Product landscaping the Bayesian way: Uncovering the evaluative dimensions of consumer dominance data

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Where are we today?
“The discovery of a new dish does more for the happiness of the human race than the discovery of a star.” – Brillat-Savarin

**BaSIC** /ˈbeɪsɪk/
1) most important or central to something
2) Bayesian Sensory model Integrated with Characteristics
The BaSIC lower model specification

\[ d_{i,j} = \alpha_{i,0} - \sum_{t=1}^{T} (x_{j,t} - y_{i,t})^2 + \varepsilon_{i,j} \]

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>(d_{i,j})</td>
<td>Preference rating for product (j) by respondent (i)</td>
</tr>
<tr>
<td>(t)</td>
<td>(1, \ldots, T) unknown dimensions</td>
</tr>
<tr>
<td>(x_{j,t})</td>
<td>The location of product (j) on dimension (t)</td>
</tr>
<tr>
<td>(y_{i,t})</td>
<td>The location of respondent (i) on dimension (t)</td>
</tr>
<tr>
<td>(\alpha_{i,0})</td>
<td>Additive constant for respondent (i) (e.g. scaling effects)</td>
</tr>
<tr>
<td>(\varepsilon_{i,j})</td>
<td>Error term for product (j) by respondent (i)</td>
</tr>
</tbody>
</table>
The BaSIC upper model specification

\[ x_{j,t} \sim N(r_j', \gamma, \sigma_x^2) \]

\[ d_{i,j} = \alpha_{i,0} - \sum_{t=1}^{T} (x_{j,t} - y_{i,t})^2 + \varepsilon_{i,j} \]

| \( x_{j,t} \) | the location of product \( j \) on dimension \( t \) |
| \( r_j' \) | Vector of predictors, e.g. expert sensory and analytic variables |
| \( \sigma_x^2 \) | Standard deviation of \( x \) |
The BaSIC upper model specification

\[ y_{i,t} \sim \sum_{s=1}^{S} \pi_s N(\beta_{0,s,t} + z_i' \beta_t, \sigma_{y,t,s}^2) \]

\[ d_{i,j} = \alpha_{i,0} - \sum_{t=1}^{T} (x_{j,t} - y_{i,t})^2 + \varepsilon_{i,j} \]

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>( y_{i,t} )</td>
<td>the location of respondent i’s ideal point on dimension t</td>
</tr>
<tr>
<td>( \pi_s )</td>
<td>Probability of being in segment s</td>
</tr>
<tr>
<td>( \beta_{0,s,t} )</td>
<td>Segment Center</td>
</tr>
<tr>
<td>( z_i' )</td>
<td>Vector of subject predictors, e.g. demographics</td>
</tr>
<tr>
<td>( \sigma_{y,t,s}^2 )</td>
<td>Standard deviation of ( y, t, s )</td>
</tr>
</tbody>
</table>
The BaSIC upper model specification

Product Predictors \[ x_{j,t} \sim N(r_j' \gamma, \sigma_x^2) \]

People Predictors \[ y_{i,t} \sim \sum_{s=1}^{S} \pi_s N([\beta_{0,s,t} + z'_i \beta_t], \sigma_{y,t,s}^2) \]

\[ d_{i,j} = \alpha_{i,0} - \sum_{t=1}^{T} (x_{j,t} - y_{i,t})^2 + \varepsilon_{i,j} \]
Bayesian parameter estimation

These full conditional distributions can be obtained by standard prior-to-posterior computations using Bayes’ theorem. The MCMC algorithm cycles through these twelve distributions, drawing a sample of the parameters from each distribution in turn, conditioning each next draw upon the realizations of the last draws of all other parameters until convergence is obtained.

Non-informative priors with sensible bounds are used to avoid prejudicing the estimation.

Upper & Lower Model Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Symbol</th>
<th>Symbol</th>
<th>Symbol</th>
</tr>
</thead>
<tbody>
<tr>
<td>Upper Model</td>
<td>(\alpha_{i,0})</td>
<td>(x_{j,t})</td>
<td>(y_{i,t})</td>
</tr>
<tr>
<td>Lower Model</td>
<td>(\alpha)</td>
<td>(\sigma^2_\alpha)</td>
<td>(\sigma^2_y)</td>
</tr>
<tr>
<td></td>
<td>(\gamma)</td>
<td>(\sigma^2_x)</td>
<td>(\beta_t)</td>
</tr>
<tr>
<td></td>
<td>(\sigma^2_{y,t,s})</td>
<td>(\beta_{0,s,t})</td>
<td>(\pi_s)</td>
</tr>
</tbody>
</table>
Why we use a Bayesian model?

MCMC Estimation of parameters

Upper Model link to lower model

Prevention of the propagation of error

Information borrowing; Natural imputation of missing data

- Easy ID of non-discriminators
- Dimension reduction
- Mitigate the influence of outliers
- Prediction for what-if scenarios

Greater reliability, even with smaller sample sizes
In Summary: HB and BaSIC combine and integrate multiple models

**Characteristics Model (Upper)**

- Demographics
- Occasions
- Behaviors
- Consumer Sensory Evaluations

- Analytics
- Expert Sensory
- Branding
- Consumer Segments

**BaSIC**

**Sensory Model (Lower)**

Fits Ideal Points into hedonic scores for products (for each person)
# Case Study: Beverage Category

<table>
<thead>
<tr>
<th></th>
<th>Traditional Landscape</th>
<th>BaSIC</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Total products tested</strong></td>
<td>16</td>
<td>14-17</td>
</tr>
<tr>
<td><strong>Number of days</strong></td>
<td>6</td>
<td>4</td>
</tr>
<tr>
<td><strong>Tastings per day</strong></td>
<td>3 each for 5 days, 1 for 1 day</td>
<td>3</td>
</tr>
<tr>
<td><strong>N</strong></td>
<td>1600</td>
<td>~300</td>
</tr>
<tr>
<td><strong>Number of products tasted per person</strong></td>
<td>16</td>
<td>2/3 – 3/4</td>
</tr>
<tr>
<td><strong>Number of tastings per product</strong></td>
<td>100</td>
<td>Minimum of 75</td>
</tr>
</tbody>
</table>
Data collected

**Consumer Information**
- Overall Liking
- Sensory Attribute Intensity
- Demographics
- Usage Occasions

**Other Data**
- Descriptive Sensory
- Analytical / Chemistry Measurements
- City/Location
2008 Landscaping Study

The client wanted to create a product similar to P22, P21 and P28, but higher liked.

Upper model reveals 3 taste segments
The client wanted to create a product similar to P22, P21 and P28, but higher liked.

Upper model reveals 3 taste segments
2012 Study – Same Market, Same Scope

This is the actual location of the new product

The product is performing better than original projections by the brand team!
Tools for Bayesian Analysis

**Software**

- OpenBUGS
- SAS
- The R Project
- in4mation insights

**Other thoughts**

- HB can be used anywhere as long as you can define a model and a prior distribution
  - (Choice Based) Conjoint Analysis
  - Just About Right Scales
  - Ideal Profile Method
Thank you!

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