

Tracking Groups in Mobile Network Traces

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Presented by Gayane Vardoyan

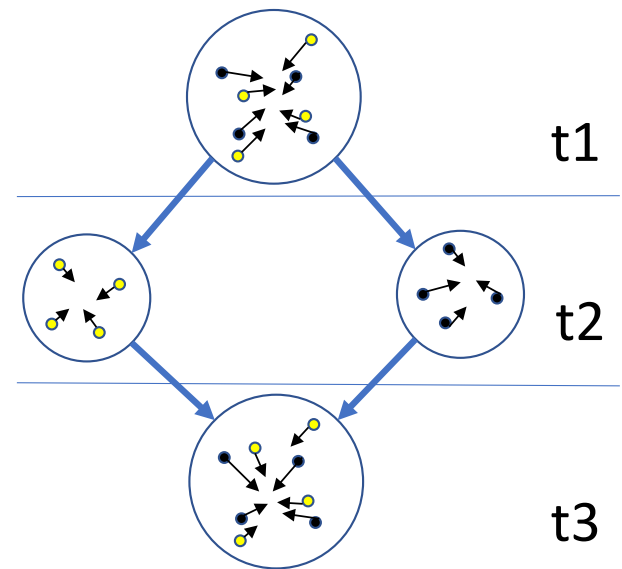
Groups in Mobile Network Trace

- Most mobility models assume independent movements
- Several ad hoc mobility models
 - Random direction, waypoint model
 - Leader based group models

Q: what is a realistic group mobility model?

Answering question requires obtaining group information from mobility data

How to do so – focus of talk

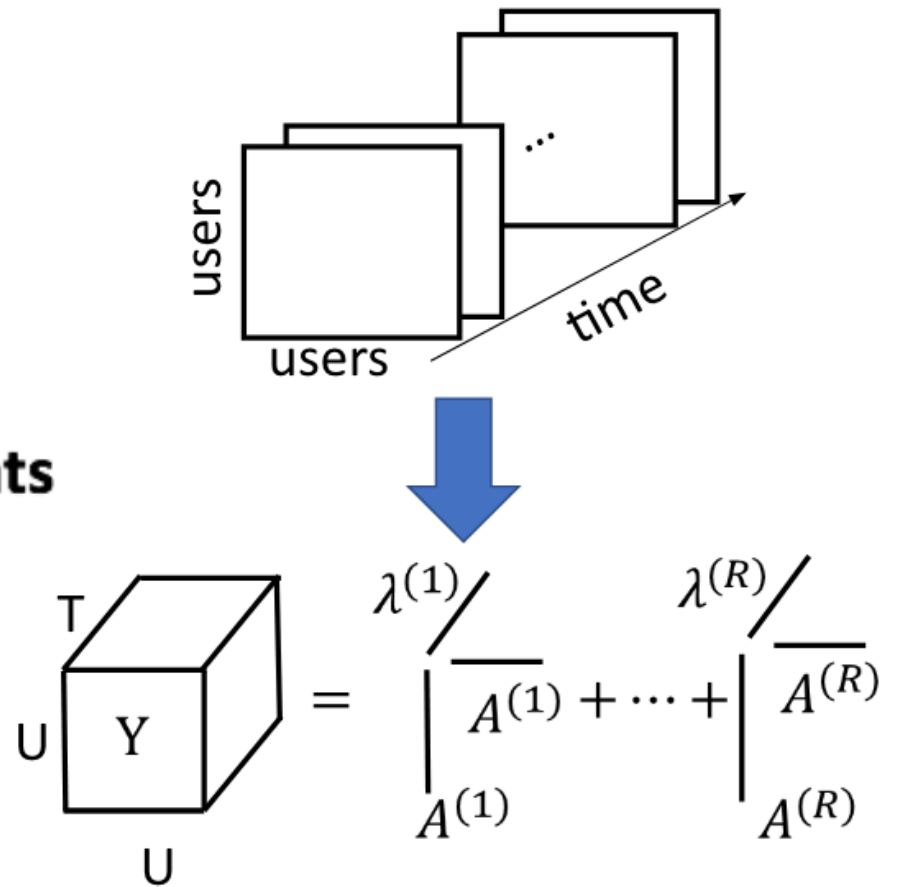


Outline

- Model and problem formulation
- Tensor decomposition
- Extracting group information from tensor components
- Experiments
- Conclusion

Idea

- Represent dataset as 3-D tensor, Y
 - Snapshots over time
 - Snapshot: adjacency matrix, Euclidean distances
- Decompose tensor into R components
- From component r
 - Identify groups from $A^{(r)}$
 - Identify group formation, dissolution times from $\lambda^{(r)}$



Challenges

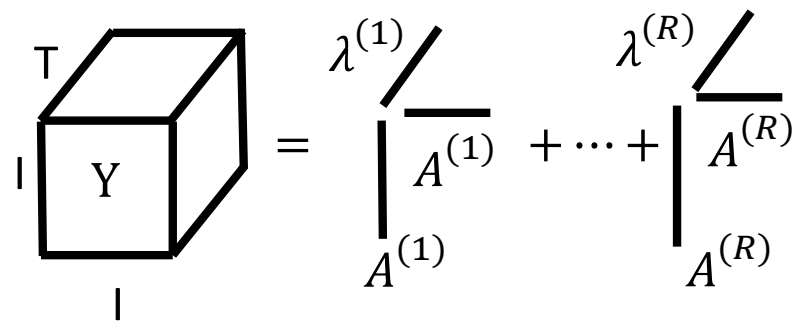
- Time granularity of snapshots
 - Fine time scale: sparse snapshot, difficult for group detection
 - Coarse time scale: loss of detailed changes, resulting in high error for lifetime detection
- Tracking changes in groups
 - creation/dissolution
 - changes in group composition
 - membership in multiple groups

Our model

- Tensor $\mathbf{Y} = [Y_{ijt}]$, Y_{ijt} - closeness of user i to user j at time t

- Approximate Y_{ijt} by R components

$$\hat{Y}_{ijt} = \sum_{r=1}^R a_{ir} a_{jr} \lambda^{(r)}(t)$$



$$\mathbf{Y} = \lambda^{(1)} \begin{matrix} \diagup \\ \text{---} A^{(1)} \\ \text{---} A^{(1)} \end{matrix} + \dots + \lambda^{(R)} \begin{matrix} \diagup \\ \text{---} A^{(R)} \\ \text{---} A^{(R)} \end{matrix}$$

- $a_{ir} \in A^{(r)}$: probability of user i in component r
- $\lambda^{(r)}$: time series representing node similarities at different time steps

Our Model

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- Approximate Y_{ijt} by R components

$$\hat{Y}_{ijt} = \sum_{r=1}^R a_{ir} a_{jr} \lambda^{(r)}(t)$$

$$Y = \lambda^{(1)} A^{(1)} A^{(1)} + \dots + \lambda^{(R)} A^{(R)} A^{(R)}$$

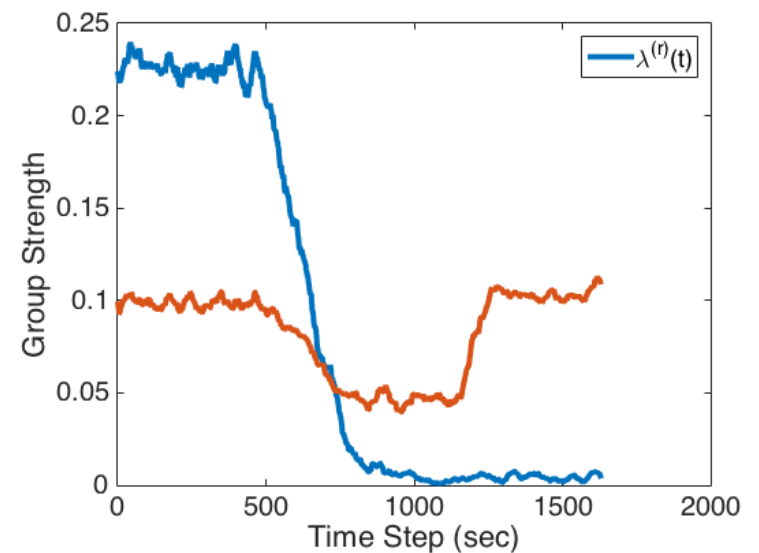
- $a_{ir}, \lambda^{(r)}(t)$ obtained from minimizing

$$\sum_{i,j \in V} \sum_t (Y_{ijt} - \sum_r a_{ir} a_{jr} \lambda^{(r)}(t))^2$$

- Use alternating least squares algorithm to solve
 - gradient descent method to compute a_{ir} and $\lambda^{(r)}(t)$ iteratively

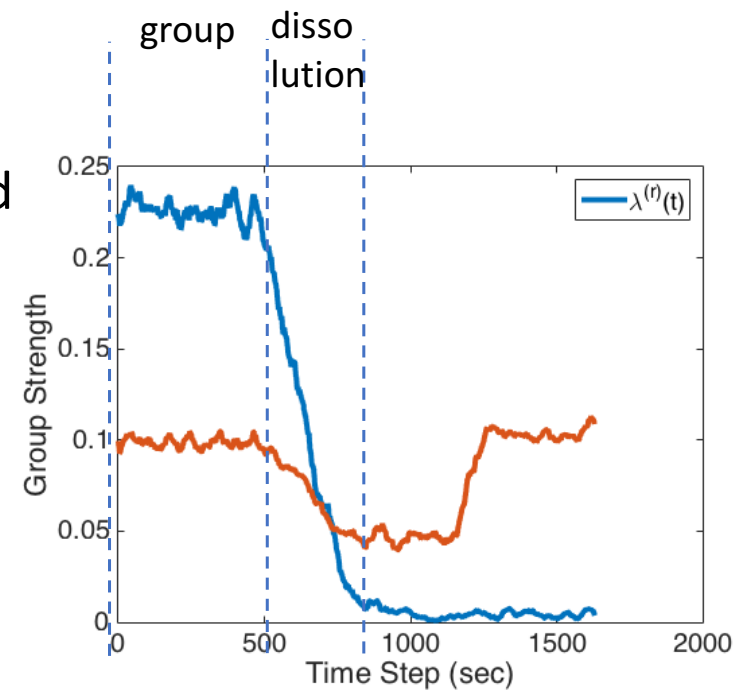
Interpretation

- Use K -means to find group(s) in $A^{(r)} = [a_{ir}]$
 - silhouette clustering criterion used to choose number of groups
- Temporal mode $\lambda^{(r)}(t)$ represents strength of group
- When R chosen properly, one meaningful group per component
- If not, can order groups according to strength using similarity ordering score



Group Lifetime Detection

- $\lambda^{(r)}(t)$ as a time series
- Compare against adaptive threshold based on average similarity
 - above – formation of group
 - below – no group
- Can detect formation, dissolution times

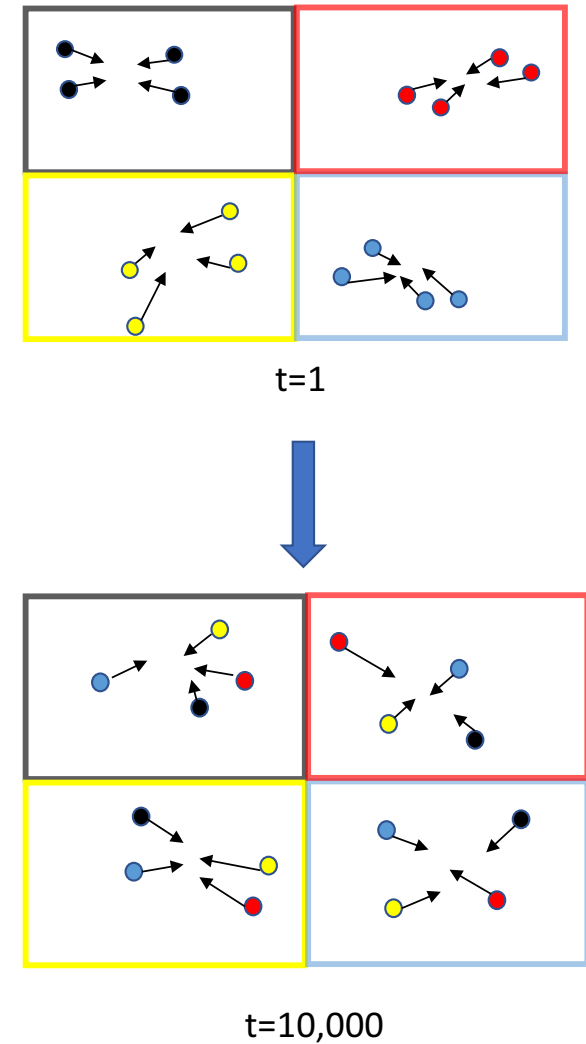


Experiments

- Synthetic datasets
- Lakehurst dataset
 - Military training exercise

Synthetic Dataset

- 400 nodes in 4 initial groups move according to random direction model (RD) for 10,000 seconds
- Each group divides into 4 subgroups, subgroups move to different areas, form new groups
- 1000 repetitions, different parameter settings



Group member detection

- \hat{C}_k : set of members in k -th detected group
- C_k^* : set of members in ground truth group mapped to \hat{C}_k using Jaccard index (intersection of two sets over their union)
- Precision: $P = \frac{|\hat{C}_k \cap C_k^*|}{|\hat{C}_k|}$
- Recall: $R = \frac{|\hat{C}_k \cap C_k^*|}{|C_k^*|}$
- F1 score: $F_1 = \frac{2PR}{P+R}$
- Precision Recall Curve (PR-curve): evaluate precision of methods when recall is similar
- Similar metrics for group lifetime: F1 score

Baseline methods:

Evolutionary Clustering (EC) (Deepayan et al., 2006)

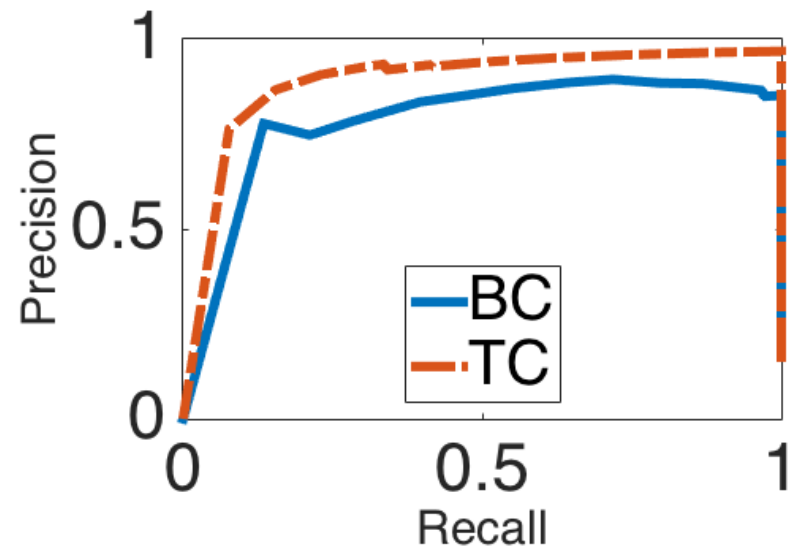
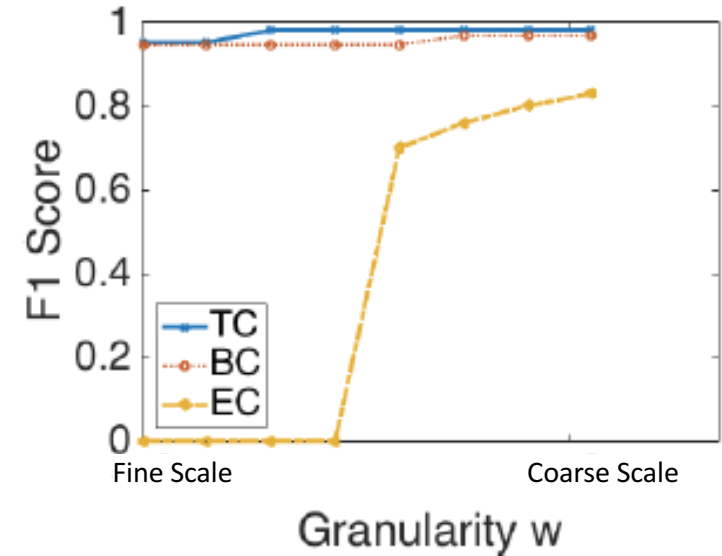
- Clustering on each network snapshot
 - Pros: fast
 - Cons: fails in multi-membership, sparse network, tracking cluster changes

Binary clustering (BC) (Laetitia et al., 2014)

- Detect cluster on tensor factorization result with fixed threshold
 - Pros: work for multi-membership, sparse network, tracking lifetime
 - Cons: difficulty in fine tuning # groups leads to high detection error

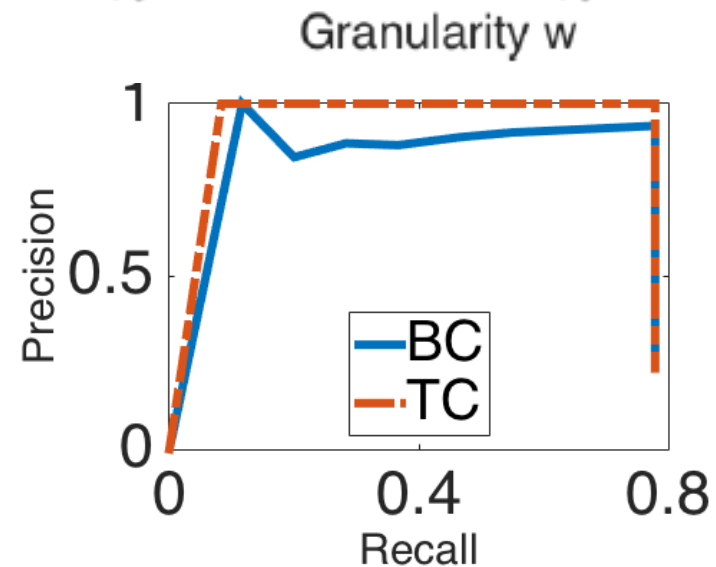
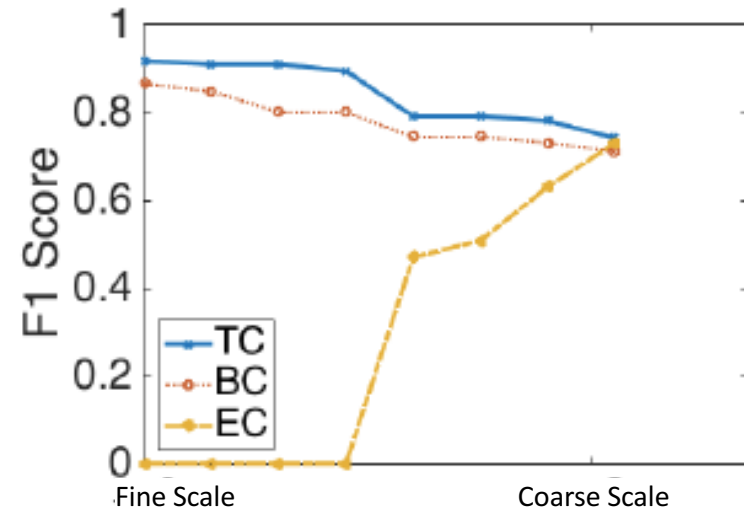
Group Member Detection

- Effect of time granularity (w)
 - Proposed method temporal clustering (TC) and BC robust to time granularity
 - EC works poorly with fine granularity
- TC has better precision than BC given same recall



Lifetime Detection

- Coarse granularity
 - reduces accuracy of TC, BC
 - improves EC performance because of increased accuracy in member detection
- TC has better precision than BC given same recall



Summary for synthetic data

- Our temporal clustering method (TC)
 - Is robust to change in time granularity in member detection
 - Performs as well as BC and better than EC

Lakehurst Military Dataset

- Three hour trace, 70 vehicles
- 64 vehicles split into 9 platoons
- Another six vehicles move separately
- Platoons combine to form large group from time to time
- 19 groups total



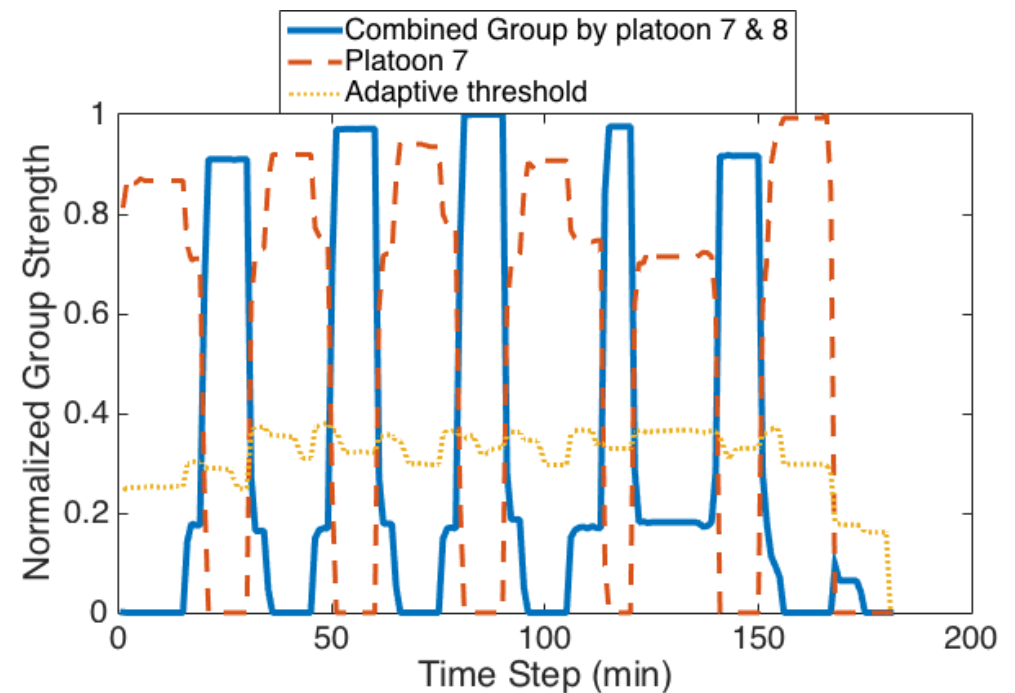
Lakehurst dataset Results

- TC performs as well or better than other methods
- Large R improves recalls for TC and BC

# component (R)	10	15	20	25	30
TC Group Recall	0.368	0.421	0.587	0.895	1.0
BC Group Recall	0.319	0.421	0.579	0.895	1.0
TC Member Recall	0.430	0.541	0.841	0.875	0.904
BC Member Recall	0.430	0.532	0.841	0.862	0.904
EC Group Recall	0.474				
EC Member Recall	0.275				

Group Lifetime Behavior

- Lifetime tracking for a group
 - Formed by platoon 7 and platoon 8 who meet at multiple waypoints
 - Formation & dissolution with time series segmentation algorithm
 - Detect lifetime using adaptive threshold (average similarity of nodes of whole network)
- Tensor time mode facilitates lifetime identification



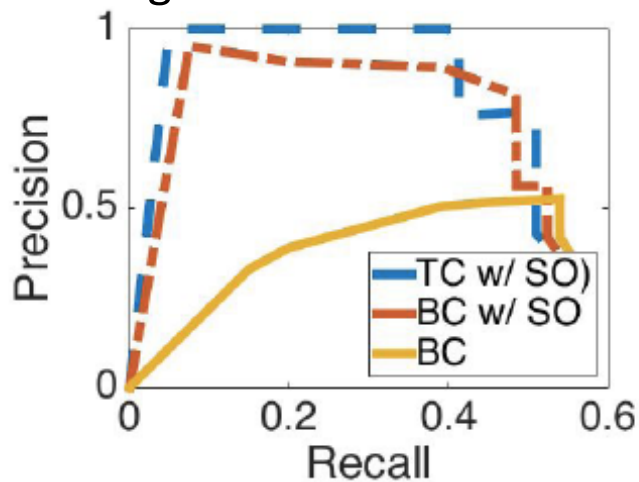
Conclusion

- Proposed temporal clustering method to detect groups in mobile trace data
- Method
 - detects multi-membership of individuals
 - robust to changes in time granularity
 - automatically determines number of groups
- Proposed method more accurate than previous methods
- Future directions
 - Model can be applied to directed temporal networks representing relations between users, location and time.

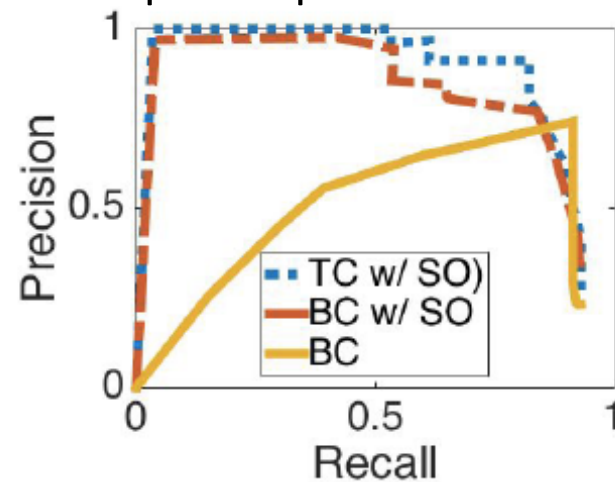
Thank you

Group Member Detection in Lakehurst

- TC has better performance measured by PR curve given different value of hyperparameter R (number of groups)
 - BC has poor precision given same Recall
 - Ranking communities with SO score improves precision on BC



(a) $R = 15$



(b) $R = 30$