Social Network Mining

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Contents

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 (in press)

Contents

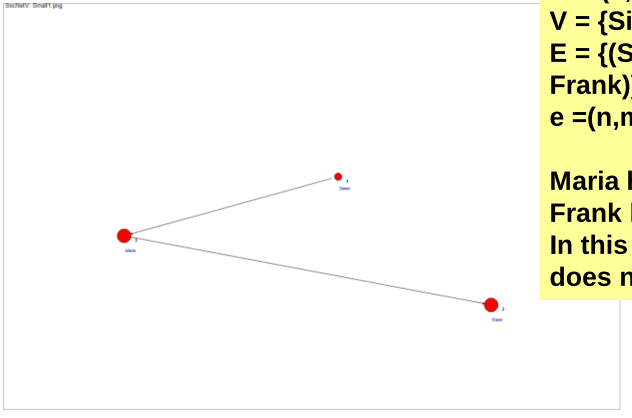
2 Data perspective

- 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



G = (V, E)
V = {Simon, Maria, Frank}
E = {(Simon, Maria), (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

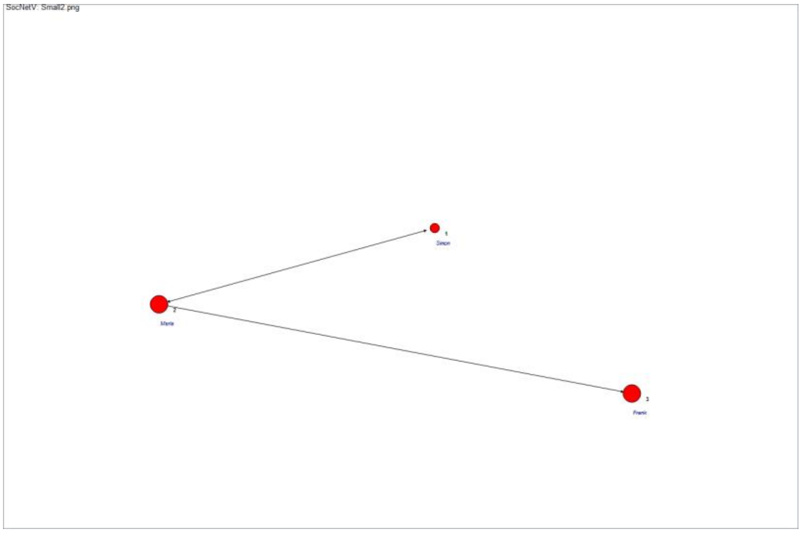
The data for example on previous slide (in .net format)

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

Difference?

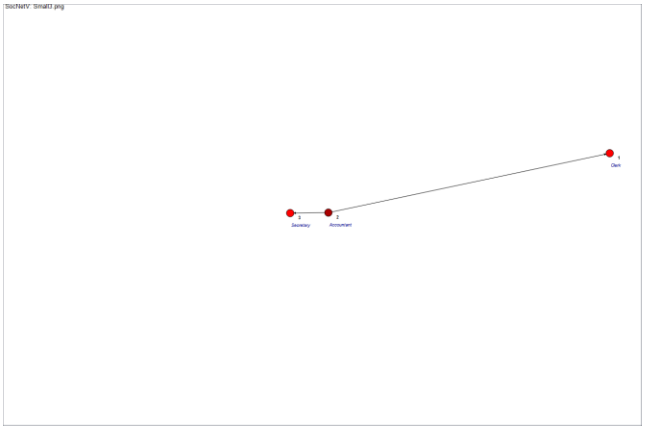
```
*Network
*Vertices 3
1 "Simon"
2 "Maria"
3 "Frank"
*Arcs
2 3 1
*Edges
1 2 1
```

2 Data perspective



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 preperation:

- 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	SID	Name
	S1	Simon
	S2	Maria
	S3	Frank
	S4	Sally
	S5	Bert

enrolled	SID	UID
	S1	U1
	S2	U1
	S1	U2
	S3	U3
	S3	U2
	S2	U2

University	UID	Name
	U1	Univie
	U2	TUWien
	U3	WUWien

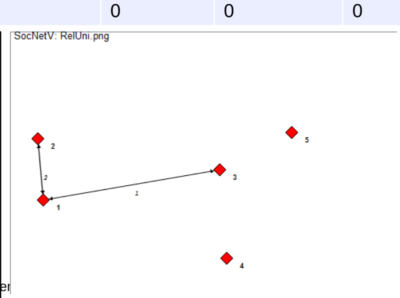
		Cases				
		S1	S2	S3	S4	S5
Cases	S1	-	2	1	-	-
	S2	2	-	1	-	-
	S3	1		-	-	-
	S4	-	1	-	-	-
	S5	-	-	-	-	-

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
```



3 Model perspective

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

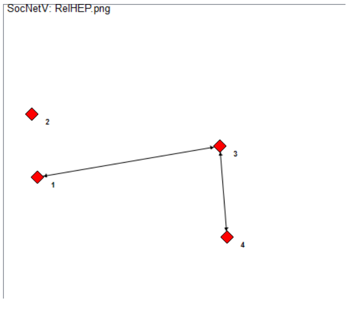
<AuditTrailEntry>
<WorkflowModelElement>Evaluate presentation 1</WorkflowModelElement>…
<Originator>person001-lecturer</Originator>
</AuditTrailEntry>
<AuditTrailEntry>
<WorkflowModelElement>Evaluate presentation 1</WorkflowModelElement>…
<Originator>person003-lecturer</Originator>
</AuditTrailEntry>
<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
```



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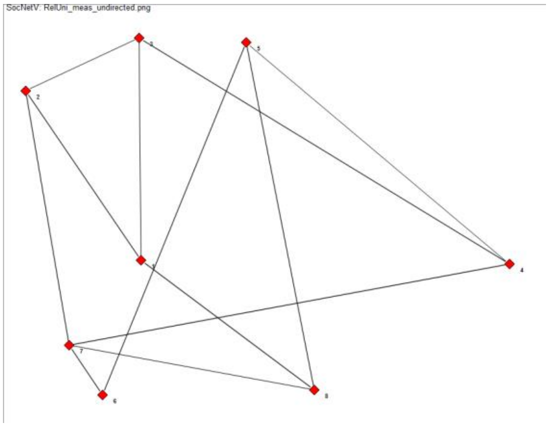
4 Analytical perspective

- 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

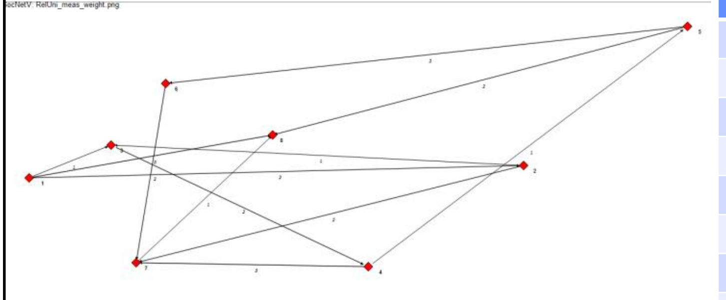


Node	Degree
1	
2	
3	
4	
5	
6	
7	
8	

4 Analytical perspective

Local measures for nodes:

1. degree, in-degree, out-degree

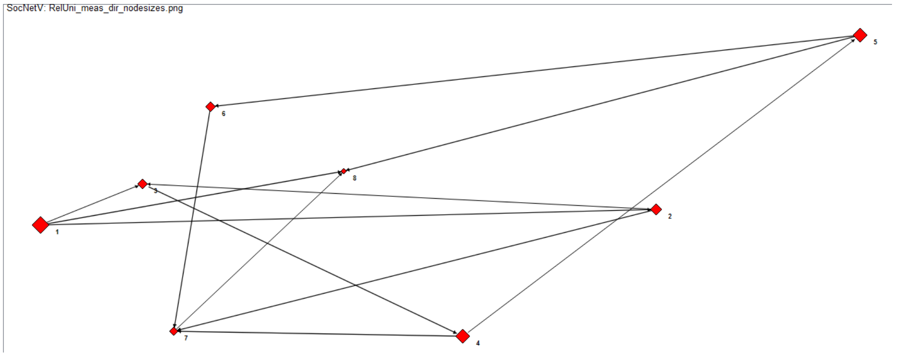


Node	In-degree	Out-degree
1		
2		
3		
4		
5		
6		
7		
8		

4 Analytical perspective

Local measures for nodes:

1. Visualization: node sizes by out-degree



4 Analytical perspective

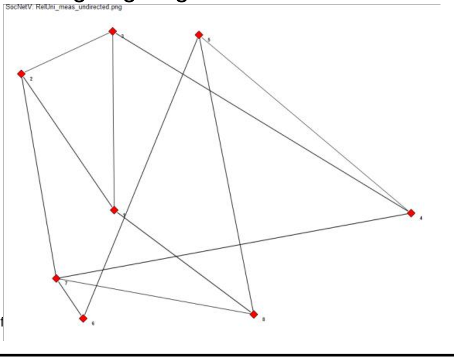
Is the degree meaningful?

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

$$DC(x) = degree(x)/(N-1)$$

where N is the number of nodes in the sociogram

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

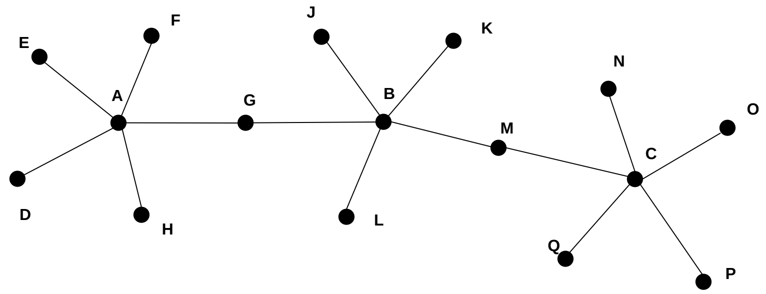


Node	DC
1	
2	
3	
4	
5	
6	
7	
8	

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

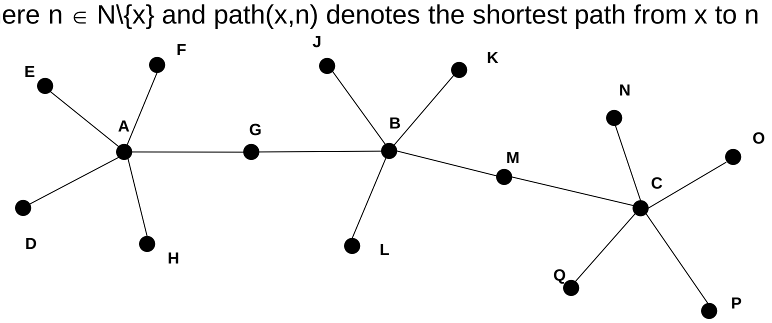


4 Analytical perspective

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

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

where n $\in$ N\{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

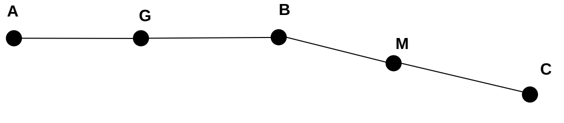
- Which nodes are locally central?
- Which nodes are globally central?
- Interpretation:

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:

BETWEENESS 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

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

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

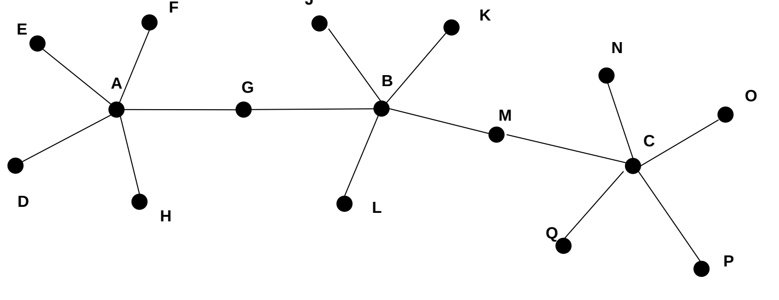
4 Analytical perspective

Graph metrics

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

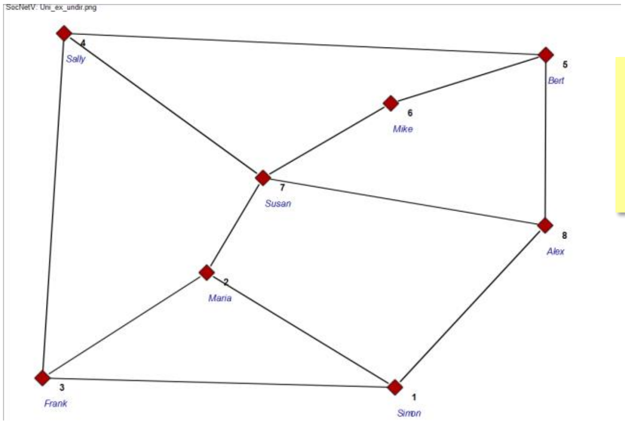
$$D(G) := \frac{2*|E|}{|V|*(|V|-1)}$$

D(G) = 30/240 = 0.125



Interpretation?

4 Analytical perspective



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

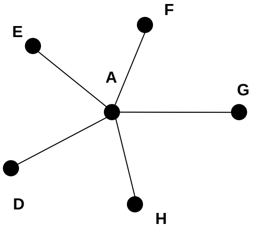
4 Analytical perspective

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:

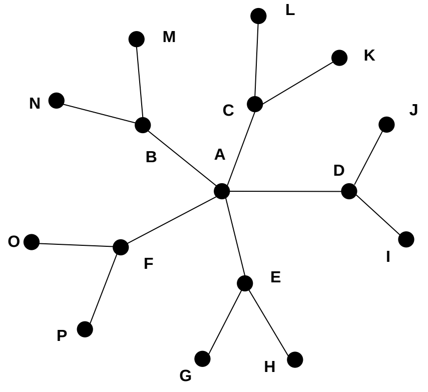
$$GC(G) = \frac{\sum_{n, n \neq x} C(x*) - C(n)}{(n-1)*(n-2)}$$



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

Contents

5 Summary

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