Know Thy Customer: Predicting How Preference Translates into Choice

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A Quick Survey (In the spirit of knowing my customer)

• How many of you have done the following:
  – Conducted an Economic Value (to the Customer) Analysis?
  – Conducted a conjoint or tradeoff analysis?
  – Estimated attribute utilities and/or demand based on purchase data?
  – None of the above?

• How many of you:
  – Have used utility estimates to build a choice or demand model?
  – Have used preprogrammed demand or choice models, such as Sawtooth?
Goals

• Improve your customer choice models so that they correspond more closely to the underlying choice process and real market data

• Enable improved estimates of customer response to price changes thus improving pricing decisions
Outline

• Brief review of preference measurement and traditional demand modeling

• Challenges in fitting predicted preferences to real world data
  – Accounting for the impact of marketing-related activities in choices
  – Accounting for individual customer choice decision processes
  – Accounting for group customer choice decision processes
Demand Modeling

• If you consider customer value when you set price, you will use a model of demand

• Types of demand models
  – *Implicit*: Using managerial judgment
  
  – *Empirical*: Generic Approaches
    • **Aggregation of individual choices**
      – Estimate preferences of individuals
      – Predict individual’s choices and how they vary with price and other product design variations
      – Aggregate across individuals

    • **Estimate from aggregate choices**
      – Estimate how aggregate sales vary over time or across markets as a function of price, marketing activities and product features
Approaches to Preference Measurement

• Economic Value to the Customer Analysis
  – Reference/Replacement Value: The present value of the incremental cost of the option to be replaced

  – Differentiation Value: The present value of differences in cost or revenue implications of the alternative to be valued
    • Cost of use (e.g. efficiency, operating speed)
    • Cost of maintenance
    • Set-up costs (installation and training)
    • Risk (likelihood of failure and resulting cost)
    • Performance quality of output
    • Adding value to customer’s customer
Approaches to Preference Measurement

- **Tradeoff analysis (e.g. Conjoint)**
  - A survey driven approach
  - Determine relevant attributes and attribute values
  - Elicit preferences based on hypothetical product profiles

**Sample Task:**

**CONJOINT TASK ILLUSTRATION**
Pairwise Comparisons

<table>
<thead>
<tr>
<th>Brand:</th>
<th>Tread Mileage:</th>
<th>Price:</th>
<th>Puncture Sealing</th>
</tr>
</thead>
<tbody>
<tr>
<td>MICHELIN</td>
<td>60,000 miles</td>
<td>$100</td>
<td>No</td>
</tr>
<tr>
<td>GOODYEAR</td>
<td>50,000 miles</td>
<td>$120</td>
<td>Yes</td>
</tr>
</tbody>
</table>

○ ○ ○ ○ ○ ○ ○ ○ ○

**Strongly Prefer Right**

**Strongly Prefer Left**
Approaches to Preference Measurement

- **Tradeoff analysis (e.g. Conjoint)**

**Sample Output: Part-Worth Utility Estimates**

**CONJOINT OUTPUT ILLUSTRATION**

Part-Worth Utilities

The utility of an alternative is given by the sum of the part-worth utilities associated with its attributes.
Basic Choice Modeling

• **Strict Utility Maximization**
  – Customers choose the most preferred alternative with certainty

• **Expected Utility Maximization**
  – Customers make random errors in estimating the utility of alternatives
  – Example: Logit Models

\[
Pr(\text{Choose Product 1}) = \frac{e^{\beta \times \text{Utility of Product 1}}}{\sum_{i \in \text{Choice Set}} e^{\beta \times \text{Utility of Product } i} + e^{\beta \times \text{Utility of No Purchase}}}
\]

  – Where \( \beta \) is an estimated parameter reflecting choice or model accuracy (ideally estimated based on past choices)
Challenges

• The reality check:

Predicted Sales

- Brand C: 37%
- Brand B: 25%
- Brand A: 16%
- Brand D: 12%
- Brand E: 10%

Actual Sales

- Brand B: 31%
- Brand C: 27%
- Brand D: 17%
- Brand A: 22%
- Brand E: 3%

• What could have gone wrong?
Challenges

• What could have gone wrong?
  – Preference model misspecification
  – A failure to account for marketing related variables
  – A failure to account for decision processes
Modeling Challenges due to Marketing Influences

• **Problem:** Customer perceptions may not correspond to what you think is reality

• **Why?**
  – May not believe that certain brands will have certain characteristics
  – Past experiences may not be representative
    • May not have used the product before so don’t know about features or benefits
    • May not know how to use a feature so don’t appreciate benefits
    • May have had bad (or good) luck in the past
  – May not have been exposed to information about a product’s features or benefits or that information may not have been processed
    • Some benefits may be taken for granted or ignored
    • Common in economic value to the customer analyses
  – You may be mistaken
Modeling Challenges due to Marketing Influences

• **Problem:** Customer perceptions may not correspond to what you think is reality

• **Pricing implications**
  – People make choices based on perceptions rather than reality
    • This may work for or against you
  
  – Price should be set to capture the desired share of customer’s perceived value rather than your perceived value
    • Perceived value may be adjusted by marketing communications
    • Be careful about charging a price to take advantage of mistaken positive beliefs if there is a good chance that those beliefs will be corrected

  – **Customers should be asked about their perceptions of different product alternatives and brand choice predictions should be based on perceptions as opposed to an “objective” measure**
Modeling Challenges due to Marketing Influences

• **Problem:** Customers evaluate product offerings in a context

• The attractiveness of a price will depend on
  – How it compares to a *reference price* based on
    • Past experience
    • The prices of other alternatives
    • A list price
    • Prices that are higher than the reference price are treated less favorably than the same price would be in the absence of a reference price
  – How the price is framed
    • A discounted price versus a lower regular price - Some product categories have “reference discounts”
    • Fixed price versus a price based on the level of use, etc.

  – A statistical analysis of historical choice data is helpful to measure these effects
Modeling Challenges due to Marketing Influences

• **Problem:** The product or brand may not be in the choice set

• **Why?**
  – Customers may not be aware of the product
  – Their chosen vendor may not carry the product or display it effectively
  – It may be incompatible with technology they currently use

• **Pricing implications**
  – Price changes won’t influence sales among these customers unless doing so brings the product or brand into the choice set
  – Non-price marketing efforts may need to be required to get the product considered
Modeling Individual Decision Processes

- Traditional choice models assume that decision-makers process all available data and they will tend to choose the alternative that yields the highest utility (value)
  - This may imply a lot of data processing on the part of the customer when making decisions, especially if there are many alternatives with many features

- **Problem:** Decision-makers will often take steps to simplify the decision-making process
Modeling Individual Decision Processes

• Example:
  – Consider a restaurant that servers hamburgers and hot dogs
    • Assume price is set so that the customer is indifferent between them
  – What is the probability of the customer’s choosing each alternative?
  – What happens if a cheeseburger is added to the menu?
    • Assume the price of the cheeseburger is just high enough to leave the consumer indifferent between all three alternatives
  – What is the probability of the customer’s choosing each alternative?
Modeling Individual Decision Processes

Nested Decision-Making

• Customers will break alternatives down into categories
  – They may eliminate some categories
  – They will choose among acceptable categories
  – When a category is chosen they will choose among alternatives within the category
Modeling Individual Decision Processes

Nested Decision-Making

• **Examples:**
  – Decide on brand first and then which alternative to choose within the brand (traditional car shopping model)
  – Decide on product form first and then brand (beverages: bottles vs. cans, diet vs. non-diet, cola vs. non-cola, etc.)
  – Decide on vendor first and then choose an alternative offered by that vendor
    • Vendors may have different product offerings (implying different choice sets), different pricing, and different promotional activity
    • Vendor choice may or may not be influenced by the product category being considered
Modeling Individual Decision Processes

Predicting Choices with Nested Decision-Making

- Example

Burgers
  - Hamburgers
  - Cheeseburgers
  - Jumbo Hot Dog
  - Sausages
    - Polish Sausage

Procedure:
1. Estimate choice probabilities within each category based on product utility
e.g. \( \text{Pr}(\text{Hamburger}|\text{Burgers}) \), \( \text{Pr}(\text{Cheeseburger}|\text{Burgers}) \)
2. Estimate the expected utility of the category
e.g. \( \text{EU}(\text{Burgers}) = \text{Pr}(\text{Hamburger}|\text{Burgers}) \times U(\text{Hamburger}) + \text{Pr}(\text{Cheeseburger}|\text{Burgers}) \times U(\text{Cheeseburger}) \)
Modeling Individual Decision Processes

Predicting Choices with Nested Decision-Making

• Example

3. Estimate category choice probabilities based on the expected utility of the category
Modeling Individual Decision Processes

Predicting Choices with Nested Decision-Making

• Example

4. Estimate product choice probabilities:
   e.g. \( \text{Pr(Hamburger)} = \text{Pr(Hamburger|Burgers)} \times \text{Pr(Burgers)} \)
Modeling Individual Decision Processes

Nested Decision-Making

• Deciding which nested structure is appropriate
  – Ask customers about their decision-making process
  – Try different structures and see what fits the best

• Pricing implications:
  – Price response estimates may be biased if they don’t separately account for:
    • The impact of price on category choice
    • The impact of price on band choice within the category
Eliminating “Unacceptable” Alternatives

- Customers may have a set of “deal-breaking” criteria and will eliminate any alternatives that don’t satisfy those criteria regardless on how they perform on other attributes.

- This effectively eliminates them from the choice set even with awareness.

- **Examples:**
  - The customer is purchasing under a strict budget and prices above that level won’t be acceptable regardless of quality.
  - An imaging device that doesn’t have improved resolution over may not be considered.
Eliminating “Unacceptable” Alternatives

• Dealing with the issue:
  – Survey customers to find out what the deal breakers are and eliminate alternatives that don’t satisfy these criteria from their choice sets
    • Note: different customers may have different deal breakers so they may have different choice sets
  – To the extent possible eliminate the unacceptable from choice tasks used to estimate utility
    • It may be desirable to give different customers different conjoint tasks
    • New adaptive conjoint methodologies allow the exclusion of “deal breaking” attribute values
Modeling Individual Decision Processes

Simplifying the evaluation of alternatives

• **Customers may not consider all attributes**
  – Products often have many relevant attributes but customers often only consider a few of them
  – Economic value to the customer and conjoint analyses will often over-estimate the importance of less-important attributes

• **Dealing with the issue:**
  – Omit “less important” attributes when computing estimated utility or value of the different alternatives in the choice set
  – Test to see if doing so improves fit with real world data
  – Note: Customers may vary in the attributes they consider to be important
Group Decision Processes

• **Problem:** There may be multiple parties who influence decisions

• Different parties may place different values on different features

• If you are estimating the value of only one party, your choice predictions will be biased
  – Example: Medical equipment
    • Physician / Practitioner will value reliability, quality and ease of use
    • Administrators will be more interested in cost and the value of the equipment in driving business
Group Decision Processes

• Dealing with the issue:
  – Estimate a joint utility function
    • Have the relevant parties take a conjoint (or similar) survey jointly
    • Have the relevant parties take a conjoint (or similar) survey independently - Estimated utility can be approximated by a weighted average of the respondents
  – Treat the decision as a sequential process (say with two decision makers)
    • View one party as reducing the choice set by eliminating unacceptable alternatives
    • The second party can be viewed as choosing among the alternatives in the reduced choice set.
  • Example: Medical Equipment:
    – Administrator sets maximum cost or minimum economic value
    – Practitioner chooses from alternatives that satisfy the administrator’s criteria
Summary

• Traditional demand modeling methodologies may provide models that have substantial biases that may give misleading predictions about customer responses to price

• Things that should be considered when building demand models:
  – The impact of marketing-related activities in choices
  – Accounting for individual customer choice decision processes
  – Accounting for group customer choice decision processes