Preference Mapping With Incomplete Blocks: A Review

Graham Cleaver
Unilever R&D
Vlaardingen, Netherlands

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Overview

- Background
- Design issues
- Sensometrics 2004: Workshop
- Examples of different analysis techniques in the context of incomplete block designs
  - External analysis: PrefMax, Latent Class
  - Internal analysis: MDPref, CLIP, PrefScal, LSA
- Summary

Acknowledgments

- *Richard Popper: Sensometrics Workshop Summary*
- *Pascal Schlich: PrefMax, CLIP*
- *Frank Busing: PrefScal simulations*
- *Danny Ennis: LSA slides*

Background: Challenge

Preference Mapping Objectives:

Systematic coverage of relevant sensory space

Robust models and understanding of drivers of liking

↓

Large no. of products – typically 12-16

Modelling Objective

At level of individual consumers

↓

Maximise no. products / respondent

Practical Constraint

Need to avoid sensory fatigue

↓

Minimise no. products / respondent

Pragmatic Solution:

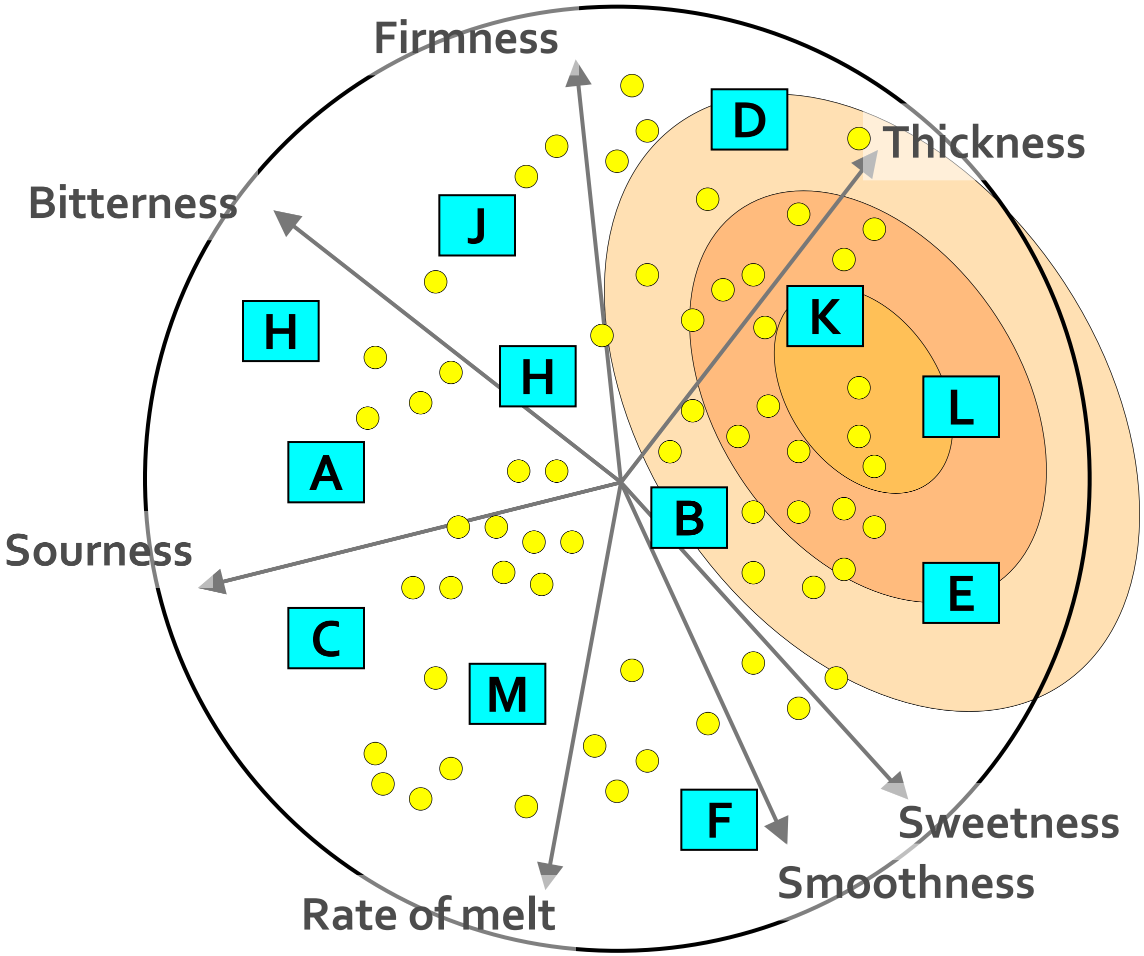
Split products to be tested over more than one day and session

Not ideal (cost, consistency over time) – need to consider alternatives

↓

Incomplete Block Designs

Design Issues



Design Considerations

Concerns

- Estimated individual ideal depends on particular set of products assessed
- Segmentation may be driven by incomplete patterns
- Single very influential product could dominate segmentation

Design aspects are critical

General good practice

Incomplete designs balanced for order and carry-over effects

Ref:
Wakeling, I.N. & MacFie H.J.H. Designing consumer trials balanced for first and higher orders of carryover effect when only a subset of k samples from t may be tested Food Quality and Preference 6 (1995) 299-308

Exploit product structure

e.g. Block designs for factorial and fractional factorials

7 factors each at 2 levels
2^7 = 128 possible products

Fractional factorial design
1/4 = 32 products

Balanced block design
8 products / consumer

Design Opportunities

Total no. of products = 12

Incomplete block design

6 products / respondent

Total no. of products = 48

Incomplete block design

12 products / respondent

Data Analysis Workshop

Consumer Segmentation & Key Drivers Analysis

7th Sensometrics Meeting
July 28-30, 2004
Davis, CA
USA

Data supplied by:
CFIFL / INRA (Pascal Schlich)

Review of findings by:
Richard Popper

Study Description

	Study Parameters
Tomato Varieties	17
Sensory Panel	14 panelists
Sensory Attributes	11
Physical/Chemical Analyses	15
Consumers	N=379 tasted 10 of 17 varieties
Hedonic Rating	Overall liking
Reason for Preference	Preference between most & least liked, with reason for preference checklist
Appearance Liking	7 varieties ranked for appearance liking
Usage and Attitudes	17 questions

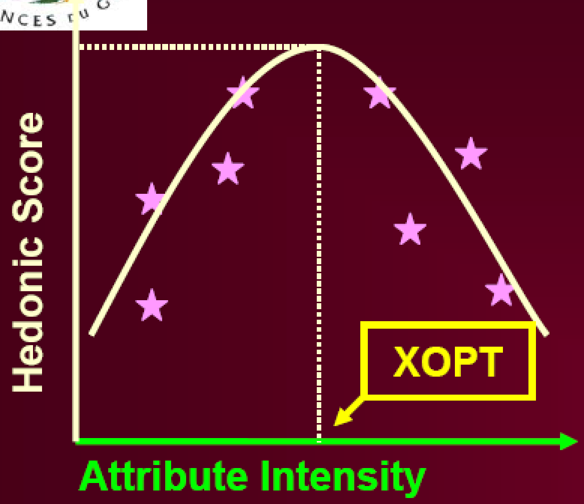
Method Comparisons

- Segmentation technique
  - liking alone
  - use external variables (e.g. sensory)
- Treatment of missing values
  - accept missing values
  - impute missing values
- Data pre-treatment
  - liking data normalized
  - data reduction technique for sensory
- Selection of number of clusters
  - judgment
  - statistical criterion
- Type of selection of drivers?
  - linear only
  - quadratic drivers included

Method Comparisons

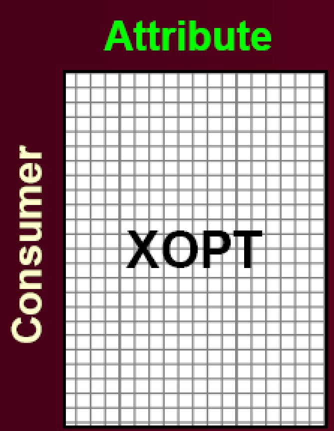
	Ledauphin	Lengard	Lundahl	Cleaver	Meullenet	Schlich	Tang	Zalila
Segmentation based on								
Liking alone		✓	✓					Yes
Liking w respect to external variables	✓			✓		✓	✓	
Impute missing values?	No	Yes	Yes	No		No	No	No
Liking data pre-treatment	No	Yes	Yes	Yes		No	Yes	Yes
Selection of number of clusters								
Judgment	✓	✓						
Statistical criterion			✓	✓		✓	✓	✓
Include quadratic drivers?	No	No	No	No		Yes	No	N/A

PrefMaX Method

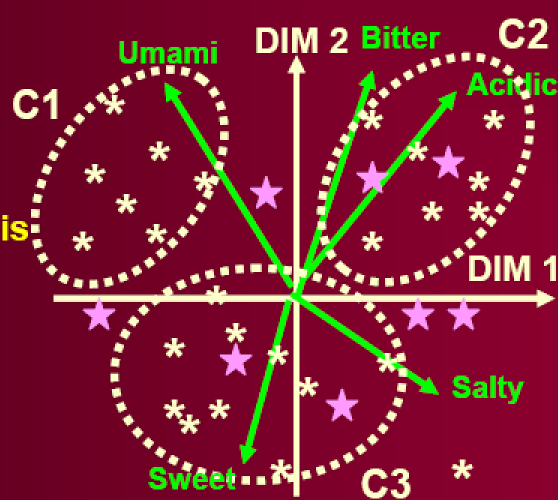


For each pair of consumer/attribute:

1. Fit a quadratic regression of hedonic scores on attribute means
2. Define optimal intensity (XOPT)
3. Store all XOPT into a *consumer x attribute* matrix
4. XOPT matrix is the input of subsequent analyses
5. In these analyses, weight each XOPT by the R^2 from the corresponding quadratic regression



Cov PCA
Cluster Analysis



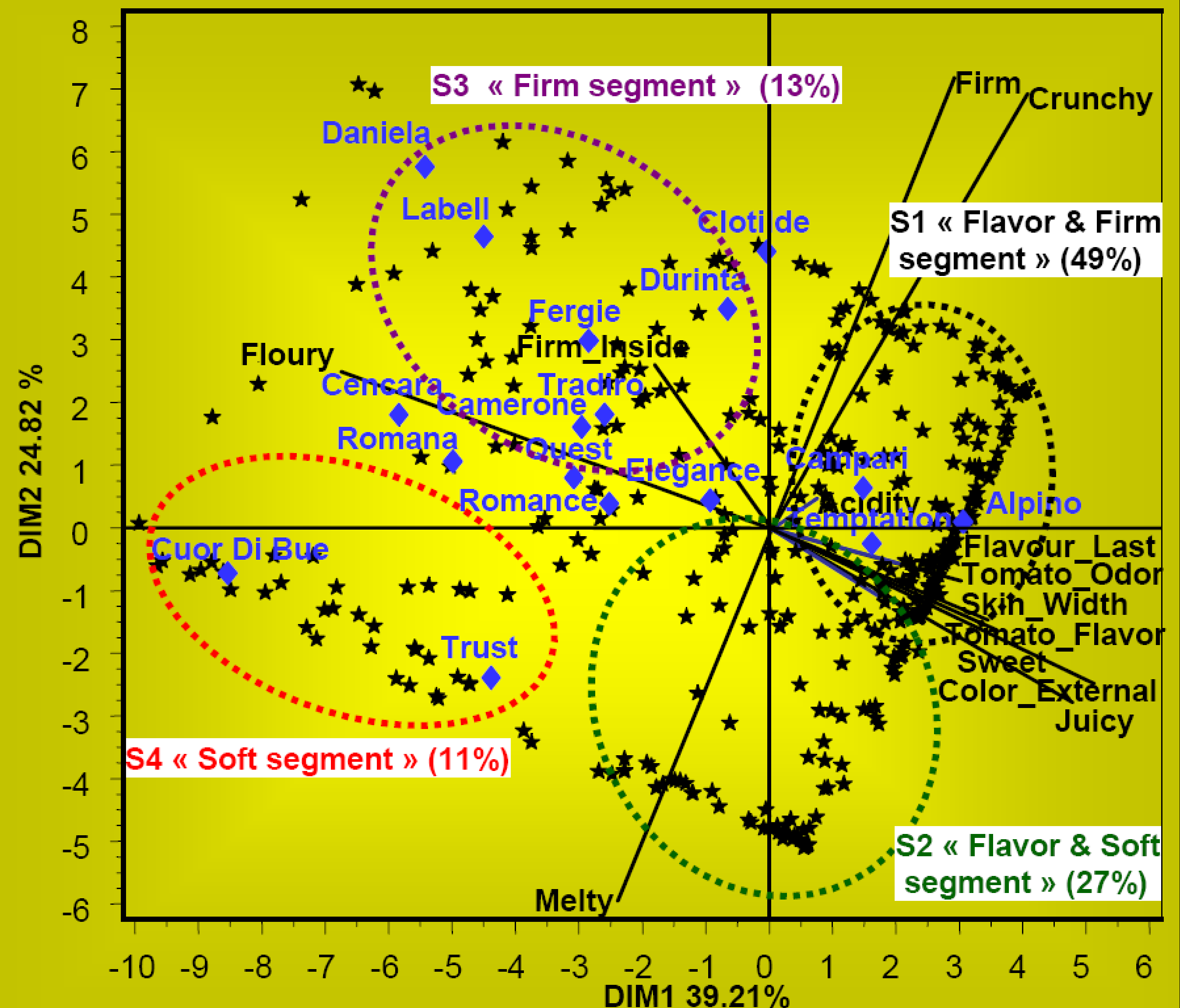
Optimal
Sensory Recipes
by Consumer Segment

Attribute	C1	C2	C3
Acidic	0	+	-
Bitter	0	+	-
Salty	-	0	0
Sweet	0	-	+
Umami	+	0	0

Each white star is the ideal point of a consumer

Each violet star is a product projected onto the map as a supplementary point using its attribute mean intensities

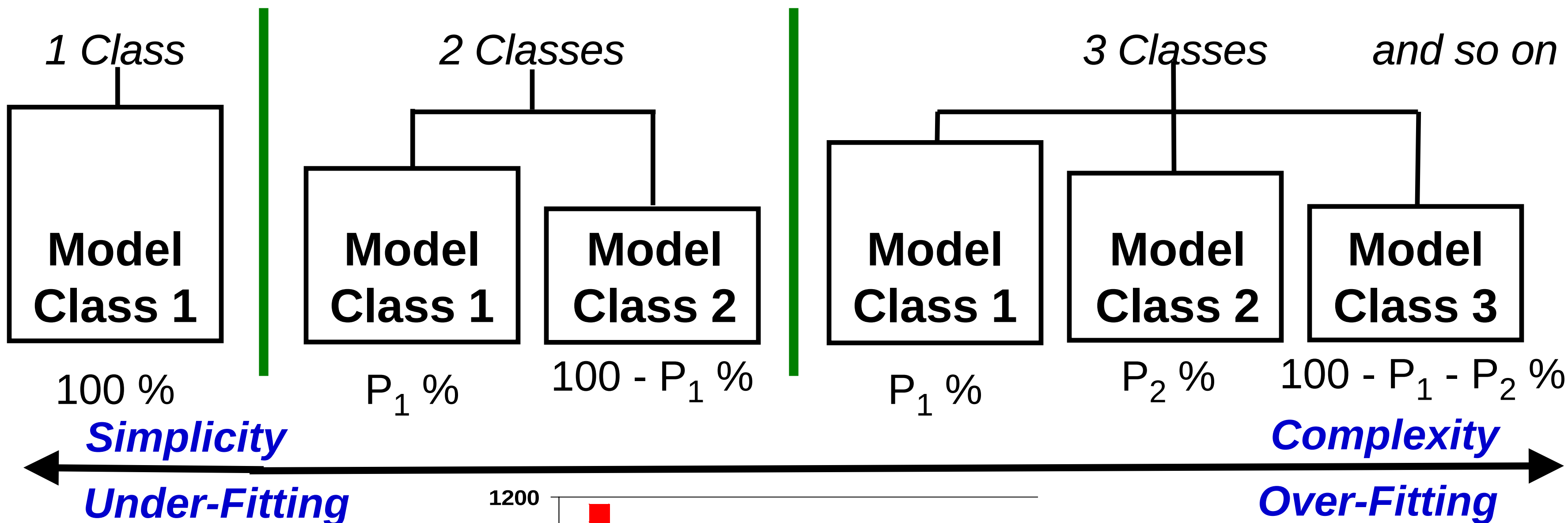
2001 Tomato PrefMaX

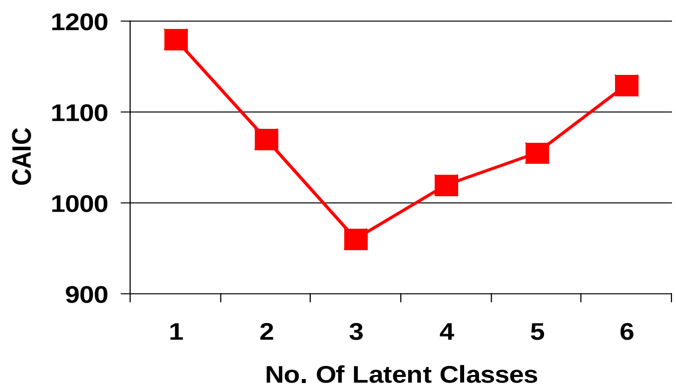


379 Consumers – 17 Tomato varieties – 13 Attributes

External: Latent Class Regression
Simultaneous Modelling & Segmentation

- Does not have pre-requirement for complete data
- Potential to work well with incomplete data: models at underlying segment level not individuals





External: Latent Class Regression
Example: Tomato Data Sensometrics (2004)

- **17 Tomato varieties**
- **Each consumer rated 10 / 17**

379 Consumers

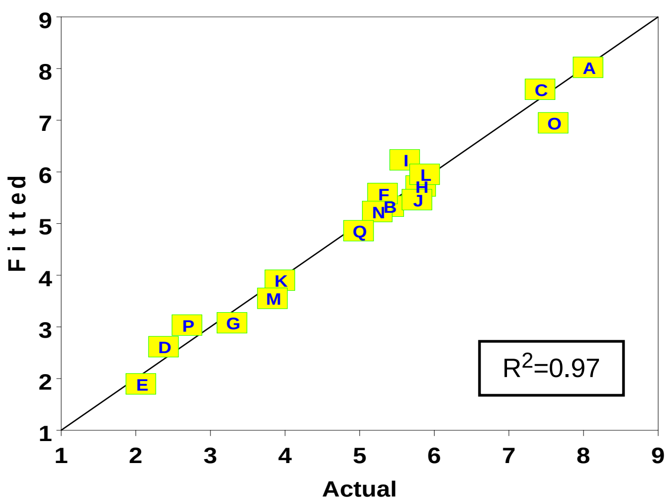
Latent Class Regression Extended Model

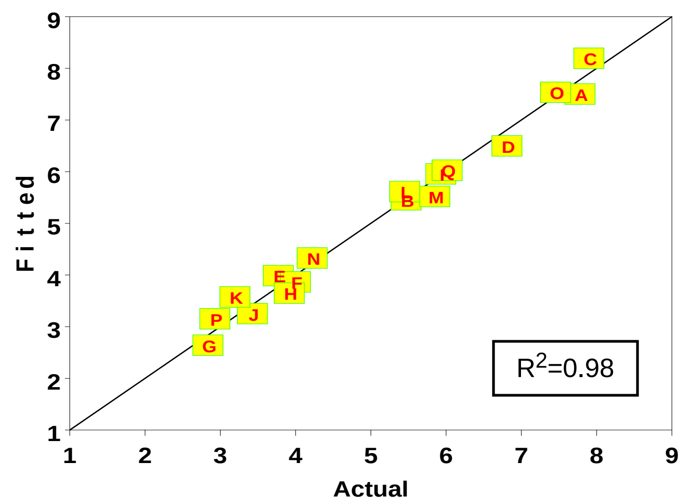
'Random Scoring'

Class 1 **49%**

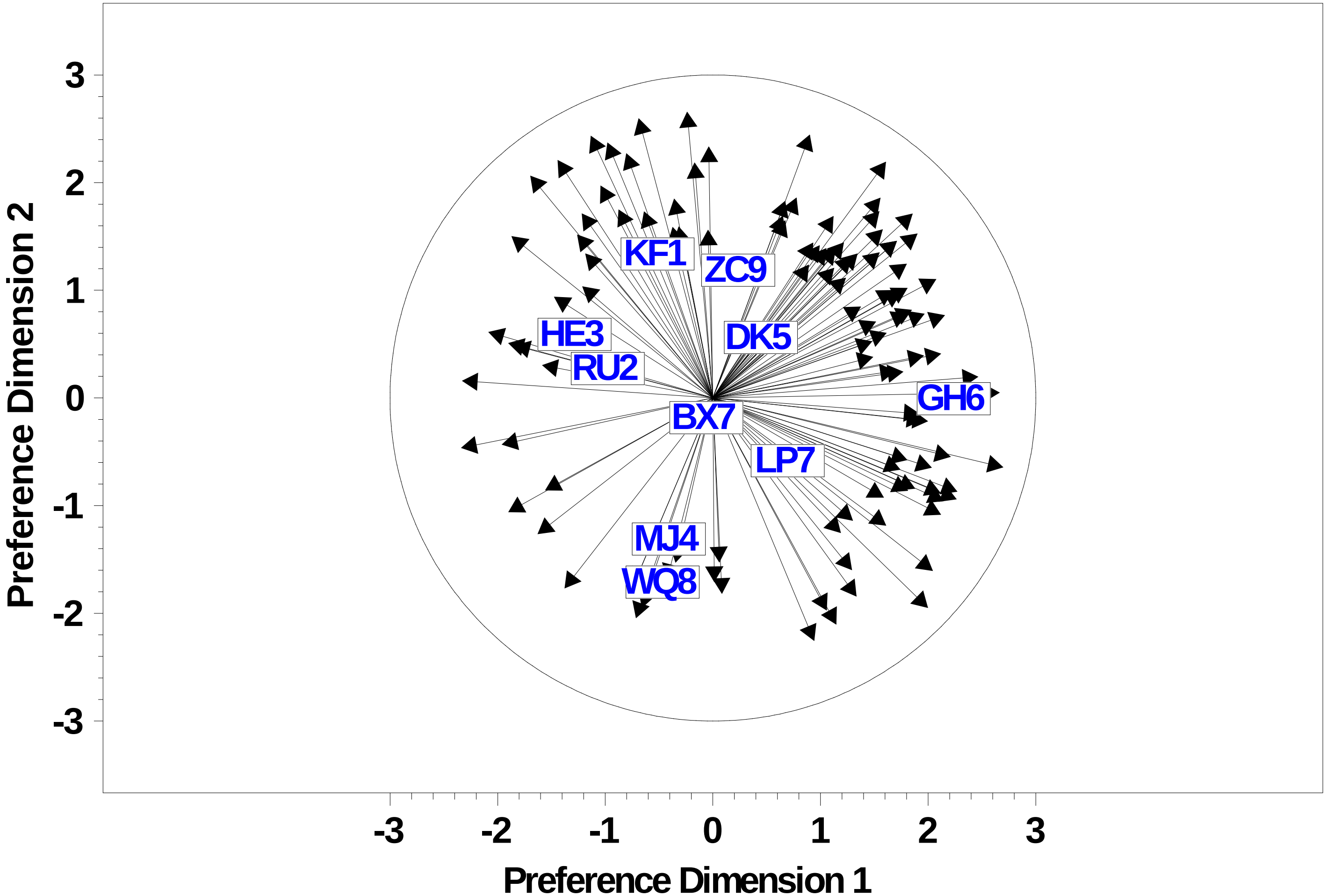
Class 2 **31%**

Class 3 **20%**





Internal: MDPref



- Ideal vectors – suitable for where ideal regions are towards the outside
- Does have pre-requirement for complete data

MDPref: Monte-Carlo Simulation

Missing value imputation

- Expectation Minimisation (Beale & Little)
- Row-Column Substitution (Krzanowski)
- Proc PRINQUAL (SAS)
- MISTRESS Algorithm (van Buuren)
- Mean substitution

Factors varied

- No. of subjects: 50 200
- No. of stimuli: 10 30
- Dimensionality of pref space: 2D 4D
- Level of noise in data: SD=1 SD=2.0
- Proportion incomplete data: 5 35 65%

Outcome

- Simple mean substitution as good as other techniques
- Level of noise was most influential factor
- Product positions stable with incomplete data
- Level of incompleteness:
  - 5% : All techniques gave good results
  - 35% : Results may be questionable
  - 65% : No technique gave good results

Ref:

- *Hedderley D. & Wakeling I. A Comparison of imputation techniques for preference mapping using a Monte Carlo simulation Food Quality & Preference 6 (1995) p281-298*

Internal: Clustering

Cluster Analysis
Usually hierarchical, applied to raw liking scores for each product to cluster respondents

Conventionally, requires complete data for each respondent

Some techniques allow missing values
eg PROC FASTCLUS (SAS)

Has not been evaluated systematically in context of incomplete block preference mapping

May be more suited to randomly distributed missing values, rather than (high) proportion of missing values for each line of data

Internal: Clustering (CLIP)

- **CL**ustering of **I**ncomplete **P**references
  - Define measure of similarity between respondents based on scores for products
  - MDS to create plot of respondents
  - Cluster analysis of respondents

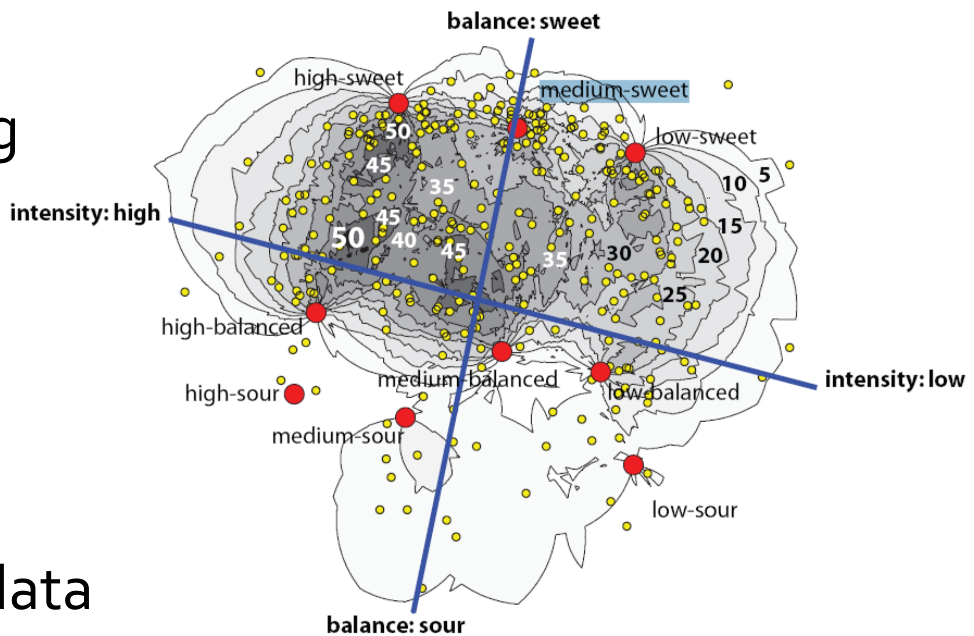
$$S_{ii'} = \frac{\sum_{j \in P_{ii'}} 1 - \frac{|x_{ij} - x_{i'j}|}{R(j)}}{k_{ii'}} \qquad (\text{si } k_{ii'} \neq 0)$$

- Three data sets used as a basis for simulation where data was systematically removed
- Results / Recommendation
  - Low noise data: Half the samples should be tasted by each assessor
  - Noisy data: Two-thirds of the samples are required.

Ref: Callier, P. and Schlich, P. (1997) La cartographie des préférences incomplétes – Validation par simulation. – Sciences Des Aliments, 17,155-172

Internal: PrefScal

- Ideal point unfolding
- With optimal scaling of liking scores
- Can incorporate external information – 'restricted unfolding'
- Does not require complete data



Refs

- ***Busing, F.M.T.A., Groenen, P.J.F., and Heiser, W.J. (2005), "Avoiding Degeneracy in Multidimensional Unfolding by Penalizing on the Coefficient of Variation", Psychometrika, 70(1), 71–98***
- ***Busing, F.M.T.A.,Heiser, W.J., Cleaver, G.J. 'Restricted unfolding: Preference analysis with optimal transformations of preferences and attributes' Food Quality and Preference 2010 Vol21 (1) p82-92***

PrefScal: Simulation study

Method

- Real and simulated of data with varying levels of completeness
- Comparison solutions based on incomplete vs complete data

Criteria

- Tucker's congruence coefficient(Φ)
- Kendall's rank order correlation (τ_b)

Outcome

Charts with guidance on proportion inclusion required, in relation to:
(a) No. of products (b) No. of respondents (c) Level of variation in data

- Small no. of products (10- products): Include complete data for each respondent
- Larger studies (15+ products and 40+ respondents): Up to 50% can be missing and still give comparable results

Ref:

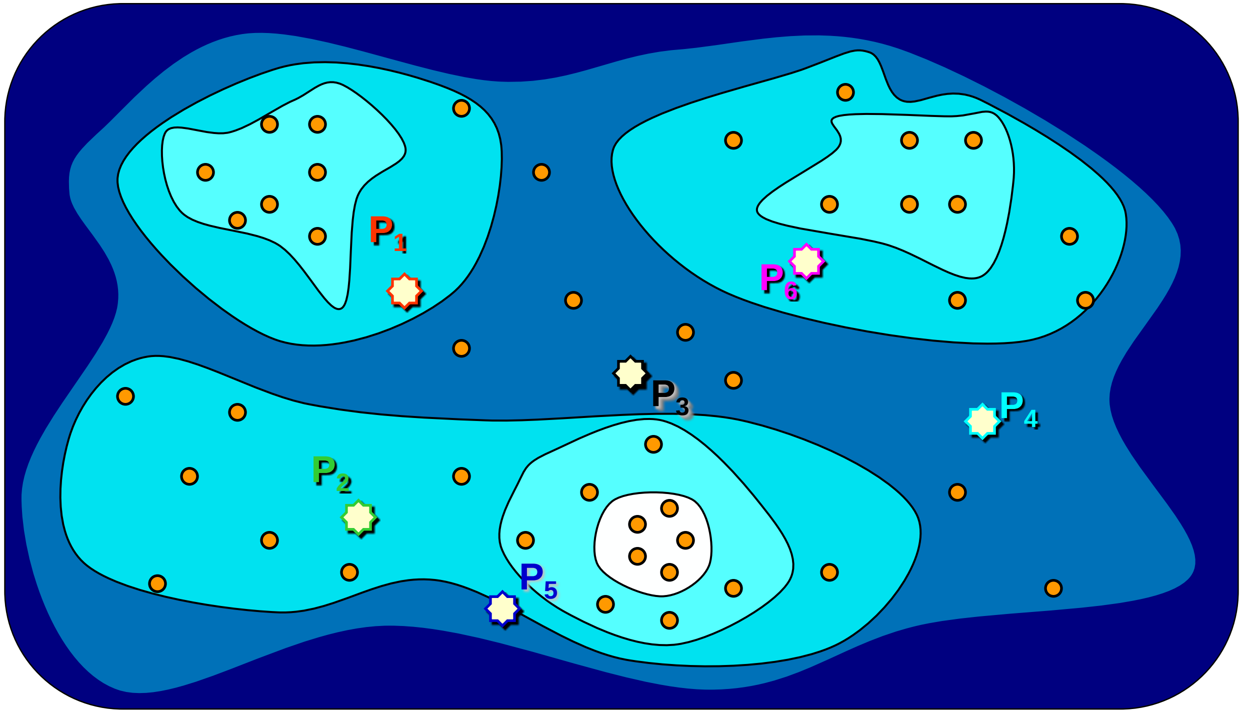
- *Busing, F. & de Rooij M. 'Unfolding Incomplete Data: Guidelines for Unfolding Row-Conditional Rank-Order Data with Random Missings' Journal of Classification 26: 329-360 (2009)*

Landscape Segmentation Analysis®

Background (1/2)

- LSA first "unfolds" liking and creates a space relevant to consumer acceptability (6 products, 44 consumers)
  - *The closer a consumer is to a product, the more he/she likes it*
  - *Contours indicate consumer densities and facilitate the visualization of potential segmentation*

Consumers



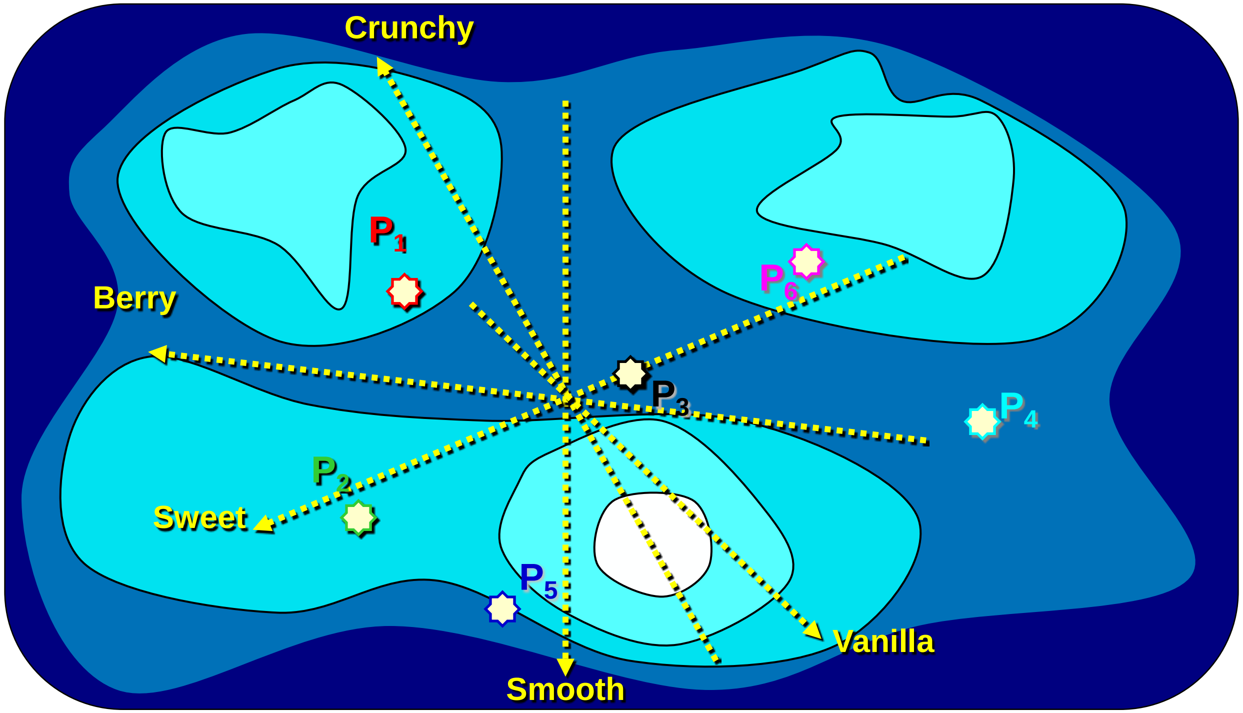
Ref

- ***IFPrograms (Institute For Perception)***

Landscape Segmentation Analysis®

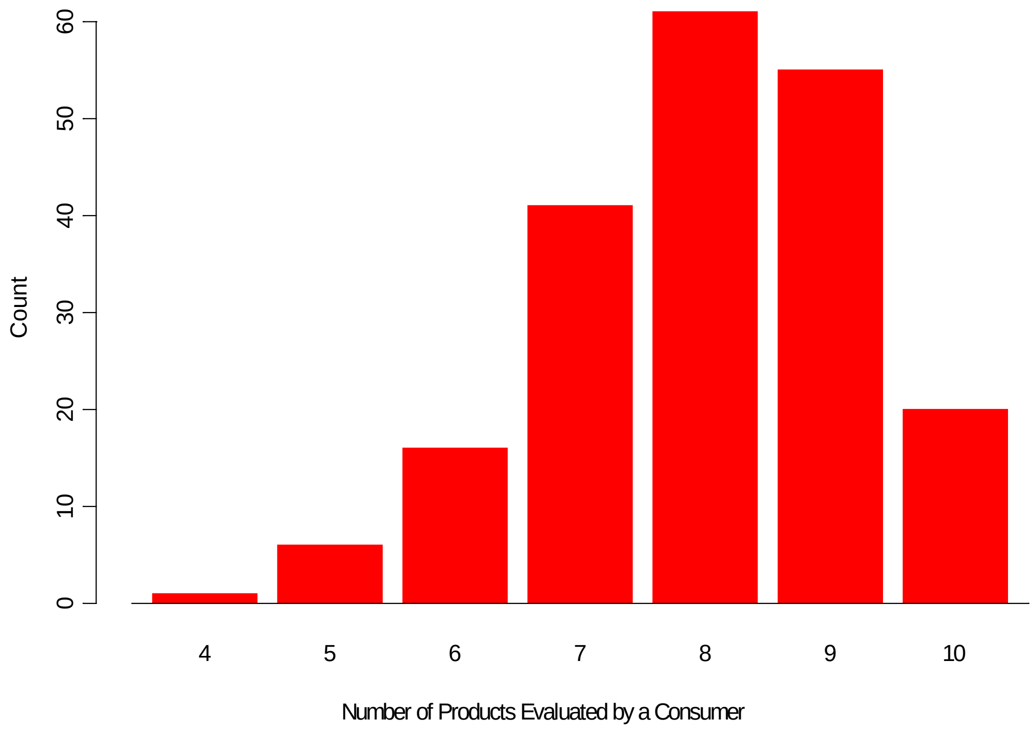
Background (2/2)

- Descriptive data is then added by regressing the attributes on the map using the relationship between the original scale data and the values predicted by projecting each product on the map's attribute
- Some attributes can be fit on the map and are drivers of liking
- Others can't and are less relevant to consumer acceptability



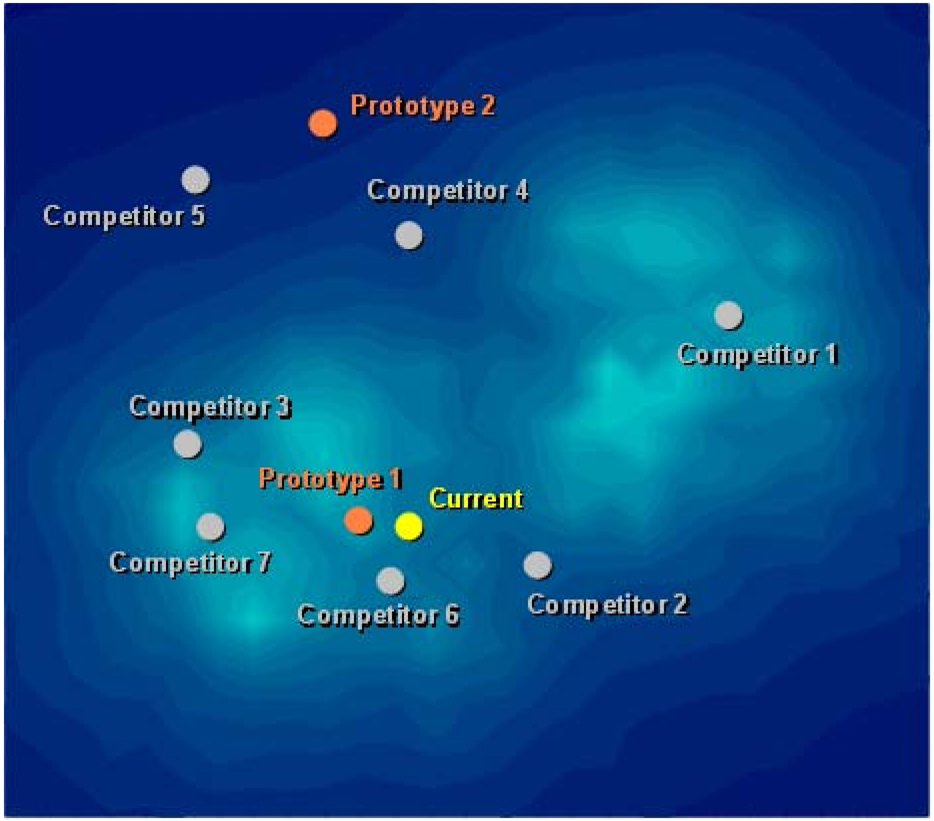
LSA results with complete block and unbalanced incomplete block arrangements

- 200 consumers, 10 cookies
- Degree of incompleteness
  - Complete block: all 200 consumers evaluate all 10 products
  - Unbalanced incomplete block: 20% of the data randomly removed
    - Should be a worse case scenario than a balanced incomplete block

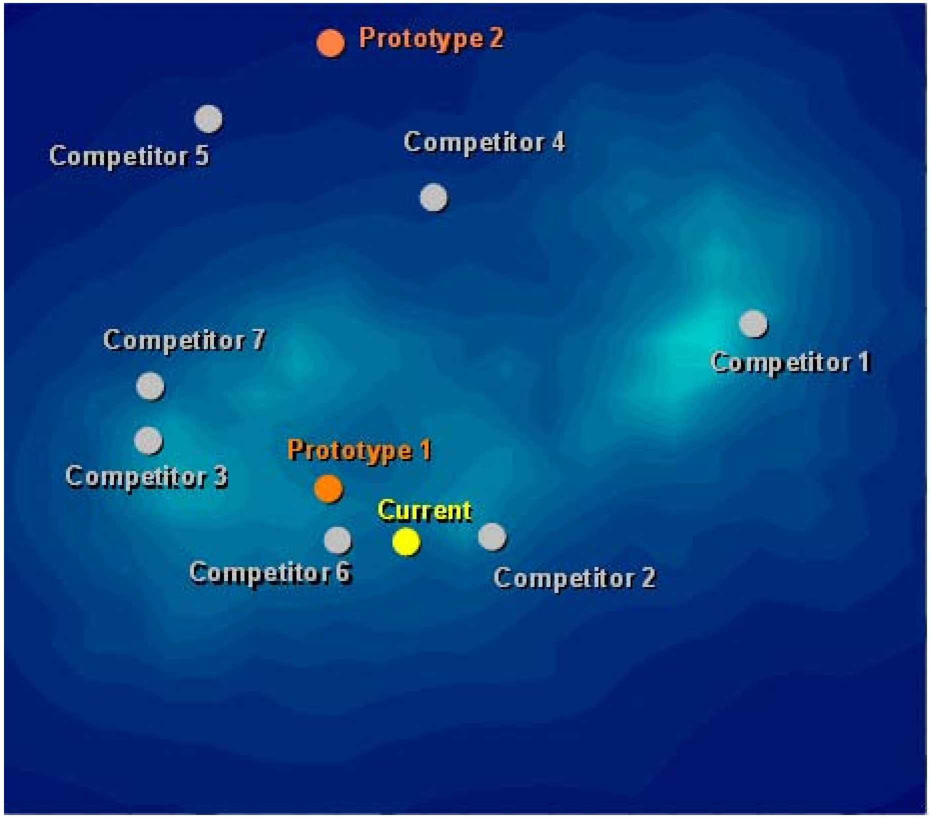


LSA results with complete block and unbalanced incomplete block arrangements

Complete block solution



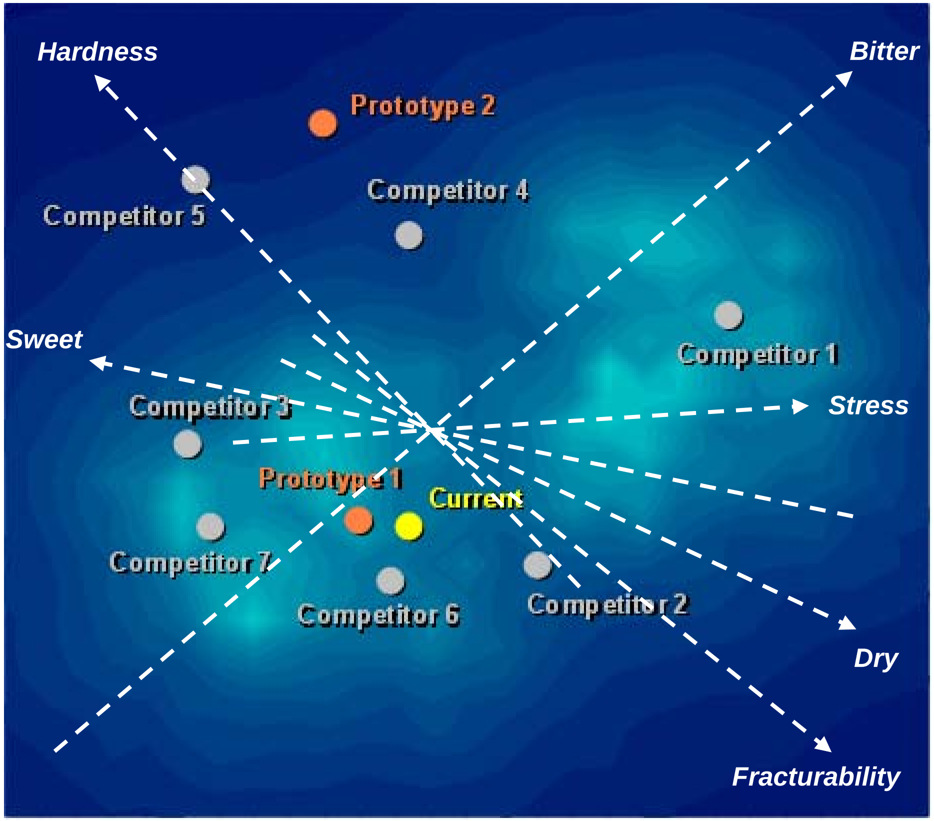
Unbalanced incomplete block solution



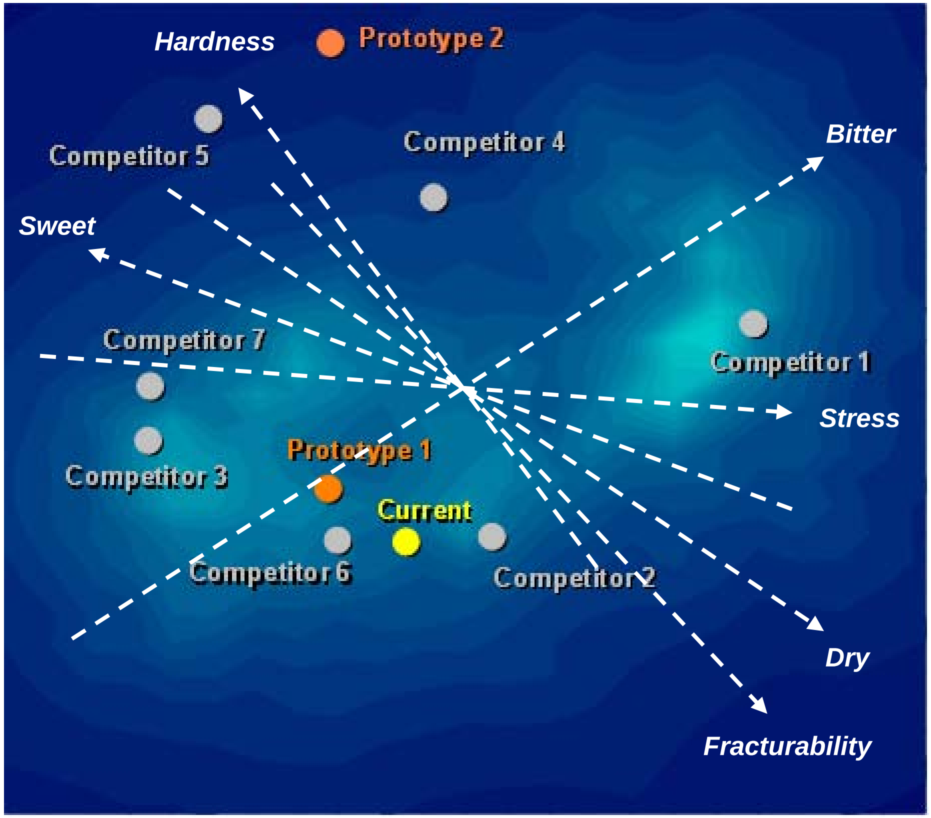
- Solutions are almost identical re products and both show two segments
- Drivers of liking highly similar (next slide)

LSA results with complete block and unbalanced incomplete block arrangements

Complete block solution



Unbalanced incomplete block solution



Driver of Liking®

Cross-Methodology Evaluation

Actual Data
Validated Models
Varying Product categories / Cultures / Size / etc

Simulated Data
Known Models
Systematic variation in Size / Noise / Dimensionality / etc

Creation Of Subsets Of Varying Completeness
Systematic removal

PrefMax | LCR | MDPref | CLIP | LSA | PrefScal

Comparison vs Validated / True Model
Based on common performance criteria

Summary

- Some analysis preference mapping techniques have a pre-requirement for complete data for each respondent, e.g. MDPref. Most do not.
- There are many examples of application of preference mapping to incomplete data and evaluations of the impact of different levels of incompleteness.
- Scope for systematic evaluation across methodologies based on common criteria.
- Recommendation may depend on absolute number of products per respondent, rather than proportion
- Design aspects are critical and deserve further attention