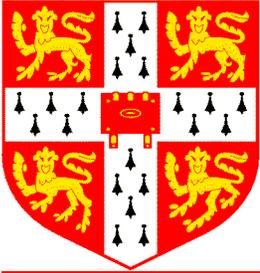


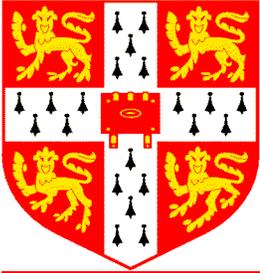
Bubble Rap: Forwarding in Small World DTNs in Ever Decreasing Circles Part 2 - People Are the Network

Jon Crowcroft
Pan Hui
Computer Laboratory
University of Cambridge



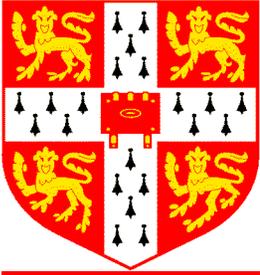
Outline

- Multiple levels human heterogeneity
 - Local community structures
 - Diversity of centrality in different scales
 - Four categories of human relationship
- Heterogeneous forwarding algorithms
 - Design space
 - RANK (centrality based forwarding)
 - LABEL (community based forwarding)
 - BUBBLE RAP (centrality meets community)
- Approximation and predictability
 - Decentralized approximation of centrality
 - Human predictability



Understanding multiple levels of heterogeneity

The first goal of this research is to move to a third generation of human mobility models, understanding heterogeneity at multiple levels of detail.



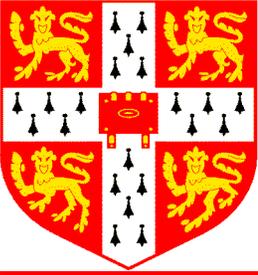
Social Structures Vs Network Structures

- Community structures
 - Social communities, i.e. affiliations
 - Topological cohesive groups or modules
- Centralities
 - Social hubs, celebrities and postman
 - Betweenness, closeness, inference power centrality

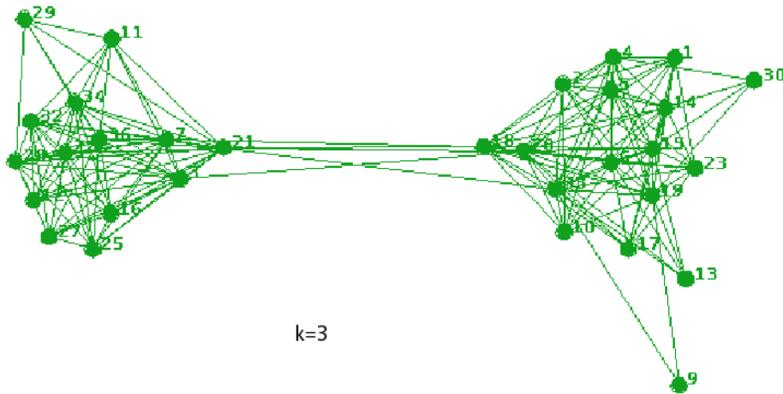


K-clique Community Definition

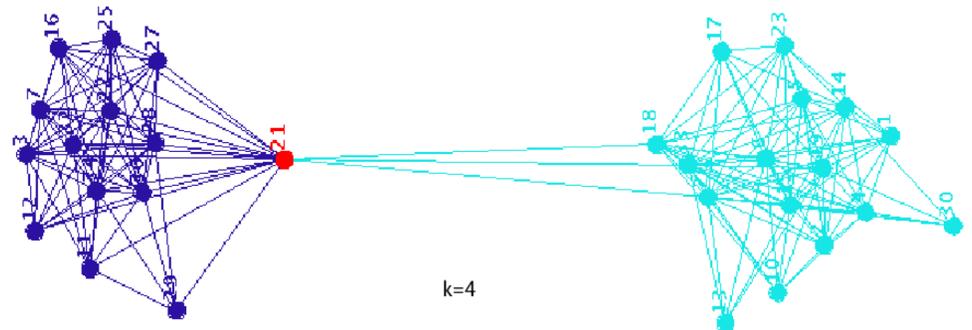
- Union of k-cliques reachable through a series of adjacent k-cliques [Palla et al]
- Adjacent k-cliques share k-1 nodes
- Members in a community reachable through well-connected well subsets
- Examples
 - 2-clique (connected components)
 - 3-clique (overlapping triangles)
- Overlapping feature
- Percolation threshold $p_c(k) = 1/[(k-1)N]^{1/(k-1)}$



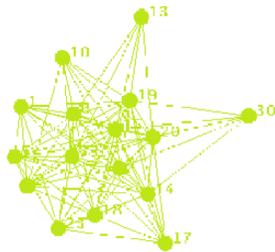
K-clique Communities in Cambridge Dataset



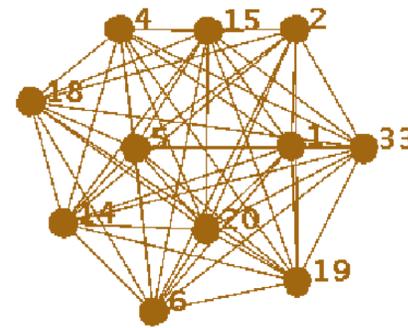
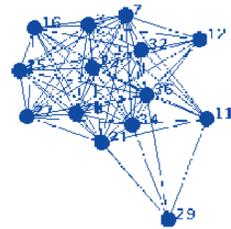
k=3



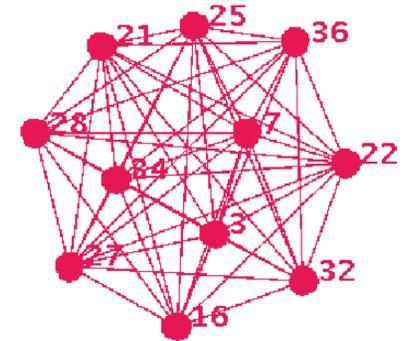
k=4

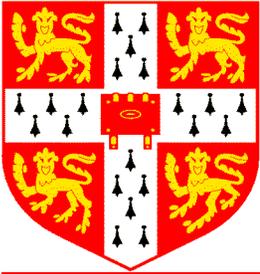


k=5

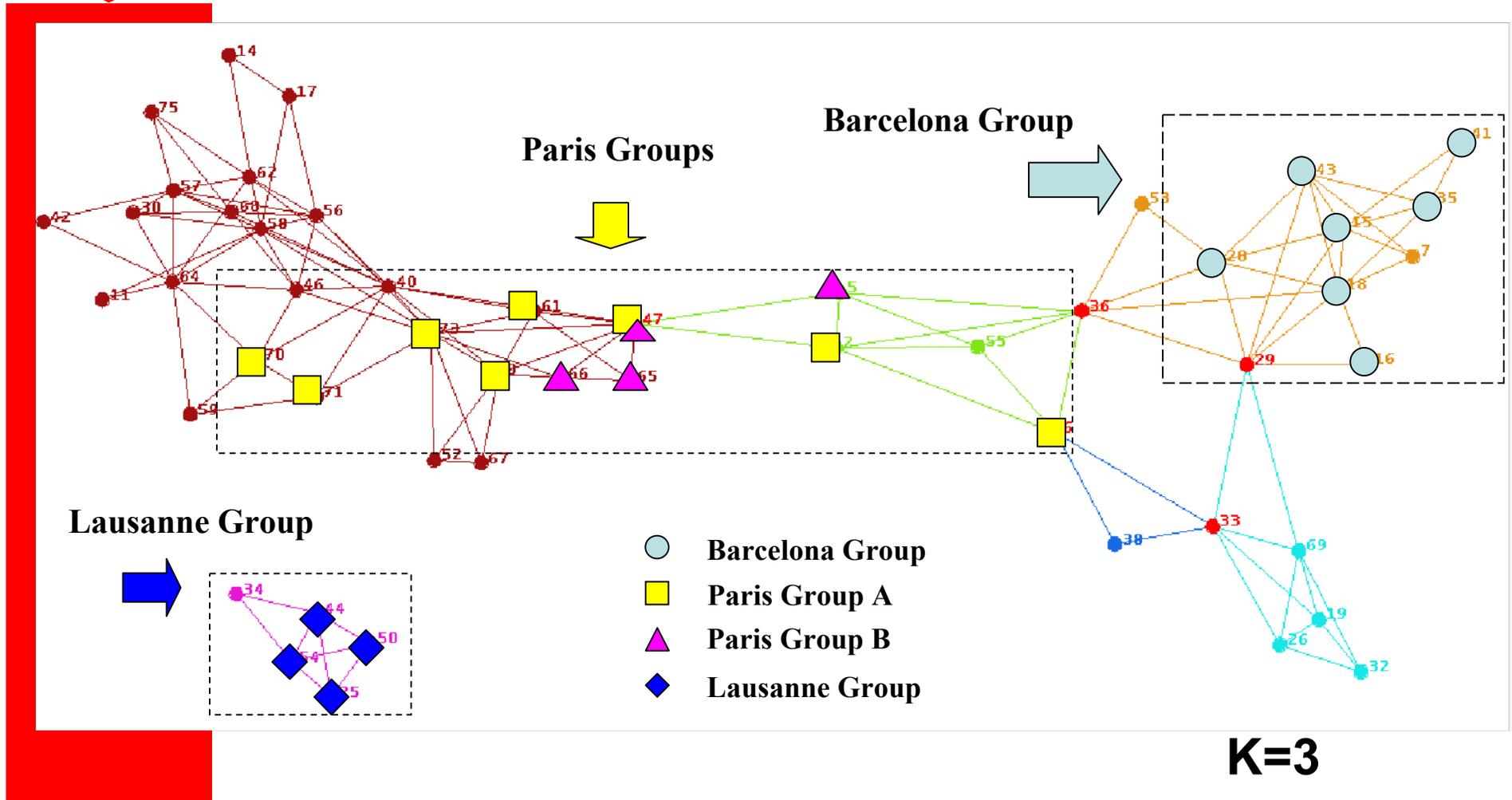


k=10



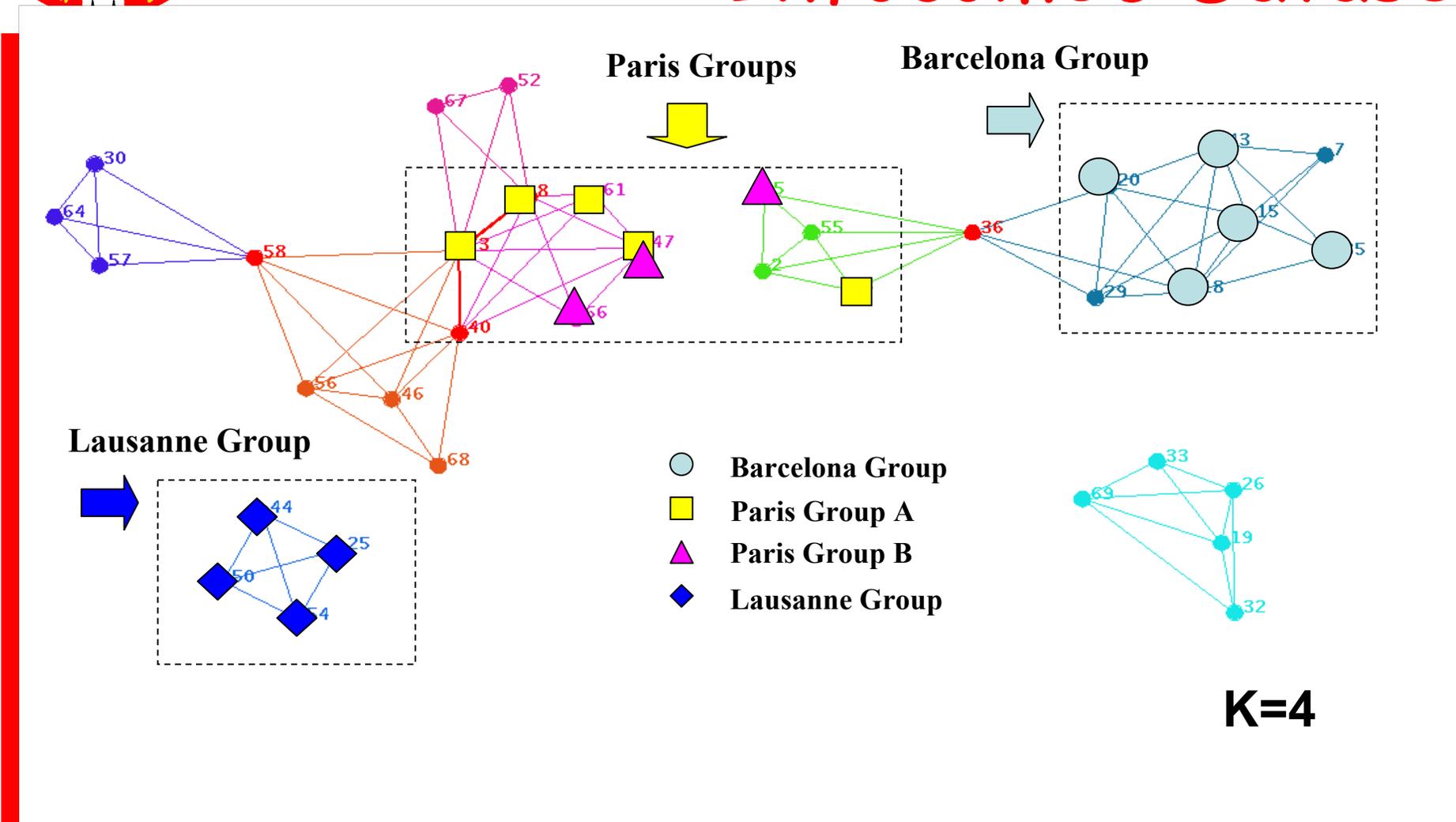


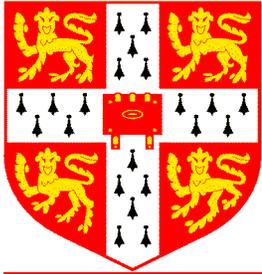
K-clique Communities in Infocom06 Dataset



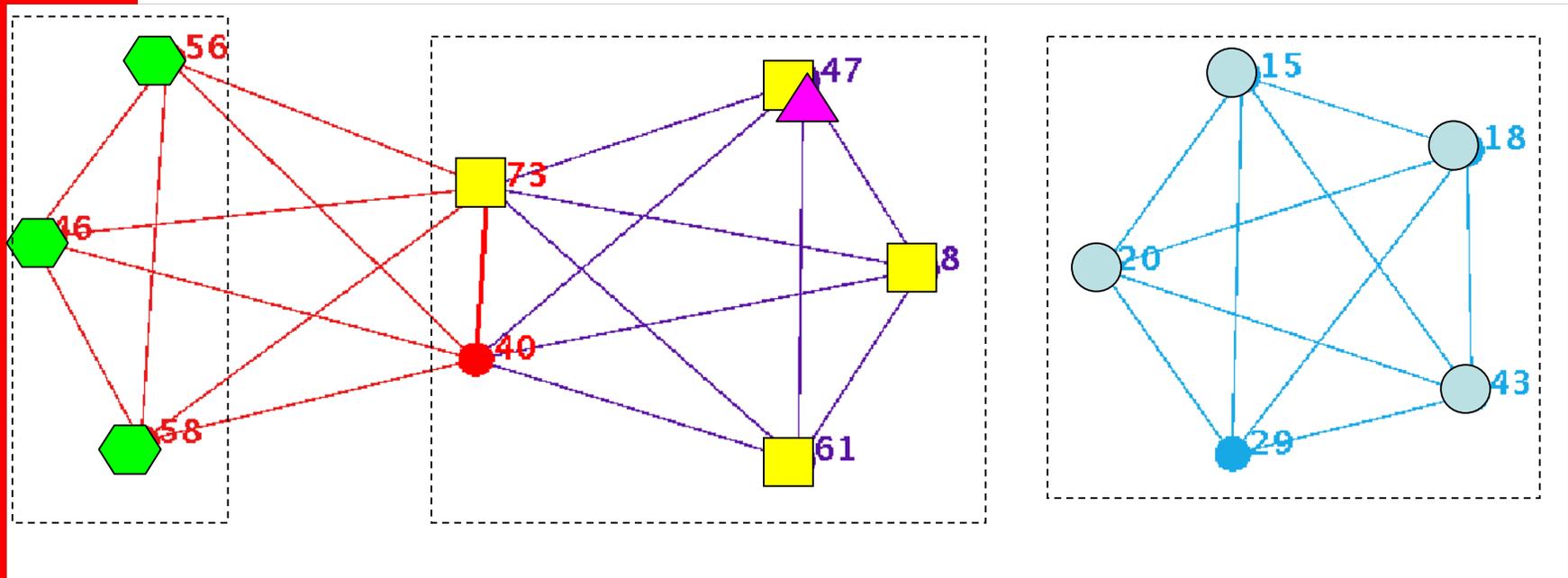


K-clique Communities in Infocom06 Dataset





K-clique Communities in Infocom06 Dataset



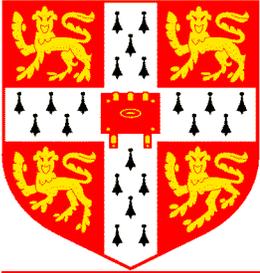
● *Italian*

■ Paris Group A (French)

▲ Paris Group B (French)

○ Barcelona Group (Spanish)

K=5



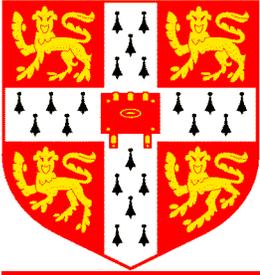
Other Community Detection Methodologies

- Betweenness [Newman04]
- Modularity [Newman06]
- Information theory[Rosvall06]

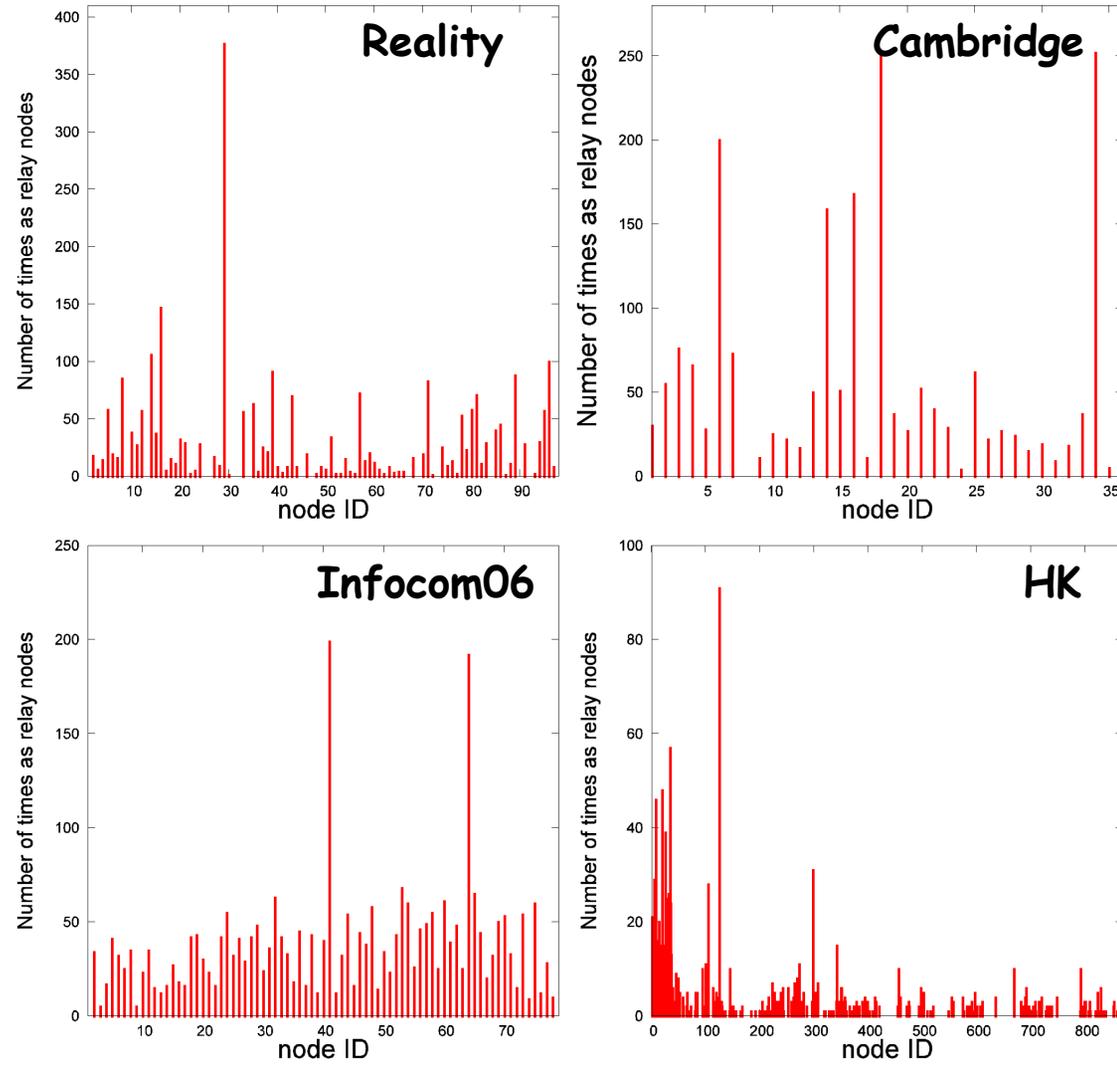
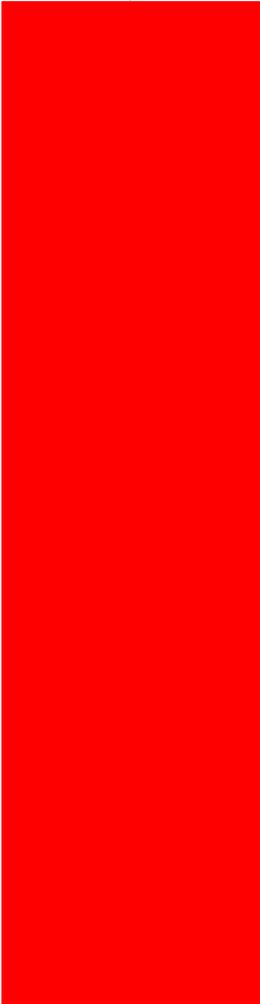


Centrality in Temporal Network

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



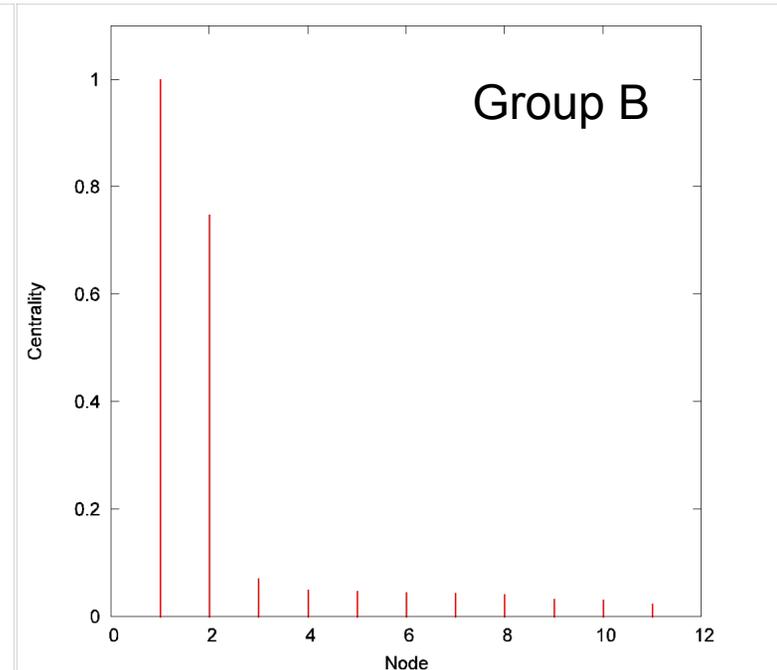
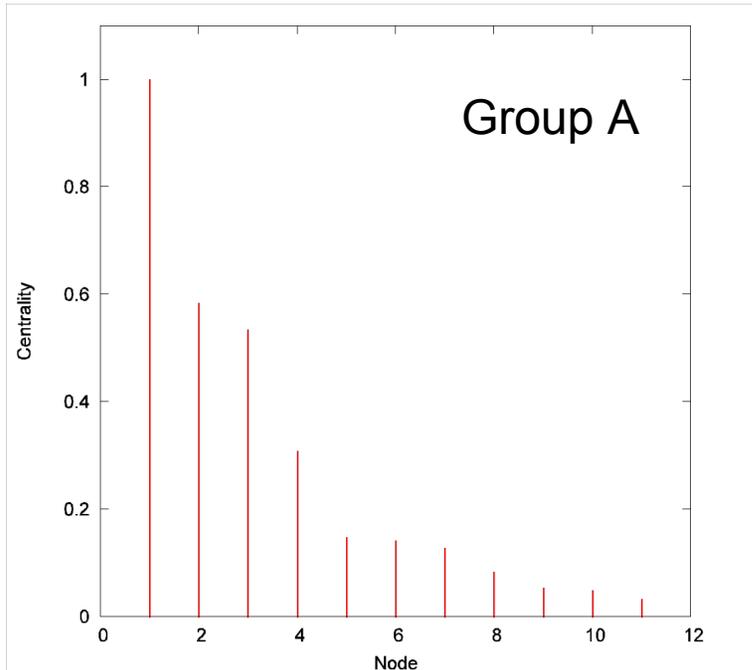
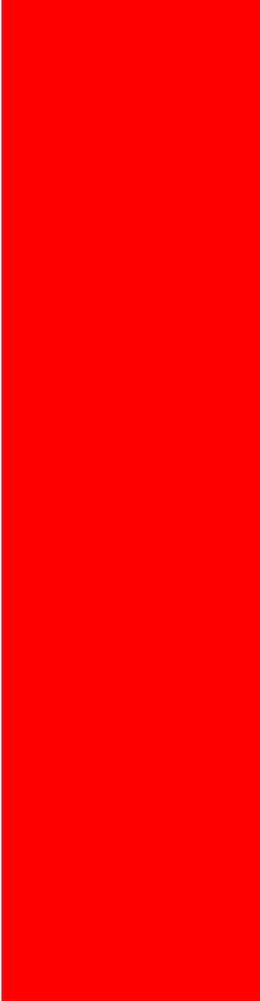
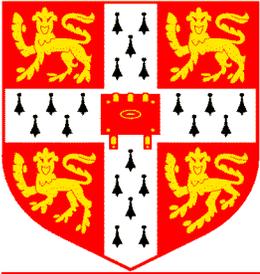
Homogenous Centrality



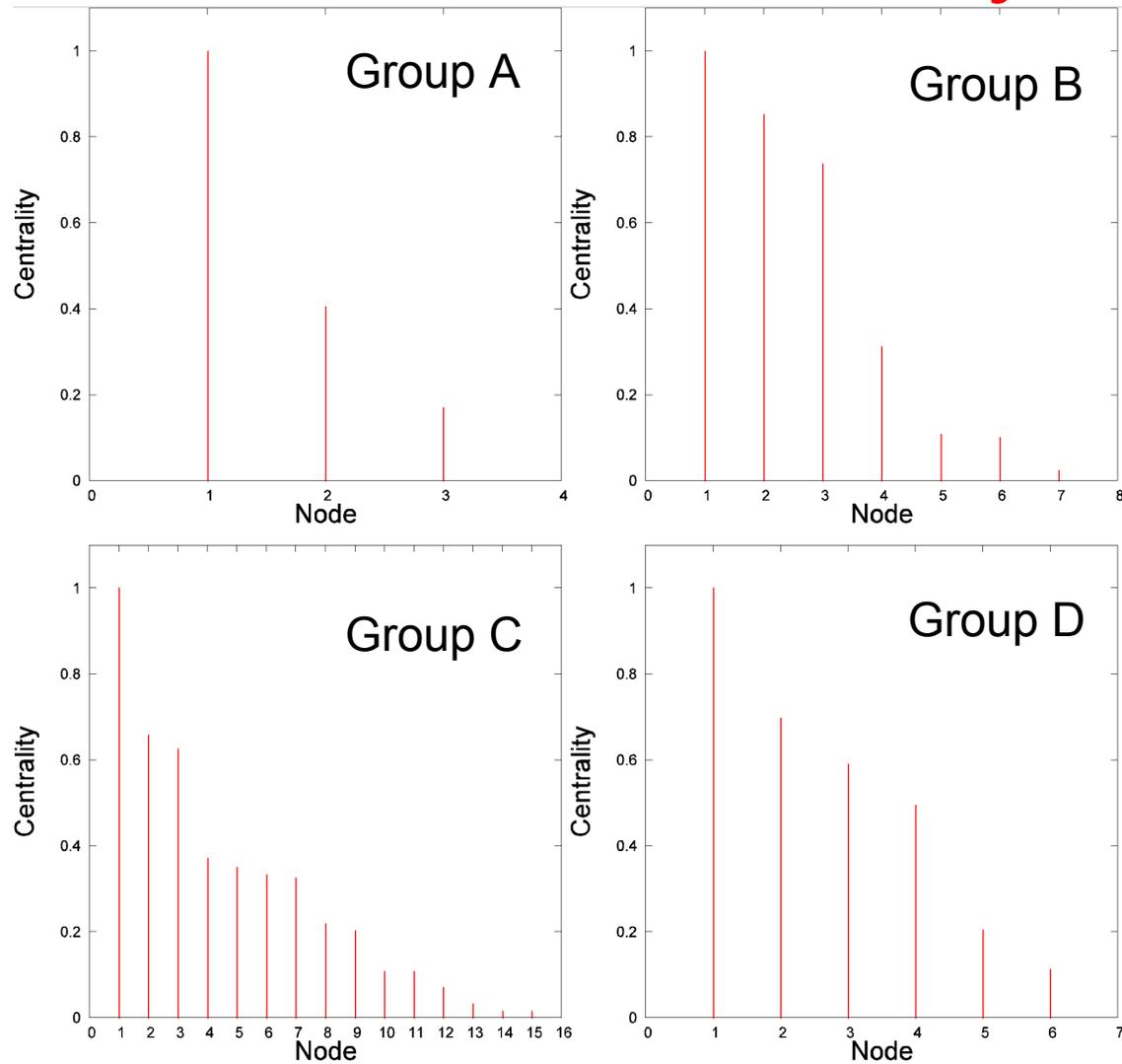
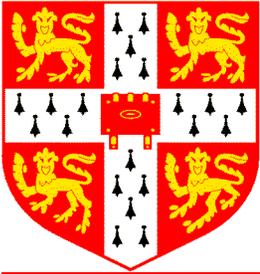
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Within Group Centrality Cambridge Dataset

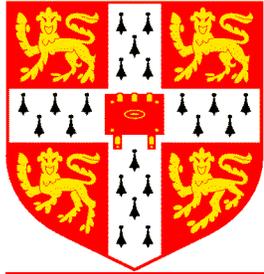


Within Group Centrality Reality Dataset



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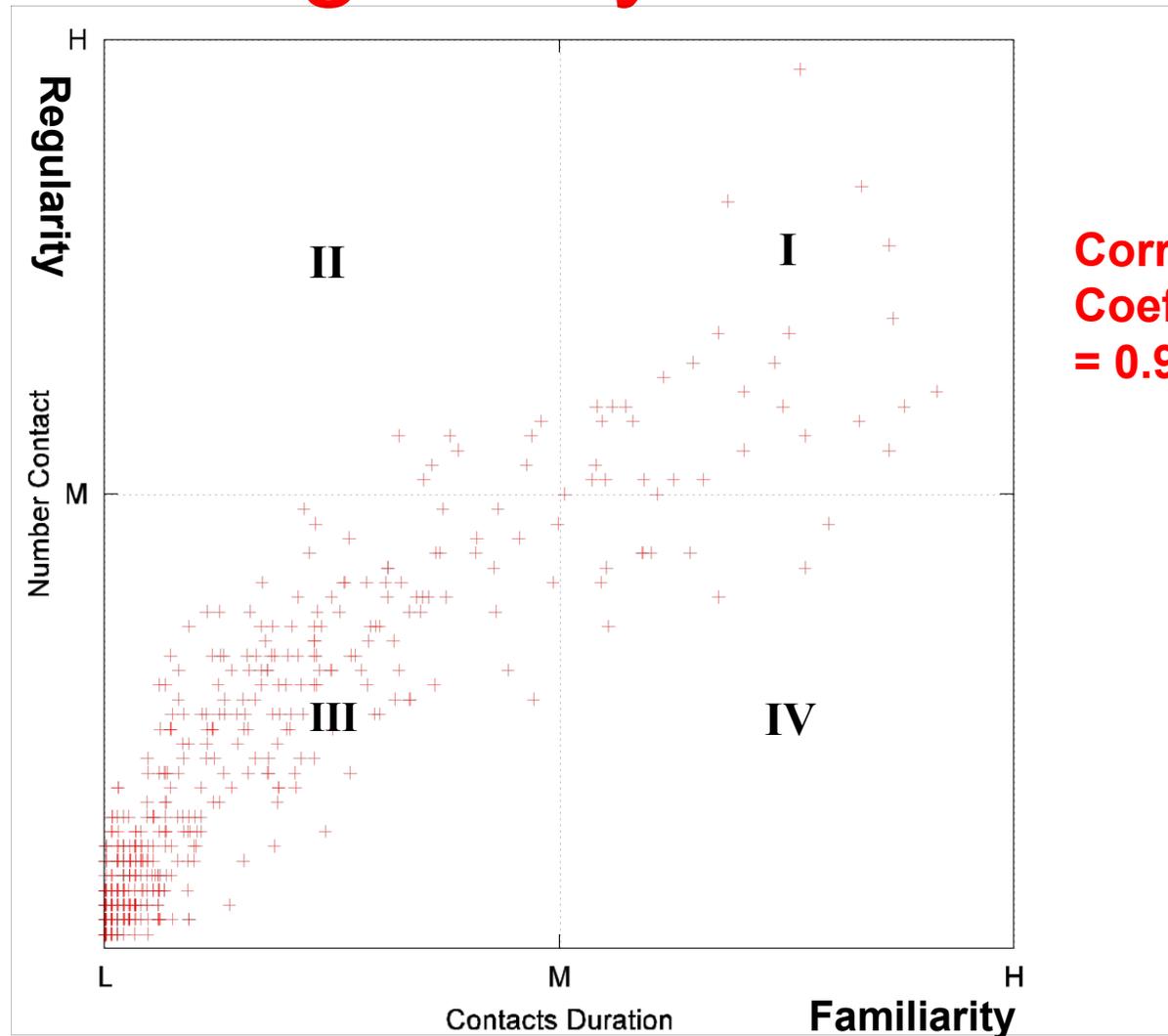


Model Node Centrality

Node centrality should be modelled in different levels of heterogeneity



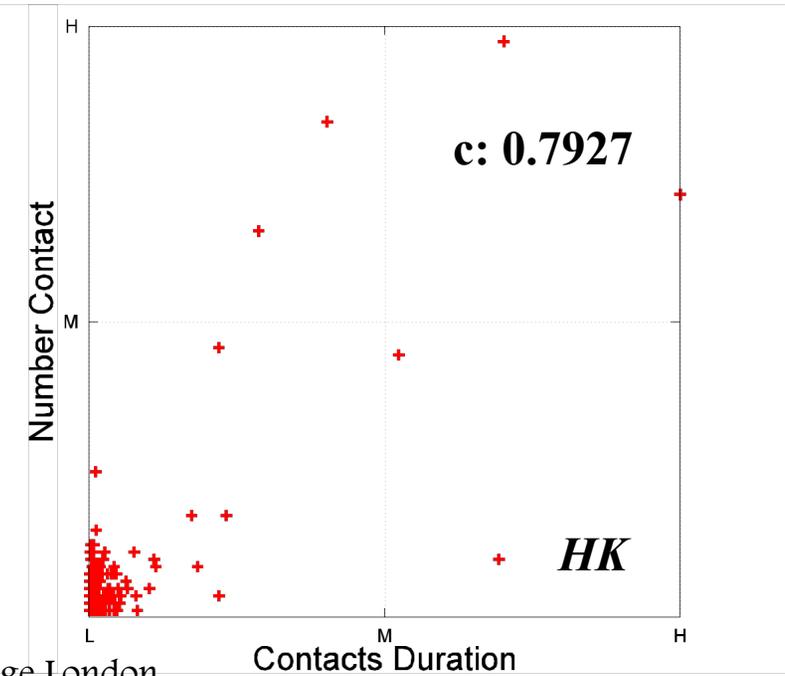
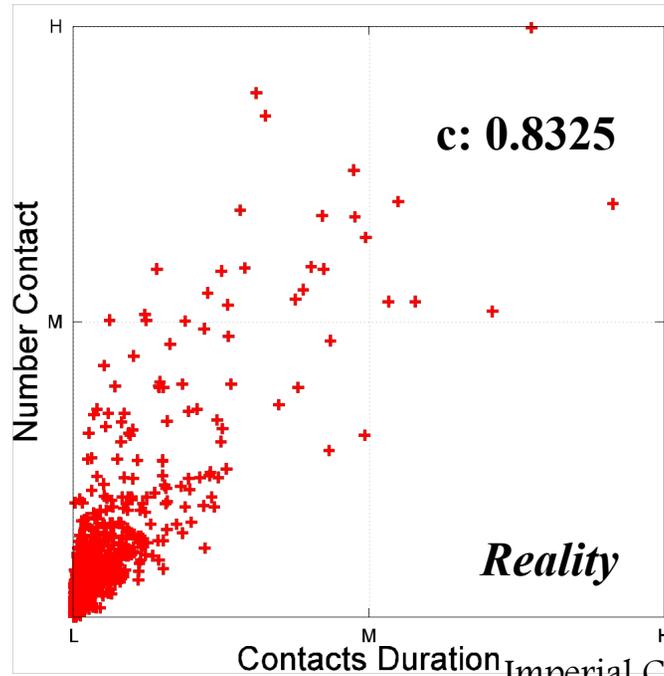
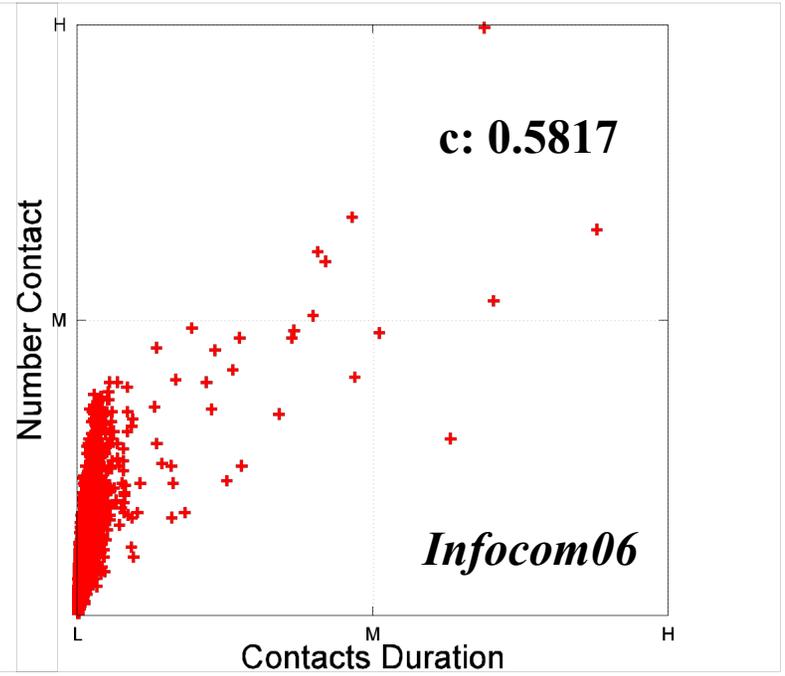
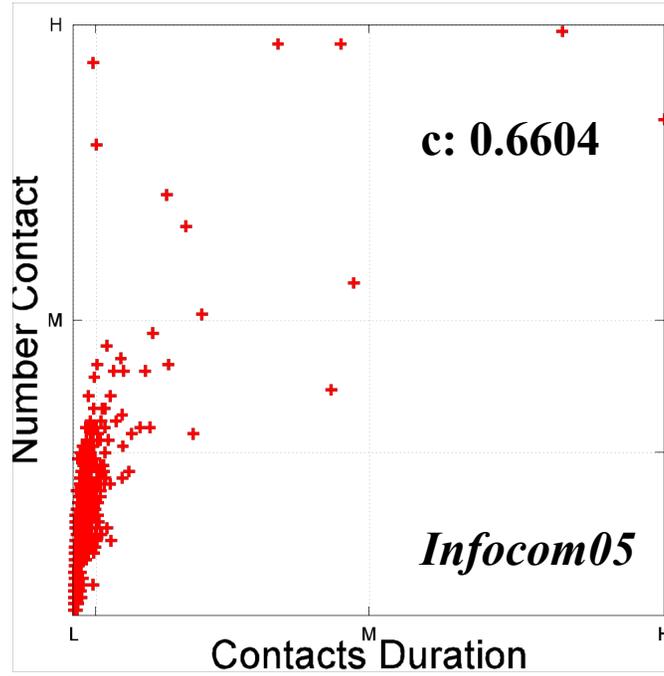
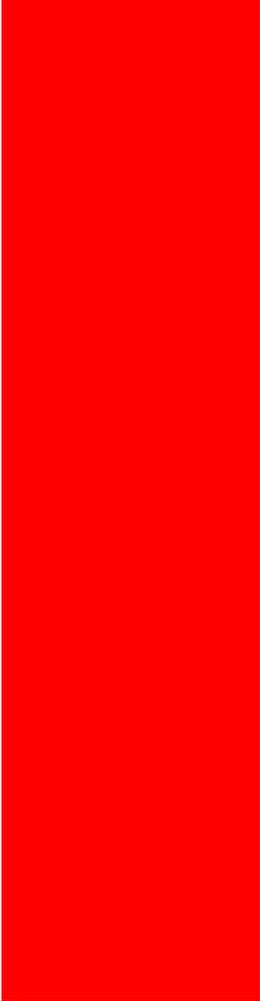
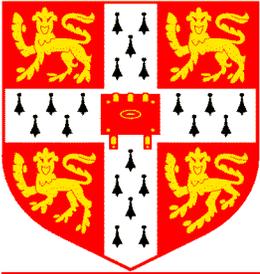
Regularity and Familiarity



I: Community II. Familiar Strangers III. Strangers IV. Friends

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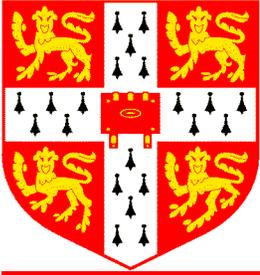
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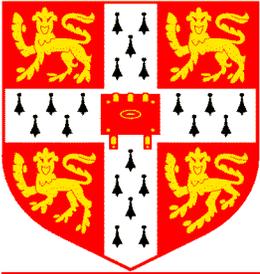
Heterogeneous Forwarding

The second goal of this research is to devise efficient forwarding algorithms for PSNs which take advantage of both a priori and learned knowledge of the structure of human mobility.

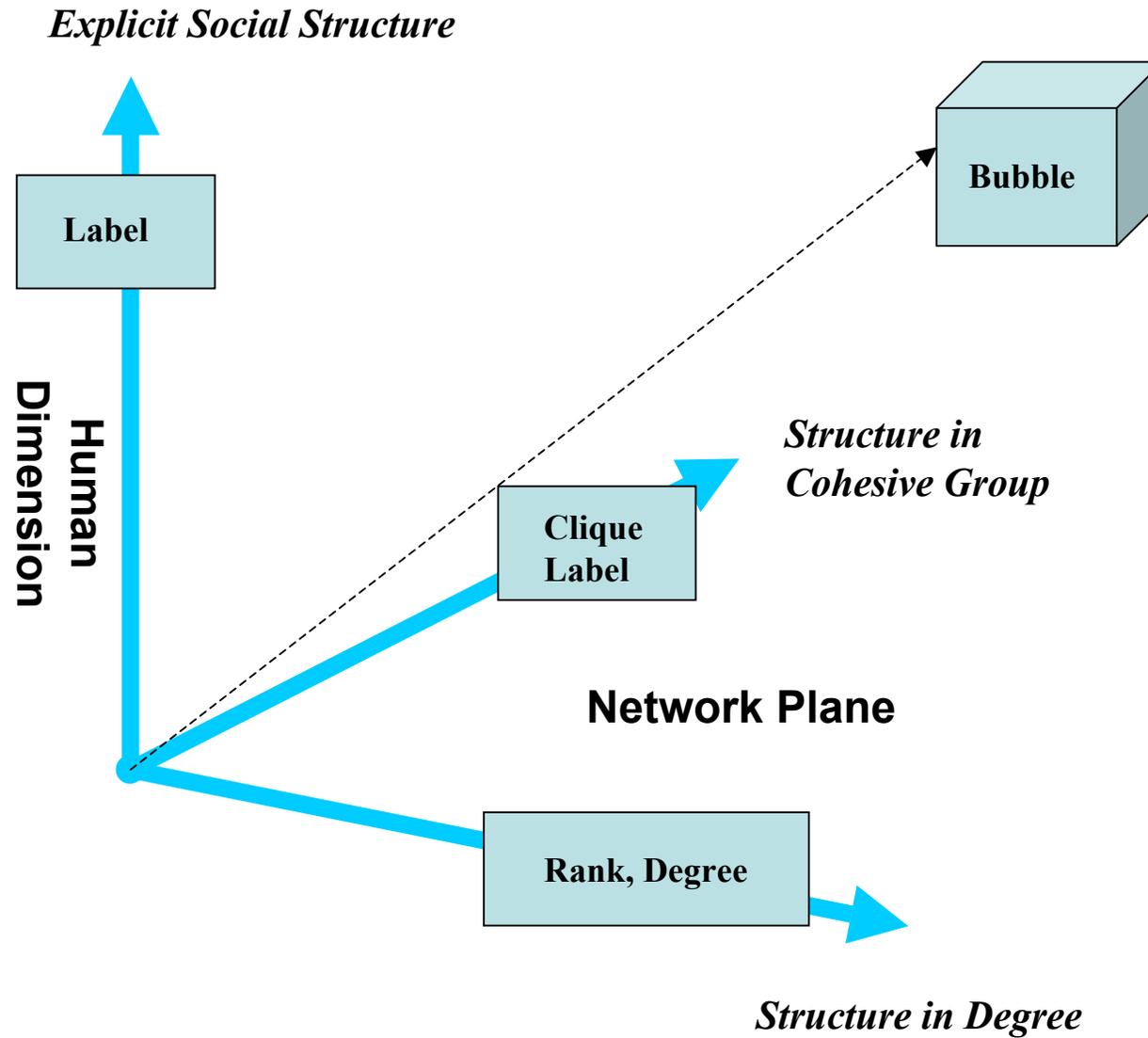


Interaction and Forwarding

- 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)



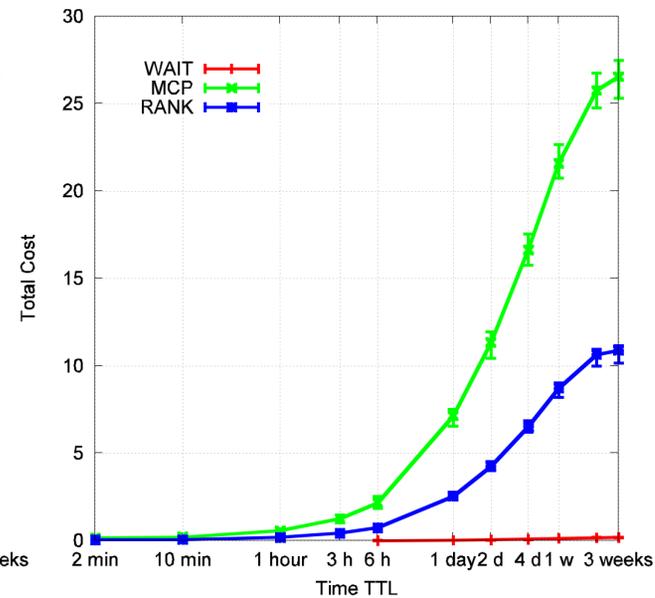
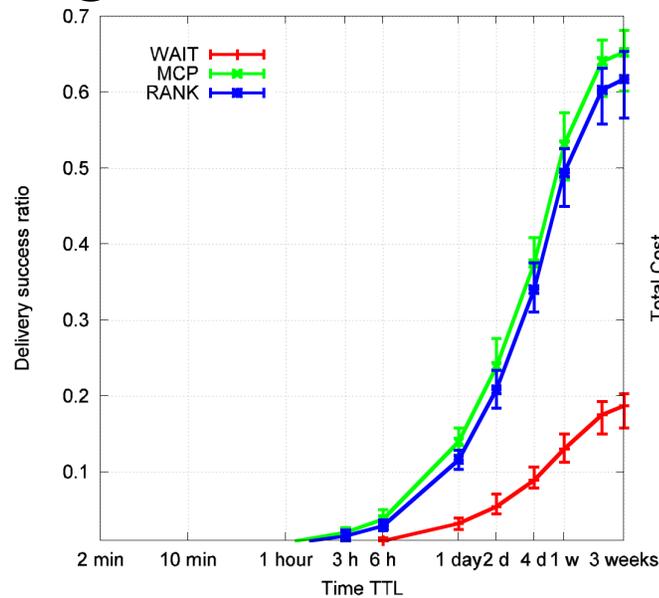
Design Space





Greedy Ranking Algorithm (RANK)

- Use pre-calculated centrality/rank
- Push traffic to nodes have higher rank
- Good performance in small and homogeneous

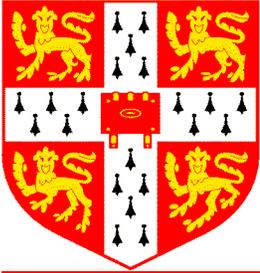




Greedy Ranking Algorithm

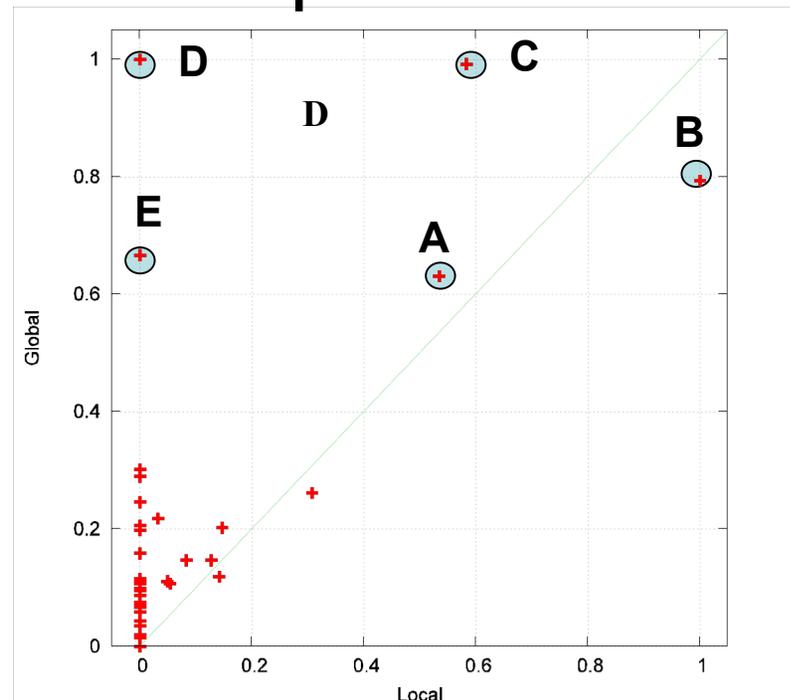
- Hierarchical organization
- Hierarchical paths [Trusina et al]
- High percentage in most dataset

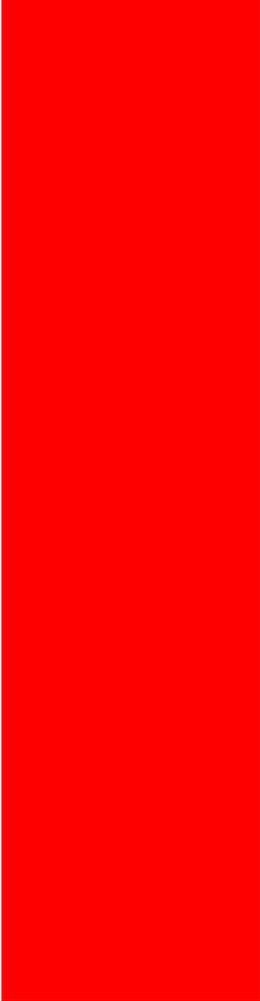
Experimental data set	% hierarchical paths
Rummidge	87.2 (-2.4,+4.3)
Reality	81.9 (-3.1,+3.3)
Infocom05	62.3 (-2.5,+2.5)
Infocom06	69.5 (-4.1,+2.4)
Hong Kong	33.5 (-4.0,+4.0)



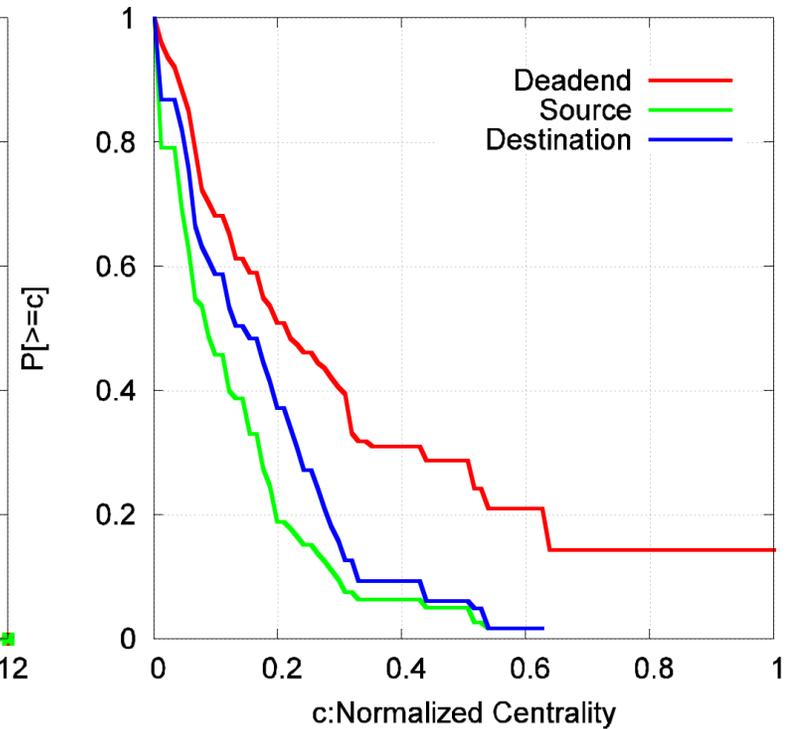
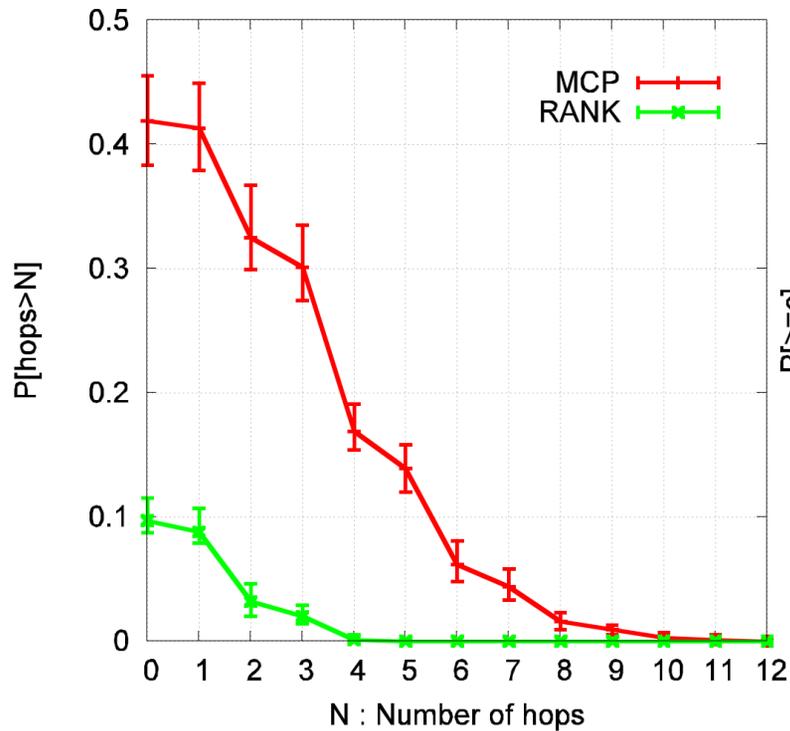
Problem with RANK

- Heterogeneous at multiple levels
- Best node for the whole system may not be best node for a specific community

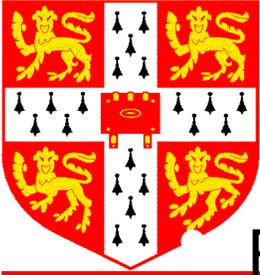




Problem with RANK



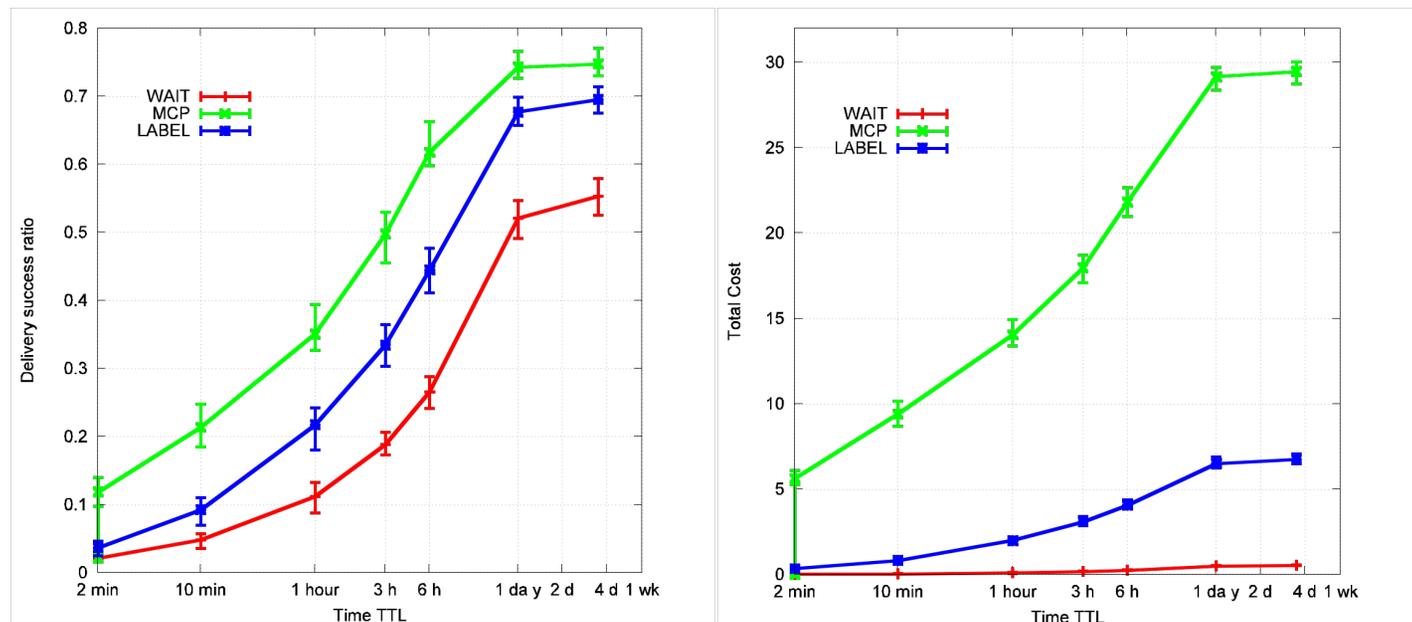
Hop distribution and rank at dead-end for HK dataset



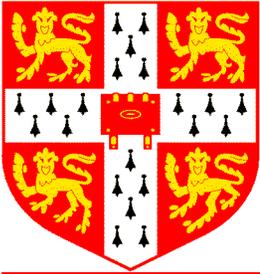
Label Strategy (LABEL)

Priori label, e.g. affiliation

- Correlated interaction
- Forward to nodes have same label as the destination
- Good performance in conference mixing environment

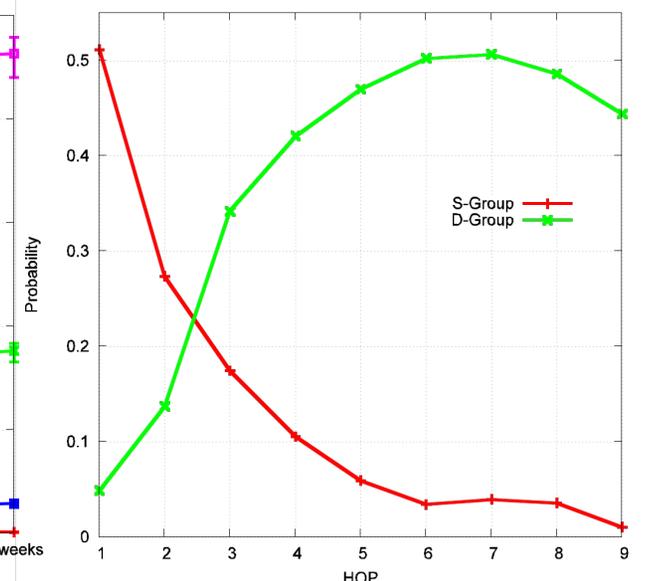
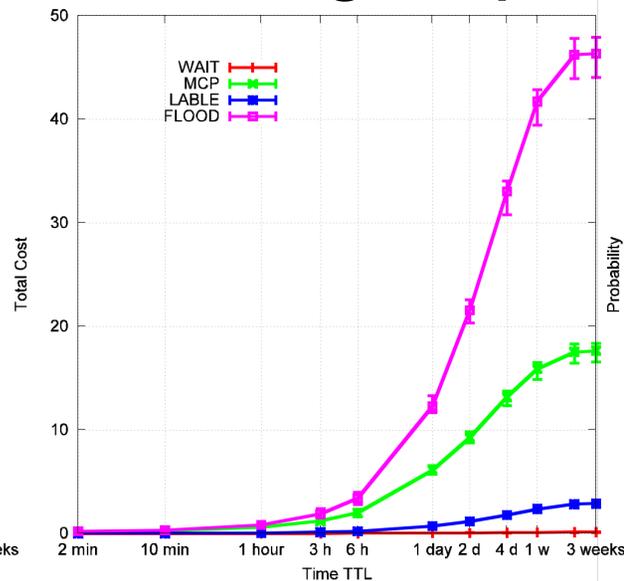
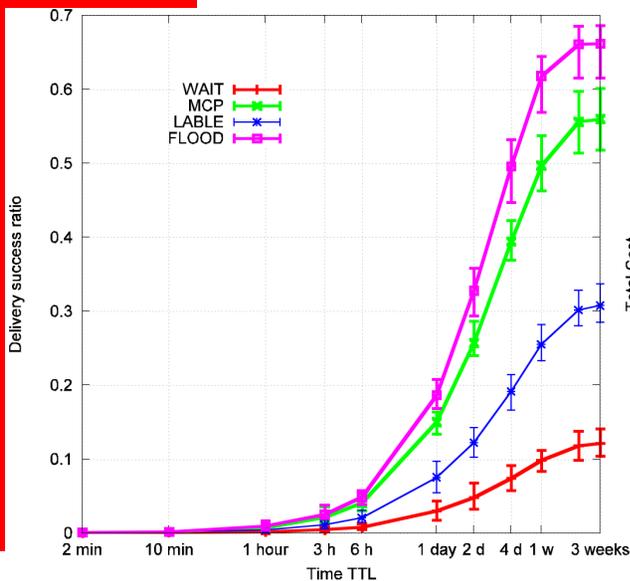


Infocom06



Problem with LABEL

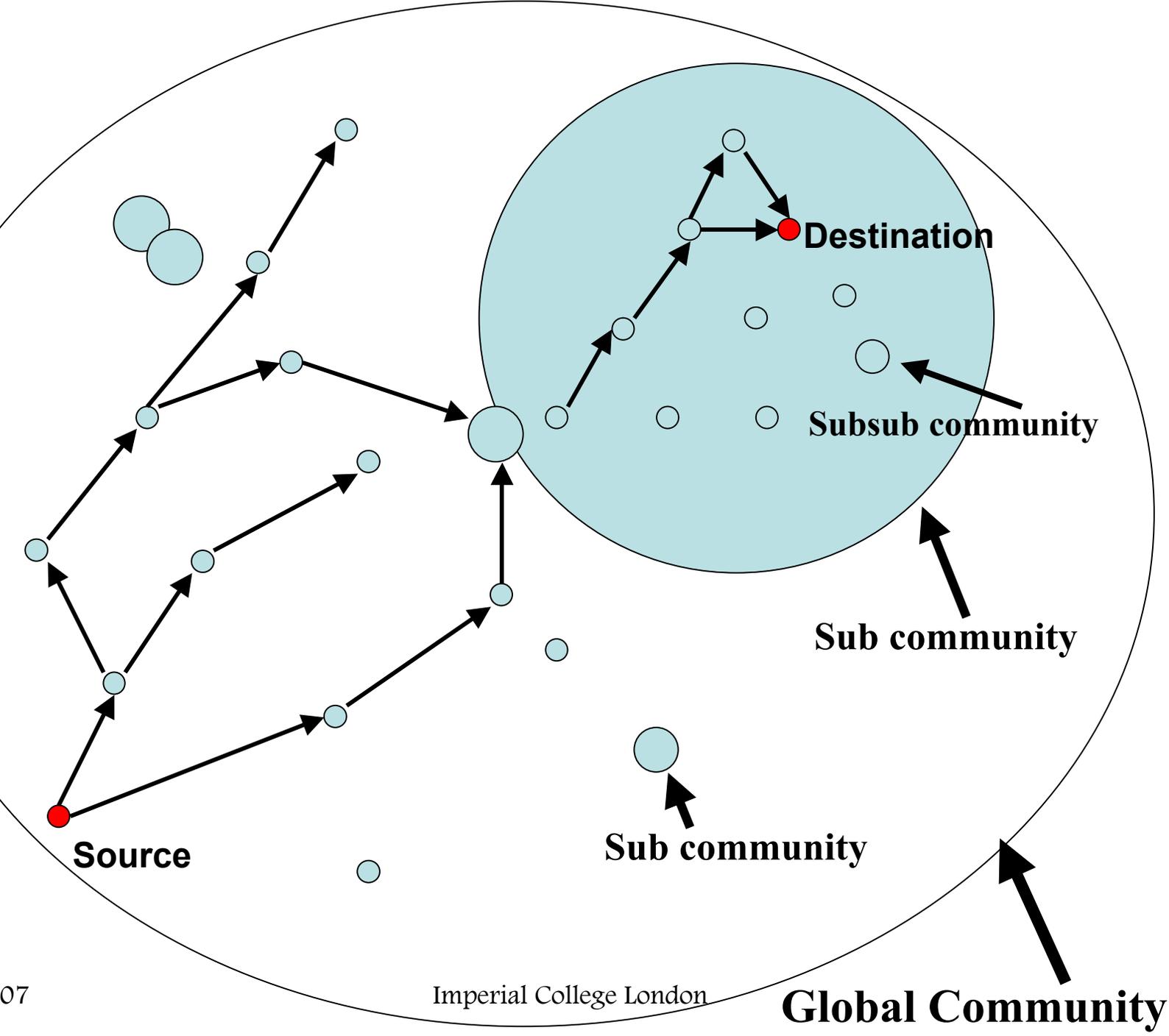
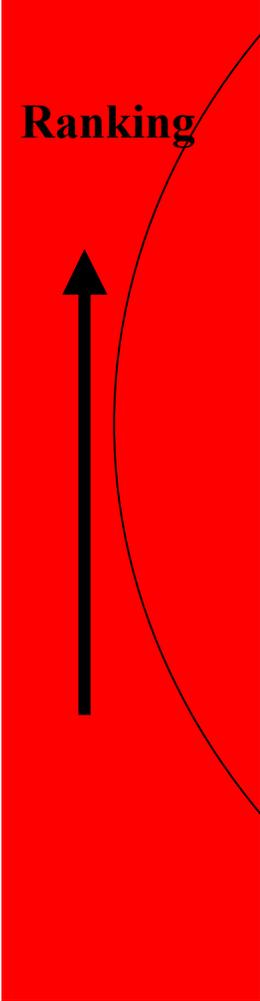
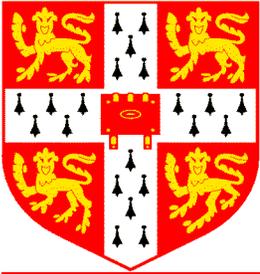
- In a less mixing environment (e.g. Reality)
- A person in one group may not meet members in another group so often
- Wait for destination group not efficient





Centrality meets Community

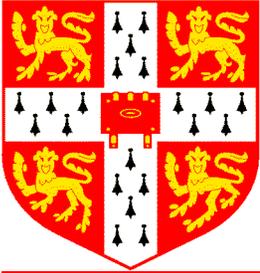
- Population divided into communities
- Node has a global and local ranking
- Global popular node like a postman, or politician in a city
- Local popular node like Christophe Diot in SIGCOMM
- BUBBLE-A
- BUBBLE-B



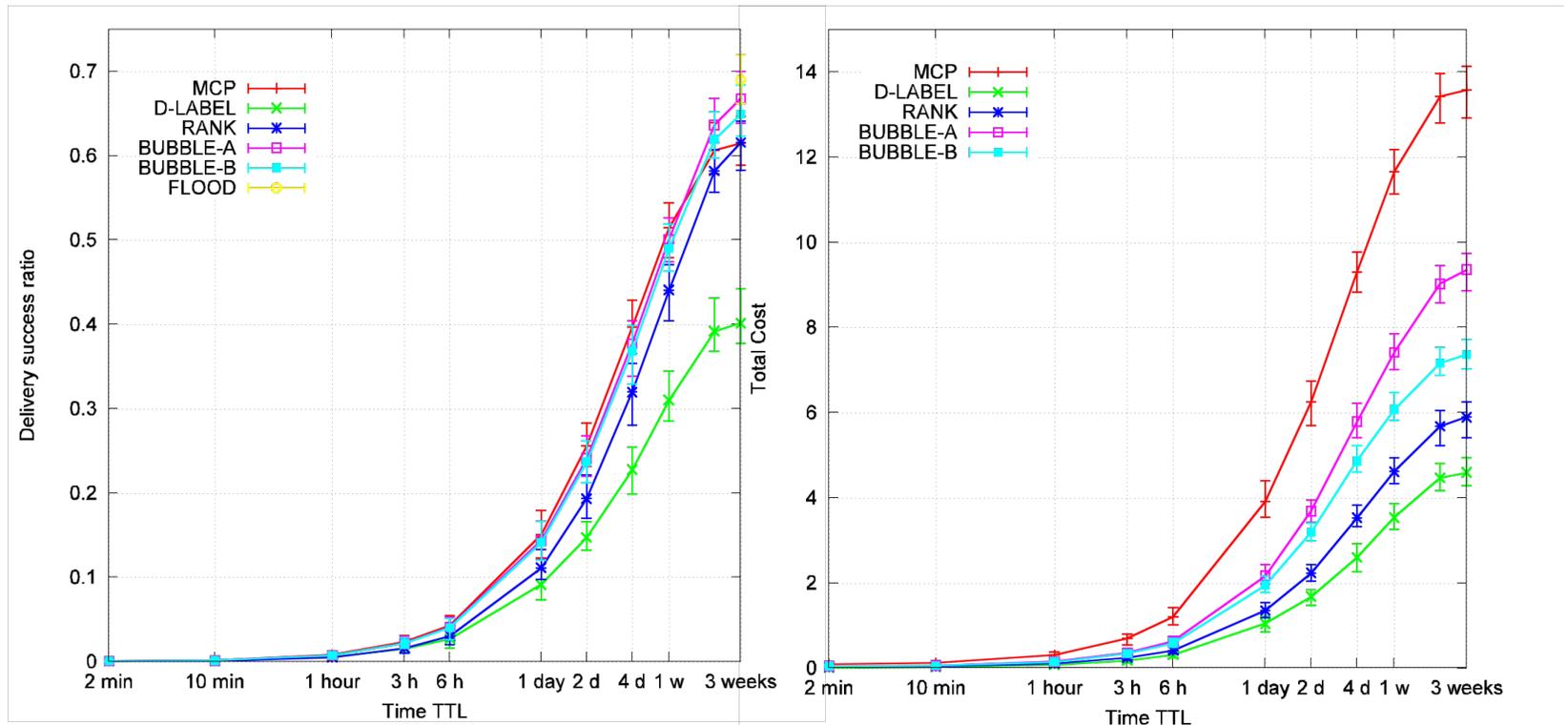
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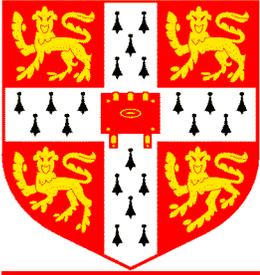
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Global Community



Centrality meets Community

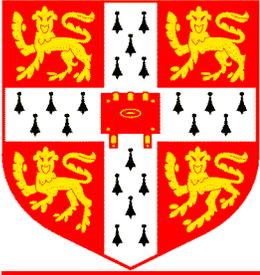




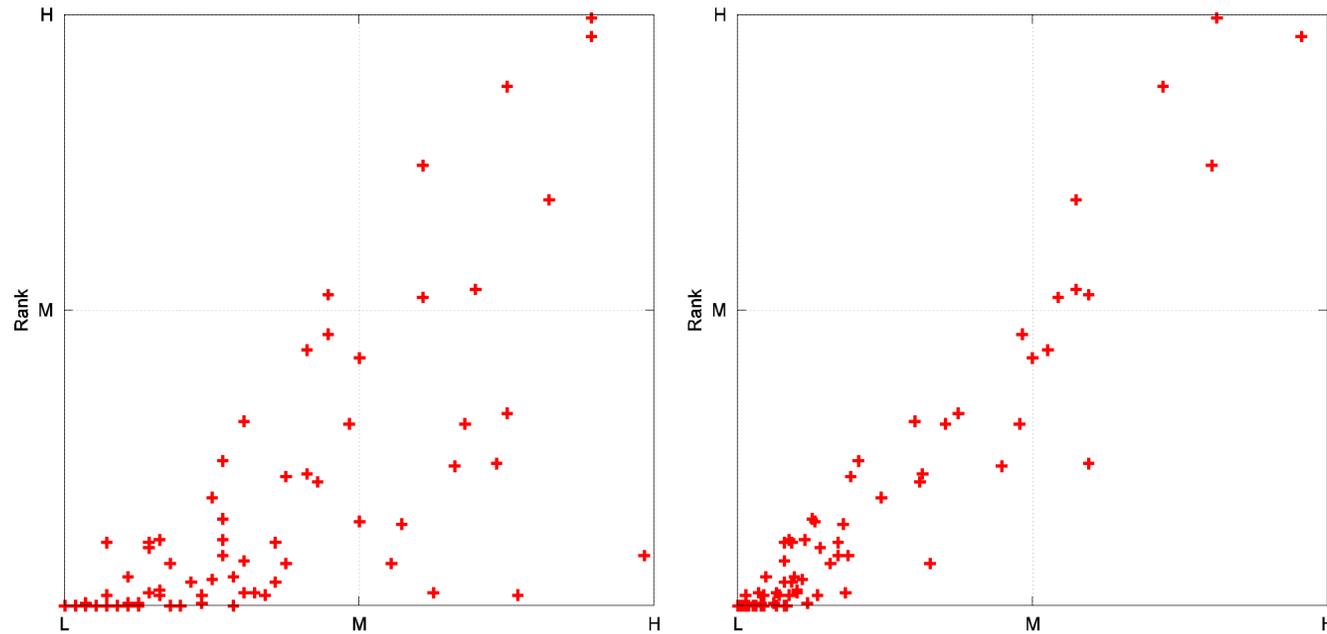
Making Centrality Practical

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

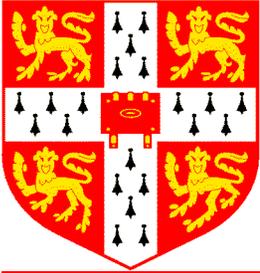
How well does past centrality predict the future?



Approximating Centrality

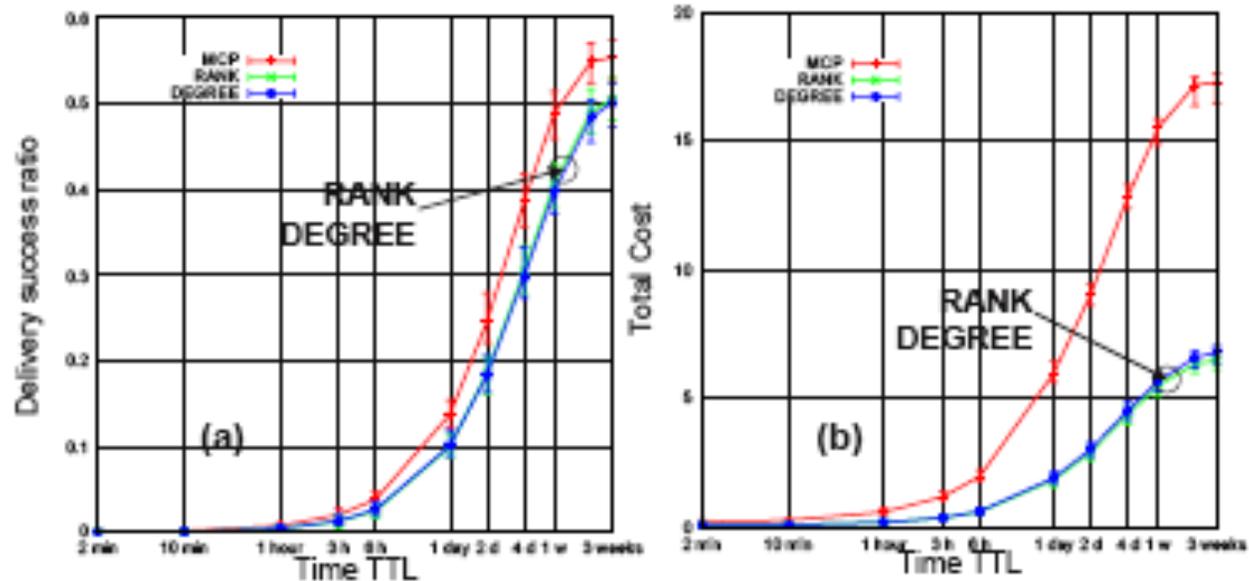


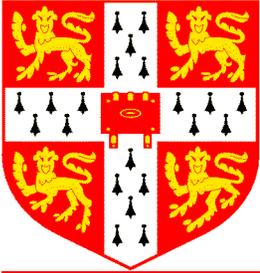
- Total degree, per-6-hour degree
- Correlation coefficients, 0.7401 and 0.9511



Approximating Centrality

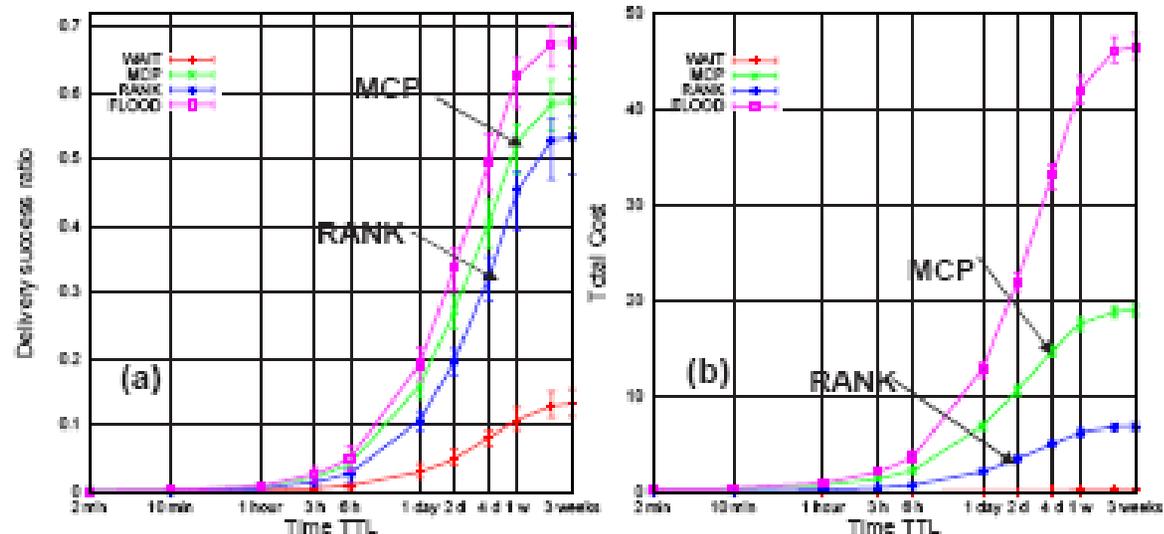
- DEGREE
- S-Window
- A-Window (Exponential Smoothing)





Predictability of Human Mobility

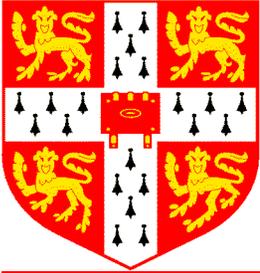
- Three sessions of Reality dataset
- Two sessions using the ranking calculated from the first session
- Almost same performance





Conclusion and Future Woks

- Forwarding using priori label or social structure inferred through observation
- Distributed k-clique building through gossiping
- Why per-6-hour?
- Weighted version of k-clique detection
- Third generation modeling



Jon.Crowcroft@cl.cam.ac.uk

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