Hierarchical Latent Space Models for Social Network Analysis

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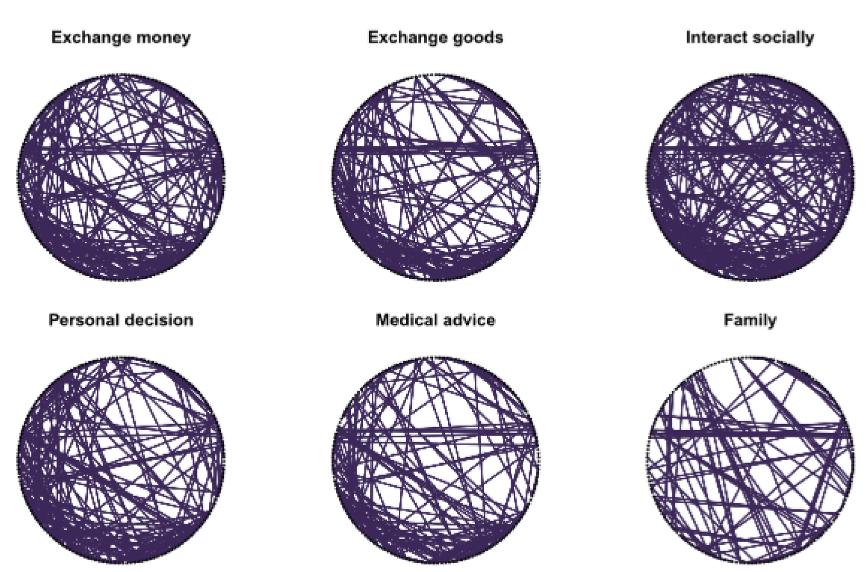
Introduction

Multigraphs: "Parallel" network models sharing identical nodes but different edges connecting nodes, used to model data where actors (nodes) maintain varying types of relationships.

Social Network Analysis (SNA), where nodes represent individual people and edges represent differing relationships, such as friendship, professional colleague, or facebook connected, for example.

Problem: Social science and network analysis rely on intuitive and interpretable models. Interpreting a graph with many nodes and differing, but related edges, is challenging.



Solution: Using a LASSO penalty, we aim to collapse sufficiently similar graphs subject to a tuning parameter.

Employee Relationships Data

Recently conducted study at a charter school in West Baltimore

Collecteda five-layer valued network between the approximately eighty employees of the school:

- Frequency of interaction
- Discussing Academics
- Discussing Behavior
- Social interaction
- Professionally Helpful Relationship

While empirically these layers are found to have very high correlations, modeling them in a way that demonstrates those correlations is challenging.

Latent Space Projection

- Map nodes, $i \mapsto z_i \in \mathbb{R}^n$ where proximity, $\|z_i - z_j\|_2 = d_{ij} < 1$, indicates nodes are connected (and not connected otherwise)
- Makes reciprocity $(j \to i \Rightarrow i \to j)$ and transitivity $(i \to j, j \to k \Rightarrow i \to k)$ probable
- Given $\sigma_{ij} = \mathbb{P}(Y_{ij} = 1 | z_i, z_j) = \text{logit}^{-1}\left(\alpha + \|z_i - z_j\|_2^2\right)$ where $Y_{ij} = 1$ indicates i, j are connected in the data, find z
- Likelihood:
$$\prod_{i<j} \sigma_{ij}^{y_{ij}} (1 - \sigma_{ij})^{1 - y_{ij}}$$

Hierarchical Models

Goal: Collapse similar networks

We include a group-wise LASSO penalty on the log-likelihood:

$$\sum_k \sum_{i<j} [y_{ijk} \ln \sigma_{ijk} + (1 - y_{ijk}) \ln(1 - \sigma_{ijk})] + \lambda \sum_i \sum_k \|\epsilon_{ik}\|_1$$

where $z_{ik} = b_i + \epsilon_{ik}$ for initialization points randomized but near the origin

Optimization Approaches:

1. Proximal Gradient Descent
2. Coordinate-Wise Optimization
3. Hamiltonian Monte Carlo methods (for comparison)

Takeaway

Convex methods have valuable contributions for fitting complex Latent Space Models, and their extensions

Model's Advantages

Our model has the additional inclusion of a hierarchy on the latent variables:

$$z_{ik} = b_i + \epsilon_{ik}$$

each node has a separate latent position to explain its ties within a single layer of the multigraph, but these multiple positions are all tied together by a single "base" position for that node b_i, and a layer-specific perturbation, ϵ_{ik}.

This allows two major advantages. One is graph-wise regularization with a group lasso penalty, allowing entire redundant layers to be removed for meaningful dimensionality reduction. Second, regularization allows a manual tuning between layouts that are expressive, and those that are comparable, solving the difficult problem of visual comparability.

Results

Figure 1: Figure caption

Nunc tempus venenatis facilisis. Curabitur suscipit consequat eros non porttitor. Sed a massa dolor, id ornare enim:

Treatments	Response 1	Response 2
Treatment 1	0.0003262	0.562
Treatment 2	0.0015681	0.910
Treatment 3	0.0009271	0.296

Table 1: Table caption

Challenges

- Negative log-likelihood is not convex in the positions
  Fix: We started from various random initializations
- Distances between positions will yield same likelihood under translations and rotation
  Fix: All initializations started near zero so that they only became as complex as necessary

Conclusion

We found that proximal gradient methods are an effective tool for refining an HLSM fit, given a good starting point.

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