Dynamic Non-negative Matrix Factorization for Role Analytics in Temporal Social Networks

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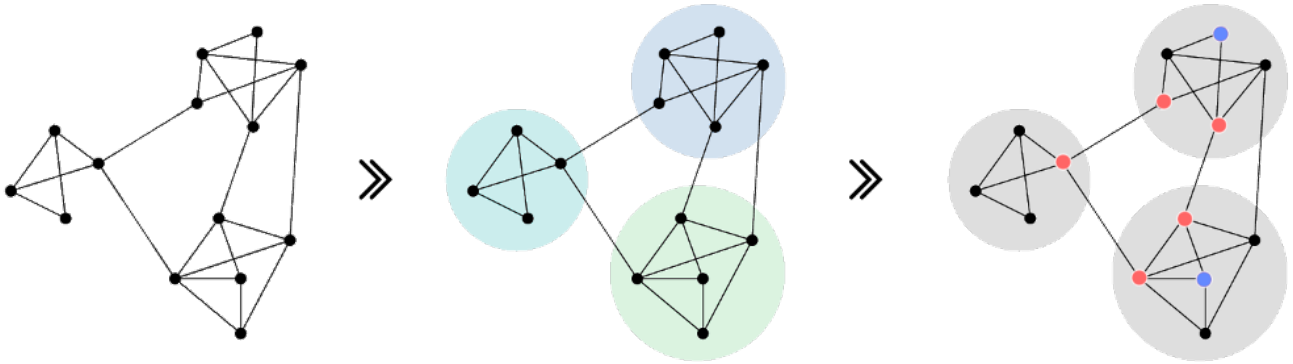
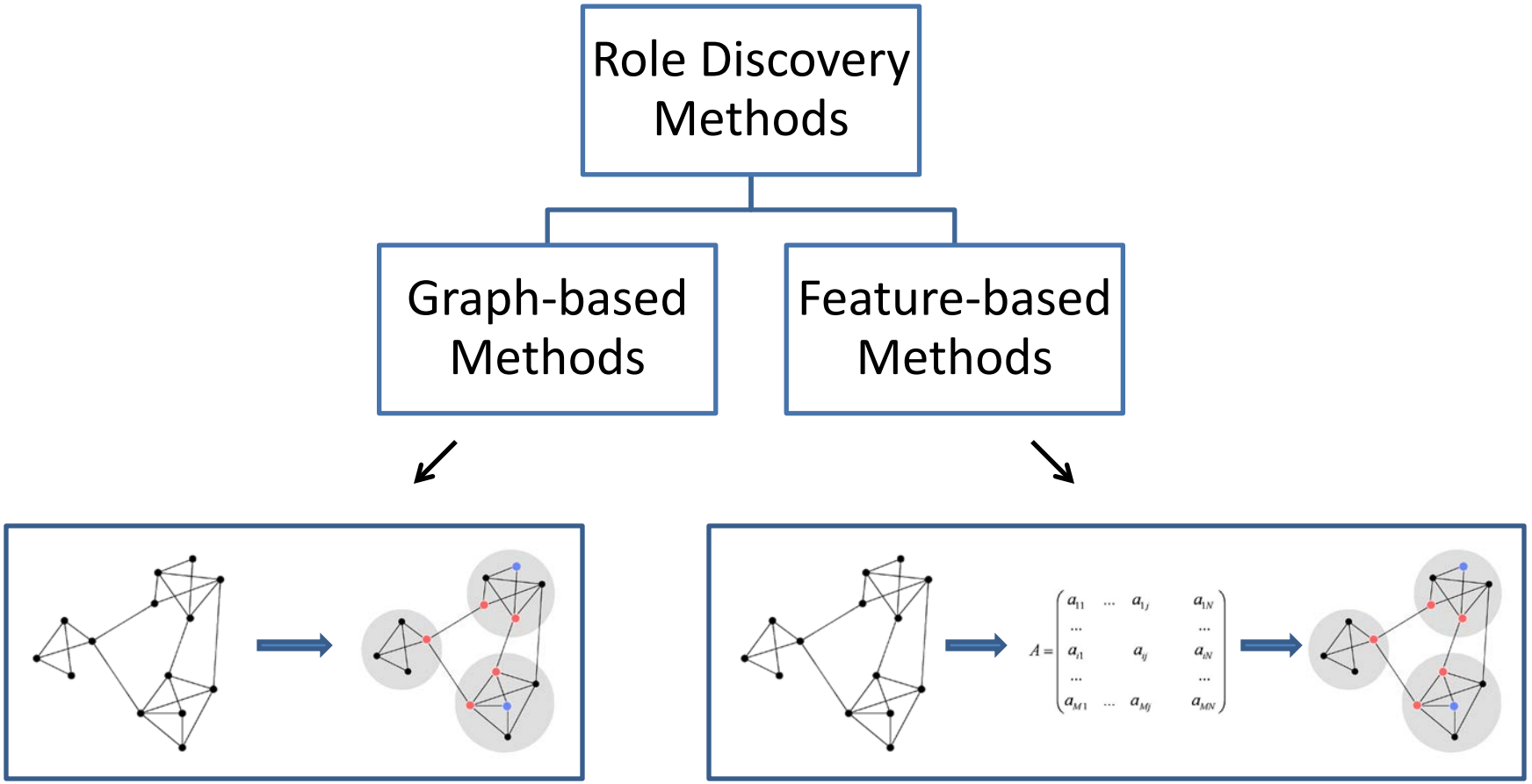
Role: Beyond Community

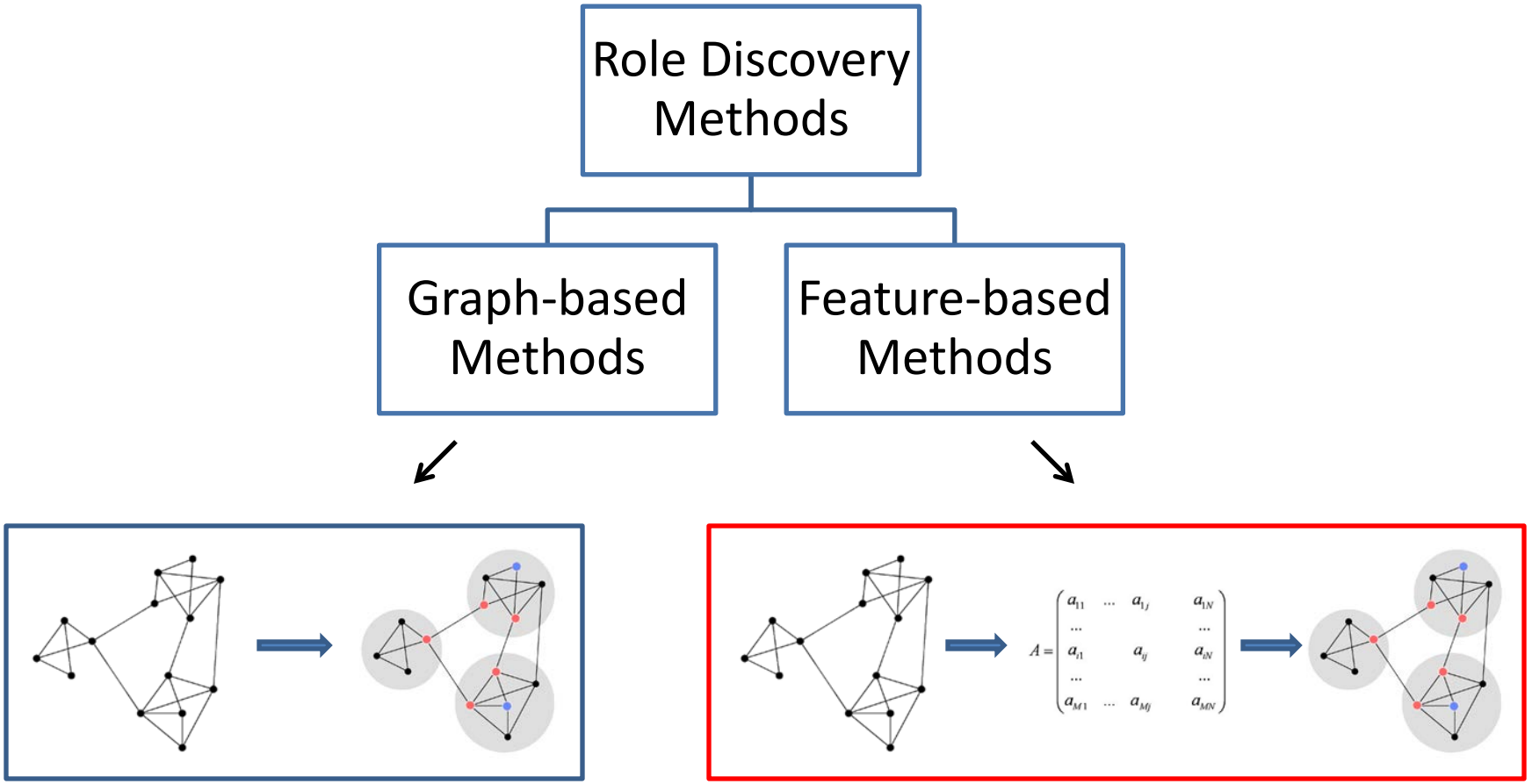


- Roles of nodes in a social network represent their **functions** and are characterized by their **structured behaviors**.
- Role discovery can be defined as the process that takes a graph and picks out sets of nodes with similar structural patterns

Methods for Role Discovery



Methods for Role Discovery



Dynamic non-negative matrix factorization (DyNMF)

- RolX
  - Given node-feature matrix V_{n*f} (n is the number of nodes and f is the number of features)
  - RolX aims to generate rank r approximation $GF=V$ (r is the number of roles, G_{n*r}: role indicator matrix, F_{r*f}: association of roles and features)

$$\min_{G,F} \|V - GF\|_F^2, \quad s.t.\ G \geq 0, F \geq 0$$

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  - Work in static graphs

Dynamic non-negative matrix factorization (DyNMF)

- Dynamic Behavioral Mixed-Role Model (DBMM)
  - Step 1: discover roles in each snapshot using RolX

$$\min_{G^{(t)},F^{(t)}} \|V^{(t)} - G^{(t)}F^{(t)}\|_F^2$$

  - Step 2: analyze role transitions based on discovered roles from Step 1

$$G^{(t-1)}M^{(t-1)} = G^{(t)}$$

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$$G^{(t-1)}M^{(t-1)} = G^{(t)}$$

  - Analyzing role transition after role discovery

Dynamic non-negative matrix factorization (DyNMF)

- Simultaneously discover roles and learn role transitions.
- Combine two views:
  - current view: capture the structural information for current snapshot
  - historical view: capture role transition and roles for previous snapshots

Dynamic non-negative matrix factorization (DyNMF)

Current view

$$\min_{G^{(t)},F^{(t)}} \|V^{(t)} - G^{(t)}F^{(t)}\|_F^2$$

Dynamic non-negative matrix factorization (DyNMF)

Current view

$$\min_{G^{(t)},F^{(t)}} \|V^{(t)} - G^{(t)}F^{(t)}\|_F^2$$

node-feature matrix

Dynamic non-negative matrix factorization (DyNMF)

Current view

$$\min_{G^{(t)},F^{(t)}} \|V^{(t)} - G^{(t)}F^{(t)}\|_F^2$$

node-feature matrix

role-feature association matrix

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$$\min_{G^{(t)},F^{(t)}} \|V^{(t)} - G^{(t)}F^{(t)}\|_F^2$$

node-feature matrix

role indicator matrix

role-feature association matrix

Dynamic non-negative matrix factorization (DyNMF)

Current view

$$\min_{G^{(t)},F^{(t)}} \|V^{(t)} - G^{(t)}F^{(t)}\|_F^2$$

node-feature matrix

role indicator matrix

role-feature association matrix

This part is same as RolX for current snapshot *(t)*.

Dynamic non-negative matrix factorization (DyNMF)

Historical view

$$\min_{F^{(t)},M^{(t)}} \|V^{(t)} - G^{(t-1)}M^{(t)}F^{(t)}\|_F^2$$

node-feature matrix

role-feature association matrix

Dynamic non-negative matrix factorization (DyNMF)

Historical view

$$\min_{F^{(t)},M^{(t)}} \|V^{(t)} - G^{(t-1)} M^{(t)} F^{(t)}\|_F^2$$

node-feature matrix

role indicator matrix from last snapshot *(t-1)*

role-feature association matrix

Dynamic non-negative matrix factorization (DyNMF)

Historical view

$$\min_{F^{(t)},M^{(t)}} \|V^{(t)} - G^{(t-1)} M^{(t)} F^{(t)}\|_F^2$$

node-feature matrix

role indicator matrix from last snapshot *(t-1)*

role transition matrix from snapshot *(t-1)* to *(t)*

role-feature association matrix

Dynamic non-negative matrix factorization (DyNMF)

Historical view

$$\min_{F^{(t)},M^{(t)}} \|V^{(t)} - G^{(t-1)} M^{(t)} F^{(t)}\|_F^2$$

node-feature matrix

role indicator matrix from last snapshot *(t-1)*

role transition matrix from snapshot *(t-1)* to *(t)*

role-feature association matrix

This part captures role transition and information from previous roles.

Dynamic non-negative matrix factorization (DyNMF)

Current view

$$\min_{G^{(t)},F^{(t)}} \|V^{(t)} - G^{(t)}F^{(t)}\|_F^2$$

Historical view

$$\min_{F^{(t)},M^{(t)}} \|V^{(t)} - G^{(t-1)}M^{(t)}F^{(t)}\|_F^2$$

$$\begin{aligned}\min_{G^{(t)},F^{(t)},M^{(t)}} L = & \min_{G^{(t)},F^{(t)},M^{(t)}} \|V^{(t)} - G^{(t)}F^{(t)}\|_F^2 \\ & + \|V^{(t)} - G^{(t-1)}M^{(t)}F^{(t)}\|_F^2 \\ & s.t.\ G^{(t)} \geq 0, F^{(t)} \geq 0, M^{(t)} \geq 0.\end{aligned}$$

Experiments

- Datasets

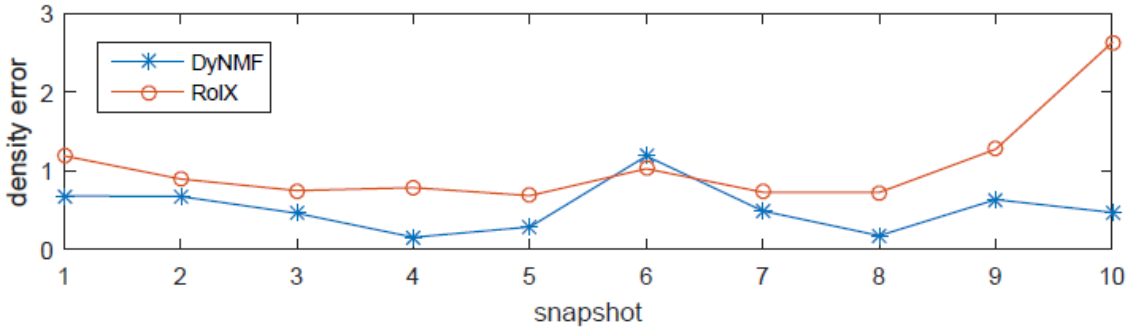
Data set	# Nodes	# Edges	# Roles	# Snapshots	Length
Enron	147	1666	7	9	9 months
Reality	6809	9467	11	10	4 months
Facebook	44416	196414	12	12	1 year
Slashdot	51068	130324	11	12	2 years

* The number of roles are determined by Minimum Description Length (MDL).

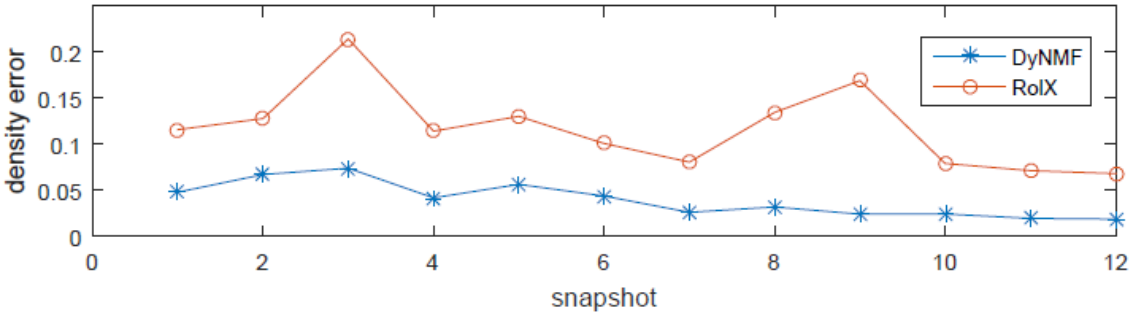
Experiments

- **Role discovery analysis**: analyze the performance of role discovery using *goodness-of-fit* indices as the measure.
- **Role identification analysis**: interpret the meaning of discovered roles by analyzing the average measures including *Degree*, *Betweenness*, *PageRank* and *HITS*.
- **Role transition analysis**: verify the role transition by calculating the trace of the role transition matrices.
- **Role prediction analysis**: another way to validate the effectiveness of the role transition by predicting roles based on previous roles and role transition.

Experiments: Role discovery analysis

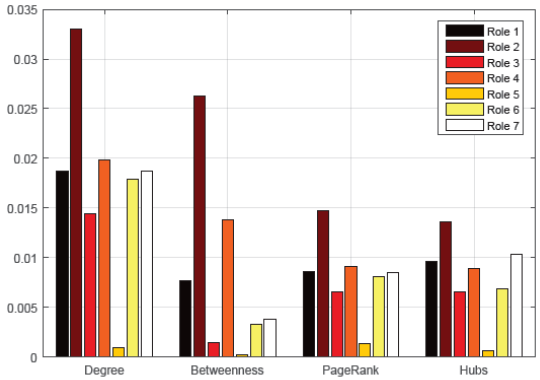


(a) Individual density error in Reality data set.

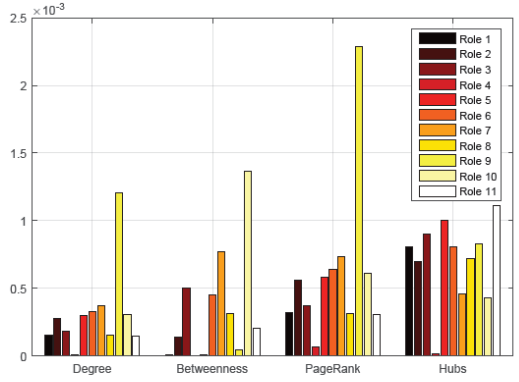


(b) Individual density error in Facebook data set.

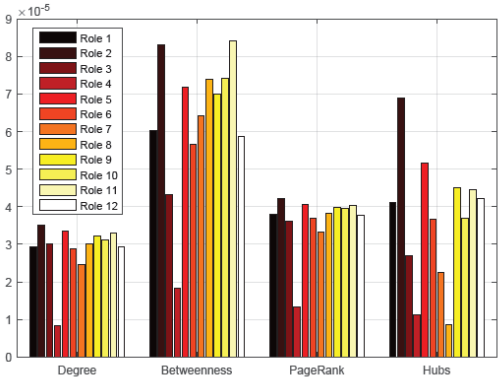
Experiments: Role identification analysis



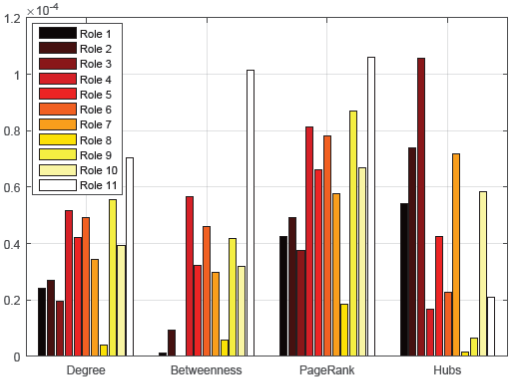
(a) Enron data set



(b) Reality data set

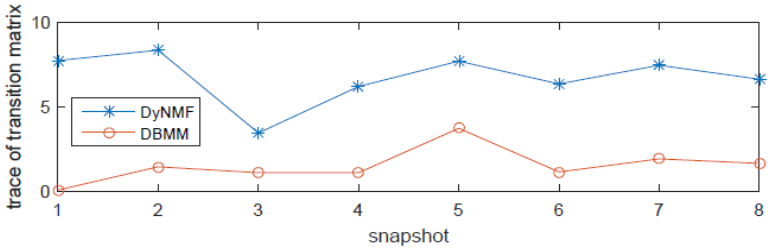


(c) Facebook data set



(d) Slashdot data set

Experiments: Role transition analysis



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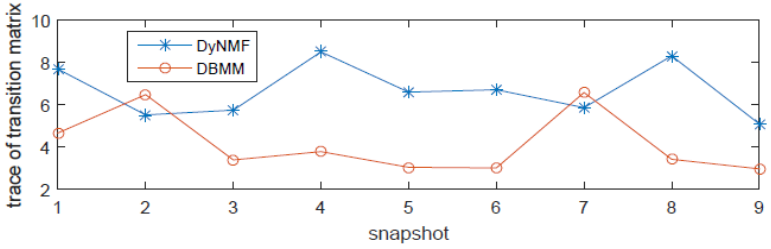

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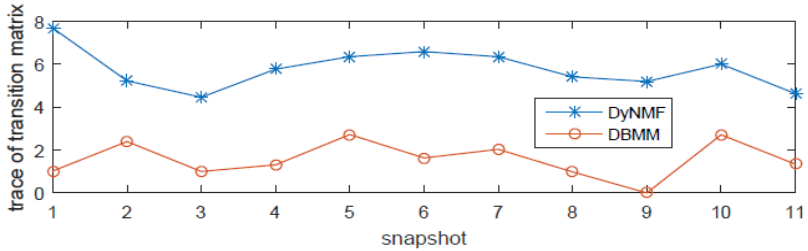
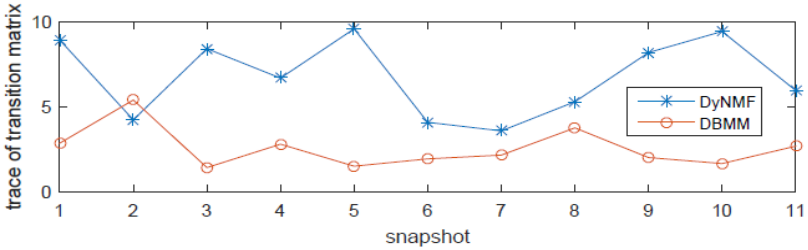


(c) Facebook data set



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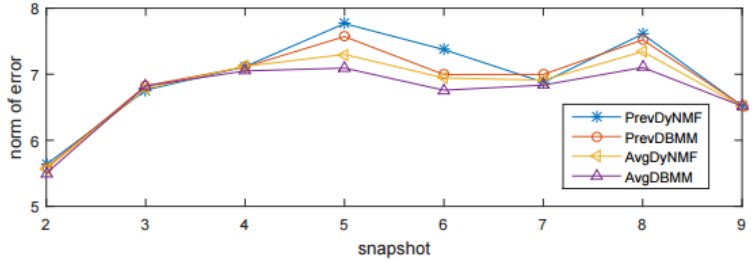

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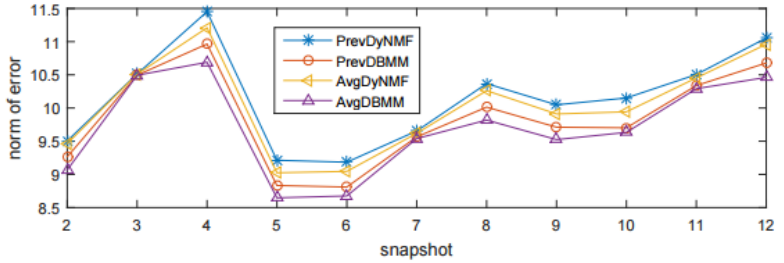
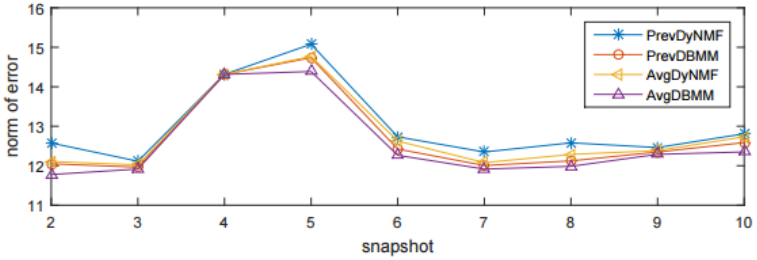


(c) Facebook data set



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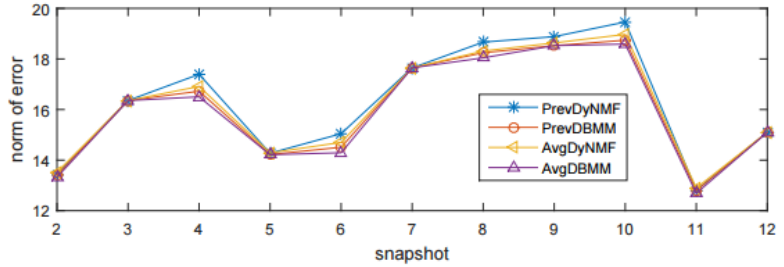

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Conclusions

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  - DyNMF approach can discover roles and role transitions simultaneously in dynamic networks.
  - Experiments validate the performance of the proposed DyNMF method in role discovery and role transition learning.
- Future Work
  - New feature extraction method
  - Role identification/transition analysis

Thanks for your attention!

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