



Data driven Product Design with optimal features and messaging

Problem Statement

- Designing products with features that users most want, like and prefer over others is crucial to new product success of our client.
- Knowing most effective brand messages from a long list of possible messages is crucial for our client to fine tune brand messaging and positioning.
- Quantifying \$ value of each potential feature is critical to our client to perform cost-benefit analysis of different competing features.

$$U_{i_1 i_2 \dots i_j, k} = \sum_{j=1}^J w_{jk} u_{ijk}$$

[Generally both u_{ijk} and w_{jk} are normalized such that $0 \leq u_{ijk} \leq 1, 0 \leq w_{jk} \leq 1$ s.t. $\sum_{j=1}^J w_{jk} = 1 \forall k$]

Where

- i_j = level i of attribute j
- j = 1, 2, 3...J attributes
- k = 1, 2, 3...K consumers
- w_{jk} = Importance of attribute j for consumer k
- u_{ijk} = Desirability of level i of attribute j for consumer k

Our Solution

- We developed a robust Product Design solution based on brand choices and the trade offs individual consumers make in the market place. This robust methodology looks outside-in leveraging input from actual users of the product.
- Using customer data we estimated the most appealing features in the product from a long list of features.
- We quantified the contribution of each feature to product success.
- We generated and validated top resonating brand messages.

Estimation of Attribute Importances

Output from constant-sum paired comparisons is a ratio of importances of 2 attributes at a time. Given these ratios, we estimate attribute importances using log-linear regression (OLS).

- Let W_j be the importance of the attribute.
- Ratio of importance of attribute j_1 to attribute j_2 is $r_{j_1 j_2} = W_{j_1} / W_{j_2}$
- Let $V_j = \log_{10}(W_j) \Rightarrow \log(r_{j_1 j_2}) = \log(W_{j_1} / W_{j_2}) = \log W_{j_1} - \log W_{j_2} = V_{j_1} - V_{j_2}$
- Without loss of generality, re-label attributes s.t. 1 denotes the most important attribute in the rankings from step 2. Let $j=1, 2, 3, \dots, J$ denote attributes involved in the constant-sum paired comparisons.
- Without loss of generality, set $V_1 = V_{\text{highest}} = a$ where $a > 0$. When $a=2 \Rightarrow V_1 = \log(W_1) = a \Rightarrow W_1 = 100$.
- Define Ω as an $N \times (J-1)$ design matrix in which columns correspond to attributes and rows to paired comparisons such that,

$$\Omega_{N \times (J-1)} = \begin{matrix} & \begin{matrix} j=1 & 2 & 3 & 4 & \dots & J \end{matrix} \\ \begin{matrix} n=1 \\ n=2 \\ \vdots \\ n=N \end{matrix} & \begin{bmatrix} 1 & -1 & 0 & & & \\ & 1 & -1 & 0 & & \\ & & 1 & -1 & 0 & \\ & & & 1 & -1 & 0 \\ & & & & 1 & -1 \end{bmatrix} \end{matrix}$$

Paired Comparisons $N \times (J-1)$ Attributes

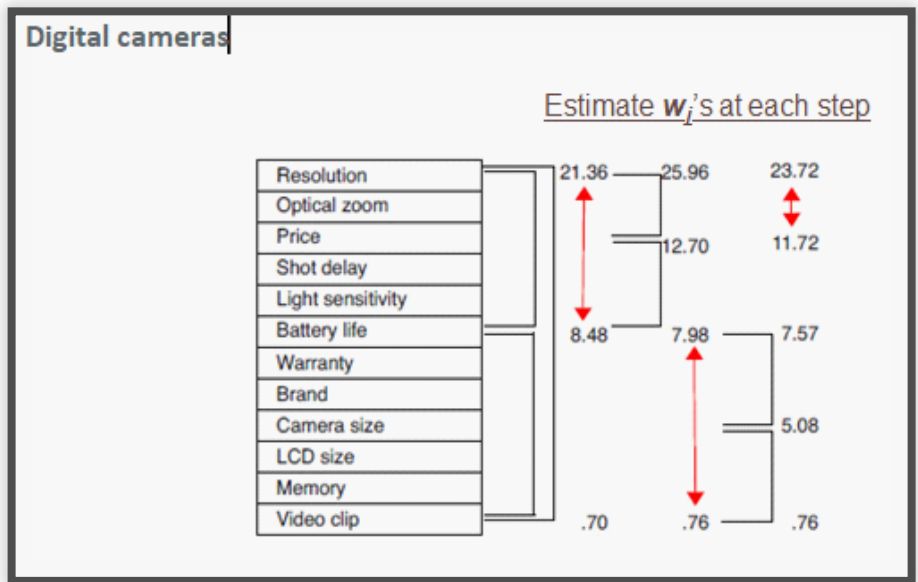
$$\Omega\{n_{ij}\} = \begin{cases} 1 & \text{if } j \text{ is the top attribute in the pair } n \\ -1 & \text{if } j \text{ is the bottom attribute in the pair } n \\ 0 & \text{if attribute } j \text{ is not in pair } n \end{cases}$$

Client Benefits

- Cost**
Reduce risk and uncertainty in product design by **50%+** in the long run compared to traditional non-data approaches.
- Integrated common goal**
Galvanize all stakeholder teams around a shared product understanding and goal via clear connection to features.
- Actionable**
Achieve tangible understanding in Product Design via direct connection to product success via data driven product feature importance.

What we do

- Design** new products and re-make existing products with winning product features and brand messages.
- Deliver** full product design and messaging solution and work with product engineering and marketing to implement the solution.
- Maintain** and periodically re-train the Product Design solution.



Optimal Digital Camera

Resolution: 24-30 megapixel
Optical zoom: 40x-50x
Digital zoom: 200x-300x
LCD size: 3'-4"
Battery life: 4-6 hours
Weight: 1.2-1.6lbs
Shot delay: Yes
Brand: XYZ
Price: \$500-\$700
Colour: Black

Process Flow

