

# Smacof at 50: A Manual

## Part 5: Unfolding in Smacof

Jan de Leeuw - University of California Los Angeles

Started December 12 2022, Version of April 26, 2024

### **Abstract**

TBD

# Contents

0.1 Metric Unfolding . . . . .	2
<b>1 Initial Configuration</b>	<b>4</b>
<b>References</b>	<b>5</b>

**Note:** This is a working manuscript which will be expanded/updated frequently. All suggestions for improvement are welcome. All Rmd, tex, html, pdf, R, and C files are in the public domain. Attribution will be appreciated, but is not required. The files can be found at <https://github.com/deleeuw> in the repositories smacofCode, smacofManual, and smacofExamples.

## 0.1 Metric Unfolding

Metric unfolding is a special case of metric MDS, as implemented for example in smacofAC. Thus we minimize stress defined as

$$\sigma(X) = \sum_{i=1}^N \sum_{j=1}^N w_{ij} (\delta_{ij} - d_{ij}(X))^2. \quad (1)$$

For unfolding

$$W = \begin{matrix} & \begin{matrix} n & m \end{matrix} \\ \begin{matrix} n \\ m \end{matrix} & \begin{bmatrix} 0 & U \\ U' & 0 \end{bmatrix} \end{matrix}$$

In other words there is a set of  $n$  row-objects and a set of  $m$  column-objects. The within-set dissimilarities are missing, or ignored, and only the between-set dissimilarities are fitted. If we partition  $X$  as

$$X = \begin{matrix} & p \\ \begin{matrix} n \\ m \end{matrix} & \begin{bmatrix} Y \\ Z \end{bmatrix} \end{matrix}$$

then we can also write

$$\sigma(Y, Z) = \sum_{i=1}^n \sum_{j=1}^m u_{ij} (\delta_{ij} - d(y_i, z_j))^2. \quad (2)$$

By defining

$$X = \begin{matrix} & p \\ \begin{matrix} n \\ m \end{matrix} & \begin{bmatrix} Y \\ Z \end{bmatrix} \end{matrix}$$

and

$$W = \begin{matrix} & \begin{matrix} n & m \end{matrix} \\ \begin{matrix} n \\ m \end{matrix} & \begin{bmatrix} 0 & U \\ U' & 0 \end{bmatrix} \end{matrix}$$

we can write

The multidimensional unfolding model for preference judgments is often attributed to (**coombs?**), (**kruskal\_carroll?**), (**roskam?**)

# 1 Initial Configuration

$$\sigma(C) = \sigma(\tilde{C} + (C - \tilde{C})) = \sum_{i=1}^n \sum_{j=1}^m ((\delta_{ij}^2 - \text{tr } A_{ij} \tilde{C}) - \text{tr } A_{ij} (C - \tilde{C}))^2$$

$$\sigma(C) = \sigma(\tilde{C}) - 2 \sum_{i=1}^n \sum_{j=1}^m (\delta_{ij}^2 - \text{tr } A_{ij} \tilde{C}) \text{tr } A_{ij} (C - \tilde{C}) + \sum_{i=1}^n \sum_{j=1}^m \{\text{tr } A_{ij} (C - \tilde{C})\}^2$$

From De Leeuw, Groenen, and Pietersz (2006)

$$\sum_{i=1}^n \sum_{j=1}^m \{\text{tr } A_{ij} (C - \tilde{C})\}^2 \leq (n + m + 2) \text{tr } (C - \tilde{C})^2$$

Define

$$B(\tilde{C}) := \frac{1}{n + m + 2} \sum_{i=1}^n \sum_{j=1}^m (\delta_{ij}^2 - \text{tr } A_{ij} \tilde{C}) A_{ij}$$

So we minimize

$$-2 \text{tr } B(\tilde{C}) C + \text{tr } C^2 - 2 \text{tr } C \tilde{C} = \text{tr } (C - \{\tilde{C} + B(\tilde{C})\})^2$$

## References

De Leeuw, J., P. J. F. Groenen, and R. Pietersz. 2006. “Optimizing Functions of Squared Distances.” UCLA Department of Statistics. <https://jansweb.netlify.app/publication/deleeuw-groenen-pietersz-u-06/deleeuw-groenen-pietersz-u-06.pdf>.