# Introduction to Social Network Analysis

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### **Co-inventorship**

Figure 1 Inventors of Silicon Valley's Largest Component in 1986-1990 by Assignee and Importance of Inventions



Notes. Node sizes reflect the number of future prior art cites to an inventor, normalized by the number of collaborators (future prior art cites correlate with value, see Albert et al. 1991). Tie width indicates number of collaborations, tie color indicates age of tie (red is five years prior, blue is two to four years prior, and green is prior year), and colors indicate assignee. Boxed area provides example of highly clustered inventors. Note that the figures do not illustrate the thousands of other (by definition) smaller components in each region; inventors need not connect to any extant component – or even another node. They can connect to small components, such as dyads or triads, or work their entire careers in complete isolation. Graphed in Pajek with Kamada-Kawai/Free algorithm (Batagelj and Mrvar 1998). Adapted from Fleming and Marx (2006).

#### Source: Fleming, King & Juda (2007)



### **Regional innovation networks**





Fig. 2. Main components of regional networks Note: Actors located within the region (headquarter or subsidiary) are marked in grey/red (electronic version), external actors are in black. Squares indicate a private actor; public research organizations are circles. The size of a node is proportional to the number of patents filed.

#### Source: Fritsch & Graf (2011)

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### Cluster knowledge network



Figure 3. Structure of knowledge network in Valle de Colchagua. The size of the nodes is proportional to the measure of their knowledge base.

Source: Giuliani (2007)

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### Patent wars



https://uk.pcmag.com/news/116009/infographic-smartphone-patent-wars-explained

### **Product space**



Fig. 1. Ine product space. UN Interacting durative processing up native representing the 775 SITC-4 product classes exported in the 1998-2000 trade, and their colors are closen according to the classification introduced by period. (B) Network representation of the product space. Unliks are color colord. Learner.

Source: Hidalgo et al. (2007)

# Some basic SNA literature

- Borgatti, SP, Everett, MG, Johnson, JC (2013) Analyzing Social Networks. London: Sage Publications
- Hanneman, RA, Riddle, M (2005) Introduction to social network methods. Riverside, CA: University of California, Riverside (published in digital form at http://faculty.ucr.edu/ hanneman/)
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### What is a network?

- A set of dyadic ties, all of the same type, among a set of actors
- Actors can be persons, organizations . . .
- A tie is an instance of a social relation



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# Relations among persons

Relational states							
Similarities		Relational roles		Relational cognition		Relational events	
Location	Participation Attribute	Kinship	Other role	Affective	Perceptual	Interactions	Flows
Same spatial and temporal space	Same clubs, Same same events gender, same attitude	Mother of, sibling of	Friend of, boss of, student of, competitor	Likes, hates	Knows, knows of, sees as happy	Sold to, talked to, helped, fought with	Information, beliefs, money

#### Note: Content matters!

Each relation yields a different structure & has different effects

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# Relations among organizations

Туре	Firms as entities	Via Individuals
Similarities	Joint membership in trade association; co-located in Silicon Valley	CEO of organization A sits on same board as CEO of organization B
Relations	Joint ventures; alliances; distribution agreements; own shares in; regards as competitor	Chief scientist of A is friend with chief scientist of B
Interactions	Sells products to; makes competitive move in response to	Representatives of A attend same conference as representatives of B
Flows	Technology transfers; cash infusions	Employee of A leaks information to employee of B

# Relations among other entities

- Patents
  - Patents citing other patents
  - Co-occurrence of technological classes
- Research fields
  - Citations between fields
  - Co-classifications of publications or patents
  - People who publish in different fields
- Sectors
  - Input-output relations
  - Labour flows

# Level of analysis

Level of analysis	Research question			
Dyad level	Are firms with overlapping technological knowledge bases more likely to form research collaborations?			
Node level	Do firms with more diverse technology partners innovate more?			
Network level	Are centralized regional networks more innovative?			

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# Data for social networks

- Network data typically as a quadratic  $n \times n$  matrix **A**, with rows and columns as observations
- $\rightarrow$ Cell aij gives the relation between i and j.



- Tie strength: Strength of relationship, frequency of interaction, ...
- Actors and attributes vs. actors and their relations

### **Direction of ties**

Ties can be directed or undirected

- Undirected ties: A and B write a joint paper, go to lunch together
- Directed ties: A cites B, A gives information to B

Logically vs empirically directed ties

- logically undirected relations can be empirically non-symmetric due to measurement error;
- logically ties might be directed, but we can only observe an undirected version.

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### Incidence and adjacency matrices

Set of vertices (nodes):  $\mathcal{V} = \{A, B, C, D, E, F\}$ Set of edges (ties):  $\mathcal{E} = \{(A, B), (A, D), (B, D), (B, F), (C, E), (C, F), (D, E), (D, F)\}$ 



# Length and distance

- Length of a path is the number of links
- Distance (dij) between two nodes is length of the shortest path (aka geodesic) between two nodes
- Distance matrix:



 Diameter of a connected graph is the length of largest distance between any nodes

### Components

- Maximal sets of nodes in which every node can reach every other by some path (no matter how long)
- A connected graph has just one component



For directed networks, we have to distinguish weak and strong components

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# **Characterizing Networks**

- Measures of cohesion
  - Density
  - Average degree / mean degree
  - Connectedness / fragmentation
- Average distance
- Clustering and transitivity
- Centralization

# Density and mean degree

- Density number of ties, expressed as percentage of potential ties
- Mean degree average number of ties
- Density is highly size sensitive!



n = 25; density = 0.26; mean degree = 12.8



n = 25; density = 0.08; mean degree = 4



n = 100; density = 0.06; mean degree = 12.7

## Connectedness and average distance

Connectedness measures use the distribution of links to measure cohesion:

- Share of actors in the main component
- Connectedness proportion of pairs that can reach each other, i.e. which are members of the same component
- Fragmentation the number of pairs that cannot reach each other

• Average distance: 
$$L = \frac{\sum_{i \neq j} d_{ij}}{n(n-1)}$$

# Clustering coefficient

- Clustering coefficient cohesion of the neighborhood
- Transitivity proportion of triples with 3 ties as a proportion of triples with 2 or more ties



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### Centralization



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# Different concepts of centrality

### Degree centrality

- Which actor has most relations?
- Degree centrality as share of all possible relations

### Closeness centrality

- Which actor is closest (least distant) to all other actors?
- Inverse of the sum of distances to all other nodes

### Betweenness centrality

- Idea: who 'controls' information flows?
- High-betweenness vertices lie on a large number of non-redundant shortest paths between other vertices
  - $\rightarrow$  'bridges' or 'boundary spanners'
- Loosely: number of times that a node lies along the shortest path between two others

### Eigenvector centrality

- Idea: connections to well connected actors are more important
- Centrality of each actor is proportional to the sum of the centralities of those actors to whom he or she is connected



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Node and label size proportional to respective centrality measure

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### Interaction in the innovation process

#### Research is increasingly teamwork

- Changes in the organization of innovative activities
- General trend: increasing team size in research



#### Source: Wuchty, Jones & Uzzi (2007)

### Innovation and interaction $\rightarrow$ networks

#### Innovation and interaction

- Collective invention (Allen 1983)
- Knowledge spillovers as major drivers of economic growth (Romer 1990, Aghion & Howitt 1992)
- Localized knowledge spillovers (LKS) (Jaffe et al. 1993)

#### Networks as structure of knowledge diffusion

- Knowledge as a latent public good
- ► Knowledge is only partly codifiable → tacit components
- Learning and exchange of knowledge through personal interaction
- Social proximity as an explanation for LKS (Breschi & Lissoni 2009)
- Consequence
  - → Access to external knowledge restricted by position within the network
  - Network structure influences rate and direction of knowledge flows

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# Types of innovation networks

#### Examples of networks from the literature

	Nodes	Edges	Application
Cooperation networks	Firms	Cooperations	Powell et al. 1996
Co-funding networks	Organizations	Cooperations	Broekel & Graf 2012
Regional networks	Regions	Cooperations	Wanzenböck et al. 2015
Co-authorship networks	Individuals	Publications	Barabasi et al. 2002
Inventor networks	Individuals	Patents	Fleming et al. 2007
Innovator networks	Patent applicants	Inventors	Cantner & Graf 2006
Citation networks	Authors, patents, publications	Citation	Sorenson et al. 2006
Product space	Product classes	Co-occurence	Hidalgo et al. 2007
Knowledge base	Industries	Labour flow	Neffke et al. 2011

### **Research topics**

Network formation and dynamics

- Network formation
- Mechanisms of formation and evolution

Networks and economic performance

- Individual ties / position and individual performance: relational embeddedness
- Creative potentials versus trust relations: structural embeddedness
- The influence of network structure on system performance

### Research topics: network formation and dynamics

- Network formation
  - Motives to cooperate / engage in network (Baum et al. 2003)
  - Innovation network dynamics and the stability of network structures (Schilling & Phelps 2007)
  - Persistence of relations (Giuliani 2011)
  - Global properties (degree distributions, small-worlds) (Watts & Strogatz 1998, Baum et al. 2003, Schilling & Phelps 2007)
- Mechanisms of formation and evolution (Cantner & Graf 2006, Barabasi at al. 2002)
  - Preferential attachment and path dependency (possible lock-in) (Abbasi et al. 2012)
  - Homophily: not too much similarity (Tomasello et al. 2017)
  - Triadic closure: creative potential vs. generating trust (ter Wal 2014)

# Research topics: networks and economic performance

- Individual ties / position and individual performance: relational embeddedness (Graf & Krüger 2011, Rowley et al. 2000)
  - Direct and indirect ties matter (Ahuja 2000)
  - Strong vs. weak ties (Rost 2011)
  - Problems of overembeddedness (Uzzi 1997)
  - Influence of more sophisticated centrality measures with mixed results
- Creative potentials versus trust relations: structural embeddedness
  - Burt–Coleman debate: structural holes vs. dense neighborhood (Gilsing & Duysters 2008)
  - Dependent on context: exploration (structural holes) exploitation (density) (Rowley et al. 2000)
- The influence of network structure on system performance (Owen-Smith et al. 2002, Fritsch & Graf 2011)
  - Small-world as a ubiquitous structural phenomenon (Watts & Strogatz 1998, Baum et al. 2003)
  - Simulations show superiority in terms of knowledge diffusion (Cowan & Jonard 2004)
  - Centralized national research networks are less embedded in the global knowledge network (Graf & Kalthaus 2018)

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- **Ozman, M. (2009)**, Inter-firm networks and innovation: a survey of literature, Economics of Innovation and New Technology, 18, 1, 39-67
- Cantner, U. & Graf, H. (2011), Innovation Networks: formation, performance and dynamics, in: Antonelli, C. (ed.) Handbook on the Economic Complexity of Technological Change, Edward Elgar, 366-394
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### Software

UCINET Easy to learn, comprehensive menu, many users (groups.io/g/ucinet/ for questions), good help files, flexible visualization with NetDraw (included), no batch mode, best for smaller networks (n < 1000), only for MS Windows

https://sites.google.com/site/ucinetsoftware/home

R (igraph) Batch mode for repetitive tasks, tables and graphics can be easily exported, platform independent, integration with other statistical packages http://cran.r-project.org/, https://igraph.org/

R (sna, network) Similar to igraph package, some algorithms are slow for large networks, might run out of memory for large networks (n > 5000), some functions that are not in igraph

Pajek Tough menu but the right choice if your network is really large, import data with txt2pajek http://mrvar.fdv.uni-lj.si/pajek/

#### RSiena Tools for testing hypotheses about network evolution

http://www.stats.ox.ac.uk/~snijders/siena/

Gephi https://gephi.org/

A 202

For qualitative analysis

VennMaker https://www.vennmaker.com/?lang=en

mynetworkmap https://mynetworkmap.com/

Small example with igraph

library(igraph)

- Character Interaction Networks for the HBO Series "Game of Thrones" from <a href="https://github.com/mathbeveridge/gameofthrones">https://github.com/mathbeveridge/gameofthrones</a>
- We read the data and select only the most important relations

#import datafile
got.edges <- read.csv("got-s8-edges.csv")
got.edges <- got.edges[got.edges\$Weight >= 35,1:3]

and turn the edgelist into an igraph object

got.ig <- graph\_from\_data\_frame(got.edges, directed=FALSE)</pre>

Let us retrieve some information about the created object

```
print (got.ig)
## IGRAPH bf322bf UN-- 20 31 --
## + attr: name (v/c), Weight (e/n)
## + edges from bf322bf (vertex names):
   [1] DAENERYS--JON
                           DAENERYS--TYRION
##
                                              JAIME
                                                      ---TYRION
##
  [4] JAIME
               --BRIENNE
                           JON
                                 --TYRION
                                              TYRION ---VARYS
   [7] TYRION --SANSA
##
                          TYRION ---DAVOS
                                              DAENERYS--SANSA
## [10] ARYA ---GENDRY
                           JON --ARYA
                                              JON
                                                      --SANSA
                          ARYA ---HOUND
## [13] JON ---SAM
                                              TYRION ---BRAN
## [16] SANSA ---ARYA
                           DAENERYS-JORAH
                                                  --GREY WORM
                                              JON
## [19] JON
              --- TORMUND
                           JON
                                  ---VARYS
                                              JON
                                                  ---DAVOS
## [22] BRIENNE -- TYRION
                                              CERSEI ---OYBURN
                           DAENERYS---VARYS
## + ... omitted several edges
```

• We can have a look at the adjacency matrix

```
get.adjacency(got.ig)
## 20 x 20 sparse Matrix of class "dgCMatrix"
##
  [[ suppressing 20 column names 'DAENERYS', 'JAIME', 'BRIENNE' ... ]]
++
## DAENERYS ... 111... 11.1... 1...
II JON
    1...11111.1..1.1..1.
    1111.11.11.11.....
## TYRION
## SANSA
    ## DAVOS
## ARYA
    ## BRAN
    ## BRONN
    ## VARYS
## GENDRY
    ## SAM
    ## HOUND
    1 . . . . . . . . . . . . . . . . . .
JORAH
## TORMUND
    . 1 1 1 . . . . . . . . . . . . . . .
## OYBURN
    ## EURON
```

 Plot the graph with labels, size proportional to degree and weighted edges

plot(got.ig,vertex.size-degree(got.ig)\*2, edge.width=E(got.ig)\$Weight/25)



• The package also has community detection algorithms, e.g. to identify densely connected subgraphs (clusters)



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# Data collection – Sampling

- Snowball methods sampling actors
  - begin with a focal actor or set of actors
  - each of these actors is asked to name some or all of their ties to other actors

 $\rightarrow$ ego-network(s)

- actors who are not connected (i.e. "isolates") are not identified
- no guaranteed way of finding all of the connected individuals in the population
- Full network methods sampling relations
  - require that we collect information about each actor's ties with all other actors: census of ties in a population of actors
  - Full network data is necessary to properly define and measure many of the structural concepts of network analysis (e.g. betweenness)
  - allows for very powerful descriptions and analyses of social structures

## Relational data sources

- Primary data
  - Snowball
  - Roster recall
  - Open list
- Patents (or publications)
  - Co-inventor networks
  - Co-applications
  - Innovator networks: applicants linked by common inventors
  - Citation networks
- Collaboration data
  - Commercial data (e.g. SDC Platinum Refinitiv)
  - Funding data (Förderkatalog in GER, CORDIS for EU)
  - . . .

### Boundaries of the Network

- Defining boundaries in primary data collection
  - What type of relation?
  - Intensity of relation?
  - Who are the focal actors?
  - Open or closed list?
- Defining boundaries with patents or publications:
  - Technological: IPC-classes, keywords or aggregates thereof (e.g. IPC4, technologies [concordance])
  - Time window: usually up to 10 years, assumption of link decay!
  - Regions: all patents (publications) with at least one inventor (author) located in the focal region

# Example for primary data collection – SCW-Networks

#### Questionnaire

- Regional clusters of actors who receive funding
- Only relations of funded actors can be observed (firms, universities, research institutes)
- We ask for the maximum of ten most important R&D partners along with link attributes

23. Bitte nennen Sie uns ihre strategisch wichtigsten FuE-Partner.

Unter strategisch wichtigen FuE-Partnern verstehen wir Partner (andere Unternehmen, und/oder nicht kommerzielle Einrichtungen), mit denen Sie gemeinsam neue Produkte, Fertigungsverfahren und sonstige Innovationen entwickeln, welche für die strategische Ausrichtung Ihres Unternehmens von großer Bedeutung sind. Eine reine Auftragsvergabe ohne aktive Zusammenarbeit wird nicht als Kooperation betrachtet.

Strategisch wichtigste FuE-Partner (Name und Standort)	Haben Sie bereits vor September 2007 mit diesem Partner gemeinsa- me FuE betrieben?		Wurde diese Beziehung durch den "Spitzencluster-Wettbewerb" ange- stoßen bzw. intensiviert?	
	ja	nein	ja	nein
1.	٩	٩	ū	٩
2.	u.	a	•	o
3.	D	٩	D I	a
			6	

### Example networks



Art des Akteurs

Columentation

O KULL KOLD
 A UniversitätHockschula
 ♥ Forschungseinischlung
 # nicht bekannt Cool Silicon 2013

Antworten: 21 - Akteure: 89

### Example networks

Cool Silicon 2011



Antworten: 17 - Akteure: 97

green = initiated by LECC lightblue = intensified by LECC



Perpion

Chasternegio Deutschark Europa Wolt

### Data cleaning

#### The "names game"

- The problem: If the character string for two nodes is exactly the same (simple string matching), we assume that they refer to the same person.
- However, this might not be the case:
  - Databases are not perfect, names might change (e.g. academic titles, middle names) or spelled differently. 'Ronald S. Burt' and 'Ronald Burt' are grouped as different nodes even though it is one person.
  - → Type I error (false negatives, different nodes refer to the same person)
  - Some names are very common. Two nodes named 'John Smith' might refer to different persons.
  - → Type II error (false positives, one node refers to more than one person)
- Parsing: reducing noise by changing case, removing double blanks, symbols, accents, etc.
- Matching: SSM or other algorithms
- Filtering: using additional information to reject false positives
- Manual check for small data
- See Raffo & Lhuillery (2009)

### Short network survey

visit <u>https://forms.gle/qDmxEBYddLybPNMP8</u>



- Please take the survey, results will be discussed in the feedback session
- Homework
  - Develop your own survey including network questions
  - Form 4 teams to work on a survey that could help you understand specific aspects of your cluster
  - Questionnaire should be finished by Workshop 3 (combined task with "data gathering" by Matthias Hügel)

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