OPERATIONS RESEARCH (ONLINE FORUM COMMENTARY)
Vol. 57, No. 1, May–June 2009, online commentary
ISSN 0030-364X | EISSN 1526-5463 | 09

INFORMS

Response to Commentary by Chong and Ho

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Thank you to Juin-Kuan Chong and Teck-Hua Ho for taking the time to write a letter and for your very helpful comments. I am quite familiar with Chong, Ho and Tang (2001) (which is referenced in Fisher (2009)) and have a high regard for this work. This was the first paper to propose a decision support model for assortment planning and to apply it to real data to derive an improved assortment. This is also one of the papers that inspired my collaborator and coauthor Ramnath Vaidyanathan and me to use an attribute approach in our own work on assortment optimization, which is reported in Fisher and Vaidyananth (2008).

Chong, Ho and Tang (2001) and Fisher and Vaidyananth (2008) describe approaches to assortment planning which differ in the required input data and demand assumptions, and hence have different domains of applicability. Chong, Ho and Tang (2001) require customer level purchase data over time and is appropriate where this data is available. Fisher and Vaidyananth (2009) require only store-SKU sales data for a recent history period and is appropriate where customer level data is not available. This would apply to other ideas suggested by Chong and Ho, such as using customer surveys to better estimate substitution. These are good approaches if the more detailed customer data can be obtained. Two demand models are commonly used. The Multinomial Logit (MNL) model, used in Chong et al, estimates the utility of a product as a function of its attributes and assumes each customer buys their highest utility product if it is above a minimum threshold, or else they don't purchase. The share of each product and of no purchase can then be found. The locational choice model assumes products are located in an attribute space. Each customer has an ideal point in attribute space and buys the available product closest to their ideal point if it is close enough, or else doesn't purchase. Fisher and Vaidyananth use this model but modify it to assume that customers buy their ideal product if it is available, or else substitute to the nearest available product with a probability that declines the further away from their ideal is the potential substitute.

Both models allow for substitution. MNL assumes that substitution demand is divided over available products in proportion to those products' market share. This assumption fits a situation in which products are similar to each other, but vary in a taste parameter, such as different flavors of yogurt or colors of apparel. By contrast, the locational choice model fits a situation in which some products are better substitutes for a given product than others. This was a very real feature of our applications; for example, the natural substitutes for a 14 inch tire are other 14 inch tires, not 15 inch tires and in the retailer segmentation of good/better/best, a best is closer to better than to good. Ramnath Vaidyanathan and I have been applying our approach at other retailers and have discovered many interesting real world nuances. For example, in the same problem, we see a variety of attribute types, some of which fit the MNL assumption and others the location model, so a blended approach would make sense.

We have also seen the interaction between attributes alluded to by Chong and Ho. For example, a given brand specializes in certain products and has a higher share for those products than for other products or consumer preference for tire price/quality depends on the age and value of the car that the tire goes on. One way to deal with this is by expressing one attribute as a function of the other e.g. the market share for the lowest price and quality tire can be made a function of the value of the car the tire fits. The phrase "with the assumption of symmetry in substitution" used by Chong and Ho suggests that it might be reasonable to assume that the rate of substitution from attribute value x to attribute value y equals the substitution rate from y to x. We have seen just the opposite. For example, in one case, the rate of substitution from Brand 1 to Brand 2 was 80%, but from Brand 2 to Brand 1 only 20%, indicating much more loyalty to Brand 2, even though the market shares of the brands were about equal. In another context, the rate of substitution from Better to Best quality level was 80%, but from Best to Better, only about 30%, in part because store associates try to persuade a customer to buy a higher quality and price, but not the reverse.

The economic significance of assortment planning is enormous. Retailing in the U.S. alone is a $3 trillion/year industry and the difference between an average and optimized assortment is easily 10% in revenue. Despite the richness of the assortment planning context and its tremendous economic importance, I am aware of only three papers that provide an algorithm and estimation process for assortment planning and apply it to real data: Chong et al (2001), Fisher and Vaidyanathan (2008) and Kök and Fisher (2007). I hope this discussion will stimulate much more research on decision support for assortment planning.

References

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