Large-scale Mining of Dynamic Networks

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Background

UNIVERSITY OF TORONTO

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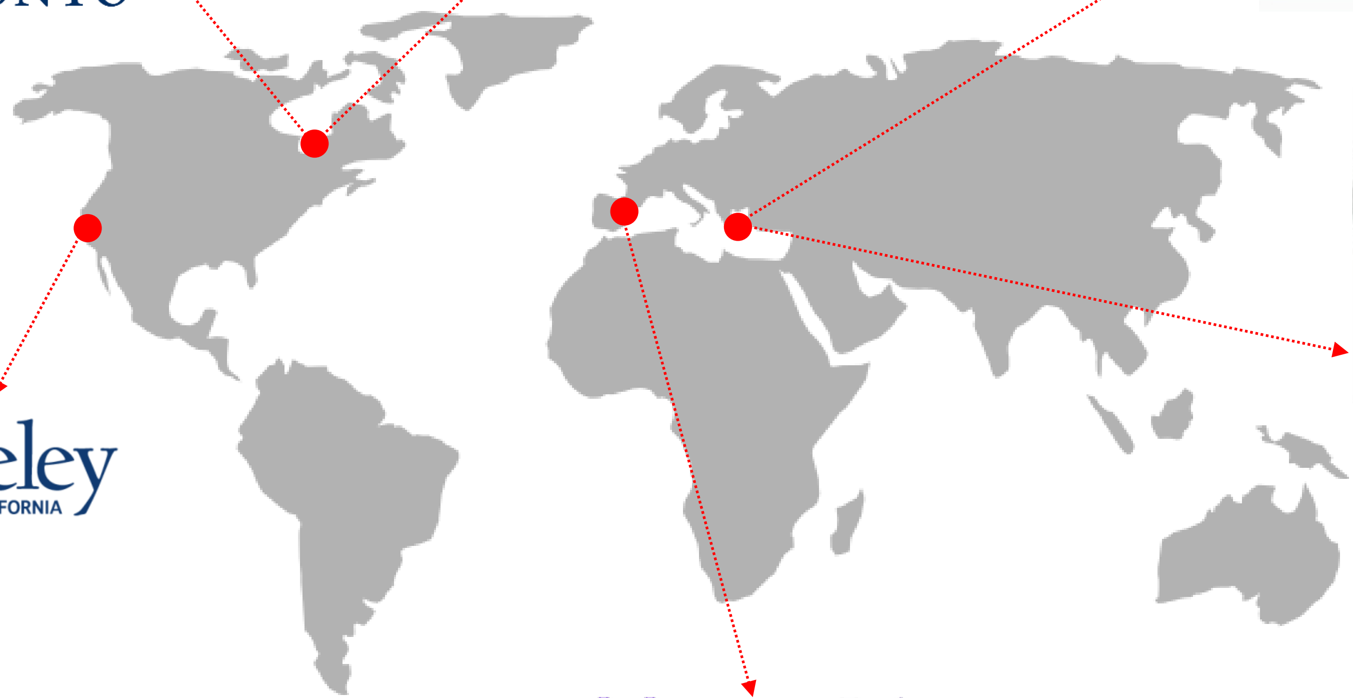
University of Crete



FORTH Institute of Computer Science

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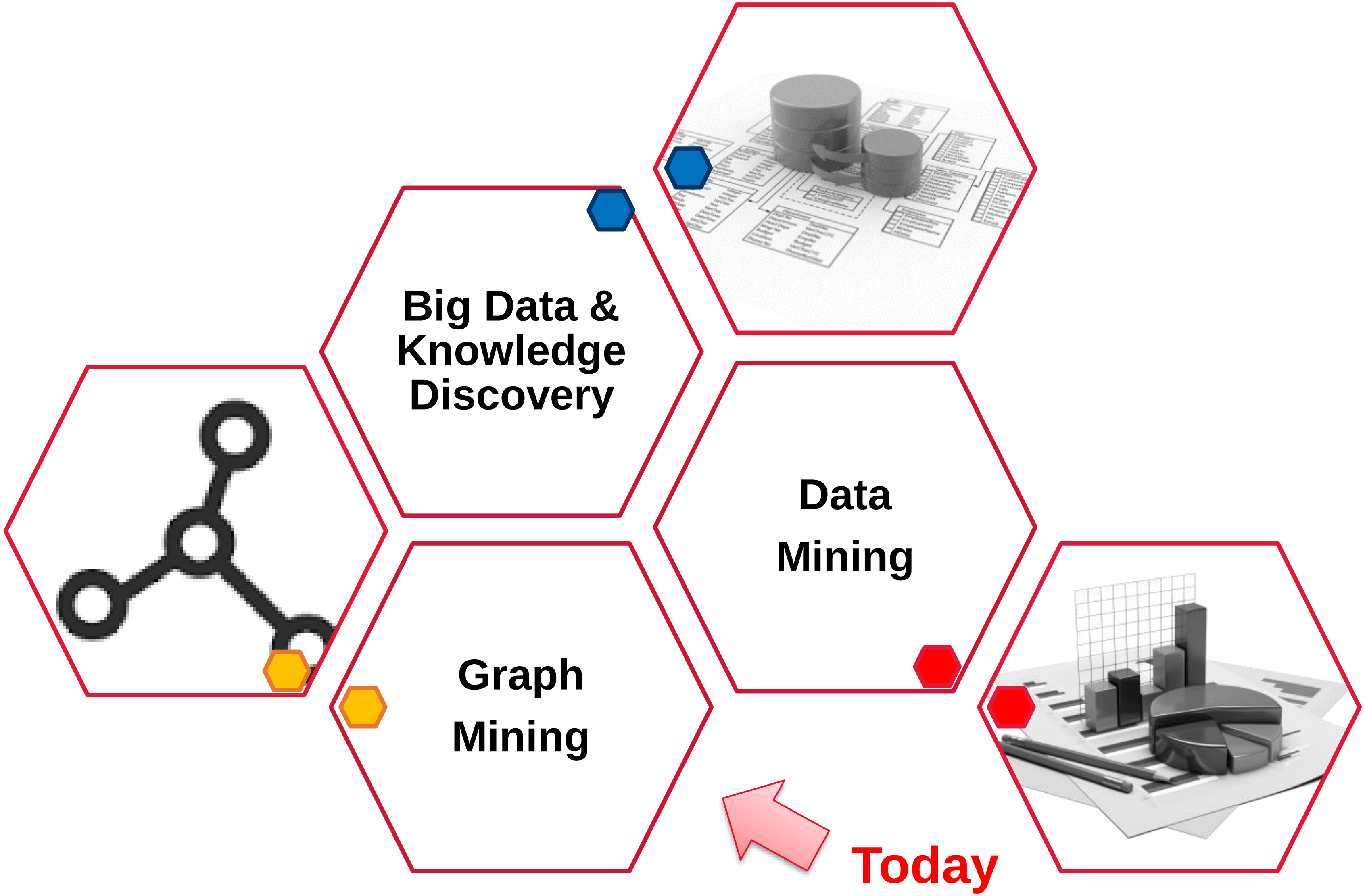
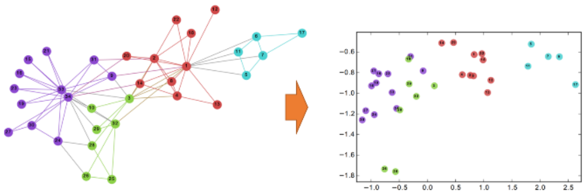
Research

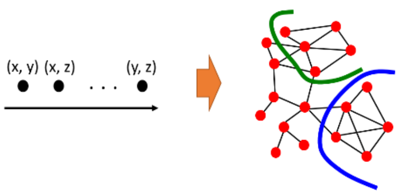

Big Data & Knowledge Discovery
Data Mining
Graph Mining
Today

Current Research focus

A. Trajectory Network Mining



B. Network Representation Learning



C. Streaming & Dynamic Graphs

D. Social Media Mining & Analysis

E. City Science / Urban Informatics / IoT

F. Natural Language Processing

Today’s Overview

Trajectory Network Mining

- Mining of Node Importance in Trajectory Networks
- Group Pattern Discovery of Pedestrian Trajectories

Evolving Network Mining

- Evolving Network Representation Learning Based on Random Walks

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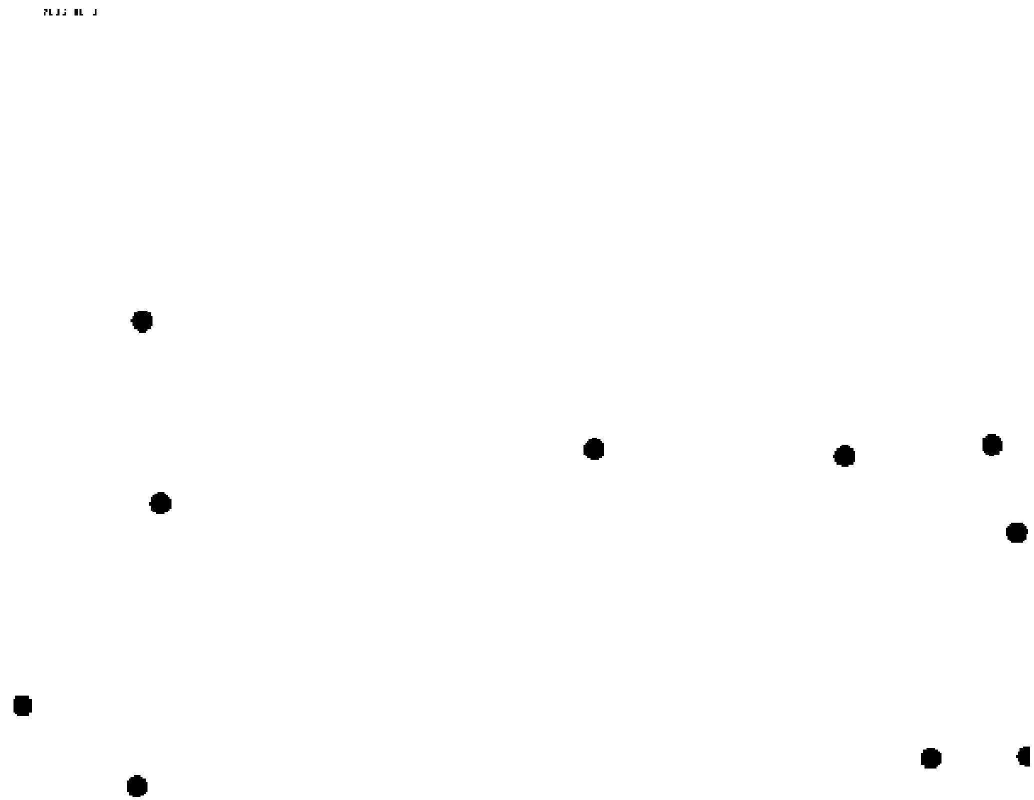
Node Importance in Trajectory Networks

Joint work with Tilemachos Pechlivanoglou

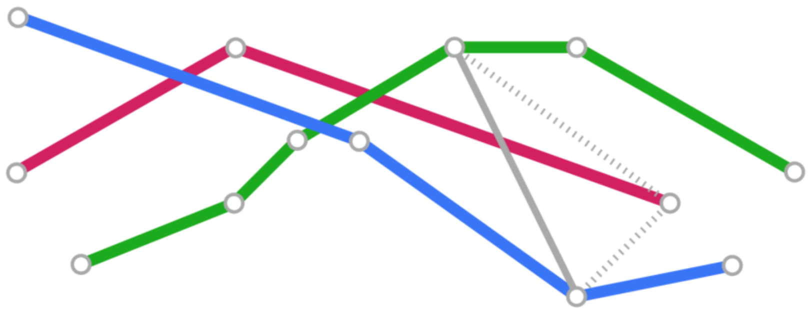
Trajectories of moving objects



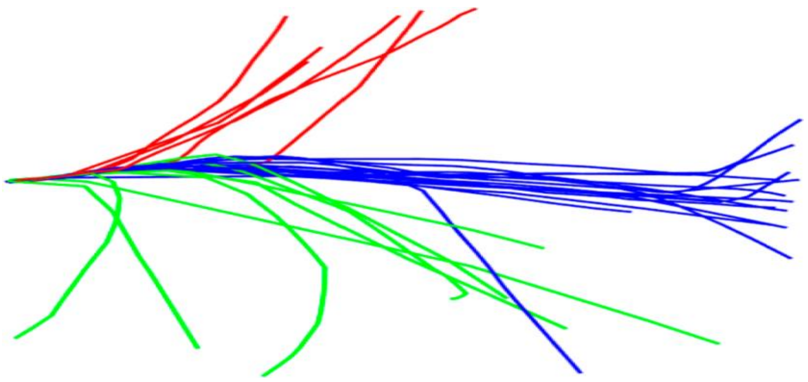
every moving object, forms a **trajectory** – in **2D** it is a sequence of (**x**, **y**, **t**)

there are trajectories of moving **cars**, **people**, **birds**, ...

Trajectory data mining



trajectory similarity

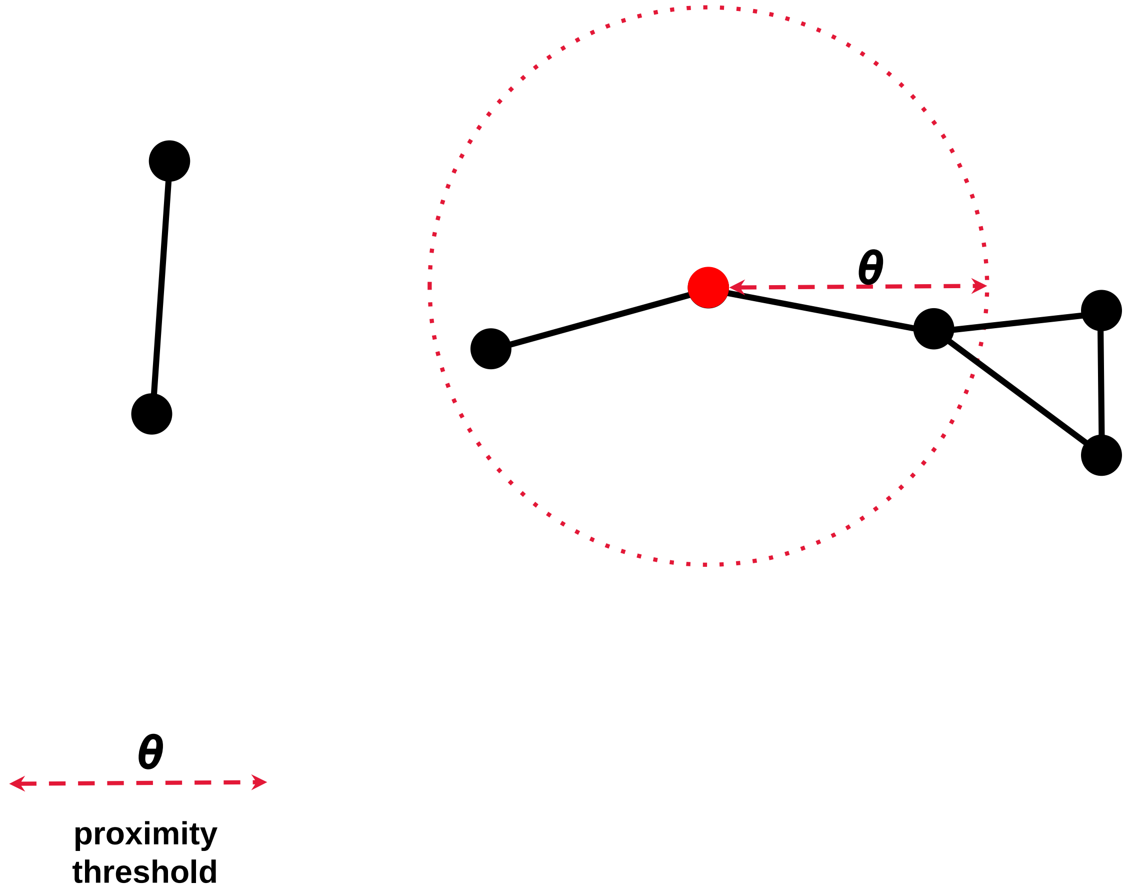


trajectory clustering

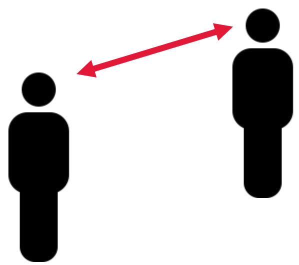
trajectory anomaly detection
trajectory pattern mining
trajectory classification
...more

we care about network analysis of moving objects

Proximity networks



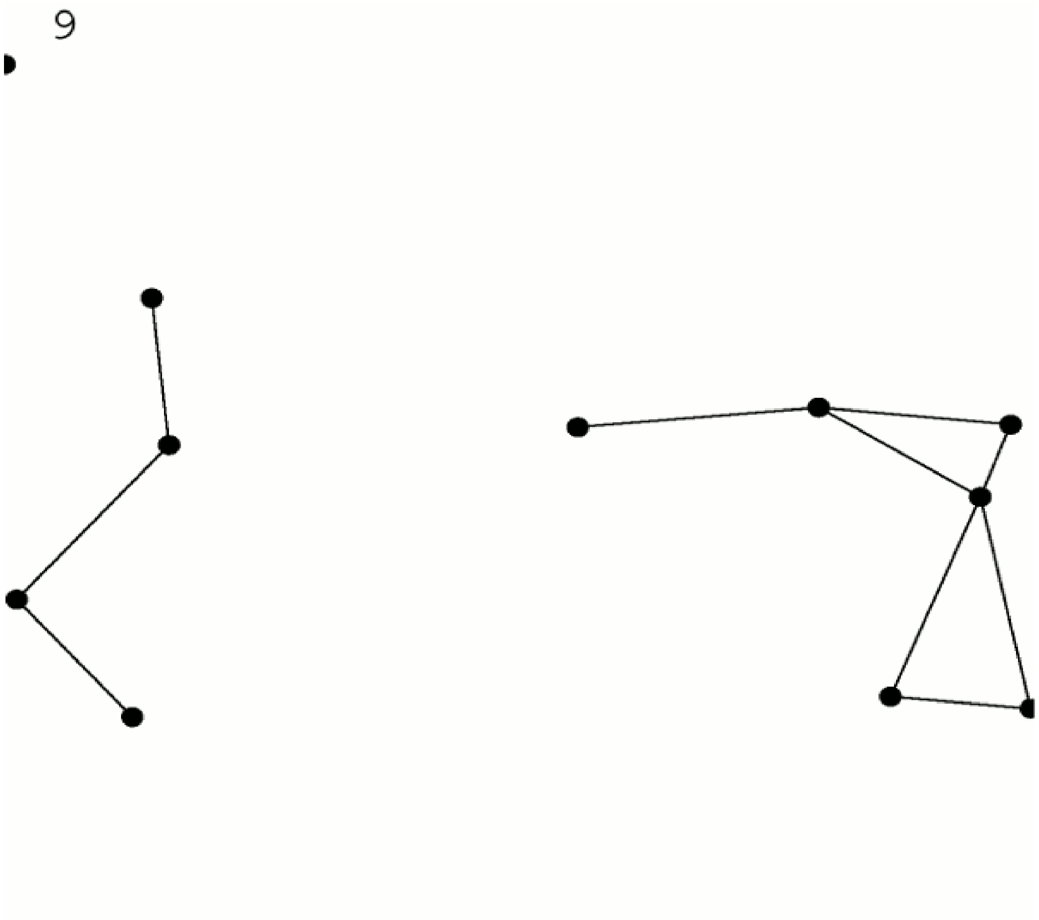
Distance can represent



line of sight

wifi/bluetooth signal range

Trajectory networks



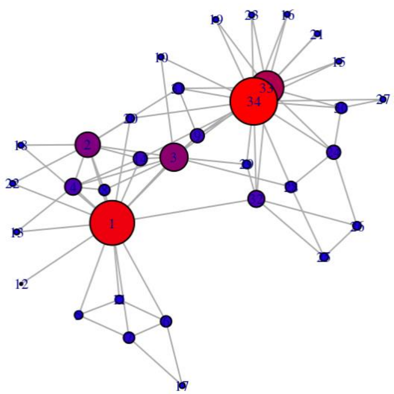
The Problem

Input: logs of trajectories (**x**, **y**, **t**) in time period [0, T]

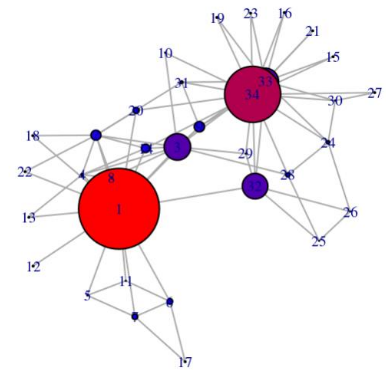
Output: node importance metrics

Node Importance

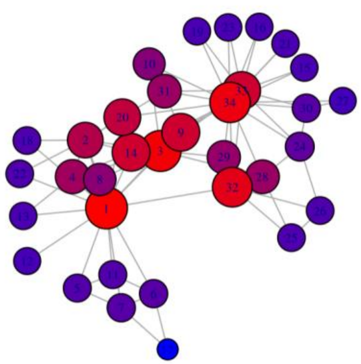
Node importance in static networks



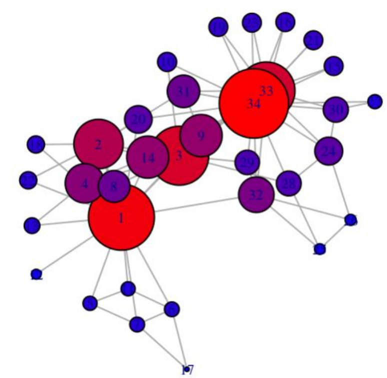
Degree centrality



Betweenness centrality

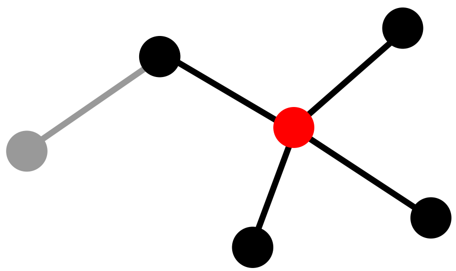


Closeness centrality

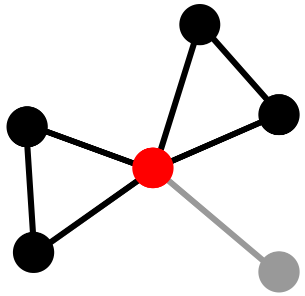


Eigenvector centrality

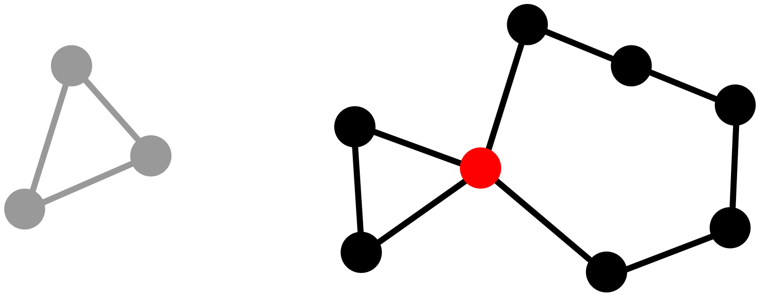
Node importance in TNs



node degree **over time**

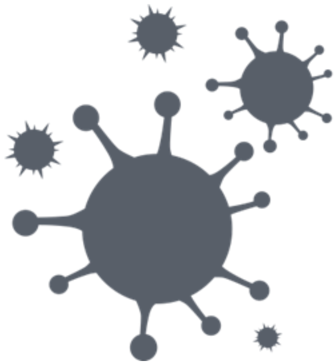


triangles **over time**



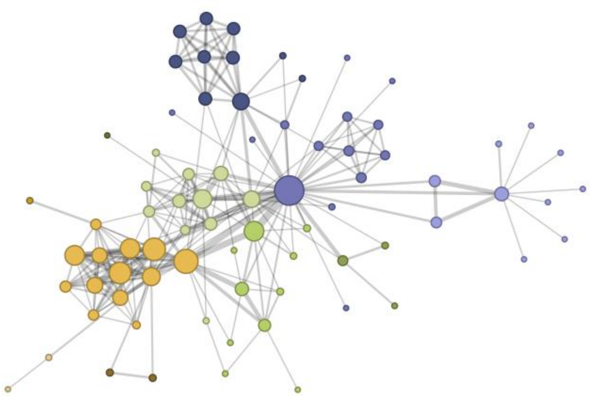
connected components **over time**
(connectedness)

Applications



infection spreading

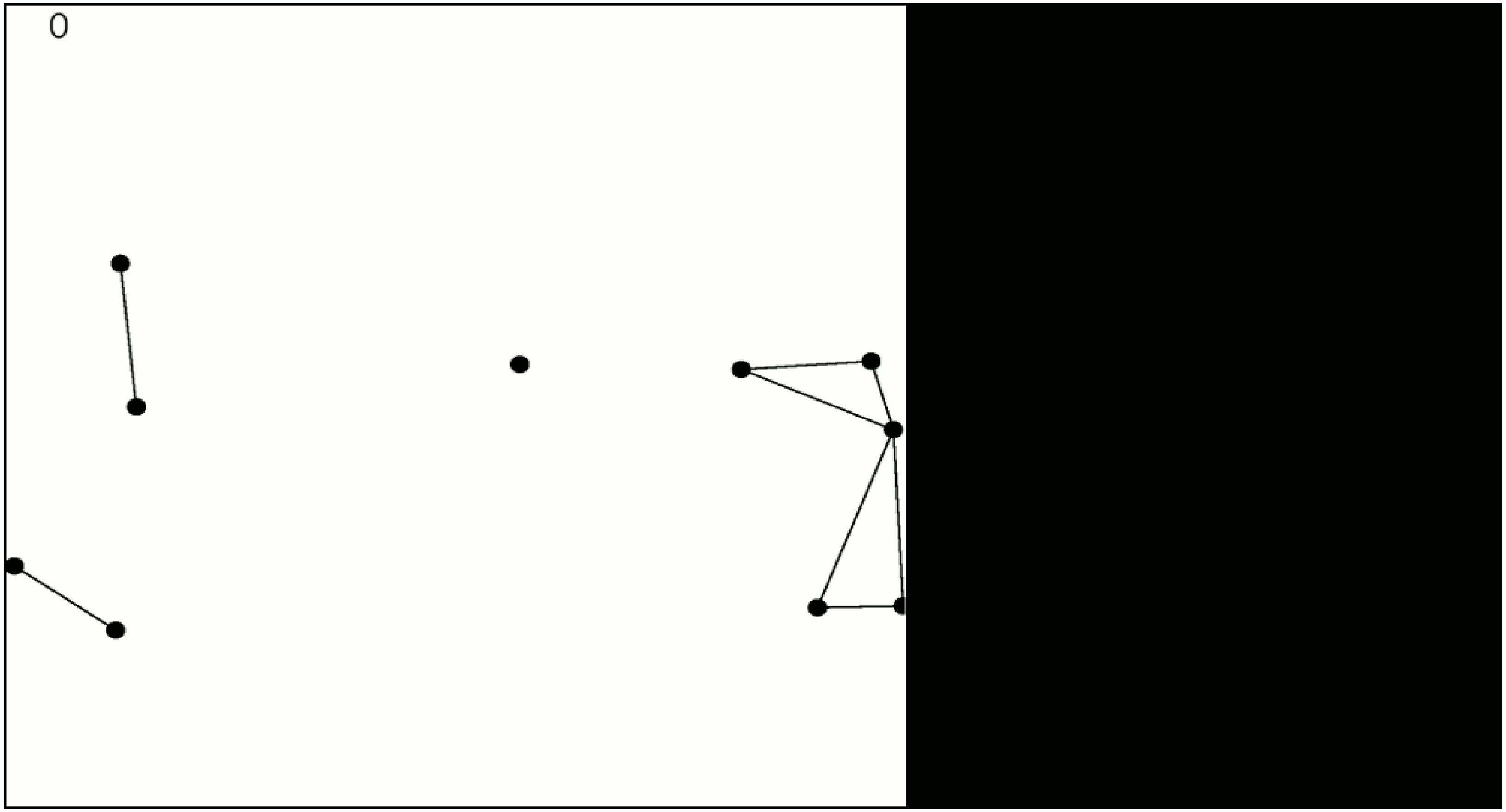
security in autonomous vehicles



rich dynamic network analytics

Evaluation of Node Importance in Trajectory Networks

Naive approach



For every discrete time unit t:

1. obtain static snapshot of the proximity network
2. run static node importance algorithms on snapshot

Aggregate results at the end

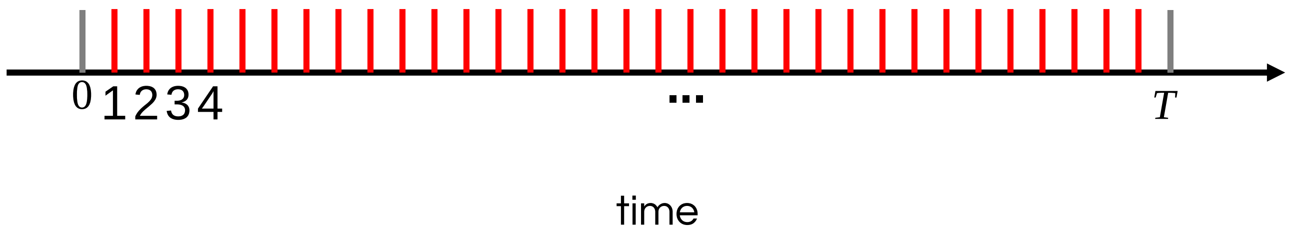
Streaming approach

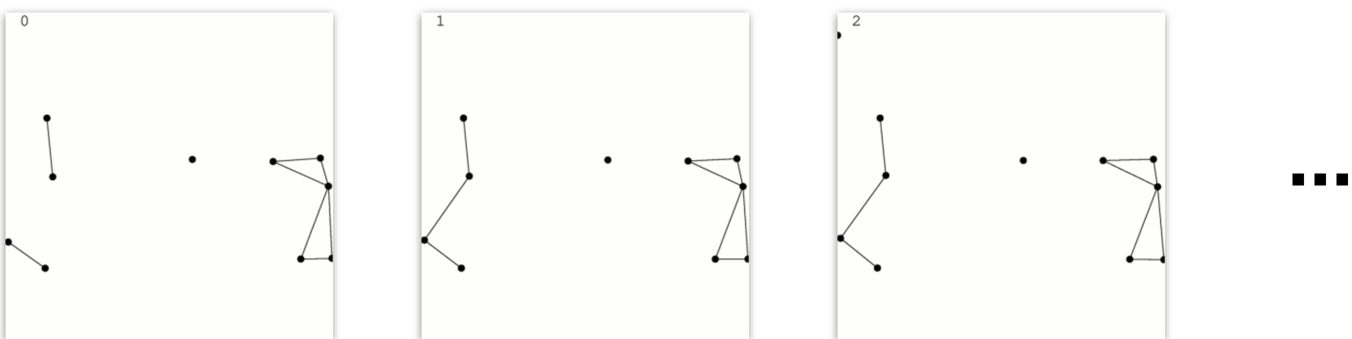
Similar to naive, but:

- **no final aggregation**
- results calculated **incrementally** at every step

Still **every time** unit

Every discrete time unit

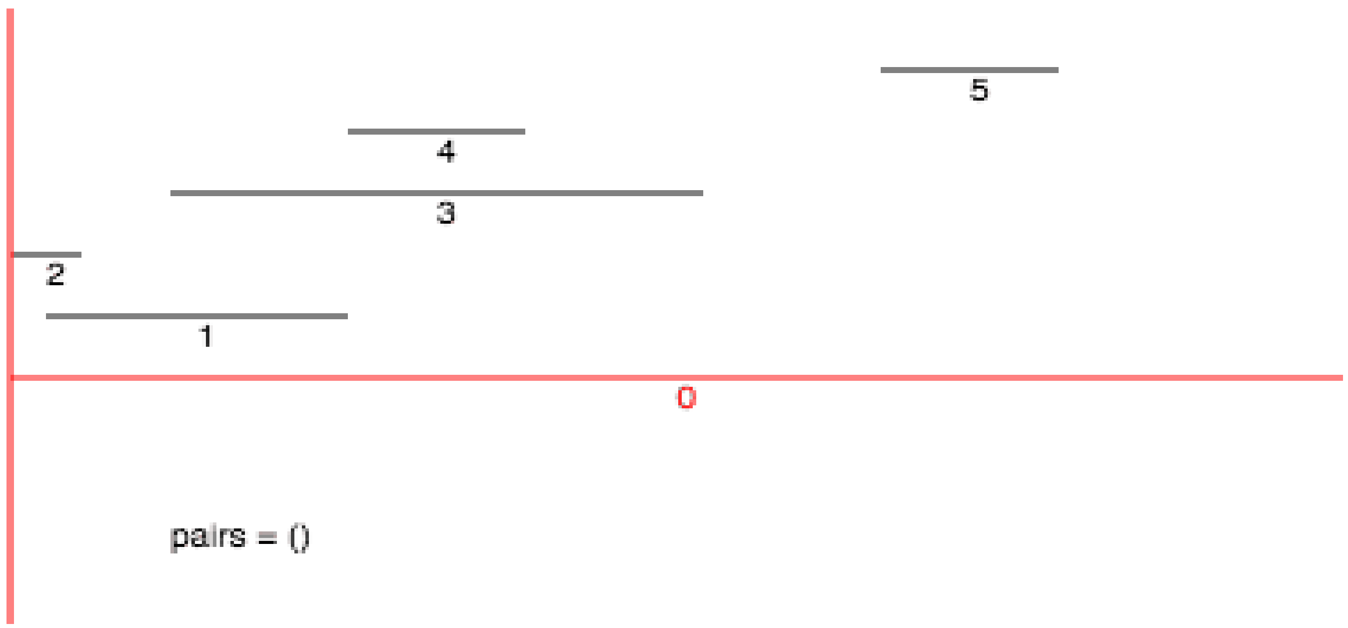




Sweep Line Over Trajectories (SLOT)

Sweep line algorithm

A computational geometry algorithm that given line segments computes line segment overlaps



Efficient one pass algorithm that only processes line segments at the beginning and ending points

SLOT: Sweep Line Over Trajectories

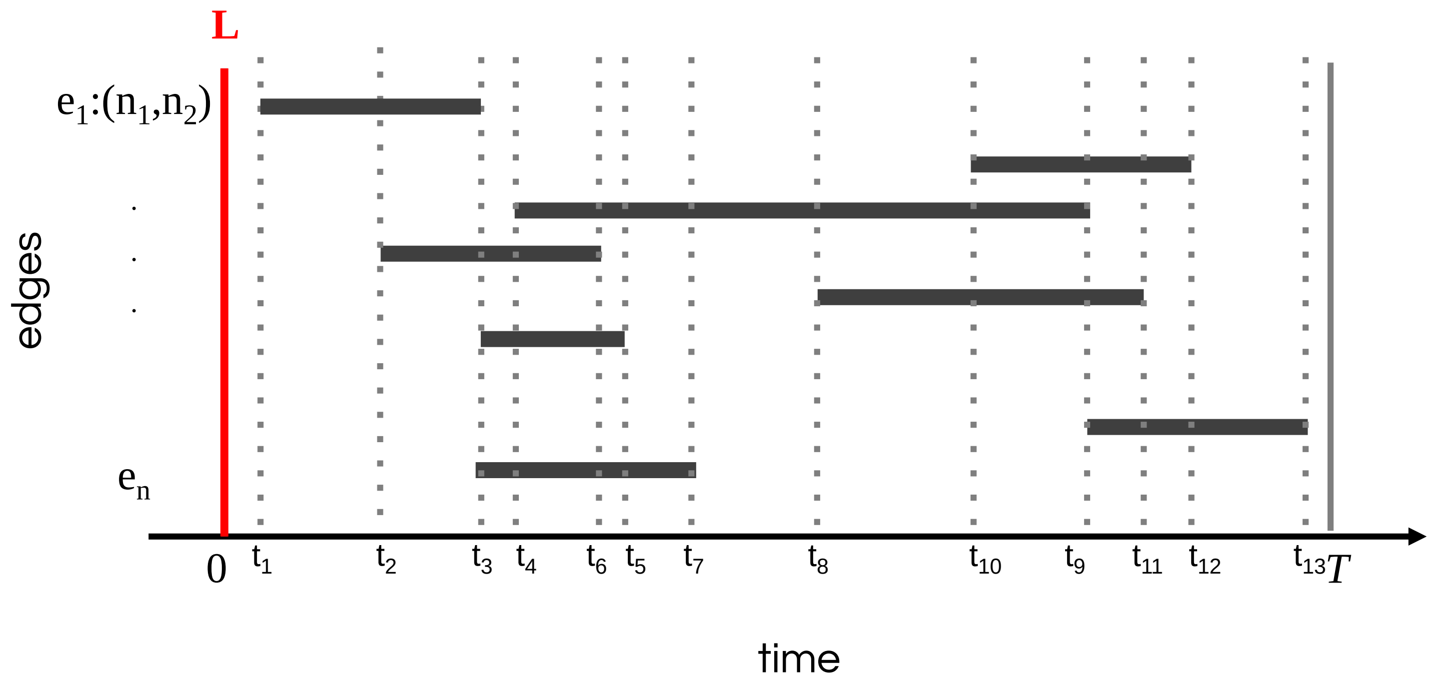
(**algorithm sketch**)

represent TN **edges** as **time intervals**

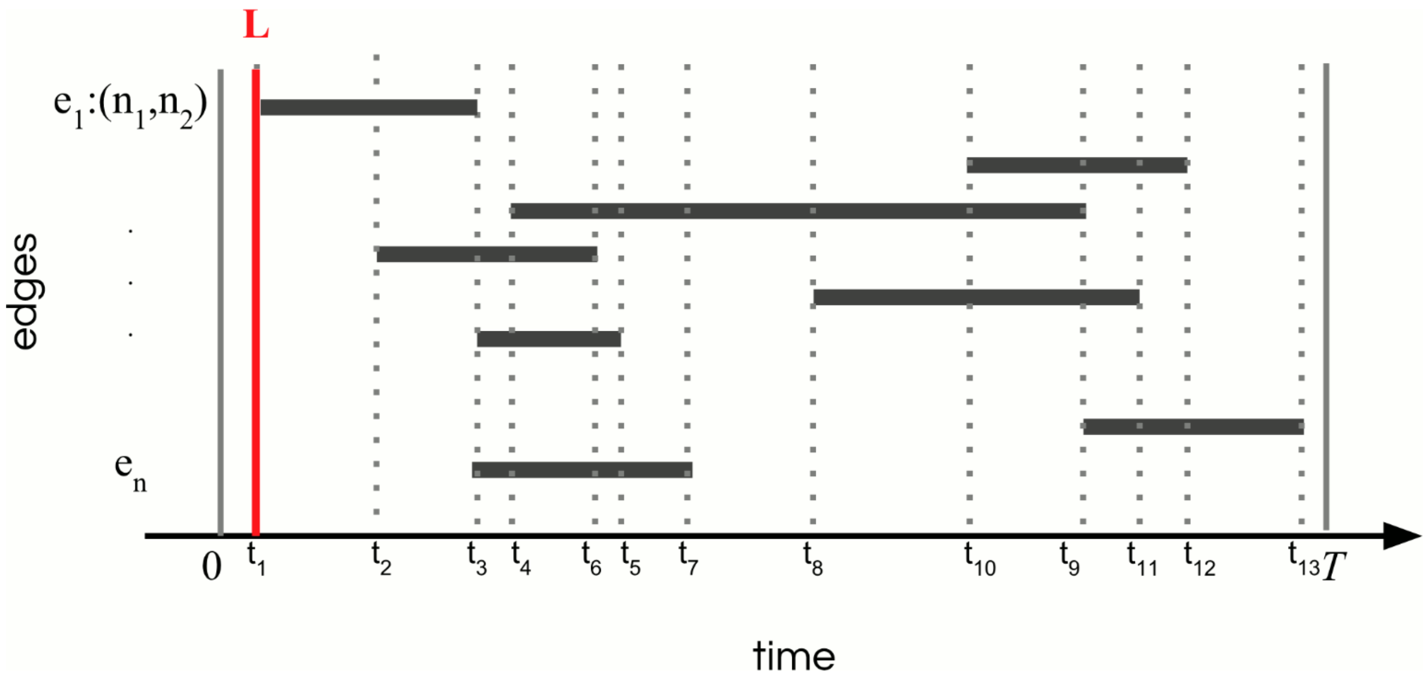
apply **variation** of sweep line algorithm

simultaneously compute *node degree, triangle membership, connected components* in **one pass**

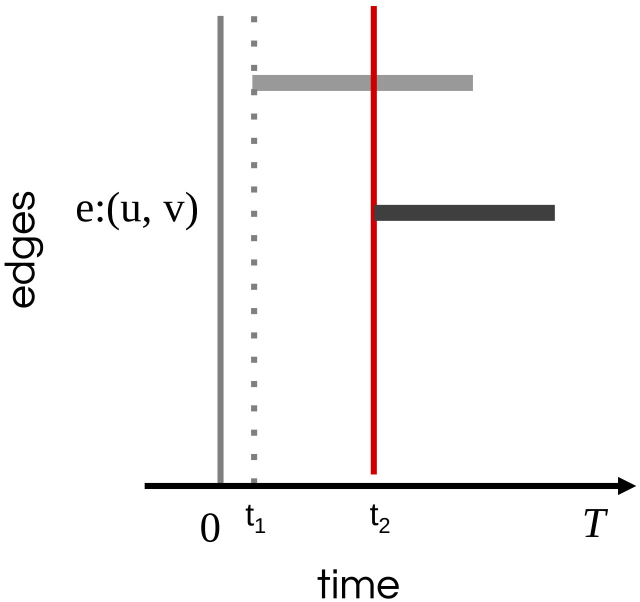
Represent edges as time intervals

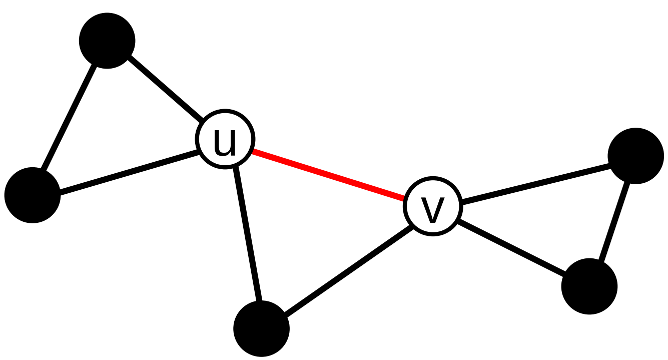


SLOT: Sweep Line Over Trajectories



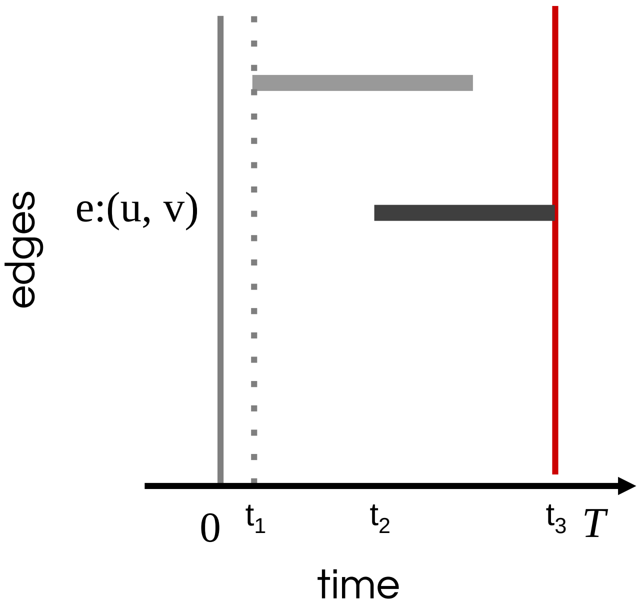
At every edge **start**

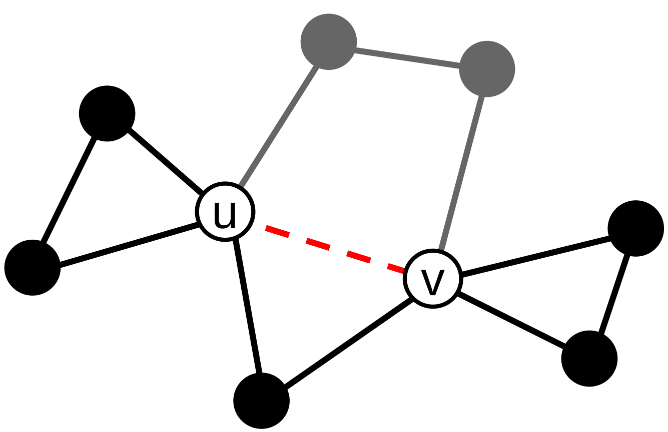




- **node degree**
  - nodes u, v now connected
  - increment u, v node degrees
- **triangle membership**
  - did a triangle just form?
  - look for u, v common neighbors
  - increment triangle (u, v, common)
- **connected components**
  - did two previously disconnected components connect?
  - compare old components of u, v
  - if no overlap, merge them

At every edge **stop**





- **node degree**
  - nodes u, v now disconnected
  - decrement u, v degree
- **triangle membership**
  - did a triangle just break?
  - look for u, v common neighbors
  - decrement triangle (u, v, common)
- **connected components**
  - did a conn. compon. separate?
  - BFS to see if u, v still connected
  - if not, split component to two

SLOT: At the end of the algorithm …

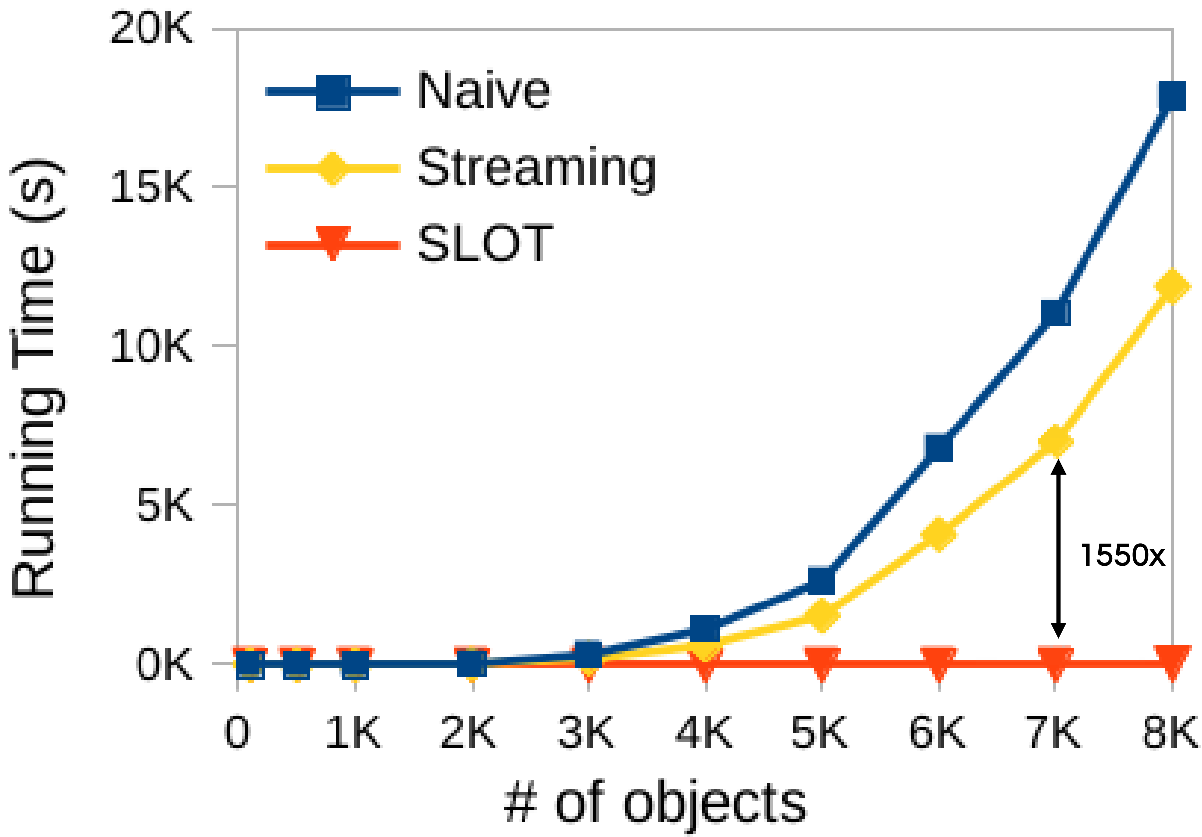
Rich Analytics

- **node degrees:** start/end time, duration
- **triangles:** start/end time, duration
- **connected components:** start/end time, duration

Exact results (not approximations)

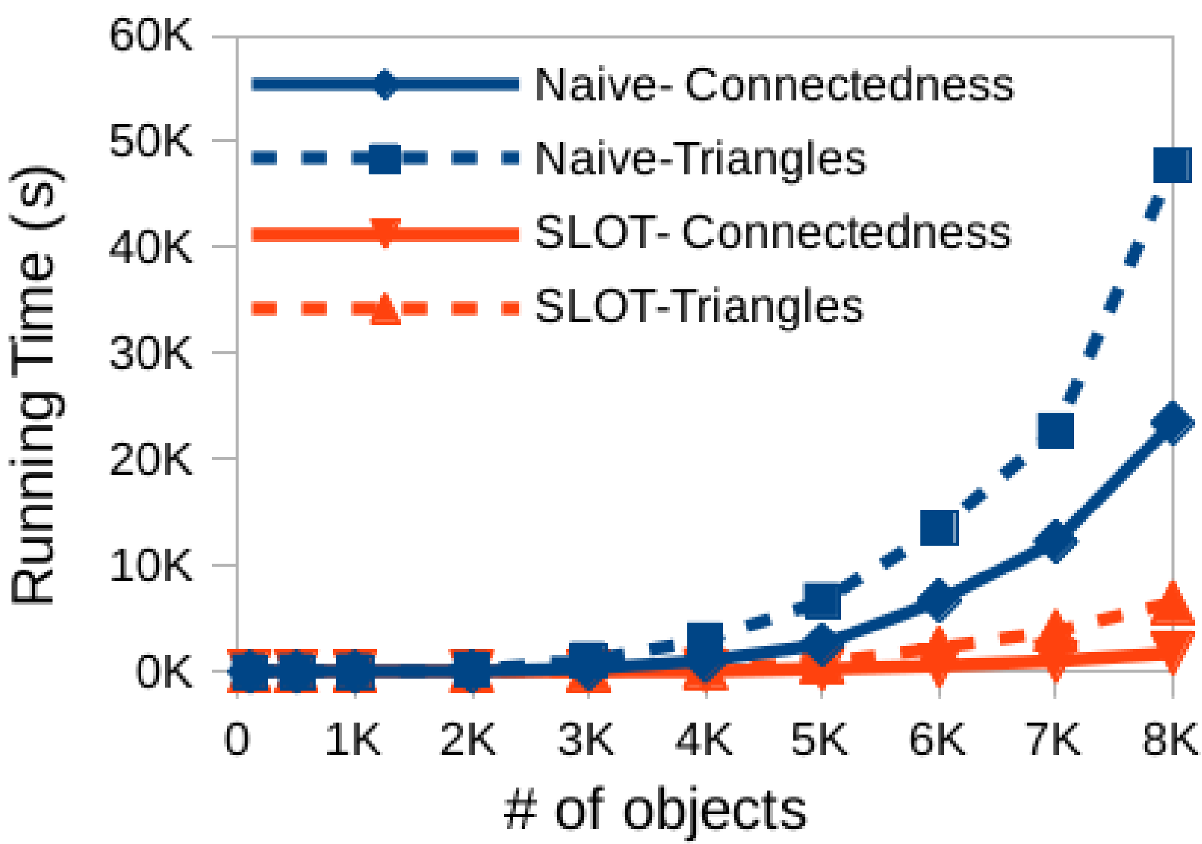
Evaluation of SLOT

Node degree

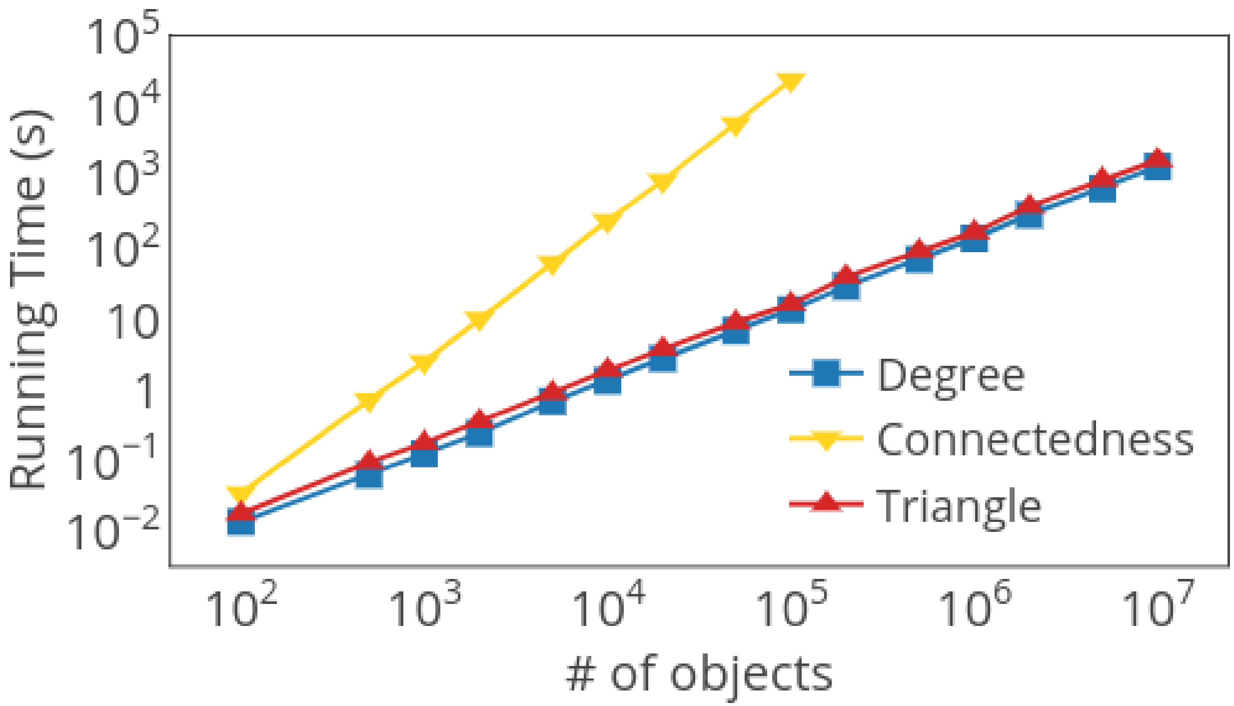


Running Time (s)
20K
15K
10K
5K
0K
Naive
Streaming
SLOT
1550x
0
1K
2K
3K
4K
5K
6K
7K
8K
# of objects

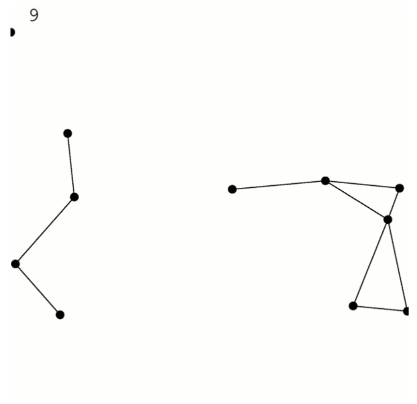
Triangle membership / connected components



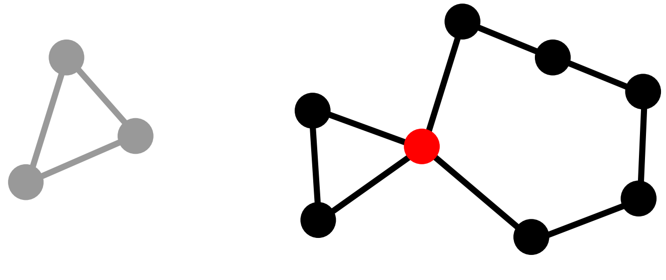
SLOT Scalability



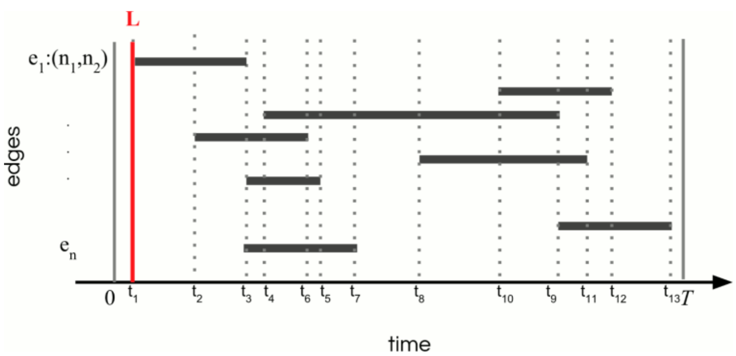
Takeaway



trajectory networks



network importance **over time**



SLOT algorithm

SLOT properties:

- fast
- exact
- scalable

Seagull migration trajectories

data from Wikelski et al. 2015

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Group Pattern Discovery of Pedestrian Trajectories

Joint work with Sawas Abdullah et al.

Pedestrian trajectories

what is a group?

many definitions,
many algorithms

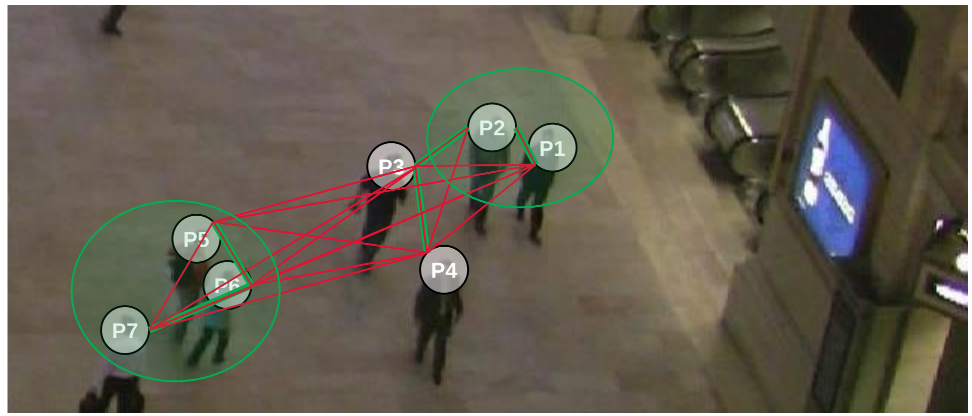
e.g., *flock*, *convoy*, *evolving-clusters*, *gathering-pattern*, ... [ACM TIST Tutorial 2015]

Finding pedestrian groups

Local Grouping

Intuitive method

Spatial-only



proximity threshold θ

key idea

find **pairs** of pedestrians **x, y** where **distance(x, y) < θ**

expand **pairs** to discover **groups**

Local grouping

expand the key idea
to include the
time dimension

Global groups vs. Time-window groups

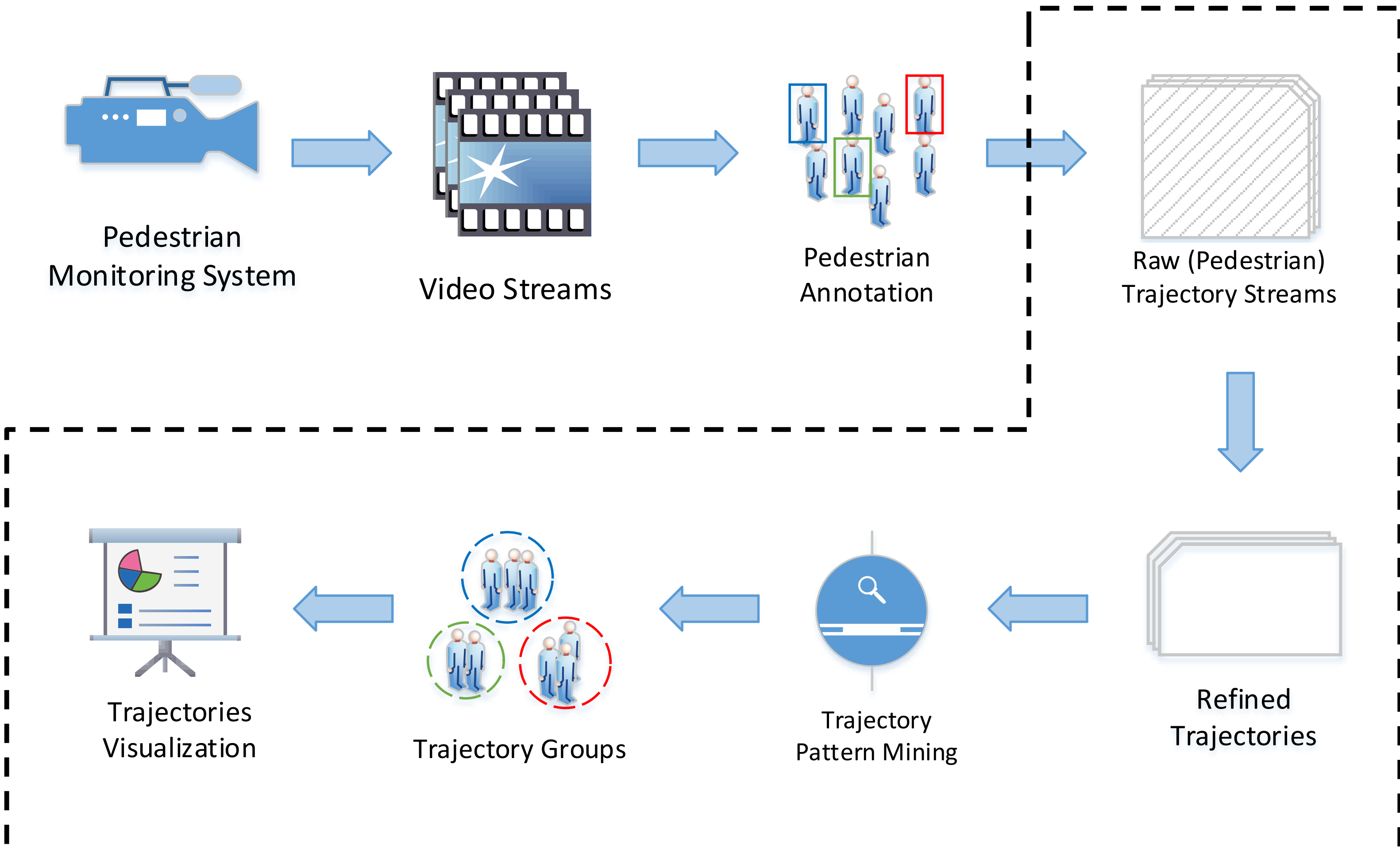
global
grouping

time-window
grouping

Trajectolizer

Demo

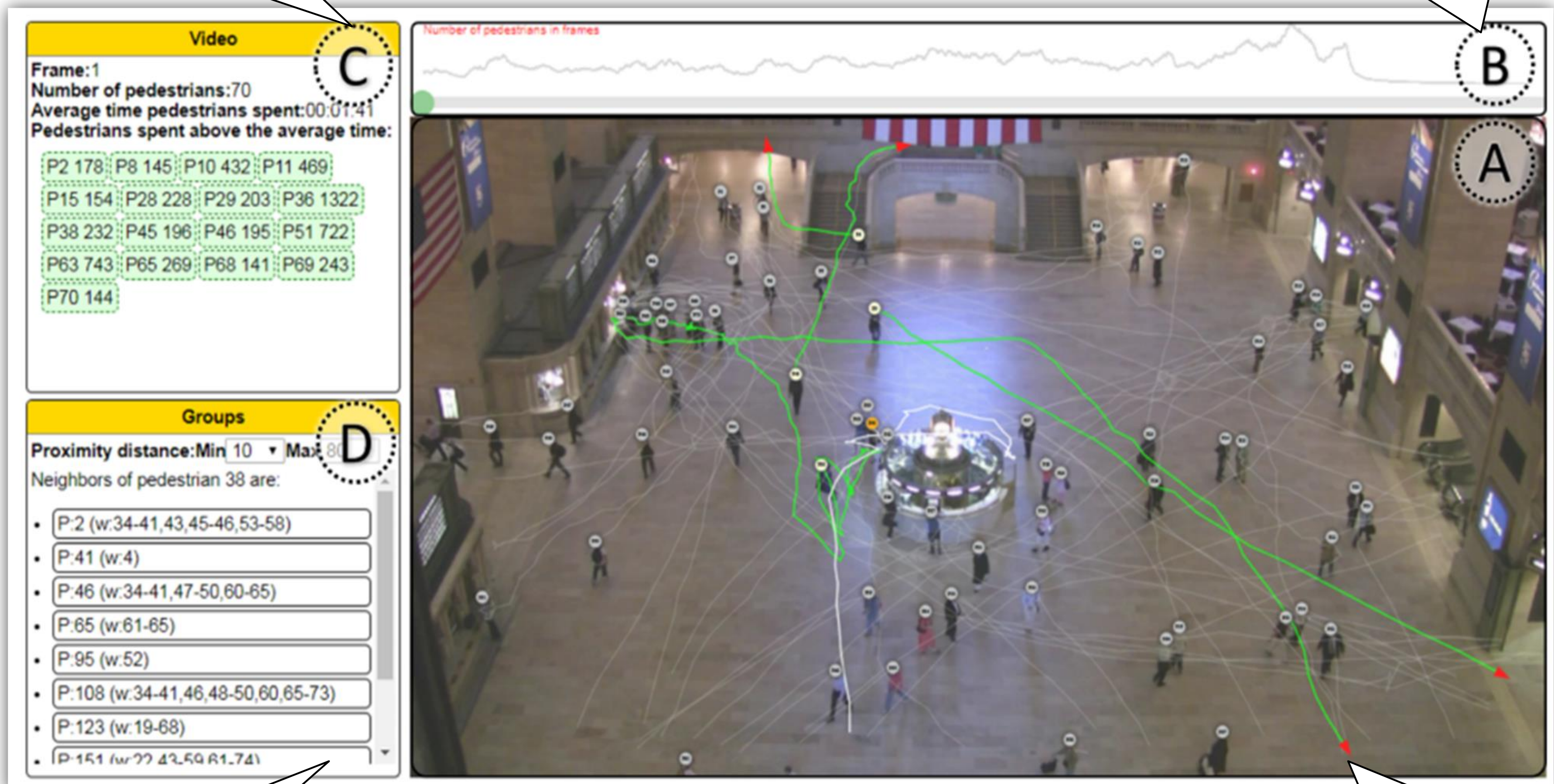
Trajectolizer: System Overview



Trajectolizer: Interactive Demo

descriptive statistics about the current frame

timeline slider area to navigate video frames



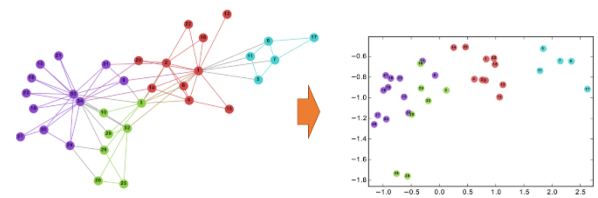
grouping analysis

current frame with pedestrian IDs and trajectories

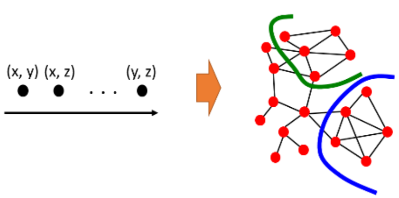
Live Demo

Current Research focus

A. Trajectory Network Mining



B. Network Representation Learning



C. Streaming & Dynamic Graphs

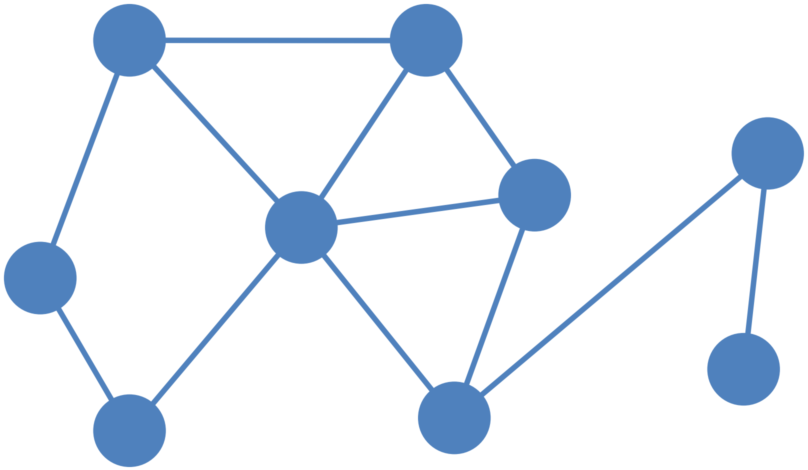
D. Social Media Mining & Analysis

E. City Science / Urban Informatics / IoT

F. Natural Language Processing

EvoNRL: Evolving Network Representation Learning Based on Random Walks

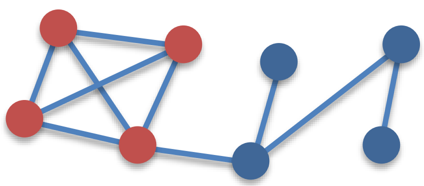
Joint work with Farzaneh Heidari



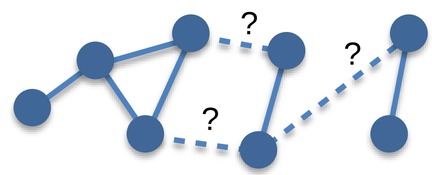
networks

(universal language for describing complex data)

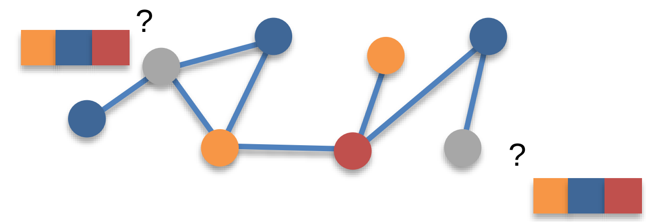
Classical ML Tasks in Networks



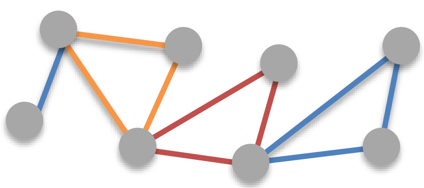
community detection



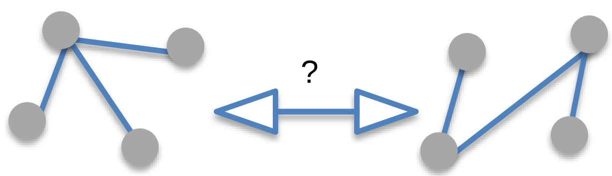
link prediction



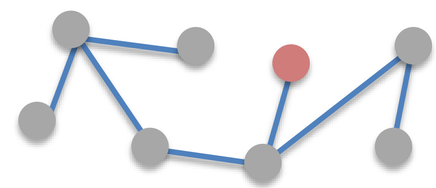
node classification



triangle count



graph similarity

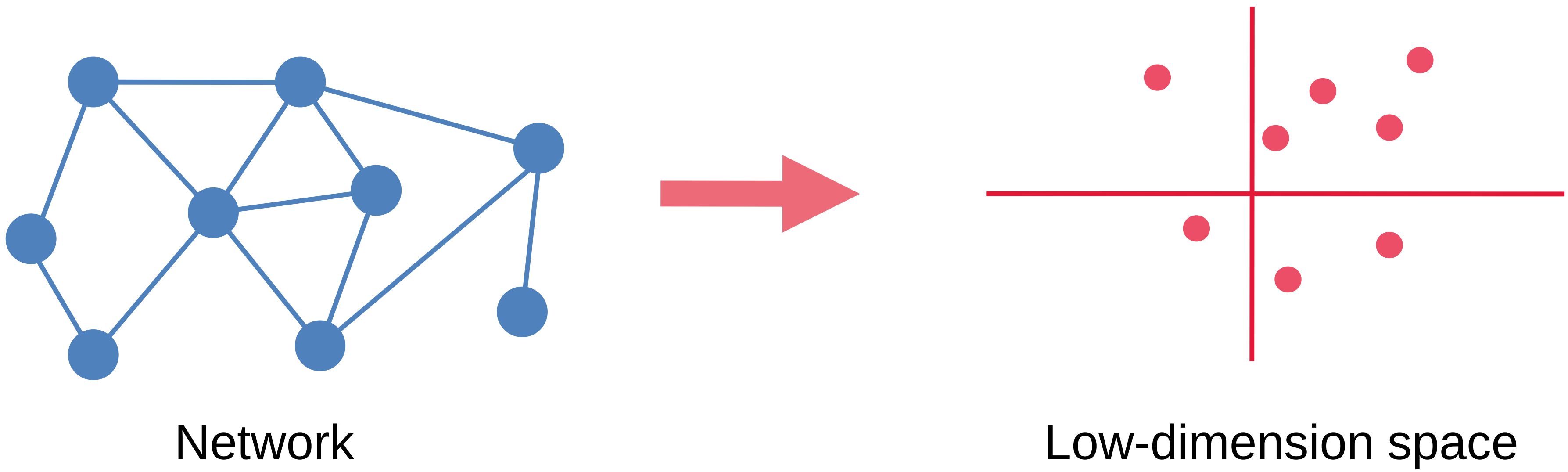


anomaly detection

Limitations of Classical ML:

- expensive computation (high dimension computations)
- extensive domain knowledge (task specific)

Network Representation Learning (NRL)

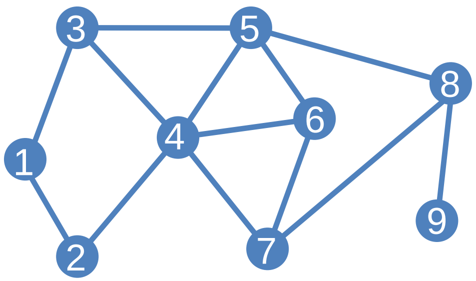


several network structural properties can be learned/embedded
(**nodes, edges, subgraphs, graphs, …**)

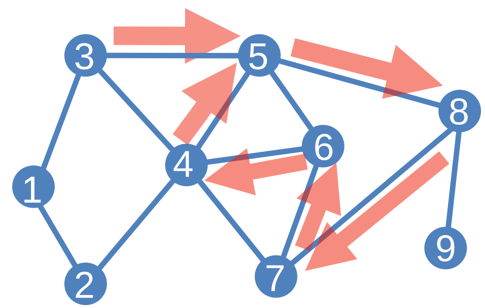
Premise of NRL:

- faster computations (low dimension computations)
- agnostic domain knowledge (task independent)

Random Walk-based NRL



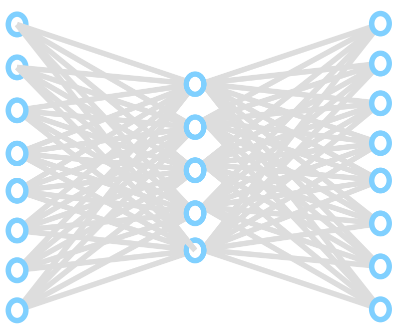
Input network



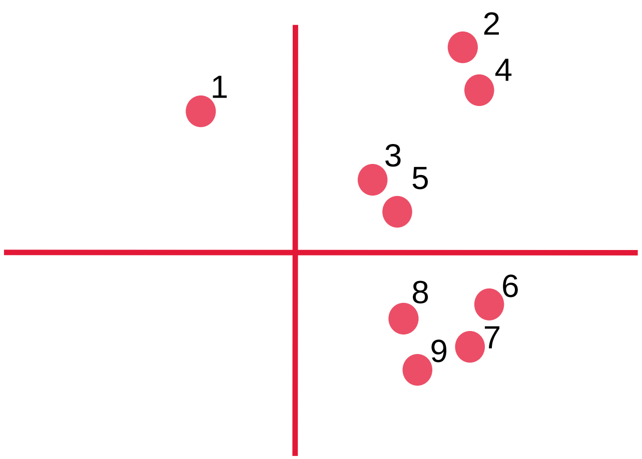
Obtain a set of
random walks

1	3 5 8 7 6 4 5
2	1 3 5 8 7 6 5
. . . .	. . . .
87	8 5 4 3 5 6 7
88	4 5 6 7 8 9
89	2 1 3 5 6 7 8
90	7 4 2 1 3 5 6

Treat the set of random walks
as sentences



Feed sentences to a
Skip-gram NN model



Learn a vector representation
for each node

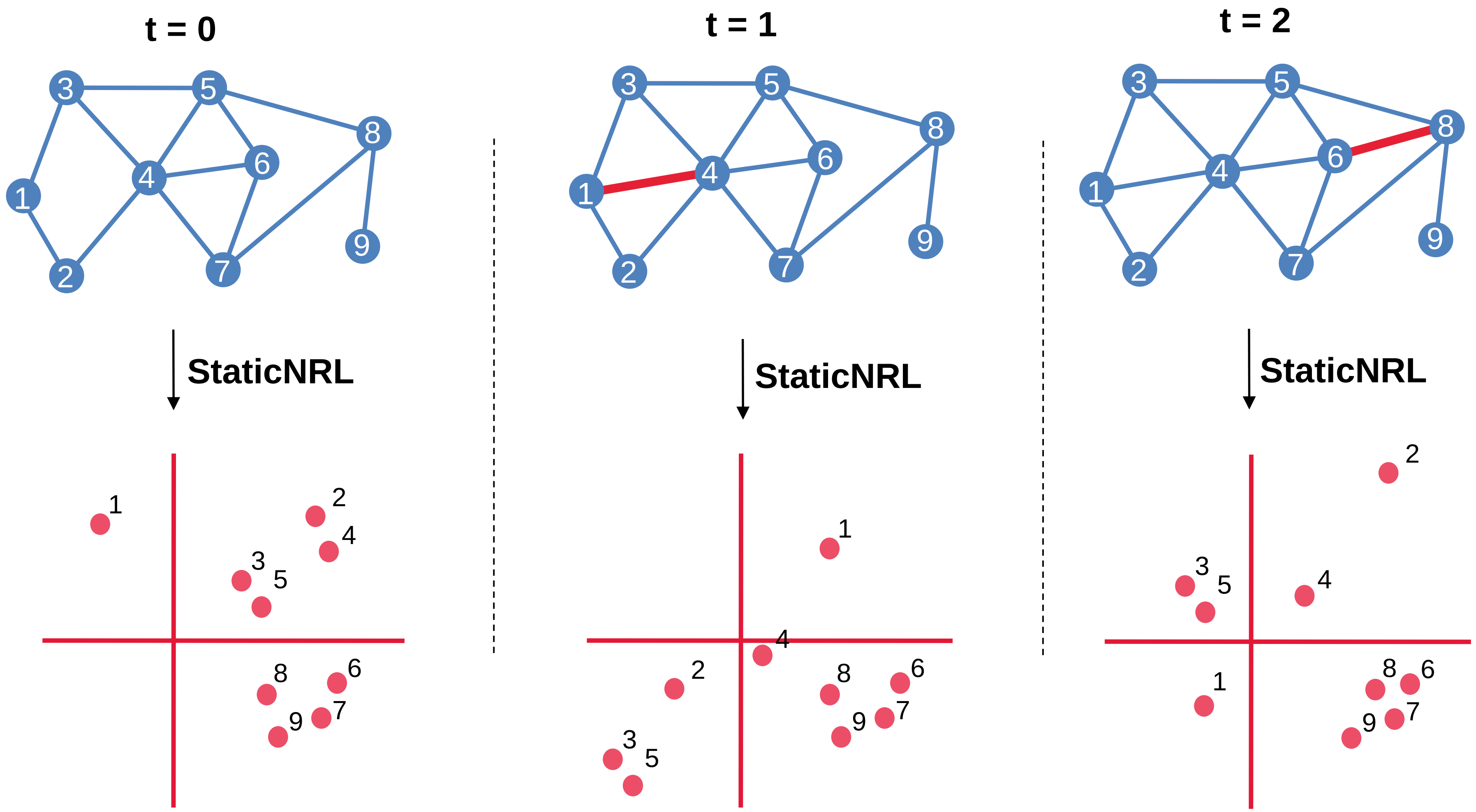
StaticNRL

(DeepWalk, node2vec, …)

but real-world networks are
constantly evolving

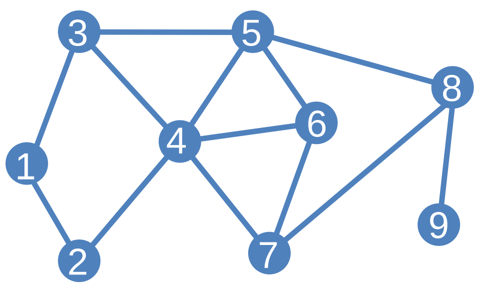
Evolving Network Representations Learning

Naive Approach

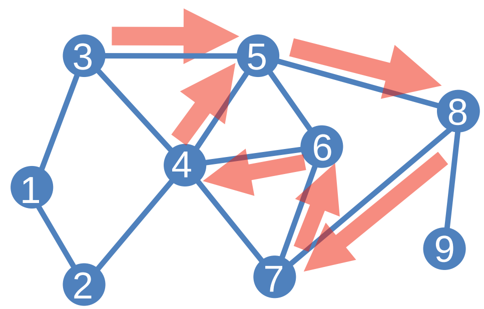


Impractical (expensive, incomparable representations)

EvoNRL Key Idea



Input network

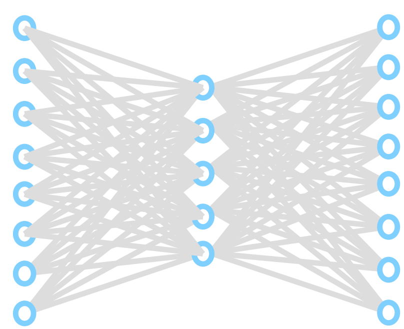


Obtain a set of random walks

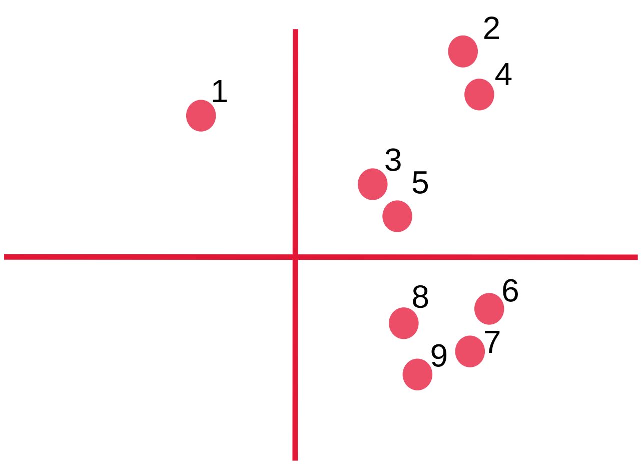
dynamically maintain a valid set of random walks for every change in the network

1	3 5 8 7 6 4 5
2	1 3 5 8 7 6 5
.	.
.	.
.	.
.	.
87	8 5 4 3 5 6 7
88	4 5 6 7 8 9
89	2 1 3 5 6 7 8
90	7 4 2 1 3 5 6

Treat the set of random walks as sentences



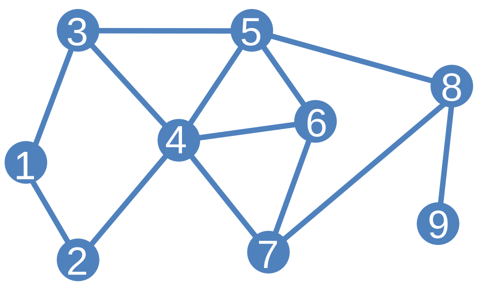
Feed sentences to a Skip-gram NN model



Learn a vector representation for each node

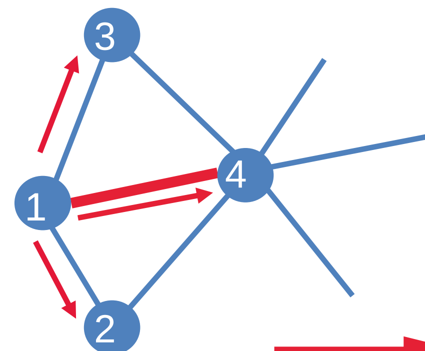
Example: Edge Addition

t = 0



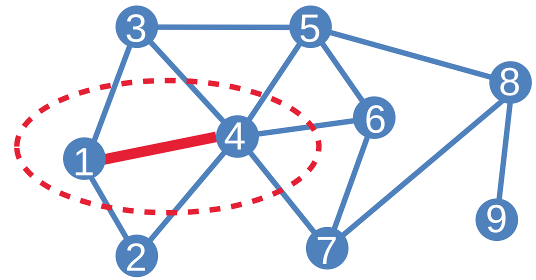
1	3 5 8 7 6 4 5
2	1 3 5 8 7 6 5
.	.
.	.
.	.
.	.
87	8 5 4 3 5 6 7
88	4 5 6 7 8 9 8
89	2 1 3 5 6 7 8
90	7 4 2 1 3 5 6

addition of edge (1, 4)



need to update the RW set

t = 1



simulate the rest of the RW

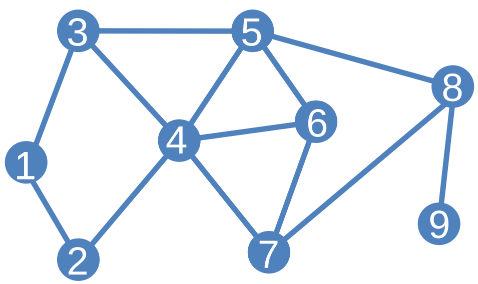
2	1 4 3 5 6 7 8

1	3 5 8 7 6 4 5
2	1 3 5 8 7 6 5
.	.
.	.
.	.
.	.
87	8 5 4 3 5 6 7
88	4 5 6 7 8 9 8
89	2 1 3 5 6 7 8
90	7 4 2 1 3 5 6

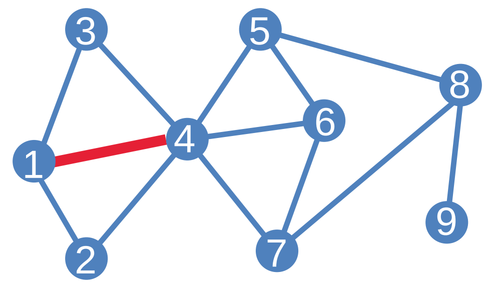
similarly for edge deletion, node addition/deletion

Efficiently Maintaining a Set of Random Walks

EvoNRL Operations



+ edge(n_1, n_2)



2	1 **4** 3 5 6 7 8

1	3 5 8 7 6 4 5
2	1 3 5 8 7 6 5
.	.
.	.
.	.
.	.
87	8 5 4 3 5 6 7
88	4 5 6 7 8 9
89	2 1 3 5 6 7 8
90	7 4 2 1 3 5 6

1	3 5 8 7 6 4 5
2	1 3 5 8 7 6 5
.	.
.	.
.	.
.	.
87	8 5 4 3 5 6 7
88	4 5 6 7 8 9
89	2 1 3 5 6 7 8
90	7 4 2 1 3 5 6

Operations on RW

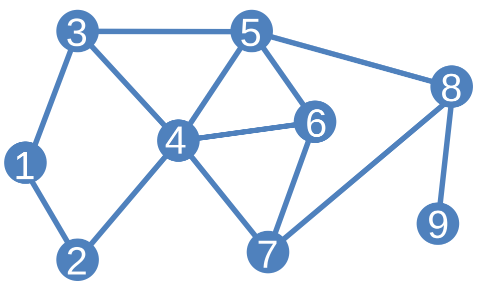
Search a node

Delete a RW

Insert a new RW

need for an efficient indexing data structure

EvoNRL Indexing



1	3 5 8 7 6 4 5
2	1 3 5 8 7 6 5
.	.
.	.
.	.
.	.
87	8 5 4 3 5 6 7
88	4 5 6 7 8 9
89	2 1 3 5 6 7 8
90	7 4 2 1 3 5 6

elastic

each node is **a keyword**
each RW is **a document**
a set of RWs is **a collection of documents**

Term	Frequency	Postings and Positions
1	3	< 2, 1 >, < 89, 2 >, < 90, 4 >
2	2	<89, 1>, <90, 3>
3	5	<1, 1>, <2, 1>, <87, 3>, <89, 3>, <90, 5>
4	4	<1, 6>, <87, 3>, <90, 2>
5	9	<1, 2>, <1, 7>, <2, 3>, <2, 7>, <87, 5>, <88, 2>, <89, 4>, <90, 6>
6	6	<1, 5>, <2, 6>, <87, 6>, <88, 3>, <89, 3>, <90, 5>
7	5	<1, 4>, <2, 5>, <87, 7>, <88, 4>, <89, 6>, <90, 7>
8	5	<1, 3>, <2, 4>, <87, 1>, <88, 6>, <89, 7>
9	1	<88, 7>

Evaluation of EvoNRL

Evaluation: EvoNRL vs StaticNRL

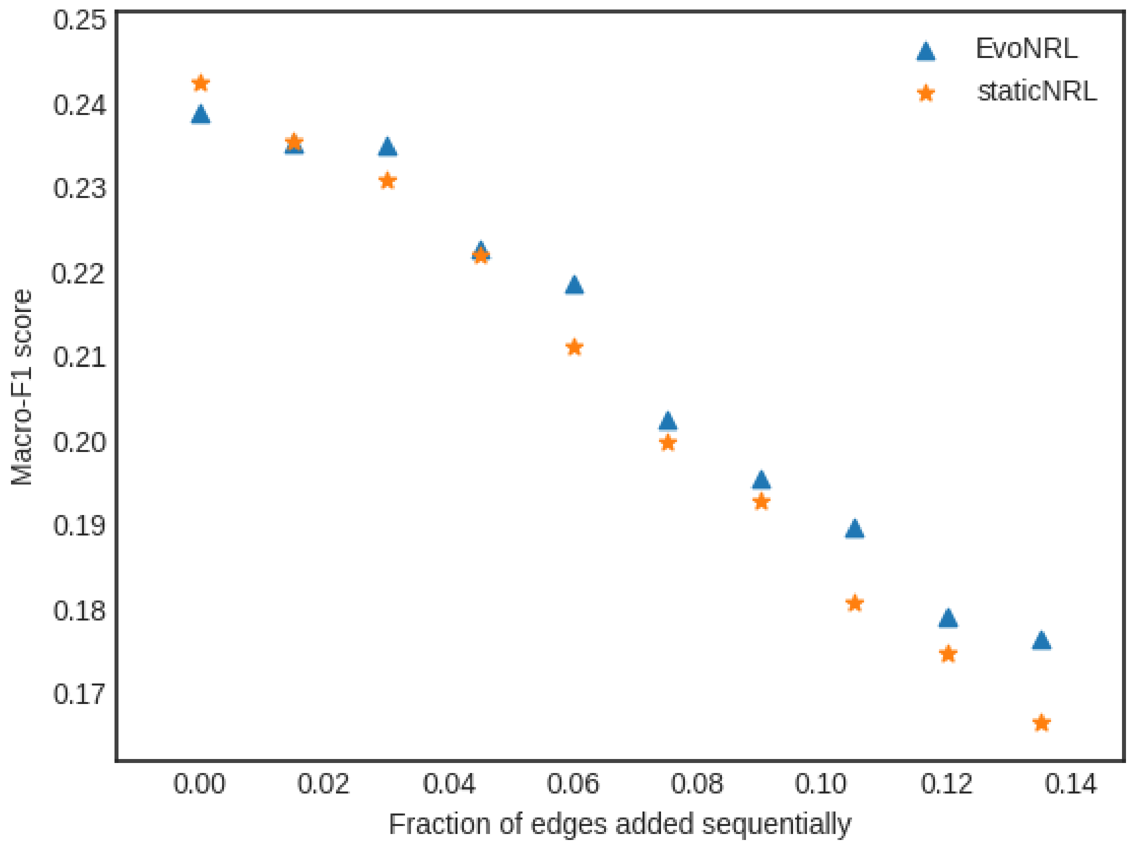
Accuracy

- EvoNRL **≈** StaticNRL

Running Time

- EvoNRL **<<** StaticNRL

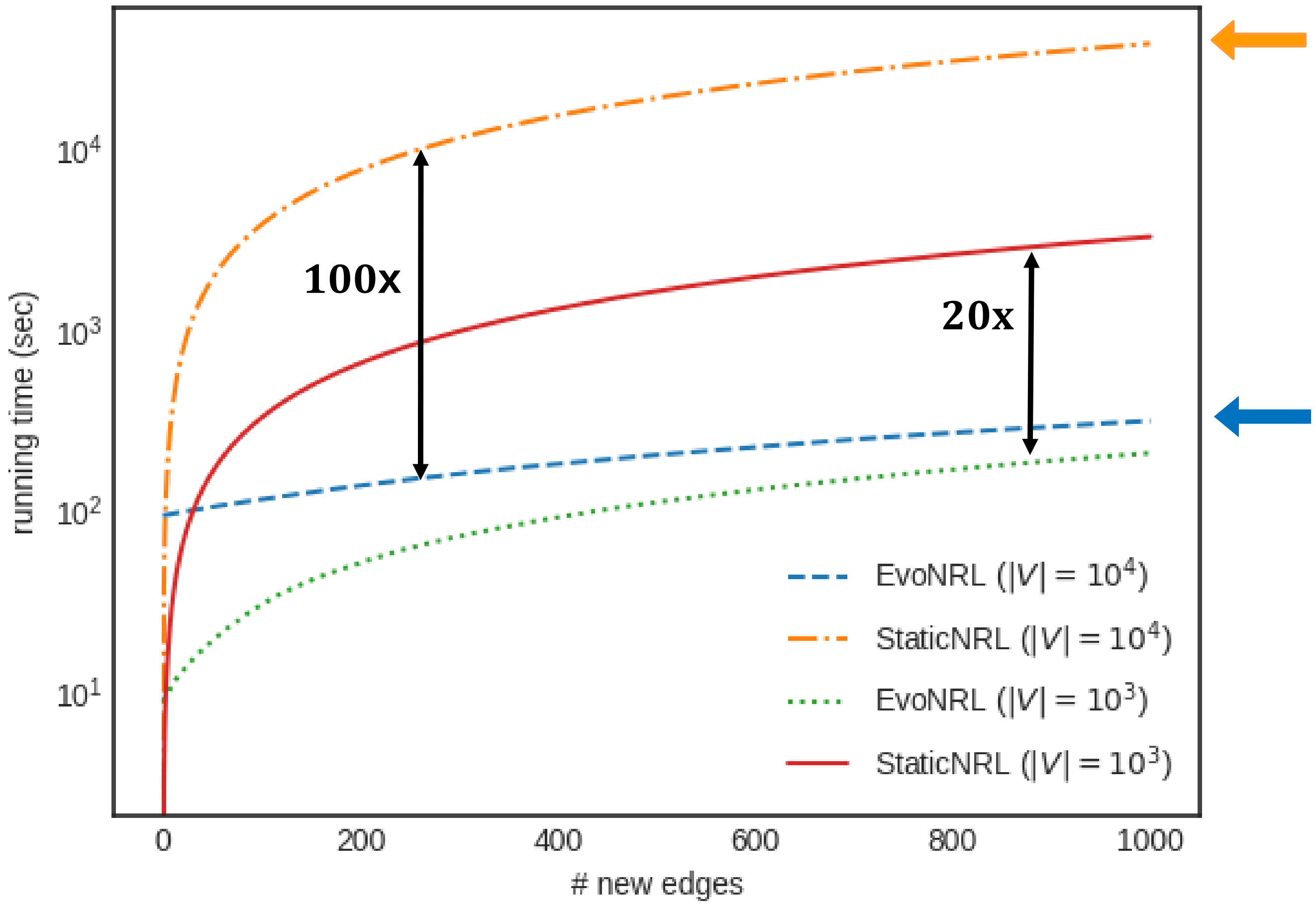
Accuracy: edge addition



EvoNRL has similar accuracy to StaticNRL

(similar results for edge deletion, node addition/deletion)

Time Performance



EvoNRL performs orders of time faster than StaticNRL

Takeaway

how can we learn representations of an evolving network?

EvoNRL

time efficient

accurate

generic method

Credits

Farzaneh Heidari

[Complex Networks 2018] EvoNRL: Evolving Network Representation Learning Based on Random Walks. Farzaneh Heidari and Manos Papagelis.

code: https://github.com/farzana0/EvoNRL/

Tilemachos Pechlivanoglou

[IEEE Big Data 2018] Fast and Accurate Mining of Node Importance in Trajectory Networks. Tilemachos Pechlivanoglou and Manos Papagelis.

code: https://github.com/tipech/trajectory-networks

Abdullah Sawas et al.

[Geoinformatica 2019] A Versatile Computational Framework for Group Pattern Mining of Pedestrian Trajectories. A. Sawas, A. Abuolaim, M. Afifi, M. Papagelis. GeoInformatica (Vol. X, No. X, 2019)

[IEEE MDM 2018] Tensor Methods for Group Pattern Discovery of Pedestrian Trajectories. A. Sawas, A. Abuolaim, M. Afifi, M. Papagelis. (**best paper award**)

demo: https://sites.google.com/view/pedestrians-group-pattern/

Thank you!

Questions?

Data Mining Lab @ YorkU

- **Mandate**
  - Conduct basic research / knowledge transfer
  - Equip students with theoretical knowledge & practical experience
  - Research focus:
    - data mining
    - graph mining
    - machine learning
    - NLP
    - big data analytics
- **Members**
  - Two Faculty Members (Prof. Aijun An, Prof. Manos Papagelis)
  - ~20 High Quality Personnel (HQP)
    - ~5 Postdoc, ~6 PhDs, ~8 MSc, ~3 Undergrads, ~1 staff