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A METHODOLOGY FOR IDENTIFYING UNOBSERVED CATEGORIES
WHEN CONSUMERS ASSIGN BRANDS TO MULTIPLE CATEGORIES

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ABSTRACT

According to previous research, consumers naturally think of brands or products as belonging to multiple categories, depending on which of various available categories come to mind. To help marketers identify the categories that consumers naturally perceive, this study proposes a new statistical procedure, in which the identification of unobserved categories varies across consumers, and brands or products may span multiple categories. As illustrated with data from 25 U.S. restaurant brands and a synthetic example, this procedure accounts for different categorization phenomena and structures, including multiple-category memberships, different levels of abstraction, and graded memberships of category representations. Finally, it is also shown that creating assortments that more closely approximate consumers’ own category structures can facilitate their search, and ultimately, their satisfaction with their choice.
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Gratitude is the memory of the heart. -- Jean Baptiste Massieu

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Chapter 1

Introduction

Consumers tend to categorize brands or products into multiple categories. For example, McDonald’s is a fast-food restaurant and a breakfast restaurant; Denny’s represents a sit-down restaurant that serves breakfast; and Taco Bell constitutes both a fast-food restaurant and one that serves Mexican food. The use of one or many categories varies across consumers, for several reasons. First, consumers may disagree about the representativeness of each brand for the respective categories (e.g., some may argue that Taco Bell sells Mexican-inspired food rather than “real” Mexican food). Second, consumers bring different categories to mind, depending on their goals, their experiences, and the presence of marketing cues (e.g., the mention of fast-food may or may not invoke Taco Bell). A category thus may be known but not necessarily brought to mind at any given point in time.

Categorization refers to the process of organizing information or knowledge into meaningful constructs, such that two items appear in the same category because they are related in some manner (Cohen and Basu 1987; Loken and Ward 1990; Rosch and Mervis 1975). The process has important impacts on consumer decision making, such that consumer categories influence ad evaluations (Goodstein 1993), product-based impression formation (Cohen and Basu 1987), inferences about performance (Gregan-Paxton, Hoeffler, and Zhao 2005), judgments of brand extensions (Boush and Loken 1991), variety-seeking behaviors (Ratner, Kahn, and Kahneman 1999), product category
assessments (Loken and Ward 1990), and category expectations (Gupta and Stewart 1996). It thus follows that products in the same categories compete closely in consumer minds.

Yet despite extensive research, it remains difficult to identify categories that consumers perceive in response to a set of products or brands. Marketing managers and researchers use a variety of research methodologies to discern these categories, including surveys, focus groups, verbal protocols, and sorting tasks. Sorting tasks require participants to put a set of items (often represented by cards) into piles, such that items assigned to the same piles are similar, according to the participants. Marketers then consider the piles to infer common category structures, such that items in the same piles are members of the same unobserved categories because of their similarity. For example, a McDonald’s brand manager might ask a sample of consumers to sort three flash cards representing three restaurants: McDonald’s, Taco Bell, and Denny’s. The manager/experimenter then would record the number of times two restaurants appear in the same pile across all consumers. If many consumers combine McDonald’s and Taco Bell in the same pile, the experimenter could infer that consumers categorize restaurants as fast-food outlets and conclude that McDonald’s and Taco Bell are more direct competitors. If most consumers combine McDonald’s and Denny’s in a pile, it suggests a breakfast category, and McDonald’s and Denny’s compete more directly. Faced with a larger set of brands, marketing managers also could use these data to perform traditional cluster analyses and infer unobserved categories based on the derived restaurant clusters.

With such an approach though, participants cannot place a brand into more than one pile; there is only one card per brand. Thus, for any given participant, McDonald’s
cannot represent both the breakfast category and the fast food category. Participants are restricted to reporting only a subset of the categories that they may find naturally salient; they may even create ad hoc categories that seem artificial, just to finish the task.

In this research, I propose a methodology that helps marketers and researchers explore unobserved category structures for a set of items in a sorting task. The contribution is twofold. First, the proposed method provides participants with multiple cards per item (e.g., products or brands) so that they can assign the items to multiple categories if they so choose. Second, I propose a new statistical methodology to help researchers and marketers explore the categories that consumers use when brands belong simultaneously to multiple categories using this new data. This method empirically suggests some different unobserved categories that consumers might use and is general enough to account for different categorization phenomena and structures. In particular, the proposed method does not restrict the categories to be mutually exclusive, nor does it make strong assumptions about the unobserved category structure. Rather, it represents an exploratory approach.

In Chapter 2, I review prior categorization literature to identify the key principles of existing category representations in marketing contexts and note the limitations of current methods to explore salient category structures. In Chapter 3, I introduce a new statistical procedure for analyzing the modified sorting data and I illustrate its capacities using a synthetic example. In Chapter 4, I further illustrate its capacities with an empirical application involving categories of restaurants brands, with insights from a traditional analysis technique as a benchmark. In Chapter 5, I explore the consequences of using different inferred category structures to design assortments, and their impact on
consumer choice. Finally in Chapter 6, I conclude by discussing the theoretical and managerial implications of the findings and offer suggestions for further research.
Chapter 2

Literature Review

Because consumers’ use of categories influences a wide range of decision processes, researchers frequently consider how marketers might influence the category structures they use. By cueing specific categories or creating new category structures, marketers can influence how consumers process information, the extent to which they perceive variety in an assortment, and their satisfaction with a choice. For example, Ülkümen, Chakravarti, and Morwitz (2010) show that exposure to broad (versus narrow) categories leads consumers to engage in more heuristic processing, which causes them to base their subsequent decisions on fewer attributes. Additionally, different assortment formats (or specified categories) have significant impacts on the choice process; organizing alternatives by brand rather than taxonomically (e.g., by product feature) increases perceived dissimilarity among category members (Poynor and Diehl 2007), whereas organizing them by brand increases the share of a low-price, low-quality alternative (Simonson, Nowlis, and Lemon 1993), and organizing alternatives by complements (rather than substitutes) increases satisfaction (van Herpen, Diehl, and Poynor 2007). The mere presence of categories, even meaningless ones, improves perceptions of variety and ultimately enhances consumer choice satisfaction (Mogilner, Rudnick, and Iyengar 2008).

The perception of products/brands to categories has significant implications for product positioning decisions, as products in the same category tend to compete with one
another to satisfy similar consumer needs. Cohen and Basu (1987) suggest categorization is central to segmentation and positioning, adding that the categorization process not only determines what products compete in consumer minds, but it also increases the salience of information relevant to the associated categories, decreases the salience of information relevant to other categories, and leads to inferences being based on category knowledge that is salient. Complicating the matter further, although products/brands in the same categories compete closely during the choice process, they are often eliminated together through non-compensatory rules to simplify the decision making process (Urban, Hulland and Weinberg 1993).

Despite the importance of the categorization process, researchers generally assume that they can easily identify the categories consumers use to make their choices. Researchers tend to assume that consumer categorize using just a few dimensions, and consequently typically design studies in with products or brands that are obvious members of one and only one category. Although this approach is methodologically simple, it appears insufficient in the face of research that shows consumers frequently categorize items into more than one category and in different ways (Loken, Barsalou, and Joiner 2008). For example, Moreau, Markman, and Lehmann (2001) find that when marketers cue two possible categories for a really new product, the first one cued obtains an undeniable advantage and serves as the main basis for inferences about the new product. The second category cued might be used to make inferences, but only when the context provides information that makes the correspondence between the second category and the new product salient. Therefore, marketer-provided cues seemingly can influence whether consumers use single or multiple categories.
Direct evidence also shows that consumers use multiple categories simultaneously to make choice inferences. Gregan-Paxton, Hoeffler, and Zhao (2005) reveal that consumer familiarity influences the extent to which consumers use different types of categories to make inferences about a new product. With a different strategy, Ross and Murphy (1999) also find that people tend to categorize items along both taxonomic dimensions (e.g., based on underlying attributes) and goal-driven categories; in one task, they even show that consumers combine information from multiple categories to make their inferences. Further, Rajagopal and Burnkrant (2008) show that primes of product attributes can induce beliefs about multiple categories, especially when category knowledge is low. Empirical evidence therefore indicates that different consumers can use multiple and varied categorization structures that involve the simultaneous membership of single brands/products to multiple categories.

Literature on market basket choice also recognizes that consumers’ choices extend beyond the traditional product categories defined by marketers (Manchanda, Ansari, and Gupta 1999; Russell and Petersen 2000). Cross-category choice occurs when high-level consumption goals lead consumers to consider products that cut across traditional product category lines (Russell et al. 1999), such as when products in different traditional categories can achieve the same goal (e.g., weight-loss shakes and treadmills both help people lose weight). Alternatively, products might be members of multiple categories (e.g., weight-loss shakes could also represent the meal replacement category). Such cross-category considerations are especially likely if consumers confront goal ambiguity with multiple conflicting goals (Ratneshwar, Pechmann, and Shocker 1996). Still though, models of cross-categorization generally focus on specific, well-known,
marketing-defined categories and assume they are known and common across consumers. Because such models inform assortment and product positioning, it is imperative that marketers identify consumers’ naturally salient category structures. In real-world contexts items are complex, which makes the effort to determine how consumers naturally categorize products or brands an empirical exercise (Kahn and Wansink 2004).

**Components of Category Representations**

To infer unobserved salient category structures, a model must be general enough to account for various categorization phenomena. It should allow for items to join multiple categories but also follow four other key principles. First, the model should not make restrictive assumptions about the underlying category structure. Second, it should represent a graded category structure. Third, it should allow categories to vary in their levels of abstraction. Fourth, the procedure should fit the input data closely. The present section details these phenomena and presents an outline for dimensions that are considered for the model presented in Chapter 3.

**Category Structures and Graded Membership**

In line with prior categorization literature, categories are a function of the underlying similarities among stimuli (Rosch 1999), such that items belong to the same category because they are similar in some manner. Traditional similarity-based models, such as exemplar and prototype models (Medin and Schaffer 1978; Nosofsky 1986; Reed
suggest that categories can be represented as clusters in an attribute space and are *taxonomic* because the similarity among items is a function of their shared features or perceptual attributes. Prototype models (Reed 1972, 1978; Rosch and Mervis 1975) instead suggest each category appears in memory as a prototype or central tendency measure, such that when a person assigns a new instance, he or she does so by choosing the category whose prototype is most similar to it. The prototype is some “average” representation of the salient features of the items in the category; the representation may or may not actually exist. Exemplar models (Medin and Schaffer 1978; Nosofsky 1986) represent categories not by prototypes but instead by a collection of stored stimuli with known category labels (exemplars). Therefore, an object gets assigned to a category through multiple similarity computations with recalled instances. Both the prototype and exemplar models use similarity judgments among the items in the category to form the basis for understanding the category structure. Despite their different representational assumptions, they also concur that exemplars vary in their prototypicality, or the extent to which an item is representative of the category (e.g., an apple is one of the most prototypical fruits, but a tomato also is a fruit). Any model that empirically identifies category structures should take graded membership into account.

Other research suggests that not all categories involve items that are similar according to their shared features. Barsalou (1983, 1985) argues that some categories emerge as needed, such that stimuli are organized in the same category because they all help support the same specific goal. For example, a category might consist of concepts that do not share similar features or attributes (e.g., protein shakes and running) but instead have the potential to help a person reach the same goal in different ways (e.g.,
(losing weight). Such goal-driven categories often cross traditional product category lines defined by taxonomic categories (Loken, Barsalou, and Joiner 2008; Loken and Ward 1990; Ratneshwar and Shocker 1991; Ratneshwar et al. 2001) as they do not typically share common features. This is consistent with other consumer research indicates consumer learning often reflects on goal-driven experiences (Huffman and Houston 1993). Additionally, Loken and Ward (1990) suggest that exemplars of goal-driven categories also vary in prototypicality, but it is no longer a function of the extent to which they share common features but rather increases as the exemplar approaches the ideal means to achieve the goal. In sum, the model should be flexible enough not to make too strong assumptions on the nature of the categories represented (it should allow exemplar-based, prototype-based and goal-driven structures), but it should be flexible enough to incorporate the principle of graded membership.

Levels of Abstraction

Categories reflect different levels of abstraction, or extents to which they are inclusive (Rosch and Mervis 1975). Traditionally, categories are believed to include subcategories, each of which may comprise additional subcategories. Such structures are often represented visually using a tree-like structure. At the highest level of abstraction, superordinate categories group items that share a few key properties; for example, grocery stores and restaurants both sell food items but share few other things in common. At a less inclusive level, basic categories (e.g., fast-food restaurants) include items that share many common features; they therefore provide a lot of information and are
generally highly differentiated (Rosch et al. 1976). Finally, at a lower level of abstraction, subordinate categories are less inclusive and all items have very similar features (e.g., Texan burger fast-food restaurants). These subordinate categories may not be differentiated from other subordinate categories at the same level though, because they share several attributes with other types of fast-food restaurants (e.g., speed of service, prices). These different levels of abstraction also have been documented in consumer research that indicates consumers use varying levels depending on their expertise (Alba and Hutchinson 1987; Sujan and Dekleva 1987).

Using Sorting Data

Traditional categorization research focuses on category learning and the use of different categorization structures, but a different research stream also considers statistical procedures that may help researchers and practitioners identify naturally salient categories. The most common data collection mechanism to infer such models uses sorting tasks (also known as card sorting), as described previously (Coxon 1999). The instructions for these tasks generally specify that participants should sort the cards into piles according to their own perceptions of similarity. Many traditional category learning paradigms establish correct category labels that participants learn to assign new instances to the correct categories, whereas a sorting task lets participants follow an unstructured path to create piles that represent their existing beliefs. When the objective is to explore salient category structures, there is no right or wrong way to create piles.
The data obtained from sorting tasks also have several advantages over other approaches to collecting similarity judgments, which are traditionally used to infer category structures. Rao and Katz (1974) suggest a sorting task can be especially useful if there are many items subject to similarity ratings. Bijmolt and Wedel (1995) show that sorting induces less fatigue, less boredom, equally good task insight, and faster completion time than paired comparison tasks, conditional rankings, and triadic combinations. Thus vast consumer and marketing research uses sorting paradigms to uncover category structures or gain other related insights (e.g., DeSarbo, Jedidi, and Johnson 1991; Huffman and Houston 1993; Isen 1984; Morales et al. 2005; Peracchio and Tybout 1996; Poynor and Diehl 2007; Sujan and Bettman 1989; Ülkümen, Chakravarti, and Morwitz 2010).

Once collected, sorting data require analyses. If the research aim is to uncover natural categories, the analyses usually involve identifying categories commonly used across a sample of participants. For example, Ross and Murphy (1999) use a sorting task with 45 different food items and find that some participants add ice cream to a dessert pile (with pie and candies), whereas others include it with dairy products (e.g., milk and cheese). Unfortunately, they could not offer conclusions beyond aggregate results because their sorting task restricted items to one and only one pile each. That is, the task restricted participants’ ability to indicate whether an item seemed representative of more than one category, even if two (or more) categories might have been very salient. Although this approach is useful for determining which potential categories are dominant across a sample of consumers, it clearly restricts the type of categorization that participants can represent.
In response to these concerns, researchers have developed multiple sorting procedures (Canter, Brown, and Groat 1985; Groat 1982), such that participants have one card per item but can categorize the whole set of cards multiple times, each time starting from scratch and using a different criterion. A downside of this approach is that if participants select the number of sorting rounds they likely offer few sequential sorts, as they prefer to minimize their cognitive and task effort. If researchers instead provide criteria to use for the sorts, researchers need previous knowledge about the criteria to use, the task may not be as exploratory as preferred, it may lead to bogus categories if participants must create categories beyond those they naturally possess.

A potential possible solution to all these limitations is to provide multiple cards per item and allow participants to assign an item to multiple piles if desired. In Ross and Murphy’s (1999) task then, participants could have put ice cream in both the dairy and the dessert piles, as well as in a “high fat content” pile or a “celebration food” pile, depending on what they considered salient at that given moment. The resulting data should mirror empirical findings in psychological and consumer research that suggest items can belong to more than one category and that consumers simultaneously can activate multiple categories simultaneously. One contribution of the present work is thus to introduce a sorting task that allows consumers to represent category structures in which brands may belong to multiple categories simultaneously.
Current Modeling Procedures to Identify Unobserved Categories from Sorting Data

Some of the earliest work on the inference of unobserved categories used sorting data. For example, latent partition analysis (Hartke 1978; Wiley 1967) employs the average number of participants who include two items in the same pile as an indication of similarity. This technique involves a factor analytic approach (Quartimax rotation) that provides partitions (i.e., no graded structure) of similar items across a sample. Thus, it is useful for determining the common structure observed across all participants, without assuming a particular representational structure. Yet it does not reveal multiple-category memberships or consider heterogeneity after the data have been aggregated over all participants.

Takane (1980) recognizes that an analysis of categorization behavior in a sorting task should incorporate some degree of individualization, so he converts each person’s piles into a similarity matrix. Given that the conversion is arbitrary, Takane suggests that the similarities should be a function of the number of items in the piles, such that the similarity between two items is greater when there are fewer additional items in the category. For example, in a sorting task, a pile of two items implies more item-level similarity than a pile of eight cards. Upon calculating all the pairwise scaled similarities, a single similarity matrix then provides input to a factor analytic technique that identifies groups of items that represent unobserved categories in a multidimensional space. The objective is to maximize the similarities of exemplars to their centroid (center of the category) while minimizing similarities between centroids. The specification of this process resembles the prototype model, such that the cluster centroid represents the
category prototype. Assuming that categories are all represented by prototype structures precludes the discovery of other categorization structures, such as goal-driven, exemplar-based or any type of hierarchical structure. Takane (1980, p. 84) notes this restriction: “Our optimization criterion is still arbitrary . . . it has nothing to do with the way that subjects perform the sorting task. It is doubtful that the subjects actually conceptualize a set of stimuli in such a way that the sum of inter-cluster distances is a maximum.” In sum, although Takane (1980) provides a rationale for aggregating similarities into a single matrix, no evidence indicates that participants convert data similarities this way.

A long tradition in psychology involves converting similarities into psychological distances in a manner that is psychologically plausible (Shepard 1957). It is assumed that the more similar two items are, the smaller their psychological distance is, and that in turn the psychological distance may be a function of the underlying attributes shared between the two items. In general, the more two items share identical features the more similar they are. Such a conversion depends on the choice of a distance metric (e.g., Euclidian), and the selection of the proper metric depends on the researcher’s assumptions about the structure of the underlying attributes, often considered an “empirical matter” and difficult to address (Torgerston 1958; for a discussion of this assumption in an exemplar model, see Nosofsky 1986). As such, the decision to convert behavior into similarities and psychological distances is controversial; for a categorization model it is preferable to fit the sorting data more directly to avoid arbitrary conversions of piles into similarities into psychological distances.

Yet as Köhn, Steinley, and Brusco (2010) document, various clustering techniques work with distances and get applied to sorting data to explore “psychological
clustering,” such as agglomerative clustering solutions including Ward’s (1963) criterion, partitioning around medoids (Kaufman and Rousseeuw 2005; Köhn, Steinley, and Brusco 2010), and K-means (MacQueen 1967). Such techniques are still widely used in practice because of their simplicity and availability in commercial statistical packages that enable managers to perform sorting and clustering tasks easily. Unfortunately though, such traditional clustering techniques also restrict representation structures, do not fit the data directly (i.e., require some aggregation and conversion of piles into similarities), do not allow items to join multiple categories, and typically impose a prototype-based representation that may not accurately represent the range of categorization structures observed in marketing contexts.

These drawbacks highlight the need for a methodology and statistical model that accurately accommodate different features of a categorization process. Some similarity-based models assume different types of categorization structures according to the prototype model. For example, multiple-tree models (e.g., Carroll 1976) identify categories that follow a hierarchical structure and allow for different levels of abstraction, such that psychological distance can be modeled as a function of ultrametric distances (inferred from dominance data) in an unspecified number of hierarchical categorization trees. Unfortunately, such methodologies usually require an arbitrary aggregation of input data, because the model requires similarity judgments. With the MAPCLUS approach, Arabie and Carroll (1980) specify piles observed across the sample as a function of unobserved, potentially overlapping categories in the data. However, MAPCLUS also assumes a common categorization structure for all participants, works with similarities rather than sorting data, and does not allow for graded membership.
Other techniques try to adjust for individual heterogeneity, such as INDCLUS (Carroll and Arabie 1983) and INDTREES (Carroll, Clark and DeSarbo 1984). Whereas INDTREES is a generalization of the multiple-tree model (Carroll 1976), INDCLUS is a generalization of MAPCLUS (Arabie and Carroll 1980) in which the degree to which items overlap across categories varies. However, neither methodology works directly with sorting or other categorization data but also requires some arbitrary conversion into similarities and distances.

Gordon and Vichi (1998) propose a direct identification of groups of participants who create similar piles in a sorting task, such that each participant gets assigned to a mutually exclusive group of members who created similar piles. Their procedure has several advantages: it works directly with the sorting data without any arbitrary aggregation or conversion, and it takes heterogeneity into account. However, it does not allow for graded structures or let items join multiple categories, because the input data were restricted by the original sorting task. This limitation carries through the mathematical formulation.

The methodology that comes close to matching all the criteria is that proposed by DeSarbo, Jedidi, and Johnson (1991). Rather than converting the sorting data into similarity judgments to be imputed into a distance-based procedure, their stochastic methodology models piles as sorting data directly, using a threshold model. If two items appear in the same pile, it must be because of a latent similarity judgment between these two items. They further suggest, on the basis of prior research into similarity judgments (Shepard and Arabie 1979), that the unobserved similarity judgment between any two items is a function of their membership in similar unobserved categories, which can be
inferred from data. The specification is similar to INDCLUS, but allows for graded membership. If two items are sufficiently similar (beyond an empirically determined threshold), they wind up in the same pile in the sorting task. This threshold formulation has received support (e.g., Hampton 1998), but again, the sorting task represents items on only one card each, so this methodology cannot infer multiple-category memberships; this inference also is prohibited by the statistical procedure.

Finally, sorting data also may support models that require similarities as input in other fields, such as multidimensional scaling models. First, multidimensional scaling models used to infer unobserved categories would be impractical in the high number of dimensions that would be required for complex/real word categories data. Second, despite the long history of research that uses sorting data to infer salient perceptual dimensions (e.g., Fry and Claxton 1971; Jain 1978; Rao and Katz 1974), these applications do not focus on the organization of stimuli into discrete constructs and therefore are beyond the scope of this research. That is, in line with existing research into the development of perceptual and categorization processes (e.g. Bahn 1986), this study distinguishes perception from categorization.
Chapter 3

The Proposed Statistical Model

To explore common unobserved consumer categories, the proposed statistical methodology must capture heterogeneity in categories between consumers, acknowledge the coexistence of multiple category structures, include different levels of abstraction, and note the membership of items to multiple categories. Therefore, I propose a sorting task in which participants have multiple cards for each item and create as many piles as they believe are representative. For the purpose of detailing the model, I simply assume that participants that can sort each item/product/brands in as many piles as they want (there is a large number of cards for each brand).

Model Specification

Assume I (i = 1, ..., I) consumers who sort a set of J items (j, k = 1, ..., J) using R unobserved categories (r = 1, ..., R). Based on the sorting task modified to include multiple cards per item, we observe $Y_{ijk}$ be the number of times items $j$ and $k$ are sorted in the same pile in the modified sorting task.

Zero-Inflated Negative Binomial Specification

The number of times two items appear in the same piles can be modeled as a count process, with $Y_{ijk}$ distributed Poisson:
where $c_{ijk}$ refers to the expected number of piles in which items $j$ and $k$ would be expected to be jointly members of, given the individuals salient category structures, and where $\Gamma(\cdot)$ is the gamma function. Despite the long tradition of modeling natural count data using a Poisson process (e.g., Ehrenberg 1988; Goodhardt, Ehrenberg, and Chatfield 1984), I note that the Poisson model herein makes some assumptions about the nature of the data that may or may not be easily satisfied.

First, count data modeled by a Poisson process are subject to dispersion issues, such that the mean is typically not equal to the variance ($E(Y_{ijk}) \neq V(Y_{ijk})$), which results in biased estimates. Overdispersion occurs when the variance is greater than the mean, and underdispersion occurs when the variance is smaller than the mean. To solve this problem, I introduce randomness into the expected rate at which two items enter the same piles, such that:

$$
\lambda_{ijk} = c_{ijk} + \nu_l,
$$

(2)

where $\nu_l$ is gamma distributed. Consequently, $\lambda_{ijk} \sim gamma(c_{ijk}, \nu_l)$, and by combining the densities of $Y_{ijk}$ and $\lambda_{ijk}$, I obtain the well-known negative binomial density (McLachlan and Nelder 1983; Ramaswamy, Anderson, and DeSarbo 1994):

$$
P[Y_{ijk} | \nu, \nu] = \frac{\Gamma(\nu_l + y_{ijk})}{\Gamma(\nu_l)\Gamma(1 + y_{ijk})} \left[ \frac{\nu_l}{\nu_l + c_{ijk}} \right]^{\nu_l} \left[ \frac{c_{ijk}}{\nu_l + c_{ijk}} \right]^{y_{ijk}},
$$

(3)

with mean $E(Y_{ijk}) = c_{ijk}$ and variance $V(Y_{ijk}) = (c_{ijk} \times (1 + \frac{c_{ijk}}{\nu_l})$. As $\nu_l$ becomes infinitely large, the model reduces to a Poisson formulation with the mean equal to the variance. The Poisson count model thus is a special case of the negative binomial model.
Second, count data often contain excess zeroes. Consider that each of the \( I \) consumer’s sorting behavior is represented by \( (J \times (J - 1)/2) \) unique cells, a number that grows quickly as the number of items in the sorting task increases. The counts reflect binary associations between pairs of items that do not necessarily end up in the same piles, so there is often a large number of zeros in \( Y = (((Y_{ijk}))) \). This excess number of zeros can lead to inconsistent estimates in both Poisson and negative binomial models (for a discussion of related issues, see Grogger & Carson, 1991). One potential option is to introduce a mixture component (e.g., Green, 1994; Li, Liechty, & Montgomery, 2002) that specifies a process that leads to more zeros than typically would be expected. To model this special process, I specify the distribution as a mixture of the negative binomial and a point mass at 0 (i.e., zero-inflated negative binomial). Therefore, \( \pi_{jk} \) denotes the probability that items \( j \) and \( k \) are not grouped together in any category, and the mass function in Equation (1) can be expressed as:

\[
P \left[ Y_{ijk} | \pi, \nu \right] = \begin{cases} 
\pi_{jk} + (1 - \pi_{jk}) \left[ \frac{\nu_l}{\nu_l + c_{ijk}} \right]^\nu_l & \text{if } Y_{ijk} = 0 \\
(1 - \pi_{jk})^\nu_l \left( \frac{\nu_l}{\nu_l + c_{ijk}} \right)^\nu_l \left[ \frac{c_{ijk}}{\nu_l + c_{ijk}} \right]^\nu_l & \text{if } Y_{ijk} > 0,
\end{cases}
\]

(4)

where \( \pi_{jk} \) is restricted to between 0 and 1 and \( c_{ijk} \) is still a parameter\(^1\). In this case, \( \pi_{jk} \) provides insight into the overall dissimilarity between items \( j \) and \( k \) across the sample.

Two items likely enter the same piles according to the number of unobserved categories in which the two items are members, as well as the extent to which the unobserved categories are salient to the consumer. Because these categories are not

---

\(^1\) Dependencies among the counts can exist in extreme cases. If \( Y_{ijk} = NP_i \) and \( Y_{ijm} = NP_i \) (where \( NP_i \) is the total number of piles an individual creates), then \( Y_{ijm} = NP_i \). Therefore, a participant would have to put two different pairs of brands in all piles, something that rarely occurs in practice.
directly observable, they must be inferred from data in a probabilistic manner. Therefore, I first define $p_{jr}$ as the probability that item $j$ belongs to unobserved category $r$ and $s_{ir}$ as the salience of unobserved category $r$ for consumer $i$. The matrices $P = ((p_{jr}))$ and $S = ((s_{ir}))$ then are the two central components of the internal category structure: category memberships for the items, and the extent to which each consumer activates each category. None are observed, and $P$ and $S$ must be estimated from the counts observed from the modified sorting task.

As such, I suggest that $c_{ijk}$, the expected number of times that two items $(j, k)$ appear together in a pile, be specified as a function of the elements of two unobserved matrices $P$ and $S$:

$$c_{ijk} = \sum_{r=1}^{R} s_{ir} p_{jr} p_{kr} .$$

(5)

That is, two items are likely to be in the same pile if they are both members of the same unobserved categories and the category is salient to the consumer performing the sorting task. The greater number of salient unobserved categories $j$ and $k$ have in common, the greater the $Y_{ijk}$ counts should be. Unless $s_{ir}$, $p_{jr}$, and $p_{kr}$ are all high, their product will be low. The total count observed thus reflects the number of salient unobserved categories in which both items are members. Because the specification in Equation (5) is not identified, I impose some constraints on the parameters. First, each $p_{jr}$ must be between 0 and 1, to represent the probability that item $j$ belongs to category $r$. Second, each $s_{ir}$ is also restricted to between 0 and 1. Salience, as the unobserved activation of categories, needs to be positive, and an upper boundary of 1 suggests that $s_{ir}$ can reflect the probability that consumer $i$ has activated unobserved category $r$. 


This formulation is equivalent to specifying the category structure and each subject’s activation. Effectively, the procedure can set \( s_{ir} = 0 \) when a category is not salient for consumer \( i \), as matrix \( P \) represents the common categories across the sample. In turn, the specification can accommodate unique categories for some consumers, simply by adding an additional category to the common categories that other consumers use and estimating high saliencies for those consumers. Salience parameters for each participant also accommodate other categorization phenomena, such as the varying perceptions of items that belong to different categories. Not all consumers may agree that item \( j \) is member of category \( r \), so the model retains two unobserved categories in \( P \): category \( r \), with item \( j \) as a member, and category \( r + 1 \) without it. This specification thus acknowledges the potential for different category structures for each consumer with appropriate salience variations.

This formulation clearly relates to prior work (Arabie et al. 1981; Carroll and Arabie 1983; DeSarbo, Jedidi and Johnson 1991; Lee 2001; Shepard and Arabie 1979). The use of similarity as a core component of categorization appears flexible enough to account for various categorization structures, including feature and functional similarity, as well as context dependence, though the specific features in similarity calculations depend on the situation (Goldstone 1994; Medin, Goldstone, and Gentner 1993; Nosofsky and Johansen 2000). However, this specification differs in several ways. Shepard and Arabie (1979) consider similarity a function of item features known to the experimenter (i.e., \( P \) was fixed and predetermined) and assumed to be binary (0 or 1), such that an item had a feature or not. Arabie et al. (1981) expanded this model by allowing \( P \) to be estimated, but their data did not pertain directly to categorization, and
their model did not allow for graded membership (entries in $P$ were restricted to 0 or 1).

In contrast, I propose that $P$ represents the probability that an item is a member of a category. For taxonomic categories, a higher value of $p_{jr}$ represents the extent to which item $j$ is representative of category $r$. In the context of a goal-driven category, a higher value of $p_{jr}$ suggests that item $j$ indicates better potential for supporting goal fulfillment.

This conceptualization also can account for different levels of abstraction and items that simultaneously belong to multiple categories. An item can be a member of multiple categories (several $P$ entries close to 1) or none (low entries for $P$ across all unobserved categories). There is no restriction on how $P$ should sum across rows ($\sum_{r=1}^{R} p_{jr}$ does not have to sum to 1, for any $j$; e.g. DeSarbo, Jedidi and Johnson 1991). Consequently, categories can be subsets of one another, and a consumer can simultaneously consider multiple categories.

In summary, the proposed specification allows for different category structures, which can vary in level of abstraction and in which items can belong to multiple categories even within a single consumer. The specification uses probabilistic membership to reflect the graded membership of an item in different ways for the different category structures.
Estimation Procedure

The joint likelihood across consumers and pairings can be formed as:

\[
L = \prod_{i=1}^{I} \prod_{j<k} \prod_{Y_{ijk} \geq 1} \left[ \left( 1 - \pi_{jk} \right) \frac{\Gamma(v_i + Y_{ijk})}{\Gamma(1 + Y_{ijk})} \frac{v_i}{v_i + c_{ijk}} \right] \frac{v_i}{v_i + c_{ijk}}^{Y_{ijk}} I_{Y_{ijk} \geq 1}
\times \left[ \pi_{jk} + (1 - \pi_{jk}) \frac{v_i}{v_i + c_{ijk}} \right]^{v_i} I_{Y_{ijk} = 0}
\tag{6}
\]

where \(I_{Y_{ijk} = 0}\) is an indicator function for when the observed count is zero and \(I_{Y_{ijk} \geq 1}\) is an indicator function for when it is greater than zero. Taking the natural logarithm of expression (6) and noting that \(\Gamma(v_i + Y_{ijk}) = \Gamma(v_i) \prod_{n=0}^{Y_{ijk} - 1} (v_i + n)\), I obtain the log likelihood:

\[
\begin{align*}
LL = & \sum_{j<k} \sum_{i:Y_{ijk} \geq 1} \left( \sum_{n=0}^{Y_{ijk} - 1} \ln(v_i + n) \right) + \ln(1 - \pi_{jk}) - \ln \left( \Gamma(1 + Y_{ijk}) \right) \\
& + \ln \left( \left[ \frac{v_i}{v_i + c_{ijk}} \right]^{Y_{ijk}} \right) + \ln \left( \left[ \frac{c_{ijk}}{v_i + c_{ijk}} \right]^{Y_{ijk}} \right) + \sum_{i:Y_{ijk} = 0} \ln \left( \pi_{jk} + (1 - \pi_{jk}) \frac{v_i}{v_i + c_{ijk}} \right). \\
& \tag{7}
\end{align*}
\]

To estimate the parameters, the log-likelihood then must be maximized subject to the constraints on \(\Pi (\Pi = ((\pi_{jk})))\), \(P\), \(S\), and \(v (v = (v_i))\) that \(0 \leq \pi_{jk}, s_{ir}, p_{jr} \leq 1\), and \(v_i \geq 0\). I can maximize the log-likelihood by setting the partial derivatives equal to 0. To enforce the positivity constraint on \(v_i\), I replace \(v_i\) with \(v_i^2\) (see Gill, Murray, and Wright 1981):
Using the chain rule and simplifying, I obtain:

\[
\frac{\partial LL}{\partial v_i} = \sum_{j < k} \sum_{l_y \in k} \left[ \lambda_{ijk} \left( \sum_{n=0}^{\lambda_{ijk}^{-1}} \frac{\partial \ln(v_i^2 + n)}{\partial v_i} \right) + \frac{\partial v_i^2 \ln(v_i^2 + c_{ijk})}{\partial v_i} - \frac{\partial v_i^2 \ln(v_i^2 + c_{ijk})}{\partial v_i} \right] \]

Using the chain rule and simplifying, I obtain:

\[
\frac{\partial LL}{\partial v_i} = \sum_{j < k} \sum_{l_y \in k} 2v_i \left[ \lambda_{ijk} \left( \sum_{n=0}^{\lambda_{ijk}^{-1}} \frac{\partial \ln(v_i^2 + n)}{\partial v_i} \right) + \frac{\partial v_i^2 \ln(v_i^2 + c_{ijk})}{\partial v_i} \right] \]

To ensure that \(\pi_{ijk}\) remains between 0 and 1, I replace \(\pi_{ijk}\) with \(\frac{\exp(q_{jk})}{(1 + \exp(q_{jk}))}\). I can then estimate \(q_{jk}\) as follows:

\[
\frac{\partial LL}{\partial q_{jk}} = \left( \sum_{l_y \in jk} \theta_{ijk} \frac{1}{1 + \exp(q_{jk})} \right) \]

Or

\[
\frac{\partial LL}{\partial q_{jk}} = \left( \sum_{l_y \in jk} \frac{\exp(q_{jk})}{1 + \exp(q_{jk})} \right) + \theta_{ijk} \frac{1}{1 + \exp(q_{jk})} \]
\[
\frac{\partial LL}{\partial q_{jk}} = \left( \sum_{i:j,i \neq j,k} \gamma_{ijk} \frac{\exp(q_{jk})}{(1 + \exp(q_{jk}))^2} \right) + \left( \sum_{i:j,i \neq j,k} \frac{\exp(q_{jk})}{(1 + \exp(q_{jk}))^2} - \gamma_{ijk} \frac{\exp(q_{jk})}{(1 + \exp(q_{jk}))^2} \right).
\]

(11)

where \( \gamma_{ijk} = \frac{r(v_i + y_{ijk})}{r(v_i) r(v_i + c_{ijk})} v_i \left( \frac{c_{ijk}}{v_i + c_{ijk}} \right)^{y_{ijk}} \) and \( \gamma_{ijk} = \left( \frac{v_i}{v_i + c_{ijk}} \right)^{y_{ijk}} \).

Because \( p_{ar} \) must be constrained between 0 and 1, I reparametrize \( p_{ar} = \frac{\exp(\gamma_{ar})}{1 + \exp(\gamma_{ar})} \).

Using the chain rule, I then can solve for \( \gamma_{ar} \):

\[
\frac{\partial LL}{\partial \gamma_{ar}} = \delta \sum_{i:a} \sum_{j:a} \ln \left( \left( \frac{v_i^2}{v_i^2 + c_{ija}} \right)^{y_{ija}} \right) + \ln \left( \left( \frac{c_{ija}}{v_i^2 + c_{ija}} \right)^{y_{ija}} \right)
\]

\[+ \sum_{i:a} \ln \left( \pi_{ja} + (1 - \pi_{ja}) \left( \frac{v_i^2}{v_i^2 + c_{ija}} \right)^{y_{ija}} \right) / \partial \gamma_{ar}, \]

(12)

\[
\frac{\partial LL}{\partial \gamma_{ar}} = \sum_{i:a} \sum_{j:a} (\gamma_{ar}^2 - \gamma_{ar}) p_{i:s_{ir}} \left( \frac{v_i^2}{v_i^2 + c_{ija}} - \frac{y_{ija}}{c_{ija}} \left( 1 - \frac{c_{ija}}{v_i^2 + c_{ija}} \right) \right)
\]

\[+ \sum_{i:a} (\gamma_{ar}^2 - \gamma_{ar}) p_{i:s_{ir}} (1 - \pi_{ja}) v_i^2 \left( \frac{v_i^2}{v_i^2 + c_{ija}} \right)^{y_{ija} - 1}
\]

\[+ \sum_{i:a} (\gamma_{ar}^2 - \gamma_{ar}) p_{i:s_{ir}} (1 - \pi_{ja}) \left( \frac{v_i^2}{v_i^2 + c_{ija}} \right)^{y_{ija}} \left( \frac{v_i^2}{v_i^2 + c_{ija}} \right)^2 \]

(13)

Likewise, I constrain the category saliencies between 0 and 1 by reparametrizing

\[s_{ir} = \frac{\exp(z_{ir})}{1 + \exp(z_{ir})} \]

and solve for \( z_{ir} \):

\[
\frac{\partial LL}{\partial z_{ir}} = \delta \sum_{j<k} \sum_{i:j} \left( l_{v_{ijk} \geq 1} \ln \left( \left( \frac{v_i^2}{v_i^2 + c_{ijk}} \right)^{y_{ijk}} \right) \right) + \ln \left( \left( \frac{c_{ijk}}{v_i^2 + c_{ijk}} \right)^{y_{ijk}} \right)
\]

\[+ l_{y_{ijk} = 0} \ln \left( \pi_{jk} + (1 - \pi_{jk}) \left( \frac{v_i^2}{v_i^2 + c_{ijk}} \right)^{y_{ijk}} \right) / \partial z_{ir}. \]

(14)
For the preceding expressions, setting the partial derivatives equal to 0 does not lead to any closed-form expression, given the extreme nonlinearity. Therefore, I use numerical optimization techniques in an alternative algorithm involving a nonlinear conjugate gradient procedure with automatic restarts (Nocedal and Wright 1999) to solve iteratively for \( \psi, \Gamma, \Pi, Z \) (Equations 9, 11, 13, and 15).

Because the number of unobserved categories is unknown, a combination of interpretation and information criteria (e.g., AIC, BIC, CAIC, MAIC) serves to determine the appropriate number of unobserved categories. Given that when estimating model parameters using maximum likelihood estimate the likelihood can always be improved by adding extra parameters, information criteria provide a way to penalize models for adding parameters that only marginally contribute to improving the likelihood. As such, a General Information Criterion (GIC) is defined as (Wedel and Kamakura 2000):

\[
GIC = -2 \times LL + nbpar \times penalty
\]  
(16)

where \( nbpar \) indicates the number of parameters estimated, and where \( penalty \) is specified differently for each criterion. For AIC, \( penalty = 2 \), for MAIC \( penalty = 3 \), for BIC \( penalty = \ln (I) \), and for CAIC \( penalty = \ln (I + 1) \). Finally, for the proposed model the number of parameters estimated can be determined by the following formula:

\[
bpar = I + R \times (J - 1 + I) + R \times \frac{I \times (I - 1)}{2},
\]  
(17)
and the number of total observations is given by $I \times \frac{J \times (J-1)}{2}$. Regardless of which criteria are used, one selects the model for which the GIC value is lowest.

**Synthetic Data Example**

I present a synthetic data example to illustrate the type of categorization structures that my methodology can recover. To do so, I generated data for 100 consumers ($I=100$) using 15 items ($J=15$) and 5 unobserved categories ($R^*=5$). To begin, a category membership $P$ (presented in Table 3-1) was proposed to illustrate the various category structures. Notice that items 1-6 are the only ones highly representative of category 1 ($p_{jr} \geq 0.94$); similarly, items 7-15 are the items that reflect category 2. Yet, all these items are clearly member of other categories, which illustrates the method’s need here to uncover multiple category memberships. For instance, item 1 is highly representative for categories 1, 4 and 5, and item 8 is highly representative of categories 2 and 3. Next, I generated the saliencies using $s_{ir} \sim beta(0.25,0.25)$, which provides values between with 0 and 1 following an inverted-U distribution. This choice reflects that consumers can use multiple categories when creating their piles in the sorting task. As such, various combinations of the saliencies may reflect entirely different category structures that vary in the extent to which they suggest the presence of multiple category memberships.

One consumer thus might consider categories 1 & 2 as salient and represent the entire set of items using these two entirely mutually exclusive categories. Another might consider categories 1, 3 and 4 and suggest a finer-grained representation of category 2 (e.g., split in categories 3 and 4). The selected representation allows each consumer to
perceive each item as potentially belonging to multiple categories simultaneously. Thus, a consumer having categories 1, 3, and 4 salient sees many items in multiple categories. Consequently, there is a large amount of heterogeneity possible with respect to the patterns of salience and category membership possible with this procedure. To demonstrate that the proposed methodology can recover these structures, I generated a dataset of counts using the parameters described above and added normally distributed error \((N(0,0.5))\) before rounding into counts\(^2\).

I estimated the model from \(R=1\ldots7\), for 5 runs each with random starts for all the parameters, and I selected the best run per value of \(R\). Log-likelihoods, and information criteria heuristics are presented in Table 3-2. Model selection heuristics BIC, CAIC and MAIC suggest that the selection of model with five unobserved categories \((R=5)\). AIC suggests the presence of 6 unobserved categories, which is somewhat expected AIC’s general tendency to select models that overfit the data (c.f., Yang and Yang 2008).

The \(R=5\) solution recovered matches the generating data \((R^*=5)\) well. For the parameters of interest, the estimated category matrix \(\hat{P} \) (RMSE: 0.09, MSE=0.01, MAD: 0.07), and the estimated saliencies matrix \(\hat{S} \) (RMSE=0.10, MSE=0.01, MAD: 0.06) were recovered very well with no substantial interpretative changes. The predicted counts \(\hat{Y} \) \((\hat{Y} = \langle \langle \langle \langle Y_{ijk} \rangle \rangle \rangle \rangle)\) also approximate well the original counts, with a Pearson Correlation of 0.96 (RMSE=0.17, MSE=0.04, MAD=0.11). As such, I am confident that the types of structures described previously can be successfully be recovered by my algorithm.

Finally given that the iterative nature of the estimation algorithm precludes from a guarantee of reaching a globally optimal solution, I estimated an additional 20 execution

\(^2\) I used \(S\) and \(P\) matricies to generate noise-free expected optimal estimates for fitting parameters \(\Pi\) and \(\nu\).
of the model for R=5 with random starting values for all parameters. I found that of the total 25 runs estimated, all 25 were within 0.9% of the best solution found (min -9612.51 vs. -9527.00), and that 20 were within 0.1% of the optima. This provides further confidence that our estimation algorithm can be successful at recovering complex structures.

The Proposed Categorization Model Summary

The proposed methodology explores differences in consumer sorts assuming that the perceived similarity between objects is a function of the unobserved categories that are particularly salient to different consumers. I explore categorization in a non-supervised context and identify common latent categories which can be the basis of further analyses. The proposed methodology takes into account the graded structure of the unobserved categories, the potential for multiple category membership within consumers, and is sufficiently flexible to account for a variety of different types of categories. It offers no specific assumption is made regarding the relationships between each of the categories (i.e., they can be inter-related). The proposed procedure also offers a way to estimate the latent categories and their individual-level saliencies through a probabilistic model using a nonlinear maximum likelihood estimation procedure.
Table 3-1. Category Structures for the Simulated Data

<table>
<thead>
<tr>
<th>Item</th>
<th>Categories</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
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<td>0.13</td>
<td>0.95</td>
<td>0.98</td>
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<td>0.10</td>
<td>0.94</td>
<td></td>
</tr>
<tr>
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<td>0.19</td>
<td>0.18</td>
<td>0.96</td>
<td>0.12</td>
<td></td>
</tr>
<tr>
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<td>0.11</td>
<td>1.00</td>
<td>0.17</td>
<td>0.98</td>
<td></td>
</tr>
<tr>
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<td>0.13</td>
<td>0.95</td>
<td>0.96</td>
<td></td>
</tr>
<tr>
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<tr>
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<td>0.99</td>
<td>0.94</td>
<td>0.11</td>
<td>0.14</td>
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Table 3.2. Simulation Results

<table>
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<th></th>
<th>LL</th>
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<th>AIC</th>
<th>BIC</th>
<th>CAIC</th>
<th>MAIC</th>
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<td>23332.11</td>
<td>21712.14</td>
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</tbody>
</table>
Chapter 4

Empirical Illustration: Categories of Restaurants

For the empirical test of the proposed model, I applied three criteria to select the
study context: sufficient control over the selection of the stimuli (which suggested a
laboratory experiment), items with sufficient variety that consumers would be proficient
in categorizing multiple brands, and participant familiarity with most brands (to avoid
having to provide them with a list of features or attributes that could cue certain
categorization structures). As such, I had undergraduate students sort locally available
restaurants. Previous research has documented that undergraduate students are familiar
with the evaluation of various restaurants (e.g., Carlson, Meloy, and Russo 2006; Laran,
Janiszewski, and Cunha 2008); these participants should also be familiar with the
dimensions, attributes, and goals related to restaurants, and have sufficient experience to
categorize them on a meaningful basis. The task context is also feasible, because there are
many restaurants from which to choose and many ways to categorize them. Some
categories represent taxonomic categories (e.g., international, Italian, ribs), and others are
more related to context (e.g., breakfast, free delivery, family dining), but some restaurants
clearly span multiple categories. For example, in a local listing of restaurants, Domino’s
can appear in the pizza, wings, takeout, and delivery categories—which may or may not
be naturally salient to consumers.
Study Procedures

One hundred thirty-two undergraduate students at a large northeastern U.S. university participated in exchange for extra course credit. Using a pretest with 12 other students, I identified the 25 restaurants listed in Table 4-1. Each participant received 250 total cards, with 10 (2 × .75 inches) pieces of paper listing each restaurant’s name. The cards were in a tray with 25 compartments, such that every compartment was specific to a restaurant and contained the 10 cards. When they entered the research lab, participants were informed that the study would be about how people think about restaurants. They looked at the set of cards in front of them and were instructed to make piles of restaurants that they thought “go together,” according to their own perceptions (Ross and Murphy 1999; see also Coxon 1999). They were told they could make as many piles as they wished, could move the cards as much as they wanted, and needed to use at least one card per restaurant.

Directly after this modified sorting task, participants completed an online questionnaire that asked them to indicate their knowledge of and experiences with each restaurant. Finally, they responded to some demographic and mood questions. The participants were 20 years of age on average; 86.5% were juniors, 94% were native English speakers, and 51% were men. They created 6.4 piles on average and completed the sorting task in an average of 12 minutes.
Results

A combination of information criteria and interpretation supported the selection of a parsimonious solution (R=9 unobserved categories; R varied from 1…11) for the restaurant data. The results are presented in Table 4. The model also fits the data reasonably well with a Pearson correlation of 0.56 between the observed and predicted counts (RMSE=0.48, MSE=0.26, MAD=0.38). Further, to investigate local optima issues I estimated an additional 20 execution of the model (total of 25) for R=9 with random starting values for the parameters. I found that of the runs estimated, all 25 were within 2.5% of the best solution found and that 12 were within 0.1% of the optima.

In Figure 4-1, I display the distribution of possible pairings of the number of cards used by participants. The $Y$ matrix has $I \times \frac{(J \times J - 1)}{2} = 132 \times 300 = 39,600$ unique cells, representing the number of possible pairings across all the participants. A rather large proportion of restaurants were never grouped together, as indicated by the dominance of zeros (77% of the cells), which offers face validity for the justification of the zero-inflated specification. The maximum number of times two items were put in the same pile by a single participant was 5, which occurred twice across the 132 participants. The mean observed number of parings was 0.34, and the observed variance was 0.17. The variance being twice as smaller than the mean provides preliminary evidence of under-dispersion.
Interpreting the Unobserved Categories

Table 4-3 contains the matrix of unobserved categories (\( \mathbf{P} \)) across the sample; Figure 4-2 provides the salience (\( \mathbf{S} \)) density plots for each derived category. The most salient category features large, dominant fast-food chains (e.g., Burger King, KFC, McDonald’s, Taco Bell, Wendy’s). The \( \mathbf{P} \) matrix for this unobserved category reflects restaurants with high or low representativeness as most entries were either 0 or 1. The associated density plot of the saliencies is highly negatively skewed, which suggest that a majority of participants activated this category.

The second category groups delivery pizza restaurants (e.g., Domino’s, Papa John’s). Of the other restaurants in the sample, only Rotelli’s (an Italian pizzeria chain) serves pizza, but is not regarded as representative. What differentiates these restaurants is their delivery service—a highly salient attribute to students who live in various forms of on-campus housing. Whereas Domino’s and Papa John’s deliver, Rotelli’s does not. This category is highly salient across the sample, with an average salience of .69, and the bimodal nature of the saliencies plot around 0 and 1 suggests that not all participants activate the category.

The third category includes restaurants such as Applebee’s, Chili’s, Olive Garden, Red Lobster, Ruby Tuesday’s, Outback, TGI Friday’s, and Texas Roadhouse, all of which typically provide waiter service and can be labeled sit-down restaurants. This unobserved category also seems highly salient (average = .67) across the sample, although the saliencies were more evenly spread out and with a large concentration near 1.
The fourth category, *Mexican restaurants* (e.g., Chipotle, Mad Mex, Qdoba, Taco Bell), reveals an average salience of .59. These restaurants serve foods associated with Mexico including burritos and tacos. Chili’s is also considered part of this category, though only partially; it is much more representative of the sit-down category for which it is highly representative. This finding reflects the strong Tex-Mex influence on Chili’s menu, even as it is positioned similarly to other sit-down restaurants. Furthermore, the saliencies suggest that a large group of participants activates this category.

For the broader set of *pizza restaurants*, the fifth category, Domino’s, Papa John’s, and Rotelli’s are all highly representative (average salience = .57). These restaurants all serve pizza, which represents a strong communality. The bimodal plot of the saliencies for this category suggests that respondents either activate the category or not.

The sixth category features Chipotle, Mad Mex, Panera Bread, Pita Pit, Qdoba, and Quiznos, with an average salience of .56. There are many sub-categories possible among these restaurants (e.g., sandwiches, burritos, wraps, subs), but they were categorized at a higher level of abstraction to include various forms of *sandwiches and subs*. Mad Mex, a local chain, was a highly representative member of the category, due to its local reputation for large, cheap burritos. With an average of .57, the category is very salient across the sample, and a significant proportion of the saliencies approach 1.

For *brunch* restaurants (average salience = .46), the category includes not only highly representative breakfast restaurants, such as Denny’s and the Waffle Shop, but also other types of restaurants. Both Applebee’s and Ruby Tuesdays offer weekend brunch and therefore join the category. Other less representative members include Chili’s, Olive Garden, Outback, and TGI Friday’s; customers can visit these restaurants
during traditional brunch times, though they do not provide a separate brunch menu. The associated salience plot is bimodal.

The eighth category, burger restaurants, induces an average salience of .25. Most representative were the traditional, fast-food burger restaurants (Back Yard Burgers, Burger King, McDonald’s, Wendy’s), though chains that offer burgers (e.g., Applebee’s, TGI Friday’s) were also regarded as somewhat representative. The density plot suggests that although a lower proportion of respondents deem this category salient, many participants experience some activation for it.

Finally, the ninth category comprises quick service restaurants. It includes both traditional fast-food restaurants (e.g., dominant fast foods, delivery pizza restaurants, subs, burritos) and restaurants such as Panera Bread that do not serve typical fast-food meals but offer fast service. As indicated by the associated salience plot, most people’s activation of this category is low.

Note that the estimated $1 - \pi_{jk}$ (mixing parameters) offers some insight into how restaurants vary in their similarity to all other restaurants. A higher value for $1 - \pi_{jk}$ indicates that focal restaurant $j$ is often in the same pile as restaurant $k$ in participants’ sorting task. Figure 2 presents a histogram of $1 - \sum_{k \neq j}^{\pi_{jk}} \pi_{jk}, \forall j = 1 ... J$, that is, one minus the average value of the mixing parameters with other restaurants (the values highly correlate with the total number of cards used for each restaurant, $r = 0.54, p < .01$). As this figure shows, some restaurants with the lowest scores appear in relatively few piles and represent categories with fewer other restaurants (e.g., pizza: Domino’s, Papa John’s; brunch: Waffle Shop, Denny’s). In contrast, some of the highest
scores involve restaurants that are in category piles that contain many restaurants (e.g., sit-down restaurants: Applebee’s, Red Lobster; burgers, quick service, and fast-food: Back Yard Burger). Figure 2 provides some insight into the perceptions and positioning of these various restaurants in this geographical area/market place. Restaurants with lower average $1 - \pi_{jk}$ values appear to have a much more definitive positioning in the market place where they are typically perceived or associated with a more limited, but clearer menu focus. For example, the major menu item at Domino’s and Papa John’s is pizza; at KFC, it is chicken, etc. While obtaining such a clear positioning in a market is typically a desirable trait, this may also limit the particular restaurant affected in terms of satisfying a limited set of food preferences or consumer goals which can often vary by use occasion. One can legitimately argue that restaurants with higher average $1 - \pi_{jk}$ values may enter into more consumers’ consideration choice sets across a wider set of food preference or goal attaining states. Applebee’s is a good example of such a restaurant given their varied menu and advertising stressing combo meals and menu diversity.

Illustrating Categorization Theory Principles

The correlations between the saliency parameters can illustrate the relationship between co-activation of categories and recover instances when consumers think at different level of abstraction. For example, the salience parameters for delivery pizza and pizza correlated negatively ($r = -0.26, p < .01$), which implies participants did not think at both these levels of abstraction simultaneously (the delivery pizza category is a subset of
the more general pizza category), and participants who thought of a pizza category did not also have the delivery pizza category as salient. Furthermore, the pizza category was more salient to those in a more positive mood, consistent with extant literature that suggests that positive moods make people more inclusive in their categories (Isen 1984). Similarly, participants who used the dominant fast food category did not generally use the quick service restaurants category ($r = -0.25, p < .01$). In the industry, fast food and “quick service” are considered synonymous. However, with these participants we notice that different participants see fast-food in different ways. One thinks of fast food including the large dominant chains (dominant fast food category), whereas others consider fast food being anything that offers a quick meal, including healthier options and sandwich restaurants (e.g. Panera Bread) that would be considered quite different from traditional fast-food chains. The quick meals category includes all the restaurants from dominant fast-food chains, such that the latter is a subset of the quick meal category. Considering the different patterns observed, it is clear that the methodology captures different levels of abstraction across consumers.

The categories generally identified were generally taxonomic, in that they reflected groups of restaurants that shared similar features like menu items (e.g., burger restaurants, pizza, sandwiches and subs). Others categories were more related to the context of consumption and may be more akin to goal-driven categories. For instance, the brunch category includes many restaurants that do not actually serve breakfast or have brunch menus (e.g., Applebee’s, Olive Garden). Intuition suggests that participants in this study were college students who generally go to breakfast/brunch away from their dorms or one of three contexts: on weekends with friends (after a long night out), when their
parents come to town, or after going to Church. In all three cases, participants not only think of having breakfast food (e.g. not quickly grabbing a McMuffin at McDonald’s prior to going to class) but rather think about a place where they can sit down and have a late morning meal which may or may not involve actual breakfast food. This example of a more context/goal-driven category of brunch & breakfast illustrates that the methodology can capture both goal-driven and taxonomic categories.

In addition, this methodology highlights that most brands belong to multiple categories. For example, Burger King, McDonald’s, and Wendy’s were all highly representative members of dominant chains, burger chains, and places to get a quick meal. Rotelli’s (local chain) was both a sit-down restaurant and a pizza restaurant. Brands also vary in their representativeness, suggesting the presence of graded membership. For example, Applebee’s was strongly identified with sit-down restaurants but also with brunch restaurants. Chili’s, though mostly considered a typical sit-down chain, shared some resemblance with Mexican restaurants perhaps due to its Tex-Mex origins. However, not all restaurants were assigned to multiple categories. For instance, the Waffle Shop, part of a local chain of breakfast restaurants, was clearly only salient to the brunch & breakfast category. Its position is a consensus among the participants, suggesting centrality and perhaps greater accessibility to those who have the category salient.

Finally, the category structure invoked provided some observations about the nature of competition between brands across multiple unobserved categories. McDonald’s and Wendy’s were representative of the same unobserved categories: dominant fast food, burgers, and quick meals. Therefore, their competition is likely
strong, and individuals’ inferences and expectations about them are likely quite similar. Furthermore, though McDonald’s serves breakfast foods, the results did not identify it as a member of the brunch and breakfast category; that is, McDonald’s had low representativeness in that category. This finding might suggest that McDonald’s positioning as a breakfast restaurant has gone unnoticed in this sample, though a more reasonable interpretation might be that the category includes restaurants mainly used for brunch. McDonald’s membership in a category focused more on breakfast might become salient if individuals’ consumption context related directly to breakfast food or they were exposed to breakfast-oriented marketing cues. Yet, at a general level, individuals in this sample do not perceive McDonald’s as part of the breakfast/brunch category.

Comparison with Aggregate Methodologies

Existing methodologies use counts of items in the same piles as an indication of similarity, so it is possible to use these methodologies to extract unobserved categories from the modified sorting task (using multiple counts). Therefore, we created a summary count matrix across all participants and used it as input for an agglomerative clustering algorithm that served as a basis for comparison with the results from the proposed method. The resulting distances are not Euclidian, so we used complete linkage as the clustering criterion. The dendrogram in Figure 4-2 then reveals the number of unobserved categories. It suggests a five-cluster solution:

(1) a breakfast cluster, including Waffle Shop and Denny’s;
(2) a sit-down cluster, with Texas Roadhouse, Outback, Red Lobster, Olive
Garden, Chili’s, Ruby Tuesday’s, TGI Friday’s, and Applebee’s;
(3) the pizza category, with Papa John’s, Domino’s, and Rotelli’s;
(4) a sandwich/subs group, featuring Qdoba, Quiznos Pita Pit, Panera Bread, Mad
Mex, and Chipotle; and
(5) a fast-food cluster, with Back Yard Burger, McDonald’s, Burger King,
Wendy’s, Taco Bell, KFC.

The dominant fast-food category, very salient in our procedure, was also evident
with this methodology. Both solutions featured a Mexican category, as well as a pizza
category, and the delivery aspect emerged from the tree structure, although no indication
about their saliencies can be obtained. Yet, the results of this aggregate methodology fails
to capture some subtleties such as the quick meal category which encompassed many
objects from other categories; here, the objects can only be assigned to one category. The
burger category also disappears as the salient fast-food category dominates instead.
Burger King, Wendy’s, and McDonald’s can appear only in one category which
undermines the intensity of perceived competition among these brands. The sit-down
category also excluded some representative members of other categories such as Rotelli’s
and Mad Mex. Finally, this methodology ignores all information about the individual-
level saliences of categories because it utilizes the aggregated data which makes it
impossible to assess whether the salience of different categories covary or inhibit one
another, make inferences about the patterns of category salience, or infer which
unobserved categories were most common.
Even when an existing clustering procedure analyzes data from the new multiple sorting task in which participants could assign restaurants to more than one pile, it cannot reveal the multiple category memberships of the various brands. Nor does this existing method address the graded membership of restaurants, and it loses information through the aggregation process and provides little information about heterogeneity in category saliencies. In sum, the new proposed procedure provides managerial insights that are not available when using other available procedures, and can recover aspects of category structures that would be unavailable otherwise.

**Implications for Competitive Market Structures**

What implications do these different empirical results have for the positioning of existing local restaurants? Consider the case of the local *Mad Mex*, part of a restaurant chain with restaurants in Pittsburgh, State College, Columbus and Philadelphia. The restaurant, known in the areas for its $5 “All you can eat burritos” Monday nights, offers a wide range of entrees ranging from traditional Mexican fares (chimichangas, enchiladas, tamales, etc.) to “Mexicanized” American options such as wings and salads. In State College, the restaurant is also very popular as a night hangout due its large patio, the ever popular $5 “Big Azz” margaritas, and its large selection of local and imported beers. Were *Mad Mex* to consider the results of the aggregate clustering analyses, the restaurant would be part of a *Sandwiches and Subs* category, competing with Chipotle, Qdoba, Pita Pit, Panera Bread and Quiznos. However, little else would be known. Which of the restaurants is *Mad Mex* more directly competing with? Using only this information,
one would conclude that the restaurant competes equally with Chipotle, Qdoba, Pita Pit, Panera Bread and Quiznos and less so with sit-down restaurants or other Mexican restaurants like Taco Bell.

When it comes to Mad Mex, it is quickly apparent that the proposed procedure captures much better the essence of the restaurant’s positioning. According to the new proposed methodology, Mad Mex is highly representative of the sandwiches and subs and Mexican (highly representative: Chipotle, Qdoba, Taco Bell) categories and less representative of the sit-down category. The information can be used to identify which of all the restaurants compete more directly with Mad Mex.

For instance, Chipotle is highly representative of both the Mexican and Sandwiches and Subs categories just like Mad Mex. However, Chipotle is not representative of the sit-down category and Mad Mex is not representative of Quick Meals. This would suggest that individuals looking for a sit-down Mexican/Burritos are more likely to think of Mad Mex, whereas those that are interested in a quick Mexican meal are more likely to consider Chipotle. Similarly, Taco Bell is likely to compete with Mad Mex on the Mexican category (both are highly representative), but less so in terms of the restaurant context as one is for a quick meal and the other is somewhat more of a sit-down restaurant. Another example involves comparing the positioning of Mad Mex and Chili’s. Chili’s is highly representative of the sit-down category but less so for the Mexican category, whereas Mad Mex is only somewhat representative of sit-down restaurants but highly representative of the Mexican category. Considering this, the two restaurants only somewhat compete with each other. Finally, one can notice that Mad
Mex only somewhat competes with Panera Bread through the *Sandwiches and Subs* category, a subtly that was lost in the clustering analyses.

Note that the estimated $1 - \pi_{jk}$ (mixing parameters) offers some additional insight into how restaurants vary in their similarity to all other restaurants and how they compete. A higher value for $1 - \pi_{jk}$ indicates that focal restaurant $j$ is often in the same pile as restaurant $k$ in participants’ sorting task. Figure 4-4 presents a histogram of $1 - \sum_{k \neq j} \frac{\pi_{jk}}{J-1}, \forall j = 1 \ldots J$, that is, one minus the average value of the mixing parameters with other restaurants (the values highly correlate with the total number of cards used for each restaurant, $r = 0.54, p < .01$). As this figure shows, some restaurants with the lowest scores appear in relatively few piles and represent categories with fewer other restaurants (e.g., pizza: Domino’s, Papa John’s; brunch: Waffle Shop, Denny’s). In contrast, some of the highest scores involve restaurants that are in category piles that contain many restaurants (e.g., sit-down restaurants: Applebee’s, Red Lobster; burgers, quick service, and fast-food: Back Yard Burger). Figure 2 provides some insight into the perceptions and positioning of these various restaurants in this geographical area/market place. Restaurants with lower average $1 - \pi_{jk}$ values appear to have a much more definitive positioning in the market place where they are typically perceived or associated with a more limited, but clearer menu focus. For example, the major menu item at Domino’s and Papa John’s is pizza; at KFC, it is chicken, etc. While obtaining such a clear positioning in a market is typically a desirable trait, this may also limit the particular restaurant affected in terms of satisfying a limited set of food preferences or consumer goals which can often vary by use occasion. One can legitimately argue that restaurants...
with higher average $1 - \pi_{jk}$ values may enter into more consumers’ consideration choice sets across a wider set of food preference or goal attaining states. Applebee’s is a good example of such a restaurant given their varied menu and advertising stressing combo meals and menu diversity.

In sum, the clustering proposed narrowly assigned the restaurant to only one category (sandwiches and subs) and failed to differentiate how the different restaurants varied in the share of mind that they compete for with each of the restaurants. In contrast, the information obtained from the proposed methodology identifies a more complex structure for Mad Mex, involving three different categories. Further, the information regarding the graded membership and overall similarity can be used to capture insights into the competitive structure that would not have been possible previously.
Notes: “Count” denotes the number of piles that a single participant put item pairs in together across the whole sample. A count of 1306 for 2 would indicate that of all the possible item pairs across the sample, 1306 items were put exactly into 2 piles across the sample of participants.

Figure 4-1. Histogram of Counts Across the Sample of the Number of Times Cards Were Used by a Single Participant
Figure 4-2. Densities for Category Saliencies.
Figure 4-3. Agglomerative Clustering Aggregate Solution
Figure 4-4. Average Values of 1-Π (Higher Values Indicate Object is in Piles with More Other Objects)
Table 4-1. Restaurants Used in the Empirical Application

<table>
<thead>
<tr>
<th>Restaurant</th>
</tr>
</thead>
<tbody>
<tr>
<td>Applebee's</td>
</tr>
<tr>
<td>Back Yard Burgers</td>
</tr>
<tr>
<td>Burger King</td>
</tr>
<tr>
<td>Chili's</td>
</tr>
<tr>
<td>Chipotle</td>
</tr>
<tr>
<td>Denny's</td>
</tr>
<tr>
<td>Domino's</td>
</tr>
<tr>
<td>KFC</td>
</tr>
<tr>
<td>Mad Mex</td>
</tr>
<tr>
<td>McDonald's</td>
</tr>
<tr>
<td>Olive Garden</td>
</tr>
<tr>
<td>Outback</td>
</tr>
<tr>
<td>Panera Bread</td>
</tr>
<tr>
<td>Papa John's</td>
</tr>
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<td>Pita Pit</td>
</tr>
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</tr>
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<td>Rotelli</td>
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</tr>
<tr>
<td>Taco Bell</td>
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<td>Texas Roadhouse</td>
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<td>TGI Friday</td>
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<tr>
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<td>Wendy's</td>
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Table 4-2. Application: Model Selection.

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<td>Sit-down</td>
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<td>Pizza</td>
<td>Sandwiches</td>
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Chapter 5

Measurement the Impact of Using Different Empirically Obtained Category Structures on Consumer Choice

Assuming that one identified the category structures held by consumers, how does one use them to create positive outcomes? Previous findings suggest that we must consider internally held category structures when organizing assortments to be presented to consumers because a mismatch may influence consumer processing and satisfaction with the choice. The present chapter investigates how organizing assortments based on categories obtained from different techniques (in chapter 4) influence consumers’ reactions and choice.

A comparison process between internally held and externally imposed category structures shows that whenever consumers receive a new stimulus, they automatically attempt to match it with salient internal category structures (Goodstein 1993). The impact of pre-specified categories (through assortments) on consumer cognitions depends though on whether they match well with those that are naturally salient to consumers (Morales 2002; Morales et al. 2005; Poynor and Wood 2010). For example, when categories are familiar to consumers, congruity between internally held and externally imposed categories used in the assortments leads to greater satisfaction (Morales et al. 2005).

What would happen if different structures based on the results obtained using the proposed methodology are imposed to consumers through different assortments? In line with the preceding research, I would expect that if the categories match well the internal
structures that consumers hold, consumers should more easily find the brands that they want, report finding the category structure to be more helpful, and ultimately be more satisfied with their choice.

Support for these expectations also comes from the literature on the design of software interfaces. To prepare an effective user interface, software designers need to consider the extent to which candidate interfaces match the users’ “mental model”. Designers recognize that approximating the users’ mental model is not an easy task that can be accomplished without acquiring knowledge from the users first. As such, a large number of interface designers exist in a variety of fields ranging from accounting software to automobile multimedia dashboard interfaces (c.f. Toms et al. 2001). In each case, designers have used sorting tasks in conjunction with clustering techniques to approximate users’ mental models. The studies, which were often oriented with respect to improving workers performance, have found that categories/options obtained using such techniques can reduce errors and increase satisfaction with the application. However, these studies did not consider the possibility that items could be in multiple categories at the same time, and that allowing this may further improve satisfaction.

In this chapter, I detail the results from an experimental study in which a restaurant community website is developed to investigate the effect of different potential category structures on the choice process and customer satisfaction. To do so, I created a website that displays different categories of restaurants (three different structures taken from the results obtained in Chapter 4) and compare the categories’ perceived helpfulness, the visitors’ browsing patterns that follow, and ultimately their satisfaction with the restaurant choices. Results show that the proposed methodology identifies
categories that reduce the consumer processing efforts, which increases the categories’ perceived helpfulness, which in turn increases consumer satisfaction with their choice.

Method

Participants

Students in an undergraduate introduction to business class were asked to participate in an extra-credit study about restaurant preferences. They were informed that they would visit a newly launched website called Happy Valley Foods, and provide feedback to the website managers. Happy Valley Foods was described as offering visitors a way to learn essential information about the restaurants available in the area.

Categories

The restaurants listed on Happy Valley Foods were organized using different category structures. The categories provided to consumers were selected based on those obtained empirically in Chapter 4: a) five categories obtained from clustering (obtained from Figure 4-2), b) nine categories obtained from clustering (also obtained from the dendrogram in Figure 4-2), and c) nine categories obtained from the proposed methodology (Table 4-2).

The labels assigned to the categories were chosen by the researcher. To ensure labels were not chosen to be more informative for the proposed methodology, 212 students from a separate sample of undergraduates were asked to evaluate the labels of
the total 23 categories by indicating if the category name fits well (1 -- fit very poorly 5 -- fits very well) the restaurants in the category. The mean fit of the label was highest for the cluster (5) solution (M=4.08, SD=.63), followed by the cluster (9) solution (M=4.05, SD=0.64) and the proposed solution (M=4.01, SD=.52). Whereas the difference between the clustering (5) and proposed solution labels was significant (p<.01) the difference with the clustering 9 solution was not significant (p>.05). We thus have evidence that the labels were not chosen "better" for the categories obtained from the new proposed methodology.

The nine-categories clustering solution was added to control for previous findings that showed that, in some cases, the mere-presence of additional categories can be sufficient to increase consumer perceptions of variety and overall consumer satisfaction with choice through a greater feeling of self-determination (Mogilner, Rudnick, and Iyengar 2008). To address this issue, I also included questions about self-determination, and perceptions of variety.

**Stimuli & Procedure**

To make the browsing experience and choice process as realistic as possible, the experiment was incentive aligned. That is, participants were probabilistically rewarded with an alternative chosen by him or her from a choice set during the visit. In the context of this study, participants were told that 1 in every 25 participants for the study would be chosen at random and given a $20 certificate to the restaurant that he or she had chosen during the visit. Consequently, they had an incentive to choose a restaurant they liked.
The website had a three level structure. At the first level, the homepage depicted in Figure 5-1, introduced the website, the incentive alignment mechanism, and the choice task. The page provided a top-menu with a locally relevant banner, and a left hand-side navigation bar or menu containing categories of restaurants. At the second level, once a category link was clicked the participant would be provided a listing of the restaurants selected a category page (see Figure 5-2 for an example). At that point, the participant can choose to visit another category (the menu on the left is still visible) or he/she could choose to get more information about a specific restaurant by clicking on it. At the third level, the restaurant page provided basic restaurant information relevant to visitors (see Figure 5-3 for an example). Restaurant pages provided a short description taken from Hoovers (hoovers.com\textsuperscript{3}) about the restaurant’s positioning and menu choices, the phone number, addresses and a map of the different locations. Further, once on a restaurant’s page, the participant can either navigate to another category by clicking the left side menu or she can make her final selection for the lottery.

Once participants had made a choice, they were redirected to a survey for students to provide feedback to the website owners. Participants were first asked how satisfied they were with their restaurant choice for the lottery. To measure their satisfaction, I asked participants on a 7-point scale (1- not at all, 7- very satisfied), “How satisfied were you with your restaurant choice?” I also asked participants about their perception of variety with the following question: “How different from one another were the restaurants listed in the Happy Valley Foods website?” (1-not different at all, 7-very different). To measure the participants’ perception of self-determination, I asked them

\textsuperscript{3} When not available, the descriptions were constructed to follow a similar structure.
four questions adapted from the Intrinsic Motivation Inventory (Deci et al. 1994; see also Mogilner, Rudnick and Iyengar 2008): “I believe I had some choice in selecting this particular restaurant.”, “For the lottery, I believe I had some choice about selecting this particular restaurant”, “For the lottery, I selected this restaurant because I had no choice”, and “For the lottery, I selected the restaurant because I had to.” (all 1- not at all true, 7- very true; Cronbach Alpha: 0.61). Further, questions were asked to inquire about the participants’ familiarity with each of the restaurants listed, their restaurant habits, and psychographics.

Finally, every participant’s visit was tracked using a database and PHP code. Information collected included the number of restaurant pages visited, the number of category pages visited, and the time spent browsing each page of the website. This allows the calculation of summary statistics, such as the proportion of total browsing time spent on category pages. This gives an indication of the relative processing effort spent required in reconciling their category structures with that offered by the website.

**Results**

One hundred and six students were recruited to participate in the experiment. Ten participants completed the browsing task in less than five seconds and paid little attention to the instructions. They were removed from all subsequent analyses. Of the remaining participants, 57.7% were male, 69.1% were juniors in college, and 28.9% had been employed as a wait staff in a restaurant, and 88.7% had English as their native language.
Satisfaction Results

A one-way ANOVA comparing the choosers’ satisfaction with their final restaurant choice suggests that participants who browsed a website employing the nine categories from the proposed methodology were more satisfied ($M=6.74$) than those who browsed the websites using categories obtained from the clustering five categories solution ($M=5.88$) and the clustering nine categories solution ($M=6.21$; $F(2,96) = 5.47, p < .01$). Contrasts showed that although there was no significant difference between the satisfaction scores for the two clustering solutions ($t(66) = 1.09, p = .26$), the categories obtained from the proposed methodology led to greater satisfaction than both the five categories clustering solution ($t(61) = 3.13, p < .01$) and the nine categories clustering solution ($t(61) = 2.89, p < .01$). There is thus evidence that the proposed methodology offered categories that led customers to be more satisfied their choice, and that the difference was not due simply to the presence of a greater number of categories.

Process Testing & Alternative Explanations

As previously stated, existing research suggests that if a category assortment more closely approximates the consumers’ mental structures, it should make it easier for consumers to find what they want, and they should find the categories more helpful in making their decision. However, it is possible that other processes explain part of the increase in satisfaction. Mogilner, Rudnick and Iyengar (2008) found that category structures that increase perceived variety also increase feelings of self-determination,
which in turn may lead to increases in satisfaction. Consequently, perceptions of variety and self-determination had to be accounted for when considering an explanation for the increase in satisfaction.

First, an ANOVA comparing the three category structure conditions on perceived helpfulness (of the categories) suggests that participants who browsed the website with categories obtained using the new methodology found the categories to be more helpful than those who browsed the websites organized using the categories obtained from the traditional clustering analyses \(F(2,94) = 5.77, p < .01\). Specifically, those who had used the nine categories from the new methodology perceived the categories to be more helpful \((M=6.21)\) than those who either saw the nine categories obtained from clustering \((M = 5.47; t(61) = 3.12, p < .01)\) or five categories obtained from clustering \((M = 5.38; t(61) = 3.20, p < .01)\). This suggests that the categories obtained from the new methodology are more helpful than the ones obtained from the clustering analyses.

Second, to provide more direct evidence of whether the increase in satisfaction was due to perceived helpfulness of the categories and not due to the perceived variety and self-determination, I performed a multiple mediation analysis using 5000 bootstrap samples for the calculation of indirect effects (c.f. Kenny, Kashy, and Bolger 1998; Preacher and Hayes 2004; Zhao, Lynch, and Chen 2010). The dependent variable was satisfaction, and the independent variable was an indicator variable as follows: 1 if the participant saw the categories from the new methodology, 0 otherwise\(^4\). I simultaneously

\(^4\) To account for the possibility that the increase in satisfaction was due to solely to an increasing number of categories, a dummy variable was added as a covariate to differentiate between the 9 category and 5 category solutions obtained from the traditional clustering analyses. Removing or adding this covariate does not impact the conclusions of the mediation analysis.
used perceived categories helpfulness, self-determination and perceived variety as additional potential mediators. Doing so permits the identification of the unique effects of the different category structures through each potential mediator, while controlling for effect of the other variables.

Like the ANOVA results, I found that categories obtained using the new methodology had a positive effect on the perceived helpfulness of the categories \( B = .52; t(91) = 2.03, p = 0.05 \) but no effect on perceived variety \( B = .12; t(91) = .32, p = .74 \) or self-determination \( B = .22; t(91) = .43, p = 0.44 \). This suggests that neither perceived variety nor self-determination can account for the observed increase in satisfaction. Further, I found perceived helpfulness to be strongly correlated with satisfaction \( B = .39; t(91) = 3.84, p < .01 \) and the relationship between the category structure and satisfaction \( B = .88; t(91) = 3.29, p < .01 \) to be weakened when the mediators were inserted into the model \( B = .65; t(91) = 2.56, p = .01 \). Note that the summary model had an adjusted \( R^2 \) of 0.21 \( F(5,91) = 6.05, p < .01 \) suggesting that the model explains the variance in the satisfaction score well.

Further, evidence for the partial mediation can be obtained by calculating the indirect effects of the potential mediations: perceived helpfulness, self-determination and perceived variety. The procedure by Preacher and Hayes (2008; 5000 bootstrap samples) was used for the calculation of the confidence intervals around the indirect effects. For perceived helpfulness, the point estimate of the indirect effect was .20 with a bias adjusted and accelerated 95% confidence interval rejecting zero \([.05, .48]\) suggesting that perceived helpfulness is a significant mediator of the relationship between category structure and satisfaction. The point estimates for perceived variety \(.0004; 95\% CI [-.04,\)
and self-determination (.02; 95% CI [-.03, .23]) do not exclude zero, suggesting that perceived variety and self-determination do not explain the difference in satisfaction observed with participants who visited the websites organized by different category structures.

**Perceived Helpfulness Results**

The current results demonstrate that the proposed methodology can be used to identify a category structure that, when used to design an assortment, is more helpful to participants. This subsequently increases their satisfaction with their restaurant choice.

The source of this increase in perceived helpfulness stems from greater search efficiency. Post-hoc analyses suggest that participants presented with the categories obtained from the new methodology spent a smaller proportion of their time on the site reading the category pages than those obtained from clustering analyses ($F(2,94) = 3.18, p = .05$). Specifically, the participants who were presented with the categories from the new methodology spent a smaller portion of their time browsing category pages (55%) than did those who were presented with either the five categories (66%; $t(61) = 2.34, p < .02$) or the nine categories (65%; $t(64) = 1.97, p = .05$) obtained from the clustering analyses. This suggests that the categories obtained from the proposed methodology were more effective at getting participants to restaurant pages. Further, a mediation analysis, following Preacher and Hayes (2008; 5000 bootstrap samples for the confidence intervals), shows that the decrease in the proportion of time spent on category pages increased perceived helpfulness ($B = 0.52; t(93) = 2.03, p = .05$). The point
estimate for the indirect effect of the proportion of time spent on category pages was .10 (95% CI: [.00, .34]) suggesting that the proportion of time spent mediates the effect of category structure on perceived helpfulness of the categories.

**Conclusion**

The present chapter investigated how the use of different category structures to create assortments can have an impact on consumers by influencing their choice satisfaction. The results show that the categories obtained using the proposed methodology helped participants spend a smaller proportion of their time on category pages, which in turn increased the perceived usefulness of the categories, and ultimately increased their satisfaction with their restaurant choice. Such findings indicate that the proposed methodology is not only helpful to investigate category structures and the relationships between products or brands, but also that it can be gainfully employed to improve aspects of the consumer choice process and increase satisfaction.
Welcome to Our Website!

Happy Valley Foods is a free service for Penn State visitor to learn more about our restaurants. We are looking for feedback regarding our website, and we would appreciate if you took a minute to look around! Enjoy :) 

Browse and Choose a Restaurant!

Learn about our restaurants and choose one that you'd like. To thank you for participating, 1 in every 25 participant will be chosen at random and given a $20 certificate for the restaurant that he chose during the visit. Make sure to make your choice wisely!

Figure 5-1. Index of Community Website
Figure 5-2. Sample Restaurant Category Page
Kentucky Fried Chicken

KFC rules the roost when it comes to serving chicken. One of the world's largest fast-food chains, the company owns and franchises more than 16,200 outlets in about 100 countries. (More than 9,100 locations are in the U.S.) The restaurants offer the Colonel's trademark fried chicken (in both Original Recipe and Extra Crispy varieties) along with chicken sandwiches, chicken pot pies, crispy chicken strips, mashed potatoes and gravy, and potato wedges.

Yes, I am choosing this restaurant for the lottery!

There is 1 KFC location in State College.

1. 2020 N Atherton St, State College, PA. Tel: (814) 238-4148.
Chapter 6

Conclusion

Marketers often face difficult decisions about how to present assortments or position new products. Yet consumers’ perceptions cause them to form their own categories, which help them simplify their environment and make inferences about existing and new products. Marketers would love to influence the perceived categories, but doing so is contingent on a correct identification of how consumers naturally categorize items. Most existing methodologies make assumptions about the nature of the unobserved natural categories, especially that items belong to one and only one category, an idea that behavioral and psychological researchers easily dismiss. The related restrictions on the modeling and data lead to misleading inferences in consumer environments. This study therefore has developed a modeling technique to infer unobserved category structures among a set of products or brands to represent what goes on inside the heads of consumers.

The approach proposed in this dissertation makes a twofold contribution. First, I extend traditional sorting tasks and integrate consumer and psychological research that acknowledges brands and products belong simultaneously to multiple categories. I do so by allowing participants in the sorting task to sort items into multiple piles, by providing participants multiple cards per brands or product. Second, I introduce a new statistical procedure that uses count data from the modified sorting task to infer the unobserved category structure directly across a sample of participants. The procedure accommodates
various well-known categorization phenomena, such as graded membership, different levels of abstraction, and consumer heterogeneity. The methodology is exploratory; it does not require any strong assumptions about the structure of the categories themselves. The illustration using a modified sorting task of 25 restaurants and a synthetic data example demonstrates the presence of the noted phenomena and shows that using traditional methodologies can lead to different inferences about which categories are most salient for which brands and which are competitors. Finally, an experiment involving showed that the category structures obtained from the proposed methodology can be used to facilitate search, increase perceptions of helpfulness, and consumer satisfaction.

The methodology can be especially useful when marketing decision makers have to make assortment decisions in contexts where brands/products can easily belong to multiple categories. For instance, consider a retailer that is interested in adding a new popular vegan & organic chocolate cake to his inventory. Where should this retailer place the product in the store, so that consumers can find it easily based on their own expectations and categorization structures? The retailer could place in the chocolate section (for those with a chocolate craving), in the vegan section (for those with dietary restrictions) and in the dessert section. Whereas putting it in all three shelf locations is probably impractical due to costs with managing inventories in multiple parts of the store, one could use the methodology to identify which of the three potential associations is the strongest for most shoppers.

In its current form then, the model is entirely exploratory; no explanatory variables attempt to explain the category memberships or category salience. All is left to
interpretation. This interpretive freedom can be useful for marketers, as a first step to identify naturally salient categories, and the methodology also might help test for the effect of different presentations or promotional programs on the natural categories that consumers form. For example, researchers could constrain unobserved category salience to be a function of a set of a priori determined individual difference measures, such as attitudes, interests, and motivations. Even a dichotomous variable representing an experimental condition might test for the effect of, say, specific marketing cues about which categories are salient. Similarly, the \( P \) matrix (unobserved category memberships) could be constrained as a function of predetermined features or usage contexts. Such reparametrizations would prove helpful for marketers who may wish to explain the unobserved category structures that they have identified. Further, such reparametrizations would allow one to engage in a more comprehensive predictive validation, for instance predicting memberships for hold-out brands that were not used in the estimation of the model’s parameters.

The statistical procedure is flexible; it accounts for the nature of sorting data (excess zeros) and dispersion through a zero-inflated negative binomial specification, for which the rate at which products join a pile is a function of the salient unobserved categories inferred from the data. It neither assumes a specific conversion of piles into similarities nor aggregates data across consumers. It instead allows each consumer to be represented by a completely different categorization structure (if necessary). The model suffers from the presence of incidental parameters, because the number of parameters increases with the sample size (Neyman and Scott 1948). A solution might be to use Bayesian estimation methods, which impose an appropriate prior distribution on the
parameters (Lancaster 2000). Bradlow, Hardie, and Fader (2002) propose closed-form solutions for the Bayesian analysis of negative binomial distributions, and their technique could be extended to accommodate the different rate function and zero inflation. Alternatively, to take heterogeneity explicitly into account, research could identify segments or groups of consumers who activate similar categories. Previous research has shown that groups of consumers tend to use similar unobserved categories (e.g., Blanchard et al. 2011; Gordon and Vichi 2002). Such a latent class formulation of the proposed model may help identify groups of consumers who would perceive similar categories, which would not only help deal with incidental parameters but also enable marketers to identify actionable, consistent category structures across different groups of consumers. It would also be possible to estimate different specifications for the parameters to account for different levels of heterogeneity, for instance by estimating a single mixture parameter $\pi$, inflation parameter $\nu$ or an additive constant.

Furthermore, the procedure does allow users to make inferences about the actual process by which participants create each pile during the sorting task. The negative binomial specification assumes a static representation, with the assumption that the inter-arrival rates of the unobserved categories are independent. However, advanced Web-based technologies could support an interface that accepts multiple categories and tracks the movement of items into different piles. Some research in this area has developed cognitive clustering heuristics that can model the sorting process (e.g., Ahn and Medin 1992; Anderson 1991; Fisher 1987), but incorporating dependency with the activation of the category into the proposed model offers a promising area for further research.
Finally, the application has involved a set of brands that may or may not have been invoked during a decision task. These brands might have been present in the physical environment, recalled from memory, or a combination thereof. The structure observed undoubtedly would change if a marketer were to add a set of brands. It thus becomes important for researchers to identify a set of items that seem likely to represent the specific situation of interest and then engage in validation with other managers using other investigative techniques. Similarly, to investigate a specific consumption context (e.g., “Imagine it’s an early weekday morning and you’re looking for breakfast” versus “Imagine it’s late evening and you’re looking for a snack”), the situation should be specified in the instructions, along with relevant brand alternatives. A context-dependent model with different consumptions situations in multiple sorting tasks would represent an interesting avenue for further research.
References


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Title: A Methodology for Identifying Unobserved Categories when Consumers Assign Brands to Multiple Categories
Committee: Wayne S. DeSarbo (Co-chair), Margaret G. Meloy (Co-chair), Duncan K. H. Fong, Richard A. Carlson

SELECTED PUBLICATIONS


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