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PREDICT 450 – Sec 55
Solo #2
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INTRO

Transitioning into a new market category can be a challenge for any business. STC, a well-known brand, is interested in entering the computer tablet market. In such a competitive market, STC wants to know which combination of attribute features are the most appealing to consumers. They are interested in the attributes effects on stated performance, the interactions between price and brand type, and impact of prior ownership of STC products on attribute selection. To improve their understanding of the new market to produce a new product, STC created a choice-based conjoint task survey that included "choice sets" for each respondent to select. We will use this quantitative research data to design a study that answers the specific questions posed by STC along with even deeper insights to facilitate the new product design decisions.

Survey

STC selected the use of choice-based conjoint tasks to quantitatively produce results for its survey. Choice-based conjoint tasks are designed so every attribute level is shown with every other attribute level at least once. This approach allows STC to score the partworths or utility levels (the average score of the tasks that include that attribute level or average preference of each attribute level) of each attribute. This information can be used to determine the "importance" score, which shows the effect each attribute has on product choice relative to all other attributes being evaluated.

Using these utility scores and importance scores with a what-if simulator, we can make predictions on the product alternative and other combinations not shown. By holding competitive product features constant, we can understand how changing product features affect preference and, for example, the direction market share and/or profitability will be moved with the changes. One disadvantage of conjoint analysis simulators is that it cannot predict the exact amount of market share or profitability a change will make. There are too many other factors that contribute to those values that are changing regularly. While outside effects can be added to the model to improve its accuracy, those extraneous effects must be considered by managers when making decisions based on conjoint simulators.

Data

The raw data contains survey responses from 1024 individuals. After removing responses with missing values, we were left with 424 respondents.

The total number of attributes measured by STC is five, based on preliminary qualitative research. Four of these attributes have three levels each (screen, RAM, processor, price) and one, brand, has four levels. This creates 3*3*3*3*4 = 324 possible combinations to evaluate, but using experimental design principles of independence and balance we use a fractional factorial design of 108 choices. These choices are broken into 36 choice sets for the respondents to evaluate. Since we use 36 choice sets, each with 3 options from which to select, we have a total of 108 (36*3=108) unique responses.

For effects coding, we must create dummy variables to represent the attribute levels of each choice set. Since dummy variables equal k-1 levels, we will have a total of 11 dummy variables. We also want dummy variables to represent the interaction between price and brand, so we created three additional dummy variables to identify the four levels of this interaction for a total of 14 unique attribute values. Finally, we need to include the responses of each respondent into the model. Thus, we create a matrix with the fourteen dummy variables (X.matrix) plus an additional matrix with the responses (ydata). In addition, we create a variable, zowner, to indicate which respondents have already owned an STC product so we can determine the effects of pre-ownership.

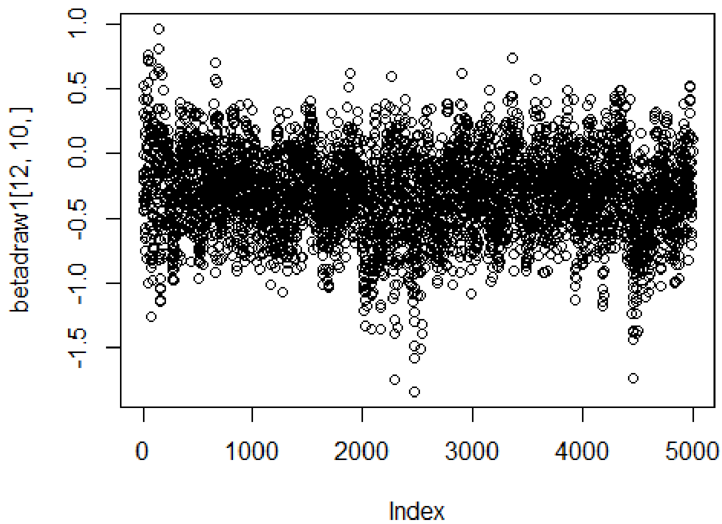
Modeling Procedures

We will use hierarchical Bayesian multinomial logit models. We will estimate the parameters in these models using Markov Chain Monte Carlo simulations, which allow us to vary the number of iterations to model and, thus, the number of samples of posterior distributions for estimating the beta parameters. By varying the number of simulations, if our assumptions and model are effective, we should eventually see the variance of the coefficients converge and stabilize (often at higher iteration amounts). It is important to locate where this convergence point begins because a "burn-in" period is required to stabilize the model before we can utilize it. By plotting all fourteen coefficient samples for a few respondents, and applying those results to all respondents, we can visually identify the "burn-in" period and begin our results testing using variables after this point.

Hierarchical Bayesian multinomial logit models with MCMC simulations are very computationally intense, but generally allow us to estimate the posterior probabilities for the attribute values (coefficients) more efficiently and accurately. The R function for conducting this type of modeling is `rhierMnlDP()` which accepts data as a list. Using X.matrix and ydata for our MCMC function we have 424 respondents remaining after we removed those with missing values. It should be noted that the X.matrix has dummy variable as effects coding and the ydata vector has responses recorded as a selection of 1, 2, or 3 (not as dummy variables).

Results

Running the first HB MLM with MCMC with 50,000 iterations and keeping every 10 (5,000 iterations) we were initially able to confirm that our model was accurate and our assumptions were correct. We determined the burn-in time by plotting the coefficients of randomly selected respondents and looking for the convergence/stabilization of the variances. Based on those plots, we selected a convergence index value of 3000 to 5000. We will use these samples to make inferences about the attributes.



Using our burn value of 2000 samples over 424 respondents we can determine the mean value for each coefficient. These coefficients tell us if, on average, a particular attribute is preferred or not. A preferred attribute will have a positive value, no preference a value of zero, and a negative value indicates a negative preference.

We are using mean beta values for the model to use for predictive purposes.

```
[1] -0.17352288  0.48965880  0.10878703  0.62994074
[5]  0.97625086  1.22461557  0.32009009 -2.79208587
[9] -0.18519047  0.05625012 -0.37044871  0.10847325
[13] 0.02090012 -0.03094506
```

We can check the variance of our beta values by comparing the density curves of individual respondents on different attribute values. If we have a bell curve, then we know we have an appropriate distribution and we can assume that using the mean of every respondent's coefficients is a valid approach to producing a model for all respondents. If the density curve is not bell shaped, then we may want to consider adding quadratic parameters because the distribution indicates a model that is non-linear for that respondent.

Validate model accuracy

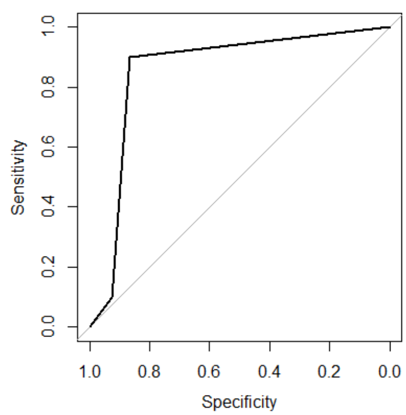
We need to validate that the model is accurate and useful. To do so we can use a confusion matrix, ROC, MSE, and/or AUC values.

Confusion matrix:

Confusion matrix: 13336/15264 = **.87368973** overall model accuracy

```
           ydatavec
custchoice    1    2    3
         1 3641  461  218
         2  254 3668  226
         3  309  460 6027
```

Area Under Curve: 0**.8565**



Attribute preferences

An easy way to understand which attributes are preferred or not preferred is to simply look at the sign preceding the coefficient value. A zero value means there is no preference while a positive value means the attribute is preferred and a negative value means not preferred. Furthermore, the extent to which the value is away from zero indicates the strength of the preference or negative preference. Hence, we can see that the $199 price and the $399 price were the most and least preferred attribute levels.

Preferred attributes:

Screen 10"- .4896588	RAM 16GB: .10878703	RAM 32GB: .62994074
PROC 2: .97625086	PROC 2.5: 1.22461557	PRICE $199: **2.47199578**
PRICE $299: .32009009	Brand STC: .49938906	Brand Pear:.05625012
Price*Somesong: .10847325	Price*Pear: .02090012	

Not-Preferred attributes:

Screen 5": -.3161363	RAM 8GB: -.3787278	PRICE $399- **-2.79208587**
Screen 7": -.17352288	PROC 1.5: -2.2008664	
Brand Somesong: -.18519047	Brand Gaggle: -.37044871	
Price*STC: -.09842831	Price*Gaggle: -.03094506	

We interpret these values by exponentiating the LOG(OR) beta value to convert it to an odds ratio which facilitates interpretation. We must remember that the odds ratio values are compared to NOT preferring the particular attribute value. For example, the attribute screen size of 10” was preferred to not preferring a 10” screen by exp(.4896588)= 1.6318 odds of preference or the probability of preference is 63% higher than non-preference for screen size of 10”. The log(OR) values from above are converted to the predicted probabilities below for easier interpretation.

Probabilities for preference for each attribute level:*

Screen 5: .72896	Screen 7: .869409	Screen 10: 1.55143
RAM 8GB: .68473	RAM 16GB: 1.1501	RAM 32GB: 1.79855
PROC 1.5: .1107072	PROC 2: 3.018013	PROC 2.5: 3.510387
PRICE $199: 11.846	PRICE $299: 1.35397	PRICE $399: .049448
Brand STC: 1.647714	Brand Somesong: .83553	Brand Pear: 1.0307
Brand Gaggle: .706313		
Price*STC: .90626	Price* Somesong: 1.08953	Price*Pear: 1.0075
Price*Gaggle: .99805		

*We interpret these probability preferences relative to 1. Greater than 1 value means the positive preference, lower than 1 value means negative preference, 1 value means no preference.

Brand * Price Interaction:

STC wanted to know the interaction effects of price sensitivity on brand preference (Log(OR)

STC vs Somesong : $199 = .89149
STC vs Somesong : $299 = .68459
STC vs Somesong : $399 = .47769

STC vs Pear : $199 = .56247
STC vs Pear: $299 = .44314
STC vs Pear: $399 = .32381

STC vs Gaggle: $199 = .93737
STC vs Gaggle: $299 = .86989
STC vs Gaggle: $399 = .80241

Pear vs Somesong : $199 = .32902
Pear vs Somesong : $299 = .24145
Pear vs Somesong : $399 = .15388

Somesong vs Gaggle : $199 = .0458
Somesong vs Gaggle : $299 = .1853
Somesong vs Gaggle : $399 = .3247

Pear vs Gaggle: $199 = .3749
Pear vs Gaggle: $299 = .42675
Pear vs Gaggle: $399 = .4786

Based on these findings there really isn’t an interaction effect between price and brand. There are no changes in trend in any of the comparison scenarios. STC is always preferred over the other brands but more so at lower prices. The same holds true for Pear vs Somesong and Gaggle, only it increases in preference vs Gaggle when the price increases. Somesong is also more preferred over Gaggle when the price increases. STC is also most preferred over Gaggle compared to the other brands regardless of price. STC is preferred by the smallest margin against Pear tablets regardless of price.

Prior STC ownership vs no prior STC ownership

Confusion matrix for zonwer model – accuracy rate: **.8738**

```
          ydatavec
custchoice    1    2    3
         1 3648  476  219
         2  249 3660  223
         3  307  453 6029
```

Area under curve: **.8558**

These values are very similar to the accuracy rate and AUC values without ownership covariate, which indicates no significant difference between the two models.

```
testrun2$Deltadraw
 [1] -0.05540648 -0.03807277  0.07016811  0.01148893  0.19765650
 [6]  0.32682548 -0.02937169 -0.70014093 -0.23034664  0.97671030
[11] -0.11545519 -0.18518414  0.06427491  0.15562500
```

These delta coefficient values indicate if a respondent had prior ownership of STC products then they will have positive preferences for: **RAM 16, RAM 32, PROC 2, PROC 2.5, and the brand Pear** and negative preference for the others. It should be noted that the baseline attributes cannot be determined right now using Deltadraw output.

The largest drawback from this comparison is the lack of available data. Only 68 out of the 424 respondents have had prior ownership of STC products, which makes it difficult to produce reliable results.

EXTRA SCENARIOS

Extra-scenarios-v3 using overall model instead of individual model

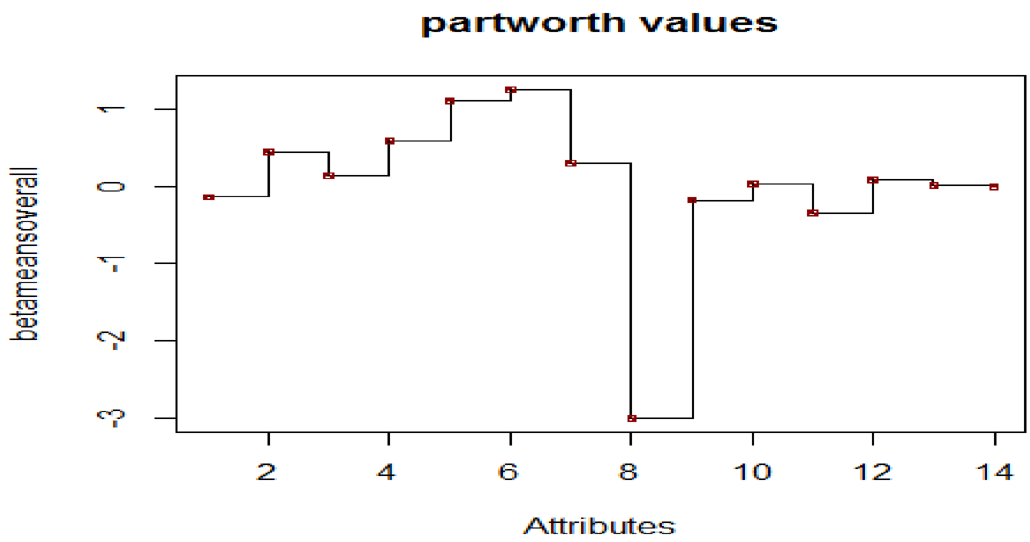
```
          [,1]      [,2]        [,3]
[1,] 0.07190093 0.6808226 0.247276472
[2,] 0.51544034 0.4818149 0.002744748
```

Predicted choice would be #2 (.68082) for additional choice set scenario #1 and choice #2 (.51544) for additional choice set scenario 2.

Choice set 1 choice #2: Screen 10”, RAM 32GB, PROC 2GHZ, $199, STC
Choice set 2 choice #1: Screen 5”, RAM 8GB, PROC 1.5GHZ, $199, STC

CALCULATING PARTWORTH AND IMPORTANCE VALUES

Calculating attribute level partworths for respondents is achieved through a number of steps. First, every choice set that includes the attribute level for analysis is identified. If the particular choice set was preferred by the respondent, add one to a cumulative total. Repeat until all choice sets that include the attribute level being analyzed are evaluated for preference or not. By dividing this cumulative total by the total number of choice sets presented, we can achieve the utility score for that particular respondent for that particular attribute level (partworth).



Once we have obtained the partworth levels for each attribute from each respondent, we can calculate the importance scores for each attribute from each respondent. This is accomplished by first determining the max and min partworth (utility scores) for each attribute used in the model. This provides the range for the partworth utility score for each attribute. To determine the importance score for that attribute, we divide the attribute utility score range value by the total attribute utility range score values of all attributes in the model.

CONCLUSION: TOP FOUR PREFERRED CHOICES

Based on output from full model and two additional scenarios, we gathered the four most preferred choices for more extensive analysis to determine a single product to create.

```
[2,]  0.994996330
[10,] 0.003555210 0.9933120846
[20,] 0.990129665
[28,] 0.005740808 0.9871804591
```

<u>Choice set 2 choice 1</u>: Screen 7”, RAM 16GB, PROC 2GHZ, $199, **STC**
<u>Choice set 10 choice 2</u>: Screen 5”, RAM 32GB, PROC 2GHZ, $199, **STC**
<u>Choice set 20 choice 1</u>: Screen 7”, RAM 16GB, PROC 2.5GHZ, $199, Pear
<u>Choice set 28 choice 2</u>: Screen 5”, RAM 8GB, PROC 1.5 GHZ, $199, Gaggle

Probability preference values lead us to select the top four preferred feature combinations. Upon further evaluation, two of the four preferred choices were for brands other than STC so we did not consider those two choices since the report is for STC.

The final two STC preferred choices differed only in screen size and available RAM. Diving deeper, both screen attribute levels (5” and 7”) were NOT preferred attributes when evaluated separately and 7” screens were preferred **only 15% more** than 5” screens. Both RAM attribute levels (16GB and 32GB) <u>were</u> <u>preferred</u> attributes when evaluated separately and 32GBs were preferred **68% more** than 16GBs, a much higher preference difference than 7” vs 5” screens.

Therefore, we determined that the RAM levels from the choices were more important to respondents than the Screen level sizes from the choices. Hence, it is our recommendation to produce choice set 10 choice 2, which is…

Screen 5”, RAM 32GB, PROC 2GHZ, $199, STC

STC should note that this analysis was conducted using a fractional factorial design of only 108 out of a 324 possible options. Thus, more options can be explored if the recommended product choice is inadequate for any reason.