

Current Practices in Perceptual Mapping

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Thomas A. Wittenschlaeger
Hughes Aircraft Company, Virginia
John A. Fiedler
POPULUS, Inc., Idaho

Abstract

This paper uses data from a proprietary Hughes survey to demonstrate the principles which underlie current practices in perceptual mapping using discriminant analysis-based maps. The paper discusses the advantages of using discriminant analysis in creating perceptual maps, criteria for selecting brands and products for respondents to evaluate, and principles for optimizing a perceptual space.

Introduction

Perceptual mapping has been used as a strategic management tool for about thirty years. It offers a unique ability to communicate the complex relationships between marketplace competitors and the criteria used by buyers in making purchase decisions and recommendations. Its powerful graphic simplicity appeals to senior management and can stimulate discussion and strategic thinking at all levels of all types of organizations.

Despite their high value as a decision-making tool, perceptual maps are easy to produce. Most currently popular mapping procedures utilize readily available ratings data which satisfy management's need for a competitive score card. Despite their having been around for thirty years, perceptual maps are still viewed as an innovative technique.

Why Use Discriminant Analysis to Produce Perceptual Maps?

From the authors' experience, two approaches are most commonly used today to produce perceptual maps: Correspondence Analysis (CA) and Discriminant Analysis (DA). CA is generally easier to use than DA; it can be used with aggregated data such as cross-tabulations while DA cannot. However, DA offers several advantages over CA which make it the authors' first choice.

1. DA has a close linkage between product points and attribute locations. When high proportions of information are accounted for by the map, the product's projections on each vector are perfectly correlated with their means on that attribute. There is a hard-to-understand relationship between products and attributes in CA, but even Michael Greenacre has argued that nobody should try to infer anything about those relationships from CA maps.

2. Unlike CA and factor-analysis-based mapping, DA maps do not change if attributes are added that are linear combinations of those already present in the space.
3. DA is alone in paying attention to “between product” information, after scaling it so that “within product” differences are equal for each dimension and uncorrelated. That means that DA uses a “yardstick” to give every dimension common metric (in terms of equal unexplained variance). Neither CA nor factor-analysis-based mapping techniques distinguish between-products differences from within-products differences at all.
4. DA is the most efficient method, in terms of cramming into a space of low dimensionality the most information about how products differ. After implicitly rescaling the data to have “spherical error,” DA provides in its map the least squares approximation to the entire data matrix for that number of dimensions. Since managers have severe problems understanding higher-dimensional structures, and DA gives you the most information in the fewest dimensions, CA permits superior communications.
5. Unlike mapping based on distances or similarities, DA makes use of attribute ratings, which are easy and natural for respondents, and useful for their content even if mapping is not done with them.
6. Fiedler (ART) showed that DA was more successful than CA at reproducing a known map than the data were distorted in various ways.

Demonstration Data Set

The authors use data from a proprietary Hughes project to demonstrate the principles of current best practices in DA-based mapping. The study dealt with air traffic management systems; it was a world-wide project with 301 decision makers from both the public and private sector. The interview was programmed in three languages, conducted at three different international conferences and via DB-M, and programmed in Ci3, ACA, and APM. The questionnaire made extensive use of visual aids.

The focus of the study was system design and development of future ATM systems which cannot be discussed due to the confidentiality requirements. Data relating to vendors' perceptions of ATM systems was tangential to the objectives of the research and was made available to the authors for this conference. Limited masking of data has protected Hughes' proprietary rights.

Adaptive Perceptual Mapping

Sawtooth Software's Adaptive Perceptual Mapping (APM) was utilized in the questionnaire. APM employs discriminant analysis

Advantages of APM

It is exceptionally easy to use. It permits the use of an incomplete design in which respondent only use rating criteria which they believe to be important, and they only rate products which they know best. This tends to result in meaningful tasks. The software offers an interactive rotation option which greatly simplifies the process of producing effective maps.

Disadvantages of APM

APM's weaknesses reflect its age. The respondent interface does not offer the flexibility of SSI's newer products. The programming interface reflects the product's Ci2 heritage.

Choosing What to Rate

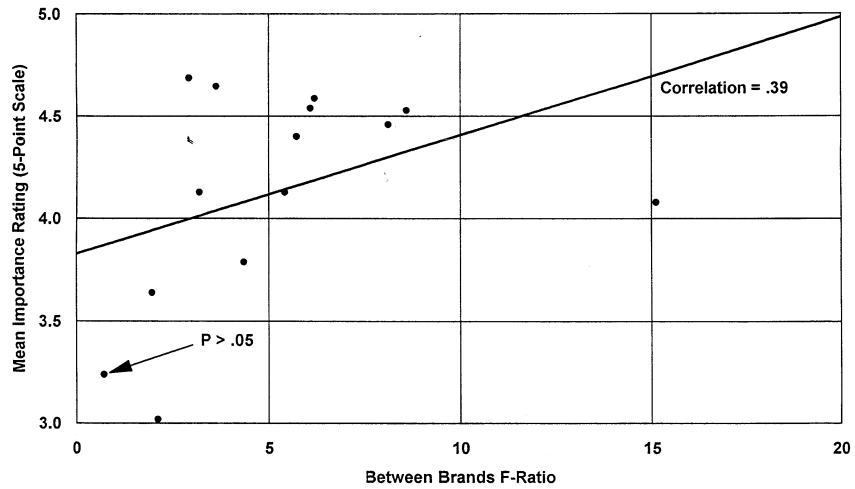
All mapping techniques attempt to show the comparative difference in how products are rated on attributes. The validity of the map depends on both the overall set of attributes and brands in the study as well as the subset of attributes and brands evaluated by the respondent.

Most studies suffer from too many attributes. Manufacturers and service providers see hundreds of ways in which their products and services differ—or might differ—from those of their competitors. Often the research analyst is unable to impose the discipline necessary to develop a reasonably short list of attributes. In most studies it is usually desirable (or necessary) to select a subset of attributes for respondents to rate. This can be accomplished by using one of two approaches.

1. *Select a subset of most important attributes.* Each respondent rates all attributes on importance. The questionnaire is programmed to select a subset of the important attributes for rating. This may assure more meaningful questionnaire tasks for respondents.
2. *Randomly select a subset of attributes.* The questionnaire randomly selects a subset of attributes for each respondent. This has the advantage that there will be roughly equal sample sizes for each of the evaluative criteria. The obvious disadvantage is that the respondent task may be less interesting.

Which approach is better? Figure 1 (below) compares average importance scores and F-ratios from the Hughes ATM study.

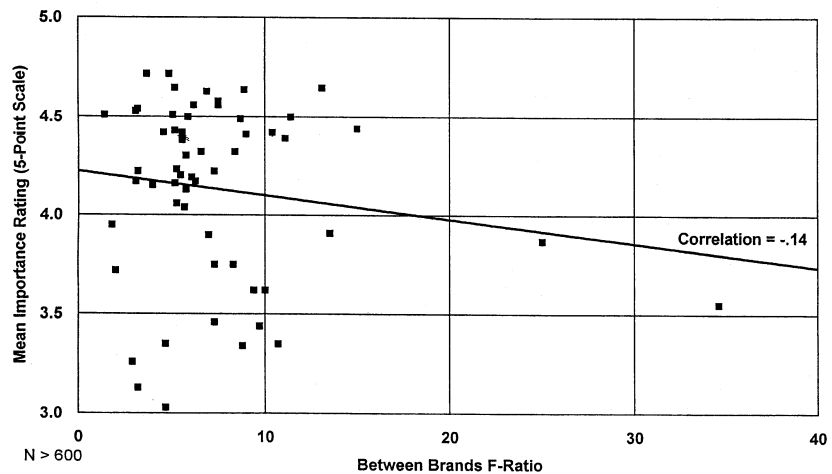
Figure 1
Discrimination Versus Stated Importance: ATM Systems



Respondents rated products on five most important attributes (of 14 altogether). Discrimination and importance are correlated; allowing respondents to use those attributes which they judged to be important was the correct decision.

Figure 2 compares discrimination and importance from another study. In this study a random subset of attributes (20 out of 57) was chosen for each respondent.

Figure 2
Discrimination Versus Stated Importance: Consumer Non-durable



Discrimination and importance are uncorrelated. Two of the most discriminating attributes are among those judged to be least important; several of the “most important” attributes are among the least discriminating

This is not an uncommon result. Very often category-defining attributes (such as “fluoride” in toothpaste or “good taste” in food) are included in a study. These define the price of entry into the category, are generally rated very important, and usually fail to discriminate. It is often difficult to successfully argue for their exclusion from a study. Conversely, brands are often differentiated by attributes which consumers judge to be irrelevant.

Conclusions and Recommendations

Restricting ratings to “most important” attributes may overlook attributes critical to marketplace differentiation; such a restriction may limit ratings to attributes which define the category rather than describe brands. The design objective should be to maximize discrimination. We believe this can be accomplished two ways:

1. *Rate more products at the expense of attributes.* We are interested in how individuals compare products. As the *APM System Manual* states: “For each attribute, we assume that the *differences* [emphasis in original] among a respondent’s ratings provide useful information, but that his *average* ratings for each attribute do not.” The entire object of perceptual mapping is to display perceptions in a reduced space. It is a waste to have a respondent rate only one or two brands on dozens of attributes when he or she could rate five or six brands on seven or eight attributes.
2. *Rate products within attributes.* This is the approach taken by APM and is most likely to maximize discrimination particularly with rational or practical benefit-oriented attributes. Occasionally the reverse is better. If a brand is viewed and evaluated holistically—such as soft drinks, cigarettes, or beer—and is being evaluated using brand personality scales and user imagery checklists, then it is typically better for the respondent to evaluate one brand in terms of all attributes before moving onto another brand.

Achieving the Benefits of APM Without its Limitations

Ten years ago, APM made producing DA-based perceptual maps easy and economical. While the system has not evolved with other Sawtooth products, it remains an easy-to-use method for producing superior DA-based maps. It is also possible to achieve all the benefits of APM—and overcome its few limitations—using Ci3, standard statistical software, and spreadsheets.

Getting the Data in Ci3

Sawtooth Software’s Ci3, with its LISTS and ROSTERS, can generate a data set with any conceivable brand and attribute selection logic. Given typical client requirements, many studies will have too many attributes with only a subset used by any one respondent and there will be many brands with only a subset used by any one respondent; thus the resulting Ci3 data file will be very large but mostly empty.

Generating a Perceptual Space

A DA-based perceptual space can be generated using SPSS or almost any other statistical package. There are nine steps in the process; SPSS code for each of these steps is included in an appendix to this paper.

1. Convert data from Ci3.
2. Build a system file with one record for each set of ratings for each brand. There will be as many records as the product of the total number of brands times the total sample size. Create a ".sav" file for product ratings for each brand. This produces as many files as there are brands.
3. Concatenate all files and sort records by brand number within respondent number.
4. Eliminate non-rated brands.

Steps 5 through 7 implement APM's approach of centering each person's attribute ratings across brands rated. This permits each person to use a unique subset of attributes and maximizes between-brand discrimination. From the APM manual: "We convert all ratings to 'deviation scores' so that each respondent's average for each attribute is zero. Experience has shown that this results in a reduction of random variation and increases precision of the measurement of the difference between products."

5. Aggregate mean attribute ratings by respondent. Create a file with each respondent's average ratings for all attributes across all brands rated (excepting an ideal brand).
6. Match the mean ratings file to each respondent's individual brand ratings record. Subtract the means from each rating.
7. Recode all non-rated data to zero.
8. Run discriminant analysis. The brand rated is the dependent variable; restrict the solution to two (or rarely three) dimensions. Aggregate mean discriminant scores by brand, segment, etc. and save to a worksheet.
9. Correlate attribute ratings with discriminant scores and copy to spreadsheet.

Creating Perceptual Maps

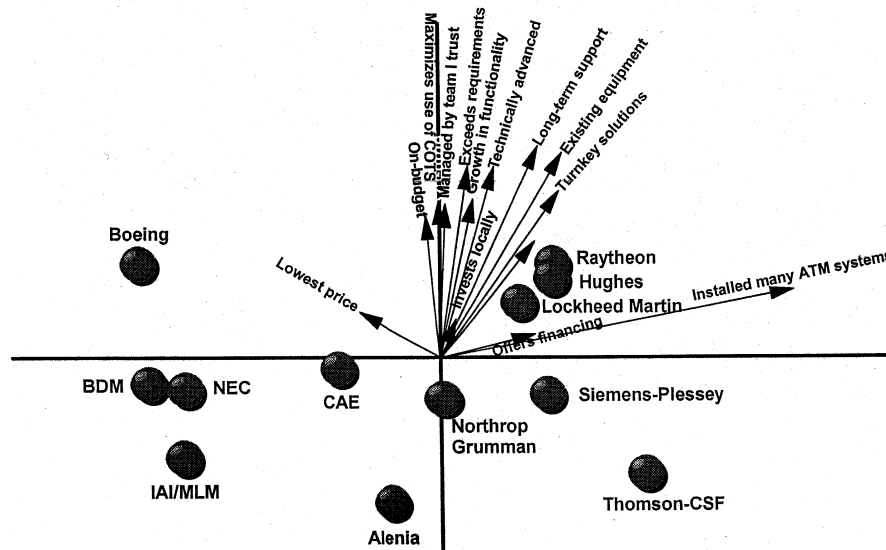
Maps can be readily created using Excel, 1-2-3 or any other spreadsheet package. There are five steps to the process.

1. Scale both the attribute and brand centroid matrices so that the largest absolute value in each is unity.
2. Insert pairs of zeros between each row of attribute correlations.
3. Add series point labels for each attribute at the end of each vector. These can be rotated manually if the chart is subsequently pasted into a graphics program.
4. Create a second X-Y chart for brand centroids and other points such as ideal point segments.
5. Overlay the two charts.

Optimizing a Perceptual Space: Five Principles for Powerful Maps

The procedures necessary to create a perceptual space using discriminant analysis are relatively straight forward. However the results may be initially disappointing or difficult to interpret and communicate.

Figure 3
First Perceptual Map



The client observed that the map failed to discriminate between the major competitors who mostly in the upper right quadrant. Most of the space is determined by the way smaller fringe companies are perceived. The client sought to capture the differences between the major competitors and then fir in the other companies.

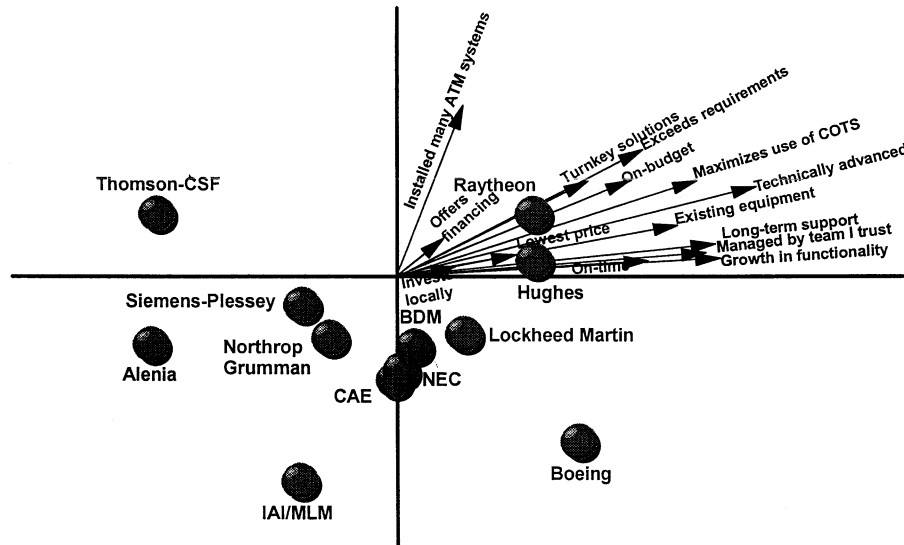
The analytic solution was to re-run the discriminant analysis using only a sub-set of brands as the dependent variable and subsequently calculating and plotting discriminant scores for non-specified companies.

The First Principle:

A perceptual map should discriminate between *major* brands. If you're trying to show the relationships between cities in Washington State, don't include Washington, D.C., in your map.

The second map based on major ATM competitors is show below:

Figure 4
Second Perceptual Map



The client observed that this second map was better, but still not very useful. All the attributes appeared highly intercorrelated. Was there some way to “fan” them out?

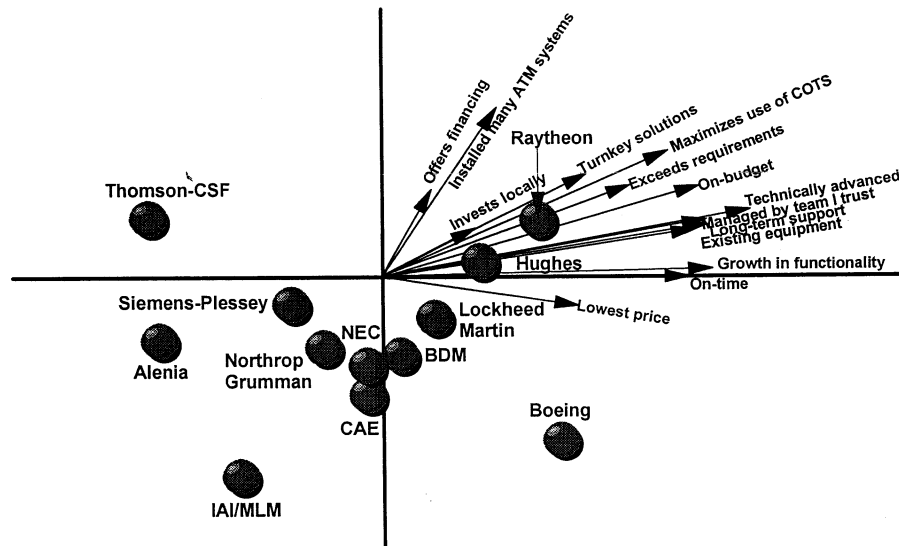
The analytic solution hypothesized that different people with different needs have different perceptual frameworks. Segmentation may reveal that companies are perceived differently by different groups. This hypothesis was tested by replacing—as sample size permitted—each brand with five “brands,” one for each of the ACA-based clusters.

The Second Principle:

Attributes should occupy as much as of the perceptual space as possible.

The *third map* based on major ATM competitors broken out by segment is show below. The segment differences are not shown to protect proprietary findings.

Figure 5
Third Perceptual Map



The client observed that, while this space accounted for need-based segment differences, variances in perceptions might be more related to regional differences rather than difference in product needs.

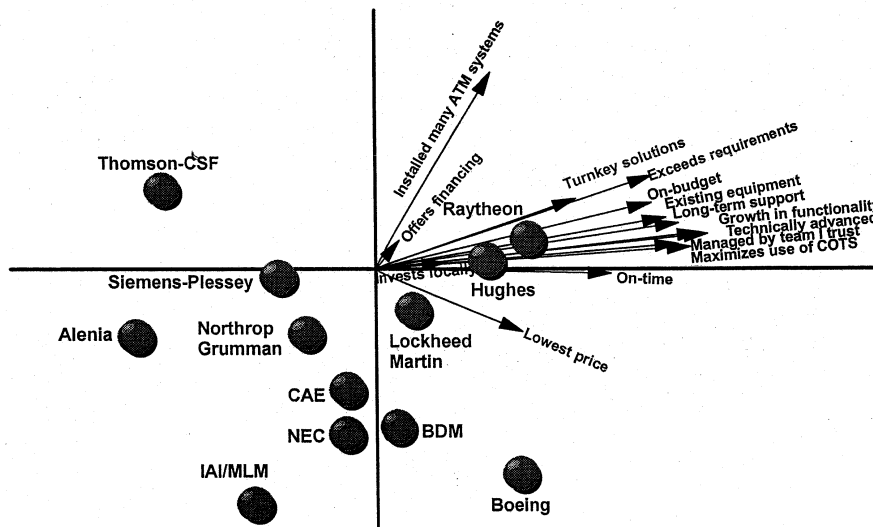
The resulting analysis was straight forward: as sample size permitted, replace each brand with six "brands," one for each of the geographic regions.

The Third Principle:

The map should capture the *most important* sources of variance between brands.

The *fourth map* based on major ATM competitors broken out by geographic region is shown below.

Figure 6
Fourth Perceptual Map



Again, the segment differences are not shown to protect proprietary findings.

The client observed that while the space was right, it would not be intuitively clear to management. Could the space be rotated so the axes are more closely aligned with some of the attributes?

The analytic solution was to rotate the space 22° counterclockwise. To rotate a perceptual space, multiply x-y coordinates of each point (or pairs of individual-level discriminant scores) by the following transformation matrix:

$$\begin{vmatrix} (1-a^2)^{1/2} & -a \\ a & (1-a^2)^{1/2} \end{vmatrix}$$

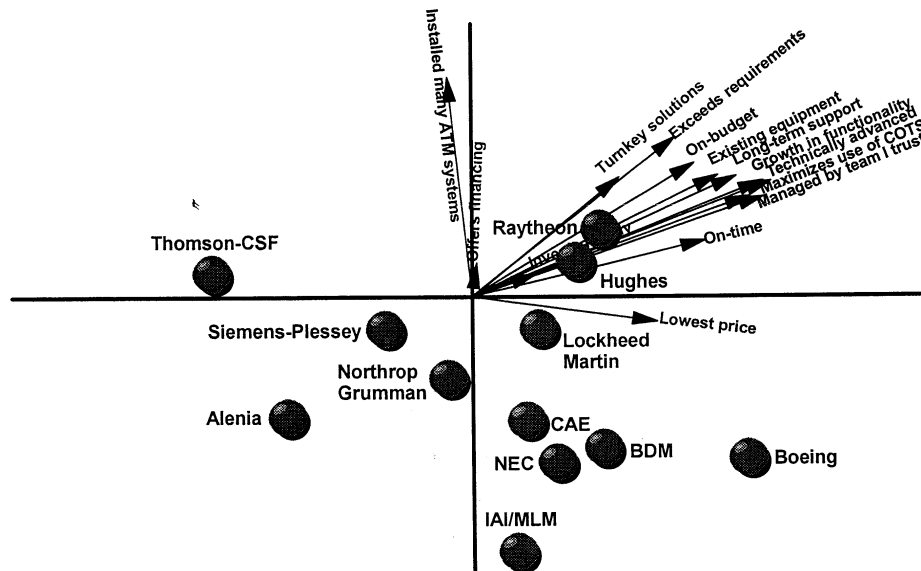
where a is the cosine of the desired angle of rotation.

The Fourth Principle:

Always rotate a map so that the axes are aligned with understandable attributes and so that desirable movement is typically “up” and “to the right.” An ideal, measured or hypothesized, should be in the upper right quadrant.

The *fifth map*, rotated, is shown below:

Figure 7
Fifth Perceptual Map



At this point, analysis begins. The types of questions that can be readily answered include:

1. How each company is perceived by each segment and in each region.
2. What is the difference in perceptions of Hughes between current customers and prospective ones?
3. What are the differences in perceptions between those who are very familiar with Hughes and those who are less familiar?
4. Is the pattern of differences in brand familiarity the same for all competitive vendors?

The Fifth Principle:

Show all major study findings in the context of a single perceptual space.

REFERENCES

APM System, Version 1, Sawtooth Software, Inc. Sequim, WA, 1987-95.

Fiedler, John A. "A Comparison of Correspondence Analysis and Discriminant Analysis-Based Maps," American Marketing Association: Advanced Research Techniques Forum. Beaver Creek, CO, June 9-12, 1996.

Greenacre, Michael J. (1989), "The Carroll-Green-Schaffer Scaling in Correspondence Analysis: A Theoretical and Empirical Appraisal," *Journal of Marketing Research*, 26 (August), 358-365.

Johnson, Richard M. "Multiple Discriminant Analysis," unpublished paper, "Workshop on Multivariate Methods in Marketing," University of Chicago, 1970.

SPSS Professional Statistics, Release 6.1. SPSS, Inc. Chicago, 1993.

Appendix

SPSS Code for Generating DA-based Perceptual Maps

Step 1

```
SAVE OUTFILE = "f:\proj\study\temp\tmp_rtgs.sav".
```

Step 2

```
COMPUTE brand = 1
COMPUTE recnum = (respnum$ * 100) + brand.
SAVE
  OUTFILE = "f:\proj\study\temp\tmpr01.sav"
  /KEEP = respnum$ recnum brand r.1.1 to r.1.14
  /RENAME (r.1.1 to r.1.14 = rate01 to rate14).
```

Step 3

```
ADD FILES
  FILE = "f:\proj\study\temp\tmpr01.sav"
  /FILE = "f:\proj\study\temp\tmpr02.sav"
      ..
      ..
  /FILE = "f:\proj\study\temp\tmprNN.sav".
SORT CASES BY recnum.
```

After Steps 1-3, the resulting data file looks like this:

```
1001 01 100101 - - - - - Respondent 1001
1001 02 100101 2 4 - 5 1 4 - - - 1 2 - 1 2 rates brands 2, 5, and 8
1001 03 100101 - - - - - on attributes
1001 04 100101 - - - - - 1-2, 4-6, 10-11, 13-14.
1001 05 100101 3 4 - 3 4 1 --- - 4 5 - 3 2
1001 06 100101 - - - - -
1001 07 100101 - - - - -
1001 08 100101 5 5 - 4 5 3 - - - 3 4 - 4 5

1002 01 100101 2 - 4 5 4 - - - 5 3 - 2 - - Respondent 1002
1002 02 100101 - - - - - rates brands 1, 5, and 6
1002 03 100101 - - - - - on attributes
1002 04 100101 - - - - - 1, 3-5, 9-10, 12
1002 05 100101 5 - 3 2 4 - - - 4 3 - 1 - -
1002 06 100101 3 - 5 4 1 - - - 2 3 - 1 - -
```

```
1002 07 100101 - - - - -
1002 08 100101 - - - - -
```

Step 4

```
COUNT emptyrec = rate01 to rate14 (1 thru 5).
SELECT IF (EMPTYREC > 0).
```

Step 5

```
AGGREGATE
  /OUTFILE = "f:\proj\study\temp\aggr_rat.sav"
  /PRESORTED
  /BREAK   = respnum$
  /avgrat01 "Avg Rtnng Att01" = MEAN(rat01)
          ..                ..                ..
          ..                ..                ..
  /avgratNN "Avg Rtnng AttNN" = MEAN(ratNN).
```

Step 6

```
MATCH FILES
  FILE      = "f:\proj\study\temp\tmp_rtgs.sav"
  TABLE    = "f:\proj\study\temp\aggr_rat.sav"
  /BY       respnum$
  /MAP.
DO REPEAT
  tmpa = rate01 TO rateNN
  /tmpb = avgrat01 TO avgratNN.
  COMPUTE tmpa = tmpa - tmpb.
END REPEAT.
```

Step 7

```
RECODE rate01 to rateNN (sysmis = 0).
```

After Steps 5-7, the resulting data file looks like this:

```
1001 02 100101 -1.3 -0.3 0.0 1.0 -2.3 1.3 0.0 0.0 0.0 -1.6 -1.6 0.0 -1.6 -1.0
1001 05 100101 -0.3 -0.3 0.0 -1.0 0.6 -1.6 0.0 0.0 0.0 1.3 1.3 0.0 0.3 -1.0
1001 08 100101 1.6 0.6 0.0 0.0 1.7 0.3 0.0 0.0 0.0 0.3 0.3 0.0 1.3 2.0
1002 01 100101 -1.3 0.0 0.0 1.3 1.0 0.0 0.0 0.0 1.3 0.0 0.0 0.6 0.0 0.0
1002 05 100101 1.6 0.0 -1.0 -1.6 -1.6 1.0 0.0 0.0 0.0 0.0 0.0 -0.3 0.0 0.0
1002 06 100101 -0.3 0.0 1.0 -0.3 -2.0 0.0 0.0 0.0 -1.6 0.0 0.0 -0.3 0.0 0.0
```

Step 8

DISCRIMINANT

```
GROUPS      = brand (1 YY)
/VARIABLES  = rate01 to rateNN
/ANALYSIS   = ALL
/METHOD    = DIRECT
/FUNCTIONS   = 2
/SAVE       = SCORES (descr)
/PRIORS     = EQUAL
/STATISTICS = MEAN STDDEV UNIVF TABLE
/CLASSIFY   = NONMISSING POOLED.
```

Step 9

CORRELATIONS

```
VARIABLES  = rate01 to rateNN
WITH       = descr1 dscr2
/MISSING   = PAIRWISE
/PRINT     = NOSIG.
```

Rotation

* Enter desired angle of rotation (-99 thru +99) in place of zero.

```
COMPUTE nag_rot = 0.
```

* Convert anngle to radians.

```
COMPUTE ang_rot = ang_rot * 3.141593 / 180.
```

*Compute cosine of angle.

```
COMPUTE alpha  = COS (rad_rot).
```

```
COMPUTE d1a    = SQRT (1 - (alpha**2)).
```

```
COMPUTE d1b    = alpha.
```

```
COMPUTE d2a    = alpha * -1.
```

```
COMPUTE d2b    = SQRT (1 - (alpha**2)).
```

```
COMPUTE r_dscr1 = (dscr1 * d1a) + (dscr2 * d1b).
```

```
COMPUTE r_dscr2 = (dscr1 * d2a) + (dscr2 * d2b).
```