STAT 3690 Lecture 26

zhiyanggeezhou.github.io

Zhiyang Zhou (zhiyang.zhou@umanitoba.ca)

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Factor scores

- Weighted least square (WLS) method
 - Given $\bar{\mathbf{Y}}$, $\hat{\mathbf{L}}$, and $\hat{\boldsymbol{\Psi}}$
 - For the *i*th observation \mathbf{Y}_i , to minimize $(\mathbf{Y}_i \bar{\mathbf{Y}} \widehat{\mathbf{L}}\mathbf{F})^{\top}\widehat{\mathbf{\Psi}}^{-1}(\mathbf{Y}_i \bar{\mathbf{Y}} \widehat{\mathbf{L}}\mathbf{F})$ with respect to \mathbf{F}
 - $\mathbf{F}_i = (\widehat{\mathbf{L}}^{\top}\widehat{\mathbf{\Psi}}^{-1}\widehat{\mathbf{L}})^{-1}\widehat{\mathbf{L}}^{\top}\widehat{\mathbf{\Psi}}^{-1}(\mathbf{Y}_i \bar{\mathbf{Y}})$

```
install.packages(c('psych'))
library(psych)
library(tidyverse)
options(digits = 4)
head(psych::bfi)
data = bfi %>%
  select(-gender, -education, -age) %>%
  filter(complete.cases(.)) # Remove demographic variable and keep complete data
decomp = psych::fa(r=data, covar=T, nfactors=q, rotate="varimax", fm="ml", scores='Bartlett')
# Follow formula
L_ml = decomp$loadings
Psi_ml = diag(decomp$uniquenesses)
Psi_ml_inv = diag(decomp$uniquenesses^-1)
Weight_mat = solve(t(L_ml) %*% Psi_ml_inv %*% L_ml) %*% t(L_ml) %*% Psi_ml_inv
scores_wls1 = scale(data, center = T, scale = F) %*% t(Weight_mat)
head(scores_wls1)
# P.S. the `scores` component of `psych::fa` is correct only when
# factoring correlation matrix/standardized data
scores_wls2 = decomp$scores
head(scores_wls2)
```

• Regression method

- Under normality $\mathbf{F} \sim MVN_p(\mathbf{0}, \mathbf{I})$ and $\mathbf{E} \sim MVN_p(\mathbf{0}, \mathbf{\Psi})$ * $[\mathbf{Y}^\top - \boldsymbol{\mu}^\top, \mathbf{F}^\top]^\top$ is of zero mean and normally distributed with covariance matrix

$$\left[\begin{array}{cc} \mathbf{L}\mathbf{L}^\top + \Psi & \mathbf{L} \\ \mathbf{L}^\top & \mathbf{I} \end{array}\right]$$

- * Hence $\mathbf{F} \mid \mathbf{Y}$ is normally distributed with mean $\mathbf{L}^{\top}(\mathbf{L}\mathbf{L}^{\top} + \mathbf{\Psi})^{-1}(\mathbf{Y} \boldsymbol{\mu})$ and covariance matrix $\mathbf{I} \mathbf{L}^{\top}(\mathbf{L}\mathbf{L}^{\top} + \mathbf{\Psi})^{-1}\mathbf{L}$
- Given $\bar{\mathbf{Y}}$, $\hat{\mathbf{L}}$, and $\hat{\mathbf{\Psi}}$,

$$\widehat{\mathbf{F}}_i = \widehat{\mathbf{L}}^{\top} (\widehat{\mathbf{L}} \widehat{\mathbf{L}}^{\top} + \widehat{\boldsymbol{\Psi}})^{-1} (\mathbf{Y}_i - \bar{\mathbf{Y}})$$

* Sometimes replace $\widehat{\mathbf{L}}\widehat{\mathbf{L}}^{\top} + \widehat{\boldsymbol{\Psi}}$ with \mathbf{S}

```
decomp = psych::fa(r=data, covar=T, nfactors=q, rotate="varimax", fm ="ml", scores='regression')

# Follow formula
L_ml = decomp$loadings
Psi_ml = diag(decomp$uniquenesses)
Weight_mat = t(L_ml) %*% solve(cov(data))
scores_reg1 = scale(data, center = T, scale = F) %*% t(Weight_mat)
head(scores_reg1)

# P.S. the `scores` component of `psych::fa` is correct only when
# factoring correlation matrix/standardized data
scores_reg2 = decomp$scores
head(scores_reg2)
```

- Comments on factor scores
 - More methods available
 - No uniformly superior way