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Accommodating the Effects of Brand Unfamiliarity in the Multidimensional Scaling of Preference Data

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Abstract

This paper presents a multidimensional scaling (MDS) methodology (vector model) for the spatial analysis of preference data that explicitly models the effects of unfamiliarity on evoked preferences. Our objective is to derive a joint space map of brand locations and consumer preference vectors that is free from potential distortion resulting from the analysis of preference data confounded with the effects of consumer-specific brand unfamiliarity. An application based on preference and familiarity ratings for ten luxury car models collected from 240 consumers who intended to buy a luxury car within a designated time frame is presented. The results are compared with those obtained from MDPREF, a popular metric vector MDS model used for the scaling of preference data. In particular, we find that the consumer preference vectors obtained from the proposed methodology are substantially different in orientation from those estimated by the MDPREF model. The implications of the methodology are discussed.

Multidimensional scaling models for the analysis of preference data have been widely used in marketing for more than two decades (Green and Carmone 1970). These models provide a spatial representation of stimulus (brand) locations as well as subjects (consumers), typically represented either as vectors or as ideal points. The input data are usually preference judgments from consumers for the various brands in the evaluation set. These consumers may not be equally familiar with the different brands in the set; indeed, they are likely to be more familiar with certain brands (e.g., those previously purchased) than others. Traditionally, MDS models have not taken into account the consumers' degree of familiarity with the different brands. If, however, a consumer's preference judgment of a brand is influenced by the degree of familiarity with the brand – and both intuition and formal evidence suggest that this is so – then the joint space representing brand locations and subject preferences derived from MDS preference models may re-

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flect some confounding of preference and the degree of familiarity. Our objective is to propose a procedure that attempts to disentangle this confounding so that the effect of unfamiliarity is, in effect, "filtered out" of the derived joint space.

Product familiarity is defined by Alba and Hutchinson (1987) as "the number of product-related experiences that have been accumulated by the consumer" (p. 411). Product related experiences are defined "at the most inclusive level . . . [to] include advertising exposures, information search, interactions with salespersons, choice and decision making, purchasing, and product usage in various situations." Our focus is on familiarity with a specific *brand* within a category; in our context, the degree of familiarity with a brand corresponds to the extent of knowledge the consumer has about that brand.[1]

We develop a methodology that seeks to derive a MDS joint space representation of brand locations and consumer preference vectors under the (unobserved) condition of complete familiarity of the consumers with all the brands in the evaluation set, while simultaneously estimating the effects of the degree of familiarity on brand preference for each consumer. In terms of input data, the procedure calls for each consumer in the sample to provide two ratings – preference and familiarity – for each brand in the evaluation set. Further, replications can be accommodated, so that the input data may be *three-way* (consumer $\times$ brand $\times$ replication) matrices of preference and familiarity measures.[2] Our methodology extends the basic vector preference model underlying MDPREF (Carroll and Chang 1964) by incorporating the impact of unfamiliarity on preference. Thus, MDPREF, which is one of the most widely used MDS procedures for analysis of preference data, serves as a natural "baseline" model – a potential benchmark for evaluating our procedure.

Among *probabilistic* MDS models that have been developed both for proximity data (Ramsay 1977; Takane 1978) and for preference data (De Soete and Carroll 1983; De Soete, Carroll and DeSarbo 1986; DeSarbo, De Soete and Jedidi 1987), those proposed by Zinnes and MacKay (1983, 1987; MacKay and Zinnes 1986; MacKay 1989) incorporate probabilistic stimulus locations. The distribution describing the brand locations is estimated from data consisting of either dissimilarity or preference ratio judgments between brand pairs. Brand unfamiliarity must be *inferred* from the estimates of the standard deviations of the brand coordinates. In contrast, our approach *separates out* the effect of unfamiliarity in deriving the joint space by using a *direct* measure of brand familiarity (along with preference ratings) to estimate a preference-familiarity relationship.

We first present the model and describe the estimation procedure, followed by an actual application of the proposed methodology involving luxury car preference. We conclude with a summary of the implications of the procedure and a brief discussion of its limitations and directions for future research.

1. Methodology

1.1. The model

Our model formulation is based on the following assumptions.

1.1.1. ***(a) Perceptions.*** Under complete unfamiliarity (no information), a brand will be perceived as "average" for the product category. With increasing familiarity, brand perceptions will move away from the category "average" toward the brand's "true" location. Further, the change in perceptions may not be linear in the degree of familiarity – in particular, the marginal impact of additional information on perceptions may be smaller at higher levels of familiarity.

The premise regarding brand perception under complete unfamiliarity follows from the phenomenon of typicality (schema)-based inference making (Alba and Hutchinson 1987; Sujan 1985). Once a product has been categorized, attributes on which a consumer is uninformed will be "filled in" with values typical for the category. Similarly, Slovic and MacPhillamy (1974) suggest that a partially described option is judged as average along the unknown dimensions; this is empirically supported by Yates et al. (1978). In marketing, Meyer's (1981; Meyer and Sathi 1985) multiattribute judgment model implies that, as a consumer obtains information on a brand's attributes, his/her belief about the level of an attribute moves away from the product class mean toward the brand-specific value.

1.1.2. ***(b) Perceptual uncertainty.*** With increasing familiarity, there will be an increase in confidence in beliefs, or (equivalently) a decrease in uncertainty about the brand's location.

This assumption follows directly from Howard's (1977) model of buyer behavior. Meyer's (1981) model also posits that uncertainty in beliefs about the brand decreases with brand-specific information. Further, the dynamics of perceptions with increasing information as stated in the above two assumptions – in terms of reduced uncertainty, trend toward "true" attribute values, and decreasing marginal impact of information – is consistent with Bayesian consumer learning models (Gatignon 1984; Roberts and Urban 1988; Chatterjee and Eliashberg 1990), as well as the information integration literature (Anderson 1981).

1.1.3. ***(c) Preference.*** Brand preference may be modeled as having two components. Given a brand's location, the first component may be represented by a standard vector preference model. The second component is an adjustment due to uncertainty (partial information about the brand). For example, under uncertainty avoiding (risk averse) behavior, this adjustment may be negative.

There is an extensive body of literature on the impact of uncertainty on preference (e.g., Lee 1971; in consumer behavior, see Bauer 1960; Bettman 1973). The notion of attitude toward risk is central to modeling preference under uncertainty (Keeney and Raiffa 1976; Pratt 1974; in marketing, see Currim and Sarin 1983; Eliashberg and Hauser 1985). Meyer (1981) models brand preference as a function of the average value and perceived dispersion (uncertainty) for each attribute, combined across attributes. The Yates et al. (1978) study found subjects discounting their preferences under uncertainty.[3]

Thus, given the above premises, the degree of brand familiarity affects preference in two ways. First, the brand location (perceptions) moves toward the true location with increasing familiarity, causing a change in preference (the "location" component). Second, increasing familiarity reduces the "uncertainty adjustment" component of brand preference.[4]

Let:

$i = 1, \cdots, I$ consumers;

$j = 1, \cdots, J$ brands;

$t = 1, \cdots, T$ dimensions;

$k = 1, \cdots, K$ replications;

f_{ijk} = consumer i's familiarity with brand j on replication k,

$0 \le f_{ijk} \le 1$ (0 = totally unfamiliar, 1 = totally familiar);

p_{ijk} = consumer i's preference for brand j on replication k;

w_{it} = the t^{th} coordinate of the terminus of consumer i's preference vector (i.e., $w_i = (w_{it})$ is consumer i's preference vector);

x_{jt} = the t^{th} coordinate of brand j's "true" location under complete familiarity on dimension t (i.e., $x_j = (x_{jt})$ is brand j's location in the derived space);

q_i = consumer i's "exponent" parameter ($q_i \ge 0$);

r_i = consumer i's "uncertainty adjustment" parameter;

a_i, b_i = consumer i's preference scaling parameters.

The input data are preference and familiarity ratings from consumers collected across all the brands, possibly with replications; i.e., $\mathbf{P} = (((p_{ijk})))$ and $\mathbf{F} = (((f_{ijk})))$.[5] Note that the preference ratings are treated as (at least) interval scale data, while the familiarity ratings are rescaled so that $f_{ijk} = 0$ corresponds to zero brand information (total unfamiliarity) and $f_{ijk} = 1$ corresponds to complete information (total familiarity). The f_{ijk}'s are treated as ratio scaled: this is reasonable since total unfamiliarity defines a meaningful zero point.

We can equate a consumer's self-explicated brand preference rating (allowing for possible rescaling) to our "two component" representation of brand preference as follows:

$$a_i\, p_{ijk} + b_i = \sum_t w_{it} \left\{ (f_{ijk})^{qi}\, x_{jt} + [1 - (f_{ijk})^{qi}] \sum_j x_{jt}/J \right\} + [1 - (f_{ijk})^{qi}]\, r_i + e_{ijk}, \quad (1)$$

where the first term on the right hand side, $\Sigma\, w_{it}\, \{.\}$, is the "location" component of brand preference (the MDS vector model), the second term is the "uncertainty adjustment" component, and e_{ijk} is error. The expression within the brackets $\{.\}$ in the first term is the expected brand location for a given degree of brand familiarity, which, following assumption (a), may be written as a weighted average of the brand location under complete familiarity and the "average" location across all brands in the set (representing expected location under complete unfamiliarity).[6] We use the same weight $[1 - (f_{ijk})^{qi}]$ in the "uncertainty adjustment" component as well to capture the impact of unfamiliarity; this seems a reasonable restriction in the interest of parsimony.

Note that when $f_{ijk} = 1$ (total brand familiarity), the right hand side of (1) reduces to $\Sigma_t\, w_{it} x_{jt} + e_{ijk}$, which is the standard vector model as in MDPREF. On the other hand, when $f_{ijk} = 0$ (total brand unfamiliarity), the right hand side of (1) reduces to $\Sigma_t\, w_{it}\, \{\Sigma_i\, x_{jt}/J\} + r_i + e_{ijk}$. Thus, in the case of total unfamiliarity, brand preference corresponds to preference (under certainty) for the "average" brand, with an adjustment for uncertainty. The consumer-specific uncertainty adjustment parameter, r_i, is negative for uncertainty avoiding (or risk averse) subjects; $r_i = 0$ and $r_i > 0$ would imply risk neutral and risk seeking consumers respectively. The consumer-specific exponent parameter, q_i, allows the impact of brand familiarity to be nonlinear in f_{ijk}. If $q_i = 1$, the adjustment is linear in f_{ijk}. If $q_i < (>)\ 1$, there is a decrease (increase) in the rate of adjustment with increasing familiarity. Thus, the smaller the value of q_i, the more rapid is the "learning" in the sense that perceptions (and consequently preferences) adjust quickly toward the "true" brand location as familiarity increases from the "zero" level. Finally, the a_i and b_i parameters allow for an optimal metric rescaling (via consumer-specific additive and multiplicative constants) on each consumer's evoked preferences.

1.2. Estimation

Given the data matrices **P** and **F**, our objective is to estimate the brand location matrix $\mathbf{X} = ((x_{jt}))$, the subject preference vector matrix $\mathbf{W} = ((w_{it}))$, the vectors of subject-specific exponent and uncertainty adjustment parameters, $\mathbf{q} = (q_i)$ and $\mathbf{r} = (r_i)$, and the optimal linear scaling parameters $\mathbf{a} = (a_i)$ and $\mathbf{b} = (b_i)$. We may restate (1) as:

$$a_i\, p_{ijk} + b_i = (f_{ijk})^{qi} \sum w_{it}\, x_{jt} + [1 - (f_{ijk})^{qi}]\, c_i + e_{ijk}, \quad (2)$$

where:

$$c_i \equiv r_i + \sum_t w_{it} \left(\sum_j x_{jt}/J \right). \tag{3}$$

We attempt to estimate the model parameters to minimize the sum of squared errors. More formally, given **P** and **F**, we estimate **c** = (c_i), **q**, **a**, **b**, **X**, and **W** to:

$$\begin{aligned} \underset{c,q,a,b,X,W}{\text{Minimize}}\ Z &= \sum_i \sum_j \sum_k (e_{ijk})^2 \\ &= \sum_i \sum_j \sum_k [a_i\, p_{ijk} + b_i - (f_{ijk})^{qi} \sum_t w_{it}\, x_{jt} - [1 - (f_{ijk})^{qi}]\, c_i]^2. \end{aligned} \tag{4}$$

Note that the above sum of squared errors is trivially minimized with $a_i = b_i = c_i = w_{ij} = 0\ \forall\ i, j$. Thus, **a** must be fixed apriori; we fix $a_i \equiv 1\ \forall\ i$. Also, we estimate **c** while the parameter set of interest is **r**; once **c**, **X** and **W** are estimated, **r** is calculated from these estimates, using (3).

For estimation, we utilize an alternating least squares (ALS) procedure where each parameter set is cyclically estimated in turn, holding all other parameter sets fixed at their current values. Analytical expressions for ALS estimates of the parameter sets **c**, **b**, **X**, and **W** are derived as follows. Differentiating (4) with respect to c_i, and equating to zero, we obtain:

$$\begin{aligned} \partial Z/\partial c_i = 0 = \sum_j \sum_k [a_i\, p_{ijk} + b_i - (f_{ijk})^{qi} \left(\sum_t w_{it} x_{jt} \right) \\ - (1 - (f_{ijk})^{qi})\, c_i] \times [-2(1 - (f_{ijk})^{qi}]. \end{aligned} \tag{5}$$

Rearranging, we obtain the conditional least squares estimator:

$$\begin{aligned} \hat{c}_i = [a_i \sum_j \sum_k p_{ijk}\, (1 - (f_{ijk})^{qi}) + b_i \sum_j \sum_k (1 - (f_{ijk})^{qi}) \\ - \sum_j \sum_k (f_{ijk})^{qi}\, (1 - (f_{ijk})^{qi})\, (\sum_t w_{it}\, x_{jt})]/\sum_j \sum_k (1 - (f_{ijk})^{qi})^2. \end{aligned} \tag{6}$$

Similarly, we obtain the following conditional least squares estimators from the appropriate stationary equations:

$$\begin{aligned} \hat{b}_i &= [-\, a_i \sum_j \sum_k p_{ijk} + \sum_j \sum_k (f_{ijk})^{qi}\, (\sum_t w_{it}\, x_{jt}) \\ &+ c_i \sum_j \sum_k (1 - (f_{ijk})^{qi})]/JR, \end{aligned} \tag{7}$$

$$\begin{aligned} \hat{w}_{it} &= [\sum_j \sum_k (f_{ijk})^{qi}\, x_{jt}\, [a_i\, p_{ijk} + b_i - (1 - (f_{ijk})^{qi}) c_i \\ &- (f_{ijk})^{qi}) (\sum_{n \neq t} w_{in}\, x_{jn})]/\sum_i \sum_k [(f_{ijk})^{qi}\, x_{jt}]^2, \end{aligned} \tag{8}$$

and

$$\hat{x}_{jt} = [\sum_i \sum_k (f_{ijk})^{qi}\, w_{it}\, [a_i\, p_{ijk} + b_i - (1 - (f_{ijk})^{qi})c_i - (f_{ijk})^{qi})(\sum_{n \neq t} w_{in}\, x_{jn})]/\sum_i \sum_k [(f_{ijk})^{qi}\, w_{it}]^2. \quad (9)$$

For the exponent parameter, the stationary equations are:

$$\partial Z/\partial q_i = 0 = \sum_j \sum_k [a_i\, p_{ijk} + b_i - (f_{ijk})^{qi} (\sum_t w_{it}\, x_{jt}) - (1 - (f_{ijk})^{qi})\, c_i] \times [2\, (f_{ijk})^{qi}\, \mathit{ln}\, f_{ijk}\, (c_i - \sum_t w_{it}\, x_{jt})]. \quad (10)$$

There is no apparent simplification here as in the case of the previous parameter sets. A conjugate gradient procedure is therefore used to estimate q_i. There is a problem if $f_{ijk} = 0$, due to the *ln* f_{ijk} term on the right hand side of (10). Thus, a "small" value (0.0001) is used for f_{ijk} whenever $f_{ijk} = 0$.

The algorithm requires the user to input the two data matrices **P** and **F** and define a control vector that specifies the selection of program options, which include the number of dimensions (T), preprocessing options for the preference data matrix (e.g., row standardization), methods for obtaining starting values (random, rational, or given),[7] restricted models (by fixing specified parameter sets), and control parameters for the estimation procedure. Since Z has a lower bound of zero and each stage can be shown to conditionally reduce Z, we can use a limiting sums argument to prove convergence (to at least a locally optimum solution) of the fixed point process. In performing Monte Carlo testing with synthetically created **P** and **F**, we find that the procedure performs quite well in converging quickly, and in correctly estimating the "true" solutions.

2. An application

We illustrate our methodology using portions of data collected as part of a larger study conducted by a major automobile manufacturer. Our objective is to compare the results obtained with those from MDPREF, which serves as our benchmark in terms of goodness-of-fit as well as substantive interpretation of the output. The raw data consist of preference and familiarity ratings (on 11-point scales) for 10 luxury car models obtained from 240 subjects. These subjects were prospective buyers of a luxury car, having stated their intention to buy such a car in the next few months. MDPREF and our proposed "full" model were fitted to the data, as were two other restricted models accommodated by our procedure. In the first restricted model (Model A), **X** and **W** were held fixed at the MDPREF estimates while all other parameter sets (**c**, **q** and **b**) were estimated by our procedure. In the second restricted model (Model B), only **X** was fixed at the MDPREF estimate.

The preference data matrix was row standardized (i.e., preference ratings were standardized for each subject across brands), while the raw familiarity data were rescaled ($0 \leq f_{ijk} \leq 1$) as required by our model. There were no replications in this study. We focus on the solution in two dimensions. Higher dimensionality added little in terms of explained variance or interpretability.

2.1.1. Goodness of Fit. The variance in the data accounted for by the four models is presented in Table 1. The full model accounts for a substantially greater percentage of the variance in the data compared to MDPREF, although we note that this model estimates many more parameters than MDPREF. Restricted Model A (with both **X** and **W** fixed from MDPREF) accounts for little more variance than MDPREF, while Model B (with only **X** fixed from MDPREF) compares favorably with the full model. The reason for this will be apparent when the estimates of **X** and **W** from MDPREF and the full model are compared below.[8]

2.1.2. Joint space. The brand locations in two dimensions for our full model and MDPREF are mapped in Figure 1. (We have not included the 240 subject vectors in these maps to avoid clutter.) The horizontal dimension appears to capture the country of origin (foreign vs. domestic), while the vertical dimension, with one exception (Cadillac Seville), seems to separate the two major domestic manufacturers, General Motors and Ford. The two stimulus maps (our model in Panel A and MDPREF in Panel B) in Figure 1 are quite similar, as is borne out by the canonical correlations of .99 and .96 between the brand locations derived from these two models. It may be noted that the foreign car models (F to J) have smaller variance with respect to the vertical dimension in the proposed model solution relative to that of MDPREF. To the extent that the vertical dimension relates to the domestic manufacturer (Ford vs. GM), the solution from the full model would appear to be somewhat more intuitively appealing in terms of the spatial representation of the foreign cars. The proposed model solution also separates the Oldsmobile 98 from the Buick Riviera more than the MDPREF solution.

While the brand locations, **X**, from MDPREF and our full model are somewhat similar, the two solutions are very different in the case of the consumer preference vectors, **W**. The canonical correlations in the latter case are .68 and .25. There is wide variation across consumers in terms of the extent of the difference between the preference vector orientations under the two solutions. Presenting plots of all

Table 1. A Comparison of Models: Goodness of Fit

Model	Variance accounted for in T = 2 dimensions
MDPREF	44.7%
Restricted Model A	45.5%
Restricted Model B	63.5%
Full Model	70.1%

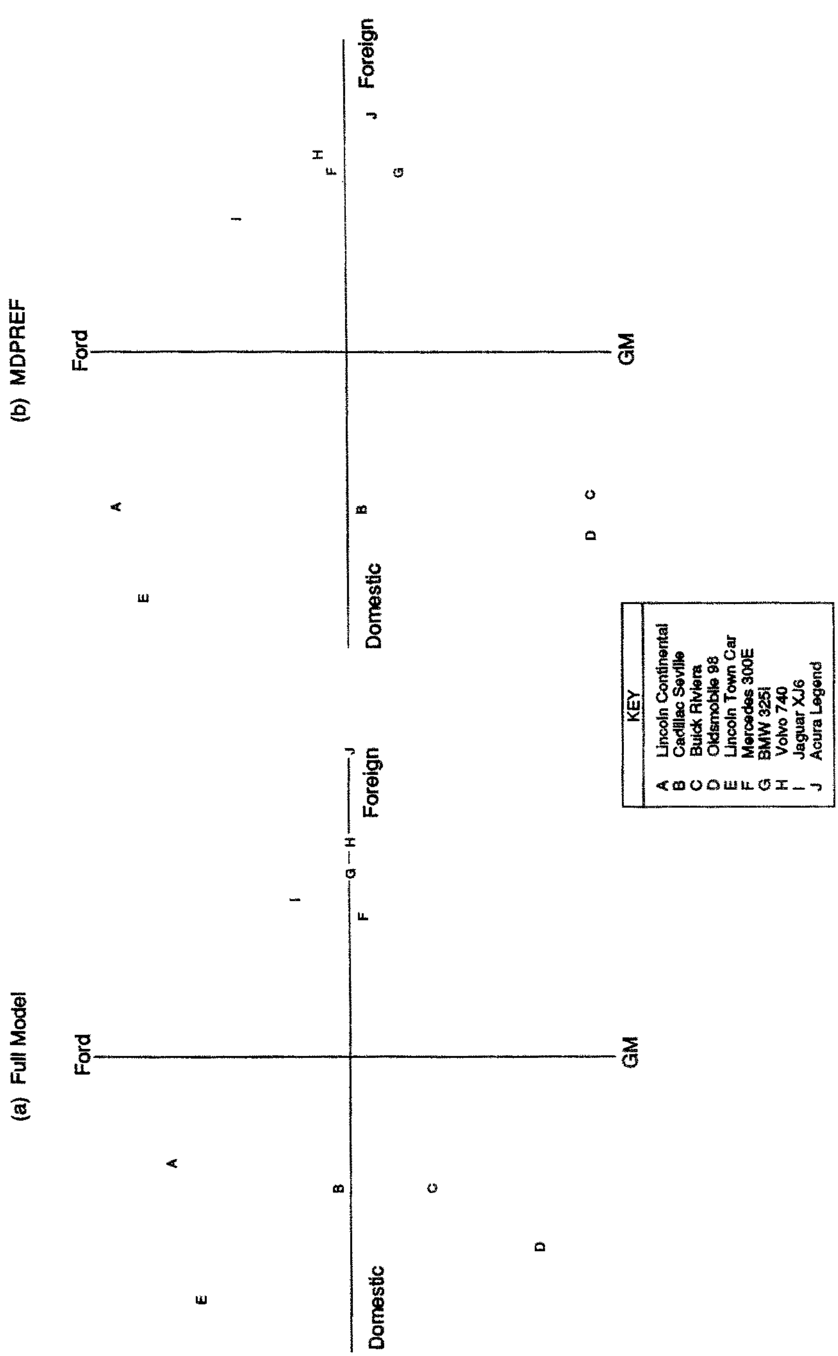
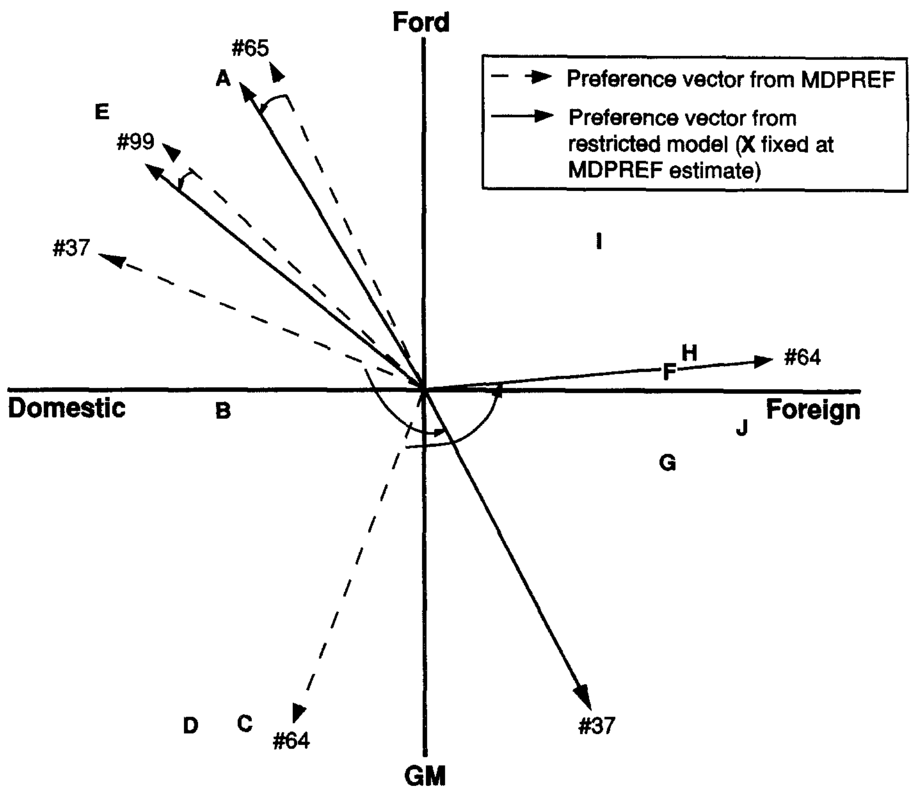


Figure 1. Two-dimensional product map.

240 vectors would be unwieldy; instead, we examine selected cases to illustrate how the methodology works. In Figure 2, we plot the preference vectors from MDPREF and from the restricted model with **X** fixed at the MDPREF values (Model B) separately for four consumers. The latter model was chosen instead of our full model to maintain a common brand map (same **X**) in both cases, so as to focus on the impact of incorporating the degree of familiarity on the consumer preference vectors. We deliberately selected two cases where the preference vec-



	Brand	A	B	C	D	E	F	G	H	I	J
Subject #37	Preference	10	10	7	7	10	9	7	4	1	8
(r = 3.0, q = 0.3)	Familiarity	0	0	6	7	0	0	4	4	4	7
Subject #64	Preference	5	7	10	1	1	3	1	2	9	5
(r = -1.3, q = 1.5)	Familiarity	9	7	0	2	3	4	2	4	9	7
Subject #65	Preference	9	8	4	6	7	4	4	3	8	8
(r = 0.3, q = 1.2)	Familiarity	9	7	7	6	0	8	7	6	6	8
Subject #99	Preference	10	3	10	1	9	1	1	1	7	1
(r = -3.2, q = 1.5)	Familiarity	8	8	9	7	8	6	6	4	8	8

Figure 2. Joint map of brand locations and preference vectors for four subjects.

tors from the two models are very similar (Subjects #65 and 99), and two others where there is a dramatic change in the estimated preference vector as the effect of the degree of familiarity is incorporated (Subjects #37 and 64). These consumers' preference and familiarity data are also provided in Figure 2.

In our model, preference ratings for unfamiliar brands receive a lower weight in determining the orientation of the preference vector. The MDPREF solution, of course, ignores unfamiliarity. Thus, subjects who give high preference ratings to unfamiliar brands are more likely to have their MDPREF based preference vector oriented quite differently from that estimated by our model. Consider Subject #64. The MDPREF based preference vector is strongly influenced by the subject's high preference rating for brand C which, however, is also rated as unfamiliar. Once familiarity is taken into account, the vector estimated by our procedure moves toward brand I, which is both highly preferred and familiar. Subject #37 is a particularly extreme case. His/her most preferred brands – A, B and E – are also the least familiar. While these three brands drive the direction of the MDPREF based vector, brands J as well as C and D, which are reasonably liked and are familiar to the subject, are most influential when familiarity effects are considered, resulting in a striking change in orientation of the preference vector, compared to the MDPREF solution. On the other hand, Subject #99 is quite familiar with all the brands; the relatively less familiar brands (H, F and G) are also less preferred. Subject #65 is unfamiliar with Brand E, but the preference rating for E is close to his/her average preference score across brands. As a result, in both these cases, the MDPREF vector is close to that estimated from our model. The small difference in orientation between the vectors appears to be driven in both cases by the presence of one most preferred and most familiar brand (A for Subject #65 and C for #99).

2.1.3. Exponent and uncertainty adjustment parameters. The two additional consumer level parameters of interest are the exponent parameter, q_i, and the uncertainty adjustment parameter, r_i. The distribution of estimates of these two parameters over the 240 subjects is summarized in Table 2. The exponent parameter estimates are almost all positive as expected; the two cases that are negative are close to zero. The uncertainty adjustment parameter exhibits much greater variation across consumers, and, somewhat surprisingly, is positive for ⅔ of the sample. This parameter should be negative for uncertainty avoiding subjects. One might expect most consumers to be uncertainty avoiding (risk averse) in the case of a high involvement product such as luxury automobiles. It is quite possible that

Table 2. Distribution of parameter estimates

Parameter	Mean	Std. dev.	Sign
q_i (exponent)	0.75	0.42	2 negative, 238 positive
r_i (uncertainty adjustment)	0.82	2.42	80 negative, 160 positive

risk becomes more salient at the time of actual behavior (i.e., the purchase decision). Thus, risk aversion is not really reflected in the preference ratings provided, without any commitment, by subjects who may be several months away from their actual purchase decision and currently in the process of external search. (See Wright and Weitz 1977 for empirical evidence of this phenomenon.)

It is insightful to examine the estimates of the uncertainty adjustment parameter for the four consumers shown in Figure 2. For Subject #99, the less familiar brands are also consistently less preferred. The pattern suggests a negative impact of unfamiliarity on preference, reflected in the strongly negative uncertainty adjustment parameter ($r_i = -3.2$). Subject #65 has an average preference rating for his/her unfamiliar brand; in this case, $r_i = 0.3$, reflecting little if any adjustment for uncertainty. On the other hand, for Subject #37, the most preferred brands are also the least familiar, suggesting a positive impact of unfamiliarity on preference ($r_i = 3.0$). For Subject #64, it may be seen that, excluding C, the more preferred brands are also more familiar. As a result, the uncertainty adjustment parameter is negative ($r_i = -1.3$).

2.1.4. Discussion. This study illustrates some key aspects of our procedure. The brand locations, **X**, were found to be similar to the MDPREF solution, while the consumer preference vectors, **W**, changed significantly. **X** is estimated across the population and, therefore, the effects of unfamiliarity may tend to "wash out," unless there is a common set of brands that is uniformly unfamiliar across consumers. At the individual consumer level, our examination of four selected cases provided some insight into factors influencing the estimates of the preference vectors. Note that merely introducing q_i, r_i, and b_i (while holding **X** and **W** at their MDPREF estimates) adds very little to the explained variance over MDPREF; it is given when **W** is freely estimated (Restricted Model B) that there is a significant improvement in goodness of fit.

3. Conclusion

We have proposed a methodology that aims to separate the effects of unfamiliarity on preferences so that the joint map is not confounded by these effects. From a diagnostic viewpoint, this yields brand locations and consumer preference vectors free of potential distortion due to brand unfamiliarity (to the extent captured by our model), as well as information on the impact of uncertainty on preference (via the exponent and uncertainty adjustment parameters). From a predictive viewpoint, once the model is estimated, preferences and expected brand locations can be inferred for any given level of familiarity for the brands in the evaluation set. An appealing aspect of our methodology is that the input data require fairly simple and intuitive responses from consumers – preference and familiarity ratings for each brand in the evaluation set.

3.1.1. Limitations and directions for future research. While there is empirical support for the premises underlying our model, there are clearly potential effects of unfamiliarity that are not captured by the specification of our model. In particular, we postulate that under complete unfamiliarity, the expected brand location lies at the average location for the category. The implicit assumption is that consumers are not aware of the brand's attributes and then learn gradually as familiarity increases. However, consumers will learn certain factual information (such as country of origin) rapidly, and use that information to form an initial impression that may not correspond to the category mean. In effect, consumers may form further subcategories within the category (e.g., German luxury cars). This may have been an issue in our application, given that the dimensions appear to be categorical (foreign vs. domestic, General Motors vs. Ford) rather than continuous. Clearly, the ideal situation is one where there are no subcategories within the main category of interest. More realistically, we recognize the opportunity to extend our framework to allow for subcategories, such that an unfamiliar brand starts at the mean location for the subcategory to which it belongs. Thus, generalizing this methodology to preference tree structures becomes a natural extension for future research.

From an estimation viewpoint, the large number of parameters in the model (given the various consumer level parameters) implies that, without a large stimulus set or replications, the degrees of freedom may be small. One approach to alleviate this problem is *reparameterization* (DeSarbo and Rao 1986), which involves specifying preference vectors as functions of prespecified consumer background variables. This approach would also serve to develop a basis for benefit segmentation.

More fundamentally, future research must address the issue of model validation. From a descriptive standpoint, behavioral studies over time are needed to record the dynamics in perceptions and preferences with changing familiarity levels.

Notes

1. It is possible that a consumer has high familiarity with – and expertise in – the product category (e.g., luxury automobiles), but is unfamiliar with a particular brand (e.g., Lexus LS400).
2. Replication would require the subjects to repeat the task of providing preference and familiarity ratings for the set of brands, after a sufficient time interval.
3. We do not explicitly consider gain/loss framing effects (Kahnemann and Tversky 1979).
4. Conceptually, we can view brand perceptions as a distribution around some expected location. With increasing familiarity, the expected location moves toward the true location and the distribution becomes tighter. We do not explicitly model this distribution; instead, our model directly captures the effect of uncertainty on preference.
5. Replications provide additional degrees of freedom in the estimation. Note that from an estimation viewpoint, it does *not* matter if some change in terms of increased brand familiarity takes place between measurements.

6. Note that we use the average of the brands in the evaluation set to define the average for the category. This implies that the evaluation set should include the relevant brands in the category, or at least that the set should be representative of the category under study.
7. In the rational start option, the starting values for **W** and **X** are obtained from MDPREF on the row standardized preference data, $q_i = 1$, and c_i is generated randomly from a unit normal distribution, for all i.
8. Because of the *deterministic* nature of these MDS models, traditional model selection heuristics such as AIC, likelihood ratio tests, etc. are not applicable in this context.

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