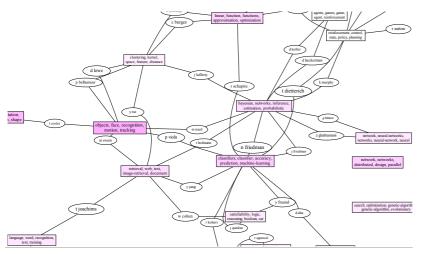
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Table 1: Example of authors and their topic preference learned by the CNTM



Colloquium

Faculty of Computer Science, HSE

Wray Buntine

Monash University

Learning on networks of distributions for discrete data

I will motivate the talk by reviewing some state of the art models for problems like matrix factorisation models for link prediction and tweet clustering. Then I will review the classes of distributions that can be strung together in networks to generate discrete data. This allows a rich class of models that, in its simplest form, covers things like Poisson matrix factorisation, Latent Dirichlet allocation, and Stochastic block models, but, more generally, covers complex hierarchical models on network and text data. The distributions covered include so-called non-parametric distributions such as the Gamma process. Accompanying these are a set of collapsing and augmentation techniques that are used to generate fast Gibbs samplers for many models in this class. To complete this picture, turning complex network models into fast Gibbs samplers, I will illustrate our recent methods of doing matrix factorisation with side information (e.g., GloVe word embeddings), done for link prediction, for instance, for citation networks.

September 11, 18.10–19.30 Kochnovskii proezd, 3, room 317 Register at computerscience@hse.ru

