3rd International Workshop on AI in Networks and Distributed Systems
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Understanding mobility in networks: A node embedding approach

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Mobility in network

Understanding the entities mobility patterns plays a fundamental role in the design, management, and performance of applications and services

Source: https://www.urban-hub.com/pt-br/smart-mobility/

Mobility in network

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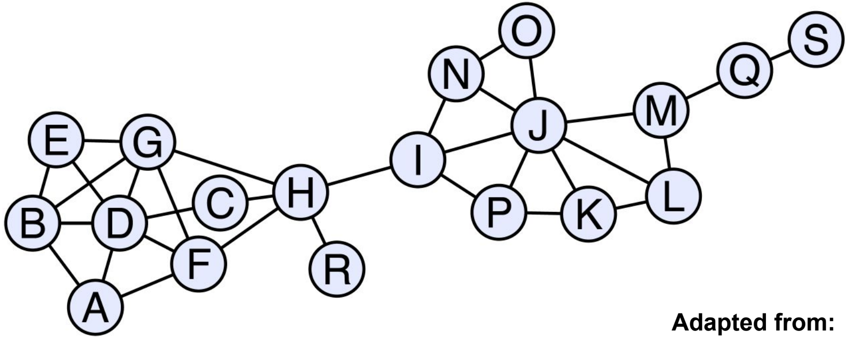

Adapted from:
https://ocw.mit.edu/courses/civil-and-environmental-engineering/1-022-introd uction-to-network-models-fall-2018/lecture-notes/MIT1_022F18_lec4.pdf

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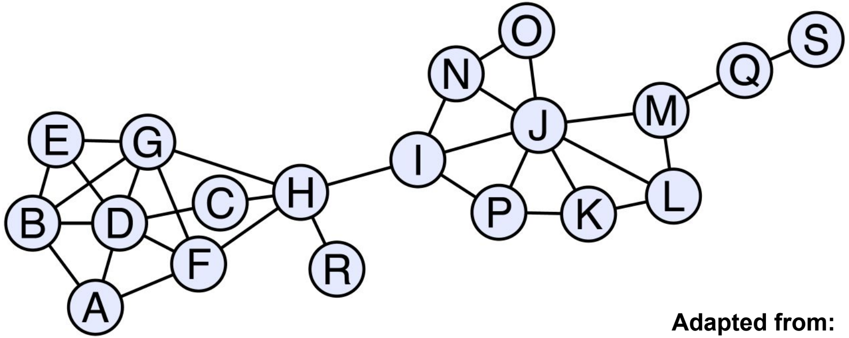

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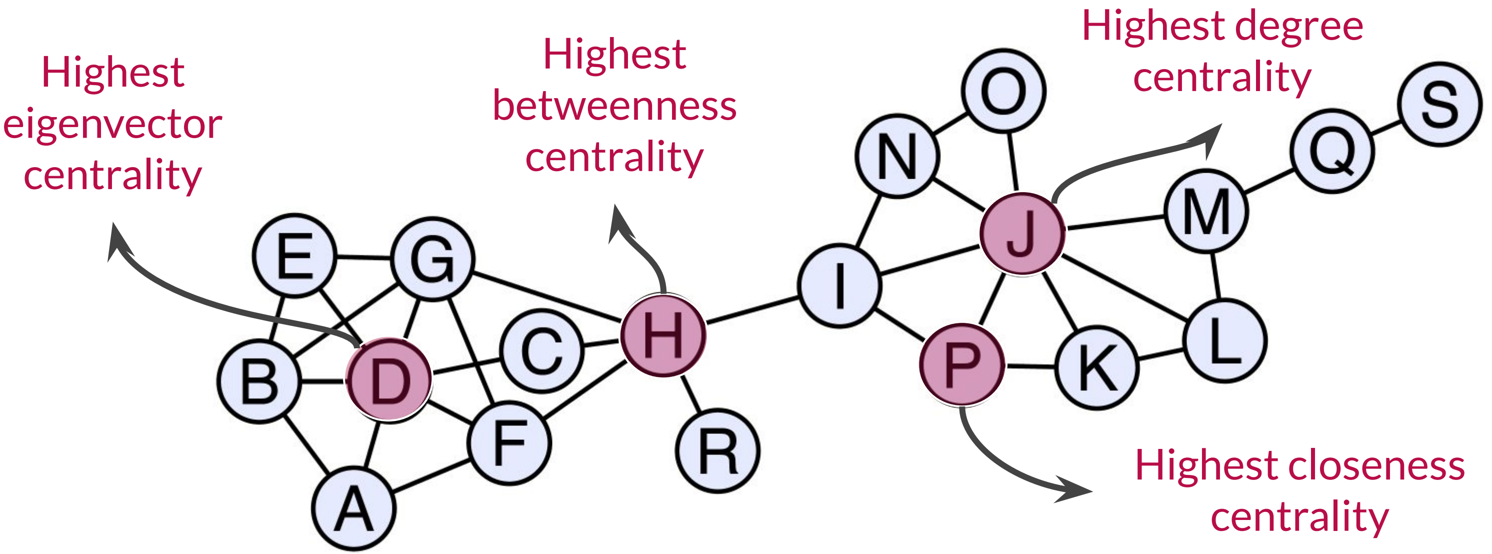
Many solutions were proposed based on topological measures

Motivation

Each measure provides a distinct notion of importance for a node!



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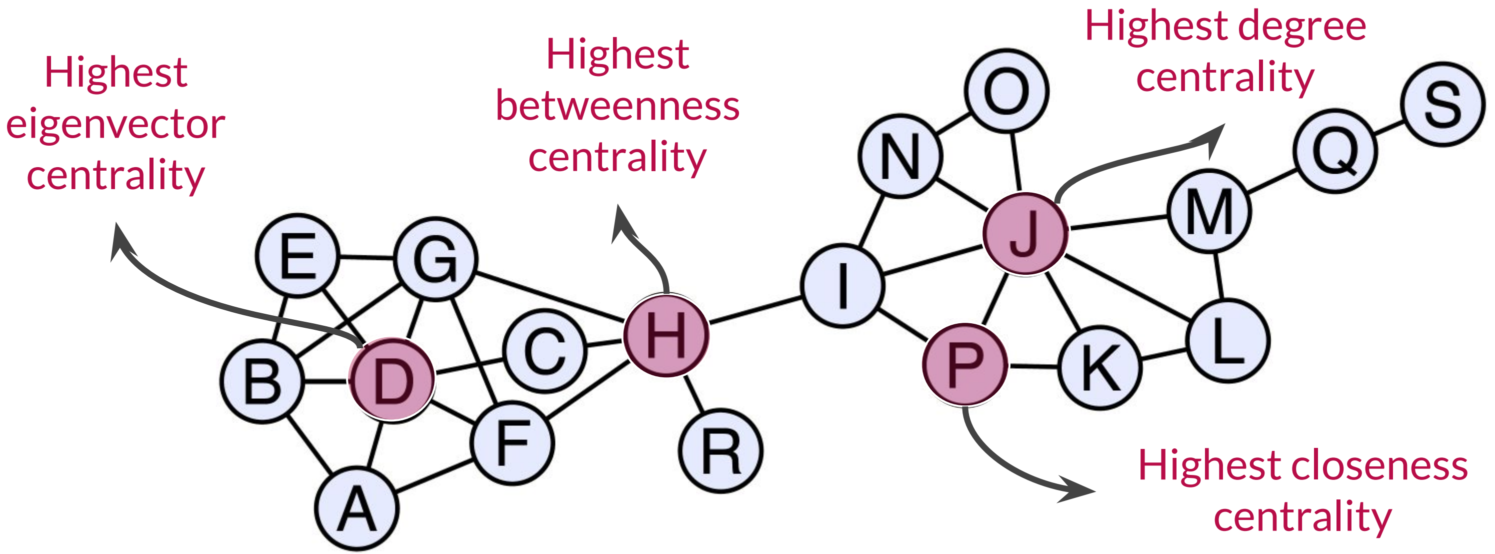

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They cannot generalize the nodes' importance criteria!

Our Goal

Propose a node embedding-based methodology to model and analyze the mobility pattern over spatial and temporal dimensions

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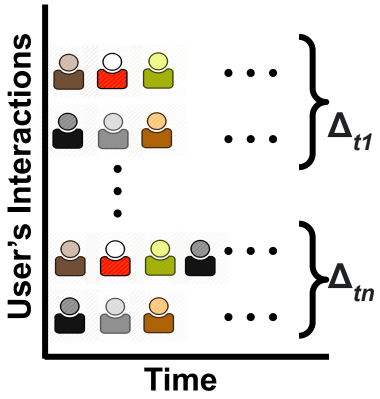
Propose a node embedding-based methodology to model and analyze the mobility pattern over spatial and temporal dimensions

Focus is to capture the **nodes' mobility** and **importance** for connectivity using the network topology and its temporal evolution

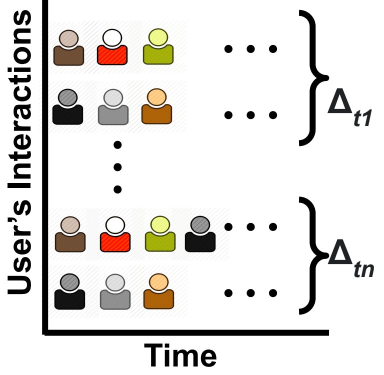
Methodology

Dataset

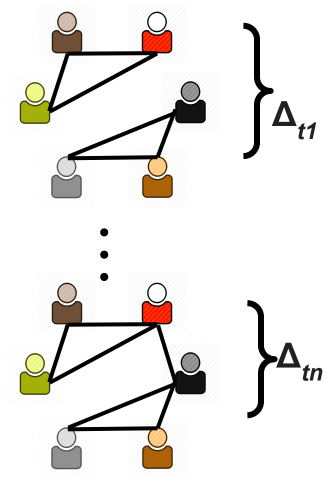


Methodology

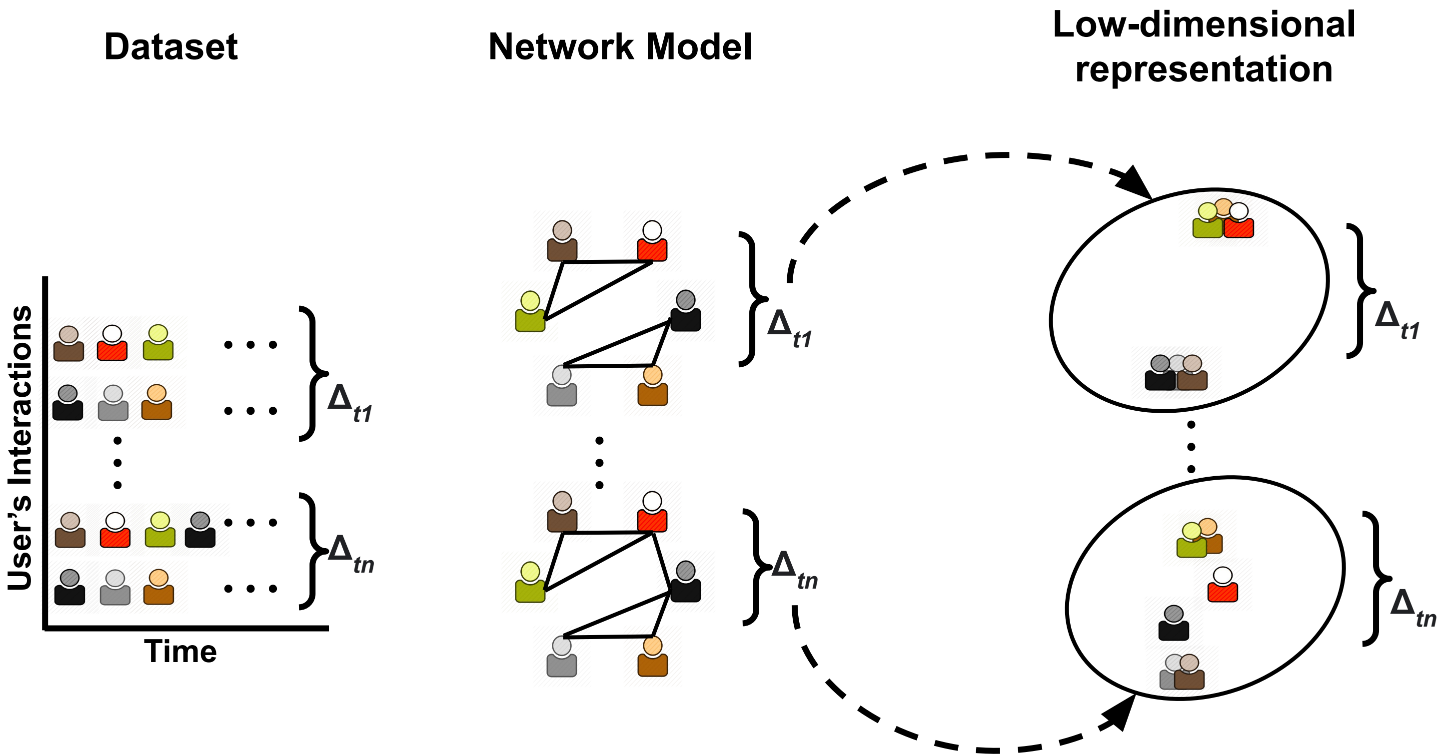
Dataset



Network Model

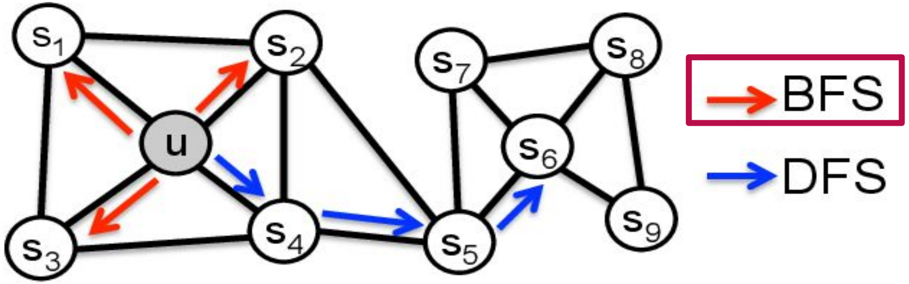


Methodology



DynamicNode2Vec

For each G_{Δ_t}, it performs a sampling using a biased random walker:



Source: Node2vec: Scalable Feature Learning for Networks. A. Grover, J. Leskovec. ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD), 2016.

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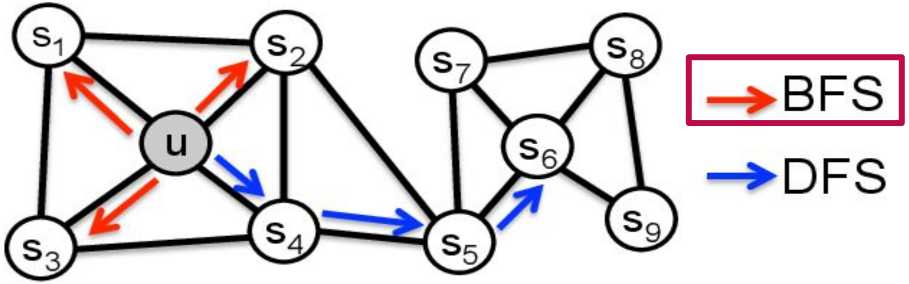

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	S1	S2	S3	S4	S5	S6	S7	S8	S9
S1	0	15	14	7	7	2	0	2	2
S2		0	12	18	6	1	1	2	1
S3			0	18	17	15	4	5	6
S4				0	13	8	3	2	7
S5					0	13	10	11	19
S6						0	15	17	20
S7							0	16	17
S8								0	15
S9									0

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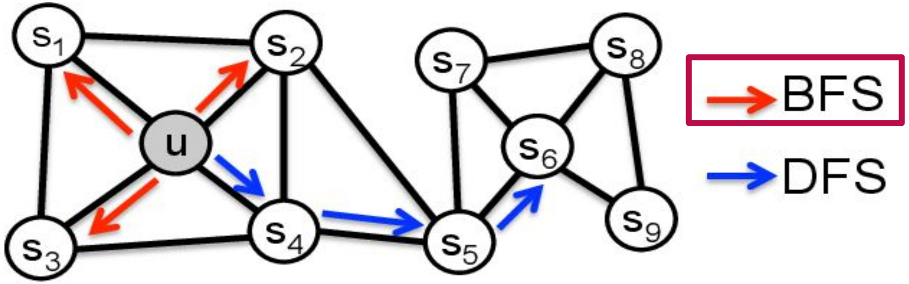

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S6						0	15	17	20
S7							0	16	17
S8								0	15
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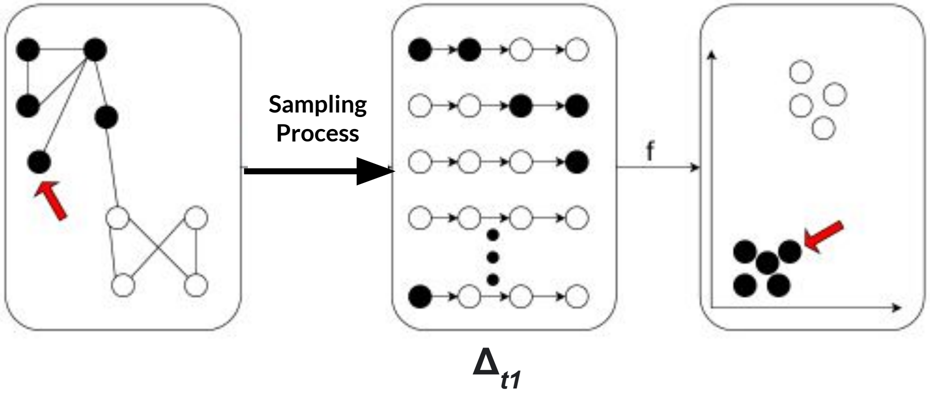
Intuition: The greater the co-occurrence between two nodes, the closer they are in the network, and the more important is the connection between them

Use the co-occurrences to produce a sequence of time-aligned embeddings

DynamicNode2Vec: The temporal embeddings



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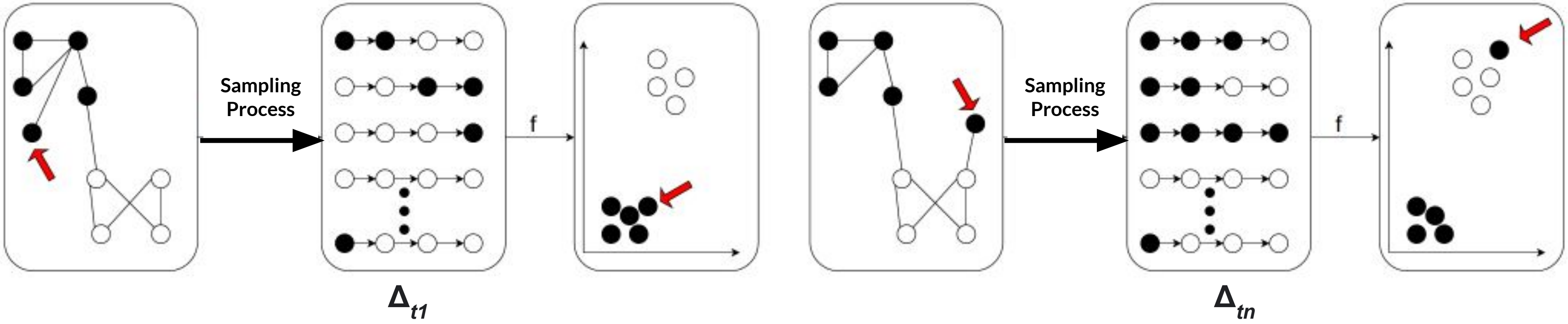
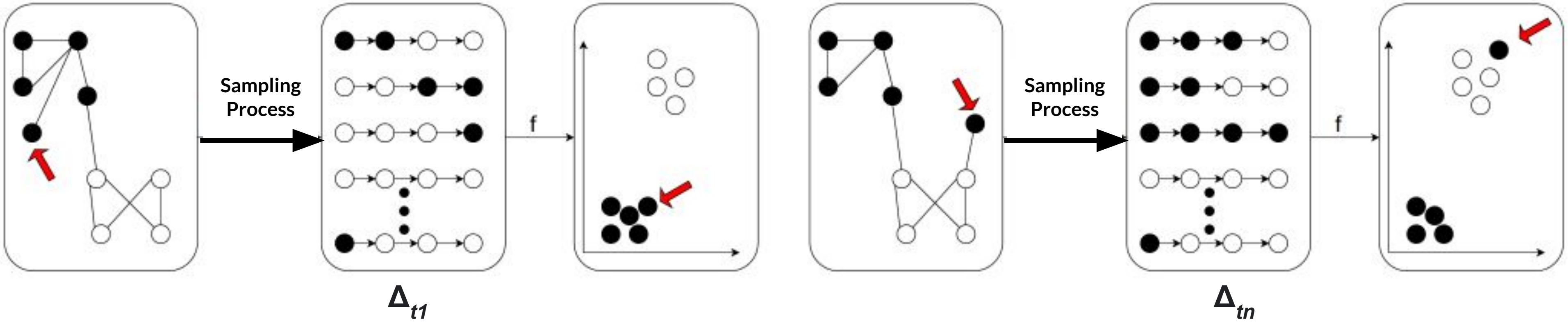
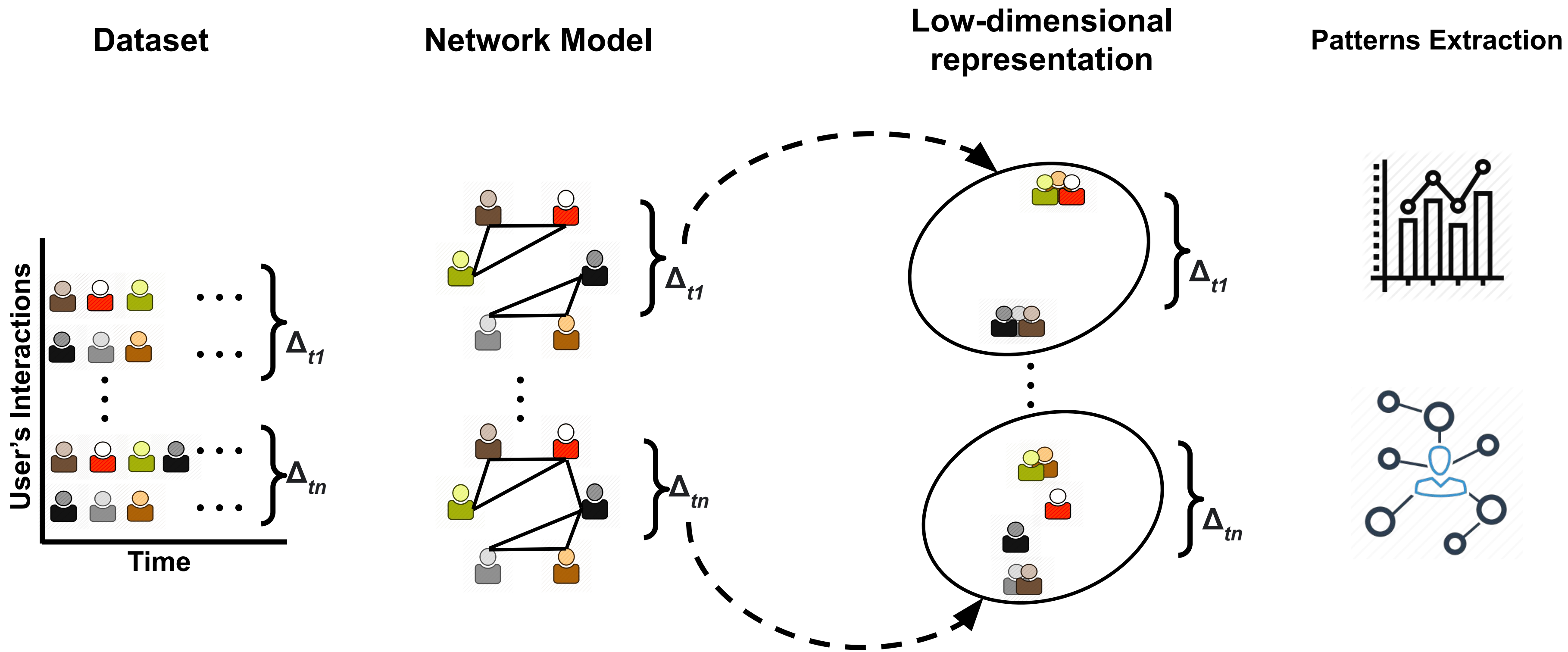


DynamicNode2Vec: The temporal embeddings



Allow tracking to what extent nodes change their connections over time!

Methodology



Extracting temporal mobility patterns

Cosine distance: Quantifies the node connection changes between two distinct time windows

- Values close to 0 indicate that the node keeps its connections to the same nodes in the two compared time windows while 1 is the opposite

Vector norm: By design, the more a node appears in the sampled paths in a given time window, the greater is the norm of its vector

- Indicates the node's importance to network connectivity

Case Study

Group Regularity Mobility Model:

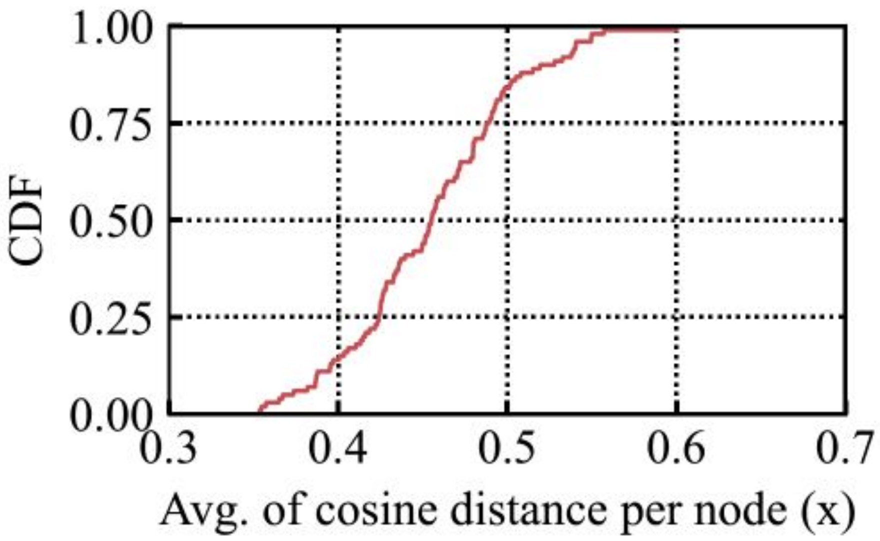
- Based on the dynamics and regularity of social meetings
  - Considers cyclical and sporadic meetings
- Generate synthetic traces with real properties

Our dataset:

- 100 users
- Covering a period of 87 days
- Daily time windows

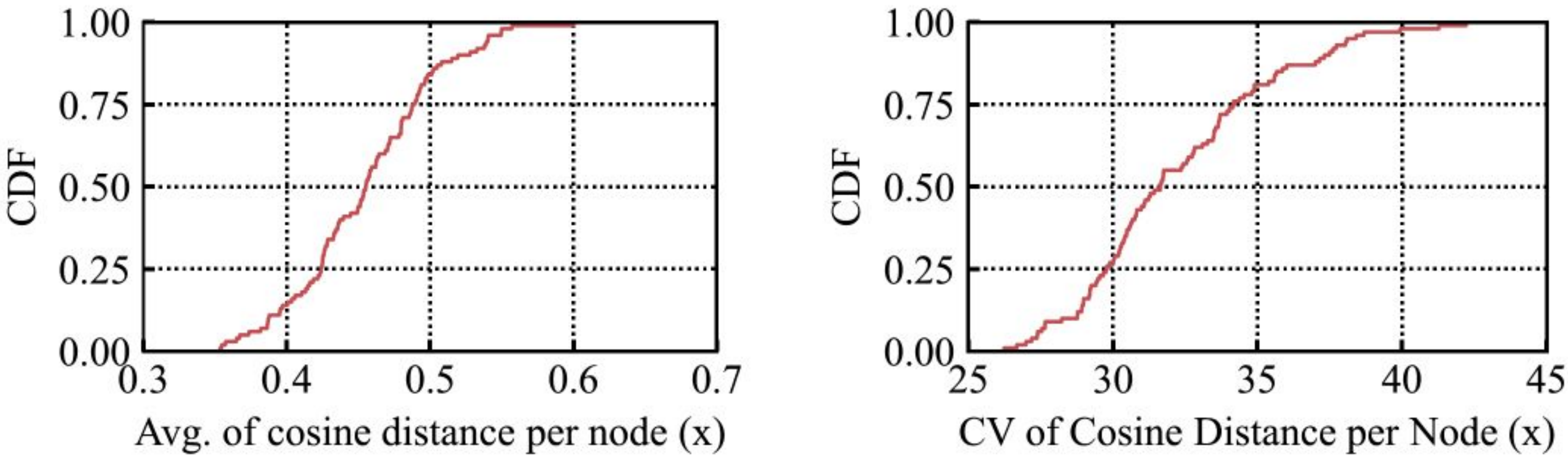
Nunes, Ivan O., et al. "GRM: Group regularity mobility model." *Proceedings of the 20th ACM International Conference on Modelling, Analysis and Simulation of Wireless and Mobile Systems*. 2017.

To what extent do nodes change their connections?



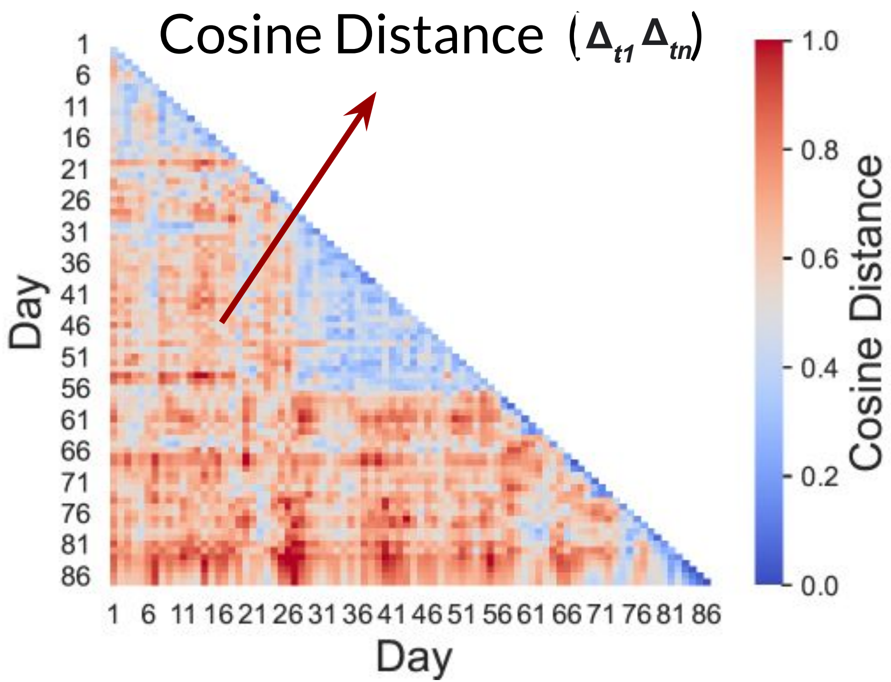
Nodes with different levels of mobility

To what extent do nodes change their connections?



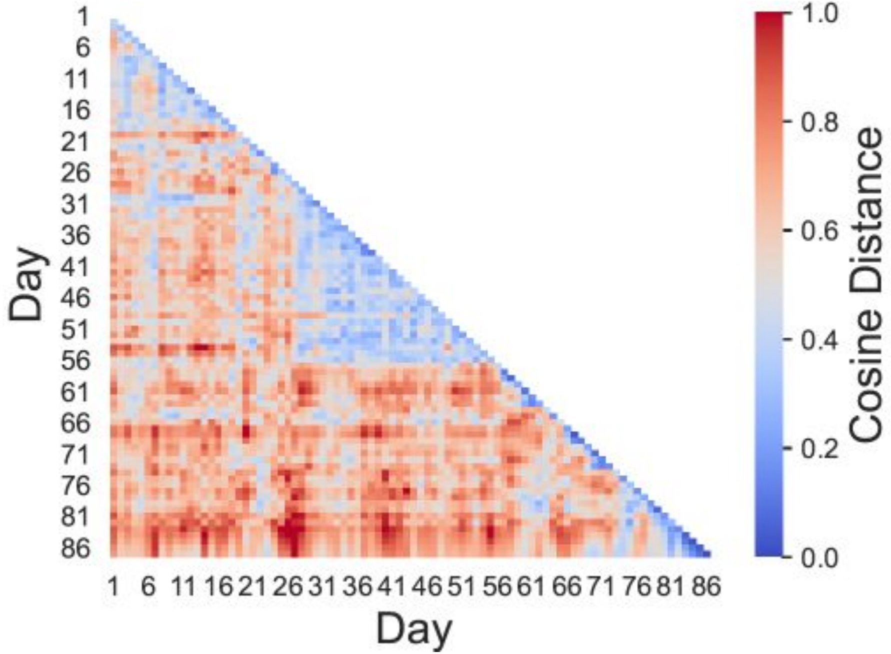
High CV indicates that these changes tend to be irregular

To what extent do nodes change their connections?



Node pattern with the **highest** avg. cosine distance

To what extent do nodes change their connections?



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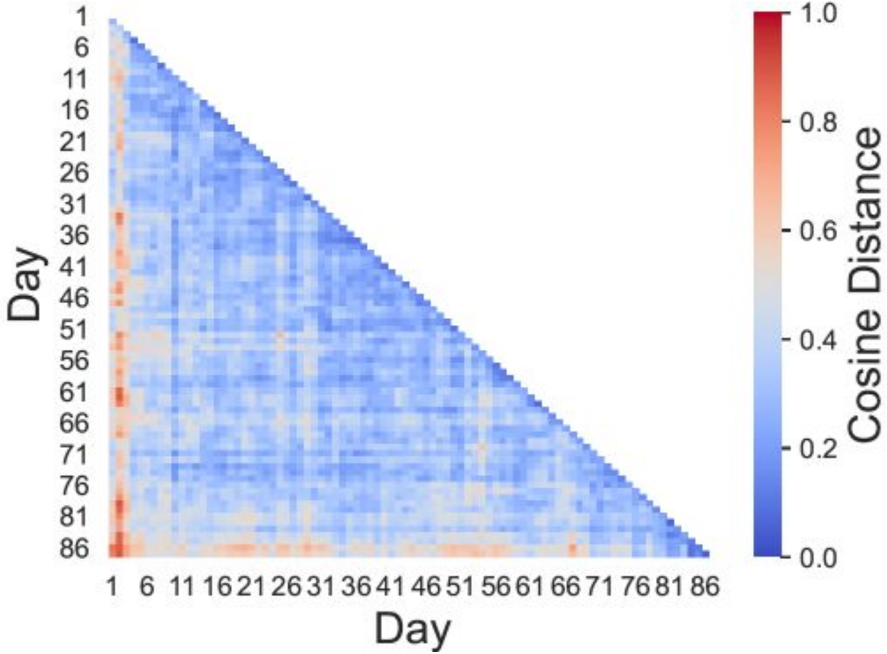
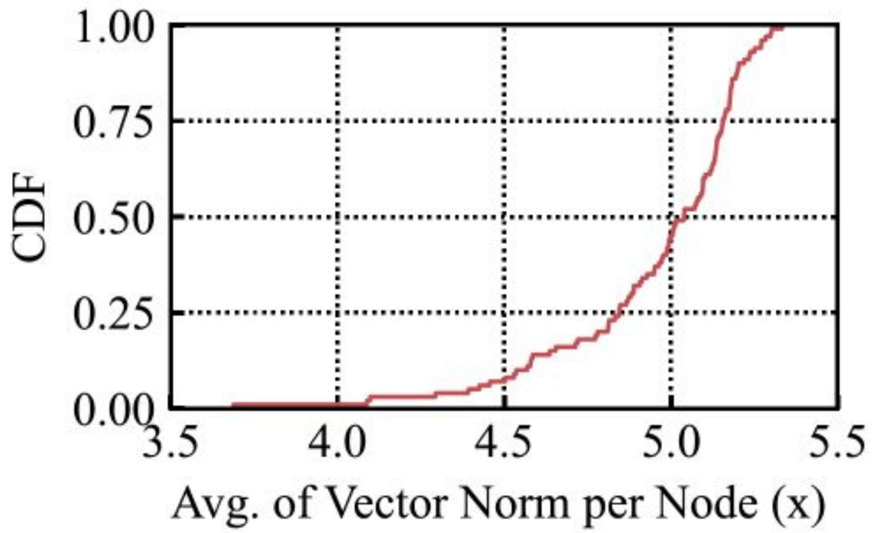


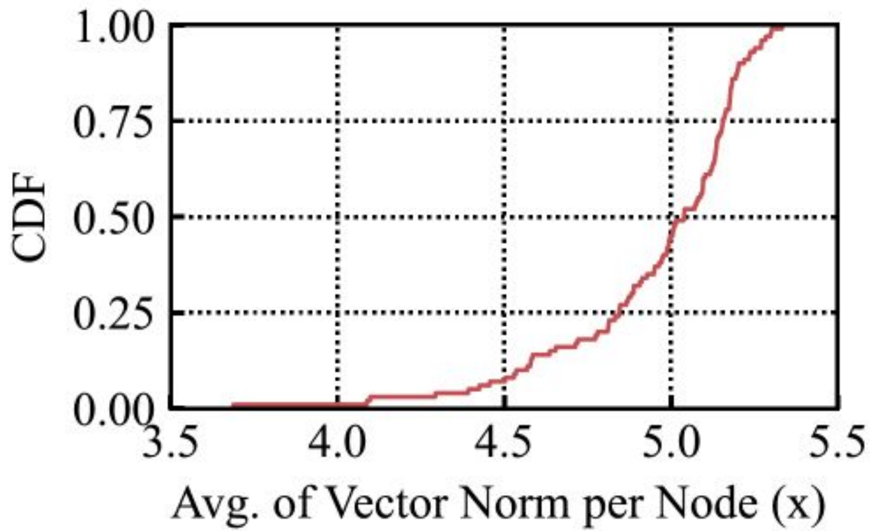
Node pattern with the **lowest** avg. cosine distance

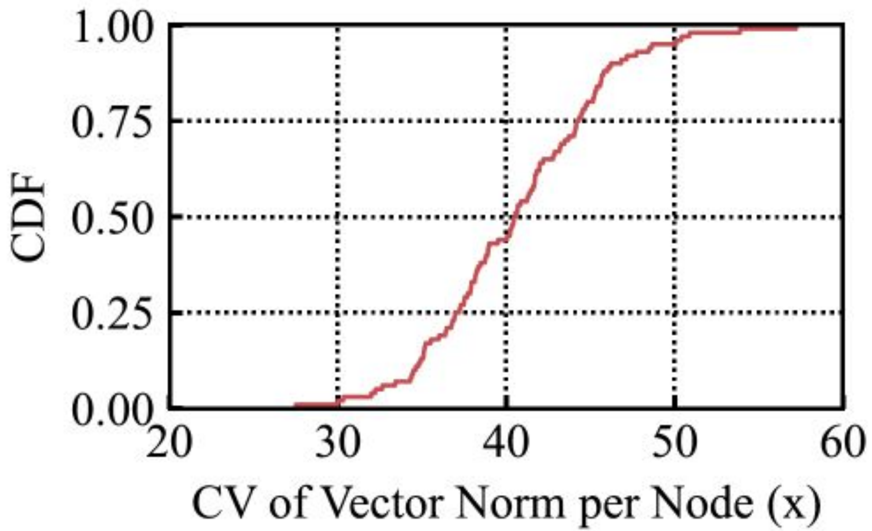
How important are the connections established by them?



Nodes with different levels of importance

How important are the connections established by them?





High variation around the average suggests that nodes have temporary importance

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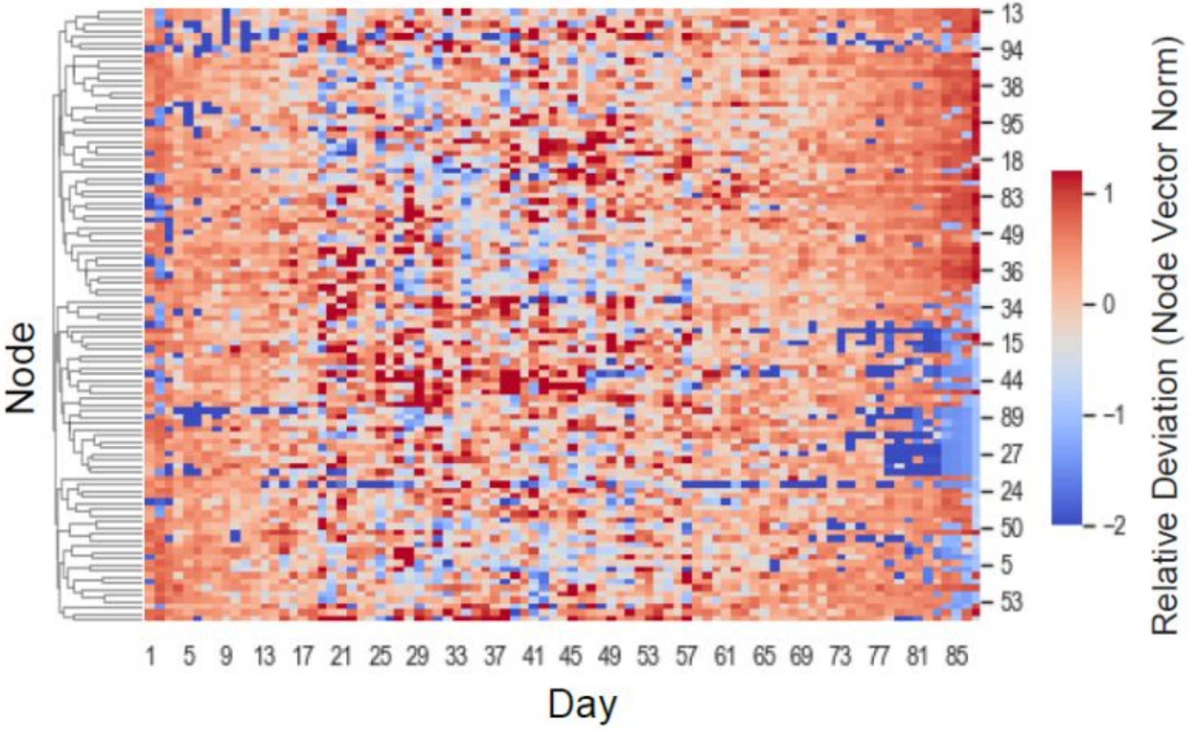

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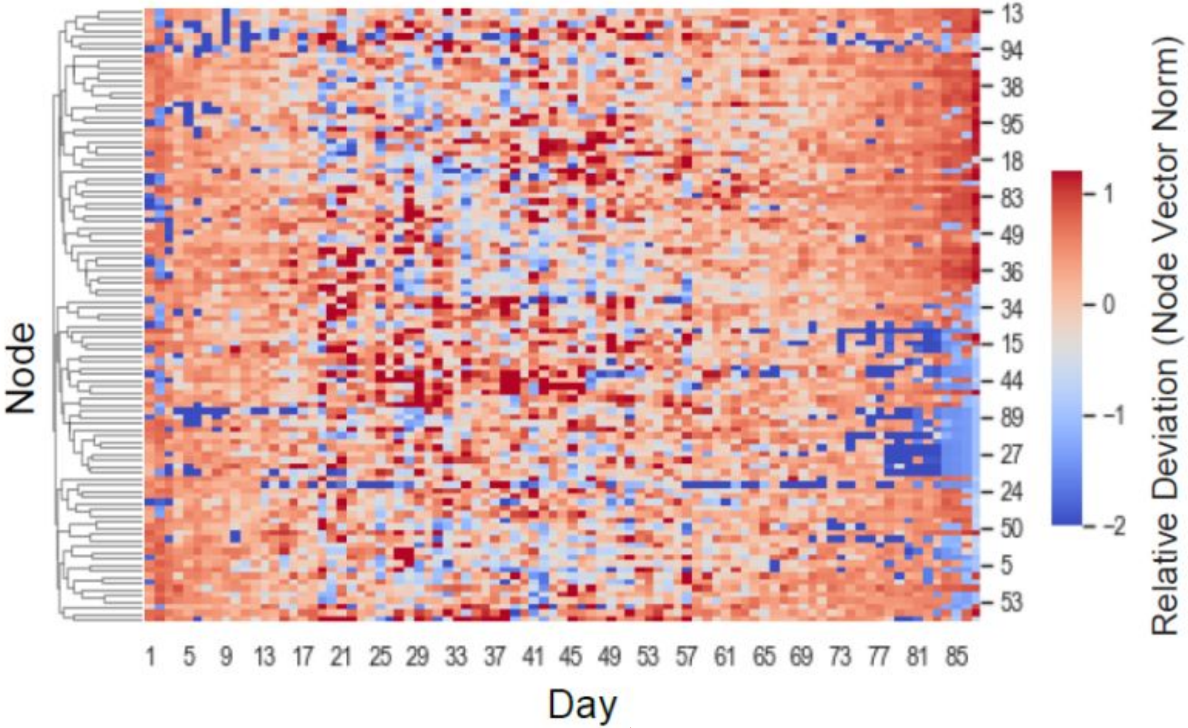
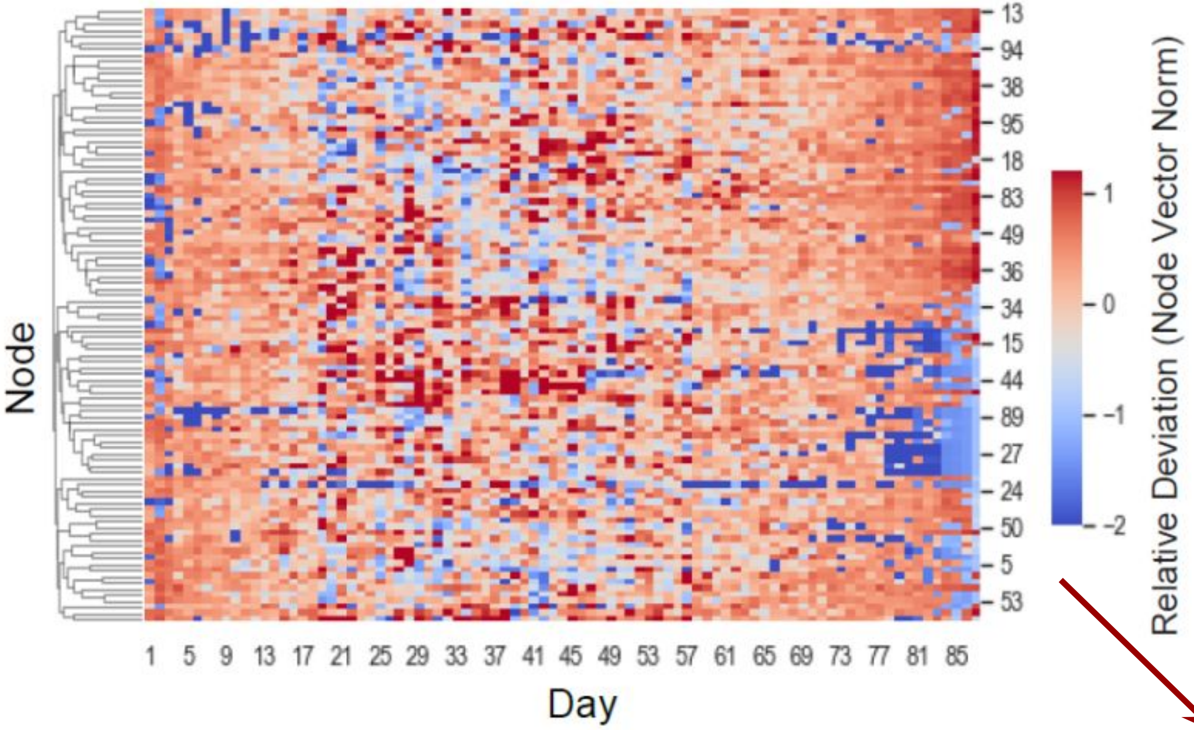


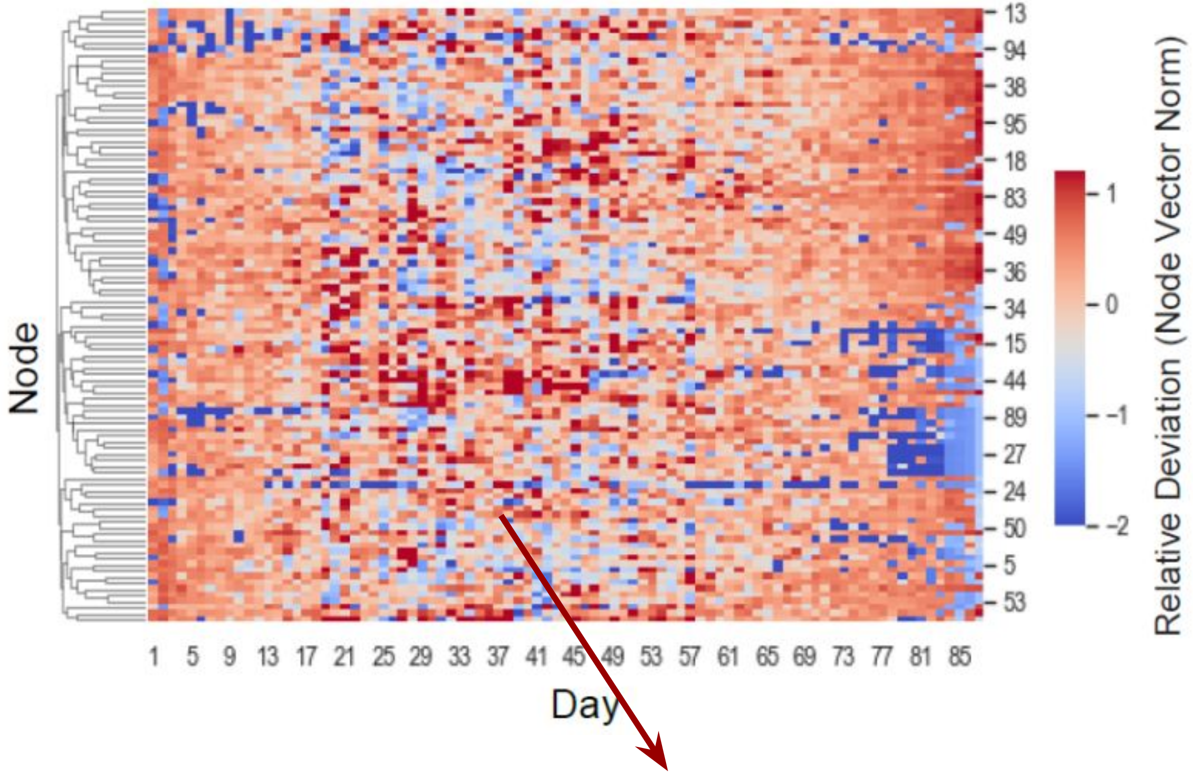
Period observed

How important are the connections established by them?



Nodes (people)

How important are the connections established by them?



Vector norm of a node representation (normalized z-score)

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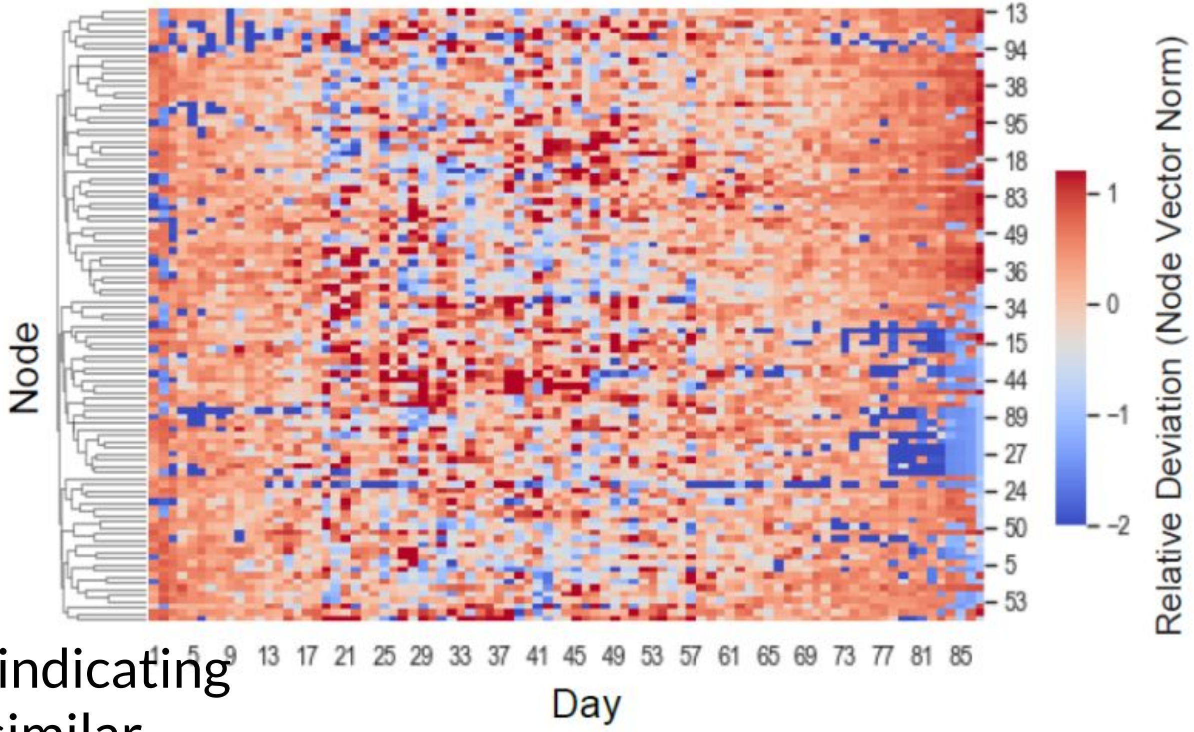
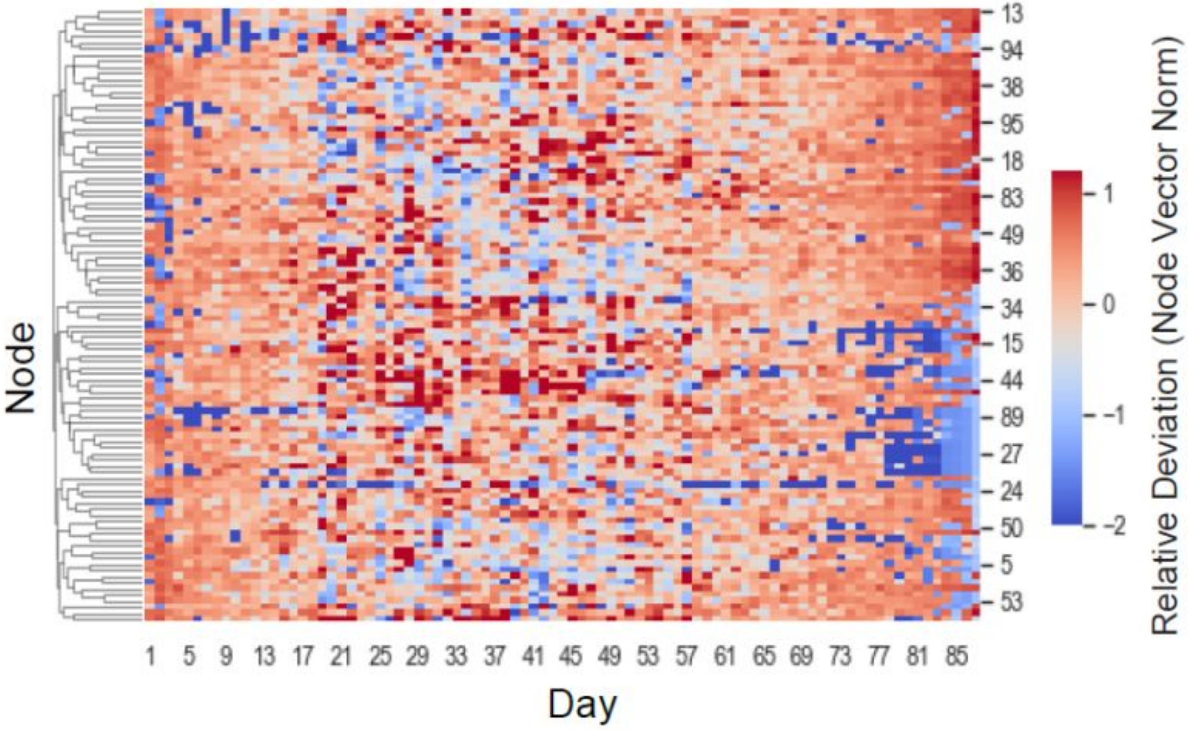


Dendrogram indicating nodes of similar importance in the same days

How important are the connections established by them?



Groups of nodes have momentary connectivity importance

What about topological measurements?

Embedding	Topological	Correlation
Avg. of Cosine Distance	Avg. of Degree	-0.64
Avg. of Cosine Distance	Avg. of Betweenness	-0.69
Avg. of Cosine Distance	Avg. of Closeness	-0.64
Avg. of Cosine Distance	Avg. of Eigenvector	-0.65
Avg. of Cosine Distance	Avg. of Clustering Coefficient	0.51
Avg. of Vector Norm	Avg. of Degree	0.33
Avg. of Vector Norm	Avg. of Betweenness	0.50
Avg. of Vector Norm	Avg. of Closeness	0.28
Avg. of Vector Norm	Avg. of Eigenvector	0.32
Avg. of Vector Norm	Avg. of Clustering Coefficient	-0.55

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They suggest that the more dynamic a node is, the lower its centrality

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Centrality measurements are not capable of generalizing the connectivity importance

Conclusions and Future Work

Our approach offers an alternative notion of connectivity importance

Allow for tracking connectivity importance while the connections in the network evolve over time

Suggest that topological network measures could not generalize the patterns of connectivity captured here

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Suggest that topological network measures could not generalize the patterns of connectivity captured here

As future work:

- Incorporate it into solutions for dissemination/collection of information in mobile networks
  - Evaluate the performance of such protocols comparing purely topological measures to those proposed here

Thanks!

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