Unfolding Models for Preference data

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AIMS Lausanne 2016
✓ Unfolding
✓ Models for Preference data
✓ A simulation
✓ Application to a preference study
Preference mapping

- MdPref: internal preference mapping
- Ideal point interpretation (EDIPM)
  
  Meullenet J.-F. et al. (2008)

- Unfolding
  - Probabilistic Unfolding (LSA)
    
    Rousseau B. et al. (2012)
  
  - Deterministic Unfolding (Prefscal)
    
    Busing F.M.T.A. et al. (2010)
    Van De Velden M., et al. (2013)

Few comparisons between different techniques

Unfolding

Objectives / Principle

\[ \Delta_{N \times P} \]

\[ \delta_{ij} \]

\[ X_{(N+P) \times Q} \]

\[ N + P \]

\[ \text{Stress1} = \sqrt{\sum_{i=1}^{N} \left( \delta_{ij} - d_{ij}(X) \right)^2} \]

\[ \text{Stress Kruskal} = \sqrt{\frac{\sum_{i=1}^{N} \left( \delta_{ij} - d_{ij}(X) \right)^2}{\sum_{i=1}^{N} d_{ij}^2(X)}} \]

Internal Preference Mapping with ideal point interpretation
Dissimilarities

\[ \delta_{ij} = m - r_{ij} \]  
\( m \) : max of the rating scale

1. \[ \delta_{ij} = m - r_{ij} \]

\[ \delta_{ij} = \alpha_j - r_{ij} \]
\( \alpha_j \) : «rating» (to be estimated) of the ideal point of subject \( j \)

3. \[ \delta_{ij} \text{ monotone transformation of } m - r_{ij} \]
Algorithm

Smacof algorithm
Borg & Groenen, 2005

- Set initial $X^0$
  $k=0$

- Compute optimal $\delta^k_{ij}$
  for distances of $X^k$

- Update $X^k$
  by Guttman transform
  $k=k+1$

- Compute $\sigma^k$

- $\sigma^{k-1} - \sigma^k \leq \varepsilon$?

- Initial solution
  (Schoneman, 1970)

- Incomplete data supported

- "Restricted" unfolding

- Optimal scaling of preference
  Non metric transformations allowed (Busing et al., 2005)
Simulated data

Design

- 9 products: $2^3$ Factorial design + central point
- Factor 3: weak vectorial effect
- 3 classes of consumers: A and B with opposite vectorial effects, C with ideal point effect

100 consumers are simulated: each one belonging to one of the 3 classes and adding - a random noise $\mathcal{N}(0,1)$ to each rating - an additive effect (uniform $[-1;1]$) to each subject
Simulated data

Proportions of the 3 classes: 33%, 33%%, 33%.
Simulated data

Mixture of classes

120 simulations: proportions of the 3 classes varying between 10% and 80%

Mean $R^2$ between reconstituted and original ratings

- Good reconstitution of the original ratings for both techniques
- Best recovery of the initial configuration for unfolding
3 opposite situations

**Unfolding**
- **1.** A single vectorial segment
  - RVs = 1.09 (p = 0.13)
- **2.** Two opposite vectorial segments
  - RVs = 3.76 (p = 0.00)
- **3.** A single ideal point segment
  - RVs = 2.22 (p = 0.02)

**MdPref**
- **1.** A single vectorial segment
  - RVs = 1.62 (p = 0.06)
- **2.** Two opposite vectorial segments
  - RVs = 2.31 (p = 0.01)
- **3.** A single ideal point segment
  - RVs = 1.63 (p = 0.06)
EuroSalmon data

30 commercial smoked salmons
1037 consumers from 5 european countries
(5 sessions ; preference rating on a 9-points scale)

Sensory profile on 33 attributes (visual, odour, texture and taste)
EuroSalmon data

Stress Kruskal (3 dim)=0.04711564
Correlations with sensory attributes

Contour plot of preference

Correlations with attributes

RV Unfolding / Profile
0.63524

RV MdPref / Profile
0.45334
Segmentation

in two classes
Possible to constraint the coordinates of the products to be a linear combination of sensory attributes

Stress Kruskal
=0.05359

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<th>D2</th>
<th>D3</th>
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Conclusion

Versatile models: transformations (metric vs non metric)
constraint (internal vs external)

Accuracy (recovery of sensory dimensions or experimental design)

Simple and direct interpretation