Latent Community Detection for Predicting Legislative Roll Call Votes

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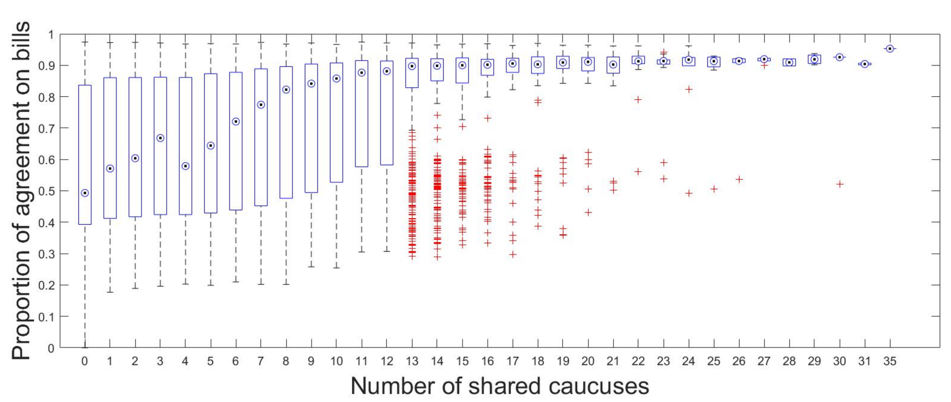
Objectives

We analyze voting data in the 110th Congress (2007-2009) House of Representatives. The ideal point model was extended to incorporate caucus membership data via a stochastic block model. In doing so, we aim to

- Use caucus membership data to infer latent communities among members
- Exploit this community structure to inform estimates for each representative's ideal point
- Predict a representative's voting behavior

Motivation

We chose to model caucus membership because we found that caucus memberships influence legislative behavior. For example, the more caucuses two legislators share, the more likely they are to vote the same way on a bill.



Moreover, representing interactions among members of the House using an undirected graphical model, we found that subgraphs corresponding to caucuses were denser than the graph of the whole House.

Model

Our model assumes each bill d and representative u has a hidden ideal point $a_d, b_d, x_u \in \mathbb{R}^S$, where S is a free parameter. We also assume the representatives belong to K latent communities.

- Sample community proportions $\pi \sim \text{Dir}(\gamma 1_K)$ and each community's ideal point $\nu_k \sim \mathcal{N}(\varpi, \sigma_\nu^2)$.
- Draw representative u's community $M_u \overset{\text{iid}}{\sim} \text{Cat}(\pi)$ and ideal point $x_u \mid M_u = k, \nu \sim \mathcal{N}(\nu_k, \sigma_x^2)$.
- Draw coexpression rates $P_{kl} \overset{\text{iid}}{\sim} \text{Gamma}(\lambda_0, \lambda_1)$.
- Observe the number of common caucuses $R_{uv} \mid P, M_u = k, M_v = l \sim \text{Poisson}(P_{kl})$.
- Draw a discrimination $a_d \sim \mathcal{N}(\eta_a, \sigma_d^2)$ and a difficulty $b_d \sim \mathcal{N}(\eta_b, \sigma_d^2)$ for each bill d.
- Observe the votes $V_{ud} \mid x_u, a_d, b_d \sim \text{Bern}(\sigma(a_d \cdot (x_u - b_d)))$.

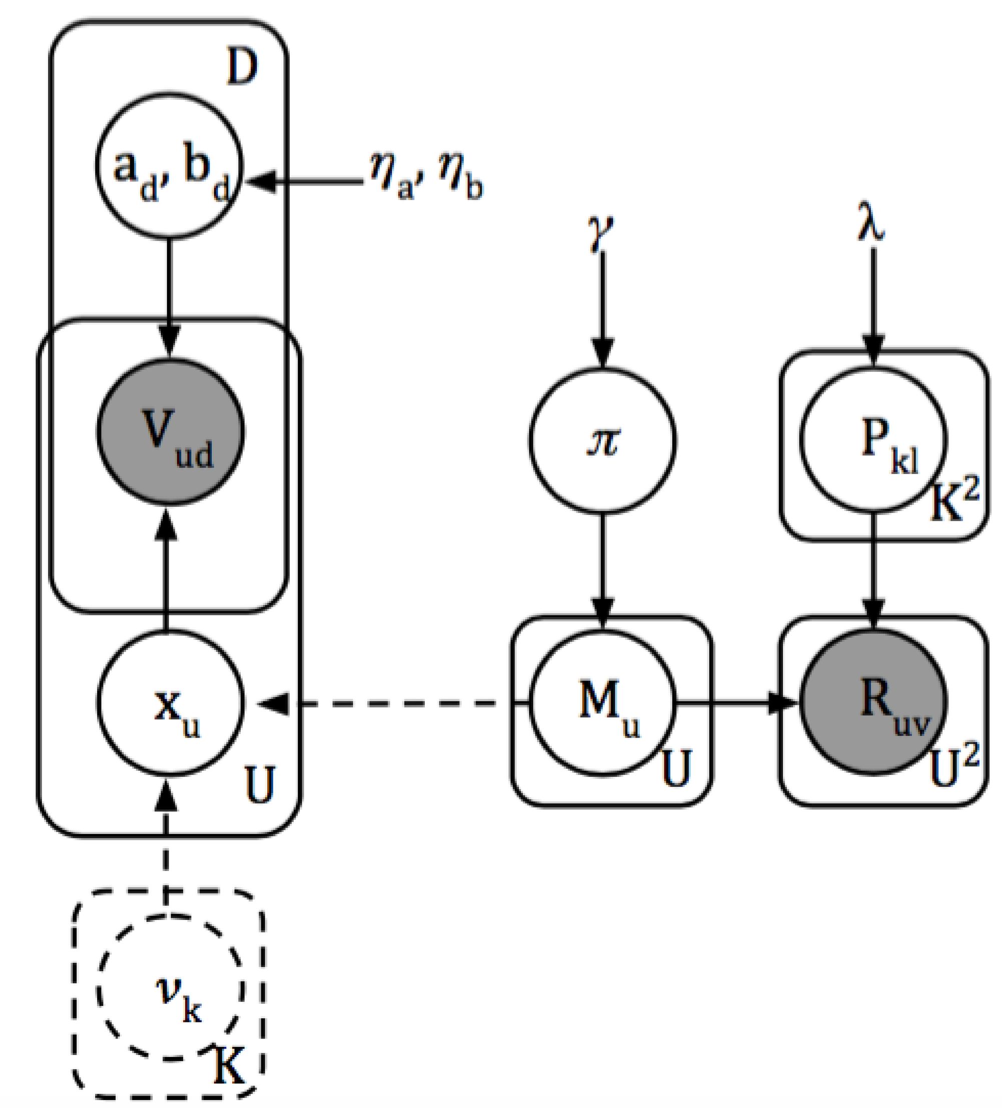


Figure: model depiction of Latent Community Ideal Point Model (LC-IPM)

Results

Variational Inference

Upon observing vote behavior $V = (V_{ud})$ and caucuses $R = (R_{uv})$, computing the posterior distribution of the latent variables given the observations is intractable. We employ *mean field variational inference*, finding the distribution q which factorizes over the latent variables closest in KL divergence to the posterior. Since the graphical model for LC-IPM joins SBM and IPM via one edge, this composabiity and the mean field factorization implies that variational updates for π, P, a_d, and b_d do not change from their respective updates in SBM and IPM, and we exploited this modularity in our implementation.

Conclusion

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Model	Acc	AUC
Logistic Reg	78.340295	85.10542
IPM ($S = 1$)	94.768623	98.418436
IPM ($S = 2$)	95.451139	98.997592
LC-IPM ($S = 2, K = 2$)	95.40514	99.013

Future Directions

By incorporating caucus data, we were able to place more informative priors on the representatives ideal points. On the other hand, we may also wish to place similarly informed priors on a bill's difficulty and discrimination. Following the example of Gerrish and Blei 2011, one may apply *supervised topic modeling* and infer the latent topics in a bill from a bill's text; these latent topics then generate a bill's difficulty and discrimination.

References

[1] Wainwright, M. J. & Jordan, M. I. (2008). Graphical models, exponential families, and variational inference. *Foundations and Trends in Machine Learning*.