

Social Network Analysis

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1 Motivation

- ❑ Enormous amounts of „social data“ available through, e.g., social networks
- ❑ Even coining of a new term „ social data revolution“ → see, for example, Wikipedia
- ❑ Possibility for asking new questions:
 - Who is interacting with whom?
 - Whom am I interacting with?
- ❑ Where „interacting“ can be any kind of „social relation“, e.g., owe money, hands over work, etc.
- ❑ Recall the three BI perspectives
 - Customer
 - Organization
 - Production
- ❑ → Social network analysis focuses on organizational perspective

1 Motivation

Questions:

- ❑ Which data is suitable?
- ❑ How has the data to be prepared?
- ❑ What analysis model is typically used?
- ❑ Which analysis techniques are there?

Reading and basis for these slides:

- ❑ [Scott] John Scott: Social Network Analysis. SAGE (2012)
- ❑ [GrRi] Wilfried Grossmann, Stefanie Rinderle-Ma: Fundamentals of Business Intelligence, Springer 2015

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2 Data perspective

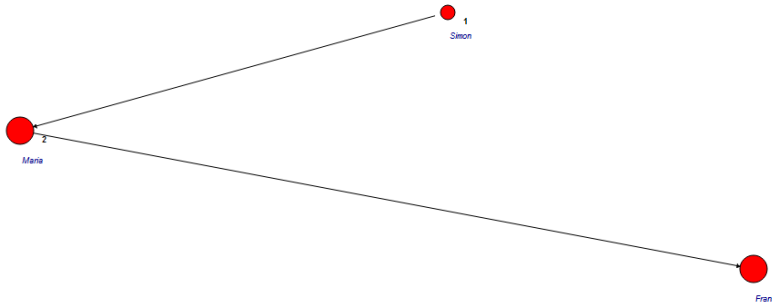
- ❑ Checking data sources → what is there?
- ❑ Checking analysis model → where do we want to go?
- ❑ Checking analysis questions → what do we want to know?

- ❑ Small lookahead: the analysis model is a sociogram, i.e., a graph $G = (V, E)$ (can be directed or undirected)

- ❑ Nodes represent the entities in the social network, e.g., persons
- ❑ Edges represent the relation between these entities, e.g., isFriendOf

2 Data perspective

SocNetV: Small1.png



$G = (V, E)$

$V = \{\text{Simon, Maria, Frank}\}$

$E = \{(\text{Simon, Maria}), (\text{Maria, Frank})\}$

$e = (n, m) \in E$: n is friend of m

Maria has friend

Frank has a friend

In this strict sense: Simon does not have a friend

2 Data perspective

The data for example on previous slide (in .net format)

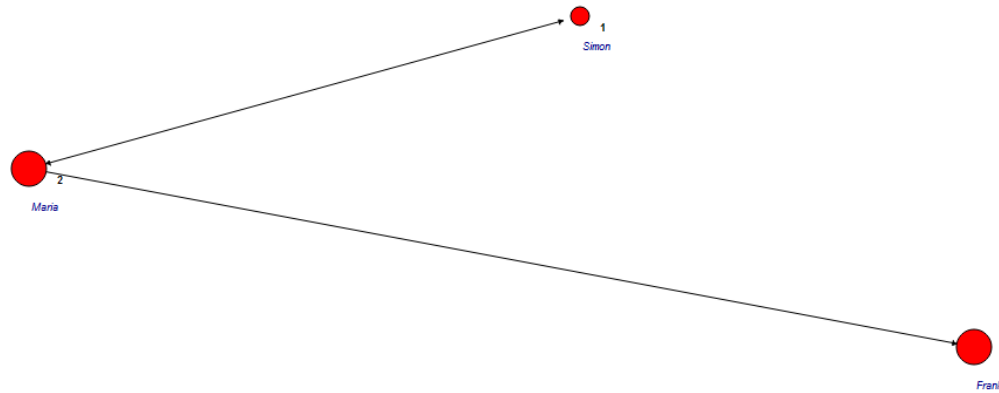
```
*Network
*Vertices 3
1 "Simon"
2 "Maria"
3 "Frank"
*Arcs
1 2 1
2 3 1
*Edges
```

Difference?

```
*Network
*Vertices 3
1 "Simon"
2 "Maria"
3 "Frank"
*Arcs
2 3 1
*Edges
1 2 1
```

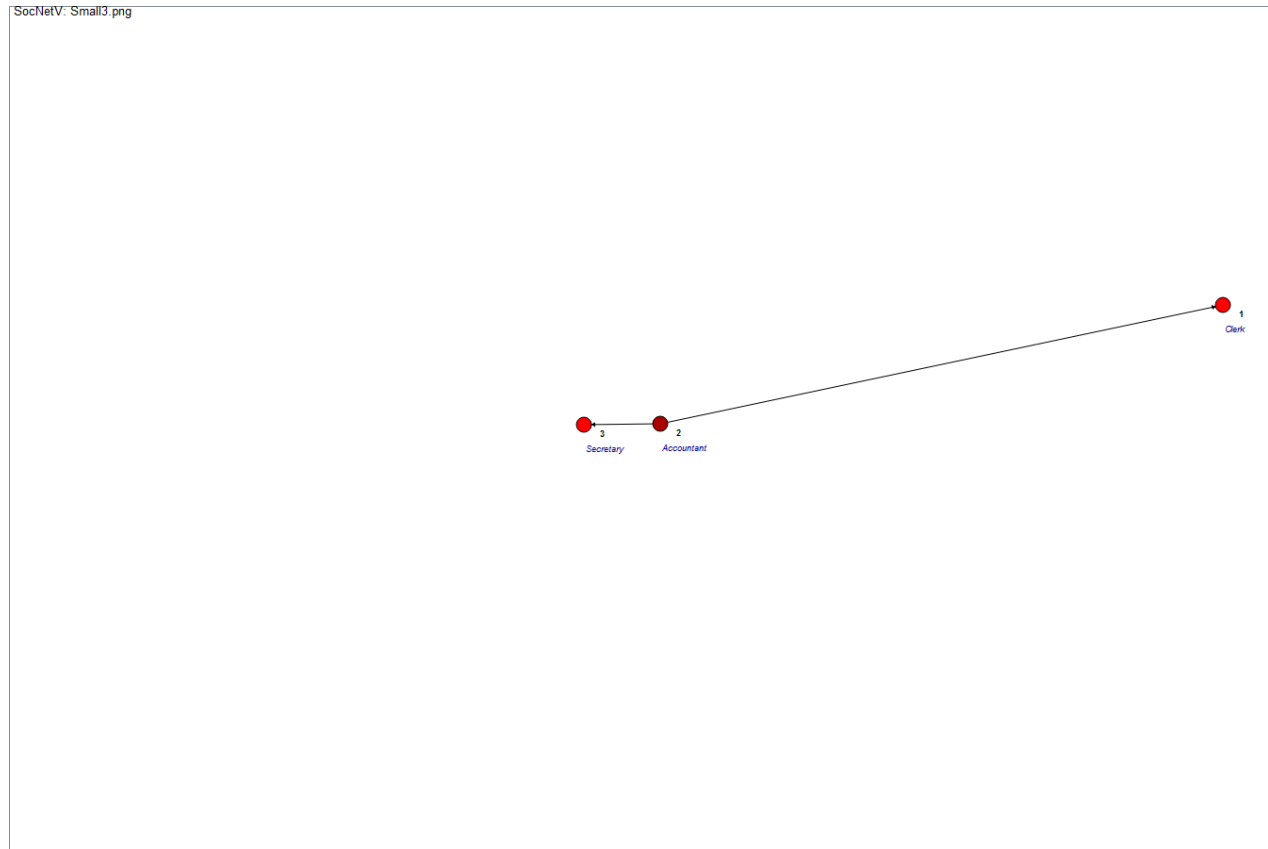

2 Data perspective

SocNetV: Small2.png



2 Data perspective

Derive the data set in .net format for the following sociogram:



2 Data perspective

Other formats:

- ❑ Adjacency matrix
- ❑ GraphML: xml-based, contains visualization information

```
<graphml> ...  
<graph id="unnamed" edgedefault="directed">  
  <node id="1">  
    <data key="d0">Simon</data>  
    <data key="d1">0.544782</data>  
    <data key="d2">0.429213</data>  
    <data key="d5">circle</data>  
  </node>  
  ...  
  <edge id="e1" directed="true" source="1" target="2"/>  
  <edge id="e2" directed="true" source="2" target="3"/>  
</graph>  
</graphml>
```

2 Data perspective

Analysis questions:

- ❑ Who or what are identified as entities?
- ❑ What are the interesting relations to be analyzed?

Basically:

- ❑ Analysis of the entire network
- ❑ Analysis for selected nodes (entities)

Job for data preparation:

- ❑ Make decisions on the questions above
- ❑ Prepare data accordingly
- ❑ If data is big, think about sampling

2 Data perspective

		Affiliations		
		A	B	C
Cases	1	1	0	0
	2	1	0	0
	3	1	0	0

What are the entities (nodes) and relations (edges) for this example (taken from [Scott])?

2 Data perspective

According to [Scott] three different representation matrices for SNA exist:

Incidence matrix		Cases		
		1	2	3
Affiliations	A			
	B			
	C			

Adjacency matrix (→ best for SNA)		Cases		
		1	2	3
Cases	1			
	2			
	3			

Adjacency matrix		Affiliations		
		A	B	C
Affiliations	A			
	B			
	C			

2 Data perspective

According to [Scott] three different representation matrices for SNA exist:

Incidence matrix

		Students		
		1	2	3
Universities	A	1	1	0
	B	0	1	0
	C	1	1	1

Adjacency matrix

		Students		
		1	2	3
Students	1	-	2	1
	2	2	-	1
	3	1	1	-

Adjacency matrix

		Universities		
		A	B	C
Universities	A	-	1	2
	B	1	-	1
	C	1	2	-

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3 Model perspective

- ❑ As mentioned before, the basic model is the sociogram
- ❑ Model structures for SNA (based on [GrRi])
 - *Undirected graphs*: an undirected graph G is defined as $G = (V; E)$ with set of nodes V and set of undirected edges E .
 - *Directed graphs*: Opposed to undirected edges, directed edges establish a relation that reflects a causal relation or a relation that is directed from one to another entity.
 - *Weighted Graphs*: It can be also useful to assign weights to the edges in the graph, i.e., a weight $w(e)$ expressing some kind of quantitative measure for the relation.
 - *Connected Subgraphs*: Special connected subgraphs might be of interest. A subgraph consisting of two nodes (with or without relations between them) describes a *dyad*, a sub-graph consisting of three nodes of interest a *triad* respectively.
 - *Dyad / triad*: Two / three actors who are connected by a relation in the social network

3 Model perspective

How to build the model from the data?

1. Step: create data matrix (as described in Section 2)
2. Step: create models for different analysis tasks

3 Model perspective

Example 1: Building model from relational data

Students		<u>SID</u>	Name	enrolled		<u>SID</u>	<u>UID</u>	University		<u>UID</u>	Name	
		S1	Simon			S1	U1			U1	Univie	
		S2	Maria			S2	U1			U2	TUWien	
		S3	Frank			S1	U2			U3	WUWien	
		S4	Sally			S3	U3					
		S5	Bert			S3	U2					
						S2	U2					
		<div>Cases</div>										
		S1	S2	S3	S4	S5						
Cases	S1	-	2	1	-	-						
	S2	2	-	1	-	-						
	S3	1		-	-	-						
	S4	-	1	-	-	-						
	S5	-	-	-	-	-						

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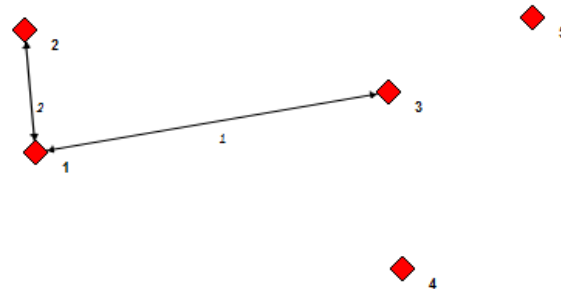
3 Model perspective

Example 1: Building model from relational data

		Cases				
		S1	S2	S3	S4	S5
Cases	S1	-	2	1	0	0
	S2	2	-	1	0	0
	S3	1		-	0	0
	S4	0	1	0	-	0
	S5	0	0	0	0	-

```
*Network
*Vertices 5
1 "Simon"
2 "Maria"
3 "Frank"
4 "Sally"
5 "Bert"
*Edges
1 2 2
1 3 1
```

SocNetV: RelUni.png



3 Model perspective

Example 2: Building model from log data (based on [GrRi])

```
<AuditTrailEntry>
  <WorkflowModelElement>Evaluate presentation 1</WorkflowModelElement>...
  <Originator>person001-lecturer</Originator>
</AuditTrailEntry>
<AuditTrailEntry>
  <WorkflowModelElement>Evaluate presentation 1</WorkflowModelElement>...
  <Originator>person003-lecturer</Originator>
</AuditTrailEntry>
<AuditTrailEntry>
  <WorkflowModelElement>plus</WorkflowModelElement>...
  <Originator>person003-lecturer</Originator>
</AuditTrailEntry>
<AuditTrailEntry>
  <WorkflowModelElement>plus</WorkflowModelElement>...
  <Originator>person004-lecturer</Originator>
</AuditTrailEntry>.000+01:00</Timestamp>
```

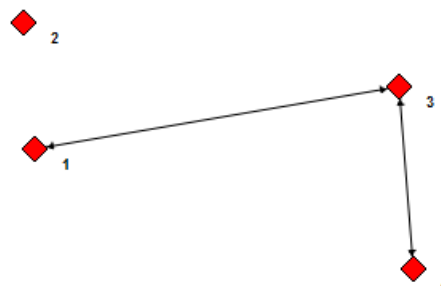
**Event Type and Time Stamp
omitted**

3 Model perspective

	Evaluate Presentation 1	plus
person001-lecturer	1	0
person002-lecturer	0	0
person003-lecturer	1	1
person004-lecturer	0	1

```
*Network
*Vertices 4
1 "person001-lecturer"
2 "person002-lecturer"
3 "person003-lecturer"
4 "person004-lecturer"
*Edges
1 3 1
3 4 1
```

SocNetV: RelHEP.png



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4 Analytical perspective

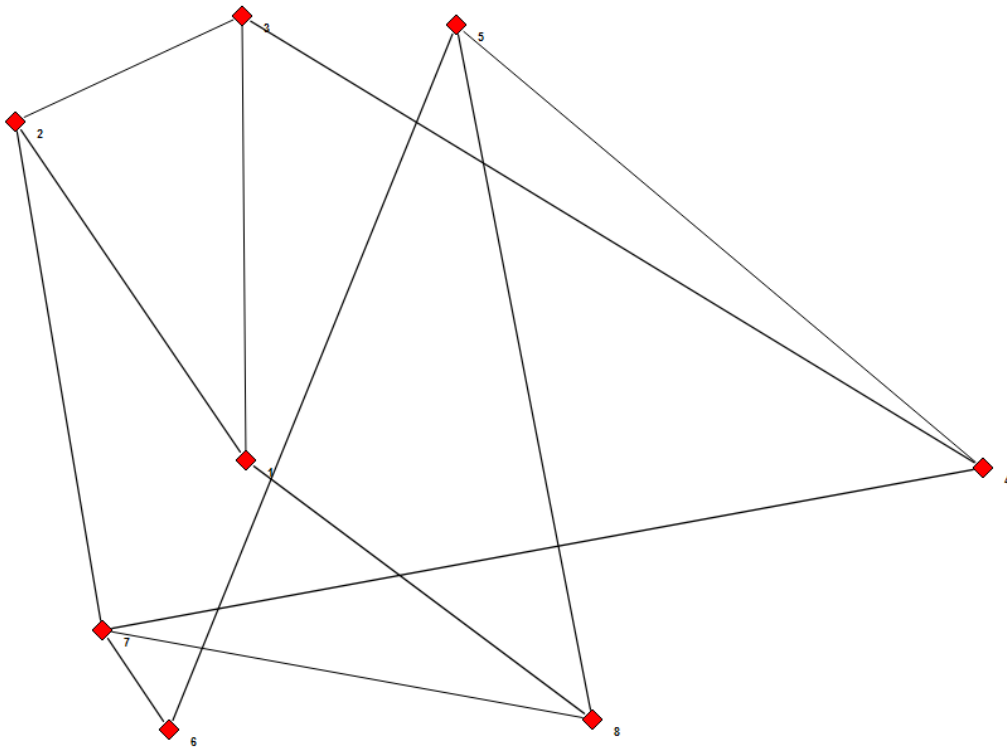
- ❑ Basically, different measures on the sociogram
 - For the entire network
 - For single nodes
- In addition: local and global measures

4 Analytical perspective

Local measures for nodes:

1. degree, in-degree, out-degree

SocNetV: RelUni_meas_undirected.png

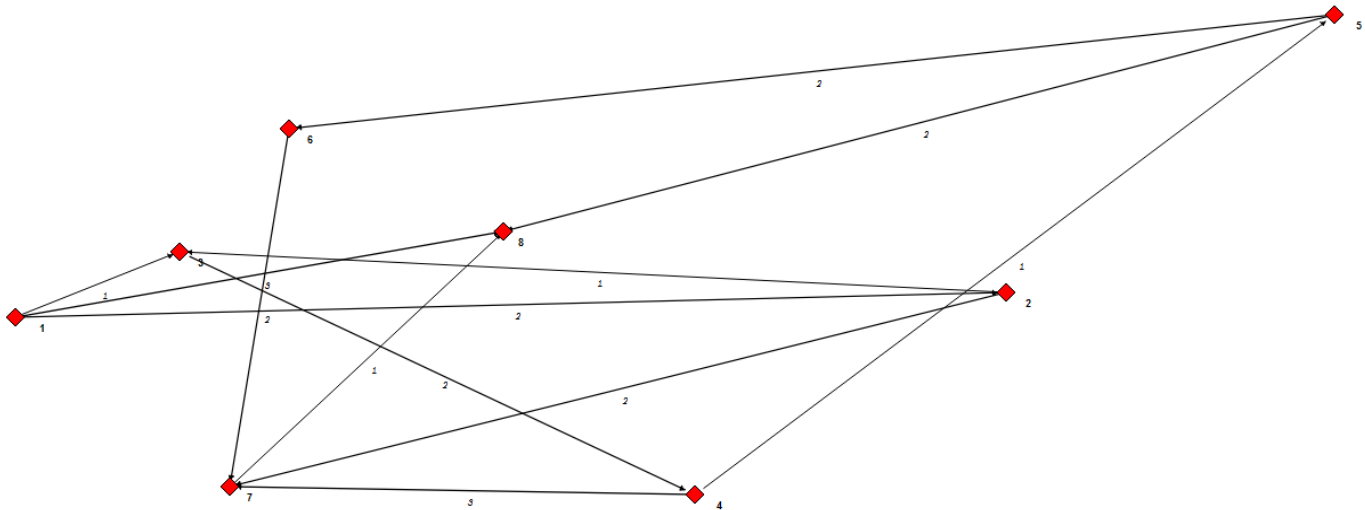


Node	Degree
1	
2	
3	
4	
5	
6	
7	
8	

4 Analytical perspective

- Local measures for nodes:
- 1. degree, in-degree, out-degree

SocNetV: RelUni_meas_weight.png



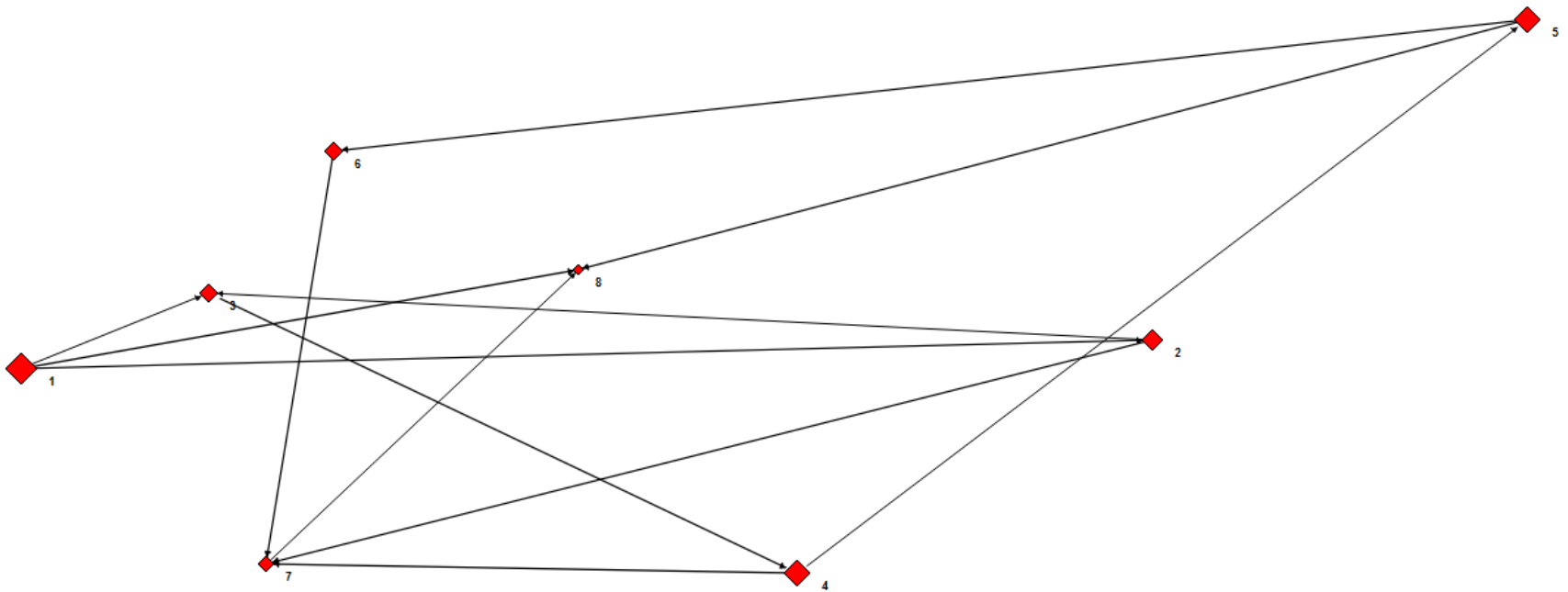
Node	In-degree	Out-degree
1		
2		
3		
4		
5		
6		
7		
8		

4 Analytical perspective

Local measures for nodes:

1. Visualization: node sizes by out-degree

SocNetV: RelUni_meas_dir_nodesizes.png



4 Analytical perspective

Is the degree meaningful?

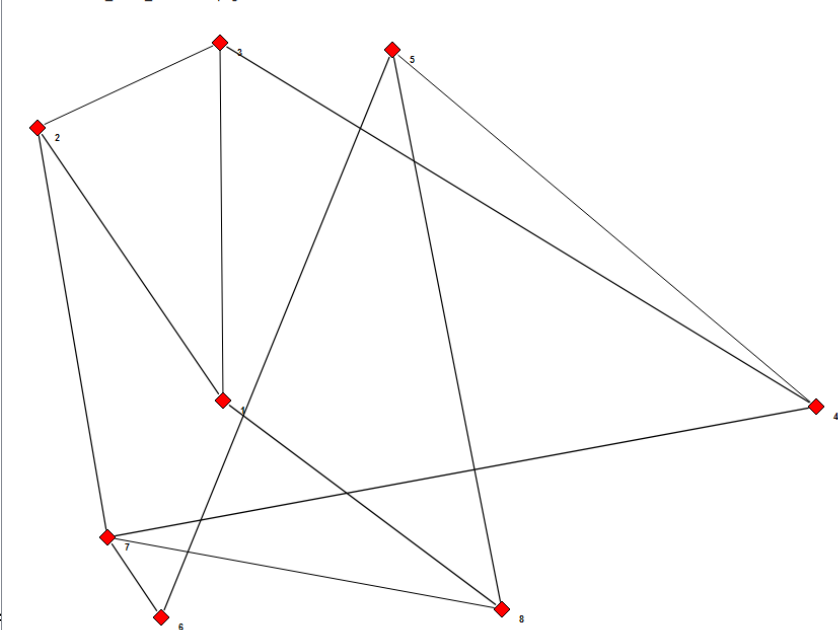
→ Degree centrality of node x (*point centrality*):

$$DC(x) = \text{degree}(x)/(N-1)$$

where N is the number of nodes in the sociogram

→ Undirected: degree; directed: out-degree; weighted: sum of all weights of outgoing edges

SocNetV: RelUni_meas_undirected.png

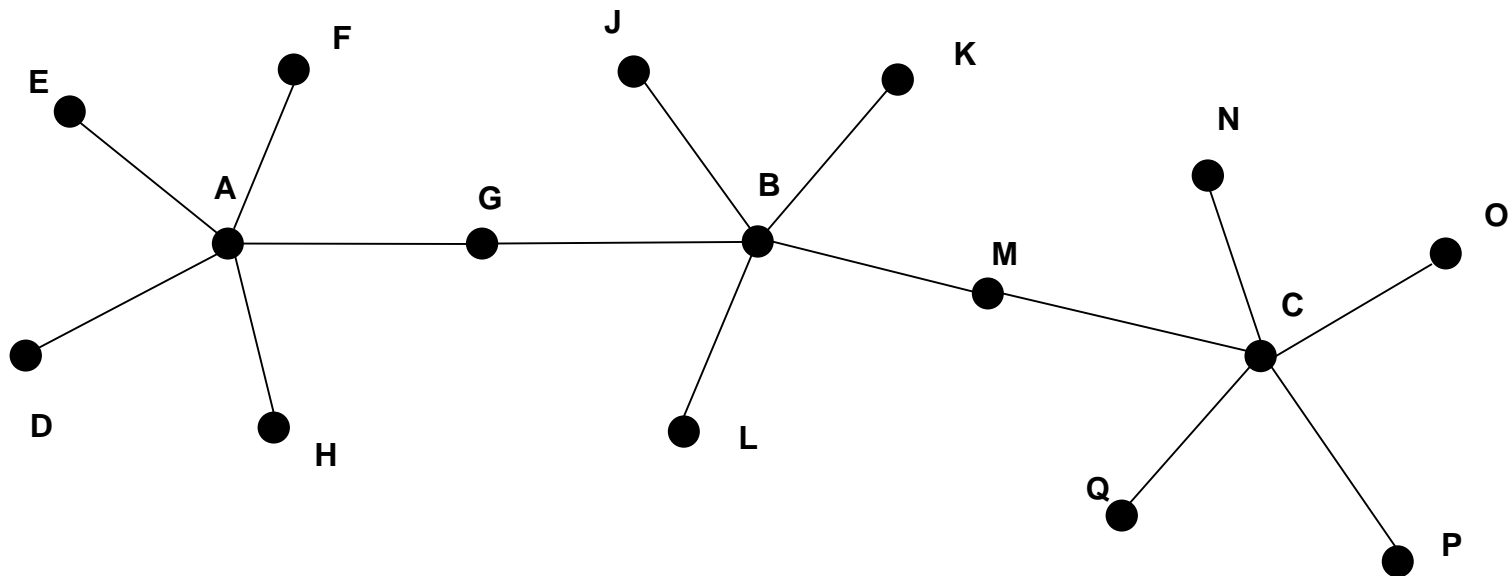


Node	DC
1	
2	
3	
4	
5	
6	
7	
8	

4 Analytical perspective

Interpretation degree centrality:

- ❑ When is this a useful measure? In which situations probably not?
- ❑ Example taken from [Scott]:
- ❑ Degree centrality is a local (node) measure

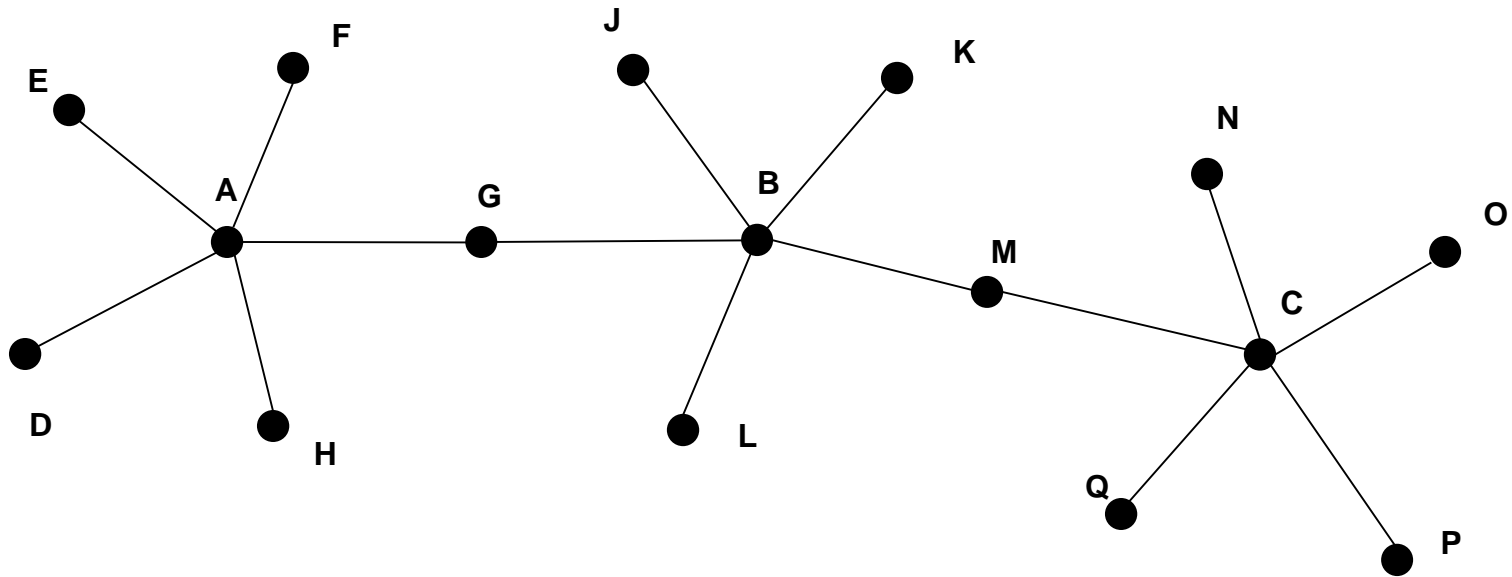


4 Analytical perspective

To come to a global measure, take paths instead of edges:

$$k\text{-path centrality of node } x = \sum_n path(x,n)$$

where $n \in N \setminus \{x\}$ and $path(x,n)$ denotes the shortest path from x to n



(based on [Scott])	A, C	B	G, M	J, K, L	others
Local centrality (abs)					
Local centrality (rel)					
Global centrality					

4 Analytical perspective

(based on [Scott])	A, C	B	G, M	J, K. L	others
Local centrality (abs)	5	5	2	1	1
Local centrality (rel)	0,33	0,33	0,13	0,07	0,07
Global centrality	43	33	37	48	57

- ❑ Which nodes are locally central?
- ❑ Which nodes are globally central?
- ❑ Interpretation:

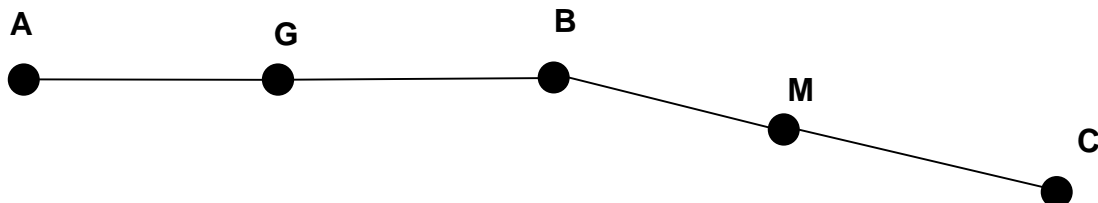
4 Analytical perspective

- ❑ Another point centrality measure: *betweenness centrality*

- ❑ Betweenness centrality BC of a node x:

$$BC(x) = \sum_{i \neq j} path(i, j, x) / path(i, j)$$

- ❑ Where $path(i, j, x)$ denotes the shortest path from i to j through x.



- ❑ $BC(B) = 3/3 + 4/4 + 2/2 + 3/3 = 4$
- ❑ $BC(G) = 2/2 + 3/3 + 4/4 = 3$
- ❑ Interpretation: betweenness centrality estimates the role of an intermediary in a SNA, e.g., a broker

4 Analytical perspective

Result Social Network Visualizer:

BETWEENNESS CENTRALITY (BC)

The BC index of a node u is the sum of $\delta(s,t,u)$ for all s,t in V where $\delta(s,t,u)$ is the ratio of all geodesics between s and t which run through u . Read the Manual for more.

BC' is the standardized BC.

BC range: $0 < BC < 12$ (Number of pairs of nodes excluding u)

BC' range: $0 < BC' < 1$ (C' is 1 when the node falls on all geodesics)

Node	BC	BC'	%BC'
1	0	0	0
2	3	0.25	25
3	4	0.333	33.3
4	3	0.25	25
5	0	0	0

Max BC' = 0.333 (node 3)

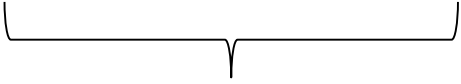
Min BC' = 0 (node 1)

BC classes = 3

BC' sum = 0.833

BC' Mean = 0.167

BC' Variance = 0.0194


Normalization with factor number
of all pairs: $(n-1)*(n-2)/2$

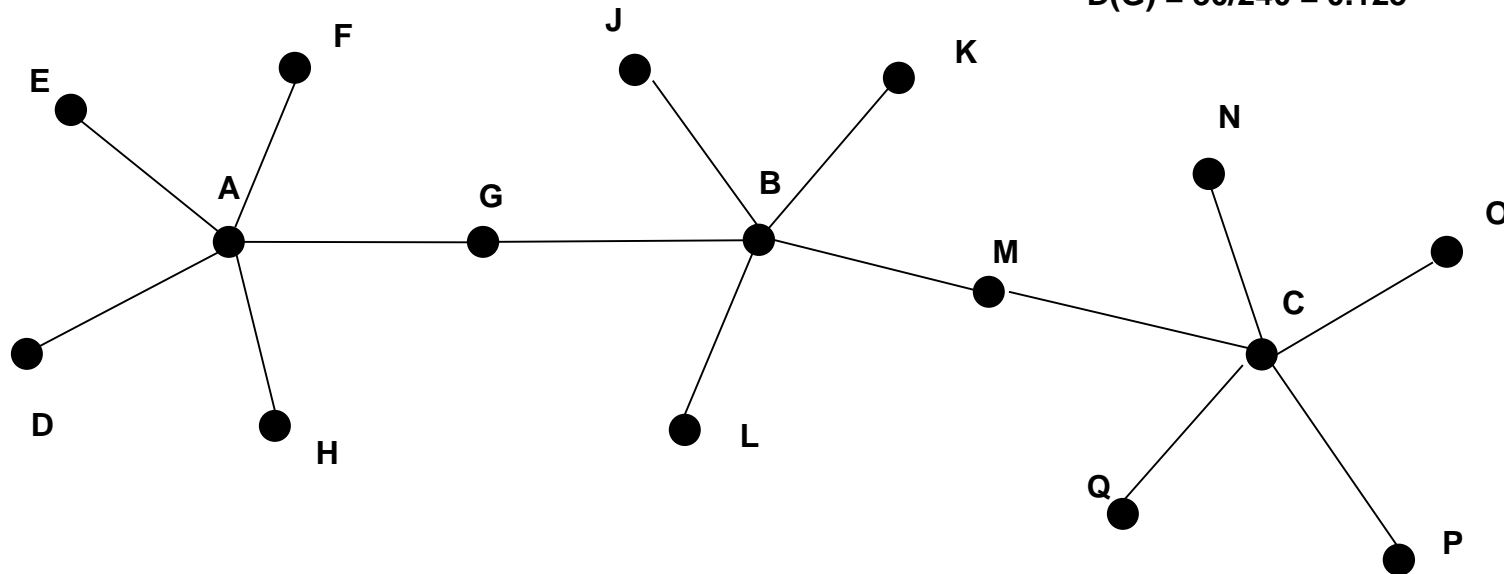
4 Analytical perspective

Graph metrics

- *density* D of a graph / sociogram $G=(V,E)$:

$$D(G) := \frac{2*|E|}{|V|*(|V|-1)}$$

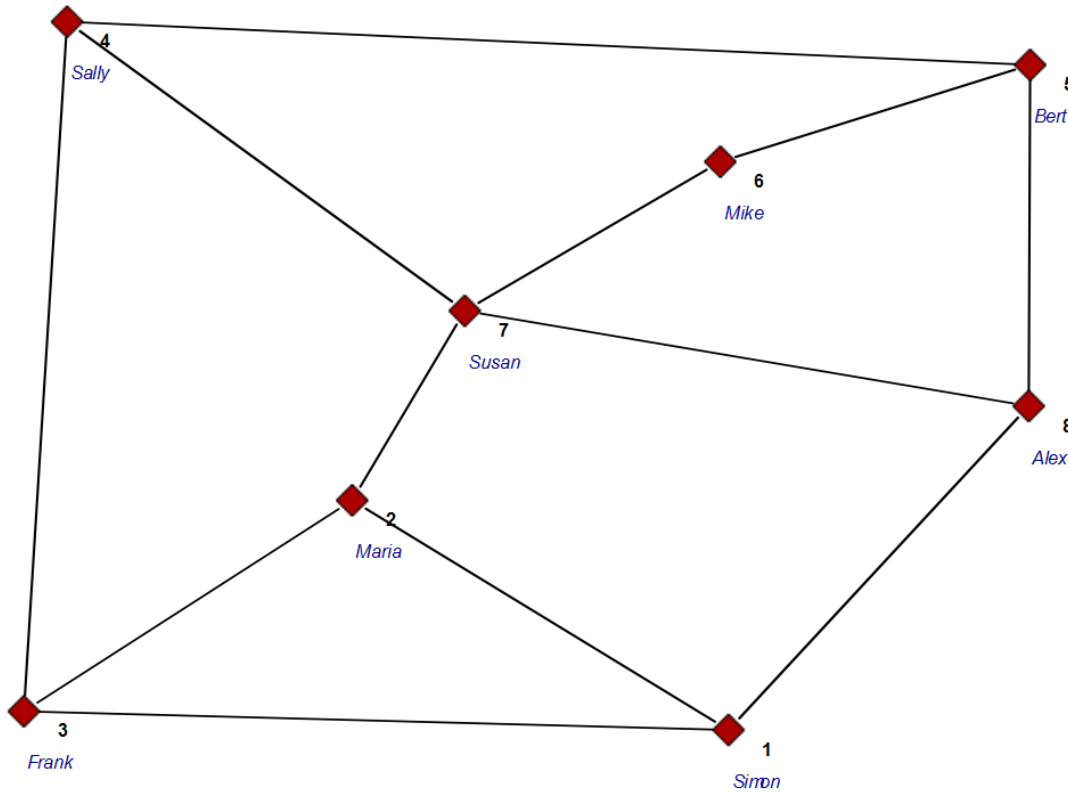
$$D(G) = 30/240 = 0.125$$



Interpretation?

4 Analytical perspective

SocNetV: Uni_ex_undir.png



Exercise:
Analyse the SNA with
the instruments we
have at hand now

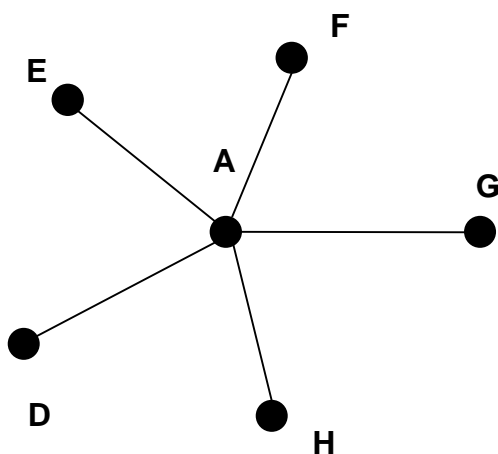
4 Analytical perspective

Graph centrality:

Measures the centrality of the nodes in the graph in relation to the most central point

Let x^* be the node with the highest centrality in the SNA G . Then:

$$GC(G) = \frac{\sum_{n, n \neq x^*} C(x^*) - C(n)}{(n-1) * (n-2)}$$



Centrality?

Assuming degree centrality

$$DC(A) = 5$$

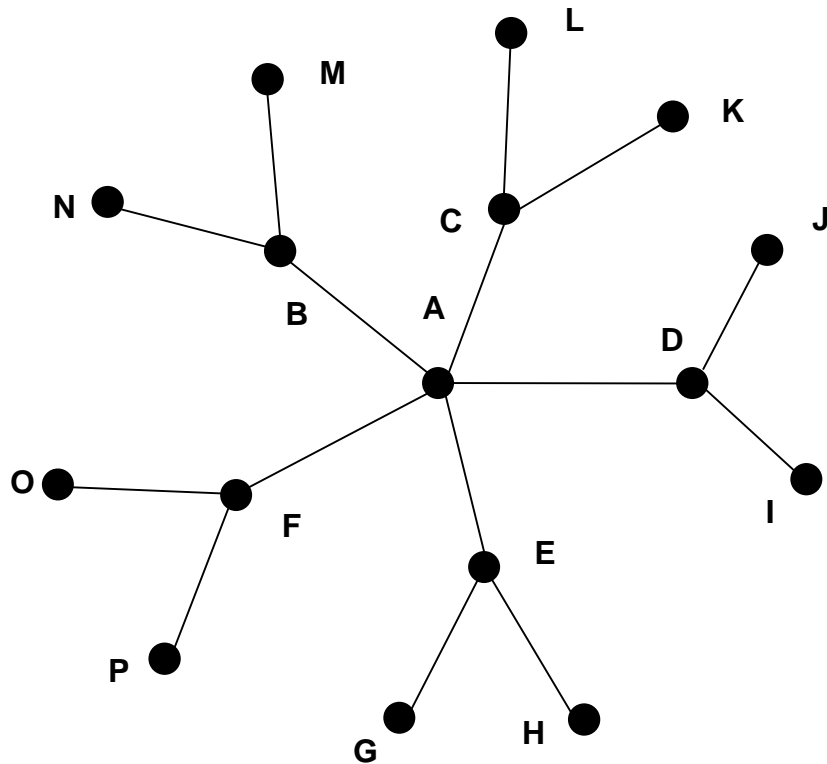
$$DC(D) = DC(E) = DC(F) = DC(G) = DC(H) = 1$$

$$GC(G) = 5 * 4 / 5 * 4 = 1$$

4 Analytical perspective

Graph centrality:

Another example based on [Scott]



node	DC
A	5
B	3
C	3
D	3
E	3
F	3
G	1
H	1
I	1
J	1
K	1
L	1
M	1
N	1
O	1
P	1

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5 Summary

- ❑ There are many more metrics to analyze SNA
 - Closeness
 - Cliques in the graph
- ❑ Tools:
 - Pajek
 - Social Network Visualizer
 - R
- ❑ Organizational mining:
 - Lies at the interface between process mining and social network mining
 - Hence at the interface between production and organization perspective