It's a matter of time!

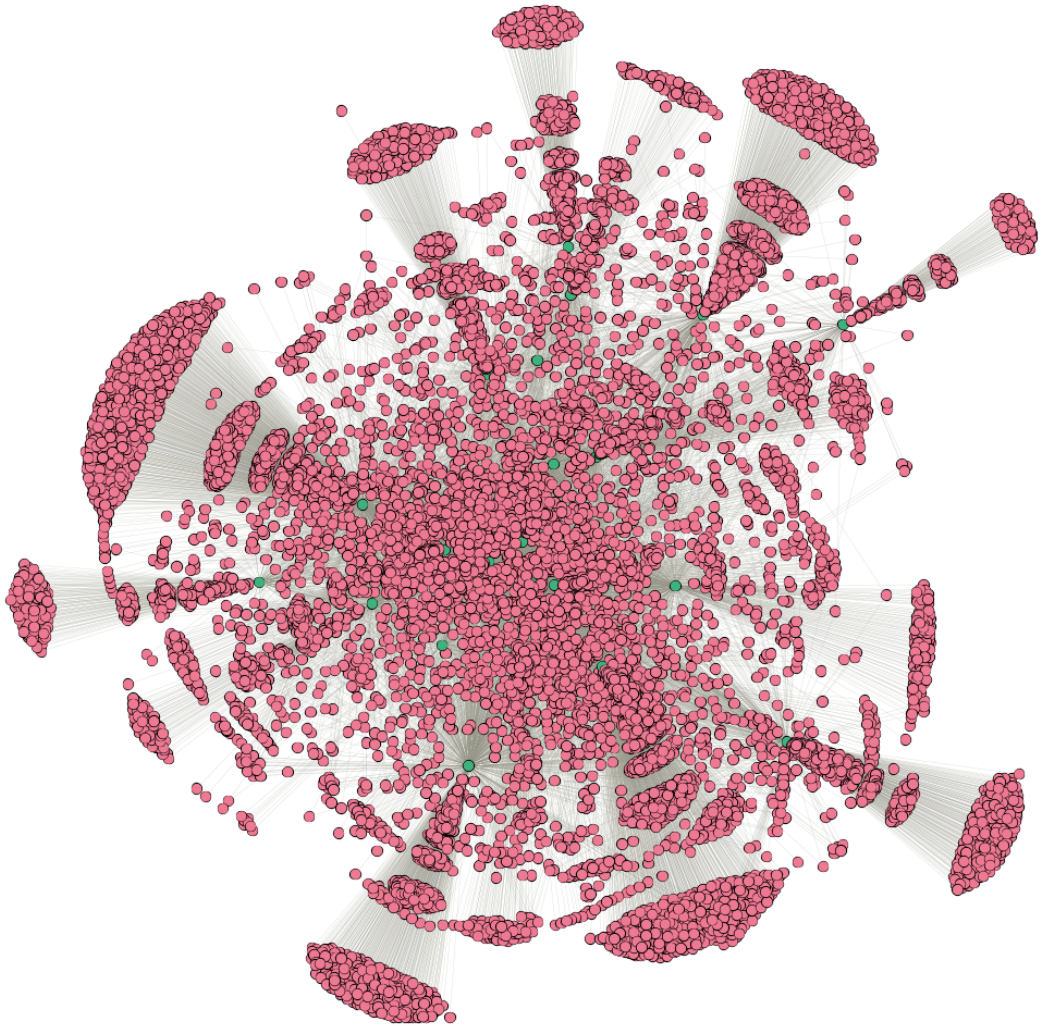
Knowledge Discovery from Temporal Social Networks

Fabíola S. F. Pereira (UFU)
João Gama (LIAAD, UPorto)
Gina M. B. de Oliveira (UFU)

Short course – SBBD – Oct 2017

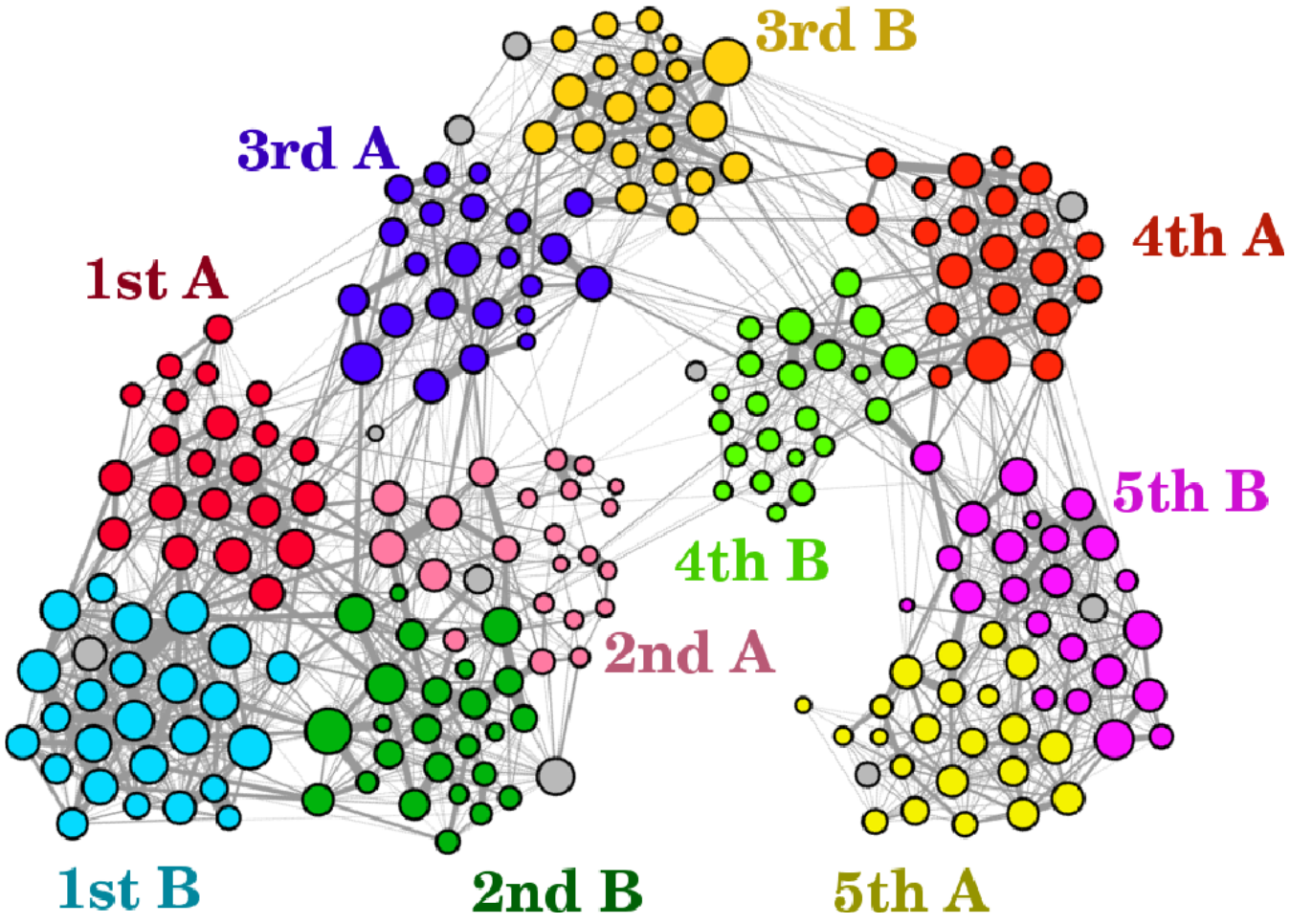
Motivation

Last.fm bipartite network (user-artist)

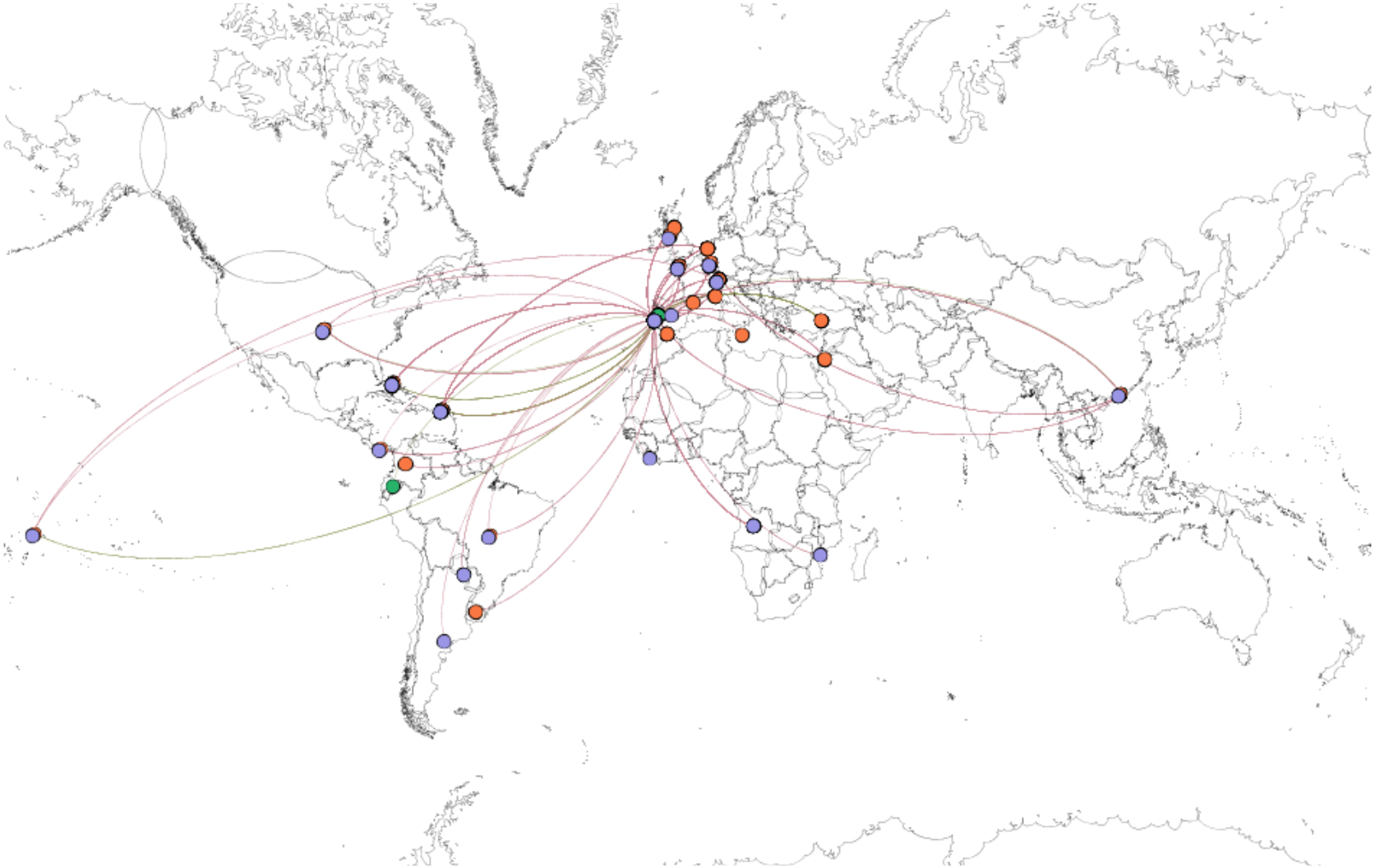


Facebook Network

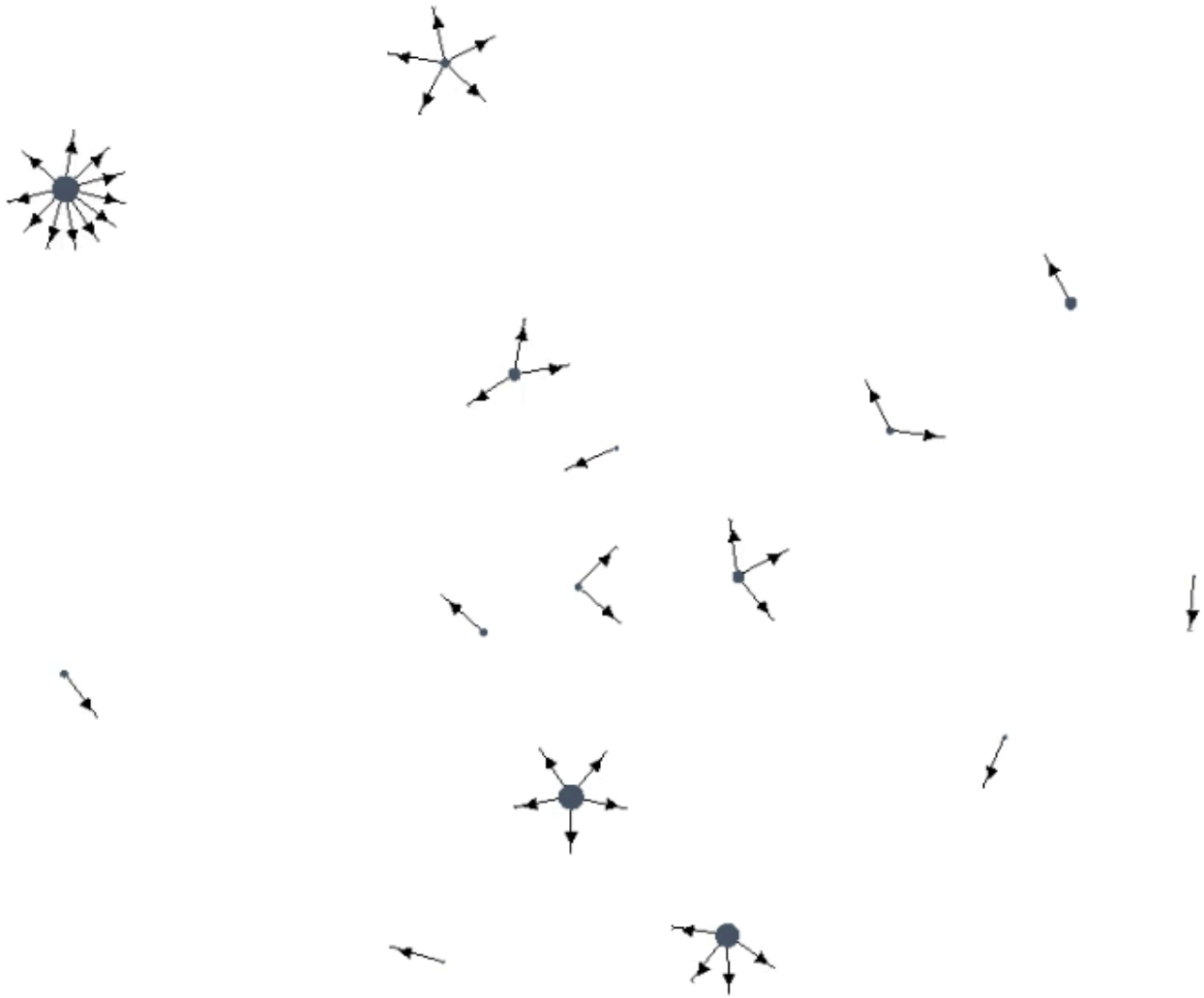
Face-to-face contact in a primary school



Panama papers - Portugal offshores



Evolving Call network



Outline

Overview

SNA Essentials

Temporal Social Networks

Processing Evolving Networks

Summary of Definitions

Case Study 1: Twitter

Case Study 2: Calls

Case Study 3: Last.fm

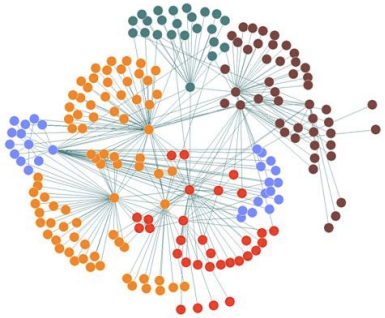
Being a Data Scientist

Final Remarks

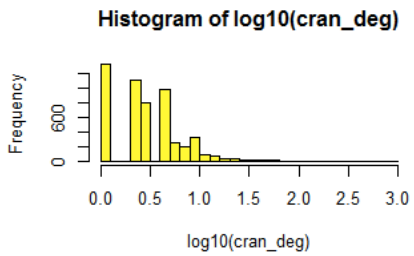
Overview

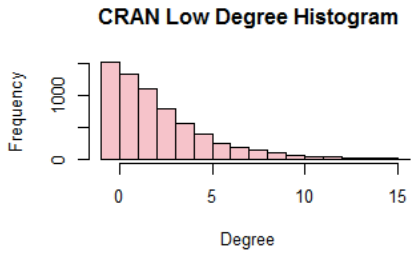
Social Media Mining is the process of...

collecting

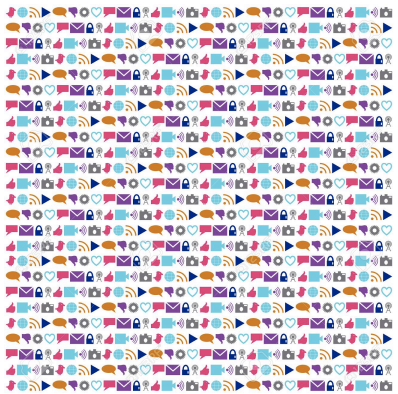


representing



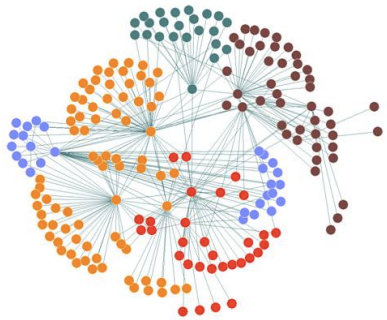


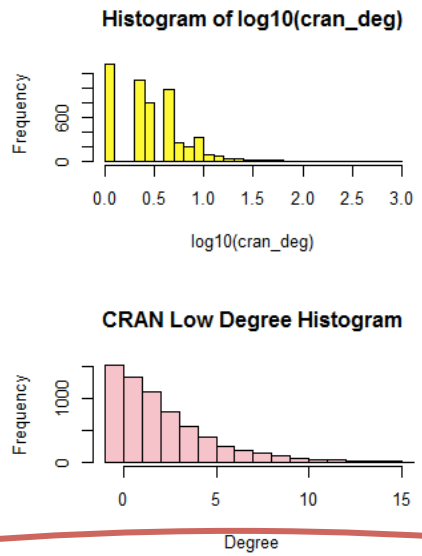
analyzing

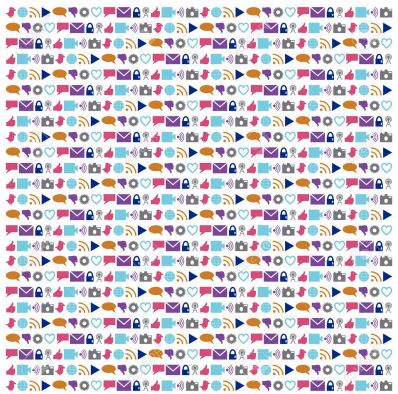


extracting patterns

This short course is about...







representing

analyzing

extracting patterns

over time

Data Science for Social Media Mining

social theory

computational theory

What we want to know about the vast social media world with computational tools?

A social media mining

data scientist

needs to do the

right questions!

How Fast Will You Get a Response? Predicting Interval Time for Reciprocal Link Creation

Vachik S. Dave, Mohammad Al Hasan
Department of Computer & Information Science
IUPUI, Indianapolis, USA
vsdave@iupui.edu, alhasan@iupui.edu

Chandan K. Reddy
Department of Computer Science
Virginia Tech, Arlington, USA
reddy@cs.vt.edu

from ICWSM'17

How Fast Will You Get a Response?
Predicting Interval Time for Reciprocal Link Creation

Chandan K. Reddy
Department of Computer Science
Virginia Tech, Arlington, USA
reddy@cs.vt.edu

Mohammad Al Hasan
Information Science

What Comments Did I Get? How Post and Comment Characteristics Predict Interaction Satisfaction on Facebook

Shruti Sannon, Yoon Hyung Choi, Jessie G. Taft, Natalya N. Bazarova
Department of Communication, Cornell University
{ss3464, yc863, jgt43, nnb8}@cornell.edu

from ICWSM'17

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What Comments Did I Get? How Post and Comment Characteristics Predict Interaction Satisfaction

Nasty, Brutish, and Short:
What Makes Election News Popular on Twitter?

Sophie Chou
MIT Media Lab
Cambridge, MA, USA
soph@media.mit.edu

Deb Roy
MIT Media Lab
Cambridge, MA, USA
dkroy@media.mit.edu

from ICWSM'17

How Fast Will You Get a Response?
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Department of Computer Science
Virginia Tech, Arlington, USA
reddy@cs.vt.edu

Are There Gender Differences in Professional Self-Promotion?
An Empirical Case Study of LinkedIn Profiles among Recent MBA Graduates

Kristen M. Altenburger
Stanford University (USA)
kaltenb@stanford.edu

Rajlakshmi De
North Carolina State University (USA)
rde2@ncsu.edu

Nikolai Avteniev
LinkedIn (USA)
navteniev@linkedin.com

Kaylyn Frazier
Google Inc. (USA)
kfrazier@google.com

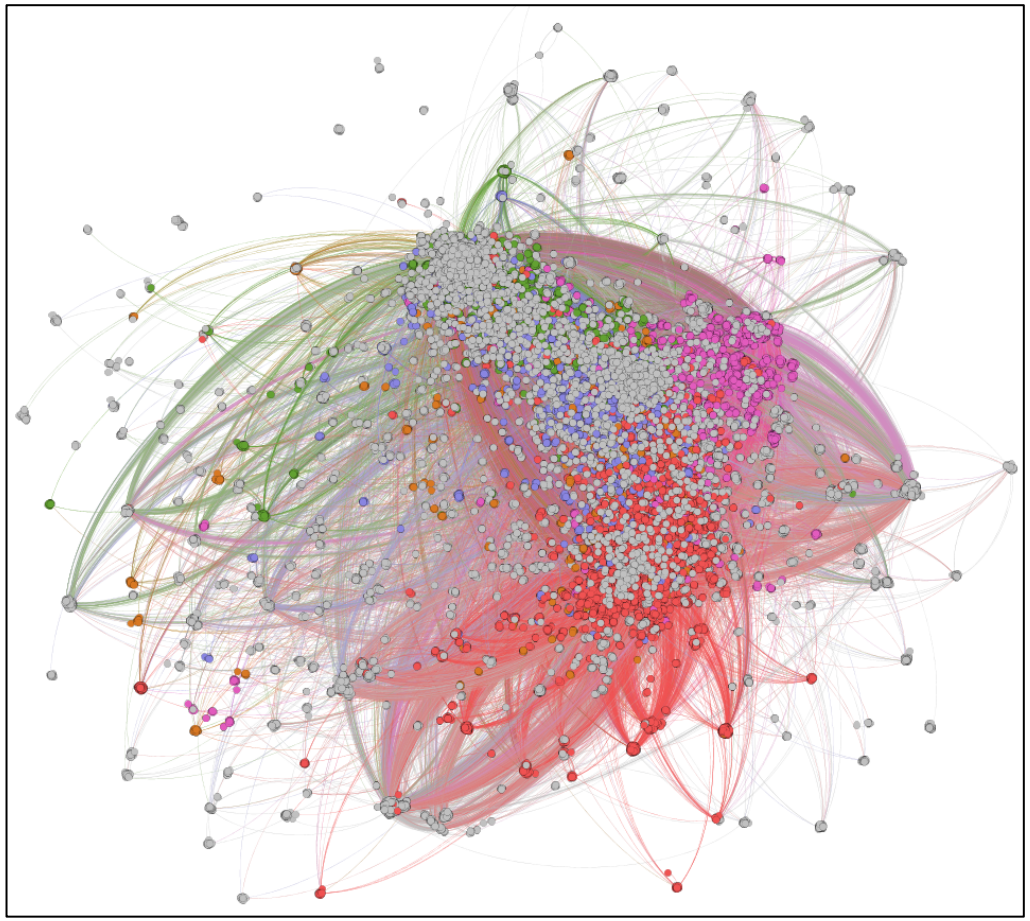
Jim Hamilton
LinkedIn (USA)
jihamilton@linkedin.com

What Makes Electi

Sophie Chou
MIT Media Lab
Cambridge, MA, USA
soph@media.mit.edu

from ICWSM'17

The network structure is our



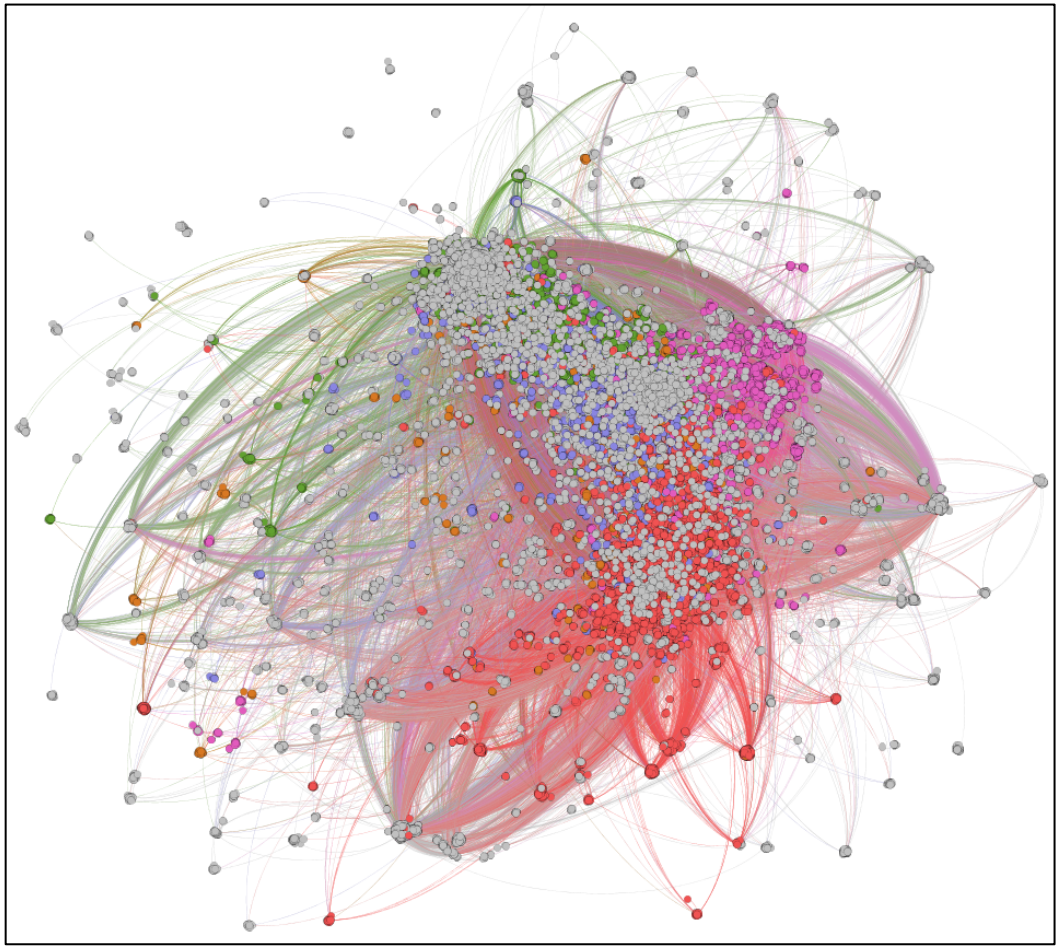
Source of knowledge

Social Network Analysis

*How can we **measure the influence** of individuals in a social network?*

*How can we **analyze the behavior** of individuals?*

*Who are the **most important people** in a social network?*



[Epinions Ego Trust Network from Massa & Avesani 2007 dataset]

Social Network Analysis

Sociology

Algorithms

Data Mining

over ***network*** *structure*

Social Network Analysis

Social Network Analysis

!=

Social Media

What are Social Networks?

- ✓ Real life (explicit)
- ✓ Online Social Networks (OSN) (explicit)
- ✓ Derived (implict)

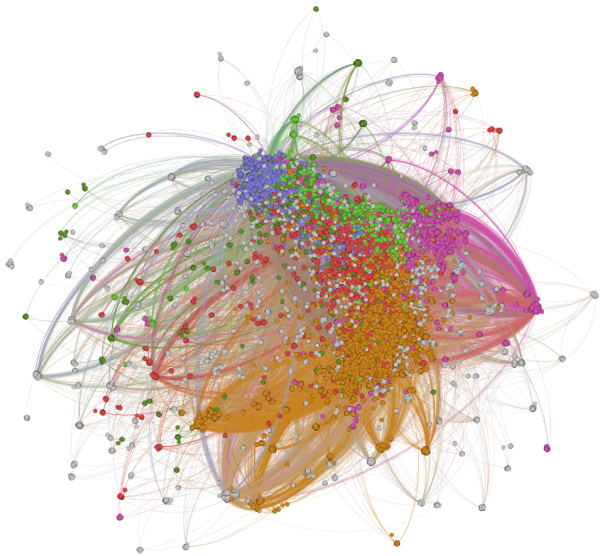
- ✓ e-mail networks,
- ✓ citation networks,
- ✓ co-author networks,
- ✓ terrorist networks,
- ✓ telecom calls networks,
- ✓ trust networks,
- ✓ contact networks,
- ✓ music listening networks,
- ✓ sexual networks,
- ✓ organized crime networks

and whatever social interaction represented as network!

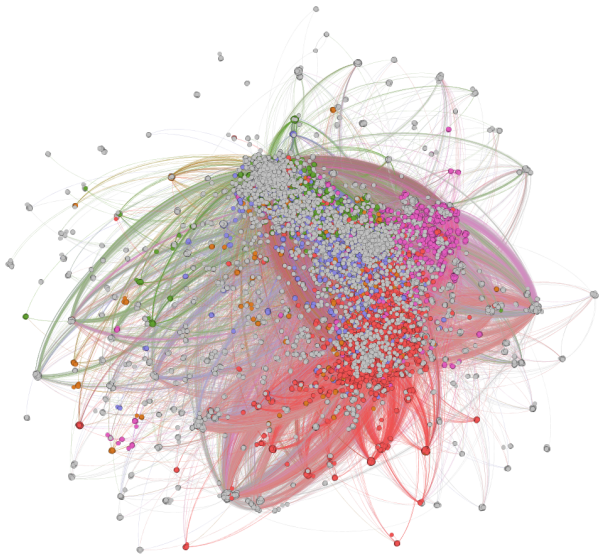
But wait....

Are social networks
evolving
as time flies?
Or are they static?

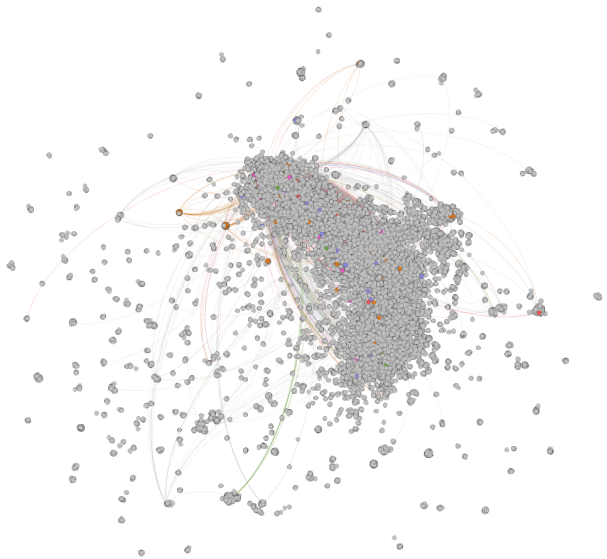
Evolving the Epinions Ego Trust Network



the whole period



2001-01-10
to
2001-07-10



2002-01-10
to
2002-07-10

top-6 modularity classes

It's a matter of time!

Social Network Analysis

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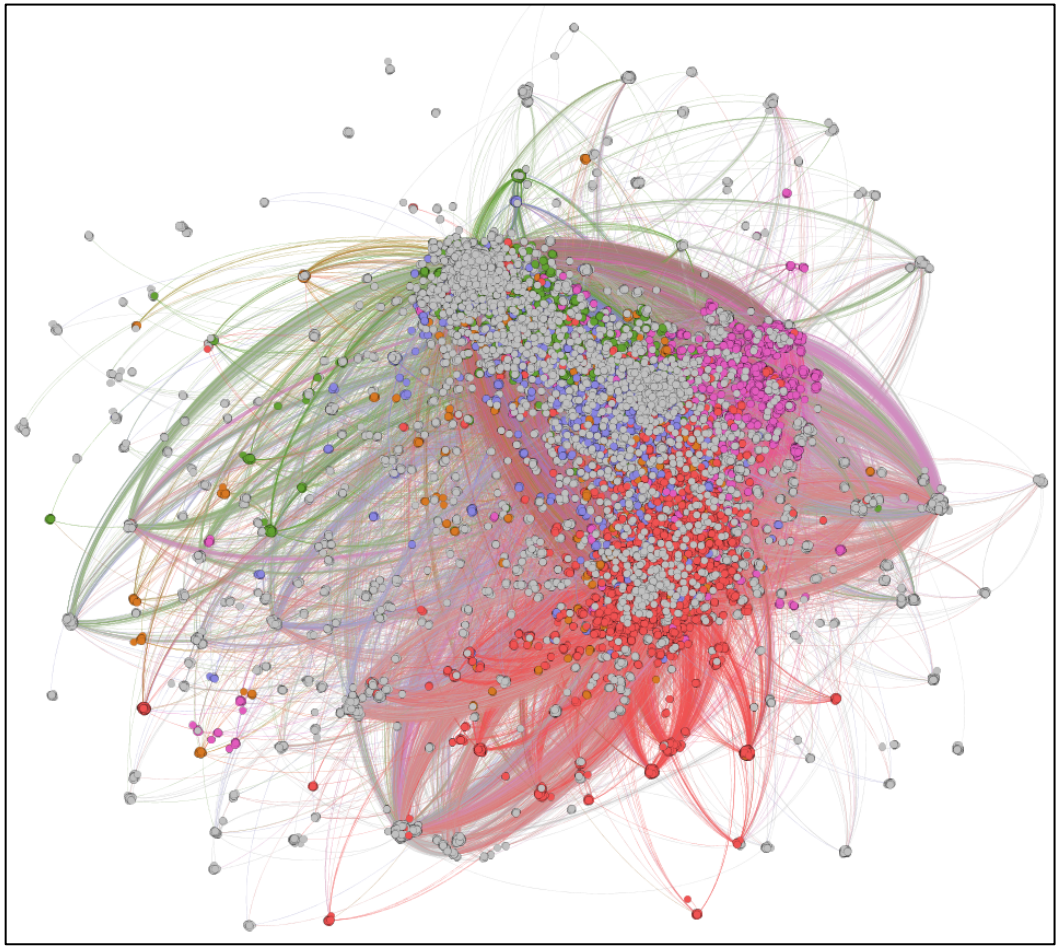

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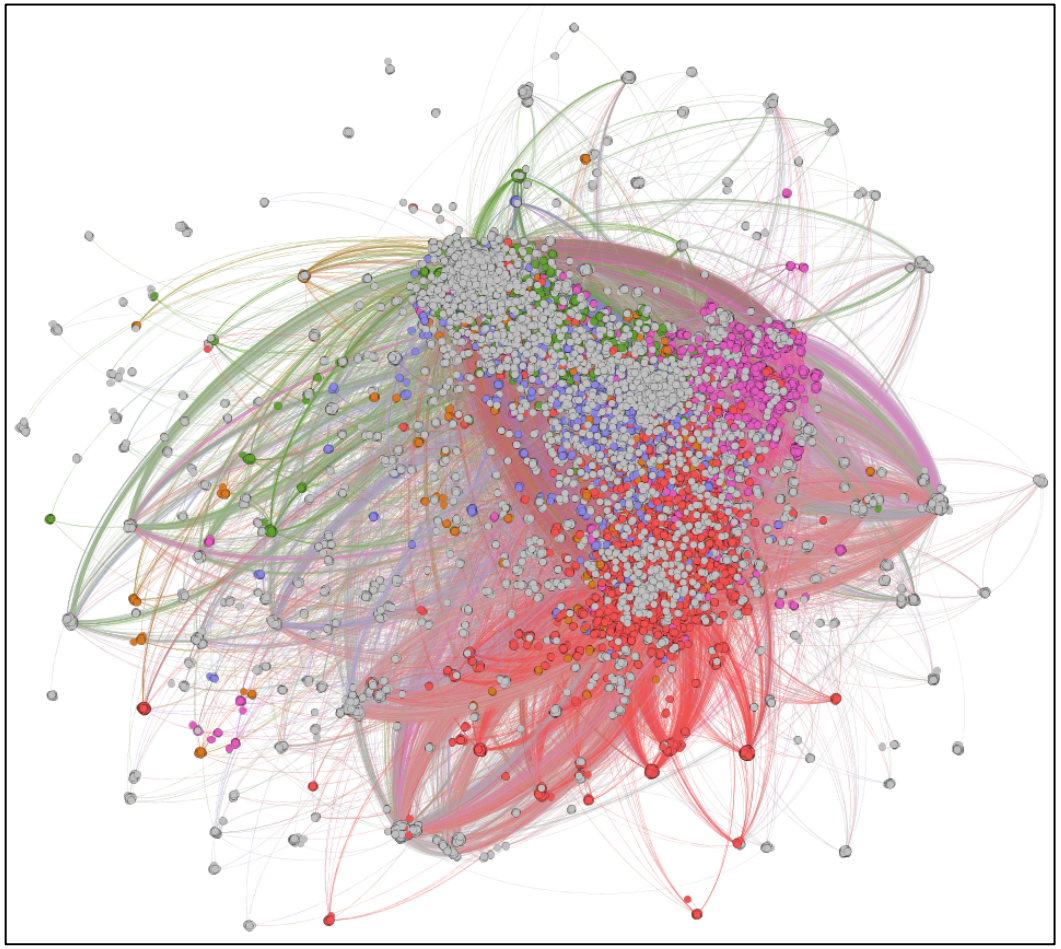

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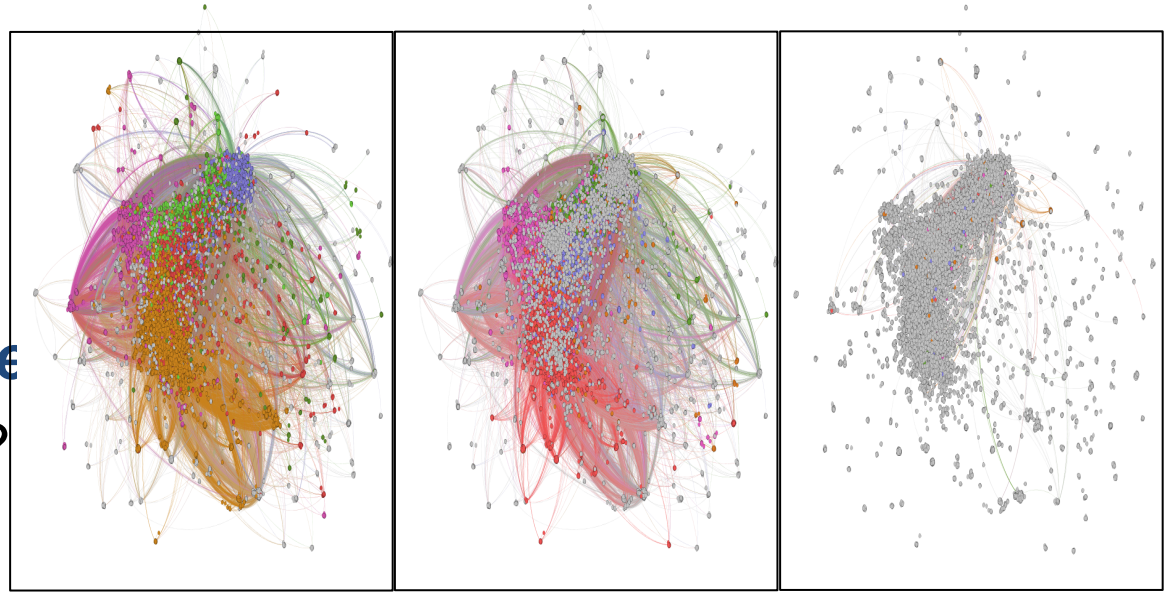

*How can we **analyze the behavior** of individuals?*

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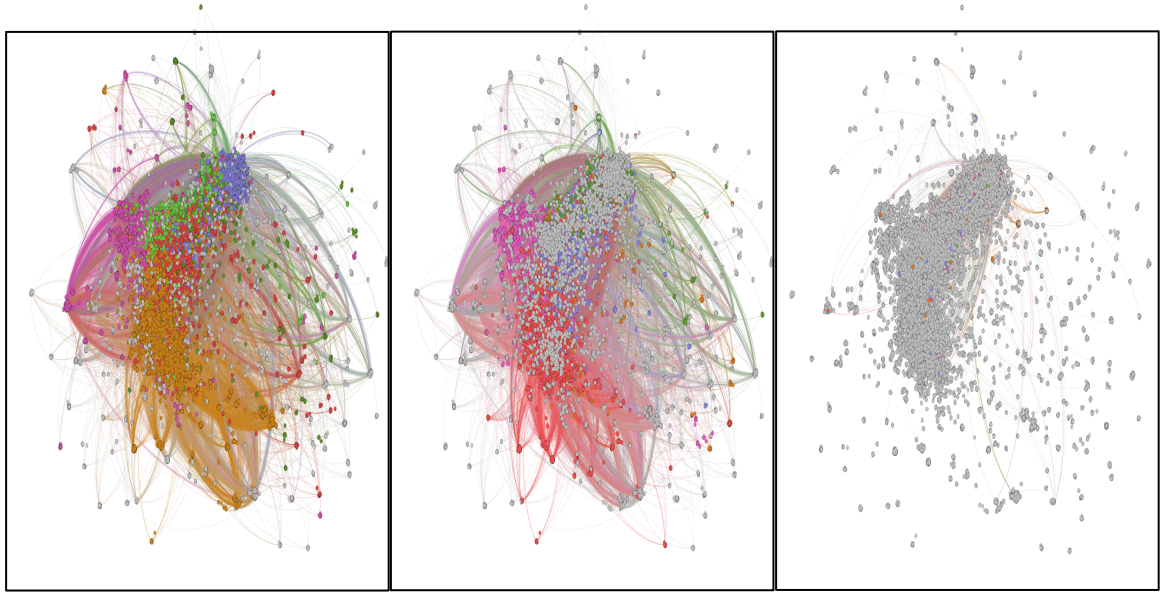
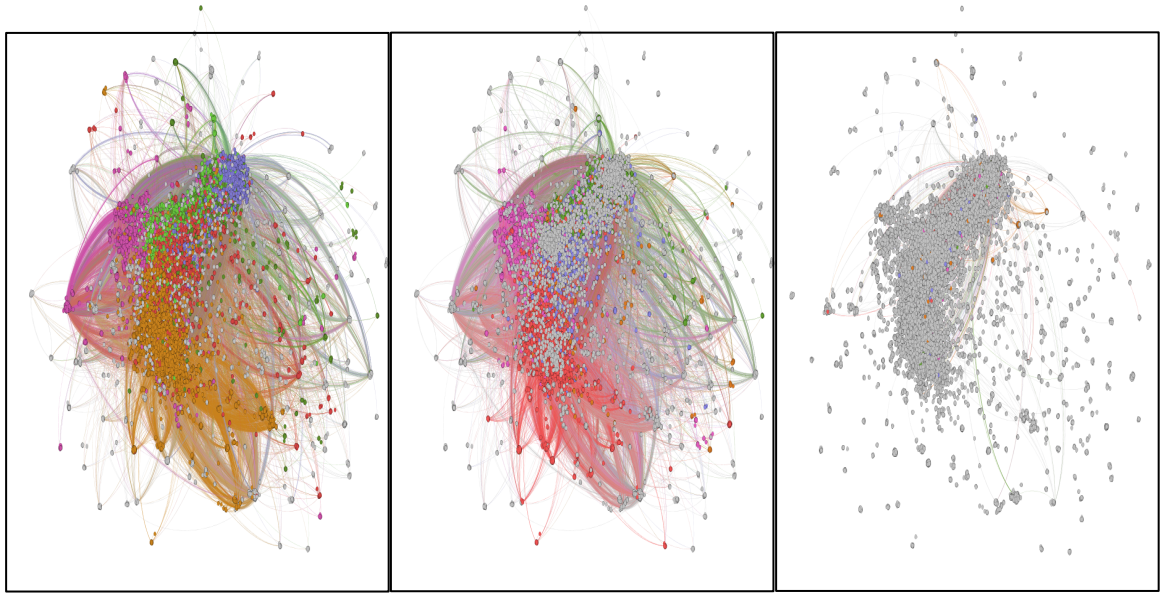
Dynamic Social Network Analysis



Dynamic Social Network Analysis

Who are likely to

become friends next?

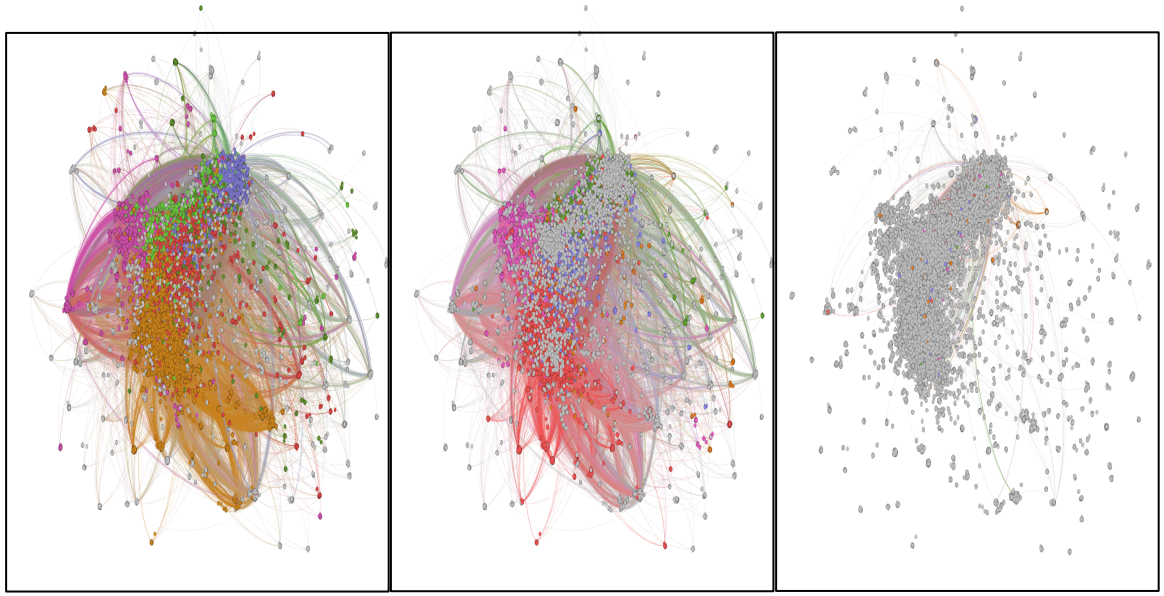


Dynamic Social Network Analysis

Who are likely to **become** friends next?

How does the **social network evolve** over time?

Can I **process** the whole network indefinitely?



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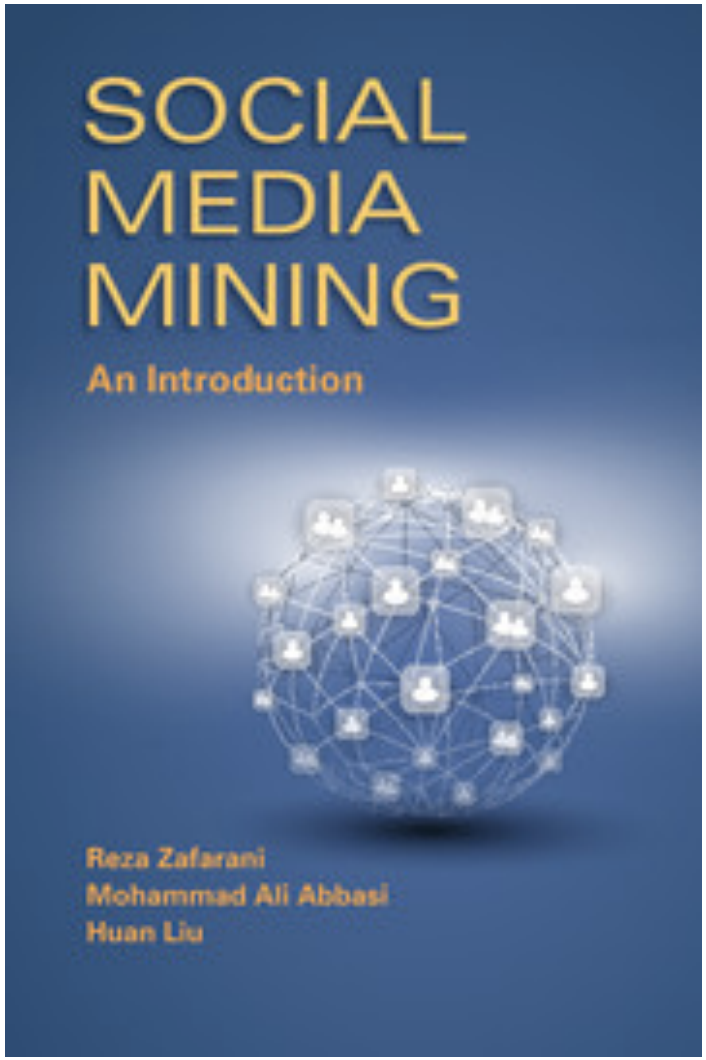
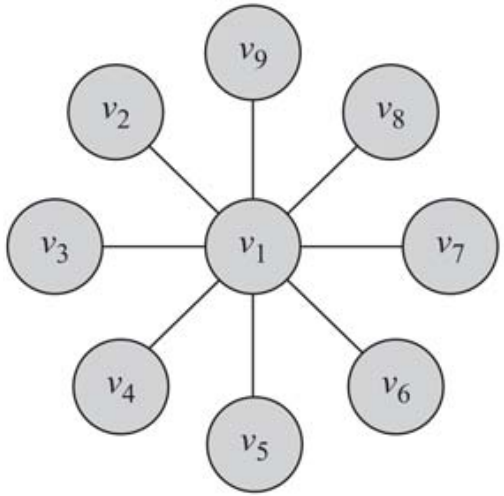
SNA Essentials

SNA Essentials



Network Measures
Degree Centrality

$C_d(v_i) = d_i \rightarrow$ number of adjacent edges



$$C_d(v_1) = d_1 = 8$$

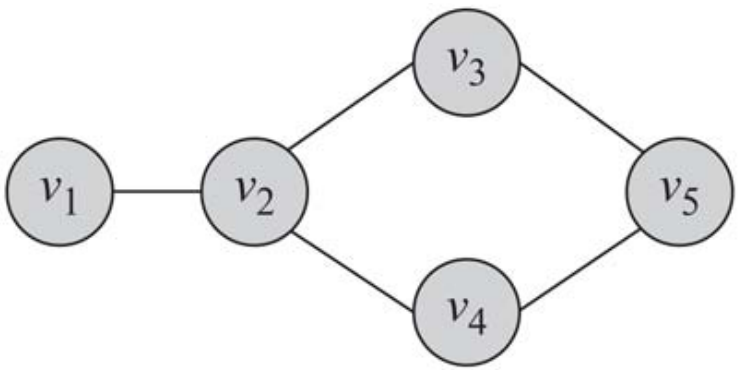
Network Measures

Betweenness Centrality

$$C_b(v_i) = \sum_{s \neq t \neq v_i} \frac{\sigma_{st}(v_i)}{\sigma_{st}}$$

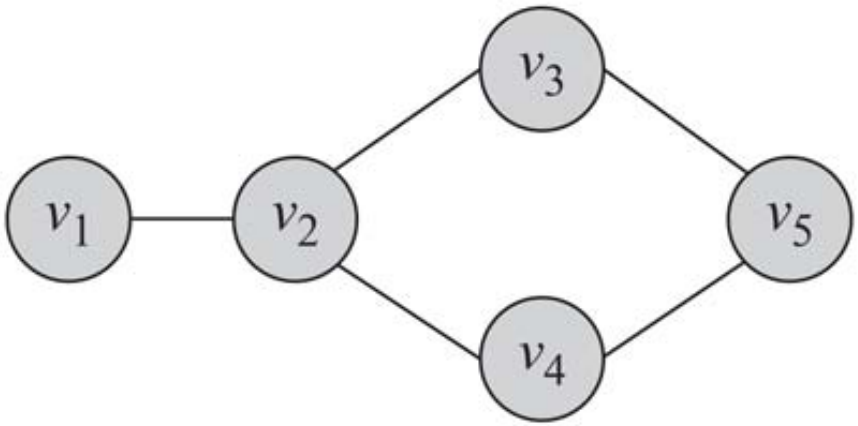
number of shortest paths from s to t passing through v_i

number of shortest paths from s to t



Network Measures

Betweenness Centrality



$$C_b(v_2) = 2 \times (\underbrace{(1/1)}_{s=v_1,t=v_3} + \underbrace{(1/1)}_{s=v_1,t=v_4} + \underbrace{(2/2)}_{s=v_1,t=v_5} + \underbrace{(1/2)}_{s=v_3,t=v_4} + \underbrace{0}_{s=v_3,t=v_5} + \underbrace{0}_{s=v_4,t=v_5})$$

$$= 2 \times 3.5 = 7$$

Network Measures

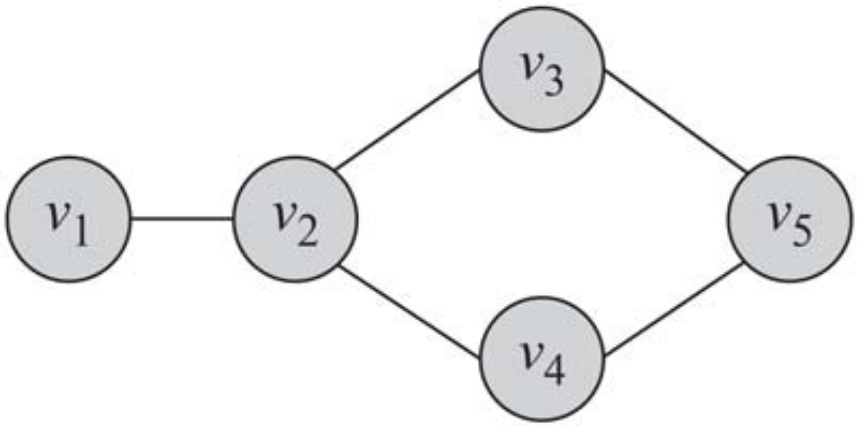
Closeness Centrality

$$C_c(v_i) = \frac{1}{\bar{l}_{v_i}}$$

vi's average shortest path length to other nodes

Network Measures

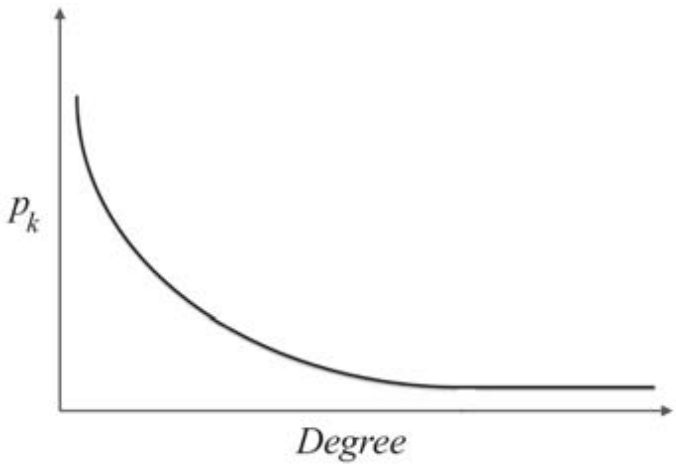
Closeness Centrality



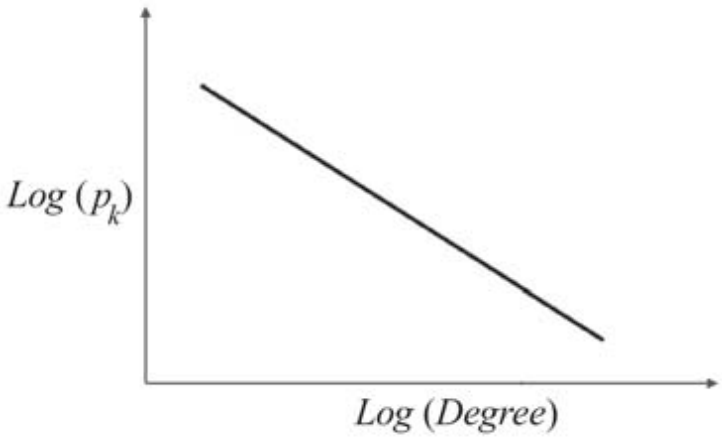
$$
\begin{aligned}
& C_c(v_1) && = 1 \,/\, (\,(1+2+2+3)/4\,) = 0.5, \\
& C_c(v_2) && = 1 \,/\, (\,(1+1+1+2)/4\,) = 0.8, \\
C_c(v_3) = \; & C_b(v_4) && = 1 \,/\, (\,(1+1+2+2)/4\,) = 0.66, \\
& C_c(v_5) && = 1 \,/\, (\,(1+1+2+3)/4\,) = 0.57.
\end{aligned}
$$

Network Models

Properties of Real-World Networks



(a) Power-Law Degree Distribution



(b) Log-Log Plot of Power-Law Degree Distribution

Degree distribution - Power Law

Network Models

Properties of Real-World Networks

Average Local Clustering Coefficient in Real-World Networks

Web	Facebook	Flickr	LiveJournal	Orkut	YouTube
0.081	0.14 (with 100 friends)	0.31	0.33	0.17	0.13

Clustering Coefficient - High average

Network Models

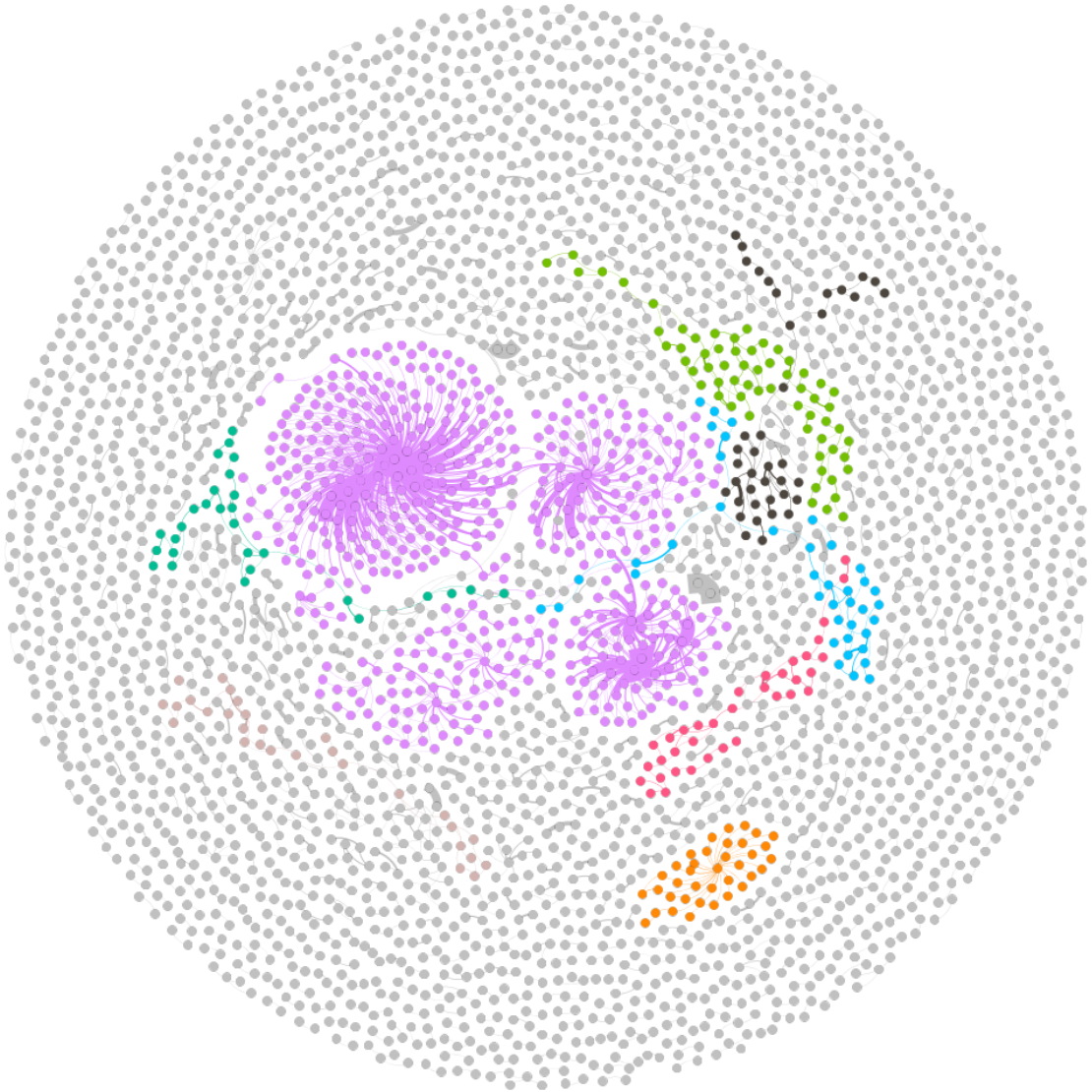
Properties of Real-World Networks

Average Path Length in Real-World Networks

Web	Facebook	Flickr	LiveJournal	Orkut	YouTube
16.12	4.7	5.67	5.88	4.25	5.10

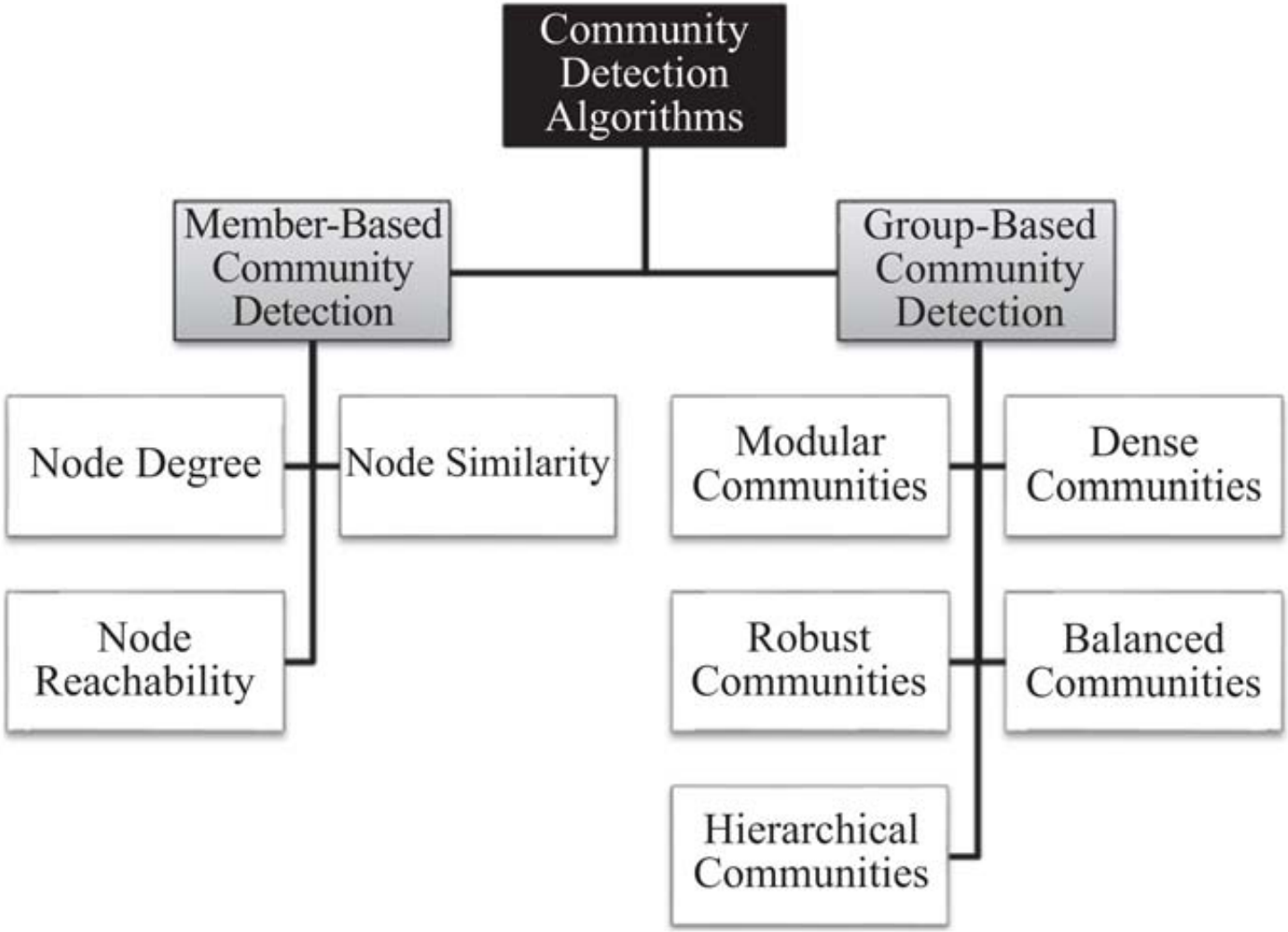
Average Path Length - Small World

Communities



Telecom calls network

Communities



Information Diffusion

The process by which a piece of information (knowledge) is spread and reaches individuals through interactions

Information Diffusion

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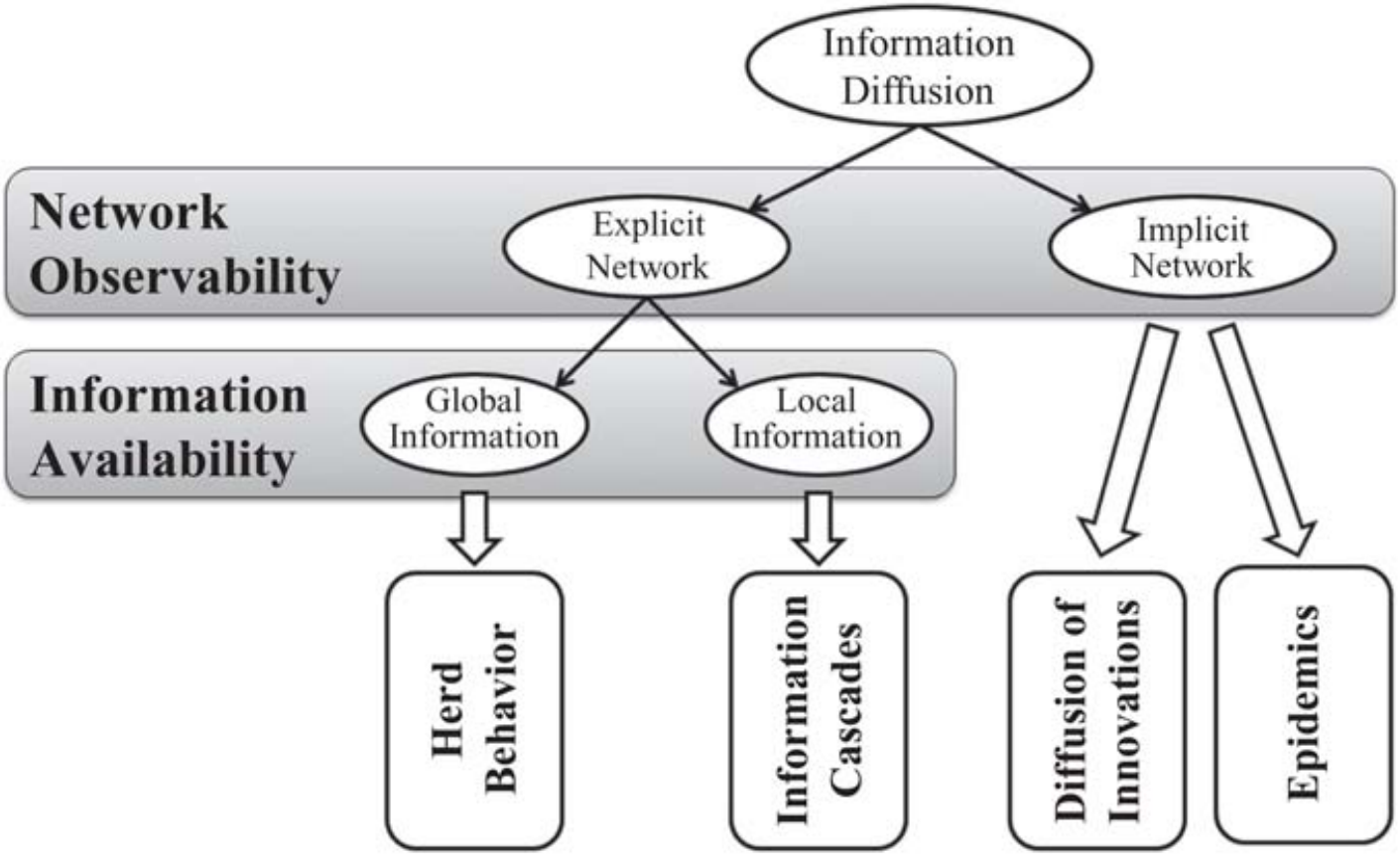
Information Diffusion



HANDS ON!!

www.lsi.facom.ufu.br/~fabiola/sbbd2017

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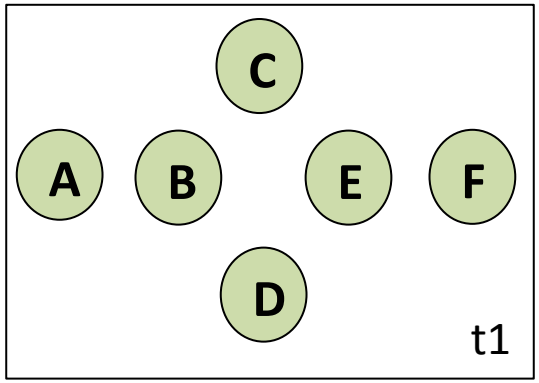
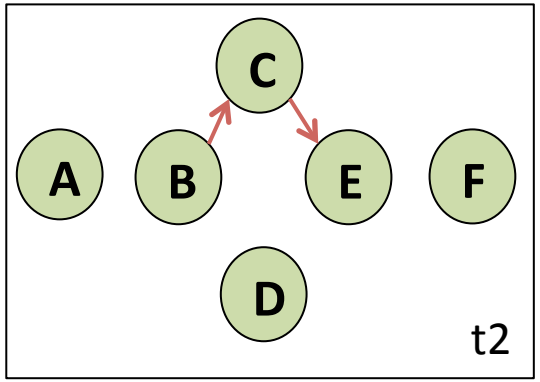
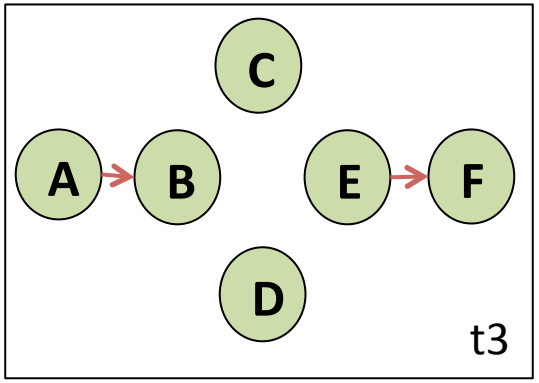
Temporal Networks



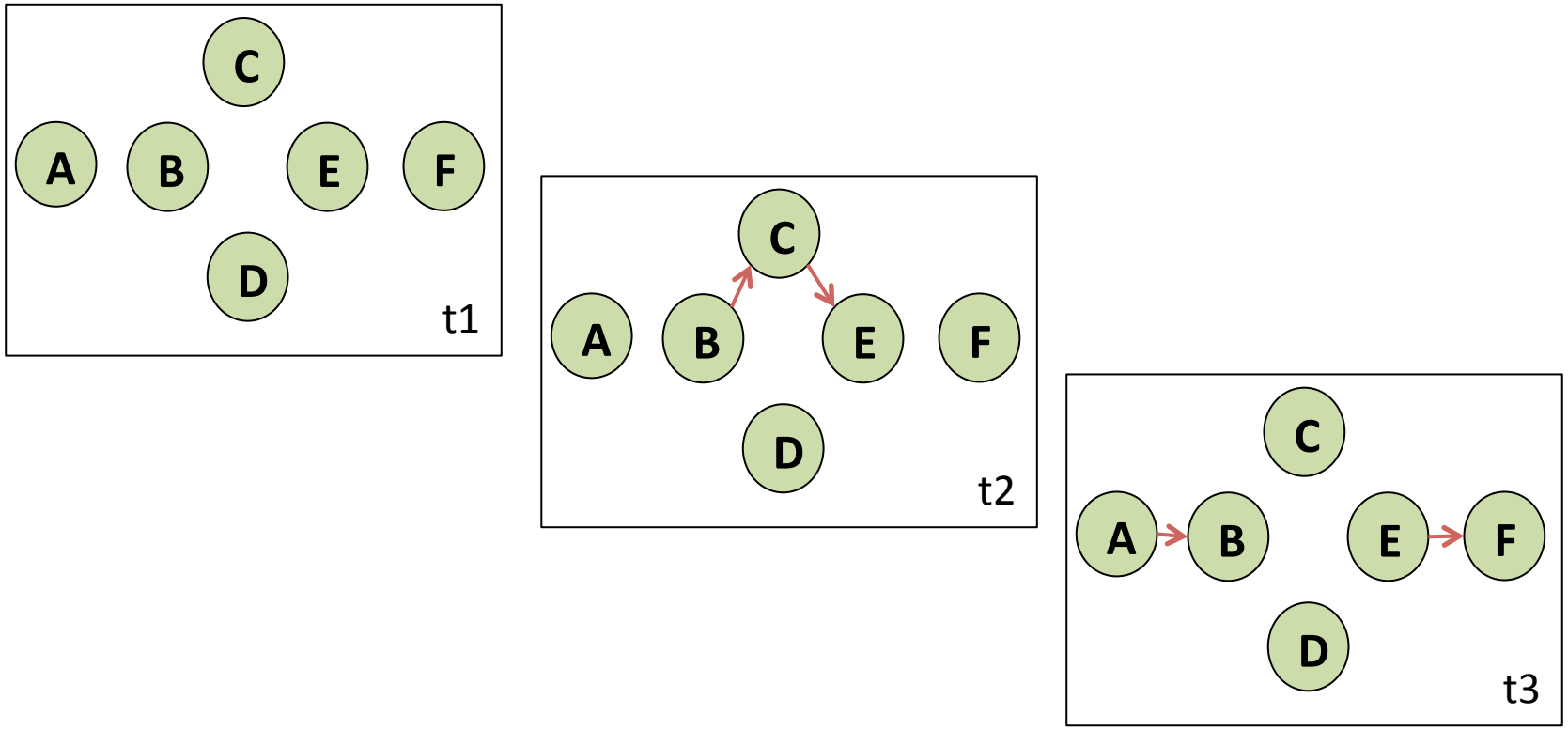
Temporal Networks

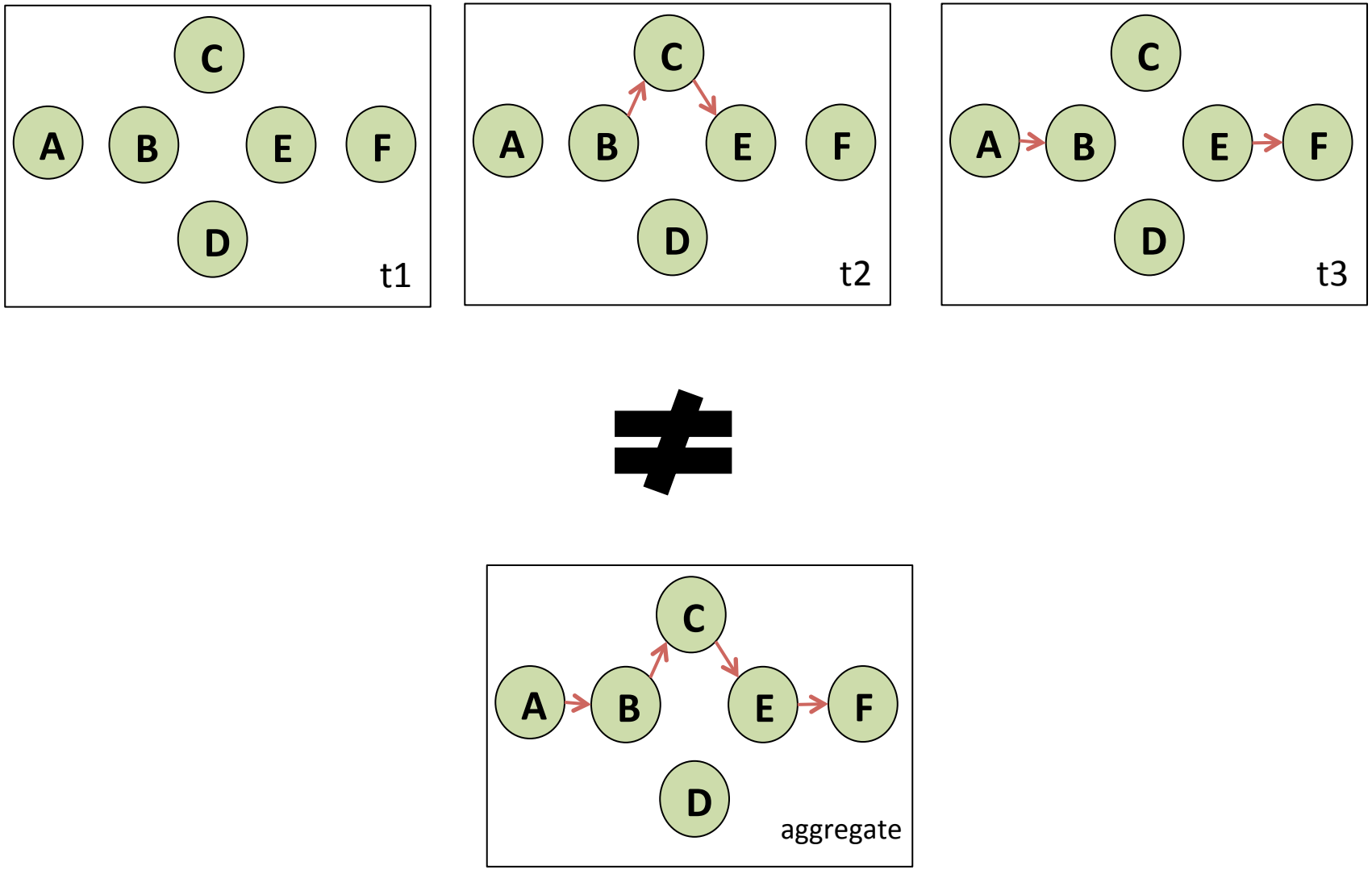


Temporal Networks



Temporal Networks




C
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F
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C
A
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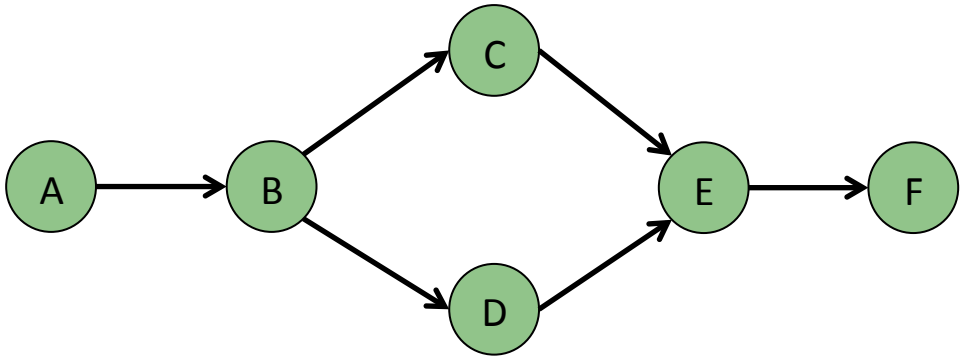
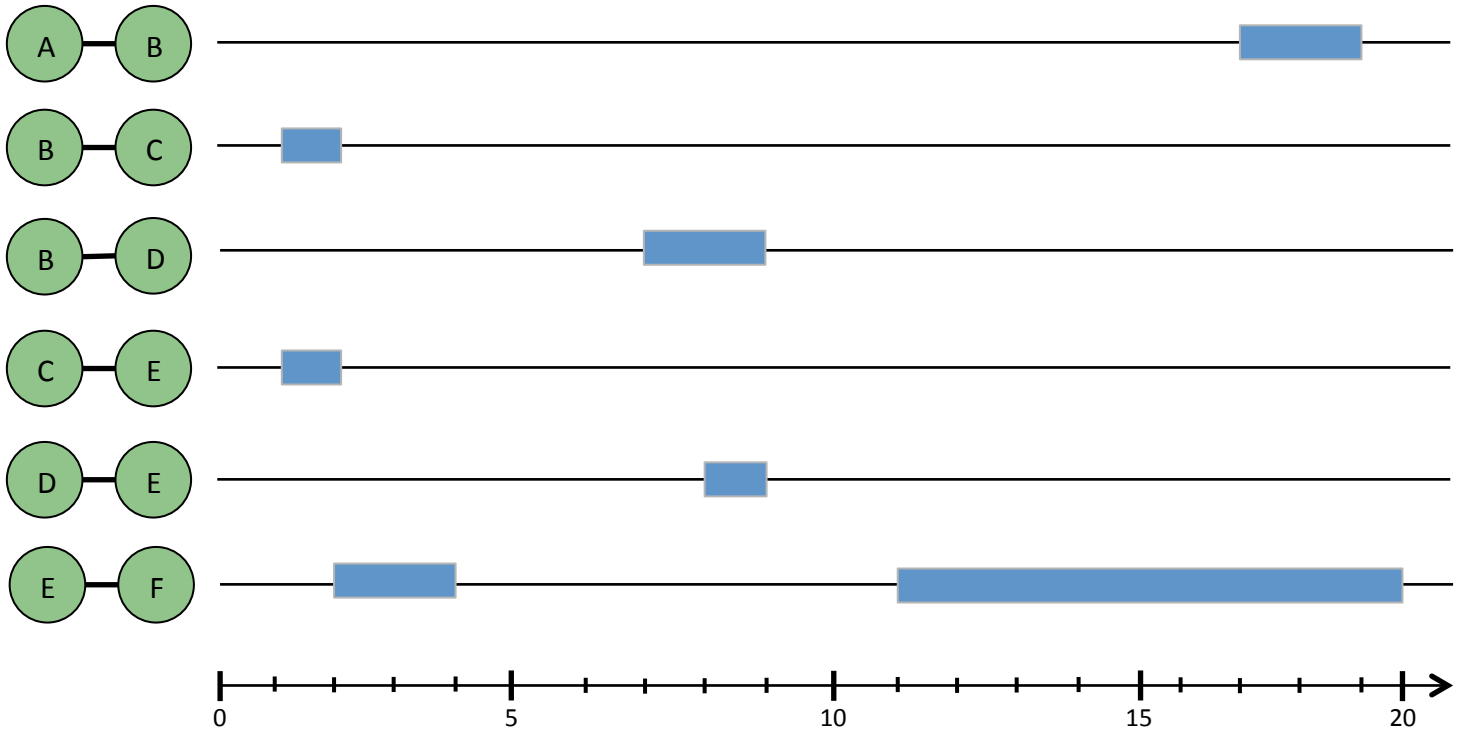
E
F
D
aggregate

Temporal Networks





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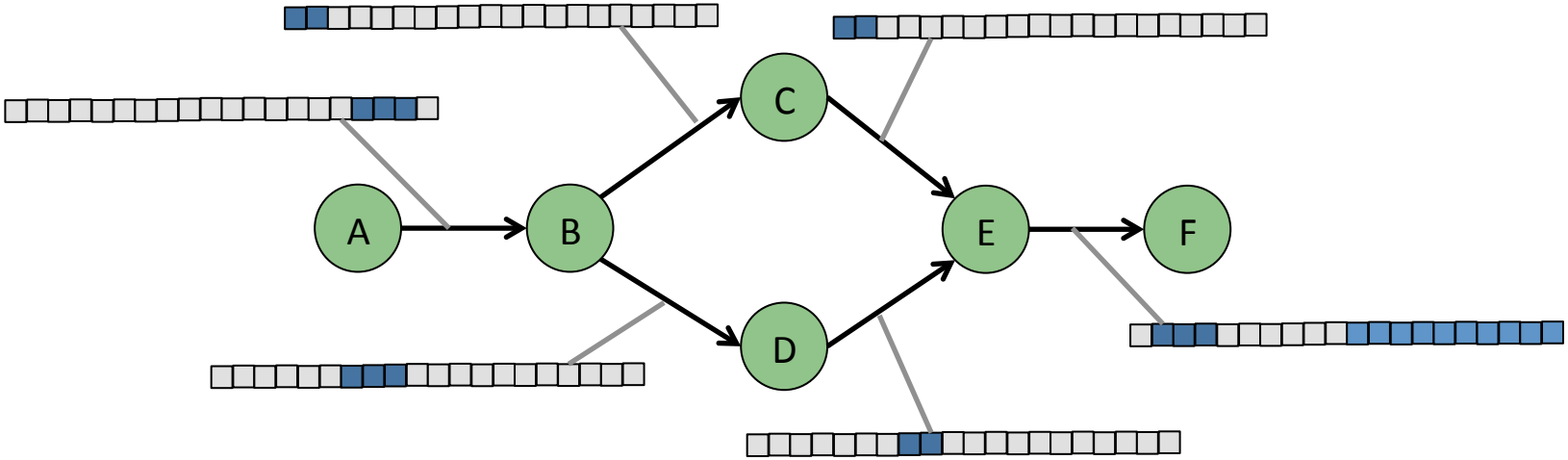
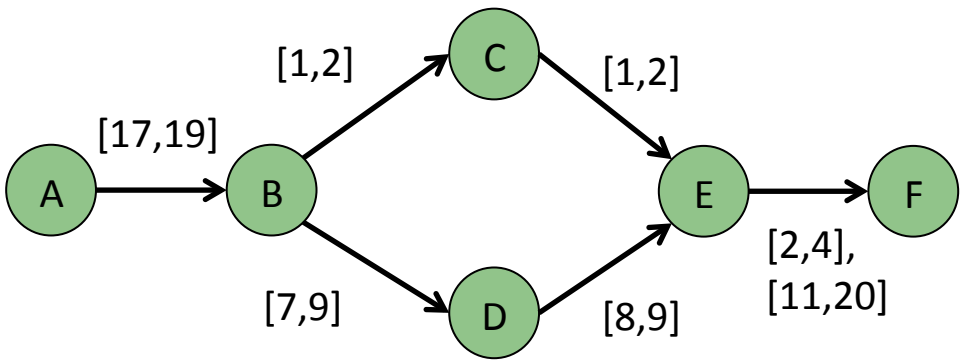
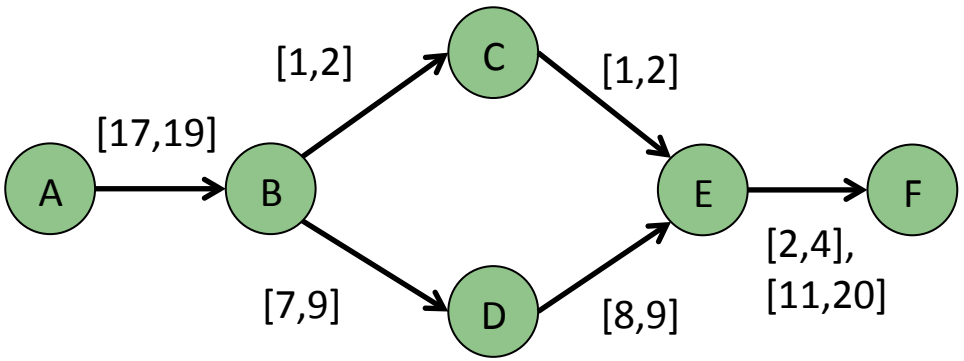


Observation window W =

Temporal Networks

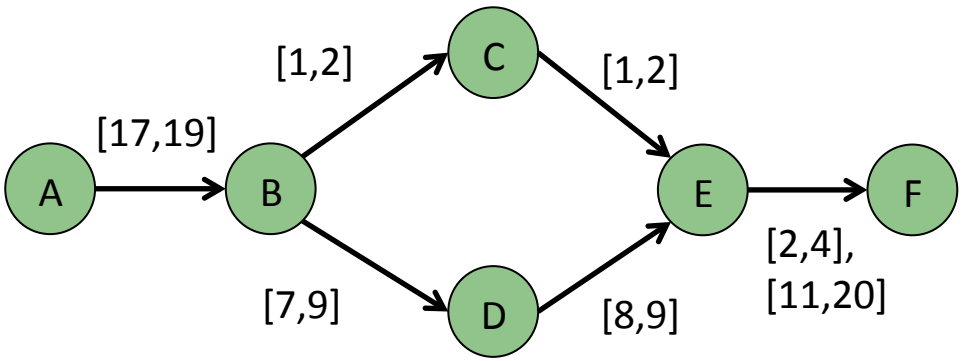


Temporal Networks



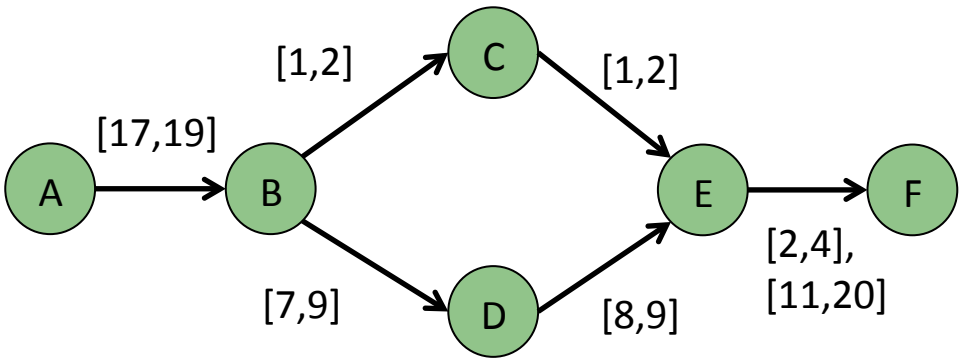
- ✓ Person-to-person communication
- ✓ Disease spreading
- ✓ Social networks
- ✓ ...

Temporal Networks



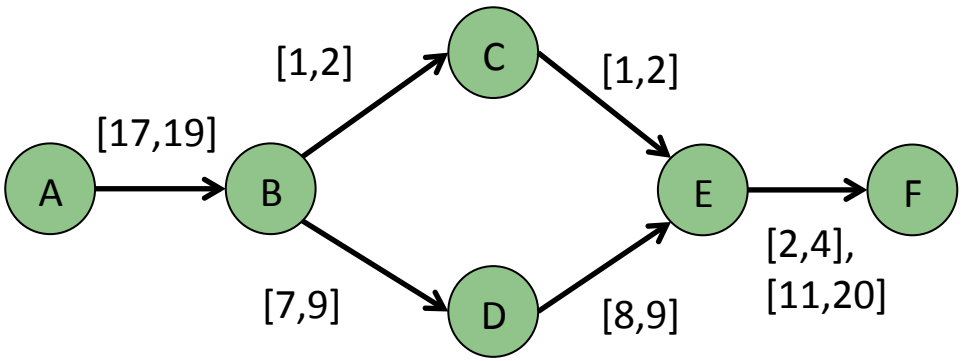
- ✓ Person-to-person communication
- ✓ Disease spreading
- ✓ Social networks
- ✓ ...

Twitter as a Temporal Network

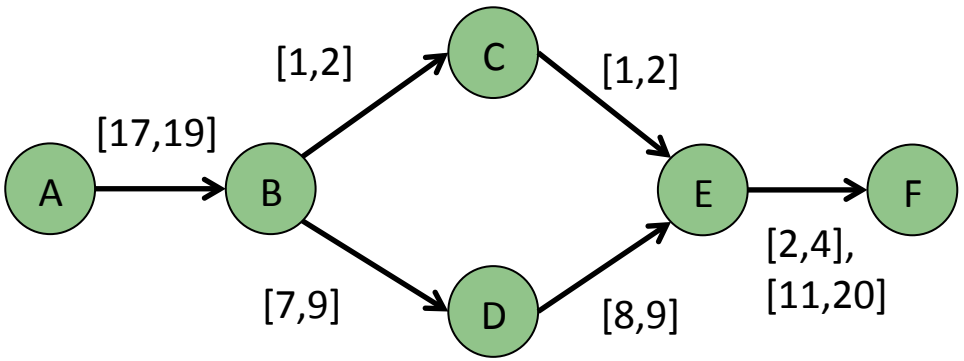


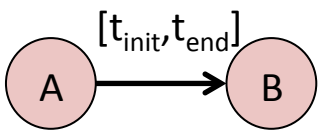
Why are we using temporal networks?

Twitter as a Temporal Network



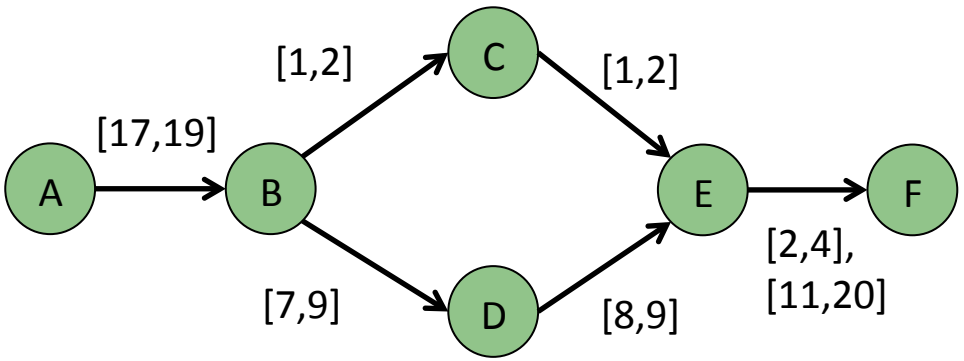
Twitter as a Temporal Network

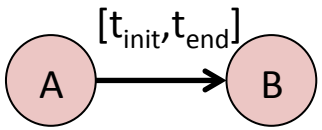


✓ 

B follows A (information flow) from t_{init} to t_{end}

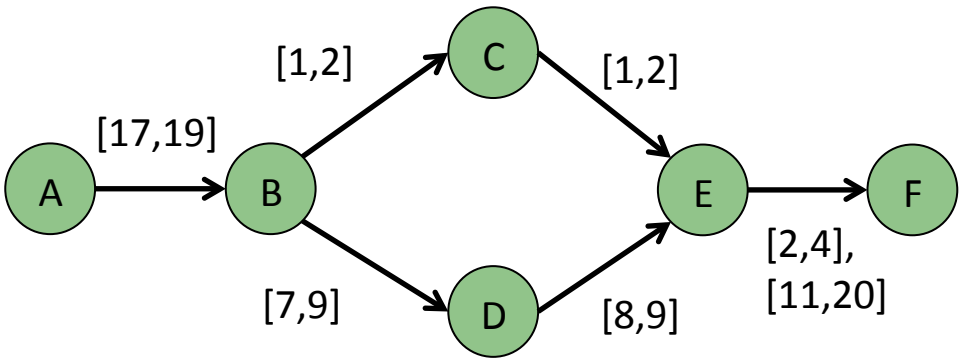
Twitter as a Temporal Network

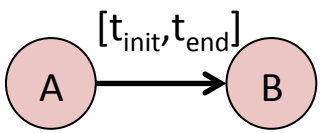


- ✓ 

B follows A (information flow) from t_{init} to t_{end}
- ✓ W = [n,N] = observation window

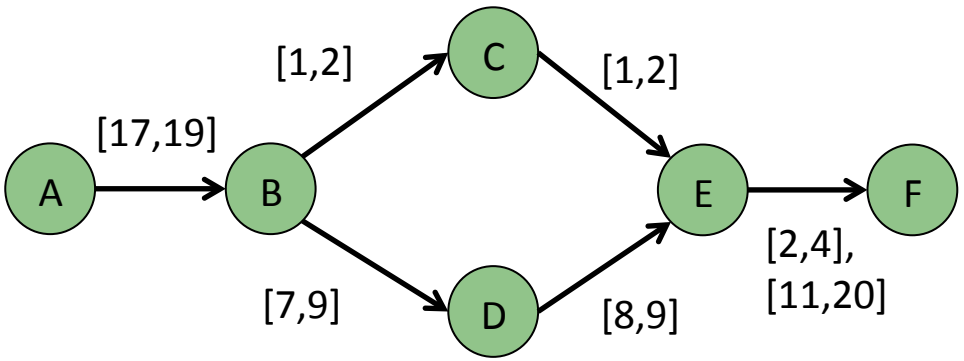
Twitter as a Temporal Network

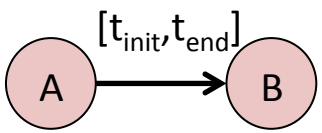


- ✓ 

B follows A (information flow) from t_{init} to t_{end}
- ✓ W = [n,N] = observation window
- ✓ R = retention time = 1 day

Twitter as a Temporal Network



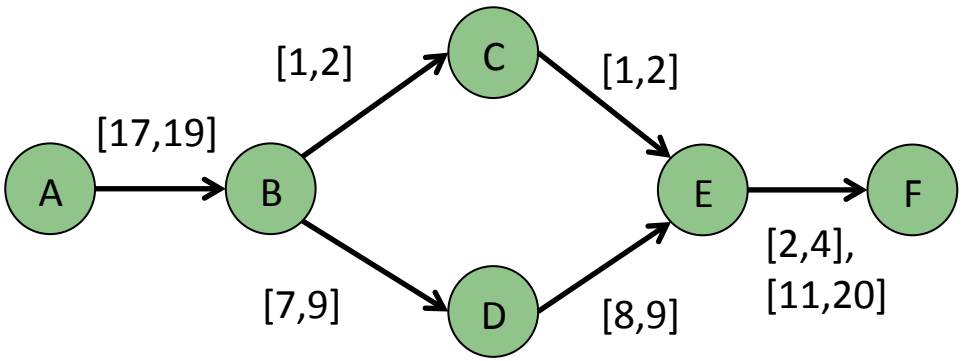
- ✓ 

B follows A (information flow) from t_{init} to t_{end}
- ✓ W = [n,N] = observation window
- ✓ R = retention time = 1 day
- ✓ T = edge traversal time = 0

Temporal Metrics

The concept of geodesic distance cannot be limited to the number of hops separating two nodes but should also take into account the temporal ordering of links.

Temporal Path



W = [1,20]

R = 1 day

T = 0

Temporal Path	Duration	Is fastest path?
P(B,E) = <(B,C,1), (C,E,2)>	1	yes
P(B,E) = <(B,D,7), (D,E,9)>	2	no
P(B,E) = <(B,D,7), (D,E,8)>	1	yes

Temporal Metrics

Revisiting centrality metrics....

$$closeness(v) = \sum_{u \in V \setminus \{v\}} \frac{1}{min(d_{P_{v,u}})}$$

Fastest path duration

- ✓ How close a node is from the others nodes in the graph
- ✓ High closeness = best visibility into what is happening

Temporal Metrics

Revisiting centrality metrics....

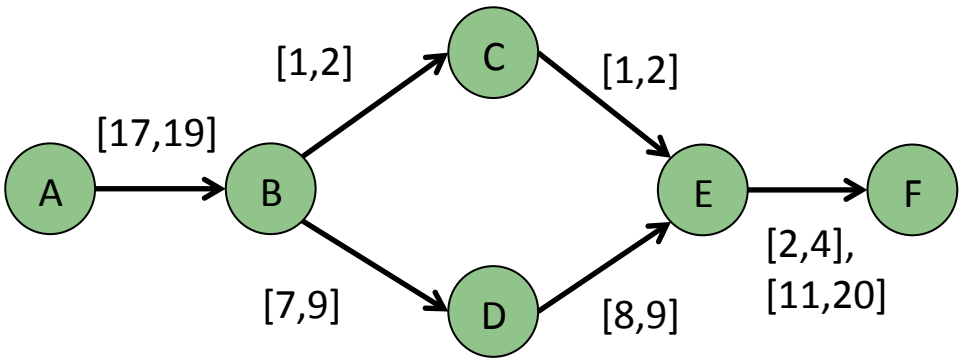
$$betweenness(v) = \sum_{v \neq j \neq k} \frac{w_v(j,k)}{w(j,k)}$$

Number of fastest paths between j and k that pass through v

Number of fastest paths between j and k

- ✓ High betweenness = great influence over what flows
- ✓ High betweenness = control the flow of information (gatekeeper)

Betweenness centrality



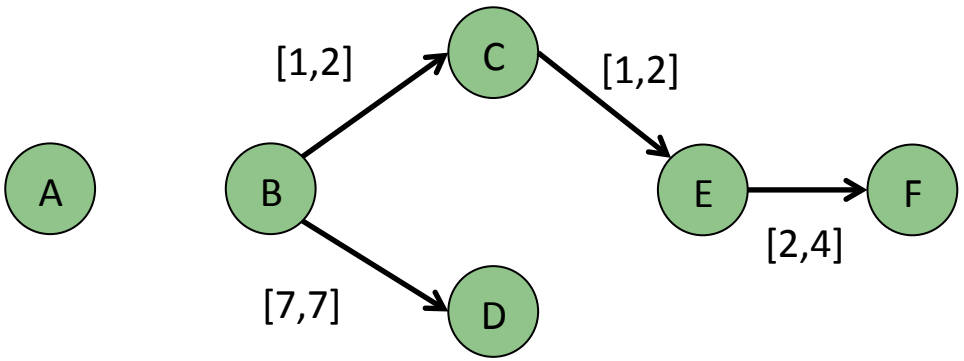
W = [1,20]

R = 1 day

T = 0

Node	Fastest Path (temporal)	Shortest Path (static)
C	1.33	2
D	0.66	2
E	3	4
B	0	4

Betweenness centrality



R = 1 day

T = 0

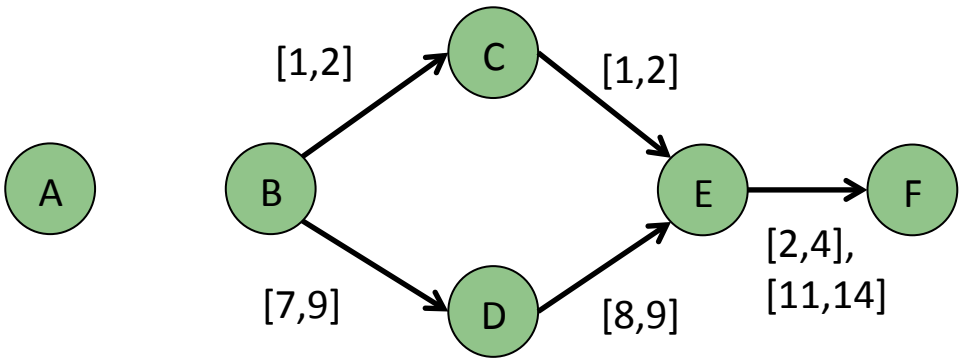
Ranking	Node
1	E, C
2	A, B, D, F
3	-
4	-

W = [1,7]

W = [1,14]

W = [1,21]

Betweenness centrality



R = 1 day

T = 0

Ranking	Node
1	E, C
2	A, B, D, F
3	-
4	-

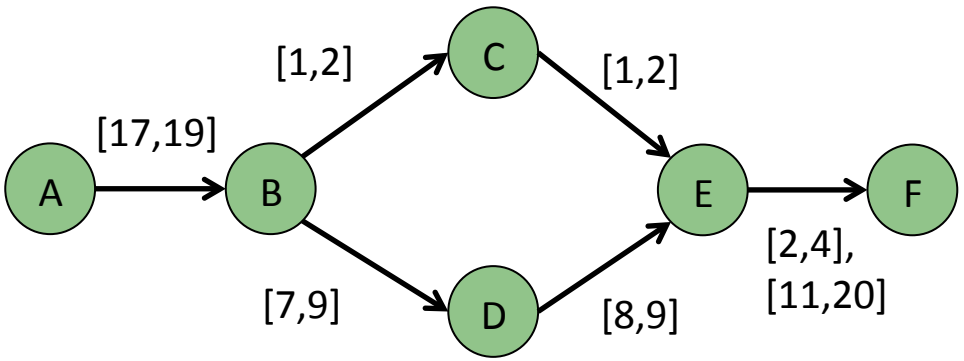
Ranking	Node
1	E
2	C
3	D
4	A, B, F

W = [1,7]

W = [1,14]

W = [1,21]

Betweenness centrality



R = 1 day

T = 0

Ranking	Node
1	E, C
2	A, B, D, F
3	-
4	-

Ranking	Node
1	E
2	C
3	D
4	A, B, F

Ranking	Node
1	E
2	C
3	D
4	A, B, F

7 14 21 t

W = [1,7]

W = [1,14]

W = [1,21]

Centrality Change

$$C_i(t) = | \, pos_i(t-1) - pos_i(t) \, | \, / \, \max(pos_i(t-1), pos_i(t))$$

ranking position of
node i in time t

Ranking	Node
1	E, C
2	A, B, D, F
3	-
4	-

Ranking	Node
1	E
2	C
3	D
4	A, B, F

Ranking	Node
1	E
2	C
3	D
4	A, B, F

7 14 21 t

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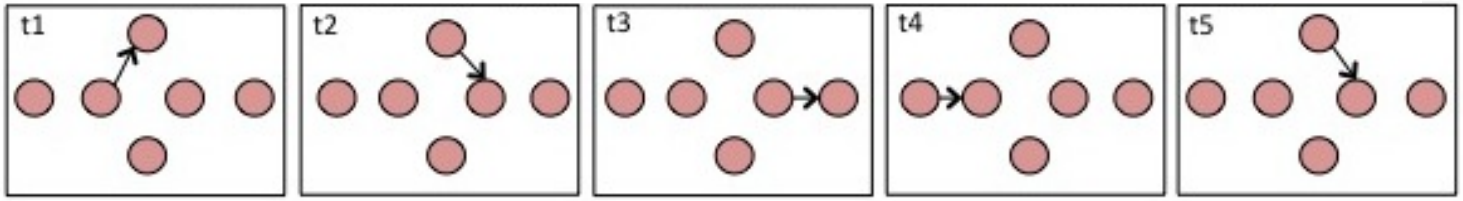
Processing Evolving Networks

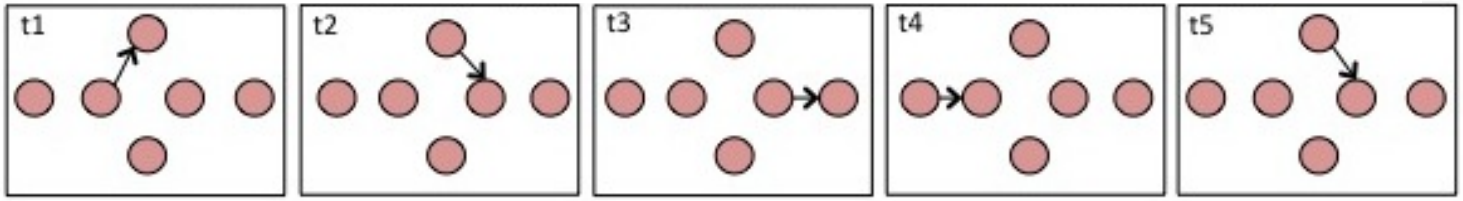
Processing Evolving Networks

Edges stream (arrival time = time granularity)



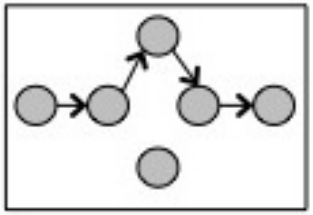
Batch Processing Evolving Networks

Edges stream (arrival time = time granularity)



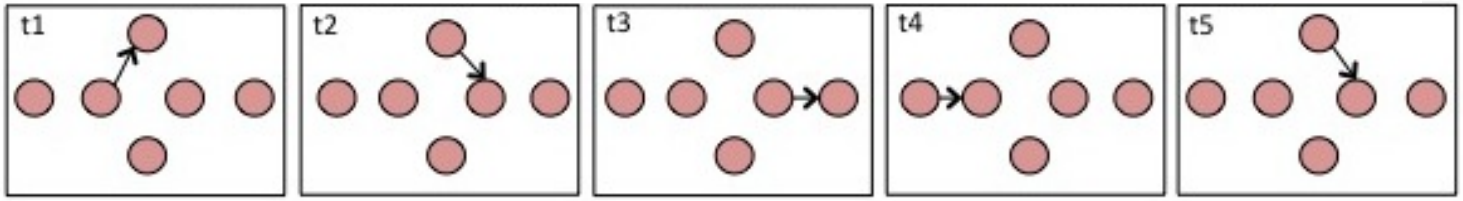
t1 t2 t3 t4 t5

Batch without
temporal info



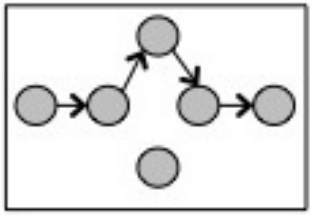
Batch Processing Evolving Networks

Edges stream (arrival time = time granularity)

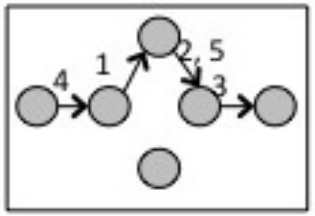


t1 t2 t3 t4 t5

Batch without temporal info

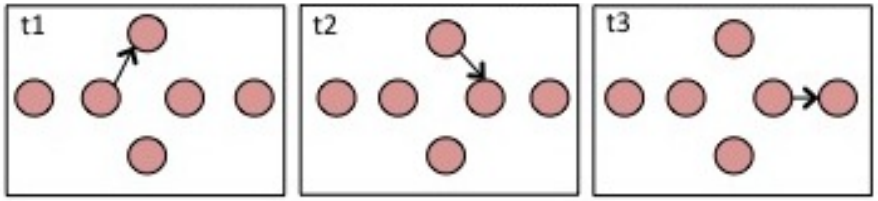


Batch with temporal info

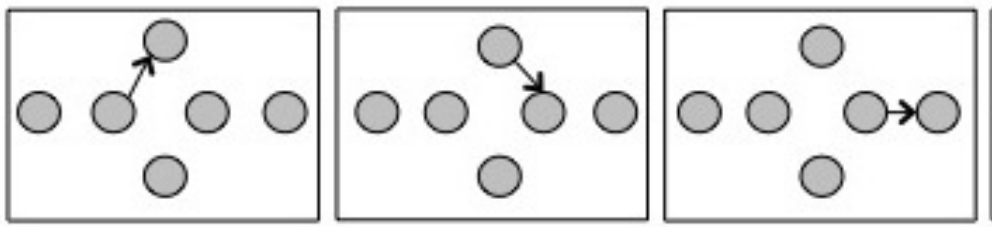


Batch Processing Evolving Networks

Edges stream (arrival time = time granularity)

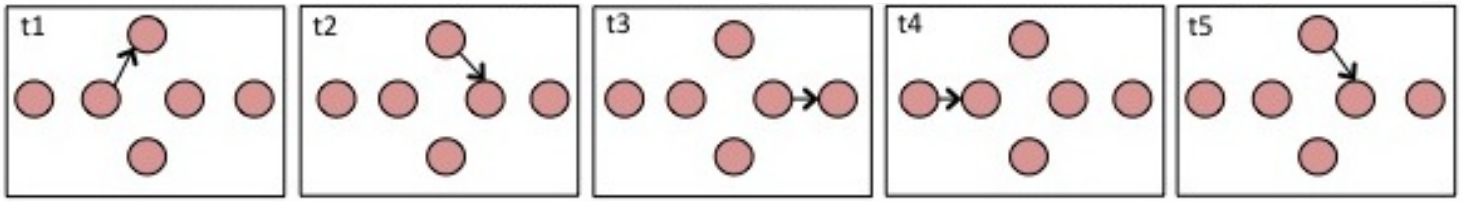


batch
temporal
snapshots
(not online)



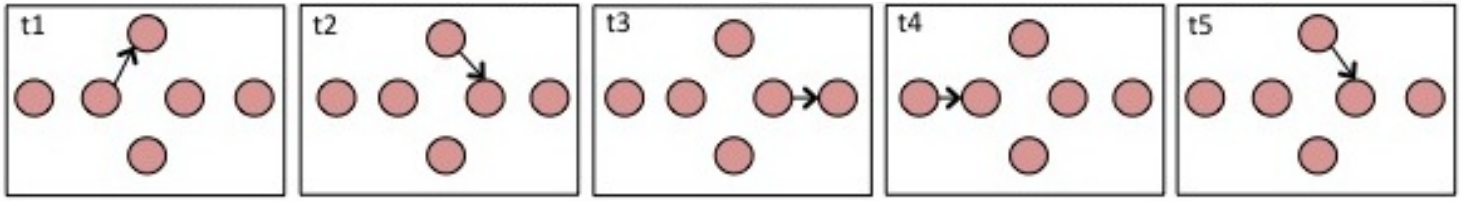
Online Processing Evolving Networks

Edges stream (arrival time = time granularity)

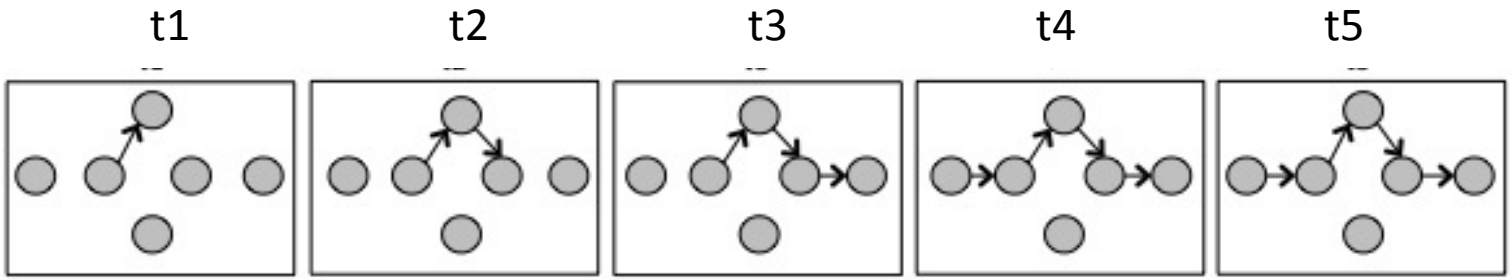


Online Processing Evolving Networks

Edges stream (arrival time = time granularity)

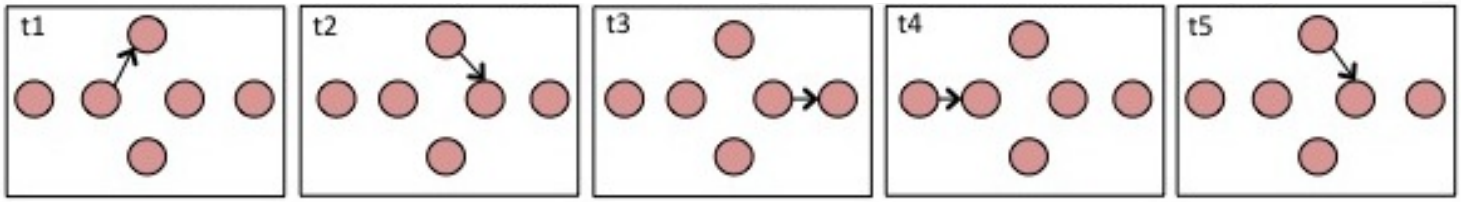


Landmark Window

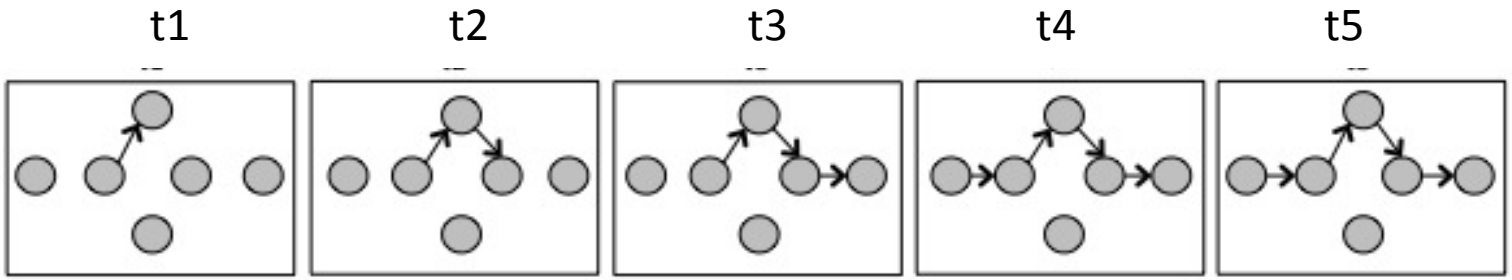


Online Processing Evolving Networks

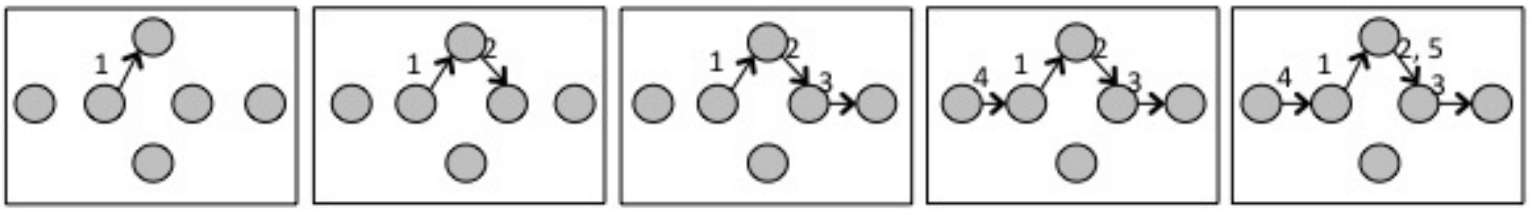
Edges stream (arrival time = time granularity)



Landmark Window

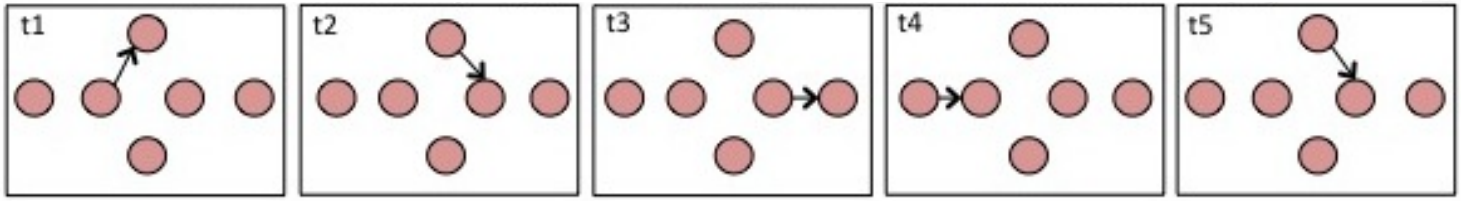


Landmark Window with temporal order



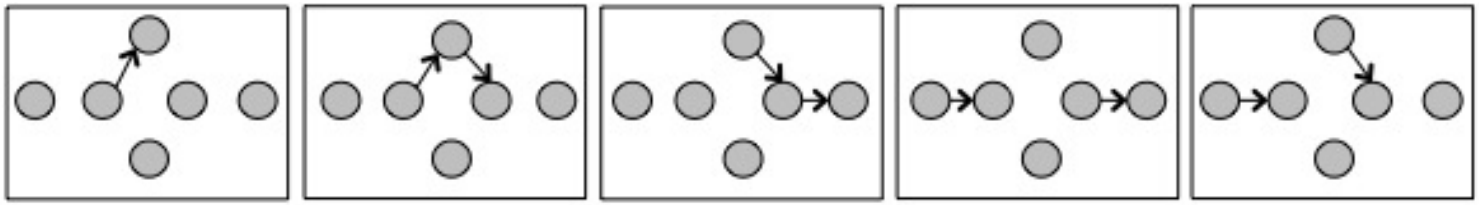
Online Processing Evolving Networks

Edges stream (arrival time = time granularity)



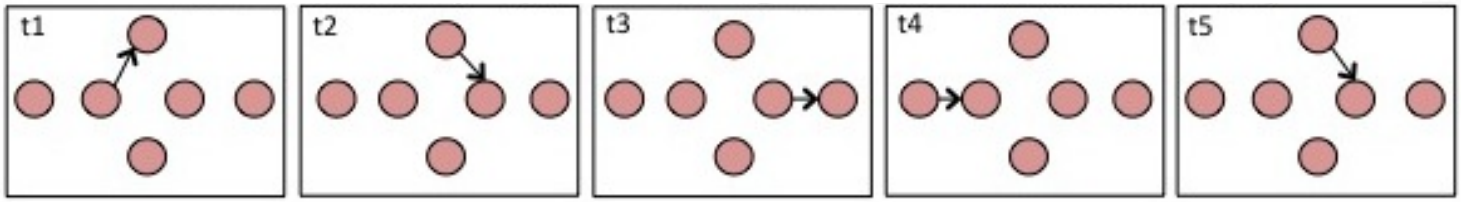
t1 t2 t3 t4 t5

Sliding Window |W| = 2



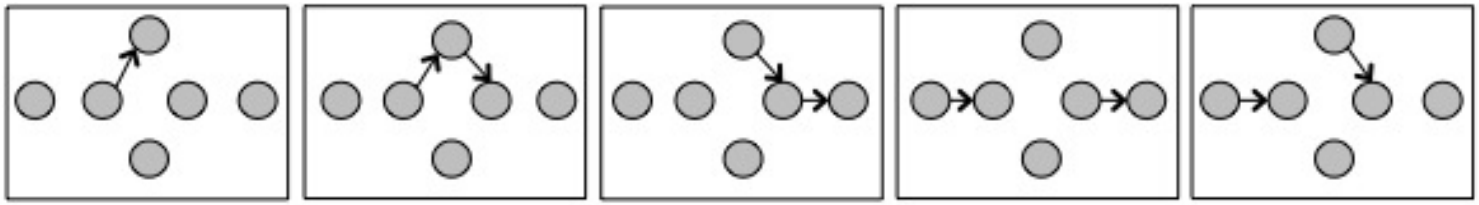
Online Processing Evolving Networks

Edges stream (arrival time = time granularity)

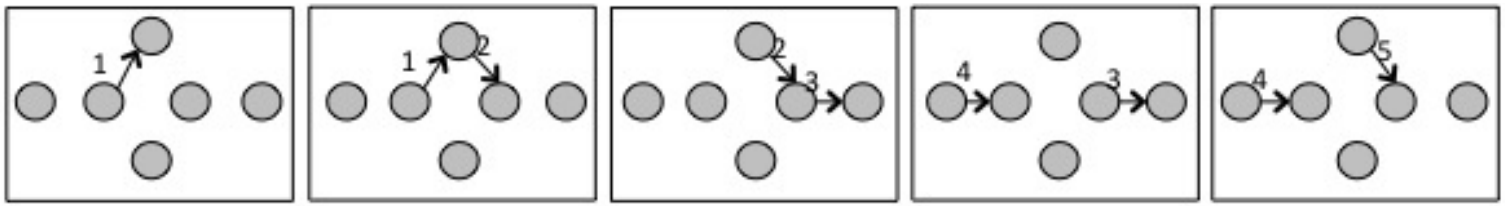


t1 t2 t3 t4 t5

Sliding Window |W| = 2

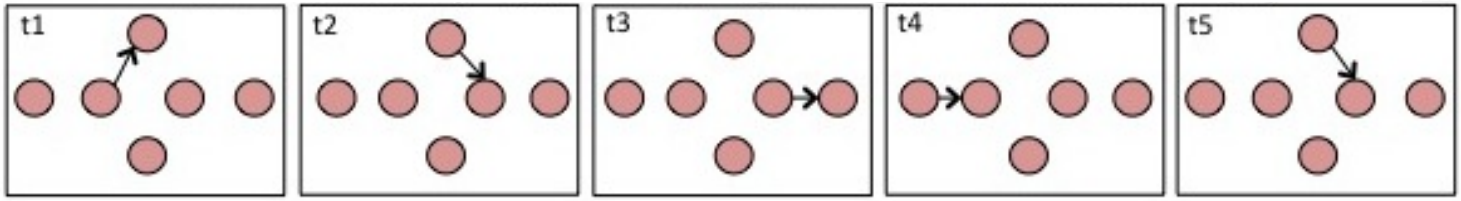


Sliding window |W| = 2 with temporal order



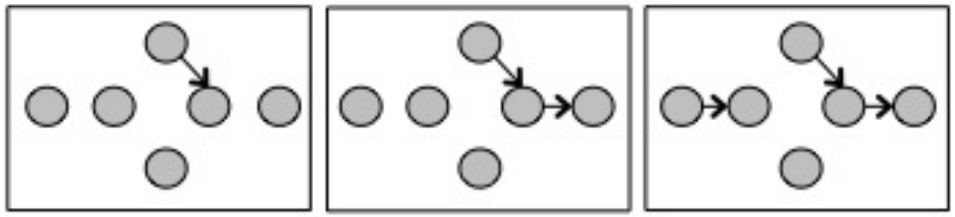
Online Processing Evolving Networks

Edges stream (arrival time = time granularity)



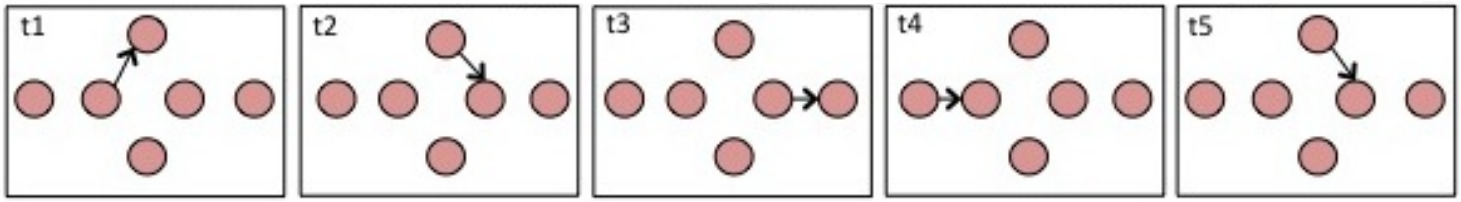
t1 t2 t3 t4 t5

Fixed Observation Window [t2,t4]



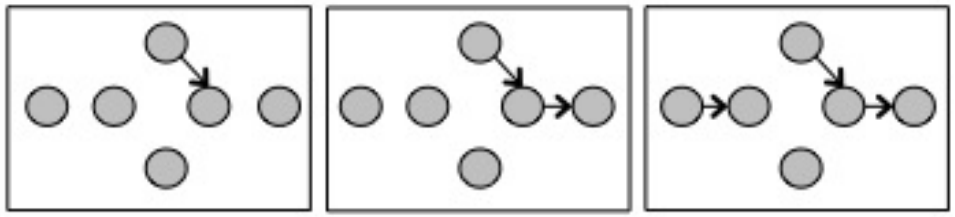
Online Processing Evolving Networks

Edges stream (arrival time = time granularity)

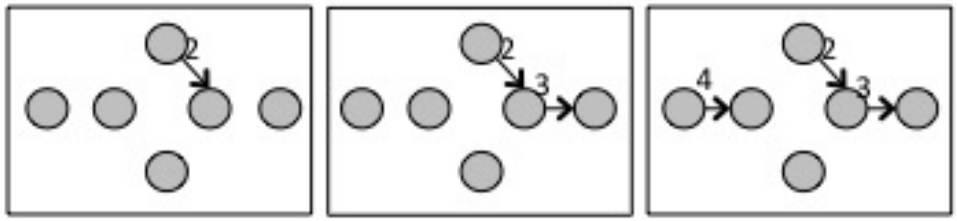


t1 t2 t3 t4 t5

Fixed Observation Window [t2,t4]



Fixed Observation Window [t2,t4] with temporal order



Processing Evolving Networks

Batch → Slowly evolving networks

Online → Streaming networks

HANDS ON!!

www.lsi.facom.ufu.br/~fabiola/sbbd2017

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Leveraging Definitions

Definitions

Network

graph with data in nodes and/or edges (semantics)

Social Network

Social interaction represented as network.
Property of nonrandomnes – relationships tend to cluster (Ullman 2011)

Definitions

{Evolving, Evolutionary, Time-evolving, Dynamic, Time-varying} Network

networks that are changing, with nodes/edges appearing and disappearing, associating and disassociating as time flies

Definitions

Temporal Network

the order that edges appear and disappear is taken into account during the analysis – the temporal order

Definitions

Streaming Network

refers to the way that the network is observed and processed, especially in scenarios where there is not the notion of begin and end of the network

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Case Study 1

Twitter Social Network

(Pereira et al 2016)

Network Statistics

Network content	
Domain	Brazilian news in Twitter
Crawling policy	tweets with @folha mention
Time span of tweets posting times	Aug 08 2016 - Nov 09 2016
# total collected tweets	1,771,435
# tweets retweeted	150,822
Network topology	
# nodes	292,310
# temporal edges (retweets)	1,392,841
Avg static path length	12.31
Avg temporal path length	5 days
Avg static degree	4.76

Centrality Metrics

Network metrics	static	temporal
Average shortest path	12.31	5 days
Average degree	4.76	-
Average closeness	1.01	2.44
Average betweenness	0.0056	0.0233

Giving a meaning to the SNA

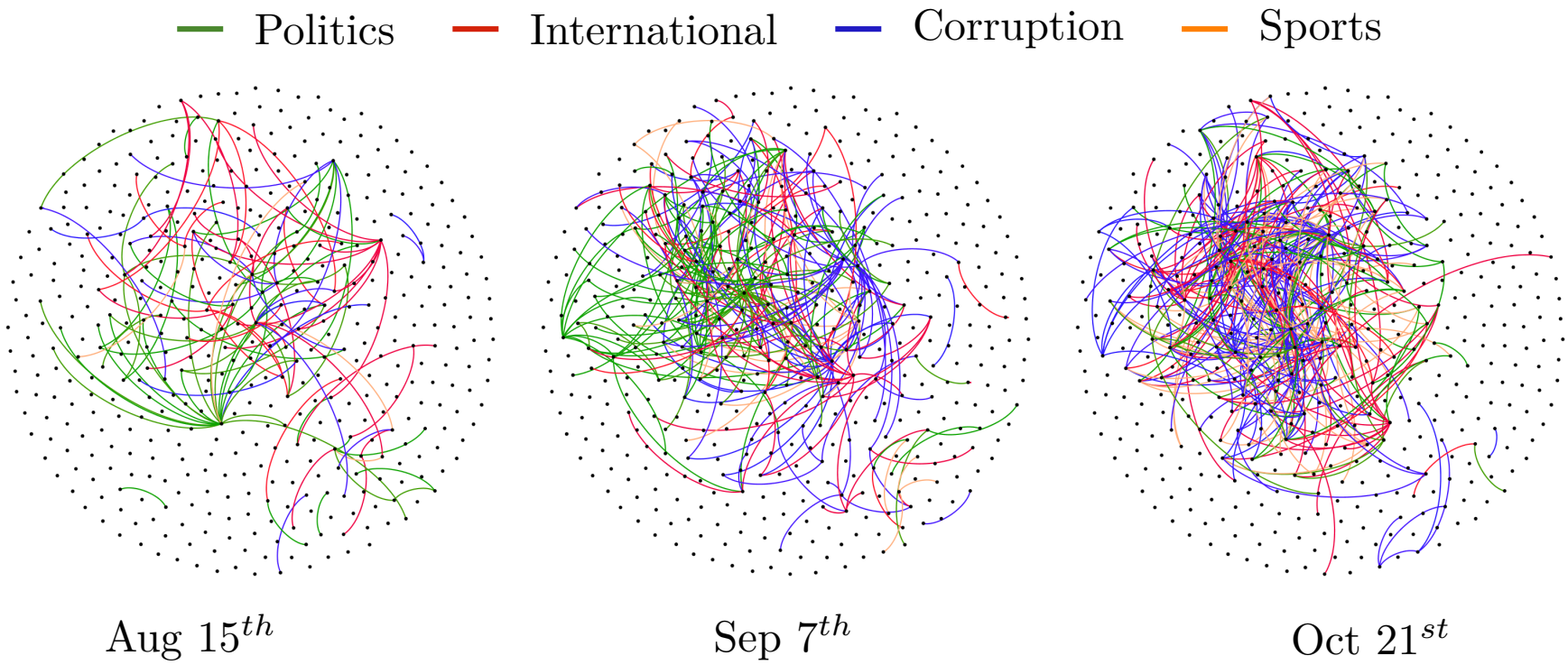


Fig. 4 Snapshots of samples of the evolving interaction network. Nodes are Twitter users. One tie from user u_1 to u_2 means that u_2 retweed at t some text originally posted by u_1. The colors represent topics that users are talking about at t. The samples were built by filtering nodes with degree between 50-22000 and edges representing the 4 most popular topics. Each snapshot corresponds to 1 day time-interval. This figure highlights the *edges* evolving aspect. Nodes are not evolving for better visualization.

The findings

User type based on retweet behavior: producer, consumer and producer&consumer

Predominant topics vary over time

Users favorite topics just analyzing the network

Case Study 2

Telecom Calls Network

(Tabassum and Gama 2016)

Network Statistics

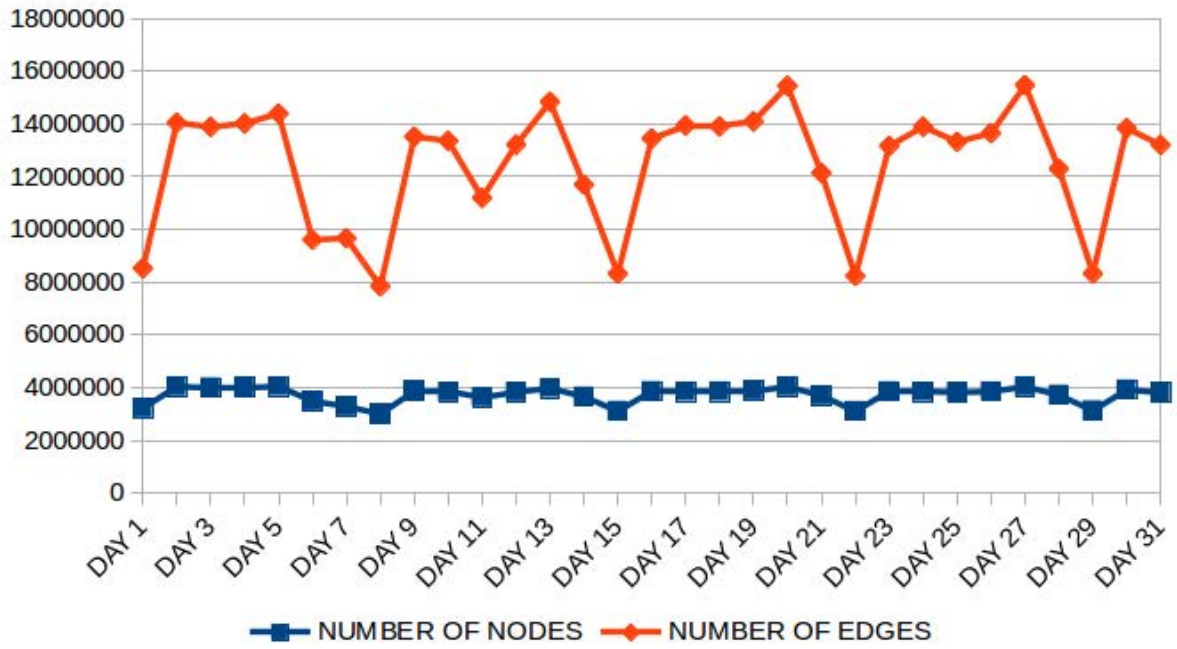
Network description

Domain	Telecom Calls
Time interval	31 days
Processing Granularity	1 day
Processing Type	streaming (online)

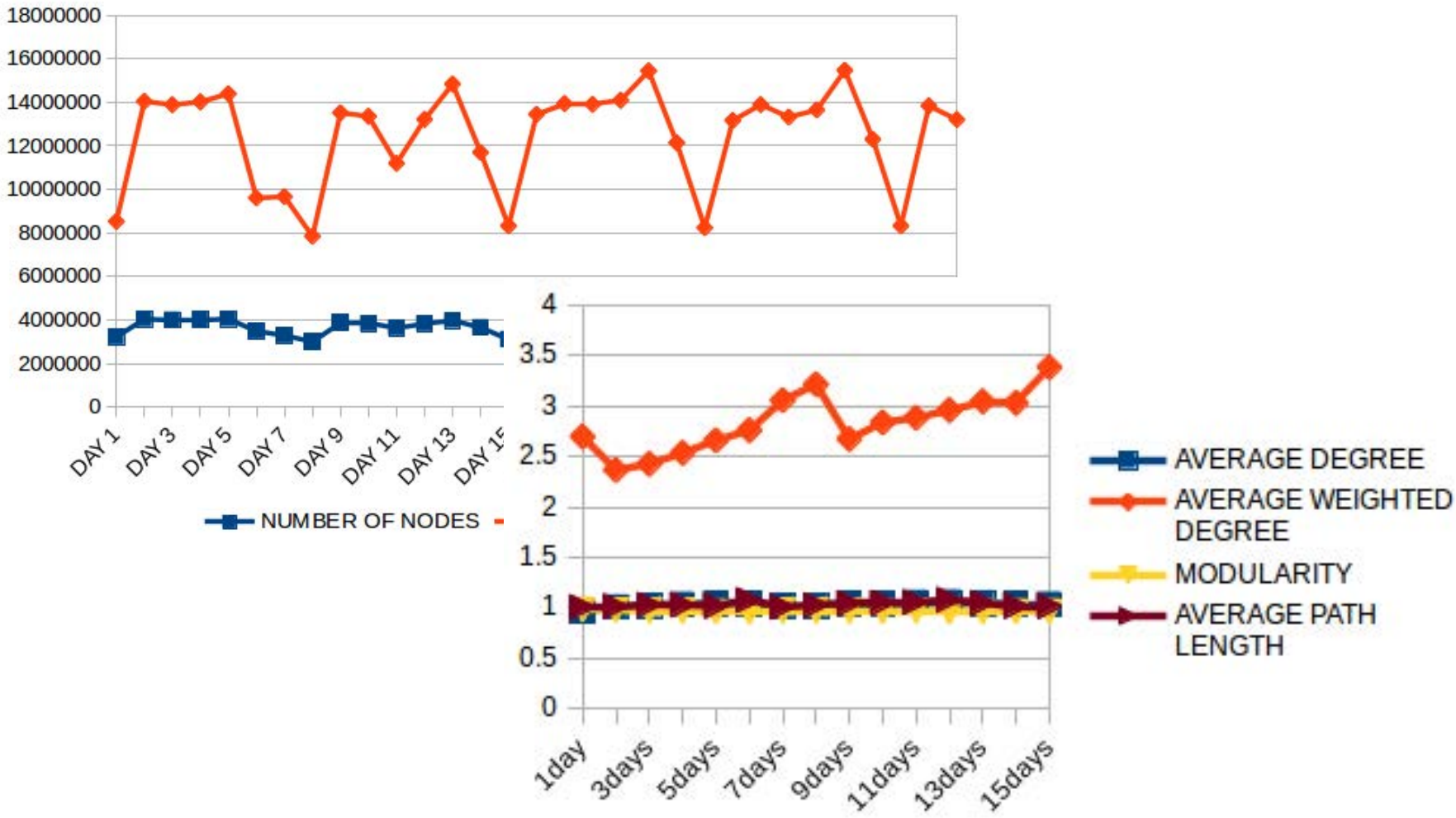
Network topology

# calls (edges)	386,492,749
# phone numbers (nodes)	11,916,442

Network Description



Network Description



Biased Random Sampling Algorithm

input : Unbounded *stream*
output: Realtime *sample* of size k

Filling the reservoir with first k items/objects;
for i = *1* **to** k **do**
  $sample[i] \leftarrow stream[i]$;
end
Inserting all new items into the stream;
while *stream!= EOF* **do**
  $i = i + 1$;
  $pos \leftarrow Random(1, k)$;
  $sample[pos] \leftarrow stream[i]$;
end

The Findings

Online processing the evolving network using sampling strategy

There is a week-pattern of calls

Constant metrics: telecom company clients are stable

Case Study 3

Last.fm Music Network

(Palovics et al 2013)

Network Statistics

Network description

Domain	Friendship in Last.fm
Time interval	1/1/2002 – 12/31/2011
Processing Granularity	1 day

Network topology

# users (nodes)	71,000
# relationships (edges)	285,241

Network Description

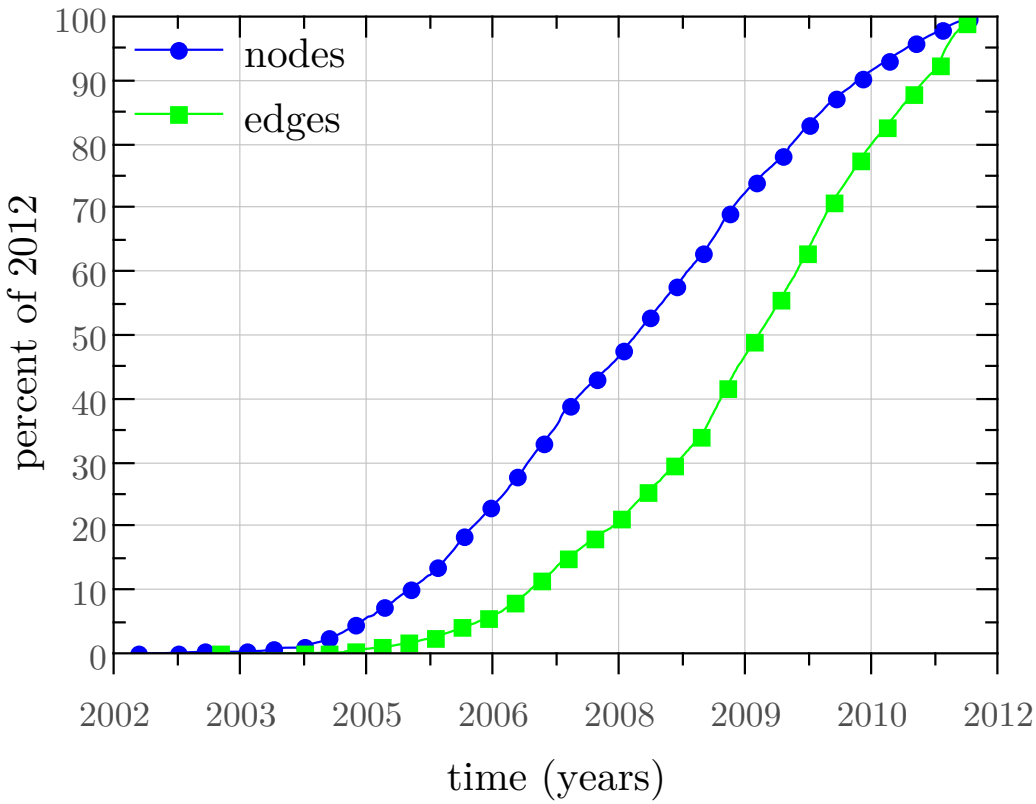


Fig. 1. The number of the users and friendship edges in time as the fraction of the values at the time of the data set creation (2012).

Network Description

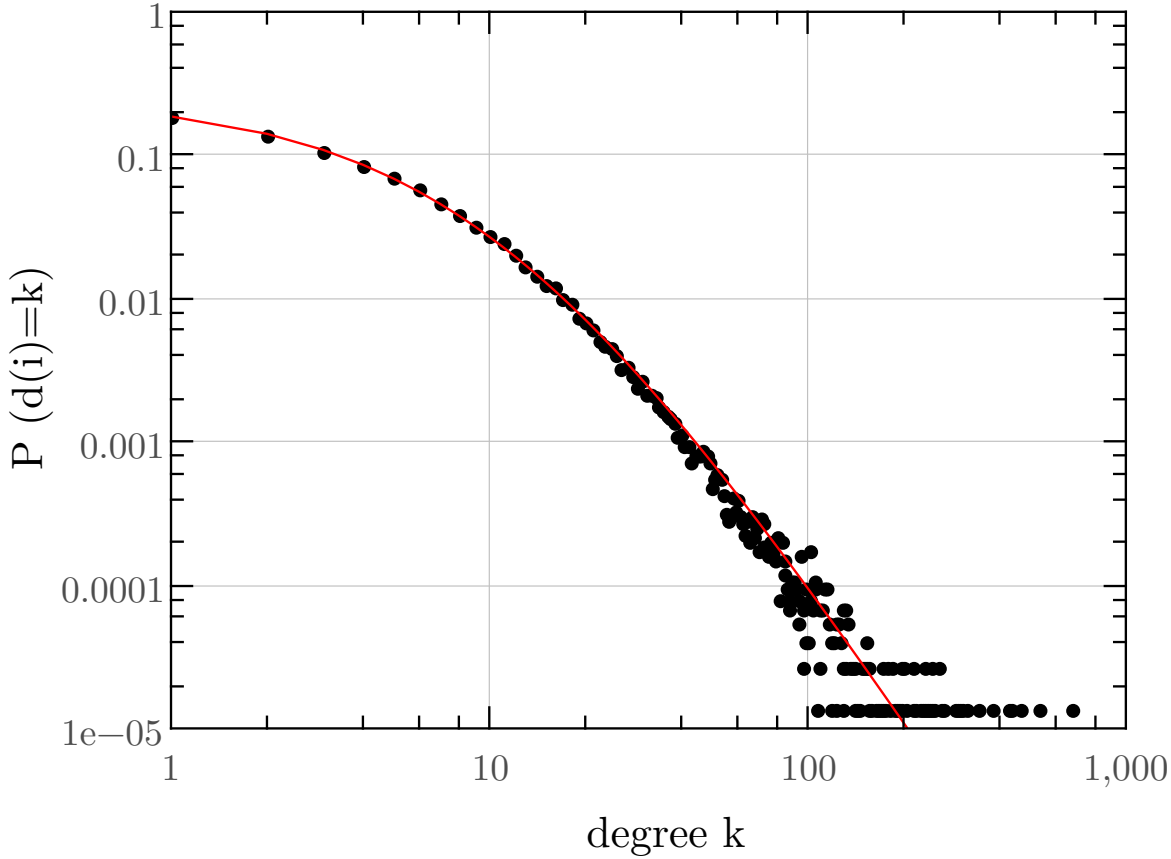


Fig. 3. Degree distribution in the friendship network.

The Findings

Influence level that friendship can exert over music tastes

Outline

Overview

SNA Essentials

Temporal Social Networks

Processing Evolving Networks

Summary of Definitions

Case Study 1: Twitter

Case Study 2: Calls

Case Study 3: Last.fm

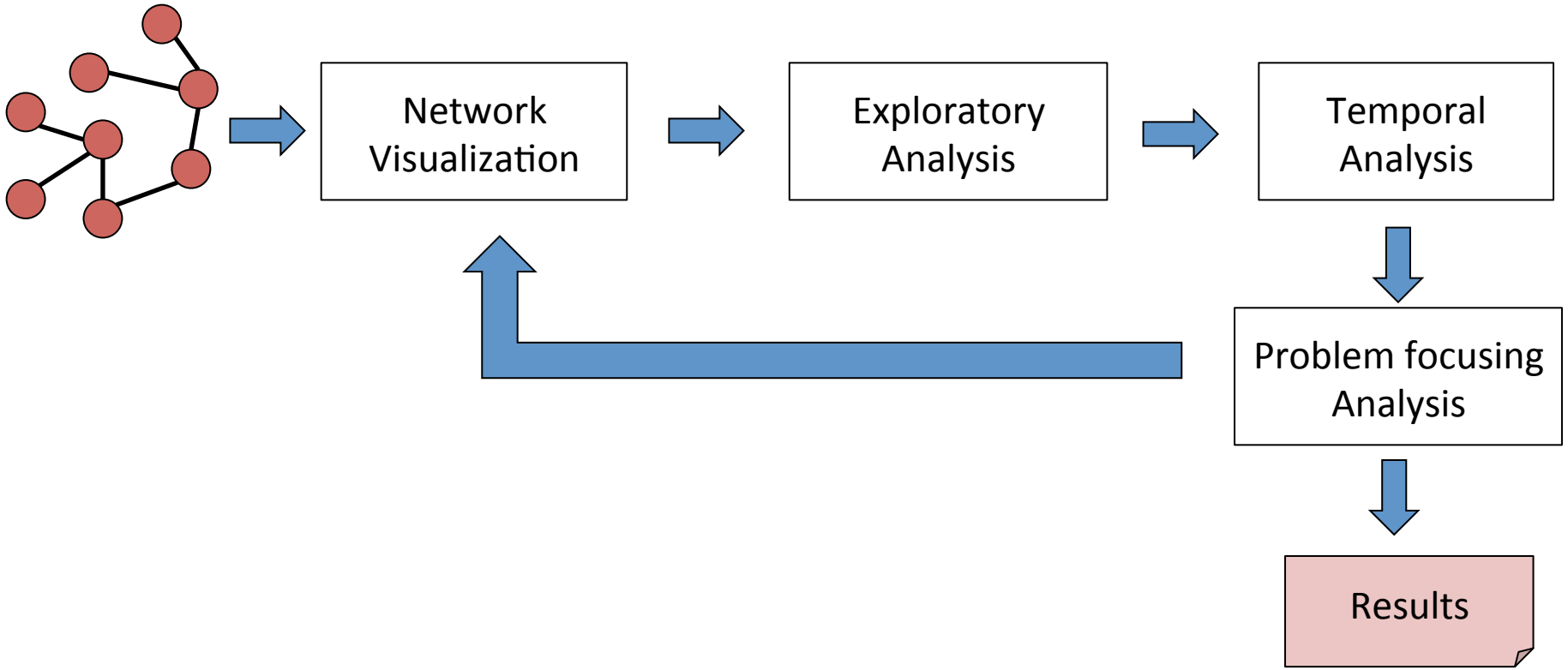
Being a Data Scientist

Final Remarks

Now...

you are a data scientist specialized on temporal social networks!

Remember...



Steps for Knowledge Discovery from Temporal Social Networks

HANDS ON!!

www.lsi.facom.ufu.br/~fabiola/sbbd2017

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Final Remarks

SNA Tools

- ✓ Gephi (visualization, basic network metrics, temporal networks)
- ✓ iGraph (programming assignments)
  - ✓ http://igraph.org/r/
- ✓ NetLogo (modeling network dynamics)

SNA Tools

- ✓ UCINet
  - ✓ sociology-focused functionality
  - ✓ Windows-only
  - ✓ not-free $

- ✓ ORA (CMU)
  - ✓ business-focused
  - ✓ Windows-only (.exe)
  - ✓ versions LITE and Professional ($)

SNA Tools

- ✓ NodeXL
  - ✓ SNA integrated into Excel
  - ✓ Windows-only
  - ✓ free

SNA Tools

- ✓ NetworkX (Python)
  - ✓ extensive functionality
  - ✓ scales to large networks
  - ✓ open source

SNA Tools

- ✓ SNA package for R
  - ✓ extensive, statistics-heavy functionality

- ✓ SoNIA – Social Network Image Animator
  - ✓ specialized for longitudinal analysis of networks

- ✓ SNAP System
  - ✓ http://snap.stanford.edu/snap/index.html

SNA Tools

- ✓ DyNetVis [Linhares et al 2017]
  - ✓ dynamic networks visualization
  - ✓ under development

- ✓ GraphStreamAPI (Java)

- ✓ Pajek
  - ✓ http://mrvar.fdv.uni-lj.si/pajek/

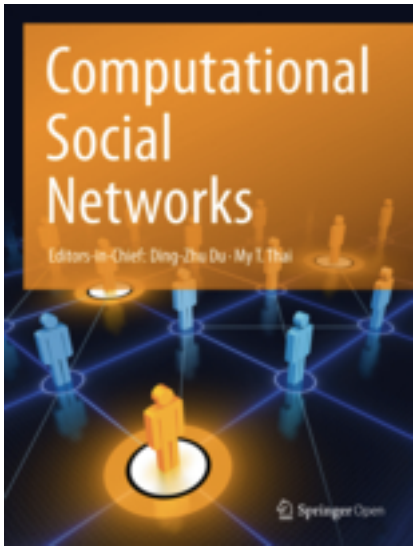
Top-3 Social Networks Repositories

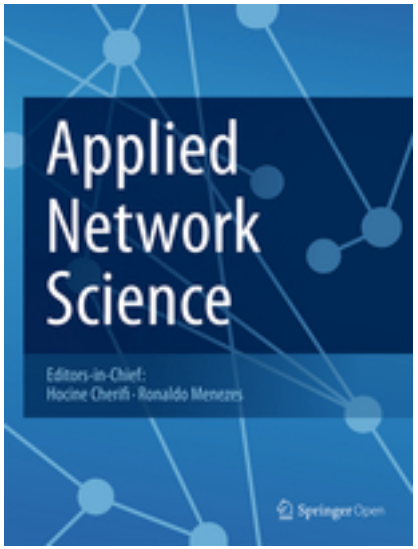
- ✓ Index of Complex Networks (ICON)
  - ✓ https://icon.colorado.edu/
- ✓ SNAP (Stanford Large Network Dataset Collection)
- ✓ KONECT (Koblenz network collection)

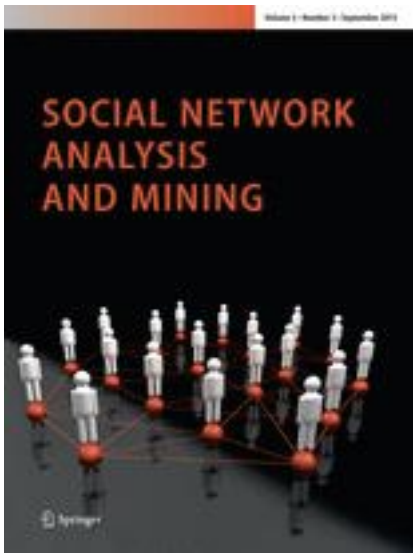
Conferences & Journals

- ICWSM
- BraSNAM
- ASONAM
- ComplexNetworks
- WSDM, HT, ICDM, DSAA, *KDD, …

Conferences & Journals







Evolving Networks Research Topics

- ✓ Evolutionary network analysis
- ✓ Social networks and social media
- ✓ Graph data analytics
- ✓ Sampling from evolving networks
- ✓ Network data mining
- ✓ Distributed network analysis and mining
- ✓ Statistical techniques for network analysis and mining
- ✓ Temporal and streaming networks
- ✓ Predictive modeling on evolving networks
- ✓ Change detection, anomaly detection
- ✓ Incorporating network content in evolution analysis
- ✓ Community detection in evolving networks

It's a matter of time!

Knowledge Discovery from Temporal Social Networks

Fabíola S. F. Pereira (UFU)
João Gama (LIAAD, UPorto)
Gina M. B. de Oliveira (UFU)

http://lsi.facom.ufu.br/~fabiola

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WELL, IF A LIKES B, BUT B LIKES C WHO LIKES D AND E WHO BOTH LIKE A WHO DOESN'T EVEN KNOW THAT D EXISTS, SHOULD F TRY TO HAVE G TALK TO B SO E WILL KNOW THAT C LIKES D AND E, AND THAT C WILL POUND H IF SHE COMES AROUND AGAIN BUTTING IN ?
MAY I THINK ABOUT THAT FOR A MINUTE ?
C