

Network Properties Revealed through Matrix Functions

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Outline

- Motivation and background
- Measuring network with matrix exponential
- New set of measures: matrix resolvent
- Relation with graph Laplacian and spectral clustering
- Resolvent vs. exponential
- Experiment
- Conclusion

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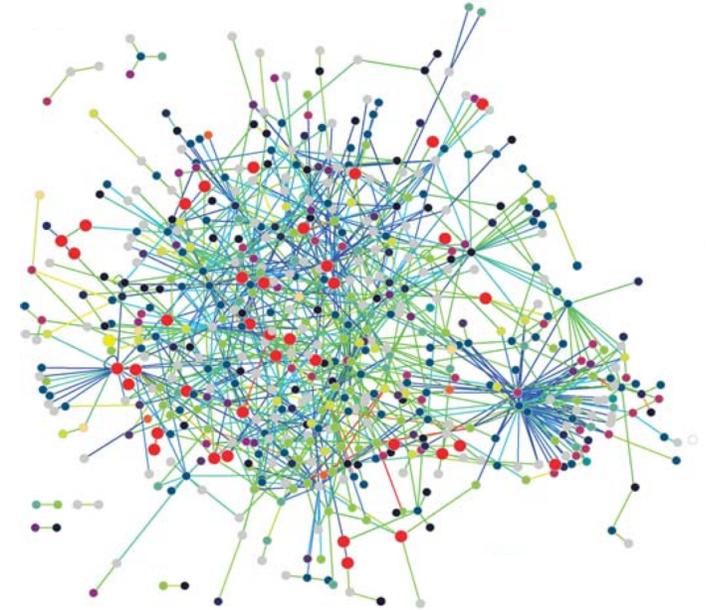
Motivation

- Analysis and characterization of networks offers valuable guidance in many areas

- Cell biology: gene-protein connections
- Brain: interconnection in neurological regions
- Epidemiology: epidemical contact of people
- Zoology: social interaction among animals
- Energy: electricity transport network
- Telecommunication
- WWW
- Movie database: costarring

- Networks are typically complex → the paper aim to describe complex networks with some simple quantities

- Network: **undirected**, **unweighted** graph with N nodes



Protein interaction network of
Treponema pallidum

Node centrality

- Measuring networks with the concept of centrality was proposed decades ago.
- Most intuitive method: Freeman centrality (Freeman, 1979), or degree

$$\text{deg}_i := \sum_{k=1}^N a_{ik} = (A\mathbf{e})_i$$

- Counts the number of edges connecting to node i
- \mathbf{e} is a vector with all elements being 1
- A is the adjacency matrix of the network
- Katz centrality (Katz, 1953), an extension of Freeman centrality

$$k_i := \sum_{j=1}^N \sum_{k=0}^{\infty} \alpha^k (A)_{ij}^k = (((I - \alpha A)^{-1} - I) \mathbf{e})_i$$

- $I = N$ -dimensional identity matrix
- α is a fixed parameter. Its upper bound is the inverse of A 's largest eigenvalue

Node centrality

- Eigenvector centrality (Bonacich, 1987), for weighted networks

$$b_i := \frac{1}{\lambda_1} \sum_{j=1}^N a_{ij} b_j = \left(\frac{1}{\lambda_1} A \mathbf{f} \right)_i$$

- λ_1 – Perron-Frobenius eigenvalue of A
- \mathbf{f} – Perron-Frobenius eigenvector of A

Walk vs. path

- A path between node i and node j (i and j are **distinct**) is an ordered list of **distinct** nodes $i, k_1, k_2, \dots, k_{n-1}, j$, in which successive nodes are connected.
- Walk between node i and node j is an ordered list of nodes $i, k_1, k_2, \dots, k_{n-1}, j$, in which successive nodes are connected.
 - The start and end of a walk may be the same ($i = j$)
 - Nodes may be revisited (k_1, k_2, \dots, k_{n-1} are not necessarily distinct)
- Lemma 1.1: The quantity $(A^n)_{ij}$ counts the number of different walks ($i \neq j$) or closed walks ($i = j$) of length n between nodes i and j .

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Matrix exponential: Centrality

- Degree of node i can be alternatively interpreted by number of closed walks of length 2 from i

$$(A^2)_{ii} = \sum_{k=1}^N a_{ik}a_{ki} = \text{deg}_i$$

- Consider lemma 1.1, $(A^n)_{ii}$ gives the number of closed walks involving node i , which reflects how i is connected to the network
- Intuitively, we write the centrality of node i as

$$(A^2)_{ii} + (A^3)_{ii} + (A^4)_{ii} + \dots$$

- Note that longer walks are less efficient than shorter walks. Hence, we need to add a weight factor to each term such that longer walks contribute less to centrality

Matrix exponential: Centrality

- Let the weight factor be $1/(n!)$ with n being the walk length and add an constant bias $(I + A)$

Arbitrary constant

Weighted sum of closed walks with all possible length

$$\left(I + A + \frac{A^2}{2!} + \frac{A^3}{3!} + \cdots + \frac{A^k}{k!} + \cdots \right)_{ii}$$

- Can be rewrite to

$$(\exp(A))_{ii}$$

Matrix exponential: Communicability

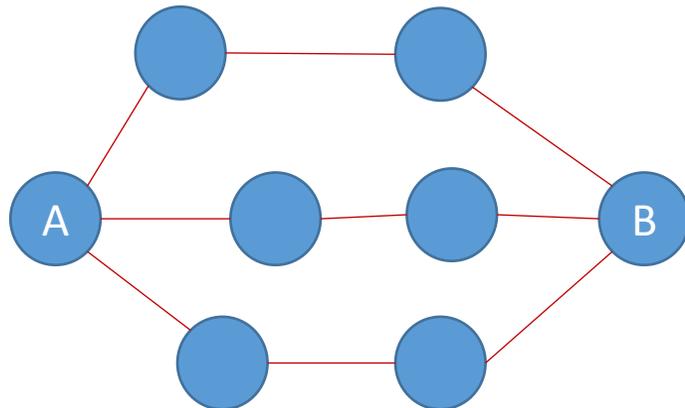
- Communicability quantifies the easiness for a piece of information to pass from node i to node j (i and j are distinct)
- A reasonable expression for communicability is sum over all walks that connect i and j .

$$(A^2)_{ij} + (A^3)_{ij} + (A^4)_{ij} + \dots$$

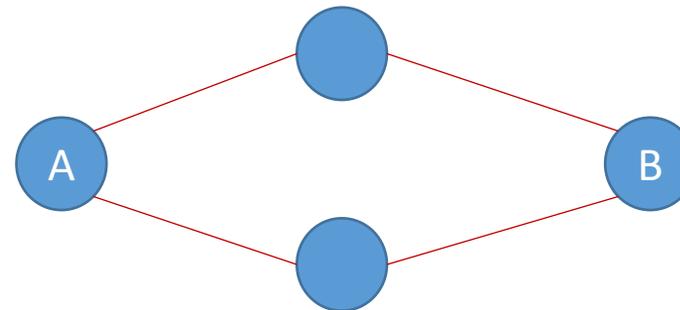
- Again, longer walks through i and j are penalized for not being efficient. If still use $1/(n!)$ as the weight and $(I + A)$ as bias, we have

$$(\exp(A))_{ij}$$

$$1/3! + 1/3! + 1/3! = 1/2$$



$$1/2! + 1/2! = 1/2$$



Matrix exponential: Betweenness

- Betweenness quantifies the importance of a particular node for information flow within the network. Alternatively, it quantifies the change of overall communicability of the network if a particular node is removed.
- Denote the node to be removed as r , and let $E(r)$ be a matrix whose components are nonzero only in (1) row and column r , AND (2) A has 1 in that position. Then the change in communicability per pair of nodes (other than r) is

$$\frac{1}{(N-1)^2 - (N-1)} \sum \sum_{i \neq j, i \neq r, j \neq r} \frac{(\exp(A)_{ij} - \exp(A - E(r))_{ij})}{\exp(A)_{ij}}$$

- $N \geq 3$
- Number of terms in the summation is $(N-1)^2 - (N-1)$
- Up to now, we developed a methodology of using matrix exponential as a measure of a network in three aspects: centrality, communicability, and betweenness

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General rule of forming new network measures

- Assumption: the graph is connected, with N nodes.
 - There must be at least one walk of length less than N between two nodes.
- Generally, to propose a new set of network measures, we write centrality in the form:

$$\sum_{n=1}^{\infty} c_n A^n$$

with $c_n \geq 0$ being the weight to scale the number of walks of length n .

- $c_n = 1/(n!)$ is not the only way of scaling.

General rule of forming new network measures

- A complete set of network measures should have the following form:
 - f -centrality: given by $f(A)_{ij}$, or in terms of the spectrum of A , $\sum_{k=1}^N f(\lambda_k) x_i^{[k]^2}$. $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_N$ are the eigenvalues of A corresponding to eigenvectors $x^{[1]}, x^{[2]}, \dots, x^{[N]}$.
 - f -communicability: given by $f(A)_{ij}$ (i and j are distinct), or $\sum_{k=1}^N f(\lambda_k) x_i^{[k]} x_j^{[k]}$
 - Betweenness: given by
$$\frac{1}{(N-1)^2 - (N-1)} \sum \sum_{i \neq j, i \neq r, j \neq r} \frac{(f(A)_{ij} - f(A - E(r))_{ij})}{f(A)_{ij}}$$
- From the factorial weight, a new f should
 - Penalize long walks ($c_n \geq 0$ decreases with n)
 - Be a convergent series
 - Lead to a matrix function

New set of measures: matrix resolvent

- Use $(N - 1)^{n-1}$ as the weight, and $c_0 = N - 1$. After some math, we get

$$f(x) = (N - 1) \left(1 - \frac{x}{N - 1}\right)^{-1}$$

rescale to

$$f(x) = \left(1 - \frac{x}{N - 1}\right)^{-1}$$

- Resolvent centrality

$$\sum_{k=1}^N \frac{N - 1}{N - 1 - \lambda_k} \mathbf{x}_i^{[k]^2}$$

- Resolvent communicability

$$\sum_{k=1}^N \frac{N - 1}{N - 1 - \lambda_k} \mathbf{x}_i^{[k]} \mathbf{x}_j^{[k]}$$

- Resolvent betweenness

$$\frac{1}{(N - 1)^2 - (N - 1)} \sum \sum_{i \neq j, i \neq r, j \neq r} \frac{(f(A)_{ij} - f(A - E(r))_{ij})}{f(A)_{ij}}$$

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Relation with graph Laplacian and spectral clustering

- Partition the nodes into two groups, where nodes in one group share more edges whereas nodes across the two groups share less edges.

- Define $x_i = 1/2$ if node i is in group A and $x_i = -1/2$ if node i is in group B
- Solve for

$$\min_{\mathbf{x} \in \mathbb{R}^N, \|\mathbf{x}\|_2=1, \sum_{i=1}^N x_i=0} \sum_{i=1}^N \sum_{j=1}^N (\mathbf{x}_i - \mathbf{x}_j)^2 a_{ij}$$

Number of edges across the two groups

Set $\|\mathbf{x}\|_2 = 1$ to eliminate trivial solution ($\mathbf{x} = 0$); set $\sum_{i=1}^N x_i = 1$ to avoid built-in redundancy

- Let $D = \text{diag}(\text{deg}_i)$, and rewrite

$$\min_{\mathbf{x} \in \mathbb{R}^N, \|\mathbf{x}\|_2=1, \sum_{i=1}^N x_i=0} \mathbf{x}^T (D - A) \mathbf{x}.$$

- $(D - A)$ is the graph Laplacian. The solution is the eigenvector ($v^{[2]}$) with the second smallest eigenvalue (μ_2), which is referred as Fiedler vector.

Relation with graph Laplacian and spectral clustering

- For two nodes i and j , given the Fiedler vector, $v^{[2]}$,
 - $v_i^{[2]}v_j^{[2]} > 0$, i and j in the same group. Larger $v_i^{[2]}v_j^{[2]}$ means i and j are more communicable.
 - $v_i^{[2]}v_j^{[2]} < 0$, i and j in different groups. Smaller $v_i^{[2]}v_j^{[2]}$ means i and j are less communicable.
- In regular graph case with monotonic f , where the degree is uniform ($deg_i \equiv deg$), graph Laplacian becomes $deg I - A$ with eigenvalues $\mu_i = deg - \lambda_i$, and eigenvectors $x^{[i]} = v^{[i]}$.
 - Dominant eigenvector ($k = 1$) contains no information as $x^{[1]} = e$.
 - Next dominate term is $v^{[2]}v^{[2]T}$, which is graph Laplacian clustering.
- In regular graph with monotonic f , $min x^T (D - A) x = min x^T (deg I - A) x \rightarrow max x^T A x$.
 - Need x_i and x_j to be large and have the same sign \rightarrow nodes that are more connected are farther from the origin.
 - $(v_i^{[2]})^2$ measures the well-connectedness of node i (same expression as f -centrality).

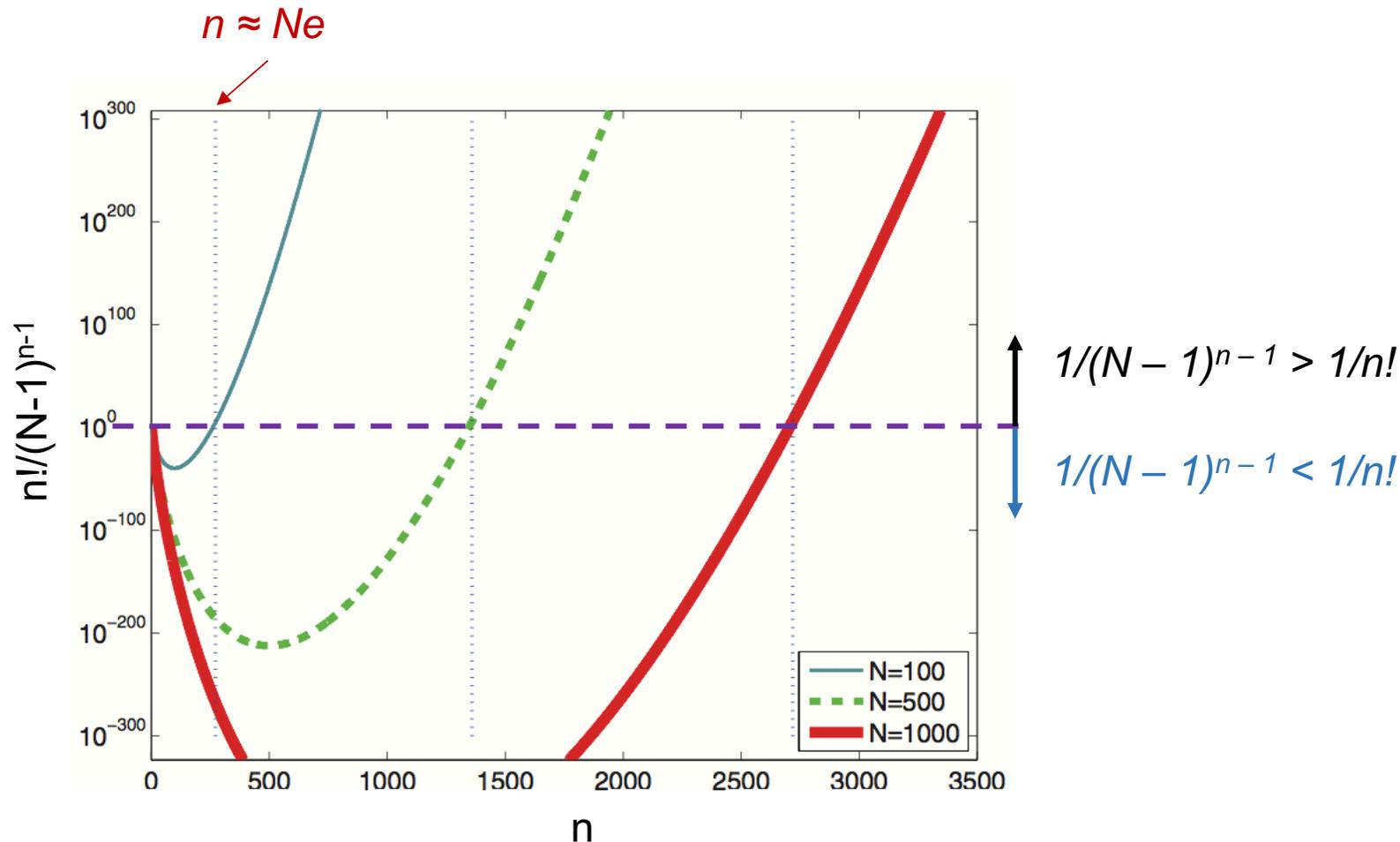
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Resolvent vs. exponential

- Exponential: $c_n = 1/n!$
- Resolvent: $c_n = 1/(N-1)^{n-1}$

- $n!$ is comparable to $(N-1)^{n-1}$ when $n \approx Ne$.



- Exponential measures penalize less on short walks ($n < Ne$), whereas resolvent measures penalize less on long walks ($n > Ne$)

Resolvent vs. exponential

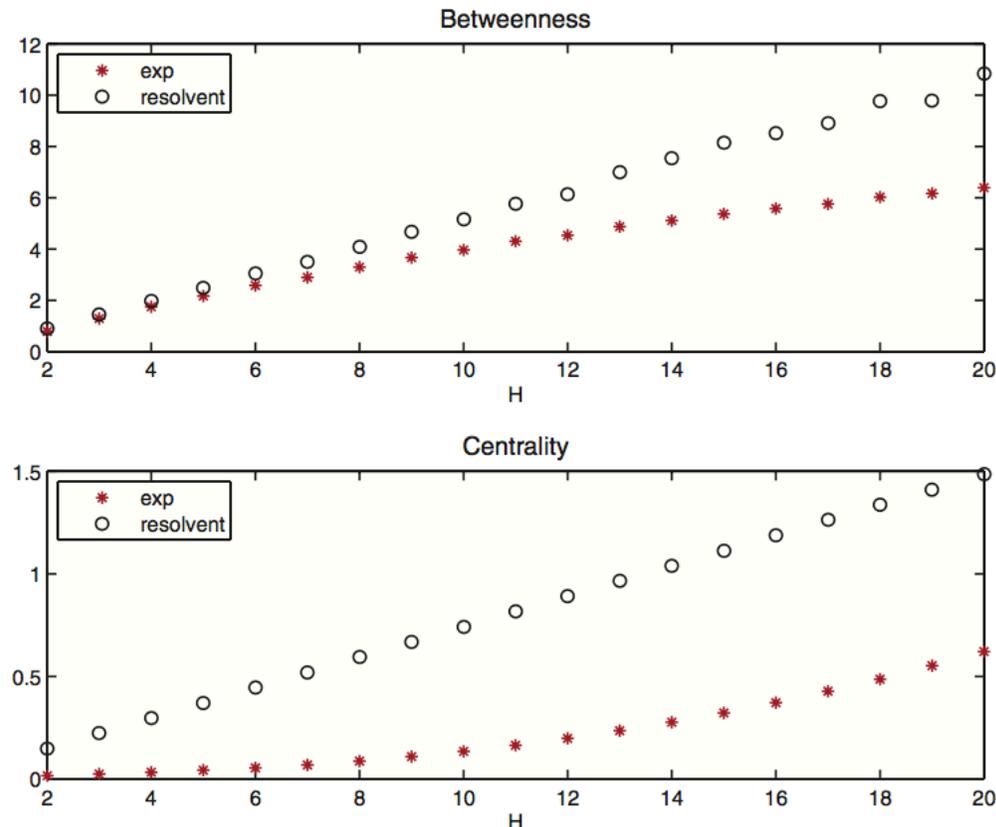
- The contribution from paths with length $\geq N$ to the resolvent communicability is bounded:

$$\begin{aligned} \sum_{n=N}^{\infty} \left(\frac{A^n}{(N-1)^{n-1}} \right)_{ij} &\leq \left\| \sum_{n=N}^{\infty} \frac{A^n}{(N-1)^{n-1}} \right\|_{\infty} \\ &\leq \sum_{n=N}^{\infty} \frac{\|A^n\|_{\infty}}{(N-1)^{n-1}} \\ &\leq \sum_{n=N}^{\infty} \frac{\|A\|_{\infty}^n}{(N-1)^{n-1}} \\ &\leq \frac{(N-1)^2}{N-1 - \|A\|_{\infty}} \left(\frac{\|A\|_{\infty}}{N-1} \right)^N \end{aligned}$$

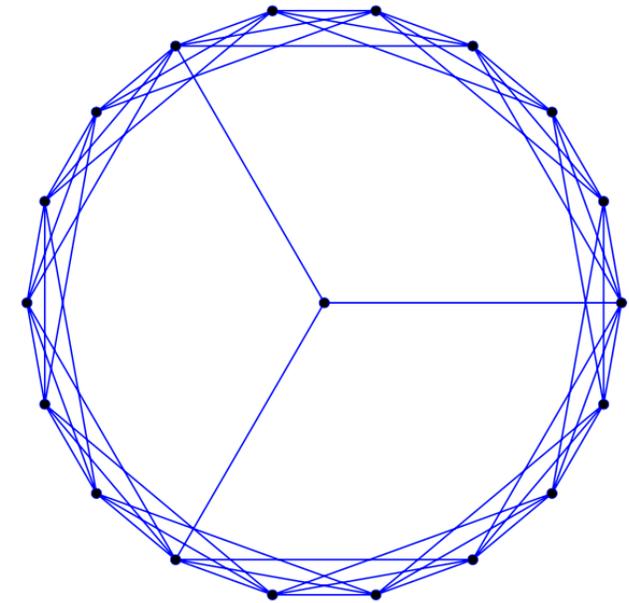
- As $\|A\|_{\infty} \ll N$, we conclude that the contribution of walks with length $O(N)$ to the resolvent communicability is negligible.

Ring of nodes with a hub

- Consider a periodic ring network. Each node is connected to K nodes clockwise and counterclockwise. Introduce a “hub” nodes that connects to H equally separated ring nodes.
- Consider such a network with $N = 200$, $K = 6$, and $H = 2 \sim 20$
- Hub removal destroys shortcuts \rightarrow more effect on resolvent communicablility
- Resolvent centrality is more similar to node degree (ratio approaches to 1 as H approaches $13 \approx 2K$)



$N = 18, K = 3, H = 3$



Betweenness and centrality of hub node relative to a ring node

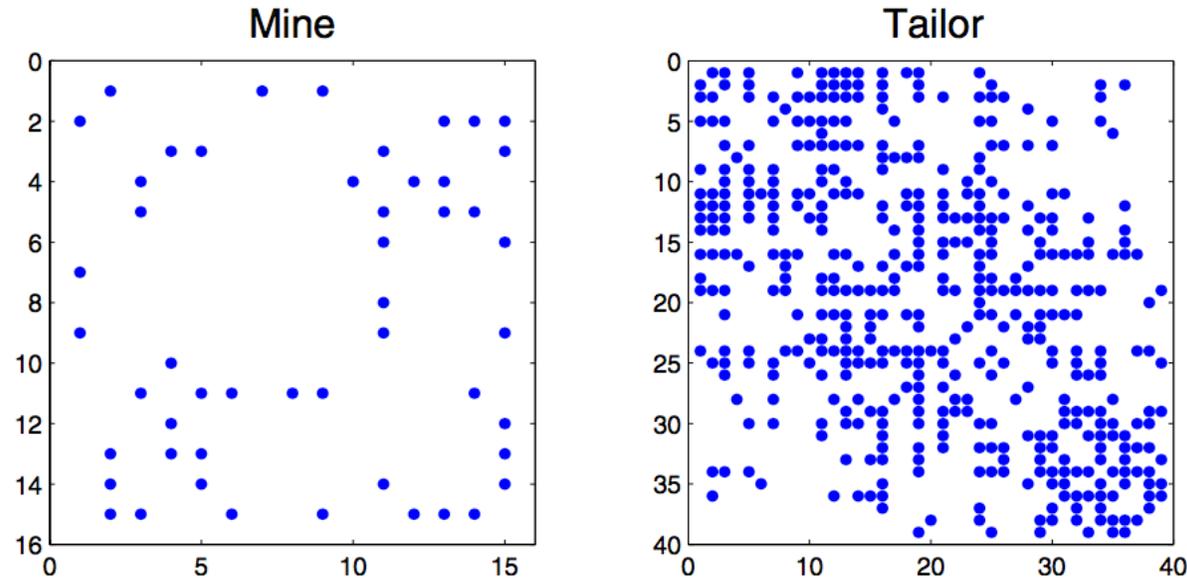
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Experiment with small scale data

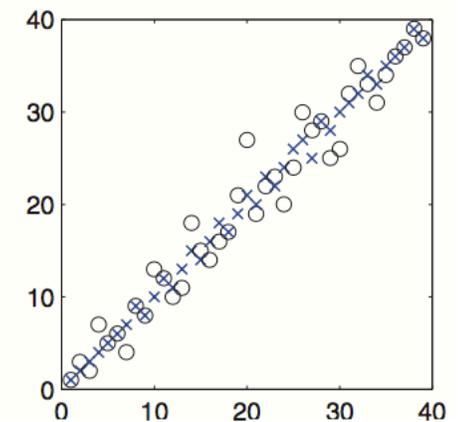
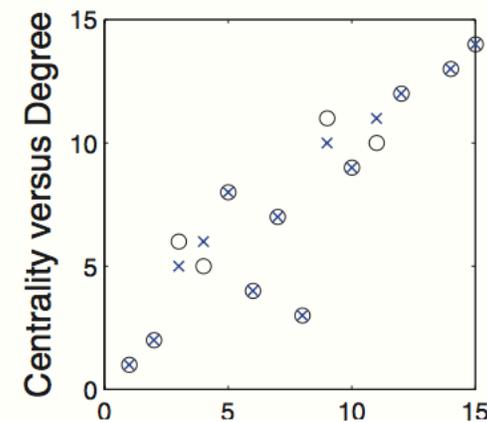
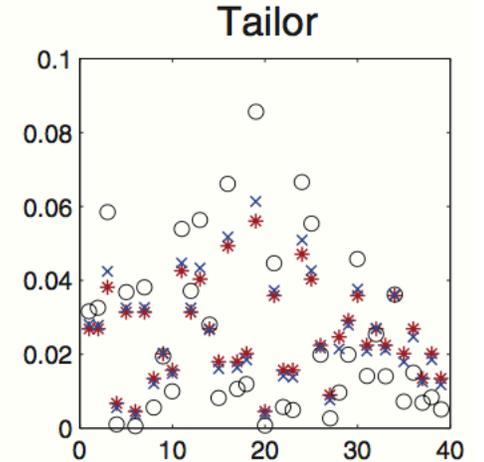
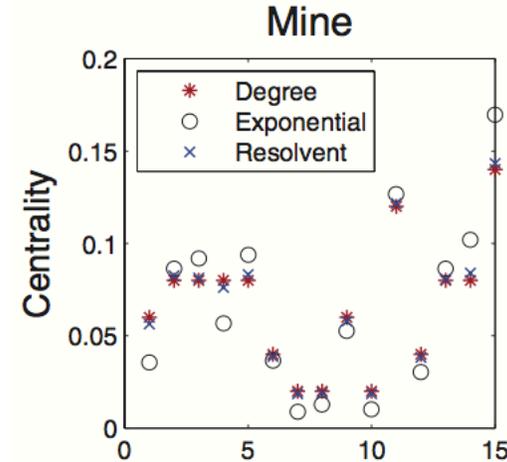
- Data set 1 – interactions (talk, joking, etc.) among 15 mine workers in Zambia
- Data set 2 – assistant-level interactions among 40 individuals in a tailor's shop in Zambia.

Adjacency matrices



Experiment with small scale data

- Resolvent centrality is close to degree, and usually locates in the middle of degree and exponential centrality.
- The three measures differ more in the mine case (smaller, sparser).
- Requires arbitrary tie-breaking if nodes have the same degree.
- Resolvent is in the middle of exponential and degree, and is more close to degree.



Position (i, j) represents the node is ranked i in degree and j in exponential (circle) or resolvent (cross) centrality

Experiment with large scale data

- Food web: 81 nodes representing marine species.
- Resolvent measure is between the degree and exponential measures, and is more close to exponential.
- Ordering of the first 10 nodes in centrality ranking (high to low) is different in each measure.
- “≡” indicates a tie-breaking

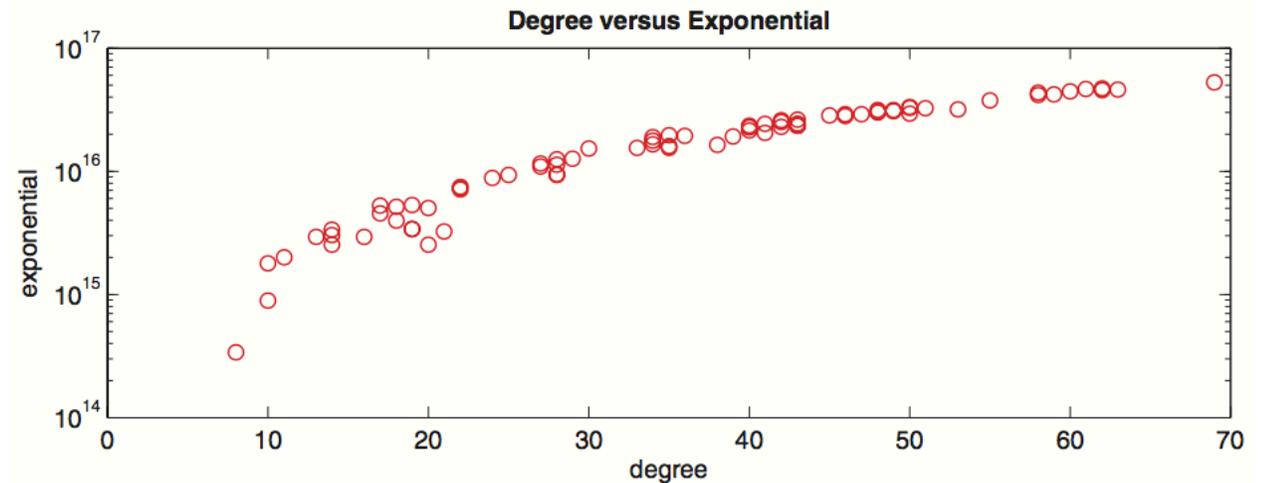
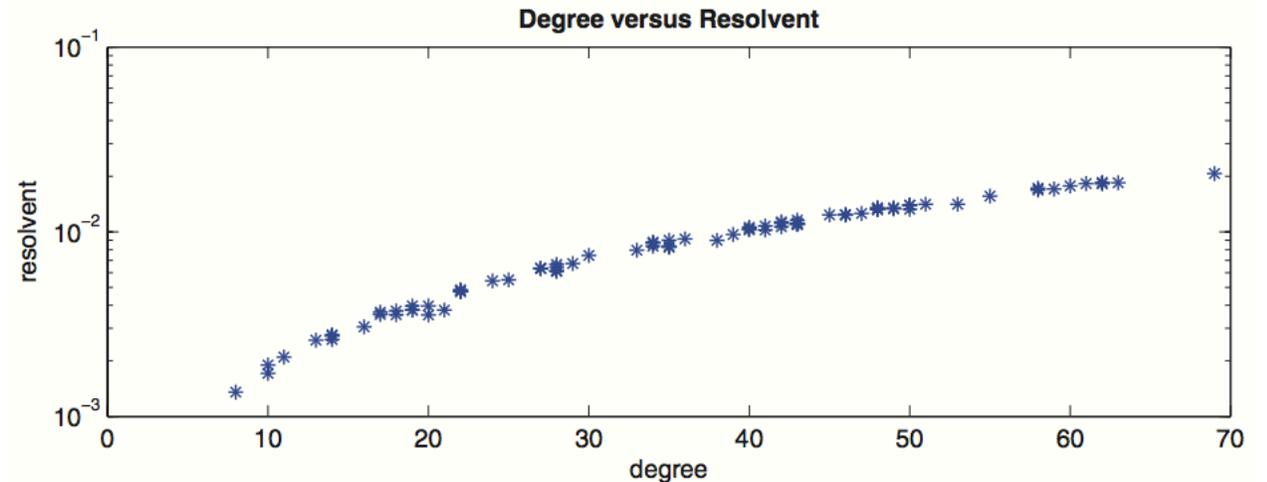
Increase centrality



degree: 50 < 49 ≡ 68 < 69 < 39 < 48 < 40 ≡ 41 < 42 < 43,

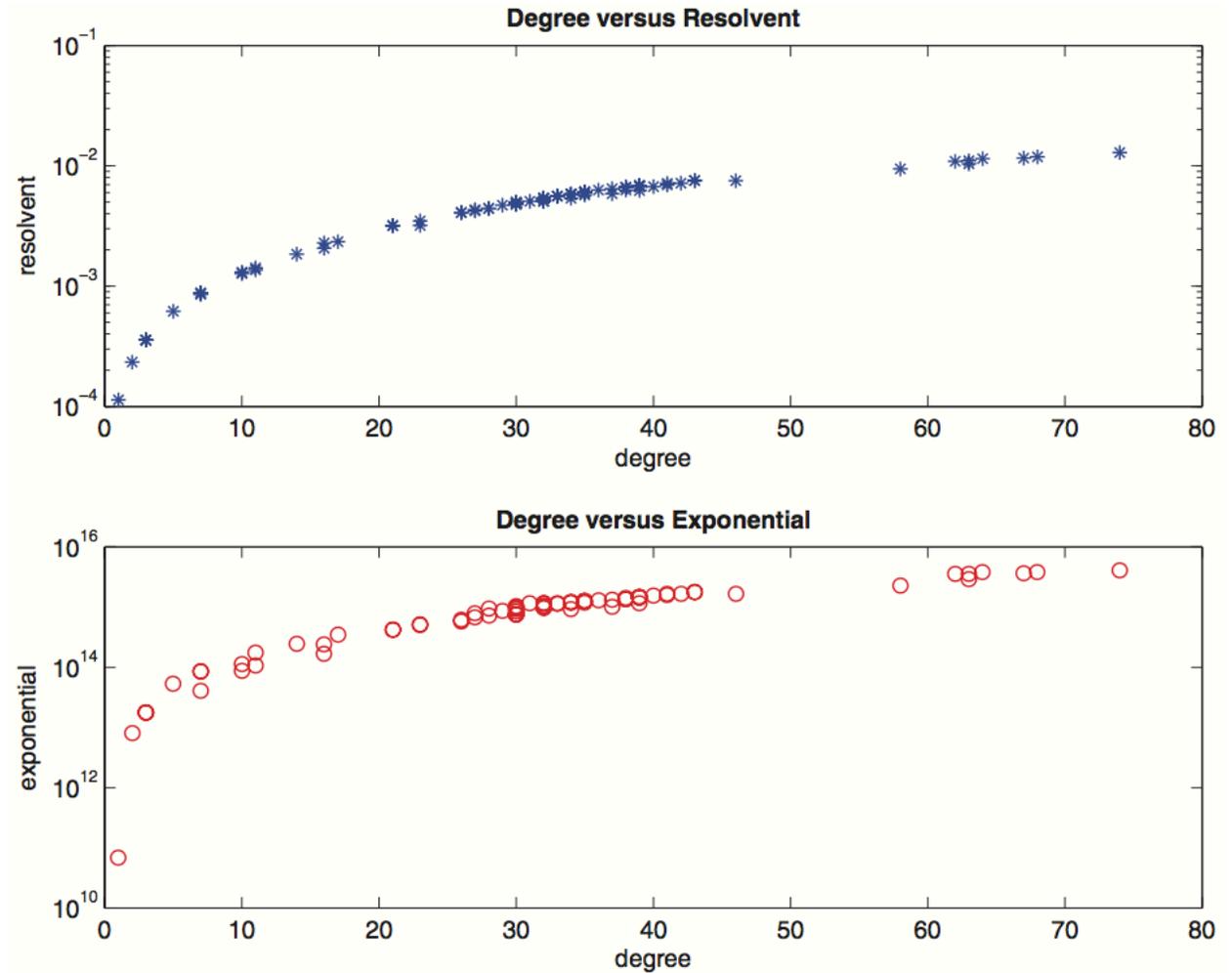
resolvent: 50 < 49 < 69 < 68 < 39 < 41 < 48 < 42 < 40 < 43,

exponential: 50 < 49 < 69 < 68 < 39 < 41 < 42 < 48 < 40 < 43.



Experiment with large scale data

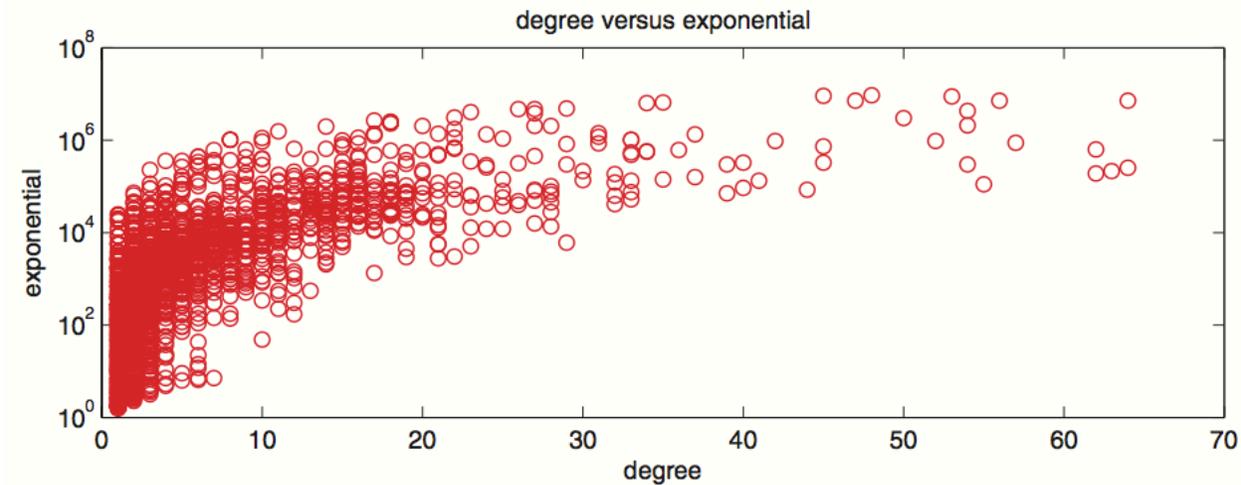
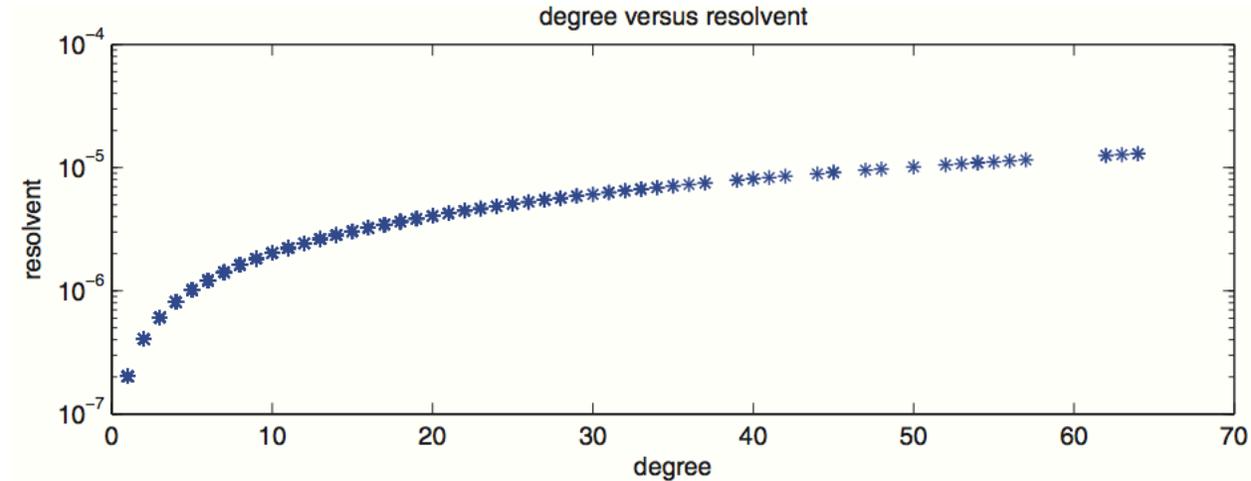
- Network of macaque cortical connectivity: 95 nodes representing regions in brain and edges are physical connections
- The three rankings are generally consistent. Difference appears at lower positions



degree: 15 < 94 < 65 < 58 < 31 ≡ 39 < 38 < 59 < 93 < 68,
resolvent: 13 < 6 < 65 < 39 < 58 < 31 < 38 < 59 < 93 < 68,
exponential: 11 < 12 < 65 < 39 < 58 < 31 < 59 < 38 < 93 < 68.

Experiment with large scale data

- Protein-protein interaction network: 2224 proteins are nodes, each edge denotes an physical interaction.
- Note that nodes 111, 607 and 1896 have the same degree. This makes degree and resolvent equivalent.



degree: 607 \equiv 1896 < 489 < 473 < 138 < 200 \equiv 739 < 1338 < 292 \equiv 535,

resolvent: 111 < 607 < 489 < 473 < 138 < 739 < 200 < 1338 < 535 < 292,

exponential: 1170 < 122 < 129 < 156 < 117 < 473 < 292 < 242 < 126 < 427.

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Conclusion

- Resolvent centrality is typically in the middle of degree and exponential centrality. Its value is often closer to degree in large networks.
- Resolvent measure has advantages of
 - Real-valued
 - Can yield analogous measures of communicability and betweenness
- Build the fundamentals of defining centrality, communicability, and betweenness using other matrix function