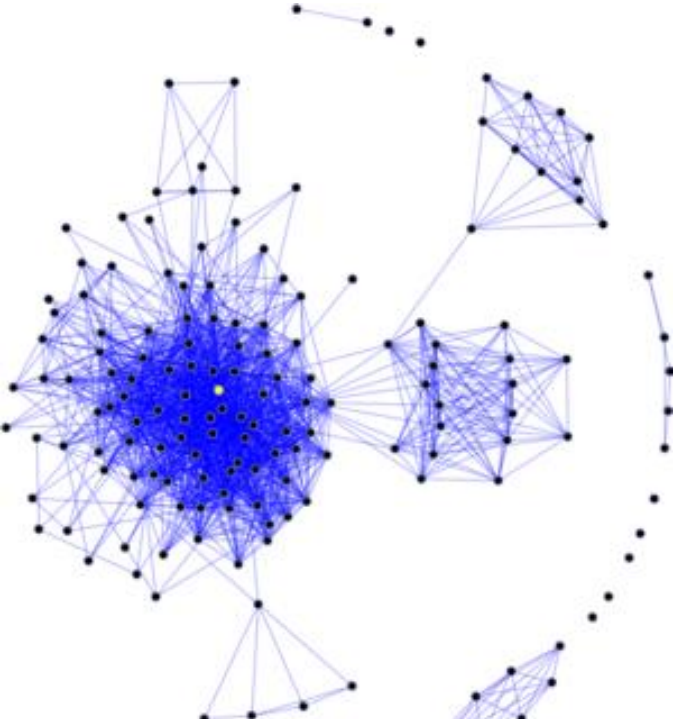
SOCIAL NETWORK ANALYSIS USING STATA



10 June 2016
German Stata User Meeting
GESIS, Cologne

Thomas Grund
University College Dublin
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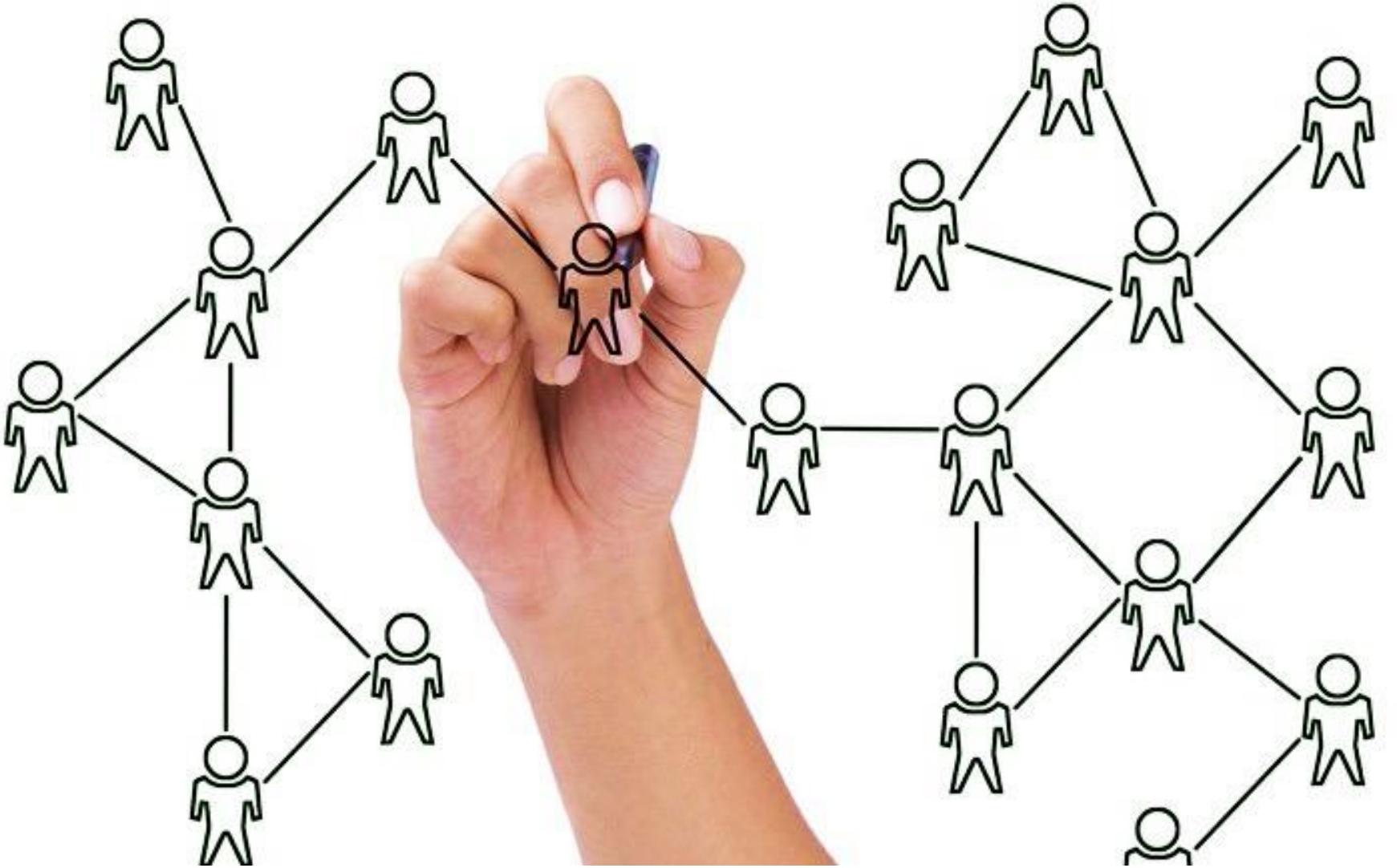
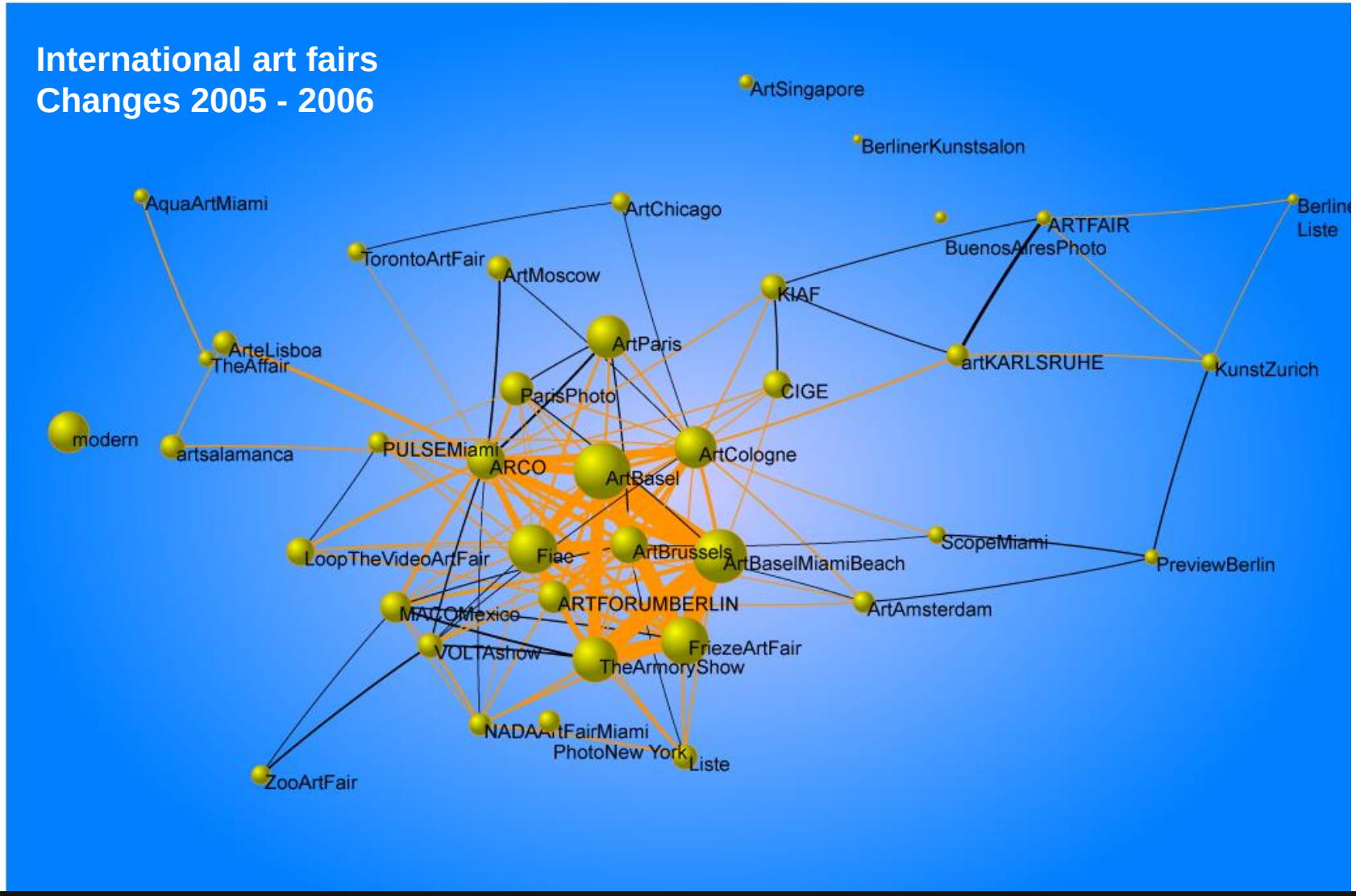
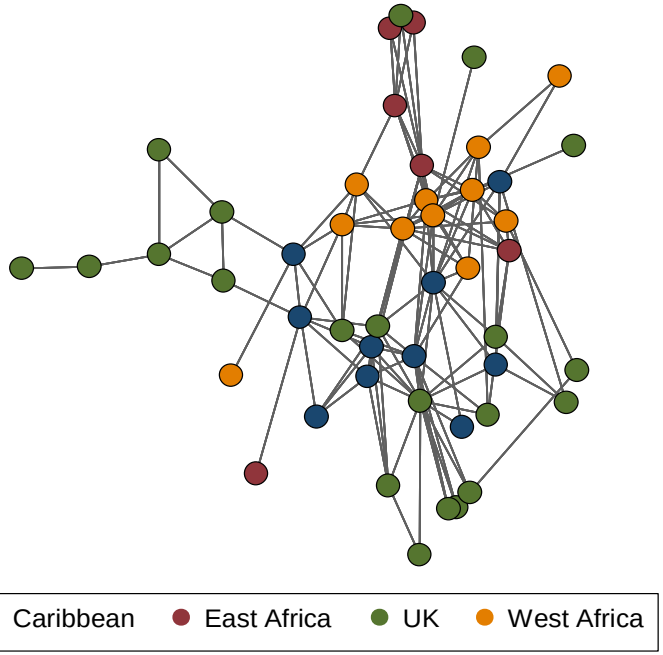
www.grund.co.uk





Yogev, T. and Grund, T. (2012) Structural Dynamics and the Market for Contemporary Art: The Case of International Art Fairs. *Sociological Focus,* 54(1), 23-40.

CO-OFFENDING IN YOUTH GANG

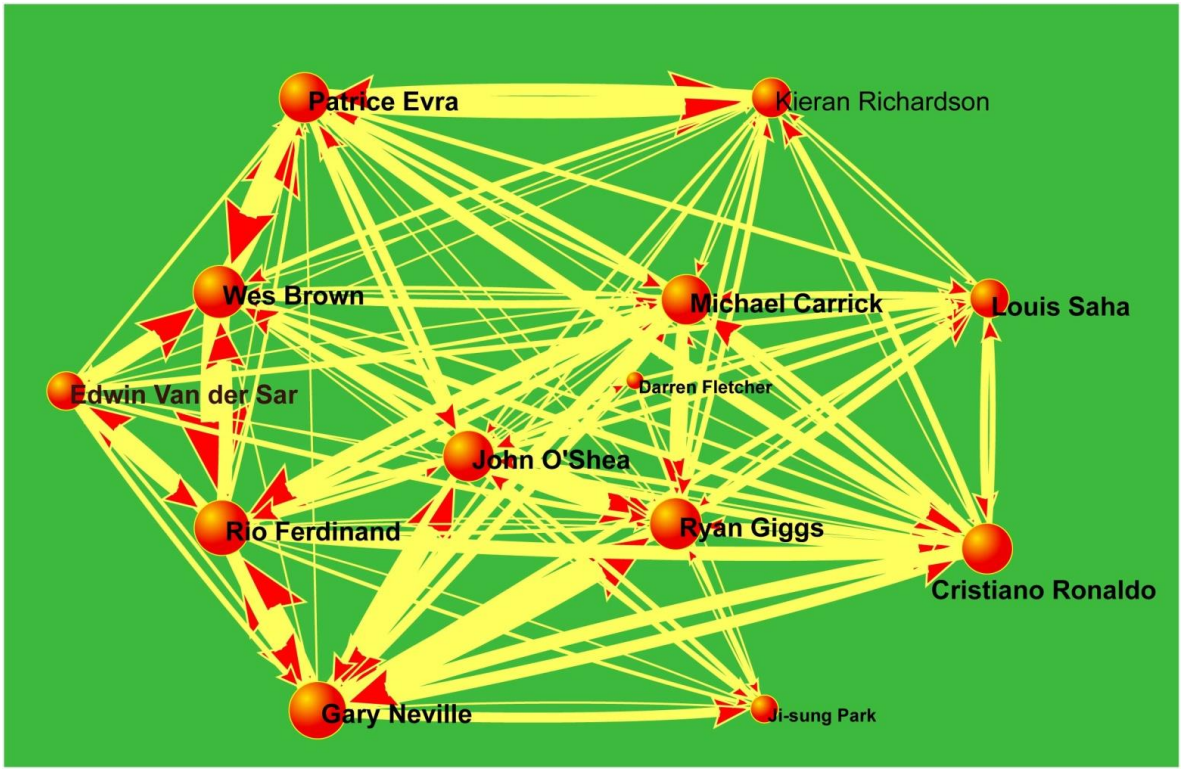


Grund, T. and Densley, J. (2012) Ethnic Heterogeneity in the Activity and Structure of a Black Street Gang. *European Journal of Criminology*, 9(3), 388-406.

Grund, T. and Densley, J. (2015). Ethnic homophily and triad closure: Mapping internal gang structure using exponential random graph models. *Journal of Contemporary Criminal Justice*, 31(3), 354–370

MANCHESTER UTD – TOTTENHAM

9/9/2006, Old Trafford



Grund, T. (2012) Network Structure and Team Performance: The Case of English Premier League Soccer Teams. *Social Networks,* 34(4), 682-690.

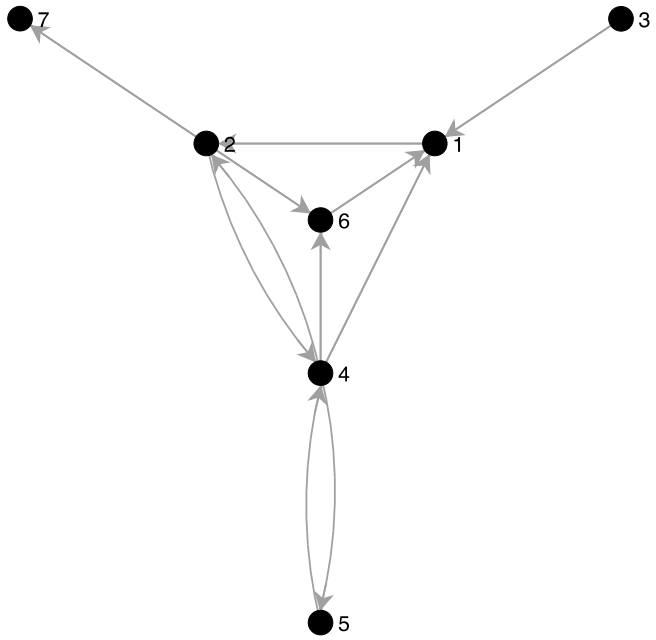
SOCIAL NETWORKS

- **Social**
  - Friendship, kinship, romantic relationships
- **Government**
  - Political alliances, government agencies
- **Markets**
  - Trade: flow of goods, supply chains, auctions
  - Labor markets: vacancy chains, getting jobs
- **Organizations and teams**
  - Interlocking directorates
  - Within-team communication, email exchange

DEFINITION

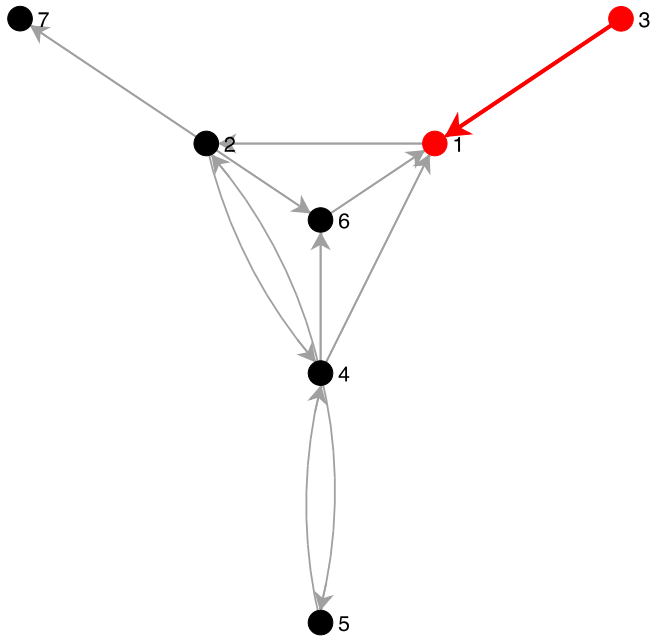
- Mathematically, a (binary) network is defined as $G = (V, E)$ where $V = \{1,2,..,n\}$ is a set of "vertices" (or "nodes") and $E \subseteq \{\langle i,j\rangle |\ i,j \in V\}$ is a set of "edges" (or "ties", "arcs"). Edges are simply pairs of vertices, e.g. $E \subseteq \{(1,2),(2,5)\ ...\}$.
- We write $y_{ij} = 1$ if actors i and j are related to each other (i.e., if $\langle i,j\rangle \in E$), and $y_{ij} = 0$ otherwise.
- In digraphs (or directed networks) it is possible that $y_{ij} \neq y_{ji}$.

ADJACENCY MATRIX



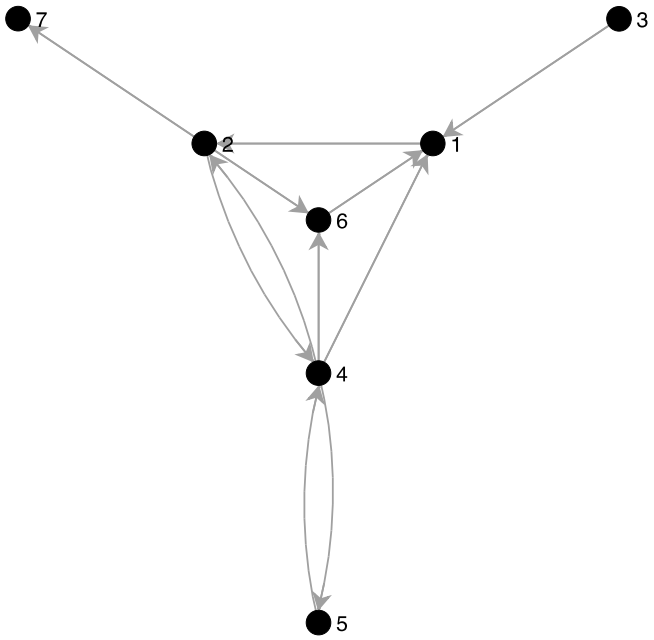
	1	2	3	4	5	6	7
1	0	1	0	0	0	0	0
2	0	0	0	1	0	1	1
3	1	0	0	0	0	0	0
4	1	1	0	0	1	1	0
5	0	0	0	1	0	0	0
6	1	0	0	0	0	0	0
7	0	0	0	0	0	0	0

ADJACENCY MATRIX



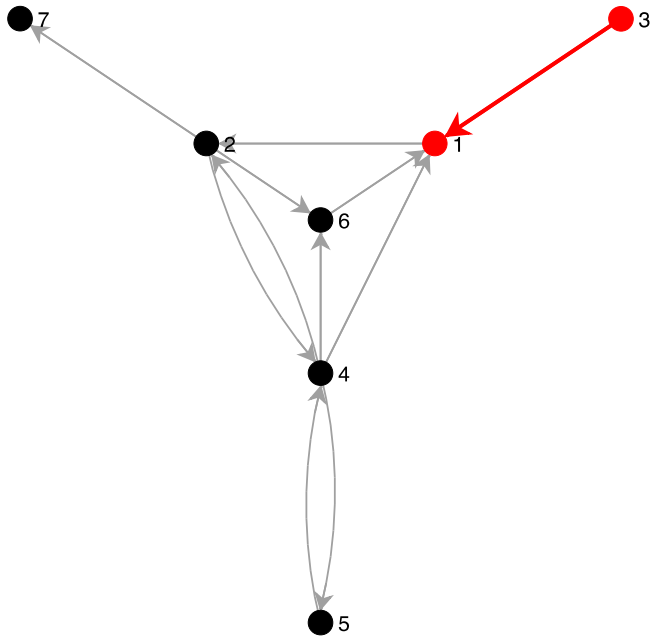
	1	2	3	4	5	6	7
1	0	1	0	0	0	0	0
2	0	0	0	1	0	1	1
3	1	0	0	0	0	0	0
4	1	1	0	0	1	1	0
5	0	0	0	1	0	0	0
6	1	0	0	0	0	0	0
7	0	0	0	0	0	0	0

ADJACENCY LIST



	ego	alter
1	1	2
2	2	4
3	2	6
4	2	7
5	3	1
6	4	1
7	4	2
8	4	5
9	4	6
10	5	4
11	6	1

ADJACENCY LIST



	ego	alter
1	1	2
2	2	4
3	2	6
4	2	7
5	3	1
6	4	1
7	4	2
8	4	5
9	4	6
10	5	4
11	6	1

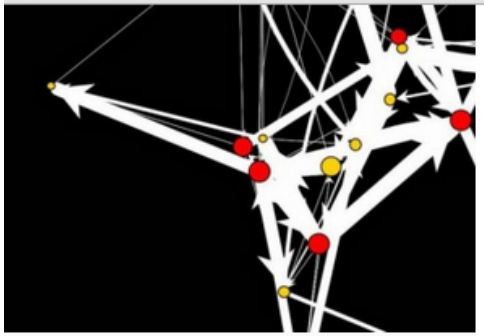
NETWORK ANALYSIS

- Simple description/characterization of networks
- Calculation of node-level characteristics (e.g. centrality)
- Components, blocks, cliques, equivalences…
- Visualization of networks
- Statistical modeling of networks, network dynamics
- ….

http://nwcommands.org

. `findit nwcommands`

http://nwcommands.org



NETWORK ANALYSIS USING STATA

nwcommands.org

- ABOUT
- NEWS
- INSTALLATION
- GETTING STARTED
- GLOSSARY
- TUTORIALS AND SLIDES

About

Here you find the the beta-version of the nwcommands – a collection of programs for social network analysis in Stata.

A more thorough description will follow.

Browse through the tutorials and the alphabetical list of the nwcommands to get a first idea about how you can do social network analysis in Stata.

Installation instructions are here.

If you have a question, you can ask it in the forum for the nwcommands. Alternatively, you can send an email to thomas.u.grund@gmail.com. You can also join the email list for the nwcommands here: https://groups.google.com/forum/#!forum/nwcommands/join. Once you are signed up you will receive information about updates, new releases and so on.

If you find any bugs in the software, please contact us by sending an email

GoogleGroup: nwcommands

Twitter: nwcommands

Search “nwcommands” to find a channel with video tutorials.

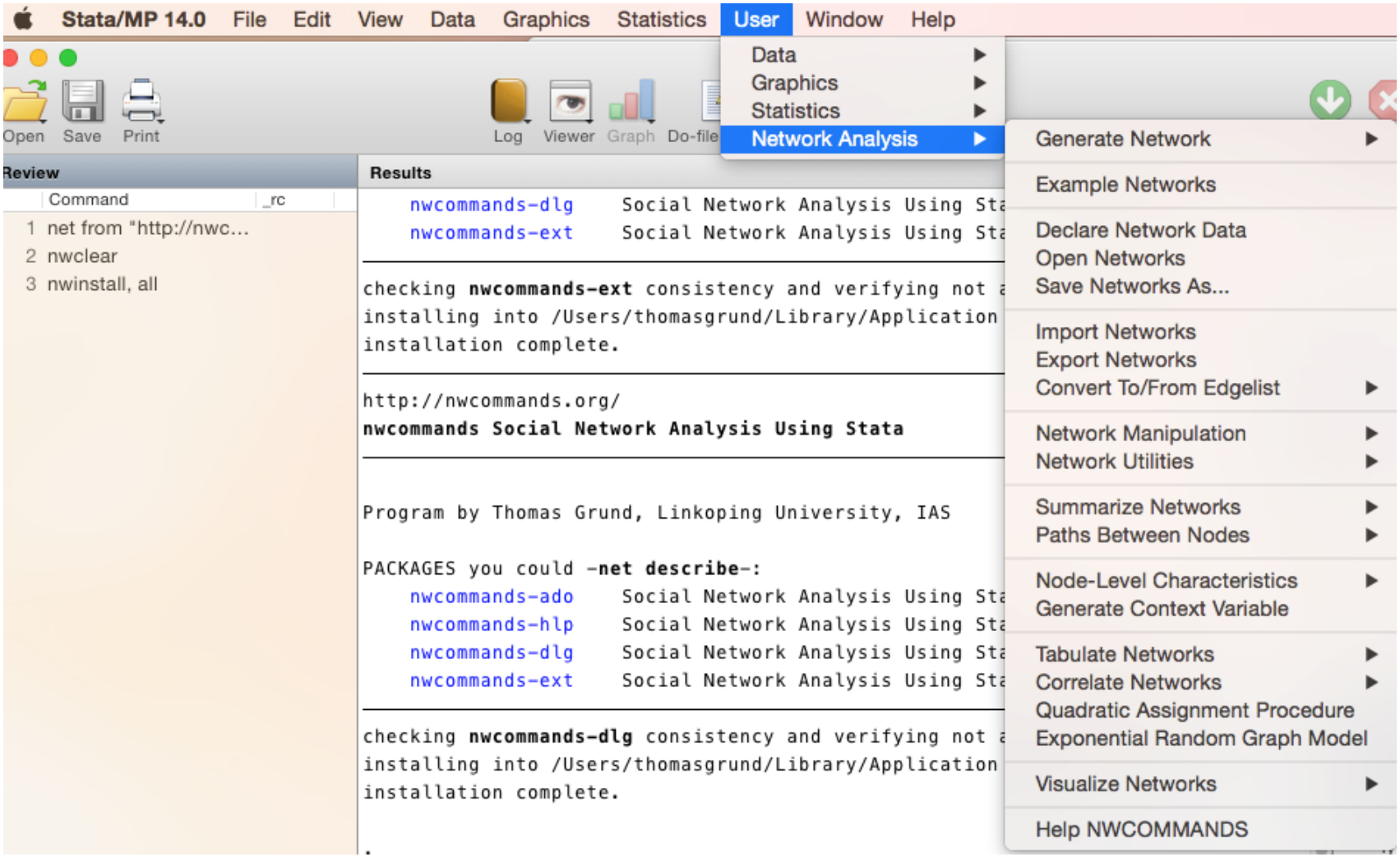
NWCOMMANDS

- Software package for Stata. Almost 100 new Stata commands for handling, manipulating, plotting and analyzing networks.
- Ideal for existing Stata users. Corresponds to the R packages “network”, “sna”, “igraph”, “networkDynamic”.
- Designed for small to medium-sized networks (< 10000).
- Almost all commands have menus. Can be used like Ucinet or Pajek. Ideal for beginners and teaching.
- Not just specialized commands, but whole infrastructure for handling/dealing with networks in Stata.
- Writing own network commands that build on the nwcommands is very easy.

LINES OF CODE

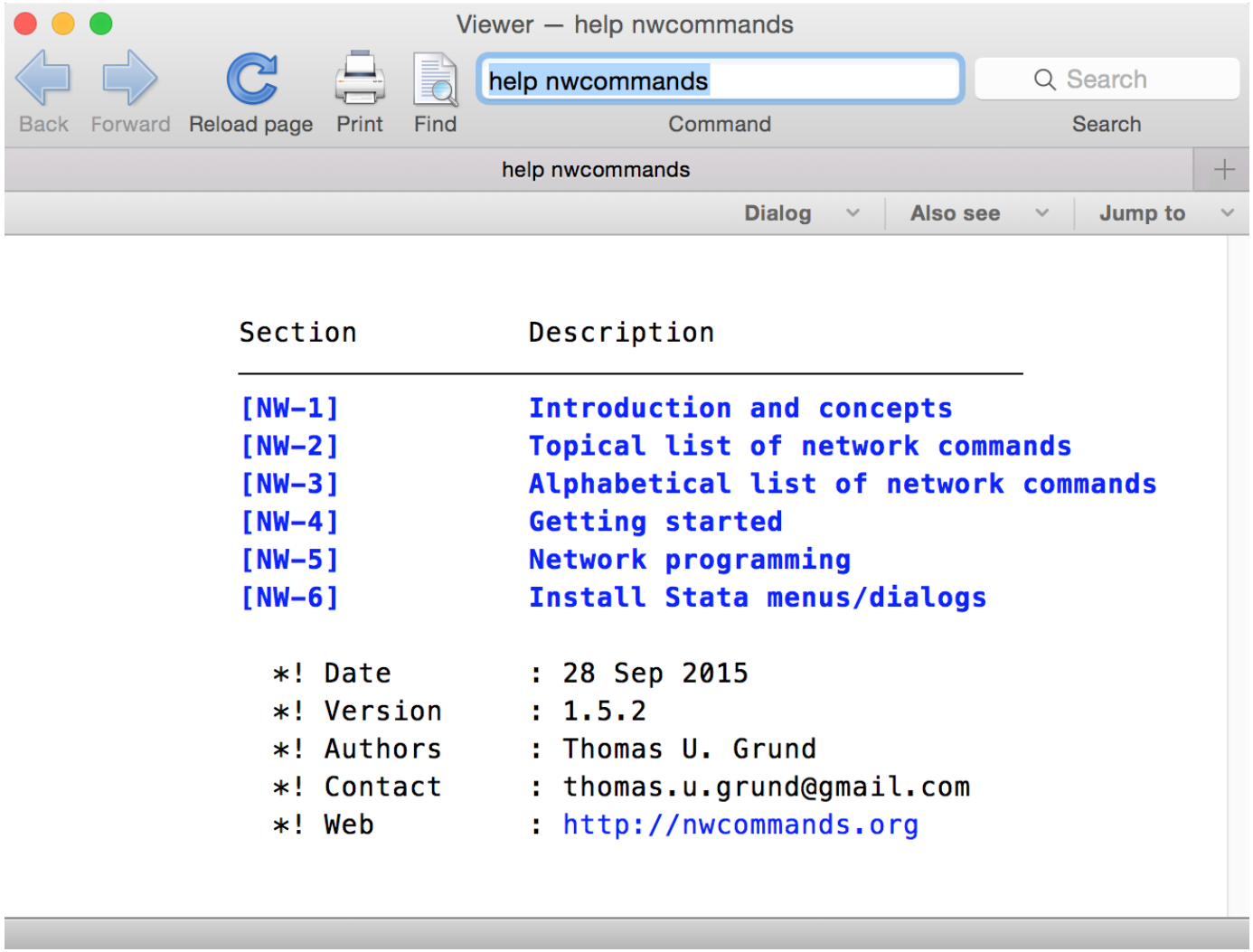
Type	Files	LoC
.ado	94	14548
.dlg	57	5707
.sthlp	97	9954

Downloads Over 13 000 (since Jan 2015)




```
. nwinstall, all
```

OVERVIEW




```
. help nwcommands
```

INTUITION

- Software introduces ***netname*** and ***netlist***.
- Networks are dealt with like normal variables.
- Many normal Stata commands have their network counterpart that accept a *netname*, e.g. nwdrop, nwkeep, nwclear, nwtabulate, nwcorrelate, nwcollapse, nwexpand, nwreplace, nwrecode, nwunab and more.
- Stata intuition just works.

SETTING NETWORKS

- "Setting" a network creates a network quasi-object that has a ***netname***.
- After that you can refer to the network simply by its ***netname***, just like when refer to a variable with its ***varname***.

Syntax:

```
nwset varlist[, edgelist directed undirected name(newnetname) labs(string)
    labsfromvar(varname) vars(string) keeporiginal xvars]

nwset, mat(matamatrix) [directed undirected name(newnetname) labs(string)
    labsfromvar(varname) vars(string) xvars]
```

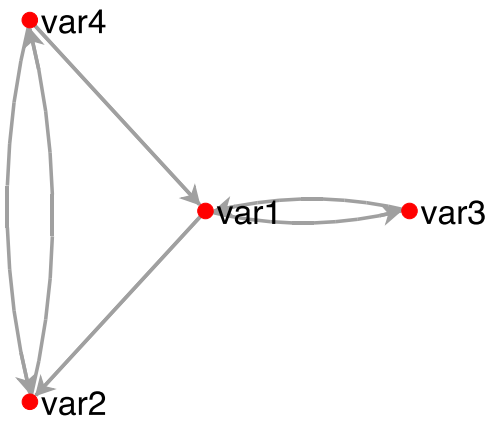
Data Edito

Edit Browse Filter Variables Properties

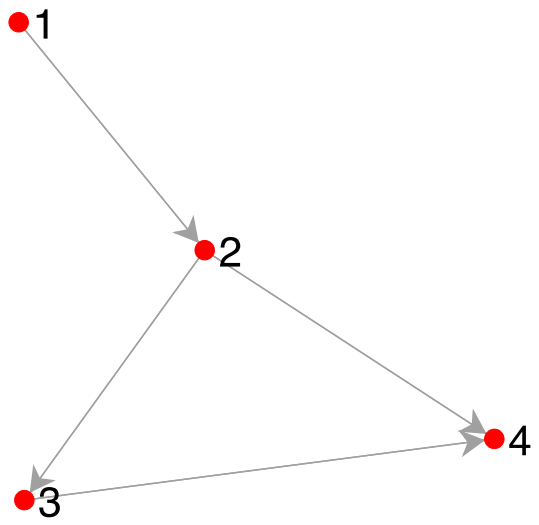
var4[5]

	var1	var2	var3	var4
1	0	1	1	0
2	0	0	0	1
3	1	0	0	0
4	1	1	0	0

Vars: 4 Order: Dataset Obs: 4




```
. nwset _all

. nwplot, lab
```



Edit Browse Filter

ego[1] 1

	ego	alter
1	1	2
2	2	3
3	2	4
4	3	4
5	5	5

Vars: 2 Order: Dataset Obs: 5

```
. nwset ego alter, edgelist

. nwplot, lab
```

LIST ALL NETWORKS

```
. nwds
network     network_1

. nwset
(2 networks)
```

```
network
network_1
```

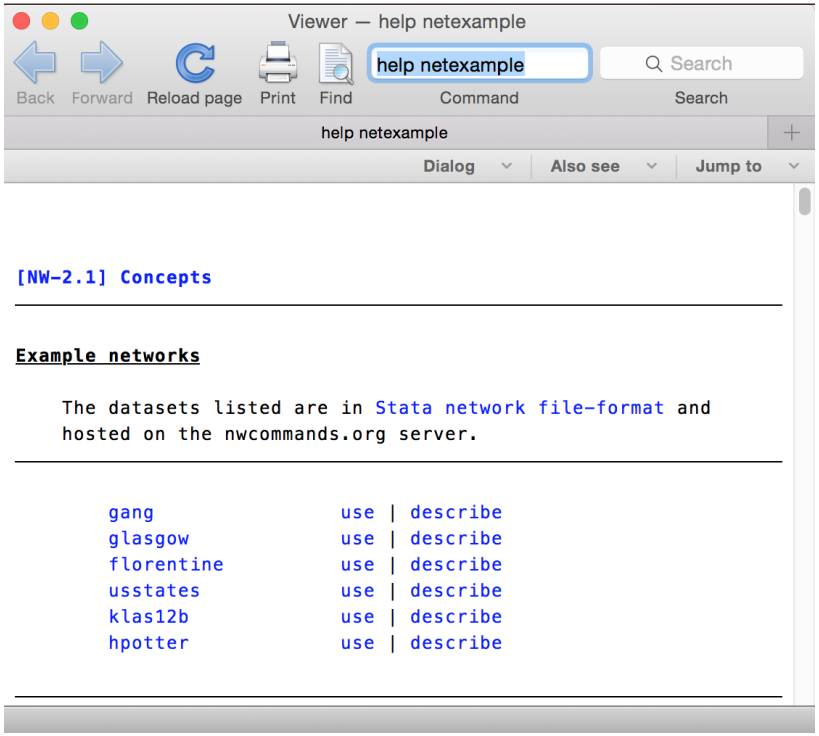
These are the names of the networks in memory. You can refer to these networks by their name.

Check out the return vector. Both commands populate it as well.

LOAD NETWORK FROM THE INTERNET

```
. webnwuse florentine

Loading successful
(4 networks)
```

```
network
network_1
flobusiness
flomarriage
```




```
. help netexample
```

IMPORT NETWORK

- A wide array of popular network file-formats are supported, e.g. Pajek, Ucinet, by **`nwimport`**.
- Files can be imported directly from the internet as well.
- Similarly, networks can be exported to other formats with **`nwexport`**.

```
. nwimport http://vlado.fmf.uni-lj.si/pub/networks/data/ucinet/zachary.dat, type(ucinet)
```

```
Importing successful
(6 networks)
```

```
      network
      network_1
      flobusiness
      flomarriage
      ZACHE
      ZACHC
```

DROP/KEEP NETWORKS

- Dropping and keeping networks works almost exactly like dropping and keeping variables.

```
. nwdrop flo*

. nwkeep ZACHE ZACHC
```


. nwclear

DROP/KEEP NODES

You can also drop/keep nodes of a specific network.

```
. nwdrop flomarriage if _nodevar == "strozzi"

. nwdrop flomarriage if _n == 1
```

NODE ATTRIBUTES

```
. webnwuse florentine, nwclear
```

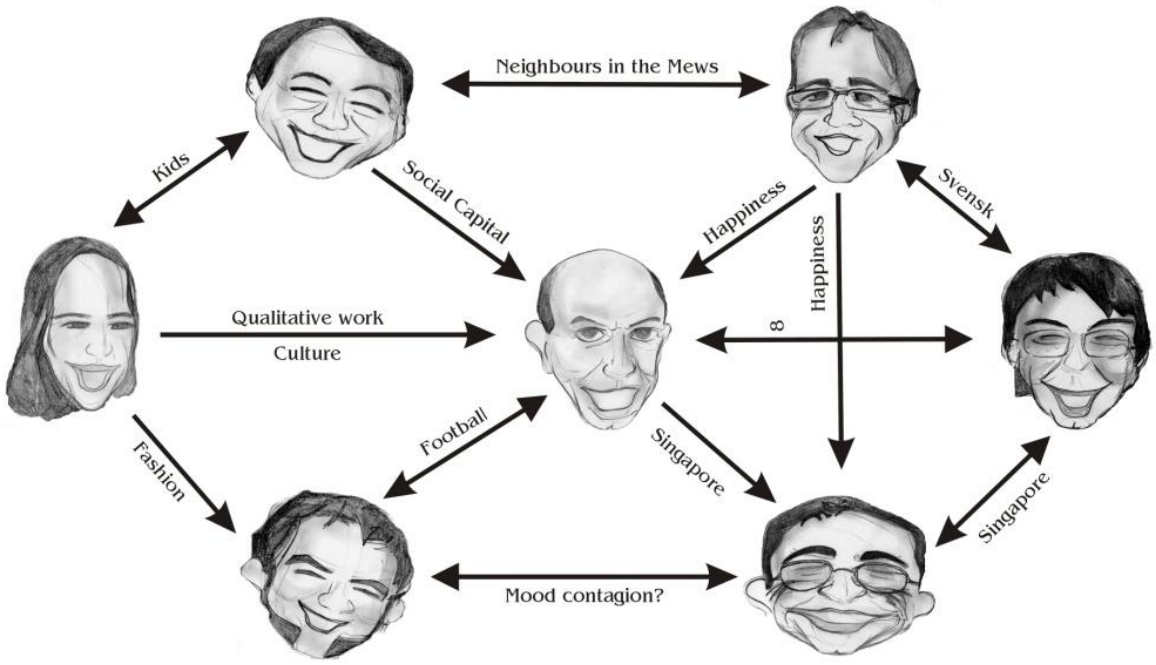
	wealth	priorates	seat	_nodelab	_nodevar	_nodeid
1	10	53	1	acciaiuoli	acciaiuoli	1
2	36	65	1	albizzi	albizzi	2
3	55	0	0	barbadori	barbadori	3
4	44	12	1	bischeri	bischeri	4
5	20	22	1	castellani	castellani	5
6	32	0	0	ginori	ginori	6
7	8	21	1	guadagni	guadagni	7
8	42	0	0	lamberteschi	lamberteschi	8

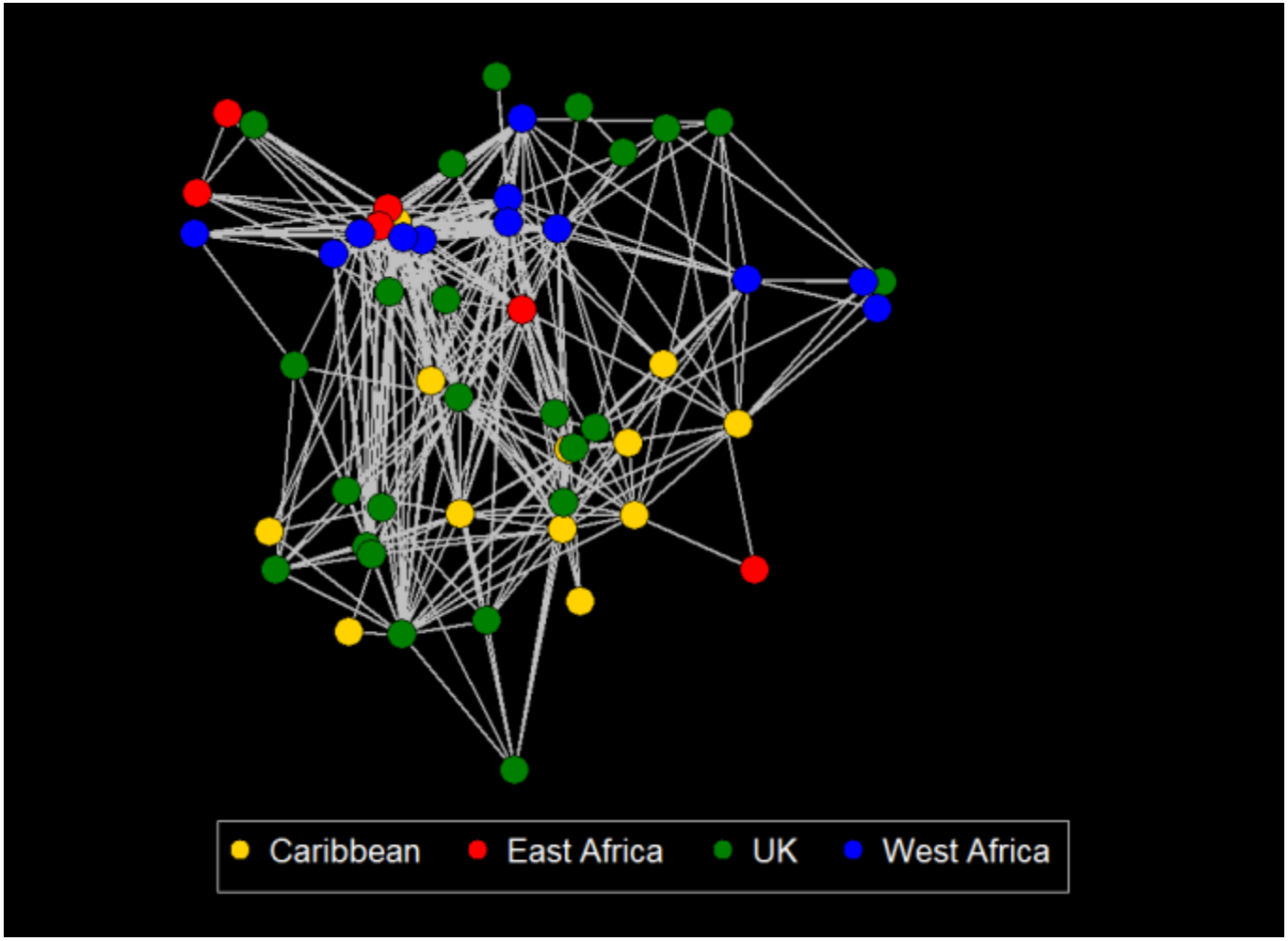
- Every node of a network has a ***nodeid***, which is matched with the observation number in a normal dataset.
- In this case, the node with ***nodeid*** == 1 is the “acciaiuoli” family and they have a wealth of 10.

OVERVIEW

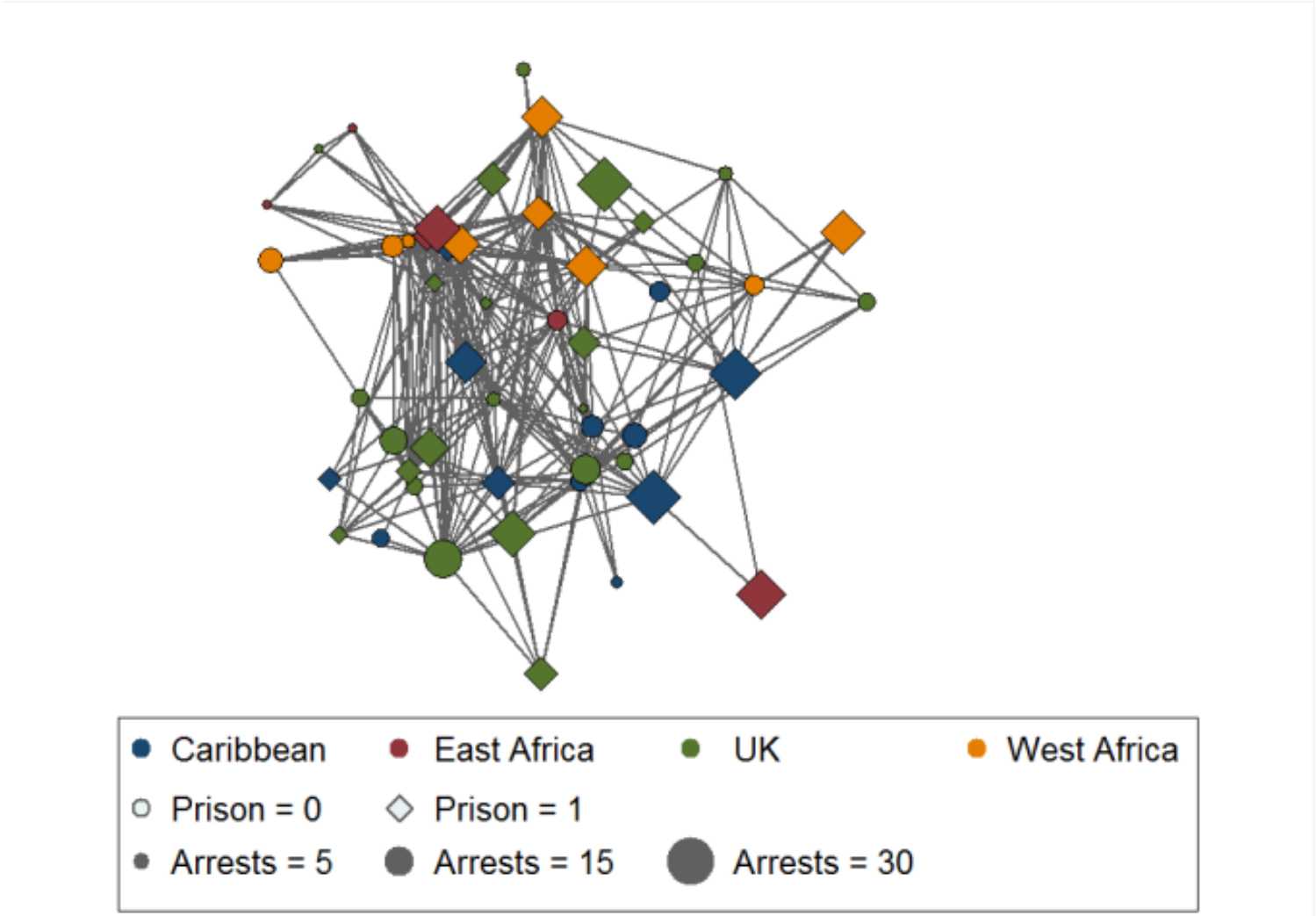
```
nwset
nwds
nwcurrent
nwimport
webnwuse
nwdrop
nwkeep
```

VISUALIZATION

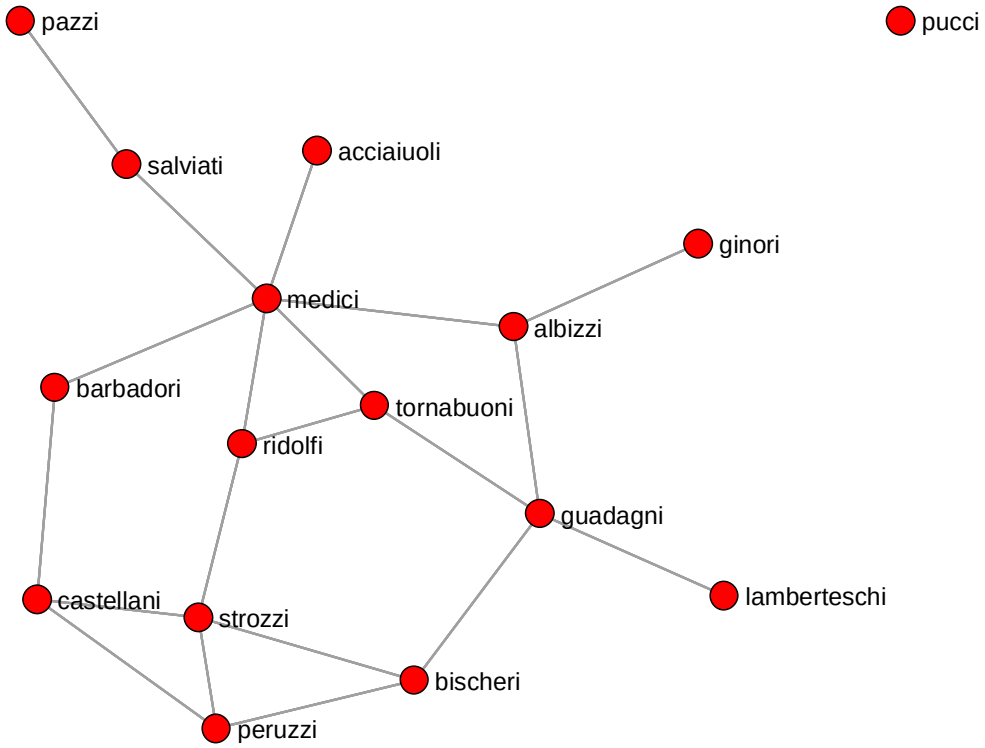

Neighbours in the Mews
Kids
Social Capital
Happiness
Happiness
Svensk
Qualitative work
Culture
8
Fashion
Football
Singapore
Singapore
Mood contagion?



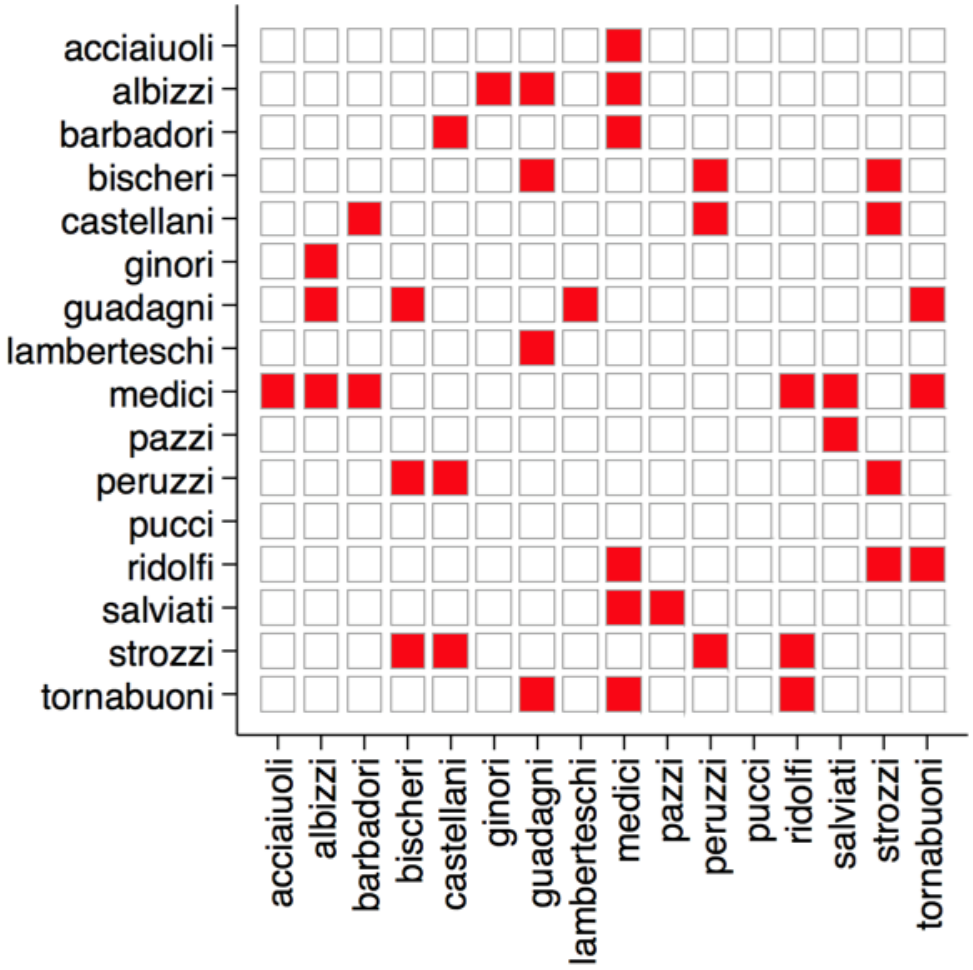

```
. webnwuse gang
. nwplot gang, color(Birthplace) scheme(s2network)
```



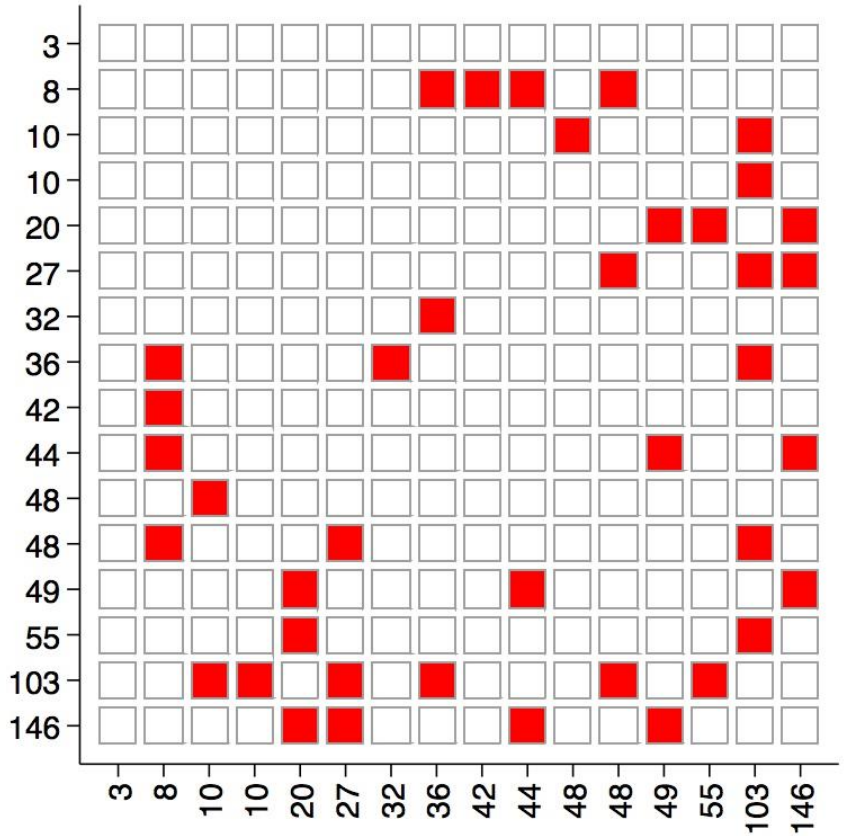

```
nwplot gang, color(Birthplace) symbol(Prison) size(Arrests)
```



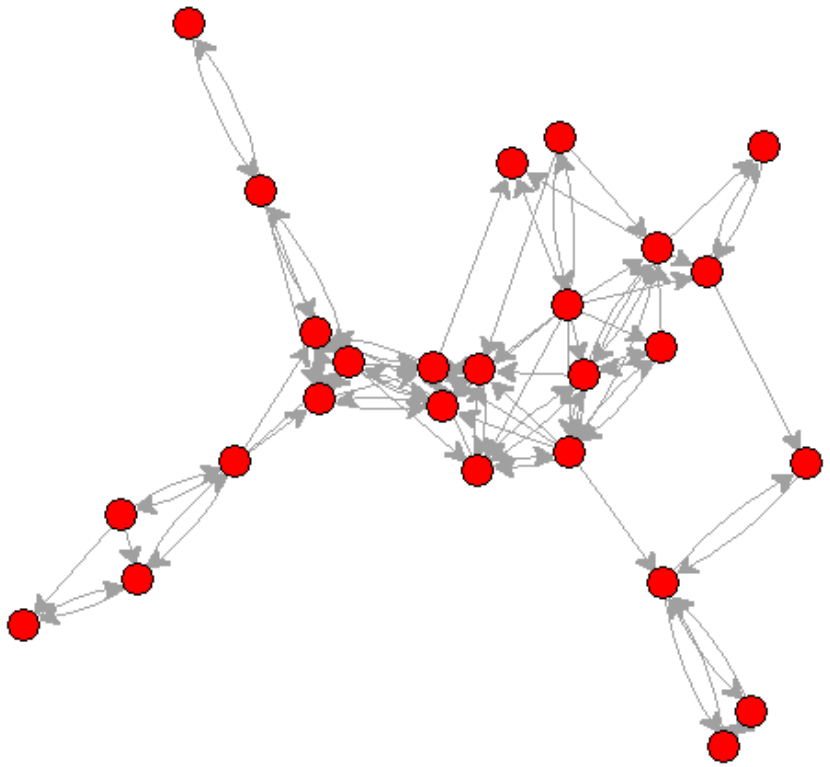

```
. webnwuse florentine
. nwplot flomarriage, lab
```



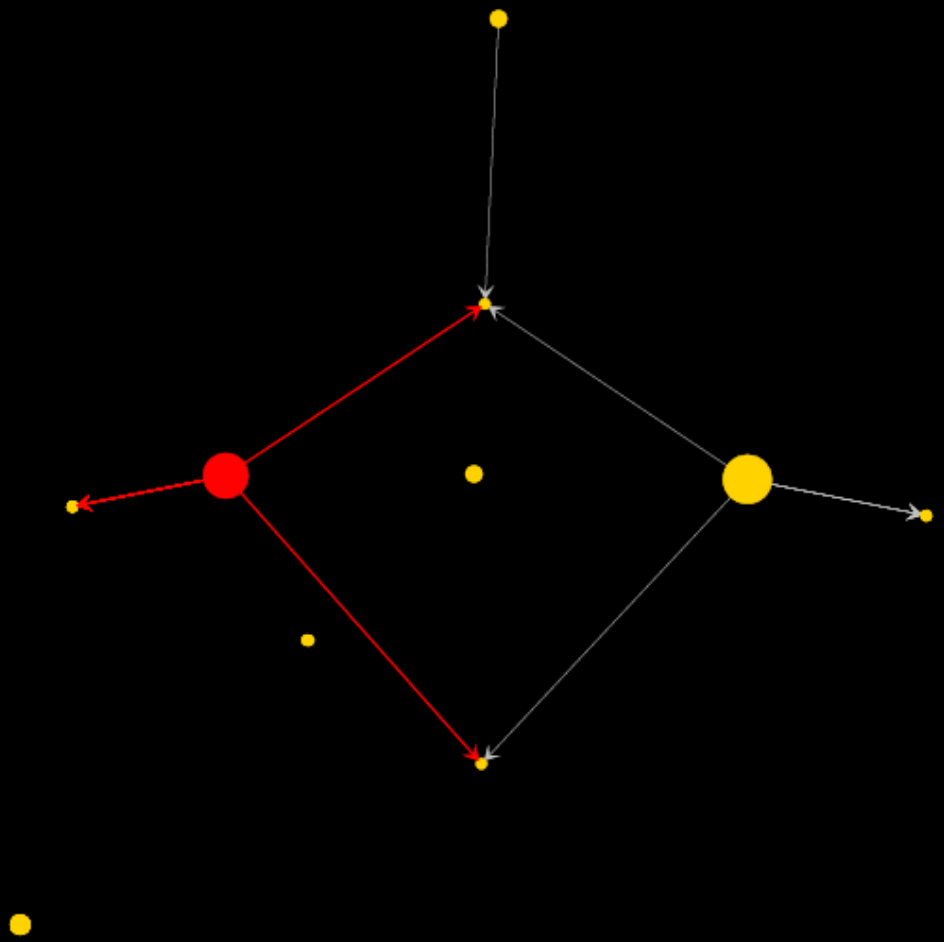

```
. nwplotmatrix flomarriage, lab
```

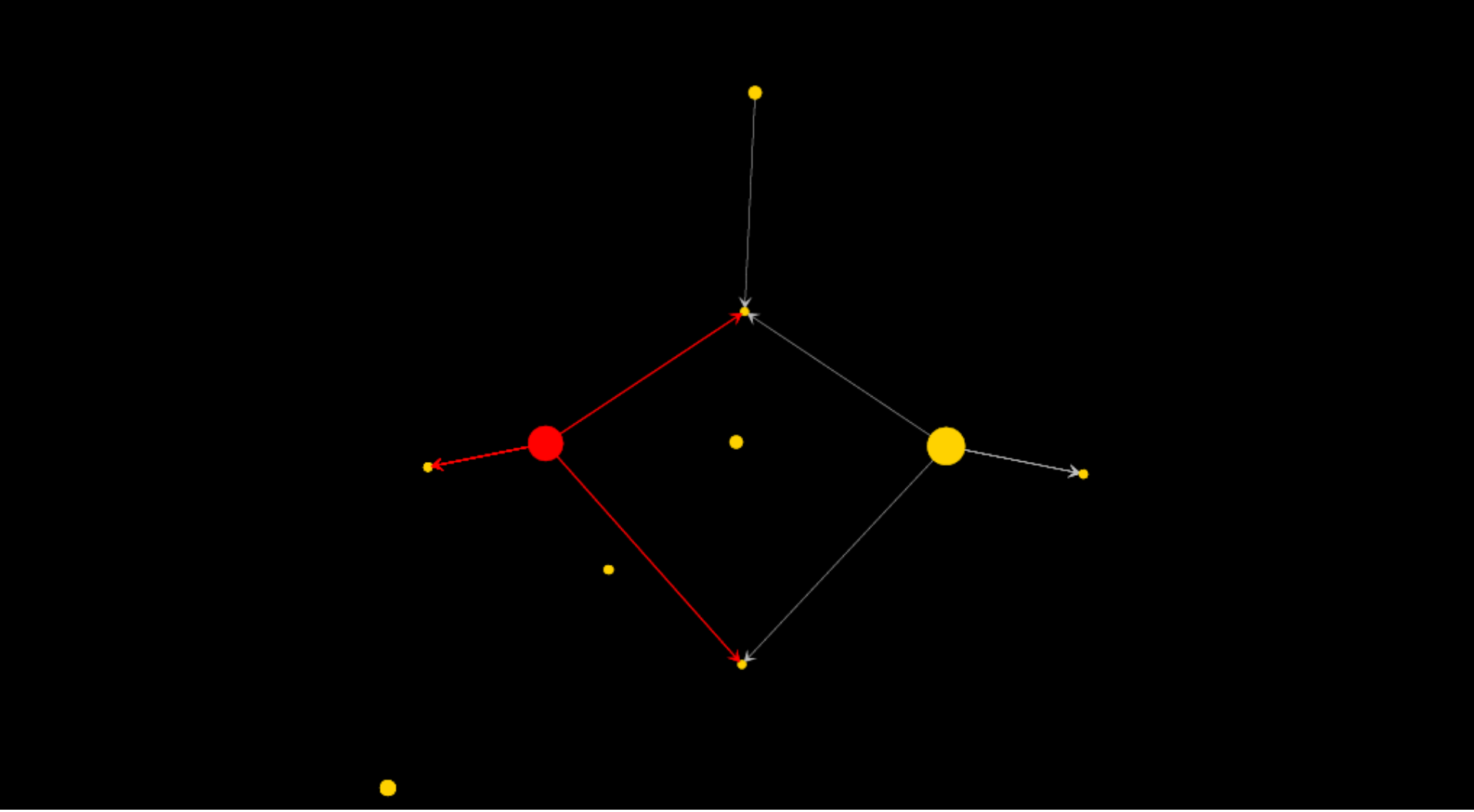



```
. nwplotmatrix flomarriage, sortby(wealth) label(wealth)
```



```
. webnwuse klas12
. nwmovie klas12_wave1-klas12_wave4
```





```
. nwmovie _all, colors(col_t*) sizes(siz_t*) edgecolors(edge_t*)
```

VISUALIZATION

nwplot
nwplotmatrix
nwmovie

EXAMINE NETWORK

SUMMARIZE

```
. nwsummarize network_1
```

```
Network name:  network_1
Network id:  1
Directed: true
Nodes: 5
Arcs: 4
Minimum value:  0
Maximum value:  1
Density:  .2
```

SUMMARIZE

```
. nwsummarize glasgow1, detail
```

```
   Network name:  glasgow1
   Network id:  1
   Directed: true
   Nodes: 50
   Arcs: 113
   Minimum value:  0
   Maximum value:  1
   Density:  .0461224489795918
   Reciprocity:  .527027027027027
   Transitivity:  .3870967741935484
   Betweenness centralization:  .0821793002915452
   Indegree centralization:: .119533527696793
   Outdegree centralization:: .0570595585172845
```

TABULATE NETWORK

```
. webnwuse florentine, nwclear

Loading successful
(2 networks)
```

---

flobusiness
flomarriage

```
. nwtabulate flomarriage
```

Network: **flomarriage** Directed: **false**

flomarriage	Freq.	Percent	Cum.
0	**100**	**83.33**	**83.33**
1	**20**	**16.67**	**100.00**
Total	**120**	**100.00**	

TABULATE TWO NETWORKS

```
. nwtabulate flomarriage flobusiness

   Network 1:  flomarriage    Directed: false
   Network 2:  flobusiness    Directed: false
```

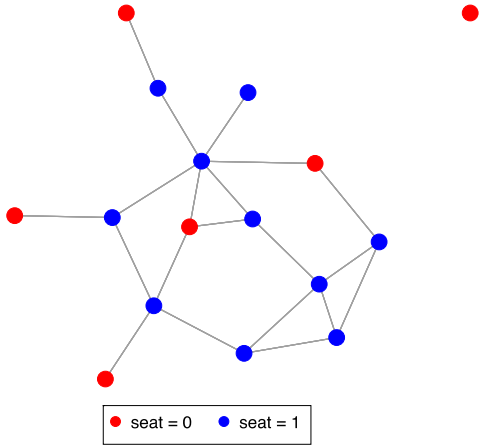
flomarriage	flobusiness		
	0	1	Total
0	**93**	**7**	**100**
1	**12**	**8**	**20**
Total	**105**	**15**	**120**

TABULATE NETWORK AND ATTRIBUTE

```
. nwtabulate flomarriage seat
(0 observations deleted)

   Network:  flomarriage      Directed: false
   Attribute:  seat

       The network is undirected.
       The table shows two entries for each edge.
```

from_seat	to_seat 0	1	Total
0	0	8	8
1	8	24	32
Total	8	32	40

```
   E-I Index: -.2    p-value: .22
```



DYAD CENSUS

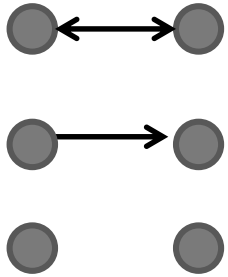
```
. webnwuse glasgow

Loading successful
(3 networks)
```

glasgow1
glasgow2
glasgow3

M: mutual

A: asymmetric

N: null



```
. nwdyads glasgow1

    Dyad census:  glasgow1
```

Mutual	Asym	Null
39	**35**	**1151**

Reciprocity: **.527027027027027**

```
. nwtriads glasgow1
```

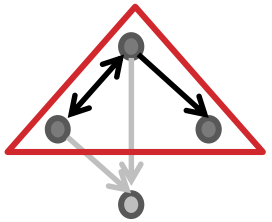
Triad census: **glasgow1**

003	012	021D	021U
16243	**1470**	**5**	**18**

021C	030T	030C	102
21	**5**	**0**	**1724**

120D	120U	120C	111D
6	**5**	**2**	**42**

111U	201	210	300
30	**15**	**9**	**5**



Transitivity: **.3870967741935484**

EXAMINE NETWORKS

```
nwsummarize
nwtabulate
nwdyads
nwtriads
```

CHANGE NETWORK

TABULATE NETWORK

```
. webnwuse gang, nwclear

. nwtabulate gang_valued

   Network:  gang_valued      Directed: false
```

gang_valued	Freq.	Percent	Cum.
0	1,116	77.99	77.99
1	182	12.72	90.71
2	92	6.43	97.13
3	25	1.75	98.88
4	16	1.12	100.00
Total	1,431	100.00	

RECODE TIE VALUES

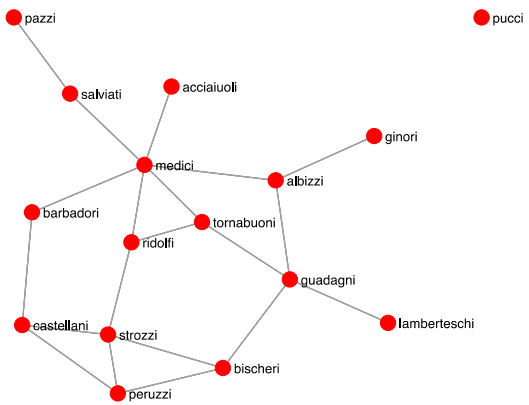
```
. nwrecode gang_valued (2/4 = 99)

(gang_valued: 266 changes made)

. nwtabulate gang_valued

   Network:  gang_valued      Directed: false
```

gang_valued	Freq.	Percent	Cum.
0	1,116	77.99	77.99
1	182	12.72	90.71
99	133	9.29	100.00
Total	1,431	100.00	

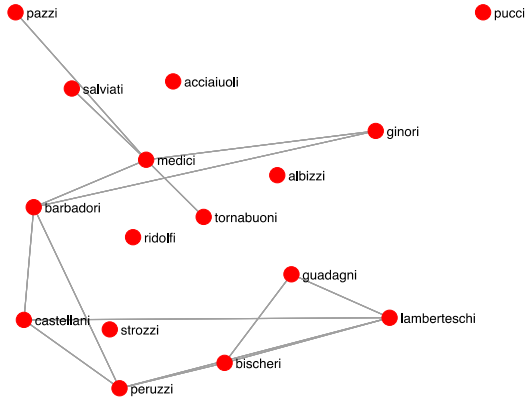
FLORENTINE FAMILIES

```
. webnwuse florentine, nwclear

Loading successful
(2 networks)
```

```
flobusiness
flomarriage
```



Marriage ties



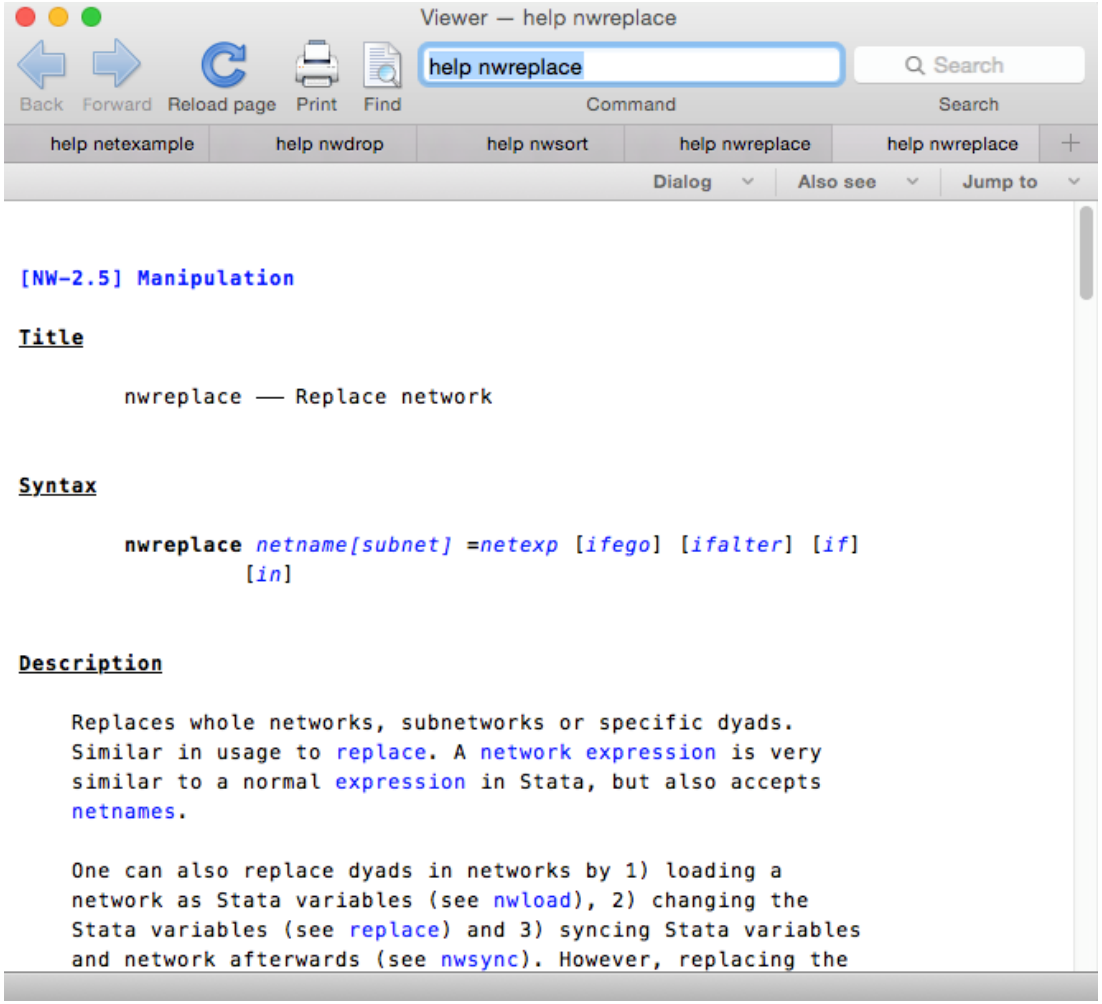
Business ties

REPLACE TIE VALUES

```
. nwreplace flomarriage = 2 if flobusiness == 1 & flomarriage == 1

. nwtabulate flomarriage
```

Network: **flomarriage** Directed: **false**

flomarriage	Freq.	Percent	Cum.
0	**100**	**83.33**	**83.33**
1	**12**	**10.00**	**93.33**
2	**8**	**6.67**	**100.00**
Total	**120**	**100.00**	

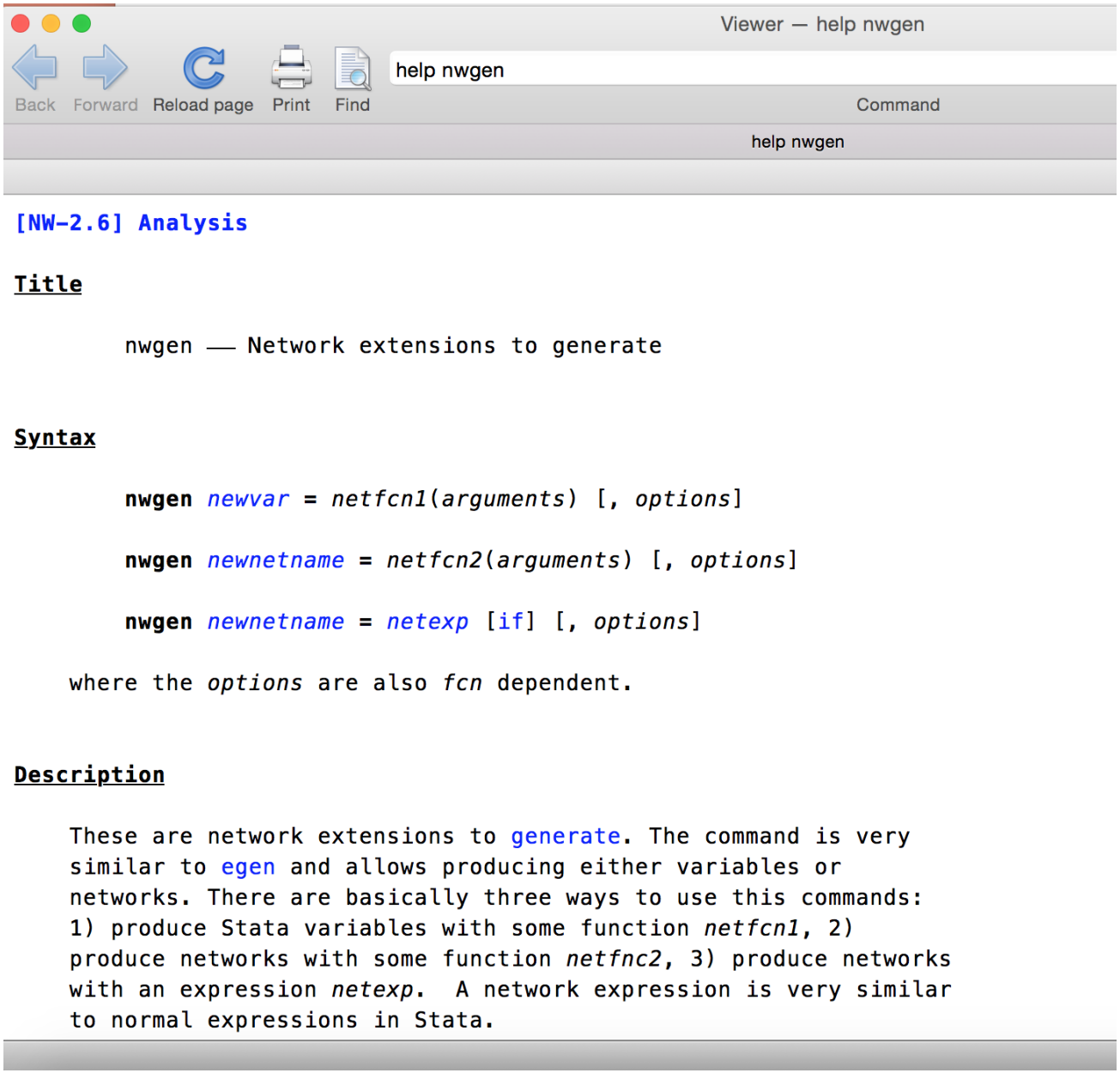


. help nwreplace

GENERATE NETWORKS

```
. nwgen both = (flobusiness & flomarriage)

. nwtabulate both

   Network:  both       Directed: false
```

both	Freq.	Percent	Cum.
0	112	93.33	93.33
1	8	6.67	100.00
Total	120	100.00	


Viewer — help nwgen
Back
Forward
Reload page
Print
Find
help nwgen
Command
help nwgen
[NW-2.6] Analysis
Title
nwgen —— Network extensions to generate
Syntax
nwgen newvar = netfcn1(arguments) [, options]
nwgen newnetname = netfcn2(arguments) [, options]
nwgen newnetname = netexp [if] [, options]
where the options are also fcn dependent.
Description
These are network extensions to generate. The command is very similar to egen and allows producing either variables or networks. There are basically three ways to use this commands: 1) produce Stata variables with some function netfcn1, 2) produce networks with some function netfnc2, 3) produce networks with an expression netexp. A network expression is very similar to normal expressions in Stata.

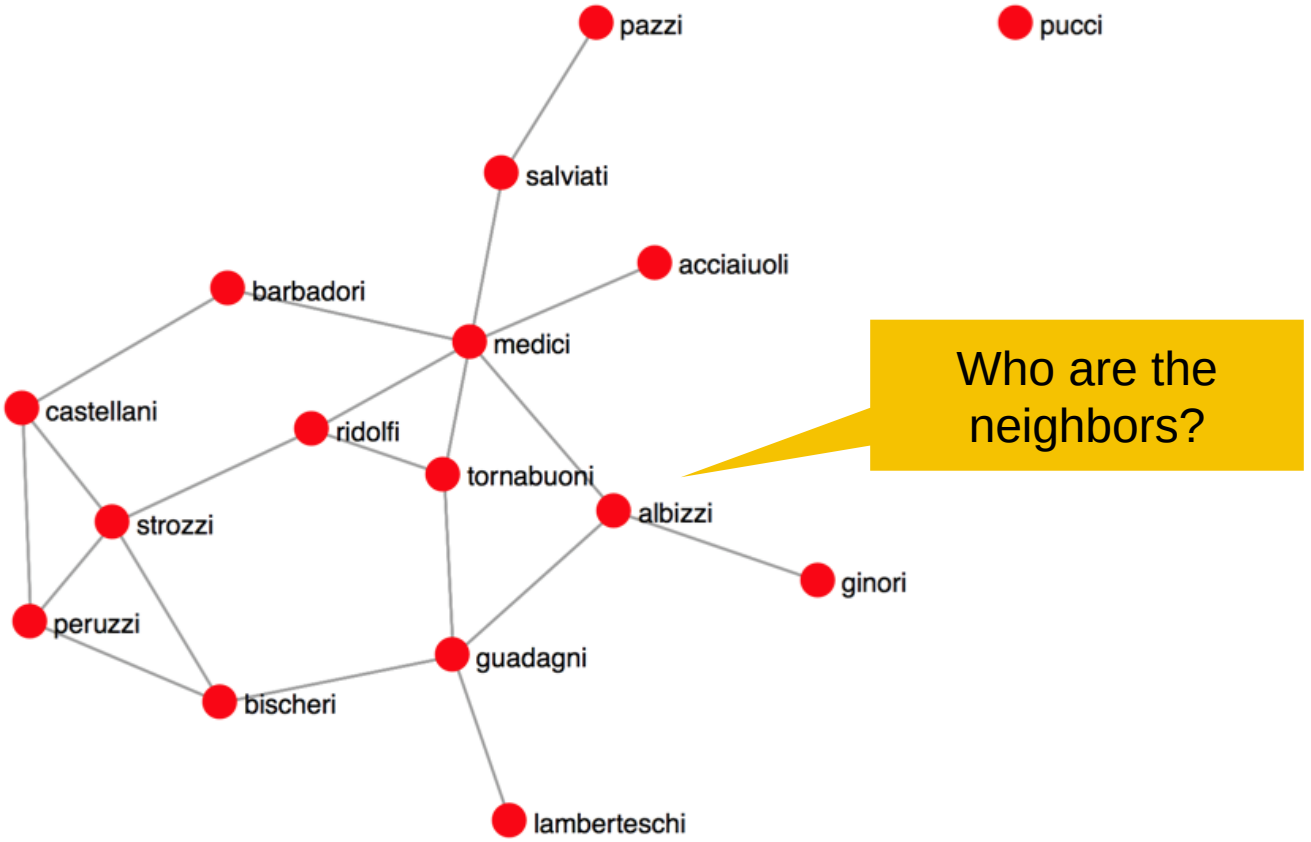
. help nwgen

CHANGE NETWORK

```
nwrecode
nwreplace
nwsync
nwtranspose
nwsym
nwgen
```

NEIGHBORS AND CONTEXT

FLORENTINE FAMILIES



NEIGHBORS

```
. webnwuse florentine, nwclear
```

```
. nwneighbor flomarriage, ego(albizzi)
```

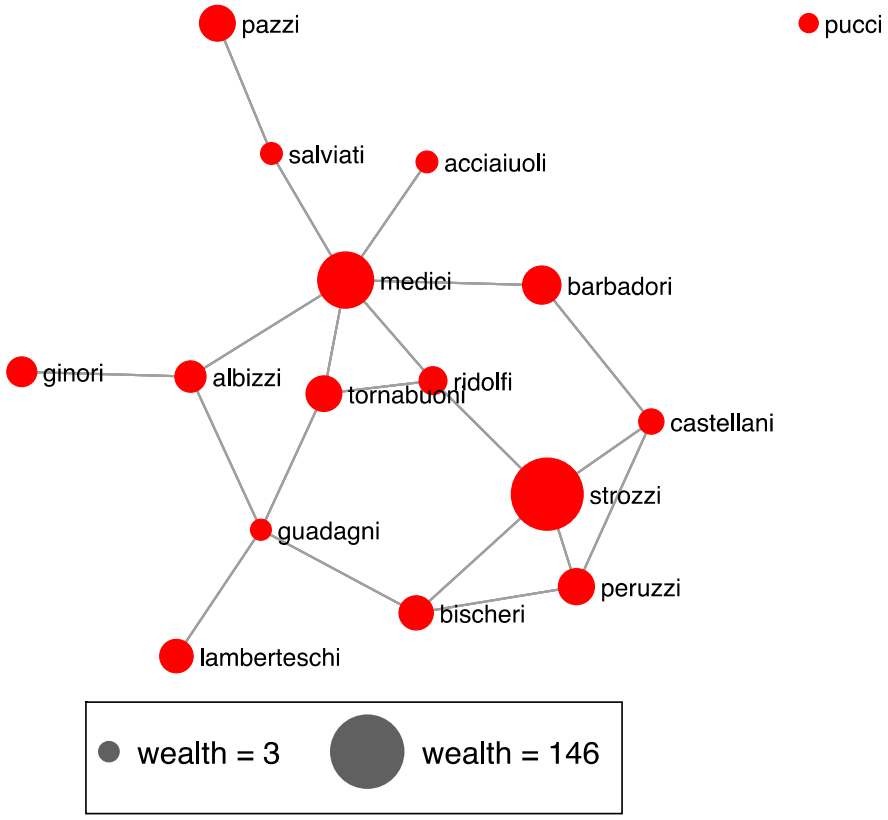
```
  Network: flomarriage
```

```
    Ego          : albizzi
    Neighbors    : ginori , guadagni , medici
```

NEIGHBORS

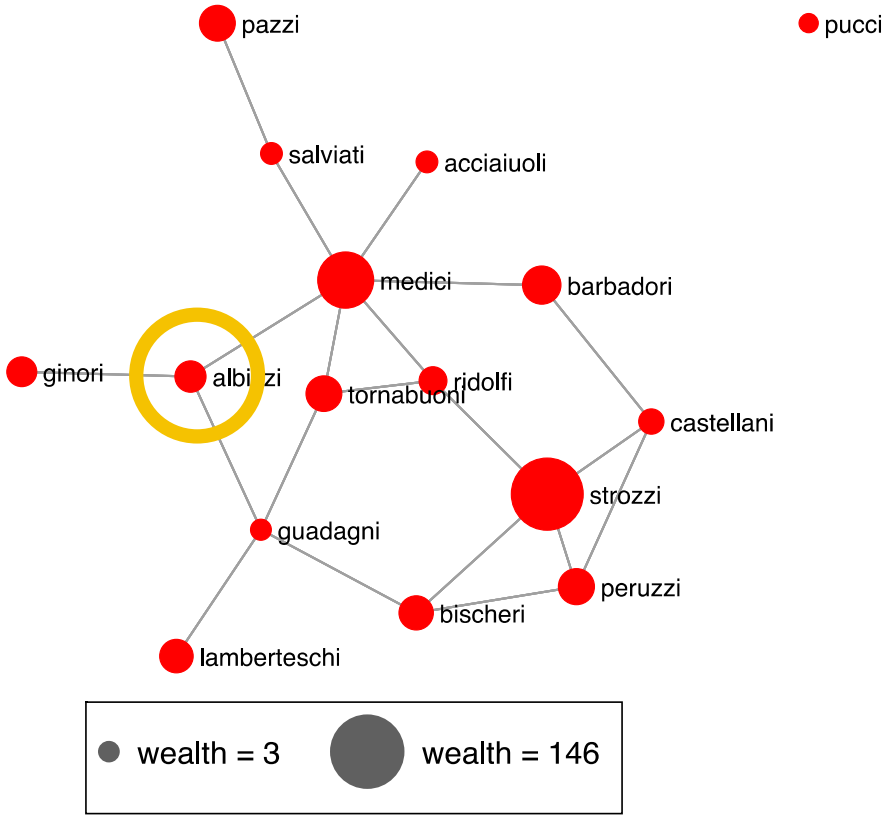
```
. return list

scalars:
                  r(ego) =  2
         r(oneneighbor) =  6

macros:
     r(neighbors_list2) : " ginori guadagni medici"
     r(neighbors_list1) : " 6 7 9"

matrices:
           r(neighbors) :  3 x 1
```

CONTEXT




```
. nwplot flomarriage, lab size(wealth)
```

CONTEXT



What is the average wealth of the “albizzi’s” network neighbors?

CONTEXT

```
. nwcontext flomarriage, attribute(wealth) stat(mean) generate(wmean)

. nwcontext flomarriage, attribute(wealth) stat(max) generate(wmax)

. nwcontext flomarriage, attribute(wealth) stat(min) generate(wmin)

. list _nodelab w*
```

	_nodelab	wealth	wmean	wmax	wmin
1.	acciaiuoli	10	103	103	103
2.	albizzi	36	47.66667	103	8
3.	barbadori	55	61.5	103	20
4.	bischeri	44	67.66666	146	8
5.	castellani	20	83.33334	146	49

CONTEXT

statistic	**Description**
`mean`	Mean of *varname* over network neighbors; defaul.
`max`	Maximum of *varname* over network neighbors.
`min`	Minimum of *varname* over network neighbors.
`sum`	Sum of *varname* over network neighbors.
`sd`	Standard deviation of *varname* over network neighbors.
`meanego`	Mean of *varname* over network neighbors and *ego*.
`maxego`	Maximum of *varname* over network neighbors and *ego*.
`minego`	Minimum of *varname* over network neighbors and *ego*.
`sumego`	Sum of *varname* over network neighbors and *ego*.
`sdego`	Standard deviation of *varname* over network neighbors and *ego*.

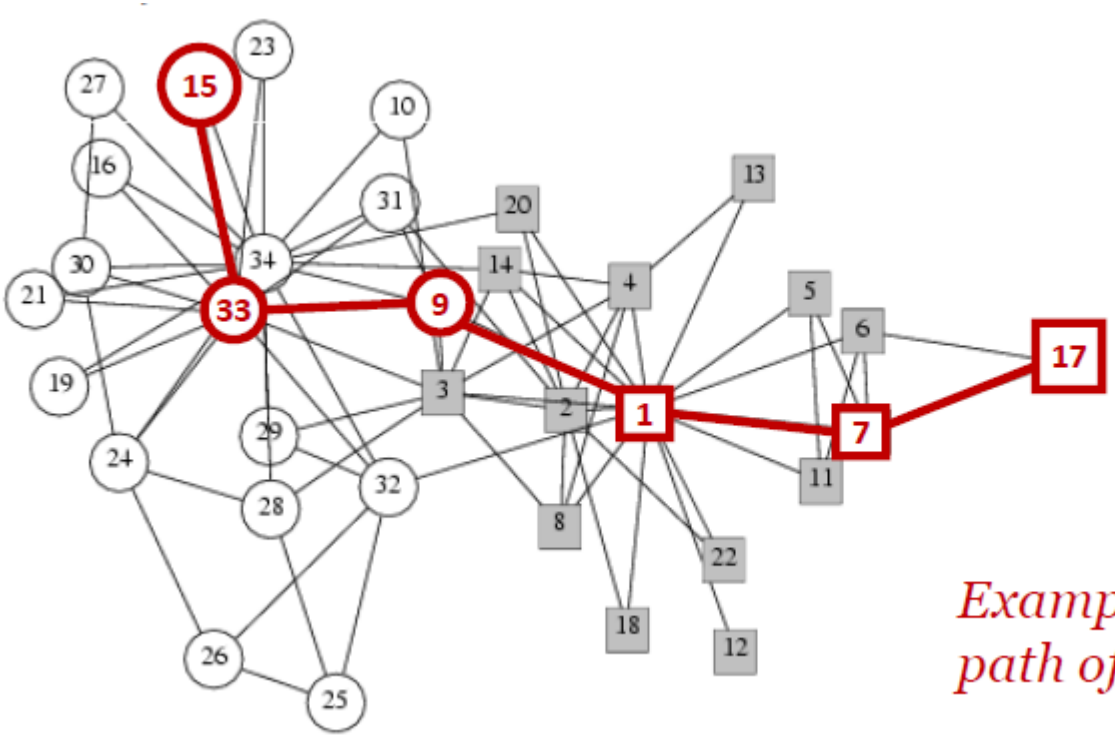
NETWORK CONTEXT

`nwneighbor`
`nwcontext`

DISTANCE AND PATH

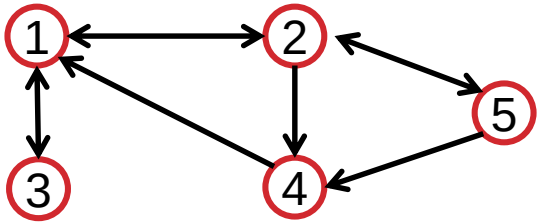
DISTANCE

Length of a shortest connecting path defines the (geodesic) distance between two nodes.



Example of a shortest path of length 5

DISTANCE



$$distances = \begin{bmatrix} 0 & 1 & 1 & 2 & 2 \\ 1 & 0 & 2 & 1 & 1 \\ 1 & 2 & 0 & 3 & 3 \\ 1 & 2 & 2 & 0 & 3 \\ 2 & 1 & 3 & 1 & 0 \end{bmatrix}$$

$$avgerage\ shortest\ path\ length = \ 1.8$$

DISTANCE

```
. webnwuse florentine, nwclear


. nwgeodesic flomarriage
```

```
  Network name: flomarriage
  Network of shortest paths: geodesic
```

```
    Nodes: 16
    Symmetrized : 1
```

```
    Paths (largest component) : 105
    Diameter (largest component): 5
    Average shortest path (largest component): 2.485714285714286
```

DISTANCE

```
. nwset
(3 networks)
```

flobusiness
flomarriage
geodesic

```
. nwtabulate geodesic
```

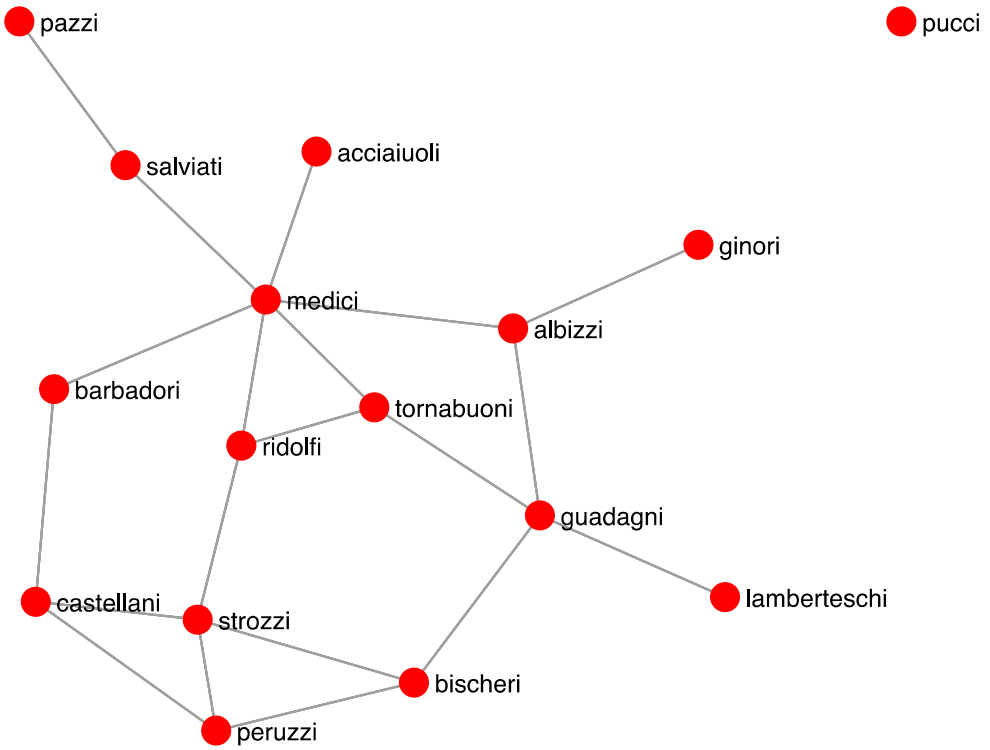
Network: **geodesic** Directed: **false**

geodesic	Freq.	Percent	Cum.
-1	15	12.50	12.50
1	20	16.67	29.17
2	35	29.17	58.33
3	32	26.67	85.00
4	15	12.50	97.50
5	3	2.50	100.00
Total	120	100.00	

PATHS

```
. webnwuse florentine, nwclear
```

How can one get from the “peruzzi” to the “medici”?

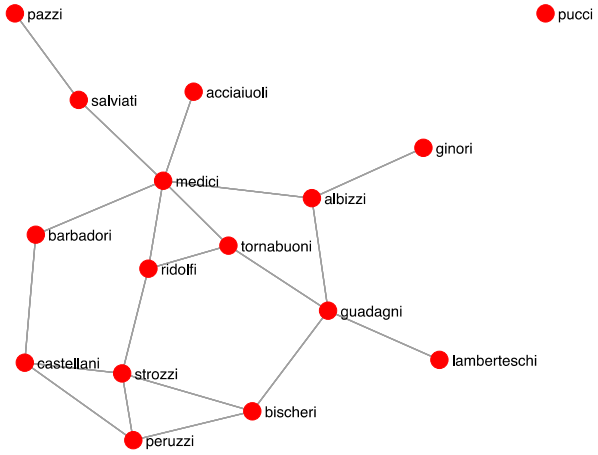


PATHS

```
. nwpath flomarriage, ego(peruzzi) alter(medici)
```

```
  Network: flomarriage
```

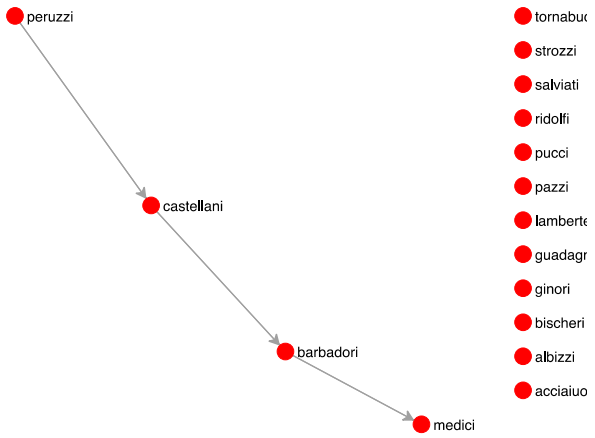
```
    Ego                    : 11 (peruzzi)
    Alter                  : 9 (medici)
    Shortest path length   : 3
    Selected length        : 3
```




```
  Path 1:  peruzzi => castellani => barbadori => medici
  Path 2:  peruzzi => strozzi => ridolfi => medici
```

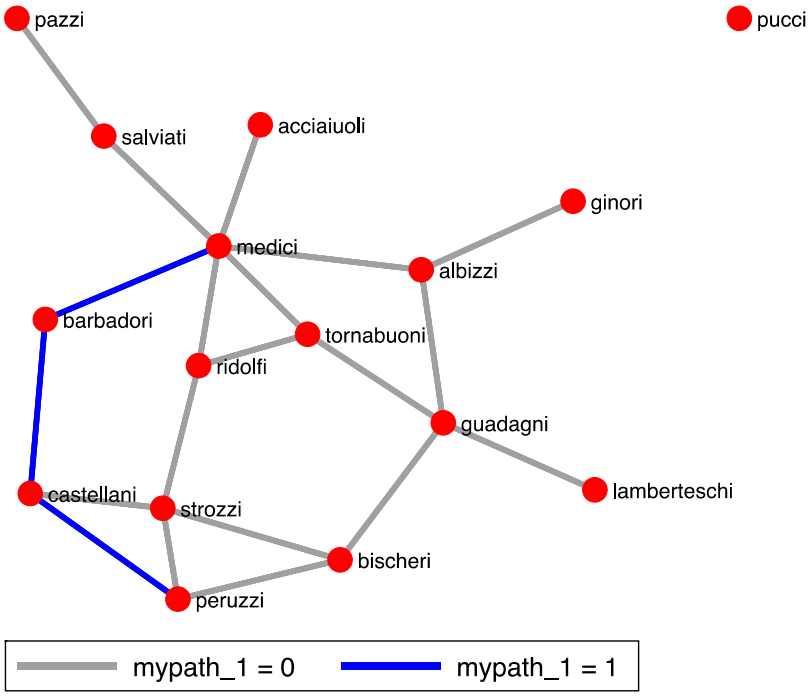
PATHS

```
. nwpath flomarriage, ego(peruzzi) alter(medici) generate(mypath)

  Network: flomarriage

    Ego                    : 11 (peruzzi)
    Alter                  : 9 (medici)
    Shortest path length   : 3
    Selected length        : 3

  Path 1:  peruzzi => castellani => barbadori => medici
  Path 2:  peruzzi => strozzi => ridolfi => medici

. nwset
(4 networks)

      flobusiness
      flomarriage
      mypath_1
      mypath_2
```



PATHS

```
. nwplot flomarriage, lab edgecolor(mypath_1) edgefactor(3)
```



DISTANCE AND PATH

```
nwgeodesic
nwpath
nwplot
```

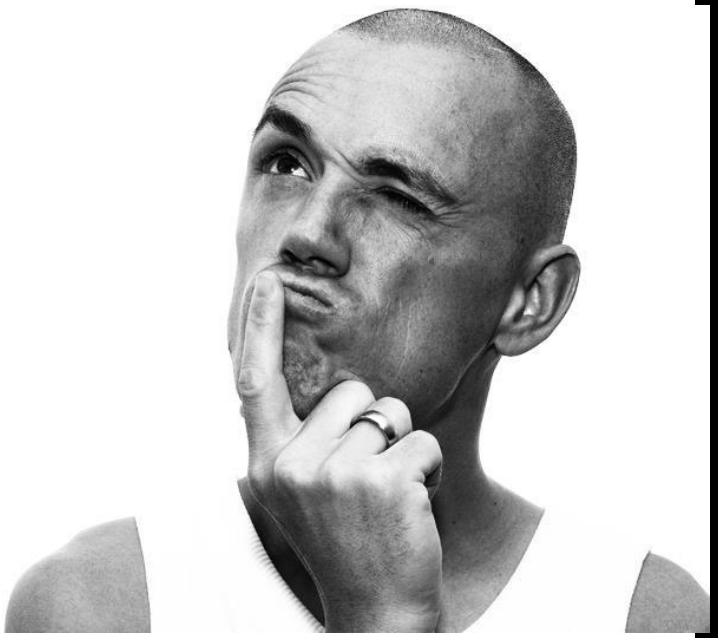
CENTRALITY

CENTRALITY

Well connected actors are in a structurally advantageous position.

- Getting jobs
- Better informed
- Higher status
- …

What is “well-connected?”



DEGREE CENTRALITY

Degree centrality

- Simply the number of incoming/outgoing ties => indegree centrality, outdegree centrality
- How many ties does an individual have?

$$C_{odegree}(i) = \sum_{j=1}^{N} y_{ij} \qquad C_{idegree}(i) = \sum_{j=1}^{N} y_{ji}$$

BETWEENNESS CENTRALITY

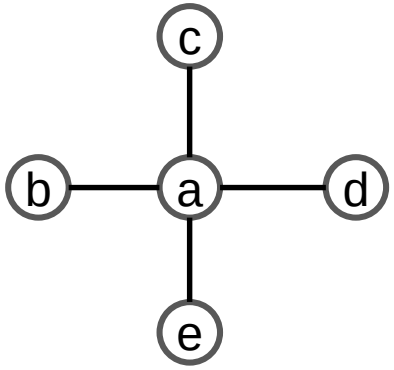
Betweeness centrality

- How many shortest paths go through an individual?

$C_{betweenness}(a) = 6$

$C_{betweenness}(b) = 0$

...

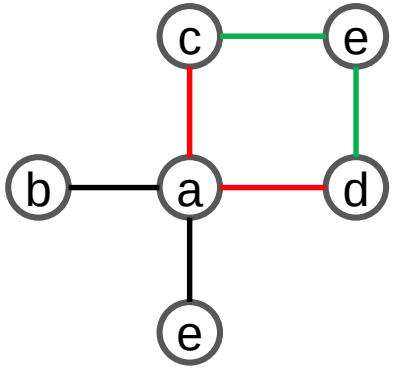


BETWEENNESS CENTRALITY

Betweeness centrality

- How many shortest paths go through an individual?

What about multiple shortest paths? E.g. there are two shortest paths from c to d (one via a and another one via e)



Give each shortest path a weight inverse to how many shortest paths there are between two nodes.

```
. nwbetween flomarriage
```

Network name: **flomarriage**

Betweenness centrality

Variable	Obs	Mean	Std. Dev.	Min	Max
_between	**16**	**19.5**	**24.60111**	**0**	**95**

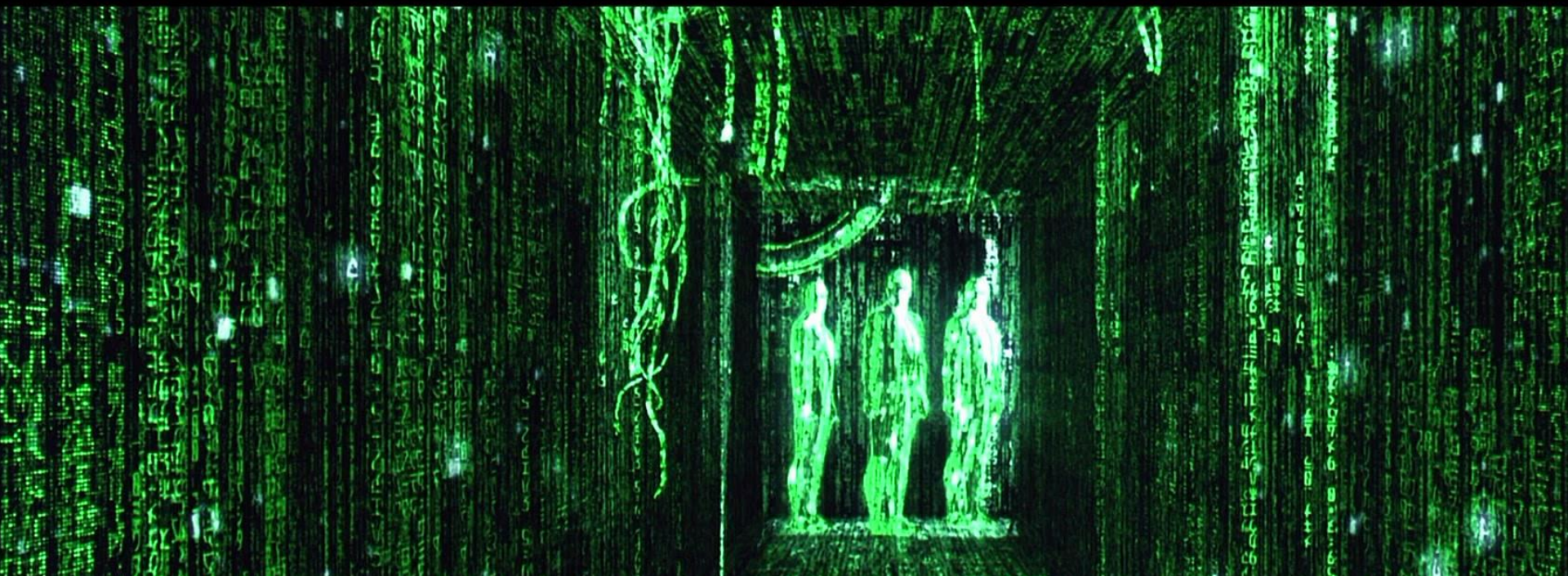
```
. list _nodelab _between
```

	_nodelab	_between
1.	acciaiuoli	0
2.	albizzi	38.66667
3.	barbadori	17
4.	bischeri	19

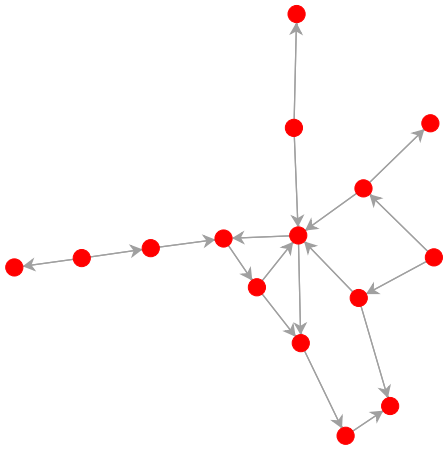
CENTRALITY

```
nwdegree
nwbetween
nwevcent
nwcloseness
nwkatz
```

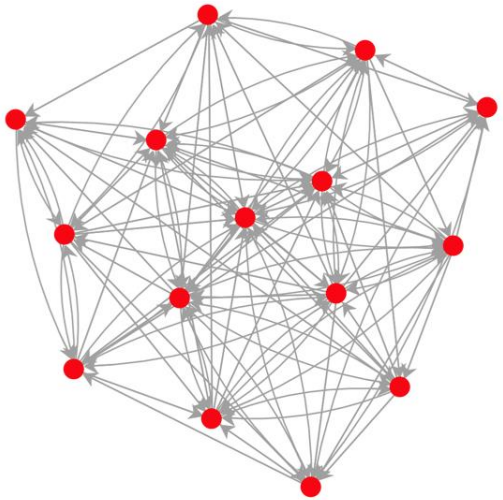
SIMULATION



RANDOM NETWORK



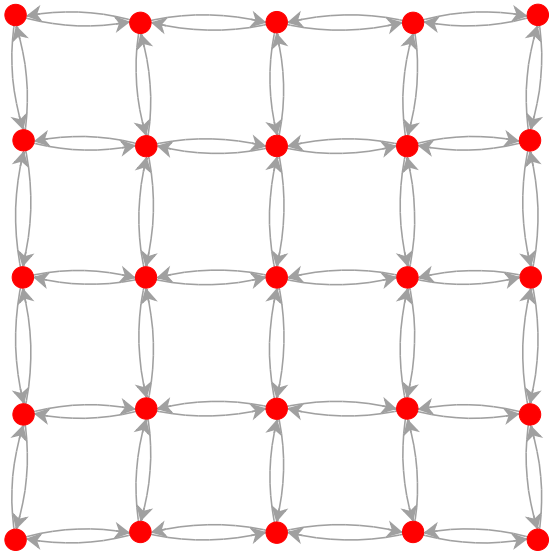
`nwrandom 15, prob(.1)`



`nwrandom 15, prob(.5)`

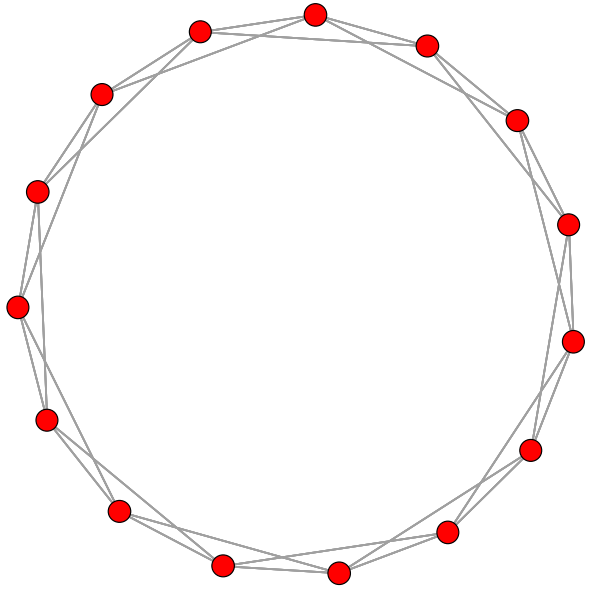
Each tie has the same probability to exist, regardless of any other ties.

LATTICE



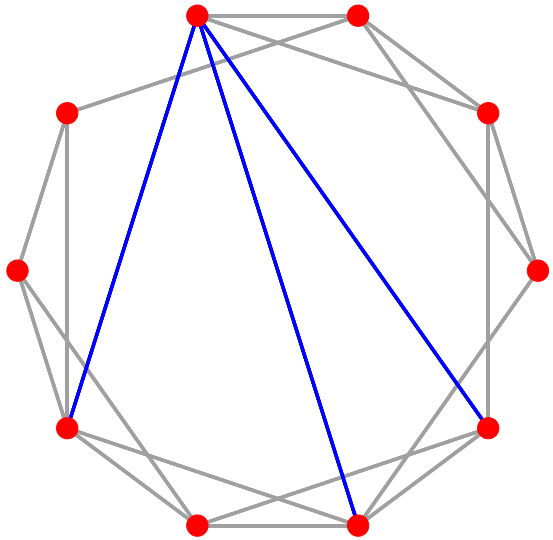
nwlattice 5 5

RING LATTICE



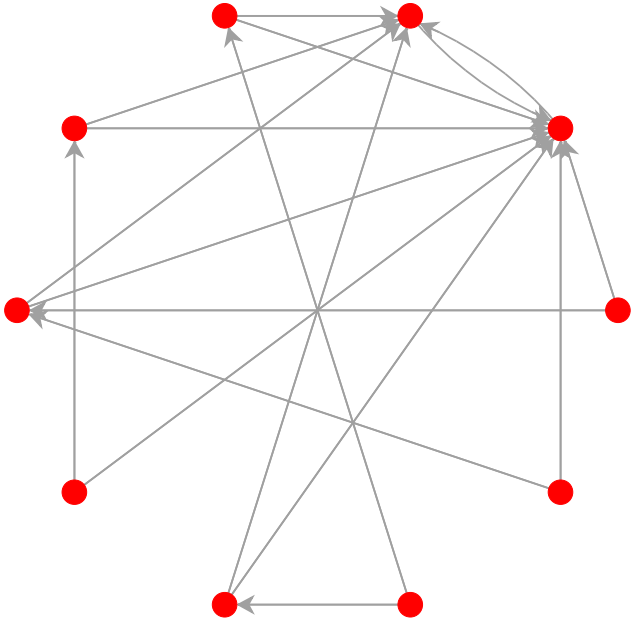
nwring 15, k(2) undirected

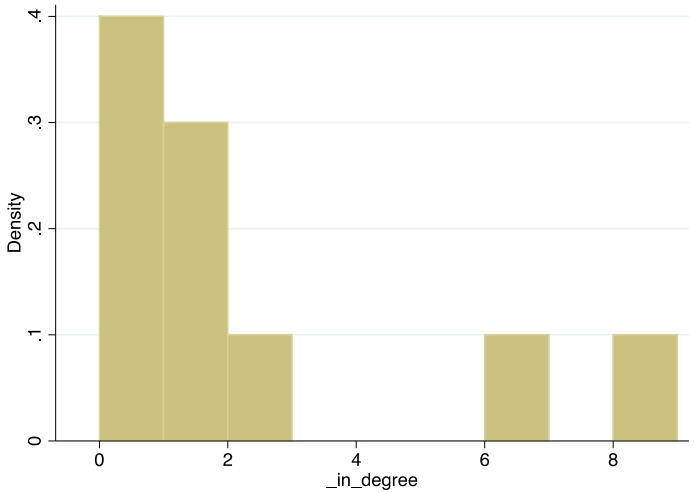
SMALL WORLD NETWORK



nwsmall 10, k(2) shortcuts(3) undirected

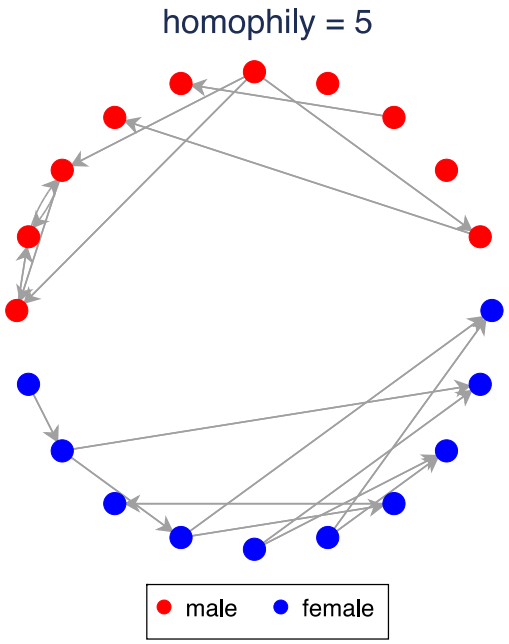
PREFERENTIAL ATTACHMENT NETWORK

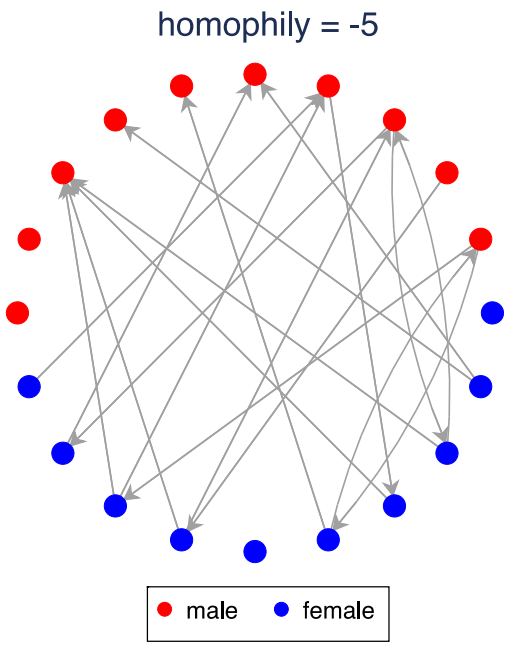





```
nwpref 10, prob(.5)
```

HOMOPHILY NETWORK






```
nwhomophily gender, density(0.05) homophily(5)
```

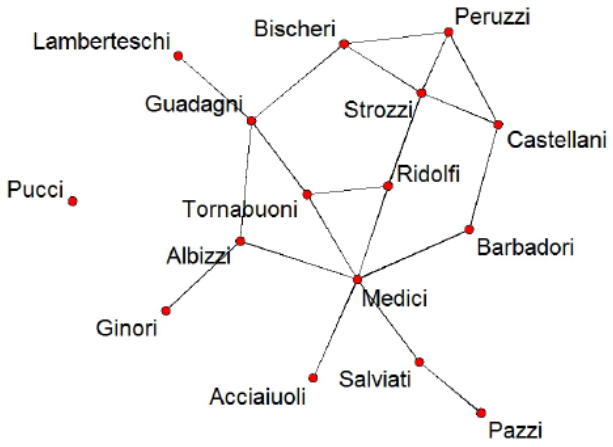
SIMULATION

```
nwrandom nwlattice
nwsmall  nwpref
nwring
nwhomophily
nwdyadprob
```

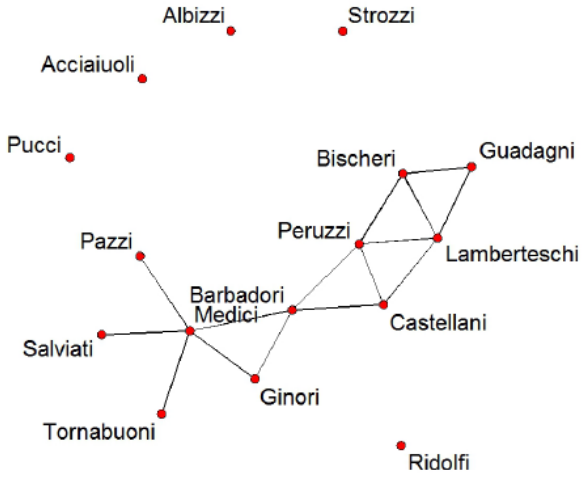
HYPOTHESIS TESTING

Is a particular network pattern more (or less) prominent than expected?

Question: Is there more or less correlation between these two networks than expected?



Florentine Marriage Network



Florentine Business Ties

$$corr_{obs} = 0.372$$

1 **Test-statistic**

$$corr_{obs} = 0.372$$

2 **Distribution of test-statistic under null hypothesis**

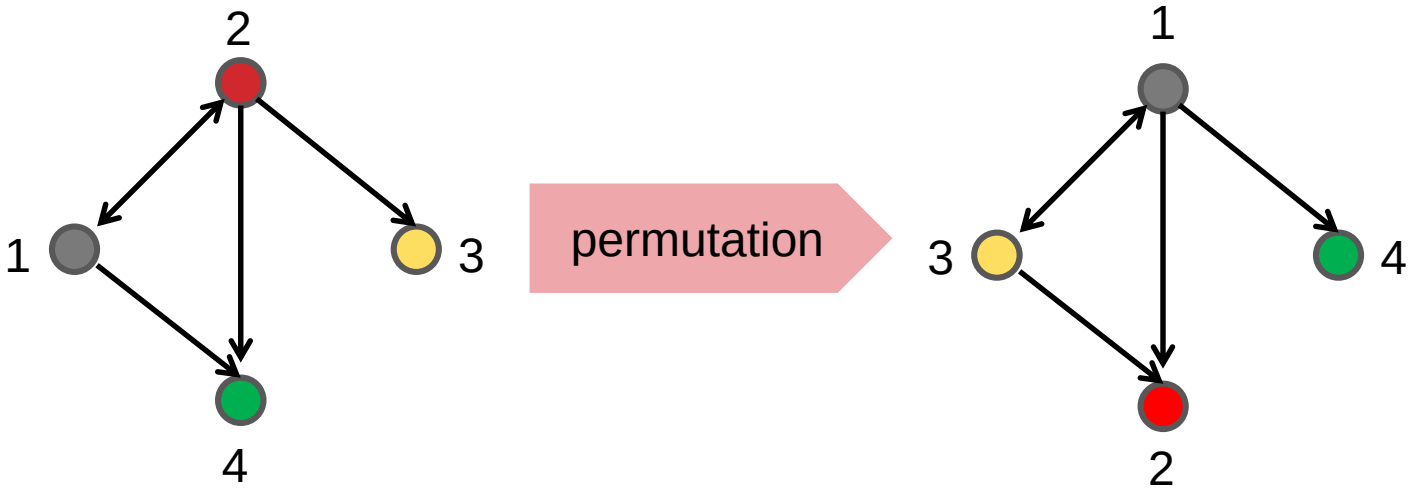
$$corr_{random} = ??$$

QUADRATIC ASSIGNMENT PROCEDURE

- Scramble the network by permuting the actors (randomly re-label the nodes), i.e. the actual network does not change, however, the position each node takes does.
- Re-calculate the test-static on the permuted networks and compare it with test-statistic on the unscrambled network.

Network structure is 'controlled' for. Keeps dependencies.

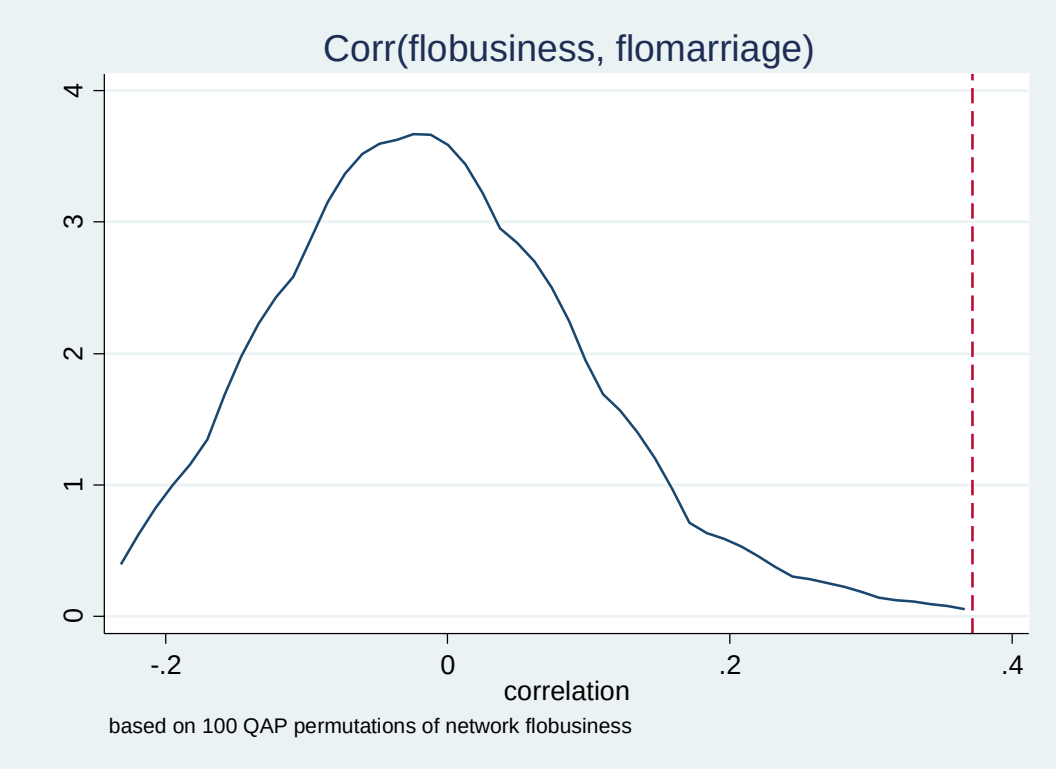
PERMUTATION TEST



-	1	0	1
1	-	1	1
0	0	-	0
0	0	0	-

-	1	1	1
0	-	0	0
1	1	-	0
0	0	0	-

GRAPH CORRELATION

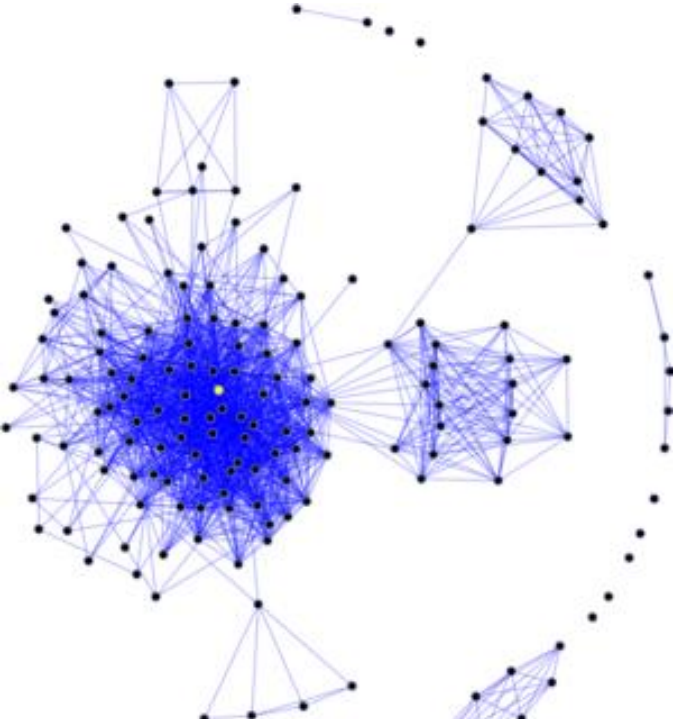



```
nwcorrelate flobusiness flomarriage, permutations(100)
```

HYPOTHESIS TESTING

```
nwcorrelate
nwpermute
nwqap
nwergm
```

SOCIAL NETWORK ANALYSIS USING STATA



10 June 2016
German Stata User Meeting
GESIS, Cologne

Thomas Grund
University College Dublin
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EXPONENTIAL RANDOM GRAPH MODELS

ERGM

Y_{ij}^{c} = all dyads other than Y_{ij}

Amount by which the feature $s_k(y)$ changes when Y_{ij} is toggled from 0 to 1.

$$\text{logit}\left[P\left(Y_{ij}=1 \middle| n\ actors, Y_{ij}^{c}\right)\right] = \sum_{k=1}^{K} \theta_k \delta s_k(\boldsymbol{y})$$

Probability that there is a tie from *i* to *j*.

Given, *n* actors AND the rest of the network, excluding the dyad in question!

ERGM

$\boldsymbol{Y = random\ variable}$, a randomly selected network from the pool of all potential networks

$\boldsymbol{y = observed\ variable}$, here observed network

$\boldsymbol{\theta = parameters}$, to be estimated

$$P(\boldsymbol{Y} = \boldsymbol{y}|\theta) = \frac{e^{\left(\theta^T s(\boldsymbol{y})\right)}}{c(\theta)}$$

A score given to our network **y** using some parameters θ and the network features **s** of **y**

Probability to draw 'our' observed network **y** from all potential networks

A score given to all other networks we could have observed

ERGM: INTEPRETATION

ERGM's ultimately give you an estimate for various parameters θ_k, which mean…

If a potential tie $Y_{ij} = 1$ (between *i* and *j*) would change the network statistic s_k by one unit.

This changes the log-odds for the tie Y_{ij} to actually exist by θ_k.

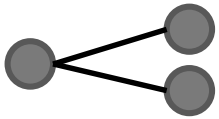
EXAMPLE

Consider an ERGM for an undirected network with parameters for these three statistics:

1) number of edges

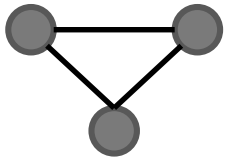
$$s_{edges}(y) = \sum y_{ij}$$

2) number of 2-stars



$$s_{2stars}(y) = \sum y_{ij}\, y_{ik}$$

3) number of triangles



$$s_{triangles}(y) = \sum y_{ij}\, y_{jk} y_{ik}$$

Then the 3-parameter ERG distribution function is:

$$P(\boldsymbol{Y} = \boldsymbol{y}|\theta) \propto e^{\left(\theta_{edges}s_{edges}(y) + \theta_{2stars}s_{2stars}(y) + \theta_{triangles}s_{triangles}(y)\right)}$$

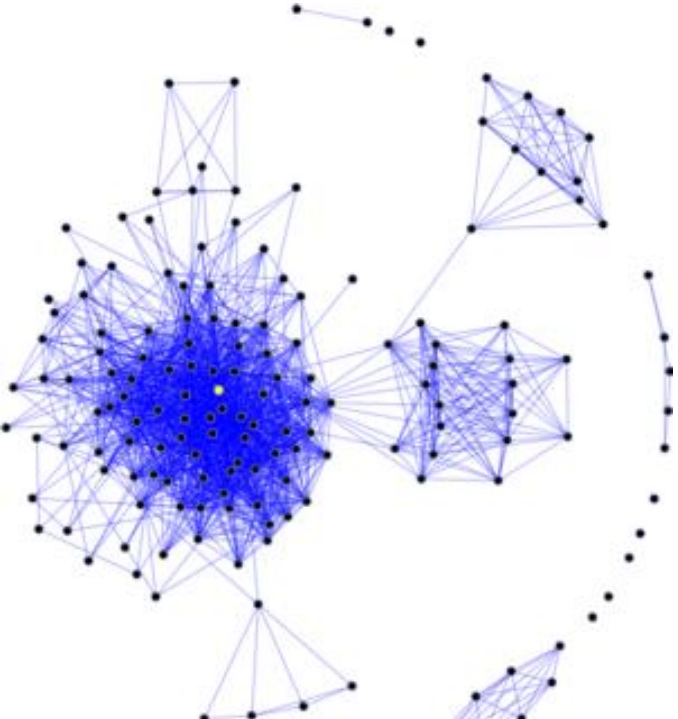
```
. nwergm gang, formula(edges + nodematch("Birthplace") + gwesp(0.5, fixed=T))

Exponential random graph analysis

 Number of vertices    =  54
 Number of edges/arcs  =  133
 Directed              =  FALSE
 Estimation            =  MLE
 Iterations            =  3 out of 20
 MCMC sample size      =  4096
 AIC                   =  741.4
 BIC                   =  757.2
```

network	Observed	Coef.	Std.Err.	MCMC%	P>|z|
edges	133	-4.585	.235	0	0
nodematch.Birthplace	63	.518	.122	0	0
gwesp.fixed.0.5	165.121	1.434	.151	0	0

SOCIAL NETWORK ANALYSIS USING STATA



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German Stata User Meeting
GESIS, Cologne

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