Methoden der Wissenschaftsforschung

Network analysis; an introduction

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Outline of brief introduction to Network Analysis

1. What is relational view and network analysis?
2. Ethnography of network ties! Context of interactions
3. How to gather and use network data?
4. Possible questions to ask!
5. A real life example from science studies!
6. Where to next?!

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What is this?!

Now what?!

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ID	Name	Age	Political view	Education
1	Tom	24	left	NA
2	Sara	22	right	BA
3	Bill	30	neutral	MA
4	Margaret	31	NA	PhD

A poll/survey results?

Variables/attributes

ID	Name	Age	Political view	Education
1	Tom	24	left	NA
2	Sara	22	right	BA
3	Bill	30	neutral	MA
4	Margaret	31	NA	PhD

A variable by observation table

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Variables/attributes

Respondents/
Observations

ID	Name	Age	Political view	Education
1	Tom	24	left	NA
2	Sara	22	right	BA
3	Bill	30	neutral	MA
4	Margaret	31	NA	PhD

What if respondents know each other?!

Variables/attributes

Respondents/ Observations

ID	Name	Age	Political view	Education
1	Tom	24	left	NA
2	Sara	22	right	BA
3	Bill	30	neutral	MA
4	Margaret	31	NA	PhD

Different contexts of familiarity

- Family, college, gym, . . .

Variables/attributes

Respondents/ Observations

ID	Name	Age	Political view	Education
1	Tom	24	left	NA
2	Sara	22	right	BA
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Stories behind ties!

- Independence of observations?

Respondents/ Observations

	Tom	Sara	Bill	Margaret
Tom	-	Instagram celebrity	Is not sure remembers	NA
Sara	NA	-	Brother	Brother's crush
Bill	(Former) same gym member	Sister	-	MA classmate / friend / smartest batchmate
Margaret	NA	NA	MA classmate	-

Respondents/ Observations

Adjacency (familiarity) matrix

Respondents/ Observations (columns); Respondents/ Observations (rows)

	Tom	Sara	Bill	Margaret
Tom	-	1	0	0
Sara	0	-	1	1
Bill	1	1	-	1
Margaret	0	0	1	-

Read Edge List as CSV

```
edge_list2_use <- read_csv("./data/humans_ties.csv")
kable(edge_list2_use)
```

source	target	weight	label
Tom	Sara	0.5	Acquaintance
Sara	Bill	1.0	Sibling
Sara	Margaret	0.5	Acquaintance
Bill	Tom	0.5	Acquaintance
Bill	Sara	1.0	Sibling
Bill	Margaret	1.0	Friend
Margaret	Bill	0.5	Acquaintance

Convert it to a graph object

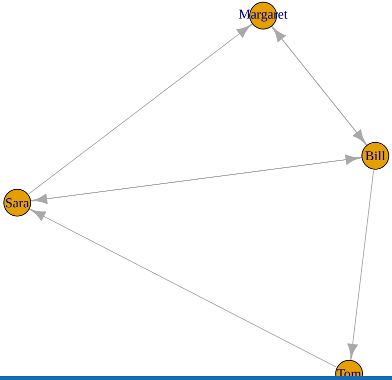
```
gg = graph_from_data_frame(d = edge_list2_use, directed = TRUE)

print(gg)
```

```
## IGRAPH 40855f1 DNW- 4 7 --
## + attr: name (v/c), weight (e/n), label (e/c)
## + edges from 40855f1 (vertex names):
## [1] Tom     ->Sara     Sara    ->Bill     Sara    ->Margaret
## [4] Bill    ->Tom      Bill    ->Sara     Bill    ->Margaret
## [7] Margaret->Bill
```

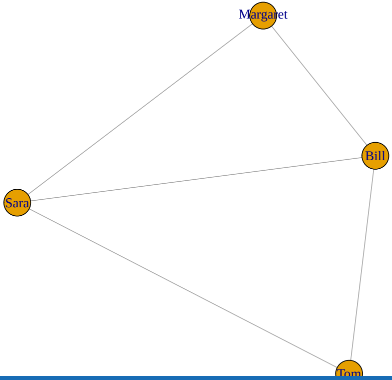
Plot the graph with a layout (directed)

```
set.seed(4535235)
gg_layout = layout.fruchterman.reingold(graph = gg)
plot(gg, layout = gg_layout, edge.label = NA)
```



Plot the graph with a layout (un-directed)

```
gg_undirected = graph_from_data_frame(d = edge_list2_use, directed = F)
gg_undirected = simplify(graph = gg_undirected, remove.multiple = T)
plot(gg_undirected, layout = gg_layout, edge.label = NA)
```



Add a new attribute to nodes?

```
print(V(gg))
```

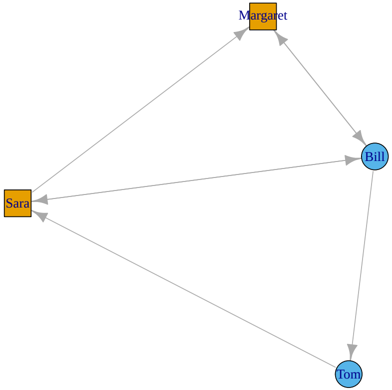
```
## + 4/4 vertices, named, from 40855f1:
## [1] Tom      Sara     Bill     Margaret
```

```
V(gg)$gender <- c('male', 'female', 'male', 'female')
V(gg)$shape <- c('circle', 'square', 'circle', 'square')
print(gg)
```

```
## IGRAPH 40855f1 DNW- 4 7 --
## + attr: name (v/c), gender (v/c), shape (v/c), weight (e/n), label
## | (e/c)
## + edges from 40855f1 (vertex names):
## [1] Tom     ->Sara     Sara    ->Bill     Sara    ->Margaret
## [4] Bill    ->Tom      Bill    ->Sara     Bill    ->Margaret
## [7] Margaret->Bill
```

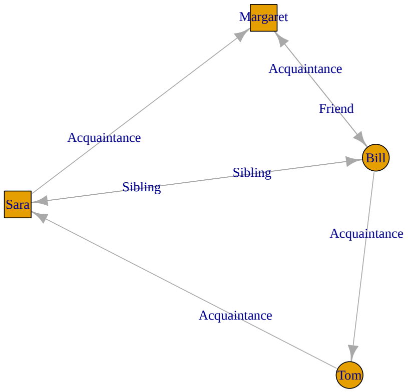
Color and shape of nodes based on gender

```
plot(gg, edge.label = NA, vertex.color = factor(V(gg)$gender),
     vertex.shape = V(gg)$shape, layout = gg_layout)
```



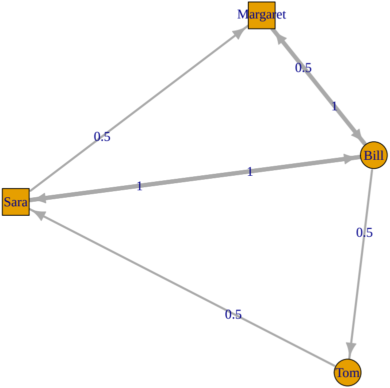
Name ties based on types

```
plot(gg, edge.label = E(gg)$label, layout = gg_layout)
```



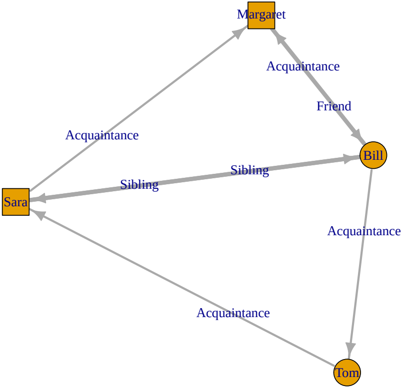
Weight ties based on importance

```
plot(gg, edge.width = E(gg)$weight*5, edge.label = E(gg)$weight, layout = gg_layout)
```



Mixture of weight/label

```
plot(gg, edge.label = E(gg)$label, edge.width = E(gg)$weight*5, layout = gg_layout)
```

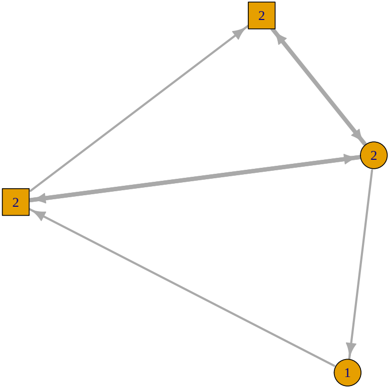


A glimpse to more serious analysis

- After simple visualization (if possible), a five number summary!
  1. **Size**: V, E
  2. **Density** (ratio of ties to possible ties, $1 =$ fully connected)
  3. **Components** & (dis)connectivity
  4. **Diameter** (how compact the network is)
  5. **Clustering Coefficient** (transitivity)
- **Centrality** in network
  - Degree, Closeness, Betweenness, Eigenvector, ...

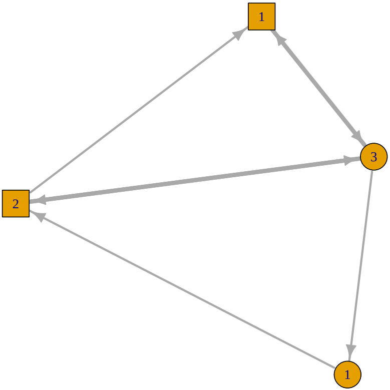
In-degree of a node

```
plot(gg, edge.label = NA, edge.width = E(gg)$weight*5,
     vertex.label = degree(gg, mode = 'in'), layout = gg_layout)
```



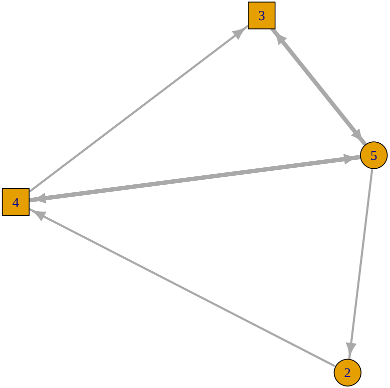
Out-degree of a node

```
plot(gg, edge.label = NA, edge.width = E(gg)$weight*5,
     vertex.label = degree(gg, mode = 'out'), layout = gg_layout)
```



Degree of a node

```
plot(gg, edge.label = NA, edge.width = E(gg)$weight*5,
     vertex.label = degree(gg, mode = 'all'), layout = gg_layout)
```

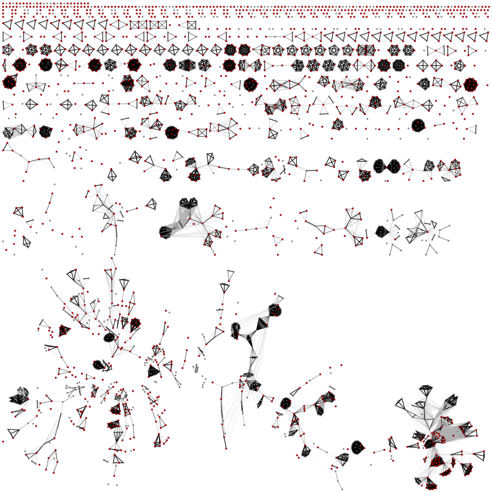


A real life example from science studies!

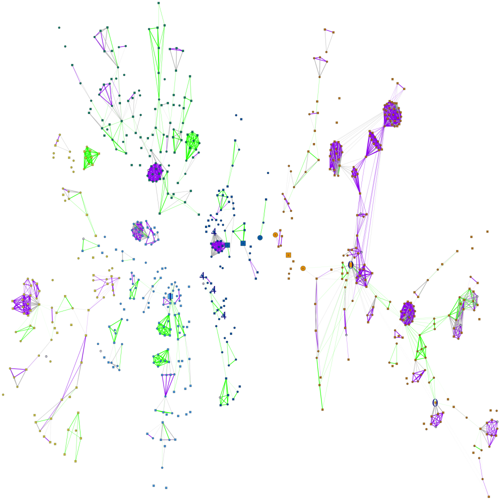
Sociological theories (& SNA conceptualization)

- **Matteo effect**, winner takes all?
  - Highly prolific scientists attract higher collaborations from other scientists?
  - Attaching preferably to a few **star scientists**/leaders?
- **Fragmentation** of ideas, sociology as a interstitial science?
  - Methodologists bridging the islands?
- [Sociological] **small world** of disconnected islands?
- **Core** of leaders and **periphery** of followers?

Coauthorship of Italian sociologists



Communities in the giant component



What can we learn from these communities? (1/2)

Table 2: Gender composition and internationality of members of the communities detected from the giant component (Percentages are calculated by rows separately for gender and country)

		Gender			Country			
Community	# members	Female	Male	Missing Gender	Europe	Italy	Other	Missing Country
0	254	43%	54%	3%	54%	29%	11%	5%
1	142	50%	49%	1%	36%	55%	6%	3%
2	122	38%	61%	1%	37%	56%	3%	4%
3	103	45%	54%	1%	41%	44%	5%	11%
4	91	47%	49%	3%	32%	57%	9%	2%

Table 3: Sectors composition of members of the communities detected from the giant component (Percentages are calculated by rows)

		Scientific Disciplinary Sectors						
Community	# members	postdoc	SPS/07	SPS/08	SPS/09	SPS/10	SPS/11	Missing Sector
0	254	2%	1%	5%	0	0%	0%	91%
1	142	2%	6%	3%	8%	1%	1%	78%
2	122	5%	10%	1%	7%	0	1%	76%
3	103	2%	4%	2%	12%	1%	0	80%
4	91	1%	7%	7%	0	1%	2%	82%

What can we learn from these communities? (2/2)

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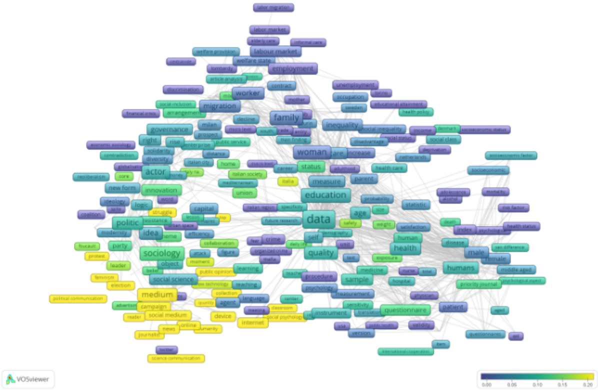
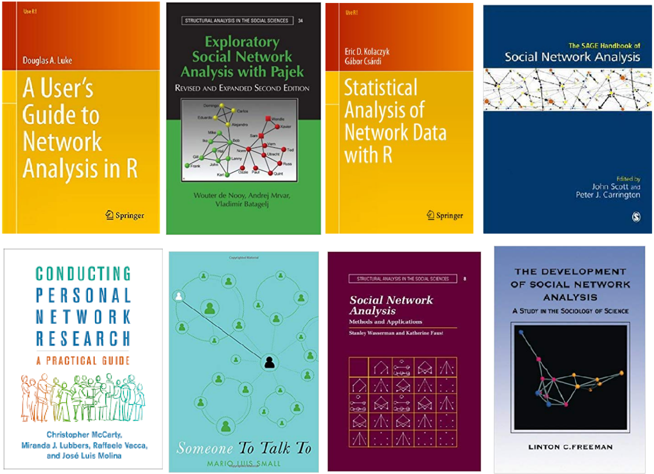
- 65% foreigners
- Medium, science communication, social medium, internet, political communication & public opinion



Where to next?!

- **Awesome network analysis** list: https://github.com/briatte/awesome-network-analysis



Best of luck in exploring networks!