

CHAPTER 24

Stage 1
Problem definition

Stage 2
Research approach
developed

Stage 3
Research design
developed

Stage 4
Fieldwork or data
collection

Stage 5
Data preparation
and analysis

Stage 6
Report preparation
and presentation

Multidimensional scaling and conjoint analysis

Objectives

After reading this chapter, you should be able to:

- 1 discuss the basic concept and scope of multidimensional scaling (MDS) in marketing research and describe its various applications;
- 2 describe the steps involved in multidimensional scaling of perception data, including formulating the problem, obtaining input data, selecting an MDS procedure, deciding on the number of dimensions, labelling the dimensions and interpreting the configuration, and assessing reliability and validity;
- 3 explain the multidimensional scaling of preference data and distinguish between internal and external analysis of preferences;
- 4 explain correspondence analysis and discuss its advantages and disadvantages;
- 5 understand the relationship between MDS discriminant analysis and factor analysis;
- 6 discuss the basic concepts of conjoint analysis, contrast it with MDS and discuss its various applications;
- 7 describe the procedure for conducting conjoint analysis, including formulating the problem, constructing the stimuli, deciding the form of input data, selecting a conjoint analysis procedure, interpreting the results, and assessing reliability and validity;
- 8 define the concept of hybrid conjoint analysis and explain how it simplifies the data collection task.

Multidimensional scaling allows the perceptions and preferences of consumers to be clearly represented in a spatial map. Conjoint analysis helps to determine the relative importance of attributes that consumers use in choosing products.



Overview

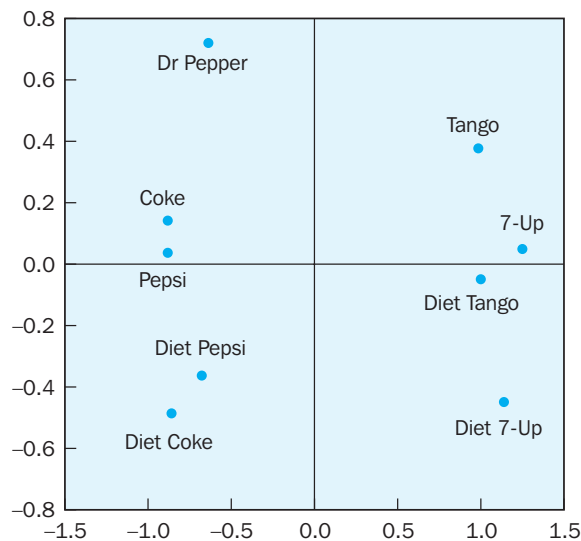
This final chapter on quantitative data analysis presents two related techniques for analysing consumer perceptions and preferences: multidimensional scaling (MDS) and conjoint analysis. We outline and illustrate the steps involved in conducting MDS and discuss the relationships among MDS, factor analysis and discriminant analysis. Then we describe conjoint analysis and present a step-by-step procedure for conducting it. We also provide brief coverage of hybrid conjoint models.

We begin with examples illustrating MDS and conjoint analysis.

example

Colas collide¹

In a survey, respondents were asked to rank-order all the possible pairs of nine brands of soft drinks in terms of their similarity. These data were analysed via multidimensional scaling and resulted in the following spatial representation of soft drinks.



From other information obtained in the questionnaire, the horizontal axis was labelled 'cola flavour'. Diet Coke was perceived to be the most cola-flavoured and 7-Up the least cola-flavoured. The vertical axis was labelled 'dietness', with Diet Coke being perceived to be the most dietetic and Dr Pepper the least dietetic. Note that Coke and Pepsi were perceived to be very similar as indicated by their closeness in the perceptual map. Close similarity was also perceived between 7-Up and Tango, Diet 7-Up and Diet Tango, and Diet Coke and Diet Pepsi. Notice that Dr Pepper is perceived to be relatively dissimilar to the other brands. Such MDS maps are very useful in understanding the competitive structure of the soft drink market. ■

example

The conjoint path over the cultural divide²

Boots the Chemist was considering whether to open new stores in the Netherlands, Japan and Thailand. Research was conducted to help decide whether to enter these markets and also to decide which element of Boots' product and service offering to prioritise.

The key research objectives were to:

- Understand the key drivers of store choice
- Assess the performance of main competitors already in the market
- Estimate the proportion of shoppers likely to visit new Boots stores.

Conjoint analysis was used to understand the key drivers of store choice, the impact of features such as range, price, quality, service and convenience, and the trade-offs made in prioritising these features.

To understand the strengths and weaknesses of existing retailers, respondents stated for each of the attributes under review what the named competitors offered. To enable take-up of the new stores to be forecast, respondents were first shown a video of the Boots concept store. The concept store was then assessed on the same series of attributes used for the existing competitors. Over 1,000 interviews were conducted in each country. The research results found:

- The characteristics of the target market in terms of age, sex, income and lifestyle, frequency of and attitudes to shopping.
- The key success factors in each product area, which influenced store design, merchandising, staff training and marketing decisions.
- Which existing players posed the greatest threat, in terms of being differentiated from current competitors and having possible areas of leverage against Boots. ■

The first example illustrates the derivation and use of perceptual maps, which lie at the heart of MDS. The Boots example involves the trade-offs that respondents make while evaluating alternatives in choosing stores and desirable features within those stores. The conjoint analysis procedure is based on these trade-offs.

Basic concepts in multidimensional scaling (MDS)

Multidimensional scaling (MDS)

A class of procedures for representing perceptions and preferences of respondents spatially by means of a visual display.

Multidimensional scaling (MDS) is a class of procedures for representing perceptions and preferences of respondents spatially by means of a visual display. Perceived or psychological relationships among stimuli are represented as geometric relationships among points in a multidimensional space. These geometric representations are often called spatial maps. The axes of the spatial map are assumed to denote the psychological bases or underlying dimensions respondents use to form perceptions and preferences for stimuli.³ MDS has been used in marketing to identify the following:

- 1 The number and nature of dimensions consumers use to perceive different brands
- 2 The positioning of brands on these dimensions
- 3 The positioning of consumers' ideal brand on these dimensions.

Information provided by MDS has been used for a variety of marketing applications, including:

- *Image measurement.* Comparing the customers' and non-customers' perceptions of the firm with the firm's perceptions of itself.
- *Market segmentation.* Brands and consumers can be positioned in the same space and thus groups of consumers with relatively homogeneous perceptions can be identified.
- *New product development.* Gaps in a spatial map indicate potential opportunities for positioning new products. MDS can be used to evaluate new product concepts and existing brands on a test basis to determine how consumers perceive the new concepts. The proportion of preferences for each new product is one indicator of its success.
- *Assessing advertising effectiveness.* Spatial maps can be used to determine whether advertising has been successful in achieving the desired brand positioning.
- *Pricing analysis.* Spatial maps developed with and without pricing information can be compared to determine the impact of pricing.
- *Channel decisions.* Judgements on compatibility of brands with different retail outlets could lead to spatial maps useful for making channel decisions.
- *Attitude scale construction.* MDS techniques can be used to develop the appropriate dimensionality and configuration of the attitude space.

The important statistics and terms associated with MDS include the following:

Similarity judgements. Similarity judgements are ratings on all possible pairs of brands or other stimuli in terms of their similarity using a Likert-type scale.

Preference rankings. Preference rankings are rank orderings of the brands or other stimuli from the most preferred to the least preferred. They are normally obtained from respondents.

Stress. Stress is a lack-of-fit measure; higher values of stress indicate poorer fits.

R-square. R-square is a squared correlation index that indicates the proportion of variance of the optimally scaled data that can be accounted for by the MDS procedure. This is a goodness-of-fit measure.

Spatial map. Perceived relationships among brands or other stimuli are represented as geometric relationships among points in a multidimensional space.

Coordinates. Coordinates indicate the positioning of a brand or a stimulus in a spatial map.

Unfolding. The representation of both brands and respondents as points in the same space.

Conducting multidimensional scaling

Figure 24.1 shows the steps in MDS. The researcher must formulate the MDS problem carefully because a variety of data may be used as input into MDS. The researcher must also determine an appropriate form in which data should be obtained and select an MDS procedure for analysing the data. An important aspect of the solution involves determining the number of dimensions for the spatial map. Also, the axes of the map should be labelled and the derived configuration interpreted. Finally, the researcher must assess the quality of the results obtained.⁴ We describe each of these steps, beginning with problem formulation.

Formulate the problem

Formulating the problem requires that the researcher specify the purpose for which the MDS results would be used and select the brands or other stimuli to be included in the analysis. The number of brands or stimuli selected and the specific brands included determine the nature of the resulting dimensions and configurations. At a minimum, eight brands or stimuli should be included to obtain a well-defined spatial map. Including more than 25 brands is likely to be cumbersome and may result in respondent fatigue.

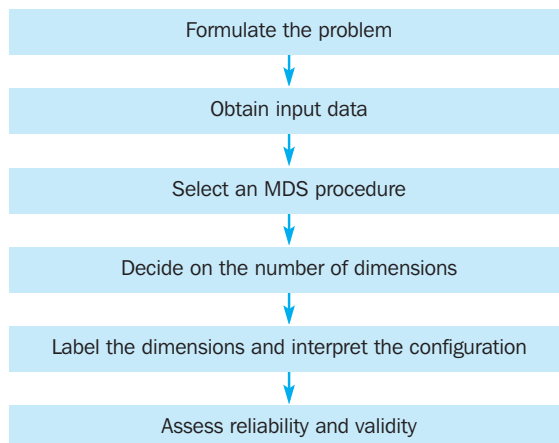


Figure 24.1
Conducting
multidimensional
scaling

The decision regarding which specific brands or stimuli to include should be made carefully. Suppose that a researcher is interested in obtaining consumer perceptions of cars. If luxury cars are not included in the stimulus set, this dimension may not emerge in the results. The choice of the number and specific brands or stimuli to be included should be based on the statement of the marketing research problem, theory and the judgement of the researcher.

Multidimensional scaling will be illustrated in the context of obtaining a spatial map for 10 brands of beer. These brands are Becks, Budvar, Budweiser, Carlsberg, Corona, Grolsch, Harp, Holsten, San Miguel and Stella Artois. Given the list of brands, the next question is: how should we obtain data on these 10 brands?

Obtain input data

As shown in Figure 24.2, input data obtained from the respondents may be related to perceptions or preferences. Perception data, which may be direct or derived, is discussed first.

Perception data: direct approaches. In direct approaches to gathering perception data, respondents are asked to judge how similar or dissimilar various brands or stimuli are, using their own criteria. Respondents are often required to rate all possible pairs of brands or stimuli in terms of similarity on a Likert scale. These data are referred to as similarity judgements. For example, similarity judgements on all the possible pairs of bottled beer brands may be obtained in the following manner:

	Very dissimilar						Very similar
Becks versus Budweiser	1	2	3	4	5	6	7
Budweiser versus Carlsberg	1	2	3	4	5	6	7
Carlsberg versus Corona	1	2	3	4	5	6	7
...							
Becks versus Stella Artois	1	2	3	4	5	6	7

The number of pairs to be evaluated is $n(n - 1)/2$, where n is the number of stimuli. Other procedures are also available. Respondents could be asked to rank-order all the possible pairs from the most similar to the least similar. In another method, the respondent rank-orders the brands in terms of their similarity to an anchor brand. Each brand, in turn, serves as the anchor.

In our example, the direct approach was adopted. Subjects were asked to provide similarity judgements for all 45 ($10 \times 9/2$) pairs of bottled beer brands, using a seven-point scale. The data obtained from one respondent are given in Table 24.1.⁵

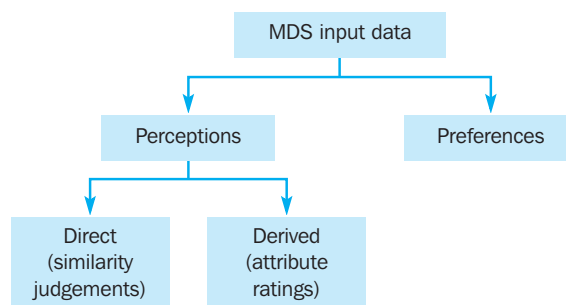


Figure 24.2
Input data for multidimensional scaling

Table 24.1 Similarity ratings of bottled beer brands

	Becks	Budvar	Budweiser	Carlsberg	Corona	Grolsch	Harp	Holsten	San Miguel	Stella Artois
Becks										
Budvar	5									
Budweiser	6	7								
Carlsberg	4	6	6							
Corona	2	3	4	5						
Grolsch	3	3	4	4	5					
Harp	2	2	2	3	5	5				
Holsten	2	2	2	2	6	5	6			
San Miguel	2	2	2	2	6	6	7	6		
Stella Artois	1	2	4	2	4	3	3	4	3	

Derived approaches
 In MDS, attribute-based approaches to collecting perception data requiring respondents to rate the stimuli on the identified attributes using semantic differential or Likert scales.

Perception data: derived approaches. Derived approaches to collecting perception data are attribute-based approaches requiring the respondents to rate the brands or stimuli on the identified attributes using semantic differential or Likert scales. For example, the different brands of bottled beer may be rated on attributes like these:

- Best drunk with food _____ Best drunk on its own
- Bottle feels good to hold _____ Bottle does not feel good to hold
- Has a strong smell of hops _____ No smell of hops

Sometimes an ideal brand is also included in the stimulus set. The respondents are asked to evaluate their hypothetical ideal brand on the same set of attributes. If attribute ratings are obtained, a similarity measure (such as euclidean distance) is derived for each pair of brands.

Direct vs. derived approaches. Direct approaches have the advantage that the researcher does not have to identify a set of salient attributes. Respondents make similarity judgements using their own criteria, as they would under normal circumstances. The disadvantages are that the criteria are influenced by the brands or stimuli being evaluated. If the various brands of cars being evaluated are in the same price range, then price will not emerge as an important factor. It may be difficult to determine before analysis if and how the individual respondent’s judgements should be combined. Furthermore, it may be difficult to label the dimensions of the spatial map.

The advantage of the attribute-based approach is that it is easy to identify respondents with homogeneous perceptions. The respondents can be clustered based on the attribute ratings. It is also easier to label the dimensions. A disadvantage is that the researcher must identify all the salient attributes, a difficult task. The spatial map obtained depends on the attributes identified.

The direct approaches are more frequently used than the attribute-based approaches. It may, however, be best to use both these approaches in a complementary way. Direct similarity judgements may be used for obtaining the spatial map, and attribute ratings may be used as an aid to interpreting the dimensions of the perceptual map.

Preference data. Preference data order the brands or stimuli in terms of respondents’ preference for some property. A common way in which such data are obtained is preference rankings. Respondents are required to rank the brands from the most preferred to the least preferred. Alternatively, respondents may be required to make

paired comparisons and indicate which brand in a pair they prefer. Another method is to obtain preference ratings for the various brands. (The rank-order, paired comparison and rating scales were discussed in Chapter 12 on scaling techniques.) When spatial maps are based on preference data, distance implies differences in preference. The configuration derived from preference data may differ greatly from that obtained from similarity data. Two brands may be perceived as different in a similarity map yet similar in a preference map, and vice versa. For example, Becks and Harp may be perceived by a group of respondents as very different brands and thus appear far apart on a perception map. But these two brands may be about equally preferred and may appear close together on a preference map.

We continue using the perception data obtained in the bottled beer example to illustrate the MDS procedure and then consider the scaling of preference data.

Select an MDS procedure

Selecting a specific MDS procedure depends on whether perception or preference data are being scaled or whether the analysis requires both kinds of data. The nature of the input data is also a determining factor. **Non-metric MDS** procedures assume that the input data are ordinal, but they result in metric output. The distances in the resulting spatial map may be assumed to be interval scaled. These procedures find, in a given dimensionality, a spatial map whose rank orders of estimated distances between brands or stimuli best preserve or reproduce the input rank orders. In contrast, **metric MDS** methods assume that input data are metric. Since the output is also metric, a stronger relationship between the output and input data is maintained, and the metric (interval or ratio) qualities of the input data are preserved. The metric and non-metric methods produce similar results.⁶

Another factor influencing the selection of a procedure is whether the MDS analysis will be conducted at the individual respondent level or at an aggregate level. In individual-level analysis, the data are analysed separately for each respondent, resulting in a spatial map for each respondent. Although individual-level analysis is useful from a research perspective, it is not appealing from a managerial standpoint. Marketing strategies are typically formulated at the segment or aggregate level, rather than at the individual level. If aggregate-level analysis is conducted, some assumptions must be made in aggregating individual data. Typically, it is assumed that all respondents use the same dimensions to evaluate the brands or stimuli, but that different respondents weight these common dimensions differentially.

The data of Table 24.1 were treated as rank-ordered and scaled using a non-metric procedure. Because these data were provided by one respondent, an individual-level analysis was conducted. Spatial maps were obtained in one to four dimensions, and then a decision on an appropriate number of dimensions was made. This decision is central to all MDS analyses; therefore, it is explored in greater detail in the following section.

Decide on the number of dimensions

The objective in MDS is to obtain a spatial map that best fits the input data in the smallest number of dimensions. However, spatial maps are computed in such a way that the fit improves as the number of dimensions increases, which means that a compromise has to be made. The fit of an MDS solution is commonly assessed by the stress measure. Stress is a lack-of-fit measure; higher values of stress indicate poorer fits. The following guidelines are suggested for determining the number of dimensions.

- 1 *A priori knowledge.* Theory or past research may suggest a particular number of dimensions.
- 2 *Interpretability of the spatial map.* Generally, it is difficult to interpret configurations or maps derived in more than three dimensions.

Non-metric MDS

A type of multidimensional scaling which assumes that the input data are ordinal.

Metric MDS

A multidimensional scaling method that assumes that input data are metric.

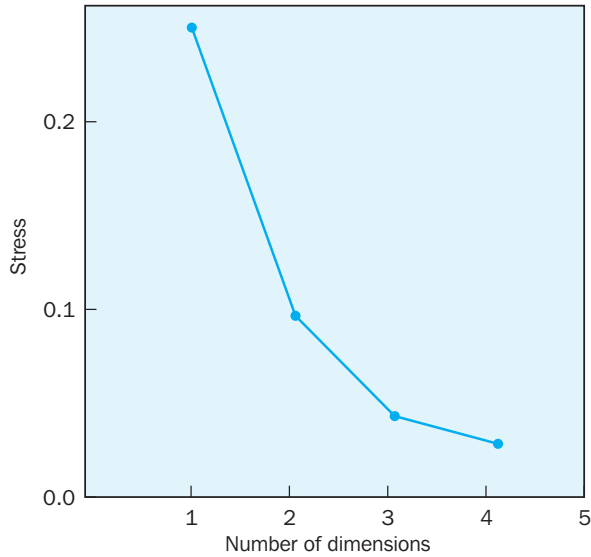


Figure 24.3
Plot of stress versus dimensionality

- 3 *Elbow criterion.* A plot of stress versus dimensionality should be examined. The points in this plot usually form a convex pattern, as shown in Figure 24.3. The point at which an elbow or a sharp bend occurs indicates an appropriate number of dimensions. Increasing the number of dimensions beyond this point is usually not worth the improvement in fit. This criterion for determining the number of dimensions is called the **elbow criterion**.
- 4 *Ease of use.* It is generally easier to work with two-dimensional maps or configurations than with those involving more dimensions.
- 5 *Statistical approaches.* For the sophisticated user, statistical approaches are also available for determining the dimensionality.⁷

Elbow criterion
A plot of stress versus dimensionality used in MDS. The point at which an elbow or a sharp bend occurs indicates an appropriate dimensionality.

Based on the plot of stress versus dimensionality (Figure 24.3), interpretability of the spatial map and ease-of-use criteria, it was decided to retain a two-dimensional solution. This is shown in Figure 24.4.

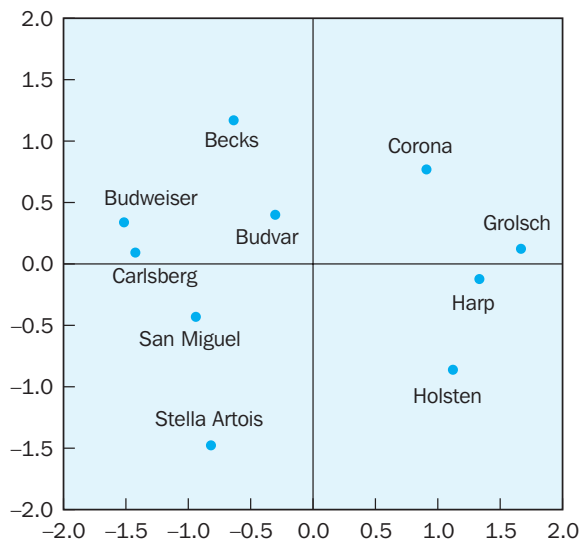


Figure 24.4
A spatial map of beer brands

Label the dimensions and interpret the configuration

Once a spatial map is developed, the dimensions must be labelled and the configuration interpreted. Labelling the dimensions requires subjective judgement on the part of the researcher. The following guidelines can assist in this task:

- 1 Even if direct similarity judgements are obtained, ratings of the brands on researcher-supplied attributes may still be collected. Using statistical methods such as regression these attribute vectors may be fitted in the spatial map (see Figure 24.5). The axes may then be labelled for the attributes with which they are most closely aligned.
- 2 After providing direct similarity or preference data, the respondents may be asked to indicate the criteria they used in making their evaluations. These criteria may then be subjectively related to the spatial map to label the dimensions.
- 3 If possible, the respondents can be shown their spatial maps and asked to label the dimensions by inspecting the configurations.
- 4 If objective characteristics of the brands are available (e.g. horsepower or kilometres per litre for cars), these could be used as an aid in interpreting the subjective dimensions of the spatial maps.

Often, the dimensions represent more than one attribute. The configuration or the spatial map may be interpreted by examining the coordinates and relative positions of the brands. For example, brands located near each other compete more fiercely than brands far apart. An isolated brand has a unique image. Brands that are farther along in the direction of a descriptor are stronger on that characteristic than others. Thus, the strengths and weaknesses of each product can be understood. Gaps in the spatial map may indicate potential opportunities for introducing new products.

In Figure 24.5, the vertical axis may be labelled as ‘strength’, representing the power of particular flavours and smells when the beer is first tasted. Brands with high positive values on this axis include Grolsch, Harp, Holsten and Corona. The horizontal axis may be labelled as ‘aftertaste’, representing the flavour of the beer that lingers on the palate after the beer has been drunk. Brands with large negative values on this dimension include Stella Artois, Holsten and San Miguel. Note that negative scores on the map do not necessarily represent negative characteristics for certain consumers. Thus, the strength of flavour from initial smell and taste through to a strong aftertaste in a brand such as Stella Artois may be seen as desirable characteristics for many beer drinkers.

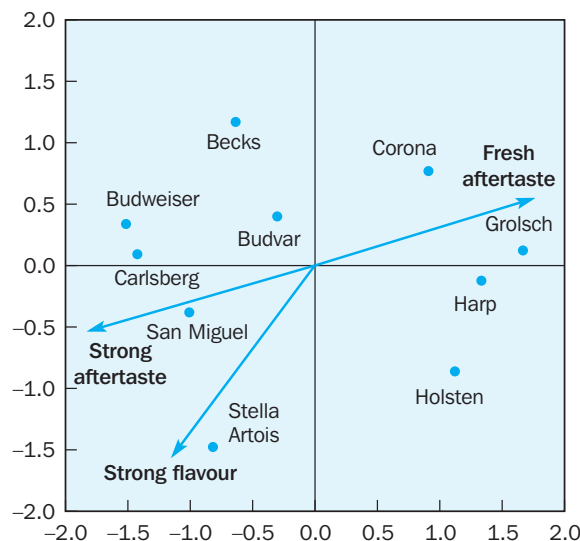


Figure 24.5
Using attribute vectors
to label dimensions

The gaps in the spatial map indicate potential opportunities for new brands, for example, one that has a strong initial taste but does not have a strong lingering aftertaste.

Assess reliability and validity

The input data, and consequently the MDS solutions, are invariably subject to substantial random variability. Hence, it is necessary that some assessment be made of the reliability and validity of MDS solutions. The following guidelines are suggested.

- 1 The index of fit, or *R*-square, should be examined. This is a squared correlation index that indicates the proportion of variance of the optimally scaled data that can be accounted for by the MDS procedure. Thus, it indicates how well the MDS model fits the input data. Although higher values of *R*-square are desirable, values of 0.60 or better are considered acceptable.
- 2 Stress values are also indicative of the quality of MDS solutions. Whereas *R*-square is a measure of goodness-of-fit, stress measures badness-of-fit, or the proportion of variance of the optimally scaled data that is not accounted for by the MDS model. Stress values vary with the type of MDS procedure and the data being analysed. For Kruskal’s stress formula 1, the recommendations for evaluating stress values are as follows.⁸

Stress (%)	Goodness of fit
20	Poor
10	Fair
5	Good
2.5	Excellent
0	Perfect

- 3 If an aggregate-level analysis has been done, the original data should be split into two or more parts. MDS analysis should be conducted separately on each part and the results compared.
- 4 Stimuli can be selectively eliminated from the input data and the solutions determined for the remaining stimuli.
- 5 A random error term could be added to the input data. The resulting data are subjected to MDS analysis and the solutions compared.
- 6 The input data could be collected at two different points in time and the test–retest reliability determined.

Formal procedures are available for assessing the validity of MDS.⁹ In the case of our illustrative example, the stress value of 0.095 indicates a fair fit. One brand, namely Stella Artois, is different from the others. Would the elimination of Stella Artois from the stimulus set appreciably alter the relative configuration of the other brands? The spatial map obtained by deleting Stella Artois is shown in Figure 24.6. There is some change in the relative positions of the brands, particularly Corona and Holsten. Yet the changes are modest, indicating fair stability.¹⁰

Assumptions and limitations of MDS

It is worthwhile to point out some assumptions and limitations of MDS. It is assumed that the similarity of stimulus A to B is the same as the similarity of stimulus B to A. There are some instances where this assumption may be violated. For example, New Zealand is perceived as more similar to Australia than Australia is to New Zealand.

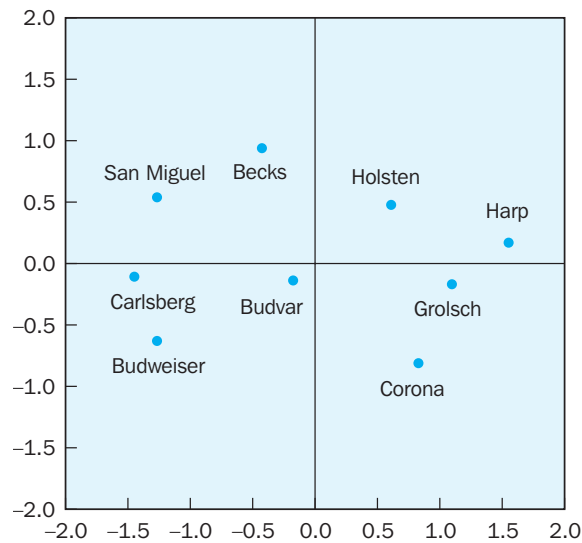


Figure 24.6
Assessment of stability
by deleting one brand

MDS assumes that the distance (similarity) between two stimuli is some function of their partial similarities on each of several perceptual dimensions. Not much research has been done to test this assumption. When a spatial map is obtained, it is assumed that inter-point distances are ratio scaled and that the axes of the map are multidimensional interval scaled. A limitation of MDS is that dimension interpretation relating physical changes in brands or stimuli to changes in the perceptual map is difficult at best. These limitations also apply to the scaling of preference data.

Scaling preference data

Internal analysis of preferences

A method of configuring a spatial map such that the spatial map represents both brands or stimuli and respondent points or vectors and is derived solely from the preference data.

External analysis of preferences

A method of configuring a spatial map such that the ideal points or vectors based on preference data are fitted in a spatial map derived from the perception data.

Analysis of preference data can be internal or external. In **internal analysis of preferences**, a spatial map representing both brands or stimuli and respondent points or vectors is derived solely from the preference data. Thus, by collecting preference data, both brands and respondents can be represented in the same spatial map. In **external analysis of preferences**, the ideal points or vectors based on preference data are fitted in a spatial map derived from perception (e.g. similarities) data. To perform external analysis, both preference and perception data must be obtained. The representation of both brands and respondents as points in the same space, by using internal or external analysis, is referred to as *unfolding*.

External analysis is preferred in most situations.¹¹ In internal analysis, the differences in perceptions are confounded with differences in preferences. It is possible that the nature and relative importance of dimensions may vary between the perceptual space and the preference space. Two brands may be perceived to be similar (located closely to each other in the perceptual space), yet one brand may be distinctly preferred over the other (i.e. the brands may be located apart in the preference space). These situations cannot be accounted for in internal analysis. In addition, internal analysis procedures are beset with computational difficulties.¹²

We illustrate external analysis by scaling the preferences of our respondent into his spatial map. The respondent ranked the brands in the following order of preference (most preferred first): Stella Artois, Holsten, Harp, San Miguel, Carlsberg, Grolsch, Budvar, Budweiser, Corona and Becks. These preference rankings, along with the coordinates of the spatial map (Figure 24.5), were used as input into a preference scaling program to derive Figure 24.7. Notice the location of the ideal point. It is close to Stella Artois, Holsten, Harp and San Miguel, the four most preferred brands, and far

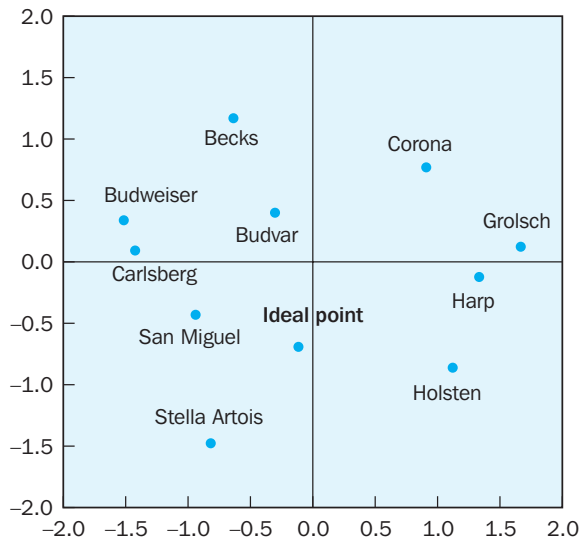


Figure 24.7
External analysis of preference data

from Corona and Becks, the two least preferred brands. If a new brand were to be located in this space, its distance from the ideal point, relative to the distances of other brands from the ideal point, would determine the degree of preference for this brand.

Although we have considered only quantitative data so far, qualitative data can also be mapped using procedures such as correspondence analysis.

Correspondence analysis

Correspondence analysis
An MDS technique for scaling qualitative data that scales the rows and columns of the input contingency table in corresponding units so that each can be displayed in the same low-dimensional space.

Correspondence analysis is an MDS technique for scaling qualitative data in marketing research. The input data are in the form of a contingency table indicating a qualitative association between the rows and columns. Correspondence analysis scales the rows and columns in corresponding units so that each can be displayed graphically in the same low-dimensional space. These spatial maps provide insights into:

- 1 Similarities and differences within the rows with respect to a given column category
- 2 Similarities and differences within the column categories with respect to a given row category
- 3 Relationships among the rows and columns.¹³

The interpretation of results in correspondence analysis is similar to that in principal components analysis (Chapter 22), given the similarity of the algorithms. Correspondence analysis results in the grouping of categories (activities, brands or other stimuli) found within the contingency table, just as principal components analysis involves the grouping of the independent variables. The results are interpreted in terms of proximities among the rows and columns of the contingency table. Categories that are closer together than others are more similar in underlying structure.¹⁴

Compared with other multidimensional scaling techniques, the advantage of correspondence analysis is that it reduces the data collection demands imposed on the respondents, since only binary or categorical data are obtained. The respondents are merely asked to tick which attributes apply to each of several brands, or in the GlobalCash study, tick which events they plan to undertake over the next two years. The input data are the number of yes responses for each brand on each attribute. The brands and the attributes are then displayed in the same multidimensional space. The disadvantage is that between-set (i.e. between column and row) distances cannot be

meaningfully interpreted. Other users have criticised the technique as causing confusion when interpreting attribute-brand relationships and complications in the tracking of perceptual changes.¹⁵ Ultimately, it must be remembered that correspondence analysis is an exploratory data analysis technique that is not suitable for hypothesis testing.¹⁶

Relationship among MDS, factor analysis and discriminant analysis

MDS, including correspondence analysis, is not the only procedure available for obtaining perceptual maps. Two other techniques that we have discussed before, discriminant analysis (Chapter 21) and factor analysis (Chapter 22), can also be used for this purpose.

If the attribute-based approaches are used to obtain input data, spatial maps can also be obtained by using factor or discriminant analysis. In this approach, each respondent rates n brands on m attributes. By factor analysing the data, one could derive for each respondent n factor scores for each factor, one for each brand. By plotting brand scores on the factors, a spatial map could be obtained for each respondent. If an aggregate map is desired, the factor score for each brand for each factor can be averaged across respondents. The dimensions would be labelled by examining the factor loadings, which are estimates of the correlations between attribute ratings and underlying factors.¹⁷

The goal of discriminant analysis is to select the linear combinations of attributes that best discriminate between the brands or stimuli. To develop spatial maps by means of discriminant analysis, the dependent variable is the brand rated and the independent or predictor variables are the attribute ratings. A spatial map can be obtained by plotting the discriminant scores for the brands. The discriminant scores are the ratings on the perceptual dimensions, based on the attributes which best distinguish the brands. The dimensions can be labelled by examining the discriminant weights, or the weightings of attributes that make up a discriminant function or dimension.¹⁸

Basic concepts in conjoint analysis

Conjoint analysis

A technique that attempts to determine the relative importance consumers attach to salient attributes and the utilities they attach to the levels of attributes.

Conjoint analysis attempts to determine the relative importance consumers attach to salient attributes and the utilities they attach to the levels of attributes.¹⁹ This information is derived from consumers' evaluations of brands or from brand profiles composed of these attributes and their levels. The respondents are presented with stimuli that consist of combinations of attribute levels. They are asked to evaluate these stimuli in terms of their desirability. Conjoint procedures attempt to assign values to the levels of each attribute so that the resulting values or utilities attached to the stimuli match, as closely as possible, the input evaluations provided by the respondents. The underlying assumption is that any set of stimuli – such as products, brands or banks – are evaluated as a bundle of attributes.²⁰

Like multidimensional scaling, conjoint analysis relies on respondents' subjective evaluations. In MDS, however, the stimuli are products or brands. In conjoint analysis, the stimuli are combinations of attribute levels determined by the researcher. The goal in MDS is to develop a spatial map depicting the stimuli in a multidimensional perceptual or preference space. Conjoint analysis, on the other hand, seeks to develop the part-worth or utility functions describing the utility consumers attach to the levels of each attribute. The two techniques are complementary.²¹

Conjoint analysis has been used in marketing for a variety of purposes, including the following:

- *Determining the relative importance of attributes in the consumer choice process.* A standard output from conjoint analysis consists of derived relative importance weights. The relative importance weights indicate which attributes are important in influencing consumer choice.
- *Estimating market share of brands that differ in attribute levels.* The utilities derived from conjoint analysis can be used as input into a choice simulator to determine the share of choices, and hence the market share, of different brands.
- *Determining the composition of the most preferred brand.* Brand features can be varied in terms of attribute levels and the corresponding utilities determined. The brand features that yield the highest utility indicate the composition of the most preferred brand.
- *Segmenting the market based on similarity of preferences for attribute levels.* The part-worth functions derived for the attributes may be used as a basis for clustering respondents to arrive at homogeneous preference segments.²²

Applications of conjoint analysis have been made in consumer goods, industrial goods and financial and other services. Moreover, these applications have spanned all areas of marketing. A recent survey of conjoint analysis reported applications in the areas of new product and concept identification, competitive analysis, pricing, market segmentation, advertising and distribution.²³

The important statistics and terms associated with conjoint analysis include the following:

Part-worth functions. The part-worth or *utility functions* describe the utility consumers attach to the levels of each attribute.

Relative importance weights. The relative importance weights are estimated and indicate which attributes are important in influencing consumer choice.

Attribute levels. Denote the values assumed by the attributes.

Full profiles. Full profiles or complete profiles of brands are constructed in terms of all the attributes by using the attribute levels specified by the design.

Pairwise tables. Respondents evaluate two attributes at a time until all the required pairs of attributes have been evaluated.

Cyclical designs. Designs employed to reduce the number of paired comparisons.

Fractional factorial designs. Designs employed to reduce the number of stimulus profiles to be evaluated in the full-profile approach.

Orthogonal arrays. A special class of fractional designs that enable the efficient estimation of all main effects.

Internal validity. This involves correlations of the predicted evaluations for the hold-out or validation stimuli with those obtained from the respondents.

Conducting conjoint analysis

Figure 24.8 lists the steps in conjoint analysis. Formulating the problem involves identifying the salient attributes and their levels. These attributes and levels are used for constructing the stimuli to be used in a conjoint evaluation task. The respondents rate or rank the stimuli using a suitable scale, and the data obtained are analysed. The results are interpreted and their reliability and validity assessed. We now describe each of the steps of conjoint analysis in detail.

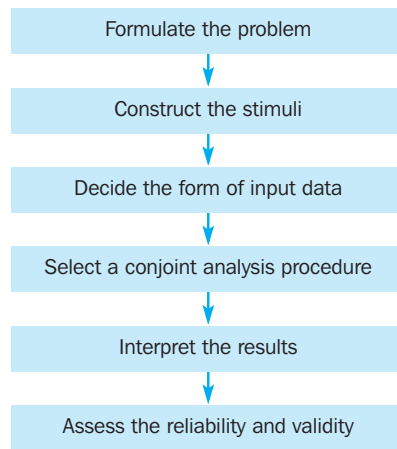


Figure 24.8
Conducting conjoint
analysis

Formulate the problem

In formulating the conjoint analysis problem, the researcher must identify the attributes and attribute levels to be used in constructing the stimuli. Attribute levels denote the values assumed by the attributes. From a theoretical standpoint, the attributes selected should be salient in influencing consumer preference and choice. For example, in the choice of a car, price, fuel efficiency, interior space and so forth should be included. From a managerial perspective, the attributes and their levels should be actionable. To tell a manager that consumers prefer a sporty car to one that is conservative-looking is not helpful, unless sportiness and conservativeness are defined in terms of attributes over which a manager has control. The attributes can be identified through discussions with management and industry experts, analysis of secondary data, qualitative research and pilot surveys. A typical conjoint analysis study may involve six or seven attributes.

Once the salient attributes have been identified, their appropriate levels should be selected. The number of attribute levels determines the number of parameters that will be estimated and also influences the number of stimuli that will be evaluated by the respondents. To minimise the respondent evaluation task and yet estimate the parameters with reasonable accuracy, it is desirable to restrict the number of attribute levels. The utility or part-worth function for the levels of an attribute may be non-linear. For example, a consumer may prefer a medium-sized car to either a small or a large one. Likewise, the utility for price may be non-linear. The loss of utility in going from a low price to a medium price may be much smaller than the loss in utility in going from a medium price to a high price. In these cases, at least three levels should be used. Some attributes, though, may naturally occur in binary form (two levels): a car does or does not have a sunroof.

The attribute levels selected will affect the consumer evaluations. If the price of a car brand is varied at €14,000, €16,000 and €18,000, price will be relatively unimportant. On the other hand, if the price is varied at €20,000, €30,000 and €40,000, it will be an important factor. Hence, the researcher should take into account the attribute levels prevalent in the marketplace and the objectives of the study. Using attribute levels that are beyond the range reflected in the marketplace will decrease the believability of the evaluation task, but it will increase the accuracy with which the parameters are estimated. The general guideline is to select attribute levels so that the ranges are somewhat greater than those prevalent in the marketplace but not so large as to impact the believability of the evaluation task adversely.

We illustrate the conjoint methodology by considering the problem of how students evaluate boots, for example brands such as Dr Martens, Timberland, Bally and

Caterpillar. Qualitative research identified three attributes as salient: the material used for the upper, the country or region in which they were designed and manufactured and the price. Each was defined in terms of three levels, as shown in Table 24.2. These attributes and their levels were used for constructing the conjoint analysis stimuli. It has been argued that pictorial stimuli should be used when consumers' marketplace choices are strongly guided by the product's styling, such that the choices are heavily based on an inspection of actual products or pictures of products.²⁴

Table 24.2 Boot attributes and levels

Attribute	Level	
	Number	Description
Uppers	3	Leather
	2	Suede
	1	Imitation leather
Country	3	Italy
	2	America
	1	Far East
Price	3	€50
	2	€125
	1	€200

Construct the stimuli

Two broad approaches are available for constructing conjoint analysis stimuli: the pairwise approach and the full-profile procedure.

In the pairwise approach, also called two-factor evaluations, respondents evaluate two attributes at a time until all the possible pairs of attributes have been evaluated.



Qualitative research revealed that students do not evaluate boots based on the sole patterns they leave on cars.

You will be presented with information on Boots in terms of pairs of features described in the form of a matrix. For each matrix, please rank the nine feature combinations in terms of your preference. A rank of 1 should be assigned to the most preferred combination and 9 to least preferred.

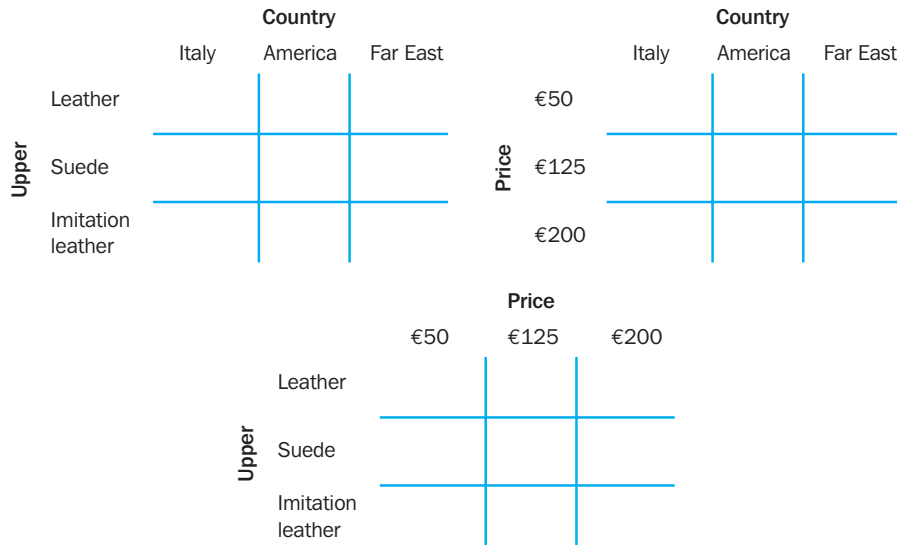


Figure 24.9
Pairwise approach to collecting conjoint data

This approach is illustrated in the context of the boots example in Figure 24.9. For each pair, respondents evaluate all the combinations of levels of both the attributes, which are presented in a matrix.

In the full-profile approach, also called multiple-factor evaluations, full or complete profiles of brands are constructed for all the attributes. Typically, each profile is described on a separate index card. This approach is illustrated in the context of the boots example in Table 24.3.

Table 24.3 Full-profile approach to collecting conjoint data

Example of boot product profile	
Upper	Made of leather
Country	Designed and made in Italy
Price	Costing €200

It is not necessary to evaluate all the possible combinations, nor is it feasible in all cases. In the pairwise approach, it is possible to reduce the number of paired comparisons by using cyclical designs. Likewise, in the full-profile approach, the number of stimulus profiles can be greatly reduced by means of fractional factorial designs. A special class of fractional designs, orthogonal arrays, allows for the efficient estimation of all main effects. Orthogonal arrays permit the measurement of all main effects of interest on an uncorrelated basis. These designs assume that all interactions are negligible. Orthogonal arrays are constructed from basic full factorial designs by substituting a new factor for selected interaction effects that are presumed to be negligible.²⁵ Generally, two sets of data are obtained. One, the estimation set, is used to calculate the part-worth functions for the attribute levels. The other, the holdout set, is used to assess reliability and validity.

The advantage of the pairwise approach is that it is easier for the respondents to provide these judgements. Its relative disadvantage, however, is that it requires more evaluations than the full-profile approach. Also, the evaluation task may be unrealistic

when only two attributes are being evaluated simultaneously. Studies comparing the two approaches indicate that both methods yield comparable utilities, yet the full-profile approach is more commonly used.

The boots example follows the full-profile approach. Given three attributes, defined at three levels each, a total of $3 \times 3 \times 3 = 27$ profiles can be constructed. To reduce the respondent evaluation task, a fractional factorial design was employed and a set of nine profiles was constructed to constitute the estimation stimuli set (see Table 24.4). Another set of nine stimuli was constructed for validation purposes. Input data were obtained for both the estimation and validation stimuli. Before the data could be obtained, however, it was necessary to decide on the form of the input data.²⁶

Table 24.4 Boot profiles and their ratings

Profile number	Attribute levels ^a			
	Upper	Country	Price	Preference rating
1	1	1	1	9
2	1	2	2	7
3	1	3	3	5
4	2	1	2	6
5	2	2	3	5
6	2	3	1	6
7	3	1	3	5
8	3	2	1	7
9	3	3	2	6

^aThe attribute levels correspond to those in Table 24.2.

Decide on the form of input data

As in the case of MDS, conjoint analysis input data can be either non-metric or metric. For non-metric data, respondents are typically required to provide rank-order evaluations. For the pairwise approach, respondents rank all the cells of each matrix in terms of their desirability. For the full-profile approach, they rank all the stimulus profiles. Rankings involve relative evaluations of the attribute levels. Proponents of ranking data believe that such data accurately reflect the behaviour of consumers in the marketplace.

In the metric form, respondents provide ratings, rather than rankings. In this case, the judgements are typically made independently. Advocates of rating data believe they are more convenient for the respondents and easier to analyse than rankings. In recent years, the use of ratings has become increasingly common.

In conjoint analysis, the dependent variable is usually preference or intention to buy. In other words, respondents provide ratings or rankings in terms of their preference or intentions to buy. The conjoint methodology, however, is flexible and can accommodate a range of other dependent variables, including actual purchase or choice.

In evaluating boot profiles, respondents were required to provide preference ratings for the boots described by the nine profiles in the estimation set. These ratings were obtained using a nine-point Likert scale (1 = not preferred, 9 = greatly preferred). Ratings obtained from one respondent are shown in Table 24.4.

Select a conjoint analysis procedure

Conjoint analysis model
The mathematical model expressing the fundamental relationship between attributes and utility in conjoint analysis.

The basic **conjoint analysis model** may be represented by the following formula:²⁷

$$U(X) = \sum_{i=1}^m \sum_{j=1}^{k_i} \alpha_{ij} x_{ij}$$

where

$U(X)$ = overall utility of an alternative

α_{ij} = the part-worth contribution or utility associated with the j th level ($j = 1, 2, \dots, k_j$) of the i th attribute ($i = 1, 2, \dots, m$)

k_i = number of levels of attribute i

m = number of attributes

The importance of an attribute, I_i , is defined in terms of the range of the part-worths, α_{ij} , across the levels of that attribute:

$$I_i = \{\max(\alpha_{ij}) - \min(\alpha_{ij})\} \text{ for each } i$$

The attribute's importance is normalised to ascertain its importance relative to other attributes, W_i :

$$W_i = \frac{I_i}{\sum_{i=1}^m I_i}$$

so that

$$\sum_{i=1}^m W_i = 1$$

Several different procedures are available for estimating the basic model. The simplest is dummy variable regression (see Chapter 20). In this case, the predictor variables consist of dummy variables for the attribute levels. If an attribute has k_i levels, it is coded in terms of $k_i - 1$ dummy variables. If metric data are obtained, the ratings, assumed to be interval scaled, form the dependent variable. If the data are non-metric, the rankings may be converted to 0 or 1 by making paired comparisons between brands. In this case, the predictor variables represent the differences in the attribute levels of the brands being compared. Other procedures that are appropriate for non-metric data include LINMAP, MONANOVA and the LOGIT model.²⁸

The researcher must also decide whether the data will be analysed at the individual respondent or the aggregate level. At the individual level, the data of each respondent are analysed separately. If an aggregate-level analysis is to be conducted, some procedure for grouping the respondents must be devised. One common approach is to estimate individual-level part-worth or utility functions first. Respondents are then clustered on the basis of the similarity of their part-worth functions. Aggregate analysis is then conducted for each cluster.²⁹ An appropriate model for estimating the parameters should be specified.³⁰

The data reported in Table 24.4 were analysed using ordinary least squares (OLS) regression with dummy variables. The dependent variable was the preference ratings. The independent variables or predictors were six dummy variables, two for each variable. The transformed data are shown in Table 24.5.

Since the data pertain to a single respondent, an individual-level analysis was conducted. The part-worth or utility functions estimated for each attribute, as well as the relative importance of the attributes, are given in Table 24.6.³¹

Table 24.5 Boot data coded for dummy variable regression

Preference ratings	Attributes					
	Upper		Country		Price	
Y	X ₁	X ₂	X ₃	X ₄	X ₅	X ₆
9	1	0	1	0	1	0
7	1	0	0	1	0	1
5	1	0	0	0	0	0
6	0	1	1	0	0	1
5	0	1	0	1	0	0
6	0	1	0	0	1	0
5	0	0	1	0	0	0
7	0	0	0	1	1	0
6	0	0	0	0	0	1

Table 24.6 Boot attributes and levels

Attribute	Level			
	Number	Description	Utility	Importance
Uppers	3	Leather	0.778	0.268
	2	Suede	-0.556	
	1	Imitation leather	-0.222	
Country	3	Italy	0.445	0.214
	2	America	0.111	
	1	Far East	-0.556	
Price	3	€50	1.111	0.500
	2	€125	0.111	
	1	€200	-1.222	

The model estimated may be represented as

$$U = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + b_5X_5 + b_6X_6$$

where X₁, X₂ = dummy variables representing upper

X₃, X₄ = dummy variables representing country

X₅, X₆ = dummy variables representing price

For upper, the attribute levels were coded as follows:

	X ₁	X ₂
Level 1	1	0
Level 2	0	1
Level 3	0	0

The levels of the other attributes were coded similarly. The parameters were estimated as follows:

$$\begin{aligned} b_0 &= 4.222 \\ b_1 &= 1.000 \\ b_2 &= -0.333 \\ b_3 &= 1.000 \\ b_4 &= 0.667 \\ b_5 &= 2.333 \\ b_6 &= 1.333 \end{aligned}$$

Given the dummy variable coding, in which level 3 is the base level, the coefficients may be related to the part-worths. As explained in Chapter 20, each dummy variable coefficient represents the difference in the part-worth for that level minus the part-worth for the base level. For upper, we have the following:

$$\begin{aligned} \alpha_{11} - \alpha_{13} &= b_1 \\ \alpha_{12} - \alpha_{13} &= b_2 \end{aligned}$$

To solve for the part-worths, an additional constraint is necessary. The part-worths are estimated on an interval scale, so the origin is arbitrary. Therefore, the additional constraint imposed is of the form

$$\alpha_{11} + \alpha_{12} + \alpha_{13} = 0$$

These equations for the first attribute, upper, are

$$\begin{aligned} \alpha_{11} - \alpha_{13} &= 1.000 \\ \alpha_{12} - \alpha_{13} &= -0.333 \\ \alpha_{11} + \alpha_{12} + \alpha_{13} &= 0 \end{aligned}$$

Solving these equations, we get

$$\begin{aligned} \alpha_{11} &= 0.778 \\ \alpha_{12} &= -0.556 \\ \alpha_{13} &= -0.222 \end{aligned}$$

The part-worths for other attributes reported in Table 24.6 can be estimated similarly. For country, we have

$$\begin{aligned} \alpha_{21} - \alpha_{23} &= b_3 \\ \alpha_{22} - \alpha_{23} &= b_4 \\ \alpha_{21} + \alpha_{22} + \alpha_{23} &= 0 \end{aligned}$$

For the third attribute, price, we have

$$\begin{aligned} \alpha_{31} - \alpha_{33} &= b_5 \\ \alpha_{32} - \alpha_{33} &= b_6 \\ \alpha_{31} + \alpha_{32} + \alpha_{33} &= 0 \end{aligned}$$

The relative importance weights were calculated based on ranges of part-worths, as follows:

$$\begin{aligned} \text{Sum of ranges of part-worths} &= [0.778 - (-0.556)] + [0.445 - (-0.556)] \\ &\quad + [1.111 - (-1.222)] \\ &= 4.668 \end{aligned}$$

$$\text{Relative importance of upper} = \frac{1.334}{4.668} = 0.286$$

$$\text{Relative importance of country} = \frac{1.001}{4.668} = 0.214$$

$$\text{Relative importance of price} = \frac{2.333}{4.668} = 0.500$$

The estimation of the part-worths and the relative importance weights provides the basis for interpreting the results.

Interpret the results

For interpreting the results, it is helpful to plot the part-worth functions. The part-worth function values for each attribute given in Table 24.6 are graphed in Figure 24.10. As can be seen from Table 24.6 and Figure 24.10, this respondent has the greatest preference for a leather upper when evaluating boots. Second preference is for an imitation leather upper, and a suede upper is least preferred. An Italian boot is most preferred, followed by American boots and boots from the Far East. As may be expected, a price of €50.00 has the highest utility and a price of €200.00 the lowest. The utility values reported in Table 24.6 have only interval scale properties, and their

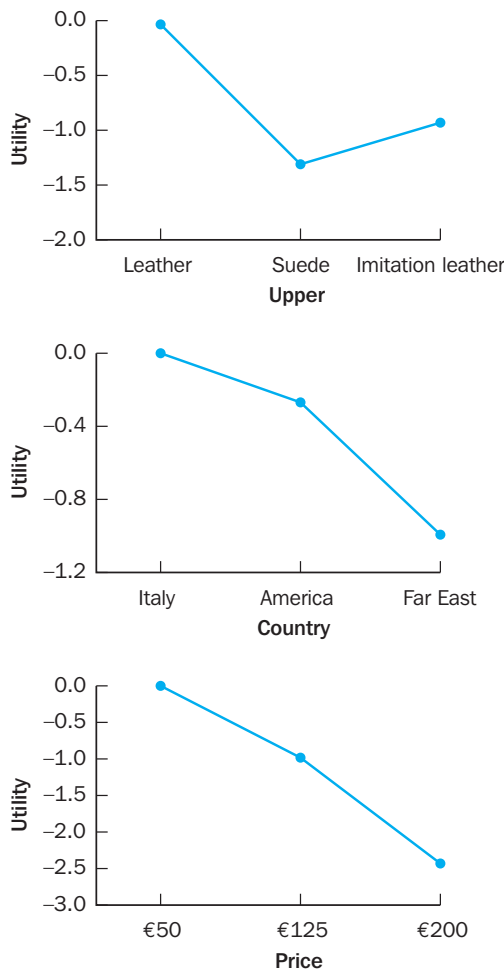


Figure 24.10
Part-worth functions

origin is arbitrary. In terms of relative importance of the attributes, we see that price is number one. Second most important is upper, followed closely by country. Because price is by far the most important attribute for this respondent, this person could be labelled as price sensitive.

Assess the reliability and validity

Several procedures are available for assessing the reliability and validity of conjoint analysis results.³²

- 1 The goodness of fit of the estimated model should be evaluated. For example, if dummy variable regression is used, the value of R^2 will indicate the extent to which the model fits the data. Models with poor fit are suspect.
- 2 Test–retest reliability can be assessed by obtaining a few replicated judgements later in data collection. In other words, at a later stage in the interview, the respondents are asked to evaluate certain selected stimuli again. The two values of these stimuli are then correlated to assess test–retest reliability.
- 3 The evaluations for the holdout or validation stimuli can be predicted by the estimated part-worth functions. The predicted evaluations can then be correlated with those obtained from the respondents to determine internal validity.
- 4 If an aggregate-level analysis has been conducted, the estimation sample can be split in several ways and conjoint analysis conducted on each sub-sample. The results can be compared across sub-samples to assess the stability of conjoint analysis solutions.

In running a regression analysis on the data of Table 24.5, an R^2 of 0.934 was obtained, indicating a good fit. The preference ratings for the nine validation profiles were predicted from the utilities reported in Table 24.6. These were correlated with the input ratings for these profiles obtained from the respondent. The correlation coefficient was 0.95, indicating a good predictive ability. This correlation coefficient is significant at $\alpha = 0.05$.

The following example further illustrates an application of conjoint analysis.

example

Fab's fabulous foamy fight³³

Competition in the clothes detergent market was brewing in Thailand. Superconcentrate detergent was fast becoming the prototype, with a market share of over 26% in the clothes detergent category. Market potential research in Thailand indicated that superconcentrates would continue to grow at around 40% a year. In addition, this category had already dominated other Asian markets such as Taiwan, Hong Kong and Singapore. Consequently, Colgate entered this new line of competition with *Fab Power Plus* with the objective of capturing 4% market share.

The main players in this market were Kao Corporation's *Attack* (14.6%), Lever Brothers' *Breeze Ultra* (2.8%), Lion Corporation's *Pao M. Wash* (1.1%) and Lever's *Omo* (0.4%). Based on qualitative research and secondary data, Colgate assessed the critical factors for the success of superconcentrates. Some of these factors were environmental appeal, hand-wash and machine-wash convenience, superior cleaning abilities, optimum level of suds for hand-wash, and brand name. Research also revealed that no brand had both hand-wash and machine-wash capabilities. *Pao Hand Force* was formulated as the hand-washing brand, and *Pao M. Wash* as the machine-wash version. Lever's *Breezematic* was targeted for machine use.

Therefore, a formula that had both hand- and machine-wash capabilities was desirable. A conjoint study was designed, and these factors varied at either two or three levels. Preference ratings were gathered from respondents, and part-worth functions for the factors were estimated both at the individual and the group level. Results showed that the factor on hand–machine capability had a substantial contribution supporting earlier claims. Based on these findings, *Fab Power Plus* was successfully launched as a brand with both hand- and machine-wash capabilities. ■

Assumptions and limitations of conjoint analysis

Although conjoint analysis is a popular technique, like MDS it carries a number of assumptions and limitations. Conjoint analysis assumes that the important attributes of a product can be identified. Furthermore, it assumes that consumers evaluate the choice alternatives in terms of these attributes and make trade-offs. In situations where image or brand name is important, however, consumers may not evaluate the brands or alternatives in terms of attributes. Even if consumers consider product attributes, the trade-off model may not be a good representation of the choice process. Another limitation is that data collection may be complex, particularly if a large number of attributes are involved and the model must be estimated at the individual level. This problem has been mitigated to some extent by procedures such as interactive or adaptive conjoint analysis and hybrid conjoint analysis. It should also be noted that the part-worth functions are not unique.

Hybrid conjoint analysis

Hybrid conjoint analysis

A form of conjoint analysis that can simplify the data collection task and estimate selected interactions as well as all main effects.

Hybrid conjoint analysis is an attempt to simplify the burdensome data collection task required in traditional conjoint analysis. Each respondent evaluates a large number of profiles, yet usually only simple part-worth functions, without any interaction effects, are estimated. In the simple part-worths or main effects model, the value of a combination is simply the sum of the separate main effects (simple part-worths). In actual practice, two attributes may interact in the sense that the respondent may value the combination more than the average contribution of the separate parts. Hybrid models have been developed to serve two main purposes: (1) to simplify the data collection task by imposing less of a burden on each respondent, and (2) to permit the estimation of selected interactions (at the subgroup level) as well as all main (or simple) effects at the individual level.

In the hybrid approach, the respondents evaluate a limited number, generally no more than nine, conjoint stimuli, such as full profiles. These profiles are drawn from a large master design and different respondents evaluate different sets of profiles so that, over a group of respondents, all the profiles of interest are evaluated. In addition, respondents directly evaluate the relative importance of each attribute and desirability of the levels of each attribute. By combining the direct evaluations with those derived from the evaluations of the conjoint stimuli, it is possible to estimate a model at the aggregate level and still retain some individual differences.³⁴

MDS and conjoint analysis are complementary techniques and may be used in combination, as the following example shows.

example

Weeding out the competition³⁵

ICI Agricultural Products did not know whether it should lower the price of Fusilade, its herbicide. It knew that it had developed a potent herbicide, but it was not sure that the weedkiller would survive in a price-conscious market. So a survey was designed to assess the relative importance of different attributes in selecting herbicides and to measure and map perceptions of major herbicides on the same attributes. Personal interviews were conducted with 601 soybean and cotton farmers who had at least 120 hectares dedicated to growing these crops and who had used herbicides during the past growing season. First, conjoint analysis was used to determine the relative importance of attributes farmers use when selecting herbicides. Then multidimensional scaling was used to map farmers' perceptions of herbicides. The study showed that price greatly influenced herbicide selections, and respondents were particularly sensitive when costs were more than €10 per hectare. But price was not the only

determinant. Farmers also considered how much weed control the herbicide provided. They were willing to pay higher prices to keep weeds off their land. The study showed that herbicides that failed to control even one of the four most common weeds would have to be very inexpensive to attain a reasonable market share. Fusilade promised good weed control. Furthermore, multidimensional scaling indicated that one of Fusilade's competitors was considered to be expensive. Hence, ICI kept its original pricing plan and did not lower the price of Fusilade. ■



Internet and computer applications

Several computer programs have been developed for conducting MDS analysis using microcomputers and mainframes. The ALSCAL program, available in the mainframe versions of SPSS and SAS, incorporates several different MDS models and can be used for conducting individual- or aggregate-level analysis. Other MDS programs are easily available and widely used. Most are available in both micro-computer and mainframe versions. Visit the following sites for further details, cases and demos.

- www.newmdsx.com/INDSCAL/indscal.htm INDSCAL, denoting individual differences scaling, is useful for conducting MDS at the aggregate level. Similarity data are used as input.
- www.newmdsx.com/MDPREF/mdpref.htm MDPREF performs internal analysis of preference data. The program develops vector directions for preferences and the configuration of brands or stimuli in a common space.
- www.newmdsx.com/PREFMAP/prefmap.htm PREFMAP performs external analysis of preference data. This program uses a known spatial map of brands or stimuli to portray an individual's preference data.
- www.sawtoothsoftware.com Sawtooth technologies include choice-based conjoint and multimedia conjoint programs that demonstrate product features rather than just describe them.
- www.statpac.com Click on 'Advanced Statistical Analysis' to see an array of multivariate data analysis programs, including correspondence analysis.
- www.tigris-software.com Click on Conjoint Analysis and then TiCon and TiCon Web.

Summary

Multidimensional scaling is used for obtaining spatial representations of respondents' perceptions and preferences. Perceived or psychological relationships among stimuli are represented as geometric relationships among points in a multidimensional space. Formulating the MDS problem requires a specification of the brands or stimuli to be included. The number and nature of brands selected influence the resulting solution. Input data obtained from the respondents can be related to perceptions or preferences. Perception data can be direct or derived. The direct approaches are more common in marketing research.

The selection of an MDS procedure depends on the nature (metric or non-metric) of the input data and whether perceptions or preferences are being scaled. Another determining factor is whether the analysis will be conducted at the individual or aggregate level. The decision about the number of dimensions in which to obtain a

solution should be based on theory, interpretability, elbow criterion and ease-of-use considerations. Labelling of the dimensions is a difficult task that requires subjective judgement. Several guidelines are available for assessing the reliability and validity of MDS solutions. Preference data can be subjected to either internal or external analysis. If the input data are of a qualitative nature, they can be analysed via correspondence analysis. If the attribute-based approaches are used to obtain input data, spatial maps can also be obtained by means of factor or discriminant analysis.

Conjoint analysis is based on the notion that the relative importance that consumers attach to salient attributes, and the utilities they attach to the levels of attributes, can be determined when consumers evaluate brand profiles that are constructed using these attributes and their levels. Formulating the problem requires an identification of the salient attributes and their levels. The pairwise and the full-profile approaches are commonly employed for constructing the stimuli. Statistical designs are available for reducing the number of stimuli in the evaluation task. The input data can be either non-metric (rankings) or metric (ratings). Typically, the dependent variable is preference or intention to buy.

Although other procedures are available for analysing conjoint analysis data, regression using dummy variables is becoming increasingly important. Interpreting the results requires an examination of the part-worth functions and relative importance weights. Several procedures are available for assessing the reliability and validity of conjoint analysis results.

Questions



- 1 For what purposes are MDS procedures used?
- 2 Identify two marketing research problems where MDS could be applied. Explain how you would apply MDS in these situations.
- 3 What is meant by a spatial map?
- 4 Describe the steps involved in conducting MDS.
- 5 Describe the direct and derived approaches to obtaining MDS input data.
- 6 What factors influence the choice of an MDS procedure?
- 7 What guidelines are used for deciding on the number of dimensions in which to obtain an MDS solution?
- 8 Describe the ways in which the reliability and validity of MDS solutions can be assessed.
- 9 What is the difference between internal and external analysis of preference data?
- 10 What is involved in formulating a conjoint analysis problem?
- 11 Describe the full profile approach to constructing stimuli in conjoint analysis.
- 12 Describe the pairwise approach to constructing stimuli in conjoint analysis.
- 13 How can regression analysis be used for analysing conjoint data?
- 14 Graphically illustrate what is meant by part-worth functions.
- 15 What procedures are available for assessing the reliability and validity of conjoint analysis results?

Notes

- 1 Green, P.E., Carmone Jr, F.J. and Smith, S.M., *Multidimensional Scaling: Concepts and Applications* (Boston, MA: Allyn & Bacon, 1989), 16-17. See also Deogun, N., 'Coke claims dominance in the Mideast and North Africa, but Pepsi disagrees', *Wall Street Journal* (3 March 1998), A4.
- 2 Barrett, P., Burr, P. and Dolman, N., 'The conjoint path over the cultural divide', *Marketing Week* (14 October 1997).
- 3 For a review of MDS studies in marketing, see Carroll, J.D. and Green, P.E., 'Psychometric methods in marketing research: Part II, Multidimensional scaling', *Journal of Marketing Research* 34 (February 1997), 193-204; Cooper, L.G., 'A review of multidimensional scaling in marketing research', *Applied Psychological Measurement* 7 (Fall 1983), 427-50.
- 4 An excellent discussion of the various aspects of MDS may be found in Davison, M.L., *Multidimensional Scaling* (Melbourne: Krieger Publishing, 1992).
- 5 The data are commonly treated as symmetric. For an asymmetric approach, see Desarbo, W.S. and Manrai, A.K., 'A new multidimensional scaling methodology for the analysis of asymmetric proximity data in marketing research', *Marketing Science* 11(1) (Winter 1992), 1-20. For other approaches to MDS data, see Bijmolt, T.H.A. and Wedel, M., 'The effects of alternative methods of collecting similarity data for multidimensional scaling', *International Journal of Research in Marketing* 12(4) (November 1995), 363-71.
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