

Skat 571

11-26-13

- D

②

$$V = \frac{1}{P} \sum_{j=1}^n \left[\sum_{i=1}^P \tilde{q}_{ij}^4 - \frac{\left(\sum_{i=1}^P \tilde{q}_{ij}^2 \right)^2}{P} \right]$$

where $\tilde{l}_{ij} = \frac{l_{ij}}{h_i}$ $\leftarrow (i,j)^{th}$ entry of L
 $h_i \leftarrow i^{th}$ communality

Note that this maximizes the variance of the squared loadings.

Quartimax rotation minimizes

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$$\sum_{i=1}^p \sum_{j \neq k} l_{ij}^2 l_{ik}^2$$

Note: this would be exactly 0 if every row contains a 0.

Minimizing $\sum_{i=1}^p \sum_{j \neq k} l_{ij}^2 l_{ik}^2$ is equivalent

to maximizing $\sum_{i=1}^p \sum_{j=1}^m l_{ij}^4$

Steps to follow:

(4)

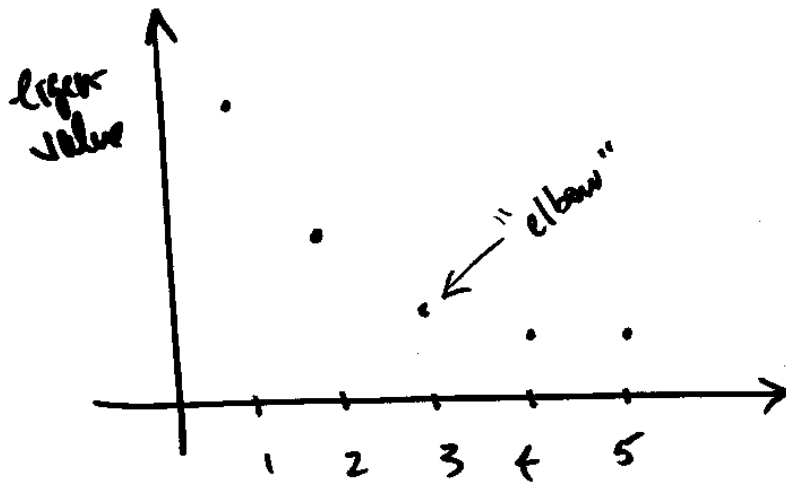
0. Decide whether to use S or R.
1. Extract the factors by PC and at least one other method (e.g. max. likelihood)
2. Decide how many factors to keep — scree plot
3. Decide on a rotation

Look at all of the solutions & choose the one with simplest structure.

4. Try to name the factors

Scree plot is a plot of the eigenvalues

(5)



Factor scores: - usually found using regression techniques

- represent the estimated values for each observation, on these latent variables

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Discriminant Analysis (Fisher, 1936)

Goal: to describe in as few dimensions as possible the features of objects from several known populations (Discrimination)

Goal 2: to sort new objects into one of the existing populations (Classification) ⑦

Fisher's method for 2 populations

Let π_1 and π_2 be the names of the 2 populations.

Let $\vec{X} = \begin{bmatrix} x_1 \\ \vdots \\ x_p \end{bmatrix}$ be a random vector.

Let $\vec{\mu}_1 = E[\vec{X} | \pi_1]$ and $\vec{\mu}_2 = E[\vec{X} | \pi_2]$

Assume that $\Sigma_1 = \Sigma_2 = \Sigma$ ⑧

Let Y be a random variable, $Y = \vec{l}' \vec{X}$

Fisher's approach: Find \vec{l} so that

$E[Y | \pi_1]$ and $E[Y | \pi_2]$ are as different as possible.

We maximize $\frac{(E[Y | \pi_1] - E[Y | \pi_2])^2}{\sigma_Y^2}$.

$$y = \vec{l}' \vec{x}$$

(9)

$$E[y | \pi_1] = E[\vec{l}' \vec{x} | \pi_1]$$

$$= \vec{l}' E[\vec{x} | \pi_1] = \vec{l}' \vec{\mu}_1$$

$$E[y | \pi_2] = \vec{l}' \vec{\mu}_2$$

$$\sigma_y^2 = \text{Var}(\vec{l}' \vec{x}) = \vec{l}' \Sigma \vec{l}$$

$$\frac{(\vec{l}' \vec{\mu}_1 - \vec{l}' \vec{\mu}_2)^2}{\vec{l}' \Sigma \vec{l}} = \frac{[\vec{l}' (\vec{\mu}_1 - \vec{\mu}_2)]^2}{\vec{l}' \Sigma \vec{l}}$$

$$= \frac{(\vec{l}' \vec{\delta})^2}{\vec{l}' \Sigma \vec{l}}$$

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Recall: $\max_{\vec{x} \neq \vec{0}} \frac{(\vec{x}' \vec{d})^2}{\vec{x}' B \vec{x}} = \vec{d}' B^{-1} \vec{d},$

achieved when $\vec{x} = c B^{-1} \vec{d}$

So the maximum is $\vec{\delta}' \Sigma^{-1} \vec{\delta}$, achieved
when $\vec{l} = c \Sigma^{-1} \vec{\delta}$

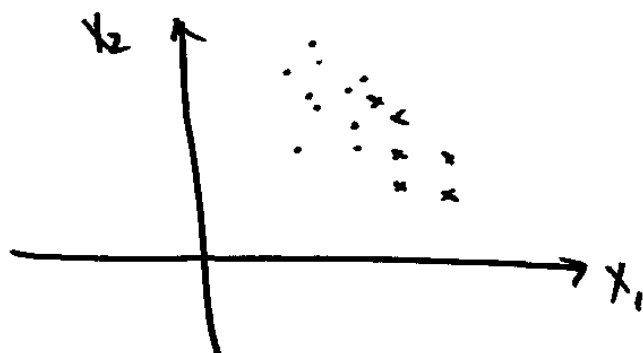
(11)

$$\text{Then } Y = \vec{\lambda}' \vec{X}$$

$$= c \vec{\delta}' \Sigma^{-1} \vec{X}$$

$$= c (\vec{\mu}_1 - \vec{\mu}_2)' \Sigma^{-1} \vec{X}$$

Defn: This is Fisher's Linear Discriminant Function



HW #7

#9.19(a,b)