

# Accelerated SMACOF Multidimensional Scaling

Jan de Leeuw - University of California Los Angeles

Started July 23 2024, Version of August 02, 2024

## **Abstract**

TBD

# Contents

<b>1</b>	<b>Introduction</b>	<b>3</b>
<b>2</b>	<b>One-point Methods</b>	<b>4</b>
2.1	Basic Iteration . . . . .	4
2.2	Rotated Basic Iteration . . . . .	5
<b>3</b>	<b>Two Point Iteration</b>	<b>8</b>
	<b>References</b>	<b>11</b>

**Note:** This is a working paper which will be expanded/updated frequently. All suggestions for improvement are welcome.

# 1 Introduction

In this paper we study minimization of the loss function

$$\sigma(X) := \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n w_{ij} (\delta_{ij} - d_{ij}(X))^2$$

over all  $n \times p$  *configuration* matrices  $X$ . Here  $W = \{w_{ij}\}$  and  $\Delta = \{\delta_{ij}\}$  are known non-negative, symmetric, and hollow matrices of *weights* and *dissimilarities* and  $D(X) = \{d_{ij}(X)\}$  is the matrix of *Euclidean distances* between the rows of  $X$ .

Define

$$\rho(X) := \sum_{i=1}^n \sum_{j=1}^n w_{ij} \delta_{ij} d_{ij}(X) = \text{tr } X' B(X) X,$$

where

$$B(X) := \sum_{i=1}^n \sum_{j=1}^n w_{ij} \frac{\delta_{ij}}{d_{ij}(X)} A_{ij}.$$

Also define

$$\eta^2(X) := \sum_{i=1}^n \sum_{j=1}^n w_{ij} d_{ij}^2(X) = \text{tr } X' V X,$$

where

$$V := \sum_{i=1}^n \sum_{j=1}^n w_{ij} A_{ij}.$$

Thus

$$\sigma(X) = 1 - \rho(X) + \frac{1}{2} \eta^2(X)$$

Both  $\rho$  and  $\eta$  are homogeneous convex functions.

$\rho(X) = 0$  iff  $d_{ij}(X) = 0$  for all  $(i, j)$  for which  $w_{ij} \delta_{ij} > 0$ .

## 2 One-point Methods

### 2.1 Basic Iteration

The *Guttman transform* of a configuration  $X$ , named after Guttman (1968), is defined as

$$\Phi(X) = V^+ B(X) X,$$

with  $V^+$  the Moore-Penrose inverse of  $V$ . If  $X = \Phi(X)$ , i.e. if  $X$  is fixed point of  $\Phi$ , then  $VX - B(X)0$ , which we can also write as  $\mathcal{D}\sigma(X) = 0$ . Thus  $X$  is a fixed point of  $\Phi$  if and only if the gradient of  $\sigma$  vanishes at  $X$ , i.e. if and only if  $X$  is a stationary point of  $\sigma$ .

We have to be somewhat careful here. Subdifferential

$$\partial d_{ij}(X) = \frac{1}{d_{ij}(X)} A_{ij} X$$

$$\partial d_{ij}(X) = A_{ij} Z$$

Using the Guttman transform we can derive the basic smacof equality

$$\sigma(X) = 1 + \eta^2(X - \Phi(X)) - \eta^2(\Phi(X))$$

for all  $X$  and the inequality

$$\sigma(X) \leq 1 + \eta^2(X - \Phi(Y)) - \eta^2(\Phi(Y))$$

for all  $X$  and  $Y$ .

Taken together „ and „, imply the sandwich inequality

$$\sigma(\Phi(Y)) \leq 1 - \eta^2(\Phi(Y)) \leq 1 + \eta^2(Y - \Phi(Y)) - \eta^2(\Phi(Y)) = \sigma(Y)$$

If  $Y$  is not a fixed point of  $\Phi$  then the second inequality in the chain is strict and thus  $\sigma(\Phi(Y)) < \sigma(Y)$ . It also follows from ... that  $\eta^2(\Phi(Y)) \leq 1$ .

Algorithm

$$\mathcal{D}\Phi_X(H) = V^+ \sum w_{ij} \frac{\delta_{ij}}{d_{ij}(X)} \left\{ A_{ij} H - \frac{\text{tr } X' A_{ij} H}{\text{tr } X' A_{ij} X} A_{ij} X \right\}$$

Thus  $\mathcal{D}\Phi_X(X) = 0$  for all  $X$ . If  $X$  is a fixed point and  $S$  is anti-symmetric  $\mathcal{D}\Phi_X(XS) = V^+ B(X)XS = XS$ , which means  $\mathcal{D}\Phi_X$  has  $\frac{1}{2}p(p-1)$  eigenvalues equal to one. At a fixed point all eigenvalues are between zero and one.

$$\mathcal{D}^2 \rho_X(G, H) = \sum w_{ij} \frac{\delta_{ij}}{d_{ij}(X)} \left\{ \text{tr } G' A_{ij} H - \frac{\text{tr } H' A_{ij} X \text{tr } G' A_{ij} X}{d_{ij}^2(X)} \right\}$$

## itel 57 sold 2.1114112739 snw 2.1114112739 chng 0.0000000000 labd 0.7669812392

stress is 2.1114112739076

```
##      [,1]
## [1,] +1.00000000000
## [2,] +0.7669965027
## [3,] +0.7480939418
## [4,] +0.7185926293
## [5,] +0.7007452300
## [6,] +0.6920114811
## [7,] +0.6859492532
## [8,] +0.6593334523
## [9,] +0.6541779410
## [10,] +0.6477573342
## [11,] +0.6237683212
## [12,] +0.6178713315
## [13,] +0.5735285948
## [14,] +0.5483330654
## [15,] +0.5260355535
## [16,] +0.5112510731
## [17,] +0.5064703617
## [18,] +0.5059294793
## [19,] +0.4919752629
## [20,] +0.4827646549
## [21,] +0.4782034983
## [22,] +0.4757907684
## [23,] +0.4682965897
## [24,] +0.4619226490
## [25,] +0.4559704883
## [26,] +0.00000000000
## [27,] +0.00000000000
## [28,] -0.00000000000
```

$$\mathcal{D}\Phi_X(H) = V^+ \sum w_{ij} \frac{\delta_{ij}}{d_{ij}(X)} \left\{ A_{ij}H - \frac{\text{tr } X' A_{ij} H}{\text{tr } X' A_{ij} X} A_{ij}X \right\}$$

Thus  $\mathcal{D}\Phi_X(X) = 0$  for all  $X$ . If  $X$  is a fixed point and  $S$  is anti-symmetric  $\mathcal{D}\Phi_X(XS) = V^+ B(X)XS = XS$ , which means  $\mathcal{D}\Phi_X$  has  $\frac{1}{2}p(p-1)$  eigenvalues equal to one. At a fixed point all eigenvalues are between zero and one.

$$\mathcal{D}^2\rho_X(G, H) = \sum w_{ij} \frac{\delta_{ij}}{d_{ij}(X)} \left\{ \text{tr } G' A_{ij} H - \frac{\text{tr } H' A_{ij} X \text{tr } G' A_{ij} X}{d_{ij}^2(X)} \right\}$$

## 2.2 Rotated Basic Iteration

```
## itel 54 sold 2.1114112739 snw 2.1114112739 chng 0.0000000000 labd 0.7669843896
```

stress is 2.1114112739076

```
##      [,1]
## [1,] +0.7669964894
## [2,] +0.7480939420
## [3,] +0.7185926297
## [4,] +0.7007452335
## [5,] +0.6920114817
## [6,] +0.6859492534
## [7,] +0.6593334543
## [8,] +0.6541779412
## [9,] +0.6477573345
## [10,] +0.6237683217
## [11,] +0.6178713316
## [12,] +0.5735285959
## [13,] +0.5483330651
## [14,] +0.5260355534
## [15,] +0.5112510730
## [16,] +0.5064703618
## [17,] +0.5059294793
## [18,] +0.4919752632
## [19,] +0.4827646574
## [20,] +0.4782035029
## [21,] +0.4757907649
## [22,] +0.4682965885
## [23,] +0.4619226493
## [24,] +0.4559704884
## [25,] -0.0000000000
## [26,] -0.0000000000
## [27,] +0.0000000000
## [28,] +0.0000000000
```

## itel 56 sold 2.1114112739 snw 2.1114112739 chng 0.0000000000 labd 0.7669940008

stress is 2.1114112739076

```
##      [,1]
## [1,] +0.7669964993
## [2,] +0.7480939419
## [3,] +0.7185926294
## [4,] +0.7007452309
## [5,] +0.6920114813
## [6,] +0.6859492533
## [7,] +0.6593334529
## [8,] +0.6541779410
## [9,] +0.6477573343
## [10,] +0.6237683213
```

## [11,]	+0.6178713317
## [12,]	+0.5735285948
## [13,]	+0.5483330653
## [14,]	+0.5260355535
## [15,]	+0.5112510731
## [16,]	+0.5064703617
## [17,]	+0.5059294792
## [18,]	+0.4919752629
## [19,]	+0.4827646550
## [20,]	+0.4782034999
## [21,]	+0.4757907672
## [22,]	+0.4682965894
## [23,]	+0.4619226495
## [24,]	+0.4559704888
## [25,]	-0.0000000006
## [26,]	-0.0000000000
## [27,]	-0.0000000000
## [28,]	+0.0000000000

### 3 Two Point Iteration

De Leeuw and Heiser (1980) suggested the update

$$\Psi(X) = 2\Phi(X) - X$$

The reasoning here is two-fold. The smacof inequality says

$$\sigma(X) \leq 1 + \eta^2(X - \Phi(Y)) - \eta^2(\Phi(Y))$$

If  $X = \alpha\Phi(Y) + (1 - \alpha)Y$  then this becomes

$$\sigma(\alpha\Phi(Y) + (1 - \alpha)Y) \leq 1 + (1 - \alpha)^2\eta^2(Y - \Phi(Y)) - \eta^2(\Phi(Y))$$

If  $(1 - \alpha)^2 \leq 1$  then

$$1 + (1 - \alpha)^2\eta^2(Y - \Phi(Y)) - \eta^2(\Phi(Y)) \leq 1 + \eta^2(Y - \Phi(Y)) - \eta^2(\Phi(Y)) = \sigma(Y)$$

Thus updating with  $X^{(k+1)} = \alpha\Phi(X^{(k)}) + (1 - \alpha)X^{(k)}$  is a stable algorithm as long as  $0 \leq \alpha \leq 2$ .

It turns out that applying the relaxed update

$$X^{(k+1)} = 2V^+B(X^{(k)})X^{(k)} - X^{(k)}$$

has some unintended consequences.

```
## itel 23 sold 3.9946270666 snw 3.9946270666 chng 3.7664315853 labd 1.0000000000
stress is 2.1114112739076
```

We see that  $\eta^2(X^{(k+1)} - X^{(k)})$  does not converge to zero, and that  $\sigma_k$  converges to a value which does not even correspond to a local minimum of  $\sigma$ .

```
##      [,1]
## [1,] -1.0000000000
## [2,] +1.0000000000
## [3,] -1.0000000000
## [4,] -1.0000000000
## [5,] +0.5339929781
## [6,] +0.4961878839
## [7,] +0.4371852597
## [8,] +0.4014904677
## [9,] +0.3840229636
## [10,] +0.3718985068
## [11,] +0.3186669088
## [12,] +0.3083558824
## [13,] +0.2955146690
## [14,] +0.2475366434
## [15,] +0.2357426633
```



```

## [16,] +0.1470571918
## [17,] +0.0966661301
## [18,] -0.0880590224
## [19,] -0.0761547015
## [20,] -0.0634068231
## [21,] +0.0520711068
## [22,] -0.0484184707
## [23,] -0.0435929937
## [24,] -0.0344706856
## [25,] +0.0225021460
## [26,] -0.0160494738
## [27,] +0.0129407235
## [28,] +0.0118589584

```

A more thorough analysis of the results show that the method produces a sequence  $X^{(k)}$  with two subsequences. If  $\bar{X}$  is a fixed point of  $\Phi$  then there is a  $\tau > 0$  such that the subsequence with  $k$  even converges to  $\tau\bar{X}$  while the subsequence with  $k$  odd converges to  $(2 - \tau)\bar{X}$ .

```

## itel 18 sold 3.9946270666 snw 3.9946270666 chng 0.0000000000 labd 0.2737973829
stress is 2.1114112739076

```

```

##      [,1]
## [1,] +1.0000000000
## [2,] -1.0000000000
## [3,] -1.0000000000
## [4,] -0.9999999999
## [5,] +0.5339930271
## [6,] +0.4961878833
## [7,] +0.4371852579
## [8,] +0.4014904541
## [9,] +0.3840229612
## [10,] +0.3718985063
## [11,] +0.3186669016
## [12,] +0.3083558816
## [13,] +0.2955146680
## [14,] +0.2475366415
## [15,] +0.2357426629
## [16,] +0.1470571877
## [17,] +0.0966661315
## [18,] -0.0880590242
## [19,] -0.0761547024
## [20,] -0.0634068192
## [21,] +0.0520711070
## [22,] -0.0484184575
## [23,] -0.0435930109
## [24,] -0.0344706938

```

```

## [25,] +0.0225021463
## [26,] -0.0160494743
## [27,] +0.0129407234
## [28,] +0.0118589585

## Warning in microbenchmark(smacofAccelerate(delta, ndim = 2, opt = 1, halt = 2,
## : less accurate nanosecond times to avoid potential integer overflows

## Unit: milliseconds
##
##                                     expr      min
## smacofAccelerate(delta, ndim = 2, opt = 1, halt = 2, verbose = FALSE) 3.188775
## smacofAccelerate(delta, ndim = 2, opt = 2, halt = 2, verbose = FALSE) 3.151875
## smacofAccelerate(delta, ndim = 2, opt = 3, halt = 2, verbose = FALSE) 3.847276
## smacofAccelerate(delta, ndim = 2, opt = 4, halt = 2, verbose = FALSE) 1.421019
## smacofAccelerate(delta, ndim = 2, opt = 5, halt = 2, verbose = FALSE) 1.564027
## smacofAccelerate(delta, ndim = 2, opt = 6, halt = 2, verbose = FALSE) 1.639467
## smacofAccelerate(delta, ndim = 2, opt = 7, halt = 2, verbose = FALSE) 1.526307
##      lq      mean    median      uq      max neval
## 3.304825 3.602914 3.358987 3.476656 6.070009   100
## 3.241993 3.521317 3.294924 3.374894 5.645618   100
## 3.939567 4.335232 4.029644 4.215682 6.634046   100
## 1.466795 1.601369 1.498222 1.541600 3.919846   100
## 1.618536 1.762409 1.650004 1.712775 3.995286   100
## 1.692829 1.827641 1.720585 1.775444 6.503174   100
## 1.578336 1.718087 1.618106 1.683132 6.439214   100

## Unit: milliseconds
##
##                                     expr      min
## smacofAccelerate(delta, ndim = 2, opt = 1, halt = 2, verbose = FALSE) 43.06710
## smacofAccelerate(delta, ndim = 2, opt = 2, halt = 2, verbose = FALSE) 44.09382
## smacofAccelerate(delta, ndim = 2, opt = 3, halt = 2, verbose = FALSE) 54.69146
## smacofAccelerate(delta, ndim = 2, opt = 4, halt = 2, verbose = FALSE) 20.16495
## smacofAccelerate(delta, ndim = 2, opt = 5, halt = 2, verbose = FALSE) 14.30547
## smacofAccelerate(delta, ndim = 2, opt = 6, halt = 2, verbose = FALSE) 22.89670
## smacofAccelerate(delta, ndim = 2, opt = 7, halt = 2, verbose = FALSE) 20.67150
##      lq      mean    median      uq      max neval
## 44.02676 45.24634 44.87503 45.65168 66.89129   100
## 45.18950 46.15677 46.23545 46.68055 50.64677   100
## 56.24936 56.93894 56.64076 57.10158 74.41721   100
## 20.85358 22.01609 22.03133 22.24851 40.76454   100
## 14.63911 15.66496 14.95206 16.28350 34.73516   100
## 24.80289 25.22137 25.04815 25.37377 44.09050   100
## 22.44541 22.52770 22.71785 22.93573 24.76105   100

```

## References

- De Leeuw, J., and W. J. Heiser. 1980. "Multidimensional Scaling with Restrictions on the Configuration." In *Multivariate Analysis, Volume V*, edited by P. R. Krishnaiah, 501–22. Amsterdam, The Netherlands: North Holland Publishing Company.
- Guttman, L. 1968. "A General Nonmetric Technique for Fitting the Smallest Coordinate Space for a Configuration of Points." *Psychometrika* 33: 469–506.