Modeling Dynamic Behavior in Large Evolving Graphs

Ryan A. Rossi, Brian Gallagher, Jennifer Neville, Keith Henderson
Modeling Dynamic Graphs

1. **Identify** dynamic patterns in node behavior
   - Evolving mixed-role memberships
   - Role contributions

2. **Predict** future structural changes
   - Transition from star to clique

3. **Detect** unusual transitions in behavior
**Dynamic Behavioral Mixed-Membership (DBMM) Model**

The **DBMM model is**: (1) Scalable for **BIG** graphs  (2) Easily parallelizable  
(3) Non-parametric & data-driven  (4) Flexible and interpretable

1. Compute set of features
2. Estimate the features on each snapshot graph
3. Learn roles from features using NMF, number of roles selected via MDL
4. Extract roles from each feature matrix over time
5. Use NMF to estimate transition model
Given $G_{t-1}$ and $G_t$ find a transition model $T$ that minimizes the functional:

$$f(G_t, G_{t-1}) = \frac{1}{2}||G_t - G_{t-1} T||_F^2$$

All models predict $G_{t+1}$ using $G_t$ as $G'_{t+1} = G_t T$

**Summary model:** Weight training examples from $k$ previous timesteps

**Baseline models:** Predict future role based on

1. previous role
2. average role distribution

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*DBMM is more accurate at predicting future behavior than baselines*
Dynamic Network Analysis with Roles

Roles exhibit many of the traditional time-series patterns

Roles are interpretable

Fit role-model to matrix of network statistics:

$$G_t E_t \approx M_t$$
Anomalous Structural Transitions

**Problem:** detect nodes with unusual structural transitions

**Anomaly score:**
1. Estimate transition model $T$ for $v$
2. Use it to predict $v$’s memberships
3. Take the difference from actual

*DBMM model finds nodes that are anomalous for only short time-periods*

Inject anomalies into synthetic data:
Detected 88.5% over 200 repeated trials