Human mobility through time and [urban] space.

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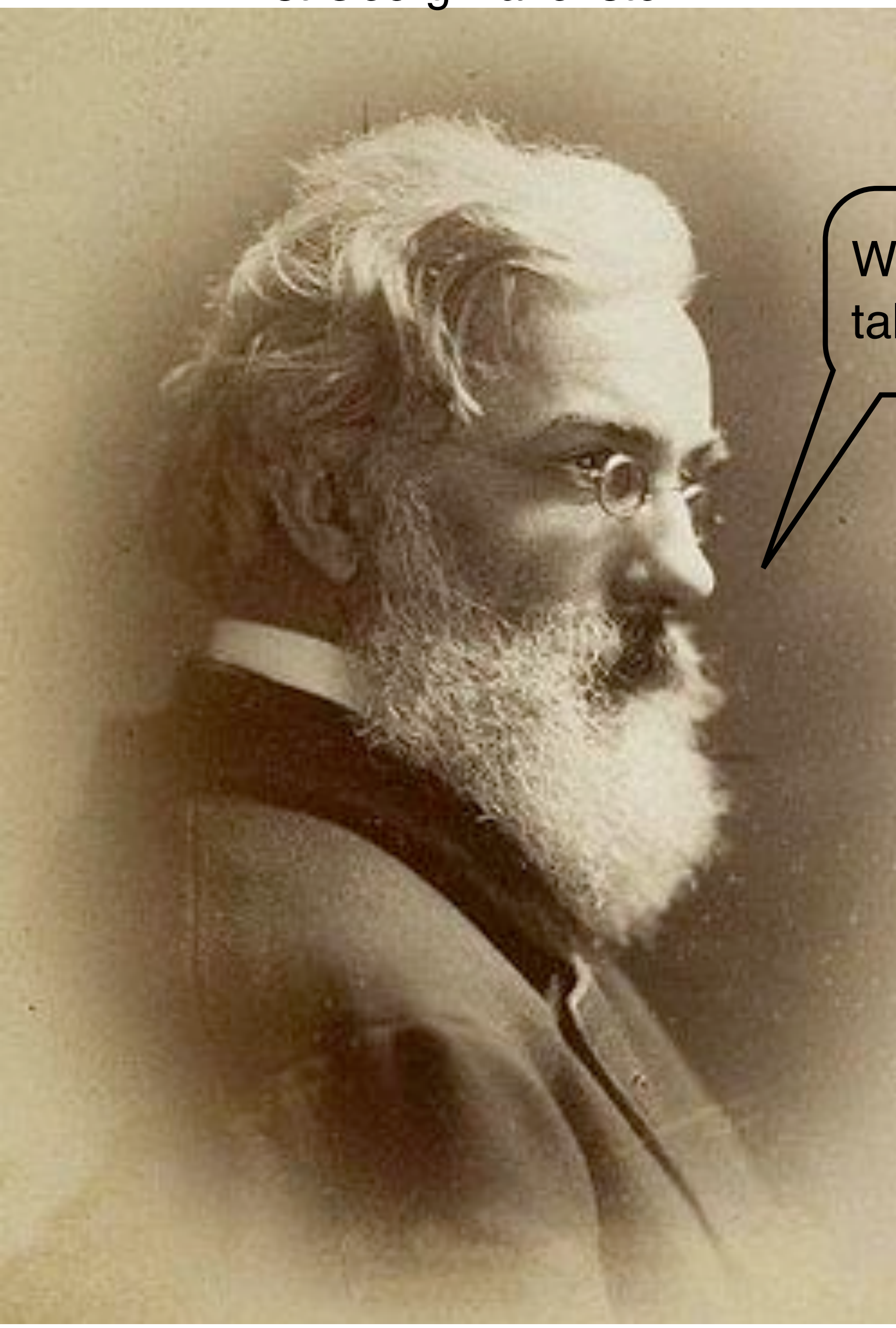
Presentation Summary

- 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

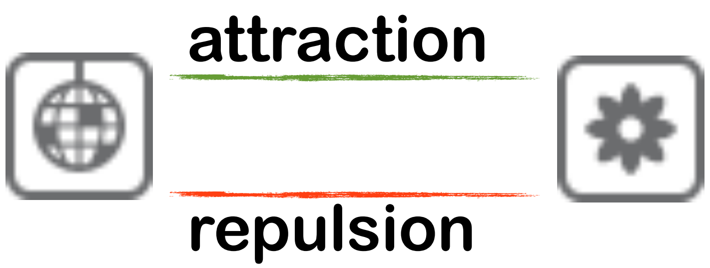
The following was a standard list after Ravenstein's (1834-1913) proposal in the 1880s. The theories are as follows:

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.*

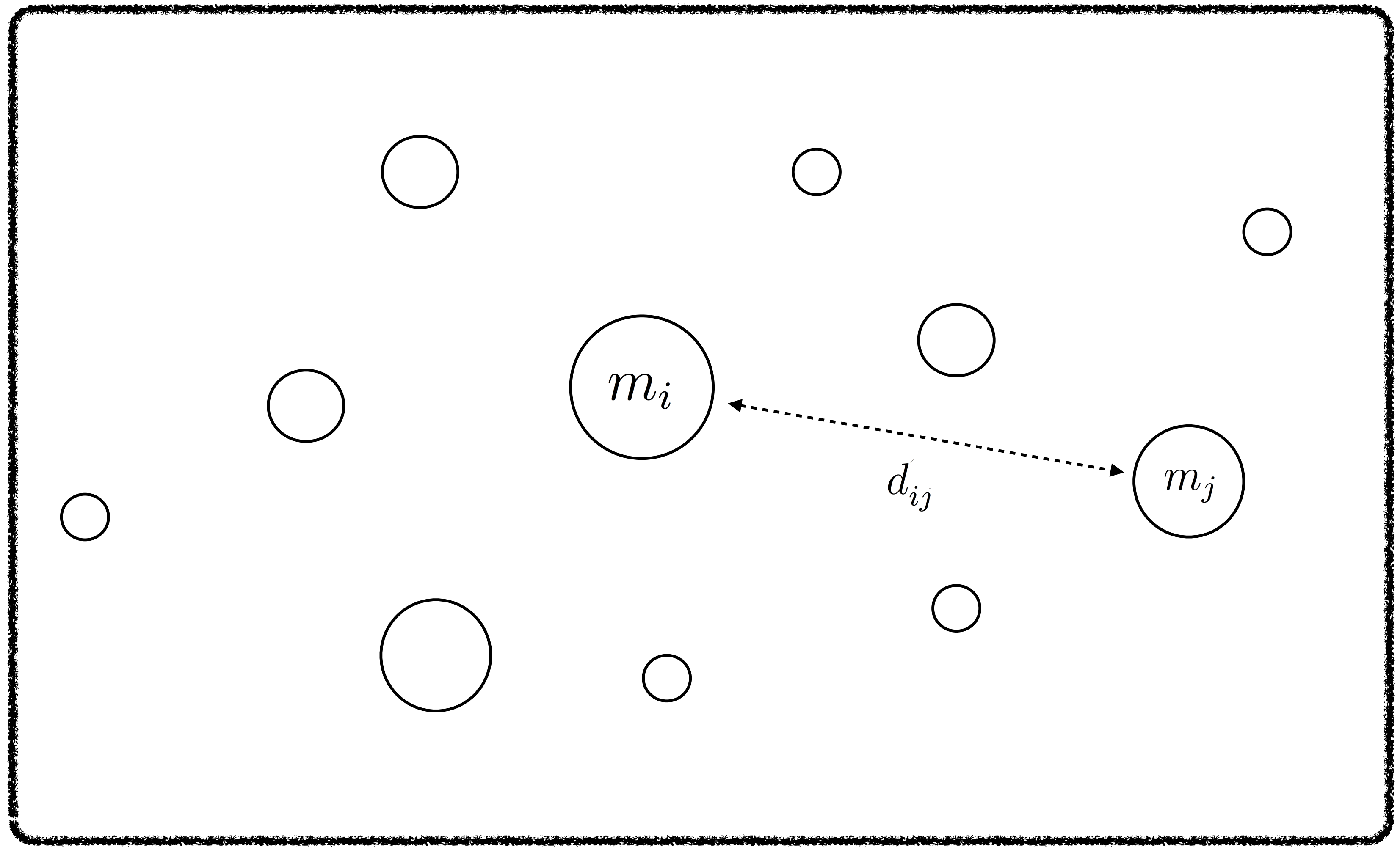
Ravenstein exploited census data from the United Kingdom to support empirically his findings ...

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

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.



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

Urban Transport Modeling

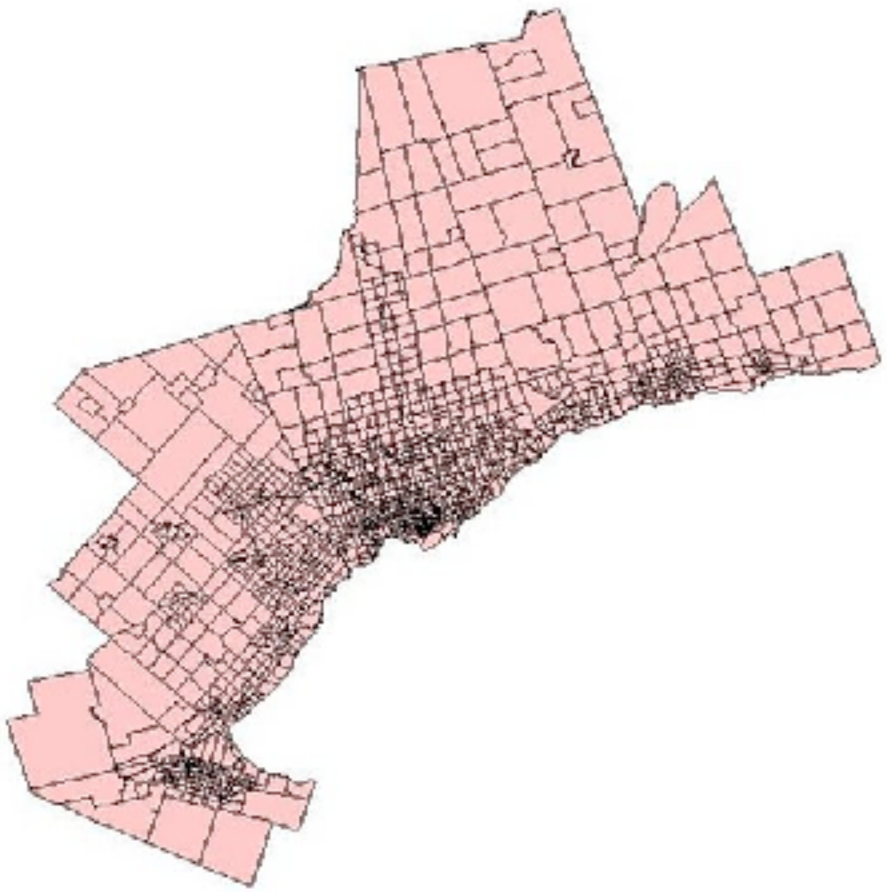


Table: Illustrative trip table

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}

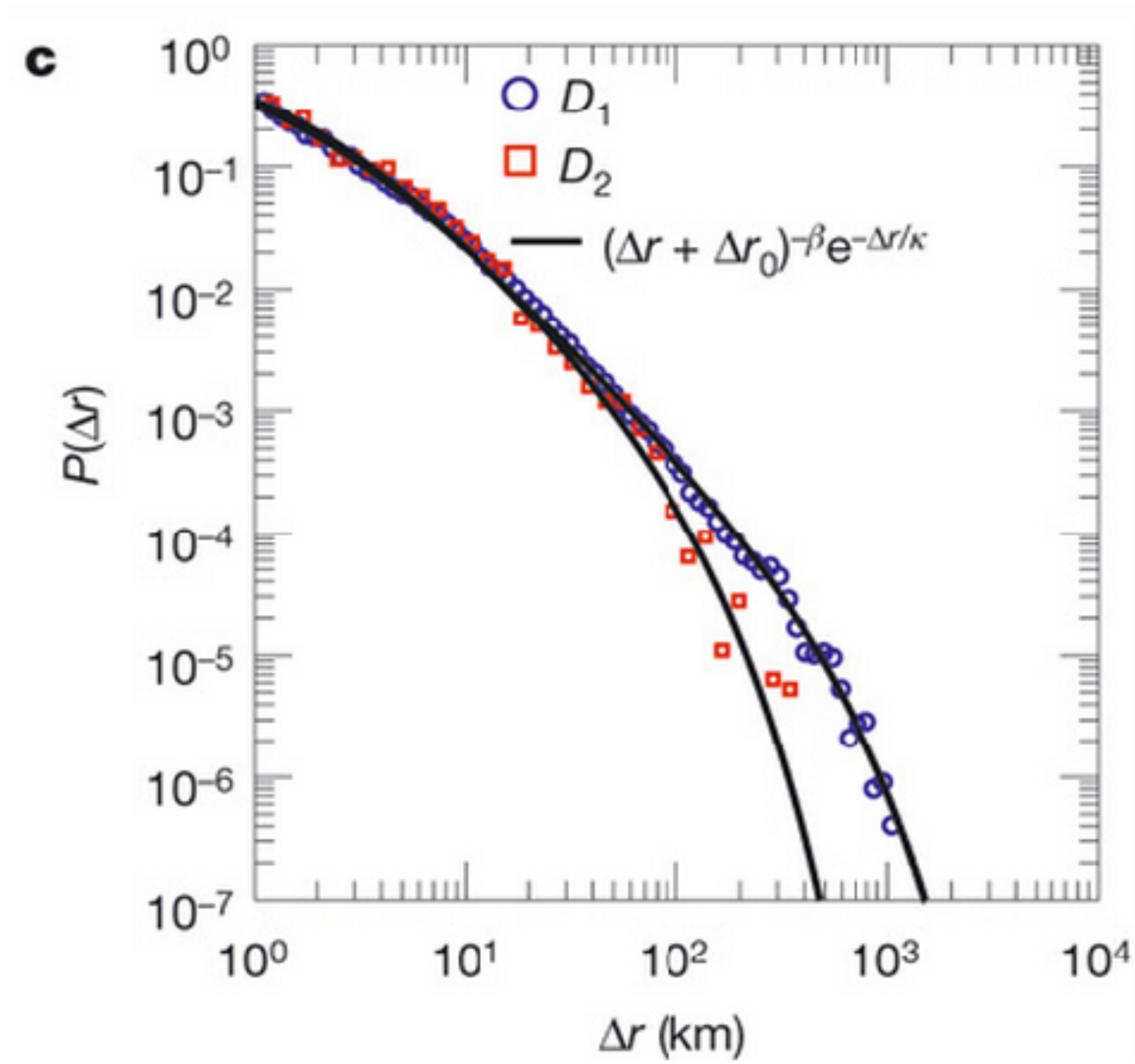
Data in urban transport modeling has been based primarily on surveys...

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

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

Cellular Datasets

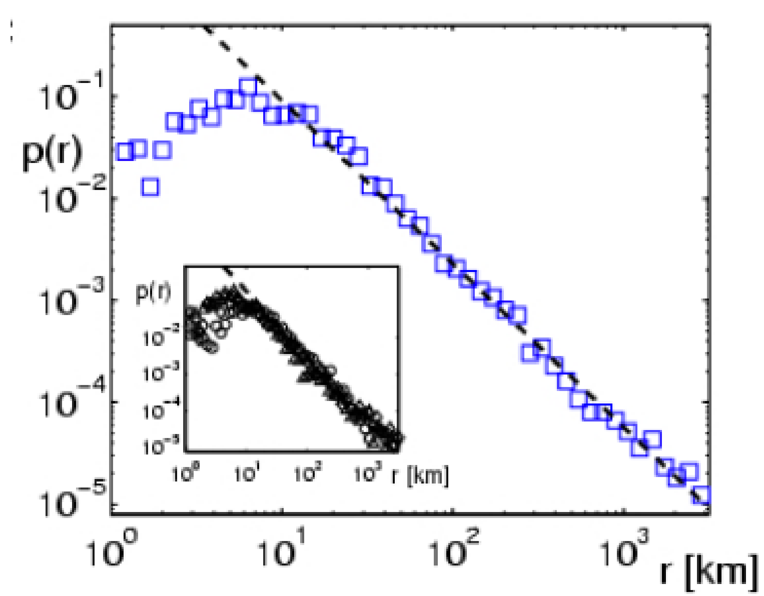
One of the first large scale studies of human movement with modern mobile datasets...

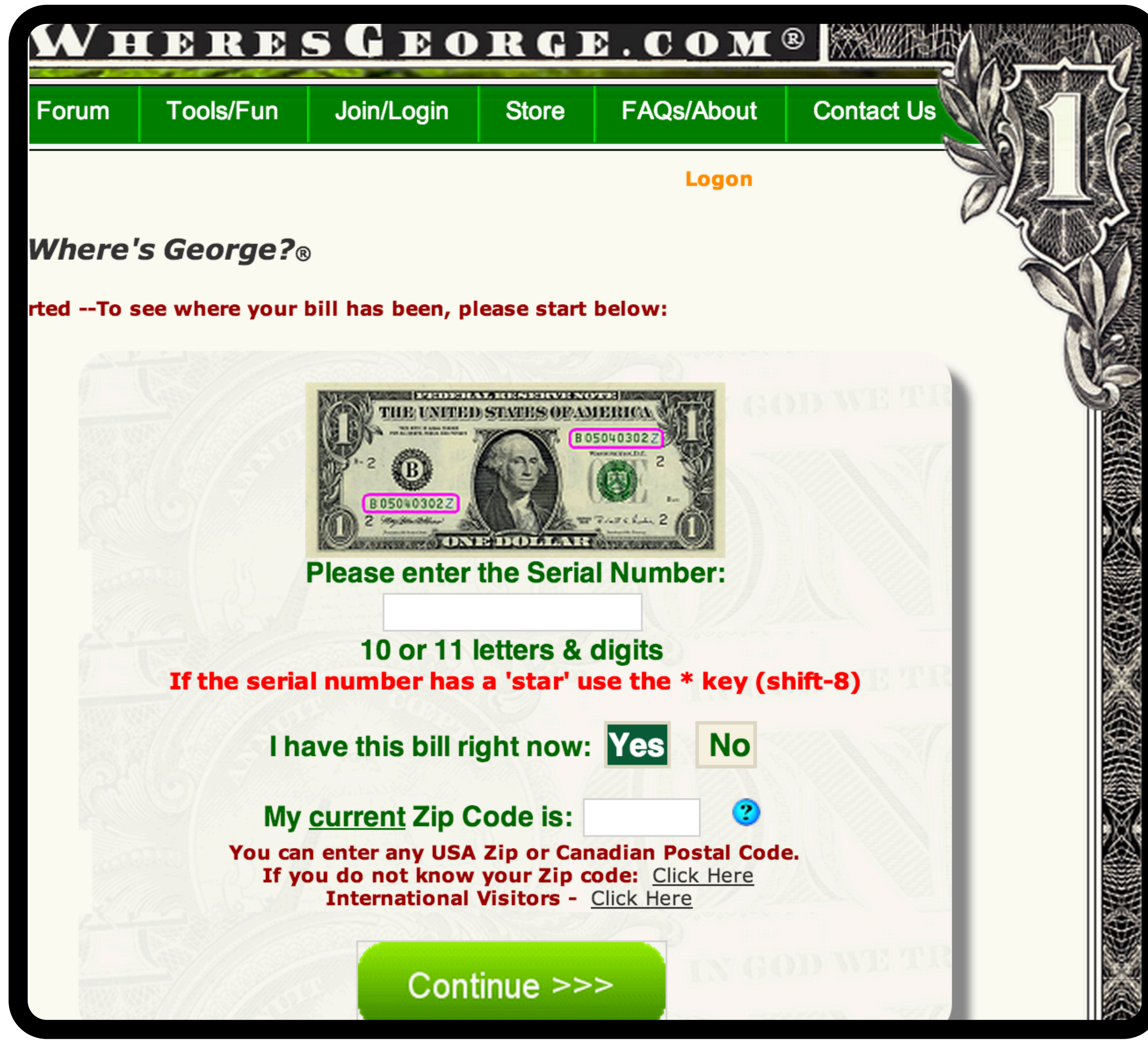


Gonzalez, Marta C., Cesar A. Hidalgo, and Albert-Laszlo Barabasi. "Understanding individual human mobility patterns." *Nature* 453.7196 (2008): 779-782.

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...





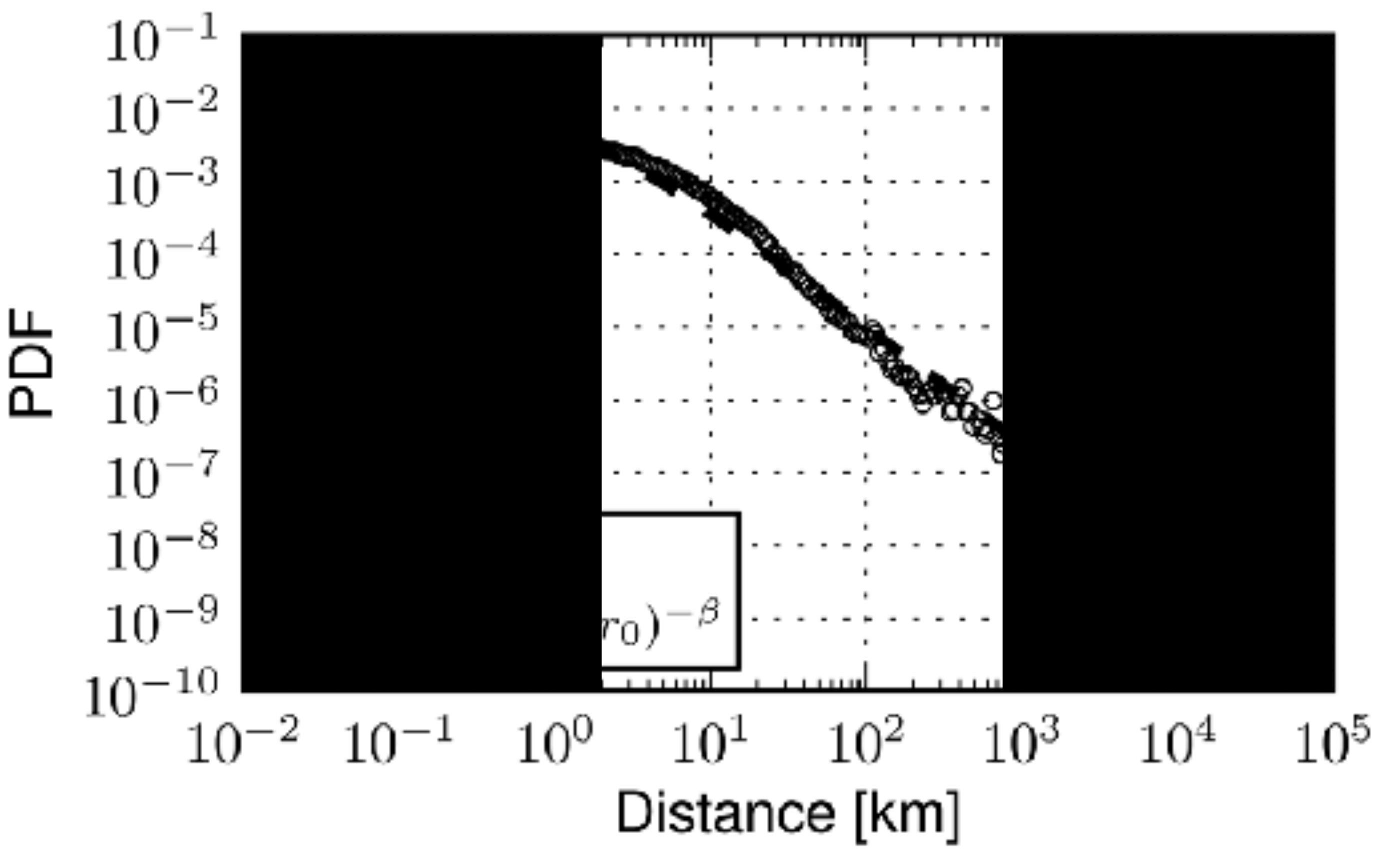
Brockmann, Dirk, Lars Hufnagel, and Theo Geisel. "The scaling laws of human travel." *Nature* 439.7075 (2006): 462-465.

Data on human movement…

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

Power-law tales ...

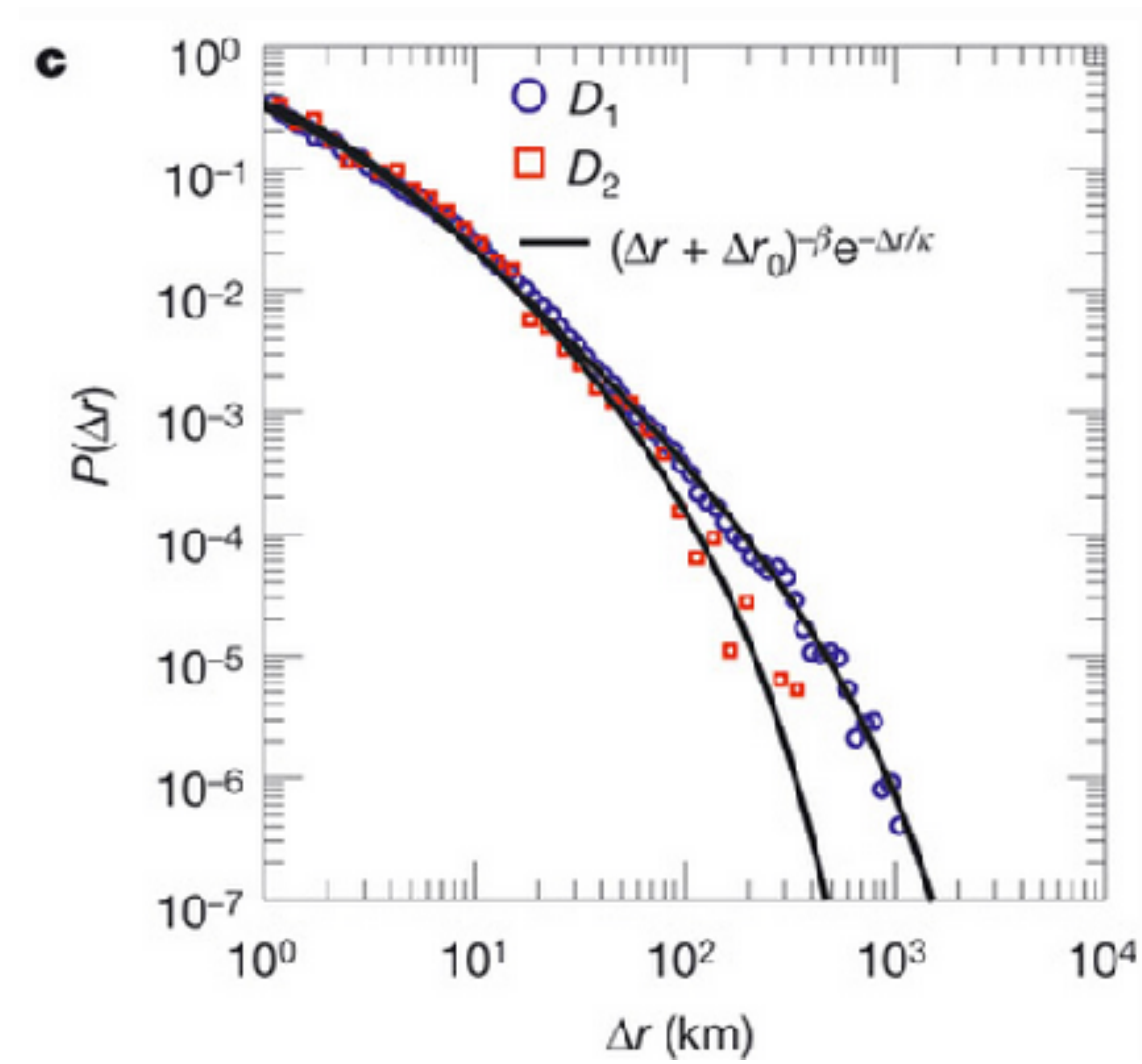
Mobile Social Network Data



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

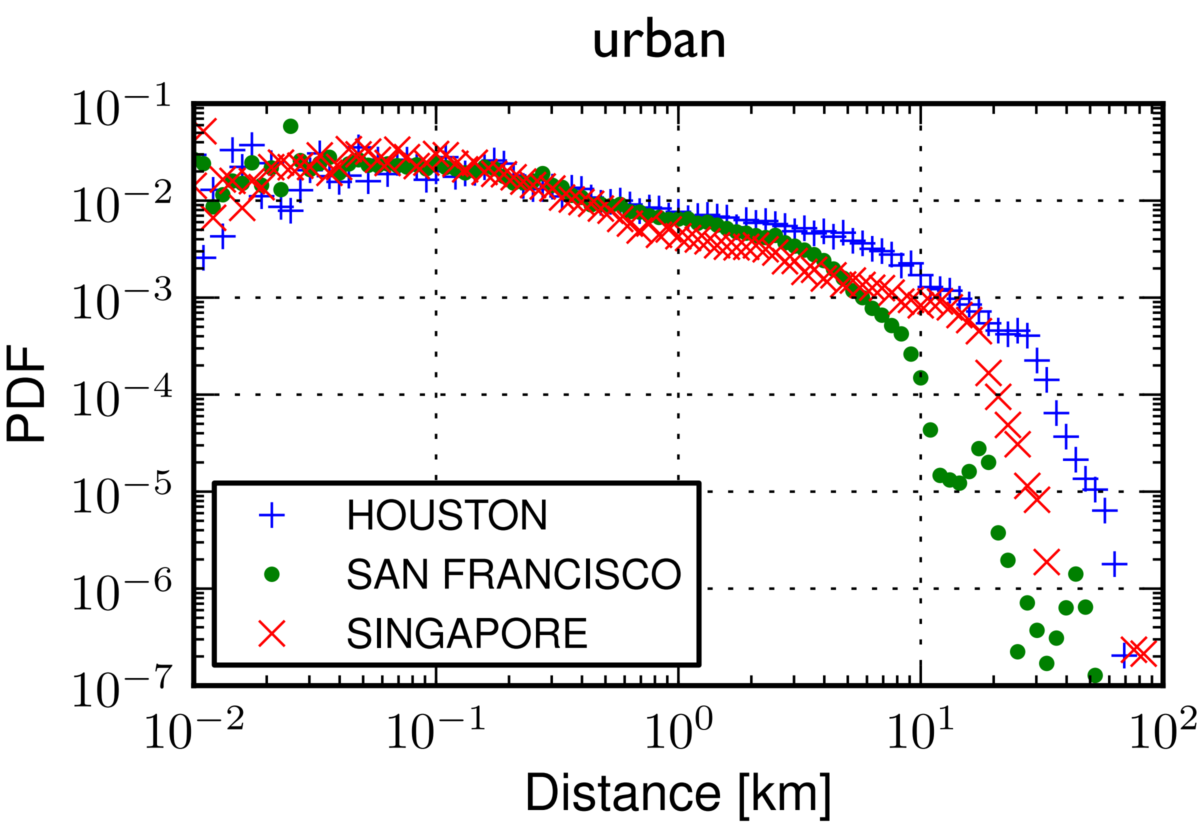
exponent β = 1.50

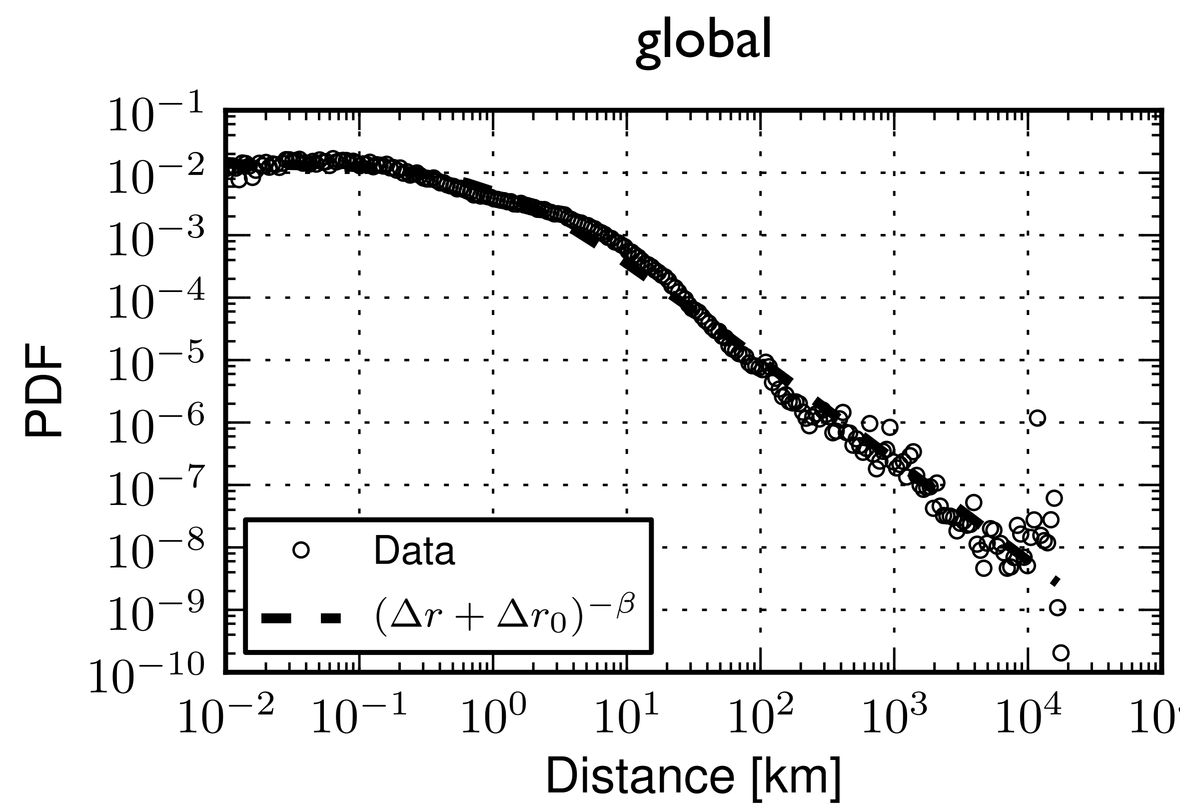
Nature **453**, 779-782(5 June 2008)



exponent β = 1.75

Urban vs Global mobility

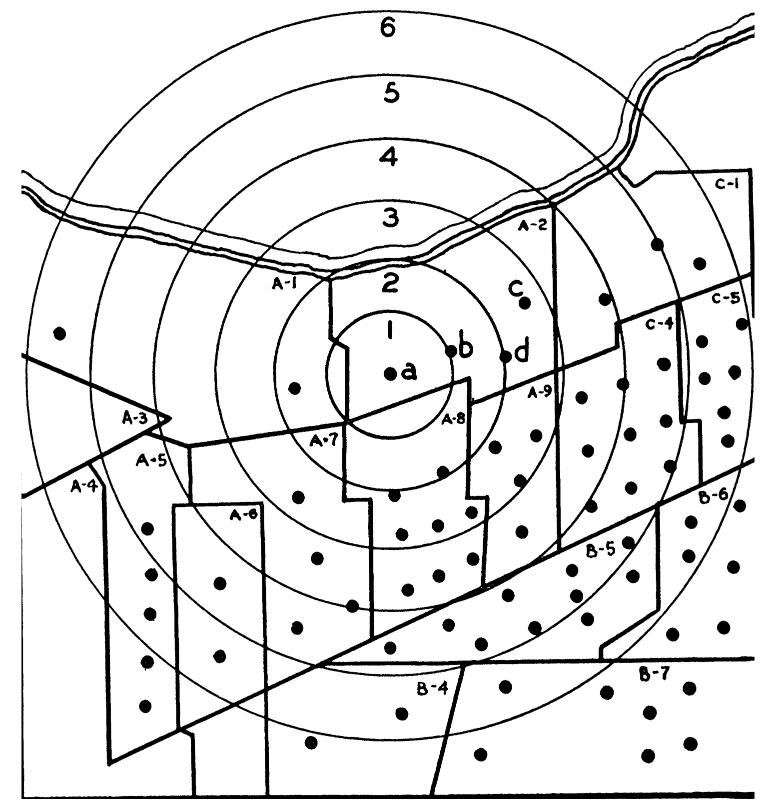




Power law kicks in at 18.42km!!!

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."* *

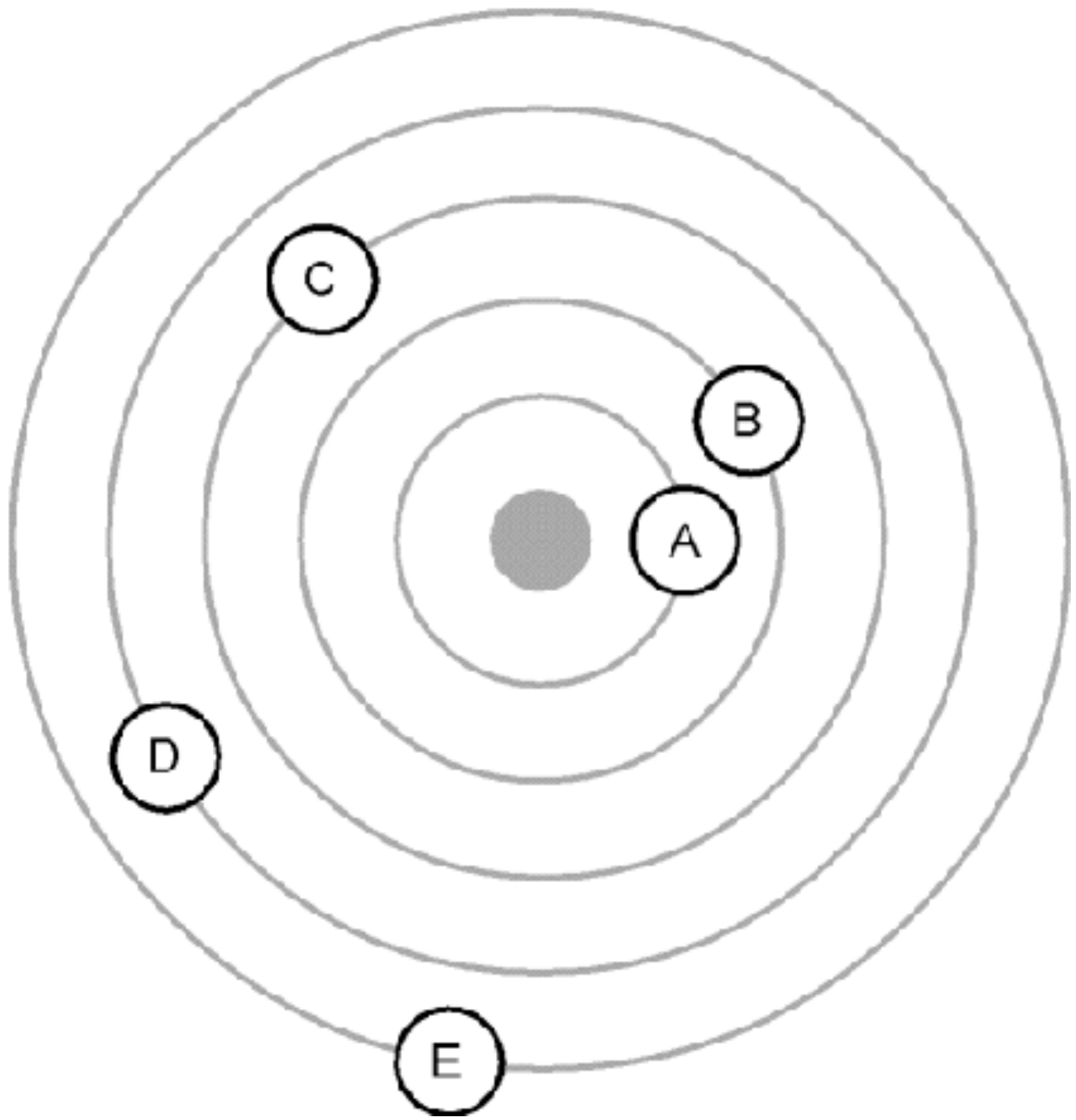


- Empirically proven using data for migrating families in the city of Cleveland.

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

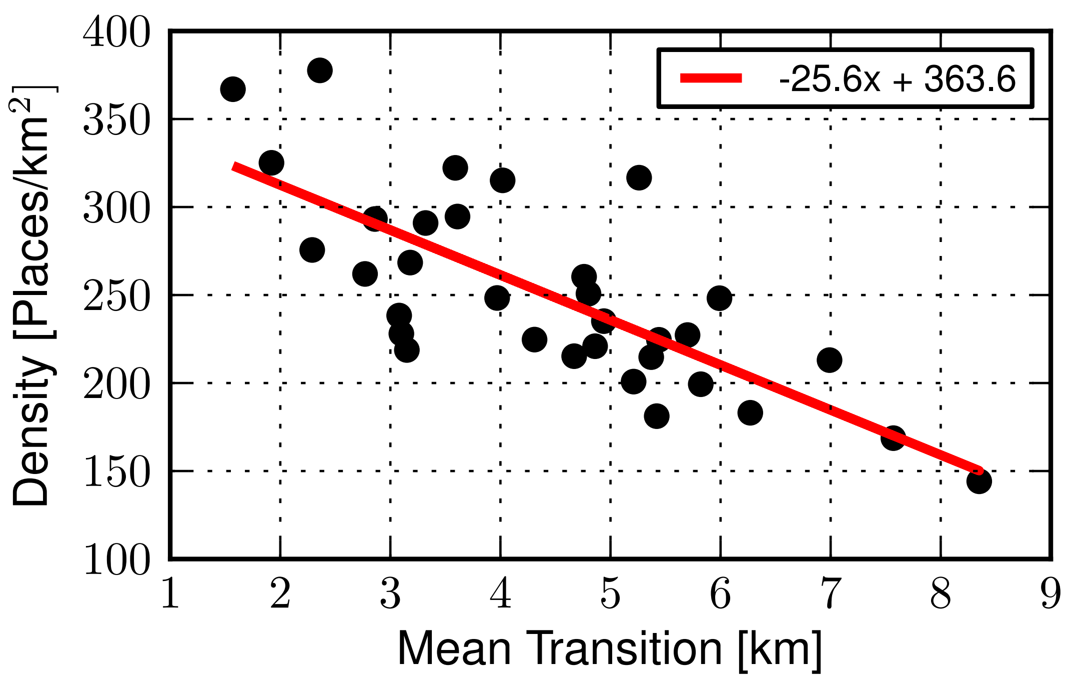
* S. Stouffer (1940) **Intervening opportunities: A theory relating mobility and distance**, American Sociological Review 5, 845-867

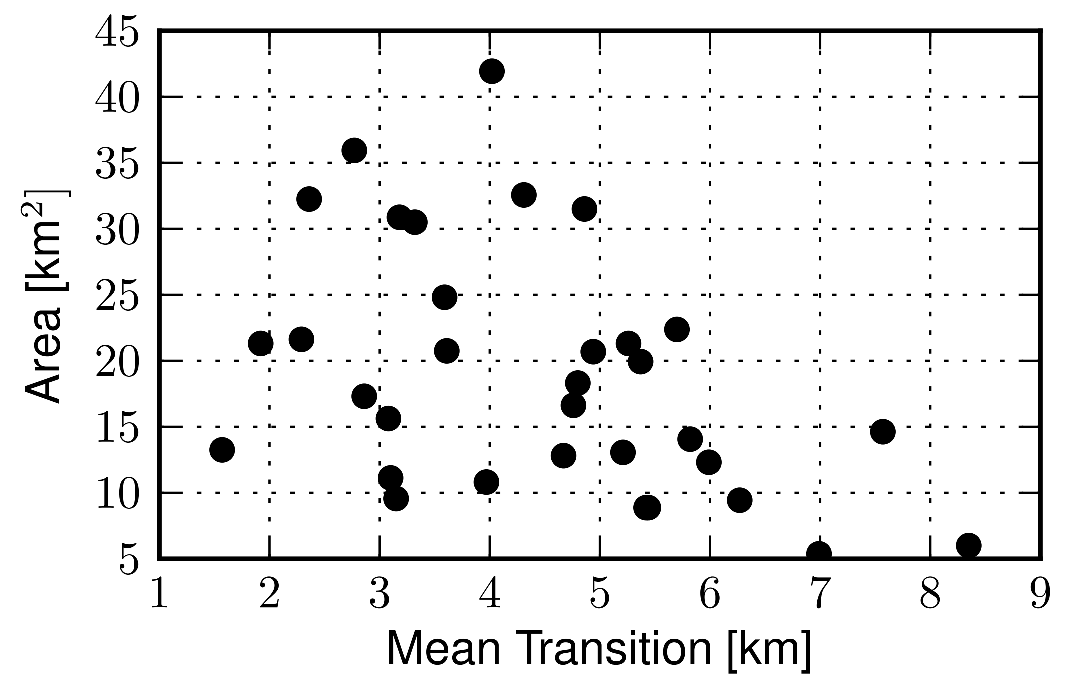
Rank-Distance



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

The importance of density

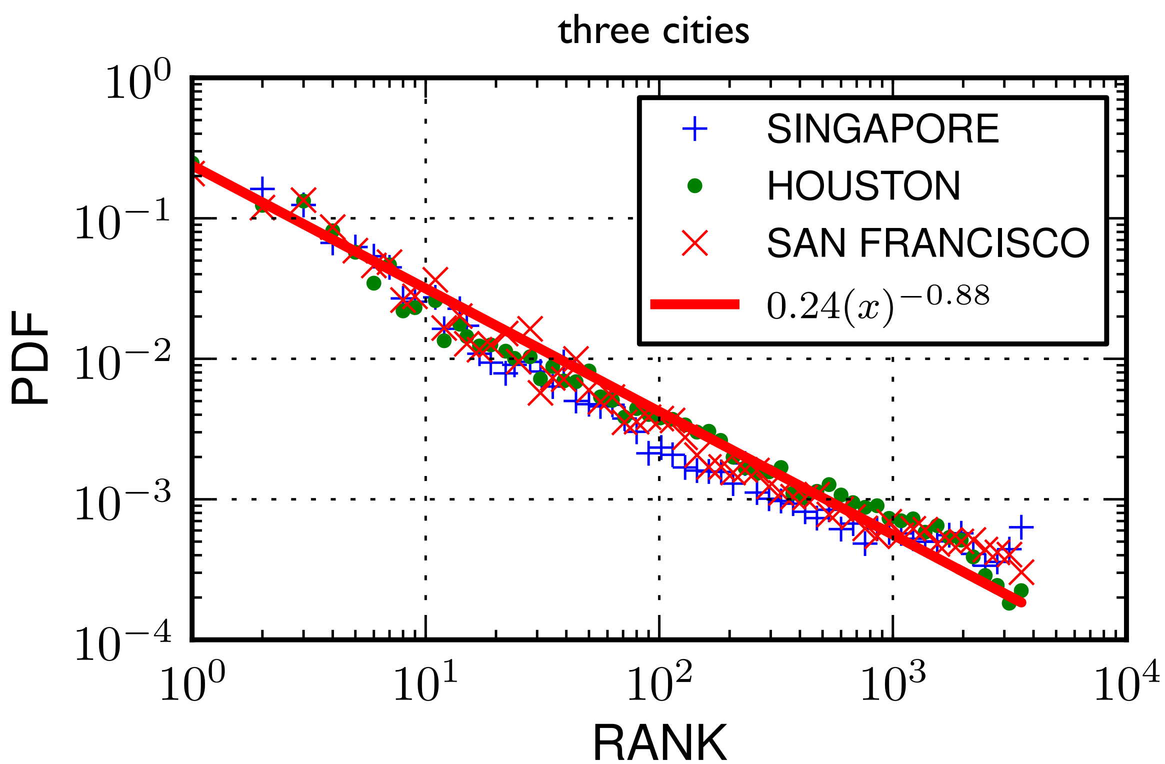


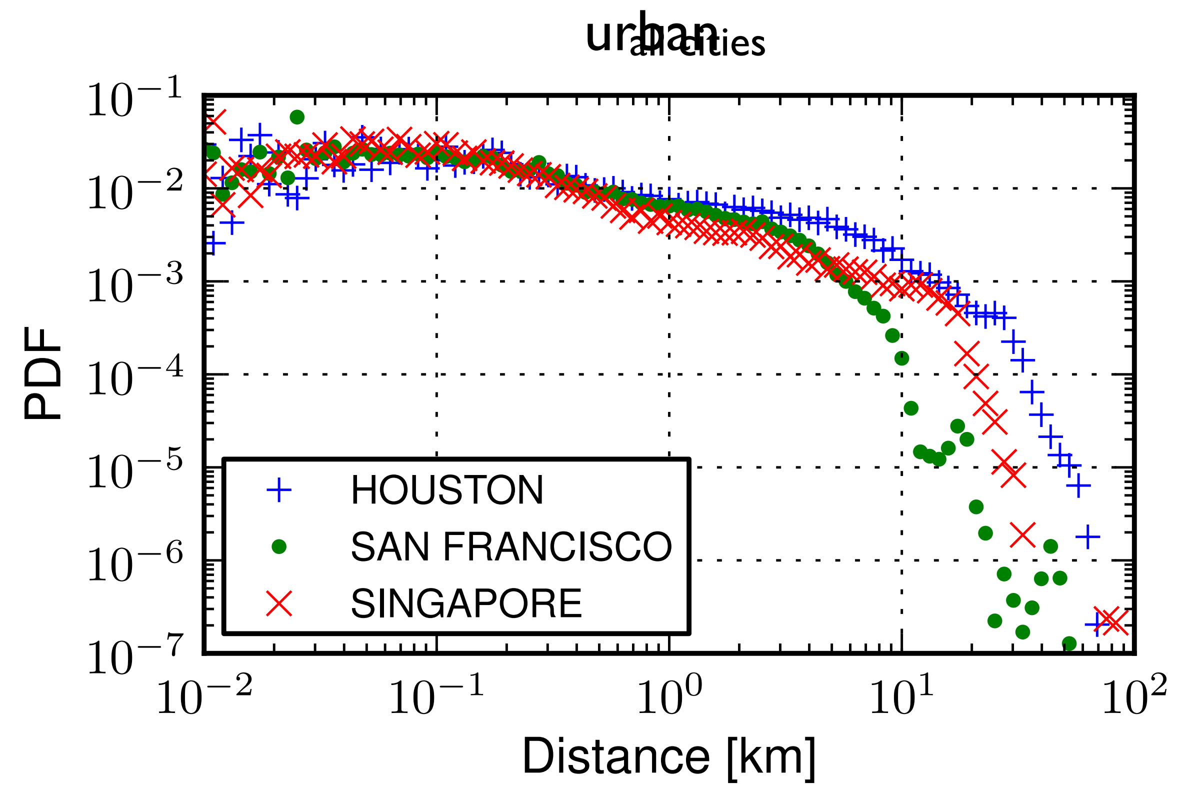


- Stouffer's Theory of Intervening Opportunities motivated us to inspect the impact of places(=opportunities) in human mobility.

- 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



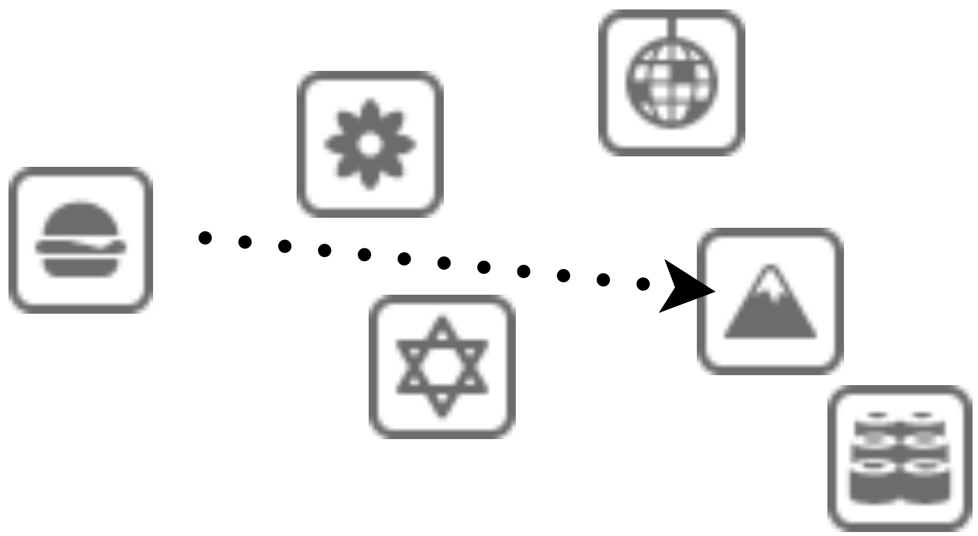


The rank of all cities collapse to a single line.

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

Decoupling cognition & space

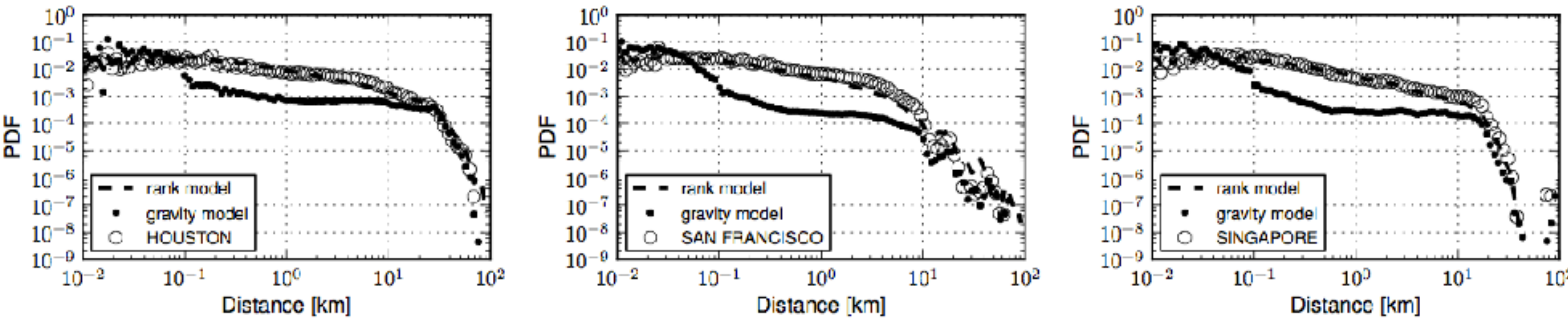
soil...



and mind!

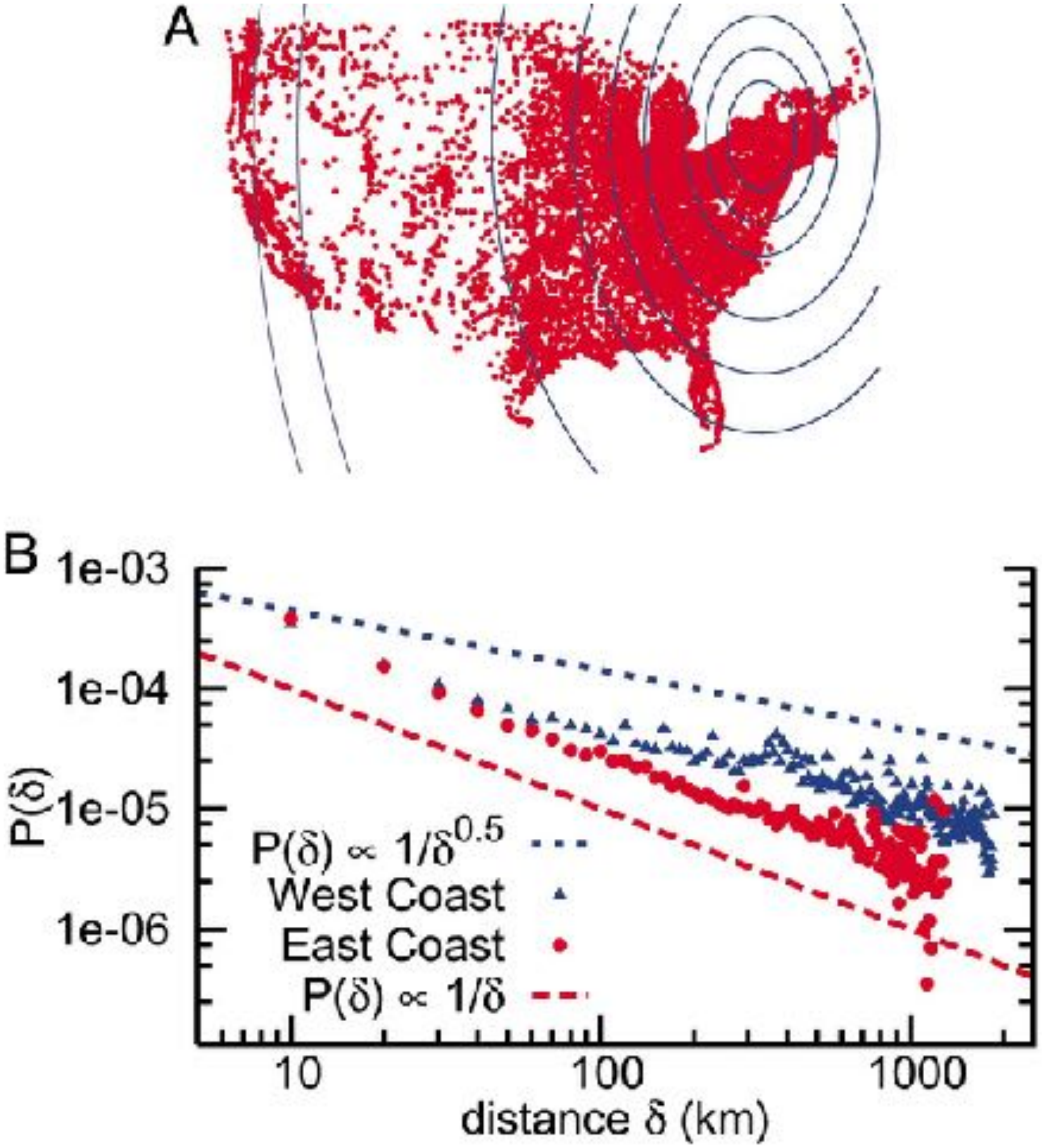
$$Pr[u \to v] \propto \frac{1}{rank_u(v)^a}$$

Rank vs Gravity

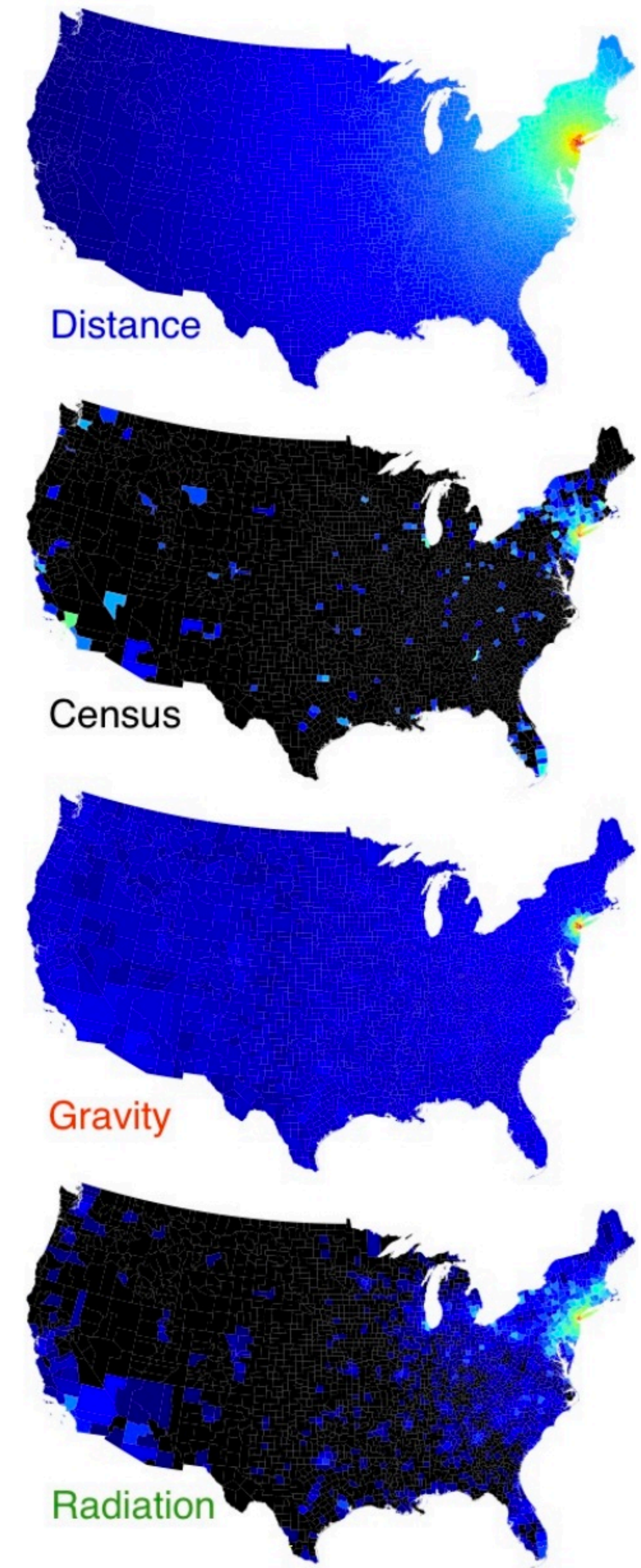


Rank is simpler and achieves better quality fits for all cities.

Gravity overestimates short transitions …

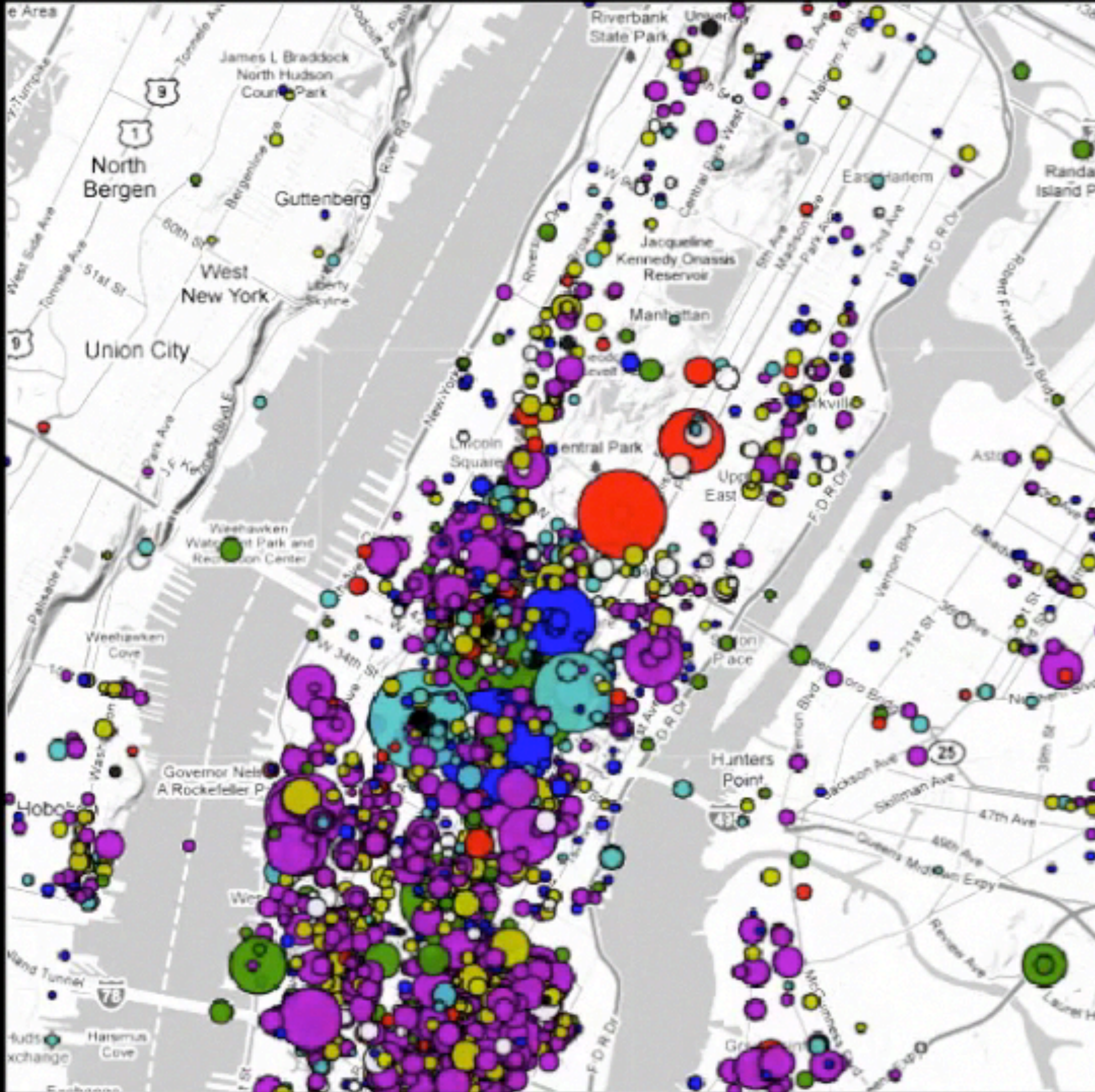


Liben-Nowell, David, et al. "**Geographic routing in social networks.”** PNAS 2005

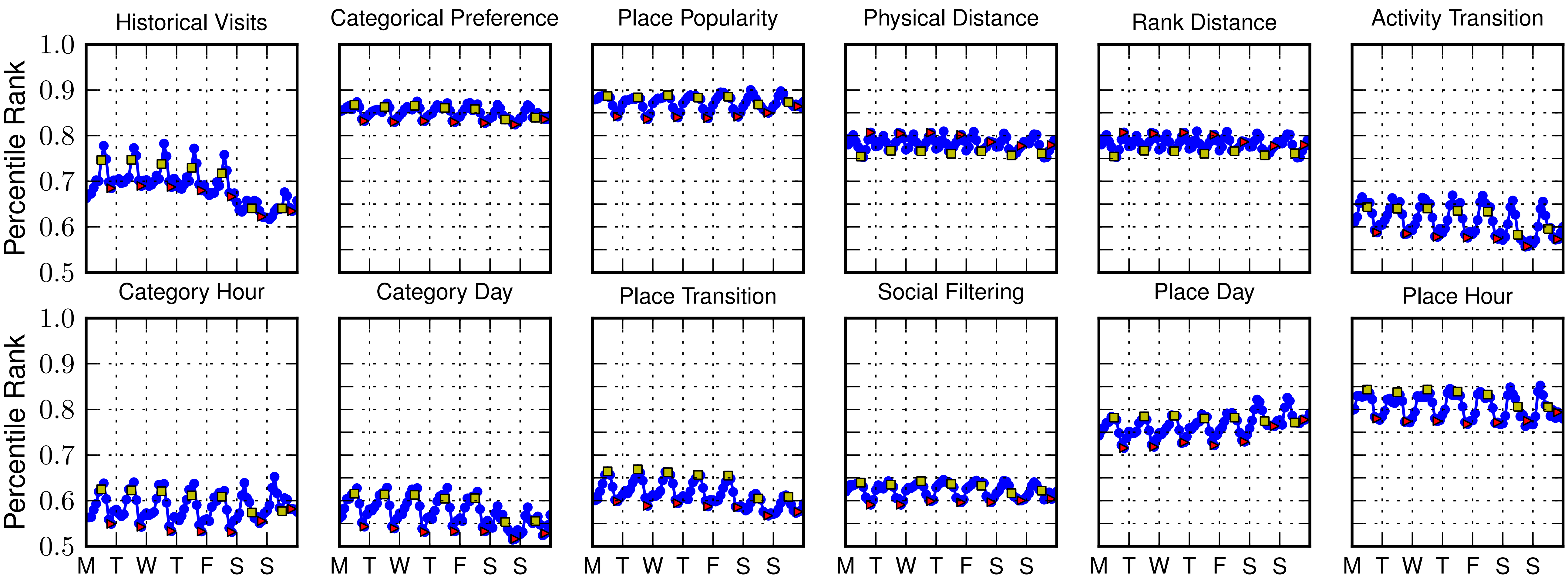


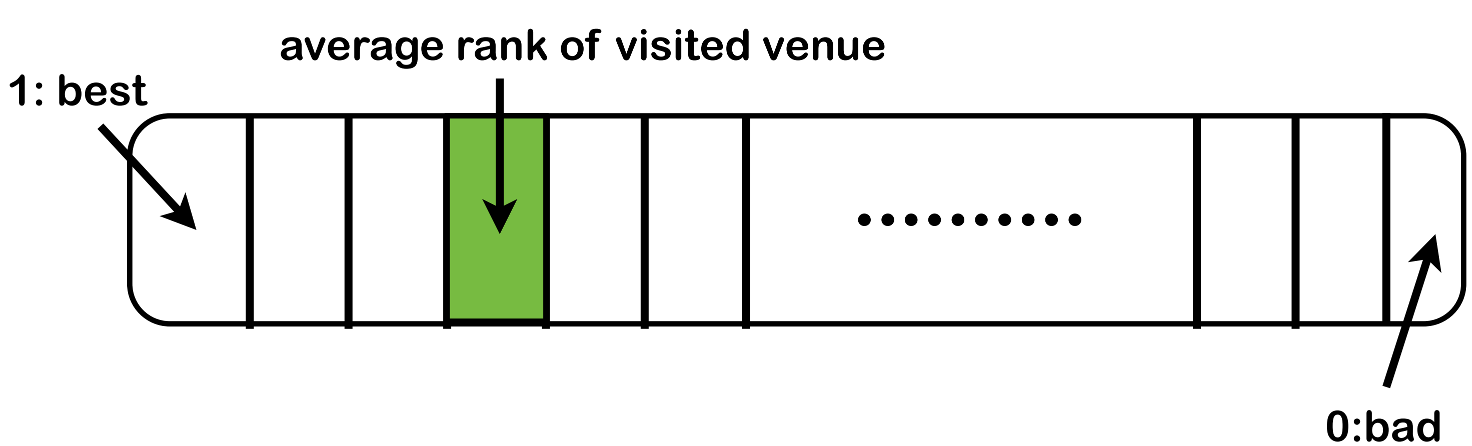
Simini, Filippo, et al. "**A universal model for mobility and migration patterns.**” Nature (2012)

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

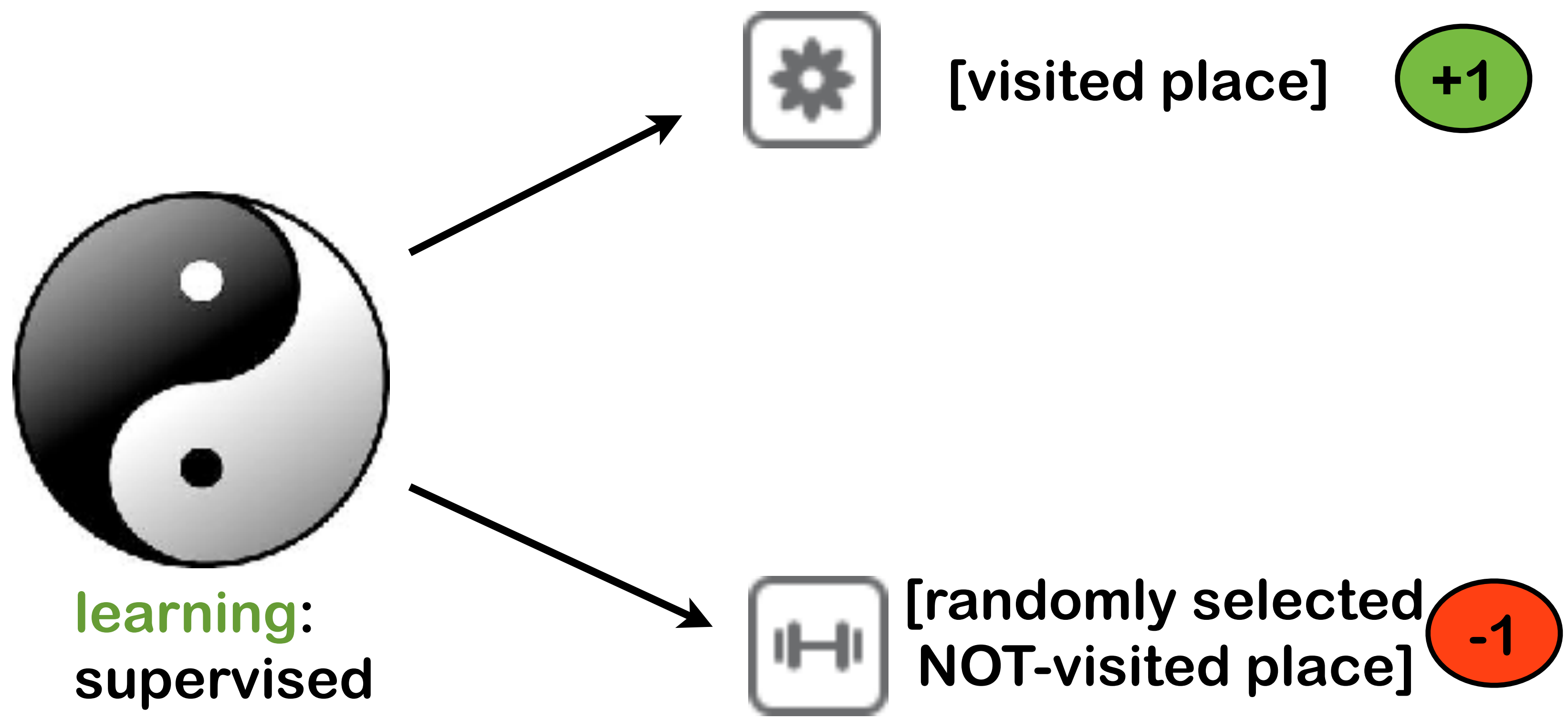

Riverbank
State Park
James L Braddock
North Hudson
County Park
North
Bergen
Guttenberg
West
New York
Union City
East Harlem
Jacqueline
Kennedy Onassis
Reservoir
Manhattan
Central Park
Weehawken
Weehawken
Cove
Hunters
Point
Harsimus
Cove
F D R Dr
W 34th St
47th Ave
Skillman Ave
Jackson Ave

Modern data is rich





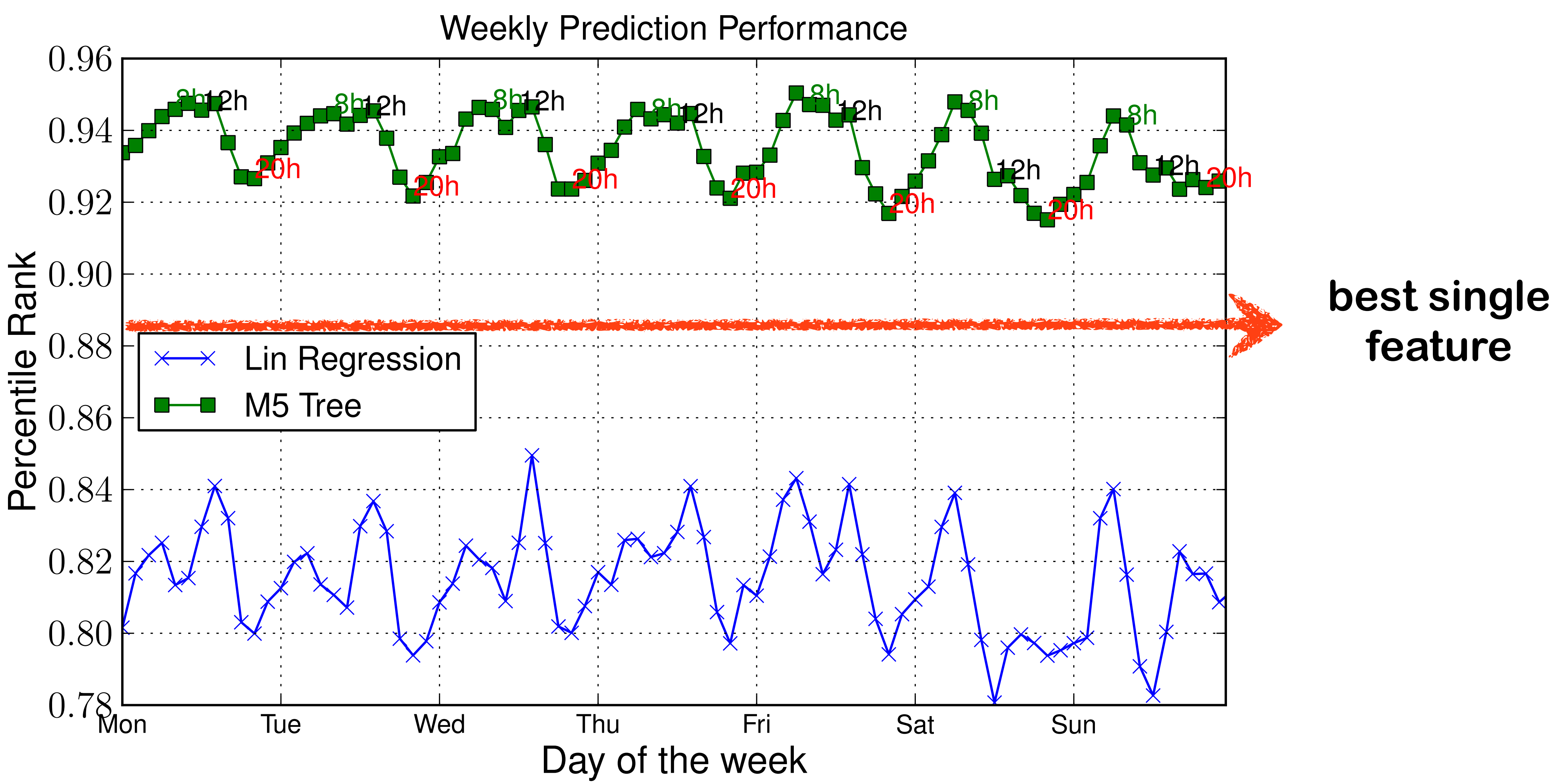
Supervised Training: teaching the good and the bad!



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!



BUT WHY?

why have we used machine learning frameworks to deal with the mobility prediction problem?

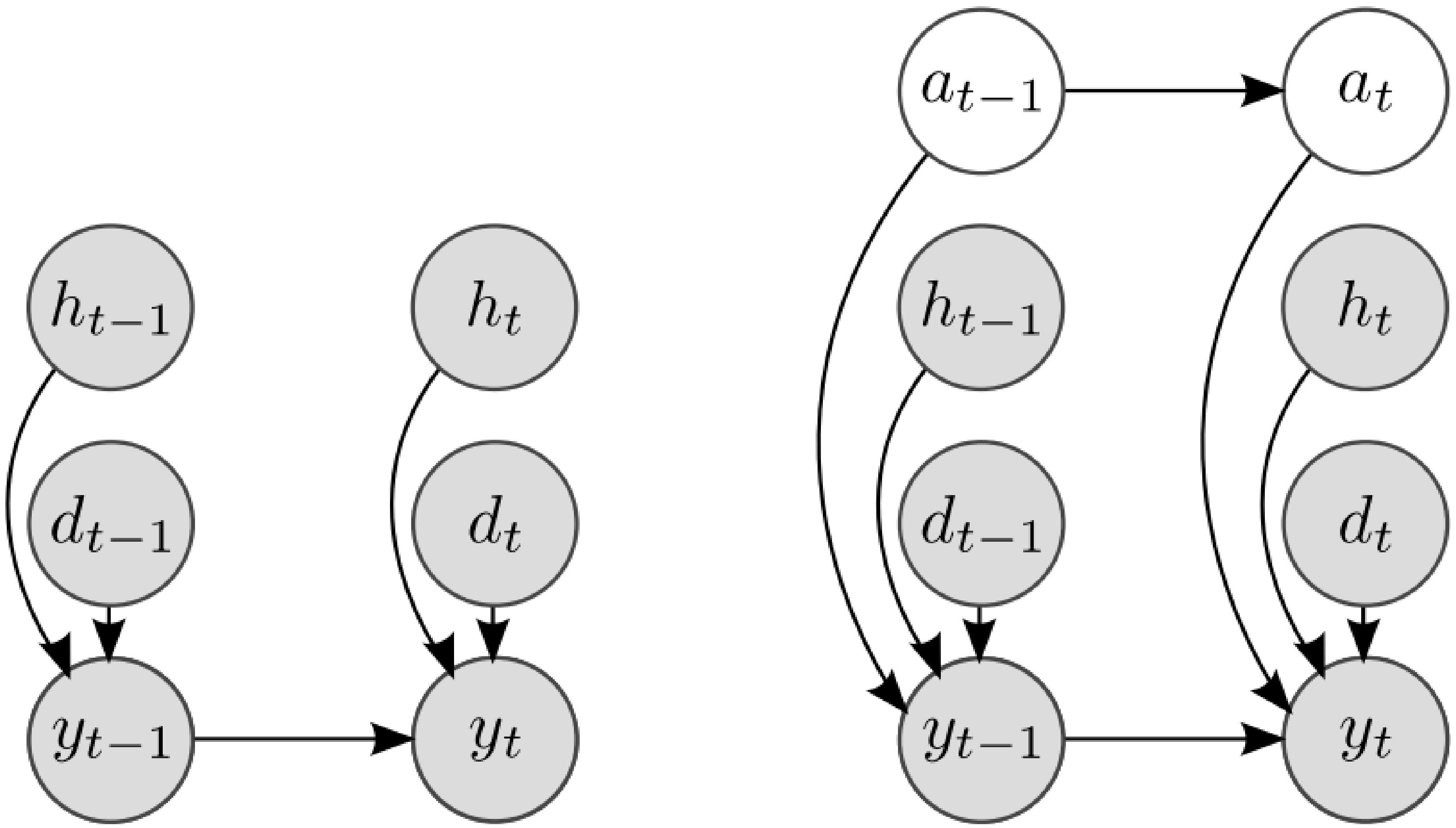
Why have we not used Markovian techniques or Bayesian probabilistic frameworks that have been applied previously to model movement may be harder to get to work in this context?

Why have we trained our models on populations of users?

Why have decision trees performed better than a linear model?

Why not using a Markov model?

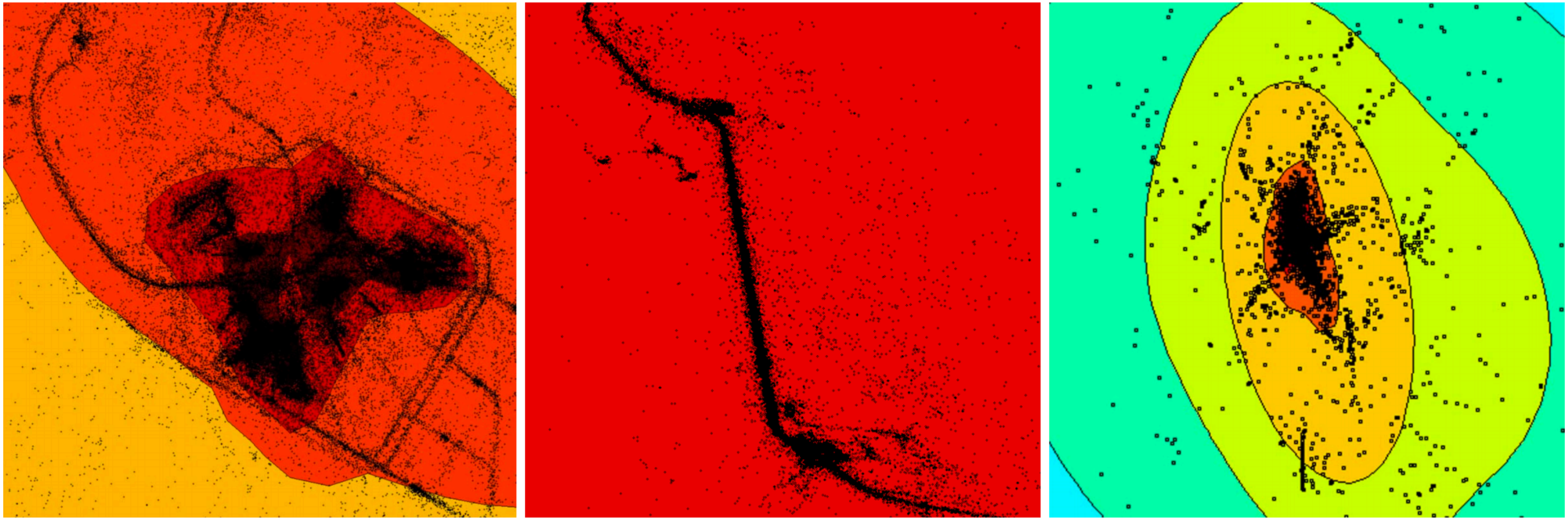
The place-network feature is a form of markov-model, but tells us only part of the truth in the prediction task.



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

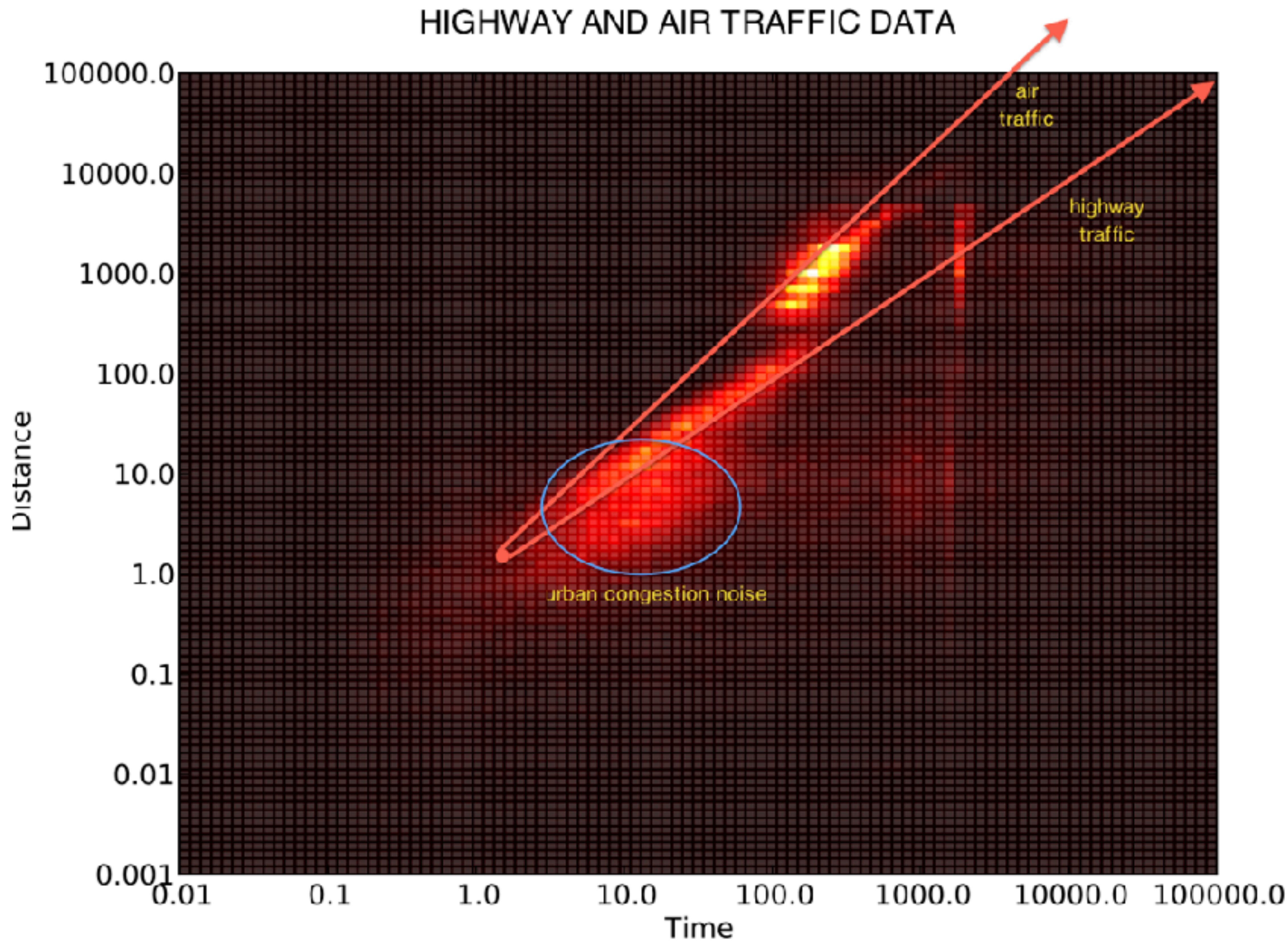
Place Shapes



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

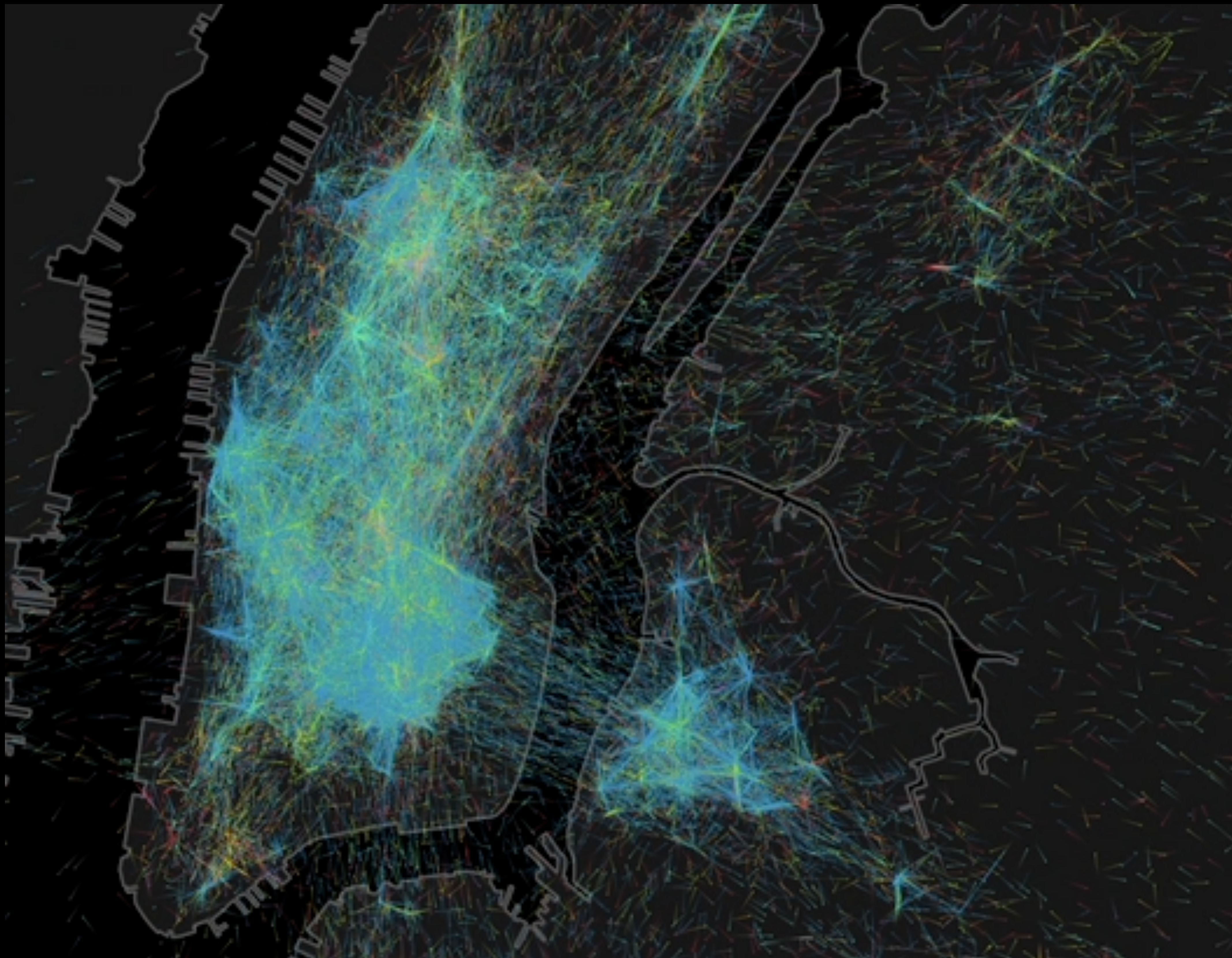
Shaw, Blake, et al. "**Learning to rank for spatiotemporal search.**" Proceedings of the sixth ACM international conference on Web search and data mining. ACM, 2013.

https://vimeo.com/145879457


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

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

New York City

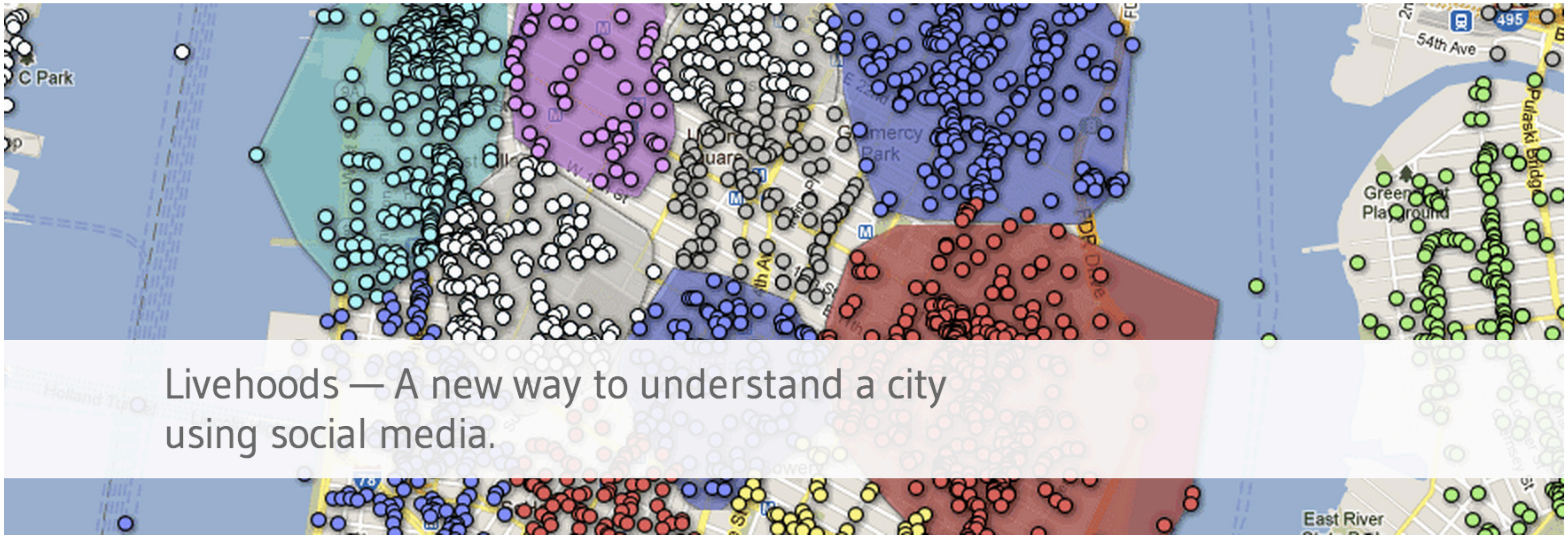


11-12PM

Place networks applications

Livehoods

Home Maps About Research Press Contact



Re-Imagining the City in the Age of Social Media

Livehoods offer a new way to conceptualize the dynamics, structure, and character of a city by analyzing the social media its residents generate. By looking at people's checkin patterns at places across the city, we create a mapping of the different dynamic areas that comprise it. Each Livehood tells a different story of the people and places that shape it.

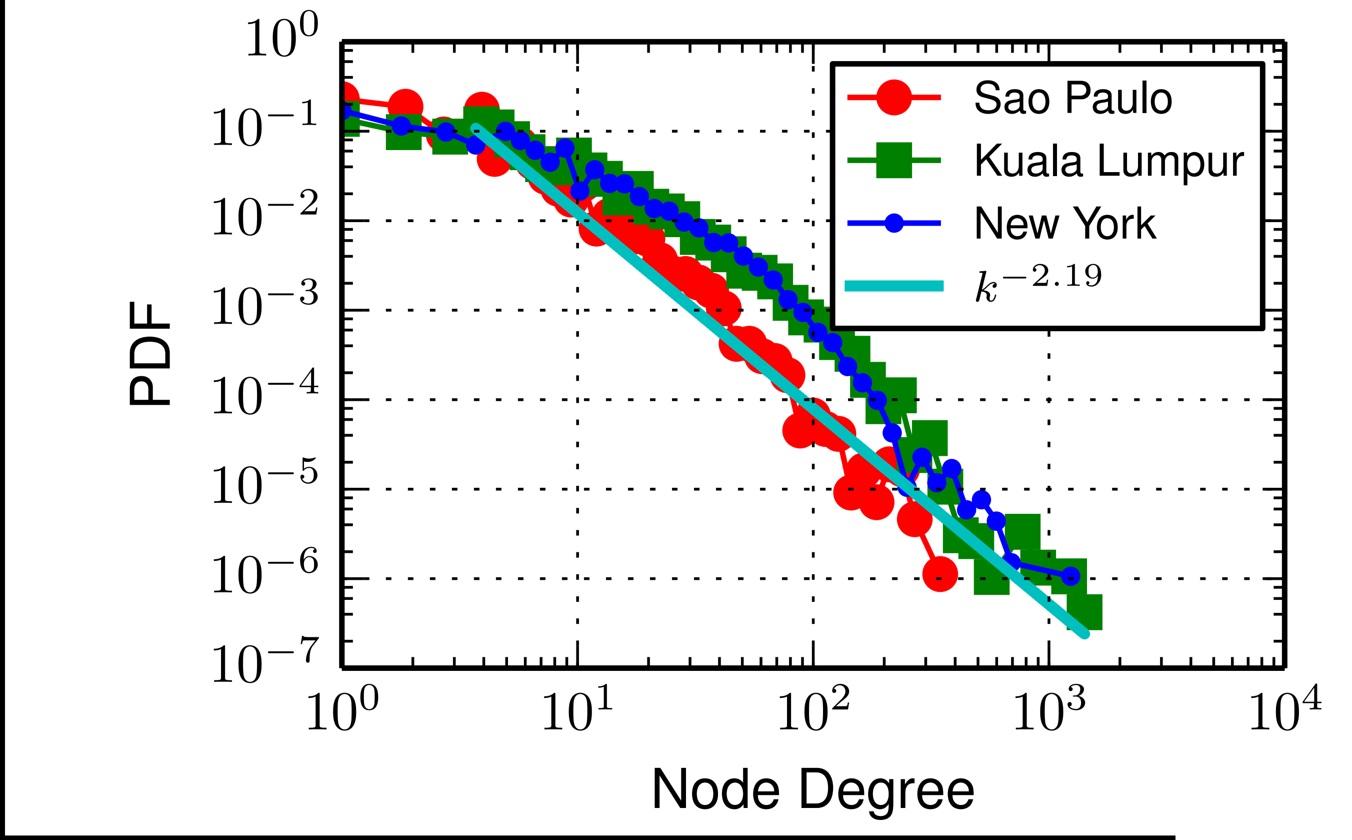
> MORE

Using Machine-Learning to Study Cities

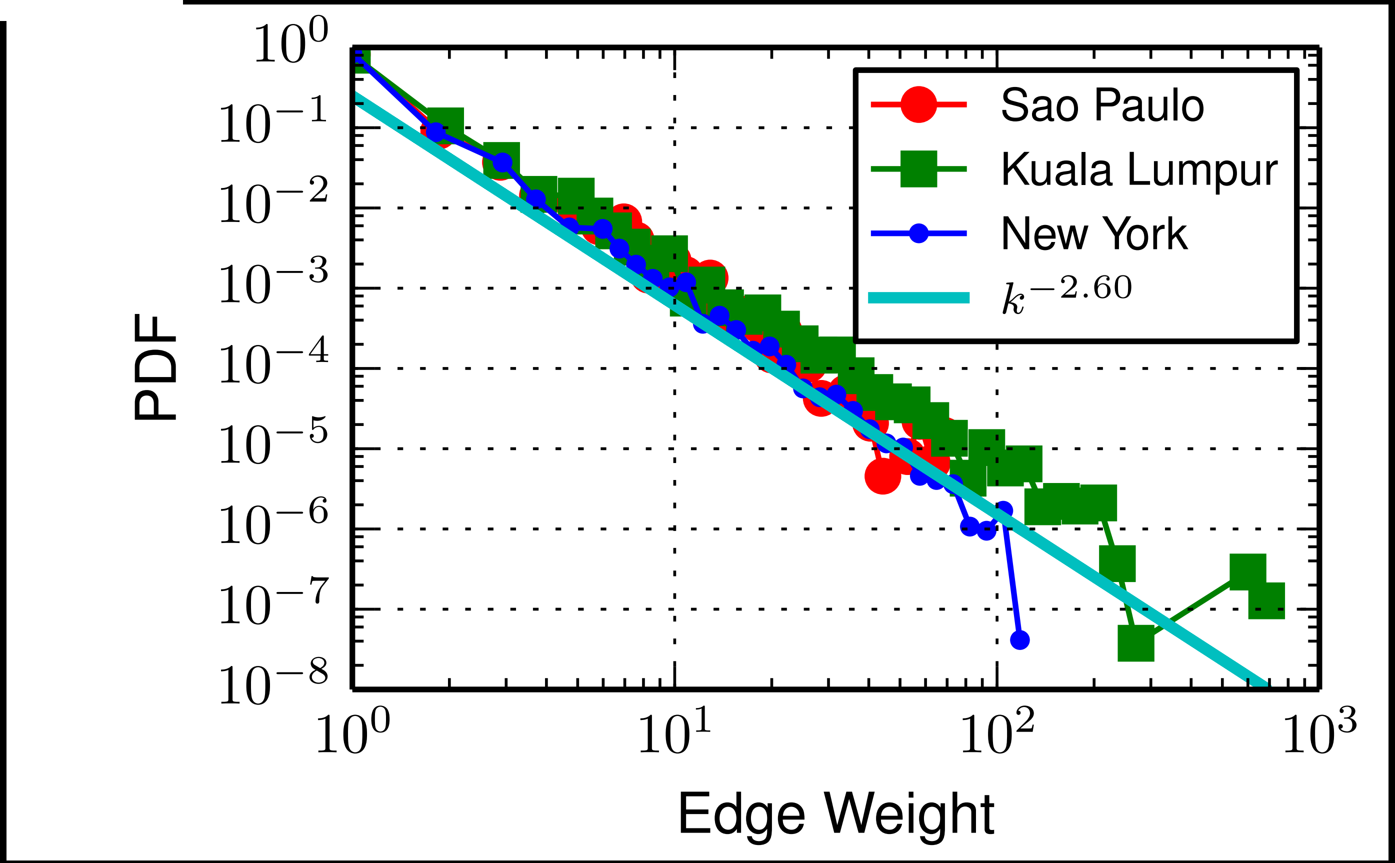
Our research hypothesis is that the character of an urban area is defined not just by the the types of places found there, but also by the people that make it part of their daily life. To explore this idea, we use data from approximately 18 million check-ins collected from the location-based social network foursquare, and apply clustering algorithms to discover the different areas of the city.

> MORE

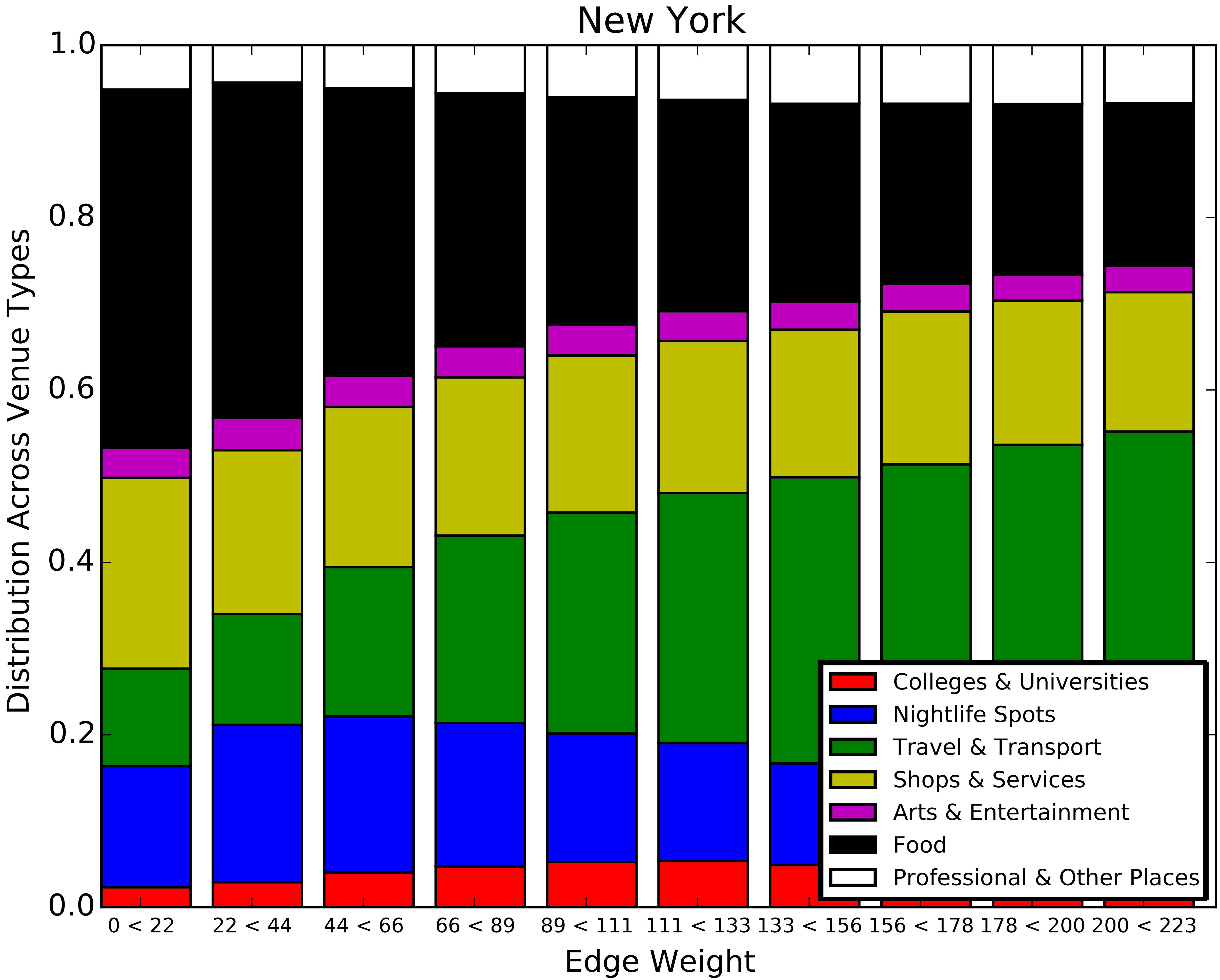
Cranshaw, Justin, et al. "**The livehoods project: Utilizing social media to understand the dynamics of a city."** International AAAI Conference on Weblogs and Social Media. 2012.



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}
10^1
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}
10^1
10^2
10^3


New York
Distribution Across Venue Types
1.0
0.8
0.6
0.4
0.2
0.0
0 < 22
22 < 44
44 < 66
66 < 89
89 < 111
111 < 133
133 < 156
156 < 178
178 < 200
200 < 223
Edge Weight
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

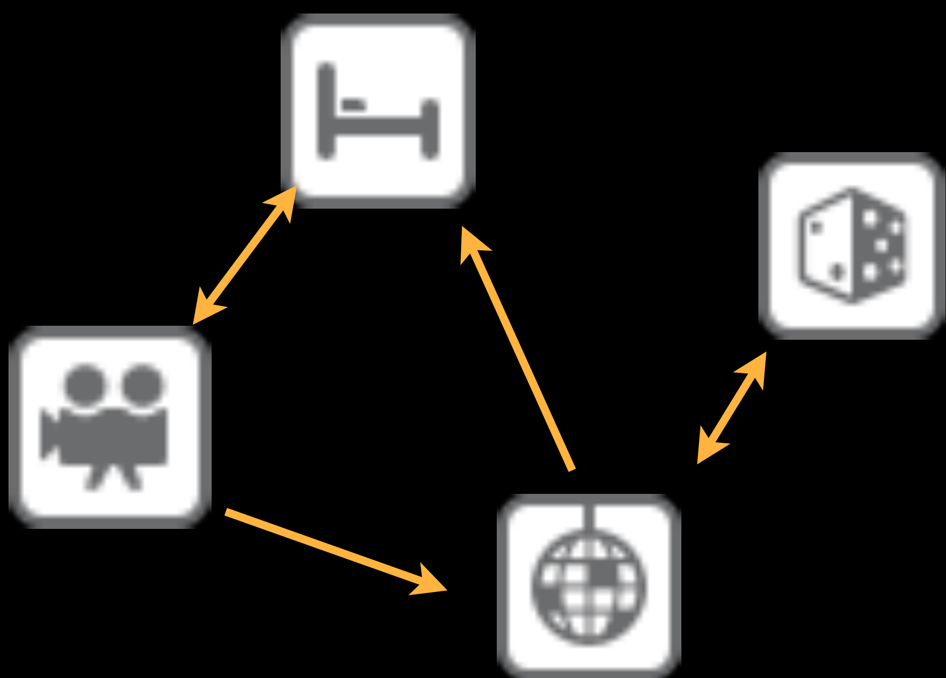
	network	n	r
real-world networks	physics coauthorship[a]	52 909	0.363
	biology coauthorship[a]	1 520 251	0.127
	mathematics coauthorship[b]	253 339	0.120
	film actor collaborations[c]	449 913	0.208
	company directors[d]	7 673	0.276
	Internet[e]	10 697	−0.189
	World-Wide Web[f]	269 504	−0.065
	protein 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.

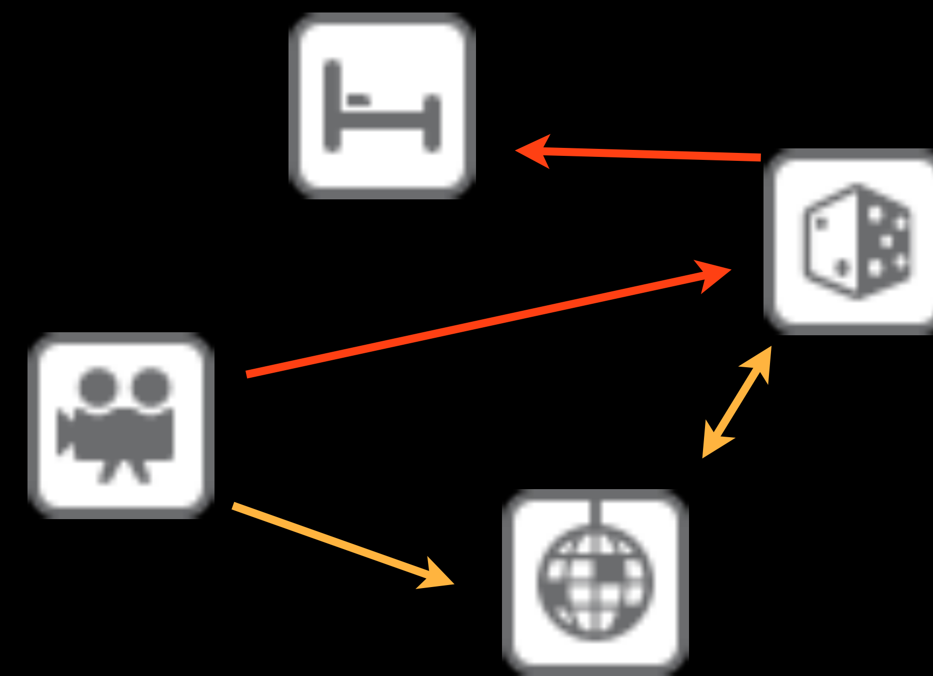
M.Newman et. al PRL, 2002

Place Networks

~75% New Links
~5% New Places



snapshot 1



snapshot 2

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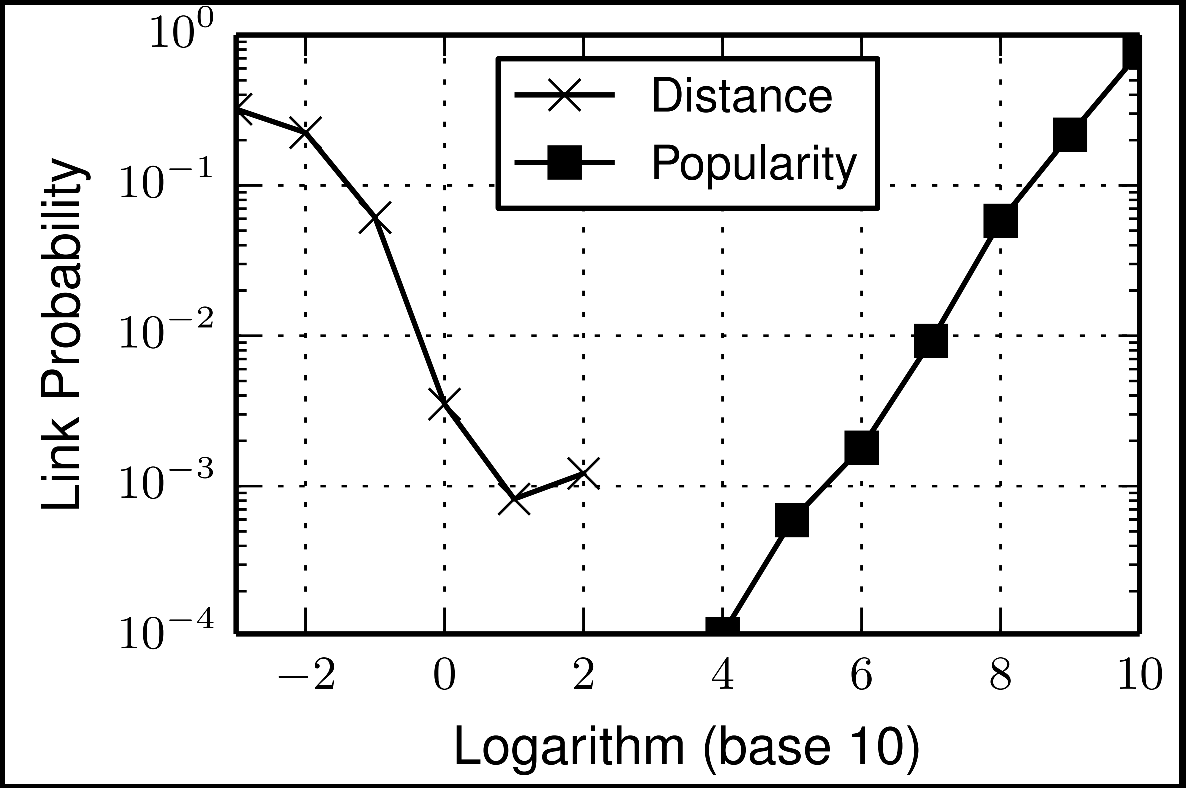
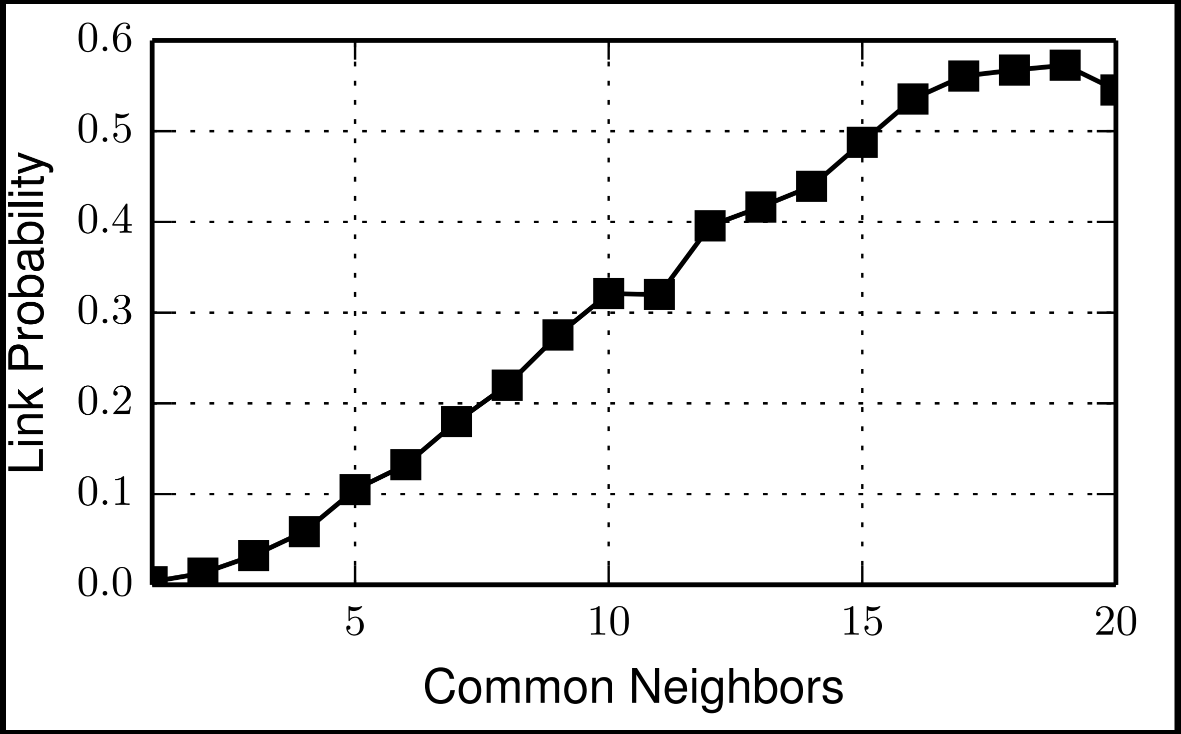
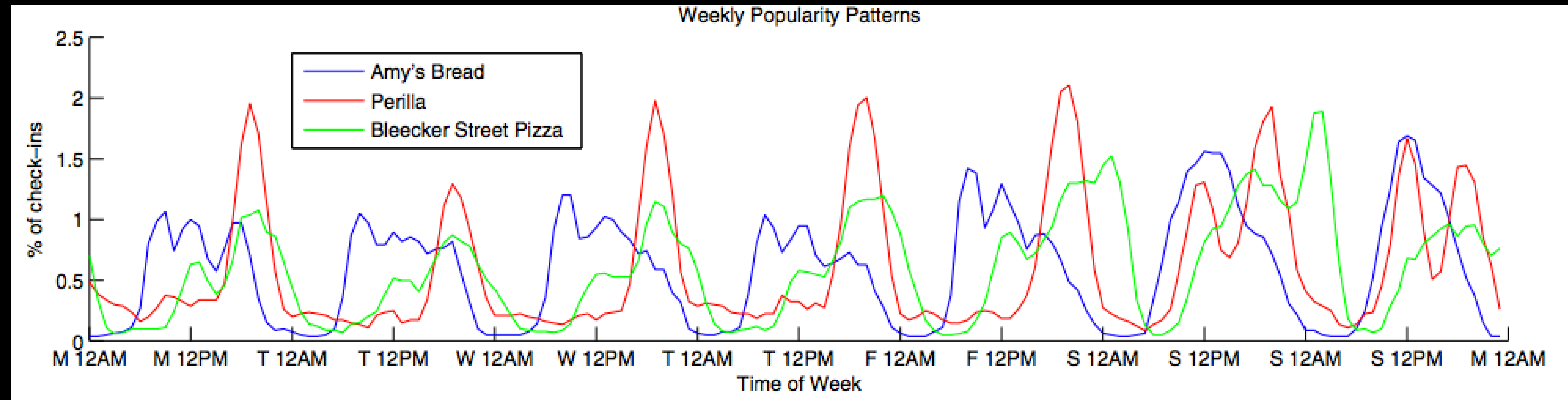
human mobility



network form

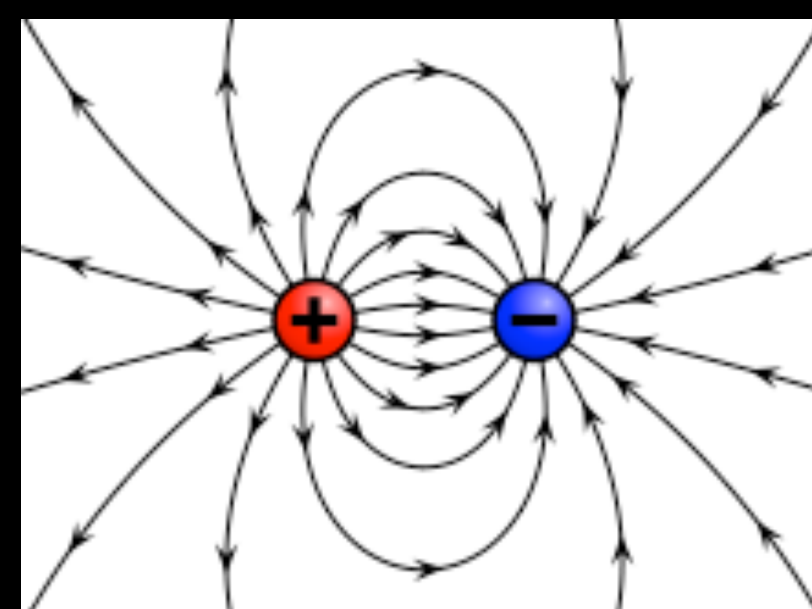


time
signal



Shaw et al. WSDM'13

place
polarity



CLASSIC GRAVITY

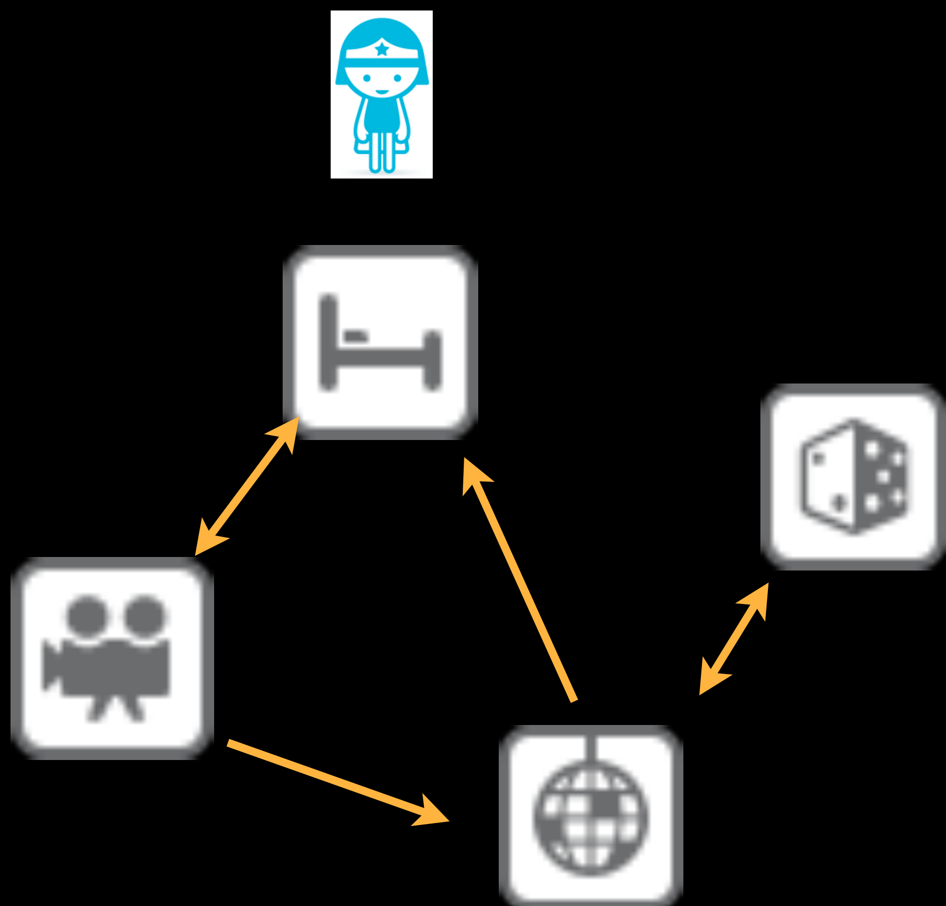
$$\frac{c_i c_j}{d(i,j)^\beta}$$

DYNAMIC GRAVITY

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

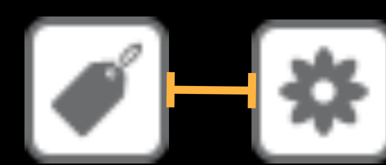
The “heavy-weights”

PLACE RANK



random walk with restart

SUPERVISED LEARNING FOR LINK PREDICTION

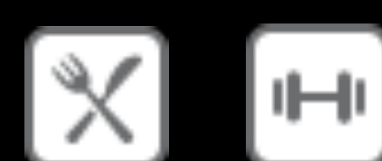


connected pair

+1

train algorithm on binary labels

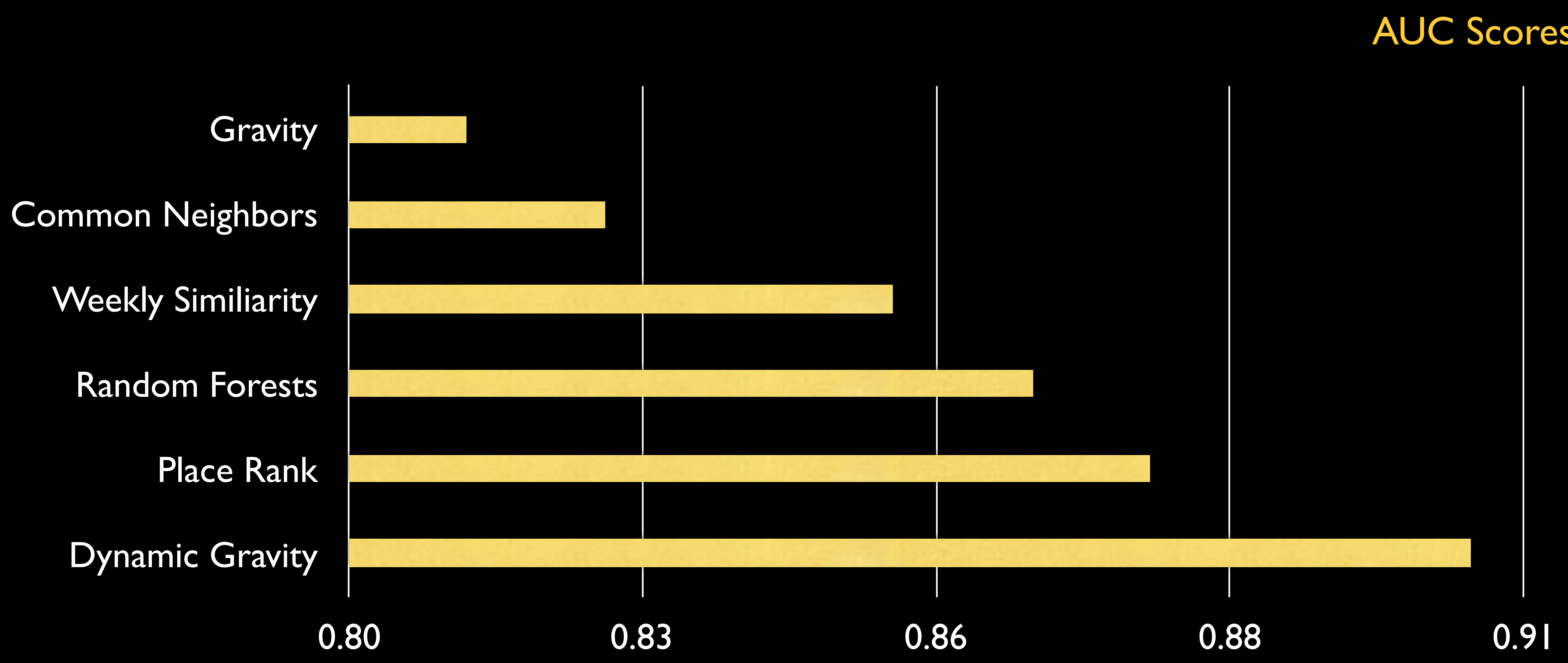
rank millions of place pairs



disconnected pair

-1

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.

Mobility prediction is much about identifying the right level of abstraction for your problem

complex systems physics

computationally demanding models

inter-mediate complexity,
the “undecided”!

simple

complex

abstraction level

favour understanding

favour applications

less data

more data

THANK YOU

@taslanous