NEW YORK UNIVERSITY

Urban Data Science: Mobility, Cities and Networks

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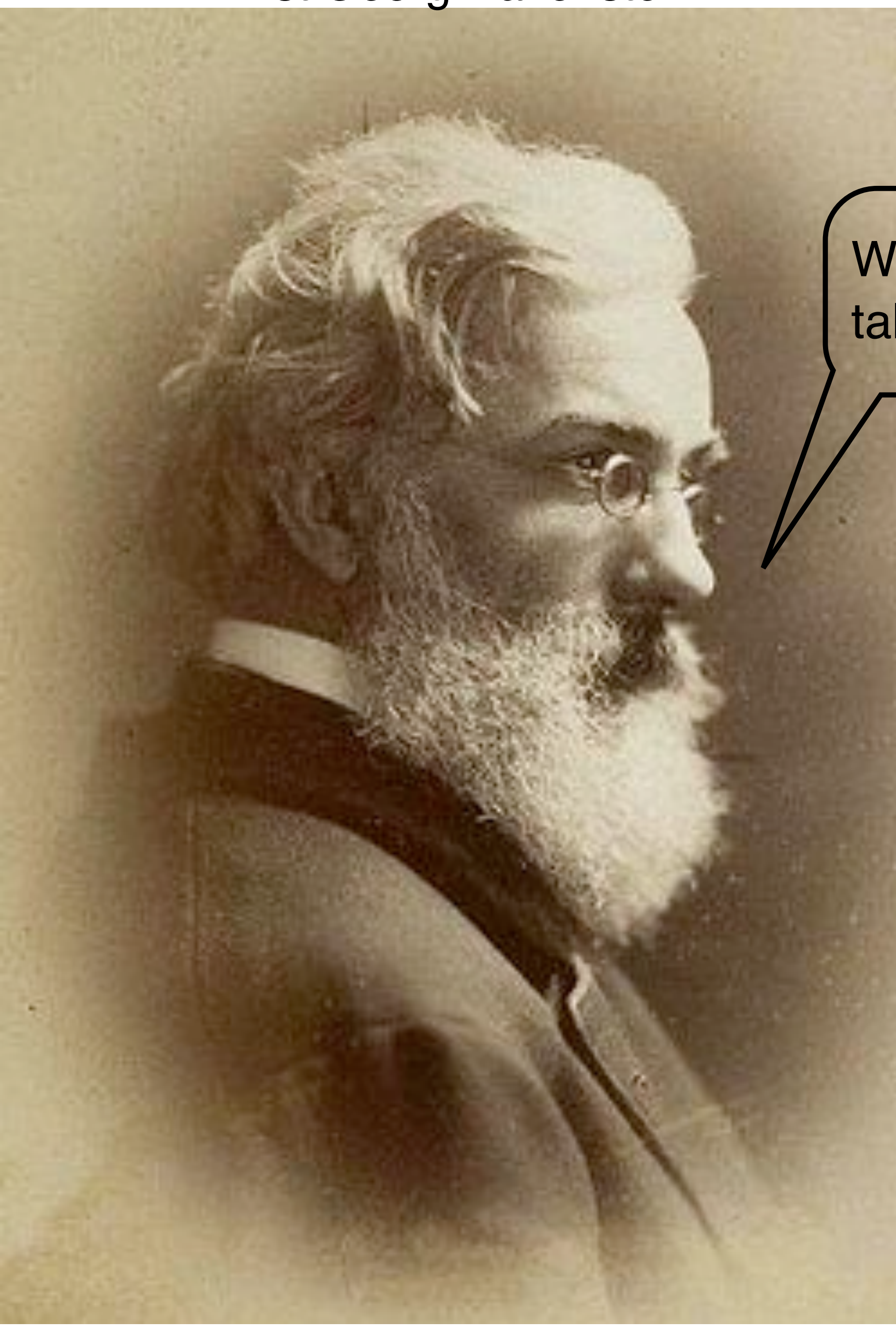
IC2S2’17, Tutorial
A Practical Introduction to Spatial Datasets and Urban Applications
Cologne, Germany

Presentation Summary

- A Historic perspective on human mobility and related datasets.
- Human mobility and transport modelling.
- Deeper in sights on urban mobility models.
- Multivariate human mobility models.
- From individual trajectories to aggregate mobility patterns.

History of modern human mobility studies

Ernst Georg Ravenstein



WTF is this dude talkin' about?

Human migration follows no definitive law ...

William Farr ... or Dark Vader

the main man ...

The laws of human migration

The following was a standard list after Ravenstein's (1834-1913) proposal in the 1880s. The theories are as follows:

1. *every migration flow generates a return or countermigration.*
2. *the majority of migrants move a short distance.*
3. *migrants who move longer distances tend to choose big-city destinations.*
4. *urban residents are often less migratory than inhabitants of rural areas.*
5. *families are less likely to make international moves than young adults.*
6. *most migrants are adults.*
7. *large towns grow by migration rather than natural increase.*

Ravenstein exploited census data from the United Kingdom to support empirically his findings ...

E. G. Ravenstein. The laws of migration. Journal of the Royal Statistical Society, 1885.

Urban Transport Modeling

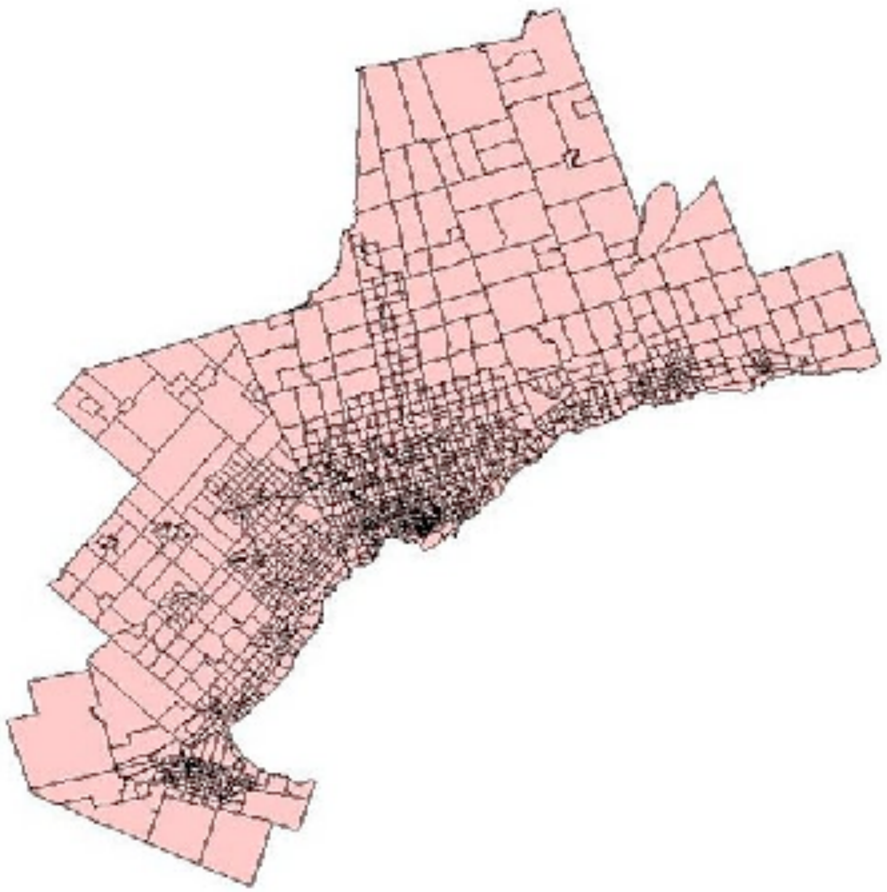


Table: Illustrative trip table

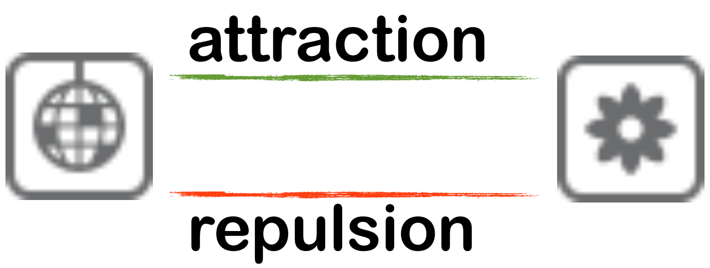
Origin \ Destination	1	2	3	Z
1	T_{11}	T_{12}	T_{13}	T_{1Z}
2	T_{21}			
3	T_{31}			
Z	T_{Z1}			T_{ZZ}

$$T_{ij} = k\frac{O_i D_j}{d_{ij}^2}$$

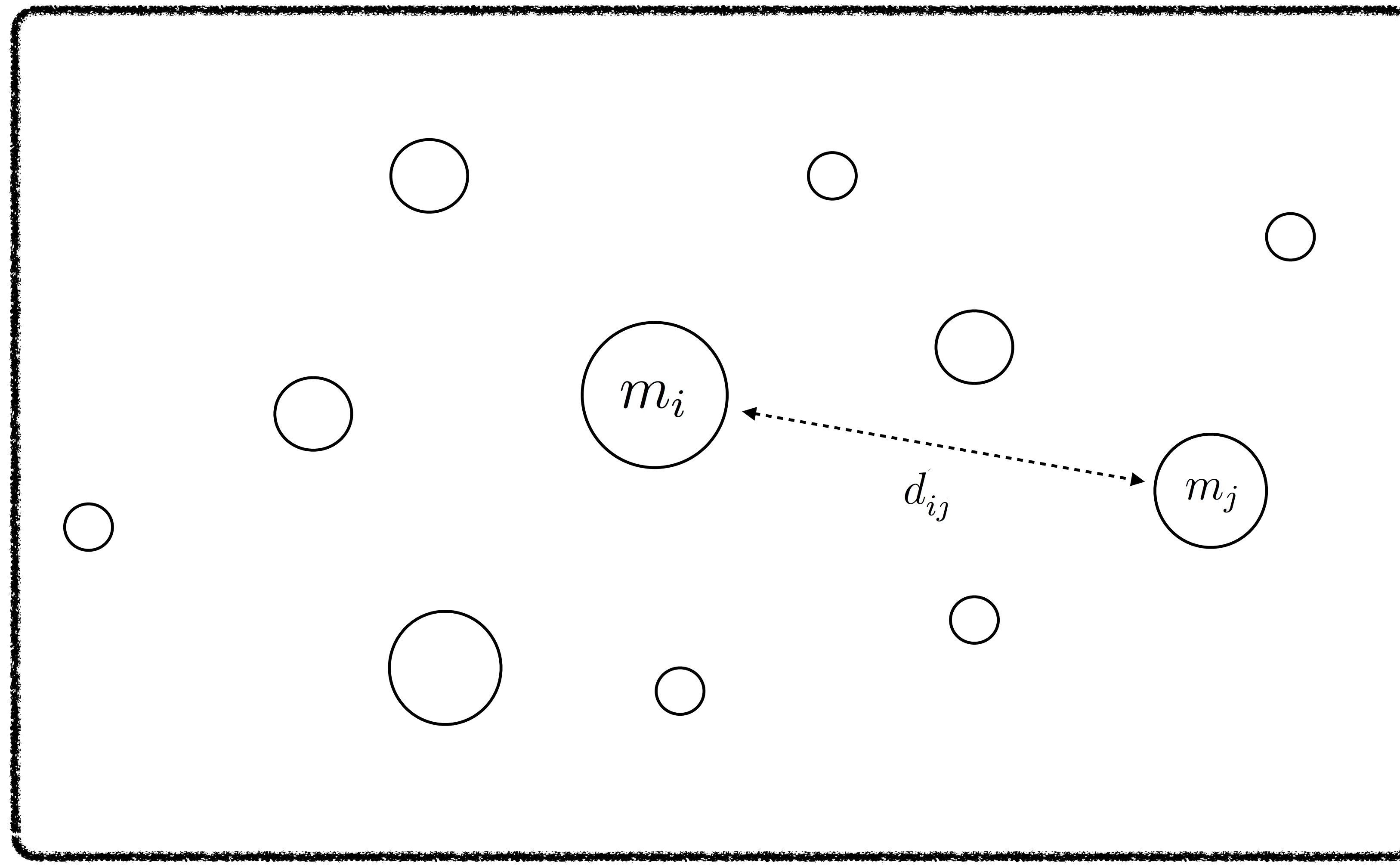
Data in urban transport modeling has been based primarily on surveys...

Ortuzar, J. de, and Luis G. Willumsen. *Modelling transport*. 2011.

Gravity Models



Inspired by Newtonian physics, gravity models suggest that two places attraction is proportional to their mass and inversely proportional to their geographic distance.

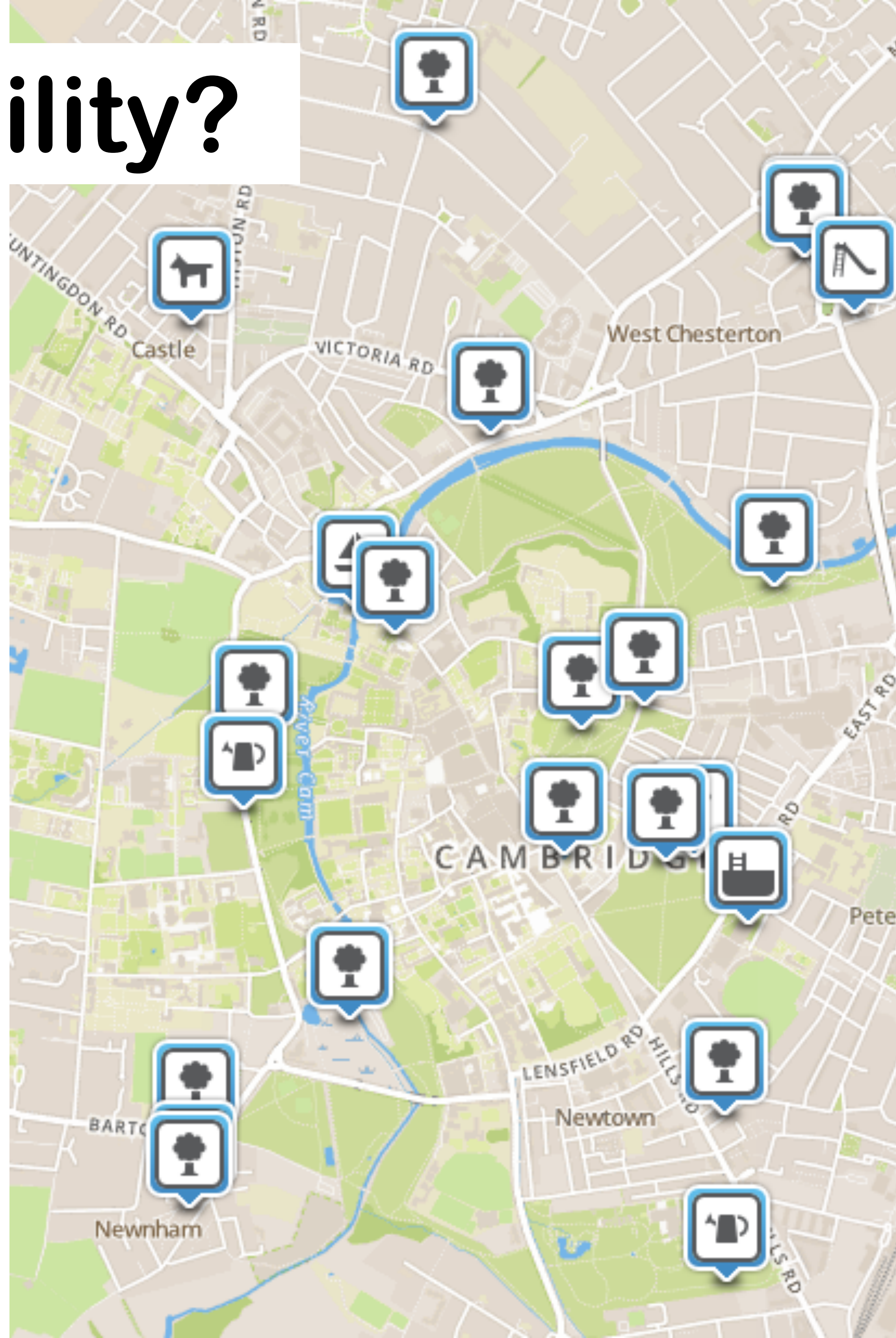


$$F_{ij} = \gamma \frac{m_i \; m_j}{d_{ij}^2}$$

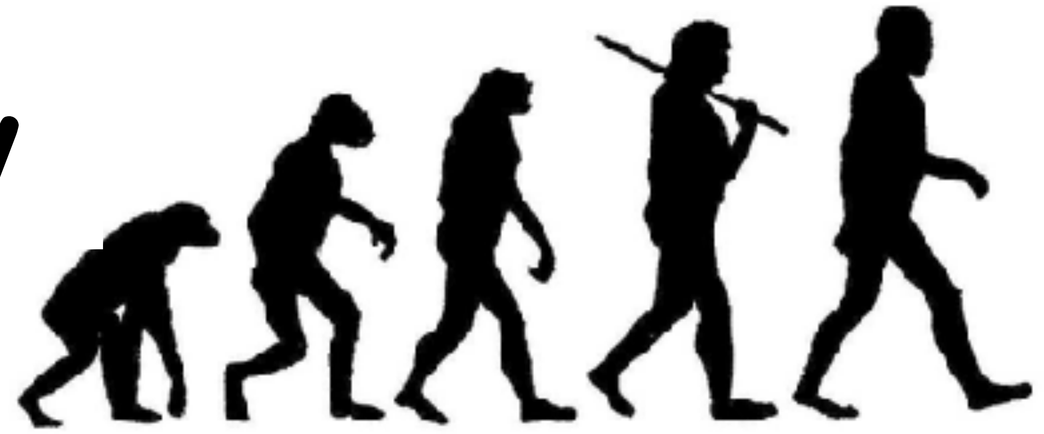
Why human mobility?

Urban planning :
understand the city and optimise services

Mobile applications and recommendations:
study the user and offer services



Why human mobility



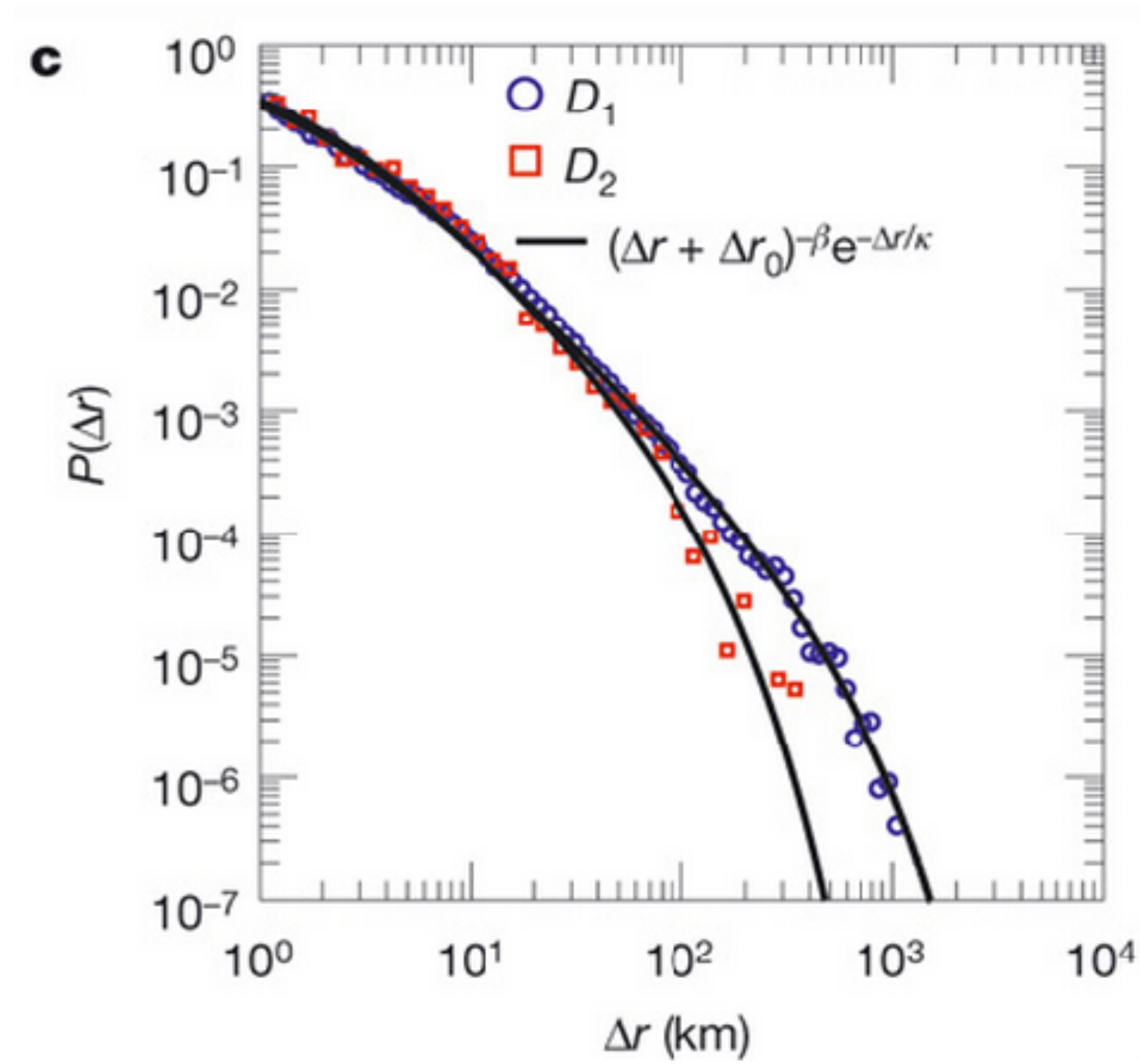
Animals have the capacity to search and navigate across space

We can understand how our brain is wired

Have we really left the monkey ?

Cellular Datasets

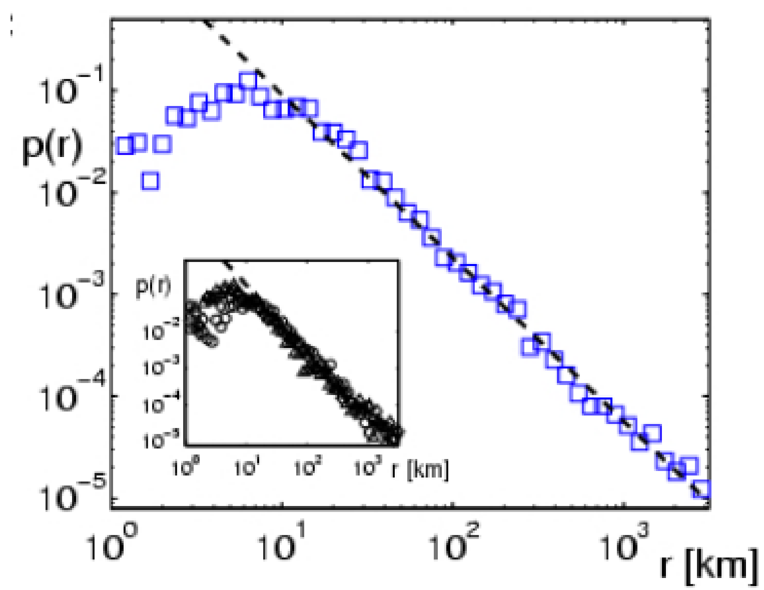
One of the first large scale studies of human movement with modern mobile datasets...

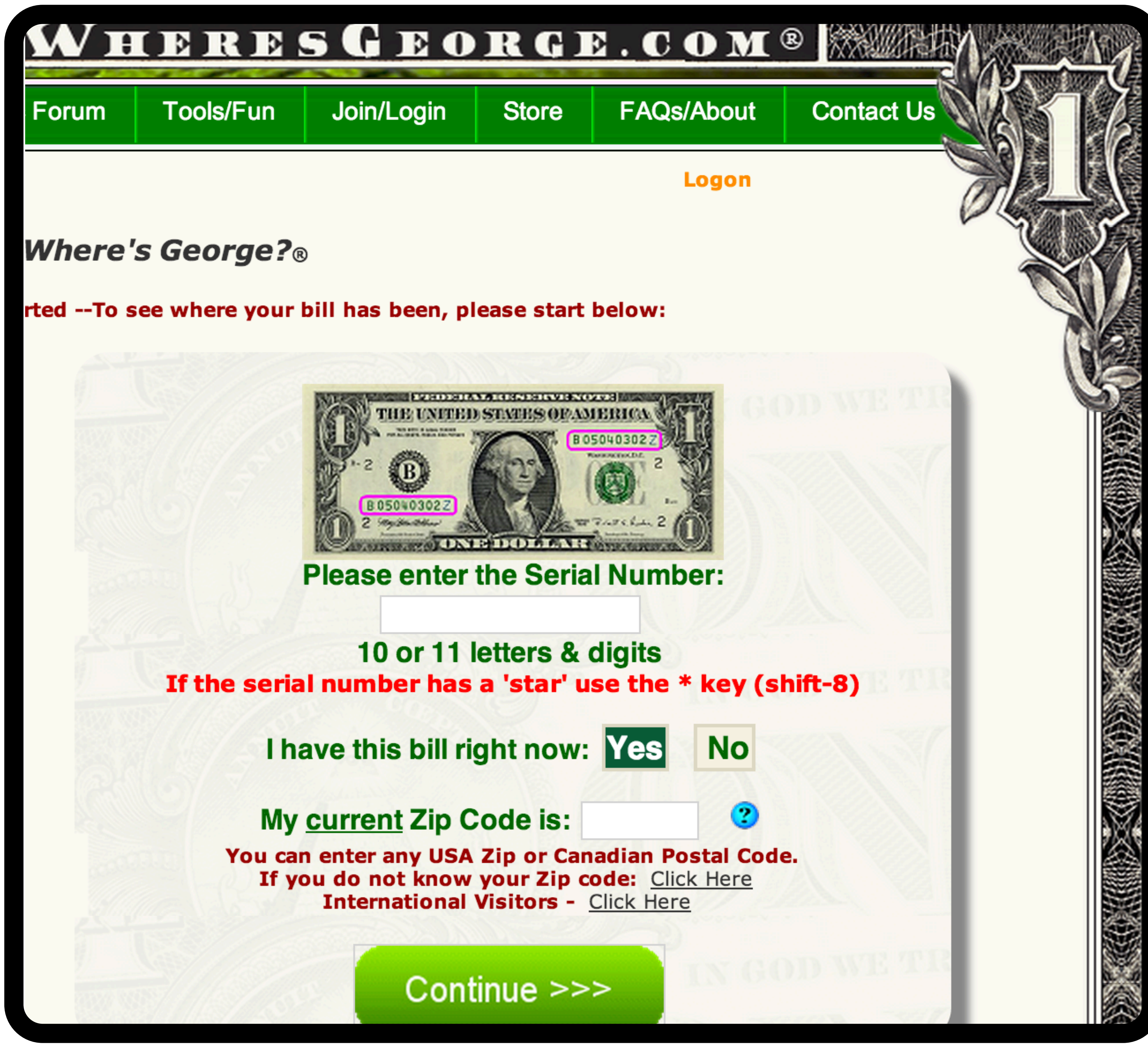


Gonzalez, Marta C., Cesar A. Hidalgo, and Albert-Laszlo Barabasi. "Understanding individual human mobility patterns." *Nature* 453.7196 (2008): 779-782.

Where's George ?

One of the most creative ways to study human movement that has used the displacement of dollar bills as a proxy to human mobility...

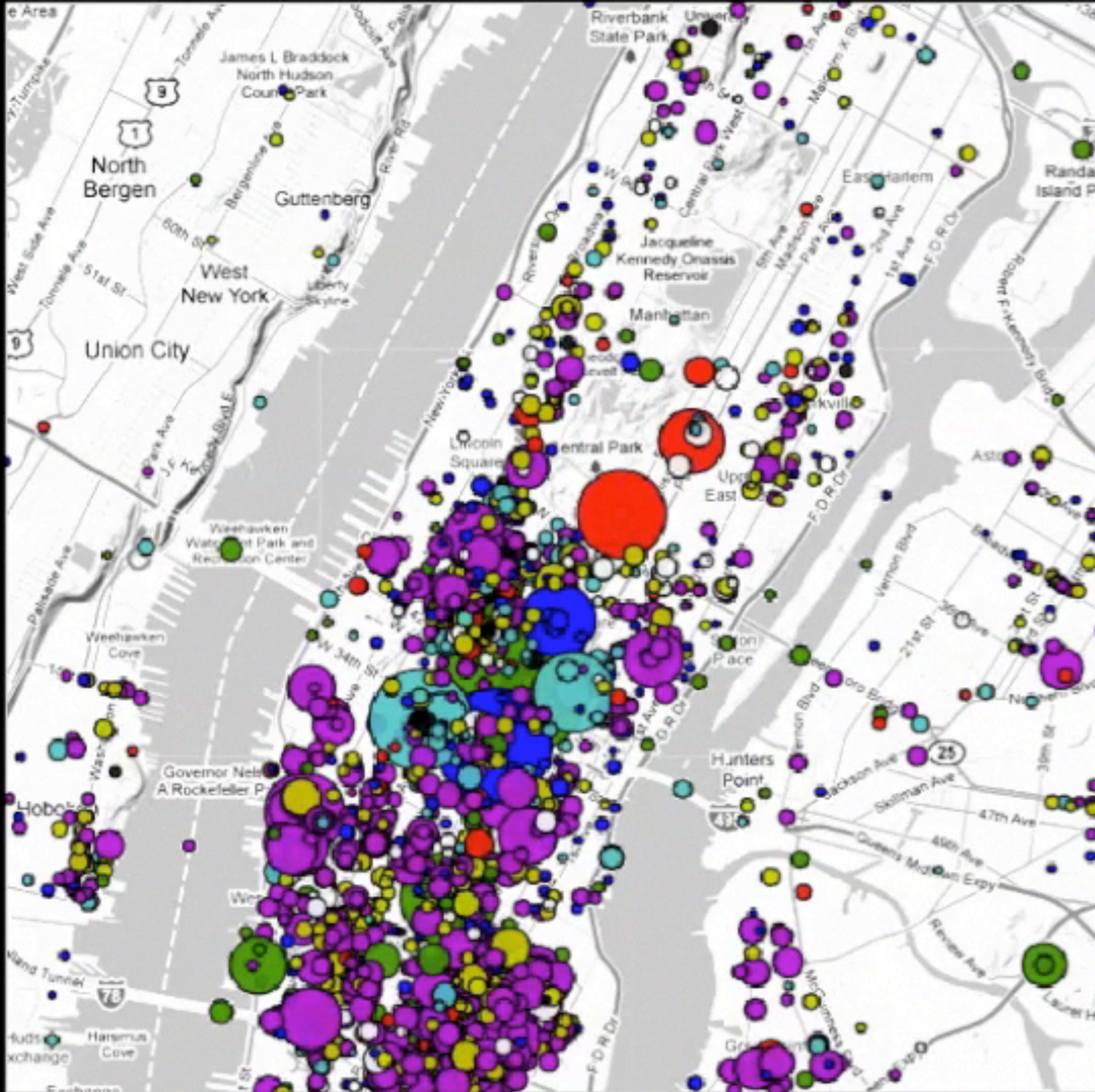




Brockmann, Dirk, Lars Hufnagel, and Theo Geisel. "The scaling laws of human travel." *Nature* 439.7075 (2006): 462-465.

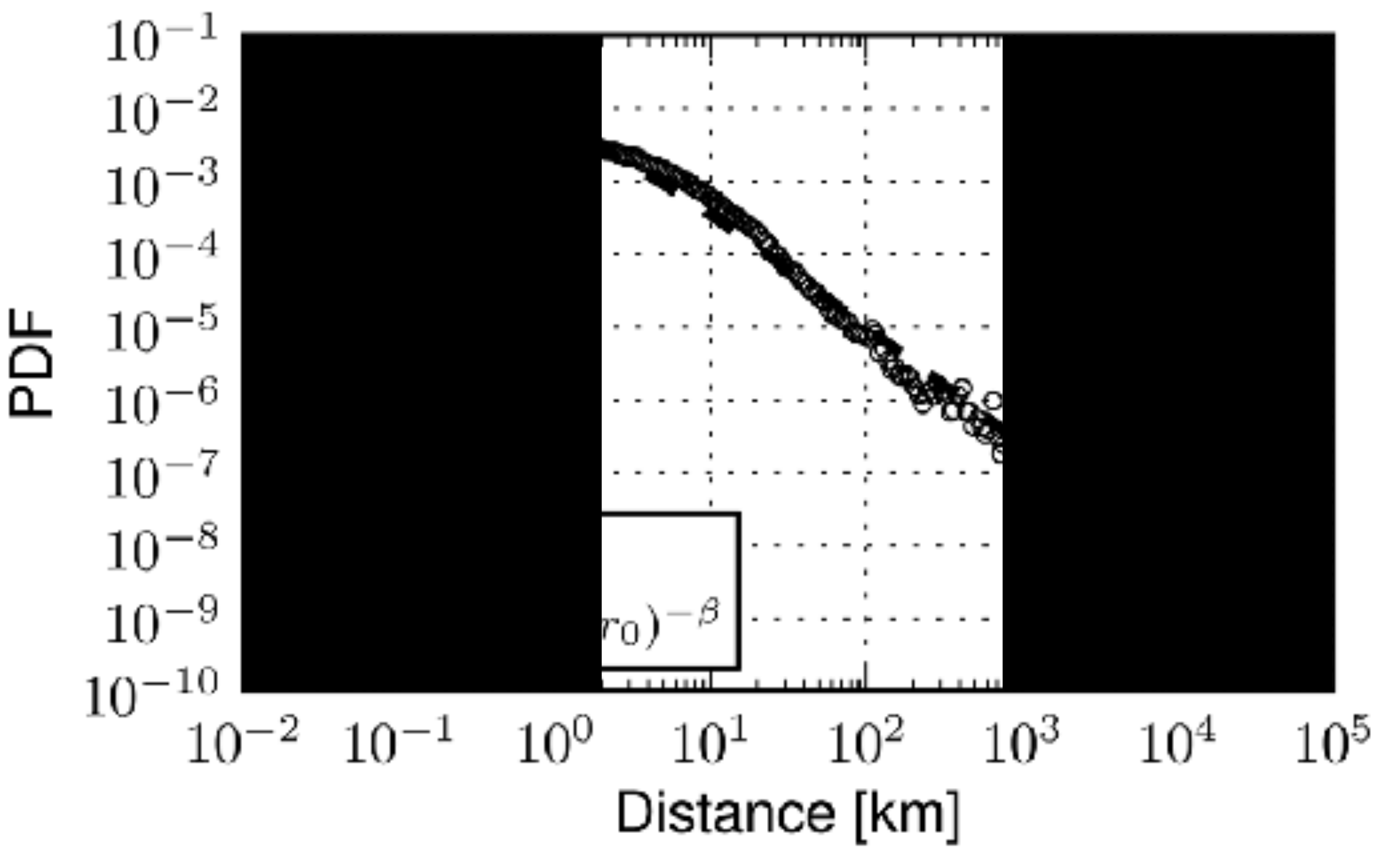
Data on human movement...

Mobile Social	VS	Cellular
GPS accuracy ~ 10 meters		BTS Tower Accuracy ~ 1KM
Global Coverage		Country Coverage
Publicly Available		Private / Corporate


Riverbank State Park
James L Braddock North Hudson County Park
North Bergen
Guttenberg
West New York
Union City
East Harlem
Randall Island Pa
Jacqueline Kennedy Onassis Reservoir
Manhattan
Lincoln Square
Central Park
Upper East
Weehawken Waterfront Park and Recreation Center
Weehawken Cove
Governor Nelson A Rockefeller Park
Hoboken
Hunters Point
Harsimus Cove
Sutton Place
W 34th St
Jackson Ave
Skillman Ave
47th Ave
49th Ave
Queens Midtown Expy
Vernon Blvd
F D R Dr
Queensboro Bridge

Power-law tales ...

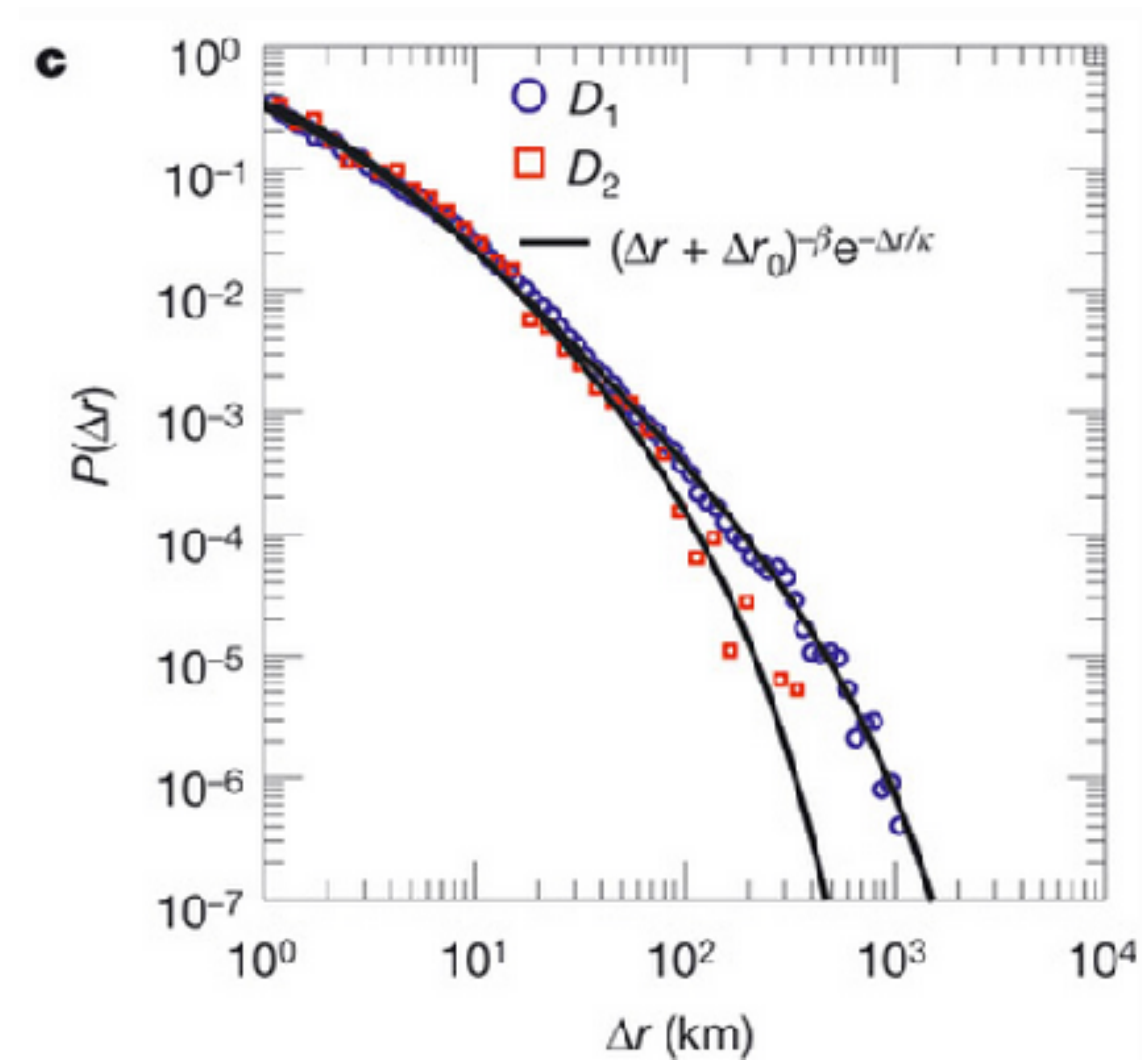
Mobile Social Network Data



$(\Delta r + \Delta r0)^{-\beta}$

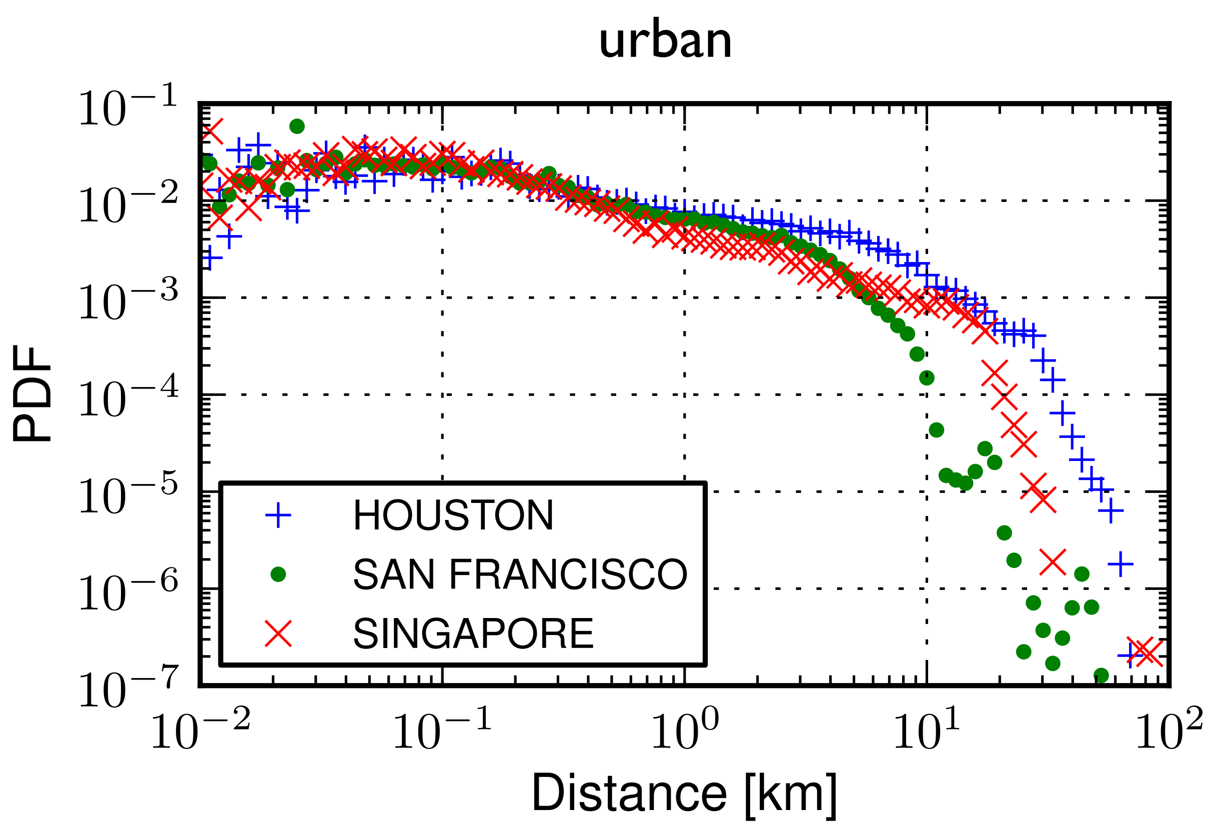
exponent $\beta = 1.50$

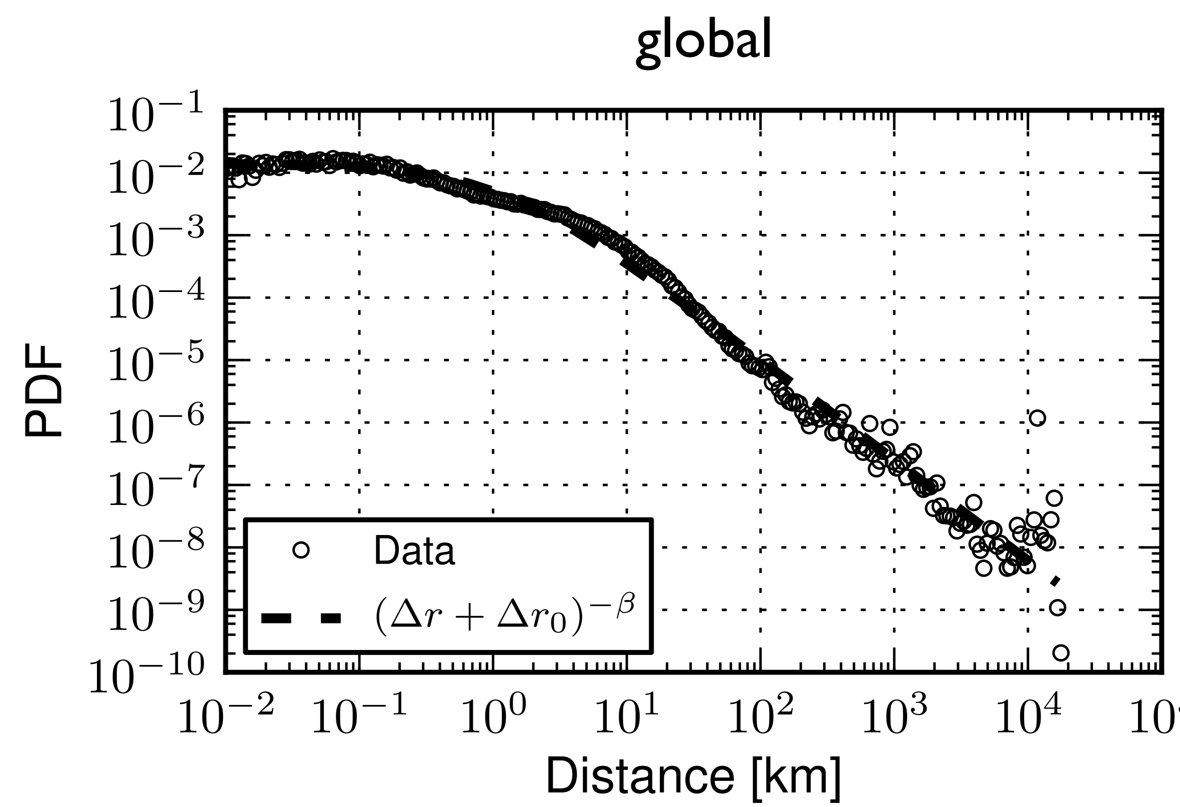
Nature **453**, 779-782(5 June 2008)



exponent $\beta = 1.75$

Urban vs Global mobility



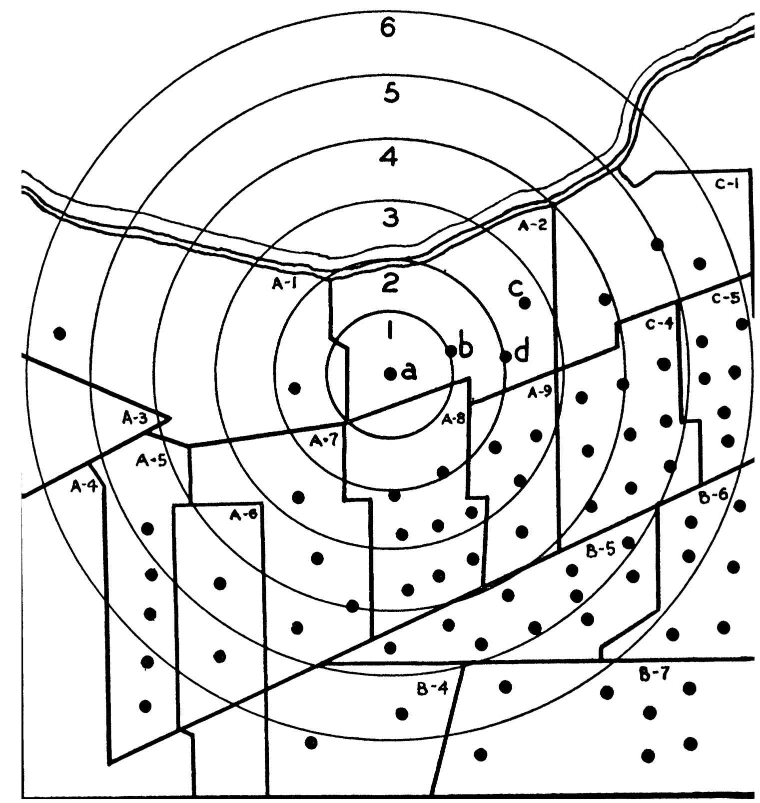


Power law kicks in at 18.42km!!!

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. doi:10.1371/journal.pone.0037027. 2012.

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." **

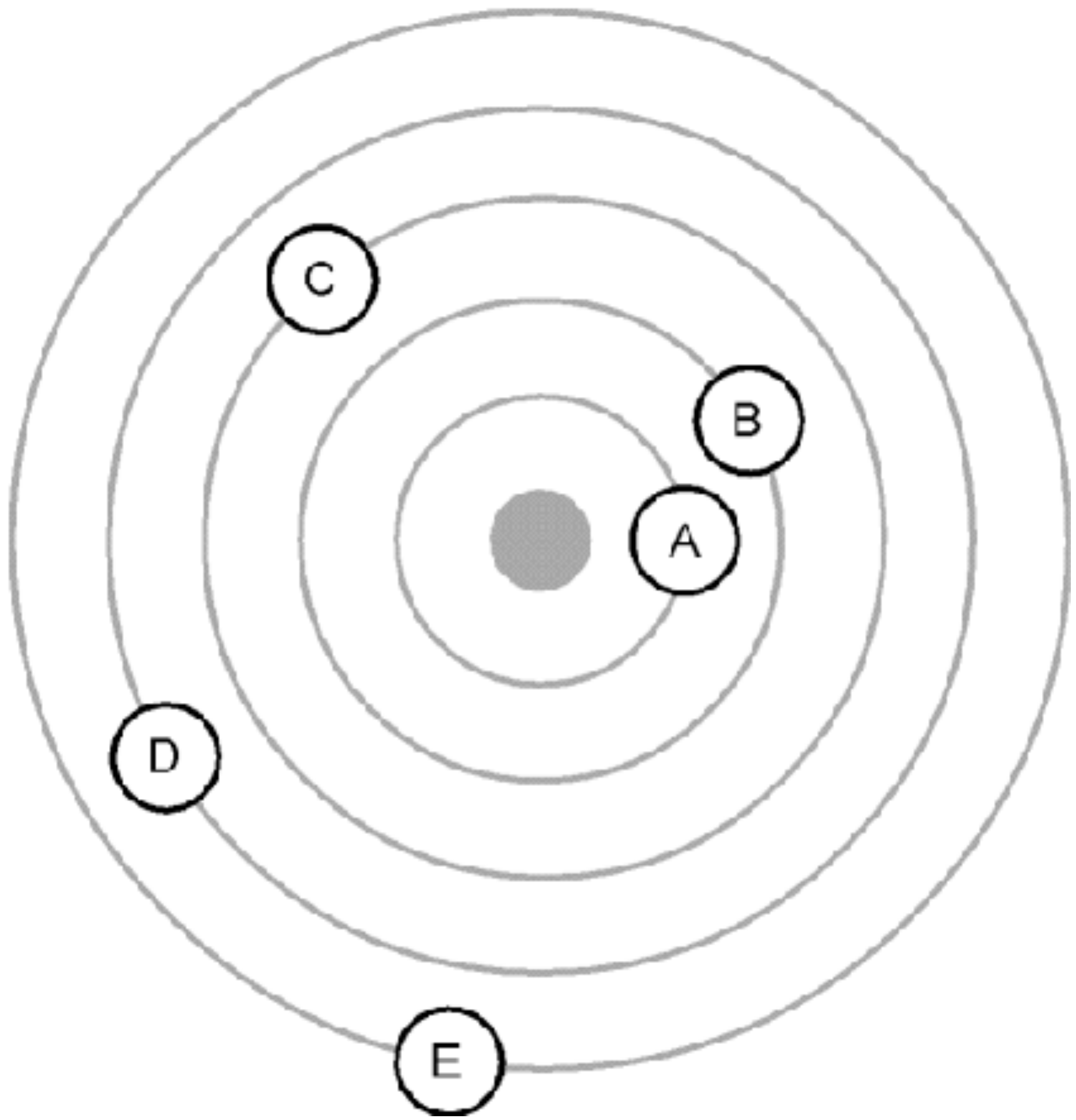


- Empirically proven using data for migrating families in the city of Cleveland.

- Inspired a host of recent works on human mobility modelling.

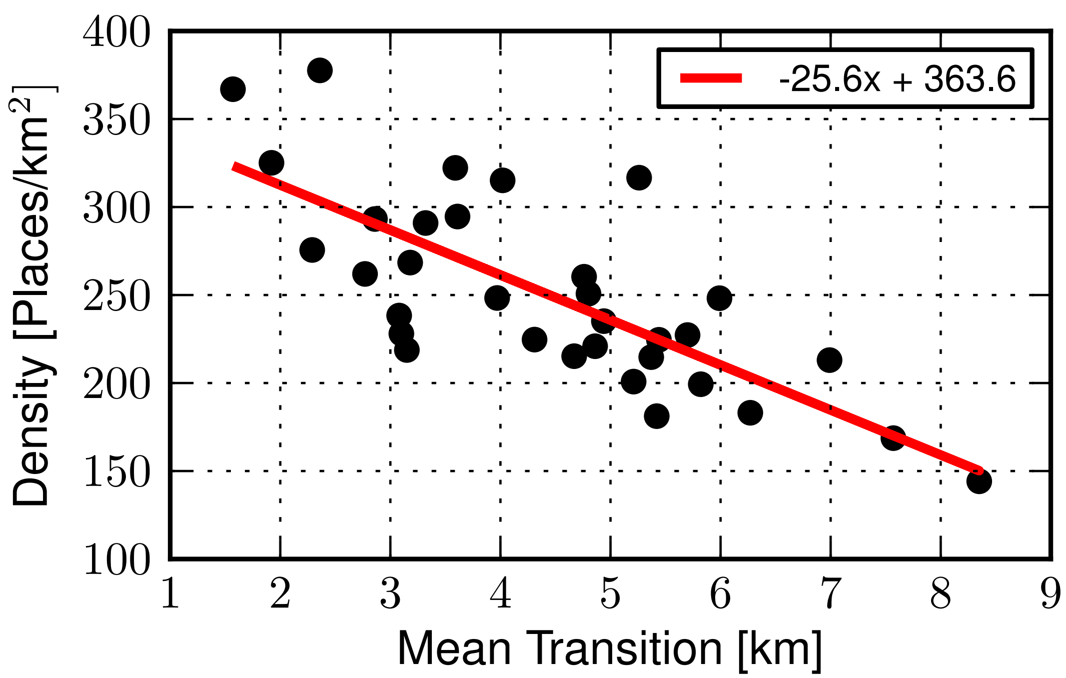
* S. Stouffer (1940) **Intervening opportunities: A theory relating mobility and distance**, American Sociological Review 5, 845-867

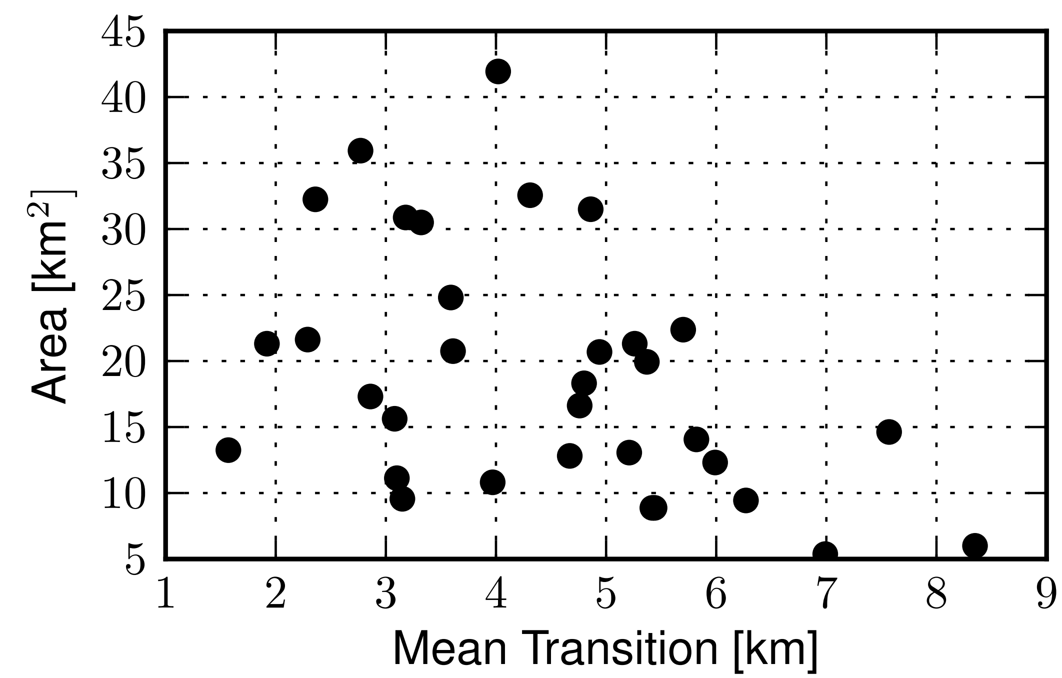
Rank-Distance



$$rank_u(v) = |\{w : d(u,w) < d(u,v)\}|$$

The importance of density

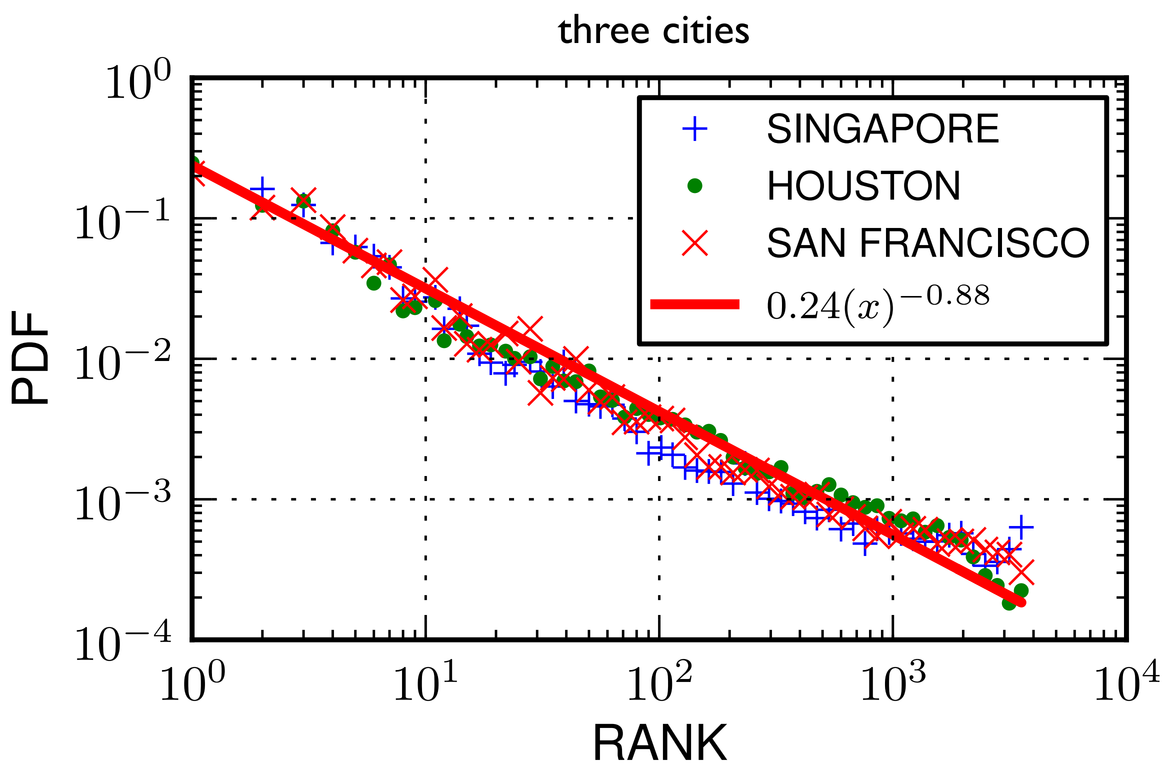


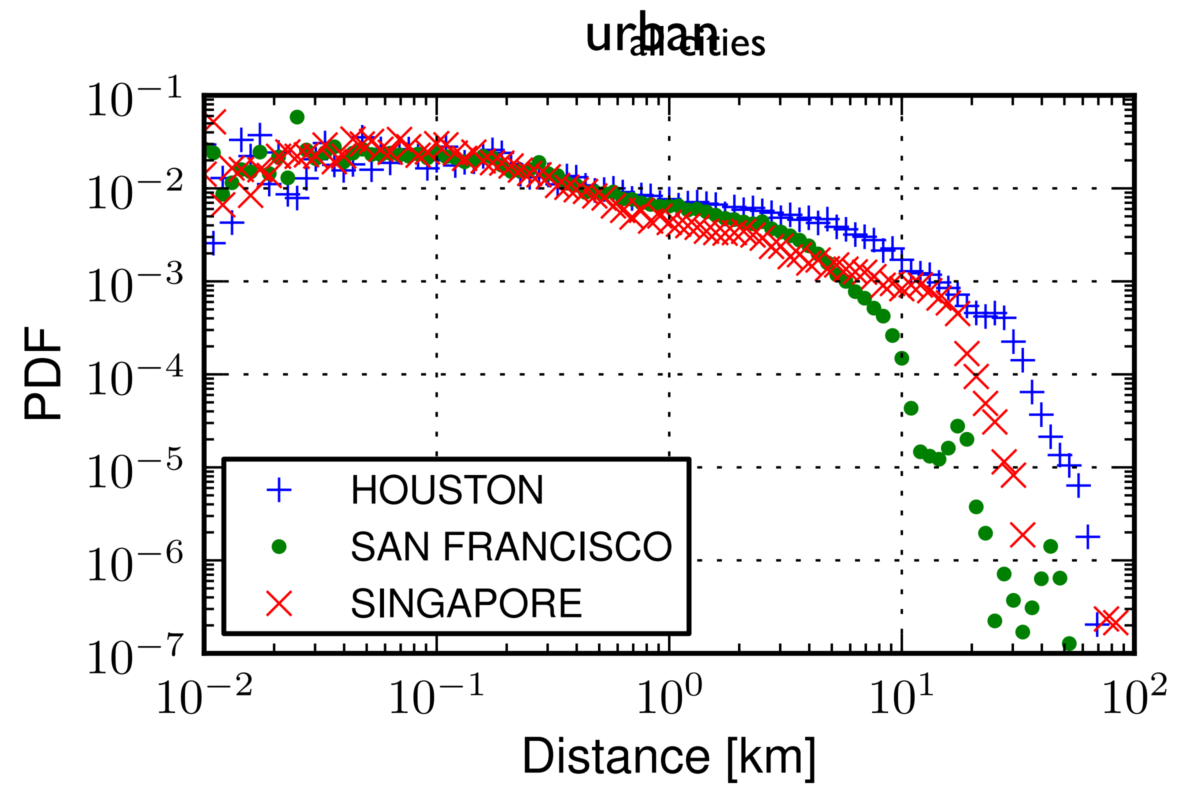


- Stouffer's Theory of Intervening Opportunities motivated us to inspect the impact of places(=opportunities) in human mobility.

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

Rank universality



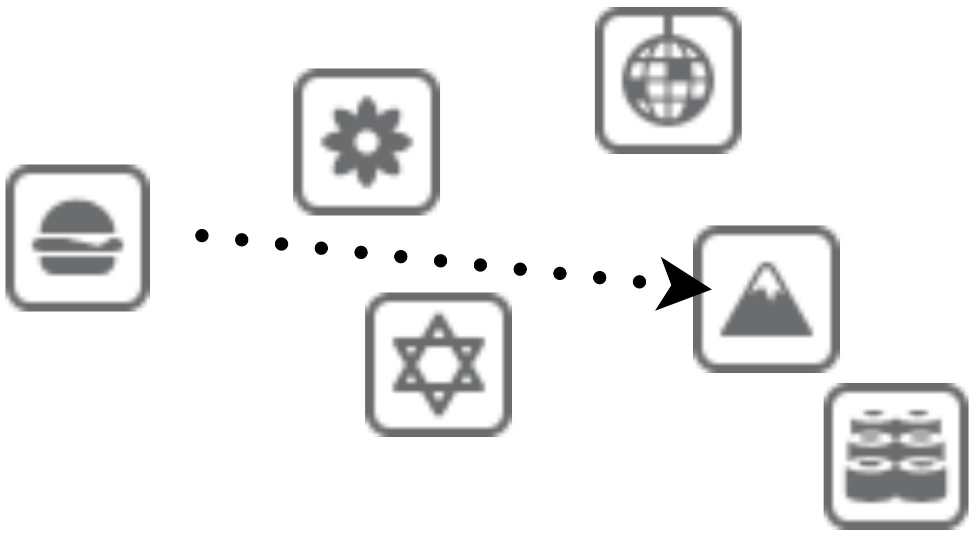


The rank of all cities collapse to a single line.

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

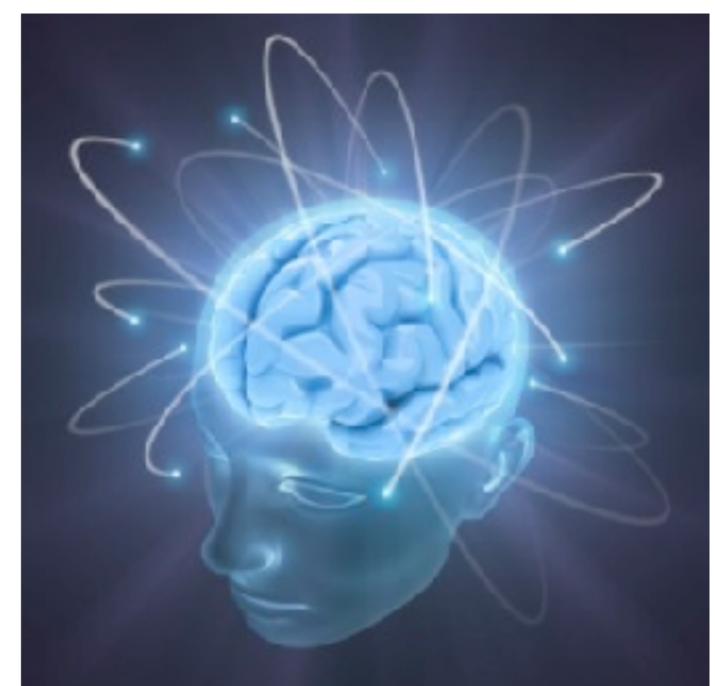
Decoupling cognition & space

soil...

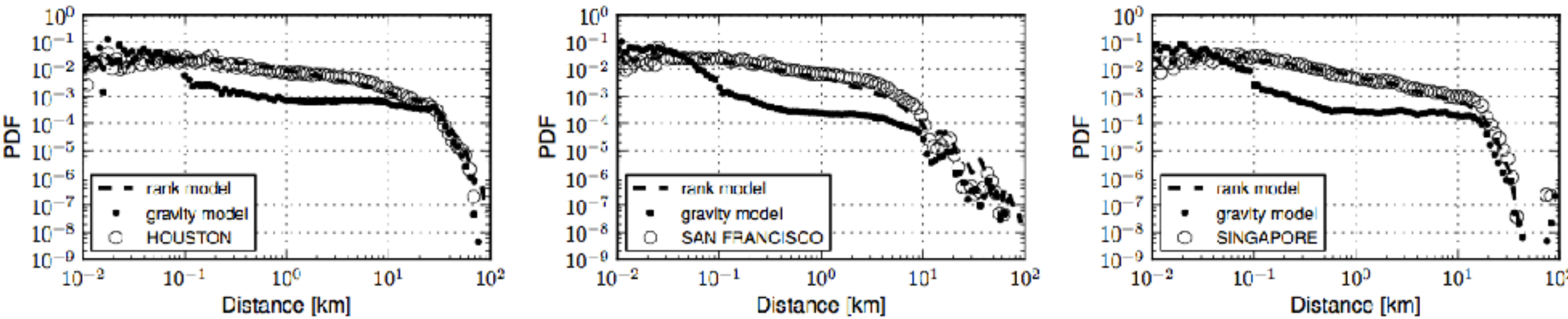


and mind!

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



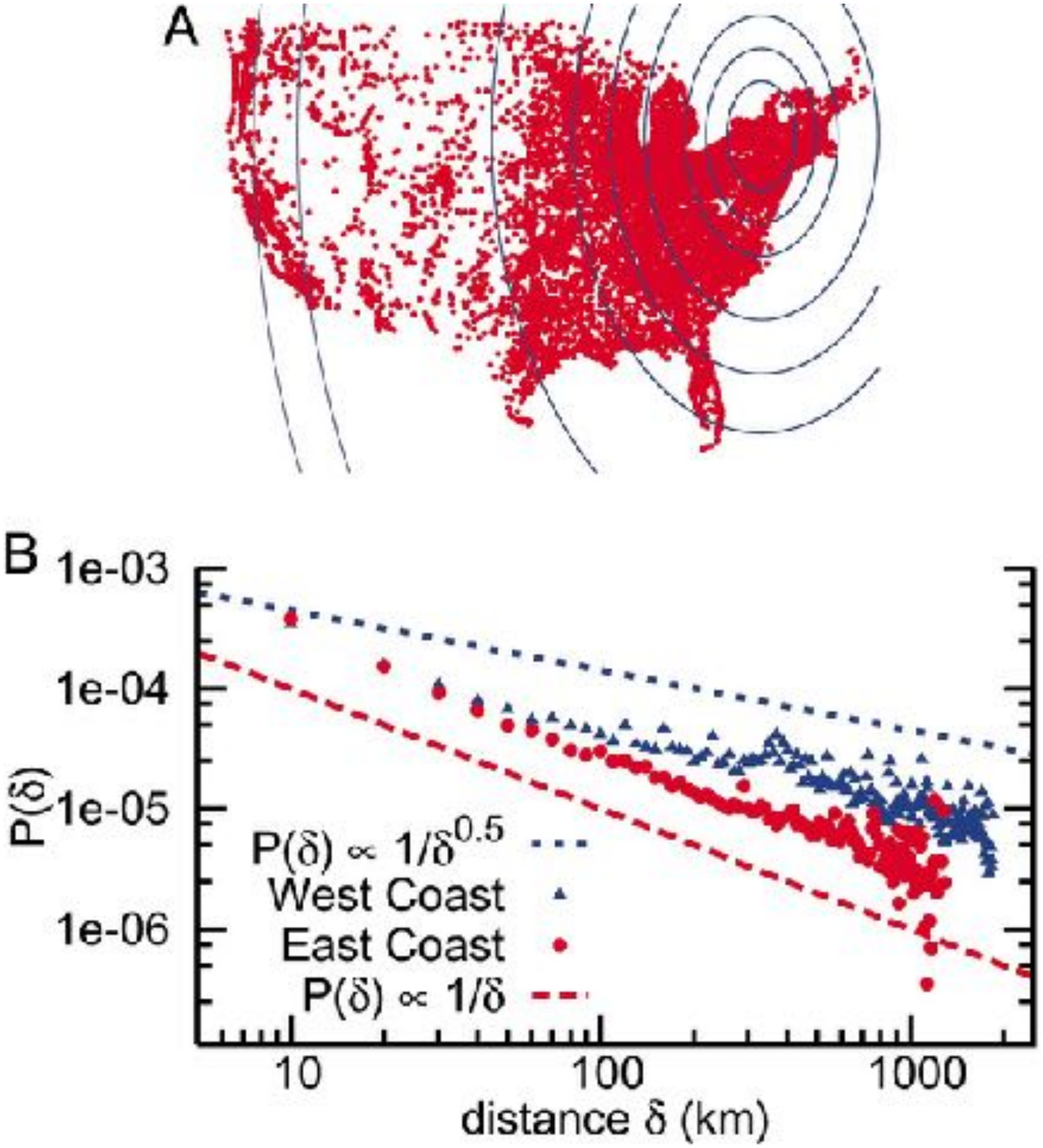
Rank vs Gravity



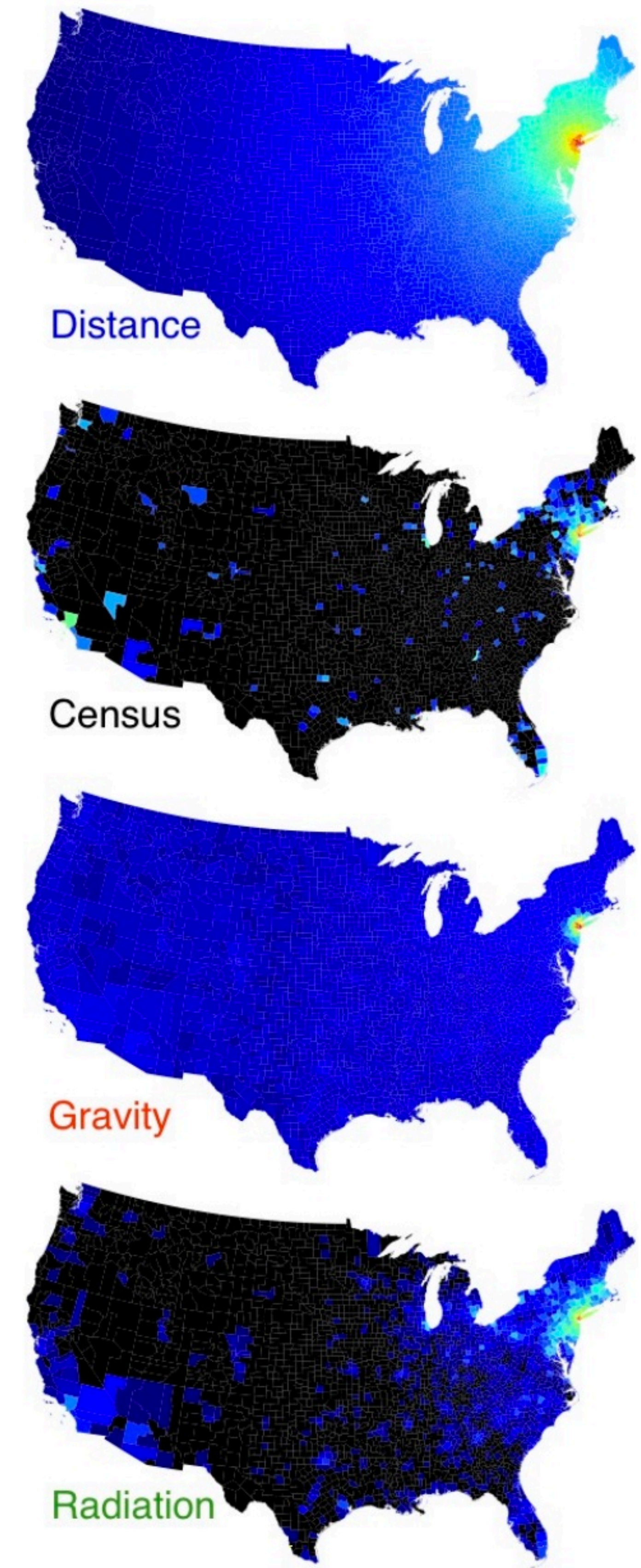
Rank is simpler and achieves better quality fits for all cities.

Gravity overestimates short transitions …

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. doi:10.1371/journal.pone.0037027. 2012.



Liben-Nowell, David, et al. "**Geographic routing in social networks.”**
PNAS 2005



Simini, Filippo, et al. "**A universal model for mobility and migration patterns.**”
Nature (2012)

$$\langle T_{ij} \rangle = T_i \frac{m_i n_j}{(m_i + s_{ij})(m_i + n_j + s_{ij})}$$

Abstraction Perspectives in human mobility

complex systems physics

computationally demanding models

inter-mediate complexity, the “undecided”!

simple

complex

abstraction level

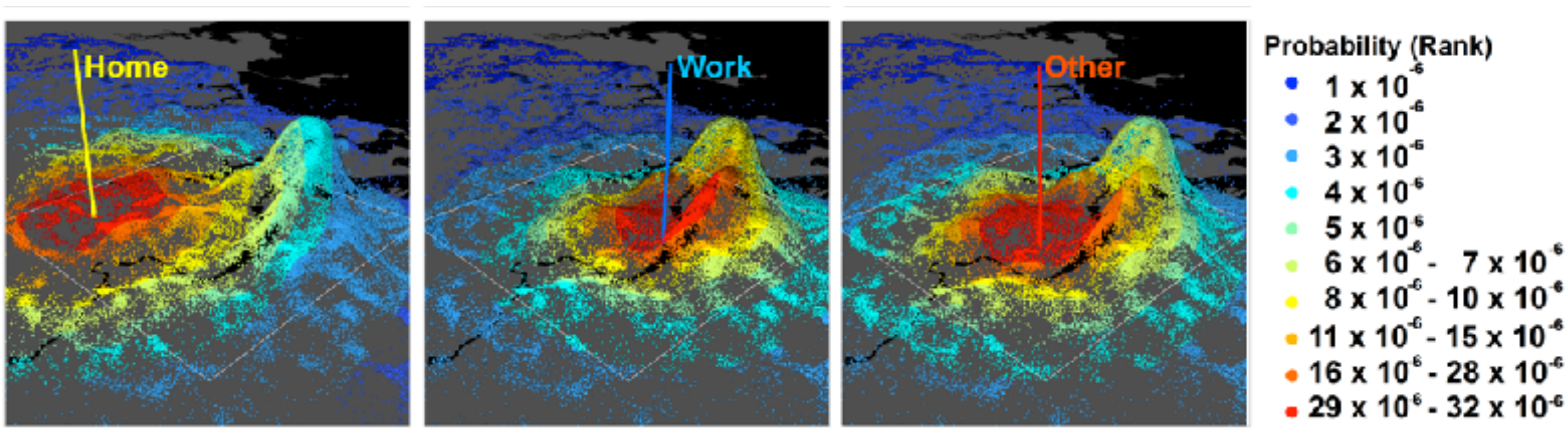
favour understanding

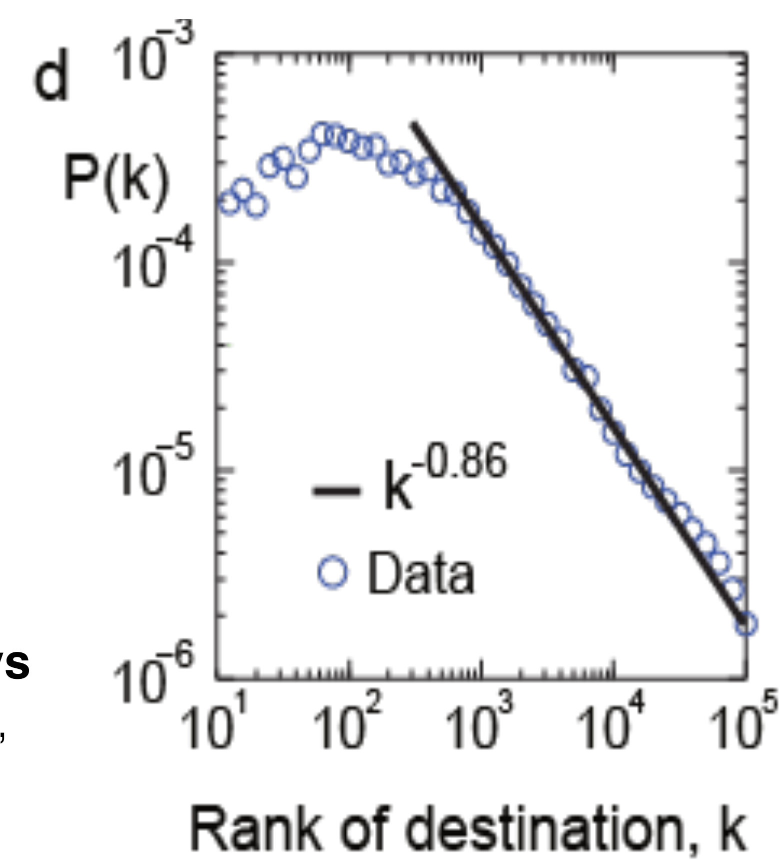
favour applications

less data

more data

Ranking of POIs to select New Destination





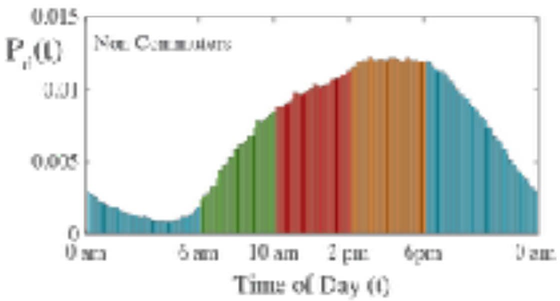
TimeGeo: a spatiotemporal framework for modeling urban mobility without surveys
Yingxiang Yang, Shan Jiang, Daniele Veneziano, Shounak Athavale, Marta C. Gonzalez,
PNAS (reviewed and resubmitted), 2016

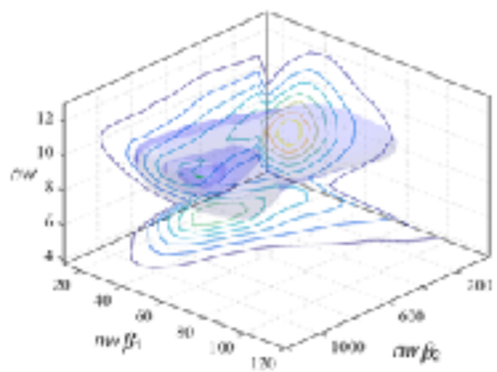
The Model

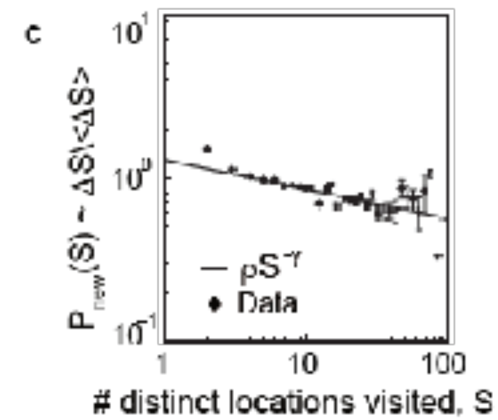
Features Extracted from data of Active Users

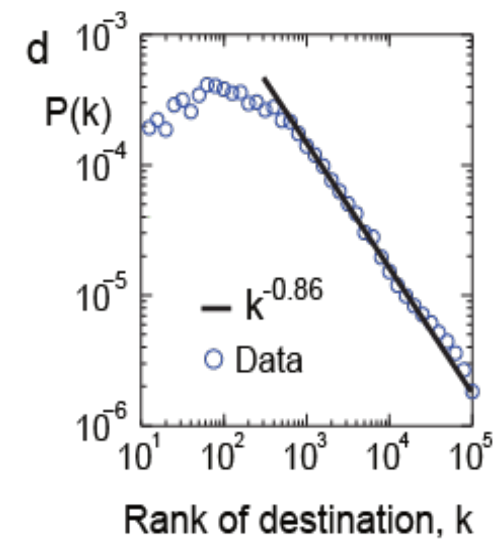
Individual Mobility Rates

Destination Rank



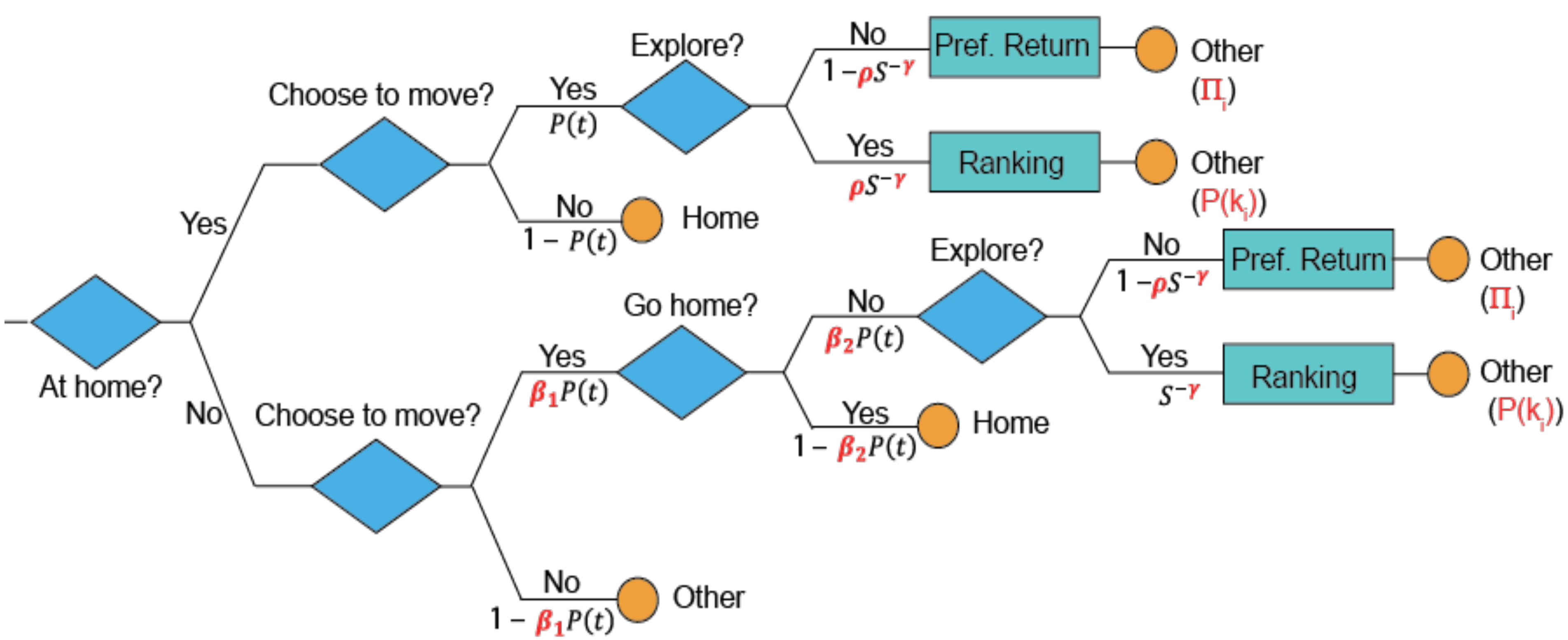






Global Trip probability

Preferential Return



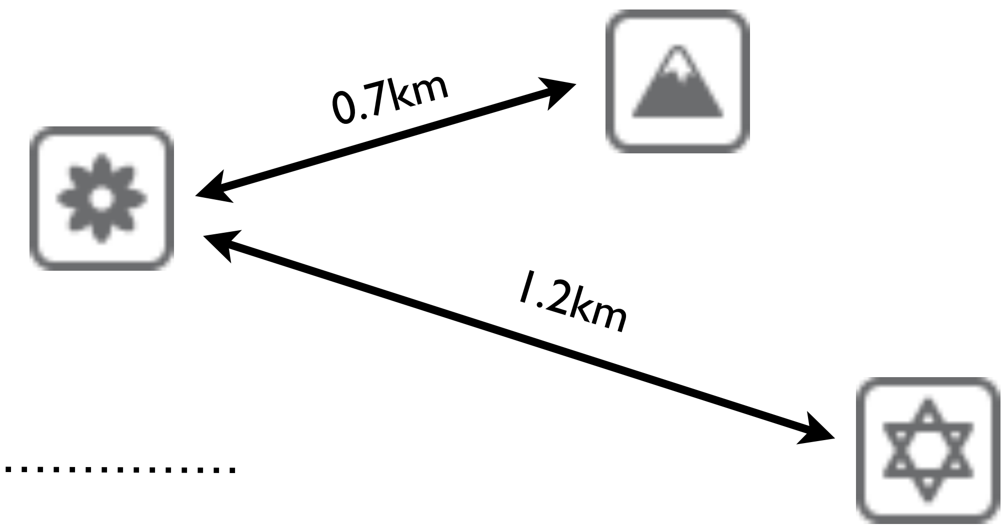
Data layers need data mining

User Specific features

- historic visits
- friend check-ins
- preferred venue types

Geographic

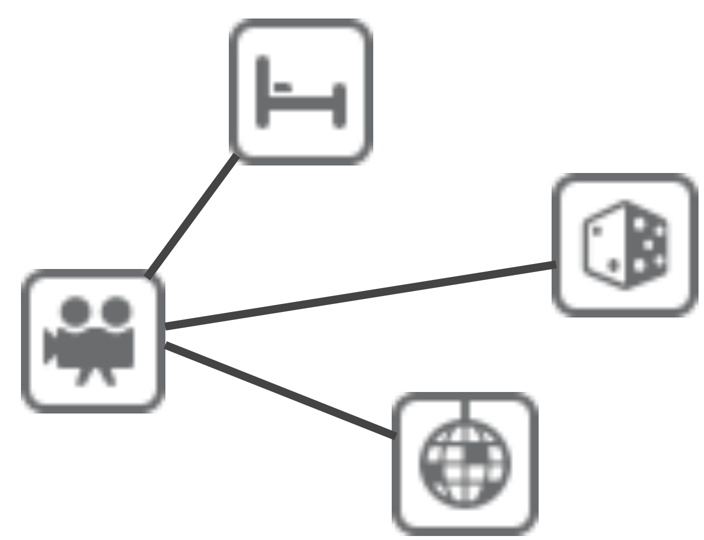
- distance and rank-distance



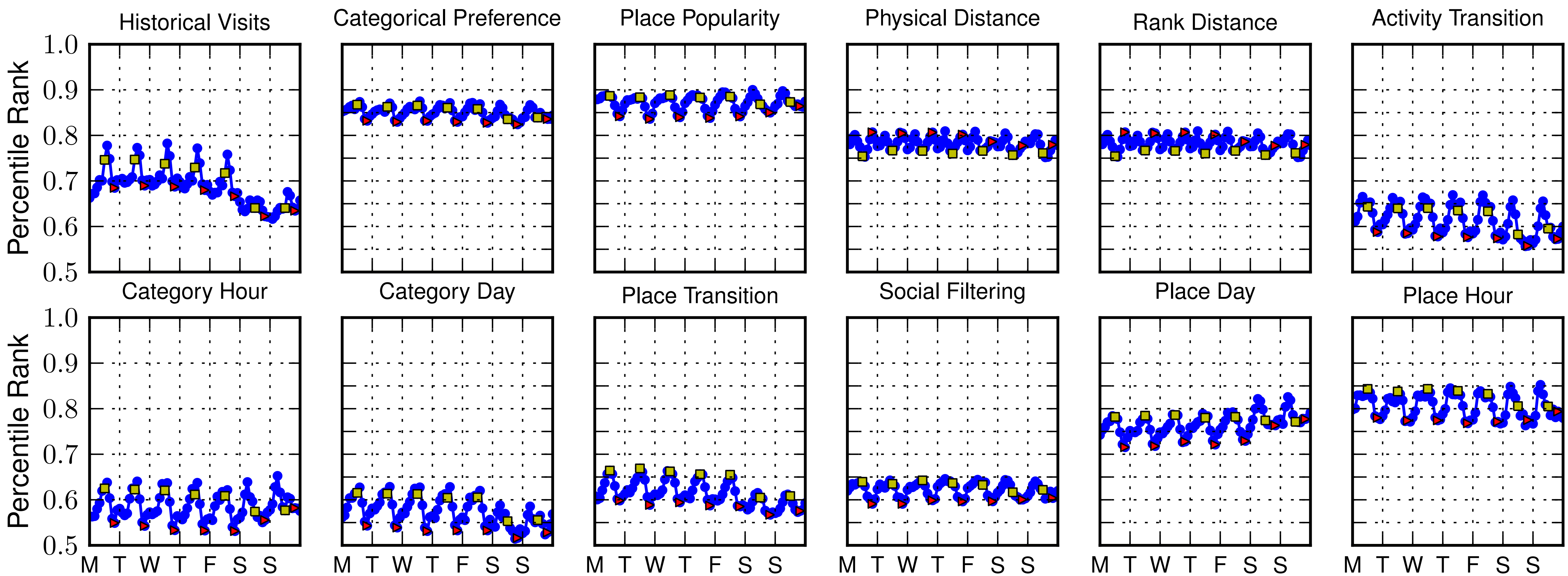
Temporal

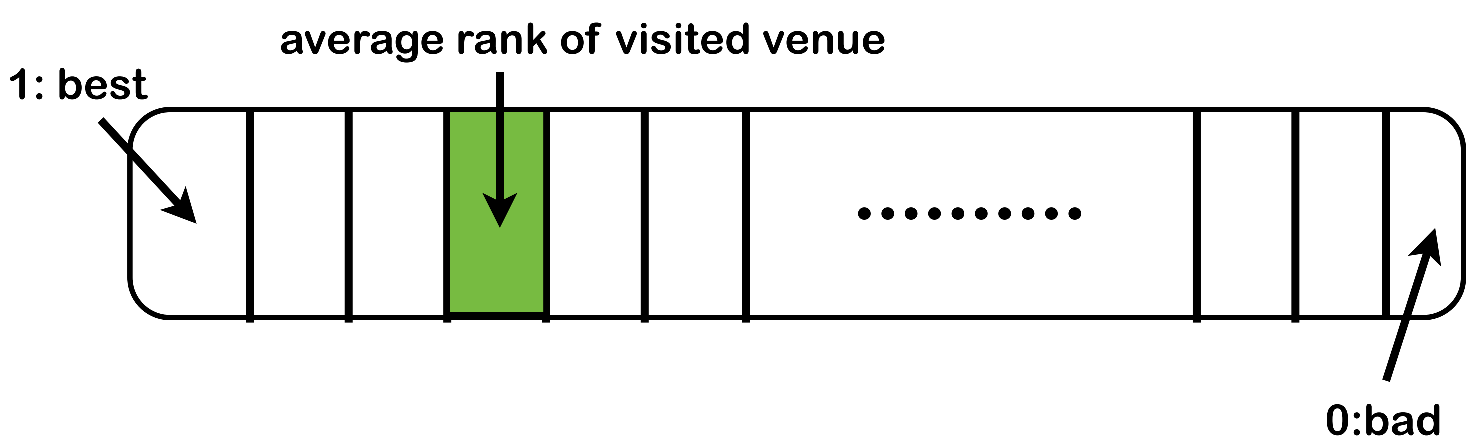
- trending places (hour/day)
- trending place types (eg. cinema at nights)

Place Network



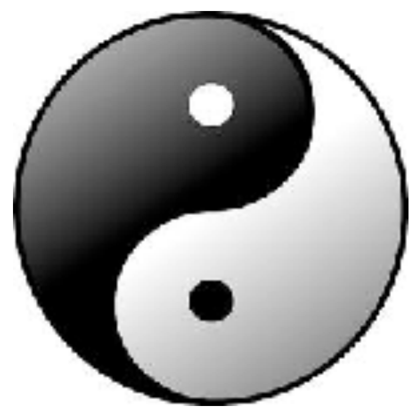
Modern data is rich



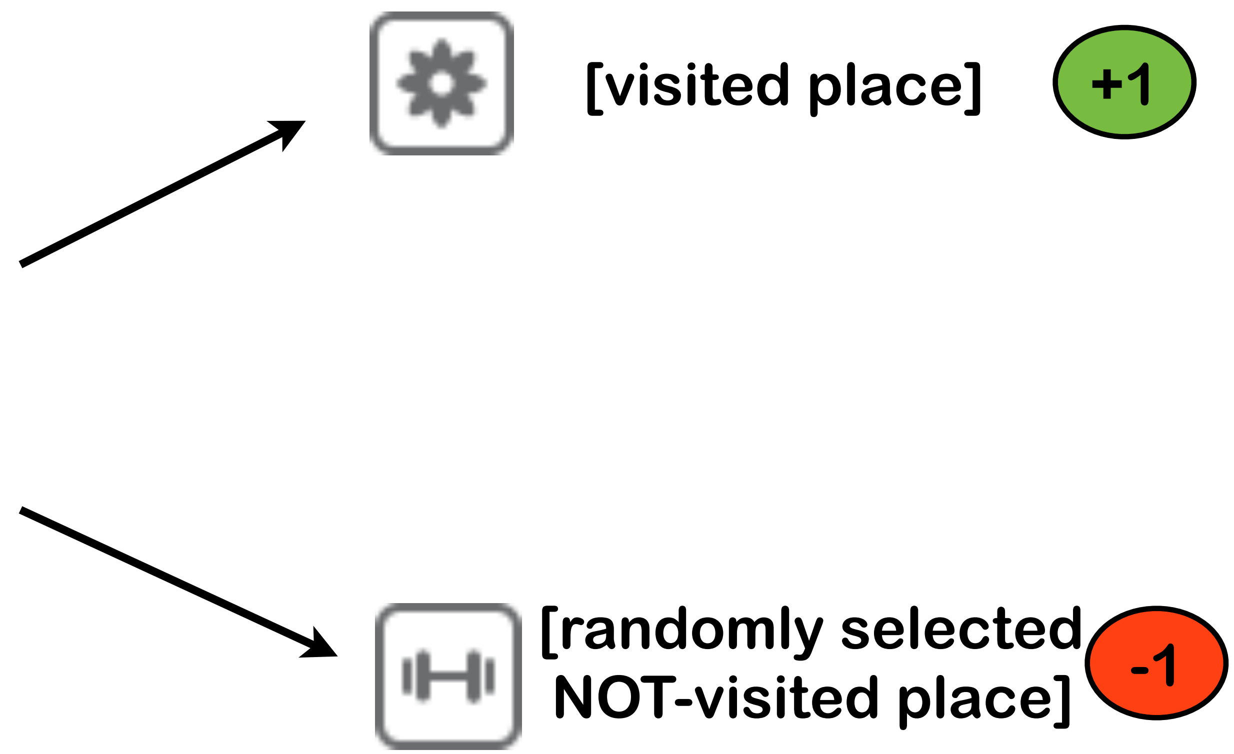


Supervised Training: teaching the good and the bad!

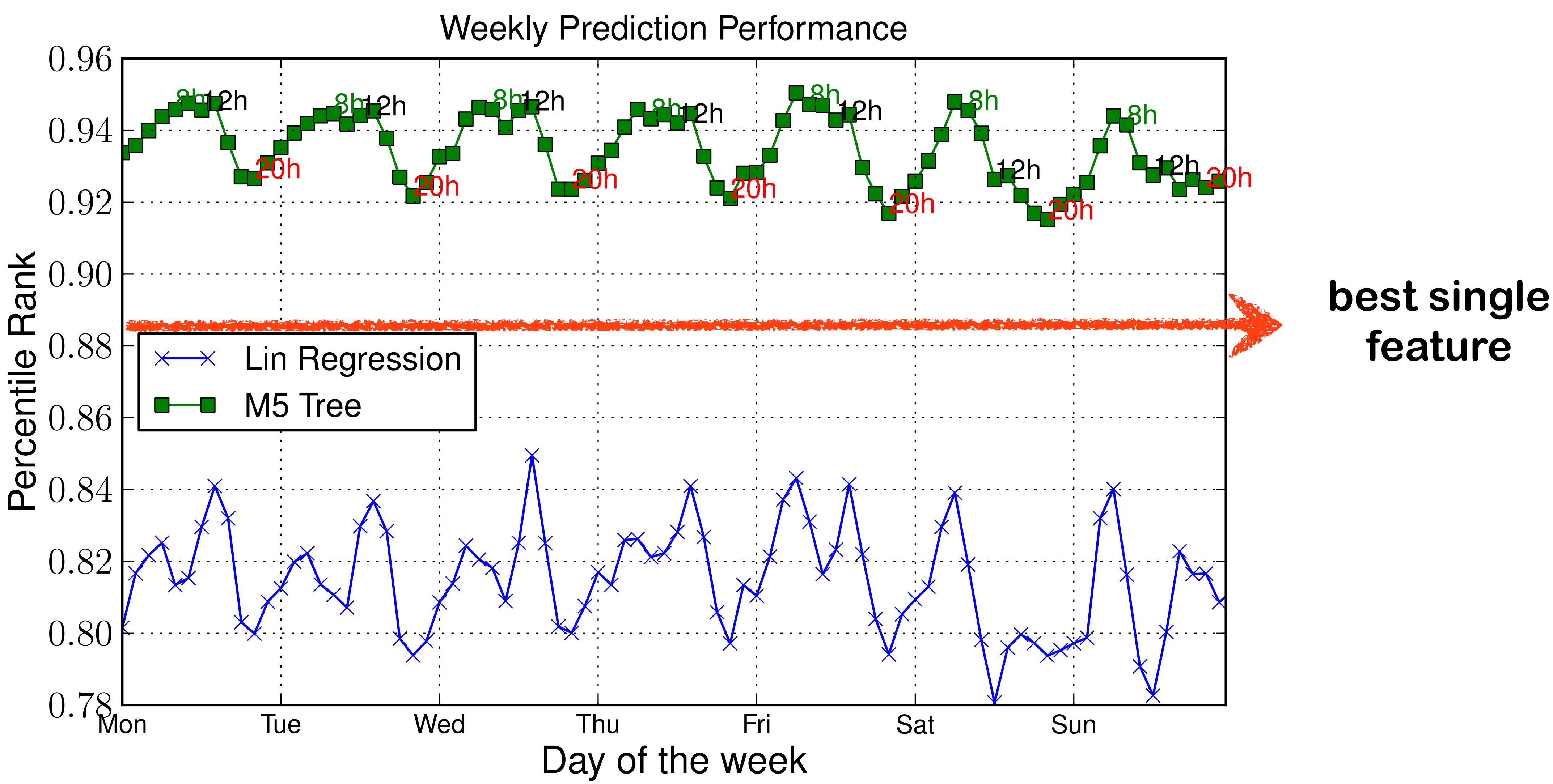
Key Insight: Every time little Amy checks-in she expresses a direct preference at a place and implicitly ignores all the rest!



learning: supervised classifier trains on millions of check-ins generated by populations of users.

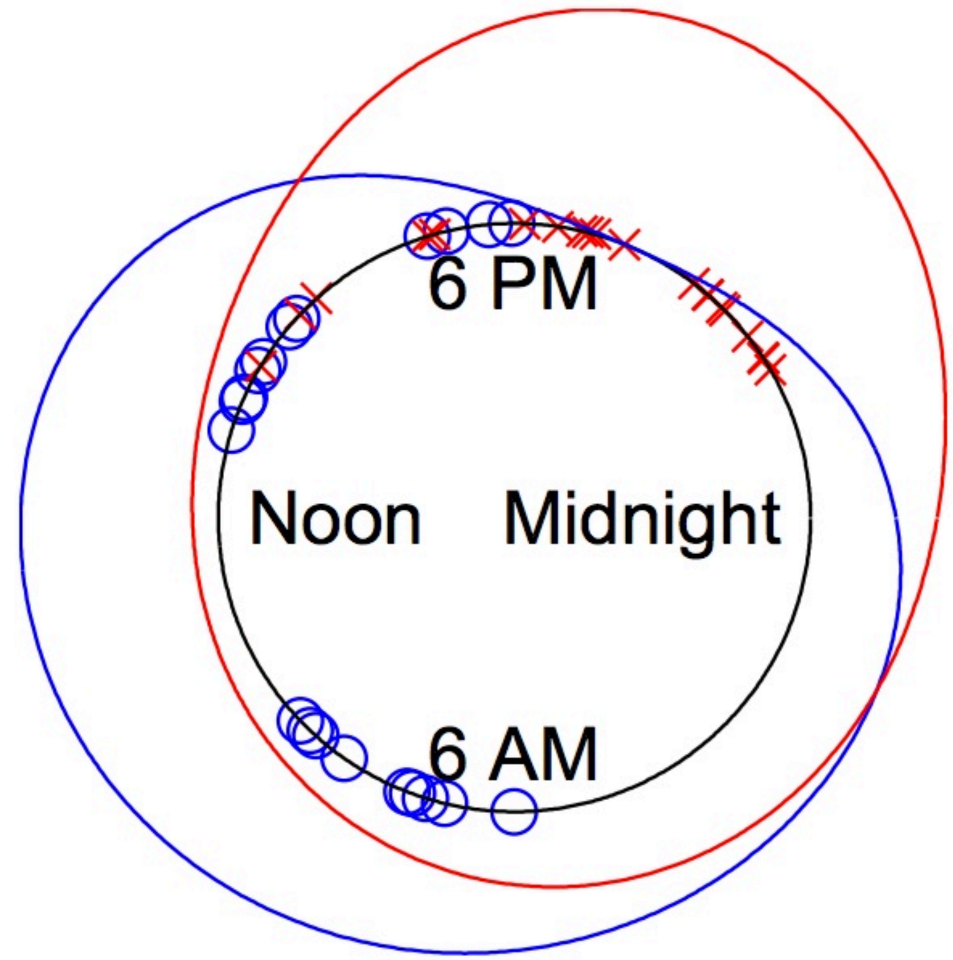


Supervised Learning Scores!



Probabilistic Models

(a) Spatial model

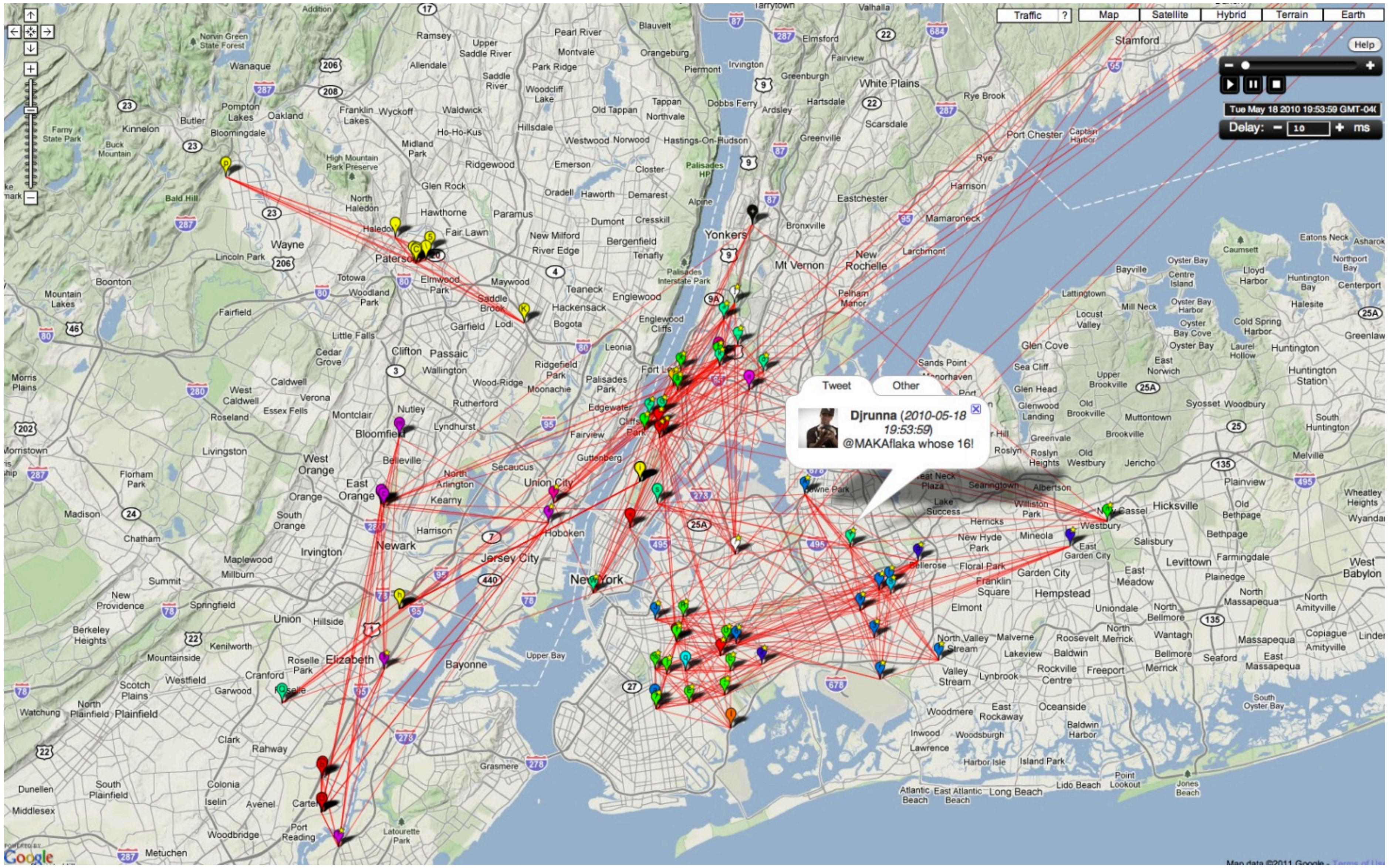


(b) Temporal model

$$P\left[x(t)=x\right] = P\left[x_u(t)=x \mid c_u(t)=H\right]\cdot P\left[c_u(t)=H\right] + P\left[x_u(t)=x \mid c_u(t)=W\right]\cdot P\left[c_u(t)=W\right]$$

Cho, Eunjoon, Seth A. Myers, and Jure Leskovec. "**Friendship and mobility: user movement in location-based social networks.**" Proceedings of the 17th ACM SIGKDD international conference on Knowledge discovery and data mining. ACM, 2011.

Probabilistic Models

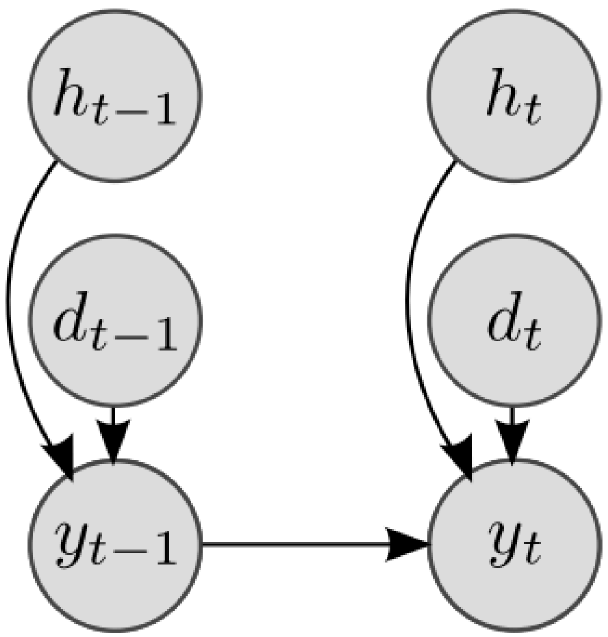


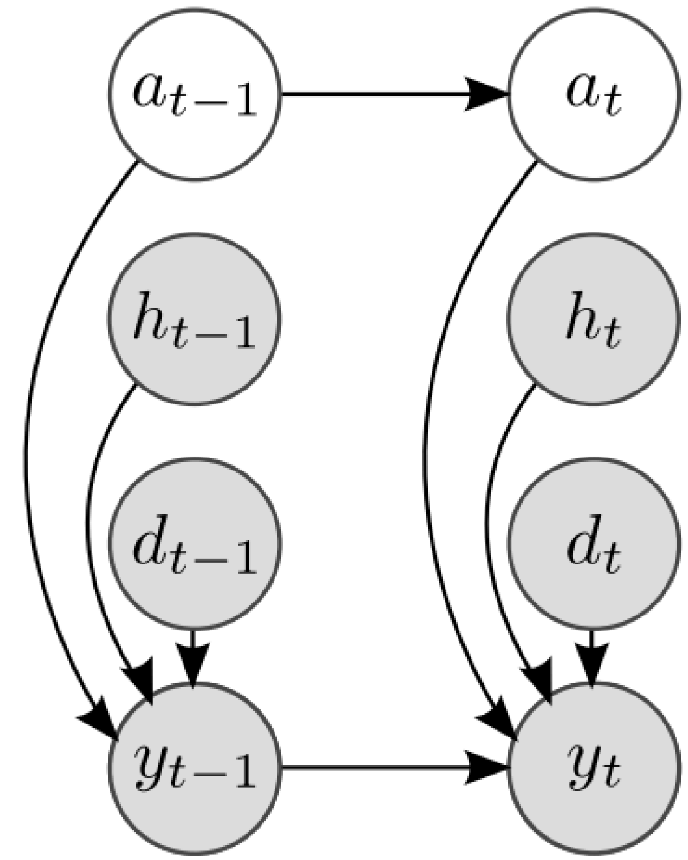
Users with known GPS positions are noisy sensors of
the location of their friends

Sadilek, Adam, Henry Kautz, and Jeffrey P. Bigham. "**Finding your friends and following them to where you are.**" Proceedings of the fifth ACM international conference on Web search and data mining. ACM, 2012.

Why not using a Markov model?

The place-network feature is a form of markov-model, but tells us only part of the truth in the prediction task.

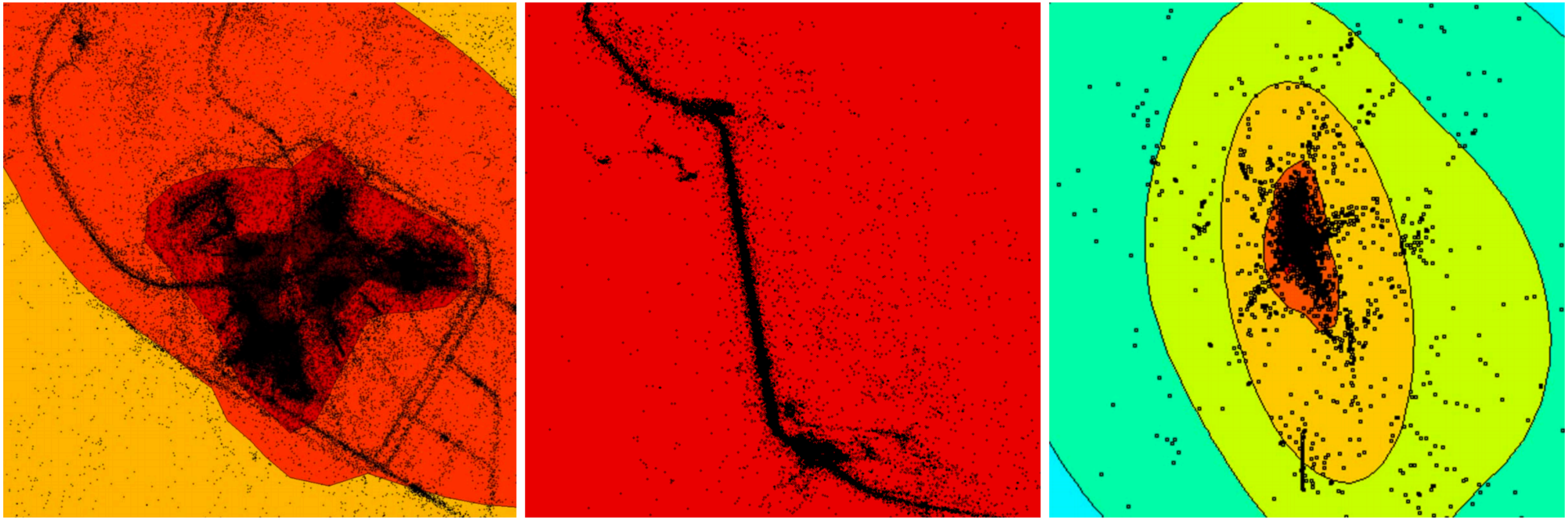




Eagle, Nathan, John A. Quinn, and Aaron Clauset. "Methodologies for continuous cellular tower data analysis." *Pervasive computing*. Springer Berlin Heidelberg, 2009. 342-353.

http://realitycommons.media.mit.edu/pdfs/pervasive09.pdf

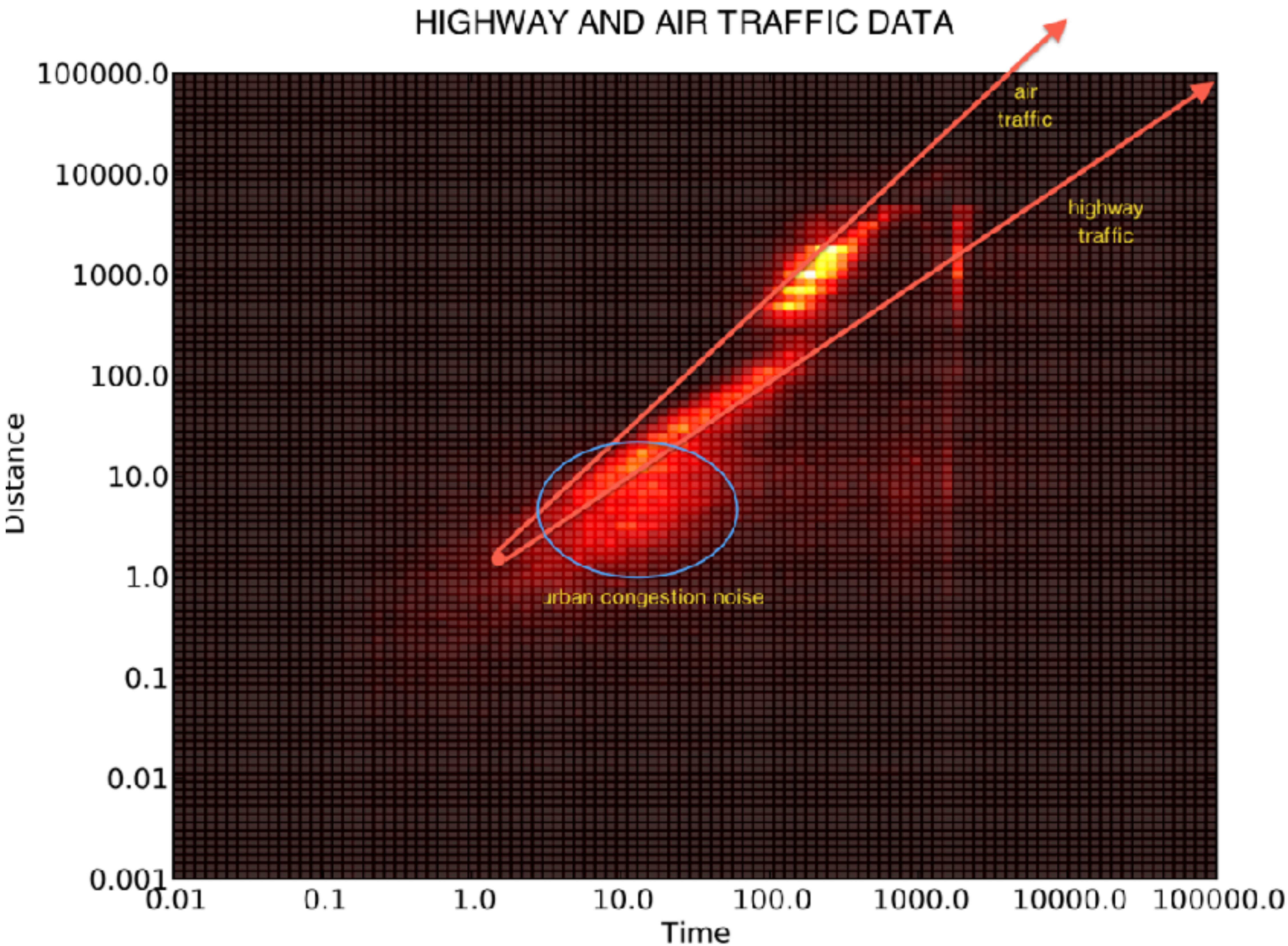
Place Shapes



(a) JFK Airport (b) Golden Gate Bridge (close up) (c) The Blind Tiger

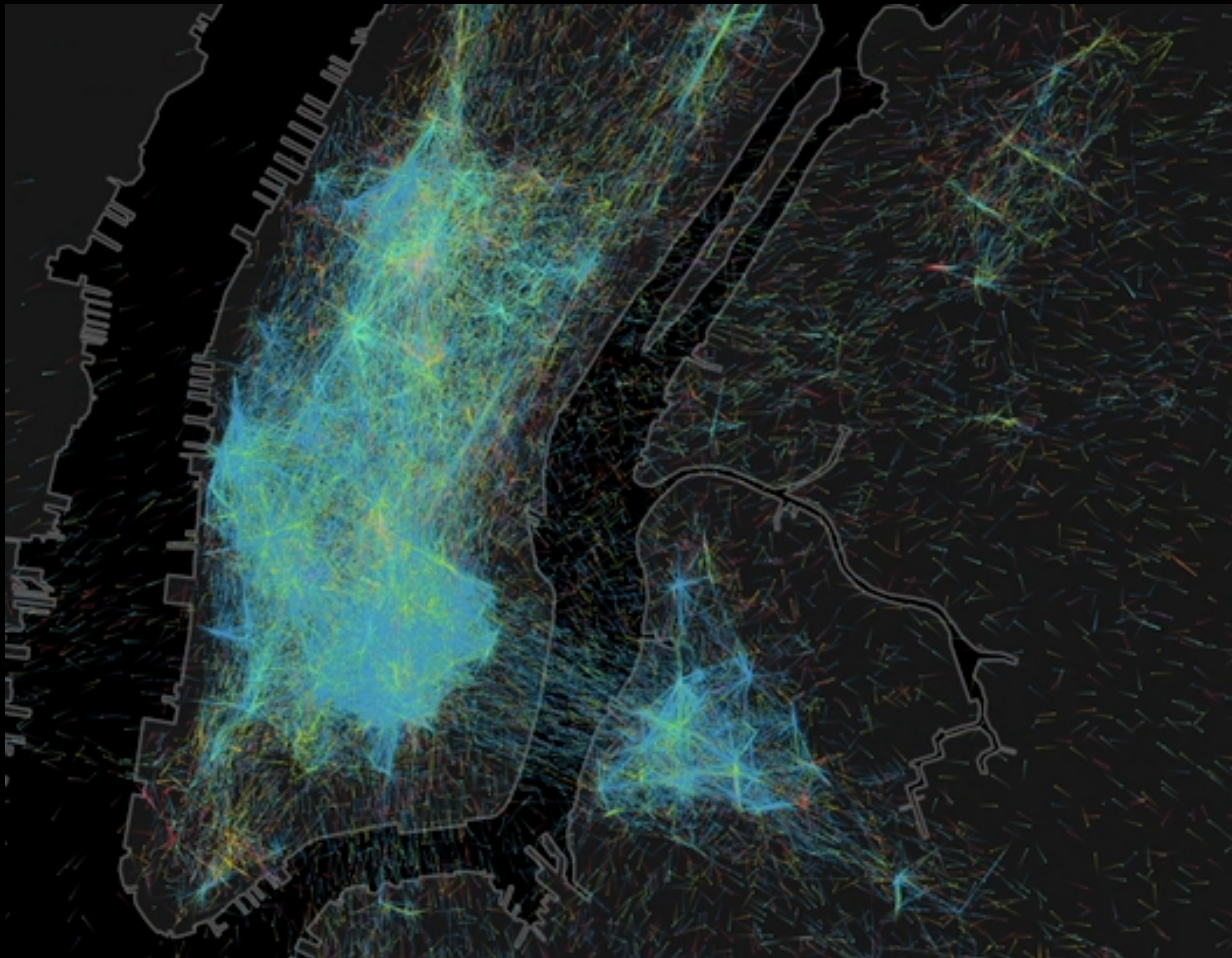
Shaw, Blake, et al. "**Learning to rank for spatiotemporal search.**" Proceedings of the sixth ACM international conference on Web search and data mining. ACM, 2013.

https://vimeo.com/145879457

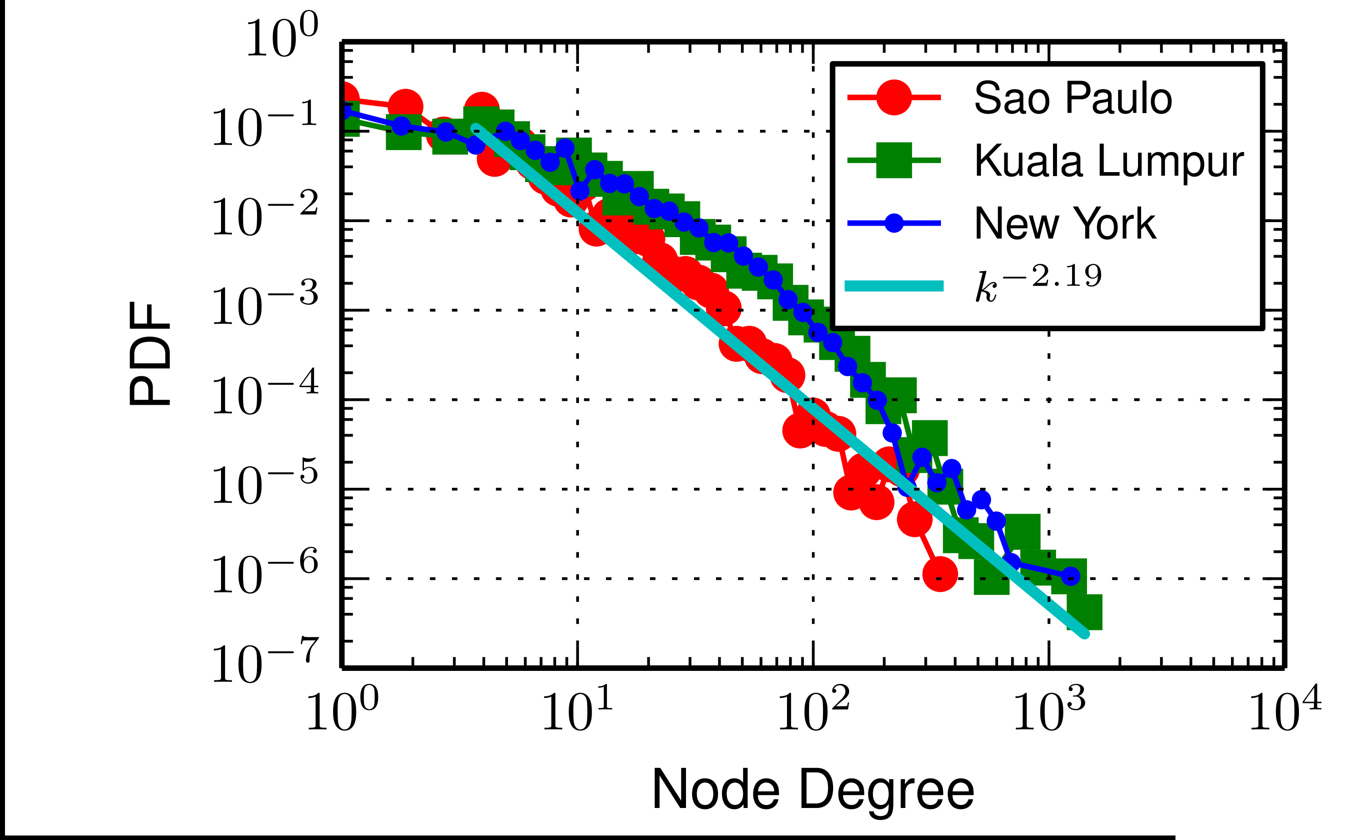

HIGHWAY AND AIR TRAFFIC DATA
air
traffic
highway
traffic
urban congestion noise
Distance
Time
100000.0
10000.0
1000.0
100.0
10.0
1.0
0.1
0.01
0.001
0.01
0.1
1.0
10.0
100.0
1000.0
10000.0
100000.0

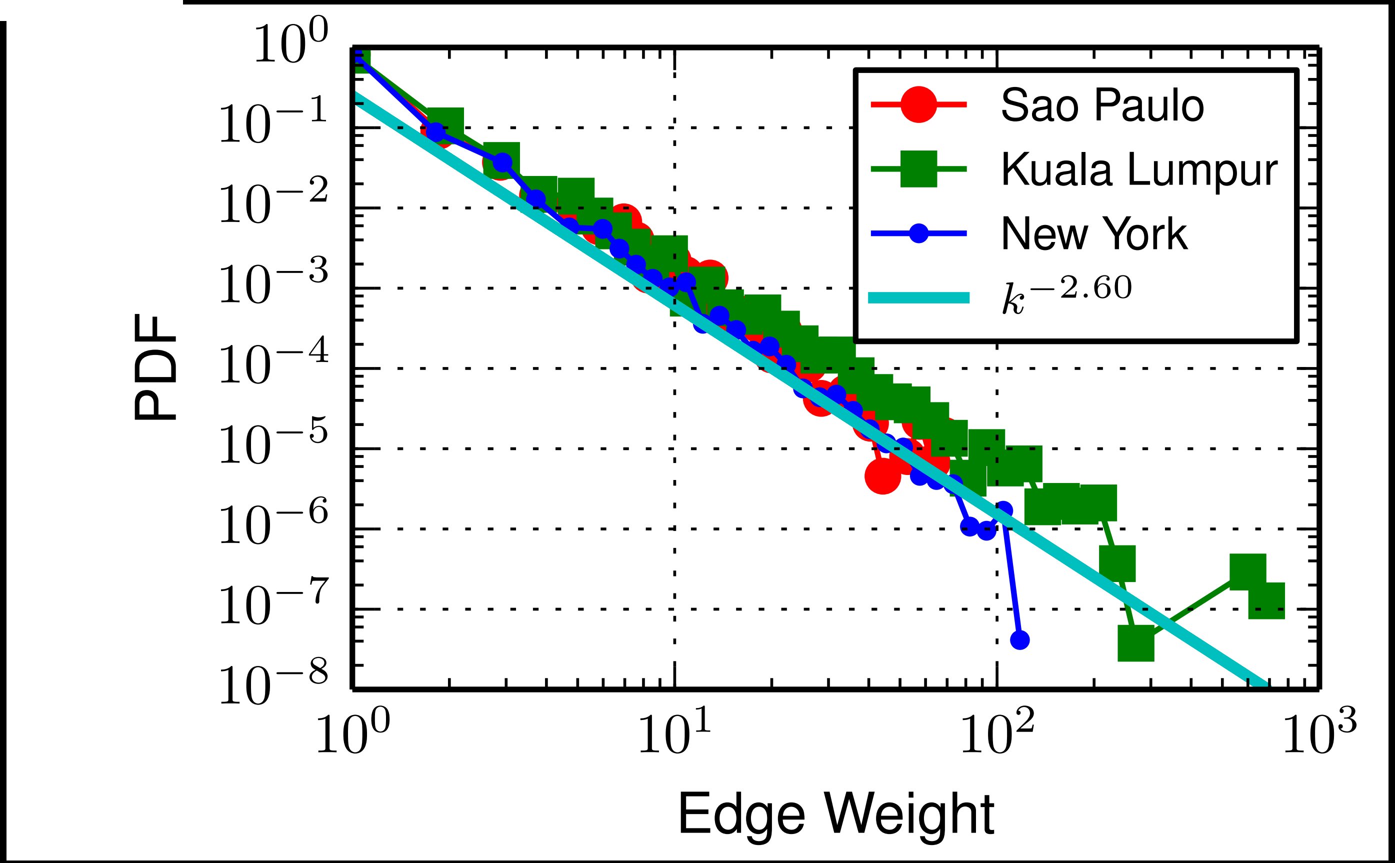
FOURSQUARE CHECK-INS SHOW THE PULSE OF **TOKYO**

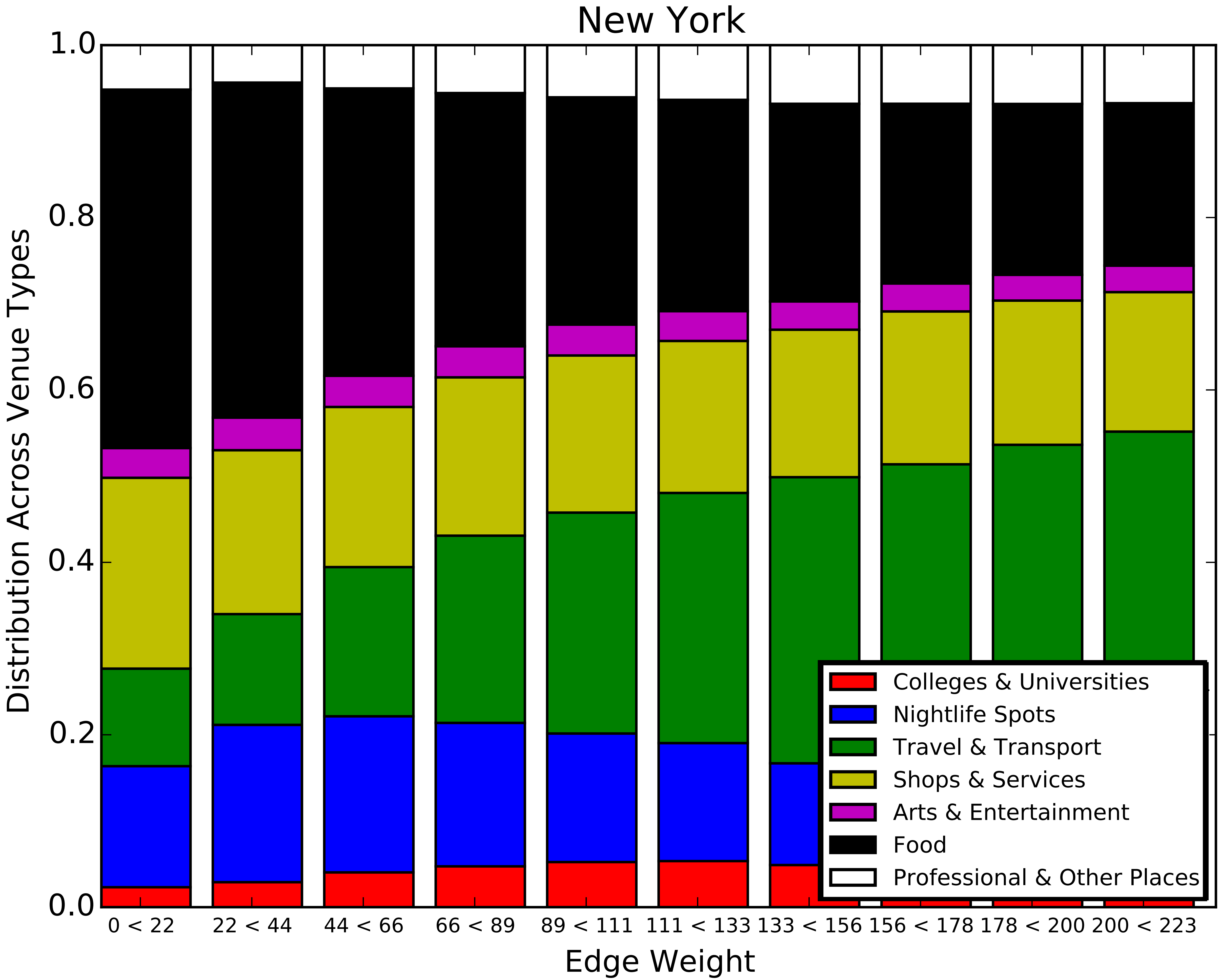
New York City



11-12PM


PDF
Node Degree
Sao Paulo
Kuala Lumpur
New York
$k^{-2.19}$
10^0
10^{-1}
10^{-2}
10^{-3}
10^{-4}
10^{-5}
10^{-6}
10^{-7}
10^0
10^1
10^2
10^3
10^4


PDF
Edge Weight
Sao Paulo
Kuala Lumpur
New York
$k^{-2.60}$
10^0
10^{-1}
10^{-2}
10^{-3}
10^{-4}
10^{-5}
10^{-6}
10^{-7}
10^{-8}
10^0
10^1
10^2
10^3


New York
Distribution Across Venue Types
Edge Weight
0.0
0.2
0.4
0.6
0.8
1.0
0 < 22
22 < 44
44 < 66
66 < 89
89 < 111
111 < 133
133 < 156
156 < 178
178 < 200
200 < 223
Colleges & Universities
Nightlife Spots
Travel & Transport
Shops & Services
Arts & Entertainment
Food
Professional & Other Places

City	$\lvert V \rvert$	$\lvert E \rvert$	C	C_r	D	D_r	d	d_r	$\langle k \rangle$	r
Saint Petersburg	9292	278099	0.20	0.08	5.83	5.91	3.30	3.25	42.57	−0.05
Moscow	8962	168945	0.19	0.07	6.25	6.00	3.21	3.37	30.96	−0.05
Sao Paulo	8643	66110	0.17	0.04	6.83	6.25	3.67	3.68	18.01	−0.05
New York	8156	145671	0.18	0.07	5.91	5.25	3.12	3.14	40.99	−0.07
Kuala Lumpur	7656	56035	0.19	0.05	6.41	6.00	3.45	3.43	23.93	−0.06
Istanbul	7389	60790	0.14	0.02	10.00	7.50	4.66	4.20	10.50	+0.05
Tokyo	7327	36627	0.23	0.07	7.58	7.16	3.79	3.79	10.40	−0.09
Bangkok	6986	33827	0.15	0.04	7.41	6.58	3.88	3.74	15.58	−0.00
Singapore	6825	30384	0.14	0.02	8.08	7.08	4.02	3.89	14.95	−0.00
Jakarta	4645	10776	0.08	0.00	10.83	9.25	5.45	5.07	5.84	+0.05

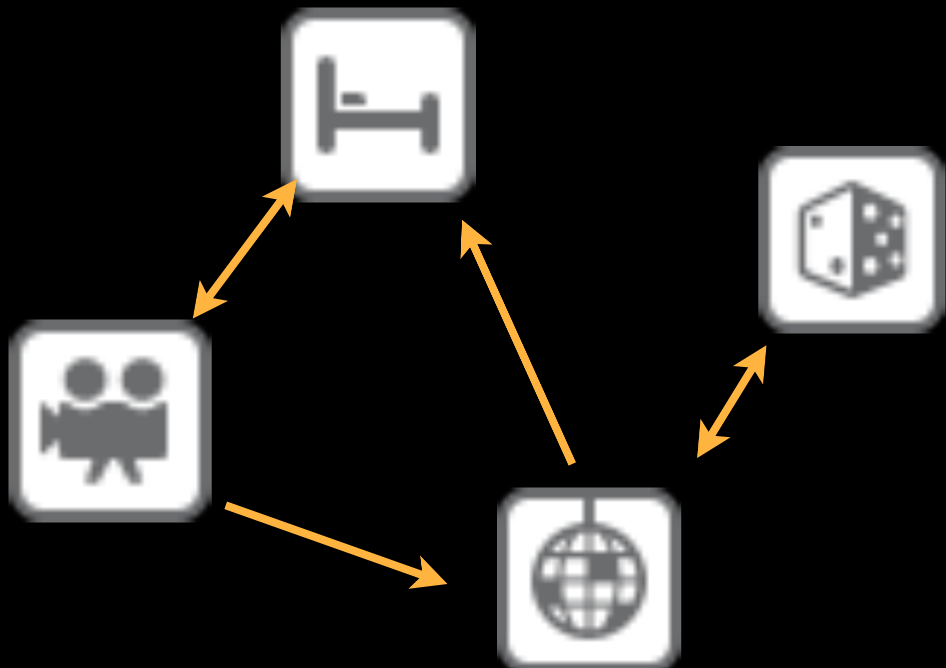
	network	n	r
real-world networks	physics coauthorship[a]	52 909	0.363
	biology coauthorship[a]	1 520 251	0.127
	mathematics coauthorship[b]	253 339	0.120
	film actor collaborations[c]	449 913	0.208
	company directors[d]	7 673	0.276
	Internet[e]	10 697	−0.189
	World-Wide Web[f]	269 504	−0.065
	protein interactions[g]	2 115	−0.156
	neural network[h]	307	−0.163
	food web[i]	92	−0.276
models	random graph[u]		0
	Callaway *et al.*[v]		$\delta/(1+2\delta)$
	Barabási and Albert[w]		0

place networks tend to be dissasortative and in that sense fundamentally different to social networks.

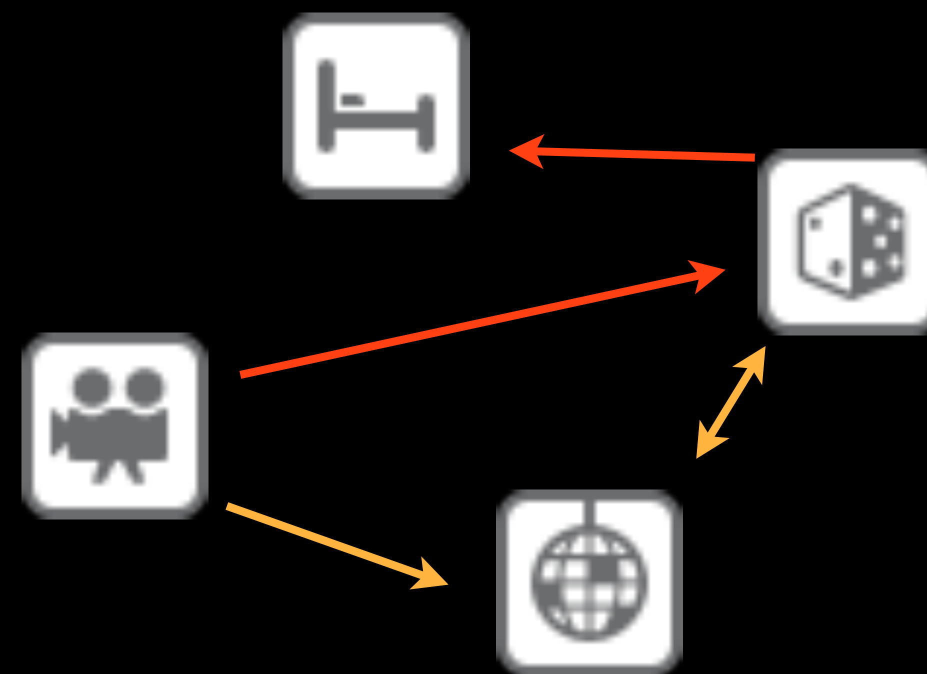
M.Newman et. al PRL, 2002

Place Networks

~75% New Links
~5% New Places



snapshot 1

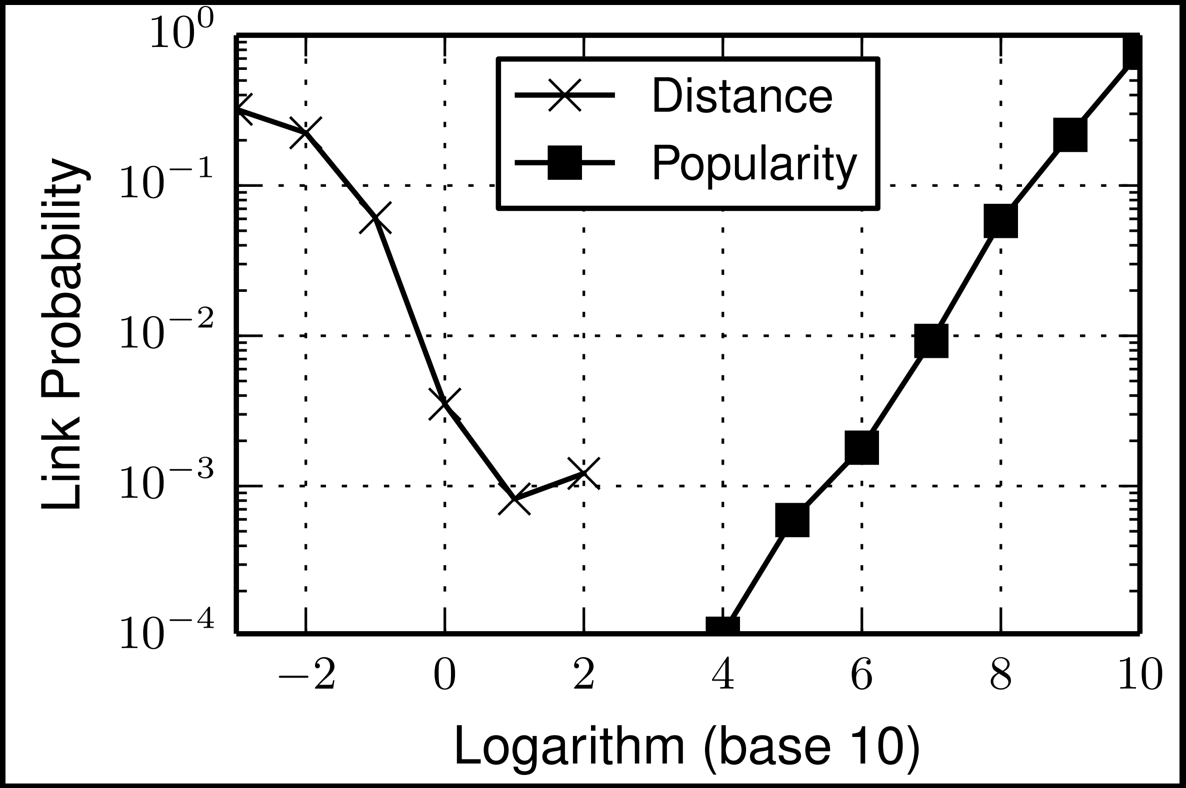


snapshot 2

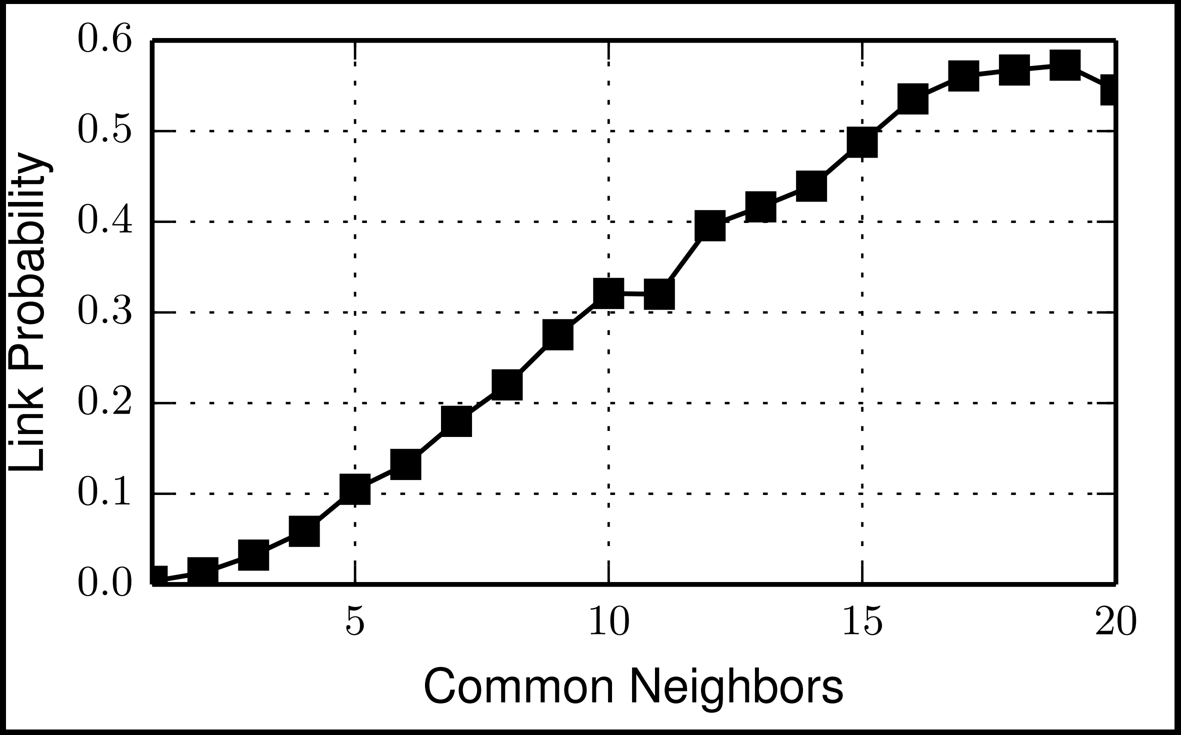
< t

> t

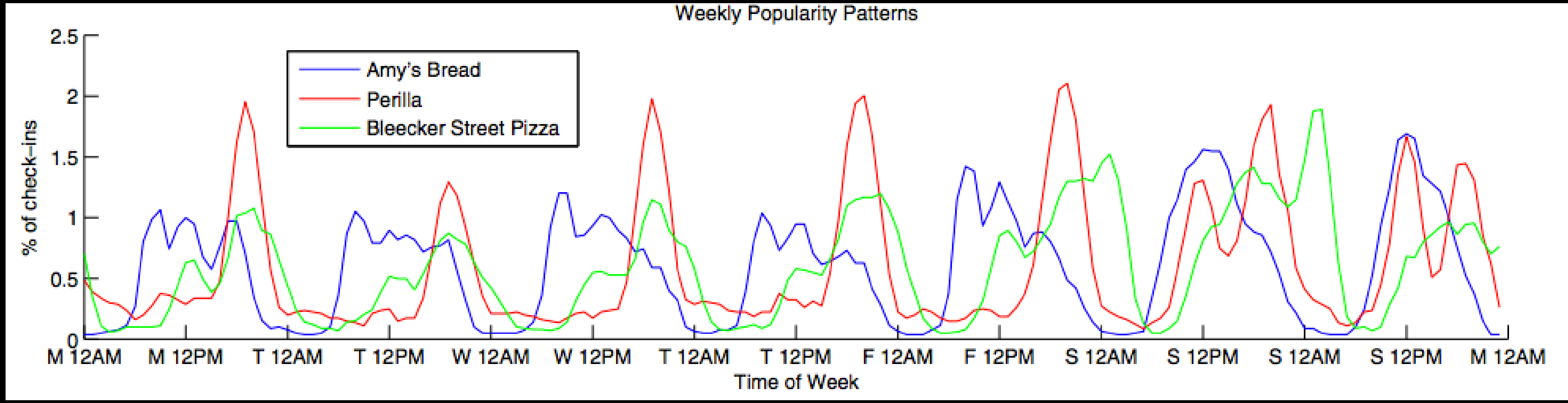
human mobility



network form

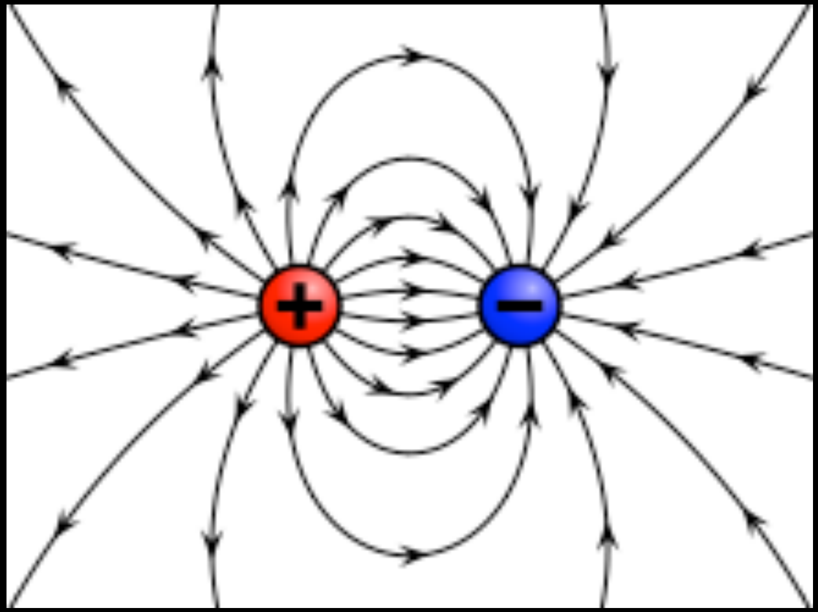


time
signal



Shaw et al. WSDM'13

place
polarity



CLASSIC GRAVITY

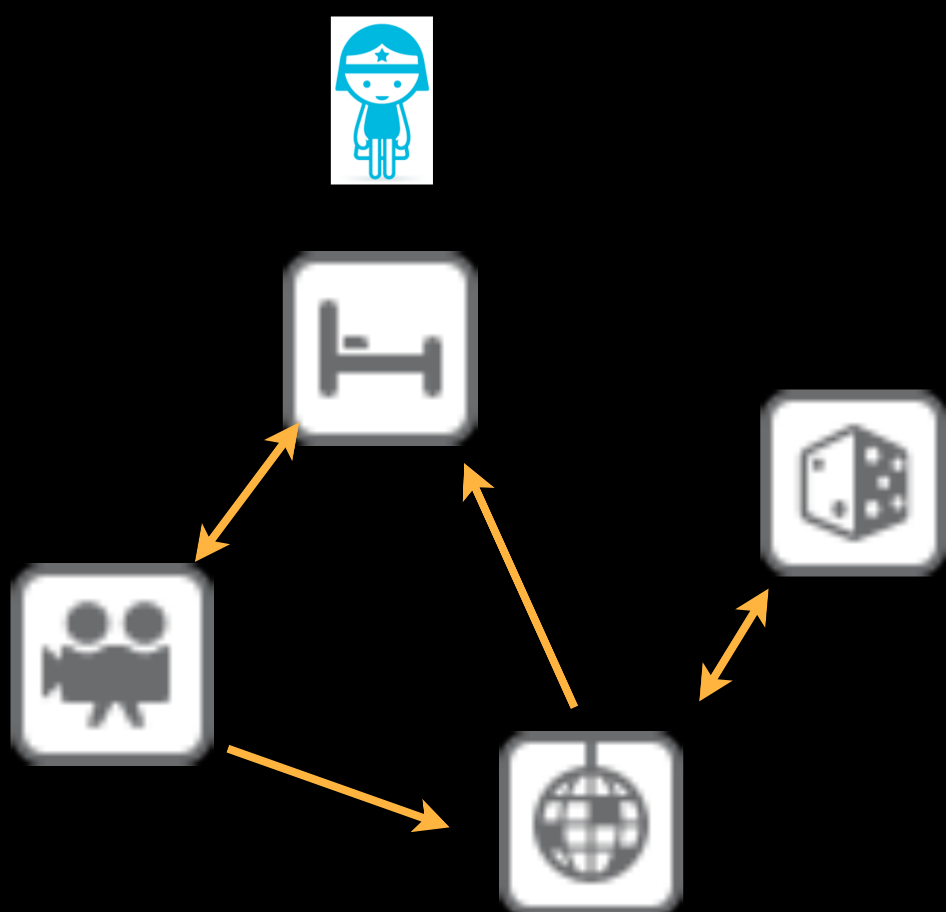
$$\frac{c_i c_j}{d(i,j)^\beta}$$

DYNAMIC GRAVITY

$$\frac{a_{ij} \sum_{\tau=1}^{T} c_i(\tau)^+ c_j(\tau)^-}{d(i,j)^\beta}$$

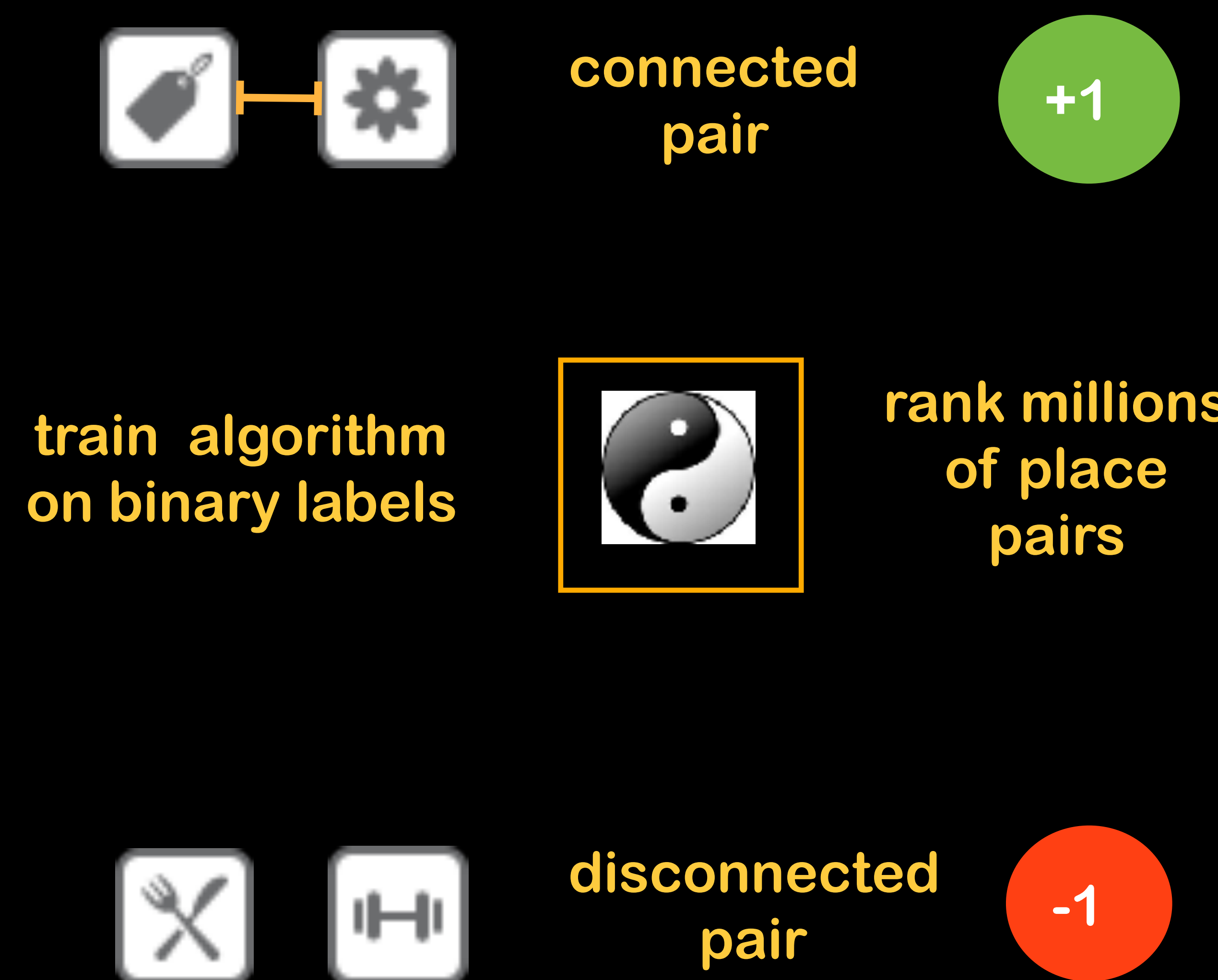
The “heavy-weights”

PLACE RANK

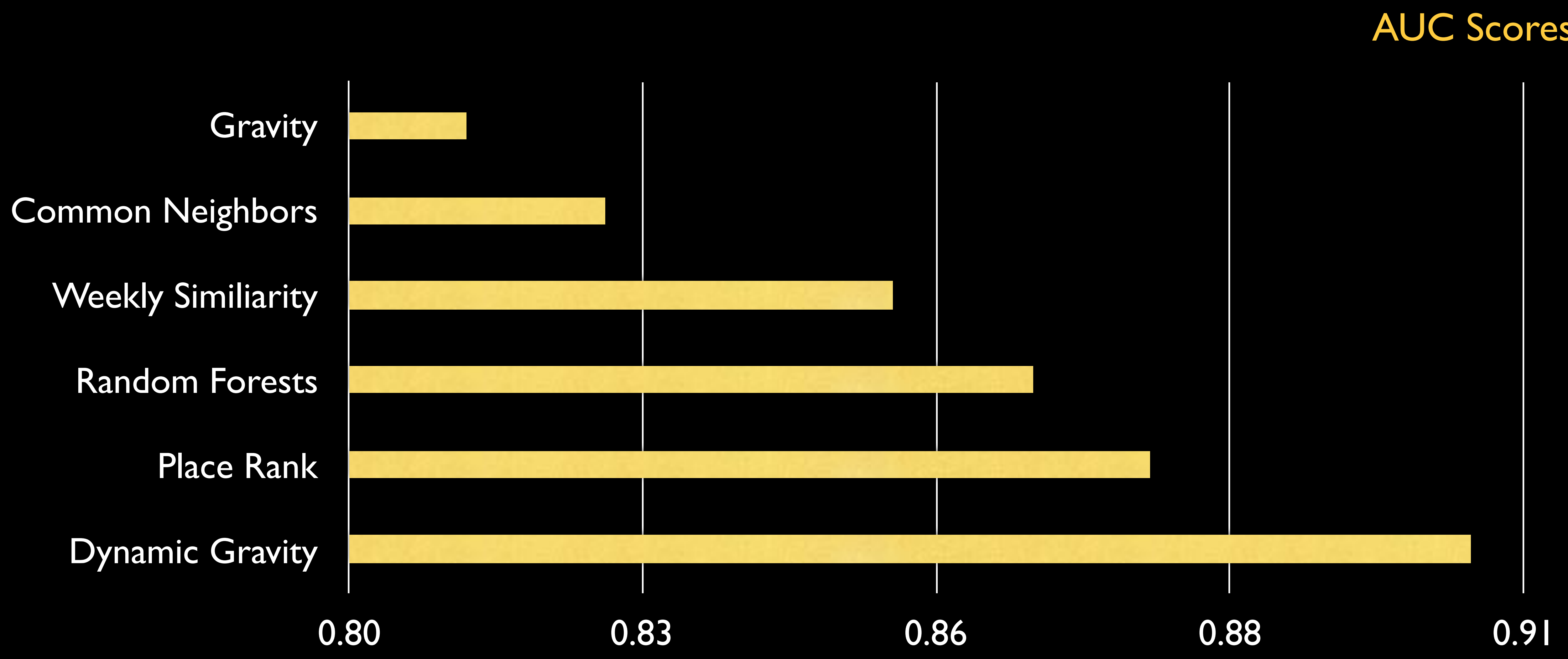


random walk with restart

SUPERVISED LEARNING FOR LINK PREDICTION



Dynamic Gravity model offers best results across 100 cities



Domain knowledge + simplicity wins

Dynamic gravity also works well in informal tests we have done on CDR

Noulas, A, et al. "Topological properties and temporal dynamics of place networks in urban environments." Proceedings of the 24th international conference on world wide web companion. International World Wide Web Conferences Steering Committee, 2015.

Cities

54% of total population in cities as of 2014

That’s up from 34% in 1960.

Of course, most of the data discussed previously is generated in urban environments.

The City as a geometric object

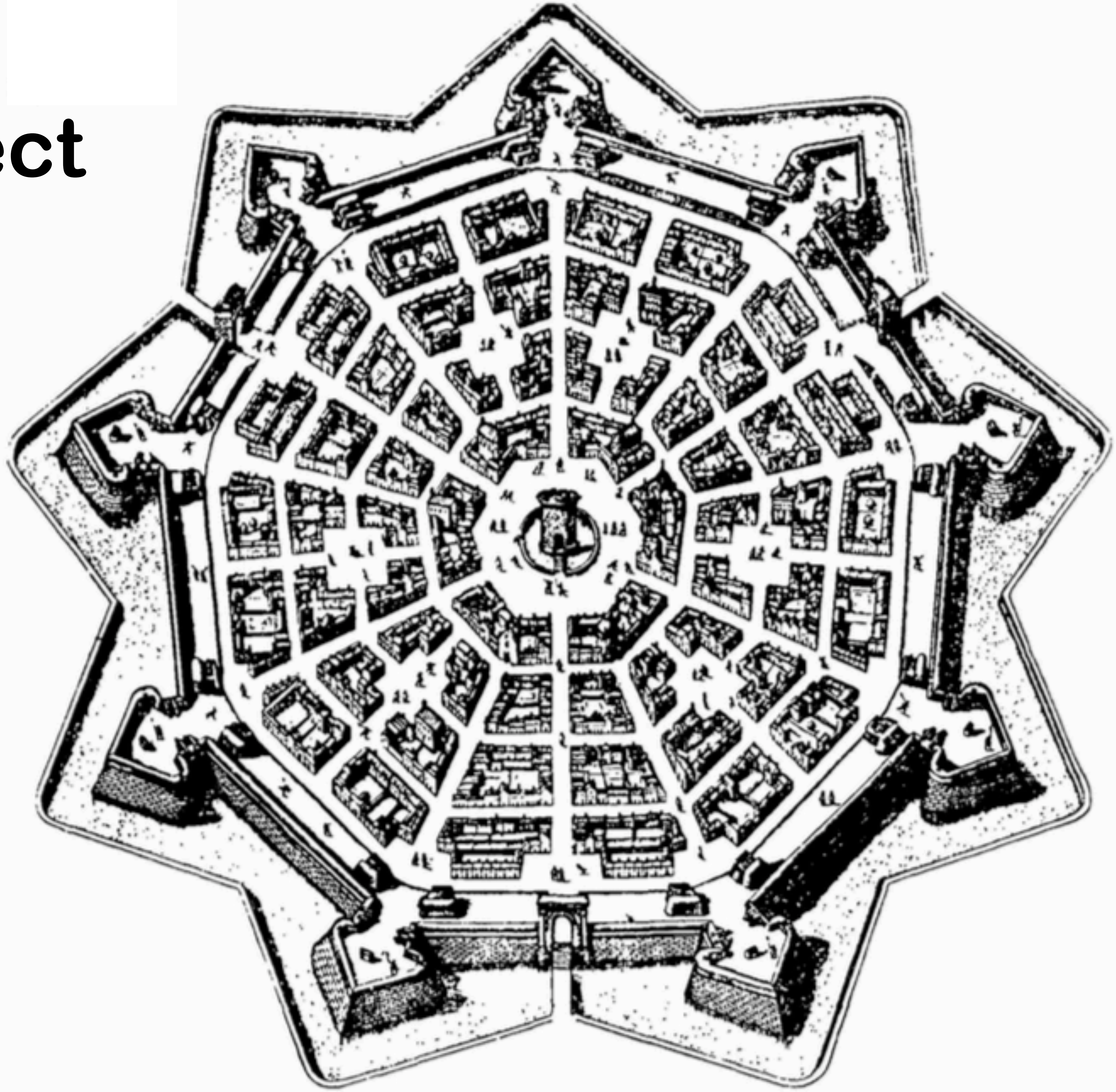
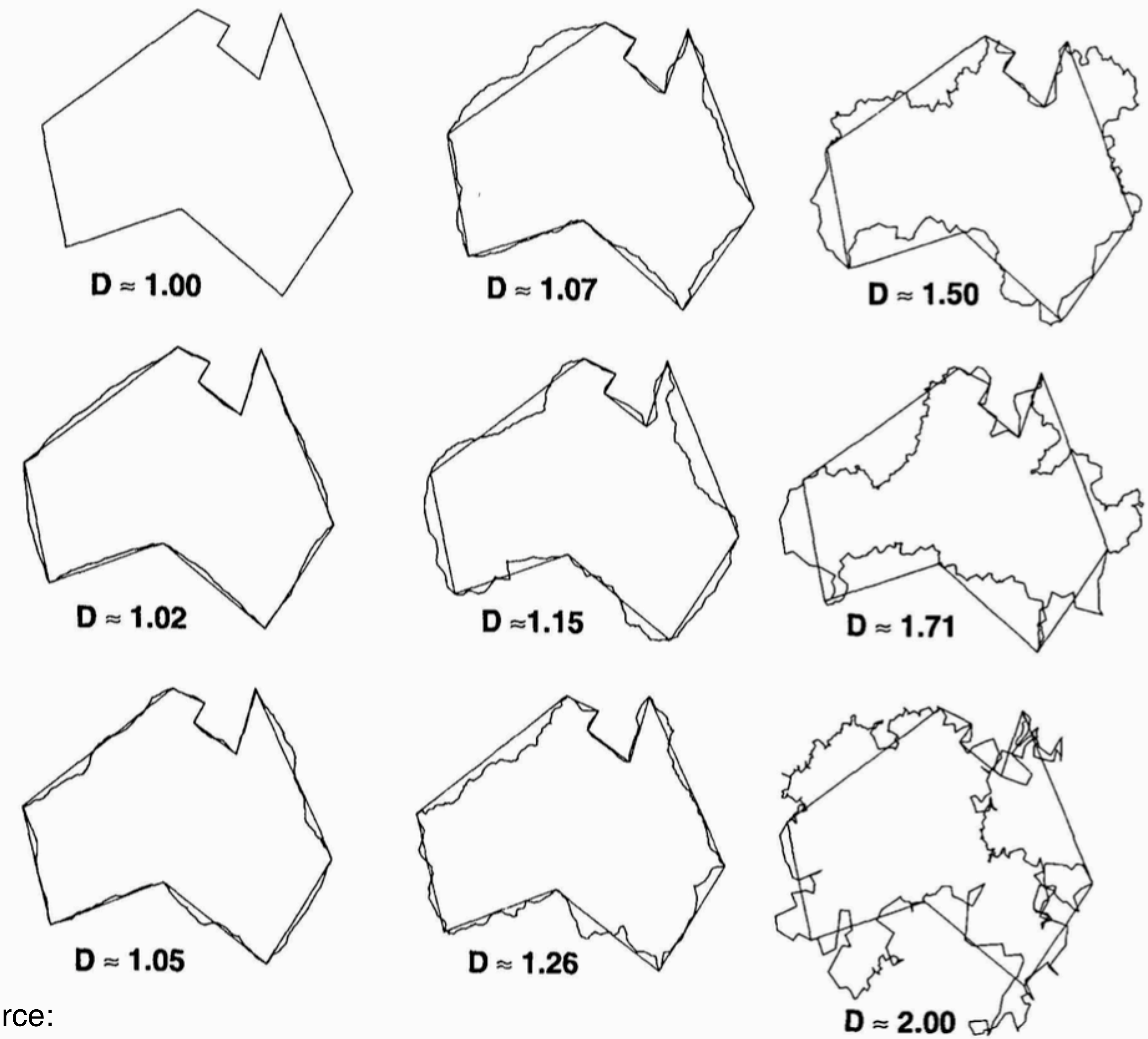


Figure 1.4. Ideal cities of the Renaissance: (a) from Vitruvius; (b) Palma Nuova after Scamozzi (from Morris, 1979).

Source:
Michael Batty
www.fractalcities.org

Fractal Cities



Self similarity

Length depends on the unit of measurement

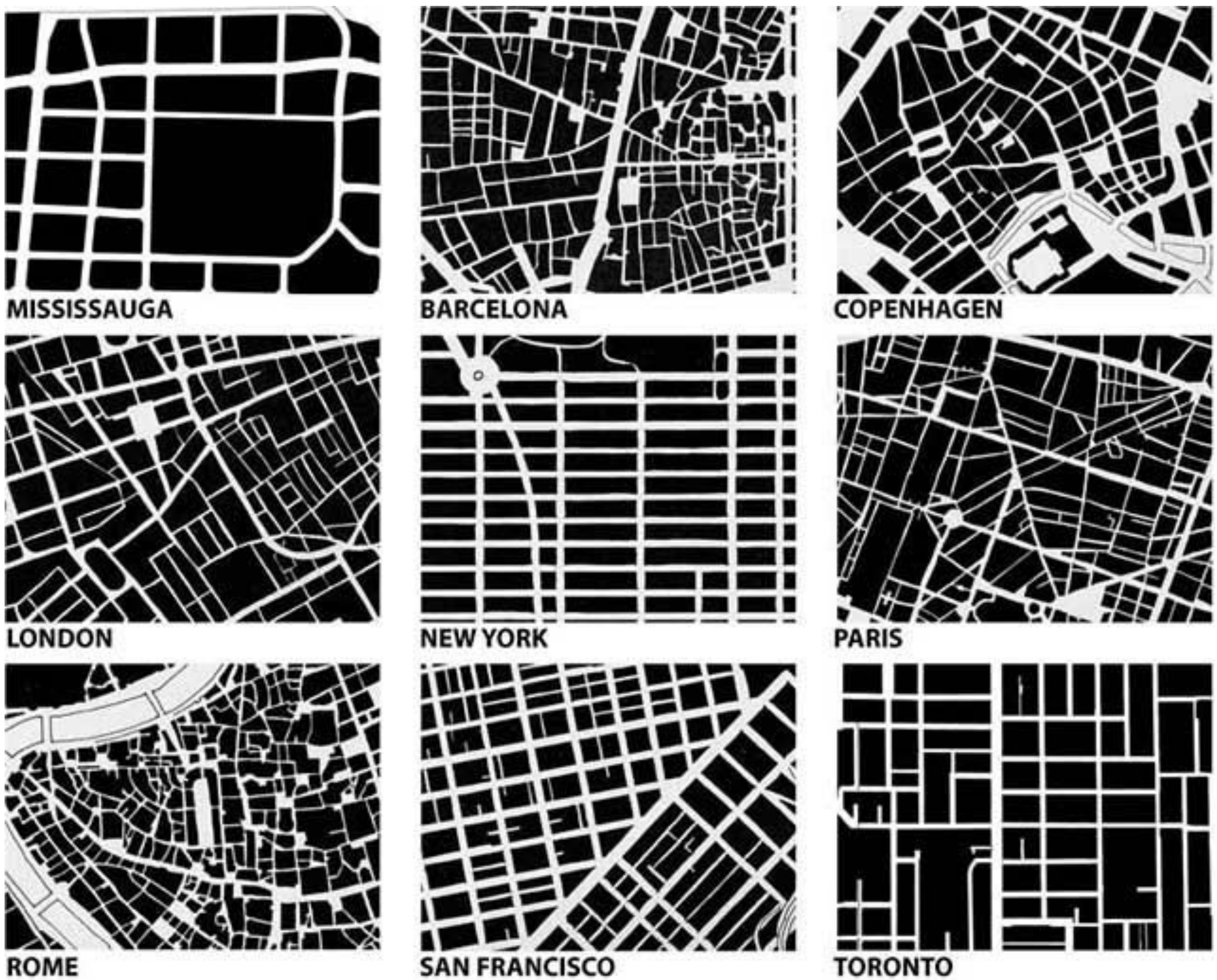
Fractal properties beyond shapes? “The city within the city”.

Source:
Michael Batty
www.fractalcities.org

Source: wikipedia

Country	The World Factbook[3]		World Resources Institute[2]		Land area km² (TWF)[4]	Coast/area ratio (m/km²)	
	#	km	#	km		(TWF)	(WRI)
World[Note 2]	—	1,162,306	—	1,634,701	148,940,000	7.80	11.
other[Note 3]	—	356,000					
Canada	1	202,080	1	265,523	9,984,670	20.2	26.
Indonesia	2	54,716	4	95,181	1,811,569	30.2	52.
Greenland[Note 4]	—	44,087			2,166,086	20.4	
Russia	3	37,653	3	110,310	16,377,742	2.30	6.7
Philippines	4	36,289	8	33,900	298,170	122	11
Japan	5	29,751	12	29,020	364,485	81.6	79.
Australia	6	25,760	6	66,530	7,682,300	3.35	8.6
Norway	7	25,148[Note 5]	7	53,199	304,282	82.6	17
United States	8	19,924	2	133,312	9,161,966	2.17	14.
Antarctica	—	17,968			14,000,000	1.28	
New Zealand	9	15,134	17	17,209	267,710[5]	56.5	64.
China	10	14,500	11	30,017	9,569,901	1.52	3.1
Greece	11	13,676	19	15,147	131,957	104	11
United Kingdom	12	12,429	16	19,717	241,930	51.4	81.
Mexico	13	9,330	14	23,761	1,943,945	4.80	12.
Italy	14	7,600	28	9,226	294,140	25.8	31.

Urban Morphology



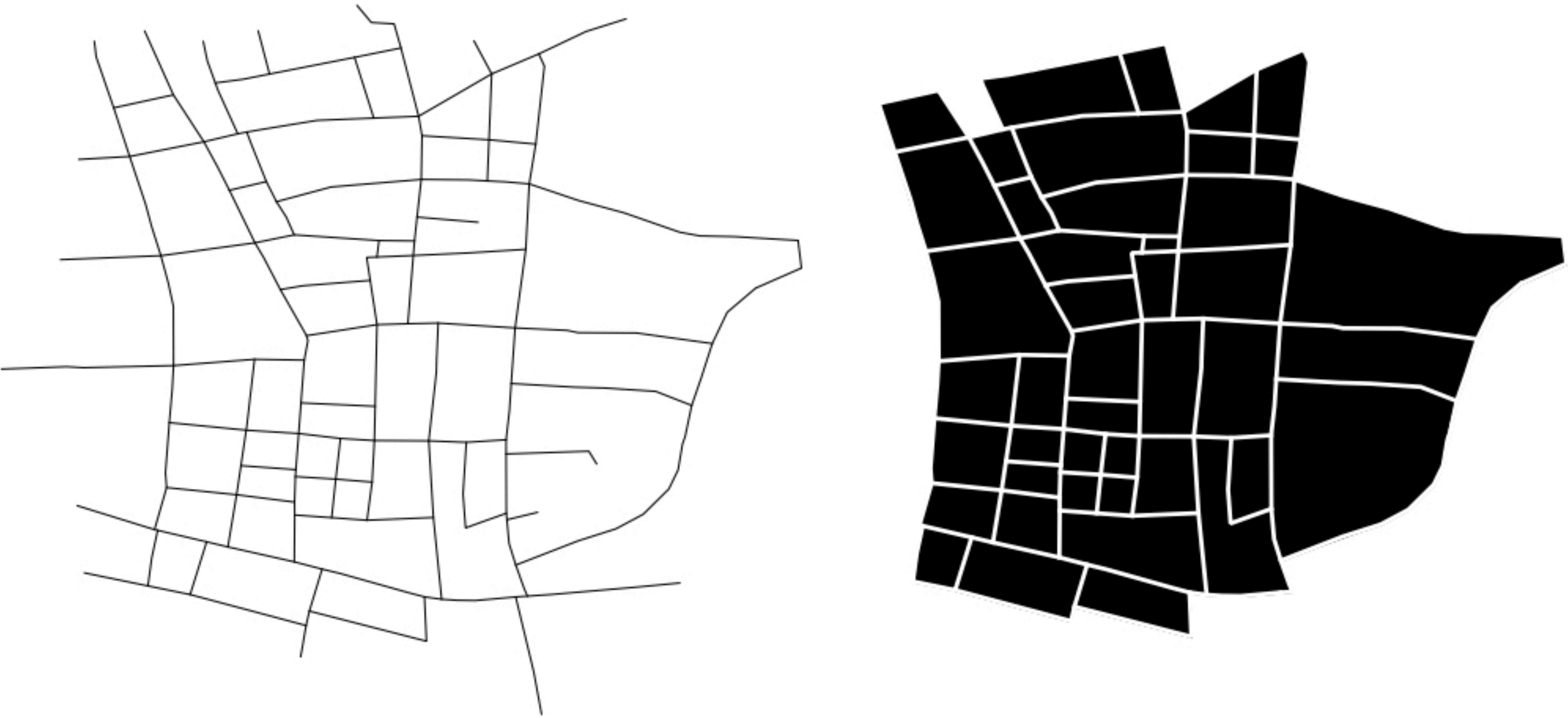
http://urbagram.stdio-london.com/v1/show/Network

https://nextcity.org/daily/entry/city-street-grid-maps-visualize-density

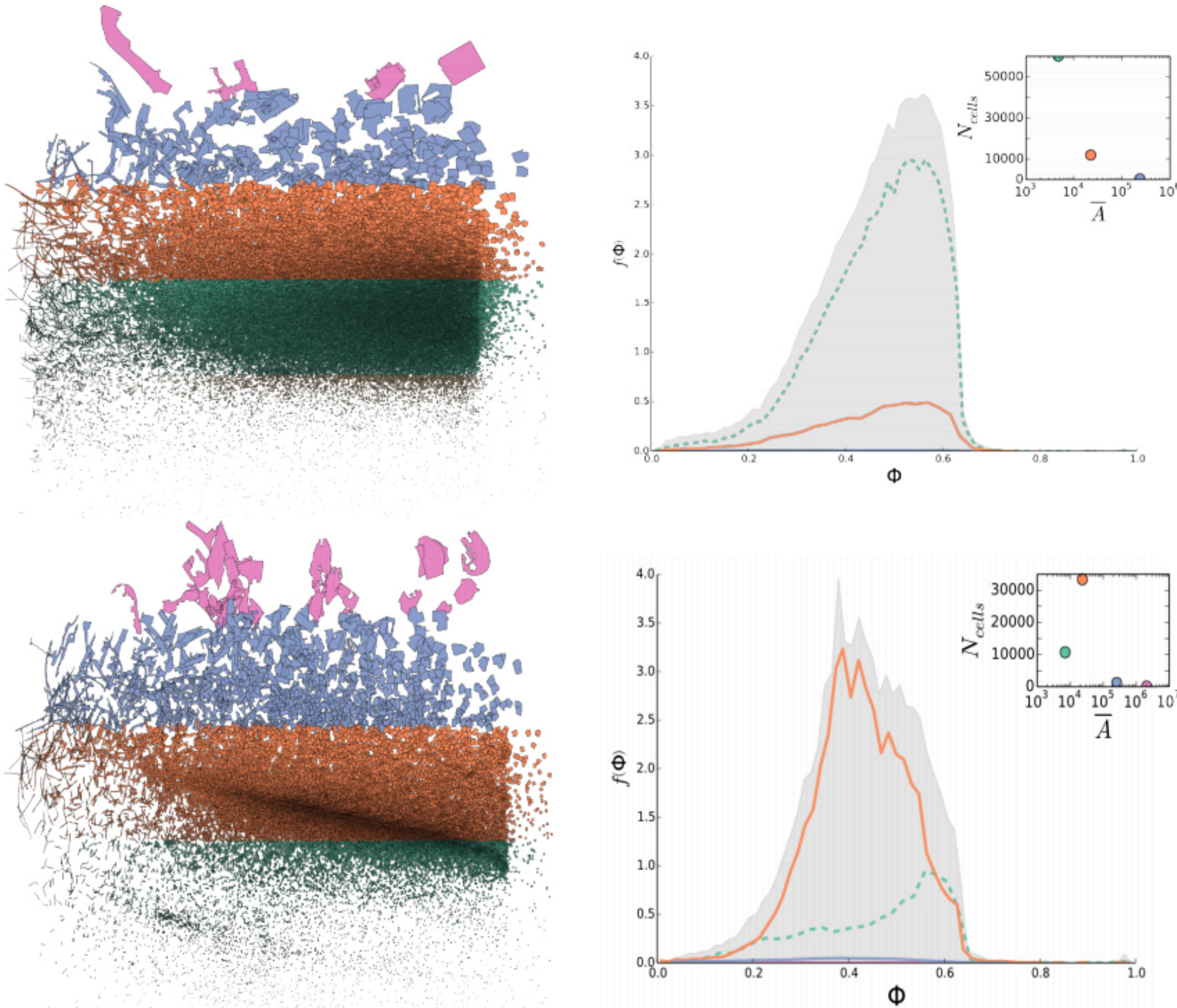
Connecting the Fractal City.

http://zeta.math.utsa.edu/~yxk833/connecting.html

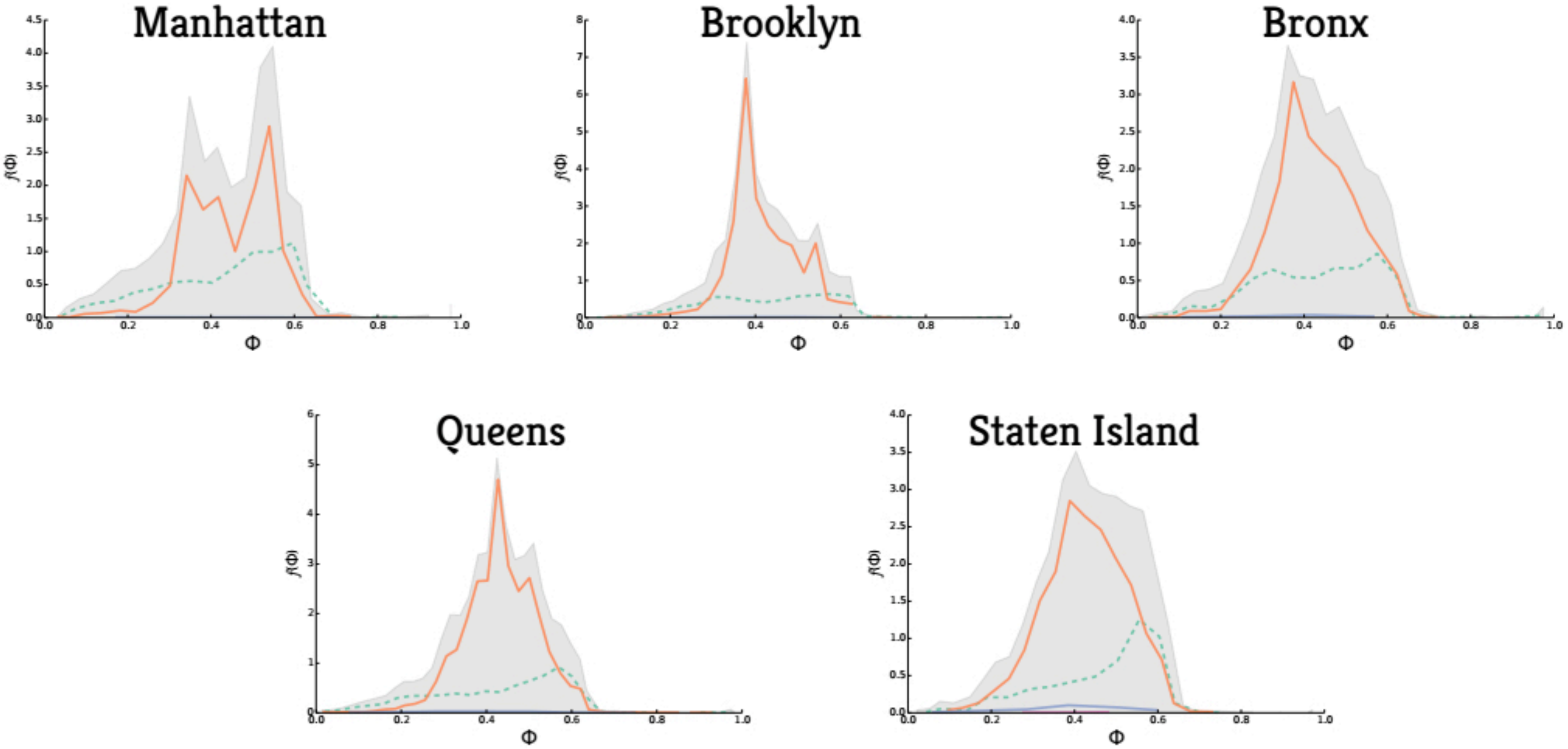
Extracting land patches

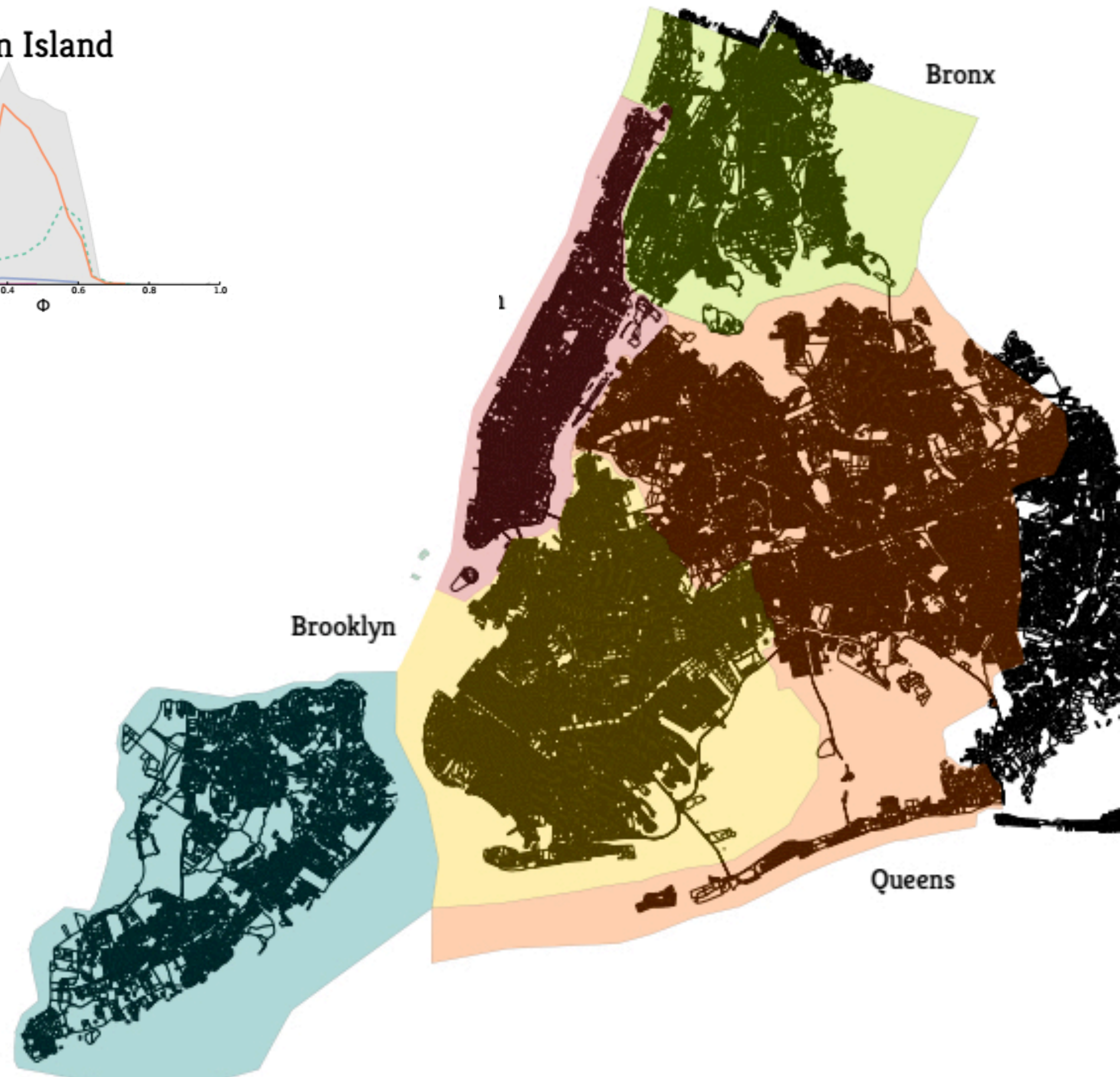


A typology of street patterns
R Louf, M Barthelemy
Journal of The Royal Society Interface 11 (101), 20140924



f(Φ)
Φ
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
0.0
0.2
0.4
0.6
0.8
1.0
N_cells
50000
30000
10000
0
10^3
10^4
10^5
10^6
A
f(Φ)
Φ
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
0.0
0.2
0.4
0.6
0.8
1.0
N_cells
30000
20000
10000
0
10^3
10^4
10^5
10^6
10^7
A





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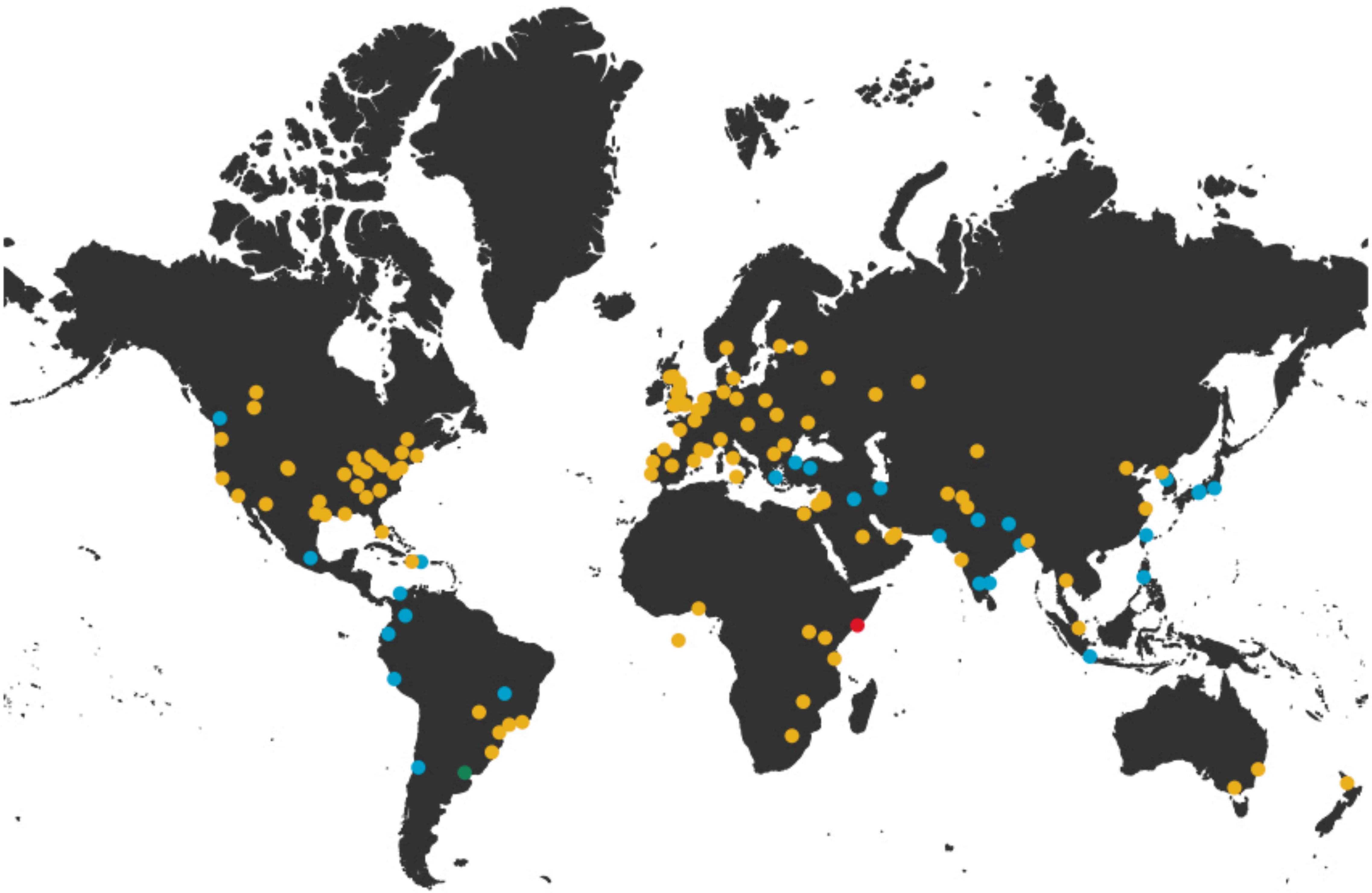
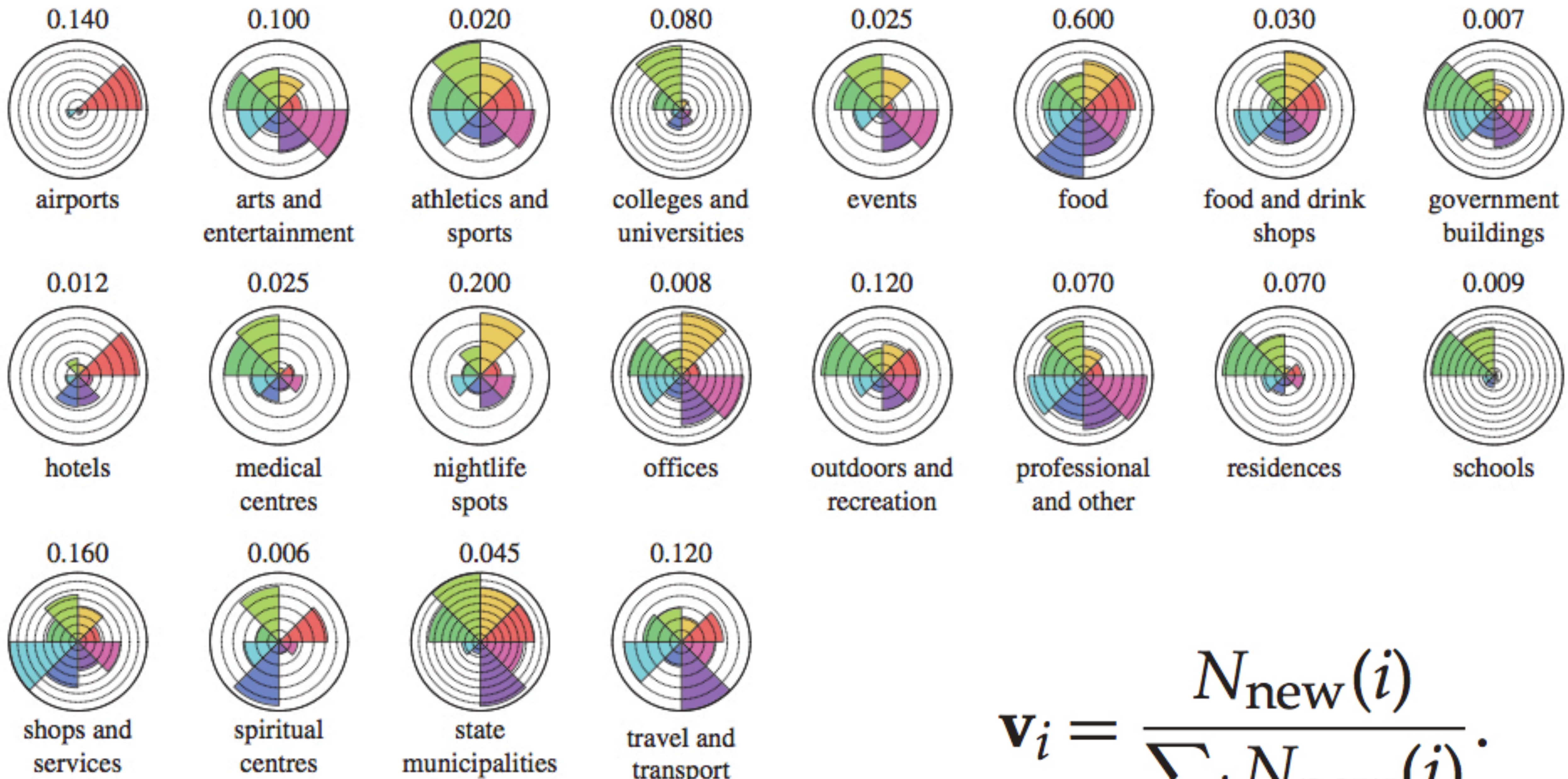


A typology of street patterns
R Louf, M Barthelemy
Journal of The Royal Society Interface 11 (101), 20140924

no.	MPD (km)	cities
1 ●	10 996	Dubai, Borough of Queens
2 ●	5800	Athens, Brooklyn, Bucharest, Portland, Sofia
3 ●	5250	Belo Horizonte, Coyoacán, Curitiba, Fortaleza, Gent, Manaus, Porto Alegre
4 ●	4924	Adana, Ankara, Bursa, Denizli, Eskişehir, İstanbul, İzmir, Lima, Santiago, Trabzon
5 ●	5887	Charlotte, Chiba, Columbus, Houston, Indianapolis, Jacksonville, Kiev, Moscow, Nashville, Orlando, Osaka, Phoenix, Raleigh, Saint Petersburg, San Antonio, San Jose, Yokohama
6 ●	3537	Bandung, Bangkok, Chiang Mai, George Town, Hong Kong, Jakarta, Kuala Lumpur, Makati City, Medan, Petaling Jaya, Pineda, Quezon City, Seoul, Shah Alam, Singapore, Surabaya, Tokyo, Toronto, Yogyakarta
7 ●	5790	Amsterdam, Barcelona, Berlin, Bogotà, Boston, Brussels, Budapest, Buenos Aires, Copenhagen, Helsinki, London, Madrid, Milano, Paris, Prague, Recife, Riga, Riyadh, Sydney, Tampa
8 ●	4276	Antwerpen, Atlanta, Austin, Brasília, Chicago, Dallas, Denver, Las Vegas, Los Angeles, Mexico City, Milwaukee, Minneapolis, New York, Philadelphia, Rio de Janeiro, San Diego, San Francisco, São Paulo, Seattle, Washington DC

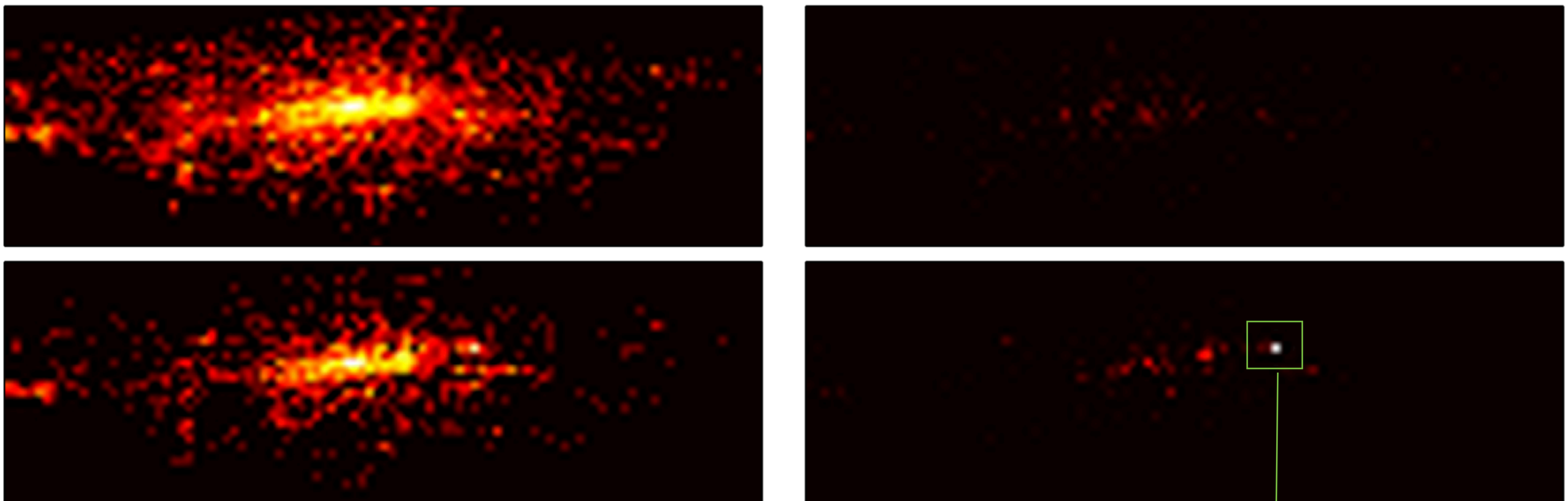


$$\mathbf{v}_i = \frac{N_{\text{new}}(i)}{\sum_i N_{\text{new}}(i)}.$$

Tracking Urban Activity Growth Globally with Big Location Data
M Daggitt, A Noulas, B Shaw, C Mascolo
Royal Society Open Science, 2015

Tracking the birth of places [London 2010-2014]

existing places | less than expected



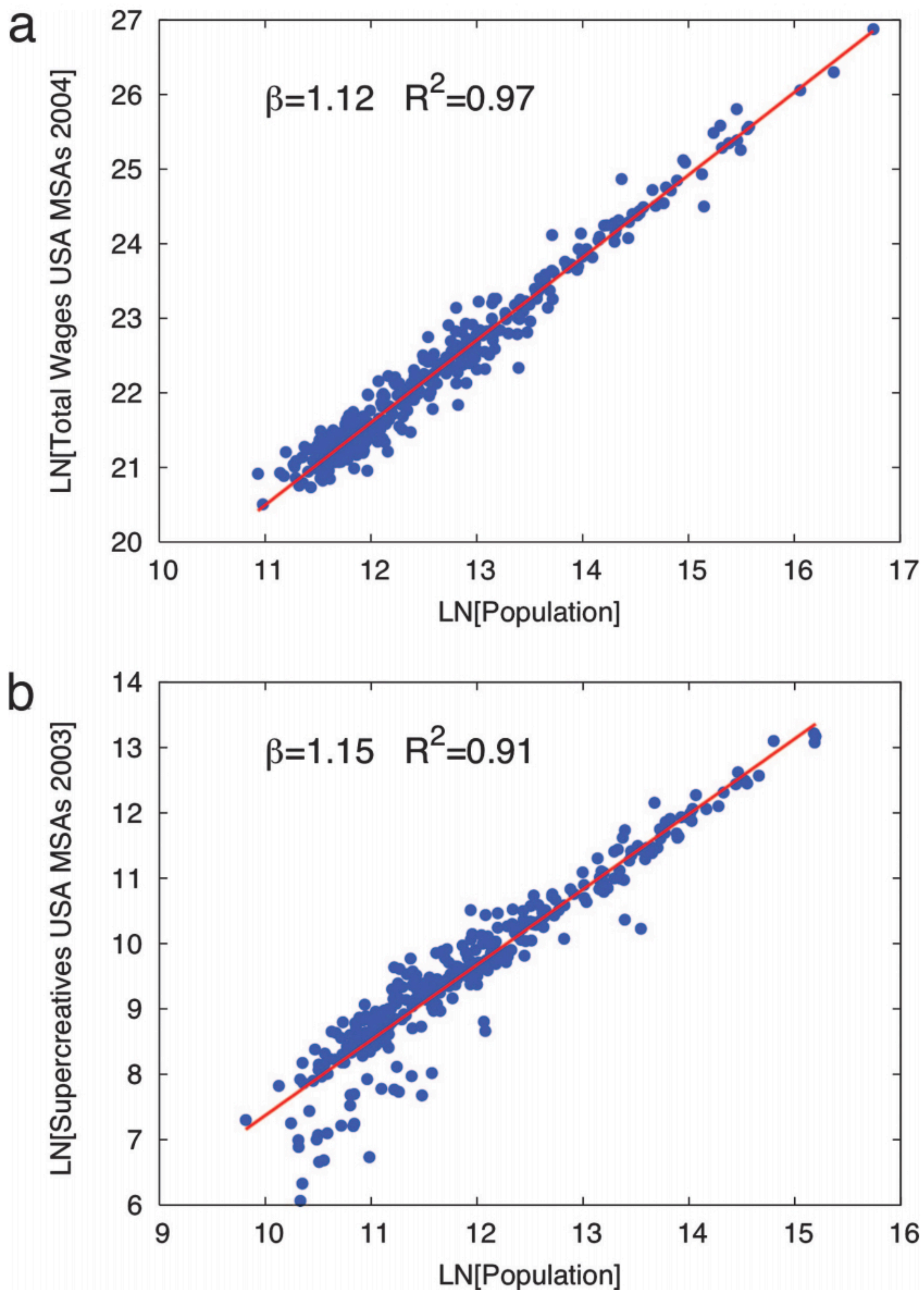
new places | more than expected

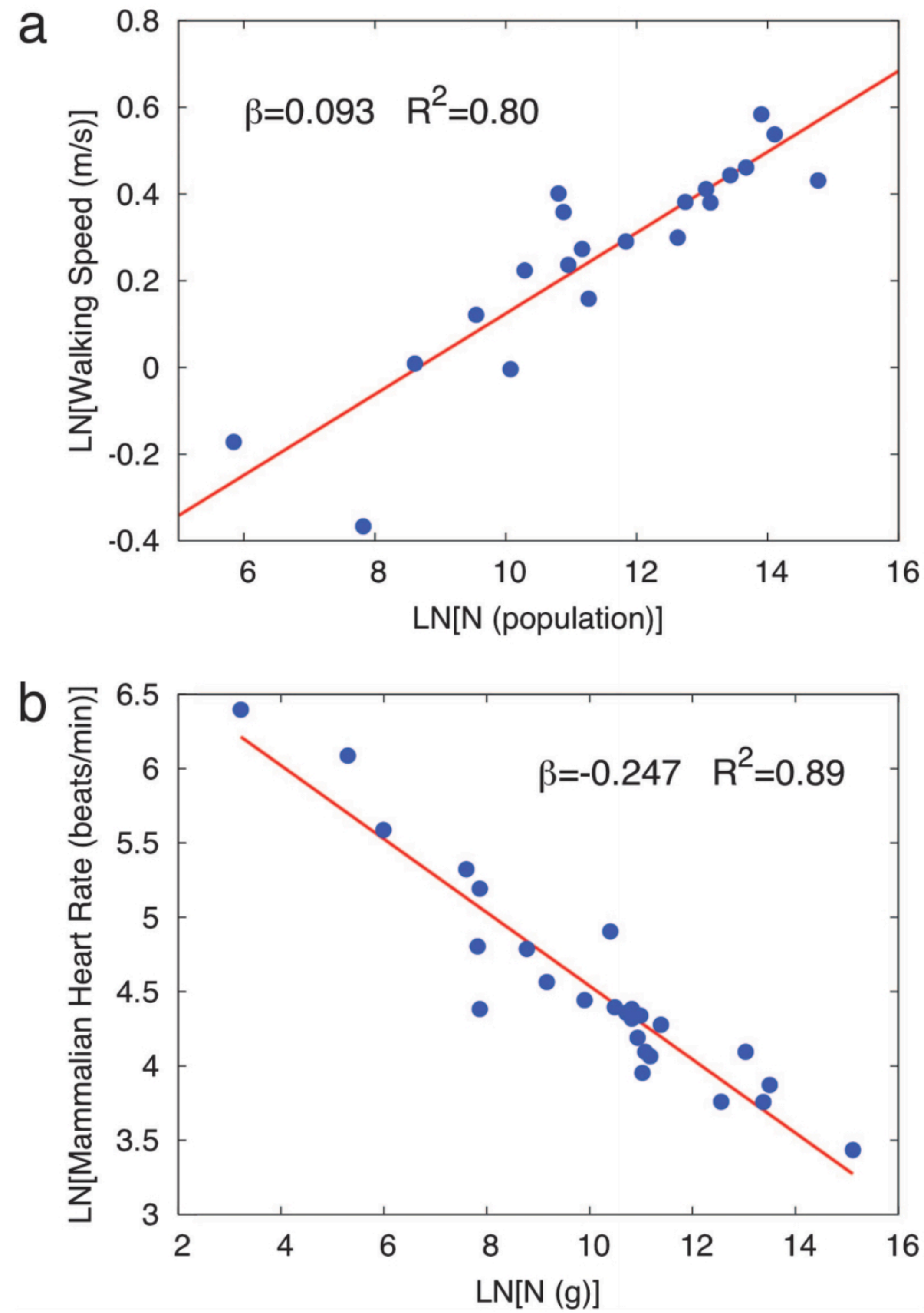
Stratford: Olympic Village

$$n_{i,j}^{\text{null}} = \frac{n_{i,j}^{\text{existing}} n^{\text{new}}}{n^{\text{existing}}}$$

$$v_{i,j} = n_{i,j}^{\text{null}} - n_{i,j}^{\text{new}}$$

Tracking Urban Activity Growth Globally with Big Location Data
M Daggitt, A Noulas, B Shaw, C Mascolo
Royal Society Open Science





Growth, innovation, scaling, and the pace of life in cities
http://www.pnas.org/content/104/17/7301.long

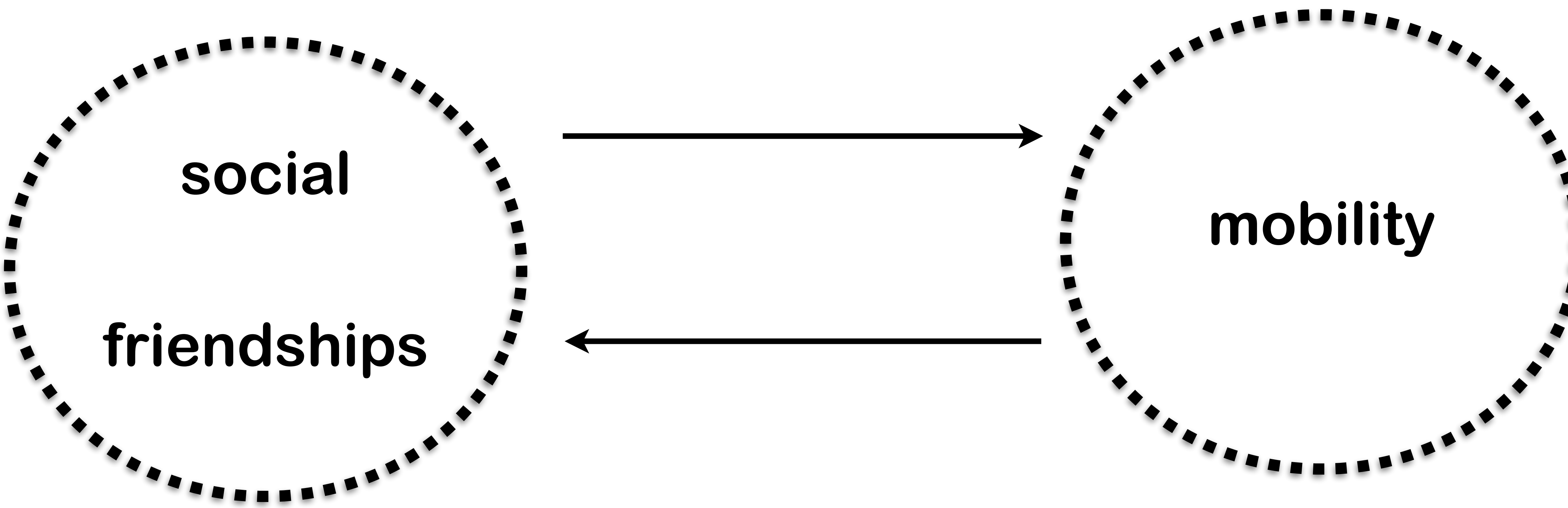
Table 1. Scaling exponents for urban indicators vs. city size

Y	β	95% CI	Adj-R^2	Observations	Country–year
New patents	1.27	[1.25,1.29]	0.72	331	U.S. 2001
Inventors	1.25	[1.22,1.27]	0.76	331	U.S. 2001
Private R&D employment	1.34	[1.29,1.39]	0.92	266	U.S. 2002
"Supercreative" employment	1.15	[1.11,1.18]	0.89	287	U.S. 2003
R&D establishments	1.19	[1.14,1.22]	0.77	287	U.S. 1997
R&D employment	1.26	[1.18,1.43]	0.93	295	China 2002
Total wages	1.12	[1.09,1.13]	0.96	361	U.S. 2002
Total bank deposits	1.08	[1.03,1.11]	0.91	267	U.S. 1996
GDP	1.15	[1.06,1.23]	0.96	295	China 2002
GDP	1.26	[1.09,1.46]	0.64	196	EU 1999–2003
GDP	1.13	[1.03,1.23]	0.94	37	Germany 2003
Total electrical consumption	1.07	[1.03,1.11]	0.88	392	Germany 2002
New AIDS cases	1.23	[1.18,1.29]	0.76	93	U.S. 2002–2003
Serious crimes	1.16	[1.11, 1.18]	0.89	287	U.S. 2003
Total housing	1.00	[0.99,1.01]	0.99	316	U.S. 1990
Total employment	1.01	[0.99,1.02]	0.98	331	U.S. 2001
Household electrical consumption	1.00	[0.94,1.06]	0.88	377	Germany 2002
Household electrical consumption	1.05	[0.89,1.22]	0.91	295	China 2002
Household water consumption	1.01	[0.89,1.11]	0.96	295	China 2002
Gasoline stations	0.77	[0.74,0.81]	0.93	318	U.S. 2001
Gasoline sales	0.79	[0.73,0.80]	0.94	318	U.S. 2001
Length of electrical cables	0.87	[0.82,0.92]	0.75	380	Germany 2002
Road surface	0.83	[0.74,0.92]	0.87	29	Germany 2002

Growth, innovation, scaling, and the pace of life in cities
http://www.pnas.org/content/104/17/7301.long

BE CRITICAL!

Reflections of two processes



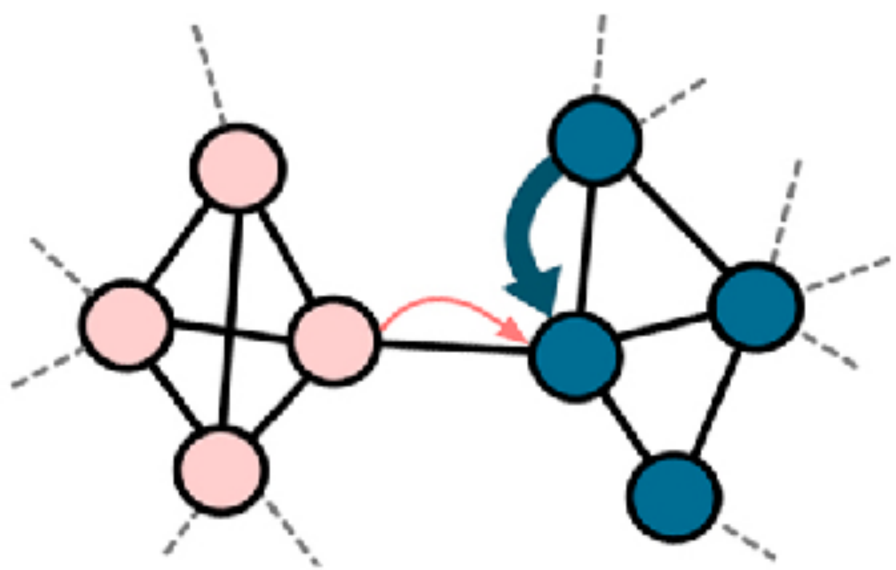
"[Cities] differ from towns and suburbs in basic ways, and one of these is that cities are, by definition, full of strangers"

–Jane Jacobs, 1961

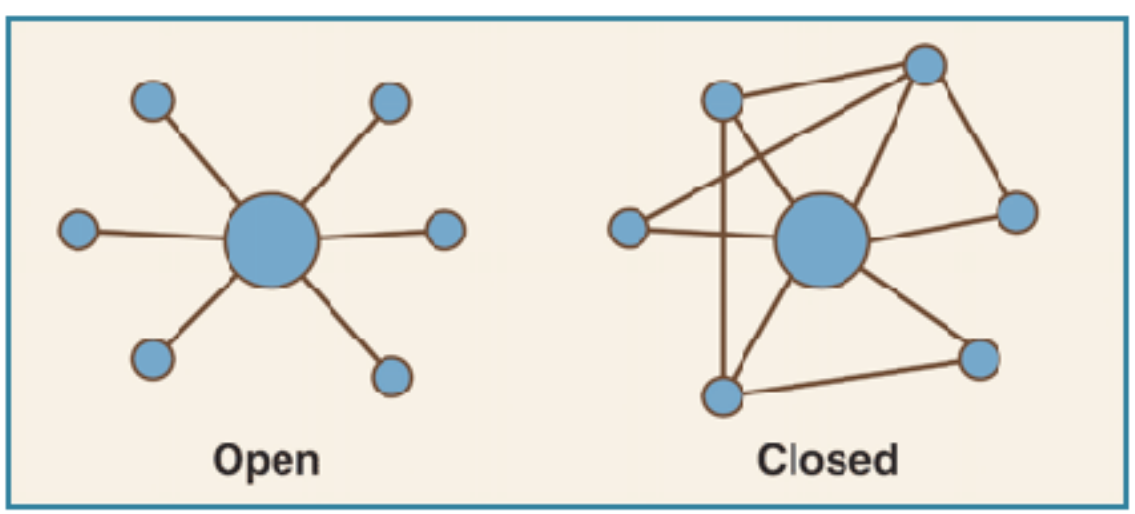
Most common non-British
Nationalities by London borough
Data: UK Census 2011
Photo: Yanko Tihov, 2015

Hristova, Desislava, et al. "Measuring Urban Social Diversity Using Interconnected Geo-Social Networks." Proceedings of the 25th International Conference on World Wide Web. International World Wide Web Conferences Steering Committee, 2016.

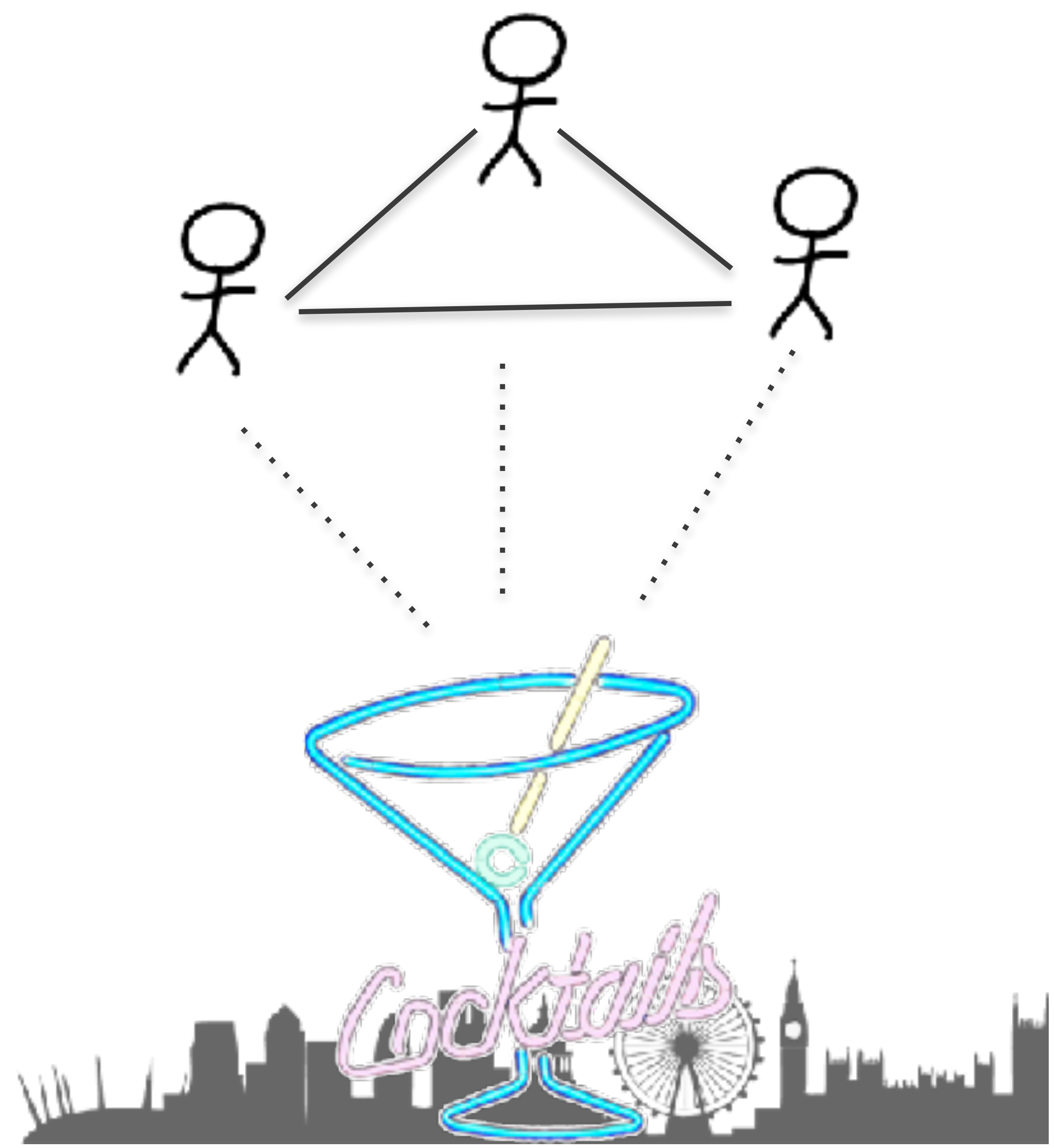
Strangers & Social Capital



Bridging vs Bonding

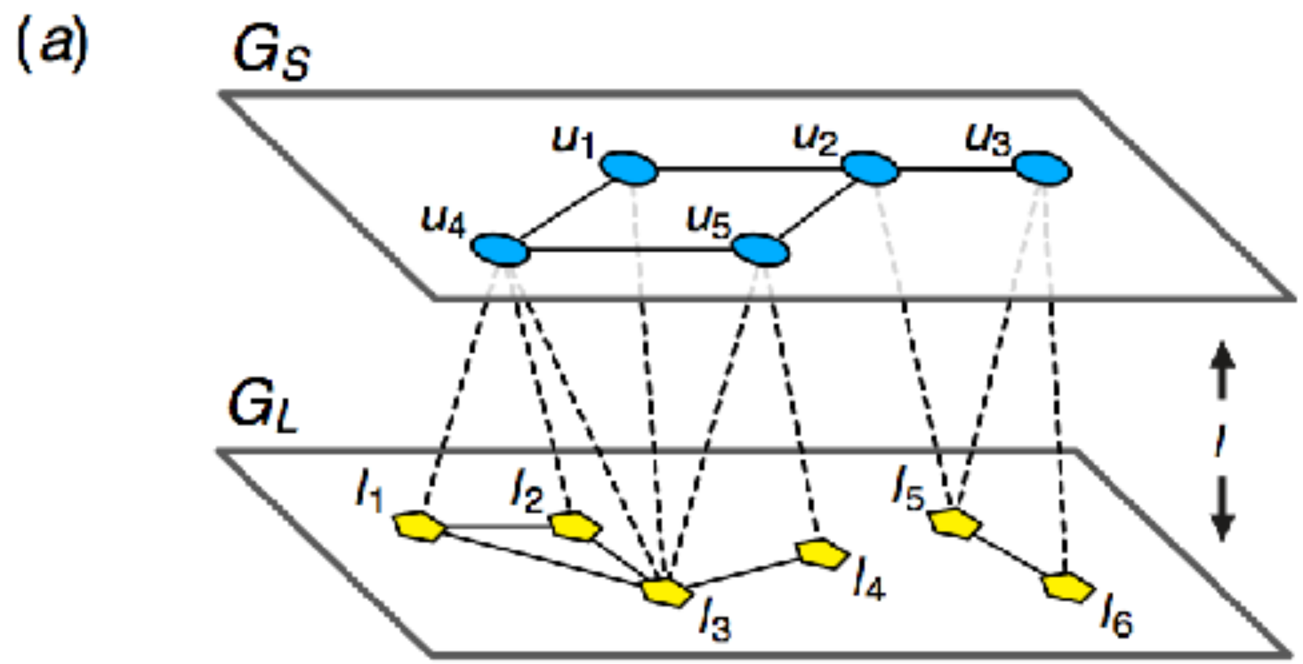


Social Brokerage



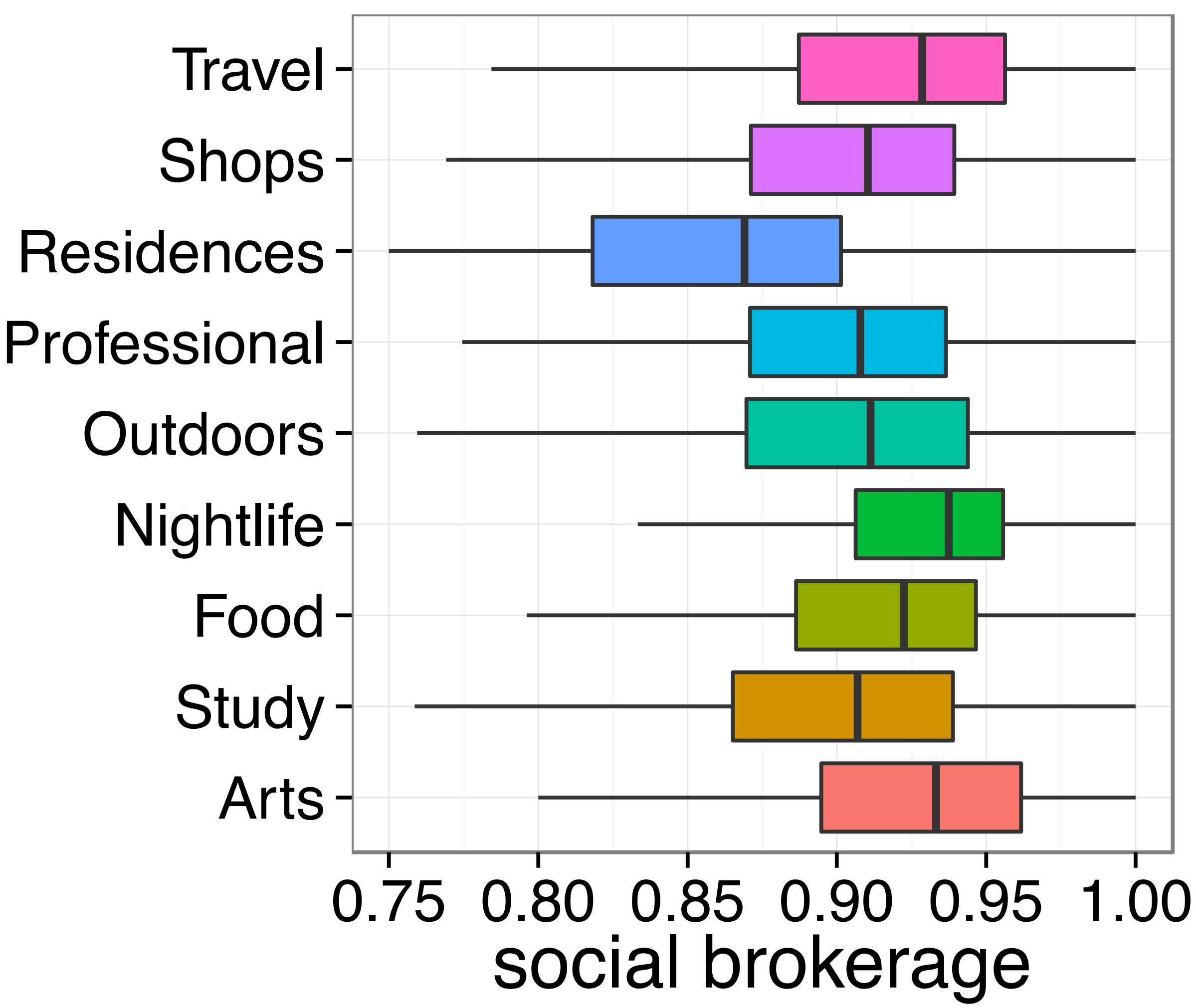
Geo-Social Brokerage

Geo-Social Interconnected Network



Social Brokerage of Places

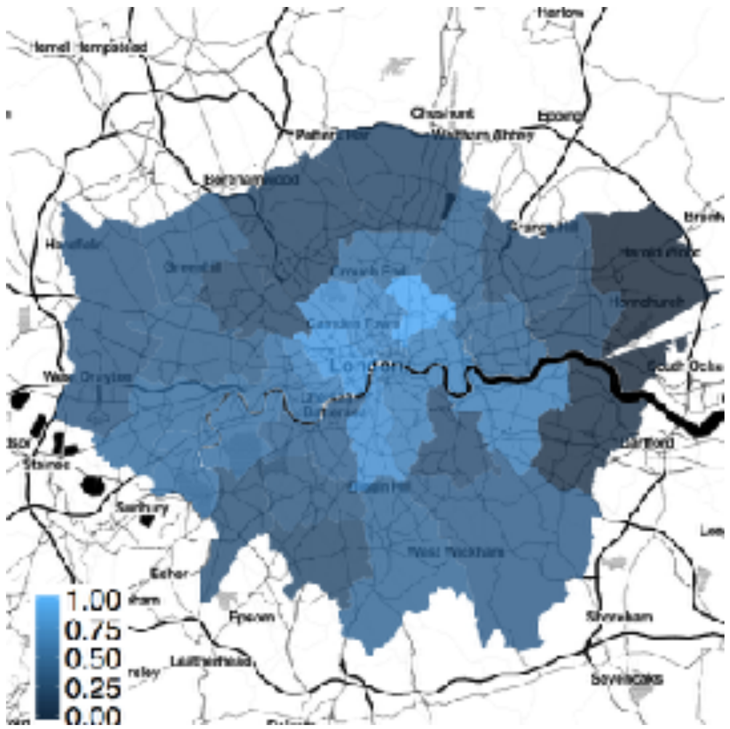
$$B(l) = |N_S^h(l)| - \frac{\sum_{u,v \in N_S^h(l)} e_{u,v}}{|N_S^h(l)|}$$



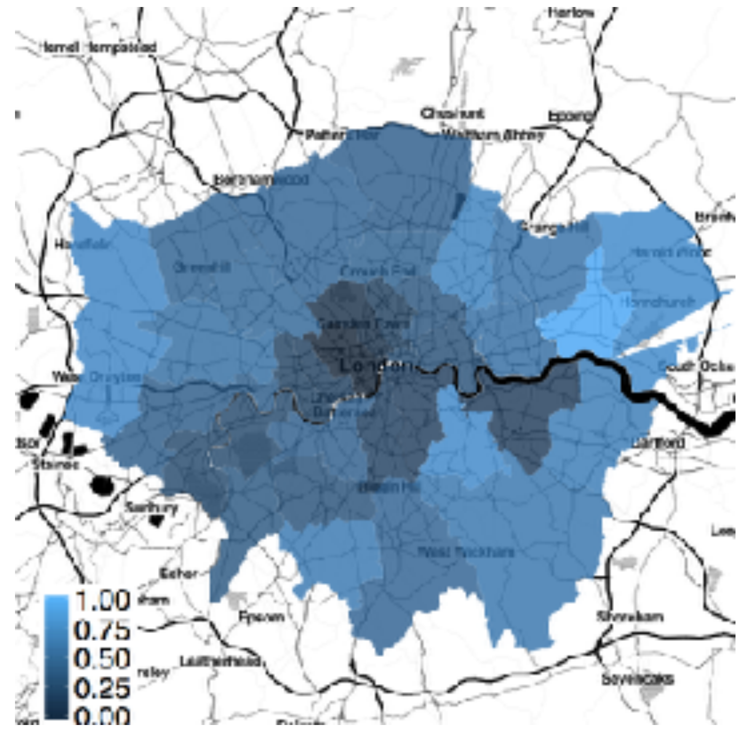
Category	**Bridging role**	**Bonding role**
Travel	Motel	B&B
Shops	Mall	Laundry
Residences	Apartment Building	Home
Professional	Courthouse	Emergency Room
Outdoors	Bridge	Vineyard
Nightlife	Gay Bar	Strip Club
Food	Dumplings	Fried Chicken
Study	Bookstore	Classroom
Arts	Art Museum	Football

Urban Diversity

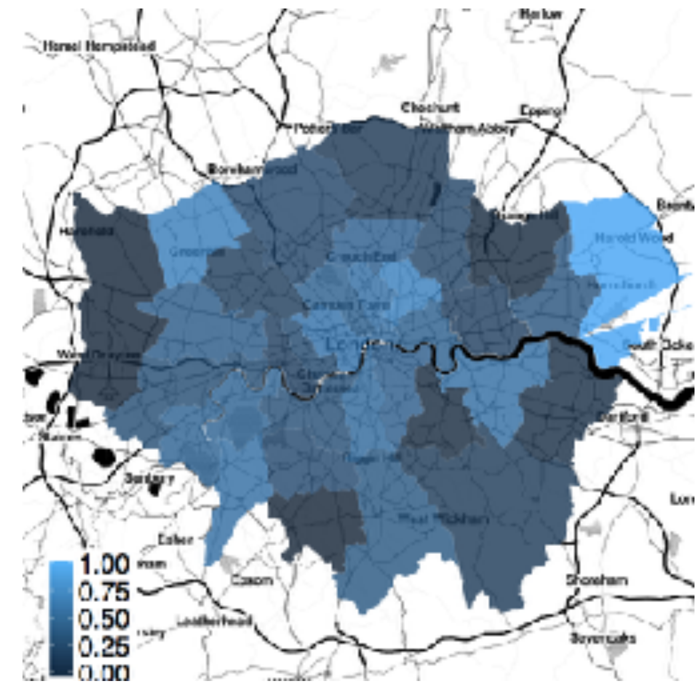
Brokerage

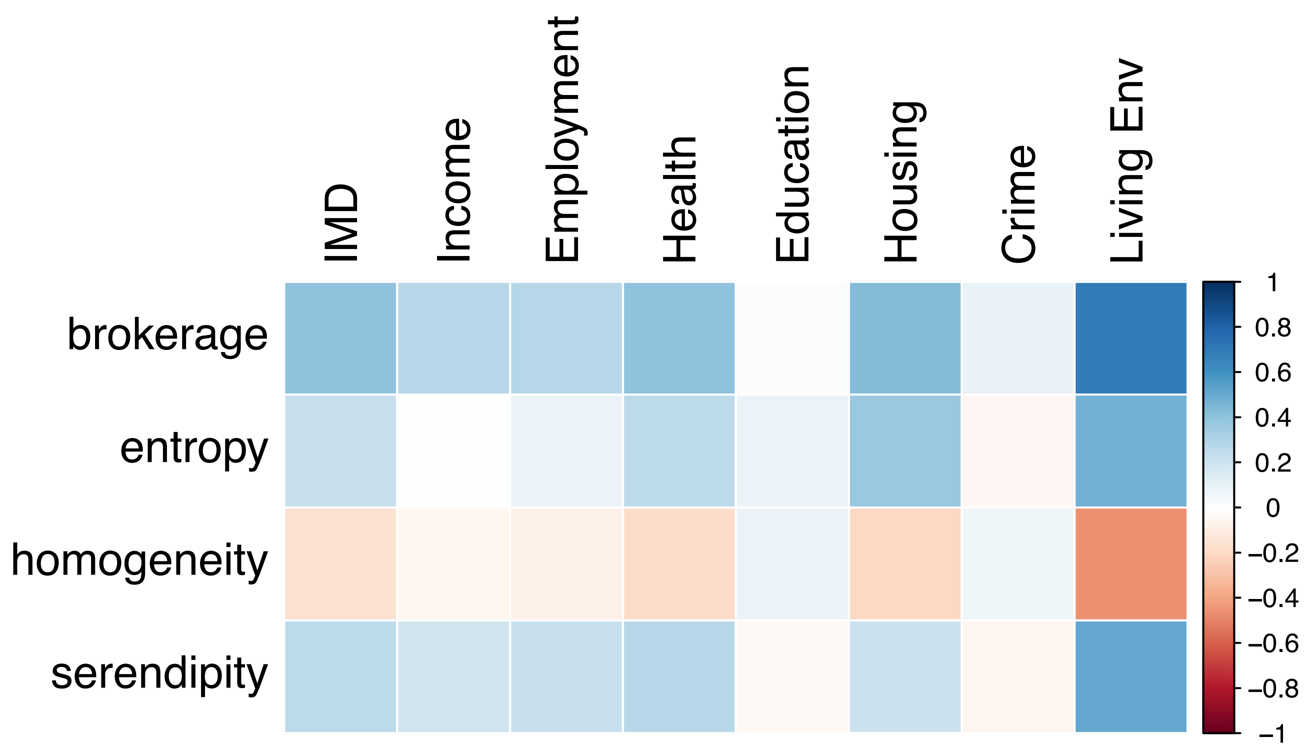


Homogeneity



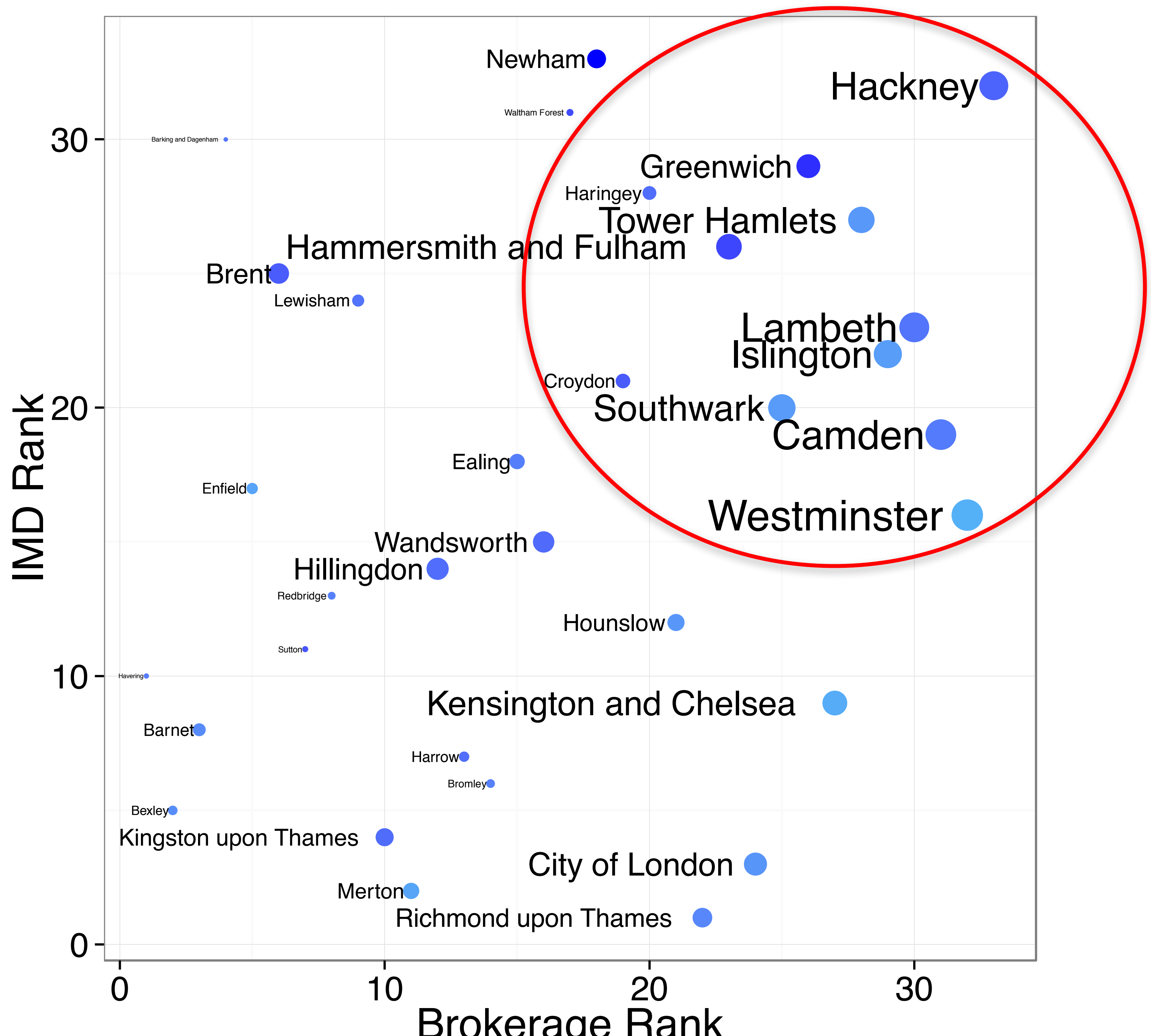
Serendipity





Deprivation is higher in areas with higher urban social diversity.

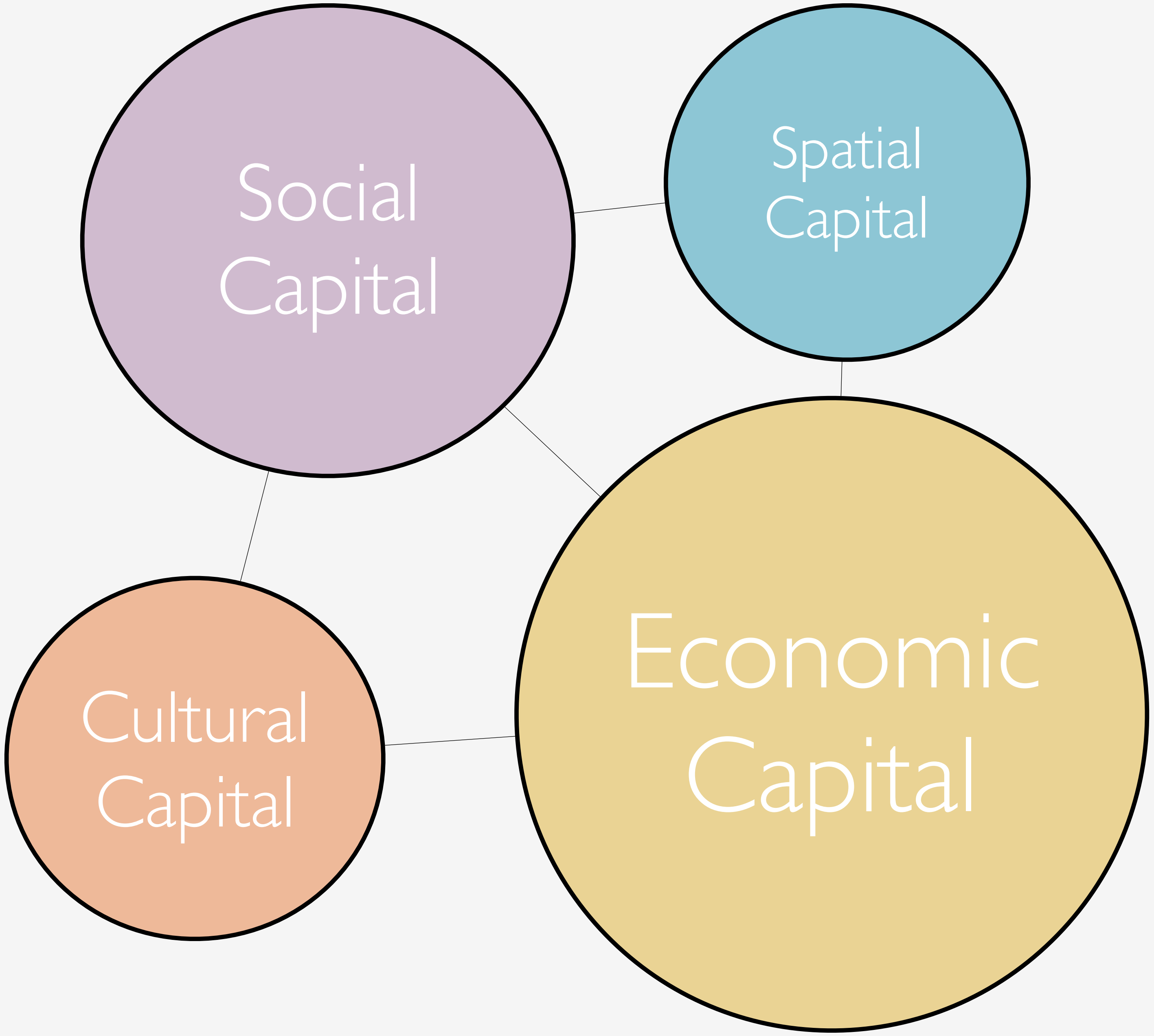
Diversity and Deprivation



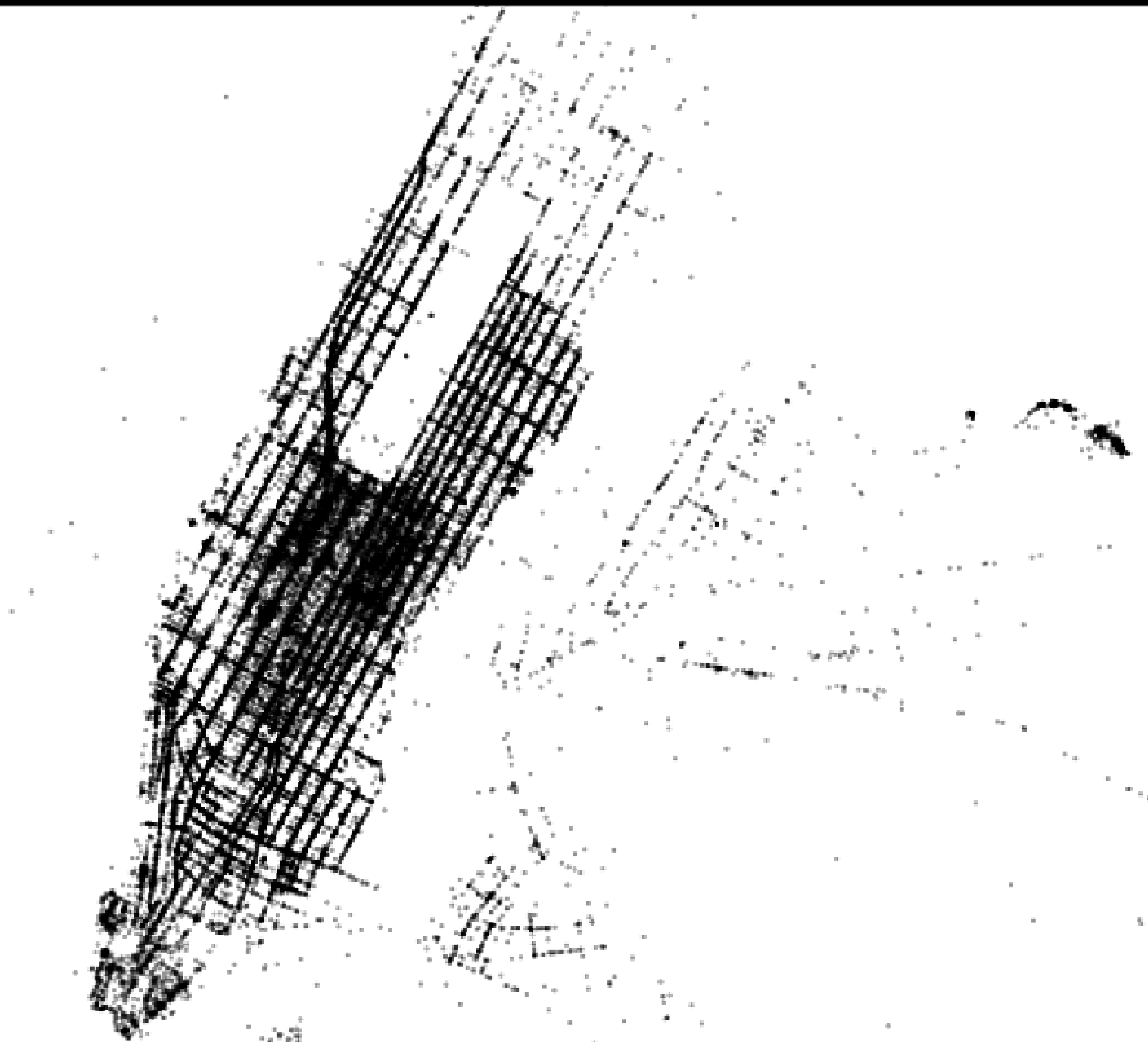
Hackney, 2011
Population: 246K
Age: 25-34
Avg. House Price: £326K
2nd most deprived

Hackney, 2016
Population: 263K
Age: 25-34
Avg. House Price: £546K
11th most deprived

Forms of Urban Capital



THE NEW YORK CITY TAXI DATASET



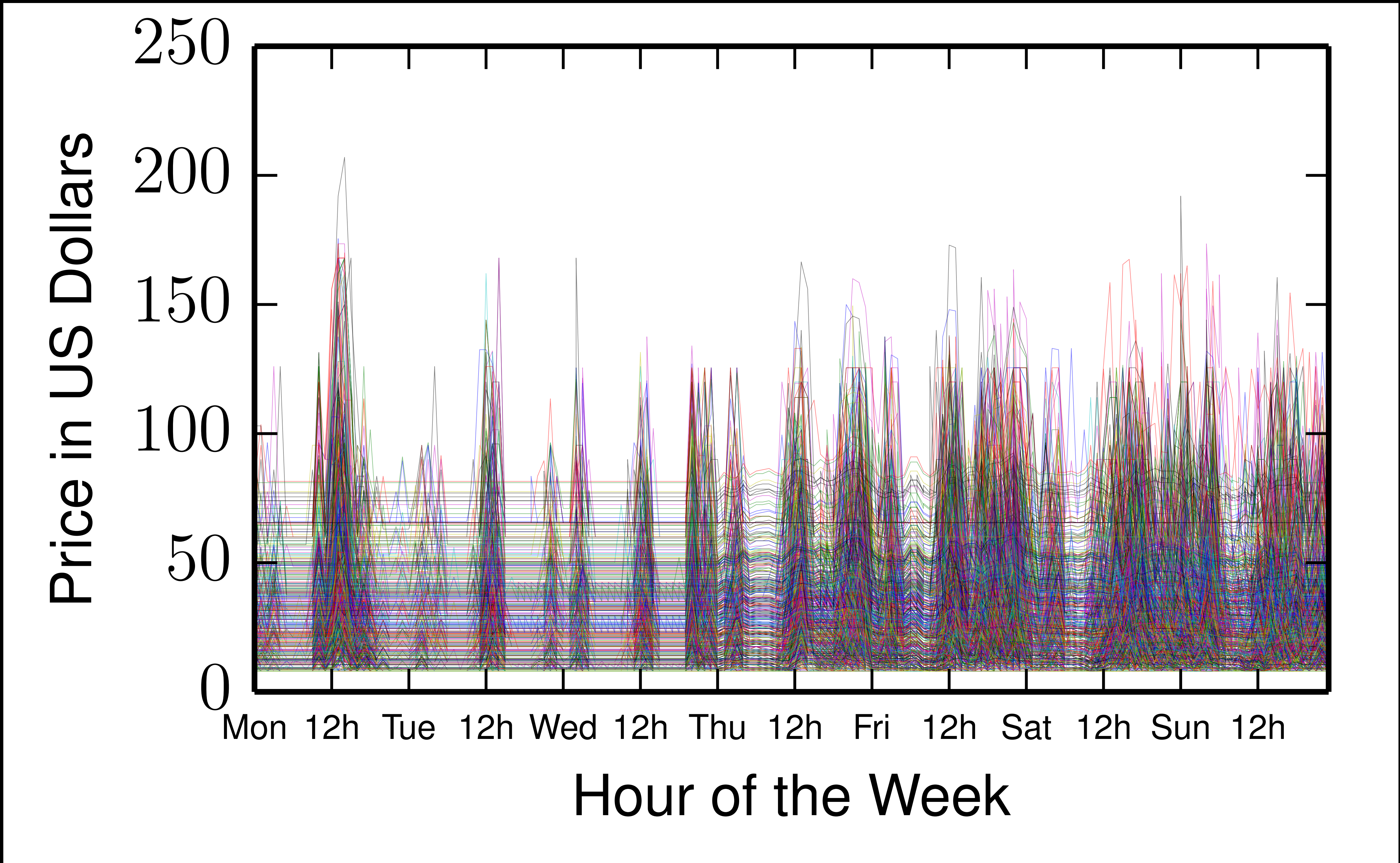
FOILing NYC's Taxi Trip Data

Freedom of Information Law

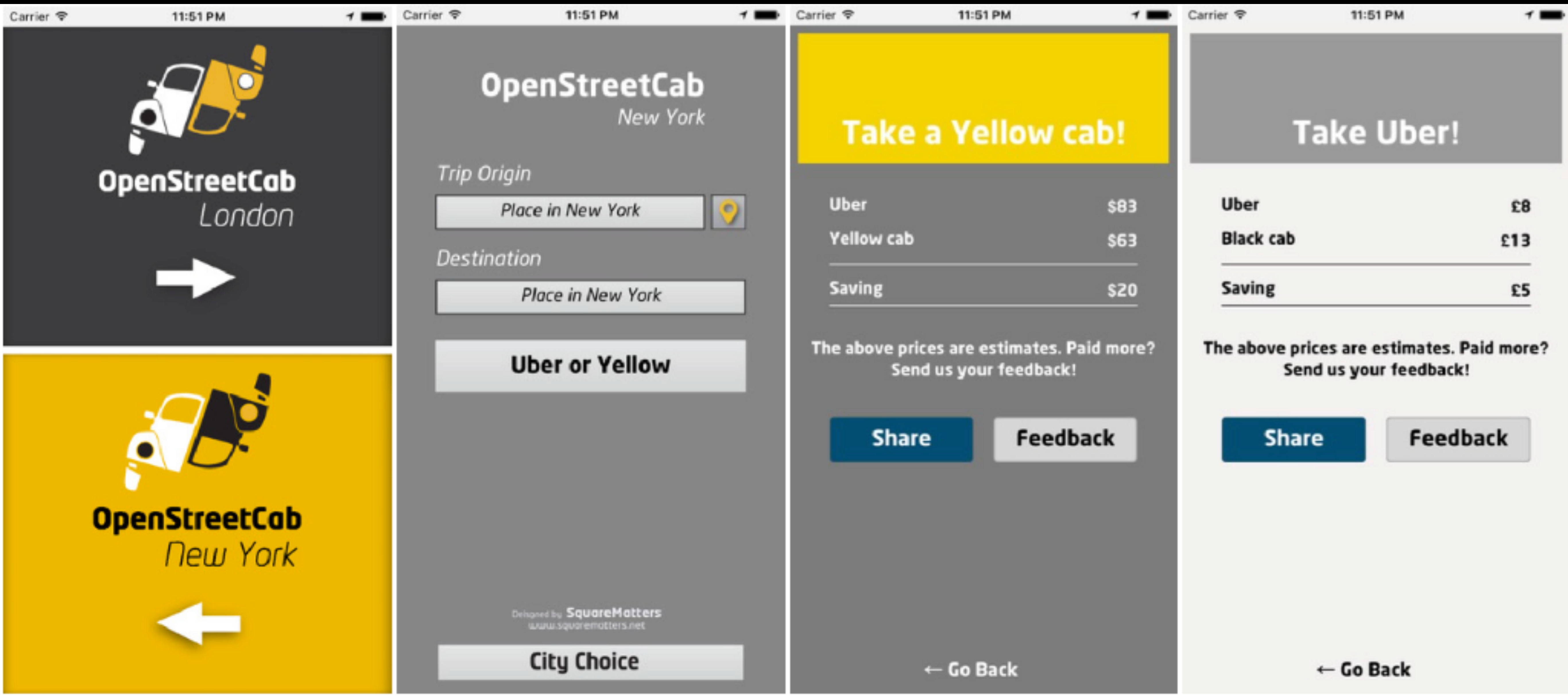
2013 Trip Data, 11GB, zipped!

2013 Fare Data, 7.7GB

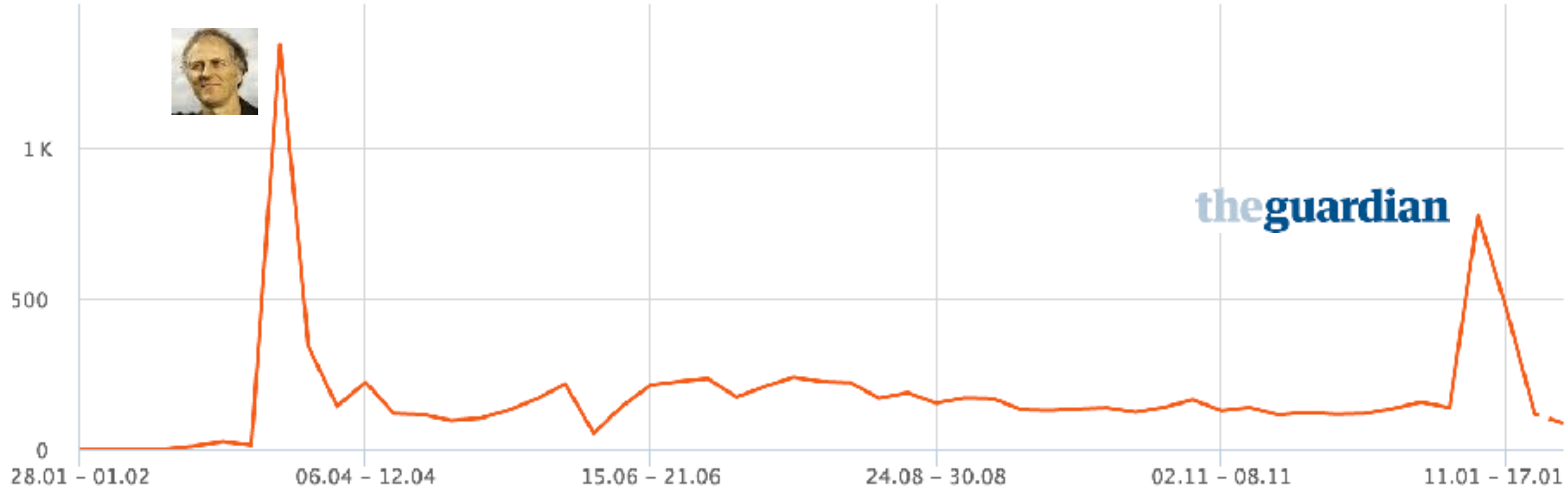
Idea: Uber Vs Yellow Taxi Price Comparison.


250
200
150
100
50
0
Price in US Dollars
Mon
12h
Tue
12h
Wed
12h
Thu
12h
Fri
12h
Sat
12h
Sun
12h
Hour of the Week

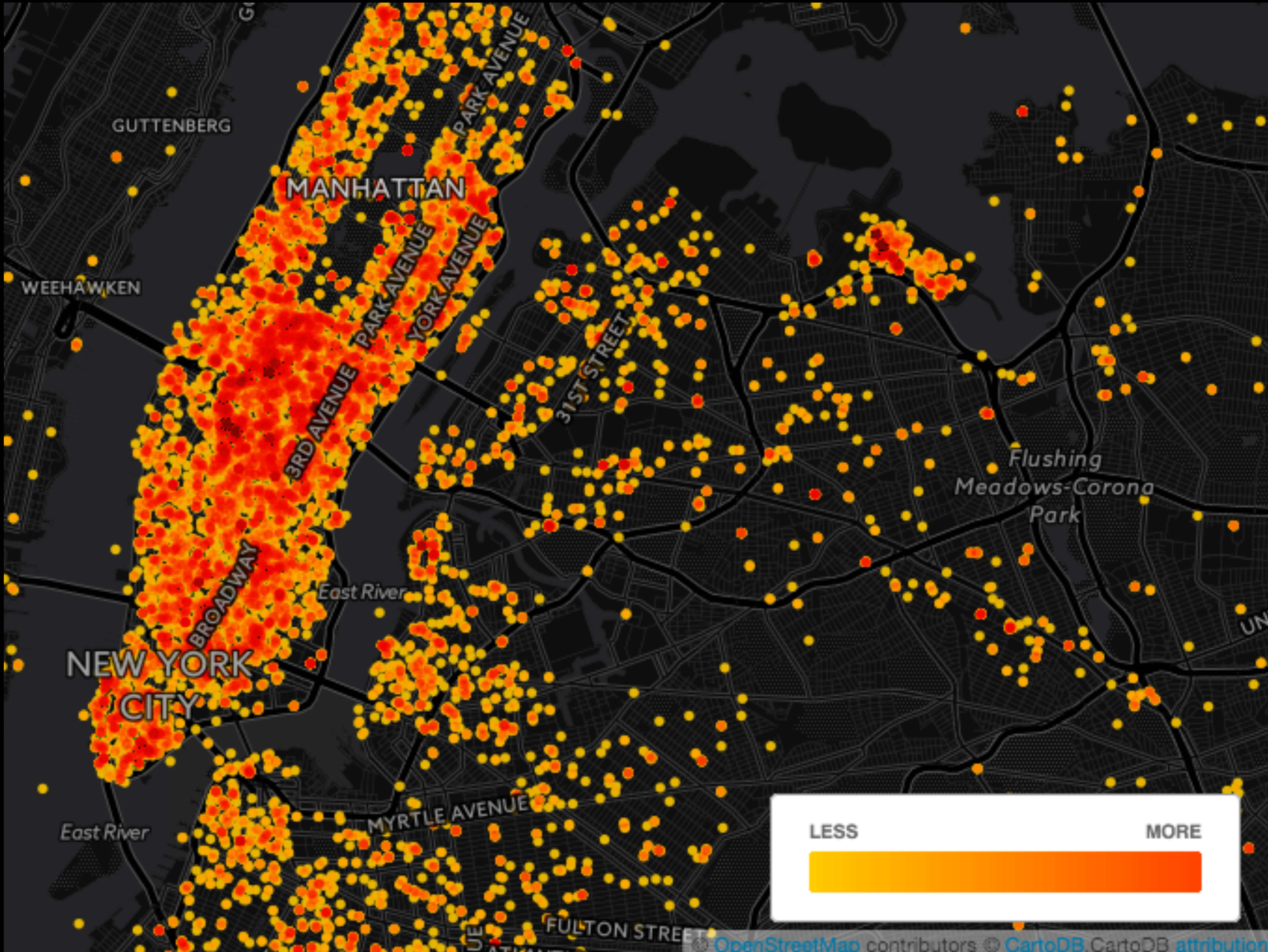
OpenStreetCab


Carrier
11:51 PM
OpenStreetCab
London
OpenStreetCab
New York
OpenStreetCab
New York
Trip Origin
Place in New York
Destination
Place in New York
Uber or Yellow
Designed by SquareMatters
www.squarematters.net
City Choice
Take a Yellow cab!
Uber $83
Yellow cab $63
Saving $20
The above prices are estimates. Paid more? Send us your feedback!
Share
Feedback
← Go Back
Take Uber!
Uber £8
Black cab £13
Saving £5
The above prices are estimates. Paid more? Send us your feedback!
Share
Feedback
← Go Back

And later on



Week	Users
Total	9 306


GUTTENBERG
MANHATTAN
PARK AVENUE
WEEHAWKEN
YORK AVENUE
3RD AVENUE
31ST STREET
Flushing
Meadows-Corona
Park
East River
BROADWAY
NEW YORK
CITY
MYRTLE AVENUE
FULTON STREET
LESS
MORE
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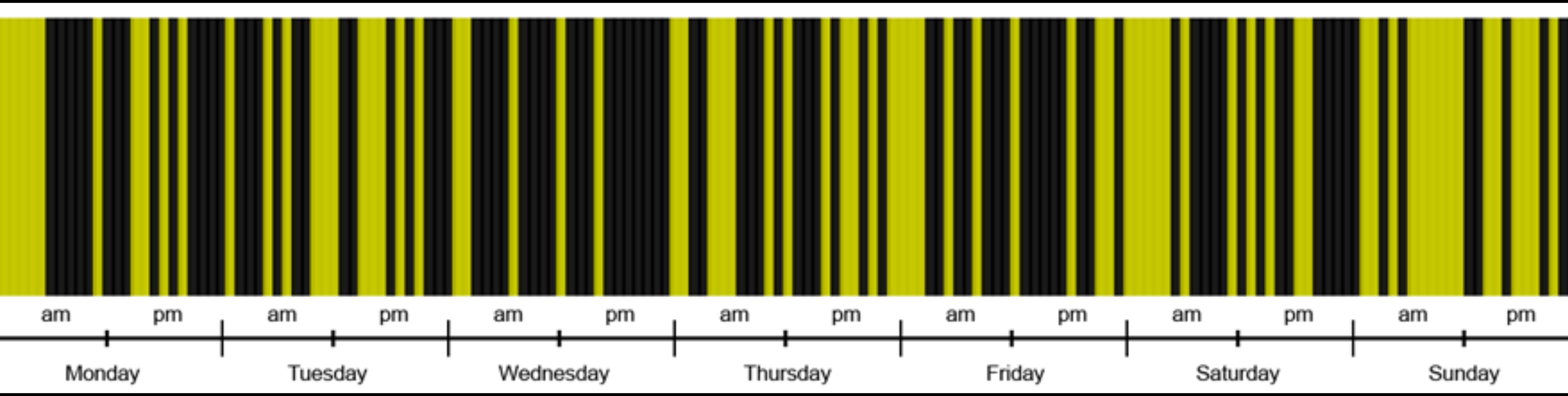
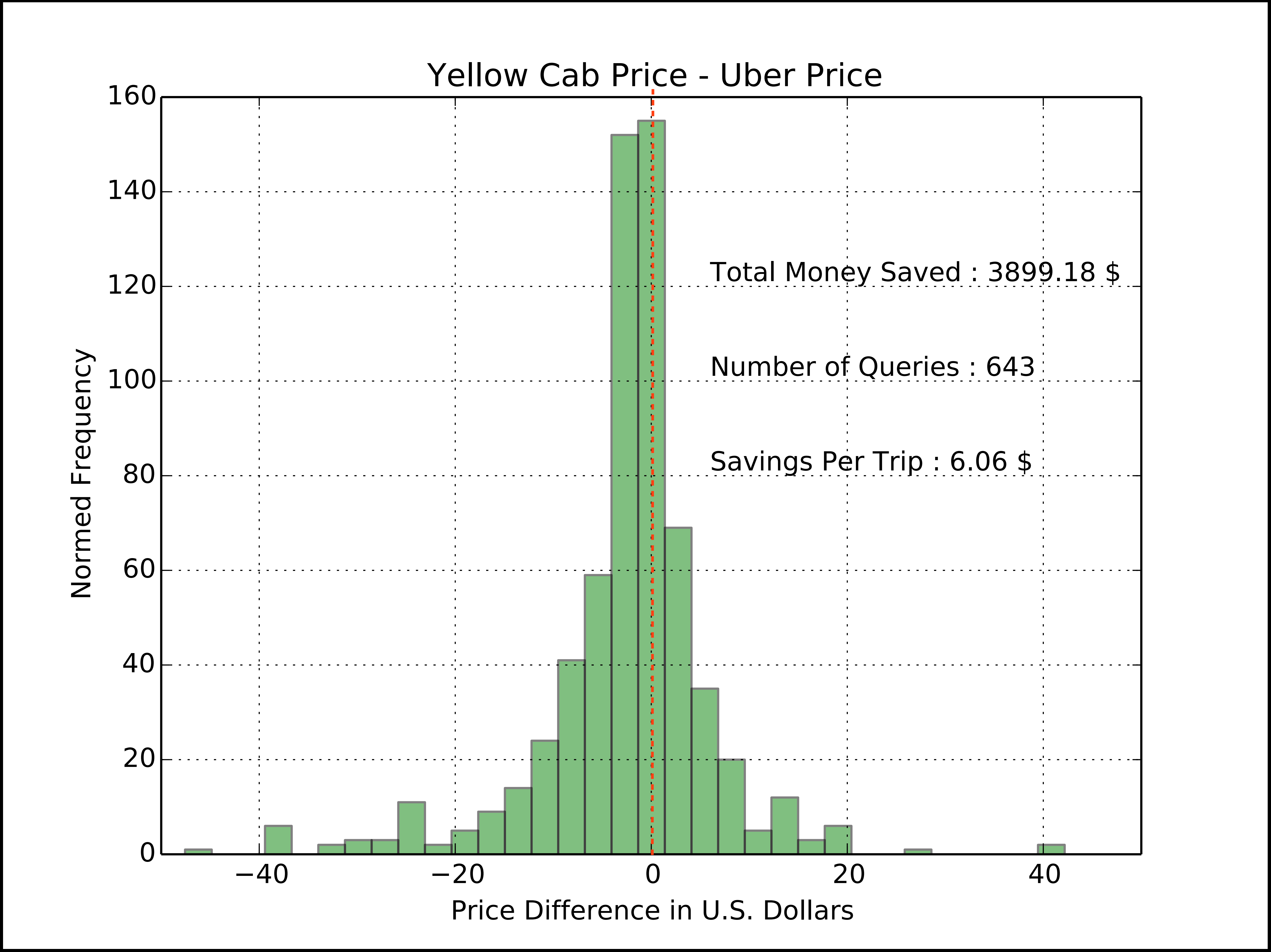
> 5K only in New York (~8K downloaded the app)

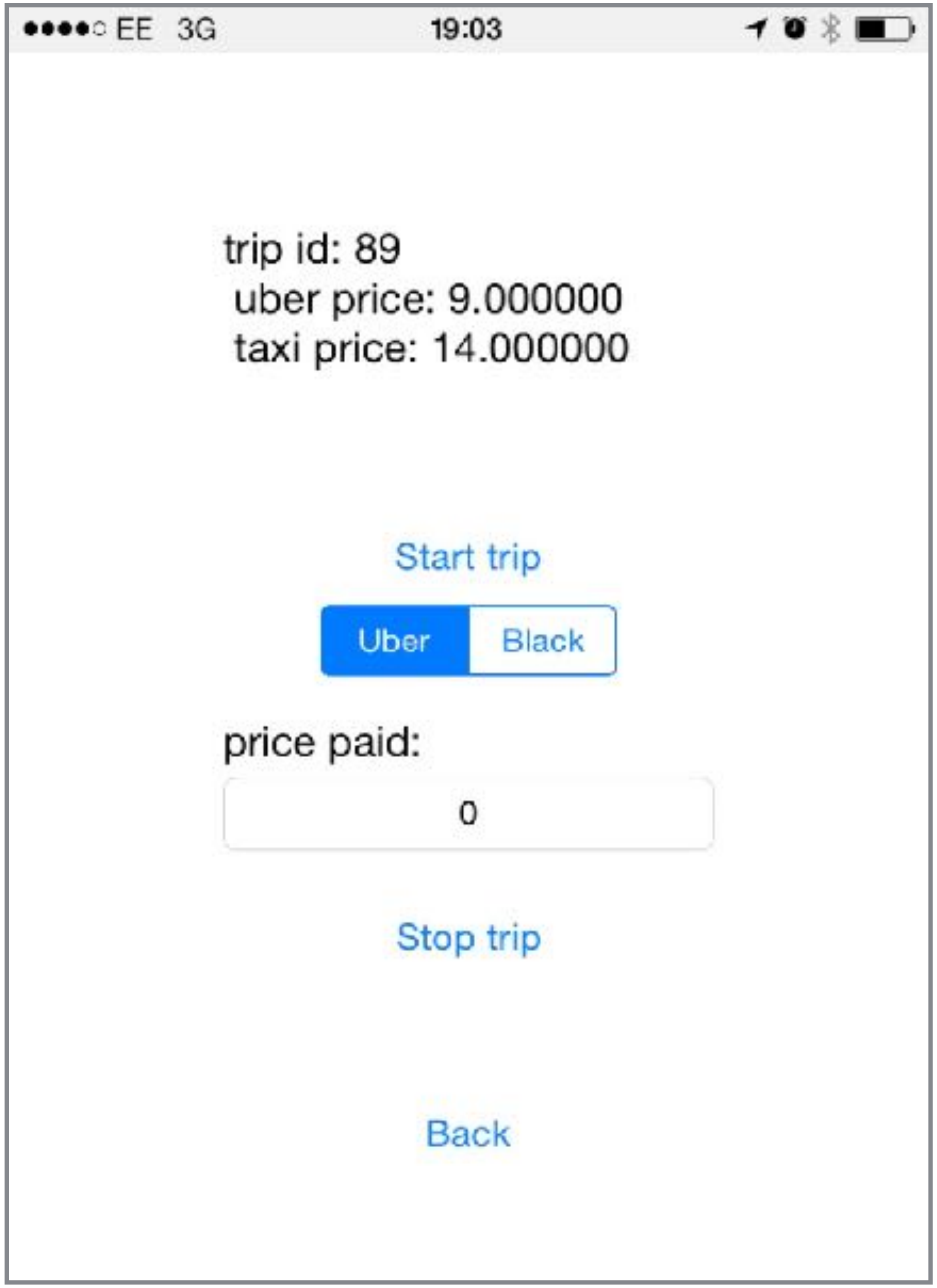
> 14000 search queries generated

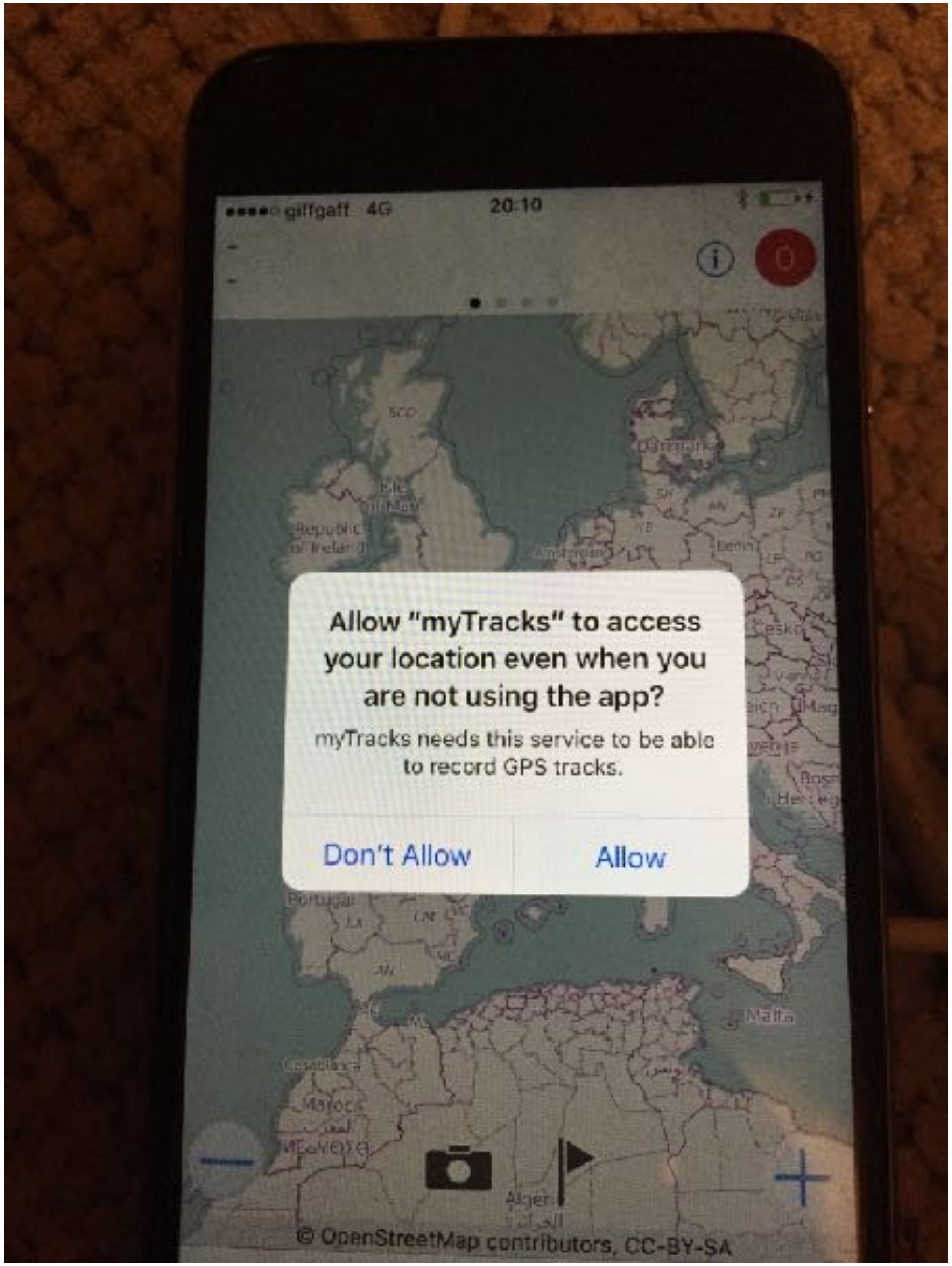




Yellow Cab Price - Uber Price
Total Money Saved : 3899.18 $
Number of Queries : 643
Savings Per Trip : 6.06 $
Normed Frequency
Price Difference in U.S. Dollars
160
140
120
100
80
60
40
20
0
−40
−20
0
20
40

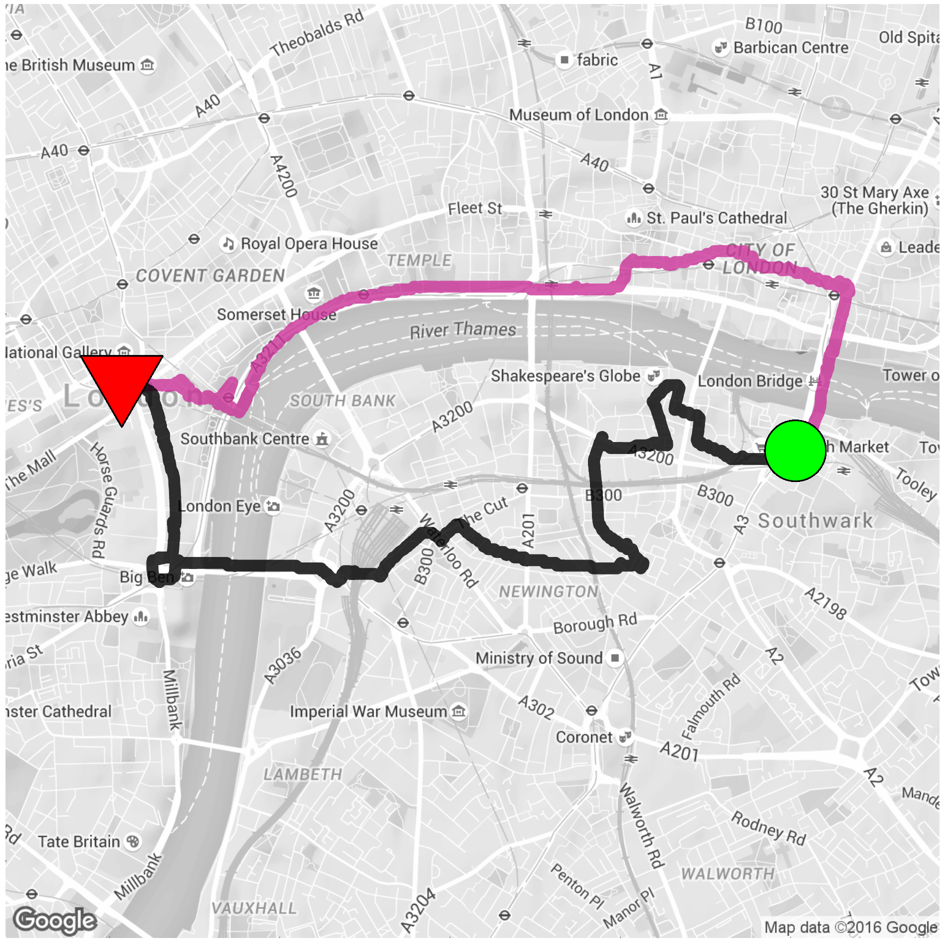
Route Tracking

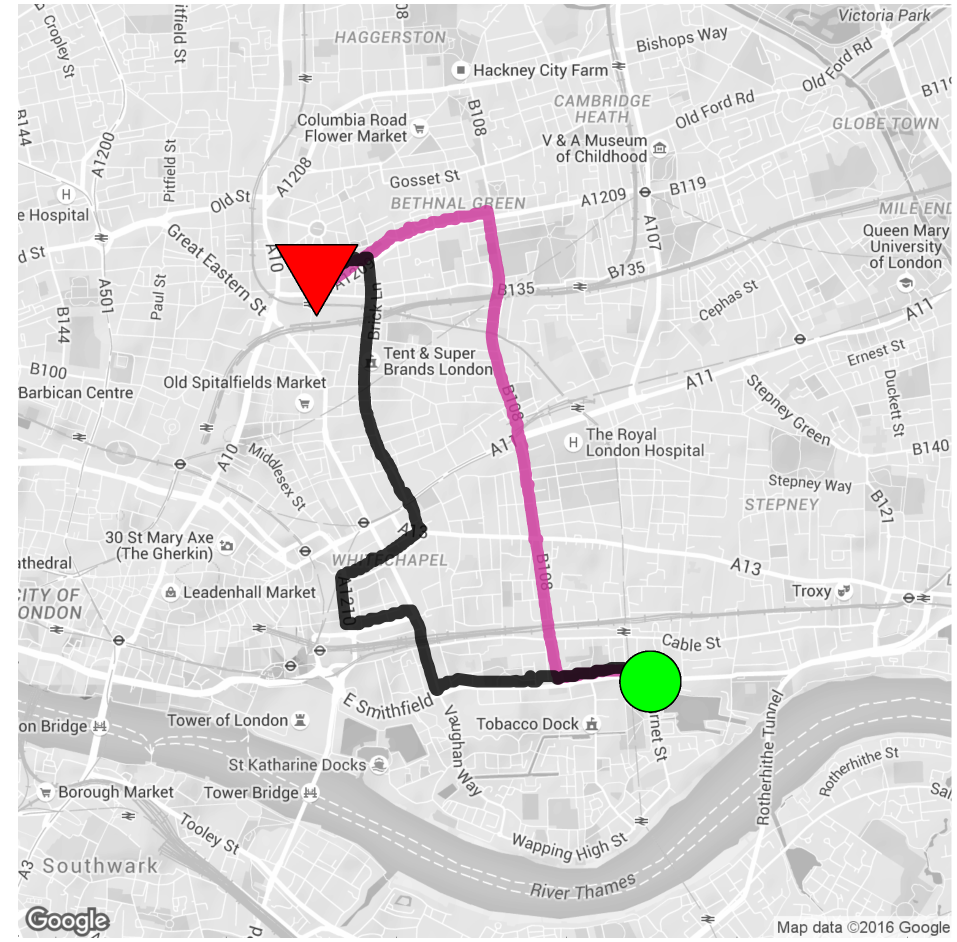


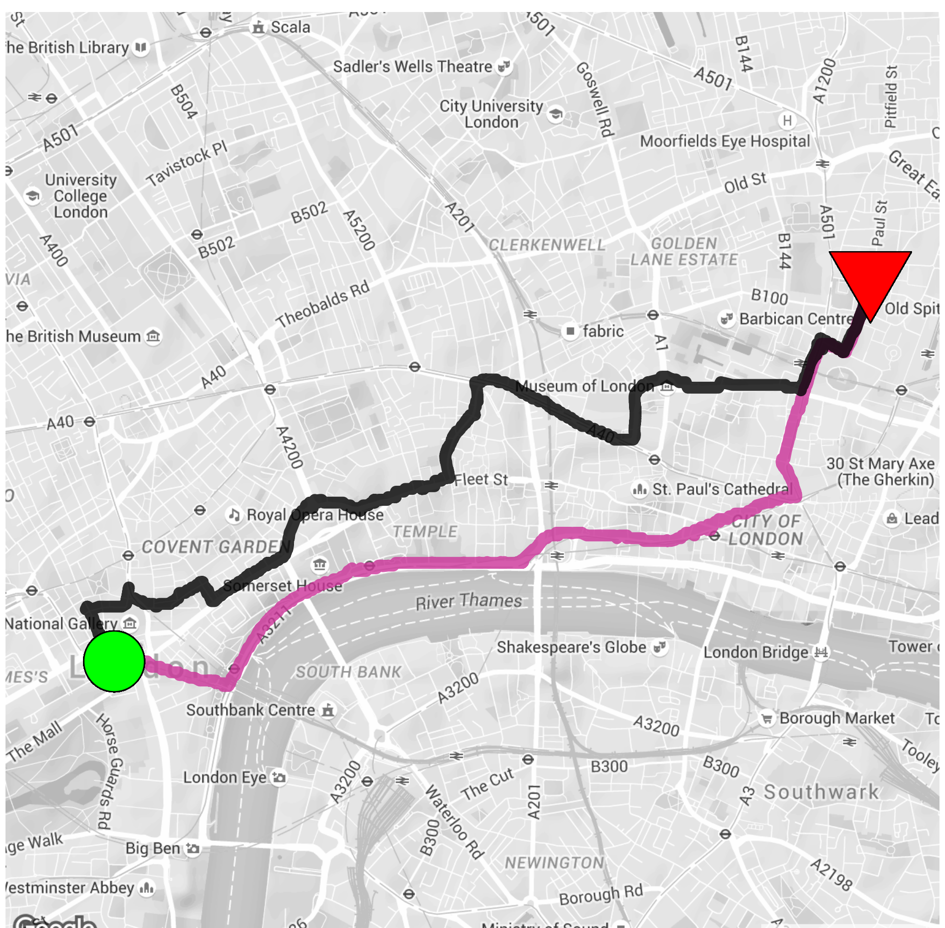


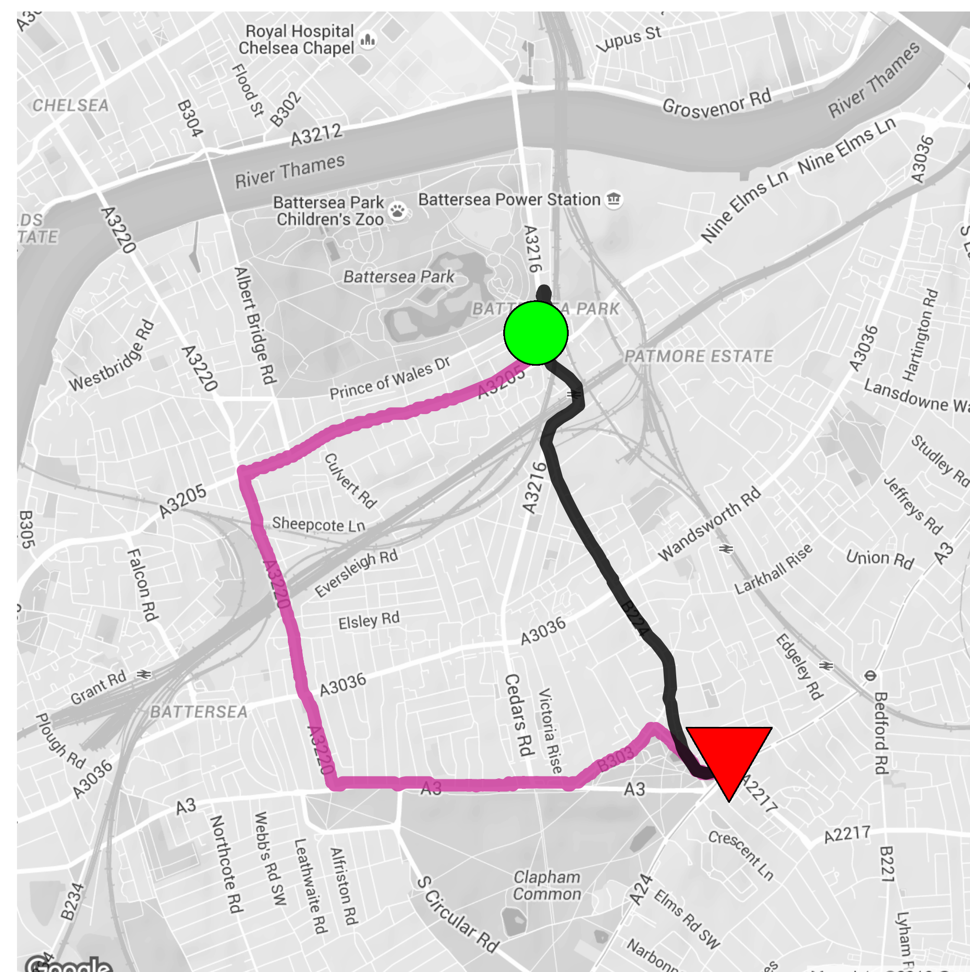

University College London
109 Camden Road
UCL
LS07 ZVX


12:00
2016/02/22
Monday


Theobalds Rd
B100
Barbican Centre
Old Spita
fabric
British Museum
Museum of London
Fleet St
St. Paul's Cathedral
30 St Mary Axe (The Gherkin)
Royal Opera House
COVENT GARDEN
TEMPLE
CITY OF LONDON
Somerset House
River Thames
National Gallery
Shakespeare's Globe
London Bridge
Tower
SOUTH BANK
Southbank Centre
Market
London Eye
The Cut
Southwark
Big Ben
NEWINGTON
Borough Rd
Westminster Abbey
Ministry of Sound
Imperial War Museum
Coronet
LAMBETH
Tate Britain
Rodney Rd
WALWORTH
VAUXHALL
Google
Map data ©2016 Google


Victoria Park
HAGGERSTON
Hackney City Farm
Bishops Way
Columbia Road Flower Market
CAMBRIDGE HEATH
V & A Museum of Childhood
Old Ford Rd
GLOBE TOWN
Gosset St
BETHNAL GREEN
MILE END
Queen Mary University of London
Great Eastern St
Tent & Super Brands London
Barbican Centre
Old Spitalfields Market
The Royal London Hospital
STEPNEY
30 St Mary Axe (The Gherkin)
WHITECHAPEL
Troxy
CITY OF LONDON
Leadenhall Market
Cable St
E Smithfield
Tower of London
Tobacco Dock
St Katharine Docks
Borough Market
Tower Bridge
Wapping High St
River Thames
Southwark
Google
Map data ©2016 Google


Scala
The British Library
Sadler's Wells Theatre
City University London
Moorfields Eye Hospital
University College London
Tavistock Pl
CLERKENWELL
GOLDEN LANE ESTATE
Old St
Theobalds Rd
B100
Barbican Centre
Old Spit
British Museum
fabric
Museum of London
Fleet St
St. Paul's Cathedral
30 St Mary Axe (The Gherkin)
Royal Opera House
COVENT GARDEN
TEMPLE
CITY OF LONDON
Somerset House
River Thames
National Gallery
Shakespeare's Globe
London Bridge
SOUTH BANK
Southbank Centre
Borough Market
London Eye
The Cut
Southwark
Big Ben
NEWINGTON
Borough Rd
Westminster Abbey
Ministry of Sound
Google
Map data ©2016 Google

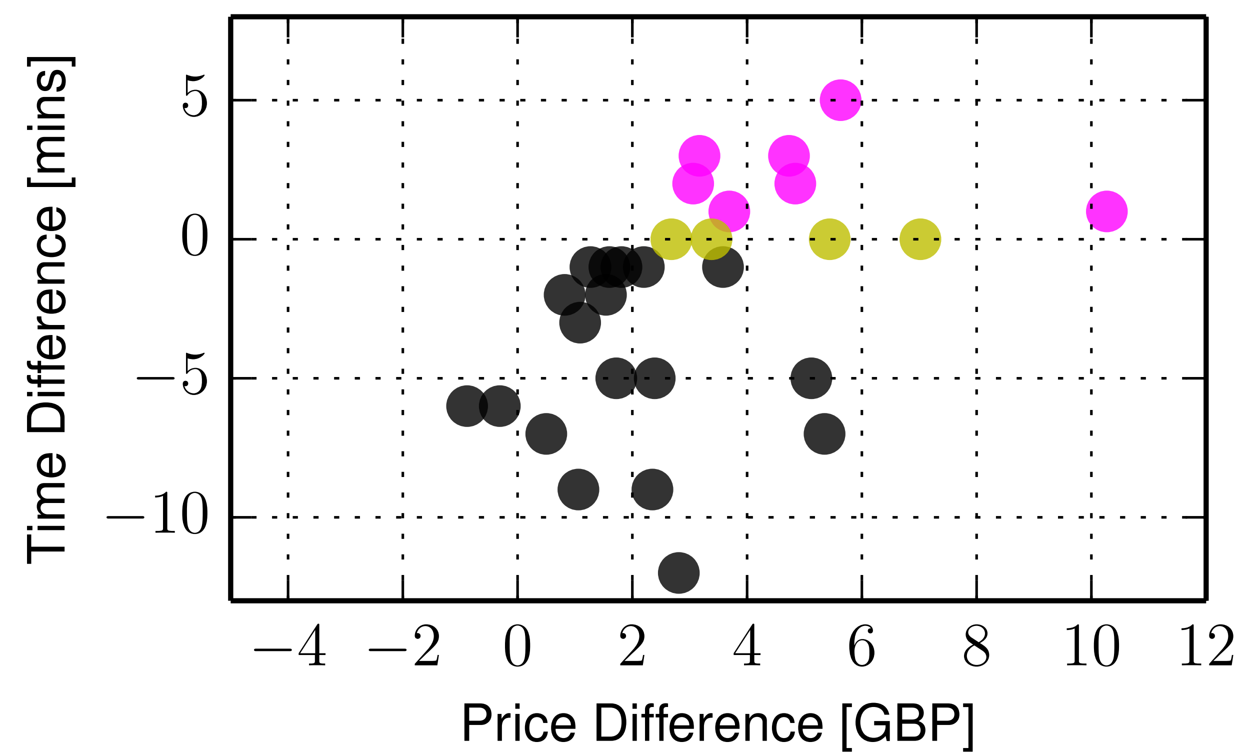

Royal Hospital Chelsea Chapel
Lupus St
CHELSEA
Grosvenor Rd
River Thames
Nine Elms Ln
Battersea Park Children's Zoo
Battersea Power Station
Battersea Park
BATTERSEA PARK
PATMORE ESTATE
Westbridge Rd
Prince of Wales Dr
Albert Bridge Rd
Lansdowne Way
Culvert Rd
Sheepcote Ln
Wandsworth Rd
Eversleigh Rd
Elsley Rd
Larkhall Rise
Union Rd
Falcon Rd
Grant Rd
BATTERSEA
Cedars Rd
Victoria Rise
Edgeley Rd
Bedford Rd
Plough Rd
Northcote Rd
Crescent Ln
Clapham Common
S Circular Rd
Elms Rd SW
Google
Map data ©2016 Google

Urban Complexity & Performance

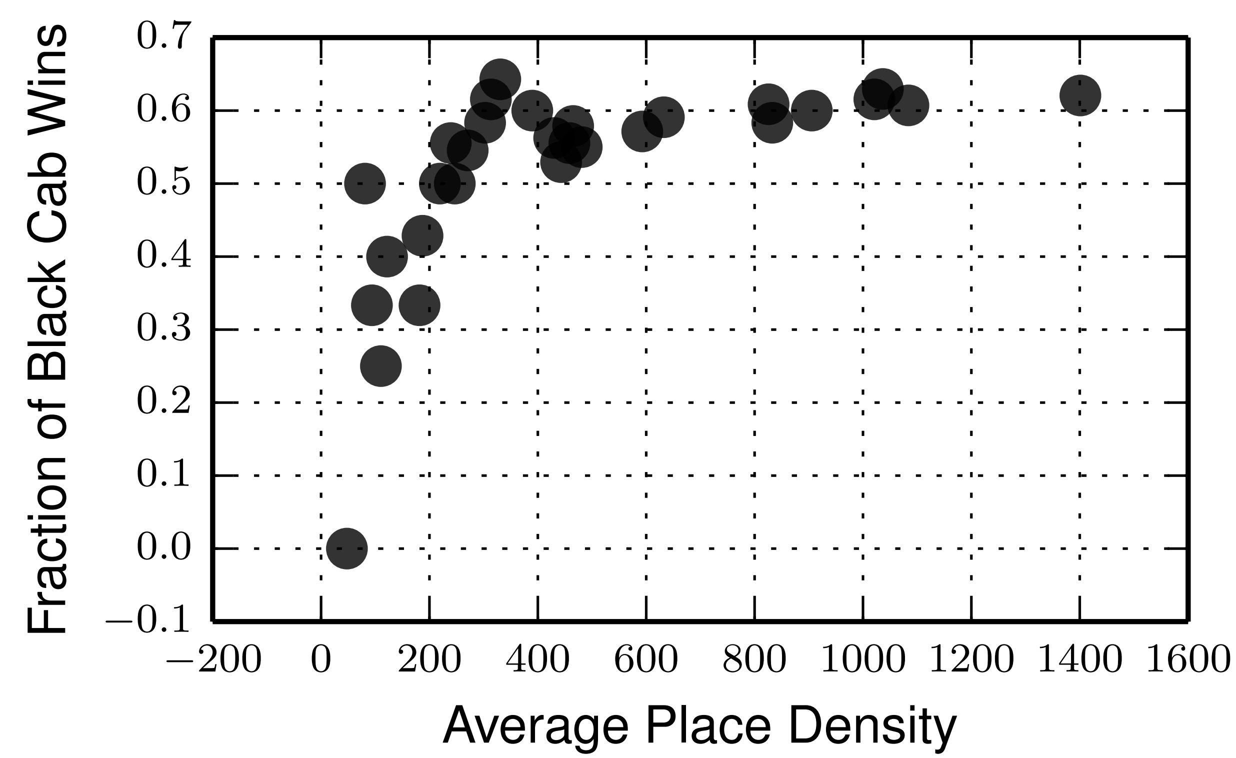
Uber faster

Black Cab faster

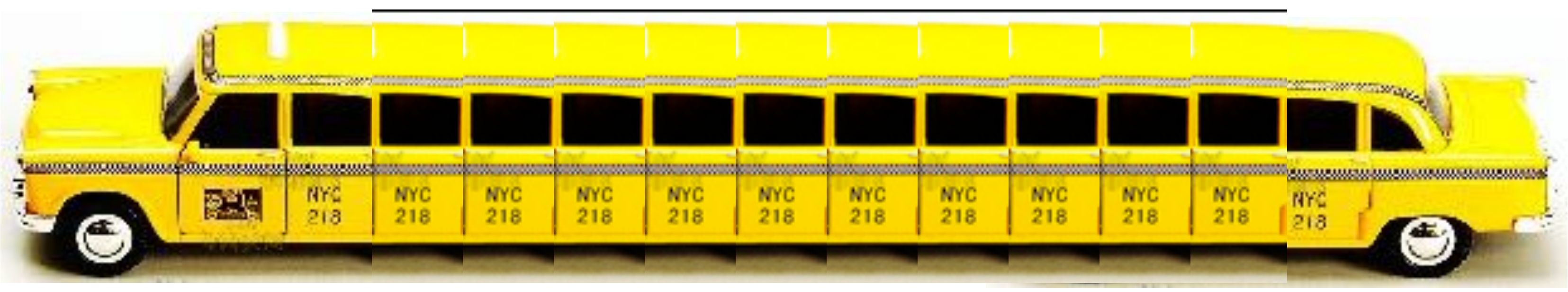
Journey duration tie



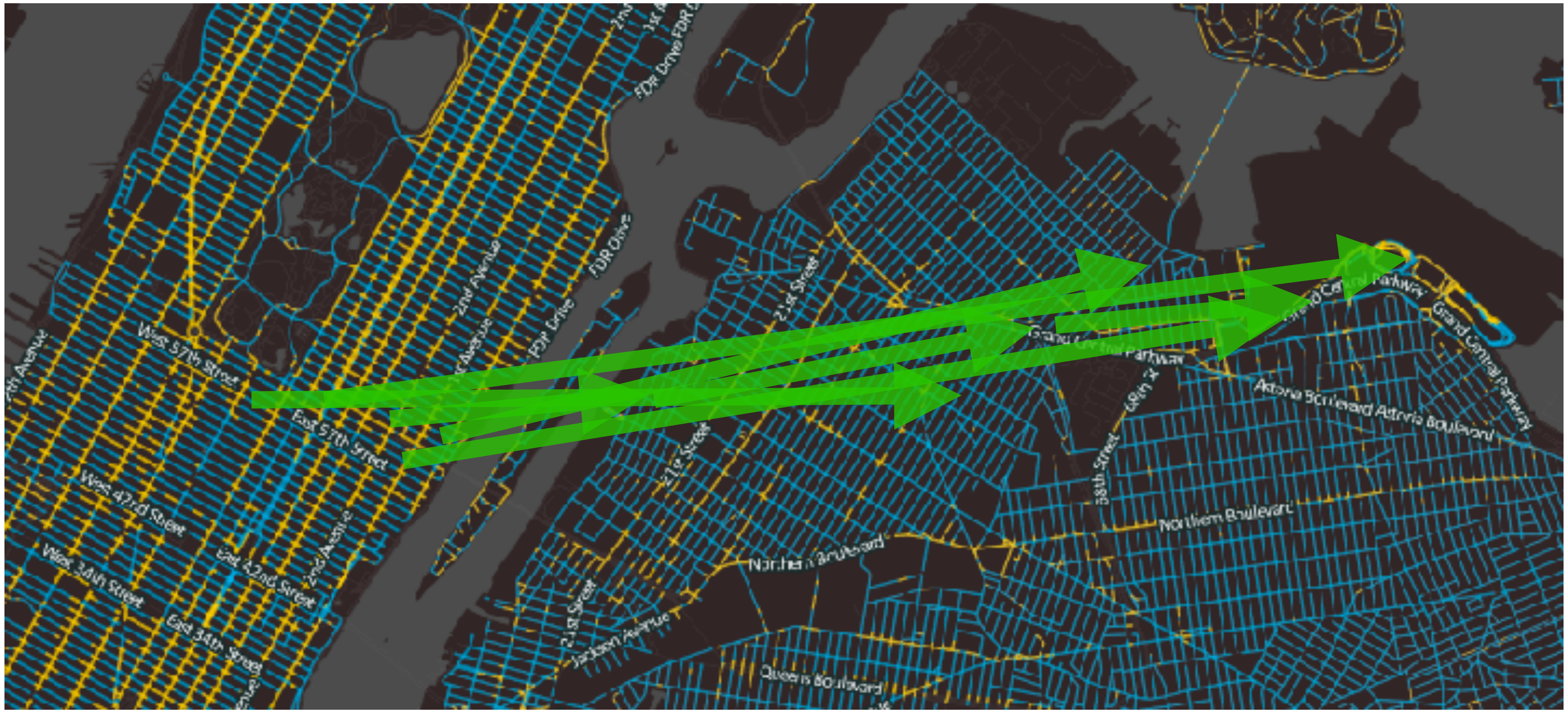
$$Trip\_Density = \frac{1}{|T|} \frac{\sum_{i=1}^{|T|} P(x = lng_i, y = lat_i, r = 200m)}{\pi r^2}$$



Taxi Sharing/Pooling



Combine k trips



http://hubcab.org/

Santi, Paolo, et al. "**Quantifying the benefits of vehicle pooling with shareability networks.**" Proceedings of the National Academy of Sciences 111.37 (2014): 13290-13294.

THANK YOU

@taslanous