Dynamics of Networks

Online Social Networks Analysis and Mining

andrea.failla@phd.unipi.it

Where next?

Two kind of dynamics:

- Dynamics of Networks
  (topological perturbations)
- Dynamics on Networks
  (diffusive phenomena: epidemics, opinion dynamics...)

Of course they can happen at the same time...

Dynamics of Networks	Dynamics on Networks	Mixed Dynamics
Assumption: Topology evolution is faster than diffusive processes unfolding (if any)	**Assumption:** Diffusive processes unfolding is faster than topology evolution (if any)	**Assumption:** Diffusive processes unfolding and topology evolution have comparable rates
Applications: - Link Prediction - Dynamic Community Discovery - ...	**Applications:** - Epidemic spreading - Opinion Dynamics - ...	**Applications:** - Diffusion shape topology - Topology shape diffusion - Feedback loops

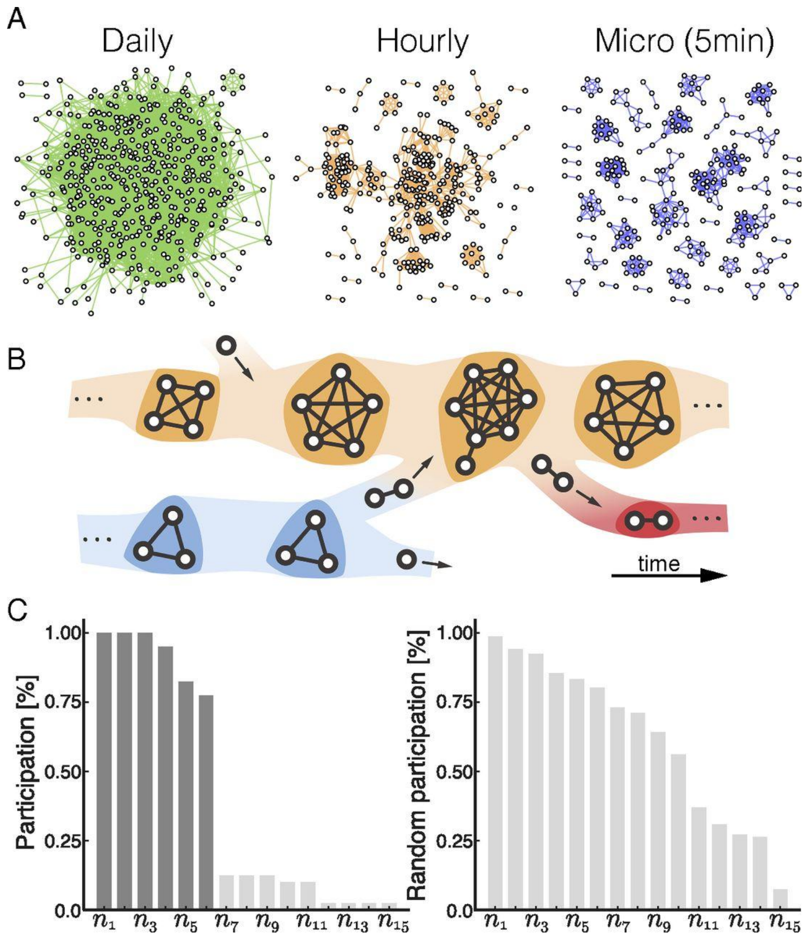
Representing Dynamic Topologies

A brief Introduction

Why bother of time?

Most real world networks are dynamic

- Facebook friendship
  - People joining/leaving
  - Friend/Unfriend
- Twitter mention network
  - Each mention has a timestamp
  - Aggregated every day/month/year => still dynamic
- World Wide Web
- Urban networks
- Protein-protein interactions
- Brain networks
- ...



Evolving Topologies

- Nodes can appear/disappear
- Edges can appear/disappear
- Nature of relations can change

How to represent those changes?

How to manipulate dynamic networks?

Three different levels of abstraction

Semantic

Relation
Vs.
Interactions

\+

Representation

Interval Graphs
Graph Series
Link Streams

\+

Data Structure

Interval List
Sequence of Graphs
Temporal edgelist

Dynamic Networks

General Paradigm

Semantics

Relations Vs. Interactions

Topological perturbations may have different temporal scales depending on their intrinsic semantic value.

Two families:

- Relations (stable ties)
- Interactions (unstable ties)

Relations

01	**Long term**	Friend Colleague Family
02	**Short term**	Collaboration in a project Same team in a game Attendees of a same class

Interactions

01	**Instantaneous**	Email Text message Co-authoring
02	**With Duration**	Phone call Discussion Attendees of a same class

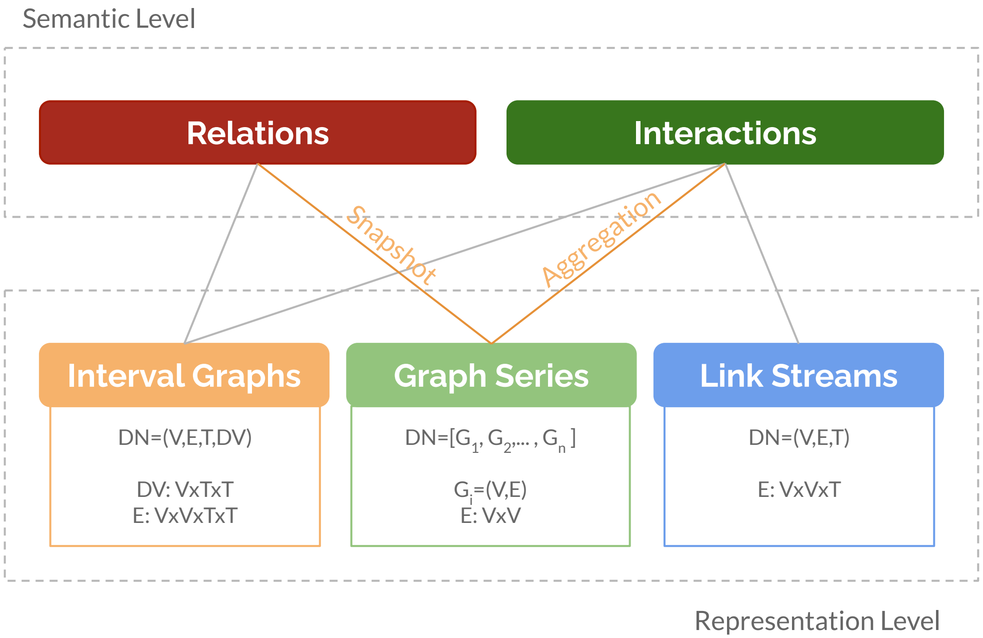
Semantics and how to represent them

Relations

The graph is more and more stable, until most observations are completely similar to previous/later ones (frequency faster than change rate)

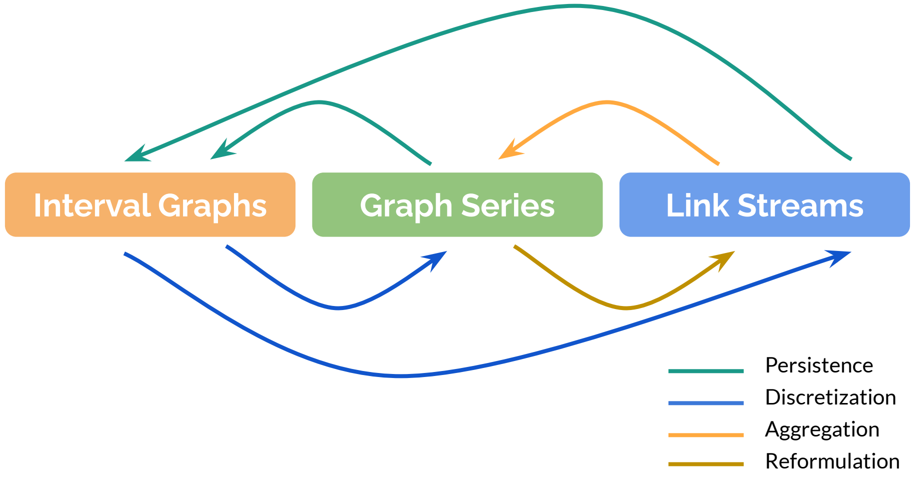
Interactions

The graph is less and less stable, until each observation is a graph in itself, thus completely different from previous/later ones (frequency faster than observed events rate)



Changing Representation

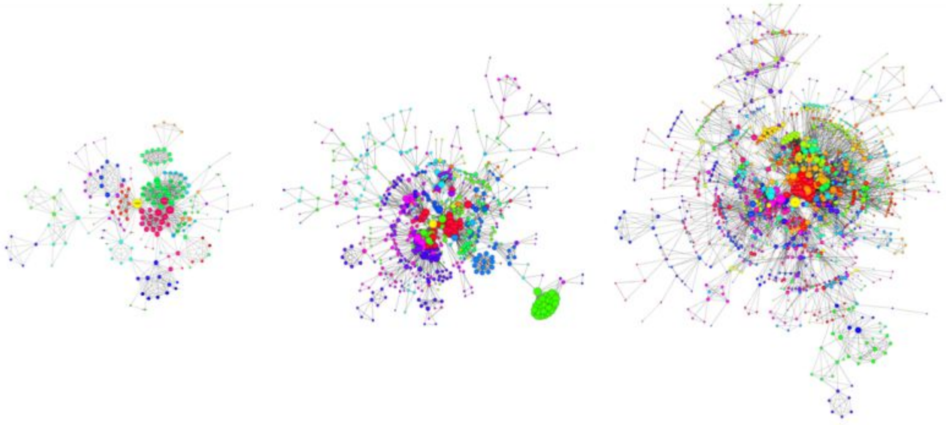
Alternative representations can be, to some extent, converted among them by applying appropriate data transformations



Unstable Snapshots

The evolution is represented as a series of a few snapshots

- Many changes between snapshots
  (Cannot be visualized as a "movie")
- Each snapshot can be studied as a static graph
- Evolution of node properties can be studied "independently"
  (e.g., node i had low centrality in snapshot t and high centrality in snapshot t+n)



Stable Network

Edges change (relatively) slowly

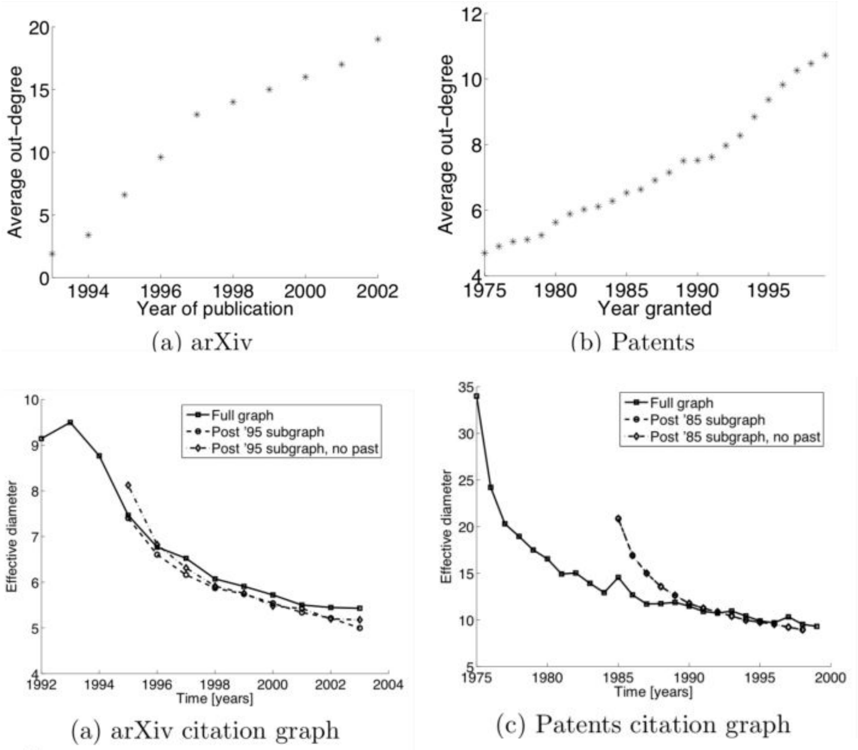
The network is well defined at any t

- Temporal network: nodes/edges described by (long lasting) intervals
- Enough snapshots to track nodes

A static analysis at every (relevant) t gives a dynamic vision

No formal distinction with previous case
(higher observation frequency)

Properties can be analyzed as time series



Leskovec, Jure, Jon Kleinberg, and Christos Faloutsos. "Graph evolution: Densification and shrinking diameters." ACM Transactions on Knowledge Discovery from Data. (2007)

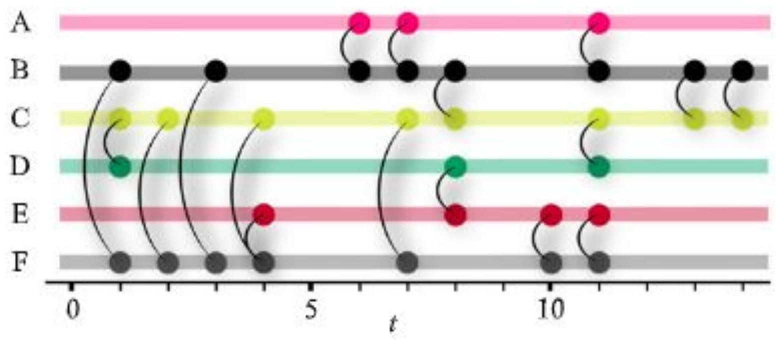
Unstable Temporal Network

The network at a given t is not meaningful

How to analyze such a network?

Until recently, network was transformed using aggregation/sliding windows

- Information loss
- How to choose a proper aggregation window size?



Holme, Petter, and Jari Saramäki. Temporal networks. Physics reports 519.3 (2012)

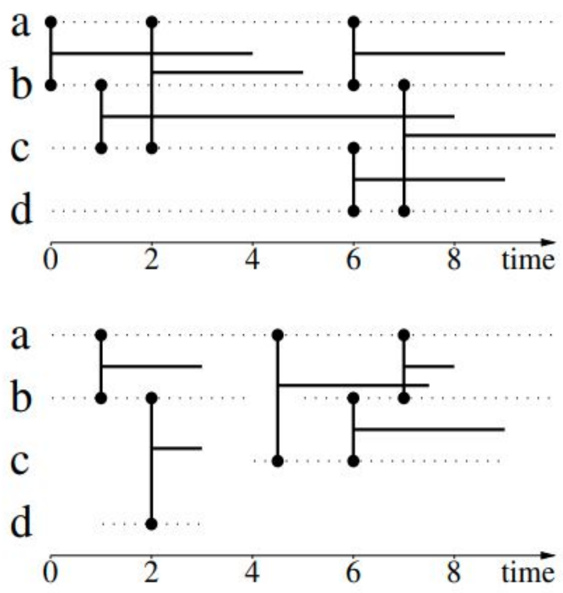
Unstable

Temporal Nets

Stream Graph

S = (T, V, W, E)

T: Possible Time
V: vertices
W: Vertices presence in time, pairs like (v, t)
E: Edges presence in time

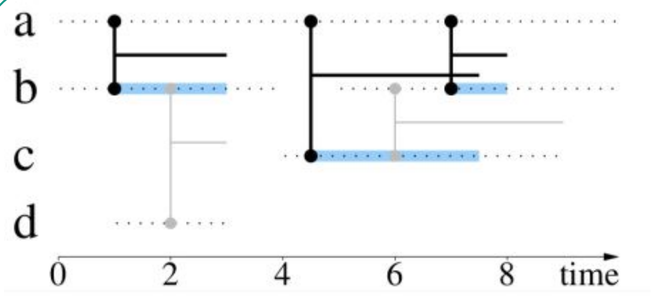


Latapy, M., Viard, T., & Magnien, C. (2018). Stream graphs and link streams for the modeling of interactions over time. Social Network Analysis and Mining, 8(1), 61.

Stream Graph

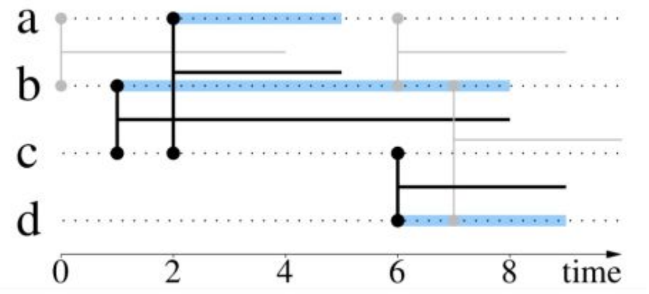
Indices

Number of nodes	$n = \sum_{v \in V} n_v = \frac{\lvert W \rvert}{\lvert T \rvert}$
Number of edges	$m = \sum_{uv \in V \otimes V} m_{uv} = \frac{\lvert E \rvert}{\lvert T \rvert}$
Neighbors of a node	$N(v) = \{(t, u), (t, uv) \in E\}$
Degree of a node	$d(v) = \frac{\lvert N(v) \rvert}{\lvert T \rvert} = \sum_{u \in V} \frac{\lvert T_{uv} \rvert}{\lvert T \rvert}$



$$N(a) = ([1,3] \cup [7,8]) \times \{b\} \cup [4.5, 7.5] \times \{c\}$$

$$d(a) = \frac{3}{10} + \frac{3}{10} = 0.6$$



$$N(c) = [2,5] \times \{a\} \cup [1,8] \times \{b\} \cup [6,9] \times \{d\}$$

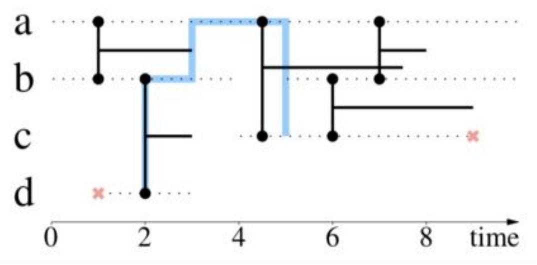
$$d(c) = \frac{13}{10} = 1.3$$

Stream Graph

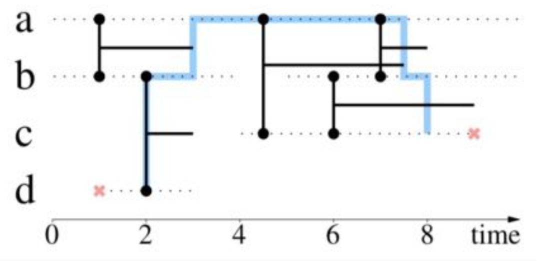
Paths and Distances

A path in a stream graphs

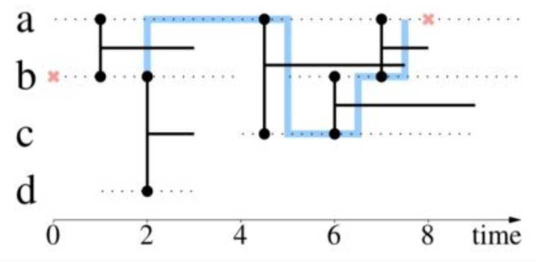
- Starts at a node and at a timestamp
- Ends at a node and at a timestamp
- Has a length
  (number of hops)
- Has a duration
  (duration from leaving node to reaching node)



Path: (d,1)(c,9)
Length: 3
Duration: 3



Path: (d,2)(c,8)
Length: 4
Duration: 6



Path: (b,0)(a,8)
Length: 4
Duration: 5

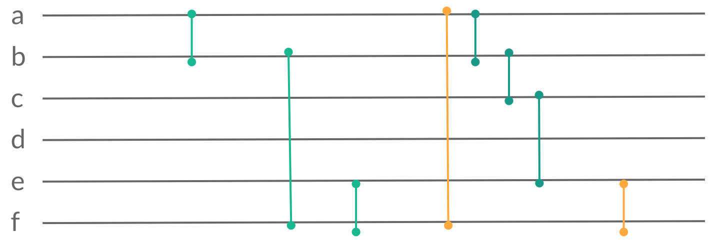
Stream Graph

Paths and Distances

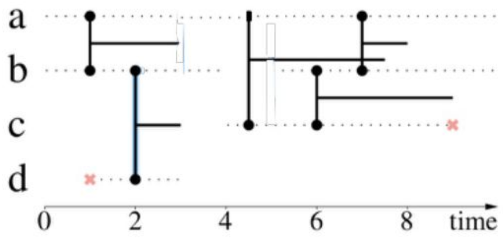
Several types of shortest paths in Stream graphs:

Type	Description
Shortest path	Minimal length
Fastest path	Minimal Duration
Foremost path	First to reach
Fastest shortest paths	Minimum duration among minimum length
Shortest fastest paths	Minimum length among minimum duration

From a to e (Foremost, Fastest, Shortest)



From (1,d) to (9,c)



Shortest path	(2.5, d, b) (3, b, a) (7, a, c)
Fastest path	(3, d, b) (3, b, a) (4.5, a, c)
Foremost path	(2, d, b) (2, b, a) (4.5, a, c)
Fastest shortest path	(3, d, b) (3, b, a) (4.5, a, c)
Shortest Fastest path from	(3, d, b) (3, b, a) (4.5, a, c)

Community Detection in Dynamic Networks

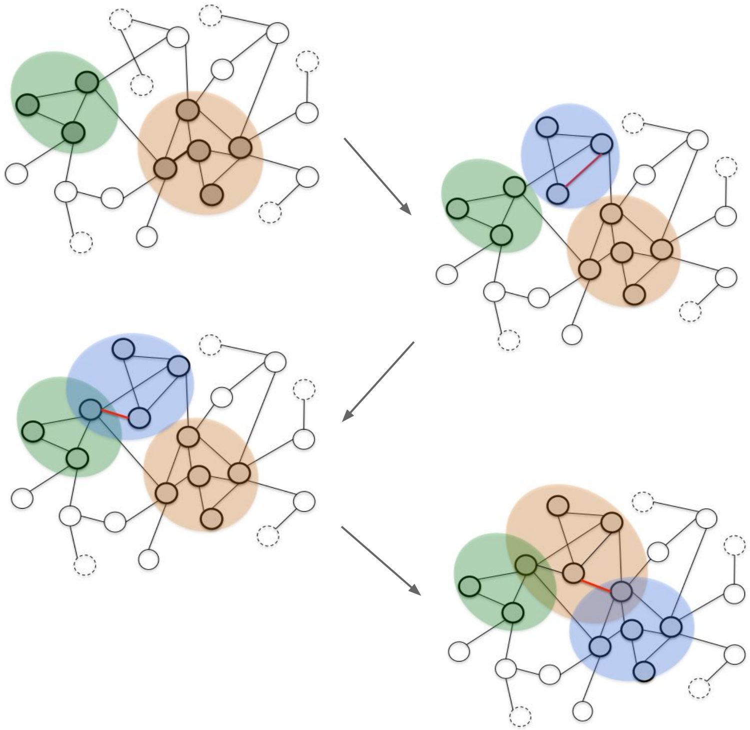
Time flies like an arrow; fruit flies like a banana

Communities
In Dynamic Networks

Networks change with time...
- Nodes appear and vanish
- Edges appear and vanish

...communities must change too!

DCD:
identify/track changes in community structure



Cazabet, Remy, and Giulio Rossetti. "Challenges in community discovery on temporal networks." Temporal Network Theory. Springer, Cham, 2019. 181-197.

A Novel Problem:

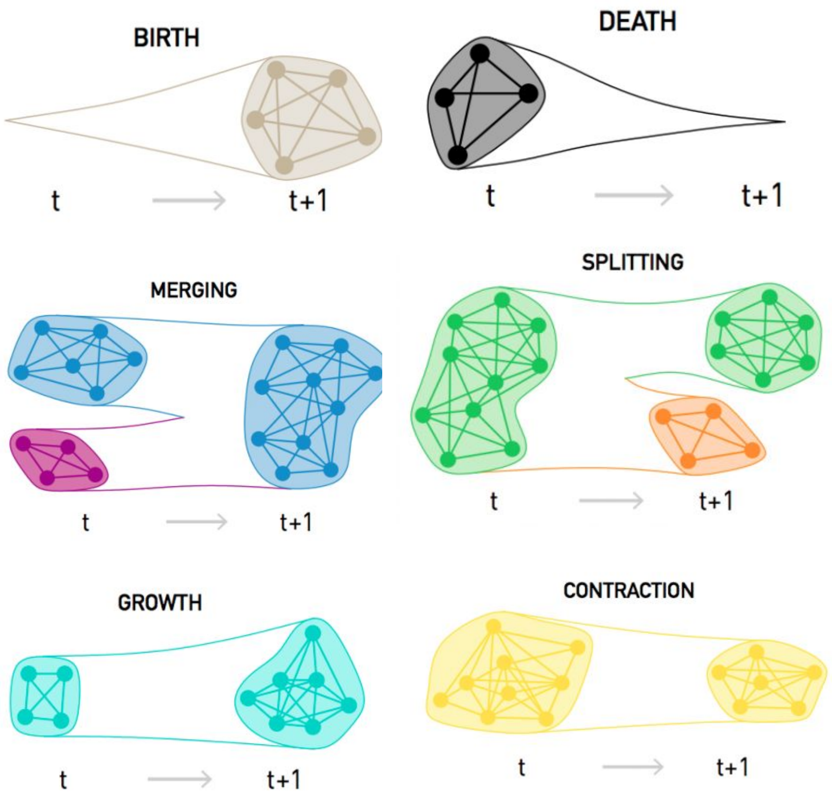
Community life-cycle tracking

As time goes by the rising of novel nodes and edges (as well as the vanishing of old ones) led to network perturbations

Communities can be deeply affected by such changes

Three main strategies:

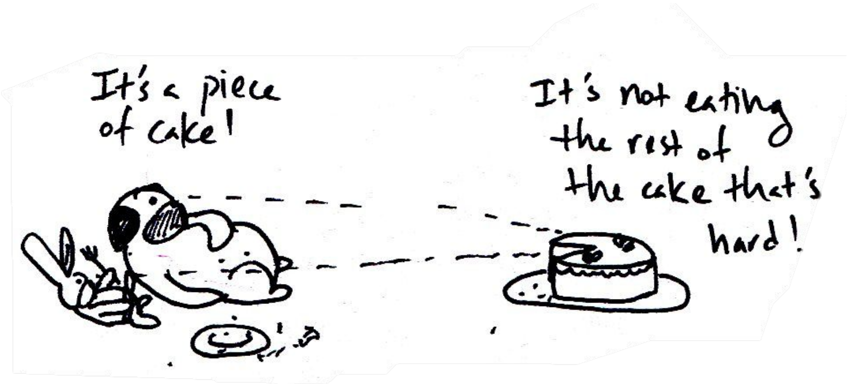
- Identify & Match
- Informed Iterative algorithms
- Stable Identification



The Optimist:

“Ok, It’s a piece of cake!”

1. Find communities at each network observation (using a static algorithm)
2. Match communities across consecutive network observations
3. Observe differences



Two major issues:

- Community Smoothing
- Theseus’ Ship Paradox

Community Smoothness

Communities are arbitrarily defined
(same issue of static CD)

Most “efficient” algorithms are stochastic

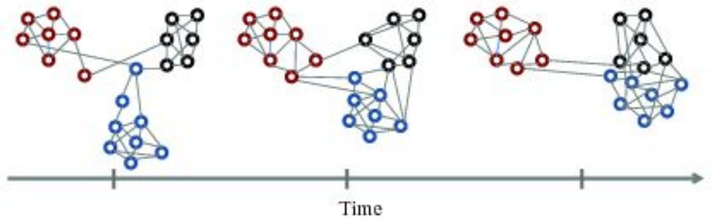
- Change in communities might be due to structural changes OR to arbitrary choices of the algorithm
- The same algorithm ran twice on the same graph *might yield* different results

Desiderata:

- a “simple” (parsimonious) model
- a trade-off between quality and simplicity (smoothness)

No Smoothness:
Partition at each t should be the same as found by a static algorithm

Smoothness:
Partition at t is a trade-off between “good” communities for the graph at t and similarity with partitions at different times



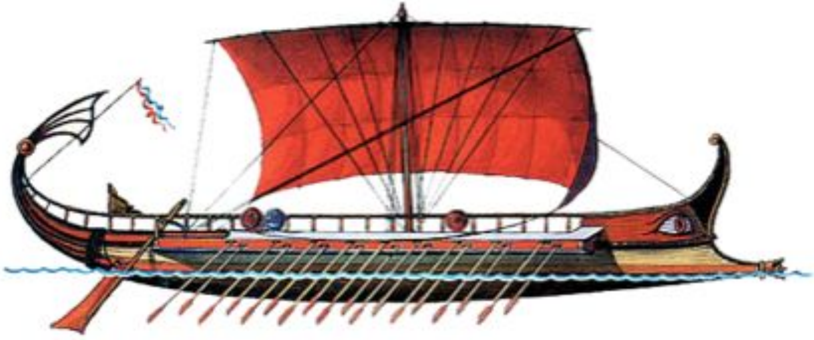
Theseus' Ship Paradox

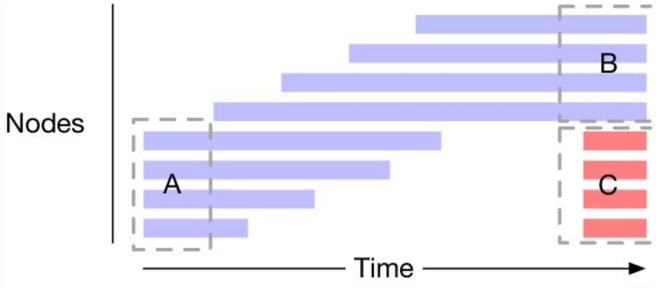
I. Theseus killed the Minotaur in Crete and came back to Athens on his boat

II. His boat was conserved as memory during a very long time

III. The boat was deteriorating, so pieces of it were gradually replaced.

IV. Until one day, all original parts were replaced





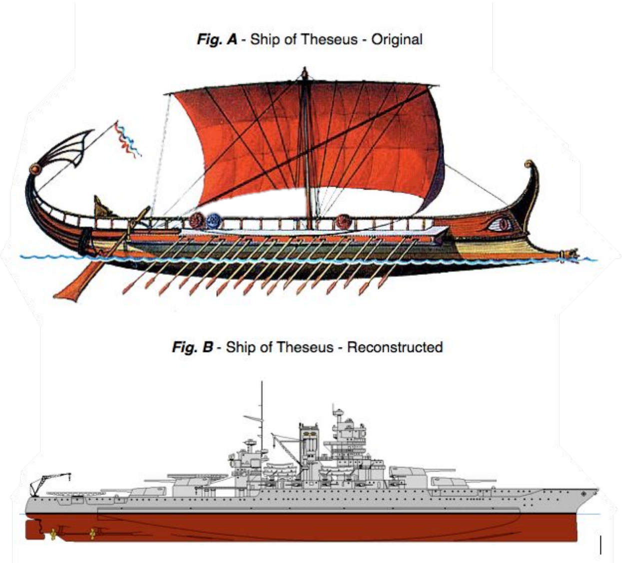
Plutarch 75

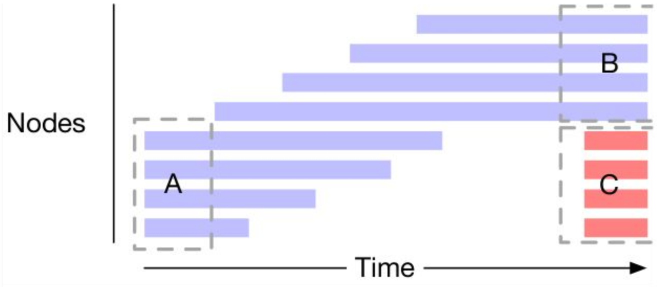
Theseus' Ship Paradox

A. Is this ship still the same as Theseus boat ?

B. If another boat was built using all pieces of the original boat, which one would be the "real" Theseus boat ?

Community evolution/identity is an <u>arbitrary</u> concept





Community Detection in Dynamic Networks

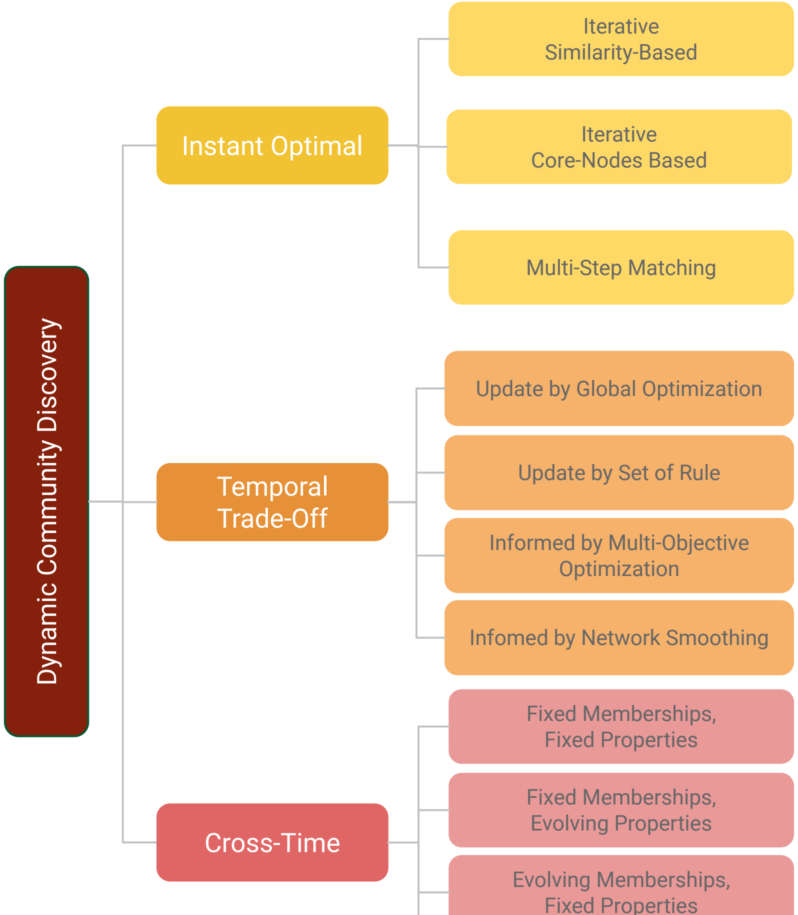
A taxonomy

DCD Algorithms Taxonomy

Hierarchical categorization

First Level:
Increasing degree of smoothness *(none -> complete)*

Second Level:
Algorithmic Approach *(how to deal with Theseus)*



G. Rossetti and R. Cazabet. Community Discovery in Dynamic Networks: a Survey. ACM Computing Surveys, 2018.

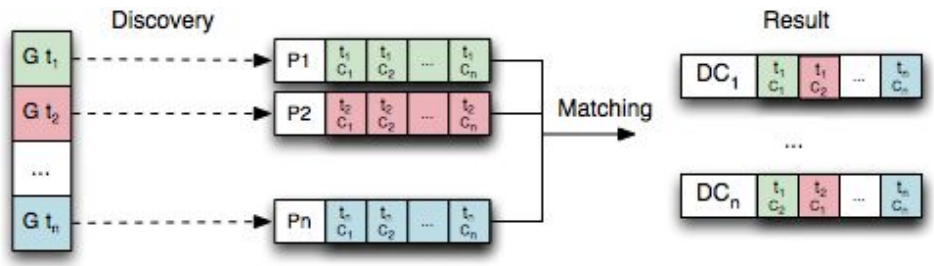
Taxonomy

Instant Optimal

“Communities found at time t are optimal for the network at time t”

Strengths
Definition consistent with static CD, parallelisation

Drawbacks
Lack of smoothness, only Snapshot Network repr.



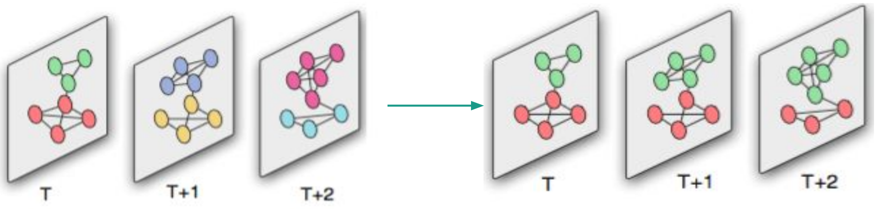
Taxonomy

Two-Step

1. Communities are detected at every step using a static algorithm (e.g. Louvain Algorithm)
2. Similarities are computed between communities in consecutive steps (at t and t+1 (e.g., Jaccard index))

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|} = \frac{|A \cap B|}{|A| + |B| - |A \cap B|}$$

3. Most similar communities are matched between t and t+1



Advantages:

- Easy to model, can extend smoothly static approaches

Drawbacks:

- The reduction to static scenarios trough temporal discretization is not always a good idea
  - How to choose the temporal threshold?
  - To what extent can we trust the obtained results?

Greene, et al. "Tracking the evolution of communities in dynamic social networks." 2010 international conference on advances in social networks analysis and mining. IEEE, 2010

Taxonomy

Temporal Trade-Off

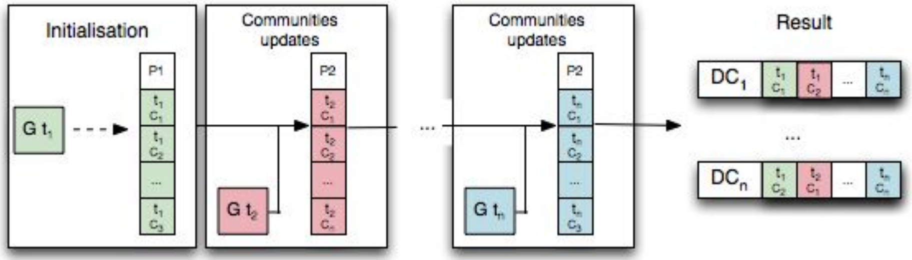
“Communities found at time t represent a trade-off between the graph at t and its previous states”

Strengths

Online, incremental, natural smoothness

Drawback

Iterative, risk of avalanche effect



Taxonomy

Tiles

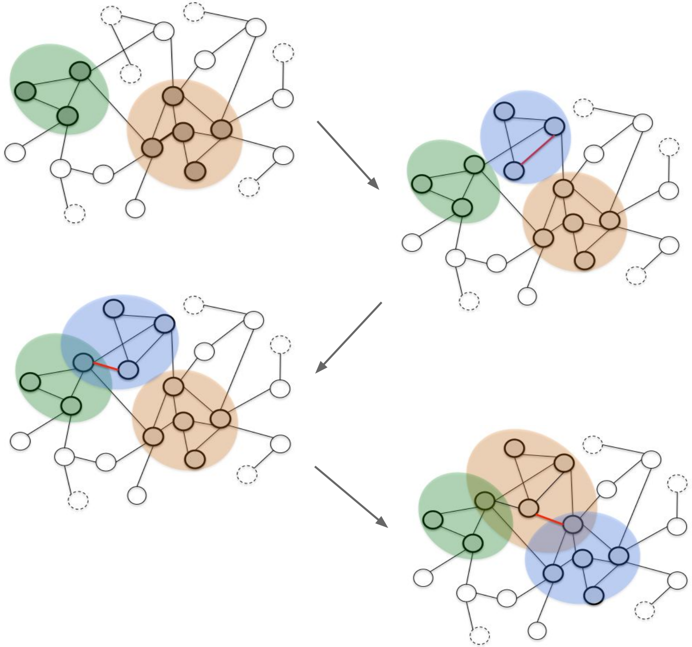
1. Social Interactions define the communities a user belongs to
2. Dynamic graphs as *edge streams*
3. Online updates of communities as nodes/edges appear/vanish

Advantages:

- Punctual updates of the community structure
- Low computational complexity

Drawbacks:

- Ad-Hoc model

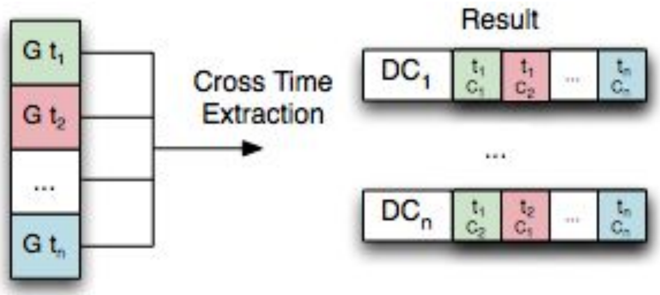


Rossetti, et al. "Tiles: an online algorithm for community discovery in dynamic social networks." Machine Learning 106.8 (2017): 1213-1241.

Taxonomy

Cross-Time

"Communities at t are defined relatively to all other steps"



Strengths

Perfectly smoothed, stable, solution

Drawback

Non online, batch computation, lacks incrementality

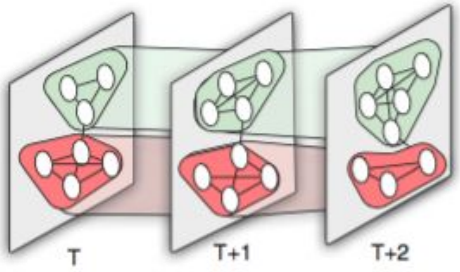
Example

Taxonomy

Transversal Network

1. A transversal network is built: nodes are couples (nodes, time), edges link the same node in adjacent snapshots
2. A community detection algorithm is run on this transversal network

   (Note: modified Modularity to avoid overestimating expected edges between nodes in different time steps, i.e., custom random graph)



Advantages:

- Maximal smoothing and stability

Drawbacks:

- No Community Events are detected
- All the network history needs to be known in advance

Mucha, Peter J., et al. "Community structure in time-dependent, multiscale, and multiplex networks." science 328.5980 (2010): 876-878

Community Detection in Dynamic Networks

Evaluation strategies

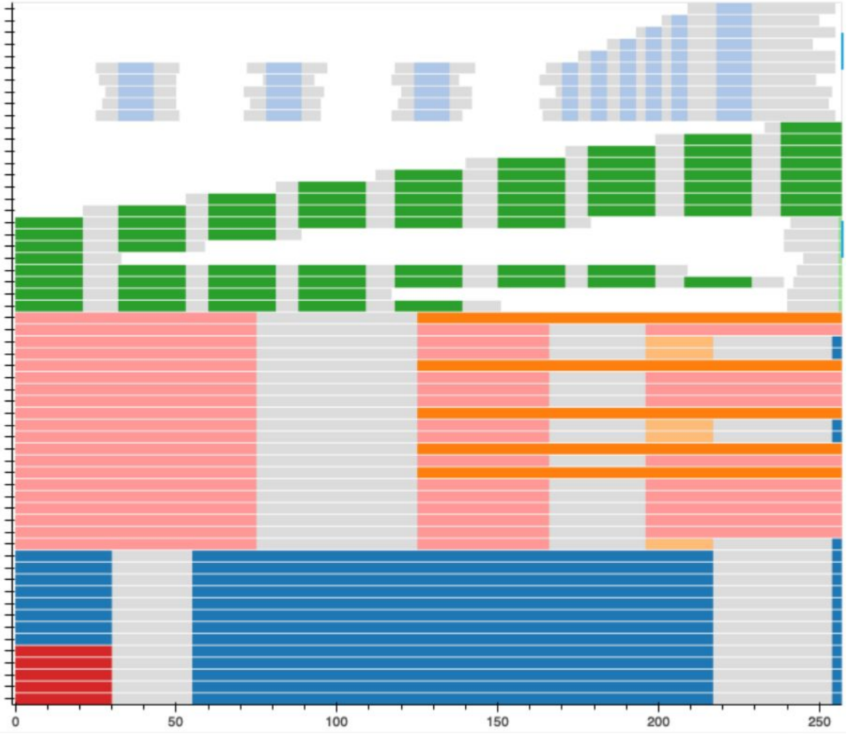
Strategies

Internal Evaluation

- Partition quality function
  (i.e., modularity, conductance, density…)
- Community characterization
  (i.e., size distribution, overlap distribution…)
- Execution time and Complexity

External Evaluation

- Ground truth testing
  (or partitions comparison)



Ground truth testing: Issues

- Few real world datasets with annotated ground truth partition are available (mostly static networks)
- Reliability of partition labelling (semantic partitions not always reflect topological ones)
- Scarcity of network generators handling community dynamics (i.e. birth, death, merge, split)

"I think we're past the point where rebooting will help."

Summarizing

Mesoscale Evolutions

Node/edge local dynamics affect community structures

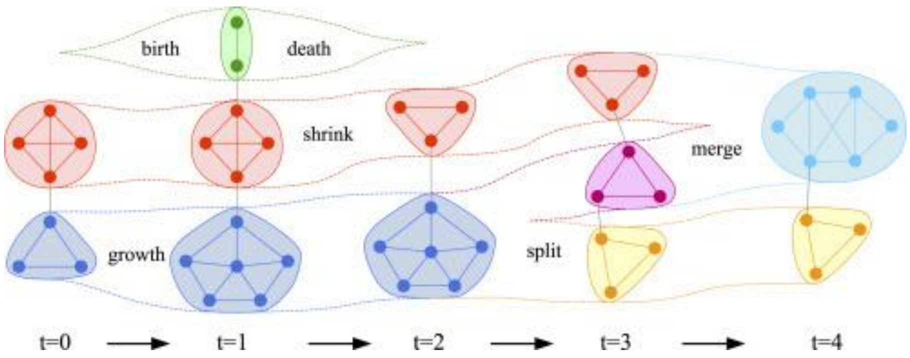
- Communities are subject to events/operations
- Life-cycles can be identified and studied

The complexity behind such ill posed problem grows

- Stability/Persistence
- Smoothness

Every family of approaches depend on

- Specific analytical needs
- Dynamic Network Representation adopted



https://andreafailla.github.io/teaching/osnam/