Introduction to Network Science

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Topic Today

IDENTIFY INFLUENTIAL SPREADERS

Influence Analysis of Nodes in Complex Networks

Introduction

Identifying the most efficient spreaders in a network is an important step towards optimizing the use of available resources and ensuring the more efficient spread of information.

Main Methods

1. Degree Centrality

2. Betweenness Centrality

3. Closeness Centrality

4. k-shell or k-core

1. Degree Centrality

Historically first and conceptually simplest is degree centrality, which is defined as the number of links incident upon a node. In the case of a directed network (where ties have direction), we usually define two separate measures of degree centrality, namely indegree and outdegree

The degree centrality of a vertex v, for a given graph G:=(V, E), with $|V|$ vertices and $|E|$ edges, is defined as

$$C_D(v) = \deg(v)$$

After normalization, the degree centrality is defined as

$$C_D(v)' = \frac{\deg(v)}{|V| - 1}$$

2. Betweenness Centrality

Betweenness centrality quantifies the number of times a node acts as a bridge along the shortest path between two other nodes

The betweenness centrality of a vertex v, for a given graph $G := (V, E)$, with $|V|$ vertices and $|E|$ edges, is defined as

$$C_B(v) = \sum_{s \neq v \neq t \in V} \frac{\sigma_{st}(v)}{\sigma_{st}}$$

where σ_{st} is total number of shortest paths from node s to node t and $\sigma_{st}(v)$ is the number of those paths that pass through v.

2. Betweenness Centrality

Betweenness centrality quantifies the number of times a node acts as a bridge along the shortest path between two other nodes

After normalization, the betweenness centrality can be represented as

$$C_B(v) = \Big(\sum_{s \neq v \neq t \in V} \frac{\sigma_{st}(v)}{\sigma_{st}} \Big) / (|V| - 1)(|V| - 2) \qquad \text{(directed)}$$

$$C_B(v) = 2 \times \Big(\sum_{s \neq v \neq t \in V} \frac{\sigma_{st}(v)}{\sigma_{st}} \Big) / (|V| - 1)(|V| - 2) \qquad \text{(undirected)}$$

3. Closeness Centrality

The farness of a node is defined as the sum of its distances from all other nodes, and its closeness was defined as the reciprocal of the farness.

The closeness centrality of a vertex x, for a given graph $G:=(V, E)$, with $|V|$ vertices and $|E|$ edges, is defined as

$$C(x) = \frac{1}{\sum_y d(y,x)}.$$

4. k-shell or k-core

The k-shell decomposition: Nodes are assigned to k shells according to their remaining degree, which is obtained by successive pruning of nodes with degree smaller than the k_S value of the current layer.

We start by removing all nodes with degree k D1. After removing all the nodes with k D1, some nodes may be left with one link, so we continue pruning the system iteratively until there is no node left with k D1 in the network. The removed nodes, along with the corresponding links, form a k shell with index kS D1. In a similar fashion, we iteratively remove the next k shell, kS D2, and continue removing higher-k shells until all nodes are removed. As a result, each node is associated with one kS index, and the network can be viewed as the union of all k shells. The resulting classification of a node can be very different than when the degree k is used.

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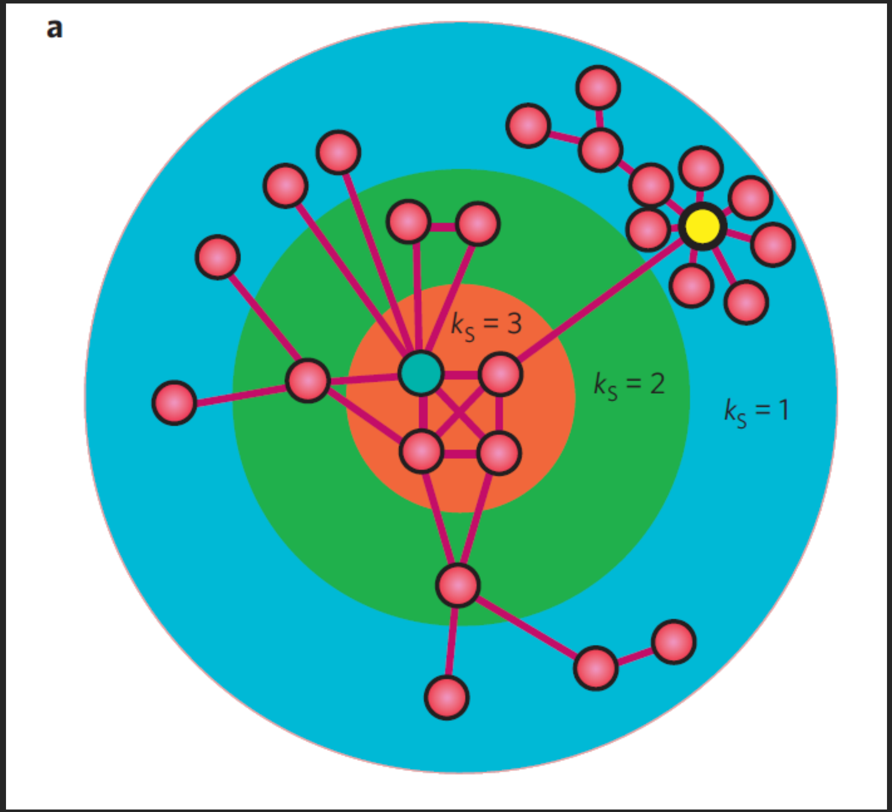
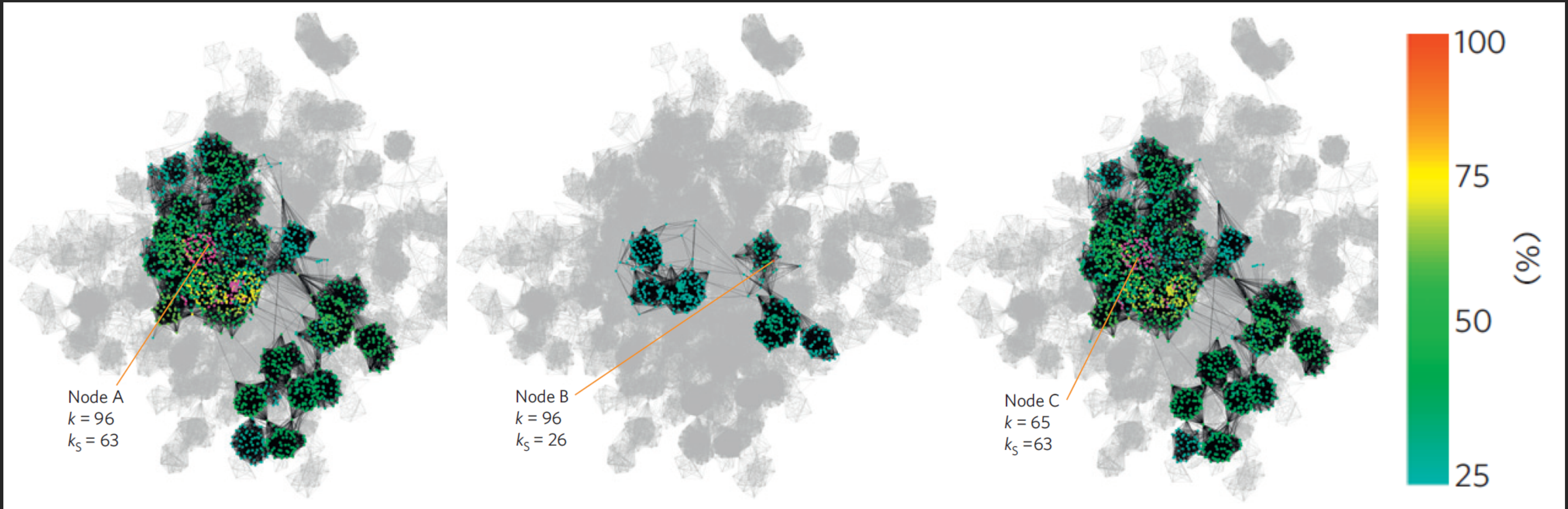


4. k-shell or k-core



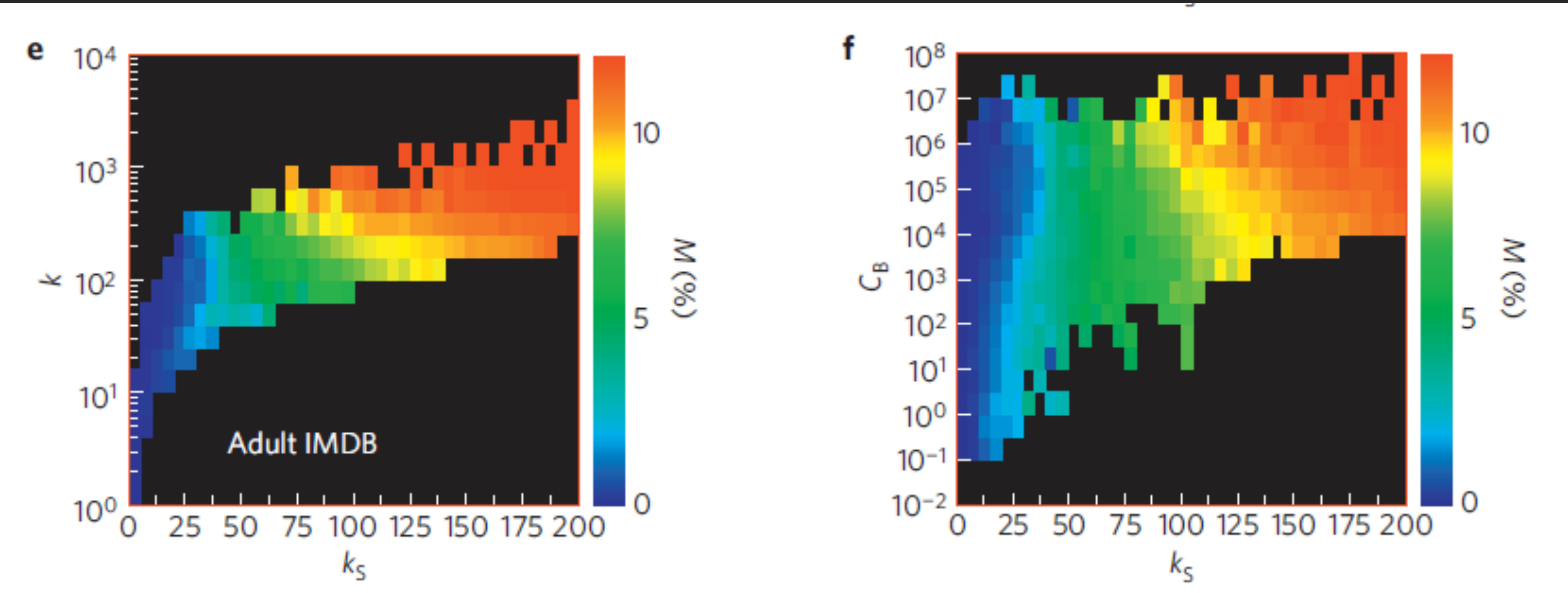
4. k-shell or k-core

$$M(k_S, k) = \sum_{i \in \Upsilon(k_S, k)} \frac{M_i}{N(k_S, k)}$$

where $\Upsilon(k_S, k)$ is the union of all $N(k_S, k)$ nodes with (k_S, k) values.

4. k-shell or k-core

The quantitative analysis: The k-shell index predicts the outcome of spreading more reliably than the degree k or the betweenness centrality C_B



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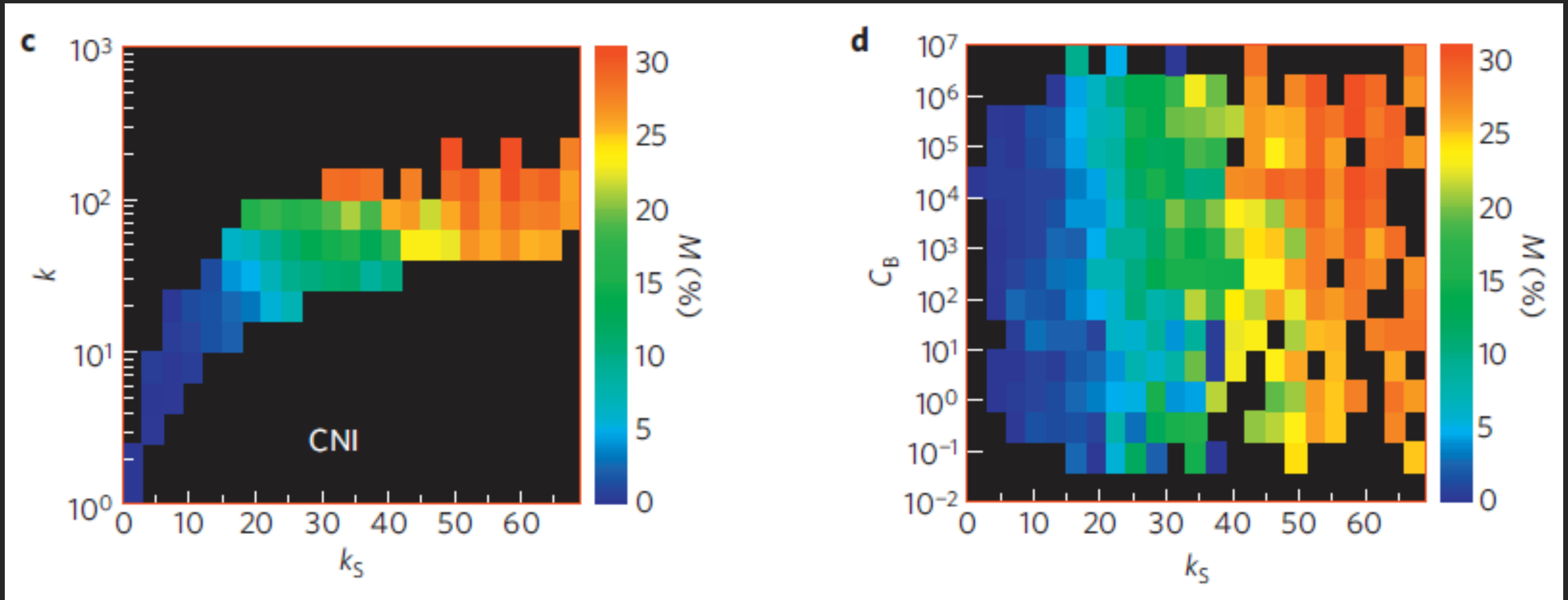

WE ARE GROUP 2

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THANK YOU

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