Large-scale Mining of Dynamic Networks

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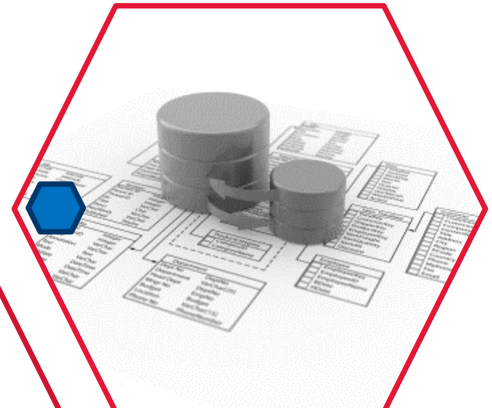
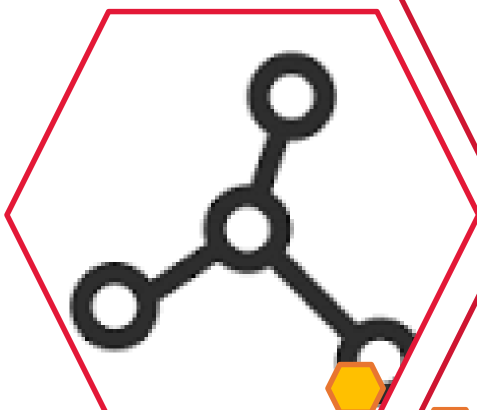
Background

UNIVERSITY OF TORONTO
YORK UNIVERSITÉ UNIVERSITY
University of Crete
FORTH
Institute of Computer Science
Berkeley
UNIVERSITY OF CALIFORNIA
YAHOO!
LABS

Research



Big Data Analytics



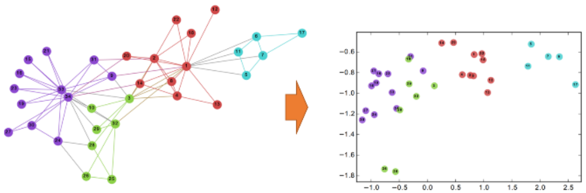
Data Mining

Graph Mining

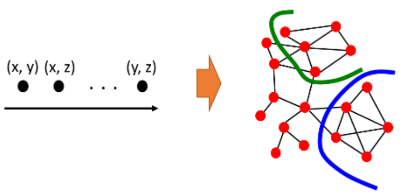
Today

Current Research focus

A. Trajectory Data Mining



B. Machine Learning with Graphs



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

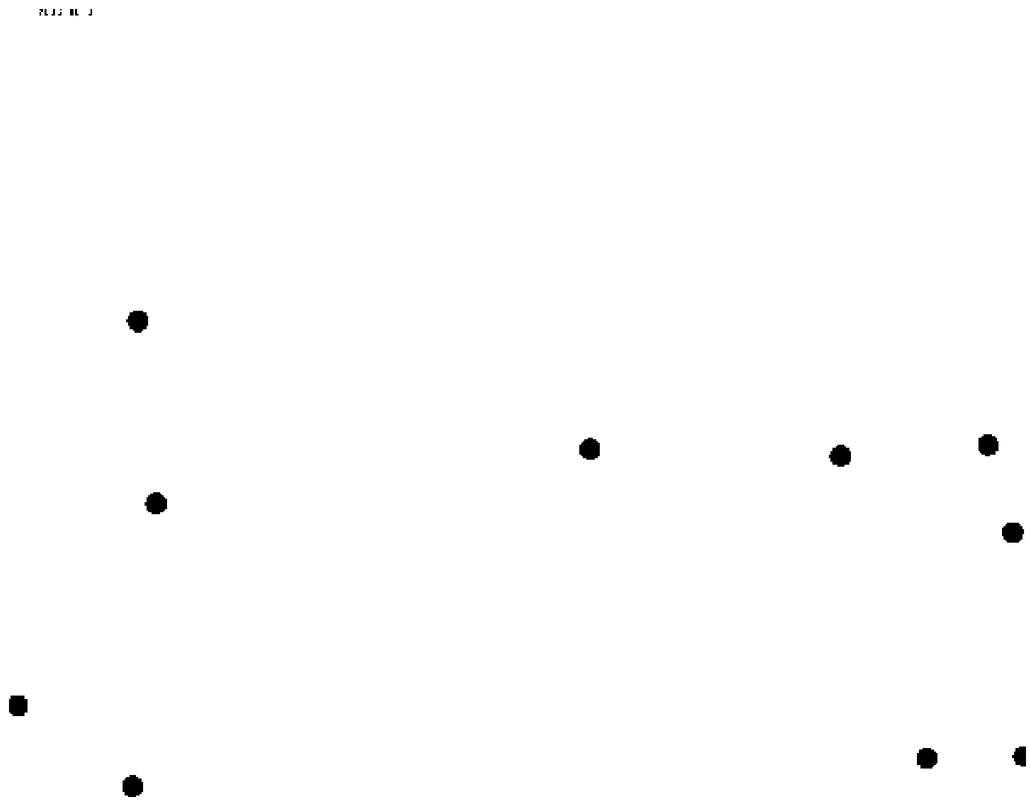
Evolving Network Mining

- Evolving Network Representation Learning Based on Random Walks

Node Importance in Trajectory Networks

Joint work with Tilemachos Pechlivanoglou

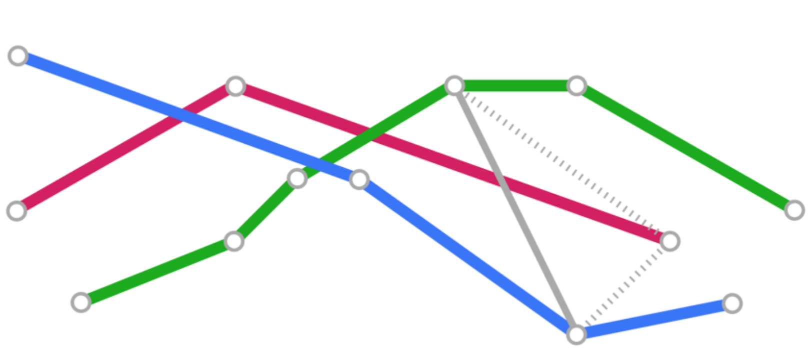
Trajectories of moving objects



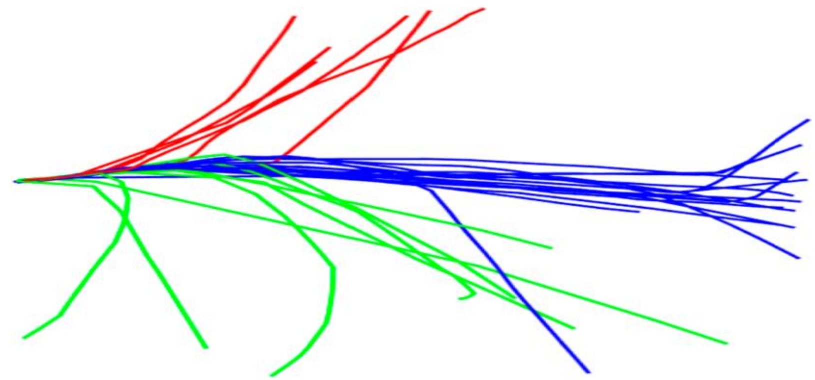
every moving object, forms a **trajectory** – in **2D** it is a sequence of (**x**, **y**, **t**)

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

Trajectory data mining



trajectory similarity

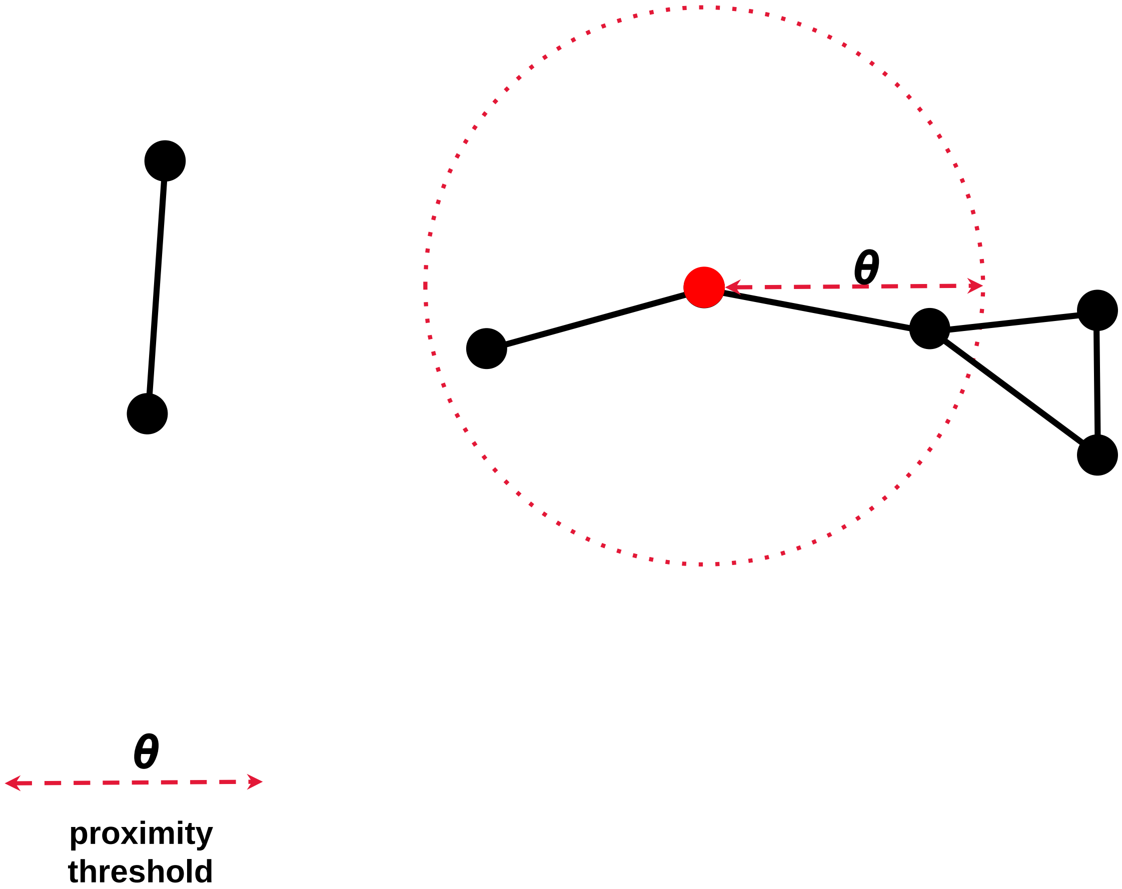


trajectory clustering

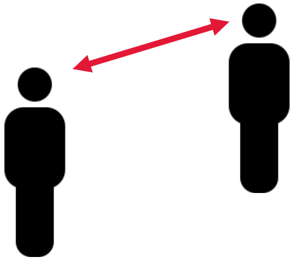
trajectory anomaly detection
trajectory pattern mining
trajectory classification
...more

we care about network analysis of moving objects

Proximity networks



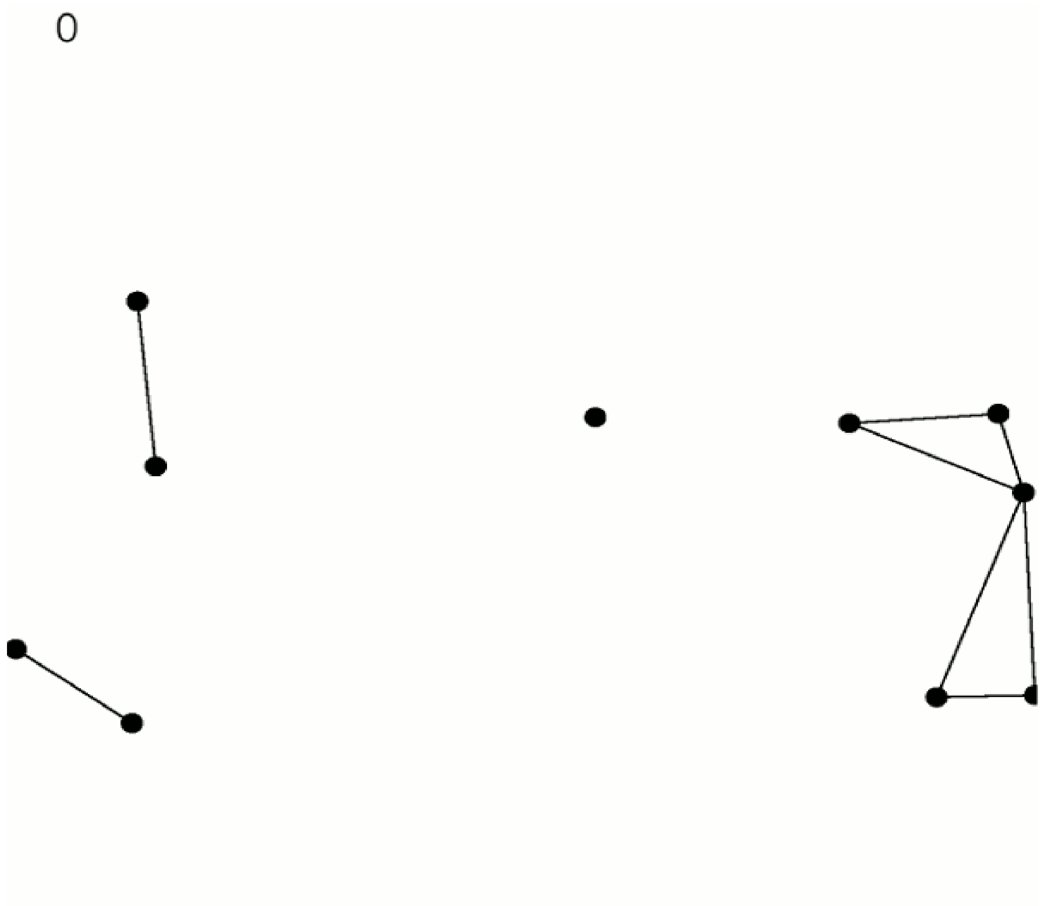
Distance can represent



line of sight

wifi/bluetooth signal range

Trajectory networks



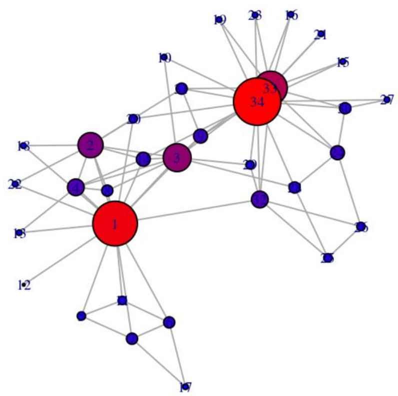
The Problem

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

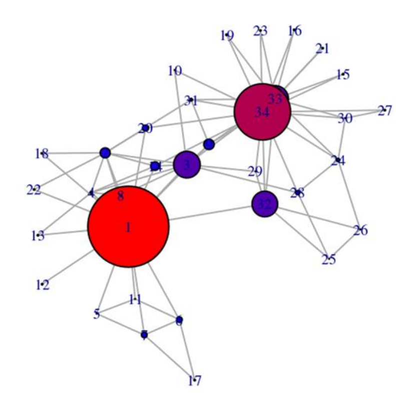
Output: node importance metrics

Node Importance

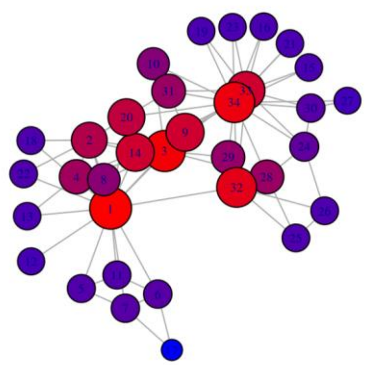
Node importance in static networks



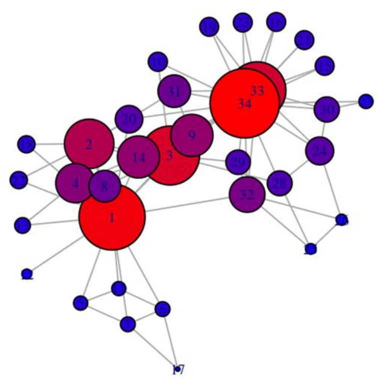
Degree centrality



Betweenness centrality

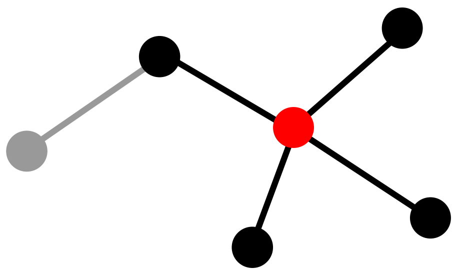


Closeness centrality

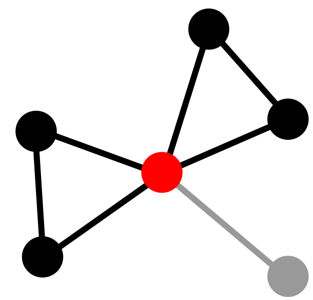


Eigenvector centrality

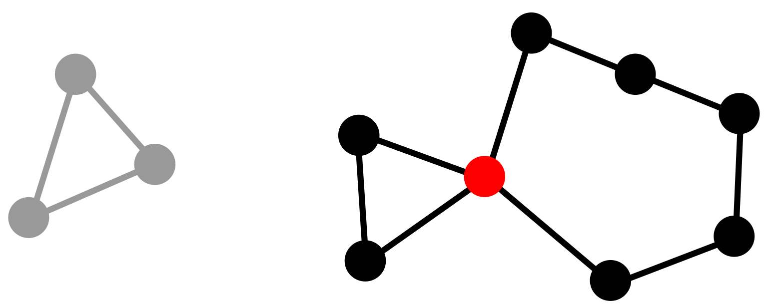
Node importance in TNs



node degree **over time**

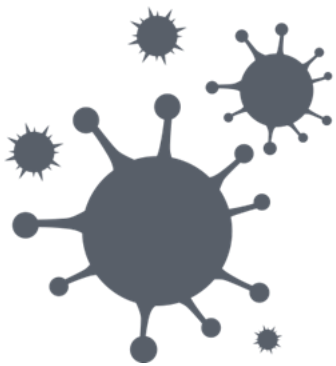


triangles **over time**



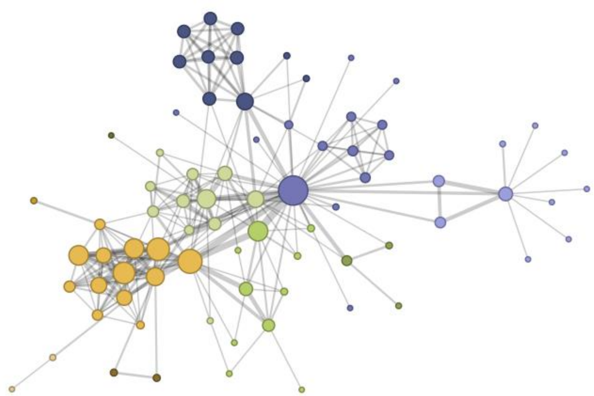
connected components **over time**
(connectedness)

Applications



infection spreading

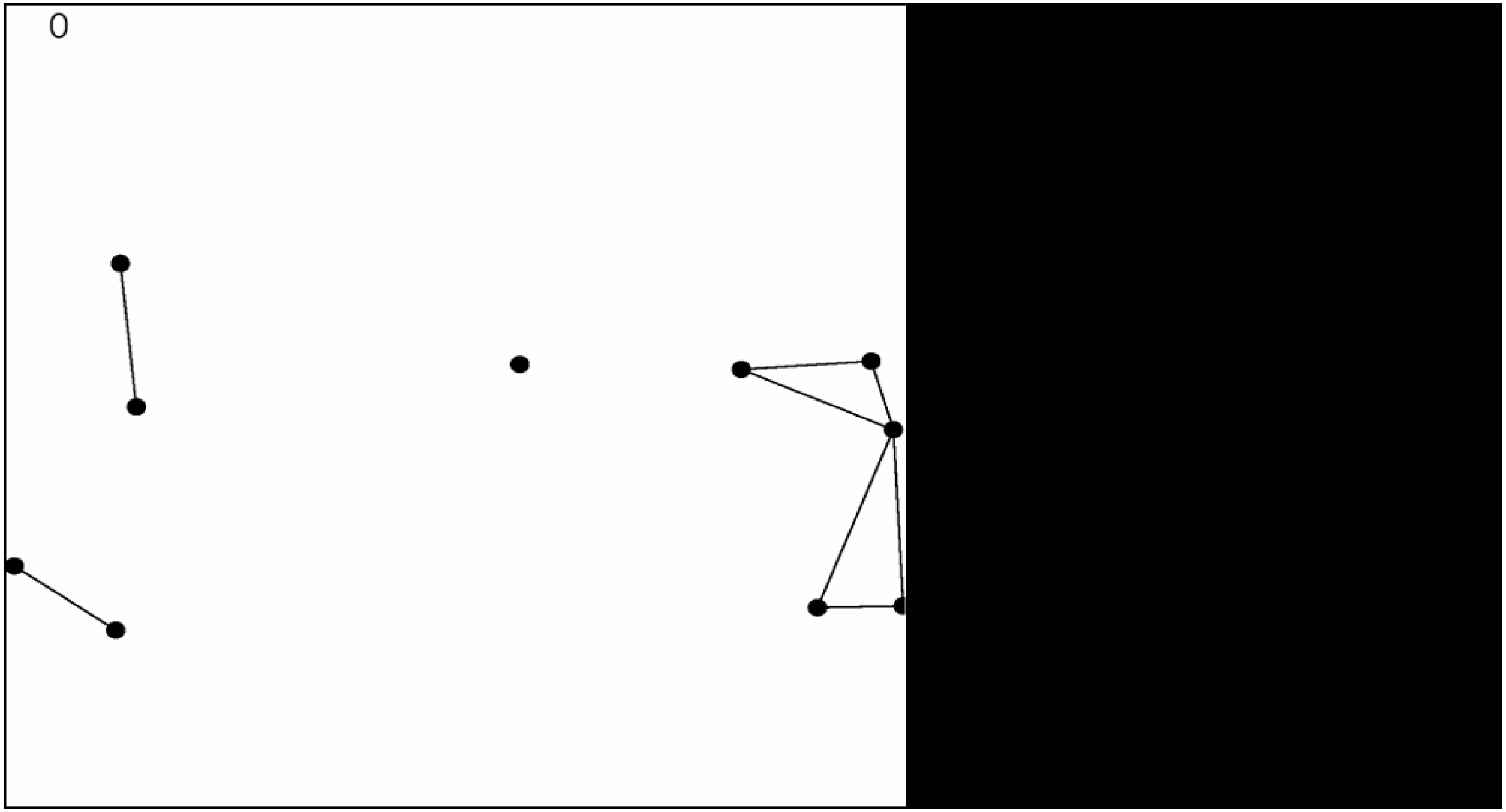
security in autonomous vehicles



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

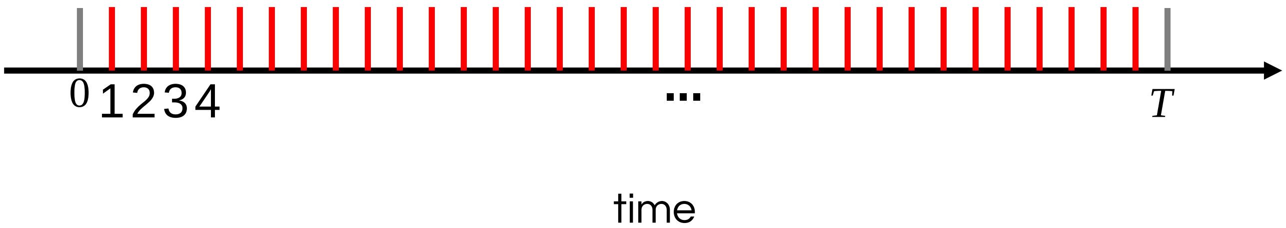
Streaming approach

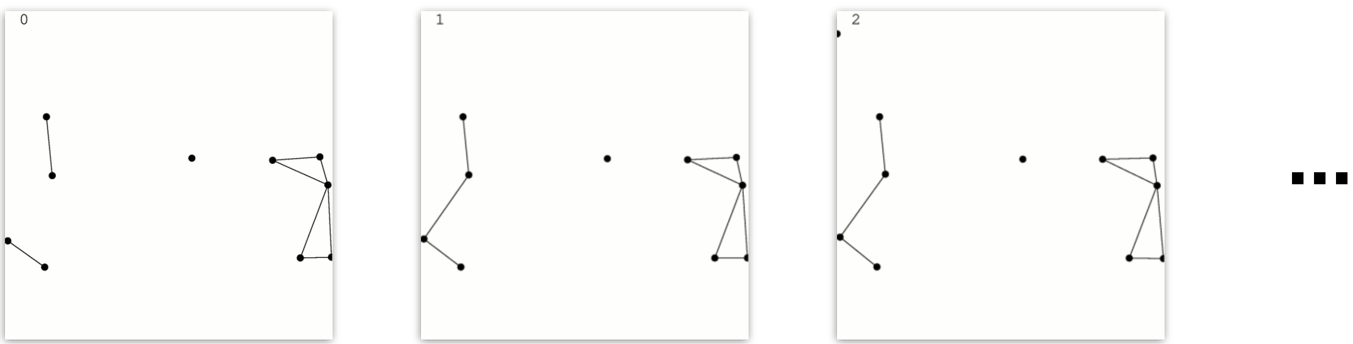
Similar to naive, but:

- **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 popular computational geometry algorithm

Input

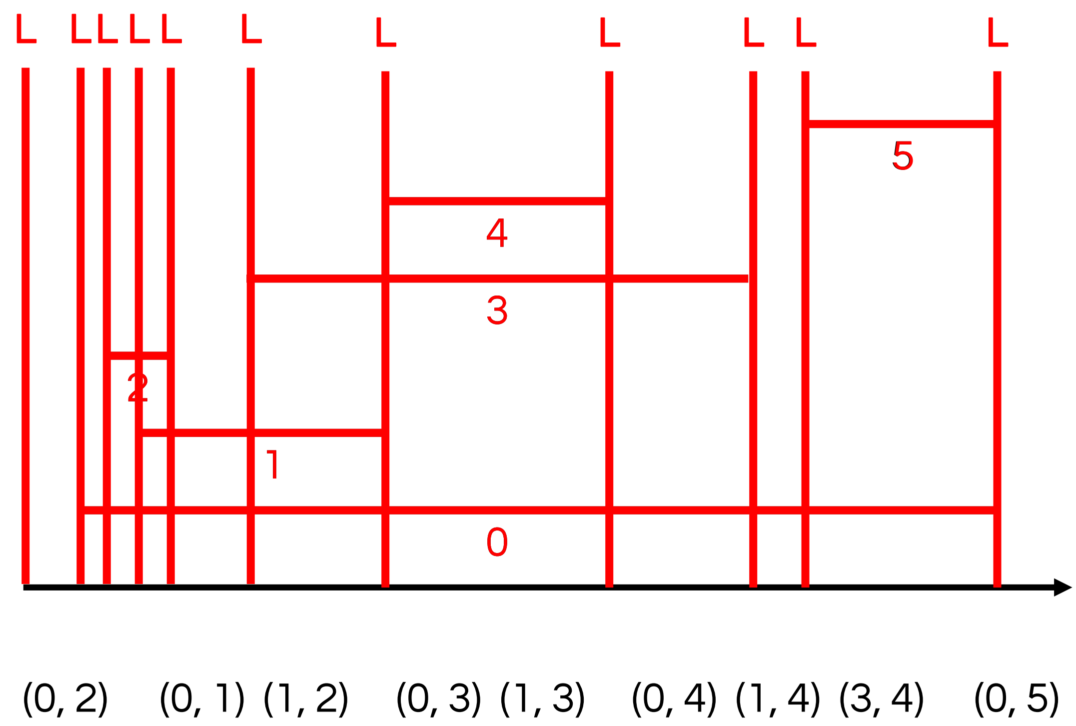
- a set of line segments (in 1D)

Output

- pairs of line segments that intersect
- size of the overlap

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

Sweep-line algorithm (1D Example)



SLOT: Sweep Line Over Trajectories

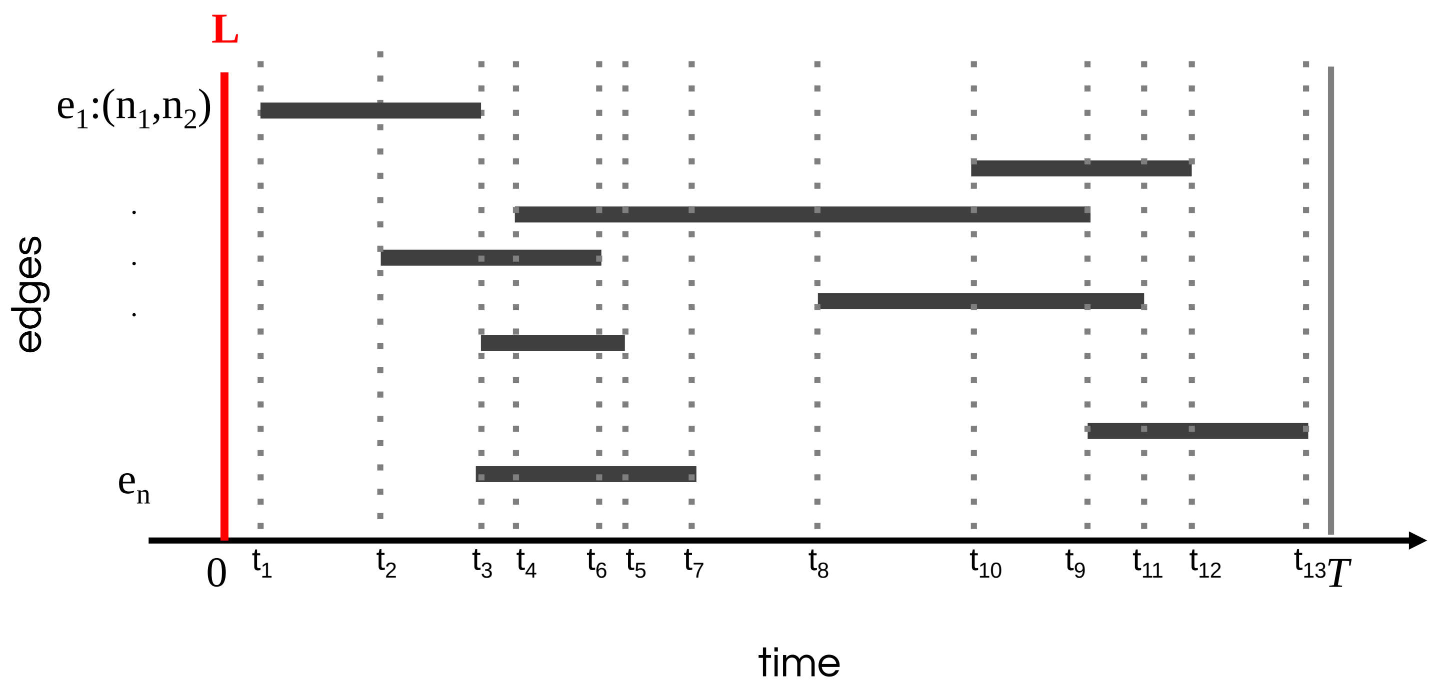
(**algorithm sketch**)

represent TN **edges** as **time intervals / line segm.**

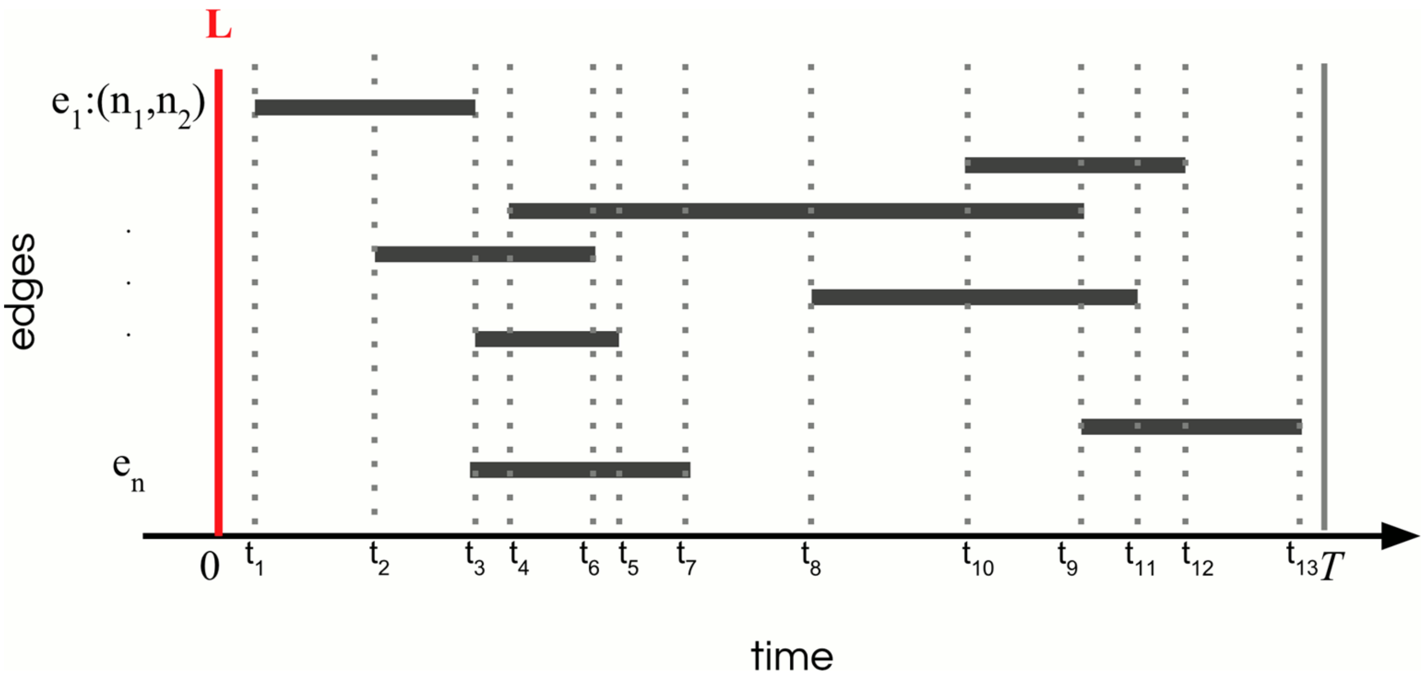
apply **variation** of sweep line algorithm

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

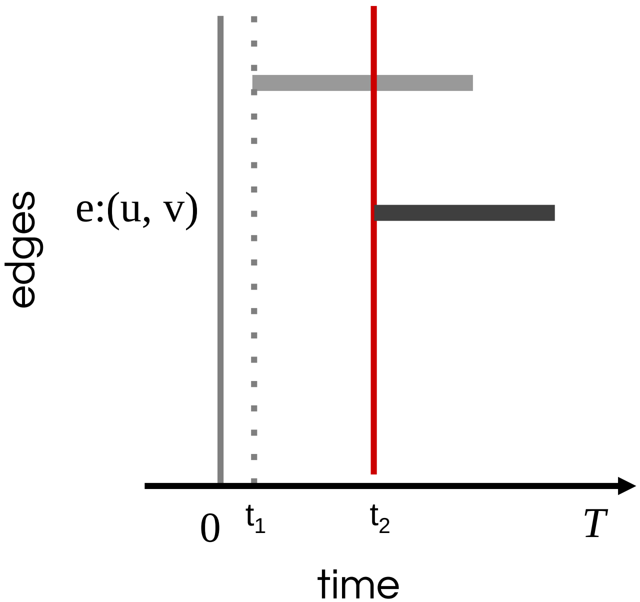
Represent edges as time intervals

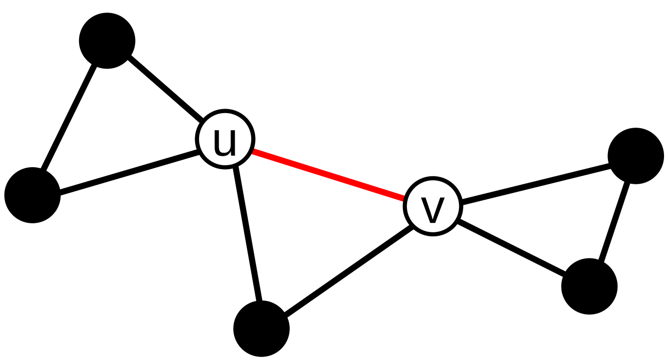


SLOT: Sweep Line Over Trajectories



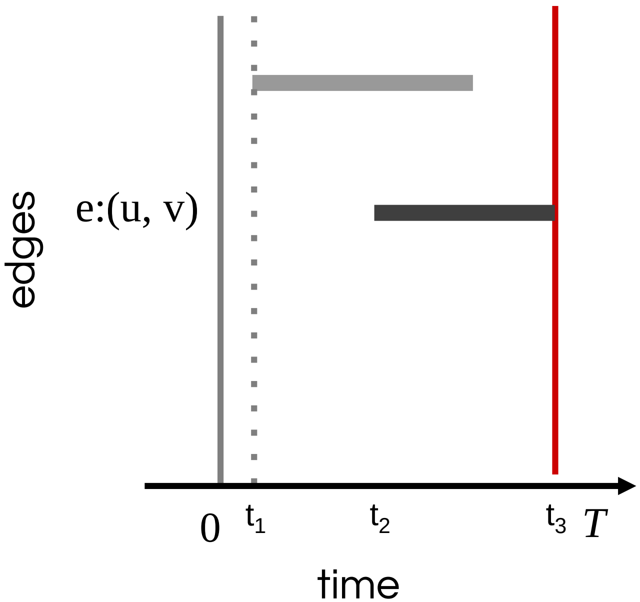
At every edge **start**

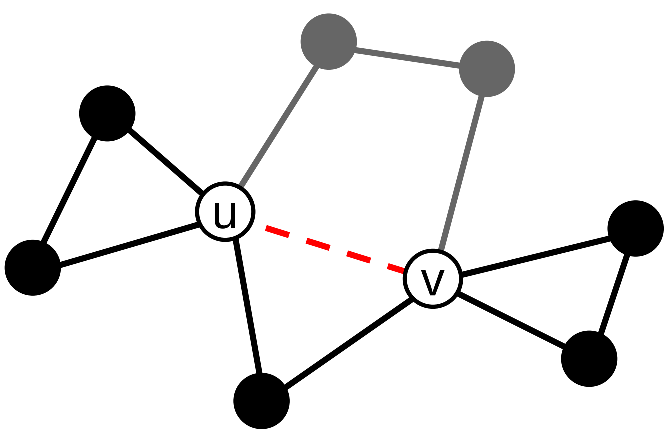




- node degree
  - nodes u, v now connected
  - increment u, v node degrees
- triangle membership
  - did a triangle just form?
  - look for u, v common neighbors
  - increment triangle (u, v, common)
- connected components
  - did two previously disconnected components connect?
  - compare old components 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 …

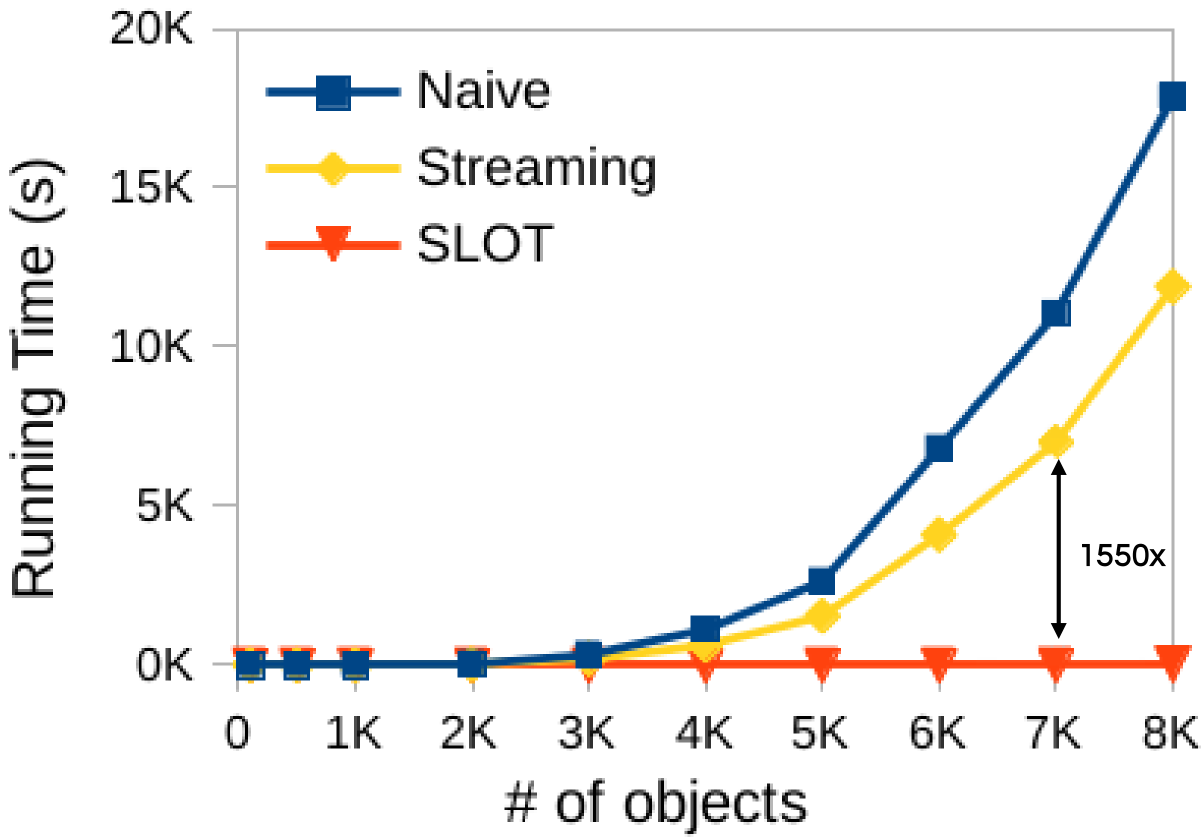
Rich Analytics

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

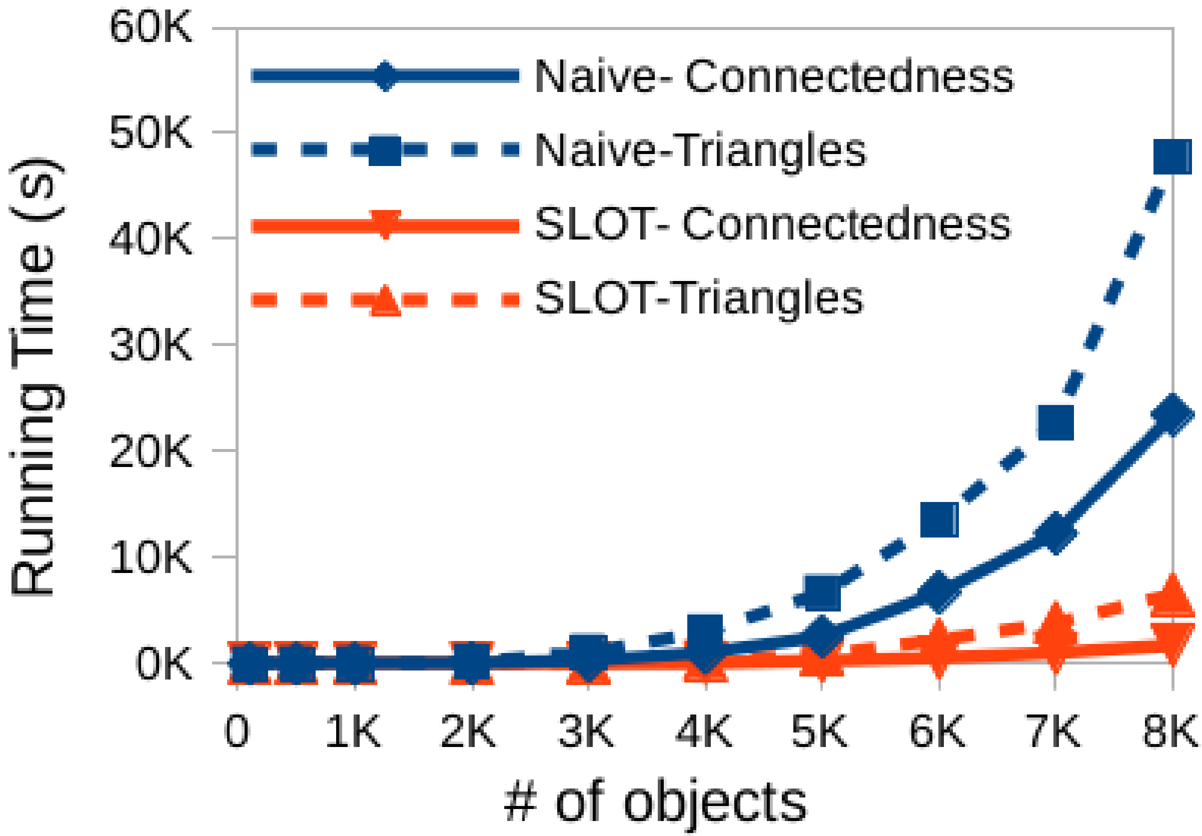
Exact results (not approximations)

Evaluation of SLOT

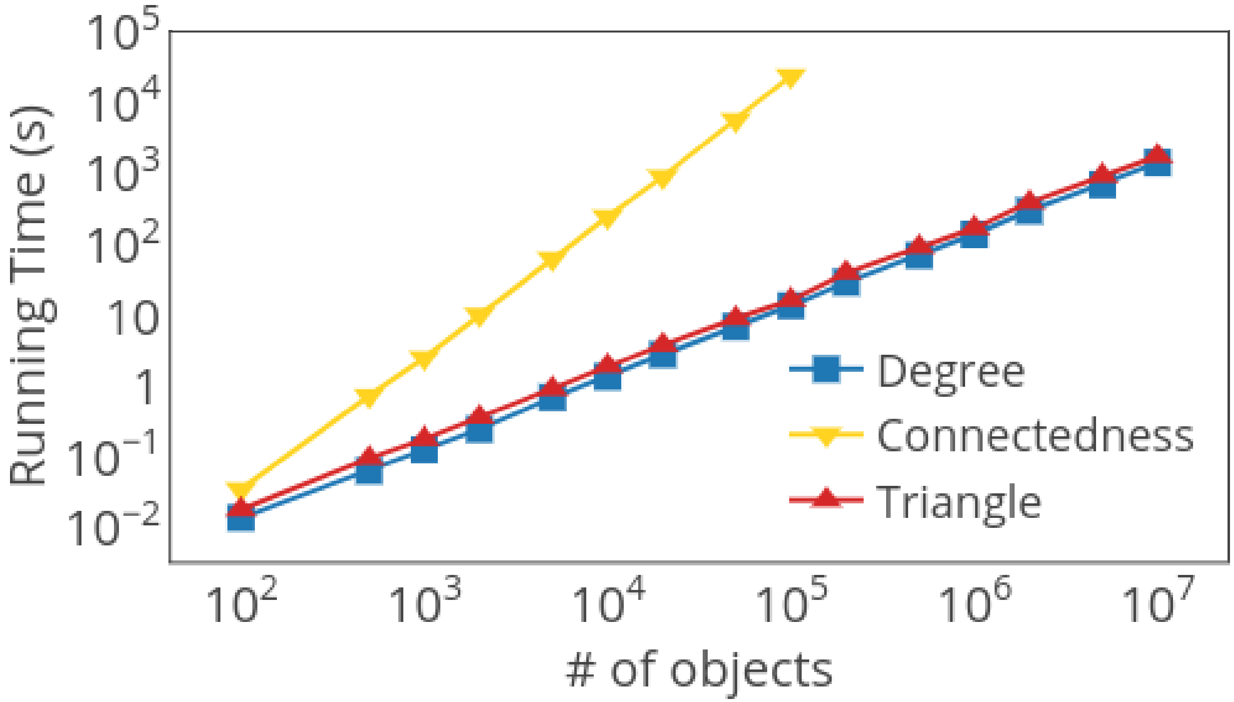
Node degree


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

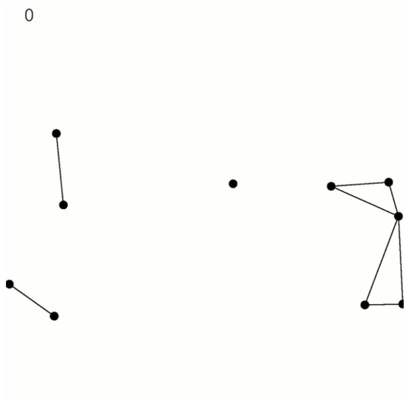
Triangle membership / connected components



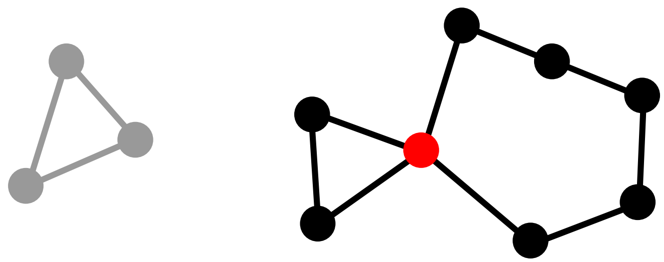
SLOT Scalability



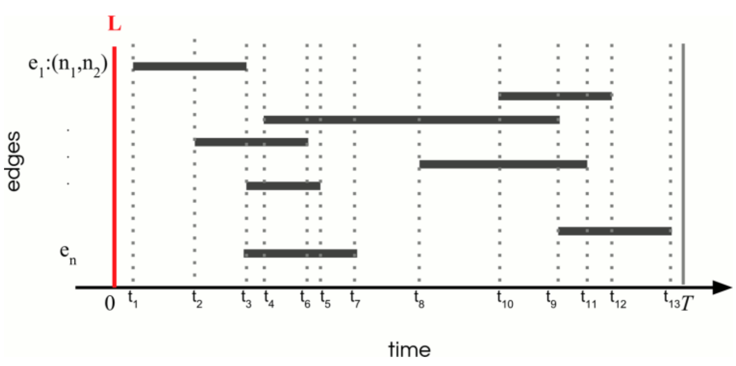
Takeaway



trajectory networks



network importance **over time**



SLOT algorithm

SLOT properties:

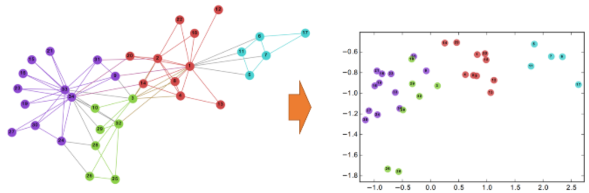
- fast
- exact
- scalable

Seagull migration trajectories

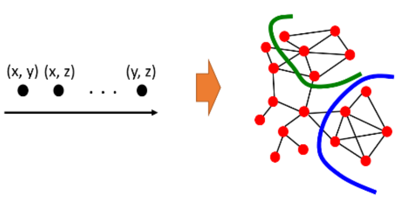
data from Wikelski et al. 2015

Current Research focus

A. Trajectory Data Mining



B. Machine Learning with Graphs



C. Streaming & Dynamic Graphs

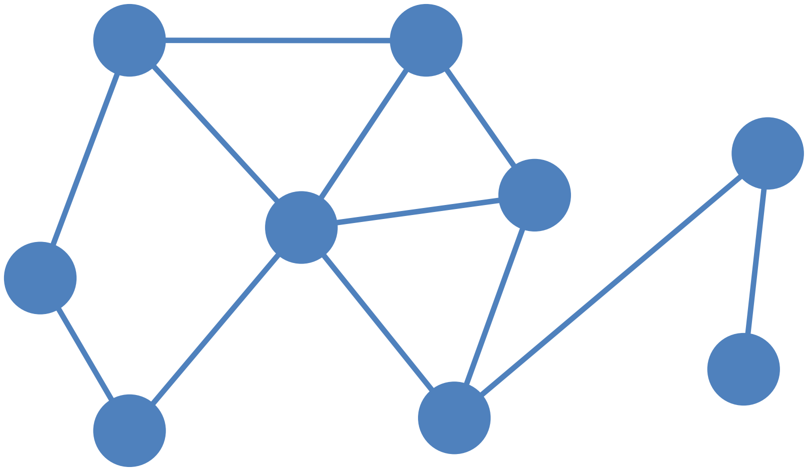
D. Social Media Mining & Analysis

E. City Science / Urban Informatics / IoT

F. Natural Language Processing

Evolving Network Representation Learning Based on Random Walks

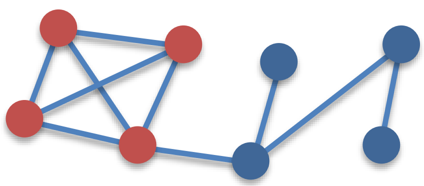
Joint work with Farzaneh Heidari



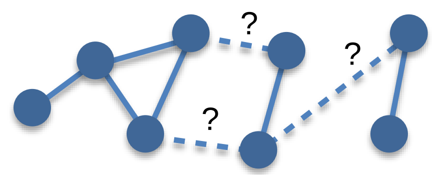
networks

(universal language for describing complex data)

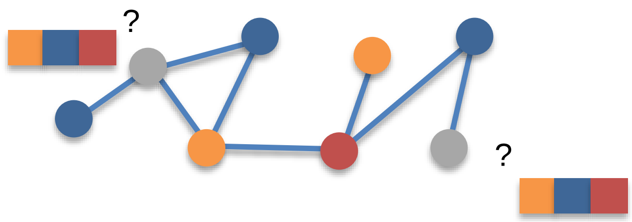
Classical ML Tasks in Networks



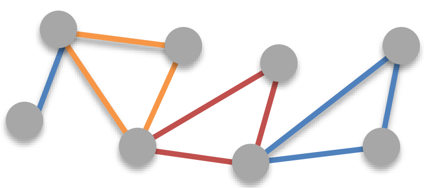
community detection



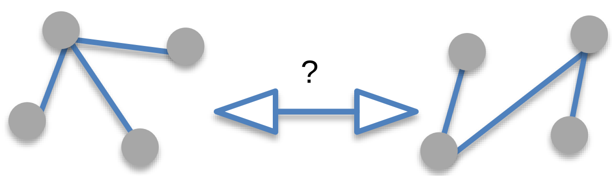
link prediction



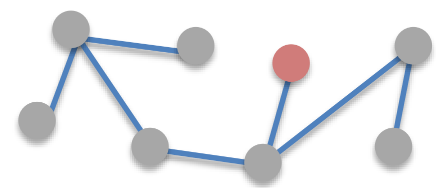
node classification



triangle count



graph similarity

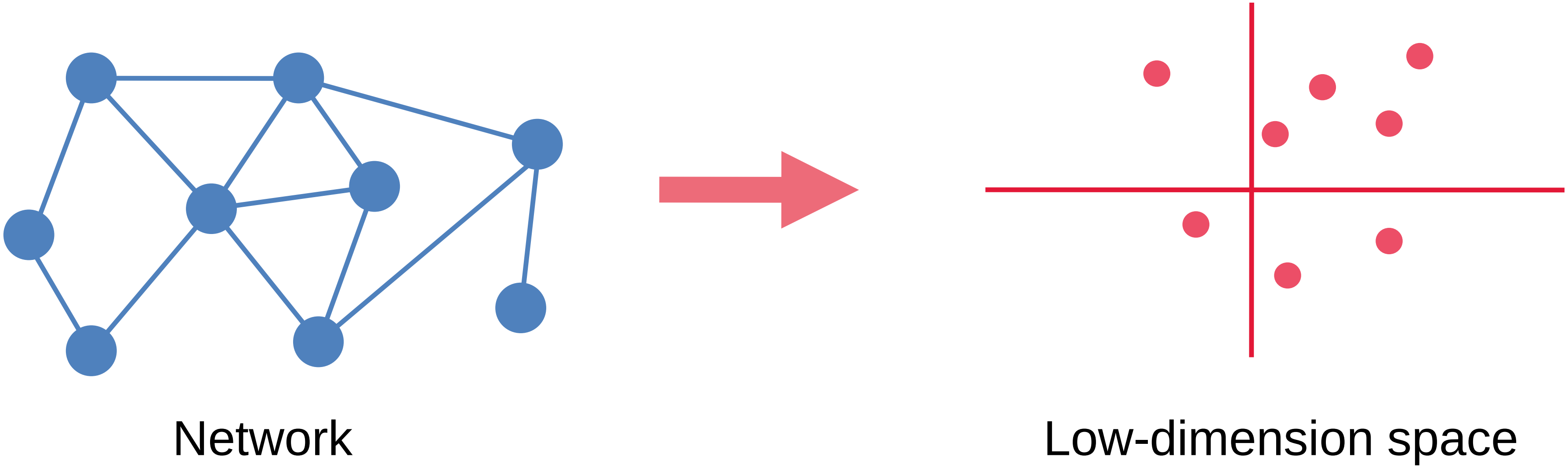


anomaly detection

Limitations of Classical ML:

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

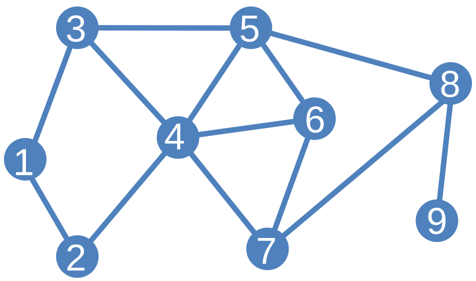
Network Representation Learning (NRL)



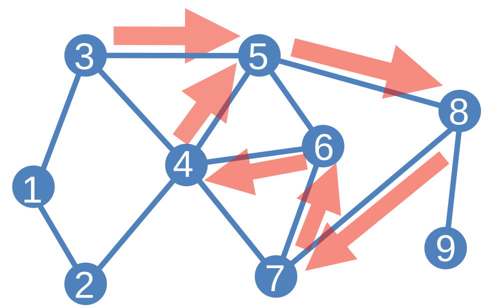
several network structural properties can be learned/embedded
(**nodes, edges, subgraphs, graphs, …**)

Premise of NRL:
- faster computations (low dimension computations)
- agnostic domain knowledge (task independent)

Random Walk-based NRL



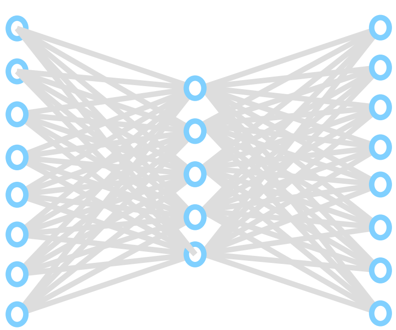
Input network



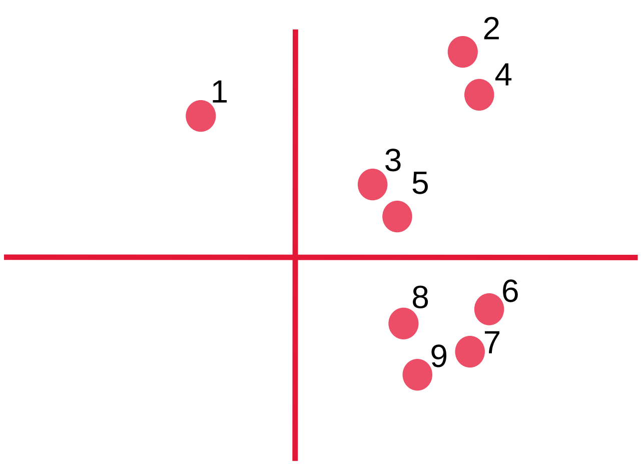
Obtain a set of random walks

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



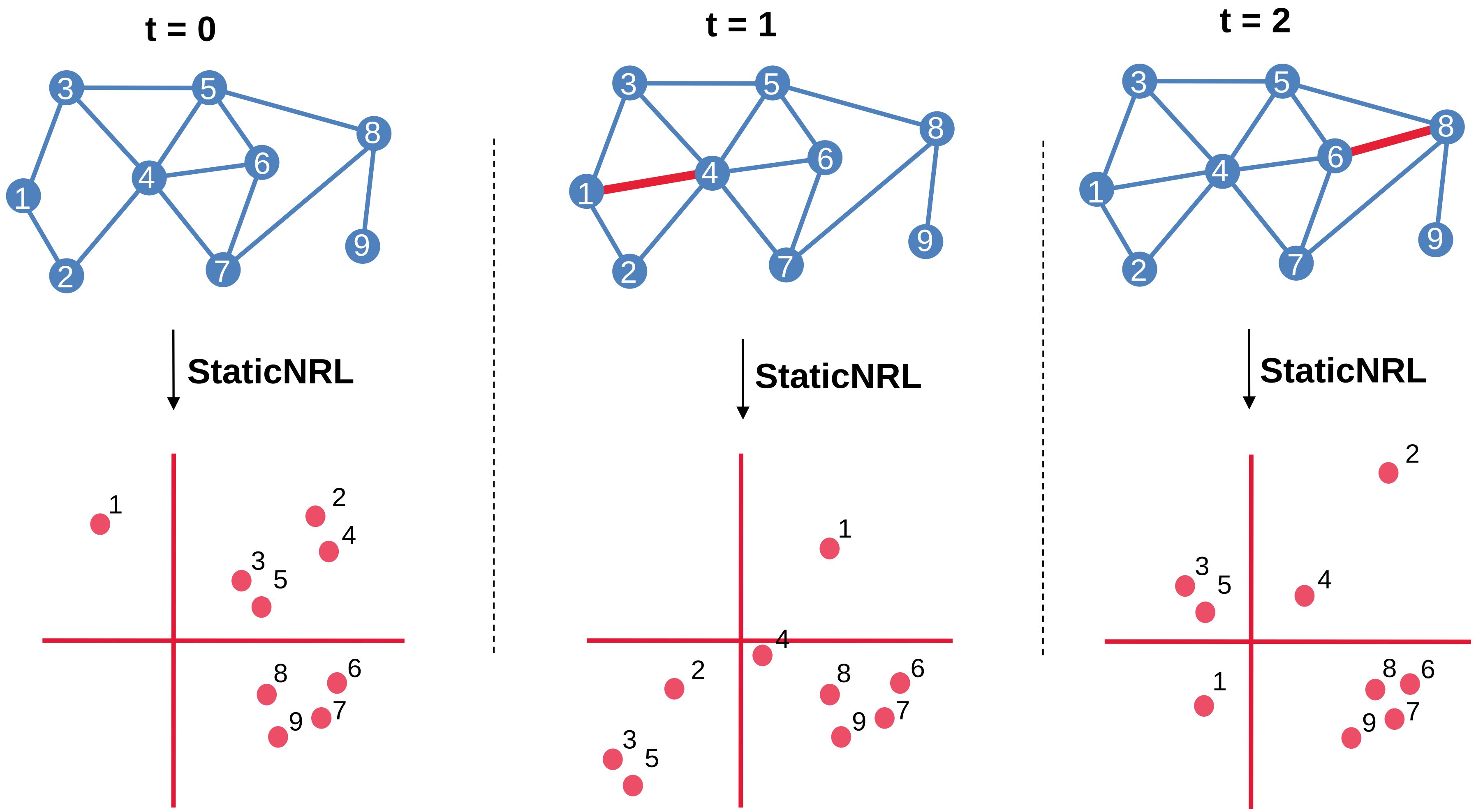
Learn a vector representation for each node

StaticNRL
(DeepWalk, node2vec, …)

but real-world networks are
constantly evolving

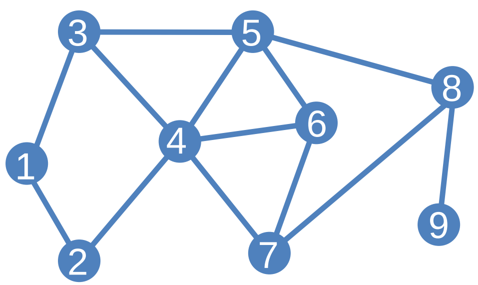
Evolving Network Representations Learning

Naive Approach

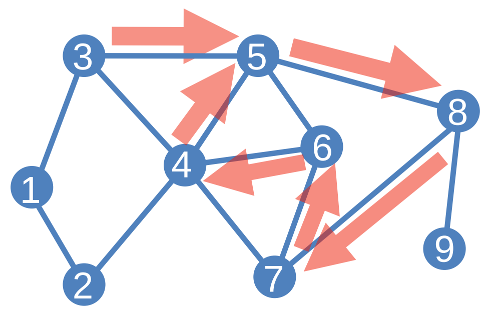


Impractical (expensive, incomparable representations)

EvoNRL Key Idea



Input network

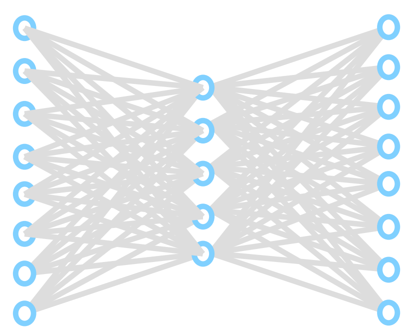


Obtain a set of random walks

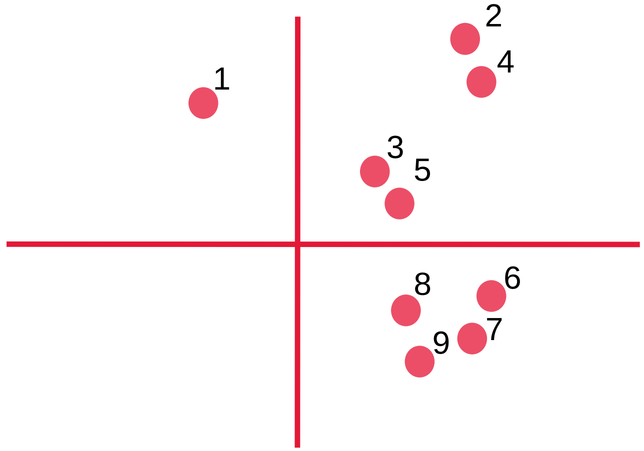
dynamically maintain a valid set of random walks for every change in the network

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



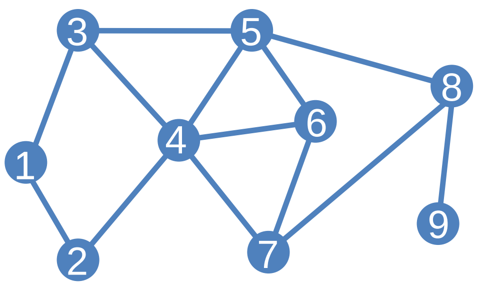
Feed sentences to a Skip-gram NN model



Learn a vector representation for each node

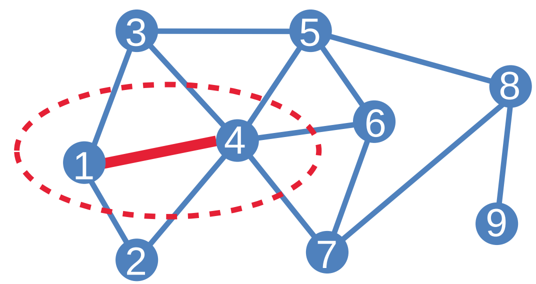
Example: Edge Addition

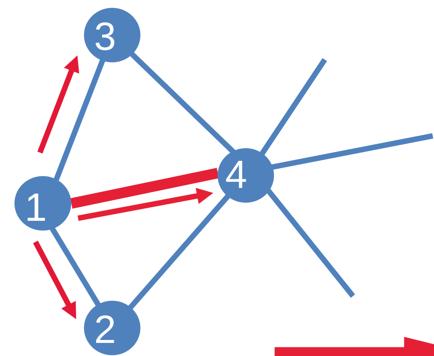
t = 0



addition of edge (1, 4)

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

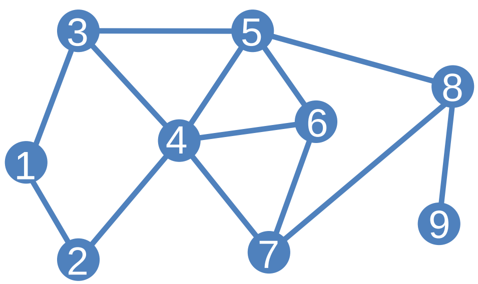
need to update the RW set

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

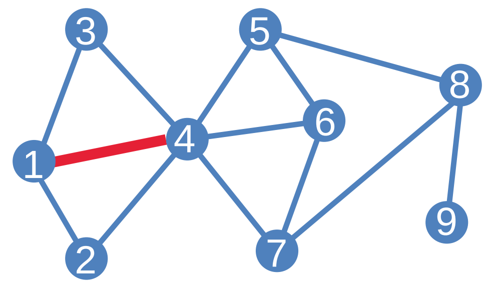
similarly for edge deletion, node addition/deletion

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

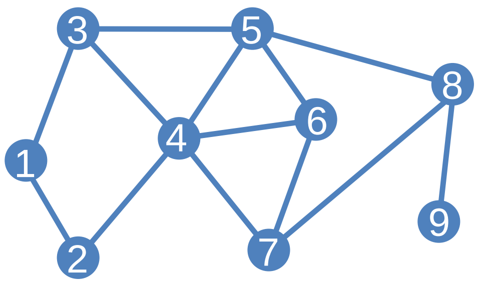
Search a node

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

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

elastic

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

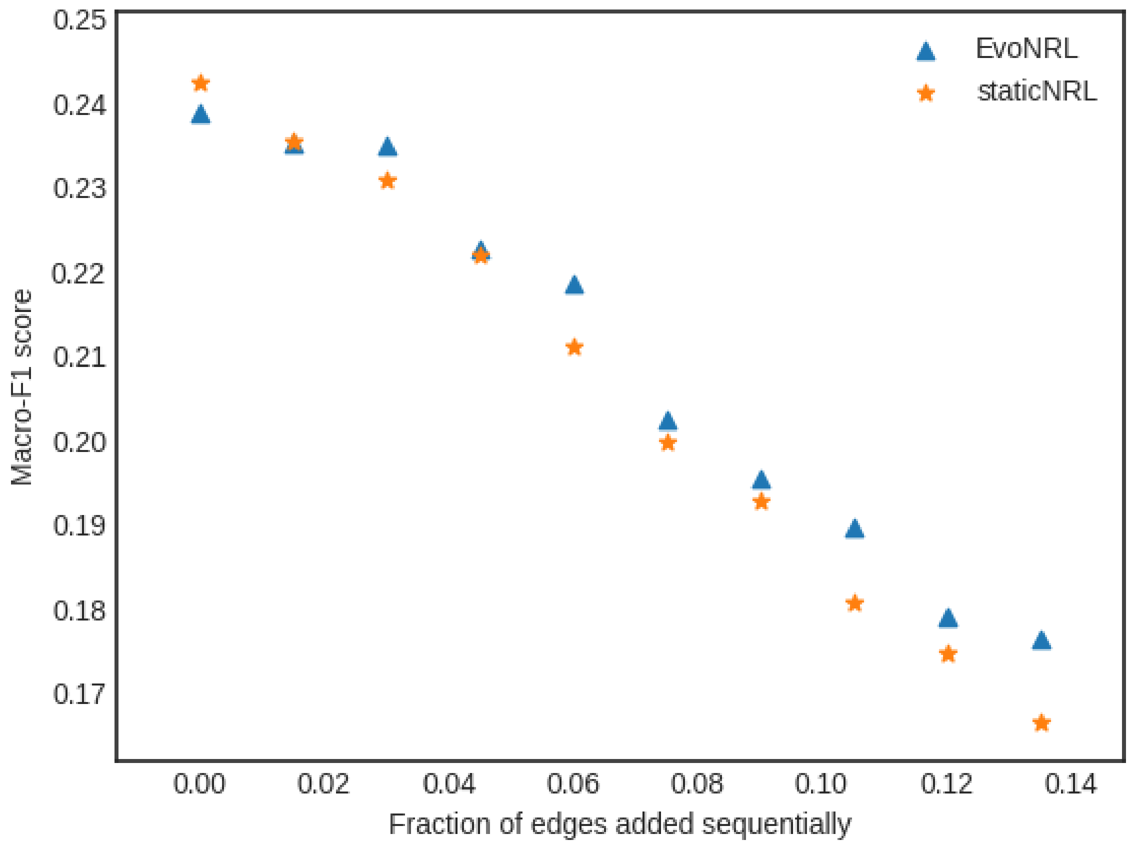
Accuracy

- EvoNRL **≈** StaticNRL (at each timestep)

Running Time

- EvoNRL **<<** StaticNRL (at each timestep)

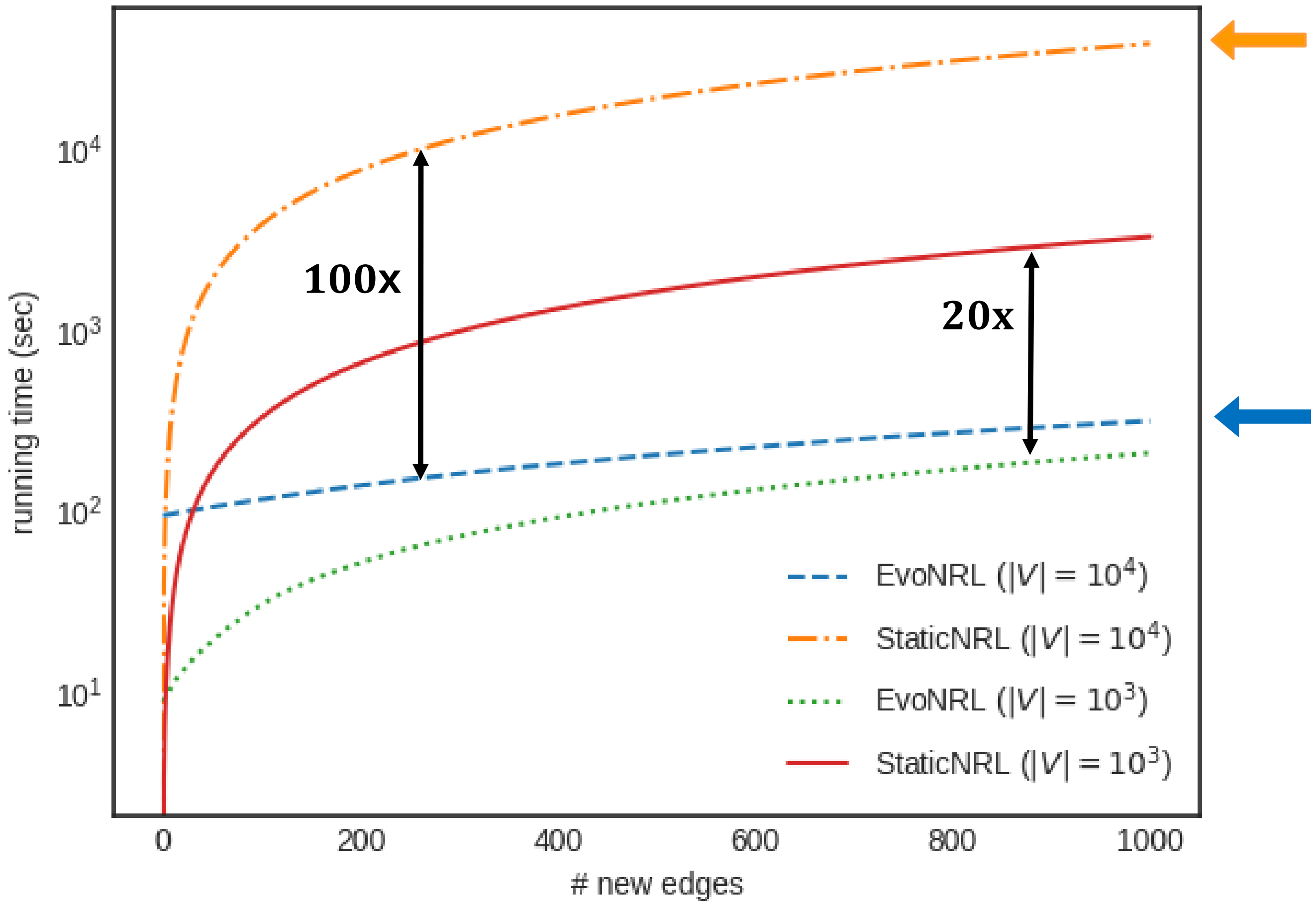
Accuracy: edge addition



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

[Applied Network Science, Vol. 5, No. 18, 2020] Evolving Network Representation Learning Based on Random Walks. Farzaneh Heidari & Manos Papagelis.

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

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

Tilemachos Pechlivanoglou

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

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

See also extensions:

[**IEEE ICDM 2019**] **Efficient Mining and Exploration of Multiple Axis-aligned Intersecting Objects**. Tilemachos Pechlivanoglou, Vincent Chu & Manos Papagelis.

[**IEEE DSAA 2020**] **MRSweep: Distributed In-Memory Sweep-line for Scalable Object Intersection Problems**. Tilemachos Pechlivanoglou, Mahmoud Alsaeed & Manos Papagelis.

Thank you!

Questions?

Working with Us

Data Mining Lab @ YorkU

http://dminer.eecs.yorku.ca

- **Members**
  - Faculty Members
    - Prof. Aijun An, Prof. Manos Papagelis
  - High Quality Personnel (HQP)
    - ~5 Postdocs, ~6 PhDs, ~8 MSc, ~3 Undergrads, ~1 staff
- **Lab Mandate**
  - Conduct basic research in the area of data mining/ML
  - Equip HQP with theoretical knowledge & practical experience
  - Knowledge transfer to industry
- **Research Area**
  - data mining, graph mining, machine learning, natural language processing (NLP), big data analytics

What We Are Looking For?

(solid)
Math & Stat

(solid)
Programming

(interest in)
Data Mining & ML

About you?

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