Combining extrinsic and intrinsic information in consumer acceptance studies

Elena Menichelli, Nina Veflen Olsen, Christine Meyer, Tormod Næs

Background

Food development studies:

- Intrinsic sensory attributes

- Extrinsic product factors

Focus

Relating sensory characteristics to additional information

Menichelli, E., Olsen, N.V., Meyer, C., Næs, T. (2012). Combining extrinsic and intrinsic information in consumer acceptance studies. *Food Quality and Preference*, *23*(2), 148-159.

Previous studies

- Independent tests may be insufficient (interaction)
- Conclusions about differences among actual products
- Limited focus on the effect of the whole sensory space and how this influences consumer preferences

Aims:

- Investigating main drivers of liking / choice probability
- Interaction with extrinsic attributes

Challenges

Design

- To select the best possible subset of the products to be tested
- To combine the selected products with extrinsic attributes in a simple way

Analysis

- To combine the large set of collinear sensory variables with the extrinsic attributes
- To allow for interactions and non-linearities, in particular with a small number of samples

Design

Requirements

- To select products that cover the sensory space
- To allow for both linear and non-linear models (ideal point) for the sensory attributes
- To estimate extrinsic effects, intrinsic effects and interactions between them
- To reveal both population structure and individual differences
- To use standard well established principles

Design

Requirements

- To select products that cover the sensory space
- To allow for both linear and non-linear models (ideal point) for the sensory attributes
- To estimate extrinsic effects, intrinsic effects and interactions between them
- To reveal both population structure and individual differences
- To use standard well established principles

Strategy

- Standard sensory profiling analysis and data reduction by PCA
- Consumers split into groups and each group is given a different set of few products (3-5)
- For each consumer, to combine each product with the same factorial design in the extrinsic attributes
- Principles from experimental design, multivariate analysis and ANOVA

Analyses: approach 1

- Mixed Model ANCOVA
  - Fixed population effects.
    Flexibility: free choice about the model for intrinsic attributes (population level: all products tested) and how these relate to the extrinsic factors
  - Random individual effects.
    Restrictions: design and number of products used for each of the consumers

$$y_{ikn} = Population\ effects + Individual\ effects + noise$$
$$= \mu + \alpha_i + \beta_1 x_{1k} + \beta_2 x_{2k} + \beta_{12} x_{1k} x_{2k} + \beta_{i1} x_{1k} + \beta_{i2} x_{2k} + \beta_{i12} x_{1k} x_{2k}$$
$$+ C_n + \alpha C_{in} + \beta_{n1} x_{1k} + \beta_{n2} x_{2k} + e_{ikn}$$

Analyses: approach 1

- Mixed Model ANCOVA
  - Fixed population effects.
    Flexibility: free choice about the model for intrinsic attributes (population level: all products tested) and how these relate to the extrinsic factors
  - Random individual effects.
    Restrictions: design and number of products used for each of the consumers

$$y_{ikn} = Population\ effects + Individual\ effects + noise$$
$$= \mu + \alpha_i + \beta_1 x_{1k} + \beta_2 x_{2k} + \beta_{12} x_{1k} x_{2k} + \beta_{i1} x_{1k} + \beta_{i2} x_{2k} + \beta_{i12} x_{1k} x_{2k}$$
$$+ C_n + \alpha C_{in} + \beta_{n1} x_{1k} + \beta_{n2} x_{2k} + e_{ikn}$$

- Analysis of the individual contributions*
  - Residuals
  - Different factor combinations
  - Average over extrinsic variables

* Endrizzi, I., Menichelli, E., Johansen, S. B., Olsen, N. V., & Næs, T. (2011). Handling of individual differences in conjoint analysis. *Food Quality and Preference*, 22(3), 241–259.

Analyses: approach 2

- Fuzzy clustering
  - Advantage of fuzzy clustering based on residual distance: different samples can be given to different consumers
  - Aim: identifying segments of consumers with similar response

*

$$\min \quad J = \sum_{j=1}^{C} \sum_{i=1}^{N} u_{ij}^{m} d_{ij}^{2}$$

Fuzzifier parameter

Distance between object i and cluster j

Membership value for object i to cluster j

$$d^2{}_{ij} = (y_i - x^t{}_i \hat{b}_j)^2$$

$$(X^T U_j X)^{-1} X^T U_j Y$$

Extrinsic and intrinsic information

Diagonal matrix with weights $u^m{}_{ij}$

Liking / choice / purchase intent

* Berget, I., Mevik, B. H., & Næs, T. (2008). New modifications and applications of fuzzy C-means methodology. *Computational Statistics and Data Analysis*, 52, 2403–2418.

Analyses: approach 2

- Fuzzy clustering
  - Advantage of fuzzy clustering based on residual distance: different samples can be given to different consumers
  - Aim: identifying segments of consumers with similar response

*

$$\min \quad J = \sum_{j=1}^{C} \sum_{i=1}^{N} u_{ij}^{m} d_{ij}^{2}$$

Fuzzifier parameter

Distance between object i and cluster j

Membership value for object i to cluster j

$$d^2{}_{ij} = (y_i - x^t{}_i \hat{b}_j)^2$$

$$(X^T U_j X)^{-1} X^T U_j Y$$

Extrinsic and intrinsic information

Diagonal matrix with weights $u^m{}_{ij}$

Liking / choice / purchase intent

- ANOVA for each cluster
  - No individual contributions: consumers already similar
  - Aim: testing significance within each group

* Berget, I., Mevik, B. H., & Næs, T. (2008). New modifications and applications of fuzzy C-means methodology. *Computational Statistics and Data Analysis*, 52, 2403–2418.

Orange juice

Consumer choice probability of orange juices with different sensory properties and in combination with two extrinsic attributes:

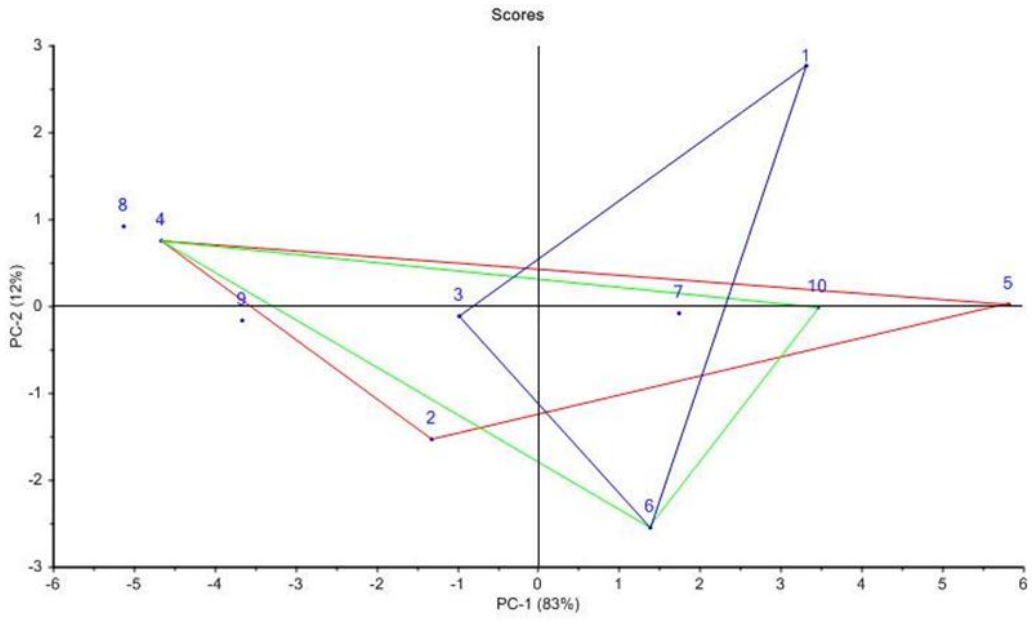
- processing method (conventional, organic)
- price (low, high).

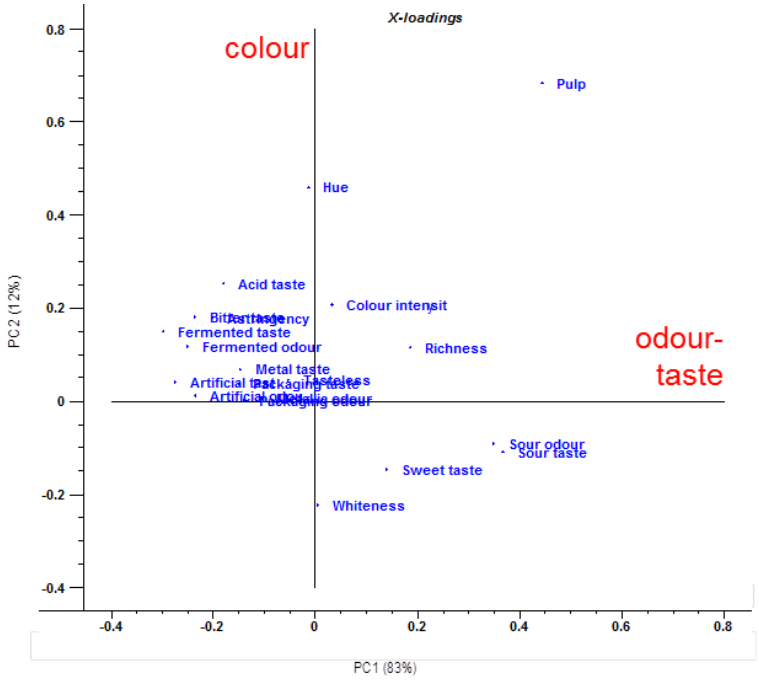
- Sensory profiling
  - 11 trained assessors (Nofima)
  - 10 orange juices
  - 20 sensory descriptors
- Consumer test
  - 105 orange juice consumers
  - 50% F, 50% M
  - 50% (20-42) years old, 50% (43-65) years old
  - Central location test (Norway)

Juice selection

PCA: sensory profile for the 10 juices

Selection of 3 sets of 3 products each
Criterion: to cover the sensory region as evenly as possible
3 product sets to 3 different consumer groups





Design

Full factorial design of 12 combinations:
- 3 products (for each consumer group)
- 2 levels of PRODUCTION (conventional, organic)
- 2 levels of PRICE (low, high)

Consumers were asked to rate all 12 combinations for their choice probability on a 7-point scale

Independent randomisation for each consumer

Mixed ANCOVA

- Fixed effects

Variable	P-value
Pc1	0.000
Pc2	0.611
Price	0.000
Production	0.092
Pc1*Pc1	0.238
Pc2*Pc2	0.149
Pc1*Pc2	0.003
Pc1*Price	0.253
Pc1*Production	0.010
Pc2*Price	0.394
Pc2*Production	0.326
Price*Production	0.944

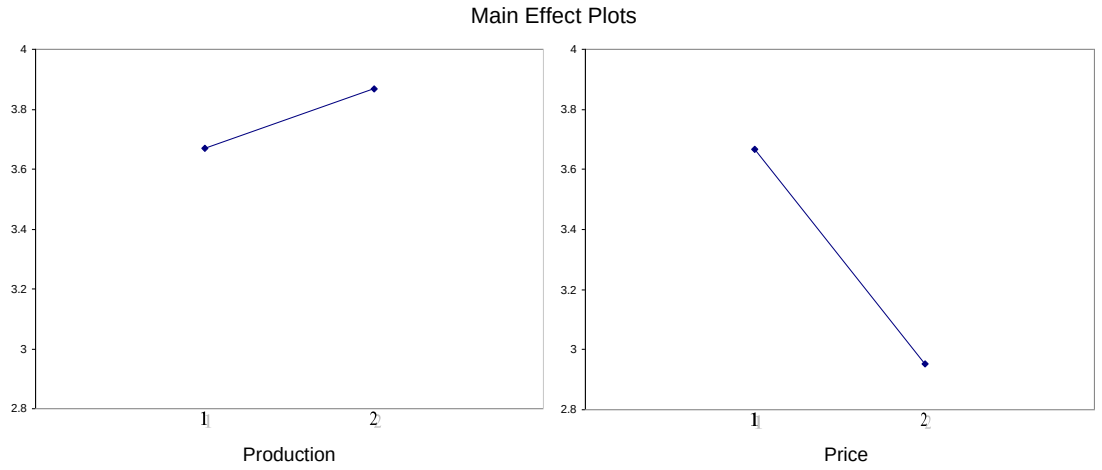
Reference level for extrinsic attributes:

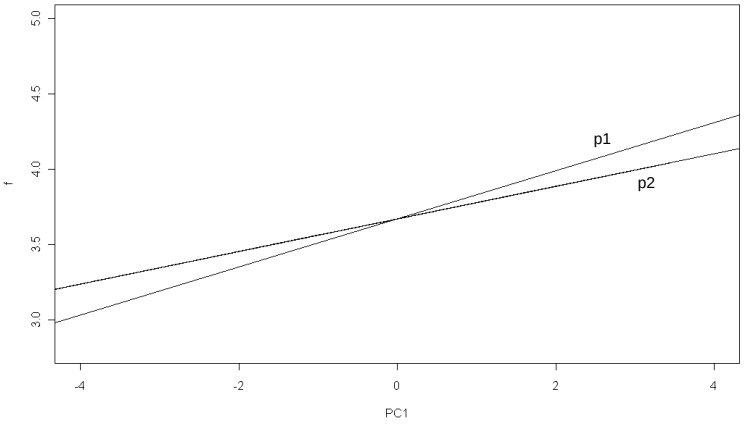
- low price
- conventional production

Mixed ANCOVA

- Fixed effects

Variable	P-value
Pc1	0.000
Pc2	0.611
Price	0.000
Production	0.092
Pc1*Pc1	0.238
Pc2*Pc2	0.149
Pc1*Pc2	0.003
Pc1*Price	0.253
Pc1*Production	0.010
Pc2*Price	0.394
Pc2*Production	0.326
Price*Production	0.944





Reference level for extrinsic attributes:
- low price
- conventional production

Mixed ANCOVA

- Regression coefficients

Effect	Coefficient
Intercept	3.67
Production 1	0
Production 2	0.20
Price 1	0
Price 2	-0.72
Pc1	0.16
Pc2	-0.06
Pc1*Pc2	0.12
Pc1*Production	-0.05

- Variance components estimates

Variable	Estimate
Cons	0.72
Cons*Price	0.22
Cons*Production	0.22
β_{n1}	0.03
β_{n2}	0.08
β_{n1}*Pc1	0.42
β_{n2}*Pc2	0.16
Residual	1.46

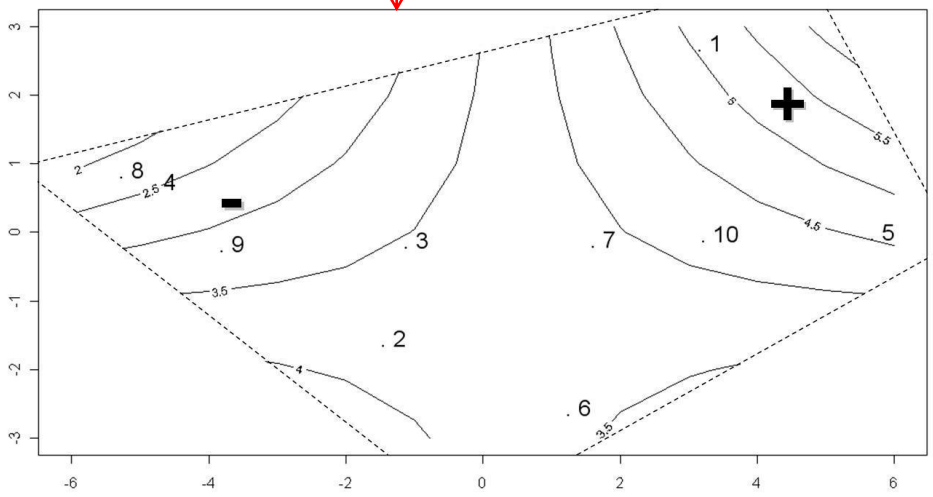
Mixed ANCOVA

- Regression coefficients

Effect	Coefficient
Intercept	3.67
Production 1	0
Production 2	0.20
Price 1	0
Price 2	-0.72
Pc1	0.16
Pc2	-0.06
Pc1*Pc2	0.12
Pc1*Production	-0.05

- Variance components estimates

Variable	Estimate
Cons	0.72
Cons*Price	0.22
Cons*Production	0.22
β_{n1}	0.03
β_{n2}	0.08
β_{n1}*Pc1	0.42
β_{n2}*Pc2	0.16
Residual	1.46

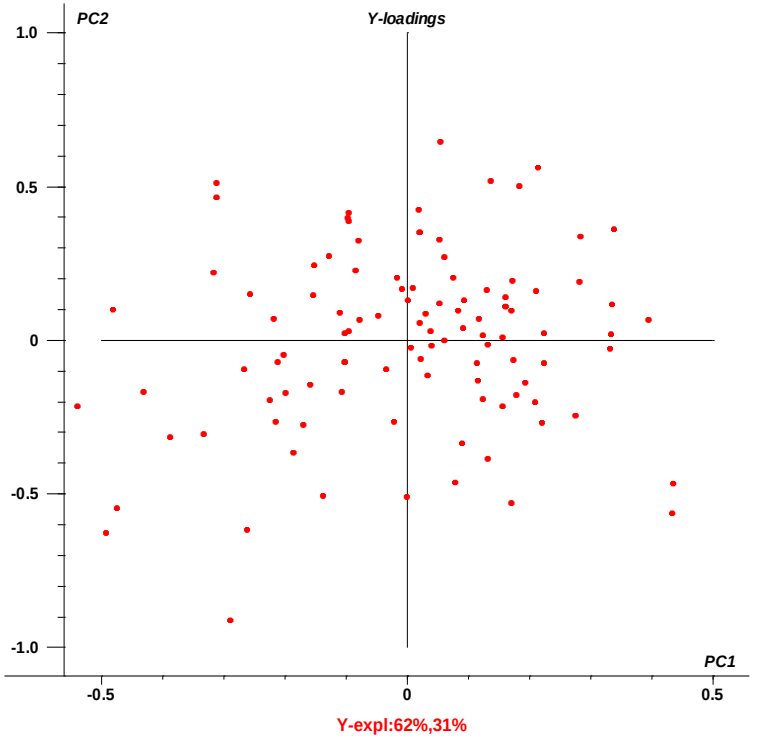


Individual differences

- Residuals comprising only the intrinsic information
- Averages over extrinsic factors

Large variation →substantial disagreement in choice probability .

For segmentation: groups with similar response pattern *



* Endrizzi, I., Menichelli, E., Johansen, S. B., Olsen, N. V., & Næs, T. (2011). Handling of individual differences in conjoint analysis. *Food Quality and Preference*, 22(3), 241–259.

Individual differences by fuzzy clustering

Different cluster numbers tried and different models used (with/ without quadratic terms).

2 cluster solution:

Effect	Cluster 1		Cluster 2	
	Estimate	Pr(>|t|)	Estimate	Pr(>|t|)
(Intercept)	3.985	<2E-16 ***	3.173	<2E-16 ***
Pc1	0.131	0.001 ***	0.134	0.000 ***
Pc2	-0.285	0.012 *	-0.012	0.908
Price	-0.621	0.001 ***	-0.824	2.02E-06 ***
Production	0.499	0.006 **	-0.129	0.452
Pc1*Pc1	0.034	0.002 **	0.017	0.089
Pc2*Pc2	0.023	0.380	0.004	0.862
Pc1*Pc2	0.170	1.72E-05 ***	0.131	0.000 ***
Pc1*Price	-0.037	0.319	-0.013	0.719
Pc1*Production	-0.034	0.366	-0.061	0.084
Pc2*Price	0.023	0.773	0.042	0.576
Pc2*Production	-0.019	0.811	-0.040	0.590
Price*Production	0.067	0.794	-0.053	0.825

Individual differences by fuzzy clustering

Different cluster numbers tried and different models used (with/ without quadratic terms).

2 cluster solution:

Effect	Cluster 1		Cluster 2	
	Estimate	Pr(>|t|)	Estimate	Pr(>|t|)
(Intercept)	3.985	<2E-16 ***	3.173	<2E-16 ***
Pc1	0.131	0.001 ***	0.134	0.000 ***
Pc2	-0.285	0.012 *	-0.012	0.908
Price	-0.621	0.001 ***	-0.824	2.02E-06 ***
Production	0.499	0.006 **	-0.129	0.452
Pc1*Pc1	0.034	0.002 **	0.017	0.089
Pc2*Pc2	0.023	0.380	0.004	0.862
Pc1*Pc2	0.170	1.72E-05 ***	0.131	0.000 ***
Pc1*Price	-0.037	0.319	-0.013	0.719
Pc1*Production	-0.034	0.366	-0.061	0.084
Pc2*Price	0.023	0.773	0.042	0.576
Pc2*Production	-0.019	0.811	-0.040	0.590
Price*Production	0.067	0.794	-0.053	0.825

3 cluster solution: cluster 1 with an even stronger and more significant effect of production;
cluster 2 with a not-significant production effect;
cluster 3 (mixed) with a not-significant production effect.

Segmentation robust with respect to the model used. Also the choice probability structure is stable across segments.

Summing up

- Methodology for joint studies of intrinsic and extrinsic attributes as an easy and effective tool to «squeeze out» the relations between the two types of attributes

Summing up

- Methodology for joint studies of intrinsic and extrinsic attributes as an easy and effective tool to «squeeze out» the relations between the two types of attributes
- Emphasis on the whole sensory profile and the main drivers of liking

Summing up

- Methodology for joint studies of intrinsic and extrinsic attributes as an easy and effective tool to «squeeze out» the relations between the two types of attributes
- Emphasis on the whole sensory profile and the main drivers of liking
- Best suited for estimating population or segment means but also for an overview of individual liking differences

Summing up

- Methodology for joint studies of intrinsic and extrinsic attributes as an easy and effective tool to «squeeze out» the relations between the two types of attributes
- Emphasis on the whole sensory profile and the main drivers of liking
- Best suited for estimating population or segment means but also for an overview of individual liking differences
- Important for product development in industry

Summing up

- Methodology for joint studies of intrinsic and extrinsic attributes as an easy and effective tool to «squeeze out» the relations between the two types of attributes
- Emphasis on the whole sensory profile and the main drivers of liking
- Best suited for estimating population or segment means but also for an overview of individual liking differences
- Important for product development in industry
- Flexible: applicability to other situations (fractional factorial design, extrinsic numerical and categorical, …)

Summing up

- Methodology for joint studies of intrinsic and extrinsic attributes as an easy and effective tool to «squeeze out» the relations between the two types of attributes
- Emphasis on the whole sensory profile and the main drivers of liking
- Best suited for estimating population or segment means but also for an overview of individual liking differences
- Important for product development in industry
- Flexible: applicability to other situations (fractional factorial design, extrinsic numerical and categorical, …)
- Use of established methods, available in standard software packages

Thank you!

www.nofimasensory.org

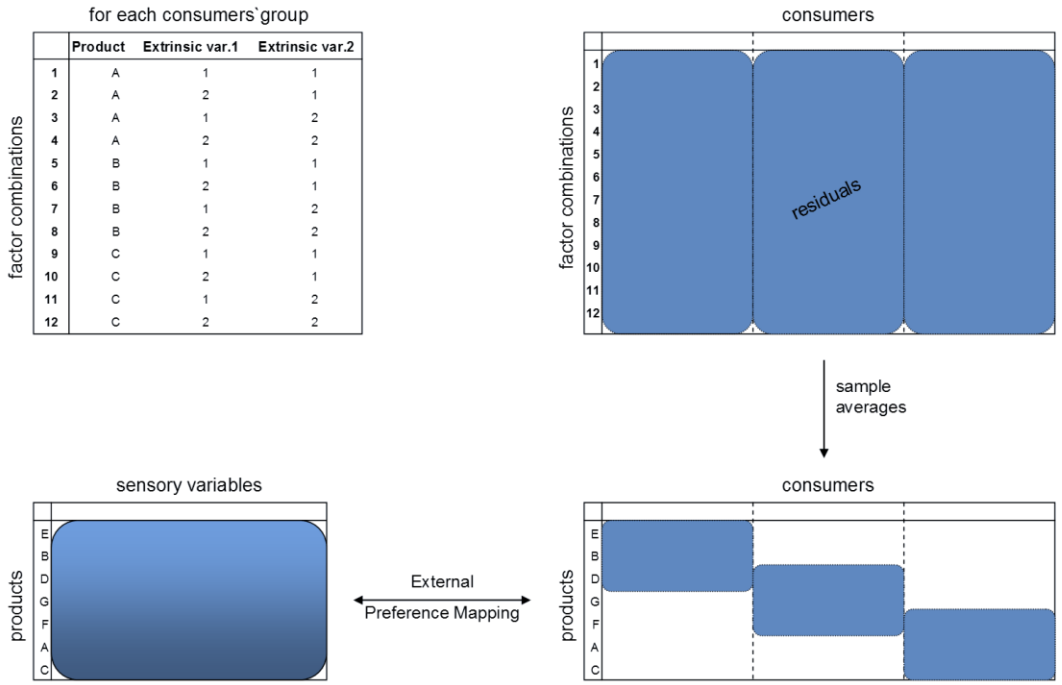
Individual differences from mixed model ANCOVA

Mixed Model ANCOVA

$$y_{ikn} = Population\ effects + Individual\ effects + noise$$
$$= \mu + \alpha_i + \beta_1 x_{1k} + \beta_2 x_{2k} + \beta_{12} x_{1k} x_{2k} + \beta_{i1} x_{1k} + \beta_{i2} x_{2k} + \beta_{i12} x_{1k} x_{2k}$$
$$+ C_n + \alpha C_{in} + \beta_{n1} x_{1k} + \beta_{n2} x_{2k} + e_{ikn}$$

Analysis of the individual contributions*

Residuals
Different factor combinations
Average over extrinsic variables



Fuzzy clustering: residual distance

The residual distance → comparing the true acceptance value with the fitted value from a regression equation in the principal components of the sensory data.
Idea: segments of consumers with similar acceptance pattern will have the same relation between x and y.

The residual distance is only dependent on the difference between the measured value and the function of the principal components. Therefore, it is essentially independent of the values of the t's.

If two consumers have the same pattern, this will be visible in the residuals without requiring that the two consumers have the same scores values, i.e. it is not necessary that they test the same products.
Also it does not require that the same number of products for each consumer.

Fuzzy clustering: choice of the number of clusters

Different measures of cluster validity and strategies for studying the quality of splitting have been developed.

A direct approach: to consider the average absolute residual value of the model used for different choices of C. This approach requires the entire clustering algorithm to be run for each potential value of *C.* The choice is related to the trade-off between a small number of clusters and a small average absolute residual.