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9/21/17
Mathematical Models in Marketing
Greedoid-based Noncompensatory Inference

Motivation:
The managerial challenge is to identify the "must have" (or "must not have") features that determine the consideration sets of consumers. Must-have features are non-compensatory in the sense that a product with must-have features is preferred to a product without these must-have features even if the product without the must-have features is better on all other features.

- Conjoint models are bad about this; part-worth models inherently assume compensatory framework
  - Could impute a super-high part-worth, but this strains the estimation

Previous studies infer that consumers generally use simplifying considerations and/or choice heuristics that are consistent with non-compensatory processes. However, identifying the choice strategy out of all possible combination of strategies is computationally challenging and even impossible when the number of features is very high.

Other benefits of using a non-compensatory approach:
Since consider-then-rank tasks are more enjoyable and require less effort, these types of questionnaires will take less amount of time with fewer nonresponses. Even though there exist compensatory models to predict consumer preferences from such data, providing a non-compensatory heuristic to analyze such non-compensatory decision processes is one of the major contribution of this research.

Broadening the scope of decision models to include consideration sets:

> *"While we expect that noncompensatory processes are common for choice tasks, we expect they are even more common for consideration tasks."*

Human decision processes:
For multi-level features, we can have four different decision processes that vary on how consumers evaluate aspects (levels) within features. These are:

- Lexicographic by features (LBF): the consumer first ranks the features and then ranks aspects within features
- Acceptance by aspects (ABA): the consumer first ranks aspects and then accepts profiles if they have the aspects
- Elimination by aspects (EBA): the consumer first ranks aspects and then rejects profiles if they do not have that aspect
- Lexicographic by aspects (LBA): the consumer first ranks aspects and then either accepts a profile if it has an aspect or rejects a profile if it does not have an aspect

Partial orders and Consistency:
Each ordered set of aspects implies a unique order of profile preferences, but the converse is not true

- i.e. a single profile preference can have many different ordered aspects. Considering only Verizon flip phones can either be ordered *L = (Verizon, flip)* or *L = (flip, Verizon)*

Lexicographic inconsistency: Preferring one profile over another given the same ordered subset of aspects

- Basically, if the aspect ordering implies a profile ordering that is not observed

Developing the algorithm:

1- If we find a lexicographic ordering of aspects that induces the profile ordering of the respondent, the aspect ordering is a greedoid language and can be solved in polynomial time.
2- If we cannot find a lexico-consistent aspect ordering, then we can find an aspect ordering with minimum number of violation using a dynamic program in 2^n steps instead of n!.
3- If each ordered pair in the profile ordering of the respondent is weighed differently, the dynamic program can find the closest aspect ordering as in 2^n steps.

Empirical study:
They study consumer preferences for smartphones with 7 features and 16 aspects. The respondents are given smart 32 phone profiles with fractional factorial design and asked to rank them successively or consider-then-rank them. In their empirical study, they compare the performance of Greedoid with additive compensatory HBRL (hierarchical Bayes-ranked logit model) and LINMAP methods on three measures: % fit of pairs, holdout hit rate and holdout % fit. Even though LINMAP had a better performance on the % fit of pairs, Lexicographic by aspect decision heuristic is significantly better at predicting the holdout data. The Greedoid method finds the solution in less than 2 seconds for 16 aspects.

Contribution:
Even though there exist compensatory models to predict consumer preferences from such data, providing a non-compensatory heuristic to analyze such non-compensatory decision processes is one of the major contribution of this research. This heuristic also gives managerial insights as “must have” and “must-not-have” aspects rather than ideal points and attribute weights which are easier to work with in the business world. The algorithm reduces the problem size from n! to 2^n while providing good estimates of the holdout data which might indicate that the heuristic aims to capture the preference of the consumer in general rather than in a given instance. However, the number of steps required by the heuristic is still exponential and computationally challenging for high number of aspects. Future studies might focus on decreasing the step size further or developing another heuristic to truncate the number of aspects into a reasonable size for greedoid method application without sacrificing the goodness of fit.