Social network methods in bird studies: analysis of interactions and corresponding statistics

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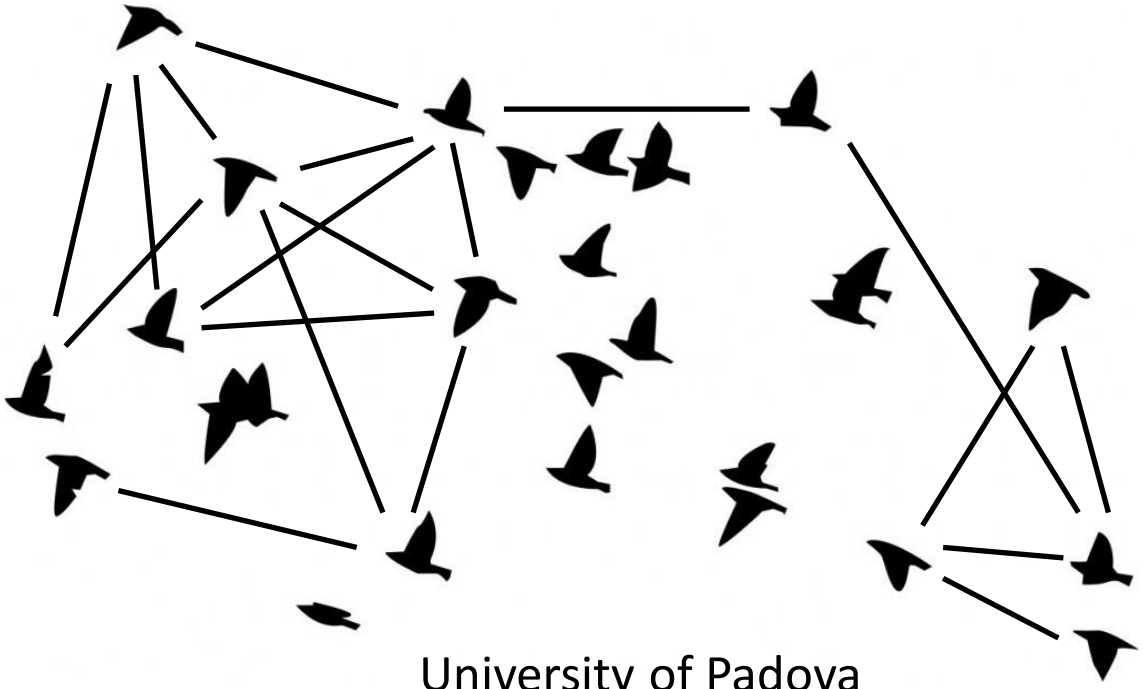


University of Padova

OUTLINE:

- **What is social network analysis (SNA)?**
  - What is a social network and what can SNA offer to behavioural ecology?
  - What are the origins of animal social network analysis?
  - Help! Notes, books, reviews, special issues

- **Analysis of social interactions**
  - Network metrics
  - *A priori* considerations
  - Example: Tóth et al. 2014 Anim Behav

OUTLINE:

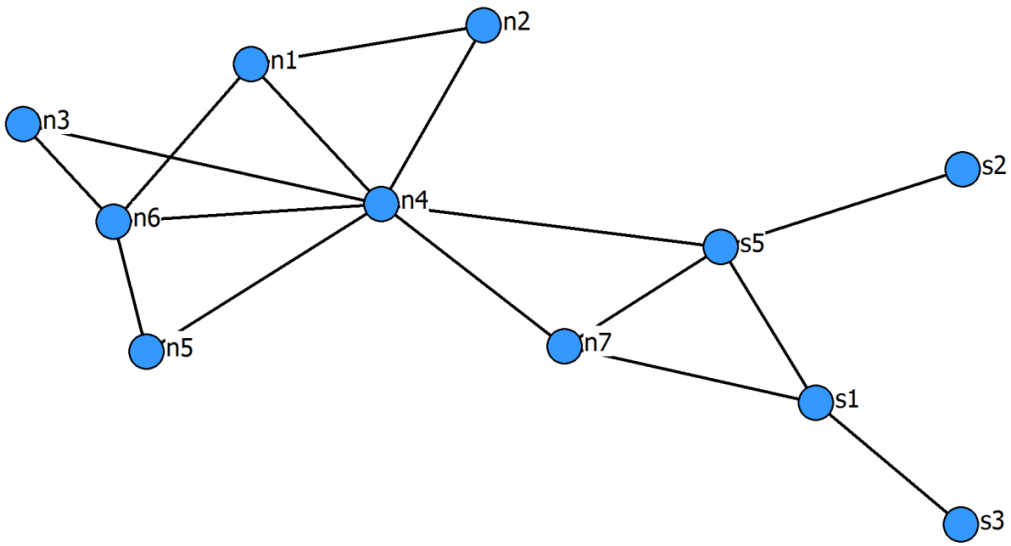
- **How to collect data for social network analysis?**
  - What should we measure and how?
  - Identification of individuals
  - Data structure

- **Analysis of the collected data**
  - Software: SOCPROG, UCINET, R
  - Examples and R scripts

What is social network analysis?

- network theory provides a formal framework, a concept and set of analytical tools, for the study of complex social relationships

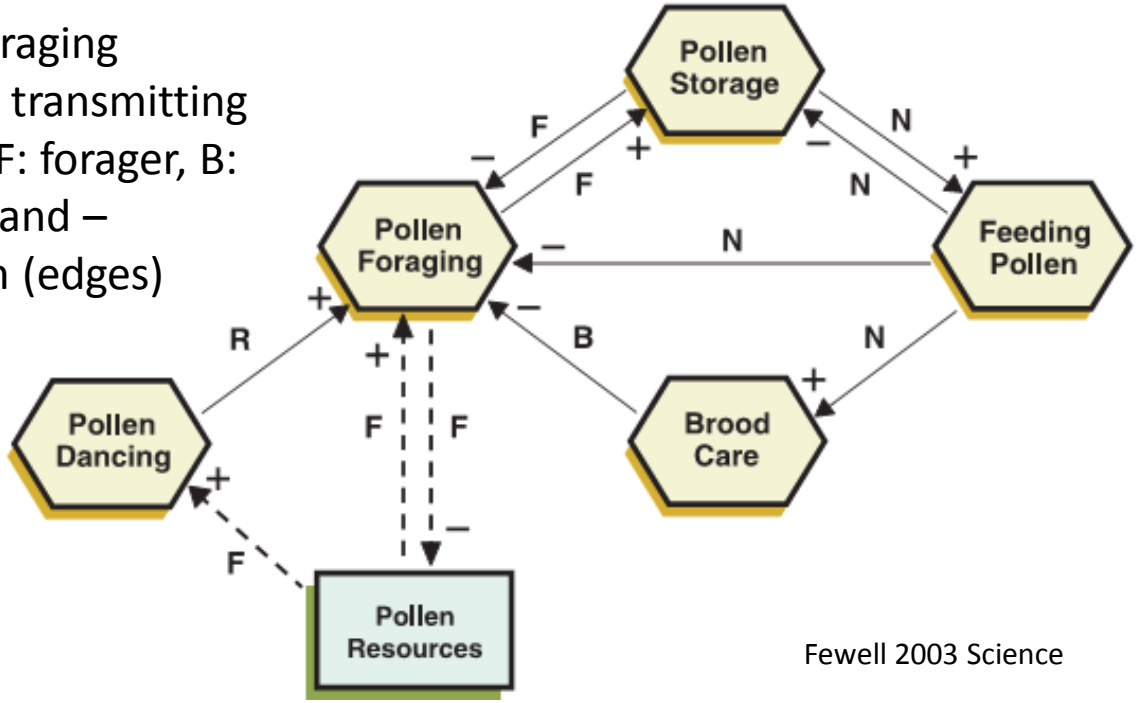
- nodes (vertices) & edges (ties): in a graph, each node is represented by a symbol, and every interaction between two nodes is represented by a line (arrow) drawn between them.



What is social network analysis?

- nodes: individuals
- edges: social interactions (aggression, allopreening, following, etc.), co-occurrence in a group

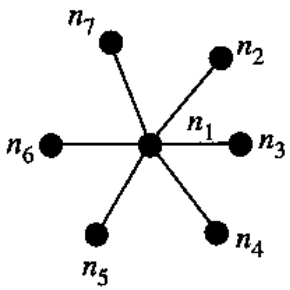
Tasks linked to pollen foraging (nodes), and individuals transmitting information (R: recruit, F: forager, B: brood, N: nurse) with + and – feedback between them (edges)



Fewell 2003 Science

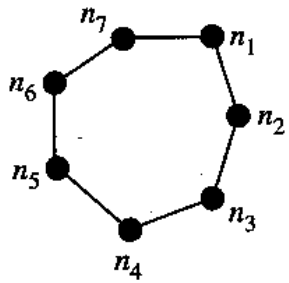
What is social network analysis?

- graph vs. matrix representation



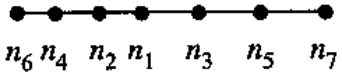
(a) Star graph

0	1	1	1	1	1	1
1	0	0	0	0	0	0
1	0	0	0	0	0	0
1	0	0	0	0	0	0
1	0	0	0	0	0	0
1	0	0	0	0	0	0
1	0	0	0	0	0	0



(b) Circle graph

0	1	0	0	0	0	1
1	0	1	0	0	0	0
0	1	0	1	0	0	0
0	0	1	0	1	0	0
0	0	0	1	0	1	0
0	0	0	0	1	0	1
1	0	0	0	0	1	0



(c) Line graph

0	1	1	0	0	0	0
1	0	0	1	0	0	0
1	1	0	0	1	0	0
0	1	0	0	0	1	0
0	0	1	0	0	0	1
0	0	0	1	0	0	0
0	0	0	0	1	0	0

Wasserman & Faust 1994

What is the advantage of SNA?

- helps to understand the link between individual behaviour and population-level phenomena, and scale up from the former to the latter:

1. individuals interact with each others: varies in strength, type and dynamics

↓

2. a diverse array of behaviours will be influenced by its structure, including finding mating partners, developing cooperation, engaging foraging or anti-predator behaviour

↓

3. population-level consequences: mating systems, habitat use, information flow, disease transmission

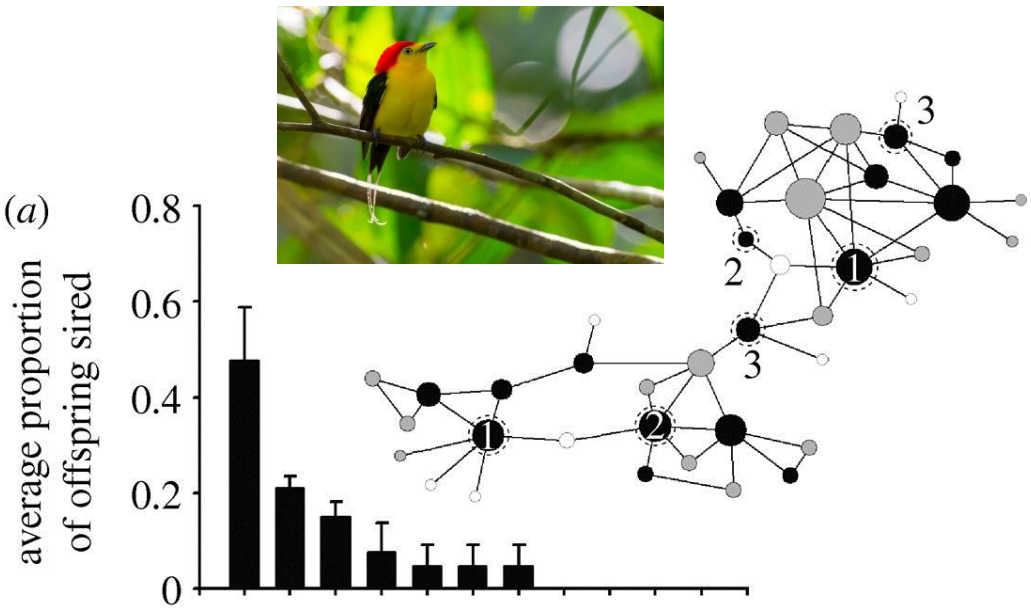
What is the advantage of SNA?

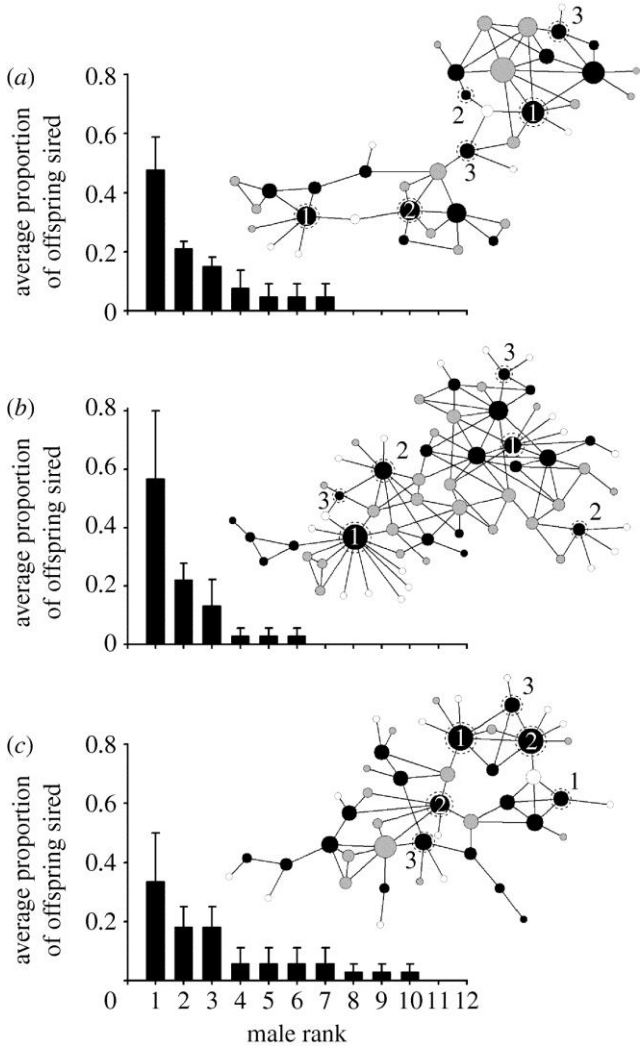
- individual attributes: age, sex, dominance, body condition (energy reserves), information (experience), parasite infection

→ improve our understanding of the function, evolution and implication of social organization, and how individuals' position is affected by intrinsic and extrinsic factors

What can SNA offer to behavioural ecology?

Example: Ryder et al. 2009 Proc R Soc B

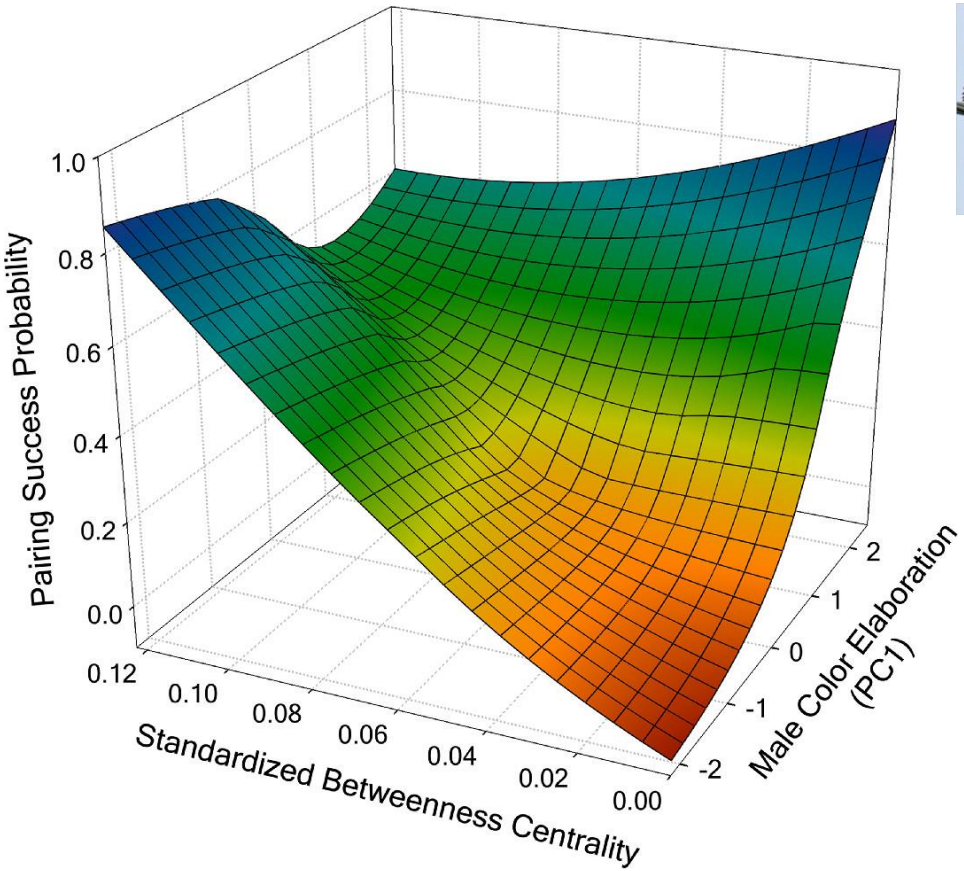


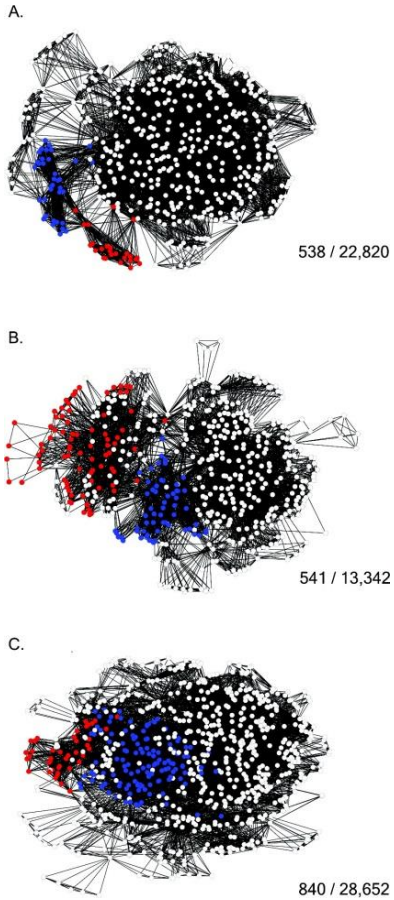


Male connectivity in the networks, measured as the number of males with whom the focal male has extended interactions, were strong predictors of the number of offspring sired.

What can SNA offer to behavioural ecology?

Example: Oh & Badyaev 2010 Am Nat

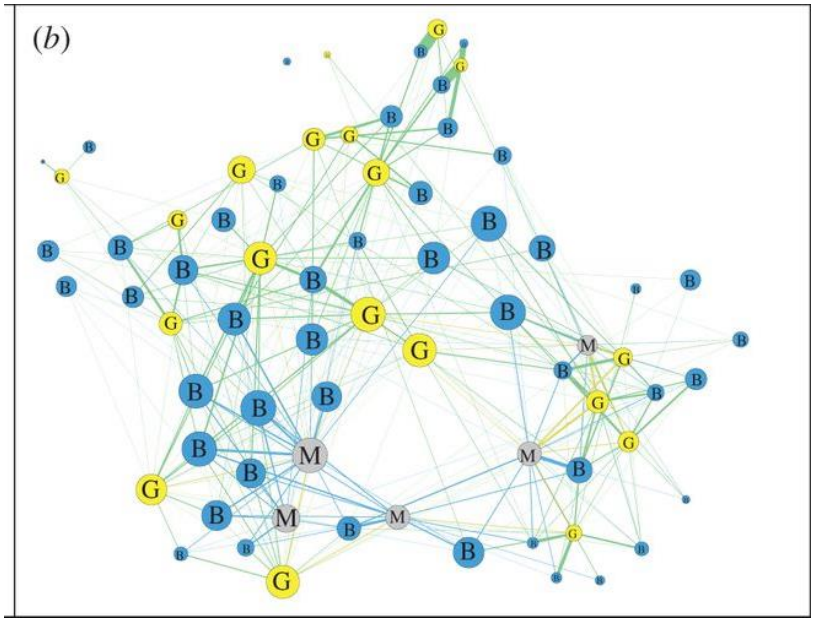


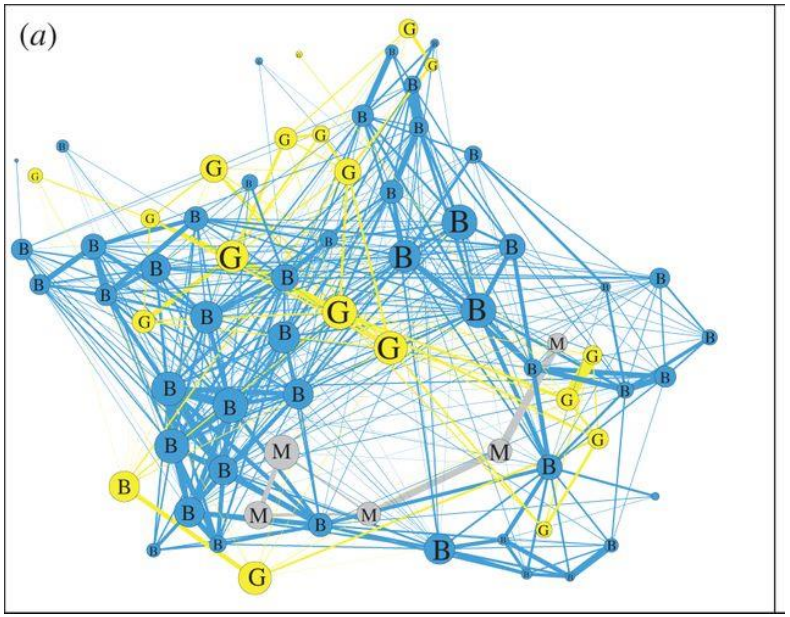


In a free-living house finch population, two distinct combinations of ornament elaboration and male social lability have roughly equivalent mating success.

What can SNA offer to behavioural ecology?

Example: Farine et al. 2015 Proc R Soc B

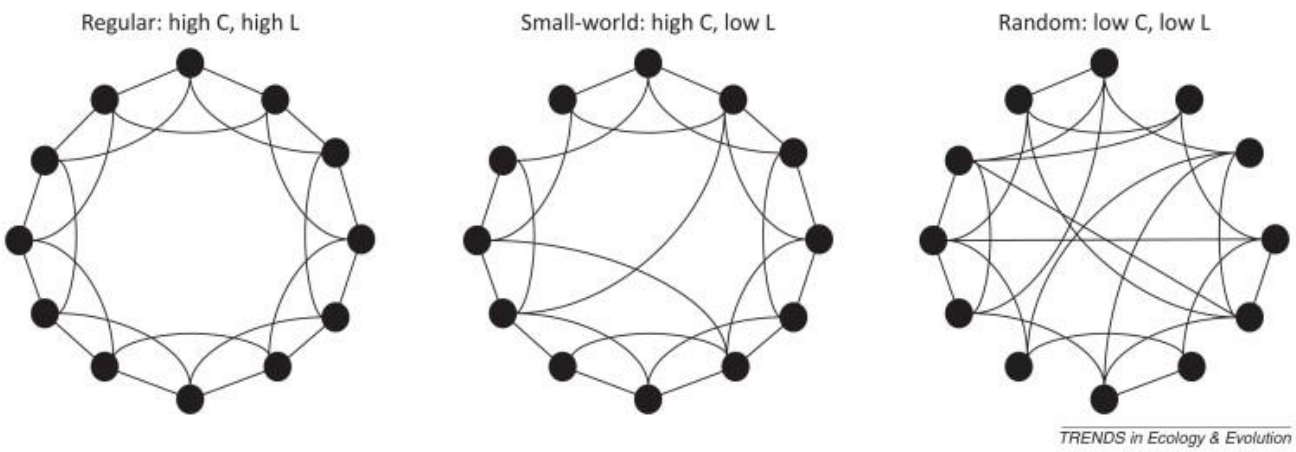




Both intraspecific and interspecific social networks contributed to the spread of information about novel food sites.

What are the origins of animal social network analysis?

- **psychology & sociology:** analysis of human interaction patterns (from the 30s)
- **mathematics and physics:** Erdős-Rényi random graphs**,** random assignments of edges and/or nodes, scale-free networks and „small worlds”



Kurvers et al. 2014 Trends Ecol Evol; originally from Watts & Strogatz 1998 Nature

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- **psychology & sociology:** analysis of human interaction patterns (from the 30s)
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→ electric power grids – vulnerability to the loss of single power plants

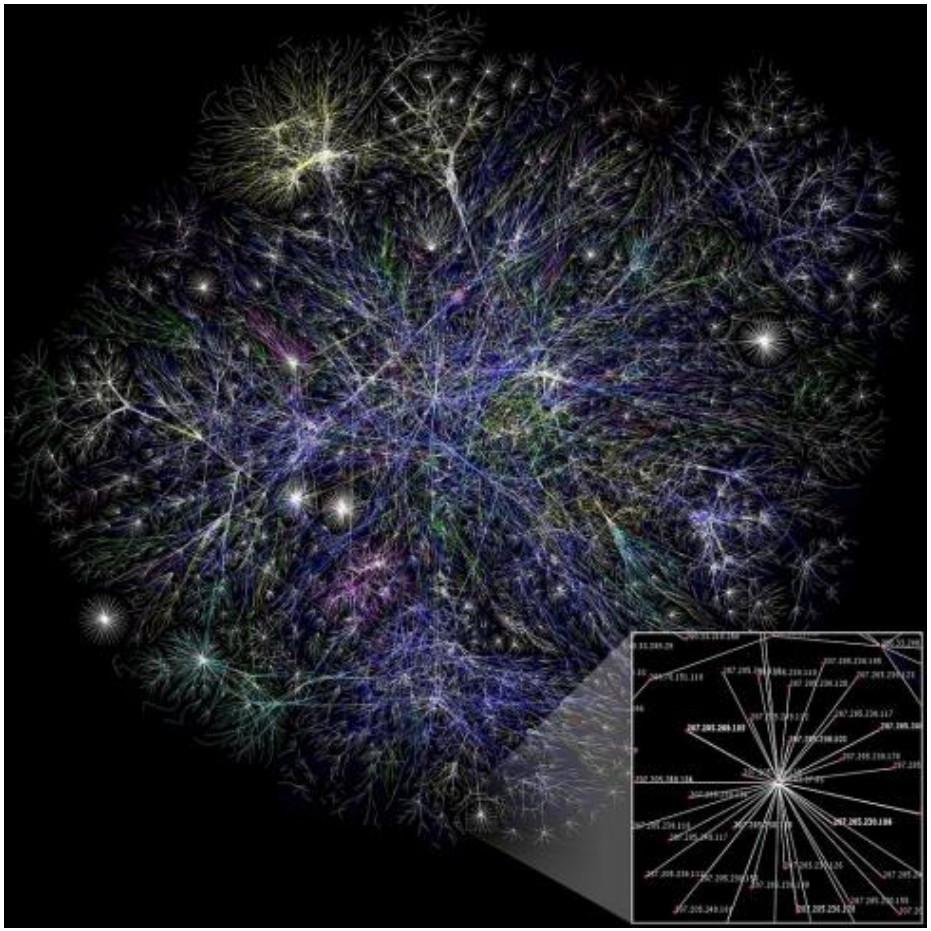
→ transport/telecommunication systems, world wide web, economy

→ gene regulatory networks, metabolic pathways

→ structure and stability of ecological systems – trophic interactions in a food web

→ disease transmission in humans

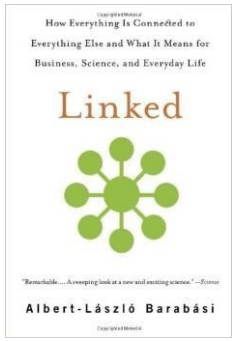
What are the origins of animal social network analysis?

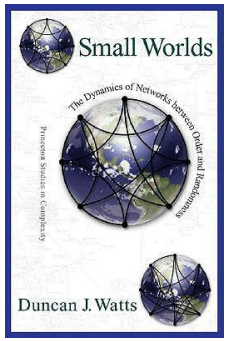


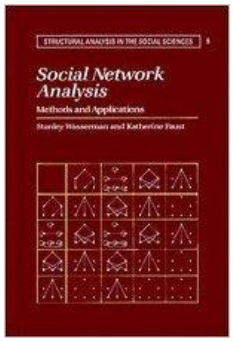
Internet map 2005 (partial)
by The Opte Project/Barrett Lyon

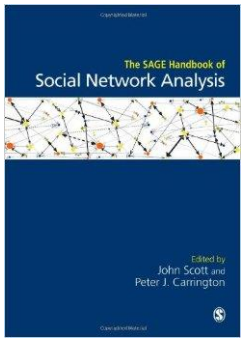
Help! books, notes, reviews, special issues

- Books 1: Barabási (2002), Watts (1999)
- Books 2: Wasserman & Faust (1994), Scott & Carrington (eds.) (2011)

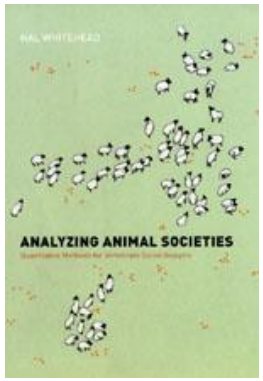


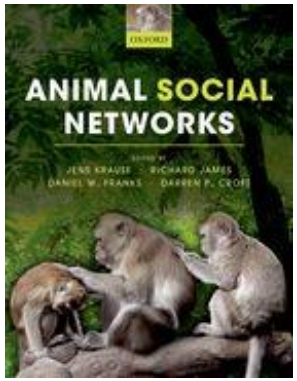






- Books 3: Croft et al. (2008) , Whitehead (2008), Krause et al. (eds) (2014)





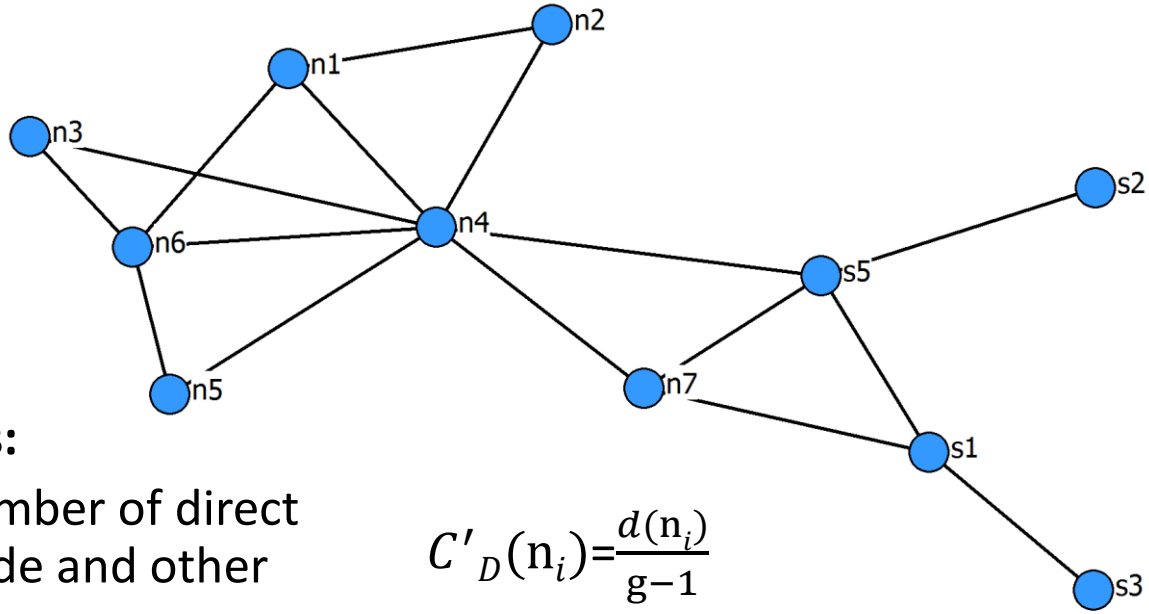
Help! books, notes, reviews, special issues

- Notes: Hanneman & Riddle 2005 http://faculty.ucr.edu/~hanneman/nettext/
- Reviews: Wey et al. 2008 Anim Behav, Kurvers et al. 2014 Trends Ecol Evol, Pinter-Wollman et al. 2014 Behav Ecol
- Researchers: N. Bode, C. Sueur, H. Whitehead, D. Lusseau, D. Croft, B. Sheldon
- Special issues/sections:

  Behav Ecol Sociobiol 2009 (vol. 63, issue 7): Social Networks: new perspectives (guest editors: J. Krause, D. Lusseau, R. James)

  Behav Processes 2010 (vol. 84, issue 3): Special section: Collective Movements.
- Programme-related websites, manuals – UCINET 6 (Borgatti et al. 2002), SOCPROG (Whitehead 2009)
- R packages – asnipe (Farine 2013), tnet (Opsahl 2009, www.toreopsahl.com), statnet (Handcock et al. 2003)
- lectures: COURSERA, http://sna.stanford.edu/rlabs.php

Network metrics (1)



- **individual measures:**

• Degree centrality: number of direct ties between a focal node and other nodes

$$C'_D(\mathrm{n}_i)=\frac{d(\mathrm{n}_i)}{\mathrm{g}-1}$$

• Betweenness: based on the number of shortest paths between every pair of other group members on which the focal individual lies

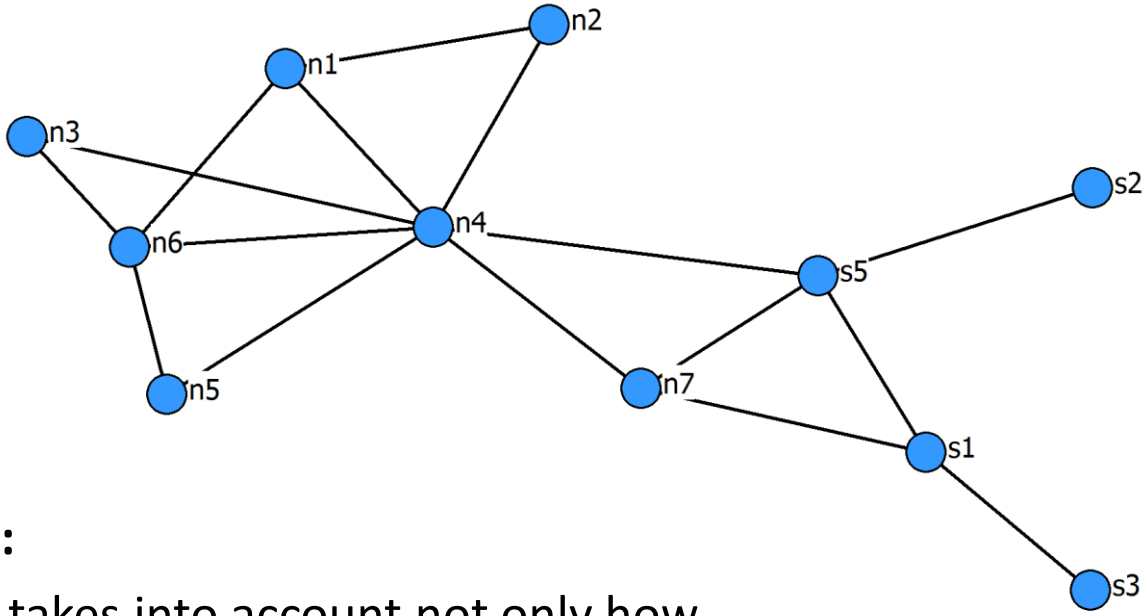
$$C_B(\mathrm{n}_i)=\sum_{j<k} \mathrm{g}_{jk}(\mathrm{n}_i)/\mathrm{g}_{jk}$$

$$C'_B(\mathrm{n}_i)=C_B(\mathrm{n}_i)/[(\mathrm{g}-1)(\mathrm{g}-2)/2]$$

• Closeness: minimum cumulative distance at which a node is connected to others in the network

$$C'_C(\mathrm{n}_i)=\mathrm{g}-1/[\sum_{j=1}^{g} d(\mathrm{n}_i,\mathrm{n}_j)]$$

Network metrics (2)

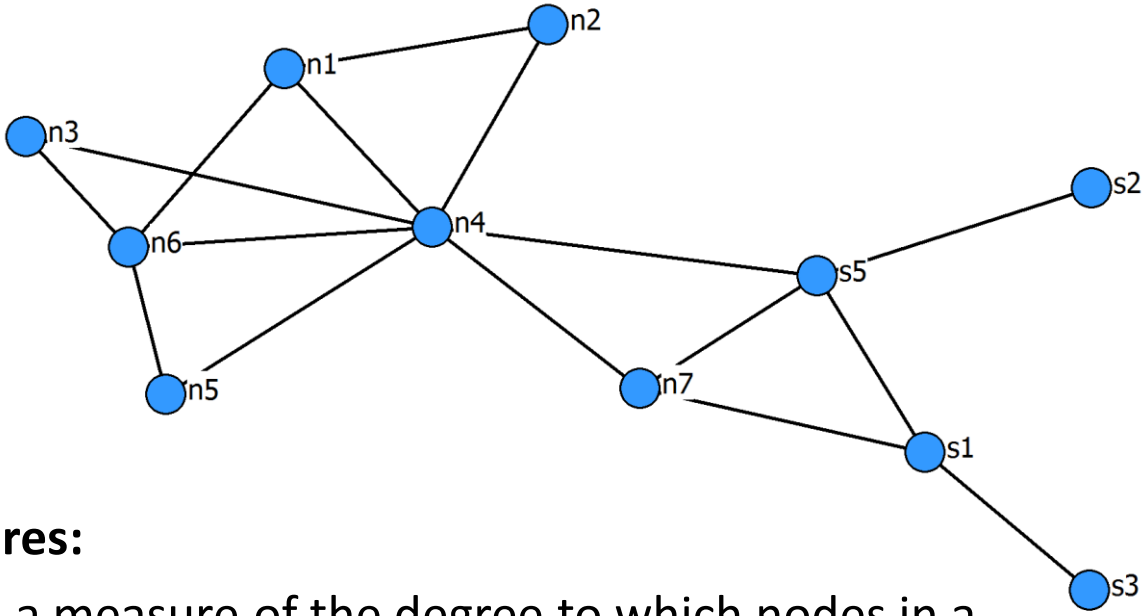


- **individual measures:**

• Eigenvalue centrality: takes into account not only how well a node is connected (degree centrality) but also how well connected each of its neighbours are

• k-reach centrality: the number of network nodes that a focal individual can reach within a specified distance (i.e. within a specified number of edges)

Network metrics (3)



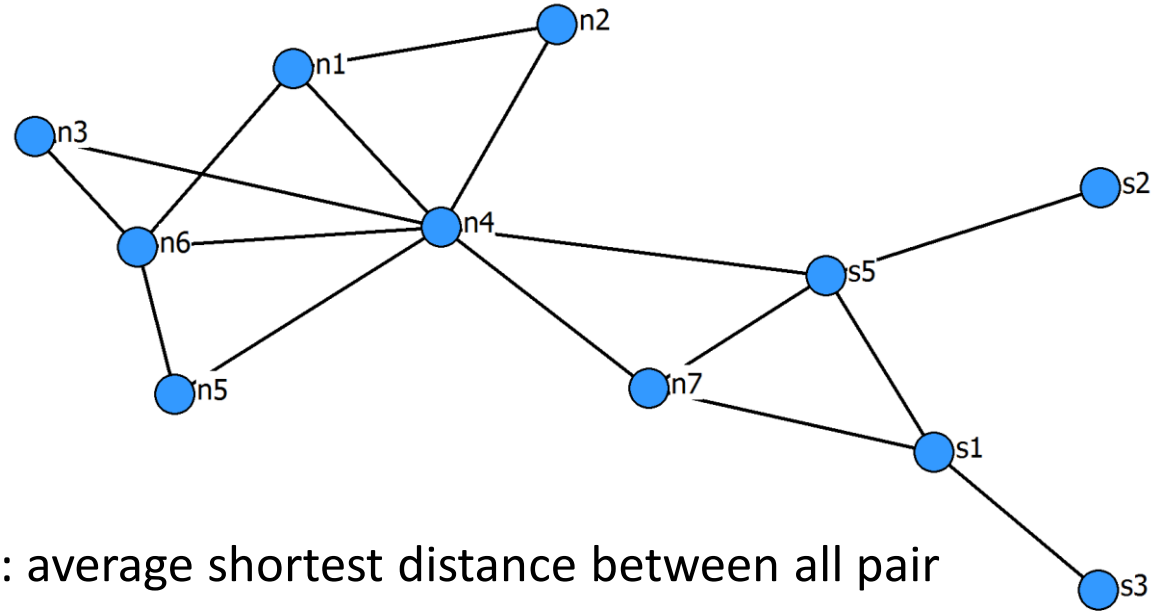
- **intermediate measures:**

• Clustering coefficient: a measure of the degree to which nodes in a graph tend to cluster together (local, global)

• Reciprocity (in directed graphs only): degree to which individuals in a group reciprocate the connections among one another

• Assortativity: a measure of the amount of mixing between subgroups of animals with certain attributes (Newman 2003)

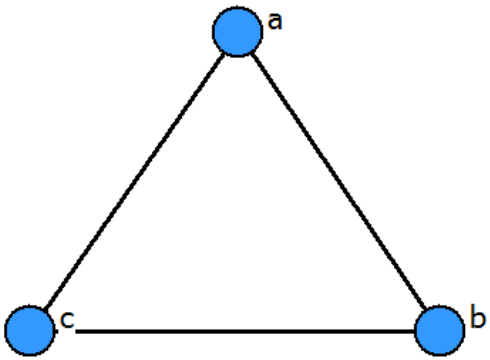
Network metrics (4)

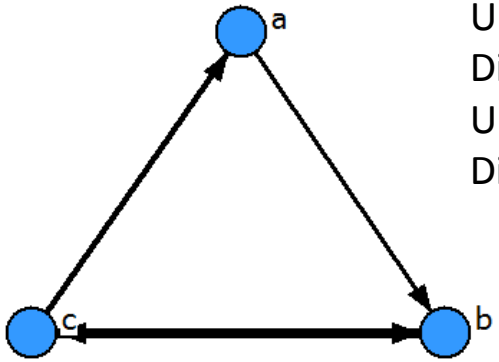


- **group measures:**
- Average path length: average shortest distance between all pair of nodes
- Density: the number of realized ties divided by the number of possible ties in the network
- Diameter: longest path length (i.e. shortest distance) in the network
- Group-level centrality indices
- Modularity: a measure of the difference between the observed density of within-cluster associations and that expected if interactions occurred randomly

A priori considerations

- binary vs. weighted, undirected vs. directed

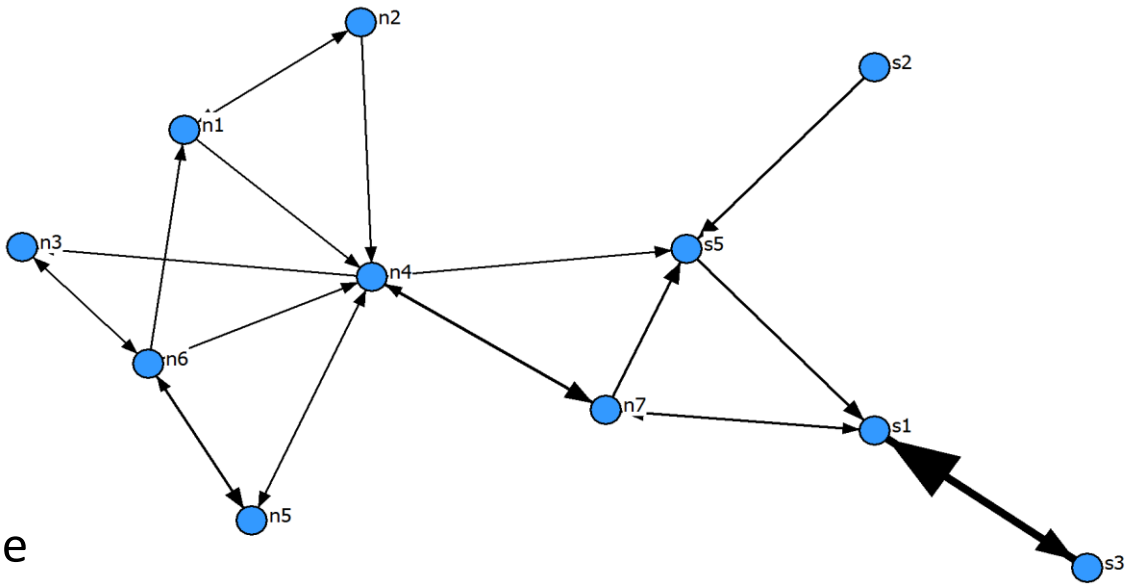




Undirected Binary Network
Directed Binary Network
Undirected Weighted Network
Directed Weighted Network

- using a threshold value: which value should we choose?

Network metrics (WDN)



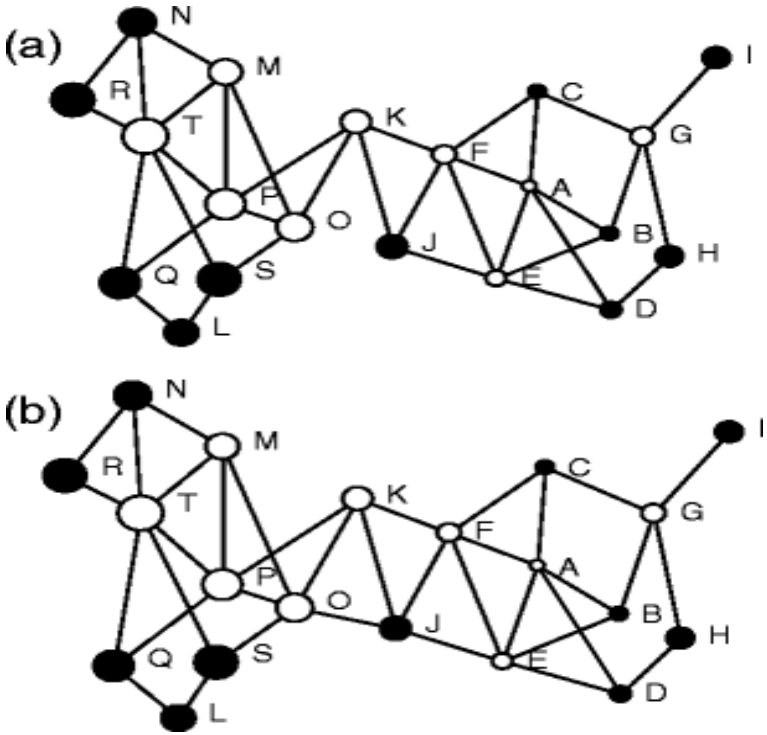
- **individual measures:**

- In-degree and out-degree
- In-strength and out-strength
- Betweenness
- Closeness
- Eigenvector centrality: only for weighted, undirected networks
- In-reach and out-reach

A priori considerations: James et al. 2009 Behav Ecol Sociobiol

- observation period and missing relationships: we should always expect that our sampling of edges is imperfect!
- **replications!**

One should be very careful not to place too much importance on the network position of single individuals!



Redrawn from Croft et al. (2008)

A priori considerations: Croft et al. 2011 Trends Ecol Evol

- SNA provides metrics to quantify social structure → these metrics can be used then to test hypotheses

- visualisation of social networks and calculating descriptive statistics: OK, but statistical analysis of hypothesis testing is much less developed

    1. Non-independence of the data
    2. Are relations observed directly or inferred?

Are relations observed directly or inferred?

- direct observation of social relationships

  ← we are essentially observing the presence, strength and direction of the network edges

  e.g. aggressive interactions, allopreening, following (specific to two individuals)

- inferring social relationships

  ← group-based data invoke the 'gambit of the group' (Whitehead & Dufault 1999)

  Sampling itself results in structured data, which influence the social network structure (especially the frequency of observations, size and number of groups)!

Randomization (1)

Null model: based on randomization of the collected data, which provide a useful solution to the problem of dependence

- What should we randomize?

  this depends on the nature of the data and the hypothesis

- **node-label permutation**: the null hypothesis is typically that any individual can occupy any network position
- **edge rearrangement**: interactions are equally likely between any pair of nodes

ONLY FOR DIRECT OBSERVATION OF SOCIAL RELATIONSHIPS

← UCINET, R packages {igraph}, {tnet}, {sna}

Randomization (2)

- **group membership swaps and shuffles**: swapping pairs of individuals between groups (group size distribution is preserved); can be phenotype-restricted

IF GROUP-BASED DATA IS COLLECTED

→ SOCPROG 'MBFM algorithm', R package {aspine}

Statistical modelling: investigate the synergistic effects of multiple factors on network structure

- exponential random graph modelling (ERGM or p* modelling): social links must be binary. R package {statnet}

- multiple regression quadratic assignment procedure (MRQAP): can be used with weighted (i.e. non-binary) networks. R package {sna}, UCINET

- generalized linear mixed-effect models (GLMMs) – can account for some forms of data non-independence, but potential structural autocorrelations should be considered

Example: Tóth et al. 2014 Anim Behav (1)

Question: How food limitation affects social organization of house sparrow flocks (both group- and individual-level effects)?

Method:

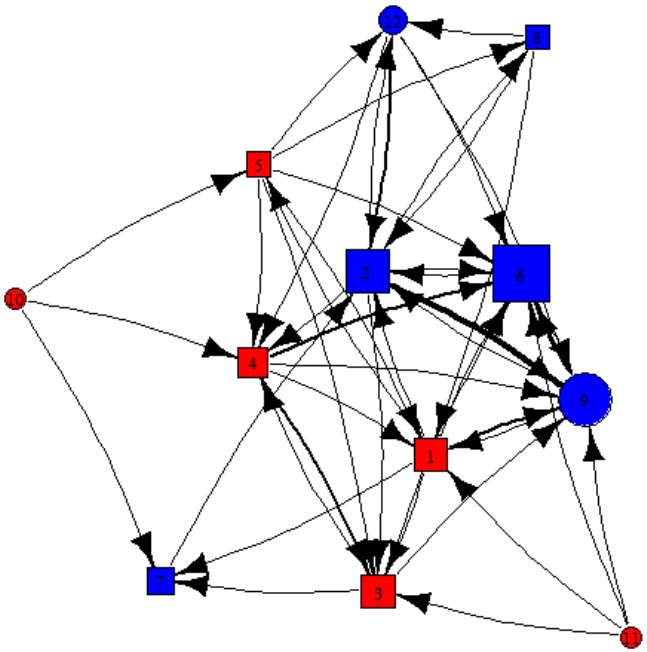
- observation of aggressive interactions and within-flock following events (→WDN)

- 2-3 days in each of the 3 sessions: before treatment, food reduction, after treatment

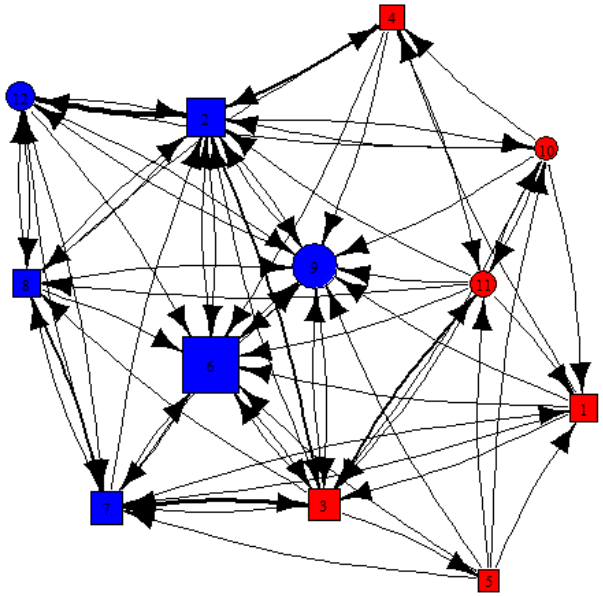
- sample size: 9 replicate flocks, 12 individuals in each

Example: Tóth et al. 2014 Anim Behav (2)

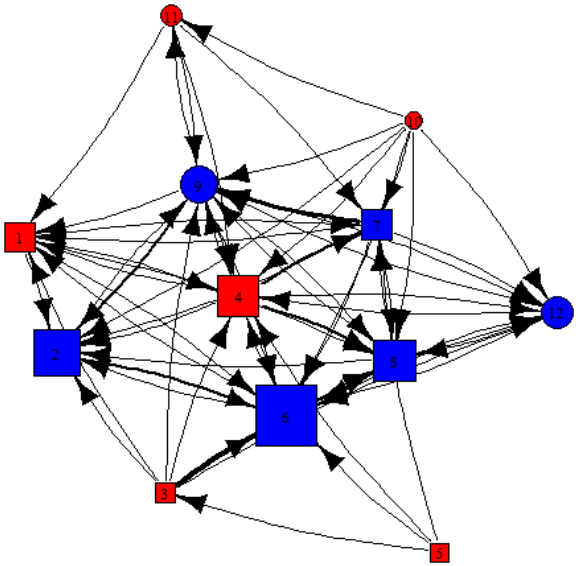
Before treatment



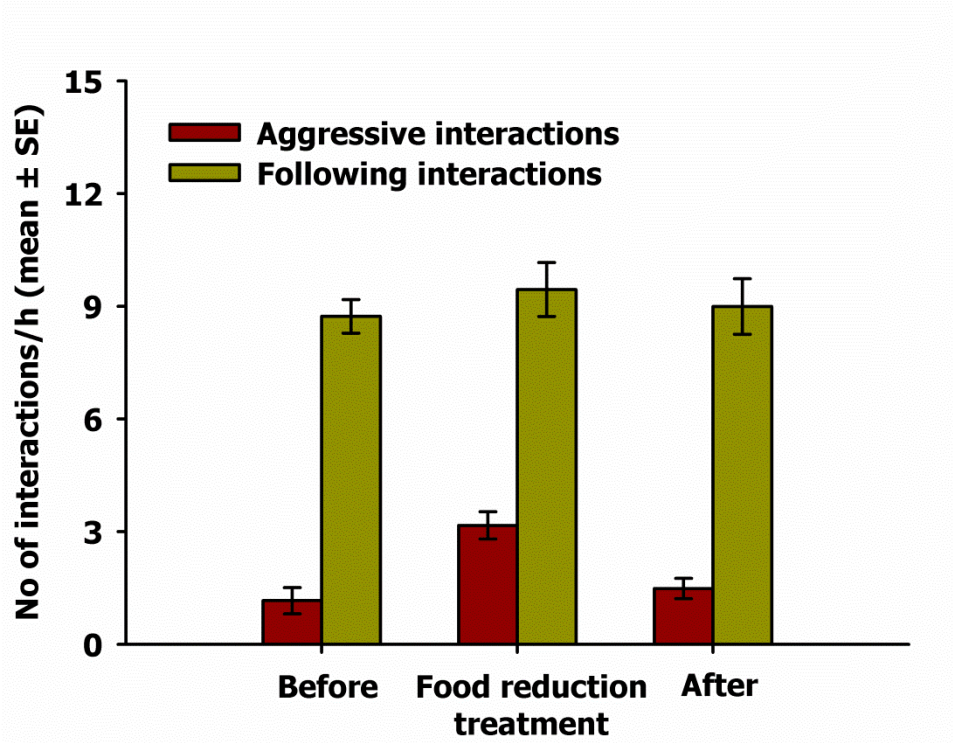
Food reduction treatment



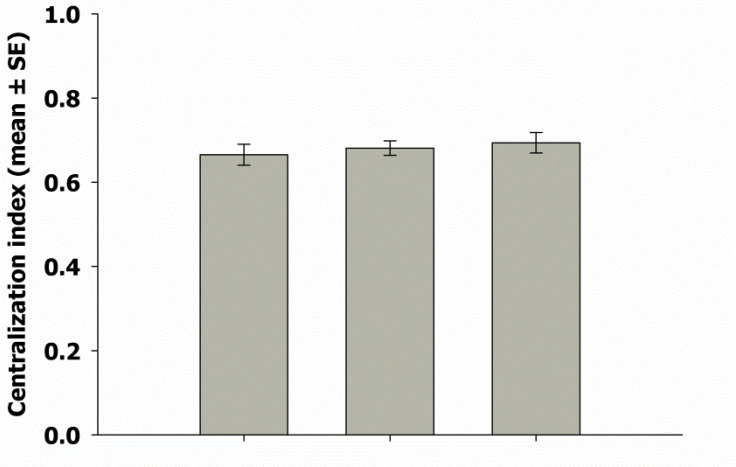
After treatment



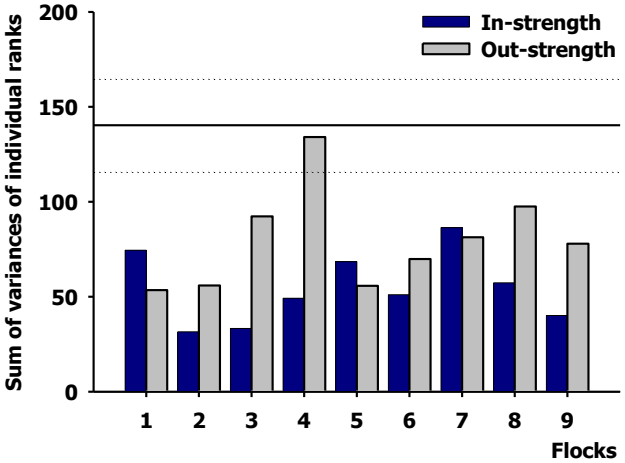
Example: Tóth et al. 2014 Anim Behav (3)



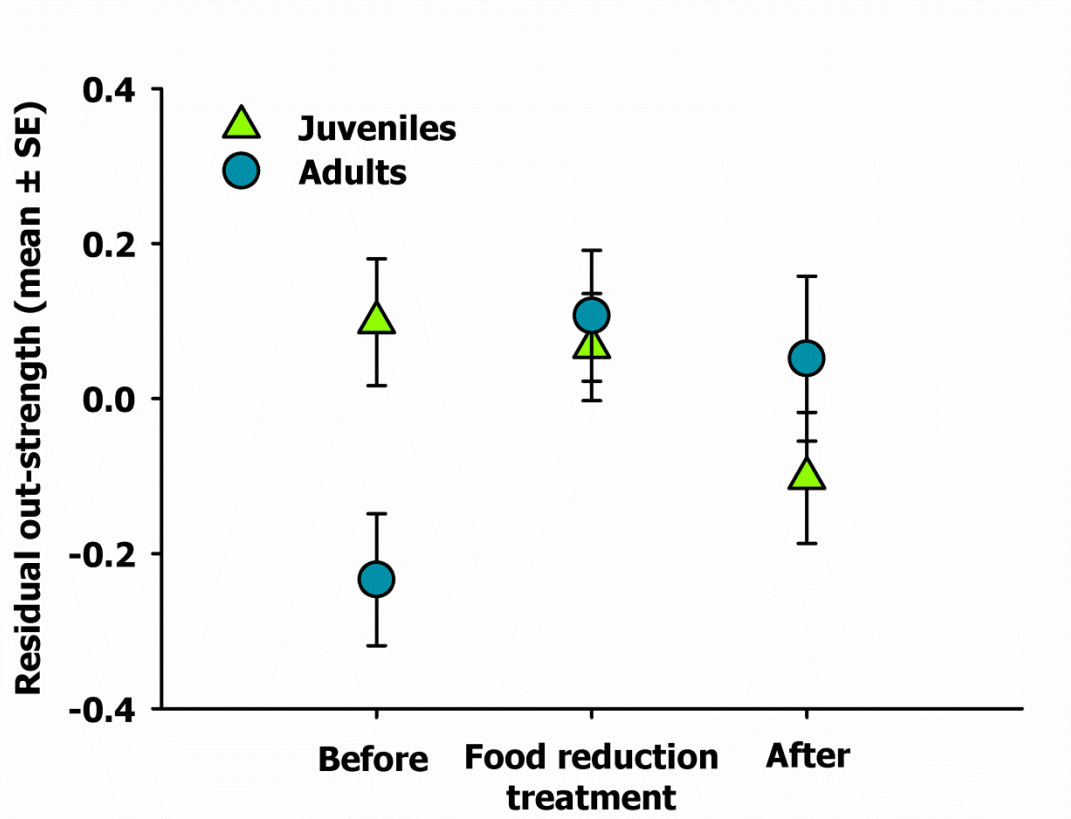
$$C_{in} = [\max(S_{in}) - \bar{S}_{in}{}^{*}] / \max(S_{in})$$

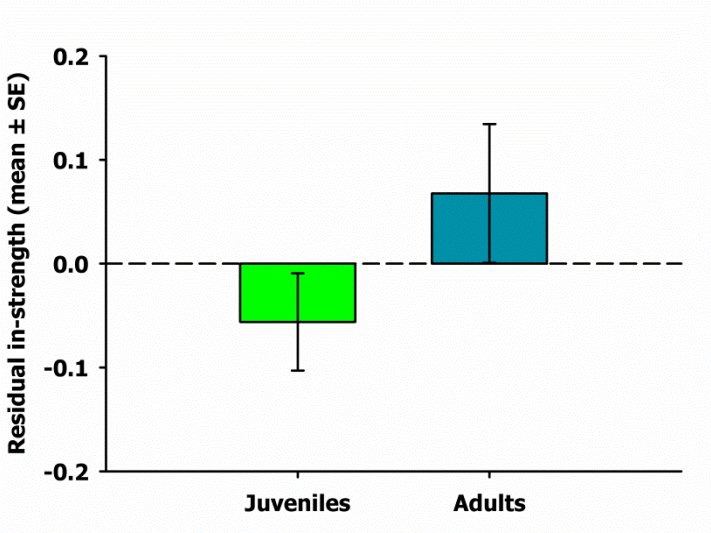


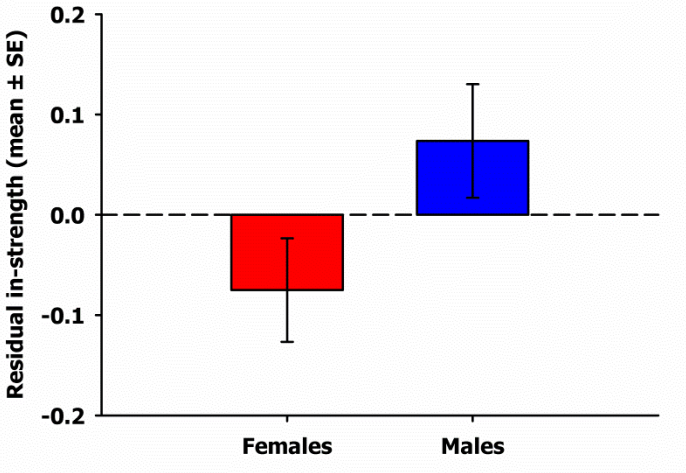
$$SV(R) = \sum_{1 \le i \le N} variance(Ri_{,1}, \ldots Ri_{,K})$$



Example: Tóth et al. 2014 Anim Behav (4)







Overall, house sparrow flocks exhibited an intermediately centralized social regime, in which an individual's position is determined by intrinsic characteristics such as sex and age.

Identification of individuals

- obviously, we should be able to identify every individual in the (captive) population if we want to collect pairwise interactions/group composition data

  e.g.: colour rings, markings (paint dots, etc.), tags

- accuracy: unidentified events should also be noted

How to collect data for social network analysis?

- human observer: direct observations, trapping (e.g. Oh & Badyaev 2010), mist netting(?)

- video recordings: more precise, but identification can be a challenge

- Automatic systems: PIT (passive integrated transponder) tags, which can be detected by receivers in the environment. For example, PIT tags can be used to record the visits of animals to known food sites (e.g. bird feeders) or nest boxes.

→ individuals visiting the same location at the same time (or within a short time period) might be socially interacting

Encounter Net project (http://encounternet.net/), Ben Sheldon's group

What should we measure?

- social interactions vs. group membership/co-occurrence

THIS HAS TO BE DECIDED BEFOREHAND, BECAUSE IT WILL SUBSTANTIALLY AFFECT THE SUBSEQUENT ANALYSES!

Data structure (SOCPROG)

- SOCPROG 2.5 (2.4 for earlier versions of Windows): MATLAB-based, but compiled (stand-alone) versions are also available

- data: linear, dyadic or group mode – xls or csv

Date	Posn	Grp-code	ID
1/1/00 9:00	279.9	1	A1
1/1/00 9:00	279.7	1	I9
1/1/00 9:00	278.2	1	N14

ID	Sex	Age
1	M	15.5
2	M	2.7
3	F	5.8
4	M	14.5

Date	Interaction	Ids
1/1/00 9:49	A	13 20
1/1/00 14:54	A	14 15

Date	Place	Behaviour	Group
1/1/00 9:49	A	2	8 11 13 20
1/1/00 14:54	A	1	1 9 14 15
1/1/00 15:41	A	2	4 7 12 17 19
1/2/00 9:11	B	1	4 7 12 17 19 20

Analysis (SOCPROG)

- SOCPROG 2.5 (2.4 for earlier versions of Windows): MATLAB-based, but compiled (stand-alone) versions are also available

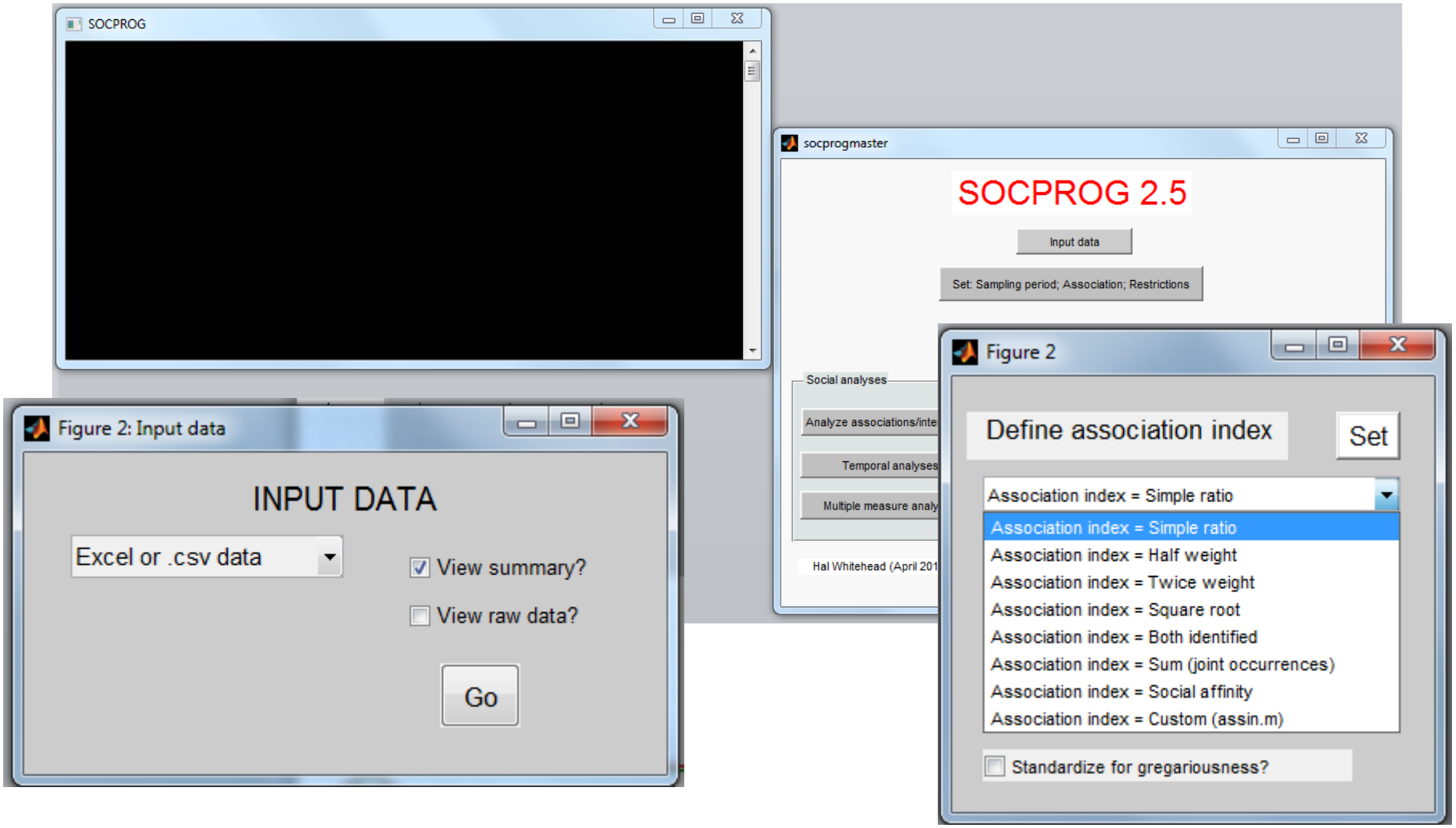
- data: linear, dyadic or group mode – xls or csv

- association indices or interaction rate → matrix output, which used as a weighted network in the subsequent social network analysis

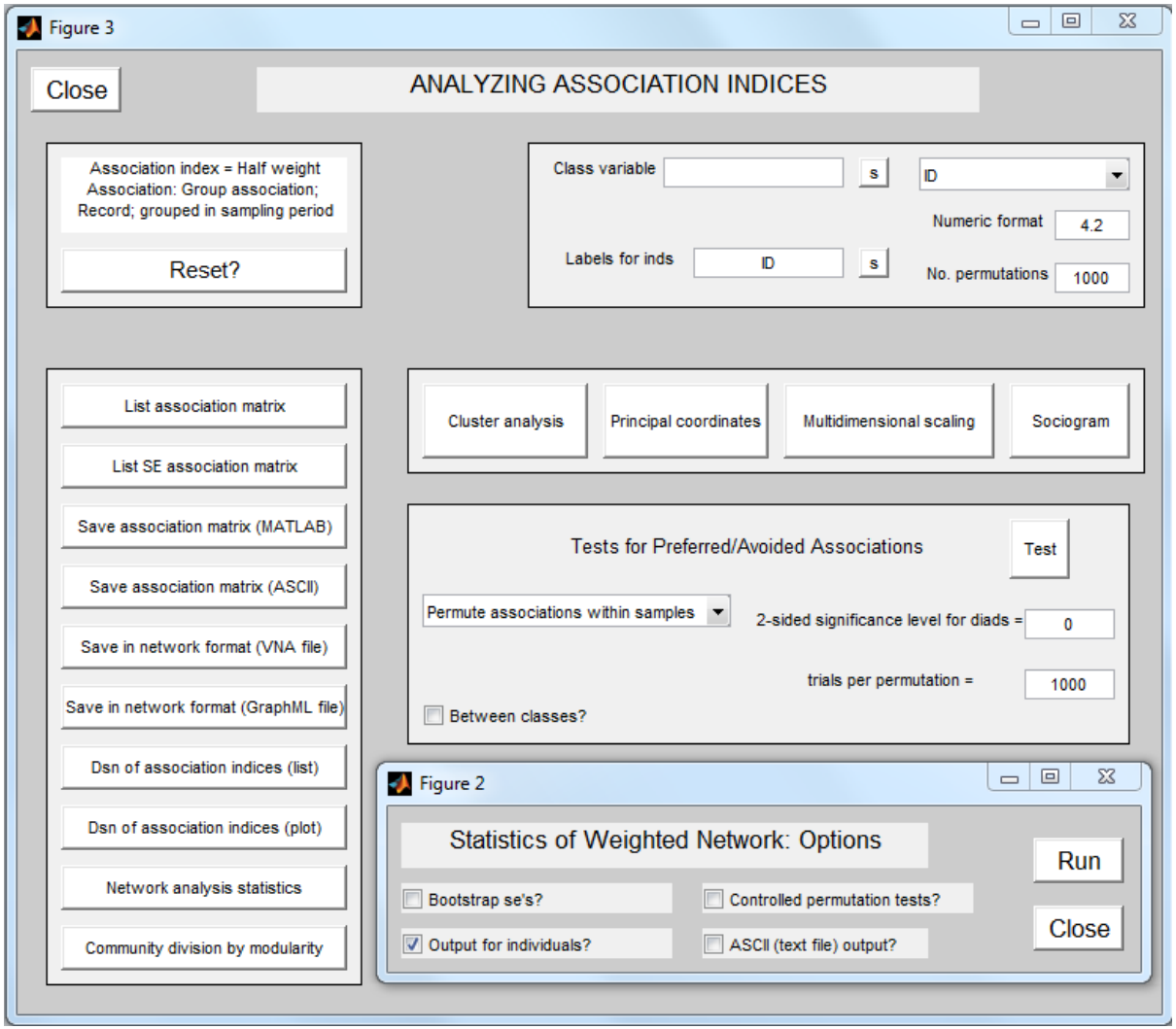
- strength, eigenvector centrality, reach, clustering coefficient, affinity

- only symmetric matrices: to obtain network measures of asymmetric data, export the data into a specialist program such as UCINET
  http://myweb.dal.ca/hwhitehe/Manual.pdf

Analysis (SOCPROG)



Analysis (SOCPROG)



Data structure (example dataset)

- 1 flock consisting of 6 birds
- 2 sessions (before and after treatment)
- following events (N=161) & fights (N=55)

D8 | f_x | 1

	A	B	C	D	E	F	G	H	I	J	K
1	Day	Hours	Flock	Session	N event	Event	Actor	Follower	Winner	Loser	
2	01-May-12	08:03:50	1	1	1	Following to the feeder	MS4	MS5	0	0	
3	01-May-12	08:09:08	1	1	2	Following to the feeder	MS1	MS4	0	0	
4	01-May-12	08:09:28	1	1	3	Following to the feeder	MS2	MS4	0	0	
5	01-May-12	08:16:19	1	1	4	Following to the feeder	MS4	MS5	0	0	
6	01-May-12	08:24:08	1	1	5	Following to the feeder	MS5	MS4	0	0	
7	01-May-12	08:29:10	1	1	6	Following	MS5	MS4	0	0	
8	01-May-12	08:37:08	1	1	7	Following	MS1	MS5	0	0	
9	01-May-12	08:51:40	1	1	8	Following	MS2	MS5	0	0	
10	01-May-12	08:54:21	1	1	9	Following	MS4	MS1	0	0	
11	01-May-12	08:59:40	1	1	10	Following to the feeder	309	MS5	0	0	
12	01-May-12	09:17:55	1	1	11	Following to the feeder	MS5	MS4	0	0	
13	01-May-12	09:20:40	1	1	12	Following to the feeder	MS5	MS4	0	0	
14	01-May-12	09:28:07	1	1	13	Following to the feeder	MS2	MS4	0	0	
15	01-May-12	09:28:57	1	1	14	Following	MS2	MS4	0	0	
16	01-May-12	09:46:25	1	1	15	Following	MS4	MS5	0	0	
17	01-May-12	10:13:55	1	1	16	Following	MS5	MS4	0	0	
18	01-May-12	10:24:17	1	1	17	Following	MS2	MS5	0	0	
19	01-May-12	10:24:27	1	1	18	Following	MS2	MS4	0	0	
20	01-May-12	10:26:30	1	1	19	Following	MS5	MS1	0	0	
21	01-May-12	10:38:35	1	1	20	Following	MS4	MS3	0	0	
22	01-May-12	10:43:03	1	1	21	Following	MS4	MS1	0	0	
23	01-May-12	10:47:39	1	1	22	Following	MS5	MS3	0	0	
24	01-May-12	10:48:00	1	1	23	Following	MS5	MS4	0	0	

Data structure (example dataset)

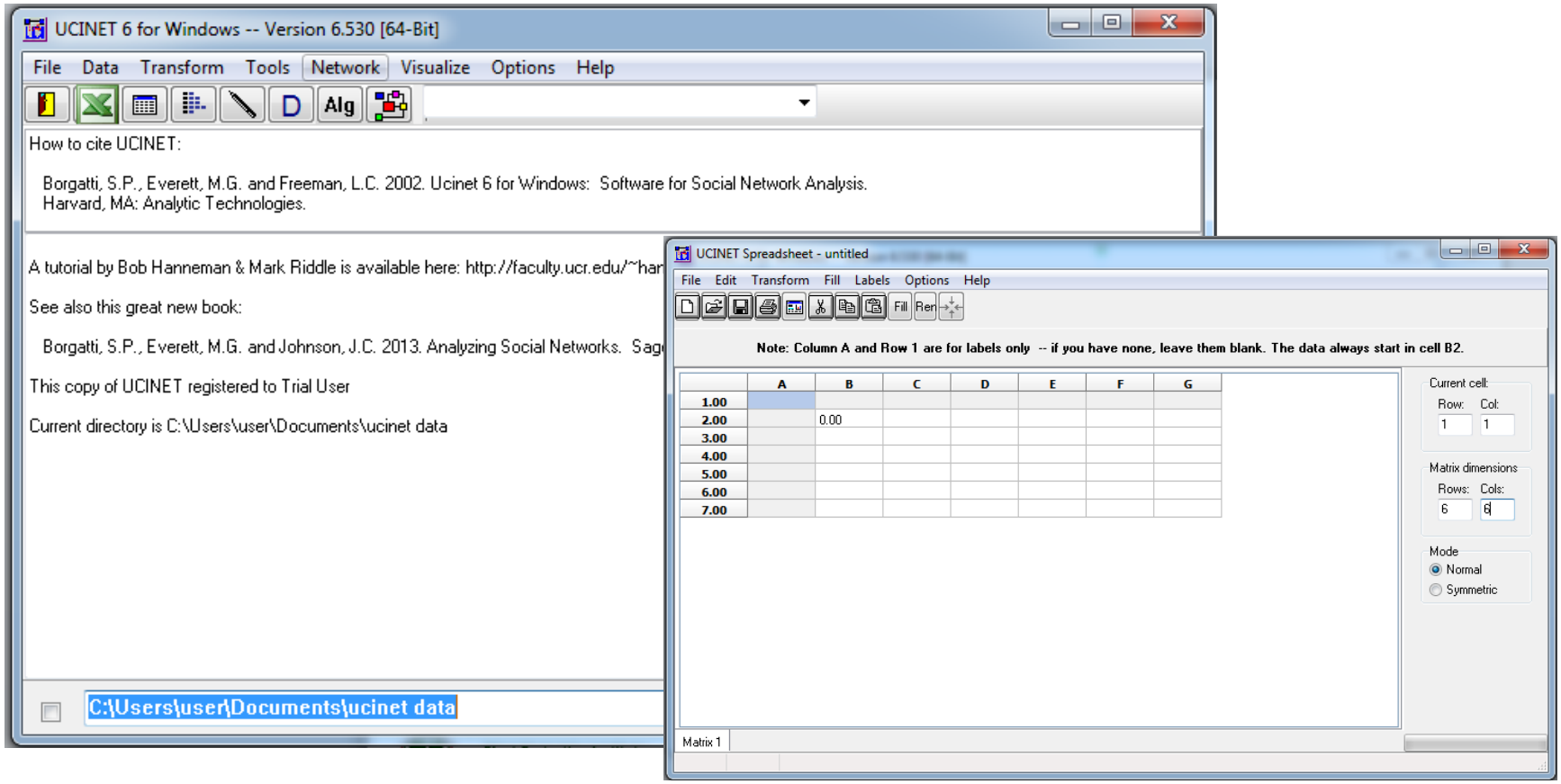
Use „insert a pivot table” to create interaction matrices!

Mennyiség / Actor		Actor						
Session	Follower	309	MS1	MS2	MS3	MS4	MS5	Végösszeg
1	309		1	1	2	4		8
	MS1	1		1	1	10	2	15
	MS2	3	1		1	1		6
	MS3		1	1		4	2	8
	MS4	2	6	5			14	27
	MS5	3	3	4		15		25
1 Összeg		9	12	12	4	34	18	89
2	309			1	1	3	2	7
	MS1			1	2	2	1	6
	MS2	13	2			2	1	18
	MS3			1		1	1	3
	MS4	7	3	4			2	16
	MS5	9		3		10		22
2 Összeg		29	5	10	3	18	7	72
Végösszeg		38	17	22	7	52	25	161

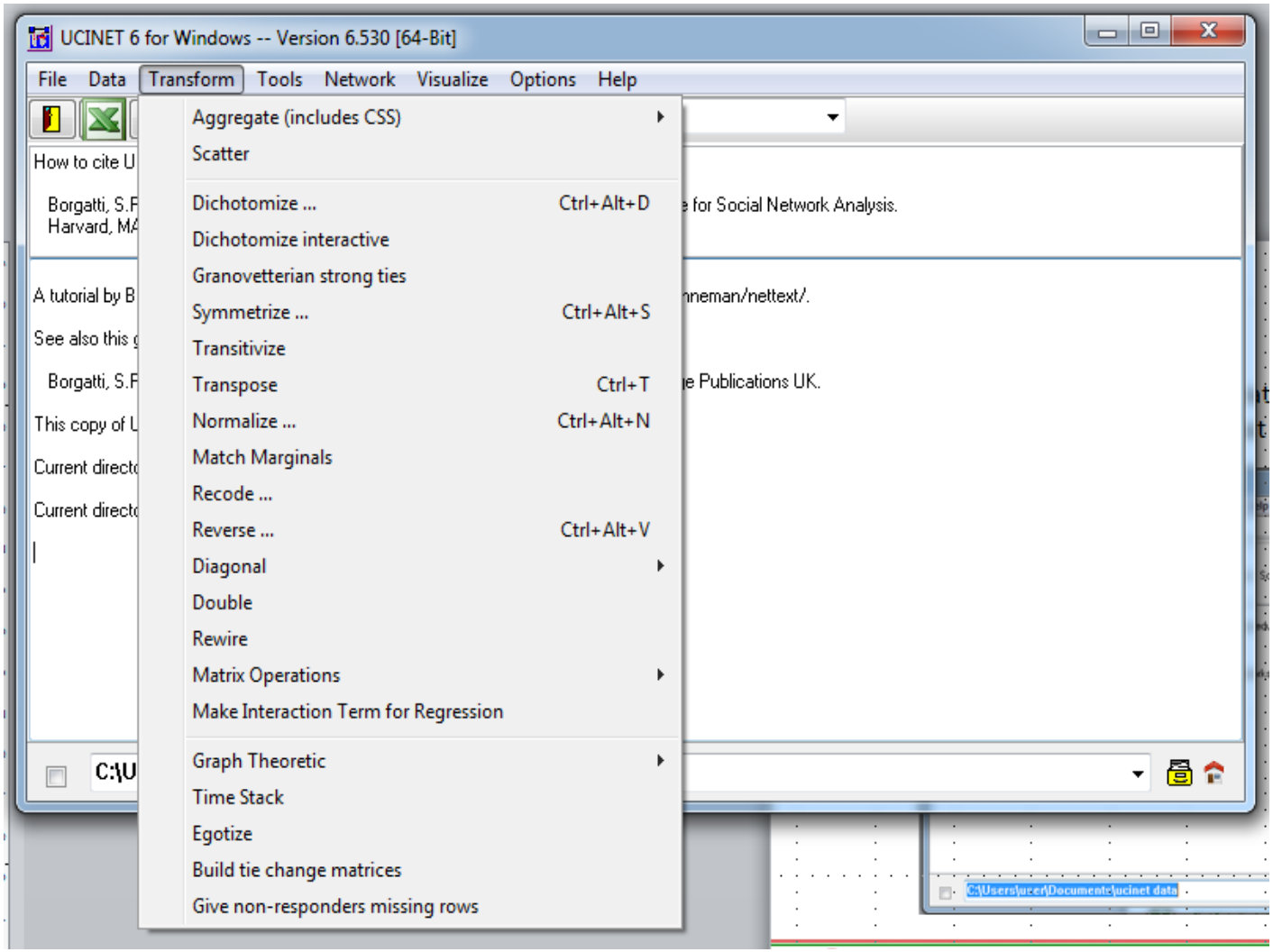
	309	MS1	MS2	MS3	MS4	MS5
309	0	1	1	2	4	0
MS1	1	0	1	1	10	2
MS2	3	1	0	1	1	0
MS3	0	1	1	0	4	2
MS4	2	6	5	0	0	14
MS5	3	3	4	0	15	0

Data structure (UCINET)

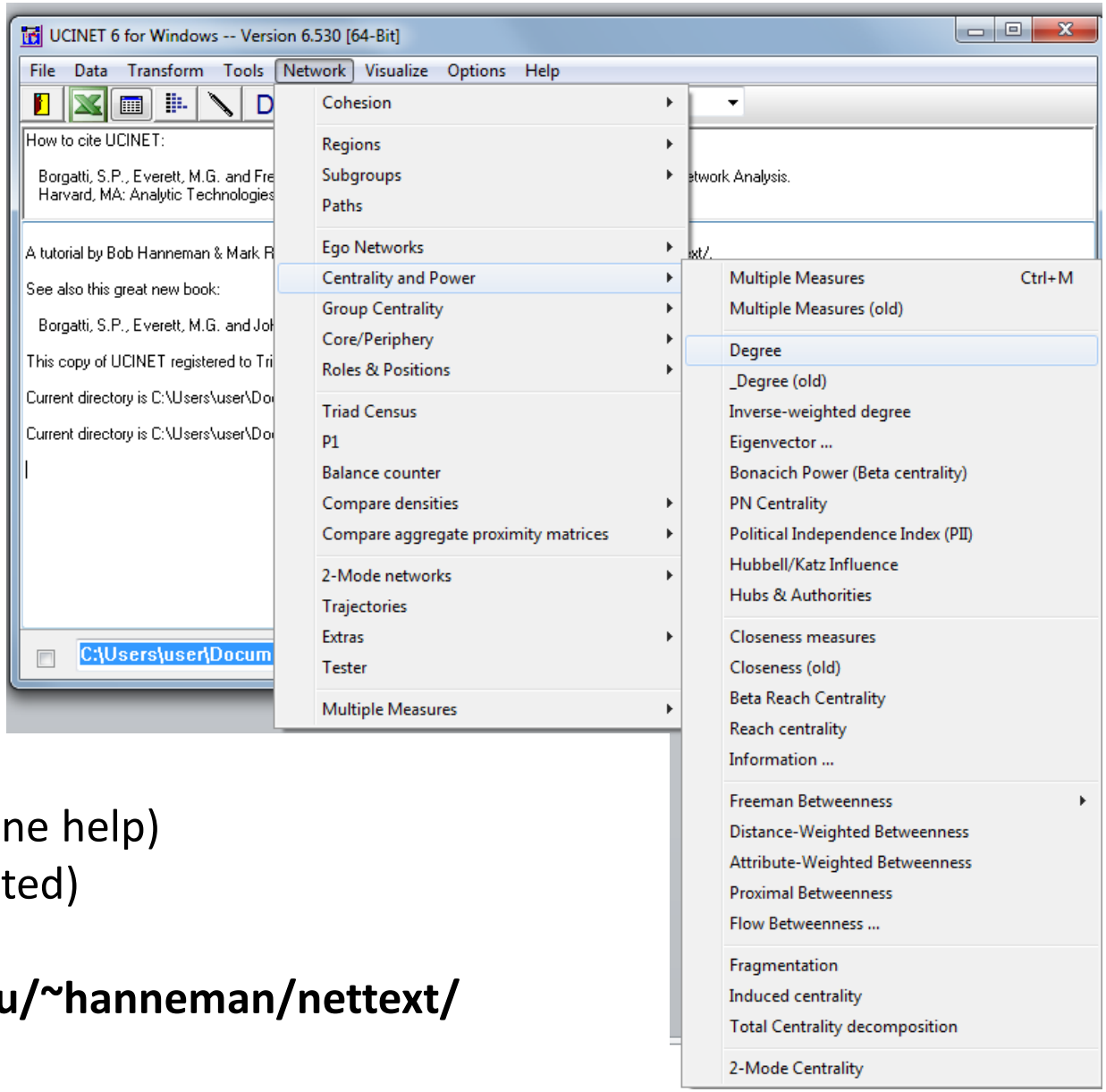
- UCINET 6.556: there is no separate trial version, but you can use the program only for 60 days without purchasing a registration code



Data structure (UCINET)



Analysis (UCINET)



Reference guide (online help)

User guide (bit outdated)

UCINET Tutorial – http://faculty.ucr.edu/~hanneman/nettext/

Analysis (UCINET)

ucinetlog2.txt - Jegyzettömb

Fájl Szerkesztés Formátum Nézet Súgó

```
FREEMAN DEGREE CENTRALITY
-------------------------------------------------------------------------------

Input dataset:                          ExampleDataset_fights (C:\Users\user\Documents\ucinet data\ExampleDataset_fights
Output degree dataset:                  ExampleDataset_fights-deg (C:\Users\user\Documents\ucinet data\ExampleDataset_fights-deg
Output centralization dataset:          ExampleDataset_fights-degcz (C:\Users\user\Documents\ucinet data\ExampleDataset_fights-degcz
Treat data as:                          Directed
Output raw scores:                      YES
Output normalized scores:               YES
Allow edge weights:                     YES
Exclude diagonal:                       YES

Degree Measures

                1       2       3       4
           Outdeg   Indeg  nOutde  nIndeg
                                g
           ------  ------  ------  ------
    1 309  16.000   4.000   3.200   0.800
    2 MS1  15.000   2.000   3.000   0.400
    3 MS2  12.000   2.000   2.400   0.400
    4 MS3   6.000   8.000   1.200   1.600
    5 MS4   5.000  23.000   1.000   4.600
    6 MS5   1.000  16.000   0.200   3.200


6 rows, 4 columns, 1 levels.

Graph Centralization -- as proportion, not percentage

                                1       2
                           Outdeg   Indeg
                           ------  ------
    1 ExampleDataset_fights 1.6400  3.3200

1 rows, 2 columns, 1 levels.


--------------------------------------
Running time: 00:00:01 seconds.
Output generated: 16 Mar 15 12:42:56
ucinet
```

Data structure

- R: versatile programming environment; packages like {sna], {igraph}, {tnet}, {asnipe} contain lots of useful functions to analyze and visualize networks

- one has to learn how to write a script (i.e. use the language) and practice a bit

A1 | fx | 0

	A	B	C	D	E	F
1	0	1	1	2	4	0
2	1	0	1	1	10	2
3	3	1	0	1	1	0
4	0	1	1	0	4	2
5	2	6	5	0	0	14
6	3	3	4	0	15	0
7						

example_following_s1.csv

Analysis of the collected data (1)

```
>setwd("d:/R_files/Padova")
>follow_s1<-read.csv2('example_follow_s1.csv',header=FALSE,dec=".",sep=",")
>follow_s1<-as.matrix(follow_s1)
>library(igraph)
>graph_f.s1<-graph.adjacency(follow_s1, mode=c("directed"),weighted=T,
diag=FALSE)              ##this is an {igraph} object now!
```

Analysis of the collected data (2)

```
> follow_s1
     V1 V2 V3 V4 V5 V6
[1,]  0  1  1  2  4  0
[2,]  1  0  1  1 10  2
[3,]  3  1  0  1  1  0
[4,]  0  1  1  0  4  2
[5,]  2  6  5  0  0 14
[6,]  3  3  4  0 15  0
```

```
> graph_f.s1
IGRAPH DNW- 6 25 --
+ attr: name (v/c), weight (e/n)
```

```
> V(graph_f.s1)
Vertex sequence:
[1] "V1" "V2" "V3" "V4" "V5" "V6"
```

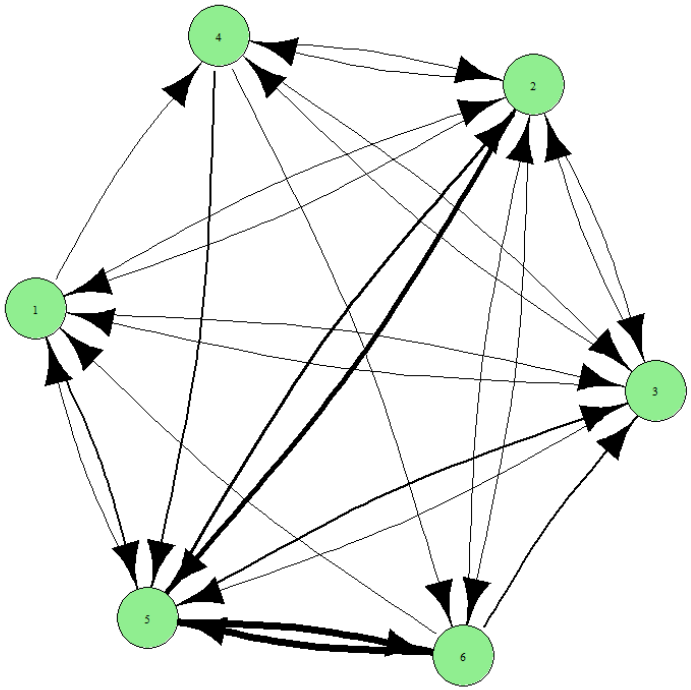
```
> E(graph_f.s1)
Edge sequence:

[1]  V1 -> V2
[2]  V1 -> V3
[3]  V1 -> V4
[4]  V1 -> V5
[5]  V2 -> V1
[6]  V2 -> V3
[7]  V2 -> V4
[8]  V2 -> V5
[9]  V2 -> V6
[10] V3 -> V1
[11] V3 -> V2
[12] V3 -> V4
[13] V3 -> V5
[14] V4 -> V2
[15] V4 -> V3
[16] V4 -> V5
[17] V4 -> V6
[18] V5 -> V1
[19] V5 -> V2
[20] V5 -> V3
[21] V5 -> V6
[22] V6 -> V1
[23] V6 -> V2
[24] V6 -> V3
[25] V6 -> V5
```

```
> E(graph_f.s1)$weight
 [1]  1  1  2  4  1  1  1 10  2  3  1  1  1  1  1  4  2  2  6  5 14  3  3  4 15
```

Analysis of the collected data (3)

```
>plot.igraph(graph_f.s1,vertex.label=c(1:6),vertex.label.color="black",layout=layout.kamada.kawai(graph_f.s1, niter=9999), vertex.label.cex=0.7, vertex.shape="circle", vertex.color="lightgreen", vertex.size=20,edge.color="black",edge.width=(E(graph_f.s1)$weight)/2, edge.arrow.size=1.2,edge.curved=0.1)
```



Analysis of the collected data (4)

```
##few examples of calculating network metrics
>indegree_f.s1<-degree(graph_f.s1, v=V(graph_f.s1), mode = c("in"), weights=NULL, loops = FALSE, normalized = FALSE)
>incloseness_f.s1<-closeness(graph_f.s1, vids=V(graph_f.s1), mode = c("out"), normalized = FALSE)
>betweenness_f.s1<-betweenness(graph_f.s1, v=V(graph_f.s1), directed = TRUE, nobigint = TRUE, normalized = FALSE)
>centrality_measures<-cbind(V(graph_f.s1),indegree_f.s1, incloseness_f.s1,betweenness_f.s1)
>write.csv(centrality_measures,file='centrality_measures.csv')
```

	A	B	C	D	E
1			indegree_f.s1	incloseness_f.s1	betweenness_f.s1
2	V1	1	4	0.111111111	4.666666667
3	V2	2	5	0.142857143	6.833333333
4	V3	3	5	0.125	4.666666667
5	V4	4	3	0.125	0.5
6	V5	5	5	0.058823529	0
7	V6	6	3	0.052631579	0

Analysis of the collected data (5)

#weighted reciprocity (library(tnet))

```
>graphTNET_f.s1<-as.tnet(follow_s1,
            type="weighted one-mode tnet")
```

```
> graphTNET_f.s1
      i j  w
 [1,] 1 2  1
 [2,] 1 3  1
 [3,] 1 4  2
 [4,] 1 5  4
 [5,] 2 1  1
 [6,] 2 3  1
 [7,] 2 4  1
 [8,] 2 5 10
 [9,] 2 6  2
[10,] 3 1  3
[11,] 3 2  1
[12,] 3 4  1
[13,] 3 5  1
[14,] 4 2  1
[15,] 4 3  1
[16,] 4 5  4
[17,] 4 6  2
[18,] 5 1  2
[19,] 5 2  6
[20,] 5 3  5
[21,] 5 6 14
[22,] 6 1  3
[23,] 6 2  3
[24,] 6 3  4
[25,] 6 5 15
attr(,"tnet")
[1] "weighted one-mode tnet"
```

Analysis of the collected data (6)

```
>recip_w<-function(g)
>{
>net_mod1<-symmetrise_w(g, method="MIN")
>help1<-degree_w(net_mod1)
>a<-help1[,3]
>help2<-degree_w(g, type="out")
>b<-help2[,3]
>help3<-a/b
>return(help3)
>}
```

```
> net_mod1<-symmetrise_w(graphTNET_f.s1, method="MIN")
> degree_w(net_mod1)
     node degree output
[1,]    1      3      4
[2,]    2      5     11
[3,]    3      4      4
[4,]    4      2      2
[5,]    5      4     23
[6,]    6      2     16
```

```
> degree_w(graphTNET_f.s1, type="out")
     node degree output
[1,]    1      4      8
[2,]    2      5     15
[3,]    3      4      6
[4,]    4      4      8
[5,]    5      4     27
[6,]    6      4     25
```

```
> recip_w(graphTNET_f.s1)
[1] 0.5000000 0.7333333 0.6666667 0.2500000 0.8518519 0.6400000
```

Analysis of the collected data (7)

- simple randomization test: will individuals' rank in terms of being followed in the flock change after treatment (compared to random changes)? (graphTNET_f.s1 and graphTNET_f.s2)

```
##first we calculate the metric in question for the observed network
>consist_pos<-function(xA, xB)
>{
>xA_instrength<-degree_w(xA, type="in")[,3]
>xA_rank<-rank(-xA_instrength)
>xB_instrength<-degree_w(xB, type="in")[,3]
>xB_rank<-rank(-xB_instrength)
>net_ranks<-cbind(xA_rank,xB_rank)
>obs_diff_sum<-sum(abs(diff(net_ranks[1,])),abs(diff(net_ranks[2,])),
abs(diff(net_ranks[3,])),abs(diff(net_ranks[4,])),abs(diff(net_ranks[5,])),
abs(diff(net_ranks[6,])))
```

Analysis of the collected data (8)

##then we reshuffle the weights of the edges to create 9999 random networks, one by one

```
>rnd_diff_sum<-rep(0,10000)
>for(d in 1:9999)  {
>rnd_net1<-rg_reshuffling_w(xA, option="weights", directed=TRUE)
>rnd_net2<-rg_reshuffling_w(xB, option="weights", directed=TRUE)
>
>rnd_net1_instrength<-degree_w(rnd_net1, type="in")[,3]
>rnd_net1_rank<-rank(-rnd_net1_instrength)
>rnd_net2_instrength<-degree_w(rnd_net2, type="in")[,3]
>rnd_net2_rank<-rank(-rnd_net2_instrength)
>
>rnd_ranks<-cbind(rnd_net1_rank,rnd_net2_rank)
>rnd_diff_sum[d]<-sum(abs(diff(rnd_ranks[1,])),abs(diff(rnd_ranks[2,])),
abs(diff(rnd_ranks[3,])),abs(diff(rnd_ranks[4,])),abs(diff(rnd_ranks[5,])),
abs(diff(rnd_ranks[6,]))) }
```

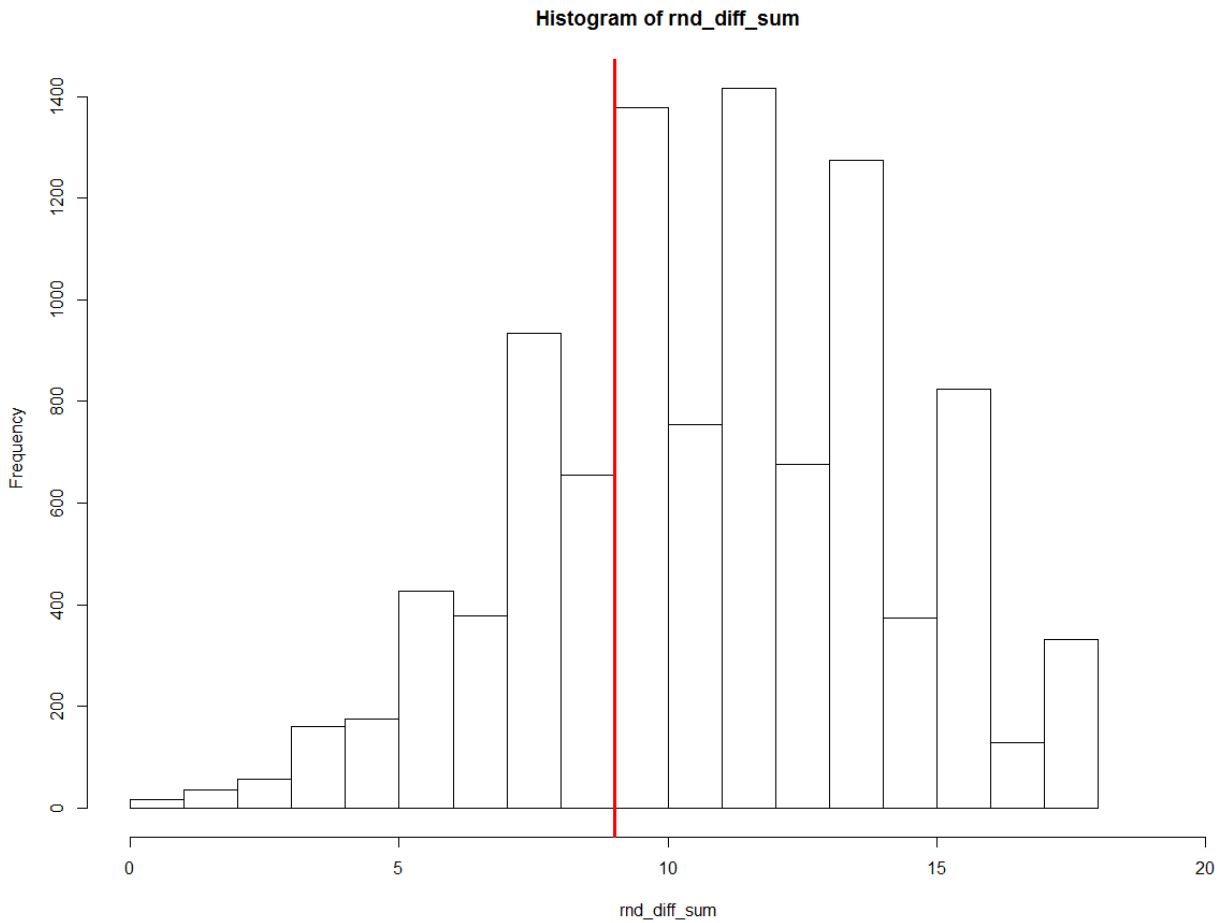
Analysis of the collected data (9)

```
##the observed value should be part of the distribution!
>rnd_diff_sum[10000]<-obs_diff_sum

##we calculate descriptive statistics of interest, and also a p-value
>mean_RN<-mean(rnd_diff_sum)
>sd_RN<-sd(rnd_diff_sum)
>print(mean_RN)
>print(sd_RN)
>print(obs_diff_sum)
>return((length(rnd_diff_sum[rnd_diff_sum==obs_diff_sum])+
length(rnd_diff_sum[rnd_diff_sum<obs_diff_sum]))/10000)
}
```

Analysis of the collected data (10)

```
> consist_pos(graphTNET_f.s1,graphTNET_f.s2)
[1] 11.3316
[1] 3.420703
[1] 9
[1] 0.2806
```



Take home message

- read some of the earlier reviews on animal social networks → advance to more recent papers/projects

- have a brainstorm: what SNA can „offer” particularly in your study system?

- be aware of the „potential banana skins” (sensu James et al. 2009) of SNA

- get familiar with one of the appropriate softwares

MTA, LP2012-24/2012

MTA, SZ-029/2013

OTKA, PD108938

Thank you for your attention!