

Higher Partial of Stress. Who Needs Them ?

Jan de Leeuw

Version 01, July 20, 2017

Abstract

Third

Contents

1	Introduction	1
2	Partials, Partials Everywhere	1
2.1	Derivatives of Distances	1
2.2	Derivatives of Stress	2

Note: This is a working paper which will be expanded/updated frequently. All suggestions for improvement are welcome. The directory gifi.stat.ucla.edu/third has a pdf version, the bib file, the complete Rmd file with the code chunks, and the R and C source code.

1 Introduction

2 Partials, Partials Everywhere

2.1 Derivatives of Distances

We start with the approximation

$$\frac{\sqrt{x + \epsilon}}{\sqrt{x}} = 1 + \frac{1}{2} \left(\frac{\epsilon}{x}\right) - \frac{1}{8} \left(\frac{\epsilon}{x}\right)^2 + \frac{1}{16} \left(\frac{\epsilon}{x}\right)^3 - \frac{5}{128} \left(\frac{\epsilon}{x}\right)^4 + o(\epsilon^4).$$

Now let $e(x) := x'Ax$ and define

$$h(x, y) := \frac{\sqrt{e(x + y)}}{\sqrt{e(x)}} = \frac{\sqrt{x'Ax + 2x'Ay + y'Ay}}{\sqrt{x'Ax}}.$$

Then

$$h(x, y) = 1 + \frac{1}{2} \left(\frac{2x' Ay + y' Ay}{x' Ax} \right) - \frac{1}{8} \left(\frac{2x' Ay + y' Ay}{x' Ax} \right)^2 + \frac{1}{16} \left(\frac{2x' Ay + y' Ay}{x' Ax} \right)^3 - \frac{5}{128} \left(\frac{2x' Ay + y' Ay}{x' Ax} \right)^4 + o(\|y\|^4).$$

If we expand powers and collect terms we get, assuming we have been lucky,

$$h(x, y) = 1 + h_1(x, y) + \frac{1}{2} h_2(x, y) + \frac{1}{6} h_3(x, y) + \frac{1}{24} h_4(x, y) + o(\|y\|^4)$$

$$h_1(x, y) = \frac{x' Ay}{x' Ax}$$

$$h_2(x, y) = \frac{y' Ay}{x' Ax} - \frac{(x' Ay)^2}{(x' Ax)^2}$$

$$h_3(x, y) = 3 \left\{ \frac{(x' Ay)^3}{(x' Ax)^3} - \frac{(x' Ay)(y' Ay)}{(x' Ax)^2} \right\}$$

$$h_4(x, y) = -3 \frac{(y' Ay)^2}{(x' Ax)^2} + 18 \frac{(x' Ay)^2 y' Ay}{(x' Ax)^3} - 15 \frac{(x' Ay)^4}{(x' Ax)^4}$$

2.2 Derivatives of Stress

The stress loss function is

$$\sigma(x) := \frac{1}{2} \sum_{1 \leq i < j \leq n} \sum w_{ij} (\delta_{ij} - d_{ij}(x))^2,$$

Here $x = \text{vec}(X)$, with X the usual MDS configuration of n points in p dimensions. The distances between points i and j in the configurations are $d_{ij}(x) := \sqrt{x' A_{ij} x}$.

The $np \times np$ matrices A_{ij} are defined using unit vectors e_i and e_j , all zero except for one element that is equal to one. If you like, the e_i are the columns of the identity matrix. Define

$$E_{ij} := (e_i - e_j)(e_i - e_j)',$$

and use p copies of E_{ij} to make the direct sum

$$A_{ij} := \underbrace{E_{ij} \oplus \cdots \oplus E_{ij}}_{p \text{ times}}.$$

Assuming without loss of generality that the dissimilarities are normalized to sum of squares one. Then

$$\sigma(x) = 1 - \rho(x) + \frac{1}{2}x'Vx,$$

with

$$\rho(x) := \sum_{1 \leq i < j \leq n} \sum w_{ij} \delta_{ij} \sqrt{x' A_{ij} x},$$

and

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

The function $\frac{1}{2}x'Vx$ is quadratic, so its derivatives are trivial to compute.

$$\rho(x + y) = \sum_{1 \leq i < j \leq n} \sum w_{ij} \delta_{ij} \sqrt{e_{ij}(x + y)}$$

$$\rho(x + y) = \rho(x) + y' \mathcal{D}\rho(x) + \frac{1}{2} y' \mathcal{D}^2(x) y +$$

$$\mathcal{D}\rho(x) = \sum_{1 \leq i < j \leq n} \sum w_{ij} \frac{\delta_{ij}}{d_{ij}(x)} A_{ij} x$$

$$\mathcal{D}^2\rho(x) = \sum_{1 \leq i < j \leq n} \sum w_{ij} \delta_{ij}$$