Conjoint analysis

4th Training

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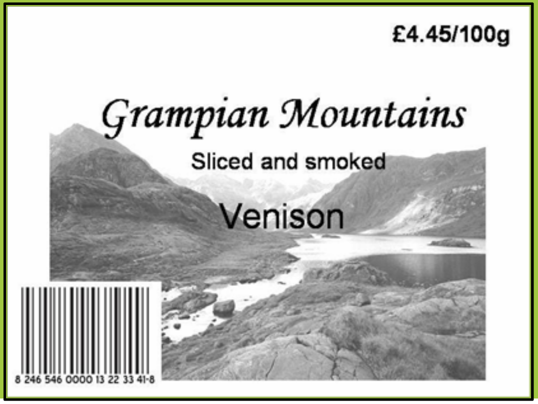
Conjoint analysis?

- "Please rank the following cards according to your preferences:"



Introduction

- Market research tool for studying consumers' preferences for a given product, regarding a set of realistic features. Development of new products
- **Goal:** know which features are important on a product by studying the trade-offs consumers are ready to make between features.
- Requires consumers to evaluate features jointly.
- **Objective of this training:** Understand construction, implementation and interpretation of conjoint analysis.

Introduction to conjoint analysis

- Idea of conjoint measurement: Luce and Tukey, **1964**. *"Simultaneous conjoint measurement: A new type of fundamental measurement"*
- Applications in consumer research.
- Review: Green and Srinivasan, **1978**. *"Conjoint analysis in consumer research«*
- New developments, partly due to development of computers

Introduction to conjoint analysis

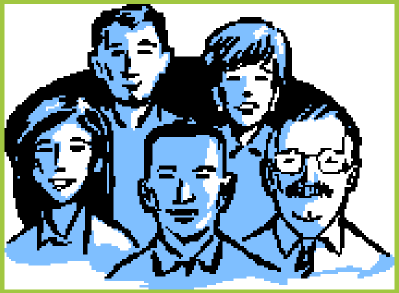
- Measures consumers' preferences for a given product.

Product: can be more or less obvious according to the research question(s)

Features: Generally visual, mostly text, sometimes images. Not sensory (taste, etc.)

- Specific research question(s) for each conjoint analysis. → groupwork

Introduction to conjoint analysis



- Ask a sample of consumers
- Rather than asking successive questions about one feature at a time
  - how important is the brand of bottled water?
  - (how much) do you prefer brand A or brand B for bottled water?
  - how important is the price of bottled water?
- CA measures trade-offs between several features
  - "how much do you prefer bottled water with brand A and price X or bottled water with brand B and price Y?"
  - how important are the brand and price of bottled water?
  - Question is too long -> present otherwise.

→ Technical aspects

Organisation of session

- 1- Card-rating conjoint analysis
- 2- Overview of other types of conjoint analysis
  - Example: chicken and honey in Italy
- 3- Group exercise on selection of attributes

Introduction to conjoint analysis

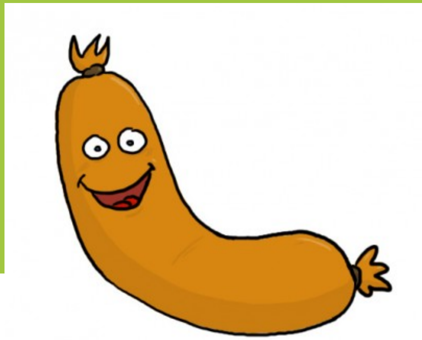
- TODAY's training: Focus on the first type of conjoint analysis:
  - Card-rating: Served as a basis for variations
- As in all research methods:
  - Preparation: Build a **set of cards** (each card = one product) each with a different combination of features
  - Experimentation: Ask the respondents to **rank the cards** according to their preferences
  - **Analysis**: See which features are most important or preferred; see what differentiates the consumers

Card-rating conjoint analysis

- Preparation
- Experimentation
- Analysis

Card-rating conjoint analysis
Preparation – Experimental design

- A short example:
  - **Product:** Dried sausage.
  - **Factors studied:**
    - Type of production: On-farm or large manufacturer
    - Origin (local/foreign)
- ➔ Two factors with two levels each.



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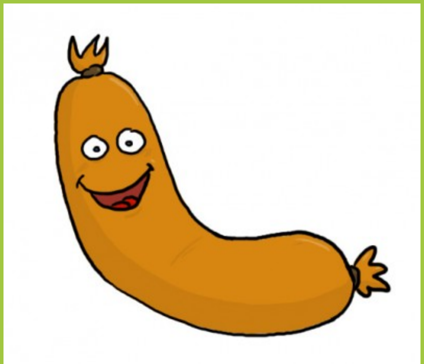
Card-rating conjoint analysis Preparation – Experimental design

- A short example:
  - **Product:** Dried sausage.
  - **Factors studied:**
    - Type of production: On-farm or large manufacturer
    - Origin (local/foreign)
- 4 combinations:

On-farm production Dried sausage Made in Croatia	On-farm production Dried sausage Made in Spain
Manufacturer Dried sausage Made in Croatia	*Manufacturer* Dried sausage Made in Spain



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Card-rating conjoint analysis Preparation – Experimental design

- Usually, many more factors and levels: cannot use all combinations otherwise too many cards
- → Use an experimental design
- For example: a fractional factorial design, orthogonal.

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Card-rating conjoint analysis
Preparation – Experimental design

- Factorial designs
- 2 factors with 2 levels each

  -> 4 (2x2) combinations possible <-> 4 cards

Card Name	Factor 1	Factor 2
A	No.1	No.1
B	No.1	No.2
C	No.2	No.1
D	No.2	No.2

=

		Factor 2	
		Level 1	Level 2
Factor 1	Level 1	Card A	Card B
	Level 2	Card C	Card D

Contingency table:

		Factor 2	
		Level 1	Level 2
Factor 1	Level 1	1	1
	Level 2	1	1

Card-rating conjoint analysis Preparation – Experimental design

- Factorial designs
- Contingency table:

		Factor 2	
		Level 1	Level 2
Factor 1	Level 1	1	1
	Level 2	1	1

- Factor 1 and Factor 2 are "**orthogonal**" factors: *Each level of one attribute is combined the same number of times with each level of the other attribute.*
- The design is **orthogonal** if each factor can be evaluated independently of all the other factors.

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Card-rating conjoint analysis Preparation – Experimental design

- Non Orthogonality and its consequences:

		Factor 2	
		Level 1	Level 2
Factor 1	Level 1	2	0
	Level 2	0	2

- If cards with level 1 for both attributes are preferred, we do not know whether it is because of Factor 1 or of Factor 2:
→ **no result**.
- If there is no clear preference, we do not know whether neither factors are important, or whether both factors are important and the levels compensated each other:
→ **no result.**

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Card-rating conjoint analysis Preparation – Experimental design

- Non Orthogonality and its consequences:

		Factor 2	
		Level 1	Level 2
Factor 1	Level 1	2	1
	Level 2	1	1

- Also not orthogonal: factor 1 and factor 2 are partly confounded

Card-rating conjoint analysis Preparation – Experimental design

- Non Orthogonality and its consequences:

		Factor 2	
		Level 1	Level 2
Factor 1	Level 1	2	2
	Level 2	1	1

- Orthogonal in a broader sense.
- *Each level of Factor 1 is presented the same number of times with each level of Factor 2. The reverse is not true.*

Card-rating conjoint analysis Preparation – Experimental design

- Fractional factorial designs
- 3 attributes with 2 levels each -> 8 (2x2x2) combinations possible: Too many?

Card Name	Factor 1	Factor 2	Factor 3
A	1	1	1
B	1	1	2
C	1	2	1
D	1	2	2
E	2	1	1
F	2	1	2
G	2	2	1
H	2	2	2

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Card-rating conjoint analysis Preparation – Experimental design

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- 3 attributes with 2 levels each -> 8 (2x2x2) combinations possible: Too many?

Card Name	Factor 1	Factor 2	Factor 3
A	1	1	1
B	1	1	2
C	1	2	1
D	1	2	2
E	2	1	1
F	2	1	2
G	2	2	1
H	2	2	2

Not an orthogonal design

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Card-rating conjoint analysis Preparation – Experimental design

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- 3 attributes with 2 levels each -> 8 (2x2x2) combinations possible: Too many?

Card Name	Factor 1	Factor 2	Factor 3
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F	2	1	2
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H	2	2	2

Not an orthogonal design

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Card-rating conjoint analysis
Preparation – Experimental design

- Fractional factorial designs
- 3 attributes with 2 levels each -> 8 (2x2x2) combinations possible: Too many?

Card Name	Factor 1	Factor 2	Factor 3
A	1	1	1
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C	1	2	1
D	1	2	2
E	2	1	1
F	2	1	2
G	2	2	1
H	2	2	2

OK, {A,D,F,G} is orthogonal

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Card-rating conjoint analysis Preparation – Experimental design

- Continuous factors (price, sugar content, etc.):
  - Can use equally spaced levels (e.g. price 1€, 1.2€, 1.4€)
  - Must cover a realistic range, may be larger than reality
  - Must be far enough apart to be considered realistically distinct
- Interactions between attributes
  - May be suspected (e.g. price and brand)
  - If of interest, include a composite factor (more levels)

Brand1
Brand2

Price1
Price2
Price2

Price & Brand
Price1 & Brand1
Price1 & Brand2
Price2 & Brand 1
Price2 & Brand 2
Price3 & Brand 1
Price3 & Brand 2

Card-rating conjoint analysis Preparation – Experimental design

- Environmental correlations
  - (e.g. for cars: engine power / acceleration time,
  - e.g. in some foods: sugar content / calories)
- Either drop one of the factors, or be very careful about cards presented

Card-rating conjoint analysis Preparation – Experimental design

- Number of cards:
- Minimum number.
- As a very general idea, the more cards you present, the more reliable the calculations, BUT the least reliable the consumers' judgment
- If a software suggests numbers of cards, do so.
- Can have more factors, can have more than 2 levels each. Whole books on experimental designs ((fractional) factorial designs, latin squares, Plackett-Burman, D-optimal, Tagushi methods, etc.). Not always strictly orthogonal factors
- Either use a very simple design with few attributes and levels (and few conclusions), or use adequate software. (SPSS, Sawtooth, online surveys, R…)

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Card-rating conjoint analysis Preparation – Experimental design

- Note:
  - Experimental designs are not the only solution
  - Can use random sampling from multivariate distribution to construct the stimuli
  - Need to be very careful

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Card-rating conjoint analysis Preparation – Experimental design

- Conclusions on experimental design
  - Decide on which attributes and levels you need
  - Consider their environmental correlations
    - If a pair are very highly correlated, consider dropping one of them
  - Consider interactions that may be of interest
    - If necessary, build composite factors
  - Make an orthogonal design with adequate software, so that
    - All pairs of levels are represented
    - The attributes can be evaluated separately

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Card-rating conjoint analysis
Preparation – Experimental design

Example on SPSS (now PASW), Conjoint add-on module :

- Presentation of the example
- Different methods to collect data
- How to create an orthogonal design ?
- How to display the orthogonal design ?
- Presentation of the data file
- EXERCISE

Card-rating conjoint analysis Preparation – EXAMPLE

- Context:

  You belong to a marketing team of a company that manufactures dairy products

- Questioning:

  You want to develop your range of yogurts.

Plain yogurts → Flavoured yogurts → Strawberry  / Orange 

Flavoured yogurts ↓ Extra production cost

⇒ **How will these new flavours be accepted ?**

⇒ **How much increase in selling price is acceptable for flavoured yogurts ?**

Card-rating conjoint analysis
Preparation – EXAMPLE

Different attributes may be considered:

- flavour,
- price,
- size of pack,
- packaging (colour, shape, size of pots, material…)
- brand name,
- display of fat content,
- display of number of calories…

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Card-rating conjoint analysis Preparation – EXAMPLE

Choice of attributes and levels:

FLAVOUR

$\Rightarrow$ Measure preferences for the new flavours comparing to plain yogurts.

$\Rightarrow$ 3 levels : plain ; traditional flavour ; innovative flavour

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Card-rating conjoint analysis Preparation – EXAMPLE

Choice of attributes and levels:

PRICE

- High correlation between price and size of pack
  - ⇒ CA does not allow to keep dependant factors
  - ⇒ Not interesting to keep the attribute Size
  - ⇒ A price per kg is not concrete for consumers
  - ⇒ **Chosen attribute : Price for pack of 4 yoghurts**
- Flavoured yogurts = + 20% production cost
- 3 levels: price of plain yogurts (reference) ; price 20% higher ; price 40% higher

Card-rating conjoint analysis Preparation – EXAMPLE

Choice of attributes and levels:

BRAND NAME

- Possibility to sell yogurts with your own brand or with a retailer brand
- 2 levels : own brand ; retailer brand

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Card-rating conjoint analysis Preparation – EXAMPLE

Choice of attributes and levels:

- A consumer survey will be carried out later concerning packaging.
- The company decided to display the fat content and the number of calories for all types of yogurts .

⇒ Conclusion : 3 factors and 3*3*2 levels

Card-rating conjoint analysis Preparation – EXAMPLE

Full-profile table

Factors and levels		Flavour		
Brand name	**Price**	Plain	Strawberry	Orange
Dukat	0,50 €	5	8	
	0,60 €		4	2
	0,70 €	3		6
Mercator	0,50 €			7
	0,60 €	1		
	0,70 €		9	

In white cells, profiles chosen by SPSS for the orthogonal design

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18 combinations of attributes possible

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Card-rating conjoint analysis
Respondents' task

- A profile becomes a stimulus card.
- The stimuli should be standardized by making sure that the profiles are all similar in physical appearance, except for the different combinations of features.
- Different supports:
  - **Product description in text paragraph**. realistic and complete description, limits number of descriptions, comparison more difficult.
  - **Verbal.** Systemized format which presents products attributes. Easier to compare but less realistic.
  - **Pictorial**. less information overload, higher homogeneity of perceptions, more interesting task, more realistic. BUT takes longer to prepare and additional unwanted information may be conveyed.
  - **Product prototypes.** Ideal but expensive.

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Card-rating conjoint analysis
Respondents' task

- With stimulus cards:
  - Change order of cards for each respondent.
  - Order (position) of attributes on cards randomized over all respondents.
  - But, for each respondent the position of the attributes is kept the same on each card.
  - Insert a number or a letter different on each card to facilitate the data entry.

Card-rating conjoint analysis
Respondents' task

- How to collect data ?

⇒ Rating : Subjects are asked **to assign a preference score** to each card (ex: Likert scale or score from 1 to 100).

⇒ Ranking : Subjects are asked **to sort the profiles** in terms of preference, from 1 to n. No equal ranks allowed.

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Card-rating conjoint analysis Respondents' task

- Ranks are **more reliable** (exercise is easier).
- Ranks **force differences** in scores as you cannot have equal ranks. BUT Ranks **insure differences** between cards (avoids middle-point rating or extreme-point rating).
- Ranks **need more explanations** and more preparation.
- Rating expresses intensity of preferences, but without comparison between products.

Card-rating conjoint analysis
Preparation – EXAMPLE

- How to generate an orthogonal design with SPSS?
- How to display an orthogonal design ?
- How to input data ?

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Card-rating conjoint analysis Questionnaires

- After the test, can ask extra questions:
  - Purchase intent (e.g. for preferred product)
  - Socio-demographic
  - Lifestyle
  - Attitudes towards a type of product.
- The answers can be related to the preferences.

Card-rating conjoint analysis

- Preparation
- Experimentation
- Analysis

Card-rating conjoint analysis Experimentation – EXERCISE

You are a customer of the supermarket Mercator and you must rank the 9 packs of yogurts proposed according to your preferences : 1 is the preferred pack, 9 is the least preferred.

Please write your answers in the table on the white sheet.

Card-rating conjoint analysis Limitations

- Difficult to apply if attributes are totally new.
- Cognitive capacities of respondents are weak:

  The number of attributes to consider to have a realistic description of the product concept is large .

⇒ CA = number limited of attributes.

- Even if we avoid the declarative biais of a questionnaire, ranking cards is artificial.

⇒ The respondent is not in real purchase situation.

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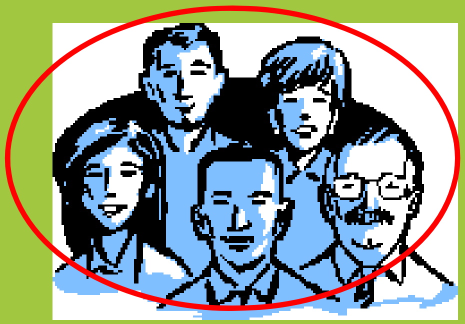
Card-rating conjoint analysis

- Preparation
- Experimentation
- Analysis

Card-rating conjoint analysis
Statistical analysis of results

- At an aggregate level
  - *which cards are most liked/disliked?*
  - *which levels are preferred?*
  - *what is the ideal product?*



- At an individual level
  - *which attributes are most important?*
  - *what are the differences in preferences between respondents?*
  - *relate preferences to characteristics of respondents.*

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Card-rating conjoint analysis

Statistical analysis of results

At the aggregate level

- Descriptive results.

Question	Method
Which card is **most / least** preferred on average?	Mean rank for each card
Which card is **most / least** often preferred? (rank 1)	For each card, proportion of respondents who placed that card at rank 1
Which card is **most / least** often at the last rank?	For each card, proportion of respondents who placed that card at the last rank

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Card-rating conjoint analysis

Statistical analysis of results

At the aggregate level

- Descriptive results.

%	Card A	Card B	Card C	Card D	Card E	Card F	Card G	Card H	Card I
Frequency at 1st Rank	18.0	2.0	2.0	4.7	6.7	12.0	13.3	27.3	14.0
Frequency at 2nd Rank	16.7	4.0	4.7	7.3	14.0	6.0	20.0	22.0	5.3
Frequency at 3rd Rank	17.3	8.0	6.7	15.3	18.7	2.7	10.0	10.0	11.3
Frequency at 4th Rank	17.3	13.3	7.3	7.3	16.7	4.7	18.7	6.7	8.0
Frequency at 5th Rank	7.3	10.7	10.7	24.7	11.3	5.3	14.0	4.0	12.0
Frequency at 6th Rank	9.3	14.7	10.0	12.0	8.7	10.0	12.7	10.0	12.7
Frequency at 7th Rank	8.7	15.3	11.3	12.7	6.7	16.0	4.7	8.0	16.7
Frequency at 8th Rank	3.3	15.3	20.7	10.0	10.0	20.0	4.0	8.0	8.7
Frequency at 9th Rank	2.0	16.7	26.7	6.0	7.3	23.3	2.7	4.0	11.3

- Limits on interpretation: Which attributes are responsible for the preferences? →Need statistics.

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Card-rating conjoint analysis

Statistical analysis of results

At the aggregate level

- Reshaped data:

Respondent	Card	Flavour	Price	Brand	Rank
Resp1	A	1	2	2	4
Resp1	B	3	2	1	2
Resp1	C	1	3	1	5
Resp1	D	2	2	1	7
...	...				
Resp2	A	1	2	2	4
Resp2	B	3	2	1	5
...	...				

- Hyp.: The rank of a card depends on the levels of the 3 factors for that card

Card-rating conjoint analysis

Statistical analysis of results

At the aggregate level

- Considering one factor: On average, we expect that a card with a **low price is more attractive**: in practice it should obtain a **smaller rank**
- We could expect something like:
  - Rank of card with **low** price = Mean rank **-3**
  - Rank of card with **medium** price = Mean rank
  - Rank of card with **high** price = Mean rank **+3**

$$Rank_{i,j} = \mu + price_i + \varepsilon_{i,j}$$

- $Price_{Low}$=-3
- $Price_{Medium}$=0
- $Price_{High}$=3
- ε represents individual variations

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Card-rating conjoint analysis

Statistical analysis of results

At the aggregate level

- <u>Hypothesis:</u> The rank of a card depends on the levels of **the 3 factors**.

$$Rank_{i,j,k,l} = \mu + flavour_i + price_j + brand_k + \varepsilon_{i,j,k,l}$$

- μ=constant
- i={Plain, Strawberry, Orange}
- j={Low, Medium, High}
- k={Own, Supermarket}
- l=repetition

Analysis of variance (ANOVA)
Or multiple regression

- Coefficients should represent "attractiveness" or "utility" of a level -> in practice we change the sign of the coefficients
- Note: Ranks are **not quantitative**, should in theory require non-parametric analysis, in practice, parametric usually used.

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Card-rating conjoint analysis

Statistical analysis of results

At the aggregate level

- Coefficients of the analysis of variance = "**Utilities**" in conjoint analysis = **part-worths** = change in rank of card if we change that factor without changing the other factors.
- Utilities are scaled to sum to zero within each attribute
- **>0** = level more appreciated
- **<0** = level not as appreciated
- we cannot directly compare values between attributes

Utilités

		Estimation d'utilité	Std. Erreur
Flavour	Plain	,040	,285
	Strawberry	,362	,285
	Orange	-,402	,285
Price	0,50	,949	,285
	0.60	,027	,285
	0.70	-,976	,285
Brand	Dukat	-,555	,214
	Mercator	,555	,214
(Constante)		5,185	,214

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Card-rating conjoint analysis

Statistical analysis of results

At the aggregate level

Factor	Level	Utility
Flavour	Plain	0.040
	Strawberry	0.362
	Orange	-0.402
Price	Low	0.949
	Medium	0.027
	High	-0.976
Brand	Dukat	-0.555
	Mercator	0.555

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Card-rating conjoint analysis
Statistical analysis of results
At the aggregate level

- Utilities summed into total utilities (ANOVA equation):
  U(Plain, Low Price, Dukat)=0.04+0.949-0.555=**0.434** (Card E)
  U(Plain, High Price, Dukat)=0.04-0.976-0.555=**-1.491** (Card C)
- Even for combinations that were not presented:
  U(Strawberry, High Price, Dukat) =0.362-0.976-0.555=**-1.169**
  Either manually, or can be added into SPSS design and noted as SIMULATIONS
  (STATUS_ column)
- Determine the ideal card (with all the most preferred levels)

Utilités

		Estimation d'utilité	Std. Erreur
Flavour	Plain	,040	,285
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(Constante)		5,185	,214

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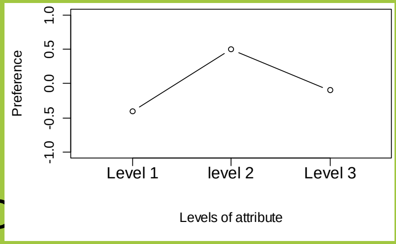
Card-rating conjoint analysis

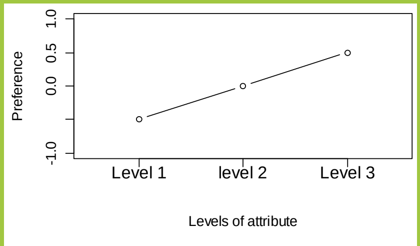
Statistical analysis of results

At the aggregate level

- Interactions:
  - We estimated main effects not interactions.
  - If the price is appreciated differently according to the brand of the product, this will not appear in the results.
  - If interactions need to be studied, in the experimental design, we need composite factors, and often, more cards.



- Models of preference:
  - Here we used part-worth func
  - We could have specified a linear relationship for the price (vector model).
  - In some cases, we can specify an ideal point model.



Card-rating conjoint analysis
Statistical analysis of results
At the aggregate level

- Conclusions on analysis at the aggregate level
  - Take a look at the data to have an idea of whether a few cards are particularly preferred or least preferred.
  - Carry out statistical analysis with adequate software
    - To know which levels are most/least preferred
    - To know how to combine attributes to make the product that is most satisfactory for « THE AVERAGE consumer »
- But « THE AVERAGE consumer » does not exist.

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Card-rating conjoint analysis

Statistical analysis of results

At the individual level

- Analysis of variance for each respondent

$$Rank_{i,j,k,l} = \mu + flavour_i + price_j + brand_k + \varepsilon_{i,j,k,l}$$

μ=constant

i={Plain, Strawberry, Orange} (I levels)

j={Low, Medium, High} (J levels)

k={Own, Supermarket} (K levels)

l=repetition

- minimum number of cards= 1+(I-1)+(J-1)+(K-1)=6
(= number of parameters to be estimated)

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Card-rating conjoint analysis

Statistical analysis of results

At the individual level

- Estimate individual utilities
  - In SPSS, add a line in the syntax -> create a file with individual utilities

Resp	Constant	Flavour1	Flavour2	Flavour3	Price1	Price2	Price3	Brand1	Brand2
1	5.33	-1.00	-0.33	1.33	-1.67	0.67	1.00	0.75	-0.75
2	5.42	-1.67	0.67	1.00	0.00	1.00	-1.00	0.75	-0.75
3	5.58	-2.00	0.67	1.33	-1.00	0.67	0.33	0.25	-0.25
...	...	...							

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Card-rating conjoint analysis

Statistical analysis of results

At the individual level

- Use individual utilities to calculate relative importance of each factor for each respondent:
  - Idea: *For an attribute, if the utilities of the various levels are not very different, that attribute is not important.*
- Utility range / Sum of all utility ranges for all Attributes.

  Imp(Flavour)=Range Flavour/(Range Flavour+ Range Price + Range Brand)

Resp	Constant	Flavour1	Flavour2	Flavour3	Price1	Price2	Price3	Brand1	Brand2
1	5.33	-1.00	-0.33	1.33	-1.67	0.67	1.00	0.75	-0.75

- *Example, respondent 1: Imp(Flavour) =(1.33-(-1.00))/(1.33-(-1.00)+1.00-(-1.67)+0.75-(-0.75)) =35.8%*

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Card-rating conjoint analysis

Statistical analysis of results

At the individual level

- Analysis of variance for each respondent
- Estimate individual utilities
- Calculate importance of each factor for each respondent
- Calculate mean importance over all respondents

Flavour	36,270
Price	38,827
Brand	24,903

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Card-rating conjoint analysis

Statistical analysis of results

At the individual level

- Analyse each respondents' preferences with adequate software
  - To know which levels are most/least preferred
  - To know which attributes are most/least important
  - To know which attributes are most/least important on average

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Card-rating conjoint analysis

Statistical analysis of results

Clustering respondents

- Respondents can be clustered according to their preferences, i.e. according to the utilities:

Resp	Constant	Flavour1	Flavour2	Flavour3	Price1	Price2	Price3	Brand1	Brand2
1	5.33	-1.00	-0.33	1.33	-1.67	0.67	1.00	0.75	-0.75
2	5.42	-1.67	0.67	1.00	0.00	1.00	-1.00	0.75	-0.75
3	5.58	-2.00	0.67	1.33	-1.00	0.67	0.33	0.25	-0.25
...	...	...							

- Cluster Analysis:
  - Calculate distance between respondents
  - Make clusters with respondents who have similar preferences (who are similar to each other but different from the others)

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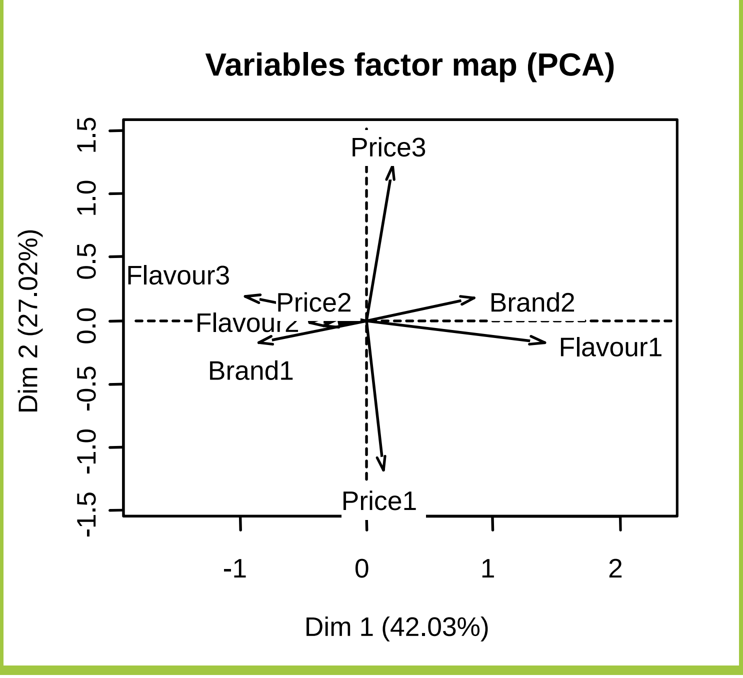
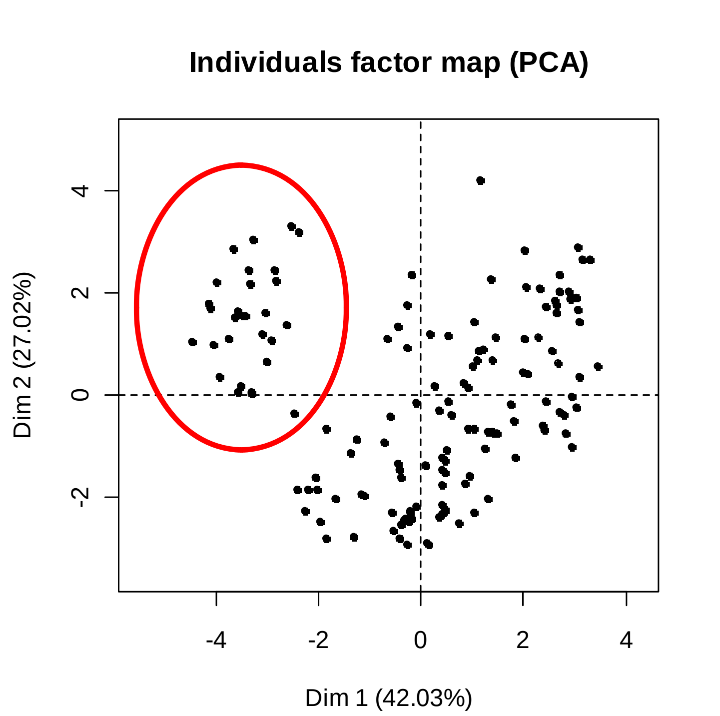
Card-rating conjoint analysis

Statistical analysis of results

Clustering respondents

- Exploration: unscaled PCA (Principal Component Analysis) allows us to visualise the differences in preference





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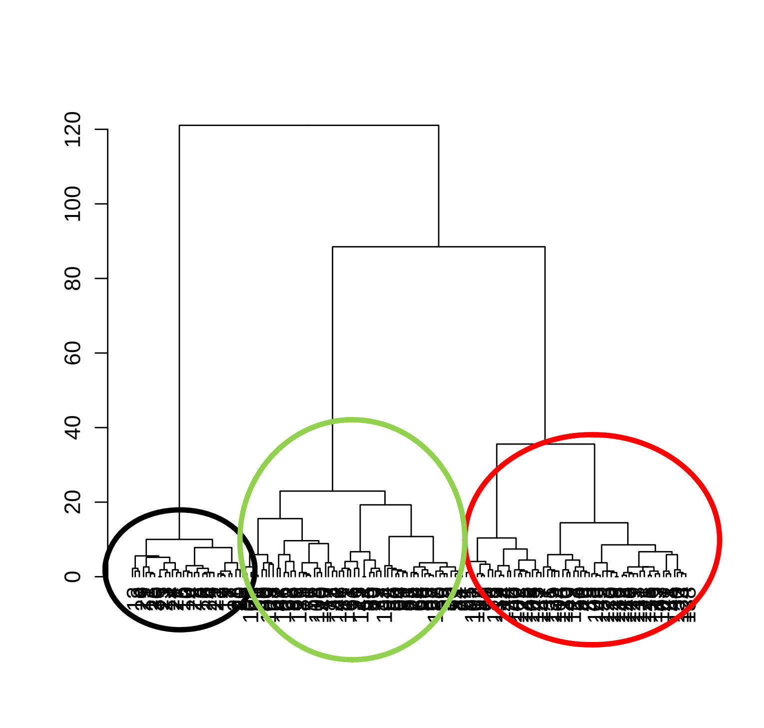
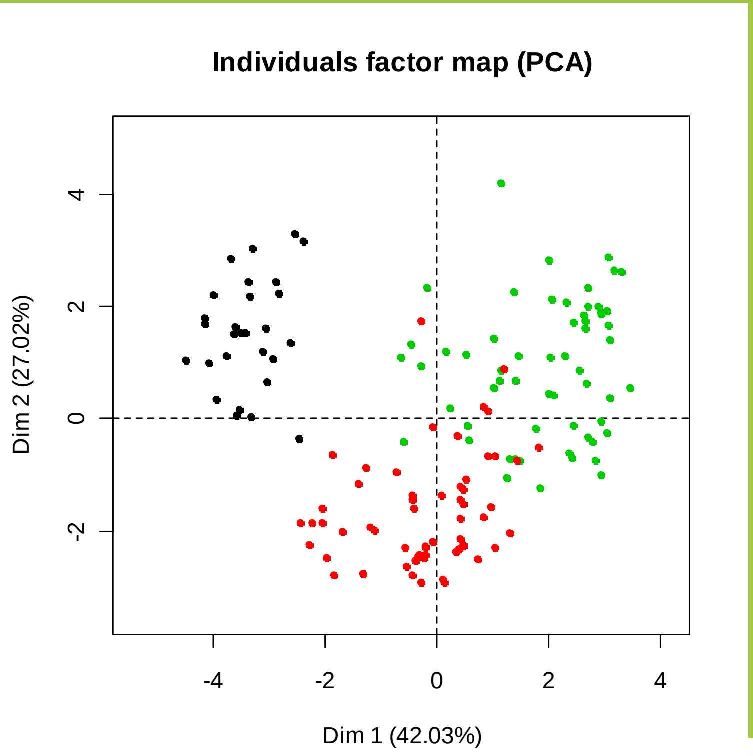
Card-rating conjoint analysis

Statistical analysis of results

Clustering respondents

- Clusters: Tree classification / k-means clustering, etc.





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Card-rating conjoint analysis
Statistical analysis of results
Clustering respondents

- Description of clusters
  - According to the preferences (e.g. in SPSS kmeans procedure): mean value of each utility for each cluster:

Centres de classes finaux

	Classe		
	1	2	3
Plain	1,30	-2,22	,07
Strawberry	-,20	,89	,57
Orange	-1,10	1,32	-,65
0,50	,38	-,26	2,00
0.60	-,46	,52	,20
0.70	,09	-,26	-2,20
Dukat	-1,41	,60	-,39
Mercator	1,41	-,60	,39

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Card-rating conjoint analysis
Statistical analysis of results
Clustering respondents

- Description of clusters
  - According to other answers (additional questionnaires: socio-demo, attitudes, etc.)
    - chi-square tests between cluster and type of shop most frequently visited, level of income etc.
    - Anova between age and cluster, etc.

	Shop at Supermarket	Shop at Green-grocers	Shop at Market
Class 1	23	3	4
Class 2	21	11	28
Class 3	15	13	32

Chi-square=23.4;
Df=4;
P-value=0.0001032

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Card-rating conjoint analysis

Statistical analysis of results

Clustering respondents

- Check variability in preferences
- Segment consumers according to their preferences
- Relate the individual preferences to other individual characteristics

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Card-rating conjoint analysis

Statistical analysis of results

Validity and reliability

- Do the signs of the utilities follow expectations?
- **Reliability:**
  - ask a subsample of respondents for preference judgments on a second set of stimulus cards which contain a subset of the original set of stimulus cards.
  - some time after, redo test with subsample of respondents, with n stimuli but avoiding duplications of the first set of stimuli

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Card-rating conjoint analysis
Statistical analysis of results
Validity and reliability

- **Predictive validity:**
  - Calculate a utility for each card of the design for each respondent (SCORES in the utility file)
  - Calculate correlation between those results and the actual ranks given: **R^2 in results**
- **Cross-validation:**
  - estimate the model using only some cards of the design (STATUS_ =1 ("design"))
  - predict the rank of the rest of the cards (STATUS_ =2 ("holdout"))
  - check with the rank actually given
- Check with **behaviour**

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Card-rating conjoint analysis
Statistical analysis of results
Validity and reliability

- Check results according to
  - expectations,
  - Behaviour
- Optionally, make extra tests to confirm results

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Methodological choices in conjoint analysis

Preparation	Selection of a model of preference	Part-worth function model
	Data collection method	Full-profile
	Stimulus set construction for the full-profile method	Fractional factorial design
	Stimulus presentation	Verbal description (stimulus card)
Test		
Analysis	Measurement scale for the dependent variable	Rank order
	Estimation method	OLS (Anova, multiple regression)

Green and Srinivasan, 1978

Our training example: Card-rating

Other types of conjoint analysis

- Full profile card-rating analysis can be boring and exacting.
- Results are relatively precise but number of attributes is limited
- Other types:
  - Adaptive Conjoint Analysis (Sawtooth, test must be computer assisted)
  - Choice-Based Conjoint Analysis (Example afterwards)
  - Partial Profile Conjoint Analysis (Not all attributes on all cards)
  - Best/Worst (B/W) Conjoint Analysis (choose attributes on a card/profile)
  - …

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