

# The Internet[work]

DSTA

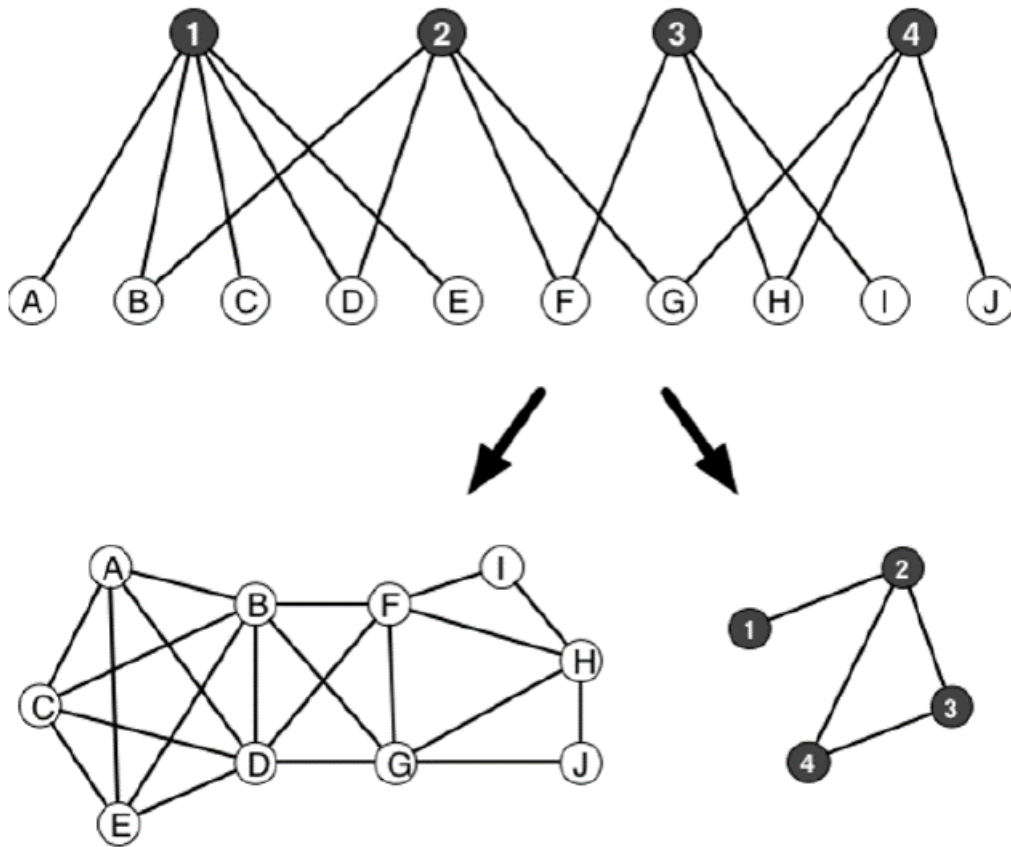
## 1 Summary of Trade Networks

### 1.1 The directed network model

Theme: discover non-trivial relationships among countries  
look at how they trade and what they trade

### 1.2 Bipartite networks

The country-to-product network induces country-to-country and product-to-product relationships.



### 1.3 Reconstruction

$$C = M_{cp} \cdot M_{cp}^T$$

$$P = M_{cp}^T \cdot M_{cp}$$

### 1.4 Analysis of neighbours

For a node  $i$ , let  $k_i$  be its degree.

For directed networks:  $k_i = k_i^{in} + k_i^{out}$ .

The distribution of degree  $P(k)$  provides a signature of the network.

The average degree is denoted  $\langle k \rangle$ .

## 1.5 Reciprocity

For a given directed network, reciprocity is the probability that of having links in both directions between two vertices.

R measures how the economies of two countries become interconnected (or interdependent).

$$r = \frac{L^{\leftrightarrow}}{L}$$

$L^{\leftrightarrow}$ : number of reciprocal links

$L$ : total number of links.

## 1.6 Assortativity

Do vertices tend to connect with those with similar/dissimilar degree?

Compute the avg. degree of  $i$ 's neighbors:

$$K_{nn}(i) = \frac{\sum_{\langle ij \rangle} k_j}{k_i}$$

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Find the avg.  $K_{nn}$  of nodes which have degree  $d$ :

$$K_{nn}(d) = \frac{\sum_{i:k_i=d} K_{nn}(i)}{n_d}$$

where  $n_d$  is the number of nodes having degree  $d$ .

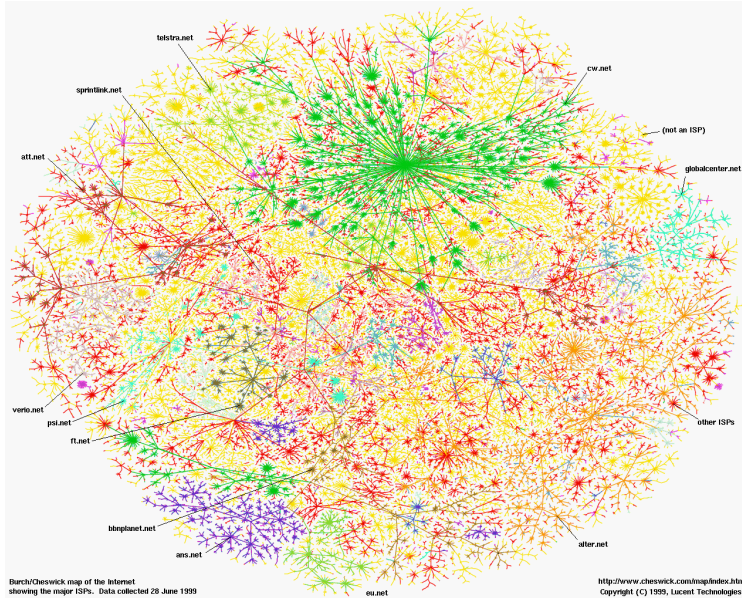
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- Are  $d$  and  $K_{nn}(d)$  close?
- does assortativity grow over time?

## 2 The Internet Network

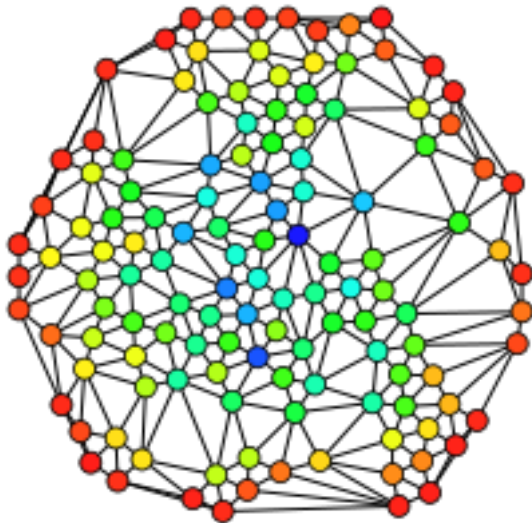
### 2.1 The need for resolution

The [Internet Service Provider network](#):



### 2.2 From visualisation back to data

Thanks to the [Beautifulsoup project](#), images of networks in `.svg` format can be imported into a Networkx structure.



```
from bs4 import BeautifulSoup

FILE = 'data/svg-example.svg'

op = open(FILE, 'r')

xml = op.read()

soup = BeautifulSoup(xml)
```

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```
G = nx.Graph()

attrs = { "line" : ["x1", "y1", "x2", "y2"] }

# what lines are there?
for attr in attrs.keys():
    tmps = soup.findAll(attr)
```

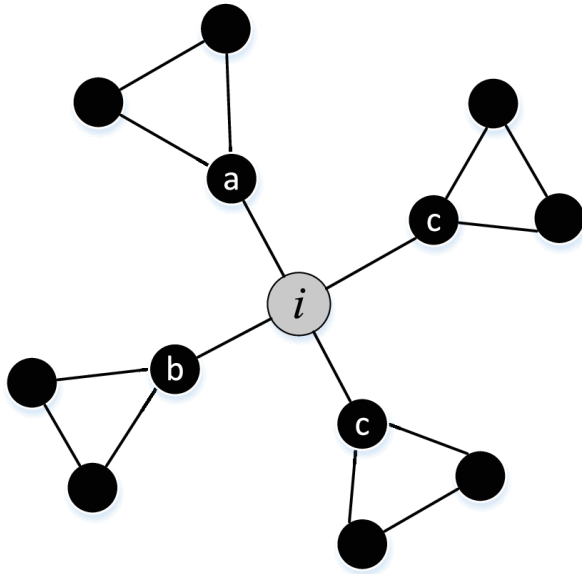
Details in Ch. 3 of the textbook.

## 3 Node Centrality

### 3.1 Find important nodes

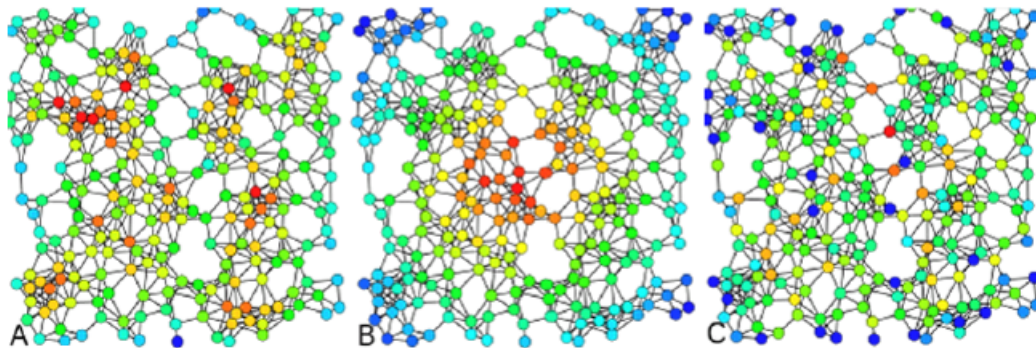
Centrality is about importance, of a vertex or edge, within the whole network.

The topology of the network should reflect such importance, so we do not need to **inspect** the entities.



### 3.2 Comparing centralities

- A Degree Centrality
- B Closeness Centrality
- C Betweenness Centrality



### 3.3 Degree centrality

High degree leads to higher centrality

### 3.4 Closeness centrality

Being in close reach to anywhere.

Let  $d_{ij}$  be the distance between  $i$  and  $j$  on the graph.

...

$$c_j = \frac{1}{\sum_{j \neq i} d_{ij}}$$

### 3.5 Harmonic centrality

Immune against isolated vertices/disconnection

$$c_j^h = \sum_{j \neq i} \frac{1}{d_{ij}} = \sum_{d_{ij} < \infty, j \neq i} \frac{1}{d_{ij}}$$

### 3.6 Betweenness centrality

Being in the middle/facilitating all contacts/conversations

Let  $D_{jl}$  be the number of distinct paths that exist between node  $j$  and node  $l$ .

Let also  $D_{jl}(i)$  be the number of those paths that go via  $i$

...

$$b(i) = \sum_{\substack{j,l=1..n, \\ i \neq j \neq l}} \frac{D_{jl}(i)}{D_{jl}}$$

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1 shortest path in 4 (or 25%) goes through  $b$ , the same with  $g$ .

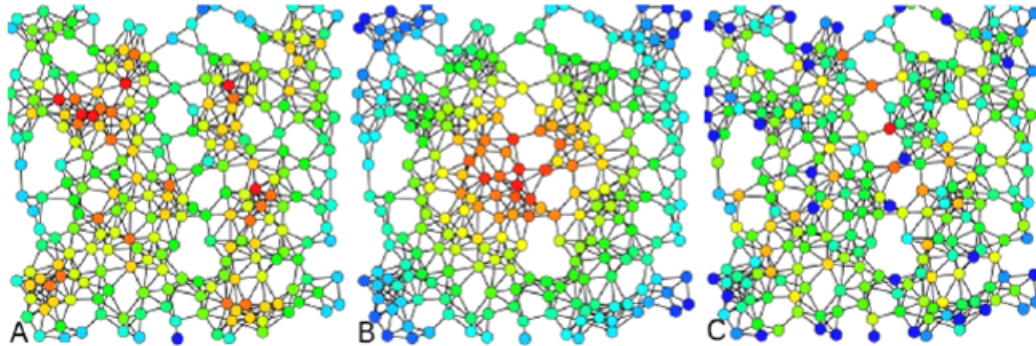
[Brandes 2001] computes  $b(i)$  in  $O(|V| \cdot |E|)$ : too slow to be practical even on small networks.

Estimates based on sampling are used instead.

Good estimates are valuable when the network evolves in a fully-dynamic way: edges and vertices are arbitrarily inserted/removed over time.

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- A Degree Centrality
- B Closeness Centrality
- C Betweenness Centrality



## 4 Eigenvector centrality

### 4.1 A reflective definition

my  $c_i$  is the average of my neighbors  $c_j$ 's,  
 which in turn depends on my own centrality.

...

The dominant e-vector  $\mathbf{v}_1$  describes the direction of maximum shape-preserving expansion

$$A\mathbf{v}_1 = \lambda_1\mathbf{v}_1$$

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$$A\mathbf{v}_1 = \lambda_1\mathbf{v}_1$$

...

$$\mathbf{v}_1 = \frac{1}{\lambda_1}A\mathbf{v}_1$$

...

For each vertex  $i$ :



$$v_{1_i} = \frac{1}{\lambda_1} \sum_j a_{ij} \cdot v_{1_j}$$

which is the needed centrality measure.

## 4.2 Computing Eigenvector centrality

1. Compute the dominant Eigenpair  $(\lambda_1, \mathbf{v}_1)$  of A;
2. sort vertices according to the  $v_{1_i}$  value they “scored.”