Classification and Analysis of Management and Marketing Data

Statistical Applications for Strategic Planning

Dissertation
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List of abbreviations

SUPV – supervisor
COMP – company
OPPTY – opportunity
QWL – quality of work-life
PCA – principle components analysis
GAM – generalized additive model(s)
HERI – Higher Education Research Institute
EI – Emotional intelligence
EILI – Emotional intelligence leadership inventory

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Introduction

This work investigates and provides examples of effective methods of statistical analysis for strategic decision making, specifically in managerial and marketing applications. The particular motivation is to bridge the gap between statistics and marketing management by presenting statistical methods that are helpful in classifying market or management segments. The contributions made are innovative approaches to applying rather traditional statistical methods to solve varied managerial and marketing issues. Three datasets are presented and analyzed, and statistical methods are applied to solve three different management and marketing problems. While the methods are not necessarily new, their application in management decision making is unique given the contexts in which they are applied.

The work is presented in three parts, each addressing a specific management issue. Varied analytical methods are applied, and a distinct contribution is made, using the classification techniques determined as most effective given the application.

The first portion investigates job-seeking behaviors and aims to classify employees as either currently seeking a new position, passive, or not seeking a new position outside the company. Knowledge of employees' seeking status provides management with a better understanding of the stability of the organization. The managerial challenge is to generate accurate classification without directly asking the employee about their job-seeking status, given that perceived risk is high, particularly for the employee. Difference analysis, factor analysis, discriminant analysis and generalized additive models are investigated and a method is created for determining the probability that an employee falls into each of the seeking status categories.

The second portion examines college student leadership behaviors. The aim is to provide a reliable self-assessment tool and understand the underlying constructs of college student leadership behaviors. Difference analysis, factor analysis, cluster analysis and discriminant analysis for validation are methods implemented. The contribution is a reliable and valid self-assessment tool to help students evaluate their current leadership behaviors and focus on behaviors that facilitate improvement of leadership skills. The self-assessment tool can be applied in managerial settings to help employees improve their leadership skills.

The third portion addresses resource allocation in a business franchise. The issue addressed is determining the most effective allocation of franchisor resources to support franchisee revenue growth. The objective is to enable a franchisor to clearly differentiate between franchisees with the same level of tenure with the franchise, yet significantly different revenue results. Discriminant analysis enables the classification of franchisees into segments of revenue results based on their perceptions of effectiveness and value, satisfaction with, and intended future use of the services offered by the franchisor. The contribution is the development of a method to effectively allocate franchisor resources which mimics the resource utilization behaviors of the higher revenue-generating franchisees.

Classification and Analysis of a Job-Seeking Market

1.1 Motivation and Literature

A method is sought that will enable the scoring of employees in a manner that reveals the probability of their job-seeking status as currently seeking, or passive in that the person would leave their current job given the right opportunity, or not seeking an alternate job at the time. The method should enable the identification of status without directly asking the employee. If the question of job-seeking status is asked by the employer, it is not likely that the employee would provide a truthful answer, particularly if passive or seeking. An analytical method is proposed that enables classification of seeking status based on a limited number of questions determined to yield the most information.

Classification and Analysis of Job-Seeking Market

This work will be presented in two parts. Part 1 will describe the dataset, with graphical and numerical support, followed by Part 2 which discusses how to classify job-seeking status based on the analysis of the sub-groups of seekers, passives, and non-seekers.

Literature Discussion

The industrial psychology literature delivers rich, relevant material regarding job satisfaction and turnover with roots in the 1950's. One consistently agreed upon element is that there is a negative relationship between job satisfaction and employee turnover (Brayfield & Crockett, 1955; Vroom, 1964: Porter and Steers, 1973; Locke 1975). Given measurements of satisfaction, researchers should be able to effectively predict potential for turnover.

March and Simon's work (1958) suggested that attitudes toward a job should affect the decision to participate (i.e., stay in the organization) more than it affects job performance. Herzberg's job satisfaction factors and techniques from the mid-1960s focused on turnover versus performance. Then, in 1972, Atchison and Lefferts studied dissatisfaction patterns that make turnover likely using Herzberg's job satisfaction factors and techniques. They found that personality, the comparison standard, and perceptions of fairness or equity all helped to distinguish subjects who stayed in their organization versus those who terminated.

Porter and Steers (1973) suggested that future research focus on the psychology of the organizational withdrawal process because they believed

that "expressed intention to leave" was the next logical step after dissatisfaction had been experienced.

In 1977, Mobley investigated this organizational withdrawal process, and highlighted variables that link job attitudes with actual turnover, finding that the job attitudes most directly related to withdrawal cognitions associated with decision to leave were only indirectly related to actual turnover behavior. In 1979 Mobley et al suggested that turnover was more than job satisfaction, and that researchers needed to look at more variables in a comprehensive attempt to identify a broad range of factors that can initiate desire to leave organization. They presented a conceptual model that identified a need to distinguish between present-oriented satisfaction and future oriented "attraction/expected utility" for both the current job versus alternatives. They further suggest the need for a mechanism to integrate aggregate-level research findings into an individual model of the turnover process (Mobley, et al, 1979).

Arnold and Feldman (1982) investigated and critiqued the existing models of turnover and their variations to create a new working model of actual turnover behavior. While this research is not directly aimed at developing another model of turnover behavior, a review of Arnold and Feldman's perceptions of then-extant research and models adds insight to the variations in causal ordering.

The Steers and Mowday (1981) model suggests the turnover process starts with job expectations and values, which are considered simultaneously; these lead to affective responses which in turn lead to intent to leave. Exogenous variables influencing job expectations and values include alternate job opportunities, economic and market conditions, and individual differences.

The Mobley et al (1979) version starts with individual values, which lead to affective responses. These in turn, lead to intent to search/quit simultaneously, yet with economic conditions and job expectations intervening between affective responses and intention to search and quit. This model may be more reflective of the currently troubled global economy. It should be noted however, that the severity of the current economic crisis was not in full effect at the time of data collection in early 2007.

Gerhart (1990) highlights the fact that voluntary turnover literature provides a recurring theme that the availability of alternative jobs influences turnover intentions and behaviors. March and Simon (1958) stated "under nearly all conditions the most accurate single predictor of labor turnover is the state of the economy…When jobs are plentiful, voluntary movement is high; when

jobs are scarce, voluntary turnover is small (p. 100). Economic literature agrees that tight labor markets (i.e. plentiful jobs relative to seekers) suggest high turnover rates, whereas loose markets experience fewer transitions in the workforce. Unemployment is a useful measure of tightness (Ehrenberg & Smith, 1982, p. 285).

March and Simon (1958) suggested that perceived ease of transition (or movement) interacts with desire to transition to influence turnover. More importantly these perceptions were suggested to be the result of general labor market conditions. Perceived ease and desirability of movement resulted in a push and pull model where dissatisfaction is more likely to push employee to consider job alternatives, and attractive alternatives would pull the employee toward transition. Again, such perceptions were suggested to be influenced by general market conditions.

Mobley's work with Horner and Hollingsworth (1978) suggests an alteration of the ordered turnover process: individual differences influence job satisfaction, and probability of finding alternatives (simultaneously) influences thinking of quitting, which in turn influences intention to search, which influences intention to leave, which results in turnover.

Evaluating the Mobley, Horner, Hollingsworth model, Miller, Katerberg, and Hulin (1979) found that the seven variables studied collapsed into four factors: withdrawal behavior (or turnover itself), withdrawal cognitions (intent to quit, intent to search, and thinking of quitting), job satisfaction and career mobility (age, tenure, probability of finding an acceptable alternative). This group suggested a more general model of career mobility which influences job satisfaction which can lead to withdrawal cognitions resulting in turnover.

Arnold and Feldman suggested the most powerful model of turnover behavior contained four significant individual predictor variables: tenure, job satisfaction, perceived job security and the intention to search for an alternative position. It is the intent to search, and the situation surrounding that intent, consideration, or lack of intent, that is the interest of the research herein.

Further, it is interesting to note other related research in the mid 70's, in which analytical activity in the field of organizational behavior takes similar approaches to those applied here, namely factor and discriminant analysis. Sims, Szilagyi, and Keller worked to improve an instrument for measuring job characteristics that could be applied to multiple organizations (Sims, et al, 1976). Similarly, the work to be presented here aims to construct and universal

instrument, that effectively distinguishes job-seeking status as seeking, passive or not seeking.

Investigating external influences on one's decision to leave a company was suggested by Mobley, Griffith, Hand, and Meglino thirty years ago, as they discussed "Attraction and Expected Utility of Alternatives: Considering both satisfaction and attraction expected utility should increase our understanding and prediction of turnover intentions and behavior." (Mobley et al, 1979).

The idea of expected utility (as well as expected value) is common in economics and decision theory. As early as 1956, Blau, Gustad, Jessor, Parnes and Wilcox took an interdisciplinary approach to the evaluation of occupational alternatives considering such evaluation as the "individual's valuation of the rewards offered by different alternatives and his appraisal of his chances of being able to realize each of the alternatives" (Blau et al, 1956).

Supporting the suggestion of a need to identify employees in the passive state is Kirschenbaum and Weisberg's work (1994). They investigated the decision process associated with turnover and suggested a causal path in which "passive search occurs before the crystallization of a turnover intent, and after an intent has emerged, an active search begins." Further, they discuss the passive job search in which minimal effort is made to generate job market information. An important point presented by Kirschenbaum and Weisberg is that the passive's behavior is reflective of a free-market economy where one compares alternatives and evaluates self-worth in the labor market both within the organization and externally. They suggest that passive search "does not necessarily lead to any particular pattern of active search associated with turnover… acting only as a springboard for the varied perceived reactions to the environment." (Kirschenbaum and Weisberg, 1994).

It is precisely this "springboard" element that this research aims to analyze and subsequently utilize for classification. Given the catalysts that lead to transition out of the organization, it is during this passive state that employees are most vulnerable to recruiters' solicitation, friends' recommendations, and other employment-networking opportunities which represent a potential loss to the organization if the passive is in fact a valued employee.

The role of the supervisor in turnover intentions was investigated by DeConick and Stilwell (2001) who found that supervisor satisfaction had a direct influence on withdrawal cognitions. Brough and Frame (2004) found that supervisor support was a strong predictor of job satisfaction and also an indirect predictor of turnover intentions. Further, Eisenberger, Stinglahamber, Vandenberghe, Sucharski, and Rhoades (2002) found that supervisor support

was negatively correlated with turnover (i.e., low supervisor support resulted in higher turnover intentions).

DeConick and Stilwell (2001) additionally investigated the role of the company in turnover behaviors with a variable referred to as organizational justice (Berkowitz et al, 1987; Folger and Cropanzano, 1998; Folger and Konovsky, 1989; Greenberg, 1990; Sweeney and McFarlin, 1993). They suggest the extreme importance of organizational justice because of its link to employees' job satisfaction, organizational commitment, and their likelihood of searching for another job. Further, DeConick and Stilwell found that the supervisor acts as a mediator between employees' perceptions of the company (organizational justice) and their commitment to the organization. Employee perceptions of their supervisor can assist management in understanding variations in organizational commitment (DeConick and Stilwell, 2001).

The impact of work-life benefits on job-pursuit intentions was studied by Cater and Buffardi (2004) who found benefits such as schedule flexibility and dependent care assistance to contribute uniquely to predicting anticipated organizational support and job pursuit intentions. Beauregard and Henry (2009) have recently tried to make the link between work-life balance and organizational performance. They concluded that there is insufficient evidence to support the notion that work-life practices enhance performance by means of reduced work-life conflict. However, they suggest a modification to the business case for work-life balance practices which reflects additional impacts of such practices on organizations.

This work validates the notion that perceptions of the company, perceptions of the supervisor, and to a lesser extent the quality of work-life and alternate opportunities, serve to discriminate between seekers, passives and non-seekers. The unique approach to analysis and classification that will be discussed here appears to be consistent with the requests for future research found in the literature.

The research instrument, methodology, and implementation process presented here were designed, and data collection implemented, prior to establishing the intent for utilizing the data for advanced analysis and classification as in this research application. Experience and intuition guided the process somewhat fortuitously as four reliable underlying constructs were ultimately uncovered which include satisfaction with current supervisor, satisfaction with current company, the influence of external opportunities, and the influence of an improved quality of work life. These constructs are used to discern the seeking status of employees within an organizational setting.

1.2 Loyalty Scores

The concept of measuring loyalty to a brand, product, or in our case, an organization, is relatively straightforward. One common method employed by market researchers is to ask the question, "How likely are you to recommend this product or service to friends or family." Typically, the researcher generates a score from the respondent, for example, on a scale from 1 = not at all likely to 10 = very likely. One can build a model based on stepwise multiple regression analysis which identifies the independent variables that serve as significant predictors of likelihood to recommend, or loyalty.

In turn, an organization can focus on promoting improvements in the variables that drive loyalty. This work is typically recommended by researchers, communicated to organizational leadership by marketers, implemented by operations personnel, and measured again by researchers to assess significance of change.

In section 1.4 the general problem of loyalty and its objective measurement is discussed in more detail, but here the use of scores for "likelihood to recommend" as a measure of loyalty are highlighted.

In recent years, the concept of measuring loyalty based on likelihood to recommend has grown in popularity thanks to Frederick F. Reichheld. First introduced by Reichheld in a 2003 Harvard Business Review article, "The One Number You Need to Grow," the net promoter score has been widely adopted as a customer loyalty metric that proponents suggest far outweighs the value of measuring customer satisfaction (Reichheld, 2003). The idea is to provide a score based on subtracting less satisfied detractors from the highly satisfied promoters and generating a net score. Reichheld further suggests that his score is the best predictor of organizational growth (Reichheld, 2006). To clarify the concept of net promoter, the following definition is provided.

Net promoter is a metric, derived from survey responses to a "likelihood to recommend" question. Respondents who provide a rating of 9 or 10 are classified as "promoters"; respondents who provide a rating of 6 or lower are classified as "detractors." Net promoter is calculated by subtracting the proportion of a firm's detractors from its proportion of promoters (i.e., Net Promoter = promoters – detractors), (Keiningham et al, 2007).

In their longitudinal examination of 21 firms, and 15,500 interviews from the Norwegian Customer Satisfaction Barometer, Keiningham, and his co-authors referenced above, debate the superiority of the metric by replicating the analyses used in net promoter research. They also compare Reichheld and colleague's findings with the American Customer Satisfaction Index.

Ultimately their research failed to replicate Reichheld's claims of clear superiority of his metric versus other measures.

Business executives like the measurement due to its simplicity, and the ease with which they can communicate improvements in the metric to employees. Academics and market researchers argue that by collapsing the 11-point scale, used to collect likelihood to recommend data points, into three components (Promoters, Passives, and Detractors), significant information is lost and statistical variability of the result increases (Business Week, January, 2006).

The important point to consider is that the net promoter metric does not facilitate any understanding of the underlying variables that affect the score, supposedly representative of loyalty. An approach such as the stepwise multiple regression analysis, mentioned above, can provide more information as to the driving forces behind loyalty as a dependent variable.

One may be likely to recommend the company to others because it is a good company for which to work. But, for varied reasons, the employee may not see one's own position as a fit for anymore. Thus, a method is sought that does not assume the link between likelihood to recommend and the propensity to seek a new position outside the organization.

1.3   Description of the Dataset – The Specific Situation

The dataset used to develop the method is comprised of a total of 2,288 online surveys administered in January 2007, through Monster.com, the largest job search engine in the world. The site is primarily used to help those seeking work to find job openings that match their skill set and location requirements. In addition to answering questions about their search behaviors, current company, and supervisor, respondents revealed their job seeking status. Segmenting seekers, non-seekers, and passives, attitudes and behaviors that differentiated the segments were analyzed, particularly as related to their current company, supervisor, quality of work life, and perceptions of opportunity outside their current situation.

Employment Status

The primary analysis was conducted on only those 1,817 respondents who reported themselves as currently employed full-time (Figure 1.3.1). Moving forward this employed group will be discussed versus the entire dataset. The intent is to reduce bias that may be introduced by those employed part-time, temporarily, or under contract, as other external factors may have substantial effects on their job-seeking behaviors and perceptions of the company, supervisor, quality of work-life, and opportunities.
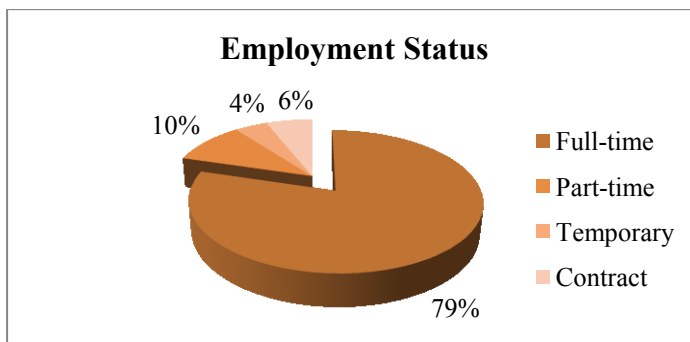
Figure 1.3.1   Employment status

Job-Seeking Status

Considering this dataset of respondents that are currently employed full-time, 69% classified themselves as currently seeking, 26% passive, and 6% non-seekers (Figure 1.3.2).

Job-Seeking Status

6%
26%
69%

■ Seeker
■ Passive
■ Non-seeker
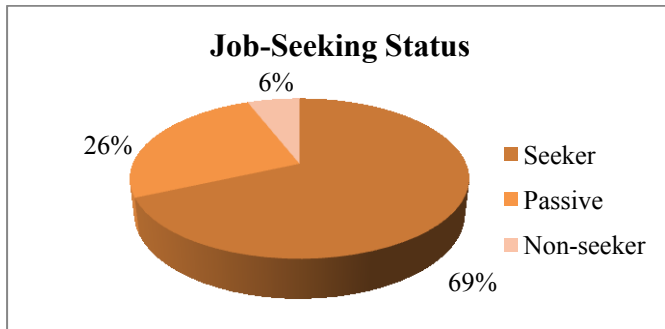
Figure 1.3.2　　Job seeking status

Level of Employment

Respondents were asked to reveal their current level of employment. Forty-four percent labeled themselves as professional/technical, 29% managerial, 17% administrative, 7% executive and 2% contract/self-employed (Figure 1.3.3).

Level of Employment

7%　　2%
17%　　　　　44%
29%

■ Prof/Tech
■ Managerial
■ Administrative
■ Executive
■ Self-empl
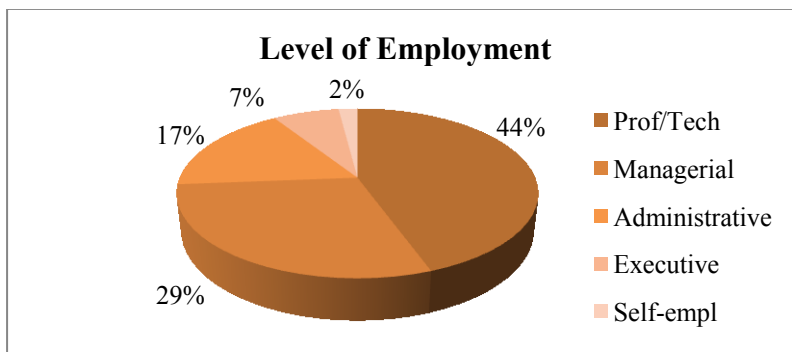
Figure 1.3.3　　Level of employment

Most Recent Job Change

In the discussion of results, significant differences between the subclasses (seeker, passive, non-seeker) are investigated. Considering only the job-seeking status of the employed respondents, distinguishing differences between states is challenging, yet some important highlights are extracted that

reflect the somewhat "dynamic" state of employees regarding their current positions.

Of those currently employed, when asked how long it had been since their last job change, 50% reported less than or equal to 2 years (Figure 1.3.4). Of that group, 65% classified themselves as seekers, and another 27% as passive, (would leave for right opportunity). Only 8% were reportedly not seeking a new job. This suggests 92% of hires within 2 years are in a "dynamic" mode, either seeking or passively seeking. However, the forum (a job search engine) in which the data was collected must be taken into consideration. Of those who had been in their current position 3-5 years, 71% were seeking, 26% passive and 3% non-seeking. The most tenured groups, 26% in their positions 6 or more years, still reflect 73% seekers, and 24% passives.

Most Recent Job Change
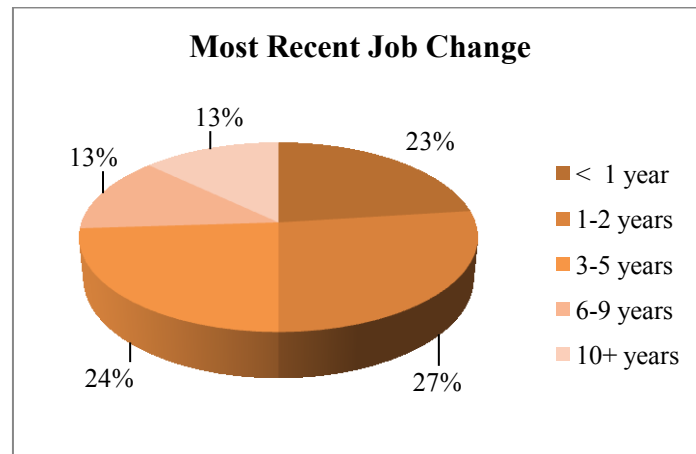
Figure 1.3.4   Most recent job change

Salary

More than half the respondents (55%) reported their current salary level to be less than $50,000 per year. Another 25% were in the $51,000 to $75,000 range, 11% earned from $76,000 to $100,000, and 7% were earning more than $100,000 annually (Figure 1.3.5).
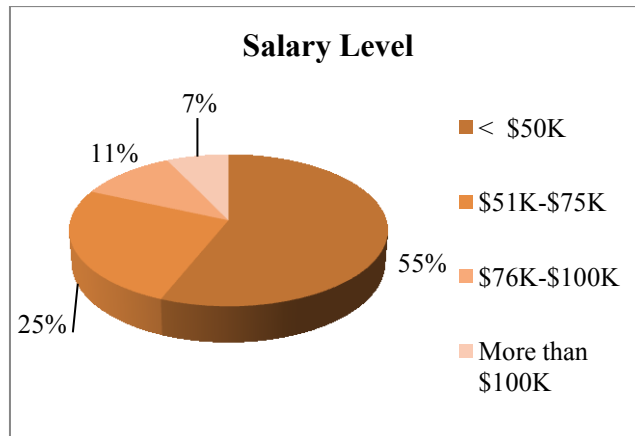
Figure 1.3.5   Salary level

Industries Represented

Over twenty industries were represented in the dataset, with 14% of the respondents from manufacturing, 12% professional, scientific, or technical services, 11% retail trade, 10% healthcare and social assistance, 9% from finance, banking, or insurance, 7% marketing, sales, communications, advertising and public relations, and 5% in education. Each of the remaining industries was represented by 4% or less of the respondents (Figure 1.3.6).
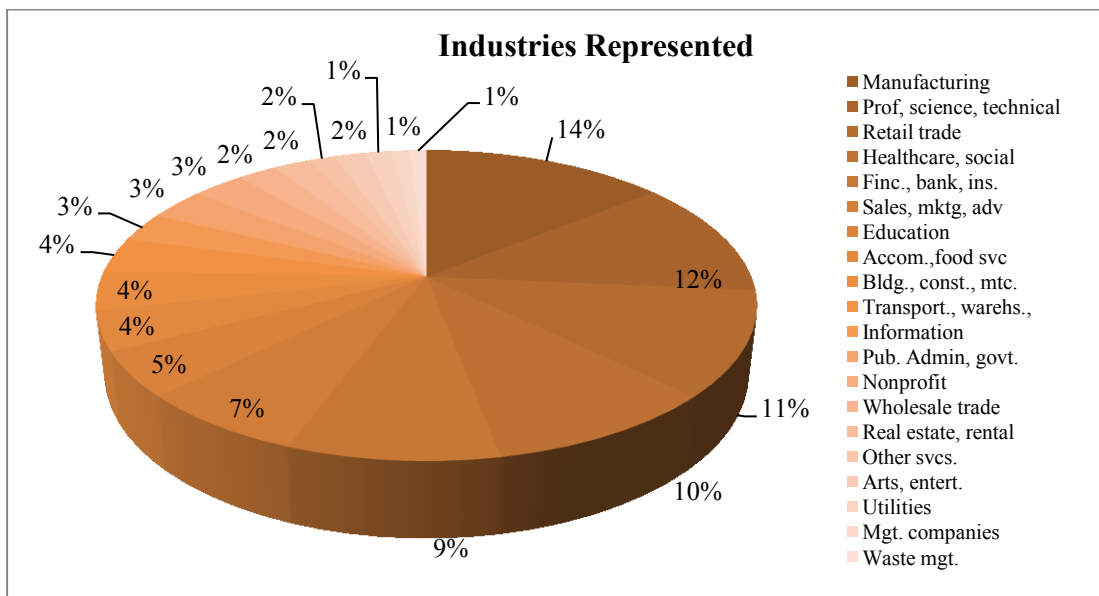
Figure 1.3.6   Industries represented

Demographics

The gender split was 57% male, 43% female (Figure 1.3.7). Thirteen percent are considered Generation Y, 17 to 28 year olds, 33% Generation X, ages 29 to 41, and 51% Baby-Boomers, ages 42 to 60. Only 3% were over 61 (Figure 1.3.8).
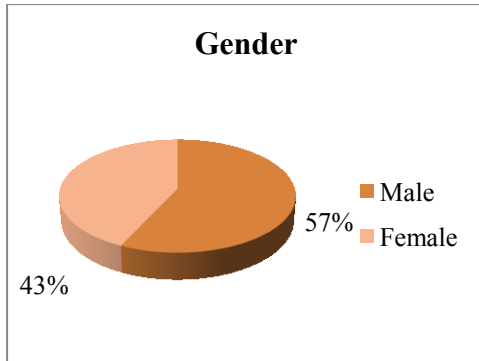
Figure 1.3.7   Respondent gender   Figure 1.3.8 Respondent age group
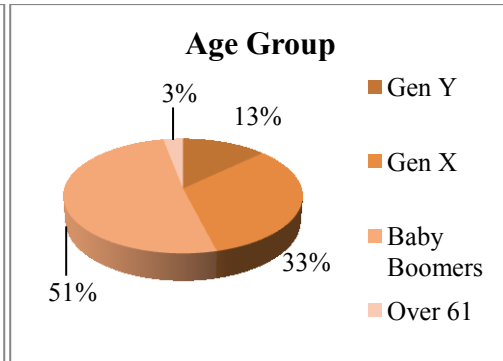
Respondents were asked to report the region of the United States in which they resided. Twenty-nine percent live in the Northeast, 21% in the Southeast, 21% in the Midwest, 18% in the Southwest, 7% in the Northwest and 4% in what is considered the Mountain Region (Figure 1.3.9).
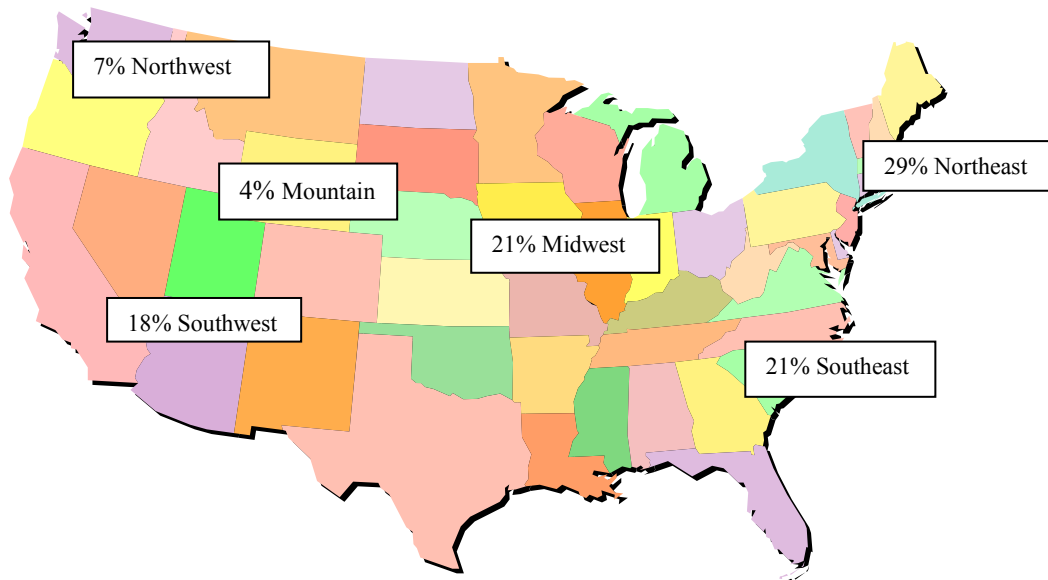
Figure 1.3.9   Respondents' geographic locations within United States

An ethnicity question was asked, with 74% reporting that they were white (not of Hispanic origin), 11% African-American (not of Hispanic origin), 8% Asian/Pacific Islander, 6% Hispanic, and 1% American Indian/Alaskan native (Figure 1.3.10).
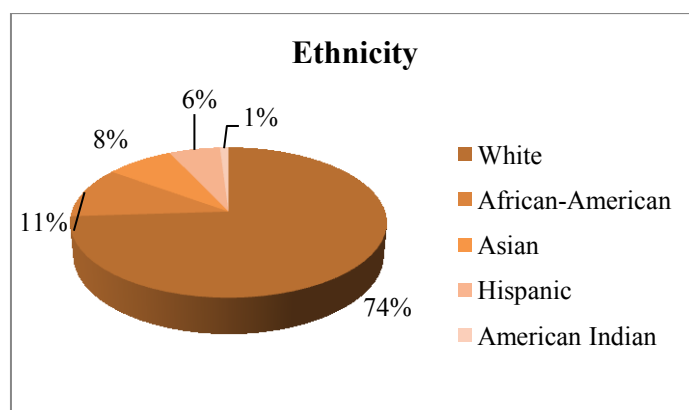
Ethnicity

Figure 1.3.10   Respondent ethnicity

Considering education, over a third, (34%) hold a bachelor's degree, and another 19% had participated in post-graduate education. Thirteen percent held an Associate's degree (2 year program, typically from community colleges). Another 24% had attended some amount of college, and 8% had only graduated high school. One percent had not completed high school (Figure 1.3.11).
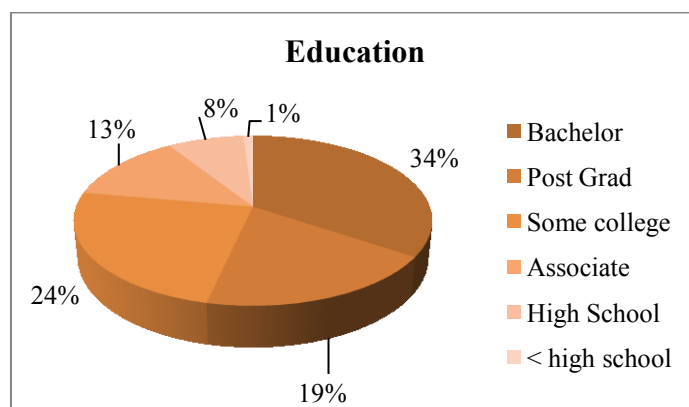
Education

Figure 1.3.11   Respondent education level

To summarize the demographics of this dataset, there is a realistic representation of both genders, more than half of the respondents held a bachelor's degree or higher, and with 90% having achieved at least some amount of college education. The respondents were primarily non-Hispanic whites (74%), with a good representation of the varied United States regions, given the population of each. Just slightly more than half are Baby-Boomers (ages 42 to 60), with another 33% considered Generation X (29-41).

Areas Investigated

While numerous questions were asked which related to job-seeking behaviors, those that would provide information about the respondent's perceptions of their current workplace and supervisor are analyzed, as well as questions about the extent to which certain external influences would draw them away from their current situation. These related to both the quality of work-life and alternate opportunities. Respondent used a 1=low to 10=high scale, and following are Table 1.3.1 to Table 1.3.5 listing the questions from which the data was drawn. These tables are presented in the order in which the respondent completed the online questionnaire. Questions about current company included:

Consider each statement relative to the company you work for and rate (1=not at all strong, 10=very strong) how strongly you agree or disagree
My company is a good place to work
My company provides a valuable product or service
My company is honest
My company provides a competitive salary
My company offers good benefits
I think other companies provide better salaries and benefits
I would recommend my company to a friend or relative
I feel proud to work at my company

Table 1.3.1   Current company questions

External influence questions:

If you were to consider a new job, how strongly (1 = not at all strong, 10=very strong) would each of these influencers impact your decision to accept the new position?
A higher salary
Better benefits
Greater advancement opportunities
Better skills training
A location with a shorter commute
A location with better perceived weather
A better company
The chance to work with a previous supervisor I enjoyed working with
The chance to work for a new supervisor
Flexible work hours

Table 1.3.2   External influence questions

Questions about current supervisor:

Consider each statement relative to your work supervisor and rate (10=strongly agree) how strongly you agree or disagree with it. My supervisor:
Is likeable
Treats me fairly
Provides clear directions for work
Offers an equitable amount of their attention
Sets clear expectation
Lets me know what is expected of my work
Supports my personal life as much as my work life
Supports an equal work/life balance
Expects too much from me
Is a good mentor
Provides me with honest feedback
Expects me to do work in off-hours

Table 1.3.3   Current supervisor questions

A fourth section of company-related questions were asked after the supervisor questions.

Consider each statement below relative to the company you work for and rate (10=strongly agree) how strongly you agree or disagree with it.
I am fairly compensated for the work I do
My company offers higher than average salaries
My company provides a competitive package of benefits

Table 1.3.4   Additional company questions

And, as mentioned earlier, respondents were then asked to report their job-seeking status.

Are you currently seeking a new job opportunity?
Yes, actively seeking
No, staying in my current job for awhile
No, but would consider a new job if it were the right opportunity

Table 1.3.5   Seeking status question and response categories

Consider the first group in the table "seekers", the second group "non-seekers" and the third group "passive seekers", who would consider leaving given the right opportunity.

1.4   General Problem

Next discussed is the general problem of loyalty and its objective measurement as it applies to the job-seeking market. Specifically, is loyalty analytically verifiable in this case?

Consider an employer who wants to understand the stability of his/her organization from a personnel standpoint. If he simply asks each employee if they are seeking, passive, or not seeking, it is highly likely that the answers would overwhelmingly sway to the not seeking side. It is not in an employee's best interest to let his employer know that he is looking for or would consider a new job given the right opportunity. Traditionally, the employer would then move to find a suitable replacement as soon as possible, in expectation of the employee's departure from the organization. Essentially, an employer cannot garner an honest, reliable response from an employee when asked about the status of job-seeking intentions in a direct manner.

The same principles apply in other settings such as business-to-business relationships, and to a certain extent, consumer behavior. If there is a significant perceived risk in allowing one's financial source (employer, client, business-to-business relation, etc.) to know one is considering other options, which could in turn damage or sever the relationship, honest and reliable admission of the potential for transition may be thwarted.

In the job-seeking application discussed here, the goal is to assess loyalty in an alternate manner which provides accurate classification of seeking status. Specifically, the intent is to generate accurate responses that enable classification, without directly asking employees the question, "are you seeking a new job?" or "do you classify yourself as seeking, passive or non-seeking?"

In section 1.2, measures of loyalty were discussed, particularly as ascertained from recommendation likelihood. In section 1.3 the dataset and the variables were discussed. It is appropriate here to elaborate on an existing method which was the catalyst in attempting to uncover an alternate, equally if not more reliable, method to measure loyalty. As mentioned in section 1.2, multiple regression analysis can be employed in an attempt to reveal the drivers of loyalty when there is a measurement for likelihood to recommend.

But, the question remains, is likelihood to recommend truly indicative of loyalty, and more importantly, in our context, is loyalty indicative of job-seeking status? Consider the following opportunity for misrepresentation of loyalty as derived from recommendation likelihood. One might honestly answer that they would not recommend the company to a friend or relative

simply because none of their friends or relatives may be qualified for the types of positions held at the company. It could be the case that the question is irrelevant to the respondent, and its intent misinterpreted. Low ratings may be the result of an honest admission that the respondent has no opportunity to recommend the company to others. Yet, low ratings would increase variance and the researcher would be investigating the other variables in search of reasoning, when the true reason was simply that the respondent had no application for the variable in question, or in effect, no or low likelihood to recommend.

Consider the question for which there is response data. In our survey, the question was posed among a set of company-related questions, which respondents rated on a 1 to 10 scale of agreement, as follows:

Consider each statement relative to the company you work for and rate (1=not at all strong, 10=very strong), how strongly you agree or disagree with it.

- *My company provides a valuable product or service*
- *My company is honest*
- *My company provides a competitive salary*
- *My company offers good benefits*
- *I think other companies provide better salary and benefits*
- *I would recommend my company to a friend or relative*
- *I feel proud to work at my company*

Next the results of a regression analysis on the data are discussed which ultimately leads to the variables considered in the factor analysis in Section 2.1.

Stepwise Regression Analysis

Using the stepwise regression procedure can be insightful, but as some researchers suggest, dangerous due to effects of collinearity, redundancy and suppression (Wuensch, 2006).

The insightful nature of stepwise regression comes into play as potential predictors are investigated that are eventually isolated for use in the factor analysis. In the dataset there were results from 8 questions about the company, 10 regarding external influences on job change, and twelve about the supervisor. These were narrowed down from thirty variables to nineteen which ultimately proved most useful in the factor analysis. Through a series of investigative tests using stepwise regression, nineteen variables were selected

based on their predictive power as related to likelihood to recommend, as well as company pride and perceptions of honesty. The stepwise regression discussion is limited to that which involves the nineteen variables under investigation.

Sequential Variable Selection Procedures

During the early 1960s, with the growth of computing capability, several variable selection procedures were developed based on sequential F-tests. The idea was to efficiently isolate a subset of the most useful regressor variables when faced with a large number of variables from which to select. Myers (1990) suggests the analyst keep the underlying motivation in mind, which at the time was computational efficiency given that it was prohibitive to gather information from all subset models. Current software packages such as SPSS and SAS offer at least some important results on all subsets. It is known that multicollinearity may cloud the results, and confuse the researcher, yet the varied methods of variable selection remain popular, probably due to their simplicity when applied from a statistical software package. The three primary methods are forward selection, backward elimination and stepwise regression. Each method adds and/or deleted regressor variables from the existing model based on F-tests.

The stepwise procedure is actually a modification of the forward selection procedure, so this is discussed first. With forward selection, the initial model contains only a constant term. The first variable for entry into the model is selected by determining the single variable that produces the largest R^2. Consider this first variable x_1. Next, a second predictor is selected that produces the largest increase in R^2 given the presence of x_1, call this x_2. This is essential in choosing the regressor with the largest partial F in the sense that the model includes the new variable being pulled into the equation, along with the existing selections.

So, at this second stage identify the largest F:

$$F = \frac{R(x_2 | x_1)}{s^2(x_1, x_2)}.$$

Here the denominator, $s^2(x_1, x_2)$ is the residual mean square for the model involving regressors x_1 and x_2. This is typically computed from the incomplete model, in other words, the existing model at that stage.   The process continues until the candidate regressor for entry does not meet the

predetermined criteria for F_{IN}, which in our case is .05, or all variables are in the equation.

The stepwise method modifies the forward selection procedure by essentially re-evaluating, through a partial F-test, all regressors currently in the model upon entry of a new candidate variable. A critical value is preselected (.10 here), for variables to be removed due to multicollinearity. So, a variable may be accepted into the equation initially, and then later removed because it is redundant. The value is that the variable, once accepted, must continue to perform effectively or it is removed. The procedure stops when no additional regressors can be entered based on our critical value $F_{.05}$ for incoming considerations, and $F_{.10}$ for those to be eliminated.

A final option is backward elimination which begins with all potential regressors and eliminates them one at a time. The first variable removed is the one with the least impact on decreasing R^2, and thus the smallest partial F-statistic. The procedure continues until the regressor under consideration for removal results in a partial F which exceeds, in this case, .10.

Chatterjee et al (2000) recommend the backward elimination procedure over forward selection because it allows the researcher to review the full model with all variables considered, even if he selects a more manageable final model. Further, Chatterjee does not recommend the use of variable selection procedures when collinearity exists, yet the backward elimination procedure handles the situation better than does the forward selection procedure (Mantel, 1970).

To check for collinearity, calculate the variance inflation factors (VIFs) or the eigenvalues of the correlation matrix of the predictor variables. The variance inflation factor is defined as

$$VIF_j = \frac{1}{1 - R_j^2} , j = 1,\ldots,p$$

Where p is the number of predictor variables. If there is no linear relationship between the predictor variables (i.e., if they are orthogonal), R_j^2 would be zero and VIF_j would be one. Increases in the variance inflation factor suggest that the predictors may not be orthogonal, and collinearity may be present. The value of VIF_j also measures the amount by which the variance of the jth regression coefficient is increased due to a linear association between X_j and the other predictor variables, relative to the variance expected if X_j were not linearly related to them.

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If none of the variance inflation factors are greater than 10, collinearity is not a problem. If they are, then multicollinearity may cause issues with estimation and interpretation.

Also, the presence of small eigenvalues indicates collinearity. If any are less than 0.01, the variables are considered collinear. Also look at the condition number, or condition index, which should not be higher than fifteen. The condition number is defined by

$$k = \sqrt{\frac{\lambda_{max}}{\lambda_{min}}}$$

where λ_{max} and λ_{min} are the maximum and minimum eigenvalues of the matrix of correlation coefficients (Chatterjee et al, 2000).

Given these criteria, Table 1.4.1 suggests there may be collinearity issues with the data using the stepwise procedure because the condition number is too high for the final variable in the model, the influence of better weather. One option is to simply delete this final variable from the model since it adds only slightly to the explanation of variance, with $R^2 change$ =.001, and the significance of the change in F, is .024. The VIFs are acceptable, with none approaching 10, not even the influence of better weather. However, the eigenvalue for this variable, which should not be less than .01, is .018, alerting the researcher of potential collinearity.

Overall, the regression model built with the stepwise procedure is a good one, with nearly 77% variance explained and strong values for the t statistic which typically exceed 2.0 if significant. However, sacrificed is all the information obtained from the other twelve variables. Subsequent analyses suggest these others add valuable insight, particularly when working to differentiate seeking status. More specifically, the regression eliminates most of the external influence variables, with the exception of the influence of a better company, and the somewhat questionable variable, the influence of better weather in a different location. Further, the supervisor variables do not survive the stepwise procedure, with the exception of fair treatment from the supervisor. Lastly, the respondent's perception of their company providing valuable products and services is lost which intuitively would seem to be a good measure of loyalty. It should be noted that the application of stepwise regression is most useful in suggesting areas of operational focus, which in this case would be developing company pride, ensuring salaries are competitive, good benefits are provided and that the company is at least perceived as honest. This loss of information is precisely the reason to move

beyond stepwise regression analysis to solve the general problem of measuring loyalty in a more scientific manner.

Variables in the loyalty regression model	R^2	T statistic	VIF	Eigenvalue	Condition number
Proud to work at company	.725	29.88	2.80	.27	5.18
Competitive salary	.751	7.44	1.84	.133	7.39
Good benefits	.761	8.20	1.70	.123	7.69
Honest	.766	5.01	2.38	.072	10.05
Supv. treats me fairly	.766	2.29	1.36	.068	10.35
Infl. better company	.767	-2.95	1.17	.039	13.60
Infl. better weather	.768	2.26	1.15	.018	20.16

Table 1.4.1   Variables in the loyalty regression model

1.5   Problem of Classification by Subclass

In this section the significant differences are discussed regarding each of the three groups including job seekers, passives that would take a new position given the right opportunity, and non-seekers who are content to stay in their current position for a while. Understanding the differences between each of the seeking statuses can help us make inferences about the most prominent catalysts for transition from state to state. Further, if one wants to be able to identify an individual as a member of one of the groups, there is a need to understand the profile and characteristics of each group, and what makes them differ from one another.

In a general sense, to test for significant differences between any two of the seeking status groups of respondent types in the dataset (i.e., passives vs. seekers, seekers vs. non-seekers, and non-seekers vs. passives), consider the mean scores for the variables measured, particular to each group, and the differences between these individual group means.

Keep in mind that one group is compared to another, one at a time, as independent samples, and therefore the t–test is used, which Lowry suggested "is probably the most widely used statistical test of all time, and certainly the most widely known. It is simple, straightforward, easy to use, and adaptable to a broad range of situations. No statistical toolbox should ever be without it." (Lowry 2009). Another practical reason for using a commonly known test such as the t-test is that the aim is to create a useful tool for applications in business settings, and most users will have had some exposure to the t-test in business school, and would be more likely to understand the methodology implemented here.

Consider the null and alternative hypotheses for each of the three examinations. As a matter of notation, seekers are coded as group 1, passives are in group 2, and non-seekers in group 3, indicative of increasing preference toward a non-seeking employee.

Research question 1: Are there significant differences between non-seekers (group 3) and seekers (group 1)?

Research question 2: Are there significant differences between non-seekers (group3) and passives (group 2)?

Research question 3: Are there significant differences between passives (group 2) and seekers (group 1)?

$$H1_0 : \mu_\_ = \iota_\_ \qquad\qquad H2_0 : \mu_\_ = \iota_\_ \qquad\qquad H3_0 : \mu_\_ = \iota_\_$$

$$H1_a : \mu_\_ \neq \iota_\_ \qquad\qquad H2_a : \mu_\_ \neq \iota_\_ \qquad\qquad H3_a : \mu_\_ \neq \iota_\_$$

In each of the above hypotheses statements, the research aims to support the alternative hypotheses, that the mean scores of the variables, examined for the two independent samples (or groups of job-seeking types), differ significantly. The hope is to reject the null hypothesis for each of the research questions, which states that any difference found between the means of the two samples should not significantly differ from zero.

Generating Difference Analysis

Consider one group compared to one other group (e.g., seekers vs. passives, passives vs. non-seekers, seekers vs. passives). Use an independent samples t-test procedure with a 95% confidence interval, and exclude cases analysis by analysis, meaning that each t-test uses all cases that have valid data for the tested variables, and sample sizes may vary from test to test.

The independent samples t-test procedure in SPSS produces two tests of difference between the two groups under observation. One test assumes variances of the two groups are equal, tested by Levene's test for homogeneity of variances (Levene, 1960). If Levene's test statistics is greater than 0.10, assume groups have equal variances and ignore the second test which does not assume equality of variances. If Levene's statistic is less than 0.10, use the *t*-statistic from this second test in which equal variances are not assumed.

Another reason to use Levene's test is because it is thought to be less sensitive to departures from normality, than say the Bartlett test (NIST SEMATECH, 2009). As will be detailed in subsequent sections, non-normality is present, thus a conservative approach was taken and Levene's test for equality of variances applied.

In this analysis, in virtually all cases, the *t*-statistic was used for which equal variances were not assumed. The exception was the variable which measured the influence of the chance to work with a new supervisor, in which case the Levene's statistic was greater than 0.10 and homogeneity of variances was assumed. Levene's test statistic is defined as follows:

$$W = \left(\frac{N-k}{k-1} \right) \frac{\sum_{i=1}^{k} N_i (\bar{Z}_{i.} - Z..)^2}{\sum_{i=1}^{k} \sum_{j=1}^{N_i} (Z_{ij} - \bar{Z}_{i.})^2}$$

where

W is the test statistic
k is the number of groups which contain the samples
N is the total samples
N_i is the number of samples in the i$^{\text{th}}$ group

and define

Y_{ij} as the value of the j$^{\text{th}}$ sample from the i$^{\text{th}}$ group

Also,

$Z_{ij} = \left| Y_{ij} - \overline{Y}_i \right|$, $\overline{Y}_i$ is the mean of the i$^{\text{th}}$ group

$Z_{..} = \dfrac{1}{N} \sum\limits_{i=1}^{k} \sum\limits_{j=1}^{N_i} Z_{ij}$ is the overall mean of all the Z_{ij}

$Z_{i\cdot} = \dfrac{1}{N_i} \sum\limits_{j=1}^{N_i} Z_{ij}$ is the mean of the Z_{ij} for group i.

Based on results from the Levene test, reject the null hypothesis that the variances are equal if

$W > F_{(a,k-1,N-1)}$, where $F_{(a,k-1,N-1)}$ is the upper critical value of the F distribution with k-1 and N-k degrees of freedom at significance level α.

Identifying Significant Differences Between Subclasses

Statistically significant differences between the subclasses (seeker, passive and non-seeker) were identified on virtually all the key variables examined. Figure 1.5.1 provides a summary of the variables that evidence significant differences between subclasses. The bulleted list is in descending order of *t*-values.   Following the summary figure, the differences are discussed thoroughly.

Non-Seeker vs. Passive
- COMP competitive salary
- SUPV work/life bal
- SUPV good mentor
- COMP good benefits
- Proud to work at COMP
- Infl new supv
- SUPV clear direction
- SUPV fair
- COMP honest
- Infl better company
- COMP valuable prod/svcs
- Infl skills training
- Infl greater advc
- Infl better benefits
- Infl higher salary

Passive vs. Seeker
- Proud to work at COMP
- COMP competitive salary
- Supv good mentor
- COMP Honest
- Infl new supv
- COMP good benefits
- SUPV work/life balance
- SUPV clear direction
- SUPV fair
- COMP valuable prdcts/svcs
- Infl better company

Seeker vs. Non
- Proud to work COMP
- COMP competitive salary
- SUPV good mentor
- SUPV work/life balance
- COMP good benefits
- COMP honest
- SUPV clear direction
- SUPV fair
- Infl new supv
- COMP valuable prdcts/svcs
- Infl better company
- Infl skills training
- Infl greater advc
- Infl better benefits
- Infl higher salary

Figure 1.5.1 Variables listed inside arrows evidenced significant differences between groups listed inside oval

Reviewing the most significant differences between an active seeker and one who is still in the passive state, (second arrow), note that the most substantial differences concern the company (pride and salary). The passive is significantly more proud to work for their company, which they perceive as significantly more honest, compared to the seeker. Further, passives are more satisfied with the competitiveness of their salary provided by the company. In fact, the most substantial differences in all states are related to the company variables, more specifically, pride in the company.

This work now transitions to a thorough review of the significant differences between each group. The discussion begins with non-seekers versus seekers, as these are the most diverse groups. The more subtle but significant differences between non-seekers and passives, and passives versus seekers are then investigated.

Non-seekers Compared to Seekers

Significance tests for mean differences indicate, as expected, substantial differences between those content to stay at their current company, versus those who are actively seeking. The largest differences are in regard to company pride which non-seekers rate 64% higher than seekers. Specifically, non-seekers rate their pride at 8.48 versus seekers at 5.17. Table 1.5.2 offers a comparative list of ratings for non-seekers versus seekers. The mean scores for

each group are provided for each of the variables which evidenced a statistically significant difference. The table also provides a simple percentage difference calculated as follows:

$$\frac{\overline{x}_{non-\,ee\,\text{ker}} - \overline{x}'_{see\,\text{ker}}}{\overline{x}_{see\,\text{ker}}}.$$

The percentage difference helps one understand the magnitude of the variation between the groups, which is subsequently supported by the t-statistic, reported in the next column, followed by degrees of freedom for the test, the p-value of two-tailed significance, mean difference and standard error of the difference. Subsequent tables of this type can be read in the same manner for easy reference to the prominent differences between groups evaluated.

Non-seekers are nearly 56% more satisfied with the competitiveness of the salaries at their current company, and rate their supervisor significantly higher as a mentor, 54% higher, and in supporting work-life balance, 47% higher.

Non-seekers are 44% more content with benefits provided by their company, and are significantly more likely to believe that their company is honest. Non-seekers rate company honesty nearly 42% higher, at 8.49 versus seekers at 6.0.

The next most substantial differences concern the supervisor again. Seekers rate their supervisor significantly lower (36% lower) on providing clear direction than do non-seekers. Further, they tend not to feel that the supervisor treats them fairly, rating their supervisors at 6.42 on this variable, versus non-seekers who rated their supervisors at 8.59, 34% higher.

It follows then that seekers are significantly more influenced by the potential opportunity to work with a new supervisor; nearly 30% more influenced.

Non-seekers rated their agreement that their company provides valuable products and services at 9.07 versus the seeker rating of 7.44, nearly 22% higher. This helps explain why seekers are significantly more influenced (15%) by the opportunity to work for a better company.

At this point the external influences become less differentiable between non-seekers and seekers. While the groups do still evidence significant differences on the influences of better skills training, greater opportunity for advancement, better benefits, and potentially higher salary, the gaps are not quite so drastic. Figure 1.5.2 provides a comparison of the means of the variables on which significant differences between non-seekers and seekers were found. Table

1.5.1 offers further clarification of the percentage difference and the t-test statistics to support these claims.
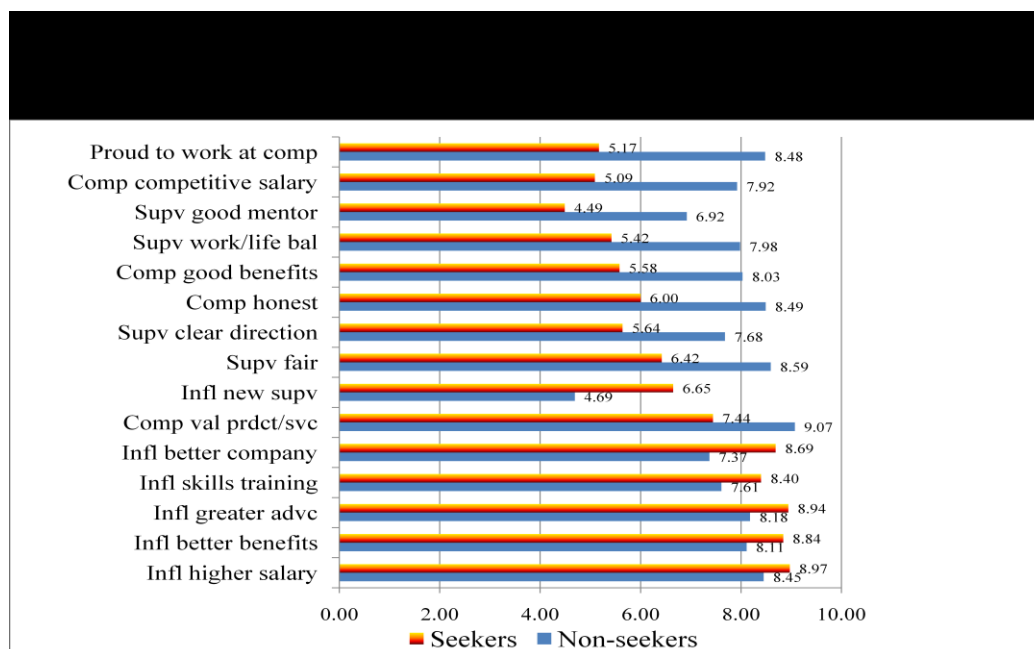
Figure 1.5.2   Non-seeker vs. seeker – significant differences between group means

	Non-seekers	Seekers	Percent difference	T stat	Degrees of freedom	Sig. 2 tailed	Mean diff.	Std. error diff.
Proud to work comp	8.48	5.17	64.02%	-17.24	149	.000	-3.31	.192
Comp competitive salary	7.92	5.09	55.60%	-13.3	134	.000	-2.82	.212
Supv good mentor	6.92	4.49	54.12%	-9.20	128	.000	-2.43	.264
Supv work/life bal	7.98	5.42	47.23%	-11.27	140	.000	-2.56	.227
Comp good benefits	8.03	5.58	43.91%	-11.12	138	.000	-2.44	.220
Comp honest	8.49	6.00	41.50%	-12.83	147	.000	-2.45	.194
Supv clear direction	7.68	5.64	36.17%	-8.72	133	.000	-2.03	.233
Supv fair	8.59	6.42	33.80%	-11.99	156	.000	-2.16	.181
Infl new supv	4.69	6.65	-29.47%	-7.39	134	.000	1.95	.264
Comp val prdct/svc	9.07	7.44	21.91%	-11.20	156	.000	-1.62	.145
Infl better company	7.37	8.69	-15.19%	5.196	109	.000	1.32	.254
Infl skills training	7.61	8.40	-9.40%	3.433	112	.001	.79	.230
Infl greater advc	8.18	8.94	-8.50%	3.327	110	.001	.75	.227
Infl better benefits	8.11	8.84	-8.26%	3.260	110	.001	.73	.224
Infl higher salary	8.45	8.97	-5.80%	2.632	112	.010	.52	.198

Table 1.5.1 Significant differences between the means of non-seekers vs. seekers

Non-seekers Compared to Passives

It is essentially simpler to state the three variables on which non-seekers and passives do not differ significantly. These are the external influences of shorter commute, better weather, and the chance to work with a previous supervisor. Aside from these three variables, non-seekers and passives differed significantly on all other variables, with non-seekers rating their current company and supervisor significantly higher in most areas, and external influences significantly lower.

Non-seekers are 21% more likely to be satisfied with salary at their current company, rating this variable at 7.92, compared to passives who rated it 6.55.

Interestingly, the largest difference quickly transitions, and to virtually the same extent, to the supervisor's support of work/life balance (7.98 non-seekers, 6.60 passives). Passives rate their supervisor as a good mentor significantly lower than the non-seekers (5.75 versus 6.92 respectively).

The extent of the differences then switch back to company related variables with good benefits garnering significantly greater satisfaction from passives versus non-seekers, nearly 18% greater. Next, it is company pride that separates passives from non-seekers who rate their sense of company pride 16% higher than passives.

The subtle yet significant differences between non-seekers and passives continue with the supervisor variables including the influence of the potential to work with a new supervisor, rated as nearly 15% more influential for passives (5.51 versus 4.69 respectively) compared to their non-seeking counterparts. On the other hand, non-seekers are significantly, 14%, more satisfied with the clarity of direction they receive from their supervisor, and 12% happier with the supervisor's fair treatment.

Company honesty plays into the differences next, rated 11% higher by non-seekers versus passives. In addition to the aforementioned differences between non-seekers and passives on other company related variables (competitive salary, good benefits, company pride, and honesty), passives are significantly more influenced (9%) by the potential opportunity to work for what they perceive to be a better company. Passives rate the value of their company's products and services significantly lower (by 8%) than do non-seekers.

The differences grow more subtle as the two groups are evaluated on the remaining external influences including skills training, greater opportunity for

advancement, better benefits and higher salary. It is interesting to note that these influences are typically rated greater than 8 on the 10 point scale by both non-seekers and passives. The groups are different, but again, the variation is subtle and may not be identified initially. Figure 1.5.3 depicts the mean scores for all the significant differences between these two groups, and Table 1.5.2 offers further clarification.
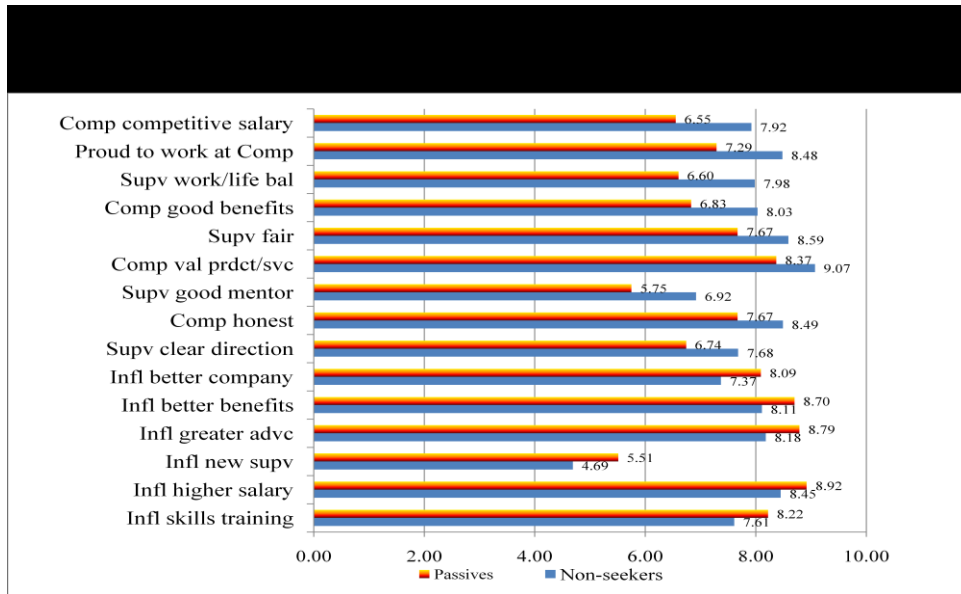
Figure 1.5.3   Non-seekers vs. passives – significant differences

	Non-seekers	Passives	Percent difference	T Stat	Degrees freedom	Sig. 2 tailed	Mean diff	Std error diff
Comp competitive salary	7.92	6.55	20.92%	-6.13	164	.000	-1.37	.224
Supv work/life bal	7.98	6.60	20.91%	-5.58	189	.000	-1.37	.247
Supv good mentor	6.92	5.75	20.35%	-4.15	166	.000	-1.17	.283
Comp good benefits	8.03	6.83	17.57%	-5.12	171	.000	-1.19	.233
Proud to work at Comp	8.48	7.29	16.32%	-5.85	184	.000	-1.1	.204
Infl new supv	4.69	5.51	-14.88%	2.87	146	.004	.81	.283
Supv clear direction	7.68	6.74	13.95%	-3.81	164	.000	-.94	.247
Supv fair	8.59	7.67	11.99%	-4.81	191	.000	-.92	.192
Comp honest	8.49	7.67	10.69%	-4.04	174	.000	-.82	.204
Infl better company	7.37	8.09	-8.90%	2.72	130	.007	.72	.265
Comp val prdct/svc	9.07	8.37	8.36%	-4.51	193	.000	-.69	.154
Infl skills training	7.61	8.22	-7.42%	2.53	132	.012	.60	.240
Infl greater advc	8.18	8.79	-6.94%	2.56	126	.012	.60	.234
Infl better benefits	8.11	8.70	-6.78%	2.59	124	.011	.59	.231
Infl higher salary	8.45	8.92	-5.27%	2.30	126	.023	.46	.203

Table 1.5.2 Significant differences between the means of non-seekers vs. passives

Passives vs. Seekers

Next investigated are the differences between passives who would consider leaving the company for a new job, given the right opportunity versus those who are actively seeking (Figure 1.5.4). Passives rate their company and supervisor significantly higher than seekers, but there are no significant differences between passives and seekers on the external influences. This is with the exception of the influence of a new supervisor or better company, where in both situations the passives rate these influences significantly lower than seekers.

More specifically, nearly a 30% difference is found between passives and seekers on company pride, with passives rating the variable at 7.29 versus seekers at 5.17. Recall, more than double this difference was seen between seekers and non-seekers (5.17 vs. 8.48). Company pride accounted for 72.5% of the variance in likelihood to recommend the company (see section 1.4).

Consider the strong and interesting relationship between company pride and perceptions of company honesty. Considering the whole dataset of full time employed respondents, the correlation between company pride and honesty is $r = 74$, significant at $p < 001$. Given each subclass, the correlation for seekers is $r = .709$, passives $r = .690$, and non-seekers at $r = .715$, all significant at $p < 001$. This sense of pride may be particularly influential in differentiating seekers from both passives and non-seekers. A 16% difference between passives and non-seekers is evident on this variable. The general indication is that company pride may serve as a catalyst to loyalty erosion and ultimately, to a transition from state to state.

A hearty significant difference between the two subclasses is found regarding agreement that their company provides a competitive salary. Seekers rated the variables at 5.09 and passives at 6.55, just over 22% higher. Recall that perceptions of being employed by a company that offers competitive salary was the largest difference between passives and non-seekers, indicating another potential catalyst to transition.

Note in Table 1.5.3 the consistent shifting between company and supervisor related variables, perhaps indicating the careful balance required to prevent a transition from passive to actively seeking. The next most prominent variation between passives and seekers is with regard to the supervisor being a good mentor which passives rated nearly 22% higher.

Company honesty was also rated nearly 22% higher by passives than seekers. Seekers rated the influence of the potential opportunity to work with a new

supervisor significantly higher than passives (6.65 vs. 5.51), a 21% difference. Recall the difference between passives and non-seeker which was 15%, with non-seekers significantly less influenced by the opportunity to work with a new supervisor. Jump from non-seekers to seekers, and the difference is substantial at nearly 30% (29.47%).

Seekers are significantly less satisfied with the benefits offered by their current company rating the variable at 5.58 whereas passives rated this at 6.83, over 18% higher.

Support of work/life balance, providing clear direction, and fairness, are all rated significantly higher by passives than seekers. Passives rate their perception of the value of the company's products and services significantly higher than seekers, 11% higher.

Lastly the influence of the potential opportunity to work for a better company is more attractive to those actively seeking versus the passives (7.42% higher for passives than seekers), but both groups rate the influence fairly high on the 1 to 10 scale, with seekers at 8.69, passives at 8.09, and recall non-seekers rated this external influence at 7.37.

Following are Figure 1.5.4 and Table 1.5.3 to clarify differentiation of passives from seekers.
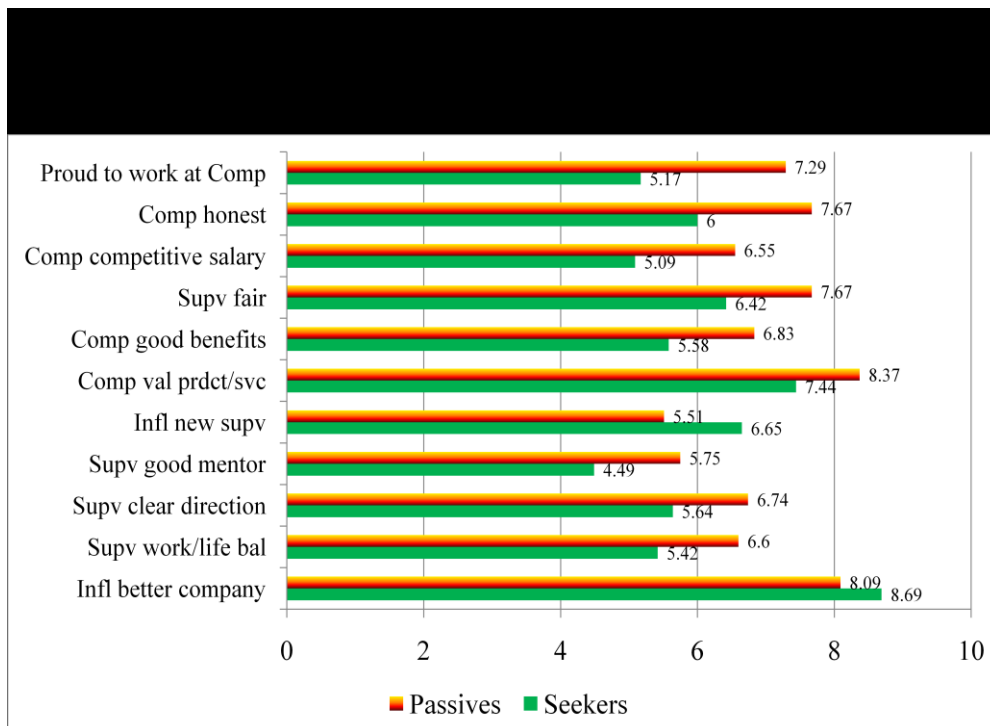
Figure 1.5.4   Passives vs. seekers – significant differences

	Seekers	Passives	Percent difference	T Stat	Degrees of freedom	p-value	Mean diff	Std. error diff
Proud to work at Comp	5.17	7.29	-29.08%	-16.130	1022	.000	-2.12	.132
Comp competitive salary	5.09	6.55	-22.29%	-11.149	978	.000	-1.45	.130
Supv good mentor	4.49	5.75	-21.91%	-7.928	875	.000	-1.25	.158
Comp honest	6.00	7.67	-21.77%	-12.84	1067	.000	-1.67	.130
Infl new supv	6.65	5.51	20.69%	8.145	1703	.000	1.14	.140
Comp good benefits	5.58	6.83	-18.30%	-8.980	967	.000	-1.25	.139
Supv work/life bal	5.42	6.6	-17.88%	-7.555	906	.000	-1.18	.157
Supv clear direction	5.64	6.74	-16.32%	-7.672	954	.000	-1.09	.143
Supv fair	6.42	7.67	-16.30%	-9.639	1047	.000	-1.24	.129
Comp val prdct/svc	7.44	8.37	-11.11%	-8.911	1037	.000	-.93	.105
Infl better company	8.69	8.09	7.42%	5.804	731	.000	.59	.103

Table 1.5.3 Significant differences between the means of seekers vs. passives

Significant Differences in Likelihood to Recommend

This section concludes with a brief discussion on the significant differences between the means of seekers, passives and non-seekers on likelihood to recommend their company.

As might be expected by now, all groups evidenced significant differences on this variable, with seekers and non-seekers evidencing the largest gap, nearly 45% (44.53%), seekers rating likelihood to recommend at 4.57 and non-seekers at 8.24

The difference between seekers and passives is substantial at 4.57 and 6.69 respectively, with passives rating likelihood to recommend nearly 32% higher (31.69%).

Further, note the significant differences between passives and non-seekers, 6.69 and 8.24, with non-seekers rating likelihood to recommend nearly 19% higher (18.81%). Table 1.5.4 highlights these differences.

Likelihood to Recommend	Mean	Percent difference	T Stat	Degrees freedom	p-value	Mean diff	Std. error diff
Seekers	4.57	44.53%	-16.53	135	.000	-3.67	.222
Non-seekers	8.24						
Seekers	4.57	31.69%	-15.03	1697	.000	-2.11	.150
Passives	6.69						
Passives	6.69	18.81%	-6.57	171	.000	-1.55	.237
Non-seekers	8.24						

Table 1.5.4 Significant differences likelihood to recommend

Deficiency Leading to Misclassification

The important point to note as in closing this section is that the mean score for likelihood to recommend (loyalty) gives us insightful points of comparison, but it is deficient in classifying seekers, passives and non-seekers.

The standard deviation for each category is so large that members cannot effectively be classified based on individual scores for likelihood to recommend, which are discrete, 1 through 10. Table 1.5.5 summarizes the means and standard deviations for each category under investigation.

Likelihood to Recommend	Mean	Standard Deviation
Seekers	4.57	2.850
Passives	6.69	2.483
Non-seekers	8.24	2.098

Table 1.5.5 Means and standard deviation by category

Therefore, a more reliable method for assessing loyalty is pursued. The aim is to utilize the information obtained from the nineteen key variables in a manner that facilitates the creation of a new, more *scientific* loyalty measure.

1.6 Conclusion of Part 1 – A Better Classification Method is Needed

An organization is comprised of primarily three types of individuals; those that are not seeking a new position, content to stay in their current situation, those that would leave given the right opportunity, and those who are actively seeking an outside alternative while currently employed at the organization.

The analysis thus far enables one to understand some of the distinguishing characteristics of each group. Each group, or subclass, has been identified to be significantly different from the others on virtually all measures tested. These measures include attitudes regarding the current organization and supervisor, as well as the influences on one's decision to transition. These influences include perceptions of external opportunities and potential for improved quality of work-life.

A sense of company pride is a very distinguishing characteristic between groups, and is highly predictive of loyalty when loyalty is measured as likelihood to recommend the company. In turn, some of the issues and potential for misclassification based on loyalty measured in this way were discussed.

It has been revealed that, in addition to perceptions of company pride and honesty, the supervisor's role as a good mentor who supports an individual's work/life balance has the potential to transition an employee from state to state.

In Part 2, several techniques are investigated in an attempt to classify employees into job-seeking status categories. First, a "loyalty score" is built with the intention of classifying seekers, passives and non-seekers based on their loyalty score. Several classification and analysis techniques are discussed including factor analysis, cluster analysis, discriminant analysis, and finally a generalized additive model is fit to the job-seeker data. The nineteen variables measured are reduced to four critical factors, namely supervisor, company, opportunity, and quality of work-life. These factors are then used to fit a generalized additive model predicting the classification of employees into seeking status categories.

2.1 Definition of Loyalty Score

Reasoning and Goal

The job turnover literature (see Section 1.1) suggests that multiple factors contribute to an employee's decision to leave the organization. Early research clarified that one's attitudes toward their job affects participation more than performance. Further, dissatisfaction is more likely to push an employee to consider alternatives, and attractive alternatives pull the employee toward transition out of the company (March and Simon, 1958). This sets a foundation for equating satisfaction with the one's job to satisfaction with the company and supervisor, both indicative of participation (i.e. staying in the company).

Recall that it was later shown that personality, the comparison standard, and perceptions of fairness all helped to distinguish subjects who stayed in the organization versus those who terminated (Atchison and Lefferts, 1972). An attempt to further validate these findings is made here with measurements for opportunity and quality of work-life. The literature later acknowledged the need to investigate external influences on one's decision to leave a company (Mobley et al, 1979). It was suggested that considering both satisfaction and external opportunities should increase understanding and prediction of turnover behavior. Researchers identified the need to distinguish between present-oriented satisfaction (e.g., company and supervisor) and future-oriented expectations for both the current situation and alternatives (e.g., opportunity and quality of work-life).

These suggestions provide sound reasoning for developing a mechanism for scoring the likelihood of turnover as reflected in a loyalty score. Further, such a score has the potential for identifying employees in a passive state, the need for which was suggested by Kirschenbaum and Weisberg (1994).

What is unclear from investigations of the withdrawal process in the literature is the appropriate amount of weight for each factor contributing to turnover. From a managerial perspective, it makes sense that satisfaction with one's supervisor, perhaps followed by or comparable to satisfaction with the company, would play a more important role in turnover than would external opportunities. Thus the goal of this section is to produce a scoring method that takes into consideration the relative importance of each of the elements potentially leading to transition.

Method

In an effort to create a more *scientific* loyalty score, factor analysis is implemented as a means to reduce the variables in a way that reveals underlying constructs. The factors are weighted and then summed to create a loyalty score which differs significantly based on seeking status. The intent is to use the loyalty score in classifying seeking status.

The definition takes a weighted sum of the four factor scores. These weights are the amount of variance explained via principle components analysis, which is selected as the method of extraction within the factor analysis procedure in SPSS. The variance explained by each of the components is used as the weight for the factor. Descriptive statistics indicate that the first two weights, for supervisor and company, are taken positive and the second two, for opportunity and quality of work-life are taken negative. This gives a high loyalty score to non-seekers and a low score to seekers. Thus, the loyalty score is defined as

$$LS = 26.91y_1 + 9.424y_2 - 3.104y_3 - 7.769y_4$$

where $y_1 ... y_4$ are the factor scores for the underlying constructs, namely supervisor, company, opportunity and quality of work-life. Details regarding the selection of methods, as well as justification of the loyalty score follow.

Factor Analysis with Principle Components Method of Extraction

In order to build the loyalty score from the nineteen questions, factor analysis is used with the data set of 1,817 currently employed respondents. The purpose of factor analysis is to describe covariance relationships among many variables, in terms of underlying, but otherwise unobservable random quantities, called factors (Johnson & Wichern, 2001). Variables are grouped by their correlations, and kept independent, or only very slightly correlated. Each group represents and independent construct that is responsible for the observed correlations. Normality, which we do not have with the job-seeker data set, is not considered a critical assumption of factor analysis. The normality assumption is required for significance testing of coefficients, and with factor analysis we are interested in clustering, or correlating, groups of like variables into underlying constructs.

Several methods are available for extracting factors from a data set. Common factor analysis, also called principle axis factoring, is a correlation-focused approach to representing the common variance of the variables under investigation, excluding unique variance. The aim is to reproduce

intercorrelations among variables. This method seeks the least number of factors which can account for the common variance (correlation) given the set of variables (Garson 2009). It is typically used for structure detection when one seeks to identify latent structures.

Alternately, the principle components method can be used as an extraction method. From principle components analysis, the idea is to build components that reflect both common and unique variance of the variables. This variance-focused approach seeks to reproduce both the total variable variance with all the components and to reproduce the correlation. It is typically used for data reduction.

To extract the first component, the principle component analysis method (an option within the factor analysis procedure in SPSS) generates a linear equation to extract the maximum total variance from the variables. To pull the second component, the PCA removes the variance explained by the first component and creates a second linear equation which extracts the maximum remaining variance, and so on. This continues until the components explain all the common and unique variance in the set of variables under investigation.

Common factor analysis is used for causal modeling, whereas the principle components analysis method of extracting factors is more appropriate for data reduction and exploration of underlying constructs. For most datasets, common factor analysis and principle components analysis will lead to similar substantive conclusions (Wilkinson, Blank, and Gruber, 1996).

Applied to the Job-Seeker Data

Given the data set of 1,817 employed respondents, common factor analysis (also called principle axis factoring) results in 53% variance explained with four factors. Using principle components analysis as the extraction method results in the same variables loading on the same four components, called factors in common factor analysis) yet with more, 62%, variance explained (Table 2.1.1). Thus, the principle components method is preferred in this application.

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5.113	26.910	26.910	5.113	26.910	26.910	3.247	17.088	17.088
2	3.691	19.424	46.334	3.691	19.424	46.334	3.209	16.888	33.977
3	1.540	8.104	54.439	1.540	8.104	54.439	2.692	14.166	48.143
4	1.476	7.769	62.208	1.476	7.769	62.208	2.672	14.065	62.208
5	.880	4.631	66.839						
6	.860	4.526	71.365						
7	.771	4.056	75.421						
8	.621	3.269	78.690						
9	.596	3.135	81.824						
10	.573	3.018	84.842						
11	.458	2.413	87.255						
12	.445	2.343	89.598						
13	.376	1.980	91.578						
14	.335	1.764	93.342						
15	.319	1.678	95.020						
16	.282	1.485	96.506						
17	.237	1.250	97.755						
18	.231	1.218	98.973						
19	.195	1.027	100.000						

Table 2.1.1 Principal component extraction method suggests 4 components explain a total of 62.2% of variance in the data from 19 variables

The component scores plotted in rotated space (Figure 2.1.1) provides graphic insight into the composition of the first three components. The company variables are clustered together, as are the supervisor variables, and the external influence variables, some related to opportunity, some quality of work-life.   .

Component Plot in Rotated Space
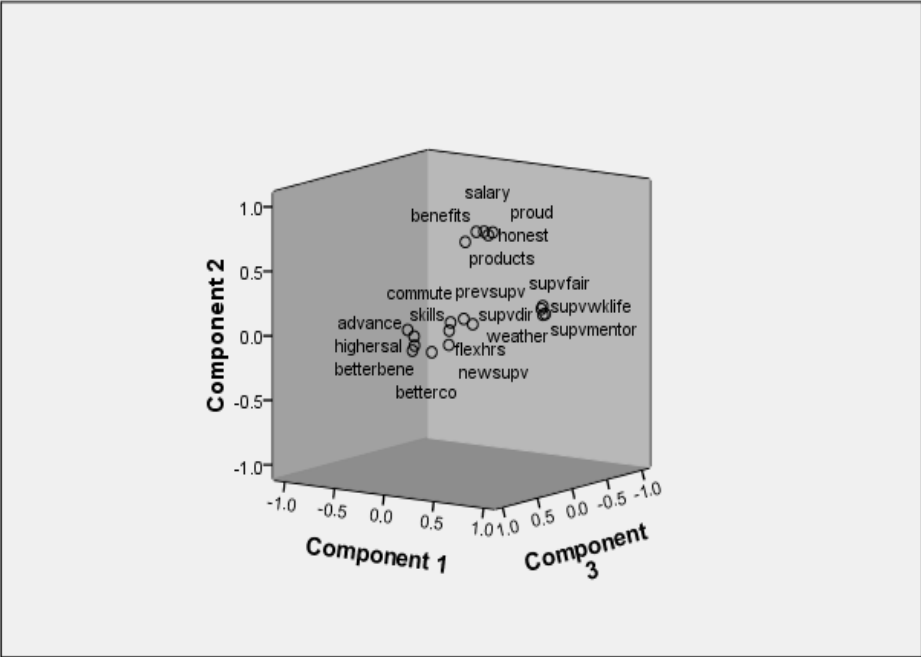
Figure 2.1.1   Component plot shows variables clustering into four components

As will be detailed in Section 2.1b, the researcher reviews the rotated component matrix to identify highest loading for each variable, given each component score (four scores for each variable), to determine the component on which the variable falls. Then, reviewing the collection of variables falling on an individual component, the researcher (somewhat subjectively) nicknames the component to reflect the underlying construct it represents. Thus the constructs are named supervisor (SUPV) for the variables falling on the first component which represent supervisor satisfaction-related variables; company (COMP) for those loading on component two and representing satisfaction with the company; opportunity (OPPTY) is represented by the third component and quality of work-life (QWL) by the fourth. See Table 2.1.7, the rotated component matrix for loadings which, when squared, represent the percent of variance in the indicator variable explained by the component.

These components will hereafter be referred to by the name of the "factor" they represent (e.g., SUPV, COMP, OPPTY, QWL). However, it is reiterated that the components actually include small portions of variance explained by each of the indicators, some of which are not considered as "loading" on the component due to their very minor contribution.

The final factors are comprised as follows in Table 2.1.2

Supervisor	*Company*	*Opportunity (influencers of job change)*	*Quality of Work-Life (influencers of job change)*
1. Treats me fairly	1. Provides valuable products and services	1. Higher salary	1. Shorter commute
2. Provides clear direction	2. Company is honest	2. Greater advancement opportunity	2. Better weather
3. Supports work-life balance	3. Competitive salary	3. Better benefits	3. Better company
4. Good mentor	4. Good benefits	4. Better skills training	4. New supervisor
	5. Proud to work at company		5. Previous supervisor
			6. Flexible work hours

Table 2.1.2 Variables that load on each component

Reliability of the Factors

To validate the reliability of the factors, as if they were scales unto themselves, consider the both inter-item correlation, and Cronbach's coefficient of reliability (Cronbach, 1951). The goal is a scale that is internally consistent, yet each variable contributes unique information. The scale variance suggests larger variance within the supervisor and company factors (Table 2.1.3). This makes sense because seekers and non-seekers are likely to rate these elements quite differently as will be clarified in Section 2.2.

Factor (# items)	Mean inter-item correlation	Inter-item variance	Coefficient of reliability for scale*	Scale variance
SUPV (4)	.722	.001	$\alpha = .91$	106.30
COMP (5)	.540	.011	$\alpha = .85$	111.11
OPPTY (4)	.551	.010	$\alpha = .83$	28.26
QWL (6)	.312	.003	$\alpha = .72$	95.82

Table 2.1.3 Factors are reliable based on inter-item correlations and coefficient of reliability

Coefficient of Reliability - Cronbach's Alpha

The coefficient, α, is based on the number of items in the scale and the ratio of average inter-item covariance to the average item variance. Cronbach (*Psycometrika*, 1951) provides a general formula:

$$\alpha = \frac{n}{n-1}\left(1 - \frac{\sum v_i}{v_t}\right)$$

Here, v_t is the variance of test scores, and v_i is the variance of the item scores after weighting. If the number of items is increased, Cronbach's alpha increases. If the average inter-item correlation is low, alpha will be low. As the average inter-item correlation increases, Cronbach's alpha increases as well. Typically, 0.6 to 0.8 indicates acceptable reliability, 0.8 or higher, good reliability, and at 0.95 or higher, the variables may be redundant. Garson (2009) suggests the widely accepted cut-off in the social sciences is .70, with some researchers using .75 to .80. Others are as lenient at .60. Garson notes that .70 is as low as one should go because at that point the standard error of measurement will be over half (0.55) of a standard deviation.

Discussion

Four distinct factors have been extracted that reliably reflect perceptions of satisfaction with company and supervisor, as well as perceptions of external influences related to opportunity and potential quality of work-life. The principal components method of extraction suggests that the first component comprised of supervisor-related variables, accounts for nearly 27% (26.9%) of the variance explained. This large amount of explanatory strength supports findings by Brough and Frame (2004) and Eisenberger et al (2002) regarding the important role of supervisor in job satisfaction and turnover intent. Variables loading on this component included "fair treatment" (DeConick and Stilwell, 2001; Fields et al, 2000; Folgers and Konovsky, 1989: Konovsky and Cropanzano, 1991; Schaubroeck et al, 1994; Sweeney and McFarlin, 1993), "clear direction", which is discussed in the literature as role ambiguity (Acquino et al, 1997; Jackson and Schuler, 1985; James and James, 1989; Mathieu, 1991; Mathieu and Zajac, 1990), "supports work/life balance" (Cater and Buffardi, 2004; Beauregard and Henry,2009) and "good mentor" (Calkins, 1987). This component is given the factor name "supervisor".

The second component extracted, explains 19.4% of the variance, and represents company-related variables. This supports findings by DeConick and Stilwell (2001) and others regarding the importance of organizational justice in understanding employees' propensity to search (Berkowitz et al, 1987;

Folger and Cropanzano, 1998; Folger and Konovsky, 1989; Greenberg, 1990; Sweeney and McFarlin, 1993). Variables including "company provides valuable products and services," company honesty and one's pride in working for the company fell on this second component as did competitive salary and good benefits. This component is given the factor name of "company".

A third component emerged, accounting for just over 8% (8.1%) of the variance, which reflects the external influences of alternate opportunities (Steers and Mowday, 1981). Variables loading on this component include the potential for higher salary, greater opportunity for advancement, and better benefits and skills training. Recall Mobley's work (1977) suggesting a need to distinguish between present-oriented satisfaction and future-oriented attraction/expected utility for both current job and alternatives. Further, Mobley et al (1979) suggest the value in such information in potentially predicting turnover intentions and behaviors. The component is named "opportunity" for the underlying construct, or factor, represented.

A final component, quality of work-life, accounts for close to an additional 7.77% of the explained variance. It is comprised of six variables reflecting exogenous influences such as shorter commute, better weather, better company, chance to work with a previous or new supervisor, and flexible work hours. Recall Cater and Buffardi's work (2004) which found that benefits such as schedule flexibility and dependent care assistance contribute uniquely to predicting anticipated organizational support and job pursuit intentions. This component is given a factor name of "quality of work-life."

Considering that the four factors extracted are representative of facets addressed in the literature, and some were suggested for future research, it is appropriate to move forward with the factor scores in the development of a loyalty score, potentially indicative of job-seeking status. Assigning weights to the factors makes sense from a managerial perspective because an employer can more realistically control company and supervisor perceptions, whereas external variables such as perceptions of alternate opportunities and the potential for better quality of work-life are influences typically beyond the control of management.

Previous research has highlighted the importance of the supervisor in turnover intent, and the supervisor factor would be expected to be more influential than other facets (thus receiving heavier weight). The literature also clarifies the importance of the employee's perception of organizational justice and the company factor clearly captures this information. The final two factors serve to "pull" employees from the organization (March and Simon, 1958) and should be negatively weighted proportionate to the variance they explain.

Thus the research proceeds with weights assigned to the factors which are representative of their importance and direction of influence. The weights assigned are the amount of variance explained by the factor which makes sense from a managerial perspective and is supported by the turnover literature.

2.1a   Justification of Loyalty Score

Each of the components (i.e., SUPV, COMP, OPPTY and QWL) of the loyalty score are weighted by the variance explained based on the principle component method of extraction. To do this, several assumptions have been met with regard to principal component analysis (PCA). PCA is used in exploratory data analysis and can be applied under any distribution, thus it is a nonparametric approach. It gives a new basis for the vectors in the dataset where the coordinates have decreasing variability. A basis is sought, which is a linear combination of the (nineteen) original variables, that best expresses the data in fewer dimensions. Thus, linearity is implicit, simplifying the problem by restricting the set of potential bases (Shlens 2010). A second assumption is the statistical importance of the mean and variance as sufficient statistics, describing the probability distribution. While deviations from normality can invalidate this assumption, the covariance matrix effectively characterizes the noise and redundancies. Further, statistical independence is the most rigorous form of eliminating redundancy, and PCA de-correlates the axes of the coordinate system.

Perhaps the most valuable assumption, given this application, is that large variances have important dynamics. This is precisely the justification for taking the weights from the principal components analysis method of extraction within the factor analysis procedural options.

Examining the questions contributing to the single factor scores, it is clear from the managerial viewpoint that some questions clearly give more information than others. Moreover, the questions for supervisor and company give high scores to non-seekers as one expects, while these same questions will be rated lower by seekers. It is expected that the influences of alternate opportunities and potentially better quality of work life will get higher scores from seekers. This intuitive reasoning is also supported by the descriptive analysis of the loyalty score. However, some questions in the dataset may be adding more noise than value, specifically, those comprising the quality of work-life factor.

Consider the variance of the loyalty score for all data combined, $\sigma = 5{,}221$. By subclass, variance is substantially reduced with $\sigma_{seeker} = 4{,}503$,

$\sigma_{passive} = 9{,}775$, and $\sigma_{non-seeker} = 6{,}576$ (Table 2.1.4). This supports the suggestion that the loyalty score has the potential to aid in the classification of employees by seeking status.

An understanding of the variability within the components adds justification to the weighting of components of the loyalty score. Compare the reduction in variance from the whole dataset to each subclass, then compare between subclasses. As stated above, larger variances indicate more important dynamics, whereas limited differences suggest potential noise.

VARIANCE	All data	Seeker	Passive	Non-seeker
Loyalty Score	15221	14503	9775	6576
SUPV	9.98	10.51	7.07	4.25
COMP	8.57	8.28	5.51	3.82
OPPTY	2.61	2.47	2.26	5.29
QWL	6.72	6.30	6.84	9.06

Table 2.1.4 Comparison of variances within full dataset vs. subclasses

The supervisor factor evidences substantial variances between the subclasses, also when each are compared to the entire dataset. Recall, 70% of the respondents classified themselves as seekers so it might be expected that the seeker variance is similar to the full dataset.

The company factor suggests reduced variability within the individual subclasses versus the full dataset, and each is distinguishable from the others given its variance.

For opportunity and quality of work-life, variance is lower in the subclasses compared to the entire dataset, with the exception of non-seekers. The forum for responding to the survey must be considered: an online job-search engine. This means that we may have respondents reporting themselves as non-seekers, yet quite varied in their responses regarding outside influences. This behavior may be indicative of underlying preferences to seek a new position. Again, this may be an effect of the administration of the survey (online job-search site). In practical application however, non-seekers may evidence more homogeneous behaviors. At this point, the related questions may be adding more noise than value.

Consider Levene's test for homogeneity of variances. The null of homogeneity between subclasses can be rejected at $p < .01$, with the exception of seekers

and passives, on OPPTY and QWL. Further, the null is rejected at only $p <$ .10 for QWL between passives and non-seekers.

Homogeneity of variances	Seeker vs. Passive		Passive vs. Non-seeker		Seeker vs. Non-seeker	
	F	Sig.	F	Sig.	F	Sig.
SUPV	42.1	.000	12.7	.000	47.07	.000
COMP	30.0	.000	8.1	.005	29.61	.000
OPPTY	.318	.574	17.8	.000	18.16	.000
QWL	.441	.507	3.5	.061	6.16	.013

Table 2.1.5 Levene's test suggests variances are not equal with the exception of OPPTY and QWL (seeker vs. passive); $p<.10$ for QWL passive vs. non-seeker

A score that indicates an employee's loyalty to the company would be beneficial to managers. Understanding an employee's loyalty can also be considered a measure of the likelihood of the employee seeking a new job. Examples of applications for a loyalty score follow.

- If a reduction in forces is required, a company would prefer to cut its less loyal employees, and retain those with a stronger commitment to the organization.
- A series of scores reflecting the proportions of seekers, passives and non-seekers within an organization, is indicative of the stability of its human resources, perhaps even morale to an extent.
- Maintaining a high proportion of seekers is indicative of a less stable organization, whereas maintaining a substantial proportion of satisfied non-seekers intuitively suggests a more dynamic culture and higher potential for growth.
- While passives are more challenging to identify, this group can potentially drain resources such as training and development without the returning the value of organizational commitment.

Further, it should be noted that one of the challenges addressed is generating such a score without directly asking the employee his/her seeking status. The method discussed enables the employer to pose nineteen questions that are used to compose the loyalty score which is in turn used to determine the probability that the employee is seeking alternative employment. The questions concerning quality of work-life should be restructured to increase variability between subclasses.

2.1b   Building the Loyalty Score

Nineteen new "component score" variables were computed for each case that are a weighted representation of the response. Specifically,

$$CS_{x_i} = \alpha_{.} \dot{\,}_i)$$

where the $\alpha_{.}$ are the highest-loading coefficients for the variable. For example, in the first line of the component score coefficient matrix (Table 2.1.6), the variable "current company provides valuable products and services" has a coefficient of .271 that is the highest of the component scores, and loads on the second component, as do the other company related variables.

Component Score Coefficient Matrix

	Component			
	1	2	3	4
curr company provides valuable product/svc	-.090	.271	.103	-.086
curr company is honest	-.038	.261	.030	-.049
curr company competitive salary	-.101	.292	-.080	.073
curr company offers good benefits	-.127	.303	-.071	.079
Proud to work at my company	-.027	.263	.016	-.028
infl higher salary	.021	-.025	.374	-.140
infl better benefits	.016	-.038	.350	-.095
infl greater advancement oppty	-.056	.044	.302	-.042
infl better skills training	-.049	.020	.207	.074
infl location shorter commute	-.016	.028	-.013	.220
infl location better weather	.001	.025	-.084	.258
infl better company	-.013	-.046	.053	.190
infl chance to work with previous supv	.022	-.002	-.149	.316
infl chance to work with new supv	-.023	-.033	-.118	.333
infl flex work hours	.000	.001	.000	.220
supv treats me fairly	.306	-.079	.008	-.033
supv provides clear direction	.322	-.102	-.011	.011
supv supports wrk/life balance	.292	-.068	-.030	.000
supv is a good mentor	.318	-.100	-.037	.028

Table 2.1.6 Component scores used as weights on each of respondent's 19 variable scores

These new component score variables were then summed to create a new "component score factor" comprised of the variables that loaded on the factor (see Table 2.1.6). For example,

$$CS_{company} = \sum CS_{value} + \ldots + CS_{proud})$$

Determining Number of Factors and Defining Factor Scores

Table 2.1.7 highlights the variables loading on each of the components as found in the rotated component matrix which offers easy interpretation. Names for the underlying constructs are assigned to each of the components and include y_1 = "supervisor" for the first component, y_2 = "company" for the second, y_3 = "opportunity" for the third and y_4 = "quality of work-life" for the final component.

Rotated Component Matrix

	Component			
	1	2	3	4
curr company provides valuable product/svc	.177	.726	.199	-.088
curr company is honest	.314	.774	.064	-.063
curr company competitive salary	.156	.761	-.101	.117
curr company offers good benefits	.095	.757	-.076	.138
Proud to work at my company	.353	.797	.055	-.022
infl higher salary	.116	.010	.842	.079
infl better benefits	.084	-.035	.826	.166
infl greater advancement oppty	-.015	.104	.752	.243
infl better skills training	-.034	.035	.632	.435
infl location shorter commute	.052	.095	.231	.572
infl location better weather	.087	.105	.090	.594
infl better company	-.050	-.129	.355	.559
infl chance to work with previous supv	.103	.049	-.015	.670
infl chance to work with new supv	-.081	-.118	.067	.735
infl flex work hours	.061	.036	.264	.588
supv treats me fairly	.854	.257	.072	-.007
supv provides clear direction	.873	.213	.075	.089
supv supports wrk/life balance	.822	.266	.006	.033
supv is a good mentor	.858	.211	.022	.101

Groupings: COMP (rows 1–5), OPPTY (rows 6–9), QWL (rows 10–15), SUPV (rows 16–19)

Table 2.1.7 Indicator variable loadings from principle components extraction method

The loadings are the correlation coefficients between the variables and the components (called factors in common factor analysis). Like Pearson's *r*, the squared loading is the percent of variance in the indicator variable explained by the component. Garson (2009) suggests a relatively high standard of .7 which corresponds to nearly half of the variance in the indicator variable being explained by the factor. Hair et al (1998) consider loadings above .6 as high and below .4, low.

Orthogonal transformation of the loadings is referred to as factor rotation because orthogonal transformations coincide with a rigid reflection of the coordinate axes (Johnson & Wichern, 2001). Loadings obtained by an orthogonal transformation have the ability to reproduce the correlation matrix.

The objective is to rotate the component axes to maximize the variance of the squared loading of a component on all the variables in the component matrix. The result is an easily-interpretable matrix with variables that have suitably high loadings for one of the components compared to low loadings on the others. The varimax orthogonal rotation method was specified in the generation of the components (Kaiser, 1958).

Another criterion that influences the number of components extracted is the Kaiser criterion. The Kaiser rule is to drop components with eigenvalues under 1.0. When this rule is relaxed to 0.8, on the job-seeker data, six components emerge, resulting in 71.3% variance explained, an improvement over 62.2% with four components. Another check is done using the Cattell scree plot (Figure 2.1.2) which suggests that the decline in eigenvalues stops with the fifth component (for which the eigenvalue is 0.88). Cattell's scree test says that when the drop ceases and the curve makes an elbow toward less steep decline, drop further components after the one starting the elbow (Garson, 2009).
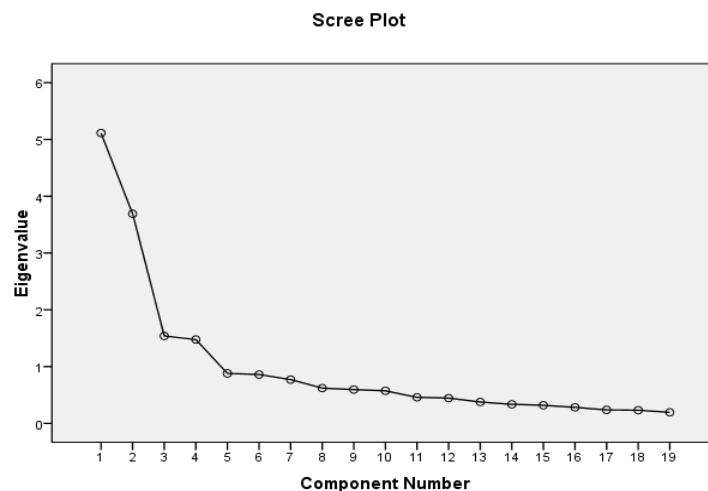
Figure 2.1.2 Cattell scree plot suggests five components

However, the complexity of using five or six variables in application is not deemed worth the price of variance explained and we proceed with the four-component model which is supported by the Kaiser rule of extracting only components with eigenvalues greater than or equal to 1. The final factors, $(y_1...y_4)$, are then composed using weights from the component score matrix. Given the literature discussed earlier (Section 1.1 and Section 2.1), the weights are logical from a managerial perspective based on what is known about the elements affecting job search and turnover (Table 2.1.8)

y_1	Supervisor	(.306*fair) + (.322*direction) + (.292*balance) + (.318*mentor)
y_2	Company	(.271*products) + (.261*honest) + (.292*salary) + (.303*benefits) + (.263*proud)
y_3	Opportunity	(.374*infl salary) + (.350 infl benefits) + (.302 infl advc) + (.207 infl train)
y_4	Quality of Work Life	(.220*commute) + (.258*weather) + (.190*better co) + (.316*prev supv) + (.333*infl new supv) + (.330*infl flex)

Table 2.1.8 Final component score factors composed with component score coefficients

2.1c   Descriptive Statistics by Seeking Status

Next, the mean scores for the four factors are investigated (Table 2.1.9). It is expected that scores for supervisor and company would be higher for non-seekers and lower for seekers. In effect, the non-seeker is expected to be more satisfied with his current situation, likely to rate the supervisor and company higher, and thus not seeking a new position outside the company.

On the other hand, one might expect seekers to be more influenced by external opportunities and potential for a better quality of work-life. Thus, the seeker is expected to rate these influences higher, but the influences impact loyalty in a negative way, so the loyalty score should reflect this negative effect.

		Seeker	Passive	Non-seeker	
y_1	Supervisor	7.4	8.9	10.15	⇧
y_2	Company	8.13	10.21	11.16	⇧
y_3	Opportunity	10.91	10.75	10.09	⇩
y_4	Quality of Work Life	10.84	10.18	9.7	⇩

Table 2.1.9 Mean scores for factors that comprise loyalty score; Opportunity and QWL negative

2.1d. Definition of Loyalty Score and Descriptive Statistics

The loyalty score, defined as

$$LS = 26.91y_1 + 9.424y_2 - 5.104y_3 - 7.769y_4$$

is thus comprised of four factors, $y_1 \ldots y_4$, weighted by the variance they explain as components extracted by the principle components analysis method

within the factor analysis procedure in SPSS. The third and fourth factors are taken negative because they influence loyalty in a negative way.

The mean loyalty score for a seeker is 186.71, increasing to 274.22 for the passive and 343.94 for the non-seeker. Descriptive statistics for the loyalty score and its components will be discussed in Section 2.2.

2.1e.   Estimations of an unknown sample series of subclasses

Let N be a known sample series of LS

Let x be the number of seekers

        y be the number of passives

        z be the number of non-seekers among the N persons.

Then we propose the following method to estimate x, y and z.

Take dataset $(s, \xi$, where $\zeta = $ LS, and $s = \begin{cases} 1 = see\text{ker} \\ 2 = passive \\ 3 = non-see\text{ker} \end{cases}$

There are 1058 seekers, 411 passives, and 93 non-seekers in the dataset, with total N= 1562.

The number of seekers, passives and non-seekers among those with scores greater than or equal to 301 is:

           200 seekers   181 passives   70 non-seekers.

The number of seekers, passives, and non-seekers among those with scores less than or equal to 280 is:

           801 seekers   180 passives   18 non-seekers.

This means that

$$
*\ \begin{cases}
\text{19\% of all seekers have a score greater than or equal to 301} \\[4pt]
\text{44\% of all passives have a score greater than or equal to 301} \\[4pt]
\text{75\% of all non-seekers have a score greater than or equal to 301} \\[4pt]
\text{76\% of all seekers have a score less than or equal to 280} \\[4pt]
\text{46\% of all passives have a score less than or equal to 280} \\[4pt]
\text{19\% of all non-seekers have a score less than or equal to 280}
\end{cases}
$$

In order to derive an estimate for *x, y* and *z* (defined above) we have 3 equations, assuming the percentage in * persists.

Let N(280)= *n* people scoring less than or equal to 280.

Let N(301)= *n* people scoring greater than or equal to 301.

$$x + y + z = N$$

$$0.76x + 0.46y + 0.19z = N(280)$$
$$0.19x + 0.44y + 0.75z = N(301)$$

Solving these three equations for the unknowns *x, y,* and *z* yields

$$x = 12.157\,N(280) + 10.588\,N(280) - 10.251N$$
$$y = 3.704\,N(280) - 0.704N - 2.111x$$
$$z = N - x - y$$

Since *x, y,* and *z* have to be integers, take the nearest integer to this solution.

Inserting *N*=1580, *N*(280) = 1030 and *N*(300) = 450, one detects

x = 1090

y = 401

z = 89,

a fairly close approximation to the dataset.

From this we can estimate the probabilities of misspecification of a randomly chosen person with a score less than or equal to 280.

$$P(\text{non-seeker} \mid \text{score} \leq 280) = \frac{\text{\# of non-seekers} \leq 280}{\text{total number of non-seekers}}$$

$$= \frac{0.19z}{N(280)}$$

which is less than 2 percent.

$$P(\text{non-seeker} \mid \text{score} \geq 301) = \frac{0.75z}{N(301)}$$

which is between 15 and 16 percent, not a good rate for detecting non-seekers.

Discussion

However, based on data inspection, if one says that a randomly selected person a non-seeker because his/her score was in the top 93 of the ordered set (the total number of non-seekers in the data), there is a 30% chance of accurate classification as a non-seeker. On the other hand, there is only a 2% chance that the person is actually a seeker. This classification is not as precise as desired, and the rest of the section discusses methods to improve it.

Using the loyalty score method, 75% of the non-seekers were identified among those with scores over 300. While the loyalty score gives more information, it is not complete. The loyalty score serves as a first and quick overview of the dataset. It is not good for specifying and predicting whether a single person is a seeker or a non-seeker. It only gives the overall picture. Analyzing the seeking status of each person is tedious and expensive in each case.

2.2 Descriptive Statistics of Loyalty Score and its Components

Reasoning and Goal

An investigation of the descriptive statistics for the loyalty score and its components clearly suggests that the data is not normally distributed. However, as will be discussed next in Section 2.3, there are multiple significant differences between the means of the subclasses with regard to the loyalty score and its components. This section will underscore the finding that turnover intentions and the attitudes and behaviors related to them, cannot be evaluated using the normal distribution. While linear models under the normal distribution may not be suitable, nonparametric approaches offer reasonable alternatives to understanding differences and predicting classification. The usefulness of evaluating subclass differences based on asymptotic normality will be addressed in Section 2.3.

Non-Normality of Loyalty Score and Factors

In the previous section, factor analysis, with the principal components method of extraction, was used to reduce a nineteen-dimensional vector into four components, each representing an independent construct that potentially influences job-seeking status. Factor score coefficients were used to create new variables that take into consideration the appropriate weights of each variable as loaded on the appropriate factor (Harman, 1979). These scores were then summed to create the loyalty score.

Checking for the normality of each factor as a new variable, as well as the new loyalty score, Shapiro-Wilk's test for normality is reported and a graphic examination conducted which includes a quantile-quantile plot, boxplot, histogram, and density plot.

For the Shapiro-Wilk's test, the W statistic is calculated as follows:

$$W = \frac{\left(\sum_{i=1}^{n} \alpha_i x_{(i)} \right)^2}{\sum_{i=1}^{n} (x_i - \bar{x})^2}$$

Where the x_i are the ordered sample values ($x_{(1)}$ is the smallest) and the α_i are constants generated from the means, variances and covariances of the order statistics of a sample of size n from a normal distribution (Royston, 1995; Pearson and Hartley, 1972).

Results from Shapiro-Wilk's statistical test for normality suggest that neither the factors nor the loyalty score evidence a normal distribution (Table 2.2.1). The *p*-values, all essentially zero, require that we reject the null hypothesis of normality.

Factor	W-statistic	p-value
SUPERVISOR (SUPV)	.9494	$p = 0$
COMPANY (COMP)	.9751	$p = 0$
OPPORTUNITY (OPPTY)	.8061	$p = 0$
QUALITY OF WORK-LIFE (QWL)	.9769	$p = 0$
Loyalty Score (LS)	.9801	$p = 0$

Table 2.2.1 Shapiro-Wilk's test suggests non-Gaussian distributions

Figure 2.2.1 through Figure 2.2.4 provide normality plots for each of the factors.. Keep in mind that the dataset is comprised of three very distinct types of respondents who differ significantly on most measures assessed.
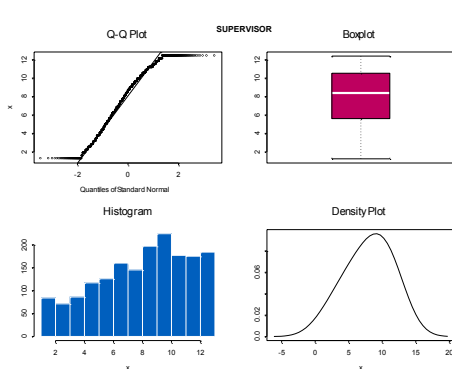
Figure 2.2.1   SUPV not normally distributed
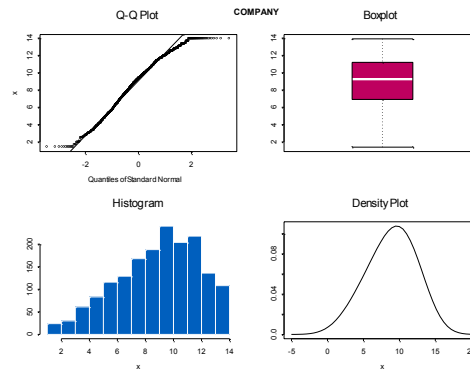
Figure 2.2.2 COMP not normally distributed
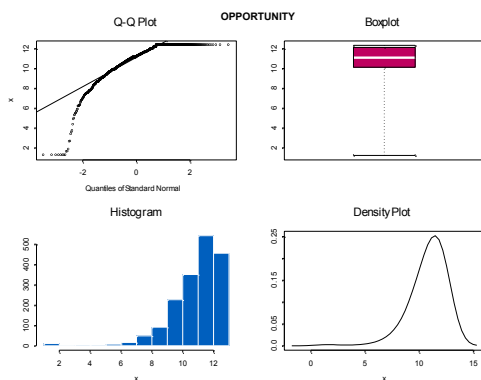
Figure 2.2.3   OPPTY not normally distributed   Figure 2.2.4   QWL not normally distributed
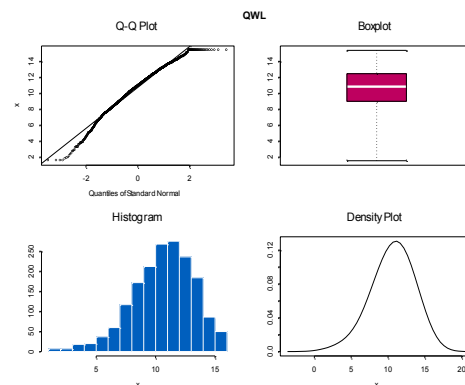
Table 2.2.2 provides a summary of the descriptive statistics for the factors and the new loyalty score. In Table 2.2.3, skewness and kurtosis statistics are presented. A negative left skew is strongest for the OPPTY factor which supports the suggestion that even non-seekers are potentially influenced by the external alternatives, namely the opportunity to work for a better company, with higher salary and better benefits. The kurtosis for OPPTY is quite leptokurtic, with $\gamma = 3.19$. The SUPV and COMP factors do not evidence as many outliers as do OPPTY and QWL.

Descriptive Statistics							
	N	Range	Min	Max	Mean		Std. Deviation
	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic
SUPERVISOR	1746	11.14	1.24	12.38	7.94	.075	3.15
COMPANY	1705	12.51	1.39	13.90	8.87	.070	2.92
OPPORTUNITY	1761	11.10	1.23	12.33	10.82	.038	1.61
QUALITY WORK LIFE	1749	13.83	1.54	15.37	10.60	.062	2.59
LOYALTY SCORE	1562	715.09	-157.95	557.13	219.10	3.12	123.26

Table 2.2.2 Descriptive statistics for factors and loyalty score

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Descriptive Statistics					
	N	Skewness		Kurtosis	
	Statistic	Statistic	Std. Error	Statistic	Std. Error
SUPERVISOR	1746	-.432	.059	-.812	.117
COMPANY	1705	-.401	.059	-.541	.118
OPPORTUNITY	1761	-2.21	.058	8.18	.117
QUALITY WORK-LIFE	1749	-.590	.059	.377	.117
LOYALTY SCORE	1562	-.443	.062	-.334	.124

Table 2.2.3 Skewness and kurtosis for factors and loyalty score

Loyalty Score

Consider the loyalty score comprised of the four factors discussed above. The loyalty score has a wide range, from a minimum of -157.95, to a maximum of 557.13, with a mean of 219.10, and standard deviation, $\sigma = 123.26$.

There is a heavy upper tail evidenced clearly the Q-Q plot (Figure 2.2.5). Skewness, $\gamma_ = -143$, and kurtosis $\gamma_ = 334$, thus the general normality of the score is not reasonable (recall Shapiro-Wilk's $= .9801$, $p = 0$, Table 2.2.1).
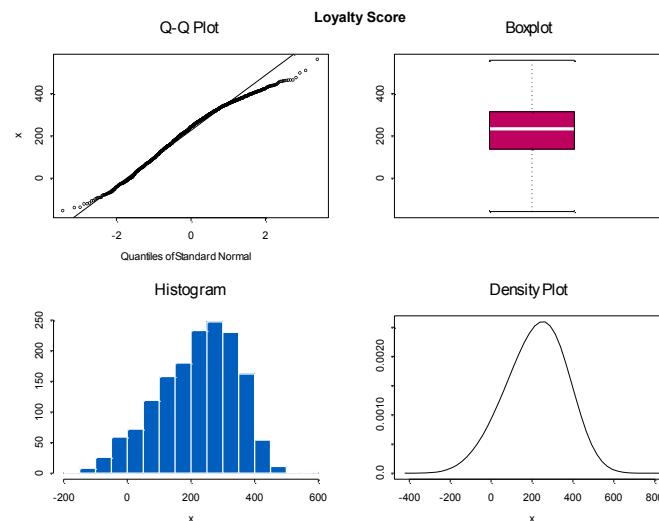
Figure 2.2.5   LS cannot be considered normally distributed

Overall the factors and the loyalty score evidence serious departures from normality. This is supported by the Shapiro-Wilk's tests as well in the graphic review of the distributions of each of the factors.

This dataset complicates the suggestion that one might survey an organization and be able to differentiate seeking status of the employees based on the questions, factors, and ultimately, the loyalty score. However, we move forward using results from the factor analysis (where normality is not required), apply discriminant analysis techniques for classification, which are robust against departures from normality, and ultimately arrive at an effective nonparametric approach, the generalized additive model, to identifying seeking status.

Next, in Section 2.3, the three subclasses of seekers, passives, and non-seekers are investigated to better understand the variations suggested by the descriptive statistics for each factor and the loyalty score.

2.3 Descriptive Statistics of Factors by Subclass

Reasoning and Goal

In this section, the three subclasses are investigated for normality and significant differences between the subclasses are examined. While the subclasses do not reflect normal distributions with regard to the factors or the loyalty score, there is valuable insight to be gained from the significant differences identified between the means of the varied seeking status categories (seekers, passives and non-seekers). These mean differences are identified using *t*-tests which are robust against non-normality with large sample sizes (PROPHET StatGuide, 1997). A proof of the asymptotic normality of the *t* statistic is provided in Ferguson (1996). The Kruskal-Wallis one-way analysis of variance by ranks also validates the significance of differences between the three subclasses with a nonparametric test. However, this test assumes identically shaped and scaled distributions for each group. It is known from Section 2.1 (Table 2.1.5) that Levene's test for homogeneity of variances suggests we have unequal variances. The results of this test are provided in Appendix A, yet the violation of the identically-scaled assumption leads to the preference for using the *t*-tests, given asymptotic normality.

Recall that *seeker*s are those who reported that they were currently seeking a new job at the time of the survey. Those considered *passives* reported that they would leave their current job, given the right opportunity. And the final group is comprised of *non-seekers* who said they were not currently seeking, and intent on staying in their current job for a while.

Seekers comprise 68.6% of the sample of full-time employed respondents (n = 1246), passives are 25.7% with n = 467, and non-seekers are the smallest group at 5.7%, with n = 104. The data does not differentiate respondents who are seeking a new position *within* their current company. The online survey question was asked specifically as follows in Table 2.3.1, where the respondent clicked on the response radial button representing their current status:

Are you currently seeking a new job opportunity?
o *Yes, actively seeking*
o *No, staying in my current job for awhile*
o *No, but would consider a new job if it were the right opportunity*

Table 2.3.1 Self-reported seeking status categories

Non-Normality within the Subclasses

Shapiro-Wilk's test for normality was conducted on the distributions for the factors and loyalty scores based on seeking status. Again the test requires rejection of the null that the distributions are normal. With the exception of the QWL factor for non-seekers, all achieve an approximate p-level $= 0$, indicating non-Gaussian distributions (Table 2.3.2).

	Factor	W-statistic	p-value
Seeker	SUPERVISOR	.958	$p = 0$
	COMPANY	.985	$p = 0$
	OPPORTUNITY	.800	$p = 0$
	QUALITY WORK-LIFE	.976	$p = 0$
	Loyalty Score	.984	$p = 0$
Passive	SUPERVISOR	.943	$p = 0$
	COMPANY	.961	$p = 0$
	OPPORTUNITY	.840	$p = 0$
	QUALITY WORK-LIFE	.978	$p = 0$
	Loyalty Score	.976	$p = 0$
Non-seeker	SUPERVISOR	.881	$p = 0$
	COMPANY	.886	$p = 0$
	OPPORTUNITY	.821	$p = 0$
	QUALITY WORK-LIFE	.981	$P = .161$
	Loyalty Score	.929	$P = .0001$

Table 2.3.2 Shapiro-Wilk's test for factor and loyalty normality by seeking status

Seeker

Graphic normality checks further support the rejection of the null of normality for seekers based on the distributions of each of the factors.
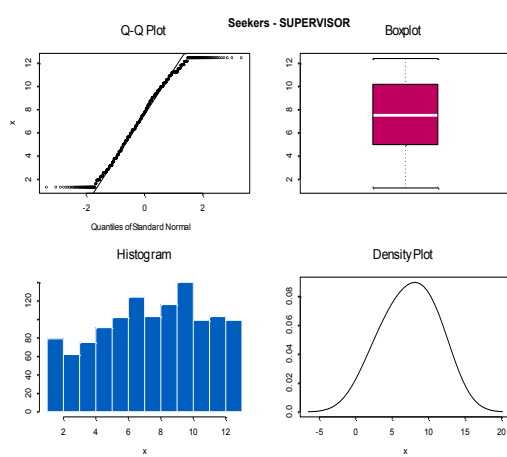
Figure 2.3.1 Seekers – Dist. not normal SUPV
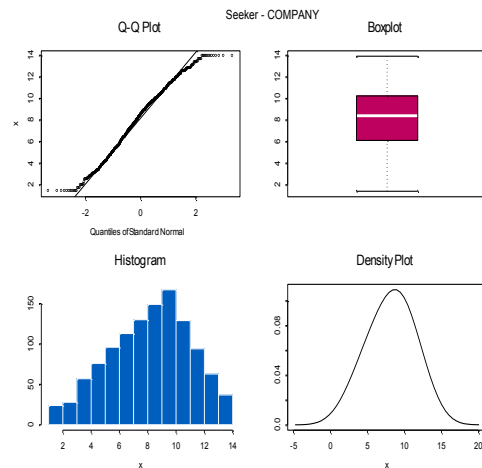
Figure 2.3.2 Seekers – Dist. not normal COMP
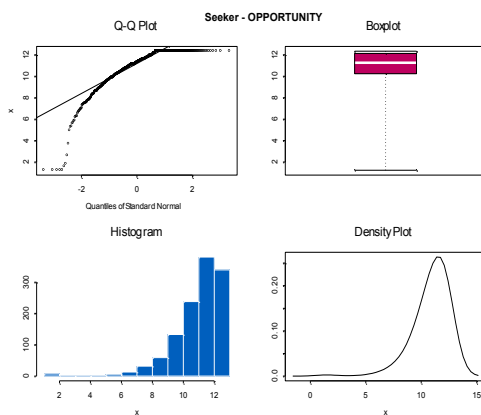
Figure 2.3.3 Seekers - Dist. not normal OPPTY
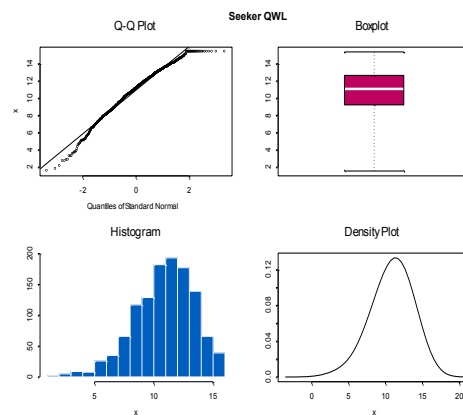
Figure 2.3.4 Seekers - Dist. not normal QWL

Seekers – Loyalty Score

Scores for seekers' loyalty range from -157.95 to 457.81, with a mean score of 186.71. There is substantial deviation with $\sigma = 20.33$. The Q-Q plot evidences heavy tails, and skewness, $\gamma_{\_} = 338$, and kurtosis $\gamma_{\_} = -185$. The loyalty score for seekers is not normally distributed.
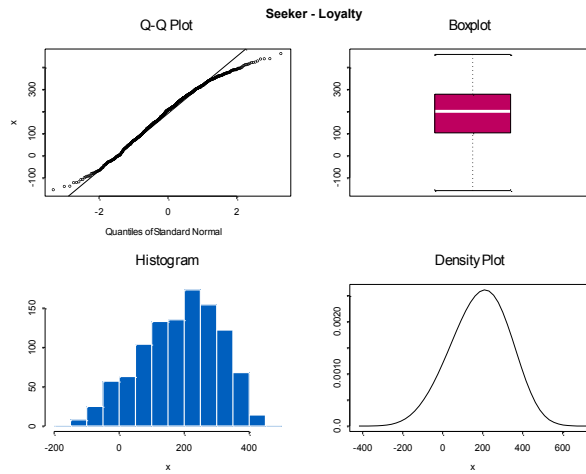
Figure 2.3.5   Seeker –Loyalty score not normally distributed

Table 2.3.3 and Table 2.3.4 summarize the descriptive statistics discussed in this section on seekers and their distributions on the factors and the loyalty score.

Seekers - Descriptive Statistics							
	N	Range	Min	Max	Mean		Std. Deviation
	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic
SUPERVISOR	1193	11.14	1.24	12.38	7.40	.093	3.24
COMPANY	1163	12.51	1.39	13.90	8.13	.084	2.87
OPPORTUNITY	1210	11.10	1.23	12.33	10.91	.045	1.57
QUALITY WORK LIFE	1193	13.83	1.54	15.37	10.84	.072	2.51
LOYALTY SCORE	1058	615.77	-157.95	457.81	186.71	3.7	120.33

Table 2.3.3   Descriptive statistics for seekers

Seeker - Descriptive Statistics					
	N	Skewness		Kurtosis	
	Statistic	Statistic	Std. Error	Statistic	Std. Error
SUPERVISOR	1193	-.230	.071	-.992	.142
COMPANY	1163	-.228	.072	-.616	.143
OPPORTUNITY	1210	-2.23	.070	8.44	.141
QUALITY WORK LIFE	1193	-.592	.071	.348	.142
LOYALTY SCORE	1058	.338	.075	-.485	.15

Table 2.3.4   Skewness and kurtosis for seekers suggest non-Gaussian distributions

Passives – Descriptive Statistics

Next consider just the passive seekers, those who would consider a new job given the right opportunity (n = 467, 25.7% of the dataset), This group is significantly different from those who report themselves as seekers on all factors with the exception of OPPORTUNITY. Passives are significantly different from non-seekers on all factors with the exception of QUALITY of WORK-LIFE. Table 2.3.8 through Table 2.3.13 provide details on significant differences between subclasses with regard to the factors and loyalty score.
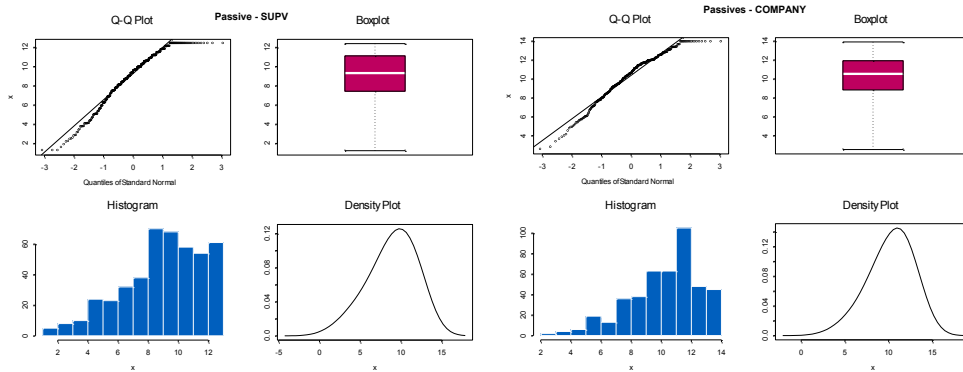
Figure 2.3.6 Passives – Dist. not normal SUPV   Figure 2.3.7 Passives – Dist. not normal COMP
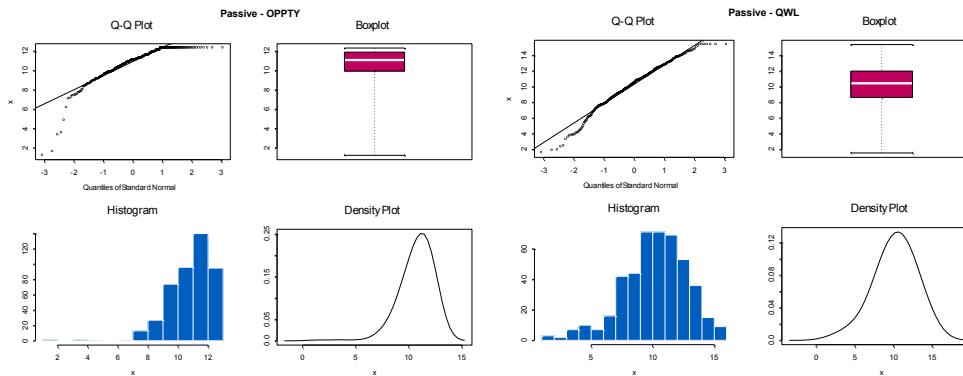
Figure 2.3.8 Passives – Dist. not normal OPPTY   Figure 2.3.9 Passives – Dist. not normal - QWL

Passives - Loyalty Score

The loyalty score for passives ranges from a minimum of -76.38 to a maximum of 504.99, with $\mu = 274.22$ and $\sigma = 98.79$. The score is significantly higher than that for seekers, where $\mu = 186.71$, and significantly lower than non-seekers at $\mu = 343.94$, differentiating the subclasses. Skewness is left again, with $\gamma = -59$ and kurtosis at $\gamma = 161$. The heavier left tail is seen in the density and Q-Q plots.
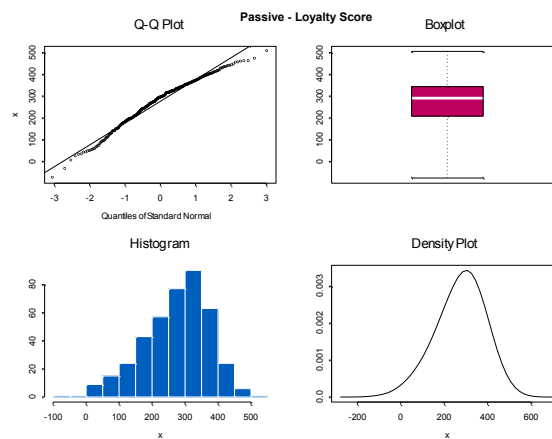
Figure 2.3.10   Passives – Loyalty score not normally distributed

Following, Table 2.3.5 and Table 2.3.6 summarize the descriptive statistics for passives discussed in this section.

Passive - Descriptive Statistics							
	N	Range	Min	Max	Mean		Std. Dev.
	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic
SUPERVISOR	451	11.14	1.24	12.38	8.9012	.125	2.65
COMPANY	442	11.38	2.52	13.90	10.213	.111	2.34
OPPORTUNITY	451	11.10	1.23	12.33	10.749	.070	1.5
QUALITY WORK LIFE	455	13.83	1.54	15.37	10.184	.122	2.61
LOYALTY SCORE	411	581.37	-76.38	504.99	274.22	4.87	98.78

Table 2.3.5 Descriptive statistics for passives

Passives - Descriptive Statistics					
	N	Skewness		Kurtosis	
	Statistic	Statistic	Std. Error	Statistic	Std. Error
SUPERVISOR	451	-.695	.115	-.164	.23
COMPANY	442	-.672	.116	.078	.23
OPPORTUNITY	451	-2.05	.115	8.17	.22
QUALITY WORK LIFE	455	-.565	.114	.450	.22
LOYALTY SCORE	411	-.590	.120	.161	.24

Table 2.3.6 Skewness and kurtosis for passives

Non-seeker Descriptive Statistics

The final subclass investigated is the non-seeker group. These people identified themselves as not currently seeking a new job, staying in their current position a while. There are 104 non-seekers, representing 5.7% of the dataset of respondents, employed full-time at the time of the survey. The non-seekers significantly differ from the seekers on all factors and the loyalty score. They also differ from passives on all factors with the exception of the influence of the variables comprising QUALITY of WORK-LIFE. There is substantial variation within the class which reflects non-normal distributions with regard to the factors.
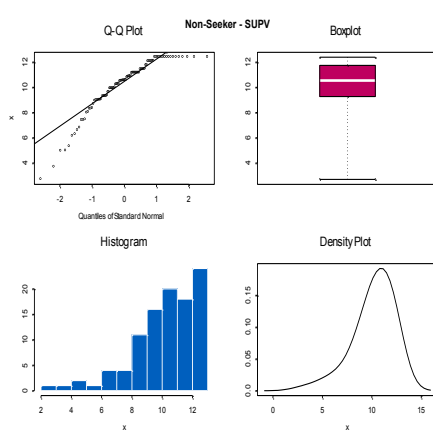
Figure 2.3.11 Non-seekers – Dist. not normal - SUPV   Figure 2.3.12 Non-seekers not normal -COMP
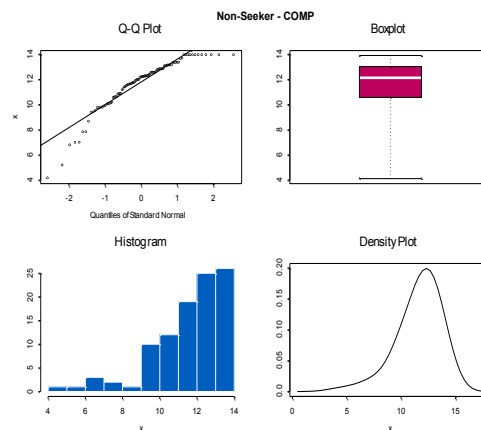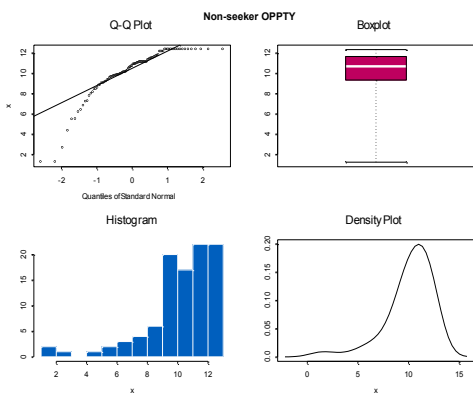
Figure 2.3.13 Non-seekers dist. not normal -OPPTY   Figure 2.3.14 Non-seekers not normal - QWL
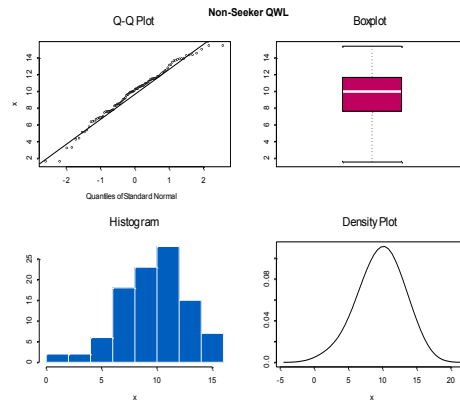
Non-seeker LOYALTY SCORE

Consider non-seeker scores for the loyalty measurement. Ranging from -11.20 to 557.14, there is a 568.34 spread. The mean loyalty score of 343.94 is significantly higher than both passives at 274.22 and seekers at 186.71. The standard deviation decreases accordingly to 80.97, whereas it was larger for passives at 98.78 and even larger for seekers at 120.33. This suggests that employees who are more loyal to their organization have less diversity in their perceptions of supervisor, company, opportunity and quality of work life, as compared to passives and seekers. The skewness statistic $\gamma = -\,83$ indicating a left skew, and kurtosis is positive, leptokurtic, at $\gamma = 554$. These statistics indicating shape are clarified by the density plot which reflects the slight bump in the fat left tail (Figure 2.3.15).
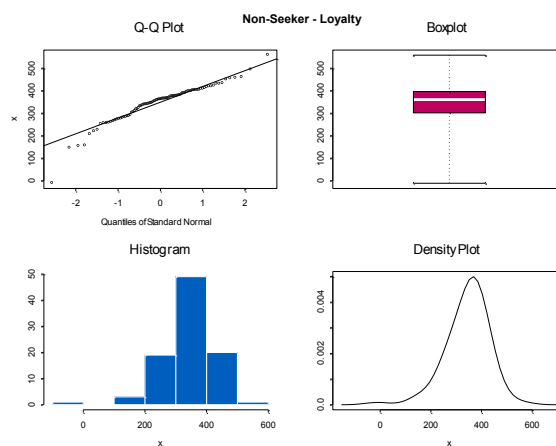
Figure 2.3.15 Loyalty scores for non-seekers are not normally distributed

The following tables (Table 2.3.7 and Table 2.3.8), provide descriptive statistics for non-seekers on the four factors and the loyalty score

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Non-Seeker - Descriptive Statistics							
	N	Range	Min	Max	Mean		Std. Deviation
	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic
SUPERVISOR	102	9.68	2.70	12.38	10.15	.20	2.06
COMPANY	100	9.78	4.12	13.90	11.60	.19	1.95
OPPORTUNITY	100	11.10	1.23	12.33	10.09	.23	2.30
QUALITY WORK LIFE	101	13.83	1.54	15.37	9.710	.29	3.01
LOYALTY SCORE	93	568.34	-11.20	557.14	343.94	8.40	80.97

Table 2.3.7 Descriptive statistics non-seekers

Non-seeker Descriptive Statistics					
	N	Skewness		Kurtosis	
	Statistic	Statistic	Std. Error	Statistic	Std. Error
SUPERVISOR	102	-1.31	.239	1.84	.474
COMPANY	100	-1.39	.241	2.43	.478
OPPORTUNITY	100	-1.83	.241	4.12	.478
QUALITY WORK LIFE	101	-.422	.240	.018	.476
LOYALTY SCORE	93	-1.14	.250	3.64	.495

Table 2.3.8 Skewness and kurtosis for non-seekers

Significant Differences Between Subclasses on Factors and Loyalty

Given the factors developed to reduce dimensionality, it is valuable to briefly summarize the areas in which significant differences between the subclasses are evident. Specifically, seekers and non-seekers evidence statistically significant differences on all factors, as well as the loyalty score. Seekers and passives differ significantly on all factors with the exception of OPPORTUNITY. Lastly, the passives differ from the non-seekers on all factors with the exception of QUALITY of WORK-LIFE (see Table 2.3.9 through Table 2.3.12). Table 2.3.13 compares loyalty scores by seeking status.

SUPERVISOR FACTOR	Mean	T Stat	Degrees freedom	p-value	Mean diff	Std. error diff
Seekers	7.40	-12.27	147	.000	-2.75	.22
Non-seekers	10.16					
Seekers	7.40	-9.59	981	.000	-1.50	.15
Passives	8.90					
Passives	8.90	-5.25	185	.000	-1.25	.23
Non-seekers	10.16					

Table 2.3.9 All subclasses differ significantly on the SUPV factor

COMPANY FACTOR	Mean	T Stat	Degrees freedom	p-value	Mean diff	Std. error diff
Seekers	8.13	-16.29	138	.000	-3.46	.21
Non-seekers	11.60					
Seekers	8.13	-14.85	968	.000	-2.07	.13
Passives	10.21					
Passives	10.21	-6.16	170	.000	-1.38	.22
Non-seekers	11.60					

Table 2.3.10 All subclasses differ significantly on the COMP factor

OPPORTUNITY FACTOR	Mean	T Stat	Degrees freedom	p-value	Mean diff	Std. error diff
Seekers	10.91	3.48	106	.000	.81	.234
Non-seekers	10.09					
Seekers	10.91	Not Significant				
Passives	10.74					
Passives	10.74	2.71	118	.000	.65	.240
Non-seekers	10.09					

Table 2.3.11 No significant difference between passives and seekers on OPPTY factor

QUALTITY of WORK LIFE FACTOR	Mean	T Stat	Degrees freedom	p-value	Mean diff	Std. error diff
Seekers	10.84	3.66	112	.000	1.12	.30
Non-seekers	9.71					
Seekers	10.84	4.68	1646	.000	.65	.14
Passives	10.18					
Passives	10.18	Not Significant				
Non-seekers	9.71					

Table 2.3.12 No significant difference between passives and non-seekers on QWL

LOYALTY SCORE	Mean	T Stat	Degrees freedom	p-value	Mean diff	Std. error diff
Seekers	186.71	-17.14	131	.000	-157.23	9.17
Non-seekers	343.94					
Seekers	186.71	-14.3	908	.000	-87.51	6.12
Passives	274.22					
Passives	274.22	-7.18	160	.000	-69.71	9.71
Non-seekers	343.94					

Table 2.3.13 Significant differences on loyalty score for all subclasses

Parallel Boxplots

This section ends with a comparison of the subclasses utilizing parallel boxplots. The idea is to compare the three subclasses of seekers, passives and non-seekers simultaneously, graphically. Visualizing these often subtle differences clarifies the descriptive statistics surrounding each of the factors and ultimately, the loyalty score.

Outliers are represented by open circles as in the following parallel boxplots. Points lying more than 3 box lengths from either end of the box are extreme outliers marked with an asterisk.

Begin with a comparative look at the SUPERVISOR factor for each of the subclasses (Figure 2.3.16).
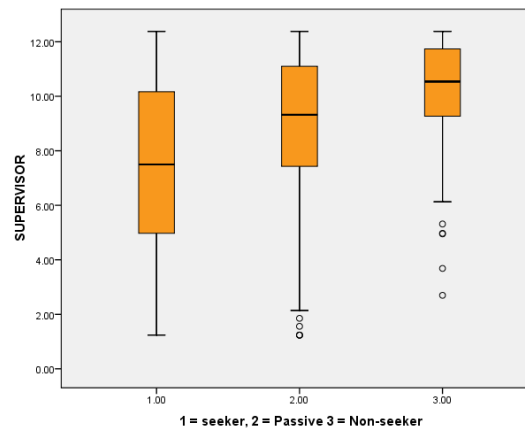
Figure 2.3.16 – Parallel boxplots of seeking status on supervisor factor

Seekers appear to be the most normally distributed of the three subclasses, yet skewed left as indicated by the longer lower whisker, yet with more variability as indicated by the interquartile range, or length of the box itself. Passives on the other hand have a more serious left skew as evidenced by the lower whisker much longer than the box. Three outliers are present in the subclass, and fall rather close to the minimum, thus not investigated further or omitted. Non-seeker scores for SUPERVISOR evidence the variability among the classes, yet with the most pronounced left skew.

Next, in Figure 2.3.17, the COMPANY factor reflects a similar pattern among the subclasses, with increasing ratings and decreasing variability. A few more outliers are present in the passive data for COMPANY than seen for SUPERVISOR but one less for non-seekers. Non-seekers evidence a median closer to the upper quartile.
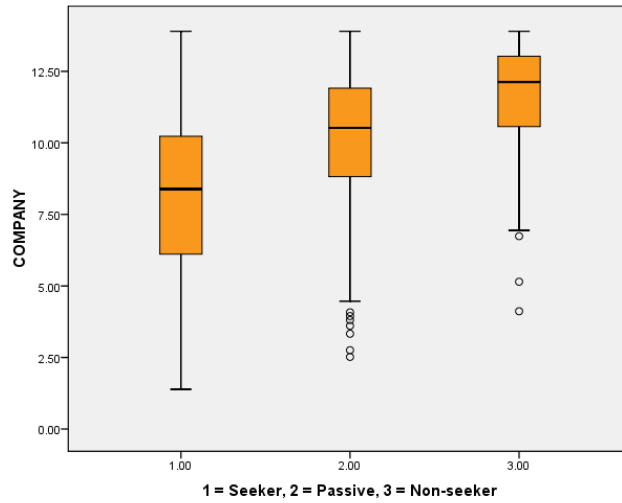
Figure 2.3.17 – Parallel boxplots of seeking status on company factor

The OPPORTUNITY factor, presented in parallel boxplots for subclasses in Figure 2.3.18 helps with visualizing the commonalities between all respondents regarding the influence of the potential for a better opportunity elsewhere. One can ascertain that all respondents are highly influenced by the potential for higher salary, better benefits, greater advancement opportunity and better skills training which is to be expected to a certain degree. It is interesting to note the very similar extent of variability for seekers and passives as evidenced by the similar lengths of the boxplots, (recall $\sigma_{seeker} = .572$ and $\sigma_{passive} = .503$), compared to the increased variability of the non-seeker with regard to the influence of potential OPPORTUNITY, where $\sigma_{nonseeker} = 1.301$.
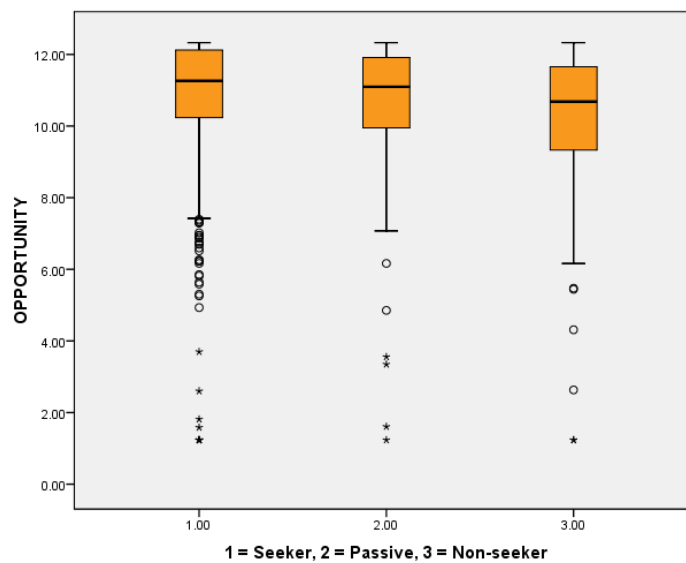
Figure 2.3.18 – Parallel boxplots of seeking status on opportunity factor

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Moving onto the QUALITY of WORK-LIFE factor (Figure 2.3.19), this is perhaps the most normal of all the factors, as evidenced by the relative symmetry of the boxplots for all subclasses.. Seekers do evidence more of a left skew and sustain more outliers, whereas non-seekers are much closer to being normally distributed with only one outlier.
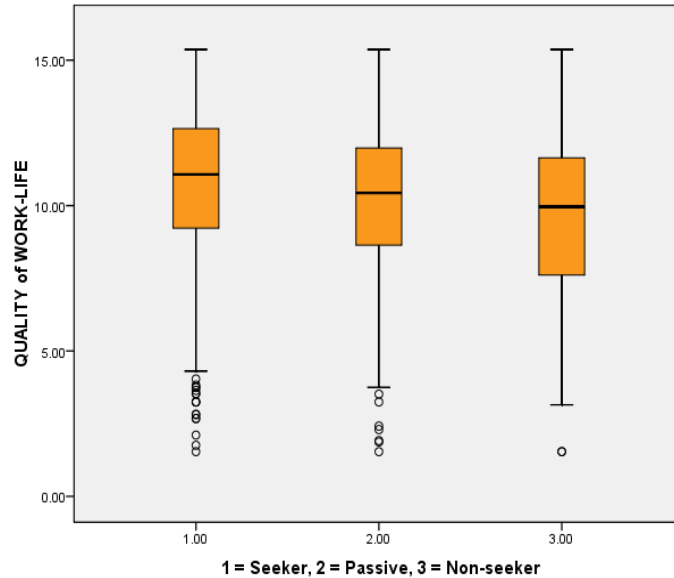
Figure 2.3.19 – Parallel boxplots of seeking status on quality of work-life factor

Lastly, the loyalty score is reviewed (Figure 2.3.20). Although there are still several outliers, it is not likely that their impact is substantial given that there are $n = 1246$ seekers with fewer than 10 outliers, $n = 467$ with one extreme passive outlier, and $n = 104$ with fewer than 5 non-seeking outliers. Variability is fairly consistent among the three subclasses and the lengths of the whiskers, relative to the boxplots, are acceptably balanced.
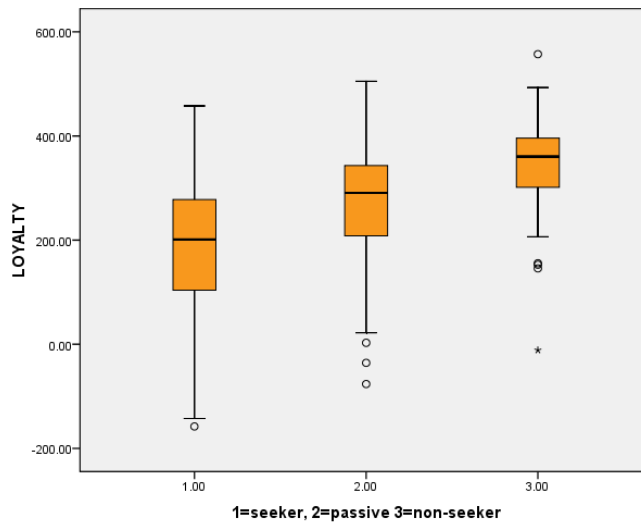
Figure 2.3.20 – Parallel boxplots of seeking status on loyalty score

Summary of Part 2 – Section 2.1 through Section 2.3

In Section 2.1 the loyalty score was developed and its components were discussed. An estimation process was detailed, and an application was made using the job-seeker dataset. In Section 2.2, the descriptive statistics for the loyalty score and its components were presented and evaluated. Both statistical and graphical checks for normality of the factors and the loyalty score suggested that generally, the data is not normally distributed. Section 2.3 focused on the subclasses, or seeking categories. The descriptive statistics for the loyalty score and its components by subclass were investigated and the distributions by subclasses were not reflective of Gaussian data.

The motivation for this portion of the analysis was not only to defend the method used to develop the loyalty score, but also to better understand the underlying factors and how they potentially differ by seeking status. It is clear from Section 2.3 that significant differences exist between the seekers, passives and non-seekers with regard to supervisor and company satisfaction as well as the influence of alternatives that may yield better opportunities or quality of work-life.

The loyalty score enabled the identification of seekers and non-seekers with 75% accuracy, based on the job-seeker dataset, but the full information, particularly that given by the passives, may not be utilized completely.

Upcoming sections will discuss alternate methods of identifying seeking status based on a dataset of job satisfaction and outside influence attitudes and behaviors.

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2.4 Conditional Probability Given Loyalty Score

Reasoning and Goal

This section considers the conditional probability of seeking status given the loyalty score. The aim is to find the empirical probability that person *x*, given the loyalty score, falls into category *y*.

Consider, if *A* and *B* are events in *S*, and P(*B*) > 0, then the conditional probability of *A* given *B*, written P(*A|B*), is

$$P(A \mid B) = \frac{P(A \cap \ )}{P(B)}$$

In the conditional probability calculation, *B* becomes the sample space P(*B|B*) = 1, and the original sample space *S* is updated to *B*. Also consider the conditional probabilities of disjoint sets, where if *A* and *B* are disjoint, $P(A \cap B) =)$. It then follows that $P(A \mid B) = P(B \mid A) =)$ (Casella & Berger, p.20).

Consider the sample space *B* to be the scientific loyalty scores, and P(*A*) to be the empirical probability that, given the loyalty score, a person *x* falls in to category *y*.

As a starting point, visual binning is used to categorize the loyalty scores. Visual binning is designed to assist in the process of creating new variables based on grouping contiguous values of existing variables into a limited number of distinct categories.

Application to Job Seeker Data

The loyalty scores are categorized into nine equally-sized bins, based on intervals of the scores. The quantity of nine bins is selected because this is a manageable number of score classifications for an employer (intuitively allowing for three levels per seeking category).

In Table 2.4.1 the exact interval is reported, the *n* respondents who fall into the interval, the *n* in each seeking category within the interval, and the percentage correctly classified. For example, 146 seekers were identified in Bin 1. Dividing this number by the total number of seekers (146/1058), we can say that 14% of the seekers were correctly classified into Bin 1, based on their loyalty scores between -157.95 and 46.97.

Bin	1	2	3	4	5	6	7	8	9
Score	-157.95 to 46.97	46.98 to 110.43	110.93 to 156.47	156.5 to 200.71	200.84 to 233.46	233.99 to 266.74	267.01 to 298.3	298.57 to 332.22	332.37 to 366.79
n	157	155	157	156	156	157	156	156	156
	% of category in bin								
Seeker	14%	13%	13%	11%	12%	10%	9%	8%	7%
Passive	2%	5%	5%	10%	8%	11%	13%	15%	15%
Non-Seeker	1%		3%		3%	6%	11%	9%	25%

Table 2.4.1 Percentage correctly classified into each interval

The method correctly classifies 51% of the seekers with scores less than or equal to 200.71. Non-seekers are found at the higher end of the ranked scores, with 54% of them scoring 200.84 or higher. Fifty-four percent of the passives had scores higher than 233.99.

Breaking the entire sample into nine equal intervals is not a particularly compelling method for identifying seeking status.

Comparative Sample with Equal Subclasses, Three Bins

Consider that the dataset is comprised primarily of seekers, nearly 70%, thus it makes sense to level the playing field by selecting equally sized subclasses for comparison. There are only 93 non-seekers with no missing data points for the loyalty score, so all are used. Out of 411 passives, 93 are randomly selected, and 93 seekers are randomly selected out of 1246. The number of bins is reduced to a more manageable three.

The first bin, comprised of scores from -124.83 to 247.73 identifies nearly 60% of the seekers in the sample. The second bin reveals 38% of the passives with scores between 247.84 and 340.35, comparable to Bin 6 through Bin 8 when all data were used (see Table 2.4.1). Sixty-two percent of the non-seekers were correctly classified into Bin 3 when equal sized subclasses were used, with scores higher than 340.35. Table 2.4.2 summarizes the results for this sample.

Bin	1	2	3
Score	-124.83 to 247.73	247.84 to 340.35	340.35 to 557.14
N	93	93	93
	% of category in bin		
Seeker	59%	31%	10%
Passive	33%	38%	28%
Non-Seeker	8%	31%	62%

Table 2.4.2 Percentage correctly classified - Sample with equal subclasses

Three Bins – all data

Next investigated is the three bin approach with all the data, calling for evenly distributed groups. The most accurately identified are the non-seekers, 76% of which are classified into Bin 3 with loyalty scores greater than 340.35. Bin 2 was not very promising, finding only a third of the passives, yet as good as chance alone. Bin 1 captured 43% of the seekers with scores less than or equal to 173.24.

Bin	1	2	3
Score	-157.95 to 173.24	247.84 to 340.35	340.35 to 557.14
N	521	521	520
	% of category in bin		
Seeker	43%	35%	22%
Passive	15%	33%	52%
Non-Seeker	4%	19%	76%

Table 2.4.3 Percentage correctly classified – All data

Three Bins – Intervals Based on Data Inspection

Lastly, the binning method is used to simply validate earlier findings in Section 2.1 based on data inspection. Three bins were used. Specifically, cases less than 280 went into Bin 1, 280 to 301 in Bin 2, and greater than 301 in Bin 3. As expected, results are reflective of that which was reported in Section 2.1. For additional clarity, Table 2.4.4 presents the results in a manner comparable to the previous tables in this section.

Bin	1	2	3
Score	-157.95 to 279.90	280.14 to 301	301.10 to 557.14
n	1009	102	451
	% of category in bin		
Seeker	76%	5%	19%
Passive	46%	10%	44%
Non-Seeker	19%	5%	75%

Table 2.4.4   Percentage correctly classified - Based on intervals from data inspection

Discussion

While seekers and non-seekers are classified fairly well, there is still difficulty classifying the passives based on the loyalty score using a visual binning approach to intervals.

The motivation for identifying passives is that an employer can take measures to enhance loyalty if the passive is valuable to the organization. Perhaps supervisory issues are affecting the passive's likelihood to seek, or there are issues related to the company (e.g., pride, honesty, valuable products, competitive salary, good benefits). Alternately, if the passive has not been performing to management expectations, or has a history of inappropriate behavior, then measures should be taken to remove the passive from the organization versus further training and development.

This leads to efforts in Section 2.5 where cluster analysis techniques are used to attempt to more reliably classify our respondents as seekers, passives, or non-seekers.

2.5   Classification Based on Intervals – Cluster Analysis

Reasoning and Goal

Cluster analysis is a method of exploring the data to see which groups are present. Here the loyalty score means are investigated along with the distances that respondent scores fall from the means of the subclasses of seekers, passives and non-seekers. Because there may be many underlying groups, or potential clusters, in a dataset, the researcher typically makes a priori decisions to simplify the process (Gentle 238). This might include deciding on the number of clusters as in K-means clustering, or comparing the computational challenges for the varied methods and selecting the one that works best for the application.

Agglomerative hierarchical clustering has three methods including single linkage, sometimes referred to as nearest neighbor, complete linkage, and average linkage. In *K*-means clustering cases are assigned to a cluster with the nearest mean. One may also consider Ward's method in which the distance measure is based on change in explained variance, R^2. In general, look for consistency in clustering methods.

In hierarchical clustering the interpoint and intercluster distance is defined. The interpoint distance is the square root of the sum of the distances squared, or Euclidean distance

$$d_E(x_1, x_2) = \sqrt{\sum_{j=1}^{p}(x_{1j} - x_{2j})^2}$$

where $x_1 = x_{11},...x_{1p})^{'}$ and $x_2 = x_{21},...x_{2p})^{'}$

are *p*-dimensional vectors in R^p. The intercluster distance is a function of the interpoint distances between pairs of points, and each point comes from a different cluster. In single linkage, this is the distance between the two closest points, for complete linkage the farthest two points, and in average linkage the average distance between every pair of points.

The basic clustering algorithm follows:

1. Start with *N* clusters, each containing a single entity and *N x N* symmetric matrix of distances (or similarities)

$$D = d_{ik}\}.$$

2. Search the distance matrix for the nearest (most similar) pairs of clusters. Let the distance between most similar clusters *U* and *V* be d_{UV}.

3. Merge clusters U and V. Label new cluster *(UV)*. Update entries in the distance matrix.

4. Repeat steps 2 and 3 a total of N-1 times. Record the identity of clusters that are merged and the levels of distances, or similarities, at which the merge takes place.

In single linkage, groups are fused according to the distance between their nearest members. For the single linkage algorithm inputs can be distances or similarities between pairs. Groups are formed from individual entities by merging the "nearest neighbors," meaning the smallest distance or largest similarity. To find the smallest distance $D = d_{ik}\}$, merge corresponding objects U and V to generate cluster *(UV)*. Distances between *(UV)* and any other cluster W are

$$d_{(UV)W} = \min\{d_{UW}, d_{VW}\}$$

where $d_{(UW)}$ and $d_{(VW)}$ are distances between nearest neighbors of clusters U and W and clusters V and W, respectively.

Complete linkage is similar to single linkage except that the distance between clusters is determined by the distance between two elements, one from each cluster, that are most distant. All items in the cluster are within some maximum distance with minimum similarity. In the algorithm for complete linkage find the minimum entry in $D = d_{ik}\}$, and merge the corresponding items to generate cluster *(UV)*. The distances between *(UV)* and any other cluster W are

$$d_{(UV)W} = \max\{d_{UW}, d_{VW}\}$$

where d_{UW}, d_{VW} are the distances between the most distant of clusters U and W and cluster V and W, respectively.

For average linkage, the distance between two clusters is the average distance between all pairs. One member of each pair belongs to each cluster. The input to the algorithm may be distances or similarities to group objects or variables. Search the distance matrix $D = d_{ik}\}$ to find the most similar (nearest) objects U and V. Them, merge them to form cluster *(UV)*. The distances are

$$d_{(UV)W} = \frac{\sum_i \sum_k}{N_{(UV)} N_W}$$

where d_{ik} is the distance between object i in cluster *(UV)* and object k in the cluster *W,* and $N_{(UV)}$ and $N_{(W)}$ are the number of items in clusters *(UV)* and *W.*

The Ward method is distinct from all the other methods discussed thus far. It uses and analysis of variance approach to evaluate the distances between clusters. It attempts to minimize the sum of squares of any two (hypothetical) clusters formed at each step. It is regarded as very efficient, however, as it tends to create clusters of small size. This method will be applied in the second essay analyzing on college student leadership behaviors.

With the *K*-means method, each item is assigned to a cluster having the nearest centroid (mean). The algorithm step 1) partitions items into *K* initial clusters. It then in step 2) proceeds through the items, assigning them to clusters with the nearest mean. The Euclidean distance is used with standardized or unstandardized observations. The mean is recalculated for the cluster receiving the new observation as well as for the cluster losing the observation. Step 2 is repeated until no more reassignments take place.

The objective of *K*-means clustering is to find and segment observations into a preset number of groups, *k*, which will minimize the variation within each group, and each group may have different variation. The variation of the jth variable in the gth group is measured by the within-sum of-squares

$$s^2_{j(g)} = \frac{\sum_{i=}^{n_g} x_{ij(g)} - \bar{x}_{j(g)})^2}{n_g -}$$

where n_g is the number of observations in the gth group, and $\bar{x}_{j(g)}$ is the mean of the jth variable in the gth group. There are *m* of these quantities. The variation of observations in the gth group is chosen as a linear combination of the sums-of-squares for all *m* variables. Partitions are created such that the pairwise dissimilarities between those assigned to the same cluster tend to be smaller than those indifferent clusters (Hastie, Tibshirani, Friedman, 459).

Hastie, Tibshirani and Friedman (p. 461) suggest that the *K*-means algorithm is one of the most popular iterative descent clustering methods, intended for use with quantitative variables. The squared Euclidean distance is chosen as the dissimilarity measure (Hastie et al., 461).

$$d(x_i, x_{i'}) = \sum_{j=1}^{p} (x_{ij} - x_{i'j})^2 = {}_{,,}x_i - x_{i'}\|^2$$

Application to the Loyalty Score

The first cluster analysis deals with only one variable, the loyalty score, which is segmented into a preselected number of clusters, a manageable nine. The *K*-means clustering method was used to generate the clusters. Table 2.5.1 reports the exact interval of the assigned cluster, the *n* respondents who fall into the cluster, the *n* in each seeking category within the cluster, and the percentage of the total category identified.

Cluster	1	2	3	4	5	6	7	8	9
Score	-157.95 to -55.53	-48.83 to 27.63	29.12 to 113.71	114.41 to 199.56	199.93 to 280.47	281.32 to 349.22	349.99 to 407.75	409.15 to 470.75	493.06 to 577.14
n	35	86	198	303	391	319	180	47	3
	% of category in cluster								
Seeker	3%	8%	16%	23%	26%	16%	7%	1%	
Passive	.02%	.07%	6%	15%	24%	31%	17%	6%	.02%
Non-Seeker		1%		3%	15%	25%	2%	13%	2%

Table 2.5.1   K-means clustering of loyalty scores

The results for the *K*-means cluster analysis on the loyalty scores are particularly more helpful in identifying seeking status. However, as discussed earlier, 76% of the seekers have scores less than or equal to approximately 280, and the *K*-means method enables one to inspect the classifications more carefully based on loyalty score.

Using just the factors in the cluster analysis, pre-selecting only three clusters yields poor results. Two of the clusters (cluster 2 and cluster 3 in Table 2.5.2) have loyalty scores that overlap too much to consider the score helpful in discriminating classes (Table 2.5.2).

Cluster	1	2	3
Loyalty Score	-159.02 to 209.41	124.96 to 557.37	125.50 to 452.79
n	518	406	638
% of category in cluster			
Seeker	42%	22%	36%
Passive	17%	34%	49%
Non-Seeker	4%	41%	55%

Table 2.5.2 K means clustering based on factors

Investigating a three-cluster solution using the loyalty scores yields an interesting result regarding non-seekers. It is known (see Section 2.1) that 75% of the non-seekers have scores greater than or equal to 301. Cluster analysis reveals 85% greater than 269.

Cluster analysis suggests a passive is not likely to have a score less than 117 (Table 2.5.3). Nearly 60% of the passives had loyalty scores over 269. Recall that if the score is greater than 301, it was suggested in Section 2.1 that they were most likely to be non-seekers. Further, the mean loyalty score for passives is 273.

Cluster	1	2	3
Loyalty Score	-159.02 to 116.74	117.89 to 269.89	269.10 to 557.37
n	326	627	609
% of category in cluster			
Seeker	28%	44%	28%
Passive	7%	35%	57%
Non-Seeker	1%	14%	85%

Table 2.5.3 K means clustering based on loyalty scores, pre-designated 3 clusters

This suggests that scores between 269 and 301 are likely to indicate passive status, and careful interpersonal analysis is required by the manager for employees scoring in this range. Given that 85% of the non-seekers are found with scores above 269, one might infer that the passive with a score over 269 (yet under 301) can be effectively transitioned to non-seeking status by the manager who focuses on improved supervisory experiences for the passive, as well as the elements comprising the company factor.

Discussion

Cluster analysis did not prove to be a particularly fruitful technique for classification based on intervals of the loyalty score. However, 85% of the non-seekers were assigned to the same cluster based on loyalty scores over 269, versus the threshold of 280 recommended in Section 2.1 (where 75% of non-seekers had scores over 280). Also, a bit more information regarding the loyalty scores of passives was interpreted. It was suggested that passives are not likely to have scores lower than 117, and those falling in the 269 to 301 range should be counseled by management in an effort to secure their loyalty to the organization, and transition them to non-seeking status.

The upcoming Section 2.6 will discuss a more effective method for discerning seeking categories, discriminant analysis.

2.6   Classification Using Discriminant Analysis

Next, a more practical and intuitive approach is taken to determining what elements of the job experience might serve as strong catalysts for a change in seeking status, ultimately leading to better classification of an employee as a seeker, passive, or non-seeker. Earlier, the many significant differences between subclasses were discussed. Particularly noted was the substantiality of the differences between all groups on perceptions of pride in the company for which they worked and its honesty. It was suggested that the supervisor's support of work/life balance was a potential catalyst to transition from non-seeker to passive. These are just a few of the intuitions that can be validated with the classification and analysis techniques within the discipline of discriminant analysis which helps the researcher build a predictive model for group membership.

Overview of Discriminant Analysis

The model can be designed to differentiate between two groups, and classify members accordingly, or for more than two groups in which case the process is called multiple discriminant analysis. The model in the case of more than two groups is composed of a set of discriminant functions that are based on linear combinations of independent predictor variables that provide the best discrimination between the groups. Functions are generated from a sample of cases for which group membership is known, and then validated by applying them to new cases that have measurements for the predictor variables but have unknown group membership.

The job-seeker data lends itself to discriminant analysis as the aim is to classify employees as members of one of three groups (seekers, passives or non-seekers). Discriminant analysis is an appropriate statistical tool when the dependent variable is categorical and independents are numeric (Hair, Black, Babin, and Anderson, p. 239).

The process involves deriving a variate, the discriminant function, which is a linear combination of two or more independent variables that best differentiate, or discriminate, between the cases (e.g., employees) in each of the job-seeker status categories which are predefined, often referred to as defined *a priori*. Weights are calculated for each independent variable with the intent of maximizing the differences between groups. Essentially, this means weighting by the between-group variance relative to the within-group variance.

The form follows:

$$Z_{jk} = a + V_1 X_{1k} + V_2 X_{2k} + ... + V_n X_{nk}$$

where

Z_{jk} = discriminant Z score of discriminant function j for object k

a = intercept

W_i = discriminant weight for independent variable i

X_{ik} = independent variable i for object k

Unique to discriminant analysis versus other multivariate techniques, is that each object, or person, may have more than one discriminant score based on multiple functions depending on the number of categories being discriminated. The number of functions is determined as number of groups (or categories) minus 1.

Hair et al clarify that discriminant analysis is used to test the hypothesis of equality of group means for a set of independent variables for two or more groups. The group mean, or centroid, is the average of discriminant scores for all cases (persons, employees, objects, etc.) within a specific group. One centroid is determined for each category, or group, and this centroid is an indication of the most typical location of any member from a particular group.

Statistical significance of the discriminant function is assessed by comparing the distance between group centroids. If the distributions of the discriminant scores for the groups overlap substantially, then the function does not discriminate well. Alternately, if the distributions overlap minimally, then the function effectively discriminates between groups.

Consider the following geometric represntation of a two-group discrimant function (Figure 2.6.1). Ellipses A and B represent two groups, and variables X_1 and X_2 are measurements for each member of each group. Envision the scatterplot representing the association of X_1 and X_2 for each member of groups A and B. In Figure 2.6.1 stars represent variable measurements for members of group A and dots represent variable measurements for gorup B. The ellipses enclose for example 95% of the points in each group. Draw a line through the point of intersection where there are both stars and dots, and project that line to a new axis, Z. The overlap in univariate distributions A' and B', where the arrow points, is less than would be obtained by any other line drawn through the ellipses formed by the scatterplots (Green, Tull, Albaum, 1988).
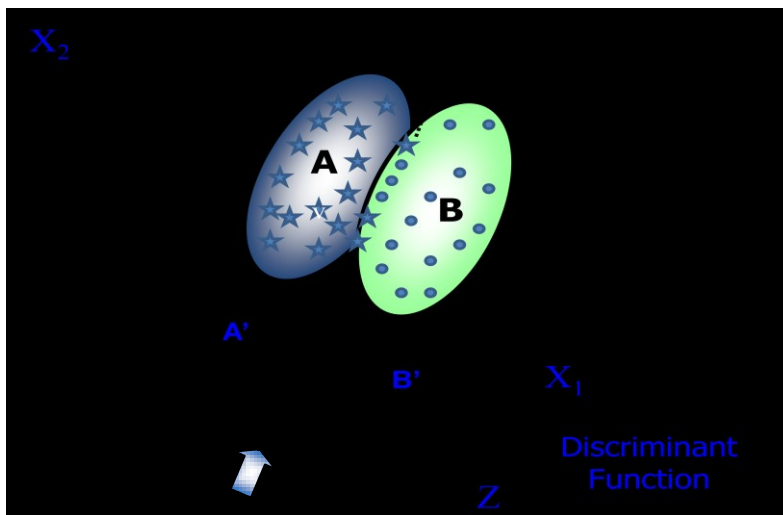
Figure 2.6.1   Two-group discriminant function

Note that on the Z axis are the discriminant scores, expressed as a single number, which represent the linear combination of original variables X_1 and X_2, condensing the profile information from both groups, inclusive of the difference information.

After deriving the linear combinations of the independent variables, there are discriminant scores for each object in each group. The aim is to maximize the variance between groups and minimize variance within groups to separate them most efficiently (Hair, et al, p. 245).

Applying and interpreting discriminant analysis is similar to regression in that information is extracted from independent variables to predict a dependent variable. The difference is that in discriminant analysis the dependent variable is categorical, versus metric as in regression. Also, consider conceptual similarities with multivariate analysis of variance (MANOVA) where the dependent variable is metric and independents are categorical. In discriminant analysis, the inverse is true. Metric independent variables are used to predict or classify cases into the categories of the dependent variable.

In regression, the researcher typically reviews correlations to select viable candidate independent variables, whereas in discriminant analysis, one considers mean differences between the groups as a directional starting point. Identifying significant differences between groups is intrinsic to beginning to develop the discriminant function.

Linear Discriminant Analysis

Hastie, Tibshirani and Friedman (2001) suggest that decision theory for optimal classification requires class posteriors $\Pr(G \mid X)$. Consider $f_k(x)$ the class-conditional density of X in class $G = k$, and the probability of k as the prior probability of class k with $\sum_{k=1}^{K} \pi_k = 1$. Applying Bayes theorem gives

.

$$\Pr(G = k \mid X = x) = \frac{f_k(x)\pi_k}{\sum_{l=1}^{K} f_l(x)\pi_l}$$

Thus, if the π_l are known, having $f_k(x)$ is virtually equivalent to having the quantity $\Pr(G = k \mid X = x)$.

Model each class density as multivariate Gaussian:

$$f_k(x) = \frac{1}{(2\pi)^{p/2} \left| \sum_k \right|^{1/2}} e^{-1/2(x-\mu_k)^T \sum_k^{-1} (x-\mu_k)}$$

Linear discriminant analysis (LDA) is used when equal covariance matrices are assumed for the classes. Test homogeneity of covariance matrices with Box's M test which will be discussed later. The comparison of two classes, say k and l, yields an equation linear in x, which can be seen by looking at the log-ratio:

$$\log \frac{\Pr(G = k \mid X = x)}{\Pr(G = l \mid X = x)} = \log \frac{f_k(x)}{f_l(x)} + \log \frac{\pi_k}{\pi_l}$$

$$=$$

$$\log \frac{\pi_k}{\pi_l} - \frac{1}{2}(\mu_k + \mu_l)^T \sum{}^{-} (\mu_k - \mu_l) + x^T \sum{}^{-} (\mu_k - \mu_l).$$

Equal covariance matrices allow for cancellation of the normalization factors, as well as the quadratic part in the exponents. Thus the linear log-odds function suggests that the decision boundary between the classes k and l (the set where $\Pr(G = k \mid X = x) = \Pr(G = l \mid X = x)$), is linear in x; in p dimensions a hyperplane (Hastie, et al, p 86).

Figure 2.6.2 attempts to show three Gaussian distributions, with the same covariance and different means. The 95% confidence contours and class centroids are included. There are 3 classes and 2 discriminating functions, *p* =*2*. The Bayes decision boundaries between each pair of classes are represented by the dashed lines, while the fitted LDA decision boundaries separating all three classes are the solid lines (a subset of the pair boundaries). These decision boundaries are not the perpendicular bisectors of the line segments joining the centroids, which would be the case if the covariance Σ were spherical $\sigma^2 \mathbf{I}$, and the class priors were equal (Hastie, et al, p. 87).
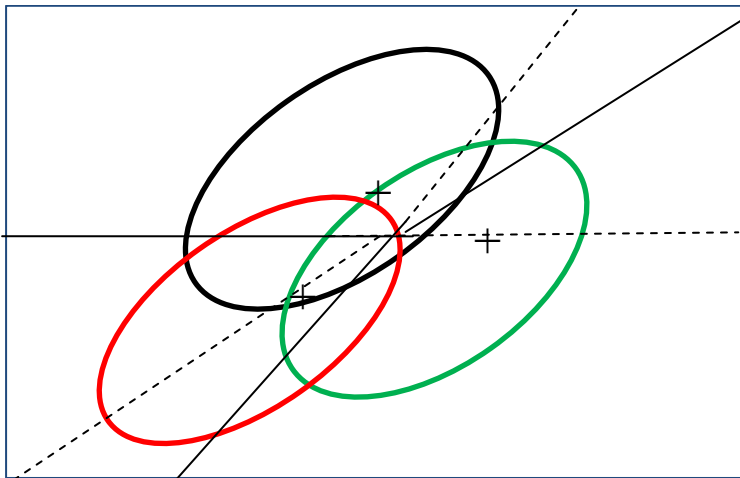
Figure 2.6.2 Solid lines representing fitted LDA boundaries, 3 Gaussians

From the log ratio of the classes as defined earlier, one can then define the linear discriminant functions as

$$\delta(x) = x^T \sum{}^{-1} \mu - \frac{1}{2} \mu \sum{}^{-1} \mu + \log \pi \quad .$$

This is equivalent to the description of the decision rule, with $G(x) = \arg\max_k \delta(x)$. Since the parameters of the Gaussian distributions are likely to be unknown in practice, they are estimated using training data where

$\pi = N_k / N$, where N_k is the number of class *k* observations

$\mu = \sum_{g_i = k} x_i / N_k$

$\hat{\sum} \sum = \sum = (x_i - \mu)(x_i - \mu)^T / (N - K).$

If the covariance matrices are unequal, which can be determined with Box's M test, there are not the convenient cancellations, and the results of our analysis will utilize quadratic discriminant functions (QDA),

$$\delta_{\cdot}(x) = -\frac{1}{2}\log\left|\sum{}_{k}\right| - \frac{1}{2}(x-\mu_{\cdot})^{T}\sum{}_{k}^{-1}(x-\mu_{\cdot}) + \log\pi_{\cdot}$$

Thus, the decision boundary between each k and l pair is described by a quadratic equation $\{x : \delta_{\cdot}(x) = \delta_{\cdot}(x)\}$.

Box's M Test

A key question then, in determining the specific procedure to be implemented, is whether the classes have a common covariance matrix $\sum_{k} \forall k$. As mentioned earlier, homogeneity of class covariance matrices is tested with Box's M test. Box (1949) derived a test statistic based on the likelihood-ratio test, for moderate to small sample sizes, with an F approximation used to compute its significance.

The jth set of r dependent variables in the ith cell are

$$y'_{\cdot} = c'_{\cdot}B + e'_{\cdot}$$

where

$$e_{ij} \sim N_{r}(0, w_{ij}^{-1}\sum{}_{i})$$
$$\text{for } i = ,...,g \text{ and } j = ,...,n_{i}$$

and where g is the number of cells with non-singular covariance matrices, and w_{ij} is the regression weight associated with y_{ij}, and $w_{ij} > 0$.

To clarify, one tests the equality of the covariance matrices of the independent variables, across the groups, or classes, of the dependent variable (Hair et al, p. 236). If the test does not exceed the critical value, it is deemed insignificant and equality of covariance matrices is assumed. If the test indicates a statistically significant difference between independent variable covariance matrices across groups, then the discriminant analysis proceeds, using techniques for separate covariance matrices.

Box's M is said to be particularly sensitive to deviations from normality (*Statsoft Electronic Textbook*, 2008), the size of the covariance matrices, and number of groups (Hair et al, 254). A conservative approach is suggested (0.01 instead of 0.05) when determining if true differences are present within the groups. As sample size increases, or the number of groups, or the number of independent variables increases, even more conservative levels are considered acceptable.

Classification can be negatively impacted by unequal covariance matrices. Hair et al suggest that if sample sizes are small and covariance matrices unequal, the statistical significance of the estimation process is compromised. What is common, is unequal covariances among groups of reasonable sample size, yet where observations are over classified into groups with larger covariance matrices. Either the sample size can be increased, or separate, group-specific, covariance matrices can be used for classification. In this case, cross-validation is required. Briefly, cross-validation assures internal validity, estimating the discriminant model by leaving out one case then predicting that case with the estimated model. Continuing the process for each observation, no one observation ever influences the model that predicts its classification.

Assumptions

In addition to a preference for multivariate normality of the independent variable, and homogeneity of variance and covariance structures of dependent variable groups as discussed, the researcher must be wary of multicollinearity as measured by tolerance values. Essentially, independent variables in the model should not be predictable by one another, thus adding limited insight into the explanation of the dependent variable, or class in the case of discriminant analysis. Review tolerance values to guard against an ill-conditioned matrix which is one with redundant variables being used to discriminate between categories. Tolerance is measured as $1 - R^2$ of a specific variable with all other variables included in the current model, indicating the proportion of variance that is unique to the specific variable. The measure should approach 1, and variables with measurements approaching 0 considered redundant. Violations of multivariate normality can impact estimation, while unequal covariance matrices yield their effects on classification, and multicollinearity among independent variables adversely affects interpretation.

Application to Job-Seeker Data

Applying the concepts discussed thus far to the job-seeker dataset, the factor scores and their interaction effects are considered as independent variables to potentially predict job-seeking status. Starting with the four factor scores for each case, namely SUPERVISOR, COMPANY, OPPORTUNITY and QUALITY of WORK-LIFE, and in order to understand the impact of interaction among these variables, six new variables were created to represent such interaction:

SUPV*COMP
SUPV*OPPTY
SUPV*QWL
COMP*OPPTY
COMP*QWL
OPPTY*QWL

Normality Issues

Shapiro-Wilk's test for normality suggests the factor scores and the interaction variables not normally distributed. In all cases, *p* values were essentially 0, thus we reject the null of normality.

Factor	W-statistic	p-value
SUPERVISOR	.9859	$p = 0$
COMPANY	.9770	$p = 0$
OPPORTUNITY	.8752	$p = 0$
QUALITY OF WORK-LIFE	.9742	$p = 0$
SUPV*COMP	.8886	$p = 0$
SUPV*OPPTY	.8146	$p = 0$
SUPV*QWL	.9124	$p = 0$
COMP*OPPTY	.7828	$p = 0$
COMP*QWL	.9213	$p = 0$
QWL*OPPTY	.5843	$p = 0$

Table 2.6.1 Shapiro Wilk's test does not suggest normality.

Garson (2009) suggests that discriminant analysis will be robust against violations of normality if the smallest group has more than twenty cases and the number of independents is fewer than six. Each of the seeking categories far exceeds the data quantity requirement, yet the final discriminant model uses seven independents, two more than the recommended number. We move forward with an understanding that the departures from normality may negatively impact estimation.

Variable Selection and Procedure

The four constructs (factors) plus their interaction effects (as six new variables) were used as independent variables in the discriminant analysis procedure. The grouping, or dependent, variable was job-seeking status, specifically job-seeker, passive or non-seeker. Within the discriminant analysis process, the stepwise estimation procedure was specified which estimates the discriminant function by entering the independent variables sequentially, according to the discriminatory power they add to the prediction of group membership.

Keeping in mind the analytical process described above, first consider the significant differences between the groups (seeker, passive, non-seeker) given the independent variables used in building the discriminant function for classification. Table 2.6.2 provides the significant differences on the 10 independent variables to be used in the analysis – 4 factors plus 6 interaction variates, with regard to seekers versus passives. For simplicity, only the variates with significant differences between the means of two groups are reported, along with their respective t-statistics derived from the independent samples t-test, and the mean difference.

	Seekers Group 1 n=1051	Passives Group 2 n=410	T Stat	Sig. 2 tailed	Mean diff
COMPANY	-.236	.413	-13.019	.000	-.650
SUPERVISOR	-.140	.228	-6.811	.000	-.369
QUALITY of WORK-LIFE	.081	-.147	3.980	.000	.228

Table 2.6.2 Significant differences seekers vs. passives on 4 factors, 6 interactions

The table suggests substantial differences between seekers and passives on perceptions of COMPANY, followed by SUPERVISOR, and QUALITY of WORK-LIFE. The implication is that these mean differences will yield good discriminators between these two groups.

Next, consider significant differences between passives and non-seekers with regard to the 10 variates that will be used in the discriminant analysis (Table 2.6.3). Recall that seekers and passives evidenced significant differences on only three factors (COMPANY, SUPERVISOR, and QUALITY of WORK-LIFE), whereas groups 2 and 3, passives and non-seekers, evidence more differences based on interaction effects. From this, one might infer that the passive candidate transitions to seeking if a significant change in the company, supervisor or quality of work-life is perceived.

Further, a non-seeker may move to a passive (would consider changing jobs given the right situation), and vice-versa, if a significant change is perceived in both quality of work-life and alternate opportunities, simultaneously. The same holds true in that there is a significant difference in perceptions of non-seeker vs. passive regarding the interaction effects of COMPANY and OPPORTUNITY. It is suggested that these factors and their interactions can serve as a catalyst for transition between seeking states. The discriminant analysis enables one to ascertain the variates that most effectively classify a case (i.e. employee).

	Passives Group 2 n=410	Non-seekers Group 3 n=93	T Stat	Sig. 2 tailed	Mean diff
QWL*OPPTY	-.044	.749	-2.68	.008	-.787
COMP*OPPTY	.078	-.435	2.84	.005	.514
OPPORTUNITY	-.033	-.490	2.95	.004	.456
COMPANY	.413	.851	-5.56	.000	-.438
SUPV*COMPANY	.052	.453	-3.81	.000	-.400
SUPERVISOR	.228	.578	-4.23	.000	-.350

Table 2.6.3   Significant differences passives vs. non-seekers on 4 factors, 6 interactions

Returning to the three-group discriminant analysis, recall that given three groups, the result will be two discriminant functions which are dimensions, each separate and distinct from the other, that separate the groups and will ultimately be used to classify new cases into group membership.

Hair et al, suggest overall sample size should be a ratio of 20 observations for each predictor variable. The approach taken here is quite conservative given that if all 10 variables are entered and used in the stepwise analysis, 200 cases would be needed. This dataset is comprised of a total of 1554 (1051 group 1 seekers, 410 group 2 passives, and 93 group 3 non-seekers). Additionally the practical guideline of at least 20 observations per category is maintained. This is particularly true with regard to cross-validation and hold-out (also called validation) samples. Subsamples are created for purposes of estimation, and both internal and external validation. The first subsample is the analysis or estimation sample, typically comprised of 70-75% of the dataset, with a second set of 25-30% held out at random. This second set, the validation or hold-out sample, is used to apply the discriminant function(s), and subsequently classify a group of new cases without having used those cases to estimate the functions, thus reducing bias and assessing external validity. As discussed earlier, internal validity is achieved with a leave-one-out cross-validation process, in which each case is individually predicted by the others yielding a more conservative estimate of classification accuracy (often by just a few percentage points, but the results add insight by category).

An additional consideration at this point is a priori knowledge of group membership, and the size of groups. The job-seeker dataset adds a level of complexity because the group sizes in the sample are substantially varied, and not necessarily representative of the population. Further, respondents completed the survey within the context of an online job-search engine, so the total sample is more representative of job-seekers. However, because the overall research objective is to be able to identify seeking status without

directly asking the question, and there are 3 groups into which the respondent will naturally fall (seeker, passive, non-seeker), utilize equal priors for all groups (i.e., .33 for each group). Hair et al (p. 261) support a conservative approach of equal priors when the researcher is unsure whether the observed proportions in the sample are representative of the population proportions.

In an optimal situation where this analysis is applied in a specific organizational setting, or is industry-specific, or applied to a particular geographic region or country, the researcher would want to ensure greater randomness in the sampling procedure, and apply any a priori knowledge of current levels of job-seekers, passives and non-seekers. Typically, these proportions are somewhat dynamic. At the time of data collection in early 2007, prior to a serious weakening in the global economic condition, job-seeking or passiveness while in a current position was likely to be more prevalent, whereas secure positions (yielding more non-seekers) are likely to be more appreciated in an economic downturn. It is important to note the value of the less biased dataset used here in that these findings are likely to be more representative of the common condition.

Another issue is that Box's M is, in fact, significant given the job-seeker dataset, suggesting the use of separate covariance matrices, which in turn negatively impacts classification accuracy. As mentioned earlier, Box's M is sensitive to large sample sizes, large numbers of predictors, and large numbers of groups, all of which are basically true here. Hair et al suggest a less conservative approach to maintaining the assumption of equal covariance matrices, and *Statsoft* researchers go so far as to suggest that because Box's M is particularly sensitive to deviations from multivariate normality (of which there is evidence), it should not be taken "too seriously."

The classification results for both methods, pooled covariance matrices and separate, were validated by running the discriminant analysis three times, producing an average result discussed in the upcoming Classification and Assessment of Accuracy section. Overall the use of separate covariance matrices resulted in negligible impact on classification of seekers, with a 1.3% reduction in accuracy; a more serious negative effect on classifying passives, at a 3.3% reduction in accuracy; and roughly a 2% (1.96) decrease in ability to classify non-seekers. These results are based on the most conservative hold-out validation sample which uses the estimation (or analysis) set to derive the discriminant function(s), and subsequently classify the hold-out sample cases without having used those cases to estimate the functions. Both methods, for all groups, surpass the standard classification hit ratio criterion of 41.25%

(Hair et al, p. 265) for one-fourth better than chance accuracy for discriminating between three groups (see Table 2.6.11 and Table 2.6.12)

Two computational methods are offered in developing the discriminant functions. Either all independent variables can be entered simultaneously, where discriminatory power is tested with Wilks' lambda, or stepwise where Mahalanobis' D^2 measures most appropriately assess fit. In most cases both methods are tested, but since ten variables are under consideration regarding the job-seeker data, the stepwise method is employed. Given utilization of the stepwise method, the advantage of using the Mahalanobis' D^2, which is based on generalized squared Euclidean distance that adjusts for unequal variances, is that it is computed in the original space of the predictor variables rather than a collapsed version as in other measures (Hair, et al, p. 258). The measure is based on correlations between variables and is useful in identifying similarities of an unknown sample set to a known one. It is different from the Euclidean distance because of the consideration of correlations and that it is scale invariant.

More specifically, Mahalanobis distance, also called quadratic distance, measures the separation of groups of objects using group means, and covariance matrix S (Mahalanobis 1936). The Mahalanobis distance of a multivariate vector $x = x_1, x_2, x_3, ..., x_n)^T$, from a group of values with mean $\mu = \mu, \mu, \mu, ..., \mu)^T$ is defined as:

$$D_M(x) = \sqrt{(x - \mu)^T S^- (x - \mu)} .$$

The measure becomes more important as the number of predictors increases because it does not result in reduced dimensionality, which would in turn, cause loss of information due to decreased variability in the independent variables. Thus Mahalanobis' D^2 is the preferred method when using stepwise procedures because the researcher utilizes the maximum amount of available information. Using this distance measure in the stepwise procedure allows the sequential selection of the variables with statistically significant differences across groups while maximizing the distance between the two closest groups. Thus, these variables maximize the discrimination between the most similar groups at each stage of the stepwise analysis.

Model Estimation and Assessment of Model Fit

The stepwise discriminant analysis procedure applied to the job-seeker data, yields two discriminant functions (number of groups minus one). The first function explains the largest amount of variance in the discriminant groups,

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and the second which is orthogonal and independent of the first, explains the largest amount of the remaining variance. The general task at hand then is to calculate the discriminant scores for each observation, evaluate group differences on the discriminant scores to ensure that the function does in fact discriminate effectively between groups, and then assess how well the function classifies.

The significance of the discriminant functions is validated by Wilks' lambda which provides a measure of how well each function separates cases into groups. It is equal to the proportion of total variance in the discriminant scores *not explained* by differences among groups. Smaller values of Wilks' lambda suggest greater discriminatory ability of the function. (Table 2.6.4).

Wilks' Lambda				
Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1 through 2	.760	302.92	14	.000
2	.984	17.88	6	.007

Table 2.6.4   Validation of significance of discriminant functions

Further, as Table 2.6.4 indicates, Chi-square values testing the null hypothesis of equality of means of the functions listed, suggest significant differences implying that the functions do far better than chance at separating the groups. Standardized discriminant function coefficients with large absolute values correspond to variables with greater discriminating power. Hair, et al suggest a threshold of .40 for significance when discerning variables with substantial contributory ability. A review of the standardized discriminant function coefficients (Table 2.6.5) suggests that COMPANY is the most discriminating variable on the first function at .786, followed by SUPERVISOR at .560. The interaction effects of QUALITY of WORK-LIFE and OPPORTUNITY play the primary discriminatory role for the second function.

Standardized Canonical Discriminant Function Coefficients		
	Function	
	1	2
SUPV	.560	-.013
COMP	.786	-.365
OPPTY	-.213	-.311
QWL	-.218	.026
SUPV*CO	.329	.325
COMP*QWL	-.202	-.169
QWL*OPPTY	.065	.678

Table 2.6.5 Discriminant function coefficients

It is also worthwhile to consider the structure matrix which provides the correlation of each predictor variable with the discriminant function (Table 2.6.6).

Structure Matrix		
	Function	
	1	2
COMP	.710	-.400
SUPV	.455	-.019
QWL	-.197	.014
SUPV*OPPTY	.042	-.023
QWL*OPPTY	.182	.786
OPPTY	-.190	-.535
SUPV*CO	.211	.342
COMP*QWL	-.112	-.253
COMP*OPPTY	-.017	-.129
SUPV*QWL	-.040	-.089

Table 2.6.6 Structure matrix, correlation of factors and interaction variables with function

Intuitively, it makes sense that an employee's perception of stability is initially impacted by the company itself, followed by one's relationship with a supervisor. Given the states of these two factors, or the first function, it then follows that the employee's perceptions of external influences (QWL*OPPTY) can serve as a catalyst to transition states, particularly if the individual is highly influenced by potential outside opportunities.

The stepwise results add insight to this intuition (Table 2.6.7) by clarifying the impact of each variable in the analysis on separating specific groups. For example, the COMPANY factor (sometimes referred to here as a variable or variate, but recall that each of these are actually factors comprised of scores from multiple variables) clearly differentiates non-seekers from passives. In effect, if the employee is highly satisfied with the company (proud to work there, thinks the company is honest, provides valuable products and services, etc.), he/she is more likely to be a non-seeker (group 3). When the score for COMPANY erodes, a transition to the passive state (group 2) is likely to follow. The same holds true for QWL*OPPTY; as these elements become more attractive, more influential, non-seekers may begin to consider seeking.

STEPWISE analysis - Variables Entered/Removed[a,b,c,]							
Step	Entered	Min. D Squared					
		Statistic	Between Groups	Exact F			
				Statistic	df1	df2	Sig.
1	COMP	.152	2.00 and 3.00	7.967	1	1105	.005
2	QWL*OPPTY	.500	2.00 and 3.00	13.075	2	1104	2.442E-6
3	SUPV	.640	2.00 and 3.00	11.135	3	1103	3.340E-7
4	SUPV*CO	.831	2.00 and 3.00	10.829	4	1102	1.298E-8
5	COMP*QWL	.860	1.00 and 2.00	35.583	5	1101	7.930E-34
6	QWL	.902	1.00 and 2.00	31.068	6	1100	1.321E-34
7	OPPTY	.919	1.00 and 2.00	27.118	7	1099	1.740E-34
At each step, the variable that maximizes the Mahalanobis distance between the two closest groups is entered.							
a. Maximum number of steps is 20.							
b. Maximum significance of F to enter is .05.							
c. Minimum significance of F to remove is .10.							

Table 2.6.7   Stepwise results – 7 variables in the final discriminant function

Group Differences on Discriminant Scores

To assess significant differences between the discriminant scores for classes of job-seeking status, t-tests for significance of differences between the means of two groups were conducted (Table 2.6.8 and Table 2.6.9). In all cases significant differences were identified between the mean discriminant scores of each group, as determined by functions 1 and 2.

	Seekers Group 1 n=1051	Passives Group 2 n=410	T Stat	Sig. tailed	2	Mean diff
Discriminant scores Function 1	-.332	.535	-15.31	.000		-.867
Discriminant scores Function 2	.024	-.170	3.46	.001		.194

Table 2.6.8 Significant differences - mean discriminant scores for seekers vs. passives

	Passives Group 2 n=410	Non-seekers Group 3 n=93	T Stat	Sig. tailed	2	Mean diff
Discriminant scores Function 1	.535	1.43	-7.61	.000		-.897
Discriminant scores Function 2	-.170	.369	-2.61	.010		.53

Table 2.6.9 Significant differences - mean discriminant scores for passives vs. non- seekers

Classification and Assessment of Accuracy

Once a set of q variables has been selected, as in the stepwise results above (Table 2.6.7), the classification function (Fisher's linear discriminant function) is computed as:

$$b_{ij} = (n - g)\sum_{l=1}^{q} w_{il}^{*}\bar{x}_{lj} \quad i = 1,2,\ldots,q \quad j = 1,2, \ldots, g \quad \text{for the coefficients, and}$$

$$a_{j} = \log p_{j} - \frac{1}{2}\sum_{i=1}^{q} b_{ij}\bar{x}_{ij} \quad j = 1,2,\ldots, q \quad \text{for the constant,}$$

where p_j is the prior probability of group j.

Table 2.6.10 provides the classification function coefficients used to assign cases to groups of seekers, passives and non-seekers. There is a separate function for each group. For each case, a classification score is computed for each function and each case is assigned by the model to the group whose classification function obtains the highest score.

Classification Function Coefficients			
	Seeker 1, Passive 2 Non-seeker 3		
	1	2	3
SUPV	-.197	.346	.834
COMP	-.315	.547	1.053
OPPTY	.077	-.066	-.431
QWL	.072	-.141	-.317
SUPV*CO	-.066	.150	.557
COMP*QWL	.044	-.108	-.369
QWL*OPPT	-.010	-.066	.269
(Constant)	-1.161	-1.286	-2.227

Table 2.6.10 Fisher's linear discriminant functions

To assess classification accuracy for discriminant analysis of the job-seeker data, the estimation sample, a hold-out sample and a cross-validation sample are considered. Moreover, three separate discriminant analyses were run, under the same procedure, yet using a new validation sample each time. The results of these three tests are averaged and discussed.

Table 2.6.11 provides a summary of three tests of validation which provide an average hold-out sample classification rate of 66.4% for seekers, 48.1% for passives, and 50.5% for non-seekers. All classifications based on the most conservative approach, the hold-out sample, surpass the three-group hit-ratio standard of 41.25% (33% standard probability for 3 groups x 1.25 as suggested by Hair et al).

In the cross-validation sample, seekers are correctly classified an average of 65.1% of the time, passives are correctly classified an average of 47% of the time, and non-seekers were correctly classified an average of 52.9% of the time, which again all exceed the standard chance criterion of 41.25%.

In the least conservative estimation (or analysis) sample, the results are 65.5% accuracy for seekers, 47.6% for passives and 55.5% for non-seekers. Full results for the classification matrices from the three validation tests (using pooled covariance matrices) are found in Appendix B.

Percent Average Correct Classification – POOLED Covariance Matrices			
	Seekers	Passives	Non-seekers
Estimation Sample			
Test 1	66.8	49.8	43.8
Test 2	64.0	50.2	56.5
Test 3	65.6	42.9	66.1
AVERAGE	65.5	47.6	55.5
Cross-validation Sample			
Test 1	66.8	49.5	43.8
Test 2	63.5	48.9	53.6
Test 3	64.9	42.6	61.3
AVERAGE	65.1	47.0	52.9
Hold-out Sample			
Test 1	67.0	50.0	45.0
Test 2	67.8	47.3	42.4
Test 3	64.4	46.9	64.1
AVERAGE	66.4	48.1	50.5

Table 2.6.11 Average correct classifications from 3 validation tests
Pooled covariance matrices

Recall the earlier discussion regarding the significance of Box's M, suggesting the use of separate covariance matrices (quadratic linear analysis). Although liberties are taken with the assumption of equal covariance matrices, an attempt is made to justify classification based on pooled covariance matrices discussed above.

Minimal change occurs by using separate covariance matrices (Table 2.6.12) with only slight deterioration of classification accuracy, primarily in the passive category with an erosion of 3.3% within the conservative hold-out sample. Accuracy deteriorates only 1.3% for seekers and 2% for non-seekers based on the hold-out sample. Comparing the estimation samples, separate covariance matrices perform slightly better for seekers and passives, yet substantially worse (by 10%) in the non-seeker category. In all analyses, and for each category, the model performs substantially better than chance.

Percent Average Correct Classification – SEPARATE Covariance Matrices			
	Seekers	Passives	Non-seekers
Estimation Sample			
Test 1	66.8	59.5	26.6
Test 2	66.9	37.7	61.9
Test 3	63.4	50.9	47.9
AVERAGE	65.7	49.3	45.5
Hold-out Sample			
Test 1	63.8	53.2	31.0
Test 2	67.3	38.1	60.0
Test 3	64.3	43.0	54.5
AVERAGE	65.1	44.8	48.5

Table 2.6.12 Average correct classifications from 3 validation tests
Separate covariance matrices

Press' Q

A final measure of classification accuracy, Press' Q, is more statistical in nature as it tests the discriminatory power of the classification matrix when compared to the chance model. The measure compares the number of correct classifications with the total sample size and the number of groups. This value is then compared with a critical chi-square value for 1 degree of freedom, with selected confidence, say .95. If the statistic exceeds the critical value (e.g. 6.68 for 95% confidence with 1 degree of freedom), then the classification matrix is considered statistically better than chance (Hair et al, p. 268).

$$Q = \frac{[N - n_{corr}g)]^2}{N(g -)}$$

where

N = Total sample size
n_{corr} = number of correctly classified observations
g = number of groups

To illustrate validity, consider the classification matrix derived from the discriminant analysis procedure described throughout this section (Table 2.6.13). Recall that validation tests were conducted three times and an average reported. Following is the classification matrix using the second validation set as the hold-out sample.

Classification Results [a,b,c,d]			True Grp	Predicted Group Membership			
				1	2	3	Total
Cases Selected	Original	Count	1	517	188	53	758
			2	86	127	73	286
			3	3	24	37	64
		%	1	68.2	24.8	7.0	100
			2	30.1	44.4	25.5	100
			3	4.7	37.5	57.8	100
	Cross-validated[a]	Count	1	516	188	54	758
			2	86	126	74	286
			3	3	26	35	64
		%	1	68.1	24.8	7.1	100
			2	30.1	44.1	25.9	100
			3	4.7	40.6	54.7	100
Cases Not Selected	Original	Count	1	196	79	18	293
			2	49	50	25	124
			3	3	12	14	29
		%	1	66.9	27.0	6.1	100
			2	39.5	40.3	20.2	100
			3	10.3	41.4	48.3	100
a. Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.							
b. 61.5% of selected original grouped cases correctly classified.							
c. 58.3% of unselected original grouped cases correctly classified.							
d. 61.1% of selected cross-validated grouped cases correctly classified.							

Table 2.6.13   Classification matrix validated with Press' Q statistic

The Press' Q statistics for the classification matrix discussed here are $Q =$ 641.86 for the estimation sample, $Q = 419.46$ for the cross-validation sample and $Q = 214.53$ for the hold-out sample. All far exceed the critical value of 6.68, suggesting a general sensitivity to large sample sizes which are more likely to evidence statistical significance for overall classification rates.

Below, Figure 2.6.3 depicts the amount of discrimination provided by the first discriminant function, based on the discriminant scores. While it is still challenging to discern seeking status based on the discriminant scores, substantial separation of the densities is evident. This first discriminant function accounts for approximately 95% of the discrimination with the second contributing only 5% (Figure 2.6.4). Thus, the balance of the discussion will cover only the first function.

Predicted Group Membership - Discriminant Function 1

Seeker=BLACK, Passive=BLUE,Non-seeker=RED
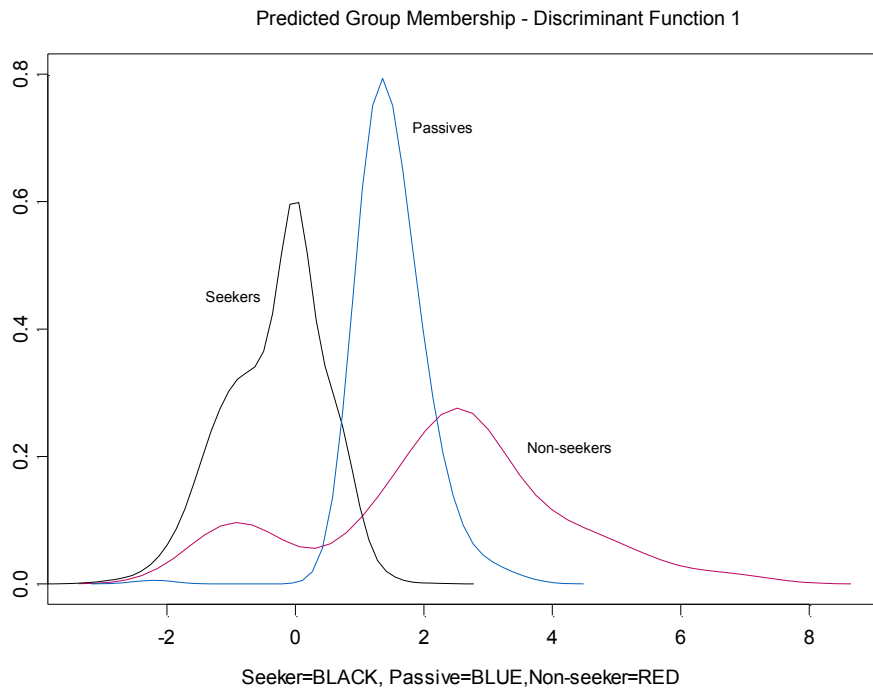
Figure 2.6.3 Separation produced by first discriminant function

Discriminant function 2

Seeker=BLACK, Passive=BLUE,Non-seeker=RED
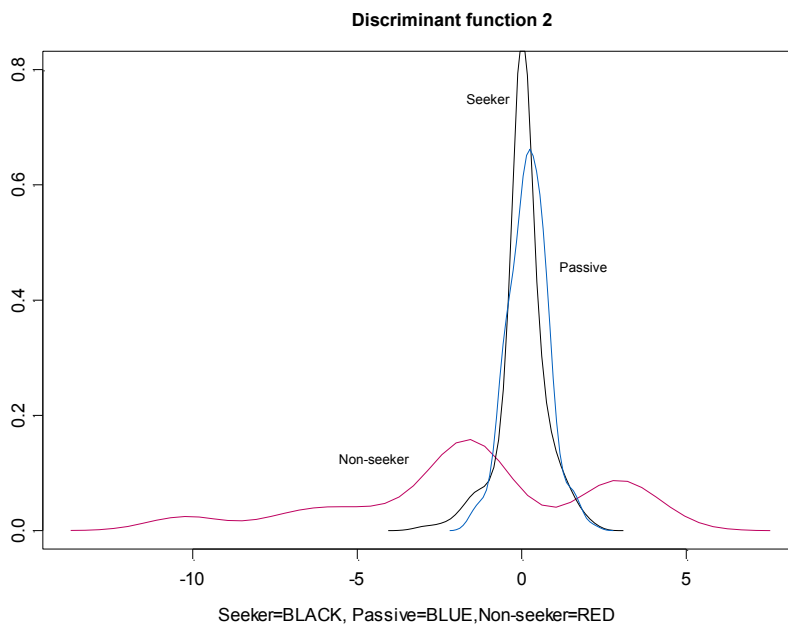
Figure 2.6.4   Separation produced by second discriminant function

A straightforward validation of the first function's discriminatory power is simply the descriptive statistics for the discriminant scores for each job-

seeking category (Tables 2.6.14 to Table 2.6.16). Seekers exhibit a mean of -.31, passives 1.5 and non-seekers 2.2.

Seekers

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
Discriminant Scores from Function 1 for Analysis 1	1555	-3.21	2.09	-.31	.754

Table 2.6.14   Seeker category discriminant score descriptive statistics

Passives

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
Discriminant Scores from Function 1 for Analysis 1	218	-2.19	3.51	1.5	.517

Table 2.6.15   Passive category discriminant score descriptive statistics

Non-seekers

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
Discriminant Scores from Function 1 for Analysis 1	44	-1.46789	6.74421	2.2	1.89

Table 2.6.16   Non-seekers category discriminant score descriptive statistics

Testing for significant differences between the discriminant score means of each of the job-seeking categories shows that all categories evidence significant differences. Between seekers (-.31) and passives (1.5), the mean difference between discriminant scores is 1.81, with a very substantial $t = -5.39$. Between passives (1.5) and non-seekers (2.2) the mean difference is -.72, with $t = -.51$

While the second function does not offer much graphic stimulation as evidenced by Figure 2.6.6, it does still serve to deliver another five percent discrimination, and there are significant differences between the mean discriminant scores for each category. Between seekers and passives, the mean difference is .15 and $t = -3.08$. Between passives and non-seekers, the mean difference for the second discriminant function .18 and $t = 3.2$, still significant at $p < .01$.

Discussion

Discriminant analysis techniques have allowed a reasonably accurate classification of job-seeking status, well exceeding chance. As expected, the most challenging group to classify is the passive employees even though significant differences are identified between this group versus seekers, and versus non-seekers.

Utilizing the stepwise procedure, plus subsequent investigation of the structure matrix (examining the correlation between variables and the discriminant function), suggests the most discriminatory constructs of satisfaction and influence to be COMPANY, followed by the interaction of QUALTIY of WORK-LIFE * OPPORTUNITY, and finally SUPERVISOR. All three are helpful in discriminating between passives and non-seekers.

2.7   Building a Generalized Additive Model to Predict Job-Seeking Status

Reasoning and Goal

In section 1.4 the general problem of classifying job-seeking status was discussed as were some of the limitations related to the objective measurement of loyalty. Regression models were briefly considered as a data analytic tool for understanding the impact of different inputs on loyalty. As clarified in Sections 2.2 and 2.3, the job-seeking status data is clearly not normally distributed. Models such as the normal linear regression model are often used for prediction and classification rules, yet these traditional linear models often fail in application because in real life effects are often not linear (Hastie, Tibshirani & Friedman, 2001). Thus, a modeling method is sought that best handles non-Gaussian data, with multiple covariates, in a manner that enables the prediction of categorical data as in the job-seeking status case.

Generalized additive models (GAM) hold promise for marketing applications, particularly because of the relaxation of linearity constraints, yet their use in management and marketing contexts has been limited. Abe (1999) used the GAM framework in a multinomial discrete-choice context to identify threshold and saturation effects of a price promotion. This is particularly useful to marketers who typically set prices and determine promotional plans. Berg (2007) used GAM in a financial context to predict bankruptcy, simultaneously showing that the GAM outperformed linear discriminant analysis.

Very recently, researchers have shown how GAM can improve marketing decision making in a customer churn context (Coussement, Benoit, Van den Poel, 2010). The identification of risky customers, or employees in the job-seeking context, coupled with increased interpretability of existing models with graphics, offers managers and marketers a valuable decision making tool.

Generalized Additive Models

Generally speaking, generalized additive models can uncover predictor-response relationships in varied data structures without the requirement of a specific model (Cai, 2008). Stone (1985) proposed additive models to estimate an additive approximation to the multivariate regression function. Univariate smoothers are used, and estimates of the individual terms explain how the response variable changes with corresponding changes in the independent variables. The additive model has the form

$$E(Y \mid \mathbf{X}) = \sum_{1}^{p} s_j(X_j)$$

Two important extensions were developed from the additive model. Friedman and Stuetzle (1981) proposed the projection pursuit regression model:

$$E(Y \mid \mathbf{X}) = \sum_{}^{p} s_j(\alpha\ \mathfrak{l})$$

where numerical search is used to find the directional vectors, $\mathbf{a}_j$, while the $s_j(\cdot$'s are estimated by smoothers.

Breiman and Friedman (1985) introduced a generalization of the additive model by estimating a transformation of the response variable. The alternating conditional expectation (ACE) model:

$$E(\theta\ Y) \mid \mathbf{X}) = \sum_{1}^{p} s_j(X_j) .$$

Hastie and Tibshirani (1986, 1987) proposed generalized additive models as an alternative to likelihood-based regression models (e.g., normal linear, linear logistic) and other parametric models. Generalized additive models replace the linear form $\sum \beta_j X_j$ by a sum of smooth functions $\sum s_j(X_j)$. The $s_j(\cdot$'s are unspecified smooth functions, estimated with a scatterplot smoother. An algorithm is developed to simultaneously estimate all functions.

Hastie et al (2001) suggest easily mixing linear and other parametric forms with the nonlinear terms. This is essential when some of the inputs are qualitative variables. Nonlinear components in two or more variables, and separate curves in the X_j for each level of the factor X_k are acceptable, adding to the flexibility of the generalized additive model (GAM). The GAM can be used to identify and characterize nonlinear regression effects. Such models assume that the mean of the dependent variable depends on each of the additive predictors via a nonlinear link function. The probability distribution of the response variable can represent any member of the exponential family of distributions. In general, the conditional mean μ(X) of a response Y is related to an additive function of the predictors via a link function g :

$$g[\mu\ x)] = \alpha\ \cdot\ f_1(X_1) +\ ..+\ f_p(X_p).$$

The functions f_j can be flexibly estimated using an algorithm based on the scatterplot smoother, and can thus reveal nonlinearities in the effect of X_j.

Gentle (2002, p.304) explains that the appropriate form of the link function depends on the nature of the probability distribution, and Hastie et al (2001, p.258) identify examples of three classical link functions including:

- $g(\mu) = \mu$ is the identity link, used for linear and additive models for Gaussian response data
- $g(\mu) = \log(\mu)$ for log-linear or log-additive models for Poisson data
- $g(\mu) = \text{logit}(\mu)$ for two-class classification where the mean of the binary response $\mu(X) = \Pr(Y = 1 \mid X)$ is related to the predictors via a linear regression model and the *logit* link function:

$$g(\mu) = \log\left(\frac{\mu(X)}{1 - \mu(X)}\right) = \alpha + f_1(X_1) + \ldots f_p(X_p).$$

For more than two classes, as in the job-seeker data, the additive logistic regression model can be generalized further using a multinomial logit formulation as will be discussed in the application that follows.

Fitting an Additive Model

As mentioned earlier, the f_j's are unspecified smooth nonparametric functions which can each be fit using a scatterplot smoother. Then one subsequently develops an algorithm for simultaneously estimating all p functions. Hastie et al (2001, p. 260) suggest using cubic smoothing splines.

In a discussion on splines, Gentle (2002, p. 139) first recalls that a smooth approximation, $\hat{f}(x)$, is one that is continuous with continuous derivatives. The polynomials in $\hat{f}(x)$ cause undesirable oscillations, and if the function being estimated has different shapes in different regions of its domain, using the same polynomial over the full domain may not be accurate. The interval over which the function is being approximated can be subdivided, and a polynomial with a low degree can be used. Then, the piecewise polynomials can be summed to approximate any point. Using more and more subintervals may be impractical and complicated, so continuity restrictions are imposed on the piecewise polynomials and their derivatives. This describes the spline approach to approximation and smoothing.

In spline approximation, the basis functions are polynomials over given intervals and zero outside of those intervals, with specified contacts or "knots" at the endpoints which are their continuous derivatives of a specified order. The approximation $\hat{f}(x)$ is then formed as the sum of the piecewise polynomials, and this is the spline. The number of free parameters in each

interval is called the "order" of the spline. A common spline basis function is the natural polynomial spline in which the second derivative of the spline expansion is 0 for all x beyond the boundary knots. For natural cubic splines with k knots, there are k basis functions.

Hastie et al (2001, p. 259) recall the additive model with the form

$$Y = \alpha \cdot \sum_{j=1}^{p} f_j(X_j) + \varepsilon ,$$

where the error term has a mean zero. Given observations $x_i y_i$ the penalized sum of squares criterion is specified where

$$PRSS(\alpha \; f_1, f_2, ..., f_p) = \sum_{i=} \left\{ {}_i - \alpha \cdot \sum_{j=} (x_{ij}) \right\} + \sum_{j=} \lambda \int f'_j t_j)^2 dt_j ,$$

where the $\lambda \geq)$ are tuning parameters. The minimizer of this is an additive cubic spline model and each of the f_j functions is a cubic spline in the component X_j with knots at each of the unique values of x_{ij}, $i = 1,...,N$. Without further restrictions, the model is not unique, so the standard convention is to assume that $\sum_1^N f_j(x_{ij}) = 0 \forall j$, the functions average 0 over the data.

An iterative procedure for finding the solution is then suggested. Set $\alpha = ive(y_i)$ which never changes. Apply a cubic smoothing spline S_k (as does Yee in the VGAM procedure in R) to the targets

$$\{y_i - \alpha \cdot \sum_{j \neq k} \hat{f}_j(x_{ij})\}_1^N$$

as a function of x_{ik} to obtain a new estimate, $\hat{f}_k$. Do this for each predictor in turn, using the current estimates of the other functions, $\hat{f}_j$ when computing

$$y_i - \alpha \cdot \sum_{j \neq k} \hat{f}_j(x_{ij})$$

This process is called "backfitting" and the resulting fit is analogous to multiple regression for linear models (Friedman and Stuetzle, 1981).

Applying Non-parametric Multinomial Regression to Job-Seeker Data

The goal is to predict whether a subject is a seeker, passive or non-seeker. We can determine the probability with which the subject falls into each of these three seeking-status categories. The additive components are SUPV, COMP, OPPTY, and QWL. The VGAM procedure in R for generalized additive models uses the logit procedure for each of the three probabilities with the constraint that the sum of the probabilities is equal to one. The model for the multinomial logit procedure is

$$\log\left(\frac{p(y = i \mid \mathbf{X})}{1 - p(y = i \mid \mathbf{X})}\right) = \alpha_j + f_{1j}(\mathbf{X}) + \ldots + f_{pj}(\mathbf{X}).$$

See Yee (2010) for more on the case of a generalized *linear* model and the logit procedure to be used, or to download the VGAM library. Utilizing the VGAM procedure in R, and calling the family function `multinomial()`, a fairly flexible model can be fit to the job-seeker data, using three degrees of freedom. A second experiment is discussed in which two degrees of freedom were specified. Figure 2.7.1 shows the estimated functions for each of the predictors. The rug plot along the bottom of the frames indicates the observed values of the corresponding predictor. The discontinuity is evidenced at zero, clarifying nonlinearity, particularly for passives' quality of work-life rating. The u shaped trend suggests seeking probability decreases until it reaches a minimum. When the values for QWL become larger the chances of seeking are greater.
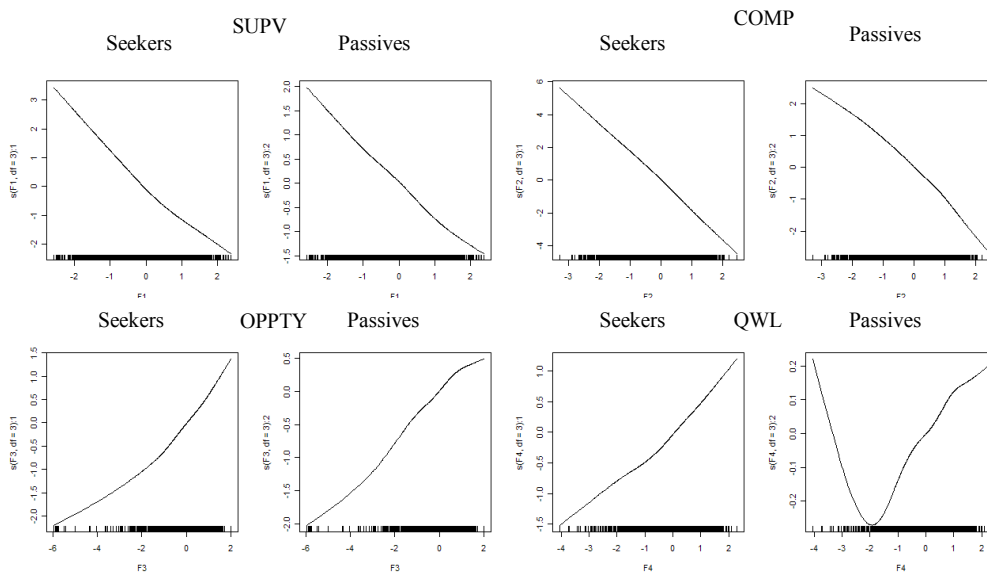
Figure 2.7.1 Functions at three degrees of freedom

For prediction, vary each of the four variables while holding the others constant. In this way, the prediction function is determined by the model (Figure 2.7.2).
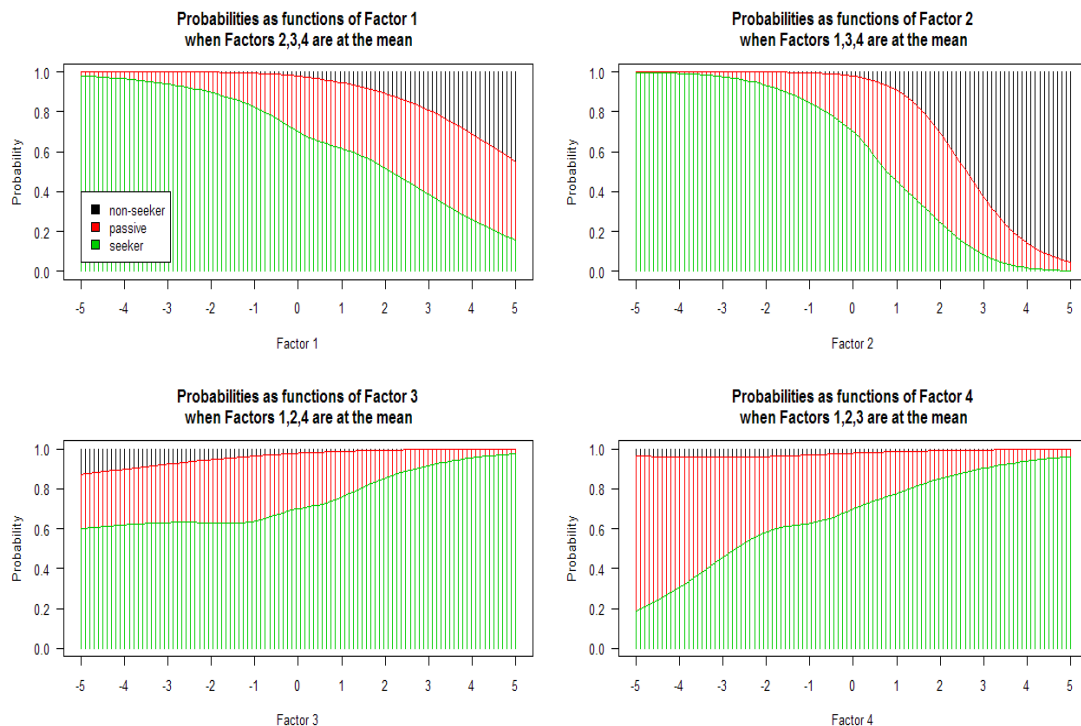
Figure 2.7.2 Varying each factor while holding others constant; three degrees of freedom

Results

Probability of seeking decreases as ratings for supervisor (factor 1, SUPV), increase. There is a fairly steep slope at the mean with a steady decrease in the likelihood of seeking as satisfaction with SUPV increases. The negative slopes separating seekers from passives, and passives from non-seekers are similar on the COMP factor 2, yet more dramatically separating passives from non-seekers as satisfaction with the company increases.

External opportunities (factor 3, OPPTY), including advancement, training, higher salary and better benefits are clearly not as influential to non-seekers. This is evident in that the non-seekers are primarily found below the mean zero, with only minor representation between zero and one. The probability of being a seeker increases steadily, but not dramatically, when external influences, or attraction/expected utility of alternatives (Mobley et al, 1979), increases. External influences related to quality of work-life (factor 4, QWL) have a fairly dramatic effect on separating seekers from passives as the influence of a potentially higher quality of work-life become more attractive.

This suggests that the probability of seeking increases as the influence of variables such as more flexible hours, the chance to work with a new supervisor, or for a potentially better company, increases.

The scores for an individual can be used in the predictive model to determine the probability of the person being in each of the seeking states. As an example, if a person scores 3 on the supervisor factor (F1), 2 on the company factor (F2), 2 on the opportunity factor (F3) and 1 on the quality of work-life factor (F4), we can specify these figures in the predictive model, resulting in an 18% probability that the subject is seeking a new position, a 26% probability that the subject is in a passive state, and a 56% probability that the subject is not seeking a new position. The person is most likely a non-seeker.

Experimenting with two degrees of freedom, the results are 13%, 24% and 63% respectively, which enhances the probability of non-seeking status (Figures 2.7.3 and 2.7.4). Overall, there is not a substantial visual difference between two and three degrees of freedom.
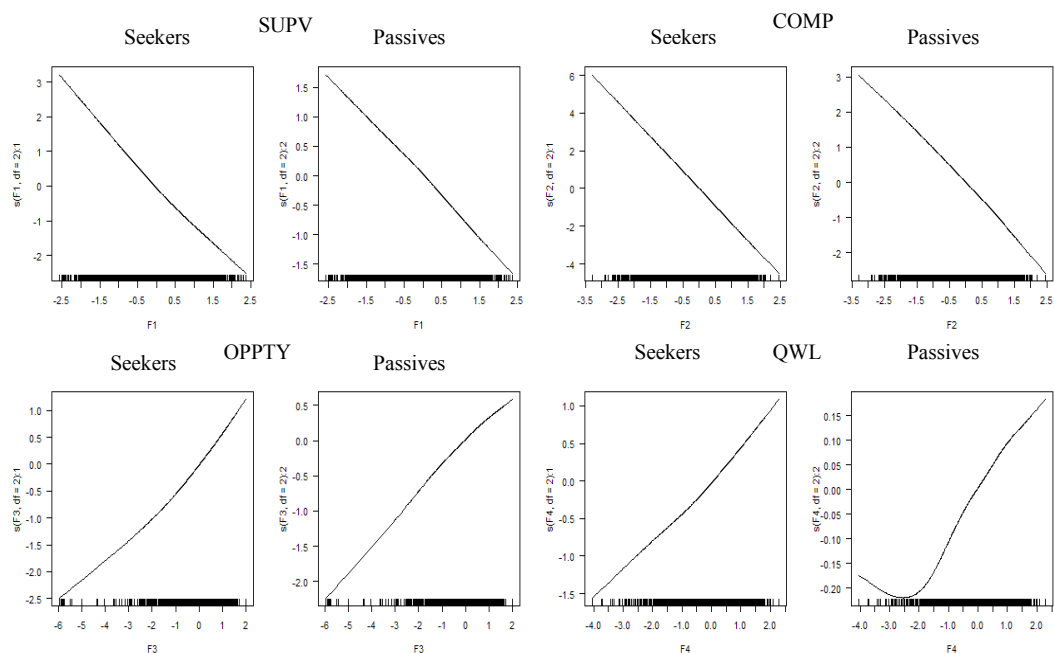
Figure 2.7.3 Functions at two degrees of freedom
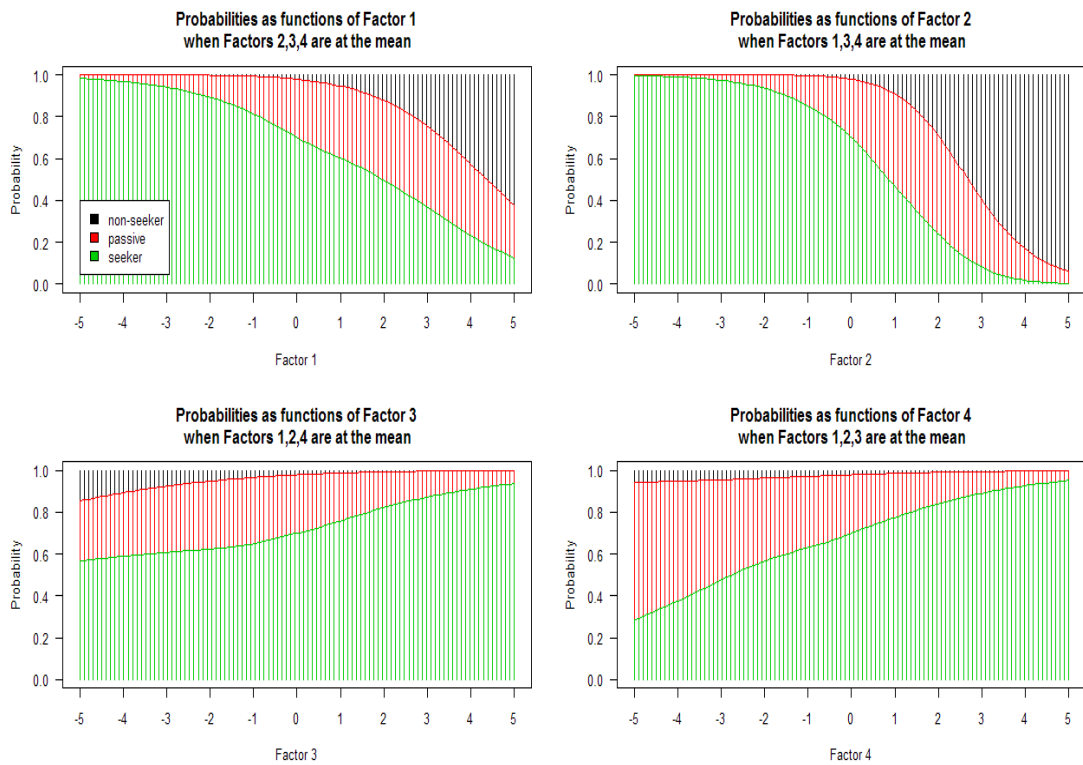
Figure 2.7.4 Varying each factor while holding others constant; two degrees of freedom

Implications

The generalized additive model provides an effective method for identifying seeking status of an individual employee. Further, the model has confirmed managerial intuitions and extant research regarding the impact of situational variables such as company and supervisor satisfaction as well as external influences related to opportunity and quality of work-life.

The predictive model enables an employer to determine an employee's probability of seeking by indirectly asking a simple set of questions.

2.8   Summary, Limitations and Future Research

The management issue addressed was measuring the stability of an organization with respect to the job-seeking status of its employees. Obtaining the true job-seeking status of an employee is challenging given the risk, or at least perceived risk, involved for the employee. A method has been developed and tested which enables the employer to ask a series of questions related to satisfaction with the company and supervisor, the influences of alternate opportunities, and quality of work-life, and ultimately use the responses to predict the likelihood that the employee is currently seeking a new position, passive, or not seeking.

A loyalty score was developed and its components were discussed thoroughly. An estimation process was detailed, and an application was made using the job-seeker dataset.

The motivation for this portion of the analysis was not only to defend the method used to develop the loyalty score, but also to better understand the underlying factors and how they potentially differ by seeking status. It is clear that significant differences exist between seekers, passives and non-seekers. The loyalty score enabled the identification of the amount of seekers and non-seekers given threshold scores, with 75% accuracy, but identifying the status of a particular employee would be impractical in a managerial setting.

The more valuable analytical methods used were factor analysis, reducing the variables to four underlying constructs; discriminant analysis to separate groups, and generalized additive models to classify seeking status. Discriminant analysis techniques delivered a reasonably accurate classification of job-seeking status, well exceeding chance. As expected, the most challenging group to classify is the passive employees even though significant differences are identified between this group versus seekers, and versus non-seekers.

A generalized additive model was built and tested which facilitates the classification of employees into seeking categories. The key contribution is that one can specify results based on factor scores in the predictive model, resulting in the probability of the subject falling into each of the three seeking-status categories. This is achieved without directly asking the employee about their current job-seeking status. Understanding the seeking status of the organization's employee base facilitates an objective measurement of stability. Further, it provides management with the ability to classify relative newcomers based on responses to satisfaction-type questions.

Limitations and Future Research

Some of the nineteen questions, related to external influences on job-seeking behaviors, may be more valuable to a loyalty scoring method if posed instead as satisfaction with the elements of one's current employment situation. Further, a response variable such as overall satisfaction with current job or with one's current company, or alternately one's supervisor, would facilitate linear regression more effectively versus using a measurement of "likelihood to recommend the company" as a dependent variable. Perhaps the question for loyalty measurement is "would you recommend your current position". However, any of these options would mean sacrificing measurements for the effects of external influences which is clearly important in the turnover literature (Mobley, 1979; Cater and Buffardi, 2004; Beauregard and Henry, 2009). The tradeoff in linearity is resolved here with nonparametric approaches, the most effective of which was the generalized additive model.

Generalized additive models (specifically the multinomial logit tested here) hold promise for predictive analytics in marketing and management applications where the data is not normally distributed. For example, brand switching behaviors in oligopolies such as wireless communication providers (e.g., three discrete choices, multinomial logit) could potentially be modeled with GAM. These models may also be appropriate for understanding leadership behaviors as related to or predictive of personal happiness. In the College Student Leadership Behaviors Study (next section) a need is identified for a response variable that measures leadership effectiveness. Perhaps the more important and valuable response outcome of leadership is one's personal happiness, self-reported in discrete categories. Resource allocation applications might include modeling franchisor or customer satisfaction, loyalty, or churn propensity, given multiple marketing and management inputs.

The challenge in management and marketing applications will be the communication of methods and results to non-statistical managers. However, managers will typically be very familiar with the variables or factors presented as covariates, and their intuitions can be supported by effective graphics that enable the visualization of non-linear relationships within customer or employee bases. Abe's work (1999) using generalized additive models to identify thresholds and saturation effects of price promotions should be of particular interest to marketers. After conducting effective modeling of the marketing or management issue with generalized additive models, software for an organization could be developed to generate easily-interpreted results.

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Classification and Analysis of College Student Leadership Data

Introduction

To briefly introduce this section, this work is comprised of a review of the leadership literature, particularly as it relates to personal development, followed by the validation of an assessment tool, and results from a survey dataset. This application focuses specifically on the development of college students as emerging leaders. Leadership studies colleagues Drs. Marcy Shankman, and Scott Allen sought this author's assistance in the development and validation of an assessment tool that would measure a student's self-perception of their own leadership behaviors. The collaborative work also resulted in a deeper focus on gender differences and involvement through the lens of emotionally intelligent leadership (Shankman, Haber, Facca, Allen, 2010).

Additional analyses were conducted to further demonstrate the appropriate applicability of statistical techniques given the dataset. These included an attempt at discriminant analysis which was not particularly fruitful given a lack of solid outcome variables since no external measurement of leadership effectiveness was available. However, cluster analysis proved to be useful in discerning groups and related leadership behaviors. Factor analysis revealed underlying constructs, and reliability analysis was used to validate the assessment tool.

The primary contribution is the development of a tool to help students self-assess their current leadership behaviors and focus on behaviors that can facilitate personal development and improvement of leadership skills. The assessment tool, or Emotionally Intelligent Leadership Inventory, is in press with Jossey-Bass, a Wiley Imprint, and will be available August 2010, as part of a collection of resources by Shankman, Allen, and Facca which also include a student workbook, a facilitator's guide, and a development guide.

1.1　College Student Leadership – Issues, Constraints and Literature

In his book, *Deeper Learning in Leadership: Helping College Students Find the Potential Within,* Roberts (2007) suggests that "leadership learning experiences will have the greatest substance and impact only when they take into account the existing research and the many available theories on leadership and its dynamics" (p. 41). Too often, leadership development lacks a foundation in theory which can limit the experience in a number of ways. Many (in varied industries) have explored the challenges inherent in translating theory into practice (e.g., Higginson, 2004; Rafferty, Allcock & Lathem, 1996). One challenge in the theory to practice gap can be the theory's ability to walk the tightrope of capturing the complexity of a topic while making the information accessible and digestible for the masses.

In the 1970s college student personnel administrators began writing about and working in the area of leadership development. One of the first comprehensive examinations of the topic was compiled by Roberts (1981), and while the topic remained present in subsequent years, it seems to have gained momentum in recent years. While there is a considerable amount of activity (Komives, Dugan, Owen, Slack & Wagner, 2006) and writing (e.g., Marshall & Hornak, 2008; Shankman & Allen, 2008; Komives & Wagner, 2009; Kouzes & Posner, 2008) on the topic, few scholars have developed theories or models specific to a collegiate audience.

However, two major models have been specifically designed with students in mind. The first, The Social Change Model of Leadership Development was funded by the Higher Education Research Institute (HERI). The authors had two primary goals for the model: (1) To enhance student learning and development; more specifically, to develop in each student participant greater leadership skills; and (2) to facilitate positive social change at the institution or in the community; to undertake actions which will help the institution/community to function more effectively and humanely (HERI, 1996, p. 19). The model examines leadership development from three different levels: (1) *The Individual*; (2) *The Group*; and (3) *The Community/Society*. In addition, the authors developed the "7 Cs" for leadership development for social change.

The second, is the Leader Identity Development Model (LID). The LID Model, identified six distinct stages: Awareness (Stage One); Exploration/Engagement (Stage Two); Leader Identified (Stage Three); Leadership Differentiated (Stage Four); Generativity (Stage Five); Integration/Synthesis (Stage Six). In essence, students move from a more hierarchical (the leader has the position) view of leadership to more of

connected/relational model of leadership (Roberts, 2007). According to Komives et al. (2009), "As that engagement happened, the student changed their *view of self with others* beginning in a dependent mode when in a follower role, then feeling independent when in a leader role, and finally recognizing interdependence with others" (p. 15).

This study introduces a third model designed specifically for young adults and emerging leaders. The goal was to provide a method to statistically assess an individual's leadership skill set, categorize them in comparison to others, and ultimately, based on the dataset, make suggestions for development. First, two primary theories are examined that comprise Emotionally Intelligent Leadership (EIL) – Emotional Intelligence and Contingency Theory. Second, an overview of the method is provided, the sample discussed, and then an examination of the research results based on the Emotionally Intelligent Leadership Inventory (EILI).

The Roots of EIL

Contingency Theory

Throughout the late 1960s and 1970s, the Contingency Model of leadership was one of the most widely studied theories of leadership (e.g., Strube & Garcia, 1981). By the mid-1990s, Contingency Model had been supported by two published meta-analyses, one of which was based on more than 145 tests of the hypotheses, making the Contingency Model the most validated leadership theory (Fiedler, 1995). However, today, other than a feature in some textbooks, Contingency Model does not seem to "live" in the community of leadership scholars and practitioners. The theory never took root, even though it dominated leadership literature for more than a decade. Research has waned and practitioners do not seem to be interested. While Blake and Mouton's (1978) *Managerial/Leadership Grid Theory* examines the leader's focus on "relationship" and "task," Contingency Theory focuses on the importance of a leader's match to a given situation. According to Fiedler and Mahar (1979), "a leader's performance is based on two interacting factors: (a) the individual's goals and needs or motivational structure and (b) the degree to which the situation provides the leader with control and influence over the outcome of the task" (p. 248). In essence, the theory is focused on the leader changing the situation, rather than changing his or her "style."

One challenge of Contingency Theory is that it is nearly impossible to categorize every possible situation a leader may face. Further, it does not take into account the notion that leaders have the ability to grow and adapt to given situations. Finally, it would be difficult to appoint and remove individuals

from positions of authority simply because their skills do not match a given situation. Regardless, Fiedler brought an important concept to the table when he suggested that leadership is relationship between the leader, the followers, and the context. Scholar David Day suggests, "These kinds of training approaches, however, ignore almost 50 years of research showing leadership to be a complex interaction between the designated leader and the social and organizational environment" (Day, 2001). Leadership is complicated and success or failure is a mix of what might be considered an almost infinite number of behavioral variables that make up the formal/informal leader, the followers (social environment) as well as variables related to the context (organizational environment).

Emotional Intelligence

So what attributes (competencies, skills) does one need to embody to successfully navigate such an environment? How does one have to behave to best approach the challenges associated with effective leadership (let alone the measurement of such)? Emotional intelligence (EI) offers a framework for approaching the complexities facing leaders today. Not only does EI promote a way of being that will serve a leader well (a focus on self awareness, self regulation, and relationship management), it highlights a number of competencies that support leadership from a behavioral perspective, (optimism, influence, conflict management, etc.).

Although a relatively new approach to thinking about intelligence, performance or personality, a number of interesting findings have been associated with Emotional Intelligence. For instance, in their meta-analytic study, Schutte, Malouff, Thorsteinsson, Bhullar & Rooke (2007) found that emotional intelligence is associated with better health. Moreover, studies associated with Bar-On's EQ-I, have found that there is a moderate yet significant relationship between EI and physical and psychological health and that the "Bar-On model is capable of identifying and predicting who will perform well at school and who will not" (Bar-On, 2006, p.14). The same is true for predicting who will perform well at work (Bar-On, 2006, p. 15). In health care settings, Akerjordet & Severinsson (2008) report that emotional intelligence has been correlated to increased job performance, resilience to stressful situations and better capacity to demonstrate a caring attitude. In addition, emotionally intelligent health care providers "nurture a greater sense of safety and provide better management performance" (Akerjordet & Severinsson, 2008, p. 569). In addition, in a study of 300 senior executives, Spencer (1997) found that the competencies of influence, team leadership, organizational awareness, self-confidence, achievement drive, and leadership

were identified in the high performers vs. average employees. Finally, along with management performance, a number of studies show that EI leads to effective leadership (e.g., Kerr, Garvin, Heaton, & Boyle, 2006; Goleman, Boyatzis & McKee, 2002; Bar-On, 2006; Cherniss, 1999).

The term *emotional intelligence* (EI) was coined by Peter Salovey and John Mayer in 1990, based on the work of many before them (e.g., Gardner 1983; McClelland, 1973; Thorndike & Stein, 1937). Many of these scholars assumed that cognitive intelligence (IQ) alone does not lead to success (or effectiveness). In fact, Hunter and Hunter (1984), concluded that intelligence accounts for around 25% of the variance in high performing employees. Others have experienced similar results (e.g., Sternberg, 1996, Singh, 2006). Salovey & Mayer's (1990) original definition of EI was, "a form of social intelligence that involves the ability to monitor one's own and others' feelings and emotions, to discriminate among them, and to use this information to guide one's thinking and action" (p. 189). Today, there are three primary approaches to the construct of Emotional Intelligence which can make it a confusing concept to understand and grasp (Caruso, 2003). However, it is important to understand that all, at their core, believe that EI is about the "abilities to recognize and regulate emotions in ourselves and others" (Goleman, 2000, p. 2). Goleman (2000) explains the three primary approaches to EI and suggests that Salovey & Mayer "framed EI within a model of intelligence" (p. 2), while Bar-On framed his model of EI in personality theory. Goleman (2000) suggests his model as a theory of performance.

As mentioned, the "competing" EIL approaches may not seem all that different at first blush. However, Bar-On (2006) effectively distinguishes the three approaches:

(a) The Salovey-Mayer model (Mayer & Salovey, 1997) which defines this construct as the ability to perceive, understand, manage and use emotions to facilitate thinking, measured by an ability based measure (Mayer et al., 2002).; (b) the Goleman model (1998) which views this construct as a wide array of competencies and skills that drive managerial performance, measured by a multi-rater assessment (Boyatzis et al., 2001); (c) The Bar-On model (1997b, 2000) which describes a cross section of interrelated emotional and social competencies, skills and facilitators that impact intelligent behavior, measured by self report (1997a, 1997b) within a potentially expandable multi-modal approach including interview and multi-rater assessment (Bar-On & Handley, 2003a, 2003b). (p. 2).

In their book *Primal Leadership,* Goleman, Boyatzis and McKee (2002) suggest that:

Primal leadership operates at its best through emotionally intelligent leaders who create resonance. Underlying that proposition is a theory of performance, one that surfaces the links between the neurology of the four fundamentals of emotional intelligence and the EI competencies that build on those fundamentals. These EI competencies are in turn the building blocks of the modes of leadership that prime resonance in a group (p. 38).

A competency is "an underlying characteristic of a person which results in effective and/or superior performance in a job" (Boyatzis, 1982, p. 21). These competencies are housed under the fundamentals of *self-awareness, self management, social awareness and relationship management.* Goleman et al. (2002) define self-awareness in the following way: "Simply put *self-awareness* means having a deep understanding of one's emotions, as well as one's strengths and limitations and one's values and motives" (p. 40). *Self-management* addresses an individual's ability to regulate his or her impulses and behaviors. This is extremely important because of the contagious nature of emotions. *Social awareness* captures a leader's ability to express his or her feelings with those around them. The leader's ability to empathize with those around them will likely determine their ability to remain in tune with those in their sphere or the organizations as a whole. Finally, *relationship management* focuses on a leader's ability to manage the emotions of those around them. To do so, the leader must have a keen sense of his or her own emotional state.

The Emotionally Intelligent Leadership Model

Emotionally Intelligent Leadership, at the heart, is a piece of integrative scholarship. Ernest Boyer (1990) of the Carnegie Foundation suggested that, "…the work of a scholar also means stepping back from one's investigation, looking for connections, building bridges between theory and practice, and communicating one's knowledge effectively to students" (p. 16). More specifically, he suggested "By integration, we mean making connections across the disciplines, placing the specialties in a larger context, illuminating data in a revealing way…serious, disciplined work that seeks to interpret, draw together, and bring new insight to bear on original research" (p. 18-19). Rather than looking at the many theories of leadership as isolated and competing concepts, here they are viewed through an inclusive lens leading to synthesis. Doing so not only aligns a number of similar concepts from the various theories, but also provides a more holistic perspective on the complex dynamic of leadership.

Emotionally intelligent leadership finds its roots in leadership theory, contingency theory and emotional intelligence. First, a number of leadership

scholars have informed this thinking and are included in the development of the model – for instance, Heifetz & Linsky's (2002) work around the context in which a leader does his or her work is captured. In addition, the need to inspire others is promoted as is highlighted in Kouzes and Posner's Five Practices (Kouzes & Posner, 1995), Transformational Leadership (Bass, 1985), charismatic leadership (Conger, 1989), relational leadership (Komives, Lucas & McMahon, 2006) and so forth. Likewise, the model includes concepts such as optimism and self-efficacy/self-confidence which are heralded by Avolio & Luthans (2006), and Goleman, Boyatzis & McKee (2002) as crucial ingredients for effective leadership to occur. Throughout the work authors are identified and categorized who promote or put forth similar viewpoints. For instance, Avolio (2005), Goleman, Boyatzis and McKee (2002), McCauley and Van Velsor (2005), and HERI (1996) all suggest that self-awareness is an important component of effective leadership. In essence, rather than promote one approach or theory, this array (transformational leadership, emotional intelligence, contingency theory, social change model, leader-member exchange, center for creative leadership, etc.) is incorporated under one roof.

The Emotionally Intelligent Leadership (EIL) model aligns most closely with Goleman's approach to Emotional Intelligence. The focus on capacities and helping college students perform more effectively when serving in a leadership role coincides with Goleman's competency model. However, EIL is comprised of three facets (consciousness of context, consciousness of self, and consciousness of others), which were also inspired by the work of HERI (1996), Fiedler (1979), Kellerman (2004) and Heifetz (1994). These approaches add a dimension not present in other models of EI – the dimension of context as a fundamental component. For instance, in her book *Bad Leadership*, Kellerman (2004) analyses each case by examining first the context, then the followers and finally the leader. The result is a rich story of how these three elements converged to create the result it did (in this case, bad). Thus, an emotionally intelligent leader must respond to and regulate the emotions in self, others, and the larger context at hand. Heifetz (1994) suggests that "Leadership is a razor's edge because one has to oversee a sustained period of social disequilibrium during which people confront the contradictions in their lives and communities and adjust their values behavior to accommodate new realities" (p. 127). To respond to this sense of disequilibrium, Heifetz suggests that the leader is responsible for "holding" followers through this period of discomfort. This is also known as a holding environment – "A holding environment is a space formed by a network of relationships within which people can tackle tough, sometimes divisive questions without flying apart…In a holding environment, with structural,

procedural, or virtual boundaries, people feel safe enough to address problems that are difficult, not only because they strain ingenuity, but also, they strain relationships" (Heifetz & Linsky, 2002, p. 102-103).

Three Facets and Twenty-one Capacities of Emotionally Intelligent Leadership

As mentioned, EIL focuses on three facets (consciousness of context, consciousness of self, and consciousness of others). Consciousness of context focuses on the environment in which leaders and followers work. Consciousness of self is being aware of oneself in terms of abilities and emotions. Consciousness of others is attending to, and working in, relationship with others and the role they play in the leadership equation. The three facets of EIL relate to a person's awareness, which is necessary but not sufficient for demonstrating emotionally intelligent leadership.

To bring this awareness to the surface and show action, the model is comprised of 21 capacities. The word *capacity* is used because many of these behaviors, skills and ways of being can be learned. According to the American Heritage Dictionary, capacity is defined as "ability to perform or produce; capability." This word is chosen because the assumption, like that of Arvey (2006; 2007), is that everyone has the capacity to develop the ability to lead others effectively. An in-depth review of the theoretical roots of each capacity is beyond the scope of this work. However, it is important that a cursory definition is provided with an explanation for each. As previously mentioned, these capacities are integrative in nature. They integrate the thinking of several scholars and theorists into one model of effective leadership (e.g., Avolio & Gardner, 2005; Bass 1995; Goleman, Boyatzis & McKee, 2002; Heifetz, 1994; Fiedler, 1972; Blanchard, Zigarmi, & Nelson, 1993; Kouzes & Posner, 2007; HERI, 1996).

Given that the context is the environment in which leaders and followers work (e.g., Fiedler, 1996; Heifetz, 1994; HERI, 1996), EIL recognizes that the settings and situations that leaders experience are always different, and may even be constantly changing. For example, people in the organizational context may be open to being led, or not. Shankman & Allen (2008) suggest that each new context requires a different set of knowledge, skills, and abilities on the part of leaders *and* followers. A leader's ability to accurately diagnose these dynamics will lead to success or failure (e.g., Day and Lance, 2004; London, 1999; Goleman, *et al*., 2002; Hartley & Hinksman, 2003; Heifetz and Linsky, 2002; and Zenger, Ulrich, & Smallwood, 2000). Once diagnosed, the

road to success or failure is dependent in large measure on the knowledge, skills, and abilities of those involved. The two capacities that comprise this consciousness of context facet include:

- *Group Savvy* – Interpreting the situation and/or networks of an organization
- *Environmental Awareness* – Intentionally thinking about the environment in any leadership situation especially the physical, psychological, and organizational elements. Harvard faculty Marty Linsky and Ronald Heifetz (2002) call this "getting on the balcony" (p. 8). This means an individual has the ability to observe, in real time, the group dynamics and factors present in the environment..

A number of authors have addressed the importance of self-awareness as a fundamental construct of effective leadership (e.g., Avolio, 2005; Conger, 1993; Goleman, Boyatzis and McKee, 2002; HERI, 1996; London, 2002; Van Velsor & McCauley, 2005). Consciousness of self requires knowing oneself and one's values, as well as how one's actions affect others (HERI, 1996). Since this is a lifelong endeavor, Shankman & Allen (2008) suggest that it's not important that introspection result in concrete answers, but it is the process that is important. This research aims to help understand that process. In addition, it must be noted that consciousness of self requires actions that are aligned with one's words. This fosters trust, which is required of leadership (Shankman & Allen, 2003, p. 26). The nine capacities that comprise this SELF facet include:

- *Emotional self-perception* – Identifying one's emotions and reactions and their impact on oneself. This capacity enables one to differentiate between emotions felt and actions taken.

- *Honest self-understanding* – Being aware of one's own strengths and limitations

- *Healthy self-esteem* – Having a balanced sense of self; holding oneself in check, evidencing humility

- *Emotional self-control* – Consciously moderating one's own emotions and reactions and regulating them

- *Authenticity* – Being transparent and trustworthy so that words match actions. This involves commitment and follow-through; being true to one's feelings and ideas; effectively aligning actions with values

- *Flexibility* – Being open and adaptive to changing situations

- *Achievement* – Being driven to improve according to personal standards

- *Optimism* – Being positive and displaying a positive regard for the future.. Research suggests that being optimistic is an important element of emotional intelligence and leadership (Avolio & Luthans, 2006; Goleman, Boyatzis, & McKee, 2002).

- *Initiative* – Wanting and assertively seeking opportunities

Consciousness of others requires one to empathize, inspire, influence, coach, manage conflict and effect change. The challenge is in the fact that context is dynamic with infinite number of variables affecting leadership, thus requiring the leader to understand others' communication patterns and preferences, desires, expectations, and work style to name just a few of the affecting variables. In perhaps the first article to truly focus on others (followers) *In Praise of Followers* Kelly (1988) suggested the following:

> *Leaders matter greatly. But in searching so zealously for better leaders we tend to lose sight of the people these leaders will lead. Without his armies, after all, Napoleon was just a man with grandiose ambitions. Organizations stand or fall partly on the basis of how well their leaders lead, but partly also on the basis of how well their followers follow. (p. 142)*

In other words, followers are an essential area of focus for effective leadership. It is leaders and followers working together that yields results (or lack thereof). In her book *Bad Leadership*, Barbara Kellerman underscores this notion and places at least part of the blame for bad leadership on followers. Kellerman (2004) suggests that "we can't expect to reduce the number of bad leaders unless we reduce the number of bad followers" (p. 21). To this end, Chaleff (2003) suggests that no leader over a long period of time can sustain their success unless they have a group of supporters willing to stand up and share their perspective. All of us are leaders *and* followers and as Kellerman suggests (2008), "we are all, every one of us, followers first" (p. xxii). To help leaders (and followers) maintain this connection, there needs to be an acute consciousness of others. The ten capacities that comprise this facet include:

- *Empathy* – Understanding others from their perspective; requires a high level of self-awareness as well as awareness of others.

- *Citizenship* – Recognizing and fulfilling one's responsibility for others or for the group. "To be a good citizen is to work for positive change

on behalf of others and the community" (Higher Education Research Institute, 1996, p. 23); requires giving for the benefit of others.

- *Inspiration* – Motivating and moving others toward a shared vision – Leaders generate feelings of optimism and a commitment to organizational goals and vision by communicating ideals and vision for the organization through verbal cues, behaviors and internal and external relationships (Bass, 1985).

- *Influence* – Demonstrating skills of persuasion – Bass (1997) suggests that "leaders display conviction; emphasize trust; take stands on different issues; present their most important values; and emphasize the importance of purpose, commitment and ethical consequences of decision making. Such leaders are admired as role models in generating pride, loyalty, confidence, and alignment around a shared purpose" (p. 133).

- *Coaching* – Helping others enhance their skills and abilities — doing what is necessary to train and prepare others for the tasks or challenges at hand.

- *Change agent* – Seeking out and working with others toward new directions. Changes may benefit one person, an organization, or a whole community. Change agents possess creative problem solving skills, and are comfortable with risk taking.

- *Conflict management* – Identifying and resolving problems and issues with others

- *Developing relationships* – Creating connections between, among, and with people – In relation to leadership, authorities have discussed the centrality and importance of relationships for years (Bass & Avolio, 1994; Blake & Mouton, 1978; Fiedler & Chemers, 1984; Graen & Uhl-Bien, 1995).

- *Teamwork* – Working effectively with others in a group – knowing how to build a team and a role model of collaboration.

- *Capitalizing on differences* – Building on assets that come from differences with others; requires flexibility in terms of a desire to learn, being open to possibilities not considered, and even changing one's mind.

Chris Lowney (2003, p.110) discusses Jesuit self-awareness and its similarities to Goleman's notion of emotional intelligence. Both wanted to identify personal traits essential to successful leadership. Goleman (1998, p. 94) summarizes five core competencies of emotional intelligence which include:

- Self-awareness – recognizing one's own moods, emotions and drives
- Self-regulation – controlling or redirecting disruptive impulses and moods; and the propensity to suspend judgment and think before acting
- Motivation – passion to work for reasons beyond money and status
- Empathy – ability to understand the emotional makeup of others
- Social skill – proficiency in managing relationships and building networks; finding common ground and building rapport

Lowney suggests the 450-year-old company of the Jesuits took it one step further by training their recruits "how" to impart these skills. Through a consistent focus on knowing oneself (and the practice of Loyola's Spiritual Exercises), recruits emerged with invaluable personal strengths including:

- The ability to systematically recognize one's own weaknesses and negative habits
- An integrated worldview, vision and value system
- Appreciation of oneself as loved and important
- Ability to meditate and reflect daily
- A method for discerning choices and making decisions

Much work has been done to study leaders, the personality characteristics of leaders, and how leaders perceive themselves and others. This work aims at capturing the importance of one's consciousness of context, and understanding how this facet of consciousness is self-perceived by college students. All three facets, consciousness of context, self and others are measured and evaluated and the results discussed.

Involvement, Gender, Leadership & Emotional Intelligence

Research demonstrates that involvement in student groups and organizations is a significant predictor for college students' leadership development (Astin, 1993; Hernandez, Hogan, Hathaway, & Lovell, 1999; Cooper, Healy, & Simpson, 1994). While involvement in organizations is found most often to positively contribute to students' leadership outcomes, involvement in too many different types of organizations can also negatively contribute to students' leadership development (Dugan & Komives, 2007). One study found breadth of involvement was negatively associated with outcome scores

of *commitment* for college men (Haber & Komives, 2009). Additional findings related to gender emerged around involvement; women tended to be involved in student organizations more often than men, and involvement in student organizations was a significant predictor of leadership outcome more often for women than men (Haber, 2006).

Gender differences also exist in how women and men engage in leadership. Literature and research on leadership styles and capacities by gender suggest that women adopt more relational, democratic, and transformational approaches to leadership than men (Eagly & Carli, 2007; Northouse, 2004; Eagly, Johannesen-Schmidt, & van Engen, 2003; Dugan, Komives & Segar, 2008; Haber & Komives, 2009). Gender differences in leadership exist in the arenas of leadership traits, leadership styles, and overall approaches and perspectives of leadership. Men and women differ in personality traits that are predictors of leadership (Eagly & Carli; Judge, Bono, Ilies, & Gerhardt, 2002). Women's personality traits tend to reflect agreeableness, warmth, positive emotions, extraversion, and openness to feelings, while men's personality traits tend to reflect greater assertiveness (Costa, Terracciano, & McCrae, 2001; Eagly & Carli). These findings on traits are reflective of similar findings on leadership behavior.

Research on gender differences in leadership style, which is a behavioral measure of leadership, indicates that women practice more democratic leadership while men tend to demonstrate more autocratic leadership (Eagly & Carli, 2007). Democratic leadership is characterized by a participative and collaborative style, which emphasizes shared power and decision-making, while an autocratic style is more hierarchical and directive (Northouse, 2004). In a study examining the leadership styles and experiences of college student women holding formal leadership roles, the participants used such terms as "nonhierarchical, interactive, accessible, one-to-one, equality and team-member" (Romano, 1996, p. 679) when describing their approaches to leadership. Another study emphasized women's leadership styles as being dependent on the larger environment and the particular role in which they are operating. For example, in male-dominated organizations or industries, women may demonstrate more autocratic leadership, which tends to reflect that of their male colleagues (Eagly & Carli).

Women also demonstrate higher levels of transformational leadership than men (Eagly & Carli, 2007; Eagly et al., 2003). Transformational leadership, characterized by inspiring and empowering followers, developing followers and responding to their needs, and aligning follower, leader, and organizational goals, is associated with greater follower satisfaction,

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performance, and commitment. Additionally, transformational leadership is associated with greater overall leader and organizational performance (Bass & Riggio, 2006).

The recent Multi-Institutional Study of Leadership (MSL) examined college students' socially responsible leadership development, which is informed by the social change model of leadership (HERI, 1996). Socially responsible leadership emphasizes a collaborative, accessible, values-based, and service-oriented process of leadership that includes three levels of the model and eight outcomes. The individual level focuses on consciousness of self, congruence, and commitment; the group level includes collaboration, common purpose, controversy with civility; the societal level includes citizenship. The overall goal of the model is change (Komives & Wagner, 2009).

Findings from MSL research indicate that women report significantly higher levels of socially responsible leadership. A single-campus study identified that women demonstrated significantly higher levels than men in all three of the group outcomes and the individual outcomes of congruence and commitment (Haber, 2006; Haber & Komives, 2009). The national study identified more prominent gender differences; women reported significantly higher scores than men in all of the outcomes with the exception of change, in which there were no significant differences by gender (Dugan et al., 2008). Interestingly, results from this study also identify that men demonstrated significantly higher measures of leadership self-efficacy, or confidence in their ability to lead, than women (Dugan & Komives, 2007). Examining these findings side by side, women demonstrated higher competence in leadership, while men demonstrated higher confidence. Higher levels of leadership self-efficacy among men were also evident in Kezar & Moriarty's (2000) study on college student leadership.

Women's more collaborative and participative style is also reflected in research on emotional intelligence. The tendency for women to demonstrate higher degrees of emotional intelligence than men has been measured in various ways, including how people perceive, use, understand, and manage emotions (Brackett, Rivers, & Shiffman, 2006). Research also suggests differences between the genders in variables of emotional intelligence such as adaptability, stress management, intrapersonal skills (i.e. awareness and connection to inner-self), interpersonal skills, and general mood (Mandell & Pherwani, 2003). Recent research, however, suggests conflicting findings for younger generations. While significant differences in women and men's emotional intelligence existed for older generations (mean age of late forties),

with women scoring higher than men, no gender differences existed for the younger, college-aged generation (Guastello & Guastello, 2003).

The literature suggests that women tend to value others in their approach to leadership as well as demonstrate intrapersonal strengths more so than men. More specifically, women demonstrate a preference for the interpersonal dynamics of leadership, particularly working with others and groups in a collaborative way. Women also tend to demonstrate higher levels of intrapersonal skills than men. While there is evidence of women's greater intrapersonal and interpersonal skills, men's self-reported self-efficacy in their leadership abilities exceeds that of women. Much research on emotional intelligence and leadership suggests significant differences by gender, with women demonstrating higher levels than men, yet a recent study examining college students does not show significant gender differences. Thus, examining gender differences in leadership and emotional intelligence among college students warrants additional research.

The examination of leadership and emotional intelligence through a model that integrates the two may shed additional light on the differences or similarities in college-aged women and men's emotionally intelligent leadership. Additional information on gender differences in leadership and emotional intelligence can allow for a better understanding of students' leadership development and awareness of themselves, others, and the larger environment. Investigating the interplay between involvement and gender will further these understandings, and can also help college student educators by helping them develop well-rounded and emotionally intelligent leaders.

This work enables a precise focus on measuring a college student's self-perceived emotional intelligence skills in leadership settings. It considers consciousness of context, self and others as underlying constructs, investigates the variables associated with differences between varied levels of consciousness in leadership settings, and investigates gender differences and involvement through the lens of emotionally intelligent leadership.

1.2   Description of the Dataset

A total of 566 students from 139 colleges and universities in the United States completed an online assessment of their leadership skills in the spring of 2009. Assessment authors Shankman and Allen composed the research tool as an eventual supplement to their book, *Emotionally Intelligent Leadership; A Guide for College Students* (2008). In their model of emotionally intelligent leadership (EIL), three fundamental facets contribute to the leadership dynamic: consciousness of context, self, and others. Student were asked to use a five-point scale to indicate the extent to which they *intentionally* participated in or focused on a total of twenty-four variables when serving in a formal or informal leadership role. The scale was assigned as follows:

Never	Infrequently	Sometimes	Frequently	Always
1	2	3	4	5

Students provided a rating for each variable to the extent that it completed the sentence at the top of Table 1.2.1

When serving in a formal or informal leadership role, I…
Take time to understand the informal traditions of the group
Learn the expressed and implicit values of the group
Monitor how my emotions affect my interactions with others
Work on my limitations
Tailor my leadership style to the situation
Capitalize on my strengths
Understand how the group's environment influences my leadership style
Help others enhance their skills and abilities
Understand how the group members relate to one another
Follow through on my commitments
Work to build a sense of team
Think about how my leadership style aligns with group culture
Establish a positive tone
Think about how my decisions are received by group members
Improve my abilities
Identify external influences on the group
Consider the needs of others in the group
Recognize the patterns of behavior in the group
Reflect on how my actions align with my values
Understand the priorities of others in the group
Listen carefully to what is and isn't being said by group members
Work with others toward a shared goal
Work to resolve conflicts within the group
Align different viewpoints within the group

Table 1.2.1 Leadership behavior questions

The 24 questions were designed to capture three constructs; consciousness of context, consciousness of self, and consciousness of others within a leadership

setting. Students simply added their scores for the variables that fell into each construct category, arriving at a self-score between 8 and 40 on each of the three constructs (assuming they responded at least "1" to each of the questions). Later we will discuss the development and testing of the reliability of the constructs using factor analysis, but at this juncture the descriptive statistics for each variable will be discussed by construct groupings (consciousness of context, self and others).

Consciousness of Context

To simplify scoring, the three constructs are each comprised of eight variables. Table 1.2.2 provides the total number of respondents for each variable that loads on the consciousness of context factor, its range, mean and standard deviation.

Recognition of patterns of behavior in the group scored high at 3.99, followed by one's tailoring of their leadership style to the situation (3.98), and learning the expressed and implicit values of the group (3.95). Later, some quite interesting and significant differences between genders as well as high-scorers, and those who are more actively involved in student organizations, will be discussed.

Consciousness of Context **Descriptive Statistics**					
	N	Min	Max	Mean	Std. Dev.
Recognize the patterns of behavior in the group	566	1	5	3.99	.776
Tailor my leadership style to the situation	564	1	5	3.98	.850
Learn the expressed and implicit values of the group	566	2	5	3.95	.790
Understand how the group members relate to one another	565	1	5	3.93	.845
Take time to understand the informal traditions of the group	566	1	5	3.84	.826
Understand how the group's environment influences my leadership style	565	1	5	3.74	.908
Identify external influences on the group	564	1	5	3.72	.867
Think about how my leadership style aligns with group culture	566	1	5	3.68	.927

Table 1.2.2   Consciousness of Context -Descriptive Statistics

Consciousness of Self

College students tended to perceive themselves as quite strong on following through on commitments (4.46), working with others toward a shared goal (4.36), and establishing a positive tone (4.30).

Consciousness of Self **Descriptive Statistics**	N	Min	Max	Mean	Std. Dev.
Follow through on my commitments	563	2	5	4.46	.651
Work with others toward a shared goal	562	2	5	4.36	.690
Establish a positive tone	562	1	5	4.30	.725
Capitalize on my strengths	564	2	5	4.13	.725
Reflect on how my actions align with my values	564	2	5	4.08	.817
Improve my abilities	561	1	5	4.06	.756
Monitor how my emotions affect my interactions with others	566	1	5	3.93	.870
Work on my limitations	561	1	5	3.53	.884

Table 1.2.3 Consciousness of Self -Descriptive Statistics

Consciousness of Others

Considering their leadership roles with regard to others, students rated their consideration of the needs of others in the group quite high at 4.25, followed by working with others to resolve conflicts within the group at 4.16, and working to build a sense of team at 4.12.

Consciousness of Others **Descriptive Statistics**	N	Min	Max	Mean	Std. Dev.
Consider the needs of others in the group	566	2	5	4.25	.728
Work to resolve conflicts within the group	565	1	5	4.16	.832
Work to build a sense of team	560	1	5	4.12	.798
Listen carefully to what is and isn't being said by group members	565	1	5	4.10	.845
Think about how my decisions are received by group members	564	2	5	4.07	.834
Understand the priorities of others in the group	563	1	5	3.95	.771
Help others enhance their skills and abilities	563	1	5	3.87	.891
Align disparate viewpoints within the group	561	1	5	3.74	.854

Table 1.2.4 Consciousness of Others - Descriptive Statistics

Gender and Ethnicity

Thirty-one percent of the sample of college students were male, and 69% female (Figure 1.2.1). An ethnicity question was asked, with 87% reporting that they were white (Caucasian), 4% Hispanic, 3% Asian/Pacific Islander, 3% multiracial, 2% African-American, and 1% were of Middle Eastern decent (Figure 1.2.2).
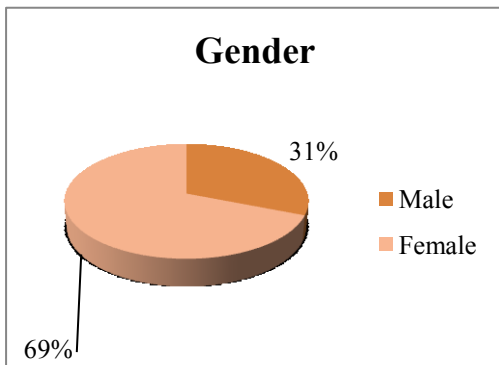
Figure 1.2.1 Respondent gender
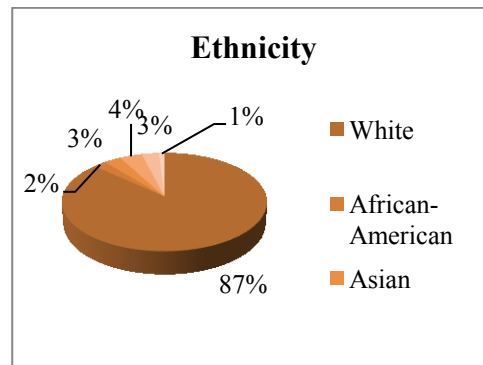
Figure 1.2.2 Respondent ethnicity

Class Rank

A reasonable distribution of class ranks participated, with 10% freshman, 28% sophomores, 32% juniors, 22% seniors and 7% graduate students (Figure 1.2.3).
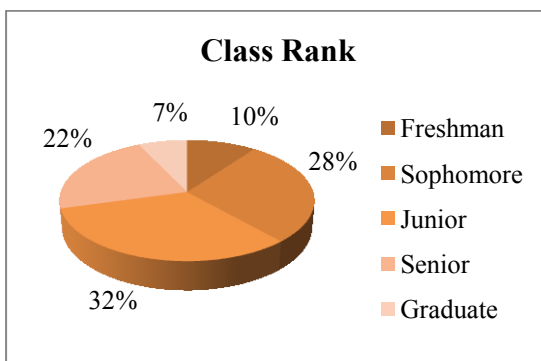
Figure 1.2.3 Percent of respondents in class

Age Category

Given the varied ages that potentially comprise each class rank, student respondents also provided their age category. Twenty-one percent were 18-19

years of age, 55% were 20-21, 16% 22-23, 2% reported their age group as 24-26 and 6% were 26 or older (Figure 1.2.4).

Age Category

18-19 21%
20-21 55%
22-23 16%
24-26 2%
> 26 6%
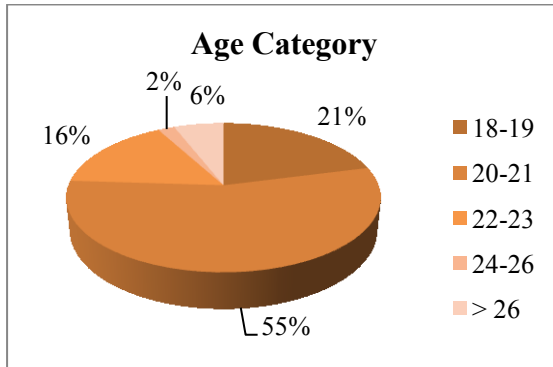
Figure 1.2.4 Respondent percent by age

Student Organization Involvement

Students were asked to provide the number of campus student organizations in which they were involved. Only 5% were not involved in any on-campus student organizations, with 54% involved in at least 3 organizations (Figure 1.2.5).

Student Organizations

None 5%
1 10%
2 31%
3 25%
4+ 29%

Leadership Role

YES 86%
No 14%
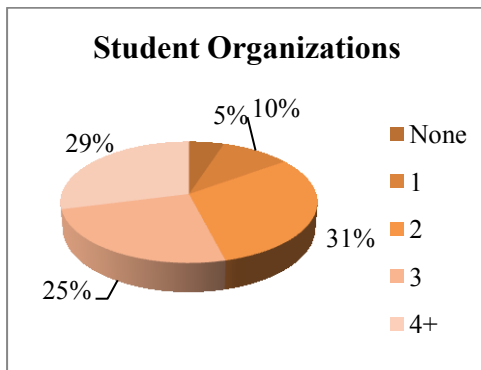
Figure 1.2.5 Student organization involvement leaders
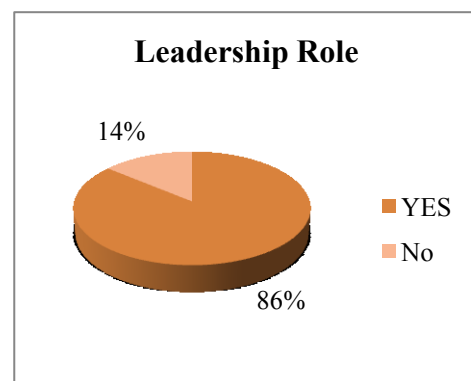
Figure 1.2.6 Percentage student -

Further, 86% reported that they were currently in some type of leadership role within an organization (Figure 1.2.6).

A final question was asked with regard to number of leadership retreats attended. All but 17% reported having participated in at least 1 leadership retreat, with nearly 40% having attended 3 or more. This high-level of involvement in leadership retreats may be somewhat reflective of the purposive sampling conducted in the administration of the survey. Authors

Shankman and Allen distributed a link to the web-enabled survey primarily to colleagues in universities who in turn distributed to their students.

Leadership Retreats
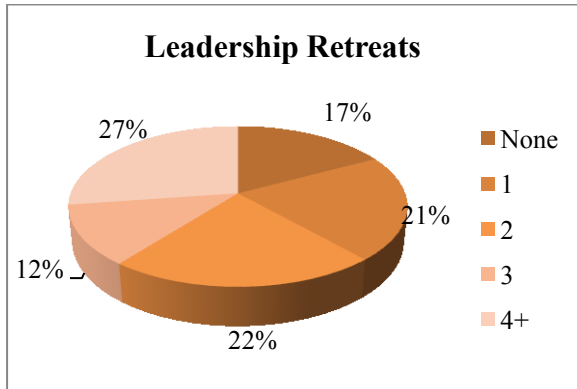
Figure 1.2.7 Participation in leadership retreats

In section 1.4 the more actively involved students will be discussed to better understand the significant differences between these students and their less-involved counterparts, as well as gender differences based on level of involvement.

1.3   General Problem – Measuring Leadership

The objective of the work herein is to provide a method to statistically assess an individual's leadership skill set, categorize them in comparison to others, and ultimately, based on the dataset, make suggestions for development.

Emotionally intelligent leadership has multiple definitions, but Shankman and Allen (2009) suggest that the most trusted include:

- "The ability to monitor one's own and others' feelings and emotions, to discriminate among them and to use this information to guide one's thinking and actions" (Salovey & Mayer, 1990, p. 189).
- Making emotions "work for you by using them to help guide your behavior and thinking in ways that enhance your results" (Weisinger, 1998, p. xvi).
- "The capacity for recognizing our own feelings and those of others, for motivating ourselves, and for managing emotions well in ourselves and in our relationships" (Goleman, 1998, p. 317).

The challenge follows: given the dataset, we seek to assess leadership skills based on self-reported levels of focus on leadership traits and techniques. Then, we need to understand significant differences between higher performing leaders and others, and subsequently utilize those findings to suggest methods for improvement.

There is not a dependent variable, preferably provided from individuals other than the respondents themselves, that offers a measurement of leadership effectiveness. Thus, the analysis is based on discriminating between groups of individuals who self-report levels of consciousness of context, self and others when they are in a leadership role. Additionally, one might consider higher levels of organizational involvement, when coupled with a leadership role, to be indicative of individuals with stronger leadership capacity. The aim is to discern the attributes that set this group apart, and ultimately provide a method for discriminating between these "max-leaders" and others.

There are three main constructs with which to work. Shankman and Allen define consciousness of context as a focus on the environment in which leaders and followers work. Consciousness of self is being aware of oneself in terms of abilities and emotions. Consciousness of others is being aware of one's relationship with others and the role they play in the leadership equation.

Given that the context is the environment in which leaders and followers work (Fiedler, 1996), the settings are often very different, and situations constantly changing, dynamic. People in the organizational context may be open to being

led, or not. Shankman and Allen suggest that each new context requires a different set of knowledge, skills, and abilities on the part of leaders and followers.

Consciousness of self requires knowing oneself and one's values, as well as how one's actions affect others (Higher Education Research Institute, 1996). Since this is a lifetime effort, Shankman and Allen suggest to their college student audience that it's not important that introspection result in concrete answers, but it is the process that is important. This research aims to help understand that process. Additionally, it must be noted that consciousness of self requires actions that are aligned with one's words. This fosters trust, which is required of leadership (Shankman and Allen, 2003, p. 26).

Consciousness of others requires one to empathize, inspire, influence, coach, manage conflict an effect change. The challenge is in the fact that context is dynamic with infinite number of variables affecting leadership, thus requiring the leader to understand others' communication patterns and preferences, desires, expectations, and work style to name just a few of the affecting variables (ibid, p. 74).

Without delving deep into the leadership "effectiveness" literature, one can safely say the concept is somewhat subjective. Given the context, one's personal goals may be spiritual, monetary, career-oriented, relationship-related, familial, etc., each requiring a sense of leadership in order to achieve one's goals effectively. Leadership can be implemented effectively, yet unethically, irresponsibly or immaturely.

Harvard Business School professor Joseph Badaracco suggests that self-reflection is vitally important to leadership, and it's this self-reflection, in our case a specific self-assessment tool, on which this analysis focuses. Badaracco interviewed corporate leaders to understand the tools they used to make decisions for their companies, concluding:

> *They are able to take time out from the chain of managerial tasks that consumes their time and undertake a process of probing self-inquiry – a process that is more often carried out on the run than in quiet seclusion. They are able to dig below the busy surface of their daily lives and refocus on their core values and principles. Once uncovered, those values and principles renew their sense of purpose at work and act as a springboard for shrewd, pragmatic, politically astute action. By repeating this process again and again throughout their work lives, these executives are able to craft an authentic and strong identity based on their own, rather than another's understanding of what is*

right. And in this way, they begin to make the transition from being a manager to becoming a leader.

(Badaracco, HBR, 1998)

In *Heroic Leadership*, Chris Lowney discusses the 450-year-old traditions of the Jesuits regarding leadership, suggesting leadership development methods must be revisited.

First, no one can make another person self-aware, so leaders must largely mold themselves. Only I can muster the will, courage and honesty to search myself. Others – coaches, managers, friends, parents, and mentors – help of course, but primarily by playing a role similar to that of the "director" in (Ignatius) Loyola's key self-awareness tool, the Spiritual Exercises…All leadership begins with self-leadership, and self-leadership begins with knowing oneself. First comes the foundation: goals and values, an understanding of personal strengths and obstacles, an outlook on the world. Then comes the invigorating daily habit of refreshing and deepening self-knowledge while immersing oneself in a constantly evolving world.

(Lowney, 2003, p.97-98)

These perspectives serve to validate the use of a self-assessment tool as a part of one's personal leadership training and development.

1.4 Problem of Classification – Significant Differences on Consciousness of Context, Self and Others

As in Section 1.5 of Classification and Analysis of a Job Seeking Market, the independent samples t-test procedure is used to identify significant differences between the means of groups of interest.

This section will first discuss the levels created for each construct and the most significant differences between the levels. Gender differences are then investigated and discussed. Also, max-leaders (involved in 3+ organizations, and currently in a leadership role) are investigated as well as the extent to which the attitudes and behaviors of this group significantly differ from the balance of the respondents.

Three levels were created for each construct based on score. Respondents with total scores less than 25 for a given construct were coded as 1, scores between 26 and 34 were coded as level 2, and those in the 35-40 range were coded the highest, at level 3. This same process was used for each of the three consciousness constructs (context, self, and others).

Table 1.4.1 details the number and percentage of respondents falling into each category, and the mean score for the group. Note that most students rated themselves in upper two tiers suggesting a general acceptance of leadership training and development.

Consciousness Construct	Level (score)	N	Percent	Mean
Context	Level 1 (8-25)	64	11.4%	22.91
	Level 2 (26-34)	388	69.3%	30.45
	Level 3 (35-40)	108	19.3%	37.08
Self	Level 1 (8-25)	12	2.2%	24.17
	Level 2 (26-34)	337	62.1%	30.96
	Level 3 (35-40)	194	35.7%	36.68
Others	Level 1 (8-25)	42	7.7%	23.36
	Level 2 (26-34)	324	59.3%	30.78
	Level 3 (35-40)	180	33.0%	37.00

Table 1.4.1 Levels of consciousness constructs

Figure 1.4.1 is provided as a supplement, to further clarify comparisons of construct scores by levels.
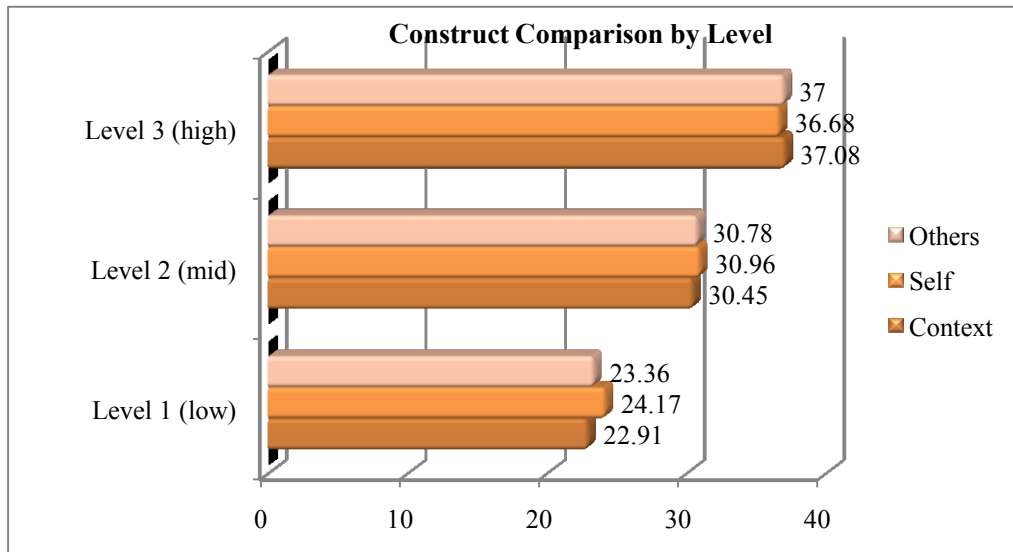
Figure 1.4.1 Construct score comparison by level

As expected, due to the groupings by low, mid and high levels, significant differences are present between variables in each group. It is insightful to note the largest of the mean differences, as these will provide a useful comparison in the discriminant analysis conducted in part two of this study. For now, consider the top three largest mean differences between each of the groups within each of the constructs. Recommendations will be made regarding areas of focus for improving to a higher level.

Consciousness of Context - Largest Mean Differences

Level 3 (high) vs. Level 2 (mid)

The highest level leaders (35-40 on consciousness of CONTEXT construct) are significantly more likely than the mid-level leaders to think about how their leadership style aligns with the group's culture. They are more likely to understand how the group's environment influences their leadership style and subsequently tailor their style to the leadership situation. Essentially, these are elements that mid-level leaders can focus on for development of consciousness of context.

Interestingly, the mid-level group's mean rating for thinking about how their leadership style aligns with group culture was rated second-lowest of the 24 attributes measured, suggesting a key area for consideration and improvement by the mid-level group.

When serving in a formal or informal leadership role, I…	$\overline{x}_{high}$	$\overline{x}_{mid}$	Mean diff.	t	df	p
*Think about how my **leadership style aligns** with group culture*	4.60	3.59	1.01	14.59	219	.000
*Understand how the **group's** environment influences my leadership style*	4.60	3.68	.921	13.61	220	.000
***Tailor my leadership style** to the situation*	4.76	3.92	.837	14.13	274	.000

Table 1.4.2 CONTEXT Level 3 (high) vs. Level 2 (mid)

Level 2 (mid) vs. Level 1 (low)

Next, compare the mid-level leaders on consciousness of CONTEXT to the lower group. The mid-level group is significantly more likely to understand how the group members relate to one another. They tend to a greater understanding of how the group's environment influences their leadership style, and they are more likely to think about how their leadership style aligns with the group culture, which again, is a focus integral to continued development.

The students in the lowest level group rated this variable dead last as far as their leadership behaviors regarding consciousness of CONTEXT, perhaps because they may still be unclear as to what their "leadership style" is or what options they have for aligning it with group culture.

When serving in a formal or informal leadership role, I…	$\overline{x}_{mid}$	$\overline{x}_{low}$	Mean diff.	t	df	p
*Understand how the **group members relate t**o one another*	3.91	2.80	1.16	9.91	76	.000
*Understand how the group's **environment influences** my leadership style*	3.68	2.66	1.02	9.86	450	000
*Think about how my leadership style **aligns with group culture***	3.59	2.62	.965	9.09	450	000

Table 1.4.3 CONTEXT Level 2 (mid) vs. Level 1 (low)

Consciousness of SELF

Level 3 (high) vs. Level 2 (mid)

Considering consciousness of SELF, level 3 leaders are significantly more likely to work on their limitations compared to their level 2 counterparts.

They intend to improve on their abilities, and they are more reflective regarding how their actions align with their values. A focus on these behaviors provides a foundation for development for the mid-level group to improve consciousness of self when in a leadership role.

Here again, as seen earlier with students at low-level consciousness of CONTEXT and their lack of focus on aligning their leadership style to the group's culture, the mid-level group is rating their propensity to work on their limitations at the very bottom of the list of behaviors. At 3.19, it is still slightly more than "sometimes" if we consider the 5-point scale, but it is still the lowest rated behavior suggesting a key area of focus for development of leadership skills with regard to consciousness of SELF.

When serving in a formal or informal leadership role, I…	$\overline{x}_{high}$	$\overline{x}_{mid}$	Mean diff	t	df	p
Work on my **limitations**	4.14	3.19	.952	14.21	529	.000
Improve my **abilities**	4.63	3.80	.831	15.65	529	.000
Reflect on how my **actions align with my values**	4.62	3.82	.805	14.15	582	.000

Table 1.4.4 SELF Level 3 (high) vs. Level 2 (mid)

Level 2 (mid) vs. Level 1 (low)

Comparing the level 2 group to the lowest level on the consciousness of SELF construct, the mid-level is significantly more likely to be working on improving their abilities when in a leadership role. They are more reflective regarding how their actions align with their values and are significantly more likely to establish a positive tone.

The lowest level group rated "improve my abilities" second last, at 2.50, halfway between infrequently and sometimes, suggesting a key area of focus for improvement toward a higher level of consciousness of SELF when in a leadership role. Aligning actions with values is a somewhat more significant result (although the mean difference is not as large) thus additional focus in this area is recommended to yield improvement.

When serving in a formal or informal leadership role, I…	$\overline{x}_{mid}$	$\overline{x}_{low}$	Mean diff.	t	df	p
Improve my **abilities**	3.80	2.50	1.29	4.47	11	.001
Reflect on how my **actions align with my values**	3.82	2.67	1.15	5.16	347	.000
Establish a **positive tone**	4.10	3.08	1.01	5.01	347	.000

Table 1.4.5 SELF Level 2 (mid) vs. Level 1 (low)

Consciousness of OTHERS

Level 3 (high) vs. Level 2 (mid)

High-level leaders are significantly more conscious of helping others enhance their skills and abilities when in a leadership role. These leaders are significantly more likely to work to resolve conflicts than the mid-level group, and they tend to a greater focus on understanding the priorities of others in the group.

The mid-level group rated their propensity to help others enhance their skills and abilities at 3.63, slightly more than half-way between sometimes and frequently behaving in this manner, suggesting a key area for improvement.

When serving in a formal or informal leadership role, I…	$\overline{x}_{high}$	$\overline{x}_{mid}$	Mean diff.	t	df	p
Help others **enhance their skills and abilities**	4.55	3.63	.923	15.35	440	.000
Work to resolve conflicts within group	4.81	3.96	.846	17.01	497	.000
Understand priorities of others in group	4.53	3.76	.765	13.47	502	.000

Table 1.4.6 OTHERS Level 3 (high) vs. Level 2 (mid)

Level 2 (mid) vs. Level 1 (low)

Differentiating mid-level leaders versus the lowest level on consciousness of others, it is clear that mid-level leaders tend to a higher likelihood of thinking about how their decisions are received by others in the group. Further, they listen more carefully to what is and is not being said in the group setting. Also, the mid-level group is significantly more likely to work to resolve conflicts within the group.

Following suit, the behavior with the most significant difference, thinking about how one's decisions are received, was rated 4th from the bottom on the list of twenty-four behavioral focuses when in a leadership role. A greater concentration on this skill is likely to help the low-level scorers move up to the mid-level.

When serving in a formal or informal leadership role, I…	$\overline{x}_{mid}$	$\overline{x}_{low}$	Mean diff.	t	df	p
Think about how my **decisions are received** by group members	3.92	2.81	1.11	9.31	364	.000
Listen carefully to what is and isn't being said	3.97	2.86	1.11	7.11	47	.000
Work to **resolve conflicts** within group	3.96	2.86	1.10	7.46	47	.000

Table 1.4.7 OTHERS Level 2 (mid) vs. Level 1 (low)

In summary, students with scores at the low and mid levels of consciousness of CONTEXT, should primarily focus on thinking about how their leadership style aligns with the group culture. This implies a potential need for effective training in this area so student understand what their leadership style actually is, and how to adapt it to the situation or context.

Concerning consciousness of SELF, mid-level leaders need to concentrate on working on their limitations, while the lowest level group should focus on improving their abilities.

A focus on helping others enhance their skills and abilities is likely to take students at the mid-level of consciousness of OTHERS to a higher level. Lastly, a stronger focus on thinking about how one's decisions are received is integral to improvement for those ranking in the lowest level of consciousness of OTHERS.

Consciousness Compared by Level of Involvement

Next, consider only those who are involved in at least one student organization. This eliminates only 5% of the sample, yet allows for comparisons by varied levels of involvement. This analytical step is certainly justified because significant differences are evidenced on all three constructs when those involved in at least one student organization are compared to those not involved in any (Figure 1.4.2). The largest mean difference, 3.89 is with consciousness of CONTEXT, followed by SELF at 3.29 and OTHERS at 2.77, clearly suggesting that involvement in student organizations serves to enhance students' perceptions of the leadership consciousness constructs.

Significant Differences by Involvement
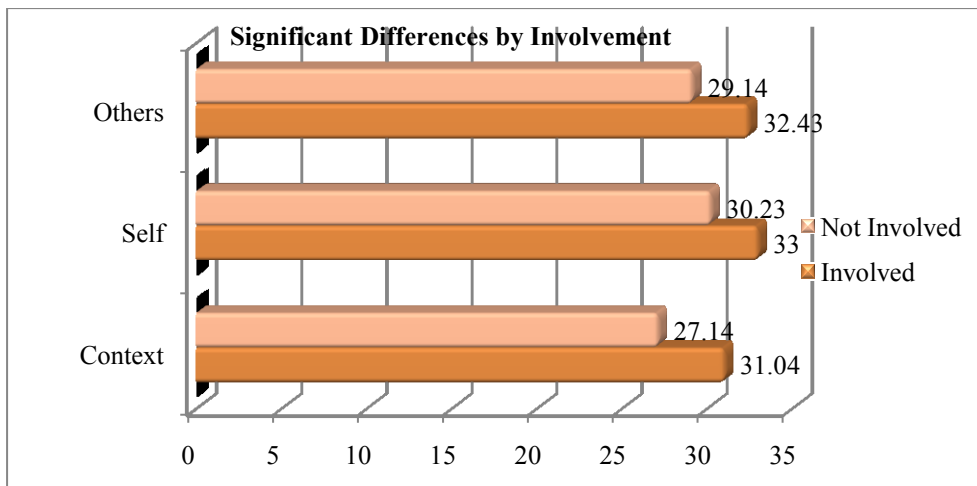
Figure 1.4.2   Comparison by involvement in at least 1 student organization; significant differences evidenced on all three constructs

Investigating the three consciousness constructs for significant differences based on level of involvement, regardless of gender at this point, the impact is found at the 4+ level of organizational involvement versus fewer. In other words, people involved in 4 or more organizations are significantly more conscious of CONTEXT, SELF, and OTHERS compared to those involved in fewer organizations. Looking deeper one finds the point at which that consciousness "kicks in". It is found at the 3 organization involvement level. So, there is a significant difference on all three constructs once the student is involved in at least one organization, then no significant change is evidenced until the student hits the 4+ involvement category, where there are significant differences in consciousness of SELF and OTHERS between those involved in 3 groups versus four or more. This 4+ group rates significantly higher on SELF (33.64) and OTHERS (33.04), compared to those involved in 3 groups, where the mean score for SELF was 32.43 and others 31.82 (with t = 2.96 and 2.41 respectively).

Note that CONTEXT has dropped from significance but only because it was negligibly close to the threshold (t = 1.994, p=.047) when compared to the larger group of all those in less than 4 groups, instead of just those involved in 3 groups where the difference in consciousness of context is insignificant. Table 1.4.9 summarizes the differences discussed above.

Max-Leaders – Significant Differences

As noted at the end of Section 1.2, the description of the dataset, a separate category was created for student respondents who participated in 3 or more student organizations, and were currently in a leadership role. Hereafter, this group is referred to as "max-leaders" although it should be noted that it is not

suggested that maximum activity necessarily implies leadership effectiveness. It is, however, worthwhile to investigate the significant differences between these high-activity student respondents versus their less-active counterparts, which are referred to as the base group. Max-leaders are significantly more conscious of CONTEXT, rated at 31.28 versus the balance of the respondents (base) at 30.44 (Figure 1.4.3).
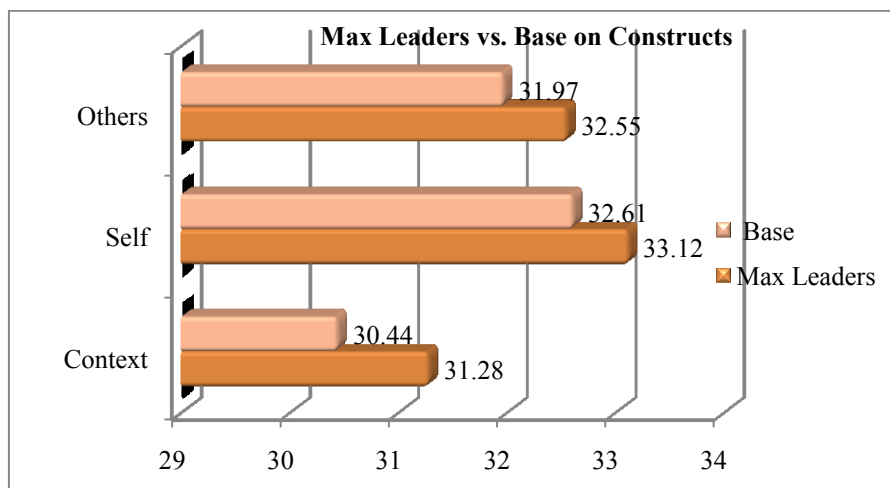
Figure 1.4.3 Max leaders scored significantly higher on consciousness of context.

This may be due to their more active involvement in student organizations (three or more) versus those not in the max-leader category, participating in two or fewer organizations. Of those in the base group 61% participate in two groups, 20% in one group. Ten percent are not involved in any student organizations, and another 9% participate in three or more groups, but are not in a leadership role, thus not qualifying for "max-leader" status.

Consider the significant differences between max-leaders and the base group on all leadership behaviors measured. Max-leaders are significantly more likely to take time to understand the informal traditions of the group, a consciousness of CONTEXT variable. Further, they are more accustomed to working with others toward a shared goal (SELF). Lastly, max-leaders put others first, significantly more so, by focusing on enhancing others' skills and this is a consciousness of OTHERS variable (Table 1.4.8).

When serving in a formal or informal leadership role, I…	Construct	$\overline{x}_{max}$	$\overline{x}_{base}$	Mean diff.	t	df	p
Take time to understand informal traditions	CONTEXT	3.95	3.73	.211	3.07	560	.002
Work with others toward a shared goal	SELF	4.44	4.28	.158	2.73	560	.006
Help others enhance skills and abilities	OTHERS	3.95	3.79	.157	2.10	561	.036

Table 1.4.8 Max Leaders vs. base – Significant Differences

Max-leaders appear to benefit from leadership positions and high levels of involvement, particularly as it relates to consciousness of context. Their significantly different behaviors appear to indicate multiple focuses because each of the consciousness constructs are represented. This suggests that a balanced sense of consciousness is required by those highly involved in organizations, and simultaneously maintaining leadership roles.

Gender and Involvement

The primary focus of this portion of the research is to explore the role that gender plays in college students' perceptions of the three facets of emotionally intelligent leadership (consciousness of context, consciousness of self, and consciousness of others). Additionally, this portion examines gender differences in students' emotionally intelligent leadership based on students' levels of involvement in campus organizations. This suggests the following two research questions:

1. What, if any, gender differences exist in students' consciousness of context, consciousness of self, and consciousness of others?

2. What, if any, gender differences exist in students' consciousness of context, consciousness of self, and consciousness of others based on level of involvement?

Looking at involvement by gender, 12% of men were involved in one organization, 27% in two organizations, 25% in three organization, and 34% in four or more organizations. Ten percent of the women were involved in one organization, 34% in two organizations, 27% in three organizations, and 29% in four our more organizations.
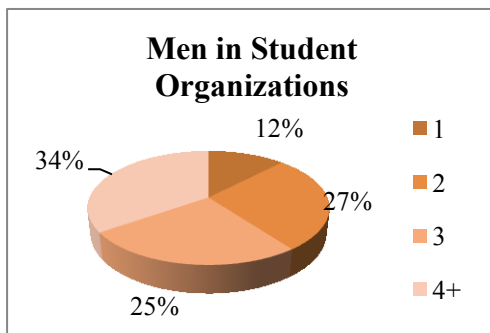
Figure 1.4.4 Men in student organizations
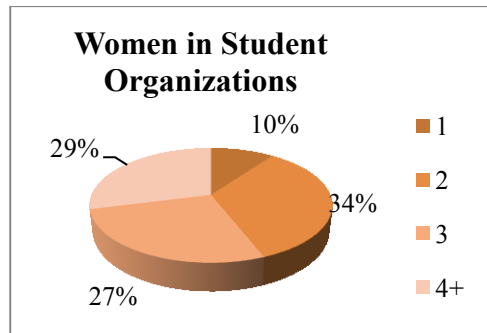
Figure 1.4.5 Women in student organizations

Research question one read: *What, if any, gender differences exist in students' consciousness of context, consciousness of self, and consciousness of others?*

Gender results for mean differences indicated significant differences between men and women on both consciousness of self and consciousness of others. Consciousness of self was significantly higher for women at 33.08 as compared to men at 32.33 ($t = 2.25$). Consciousness of others was also significantly higher for women at 32.56 as compared to men at 31.64 ($t = 2.16$). No significant differences by gender were identified between the mean ratings on the consciousness of context construct.

Table 1.4.9 highlights the results for specific measures in which significant differences were identified between the means of the gender groups. Three of the measures load on the consciousness of others construct, and three load on the consciousness of self construct. Women appear to demonstrate greater consideration of others in the group and think about how their decisions are received by others. Additionally, women tend to monitor how their emotions affect their interactions (self) more so than men, and they place a significantly stronger focus on following through on commitments (self). Women also demonstrate a greater likelihood to reflect on how their actions align with their values (self), and they listen more carefully to what is said and unsaid (others). The only variable in which men demonstrated higher mean scores than women was capitalization on strengths (self).

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When serving in a formal or informal leadership role, I…	Construct	$\bar{x}_{women}$	$\bar{x}_{men}$	Mean diff	t	df	p
Consider needs of **others** in the group	Others	4.32	4.09	.23	3.47	315	.001
Monitor how my **emotions affect my interactions** with others	Self	3.99	3.79	.20	2.41	558	.010
Think about how my **decisions are received**	Others	4.13	3.94	.19	2.60	319	.016
Follow through on commitments	Self	4.52	4.33	.19	3.11	303	.002
Reflect on how my **actions align** with my values	Self	4.13	3.97	.16	2.16	558	.031
Listen carefully to what is and isn't being said	Others	4.15	3.99	.16	2.01	559	.045
Capitalize on my strengths	Self	4.08	4.23	-.15	-2.24	558	.026

Table 1.4.9 Gender Differences for individual measures from research question one

In examining those respondents who scored in the highest levels across all three constructs of consciousness (between 35-40 on each, 13% of total respondents), there was only one significant difference by gender. Women reported significantly higher scores (4.93) than men (4.56) for the measure of "consider the needs of others in the group" (t = 3.01). Even among the students with the highest levels of self-reported leadership behaviors, women tend to consider the needs of others in the group more often than men.

Research question two reads: *What, if any, gender differences exist in students' consciousness of context, self and others, based on level of involvement?*

When gender differences within the three constructs were examined in relation to respondents' level of involvement, a few significant differences emerged. Similar to findings from research question one, there were no significant differences by gender for the construct of consciousness of context. Significant differences by gender did exist, though, for consciousness of self and consciousness of others when taking into consideration involvement. Additionally, there were many significant differences by gender across all levels of involvements for individual measures of consciousness of context, self, and others. The findings on gender differences for the individual measures are summarized in Table 1.4.10.

For students involved in only one organization, significant differences by gender were minimal. One significant difference emerged within this group of less-involved students for the consciousness of self measure of capitalizing on strengths, with mean scores of 4.53 for men compared to 4.03 for women (t = 2.46). No significant differences were evident by gender for the three constructs.

For respondents involved in two student organizations, women scored significantly higher on the construct of consciousness of self than men (33.21 vs. 31.54; t=2.74). The specific measure in which gender differences were particularly evident was following through on commitments (4.51 for women and 4.21 for men; t=2.68). While significant differences were not evident on the other two facets (others and context) for the students involved in two organizations, there are some interesting differences for some of the specific measures. Women involved in two organizations are significantly more likely to work on building a sense of team (others), rating themselves at 4.15 compared to men at 3.80 (t= 2.61). They are also more likely to consider the needs of others in the group (4.34) as compared to men (4.07; t = 2.15). Last, one of the measures of consciousness of context was significant; women are more likely to recognize patterns of behavior in the group (4.11 vs. 3.78; t = 2.60).

For respondents involved in three student organizations, women (32.35) were significantly higher in the construct of consciousness of others than men (32.35 for women and 30.55 for men; t=2.66). Women in three organizations were significantly more likely to consider others' needs (4.30 vs. 3.92; t=2.73), think about how their decisions were received by the group (4.09 vs. 3.75; t=2.19), and try to understand the priorities of others in the group versus their male counterparts (4.0 vs. 3.69; t=2.24). All three are measures within the consciousness of others construct.

For those involved in at least four organizations, there were no significant differences by gender in the three overall consciousness constructs. For individual measures, though, there were a few significant differences. Men were significantly more likely to work on their limitations (3.83 vs. 3.48), align disparate viewpoints within the group (3.93 vs. 3.64), (others), and capitalize on their strengths (4.38 vs. 4.11) as compared to women.

Number of Organiza-tions	When serving in a formal or informal leadership role, I…	Construct	$\bar{x}_{women}$	$\bar{x}_{men}$	Mean diff.	t	df	p
One	*Capitalize on my strengths*	Self	4.03	4.53	-.50	-2.46	56	.017
Two	*Building a sense of team*	Others	4.15	3.80	.35	2.61	167	.010
	Recognize patterns of behaviors in the group	Context	4.11	3.78	.33	2.60	169	.010
	Follow through on commitments	Self	4.51	4.21	.30	2.68	169	.008
	Consider needs of others in the group	Others	4.34	4.07	.27	2.15	169	.033
Three	*Consider needs of others in the group*	Others	4.30	3.92	.38	2.73	136	.007
	Think about how my decisions are received	Others	4.09	3.75	.34	2.19	136	.030
	Understand priorities of others in group	Others	4.00	3.69	.31	2.24	134	.027
Four or More	*Work on my limitations*	Self	3.48	3.83	-.35	-2.25	155	.026
	Align disparate viewpoints within group	Others	3.64	3.93	-.29	-2.07	158	.040
	Capitalize on my strengths	Self	4.11	4.38	-.27	-2.27	157	.025

Table 1.4.10 Gender differences for individual measures based on level of involvement

Next, this work transitions to the application of analytic methods to better understand the reliability of the self-assessment tool used to determine a college student's leadership behaviors. Classification methods will be demonstrated with discriminant analysis. Cluster analysis is also discussed which proves to be a worthwhile method, yielding reliable results and valuable insights into the assessment of college student leadership behaviors.

2.1 Reliability of Consciousness Constructs and Factor Analysis

To better understand the constructs of consciousness, both reliability analysis and factor analysis were implemented. In reliability analysis, Cronbach's alpha is the primary criterion to be examined. For the factor analysis, principal components analysis was the extraction method, and Varimax the rotation method, with Kaiser normalization (for more details, see Section 2.1 in Job Seeker Classification and Analysis).

Reliability of Constructs as Scales of Measurement

Several iterations of construct development led to breaking down the original 24 variables included in the assessment of emotionally intelligent leadership, to three constructs considered as reflective of consciousness of context, consciousness of self, and consciousness of others. Table 2.1.1 through Table 2.1.3 supply the variables comprising each construct.

Consciousness of CONTEXT
Take time to understand the informal traditions of the group
Learn the expressed and implicit values of the group
Tailor my leadership style to the situation
Understand how the group's environment influences my leadership style
Understand how the group members relate to one another
Think about how my leadership style aligns with group culture
Identify external influences on the group
Recognize the patterns of behavior in the group

Table 2.1.1 Variables comprising consciousness of context construct

Consciousness of SELF
Monitor how my emotions affect my interactions with others
Work on my limitations
Capitalize on my strengths
Follow through on my commitments
Establish a positive tone
Improve my abilities
Reflect on how my actions align with my values
Work with others toward a shared goal

Table 2.1.2 Variables comprising consciousness of self construct

Consciousness of OTHERS
Help others enhance their skills and abilities
Work to build a sense of team
Think about how my decisions are received by group members
Consider the needs of others in the group
Understand the priorities of others in the group
Listen carefully to what is and isn't being said by group members
Work to resolve conflicts within the group
Align disparate viewpoints within the group

Table 2.1.3   Variables comprising consciousness of others construct

Reliability of the assessment tool is ensured in that the constructs (also referred to as scales), comprised of 8 questions each for simplicity of student self-scoring, achieve strong levels of reliability as measured by Cronbach's alpha coefficient. (Table 2.1.4).

FACTOR	Cronbach's Alpha	Sample size
Consciousness of Context	$\alpha = .81$	n = 560
Consciousness of Self	$\alpha = .73$	n = 543
Consciousness of Others	$\alpha = .82$	n = 546

Table 2.1.4 Reliability of factors

The goal of each scale (consciousness of context, consciousness of self, consciousness of others) is to use several questions that are consistent in measuring the construct, yet each must contribute unique information. The coefficient, α, is based on the number of items in the scale and the ratio of average inter-item covariance to the average item variance (Cronbach, 1951). As the number of items, or questions, increases, the measurement of Cronbach's alpha is likely to increase. If the average inter-item correlation is low, alpha will be low. As the average inter-item correlation increases, Cronbach's alpha increases as well. Typically, 0.60 to 0.80 indicates acceptable reliability, 0.80 or higher means good reliability, and coefficients greater than 0.95 may indicate redundancy in the questions. Garson (2009) suggests the widely accepted cut-off in the social sciences is 0.70 with some researchers using 0.75 to 0.80. Others are as lenient as 0.60. Garson notes that 0.70 is as low as one should go because at that point the standard error if measurement will be over half (0.55) of a standard deviation.

Factor Analysis – College Student Leadership Data

Factor analysis yields interesting results, with a total of five factors explaining nearly 53% of the variance (52.6%, based on eigenvalues greater than 1, n= 546). The factor loadings from the rotated component matrix reveal important insights, particularly regarding the "interaction" of SELF and OTHER variables on the first component which explains the most (14.29%) variance. The second component maintains the concept of consciousness of context, and explains an additional 13.18% of the variance; with the third component offering another 10.82%, the fourth 8.35% and the fifth component 6.15%. Table 2.1.5 provides the rotated component score matrix with loadings highlighted in matching colors.

Rotated Component Matrix[a]

	Component				
	1	2	3	4	5
1. Take time to understand the informal traditions of the group	.221	.704	.058	-.036	.032
4. Learn the expressed and implicit values of the group	.094	.689	.139	.131	.159
5. Monitor how my emotions affect my interactions with others	.064	.180	.264	.649	-.094
6. Work on my limitations	.054	.091	.580	.449	.057
7. Tailor my leadership style to the situation	.216	.137	.702	.150	.127
8. Capitalize on my strengths	.134	.156	.602	-.112	.452
9. Understand how the group's environment influences my leadership style	.198	.350	.577	.171	-.029
11. Help others enhance their skills and abilities	.455	.377	.351	.057	.024
12. Understand how the group members relate to one another	.239	.549	.186	.199	.071
13. Follow through on my commitments	.224	.027	.064	.014	.756
14. Work to build a sense of team	.631	.276	.210	.012	.146
15. Think about how my leadership style aligns with group culture	.255	.498	.364	.125	-.050
16. Establish a positive tone	.688	-.043	.048	.330	.061
17. Think about how my decisions are received by group members	.521	.164	.176	.420	-.015
18. Improve my abilities	.378	.159	.411	.220	.249
20. Identify external influences on the group	.029	.575	.258	.246	.060
22. Consider the needs of others in the group	.421	.169	-.019	.534	.298
23. Recognize the patterns of behavior in the group	.138	.523	.067	.470	.164
24. Reflect on how my actions align with my values	.055	.356	.171	.393	.452
25. Understand the priorities of others in the group	.386	.383	.094	.356	.175
26. Listen carefully to what is and isn't being said by group members	.387	.267	.108	.229	.319
27. Work with others toward a shared goal	.685	.225	.090	-.002	.225
28. Work to resolve conflicts within the group	.677	.146	.322	.000	.112
29. Align disparate viewpoints within the group	.411	.343	.454	.078	-.172

Table 2.1.5 Rotated component score matrix evidencing 5 unique factors from college student leadership data

2.2 Classification using Discriminant Analysis – College Student Leadership Assessment

Given no variable which actually measures the respondent's effectiveness as a leader, an attempt is made to utilize the data for "number of student organizations involved in" which ranges from 0 to 4 or more, and the binary variable "are you currently in a leadership role?" Fifty-four percent reported involvement in at least 3 organizations and nearly 86% said they were currently involved in a leadership role.

Consider respondents involved in three or more organizations, who are also in a leadership role. As a matter of convenience we call them max-leaders, and this group represents 49% of the sample.

Next, discriminant analysis is used to investigate the attributes that distinguish these highly active leaders from their less active counterparts. The discriminant analysis function is further validated by t-tests for significance of difference between the means of groups, which show that the max-leaders are significantly different from the rest of the dataset on several discriminating variables including taking the time to learn the informal traditions of the group, working toward a shared goal, and helping others enhance their skills and abilities (see Section 1.4).

Recall that 86% of the students said they were in a leadership role, and 89% are involved in at least 2 organizations. This commonality of involvement and leadership motivation portends a challenge in discerning the composition of the respondents' consciousness of context, self and others, without considering the high-involvement/activity respondents separately. Keep in mind that the measurement is not that of leadership effectiveness, but one that indicates a high level of involvement (three or more organizations), coupled with a current leadership role. This group of max-leaders, approximately half the dataset, will be compared to the less-involved second half to better understand which attributes best discriminate between the two groups.

Each construct is comprised of 8 variables, rated from 1 to 5, reflecting consciousness of context, self, and others, and has a maximum score of 40. Three generally even levels are created for each consciousness construct. Low ratings are those ≤ 25, mid-level ranges from 26 to 34, and high scores are those ranging from 35-40. Given that virtually all respondents fell into the mid and high ranges, a greater focus is placed on understanding the composition of the mid and high levels, and the variables that can help discern the attributes of max-leaders in each of these groups versus others. First,

however, the entire group of college student respondents is investigated to discern between the characteristics of the max-leaders versus others.

Results

Overall, discriminant analysis techniques, applied to the college student leadership dataset, effectively identify the variables which discriminate between the max-leaders and their less involved counterparts, but classification is not particularly fruitful. The same holds true as gender differences are investigated, where reasonable discrimination is evident, yet classification is weak. This is most likely the result of not having a good "outcome" variable such as a leadership effectiveness score. Several attempts were made to categorize respondents in meaningful ways that would lead to better classification, but again, without a useful outcome variable, such as effectiveness as determined externally, the classification results just border significance.

The stepwise discriminant analysis procedure (as described in Section 2.6 of the job-seeker analysis) was used to isolate the most discriminating variables. Box's M was insignificant, so pooled covariance matrices were used. To clarify focus on the discriminatory power of each relevant independent variable, the partial F value is reported. Large F values indicate stronger discriminatory power (Hair, et al, p. 269).

The structure matrix further validates the correlation of each predictor variable with the discriminant function, and also identifies the variables that are correlated with the discriminant function, yet may not have survived the stepwise analysis.

Effectiveness of the discriminant function is validated by Wilks' lambda which reveals how well each function separates cases into groups. It is the proportion of total variance in the discriminant score not explained by differences among groups. Smaller values mean better discriminatory ability.

Discriminating Max-Leaders with Leadership Skills Variables

It is fair to consider the most discriminatory variables as the behaviors that distinguish max-leaders from others. Thus, the stepwise discriminant analysis suggests that max-leaders work with others toward a shared goal (F =12.28), take time to understand the informal traditions of the group (F = 9.69), and consider the needs of others in the group (F = 7.91). Table 2.2.1 provides details.

MAX-LEADERS STEPWISE DISCRIMINANT ANALYSIS Variables Entered/Removed							
Step	Entered	Min. D Squared					
		Stat	Between	Exact F			
			Groups	Statistic	df1	df2	Sig.
1	Work with others toward a **shared goal**	.135	1.00 and 2.00	**12.279**	1	363	.001
2	Take time to understand the **informal traditions** of the group	.213	1.00 and 2.00	**9.690**	2	362	7.954E-5
3	Consider the **needs of others** in the group	.262	1.00 and 2.00	**7.909**	3	361	4.016E-5
At each step, the variable that maximizes the Mahalanobis distance between the two closest groups is entered.							

Table 2.2.1   Stepwise results for most discriminatory variables distinguishing max-leaders from others

The structure matrix further supports the importance of the primary independent variables by providing the correlation of these variables with the discriminant function. Specifically, working with others toward a shared goal has a loading of .72 and understanding informal traditions, .70. It is insightful to note that "considering the needs of others" is a predictor, yet does not hold correlational value with the discriminant function. One might infer that this is related to the fact that males and females differ significantly on "considering needs of others", with females significantly more likely to evidence this behavior in a leadership setting.

Discriminating Gender with Leadership Skills Variables

This leads again to the gender question, and whether discriminant analysis offers any insights as to how the genders might be discriminated given the leadership behavior variables measured. Stepwise discriminant analysis using pooled covariance matrices (Box's M was insignificant), reveals three key discriminators which are all reflective of the consciousness of SELF construct, two which women rate significantly higher, and one which males perceive as significantly more common behavior (Table 2.2.2)

The interesting result is that the variables that most distinguishes the genders are reflective of extant leadership theories. The first highly discriminating variable, "monitor how my emotions affect my interactions with others" ($F = 7.80$) is characteristic of the emotionally intelligent leader who monitors emotions and focuses on the more affective elements of leadership (Mayer,

Salovey, & Caruso, 2000). Recall from Section 1.4 that females rated their participation in this behavior significantly higher than males.

The second discriminating behavior, "follow through on my commitments" ($F = 7.02$) was also rated significantly higher by females and might be considered to affirm path-goal theory where leaders are achievement-oriented (Northouse, p. 130).

The final discriminator, "capitalize on my strengths" ($F = 6.86$), was rated significantly higher by males, and is reflective of the skills approach to leadership which emphasizes learning and development of skills, suggesting that knowledge and abilities are needed for effective leadership (Northhouse, p. 39).

Examination of the structure matrix supports the three discriminatory variables with loadings of -.569 for capitalizing on strengths, .533 for monitoring emotions, and .386 for following through on commitments (recall the threshold of .40). Wilks' lambda is not particularly encouraging as reflected in the classification results, with $\lambda = .945$. However $\chi = 20.49$, significant at $p < .000$, clearly supports the hypothesis that the means of the functions are equal across groups.

GENDER – Discriminating Variables Entered/Removed							
Step	Entered	Min. D Squared					
		Stat	Between Groups	Exact F			
				Stat	df1	df2	Sig.
1	**Capitalize** on my strengths	.089	Male and Female	**6.863**	1	363.000	.009
2	Monitor how my **emotions affect my interactions** with others	.203	Male and Female	**7.804**	2	362.000	.000
3	**Follow through** on my commitments	.274	Male and Female	**7.020**	3	361.000	.000

Table 2.2.2 Stepwise discriminant analysis distinguishing gender

Given Max-Leaders, Discriminate Gender

Consider only the max-leaders. Using discriminant analysis, stepwise method, with separate covariance matrices since Box's M is significant in this case, two variables surface which discriminate the genders, given that they are max-

leaders involved in more than 3 student organizations, and in a leadership role. The most discriminating variable, considering the needs of others in the group ($F = 11.01$), was rated significantly higher by females (Table 2.2.3). Interestingly, this behavior is characteristic of a transformational leader who emphasizes intrinsic motivation, and is concerned with assessing followers' motives and satisfying their needs (Northouse, p. 175). Results from the structure matrix support the usefulness of the variable which has a loading score of - 475.

Discriminating Gender of MAX-LEADERS, Variables Entered/Removed							
Step	Entered	Min. D Squared					
		Stat	Between	Exact F			
			Groups	Statistic	df1	df2	Sig.
1	**Improve my abilities**	.221	Male and Female	7.897	1	180	.005
2	**Consider the needs of others** in the group	.618	Male and Female	11.007	2	179	3.101E-5

Table 2.2.3 Stepwise discriminant analysis distinguishing gender among max-leaders

The second discriminating variable, improving one's abilities, ($F = 7.89$, structure matrix loading = .597) did not evidence significant mean differences between the genders in the entire dataset, nor among the max-leaders. This suggests that discriminant analysis permits the identification of important variables that distinguish the genders yet may not be obvious from difference analysis such as in t-tests for significant differences between means. Thus, discriminant analysis is a necessary step, particularly in behavioral research, toward a better understanding of underlying differences between groups or categories of respondents.

Evaluating the ability of the discriminant function to separate cases into gender groups, $\lambda = 89$, and classification results indicate better than chance accuracy with 72.4% of the estimation set classified correctly and 63% of the hold-out sample correct. Both exceed the better-than-chance criterion of 61.25%.

Discriminating Max-Leaders Given Gender

Consider only males, and which variables might discriminate max-leaders from others of the same gender. Results from the discriminant analysis suggest

that it is simply working to build a sense of team ($F = 8.18$) that distinguishes the male max-leader from his less involved and leading counterparts (Table 2.2.4). Team leadership is typical of the organizational setting, where the leader processes complex information for action taking (Northouse, p.224). No significant differences between genders are evident with regard to team building. Again, discriminant analysis has provided information not clarified through analysis of mean differences.

MALES ONLY - Discriminating Max-Leaders - Variables Entered/Removed							
Step	Entered	Min. D Squared					
		Stat	Between Groups	Exact F			
				Statistic	df1	df2	Sig.
1	Work to build a **sense of team**	.295	1.00 and 2.00	8.182	1	109.000	.005

Table 2.2.4 Male category, discriminating max-leaders from base

On the other hand, female max-leaders focus on identifying external influences on the group ($F = 4.05$), $p < .05$ (Table 2.2.5). The behavior may be considered reflective of a situational approach where the leader adapts his/her leadership style to the situation, perhaps as a result of external influences. Additionally, contingency theory states that effective leadership is contingent on matching a leader's style to the right setting. Identifying external influences serves to evaluate the situation, which the female max-leader leader then adapts to the setting.

FEMALES ONLY – Discriminating Max-Leaders - Variables Entered/Removed							
Step	Entered	Min. D Squared					
		Stat	Between Groups	Exact F			
				Statistic	df1	df2	Sig.
1	Identify **external influences** on group	.061	1.00 and 2.00	4.053	1	262.000	.045

Table 2.2.5 Female category, discriminating max-leaders from base

These methods of creating variables to enable discriminant analysis do offer interesting insights, but without a specific categorical dependent variable, the application of discriminant analysis is limited. Thus in the following and final section, cluster analysis is investigated as a more appropriate tool for classification and analysis of the college student leadership data.

2.3   Cluster Analysis to Segment Students on Leadership Behaviors

This section investigates the application of clustering techniques to the college student leadership behavior data, then profiles and validates the resulting clusters. See Section 2.5 of the Job Seeker analysis for additional details on the methods and options for using cluster analysis.

Cluster analysis allows the researcher to take a different look at the data, with no preconceived notions regarding profiles, similarities, or performance measures. This analysis simply aims to segment the college student leadership data into meaningful clusters. Then these clusters are reviewed, evaluated and discussed to better understand the behaviors that link those within a cluster, and differentiate them from those in other clusters.

The final clustering method used here is a two-step cluster program which has the ability to quickly determine the appropriate number of clusters, then classify them using a nonhierarchical routine. The procedure is relatively new, but as recommended by Hair et. al. (p. 497), it does prove to be useful in this application due to the sample size, over 500 cases, and the number of variables be analyzed (the 24 leadership behaviors). Garson (2009) further encourages the use of the two-step method for large datasets using both continuous data and categorical variables with three or more levels.

The two steps are a pre-clustering step where cases are divided into small sub-clusters, followed by a second clustering of the sub-clusters into the desired or pre-defined number of clusters. An automatic selection of clusters is optional, but results in only two clusters given the leadership dataset, which does not yield the interpretability being sought. Thus, the appropriate number of clusters must be determined which will be discussed further below.

The two-step procedure is based on Banfield and Rafferty's (1993) work with clustering methods for continuous variables based on the reduction in log-likelihood when two clusters are merged. Further, the two-step procedure extends the work of Melia and Heckerman (1998) who took a similar probabilistic approach to clustering categorical variables. Zhang et al, 1996 developed BIRCH clustering for larger datasets, reducing them to sub-clusters which are analyzed in a second step much like traditional clustering methods. The two-step procedure innovatively combines these works, resulting in an effective clustering solution for the leadership dataset due to its size and the number and types of variables being investigated.

The pre-clustering stage uses a cluster-feature tree (CF tree) with nodes leading to leaf nodes, the result of a sequential clustering method described by Theodoridis and Koutroumbas (1999). Cases begin at the base, or roots of the

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tree, and climb toward nodes and up to leaf nodes with the closest match. If the distance measure for the case is above the threshold level, thus no adequate match is found, the case begins a new leaf node. If the CF tree fills and cannot accept new leaf entries in a node, it is split, using the most-distant pair in the node as seeds. Should this recursive process build the tree beyond maximum size, the threshold distance is increased and the tree is rebuilt, allowing new cases, and continuing the process until all cases are read. For the leadership dataset, the clustering specified includes maximum of three levels of nodes for the CF tree, with eight entries per node maximum.

The log-likelihood distance measure is used because it can handle both continuous (normal distribution assumed) and categorical variables (multinomial distribution assumed). The distance between two clusters is based on the decrease in log-likelihood as they are combined into one cluster. With the log-likelihood distance for two-step clustering algorithm, the distance between clusters is defined as

$$d(i, j,) = \xi_{} + \xi_{} - \xi_{,j>}$$

where

$$\xi_{} = -N_v \left(\sum_{k=1}^{K^A} \frac{1}{2} \log(\sigma_{} + \sigma_{}) + \sum_{k=1}^{K^B} \hat{E}_{vk} \right)$$

and

$$\hat{E}_{vk} = -\sum_{l=1}^{} \frac{{}_{vkl}}{{}_v} \log \frac{N_{vkl}}{N_v}.$$

K^A Total number of continuous variables used in the procedure.
K^B Total number of categorical variables used in the procedure.
R_k The range of the kth continuous variable.
N Number of data records in total.
N_k Number of data records in cluster k.
$\hat{\mu}_{}$ The estimated mean of the kth continuous variable across the entire dataset.

$\sigma_{}$ Estimated variance of the kth continuous variable across the entire dataset.
$\hat{\mu}_{}$ Estimated mean of the kth continuous variable in cluster j.

$\sigma_{}$ Estimated variance of the kth continuous variable in cluster j.

d(j,s)   Distance between clusters *j* and *s*.

<j,s>   Index that represents the cluster formed by combining clusters *j* and *s*.

Variable Importance

The relative contribution of each variable to the cluster can be computed for both categorical and continuous variables. For categorical variables, the importance measure is chi-square distributed and for continuous variable the measure is based on Student's t-test. Computations for both are given here, but the application to the college student leadership data will discuss the significance of the probability measures which are more straightforward graphically.

Categorical variables are based on the importance measure:

$$\chi = \sum_{l=}^{L_k} \left(\frac{N_{jkl} - N_{kl}}{N_{kl}} \right)$$

Where

N_{jkl} is the number of data records in cluster *j* whose k^{th} categorical variable takes the lth category.

N_{kl} is the number of data records in the kth categorical variable that take the lth category.

L_k is the number of categories for the kth categorical variable.

Under the null hypothesis the above measure is distributed as χ with L_k degrees of freedom. Again, the importance measure can be reported as χ or its significance.

Continuous variables are based on the importance measure:

$$t = \frac{\mu_. - \iota_{j.}}{\sigma_{j.} / \sqrt{N_k}}.$$

Under the null hypothesis, this is distributed as *t* with $N_k - 1$ degrees of freedom. Significance level is two-tailed, and again, either the statistic or its significance level can be reported as the importance measure.

Determining Number of Clusters

The procedure uses an algorithm based in part on Bayesian (BIC) or Akaike (AIC) information criteria loss to determine the optimal number of clusters. As mentioned earlier, this automatic determination results in only two clusters which is not preferred given the leadership application. The preference is to identify clusters comprised of cases that behave similarly. The objective is to profile and understand the behaviors within the cluster, and differences between the clusters, so as to suggest improvements that have the potential to transition members to a cluster evidencing stronger leadership tendencies. The automatic cluster number option was overridden and a random sample of 100 cases taken through several variations of hierarchical clustering procedures to determine the appropriate number of clusters as suggested by Garson (2009).

To determine the appropriate number of clusters, the agglomeration schedule was reviewed, looking for substantial changes in heterogeneity, meaning how different observations in one cluster are from those in another (Hair et al, p.526). The agglomeration coefficient measures the increase in heterogeneity occurring from the combination of two clusters. Hair et al. suggest a reasonable approach to determining the number of clusters is to measure the percentage change in heterogeneity. "When large increases occur in moving from one stage to the next, the researcher selects the prior cluster solution because the new combination is joining quite different clusters." (Hair, et al, p. 527). A 27% change in the agglomeration coefficient is evident between three and four clusters using a complete linkage method, thus the three cluster solution was selected.

Several steps were initially taken which further validate the use of a three cluster solution. A random sampling of 100 cases were tested using only the three construct variables (SELF, CONTEXT, OTHERS). Complete linkage and Ward's method resulted in four cluster solutions, while single linkage returned three clusters. Next, all cases and all 24 leadership variables were tested under the Ward's linkage method which resulted in a three cluster solution with a 4.4% change between three and four clusters. As mentioned above, results from the complete linkage agglomeration schedule supported a three cluster solution.

Cluster Profiles

As discussed earlier, the two-step clustering method was used on the college student leadership data because of its ability to handle both continuous and categorical data, as well as its flexibility with larger sample sizes. The cluster

analysis yields three uniquely profiled groups, with membership distributed in a reasonable manner with 22% in cluster 1, 54.3% in cluster two and 23.7% in cluster 3. The cluster sizes are reasonable in that one might expect around 20-25% of college student respondents to fall in the lowest and highest cluster categories based on self-assessments of leadership skills, the balance falling in the middle category.

Based on the profiles to be discussed, the clusters are nicknamed as follows: Cluster 1, less involved, less others-oriented, cluster 2 are the self-improvers, and cluster 3 are the more involved leaders with some distinctive characteristics.
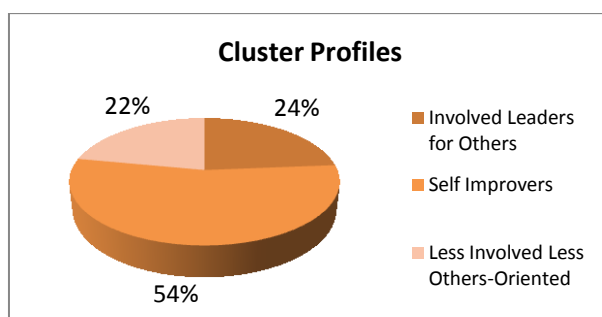
Figure 2.3.1 Cluster Profiles

Cluster 1 – Less Involved, Less Others-Oriented

Variable importance plots are used to graphically display the variables' relative contribution to the cluster. The first cluster is profiled as "less involved, less others oriented." These are essentially the lowest self-scoring students. Figure 2.3.2 suggests significant chi-square values for the categorical variables in the analysis, level of involvement, year in school and gender. The most differentiating impact from categorical variables is from involvement level. This group holds nearly 85% of the students who were not involved in *any* student organizations. Members tend to be seniors and graduate students which may explain a lower level of involvement in on-campus student organizations.
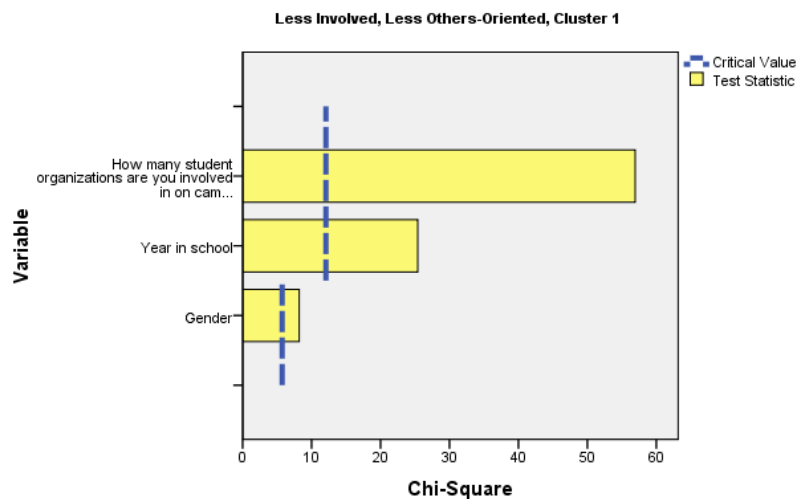
Figure 2.3.2 Cluster 1 – Categorical discriminators for less involved, less others-oriented group

The top five most important variables contributing to cluster membership will be discussed. While others do contribute significantly, five is a manageable number to recall for reference and discuss here.

The top two are both variables related to consciousness of OTHERS; thinking about how decisions are received by others in the group, as well as being concerned about resolving conflicts within the group. The next most important variables affecting cluster membership are two CONTEXT variables which are thinking about how the environment influences their leadership style, and tailoring their style to the situation. Willingness to help others enhance their skills was the fifth most important variable in contributing to group membership. These are the five variables with the most significant probability scores with regard to each variable's contribution to group membership in the less involved, less others-oriented cluster (Table 2.3.1).

Less Involved, Less Others-Oriented Cluster Variable	*t*-statistic	p-value
Think about Decisions Received	-9.6	.000
Resolve Conflicts	-9.2	.000
Environment Influences Style	-9.1	.000
Tailor Style to Situation	-9.0	.000
Help Others Enhance Skills	-8.9	.000

Table 2.3.1 Variables most significantly contributing to membership in "Less-involved, less others-oriented" cluster 1.

Again, as this is the lowest-scoring group, a development focus on improving in these areas could potentially move this group to a higher level of leadership.

Cluster 2 – Self Improvers

Given that three clusters were specified, this middle group had no variables that significantly contributed to group membership. Working on one's limitations approached significance, thus the cluster is nicknamed "self-improvers". None of the categorical or continuous variables serve as significant discriminators of group membership, but the variable importance plots offer a directional view into the respective importance of each variable within the cluster. This group may be more self-oriented, working on their limitations, improving abilities, capitalizing on personal strengths, and following through, all variables of the SELF construct.. Note that the second most important variable (although insignificant) is thinking about how one's leadership style aligns with group culture, a consciousness of CONTEXT variable, suggesting a willingness to learn leadership skills. Recall that this second cluster of self-improvers rates significantly lower on their mean scores for all these variables compared to their cluster 3 counterparts.

Cluster 3 – Involved Leaders for Others

Members of the third cluster, dubbed "Involved Leaders for Others" are significantly differentiated by their high level of involvement in student organizations on campus (Figure 2.3.3).
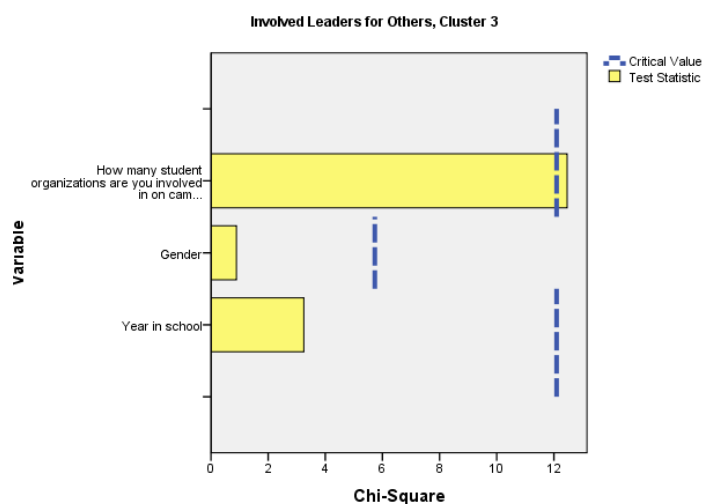
Figure 2.3.3 Level of involvement differentiates "Involved Leaders for Others" – Cluster 3

This top-ranking group is distinguished by their others-centeredness including working to resolve conflicts within the group, team-building, and considering the needs of others in the group, all variables from the OTHERS consciousness construct. They next look internally and think about how they might improve their abilities and establish a shared goal (SELF variables). Table 2.3.2 reviews Student's t for each variable and its significance.

Involved Leaders for Others Cluster Variable	t-statistic	p-value
Resolve Conflicts	16.9	.000
Work to Build Team	16.3	.000
Consider Needs of Others	15.8	.000
Improve my Abilities	15.6	.000
Work Toward a Shared Goal	14.8	.000

Table 2.3.2 Variables most significantly contributing to membership in Involved Leaders for Others – cluster 3

Validating the Cluster Solution with Discriminant Analysis

Cluster membership can be used as the grouping variable in discriminant analysis as a means for validating the final cluster solution (Punj, 1983, Garson, 2009;). Punj suggests that after developing the cluster solution on one sample, discriminant functions are derived and applied to a second (hold out) sample. Figure 2.3.4 shows the distribution of the discriminant scores for the first discriminant function applied to each of the three clusters derived in the two-step cluster analysis. The distribution of discriminant scores for each cluster is substantially separate..

cluster1=RED, cluster2=BLACK,cluster3=BLUE
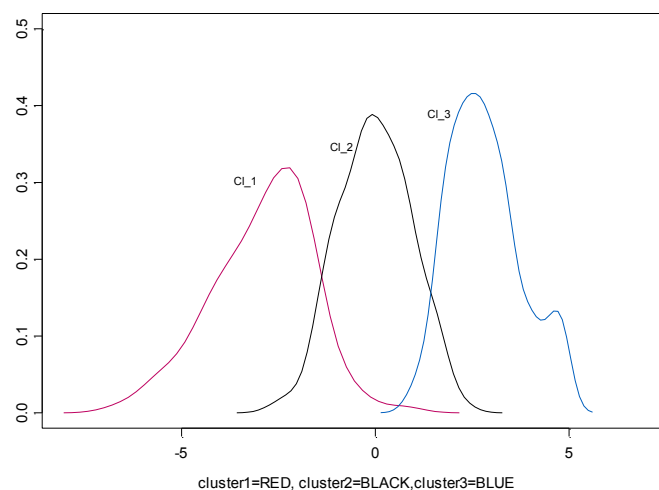
Figure 2.3.4 Discriminant scores for each cluster from first discriminant function

To assess model fit, consider Wilks' λ = .186 for the first discriminant function, which suggests that the model separates cases into groups very effectively with the proportion of total variance in the discriminant scores not explained by differences among the groups at only 18.6%. Recall, smaller values of lambda suggest greater discriminatory power of the function.

The stepwise procedure was used, where at each step the variable that maximizes the Mahalanobis distance between the two closest groups is entered into the solution. Interestingly, "work to build a sense of team" is the first variable entering the procedure, followed by considering the needs of others in the group. These two variables, elements of the consciousness of OTHERS construct, serve to differentiate clusters 1 and 2. This supports the profiling of cluster 1 members who tended to be significantly less conscious of others given the attribute importance ratings supplied by the two-step cluster procedure.

Substantially separating cluster 2 (Self-Improvers) and cluster 3 (Involved Leaders for Others) are propensity to improve one's abilities and monitoring how emotions affect interactions with others, both SELF construct variables. A simple tally of the variables and the clusters they differentiate reveals that the less involved, less others-oriented members of cluster 1 were differentiated from cluster 2, Self-Improvers, primarily on OTHERS and CONTEXT variables. It is primarily CONTEXT and SELF variables that distinguish Self-Improvers (cluster 2) from the Involved Leaders for Others in cluster 3. Further, extent of organizational involvement on campus further discriminates between Self-Improvers and Involved Leaders. These findings clearly support the suggestion that if the less involved, less others-oriented members in cluster 1 were to focus on being more conscious of others and the context of the leadership situation they could potentially transition to a higher level in cluster 2. They could potentially improve these skills through greater involvement in campus organizations. Such involvement, plus additional focus on the SELF attributes has the potential to transition them all the way to cluster 3, Involved Leaders for Others.

The second function offers some discrimination, but just borders significance with λ=.937, significant at .066, somewhat outside a useful threshold. Figure 2.3.5 provides graphic support for the second discriminant function.
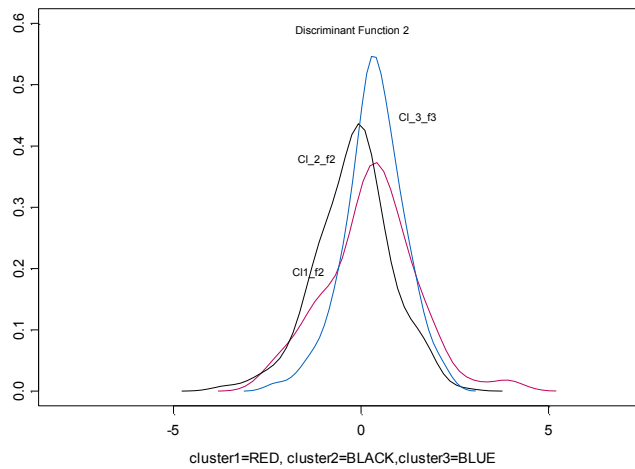
Figure 2.3.5 Second discriminant function

Looking to the classification table (Table 2.3.3) for practical results, it is found that 92% of the cases from which the function was built are classified correctly, and 87% of the holdout sample is correctly classified. Specifically, cluster 1, whose members are less involved, less-others-oriented, are classified correctly 83.9% of the time, and cluster 2 Self-Improvers 84.5% of the time. Also, 94.6% of the hold-out sample cases of the involved, more others-oriented, leaders, cluster 3, were correctly classified. Overall the discriminant analysis approach to validating the clusters proves worthwhile, and suggests the clusters are stable.

Classification Results[a,b]				with gender, yrsch, orgs	Predicted Group Membership			
					Cluster 1	Cluster 2	Cluster 3	Total
Cases Selected	Original	Count	1		78	3	0	81
			2		9	168	14	191
			3		0	2	82	84
			Ungrouped cases		5	3	3	11
		%	1		**96.3**	3.7	.0	100.0
			2		4.7	**88.0**	7.3	100.0
			3		.0	2.4	**97.6**	100.0
			Ungrouped cases		45.5	27.3	27.3	100.0
Cases Not Selected	Original	Count	1		26	5	0	31
			2		8	73	5	86
			3		0	2	35	37
			Ungrouped cases		3	6	3	12
		%	1		**83.9**	16.1	.0	100.0
			2		9.3	**84.9**	5.8	100.0
			3		.0	5.4	**94.6**	100.0
			Ungrouped cases		25.0	50.0	25.0	100.0
a. **92.1**% of selected original grouped cases correctly classified.								
b. **87.0**% of unselected original grouped cases correctly classified.								

Table 2.3.3 Discriminant analysis classification results using cluster membership as grouping variable

2.4   Summary and Future Research

The management issue was to validate a self-assessment tool employed by researchers studying college student leadership behaviors. The methods used were factor analysis to assess reliability of the assessment tool, discriminant analysis to understand the variables separating higher performing leaders from others, and cluster analysis to ascertain the natural clustering of behavioral variables related to leadership. Three underlying constructs of the leadership experience were identified and validated. These include consciousness of context, self and others.

Another objective was to use the data to suggest areas for improvement in the consciousness constructs (context, self and others) which reflect the behaviors of higher level leaders (at least from the perspective of self-perceptions). Starting from oneself, it was recommended that the initial focus be on improving one's abilities, aligning one's actions with values, then working on one's limitations. Considering consciousness of others, the immediate focus that most differentiated low from mid-level leaders was thinking about how one's decisions are received by the group. To generate improvement from there, a focus on helping others enhance their skills and abilities was suggested. Also, context must be considered. The data suggests that those scoring lowest on consciousness of context are primarily different from their mid-level counterparts in their thinking about how they align their leadership style with group culture. The next step suggested was to understand how the group's environment influences one's leadership style, then tailoring the style to the situation. These elements most differentiated college students in their self-perceived leadership behaviors. The differences evident in the behavioral data were effectively interpreted to make suggestions for improvements.

Cluster analysis enabled the division of respondents into meaningful clusters based on specific, self-reported behaviors. In leadership settings, those who are more involved were also more others-oriented. They prioritize resolving any conflicts within the group, then they work on team-building. Considering the needs of others plays a key role as does improving one's abilities. Working toward a shared goal further contributed to a student being categorized into this leadership group.

The investigation of gender differences was fruitful. Findings from research question one suggested that women and men college students lead differently. Women demonstrated significantly higher levels of emotionally intelligent leadership in the constructs of consciousness of self and consciousness of others. This supports findings that women tend to demonstrate higher

competence in individual and group values of the social change model of leadership than men (Dugan et al., 2008). It also supports the idea that women have more democratic and relational leadership styles than men (Eagly & Carli, 2007).

In examining the individual measures from research question one, women more specifically tend to put the needs of others in front of their own, listen to others, and think about how their decision will be received more often than men. This concern for others also reflects democratic leadership, which emphasizes collaboration, shared power, and group decision-making (Northouse, 2007). Women's greater capacities for the consciousness of self measures of following through on their commitments and aligning their actions with their values reflect findings by Dugan et al. (2008) and Haber and Komives (2009) that women demonstrate higher levels of commitment and congruence from the social change model of leadership than men.

The behavior of considering needs of others was particularly prominent, and among the students with the highest scores of all three levels of consciousness, women still held significantly higher scores than men on this measure. Considering the needs of others seems to be the behavior that most differentiates the genders at the highest self-perceived levels of leadership. This finding along with the overall pattern of findings from this study suggest that women have higher levels of many of the consciousness of others measures than men, which is consistent with the literature on gender differences in transformational leadership (Bass & Riggio, 2006; Eagly & Carli, 2007) and the group values of socially responsible leadership (Dugan et al., 2008; Haber, 2006).

Men in the study demonstrated higher levels of the consciousness of self measure of capitalizing on strengths than women. While this measure does not specifically have to do with self-esteem, it does reflect acknowledgement of strengths and self-perception of ability to use strengths. This could reflect past research that men tend to demonstrate greater confidence and self-efficacy in leadership than women (Dugan & Komives, 2007; Kezar & Moriarty, 2000). Additionally, highly involved men also worked on their limitations more often than women. This goes hand in hand with trying to build strengths and capitalizing on them.

In examining gender differences based on levels of involvement, it does not appear that levels of involvement by gender provide many significant findings. For men and women involved moderately (two or three organizations), women scored significantly higher than men in the constructs of consciousness of self (for two organizations) and consciousness of others (for three organizations).

There were no overall differences in levels of consciousness for respondents with low involvement (one organization) or high involvement (four or more organizations). It appears as if moderate involvement is associated with gender differences in measures of emotionally intelligent leadership. This emergence of gender differences for moderate involvement but not for high or low involvement warrants additional exploration as to the role that gender plays based on different levels and types of involvement in developing students' emotionally intelligent leadership.

Although there were no differences by gender in the three constructs of consciousness for those students involved in four or more organizations, gender differences did emerge for the individual measures. Unlike other findings throughout this study, men tended to work on their limitations, capitalize on their strengths and align different points of view more than women. In examining the shift in gender differences from the moderately involved students to the highly involved students, there may be something to be said about women being overburdened or overwhelmed with higher levels involvement or men benefiting more from higher levels of involvement. These possible phenomena would be worth exploring to understand what may contribute to these differences along with or beyond the sheer number of organizations in which one is involved. Further exploration into how men and women's emotionality intelligent leadership measures shift depending on levels of involvement would also provide additional insight into the role of involvement in college men and women's emotionally intelligent leadership outcomes.

It is important to note that throughout both research questions there were no significant differences for the construct consciousness of context. A significant difference emerged for one of the consciousness of context measures, whereby women involved in two organizations recognize patterns or behaviors in a group more often than men. Beyond this narrow finding, it appears as if men and women have similar levels of awareness of the larger environment in which they operate. Overall, women tend to demonstrate higher levels of the consciousness of self and consciousness of others capacities of emotionally intelligent leadership than men.

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Classification and Analysis of Franchise Resource Data

1.1   Franchising market – Issues, Constraints and Literature review

Over 30 years ago, investigating the effects of tying agreements on the franchise system of distribution, Hunt and Nevin (1975) suggested that legislation and franchisee vs. franchisor litigation had proliferated to crisis proportions. Legal expert Glosband (1972) believed the problem of restrictions on the source of supplies or services was at the heart of virtually every complaint pending against franchisors.

This work initially investigates satisfaction with services provided by the franchisor to the franchisee, as well as overall satisfaction levels. These services can be considered marketing services in that the programs are aimed at assisting the franchisee in generating revenue. Such programs, products and services are typically provided by the franchisor to the franchisee as revenue-generating tools, thus increasing royalty fees paid to franchisor. The aim then is to use analytical techniques to better understand franchise market segments and make suggestions for more effective allocation of franchisor resources. Analytical methods are applied that may potentially reduce franchisee/franchisor conflict by understanding franchisees' perceptions of effectiveness, value and satisfaction with franchisor programs and services. Such understanding can be used by the franchisor to guide lesser performing franchisees. In effect, the franchisor can investigate the behaviors of higher performers, design programs that are reflective of these behaviors, and implement them with lower performing franchisees, with the intent of generating increased revenue and/or enhanced performance.

Two primary streams of research are found in the franchising literature, the first being a more theoretical discussion of owning versus franchising, and the second investigating factors that affect royalty fees (Agrawal and Lal, 1995). Literature specifically addressing marketing issues affecting the franchise relationship is limited. Marketers in a franchised organization are vulnerable to criticism for a number of reasons including misguided strategic decision-making at higher levels, misperceptions of effectiveness, and miscommunication, particularly in large franchises where messages are often stopped at the franchisee-owner level, and not disseminated down to the operational level. Further, marketers often fail to communicate sufficient quantitative evidence required to garner system-wide participation in programs.

Bridging the Marketing-Finance Gap in a Franchise System of Distribution

In the past decade, there has been an explosion of literature in marketing theory about validating marketing's impact (Rao, 2008; Doyle, 2000; Srivastava, 1998) and the link between customer satisfaction and shareholder value (Aksoy, 2008; Luo, 2008).

In 2001, at the forefront of a then-impending dot.com meltdown, Shaw editorialized that marketing and finance needed to agree on a common measurement framework (Shaw, 2001). His summary insights and recommendations at the time were clearly reflective of the instability of the marketing function with regard to financial responsibility. Shaw suggested,

"More progressive finance directors are driving towards a more integrated framework. They have taken on the customer and competitive measurement problem themselves, something which entails creating several new roles. Market research is moved into the finance department, thus guaranteeing a degree of objectivity not found when marketing runs market research. Predictive modeling also gets commissioned by the finance department, either by using outside consultants or in-house analysts. Balanced scorecards are developed by the finance department: marketing objectives and strategies thus are quantified in ways that are rare when marketing are responsible for marketing plans."

While Shaw's comments may slice through the core of a marketer's heart, his position is warranted. In 2003, Tim Ambler addressed the marketing-finance gap issues, questioning whether the over-popularized philosophy of managing for shareholder value was assisting or damaging the generation of inward cash flow (Ambler, 2003). He suggested that the analysis of shareholder value is a worthwhile technique for identifying assets and costs that can be adjusted, but when used as a 'universal framework for decision making', it may be misleading, particularly for marketing measurements. Typically, finance does not look at future returns as a result of brand building activities today, nor does it evaluate the financial impact of marketing activities from a perspective that acts as a managerial control mechanism on specific marketing activities.

Ambler also suggested using quantitative metrics in a way that leads to effective action. Day (1990), suggested that effective use of metrics includes linking marketing activities to market response and then to subsequent financial impact.

In 2002, between Shaw's lambasting and Ambler's tactful rebuttal (the two not necessarily related), marketing scholars (Ambler, Carpenter, Jacobson, Kumar, Rust, Srivastava, 2004) responded with a partnership between the

American Marketing Association and the Marketing Science Institute to research the need for bridging the metrics gap between marketing and finance.

A special section of the Journal of Marketing in 2004 was the result of a push for more research on the connection between marketing and finance from the Marketing Science Institute. In the introduction to this issue, Lehmann (2004) suggested that although measurements of return-on-investment or margins are accepted standards, in order to accurately assess marketing performance these measures need to be used in conjunction with financial measures of the value of marketing assets that have long-term value such as brand equity, or customer attitudes, behaviors and other evaluative criteria. Acknowledging the data and methodological issues and constraints related to developing an accurate value chain (or the bridge between customer associations and stock price), Lehmann asserted,

"...an attempt to lay out such a value chain and estimate the links seems to be critical. This means there can be no overreliance on a single measure...but there needs to be measures at all the levels. Put simply, if marketing wants "a seat at the table" in important business decisions, it must link to financial performance."

Without a seat at the table, Lehmann predicted that marketing would lose ground to other areas such as product development, and devolve into departments of "ad copy and cents-off coupons" (Lehmann, 1996).

The collaborative efforts by Rust, Ambler, Carpenter, Kumar and Srivastava (2004) suggest that a lack of accountability among marketers has undermined their credibility. Without evidence of the impact of marketing effectiveness on shareholder value, the marketer's very existence in the organization is threatened. Rust, et. al., suggest that it is possible to show how marketing expenditures add to shareholder value. Dissemination of methods of assessing marketing productivity to the business community serves to validate marketing's position within the firm. They recommend dynamic models that link tactics to financial impact. Research and models are necessary in many areas, including strategies and tactics, brand equity, customer equity, market impact, financial impact, the environment and competition.

While academics busily collected, evaluated, and honed the available analytical techniques appropriate for measuring and validating marketing effectiveness, executives in finance began to realize that the union of finance and marketing was essential to spawn growth initiatives from within (organic growth) vs. acquiring other companies. Earnings at industry leaders like Best Buy Co., Inc., Genetech Inc., Barclays PLC and Roche Holding AG, all stock-

market stars in the recent years prior to 2005, came primarily from organic growth. Further, companies in the top quartile of organic growth are 13 times more likely to be in the top quartile of shareholder returns (Jenkins and Meer, 2005).

Practitioners recognize inherent challenges in bridging the gap between finance and marketing, particularly the obvious differences in perspectives. Where finance is motivated by measurement, stability and that which is known, marketing thrives on vision, creativity and innovation. Jenkins and Meer (2005) suggest that requests for budget increases rarely explain how they will boost revenue and profitability. Barclay's former finance director for private client business, Mike Murray suggests marketing's lack of explanation leads to finance "taking the easy way out and cutting marketing spending instead of finding less productive costs that should be reduced to meet profit targets." Jenkins and Meer point to innovation, evaluation of growth opportunities and portfolio management as areas in which a strong marketing and finance partnership can drive firm benefits. Finance executives can help marketers better evaluate the top and bottom line impact of their plans and secure funds for their programs.

Confirming the seriousness of the issue, a 2005 study by Forrester Research, Marketing Management Analytics, and the Association of National Advertisers (ANA) found that only one in three marketers surveyed said they build marketing budgets based on knowledge of the spending required to meet corporate goals. If faced with a 10% budget cut, only 40% felt they could predict the impact of the cut on sales (See, 2006).

A common language between marketing and finance is integral to improving the alignment between the two functions. Ed See (2006) suggests that language should include marketing based drivers, such as consumption, distribution, displays and retailer publication features and their supporting data. Interviewing the VP Finance for a Fortune 500 cosmetics company, See reports that the company's financial projections are the outcomes of their marketing plan, and are thus closely linked. The VP Finance says, "We need to quantify, track and measure everything that we can, including marketing activity. Marketing is not just art – it can also be science, thus bringing it closer to a numbers function like finance."

Both academics and practitioners recognize the need for marketing metrics that satisfy the firm's financial reporting requirements, as well as accurately predict future market behaviors and potential responses to changes in firm strategy. Perhaps the complexity of academic models inhibits general acceptance by managerial practitioners. As Wübben and Wangenheim (2008)

suggest, while stochastic customer base analysis models, designed by academics, are available, managerial application is not widespread.

The good news is that there are ample models and methods designed to measure marketing effectiveness. Just as an example, Srinivasan, Pauwels, Silva-Risso and Hanssens (2009) examined how product innovations and marketing investments for innovations lift stock returns by improving the outlook on future cash flows. They found adding 'information about marketing actions to the established finance benchmark model greatly improves the explained variance in stock returns.' Trusov, Bucklin and Pauwels add substantial insight to the effects of word-of-mouth (WOM) versus traditional marketing. Their method utilizes a vector autoregressive (VAR) modeling approach to show that WOM referrals have "substantially longer carryover effects and produce substantially higher response elasticities. They quantify the monetary value of a WOM referral, based on revenue from advertising impressions served to a new member. These innovative techniques and methods for quantifying the impact of marketing efforts are available but have not yet found their way into average marketing departments.

Rust et al (2004) suggest a greater emphasis on developing aggregate-level models that link tactics to financial impact. Further, they recommend research in the area of accounting for customer heterogeneity. Specifically, they mention the identification of high-profit customers as being central to market segmentation, strategic marketing and related tactics. The marketing scholars summarize their review suggesting that the evaluation of marketing productivity ultimately involves projecting the differences in cash flows that will occur from implementation of marketing action. An understanding of how marketing actions impact financial assets is likely to transform the way businesses are managed.

Marketing and Resource Allocation Challenges in a Franchise Organization

The franchisor faces substantial challenges related to resource allocation regarding franchisees. New members of the franchise system require substantial training resources, while more tenured franchisees typically seek assistance with revenue generating programs such as sales incentive contests, cooperative advertising or perhaps financing options for renovations or development. The franchisor's challenge is in identifying the franchisees that hold the most promise for future revenues, then allocating the appropriate resources. .

Eliashberg and Michie (1984) investigated how multiple business goal sets determined marketing channel conflict. They highlight the fact that in many marketing distribution systems the channel members operate under different business philosophies. Wittreich (1962) suggested that independent owner-operators do not typically share the growth philosophy that corporate managers do. This individual's business philosophy is oriented toward reaching a point and leveling off into a continuously satisfying plateau. This is reflected in the franchising dataset in the segment nicknamed "Glory Days". This group of franchisees have been with the organization over 16 years and are in the lowest revenue category, earning less than $500,000 in annual revenues. This segment reveals low levels of satisfaction with the franchisor, comparable to their higher revenue counterparts of the same tenure. Resource demands placed on the franchisor by this segment can diminish productivity without the financial return that can be anticipated from higher revenue segments.

Eliashberg further suggests that two different business philosophies are likely to result in two different business goals sets in many marketing channels – the overall system goals set and the individual members' informal but operationally tractable business goals set. The franchisor is the channel administrator who sets the overall system goals, but franchisees are likely to have different *operative goals* (Perrow, 1970). Usually, these operative goals are actively being pursued by the organization's members and the pursuit is reflected in the members' activities and resource allocation patterns (Connor and Bloomfield, 1970). It is fair to assume that different goal sets between the franchisor and franchisee can be a source of conflict resulting in lower levels of satisfaction.

Franchisors typically have a goal of standardizing the marketing practices of franchisees (Anand, 1987). The goal is usually addressed in franchise agreements, but federal, state and local regulations preserve the franchisees' discretion in making certain decisions. The franchisor must then be highly persuasive to generate franchisee support for programs. Anand and Stern (1985) found that franchisees would relinquish control when

- profitable decisions initiated by the franchisor were attributed to internal characteristics of the franchisor, such as ability and effort
- unprofitable decisions initiated by the franchisor were attributed to factors external to the franchisor, such as store location and luck
- their own profitable decisions were attributed to external factors, and

- their own unprofitable decisions were attributed to internal causes, such as lack of ability or effort.

Anand (1987) suggests that management consider using subsamples to influence lower performers to act like their higher performing counterparts. If, for example, the "top 10%" is revealed to have relinquished control to the franchisor (implying participation in programs and services), then this news should be spread within the organization, hopefully garnering support for the franchisor's decision making skills. Channel members who perceive they are doing well (or badly) on their own (or the franchisor's decisions) might be influenced by performance of the top 10% or bottom 10%.

In the dataset analyzed here, it can be seen that higher level performers participate in franchisor meetings, they perform benchmarking against other channel members, and share best practices. The analysis digs deeper to understand the specific programs and services that yield usage and satisfaction from the higher level performers. Thus, the lower levels can be encouraged to participate in a like manner, with the intent of moving them upward in profitability segments.

1.2   Description of the Dataset - Franchise Community Survey

The subject organization is a 40-year-old franchise network of employment recruiting service offices, with an estimated 1100 offices in 40 countries (800 in the United States, 300 international). Franchise offices target employers, contracting their services to find, pre-screen and present potential candidates for positions within the employer's organization. An average fee of 30% of the recruit's first year salary is paid by the employer to the franchise office for the aforementioned services. A fee of approximately 7.5% of top-line sales revenue is paid by the franchisee to the franchisor who offers no competing recruiting services, only support services to the franchisees. Franchises are sold by geographic area, but each works in an industry niche with no boundaries, borders or competitive protection resulting from the franchise agreement.

The dataset was collected in March 2009, with the following objectives defined:

- *Generate valid and reliable research from members of the franchise community that will enable the effective design of a strategic plan for growth that is perceived as equitable and valuable to both the franchisor and its franchisees.*
- *The research investigates services provided by the franchisor including operations, marketing, training and information technology, and the levels of utilization and satisfaction within the franchise community.*

The dataset was collected via a web-enabled survey, introduced and sent in an email as link in late January 2009. The invitation to participate was sent to the entire franchise network in the United States, yet only approximately 300-400 franchisees are considered active participants in the franchise community. Varied size and tenure offices are represented in the final sample of 225 respondents. A total of 447 variables measured, with over 100,000 data points considered in the initial analysis reported to the franchisor. This work will discuss only the most relevant areas investigated, those that are utilized in the final discriminant analysis.

Nearly 30% (26.7%) of the respondents had been with the network for over 20 years. Varied tenure of franchise ownership were comparably represented, with the exception of those in business 1-3 years (10%) and less than one year (4%), see Figure 1.2.1.
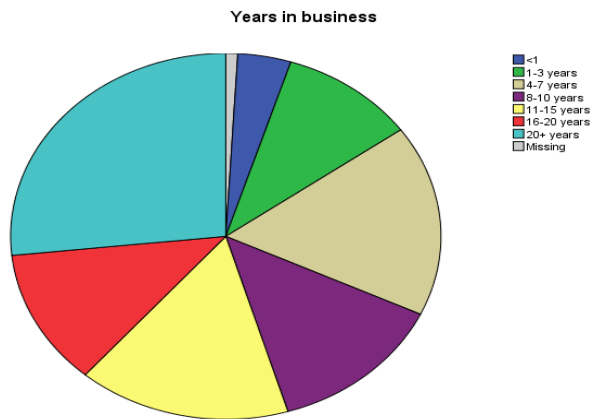
Years in business

Legend:
- <1
- 1-3 years
- 4-7 years
- 8-10 years
- 11-15 years
- 16-20 years
- 20+ years
- Missing

Figure 1.2.1 Franchisee tenure distribution

Forty percent reported less than $500K in annual revenues, followed by nearly 25% (24.4) in the $1-3MM range. Another 18% reported average annual revenues at $500,000-$750,000 (Figure 1.2.2).

Average Annual Revenue

Legend:
- <$500,000
- $500K - $750K
- $751K - $1MM
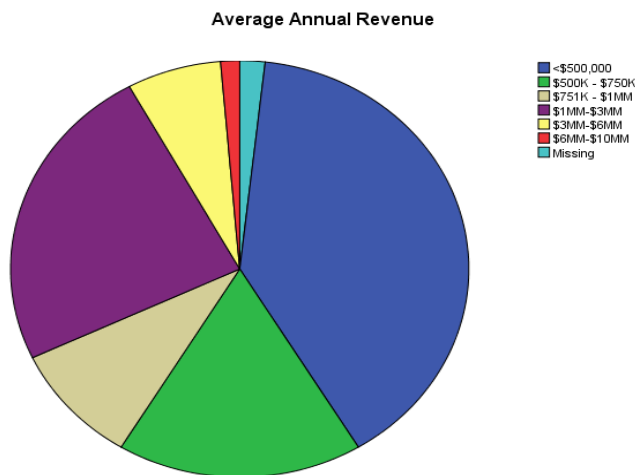- $1MM-$3MM
- $3MM-$6MM
- $6MM-$10MM
- Missing

Figure 1.2.2 Franchisee sales distribution

Thirty-seven percent employed 1-3 staff members (including themselves), and another 33% ran their business with 4-7 employees (Figure 1.2.3). Thirteen percent of respondents managed their office with a staff of 8-10, and 7% had twenty or more staff.

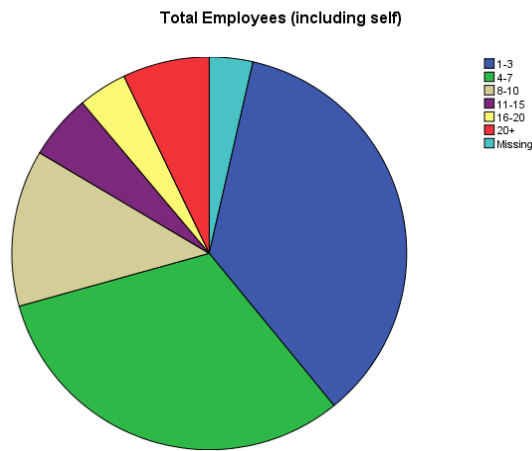**Total Employees (including self)**

Figure 1.2.3   Number of employees in franchisee office

Satisfaction with functional areas was assessed, indicating overall satisfaction with franchisor programs and services was rated at 5.44 on the 1=low to 10=high satisfaction scale. Legal services (7.48) and Learning and Talent Development (6.5) were rated at the top whereas marketing and vendor programs rated lowest, just above overall satisfaction (Figure 1.2.4).
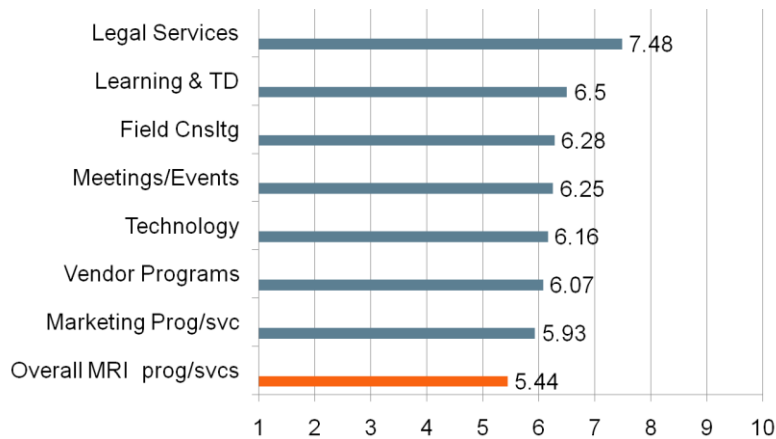

Figure 1.2.4 Franchisee satisfaction with functional areas of service; overall satisfaction with franchisor

Satisfaction regarding specific programs and services was highest with office supplies and services at 6.52, followed by The Resource at 6.5. This is the website database for all franchise-related documentation including marketing and training materials, communications, benchmark ratings, etc. Revenue generating programs were rated alarmingly low at 3.76 (Figure 1.2.5)
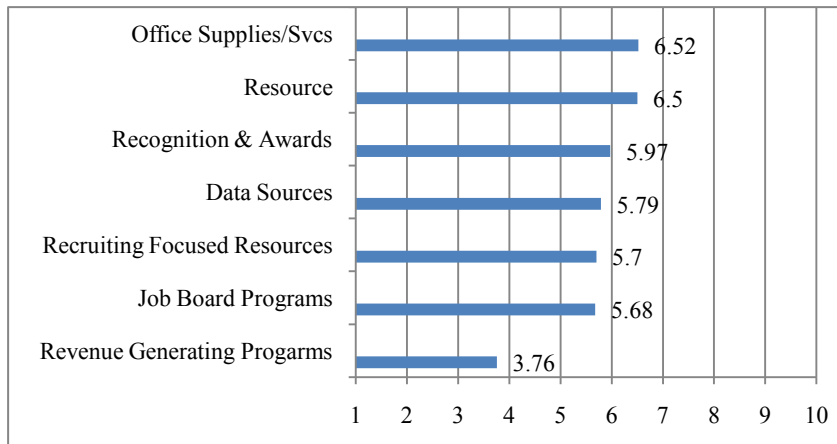
213

Figure 1.2.5 Franchisee satisfaction with specific programs and services provided by franchisor

Satisfaction with field consulting services was rated at 6.28 on the 10-point scale. These services typically involve telephone calls, emails and personal office visits from representatives of the franchisor. The representative provides guidance, direction, and assistance with all matters related to managing and developing the business in the prescribed manner suggested by franchisor management. Use and satisfaction with these services are integral to value perceptions perceived by franchisees. Seventy-four percent report usage of field services. Note that the "aware" box was checked by 57%, but we infer that if one used, they must be "aware". Responsiveness was rated fairly high at 7.92, while value perceptions, effectiveness and future usage intent hover near 7 on the 10 point scale.
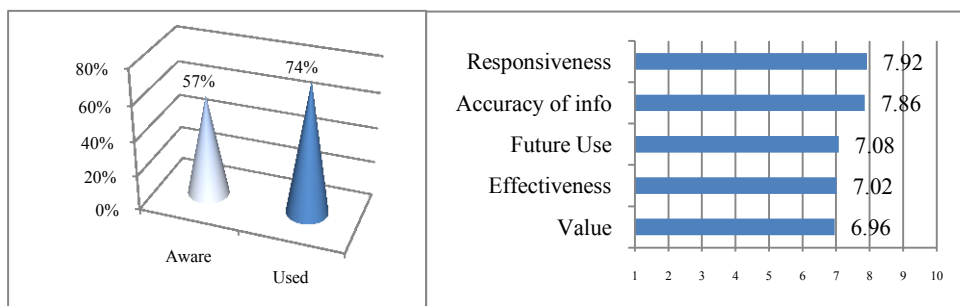

Figure 1.2.6 Field consulting services – overall satisfaction 6.28

While a substantial 83% reported awareness of public relations services, only 20% had used them. Information was rated relatively accurate as this is primarily supplied by participating franchisee. Responsiveness was rated at 6.15, value perceptions were not strong and intent of future use of public relations services rather limited at less than 5 (Figure 1.2.7).
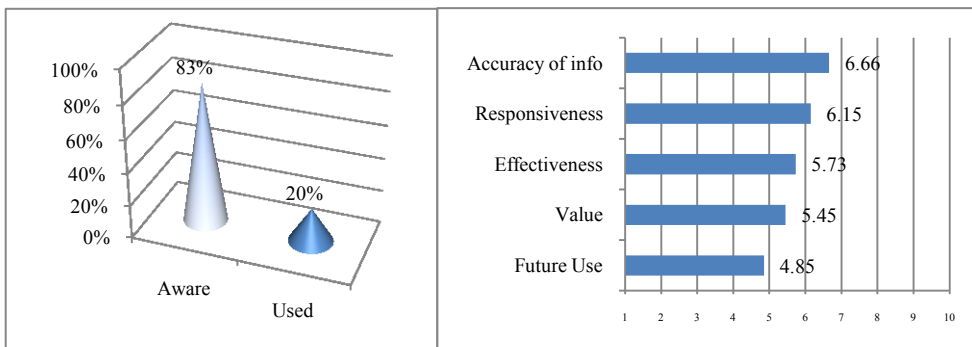
Figure 1.2.7 Public relations services – usage , value perceptions and intent of future use low

Assuming awareness if used, 90% of the respondents reported using the "Resource", the website for franchise information. Satisfaction with the information website was rated at 6.5, with intent of future use fairly high at 8.46 and value perceptions relatively strong at 7.27. Information was perceived to be acceptably accurate at 7.24 (Figure 1.2.8).
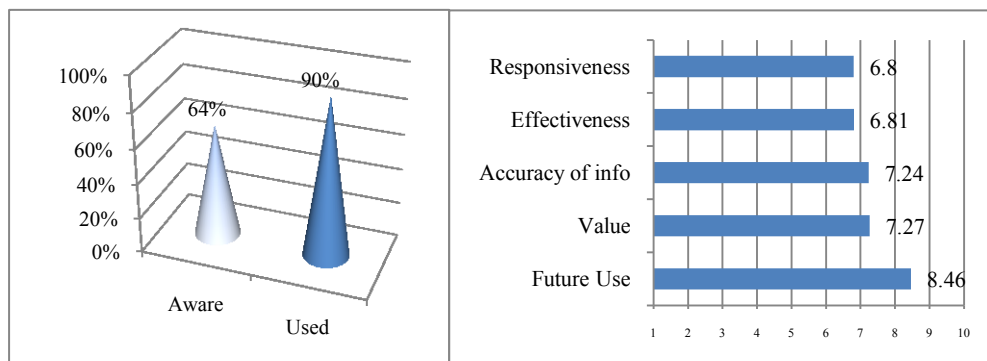

Figure 1.2.8 The Resource, franchise information website; usage , value perceptions , future use intent

Training and development programs offered by the franchisor managed a 6.5 satisfaction rating. In general, awareness of the training and development programs was strong, ranging from roughly 60-80%. Training videos were the
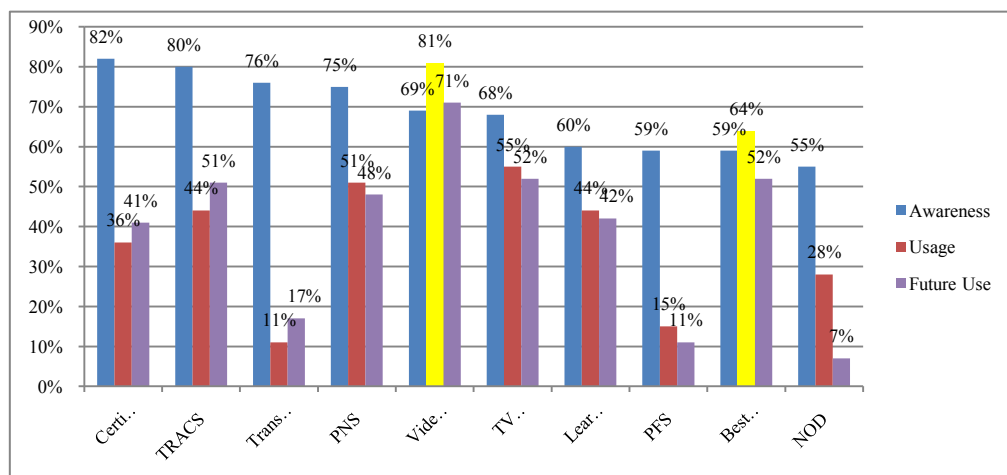

Figure 1.2.9 Awareness, usage and intent to use training materials in the future. Videos and best practice sharing most utilized resources

Best Practice Sharing results in the strongest value perceptions at 8.19, followed by the franchisor's online television-type resource at 8.13, and the Video Vault at 8.02 (Figure 1.2.10). These same tools are considered the most effective as well. The training resources are similar in that they all serve as "how to" resources for recruiters, but the media vehicles differ. Typically a recruiter might watch the franchisor's "TV" network online, downloading video clips of presentations delivered at former meetings, workshops and seminars. The videos in the "vault" may be older, but still worthwhile and shared in an office group meeting as a training element. Sharing best practices happens in all these situations, yet this typically implies learning from an "expert" colleague within the franchise community or within one's own office.
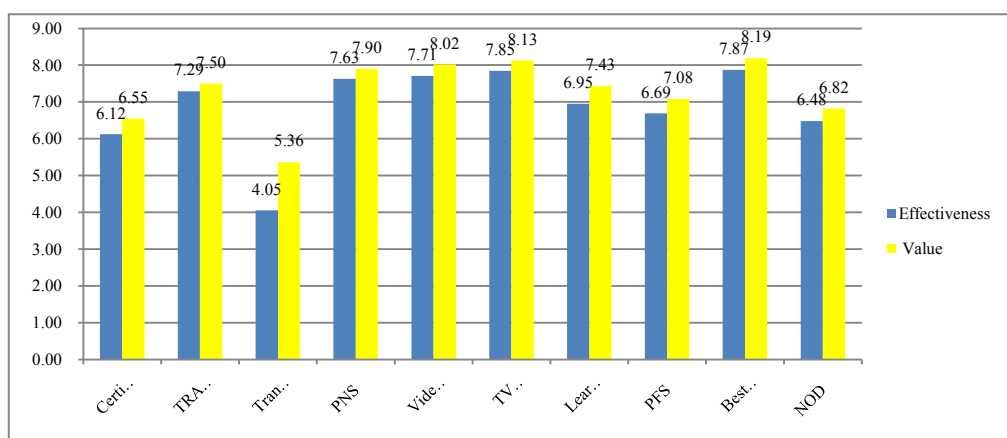

Figure 1.2.10 Franchisee's effectiveness & value perceptions regarding training and development programs

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Assuming awareness, usage of the global conference and regional meetings were nearly 90%, yet future intention of use was only 64% for the global conference and 75% for regional meetings (Figure 1.2.11)
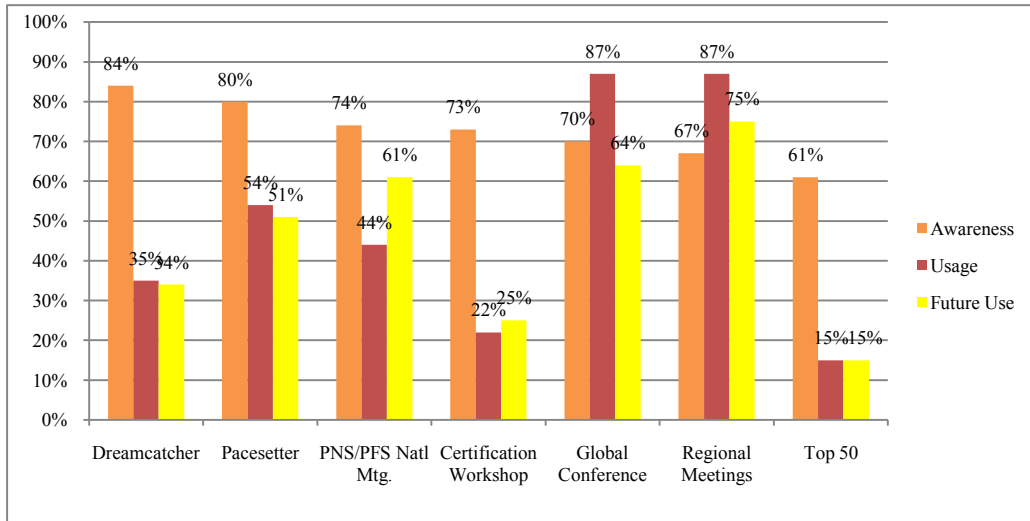
Figure 1.2.11 Franchisees' awareness, usage and intent of future use of franchisor sponsored meetings and events

For regional meetings, value perceptions were rated 7.18 and global conference at 6.54. As far as effectiveness, regional meetings were rated highest at 7.29, and the global conference perceived as fairly effective at 6.8, with value perceptions slightly lower at 6.54 (Figure 1.2.12).

Figure 1.2.12 Franchisees' effectiveness and value perceptions for meetings and events

Breaking out the system into roughly thirds, (low, mid, high) on revenue and tenure, it can be seen that satisfaction erodes as revenue increases. The mid-level 8-15 year old offices report the lowest level of sa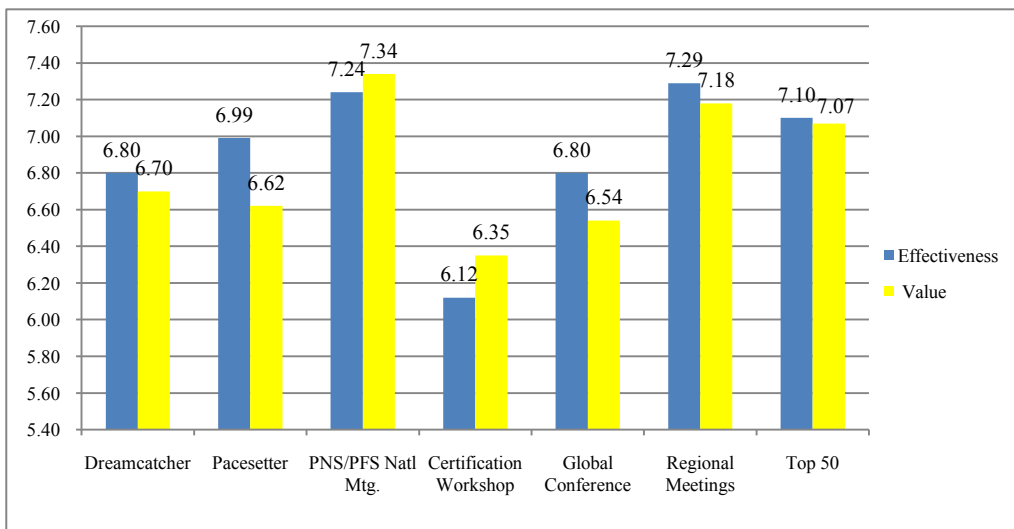tisfaction (Figure 1.2.13) Interestingly however, there is no significant correlation between satisfaction with the franchisor's programs and services and either revenue or tenure. There is a slight, but significant, relationship between tenure and revenue.
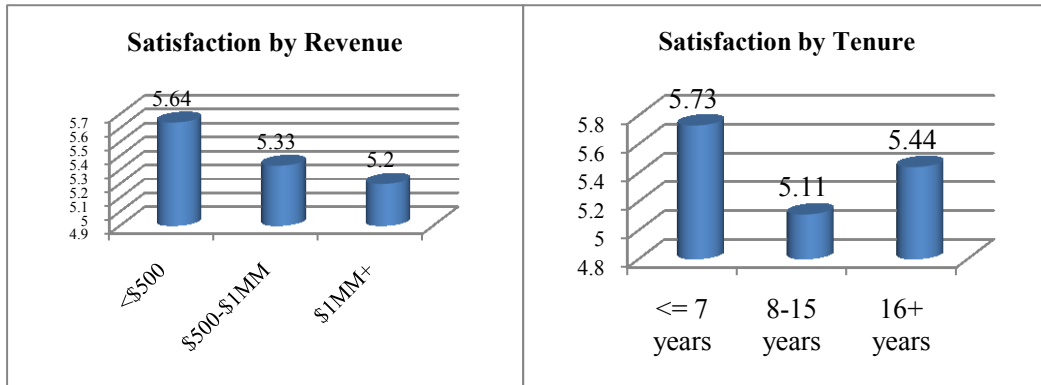
Figure 1.2.13 Franchisee satisfaction by revenue segment and by tenure

Overall, the description of the dataset allows a glimpse into the satisfaction problem of a large, well-established franchise organization in a service industry. Without the tangible assets often found in successful franchises, such as secret recipes, brand equity, or national advertising campaigns, maintaining franchisees' value perceptions and subsequent satisfaction with the resources provided by the franchisor, is challenging at best. This leads to a discussion of the managerial problem at hand.

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1.3   General problem – where to focus franchisor's resources?

Given that the franchise organization under analysis was established over 40 years ago, there is a rich history of recruiting skills required to execute effectively, and techniques to apply in virtually any situation (e.g., candidate wants more money, job description changes after recruiting has begun, etc.). As evidenced in the previous section, satisfaction declines as revenue increases (see Figure 1.2.13). Recall, however that there is no evidence that an individual franchisee's satisfaction decreases over time, but if one considers the segments utilizing the services of the franchisor, it is clear that franchisees with revenues under $500,000 hold the highest level of satisfaction, as do those who have been in the franchise system for seven years or less. The implication is that the franchisee "outgrows" the resources of the franchisor as tenure and revenue increase. Without addressing this vulnerability, the franchise organization remains unstable.

If the franchisor elects to address the questionable sustainability of growth, it must consider allocation of resources. Each franchise contract essentially promises the same support, regardless of tenure or revenue, in exchange for a franchise fee. Contracts are typically 10 years in duration. An assessment of renewed contracts and the status and satisfaction at the time of renewal would prove fruitful for future research, but the data are not available here. So, the question remains to be framed around the best use of both human and physical material resources to support the franchise network as a whole, yet providing ample individual opportunity for business development and growth at the franchisee office level. Top line revenue growth for the franchisee directly results in increased franchise fees, or revenues, paid to the franchisor.

Often times the reality is that struggling franchisees can be the most demanding on the franchisor's limited resources. Time and resources are spent on field visits, developing individual marketing and sales strategies, assisting with implementation, providing guidance, and encouraging progress toward these single-unit goals. The undertaking may increase the franchisee's satisfaction and value perception in the short-term, but the consistent strain on resources tends to outweigh the long-term effectiveness, and ultimately, the franchisor's revenue results. It is common in a franchise organization to have franchisor representatives serve anywhere from a 10:1 to 30:1 ratio of franchisees to franchisor representative. As the system grows, field service representatives tend to take on one or two new franchisees annually, depending on industry growth trends, but increasing staffing to support individual unit additions is seldom considered unless the growth rate exceeds obvious capacities.

Thus, a plan for effective allocation of resources, including material resources, time, and human resources, is essential to the franchisor's growth strategy. A method of discerning the differences between the attitudes and behaviors of the highly successful versus those less productive franchisees, is integral to establishing a strategic plan for servicing the franchise community. While this work does not differentiate the types of resources allocated (time, human, material) it will enable a method for determining significant differences between franchisee performance levels, the resources they use and intend to use in the future, value and effectiveness perceptions, and satisfaction states of the varied segments.

Essentially, if the franchisor can understand the resources utilized and preferred by franchisees with better performance, preferably in a shorter period of time, it can focus on encouraging the use of similar resources by those in a less effective position, and potentially move them "upward" to a higher performance position. These segments and their preferences will be discussed in the next section.

1.4 Problem of classification – by tenure and revenue segments

Franchisee respondents were segmented into like groups for comparative analysis. Nine groups were created based on two variables, annual revenue and tenure with the franchise. The low revenue segment includes franchisees with average annual revenue less than $500,000. The mid-level revenue segment includes those with sales from $500,000 to $1 million. The high revenue group achieves an average annual revenue greater than $1 million. Tenure with the franchise network was segmented as low if the franchisee had been in the system up to seven years; mid-level means 8 to 15 years, and high level are those in the system 16 or more years. Each group was assigned a name to reflect the segment to which they belonged, based on revenue and tenure. The following chart provides the segment name, percentage of respondents in the segment, and that segment's overall satisfaction with the franchisor's programs and services (Figure 1.4.1).

	Low	Mid	High
High	SHOOTING STARS 6% 4.7	CLASSIC ROCKERS 9% 5.2	ROLLING STONES 18% 5.4
Mid	UP n' COMERS 7% 4.5	ROCK STEADY 10% 5.6	ROCK & a HARD PLACE 10% 5.4
Low	BRAT PACK 18% 6.4	WORKING CLASS HERO 10% 4.5	GLORY DAYS 12% 5.6

(Revenue on vertical axis; Tenure on horizontal axis)

Figure 1.4.1   Franchisee segments, percentage in segment and satisfaction with franchisor (1 to 10 scale)

Resource Requirements by Segment

Next investigated were the resources each segment intended to use in the future. Intent to use some of the products and services provided by the franchisor was rated on a 1 to10 scale which is depicted in the upper right of the following figures. In most instances intent to use a given product or service was indicated by marking a check box, thus the most common frequency figures are reported in the lower left of the figure. Figure 1.4.2 explains how to read each of the upcoming figures for resource requirements by segment.
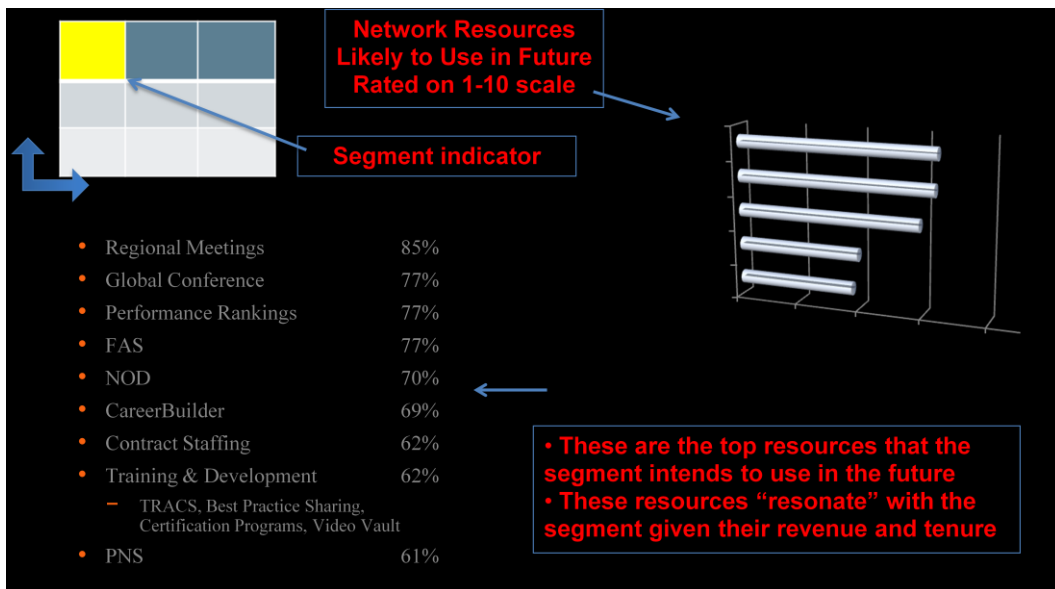
Figure 1.4.2   How to read each of the upcoming figures for resource requirements by segment

Shooting Stars - Low Tenure, High Revenue

This stellar group had risen quickly with low tenure, less than 8 years with the franchise and reporting high annual revenues, over $1 million. They reported being involved in the franchise network meetings, and practiced benchmarking with performance rankings. They intended to continue building on their initial training received from the franchisor (NOD is "new office development").

Shooting Stars typically intended to use or continue to use a franchisor program called "Contract Staffing" as a revenue generating resource. This version of recruiting is a bit different in that the recruit is hired as a contractor to the employing company, but actually works for the franchisee who takes a percentage of the hourly fee.

This high-level segment intended to use varied training and development resources, including a support group program (PNS) which encourages open dialog and information exchange among new franchisees. The segment would continue to use the website information resource and wanted field consulting expertise (Figure 1.4.3).

Shooting Stars – Low Tenure, High Revenue

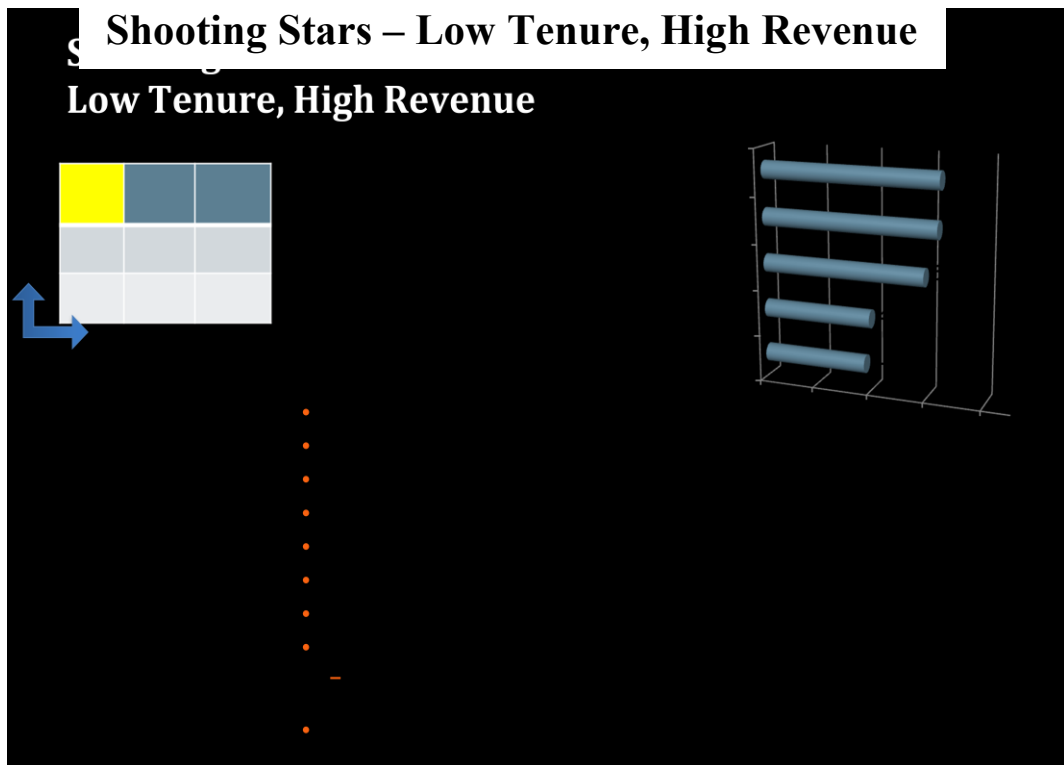Low Tenure, High Revenue

Figure 1.4.3   Low tenure, high revenue segment – franchisor resources required

In the upcoming discriminant analysis, this group will primarily be compared with their low tenure yet low revenue counterparts, the Brat Pack. Thus this segment with low tenure and revenue is discussed next.

Brat Pack – Low Tenure, Low Revenue

The Brat Pack joined the franchise within the previous 8 years, and had reported annual sales under $500,000. These new kids on the block intended to continue participating in franchisor-sponsored events, and intended to continue using a new best practices video series as well as older training tapes (from the Video Vault). This group was open to franchisor training guidance and communication as well as its recommended vendors and technology. Future field consulting was reportedly important to this group, which was open to new offerings such as a training program for new recruiters and inter-office referrals (TRACS and IOR) to continue their own development (Figure 1.4.4)
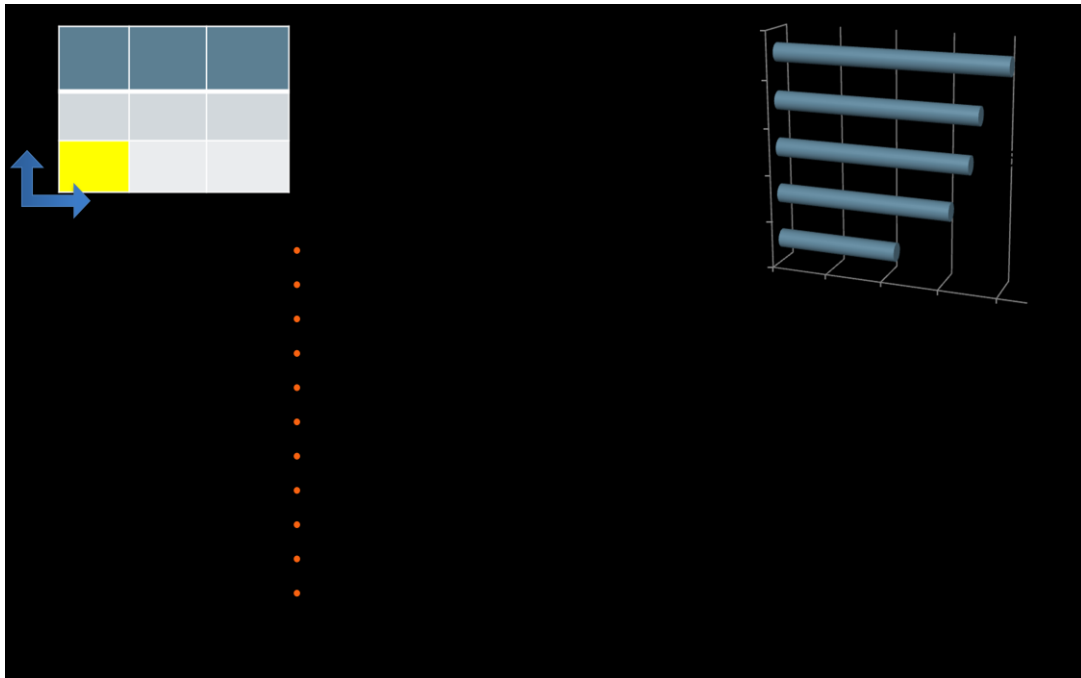
Brat Pack – Low Tenure, Low Revenue

Figure 1.4.4   Low tenure, low revenue segment – franchisor resources required

As mentioned earlier, the key question is, "What can we learn about the differences between higher revenue performers versus lower revenue performers, with the same tenure, that can help the franchisor evaluate needs and allocate resources more effectively?"

Consider the significant differences between these two groups, as indicated by t-tests for significance of difference between their means on the continuous variables measured. Statistically significant differences between these two low tenure segments include overall satisfaction with the franchisor, value in sharing best practices, value perceived in archival training videos, and value perceptions regarding franchise regional meetings. Franchisees with higher revenues rated these resources significantly lower than their lower revenue counterparts of similarly short tenure (Table 1.4.1). Regional meetings are designed to provide hands-on workshops and training for employees of the franchisee (i.e. employment recruiters). The franchisee incurs hotel accommodation expenses, travel, and meeting expenses. Keep in mind that 85% of the Shooting Stars (high revenue, low tenure) intended to continue to utilize regional meetings as a resource. This higher-revenue segment of newer franchisees finds limited value in these meetings, rating them at 5.85 on the 10 point scale. This may signal the franchisor that a different approach is required for franchisees at a higher performance level. The "Stars" willingness to

continue to participate is a positive signal to the franchisor, who remains vulnerable to reduced overall satisfaction (rated at 4.82) if improvements to specific resources such as regional meetings are not addressed.

	$\overline{x}_{brats}$	$\overline{x}_{stars}$	Mean diff.	t	df	p
Overall satisfaction with franchisor	6.32	4.82	1.49	2.32	51	.025
Value best practice sharing	8.67	6.77	1.90	2.18	13	.047
Value of archived videos	7.95	7.00	.95	2.03	51	.048
Value of regional meetings	7.77	5.85	1.92	2.11	14	.053

Table 1.4.1   Significant differences between low tenure high revenue (Stars) and low tenure   low revenue (Brats) segments

Rolling Stones – High Tenure, High Revenue

This segment, comprised of franchisees with 16 or more years' tenure, and revenues exceeding $1MM, reported a fairly low satisfaction level at 5.4. This segment represents 18% of the sample, proportionate to new franchisees at low revenue (Brat Pack at 18%). This segment is considered by the franchise community as the foundation of the network, with high tenure and revenue, and strong support of existing programs. Communications were reportedly considered top priority, and there was a continued demand for classic training materials from the archived videos as well as newer best practices videos. They practiced benchmarking with system-wide performance rankings, and regional meetings were used to motivate teams. They are likely to participate in the international meeting of franchisees with the franchisor (i.e., global conference). They utilize and operating ratio study published by the franchisor and are open to new training programs for new hires. Field consulting is still needed, yet expertise must be substantial (Figure 1.4.5).

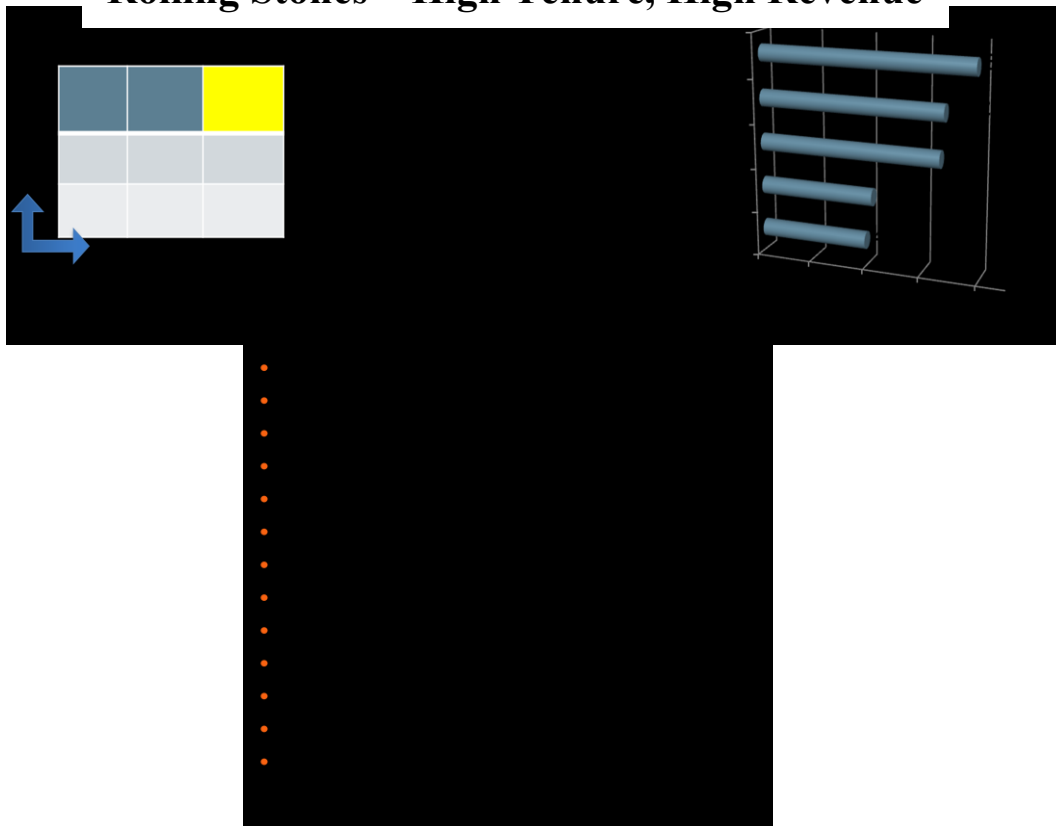# Rolling Stones – High Tenure, High Revenue

Figure 1.4.5   High tenure, high revenue segment – franchisor resources required

This group is then compared to the high tenure, low revenue group nicknamed Glory Days.

Glory Days – High Tenure, Low Revenue

This segment has been with the franchise over 15 years yet still reports annual revenues under $500,000. Their overall satisfaction with franchisor programs and services is just slightly higher than that of most other segments. Not very interested in field consulting or new programs, this group is loyal to the network vendors, happy to participate in regional meetings, but not exceptionally motivated toward growth at this juncture.

Glory Days – High Tenure, Low Revenue
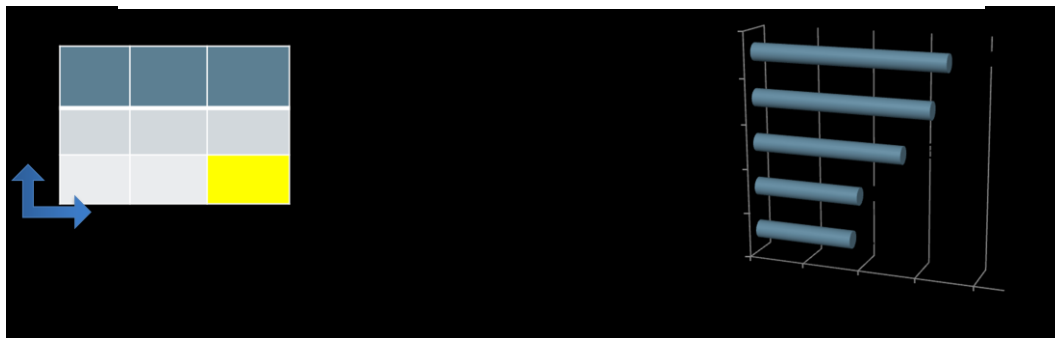
• FAS	85%
• Regional Meetings	77%
• Digest	77%
• Operating Ratio Study	69%
• Video Vault	62%
• FedEx	58%
• Monster	54%
• Best Practices Video	54%
• IOR Program	54%
• Manager's Video Catalog	50%

Figure 1.4.6   High tenure, low revenue segment – franchisor resources required

Considering the significant differences between these two high tenure groups, it is found that satisfaction with field consulting services provided by the franchisor, and intent of future use, is significantly higher among the high tenure, high revenue group (Rolling Stones), versus high tenure, low revenue (Glory Days). If the high tenure, low revenue segment is exerting substantial demand on the franchisor's resources, yet rate intent of future use at 4.96, one must discern the potential effectiveness of allocating resources to this high tenure, low revenue segment. Alternately, they may be interested in field consulting, but given the effectiveness of the franchisor's representative (i.e. extent to which the field service representatives help increase sales), dissatisfaction may be leading to low intent of future use.

	$\overline{x}_{Stones}$	$\overline{x}_{GloryDays}$	Mean diff	t	df	p
Satisfaction with field consulting	6.75	4.53	2.21	3.45	64	.001
Intent to use field consulting in future	7.59	4.96	2.57	3.58	64	.001

Table 1.4.2   Significant differences between high tenure *high* revenue (Stones) segment and high tenure, *low* revenue (Glory Days) segment

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Discussion

In this section it has been made clear that there are significant differences within the low tenure group that provide insight. Value perceptions regarding regional meetings, best practice sharing, and video archives are all significantly lower among those franchisees in the high revenue category vs. those in the low revenue category. Further, overall satisfaction with the franchisor is significantly lower among the high revenue group as compared to the low revenue group.

The implication is that the franchisor evidences uncertainty and potential risk among the high revenue group of newer franchisees. Renewal of the franchise contract (e.g., at the ten-year mark), is less likely if value perceptions and satisfaction are low.

Franchisees that have been with the system the longest, over sixteen years, and are in the highest revenue category, evidence higher satisfaction with field consulting services provided by the franchisor, than those in the lower revenue category of the high tenure segment. This signals the franchisor to carefully review the low revenue segment's interest in utilizing franchisor resources, particularly in the area of field consulting where satisfaction and future usage intent are significantly lower than among those with higher revenue.

The challenge then, is to identify not only the significant differences between performance levels, but also to identify the variables that will help the franchisor understand a franchisee's propensity to work toward and succeed at a higher level if a focus is placed on utilization of and satisfaction with specific franchisor resources. Discriminant analysis will assist in identifying those variables.

Recall that in the franchise system studied here, the least tenured segment of franchisees had been in the system less than eight years. This group is considered the relative newcomers. The franchisor spends time and resources on training, monitoring, and development this segment. It makes intuitive sense that if the newcomer is encouraged to focus on behaviors reflective of higher performers, particularly with the same level of tenure, then the newcomer is more likely to achieve better results. This research aims at isolating the specific resources used by higher level performers that most differentiate them from their lower performing counterparts, thus providing the franchisor with a tactical guideline for development of franchisees and utilization of resources.

2.1   Classification of Franchisees Using Discriminant Analysis

A logical start to using discriminant analysis to classify franchisees is to use the variables which are known to be significantly different between groups. These variables separate the two groups to a certain extent, yet adding others to the analysis yields better discrimination. This process will be discussed in this section.

Shooting Stars vs. Brat Pack – Discriminant Analysis using Significant Differences

Recall from Section 1.4, the significant differences between the high (Shooting Stars) and low revenue producers (Brat Pack) in the less tenured group. These included value found in regional meetings, value in sharing best practices, value perceived from viewing archived training videos, and overall satisfaction with the franchisor. In all cases, the higher revenue segment rated these variables significantly lower than their lower revenue counterparts.

Franchisees achieving higher revenue, over $1 million, in their early years with the franchisor, less than 8 years, perceived programs and services related to training as less valuable. Regional meetings may not be effectively meeting expectations because the training for newer franchisees is directed toward those with lower revenue. The franchisor might consider training sessions offered by revenue segment instead of tenure. In general, the franchisor's concern is likely to be with overall satisfaction and how to improve it for this higher revenue segment since the royalty stream is more substantial from this group.

Using only the variables with identified significant mean differences in the discriminant analysis, the low tenure group can be classified correctly about 70% of the time (Table 2.1.1). In the most rigorous test, classification using the holdout sample, the Brats (low tenure, low revenue) were classified correctly 69.2% of the time and the Stars (low tenure, high revenue) 66.7% of the time. Recall from Section 2.6 of the Job Seeker analysis, the threshold is 62.5% for discriminating between two groups.

The discriminant function does a reasonable job differentiating the groups with $\lambda = 87$. Recall, Wilks' lambda measures how well each function separates cases into groups. It is equal to the proportion of the total variance in the discriminant scores not explained by differences among the groups. Smaller values of Wilks' lambda indicate greater discriminatory ability of the function.

Based on the structure matrix (Table 2.1.2), three of the four variables evidence moderate correlation with the discriminant function. These include value of the regional meetings, at .75, value of best practice sharing at .72 and overall satisfaction with the franchisor at .67. Value regarding the archival training videos did not evidence significant correlation with the discriminant function.

Classification Results[a,b,c]				Predicted Group Membership		
			tenure and revenue	Brat Pack low ten low rev	Shooting Stars low ten hi rev	Total
Cases Selected	Original	Count	Brat Pack low ten low rev	21	6	27
			Shooting Stars low ten hi rev	4	6	10
		%	Brat Pack low ten low rev	77.8	22.2	100.0
			Shooting Stars low ten hi rev	40.0	60.0	100.0
	Cross-validated	Count	Brat Pack low ten low rev	21	6	27
			Shooting Stars low ten hi rev	5	5	10
		%	Brat Pack low ten low rev	77.8	22.2	100.0
			Shooting Stars low ten hi rev	50.0	50.0	100.0
Cases Not Selected	Original	Count	Brat Pack low ten low rev	9	4	13
			Shooting Stars low ten hi rev	1	2	3
		%	Brat Pack low ten low rev	**69.2**	30.8	100.0
			Shooting Stars low ten hi rev	33.3	**66.7**	100.0
a. 73.0% of selected original grouped cases correctly classified.						
b. 68.8% of unselected original grouped cases correctly classified.						
c. 70.3% of selected cross-validated grouped cases correctly classified.						

Table 2.1.1   Low tenure franchisees - Classification results from discriminant analysis using only the variables that evidence significant differences between lower tenured franchisees at low revenue vs. high revenue

Structure Matrix	
	Function 1
Value regional meetings	**.749**
Value best practices	**.719**
Overall satisfaction with franchisor	**.674**
Video vault – archived training videos	.028

Table 2.1.2   Low tenure franchisees - Pooled within-groups correlations between discriminating variables and standardized canonical discriminant function.

Rolling Stones vs. Glory Days - Discriminant Analysis using Significant Differences

Next examined is the discriminant function comprised of variables that were determined to be significantly different between the high tenure (16+ years) franchisees with high revenue (Rolling Stones) versus those with low revenue (Glory Days).

Again the Rolling Stones are those with annual revenues over $1MM, and the Glory Days are those with lower revenue, under $500,000 yet the same long tenure as franchisees. Recall that the significant differences between these groups included satisfaction with field consulting services and intent to use field consulting services in the future. In both cases, the higher revenue segment (Rolling Stones) rated field consulting higher than did their lower revenue counterparts (Glory Days).

Using just these two variables to build the discriminant function yields proper classification in about 60% of the holdout sample cases, with 66.7% of the Rolling Stones high revenue group correctly classified and 60% of the Glory Days low revenue group correctly classified (Table 2.1.3).

The discriminant function does a reasonable job differentiating the groups with $\lambda = 70$. Based on the structure matrix (Table 2.1.4), both variables evidence strong correlation with the discriminant function. Satisfaction with field services provided by the franchisor offers substantial discrimination in the function, with a coefficient of .90, and the franchisees' intent to use these field services in the future also contributes substantially, with a coefficient of .87 (Table 2.1.5).

Note that the classification results for the holdout sample for the Glory Days segment does not meet the threshold requirement of 62.5% for discriminating between two groups.

Classification Results[b,c,d]							
			tenure and revenue	Predicted Group Membership			
				Glory Days hi ten low rev	Rolling Stones hi ten hi rev	Total	
Cases Selected	Original	Count	Glory Days hi ten low rev	17	6	23	
			Rolling Stones hi ten hi rev	5	20	25	
		%	Glory Days hi ten low rev	73.9	26.1	100.0	
			Rolling Stones hi ten hi rev	20.0	80.0	100.0	
	Cross-validated	Count	Glory Days hi ten low rev	17	6	23	
			Rolling Stones hi ten hi rev	6	19	25	
		%	Glory Days hi ten low rev	73.9	26.1	100.0	
			Rolling Stones hi ten hi rev	24.0	76.0	100.0	
Cases Not Selected	Original	Count	Glory Days hi ten low rev	2	1	3	
			Rolling Stones hi ten hi rev	6	9	15	
		%	Glory Days hi ten low rev	**66.7**	33.3	100.0	
			Rolling Stones hi ten hi rev	40.0	**60.0**	100.0	
a. 77.1% of selected original grouped cases correctly classified.							
b. 61.1% of unselected original grouped cases correctly classified.							
c. 75.0% of selected cross-validated grouped cases correctly classified.							

Table 2.1.3 Highly tenured franchisee segments - Classification results from discriminant analysis using only the variables that evidence significant differences between high tenured franchisees at low revenue vs. high revenue

Structure Matrix	
	Function 1
Satisfaction with field consulting	**.899**
Future use field consulting	**.868**

Table 2.1.4   Highly tenured franchisee segments - Pooled within-groups correlations between discriminating variables and standardized canonical discriminant function.

Classification Using Additional Variables

Next, the aim is to improve these classifications by adding significantly discriminatory variables to the analysis, with the intent of generating a function that yields better classification results. A trial and error method was employed with numerous variables, ultimately resulting in the final discriminant functions and classifications that follow.

Shooting Stars vs. Brat Pack (low tenure segment)

The final model to discriminate the high and low revenue segments of newer franchisees includes six variables which in future applications can be measured fairly easily. These include:

1. Value of best practices sharing
2. Value of regional meetings
3. Intent to use franchisor's information website
4. Overall satisfaction with franchisor
5. Intent to use franchisor's field consulting services in the future
6. Satisfaction with field consulting services

Value of archival videos was eliminated from the first model because it did not usefully discriminate the groups. Satisfaction with and intent to use field consulting services were added in because they play a prominent role with more tenured franchises. Further, this is a key area of service from the franchisor to franchisees, and requires proper allocation of resources due to its labor-intensive nature.

In building the final model, separate covariance matrices were used because Box's M was significant at $p < 001$. The canonical correlation for the discriminant function evidences a moderate relationship between the variables and the function at .56, and Wilkes' lambda is lower, .68, showing improvement from the first model where $\lambda = 87$.

The structure matrix suggests that value in best practices, and value found in regional meetings as well as future intent to utilize the franchisor's information website, and overall satisfaction with the franchisor all served to effectively discriminate the groups (Table 2.1.5).

Structure Matrix	
	Function 1
Value best practices	**.660**
Value regional meetings	**.583**
Future use informational website	**.527**
Overall satisfaction with franchisor	**.478**
Future use field consulting services	.134
Satisfaction with field consulting services	.002

Table 2.1.5 FINAL discriminant function for Low tenure franchisee segments - Pooled within-groups correlations between discriminating variables and standardized canonical discriminant function.

Classification is improved with the final model with 85% of the low-tenure, low-revenue segment classified correctly, and 77% of the low-tenure, high revenue segment classified correctly (Table 2.1.6).

Given that the validation sets from the first model were used as a basis for improvement, and were acceptable on their own, the validation set is eliminated from the final model because the total number of observations is rather low (n = 40 for Brat Pack and n = 13 for Shooting Stars).

Classification Results[a]					
		tenure and revenue	Predicted Group Membership		
			Brat Pack low ten low rev	Shooting Stars low ten hi rev	Total
Original	Count	Brat Pack low ten low rev	34	6	40
		Shooting Stars low ten hi rev	3	10	13
	%	Brat Pack low ten low rev	**85.0**	15.0	100.0
		Shooting Stars low ten hi rev	23.1	**76.9**	100.0
a. 83.0% of original grouped cases correctly classified.					

Table 2.1.6   Final classification results for low tenure segments using 6 easily measured variables

Rolling Stones vs. Glory Days (high tenure segment)

The final model to discriminate the high and low revenue segments of the most tenured franchisees includes eight easily measured variables. These include:

1. Intent to use field consulting services in the future
2. Satisfaction with field consulting services
3. Intent to use franchisor's information website in the future
4. Value in sharing best practices
5. Effectiveness of performance rankings (benchmarking)
6. Overall satisfaction with franchisor
7. Value in performance rankings
8. Value in regional meetings

These variables reflect the discriminators for the lower tenure segment with the addition of effectiveness and value of performance ranking (benchmarking).

The final model results in a canonical correlation of .69 for the discriminant function and $\lambda = 53$, both improvements over the model with only satisfaction and future usage intent for field consulting. The structure matrix (Table 2.1.7) suggests however, that these are still the most discriminatory variables, yet the information gained from the other six variables yields better classification as will be discussed.

Structure Matrix	
	Function 1
Future field consulting	**.472**
Satisfaction field consulting	**.455**
Future informational website	.252
Value best practice sharing	-.218
Effectiveness of performance rankings	.096
Overall satisfaction with franchisor	-.062
Value of performance rankings	-.056
Value of regional meetings	-.049

Table 2.1.7 - FINAL discriminant function for high tenure franchisee segments. Pooled within groups correlation between discriminating variables and standardized canonical discriminant function.

Classification is improved with the final model with 81% of the high tenure, low-revenue segment classified correctly, and 85% of the high tenure, high revenue segment classified correctly (Table 2.1.8).

Given that the validation sets from the first model were used as a basis for improvement, and were acceptable on their own, the validation set is eliminated from the final model because the total number of observations is rather low with n = 26 for Glory Days (low revenue), and n = 40 for Rolling Stones (high revenue).

Classification Results[a]					
		tenure and revenue	Predicted Group Membership		
			Glory Days hi ten low rev	Rolling Stones hi ten hi rev	Total
Original	Count	Glory Days hi ten low rev	21	5	26
		Rolling Stones hi ten hi rev	6	34	40
	%	Glory Days hi ten low rev	**80.8**	19.2	100.0
		Rolling Stones hi ten hi rev	15.0	**85.0**	100.0
a. 83.3% of original grouped cases correctly classified.					

Table 2.1.8   Final classification results for high tenure segments using 8 easily measured variables.

Densities Based on Discriminant Scores by Class

Consider the assigned groupings for both the low and high tenure segments. Comparing the discriminant scores of Shooting Stars vs. Brat Pack, separation between segments is clear (Figure 2.1.1), as is that of Rolling Stones vs. Glory Days (Figure 2.1.2).
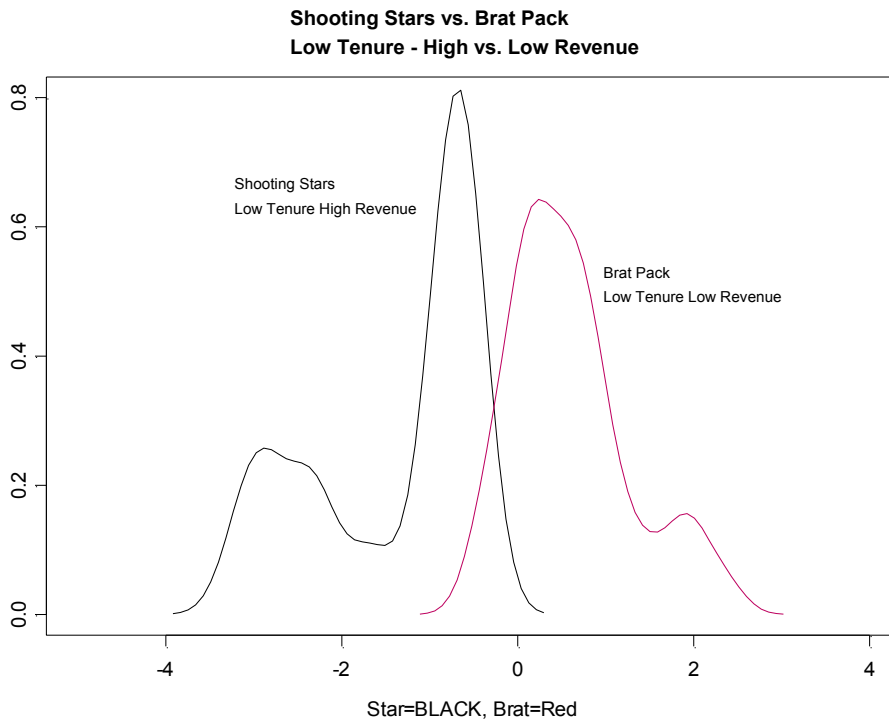
Shooting Stars vs. Brat Pack
Low Tenure - High vs. Low Revenue

Shooting Stars
Low Tenure High Revenue

Brat Pack
Low Tenure Low Revenue

Star=BLACK, Brat=Red

Figure 2.1.1 Discriminant scores for low tenure segment based on group classification

Rolling Stones vs. Glory Days
High Tenure - High vs. Low Revenue

Glory Days
High Tenure, Low Revenue

Rolling Stones
High Tenure, High Revenue
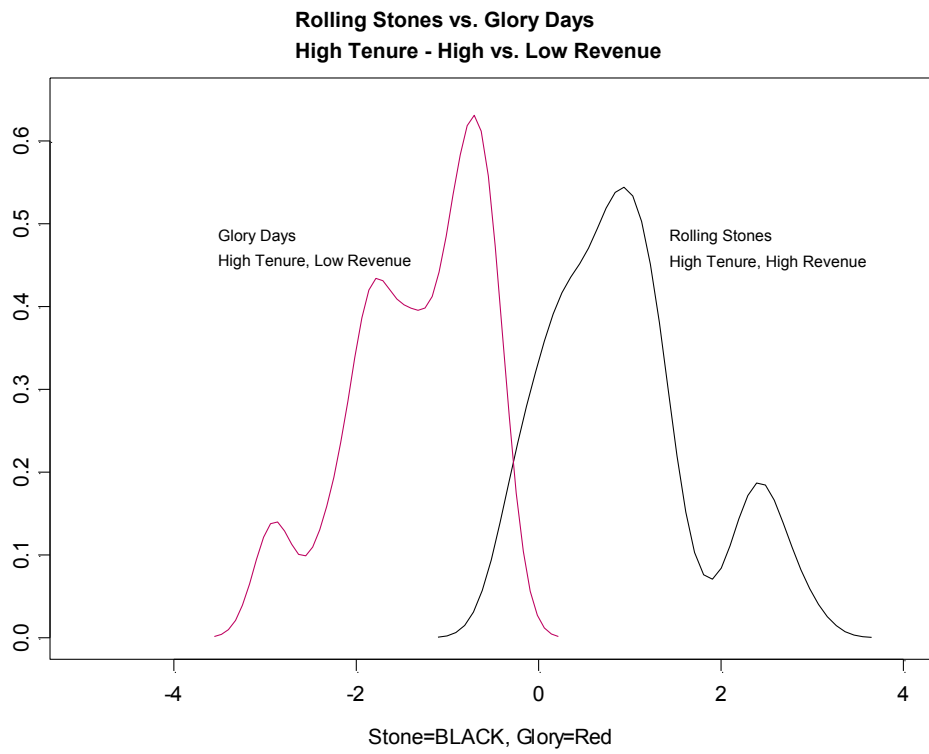
Stone=BLACK, Glory=Red

Figure 2.1.2 Discriminant scores for high tenure segment based on group classification

2.2 Summary – Classification and Analysis of Franchise Resource Data

In the first portion of this study, the focus was on newer franchisees. The discriminating variables suggest lower satisfaction and value in the services provided by the franchisor within the higher revenue segment compared to the lower revenue. The suggested franchisor response is to tailor services to more effectively address the needs of the segment which earns higher revenues, thus higher royalties are paid to the franchisor. This action would reduce the franchisor's risk of the high-revenue new franchisee not renewing their franchise agreement due to dissatisfaction with value provided by franchisor.

In the second situation, where the focus was on the most tenured franchisees, the higher revenue segment is significantly more satisfied with the franchisor's field consulting services. Thus, resources should be allocated to maintain these satisfaction levels.

Classification of a franchisee into one of these segments is facilitated by discriminant analysis, with an accuracy of over 80%. Applying the technique, one can generate scores for as few as eight variables and determine fairly well the potential revenue segment of a franchisee for a current year. The franchisor's field consultants should focus on resources used by the higher revenue segments (e.g., benchmarking with performance rankings) to guide the lower revenue segments, particularly as tenure increases.

The management issue addressed was allocation of resources to most effectively support franchisee revenue growth. The most effective classification and analytic method was discriminant analysis to understand the resources that discriminate revenue performance groups. The contribution is the presentation of a tool for effectively allocating franchisor resources which mimics the resource utilization behaviors of the highest revenue-generating categories.

The approach taken here supports Ananad's (1987) suggestion that management consider using subsamples to influence lower performers to act like their higher performing counterparts. However, the practical applications may require varied forms. For example, given the dataset investigated here, the least tenured group was considered the relative newcomers. This group provided feedback on services they were currently receiving, within the franchise system, from the franchisor. If the franchisor wanted to classify "potential" franchisees, say those who were investigating the option of buying a franchise (i.e., becoming a franchisee), they could not provide comparable usage, effectiveness, value and satisfaction data because they would not have yet used the services. However, this tool can be used as a directional guide for

those within the system, yet for a short period of time. The focus of servicing the low revenue group should be encouraging the service-usage behaviors of their higher revenue counterparts with equal tenure in the franchise system.

Alternately, a screening interviewer for the franchisor might discuss the potential franchisee's likelihood to use certain services which are reflective of the higher performers' preferences. For example, would the potential franchisee be willing to participate in regional meetings, benchmarking, and sharing of best practices?

The value to the franchisor is in isolating the behaviors (in the form of services used), that are most likely to spawn revenue growth. Also, a potential franchisee can more clearly identify the requirements of success, and make a more informed decision regarding purchasing a franchise. Analytic tools such as those discussed here can be designed specifically for a particular franchise system. Such tools can aid in reducing conflict regarding marketing services provided by the franchisor to the franchisee.

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Appendix A – Classification and Analysis of Job-Seeking Market

Section 2.3 – Descriptive Statistics for Factors and Loyalty Scores by Subclass

The Kruskal-Wallis test is a nonparametric method for testing the equality of population medians among group. The results suggest that the medians of the rank ordered groups are significantly different. However, the test assumes identically shaped and scaled distributions, and it is known that the non-Gaussian distributions have unequal variance. A focus was placed instead on the asymptotic normality of the t statistic and its usefulness applied to the job-seeker dataset.

	Seeker=1 Passive=2 Non=3	N	Mean Rank
SUPV	1	1193	787.66
	2	451	1017.92
	3	102	1238.91
	Total	1746	
COMP	1	1163	725.27
	2	442	1079.28
	3	100	1338.32
	Total	1705	
OPPTY	1	1210	914.46
	2	451	828.57
	3	100	712.56
	Total	1761	
QWL	1	1193	920.27
	2	455	791.06
	3	101	718.36
	Total	1749	

	SUPV	COMP	OPPTY	QWL
Chi-Square	125.25	268.82	21.26	31.87
df	2	2	2	2
Asymp. Sig.	.000	.000	.000	.000

	Subclass	N	Mean Rank
Loyalty	1	1058	660.91
	2	411	982.91
	3	93	1263.24
	Total	1562	
Chi-Square	263.651		
df	2		
Asymp. Sig.	.000		

Appendix B – Classification and Analysis of a Job-Seeking Market

Section 2.6   Discriminant Analysis - Validation test results

Classification Results[b,c,d]

			1=seeker 2=Passive 3=not seeking	Predicted Group Membership			
				1	2	3	Total
Estimation Sample	Original	Count	1	483	198	42	723
			2	93	150	58	301
			3	5	36	32	73
		%	1	66.8	27.4	5.8	100.0
			2	30.9	49.8	19.3	100.0
			3	6.8	49.3	43.8	100.0
	Cross-validated[a]	Count	1	483	198	42	723
			2	94	149	58	301
			3	5	36	32	73
		%	1	66.8	27.4	5.8	100.0
			2	31.2	49.5	19.3	100.0
			3	6.8	49.3	43.8	100.0
Hold-Out Sample	Original	Count	1	217	91	16	324
			2	36	53	17	106
			3	2	9	9	20
		%	1	67.0	28.1	4.9	100.0
			2	34.0	50.0	16.0	100.0
			3	10.0	45.0	45.0	100.0

a. Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.

b. 60.6% of estimation sample cases correctly classified.

c. 62.0% of hold-out sample cases correctly classified.

d. 60.5% of estimation sample cross-validated grouped cases correctly classified.

Validate 2

Classification Results[a,b,c]

			1=seeker 2=Passive 3=not seeking	Predicted Group Membership			
				1	2	3	Total
Estimation Sample	Original	Count	1	554	226	86	866
			2	89	158	68	315
			3	4	26	39	69
		%	1	64.0	26.1	9.9	100.0
			2	28.3	50.2	21.6	100.0
			3	5.8	37.7	56.5	100.0
	Cross-validated	Count	1	550	228	88	866
			2	91	154	70	315
			3	4	28	37	69
		%	1	63.5	26.3	10.2	100.0
			2	28.9	48.9	22.2	100.0
			3	5.8	40.6	53.6	100.0
Hold-Out Sample	Original	Count	1	217	79	24	320
			2	34	62	35	131
			3	3	16	14	33
		%	1	67.8	24.7	7.5	100.0
			2	26.0	47.3	26.7	100.0
			3	9.1	48.5	42.4	100.0

a. 60.1% of estimation cases correctly classified.

b. 60.5% of holdout cases correctly classified.

c. 59.3% of estimation cross-validated grouped cases correctly classified.

Validate 3

Classification Results[a,b,c]

			1=seeker, 2=Passive 3=not seeking	Predicted Group Membership			
				1	2	3	Total
Estimation Sample	Original	Count	1	529	201	77	807
			2	88	137	94	319
			3	2	19	41	62
		%	1	65.6	24.9	9.5	100.0
			2	27.6	42.9	29.5	100.0
			3	3.2	30.6	66.1	100.0
	Cross-validated	Count	1	524	206	77	807
			2	89	136	94	319
			3	2	22	38	62
		%	1	64.9	25.5	9.5	100.0
			2	27.9	42.6	29.5	100.0
			3	3.2	35.5	61.3	100.0
Holdout sample	Original	Count	1	241	95	38	374
			2	36	61	33	130
			3	2	12	25	39
		%	1	64.4	25.4	10.2	100.0
			2	27.7	46.9	25.4	100.0
			3	5.1	30.8	64.1	100.0

a. 59.5% of estimation cases correctly classified.

b. 60.2% of holdout cases correctly classified.

c. 58.8% of estimation sample cross-validated grouped cases correctly classified.

Die Dissertation hat folgende Erklärung zu enthalten:

"Ich versichere an Eides Statt, dass ich die eingereichte Dissertation "Classification and Analysis of Management and Marketing Data: Statistical Applications for Strategic Planning" selbstständig verfasst habe. Anderer als der von mir angegebenen Hilfsmittel und Schriften habe ich mich nicht bedient. Alle wörtlich oder sinngemäß den Schriften anderer Autorinnen und/oder Autoren entnommenen Stellen habe ich kenntlich gemacht."

_____   __11 March 2010_____

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