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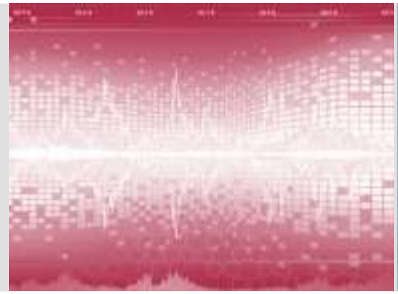
Engineering Your Competitive Advantage



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

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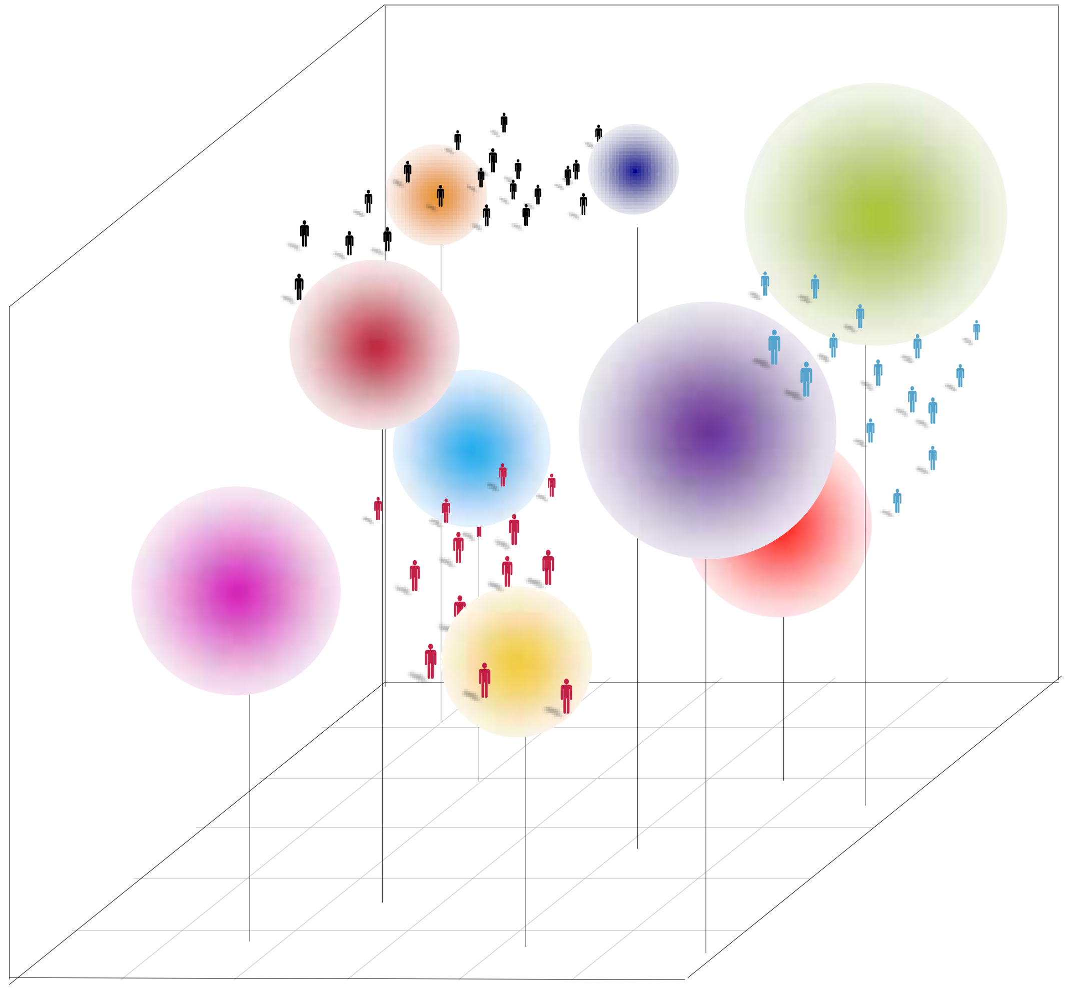
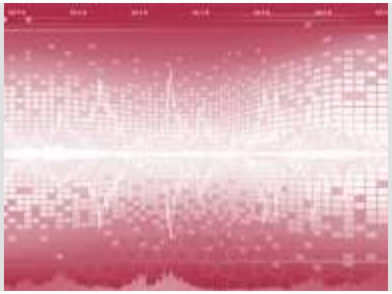
Where are we today?



"The discovery of a new dish does more for the happiness of the human race than the discovery of a star." – Brillat-Savarin





BaSIC /ˈbeɪ·sɪk/

1) most important or central to something

2) **Ba**yesian **S**ensory model **I**ntegrated with **C**haracteristics

The BaSIC lower model specification

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

$d_{i,j}$	=	Preference rating for product j by respondent i
t	=	$1, \ldots, T$ unknown dimensions
$x_{j,t}$	=	The location of product j on dimension t
$y_{i,t}$	=	The location of respondent I on dimension t
$\alpha_{i,0}$	=	Additive constant for respondent i (e.g. scaling effects)
$\varepsilon_{i,j}$	=	Error term for product j by respondent i

The BaSIC upper model specification

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

$$d_{i,j} = \alpha_{i,0} - \sum_{t=1}^{T} \left(\boldsymbol{x_{j,t}} - y_{i,t}\right)^2 + \varepsilon_{i,j}$$

$x_{j,t}$	=	the location of product *j* on dimension *t*
r_j'	=	Vector of predictors, e.g. expert sensory and analytic variables
σ_x^2	=	Standard deviation of *x*

The BaSIC upper model specification

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

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

$y_{i,t}$	=	the location of respondent i's ideal point on dimension t
π_s	=	Probability of being in segment s
$\beta_{0,s,t}$	=	Segment Center
z_i'	=	Vector of subject predictors, e.g. demographics
$\sigma^2_{y,t,s}$	=	Standard deviation of y, t, s

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

Upper & Lower Model Parameters		
$\alpha_{i,0}$	$x_{j,t}$	$y_{i,t}$
α	σ_α^2	σ_y^2
γ	σ_x^2	β_t
$\sigma_{y,t,s}^2$	$\beta_{0,s,t}$	π_s

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.

Why we use a Bayesian model?

MCMC Estimation of parameters → Information borrowing; Natural imputation of missing data

Upper Model link to lower model →

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

↓

Prevention of the propagation of error → Greater reliability, even with smaller sample sizes

In Summary: HB and BaSIC combine and integrate multiple models

Characteristics Model (Upper)

Demographics	Analytics
Occasions	Expert Sensory
Behaviors	Branding
Consumer Sensory Evaluations	Consumer Segments

BaSIC

Sensory Model (Lower)

Fits Ideal Points into hedonic scores for products (for each person)

Case Study: Beverage Category

	Traditional Landscape	BaSIC
Total products tested	16	14-17
Number of days	6	4
Tastings per day	3 each for 5 days, 1 for 1 day	3
N	1600	~300
Number of products tasted per person	16	2/3 – 3/4
Number of tastings per product	100	Minimum of 75

Data collected

Consumer Information

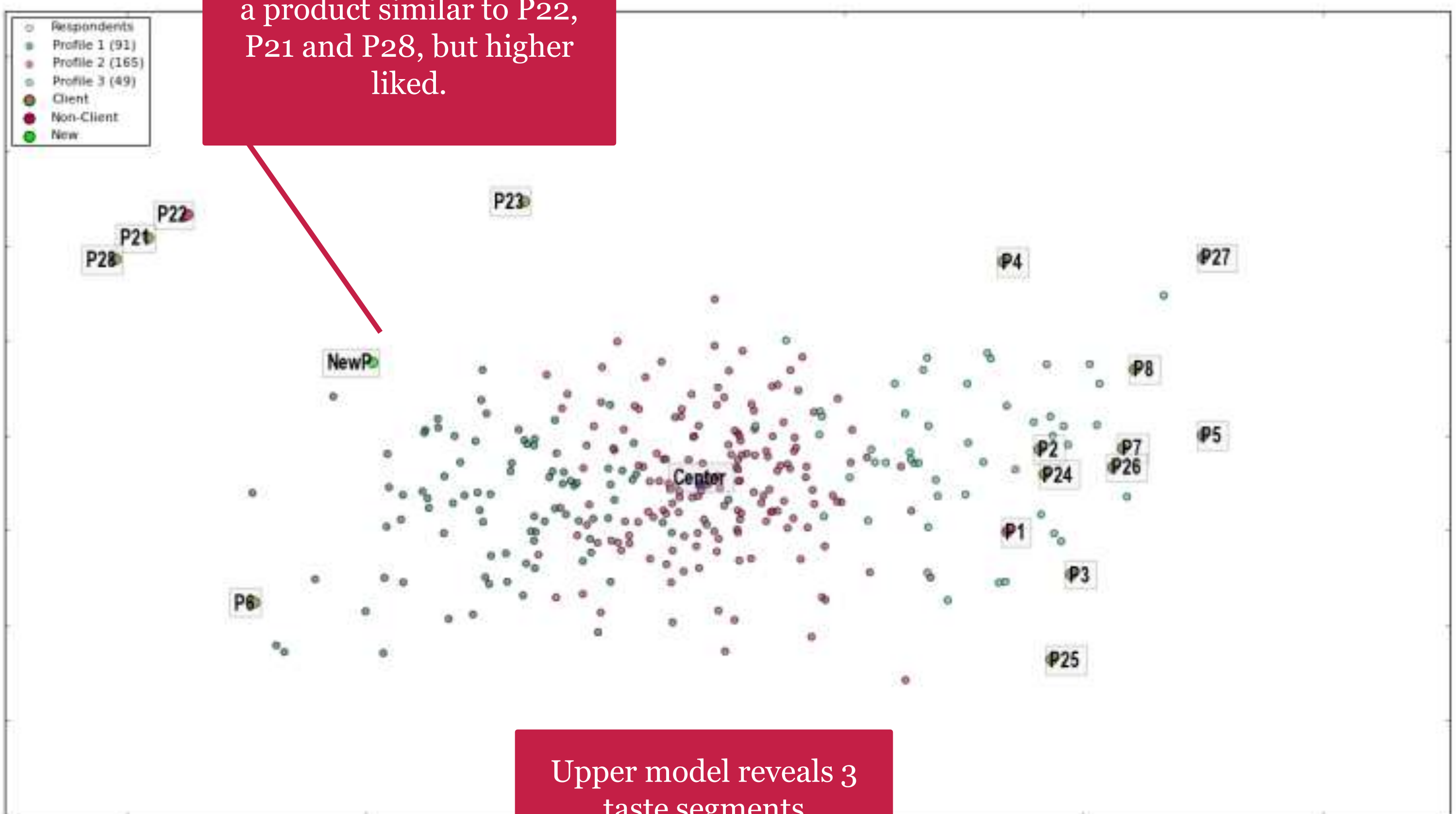
- Overall Liking
- Sensory Attribute Intensity
- Demographics
- Usage Occasions

Other Data

- Descriptive Sensory
- Analytical / Chemistry Measurements
- City/Location

2008 Landscaping Study

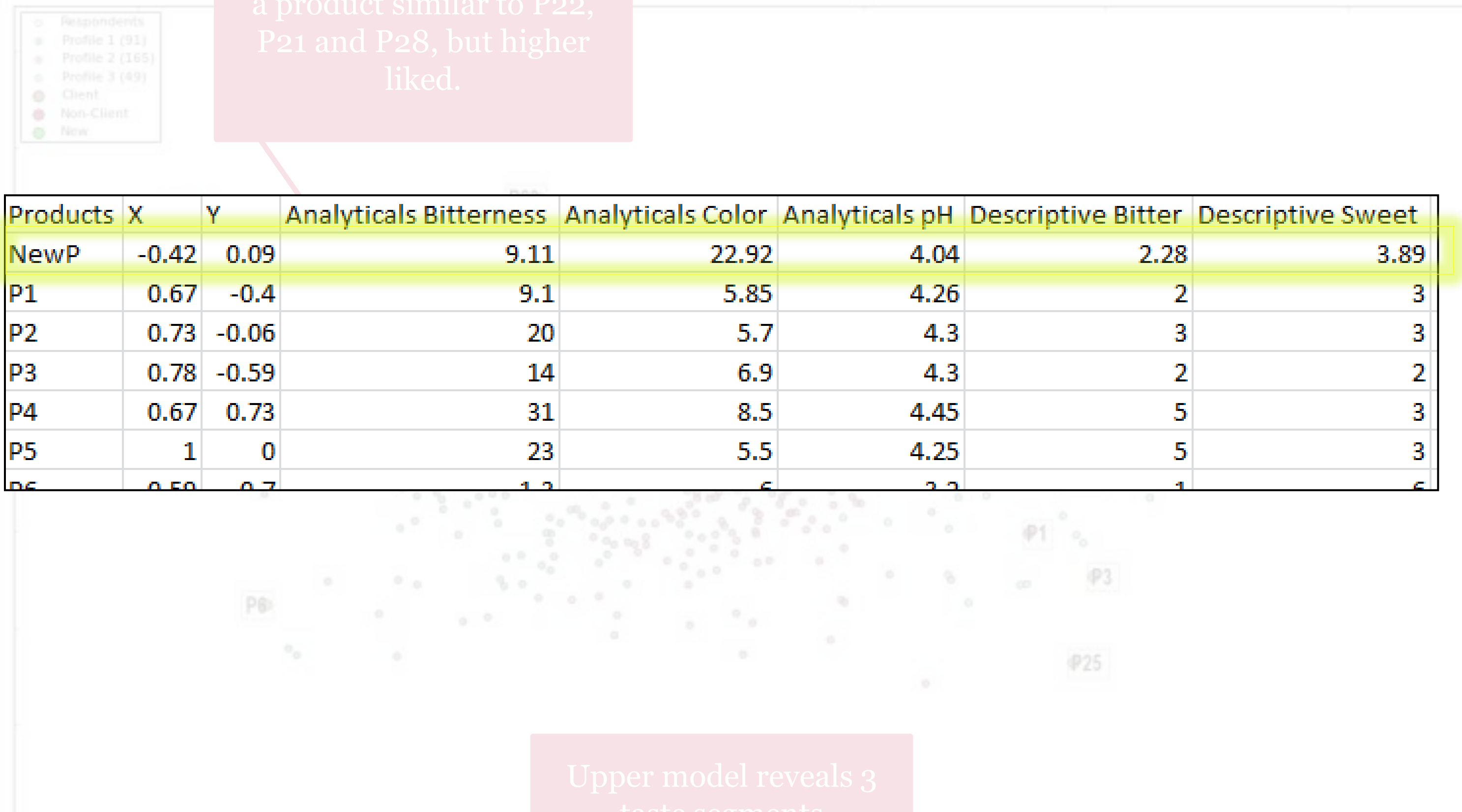
The client wanted to create a product similar to P22, P21 and P28, but higher liked.



Upper model reveals 3 taste segments

2008 Landscaping Study

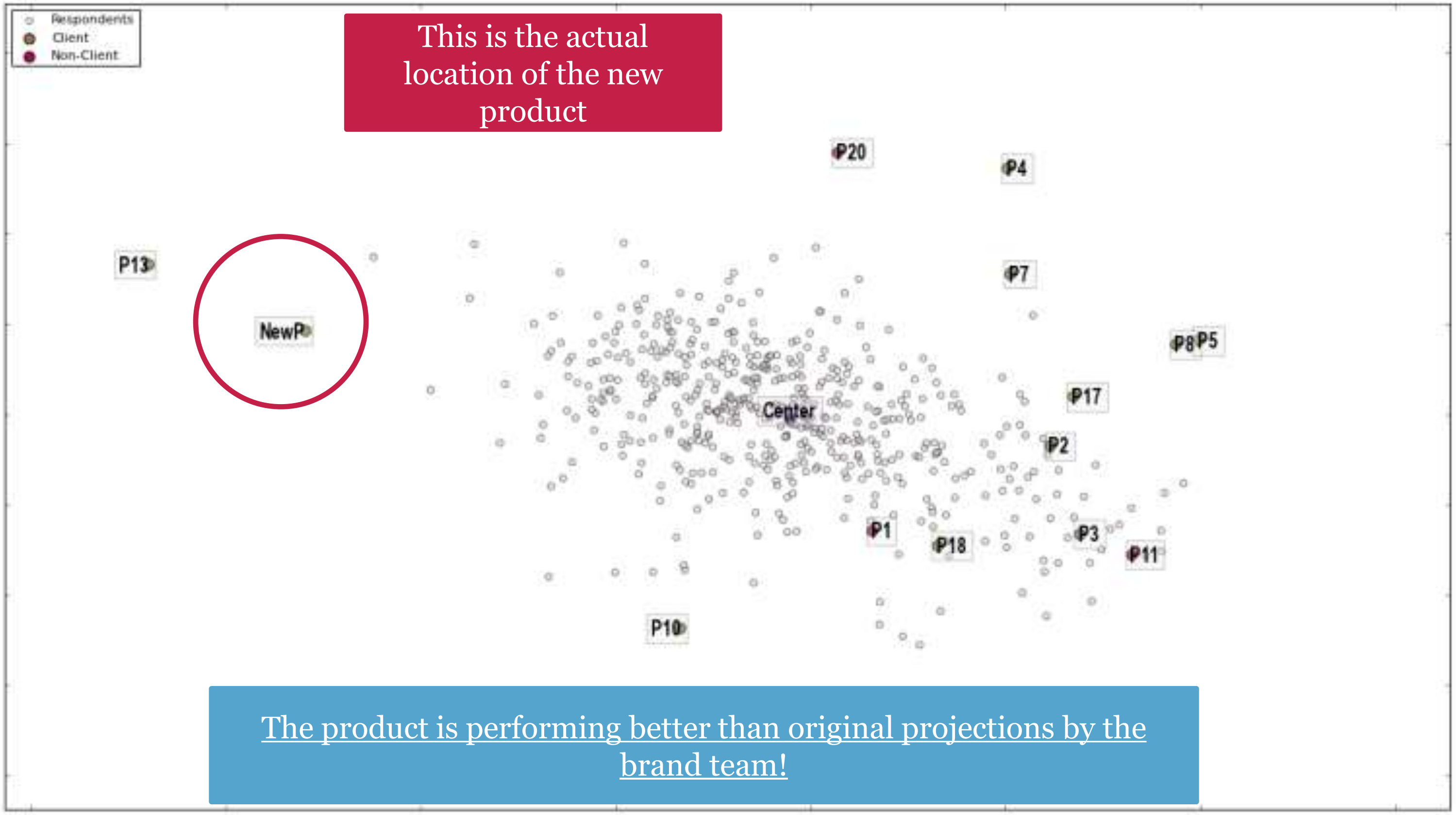
The client wanted to create a product similar to P22, P21 and P28, but higher liked.



Products	X	Y	Analyticals Bitterness	Analyticals Color	Analyticals pH	Descriptive Bitter	Descriptive Sweet
NewP	-0.42	0.09	9.11	22.92	4.04	2.28	3.89
P1	0.67	-0.4	9.1	5.85	4.26	2	3
P2	0.73	-0.06	20	5.7	4.3	3	3
P3	0.78	-0.59	14	6.9	4.3	2	2
P4	0.67	0.73	31	8.5	4.45	5	3
P5	1	0	23	5.5	4.25	5	3

Upper model reveals 3 taste segments

2012 Study – Same Market, Same Scope



Tools for Bayesian Analysis

Software

OpenBUGS

SAS

The R Project

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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!

Q&A

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