### High Dimensional Data Visualisation: the Textile Plot

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## Building good models from data

- Exploring data through visualisation
  - Finding outliers
  - Clustering observations
  - Investigating relationships between variables



#### **Parallel Coordinate Plots**

(Inselberg 1985, Wegman 1990)

- Visualising a set of points in high dimensional space
  - Axes are placed in parallel (not right angle)
  - Coordinates of each point are connected by segments









Iris







Iris



























#### One polygonal line indicates one observation



# Difficult to understand any mechanism behind the data





#### The number of the intersections increases

# Location and scale of each axis are independently chosen



All coordinate points fill up the range of the axis.



# Choosing appropriate locations and scales and the order of the axes





## **Textile plot**

#### (Kumasaka and Shibata, submitted)

- A parallel coordinate plot
  - Locations and scales are simultaneously chosen
    - All polygonal lines are aligned as horizontally as possible
  - Order of axes is carefully chosen
    - To provide a clear image of the data to the user
  - Any kind of data can be displayed
    - Numerical data
    - Unordered categorical data
    - Ordered categorical data
    - Missing values
- Named by analogy to a fabric
  - Warp and Weft





Data (p-dimensional n observations)

$$\left(\begin{array}{ccc} x_{11} & \cdots & x_{1p} \\ \vdots & & \vdots \\ x_{n1} & \cdots & x_{np} \end{array}\right) = (\boldsymbol{x}_1, \dots, \boldsymbol{x}_p)$$

• Data vector

$$x_j, \ j = 1, \dots, p$$
  
 $(\mathbf{1}^T x_j = 0, \ \|x_j\| = 1)$ 

$$\boldsymbol{y}_j = \alpha_j \boldsymbol{1} + \beta_j \boldsymbol{x}_j \ (j = 1, \dots, p)$$





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• Data vector

$$m{x}_{j}, \ j = 1, \dots, p$$
  
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# Criterion



Coordinate vector

 $\boldsymbol{y}_j = \alpha_j \boldsymbol{1} + \beta_j \boldsymbol{x}_j \ (j = 1, \dots, p)$ 

- Location parameter vector  $\boldsymbol{\alpha} = (\alpha_1, \dots, \alpha_p)^T$
- Scale parameter vector

$$\boldsymbol{\beta} = (\beta_1, \dots, \beta_p)^T$$

Ideal coordinate vector

$$\boldsymbol{\xi} = (\xi_1, \dots, \xi_n)^T$$



• The sum of squared deviations is minimised

$$S^{2}(\boldsymbol{lpha}, \boldsymbol{eta}, \boldsymbol{\xi}) = \sum_{j=1}^{p} \left\| \boldsymbol{y}_{j} - \boldsymbol{\xi} \right\|^{2} o \min$$

# Solution of the ideal coordinate vector

By introducing the mean vector

$$\boldsymbol{m} = \frac{1}{p} \sum_{j=1}^{p} \boldsymbol{y}_j,$$

we can decompose  $S^2$  into

$$S^{2}(\boldsymbol{\alpha},\boldsymbol{\beta},\boldsymbol{\xi}) = \sum_{j=1}^{p} \|\boldsymbol{y}_{j} - \boldsymbol{\xi}\|^{2}$$
$$= \sum_{j=1}^{p} \|\boldsymbol{y}_{j} - \boldsymbol{m}\|^{2} + p\|\boldsymbol{m} - \boldsymbol{\xi}\|^{2}.$$
$$\hat{\boldsymbol{\xi}} = \boldsymbol{m}$$



## Constraint



We need a constraint for  $\alpha$  and  $\beta$  to avoid trivial solutions like

$$\boldsymbol{\alpha} = \boldsymbol{\beta} = \mathbf{0} \quad \Rightarrow \quad S^2(\mathbf{0}, \mathbf{0}, \mathbf{0}) = 0.$$

The constraint would be that

$$\sum_{j=1}^{p} \|\boldsymbol{y}_{j} - \bar{y}_{j} \mathbf{1}\|^{2} = \|\boldsymbol{\beta}\|^{2} = np,$$

where  $\bar{y}_{.j} = \sum_{i=1}^{n} y_{ij}/n$ .

#### **Solution of location parameter**

By introducing the mean  $\bar{y}_{..} = \sum_{i,j} y_{ij}/np$ , we can decompose

$$S^{2}(\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{m}) = \sum_{j=1}^{p} \|\boldsymbol{y}_{j} - \boldsymbol{m}\|^{2}$$
$$= \sum_{j=1}^{p} \|\boldsymbol{y}_{j} - \bar{\boldsymbol{y}}_{\boldsymbol{\cdot} j} \mathbf{1}\|^{2} - p \|\boldsymbol{m} - \bar{\boldsymbol{y}}_{\boldsymbol{\cdot} \boldsymbol{\cdot} 1}\|^{2} + \sum_{j=1}^{p} \|\bar{\boldsymbol{y}}_{\boldsymbol{\cdot} j} \mathbf{1} - \bar{\boldsymbol{y}}_{\boldsymbol{\cdot} \boldsymbol{\cdot} 1}\|^{2}$$

Since the first two terms on the right hand side of the equation are independent of  $\alpha$ , minimisation with respect to  $\alpha$  yields the solution  $\hat{\alpha}$ , such that

$$\hat{\alpha}_j = \alpha_0, \ j = 1, \dots, p,$$

for an arbitrary constant  $\alpha_0$ .

we can assume  $\alpha_0 = 0$ 



## **Solution of scale parameter**



 $S^{2}(\hat{\boldsymbol{\alpha}},\boldsymbol{\beta},\boldsymbol{m}) = \sum_{i=1}^{p} \|\boldsymbol{y}_{j} - \bar{\boldsymbol{y}}_{i} \mathbf{1}\|^{2} - p \|\boldsymbol{m} - \bar{\boldsymbol{y}}_{i} \mathbf{1}\|^{2}$  $= \|oldsymbol{eta}\|^2 - rac{1}{n}oldsymbol{eta}^T \mathbf{R}oldsymbol{eta}$ (**R**: sample correlation matrix of the  $x_i$ ) maximise  $\boldsymbol{\beta}^T \mathbf{R} \boldsymbol{\beta}$ subject to  $\|\boldsymbol{\beta}\|^2 = np$ 

The solution  $\hat{\beta}$  is the eignevector of **R** with the largest eigenvalue, such that  $\|\hat{\beta}\|^2 = np$ .

#### **Optimal choice of locations and scales**





## **Order of axes**

- According to the squared distance  $\| \boldsymbol{y}_j \boldsymbol{m} \|^2$ 
  - The further left axis is closer to the mean vector



$$S^{2}(\hat{\boldsymbol{\alpha}}, \hat{\boldsymbol{\beta}}, \boldsymbol{m}) = \sum_{j=1}^{p} \|\boldsymbol{y}_{j} - \boldsymbol{m}\|^{2} \qquad \qquad \begin{array}{c} \text{Petal Length} \quad \text{Petal Width} \quad \text{Sepal Length} \quad \text{Sepal Width} \\ \hline \|\boldsymbol{y}_{j} - \boldsymbol{m}\|^{2} \quad 16.62 \quad 21.53 \quad 34.63 \quad 89.45 \end{array}$$





# Categorical data vector

- To determine a coordinate of each level
  - Encoding the categorical data vector x by a set of contrasts







columns of  $\mathbf{X}$  are linearly independent to  $\mathbf{1}$ 

# Choice of locations and scales for numerical and categorical data

- Data Matrix  $\mathbf{X}_j \in \mathbb{R}^{n \times (q_j 1)}$   $(j = 1, \dots, p)$ 
  - Encoded matrix for a categorical data vector  $x_j$  with  $q_j$  levels
  - Original data vector  $x_j$  for a numerical data vector  $(q_j = 2)$
- Coordinate vector

 $\boldsymbol{y}_j = \alpha_j \mathbf{1} + \mathbf{X}_j \boldsymbol{\beta}_j \quad (j = 1, \dots, p)$ 

Location parameter vector

$$\boldsymbol{\alpha} = (\alpha_1, \dots, \alpha_p)^T$$

- Scale parameter vector  $\boldsymbol{\beta} = (\boldsymbol{\beta}_1^T, \dots, \boldsymbol{\beta}_p^T)^T \quad (\boldsymbol{\beta}_j \in \mathbb{R}^{q_j - 1})$
- Sum of squared deviations is minimised

$$S^2(oldsymbol{lpha},oldsymbol{eta},oldsymbol{\xi}) = \sum_{j=1}^p \left\|oldsymbol{y}_j - oldsymbol{\xi}
ight\|^2 o \min \left( ext{under } \sum_{j=1}^p \|oldsymbol{y}_j - oldsymbol{ar{y}}_{.j} \mathbf{1}\|^2 = np 
ight)$$



## Solution of location and scale

By introducing the following matrix notations

$$\mathbf{A} = \frac{1}{p} \left( \mathbf{X}_j^T \mathbf{X}_k - \frac{1}{n} \mathbf{X}_j^T \mathbf{1} \mathbf{1}^T \mathbf{X}_k; \ 1 \le j, k \le p \right)$$
$$\mathbf{B} = \operatorname{diag} \left( \mathbf{X}_j^T \mathbf{X}_j^T - \frac{1}{n} \mathbf{X}_j^T \mathbf{1} \mathbf{1}^T \mathbf{X}_j; \ 1 \le j \le p \right)$$

The optimal choice for the locations is given by

$$\hat{\alpha}_j = \alpha_0 - \bar{\boldsymbol{x}}_{\boldsymbol{\cdot}j}^T \hat{\boldsymbol{\beta}}_j, \ j = 1, \dots, p$$

for an arbitrary constant  $\alpha_0$ , where  $\bar{x}_{j}^T = \mathbf{1}^T \mathbf{X}_j / n$ . That of the scales is given by  $\hat{\beta}$  which is the eigenvector of  $\mathbf{A}$  with respect to  $\mathbf{B}$  with the largest eigenvalue, such that  $\hat{\beta}^T \mathbf{B} \hat{\beta} = np$ .

#### Categorical data on parallel coordinate plot











# **Ordered categorical data**



$$\mathbf{C} = \begin{pmatrix} 0 & \cdots & 0 \\ 1 & \ddots & \vdots \\ \vdots & \ddots & 0 \\ 1 & \cdots & 1 \end{pmatrix}$$

Additional constraints

$$oldsymbol{eta}_j \geq \mathbf{0} ~~\mathrm{or}~~oldsymbol{eta}_j \leq \mathbf{0}$$

#### Example

$$\boldsymbol{x} = \begin{pmatrix} Small \\ Small \\ Medium \\ Large \\ Large \end{pmatrix} \rightarrow \boldsymbol{y} = \alpha \mathbf{1} + \begin{pmatrix} 0 & 0 \\ 0 & 0 \\ 1 & 0 \\ 1 & 1 \\ 1 & 1 \end{pmatrix} \begin{pmatrix} \beta_1 \\ \beta_2 \end{pmatrix} = \begin{pmatrix} \alpha & \lambda \\ \alpha \\ \alpha + \beta_1 \\ \alpha + \beta_1 + \beta_2 \\ \alpha + \beta_1 + \beta_2 \end{pmatrix}$$

The order of levels is retained if  $\beta_1, \beta_2 \ge 0$  or  $\beta_1, \beta_2 \le 0$ 



# **Missing values**



Indicator matrix reflecting missing information

$$\left( egin{array}{cccc} w_{11} & \cdots & w_{1p} \ dots & & dots \ dots & & dots \ & & dots \ & & w_{n1} & \cdots & w_{np} \end{array} 
ight) = (oldsymbol{w}_1, \dots, oldsymbol{w}_p)$$

where  $w_{ij} = \begin{cases} 0 & \text{if } x_{ij} \text{ is missing,} \\ 1 & \text{otherwise.} \end{cases}$ 

• Sum of squared deviations

$$S^2(oldsymbol{lpha},oldsymbol{eta},oldsymbol{\xi}) = \sum_{j=1}^p \left\|oldsymbol{y}_j - oldsymbol{\xi}
ight\|_{oldsymbol{w}_j}^2$$

• Constraint

$$\sum_{j=1}^{p} \left\| \boldsymbol{y}_{j} - \bar{\boldsymbol{y}}_{j} \right\|_{\boldsymbol{w}_{j}}^{2} = \sum_{i,j} w_{ij}$$



$$\left( \| \boldsymbol{x} \|_{\boldsymbol{v}}^2 = \sum_{i=1}^n v_i x_i^2 : \text{ weighted norm} \right)$$

# **Design of display**



#### • Textile plot

- Understanding various aspect of data
- Points displayed on a axis are carefully chosen
- Further classification of data types



# Way of displaying points on a axis



- Numerical data
  - Continuous data
    - Continuous line
  - Discrete data
    - Tick marks
  - Arrow head to show the orientation
  - Possible minimum and maximum
- Non-numerical data
  - Possible levels
  - Ordered categorical data
    - Arrows
  - Logical
    - Coloured
- All data
  - Multiplicity on the coordinate is represented by the area of the circle
  - Missing value
  - Label (with unit or numeral)



#### **Textile plot of Iris data**





#### **TOPIX (Tokyo Stock Price Index)** from Jan 1991 to Oct 2002



TOPIX = (Today's whole price / the whole price on the 4th of Jan 1968)  $\times$  100

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# **Two significant features**



#### • Knot

- A point on a axis, where all polygonal lines are pass through
- Isolated data vector

#### • Parallel wefts

- Segments horizontally aligned between two axes
- Perfect linear relationship or mapping between two data vectors



# **Preparation**

#### • Assumption

- No missing values and no ordered categorical data
- Normalisation

$$\mathbf{1}^T \mathbf{X}_j = \mathbf{0}$$
 and  $\mathbf{X}_j^T \mathbf{X}_j = \mathbf{I}, \quad j = 1, \dots, p$ 

#### Matrix notations

$$\begin{aligned} \mathbf{X}_{-j} &= (\mathbf{X}_1, \dots, \mathbf{X}_{j-1}, \mathbf{X}_{j+1}, \dots, \mathbf{X}_p) \quad (\in \mathbb{R}^{n \times q}) \\ &= \mathbf{U} \mathbf{D} \mathbf{V}^T \\ &= (\boldsymbol{u}_1, \dots, \boldsymbol{u}_q) \mathrm{diag}(d_1, \dots, d_q) \mathbf{V}^T \\ &\quad (\text{where } d_1 > d_2 \ge \dots \ge d_q \ge 0) \end{aligned}$$



## Knot



A knot is produced on the *j*th axis when the selected scale parameter is zero, that is,  $\hat{\beta}_j = 0$ .

**Theorem** A necessary and sufficient condition for a knot to occur on the jth axis is that

$$\mathbf{X}_j^T oldsymbol{u}_1 = \mathbf{0}$$

and all eigenvalues of  $\mathbf{X}_{j}^{T} \mathbf{U} \Delta \mathbf{U}^{T} \mathbf{X}_{j}$  are less than  $d_{1}^{2} - 1$ , where

$$\mathbf{\Delta} = \operatorname{diag}\left(0, \frac{d_2^2}{d_1^2 - d_2^2}, \dots, \frac{d_q^2}{d_1^2 - d_q^2}\right).$$

# Simplified condition for a knot to occur



**Corollary** If  $\mathbf{X}_{j}^{T}\mathbf{X}_{-j} = \mathbf{O}$ , a knot is always produced on the *j*th axis.



## **Parallel wefts**



Parallel wefts between the *j*th and the j + 1th axes occur when the coordinate vectors  $y_j$  and  $y_{j+1}$  are identical.

**Theorem** A necessary and sufficient condition for  $y_j = y_k$  is given by

$$\operatorname{Proj}_{\mathbf{X}_{j}}(\boldsymbol{m}) = \operatorname{Proj}_{\mathbf{X}_{k}}(\boldsymbol{m}),$$

where  $\operatorname{Proj}_{\mathbf{M}}(\boldsymbol{v})$  is the projection of  $\boldsymbol{v}$  on the range space of a matrix  $\mathbf{M}$  and  $\boldsymbol{m} = \sum_{j=1}^{p} \boldsymbol{y}_j/p$ .

**Example** Parallel wefts occur when there exist two numerical data vectors  $\boldsymbol{x}_j = (1, 2, 3, 4, 5)^T$  and  $\boldsymbol{x}_k = (10, 8, 6, 4, 2)^T$ , or two categorical data vectors  $\boldsymbol{x}_j = (A, A, B, C, C)^T$  and  $\boldsymbol{x}_k = (b, b, c, a, a)^T$  in the given data.

#### TOPIX (Tokyo Stock Price Index) from Jan 1991 to Oct 2002





# **Textile plot**

- Visualisation for understanding data
  - Polygonal lines are aligned as horizontally as possible
  - Any kind of data can be displayed
  - Symbols for points displayed are carefully chosen
  - Knot and Parallel wefts
- Implemented on R
  - DandDR (<u>http://www.stat.math.keio.ac.jp/DandDIV/</u>)
    - Add-on package for R
    - Interface between DandD and R
    - Receiving data and necessary information
    - Creating a dad object on R
      - List object which consists of data and attributes
      - Own plot method producing the textile plot





# **Further developments**

- Non-linear transformations
- Design enhancements
  - Using colour
  - Line width and thickness
- Dynamic or interactive display
  - Improving user interface
  - Java Language

Thank you for your attention.

#### Reference



- A. Inselberg, The plane with parallel coordinates, *The Visual Computer* 1 (1985) 69-91.
- E. Wegman, Hyperdimensional data analysis using parallel coordinates. *Journal of The American Statistical Association* **85** (1990) 664--675.