A Statistical Method for Synthetic Power Grid Generation based on the U.S. Western Interconnection

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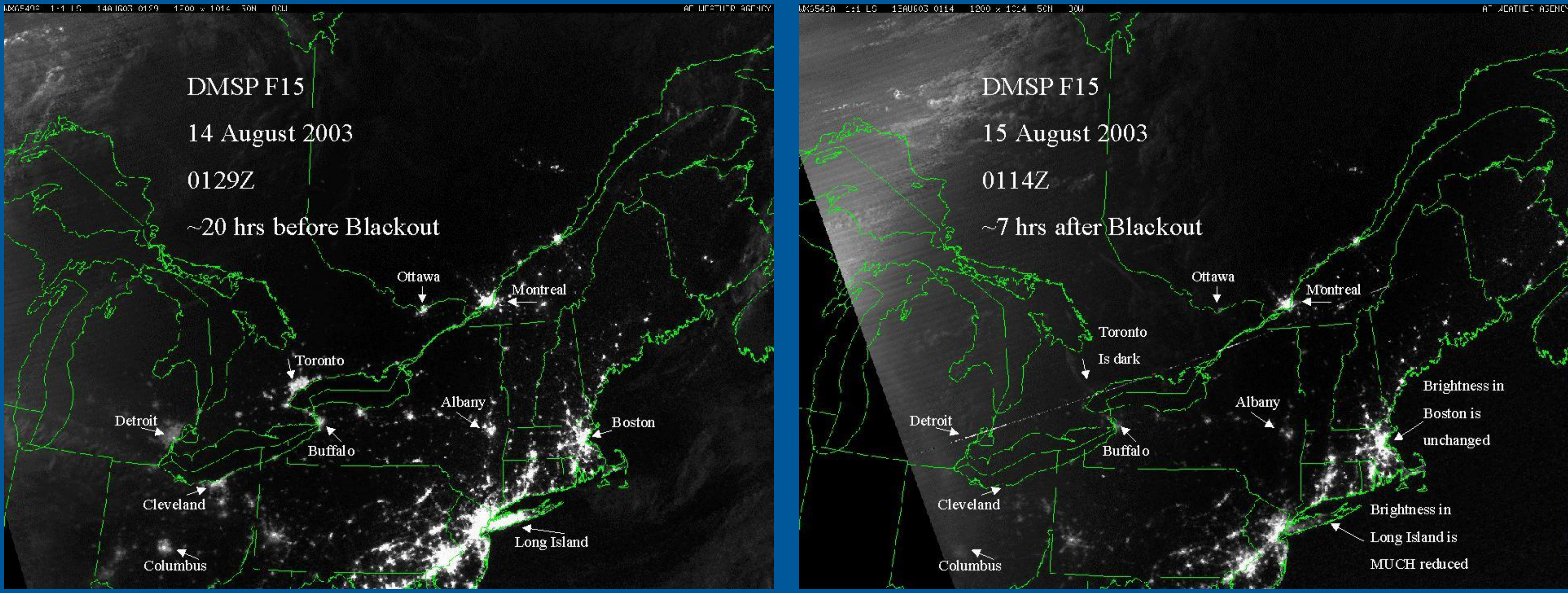
Failures in Power Grids

- One of the most essential infrastructures in modern life
- Rely on physical components → Vulnerable to physical attacks/failures
- Failures may cascade → Blackouts (US’03, India’12, Turkey’15)

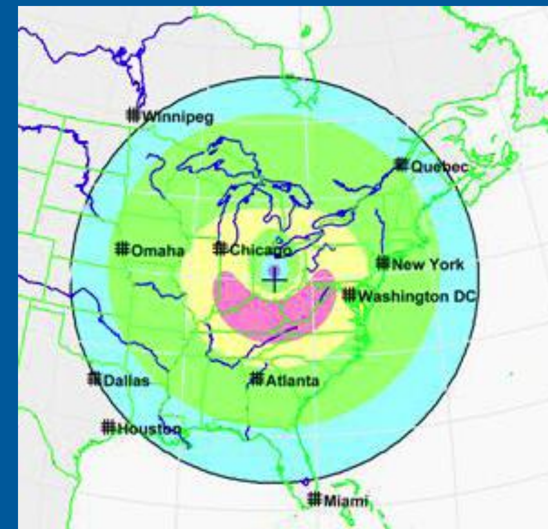


- An attack/failure will have a significant effect on many interdependent systems (communications, gas, water, etc.)

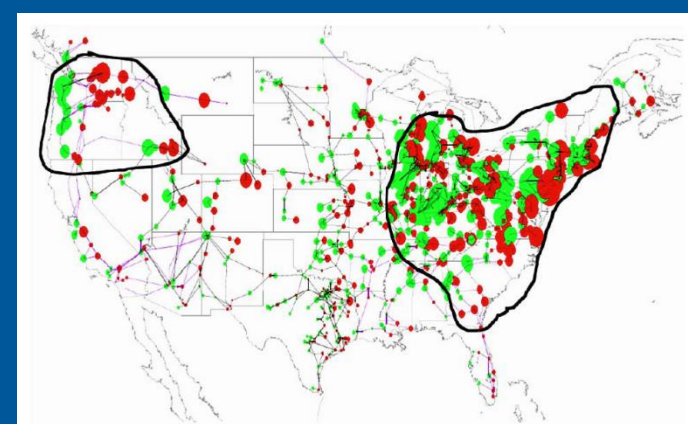
Failures/Attacks/Disasters

- Mismanagements
- EMP (Electromagnetic Pulse) attack
- Solar Flares - Federal Energy Regulatory Commission (FERC) has recently issued a rule for transmission grid operators to develop a plan to deal with the Geomagnetic disturbances

- Other natural disasters
- Physical attacks



Source: Report of the Commission to Assess the threat to the United States from Electromagnetic Pulse (EMP) Attack, 2008



FERC, DOE, and DHS, Detailed Technical Report on EMP and Severe Solar Flare Threats to the U.S. Power Grid, 2010

Power Grid Attack in San Jose

- "A sniper attack in April 2014 that knocked out an electrical substation near San Jose, Calif., has raised fears that the country's power grid is vulnerable to terrorism. " –The Wall Street Journal

Shots in the Dark

A look at the April 16 attack on PG&E's Metcalf Transmission Substation

1	2	3	4	5	6	7
12:58 a.m., 1:07 a.m. Attackers cut telephone cables	**1:31 a.m.** Attackers open fire on substation	**1:41 a.m.** First 911 call from power plant operator	**1:45 a.m.** Transformers all over the substation start crashing	**1:50 a.m.** Attack ends and gunmen leave	**1:51 a.m.** Police arrive but can't enter the locked substation	**3:15 a.m.** Utility electrician arrives

Sources: PG&E; Santa Clara County Sheriff's Dept.; California Independent System Operator; California Public Utilities Commission; Google (image)
The Wall Street Journal

Motivation

- Need to study vulnerabilities in the real grid topologies
- Real data may **not be available** to all researchers or **hard to obtain** due to security reasons
- **Not wise** to publish vulnerabilities of the real grid
- Current situation
  - Small-world, scale-free networks, etc. do not consider the geographical locations (The reactance value and type of a line is directly correlated to its length)
  - Spatial networks (e.g., random geometrics graphs) are not designed to generate networks with properties similar to power grid networks
  - Limited reference test cases (Polish Grid, IEEE benchmark systems, etc.) that do not contain the coordinates of the lines
- We present a procedure to generate synthetic networks with similar structural properties to power grids

Related Work

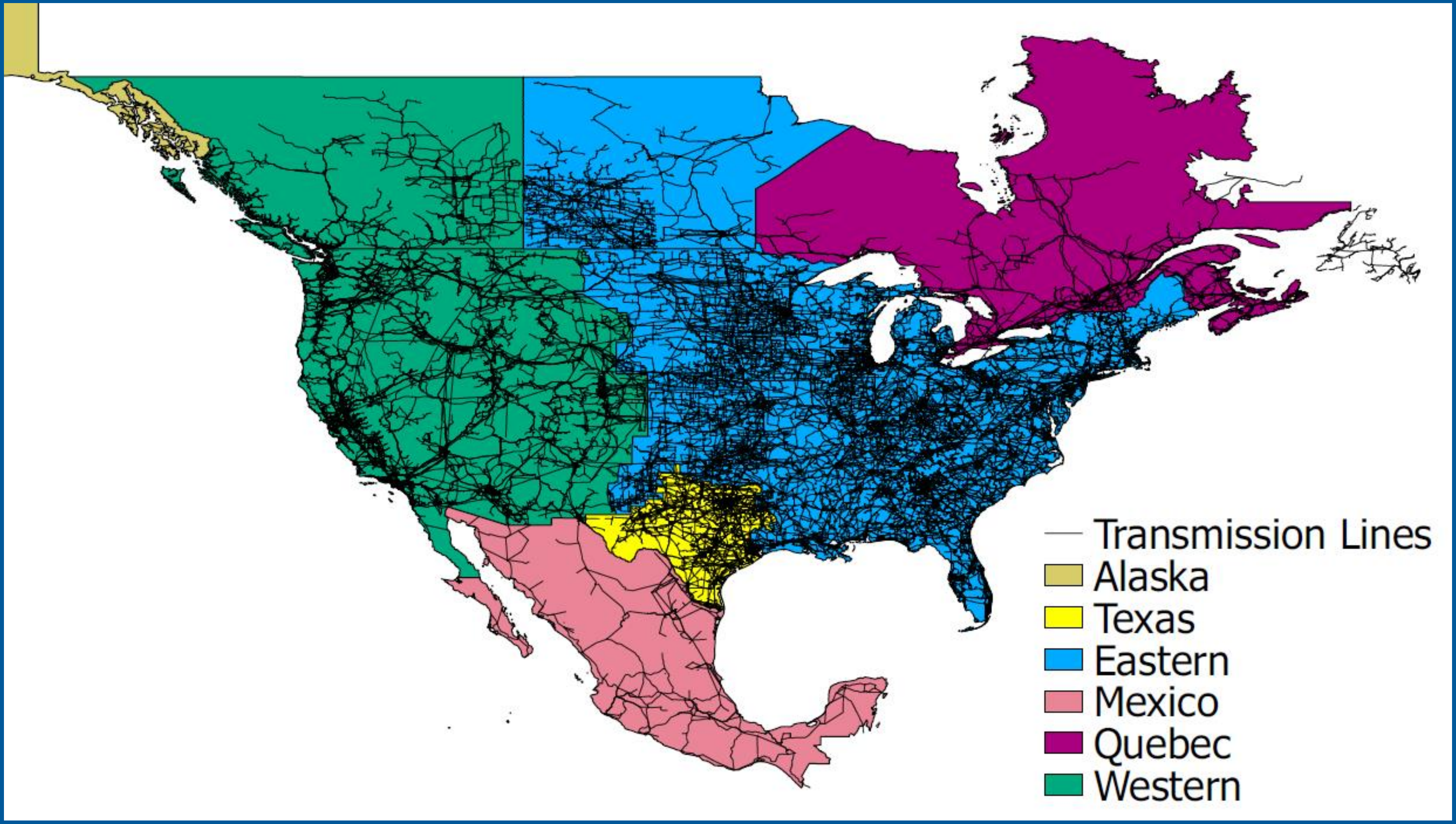
- The structural properties of the power grids around the World (North America, Europe, etc.) has been widely studied
  - Watts and Strogatz (1998)→ small-world property (average path length and clustering coefficient)
  - Barabasi and Albert (1999)→ the power-law degree distribution
  - Studies of the power grids in European countries shows similar properties (2007)
  - Wang, Scaglione, et. al. (2010)→Algebraic connectivity
  - Recent work by Hines et. al. (2012) → show existent topological models do not satisfy all the structural properties of power grids
- Few synthetic models are available
  - Random Networks (Small-world, scale-free, etc.)
  - Wang, Scaglione, et. al. (2010)
  - Recent work by Schultz et. al. (2014)
- None has considered the spatial distribution of the nodes and the length distribution of the lines

Structural Properties

- What is important?
  - **Number of Nodes**
  - **Number of Edges**
  - **Average path length**: The average shortest path lengths (number of edges) between all pairs of nodes
  - **Clustering coefficient**: The fraction of connected pairs between all the neighbors of a node i, averaged over all nodes i
  - **Degree distribution of the nodes**
  - **Length Distribution of the lines:** Is directly correlated with physical properties of the lines (e.g., resistance, reactance)

North America Power Grid

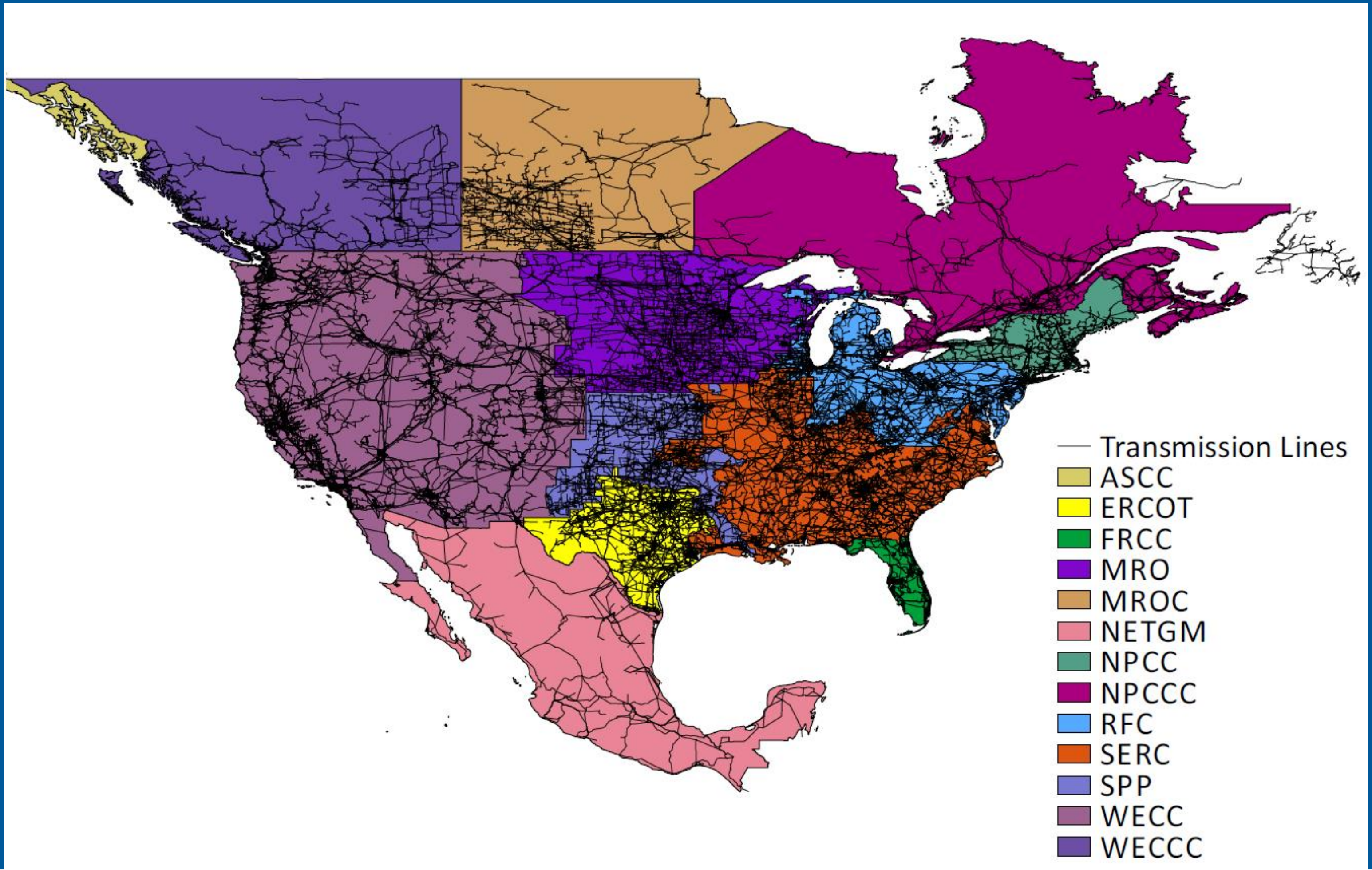
- Two major: The Western (WI) and Eastern Interconnections (EI)
- Three minor: The Texas, Québec, and Alaska Interconnections



The data is obtained from the Platts Geographic Information System (GIS)

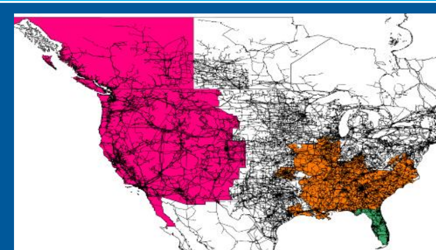
Regional Entities

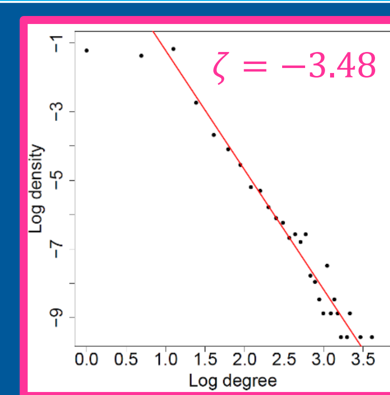
- North American Electric Reliability Corporation (NERC) regional entities and the National Electricity Transmission Grid of Mexico (NETGM).

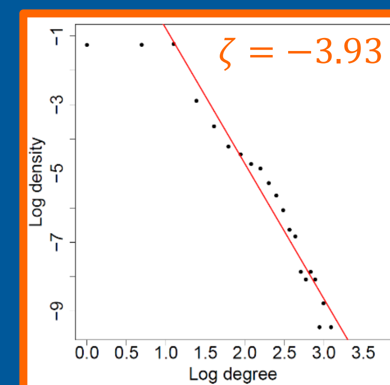


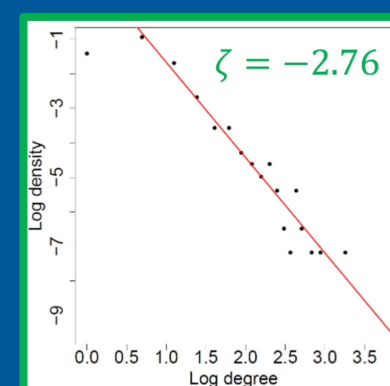
Structural Properties

- We consider
  - Western Interconnection (WI)
  - SERC Reliability Corporation (SERC)
  - Florida Reliability Coordinating Council (FRCC)







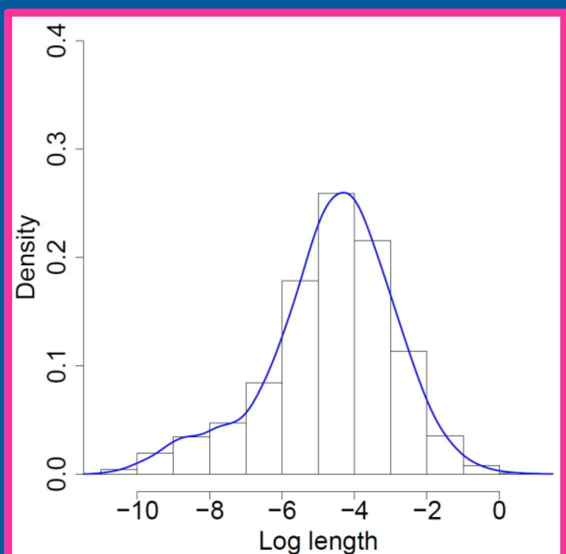


Network	WI	SERC	FRCC
# of Nodes	14302	12946	1312
# of Edges	18769	16658	1780
Average Path Length	17.33	19.71	11.68
Clustering Coefficient	0.049	0.049	0.075
Power-law exponent ζ	-3.48	-3.93	-2.76

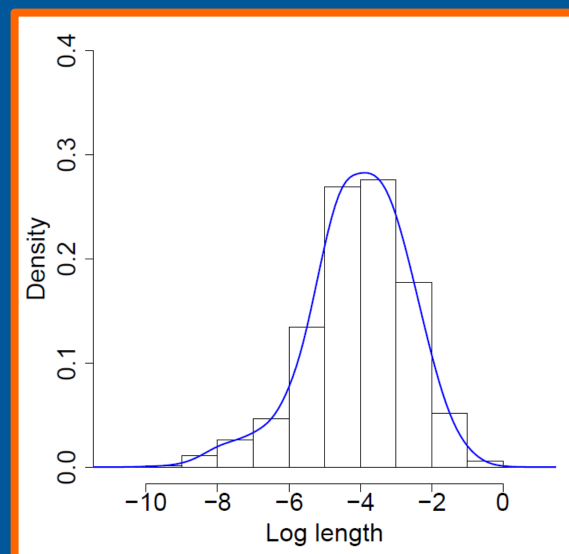
The Length Distribution of the Lines

- First time that has been studied
- Non-parametric fit

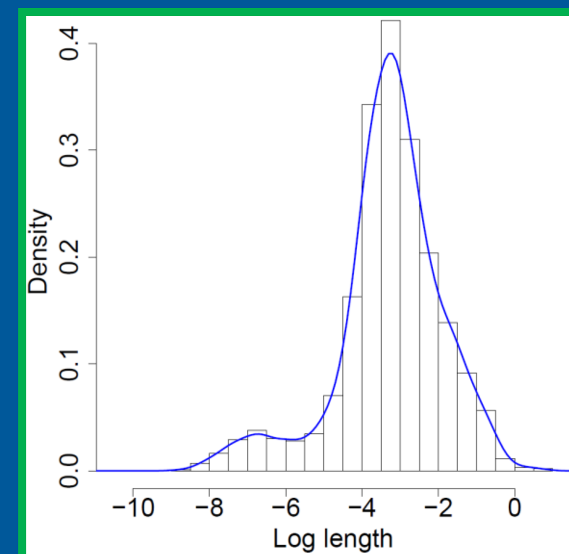
WI



SERC

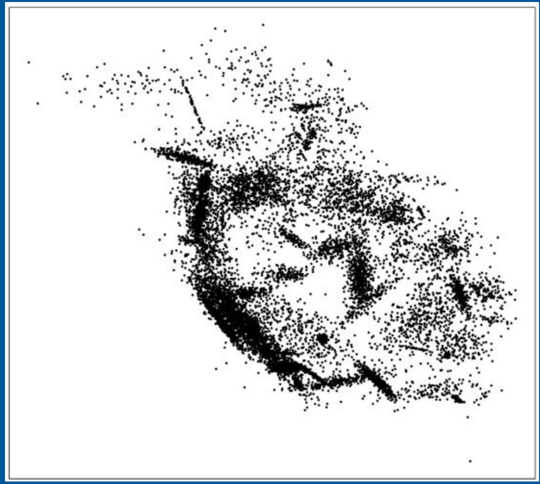


FRCC

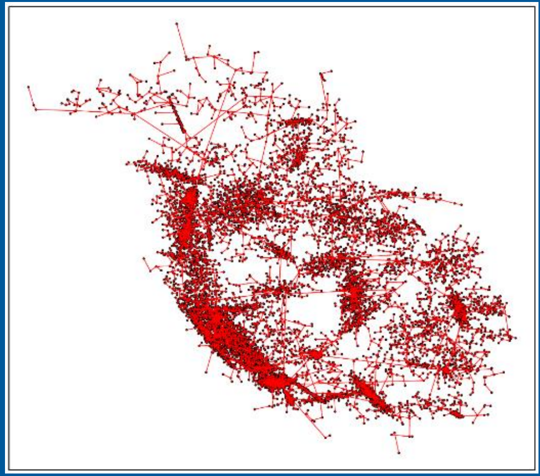


Outline of our Method

1. Generate nodes with the similar spatial distribution to a given network with n nodes and m edges

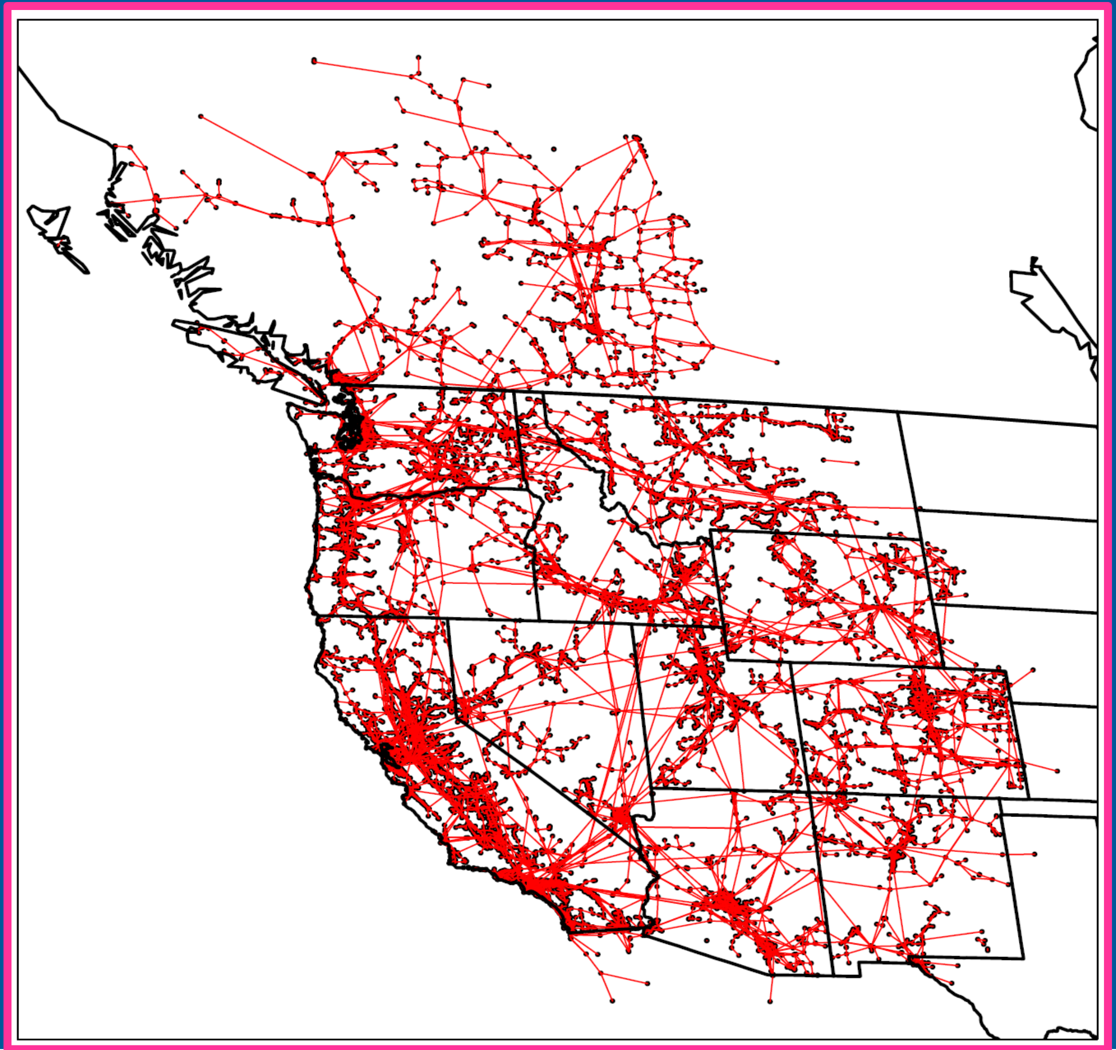


2. Connect nodes based on the distances and degrees



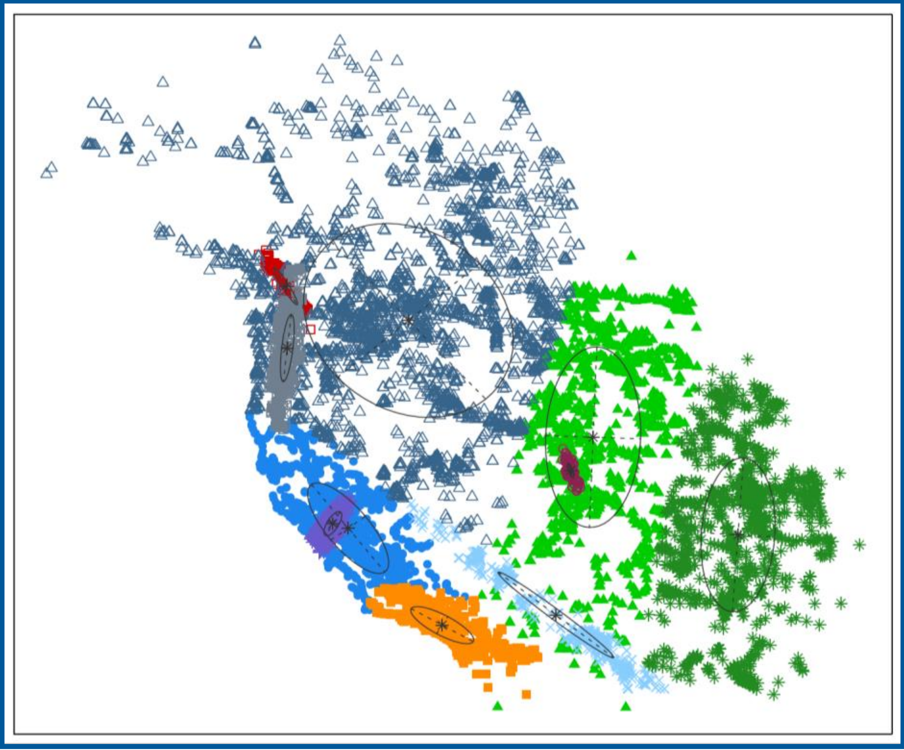
Western Interconnection

- Western interconnection with n =14302 substations (nodes) and m =18769 lines (edges)



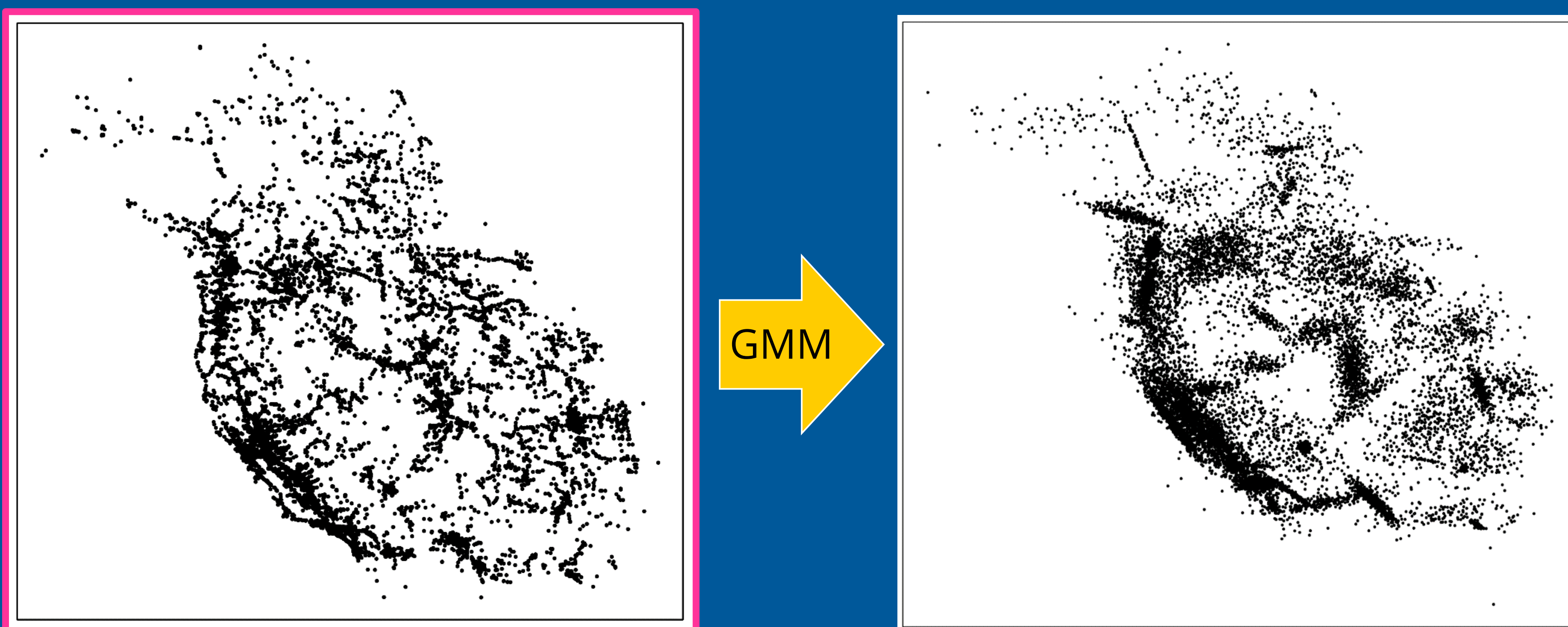
Spatial Distribution of the Nodes

- Cluster points based on their geographical proximity
- Gaussian Mixture Models (GMM) are commonly used for clustering and density estimation
- Mixtures describe two-stage sampling procedure
  - Sample $j \sim \pi = (\pi_1, \ldots, \pi_c)$ → Categorical distribution
  - Sample $X_i \sim \mathcal{N}(\mu_j, \Sigma_j)$ → Gaussian distribution
- Given a network, π and (μ_j, Σ_j)s can be estimated using algorithms like EM algorithm
- Example of clustering nodes in WI into 10 clusters
  - Each color represents nodes assigned to a cluster



Position of the Nodes

- Use the Bayesian Information Criterion (BIC) to select number of clusters → 55 clusters
- Use the obtained parameters from GMM to generate n nodes with similar spatial distributions as the nodes in WI



Outline of our Method

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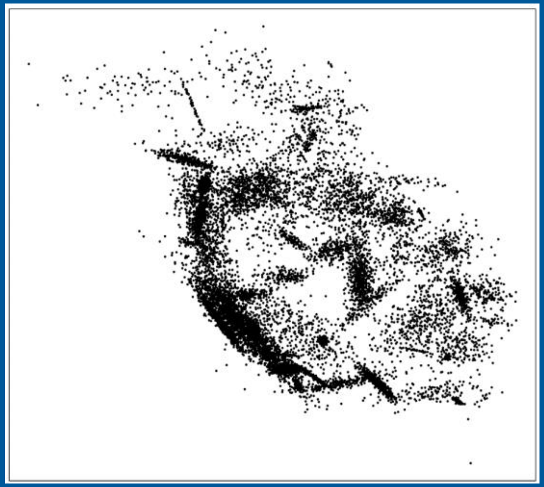

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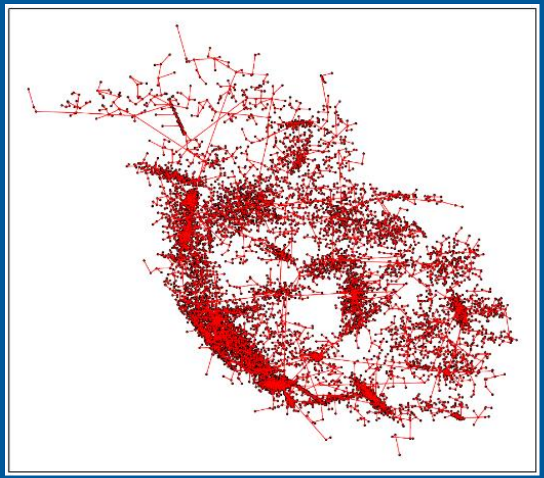
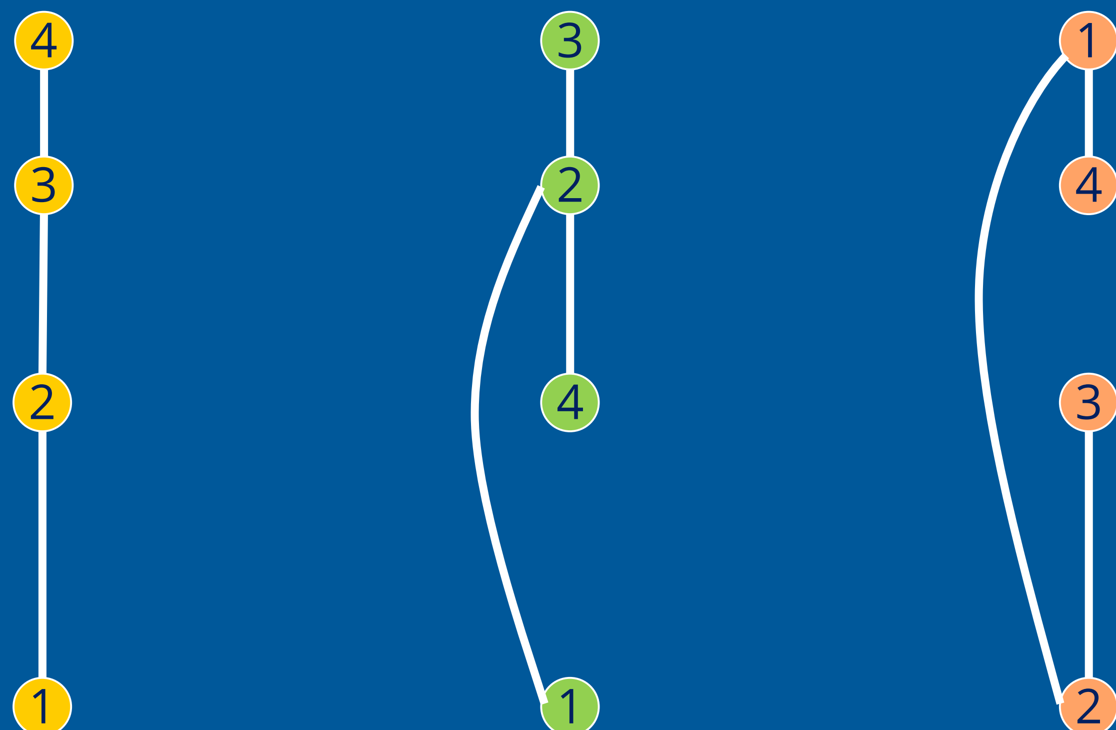


Connection Between the Nodes

- Inspired by the way the power grids have evolved through time
- Find a spanning tree of nodes (Connectivity) ⟶ $n-1$ edges
- Add more edges to the graph (Robustness) ⟶ $m-n+1$ edges
  - Number of edges
  - Clustering coefficient
  - Degree distribution of the nodes

Connectivity

- Minimum weight Spanning Tree (MST)→ high average path length
- Connect node i to its geographically closest node with index less than i
- Depends on the ordering of the nodes



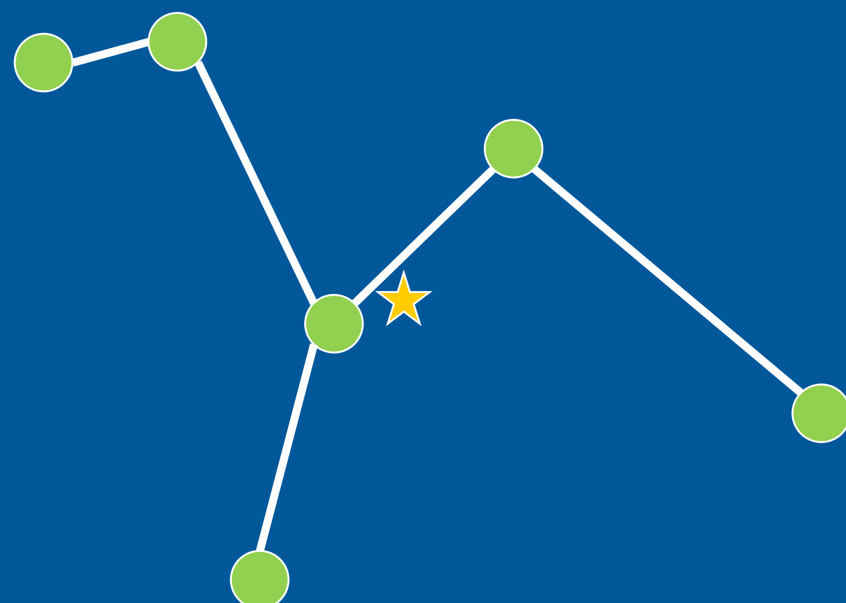
- There is an ordering that obtains the minimum spanning tree using this process

Tunable Spanning Tree

Position of node i

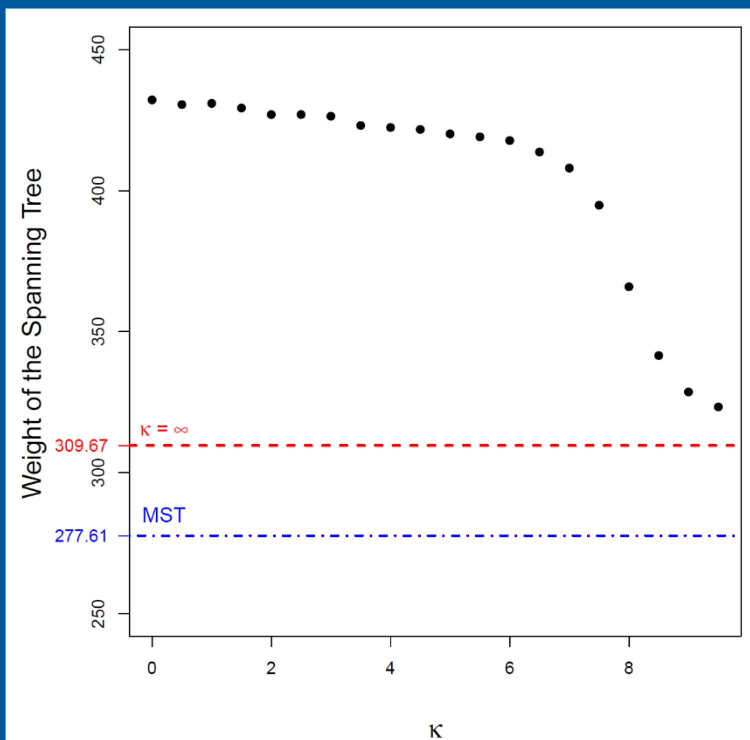
Average point

- Finding a spanning tree (tunable parameter κ):
  - Randomly order nodes with probability proportion to $||X_i - \bar{X}||^{-\kappa}$
  - Connect node i to its geographically closest node with index less than i

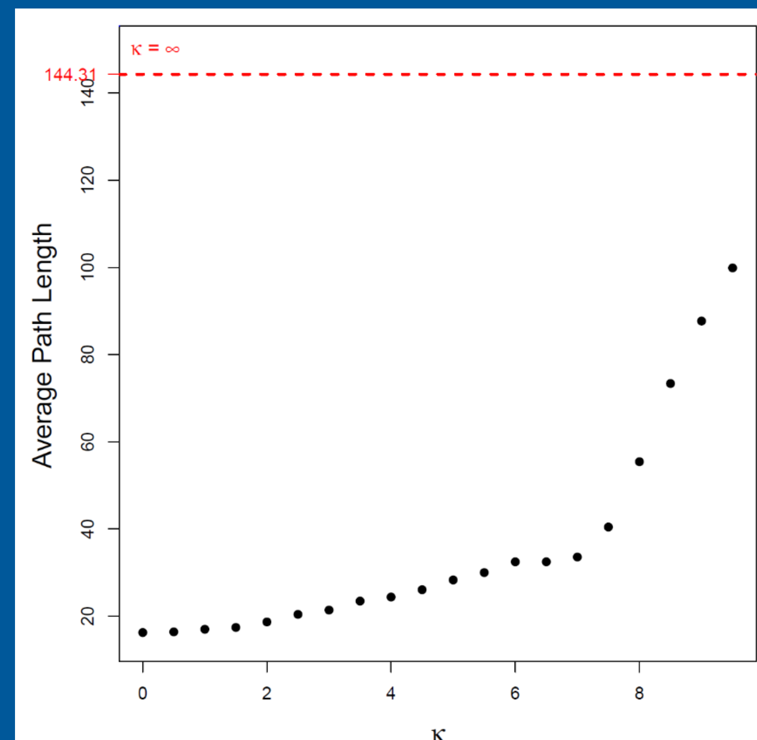


Tunable Parameter κ

- κ controls the total weight and the average path length of the obtained tree
- Average path length in MST is ≈ 505

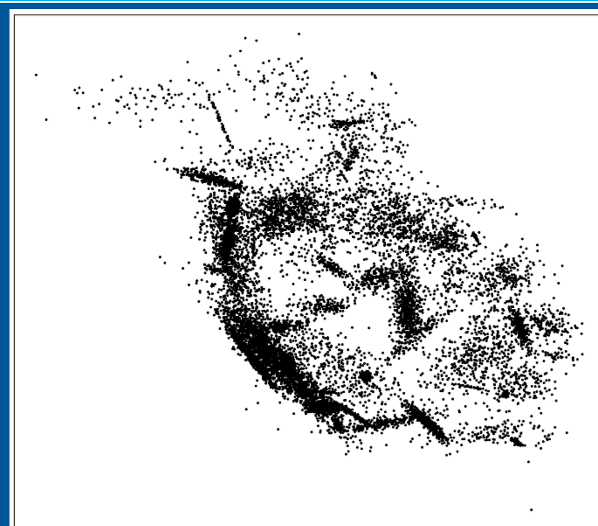


Geographical weight of the spanning tree

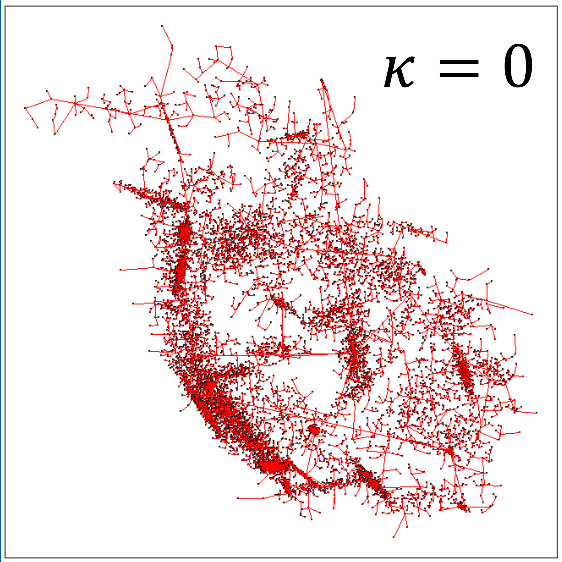


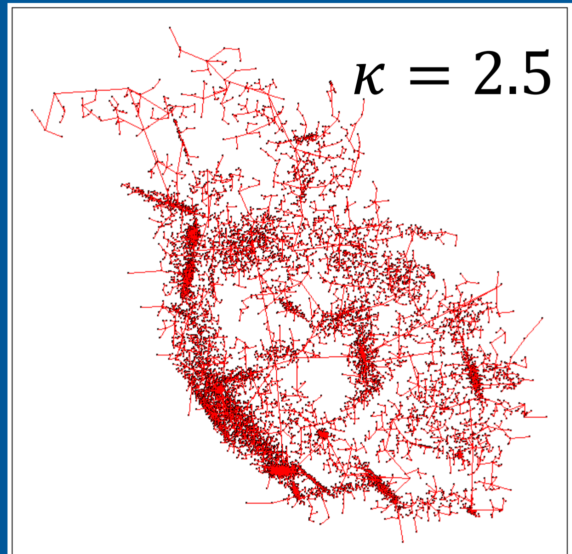
Average path length (hops)

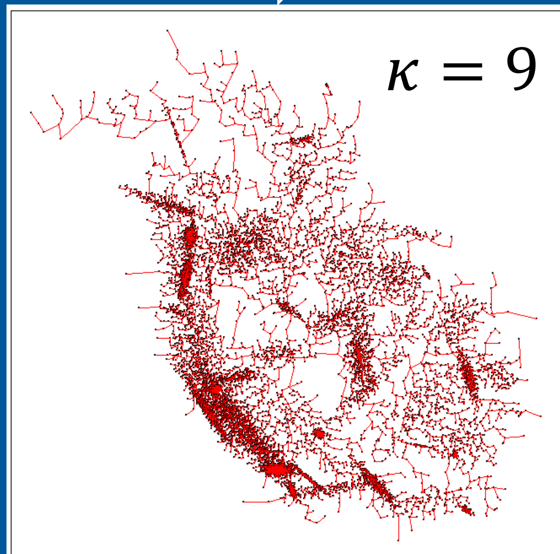
Tunable Parameter κ



Get closer to the MST







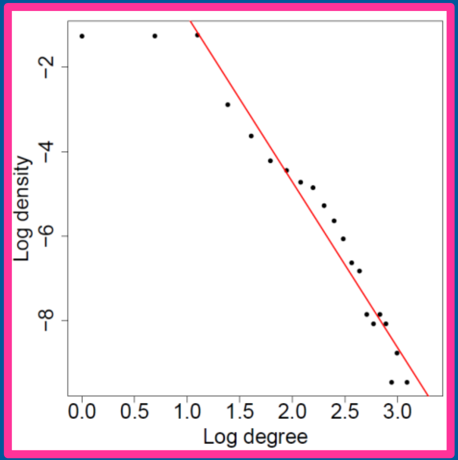
Connection Between the Nodes

- Find a spanning tree of nodes (Connectivity) ⟶ $n - 1$ edges
- Add more edges to the graph (Robustness) ⟶ $m - n + 1$ edges
  - Number of edges
  - Clustering coefficient
  - Degree distribution of the nodes

Add More Edges to the Graph: Observations

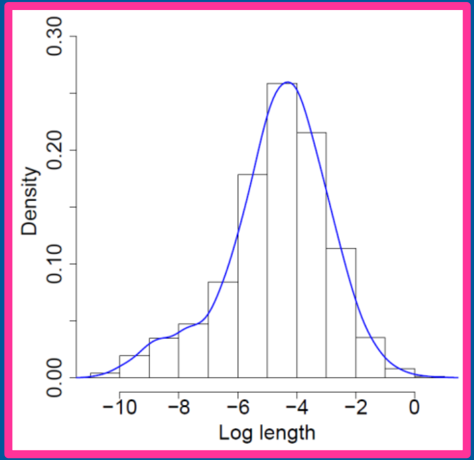
1

- Power-law degree distribution
  →Preferential attachment
- Less degree 1 & 2 nodes



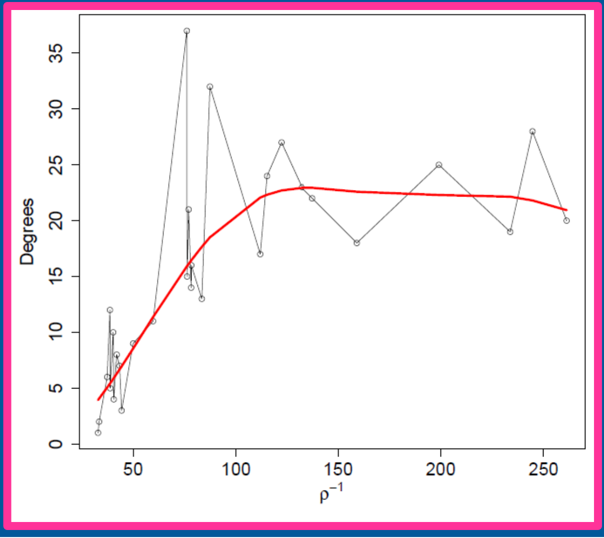
2

- Longer edges have lower probabilities



3

- Nodes in denser areas have higher degrees
- Define ρ_i as the average geographical distance of the node i from its k closest nodes
- $\rho_i^{-1} \equiv$ density of nodes around node i



Add more Edges to the Graph

- Repeat $m - n + 1$ times:
  1. Pick a low degree node in a dense area

d_i: Degree of the node i
ρ_i^{-1} : Density of the nodes around the node i

> - If Small Network: Sample node i with probability $\propto d_i^{-\eta} \rho_i^{-\alpha}$
> - If Large Network: From all nodes with degree less than 3, sample node i with probability $\propto \rho_i^{-\alpha}$

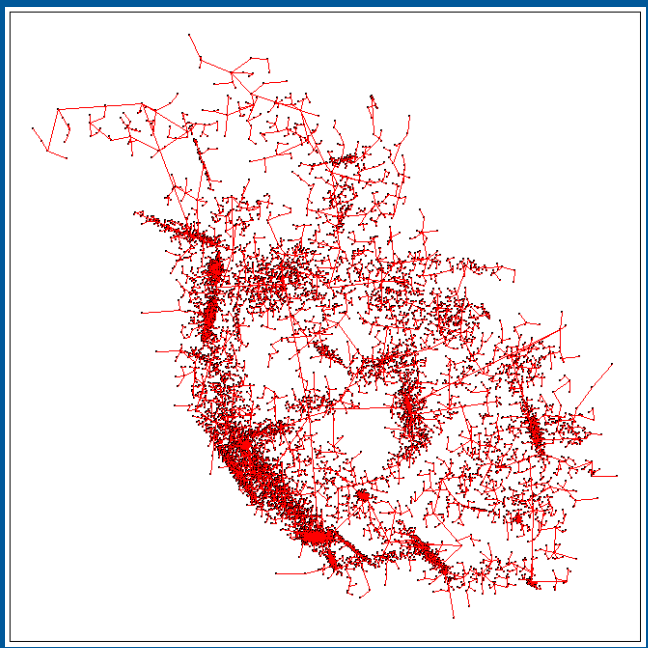
  2. Connect it to a high degree but close node

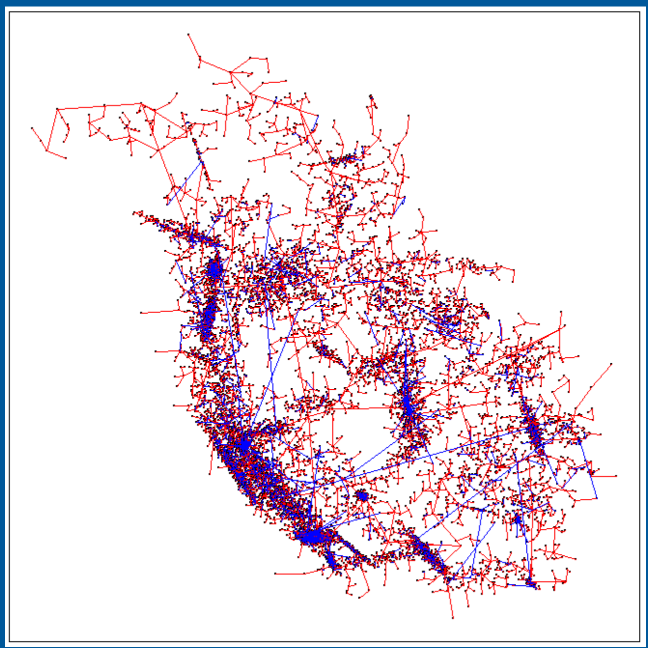
X_i: Position of the node i

> - Connect node i to node j sampled from all other nodes with probability $\propto ||X_i - X_j||^{-\beta} d_j^{\gamma}$
>   - β tune the probability distribution of length of the lines
>   - γ tune the exponent of the power-law distribution for degrees

- $\alpha, \beta, \gamma, \eta$ are tunable parameters

Add more Edges to the Graph





Evaluation

Kullback-Leibler (KL) divergence

- Measure the similarity between the length distribution of the lines in two networks

- The KL-divergence is a non-symmetric measure of the difference between two probability distributions P and Q

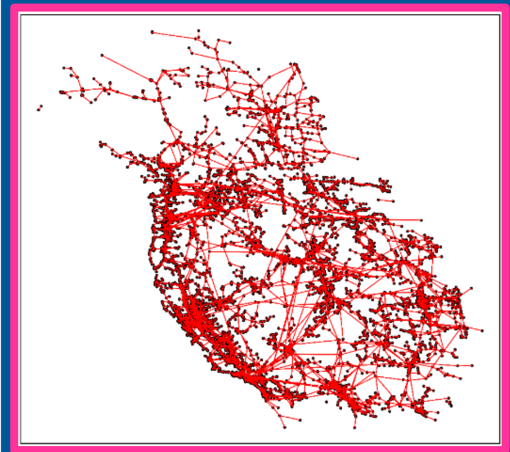
$$D_{KL}(P||Q) = \sum_i P(i) \, \ln \frac{P(i)}{Q(i)}$$

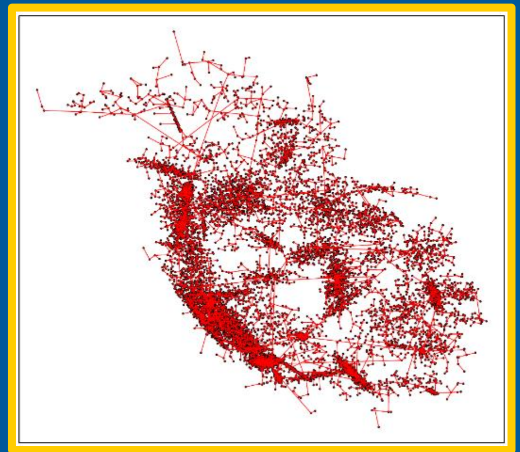
$$D_{KL}(P||Q) = \int_{-\infty}^{\infty} p(x) \ln \frac{p(x)}{q(x)} dx$$

- We do not have the actual distribution → use samples to estimate the KL-divergence as in the paper by Boltz et. al.

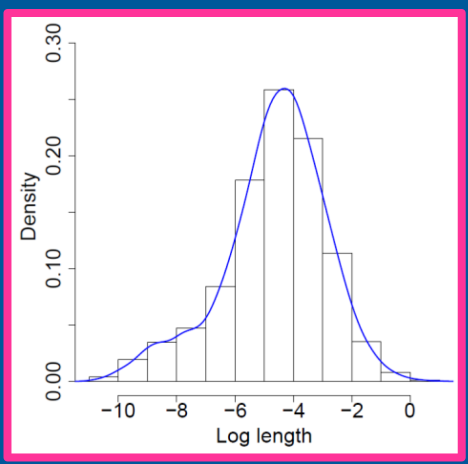
S. Boltz, E. Debreuve, and M. Barlaud, "High-dimensional statistical measure for region-of-interest tracking," IEEE Trans. Image Process., vol. 18, no. 6, pp. 1266–1283, 2009.

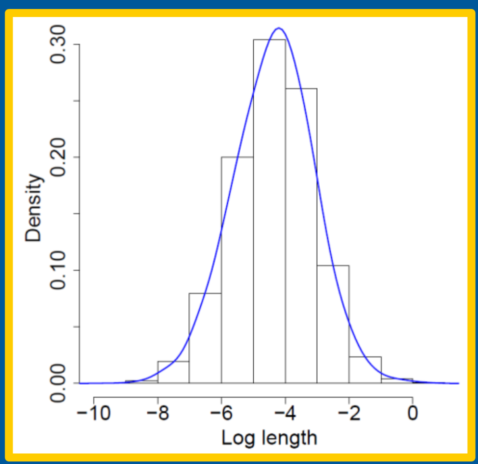
Evaluation: WI



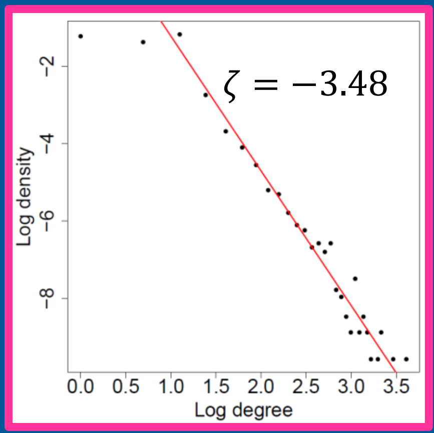


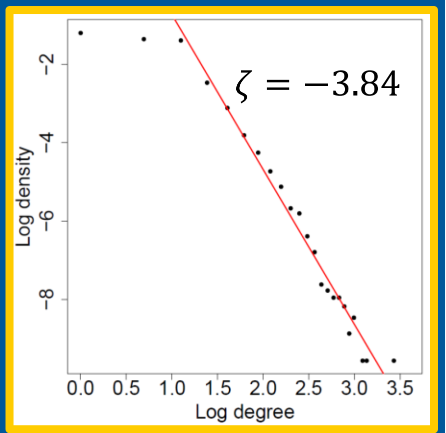
	Actual	Gen.
# of Nodes	14302	14302
# of Edges	18769	18769
Average Path Length	17.33	17.28
Clustering Coefficient	0.049	0.050
ζ	-3.48	-3.84
D_{KL}	0	0.1





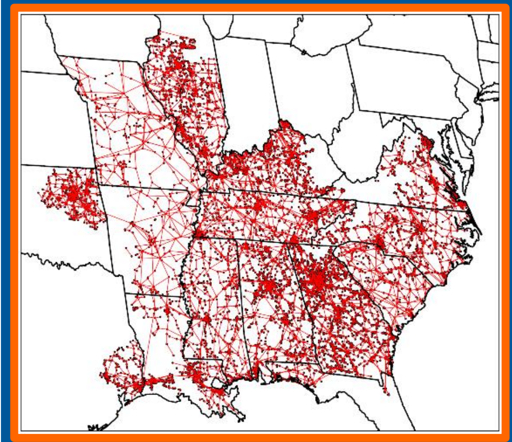
Length Distribution $D_{KL} = 0.1$

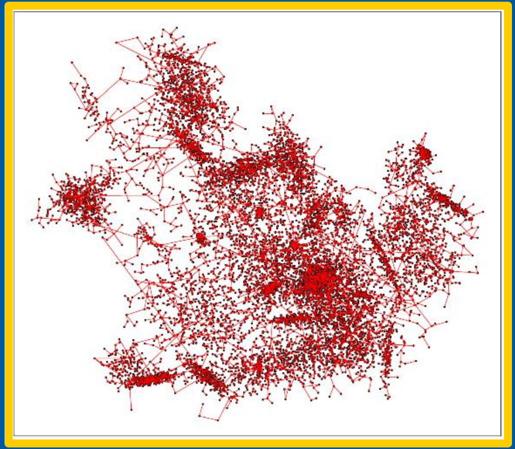




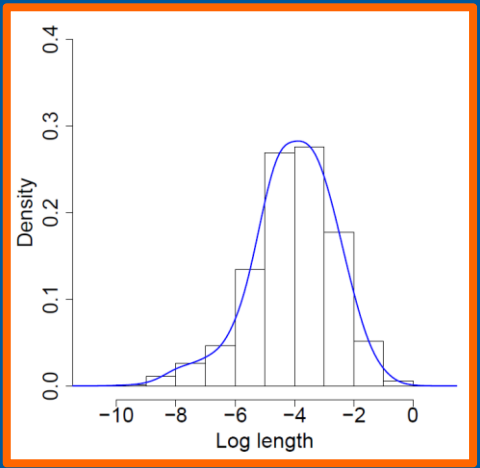
Degree Distribution

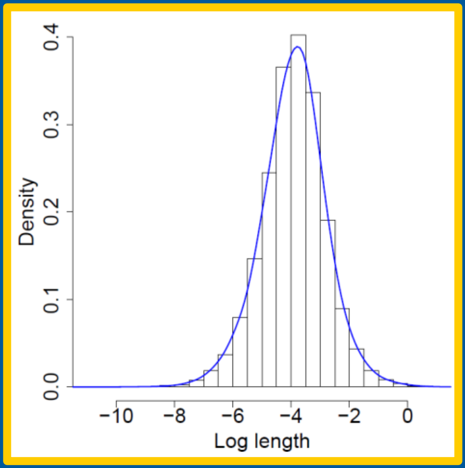
Evaluation: SERC



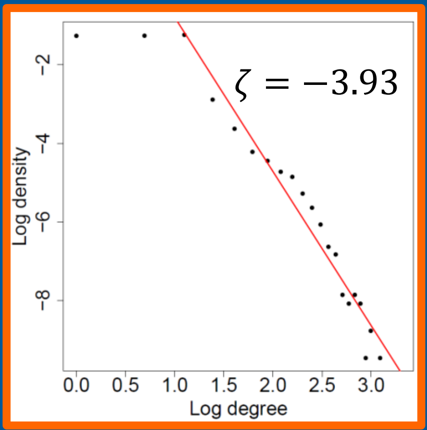


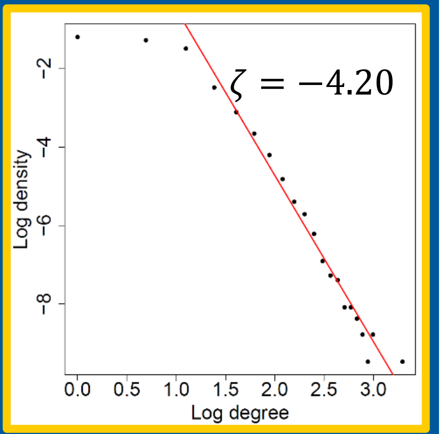
	Actual	Gen.
# of Nodes	12946	12946
# of Edges	16658	16658
Average Path Length	19.71	20.46
Clustering Coefficient	0.049	0.049
ζ	-3.93	-4.20
D_{KL}	0	0.064





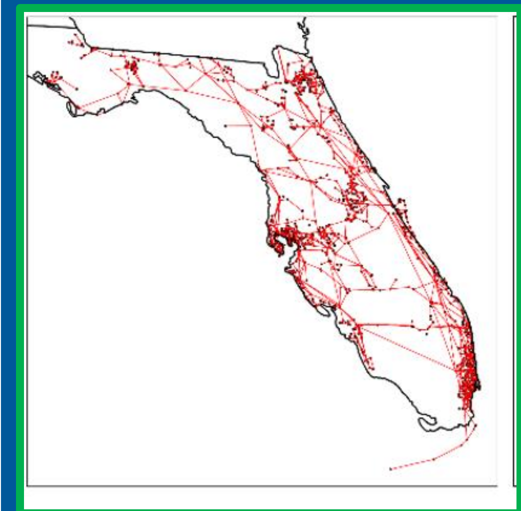
Length Distribution $D_{KL} = 0.064$

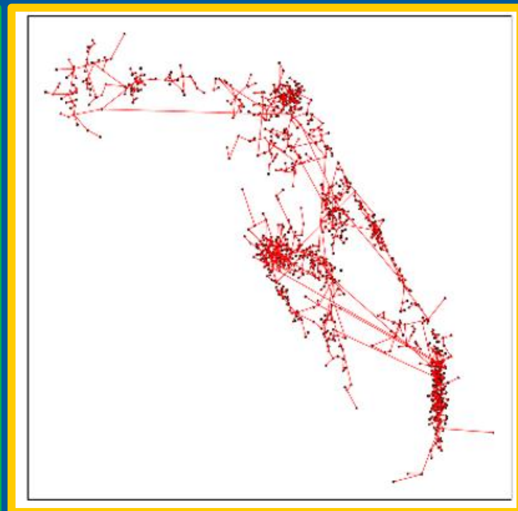




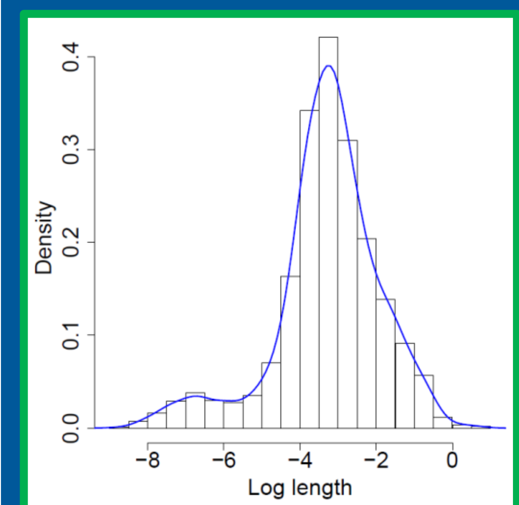
Degree Distribution

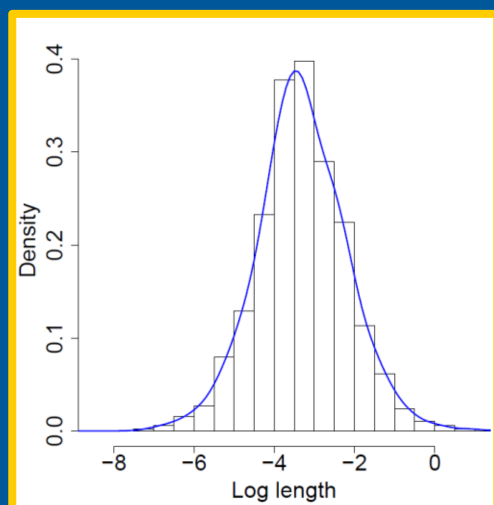
Evaluation: FRCC



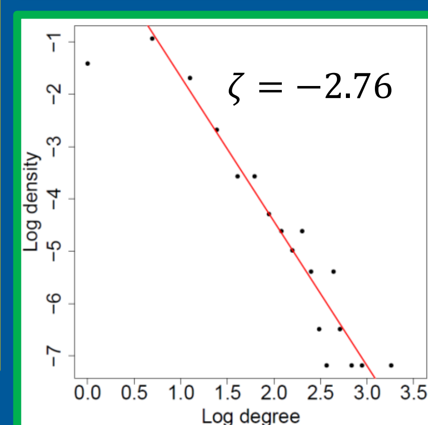


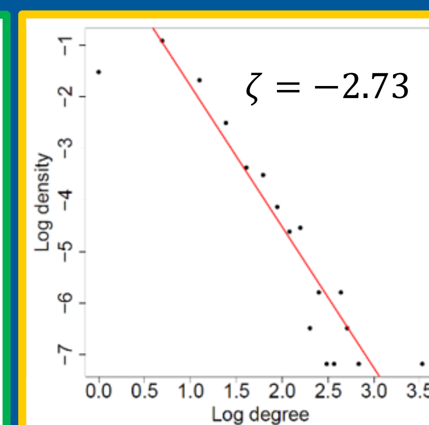
	Actual	Gen.
# of Nodes	1312	1312
# of Edges	1780	1780
Average Path Length	11.68	10.65
Clustering Coefficient	0.075	0.057
ζ	-2.76	-2.73
D_{KL}	0	0.08





Length Distribution $D_{KL} = 0.08$





Degree Distribution

Conclusion/Future Work

- A method to generate synthetic networks with structural properties similar to a given network
- Applied it to different parts of the North America grid
- It can be applied to any spatial network (e.g., transportation, gas pipes)
- It can be used to generate networks similar to a given network with less number of nodes and edges (turn back the time!)

- Publish our code as a Library in *R* for generating synthetic networks similar to any part of the North America grid as well as any given network
- Submit our work to the IEEE Transactions on Network Science and Engineering

Thank You!

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