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# Social and Technological Network Analysis

## Lecture 11: Spatial and Social Network Analysis

Dr. Salvatore Scellato  
Google



# In This Lecture

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- In this lecture we will study spatial networks and geo-social networks through examples from our work.

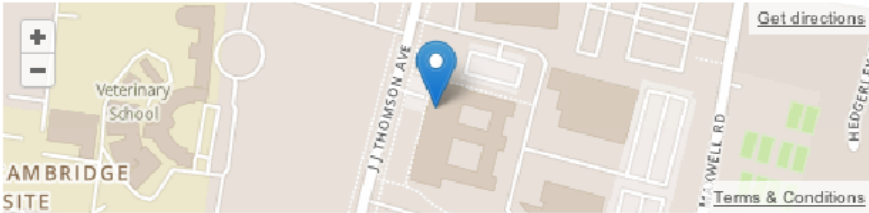
# Places and Friends



foursquare  Activity Explore Lists Cecilia

## Computer Lab, University of Cambridge

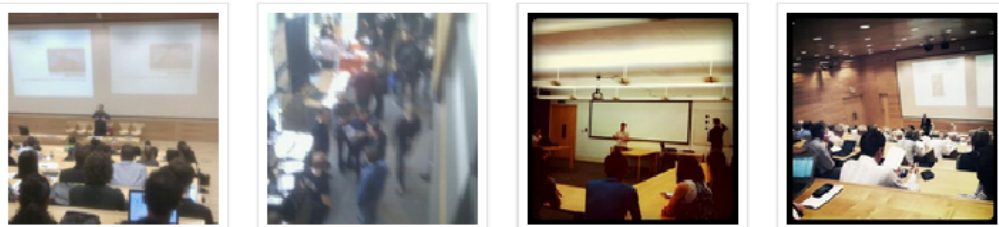
15 JJ Thompson Avenue, Cambridge, UK CB3 0FD  
University (Edit)



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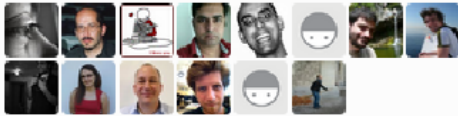


SAVE  DONE

YOUR CHECK-INS	TOTAL PEOPLE	TOTAL CHECK-INS
57	120	1,197

**Mayor: Chloë**  
44 check-ins in last 60 days 

**14 friends have been here**



**Similar places**  
[Imperial College](#), [Queens' College](#), [Sidney Sussex College](#), [Newnham College](#), [Fitzwilliam College](#)

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# Geo-social Network Analysis can lead to insights into social behaviour

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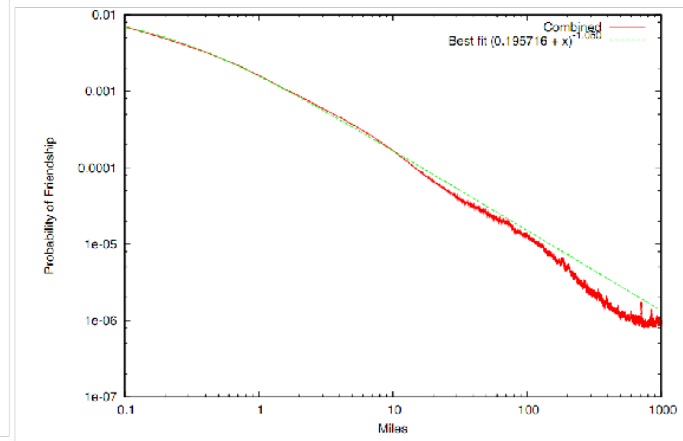
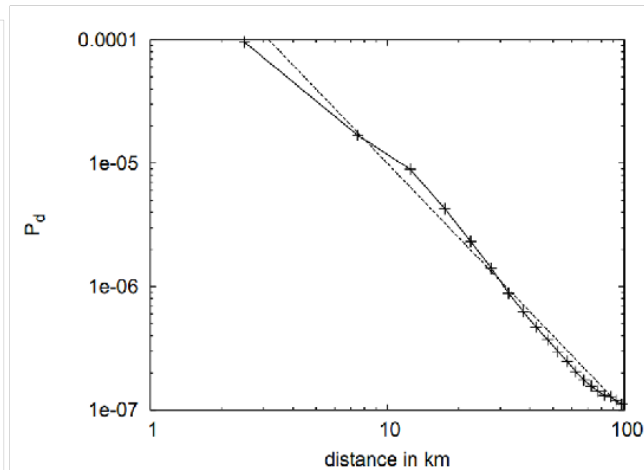
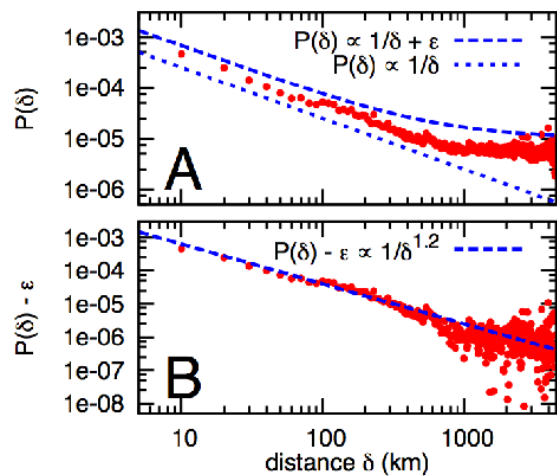
# Effect of Distance on Social Connections



LiveJournal (2005)

Mobile phones (2008)

Facebook (2010)



$$P(d) \propto d^{-1} + \epsilon$$

$$P(d) \propto d^{-2}$$

$$P(d) \propto d^{-1}$$



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# Effect of geography over social link formation

# What do we see in Geo-social Networks?

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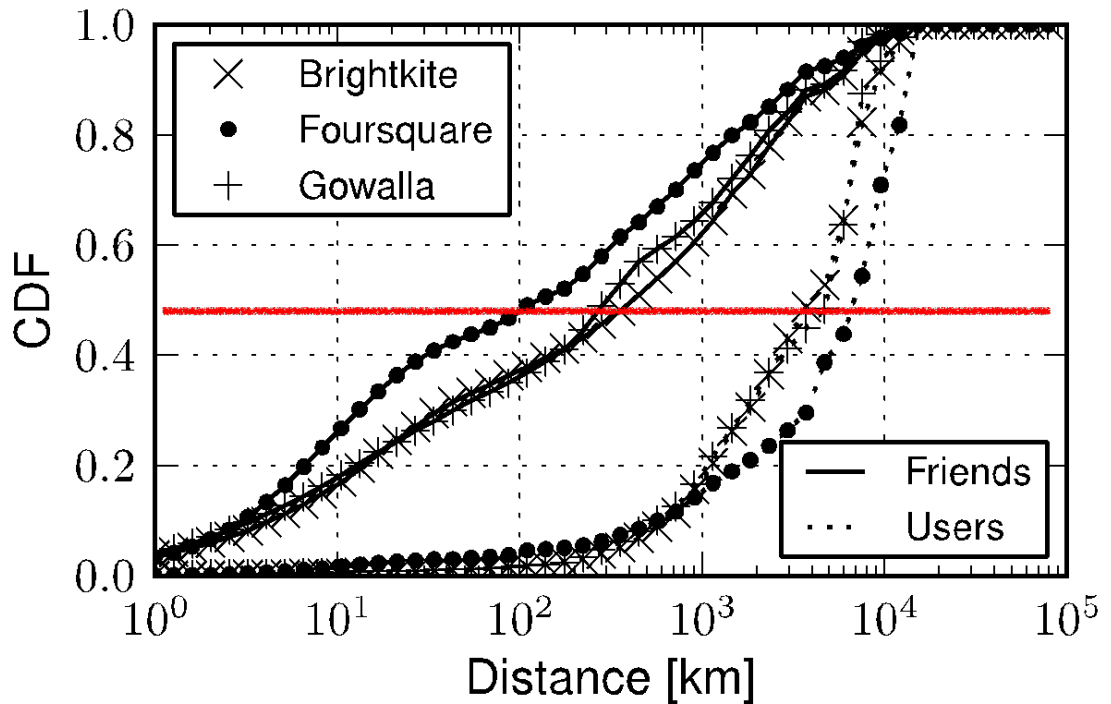


- We have acquired data about the socio-spatial network of **3 real-world location-based services**
- We design **two randomized models** of a socio-spatial network to better understand which factors shape the real networks.
- We study how individual users create their **social links** and their **social triangles** over space.

# Distance between Friends

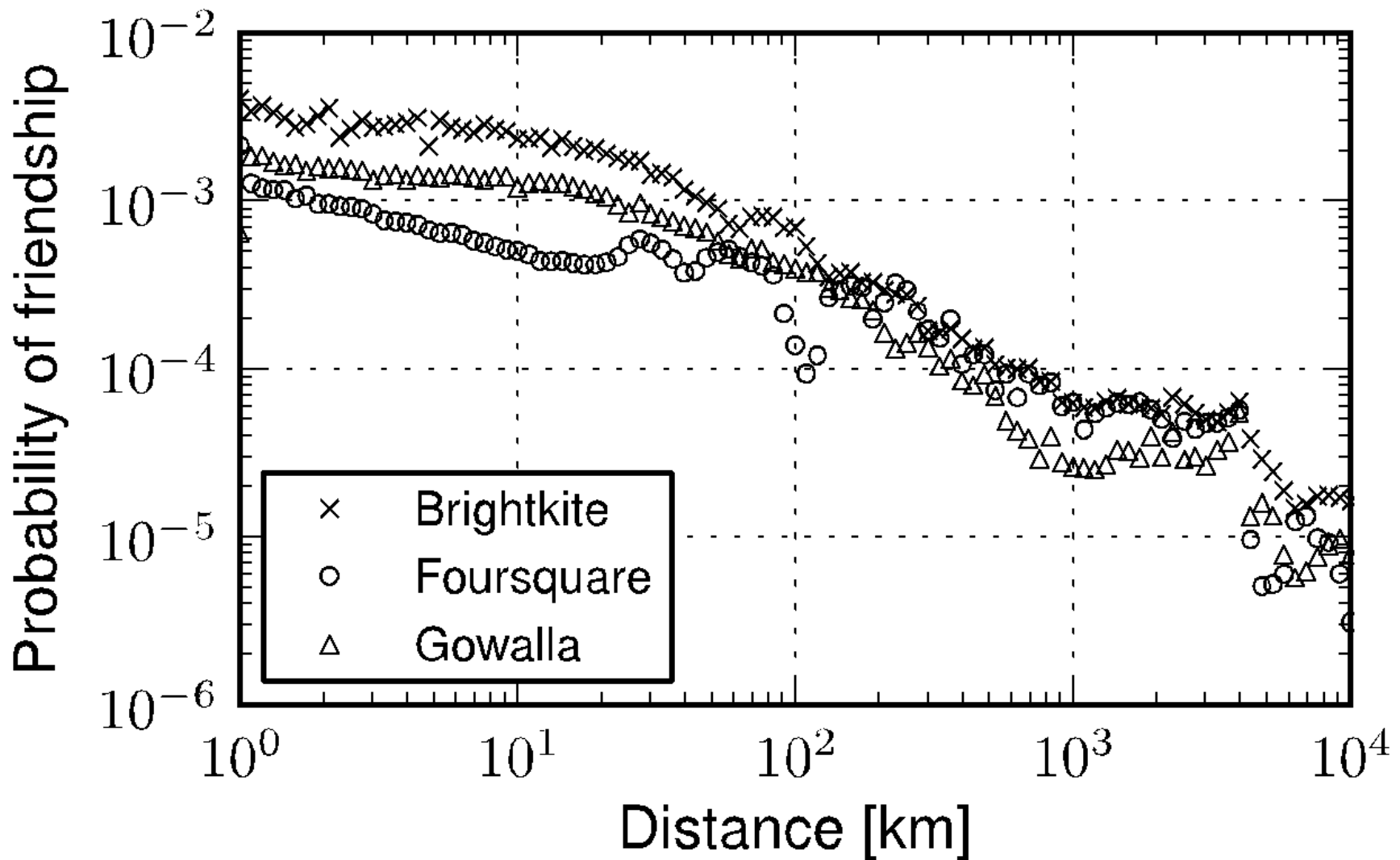
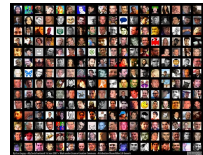


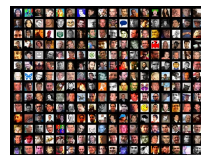
**Friends tend to be much closer than random users:** about 50% of social links span less than 100 km, while about 50% of users are more than 4,000 km apart.





# Probability of Friendship vs Distance





# Network Randomization

	Description	Social properties	Spatial properties
<b>Original data</b>	No modification.	✓	✓
<b>Geo model</b>	Fix node locations and reassign all links according to probability $P(d)$ .	✗	✓
<b>Social model</b>	Fix links and shuffle all node locations.	✓	✗

# Users have heterogeneous friend distances

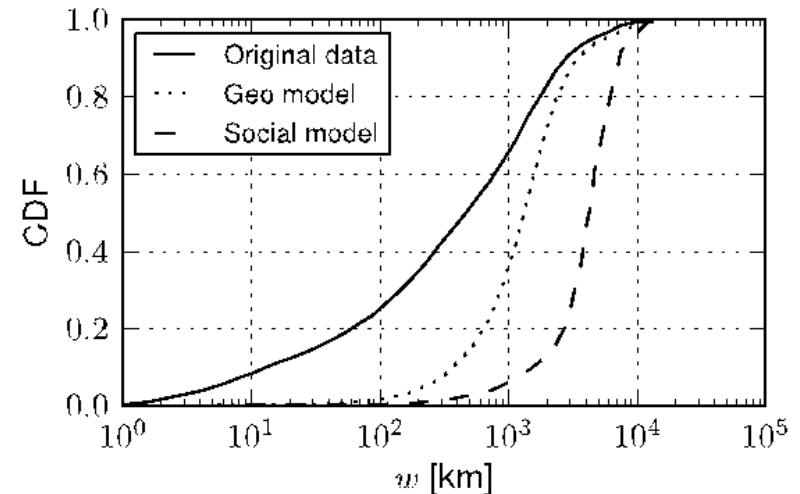
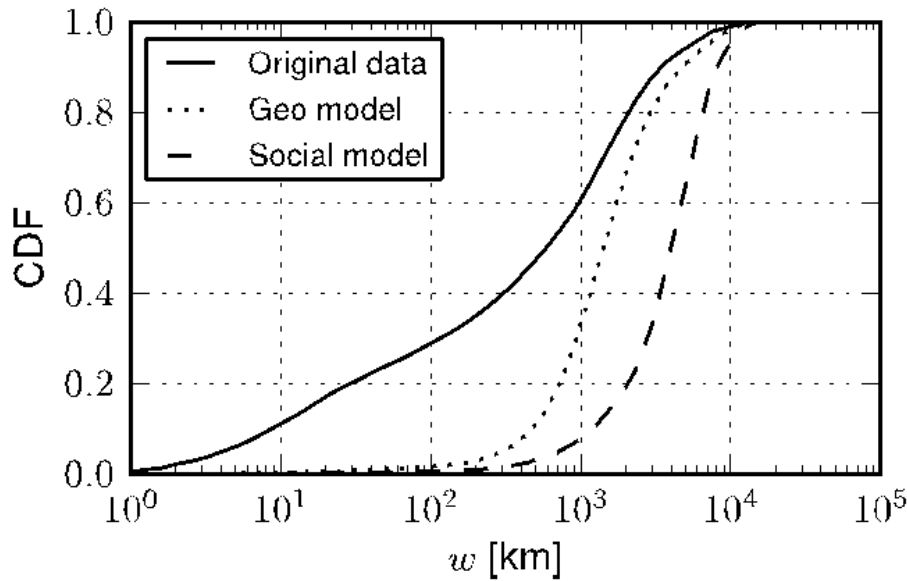
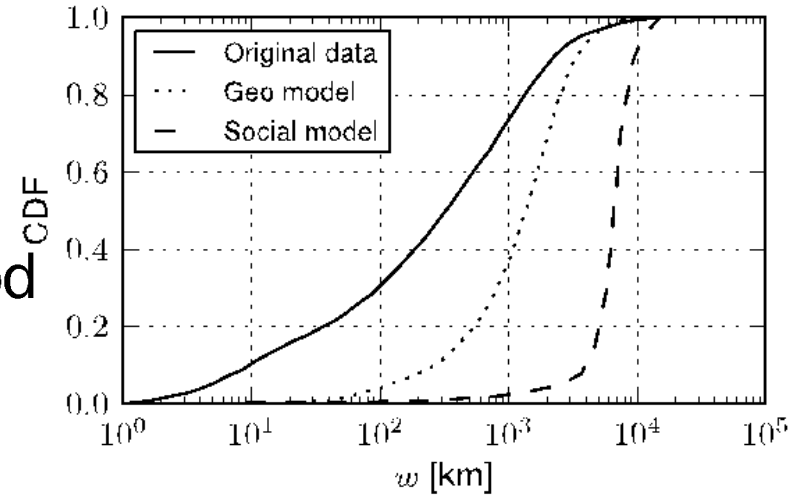


$$w_i = \frac{1}{k_i} \sum_{j \in \Gamma_i} l_{ij}$$

Node degree

Node neighborhood

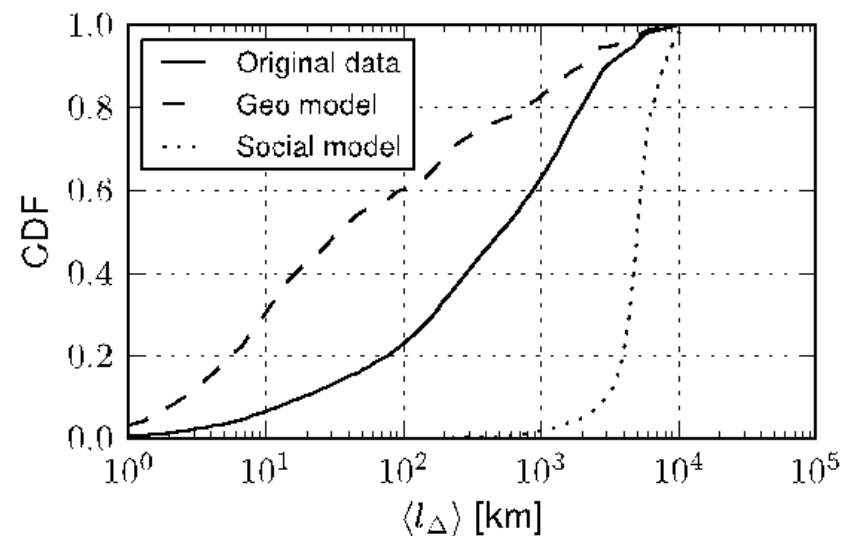
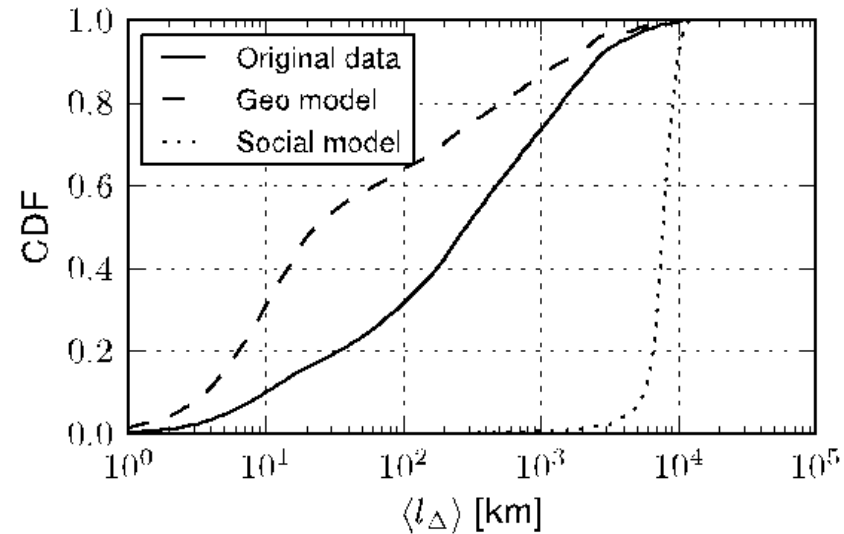
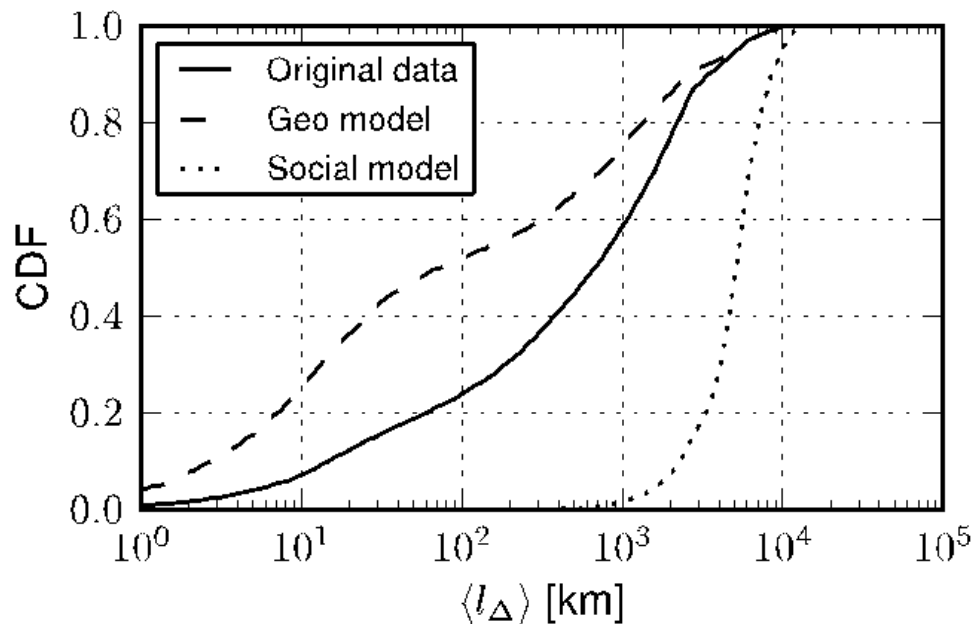
Link length



# Average triangle geographic length



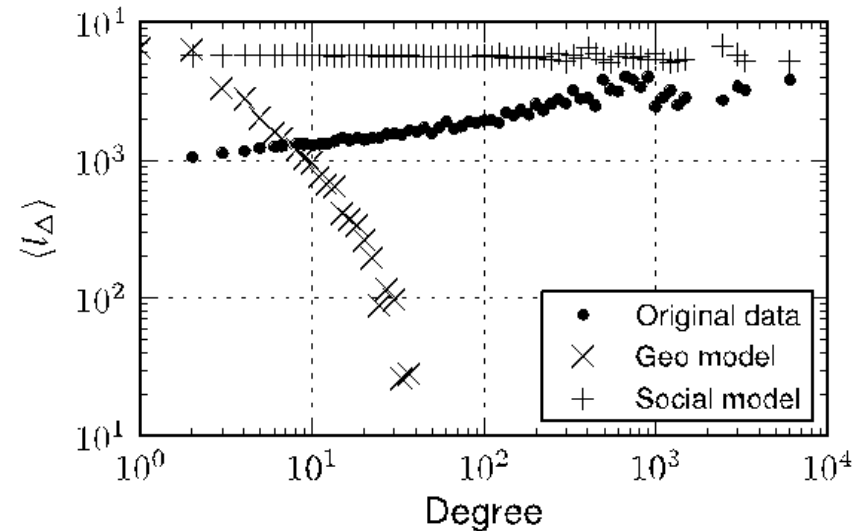
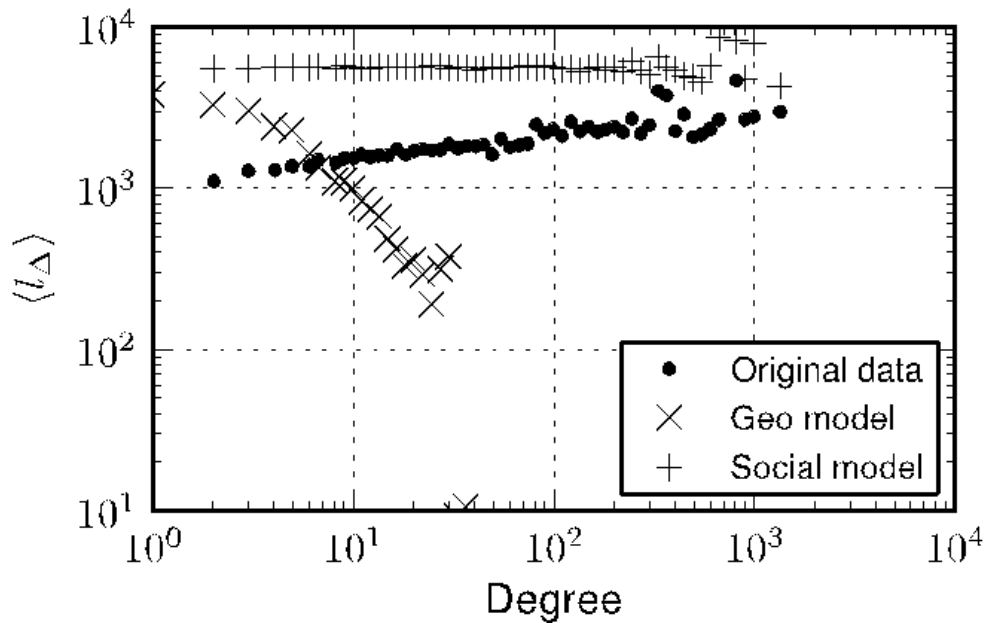
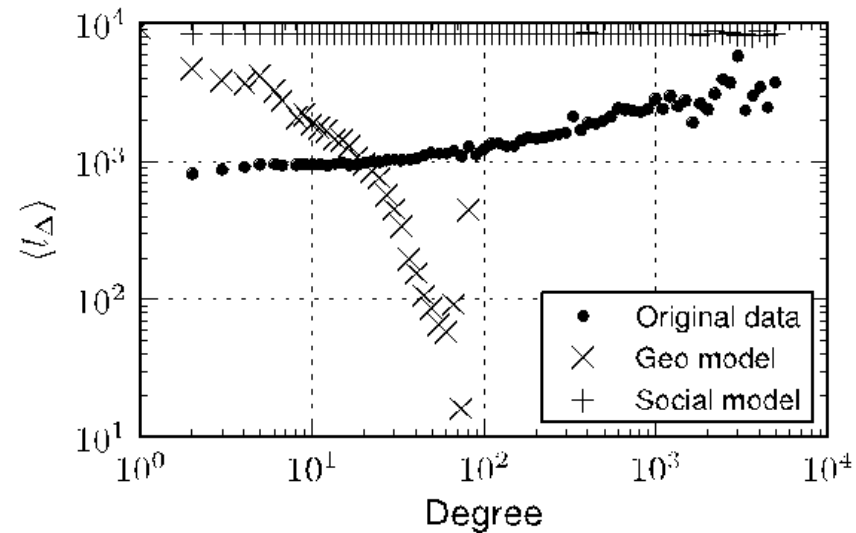
$\langle l_{\Delta} \rangle$  is the average length of the triangles of a user



# Correlation triangle length/degree



Correlation with degree: users with many friends belong to bigger triangles



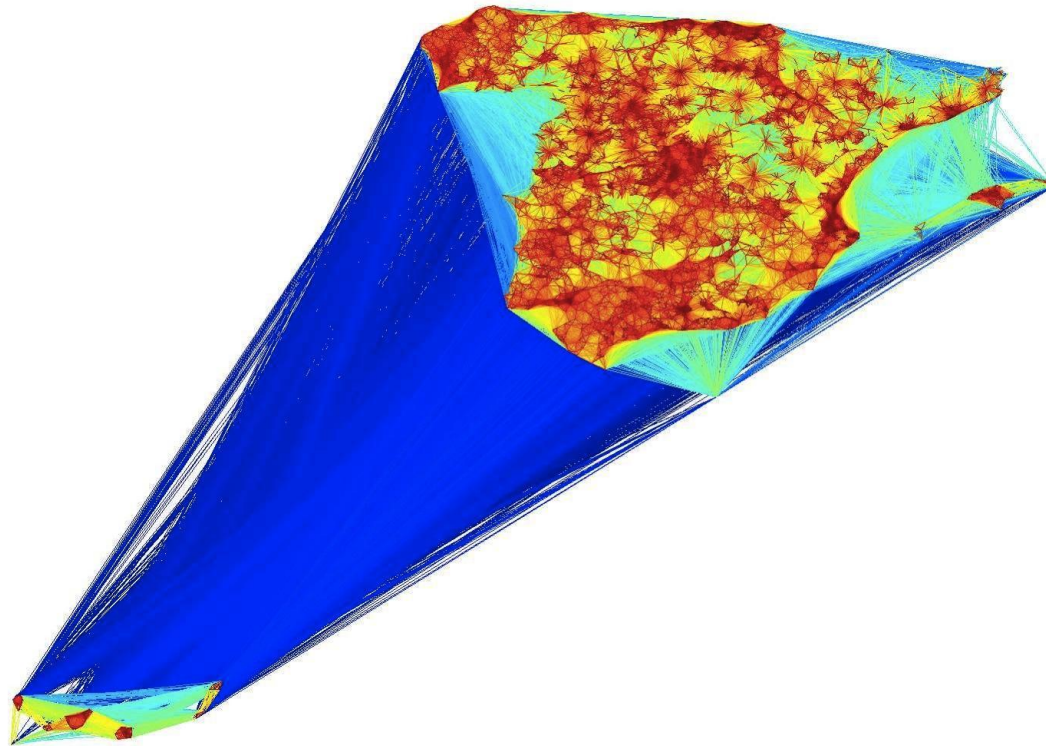


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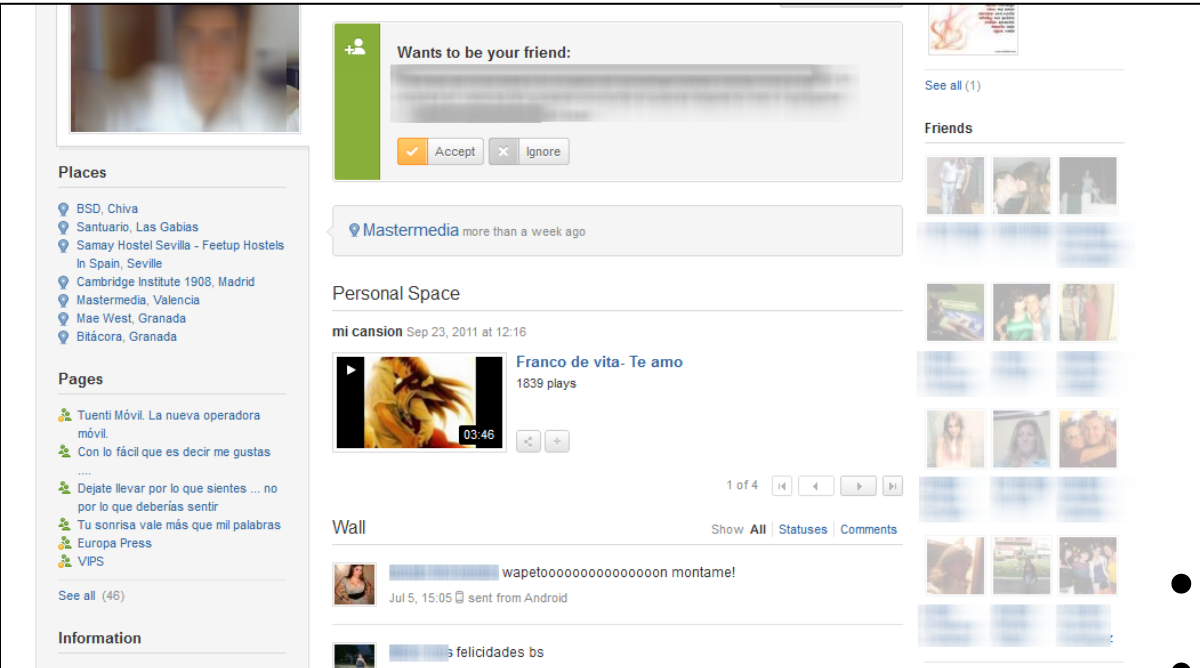
# Effect of geography over interaction

# How does geography affect interaction?

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# Tuenti



- Tuenti dataset (Nov 11)
- 9.88 million registered users
- ~1 174 million friendship links
- 500 million messages in 3 months

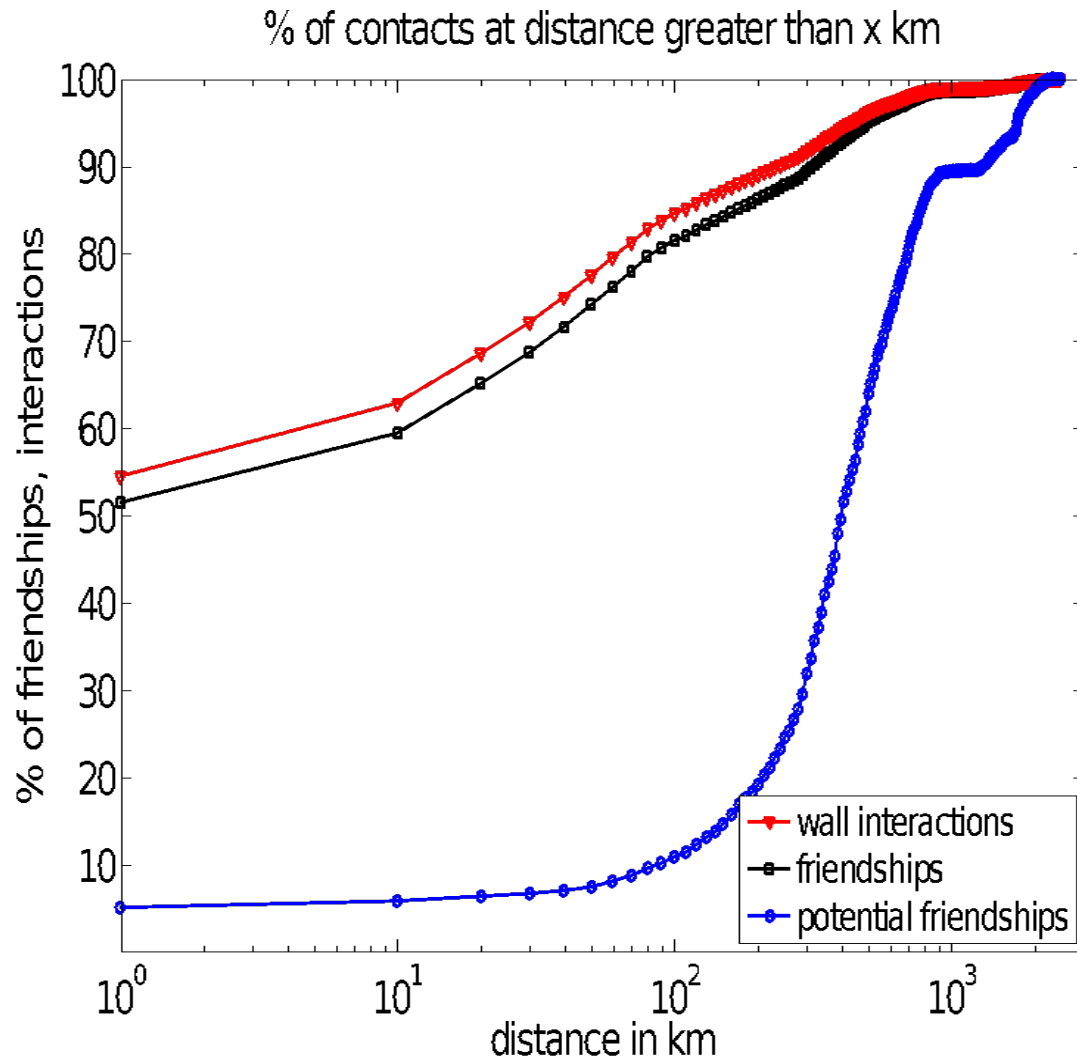


# Geographic Properties



60% of social connections are at a distance of  $\leq 10$ km.

Only 10% of all distances between users are below 100km

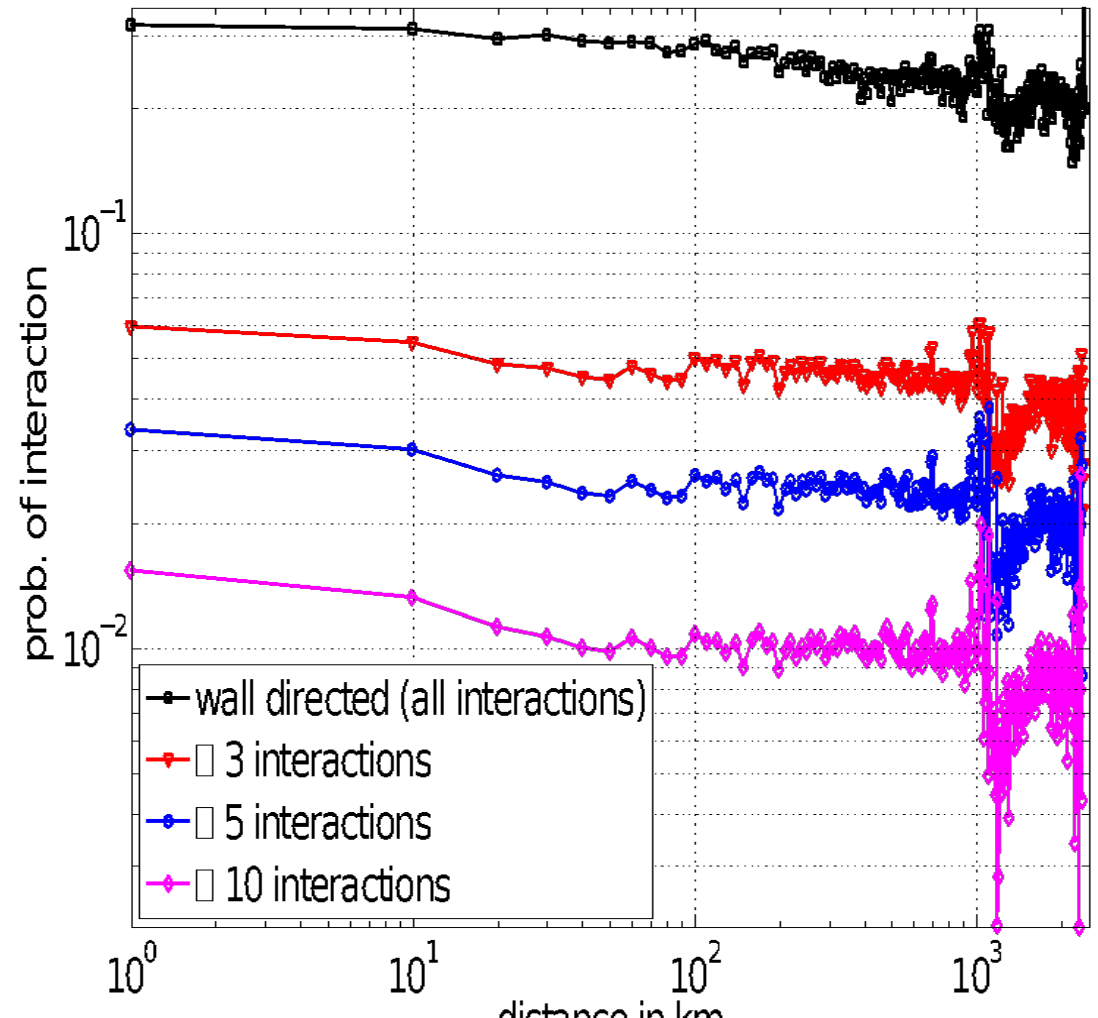


# Effects of geography on interactions



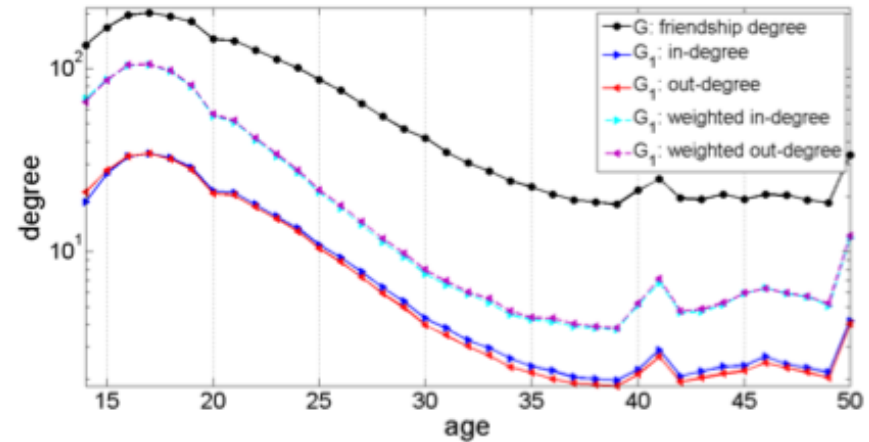
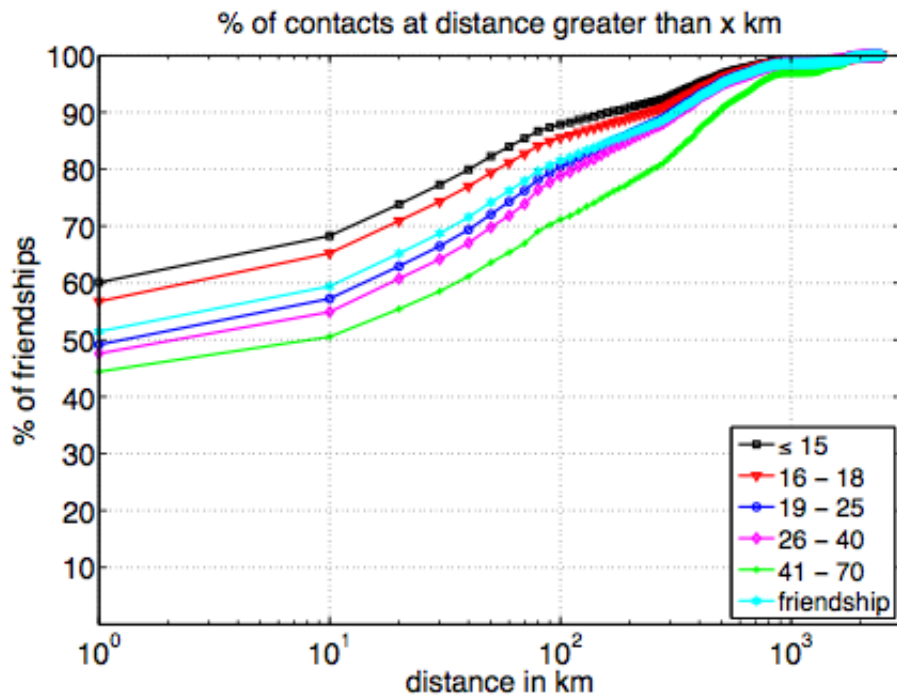
Probability that a message is exchanged over a friendship link seems not to be very affected by distance

fraction of wall posts between friends

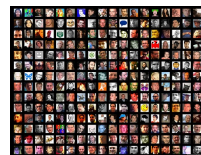




# Effect of Age

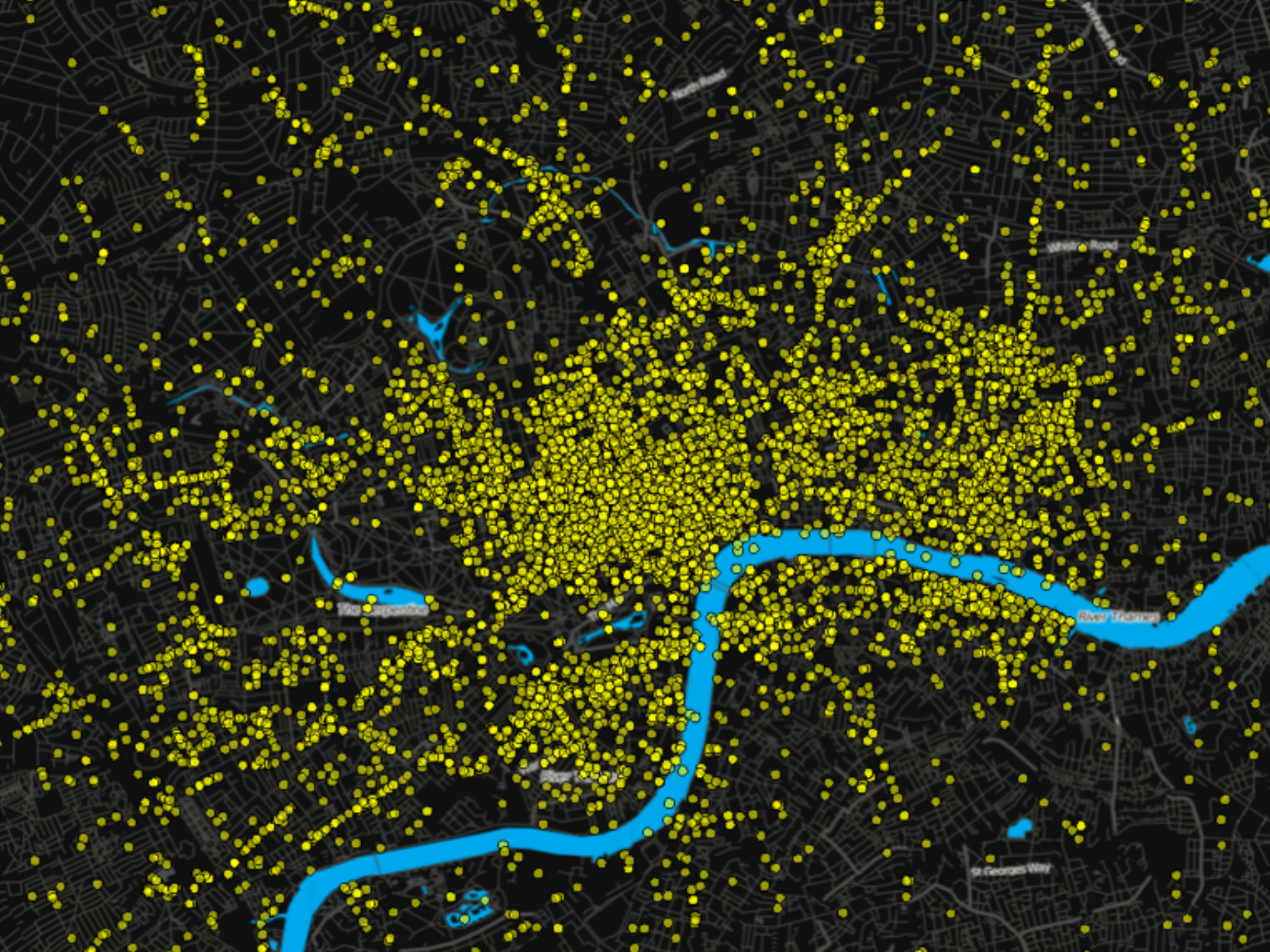


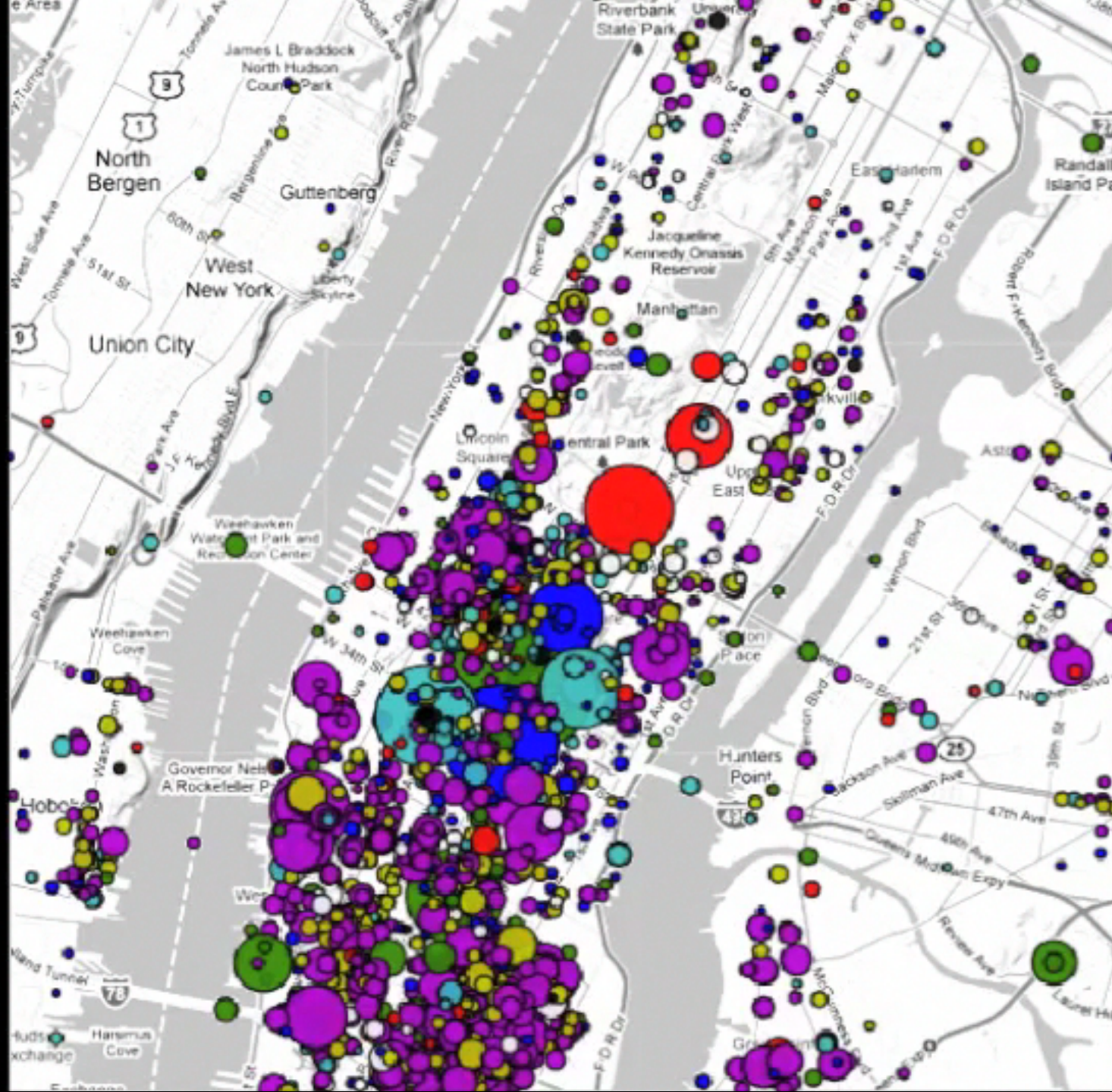
Under 15 have 70% friends within 10km. They also have more friends and interact more.



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# Understanding human mobility







# Samuel A. Stouffer

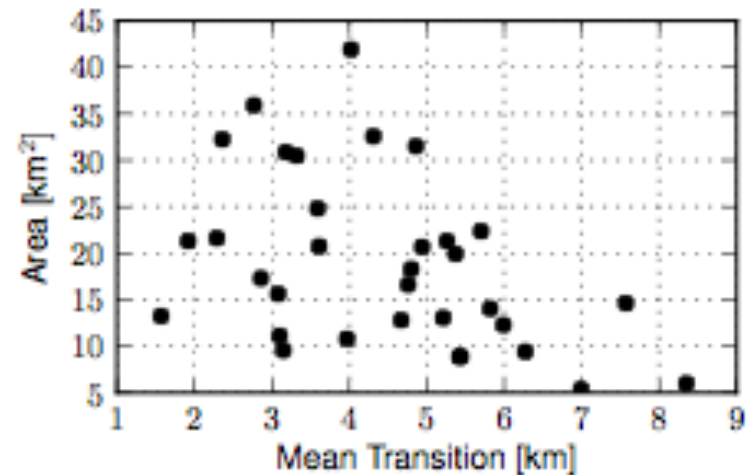
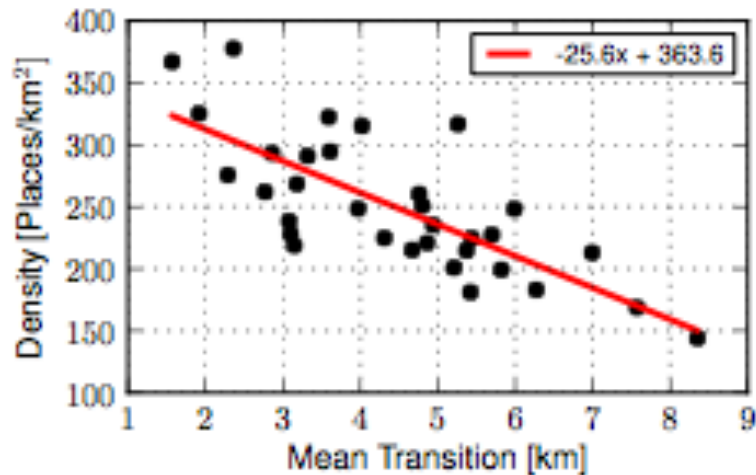


Stouffer's **law of intervening opportunities** states, "The number of persons going a given distance is directly proportional to the number of opportunities at that distance and inversely proportional to the number of intervening opportunities." \*

- Empirically proven using data for migrating families in the city of Cleveland.
- Is this true in our data?

\* S. Stouffer (1940) Intervening opportunities: A theory relating mobility and distance, American Sociological Review 5, 845-867

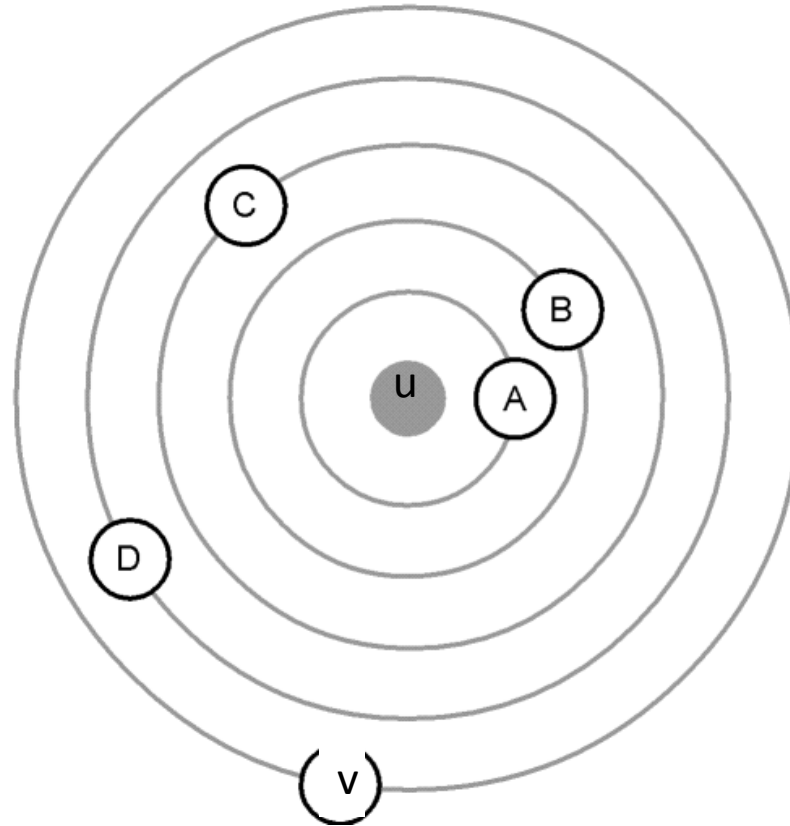
# The importance of density



Place density by far more important than city area size with respect to mean length of human movements ( $R^2 = 0.59$  and  $0.19$  respectively).

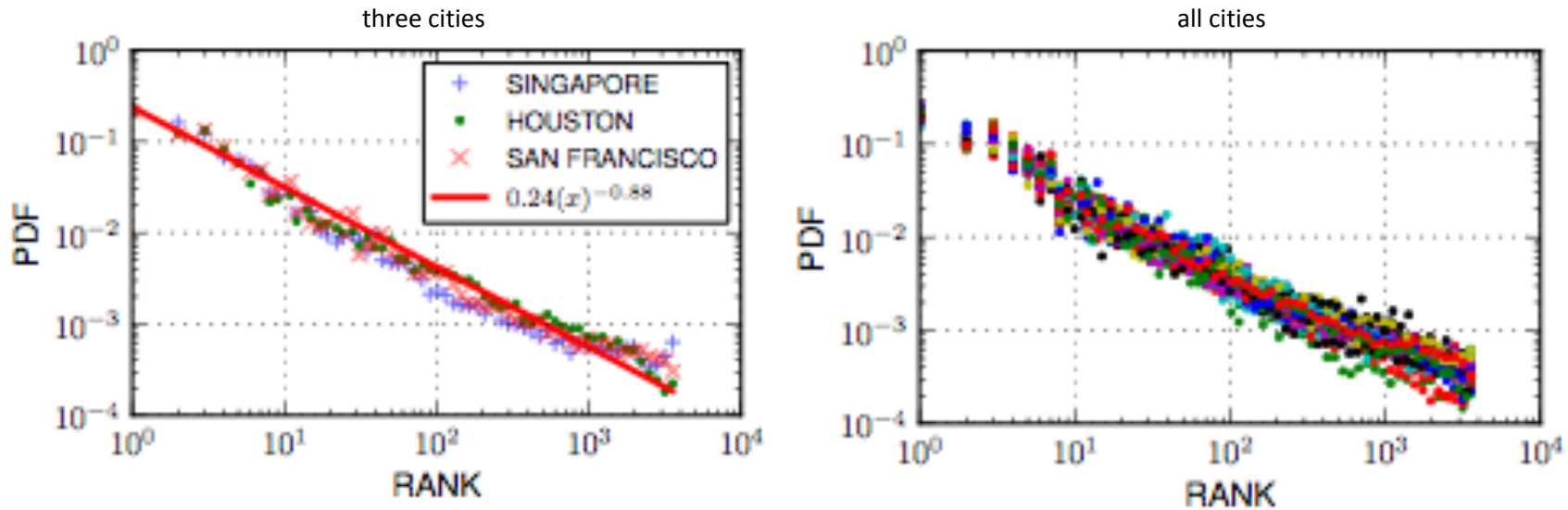


# Rank Distance



$$\text{rank}_u(v) = |\{w : d(u, w) < d(u, v)\}|$$

# Rank universality



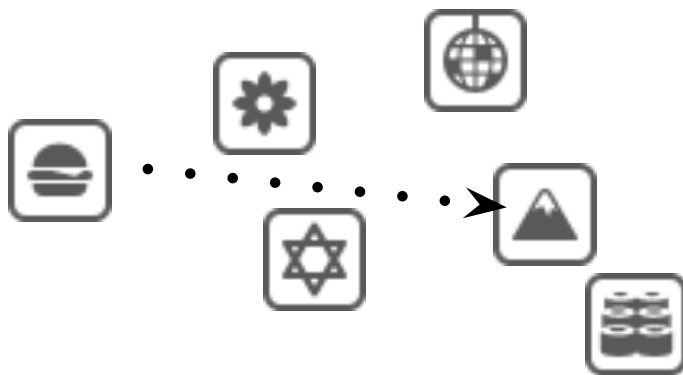
The rank of all cities collapses to a single line.

We have measured a power law exponent  $\alpha = 0.84 \pm 0.07$



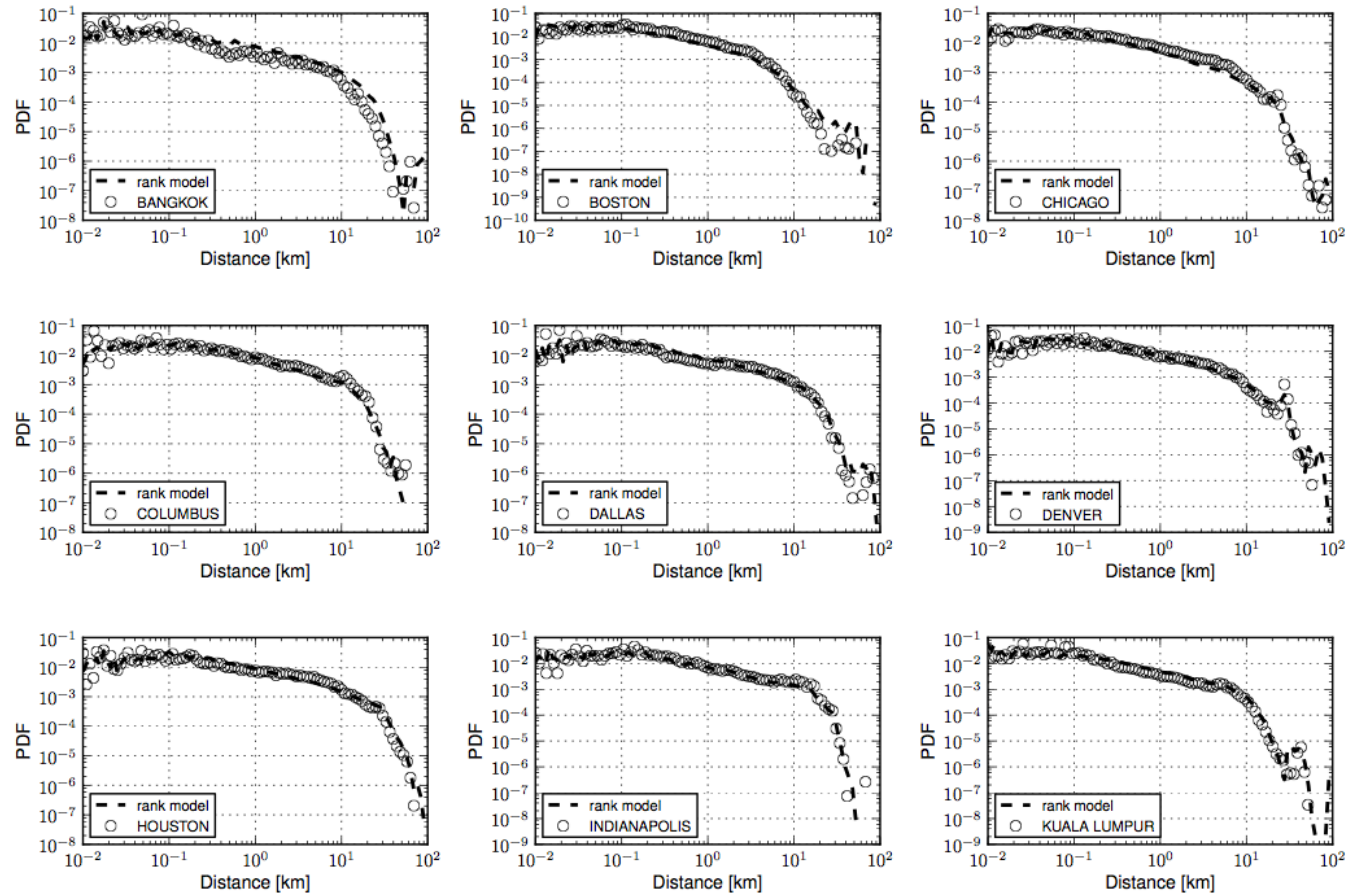
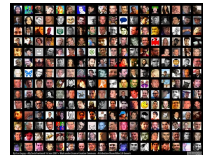
# A new model for urban mobility

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$$Pr[u \rightarrow v] \propto \frac{1}{rank_u(v)^a}$$

# Simulation Results ...





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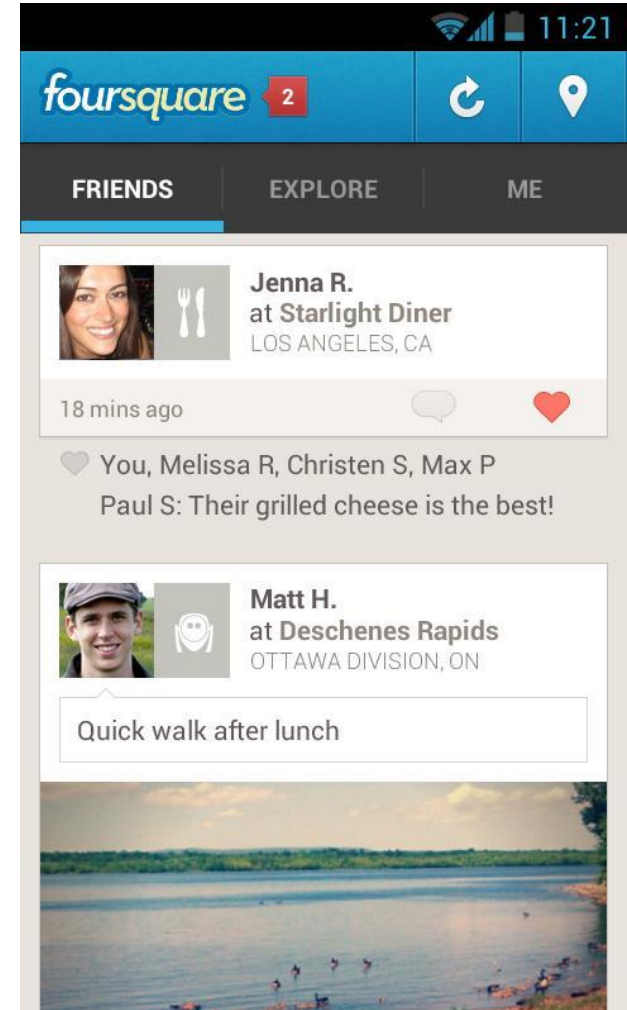
# Understanding communities and role of places

# City-scale social networks



- We look at **intra-city** social networks
- People who have checked in at a place in a given city, and their friends **who have also checked in** at those places

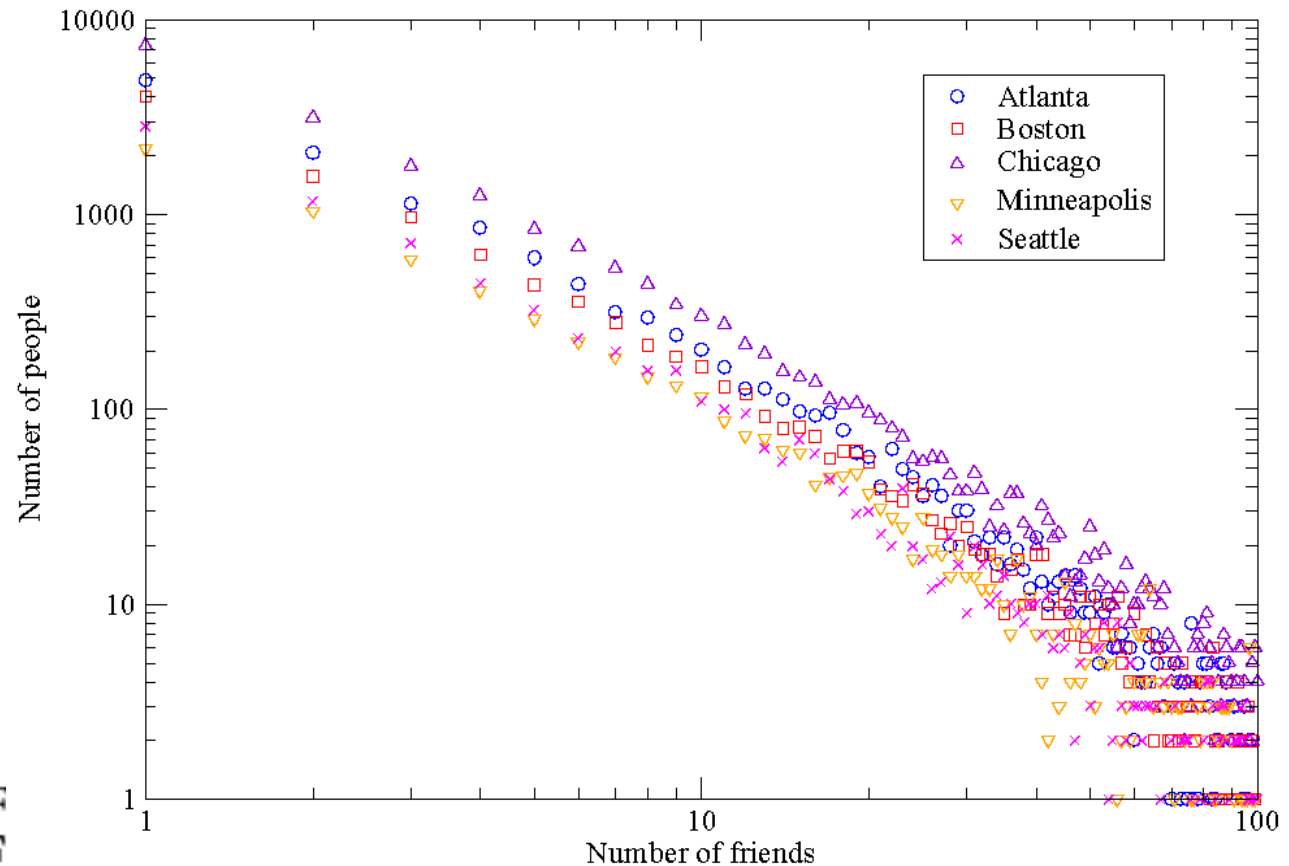
**What do these place-based social networks look like?**



# City-scale social networks



- **Degree:** power-law distribution





# City-scale social networks

- **Degree:** power-law distribution
- **Clustering coefficient:** high (between 0.1 and 0.2, in random graph of the same size  $<0.001$ )
- **Average shortest path length:** small (about 4 hops), comparable to random graph (Clustering coeff. + average path length = “small world”)
- **Community structure** (modularity  $> 0.4$ )

Our city-level graphs have well-known structural properties of social networks.

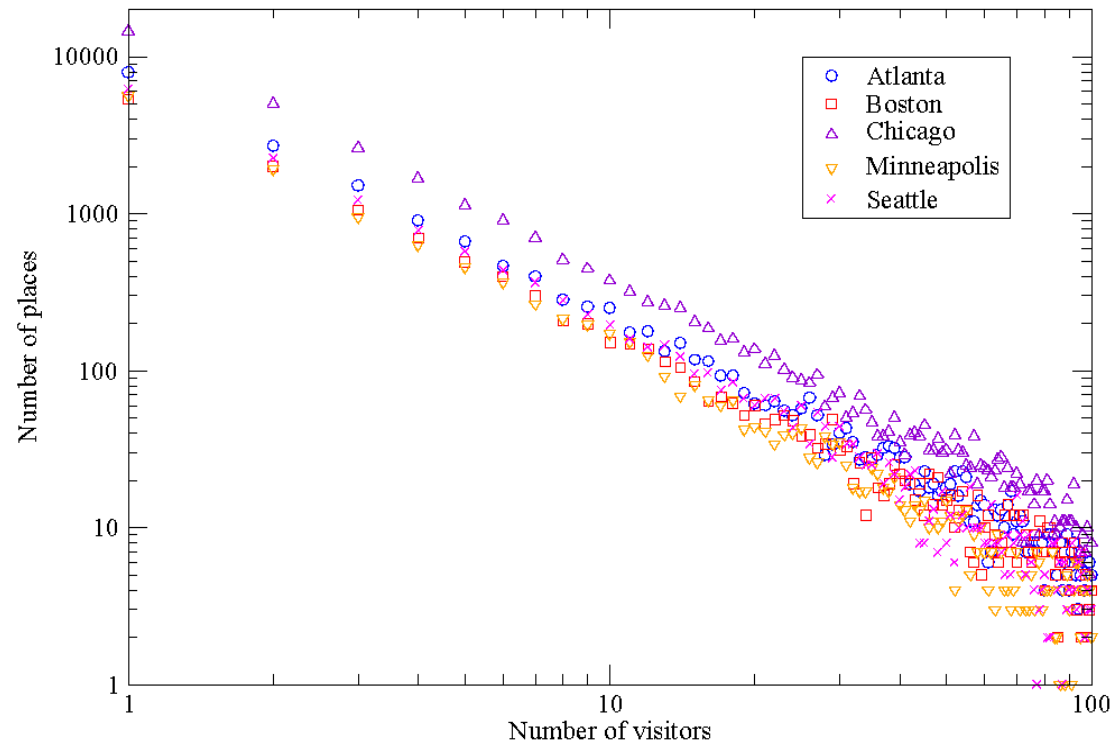


# The role of places



- Power-law distribution of **place popularity**

...like the degree distribution in the social network





# Places vital for tie formation

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- Power-law distribution of **place popularity**
- **Analyze triangles:** >70% of triangles have one place shared between all three people  
→ **clustering around certain places**

**These places could act as foci for tie formation...**



# Role of categories...

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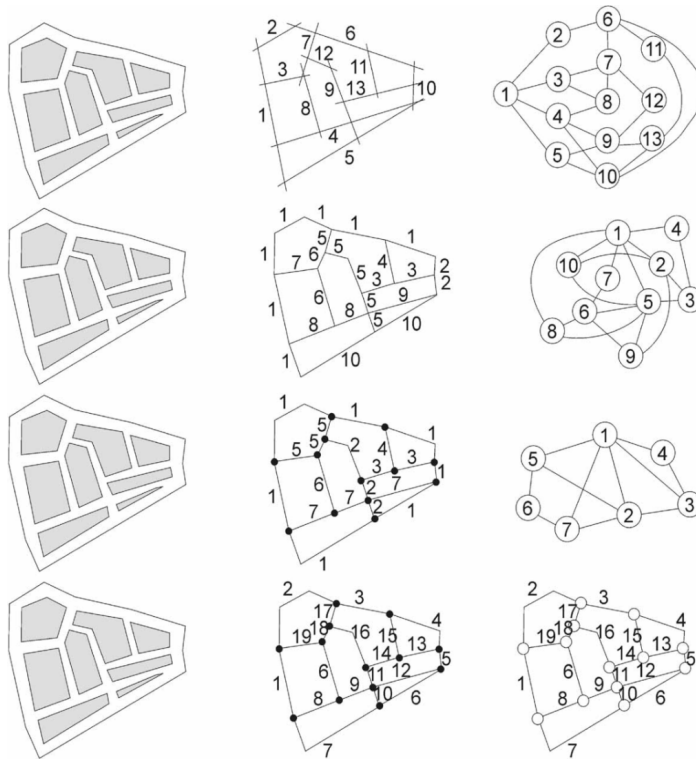
- What is the role of place categories?
  - Probability of friendship between **colocated people** at places in each Foursquare **category**
  - Some kinds of places are **much more likely to reinforce friendship** than others



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# Urban analysis with spatial networks

# Model cities with networks



## DUAL

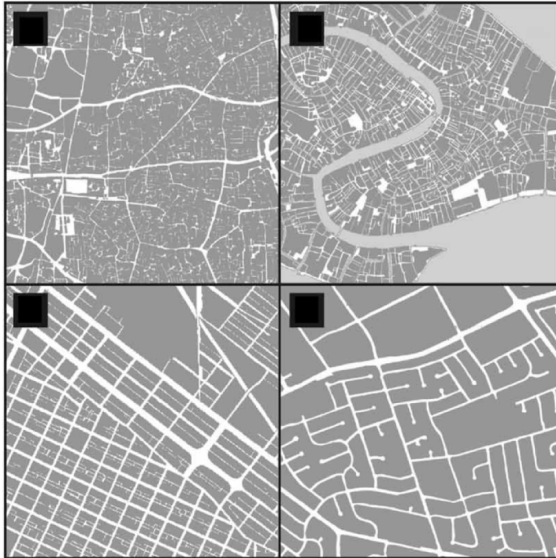
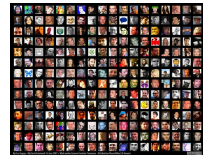
- Named Street Approach
- Axial Line, Space Syntax
- Good Continuation Approach

## PRIMAL

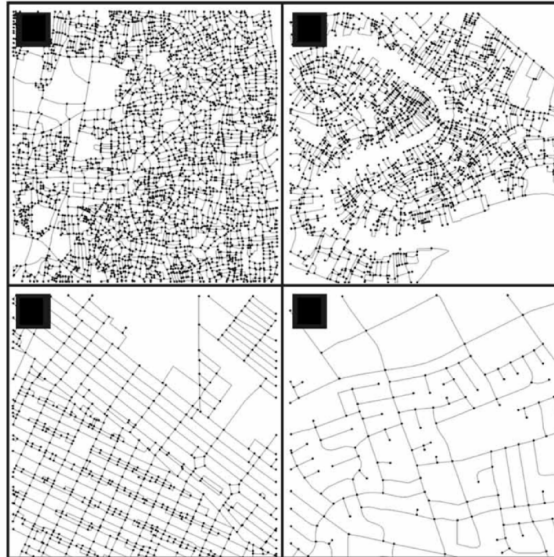
Pure Primal

Porta S, Crucitti P, Latora V. (2006), The network analysis of urban streets: a primal approach, «Environment and Planning B: planning and design», 33

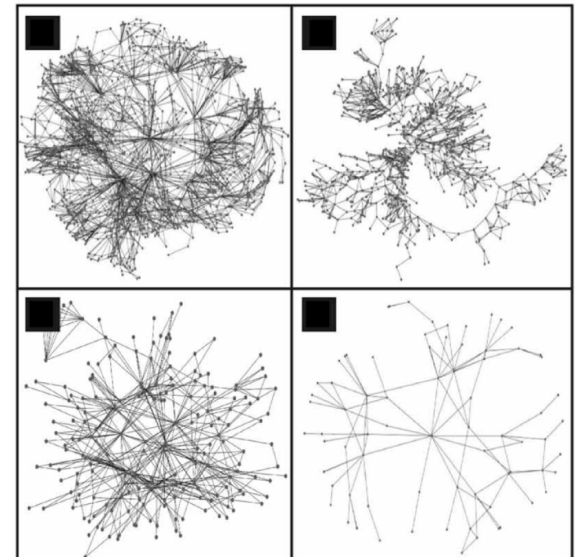
# Street networks models



Urban Map



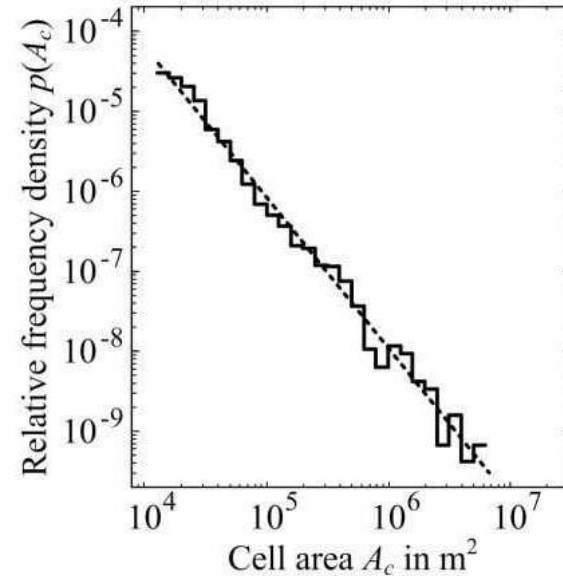
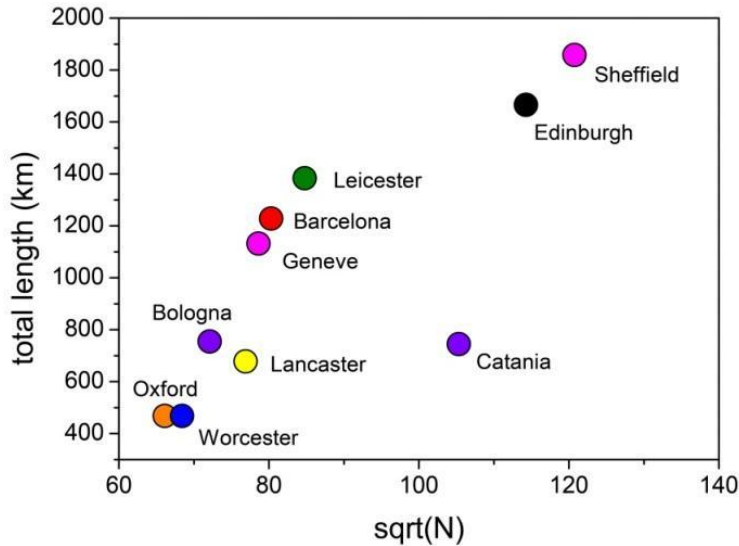
Primal Representation



Dual Representation

Porta S, Crucitti P, Latora V. (2006), The network analysis of urban streets: a primal approach, «Environment and Planning B: planning and design», 33

# Street networks analysis



- Barthelemy, M. Spatial Networks, Physic Report, 2011
- Strano, E. Viana, M. Cardillo, A. Porta, S. Da Costa, L Latora, V. "Urban street networks, a comparative analysis of ten European cities." Environment and Planning B (in print).
- S. Lämmer, B. Gehlsen, and D. Helbing (2006) Scaling laws in the spatial structure of urban road networks. *Physica A* **363**(1) 89-95.

# Betweenness Centrality



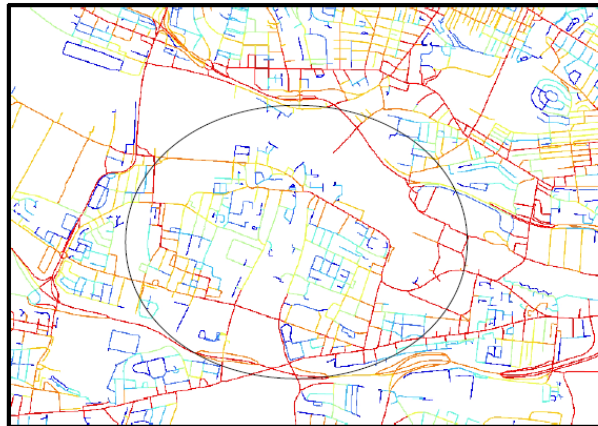
1

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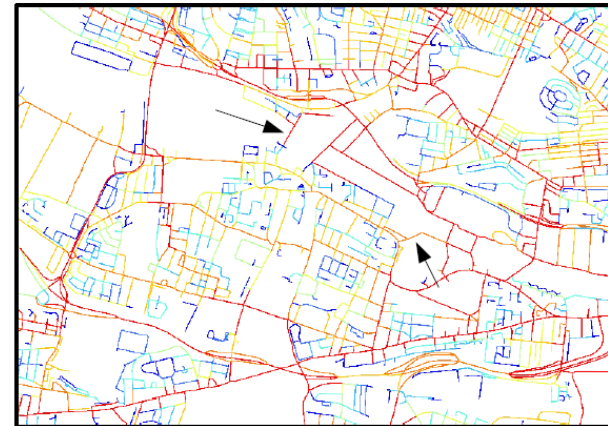
## Betweenness

BetC is based on the idea that a node is more central when it is traversed by a larger number of shortest paths connecting all couples of nodes in the network.  $n_{jk}$  is the number of shortest paths between nodes  $j$  and  $k$ , and  $n_{jk}(i)$  is the number of these shortest paths that contain node  $i$ .

$$C_i^B = \frac{1}{(N-1)(N-2)} \sum_{j=1; k=1; j \neq k \neq i}^N \frac{n_{jk}(i)}{n_{jk}}$$



Current situation

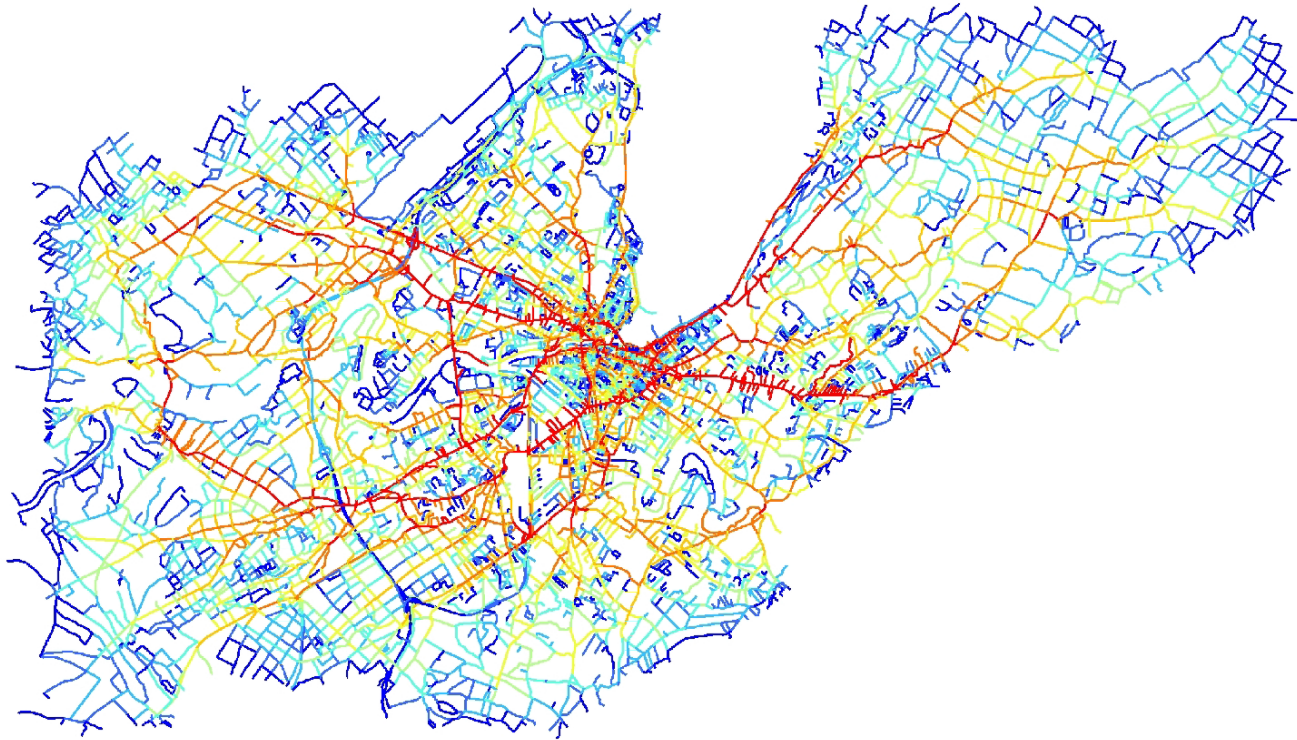


Simulation

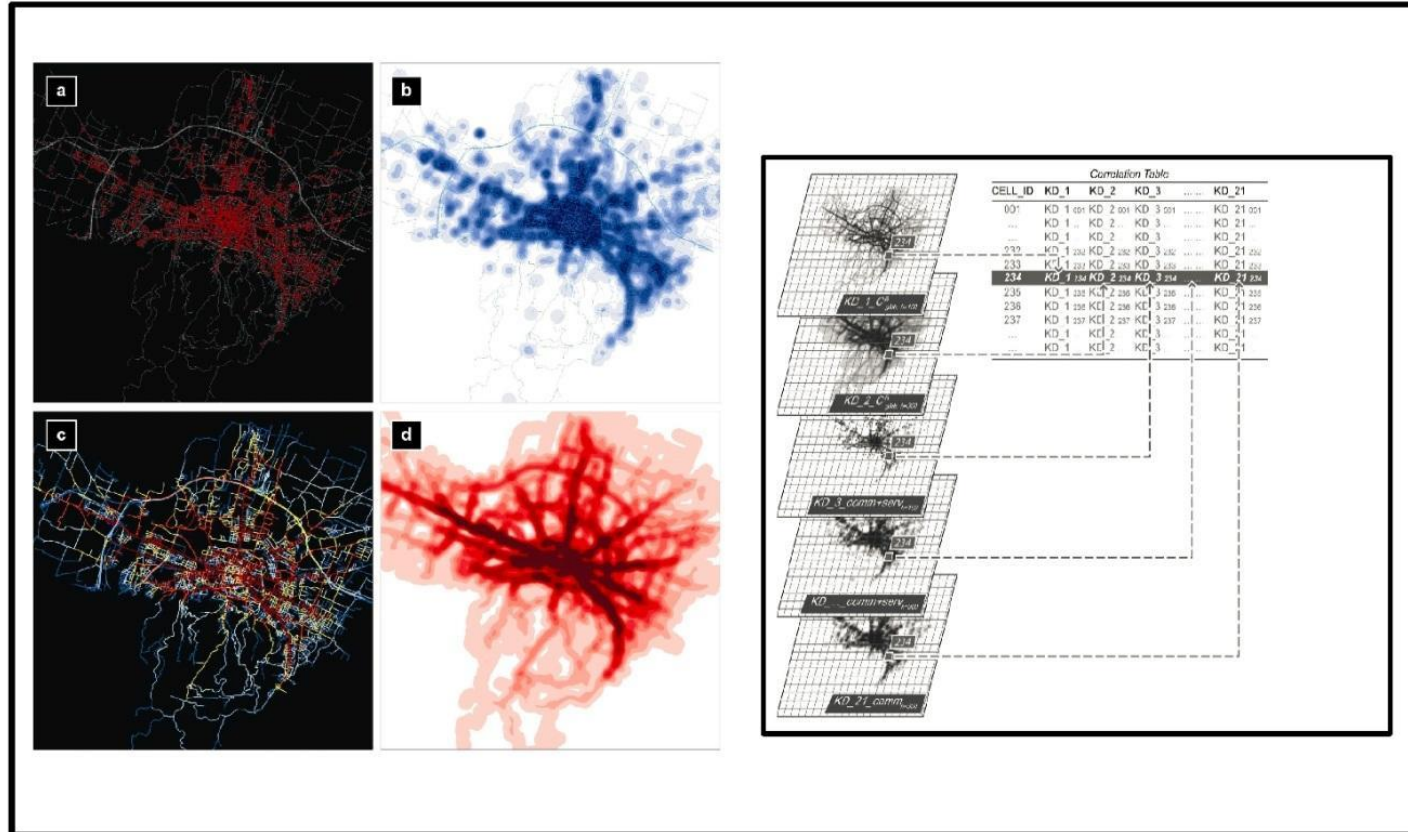


# Betweenness Centrality

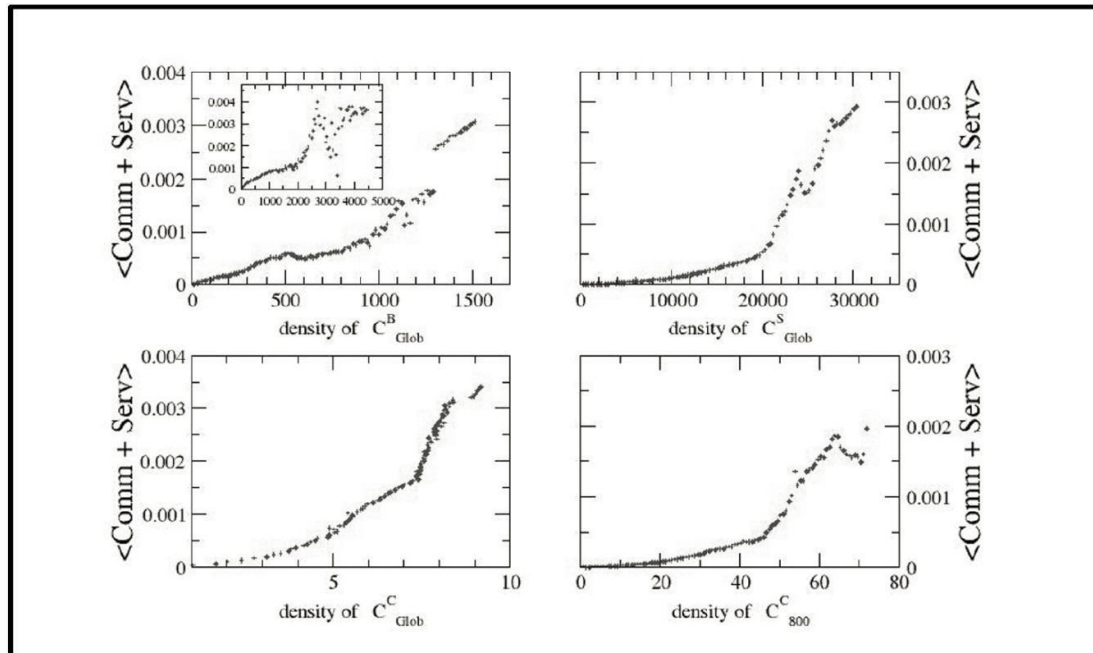
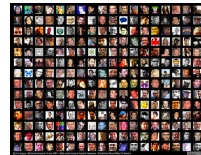
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# Example 1: Betweenness and Economic Activities



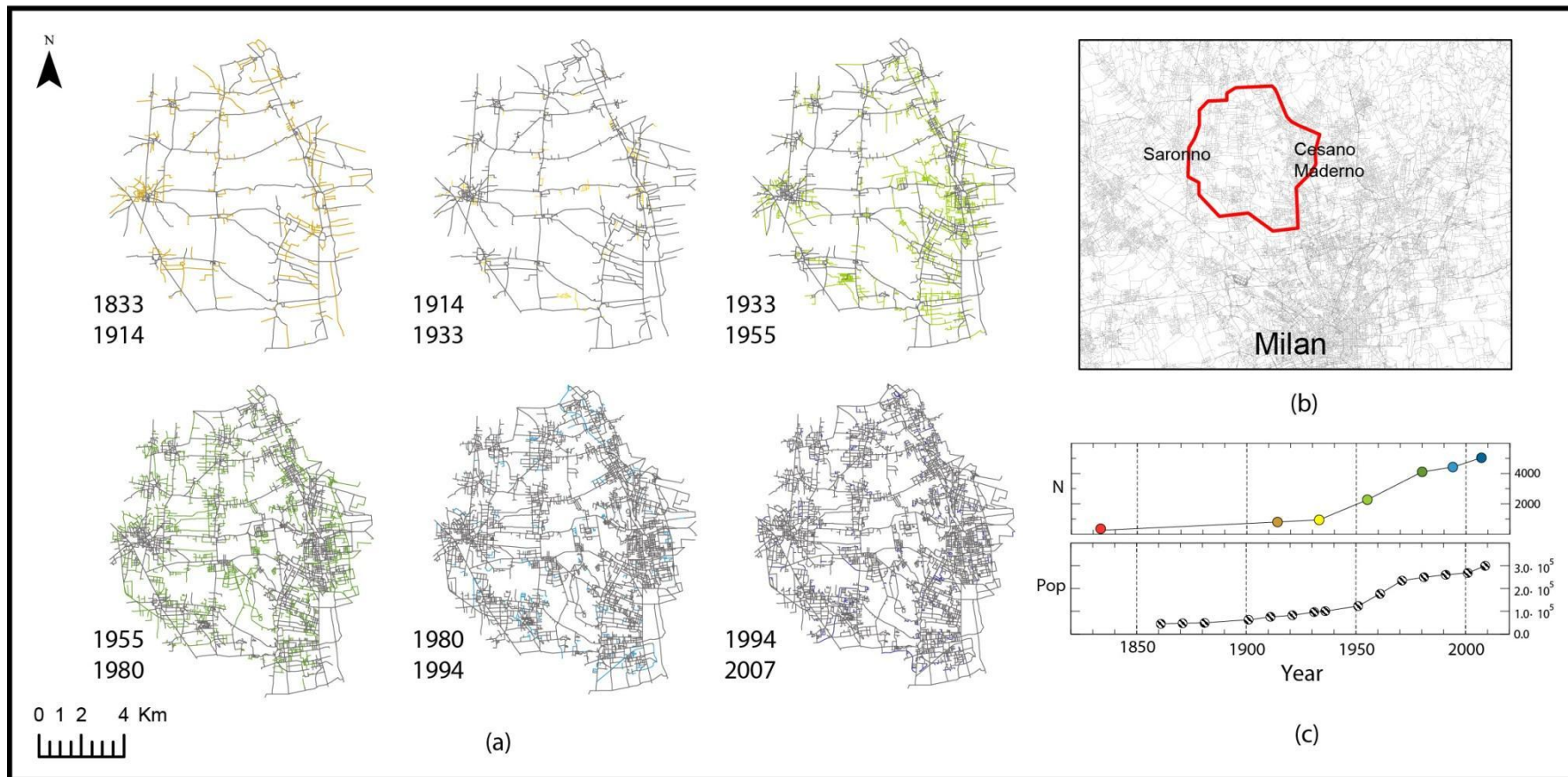
# Example 1: Betweenness and Economic Activities



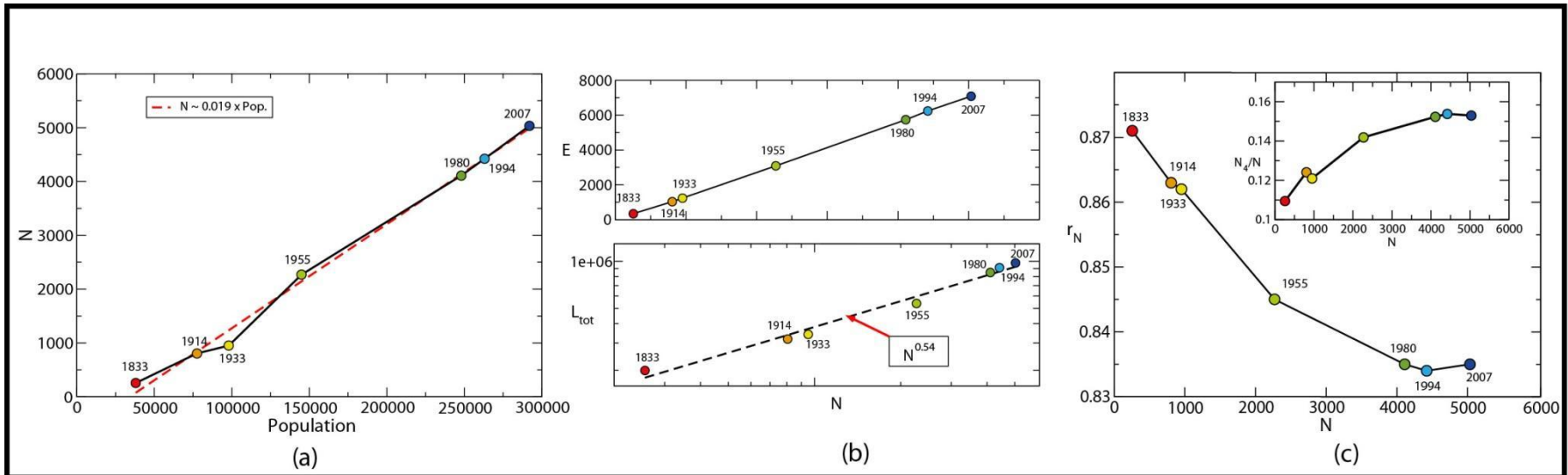
**It seems that centralities are correlated to the location of micro economic activities**

Porta, S. Latora, V, Strano, E, et al "Street centrality and densities of retail and services in Bologna, Italy", Environment and Planning B: Planning and design, 36,3,450-465,2009.

# Example 2: Network Evolution and urbanization



# Example 2: Network Evolution and urbanization



Pop Vs  $N$ , it seems that we all own a fraction of a street intersection.

$$L_{tot} \sim N^\gamma$$

$$\gamma = 0.54$$

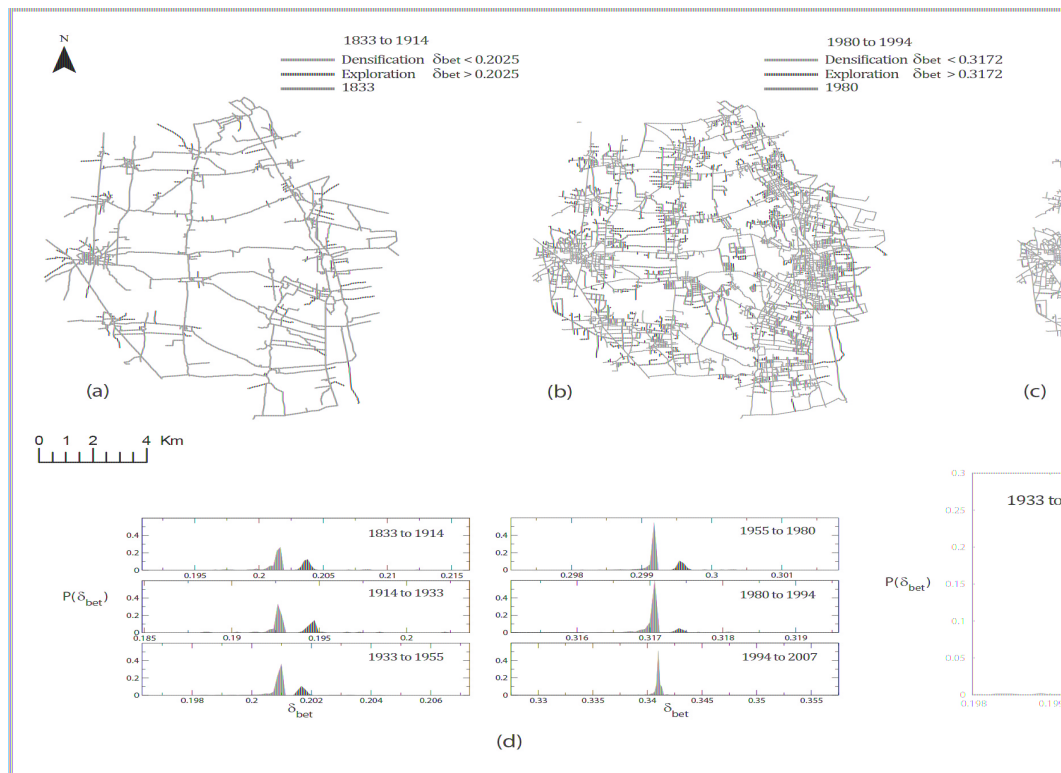
$$r(N) = \frac{N_1 + N_2}{\sum_{k \neq 2} N_k}$$

# Example 2: Network Evolution and urbanization



**Betweenness Centrality is strongly correlated to the age of each street!**

# Example 2: Network Evolution and urbanization



Betweenness contribution of each new street can be assigned to two main processes: exploration and densification

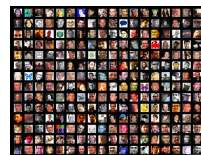
Strano et al: Elementary Processes Governing the evolution of Street Network. Nature Scientific Report (2012)

# What can all this be used for?



- **Friendship Recommendation:**
  - **Exploiting Place Features in Link Prediction on Location-based Social Networks**, Salvatore Scellato, Anastasios Noulas, Cecilia Mascolo. In Proceedings of 17th ACM International Conference on Knowledge Discovery and Data Mining (KDD 2011). San Diego, USA. August 2011.
- **Place Recommendation:**
  - **Mining User Mobility Features for Next Place Prediction in Location-based Services**. Anastasios Noulas, Salvatore Scellato, Neal Lathia and Cecilia Mascolo. In Proceedings of IEEE International Conference on Data Mining (ICDM 2012). Short Paper. Brussels, Belgium. December 2012.
  - **A Random Walk Around the City: New Venue Recommendation in Location-Based Social Networks**. Anastasios Noulas, Salvatore Scellato, Neal Lathia and Cecilia Mascolo. In Proceedings of ASE/IEEE International Conference on Social Computing (SocialCom). Amsterdam, The Netherlands. September 2012.





# What can all this be used for?

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- **More Modelling:**

- **Talking Places: Modelling and Analysing Linguistic Content in Foursquare.** Sandro Bauer, Anastasios Noulas, Diarmuid Ó Séaghdha, Stephen Clark and Cecilia Mascolo. In Proceedings of ASE/IEEE International Conference on Social Computing (SocialCom). Amsterdam, The Netherlands. September 2012.
- **Exploiting Foursquare and Cellular Data to Infer User Activity in Urban Environments.** Anastasios Noulas, Cecilia Mascolo and Enrique Frias-Martinez. In Proceedings of 14th International Conference on Mobile Data Management (MDM 2013). Milan, Italy. June 2013.
- **Evolution of a Location-based Online Social Network: Analysis and Models.** Miltiadis Allamanis, Salvatore Scellato and Cecilia Mascolo. In Proceedings of ACM Internet Measurement Conference (IMC 2012). Boston, MA. November 2012.

# References



- **The length of bridge ties: structural and geographic properties of online social interactions.** Yana Volkovich, Salvatore Scellato, David Laniado, Cecilia Mascolo and Andreas Kaltenbrunner. In Proceedings of Sixth International AAAI Conference on Weblogs and Social Media (ICWSM 2012). Ireland. June 2012.
- **Far from the eyes, close on the Web: impact of geographic distance on online social interactions.** Andreas Kaltenbrunner, Salvatore Scellato, Yana Volkovich, David Laniado, Dave Currie, Erik J. Jutemar, Cecilia Mascolo. In ACM SIGCOMM Workshop on Online Social Networks (WOSN 2012). Finland. 2012.
- **A tale of many cities: universal patterns in human urban mobility.** Anastasios Noulas, Salvatore Scellato, Renaud Lambiotte, Massimiliano Pontil, Cecilia Mascolo. In PLoS ONE. PLoS ONE 7(5): e37027.
- **The Importance of Being Placefriends: Discovering Location-focused Online Communities.** Chloë Brown, Vincenzo Nicosia, Salvatore Scellato, Anastasios Noulas, Cecilia Mascolo. In ACM SIGCOMM Workshop on Online Social Networks (WOSN 2012). August 2012.