Social and Technological Network Analysis

Lecture 13: Temporal Social Network Metrics and Applications

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In This Lecture

- We will show metric extensions for complex networks which keep time into account.
- We will also show how these can be applied to applications.

Why Temporal Social Network

- Most of the analysis we have seen has been done on aggregated network graphs
- Time has not been kept into account by the metrics
- Why does this matter?

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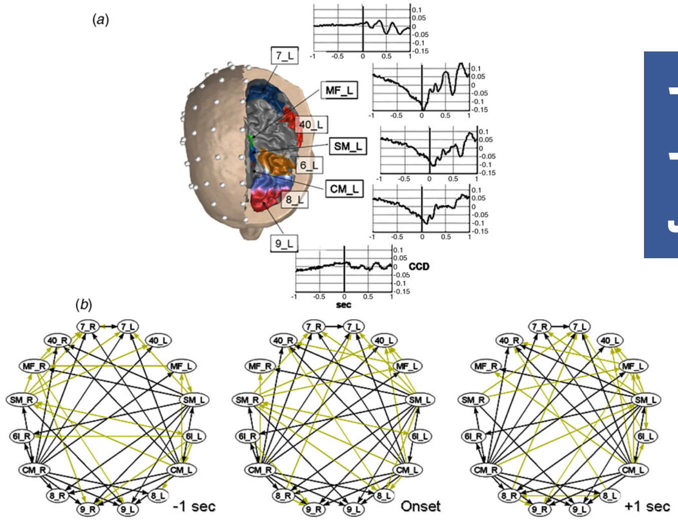
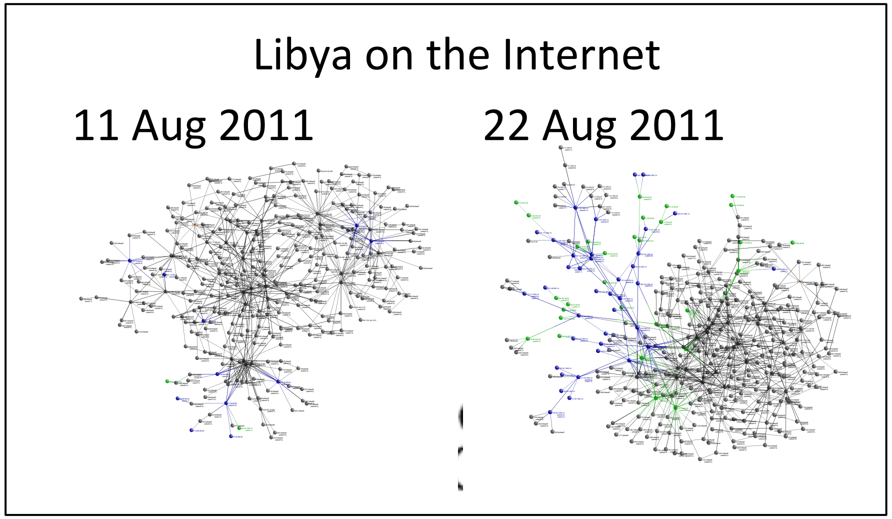
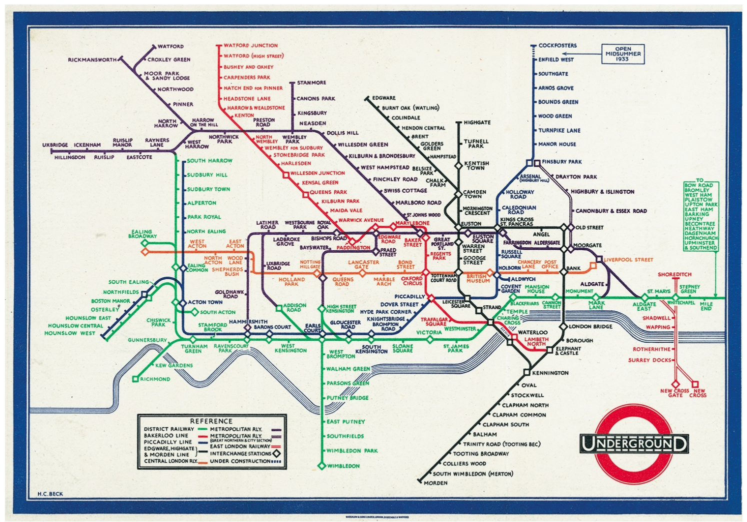
Empirical Networks







Time in networks

- Timestamps
  - e.g. Facebook: friends added and removed over time
- Duration
  - e.g. Spending time with friends
- Frequency
  - e.g. Friends, colleagues, strangers
- Time-order
  - e.g. Timetables in public transport systems

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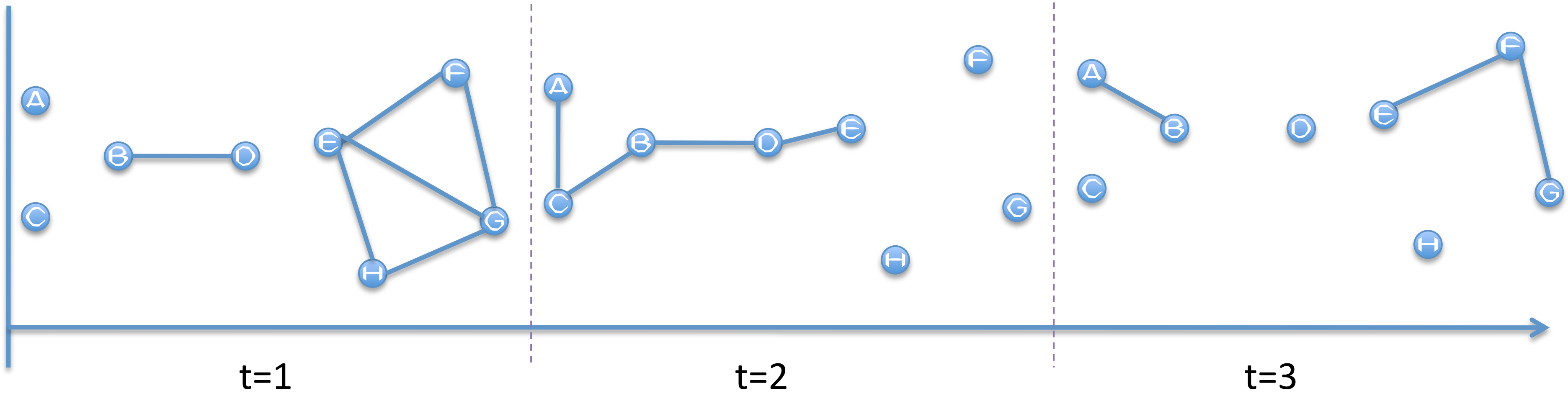
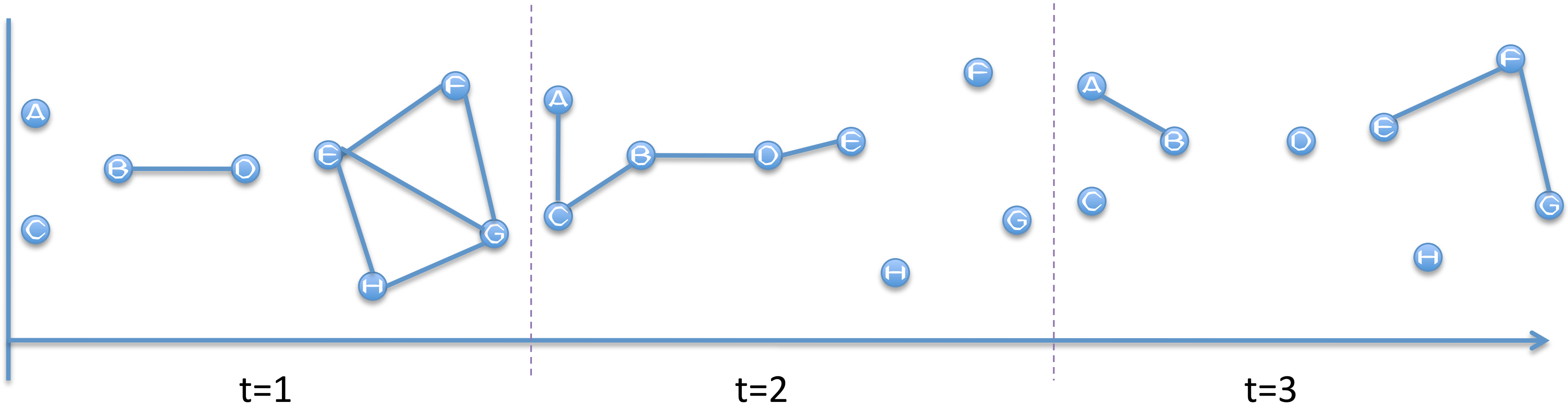
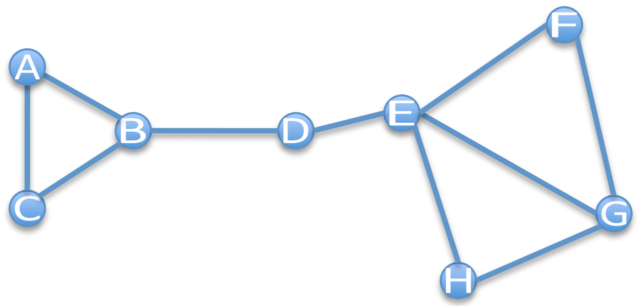
Temporal Graph



Temporal Graph





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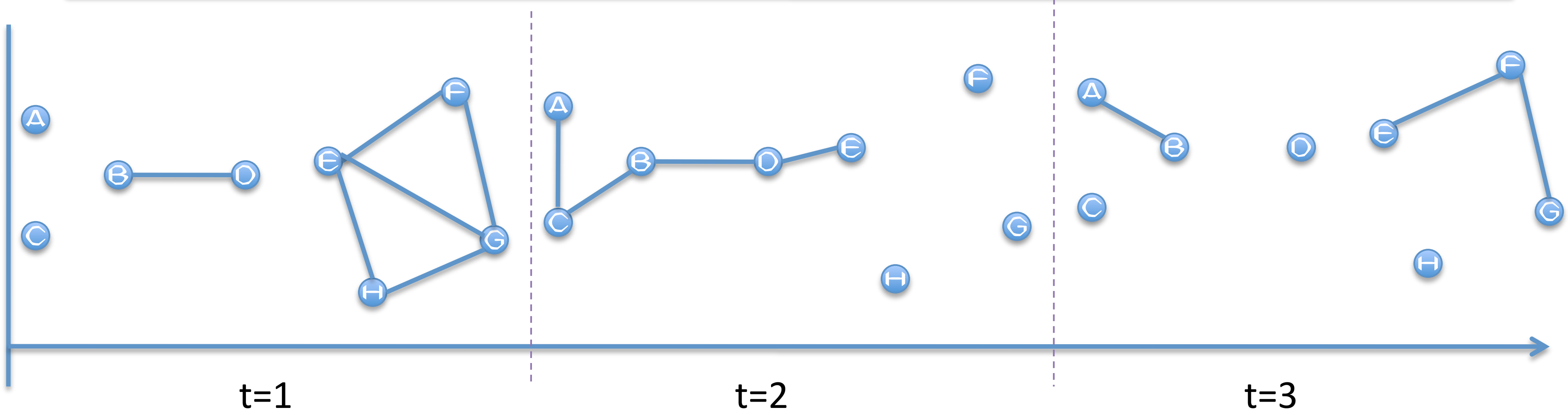
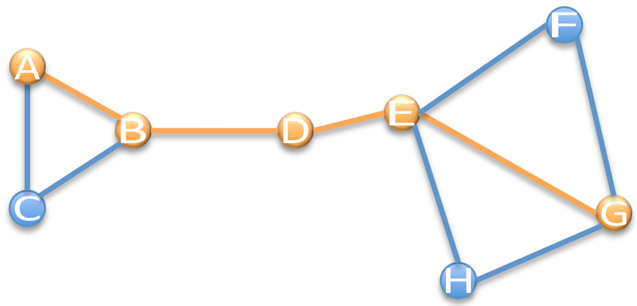
Temporal Graph



- Static
    - Shortest path (A,G) = [A,B,D,E,G]
    - Shortest path length (A,G) = 4 hops



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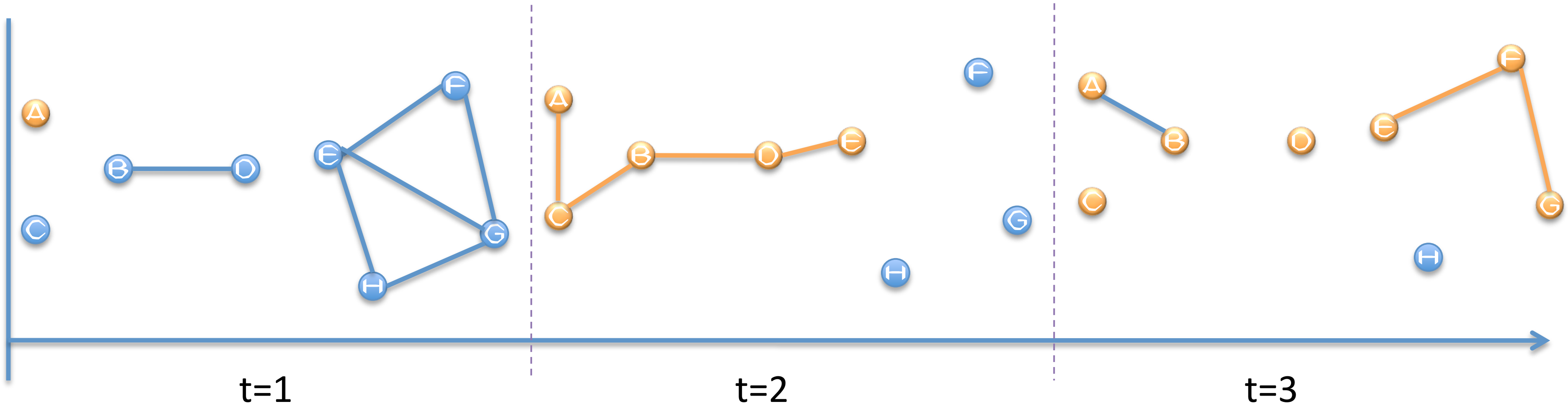
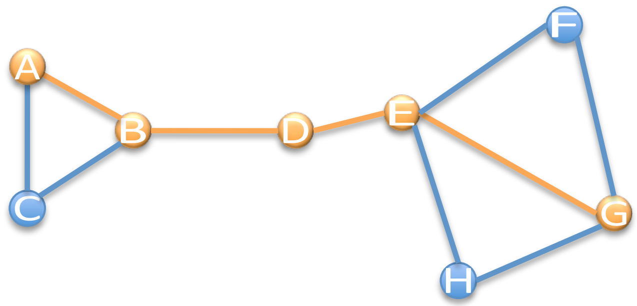
Temporal Graph



- Static
  - Shortest path (A,G) = [A,B,D,E,G]
  - Shortest path length (A,G) = 4 hops
- Temporal
  - Shortest path (A,G) = [A,C,B,D,E,F,G]
  - Shortest path length (A,G) = 6 hops
  - Time=3 seconds



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Temporal Measures

- d_{ij} Shortest Temporal Path Duration
- d^*_{ij} Number of Hops in shortest temporal path
- $E_{ij} = \frac{1}{d_{ij}}$ Temporal Efficiency of communication

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Temporal Measures

- Average Temporal Path Duration

$$L = \frac{1}{N(N-1)} \sum_{ij} d_{ij}$$

- Average Temporal Path Hops

$$L^* = \frac{1}{N(N-1)} \sum_{ij} d^*_{ij}$$

- Average Temporal Efficiency

$$E_{glob} = \frac{1}{N(N-1)} \sum_{ij} E_{ij}$$

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Does it really matter?

- Infocom 2005 conference environment
- Bluetooth colocation scans
- 5 Minute Windows
- Measure 24 hours starting 12am

					Static		Temporal		
Day	N	<k>	Activity	Contacts	L	Eglob	L*	L	Eglob
1	37	25.73	6pm-12pm	3668	1.291	0.856	4.090	19h 39m	0.003
2	39	28.31	12am-12pm	8357	1.269	0.870	4.556	9h 6m	0.024
3	38	22.32	12am-12pm	4217	1.420	0.798	4.003	10h 32m	0.018
4	39	21.44	12am-5pm	3024	1.444	0.781	4.705	9h 55m	0.013

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Temporal Centrality Measures

- Static Closeness and Betweenness based on *static shortest paths*
- Reformalise *closeness* and *betweenness* with temporal paths:
  – Duration
  – Time Order
  – Frequency

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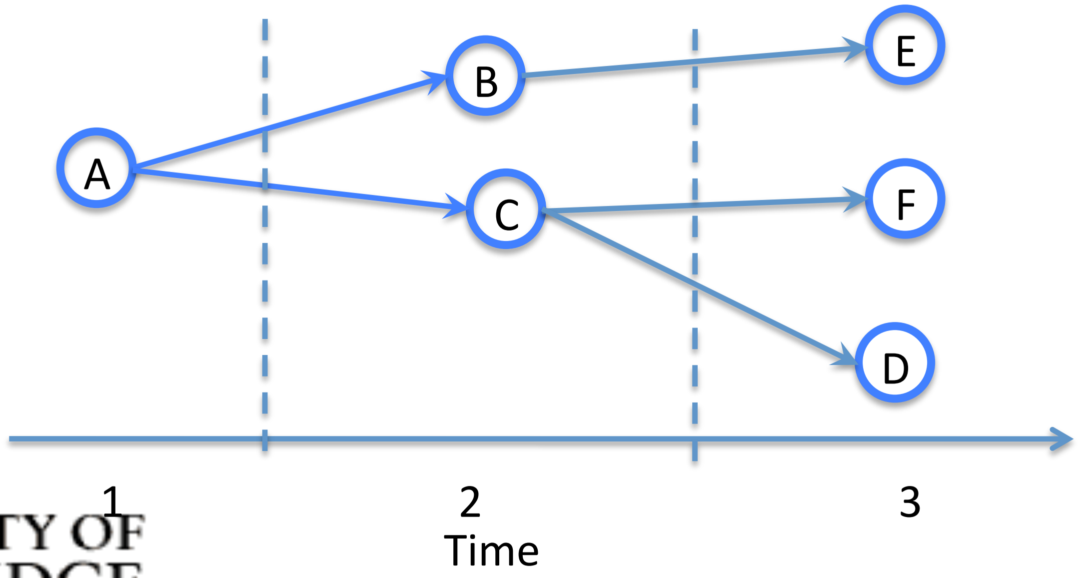
Temporal Closeness

$$C_i^C = \frac{N-1}{\sum_j d_{ij}}$$



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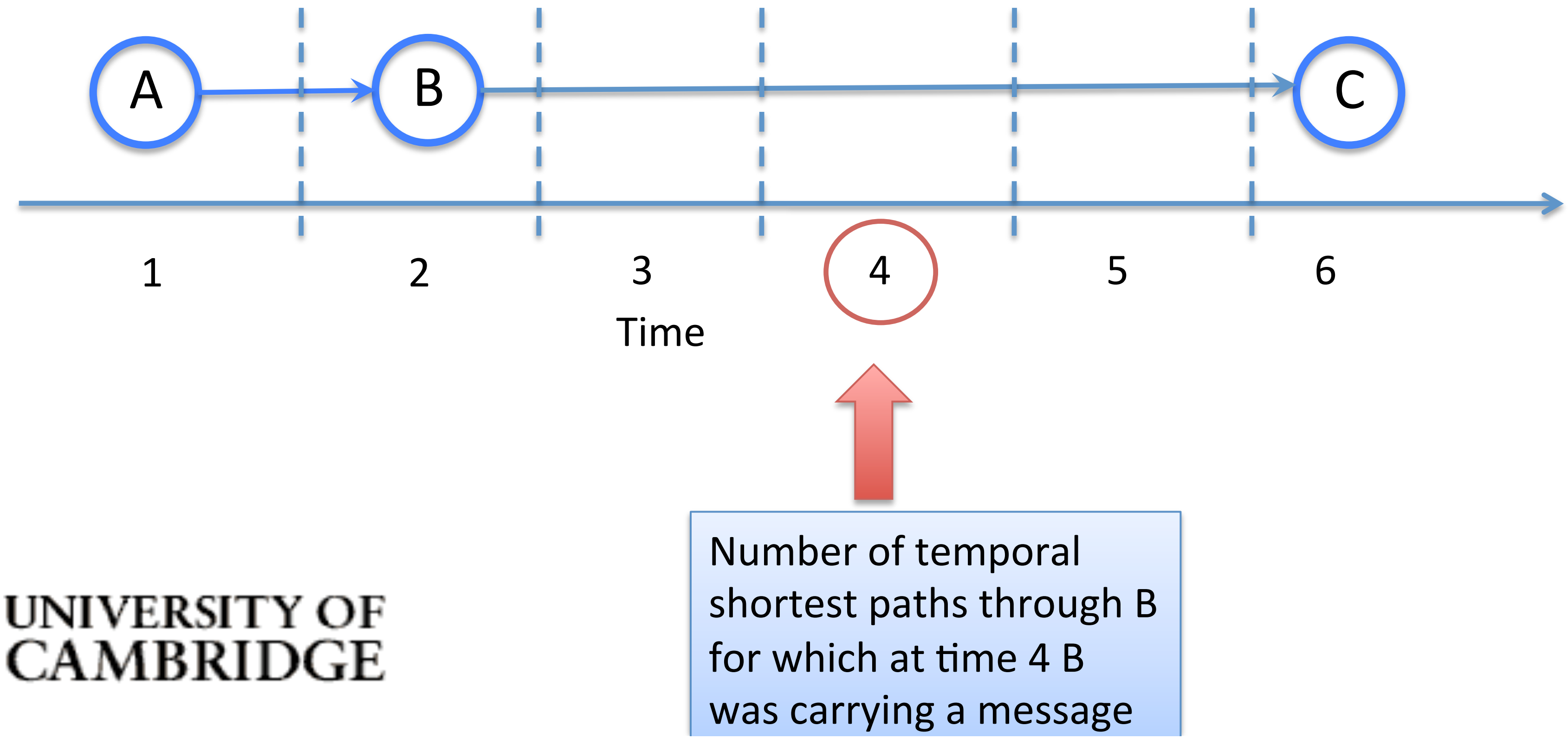
Temporal Betweenness

- Using temporal path length



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Formally…

Num of temp. shortest paths between j and k in i at tm

$$C_i^B(t_m) = \frac{1}{(N-1)(N-2)} \sum_{j \neq i} \sum_{\substack{k \neq j \\ k \neq i}} \frac{U(i, t_m, j, k)}{\sigma_{jk}}$$

Num of temp. shortest paths between j and k

$$C_i^B = \frac{1}{M} \sum_m C_i^B(t_m)$$

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Evaluating Centrality

- Two perspectives:
  - Semantic: known roles of nodes
  - Dynamic Processes: mobile malware containment

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Enron in the News

Public Investigation

- Telephone logs
- Documents
- Financials
- Emails

  - 151 user mailboxes
  - May 1999 to Jun 2002
  - 250,000 emails
  - NOT anonymised

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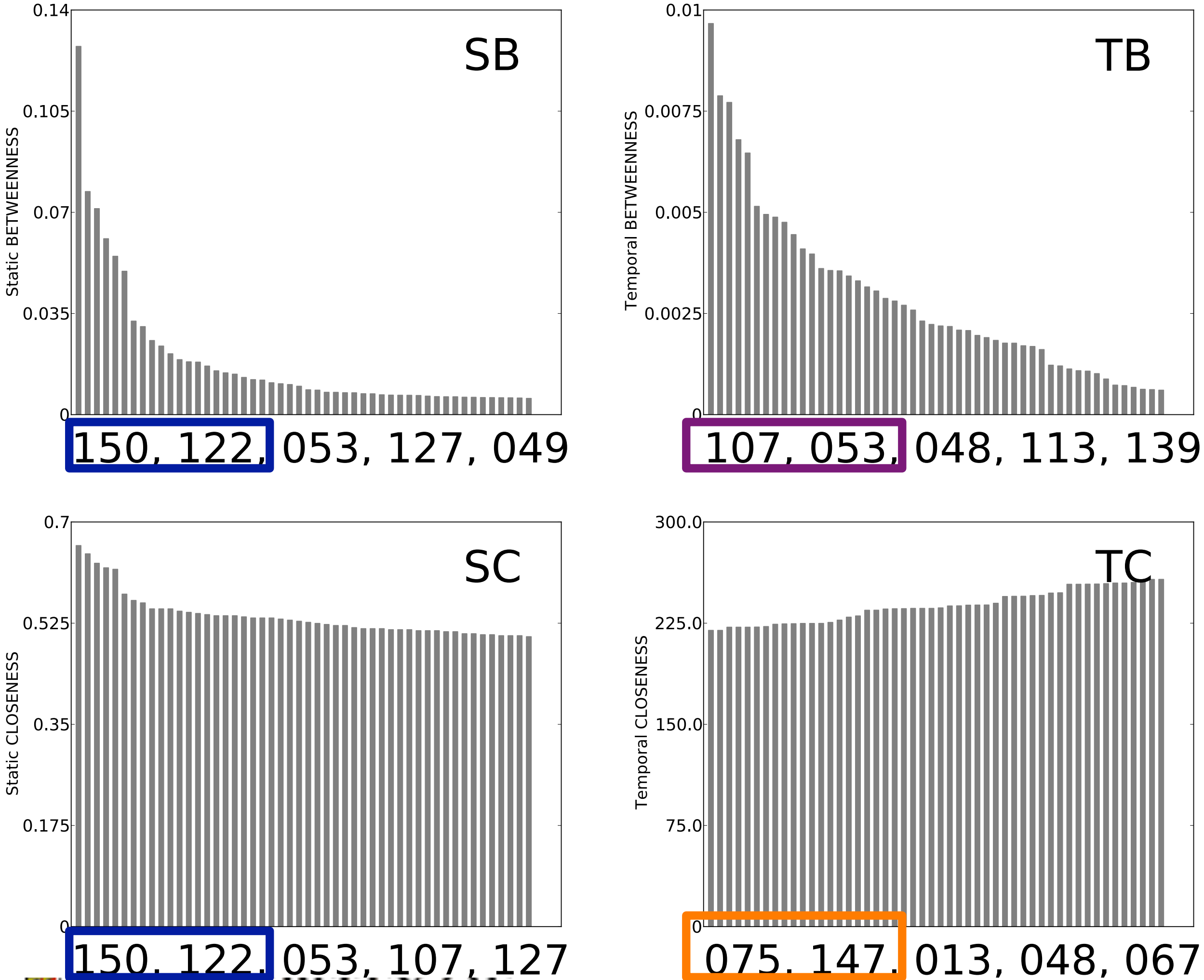
Semantics



ID	Role
009	(Unknown)
013	Legal
017	Manager
048	Executive
053	Trader
054	President
067	Vice President
073	Trader
075	Director of Trading
107	Trader
122	Managing Director
127	Manager
139	Director
147	Trader
150	Secretary

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Semantics

ID	Name	Role
9	Stephanie Panus	(Unknown)
13	Marie Heard	Legal
17	Mike Grigsby	Manager
48	Tana Jones	Executive
53	John Lavorato	Trader
54	Greg Whalley	President
67	Sara Shackleton	Vice President
73	Jeff Dasovich	Trader
75	Gerald Nemec	Director of Trading
107	Louise Kitchen	Trader
122	Sally Beck	Managing Director
127	Kenneth Lay	Manager
139	Mary Hain	Director
147	Carol Clair	Trader
150	Liz Taylor	Secretary

CNN.com/LAWCENTER

Top bonuses awarded

John Lavorato: $5 million
Louise Kitchen: $2 million
Jeffrey McMahon: $1.5 million
James Fallon: $1.5 million
Raymond Bowen Jr.: $750,000
Mark Haedicke: $750,000
Gary Hickerson: $700,000
Wesley Colwell: $600,000
Richard Dimichele: $600,000

- Big bonuses linked with information mediators

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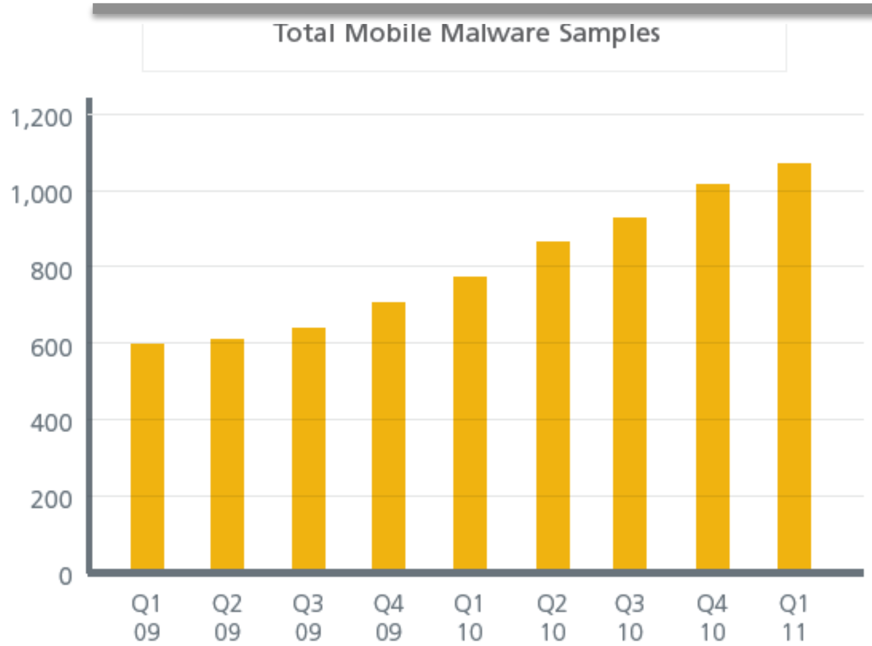
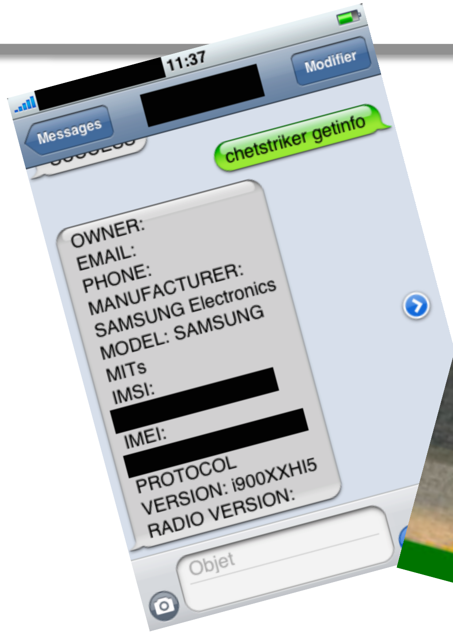
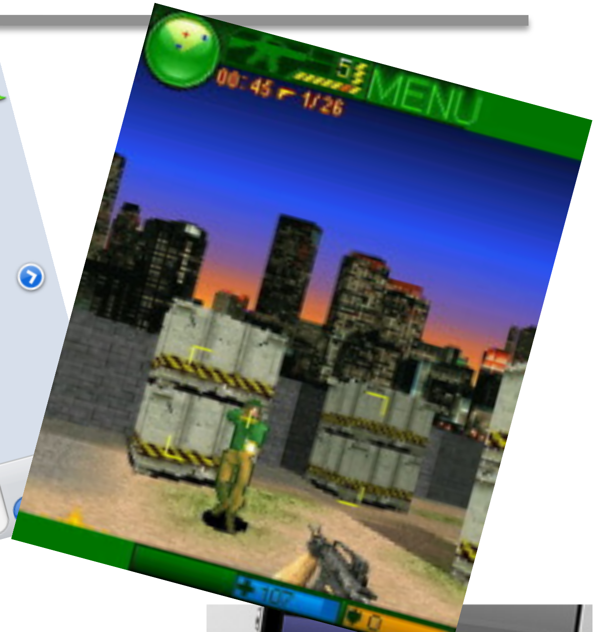
Mobile Phone Malware







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Mobile Malware Propagation

- Long Range
  - Sms, mms, email
  - Can be filtered by central service provider
- Short Range
  - Bluetooth, wifi
  - Evades central service provider

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Limitations

- Devices
  - Resource constrained
- Infrastructure
  - Limited bandwidth
- Prioritise Devices using SNA
  - Patch individual devices via nodes with high **Betweenness**
  - Flood patch via nodes with high **Closeness**

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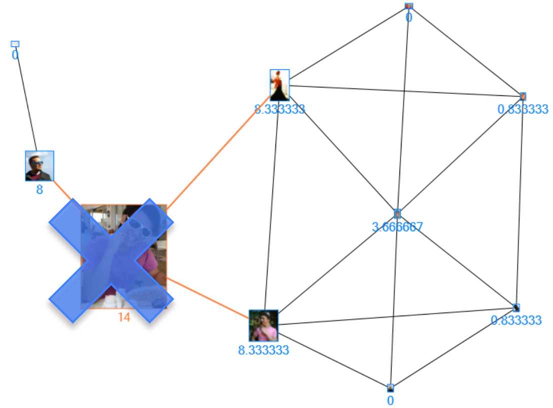
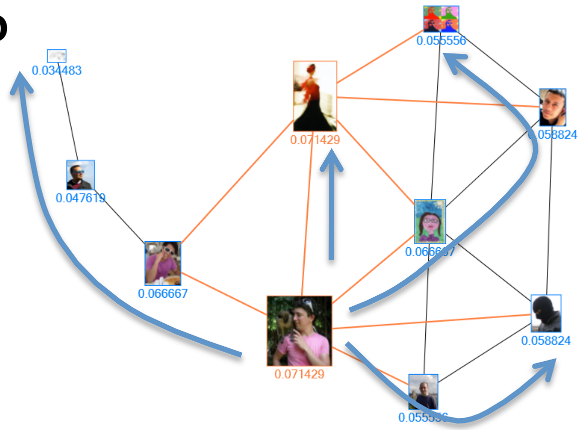
Priority Patching Schemes

1. Traditional Patching
   ➔Can we block path of malware?
   ➔**Betweenness**



2. Opportunistic Patching
   ➔Can we compete with malware?
   ➔**Closeness**



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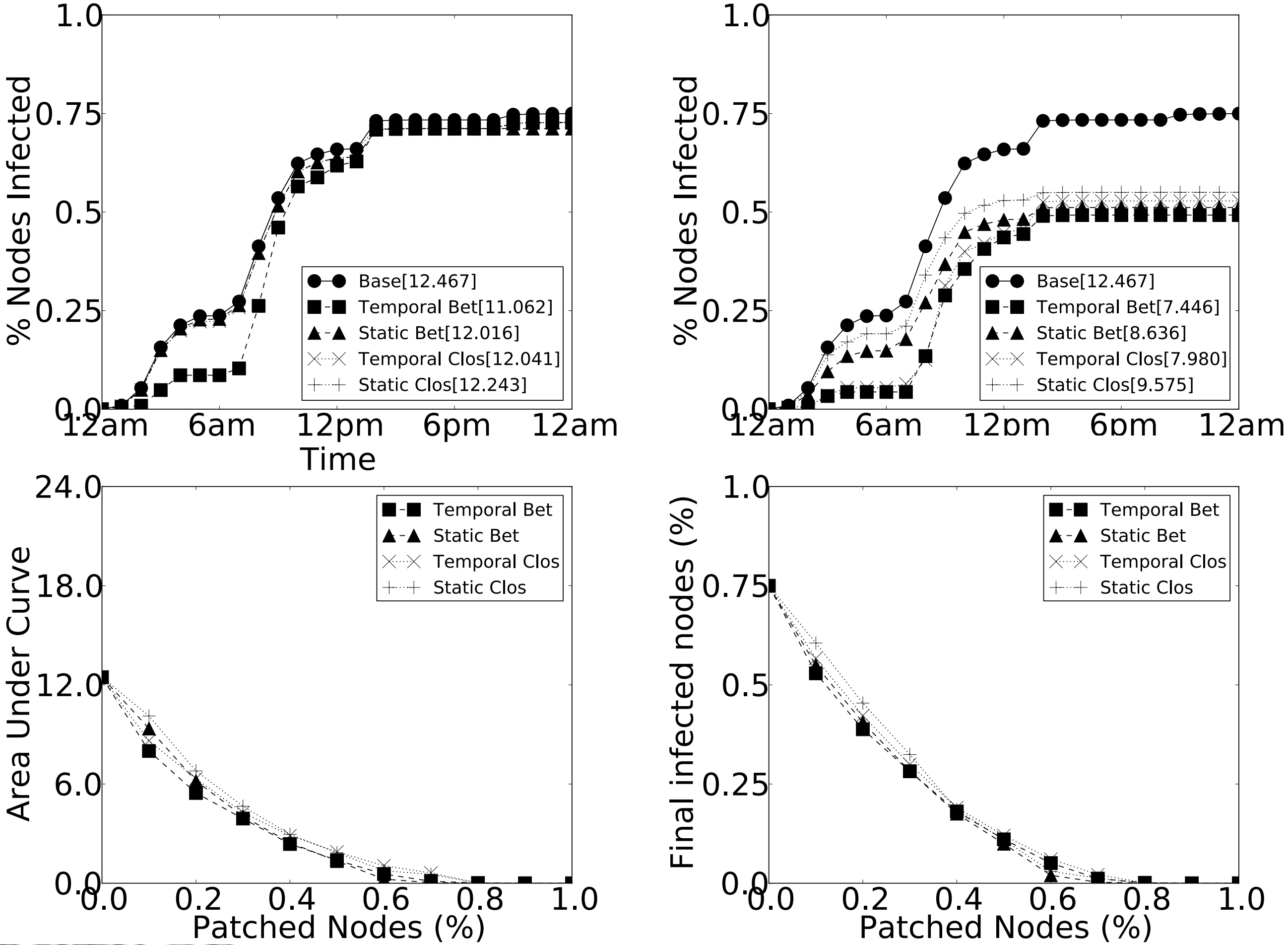
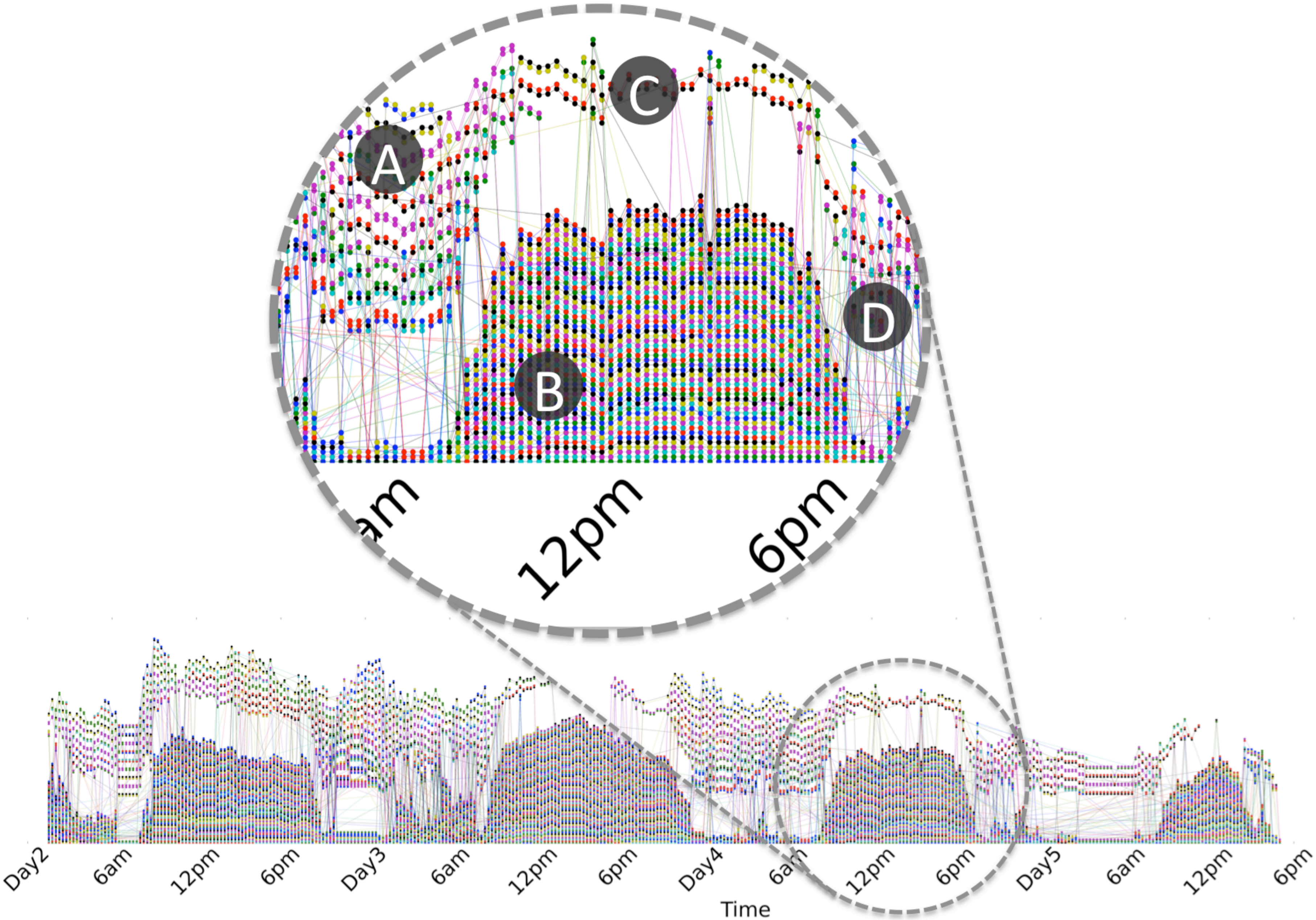
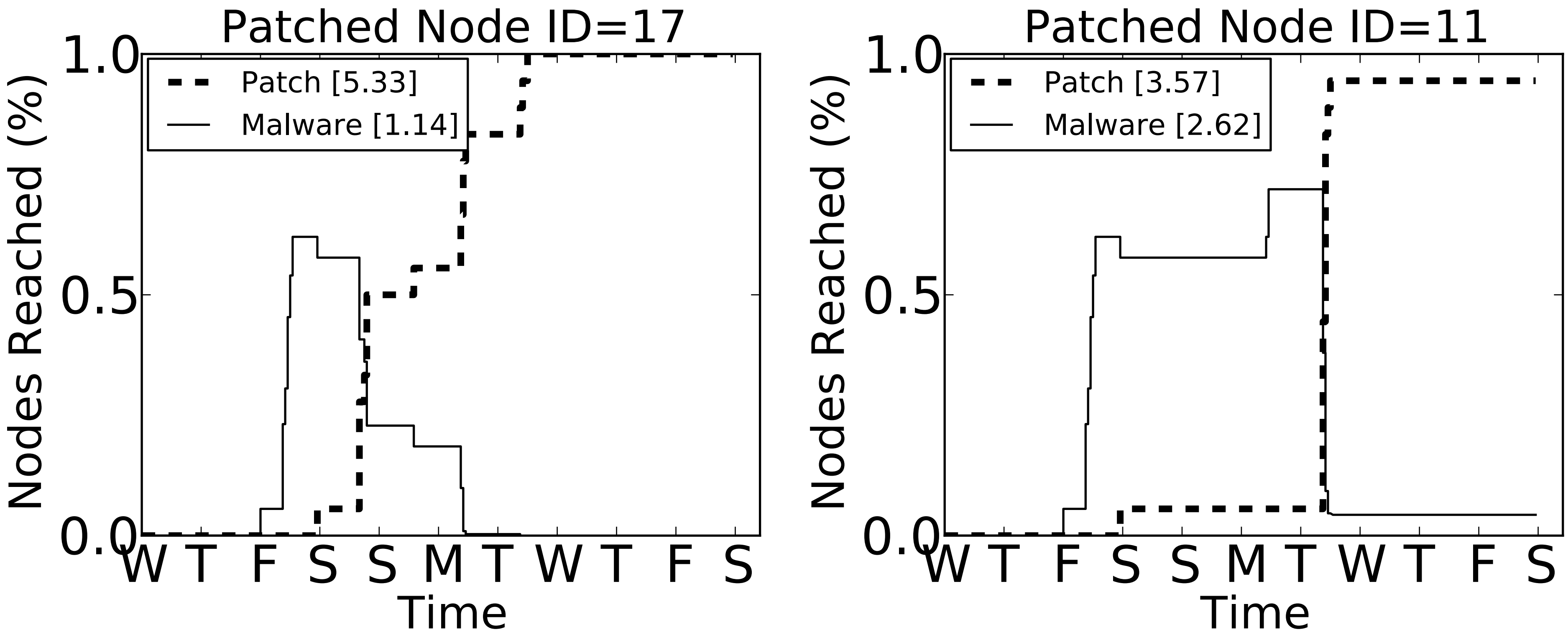
Patching Nodes





A
B
C
D
12pm
6pm
Day2
6am
12pm
6pm
Day3
6am
12pm
6pm
Day4
6am
12pm
6pm
Day5
6am
12pm
6pm
Time

Flood Network with Patch



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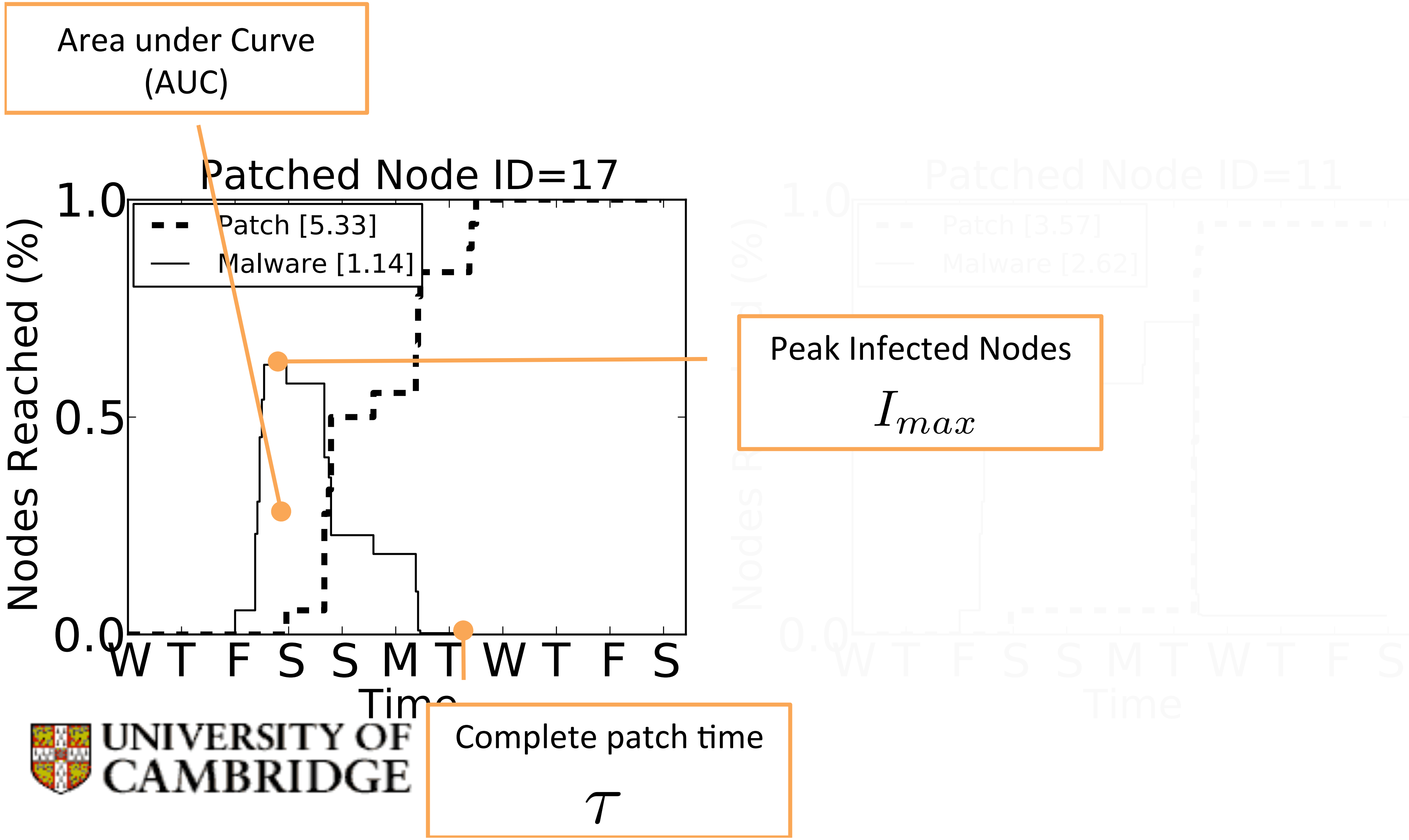
Flood Network with Patch



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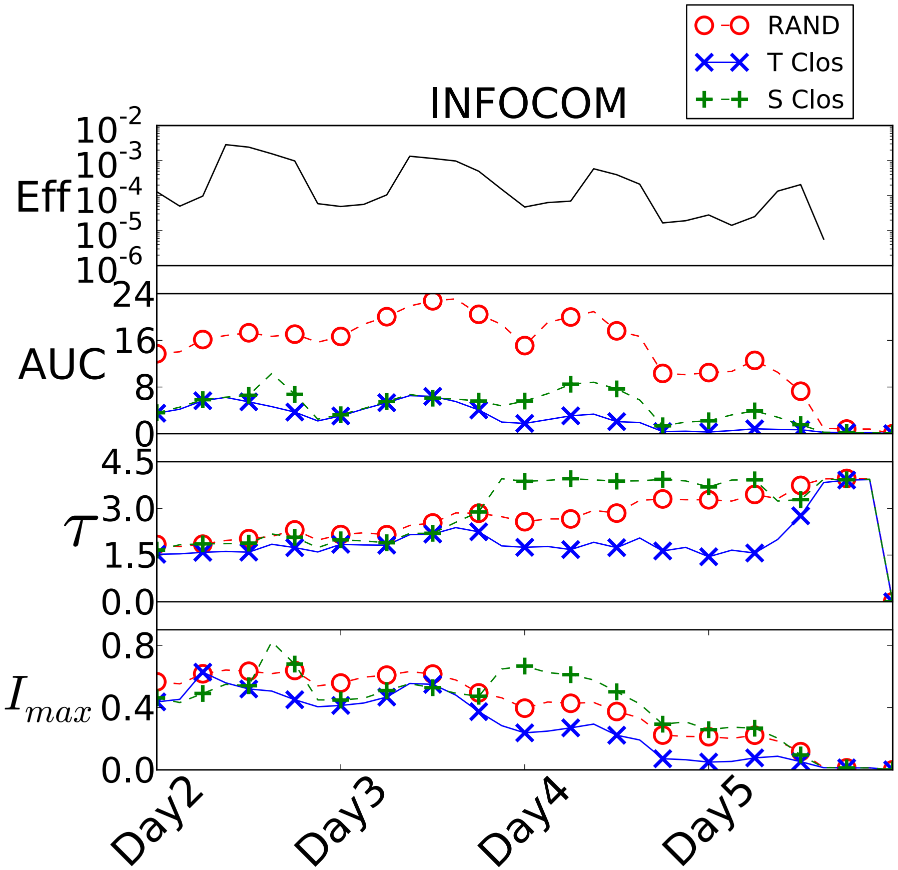
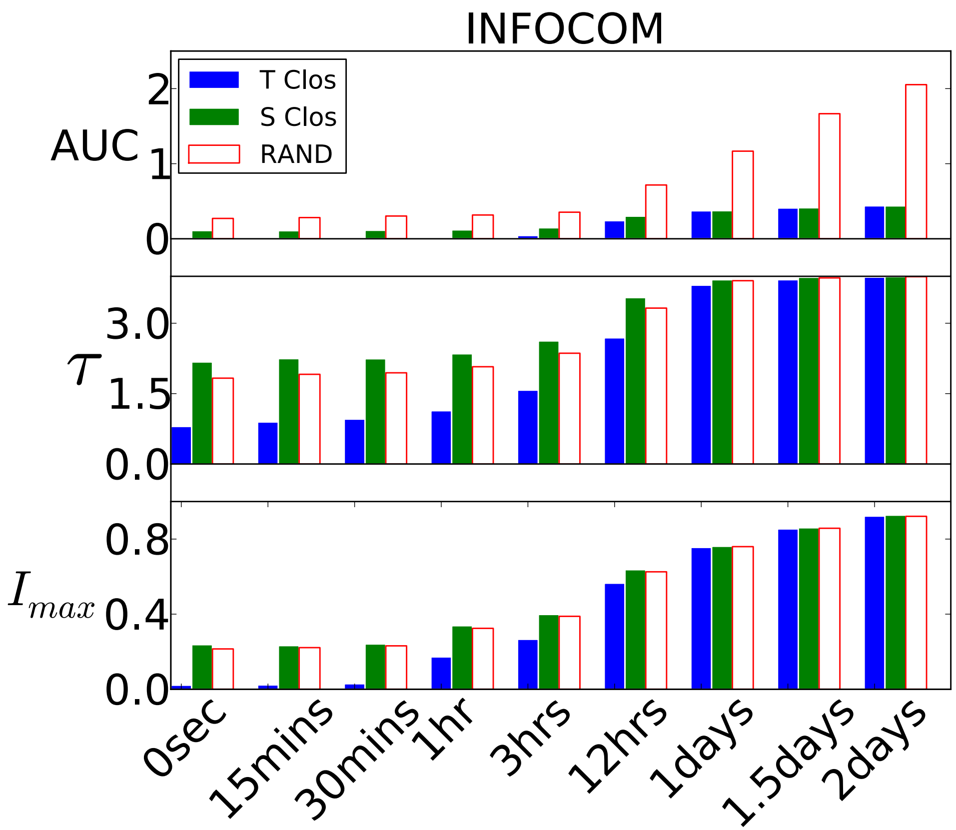
Opportunistic Patching



Malware Start Time



Patch Delay

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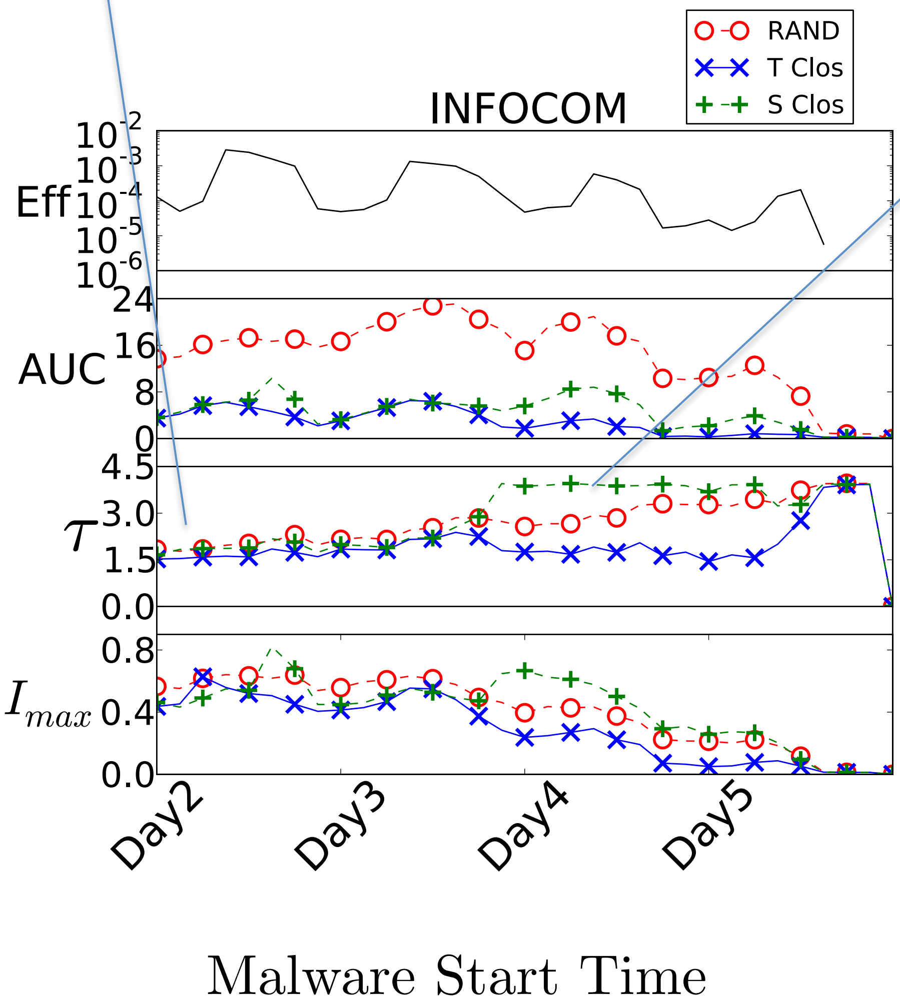
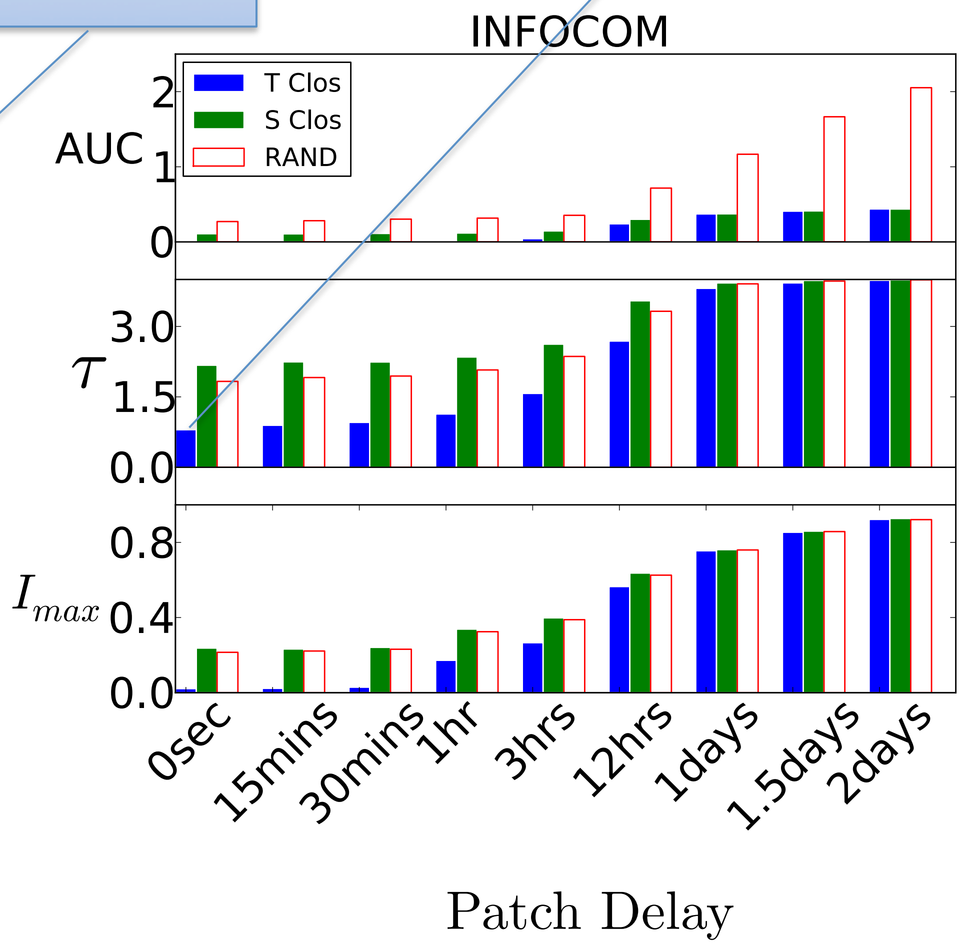
Opportunistic Patching

1. Finite Time

2. Static is Poor

3. Temporal is Best





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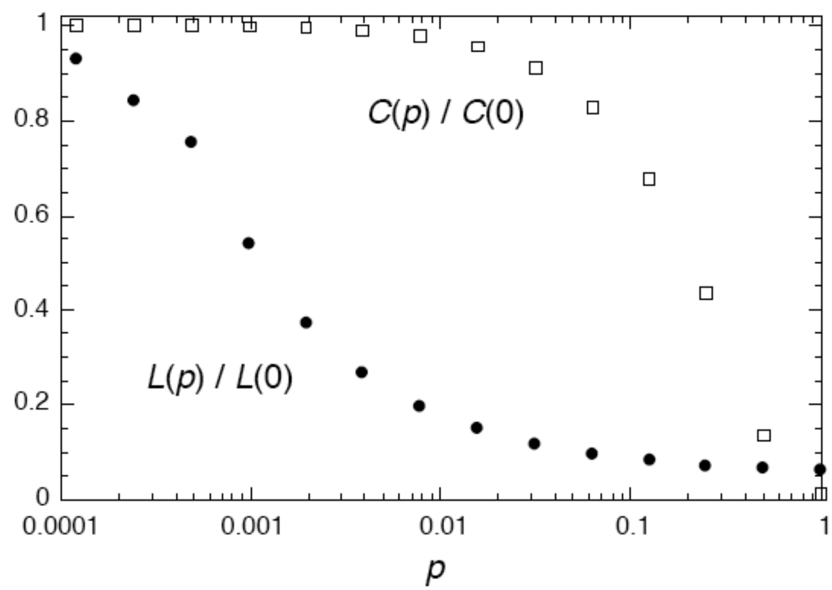
Static Small World

- Graphs which both are locally clustered but with small average path length
  – High local clustering but long paths => Lattice
  – Small average paths but low clustering => Random



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Temporal Small World

- Does this hold in time-varying graphs
- Temporal small world:
  - quick paths from one node to another and
  - have some temporal local persistence of links

Testing for Temporally Small World

- Measure
  - communication efficiency
    - Temporal shortest path length
  - speed of change
    - Temporal correlation coefficient
    - Measure persistence of links
- Model
  - Recreate a slowly changing and quickly changing temporal graph
  - Brownian motion with prob(jump)

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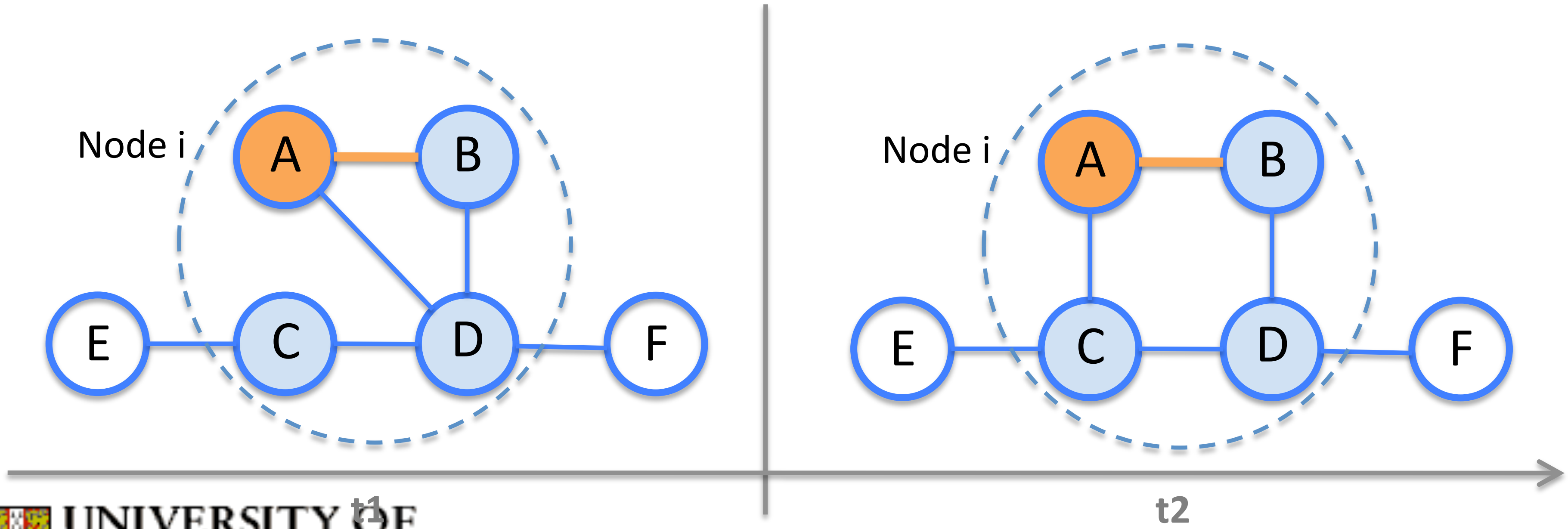
Coefficient of Temporal Clustering

$$C = \frac{\sum_i C_i}{N} \quad C_i = \frac{1}{T-1}\sum_{t=1}^{T-1}\frac{\sum_j a_{ij}(t)a_{ij}(t+1)}{\sqrt{[\sum_j a_{ij}(t)][\sum_j a_{ij}(t+1)]}}$$

C(A)=1/3



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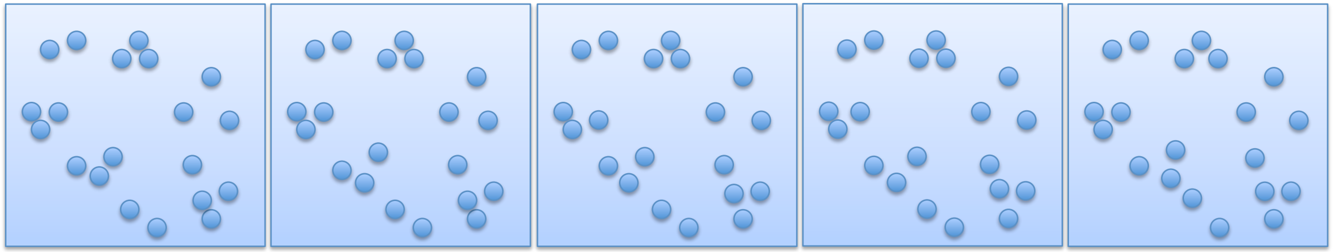
Temporal SW Model

- N Random Walkers with Prob Jumping P_j

P_j=0.0



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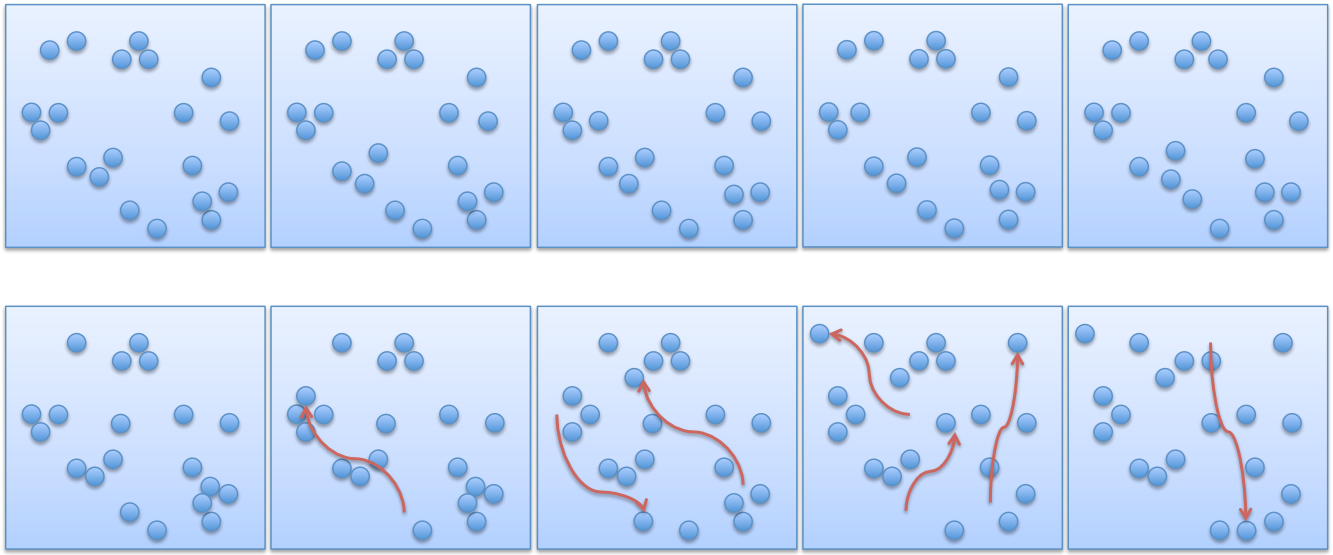
Temporal SW Model

- N Random Walkers with Prob Jumping P_j

$P_j=0.0$

$P_j=0.5$



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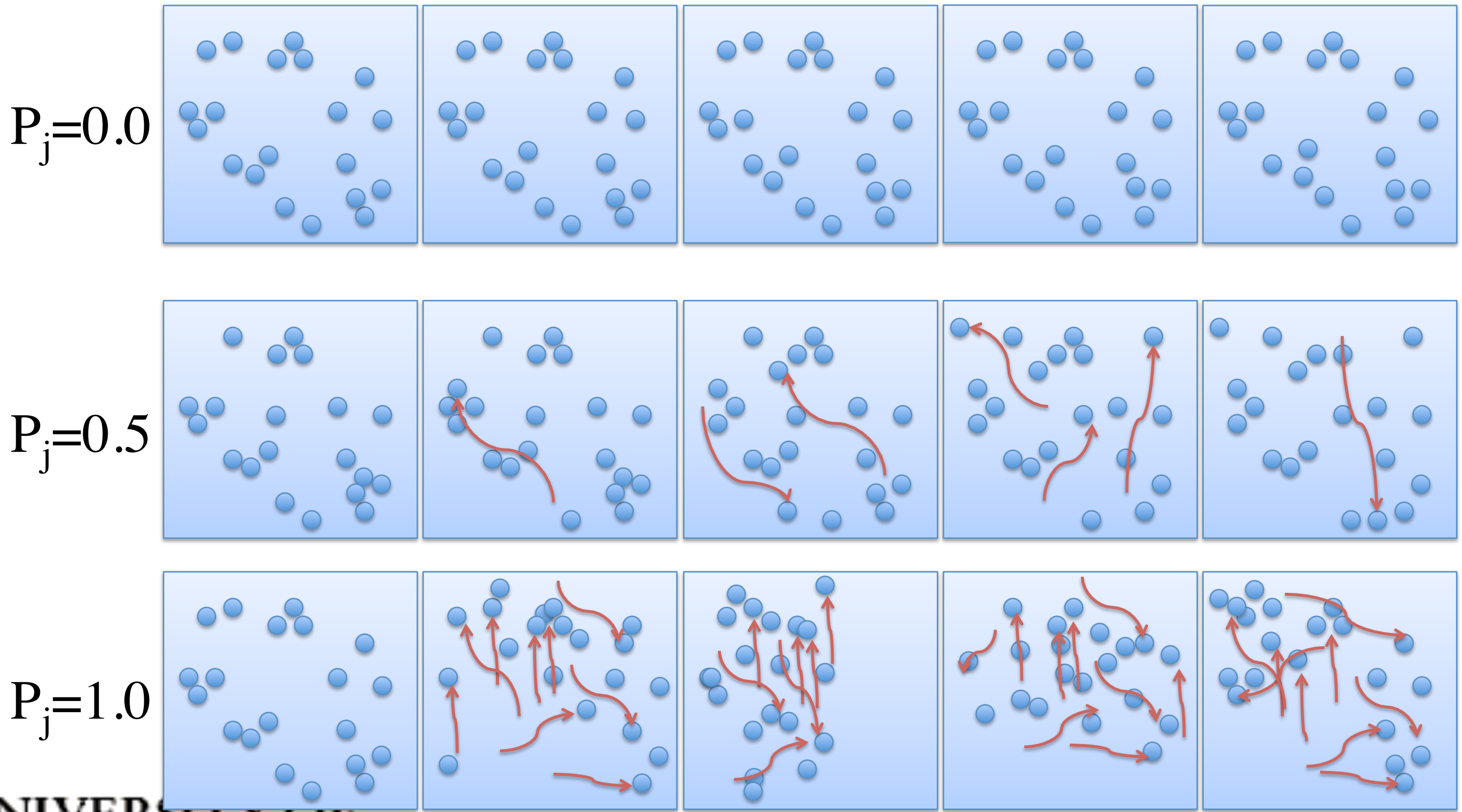
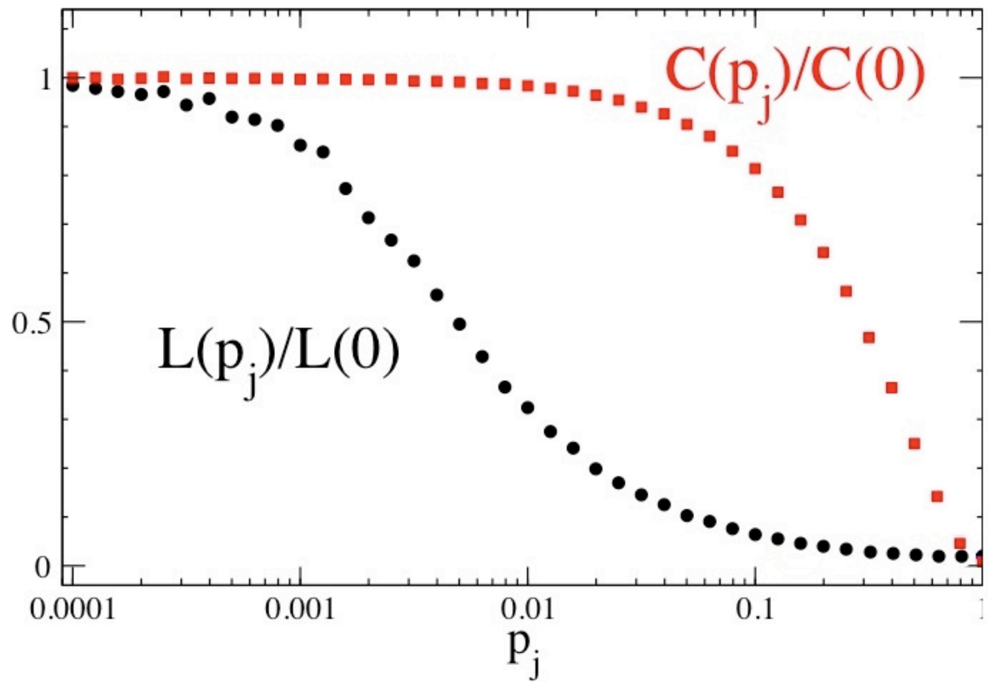
Temporal SW Model

- N Random Walkers with Prob Jumping P_j



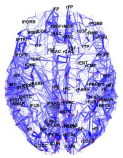
Temporal Small World

- Graphs which evolve slowly over time can still exhibit high communication efficiency
  - Highly temporal-clustering => non-jumping model
  - Low temporal-delay => fully-jumping model



Small-world Behaviour in Real Data

Network		C	C^{rand}	L	L^{rand}	E	E^{rand}
Brain network	α	0.44	0.18	3.9 (100%)	4.2 (98%)	0.50	0.48
	β	0.40	0.17	6.0 (94%)	3.6 (92%)	0.41	0.45
	γ	0.48	0.13	12.2 (86%)	8.7 (89%)	0.39	0.37
	δ	0.44	0.17	2.2 (100%)	2.4 (92%)	0.57	0.56
Bluetooth contacts (INFOCOM'06)	d1	0.80	0.44	8.84 (61%)	6.00 (65%)	0.192	0.209
	d2	0.78	0.35	5.04 (87%)	4.01 (88%)	0.293	0.298
	d3	0.81	0.38	9.06 (57%)	6.76 (59%)	0.134	0.141
	d4	0.83	0.39	21.42 (15%)	15.55(22%)	0.019	0.028
facebook (London network)	Mar	0.044	0.007	456	451	0.000183	0.000210
	Jun	0.046	0.006	380	361	0.000047	0.000057
	Sep	0.046	0.006	414	415	0.000058	0.000074
	Dec	0.049	0.006	403	395	0.000047	0.000059



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Summary

- We have introduced metrics for time varying social networks
- We have shown examples of use on real networks

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