

Centrality Measures

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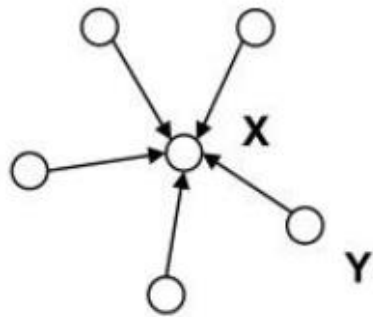
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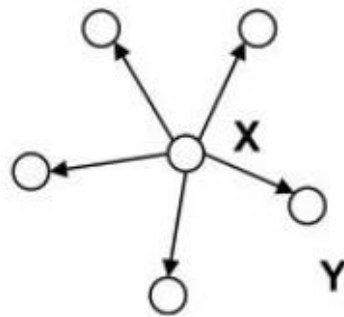
- Degree centrality
- Betweenness centrality
- Closeness centrality
- Eigenvector centrality
- PageRank and its application in web search

- Knowing the network structure, we can calculate various useful quantities or measures that capture features of network topology
- Centrality measures represent the most important nodes in graphs:
 - The most influential person in a social network.
 - The most critical nodes in a infrastructure.
 - The highest spreaders of disease.

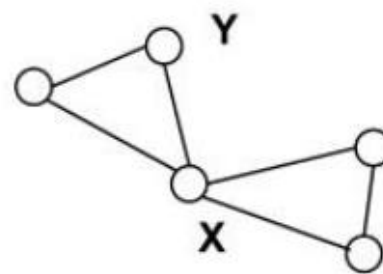
- Who is important based on the network position?
- In each of the networks, X has higher centrality than Y according to a particular measure.



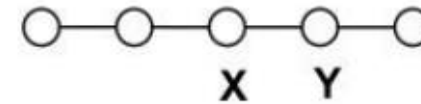
indegree



outdegree

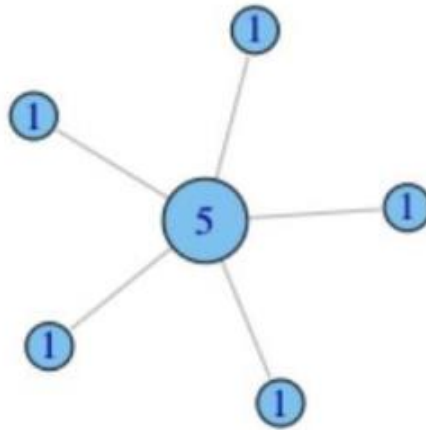


betweenness



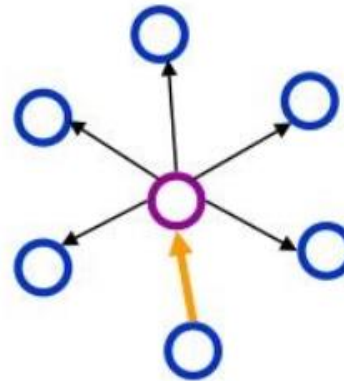
closeness

- People who have many friends is most important.
- When is the number of connections the best centrality measure?
 - People who will do favors for you
 - People you can talk to (influence set, information access, ...)
 - Influence of several actions.

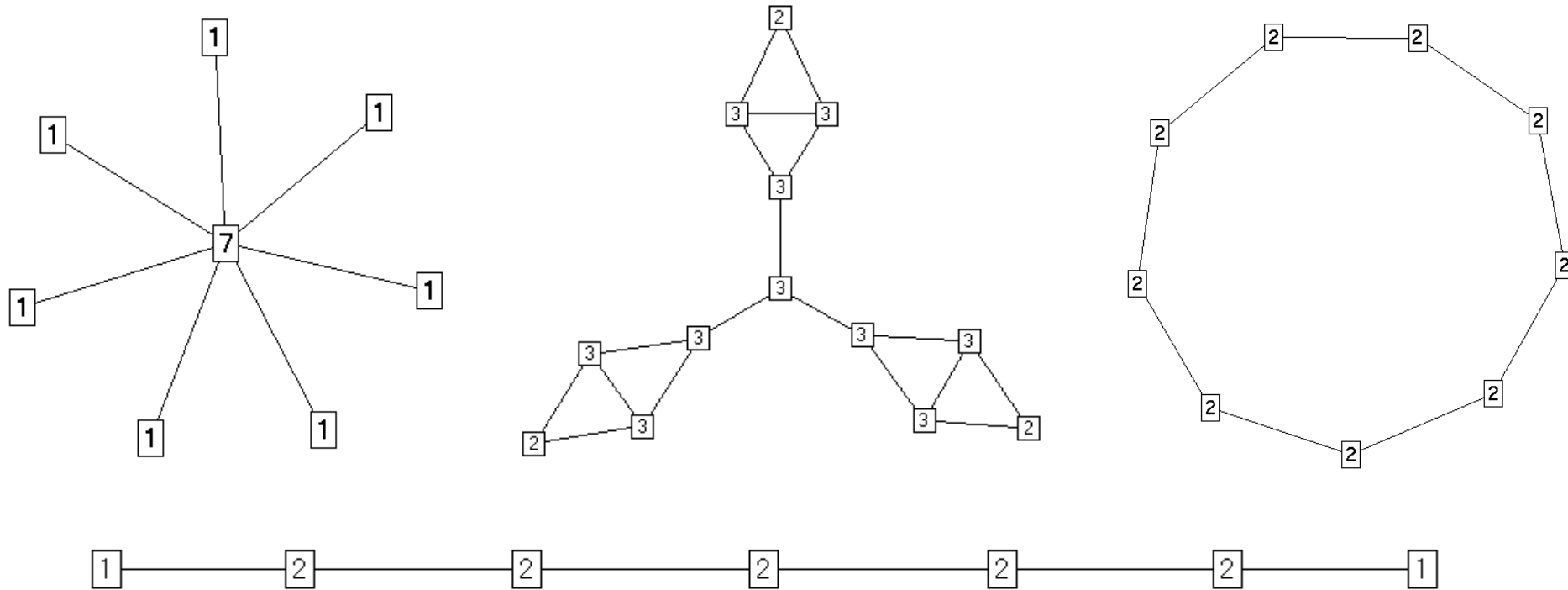


- When 'prestige' may be the right word
 - Admiration
 - Influence
 - Gift-giving
 - Trust

- Degree centrality
- Indegree centrality
 - A paper that is cited by many others has high prestige
 - A person nominated by many others for a reward has high prestige

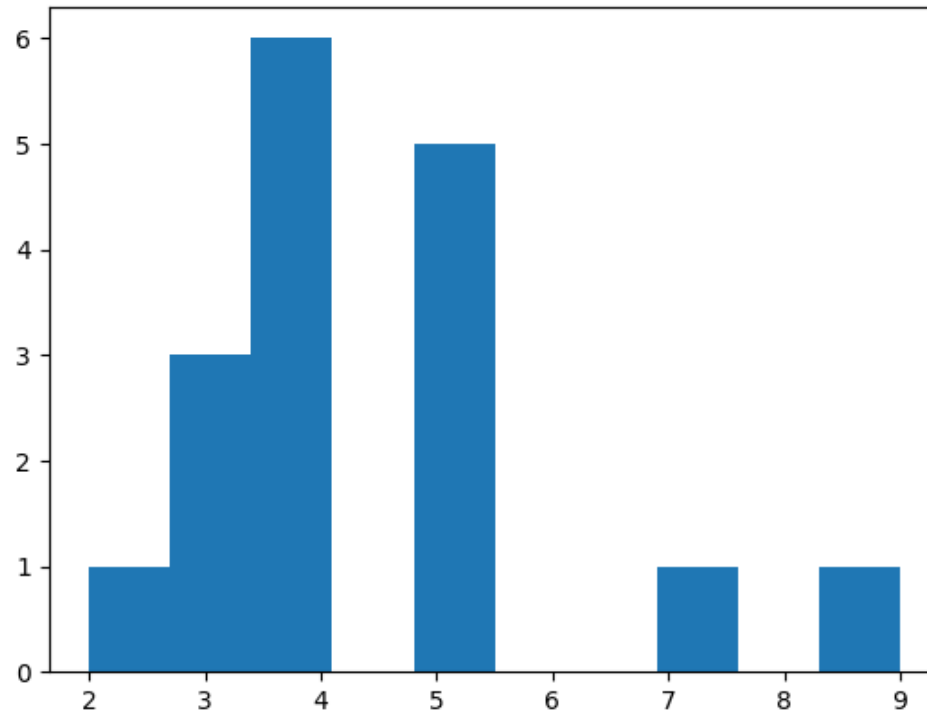


- The most intuitive notion of centrality focuses on degree:
 - The actor with the most ties is the most important:



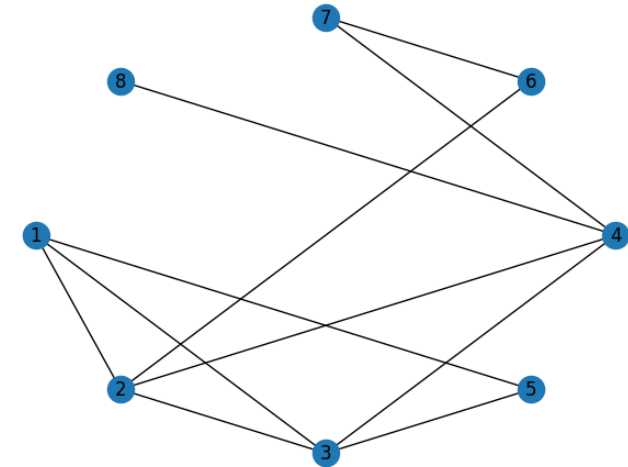
$$C_D(v_i) = d(v_i) = \sum_{j=1}^n A_{ij}$$

- In a simple random graph, degree will have a Poisson distribution, and the nodes with high degree are likely to be at the intuitive center.
- Deviations from a Poisson distribution suggest non-random processes, which is at the heart of current “scale-free” work on networks.



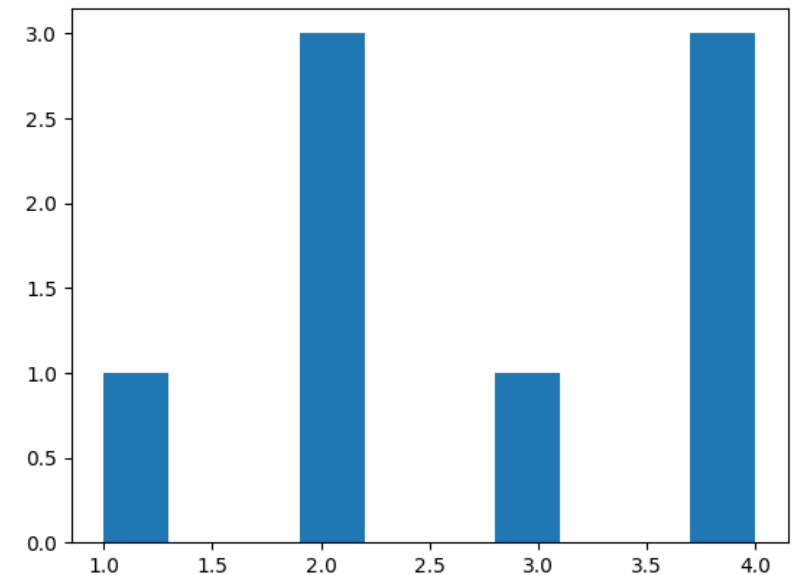
Create graph using edgelist from edge_list.txt file

```
# Undirected graph
G = nx.read_edgelist('./data/edge_list.txt')
nx.draw(G, pos=nx.shell_layout(G), with_labels = True)
#nx.draw(G, pos=nx.spiral_layout(G), with_labels = True)
# Directed graph
# G = nx.read_edgelist('edge_list.txt', create_using=nx.DiGraph())
```



Histogram degree plot

```
degrees = [G.degree(n) for n in G.nodes()]
plt.hist(degrees)
```



- If we want to measure the degree to which the graph as a whole is centralized, we look at the *dispersion* of centrality:
 - Simple: variance of the individual centrality scores.

$$S_D^2 = \left[\sum_{i=1}^n (C_D(v_i) - \bar{C}_d)^2 \right] / n$$

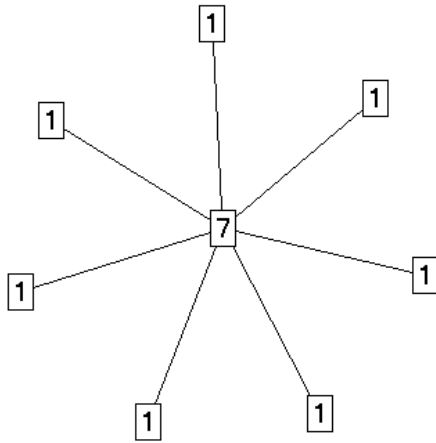
- Or, using Freeman's general formula for centralization (which ranges from 0 to 1): How much variation is there in the centrality scores among nodes?

$$C_D(G) = \frac{\sum_{i=1}^n [C_D(v^*) - C_D(v_i)]}{(n-1)(n-2)},$$

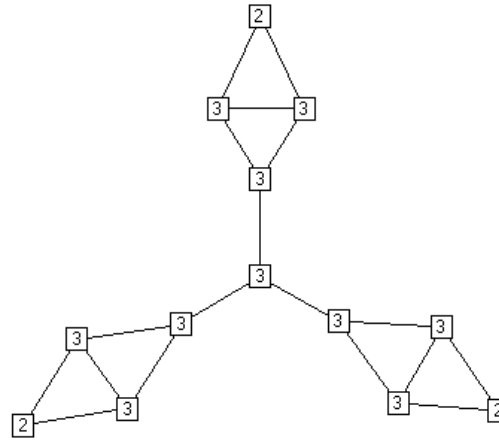
where :

v^* : the node with the highest degree in G

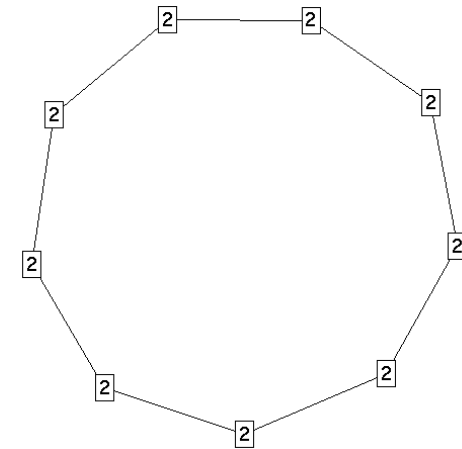
➤ Degree centralization scores



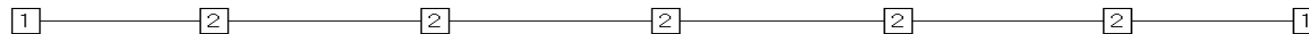
Freeman: 1.0
Variance: 3.9



Freeman: .02
Variance: .17

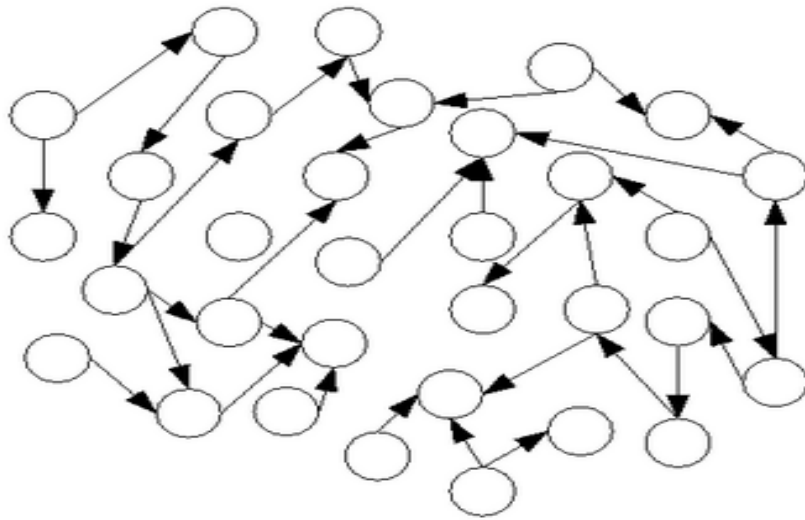


Freeman: 0.0
Variance: 0.0



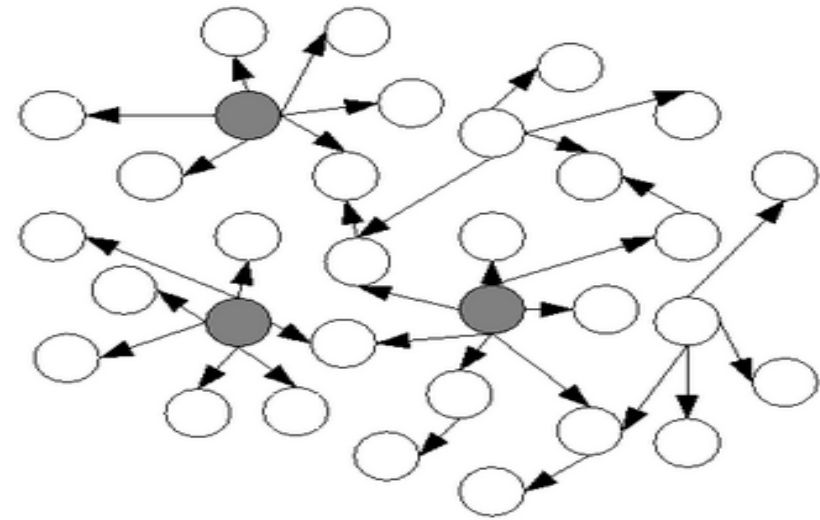
Freeman: .07
Variance: .20

- Random network models introduce an edge between any pair of vertices with a probability p .
- The problem here is NOT randomness, but rather the distribution used (which, in this case, is uniform)



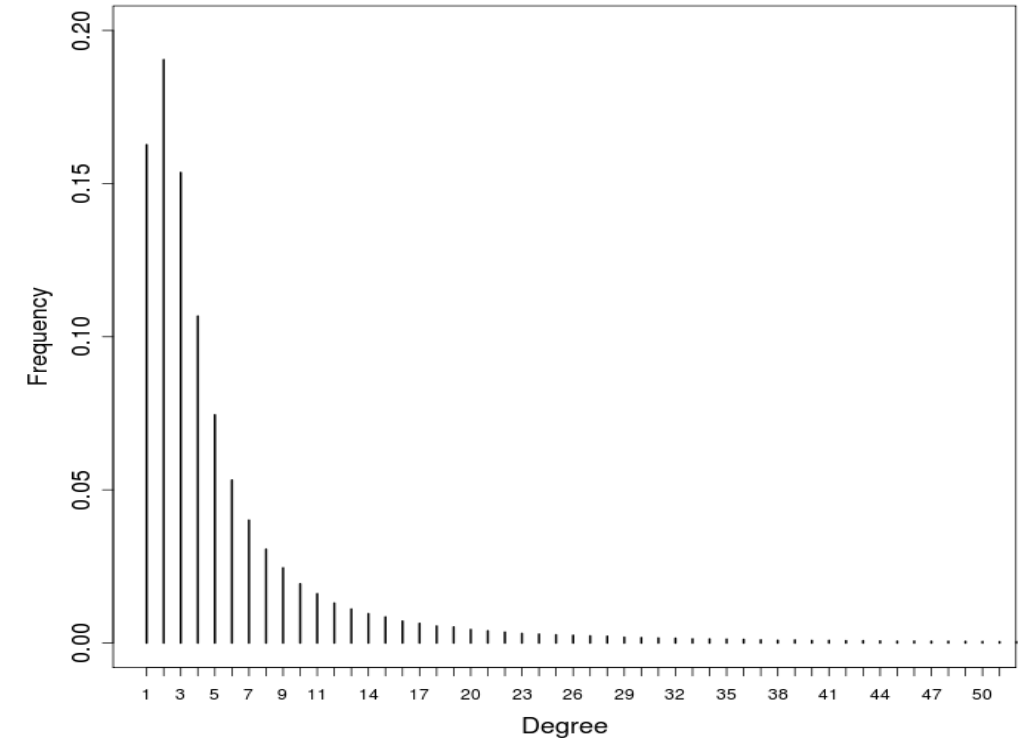
(a) Random network

- Real networks are not exactly like these:
 - Tend to have a relatively few nodes of high connectivity (the “Hub” nodes)
 - These networks are called “Scale-free” networks

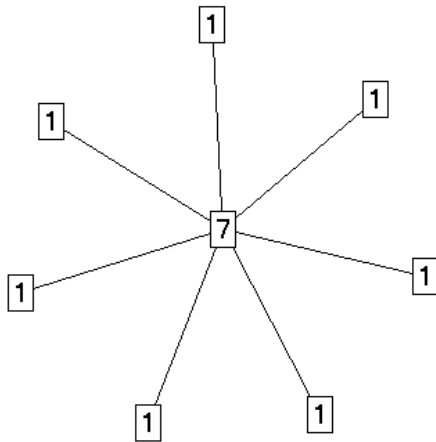


(b) Scale-free network

- In most real networks, the degree distribution is highly asymmetric:
 - Most of the nodes (the trivial many) have low degrees
 - A small but significant fraction of nodes (the vital few) have an extraordinarily high degree. A highly connected node, a node with remarkably high degree, is called hub showing a long tail.



➤ Degree centralization scores



Freeman: 1.0

Variance: 3.9

```
: import networkx as nx
import numpy as np
import matplotlib.pyplot as plt

# Instantiate the graph
G = nx.Graph()
# add node/edge pairs
G.add_edges_from([(1, 0), (1, 2), (1, 3), (1, 5), (1, 4), (1, 6), (1, 7)])
#Degree plot for undirected and weighted graph
degrees = [G.degree(n) for n in G.nodes()]

#degrees = [G.degree(n, weight='weight') for n in G.nodes()]
plt.hist(degrees)
mean = sum(degrees) / len(degrees)

v_start = max(degrees)
n = len(degrees)
var = sum((i - mean) ** 2 for i in degrees) / n
freeman = sum((v_start - i) for i in degrees) / ((n-1)*(n-2))
print(f'variance: {var}')
print(f'Freeman: {freeman}')
```

```
variance: 3.9375
Freeman: 1.0
```


- Using Freeman's general formula for centralization (which ranges from 0 to 1):

$$C_D(G) = \frac{\sum_{i=1}^n [C_D(v^*) - C_D(v_i)]}{(n-1)(n-2)},$$

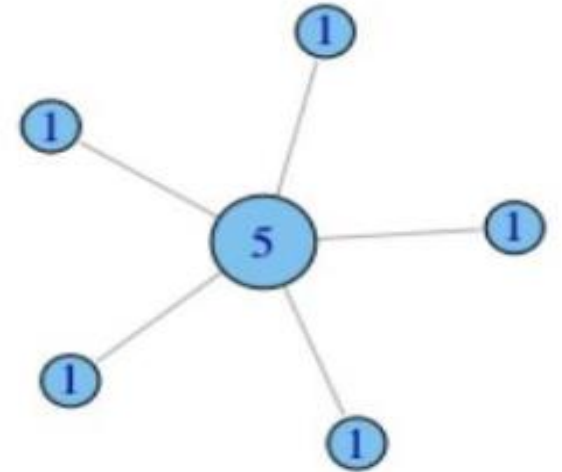
where:

v^* : the node with the highest degree in G



$$C_D = 0.167$$

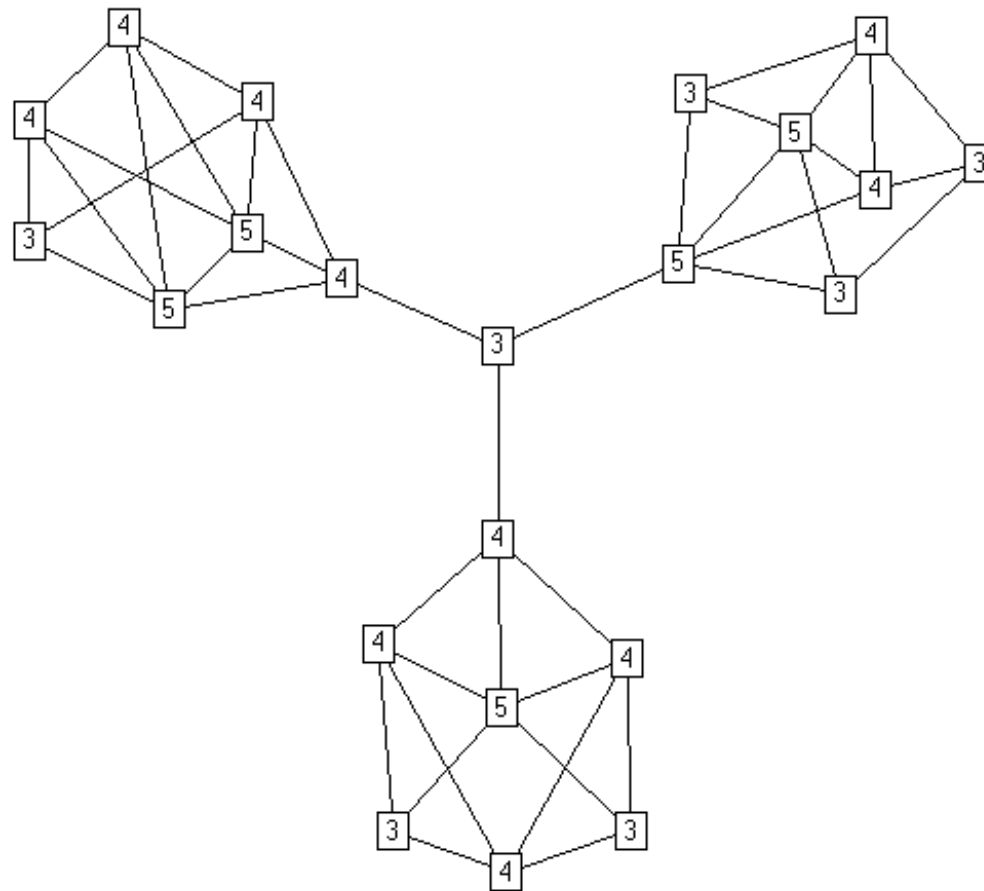
$$C_D(G) = \frac{(2-1) + (2-0) + \dots + (2-1)}{(5-1)(5-2)} = 0.167$$



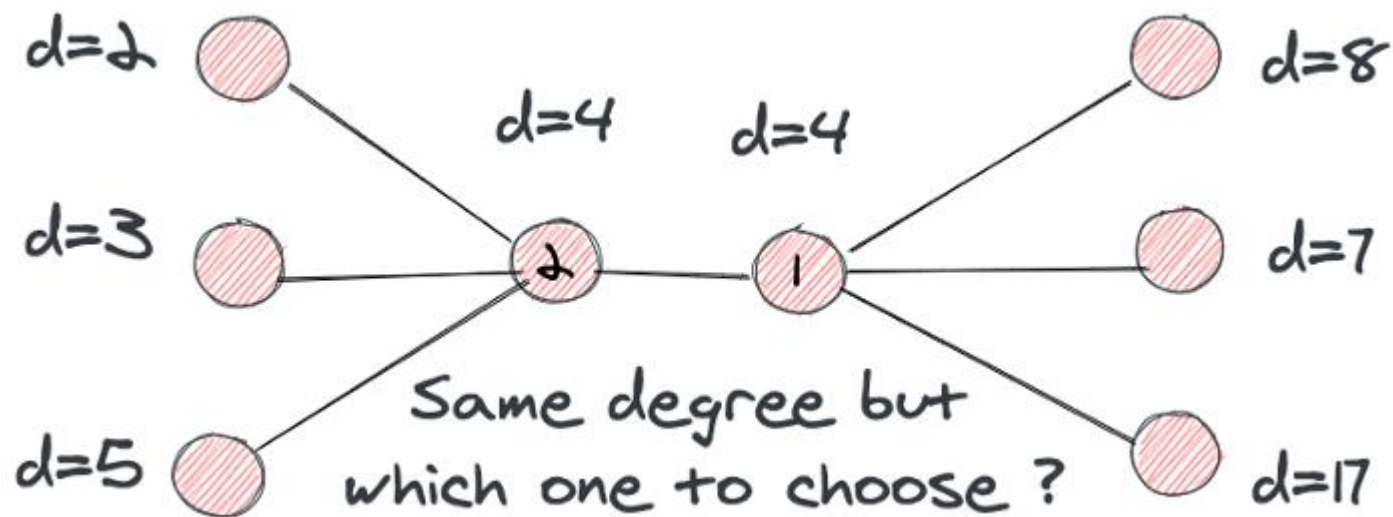
$$C_D = 1.0$$

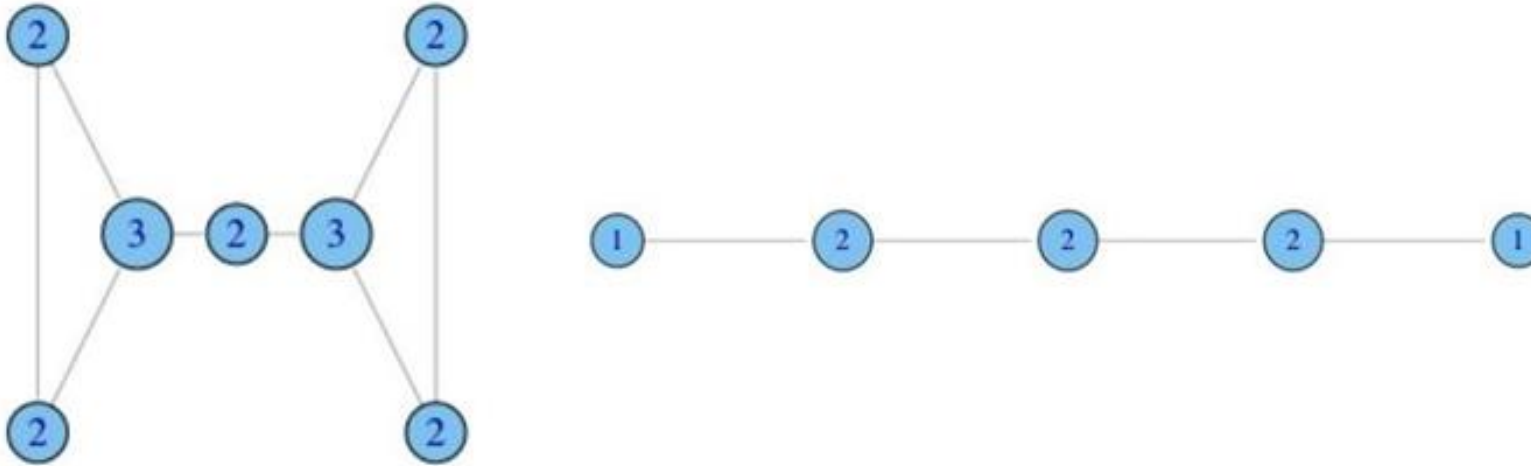
$$C_D(G) = \frac{(5-1) + \dots + (5-1)}{(6-1)(6-2)} = \frac{20}{20} = 1$$

- Degree centrality, however, can be deceiving, because it is a purely local measure.



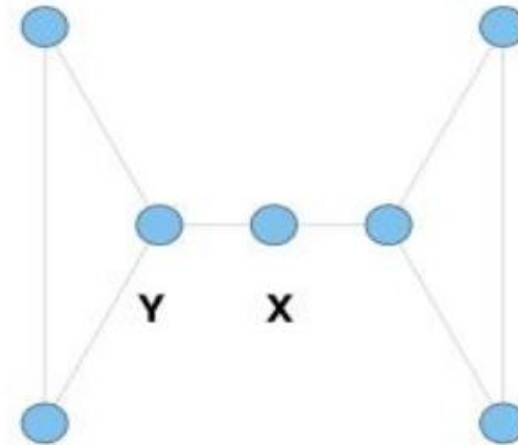
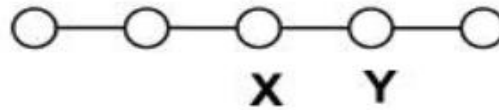
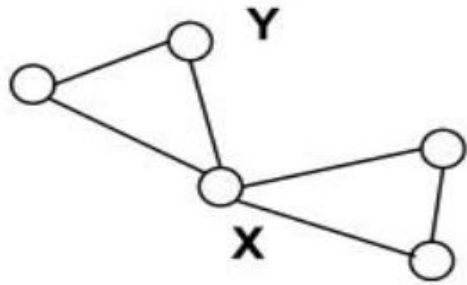
- Node degree is local, not global



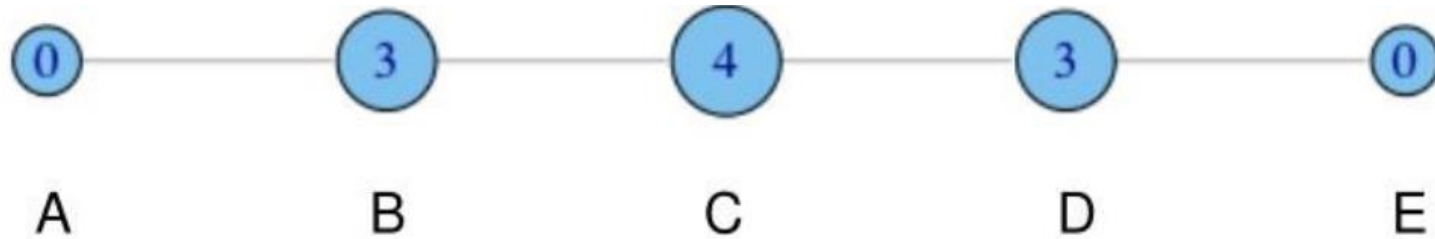


- Ability to broker between groups.
- The likelihood that information originating anywhere in the network reaches you.

- Intuition:
 - How many pairs of individuals would have to go through you in order to reach one another in the minimum number of hops?
- Who has higher betweenness, X or Y?



- Non-normalized version:
 - A lies between no two other nodes
 - B lies between A and 3 other nodes: C,D,E
 - C lies between 4 pairs: (A,D), (A,E), (B,D), (B,E)



- Betweenness centrality of node v_i :

$$B(v_i) = \sum_{v_j, v_k \in G} |SPD_{v_j \rightarrow v_k}(v_i)|$$

The number of shortest paths between v_j and v_k that pass through the vertex v_i

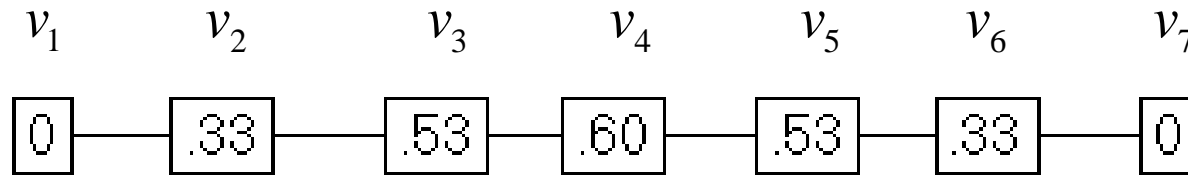
- Usually normalized by:

$$\bar{B}(v_i) = B(v_i) / [(n-1)(n-2) / 2]$$

No. pairs of nodes excluding the node itself

- Vertices with high betweenness centrality have influence in the network by virtue of their control over information passing between others.
 - They get to see the messages as they pass through
 - They could get paid for passing the message along
- Thus, they get a lot of power: their removal would disrupt communication

➤ Betweenness centrality of node v_2 :



$$B(v_2) = \sum_{v_j, v_k \in G} |SPD_{v_j \rightarrow v_k}(v_2)| = |\{v_1, v_3\}, \{v_1, v_4\}, \{v_1, v_5\}, \{v_1, v_6\}, \{v_1, v_7\}| = 5$$

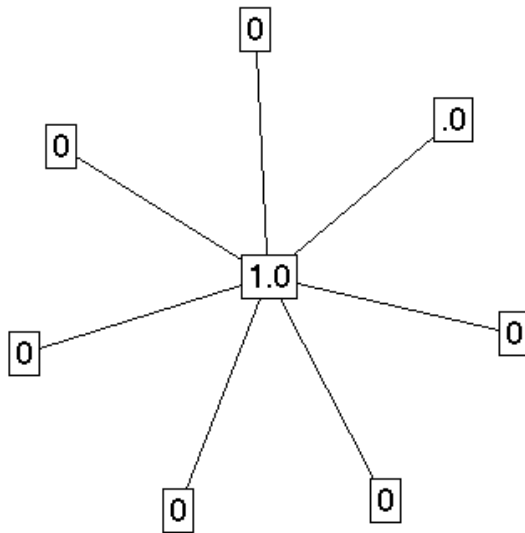
$$\bar{B}(v_2) = \frac{B(v_2)}{(n-1)(n-2)/2} = \frac{5}{(7-1)(6-2)/2} = 0.33$$

➤ Centralization:

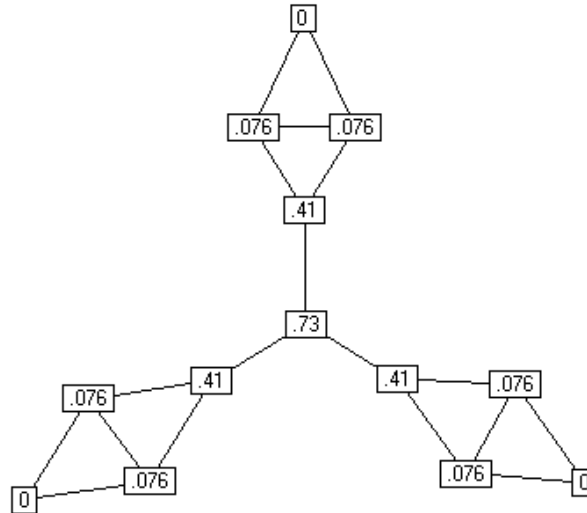
$$C_D(G) = \frac{\sum_{i=1}^n [B(v^*) - B(v_i)]}{(n-1)},$$

where : v^* is the node with the highest betweenness in G

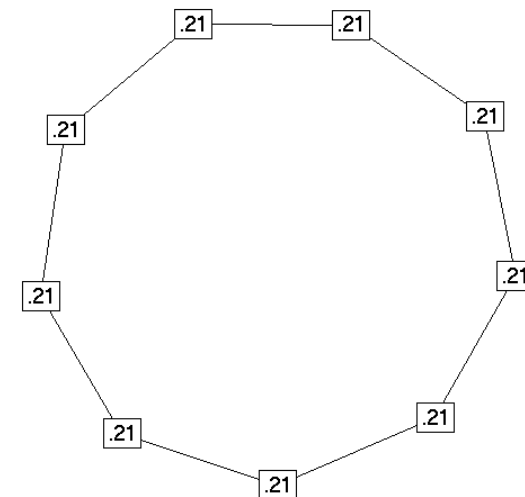
B: Betweenness centrality



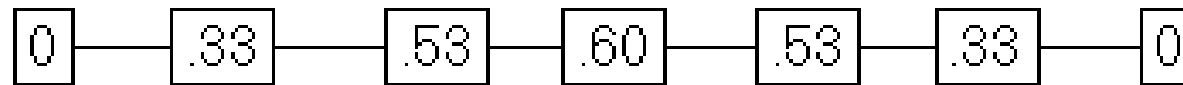
Centralization: 1.0



Centralization: .59



Centralization: 0



Centralization: .31

```
: import networkx as nx
import numpy as np
import matplotlib.pyplot as plt
```

```
# Instantiate the graph
```

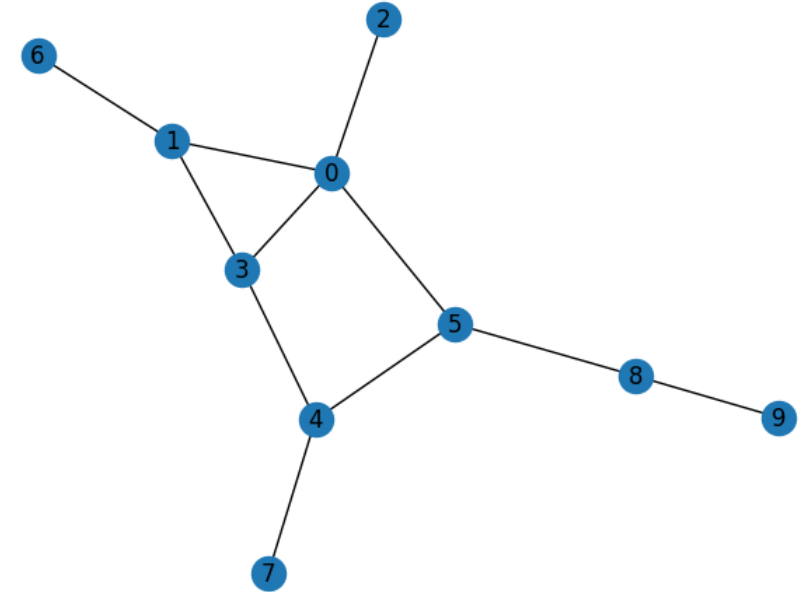
```
G = nx.Graph()
```

```
# add node/edge pairs
```

```
G.add_edges_from([(0, 1),
                  (0, 2),
                  (0, 3),
                  (0, 5),
                  (1, 3),
                  (1, 6),
                  (3, 4),
                  (4, 5),
                  (4, 7),
                  (5, 8),
                  (8, 9)])
```

```
: #Sort for identifying most influential nodes using betweenness centrality
for node in sorted(betweenness_centrality, key=betweenness_centrality.get, reverse=True):
    print(node, betweenness_centrality[node])
```

```
5 0.4444444444444444
0 0.4305555555555555
4 0.2638888888888889
1 0.2222222222222222
8 0.2222222222222222
3 0.16666666666666666
2 0.0
6 0.0
7 0.0
9 0.0
```



- Problem:
 - What if: It is not so important to have many direct friends? Or be “between” others.
- But one still wants to be in the “middle” of things
 - Node v_i not too far from the center

- The closeness is defined so that if a vertex is close to every other vertex, then the value is larger than if the vertex is not close to everything else.

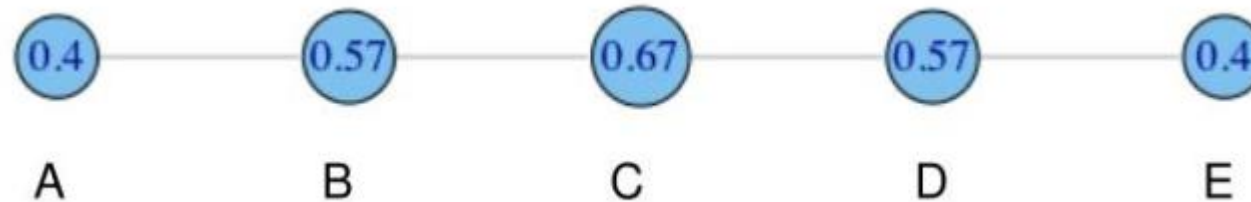
SPD: The number of nodes in the shortest path between 2 nodes

$$C(v_i) = \left[\sum_{j=1}^n \text{SPD}(v_i, v_j) \right]^{-1}$$

- Normalized Closeness Centrality:

$$\bar{C}(v_i) = C(v_i) / (n-1)$$

- The Closeness centrality of node A = Sum of the number of nodes between A and other nodes:
 - SPD(A,B)=1
 - SPD(A,C)=2
 - SPD(A,D)=3
 - SPD(A,E)=4



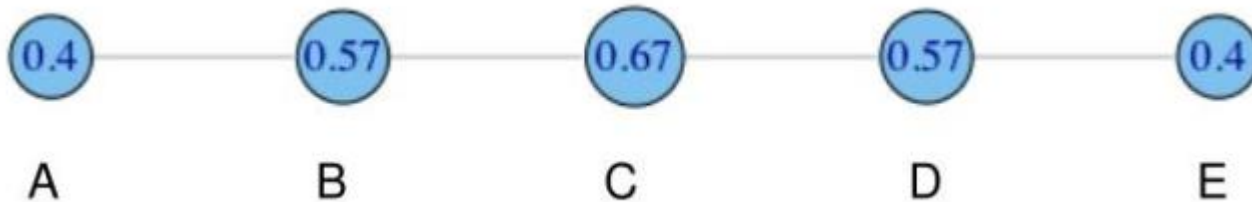
$$C'_c(A) = \left[\frac{\sum_{j=1}^N d(A,j)}{N-1} \right]^{-1} = \left[\frac{1+2+3+4}{4} \right]^{-1} = \left[\frac{10}{4} \right]^{-1} = 0.4$$


```
G = nx.Graph()
# add node/edge pairs
G.add_edges_from([(0, 1),
                  (1, 2),
                  (2, 3),
                  (3, 4)])

nx.draw(G, with_labels = True)

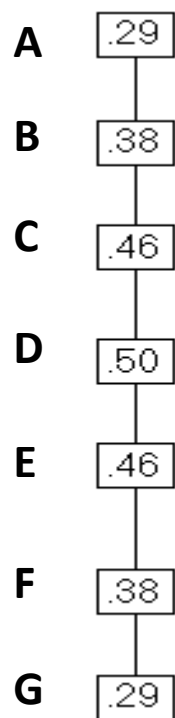
closeness centrality = nx.closeness centrality(G)
print(closeness centrality)
#Sort for identifying most influential nodes using closeness centrality
#for node in sorted(closeness centrality, key=closeness centrality.get, reverse=True):
# print(node, closeness centrality[node])
```

{0: 0.4, 1: 0.5714285714285714, 2: 0.6666666666666666, 3: 0.5714285714285714, 4: 0.4}



$$C'_c(A) = \left[\frac{\sum_{j=1}^N d(A, j)}{N-1} \right]^{-1} = \left[\frac{1+2+3+4}{4} \right]^{-1} = \left[\frac{10}{4} \right]^{-1} = 0.4$$

- Given a graph with 7 nodes: A,B,C,D,E,F,G
- Distance matrix denotes the shortest path distance between two nodes



Distance							Closeness normalized	
A	B	C	D	E	F	G		
	0	1	2	3	4	5	.048	.286
B		0	1	2	3	4	.063	.375
C	1		0	1	2	3	.077	.462
D	2	1		0	1	2	.083	.500
E	3	2	1		0	1	.077	.462
F	4	3	2	1		0	.063	.375
G	5	4	3	2	1		.048	.286

- Comparing across these 3 centrality values
 - Generally, the 3 centrality types will be positively correlated
 - When they are not (low) correlated, it probably tells you something interesting about the network.

	Low Degree	Low Closeness	Low Betweenness
High Degree		Embedded in cluster that is far from the rest of the network	Ego's connections are redundant - communication bypasses him/her
High Closeness	Key player tied to important important/active alters		Probably multiple paths in the network, ego is near many people, but so are many others
High Betweenness	Ego's few ties are crucial for network flow	Very rare cell. Would mean that ego monopolizes the ties from a small number of people to many others.	

- An extension of degree centrality
 - Centrality increases with number of neighbors
- Not all neighbors are equal
 - Having connection to more central nodes increases importance
 - For example, a node with 300 relatively unpopular friends on Facebook would have lower eigenvector centrality than someone with 300 very popular friends (like Barack Obama).

- Computing Eigenvector centrality:

$$x_i(t) = \sum_j A_{ij} x_j(t-1)$$


with the centrality at time $t=0$ being $x_i(0) = 1, \forall j$

- Define the centrality x'_i of i recursively in terms of the centrality of its neighbors:

$$x'_i = \sum_{v_j \in N(v_i)} A_{ij} x_j \quad \text{with the initial node centrality } x_j = 1, \forall j$$

- That is equivalent to:

$$x_i(t) = \sum_{v_j \in N(v_i)} A_{ij} x_j(t-1) \quad \text{with the centrality at time } t=0 \text{ being } x_j(0) = 1, \forall j$$



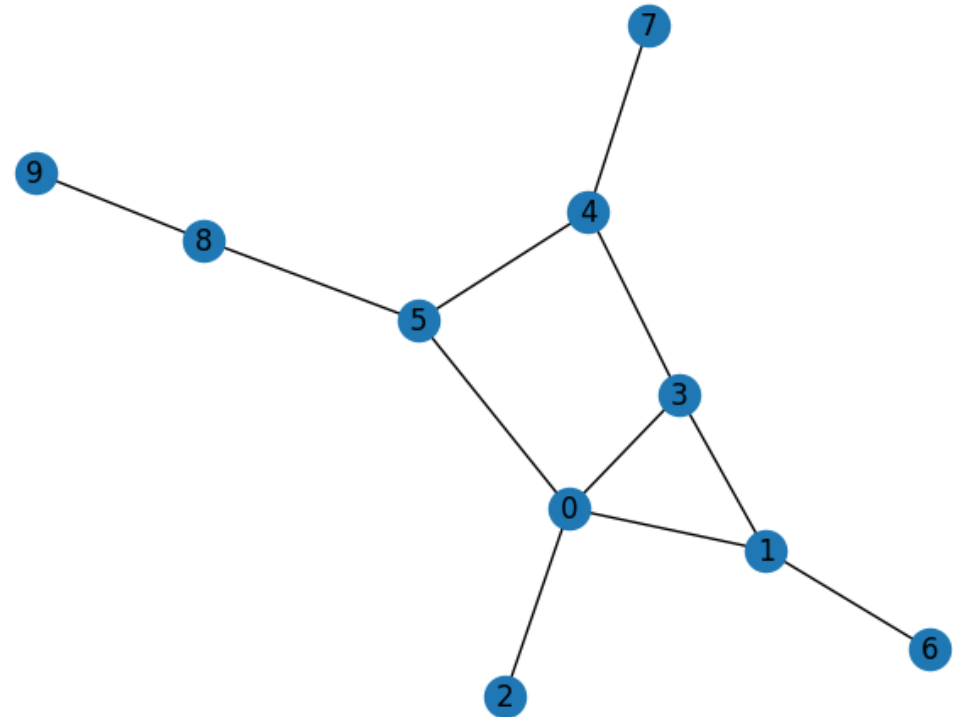
The centrality of nodes x_i and x_j at time t and $(t-1)$, respectively.

```
import networkx as nx
import numpy as np
import matplotlib.pyplot as plt

# Create a graph
G = nx.Graph()
# add node/edge pairs
G.add_edges_from([(0, 1),
                  (0, 2),
                  (0, 3),
                  (0, 5),
                  (1, 3),
                  (1, 6),
                  (3, 4),
                  (4, 5),
                  (4, 7),
                  (5, 8),
                  (8, 9)])

# Calculate eigenvector centrality
eigenvector centrality = nx.eigenvector centrality(G)
# Sort for identifying most influential nodes using eigenvector centrality
for node in sorted(eigenvector centrality, key=eigenvector centrality.get, reverse=True):
    print(node, eigenvector centrality[node])
```

```
0 0.5163311132778224
3 0.4605589097129744
1 0.40781116737108153
5 0.3684701926326299
4 0.34608812874643025
2 0.18721071680314055
8 0.15382393197189426
6 0.14786314470285283
7 0.12548504820698178
9 0.05577442762250838
```



- Katz centrality computes the centrality for a node based on the centrality of its neighbours. It is a generalization of the eigenvector centrality.
- The Katz centrality for node v_i is:

$$x_i = \alpha \sum_j A_{ij} x_j + \beta,$$

where:

α is a constant called damping factor, and β is a bias constant,

A is the adjacency matrix.

- When $\alpha = 1 / \lambda_{\max}$, $\beta = 0$, Katz centrality is the same as eigenvector centrality

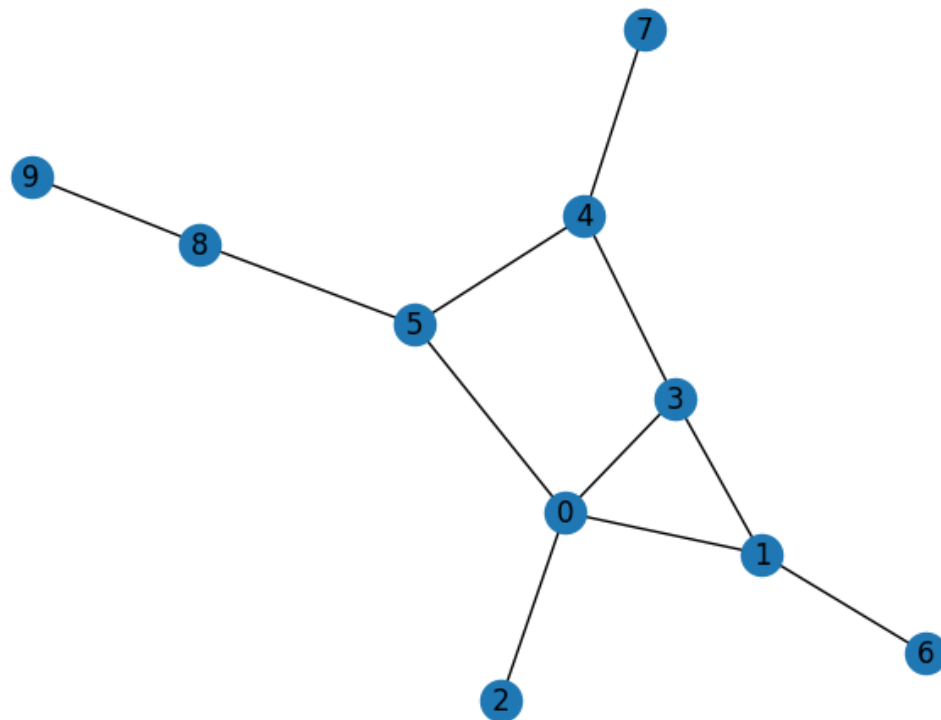
```
import networkx as nx
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# Create a graph
G = nx.Graph()
# add node/edge pairs
G.add_edges_from([(0, 1),
                  (0, 2),
                  (0, 3),
                  (0, 5),
                  (1, 3),
                  (1, 6),
                  (3, 4),
                  (4, 5),
                  (4, 7),
                  (5, 8),
                  (8, 9)])
nx.draw(G, with_labels = True)
# Caculate kat centrality

kat centrality = nx.katz centrality(G)

#Sort for identifying most inflential nodes using kat centrality
for node in sorted(kat centrality, key=kat centrality.get, reverse=True):
    print(node, kat centrality[node])
```

```
3 0.39837116164016045
2 0.3979957464558509
4 0.3912885477686667
1 0.3627994945952694
5 0.3266180854671848
6 0.32248848309558037
7 0.3218787410123867
8 0.28962990709484226
```



- Eigenvector centrality: i 's Rank score x_i is the sum of the Rank scores x_j of all pages j that point to i :

$$x_i := \sum_{(j,i) \in E} x_j$$

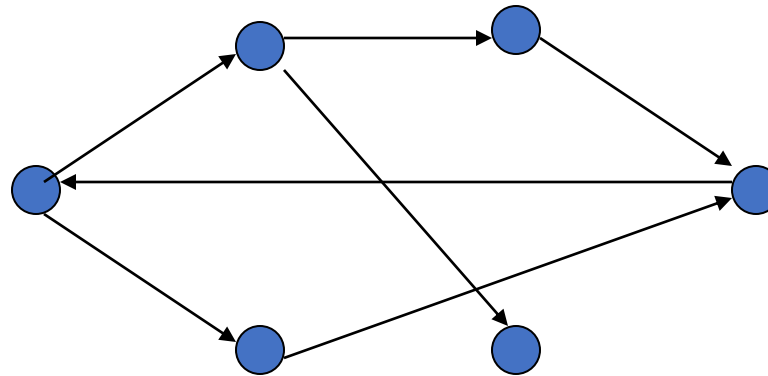
- Then Katz centrality adds **the teleportation** by adding a small weight edge to each node (using a weight of β):

$$x_i := \sum_{(j,i) \in E} x_j + \beta$$

- BUT, since a page j may point to many other pages, its prestige score should be shared among these pages.
(For example NPS pointing to many sites)

$$x_i := \sum_{(j,i) \in E} \frac{x_j}{\text{out deg } j} + \beta$$

- Web pages are organized in a network.
 - Each webpage is represented as a node.
 - Each hyperlink is a directed edge
 - The entire web can be viewed as a directed graph.

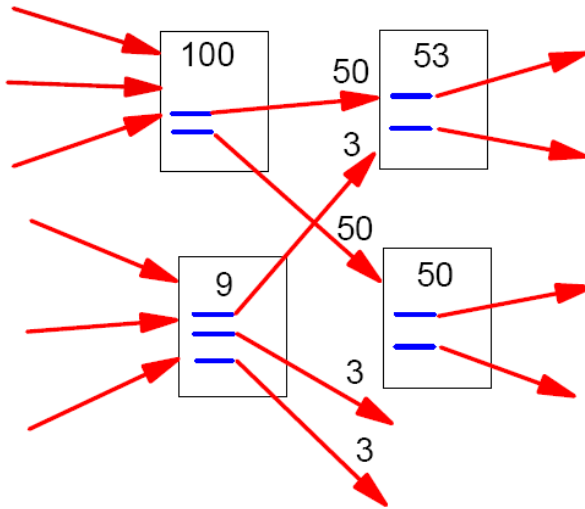


PageRank is a numeric value that represents how important a page is on the web.

- Webpage importance
 - One page links to another page = A vote for the other page A link from page A to page B is a vote on A to B.
 - If page A is more important itself, then the vote of A to B should carry more weight.
 - More votes = More important the page must be
- How can we model this importance?

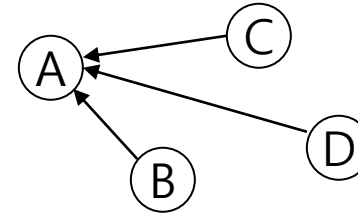
➤ Importance Computation

- The importance of a page is distributed to pages that it points to.
- The importance of a page is the aggregation of the importance shares of the pages that points to it.
 - If a page has 5 outlinks, the importance of the page is divided into 5 and each link receives one fifth share of the importance.

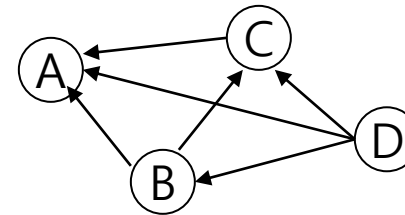


- Assume four web pages: A, B, C and D. Let each page would begin with an estimated PageRank of 0.25.

$$PR(A) = PR(B) + PR(C) + PR(D)$$



$$PR(A) = \frac{PR(A)}{2} + \frac{PR(C)}{1} + \frac{PR(D)}{3}$$



- $L(A)$ is defined as the number of links going out of page A. The PageRank of a page A is given as follows:

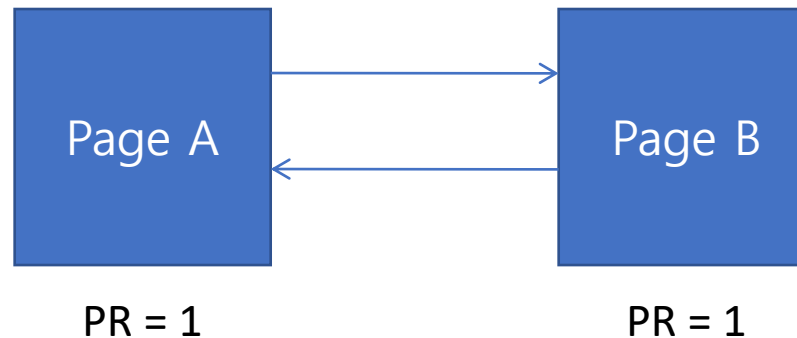
$$PR(A) = \frac{PR(A)}{L(B)} + \frac{PR(C)}{L(C)} + \frac{PR(D)}{L(D)}$$

- Assume page A has pages B, C, D ..., which point to it.
- The parameter d is a damping factor which can be set between 0 and 1.
- Usually set d to 0.85.
- The PageRank of a page A is given as follows:

$$PR(A) = 1 - d + d \left(\frac{PR(B)}{L(B)} + \frac{PR(C)}{L(C)} + \frac{PR(D)}{L(D)} + \dots \right)$$

- Where:
 - d is a damping factor which can be set between 0 and 1 (usually set to 0.85)
 - L(X) is the number of outbound links on page X

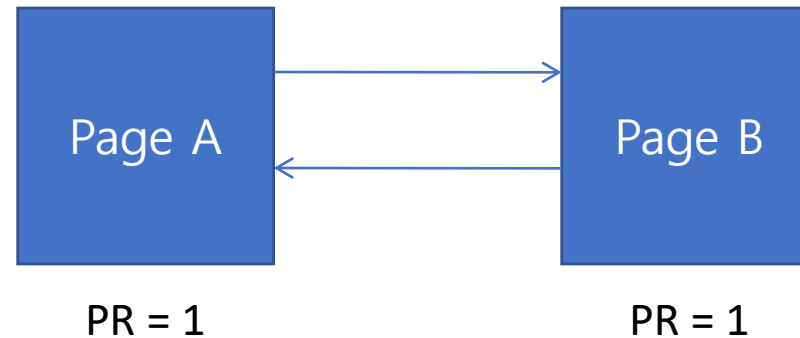
- We can't work out A's PageRank until we know B's PageRank, and we can't work out B's PageRank until we know A's PageRank.
- Iterations are necessary to calculate the most accurate values by using inaccurate values



$$PR(A) = 0.15 + 0.85 * PR(B)$$

$$PR(B) = 0.15 + 0.85 * PR(A)$$

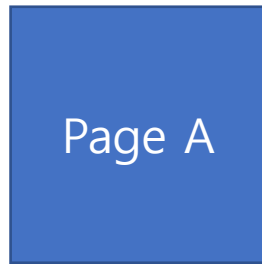
- A website has a maximum amount of PageRank that is distributed between its pages by internal links
- The maximum amount of PageRank in a site increases as the number of pages in the site increases
- By linking poorly, it is possible to fail to reach the site's maximum PageRank, but it is not possible to exceed it



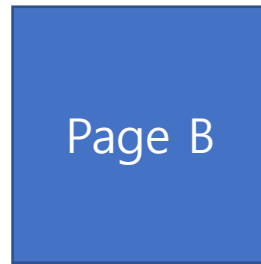
$$PR(A) = 0.15 + 0.85 * PR(B)$$

$$PR(B) = 0.15 + 0.85 * PR(A)$$

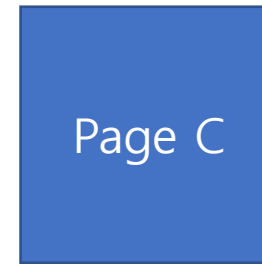
- Maximum PageRank is the amount of PageRank in the site.
- So this site's maximum PageRank is 3.



PR = 1



PR = 1



PR = 1

$$PR(A) = 0.15 + 0.85 * (0) = 0.15$$

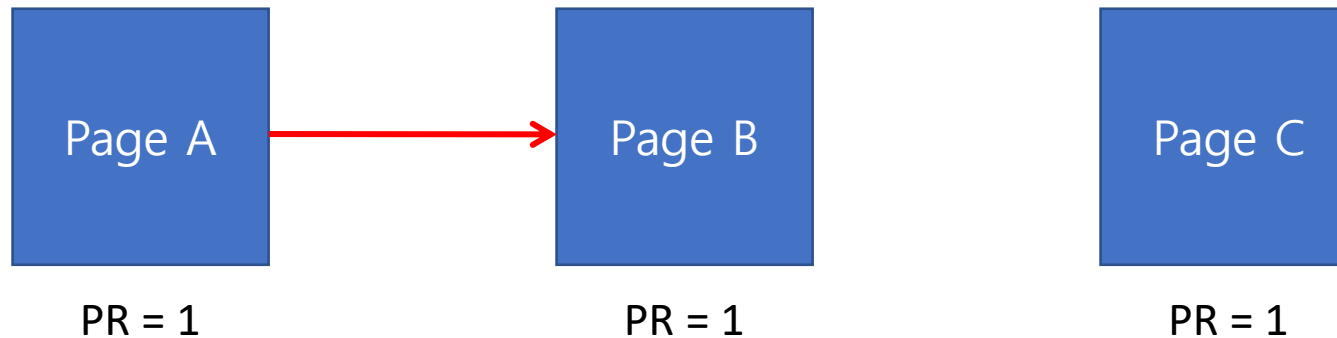
$$PR(B) = 0.15 + 0.85 * (0) = 0.15$$

$$PR(C) = 0.15 + 0.85 * (0) = 0.15$$

Total PageRank in this site = 0.45

Wasting most of its potential PageRank!

- Maximum PageRank is the amount of PageRank in the site.
- So this site's maximum PageRank is 3.



$$PR(A) = 0.15 + 0.85 * (0) = 0.15$$

$$PR(B) = 0.15 + 0.85 * (PR(A)/1) = 0.15 + 0.85 * (1) = 1$$

$$PR(C) = 0.15 + 0.85 * (0) = 0.15$$

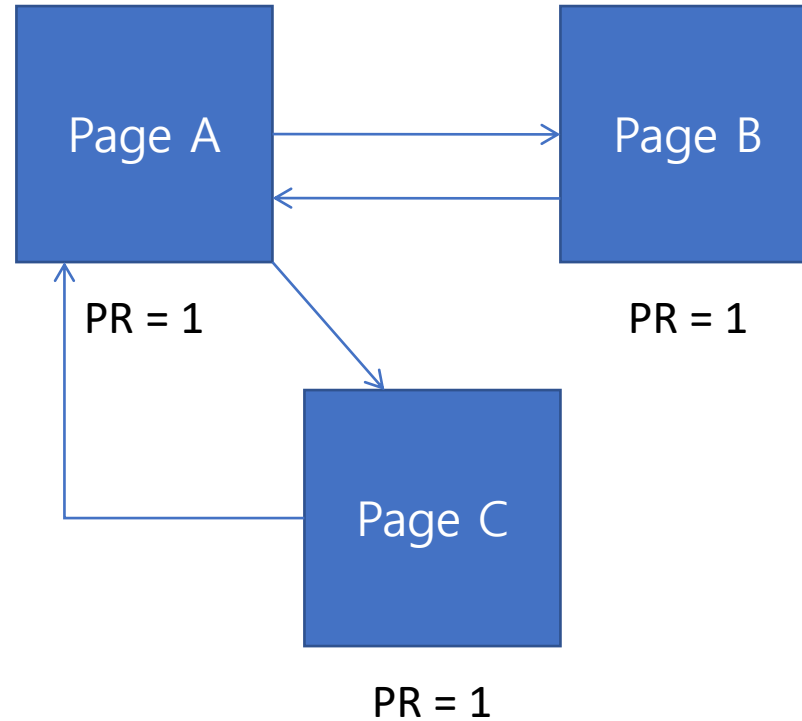
After 100 iterations....

$$\begin{aligned} \text{PR}(A) &= 0.15 + 0.85 * (\text{PR}(B)/1 + \text{PR}(C) / 1) \\ &= 0.15 + 0.85 * (1 + 1) \\ &= 0.15 + 1.7 \\ &= 1.85 \end{aligned}$$

$$\begin{aligned} \text{PR}(B) &= 0.15 + 0.85 * (\text{PR}(A)/2) \\ &= 0.15 + 0.85 * (0.5) \\ &= 0.15 + 0.425 \\ &= 0.575 \end{aligned}$$

$$\begin{aligned} \text{PR}(C) &= 0.15 + 0.85 * (\text{PR}(A)/2) \\ &= 0.15 + 0.85 * (0.5) \\ &= 0.15 + 0.425 \\ &= 0.575 \end{aligned}$$

After 100 iterations...



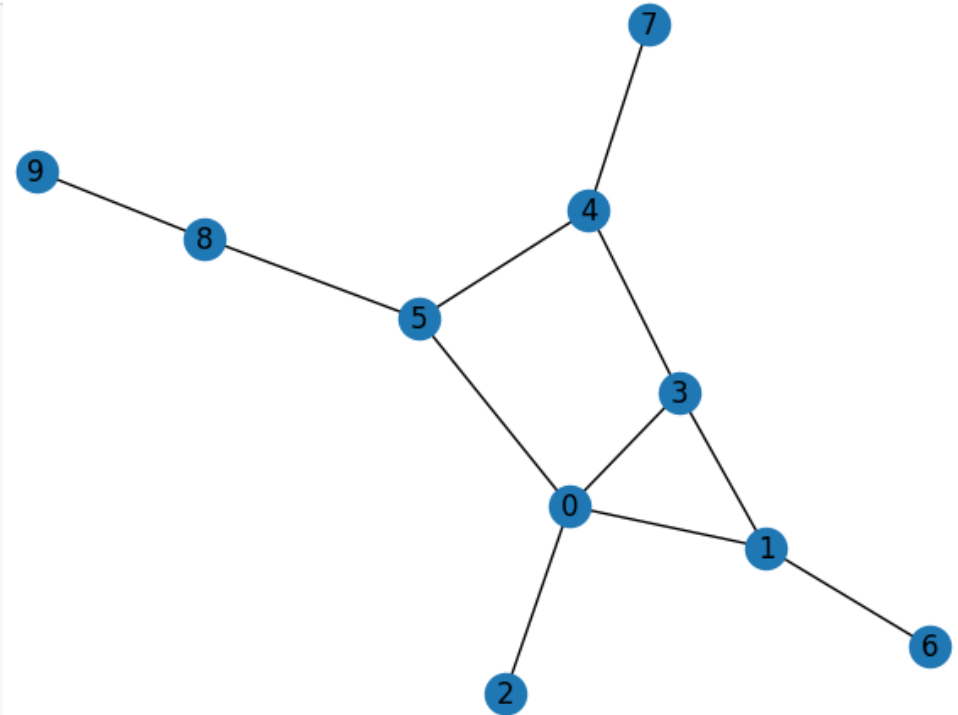
Page A = 1.459459
Page B = 0.7702703
Page C = 0.7702703

```
import networkx as nx
import numpy as np
import matplotlib.pyplot as plt

# Create a graph
G = nx.Graph()
# add node/edge pairs
G.add_edges_from([(0, 1),
                  (0, 2),
                  (0, 3),
                  (0, 5),
                  (1, 3),
                  (1, 6),
                  (3, 4),
                  (4, 5),
                  (4, 7),
                  (5, 8),
                  (8, 9)])

# Calculate pagerank
nx.pagerank(G, alpha=0.1)
```

```
{0: 0.10949439969135805,
1: 0.10541496772119344,
2: 0.09273734992283952,
3: 0.09978650527263376,
5: 0.10141741370884774,
6: 0.09351382767489713,
4: 0.10606037911522635,
7: 0.09353532767489713,
8: 0.1028950931069959,
9: 0.09514473611111113}
```



- Estimating Web Traffic
 - On analyzing the statistics, it was found that there are some sites that have a very high usage, but low PageRank.
 - eg: Links to pirated software
- PageRank as Backlink Predictor
 - The goal is to try to crawl the pages in as close to the optimal order as possible i.e., in the order of their rank.
 - PageRank is a better predictor than citation counting
- User Navigation: The PageRank Proxy
 - The user receives some information about the link before they click on it
 - This proxy can help users decide which links are more likely to be interesting



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