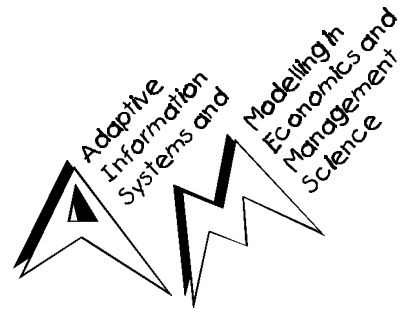


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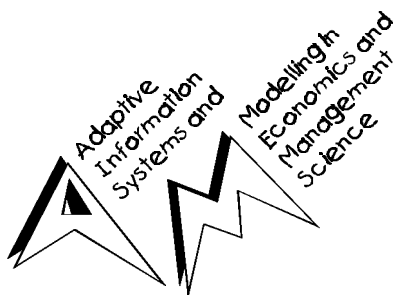


## THE SIMSEG PROJECT: A SIMULATION ENVIRONMENT FOR MARKET SEGMENTATION AND POSITIONING STRATEGIES

Thomas Baier and Josef A. Mazanec

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# THE SIMSEG PROJECT: A SIMULATION ENVIRONMENT FOR MARKET SEGMENTATION AND POSITIONING STRATEGIES

T. Baier and J. A. Mazanec<sup>1</sup>

## **Abstract**

A simulation environment for exploring analytical tools and joint segmentation and brand positioning strategies is tailored to comply with the perceptions-based approach to market segmentation. The initial version contains a number of *ad hoc* segmentation strategies. It also indicates how the strategy agents in a more fully elaborated version may autonomously decide on their selection of target segments and brand profiles. With a reasonably sized parameter set the SIMSEG brands are subject to perceptual dynamics that respect the basic principles of attribute learning through advertising and promotion. SIMSEG is conceived for interfacing with an Artificial Factory simulation background where the consumers' fuzzy perceptions of rivaling brands are translated into physical or functional characteristics.

## **A. Conceptual foundation** (J. Mazanec)

Returning from a guest lecture at the INSEAD, Fontainebleau, in 1979, J. Mazanec brought the MARKSTRAT simulation game (Larréché and Gatignon, 1977) to the WU Wien. Since then many generations of business studies graduates improved their management and marketing skills by exercising this business strategy game. Now in its 3<sup>rd</sup> release (Larréché and Gatignon, 1997) it may still be considered the leading software in the field. MARKSTRAT has sometimes been used as a marketing laboratory to analyze the participants' decision styles (van Bruggen, Smidts and Wierenga, 1998). Twenty years experience with this implementation (sometimes with mixed managers-students groups) of a fairly sophisticated simulation model led to the conviction that,

- while it would be a stupid claim to replace practical work experience by classroom simulation,
- the participants have always been successfully trained to relate textbook 'recipes' to a particular firm and market situation. It did not matter too much that there was a laboratory-generated setting. MARKSTRAT was not considered to oversimplify on the fundamental criteria of a competitive world with opportunities and threats which may emerge quite unexpectedly.

An educational simulation setting is different from a research-driven model. Here, one wants to add complexity to challenge the students' capabilities to come to terms with ill-

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<sup>1</sup> Thomas Baier and Josef Mazanec are with the Research Initiatives #1 and #3 of the Joint Research Program (SFB) 010 on Adaptive Systems and Modelling funded by the Austrian Science Foundation. They happen to have written this paper while all members of the SIMSEG team were involved in some of the design sessions, alphabetically these are Christian Buchta (#3), who made valuable suggestions to this paper and also programmed two of the thirty functions of the MATLAB/OCTAVE version, Sara Dolnicar (#3), Andreas Geyer-Schulz, Fritz Leisch (#1), Martin Natter (#5), Thomas Reutterer (#3), Helmut Strasser (#2), Andreas Weingessel (#1).

structured problems; there, one likes to reduce complexity to trace the cause-effect relationships in an artificial — and imperfectly separable — subsystem of a sector of the economic reality. The SIMSEG Project has been launched to create an artificial market environment. It serves not only the consumer modeling requirements of the Research Initiative #3 on Market Segmentation and Product Positioning but also corresponds to the integrating exercise of the SFB long-term goal.

### **1. Objectives and research motivation**

SIMSEG serves a double purpose. It allows for

- assessing experimentally varied alternatives of segmentation analyses and strategies, and for
- generating artificial data with controlled properties.

Vis-à-vis the Artificial Factory the simulation mechanism provides the market response to marketing strategy and action. At the same time it generates periodic results and thus creates market data with known properties.

The rationale for the SIMSEG project refers to the basic characteristics of the SFB 010 on 'Adaptive Modeling':

- While the contemporary world of marketing scholars seem to be fully absorbed by modeling brand choice out of scanner (panel) data the SIMSEG group emphasizes perceived attributes. Efforts to analyze the competitive behavior of firms with regard to product attributes have been very rare (Hauser and Shugan, 1983; Hauser and Clausing, 1988; Urban and Hauser, 1993; Ansari, Economides and Ghosh, 1994). But how do you proceed if you are a marketing manager facing an inquisitive engineer from your firm's R&D department? (Or a marketing researcher collaborating with your liaison counterpart from the 'Artificial Factory' research group, where they are waiting for the consumer expectations of product attributes?)
- SIMSEG utilizes the exploratory and inferential methodology newly developed for optimizing market segmentation and brand positioning decisions. These methods become analytical agents (A-agents) in the simulation experiments.
- As it needs automated versions of the analytical tools it uncovers the weaknesses of the analytical methods. Normally, the real world application gaps are bridged by taking recourse to 'human judgment'. For the A-agents these rules of managerial judgment must be made explicit. In the more advanced SIMSEG versions they will become subject to learning.
- The simulation assists in revealing the consequences of the assumptions which are (implicitly) made in the empirical applications. It helps separating the non-essential from the crucial ones.
- The A-agents may function in competition with each other. Therefore, the economic consequences of alternative modeling and information processing techniques become apparent.
- The same principles of competition apply to the strategic agents (S-agents) and also for the combined effects or interaction between analysis and strategy.
- The experimenters exercise control over consumer heterogeneity in their artificial markets. Segmentation analysis and strategy will be exposed to the systematic variation and mixing of the choice rules ('cognitive algebra') in the consumer population ('inter-personal' parameter and model variety).

- The simulation refinements are then straightforward. Dynamic effects and adaptivity ('intra-personal' parameter and model variety) will be introduced for the consumers to challenge the A and S agents.

## **2. A brief review of the requirements for 'second generation marketing simulation'**

In marketing research simulation models have a tradition which dates back to the Sixties and Seventies (Topritzhofer, 1974). From a contemporary perspective the early attempts to mimic (consumer) market phenomena by computer simulation were bound to fail. They applied a micro-simulation approach and tried to incorporate producers, consumers and the distribution systems all at once. The 'all-encompassing' simulation models (Nicosia, 1966; Amstutz, 1967; Lavington, 1970; Klenger and Krautter, 1972) were over-ambitious in terms of defining a reasonably sized and manageable sector of market reality. As a consequence the simulation model builders were forced to introduce many *ad hoc* parameters with deliberate value settings to capture some faint cause-effect relationships they deemed important. In the end the model builders were unable of unambiguously tracing back the model output and the attempts failed because of the inverse relationship between model complexity and interpretability of the results (Mazanec, 1978, p. 32; Rangaswamy, 1993, p. 744). So is it still valid what A. S. C. Ehrenberg (1968) wrote in a JMR review of Nicosia (1966): "The book illustrates the modern model-builders syndrome of falling over himself by trying to run before he can walk."?

For 'second generation marketing simulation' the view is different. Increasing the coverage of real market phenomena is no longer a valid goal of its own. Instead, the concern about 'noncritical' abstraction and parameter parsimony becomes paramount. There is a safe way of avoiding overparameterization by a piecemeal process. One has to assure modularity, start with a system of very modest size, and gradually add complexity once the cause-effect relationships in the previous step have been properly understood. This sounds like a simple recipe. The analyst, however, faces the problem of deciding on where the abstraction and simplification threaten to destroy the homomorphic relation between market reality and the scope of the simulation model. In other words, there is a 'representation threshold'. Even the initial version of the simulation environment has to respect a number of requirements which — if they were abandoned — would render the simulation output meaningless.

### **3. The initial version of SIMSEG**

#### *3.1 Outline of the SIMSEG macro structure*

There is a latent process which generates the consumers' brand perceptions, their segment-specific preferences, and their reservation prices. The probability of a purchase in the product class and of choosing a particular brand depends on the initial perceptions-preferences structure and on the firms' relative investments into market operation such as brand variation and differentiation or market communications. It is a strong and very realistic assumption that the domain of unobservables and empirically inaccessible mechanisms is actually unknown to the firms competing on the artificial market. Beyond this

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#### **„line of visibility“**

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the firms monitor the brands perceptual (image) profiles as 0-1 data vectors. They watch the brand choice and calculate market shares for  $k$  brands. To achieve this they draw  $k$ -block samples, apply analytical tools (A-agents) to extract perceptual prototypes, assess the brand positions and their height of preference. They develop strategies (S-agents) according to prespecified corporate goals and budget limits. They interpret the competitive situation and derive segment-specific positioning targets under predetermined (or adaptively optimized) decision rules. The marketing strategy comprises target segments, a target profile of perceptual brand attributes, segment-specific prices, and an overall budget for market operation.

*[Not yet implemented in the initial version: The*

#### **----- Artificial Factory interface -----**

*is intervening in this stage as the AF product engineers interpret the fuzzy perceptual and preferential information transforming them into technical and functional attributes. The AF simulation ensues. A negotiation process between the marketing and the production subsystems regarding revenue and cost forecasts will be part of practicing the 'learning organization' paradigm ( see Mild et al., 1999).]*

Jumping over the

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#### **„line of visibility“**

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the market reaction will be mediated through the latent responsive process depending on the firms' relative budget appropriations accompanying their segmentation and positioning decisions. While the market responds with a change in the perceptions and preference generating probabilities the firms again will be restricted to exploiting the manifest 0-1 perceptual data and the actual brand choices indicative of latent 'ideal attribute vectors' and brand preferences.

#### *3.2 Current limits to market structures and market dynamics*

SIMSEG assumes a simplified market structure tailored to emphasize the segmentation and positioning phenomena for a convenience product. However, it does not simplify on all respects and certainly not on brand perceptions. The brands in the product class are rivaling for consumer awareness by emphasizing connotative and emotional (pseudo-) characteristics. They are subject to tough competition in terms of promotional claims and

emotional loading of brand names. To grasp the idea imagine a product class such as beer. The product attributes may be condensed into three latent perceptual dimensions with four observable perceptual indicators each:

- „intensity of taste“ (strong, tasty, spicy, rich)
- „lightness“ (low in alcohol, low caloric content, refreshing, light)
- „life style“ (cool, young, 'in', dynamic)

The brand differentiation is supported by add-ons such as Lager, Special, Pils, Premium, Medium, Light, Cult, Ice. (More extreme examples are cigarettes, perfumes, liquors, and all sorts of fashion accessories.)

Each producer offers one brand which compete in a homogeneous product class. 5 to 7 is an appropriate number of brands considering the normal size of consumers' evoked set. Each producer can deliver any combination of attributes; initially there are no technically incompatible product characteristics. This is a market place without a distribution system. It lacks intermediaries such as wholesalers and retailers.

There are no life cycle or saturation effects. The market potential is constant and equals the maximum market volume resulting from each consumer buying one and only one unit per period. Therefore, firms' planning periods coincide with the consumers' purchasing cycles and the buying frequency is 1. The quantities sold equal the number of units produced; there is no bottleneck in production or distribution, no inventory and no allocation of excess demand.

The cost for brand variation and differentiation include production and market communication. The number of brand attributes addressed in an advertising message affects the cost-effect ratio. Given the same budget for targeting a particular market segment, the consumers' learning effect will decrease in proportion with the number of attributes to be moved towards the 'target profile'.

By focussing on perceptual and preference analysis and strategy the SIMSEG firms are hooked on a truncated marketing mix. It consists of product variation and differentiation, pricing, and advertising. Segmentation is by psychographics only where the firms may rely on idealized segment reachability ignoring segment overlap or spill-over effects. Prices need not, but may be varied by brand and by market segment.

The consumer population is constant and consumers are modeled on a semi-aggregate level. This means that there is no individual memory of the history of purchase incidences. Consumers have a 100 per cent awareness of all brand names. They are prepared to rate all brands in their consideration set. Their judgments, however, are subject to learning and forgetting product knowledge and brand comprehension. This is the core element of the simulation procedure. In the basic data scenario the consumers' 0-1 brand perceptions are based on mutually independent probabilities of associating an attribute with a brand (i.e. a "1" response) when personally interviewed in a market survey. A "0" denotes either an attribute misfit or a "don't know", irrelevance, or "don't care" reaction. Consequently, a zero in the latent vectors of 'ideal' attribute profiles means "irrelevant" while unity indicates a desirable attribute. Desired attributes and preferences are not situation-specific; they do not vary over purchasing or consumption scenarios. It is of utmost importance to note that the ideal vectors are not accessible by direct questioning. The firms have to deduce them indirectly or do without explicit and attribute-specific preferences. An indirect measurement of attribute part worths which is common in conjoint analysis for new product planning is permitted. The conjoint

analysts, however, would have hard times coping with the large number of (fuzzy) attributes typically governing brand choice in an emotions-dominated product class.

As an *ad hoc* example consider a market with  $S$  perceptually homogeneous consumer segments and  $B$  brands.<sup>2</sup> If there are, say, 12 product attributes each perceptions data vector  $x_{ij} \in \{0,1\}^{12}$ . The data generating probabilities are arranged in a latent supermatrix  $\Theta$ , where the columns consist of the perceptions each consumer segment  $s = 1, \dots, S$  attaches to brand  $b = 1, \dots, B$ . The marketing mix applied by brand  $b$  influences one or more selected  $\Theta_{sb} = \text{Prob}(X=1)$  in the respective column  $b$ . This implies that there are  $S \times B$  hidden prototypes of perceptual patterns unknown to the firms on the market. If the consumers are surveyed they respond with the binary brand ratings in each attribute correspondingly arranged in the respondents  $\times$  attributes  $\times$  brands matrices in  $X$ :

$$\left( \begin{array}{c|c|c} \Theta_{11} & \Theta_{12} & \dots & \Theta_{1B} \\ \Theta_{21} & \Theta_{22} & \dots & \Theta_{2B} \\ \dots & \dots & \dots & \dots \\ \Theta_{S1} & \Theta_{S2} & \dots & \Theta_{SB} \end{array} \right) \rightarrow \left( \begin{array}{c|c|c} X_{11} & X_{12} & \dots & X_{1B} \\ X_{21} & X_{22} & \dots & X_{2B} \\ \dots & \dots & \dots & \dots \\ X_{S1} & X_{S2} & \dots & X_{SB} \end{array} \right)$$

The SIMSEG firms are also unaware of the 'true' perceptual segment structure  $1, \dots, S$ . They only hypothesize that such a structure exists when they observe the perceptual variables

$(X_1|X_2|\dots|X_B)$  and try to extract 'typical' patterns named prototypes. Each firm may

detect a different set of prototypes  $\left( \begin{array}{c} \mathbf{y}_1 \\ \mathbf{y}_2 \\ \dots \\ \mathbf{y}_{S'} \end{array} \right)$  with a presumable structure of  $S' \sim S$

according to the A-agent used for uncovering perceptually homogeneous consumer groups.

### 3.3 Consumers' cognitive algebra and brand choice modeling

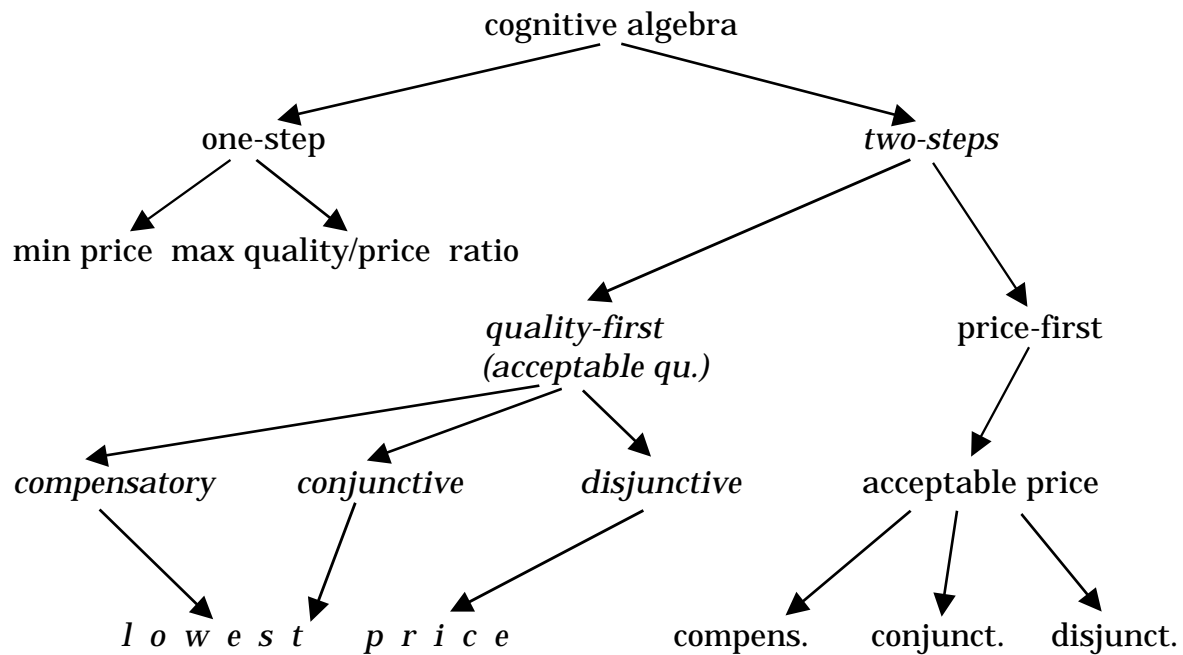
The number and contents of perceptual dimensions and corresponding indicator variables are constant. The consumers learn and unlearn (forget) the brand perceptions depending on the firms' relative investments into communicational efforts. The brand preferences originate from latent 'ideal' attribute profiles which are held constant in the initial version. So far there is no adaptation of aspiration levels according to consumers' experience. The number and size of the perceptual and preferential segments stays the same over the simulation iterations.

Each artificial consumer sticks to a preassigned decision rule for making brand choices. The choice rules given in *italics* are currently implemented (for a recent update on choice rules see Bettman, Luce and Payne, 1998):

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<sup>2</sup> The generation of artificial data for SIMSEG experiments is not elaborated here. For a more rigorous treatment see Chr. Buchta, Modelling Market Scenarios for Simulation Studies on the Joint Segmentation and Positioning Problem, Working Paper No. 59, SFB 'Adaptive Information Systems and Modelling in Economics and Management Science.





Actual brand choices originate from the consumers' confronting of brand perceptions with their 'ideal' vectors of desired attributes. Again, the SIMSEG firms have no empirical access to this piece of information. Attribute-related preferences are latent and have to be inferred from revealed preferences i.e. brand choices.

Consider a consumer's latent profile of desired attributes  $y \in \{0,1\}^{12}$  for 12 attributes. He belongs to one of several preferential segments where he shares the same  $y$ -pattern with his market compatriots. In the initial version the  $y$ -vectors are constant, but will be subject to adaptation (reinforcement learning or aspiration level adjustment) in later SIMSEG versions. Preferential segments are superimposed on the perceptual segments. During the SIMSEG runs they may either be independent from the perceptual patterns or experimentally made dependent on them. Each buyer with his  $B$  perceived brand profiles pursues one preferred pattern. So how is all of this transformed into brand choice?

SIMSEG first determines the consumers' consideration sets of acceptable brands. Thus brand  $b$  being part of a consumer's consideration set is indicated by  $a_b$ :

$$a_b = \begin{cases} 1, & \text{if } y' x_b = \max(y' x_1, y' x_2, \dots, y' x_B) \\ 0, & \text{else} \end{cases}$$

for a compensatory choice rule, and

$$a_b = \begin{cases} 1, & \text{if } y' x_b = y' y \\ 0, & \text{else} \end{cases}$$

for the binary equivalent of a conjunctive rule, or

$$a_b = \begin{cases} 1, & \text{if } y' x_b \geq 1, 2, \dots \\ 0, & \text{else} \end{cases}$$

for a disjunctive rule describing a consumer satisfied with finding a small number of 1 or 2 brand  $b$  attributes matching his 'ideal' profile.

A number of brands surviving this first screening stage gets now evaluated in terms of price. The brand choice indicators  $c_1, \dots, c_B$  depend on the consumer's reservation price  $r$ . This reservation price  $r$  is specific for each preferential segment and varies around the average price of all brands within the range  $0 < b_i < b_{max}$ :

$$r_i = b_i \bar{p}$$

$$c_b = \begin{cases} 1, & \text{if } r - p_b = \max[a_1(r - p_1), \dots, a_B(r - p_B)] \\ 0, & \text{else} \end{cases}$$

If  $c'c > 1$  indicating that more than one brand remain in the final choice set, a random choice takes place.

The SIMSEG firms are monitoring brand choice on the disaggregate level. The resulting criteria of market success on aggregate level for making a single-period assessment are sales, revenue, and market share. Cumulative sales and revenue for judging multi-period achievements are sufficient as long as the firms/brands operate on predetermined budgets. The output criteria are easily complemented by (discounted) profit figures and ROI ratios. These are required by the interfacing with the Artificial Factory and its simulation of investment decisions.

The initial version of SIMSEG makes no provision for time-lags in market response and for cumulative carry-over effects. The firms' actions and consumers' reaction entirely occur in the same planning period.

### 3.4 SIMSEG strategy formulation: Ad hoc vs. systematically derived strategies

The SIMSEG firms are measuring brand perceptions and brand choices in each planning period (e.g. through purchasing consumer/household panel data). Very much like their real world counterparts, however, they adhere to the same segmentation strategy during a number of subsequent periods.

In perceptions-based market segmentation (PBMS) the marketing manager takes advantage of the data compression that leads to a representation of competing brands by perceptual prototypes. The brand profiles represented by one perceptual prototype make up a perceptual class. As each respondent in the consumer sample rates each brand, a perceptual class normally consists of more brand profiles than respondents underlying these profiles. Only a minority of the perceptual profiles belong to those chosen for a purchase. Owing to the k-block design  $r_{isb} = 1$  (0) denotes a respondent  $i$  (not) perceiving brand  $b$  according to the prototype (perceptual class)  $s$ . Then the number  $r_s$  of respondents underlying the perceptual class  $s$ ,

$$r_s = \sum_i r_{is}$$

where

$$\forall i: r_{is} := \begin{cases} 1, & \text{if } \sum_b r_{isb} > 0 \\ 0, & \text{else} \end{cases}$$

The market structure information resides in the two contingency tables of prototypes  $\times$  brands for perceptions ( $p$ ) and for choices ( $c$ ):

Absolute frequencies for perceptual profiles							
	b	r	a	n	d	s	$\Sigma$
p	$p_{11}$	$p_{12}$	...	$p_{1b}$	...	$p_{1B}$	$p_{1.}$
r	...						...
o	$p_{s1}$	$p_{s2}$	...	$p_{sb}$	...	$p_{sB}$	$p_{s.}$
t	...						...
s.	$p_{S1}$	$p_{S2}$	...	$p_{Sb}$	...	$p_{SB}$	$p_{S.}$
	$p_{.1}$	$p_{.2}$	...		...	$p_{.B}$	$p_{..}$

An analogous table exists for the brand choices ( $c_{sb}$ ).

A series of nonparametric significance tests (adaptive partitioning followed by permutational testing) to examine various hypotheses about the competitive relationships among the brands have been developed for pairwise comparisons (Strasser, 1998). The initial version of SIMSEG does not yet incorporate these tests into strategy formation. So far, it employs a number of managerial heuristics to decide on the selection of target segments. The consequences of these rules have to be properly understood, before more refined S-agents will be added.

Processing the contingency information the firms construct three descriptive ratios for each perceptual class  $s$ :

$$SC := 1 - \frac{r_s}{p_{s.}}, \quad 0 \leq SC < 1,$$

is 1 less the ratio of respondents and perceptual profiles in  $s$  and serves as a measure of the strength of 'similarity competition' among the brands represented by prototype  $s$ .

$$BI := \frac{c_{s.}}{r_s}, \quad 0 \leq BI \leq 1,$$

is the ratio of brand profiles purchased by the consumers underlying the perceptual class  $s$  and indicates the 'buying intensity' for prototype  $s^3$ .

$$AT := \frac{c_{s.}}{p_{s.}}, \quad 0 \leq AT \leq 1,$$

is the share of brand profiles purchased of all profiles in the perceptual class  $s$  and indicates the 'attractiveness' of prototype  $s^3$ .

<sup>3</sup> Note that brand-specific values for  $BI$  and  $AT$  may also be relevant, where the managerial attractiveness of a prototype interacts with the brand name.

Finally,

$$AT = SC \times BI.$$

The SIMSEG sample output below shows a prototypes  $\times$  perceptions and a prototypes  $\times$  choices table and the row sums for the  $p$ -values and the number of respondents affiliated with each prototype.

6 segments detected for BRAND 4 (817 respondents  $\times$  4 brands)

Perceptual\_prototypes\_by\_brands =

41	158	41	46	
64	76	12	84	
81	174	52	192	
295	72	86	106	( $p_{sb}$ )
300	229	604	308	
36	108	22	81	

Sum\_of\_profiles\_and\_respondents =

286	260	
236	198	
499	378	$p_s$ and $r_s$
559	446	
1441	724	
247	228	

Purchases\_in\_prototypes\_by\_brands =

5	37	2	8	
32	61	8	63	
26	121	20	101	
52	21	16	22	( $c_{sb}$ )
37	41	48	37	
6	29	3	21	

Brands\_sold\_units =

158	310	97	252	$c_b$
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Nonexistent price strategy. Default selected.

budget\_assigned\_to\_segments =

...

Similarity competition is lowest for prototype 6 with  $SC = 1 - 228/247 = .08$  and toughest for 5 where 724 respondents account for twice as many (1441) perceptual profiles ( $SC = 1 - 724/1441 = .50$ ). Buying intensity is computed by using the number-of-choices row sums from ( $c_{sb}$ ). It is by far the highest for prototype 2 with  $BI = 164/198 = .83$  and beats all others except the second-best (i.e. 3) by a wide margin. Prototypes 2 and 3 frequently translate perceptions into choices and thus stay the most attractive ones with  $AT = 164/236 = .69$  and  $268/499 = .54$ .

The market segments are made up of consumers. The SIMSEG firms define them in terms of perceptions and evaluate them by judging the sales potential and competitive threat. When a brand prototype and its associated perceptual class gets selected for market operation, the underlying consumers build the target segment. In choosing market segments the firms are compelled to draw a compromise between targeting the attractive but highly competitive markets. This is a matter of strategy formation and cannot be resolved without a corporate objective giving priority to utilizing opportunities or avoiding hazards.

In their joint segmentation-positioning decision making the SIMSEG firms always define a 'target profile' for their brands when choosing among market segments. These strategic issues are two sides of the same medal. Targeting 'how to whom' means elaborating an attractive brand profile for one or several target segments. As it would be naive for the firms to directly question the consumers' about their 'ideal' product profiles, this piece of knowledge is rarely available. A very clever A-agent may be capable of extracting the latent preferences in a segment-specific manner. This is exactly what the enthusiasts of response-based segmentation, e.g. via ML estimation of mixture models, try to do. Here the skepticism prevails and, thus, for the SIMSEG firms the only hint the market provides is the actual sales information.

*Ad hoc* strategies (currently implemented):

segmentation strategy for brand <i>b</i>	segment(s) selected	target profile(s) <sup>4</sup> equal(s)
"one-for-all"	all	average of all profiles sold
"one-for-each"	each	average of the profiles sold in each segment
"follower"	with max $c_{sb}$ '	profile of the best-selling brand $b'$ in this segment
"niche-seeker"	with max $c_{sb}$ of brand $b$ from among the segments with a below-average $p$	average of the profiles sold in $s$
"risk-avertter"	with max $c_{sb}$ of brand $b$ from among the low competition segments i.e. those with above-average $SC$	average of the profiles sold in $s$
"use-your-strengths"	with max $c_{sb}$ of brand $b$ from among the segments where $b$ has a competitive advantage i.e. its choices share $c_{sb} / \sum_b c_{sb} >$ its perceptions share $p_{sb} / \sum_b p_{sb}$	average of the brand $b$ profiles in $s$

Systematically derived strategies are based on the  $SC$ ,  $BI$ , and  $AT$  ratios and a little 'theory' related to ordinary portfolio analysis for SBUS (strategic business units) or brands (cf. Kerin, Mahajan and Varadarajan, 1990). These are not yet implemented in the initial version of SIMSEG:

<sup>4</sup> The target profiles are derived from the market or segment averages by rounding the attributes toward unity which are desired by a qualified majority of the consumers.

Segment selection matrix (for comparative strategies)		
Attractiveness <i>AT</i> (all brands) is ...	hi	"build"                      "maintain"
	lo	(disregard)                "harvest"
<div style="text-align: center;">           competitive advantage of <i>b</i>            (<math>AT_b = BI_b</math>) is ...            lo    hi         </div>		

Joint segmentation-positioning strategies that may be automated or implemented by an autonomous agent are then derived in the following manner:

Segmentation strategy for brand <i>b</i>	select the segment(s) with	target profile(s) equal(s)
<div style="text-align: center;">           These strategies exploit ratios on segment level only:         </div>		
"max conversion"	highest <i>AT</i>	average of all profiles sold
"offensive"	hi <i>BI</i> (i.e. many buyers) but lo <i>SC</i> (ie. tough competition)	average of all profiles sold
"defensive"	lo <i>BI</i> (i.e. few buyers) but hi <i>SC</i> (i.e. mild competition)	average of all profiles sold
<div style="text-align: center;">           This strategy exploits a brand-specific ratio only:         </div>		
"cost optimizer"	highest $BI_b$	average of all brand <i>b</i> profiles sold

These strategies are comparative i.e. exploit ratios on segment and brand-specific levels as well:

"build"	hi $AT$ and lo $BI_b$	average of all profiles sold
"maintain"	hi $AT$ and hi $BI_b$	average of all brand $b$ profiles sold
"harvest"	lo $AT$ and hi $BI_b$	average of all brand $b$ profiles sold

### 3.5 Perceptual response modeling

Marketing research has a long tradition of market response modeling (Parsons and Schultz, 1976; Hanssens and Parsons, 1993; Hruschka, 1996; Lilien and Rangaswamy, 1998). Therefore, it is a straightforward exercise to state the desirable properties which are required for the SIMSEG version of the perceptual response mechanism. Perceptual response in SIMSEG means changing the perceptions-generating probabilities in  $Q$  on disaggregate level. For each consumer, brand, and attribute the probability in simulation period  $t$  is subject to perceptual change; this  $\Theta_{change}$  depends on the 'perceptual change factor' ( $PCF$ ) and the 'perceptual change potential' ( $PCP$ ):

$$\Theta_t = \Theta_{t-1} + \Theta_{change}, \text{ where}$$

$$\Theta_{change} = PCF \cdot PCP, \text{ and the } PCP = (1 - \Theta_{t-1}).$$

Brand positioning in SIMSEG implies that the firms state their positioning objectives in terms of planned perceptual change for the attributes they deem decisive in the consumers' choice. Thus they aim at a 100 per cent probability that the consumers in their target segments associate a desired attribute with their brand. The higher this probability has become, the smaller is the maneuvering margin for further improvement. Even for the initial version it is inevitable that

- the perceptual change factor ( $PCF$ ) increases less than proportional and approaches a saturation level with a growing relative marketing budget.
- Second, a 'forgetting effect' is mandatory: Brand perceptions are subject to a constant decay rate unless the consumers' brand comprehension gets reinforced.
- Third, the perceptual response should exhibit a 'threshold effect'; reinforcement and brand attribute learning do not occur as long as the relative marketing budget lurks below a minimum level (i.e. a brand's 'fair share' of market operation).

In a simulation model each new parameter necessitates the analyst to account for an additional factor in the experimental design. A lean **two-parameters specification** fulfils the above mentioned requirements, if one accepts the restriction that the magnitudes of the perceptual change saturation level, the decay rate and the cutoff point, where the relative marketing impact gets strong enough to trigger learning and cease forgetting, cannot be separated from the slope of the response function. This implies that the consumers behave 'symmetrically'. In a 'nice' and highly responsive



market they start learning earlier and learn more and more quickly than in a 'nasty' and irresponsible market.

Under this rigid specification few variables and parameters are needed to yield the *PCF* for each consumer and each brand:

- The 'responsiveness'  $r$ , where  $0 < r$ , depicts the consumers' sensitivity for learning brand attributes.  $r$  determines the slope of the response function, the learning threshold and the upper limit (to be reached with a 100 per cent relative budget) at the same time.
- The persistency  $p$ , where  $0 < p < 1$ , describes lag effects; e.g.  $p = .8$  implies that 80 per cent of the perceptual level is maintained in case of an insufficient budget or for a brand attribute which is ignored in a promotional campaign. For high values of  $r$  the persistency also equals the perceptual change saturation level and the highest relative budget will not be able to boost the *PCF* to more than  $p$ .
- The decay rate  $(p - 1)$  denotes the magnitude of the forgetting effect in case of a 'below threshold' budget or an intentional neglect of some brand attribute.
- As a consequence of its segmentation and positioning strategy each brand assigns a marketing budget to the consumer segments  $s=1,\dots,S$  while respecting the budget limit  $\sum_{s=1,\dots,S} K_s \leq K_{max}$ .
- The marketing budgets of each brand are projected down to the disaggregate level of the individual consumer. Therefore, a 'personal' budget on the micro level for each brand and for each consumer results after dividing the segment-assigned budget by  $(\text{segment size})^{sf}$ . A 'scale factor'  $sf < 1$  is recommended to account for scale effects in market operation. A firm targeting more sizeable segments than its competitors employs more efficient mass media and achieves a better ratio of advertising OTS ('opportunity to see') and cost.
- Another step is required to transform this 'consumer-individual budget' into an 'impact-producing' quantity which serves as an appropriate independent variable in the response function. For all what is known about market communication mechanisms, a positioning strategy supported by a given amount of promotional funds is more effective if it offers focus in message content. The initial version of SIMSEG divides the 'consumer-individual budgets' by the number of attributes the brand managers decided to include in their target profile for a particular group of consumers. This number is raised to the  $pf^{\text{th}}$  power where  $pf > 1$  is recommended for the 'penalty factor'. Very realistically, a brand is penalized for trying to improve on many perceptual attributes all at once.<sup>5</sup>
- Finally, what matters on micro level is the brand's  $b$  relative marketing effort  $0 \leq K_b / \sum_{b=1,\dots,B} K_b \leq 1.0$  directed to a particular consumer.
- Noise  $\epsilon$  may be added in controlled portions.

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<sup>5</sup> Note that this is not a cost-driven rationale. For producing an advertising message and spreading it via mass media it makes little difference how many claims one squeezes into promotional appeals and arguments. The bottleneck is the recipients' selective awareness and processing capability. See the convincing results on information overflow repeatedly published by Werner Kroeber-Riel and his research team (e.g. Kroeber-Riel, 1980, pp. 226 ff.).

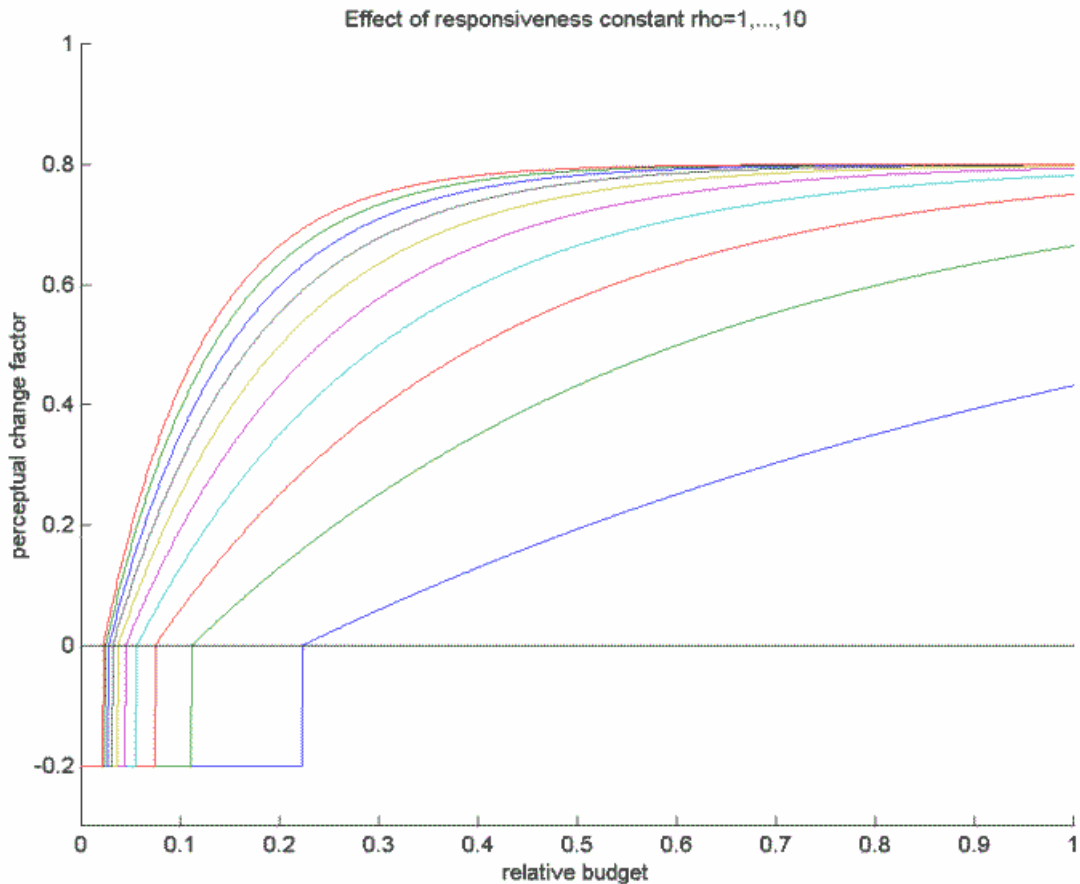
Let  $K_b$  be the budget for brand  $b$  and  $x_{tar}$  and  $x_{act}$  denote a variable of the brand's target and actual perceptual profiles in a market segment. An actual profiles corresponds to the average perceptual profile encountered in a market segment. It reflects the consumers' current perceptions in the beginning of the simulation period. Then the perceptual change factor for this perceptual variable amounts to a provisional value  $PCF_{pro}$ :

$$PCF_{pro} = \begin{cases} p - (e^{-r \frac{K}{\Sigma K}}) & \text{if } (x_{tar} - x_{act}) \geq 0 \wedge x_{tar} > 0 \\ p - 1 & \text{else} \end{cases}$$

and, according to the threshold effect, has to be reset to

$$PCF = p - 1 \quad \text{if } PCF_{pro} < 0.$$

The subsequent figure demonstrates how the responsiveness parameter  $r$  shapes the perceptual response curve. For a large  $r$  the learning gets accelerated fast, exceeds the learning-unlearning threshold at a lower budget level and approaches saturation earlier. For small values of  $r$  the response curve resembles a linear function which requires a higher relative budget to surpass the learning threshold and to attain a significant amount of perceptual change. The functions are based on a decay rate of .2 equivalent to a persistency (saturation) of .8.



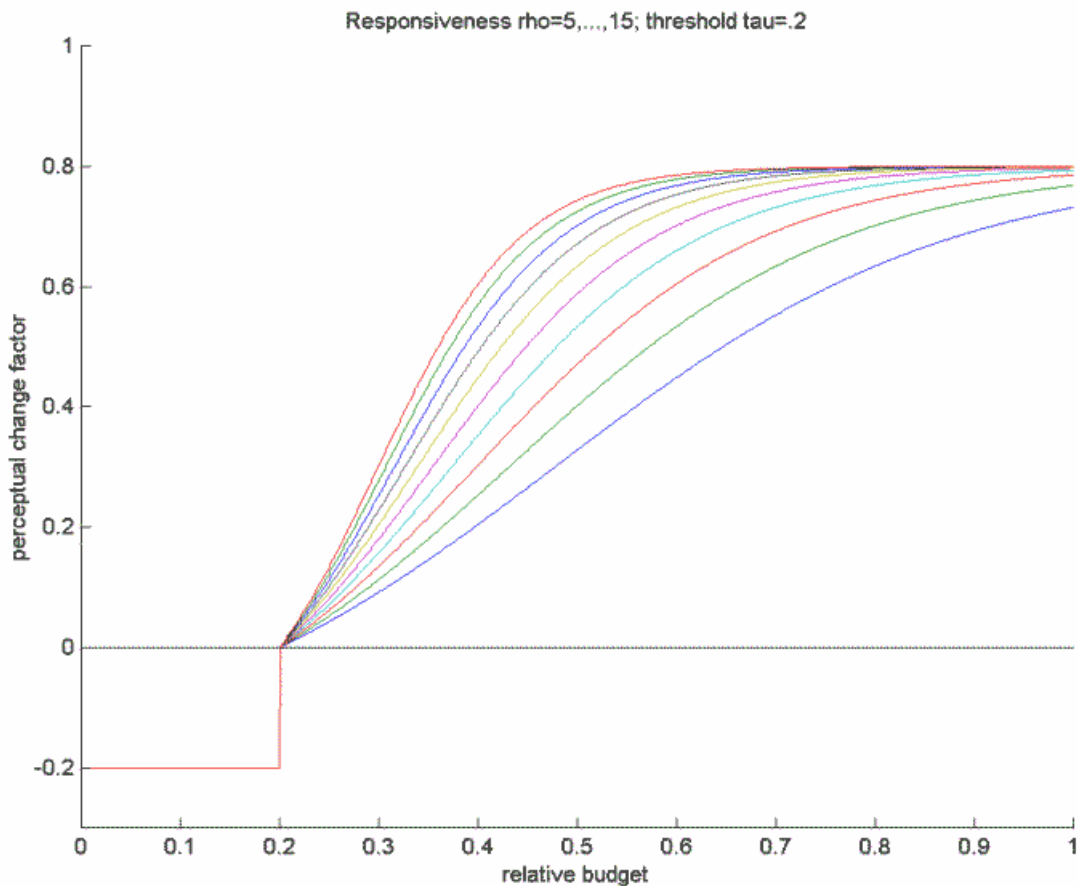
If the experimental design should allow for the separate control and variation of the response slope, threshold and saturation a **three-parameter specification** is adequate<sup>6</sup>. A realistic shape is logistic with a freely movable threshold budget governed by the parameter  $t$ :

$$PCF_{pro} = \begin{cases} \mathbf{p} \left( e^{r \left( \frac{K}{\Sigma K} - t \right)} - 1 \right) / \left( e^{r \left( \frac{K}{\Sigma K} - t \right)} - \mathbf{p} \right) & \text{if } (x_{tar} - x_{act}) \geq 0 \wedge x_{tar} > 0 \\ \mathbf{p} - 1 & \text{else} \end{cases}$$

Again,

$$PCF = \mathbf{p} - 1 \text{ if } PCF_{pro} < 0.$$

The figure below demonstrates how the three-parameter specification differs from its two-parameter alternative. Again the responsiveness and the persistency together determine the shape and the lower and upper limits, while the curve respects the budget threshold  $t$  for all values of the responsiveness  $r$  (persistency  $p$  uniformly set to .8).



<sup>6</sup> This specification was suggested by C. Buchta in the discussion of parsimonious vs. realistic response modeling.

The perceptual dynamics result from each simulation iteration creating a new perceptions-generating  $\Theta_{new}$  according to

$$\Theta_{new} = \begin{cases} \Theta_{old} + PCF (1 - \Theta_{old}) & \text{if } PCF \geq 0 \\ \Theta_{old} - |PCF| \Theta_{old} & \text{if } PCF < 0 \end{cases}$$

Perceptual change occurs if the firm decides to manipulate (some of) the brand's perceived attributes and its relative marketing budget directed to a consumer segment exceeds the threshold value. Any other situation results in attribute decay. This is of no harm if the brand has already attained a high level of an attribute assignment or the attribute is deemed irrelevant.

SIMSEG is not necessarily confined to artificial data operation. One may construct a zero period scenario by utilizing real world information. Consider a simulation run with four brands rated in 21 perceptual variables, six perceptual and three preferential segments in a total sample of 817 cases.<sup>7</sup> The perceptual and choice data in the starting period originate from an empirical example (Mazanec, 1999). The perceptions-generating probabilities for the brand profiles are initially set to equal the perceptual prototypes extracted from the observed data. Brand preferences are initially adjusted to the observed brand choices. Henceforth, each respondent seeks an 'ideal' profile according to the brand actually chosen in period zero. All consumers are compensatory decision makers and (randomly) choose one of these brands which offer the maximum number of attribute matches between the perceived and the desired profiles. Each firm receives the same information on the perceptual segment structure, which remains the constant basis of the firms' partitioning of the market. The information on brand choices is periodically updated and available to everybody. The 'ideal' profiles of desired attributes are hidden. The firms watch the profiles actually purchased. They adapt their own brand profiles according to what a qualified consumer majority (with a share of  $ml$  or greater) in their target segments seem to desire. The subsequent 10 iteration cycles assume that brands #1, #2, and #4 pursue "one-for-all" strategies. #3 aims to appeal to each segment individually by favoring a "one-for-each" strategy. Each brand invests an equally sized marketing budget of 1000 units and allocates it in proportion to the number of consumers accommodated by each market segment. Price effects are switched off. The parameters are set:

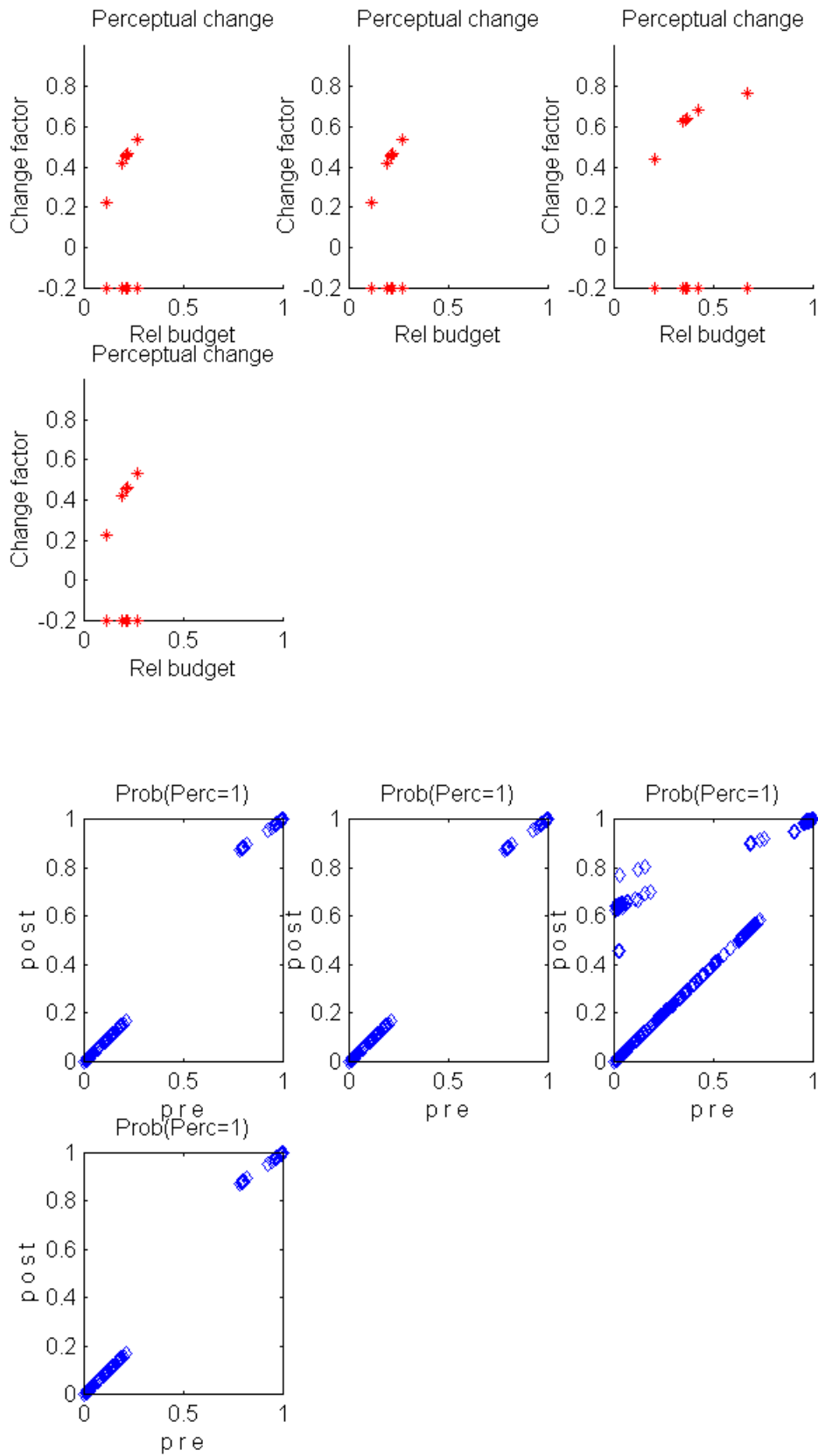
- persistency  $p = .8$ , i.e. decay = .2
- responsiveness  $r = 5$
- (economies of) scale factor  $sf = .9$
- (attribute exuberance) penalty factor  $pf = 2$
- desired attribute majority limit  $ml = .4$ .

The  $PCF$  functions in the subsequent graphs (upper panel) for period 8 demonstrate that brand #3 specializes in each segment. Being more selective in adapting its target profiles it achieves a higher perceptual response level than #1, #2, and #4 as these brands indiscriminately try to mimic the market average of the brand profile preferred. The same selectivity effect becomes apparent in the 'before-after' chart (lower panel) which

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<sup>7</sup> A MATLAB implementation `simseg.zip` of this simulation setup is available from the server <ftp://leisure.wu-wien.ac.at/pub/software/>. To launch a ten periods' simulation run start the `SSS_main_e` script.

compares the perceptions-generating probabilities before and after the promotional intervention in period 8.



The diamonds in the 'before-after' charts lying above the diagonal — like so many for brand #3 — point to those consumers, who experienced a learning effect regarding a brand attribute. Brand #3 steadily approaches the profile preferred by the consumers in each segment. Though it started in the 'dog' position in this product class brand #3 manages to excel the other three competitors after period 6. It finishes second-best in terms of accumulated revenues. As all brands applied the same amount of promotional funds and price effects are neutralized the market dynamics exclusively depend on the brands' segmentation-positioning decisions.

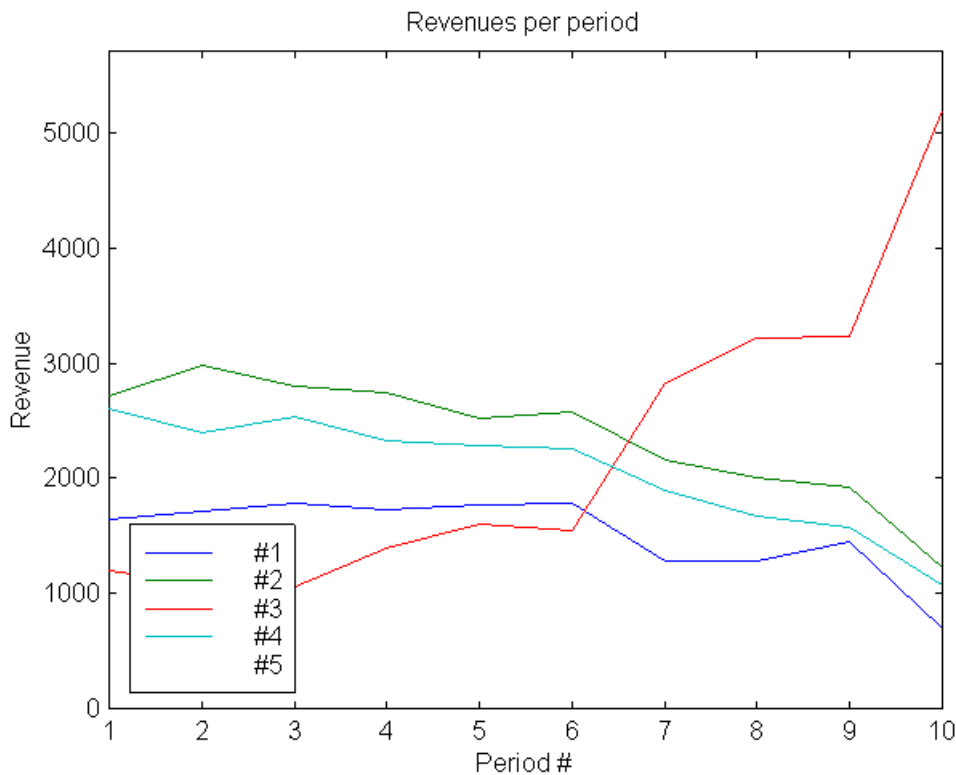
>>> implementing strategy for period # 10 <<<

one\_period\_revenues =

1650	2710	1200	2610
1710	2980	1080	2400
1780	2800	1060	2530
1720	2740	1390	2320
1770	2520	1600	2280
1780	2580	1550	2260
1280	2160	2830	1900
1280	2010	3210	1670
1450	1920	3230	1570
690	1220	5190	1070

Brands\_summed\_revenue =

15110	23640	22340	20610
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Note that #3, #2, #4, #1 is the revenue rank order in period 10.

#### **4. Future enlargement and refinements: Short and long-term prospects**

##### *4.1 Scenario setting for experimental designs and generation of artificial data*

The very simple example of the previous section already tells a lot about the controlled experiments which are required in the next stage of the SIMSEG project. Though there is a very limited set of parameter values a careful exploration of the sensitivity of the results will have to follow. The  $pf$  factor which penalizes the firms for practicing attribute exuberance or the 'desired attribute majority limit' ( $m$ ) are particularly suspect of exerting a crucial influence on the perceptual dynamics. These factors, however, have a distinct empirical meaning. They are likely to inspire the formulation of managerially relevant hypotheses in an explanatory model.

One also has to bear in mind that the periodical generation of new perceptions data is subject to random variation; a sufficient number of repetitive runs is necessary for each parameter setting. Once the crucial settings are better understood it makes sense to systematically explore the results of alternative brand strategies.

SIMSEG offers an environment for experimenting with artificial data of prespecified properties. This is particularly useful in analyzing the predictive power of various choice models, which are trying hard to master consumer heterogeneity. While MNL models make significant progress in incorporating nonlinear utility functions (Hruschka, Fettes and Probst, 1999) the effects of consumers' parameter heterogeneity are still largely unexplored. Things become still more intricate if the artificial market permits the consumers to follow different choice rules. It is worthwhile to ascertain where the limits of a parametric representation of brand choice decision making are under controlled 'model heterogeneity'. It will also be rewarding to examine the conjoint effects of A and S agent combinations as some segmentation strategies may be less dependent on highly accurate choice modeling on micro level.

##### *4.2 Relaxing restrictive assumptions and coupling with the 'Artificial Factory'*

It is a long-term goal that SIMSEG develops into a market simulation environment for the 'Artificial Factory' (AF) as conceived by the SFB Research Initiative #5 (Mild et al., 1999). Obviously, this will add further complexity. "Do we really need this to capture the phenomena under study?" will be a question regularly raised. Coupling with the AF tackles one of the unresolved puzzles in marketing modeling i.e. interfacing between the consumer expectations and the physical/functional product/service attributes. The AF decided to center their simulation on the House of Quality concept (Hauser and Clausing, 1988). It is a framework to assist a company in securing customer-driven product design; the interfacing between the customer perceptions and the product engineers' objective measures is portrayed in a 'relationship matrix' (Urban and Hauser, 1993, p. 343). It would be too simple to have the market simulation responsibility end with feeding perceptual response into this 'relationship matrix'. The process is two-way and the market research specialists are encouraged to suggest the instruments for measuring consumers' reactions to new or modified product features. There is a negotiation, mutual consulting, forecasting, or test marketing process and, of course, the measurement of actual sales results — frankly — a research agenda for decades ...

If the SIMSEG—AF connection is to avoid the simulation overflow syndrome the system dynamics must be expanded prudently. Under the 'learning organization' paradigm the

collaborative agents involved in market analyze, marketing strategy building, product design, production, finance, etc. must not become 'smart' simultaneously. In the market domain of simulation research a stepwise introduction of learning agents performing analysis and strategy is recommended. These new sources of marketing intelligence for the AF may then be confronted with a consumer population exhibiting an individual memory of past brand choices and acquiring brand loyalty. (So far, the learning has been limited to perceptions.) Another step in consumer learning relates to preferences. As startling as it is, very few authors in economics and marketing have investigated the evolution of preferences (Ramaswamy, 1997; Brenner, 1999). It is tempting to check for oscillation or convergence when the consumers adapt their (hidden) 'ideal' profiles according to the actual brand attributes encountered in repetitive simulation periods.

A fundamental issue of linking SIMSEG to the AF deals with the firm's habits of setting objectives. So far, the SIMSEG brands have operated on predetermined marketing budgets. Once the integration of the AF/market system has progressed to include cost functions a superior level of corporate planning comes into play. In principle, the marketing simulation can easily be transformed into a gross profit or contribution maximizing exercise. Conventionally, this is achieved by 'misusing' the simulation mechanism to provide forecasts. In SIMSEG this is straightforward on condition that the firm (brand) makes explicit assumptions about the competitors' synchronous budget appropriations.

There is also room for unlimited imagination concerning the dynamic aspects of marketing strategies. Multiperiod planning may become an issue for simulation experiments when the firms are free to define long-term goals. Finally, the multi-faceted notion of adaptivity offers a hierarchical interpretation too. Once an S-agent has become smart enough to autonomously improve through rule-learning, adaptivity hops one level upward: Meta-strategies govern the way a lower-level marketing strategy is optimized by trial and error. Thus one ends up in learning rules of how to learn rules ...

#### *4.3 A real-world electronic market: Adjustments for experimenting with the information products of the WU Virtual University*

If the SIMSEG team were to get bored by lab-only experiments they may turn to another option. The WU Virtual University has agreed to conduct controlled field experiments by streamlining their information services and by monitoring customer behavior. The VU mobilizes a worldwide market of Internet users who are willing to abandon their anonymous status and participate in accessing distance learning and information products. The VU does not yet charge their clients any fees and does not advertise in the mass media other than the WWW (except some occasional reports in a daily). The most promising marketing instrument is customizing its products in a segment-specific manner. The SIMSEG philosophy lends itself for intangibles as well. The research team is also optimistic to identify VU services which are competing with each other and considered as marketable units of sufficient distinctiveness. Special incentives may be appropriate to obtain the required feedback on perceived service attributes.

It pays off to make major investments into the VU option; once equipped to do the job it will generate an instantaneous and never-ending influx of customer and product data



## **B. The SIMSEG 1.0 technical implementation** (T. Baier)

The current version of the SIMSEG software represents an implementation of the concepts described in Part A of this paper. This Part B will outline the design of the SIMSEG implementation and the ideas underlying this design.

The first section will focus on the requirements which led to this design, then the logical structure of the simulation is presented. After a summary of the computational model used for SIMSEG 1.0 the object-oriented approach to the current implementation is discussed. Part B concludes with an overview of how to customize and extend the current system.

### **1. Requirements**

#### *1.1 A highly configurable computational engine*

Besides the structure of the simulation process in general, all computational parts shall be configurable.

On the one hand, the simulation shall provide means to test different marketing strategies for different brands, so it is absolutely necessary for the user to be able to implement these strategies himself and integrate new strategies into the simulation. On the other hand, even the “computational back-end“, i.e. the process of the customers choosing the brands and the update of the customers' perceptions after every brand applying a marketing action, shall be customizable to test various assumptions on the behavior of customers and the effects of marketing action on these behaviors.

#### *1.2 Extensibility and ease of maintenance of the system*

While the overall structure of the simulation is constant, data processing, logging and the presentation of simulation results varies. Furthermore, one of the goals of this simulation environment is to become part of some much larger marketing simulation, possibly a distributed simulation environment, where modules of the current simulation (e.g. the customers) will be completely replaced with different functionality.

#### *1.3 Providing different views of the simulation to different users*

Because of the highly configurable design of the simulation, the whole system will be of fairly high complexity—even to the user. However, the users of the system should only be exposed to a minimum amount of complexity. If, e.g., a user just wants to test some (already implemented) marketing strategies, he should not be bothered with the internal structure of the simulation. The only thing he should have to know is how to specify the use of the strategy he intends to test.

These requirements are met by a mixture of an *object oriented* design and a partly procedural interface. Additionally, the objects required for initializing a simulation are created using *high-level constructor function* where only the absolutely minimum knowledge of the system is required.

In addition to designing different views of the system, it is also an intended goal to provide a graphical user interface for the most common actions to allow easy access to simply “using” the simulation.

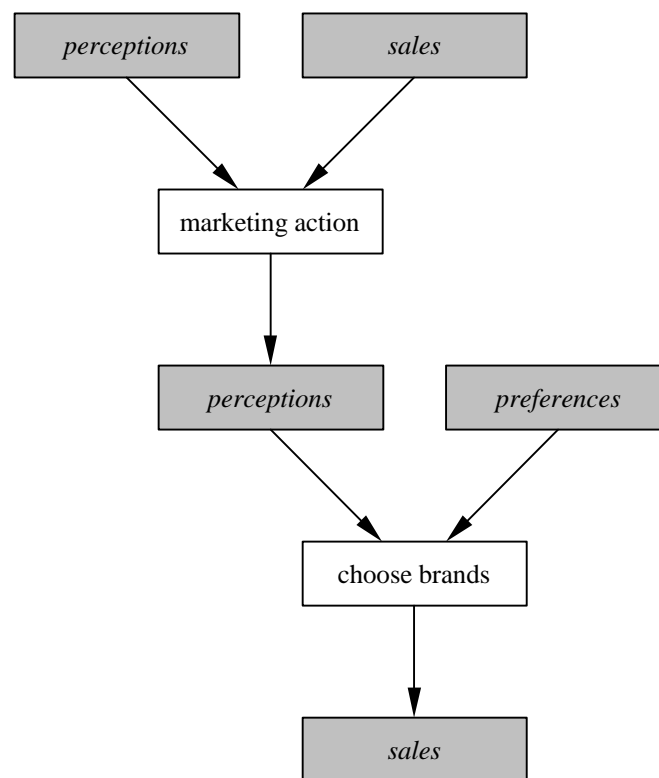
#### 1.4 Provide means for multiple (replaceable) front-ends

While the first implementation of SIMSEG is an environment, which combines both front-end (providing means of configuration and a runtime module) and computational back-end, it should be possible to offer various front-ends to different users while still using the same back-end functionality.

Therefore the front-end part of SIMSEG is designed as a very simple — replaceable — part of the system, which maintains much of its functionality in a form that provides *re-usable* components for other possible front-ends.

## 2. Logical structure of the simulation process

The following figure illustrates the (repeated) simulation process concerning control and data flow:



This figure highlights the data and the control flow in a single computational unit of the simulation process. As this unit is executed repeatedly, it is called a *simulation cycle* and consists of

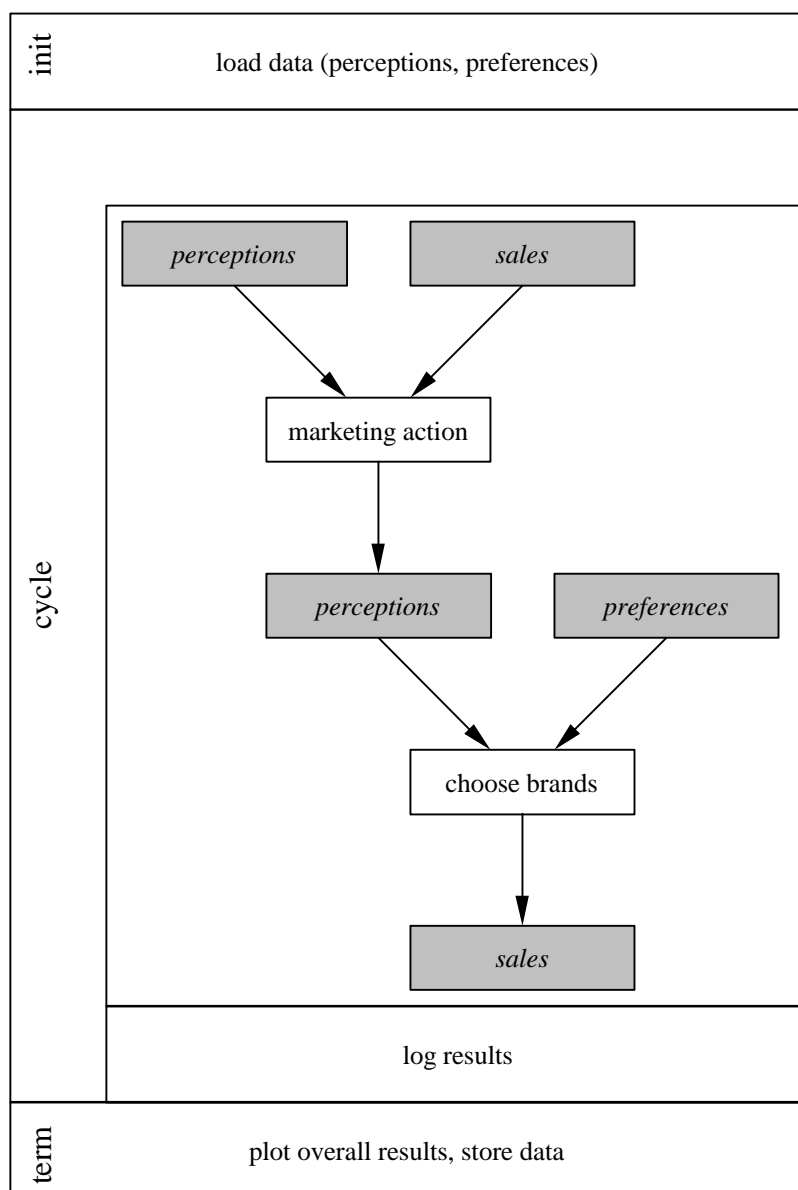
- a *marketing action*, based on the perceptions of the customers and the most recent sales record. Every brand has the chance to set its own marketing actions, while the simulation framework is responsible for updating the perceptions of the customers according to the results of the brands' market operations;

- the customers *choosing brands*; this action — based solely on the perceptions and the preferences of the individual customers — will then lead to new sales data and so to required information for the next simulation cycle.

The process of simulation itself consists of three phases,

- initialization, where eventually data is loaded and the whole system is initialized. this also includes a first step of choosing brands to provide the necessary input (sales records) for the first simulation cycle;
- cycle, as described above, and
- termination, where normally the overall results are visually displayed.

This overall simulation process is illustrated by the following figure:



### 3. The computational model used in SIMSEG 1.0

In this section, the simulation environment is outlined, where

- $n_b$  denotes the total number of brands (products) in the simulation,
- $n_a$  is the number of attributes of brands as seen by the customers and
- $n_c$  is the number of customers in the virtual market.

#### 3.1 Initialization

To start the simulation process (i.e. the computations for every simulation cycle), initial data must either be loaded from a file or generated (randomly). Persistent data, which can be loaded to initialize a simulation, represents the full internal state of the simulation environment ready to compute a simulation cycle. If a simulation is started from scratch, in most cases the data is generated randomly according to some suitable algorithm (see Dolnicar, Leisch and Weingessel, 1998) for more information on generating artificial data).

The customers' internal data structure is represented by

- a three-dimensional array of probabilities ( $R \in [0,1]^{n_c \times n_a \times n_b}$ ), where  $R_{i,j,k}$  represents the probability that customer  $i$  believes brand  $k$  has the attribute  $j$  and
- a  $n_c \times n_a$  matrix  $\in [0,1]^{n_c \times n_a}$  called  $P$ , where  $P_{i,j}$  denotes the importance of the availability of attribute  $j$  in a brand for customer  $i$ , viz. the customers' preferences.

In a very simple approach,  $R$  is initialized with random deviates from the uniform distribution. To provide better results,  $R$  is generated according to some pre-defined parameters (see Dolnicar, Leisch and Weingessel, 1998), or  $R$  can even be initialized with the results of a real world survey amongst customers.  $P$  is normally loaded from a file.

The step of (random) initialization is completed with the computation of the customers' array of (binary) perceptions and of the simulation's initial sales records.

#### 3.2 Computing the perceptions

The customers' perceptions of the set of brands (and their attributes) are represented by another three-dimensional array, where  $\dim(R)=\dim(S)$  and  $S_{i,j,k}$  is 1 iff customer  $i$  thinks brand  $k$  has attribute  $j$ . Else,  $S_{i,j,k}$  is 0.

The perceptions  $S$  are computed from the probabilities  $R$  randomly, where  $R_{i,j}$  denotes the probability of  $S_{i,j}$  being 1.

$$f : [0,1]^{n_c \times n_a \times n_b} \rightarrow \{0,1\}^{n_c \times n_a \times n_b} \mid R_{i,j} \rightarrow \begin{cases} 1 & \text{if } \text{rand}() > 1 - R_{i,j} \\ 0 & \text{else} \end{cases}$$

This function is a property of the concrete implementation of the customers and can be configured or completely replaced by the user.

### 3.3 Computing sales data

Based on the customers' preferences ( $P$ ) and their perceptions ( $S$ ) every customer will choose exactly one brand in every simulation cycle (and in the initialization phase).

The choices of the customers are stored in a matrix  $C \in \{0,1\}^{n_c \times n_b}$ , where  $C_{i,j}$  is 1 if customer  $i$  chose brand  $j$ , 0 else. From every customer's individual choice, the total sales data is computed.

In the first version of SIMSEG, every customer is assumed to choose exactly one brand in every simulation cycle.

Brand  $j_i$  chosen by customer  $i$  is the brand having the minimum deviation from the customer's perceptions of this brand (with a 5 per cent noise ratio) from his preferences. Assuming  $\bar{R}$  to be the array of perceptions with a noise ratio of 5 per cent,

$$j_i = \min_b \sum_a |\bar{R}_{i,a,b} - P_{i,j}|$$

Again, this formula is a replaceable property of the concrete implementation.

This results in a vector of sales  $T \in \mathbb{N}^{n_b}$ , where

$$T_j = \sum_i C_{i,j}.$$

### 3.4 Setting a marketing action

Every simulation cycle gives every brand the chance to set a marketing action used in computing the sales in the current cycle.

Setting a marketing action consists of mainly two distinct steps,

- a step of *data analysis*, where a segmentation of the data is performed and
- applying a *marketing strategy* on the clusters found in the segmentation process. The result of this step is a modification in the perceptions of every cluster as requested by the brand.

The simulation environment then applies the results of the marketing strategy on the customers' probability matrix  $R$  and then re-computes their perceptions  $S$ .

#### 3.4.1 Segmentation of perceptual data

Every brand is passed the customers' current perceptions and the latest sales data (matrix  $C$  from the previous simulation cycle or from the initialization step).

The segmentation process either applies a predefined segmentation algorithm (locally defined for each brand) on the perceptions or a pre-computed segmentation is "bought" i.e. provided by an outside market research unit.

In any case, the segmentation process is a function based on the customers' perceptions and the last sales data resulting in a number of clusters of customers. The number of segments depends on the brand's marketing objectives and its budget limit.

$$f(S, C) = U$$

Data partitions computed for different brands based on the same analytical tool are controlled to result in the same segmentation.

### 3.4.2 Choosing marketing action

The results of the segmentation process are then passed to a marketing function, where a marketing action for each segment is computed and changes to the segment's perceptions are requested by setting positioning objectives.

The results of the marketing strategy are based on the customers' perceptions, the last sales data, the segmentation scheme, and the budget available.

This function returns the requested changes in the customers' perceptions.

Again, each brand can either choose a new marketing action in every cycle, apply the same market operation again for a pre-defined number of cycles, or stick to the same strategy throughout the whole simulation.

### *3.5 Applying the brands' strategy changes to the market*

The simulation framework collects the action plans of each brand's marketing strategy per simulation cycle and applies these influential patterns to the customers. See part A, section 3.5 for a description of one algorithmic approach to this functionality.

## **4. Design of the simulation framework**

To meet all these requirements and to keep the whole system open for enhancements, an object-oriented approach to the design of the simulation framework has been chosen. This section describes the data model, a completely object-oriented design of a simulation framework, and some simplifications to provide easier access to configuring and extending the system.

### *4.1 Data model and data encapsulation*

Data encapsulation provides many advantages. One of the most appealing features of this technique is that, because every access to the data is achieved by using designated *accessor functions*, the internal data structure itself is of no concern to its clients, e.g. to some concrete implementation of a marketing action.

Therefore the clients (in our case, e.g., new implementations of marketing strategies) are not affected, if the internal data structure is completely redesigned or enhanced to meet new requirements.

The simulation's data model has already been mentioned in the previous section. It mainly consists of

- a number of *brands*, their marketing strategies and some internal data required by the strategies,
- the customers' *preferences*,
- their *perceptions*, resulting from previous marketing actions of the brand-owners and
- the last *sales data*, which is a required input for the marketing strategies.

Additionally some internal data is stored, e.g. some shared segmentation data required by all brands. Access to this data is provided totally transparently to the individual clients of this data.

Basically, the individual brands are not required to store any data for themselves, because they are provided with current data every time some of their functionality ("methods") is invoked. Only if, e.g., a brand requires access to historic data for the marketing actions, concrete implementations of brands will have to manage instance data. For this case, generic mechanisms for storing data with a brand are provided.

Both *preferences* and *perceptions* are attributes of customers, while *sales data* is a property of the simulation engine in general.

From the data model view, three classes can be identified,

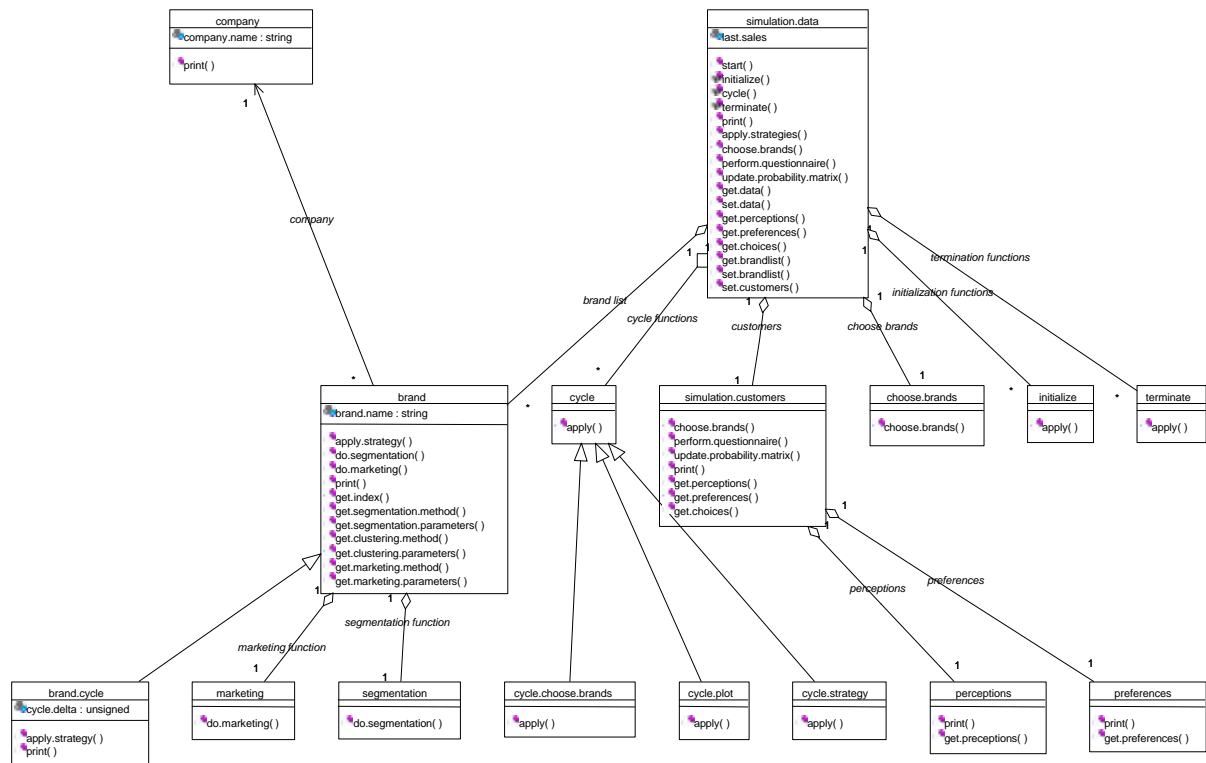
- *brand* only containing internal data used by the brand-owners for applying marketing actions,
- *customers* encapsulating the customers' preferences and their perceptions of the various brands and
- *simulation* being responsible for the most recent sales data.

#### 4.2 Full OO design of the simulation environment

To simplify the simulation process from the user's viewpoint, the whole simulation is encapsulated in a single data structure. The class contains all required data, mostly a list of brands and the customer data (perceptions and preferences).

The main entry point to the simulation is the function `start()`. It is responsible for performing initialization, simulation cycles and termination. Furthermore, it contains the logic for starting the brand owner's marketing actions and letting the customers choose brands or perform surveys.

The following figure is the result of this design as a class diagram in UML notation as described in Booch, Jacobson and Rumbaugh (1998). This diagram shows the main classes and their relations.



This design relies heavily on the “strategy pattern” as described in Gamma, Helm, Johnson and Vlissides (1995) to provide encapsulation of algorithms and easy replacement of one “strategy” with another. E.g. the main simulation engine (class `simulation.data`) delegates all concrete computations to the various brand and customers objects. Even basic functionality, like initialization, cycle and termination are assigned to distinct objects providing the real implementations. Brand and customers objects in their case delegate computational work to objects like “marketing”, “segmentation” etc.

The idea behind this design philosophy is its capability of providing a simulation framework that can be used for most purposes, while the specific implementation is taken care of by some “objects” and external functions.

#### 4.2.1 `simulation.data`

Objects of the class `simulation.data` represent a whole simulation. All required data and processing capabilities are encapsulated in this class or one of its related classes.

It consists of

- a *list of brands*, responsible mostly for applying the marketing actions for the brands,
- a *customers* object, which represents the set of customers in the simulation environment, including their perceptions of the brands, and their preferences and
- a number of *initialization*, *cycle* and *termination* objects, all conforming to some abstract interface and representing the whole simulation logic.



From an abstract viewpoint, `simulation.data` does not have any computational capabilities itself; it is only responsible for encapsulating all data required by the simulation and *delegates* the concrete functionality to *external objects*.

The delegation approach enables the user to fully configure the simulation by simply providing a list of objects, which then implement the concrete simulation process.

All instance methods of this class only delegate responsibility to external objects or forward the request to the direct relatives (e.g. a request to choose brands is forwarded directly to the related customers object).

An instance of this class represents the runtime environment and a very simple front-end for the user in the first version of SIMSEG.

#### 4.2.2 `simulation.customers`

Concerning data management, it is clear, that a customers object is responsible for managing the customers' *preferences*.

In the current design, the customers object is also responsible for “caching” the last questionnaire data, the customers' *perceptions*.

From an algorithmic viewpoint, the class `simulation.customers` is responsible for implementing algorithms to let the customers *choose brands*, to answer to a *questionnaire*, and to update the perceptions according to the marketing actions taken by the brand-owners.

#### 4.2.3 `simulation.brand`

Objects of the class `simulation.brand` are used to encapsulate the functionality and the data required for brands.

The functionality implemented for concrete brands is the computational method used for applying a marketing strategy according to the current marketing data. Our “standard” brand's strategy consists of

- a segmentation phase to identify various clusters of customers. The clusters (or to be more precise, their centers) is then targeted for the concrete
- marketing action. The marketing action then returns the requested change in the preferences the brand owner is aiming at.

The segmentation algorithm can compute a new segmentation per brand per cycle, use one *shared* segmentation for all brands in a cycle, or just use a previously computed segmentation again and again for many cycles. Like the segmentation algorithm, the marketing action unit can compute new results in every cycle or can use previously computed results for a number of cycles or throughout the whole simulation.

The simulation framework then will send the customers the brand owners' requests and the customers will adjust their perceptions according to these *marketing actions*.

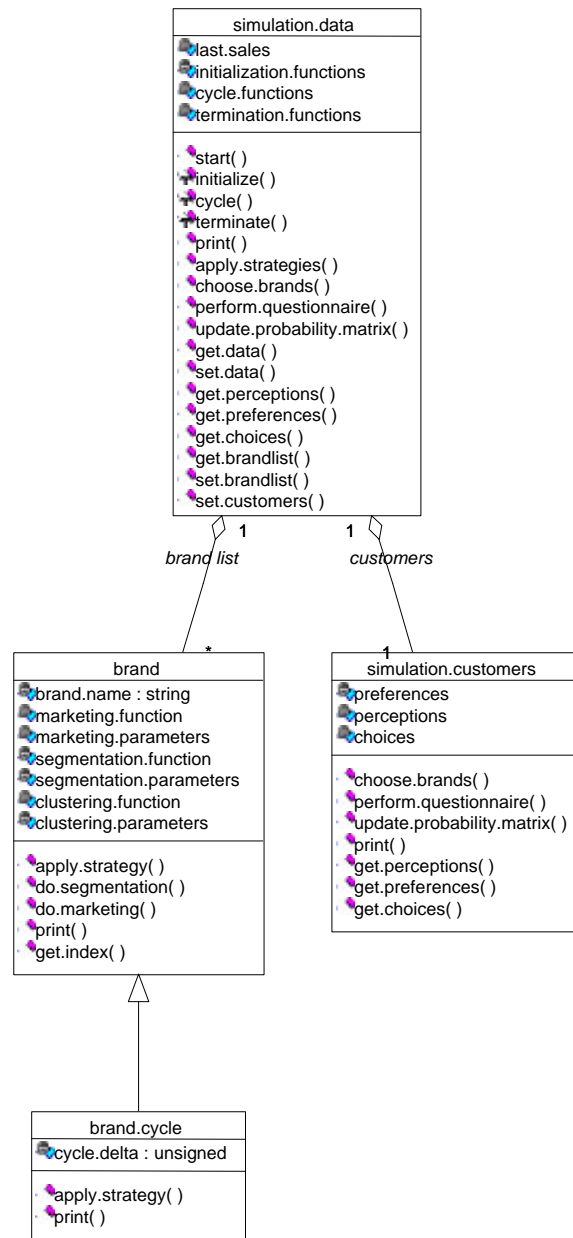
### *4.3 Simplified design*

To simplify the process of implementing and testing new marketing strategies, the object-oriented design as presented in the previous section has been relaxed to integrate a more procedural — and so for most of the users of the system a much simpler — approach.

Wherever it is likely that users will add their own functionality, the object-oriented design is replaced by mere function calls. It is assumed, that most of the users of the simulation are familiar with the concepts of procedural programming, but not with object-oriented programming.

Nevertheless, the basic design philosophy underlying the simulation framework is truly object-oriented. To totally change the behavior of the simulation, to change the way, customers choose the products, to break up the factory-settings for brands, one must inherit from the corresponding classes and override the methods.

The simplification of the design is depicted in the following figure.



## 5. Configuring a simulation

### 5.1 Creating an object model

For the end-user the whole simulation is represented by a single object, an instance of `simulation.data`. To run a simulation, the user either creates a simulation object from scratch (normally by using some of the provided prototypical simulation objects) or an object is loaded from a file.

Creating and initializing a simulation object is a process normally consisting of three steps:

1. create and initialize a list of brands used in the simulation,
2. create and initialize an object representing the market itself, a “customers” object and

3. create a simulation object and tell it which brands and which customers object to use.

To provide easy access to the simulation, a rich set of prototypical objects is provided, which can be used as “templates” for creating new brands, customers objects or the simulation itself.

### *5.2 Using object prototypes*

SIMSEG provides a number of prototypical objects (see Gamma, Helm, Johnson and Vlissides (1995)) used in building a concrete simulation. To create an object model, you normally choose from the prototypes (prototypical brands, prototypical customers and prototypical simulation) the ones most closely matching your needs, *clone* these prototypes to get your own objects and modify the copies to your needs.

### *5.3 Changing prototype instances*

As the prototypes provided by SIMSEG will in most cases not be exactly what one wants, one will have to slightly modify the prototypical instances created by cloning an object prototype.

E.g. when creating and configuring a brand for a simulation, you will normally choose from the prototypical brands one using the marketing strategy you want to use and then simply modify the properties of the clone you created from this — normally just set the brands’ names — and add it to the simulation.

## **6. Extending the system**

The simulation system can be extended by means of adding simple functions (e.g. the user’s own implementations of marketing strategies) or by subclassing some of the system-provided classes.

### *6.1 Providing functions*

In most cases, users can simply add functions for enhancing the simulation system or changing its current behavior. At the moment, the whole simulation process can be customized by providing user-defined functions.

#### 6.1.1 Segmentation and marketing action

When testing new marketing strategies, probably one of the first places where to extend the current simulation is to implement your own segmentation functions and marketing actions.

The standard implementation of a brand will call both a brand’s segmentation function and its marketing function. The user may simply create new functions conforming to the standard interface and use them in the simulation. Just set the brand’s `segmentation.method` and `marketing.method` properties to the names of your functions. Additionally, specify parameters passed to your functions in the brand’s properties `segmentation.parameters` respectively `marketing.parameters`.

### 6.1.2 Providing custom initialization and termination functions

The open design of the simulation environment makes it possible to add user-defined functions to every phase of the simulation process.

One may simply write functions to be used as initialization, cycle or termination functions and add them to the simulation object (`simulation.data`). The simulation object contains lists of initialization, cycle and termination functions, which are invoked automatically. Just add new functions to these lists and they will be called by the simulation framework SIMSEG.

The user-specified initialization functions are executed *after* the framework has initialized itself, the cycle functions are called when all computations for the current cycle have been done, and the termination functions are called before the framework terminates.

In all three cases, unlimited access to all the data managed by the simulation framework is granted.

You should provide your own initialization, cycle or termination functions e.g. when implementing custom logging or plotting functions.

SIMSEG's internal logging and plotting capabilities are implemented using these extension mechanism.

### *6.2 Subclassing*

While most customization and enhancements can be achieved simply by installing user-defined functions, some of the frameworks behavior can only be changed by means of a technique called *subclassing*.

E.g. changing the application of a marketing strategy for a brand or updating the customers' perceptions in response to the marketing strategies requires subclassing brands or customers respectively.

Consider the need for a brand type where the marketing actions should only be applied every two simulation cycles. This can be achieved by *overriding* the current's `simulation.brand` function `apply.strategy()` and using the newly created subclass for simulation.

Other examples of functionality enhancements requiring subclassing are implementing new algorithms for updating the customers perceptions or for the customers choosing brands — both requiring subclassing `simulation.customers`.

To simplify the use of subclassing, each of the classes in SIMSEG provides means for dynamically storing and retrieving data with every object. So you can access new instance data when subclassing without structurally modifying or extending internal data structures or even in cases, where you just provide replacement functions for, e.g., a segmentation or marketing strategy.

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