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Replicated Preference Testing to Diagnose Consumer Segmentation

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Background: In blind consumer preference testing, consumers do not always make consistent choices. This situation will most likely occur when the products tested are similar or exhibit significant variability. The variability may arise from the products themselves, called *stimulus variability*, or from consumer perception of the products, called *neural variability*[1]. Consistency in preference responding can inform the degree of segmentation among consumers. Diagnostics for degrees of preference segmentation can be valuable before conducting a large-scale category appraisal. A useful, simple diagnostic for preference segmentation was discussed in a previous technical report on identicality norms[2]. In that report, it was shown that preference segmentation can be diagnosed by comparing preference counts, obtained from a ballot with a no preference option, to expected results if the products are identical. In the same report it was also shown how to establish identicality norms by conducting preference tests on identical products or by predicting the norms using a Thurstonian model of two-alternative choice data[3,4]. A different way to study potential segmentation is to use replicated testing, which is the subject of this technical report.

Scenario: You are making an ingredient change in a snack food product that may affect its texture and, in particular, its hardness. It is possible that consumers differ regarding their preferences for softer or harder products in this category. Before deciding on the methodology you will use to study consumer response to a broad array of products in the category, you would like to determine if there is evidence for preference segmentation. If there is segmentation, you will probably favor an unfolding approach to find individual ideal point clusters. If there is not, you will consider a modeling approach that assumes a homogenous group of consumers with respect to the drivers of liking. Using two prototypical products, you conduct a double replicated pilot study by recruiting 65 consumers of the product category. The results of the study are shown in Table 1. The question you need to answer is whether you have evidence for segmentation in which some consumers consistently prefer one product and others prefer the other product, or do all consumers share a common preference probability favoring one or neither of the products. This diagnosis will help you to decide your next steps regarding the choice of category appraisal analysis approach. The results may also influence the type of design and the sample size you choose for your category appraisal.

Product A vs Product B	
Number of Times Product A is Preferred	Number of Consumers out of 65
0	17
1	23
2	25

Table 1. Replicated preference testing of two snack foods among 65 consumers of the category.

Limitations of the Binomial Model: Preference segmentation occurs because consumers differ regarding their preferences and this leads to *inter*-trial variability. Variability within a trial, or *intra*-trial variability, occurs when a particular consumer responds differently to the same two products and is typically analyzed using the binomial distribution. However, the binomial model does not take *inter*-trial variability into account which means that it does not account for differences among consumers in their choice probabilities. In fact, it assumes that the choice probability is constant across consumers or that consumers have the same underlying preferences. Consumers, in other words, are assumed to be homogeneous. If consumers are heterogeneous with regard to their preferences, the binomial model will not diagnose segmentation. It has been suggested that replicated testing can be analyzed using the binomial model without accounting for *inter*-trial variability. However, the analysis provides no guidance, when the model is rejected, on whether the rejection occurred because of inter-trial variability or because there is a difference in the mean preference response, or both. When the model is not rejected, no conclusions can be reached including those regarding inter-trial variability, so segmentation will not be diagnosed.

Binomial, Beta and Beta-Binomial Models: The binomial distribution is a discrete distribution and when applied to preference data it models the probability that a particular choice outcome will occur. For instance, in the snack food example, the binomial distribution models the probability within a consumer that Product A will be preferred 0, 1, or 2 times. If we pool data across consumers, we assume that each consumer's preference response to each product on average is the same as every other consumer. But this assumption may not be correct because consumers may have different preference probabilities. By combining data, we are mixing data that may have different real choice probabilities. Figure 1 shows the binomial distribution for $n = 2$ and $\mu = 0.562$, the mean result from the experiment, along with the actual results. Visual inspection shows that these two distributions do not appear to be similar. We would not expect the likelihood of getting 2/2 preference responses for Product A to be the highest if the results were binomial with a mean choice probability of 0.562.

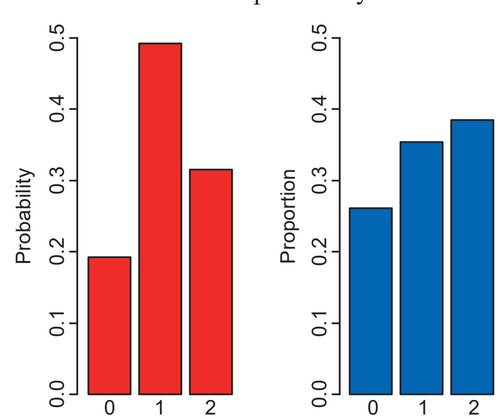

Figure 1. Binomial probabilities for $n = 2$ and $\mu = 0.562$ and the actual results of the snack food experiment.

We now consider the possibility that the mean choice probability may change from consumer to consumer due to segmentation. One very general possibility is to consider that the means follow a beta distribution. The beta distribution allows a broad variety of shapes for the distribution of the preference probabilities. Four shapes are shown in Figure 2.

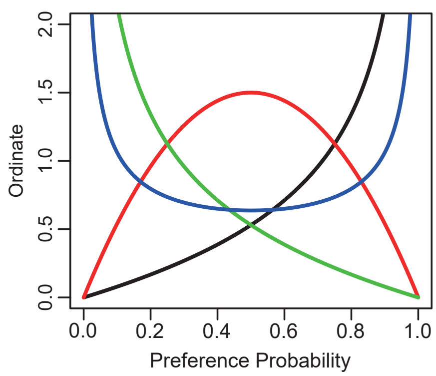

Figure 2. Four shapes for the beta distribution for the preference probability among consumers. The black line shows a preponderance of preference for Product A, the green line the opposite, the red line shows that consumer preferences vary symmetrically around 0.5 with few extremes in either direction, and the blue line shows the opposite.

Combining the binomial and beta distributions produces the beta-binomial (BB) distribution[5]. In this distribution, we assume that a binomial distribution applies to a particular consumer choice but that from consumer to consumer, the preference probabilities follow a beta distribution, like the black line in Figure 2. In order to estimate the parameters of the beta distribution, we need more than one evaluation per consumer. The beta-binomial model estimates two parameters of interest. The parameter that accounts for differences in the preference probabilities across consumers is called γ (gamma), which takes values from 0 to 1. When γ is zero, there is no heterogeneity and therefore no evidence of segmentation. When γ is 1, there is the most extreme heterogeneity. Between these extremes lie various degrees of heterogeneity or various degrees of preference segmentation. The second parameter is the mean, μ, which measures the average preference probability.

Application of the BB Model to Snack Food Preferences: You analyze the data from the snack food experiment shown in Table 1. This analysis can be performed in *IFPrograms*™ or using other available software that fits the BB model. Your estimate of the mean preference probability is 0.56 and the estimate of γ is 0.28. In order to decide whether the BB model is superior to the binomial because of the preference segmentation, you conduct a statistical test on the difference between the BB and binomial model fits[5]. This test is significant with a p-value of 0.03. This means that you have evidence for preference segmentation and that consumers do not share a common preference probability.

Figure 3 shows that the model fit for the BB perfectly fits the data in Table 1. This is because, in this case, the data involve two independent observations and the BB has two parameters. The analysis also shows that the estimate of the mean preference probability is not significantly different from 0.5 ($p = 0.21$). When the binomial was used to compare products on the combined data from consumers, the mean preference probability was also not significantly different from 0.5 ($p = 0.19$). The difference between this test and the BB test is that the binomial model analysis confounds differences due to products and preference segmentation, which it cannot separate and the BB model does not.

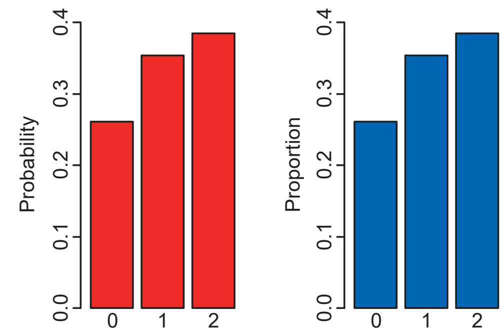

Figure 3. Beta-Binomial probabilities for $\mu = 0.562$ and $\gamma = 0.28$ and the actual results of the snack food experiment.

Conclusion: Preference segmentation can be studied in a variety of ways, some more complex than others. One way, as mentioned in the introduction, is to compare preference counts with a no preference option to an identicality norm, such as 40:40:20 (Prefer A : Prefer B : No Preference). Another way to conduct this research is through the use of replicated testing. In the example chosen to illustrate this method, a test involving 65 consumers was used in which each consumer conducted a double-replicated preference test where each replicate was independent of the other. This approach led to a quantitative measure of segmentation, called γ. Our interest in γ is to find out whether it is greater than zero and thus support a conclusion that consumers are heterogeneous with respect to their preferences. This type of analysis will inform the next stages in the exploration of a category because in this case we know that we need to consider how to estimate the location and effect of individual ideals in the analysis of the category appraisal. If there had been no segmentation, then other approaches could have been considered that treat consumers as interchangeable with regard to their product preferences.

References and Notes

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