Hierarchical Bayes: A Better Conjoint Analysis

When most researchers think of conjoint studies, they're focused on writing and fielding the questionnaire and ultimately drawing conclusions based on utility scores. The question of how we get from raw data to utility scores (and more specifically which type of model is used) is rarely questioned, even though the type of analysis can greatly impact the results.

For decades, the analysis method of choice was Multinomial Logit (MNL), which solves for the average opinion. The flaw, of course, in the logic of solving for the average is that consumers are seldom a homogenous group. Hierarchical Bayes (HB), born partially out of the significantly increased computing power available today, has gained favor because it assumes that there will be some variability in opinions (i.e., that consumers are heterogeneous).

Why is Hierarchical Bayes Better than Traditional Analysis?

Statisticians and researchers have compared conjoint results using HB analysis to those using an MNL model using both hypothetical and real-world datasets. HB has consistently been proven to produce results that are at least as good as, and usually better than, MNL models. Specifically:

- HB has **greater predictive validity** (i.e., results are more realistic)
- HB is **more robust** than traditional models because it looks for patterns at both the individual and group levels rather than just at the group level
- The **importance assigned to each attribute** is somewhat **more discriminating** because noise can be isolated
- Since utilities are calculated at the individual level, **subgroup analyses are more reliable**
- **If using HB with an ACA** (Adaptive Conjoint Analysis) study, the **calibration concept data is not necessary**. In the end, this means a shorter survey. Of course, if you're interested in purchase likelihood simulations, the calibration concept data can be included.

How does Hierarchical Bayes Analysis work?

HB seeks to maximize individual differences, while minimizing noise. This is achieved using a multi-step, or hierarchical, analysis. First, a micro approach is taken; utilities are calculated for each individual in the dataset. Next, a macro approach is taken; the model is rerun incorporating data from all individuals simultaneously. Bayes theorem (a formal rule used to solve for conditional probability) is used to understand how well the utilities derived from each micro-level model predict the utilities from the macro-level model. The macro level step is repeated for a large number of iterations (10,000+); with each iteration the noise level is adjusted until the model best represents the dataset.

Are there any Drawbacks to Hierarchical Bayes Analysis?

There are no analytic downsides to HB. MNL analyses were traditionally favored for logistical reasons; the calculations going into HB are extremely complex, which up until recently, proved daunting, even to the most powerful computers. While HB analysis may still take 10+ hours for an extremely complex study, the average market research study can be analyzed with HB in under an hour.

What do I need to?

In short; nothing, when working with RTi. HB is applied by our analysts on the back end, and can be used with all types of conjoint analysis. Because of the clear benefits of HB over MNL analysis, RTi uses HB when analyzing all conjoint studies.

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