Project description

Rico Krueger

Filipe Rodrigues

DTU Management Engineering
Department of Management Engineering

Outline

- Rules
- Important dates
- Peer feedback and project evaluation
- Common mistakes, misconceptions and advice
- Great projects from last year
- Take-away ideas

work with one problem in depth, not many problems superficial

Rules

- Topic is **free** (creativity highly encouraged!)
- No constraints on the dataset
- If in doubt, talk with us!
- We also provide some suggestions for projects

Important dates

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- 31 March - Milestone report (in groups, mandatory)
  - Project outline (1-2 pages):
    - Dataset and research question(s)
    - First draft of model(s) that you plan to try out (PGM + generative process)
  - Initial notebook (descriptive stats, data preparation) can be revised later
  - Save notebook as PDF and append to project outline.
  - Submit one PDF to the peer feedback platform (we will provide more details soon).

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- 22 May - Final delivery (in groups)
  - Fully self-explanatory notebook
  - 5-10 page report (incl. figures and tables)

Peer feedback and project evaluatione

- Peer feedback
  - We will use peergrade.io to organise the peer feedback.
  - Each group makes one submission.
  - Everyone provides feedback on two milestone reports (individually)
  - Provide fair, respectful, caring and constructive feedback to your peers.
  - Consider the grading rubric for the final evaluation of the project when giving feedback.
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- Project evaluation
  - We provide a detailed grading rubric on DTU Learn. Please read it carefully.

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  - Consider for example: Intelligence $\rightarrow$ Course grade $\rightarrow$ Recommendation letter
  - If course grade is always observed, then it blocks the path between intelligence and recommendation letter. Therefore, "Intelligence $\rightarrow$ Course grade" and "Course grade $\rightarrow$ Recommendation letter" become two independent models.
  - There is no point estimating them jointly because there is no flow of information between the two (unless there is an alternative path, of course...)

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  - There is no point estimating them jointly because there is no flow of information between the two (unless there is an alternative path, of course. . .)
- Don't just think about what variables depend on other variables, and their distribution types. Think also of how you should model those dependencies (e.g. how to condition the parameters of a Beta distribution on another variable?)

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- Use ancestral sampling to generate artificial data, and run inference on the model using Pyro/STAN to see if it is able to recover the true values/parameters that were used to generate the data. This is a great way of guarantying that the model is correctly implemented, and that inference is working correctly

2019 proj.: Analysis group membership in Social Networks I

- Graph data of human interaction is called social networks. The interaction could for example being friends on Facebook or talking to each other.
- The project inferred groups in social networks based on Game Of Thrones. Take a look at the data here https://github.com/mathbeveridge/gameofthrones
- Tried different models. Results below is from a Mixed membership stochastic block model - MMSBM.

2019 proj.: Analysis group membership in Social Networks II

1. For $n = 1..N$
   1. draw $\boldsymbol{\pi}_n \sim \text{Dirichlet}(\boldsymbol{\alpha})$
2. For $k, k' = \{1, 2, \ldots, K\} \times \{1, 2, \ldots, K\}$ where $k \neq k'$
   1. draw $\lambda_{k,k'} \sim \text{Gamma}(a, b)$
3. For k in $1..K$
   1. draw $\lambda_{k,k} \sim \text{Gamma}(c, d)$
4. For all pairs $i, j \in \{1, 2, ...N\} \times \{1, 2, ...N\}$ where $i \neq j$
   1. $x_{i,j} \sim \text{Poisson}(\boldsymbol{\pi}_i^T \lambda \boldsymbol{\pi}_j)$;

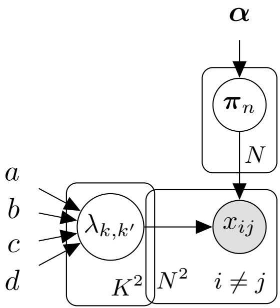


Figure: PGM for Mixed membership stochastic block model

2019 proj.: Analysis group membership in Social Networks III

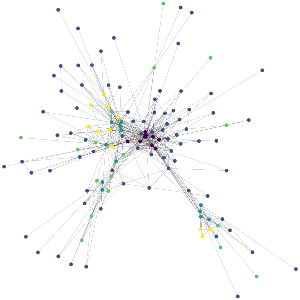


Figure: Each node is a GoT character from season 5. Colors indicate one of 5 inferred groups.

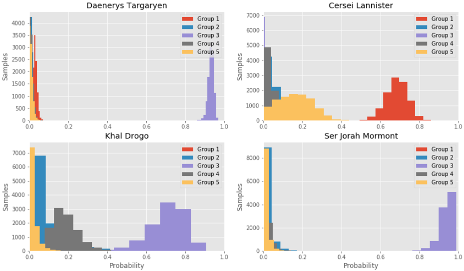


Figure: The histogram shows posterior probabilities of belonging to one of 5 groups for 4 main characters of GoT

2019 project: Bayesian semi-parametric soccer analysis

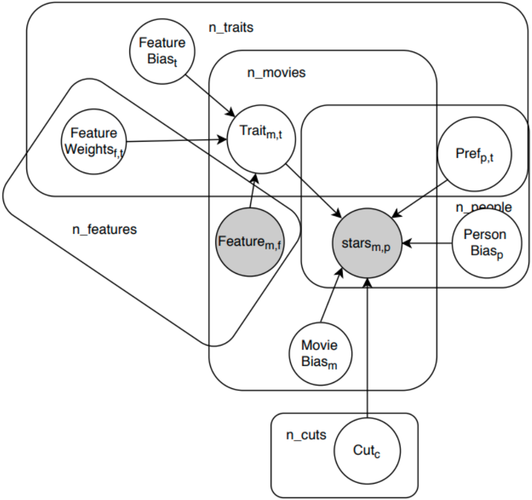
- Apply the time-to-event analysis methods to analyze the intensity with which goal scoring occurs in soccer matches
- Tried different time-to-event models from the class of Cox proportional hazards models and extend these to incorporate non-linear effects by use of the highly flexible Gaussian processes from the Bayesian non-parametrics toolbox
- The hazard in the i-th match at time interval j is

$$\lambda_{ij} = \lambda_j \exp(\beta_1 * skill\_gap + \beta_2(t) * x\_goal)$$

- Baseline of Cox model is a GP: $\log \lambda_0 \sim \mathcal{GP}(\mathbf{0}, K(t, t'))$
- Implemented everything in STAN and did a very good experimental evaluation

2019 project: Movie recommendations - MovieLens dataset

- Inspired by the example in Bishop's "Model-based Machine Learning" book, but with a good mix of creativity, lots of experimentation and insightful discussions



EV charging demand prediction incorporating demand diffusion

- Demand diffusion: Propagation of customers to different charging stations when the capacity of the desired station is met
- Bayesian autoregressive model with latent propagation process to predict EV charging demand
- Comparison with two other models: Without censoring or propagation variable

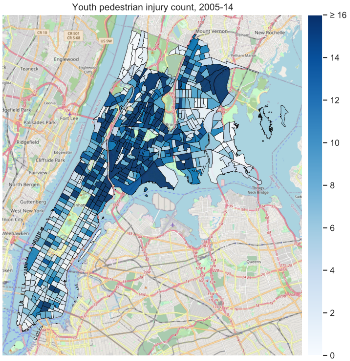
EV charging demand prediction incorporating demand diffusion

1. Draw propagation probability $p_{i,j} \sim$ Dirichlet(α) with α being a proximity measure
2. For each charging station i:
   1. Draw transition coefficient $\beta_i \sim N\left(0,1\right)$
   2. Draw standard deviation $\sigma_i \sim HalfCauchy(0.1)$
   3. Draw demand for initial time step $y_i^0 \sim N\left(\mu,1\right)$
   4. Calculate censored demand $y_i^{*0} = \min(Cap_i, y_i^0)$
3. Draw coefficients $\tau \sim N\left(\mathbf{0},\mathbf{1}\right)$
4. For each charging station i:
   1. For each time step t:
      1. Draw non-censored demand:
      $$\mathbf{y_i^t} \sim N\left(\beta_i y_i^{t-1} + \tau X_i^t + \sum_{j!=i} p_{i,j}(y_j^{t-1} - y_j^{*t-1}), \sigma_i^2\right)$$
5. Calculate censored demand ${y_i}^{*t} = \min(Cap_i, y_i^t)$

Kaggle datasets

- Find a cool/crazy dataset on Kaggle - e.g. Avocado Prices (`https://www.kaggle.com/neuromusic/avocado-prices`)
- Formulate a research question(s) - e.g. how do the temporal dynamics of price change across regions
- Propose a PGM to model the data based on domain knowledge and assumptions of research question - e.g. hierarchical temporal model
- Fit model, extract results, revise model and data, propose model extensions, formulate new research questions... and iterate...

Bayesian Spatial Count Models



- For each area i, the observed count y_i follows a Negative Binomial distribution

$$y_i \sim \text{NB}(r, p_i), \qquad \text{(likelihood)}$$

$$p_i = \frac{\exp(\psi_i)}{1 + \psi_i}, \qquad \text{(link function)}$$

$$\psi = \boldsymbol{\beta}^T \mathbf{X}_i + \phi_i, \qquad \text{(linear function of inputs } \mathbf{X}_i\text{)}$$

where $\mathbf{X}_i$ are the characteristics of the area and ϕ_i is a correlated error term

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- **Research topic 1**: How to have non-linear dependencies on inputs $\mathbf{X}_i$?
  - Neural networks?
  - Hierarchical modelling?

[1] Reference: `https://arxiv.org/abs/2007.03681`

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- **Research topic 1**: How to have non-linear dependencies on inputs $\mathbf{X}_i$?
  - Neural networks?
  - Hierarchical modelling?
- **Research topic 2**: How to capture spatial correlations between areas?
  - Capture correlations through the noise term?[1]

$$\exp(\tau \mathbf{W})\boldsymbol{\phi} \sim \mathcal{N}(0, \sigma^2 \mathbf{I})$$

  - Neural networks? E.g., convolutions or graph convolution neural nets?

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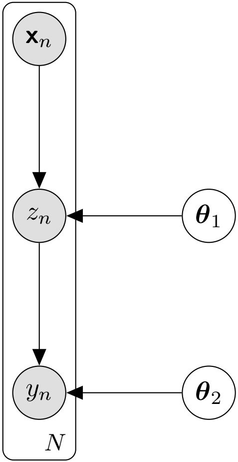
Do Bayesian Neural Networks Need To Be Fully Stochastic?

- Bayesian neural network is a very active area of research
- Generative process
  1. Draw NN parameters $\boldsymbol{\theta} \sim \mathcal{N}(\boldsymbol{\theta}|\mathbf{0}, \tau\mathbf{I})$
  2. For the n^{th} observation
     a. Draw target $y_n \sim \mathcal{N}(y_n|f_{\text{nnet}}(\mathbf{u}_n), \sigma^2)$
- But do they need to be fully stochastic[2]?
- **Research Ideas**:
  - ... can we only keep a fraction of θ_1 stochastic?
  - ... how do these work with time series?
  - ... analyse the Bayesian approach to neural networks.
-



[2] https://arxiv.org/pdf/2211.06291.pdf