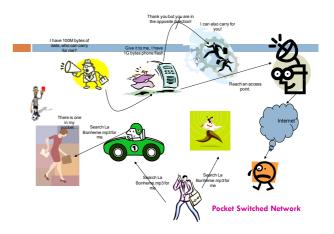
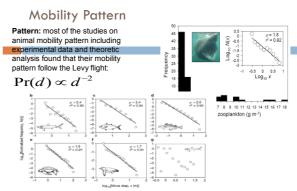
LECTURE 14 : MOBILITY AND OPPORTUNISTIC NETWORKING

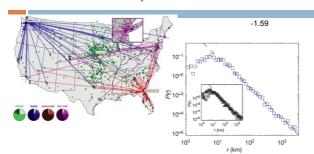


People Are the Network



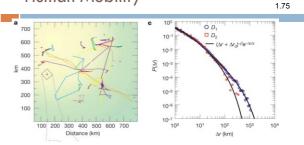
Levy flight search patterns of wandering albatrosses, Nature 381, (1996) Revisiting Le'vy flight search patterns of wandering albatrosses, bumblebees and deer, NATURE] Vol 449[25 October 2007 Scaling laws of marine predator search behaviour, Nature (2008)

Human Mobility



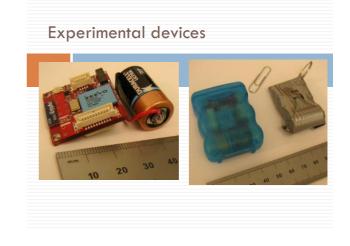
D. Brockmann, L. Hufnagel and T. Geisel, The scaling laws of human travel, Nature, 439, 462-465, (2006).

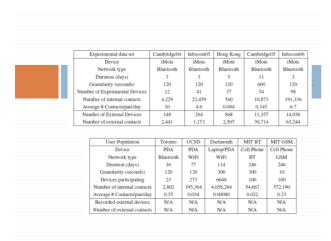
Human Mobility

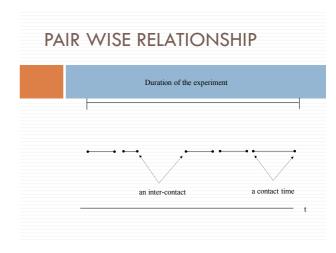


Understanding individual human mobility patterns
Marta C. Gonza´lez, Ce´sar A. Hidalgo & Albert-La´szlo´ Baraba´si, NATURE| Vol
453l5 June 2008

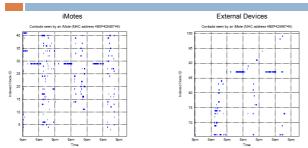
EXPERIMENTAL SETUP iMotes ARM processor Bluetooth radio 64k flash memory Bluetooth Inquiries 5 seconds every 2 minutes Log {MAC address, start time, end time} tuple of each contact





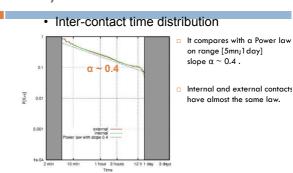


Contacts seen by an iMote

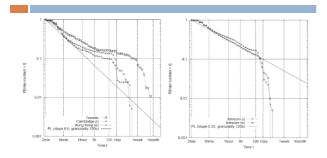


- x-axis shows the time of the day and the y-axis shows the node $\ensuremath{\mathsf{ID}}$
- Contacts are sparse
- iMote sees node 28 every night and they stay together the whole night $\ensuremath{\textcircled{\scriptsize 0}}$

Heavy Tailed Distributions



OTHER EXAMPLES



Implication on Opportunistic Forwarding:

□ For $\alpha > 2$

Any stateless algorithm achieves a finite expected delay.

 \square For $\alpha \ge \frac{m+1}{m}$ and $\# \{ \text{ nodes } \} \ge 2m$

There exist a forwarding algorithm with m copies and a finite expected delay.

□ For α < 1

No stateless algorithm (even flooding) achieve a bounded delay (Orey's theorem).

Social Structures Vs Network Structures

□ Community structures

- □ Social communities, i.e. affiliations
- □ Topological cohesive groups or modules

□ Centralities

- Social hubs, celebrities and postman
- Betweenness, closeness, inference power centrality

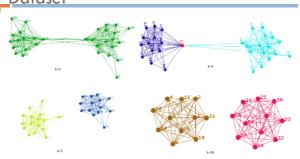
K-clique Community Definition

- □ Union of k-cliques reachable through a series of adjacent k-cliques [Palla et al]
- □ Adjacent k-cliques share k-1 nodes
- □ Members in a community reachable through well-connected well subsets

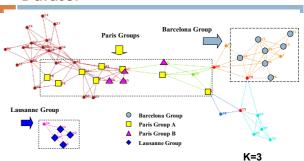
□ Examples

- 2-clique (connected components)
- □ 3-clique (overlapping triangles)
- Overlapping feature

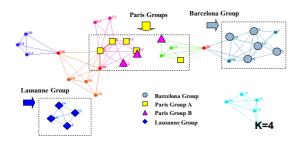
K-clique Communities in Cambridge Dataset



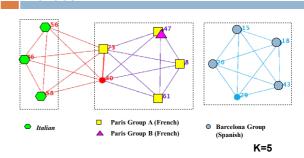
K-clique Communities in Infocom06 Dataset



K-clique Communities in Infocom06 Dataset



K-clique Communities in Infocom06 Dataset



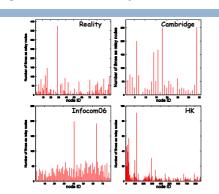
Other Community Detection Methods

- □ Betweenness [Newman04]
- □ Modularity [Newman06]
- □ Information theory[RosvallO6]
- □ Statistical mechanics[Reichardt]
- □ Weighted Network Analysis[Newman05]
- □ Survey Papers[Danon05][Newman04]

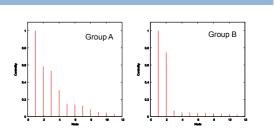
Centrality in Temporal Network

- $\hfill\Box$ Large number of unlimited flooding
- □ Uniform sourced and temporal traffic distribution
- □ Number of times on shortest delay deliveries
- □ Analogue to Freeman centrality [Freeman]

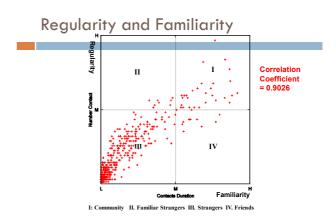
Homogenous Centrality

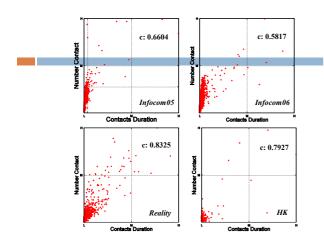


Within Group Centrality Cambridge Dataset



Within Group Centrality Reality **Dataset** Group A Group B Group D Group C







Third generation human interaction model

- Categories of human contact patterns
- □ Clique and community
- Popularity/Centrality

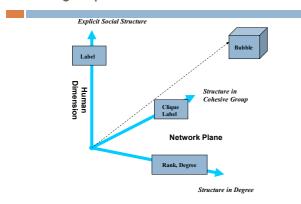
Dual natures of mobile network

- Social network
- Physical network

Benchmark Forwarding strategies

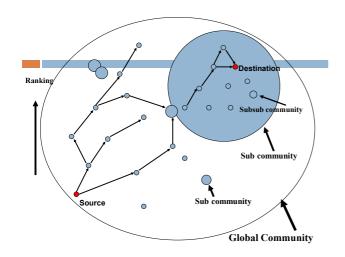
□ Flooding, Wait, and Multiple-copy-multiple-hop (MCP), **PROPHET**



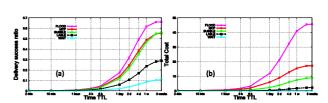


Centrality meets Community

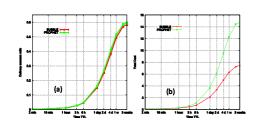
- □ Population divided into communities
- □ Node has a global and local ranking
- □ Global popular node like a postman, or politician in
- □ Local popular node
- □ BUBBLE



Centrality meets Community



Centrality meets Community

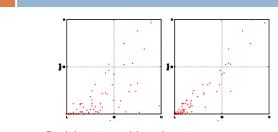


Making Centrality Practical

How can each node know its own centrality in decentralised way?

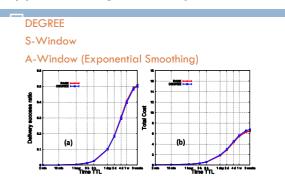
How well does past centrality predict the future?

Approximating Centrality



- □ Total degree, per-6-hour degree
- □ Correlation coefficients, 0.7401 and 0.9511

Approximating Centrality



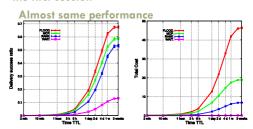
Approximating Centrality

(a) (b)

Predictability of Human Mobility

Three sessions of Reality dataset

Two sessions using the ranking calculated from the first session



Distributed Community Detection

SIMPLE, K-CLIQUE, MODULARITY

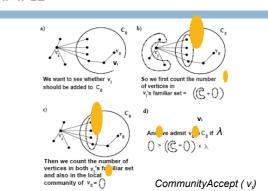
Terminology: Familiar Set (F), Local Community (C)

Update and exchange local information during

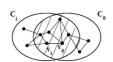
Build up Familiar Set and Local Community

☐ CommunityAccept(), MergeCommunities()

SIMPLE



SIMPLE



We only consider merging the two communities $C_a \& C_i$ if the fraction of them in common /// > /

MergeCommunities (C_o , C_i)

Results and Evaluations

| Data Set | SIMPLE | K-CLIQUE | MODULARITY |
|------------|-----------|--------------------|------------------------------------------------------|
| Reality | 0.79/0.76 | 0.87 | 0.82 |
| UCSD | 0.47/0.56 | 0.55 | 0.40 |
| Cambridge | 0.85/0.85 | 0.85 | 0.87 |
| Complexity | O(n) | O(n ²) | O(n ⁴)/O(n ² k ²) |

Newman weighted analysis Palla et al, k-Clique

 $\sigma_{Jaccard} = \frac{|\Gamma_i \cap \Gamma_j|}{|\Gamma_i \cup \Gamma_j|}$

Distributed BUBBLE RAP (DiBuBB)

