technische universität
dortmund

New Methods for Statistical Learning

Andreas Groll

June 16^{th} 2020

Dortmund Data Science Center
Department of Statistics

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- Diploma (2007) in Business Mathematics (LMU Munich)

Research interests (general)

- Methods for variable selection and regularization, in particular in Generalized Linear/Additive (Mixed) Models and time-to-event data analysis
- Modeling of categorical data
- Semiparametric regression
- Sports Statistics, in particular modeling and prediction of international football tournaments

Effects selection in Cox frailty models

Cox frailty model with time-varying coefficients:

$$\lambda(t|\boldsymbol{x}_{ij}, \boldsymbol{z}_{ij}, \boldsymbol{u}_{ij}, \boldsymbol{b}_i) = \lambda_0(t) \exp\left(\boldsymbol{x}_{ij}^T\boldsymbol{\beta} + \sum_{k=1}^{r} z_{ijk}\gamma_k(t) + \boldsymbol{u}_{ij}^T\boldsymbol{b}_i,\right)$$

with covariates $z_{ij1}, \dots, z_{ijr}$ being associated with time-varying effects.

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Estimation: expand time-varying effects $\gamma_k(t)$ in B-splines:

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- Classical variable selection via LASSO
- Effects selection of potential time-varying coefficients via L_1-penalization
- Effects selection of potential time-varying coefficients via boosting

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1. A good (ML) model is fitted on `iris` data
2. Labels are predicted for all observations
3. The value of the feature *Petal.Width* is raised by a very small amount for all observations
4. New labels are predicted for the manipulated data
5. Changes found are interpreted as "classes modeled next to each other" and visualized

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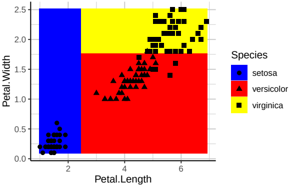

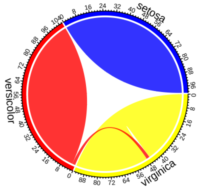

Penalized Joint Regression Modeling

Bivariate count obervations (y_1, y_2) and marginal regressions:

- $\hat{y}_1 = \exp(\beta_0^{(1)} + \beta_1^{(1)} x_1^{(1)} + \ldots + \beta_p^{(1)} x_p^{(1)})$
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With dependency between y_1 and y_2 taken into account via Copulae C

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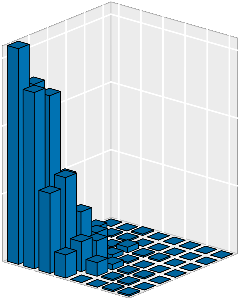
New: Penalization for competitive settings

- $\ell_p(\boldsymbol{\beta}) = \ell(\boldsymbol{\beta}) - \frac{1}{2}\xi \sum_{j=0}^{p} \omega_j \left(\beta_j^{(1)} - \beta_j^{(2)}\right)^2$



$\Longrightarrow$ Probabilities for football scores (y_1, y_2) and interpretable coefficients

Regularization in complex regression settings

1. Causal inference using Distributional Regression with instrumental variables.
   - Causal effects of treatments on various distributional quantities, e.g. expectation, variance, coefficient of variation.
   - Data-driven variable selection via gradient-based-boosting.

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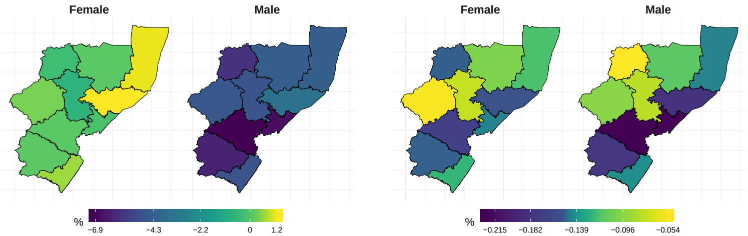

Effect of electricity on mean (left) and standard deviation (right) on employment rates.

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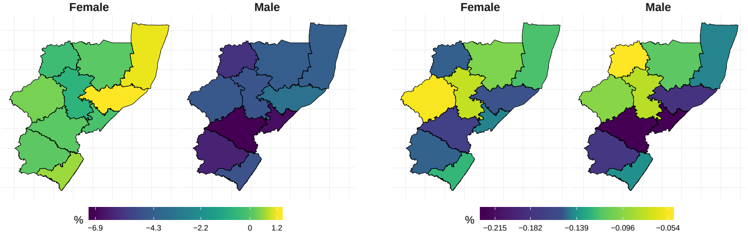

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2. Regularized bivariate mixed binary-continuous copula regression.
   - Joint modeling of e.g. match winner and match duration in tennis.

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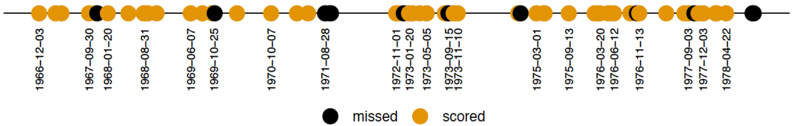

Example data – penalties taken by Gerd Müller

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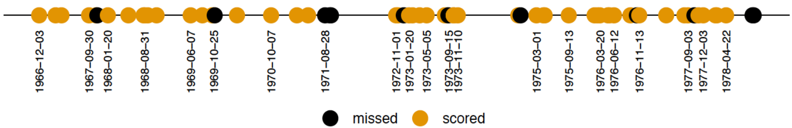

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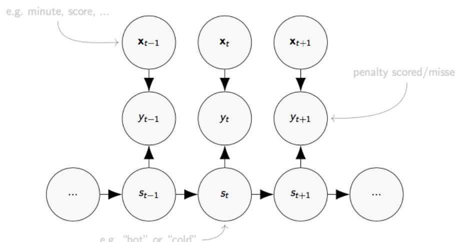

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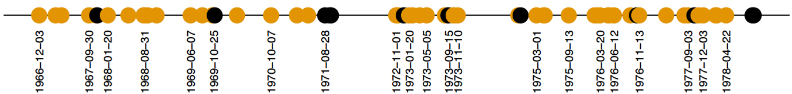

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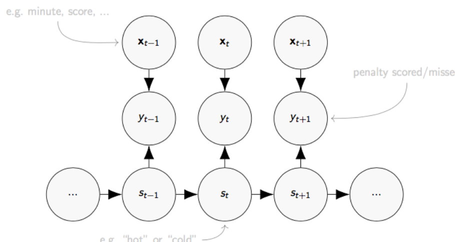

- Planned: Analysis on “hot glove” effect

Current grant proposals

- Gemeinsamer Bundesausschuss Innovationsausschuss: PREMISE (ongoing)
- Marie-Curie ITN: S-TRAINING (recently rejected; currently under revision)
- 2 DFG Research Training Groups:
  - Biostatistical methods for high-dimensional data in toxicology (submitted)
  - Domain knowledge in the data-driven sciences from basic research to industrial applications (submitted)

Planned grant proposals

- 2 DFG Research Units
- DFG Individual Research Grant
- DFG Collaborative Research Centre

References

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