

# Spatial Dissemination Metrics for Location-Based Social Networks

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Joint work with Mirco Musolesi

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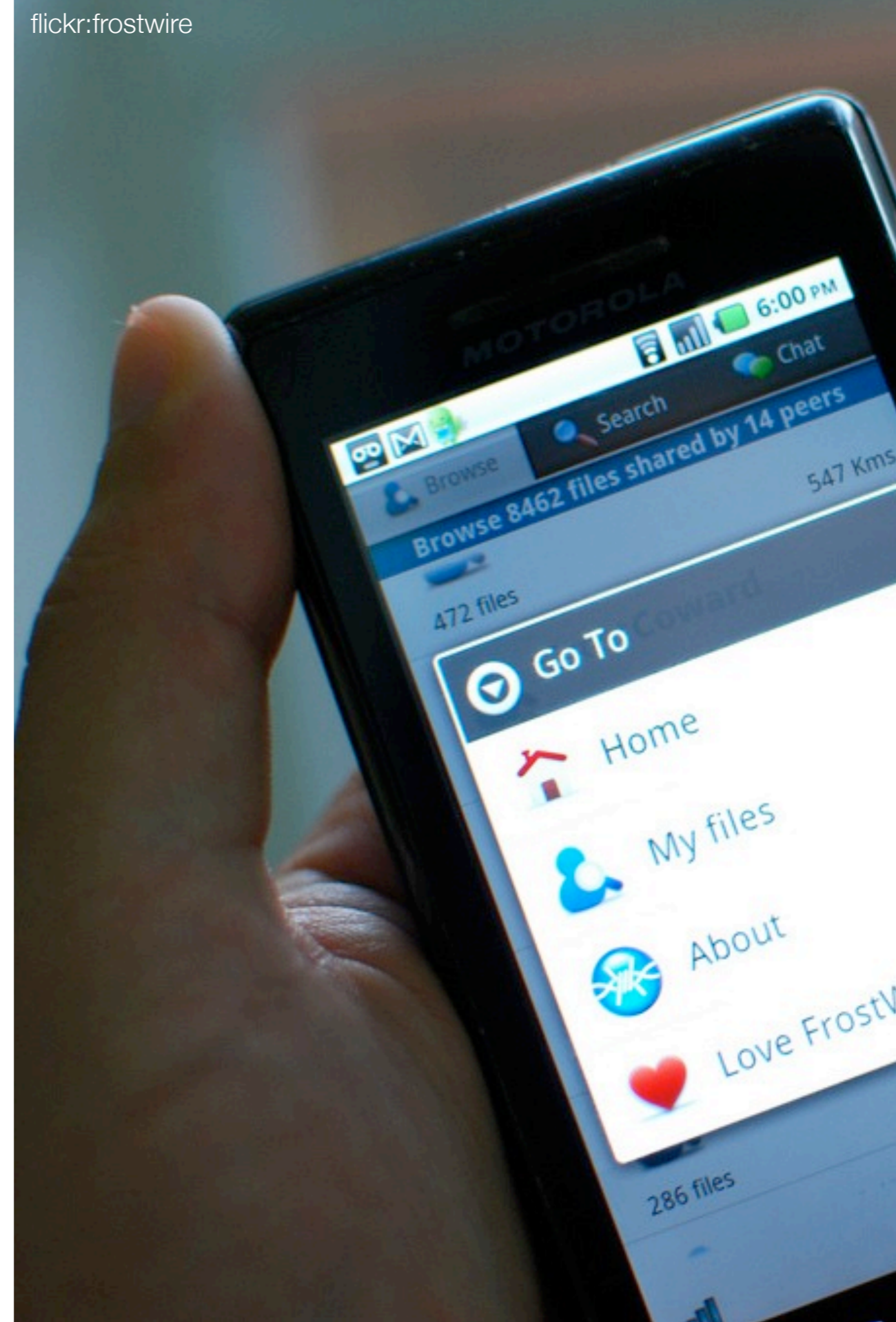


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# Information dissemination

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- Mobile access to online services and social networks is increasingly common.
- Realtime information dissemination through these channels is important and in some contexts predominant.
- Who are the most important people in the network?



# TIME THE 2012 TIME 100

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Influence is not global

Even the most influential people are influential in their field of action and in selected regions.

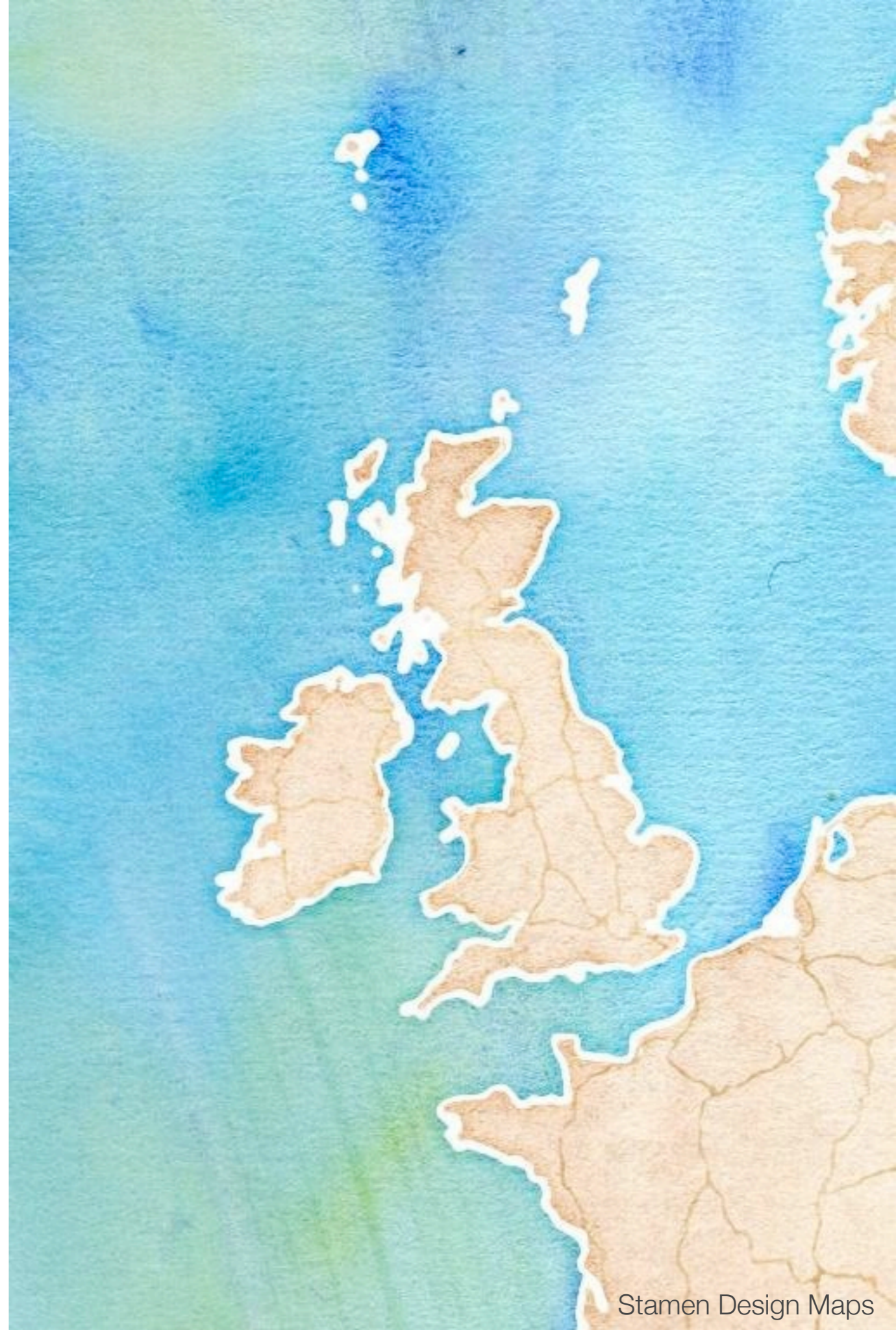


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# Research Question

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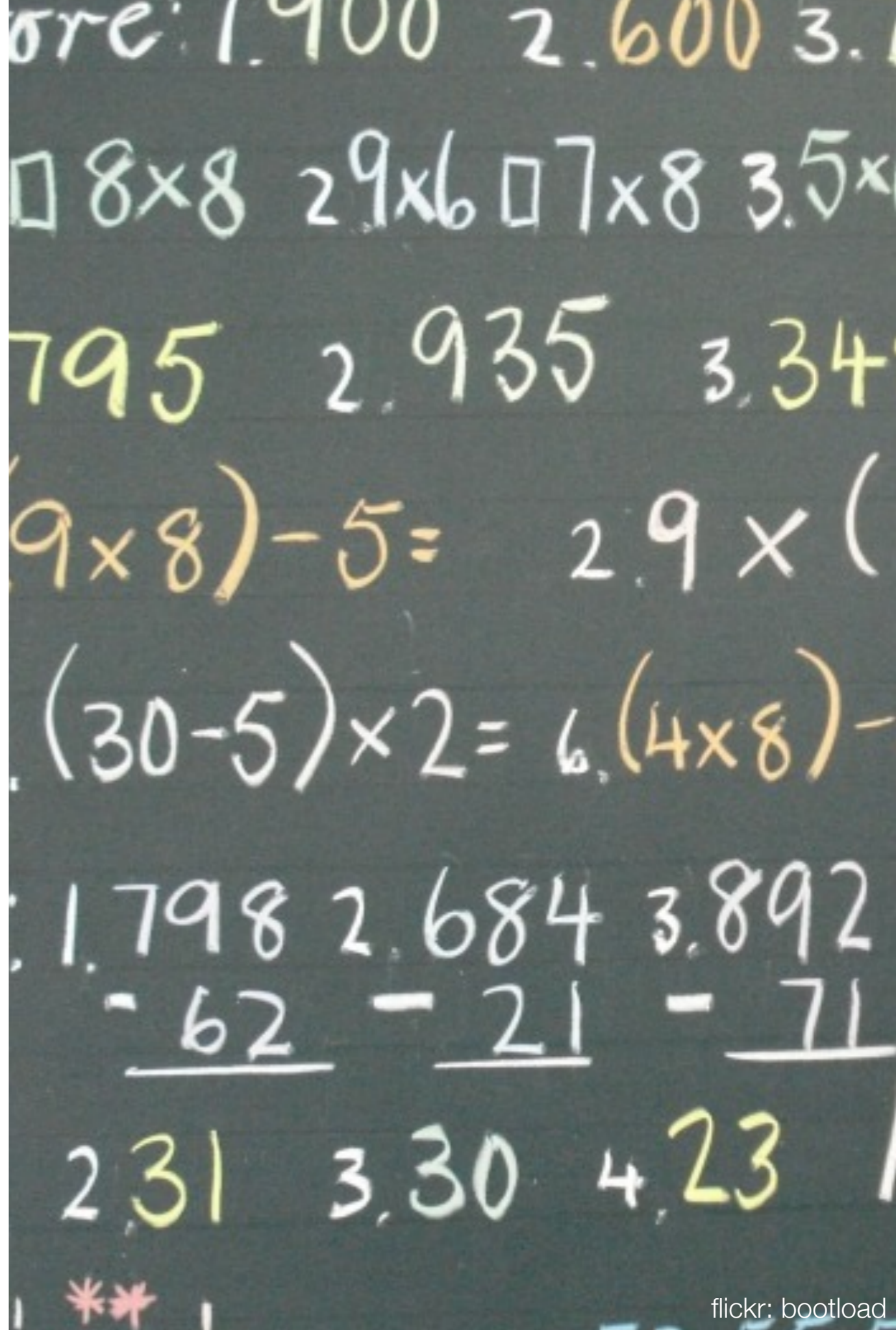
- Complex networks metrics allow us to find most central users in a social network.
- How to find people that are most central to a certain *geographic* region?
- Potential applications in a targeted information spreading and in building models of cultural influence.

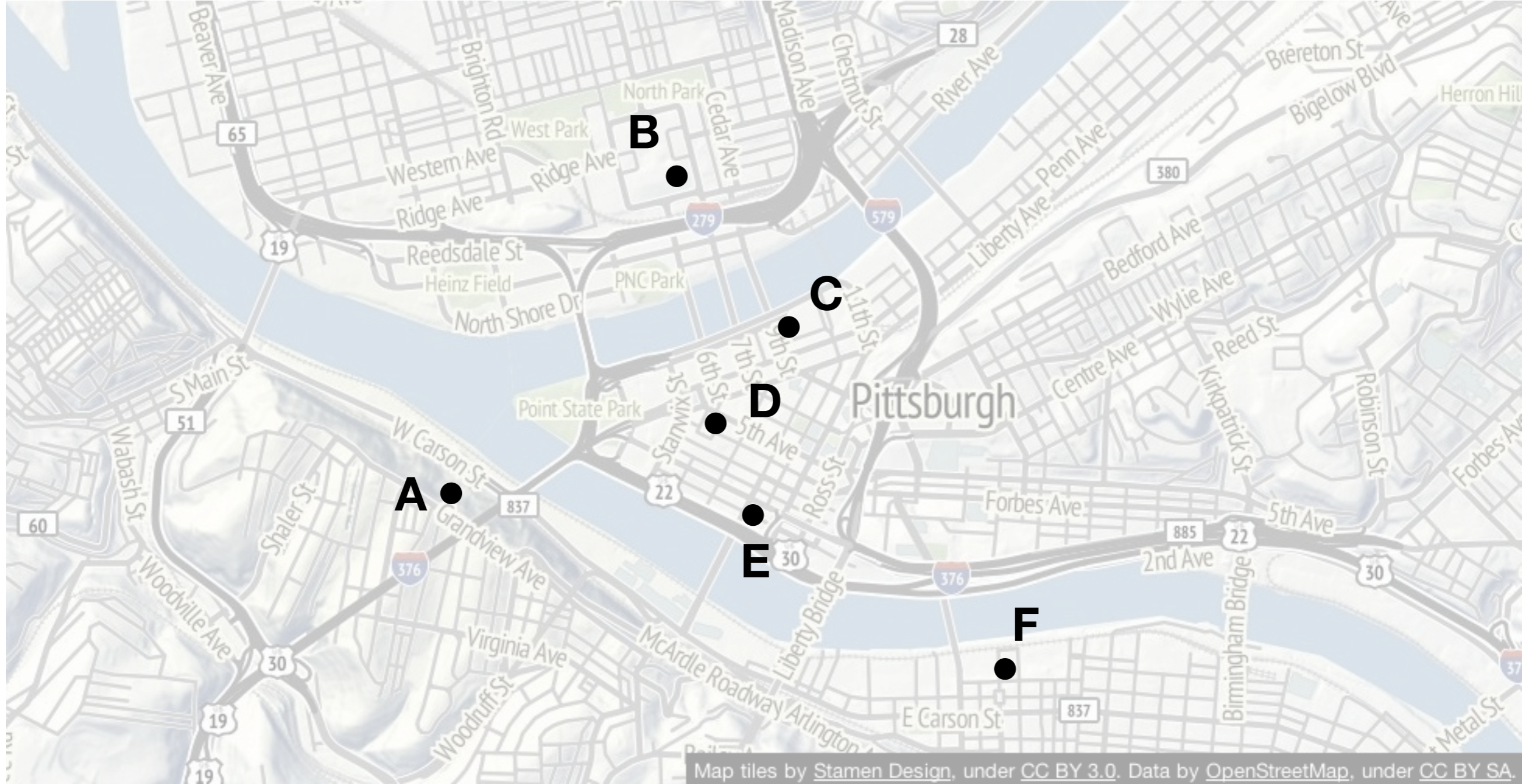


# Our Approach

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- A geo-social network model.
- Geographic extension of centrality measures defined for complex (social) networks. These are *structural* metrics.
- Analysis of real-world scenarios on two major social networks websites, Twitter and Foursquare.

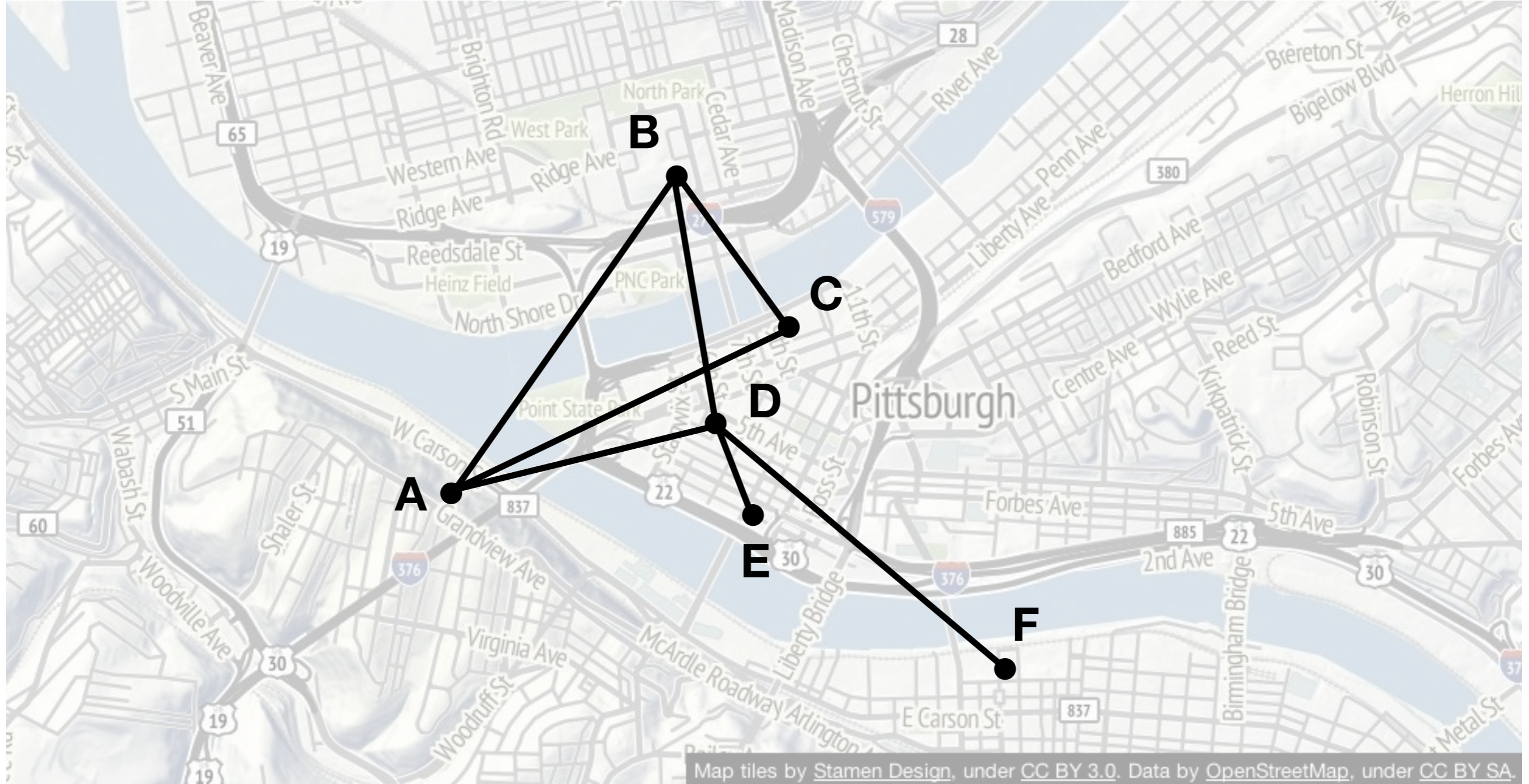




# Geosocial Network Model

Every user is associated one or more significant point in a geographic space (home, office, favorite café, ...)

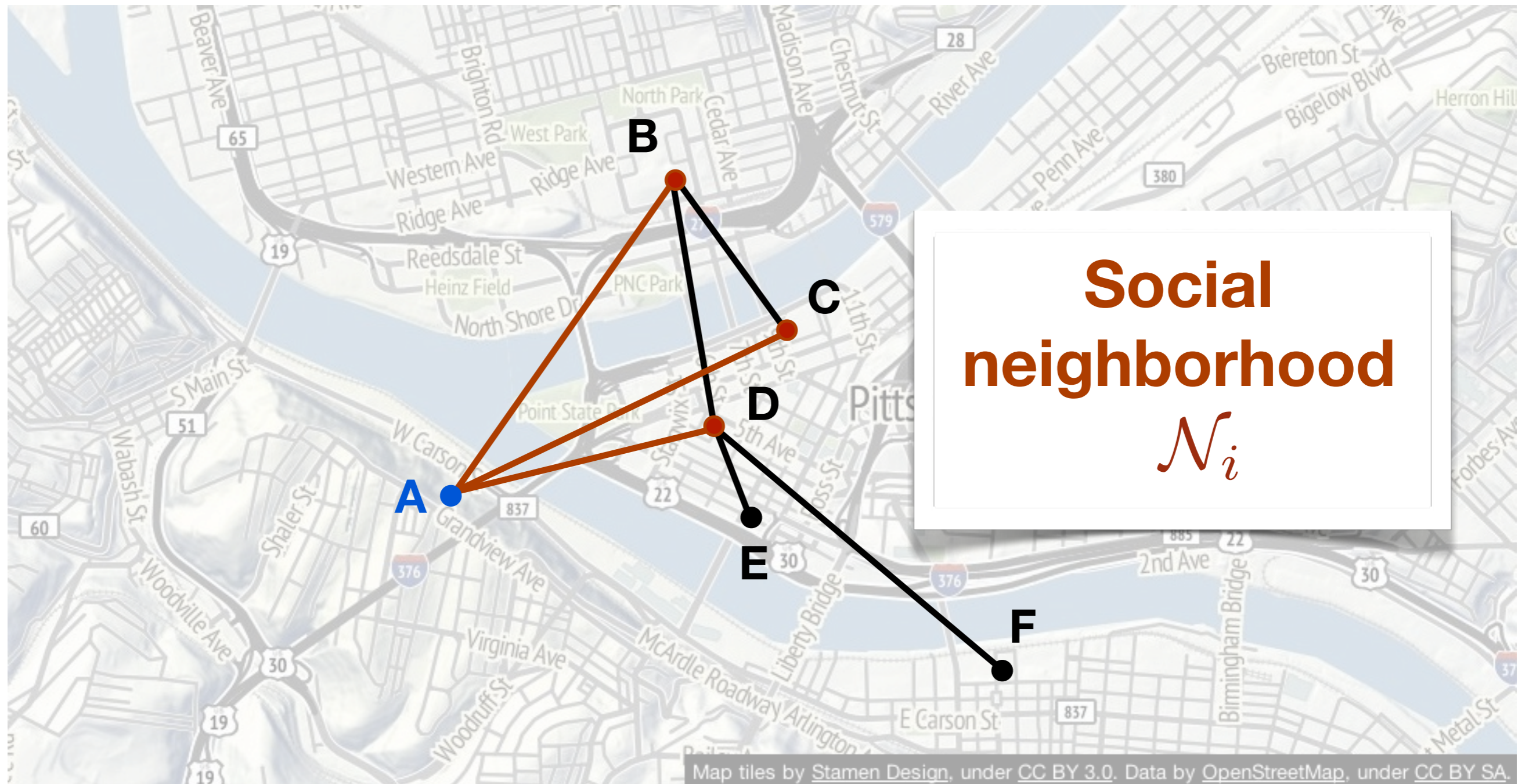




# Geosocial Network Model

We also know the social network of this group of people.



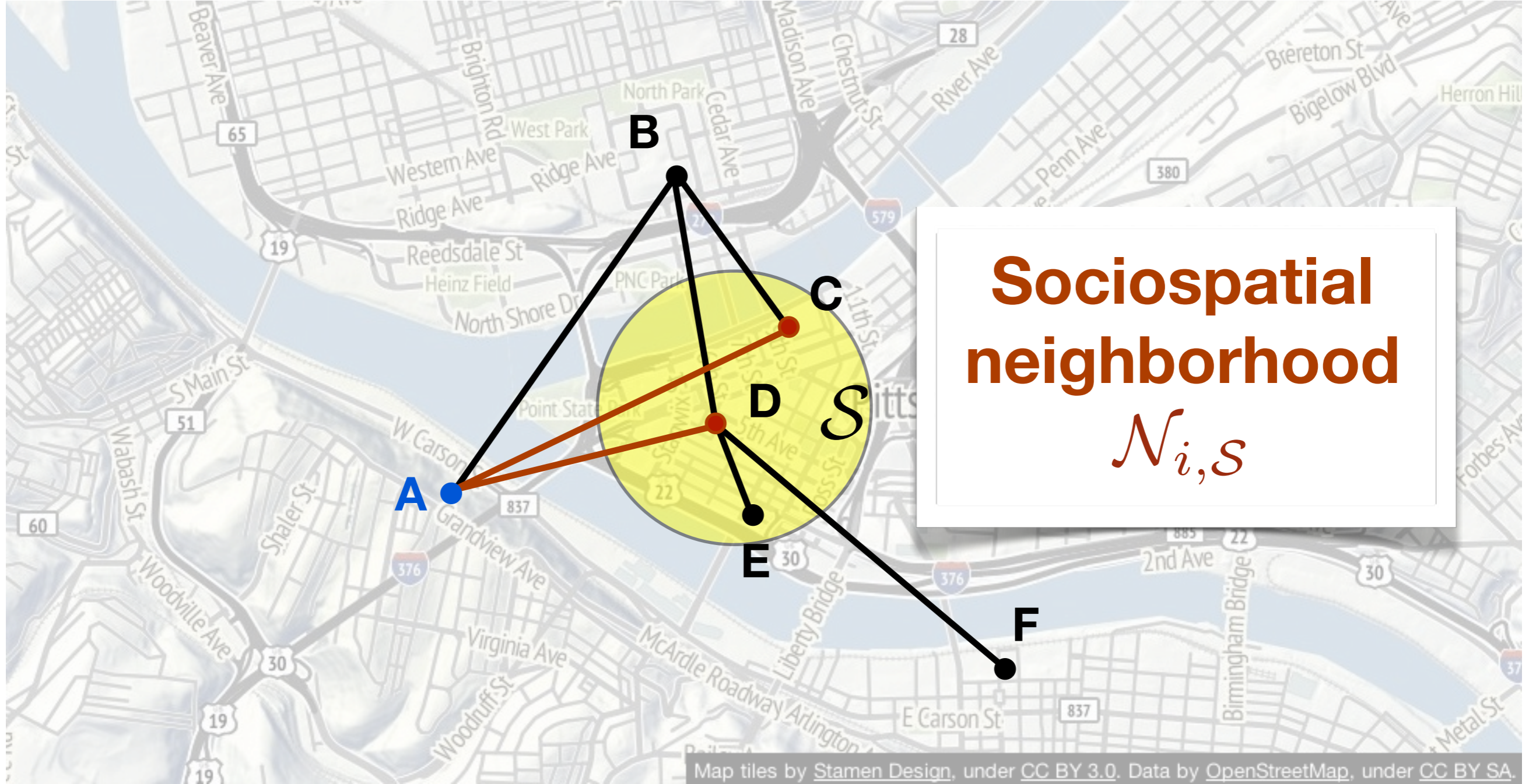


# Geosocial Network Model

Social neighborhood of a node. It is defined only on the social graph (no geographic info).







# Geosocial Network Model

Spatio-Social neighborhood of a node w.r.t. to the yellow region.



# Twitter Dataset

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- Snowball sampling.
- 1375 seed users in San Francisco, CA and London, UK. 657K users (1375 seeds) and their social links.
- User significant point specified in their profile (location field).
- Location was geocoded using Google Geocoding API.



# Foursquare Dataset

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- Mayor of a venue: user with the highest number of check-ins in the last 60 days.
- Random crawling of venues in selected urban areas, their mayors' profile and friends.
- 177K users and their social links.
- Mayorships describe users significant points.



# Spatial Degree Centrality and Spatial Degree Ratio

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$$C_{i,S} = |\mathcal{N}_{i,S}|$$

Quantifies how many neighbors of  $i$  have significant points inside the region  $S$ .

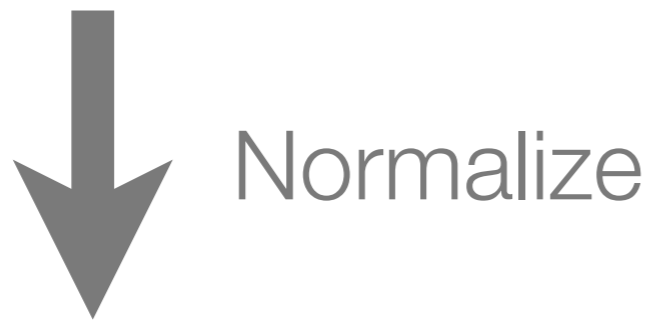


# Spatial Degree Centrality and Spatial Degree Ratio

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$$C_{i,S} = |\mathcal{N}_{i,S}|$$

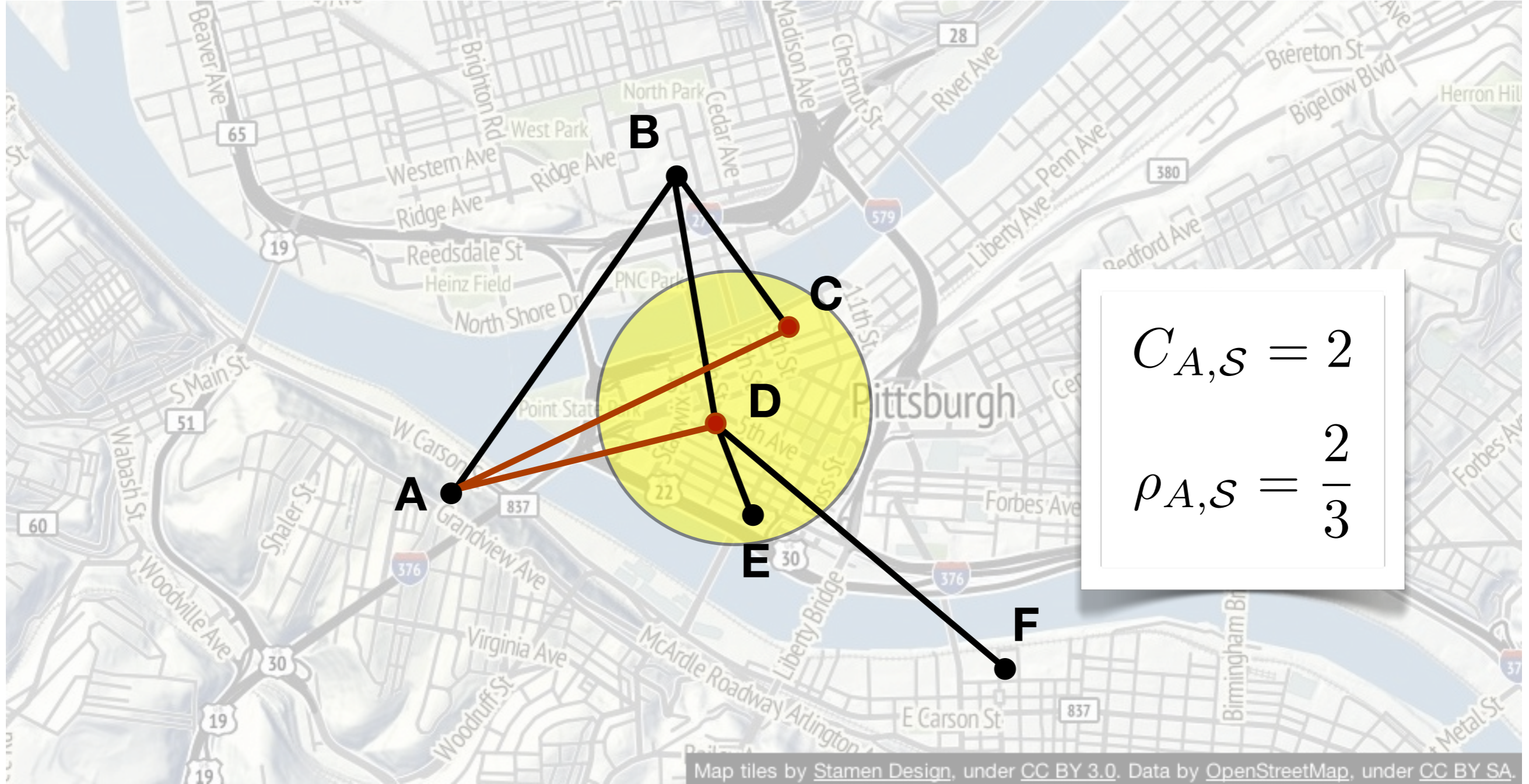
Quantifies how many neighbors of  $i$  have significant points inside the region  $S$ .



$$\rho_{i,S} = \frac{|\mathcal{N}_{i,S}|}{|\mathcal{N}_i|}$$

Quantifies the fraction of neighbors of  $i$  have significant points inside the region  $S$ .



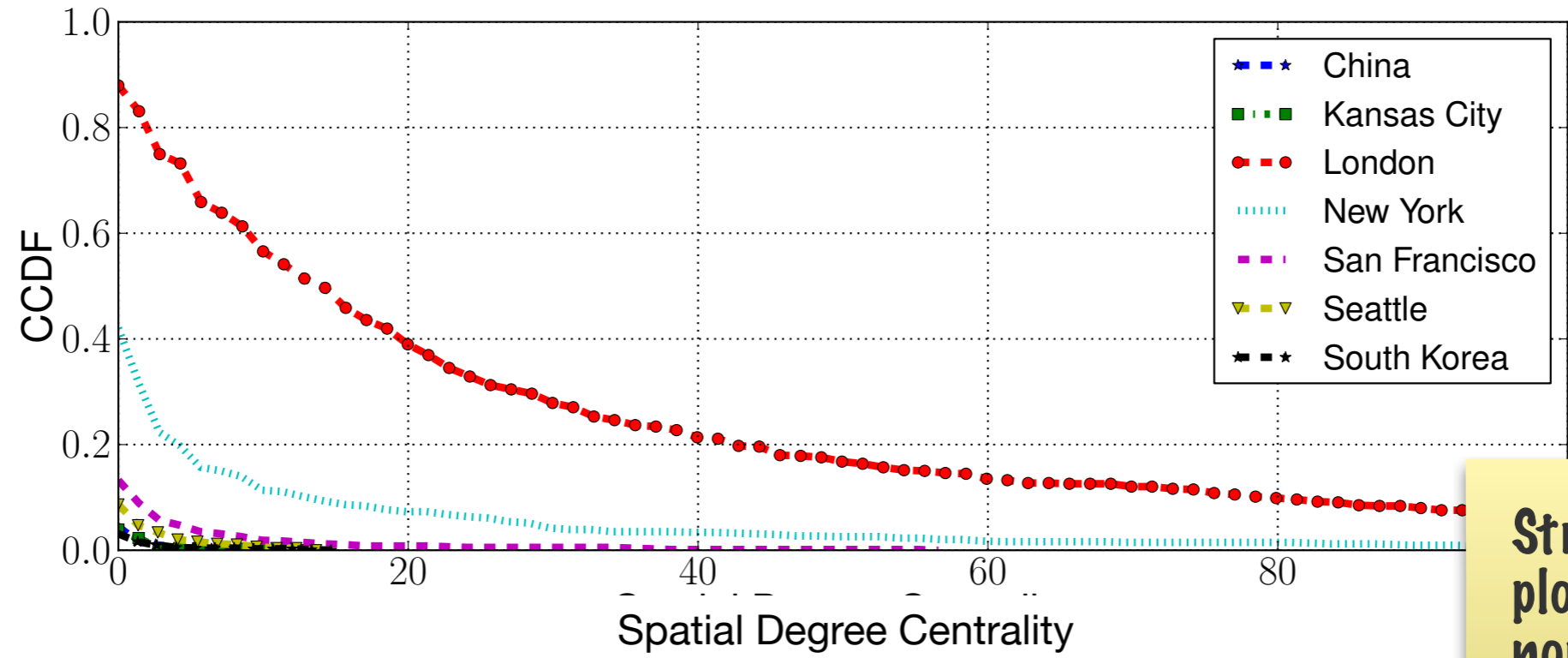


$$C_{A,S} = 2$$

$$\rho_{A,S} = \frac{2}{3}$$

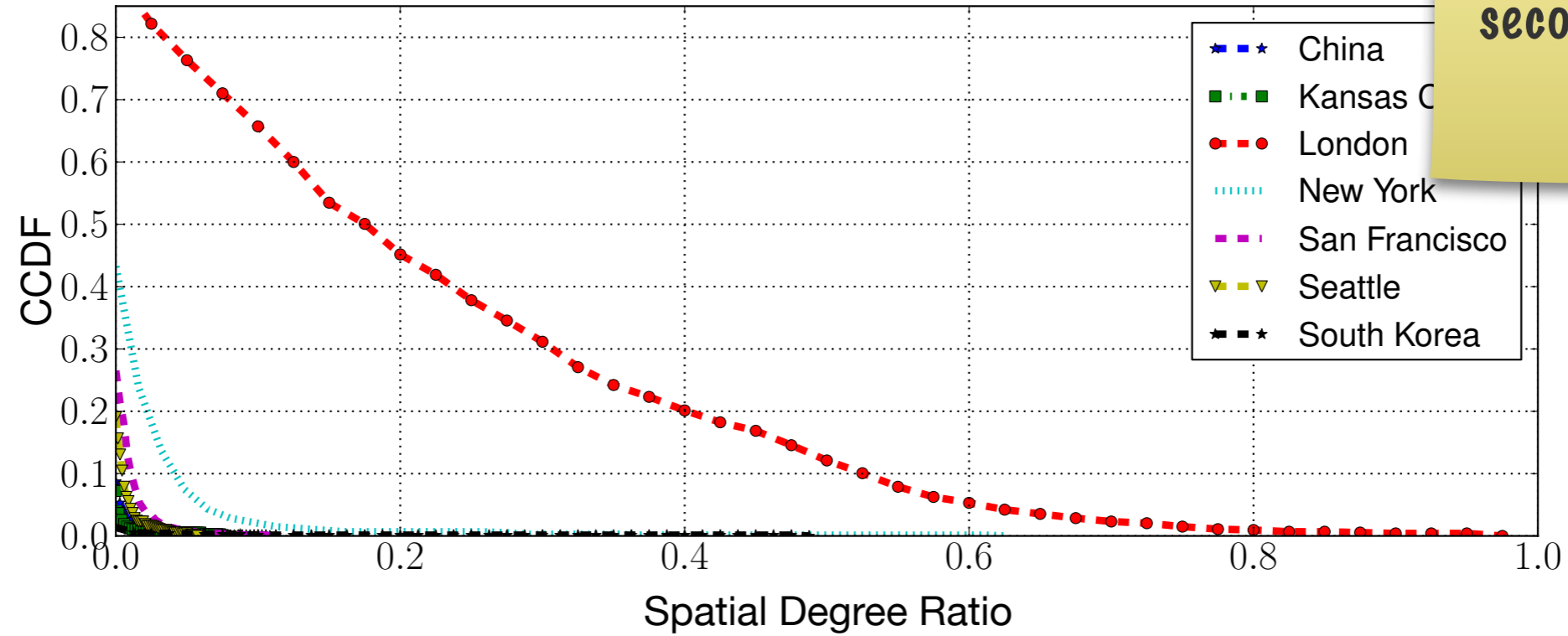


$C_{i,S}$



Stress that first plot is not normalized, second is

$\rho_{i,S}$

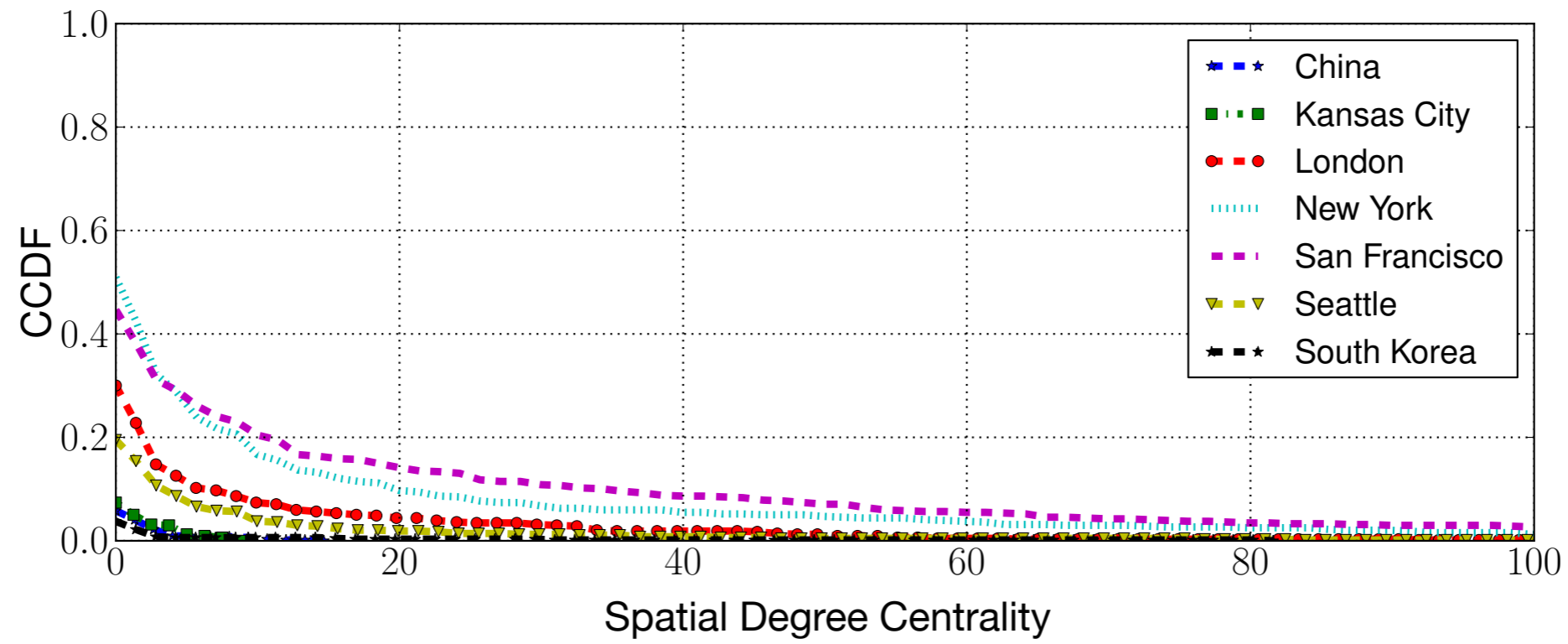


Users in London (Twitter)

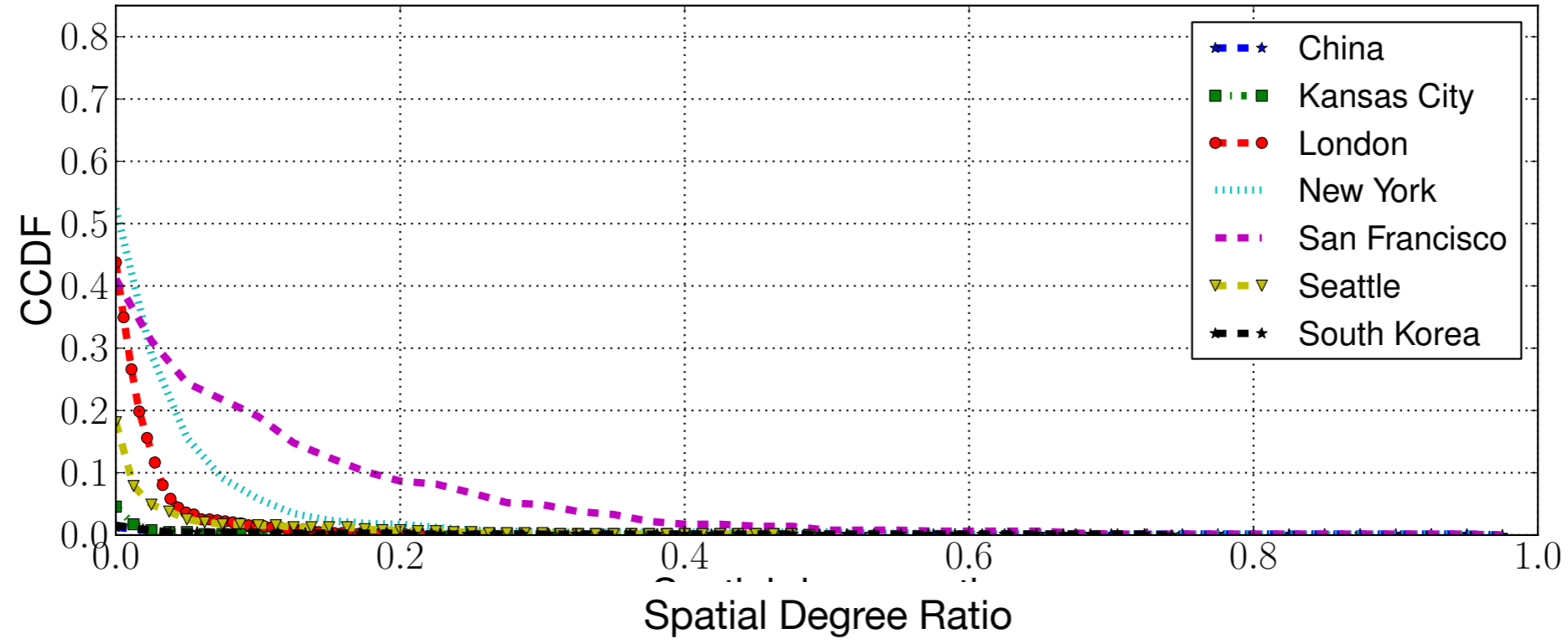
Londoners are mostly central towards London and somewhat central to New York as well.



$C_{i,S}$



$\rho_{i,S}$

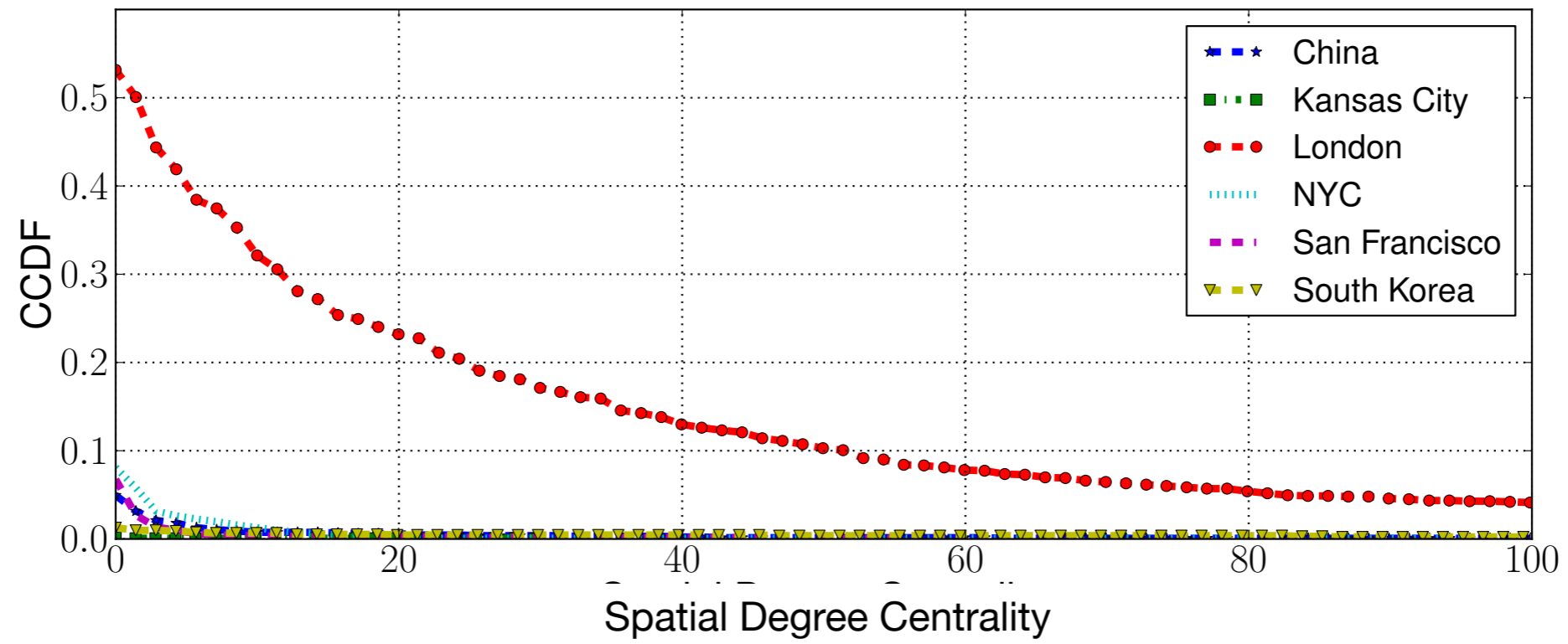


Users in San Francisco  
(Twitter)

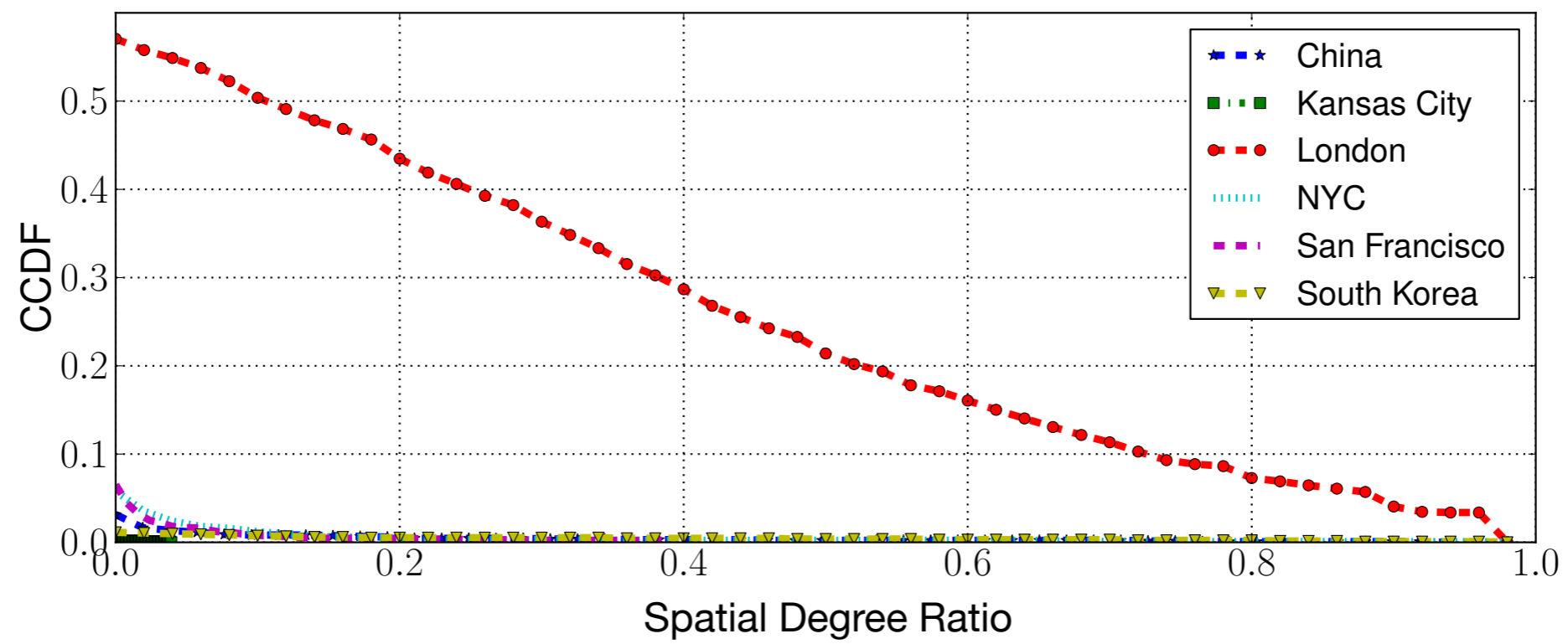
Interestingly, San Franciscan users have a similar distribution of centrality w.r.t. New York and San Francisco.



$C_{i,S}$



$\rho_{i,S}$

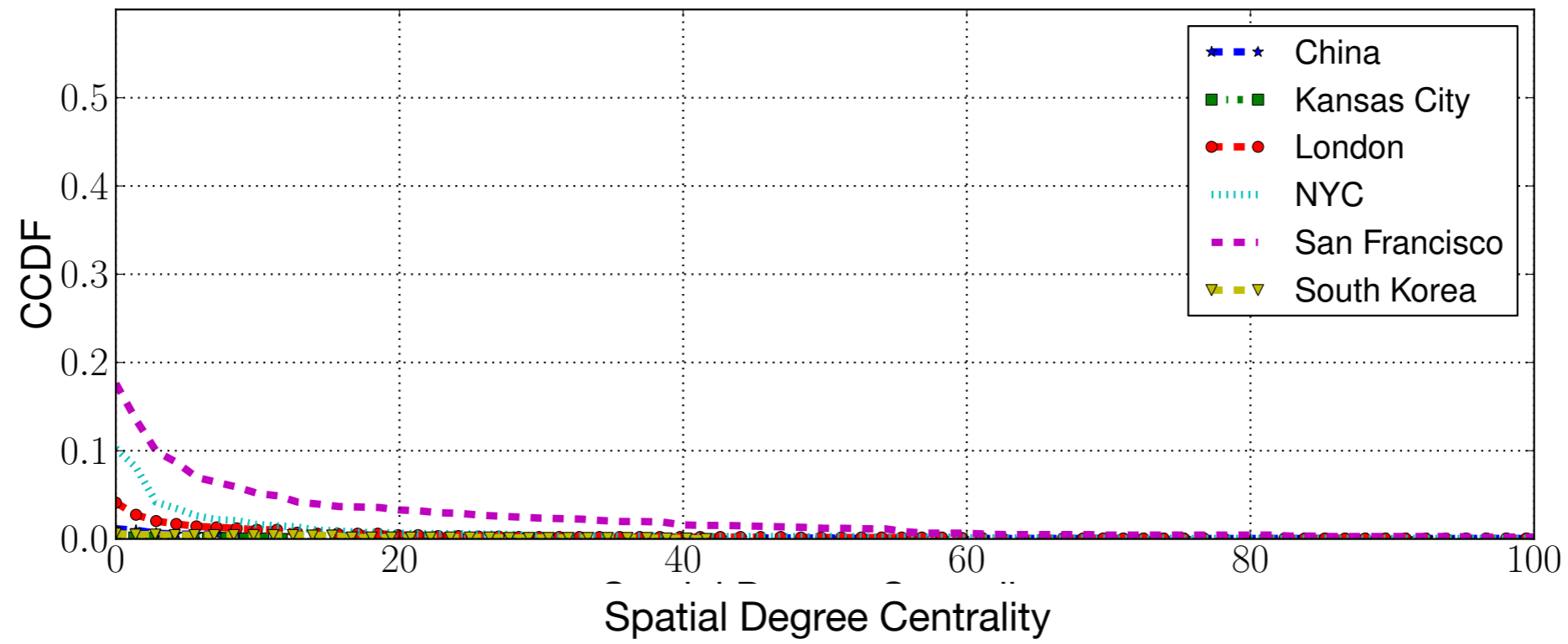


Users in London  
(Foursquare)

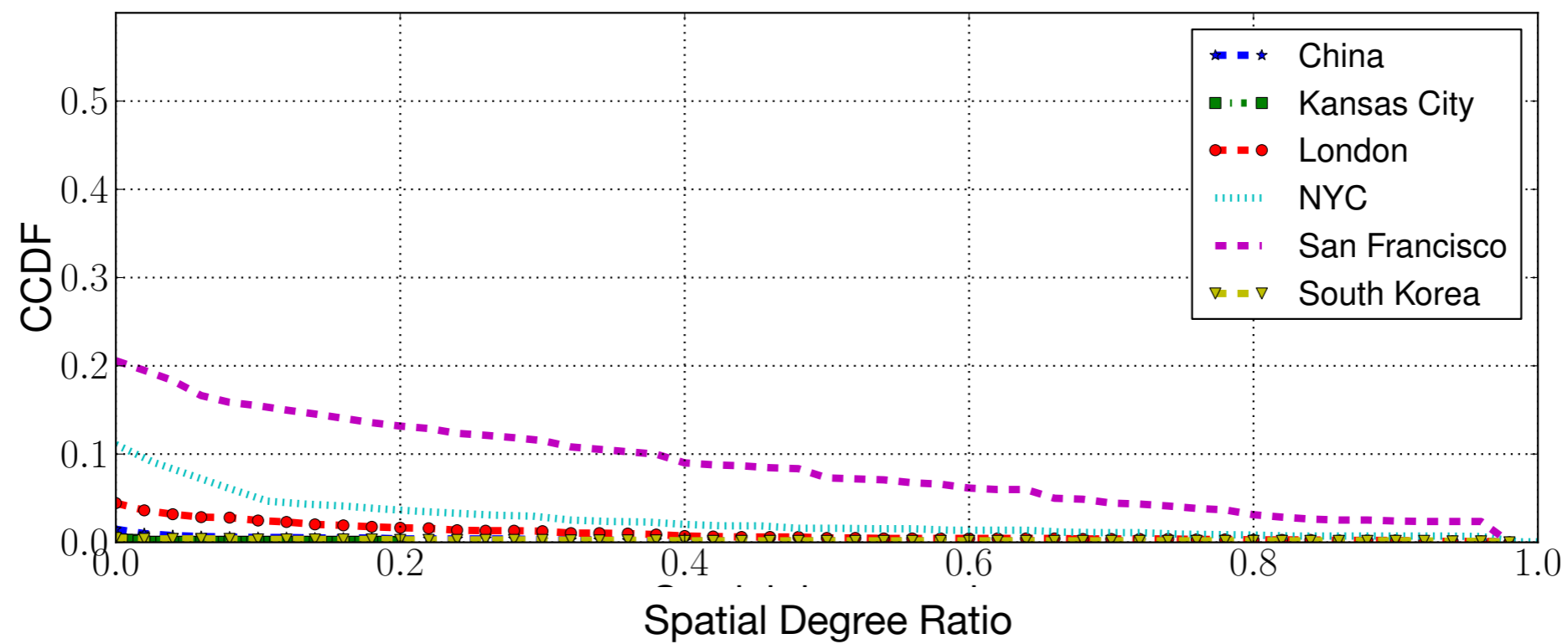
Foursquare exhibits lower avg degree (due to lower penetration rate). Results are in accordance with those observed for Twitter.



$C_{i,S}$



$\rho_{i,S}$



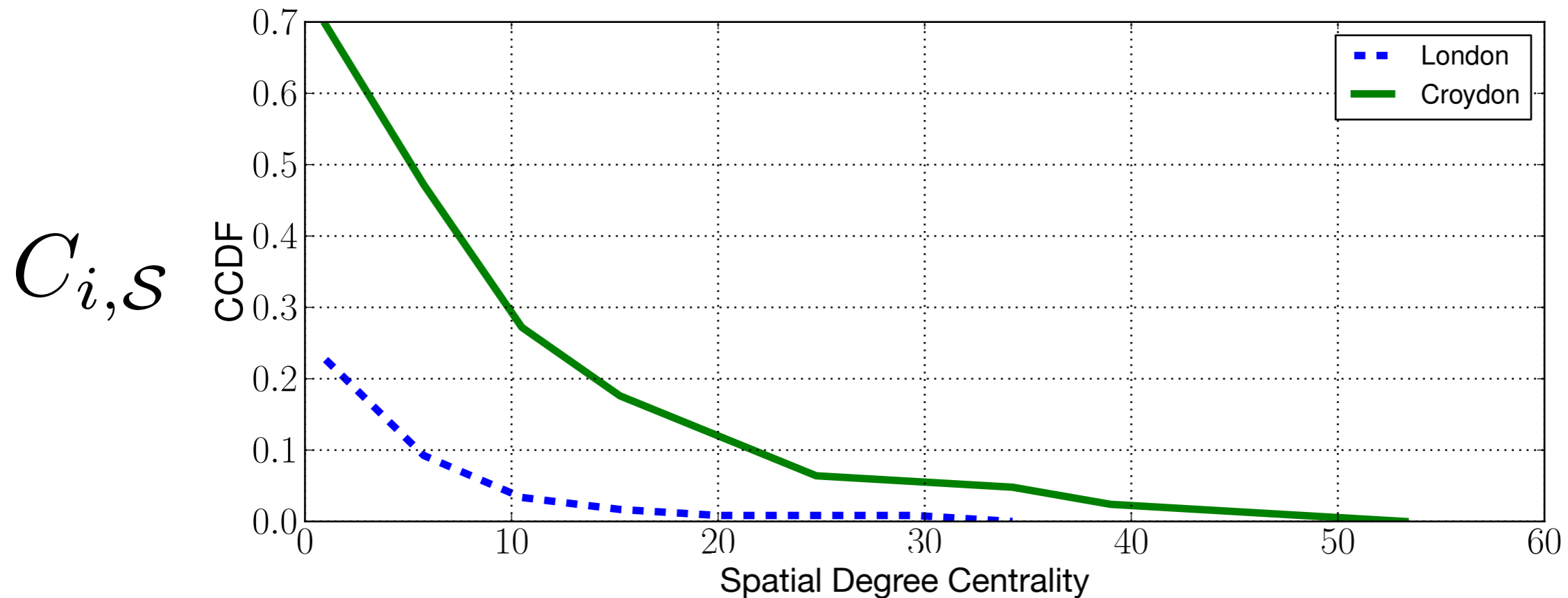
Users in San Francisco  
(Foursquare)

While London had no “influence” over other areas, San Francisco still has some influence on New York, as seen for Twitter.



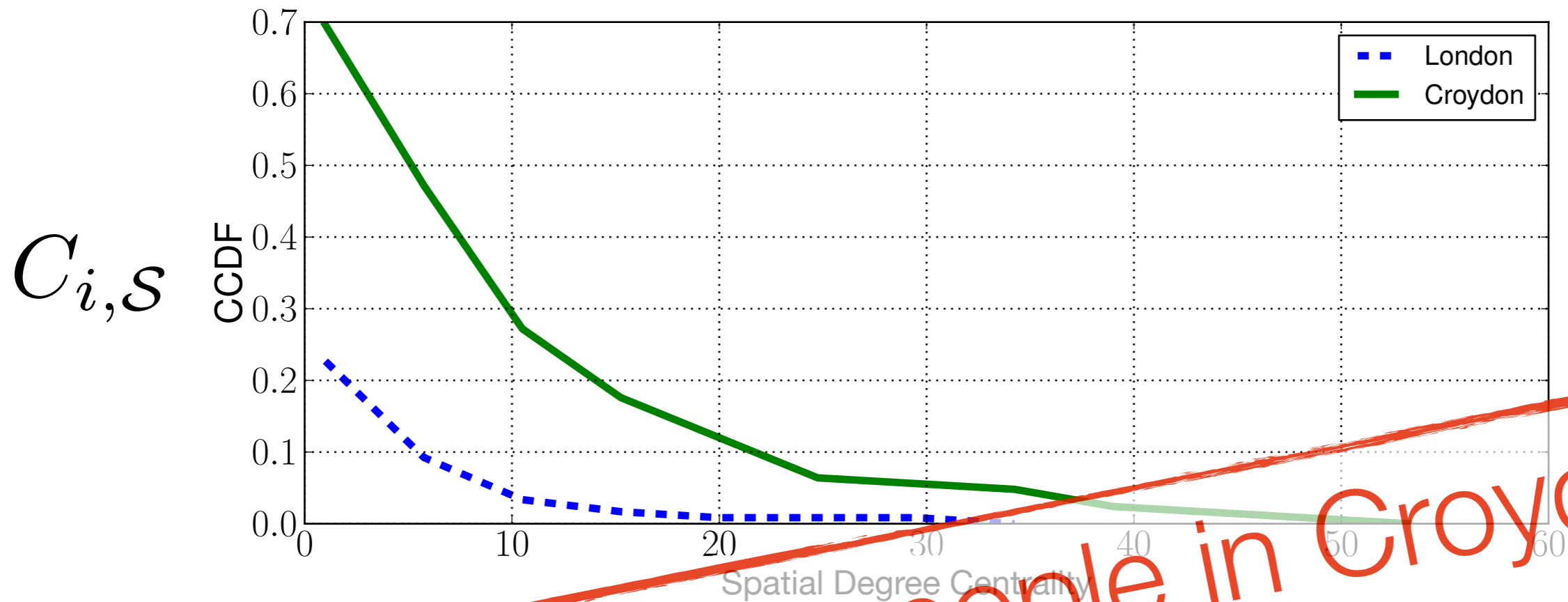
# Spatial Degree Centrality for Foursquare L Croydon and London w.r.t. Croydon

The intra-city analysis cannot be carried out on the Twitter dataset.



# Spatial Degree Centrality for Foursquare L Croydon and London w.r.t. Croydon

The intra-city analysis cannot be carried out on the Twitter dataset.



Targeting people in Croydon  
might give an advantage



# Spatial Degree Centrality for Foursquare Users in SF Chinatown and SF w.r.t. San Francisco

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- Avg centrality of Chinatown and San Francisco users w.r.t. Chinatown are comparable (3.20 vs 3.06).
- Avg centrality of Chinatown users w.r.t. to China is three times bigger than the centrality from San Franciscans (32.24 vs 11.87).



Potential  
cultural  
influence



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- Avg centrality of Chinatown users w.r.t. to China is three times bigger than the centrality from San Franciscans (32.24 vs 11.87).

Advantage towards China,  
not SF Chinatown



# Spatial Closeness Centrality

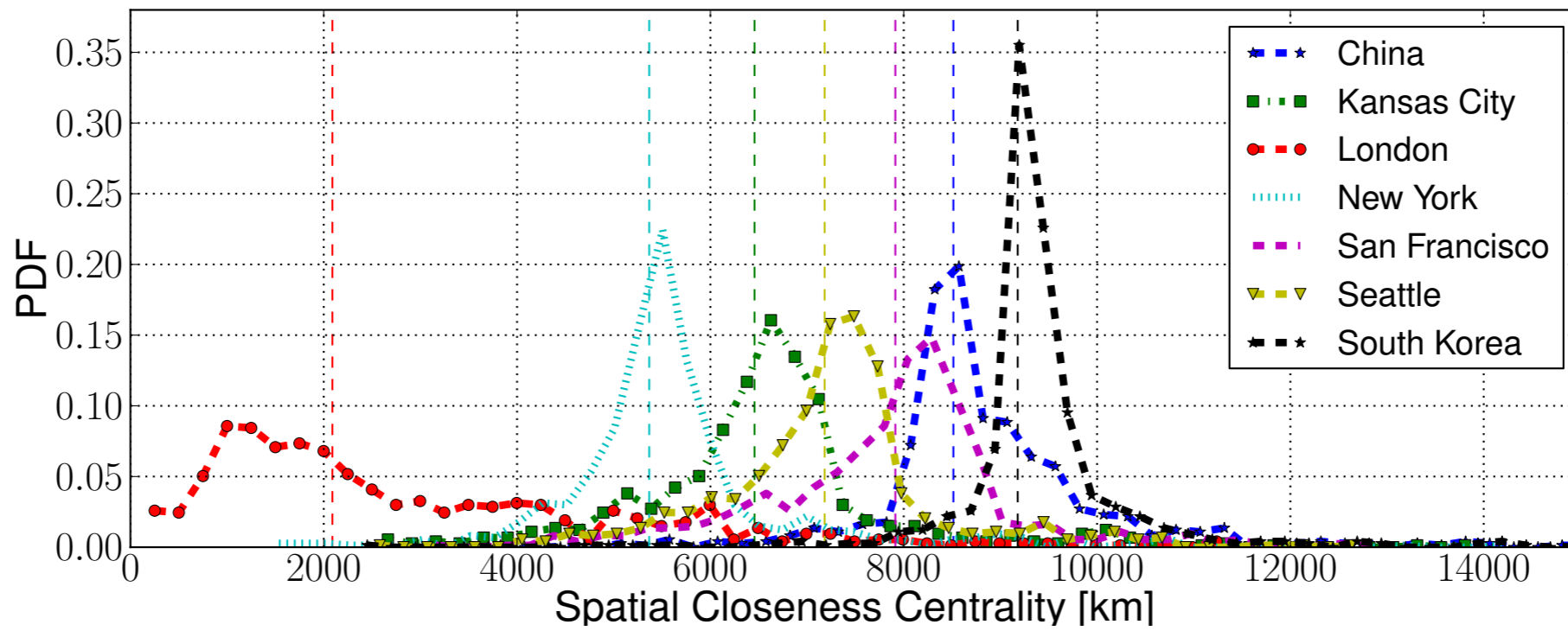
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$$C_{i,p^*}^C = \frac{1}{|\mathcal{N}_i|} \sum_{j \in |\mathcal{N}_i|} d_G(p_j, p^*)$$

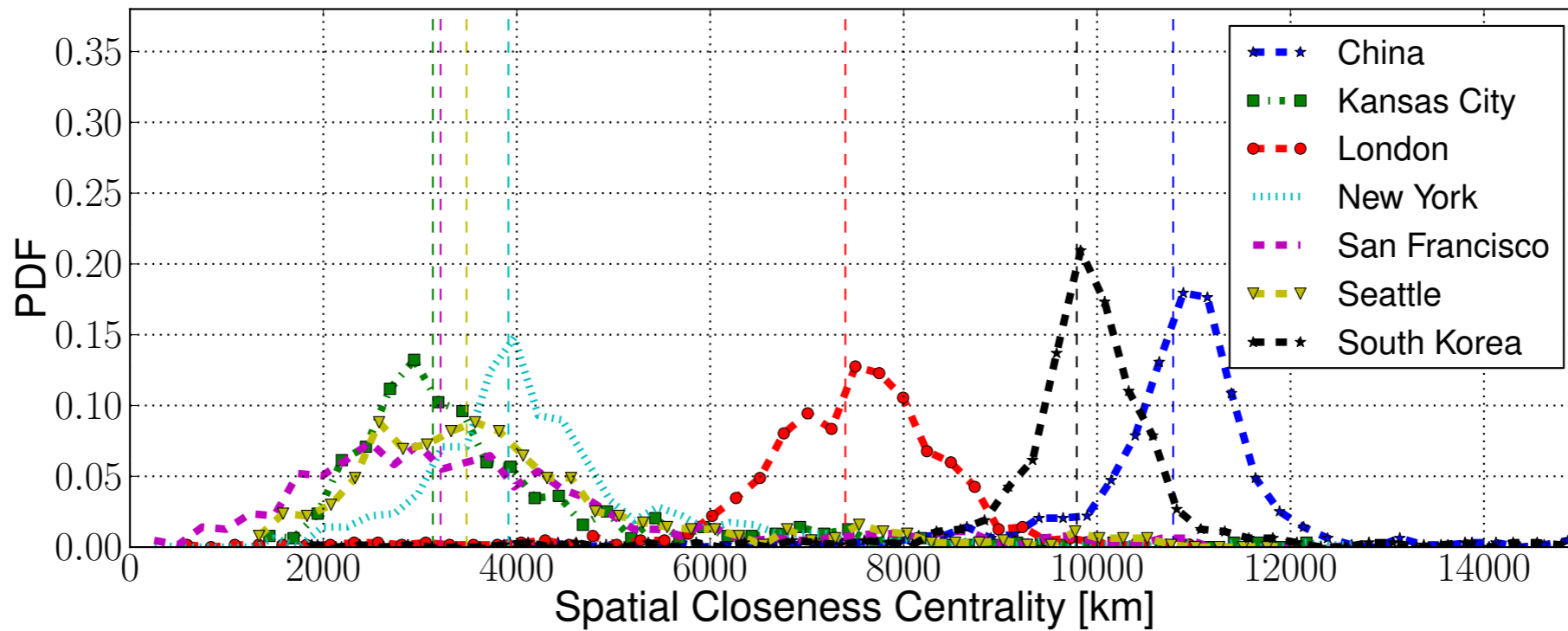
It is the average geographic distance of all neighbors' significant places from a specific geographic point.

It is an indicator of how the influenced audience of a user is geographically close to a certain location.





from  
London



from San  
Francisco

Stress that it is London vs other cities and SF vs other cities

# Spatial Closeness Centrality (Twitter)

Peak/median very close to the distance between considered locations.



# Spatial Efficiency Centrality

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$$C_{i,p^*}^E = \frac{1}{k_i} \sum_{j \in \mathcal{N}_i} \frac{1}{d_G(p_j, p^*)}$$

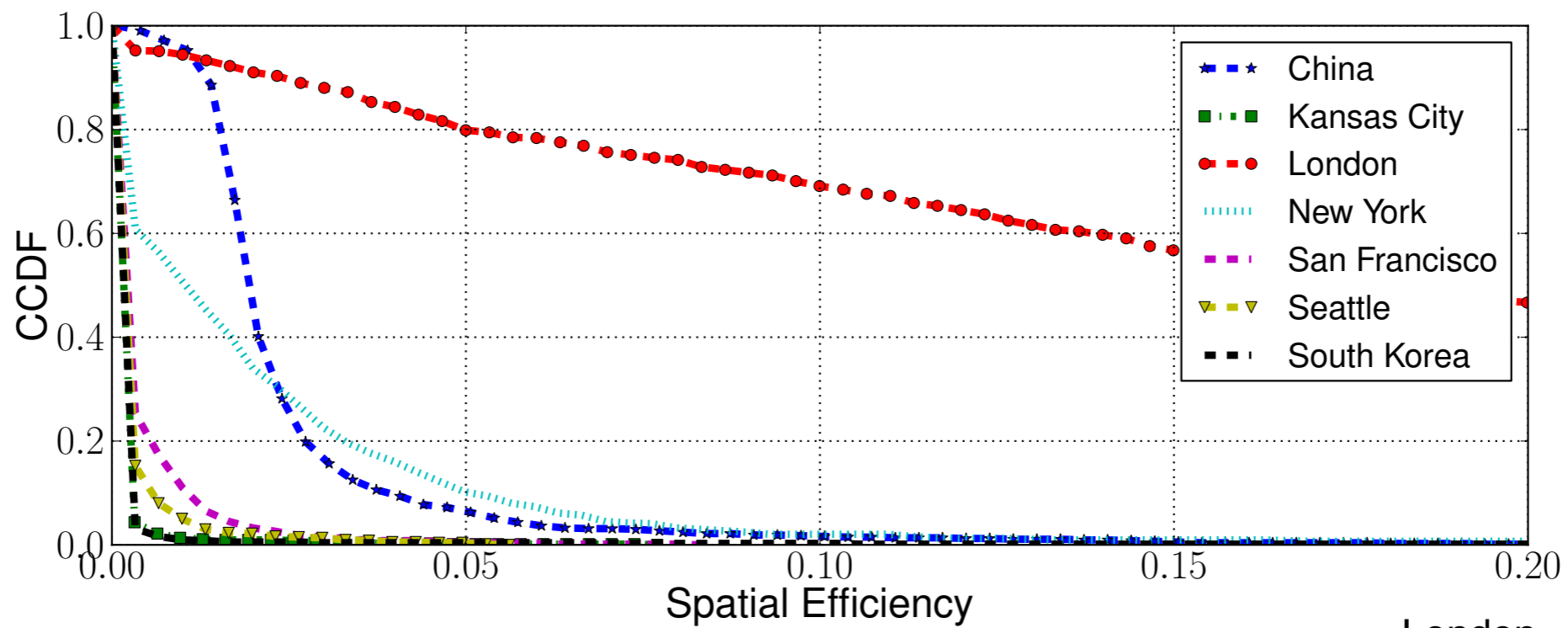
It can be thought of as a spatial extension of efficiency of traditional graphs.

Not defined if  $i$  and  $p^*$  are coinciding!

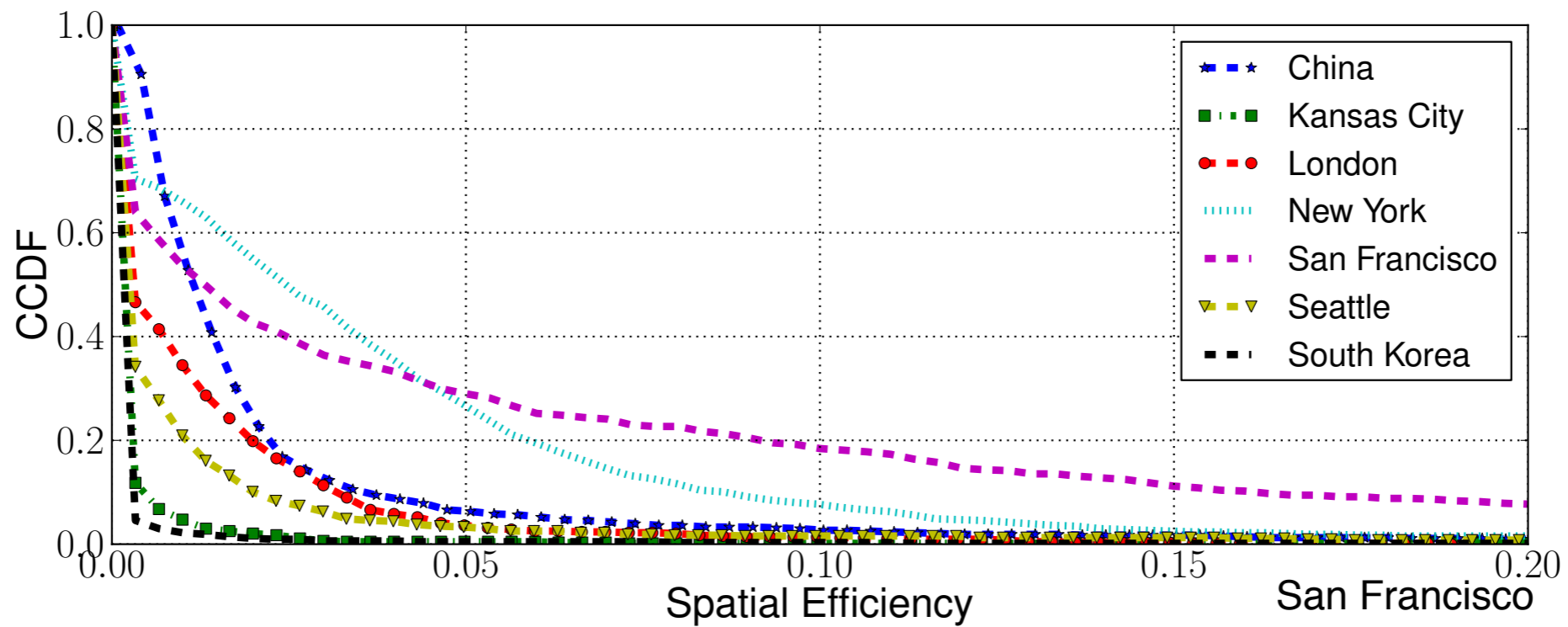


$$C_{i,p^*}^E = \frac{1}{k_i} \sum_{j \in \mathcal{N}_i} e^{-d_G(p_j, p^*)/\gamma}$$





from  
London



from San  
Francisco

## Spatial Efficiency Centrality (Twitter)

High values of self-efficiency for Londoners. Distributions for SF more uniform.



# Local Spatial Clustering Coefficient

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$$C_{i,S} = \frac{|\{e_{jk} \in E : j, k \in \mathcal{N}_{i,S}\}|}{k_{i,S}(k_{i,S} - 1)}$$

It represents the fraction of users of  $i$  which form social triangles in the considered region  $S$ .

Nodes scoring high values are part of social circles in the region, making them potentially very influential.



# Complexity

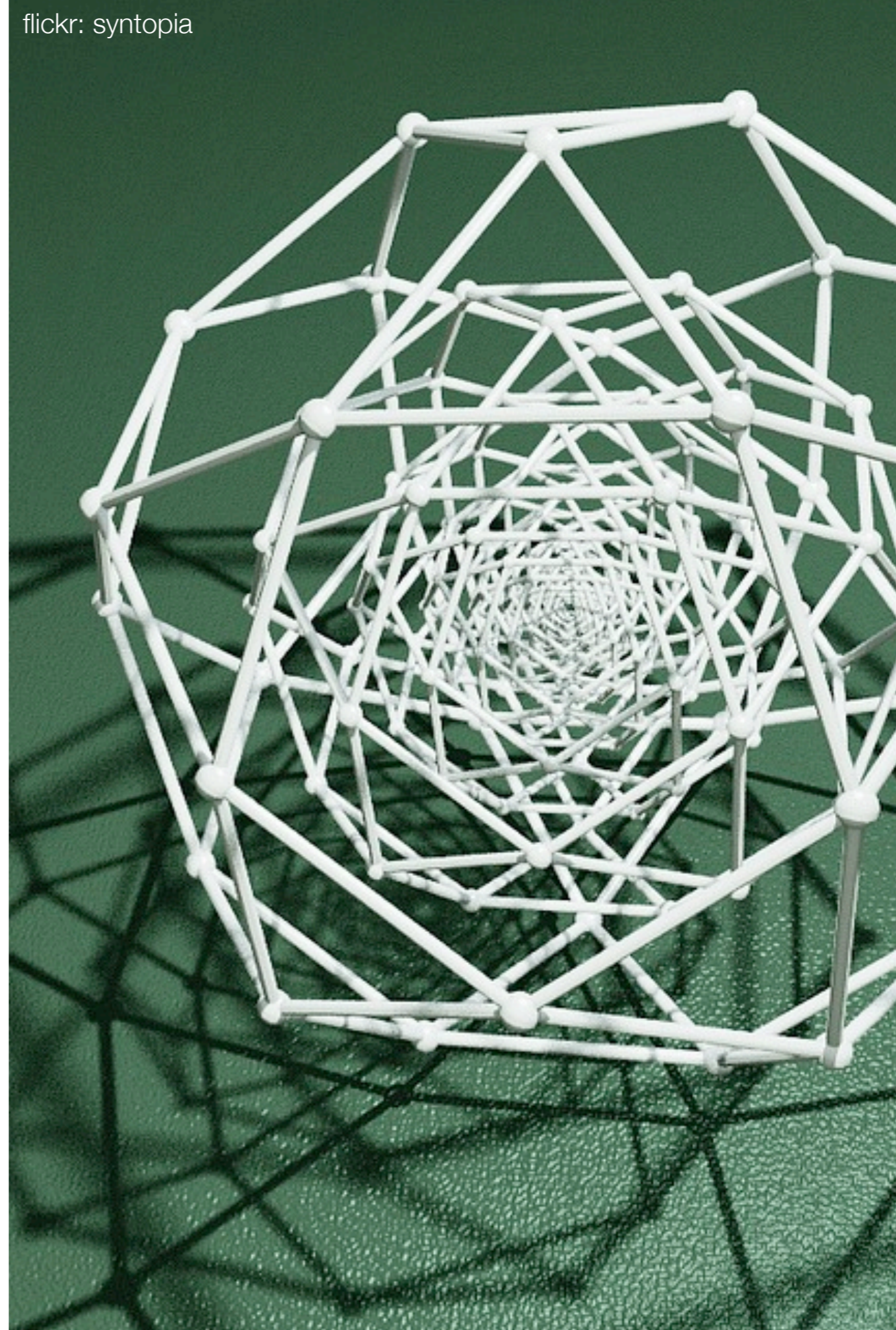
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- All the defined metrics are *local*: no need to explore the whole graph.
- Spatial degree/ratio/closeness centrality and spatial efficiency scale as

$$\mathcal{O}(nkt)$$

Local spatial clustering coefficient scales as

$$\mathcal{O}(nk^2t^2)$$



# Complexity

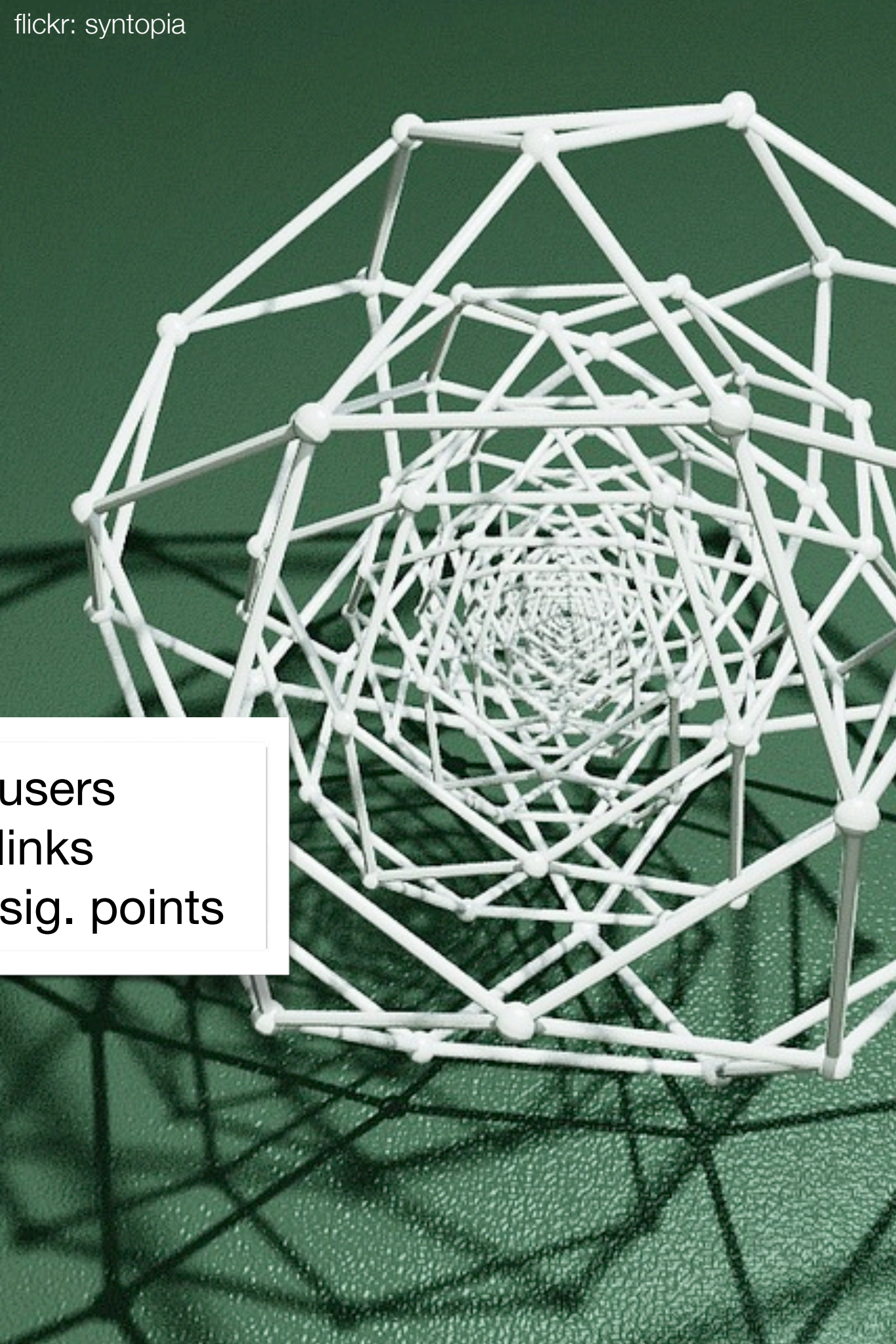
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- Spatial degree/ratio/closeness centrality and spatial efficiency scale as

$$\mathcal{O}(nkt)$$

Local spatial clustering coefficient scales as

$$\mathcal{O}(nk^2t^2)$$



n	# users
k	# links
t	# sig. points

# Future work

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- We analysed *structural* properties, not processes dynamics (e.g. information diffusion).
- We plan to analyse processes happening on a network (e.g. retweets, mentions) and quantify the impact of spatial structure over these processes.
- We plan to explore real-time computation aspects.



## Take-away Messages

Centrality metrics can be extended to measure spatio-social centrality.

Such metrics can be used to rank users according to their importance.

The presented metrics are local and scale well.

# Thanks!

# Questions?

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