Planning new tariffs at *tele.ring* – the application and impact of an integrated segmentation, targeting and positioning tool

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Abstract

tele.ring is a mobile phone organization selling contracts and cell phones in the Austrian market. The market situation in 2005 was highly competitive and dynamic resulting in relatively short tariff life cycles. Excessively long lead times made *tele.ring's* management feel dissatisfied with their new tariff development process. Furthermore, a new competitor had entered the market posing a major threat and it was unclear how to effectively safeguard *tele.ring's* position in the market. In cooperation with the management, we implemented and tested a new segmentation, targeting and positioning tool, which provides managers with information on their target markets, customer preferences, competitors' strengths, and customer segments. It allows for the simultaneous visualization of this data on a single map and facilitates timely and accurate decision making. In particular, we report on the design and the implementation of a new pricing scheme, "Formel 10", which became the most successful new tariff introduction in this competitive market. *tele.ring's* managers were very much impressed with our tool's ability to represent the market on a single map and with its capacity to allow for intuitive interpretation. In addition, the tool enhanced internal communication between its users and different stakeholders during the new tariff development process.

Keywords: segmentation, targeting, positioning; preference mapping; pricing; mobile phone market

1 Company background and management problem

In 2005, *tele.ring* served more than one million customers in the Austrian market, i.e. 1,029,000 cell phone users and 98,500 conventional telephone network customers. At that time, there were five providers selling contracts and cell phones through their own retail outlets and other distributors. These were *Mobilkom,* the former monopolist (41 % market share in 2004), *T-mobile* (26 %), *One* (19 %), *tele.ring* (12 %), and *Hutchison 3G Austria* (2 %). With a market penetration as high as 106 %, the Austrian mobile phone market is worth about $ 4.5 billion per year and is therefore highly competitive[1] and dynamic (see Figure 1), which has resulted in providers introducing new tariff schemes every six to eight months. A reduction in tariff life cycles combined with high market dynamics made *tele.ring* aware that their new tariff development process was lacking in efficiency. With an average lead time of seven months at its disposal, *tele.ring* decided to develop a new pricing scheme for April 2005. In dynamic markets, long lead times limit predictive accuracy and, although *tele.ring* recognized this problem, poor communication between departments hindered a significant reduction in throughput times for new ideas and the incorporation of up-to-date market information in the final planning phase.

The new tariff introduction for April 2005 was an important project since the new rival in the market, *Hutchison 3G Austria*, had started to significantly gain market share and, consequently, *tele.ring's* new tariff scheme would need to be sufficiently attractive to slow down *Hutchison's* growth rate. Figure 1 highlights that in the past every new entrant into the market immediately stopped the growth of the previous entrant in terms of market share. Although it was clear that something had to be done to avoid this, it was not clear **who** *Hutchison's* potential new customers were nor **how** to attract them. In saturated markets with strong competition, it is difficult to gain market share without negatively affecting the price. In a situation like this, a segment-based positioning strategy can be a source of competitive advantage and provide solutions for the selection of an appropriate target group (i.e. who) and the definition of a suitable offer (i.e. how).

[1] A comparison of the Herfindahl index for market concentration between 19 European countries ranks the Austrian market in third place, confirming its competitiveness.

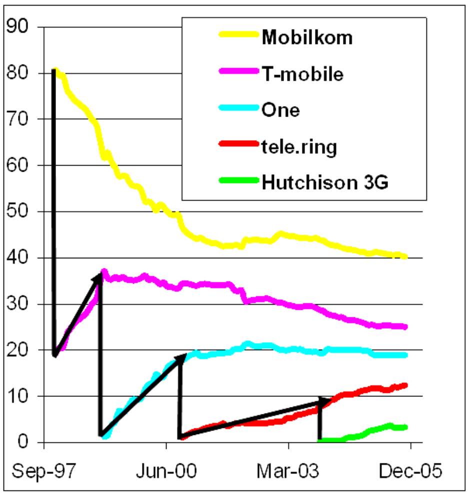

Figure **1:** *tele.ring's* threat**:** Every new entrant into the market immediately stopped the growth of the previous entrant in terms of market share. This was the case for *T-mobile* which took away market share from *Mobilkom,* for *One* which stopped *T-mobile's* growth and for *tele.ring* stopping *One.*

As a result of the economic importance of this market, competitors commonly use state-of-the-art techniques to explore business opportunities. Pricing studies and what-if analyses, for example, are usually undertaken using commercially available conjoint analyses software. As the use of these tools is common practice in this market, it is no longer a source of competitive advantage for a company. Being aware of this, the management at *tele.ring* began to look for another success factor and was willing to adopt an alternative marketing science method[2]. As a result, the management decided to use the marketing science tool that we developed to support their new tariff development process.

The tool's basic methodological components consist of procedures for representing heterogeneous competitive market structures (for an overview, see e.g., Lattin, Carroll and Green 2003). The primary aim of this class of methods is to derive a configuration of brands in a product class on the basis of competitive relationships between brands. The degree of inter-brand competition serves as a measure for substitution as perceived by customers (cf. Day, Shocker and Srivastava 1979).

[2] In a sense this situation is similar to the situation described by Kumar and Rao (2006), however, for a different marketing context (i.e., pricing in a highly competitive supermarket environment). They found that data analysis was profitable whether or not a competitor undertook data analysis since implementing data analysis was a dominant strategy.

Multidimensional scaling (MDS) methods are primary vehicles used to visualize product positioning in marketing (DeSarbo, Young and Rangaswamy 1997). However, the positioning and analysis of competitive market structures are not independent tasks; instead, they are often integrated into more encompassing frameworks such as the segmentation-targeting-positioning (STP) approach (Lilien and Rangaswamy 2004). In integrated frameworks like these, in which a firm targets one or more groups of customers, product positioning analysis shows itself to be a segment specific concept. In many cases, applying clustering and MDS to the same proximity data can result in much greater insight into the data's structure than either approach on its own (Carroll and Chaturvedi 2002). This justifies the need to develop models that integrate measurement, segmentation, targeting and positioning.

With regard to segmentation, there is an apparent gap between academic research that has followed normative and rational routes and actual business practices (Kalafatis and Cheston 1997). Wind and Cardoza (1974), for instance, point out that marketers judge segments on the basis of appropriateness and ease of implementation. Fish, Barnes and Aiken (1995) see the main constraint of these methods in a manager's limited capacity to cope with the complexity of multivariate segmentation. One of the limitations of the use of preference mappings is that they can be difficult to interpret (e.g., DeSarbo, Young and Rangaswamy 1997, Lilien and Rangaswamy 2004).

In view of this situation, we designed a new software tool to assist management decision making. This tool takes the STP approach and guides market analysts through the STP process. The algorithmic procedures used employ a mix of existing methods in this field, combined in an innovative way. In contrast to the step-by-step approach taken by independent methods, our tool provides a comprehensive picture of the market, explicitly takes trade-offs between different performance measures into account, and facilitates interpretation and use. The software also integrates additional features to assist managers in charge of new product (tariff) development, e.g., a segment-based analysis of preferences and questionnaire responses, a conjoint modeling and market simulation framework as well as interactive target group selection and positioning functionalities.

In the remainder of this paper, we firstly outline the ideas behind the modeling approach adopted in the development of the tool and discuss the procedural approach to the modeling. Then, we describe the project and the tool's implementation at *tele.ring* and, finally, we report on the impact on profits and sales.

2 Basic idea behind the modeling approach

2.1 Desired properties of the management tool for STP decision making

Over the years, researchers have developed a large number of models and algorithms for the integration of segmentation and MDS. At the same time, market researchers, managers and analysts have developed and applied a large number of graphic representations to analyze (segment-specific) market structures. There seems to be some relationship between graphic representations of perceptual mappings and managerial applications (i.e., ease of interpretation tends to stimulate practical usage).

Designing a marketing science tool requires developers to study the needs and preferences of its potential users. Since the targeted users are not members of the scientific community but managerial decision makers, we interviewed managers from new product development companies, strategy consultants, marketing analysts from customer focused companies, and marketing students. This empirical survey (Natter, Wagner and Cornelius 2006) identified first of all that the most important criterion in assessing different visual designs is the ability to intuitively understand graphic representations. Secondly, it found that the use of distance rather than vector models results in better decisions. Thirdly, it also highlighted that managers consider information on market structure, preference structure and customer heterogeneity to be relevant for decision-making and regard the incorporation of segment-specific information in a graphic representation of the market as essential.

When creating so-called "homogeneous" segments, a certain degree of customer heterogeneity[3] is bound to exist, which could be of significant relevance to marketing decision makers. While analyzing twenty different empirical data sets, it became very obvious that segment structures are by no means clear-cut. This finding is in line with the literature (e.g., Wedel and DeSarbo 1996) and therefore we decided to include individual preference information in addition to segment membership in the graphic representation. To be specific, customers are assigned a different location

[3] See e.g., Horsky, Misra and Nelson (2006) for a recent contribution that considers observed and unobserved customer heterogeneity within a model.

on the map depending on their individual heterogeneity[4], and specific colors portray their segment membership.

It was the desired properties of suitable graphic representations and the means of communication outlined above that guided the development of the marketing engineering tool. The approach taken is based on the assumption that the different aspects of segmentation, targeting and positioning need to be integrated into the tool and that managerial applicability is of prime importance, i.e., practitioners should find the map generated by the model easy to interpret. In summary, the tool should fulfill the following five requirements:

(R1) The two-dimensionality of the maps is an essential requirement for practical usage. Maps of greater dimensionality are neither understood nor do they support group decision making. Two dimensional maps provide a unique view of the market, which is of great importance when several departments are involved, whereas three-dimensional (or even greater) solutions are often represented by several two-dimensional partial views or by three-dimensional graphs, and usually have to be rotated in order to perceive relationships of interest.

(R2) Brands, attributes and consumers should be incorporated into a single map to provide an encompassing view of the market comprising the three important aspects of the STP approach. The size of the corresponding labels should reflect the brand's strength and the perceived importance of the attributes.

(R3) Spatial distances on the map should directly mirror substantive differences (i.e., the farther apart brands, attributes, and consumers are located on the map, the greater the difference in their perception). An overall performance measure should reflect whether a map is reliable.

(R4) Consumers should be grouped into distinct segments with clear boundaries (i.e., segment overlap should be minimized). The procedure we used in this case for segmentation (K-means clustering) assigns each customer to their most appropriate segment. Nevertheless, there may be customers located close-by on the map who have been assigned to different segments. This creates sectors of customers with different segment membership; in other words, overlapping

[4] Thus discrete market segments are formed and customers are not allowed to be fractional members of multiple segments as is proposed, for example, by DeSarbo, Ramaswamy and Cohen (1995) in a similar

segments. From a managerial point of view, decisions have to be made with or without clear-cut evidence from a formal model. For this reason, we feel that in our case managerial relevance has to prevail over formal rigor, i.e., our approach attempts to form non-overlapping segments even if traditional models (e.g., K-means clustering) do not result in a well-defined picture.

(R5) Additional information linked to objects (brands, regions, attributes, customers, segments) on the map should be easily accessible via interactive features.

2.2 Procedural outline of the modeling approach

As already highlighted, our tool draws on two different concepts: the general marketing concept of segmentation–targeting–positioning, and the more technical issue of alternative ways of perceptual mapping. These concepts were combined by:

(1) integrating STP into a single procedure rather than viewing it as a linear sequence of subsequent decisions.

(2) concentrating on producing a graphic representation which managers can immediately implement in their decision making.

From a methodical point of view, we combined two well-known procedures into a single framework to accomplish these goals, i.e., multidimensional scaling (MDS) by means of iterative majorization (e.g., Borg and Groenen 2005) and K-means clustering (e.g., McQueen 1967). However, these two procedures are linked so that the results from the MDS[5] are used as further input for K-means clustering. Moreover, since these two procedures were developed independently, they each employ individual measures of goodness-of-fit. Our approach applies a range of fit–criteria to account for this diversity. By including a criterion measuring segmentation overlap, we took into consideration that the results need to be suitable for managers. Since the basic procedures applied are

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context.

[5] Researchers have criticized MDS for stability problems which arise when the number of objects is small. Stenson and Knoll (1969) and Klahr (1969) study the properties of nonmetric multidimensional scaling when these algorithms are applied to randomly generated data. They report that, for a small number of objects (six or seven), it is very likely that a good fit can be found even if the data is generated by a random process. Therefore they doubt the stability of MDS solutions in such situations. We do not expect stability problems to occur in our application, as we are dealing with a very large number of objects (i.e. more than a thousand, since products, attributes and customers are to be positioned on the map simultaneously).

well known, Table 1 provides a simplified flow chart of the modeling approach. A more detailed technical appendix is available on the *Marketing Science* website.

1) Provide **input data:** rankings of brands and attributes
2) Calculate **intermediate results to represent:** • (metric) distances between brands/attributes and respondents • respondents' heterogeneity • brands' and attributes' heterogeneity
3) **Positioning:** MDS procedure in two-dimensional space based on distances between brands and attributes for all respondents Result: positions of respondents, brands and attributes on a two-dimensional map Stress measures describing the solution's ability to replicate o distances (based on ranks) between brands/attributes and respondents (C_1) o respondents' heterogeneity (C_2) o brands' and attributes' heterogeneity (C_3)
4) **Segmentation:** K-means clustering based on respondents' heterogeneity **and** positions of respondents on the two-dimensional map Result: number of segments and segment membership for all respondents Goodness-of-fit measure for the cluster solution (C_4)
5) **Reduce segment overlap** based on positions of respondents and their preliminary segment membership Result: revised segment membership for all respondents Percentage of non-overlapping segments (C_5)
6) **Check derived solution** based on $C_1 - C_5$ if necessary reiterate steps 3), 4) and 5) Result: overall goodness-of-fit $\overline{C}$

Table 1: Simplified flow chart of the mapping / segmentation approach

The analysis of market structure has a long-standing tradition in marketing. One stream of research tackles this issue by studying patterns of substitution implied by brand switching. Partitions of the market into consumer segments are determined by means of modeling choice behavior, and the positioning of the brands on offer is established by taking certain attributes (e.g., price sensitivity) into account (cf. Kamakura and Russell, 1989; DeSarbo, Ramaswamy and Cohen, 1995). Another stream of research is based on a kind of unfolding procedure originating from the psychometric literature (e.g., Kruskal, 1964). Marketing scholars have successfully developed models which simultaneously represent brand and attribute positions on a single map.

When considering heterogeneity, there are two important classes of models. On the one hand, there is the class of STUNMIX models (Wedel and DeSarbo 1996) which provide segment information in terms of a vector or ideal point, but no individual level preference information. On the other hand, there are models like GENFOLD2 (DeSarbo and Rao 1984) or PARFOLD (DeSarbo, Young and Rangaswamy 1997) which reflect customer heterogeneity. However, this group of models does not account for segment membership.

approach	provides segment information	provides individual preferences	considers segment overlap
STUNMIX	+	-	-
GENFOLD2 PARFOLD	-	+	-
our approach	+	+	+

Table 2: Comparison between related methods and our approach with respect to mapping features

The procedure we propose in this paper builds heavily upon research in the latter area of mapping and tries to improve on the graphic representation of customer heterogeneity, i.e., by portraying both individual level customer preferences and segment membership. As a consequence, segment overlap becomes an issue and has to be considered. Table 2 compares the standard models in marketing outlined above with the approach we adopted in terms of relevant mapping features.

3 Project outline and implementation at *tele.ring*

Having outlined the basic ideas behind the new marketing engineering tool, we now focus on its implementation at *tele.ring*.

3.1 Design of "Formel 10"

In August 2004 the project to design a new tariff scheme began with a workshop to define the market (i.e., competitors, tariff attributes, characterization of customers). Subsequently, we designed a questionnaire and, in October and November 2004, carried out 988 CAPI interviews. By the middle of December 2004, analysis and service development had also been completed and, after a three-month preparation period, *tele.ring* launched their tariff scheme, "Formel 10", on April 1st, 2005.

The analysis and design phase started with an investigation of the overall market, from which it was evident that *tele.ring* was perceived as a cost leader. *tele.ring* was also stronger in terms of share of preference rather than current market share, which was confirmed in an analysis of switching intentions. It was clear that a new tariff scheme's perceptual position should not deviate greatly from its present positioning to avoid inconsistency with the current image. Additionally, managers agreed that the fact that the new position was remote from that of its competitors, might be of strategic advantage and could reduce the risk of imitation. At the time, the tariff scheme was based on attractive "free-minute" packages and an enticing one-cent tariff within the *tele.ring* network.

In the next step, we studied the integrated market map and identified four segments (Figure 2); we estimated the segment sizes to be 31 % (segment 1), 29 % (segments 2 and 3), and 11 % (segment 4). As this map could be interpreted based on distance, segment specific colors[6] and label size alone (overall importance of attributes and overall market share), the whole development team was quickly able to gain a mutual understanding of the market situation. Tentatively, the horizontal axis corresponds to the market entry time of the competing brands. Whereas the latest entrant *Hutchison 3G Austria* is positioned on the very left hand side, the former monopolist *Mobilkom* is positioned on the right hand side. Usually, the perceived quality of a mobile phone provider increases with its time in the market, as the firm can improve its network and services. Consequently, only customers on the very right hand side of the map view a provider's image as their most important criterion.

The vertical axis represents customers' perceived importance of various price components. The position of the different price components suggests that usage intensity might explain a customer's location on the map. Customers with low usage intensity seem to put more emphasis on the fixed components of their bills ("base fee" and the price for "free-minute" packages), whereas customers with a high usage profile focus more on the various variable components of a mobile phone tariff scheme (labeled "tariff-other nets", "tariff-conventional net", "tariff-own-net"). In fact, the average monthly bill in segment 1 is approximately 35 % higher than in segments 2 and 3.

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[6] Due to the restriction imposed by the publisher, Figure 2 is replicated here in black and white only.

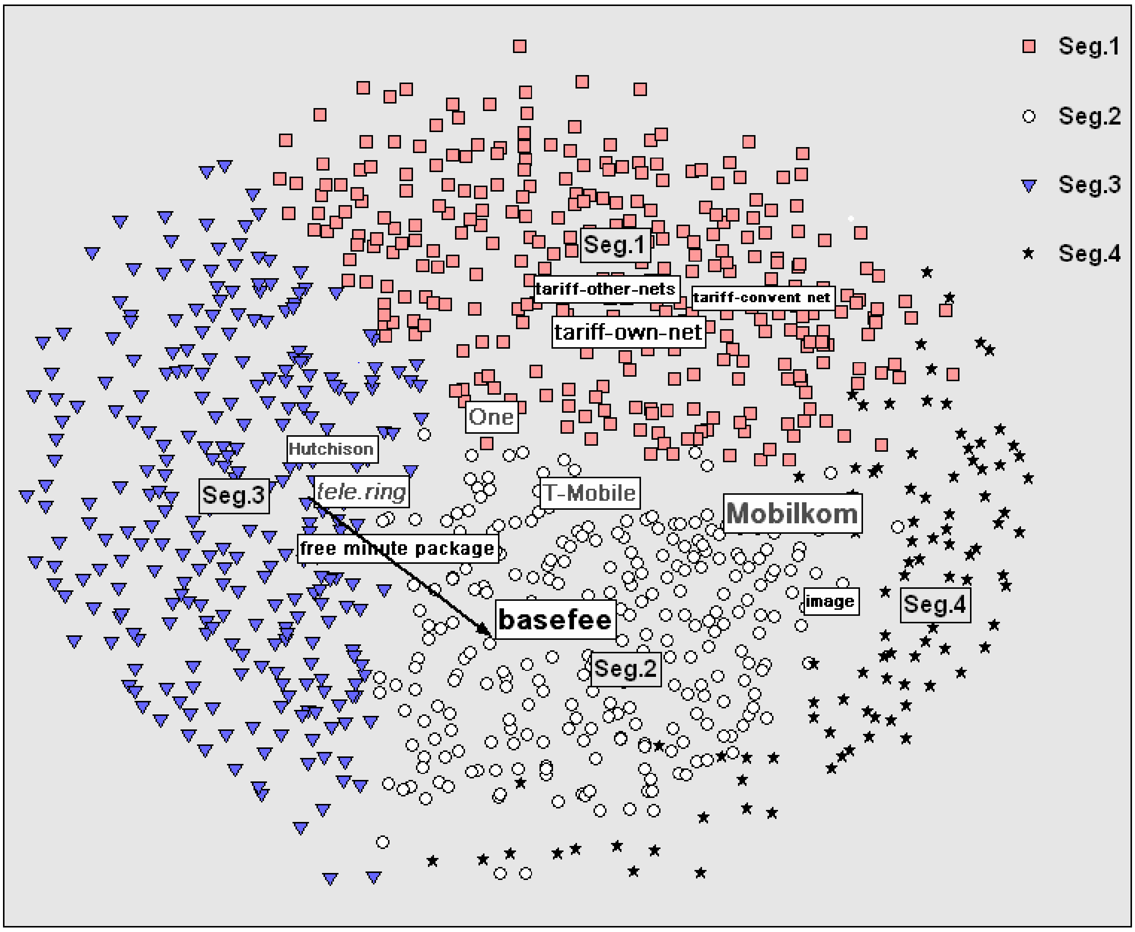

Figure 2: Market map with providers, attributes and customer segments 1-4

To be more specific, while members of segment 1 tended to evaluate variable tariffs highly, "base fee" seemed to be most relevant within segment 2, "base fee" and "free minute package" within segment 3, and "image" was seen as the most important attribute in segment 4 (cf. Figure 2 and Table 4). The market leader, *Mobilkom*, dominated segment 4 and *tele.ring* was competing with *Hutchison 3G Austria* in particular for customers in segment 3.

3.2 Strategic considerations

Considering the above mentioned criteria as well as the trade-off between attribute importance and relative distance toward the target position, *tele.ring's* management found that "base fee" was the most promising attribute to focus on. This attribute proved to be the most relevant attribute for segment 2 (see Figure 2), which is adjacent to the segment currently dominated by *tele.ring* (segment 3), and none of the competitors were well positioned there (i.e., undefended territory). The arrow in Figure 2 points to the proposed new position. A separate analysis for customers located around this position indicated that the attribute “base fee” was the most relevant feature, both in absolute and relative terms.

While the map provides a comprehensive view of the market and supports strategic thinking well, we adopted Choice-Based Conjoint analysis[7] to fine tune the tariff for the target group (i.e., segments 2 and 3 in Figure 2). It became apparent that the level of the “base fee” had a non-linear impact on tariff choice probability, inspiring the idea to offer the first tariff scheme with no base fee at all. This type of offer has a very obvious advantage to (low usage) customers as they are only invoiced for their actual telecommunication service usage and in proportion to the amount of usage. Therefore, the development team devised “minimum turnover” as a new attribute, which was a compromise between cost covering and utility goals. Since variable tariffs for all available nets amount to 10 cents per minute each, *tele.ring’s* communication activities also point out that customers only have to divide their actual usage time by 10 in order to calculate the amount they have to pay (in €). This was also the reason for calling this tariff scheme “Formel 10” (i.e. Formula 10).

Survey data also highlighted that the respondents were extremely confused by the different tariffs in this market. It is interesting to note that this observation is in line with the literature on perceived financial risk since the actual price paid for a specific telecommunication service remains hidden from the individual consumer (e.g., Sheth and Venkatesan 1968).

Besides defining this service concept and its target group, analysis of other survey data such as media preferences gave clear indications with regard to the potential communication strategy and sales channel (cf. Iyer, Soberman and Villas-Boas 2005). Moreover, after about four months on the market, comparison of the conjoint-based forecasts with actual market share of new contracts revealed that the (ex-ante) forecasts were accurate within a range of 1 %. This was an additional benefit given that *tele.ring* is owned by financial investors who place great value on these aspects.

It was not only the efficient new service development within a four-month timeframe which was the novelty, but the new method also profoundly transformed the way *tele.ring* designed its new

[7] See Jank and Kannan (2005) for an approach to considering graphical relationships within choice models.

offers. In addition, internal communication between managers using this tool at *tele.ring* improved considerably. Traditionally, *tele.ring's* marketing analysts compiled the market analysis, and then the results were transferred to other functional areas, in particular to managers concerned with internal auditing. This often led to information loss and disagreements caused by conflicting interests, and additional feedback loops. Now, for the first time, using the integrated market map, managers could check the feasibility of a new idea quickly and could clearly understand the rationale for the new offer from the outset[8].

On completion of the analysis stage, we discussed the segment-specific outcomes and the importance assigned to the different attributes with strategic decision makers. It transpired that the results provided were very helpful in convincing the external stakeholders, i.e. those not involved in the development team (owner, lower level management). In the beginning, they were very skeptical of the success of Europe's first tariff without a base fee. Using a data-driven calibration of concepts, which they were familiar with from their strategic marketing studies such as Porter's analysis of the situation in question, they were quickly shown that "Formel 10", which attacked poorly defended "territory" but did not cannibalize their current customers, was the correct strategic choice for *tele.ring.*

The speed of development, the quality of the results, the accuracy in forecasting, and the improvement in internal and external product concept communication have convinced *tele.ring* to organize its service development process around this new method. Currently, *tele.ring* is working on the development of another new tariff using this tool.

4 Impact on Profit and Sales

When assessing the proposed solution from a statistical point of view (i.e., by considering the goodness-of-fit measures), the results are satisfactory. Statistical measures alone, however, are not a conclusive proof that the use of the new method was the only success factor. We took great care to

[8] This observation is in line with remarks made by Divakar, Ratchford and Shankar (2005) who also experienced that their CHAN4CAST model was being rolled out for more users and more divisions in the company they were working with than initially expected and that CHAN4CAST changed (or modified) the way senior management looked at the forecasting process.

identify potential violations of the "ceteris paribus assumption" (caused, e.g., by effects of other marketing instruments, organizational or structural changes). Share-of mouth of all competitors over time, for instance, did not show any striking patterns, and *tele.ring*'s advertising expenditure remained relatively constant during that period of time.

In the following section, we provide further reasoning to support the link between the usage of our tool and the success of the new tariff.

4.1 Benchmarking the new tariff scheme against earlier tariff launches

To measure the impact of the method proposed, we benchmarked[9] the success of the newly introduced tariff scheme against seven former new tariff launches in the Austrian mobile phone market in terms of the increase in share-of-new-customers relative to the share-of-new-customers in the month before the launch. All new tariff scheme launches show a life cycle pattern of relatively short durations (six to eight months). As expected, the share-of-new-customers increases for a few months after tariff launch before starting to decline. Usually after about eight months, only a few additional new customers are acquired. In the beginning, there was a 20 percentage point increase in new customers with the new *tele.ring* tariff scheme, which rose to 23 percentage points in the third month after its introduction. Seven months after its launch, the newly introduced tariff scheme was still outperforming other new tariff schemes. On average (over seven months), the increase in share-of-new-customers was 17 percentage points, compared to the 2.4 percentage points benchmark (the average of the seven other tariff scheme launches). This benchmark shows a standard deviation of 4.3 percentage points.

Based on an average of 45,500 new registrations per month and on the observed changes with regard to the increase in share-of-new-customers in the seven months of available data, *tele.ring* acquired 46,350 additional (compared to other tariff scheme launches) customers. Since on average customers maintain this tariff scheme for 24 months (18 months is the contractual minimum period) and, since the average monthly profit per customer amounts to approximately $ 25.2, the additional

[9] While scientifically appealing, we could not set up a control group using other tools and introducing a rival tariff scheme to the market at the same time for obvious reasons and also cannot repeat the "*Formel 10"* case

(i.e. above-benchmark) profit generated using our method amounts to about $ 28,000,000. *tele.ring's* CEO, Michael Krammer, also pointed out that *tele.ring's* newly improved market position had even made them an attractive candidate for a takeover by one of its competitors at the end of 2005.

4.2 Assessing targeting precision

Share-of-new-customers

Having analyzed the impact of the new tariff scheme launch on the share-of-new-customers for various competitors, the mapping approach supported our view of the competitive structure of the market (cf. Figure 2). Based on this analysis, we expected *Hutchison 3G Austria* and *One* to be the main competitors because of their proximity to *tele.ring*. Table 3 compares the average share-of-new-customers over a period of six months for all major providers before and after the introduction of the "Formel 10" tariff scheme. The share-of-new-customers for all competitors decreased from 80.6 % to 68.9 % after the introduction of "Formel 10". The (weighted) average loss in the share-of-new-customers was 15 %. However, this did not affect all competitors equally. Those competitors positioned (cf. Figure 2) closest to *tele.ring*, i.e., *One* (-25 %) and *Hutchison 3G Austria* (-33 %), suffered a significantly higher decrease in their share-of-new-customers in comparison to *Mobilkom* or *T-mobile,* who were located farther apart. This further supports the conjecture that a large proportion of the new customers attracted by the "Formel 10" tariff scheme were from the targeted group.

Provider	**avg. share before introduction**	**avg. share after introduction**	**change in %**
Mobilkom	29.5	26.8	-9%
T-mobile	22.0	21.2	-4%
One	14.8	11.2	**-25%**
Hutchison 3G	14.3	9.7	**-33%**
$\sum$	80.6	68.9	

Table 3: Average share-of-new-customers of all major competitors over a period of six months before and after the introduction of *tele.ring's* new tariff scheme "Formel 10"

with rival STP models due to changed environmental conditions. We thus have to turn to prior/alternative tariff scheme introductions, conducted with rival approaches, as proxies.

Competitive analysis

One year after the introduction of the "Formel 10", a similar market survey was conducted to investigate the targeting precision of the method applied. For this purpose, the characteristics of *tele.ring's* customers were compared in terms of their favorite product attributes (most important product feature) before and after the introduction of the new tariff. Table 4 shows the results of the studies conducted in 2005 and 2006 and gives segment specific figures for 2005 (e.g., 38 % of all respondents stated "base fee" was the most important attribute in 2005, in contrast to 48 % in 2006; however, 91 % of the respondents belonging to segment 2 felt that "base fee" was the most important attribute in 2005).

Based on this data, we performed a formal analysis and estimated that 56 % of *tele.ring's* new customers had come from segment 2, and 34 % from segment 3; i.e. 90 % belonged to the target group. If the targeting had not been effective, new customers' preferences in 2006 would have been similar to those in 2005 and new customers would have switched to *tele.ring* in proportion to segment sizes in 2005, i.e., 29 % from both segments 2 and 3. This provides further evidence that the targeting procedure applied was highly effective and responsible for the success of "Formel 10".

Given the significant increase in profitability and the fact that no violations of the "ceteris paribus assumption" could be identified, the marketing science method implemented appears to be responsible for this success.

	study 2005	study 2006	Seg. 1	**Seg. 2 (target)**	**Seg. 3 (target)**	Seg. 4
base fee	38%	48%	0%	91%	46%	3%
price into own net	32%	21%	61%	1%	17%	5%
Image	3%	3%	0%	0%	1%	78%
free minutes	18%	15%	4%	5%	28%	4%
price into other mobile nets	6%	10%	24%	1%	6%	8%
price into fixed network	3%	3%	11%	2%	2%	2%

Table 4: A comparison of *tele.ring* customer preferences for 2005 and 2006 and segment specific customer preferences in 2005. The cells show percentages of top-ranked attributes.

As of May, 2007, *tele.ring* has reported that their tariff called “Ätschpeck” which was also designed by our tool generated as much as 200.000 new customers. Due to the success of *tele.ring*, other providers in the market (*Hutchison 3G* and *Mobilkom*) have adopted this tool as well.

5 Managerial Learning and Take-Aways

In this paper we have provided insights into the design of a new tariff scheme for a provider of mobile phone services in Austria by making use of marketing science techniques. As it turned out, the introduction of the new tariff scheme was very successful from an economic point of view. Although the report has focused on a single case only, several aspects of it seem to be of more general character. Therefore these results might be interesting for a broader audience.

5.1 Internal commitment

An external consultant depends heavily on the information provided by company members and their willingness to cooperate. Moreover, support from top-management is essential in establishing teamwork, rapport and trust in new research techniques. In our case, *tele.ring's* CEO enthusiastically supported our segmentation, targeting and positioning tool and decided to use it at the beginning of the project. This pre-condition helped to facilitate the co-operation and gain the commitment of *tele.ring's* managers.

This observation is in line with remarks made by Divakar, Ratchford and Shankar (2005) who reported on the implementation of a forecasting model for a consumer packaged goods company.

5.2 Visualization of results

Information needs to be disseminated efficiently across an organization, beyond those who have acquired it, and in a format that facilitates rapid interpretation and communication (DeSarbo et al. 2001). Graphic representations provide this type of format and often serve to communicate the very essence of marketing research results. Using the intuitively appealing concept of distance, the tool we developed visualizes the market structure in a two-dimensional graph supporting easy interpretation by managers. Furthermore, strategic considerations based on market positioning are familiar not only to marketing specialists, but also to managers with more general business training. This also enhanced adoption of our tool since it assisted management decision making.

These findings reinforce Lodish's (2005) experience that "it is much easier to get managers to adopt aids to help them to do their jobs *more easily*, than it is to adopt aids to help them to do their jobs *better*."

5.3 Communication between different stakeholders

By generating easy to interpret graphic representations of the market, the tool improved communication between market analysts and top management and therefore had an important impact on the process of developing new tariffs within the organization. In particular, the tool facilitated the participation of top managers in defining the target group and the positioning statement. The development process also benefited from the tool's ability to shorten the new product development process from idea generation to analysis of resulting consequences.

5.4 Results are judged upon face validity and usability

Managers did not question the methodological correctness of the underlying model nor did they doubt its formal rigor. Rather, they evaluated the results provided by looking at face validity issues and the tool's features, e.g., easy-to-use and flexibility (cf. Little (2004) for a similar finding). An important feature of the procedure supporting the STP process is that it steers the idea generation process in the right direction. Managers at *tele.ring* found that the merits of this tool lay in its interactive and intuitive nature. Interestingly, they also paid considerable attention to descriptive statistics, e.g. goodness-of-fit measures, and, of course, to predictive accuracy.

5.5 Transportability

The mobile phone market in Austria is highly competitive and the competitors in this market use state-of-the-art market research techniques. *tele.ring's* management considered the tool described here to provide a source of competitive advantage over other providers and demanded our exclusive cooperation. We, however, designed the tool for a variety of market situations with data available on brand and attribute rankings from a sample of customers. In fact, our tool has already been successfully applied to other markets (e.g., utilities, prefabricated homes, e-government, banking). The case presented here demonstrates its capabilities and illustrates further issues to consider when implementing it in a real-life setting.

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Appendix: Procedural outline of the modeling approach

Table 1 provides a simplified schematic representation of the modeling approach. This appendix aims at giving more technical details to further explain this model. Its structure follows the six steps outlined in Table 1.

1 Provide input data

To explain the rationale behind the modeling approach and in order to demonstrate the modest data requirements of the procedure, the sequel focuses on a situation in which marketing research provides data on respondents' rankings of the brands and attributes of the market under consideration. However, the marketing engineering tool is also capable of dealing with more complex input data. This applies in the case study of the Austrian mobile phone market.

These two-way preferences are arranged in the data matrix $Q = (q_{ij})_{(I,J)}$. Each row i contains the rankings of respondent *i* on all J_1 brands and all J_2 attributes ($J = J_1 + J_2$). The rankings are such that the lower values indicate a stronger preference than the higher values. The index *j* is used for brands and attributes.

2 Calculate intermediate results

In order to represent respondent, brands and attributes in a single map simultaneously (MDS) and to segment respondents according to their degree of homogeneity (clustering), Q has to be transformed/extended appropriately. These transformations are described below.

i) Calibration of *metric* disparities $\hat{\delta}_{ij}$ reflecting the *distances* between the brands and the attributes for all respondents (upper right block of input matrix in Figure A1).

Since the input data Q is of ordinal type only, but unfolding algorithms require metrically scaled data, a monotonic transformation is applied (cf. Borg and Groenen 1997), and results in disparities $\hat{\delta}_{ij}$, such that $(q_{ij} > q_{ij'})$ implies $(\hat{\delta}_{ij} > \hat{\delta}_{ij'})$ for all i

respondents and all brands, and attributes j, j'. The notation "$\hat{\cdot}$" is used to emphasize that $\hat{\delta}_{ij}$ were derived rather than calculated directly.

ii) Calibration of a measure of *respondent* heterogeneity $\delta_{ii'}$ (upper left block of input matrix in Figure A1).

As a measure of respondent heterogeneity/dissimilarity, the amount of correspondence between stated rankings is taken. Spearman's rank correlation coefficient is modified so that $0 \le \delta_{ii'} \le 1$, where 0 and 1 indicate high and low similarity of respondents i, i' respectively.

$$\delta_{ii'} = c_1 \cdot \sum_{j=1}^{J} \left(q_{ij} - q_{i'j}\right)^2$$

c_1 - scaling constant

iii) Calibration of measure of heterogeneity/dissimilarity with respect to preferences for *brands and attributes* $\delta_{jj'}$ (lower right block of input matrix in Figure A1).

In a similar vein, the amount of correspondence between brands and/or attributes j, j' across respondents is calculated.

$$\delta_{jj'} = c_2 \cdot \sum_{i=1}^{I} \left(q_{ij} - q_{ij'}\right)^2$$

c_2 - scaling constant

Again, small values for $\delta_{jj'}$ coincide with high similarity.

iv) Since $\hat{\delta}_{ij} = \hat{\delta}_{ji}, \forall i, j$, $\delta_{ii'} = \delta_{i'i}, \forall i, i'$ and $\delta_{jj'} = \delta_{j'j}, \forall j, j'$, the lower left block of the input matrix in Figure A1 is extended symmetrically.

3 Positioning

The matrix in Figure A1 is used as input for both MDS and K-means clustering. First, full multidimensional scaling is applied to the whole matrix and the dimensionality of the resulting perceptual map is fixed to two a priori. Thereby, requirements (R1) and (R2) of section 2.1 are dealt with.

The main output of MDS therefore refers to the position of brands, attributes and respondents in a single *two-dimensional* map, i.e., it results in

- x_{it}, coordinate of respondent i in dimension t $(t=1,2)$,
- y_{jt}, coordinate of brand, attribute j in dimension t.

In accordance with requirement (R3), distances are measured as the Euclidean norm, i.e.,

$$d_{ij} = \sqrt{(x_{i1} - y_{j1})^2 + (x_{i2} - y_{j2})^2}$$

$d_{ii'}$ and $d_{jj'}$ are defined analogously.

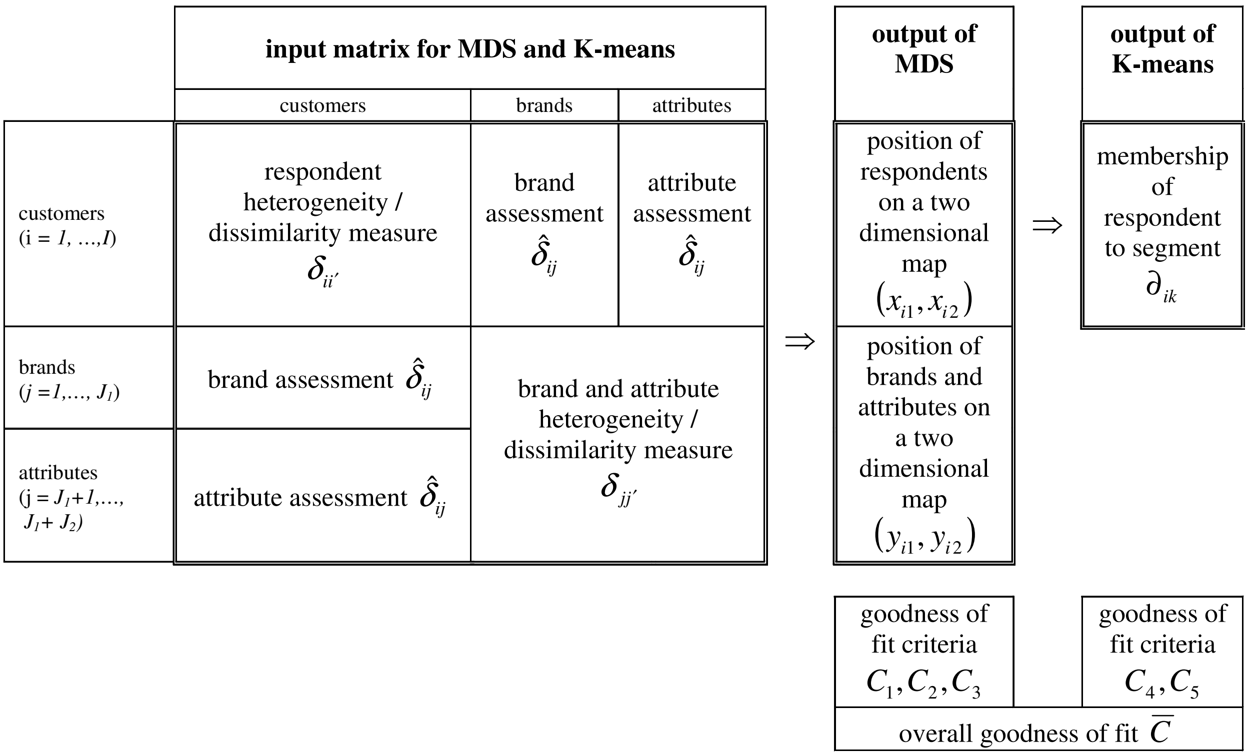

Figure A1: Data matrix used for procedure

The MDS-algorithm identifies $\left(x_{it}, y_{jt}\right)$ in order to fit the data best. However, this fit could be evaluated in several ways. In particular, five different aspects and an overall measure are focused on.

The first three aspects deal with mapping and therefore all measures are essentially based on some kind of stress $S^{[..]}$ (Kruskal 1964) which is applied to the three different blocks of the input matrix displayed in Figure A1.

(C1) Replication of brand/attribute ranks (unfolding) — C_1

(stress applied to the upper right block of the input matrix in Figure A1)

Preferences of respondent *i* for brand or attribute *j* should be reflected by the distances on the map, facilitating the targeting task and the interpretation of the map.

$$S^{[ij]} = \sqrt{\sum_{i=1}^{I}\sum_{j=1}^{J}\left[w_{ij}\cdot\left(d_{ij}-\hat{\delta}_{ij}\right)^2\right] \Big/ \sum_{i=1}^{I}\sum_{j=1}^{J}\left(w_{ij}\cdot d_{ij}^2\right)} \qquad (1)$$

The weights w_{ij} can be used to exclude missing proximity data, or to account for data with varying confidence levels (cf. Quist and Yona 2004). For the application at hand, these weights are also used to permit a balance between measures C_1, C_2, C_3.

$S^{[ij]}$ shows the suitability of the collected data for targeting and positioning purposes. In this sense $S^{[ij]}$ can be used as a measure of evaluation. Alternatively, $S^{[ij]}$ could serve as an optimization criterion. $S^{[ij]}$ is minimized by iterative majorization (implemented in the SMACOF-III algorithm; Heiser and De Leeuw 1979). Hence the first measure, C_1, is defined as $C_1 = \left(1 - S^{[ij]}\right)$, $0 \le C_1 \le 1$ and therefore it may be interpreted as a goodness-of-fit measure (with values of C_1 near 1 and 0, denoting a good or poor fit respectively).

(C2) Replication of *respondent* heterogeneity — C_2

(stress applied to the upper left block of the input matrix in Figure A1)

The procedure is very much in line with the one described above. In a more formal sense, it yields $S^{[ii']}$ by means of equation (1). $S^{[ii']}$ can be used as the minimization criterion as well as a goodness-of-fit measure $C_2 = \left(1 - S^{[ii']}\right)$.

(C3) Replication of *brand and attribute* heterogeneity — C_3

(stress applied to the lower right block of the input matrix in Figure A1)

Once again the procedure described above is followed and $S^{[jj']}$ and C_3 are arrived at.

4 Segmentation

Segmentation is based on respondent heterogeneity $\delta_{ii'}$. In order to link unfolding and clustering, the coordinates $\left(x_{i1}, x_{i2}\right)$ of all respondents on the map (as derived from MDS) are also used.

For ease of presentation, the data is arranged to form a vector Z_i for each respondent i: $Z_i = \left(\delta_{i1}, ..., \delta_{iI}; x'_{i1}, x'_{i2}\right)$. In order to make the elements of Z_i comparable in size, x'_{it} are scaled from x_{it} such that $0 \le x'_{it} \le 1$. $\left(Z_i, i = 1, ..., I\right)$ is used as input data for the segmentation procedure.

Thus, each respondent is assigned to a certain segment k' ($k = 1, ..., K$ and K is the number of segments in the market):

$$\partial_{ik'}^{(K)} = \begin{cases} 1 & \text{if} \quad i \quad \text{belongs to segment} \quad k' \\ 0 & \text{otherwise} \end{cases}$$

There is a large body of literature (cf. Lilien and Rangaswamy 2004) on different segmentation approaches to marketing data. Since analyzing different segmentation procedures is not the aim of our paper, we have restricted ourselves to the K-means procedure (McQueen

1967), a popular method for analyzing marketing data (e.g., Green and Krieger 1995). K-means looks for solutions in which distances $d_{ik}^{(K)}$ between respondents and their segment centers $\bar{z}_{t'}^{(k,K)}$, $(t' = 1,...I+2)$ are minimal.

$$\bar{z}_{t'}^{(k,K)} = \sum_{i=1}^{I} \partial_{ik}^{(K)} \cdot z_{it'} \Big/ \sum_{i=1}^{I} \partial_{ik}^{(K)} \qquad \forall t', k$$

$$d_{ik}^{(K)} = \sqrt{\sum_{t'=1}^{I+2} \left(z_{it'} - \bar{z}_{t'}^{(k,K)} \right)^2} \qquad \forall i, k$$

$$d_{ik'}^{(K)} = \min_{k=1,...,K} \left\{ d_{ik}^{(K)} \right\} \qquad \forall i$$

Since the outcome of K-means depends on the initialization of $\partial_{ik'}^{(K)}$, K-means needs to be replicated from different starting points and furthermore run for different numbers of segments K. The optimal number of segments K^* is chosen on the basis of the Davies-Bouldin Index (Davies and Bouldin 1979).

Conditioned on the optimal number of segments, another goodness-of-fit measure is calculated.

(C4) Variance accounted for by segmentation — C_4

C_4 corresponds to the VAF (variance accounted for) measure frequently applied in segmentation studies (cf. Arabie et al. 1981) and can be interpreted as the advantage (in terms of squared distances) of the solution at hand over a single segment solution, i.e., a non-segmented market.

$$C_4 = 1 - E(K^*) / E(1)$$

with $E(K^*) = \sum_{i=1}^{I} \sum_{k=1}^{K} \partial_{ik}^{(K^*)} \cdot d_{ik}^{(K^*)^2}$

5 Reduce segment overlap

In accordance with requirement (R4), the creation of non-overlapping segments is the objective. For managerial application, the segment overlap needs to be low otherwise the targeting step becomes cumbersome. Therefore, a solution in which the percentage of non-overlapping sectors on the map is large is preferable.

In order to get a measure of segment-overlap, the map is divided into a $(m*m)$ grid. Granularity might be varied (e.g., according to the number of respondents *I*) but the proposed measure was not found to be extremely sensitive with respect to m (cf. Figure A2 for an empirical example). Therefore, $m = 20$ was heuristically defined for subsequent calculations.

Each respondent is assigned to one sector of the grid. Sectors with respondents belonging to different segments are defined as overlapping sectors, and OL^o is the number of these sectors found. OL^n, on the other hand, corresponds to the total number of sectors that contain at least one respondent. Thus, a final goodness-of-fit measure, the percentage of non-overlapping segments, is calculated as:

(C5) Percentage of non-overlapping segments — C_5

$$C_5 = 1 - OL^o / OL^n$$

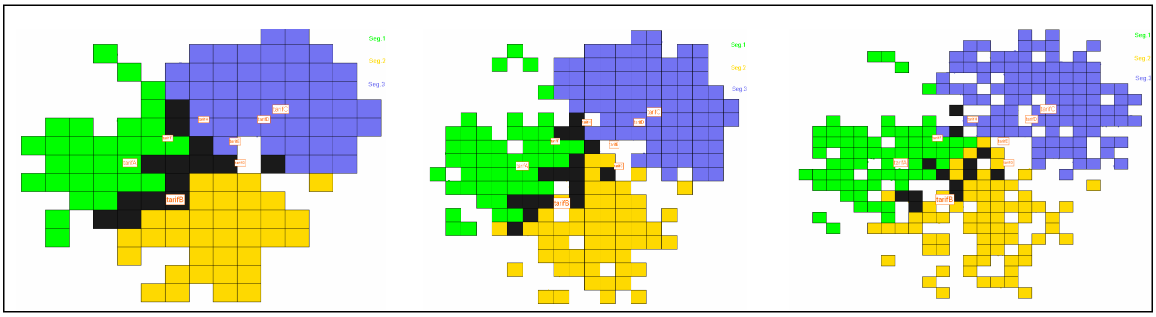

Figure A2: Measuring the segment overlap (black fields) with different grid sizes m=15 (C_5 = 0.89); m=20 (C_5 = 0.92) and m=25 (C_5 = 0.95). Overlapping sectors are detected always in similar regions of the map.

C_4 and C_5 are used as optimization criterion for the K-means clustering procedure as well.

6 Check derived solution

Based on the goodness-of-fit criteria C_1 - C_5 the derived solution is evaluated. If the fit is found inappropriate steps 3), 4) and 5) are reiterated. This time, however, $\partial_{ik'}^{(K)}$ are also used as an input for the MDS procedure.

In view of the different aspects of the problem, a global measure of the goodness-of-fit is calculated as the mean over the individual C_1 - C_5 measures.

($\overline{C}$) Overall fit measure — $\overline{C}$

$$\overline{C} = \frac{1}{5} \cdot \sum_{l=1}^{5} C_l$$

Obviously, the overall fit measure can be computed by giving different weights to the individual C_l or by using geometric means.

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