

January 1999

Analyzing Destination Images: A Perceptual Charting Approach

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Recommended Citation

Dolnicar, Sara; Grabler, K.; and Mazanec, J. A.: Analyzing Destination Images: A Perceptual Charting Approach 1999.

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Keywords

destination image, positioning, market structure analysis

Disciplines

Business | Social and Behavioral Sciences

Publication Details

This article was originally published as Dolnicar, S, Grabler, K & Mazanec, JA, Analysing Destination Images: A Perceptual Charting Approach, *Journal of Travel & Tourism Marketing*, 8(4), 1999, 43-57.

Analyzing Destination Images: A Perceptual Charting Approach¹

Sara Dolnicar, Klaus Grabler, and Josef A. Mazanec²

Abstract

Heterogeneity of perceptions is a neglected issue in market segmentation studies. Only recently parametric approaches toward modeling segmented perception-preference structures such as combined MDS and Latent Class procedures have been introduced. A completely different nonparametric method is based on topology-sensitive vector quantization (VQ) for consumers-by-brands-by-attributes data. It maps the segment-specific perceptual structures into bar charts with multiple brand positions exhibiting perceptual distinctiveness or similarity. A brief introduction into the VQ methodology is followed by a sample study on three urban destinations competing on the world travel markets. City images serve as the underlying behavioral constructs. Preferential data are based on respondents' comes-closest-to-ideal-city judgments and incorporated into the perceptual positions of city profiles. Perceptual charting works on two levels of aggregation named prototypes and perceptual sub-structures. The results demonstrate how this method prevents the analyst from drawing erroneous conclusions due to uncontrolled aggregation.

Neural Network reduction techniques for condensing three-way data

The data techniques to be discussed in the forthcoming sections deal with descriptive market structuring and with the non-normative part of positioning models. The common assumption is that the raw data arrive in a three-way format. This means that three directions of variation are involved, viz. respondents, objects, and their attributes. Data reduction, therefore, is an implicit objective as the measurement of attitudes toward product brands and, particularly, of highly emotional brand images requires a substantial amount of redundancy in one's data gathering instruments. To bridge the gap between the fuzzy language of the consumers and the more concise jargon of marketing managers the symptomatic patterns of brand-attribute associations should be automatically respected by the data processing methodology. Given a battery of numerous image or attitudinal items the respondents'

¹ This piece of research is part of the Special Research Program 010 on "Adaptive Systems and Modeling in Economics and Management Science" funded by the Austrian Science Foundation (FWF).

willingness to collaborate must not be challenged by cumbersome rating scales. The data techniques should be capable of processing binary data. As a third requirement the methodology should accept an arbitrarily small number of brands if the typical size of the consumers' choice set does not exceed, say, three or four alternatives. Classical MDS procedures then would not be applicable because of too few restrictions in the proximity data. A pictorial display of the results that does not sacrifice crucial information is desirable. A more fundamental criterion to value the merits of market structuring and positioning procedures will be whether the technique preserves the consumer segment information by avoiding rigorous homogeneity assumptions and rude aggregation steps during the data processing.

Since the second half of the 1980ies neurocomputing techniques for unsupervised learning have been added to the marketing research toolkit (Krycha and Wagner, forthcoming). In particular, the LBG and other K-means related adaptive vector quantization (VQ) methods are attractive for marketing analysts (Linde, Buzo and Gray 1980). They can operate online and thus may be used to classify customers by processing samples of unlimited size (such as a steady influx of scanner data). This gives them an advantage over other K-means extensions like the overlapping K-centroids approach proposed by Chaturvedi et al. (1997).

The neurocomputing tools offer more than that. It has been claimed that Self-Organizing Maps (SOMs) assist in solving clustering problems while preserving topological properties of the data (Kohonen 1982, 1984, 1990, 1997; cf. Nour and Madey, 1996, for a review and Mazanec 1995a, 1995b, forthcoming, for marketing research applications). The SOM does not produce a spatial configuration like MDS. Instead, the brand positions are topologically ordered telling the analyst about the order of perceptual similarity. Like many other neural networks SOMs operate on disaggregate data by learning from examples, one at a time (e.g. data vectors from individual respondents). As no prior aggregation is required during the training of a SOM network any subset of data vectors can be processed in

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subsequent recall runs. The SOM is mainly criticized for two reasons. (1) The SOM update rule — for continuous variables — is not a gradient descent process and thus hinders the mathematical analysis of the asymptotic behavior of an explicit objective ('energy') function. (2) SOMs impose a rigid framework (a predetermined 'grid') of neighborhood relations among cluster centers ('prototypes') the update algorithm has to respect during the training.

It may be desirable not to impose rigorous neighborhood connections among prototypes but either to have them learned and unlearned during the training or to introduce them after the quantization step. A procedure of this type was developed by Martinetz and Schulten in 1994. This model was introduced under the name Topology Representing Network. It employs the "neural-gas" algorithm by Martinetz, Berkovich and Schulten (1993) to perform a topology-sensitive vector quantization³. The training rule adjusts not only the most similar ('winning') prototype for each randomly selected data point but also the adjacent prototypes according to the rank order of distances to the 'winner'. Thus the "neural gas" method exploits a higher amount of information stored in a system of prototypes. As in SOMs the 'similarity' between data points and their prototypes (cluster centers) is also measured by the Euclidean distance between the *i*-th prototype's coordinates or weights' vector and a data vector arriving as input. During the training the system of prototypes is repeatedly exposed to input vectors randomly selected from the data set. Starting from an initial weight distribution of small random coordinates it learns to adapt its weight structure according to the distribution pattern of the input data. Each of the prototypes learns to take responsibility for a homogeneous set of data vectors. As in the SOM the prototypes compete with each other and only the winner gets full update. The units in its neighborhood are allowed to improve their fit by a weight update lower than the one defined for the winner with a decay constant decreasing during the training. For a decay constant of zero the process is equivalent to the

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³ A Windows95/NT implementation with special features for processing three-way data (TRN32 by J. Mazanec (c) 1997) may be obtained from the website <http://leisure.wu-wien.ac.at/software/>.

online version of the popular K-means clustering. The update rules have been shown to optimize an explicit cost function where the co-updating of adjacent prototypes resembles a 'fuzzy' assignment of data points to the best, second-best, third-best prototype. The "neural gas" algorithm was shown to excel K-means as well as the SOM and the maximum-entropy clustering procedure (Martinetz et al., 1993).

Up to this point the training process does not enforce a topographic mapping of the data points into a set of prototypes subject to a learned adjacency structure. This step was added by Martinetz and Schulten (1994). Adjacency is conceived as a dichotomous concept in the Topology Representing Network. Two prototypes are neighbors or not. The adjacency learning and unlearning process is based on the similarity of the winning prototype and its 'toughest' competitor. Each data point arouses a winner co-winner pair for which it either confirms or establishes the adjacency relation. Adjacency connections for pairs that do not get confirmed for a number of successive updates die out but may again emerge later on in the training. In a simulation experiment the authors demonstrate that the TRN is capable of preserving rather complicated topological structures. It seems to render a perfect topological mapping as long as the grid of prototypes is dense enough to approximate a manifold of lower dimensionality embedded in the high-dimensional data space.

Topological models like the SOM and the TRN do not enforce a disjunctive partitioning of brands or consumers. They neither classify brands nor consumers but brand profiles as perceived by individual consumers. Therefore, the resulting brand prototypes may represent different real brands for different subjects. Brands as well as consumers usually occupy more than one position in a topological graph with varying frequency. These frequencies report on the distinctiveness or vagueness of the brand perceptions. The choice or preference information is easily incorporated into this framework as each brand profile position reflects an observed number of past purchases or buying intentions. The results are conveniently visualized by a series of bar charts or by a combined pie-bubble-bar chart; hence the term 'perceptual charting'.

Exploiting the adjacency structure: The TRN generates a system of prototypes in conjunction with the accompanying information on the mutual similarity of the prototypes. The frequency of 'winner co-winner' pairs as aroused by the data points (the 'statistical neighborhood') serves as the proximity measure. Two prototypes which are more frequently activated as the first and the second 'winner' by the data vectors are expected to be more similar to each other than prototypes less frequently tied in a winner co-winner relationship. The 'strength of adjacency' or similarity usually is strong for a limited number of prototypes thus producing prototype sub-structures. Strong similarity is visualized as a connecting path in the adjacency graph.

From the positioning/segmentation point of view the adjacency graph fulfills a double function: (1) It indicates groups of 'neighboring' brand profiles (and respondents having these profiles on their minds); this means that market structuring occurs on a second level of aggregation in addition to the first level of the prototypes. (2) It indicates which (brand) prototypes may be merged if the analyst seeks a representation with larger perceptual segments; this may happen if the competing brands do not differ markedly in their prototype affiliation, or the perceptual prototypes do not vary in terms of consumer preferences.

A sample application of perceptual charting

This sample application is a typical positioning study. It is part of the Austrian national guest survey conducted in three years' intervals. The aim of this survey is to monitor travel trends and the service quality offered by the Austrian tourism industry. The master sample comprises 10,000 respondents annually with about 7,000 interviewed during the summer season and 632 in the capital city Vienna. This subsample of 632 cases is used to analyze the images of three Central European cities which compete in the international travel markets. Budapest, Prague, and Vienna are hypothesized to share a number of attributes in the travelers' perceptions. The perceptions, however, are expected to vary by perceptual segments.

Each respondent judges the three cities in terms of image attributes such as "authentic", "calm", "romantic", "friendly" etc. Each of the 20 attributes may be considered appropriate for a destination or not. The disaggregate image profiles of binary data are subject to vector quantization. In this stage the three-way data are stacked into an elongated two-dimensional data matrix. During the data reduction step the block structure (due to repeated measurements) in the $(632 \text{ cases} \times 3 \text{ cities}) \times 20 \text{ vars}$ data is ignored. Given the large number of data vectors (1,896 city profiles) it is evident that a partitioning procedure will have to be applied rather than a hierarchical clustering method. The decision regarding the number of image prototypes was made by using the 'simple structure index' (for details see Dolnicar et al., forthcoming). The SSI recommends two cluster solutions to be examined in more detail. Six or ten prototypes promise to offer ease of interpretation. The six prototypes alternative was discarded due to inferior results on reproducibility (for details see Dolnicar et al., forthcoming).

Pairs of prototypes	Statistical Neighborhood
#9-#10	22.47
#1-#7	10.55
#8-#10	7.02
#5-#8	6.17
#4-#5	5.06
#1-#3	3.96
#3-#6	3.32
#5-#6	2.85
#2-#6	2.79
...	...

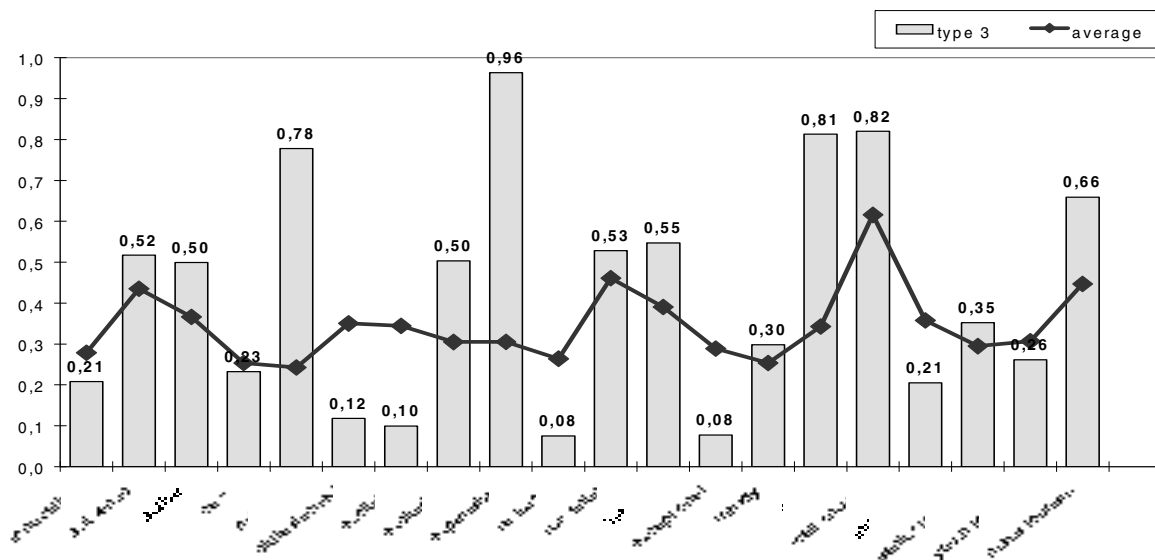
Having opted for the 10 prototypes solution the data matrix of perceptual judgments by 632 tourists for Vienna, Prague, and Budapest was used to train a TRN. After the training of the prototypes a recall run through the 1,896 data vectors was performed. Each pair of prototypes exhibits some frequency of being tied in a winner co-winner relationship (called the 'statistical neighborhood') giving an appropriate measure for the similarity. The statistical neighborhood usually

is strong for a limited number of prototype pairs and then levels off. It helps to delineate the perceptual structures on a 'macro' level:

A cut-off value of 3.0 for the statistical neighborhood measure leads to three groups of prototypes. One group consists of five prototypes (#4, #5, #8, #10, #9), one of four types (#6, #3, #1, #7), and the

remaining node (#2) represents a unit of its own. A smaller cut-off point of 2.8 causes an additional link in the neighborhood graph as #5 and #6 get connected; the resulting structure is degenerate, because #2 (representing 8 per cent of all data points) remains unconnected while all the rest forms one undifferentiated sub-structure. The prototypes and their proximities are of double interest. The statistical neighborhood between the prototypes may be regarded as a measure of intensity of competition due to perceptual similarity. At the same time each prototype represents a distinct attribute profile as shown in Figure 1. For prototype #3, e.g., the respondents judged the city under consideration to be modern, expensive, safe, and well-known.

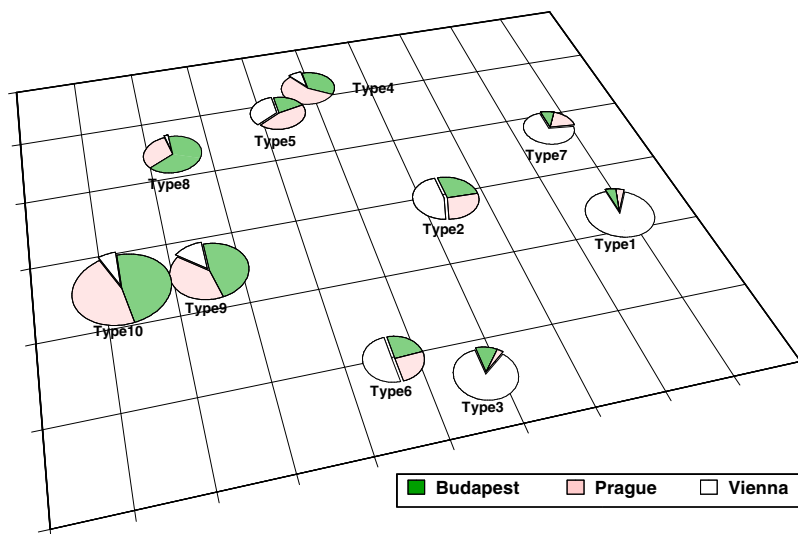
Figure 1: Image profile for prototype #3



By means of Sammon mapping as in the TRN program (Sammon 1969) or by using standard MDS software the 20-dimensional prototypes are mapped onto a two-dimensional plane. However, it is important to emphasize that the chart conveys topological rather than spatial information. The distances between the prototypes are meaningless and not exploited for drawing conclusions. (Therefore, no stress value is given.) However, arranging the prototypes pictorially by a Sammon or MDS projection may assist the reader familiar with perceptual mapping in getting accustomed to the more elementary perceptual charting display. Figure 2 shows a combined perceptual bubble-pie chart for all three cities. The size of the bubbles indicates the number of city profiles located in this position.

It represents the singularity or the generality of a perceptual position: the larger the bubble, the more frequent is the bundle of attributes indicating a higher risk of being substituted. The three cities share each bubble position as portrayed by its pie structure. For example, Prague and Budapest are highly concentrated in the positions #8, #9, and #10. Vienna most strongly coincides with the Type #1 and #3 positions. One cautious remark regarding the conclusions about competitive threat is in order here. Interpreting the aggregate frequencies as given in Figure 2 may be misleading. The respondents placing several cities into a perceptual position may belong to different subsamples which are partially or even completely non-overlapping. Competition, however, is likely to occur where a number of identical respondents perceive two or more cities in the same position or in the same sub-structure of prototypes.

Figure 2: Three cities occupying the perceptual positions



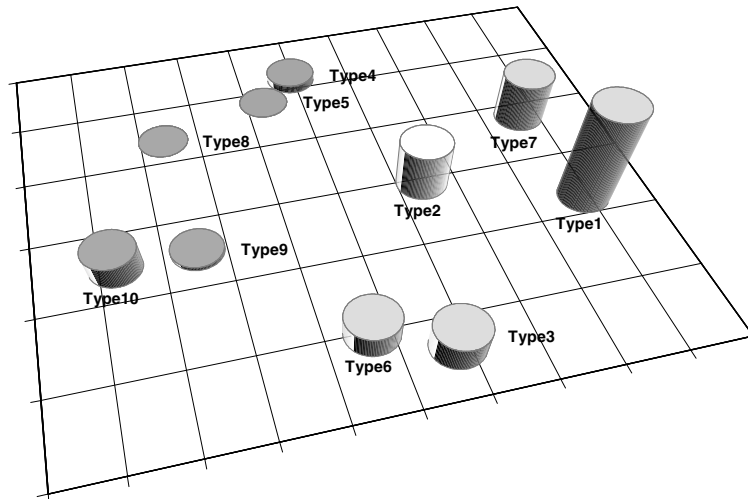
The prototypes system resulting from the vector quantization may be employed to derive individual charts for each city. Figure 3 shows the prototypes configuration for Vienna, where the bubble size denotes the number of respondents placing Vienna in the respective position. In addition to what was presented in Figure 3 the sub-structures of similar prototypes are identified by their grey-scale shading. The charting thus incorporates the statistical neighborhood results i.e. three sub-structures, where prototype #2 stands aloof, prototypes #1, #3, #6, and #7 are grouped together, the remaining types form

the third sub-structure. Figure 3 thus informs about the image positions and the corresponding segment sizes for Vienna. Obviously, there are popular image positions of Vienna in sub-structure 1 (prototypes #1, #3, #6, and #7). These perceptual segments account for 68 per cent of all respondents. The sub-structure profiles indicate that this subgraph of the perceptual chart implies strong agreement of the respondents with the majority image items. Position #1 (23 per cent of respondents placing Vienna there) is characterized by above average ratings on all attributes except "calm", similar to position #7 (17 per cent), where only the attributes "modern" and "trendy" are not in compliance with Vienna. Position #3 (18 per cent) stands for the modern and expensive Vienna image, the segment underlying position #6 (10 per cent) believes that Vienna is "calm", "relaxing", and "friendly". Few perceptual segments place Vienna in structure 3 (consisting of types #4, #5, #8, #9, and #10). These five tourist groups account for only 21 per cent of the respondents. Position #10 indicates that no attribute matches with the Viennese image, position #9 is very similar to this view, except for the above-average rating on the "well-known" item. Position #8 is based on "old-fashioned" as a stand-alone item, whereas "authentic" is the attribute a respondent of type #5 would assign. Finally, position #4 is related to the images of "mass tourism" and "youth tourism". The remaining 11 per cent of respondents place Vienna on position #2 meaning that this city is an "active" and "exciting" destination with plenty of opportunities for "individuality".

Regarding the different image positions for Vienna it is desirable for the destination manager to learn about the preferences attached to the prototype positions. The survey contains information on which of the three cities comes closest to the subjective 'ideal' urban destination. Adding this piece of knowledge to the chart yields a joint representation of perceptions and preferences. The height of the bars in Figure 3 denotes the amount of preference. Only those respondents positioning Vienna into a prototype coinciding with their 'ideal' profile are considered. A chi square test against a uniform distribution clearly supports the preferential differences between perceptual positions ($p < .01$). There is no doubt that respondents placing Vienna in position #1 are most satisfied with the destination image. 35 per cent of the image profiles coinciding with a 'closest to ideal' statement can be found in this segment. It

seems that the image of Vienna offering nearly everything — except calmness — is fairly desirable, followed by positions #7 and #2 with equal preferential strength (17 per cent). These findings demonstrate, how important the preference information is on single segment level. 17 per cent

Figure 3: Image positions and height of preference for Vienna



believe that Vienna is "exciting" and "active" and like it to stay this way while another 17 per cent tend to avoid a "modern" and "trendy" destination valuing the attribute "old-fashioned". Obviously, there is some amount of contradiction in the ideal positions of these two segments. The destination manager has to take this into consideration when deciding on how to channel marketing efforts. The charting exercise proves the usefulness of processing the perceptual and preference information on disaggregate level.

So far the sample application only dealt with segmenting the image of one choice alternative (Vienna) into several perceptual groups exhibiting different preferences. Perceptual charting, however, aims at detecting the positions of competitors and the degree of competition. In the TRN solution, therefore, the information on competitive relationships resides in the distribution of individual cities over the ten prototypes. Competitive threat is likely to occur if a number of respondents perceive two or more cities in the same position or in the same prototype sub-structure. Thus a crosstabulation of the classification of cities into prototypes is required. The number of respondents classifying a pair of cities into the same prototypes serves a measure of competitive threat. The 'identically classified' index (ICI) for the

three cities clearly identifies Budapest and Prague as the toughest competitors (43.8 per cent). It reveals an almost identical degree of competition for Vienna versus Prague (10.8 per cent) and Vienna versus Budapest (10.1 per cent). The ICI is a measure for the overall intensity of competition between pairs of cities. A 'micro' analysis of competition may differentiate by perceptual positions. For identifying those prototype positions where intense competitive relationships prevail, a series of crosstabulations of city pairs in terms of identical versus non-identical positions is appropriate. For the 2x2 tables a measure of association such as the Phi coefficient then may be interpreted as a competitive intensity measure. Owing to the small sample size the Exact Tests version of SPSS was used ($p < .05$):

Vienna competing with ... in ...	Budapest	Prague
Position #1	.10	.06
Position #2	.15	.11
Position #3	.04 (n.s.)	.11
Position #4	.08 (n.s.)	.05 (n.s.)
Position #5	.01 (n.s.)	.01 (n.s.)
Position #6	.11	.01 (n.s.)
Position #7	.11	.08 (n.s.)
Position #8	.05 (n.s.)	.08 (n.s.)
Position #9	.10	.15
Position #10	.16	.18

Obviously, the intensity of competition varies among different perceptual positions and is particularly strong in positions #10 (which in fact is indicative of a single response pattern) and #2. Different competitive relationships emerge for different city pairs. Generally, the intensity of competition between Vienna and Prague or Budapest appears to be rather

low (which is partly attributable to the sampling of guests staying in Vienna). Nevertheless, the Phi values for Budapest versus Prague demonstrate their usefulness as a measure for competitive intensity. Excluding position #3, which reveals no significant relationship, the Phi values for these two cities range from .137 (in #8) to .549 (in #10).

The ICI also confirms the strong competitive relationship between Budapest and Prague (77.4 per cent) and the comparable results for Vienna versus Budapest (25.9 per cent) and Vienna versus Prague (29 per cent) on the macro level, taking the three perceptual sub-structures as competitive clusters. The

intensity of competition becomes uniform on this higher aggregation level, indicating that a cluster solution with only three prototypes — something that strikes one's mind in a tale of three cities — would have failed to extract accurate market structure results.

Managerial implications

Perceptual charting teaches the managers in a City Tourism Organization (CTO) three lessons: (1) The individual city charts (Figure 3) inform them about segment-specific image positions of the destination they are responsible for and about the size of each underlying perceptual segment. The attribute pattern corresponding to each prototype shows the perceptual characteristics of the positions, e.g. the image a particular segment has of this city (Figure 1). (2) By relying on past choice behavior or by direct questioning the height of preference for each destination-position is added (Figure 3). It indicates the segment-specific preference attainable in each position. (3) The contingency tables of image profiles classified into prototypes for one city versus another highlight the segmentwise competitive relations among cities.

The results under (1) assist in spotting perceptual strengths and weaknesses. The uniqueness of attributes is easily verified. The variability of the images also becomes apparent. A brand evenly scattered over many prototypes lacks distinctiveness. In the city case study Vienna is strongly represented and highly valued in those perceptual positions where the respondents tended to attribute many characteristics to the city. (This may be partly due to the fact that the respondents were interviewed during their stay in Vienna.) The perceptual profiles of this destination are concentrated on few positions rather than being scattered all over the chart.

The findings under (2) are linked to setting positioning objectives. In the absence of interaction effects between a brand name and the preference for a perceptual profile attached to it, the height of preference (number of actual choices, stated first rank) may be accumulated over brands. The manager then gets brand-independent information on which positions are more or less desirable. These cumulative results are also relevant for placing new product profiles under a new brand name.

Objectives for product positioning are set in terms of a target frequency distribution rather than spatial coordinates. In the city case study the interaction between the destination name, the perceptual profiles, and the preferences is apparent. The profiles must not be merged. Drawing conclusions for one city the CTO of Vienna ought to convince the members of segment #6 not satisfied with this position of the additional strengths of Vienna these tourists had underestimated in the past. This would shift tourists from segment #6 to the more preferred position #1. As in any psychographic segmentation more information on demographics and socioeconomic characteristics is needed to implement such a strategy.

The competitive pressure expected from the rivaling brands follows from the cross-classifications under (3). In the city case study position #7 represents a high preference profile for Vienna, where fairly strong competition with Budapest can be detected. Marketing managers may want to put more emphasis on the attributes appreciated by this group. Clear distinction from Budapest is necessary, whereas competitive action to get more distinct from Prague is not urgent.

The entire planning process benefits from the disaggregate findings, as the perceptual positions, the preference information, and the competitive relations are analyzed from a strictly segment-specific point of view. It requires no parametric assumptions regarding the generation of perceptual response and the formation of preferences. For marketing applications a parsimonious model in terms of the number of perceptual positions is desirable. Besides the similarity of profiles the information on preferences or brand choice may assist in selecting the appropriate number. Ideally, positions with similar perceptual profiles and the same height of preference should be grouped together. In the city case study the 10 prototypes solution was compared with a reduced sub-structure solution that originated from the statistical neighborhood. Whereas the large number of 10 positions bothers the destination manager and makes decisions more complex, the sub-structures - in this application - blur the information about individual differences. Chi-square tests against an uniform distribution of preferences within both sub-structures containing more than one prototype confirm significant

differences in sub-structure 1. Given the diverse competitive relationships among prototypes even within the same sub-structures an automatic grouping of prototypes into sub-structures is not advocated. A more refined methodology for identifying the most parsimonious model is needed. A two-stage procedure combining data reduction via vector quantization with a subsequent latent class analysis seems to be a promising alternative.

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