On the delay performance of wireless networks: from hard real-time to delay-tolerant opportunistic networking

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Colorado School of Mines

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I am from

Toulouse

ENSEEIHT

the University of Toulouse (1229)

- Maîtresse de conférence at **ENSEEIHT** since Sept. 2011 - Engineering school
- 5 teaching departments : Electronics and signal processing, Electrical engineering and control, Computer science and applied maths, **Telecommunications and Networking**
- Member of the **IRIT lab**: Research Institute for Computer Science of Toulouse

Where did I go before Toulouse ?

2002-2005 ▷ **PhD in Computer Science**
Inria Rhône-Alpes, CITI lab, University of Lyon / INSA Lyon
"Wireless LAN planning"

2006-2007 ▷ **Post-doc**, Stevens Institute of Technology, NJ, USA
(working with Cristina Comaniciu)
"Cross-Layer Cooperation for Energy Efficiency in WSNs"

Paul

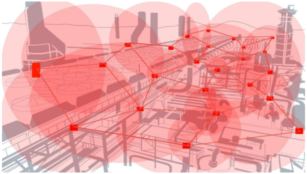
2007-2010 ▷ **Researcher**, Outgoing International Fellowship, European Union FP7
2007-2009 : Stevens Institute of Technology

Lucie

2010 : Inria Rhône-Alpes, CITI lab, University of Lyon / INSA Lyon
"Distributed MultiObjective Optimization for Wireless ad hoc nets"

2011-? ▷ **Maîtresse de conférences**, University of Toulouse, INPT-ENSEEIHT

Wireless networking



Very wide range of applications now

- Telecommunications (3G, 4G...)
- Wireless Internet access (WiFi, Bluetooth, ...)
- Factory automation (WirelessHART, ISA100.11a, ...),
- Sensor networking (802.15.4)
- Wireless social networking,
- Body area networking...

All wireless, but... different performance are expected

Performance evaluation

Research on performance evaluation of wireless networks

Different metrics may be of interest:

- Capacity, throughput, reliability, ...
- End-to-end communication delays, jitters, ...
- Energy consumption,

During this talk, we will concentrate on the **end-to-end communication delay**, primarily, in the following two case studies:

- Part 1: Real-time wireless networking
- Part 2: Large scale dynamic wireless networking

Part 1: Real-time wireless networks

Wireless is gaining momentum to carry delay-sensitive data

- wireless industrial fieldbuses (WirelessHART, ISA100.11a),
- real-time sensing,
- wireless embedded networks, etc.

For safety-critical applications, **real-time guarantees** have to be provided!

"Rien ne sert de courir ; il faut partir à point"

Jean de la Fontaine,

Is wireless compatible with hard real-time?

The main pitfall of wireless communications: its unreliability
due to interference, pathloss, fading, collisions, hidden nodes, ...

If you embark on a plane 

.....you expect all avionics communication flows to arrive on time to the core processing modules, no?

Is wireless compatible with hard real-time?

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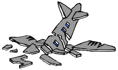


.....you expect all avionics communication flows to arrive on time to the core processing modules, no?

Thus, using wireless to send hard real-time avionics data

..... has to be proved to be safe!!!....

Why wireless for avionics?

Gain in weight

In an A380, total cabling weights around 21 tons, which represents 8.5% of the typical empty operating weight of the airplane.

Simplified maintenance and installation

There are 3 redundant networks on board (source: http://www.airliners.net)

Upgrading aircraft

Which type of wireless medium access?

A380 network carries $\sim$1000 real-time multicast flows emitted by $\sim$100 core processing modules.
Current 100Mbps switched Ethernet network loaded up to 25%.

Time division multiple access

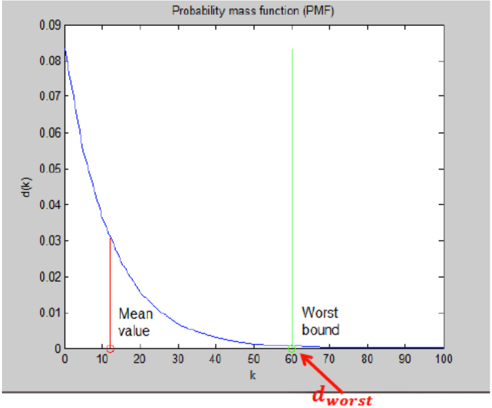
- ☺ Strong real-time guarantees
- ☹ Necessitates a common clock for all end systems
- ☹ May require dedicated hardware

Carrier sense multiple access (CSMA/CA)

- ☺ Purely distributed, works well for low loaded networks
- ☺ Off the shelf components widely available
- ☹ May not provide real-time guaranties.

Calculating a probabilistic bound

Characterize and model the **end-to-end delay distribution**



Worst-case delay $\mathbf{d_{worst}}$:

$P(K > d_{worst}) = 10^{-8}$

with real-time guarantee 10^{-8}

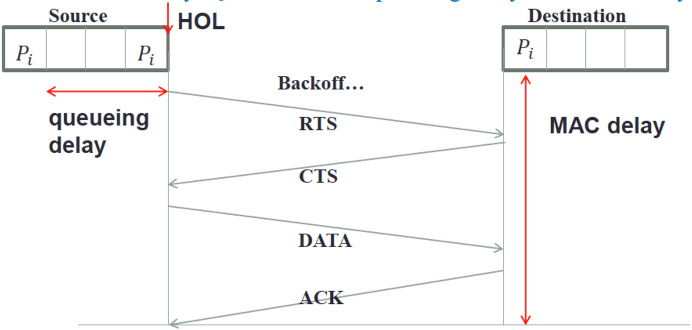
Probability Mass Function (PMF): $d(k) = P(K = k)$

Bound for a point-to-point communication

For a point-to-point communication using CSMA/CA

- N stationary nodes sharing a common wireless medium
- IEEE802.11 DCF MAC protocol: with or without RTS/CTS mechanism
- M/M/1 and M/G/1 queue and ideal channel conditions

Total transmission delay d_t is the sum of queueing delay and MAC delay



Bound for a point-to-point communication

Overall analytical distribution derivation

Previous works have addressed this problem (cf. refs in [1] [1])

Main assumption: **MAC and queueing delays are independent** discrete random variables.

MAC delay is a function of the number of nodes N contending for the medium, not the number of packets in the queue

- Calculate the Probability Generating Function (PGF) (i.e. Z-transform of PMF) for MAC and Queueing delays: $D_m(Z)$ and $D_q(Z)$
- Total delay PGF follows $D_t(Z) = D_m(Z) \times D_q(Z)$
- Invert total delay PGF to retrieve PMF using numerical inversion techniques.

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[1] [1] "A thorough analysis of the performance of delay distribution models for IEEE 802.11 DCF", Q. Wang, K Jaffrès-Runser, JL Scharbarg, C Fraboul, Y Sun, J Li, Z Li, in Press, Ad Hoc Networks

PGF of total delay

Calculated for M/M/1 and M/G/1 queues, where

- $E[D_m]$ is the mean MAC delay
- $D_m(Z)$ is the PGF of MAC delay

➢**with M/M/1 queue**, the PGF of total delay $D_t(Z)$

$$D_t(Z) = \frac{\frac{1}{E[D_m]} - \lambda}{-lnZ + \frac{1}{E[D_m]} - \lambda}$$

➢**with M/G/1 queue** , the PGF of total delay $D_t(Z)$

$$D_t(Z) = \frac{D_m(Z)(1-Z)(1-\rho)}{1-Z-\lambda(1-D_m(Z))}$$

where

$$D_m(Z) = (1-p)S(Z)\sum_{x=0}^{m}\left[(pC(Z))^x \prod_{i=0}^{x} B_i(Z)\right] + (pC(Z))^{m+1} \prod_{i=0}^{m} B_i(Z)$$

PGF of MAC delay

Mean and PGF of MAC delay are extracted from the well-known Markov chain designed by Bianchi[2] for IEEE802.11 DCF.

- MAC delay distribution

$$D_m(Z) = (1-p).S(Z).\sum_{x=0}^{m}[(p.C(Z))^x \prod_{i=0}^{x} B_i(Z)] + (p.C(Z))^{m+1}.\prod_{i=0}^{m} B_i(Z) \quad (1)$$

- Mean MAC delay

$$E[D_m] = D'_m(Z)|_{Z=1} \quad (2)$$

[2] G. Bianchi. Performance analysis of the ieee 802.11 distributed coordination function. Selected Areas in Communications, IEEE Journal on, 18(3):535-547, 2000

Numerical inversion step

- **Probability generating function(PGF)**
- $D(Z) = \sum_{k=0}^{\infty} d(k) Z^k \xrightarrow[\textbf{inversion}]{\textbf{Numerical}} d(k)$
- **Numerical inversion methods:**
  - Lattice-Poisson **(LP)** algorithms[1]
- **Two different usage of the LP algorithms**
  - The LP inversion formula of Vardakas et all. [9]

$$d(k) \approx \frac{1}{2kr^k} \sum_{j=1}^{2k} (-1)^j Re(D(re^{i\pi j/k}))$$

  - The LP inversion formula of Vu et Sakurai [10]

$$d(k) \approx \frac{1}{2klr^k} Re\left(\sum_{j=-kl}^{kl-1} D(re^{-i\pi j/(kl)}) e^{i\pi j/l}\right)$$

where $r = 10^{-\frac{\gamma}{2k}}$, which results in an accuracy of $10^{-\gamma}$

Are all these model accurate?

Errors can be introduced by

- MAC or queuing model inaccuracies
- Numerical inversion step.

Goal of this work

Propose a **performance evaluation framework** to:

- select the best MAC and queuing models
- limit inversion errors

where we **decouple the error** introduced by the model and the numerical inversion.

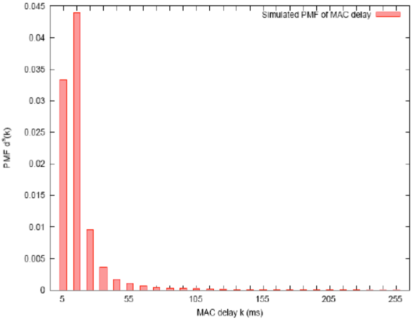
Quantifying the modeling error (1)

Total delay model directly produces the PGF

Compare to extensive simulations

But **without inverting the analytical total delay PFG !**

Calculated the PMF $d^s(k)$ from the statistics of the delay obtained by simulation



$d^s(k)$

$$D^s(Z) = \sum_{k=0}^{\infty} d^s(k) Z^k$$

Compare

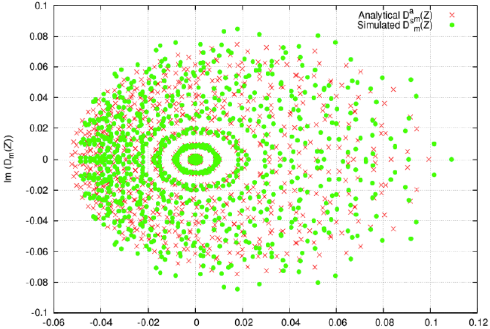
$$D^a(Z), Z \in \mathbb{C}$$

Quantifying the modeling error (2)

- **Normalized root mean squared error (NRMSE) as**

$$f_{model} = \frac{1}{Card(C)} \sum_{Z \in C} \sqrt{\frac{|D^S(Z) - D^a(Z)|^2}{|D^S(Z)|^2}}$$

- **Results**



Number of nodes	$\bar{f}_{model}$ for Markov model
$n = 5$	0.0547
$n = 15$	0.0789
$n = 30$	0.0729

Quantifying the inversion error (1)

- **A perfect PGF inversion is characterized by**

$$Z\{Z^{-1}\{D(Z), Z\epsilon\mathbb{C}\}\} \equiv \{D(Z), Z\epsilon\mathbb{C}\}$$

Procedure:

$$D_m^a(Z) = (1-p)S(Z)\sum_{x=0}^{m}\left[(pC(Z))^x \prod_{i=0}^{x} B_i(Z)\right] + (pC(Z))^{m+1}\prod_{i=0}^{m} B_i(Z)$$

LP algorithm

$$Z^{-1}\{D_{m(Z)}^a\}: \ \widehat{d(k)} \approx \frac{1}{2klr^k} Re\left(\sum_{j=-kl}^{kl-1} D_m^a\left(re^{-\frac{i\pi j}{kl}}\right)e^{\frac{i\pi j}{l}}\right)$$

Z-transform

$$Z\{Z^{-1}\{D_{m(Z)}^a\}\}: \sum_{k=0}^{\infty}\widehat{d(k)}Z^k$$

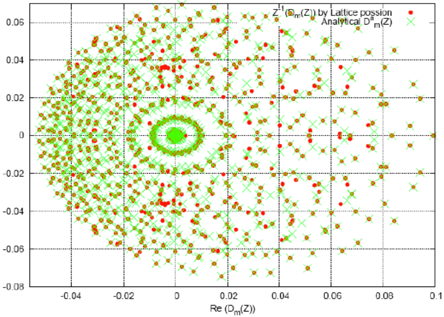
Compare ⟷ $D_m^a(Z)$

Quantifying the inversion error (2)

- **Normalized root mean squared error (NRMSE) as**

$$f_{inv} = \frac{1}{Card(C)} \sum_{Z \in C} \sqrt{\frac{|D(Z) - Z\{Z^{-1}\{D(Z)\}\}|^2}{|D(Z)|^2}}$$

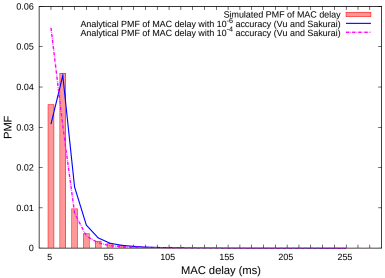
- **Results**



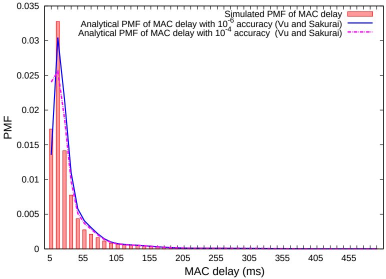
Error bound	Inversion method	f_{inv}
$\gamma = 10^{-6}$	Vu and Sakurai	0.0195
	Vardakas et al.	0.0688
$\gamma = 10^{-4}$	Vu and Sakurai	0.0232
	Vardakas et al.	0.1814

Results: MAC delay PMF

MAC model is good - Inversion accuracy needs to be controlled



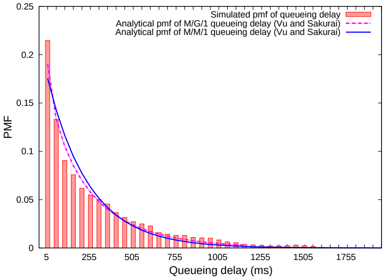
(a) $n = 5$



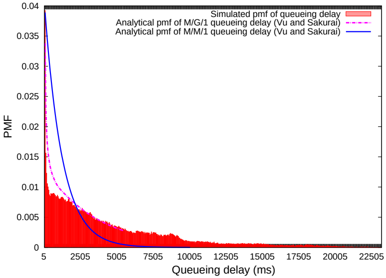
(b) $n = 15$

Figure: MAC delay PMF for different accuracies using Vu and Sakurai's LP formula with different accuracies.

M/G/1 much better for large networks. For small networks, M/M/1 is sufficient!



(a) $n = 5$

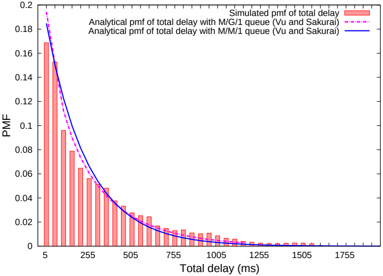


(b) $n = 15$

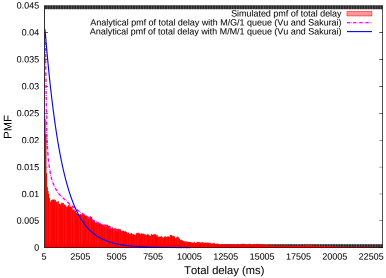
Figure: Analytical queueing delay PMFs for M/M/1 and M/G/1 queues vs. simulations.

Results: Total delay PMFs

Total delay is dominated by queuing.



(a) $n = 5$



(b) $n = 15$

Figure: Analytical total delay PMFs for M/M/1 and M/G/1 queues vs. simulations.

Results: Extension to 2-hop communications

cf. Paper for details.

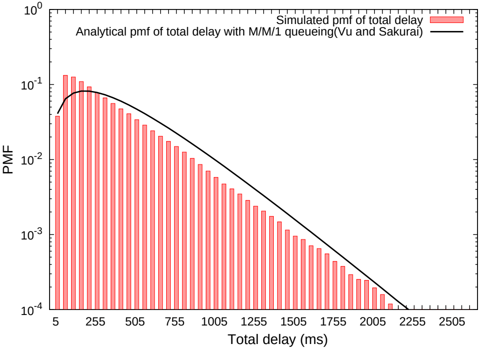


Figure: Results for a 2-hop communication of $n = 5$ nodes, M/M/1 queues.

☹Arrival distribution at the relay node is not Poisson (but log-normal)

Conclusion Part 1:

Is wireless compatible with real-time?

- ☺ For a point-to-point communication, worst-case probabilistic bounds can be extracted analytically for CSMA/CA.
- ☺ There is performance evaluation framework to test various models and methods that could be used for certification

Main challenges

- Extend to multi-hop communications.
  But will we really need multiple hops in a plane?
- Compare to TDMA solutions with synchronization.

Part 2: Large scale dynamic wireless networks

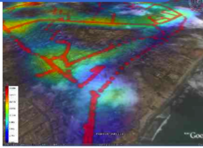
Smartphones have the potential to be:

visually-aware
sonically-aware
always-connected
directionally-aware
location-aware
motion-aware

+

=

User-aided wireless networks/
Disruption-Tolerant networks

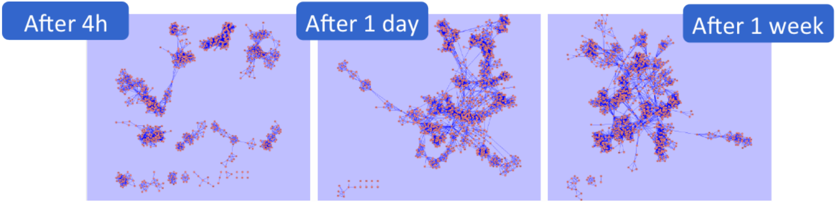


Creates a dynamic network with high potential for wireless and pervasive applications

- Wireless social networking, global sensing, content distribution,
- More and more data in transit: 3/4G network offloading...

Internetworking human beings!

Real-world mobility scenarios create neither purely regular nor purely random connections among the entities composing the network



Dynamic Complex Wireless Networks (DCWN)

- Have large number of vertices and edges that exhibit a pattern
- Evolves according to semi-rational decisions of its entities
- Semi-rational decisions:
  - are mostly regular and repeat themselves
  - but may be influenced by random events

Data sets

Data collection to build *contact traces*

- Log the contact time and duration of a node to an access point
- Log the GPS coordinates of mobile nodes regularly

Derive a time-varying contact graph

Dataset	Local	# entities	Duration	Type	Avg. # encounters/ node/day
Dartmouth [3]	campus	1156	2 months	Individuals	145.6
USC [4]	campus	4558	2 months	Individuals	23.8
San Francisco [5]	City	551	1 month	Cabs	834.7

- Dartmouth and USC collect connection dates/durations to WiFi APs,
- San Francisco collects GPS locations of taxi cabs.

[3] T. Henderson et al. "The changing usage of a mature campus-wide wireless network," in Proc. of ACM MobiCom 2004

[4] W. jen Hsu et al. "Impact: Investigation of mobile-user patterns across university campuses using wlan trace analysis," CoRR, vol. abs/cs/0508009, 2005

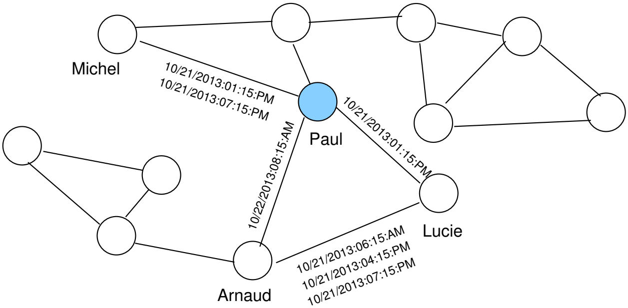
[5] A. Rojas et al. "Experimental validation of the random waypoint mobility model through a real world mobility trace for large geographical areas," in Proc. of the 8th ACM MSWiM 2005

Rationale and related initiatives

Characterize interactions, i.e. edges of contact graph

- Regularity of contacts : How often did Arnaud and Paul meet per day? during the whole trace?

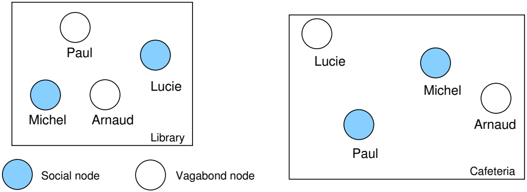
Miklas et al.[6] determine whether 2 nodes are *friends* or *strangers* using an empirical threshold (friends encounter 10 times or more within 14 weeks).



6 A. G. Miklas et al., "Exploiting social interactions in mobile systems," in *Proceedings of the UbiComp '07*

Characterize node's behavior, i.e. vertices of contact graph

Using localization information, Zyba et al.[7] differentiate *social* from *vagabond* nodes. Socials appear regularly in a given area while vagabonds visit an area rarely and unpredictably.



- Monitor the total appearance and regularity of appearance

Paul is social at the cafeteria but vagabond at the library: a per node/per area approach → *geographical dependency*

[7] G. Zyba, G. Voelker, S. Ioannidis, and C. Diot, "Dissemination in opportunistic mobile ad-hoc networks: The power of the crowd, in *Infocom'11*

Rationale and related initiatives

RECAST[8]

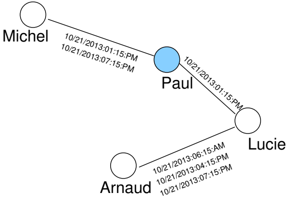
- Characterizes the interactions of nodes based on their probability to originate from a random or social behaviour
- Identify different kinds of social interactions (friends, acquaintances, bridges or random)
- No geographical dependency, i.e., is of general validity

[8] "RECAST: Telling Apart Social and Random Relationships in Dynamic Networks", P. Olmo Vaz de Melo, A. Viana, M. Fiore, K. Jaffrès-Runser, F. Le Moüel and A. A. F. Loureiro, in MSWiM'13.

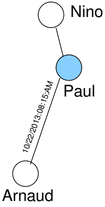
Temporal social graphs from contact traces

Two possible representations

1. δ event graph: $\mathcal{G}_k(\mathcal{V}_k, \mathcal{E}_k)$
   There is an edge in $\mathcal{E}_k$ if contact within $\delta = 1$ day for instance.



Day 1 event graph $\mathcal{G}_1(V_1, E_1)$



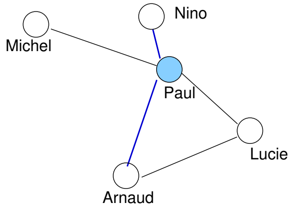
Day 2 event graph $\mathcal{G}_2(V_2, E_2)$

2. Accumulative graph $G_t(V_t, E_t)$

Temporal social graphs from contact traces

Two possible representations

1. δ event graph: $\mathcal{G}_k(\mathcal{V}_k, \mathcal{E}_k)$
   There is an edge in $\mathcal{E}_k$ if contact within $\delta = 1$ day for instance.
2. Accumulative graph $G_t(V_t, E_t)$: $G_t = \{\mathcal{G}_1 \cup \mathcal{G}_2 \cup \ldots \cup \mathcal{G}_t\}$



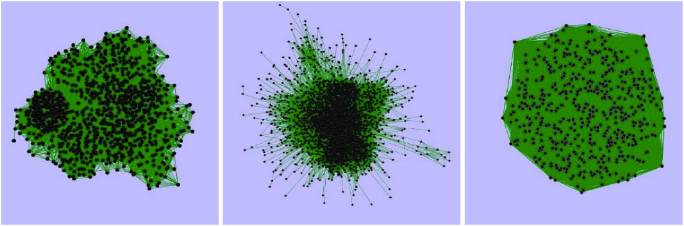
$G_2(V_2, E_2)$ Accumulative graph up to Day 2

Accumulates all event graphs up to time step t.

Temporal graphs generation from contact traces

Example accumulative graph G_t for $t = 2$ weeks

For $\delta = 1$ day and using force-direct layout algorithm for plotting



(a) Dartmouth (b) USC (c) San Francisco

Seems difficult to extract any knowledge from these social graphs:
$\rightarrow$ gathers all social AND random interaction!

Comparing a social graph to its random counterpart

Random graph equivalent of G

Calculate a random graph G^R from a graph $G(V,E)$:

- Keep same number of vertices and edges,
- Randomly assign edges to keep the same node degree distribution using *RND* algorithm[9]:

An edge is set between nodes of degree d_i and d_j with probability $p_{ij} = (d_i \times d_j)/\sum_{k=1}^{|V|} d_k$

Random accumulative graph G_t^R

Random accumulative graph derived from event graphs $\{\mathcal{G}_i\}_{i\in[1,..,t]}$

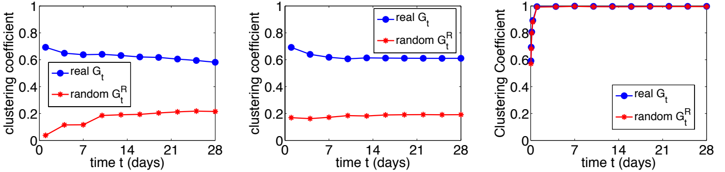
$$G_t^R = \{RND(\mathcal{G}_1) \cup RND(\mathcal{G}_2) \cup \ldots \cup RND(\mathcal{G}_t)\}$$

[9] F. Chung and L. Lu, "Connected Components in Random Graphs with Given Expected Degree Sequences," Annals of Combinatorics. Nov. 2002

Comparison social vs. random graphs

Network clustering coefficient can identify a network with an elevated number of clusters (i.e. communities).

- If $\bar{cc}(G) >> \bar{cc}(G^R)$, parts of the decisions of the nodes of G are NOT random



(a) Dartmouth (b) USC (c) San Francisco

- Dartmouth / USC traces have an order of magnitude higher $\bar{cc}$ than G^R $\rightarrow$ social decisions
- San Francisco: each individual taxi in the trace encounters most of the other taxis $\rightarrow$ closer to a random behavior

Social network features: Regularity and Similarity

Social nodes' behavior tend to

- repeat on a regular basis (because of daily activities for instance) $\rightarrow$ Regularity
- build persistent communities and generate common acquaintances $\rightarrow$ Similarity

Mathematical metrics

- Edge persistence $per(i,j)$ [10] :
  Percentage of time steps an edge exists over the past discrete time steps in the event graphs $\{\mathcal{G}_i\}_{i\in[1,..,t]}$
- Topological overlap $to(i,j)$ [11]:
  Ratio of neighbors shared by two nodes calculated for the accumulative graph G_t.

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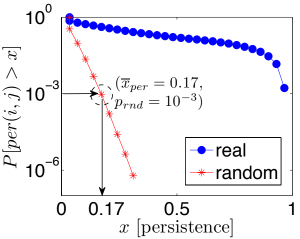
[10] N. Eagle et al., "From the Cover: Inferring friendship network structure by using mobile phone data," Proceedings of the National Academy of Sciences, Sept. 2009

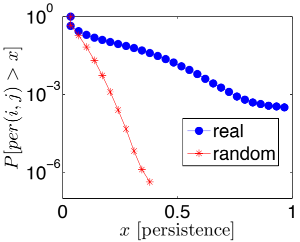
[11] J. P. Onnela et al., "Structure and tie strengths in mobile communication networks", Proc. of the National Academy of Sciences, May 2007

CCDF of edge persistence $per(i,j)$ after 4 weeks

Individuals tend to see each other regularly

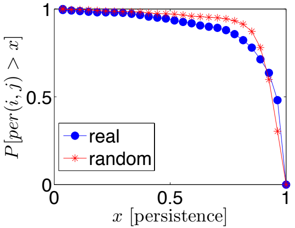


(d) Dartmouth



(e) USC

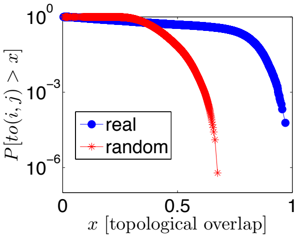
Encounters occur almost in a random fashion



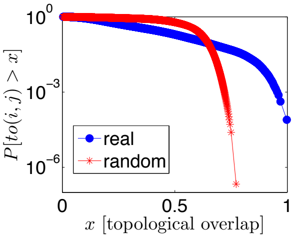
(f) San Francisco

CCDF of topological overlap $to(i,j)$ after 4 weeks

Individuals of G_t have common neighbors

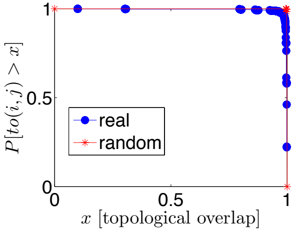


(g) Dartmouth



(h) USC

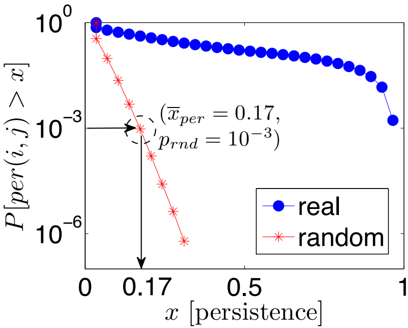
Common neighbors occur in a random fashion



(i) San Francisco

Social vs. random edges

In the random network, we only have a probability of 10^{-3} to have edges with a persistence of more than $\bar{x}_{per} = 0.17$.



$\rightarrow$ Thus, in the social graph G_t:

- edges with $per(i,j) > \bar{x}_{per}$ can be classified as *social edges*
- edges with $per(i,j) < \bar{x}_{per}$ can be classified as *random edges*

Note that there is a p_{rnd} chance that a social edge is actually random (mis-classification)

RECAST classification algorithm

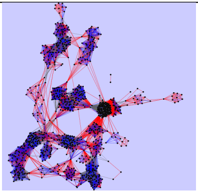
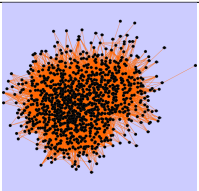
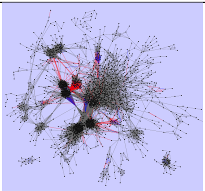
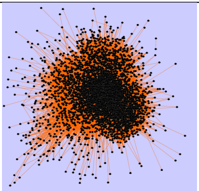
Only parameter of RECAST: p_{rnd}, the mis-classification error bound.

Main steps

- Calculate the $per(i,j)$ and $to(i,j)$ for each edge
- Knowing p_{rnd}, calculate $\bar{x}_{per}$ and $\bar{x}_{to}$ from CCDF's
- For each edge,
  - if $per(i,j) > \bar{x}_{per} \rightarrow (i,j)$ is social for edge persistence
    else (i,j) is random for edge persistence
  - if $to(i,j) > \bar{x}_{to} \rightarrow (i,j)$ is social for topological overlap
    else (i,j) is random for topological overlap
- Classify edges into classes of relationships according to:

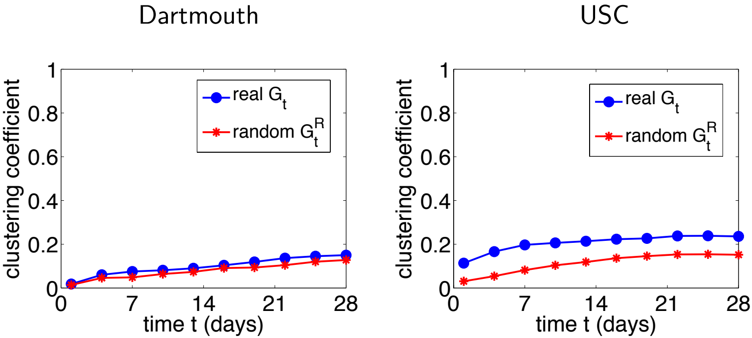
Class	Edge persistence	Topological overlap
Friends	social	social
Acquaintances	random	social
Bridges	social	random
Random	random	random

Snapshots after 2 weeks

Dartmouth		USC	
			
Social edges	Random edges	Social edges	Random edges

Friends edges are in blue, Bridges edges are in red
Acquaintance edges are in gray, Random edges are in orange

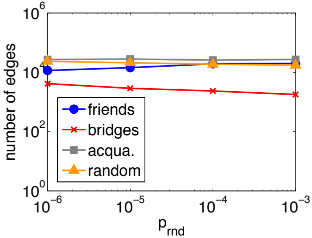
Cluster coefficient analysis for **only random edges**



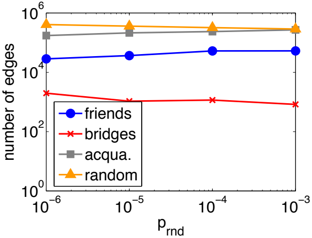
Validates the efficiency of RECAST to identify random edges for Dartmouth and USC

Classification results after 4 weeks

Number of edges of a each class that appear in the first 4 weeks vs. p_{rnd}



Dartmouth



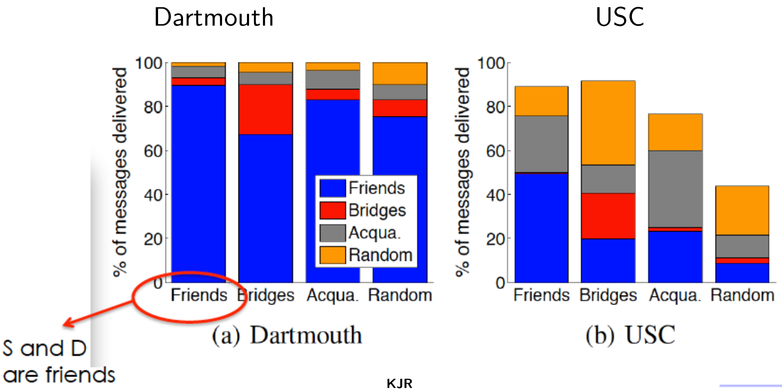
USC

RECAST is not sensitive to p_{rnd} !

Epidemic data dissemination results

Is it worth accounting for the social edges?

- Let's assume we start an epidemic transmission between a source and a destination that share a edge in the social network. (Social graph calculated with 4 first weeks of data set)
- Which edges participate in the forwarding in the following 2 weeks?

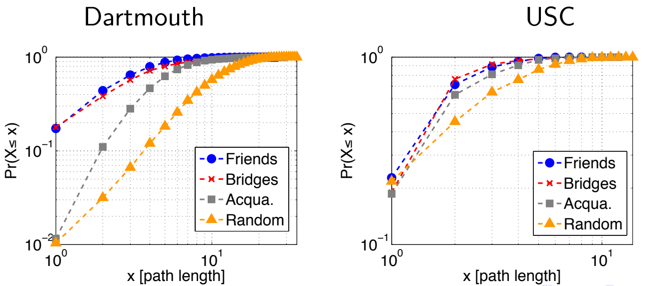


(a) Dartmouth (b) USC

Epidemic data dissemination: Path length

Is it worth accounting for the social edges?

- For both data sets, a majority of routes to social edges have a path length ≤ 3, while only a few percents of routes to random edges do.
- The transfer is much faster between nodes that share a social relationship.
- Edge persistence has a strong impact on the routing efficiency
- But random edges help as well...



Conclusions and future works

RECAST

- requires a unique parameter
- combines user encounter frequency with their 2-hop social network ties
- identifies different kinds of social interactions: friendship, acquaintanceship and bridges

Different mobility traces may have completely different behaviors (San Francisco vs. USC)

Future works

- Provide a distributed RECAST classification
- Assess RECAST using data sets with ground truth
- Study spatio-temporal correlations of data sets

Thank you for your attention

First beta-version of RECAST classifier available on :
http://www.irit.fr/~Katia.Jaffres/RECAST/Recast-code.zip