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Engineering Your Competitive Advantage

A Bayesian stochastic unfolding model for sensory dominance judgments

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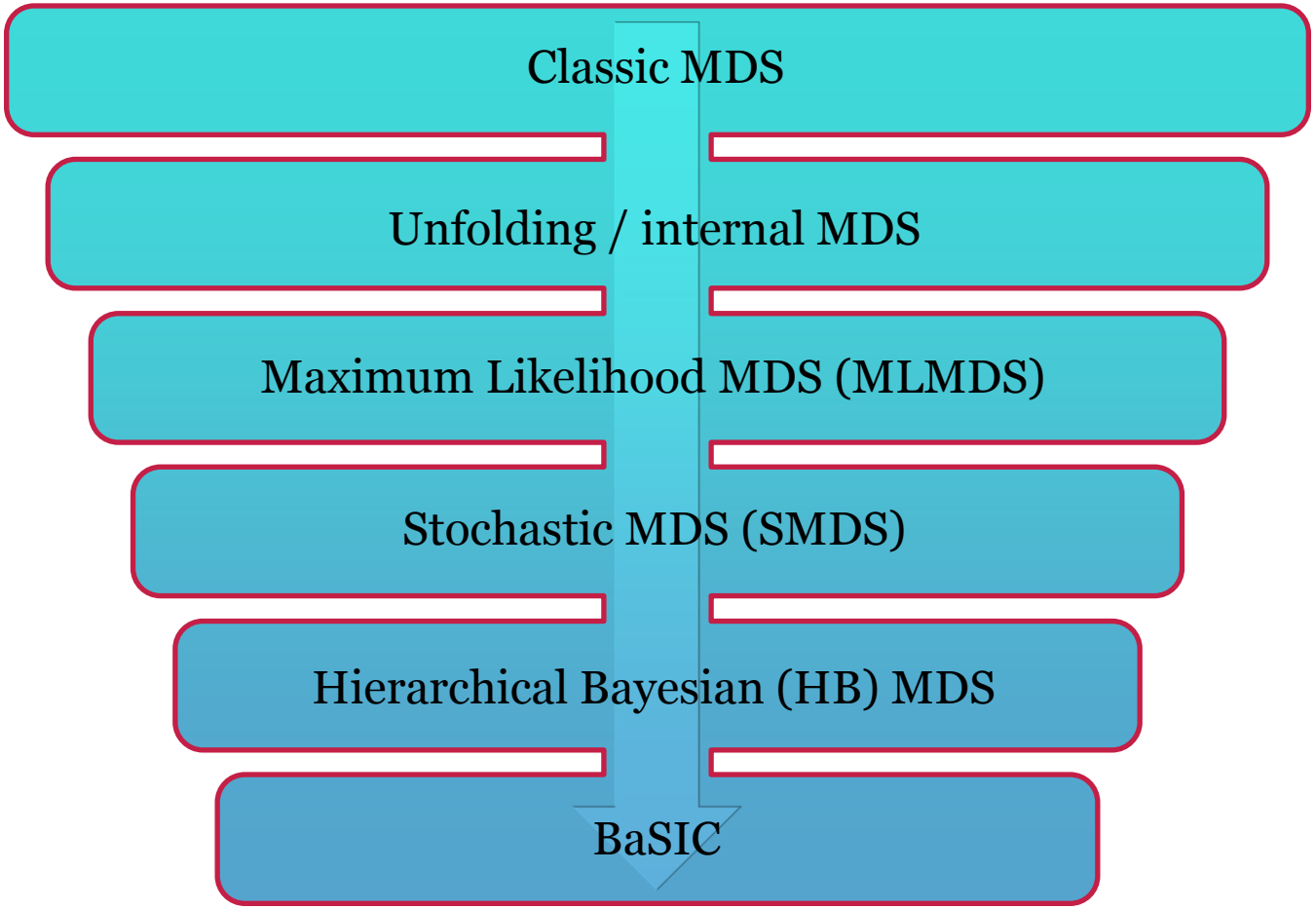
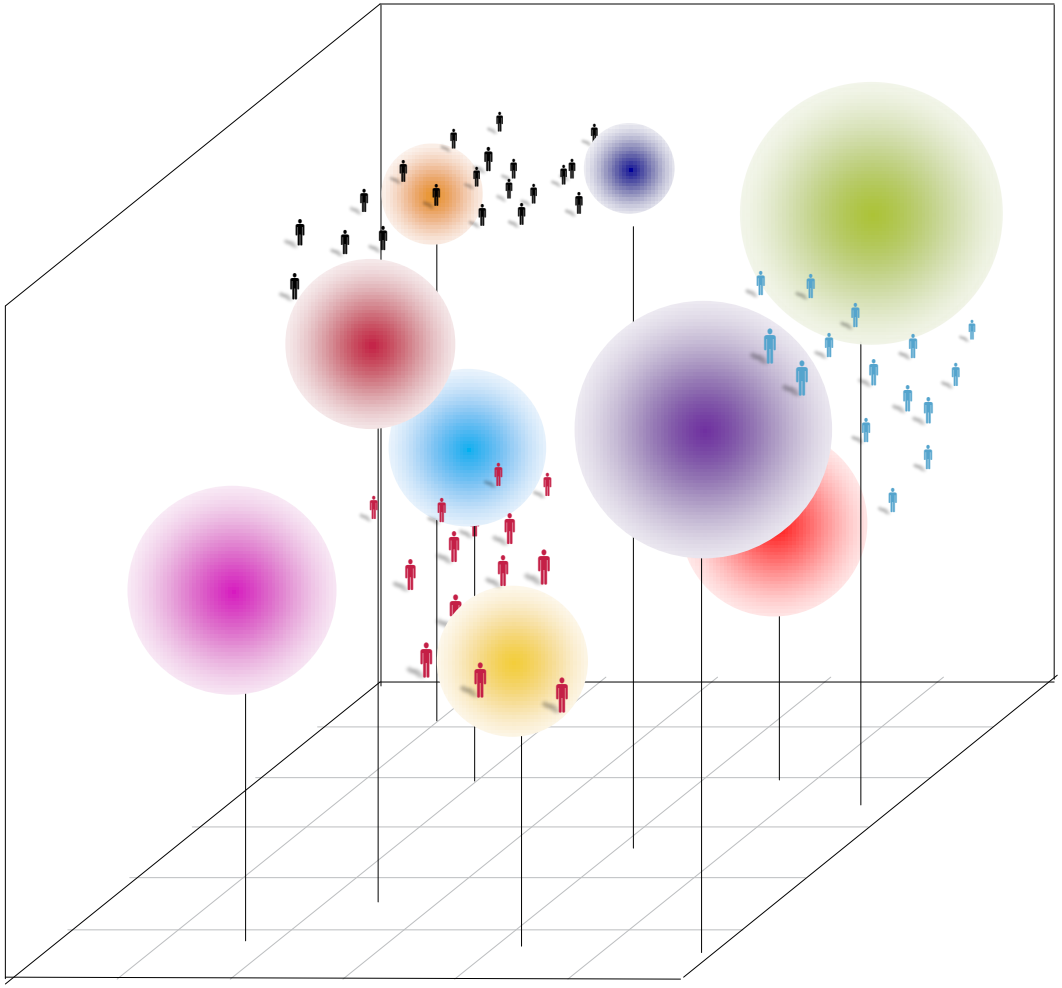
A (Very) Brief History of Multidimensional Scaling Advances (in somewhat chronological order)



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

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

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

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

The BaSIC upper model specification

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

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

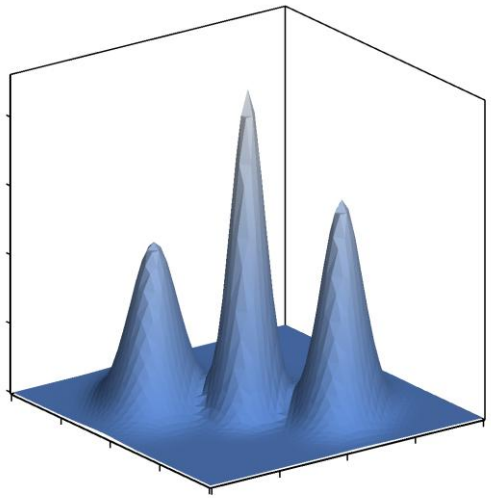
$y_{i,t}$	=	the location of respondent i's ideal point on dimension t
π_s	=	Probability of being in segment s
$\beta_{0,s,t}$	=	Segment Center
z_i'	=	Vector of subject predictors, e.g. demographics
$\sigma^2_{y,t,s}$	=	Standard deviation of y, t, s

The BaSIC upper model specification

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

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

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



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?

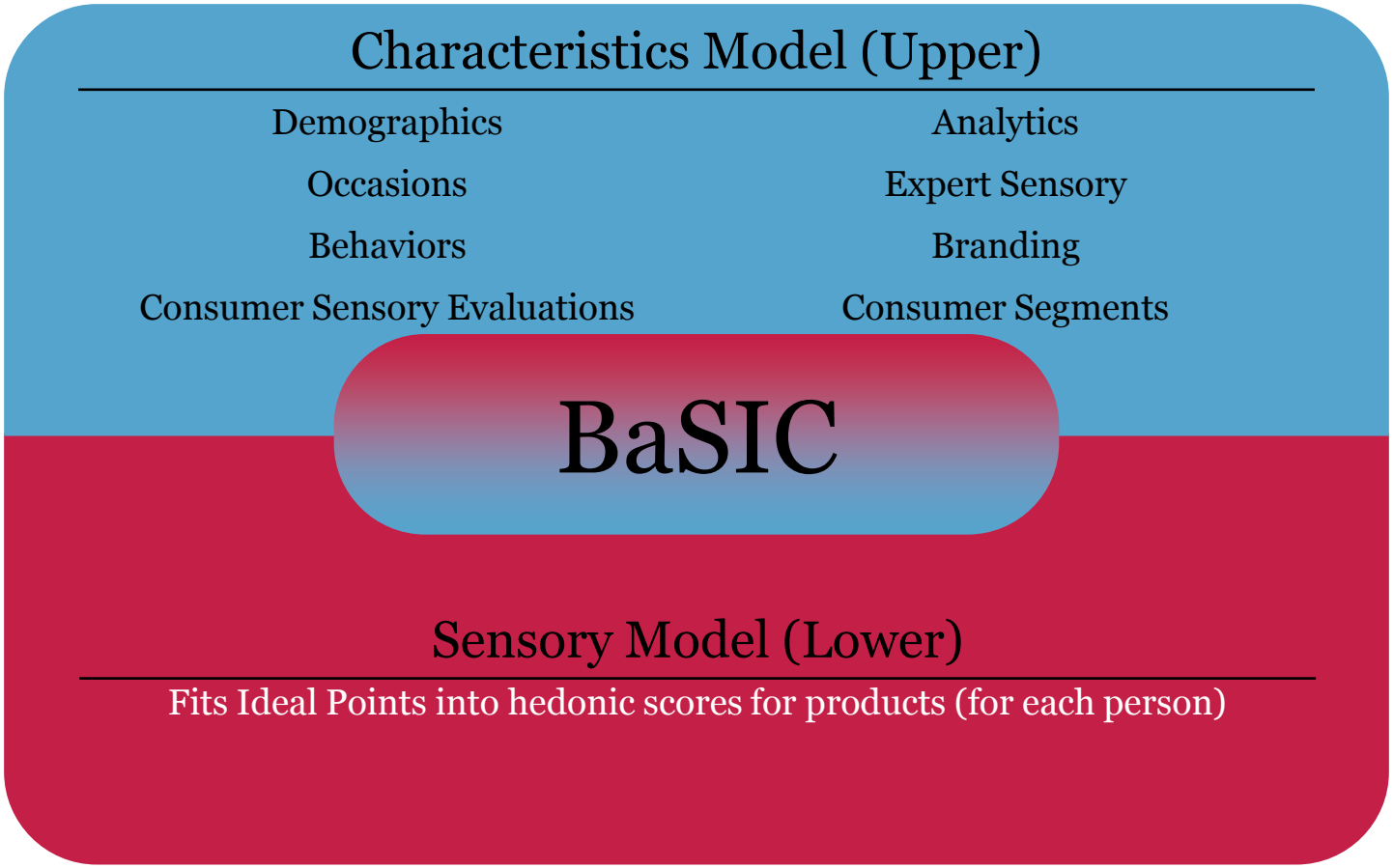
MCMC Estimation of parameters → Information borrowing; Natural imputation of missing data

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



Case Study: Beverage Category

	Traditional Landscape	BaSIC
Total products tested	16	16
Number of days	6	4
Tastings per day	3 each for 5 days, 1 for 1 day	3
N	1600	900
Number of products tasted per person	16	12
Number of tastings per product	100	75

Data collected

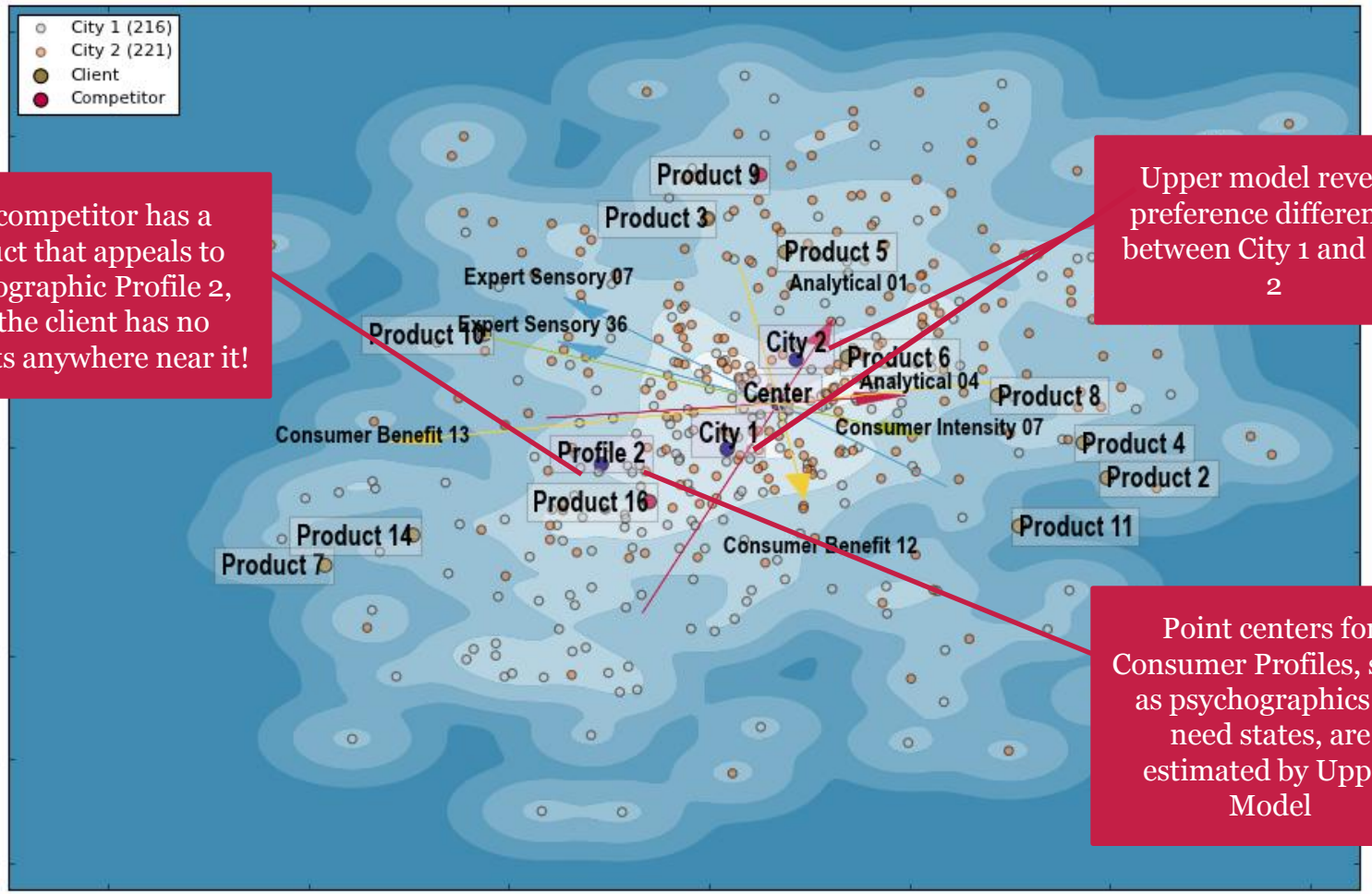
Consumer Information

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

Other Data

- Expert Sensory Evaluations
- Analytical Measurements
- City/Location

Profile Map



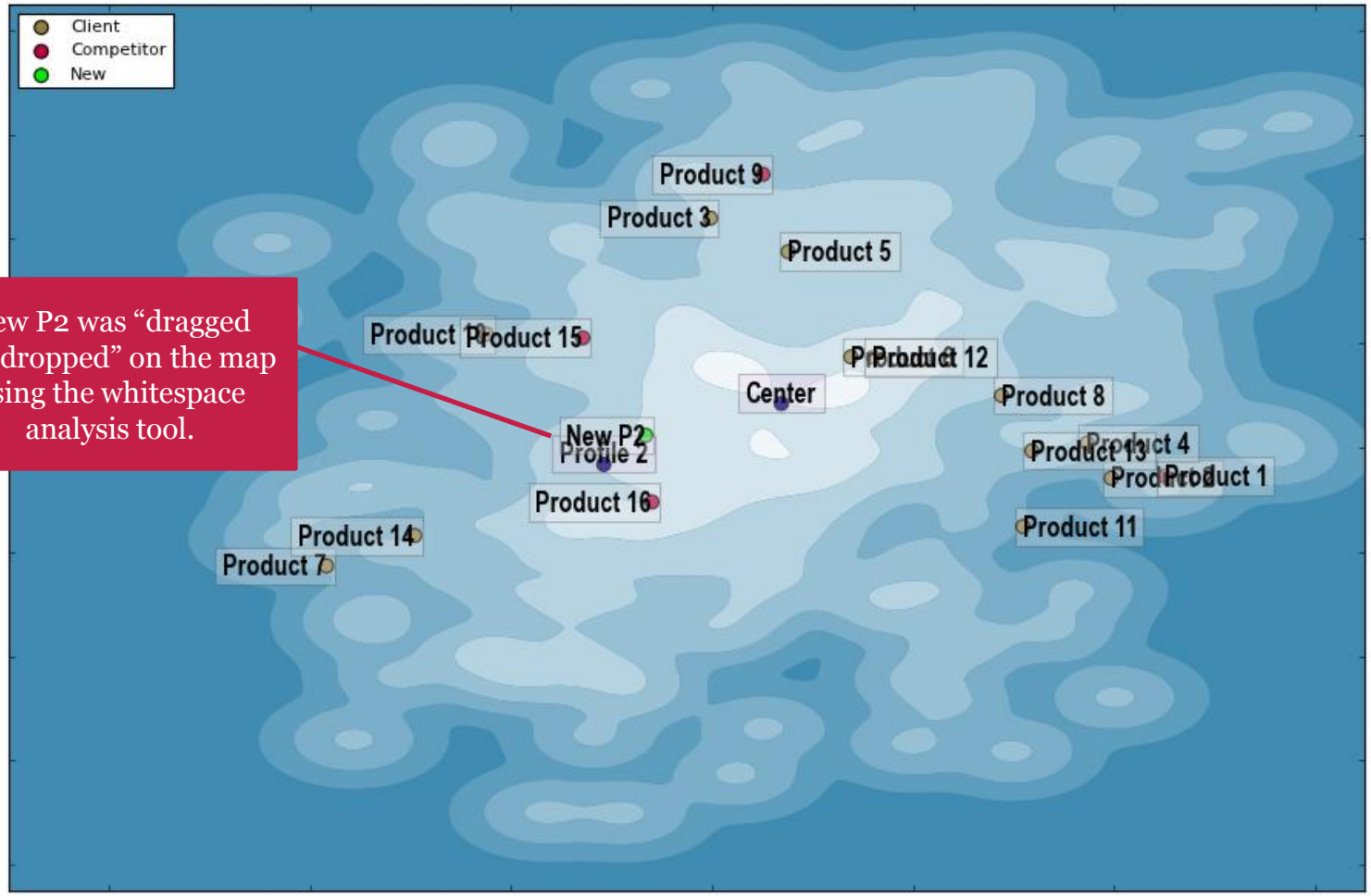
The competitor has a product that appeals to psychographic Profile 2, and the client has no products anywhere near it!

Upper model reveals preference differences between City 1 and City 2

Point centers for Consumer Profiles, such as psychographics or need states, are estimated by Upper Model

Predictive capabilities of upper model

New P2 was "dragged and dropped" on the map using the whitespace analysis tool.



Predicted liking, including the expert sensory and analyticals associated with the new product

	X	Y	Analytical Analytical 01	Analytical Analytical 02	Analytical Analytical 03	Analytical Analytical 04	Analytical Analytical 05	Expert Sensory Expert Sensory 01	Expert Sens Expert Senso
Product 1	1.30	-0.11	4.28	4.76	19.40	4.17	2.80	0.00	0.00
Product 2	1.19	-0.12	3.89	6.80	20.60	4.26	2.36	0.00	0.00
Product 3	0.40	0.88	5.92	214.00	31.40	4.35	5.13	0.00	0.00
Product 4	1.15	0.02	4.50	5.65	20.60	4.36	2.90	0.00	0.00
Product 5	0.55	0.75	6.92	70.85	20.10	3.99	4.56	0.00	0.00
Product 6	0.68	0.35	6.48	7.52	21.40	4.02	4.25	0.00	0.00
Product 7	-0.37	-0.45	0.03	175.00	10.00	4.71	14.51	0.00	0.00
Product 8	0.98	0.20	4.74	9.00	19.20	4.34	3.55	0.00	0.00
Product 9	0.50	1.05	6.46	171.00	44.00	3.81	5.69	0.00	0.00
Product 10	-0.05	0.43	4.98	127.00	12.60	4.20	3.51	0.00	0.00
Product 11	1.02	-0.30	4.52	7.37	9.70	4.43	3.67	0.00	0.00
Product 12	0.72	0.35	4.82	14.33	16.30	4.14	3.53	0.00	0.00
Product 13	1.04	-0.01	5.62	6.89	20.20	4.43	3.34	0.00	0.00
Product 14	-0.19	-0.34	4.79	3.72	0.00	2.83	4.88	0.30	0.20
Product 15	0.14	0.42	5.72	8.22	10.90	3.72	2.66	0.00	1.70
Product 16	0.28	-0.21	7.05	4.00	0.00	2.93	9.44	0.00	0.40
New P2	0.27	0.04	4.45	63.93	12.38	3.98	6.64	0.03	0.28

Predicted analytical and sensory profiles.

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

Merci!

Q&A

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J'adore les huîtres, on a l'impression d'embrasser la mer sur la bouche. -Léon-Paul Fargue (Moi aussi!)