Joint modelling of a multilevel factor analytic model and a multilevel covariance regression model

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Outline

- RN4CAST project and research questions
- Multilevel covariance regression (MCR) model
- Multilevel higher-order factor (MHOF) model
- Conclusions

The RN4CAST project

- Registered Nurse Forecasting (Sermeus et al., 2011)
- Nurse survey across Europe (2009-2011)
- 33,731 nurses, 2,169 nursing units, 486 hospitals and 12 countries
- Aim: Study the impact of system-level features of nursing care on nurse wellbeing and patient safety outcomes

Variables of interest

- Three dimensions of burnout
 - Emotional exhaustion (EE)
 - Depersonalization (**DP**)
 - Reduced personal accomplishment (PA)
- Measured using the 22-item Maslach Burnout Inventory
 - Q: "I feel emotionally drained from my work" (EE)
 - A: 0-never; 1-a few times a year or less; ...; 6-every day

Covariates

- Covariates of interest:
 - Nurse level: working experience (yrs), fulltime/part-time
 - Nursing unit level: work environment, size, surgical/medical, work load
 - Hospital level: teaching, technical, size
 - Country level: aggregated variables

Research questions

- **RQ 1**: Are the **means** of the three burnout dimensions correlated with the organizational-level and individual-level characteristics?
- RQ 2: Are the variances/correlations among the three burnout dimensions stable across hospitals, nursing units and nurses, after taking into account a rich set of confounders at different levels?
 - Original English-written questionnaire was translated into several languages
 - Might be some variability in interpreting the questions
 - Reflected by not only the mean of burnout, could be also the correlation of the the burnout dimensions

Proposed solutions

A multivariate multilevel model for

- The mean structure
- The covariance structure
- Different types of responses:
 - Sum scores with each dimension (continuous)
 - Multilevel covariance regression (MCR) (Li et al., 2014b)
 - The original 22 burnout items (ordinal)
 - Multilevel higher-order factor (MHOF) model (Li et al., 2014a)

MCR model: Specification

A 2-level MCR model:

 $m{y}_{ij} = m{B} m{x}_{ij} + m{u}_j + m{\delta}_{ij}, \qquad \longrightarrow \text{A random intercept model}$ $m{\delta}_{ij} = m{\lambda}_{ij} F_{ij} + m{\varepsilon}_{ij}, \ m{\lambda}_{ij} = m{B}^* m{x}_{ij}^* + m{u}_j^*, \longrightarrow \text{A factor model}$

$$\begin{aligned} \boldsymbol{u}_j &\sim N(\boldsymbol{0}, \boldsymbol{\Sigma}_u), \quad \boldsymbol{u}_j^* \sim N(\boldsymbol{0}, \boldsymbol{\Sigma}_u^*), \\ F_{ij} &\sim N(0, 1), \quad \boldsymbol{\varepsilon}_{ij} \sim N(\boldsymbol{0}, \boldsymbol{\Sigma}_{\varepsilon}) \end{aligned}$$

MCR model: Specification



MCR model: Implied marginal distribution

• The marginal covariance matrix of the responses is:

$$\Psi_{ij} = ({m B}^* {m x}_{ij}^* + {m u}_j^*) ({m B}^* {m x}_{ij}^* + {m u}_j^*)^T + \Sigma_{arepsilon}$$

- Both level covariates could be added
- The factor model guarantees a positive definite covariance matrix Ψ_{ij}
- Easy interpretation: Ψ_{ij} depends on covariates quadratically

MCR model: Implied marginal distribution

• Relationship between covariance/correlation and covariate



MCR model: Implied marginal distribution

- The marginal distribution of the response is not normal
- Skewness is zero if all random effects are independent
- (excess) Kurtosis is always non-negative
- The ability to handle heavy-tailed distributions

MCR model: Identification issues

- "Flipping states" issue in factor model
- More complex with random effects in the loadings
- Leads to biased estimates if not properly taken care of
- Solution: use mixture prior for the random loadings
- Mixture of two multivariate normal distributions

MCR model: Identification issues



MCR model for the RN4CAST study

• A 3-variate 4-level MCR model:

 $\begin{aligned} \boldsymbol{y}_{ijkl} &= \boldsymbol{B}\boldsymbol{x}_{ijkl} + \boldsymbol{u}_{jkl} + \boldsymbol{u}_{kl} + \boldsymbol{u}_l + \boldsymbol{\delta}_{ijkl} \\ \boldsymbol{\delta}_{ijkl} &= \boldsymbol{\lambda}_{ijkl}F_{ijkl} + \boldsymbol{\varepsilon}_{ijkl}, \quad \boldsymbol{\lambda}_{ijkl} &= \boldsymbol{B}^*\boldsymbol{x}_{ijkl}^* + \boldsymbol{u}_{jkl}^* + \boldsymbol{u}_{kl}^* + \boldsymbol{u}_l^* \end{aligned}$

$$\begin{split} \boldsymbol{u}_{jkl} &\sim N(\boldsymbol{0}, \Sigma_u), \quad \boldsymbol{u}_{kl} \sim N(\boldsymbol{0}, \Sigma_h), \quad \boldsymbol{u}_l \sim N(\boldsymbol{0}, \Sigma_c), \\ \boldsymbol{u}_{jkl}^* &\sim N(\boldsymbol{0}, \Sigma_u^*), \quad \boldsymbol{u}_{kl}^* \sim N(\boldsymbol{0}, \Sigma_h^*), \quad \boldsymbol{u}_l^* \sim N(\boldsymbol{0}, \Sigma_c^*), \\ F_{ijkl} &\sim N(0, 1), \quad \boldsymbol{\varepsilon}_{ijkl} \sim N(\boldsymbol{0}, \Sigma_\varepsilon) \end{split}$$

Computational aspects

- Bayesian approach (MCMC method) was used
 - Large number of random effects
 - Various distributions for the random effects
 - Various transformations of parameters
- JAGS through R packages rjags/dclone
- Model comparison: DIC and PSBF (Pseudo Bayes Factor)
- Convergence check: BGR plots and PSRF (Potential Scale Reduction Factor)
- Goodness of fit: PPC (Posterior Predictive Check) with χ^2 discrepancy function

MCR model: Main results

- Mean part of burnout:
 - Fulltime nurses ⇒ more burnout

 - Better work environment ⇒ less burnout
 - Heavier work load ⇒ more burnout

MCR model: Main results

- Covariance part of burnout:
 - Experienced nurses have a larger variance of burnout
 - Burnout feelings get pronounced over years
 - Random effects: variance of burnout differs across units
 - Measure the degree of equality of work load "harmonic burden"

Working on 22 items directly

- Burnout was originally measured through 22 items
- The three dimensions was proposed by Maslach and Jackson (1981) on different population
- These dimensions might change
- Alternative: model the original 22 items directly
- MCR not efficient to hand high-dimensional response
- A factor model to find the correct burnout dimensions (MFA)
- Jointly estimate the MFA and MCR MHOF model (Li et al., 2014a)

MFA model: Specification

- Find the latent factors underlying a group of variables in a multilevel context
- A two level MFA model is:

$$\begin{aligned} \boldsymbol{y}_{ij} &= \boldsymbol{\mu} + \boldsymbol{L}_B \boldsymbol{f}_j + \boldsymbol{u}_j + \boldsymbol{L}_W \boldsymbol{f}_{ij} + \boldsymbol{\varepsilon}_{ij}, \\ \boldsymbol{f}_j &\sim N(\boldsymbol{0}, \boldsymbol{\Sigma}_{fB}), \quad \boldsymbol{u}_j \sim N(\boldsymbol{0}, \boldsymbol{\Sigma}_u), \\ \boldsymbol{f}_{ij} &\sim N(\boldsymbol{0}, \boldsymbol{\Sigma}_{fW}), \quad \boldsymbol{\varepsilon}_{ij} \sim N(\boldsymbol{0}, \boldsymbol{\Sigma}_{\varepsilon}), \\ &i = 1, 2, ..., n_j; \ j = 1, 2, ..., k, \end{aligned}$$

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MFA model: Specification



MHOF model

- The MFA part:
 - Factor structure at the lowest level only
 - Estimate the whole covariance matrix at higher levels
- The MCR part:
 - Use the nurse-level factor scores as responses
 - Include covariates at each level

MHOF model: Specification

The MFA part :

$$\begin{split} \boldsymbol{y}_{ij} &= \boldsymbol{\mu} + \boldsymbol{b}_j + \boldsymbol{L} \boldsymbol{z}_{ij} + \boldsymbol{\varepsilon}_{ij}^{FA}, \\ \boldsymbol{b}_j &\sim N(\boldsymbol{0}, \boldsymbol{\Sigma}_u), \quad \boldsymbol{\varepsilon}_{ij}^{FA} \sim N(\boldsymbol{0}, diag(\sigma_1^2, \sigma_2^2, ... \sigma_p^2)) \end{split}$$

The MCR part :

$$oldsymbol{z}_{ij} = oldsymbol{B} oldsymbol{x}_{ij} + oldsymbol{\delta}_{ij},$$

 $oldsymbol{\delta}_{ij} = oldsymbol{\Lambda}_{ij} F_{ij} + oldsymbol{arepsilon}_{ij}^{CR}, \quad oldsymbol{\Lambda}_{ij} = oldsymbol{B}^* oldsymbol{x}_{ij}^* + oldsymbol{u}_j^*,$
 $oldsymbol{u}_j^* \sim N(oldsymbol{0}, \Sigma_u^*), \quad F_{ij} \sim N(0, 1), \quad oldsymbol{arepsilon}_{ij}^{CR} \sim N(oldsymbol{0}, \Sigma_arepsilon)$

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MHOF model: Specification



MHOF model: Identification issues

- All the cross loadings in the MFA part are estimated, but with informative priors (e.g. N(0, 0.05)) (BSEM, Muthén and Asparouhov (2012))
- Same as MCR model, mixture prior is applied to the factor loading parameters in the MCR part

MHOF model: Implied marginal distribution

- The MCR part of the MHOF model shares the same properties with the MCR model
- The lower-order factor scores have a non-normal distribution with zero skewness and non-zero kurtosis

Apply to the RN4CAST study

- Applied to Belgian part of RN4CAST study
 - 2809 nurses, 268 nursing units, 55 hospitals
- A 3-level MFA model based on 22 items and a 3-variate 3-level MCR model are jointly estimated
 - Quite similar findings as from the MCR model: Mean part and covariance part

Conclusions

- MCR model provides a novel way of modeling covariance matrix hierarchically
- Model both the mean and the covariances simultaneously
- MHOF model could handle high-dimensional data well
- It can be seen as a multilevel SEM, with a complex structural part not being done before
- Find "hidden" information:
 - Variance varies across unit, indicating different degrees of work load equality

Main references

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Thanks for your time!