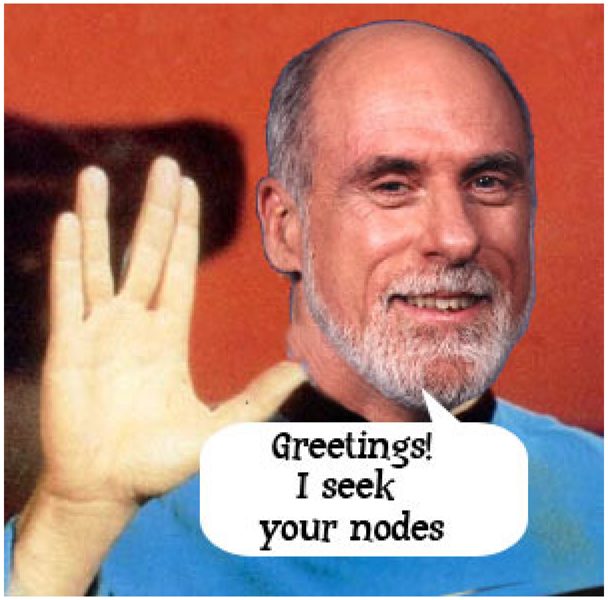

Telling apart social and random relationships in wireless networks

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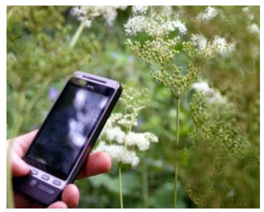
The smartphone phenomena
and the ***culture of the small screen****…*

Smartphones have the potential to be:

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



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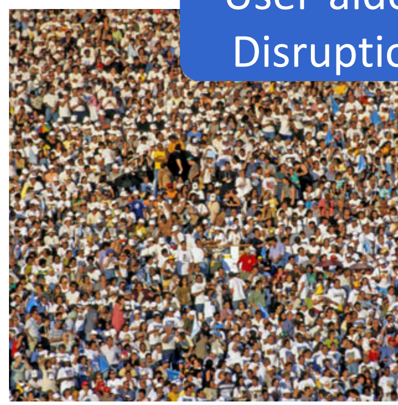
User-aided wireless networks/ Disruption-Tolerant networks



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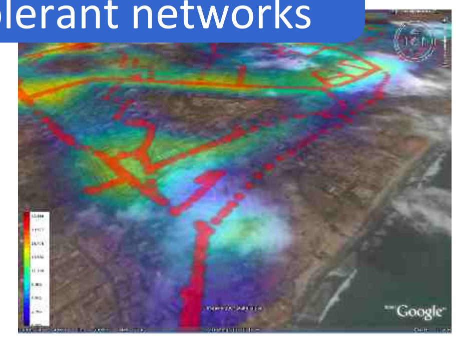
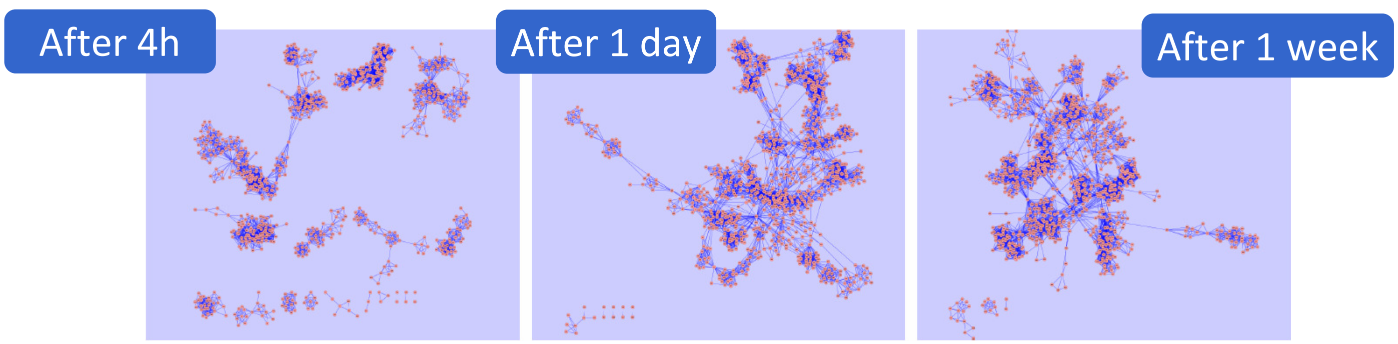


- New potential wireless and pervasive applications
  - Wireless Social networks, global sensing, content distribution
  - Increasing volume of mobile data between 2010-2015

…involving. devices carried by humans

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

- Decision-Based Wireless Networks (DbWN)
  - Have large number of vertices and edges that exhibit a pattern
  - Communities are naturally formed, reflecting social decisions of entities



  - Evolves according to semi-rational decisions of entities ≠ random networks
    - Semi-rational decisions tend to be regular and to repeat themselves

Random events are always possible in humans routines

- But…
  - …introduce significant amount of noise in predictable patterns
  - …make the process of knowledge discovery in datasets a complex task

- Proposal: Random relationship classifier strategy (RECAST)
  - Accurately identify random from social interactions (nodes wireless encounters) in large datasets

- Application scenarios:
  - Recommendation systems
  - Forwarding strategies
  - Ad-hoc message dissemination schemes (high coverage and limited number of messages)

Outline

1. Considered real-world datasets
2. Comparison with random graphs
   – Temporal graph generation
3. Random relationship classifier strategy (RECAST)
   – Identified features
   – Algorithm
4. Classification results
5. Case of study
   – Data dissemination
6. Conclusion

Considered real-world datasets

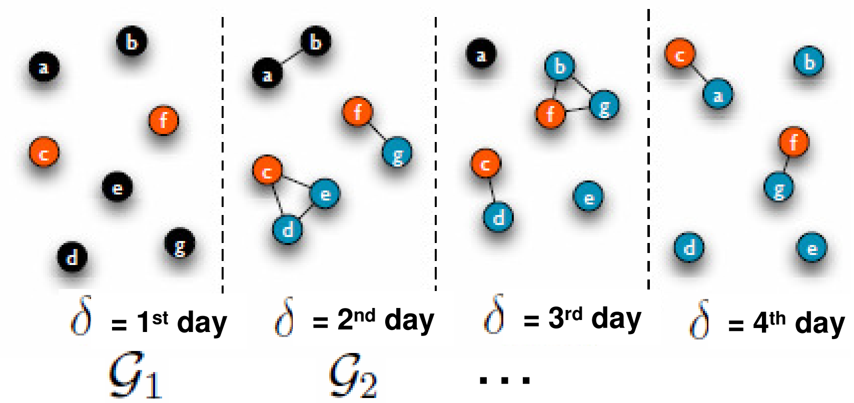
Dataset	Local	Number of entities	Duration	Entities type	Avg. # encounters/node/day
Dartmouth [30]	University campus	1156	2 months	Devices	145.6
USC [31]	University campus	4558	2 months	Devices	23.8
San Francisco [32]	City	551	1 month	Cabs	834.7

- [30] T. Henderson et al. "The changing usage of a mature campus-wide wireless network," in *Proc. of ACM* MobiCom 2004.
- [31] W. jen Hsu et al. "Impact: Investigation of mobile-user patterns across university campuses using wlan trace analysis," *CoRR*, vol. abs/cs/0508009, 2005.
- [32] 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.

Comparison with Random Graphs

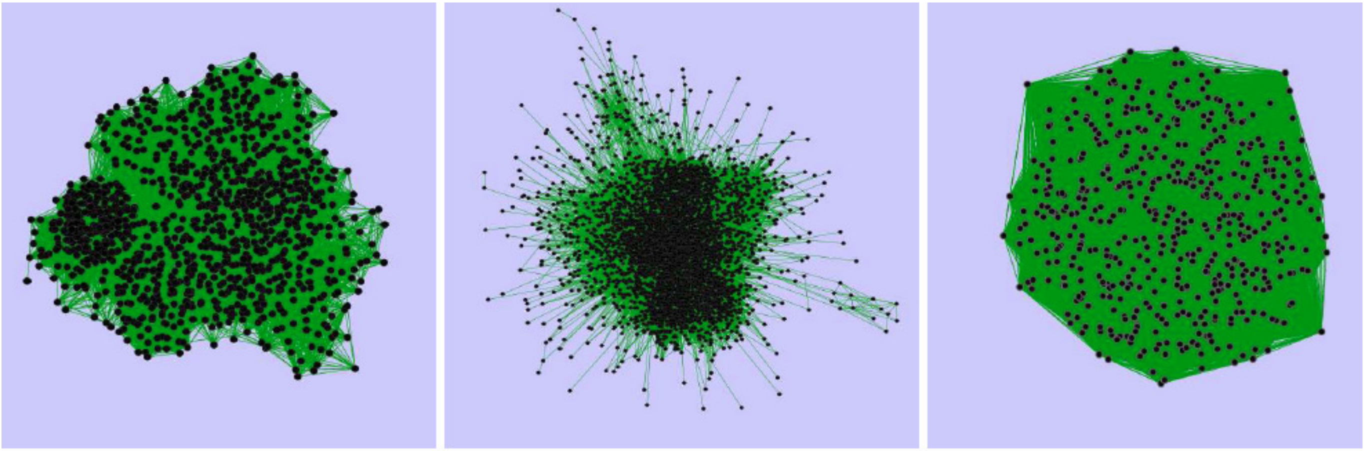
Temporal graph generation

- Time steps δ = 1 day
- Event graph: $\mathcal{G}_k(\mathcal{V}_k, \mathcal{E}_k)$
- Time accumulative graph:
  - $G_t = (V_t, E_t)$
  - $G_t = \{\mathcal{G}_1 \cup \mathcal{G}_2 \cup \ldots \cup \mathcal{G}_t\}$



- G_t for δ = 1 day and t = 2 weeks

Difficult to extract any knowledge!!



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

- **1st step:** from $\mathcal{G}_k(\mathcal{V}_k, \mathcal{E}_k)$ generates its random version $G^R(V, E^R) = \texttt{RND}\ (G)$ [1]
  - with the same number of nodes, edges, and empirical degree distribution
  - assigns edges with probability

$$p_{i,j} = (d_i \times d_j) / \sum_{k=1}^{|V|} d_k$$

  - the only difference is in the connections among nodes
    - G : nodes connect in a "semi-rational" way
    - G^R: the connections happen in a purely random fashion

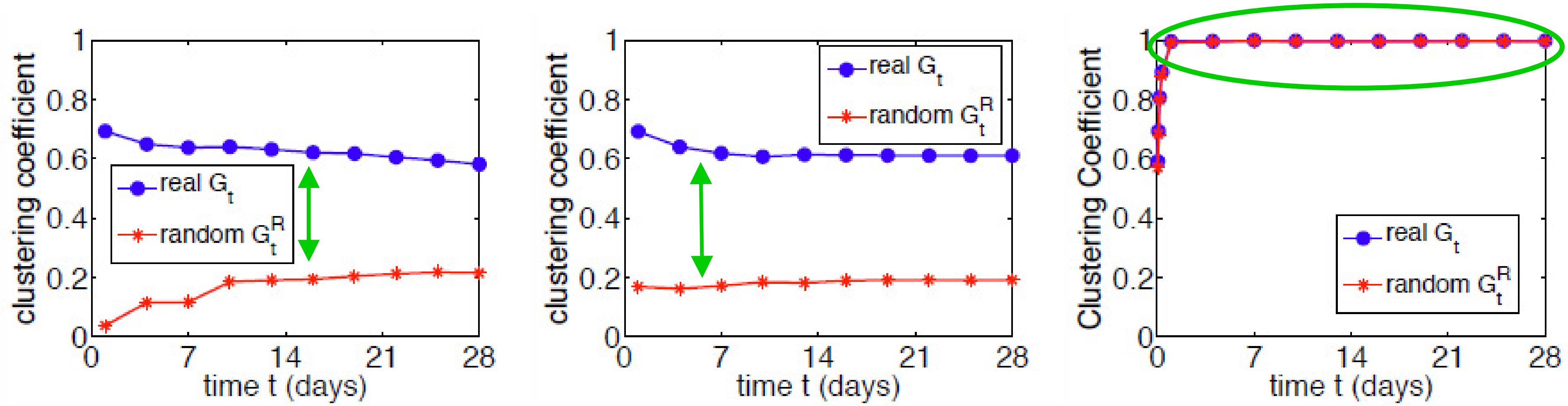
- **2nd step:** generates the temporal random version of G_t : G_t^R
  - T-RND algorithm
  - $G_t^R = \texttt{T-RND}\ (\mathcal{G}_1, \mathcal{G}_2, \ldots, \mathcal{G}_t) = \{\texttt{RND}(\mathcal{G}_1) \cup \texttt{RND}(\mathcal{G}_2) \cup \ldots \cup \texttt{RND}(\mathcal{G}_t)\}$

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

Comparison with Random Graphs (2)

- Clustering coefficient (cc): probability of two neighbors of a node to be directly connected
  - good metric to differentiate social networks from random networks
  - when cc $_G$ >> cc $_{G^R}$ $\Rightarrow$ (part of) the decisions made by the agent of G are non-random

Each individual taxi encounters most of the other taxis $\Rightarrow$ similar to a random network



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

RECAST classifier

Social relationships

- Two main features:
  - Regularity [2]
    - Encounters between "friends" repeat often
  - Similarity [3]
    - two "friends" share common "friends"

- How to represent them mathematically?
  - Edge persistence
  - Topological overlap

[2] N. Eagle, A. Pentland, and D. Lazer, "From the Cover: Inferring friendship network structure by using mobile phone data," *Proceedings of the National Academy of Sciences*, Sept. 2009.
[3] J. P. Onnela, J. Saram¨aki, J. Hyvoonen, G. Szab´o, D. Lazer, K. Kaski, J. Kert´esz, and A. L. Barab´asi, "Structure and tie strengths in mobile communication networks," *Proc. of the National Academy of Sciences*, May 2007.

Edge persistence

- Percentage of times an edge occurred over the past discrete time steps 1,2, …, t
- Applied at the event graphs $\{\mathcal{G}_1, \ldots, \mathcal{G}_t\}$

day	Mon	Tue	Wed	Thu	Fri	Sat	Sun
encounter between Smith and Johnson	x		x		x		

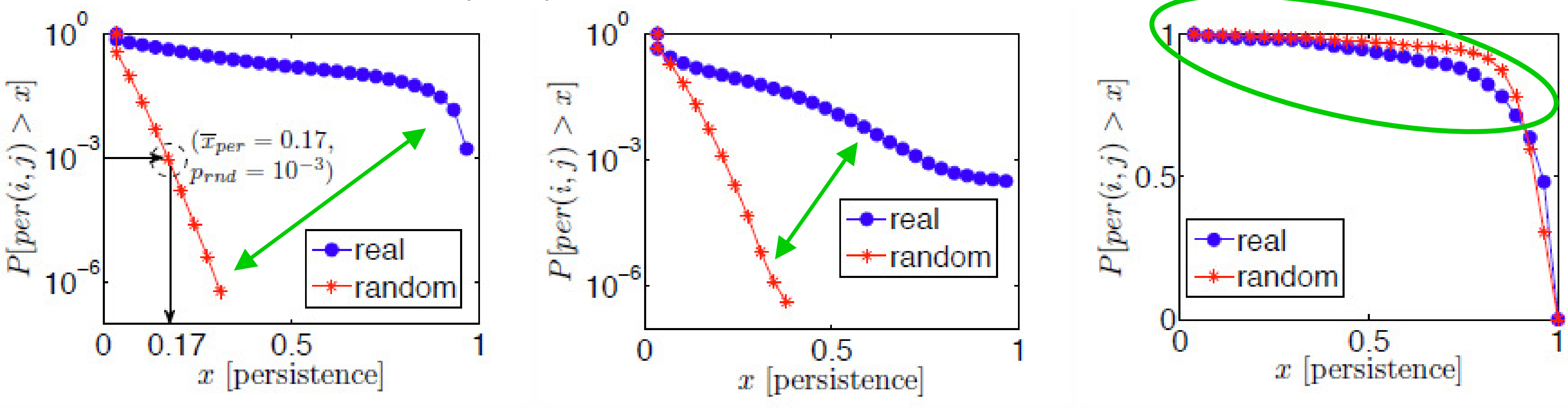
Edge Persistence: 3/7

Edge persistence

- Complementary cumulative distribution function of *per (i, j)*
- 4 weeks of contacts of each dataset

Individuals tend to see each other regularly, for reasons beyond pure randomness

Encounters occur almost in a random fashion

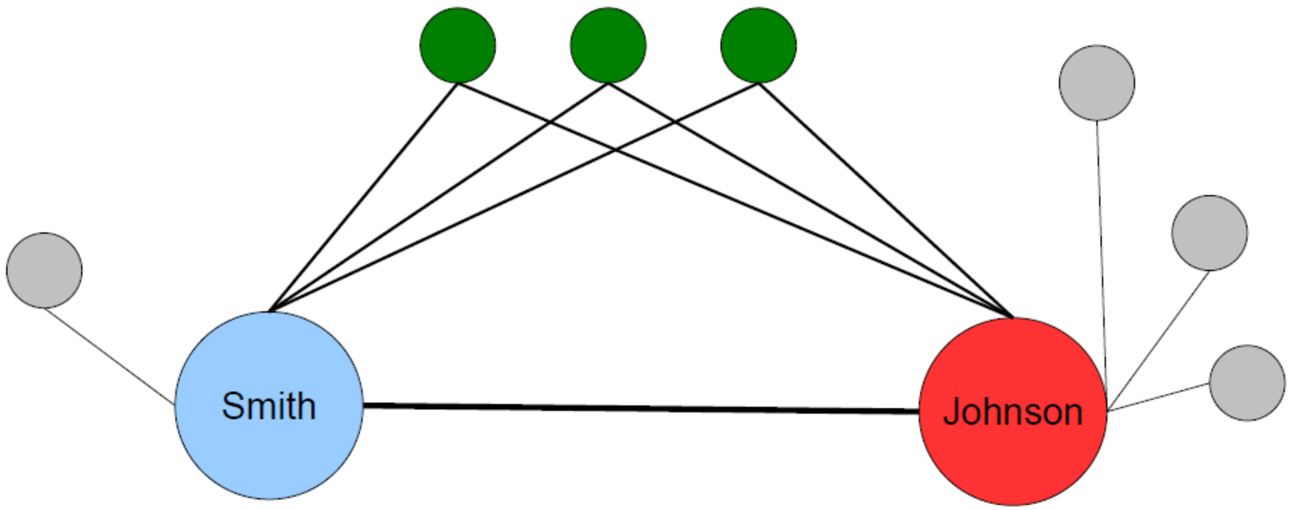


(a) Dartmouth (b) USC (c) San Francisco

Feature values > x are very unlikely to occur in a random network ⇒ are most probably due to actual social relationships

Topological overlap

- Ratio of neighbors shared by two nodes
- Extracted from the aggregated temporal graph $G_t = \{\mathcal{G}_1 \cup \mathcal{G}_2 \cup \ldots \cup \mathcal{G}_t\}$



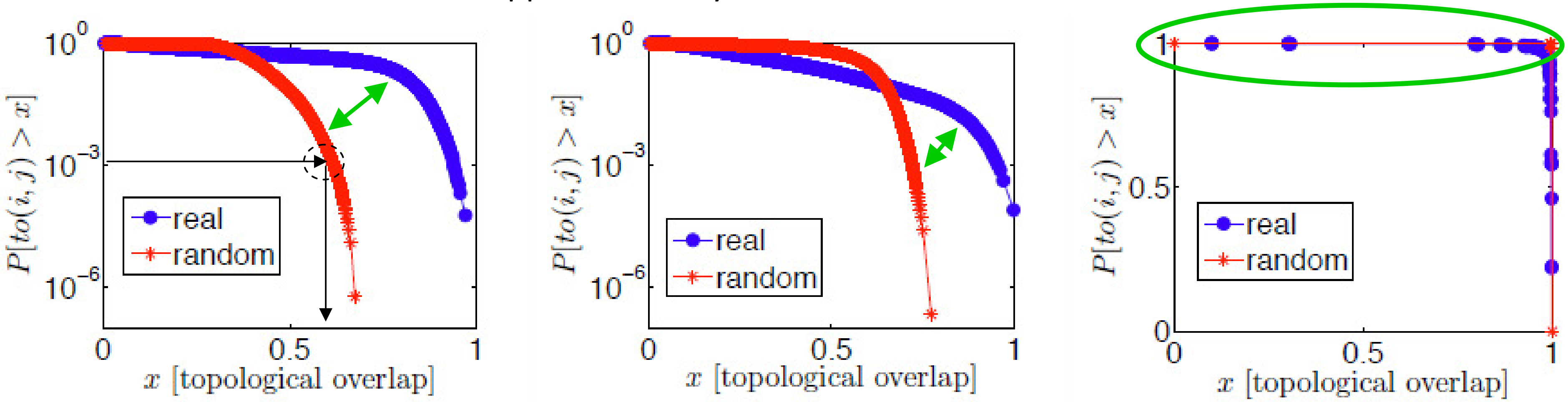
Topological Overlap = 3 / [(5-1) + (7-1) – 3] = 3/7

Topological overlap

- Complementary cumulative distribution function of *to (i, j)*
- 4 weeks of contacts of each dataset

Individuals share common neighbors in a way that could not happen randomly

Common neighbors occur in a random fashion



(d) Dartmouth (e) USC (f) San Francisco

Feature values > x are very unlikely to occur in a random network ⇒ are most probably due to actual social relationships

RECAST algorithm

- For each edge (i,j)
  - compute *per(i,j)* using the event graphs $\{\mathcal{G}_1, \ldots, \mathcal{G}_t\}$
  - compute *to(i,j)* using the aggregated temporal graph $G_t = \{\mathcal{G}_1 \cup \mathcal{G}_2 \cup \ldots \cup \mathcal{G}_t\}$

- Compare these values with the ones from the random graph
  - prnd can be seen as the expected classification error percentage

$$\text{Get } \bar{x}_{to} \mid \overline{F}_{to}(\bar{x}_{to}) = p_{rnd} \text{ and } \bar{x}_{per} \mid \overline{F}_{per}(\bar{x}_{per}) = p_{rnd}$$

- Classify edges into classes of relationships

3 types of social relationships

Class	Edge persistence	Topological overlap
Friendship	social	social
Acquaintanceship	random	social
Bridges	social	random
Random	random	random

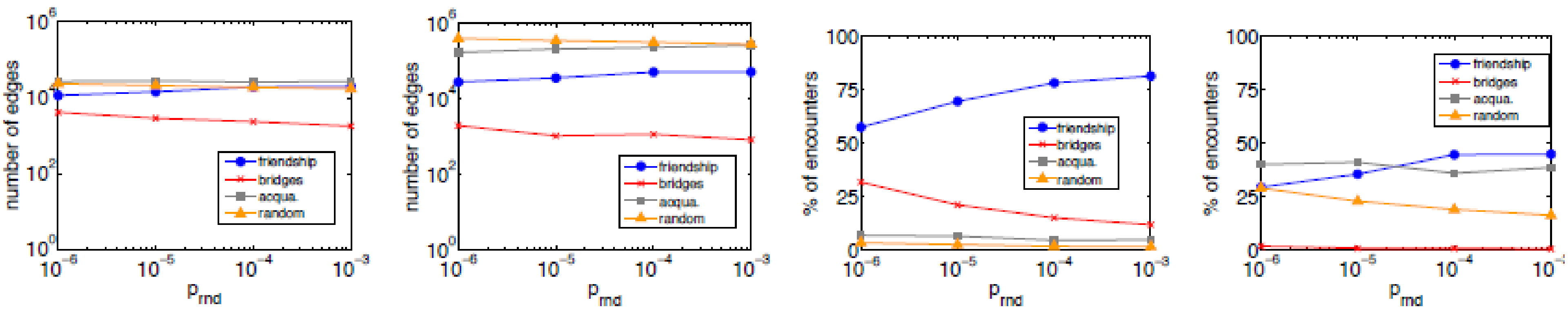
Classification results

Number/Percentage of edges per class *vs* p_{rnd} value

- 4 weeks of contacts of each dataset

Similar dynamics in tight relationships among individuals in the two campuses

USC has a significantly higher tendency to evolve to a random topology than the Dartmouth

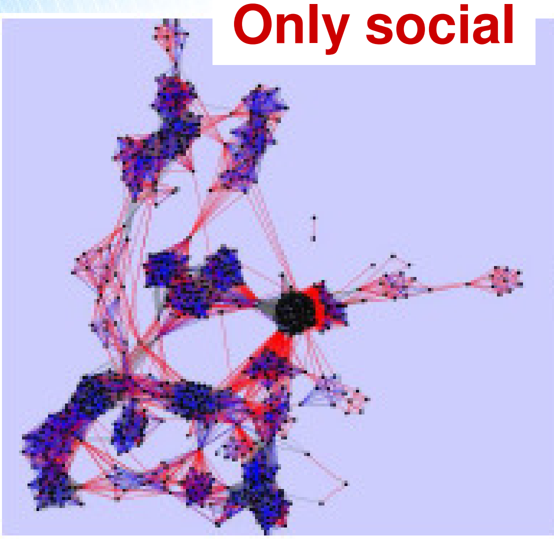


(a) Dartmouth (b) USC (c) Dartmouth (d) USC

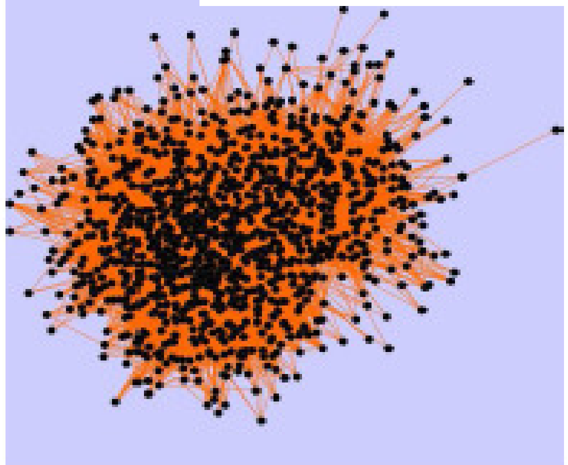
RECAST does not need a fine calibration of p_{rnd} to return a consistent edge classification

Snapshots after two weeks of interactions

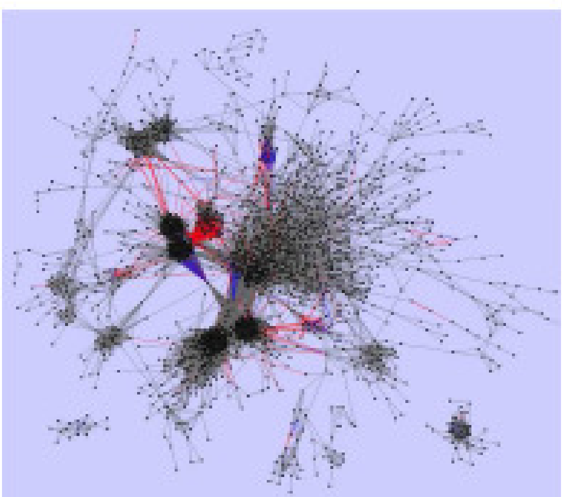
Only social **Only random**



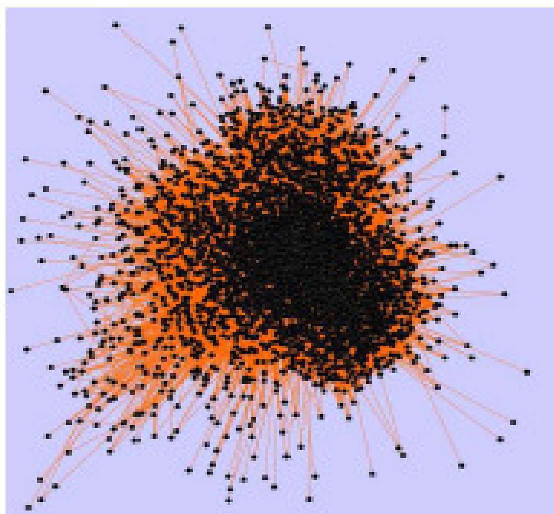
(a) Dartmouth, only social edges



(b) Dartmouth, only random edges



(c) USC, only social edges



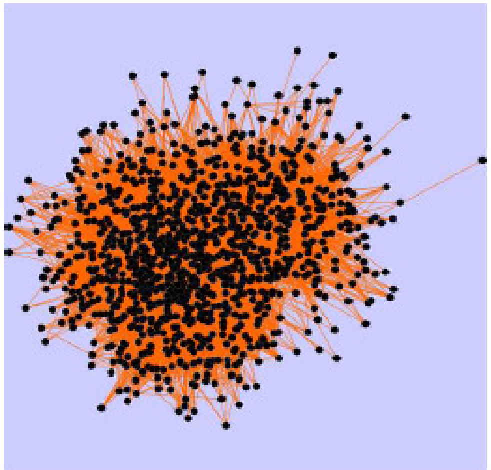
(d) USC, only random edges

- **Social-edges net.**: Complex structure of *Friendship* communities, linked to each other by *Bridges* and *Acquaintanceship*

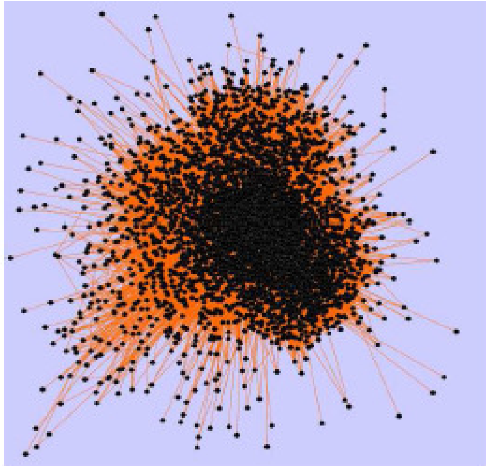
- **Random-edges net.**: No structure appears, looking like random graphs

Friendship edges are in **blue**
Bridges edges are in **red**
Acquaintance edges are in **gray**
Random edges are in **orange**

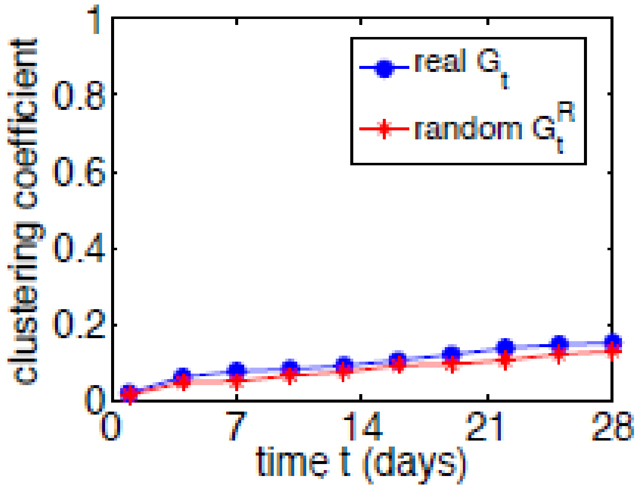
Cluster coefficient analysis, **only** Random edges



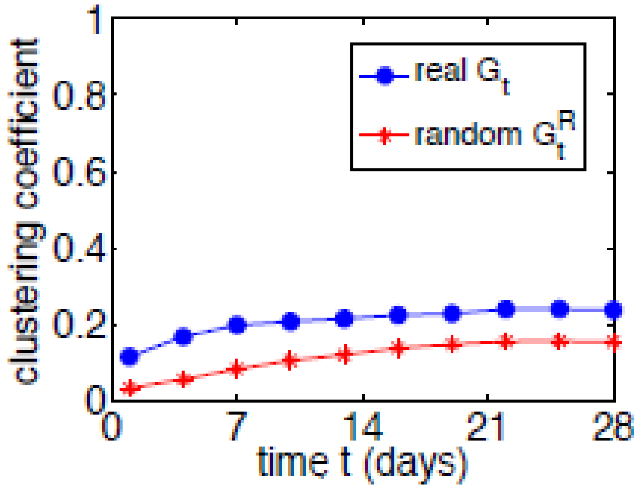
(b) Dartmouth, only random edges



(d) USC, only random edges



(a) Dartmouth



(b) USC

Validates the efficiency of RECAST classification!

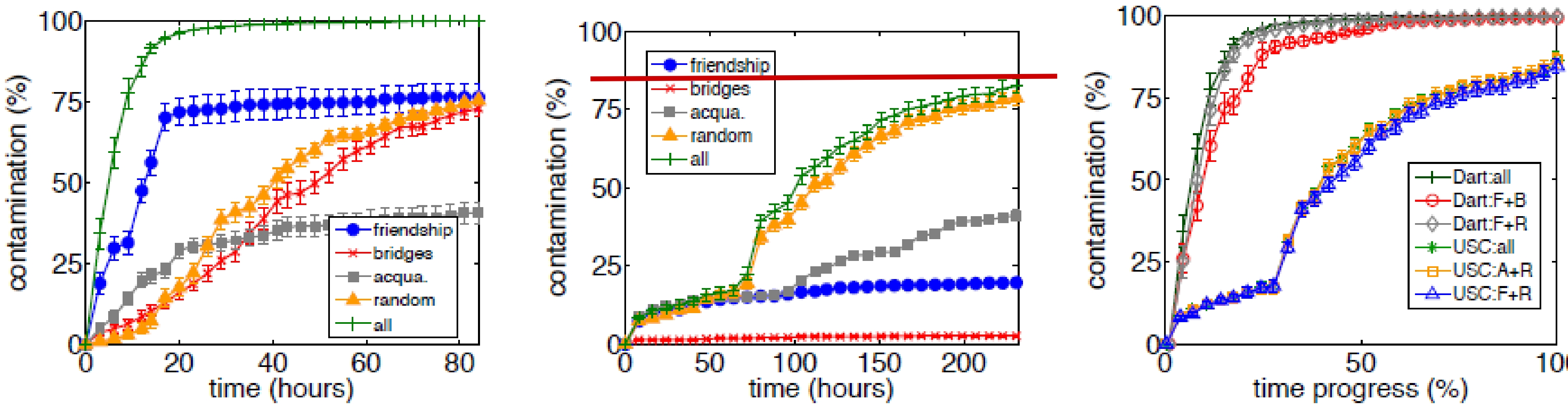
Case of Study

Data dissemination: when only edges of each class are used

Dartmouth dataset:

Training set of 4 weeks

Test set at the 5th week



(a) Dartmouth (b) USC (c) Mix of Classes

USC dataset:

Training set of 6 weeks

Test set at the 7th, 8th, 9th weeks

Data dissemination: results summary

- Efficient contamination needs:
  - edges that provide a high number of encounters inside communities (*Friendship* in Dartmouth and *Acquaintanceship in* USC)
  - edges that provide a high number of connections among individuals in different communities (*Random* and *Bridges* in Dartmouth and *Random in* USC)

- Contamination when *Bridge + Friendship* edges in the Dartmouth ≅ *Random + Friendship*
  - Number of *Bridge* edges ≅ 12% the number of *Random* edges
  - Using *Bridge* edges help to save computational resources

Related initiatives

- Users classification into social and vagabonds [Zyba et al., Infocom 2011]
  - regularity of appearance and duration of visits in a given area
  - only works on a per-individual per-area basis

- Links classification into friends and strangers [Miklas et al., UbiComp 2007]
  - pairs of users meeting 10 days or more out of 101 days are friends
  - otherwise are strangers

- A. G. Miklas et al., "Exploiting social interactions in mobile systems," in *Proc. of the UbiComp '07*.
- G. Zyba et al. "Dissemination in opportunistic mobile ad-hoc networks: The power of the crowd," in *Proc. of IEEE INFOCOM 2011*.

Summary and outlook

- RECAST
  - has no geographical dependency
  - combines user encounter frequency with their 2-hop social network ties
    - periodic behaviors can explain **50% to 70%s** of the human movement patterns
    - but a non-negligible percentage of mobility (**about 10% to 30%**) is due to social relationships
  - identifies different kinds of social interactions
    - friendship, acquaintanceship and bridges

- Different mobility traces may have completely different behaviors

- Researchers should not generalize their results based on the analysis of a single trace

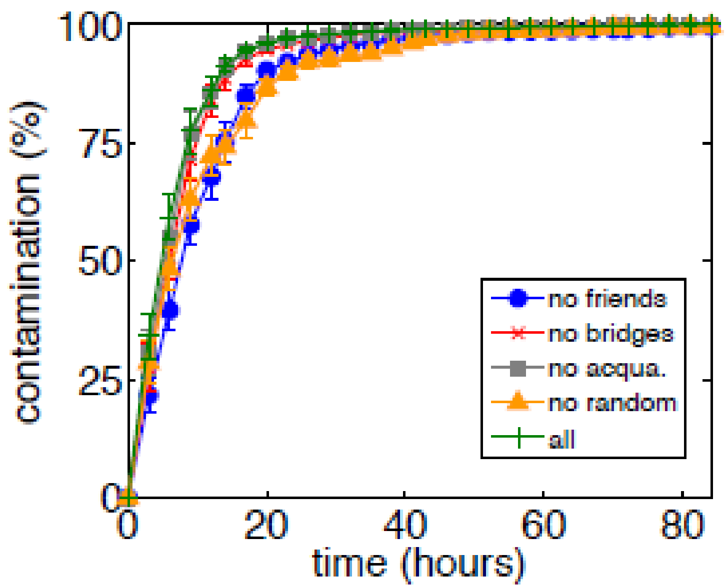
Thanks for your attention!

Questions?

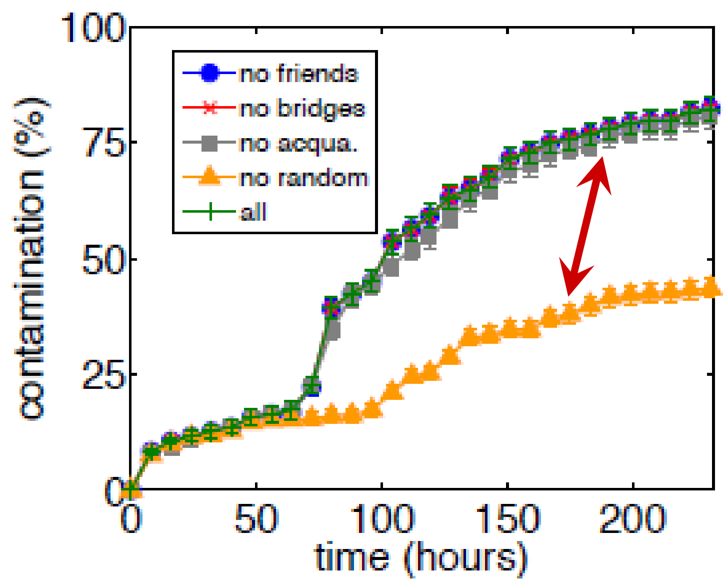
Data dissemination: when only edges of each class are used

Dartmouth dataset:
Training set of 4 weeks
Test set at the 5th week

USC dataset:
Training set of 6 weeks
Test set at the 7th, 8th, 9th weeks



(a) Dartmouth



(b) USC

Link prediction (training set = 4 weeks/test set = 5th week)