Urban morphology and structural invariants in street networks

Alec Kirkley[1] ,Hugo Barbosa[1], Marc Barthelemy[2] and Gourab Ghoshal[1]

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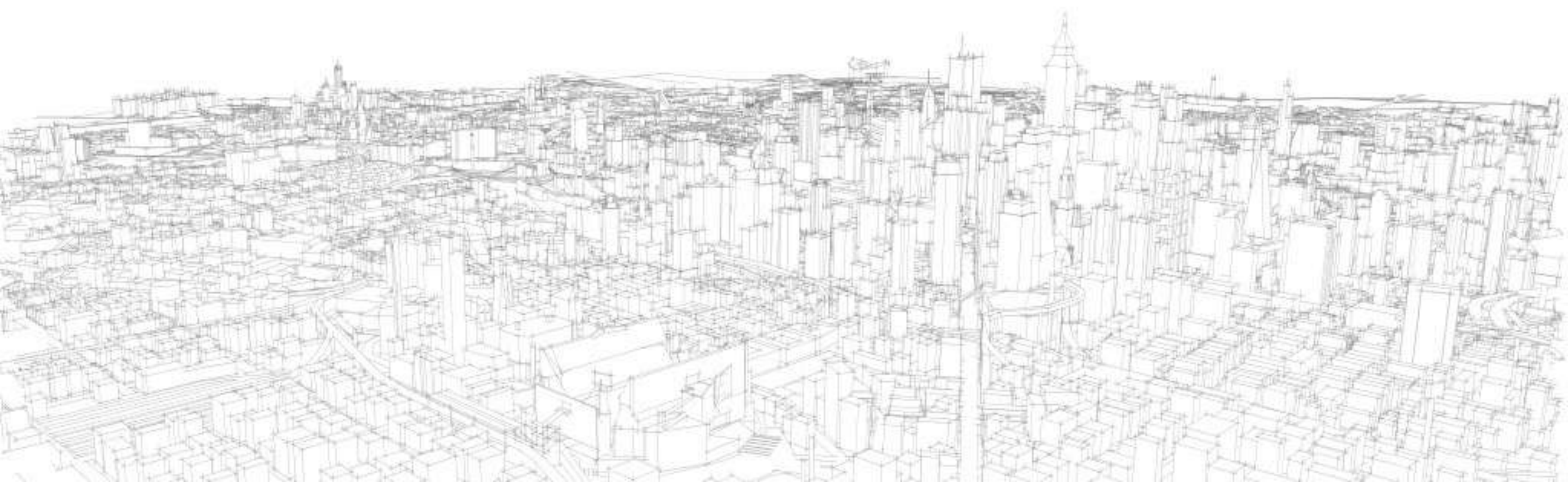
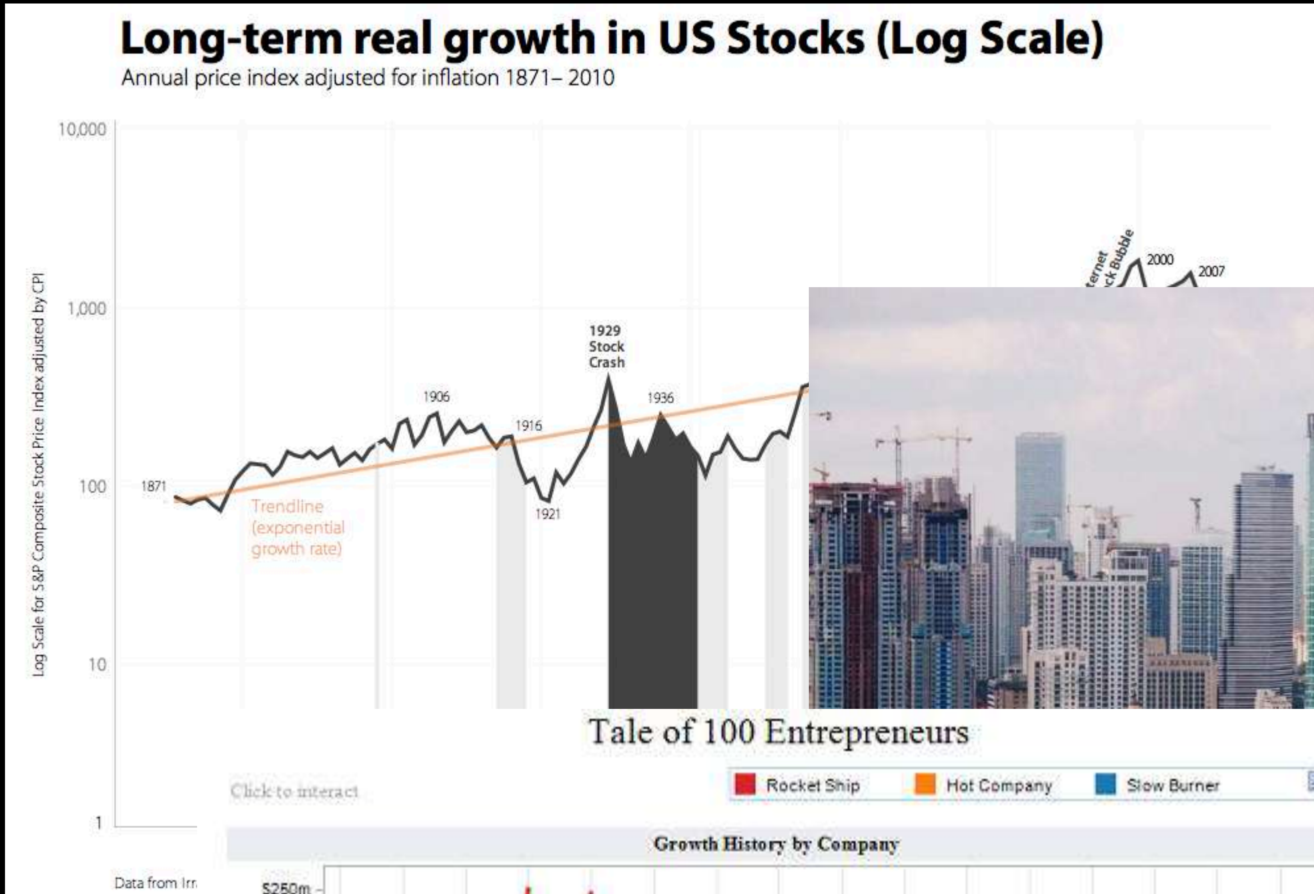
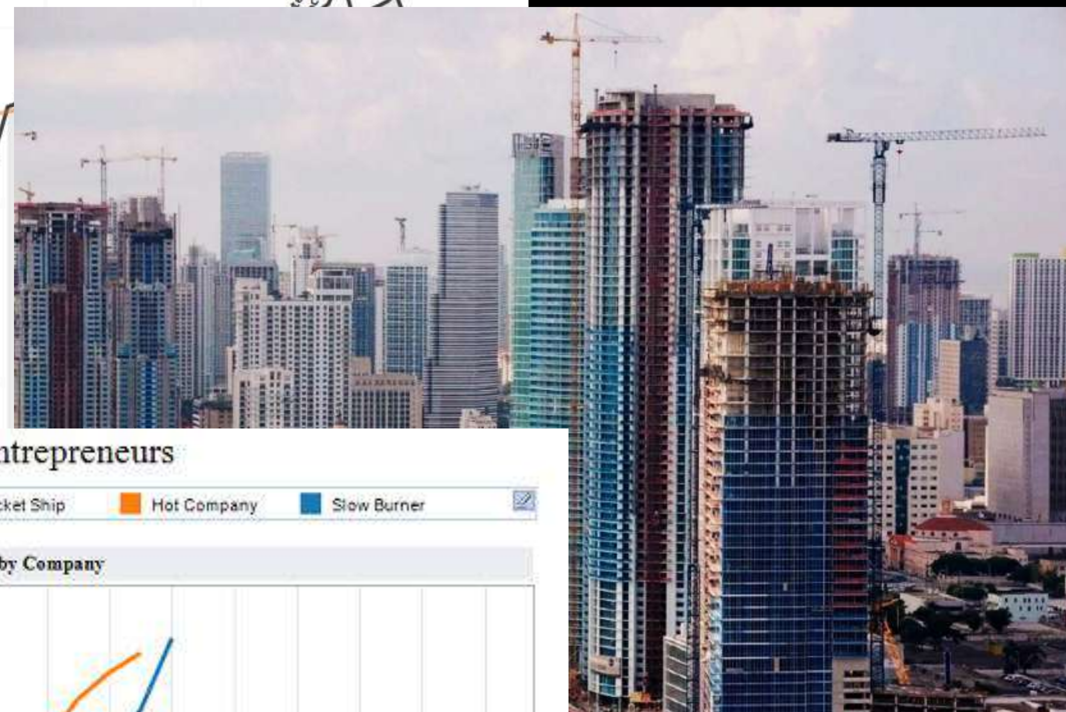
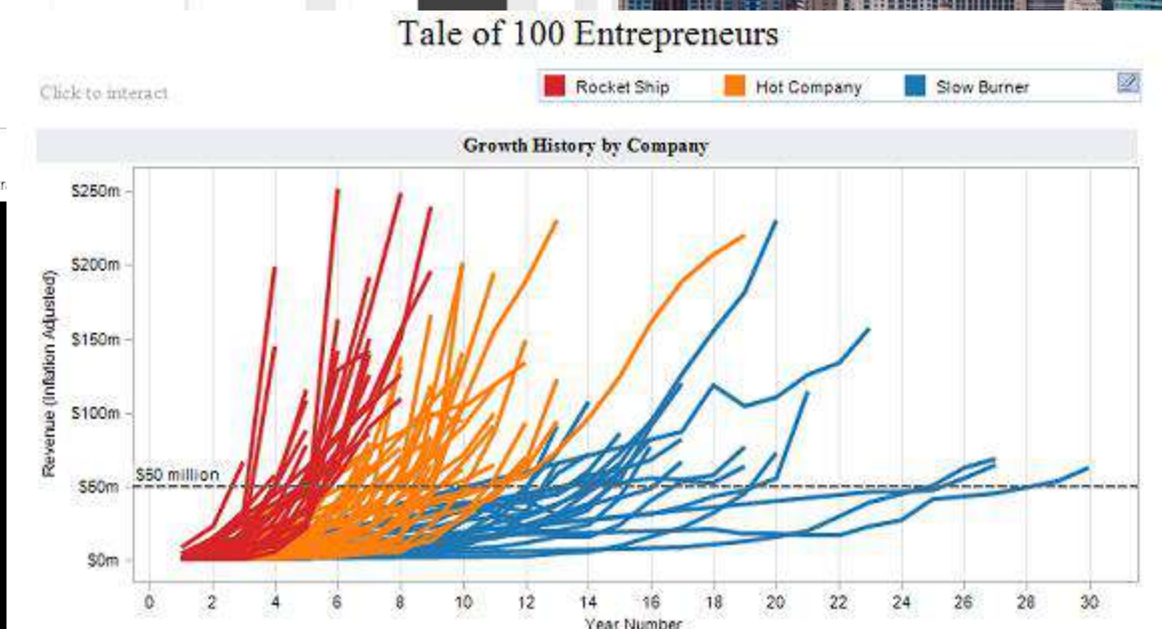



Google


Long-term real growth in US Stocks (Log Scale)
Annual price index adjusted for inflation 1871– 2010
Log Scale for S&P Composite Stock Price Index adjusted by CPI
10,000
1,000
100
10
1
1871
Trendline (exponential growth rate)
1906
1916
1921
1929 Stock Crash
1936
2000
2007




Tale of 100 Entrepreneurs
Click to interact
Rocket Ship
Hot Company
Slow Burner
Growth History by Company
Revenue (Inflation Adjusted)
$250m
$200m
$150m
$100m
$50m
$0m
$50 million
0
2
4
6
8
10
12
14
16
18
20
22
24
26
28
30
Year Number

Growth, innovation, scaling, and the pace of life in cities

Luís M. A. Bettencourt*†, José Lobo‡, Dirk Helbing§, Christian Kühnert§, and Geoffrey B. West*¶

Urban indicators scale **super-linearly** with population size

$$Y(t) \sim N(t)^{\beta}$$

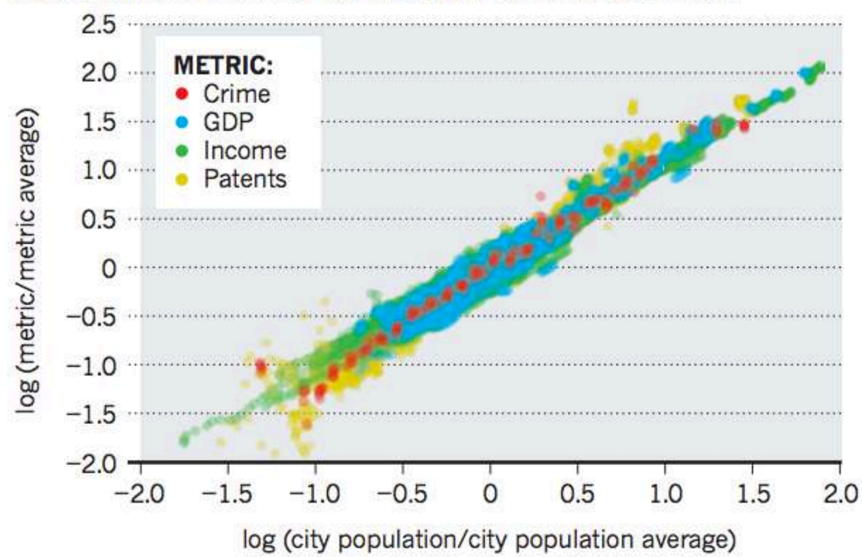
Table 1. Scaling exponents for urban indicators vs. city size

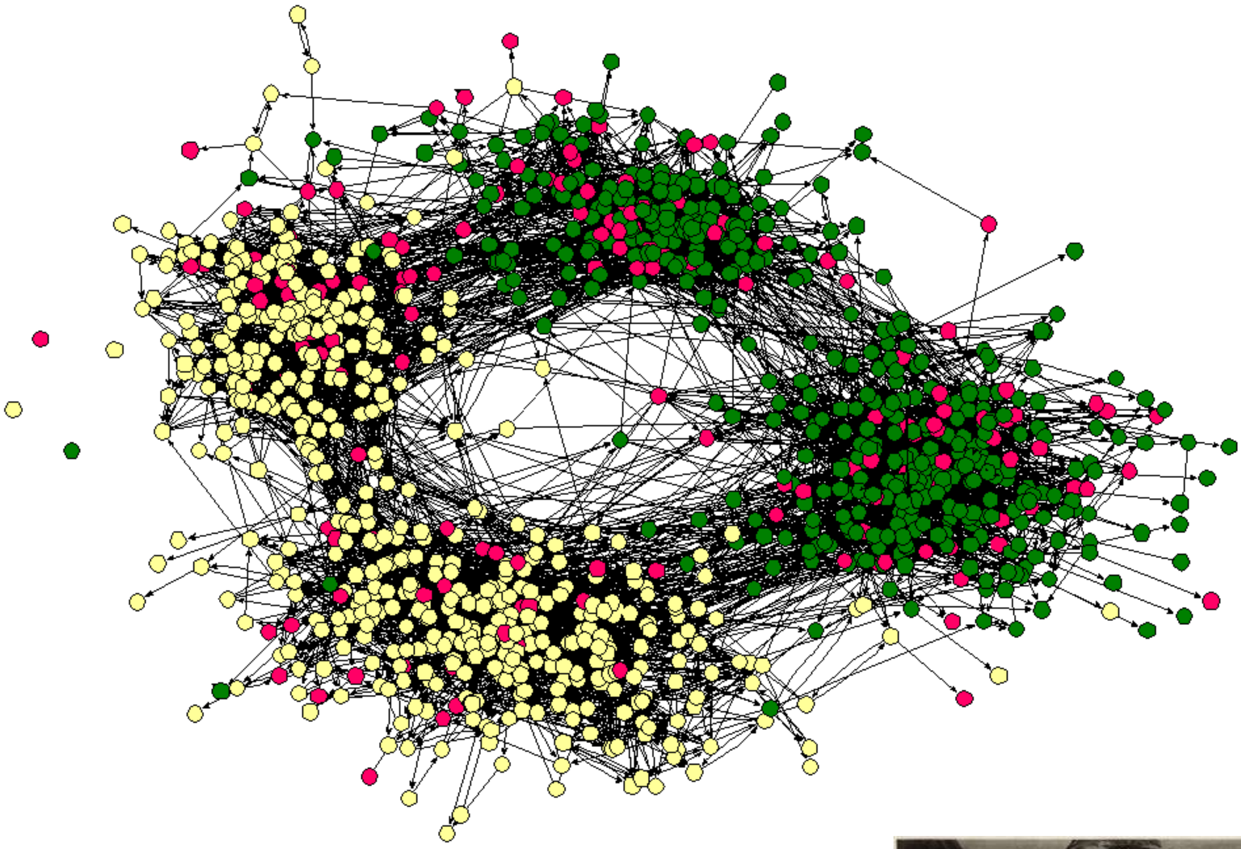
Y	*β*	95% CI	Adj-R^2
New patents	1.27	[1.25,1.29]	0.72
Inventors	1.25	[1.22,1.27]	0.76
Private R&D employment	1.34	[1.29,1.39]	0.92
"Supercreative" employment	1.15	[1.11,1.18]	0.89
R&D establishments	1.19	[1.14,1.22]	0.77
R&D employment	1.26	[1.18,1.43]	0.93
Total wages	1.12	[1.09,1.13]	0.96
Total bank deposits	1.08	[1.03,1.11]	0.91
GDP	1.15	[1.06,1.23]	0.96
GDP	1.26	[1.09,1.46]	0.64
GDP	1.13	[1.03,1.23]	0.94
Total electrical consumption	1.07	[1.03,1.11]	0.88
New AIDS cases	1.23	[1.18,1.29]	0.76
Serious crimes	1.16	[1.11, 1.18]	0.89

$$1.1 \leq \beta \leq 1.3$$

PREDICTABLE CITIES

Data from 360 US metropolitan areas show that metrics such as wages and crime scale in the same way with population size.





What is a city but the people?

-William Shakespeare, Tragedy of Coriolanus

nature COMMUNICATIONS

ARTICLE

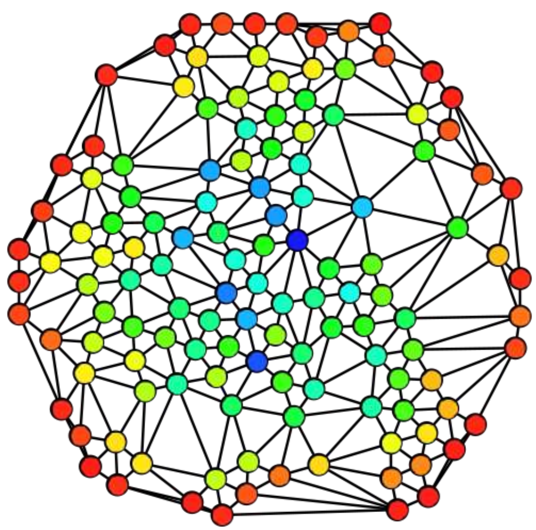
Received 4 Dec 2012 | Accepted 30 Apr 2013 | Published 4 Jun 2013

DOI: 10.1038/ncomms2961

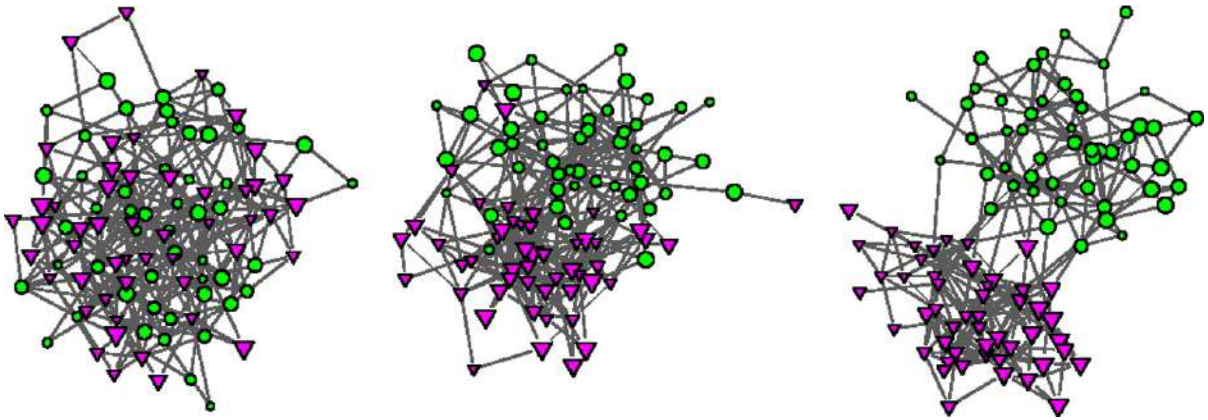
Urban characteristics attributable to density-driven tie formation

Wei Pan[1], Gourab Ghoshal[1,†], Coco Krumme[1], Manuel Cebrian[1,2,3] & Alex Pentland[1]

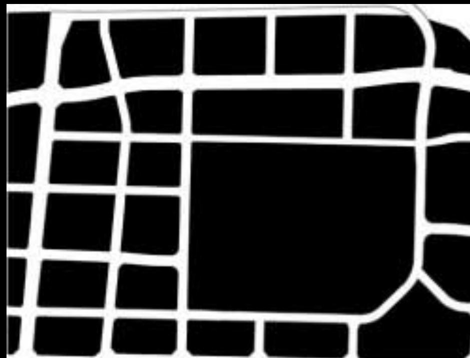
- **Generative theory** that **links** urban **geography** and **population density** and naturally reproduces scaling behavior found in urban data.
- The density of **social ties** is a scaffold on which rate of information exchange and interactions takes place.
- Thus this may well be **one** of the primary mechanisms behind innovation and productivity.



Limitations



- While the network is growing, it is static in the sense that there is no opportunity to reshape links.
- Relations are treated homogenously, in the sense that no differentiation based on social, functional, commuting behavior.
- Most importantly the predictions of the model fail when compared to economic data from developing countries.

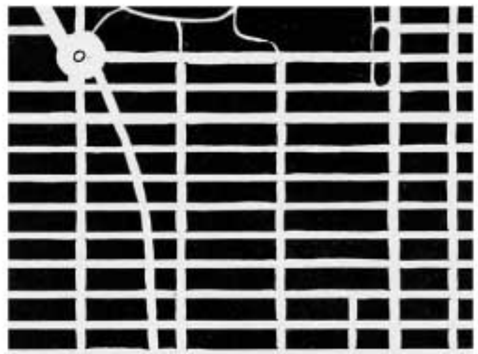


MISSISSAUGA

BARCELONA

COPENHAGEN

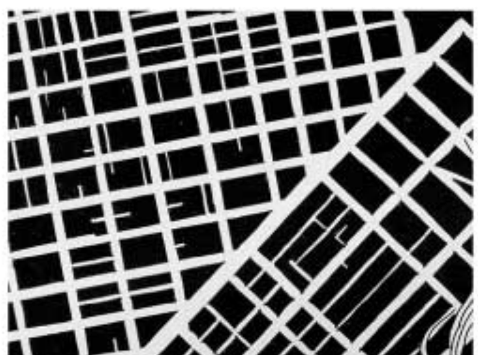
LONDON



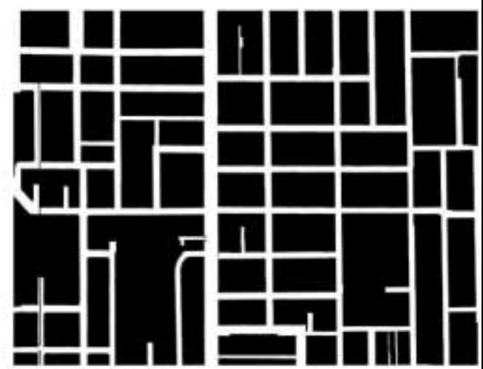
NEW YORK

PARIS

ROME



SAN FRANCISCO



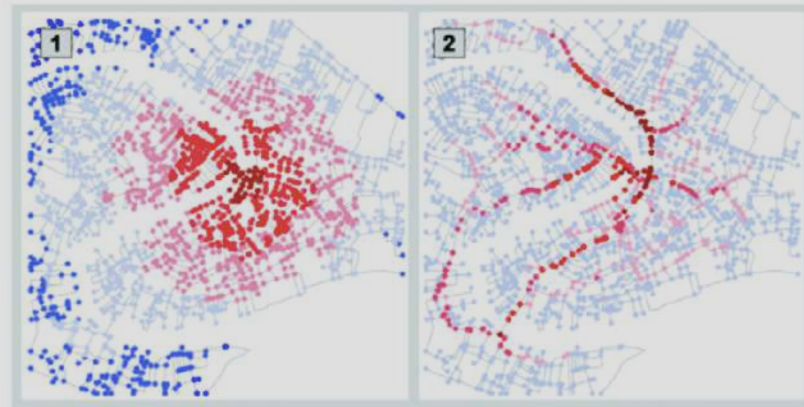
TORONTO

Urban Street networks

Fractal structure

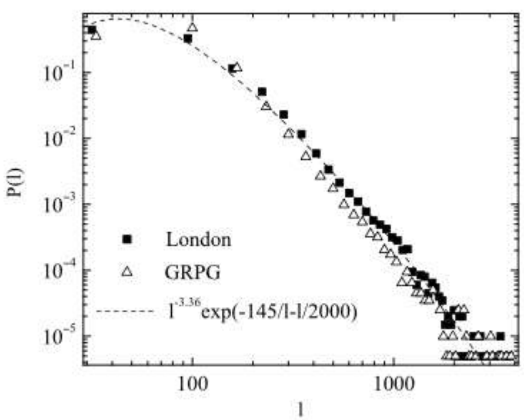
R. Murcio el al. (2015) PRE

Street network analysis



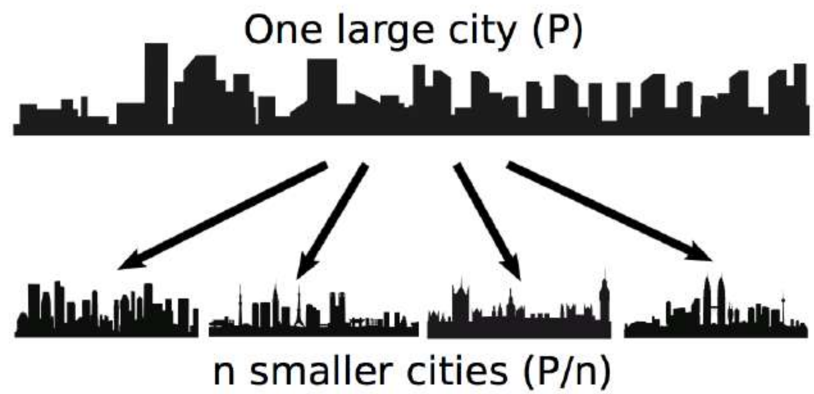
Crucitti et al. (2006) PRE

Statistical properties



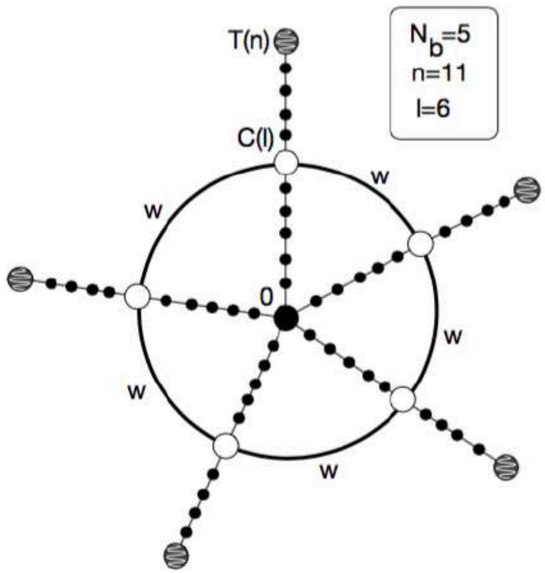
Masucci (2009) Eur. Phys. J. B

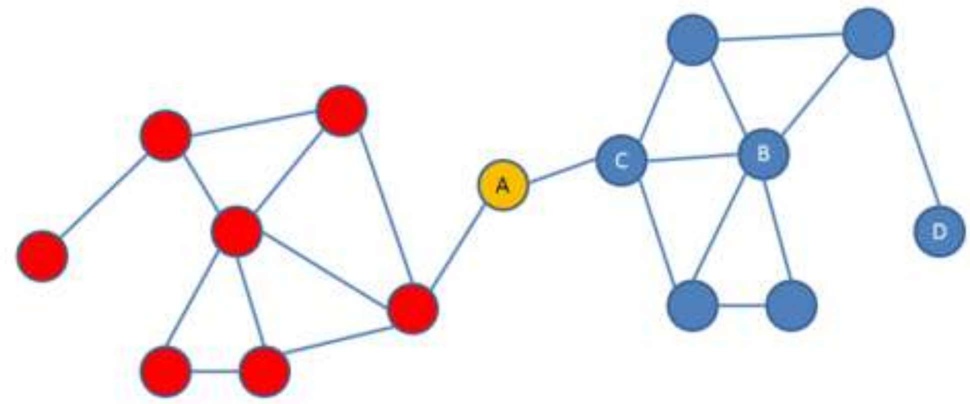
Polycentric or monocentric

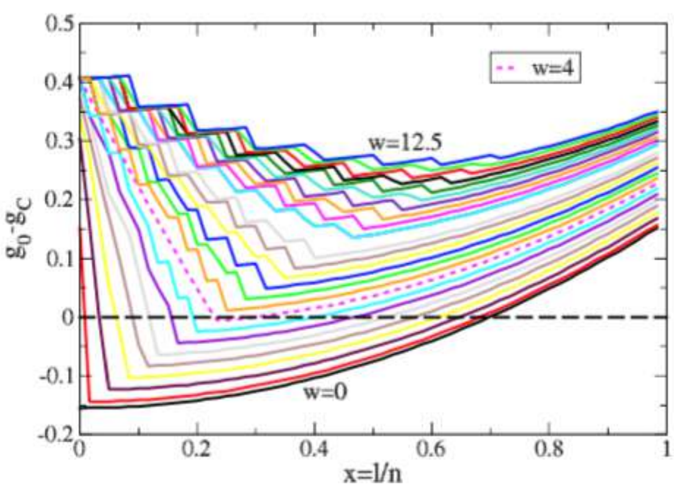


R. Loufand M. Barthelemy (2014) Scientific report

Betweenness Centrality







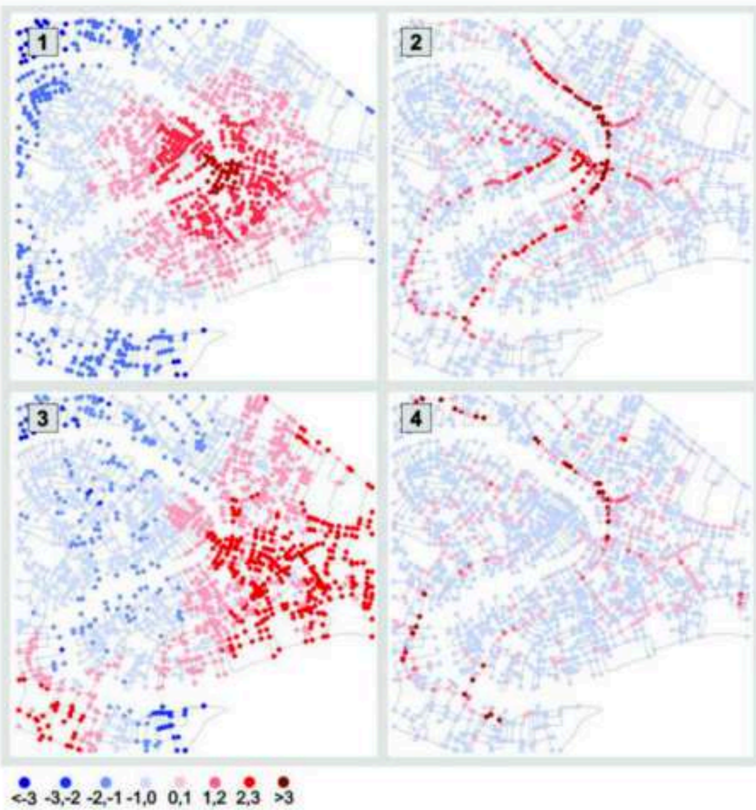
$$g_B(v) = \mathcal{N} \sum_{s,t \in G} \frac{\sigma_{st}(v)}{\sigma_{st}}$$

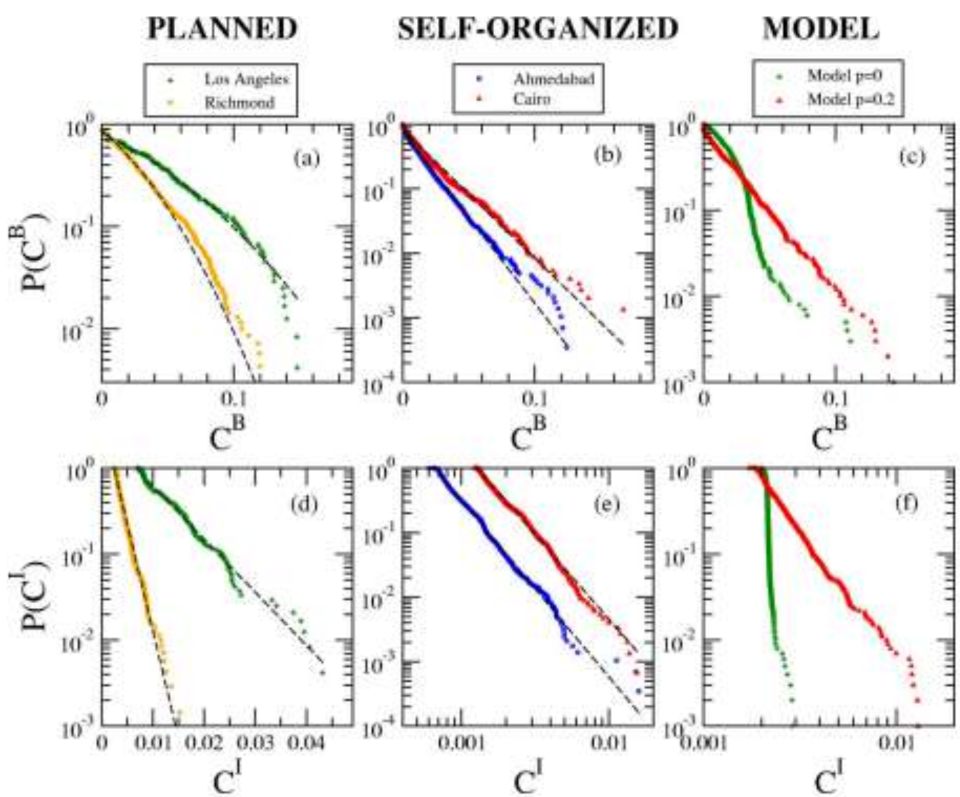
B. Lion and M. Barthelemy, *Betweenness centrality patterns in random planar Graphs,* arXiv:1611.03232

PHYSICAL REVIEW E **73**, 036125 (2006)

Centrality measures in spatial networks of urban streets

Paolo Crucitti,[1] Vito Latora,[2] and Sergio Porta[3]
[1]*Scuola Superiore di Catania, Italy*
[2]*Dipartimento di Fisica e Astronomia, Università di Catania, and INFN Sezione di Catania, Italy*
[3]*Dipartimento di Progettazione dell'Architettura, Politecnico di Milano, Italy*
(Received 20 October 2005; published 24 March 2006)

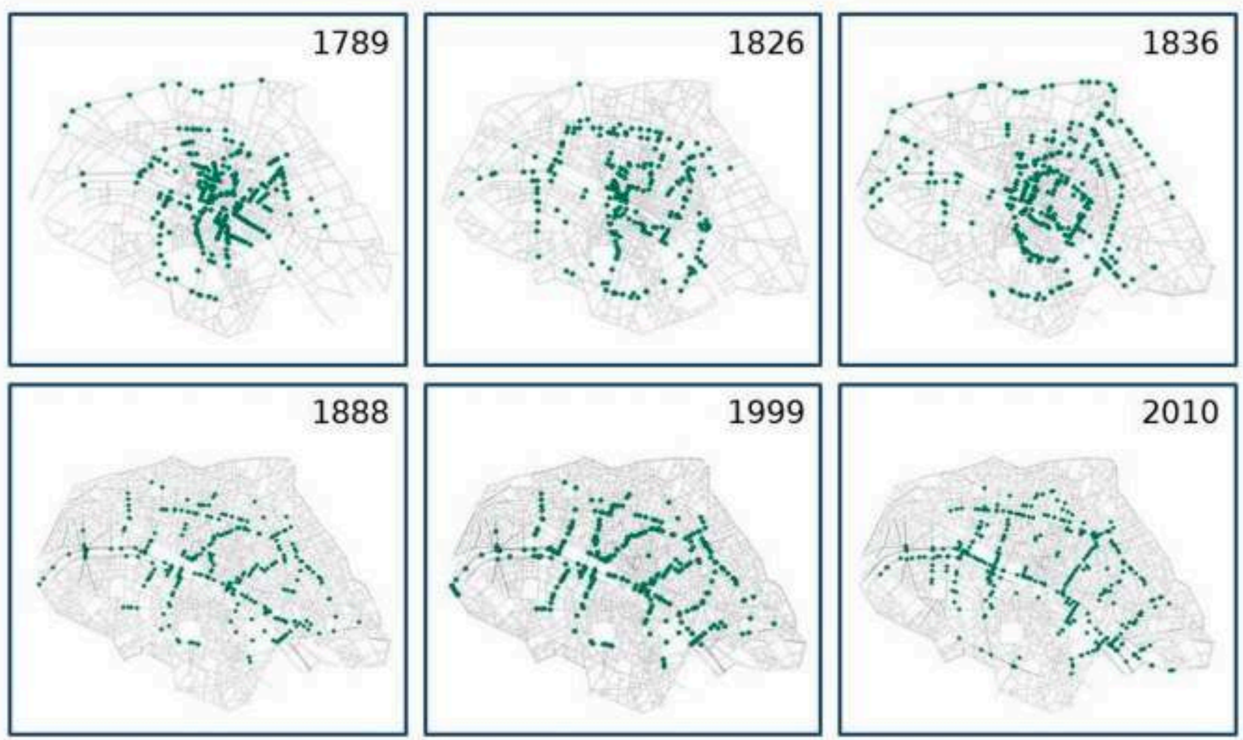




Article | OPEN

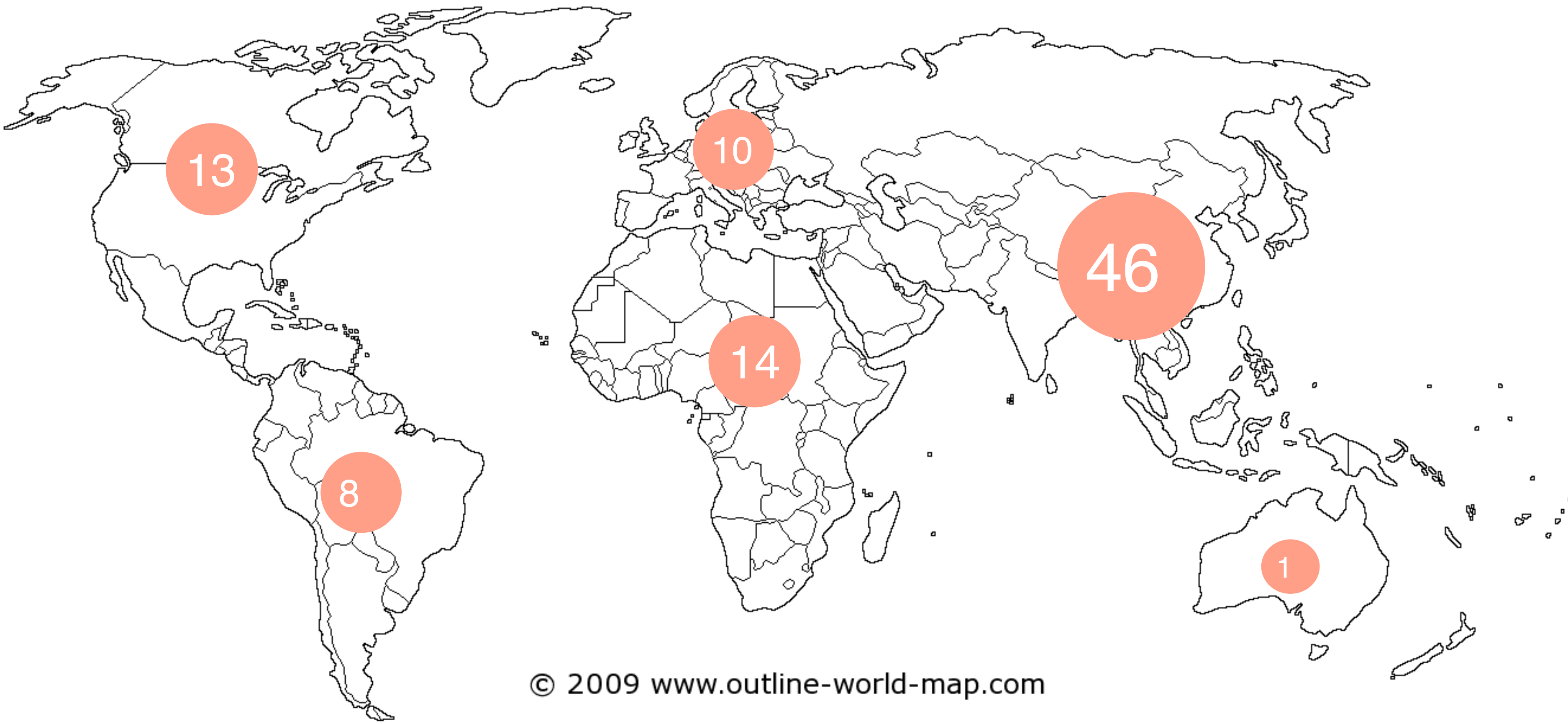
Self-organization versus top-down planning in the evolution of a city

Marc Barthelemy, Patricia Bordin, Henri Berestycki & Maurizio Gribaudi

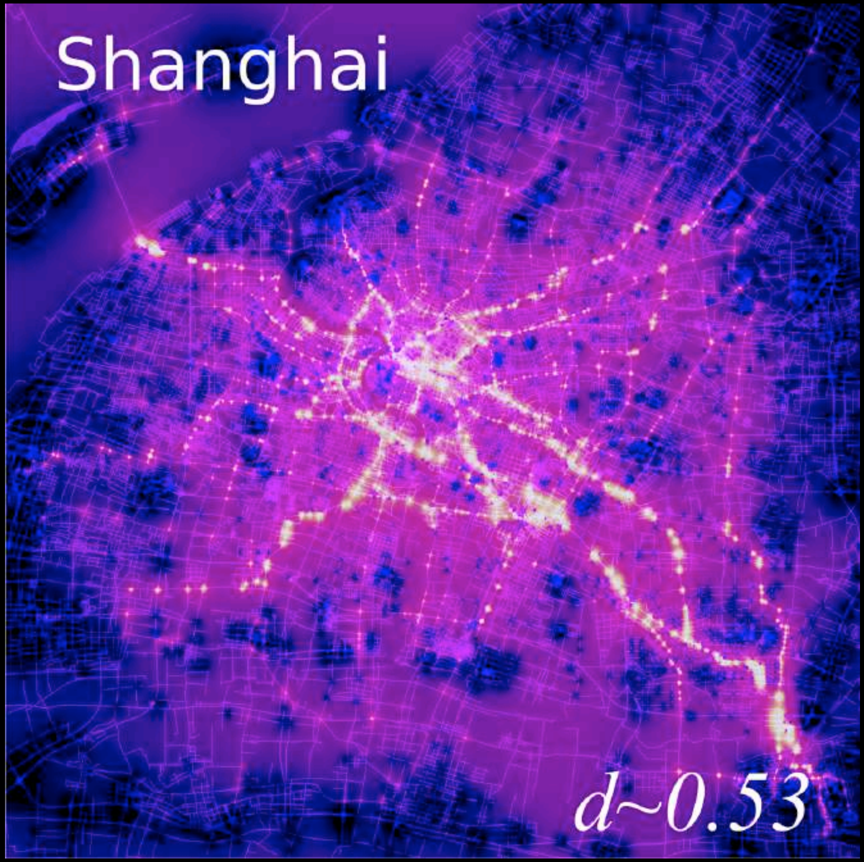


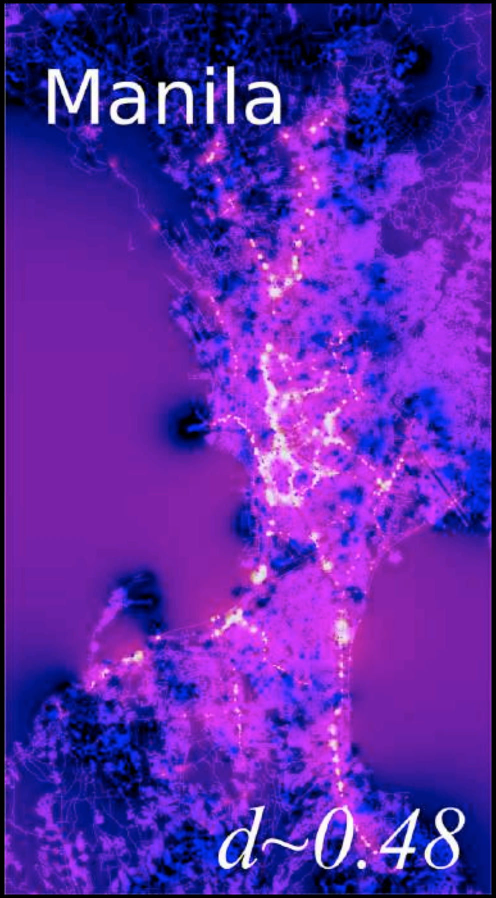
Data Source

OpenStreetMap API
92 most populous cities

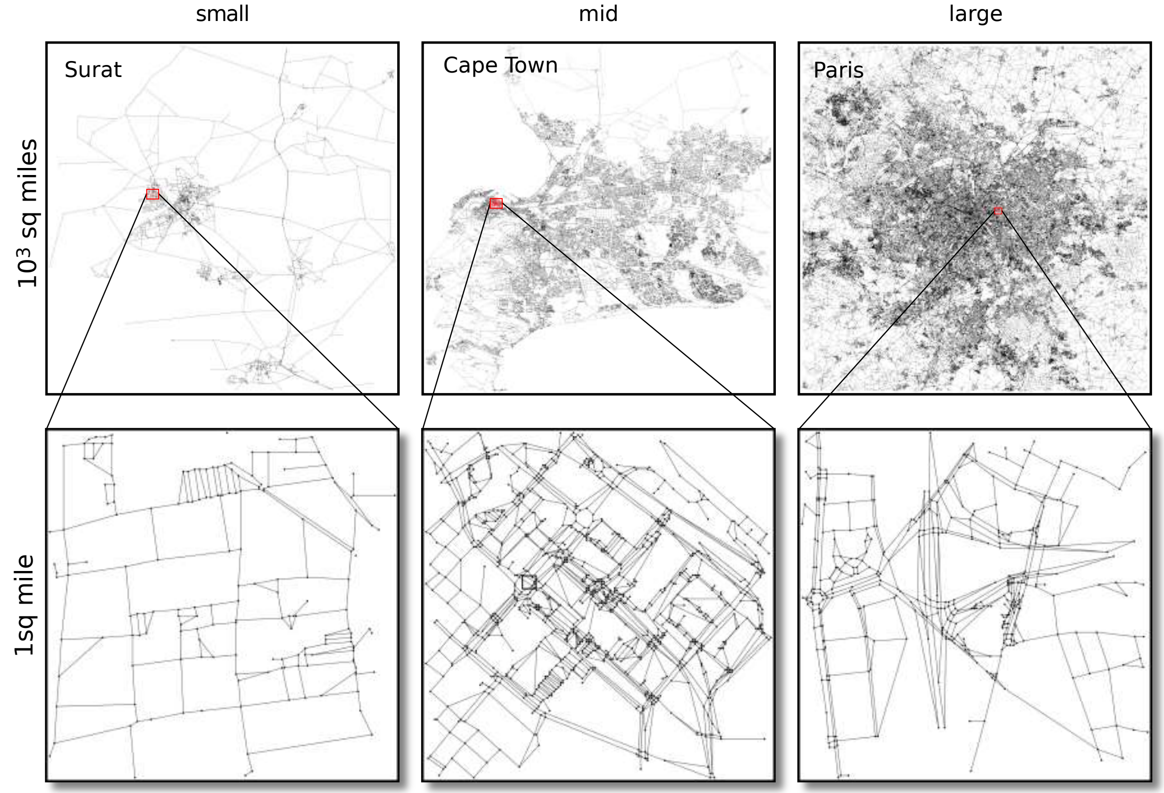


Betweenness distribution of cities



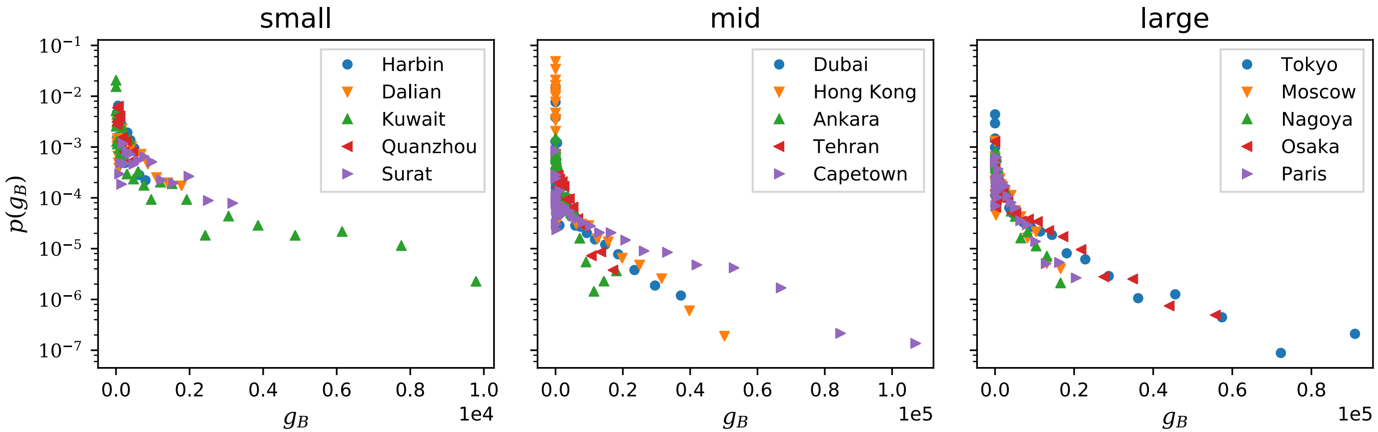


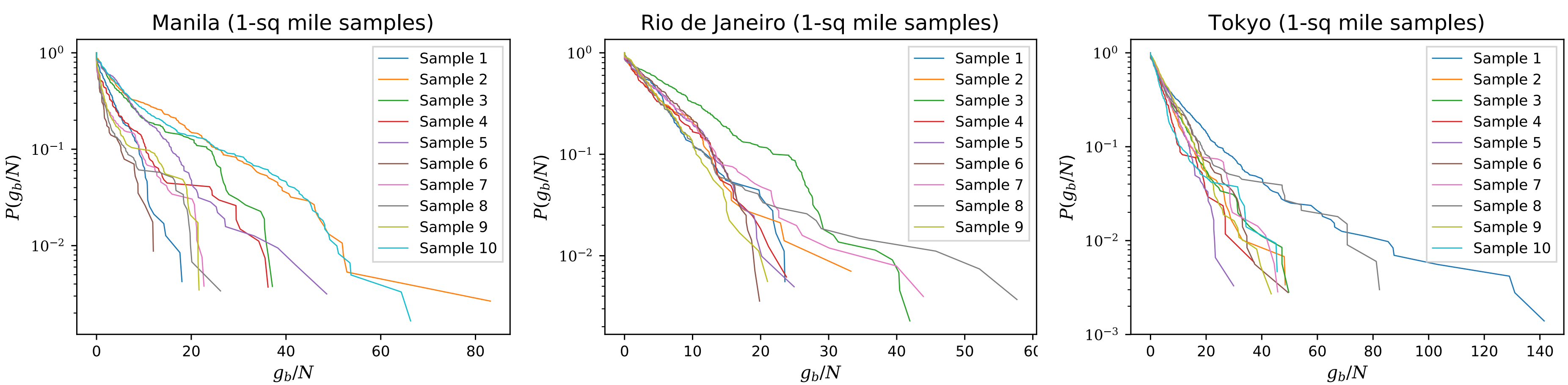
Street network statistics



	Area A(sq miles)	Nodes N	Length ℓ (miles)	Density ρ	Edges e
mean	1776	83529	10850	46	130253
stdev	744	90335	9353	40	143060
min	300	3349	1114	3	5020
25%	1229	18925	3597	14	28518
50%	1703	62451	7961	39	95797
75%	2268	118712	14758	69	178773
max	4464	612418	51316	242	976040

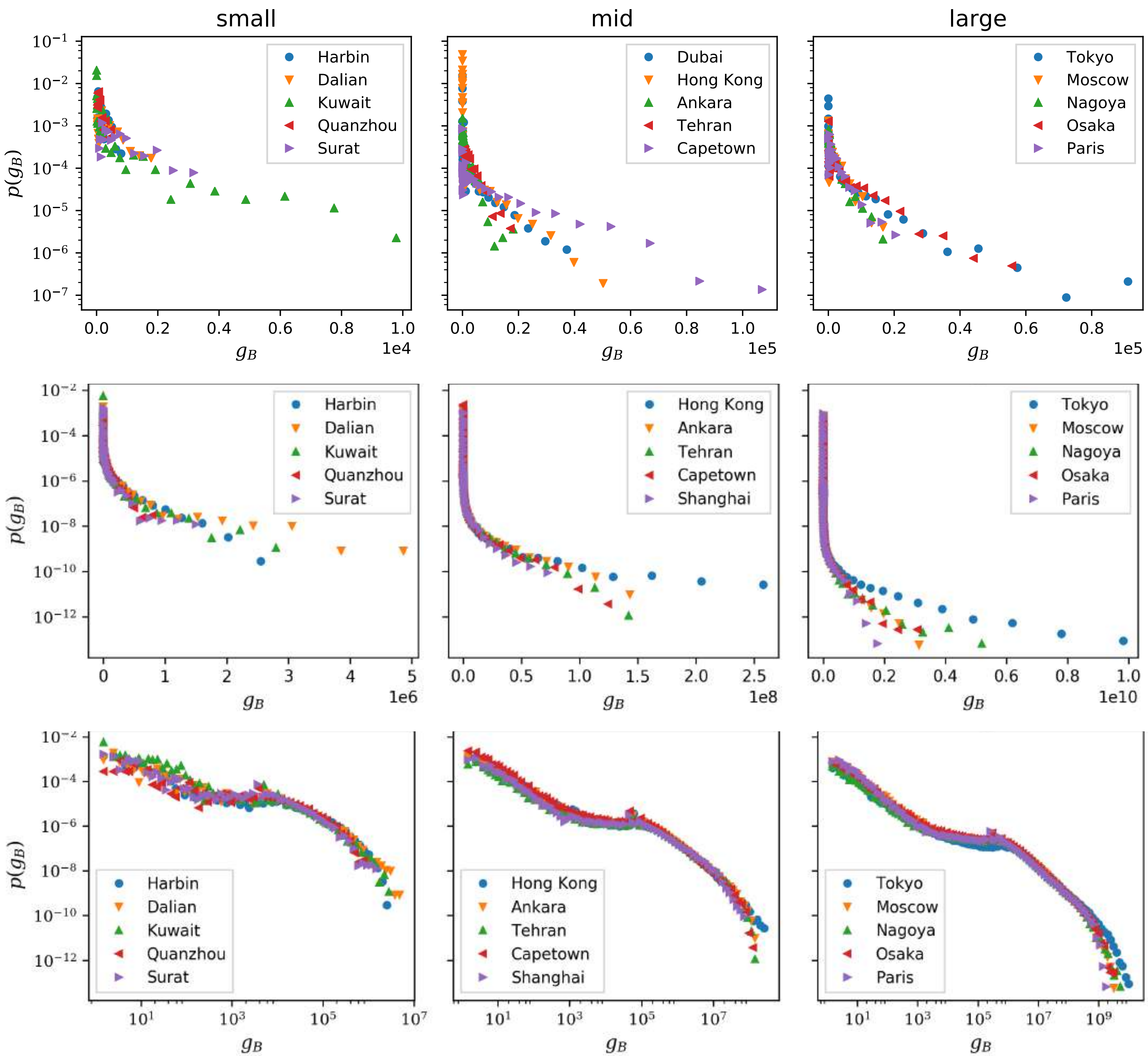
Betweenness (1 sq. mile)



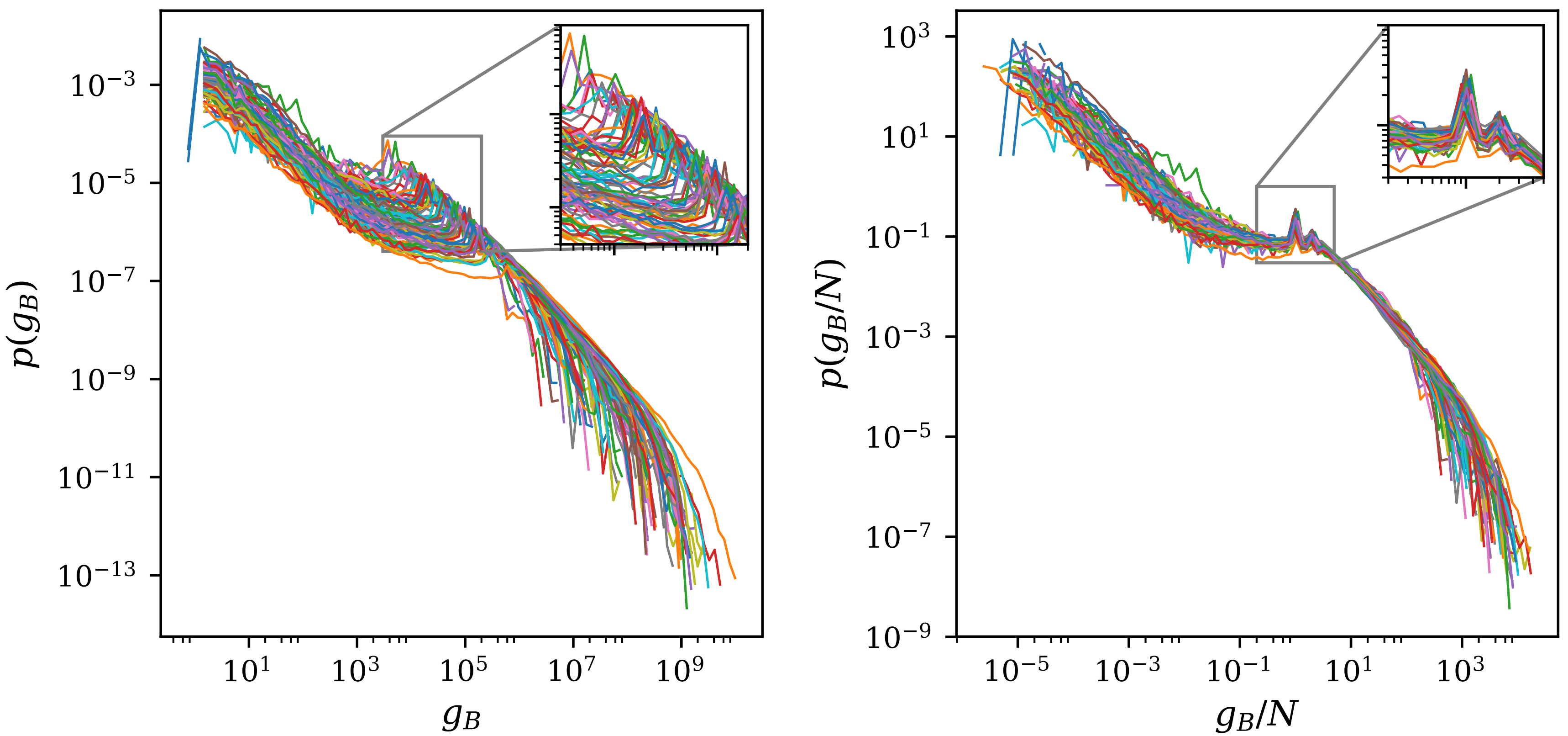


P. Crucitti, V. Latora and S. Porta, *Phys. Rev. E* **73** 036125 (2006)

Betweenness (different scales)

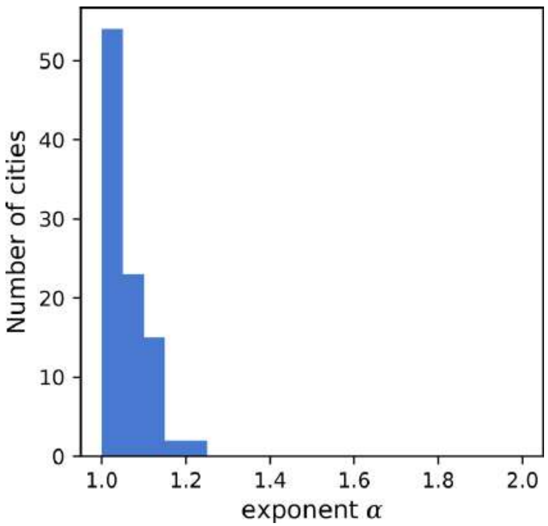


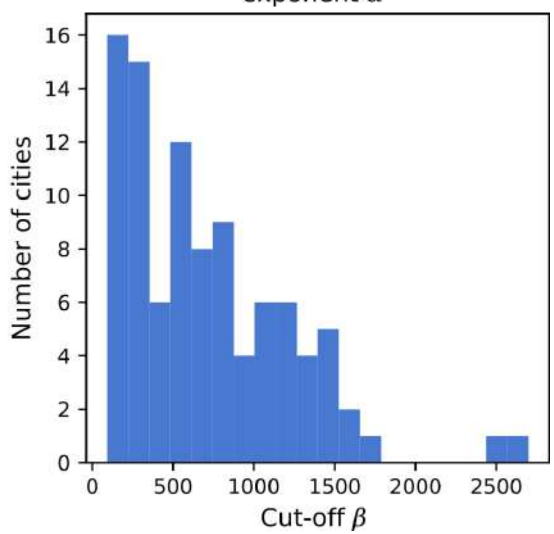
Betweenness (1000 sq. miles)

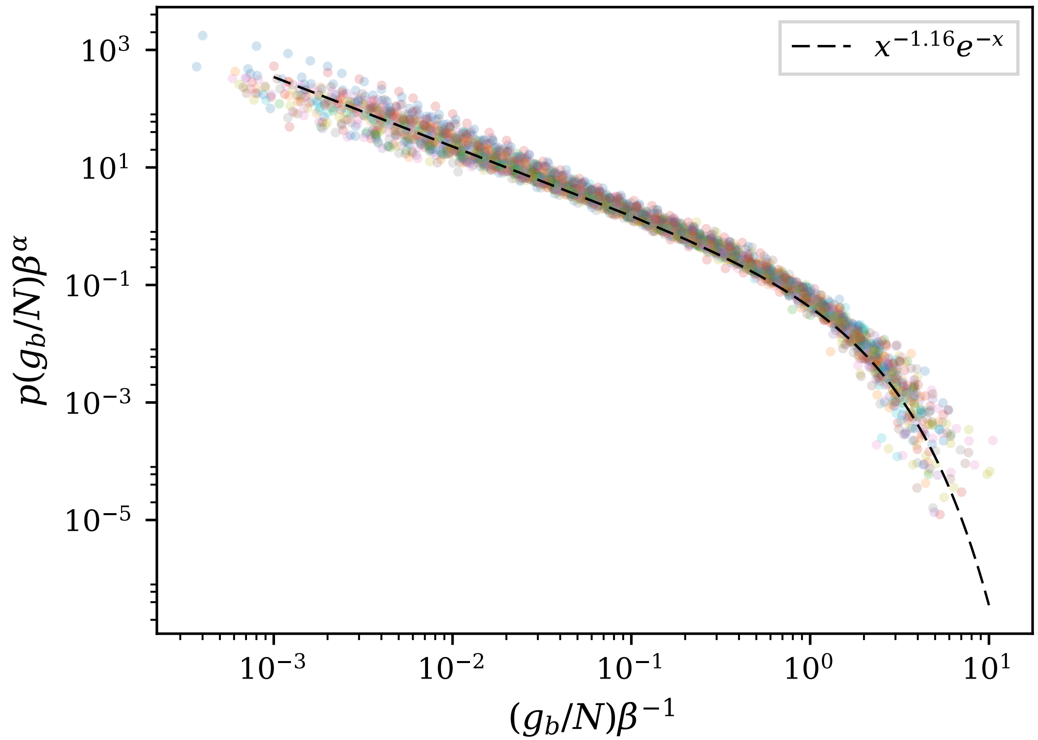


Betweenness invariance

Truncated power law: $p(\tilde{g}_B) \sim \tilde{g}_B^{-\alpha} e^{-\tilde{g}_B/\beta}$



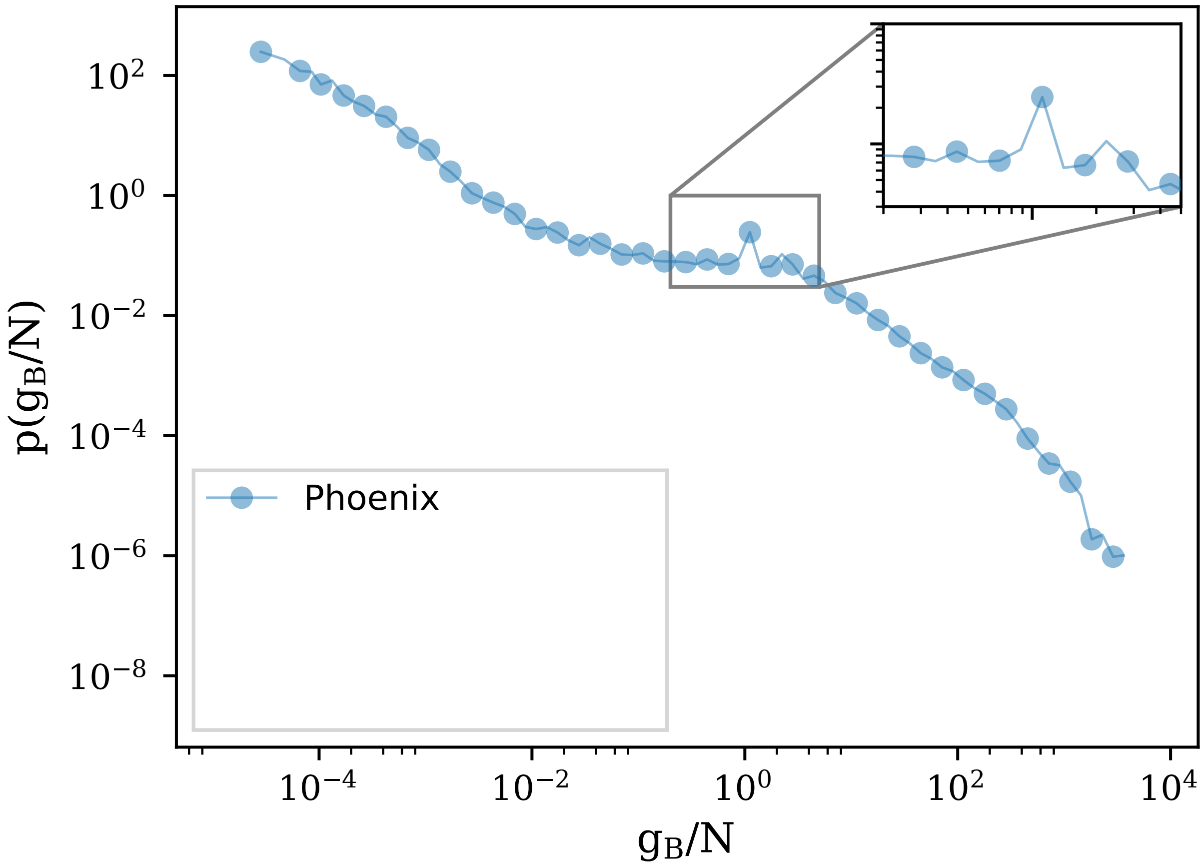




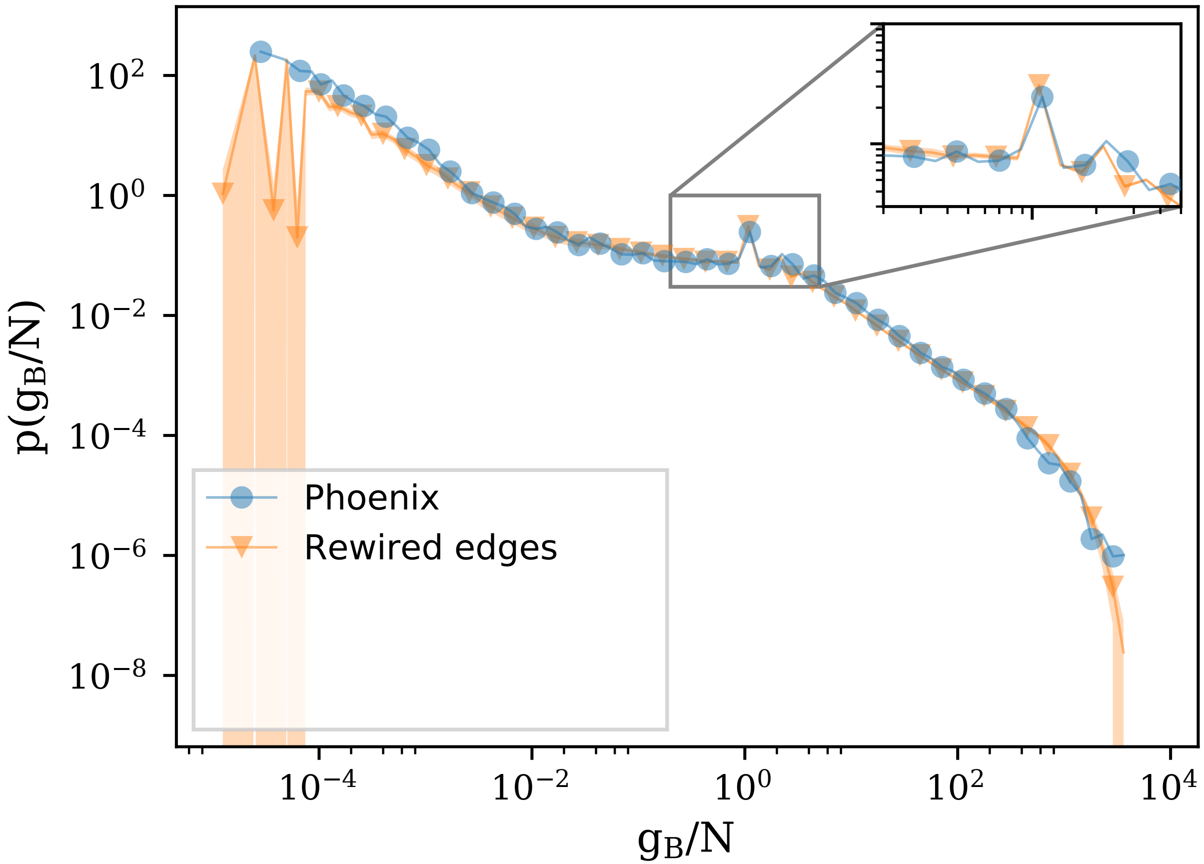
After appropriate re-scaling, Betweenness distribution for all cities look the same!

What are the factors behind this remarkable invariance?

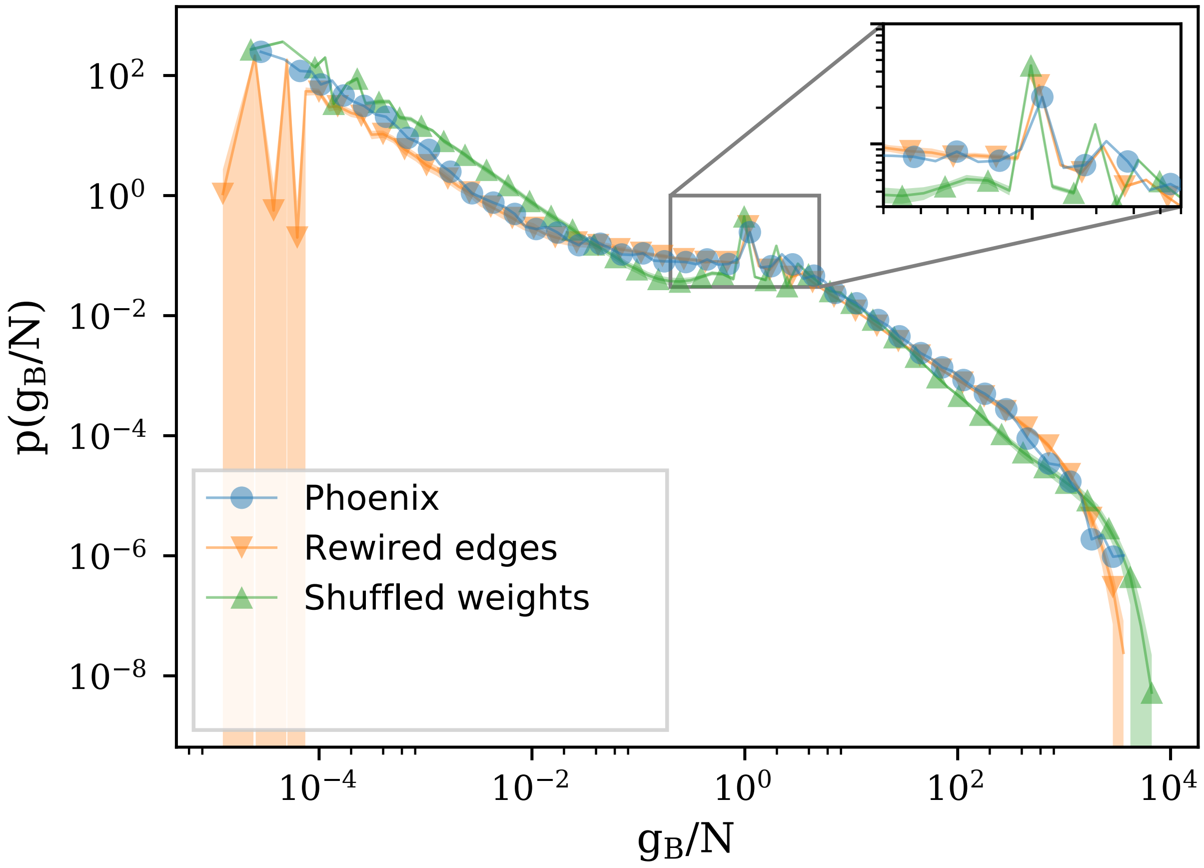
Random planar graphs



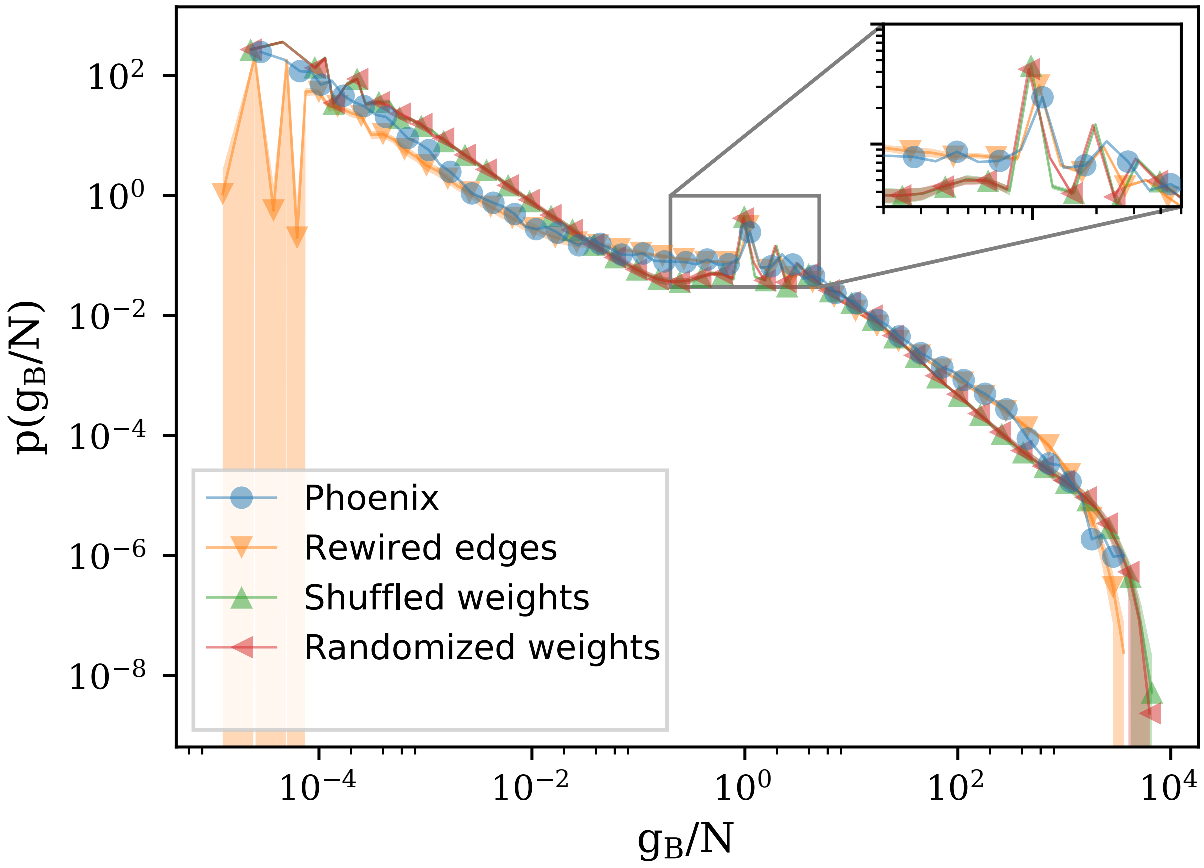
Random planar graphs



Random planar graphs



Random planar graphs



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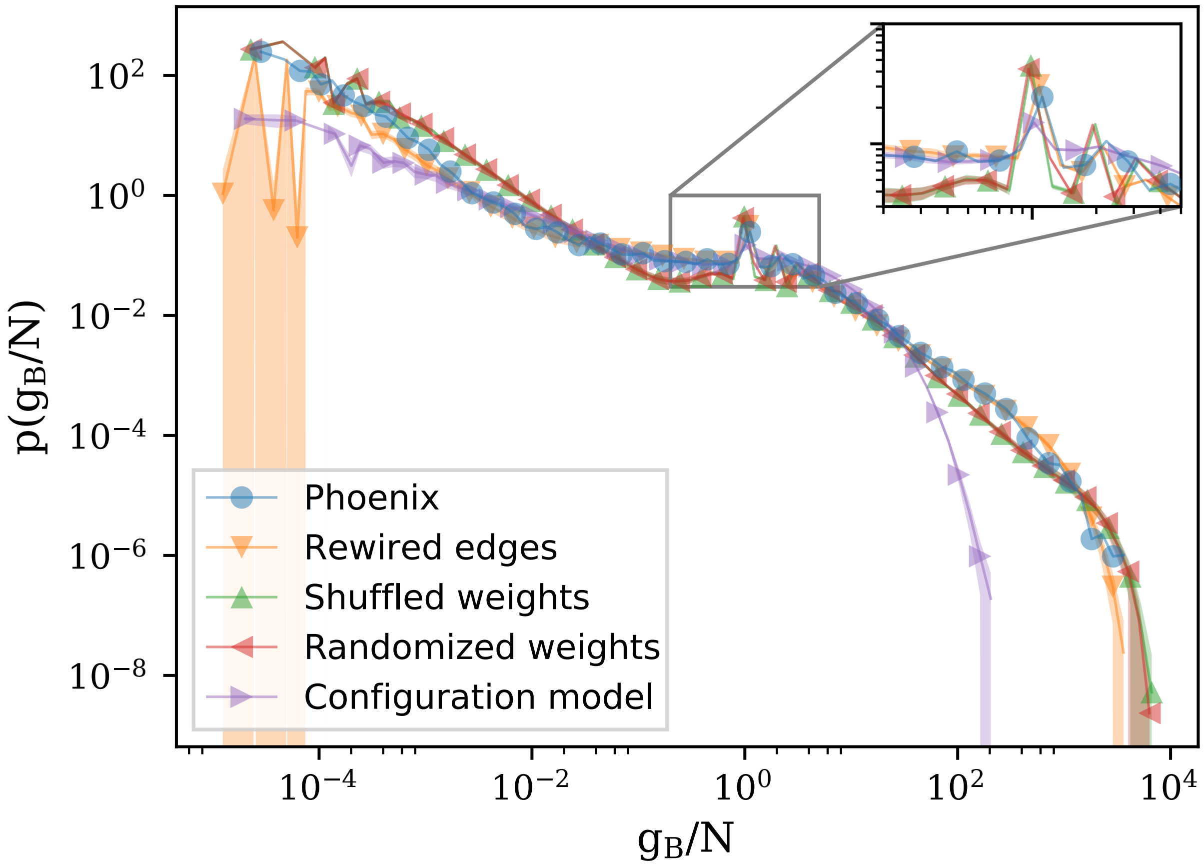
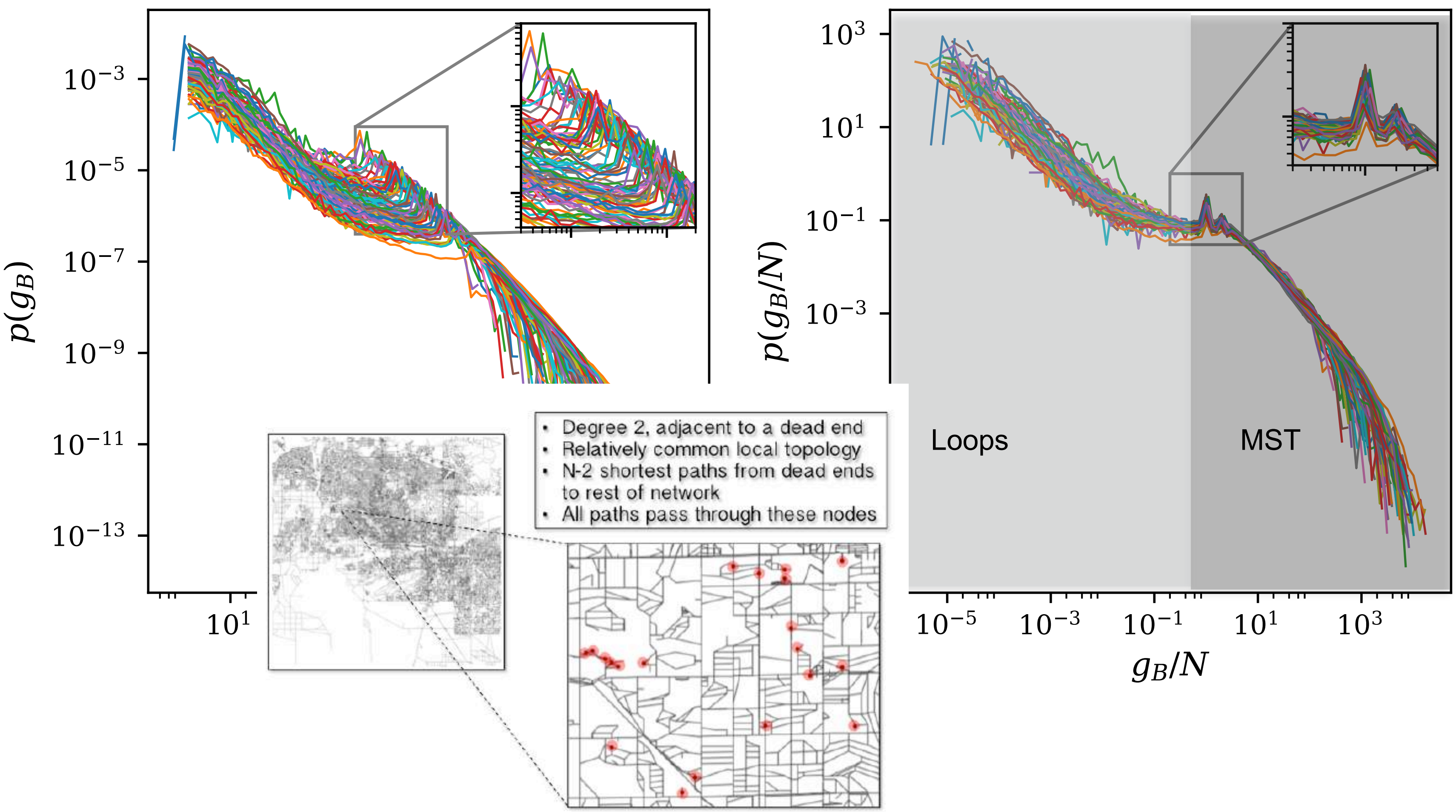


$P(g_B)$ only specified by planarity, number of intersections N and roads e!

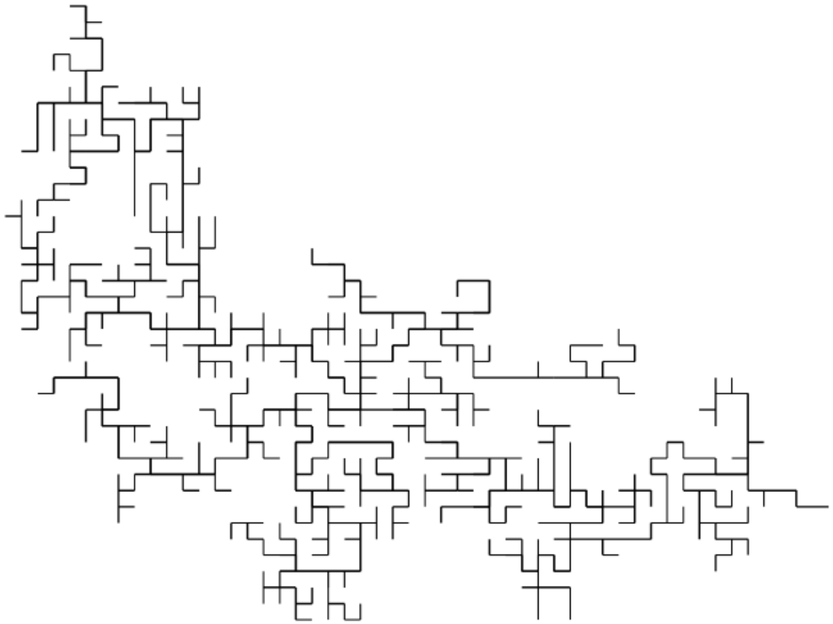
Explanation for bimodality and Size-scaling?

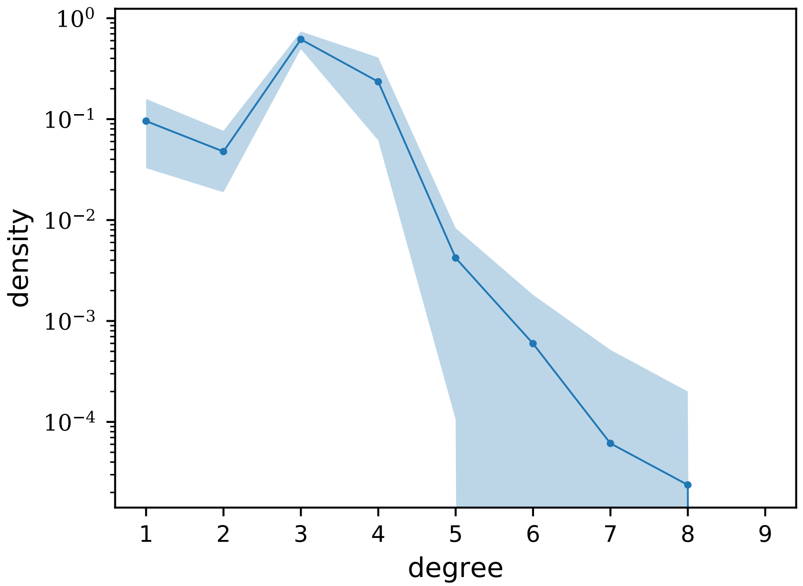
Betweenness (1000 sq. miles)



Quasi-analytical description

K-ary Tree (Cayley) approximation





Nodes N
Vertex v
Branching-ratio k
Depth l
Leaf-level L

$$g_b(v|k,l) \sim O\left(Nk^{L-l}\right)$$

$$P\left(g_b(v|k,l)\right) \sim \frac{k^l}{N}$$

$$P(g_b/N) \sim \left(\frac{g_b}{N}\right)^{-1-\frac{1}{L-l}}$$

How does one explain the low betweenness regime?

Effect of loops

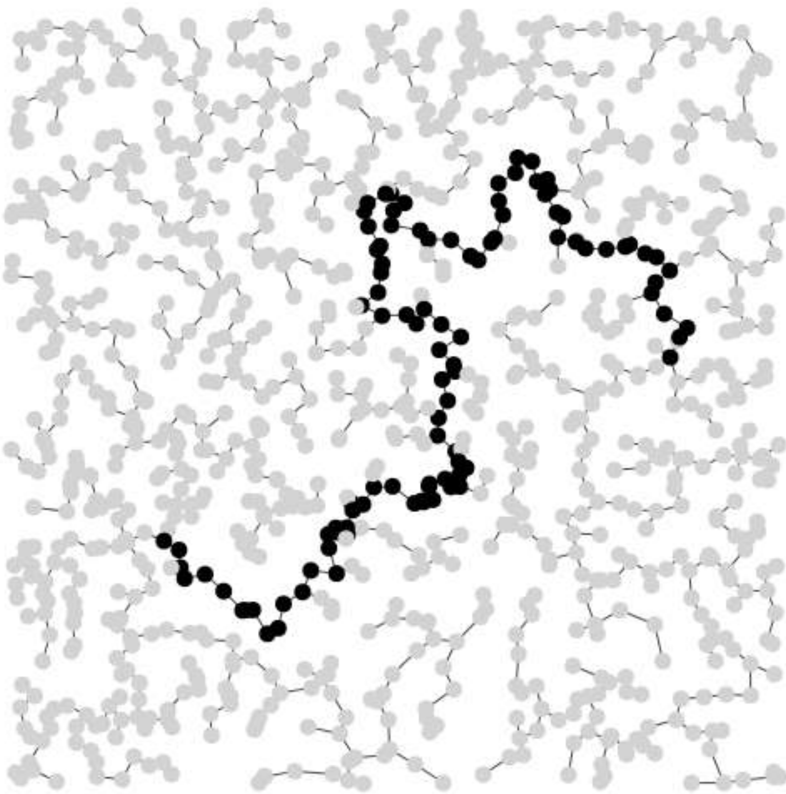
Effect of Edge-Density

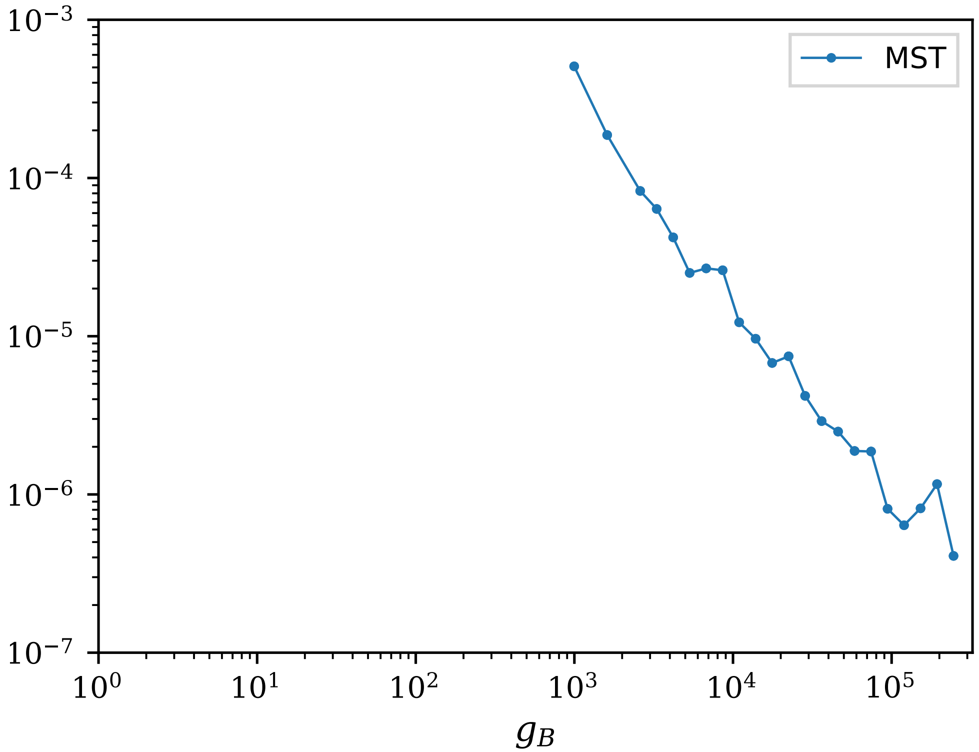
Euler's formula

$$N - e + f = 2$$

Edge Density

$$d_e = \frac{e}{e_{DT}}$$





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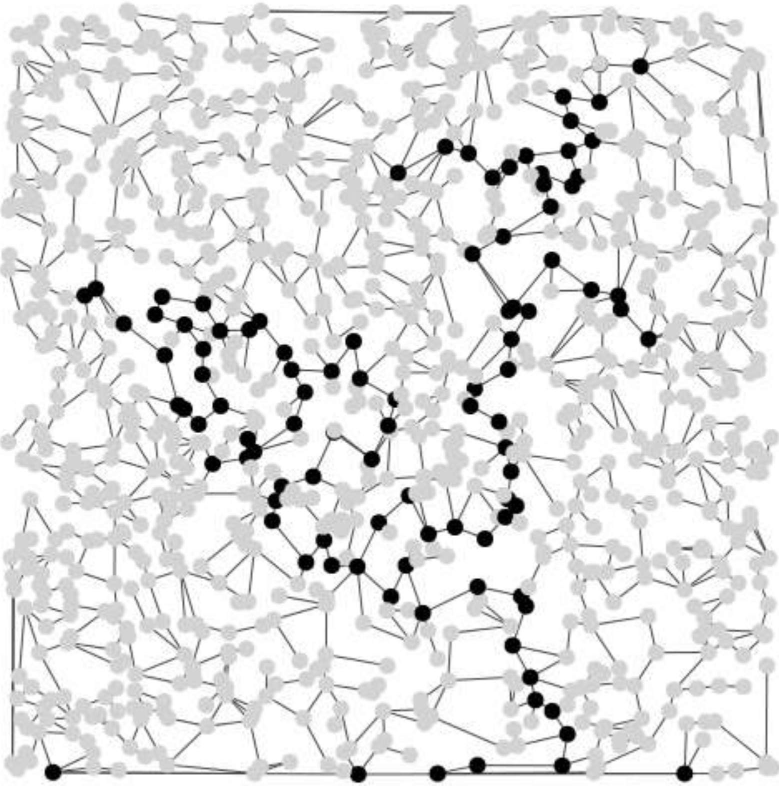

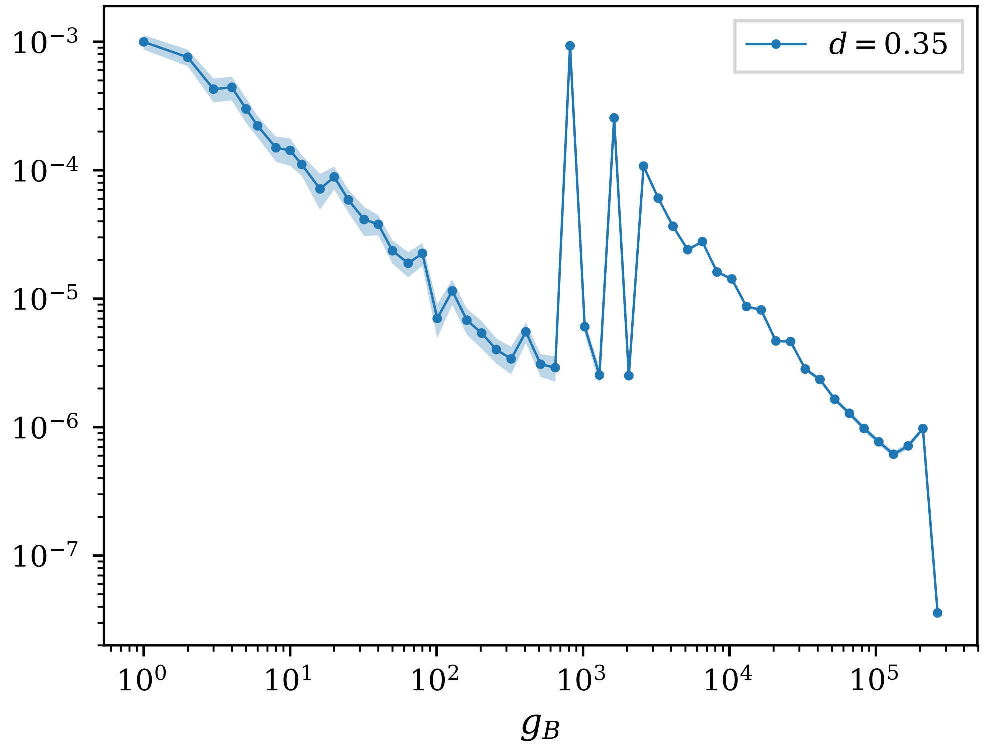

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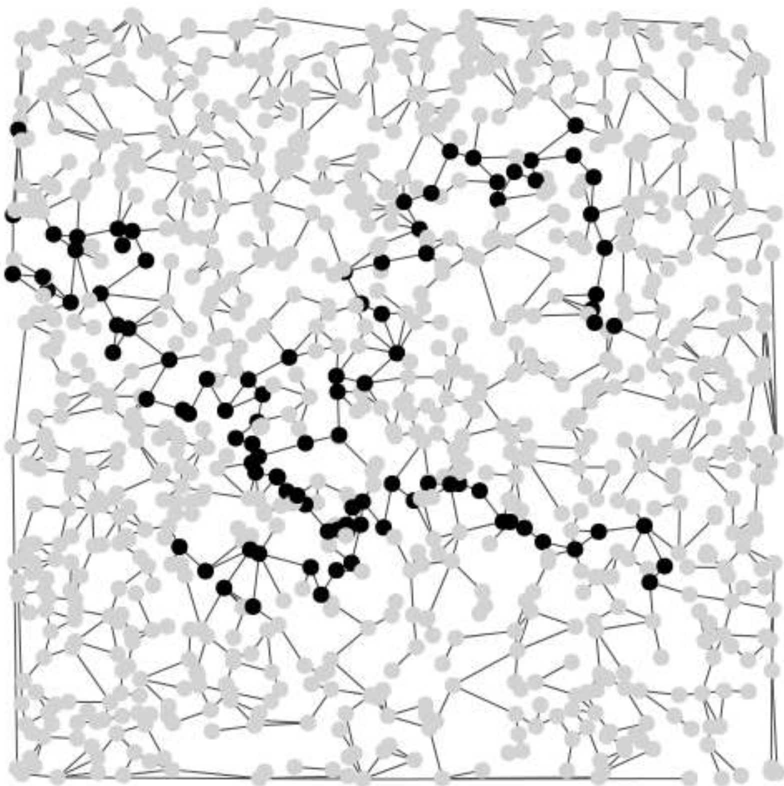

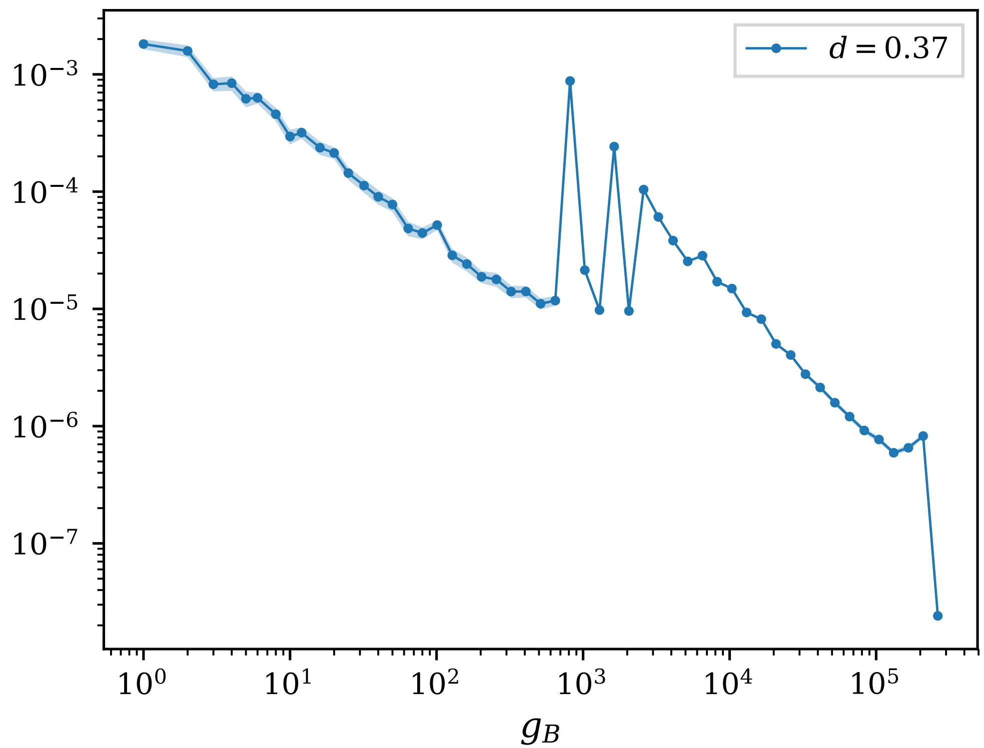

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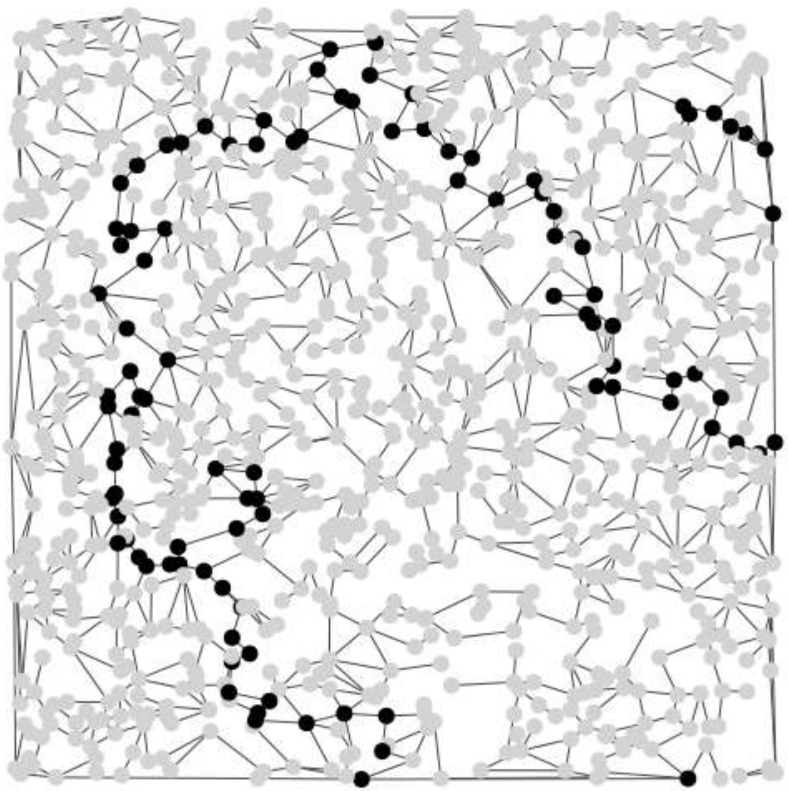

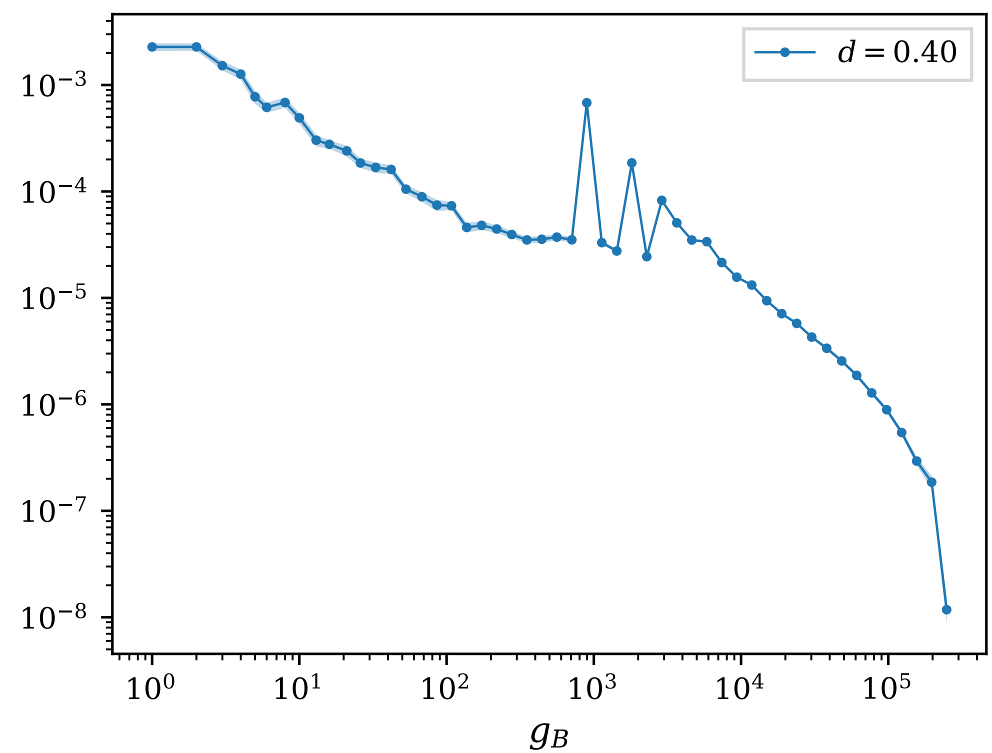

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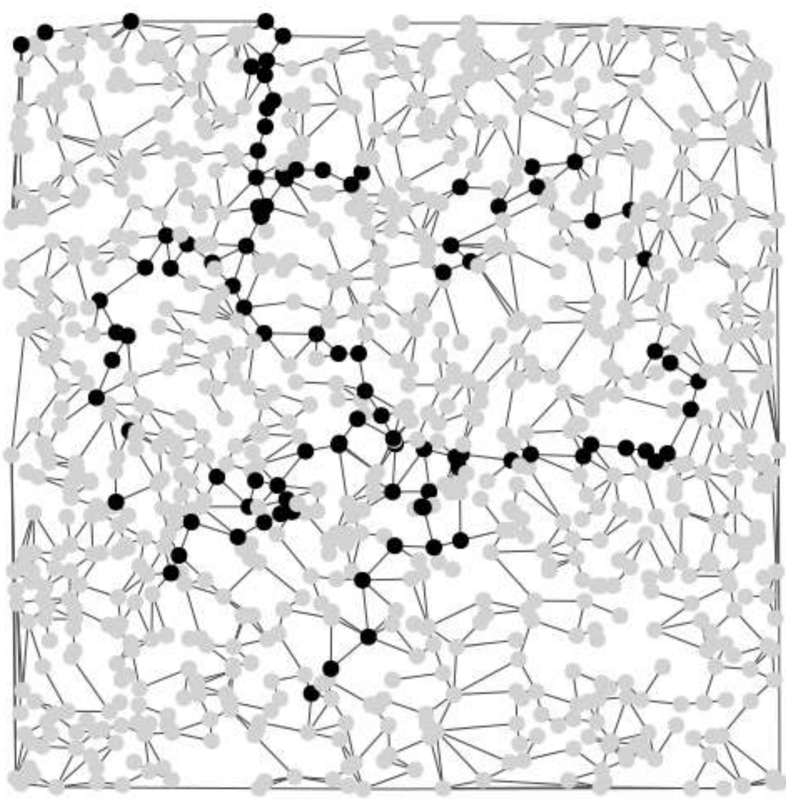

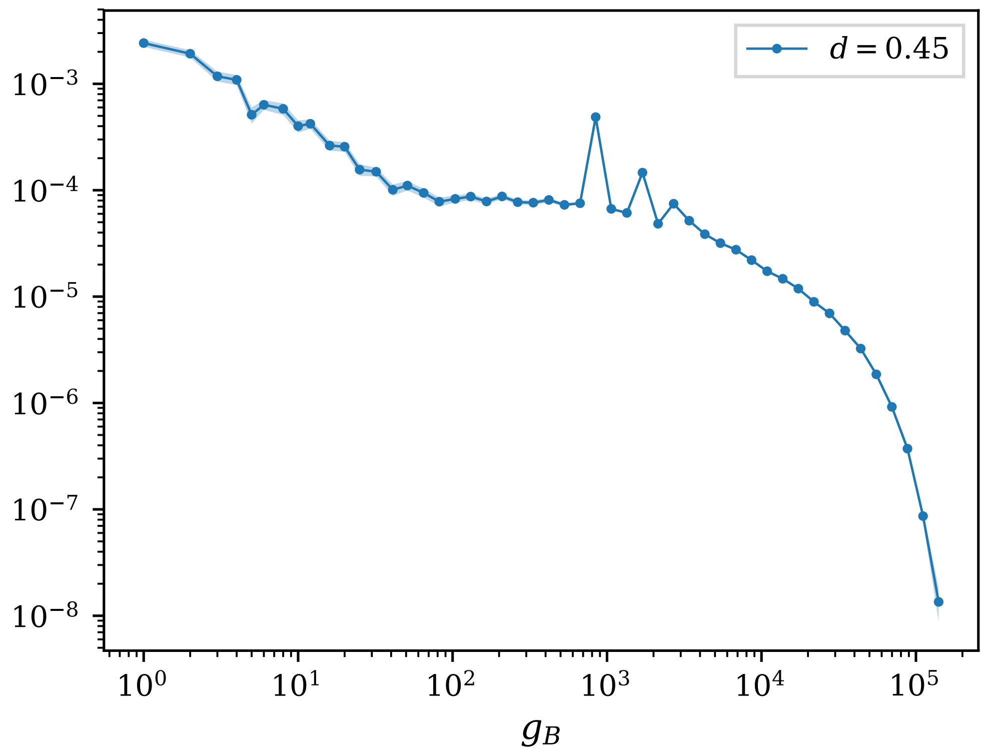

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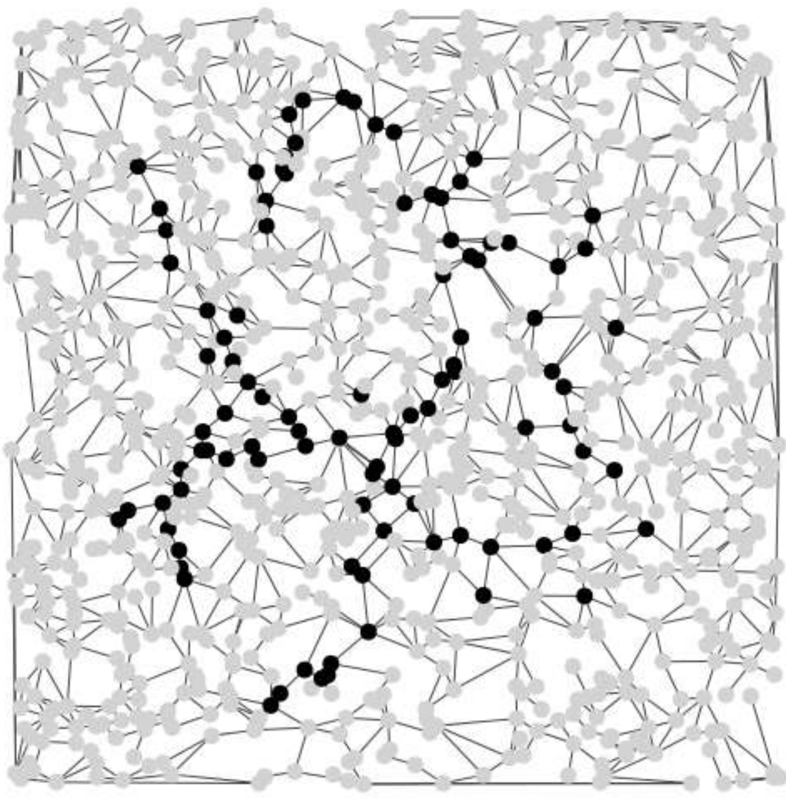

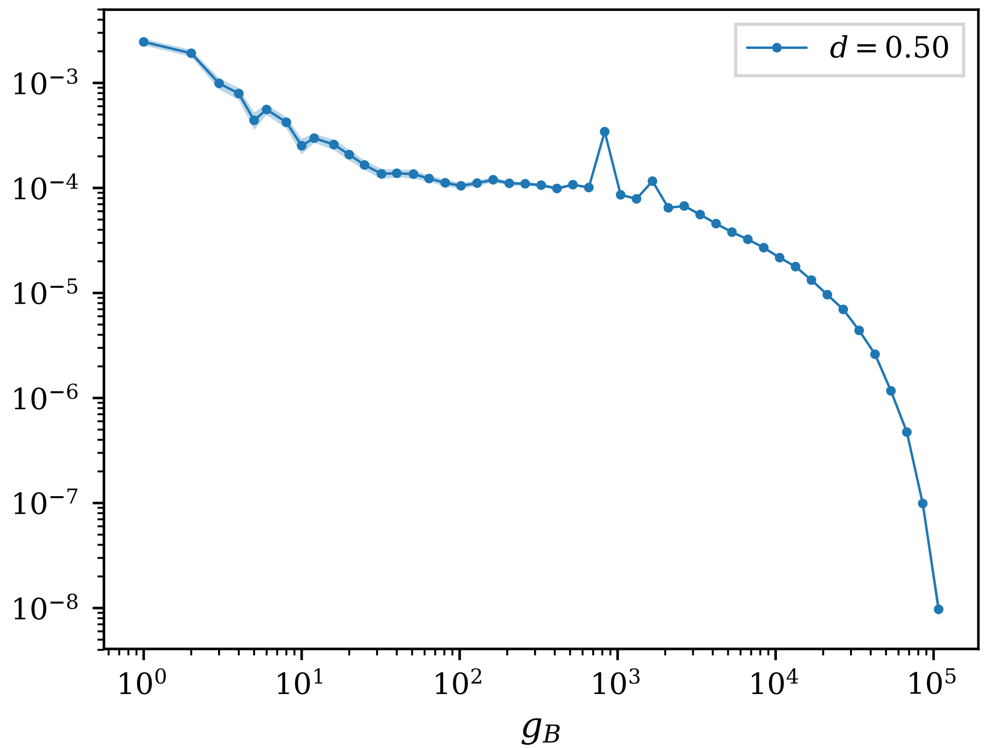

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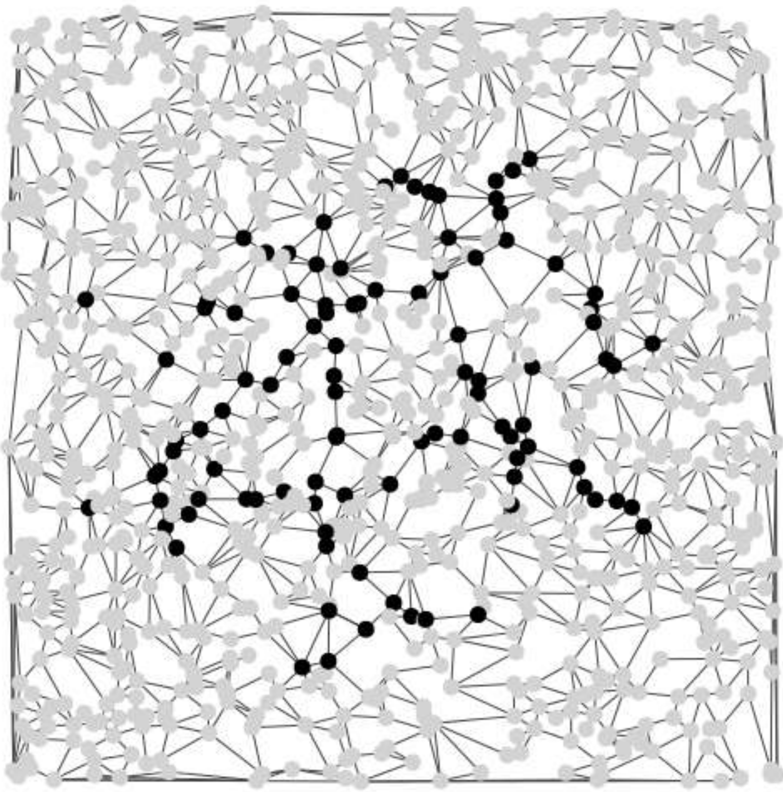

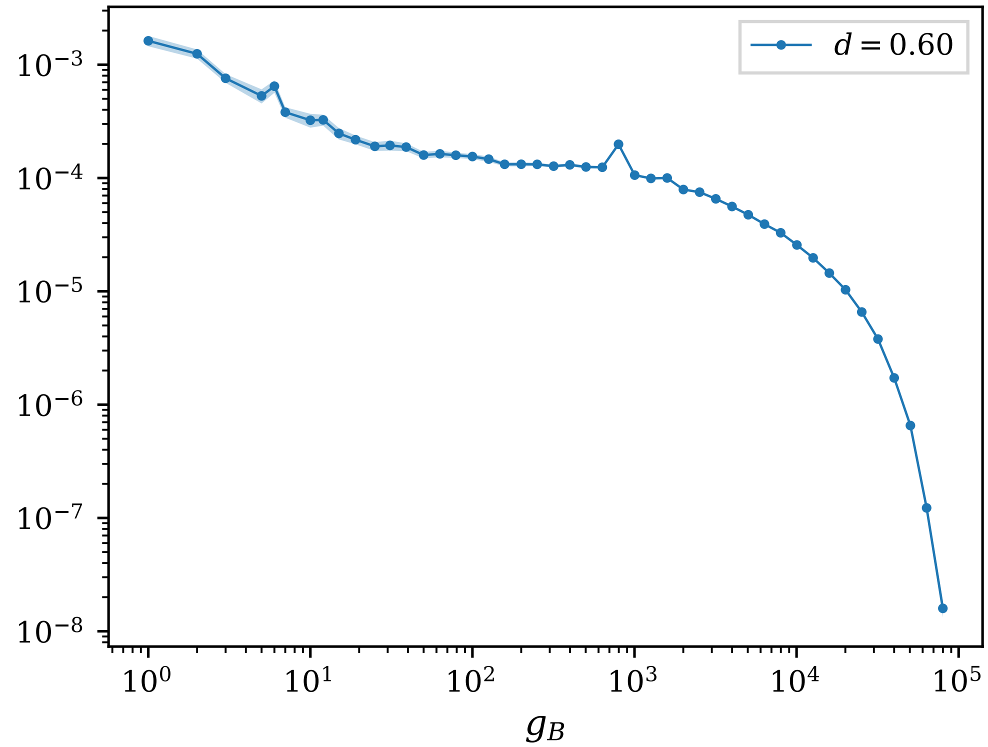

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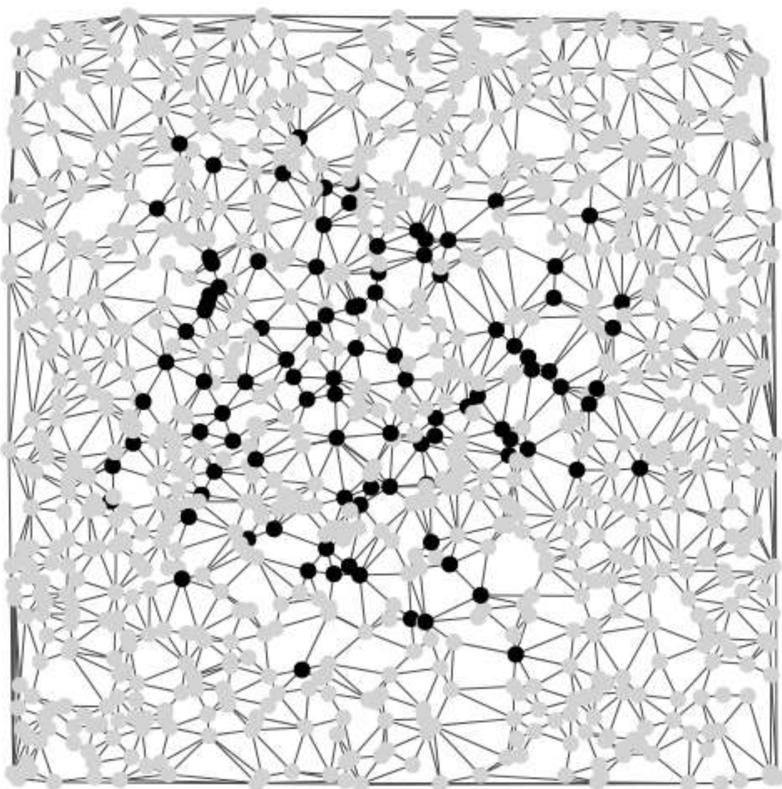
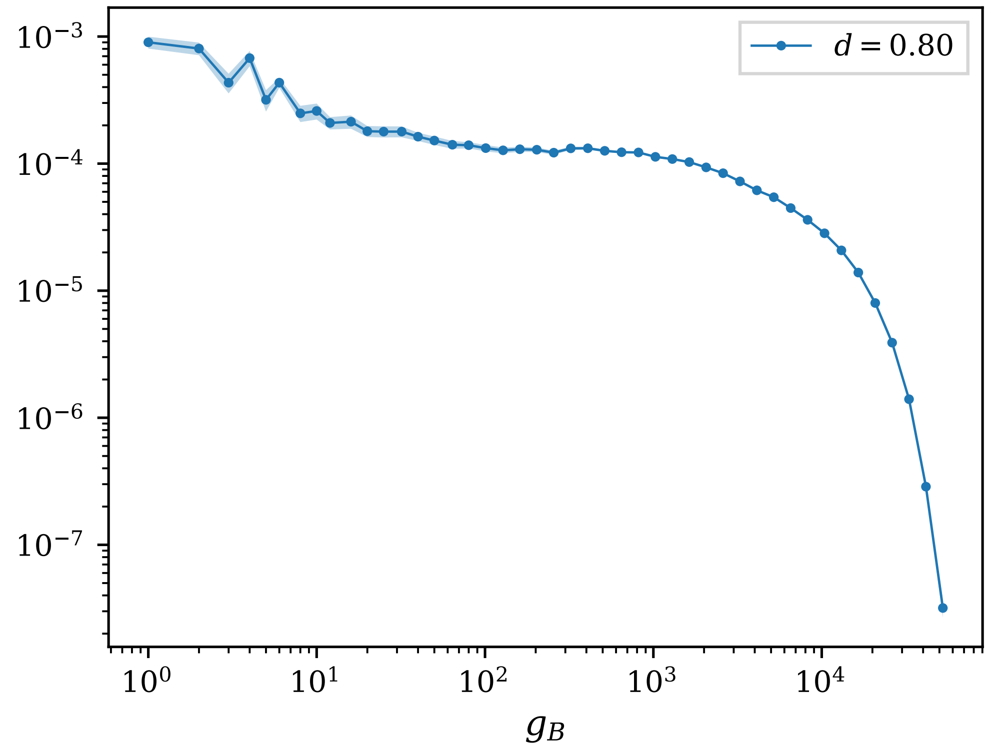
$$d_e = \frac{e}{e_{DT}}$$





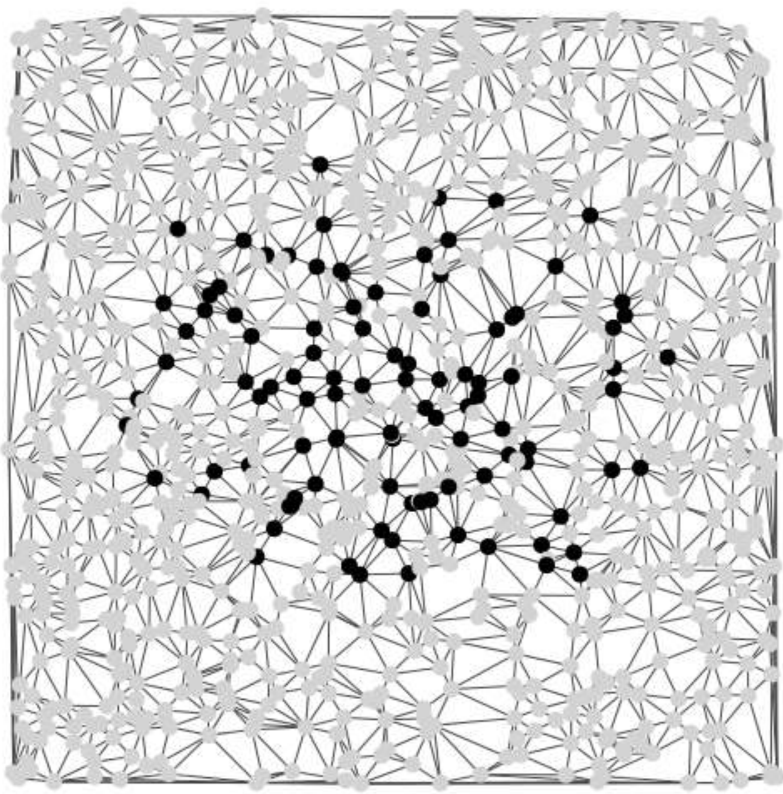
Effect of Edge-Density

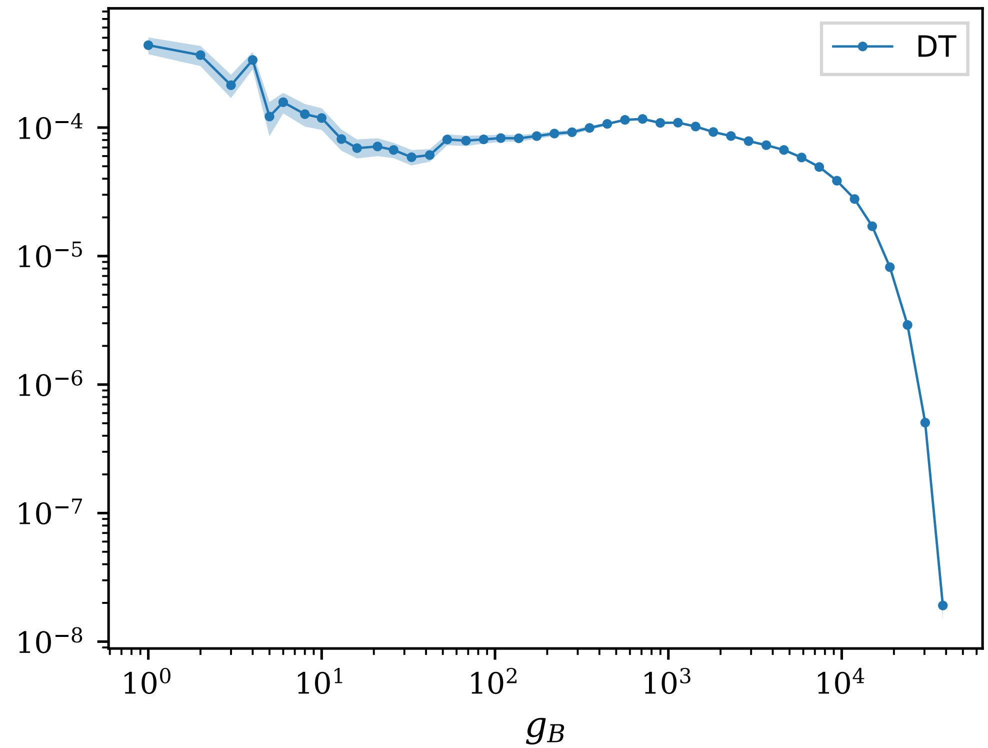
Euler's formula

$$N - e + f = 2$$

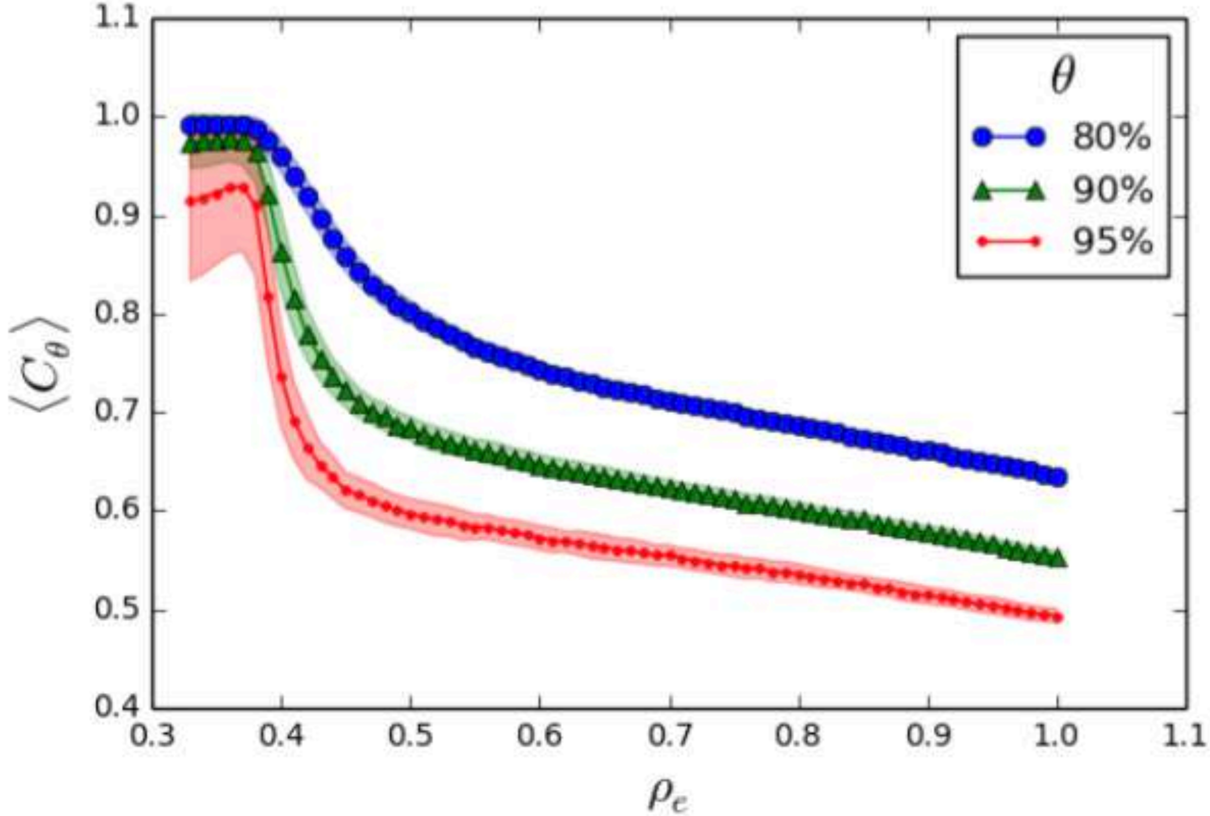
Edge Density

$$d_e = \frac{e}{e_{DT}}$$



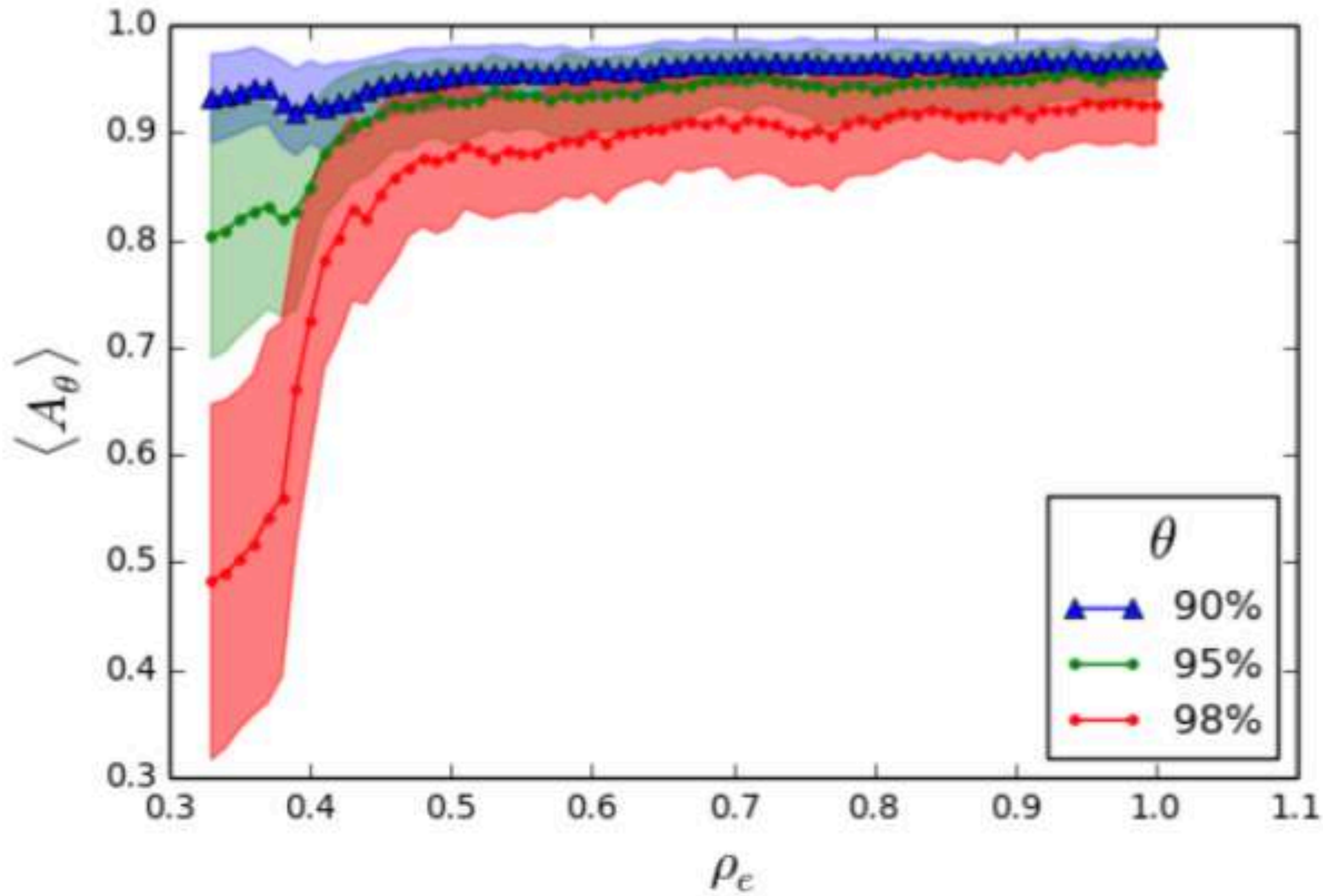


Spatial Clustering



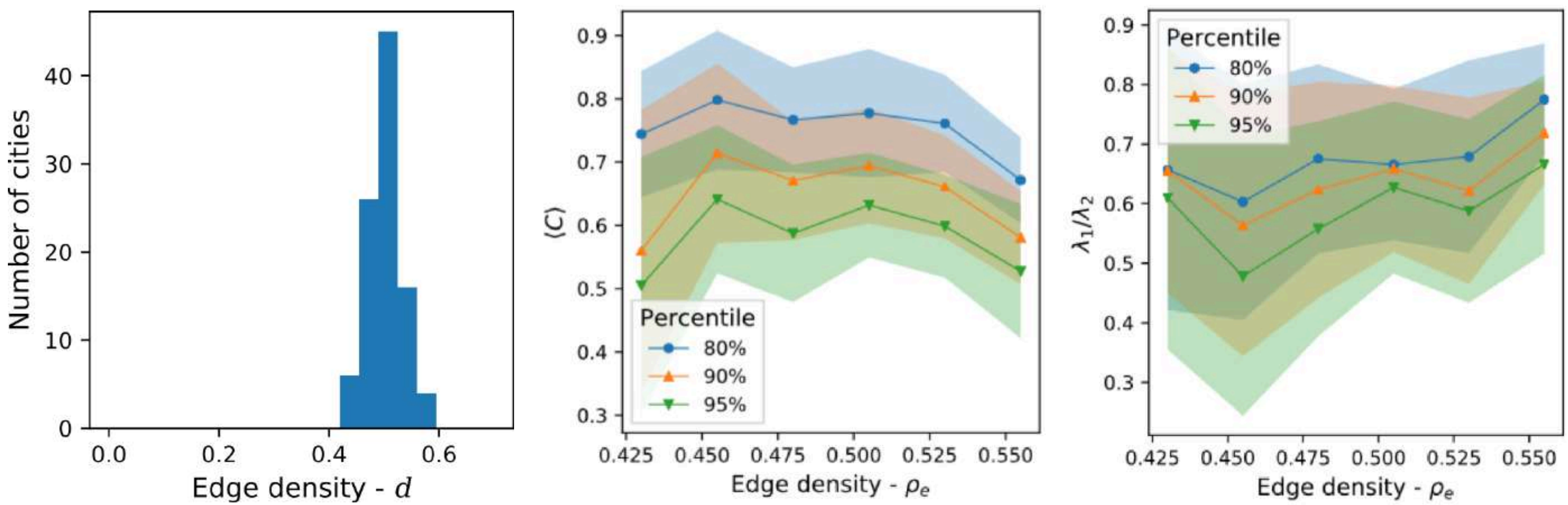
$$C_\theta = \frac{1}{\langle w \rangle N_\theta} \sum_{i=1}^{N_\theta} ||\mathbf{x}_i - \mathbf{x}_{\rm cm}||; \quad \mathbf{x}_{\rm cm} = N_\theta^{-1} \sum_{i=1}^{N_\theta} \mathbf{x}_i$$

Measure of anisotropy

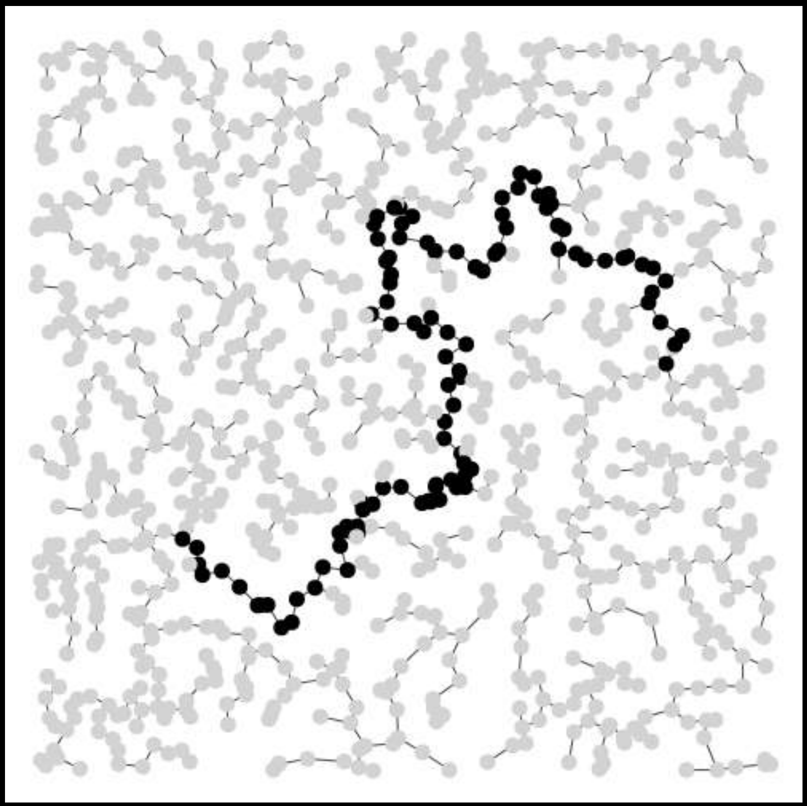


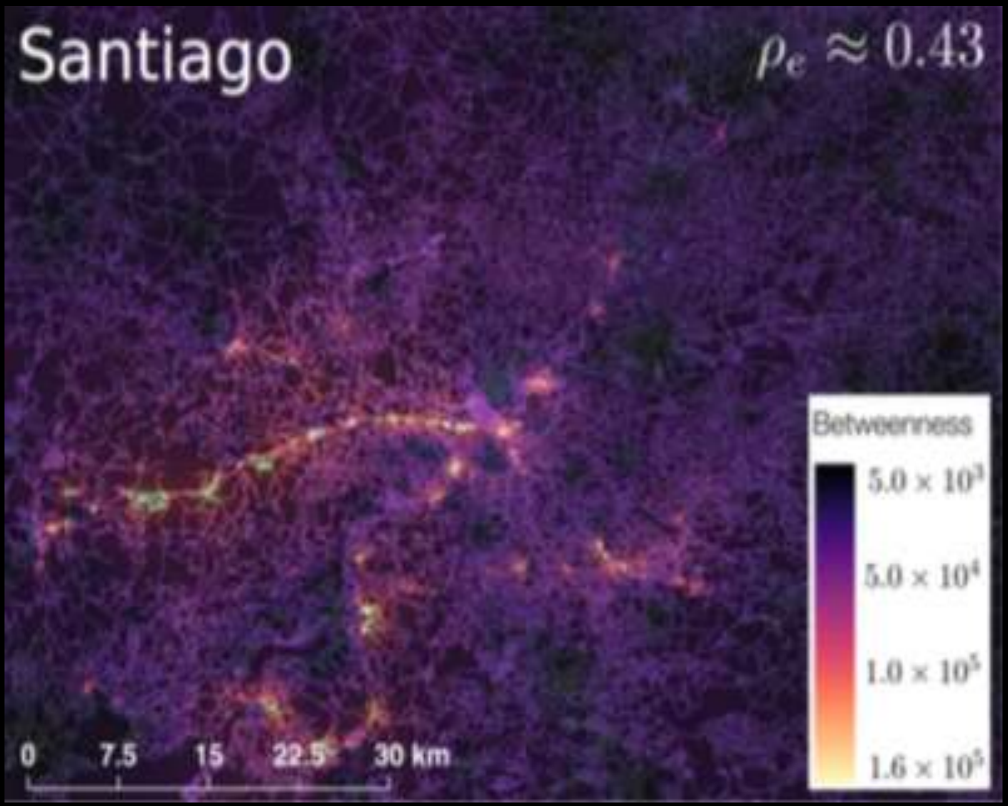
Eigenvalue ratio of covariance matrix: $$A_\theta = \frac{\lambda_1}{\lambda_2}; \quad \lambda_1 > \lambda_2$$

Spatial Clustering and anisotropy in real cities

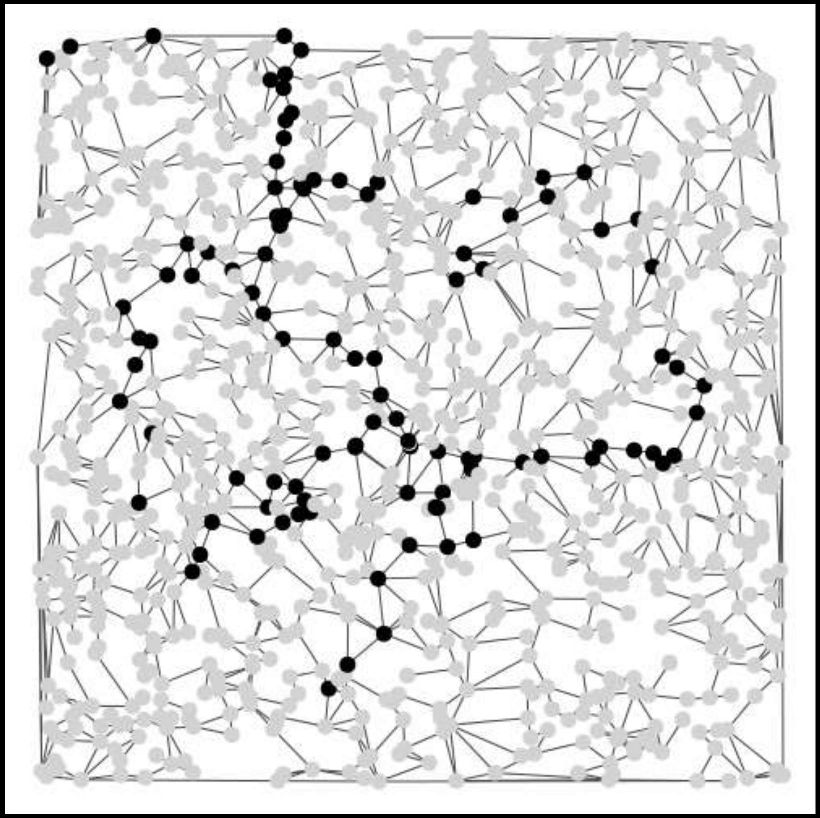


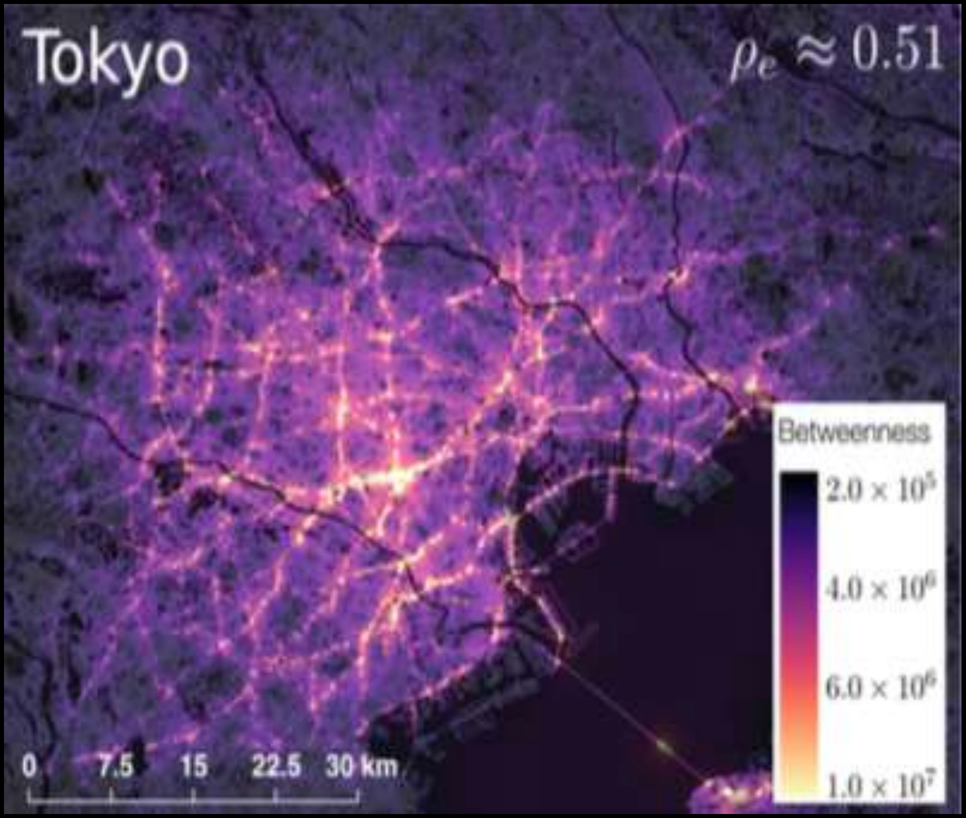
Archetypes in real cities



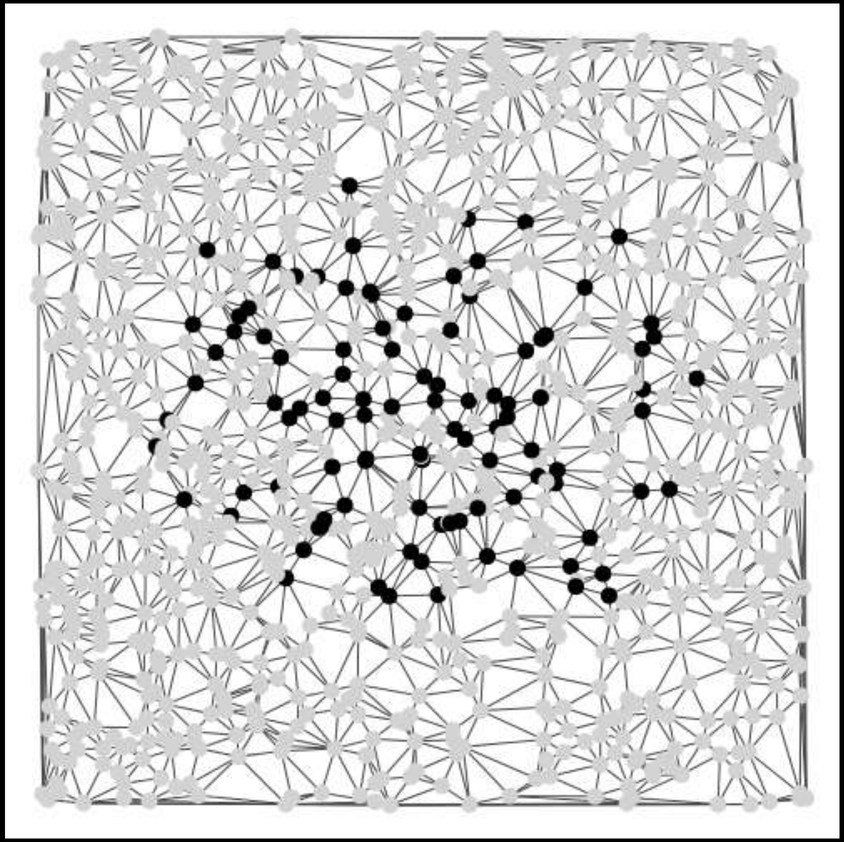


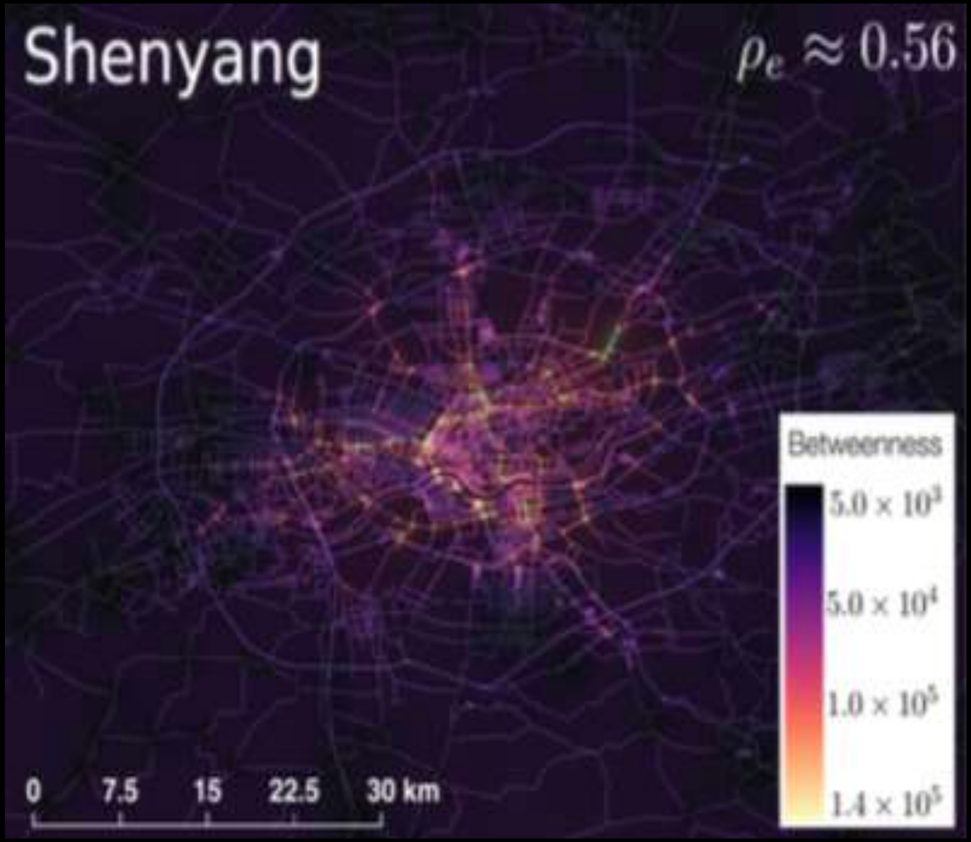
Archetypes in real cities





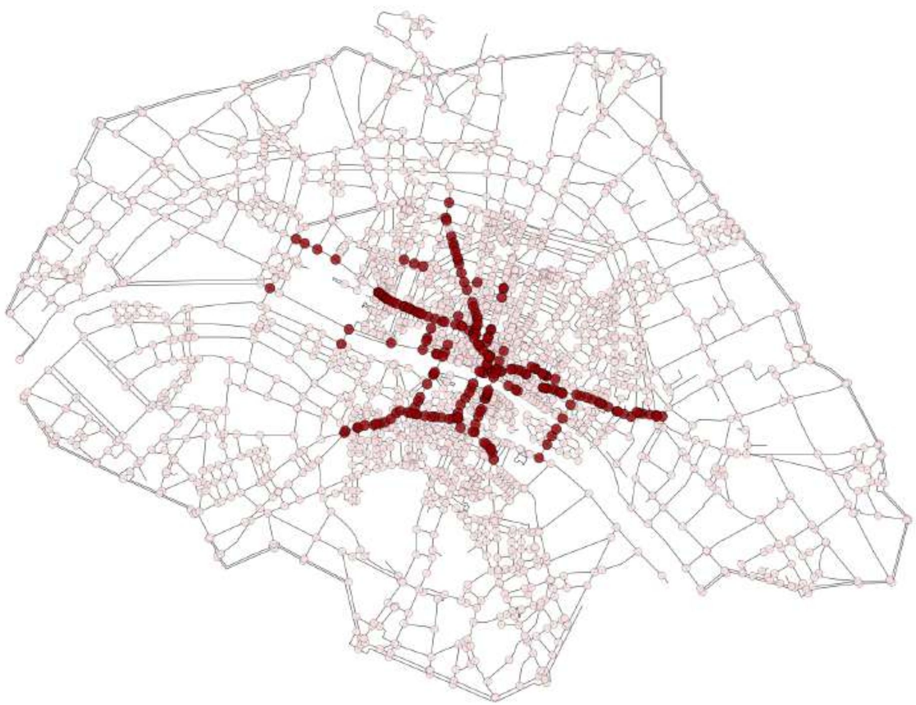
Archetypes in real cities





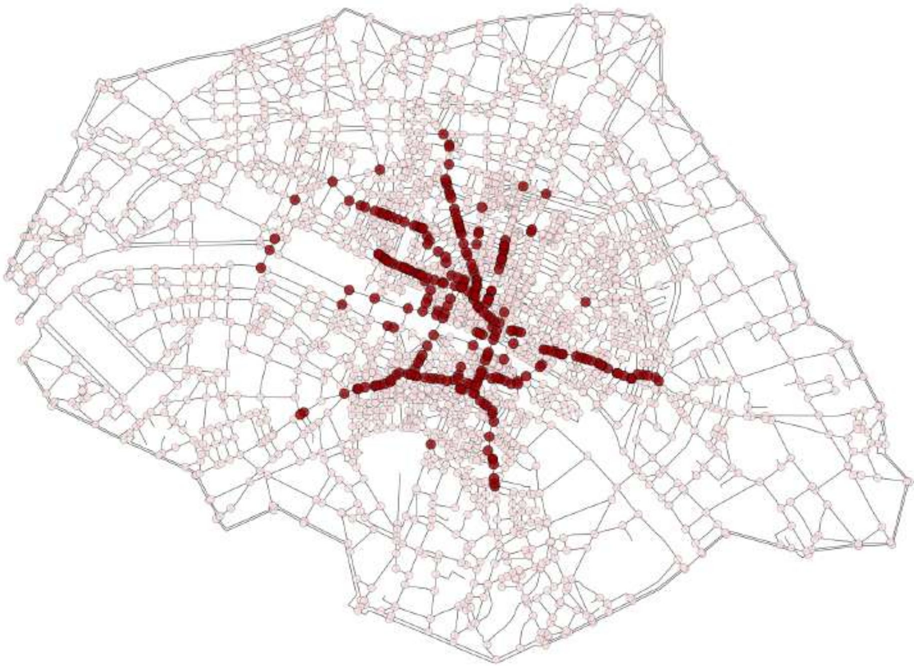
Evolution of Paris

1790



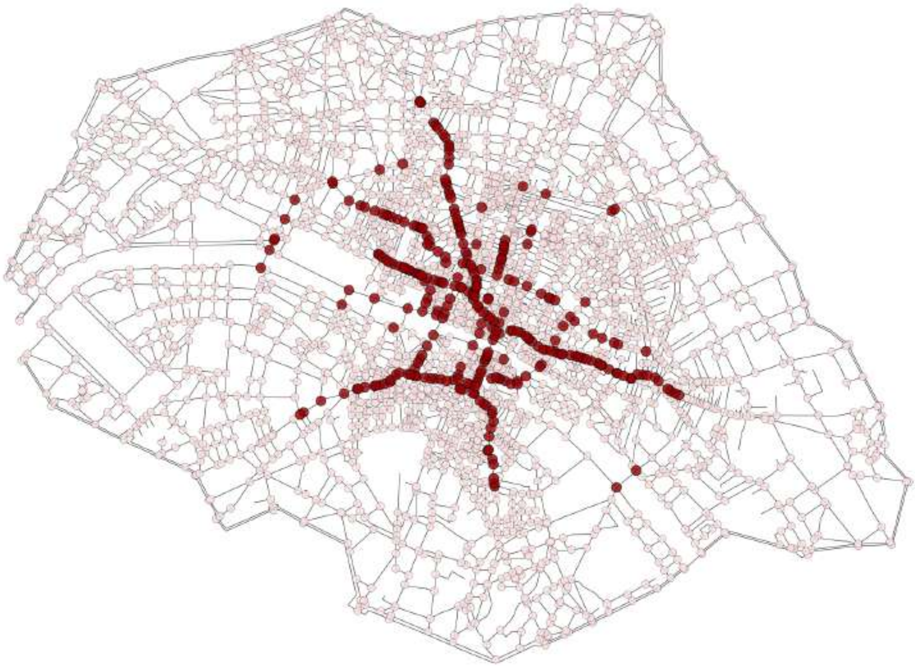
Evolution of Paris

1836



Evolution of Paris

1849

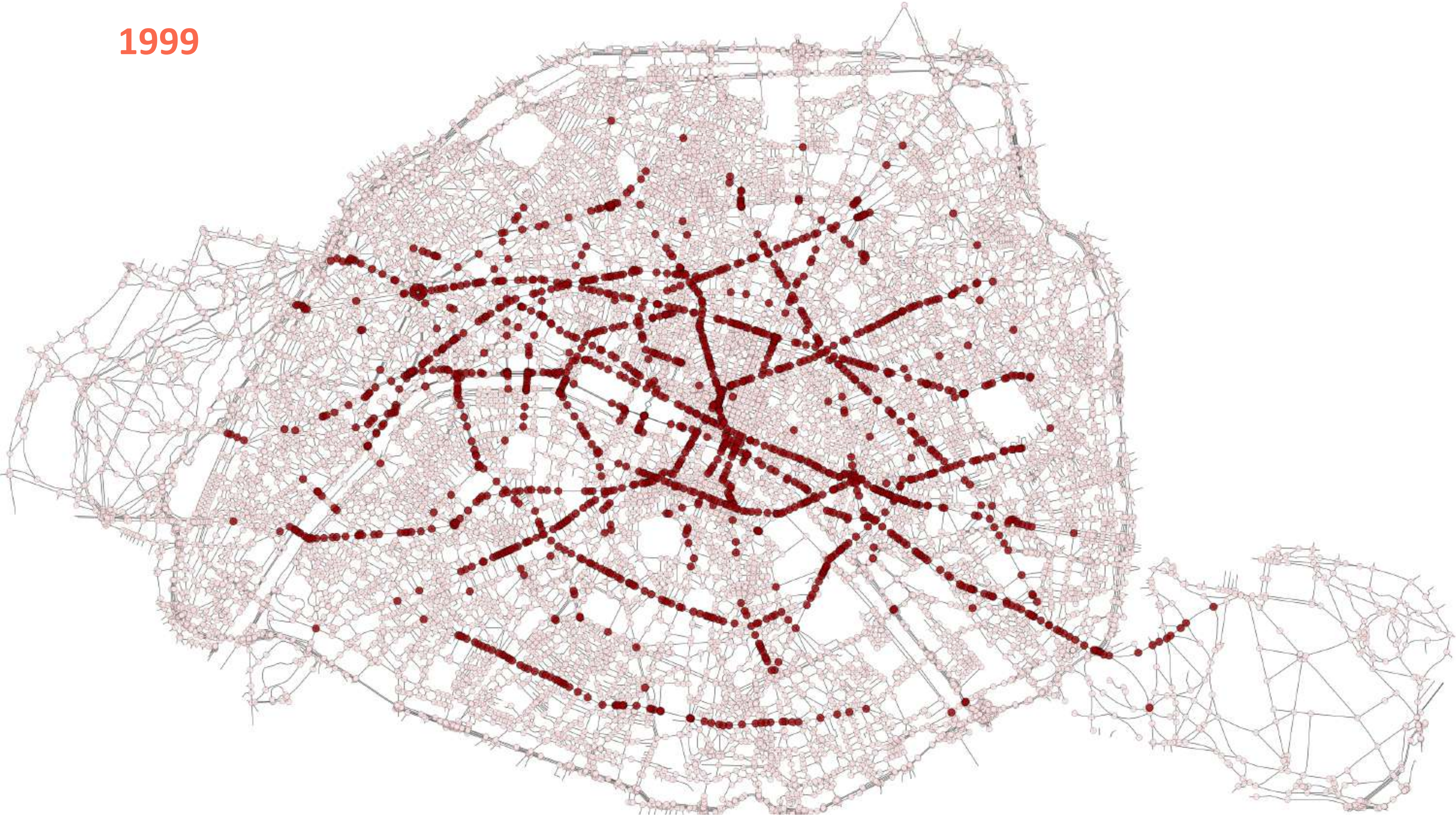


Evolution of Paris

1888 (Haussmann)

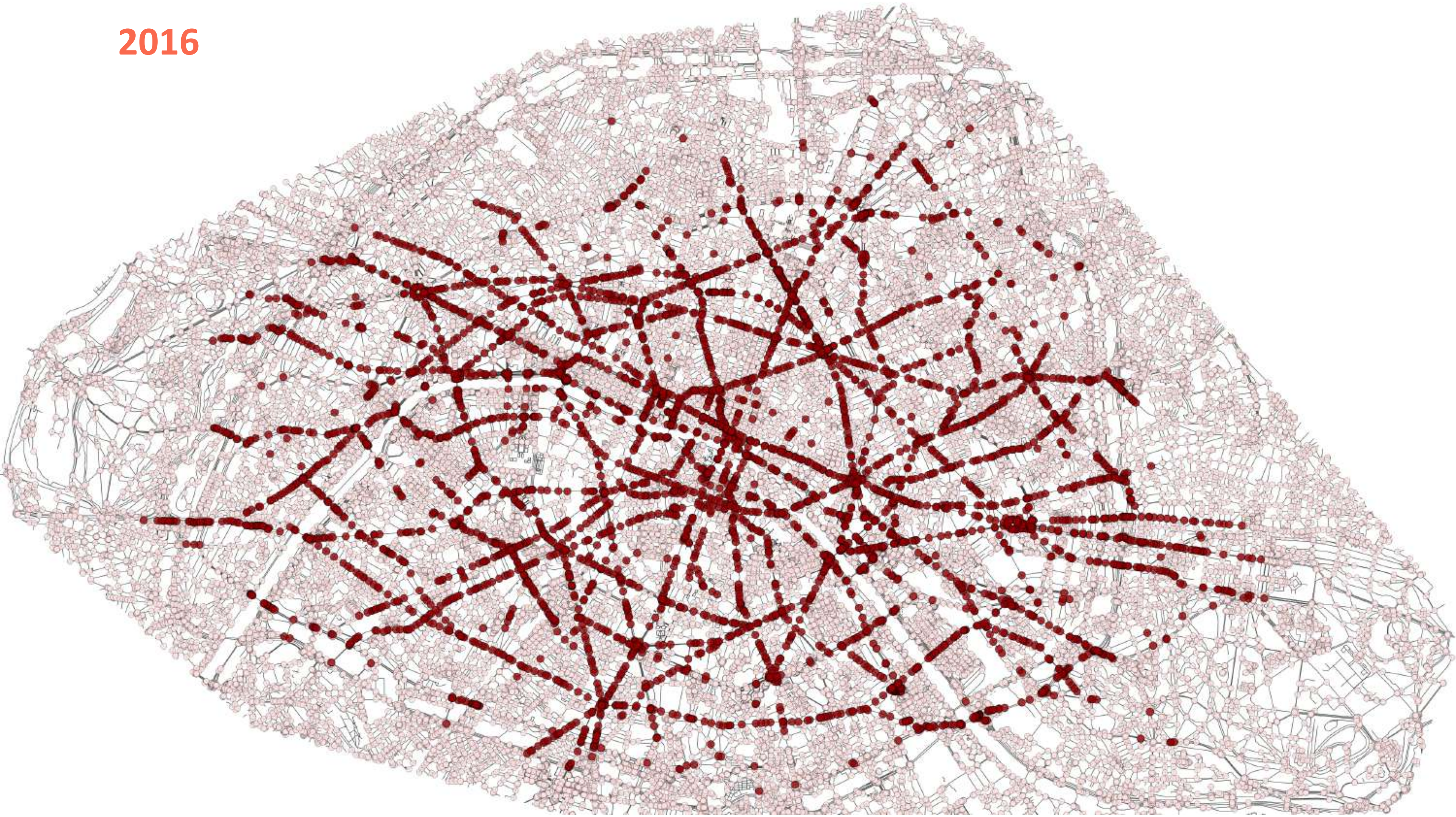
Evolution of Paris

1999

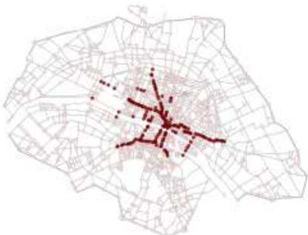


Evolution of Paris

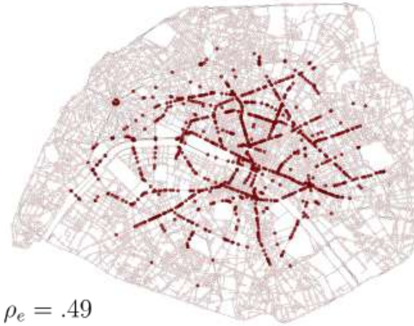
2016



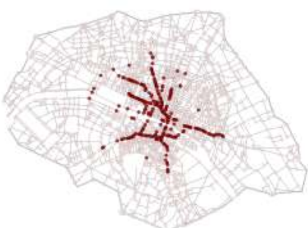
Evolution of Paris



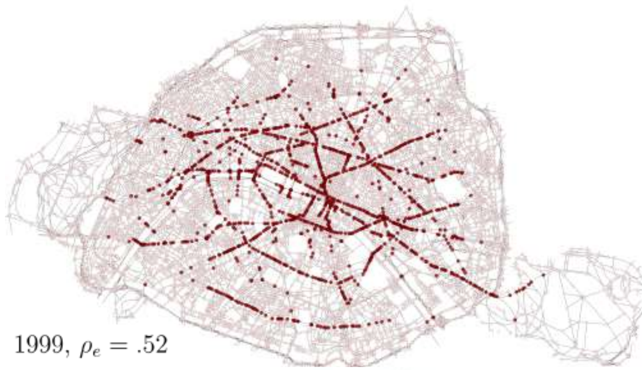
1790, $\rho_e = .51$



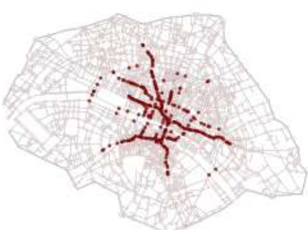
1888, $\rho_e = .49$



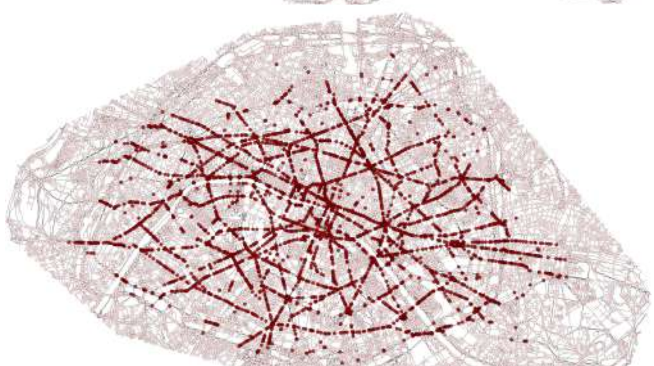
1836, $\rho_e = .53$



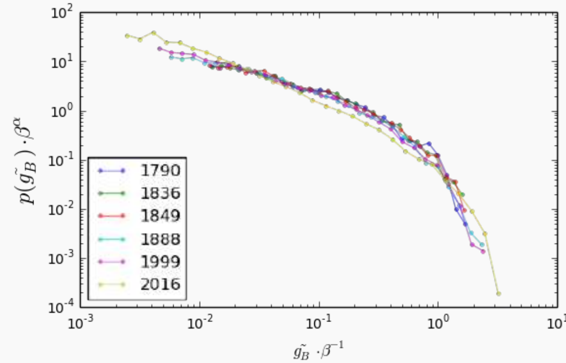
1999, $\rho_e = .52$

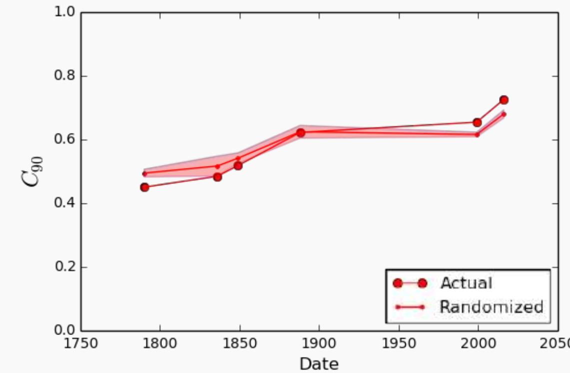


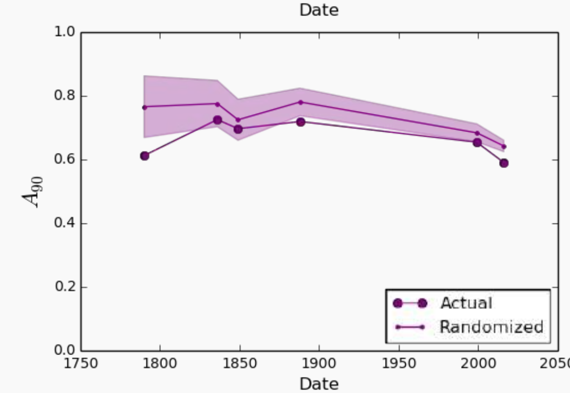
1849, $\rho_e = .53$



2016, $\rho_e = .48$







Takeaways

- Betweenness centralities of streets is sensitive to the scale of measurement.
- At the level of the "full" city, the distribution is bimodal composed of a backbone tree (high betweenness) decorated by loops and dead-ends (low betweenness).
- After a appropriate rescaling, the distribution appears to be invariant across cities, indicating that the "total" flow in cities is a conserved quantity determined entirely by the spatial extent and number of streets.
- On the other hand high betweenness nodes have a complicated spatial dependence, with a "decoupling" between topology and space at a "critical" edge density.
- Results suggest the interesting behavior occurs only in the tail of the distribution. "Neighborhood" of high betweenness nodes of particular interest.
- **Lessons for Central Planners**. Spatial and topological constraints limit room for maneuver. Multimodal transport seems the most efficient choice.

A. Kirkley, H. Barbosa, M. Barthelemy and G. Ghoshal, (working paper)

Human Mobility: Models and Applications

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Abstract

Recent years have witnessed an explosion of extensive geolocated datasets related to human movement, enabling scientists to quantitatively study individual and collective mobility patterns, as well as generate models that can capture and reproduce the spatiotemporal structures and regularities in human trajectories. The study of human mobility is especially important for applications such as estimating migratory flows, traffic forecasting, urban planning, and epidemic modeling. In this survey, we review some of the historical approaches developed to reproduce various mobility patterns. However, the main focus is on recent works in light of the explosion of relevant data. This review can be used both as an introduction to the fundamental modeling principles of human mobility, and as a collection of technical methods applicable to specific mobility-related problems. The review organizes the subject by differentiating between individual and population mobility and also between short-range and long-range mobility. Throughout the text the description of the theory is intertwined with real-world

Many Thanks!

Hugo Barbosa

Alec Kirkley

Marc Barthelemy

http://gghoshal.pas.rochester.edu/