Modelling of mixed type intensive longitudinal data via Semiparametric Gaussian Copula and its application to real-time mobile monitoring of daily health behaviours

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## **Electronic Diaries (EMA)**



- Real-time self-reports of mood, energy, stress, pain-level, anxiety, headache recorded through smartphones.
- Objectively recorded physical activity and sleep through smartwatches.
- Intensive longitudinal data.
- Different measurement scales (binary, ordinal, truncated, continuous, categorical).
- Differences in subjective interpretation of scales.



#### **NIMH Family Study**

- A nested case-control design of 499 adults with cases being subjects with different mood disorders.
- An actigraphy device worn on the nondominant wrist plus EMA 4 times per day for 2 weeks.



# **Trajectories of Energy (scale 1-7)**

4





# Case Study: Migraine

### Headache incidence Sleep, mood, medical history





History of mood/anxiety disorder History of migraine



Self-reported sleep quality (1-7) Actigraphy measured sleep duration Actigraphy measured sleep midpoint

Morning headache incidence

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Mood Anxiety Energy



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### **Time-dependent covariates**





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#### **Significant associations** Linear mixed effects model



Morning headache incidence



Anxiety (-) Energy (-)



# Challenges

- Self-reported mood/sleep variables need to be treated as ordinal variables rather than continuous.
- How can we tackle different subject-specific scales for EMA variables?
- Can we build a joint modeling framework for all our binary, ordinal and continuous variables?



# Semi-parametric Gaussian Copula

### Illustration



#### Latent

#### **Observed**



#### Semi-parametric Gaussian Copula/ Non-paranormal Distribution (NPN)

Observed variables are monotone transformations (f) of jointly standardized correlated normal latent variables  $(N_p(0, \Sigma))$ .

# **Generalized Latent NPN (GLNPN)**

Observed variables are truncated, categorized or binarized version of monotone transformations (f) of jointly standardized correlated normal latent variables  $(N_p(0, \Sigma))$ .



#### Joint model

- Time-points:  $t_1, t_2, \dots, t_m$
- Time-varying outcome (e.g. Mood):  $Y_i(t_1), \dots, Y_i(t_m)$
- Time-varying covariate (e.g. Physical activity):  $X_i(t_1), \dots, X_i(t_m)$
- $(Y_i(t_1), \dots, Y_i(t_m), X_i(t_1), \dots, X_i(t_m)) \sim GLNPN(0, \Sigma, f)$



# **Regression and PCA**

- Σ is assumed to be cross-correlation matrix from known functional covariance Kernels of Gaussian processes.
- Function-on-function Regression coefficients can be estimated from conditional distribution derived from the latent smooth correlation matrix.
- We can also perform functional PCA on the latent space for dimension reduction.



## Advantages

- Takes care of mixed type of variables representing subject-specific heterogeneous scales,
- Identifies within-day patterns of mode-specific and domain-specific behavioral measures;
- Evaluates cross-domain inter-relationships to characterize mode-specific and multi-modal dynamic behavioral phenotypes,
- Develops individualized prediction models for dynamic prediction of adverse short-term health and behavioral events.



# THANK YOU!

