

Jack Reilly

CRASH COURSE

Social Networks: Description and Visualization

Agenda

Why do we study social networks?

What are social networks?

How do we visualize networks in R?

Where can I go for more?

Learning outcomes

- When we're done, you should be able to:
 - **Describe social networks** using formal language
 - **Construct network data** for analysis and visualization
 - Use the **iGraph** library in R to draw and manipulate basic networks
 - Know where to go for other options

Part One

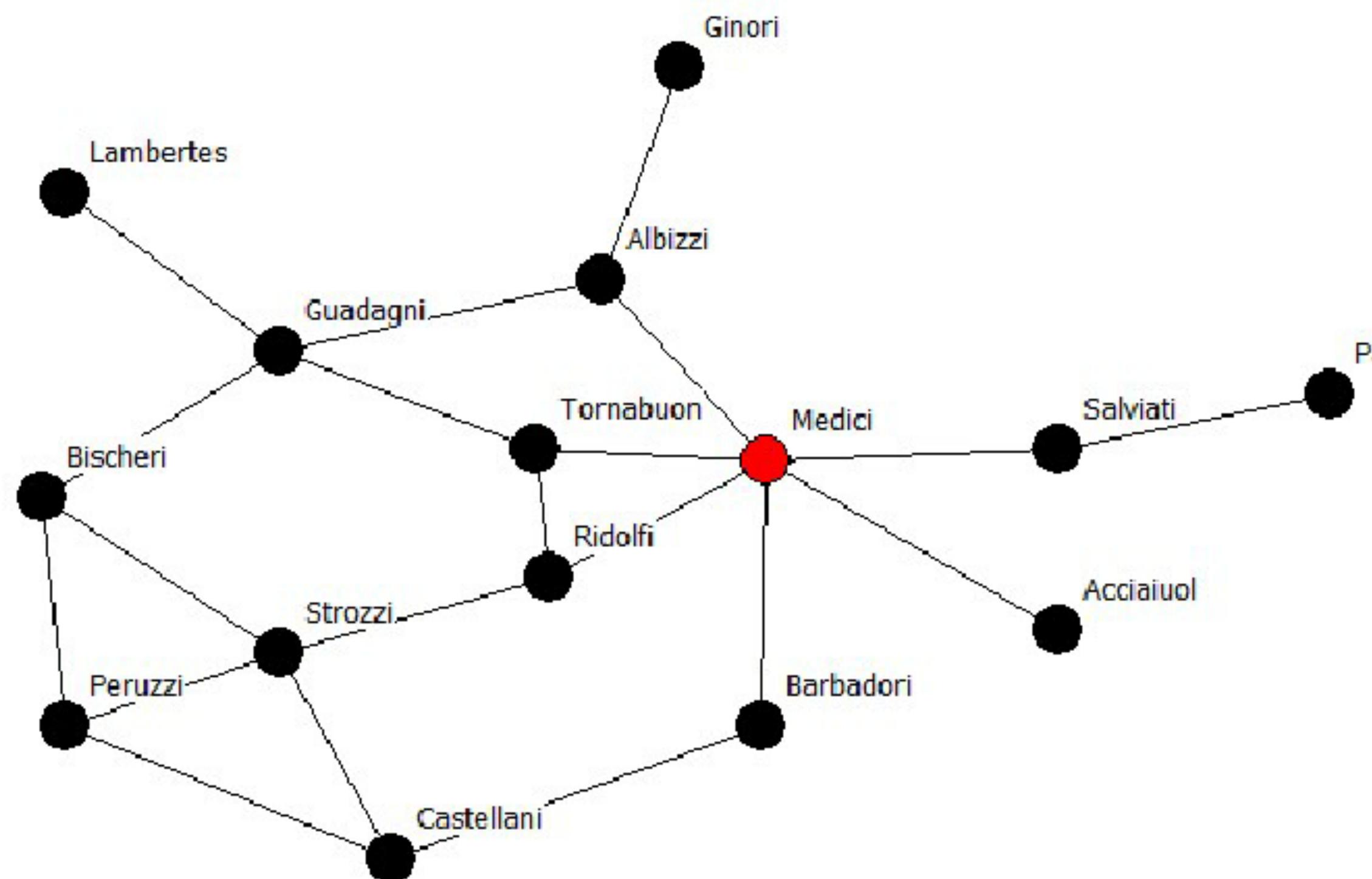
Why do we study social networks?

#1

Social network connections can tell us
valuable things about how individual
actors behave and perform

Networks in politics and history

- Why did the Medici emerge to be so powerful? (Padgett & Ansell, 1993)



Networks in politics and history

- Why was medieval Constantinople so rich, even after and as the Roman empire crumbled?



*There are characteristics of the **city** and the city's **network***

Networks in politics and history

- Why was medieval Constantinople so rich, even after and as the Roman empire crumbled?



Sources: wikipedia (https://en.wikipedia.org/wiki/Constantinople#/media/File:Byzantine_Constantinople-en.png);

#2

Social networks help illuminate complex
collective dynamics of human behavior
that emerge and cascade unexpectedly





Bird behavior or human behavior?

- Collective network dynamics yield complex human behavior, as well
 - Why do riots start in some towns but not others? (Granovetter 1978)
 - *Because someone needs to throw the first stone*
 - Why do some musical artists become popular and others done? (Salganik, Dodds, and Watts 2006)
 - *Talent, but also network popularity effects*
 - Why do some news stories “go viral” and others don’t? (Boydston, Walgrave, and Hardy 2014; Nahon & Hemsly 2013)

#3

The macro structure of social networks can tell us important things about large scale changes and continuity in society

A contemporary story: Polarization

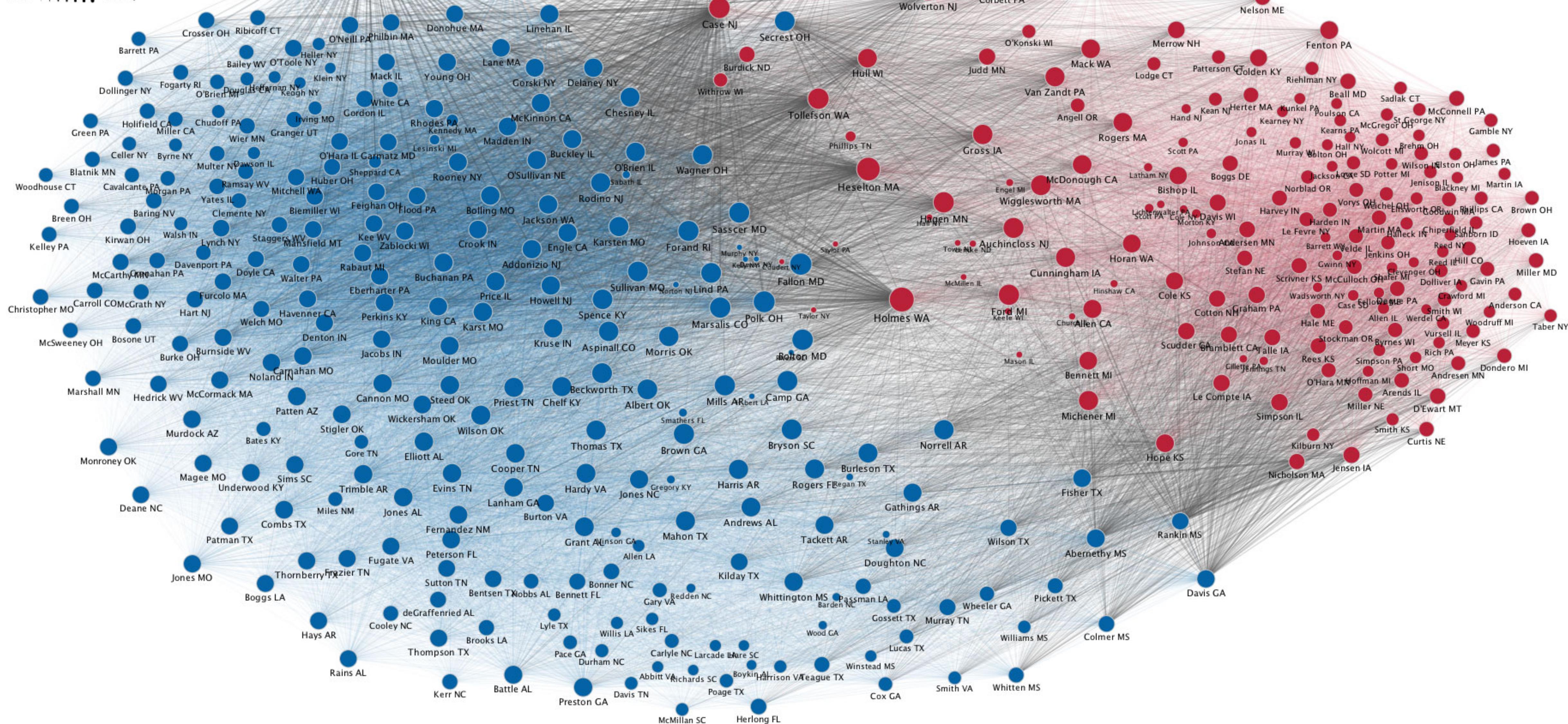
- Specifically, polarization in the United States House of Representatives
 - Based on roll call data, we can see how often different pairs (or “dyads”) of legislators agree
 - For all pairs of legislators:
 - Votes in common (both “aye” or both “nay”) increased the agreement score
 - Votes not in common (one “aye” and one “nay”) decreased the agreement score
 - What does it look like? And does it change?

Year: 1949

D-D D-R R-R

Degree 1 o 400

Few ||| Many

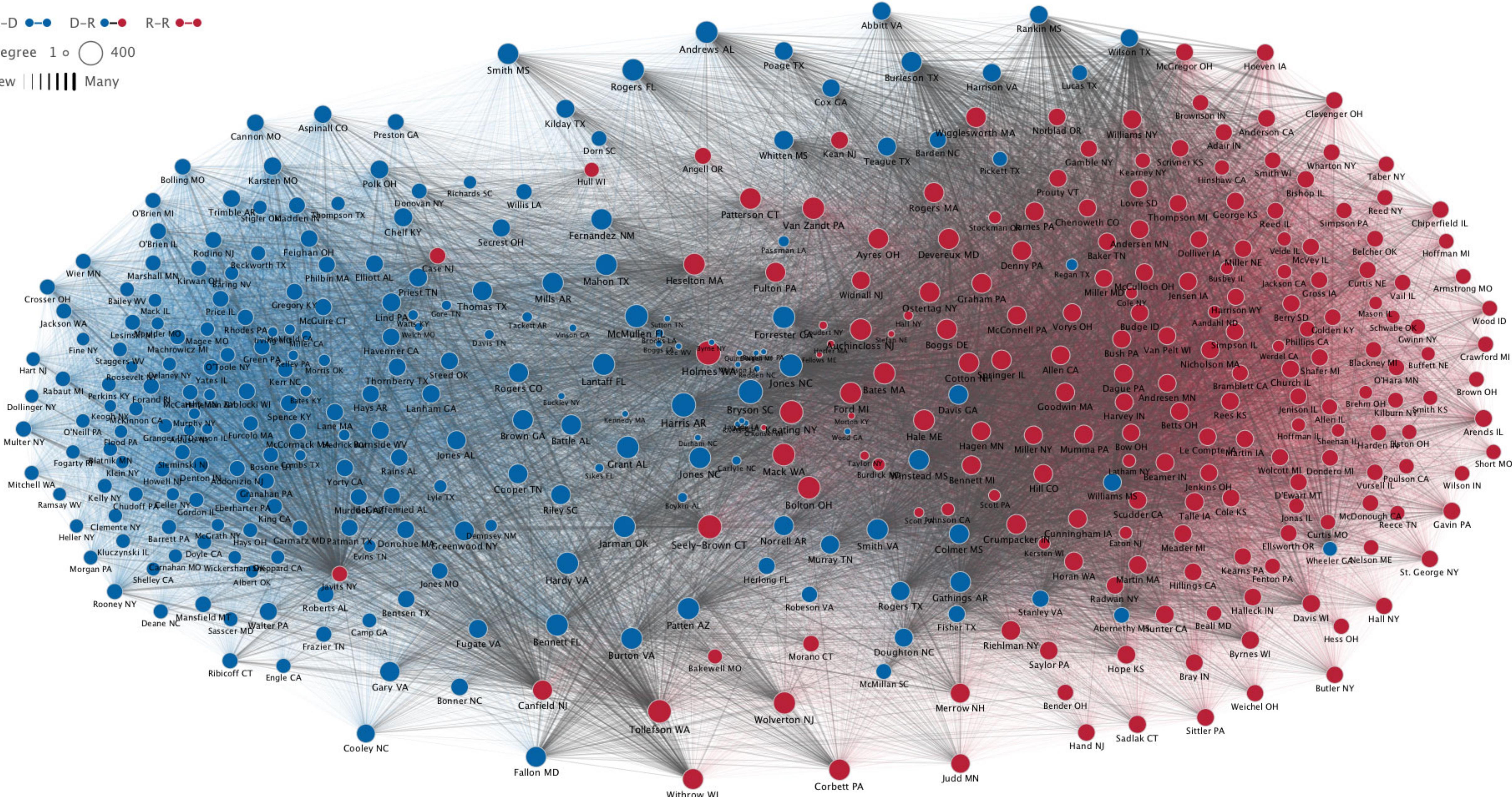


Year: 1951

D-D D-R R-R

Degree 1 o 400

Few ||| Many

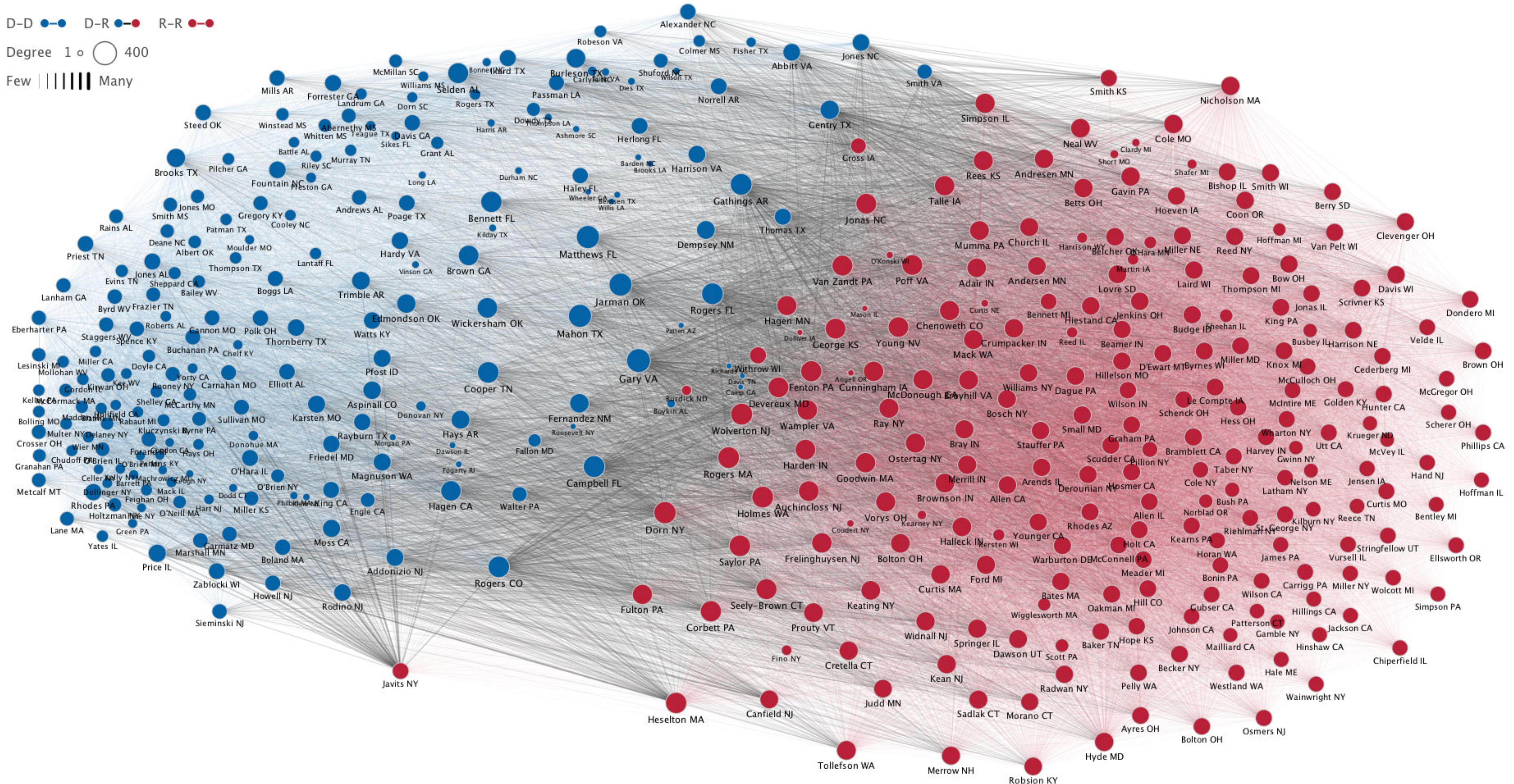


Year: 1953

D-D •— D-R •— R-R •—

Degree 1 o 400

Few |||| Many

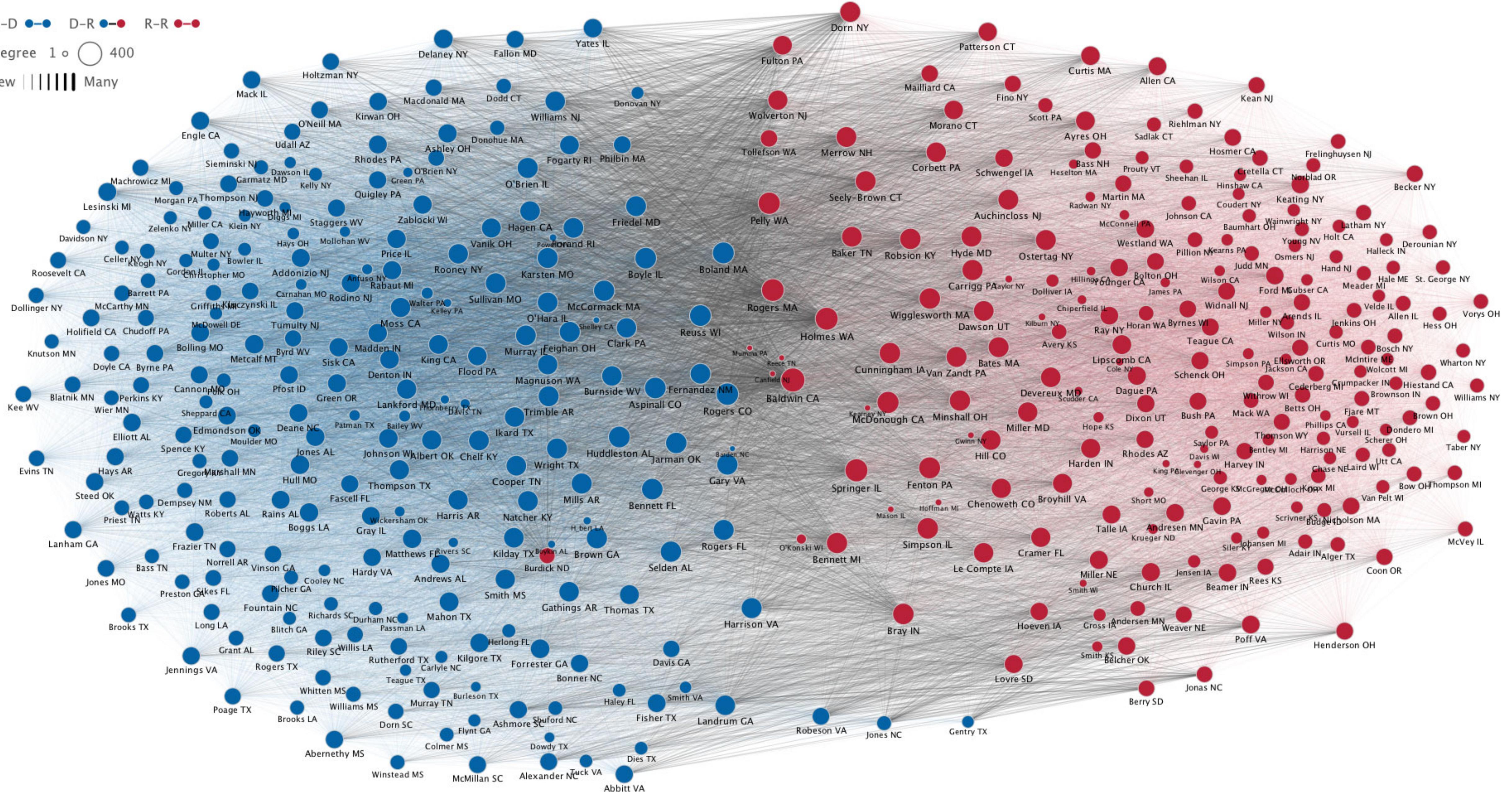


Year: 1955

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Degree 1° 400

Few | | | | | Many

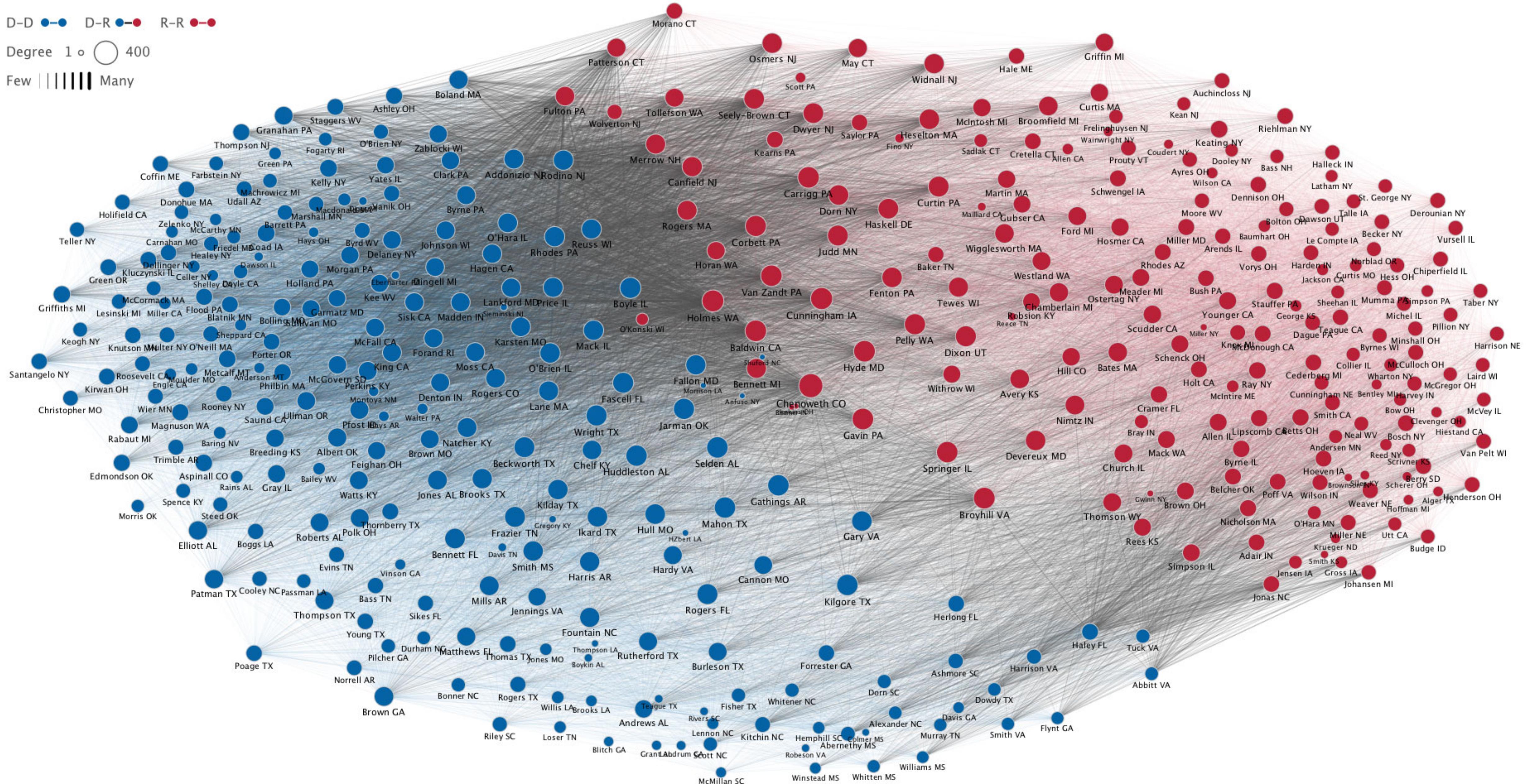


Year: 1957

D-D D-R R-R

Degree 1 o 400

Few ||| Many

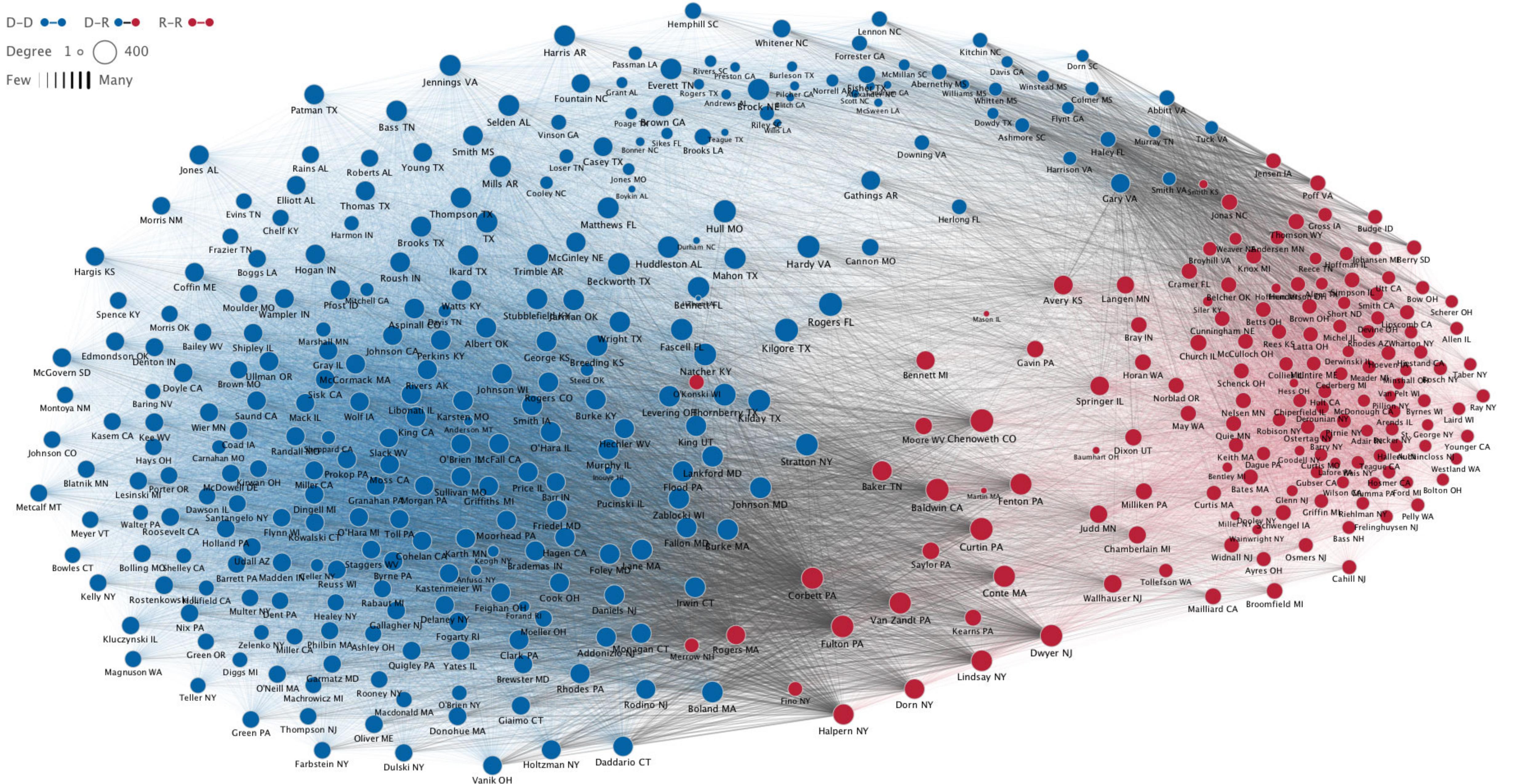


Year: 1959

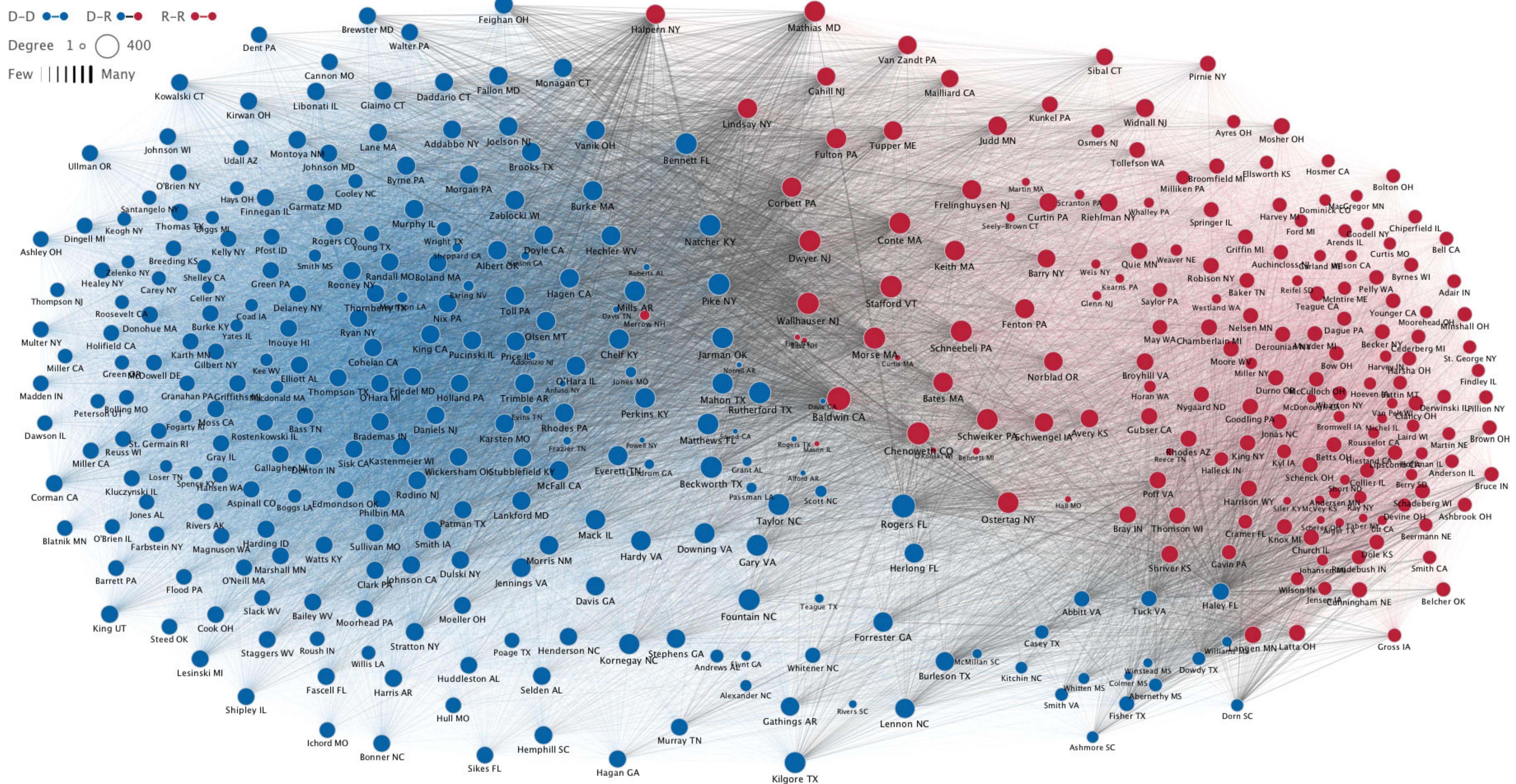
D-D D-R R-R

Degree 1 o 400

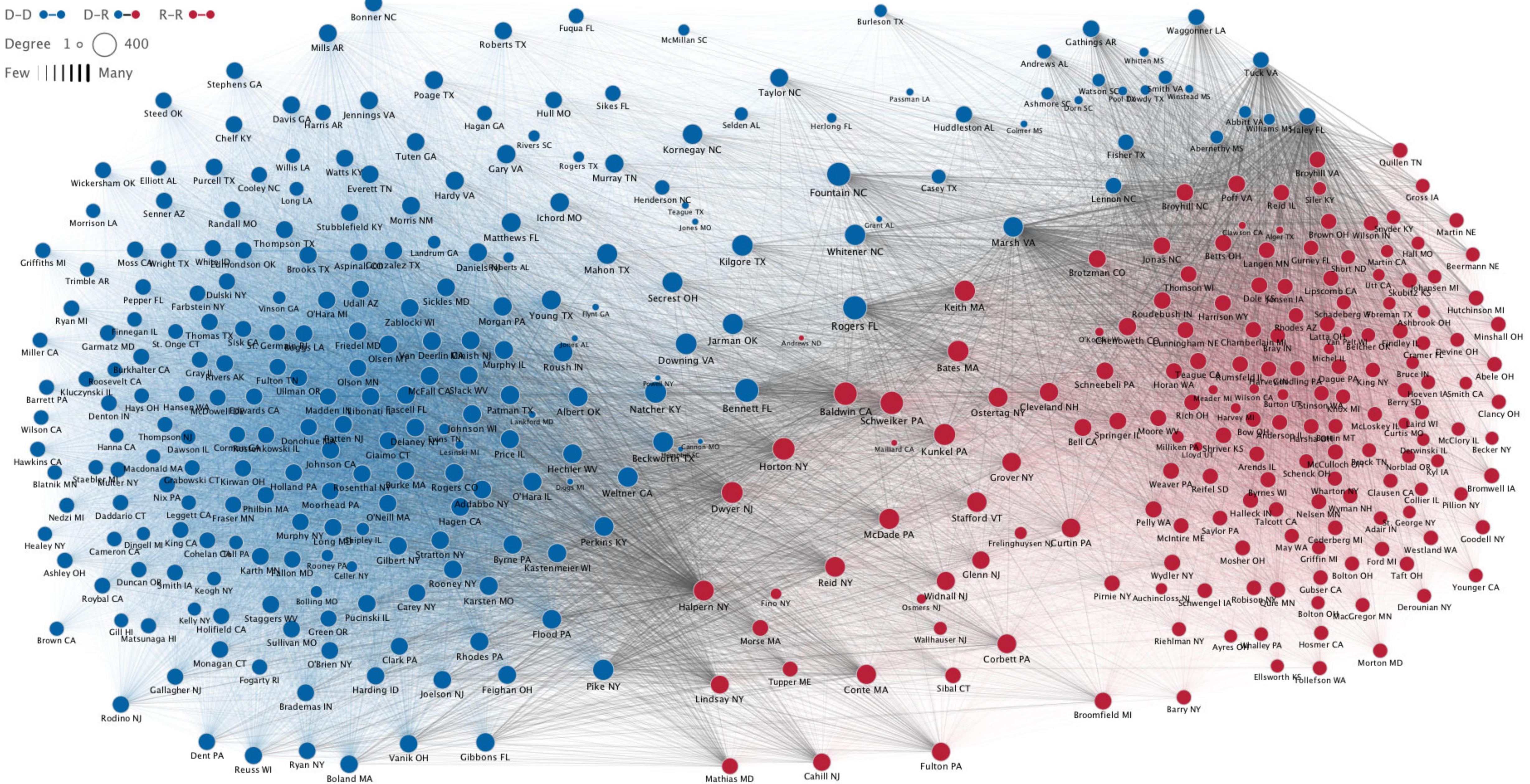
Few ||| Many



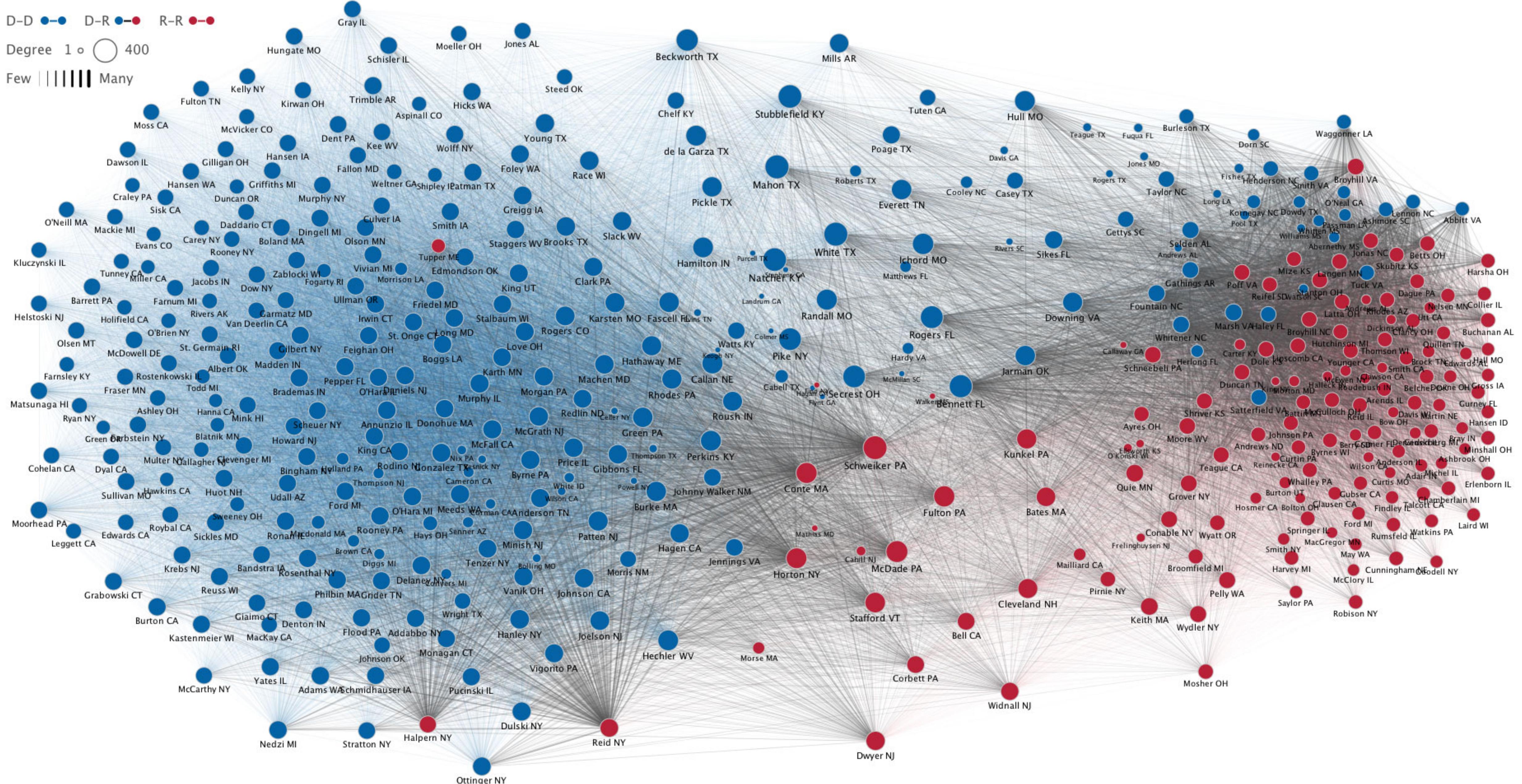
Year: 1961



Year: 1963



Year: 1965

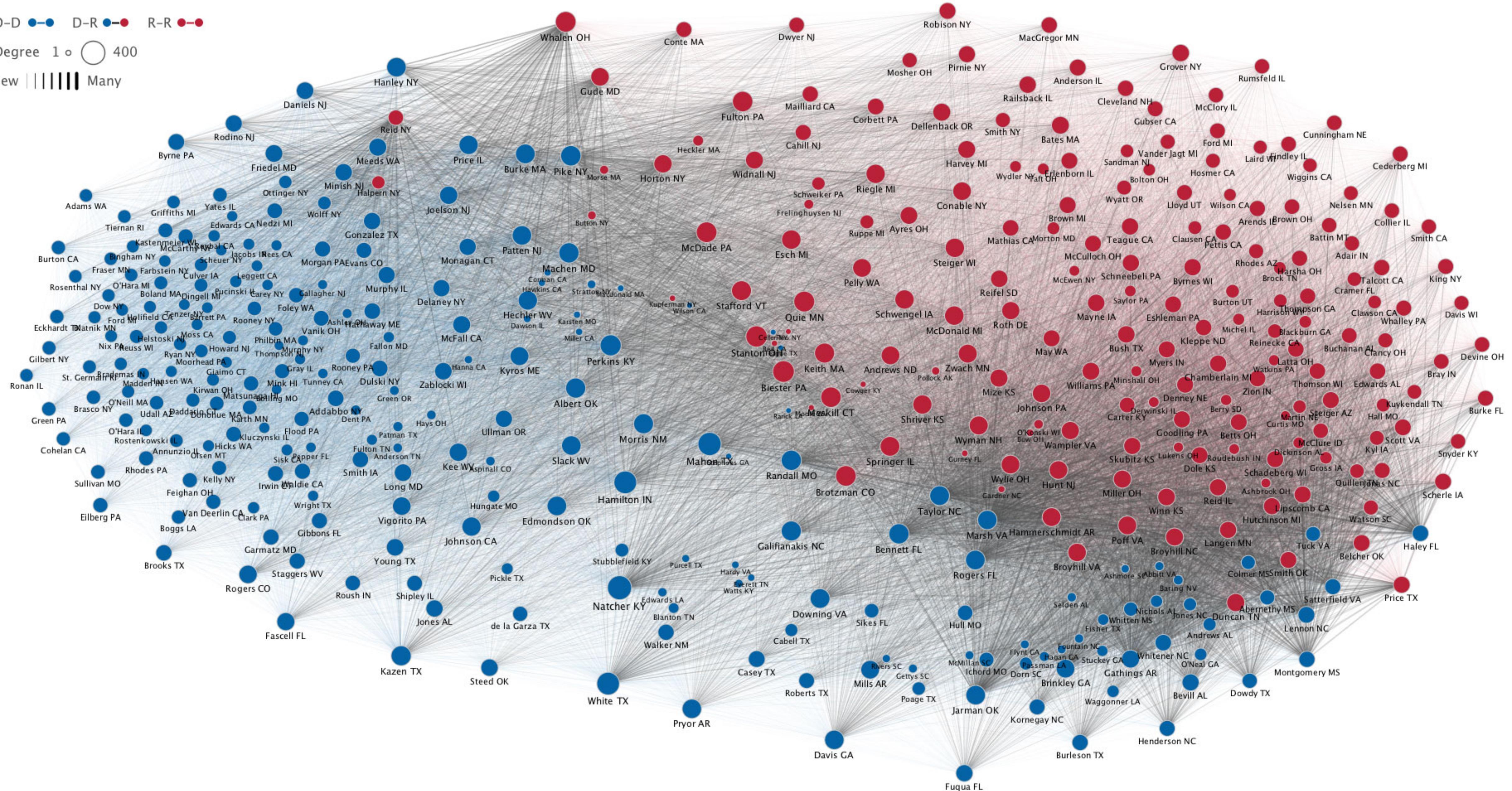


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Degree 1 o 400

Few ||| Many

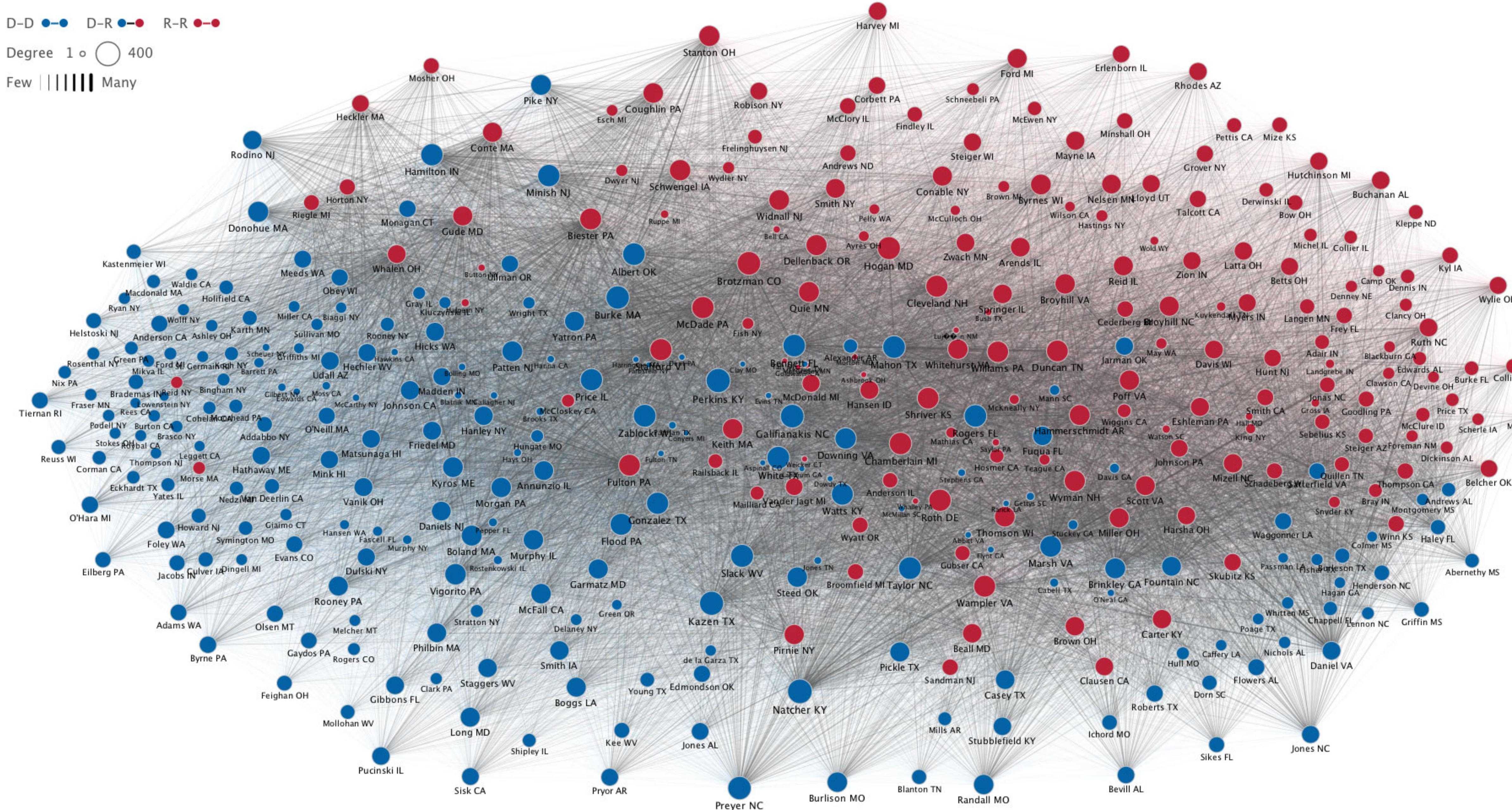


Year: 1969

D-D D-R R-R

Degree 1 o 400

Few ||| Many

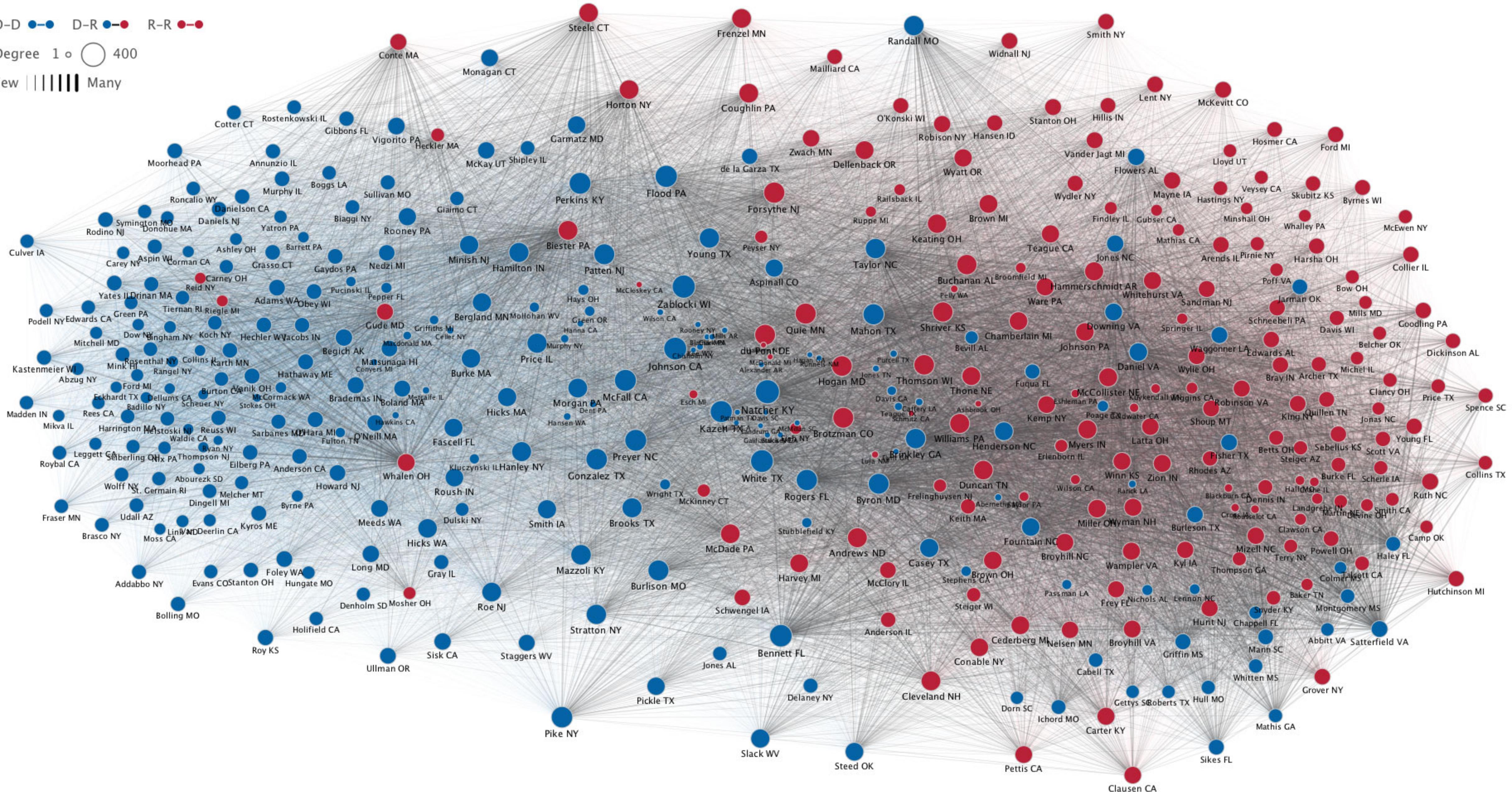


Year: 1971

D-D D-R R-R

Degree 1 o 400

Few ||| Many

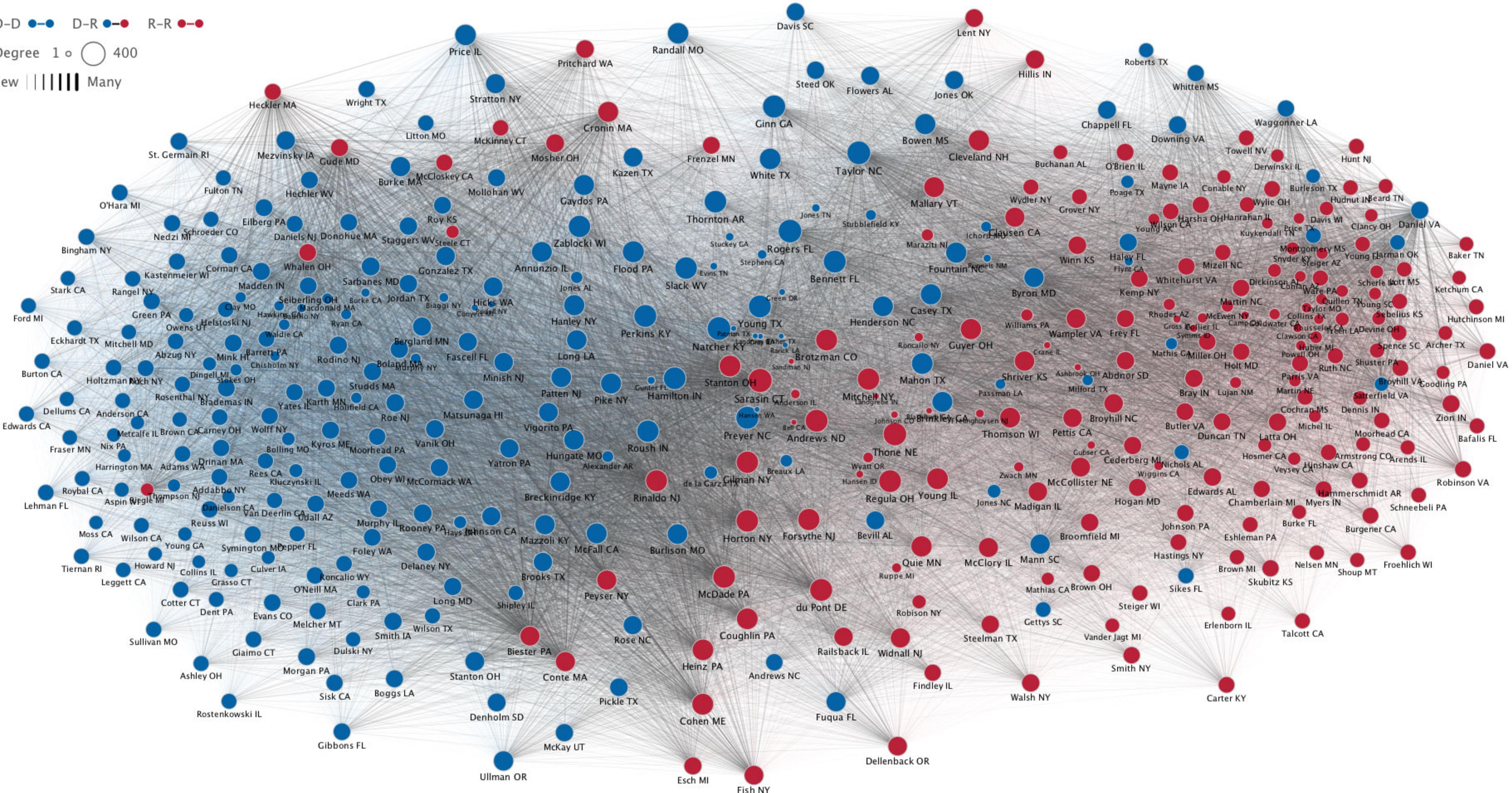


Year: 1973

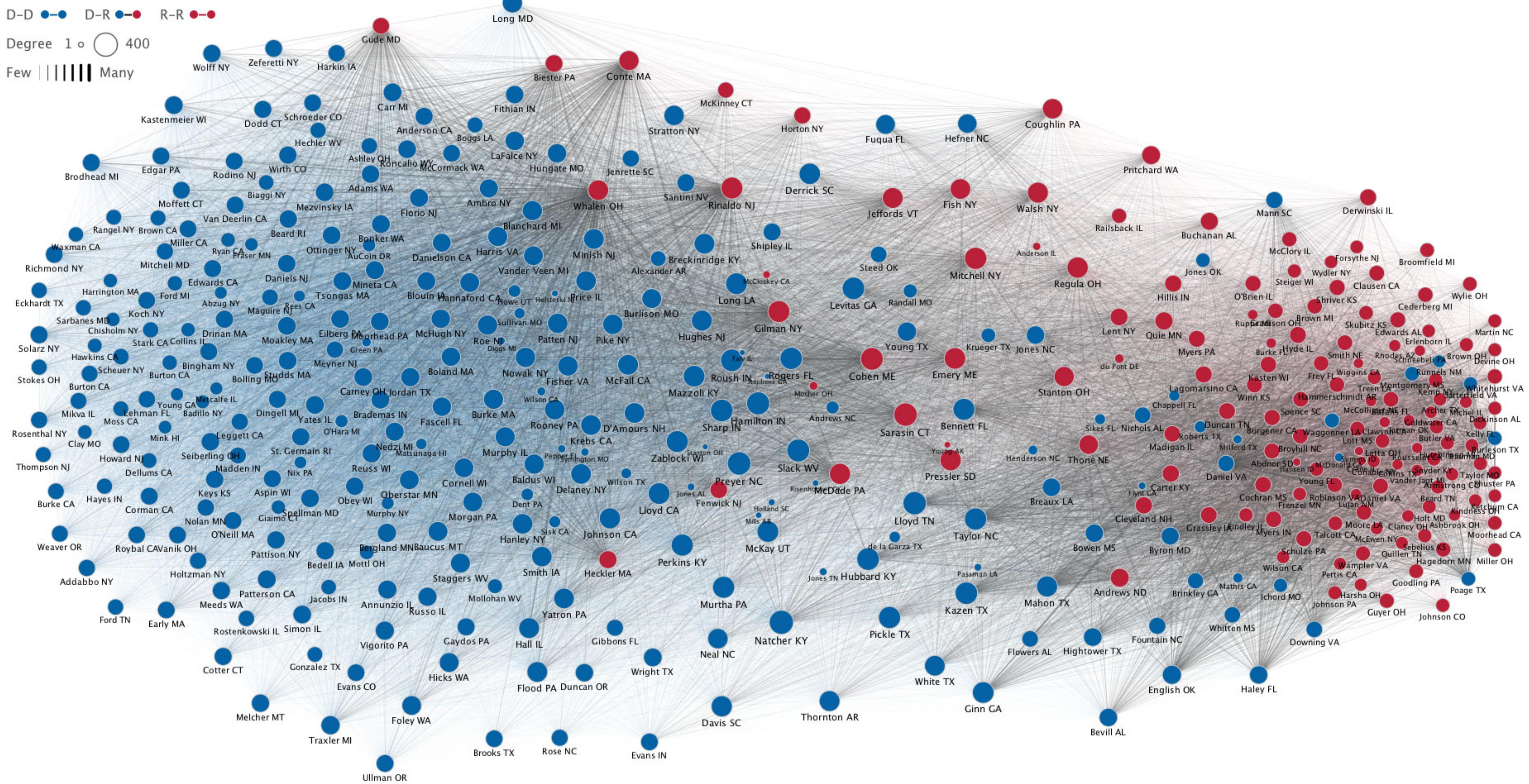
D-D D-R R-R

Degree 1° 400

Few | | | | | Many



Year: 1975

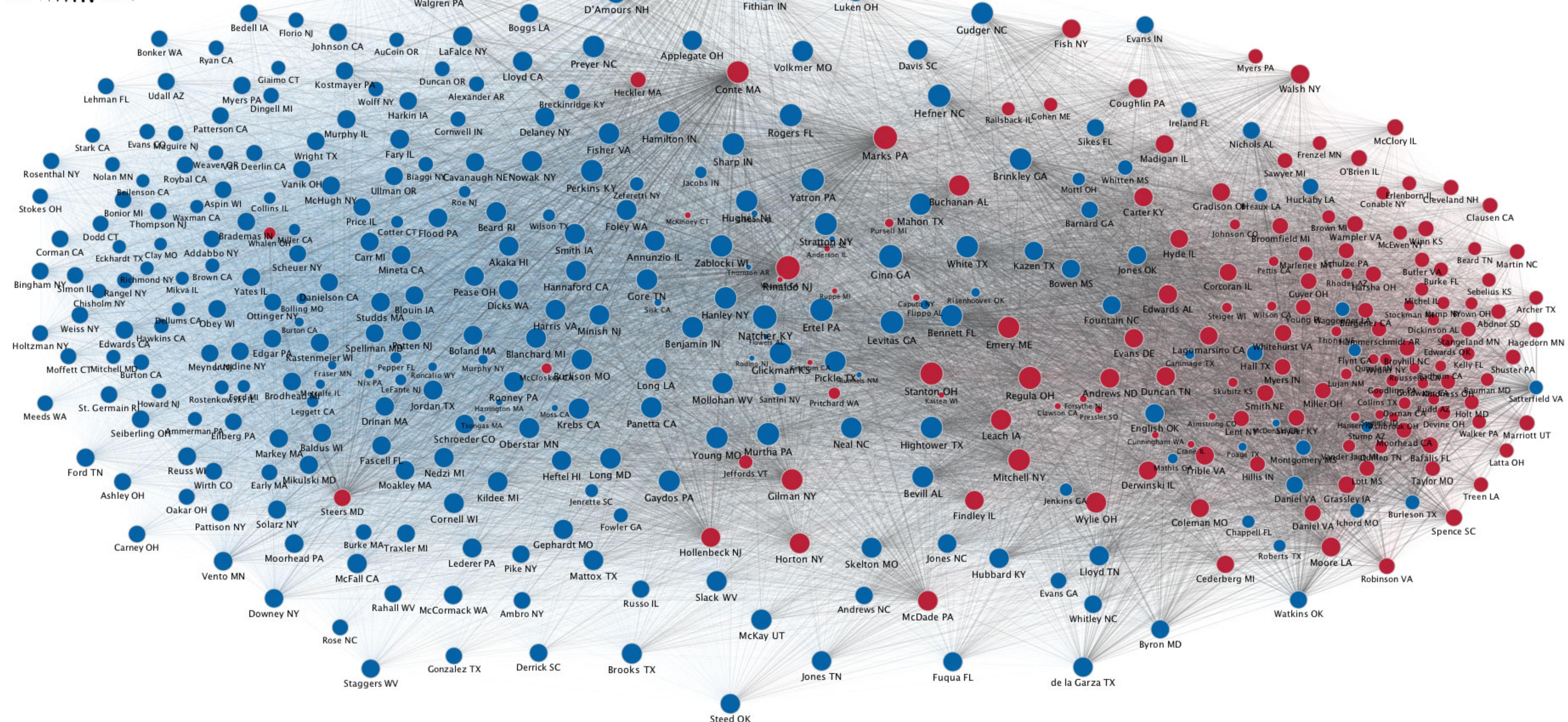


Year: 1977

D-D •—• D-R •—• R-R •—•

Degree 1 o 400

Few ||| Many

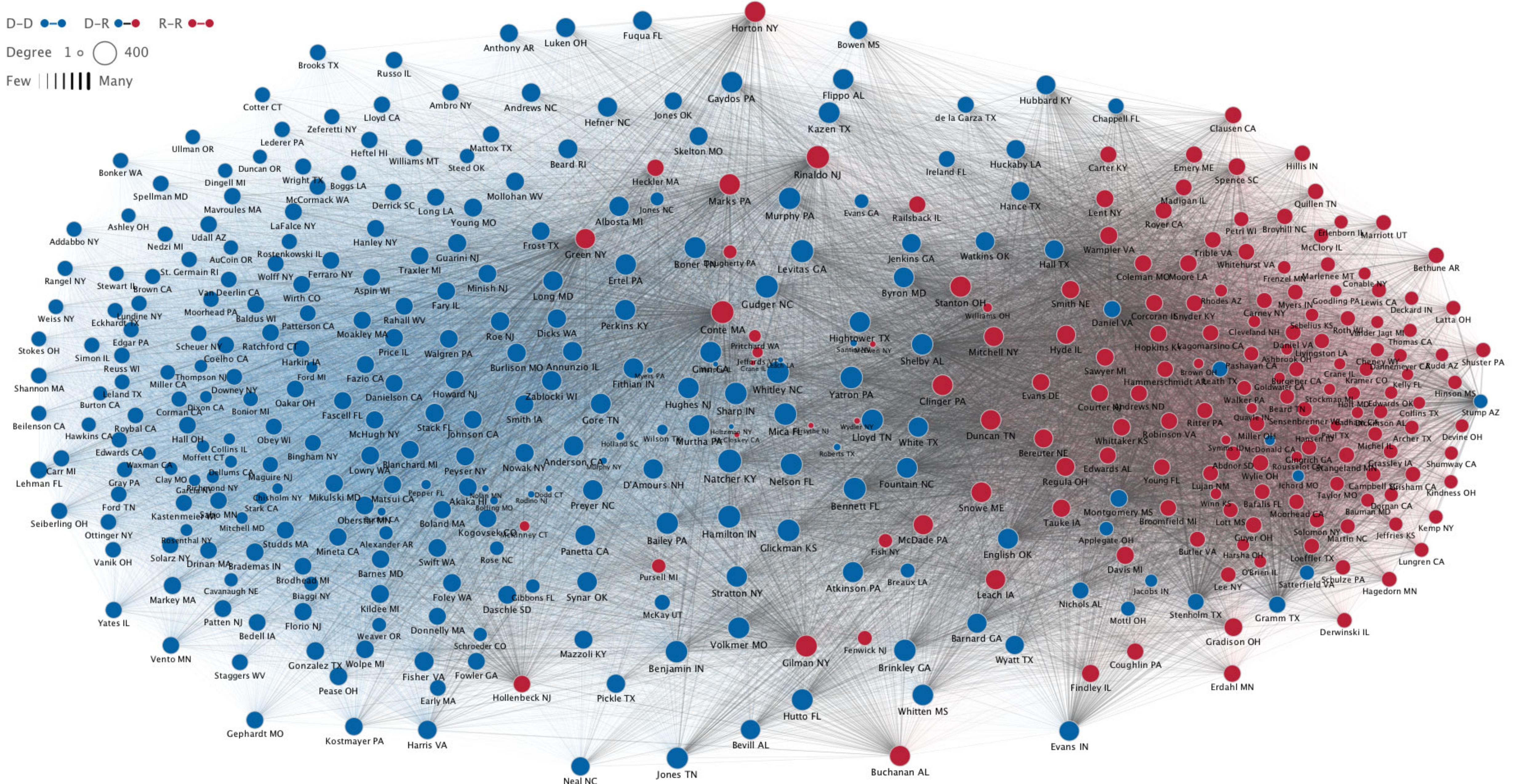


Year: 1979

D-D D-R R-R

Degree 1 ° 400

Few | | | | | Many

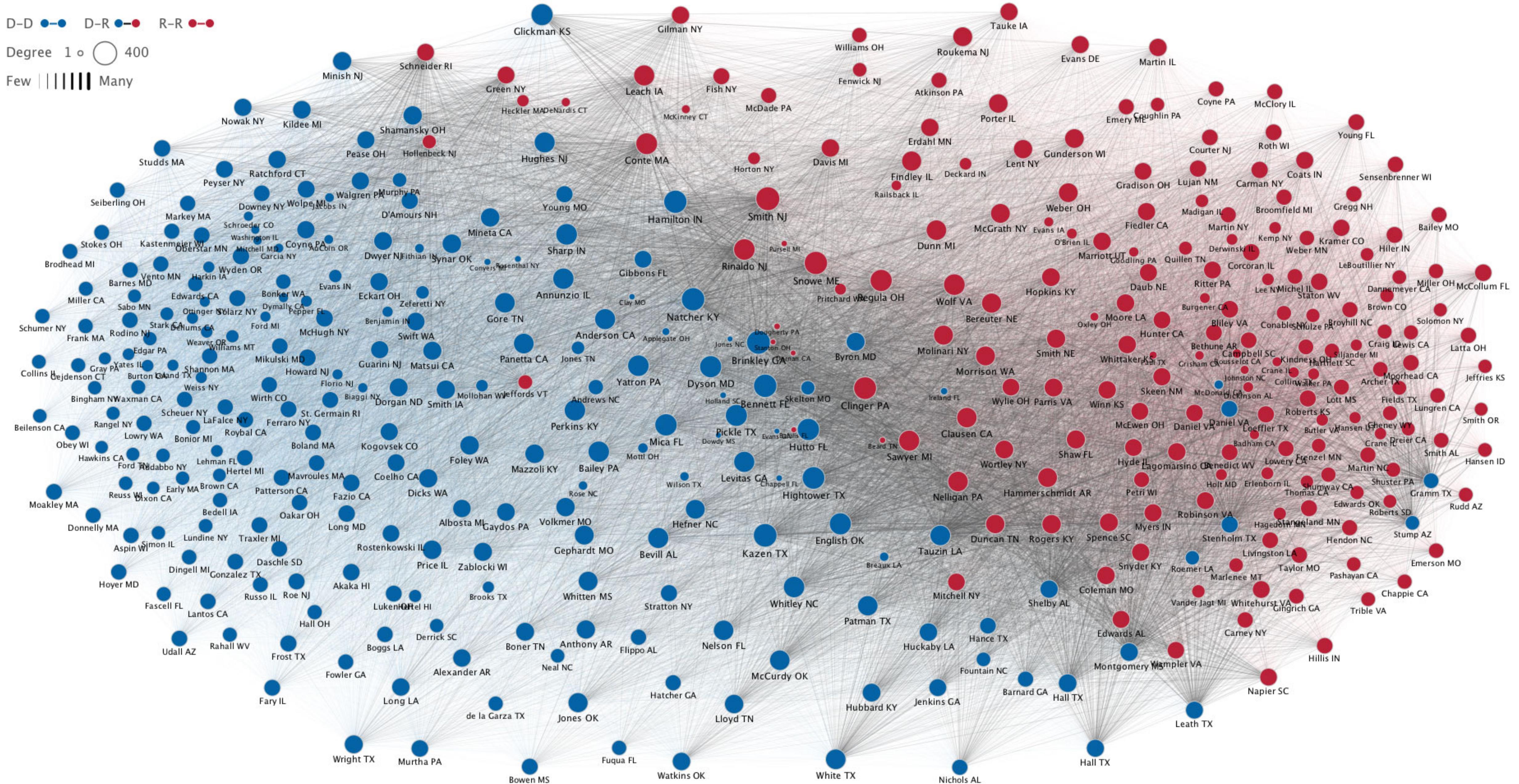


Year: 1981

D-D D-R R-R

Degree 1° 400

Few | | | | Many

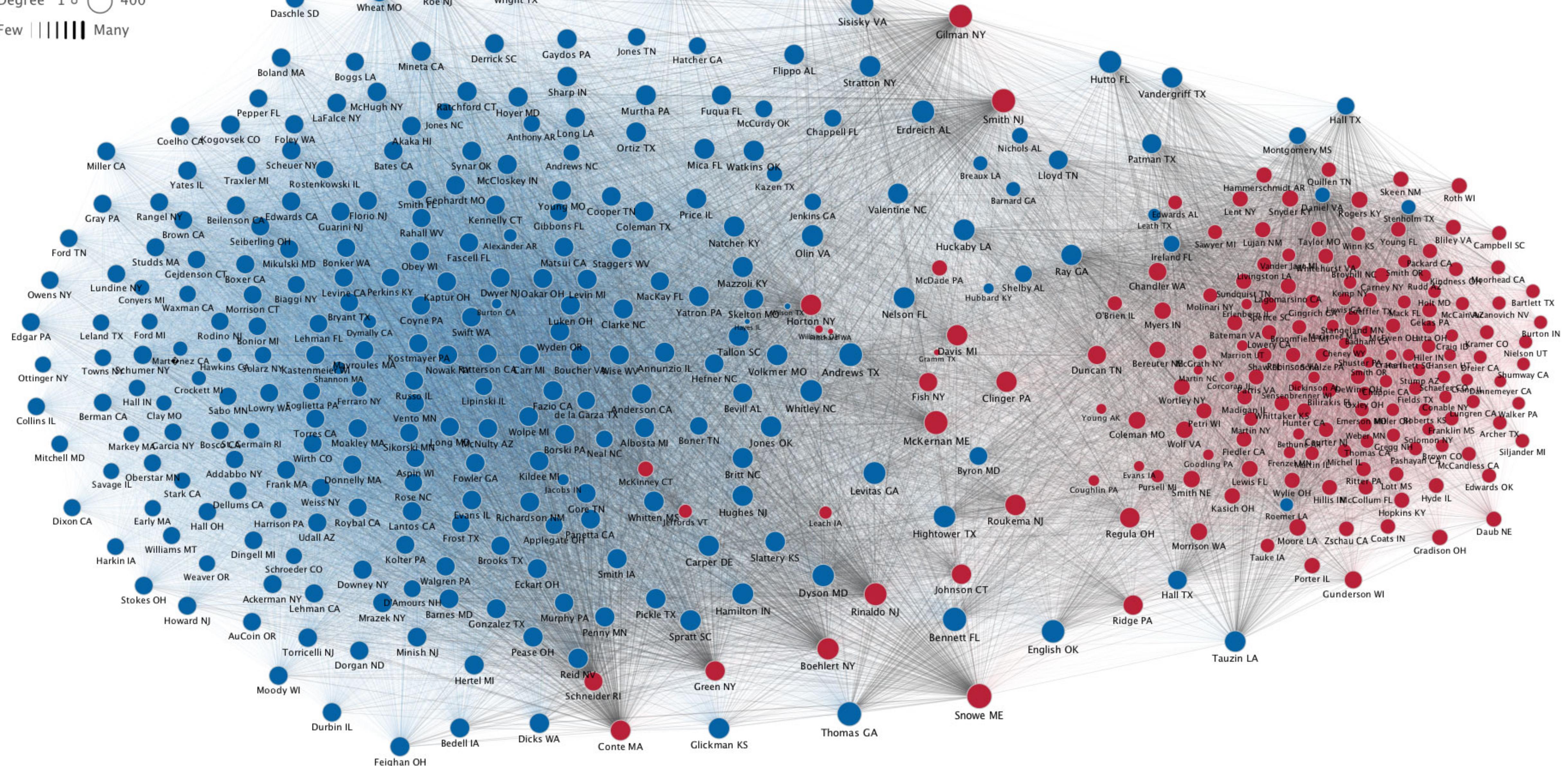


Year: 1983

D-D D-R R-R

Degree 1 o 400

Few ||| Many

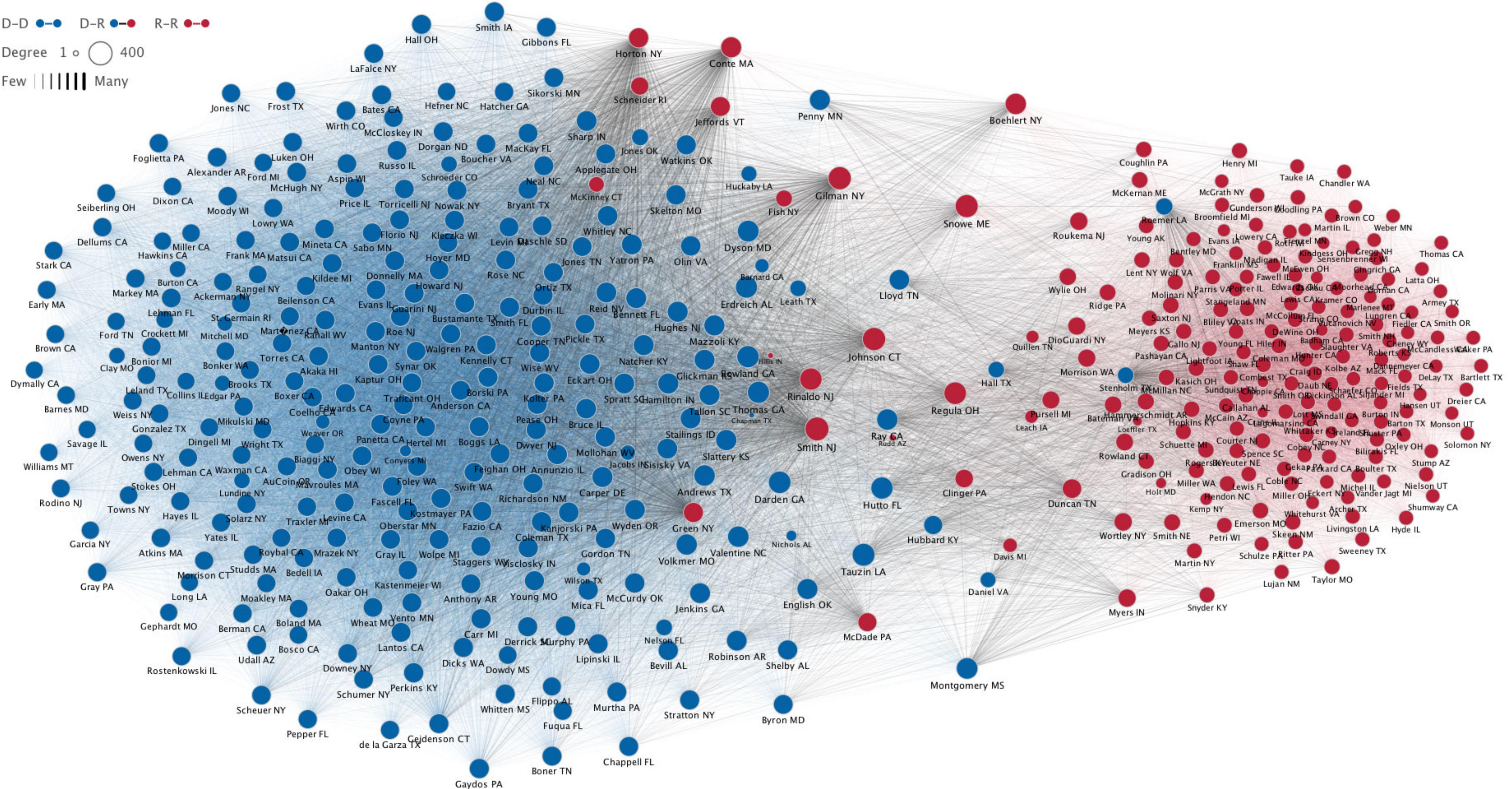


Year: 1985

D-D D-R R-R

Degree 1 o 400

Few ||| Many

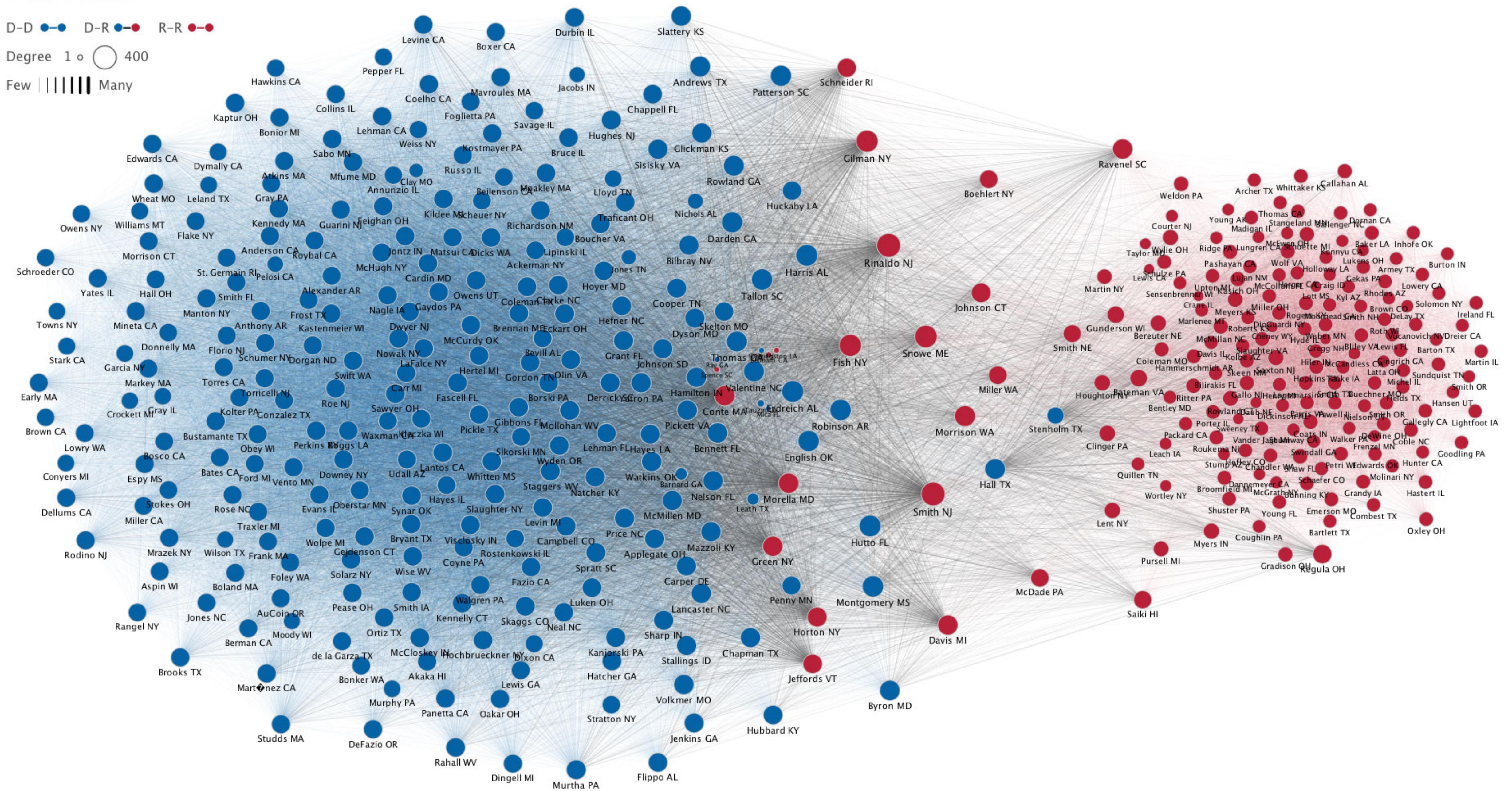


Year: 1987

D-D D-R R-R

Degree 1 ° 400

Few | | | | Many

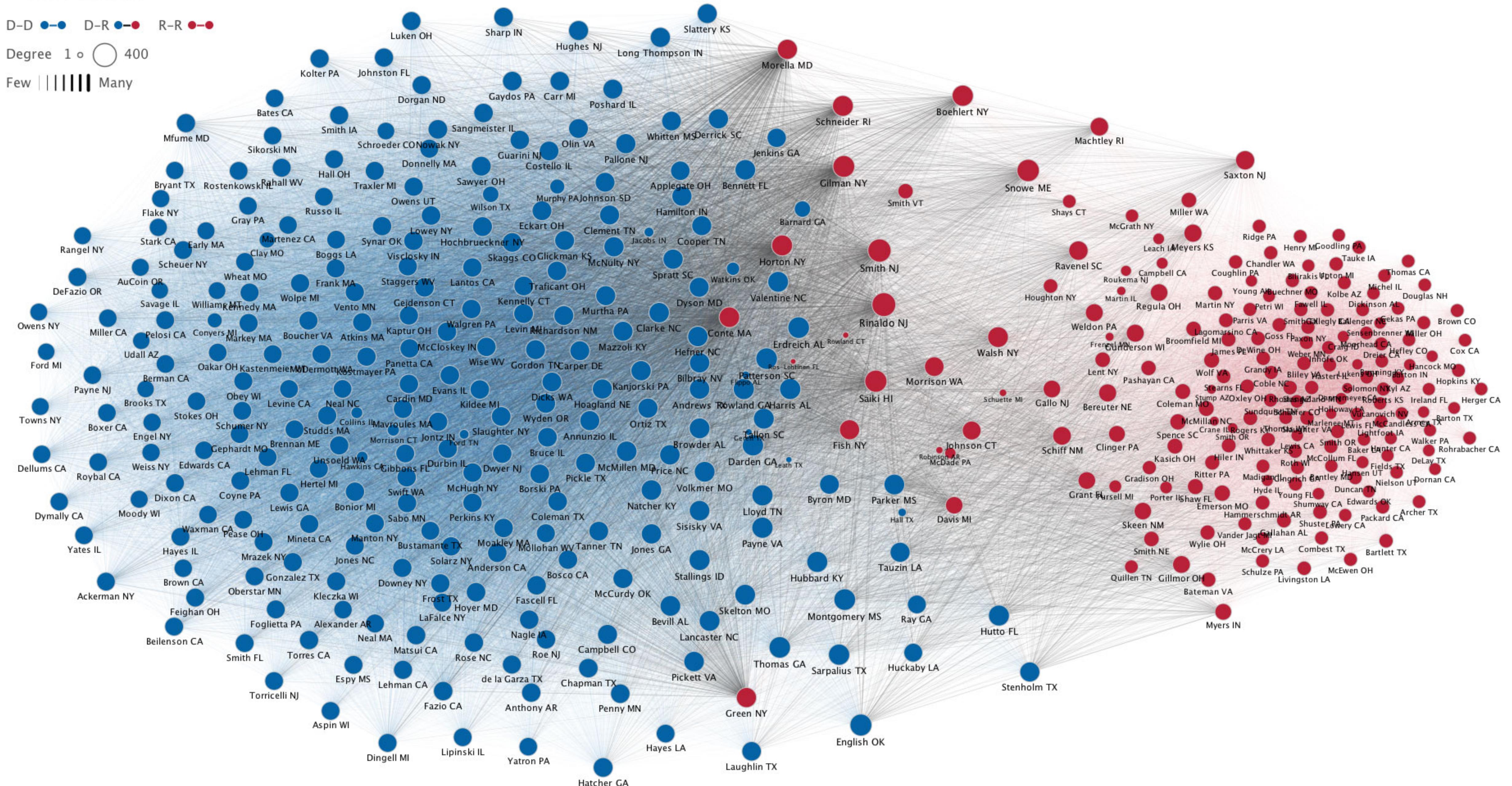


Year: 1989

D=D D=R R=R

Degree 1 ° 400

Few | | | | | Many

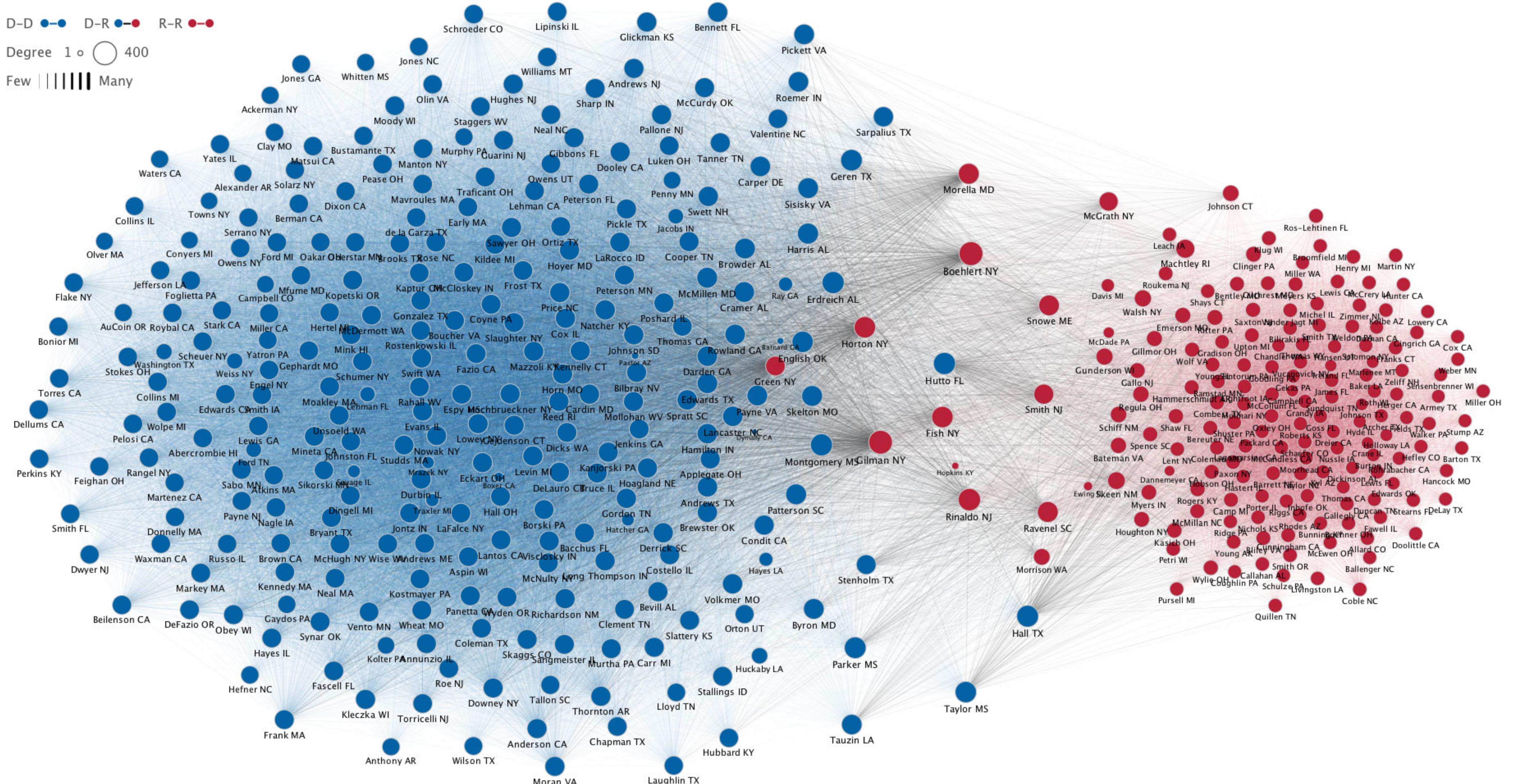


Year: 1991

D-D D-R R-R

Degree 1 o 400

Few ||| Many

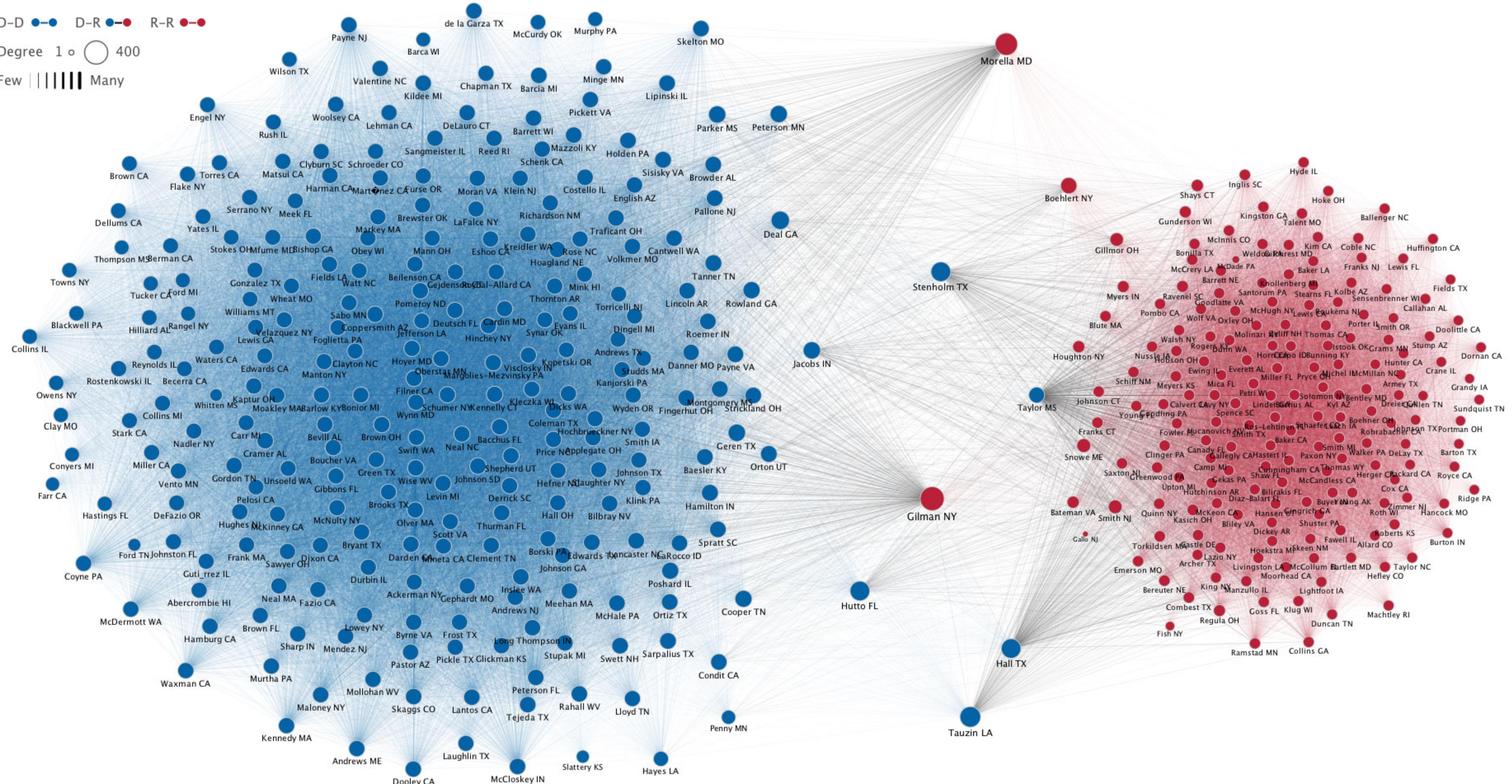


Year: 1993

D-D D-R R-R

Degree 1 o 400

Few ||| Many

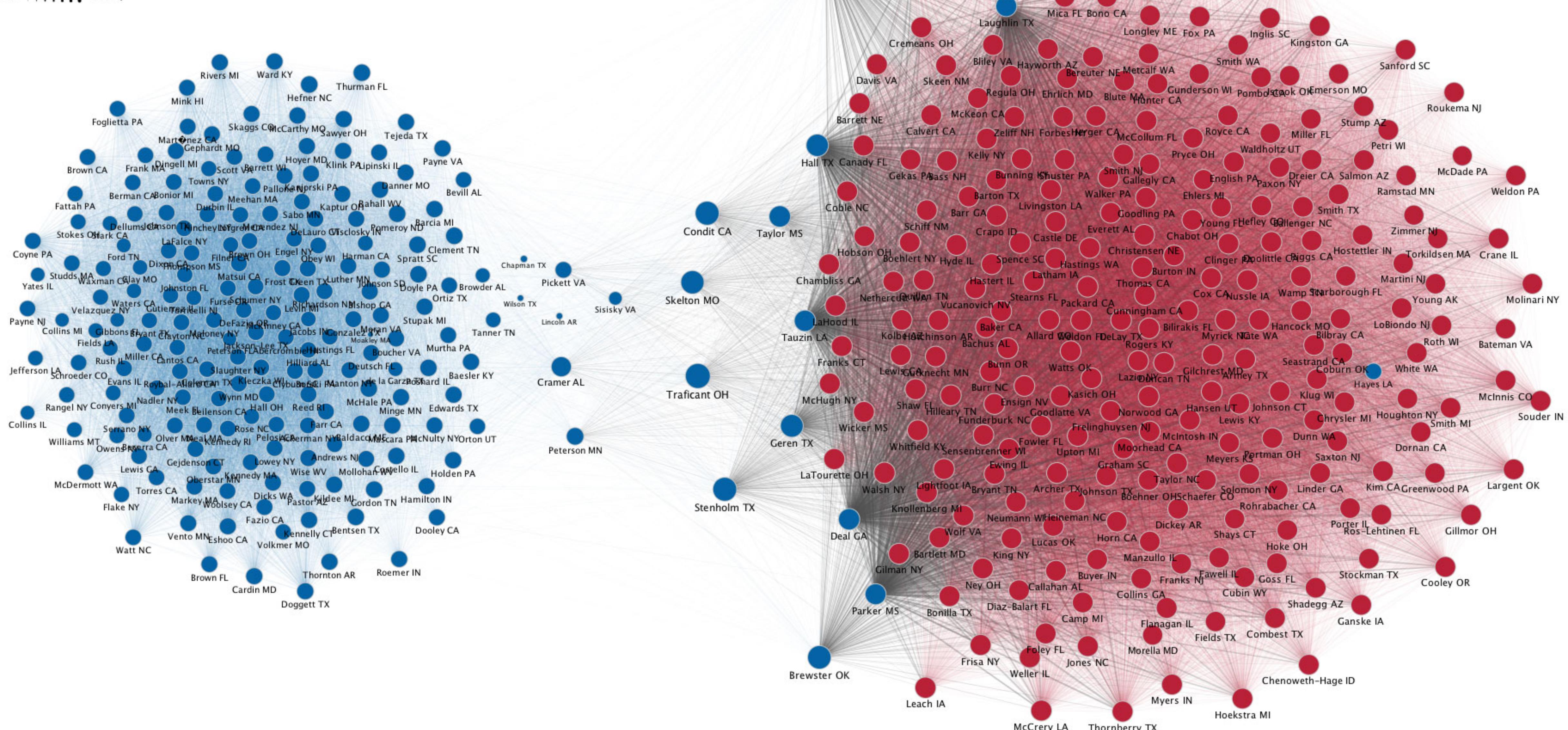


Year: 1995

D-D D-R R-R

Degree 1° 400

Few | | | | | Many

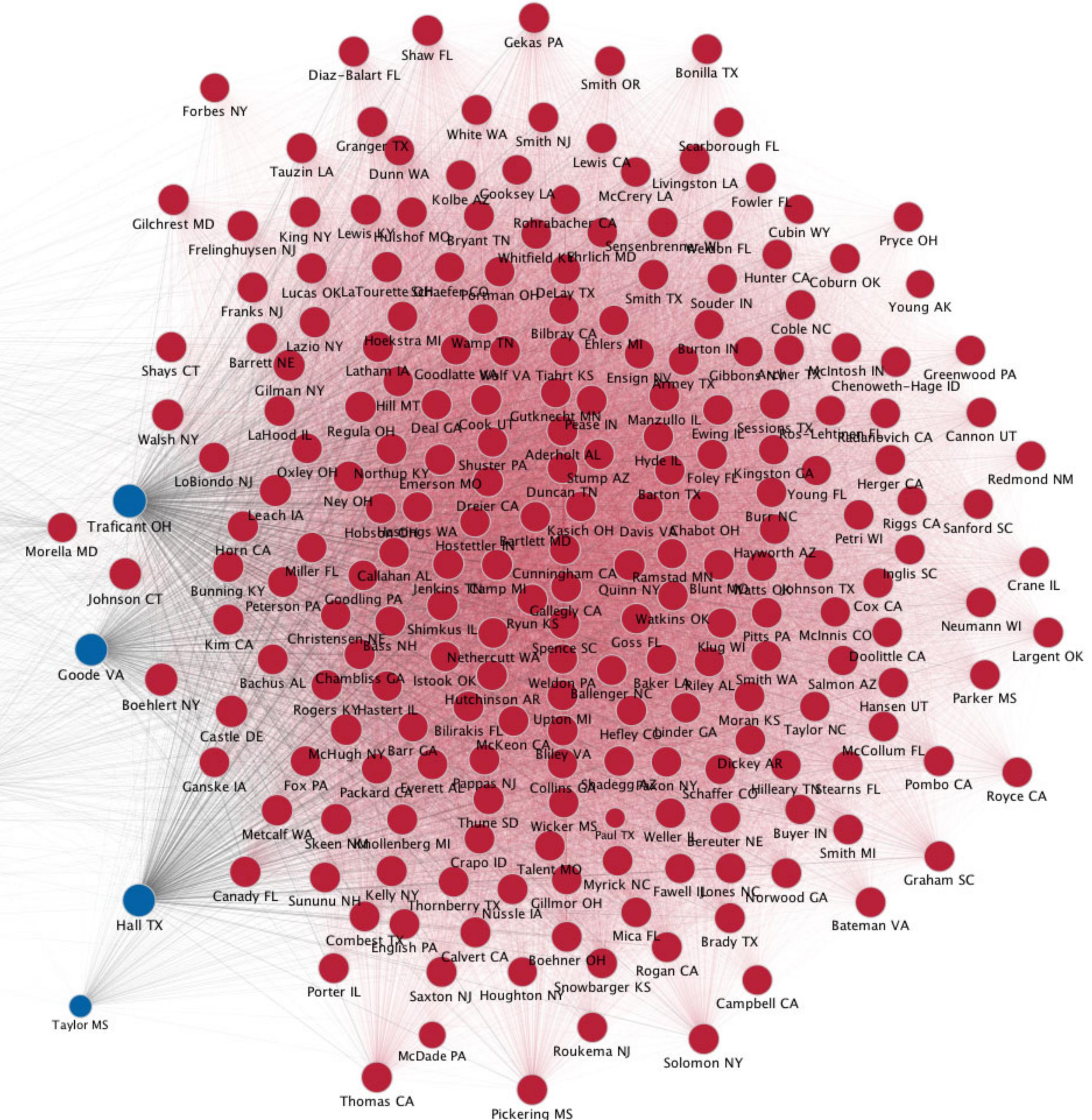
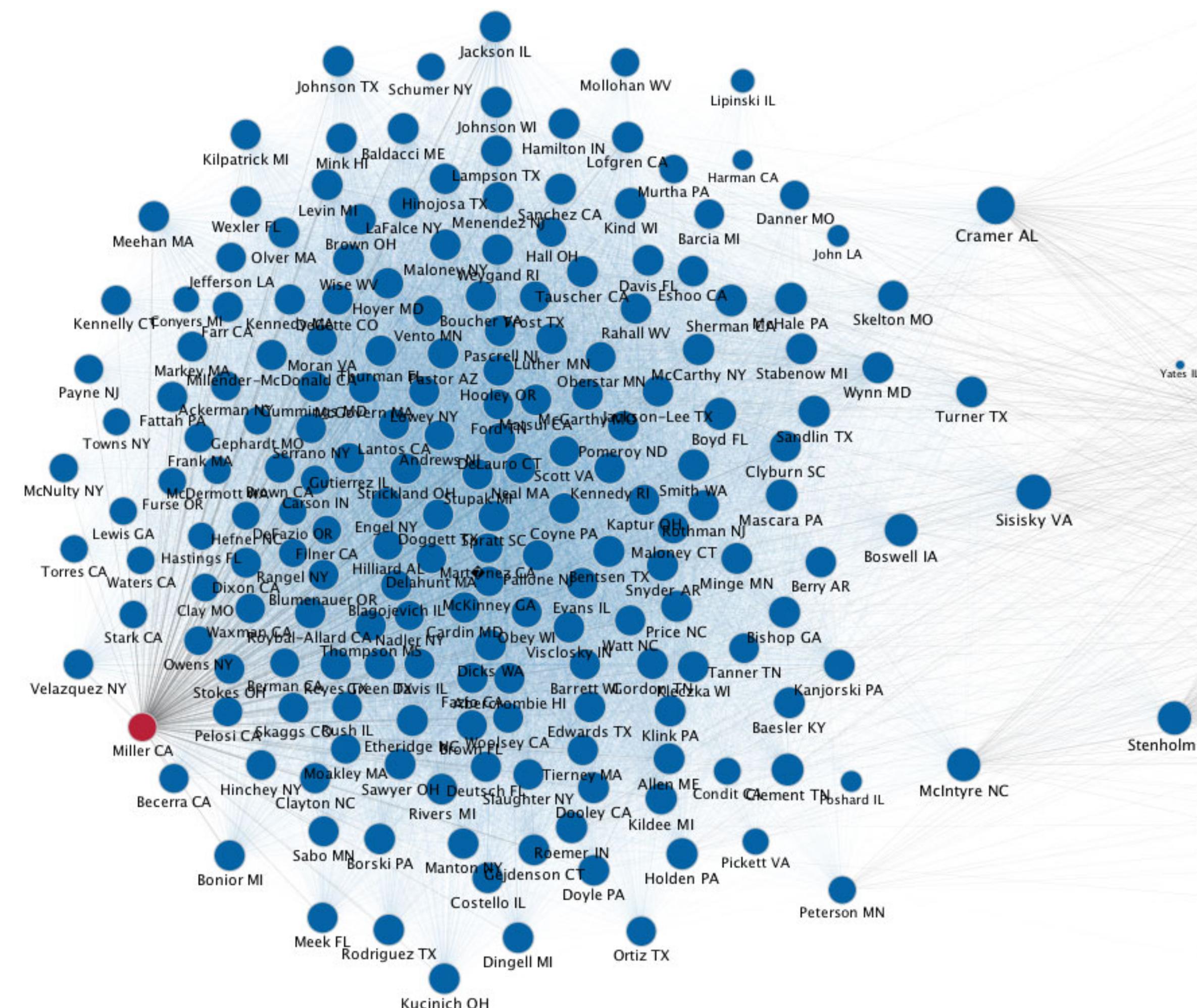


Year: 1997

D-D D-R R-R

Degree 1 ° 400

Few | | | | Many

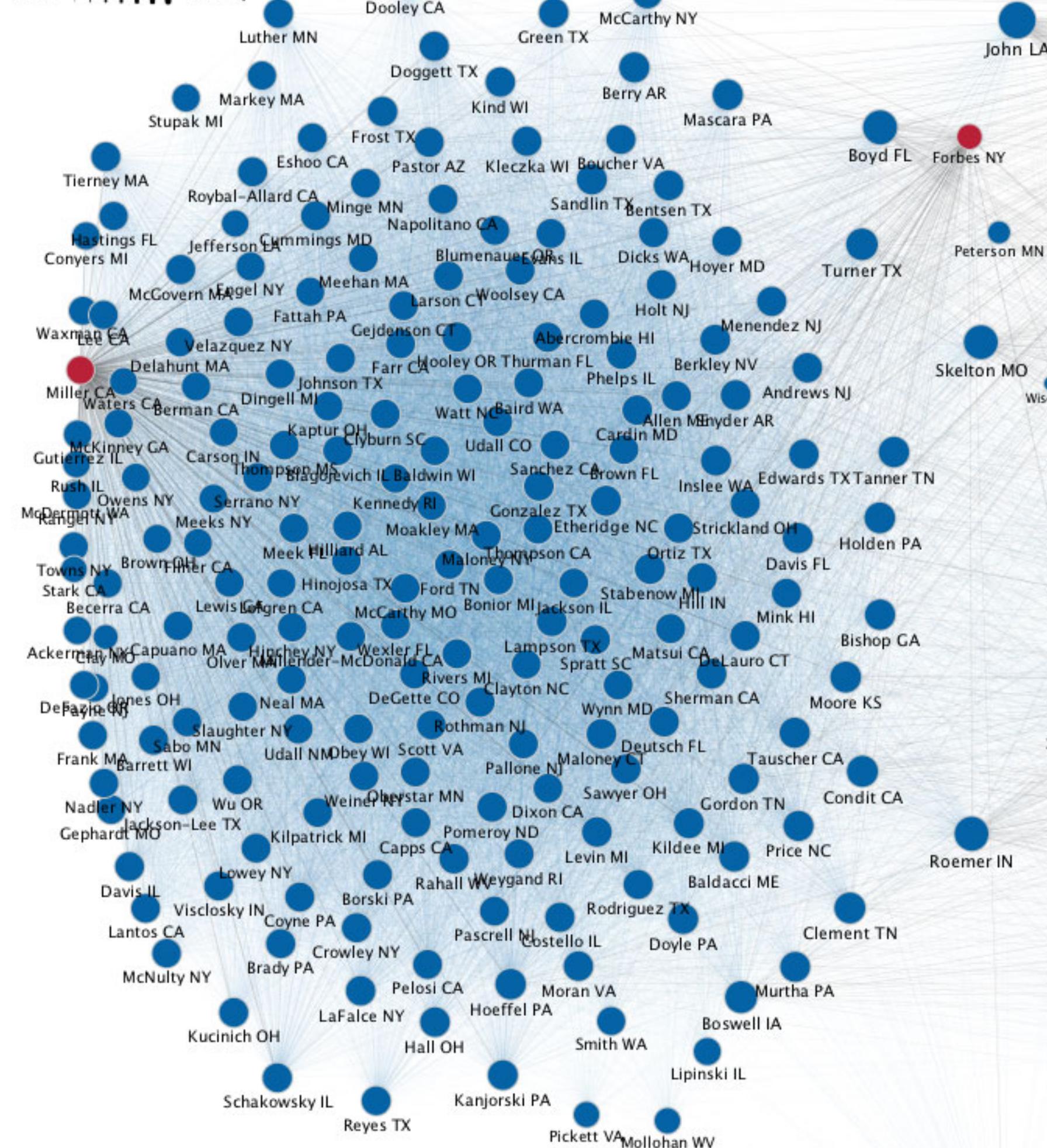


Year: 1999

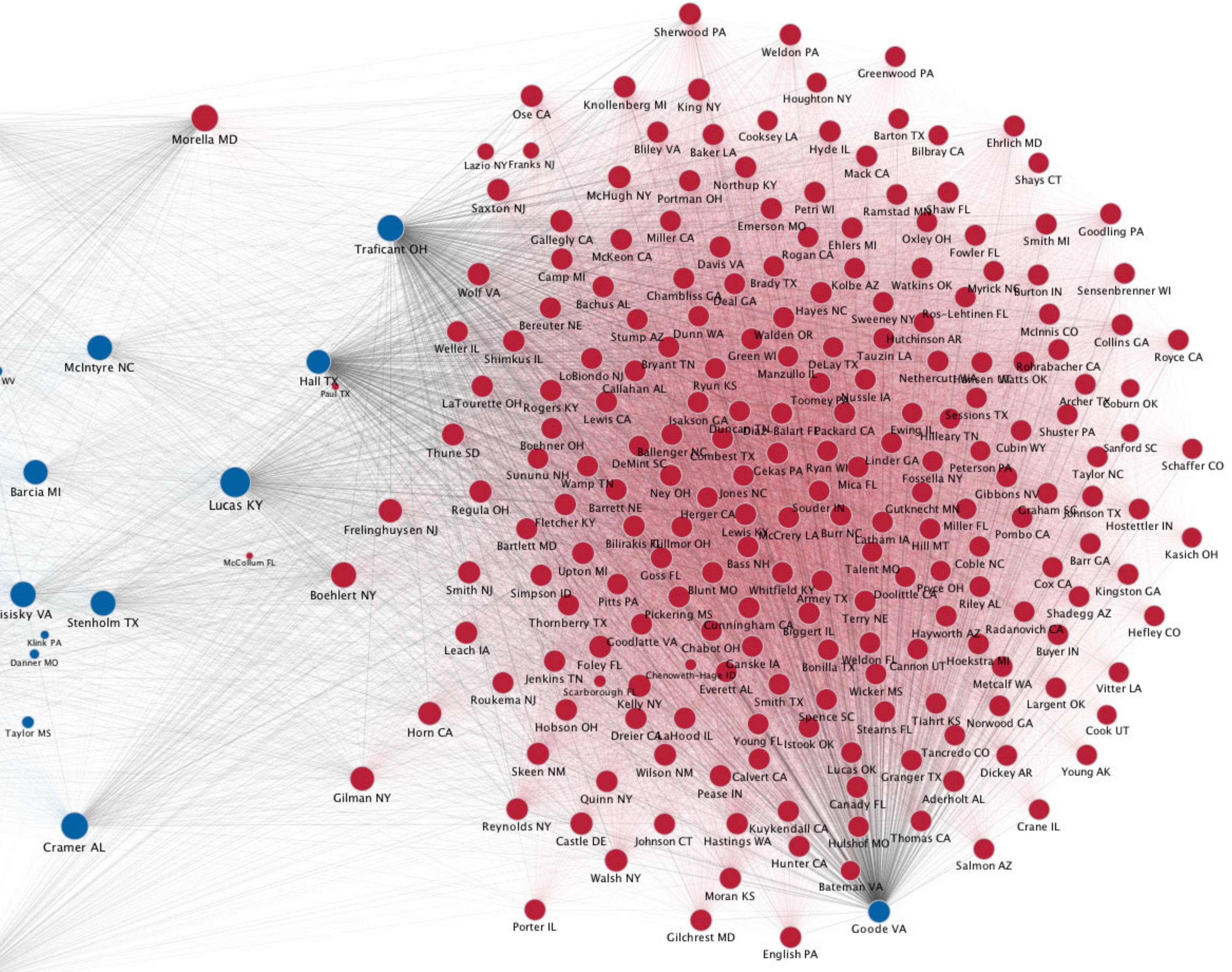
D-D D-R R-R

Degree 1 o 400

Few ||| Many



Show MS



Goode VA

English PA

Bateman VA

Hunter CA

Hulshof MO

Thomas CA

Kuykendall CA

Calvert CA

Pease IN

Wilson NM

Young FL

Istook OK

Spence SC

Stearns FL

Tiahrt KS

Norwood GA

Cook UT

Crane IL

Dickey AR

Young AK

Aderholt AL

Granger TX

Tancredo CO

Dickerson CO

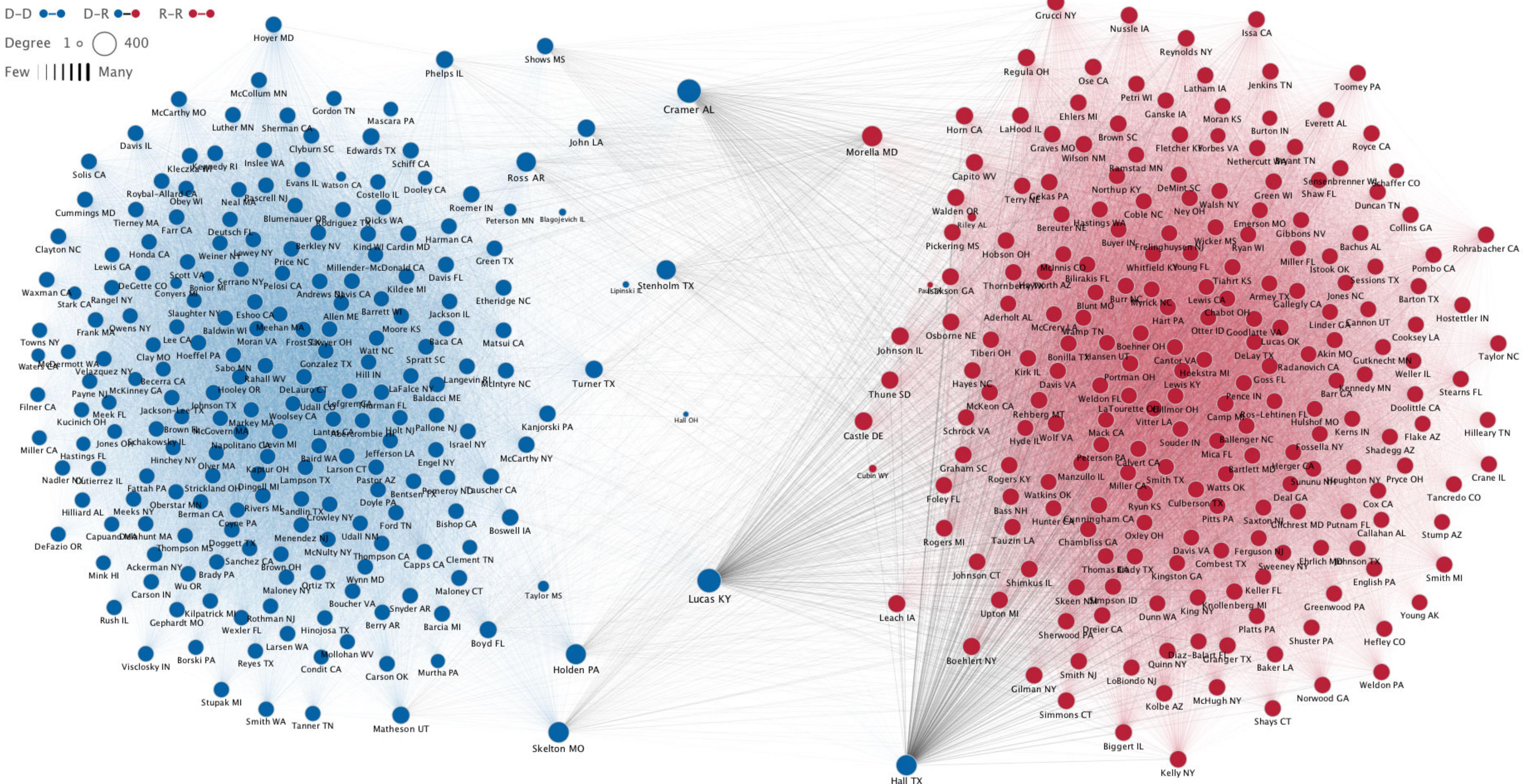
Salmon AZ

Bateman VA

Goode VA

English PA

Year: 2001

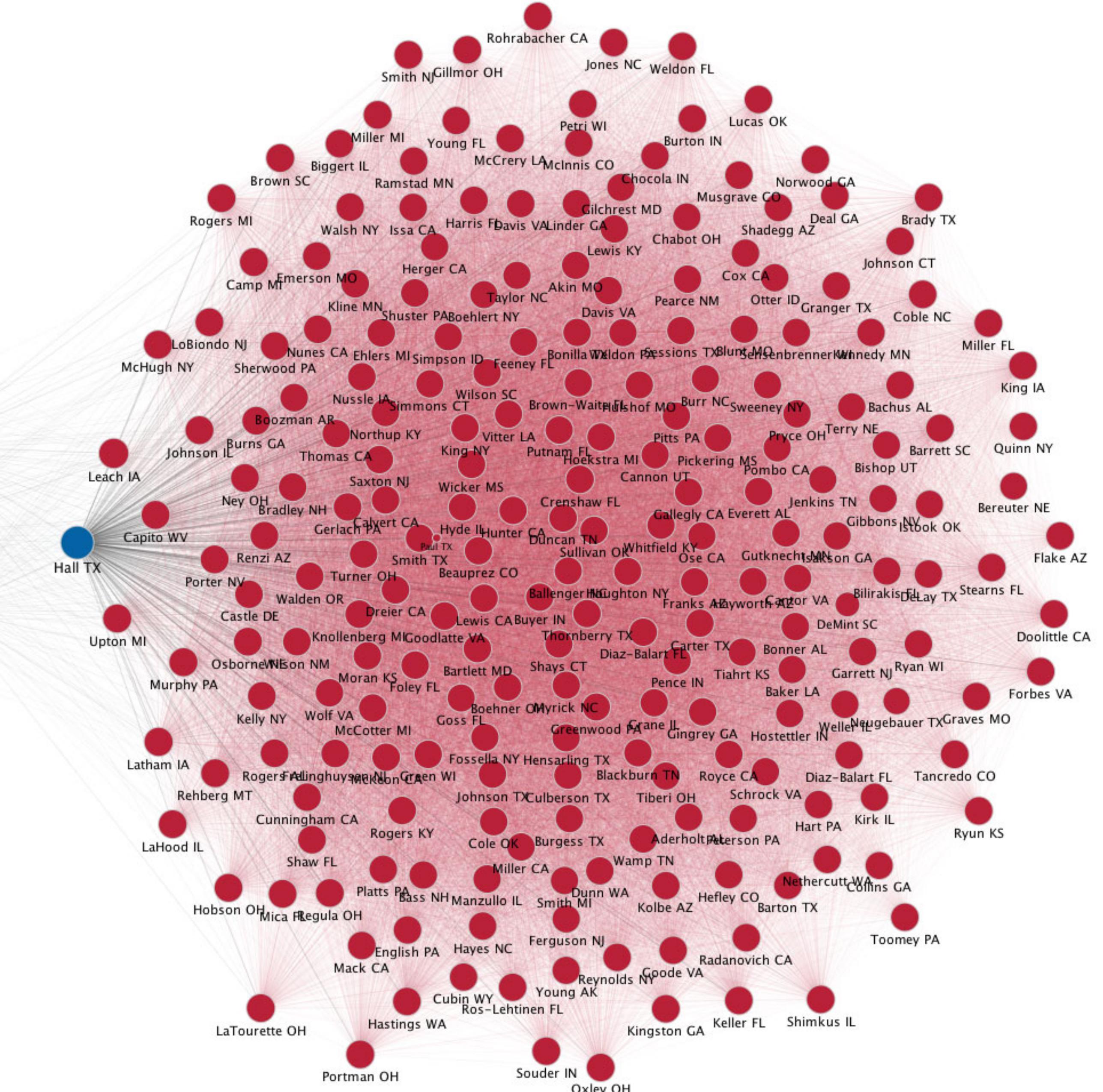
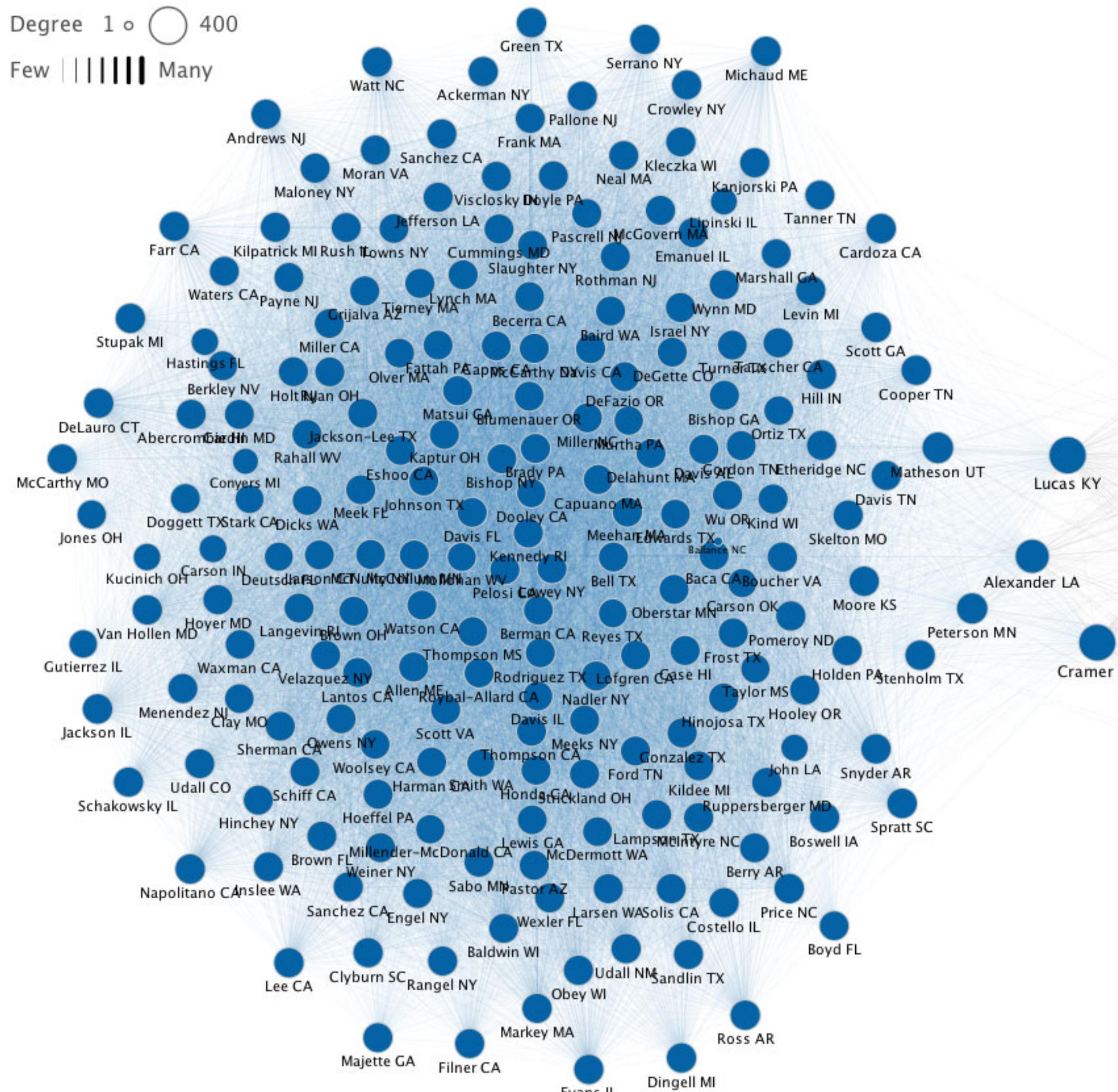


Year: 2003

D-D D-R R-R

Degree 1 o 400

Few |||| Many

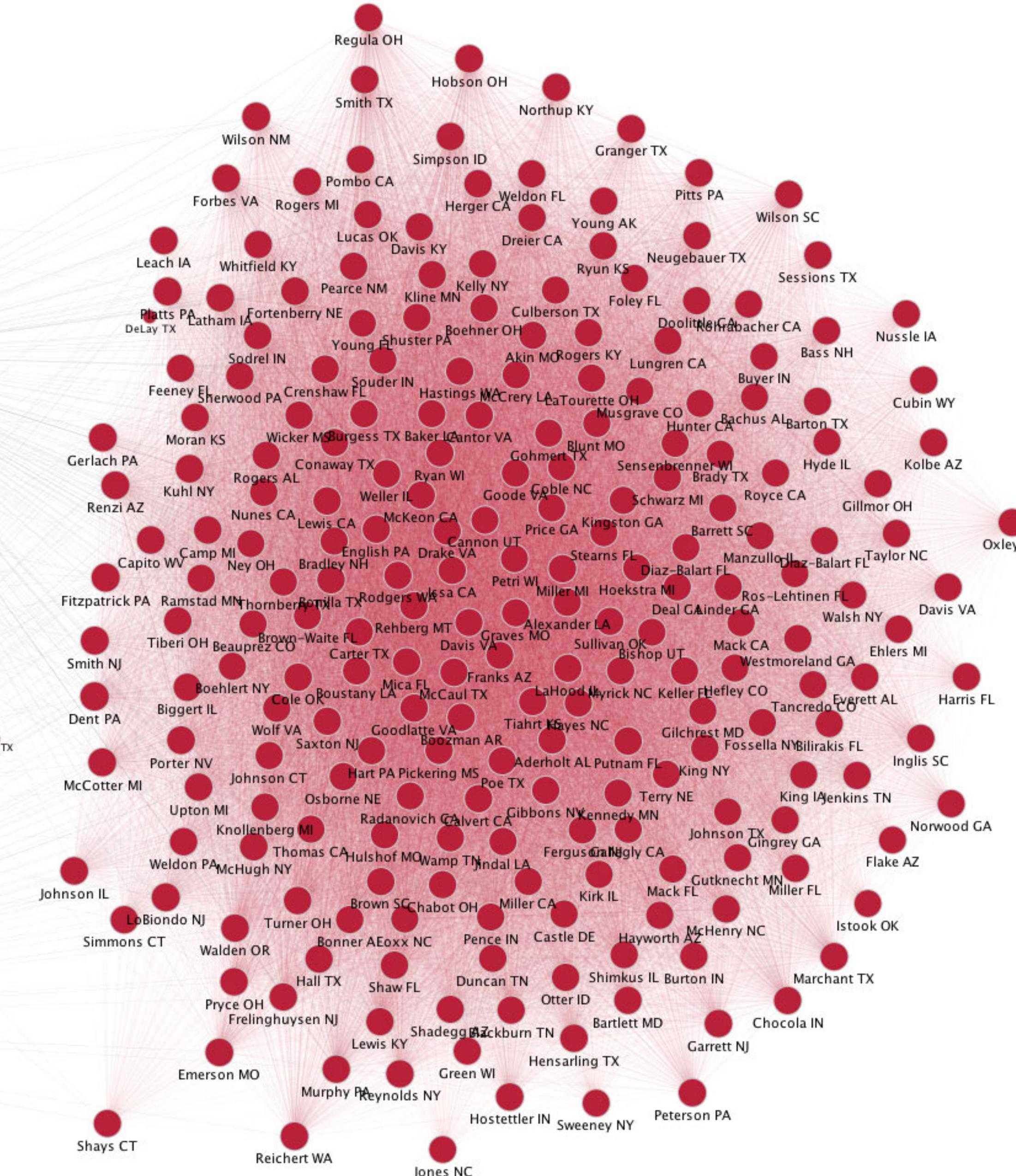
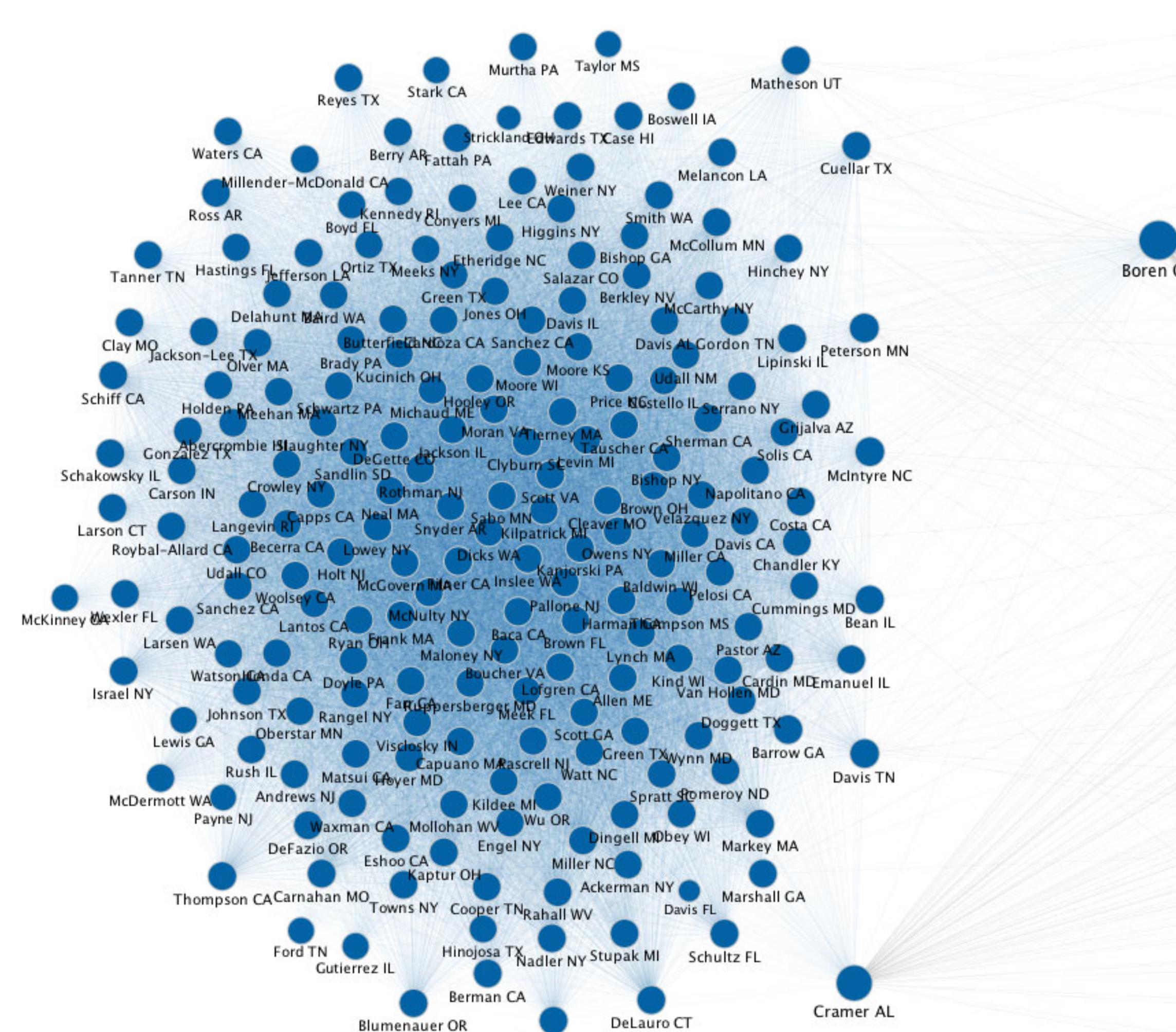


Year: 2005

D-D •—• D-R •—• R-R •—•

Degree 1 o 400

Few ||| Many

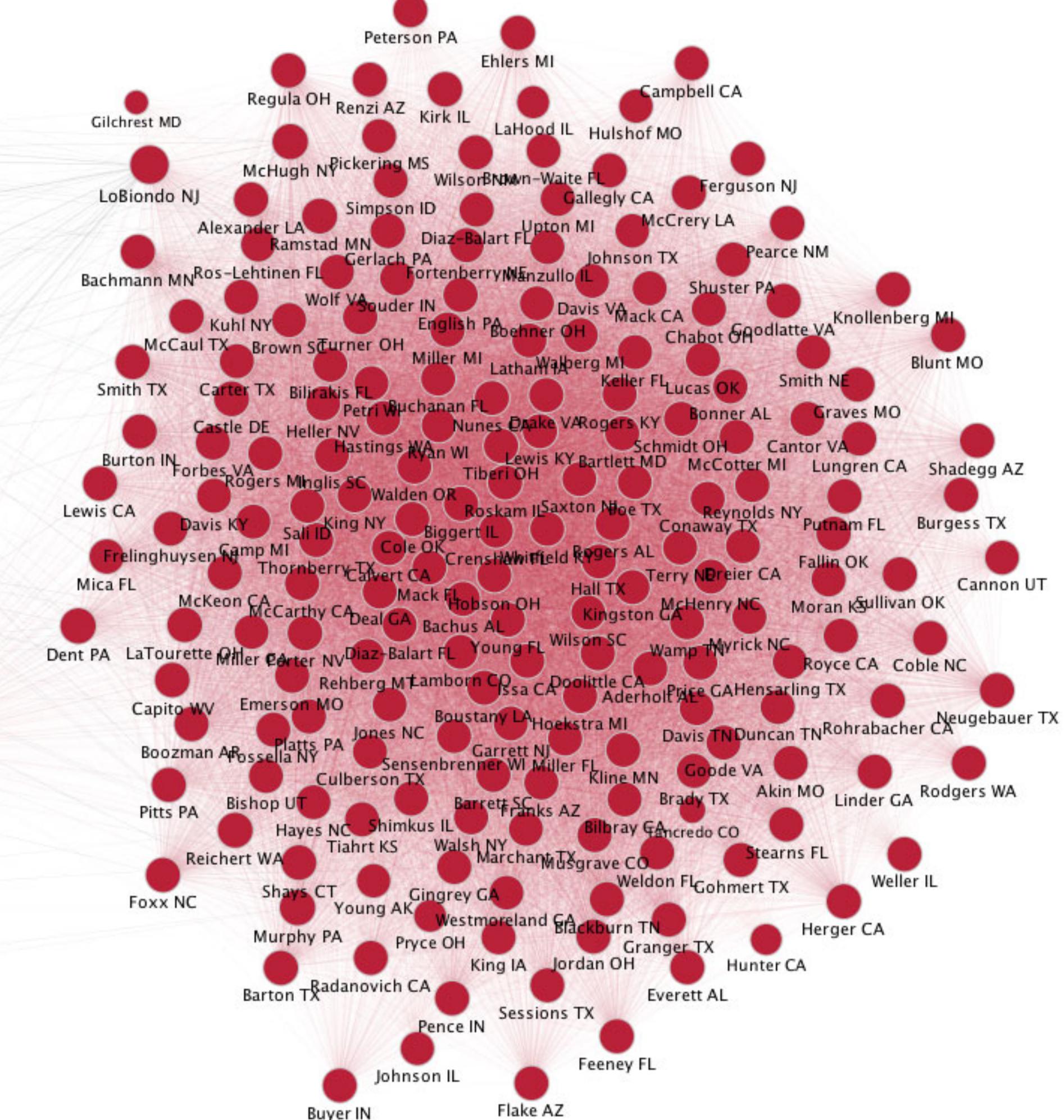
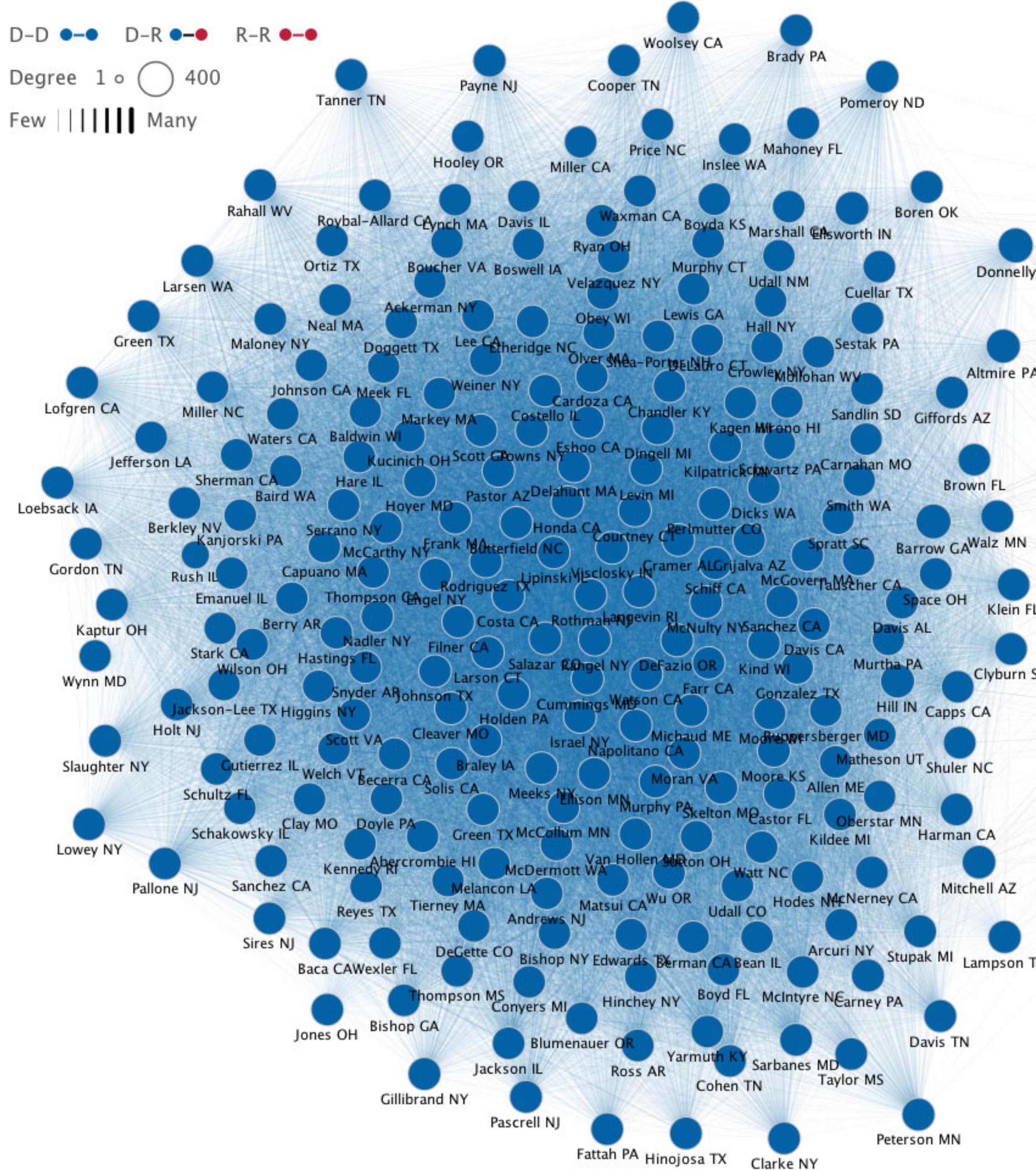


Year: 2007

D-D D-R R-R

Degree 1 o 400

Few ||| Many

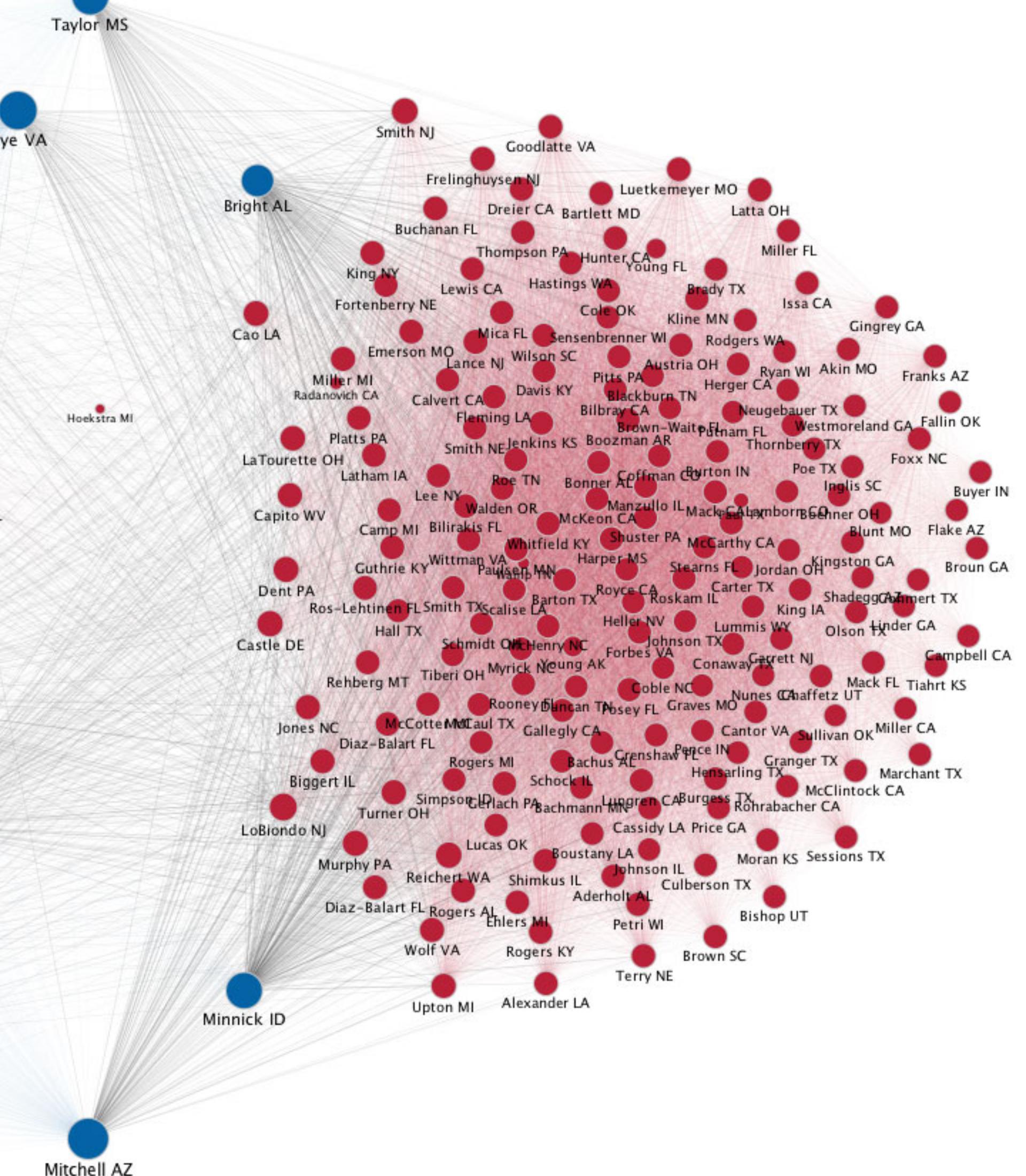
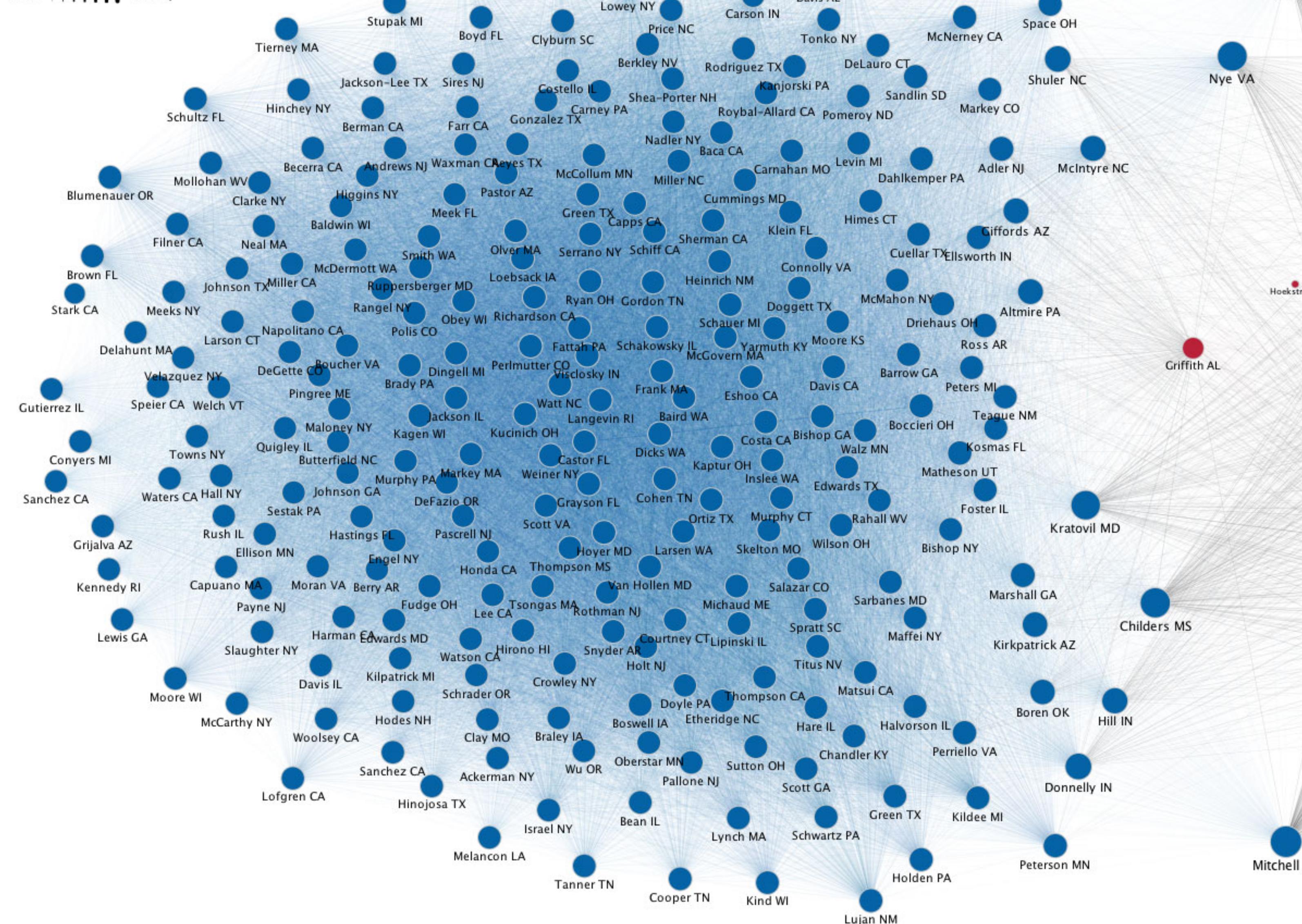


Year: 2009

D-D D-R R-R

Degree 1 o 400

Few ||| Many

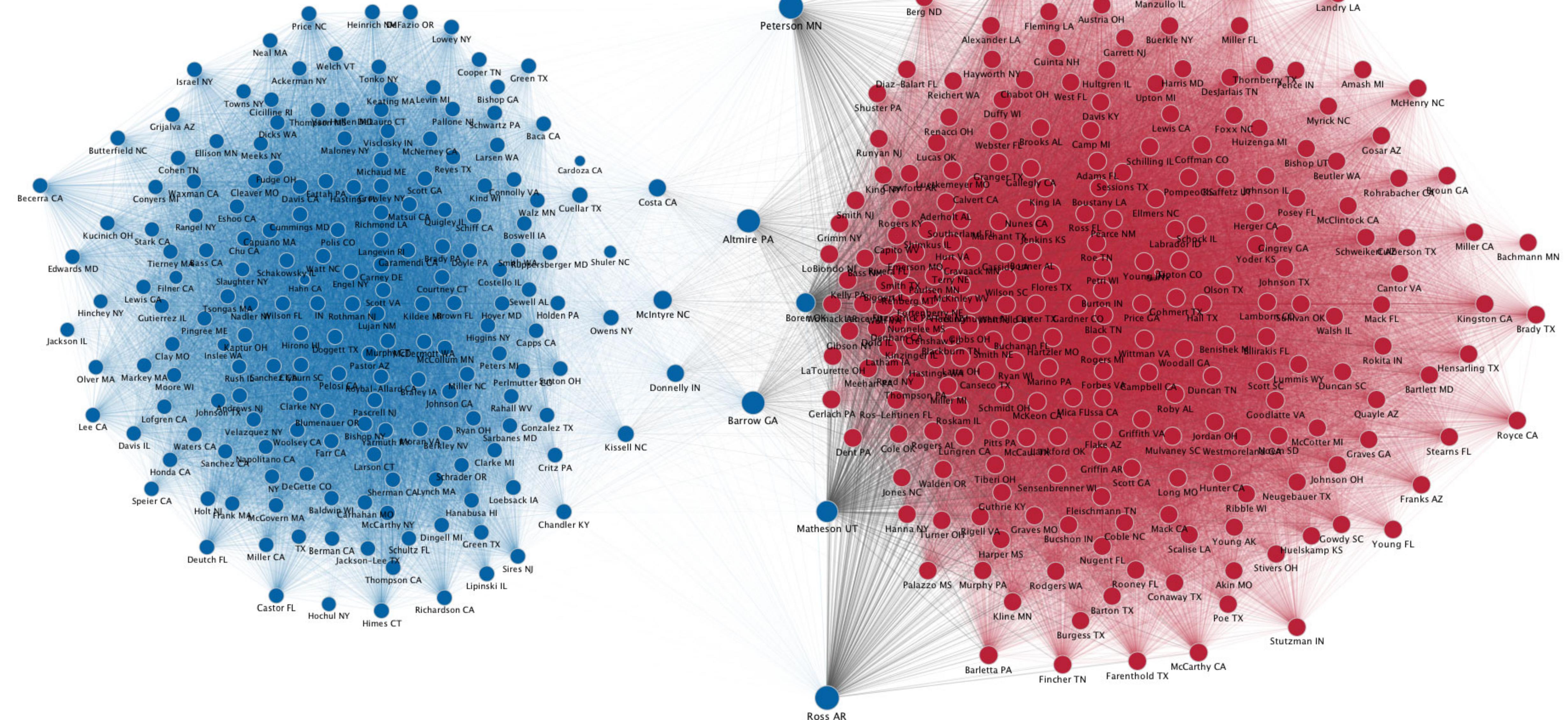


Year: 2011

D-D D-R R-R

Degree 1 ° 400

Few | | | | | Many



Part Two

What are social networks?

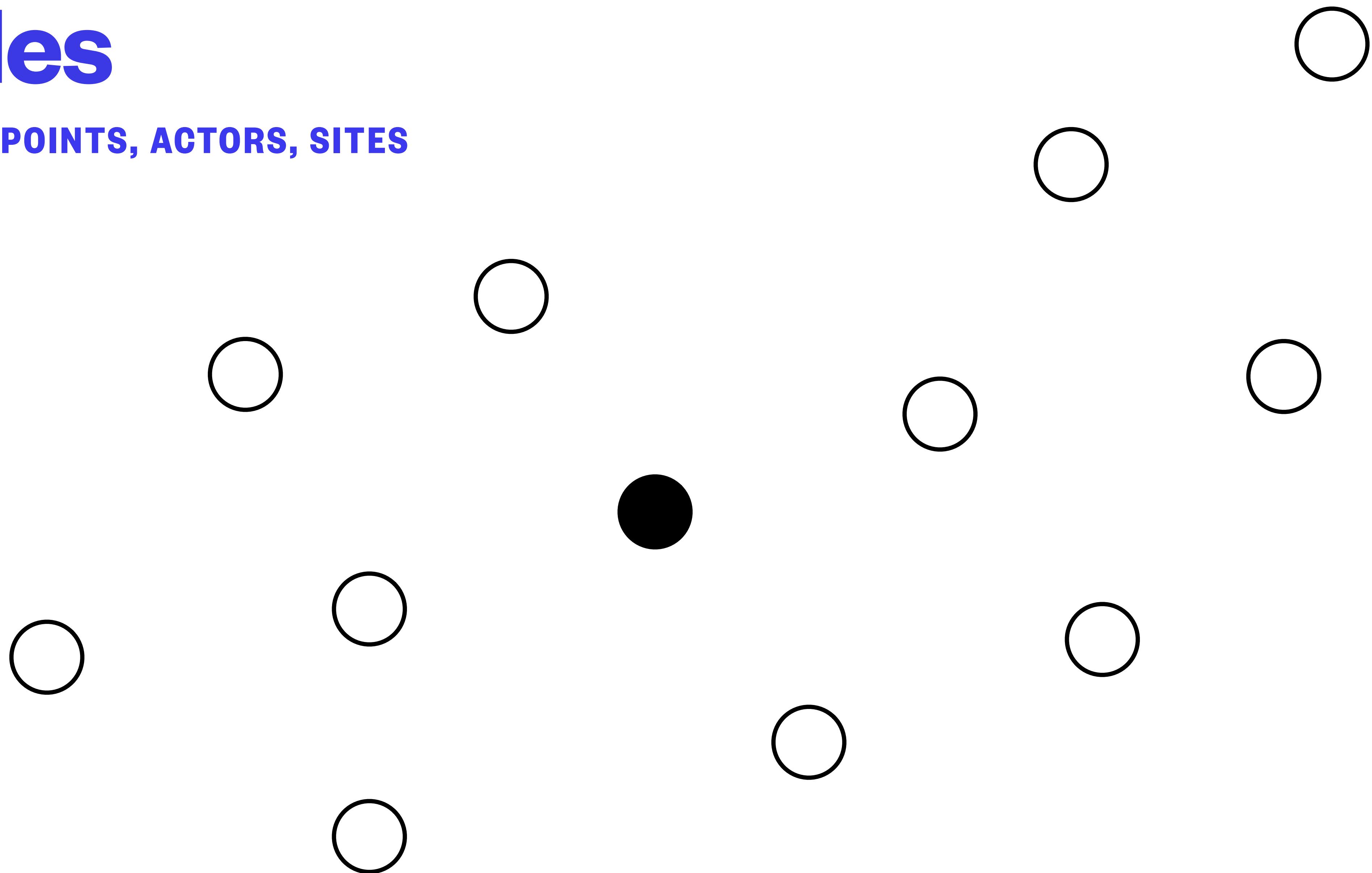
Networks have two basic elements:

Nodes & Edges

- Let's take an imaginary ego-centric friendship network to illustrate
 - Ego-centric: A network focused on a particular individual

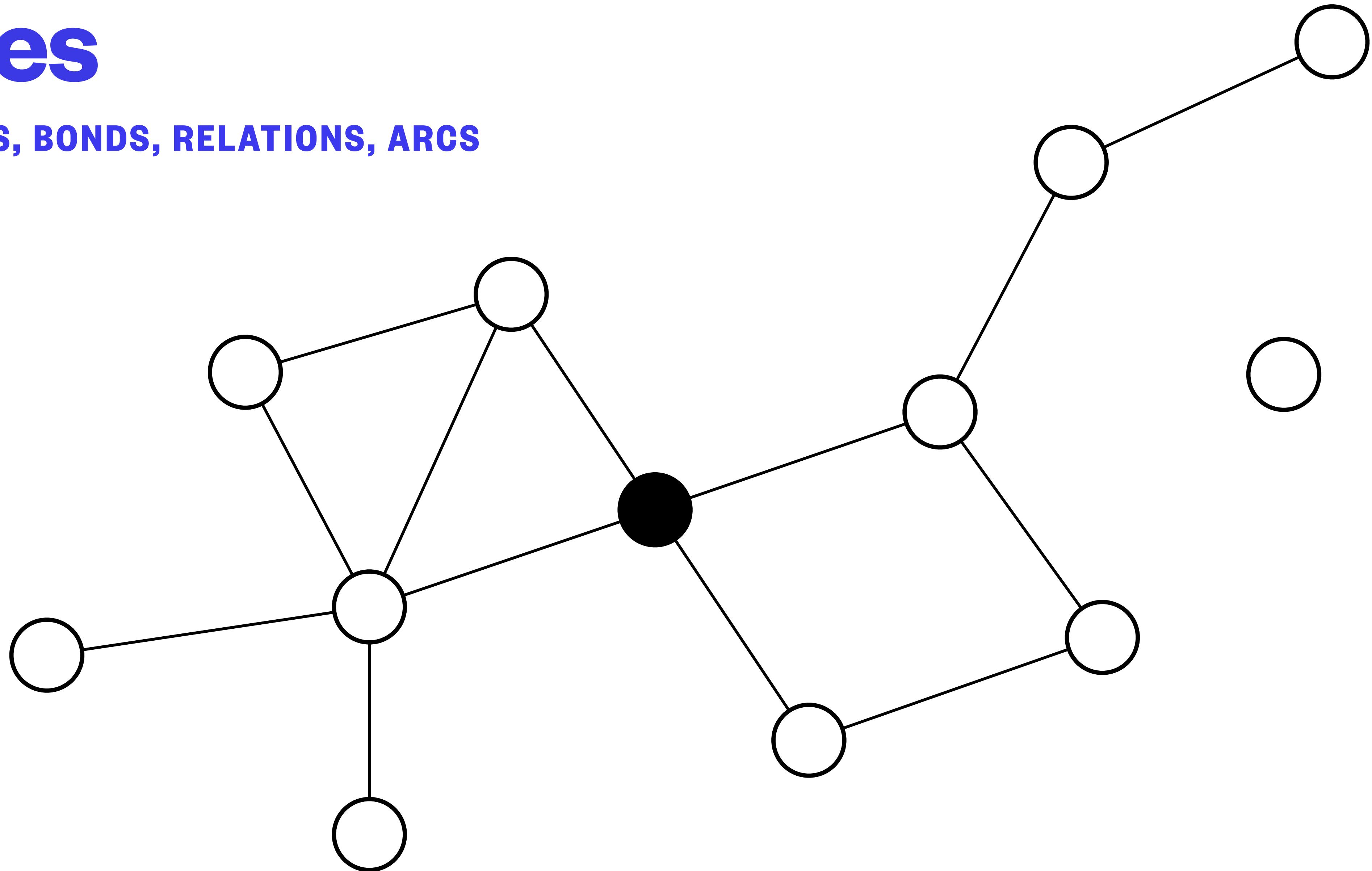
Nodes

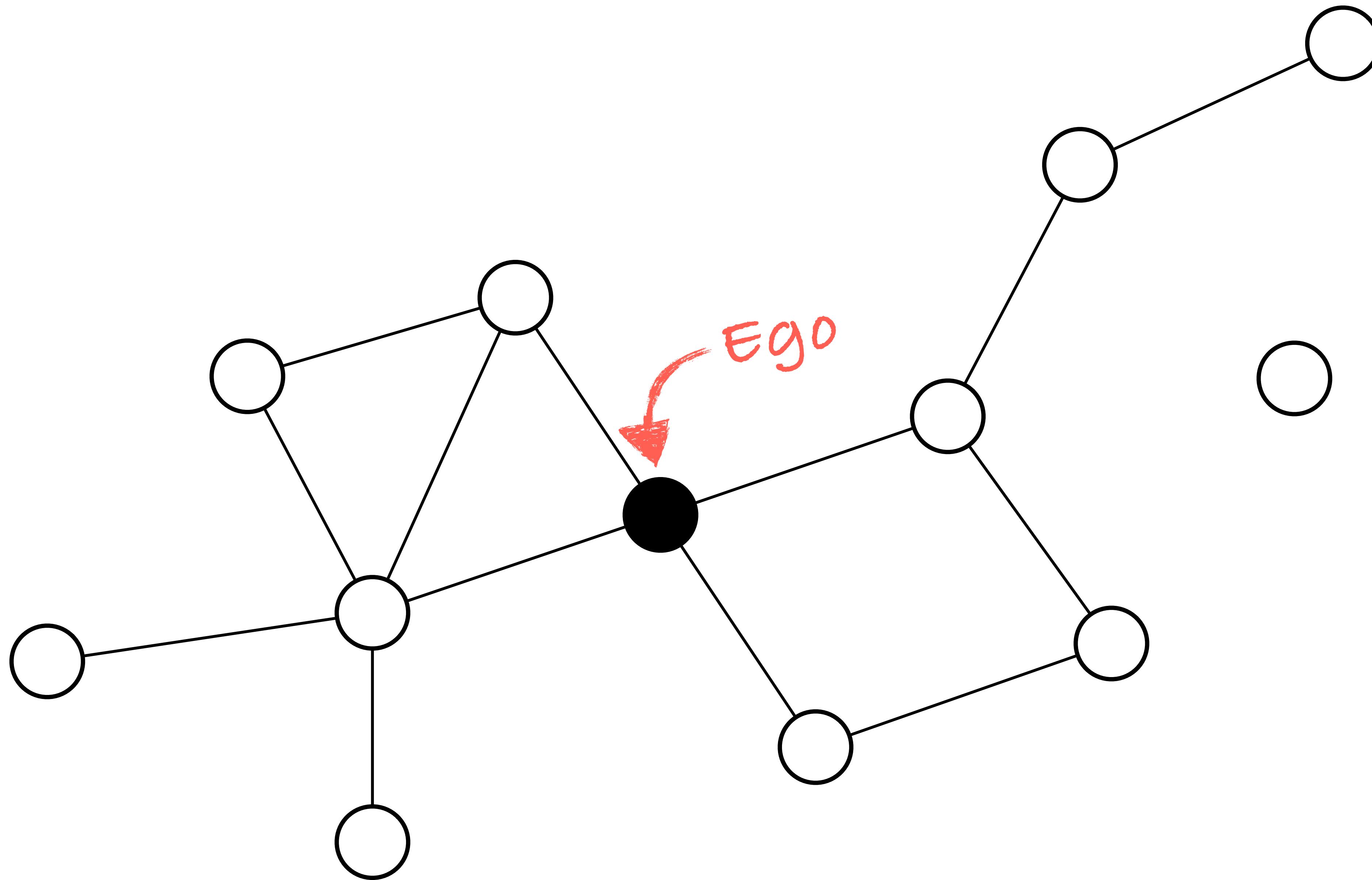
VERTICES, POINTS, ACTORS, SITES

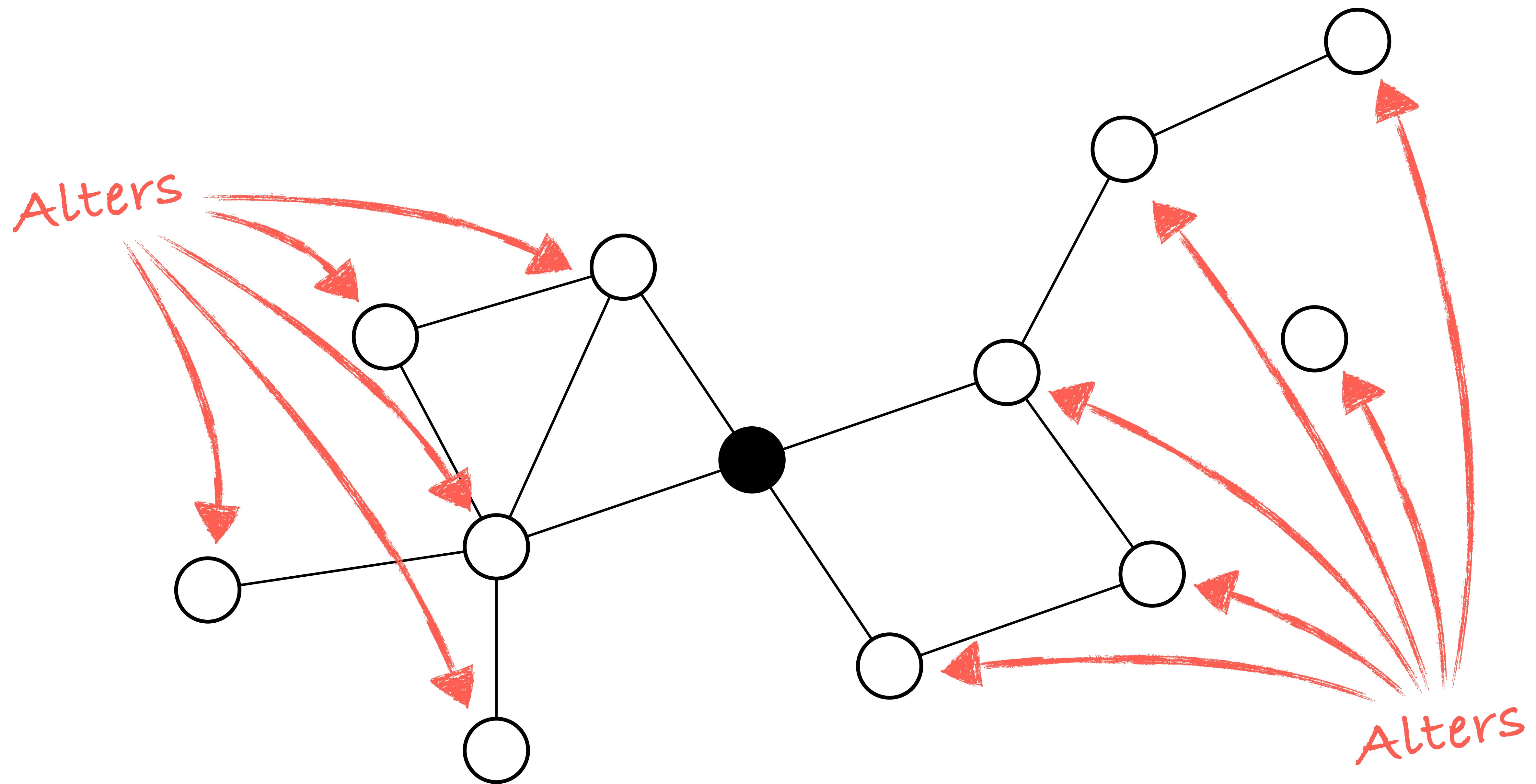


Edges

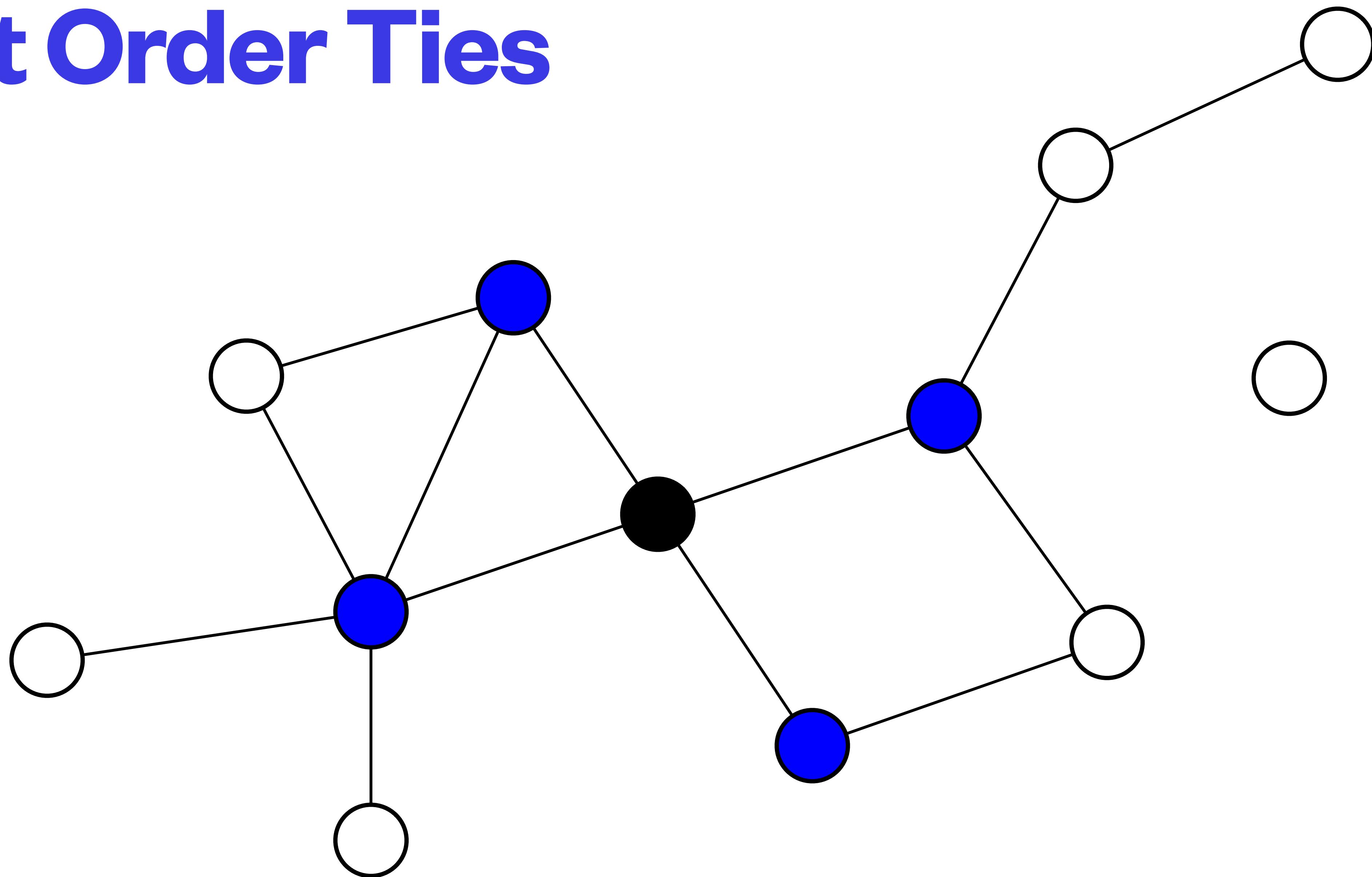
TIES, LINKS, BONDS, RELATIONS, ARCS





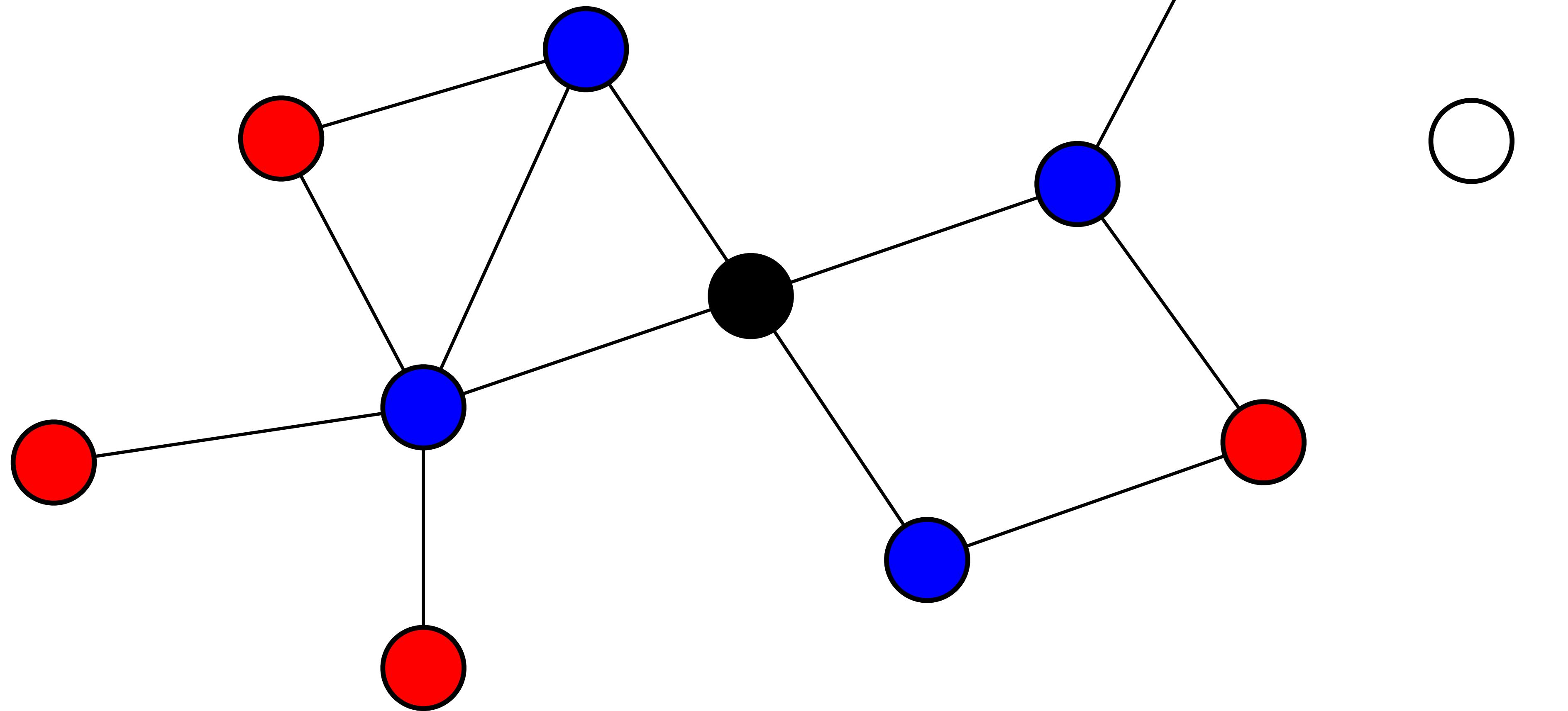


First Order Ties

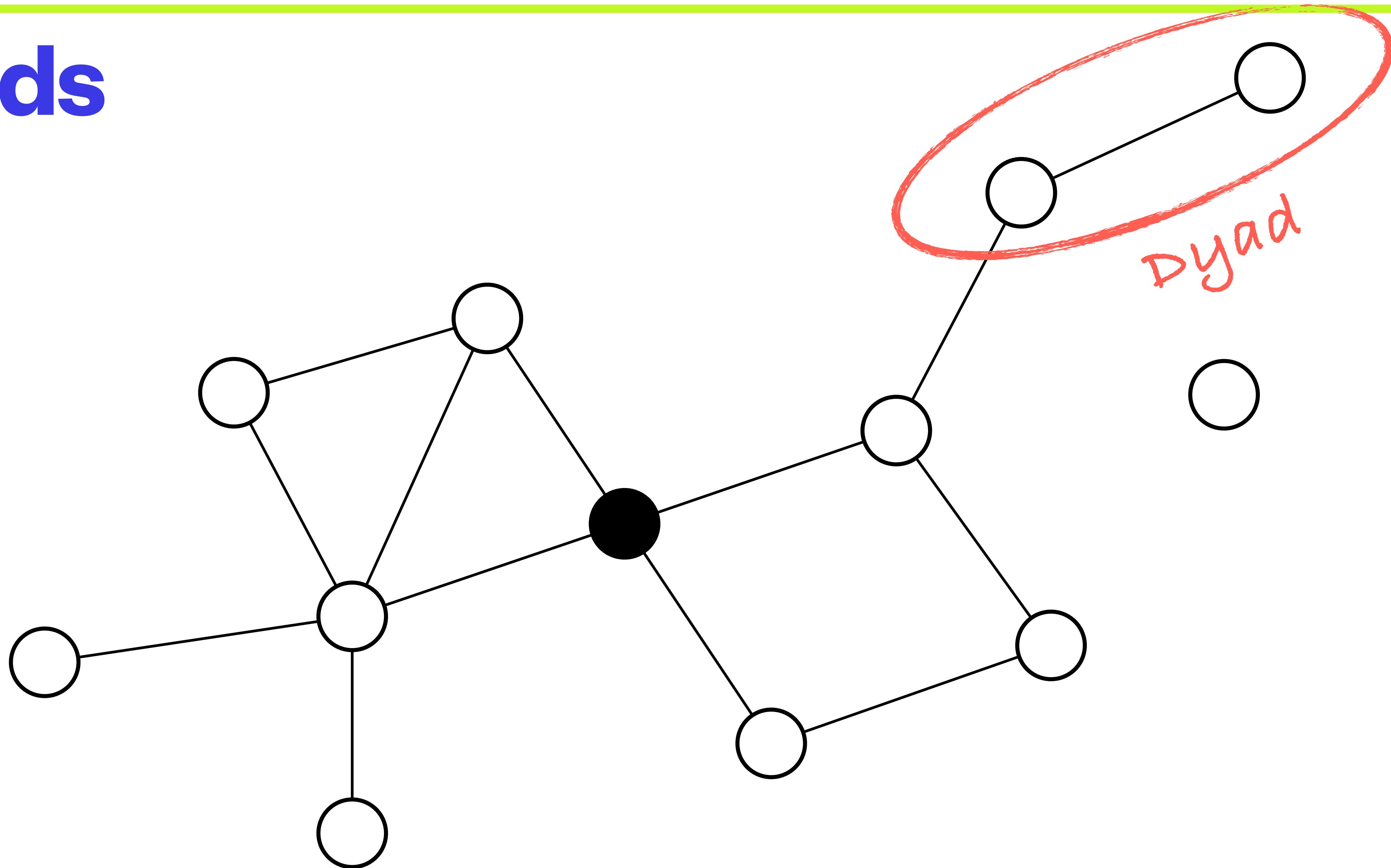


First Order Ties

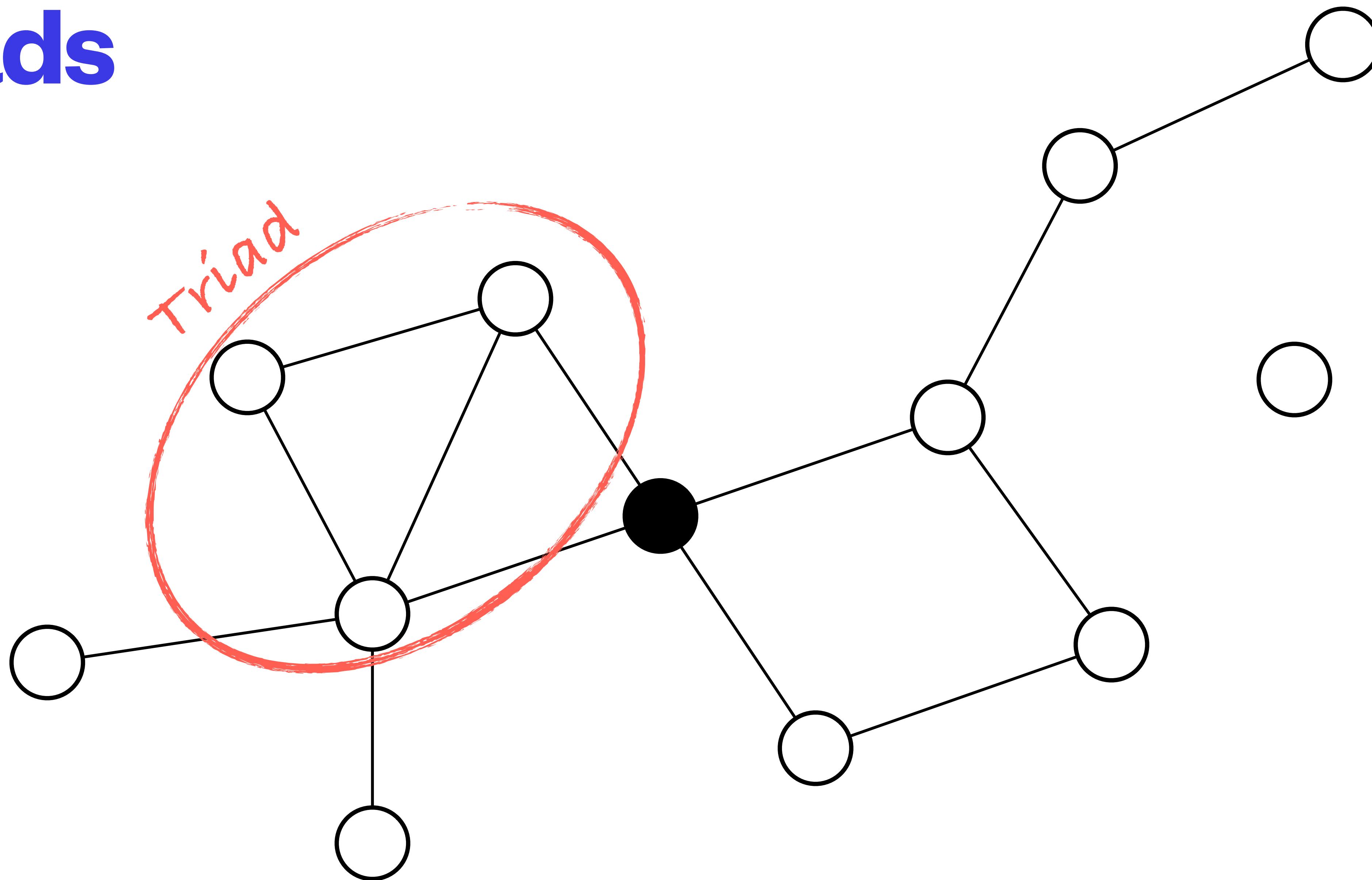
Second Order Ties



Dyads

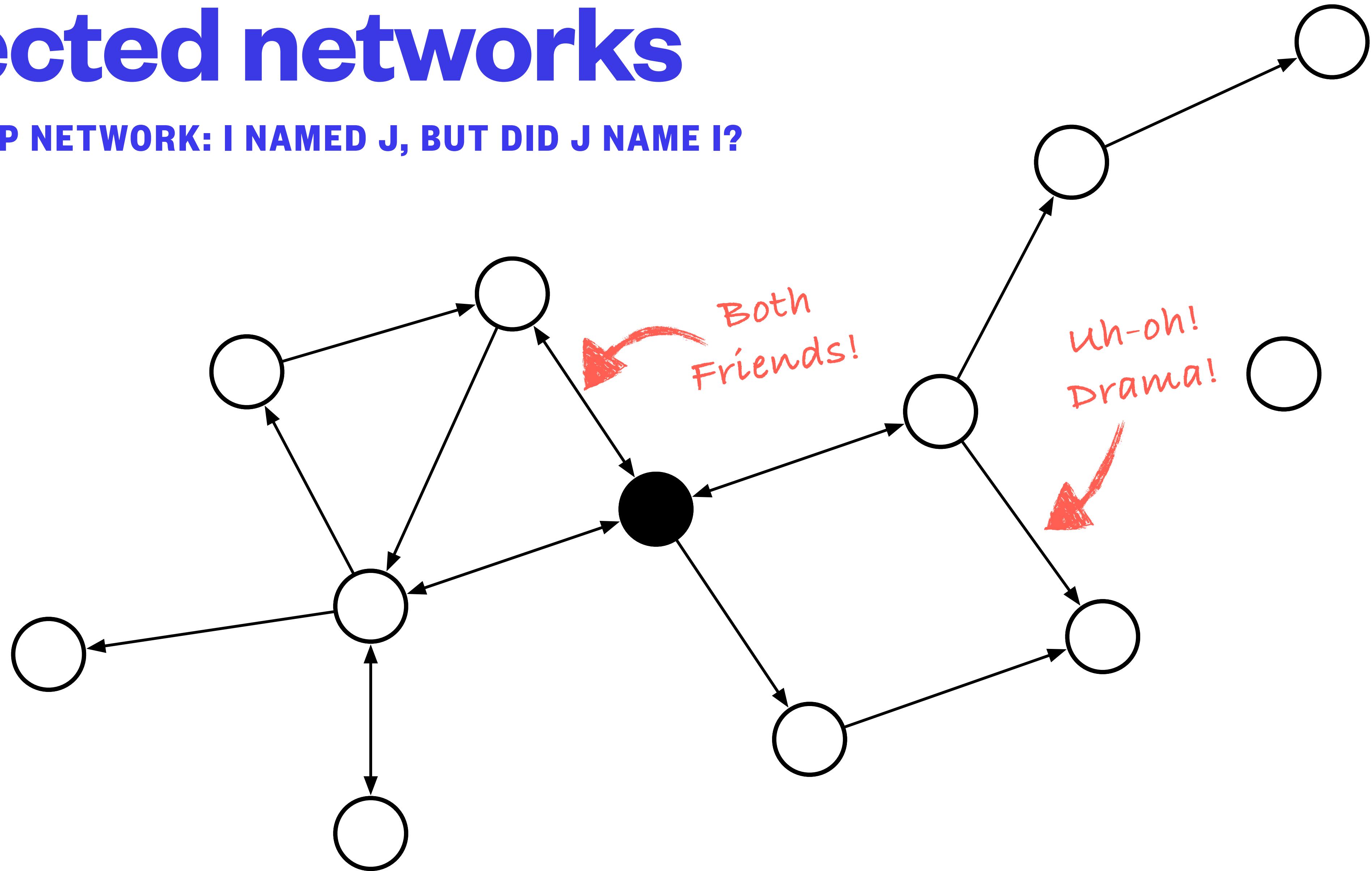


Triads



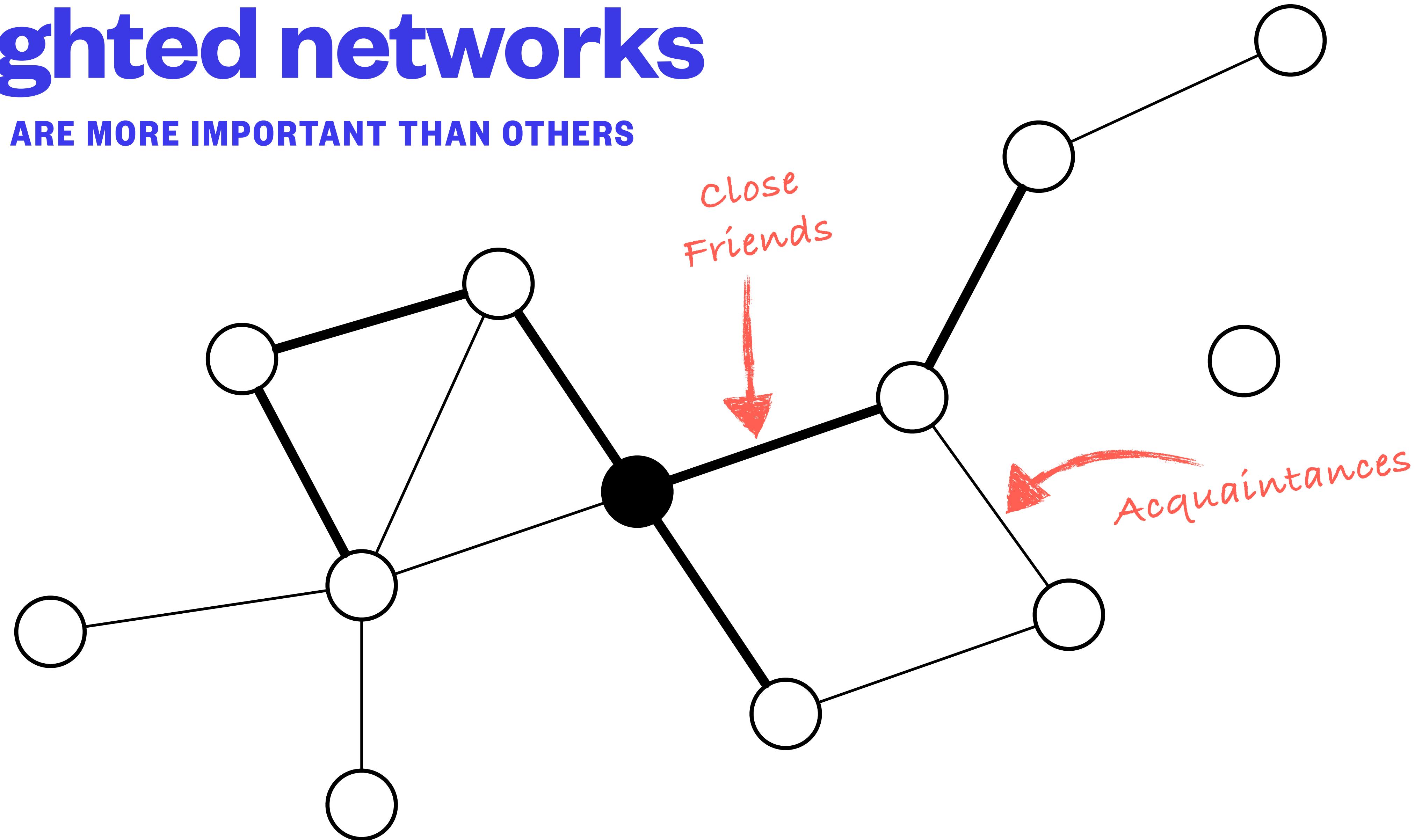
Directed networks

FRIENDSHIP NETWORK: I NAMED J, BUT DID J NAME I?



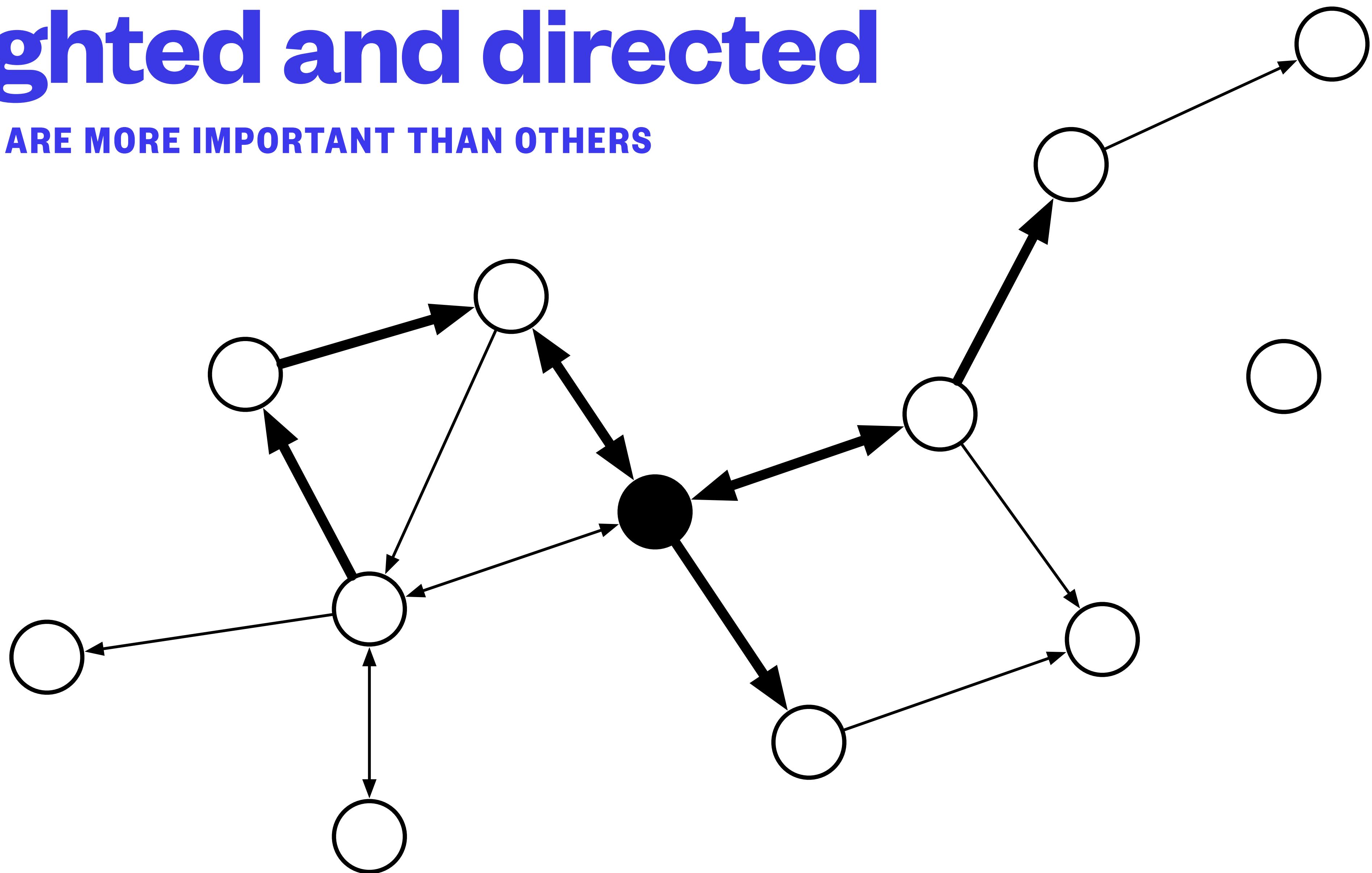
Weighted networks

SOME TIES ARE MORE IMPORTANT THAN OTHERS



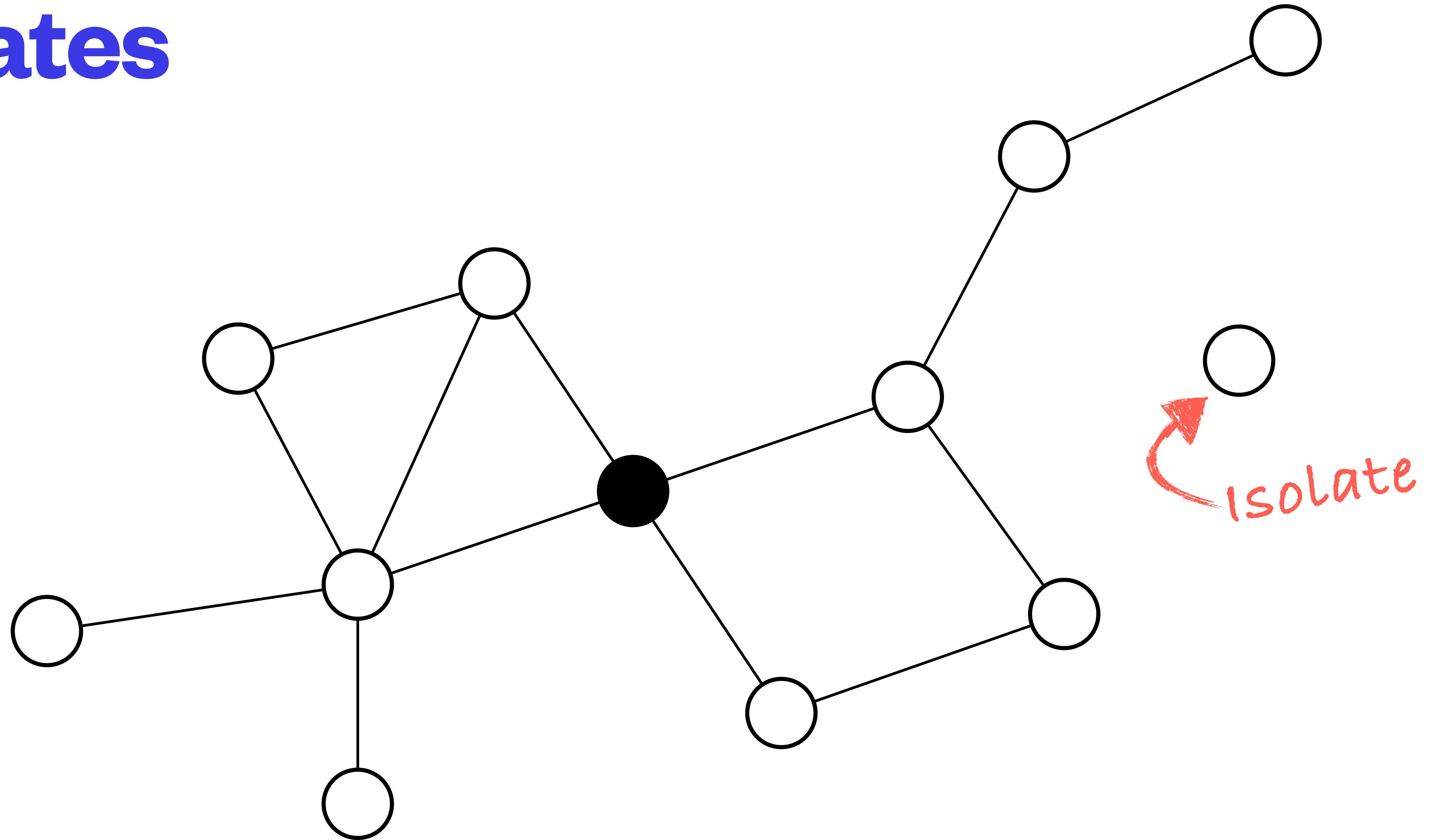
Weighted and directed

SOME TIES ARE MORE IMPORTANT THAN OTHERS

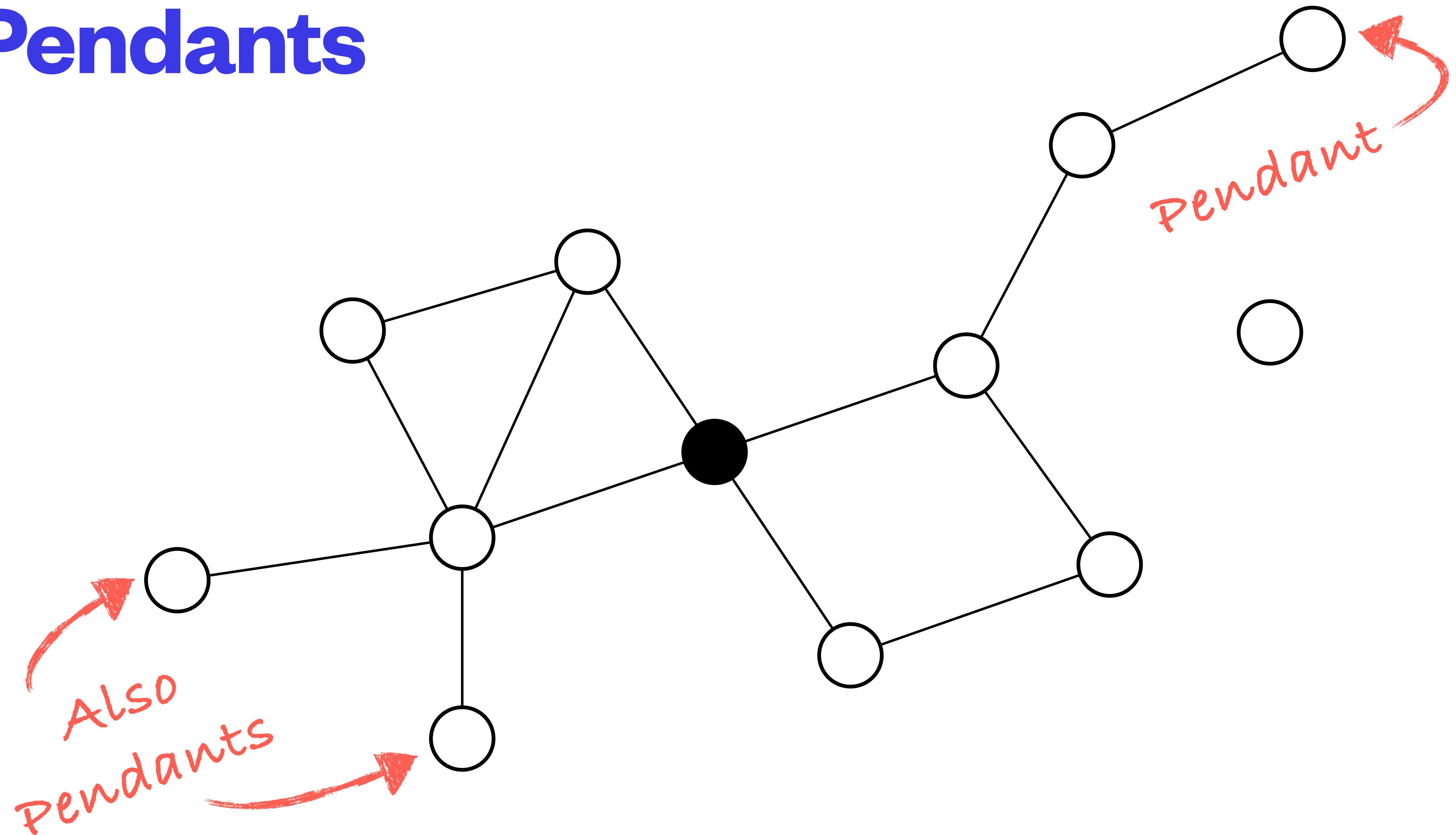


Describing Parts of Networks

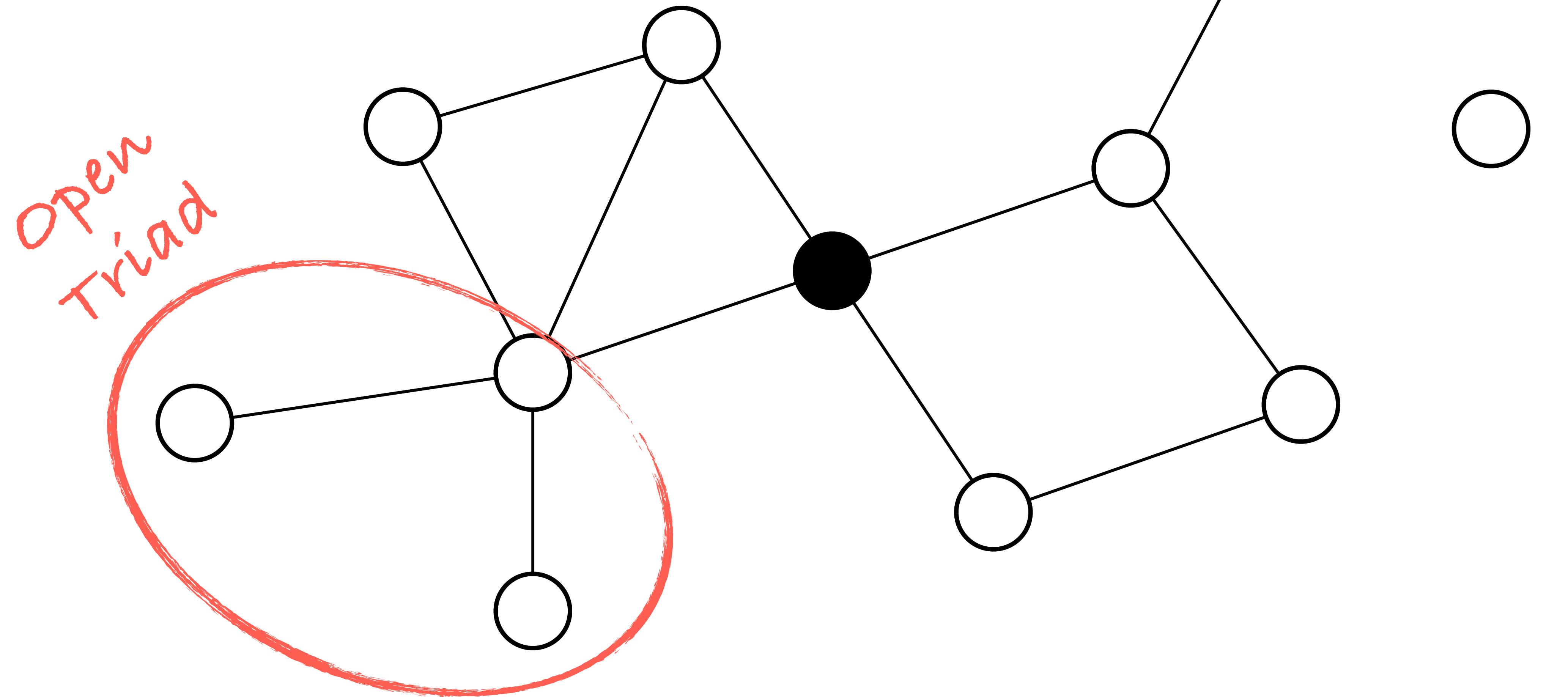
Isolates



Pendants

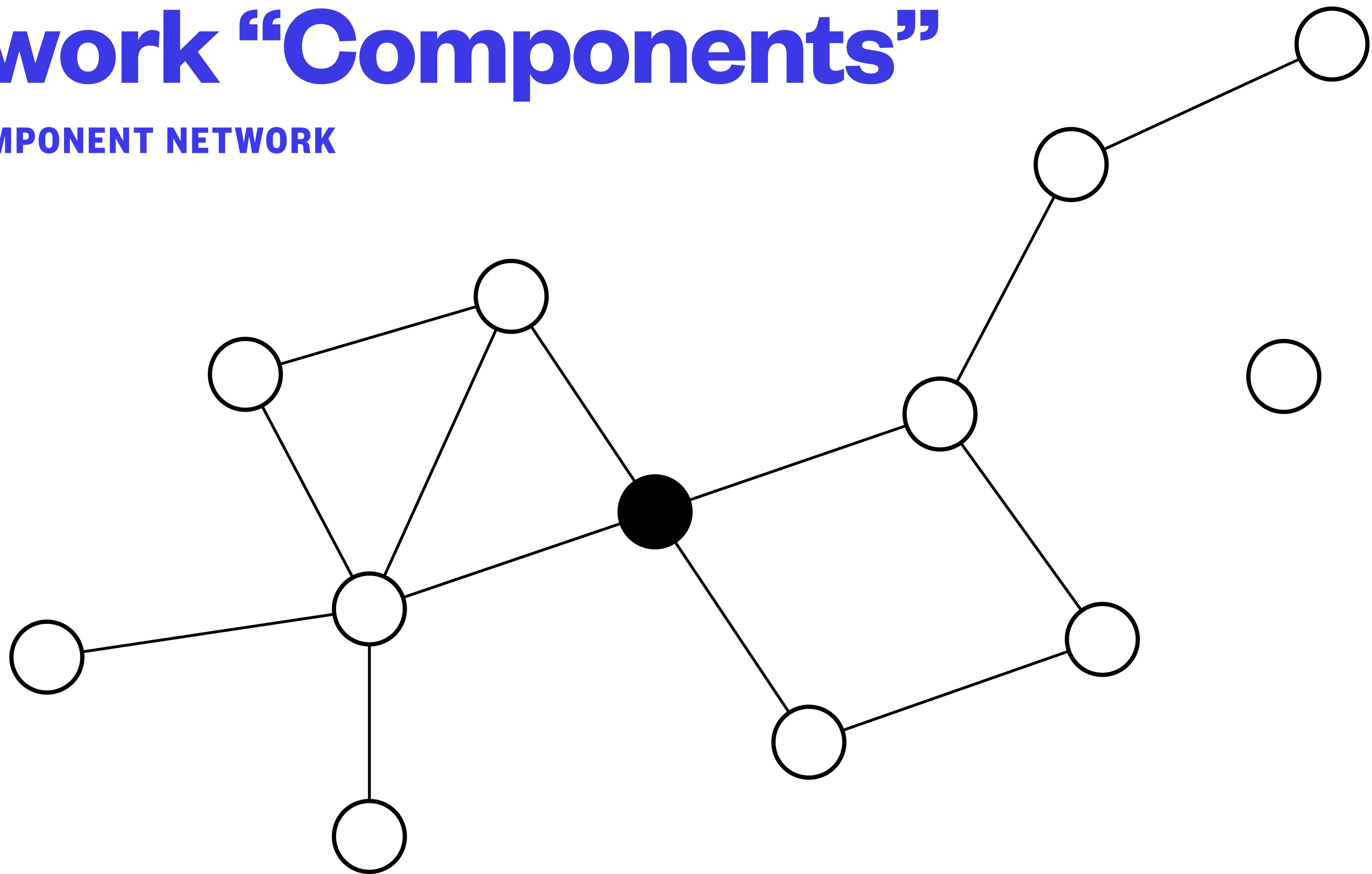


Triad



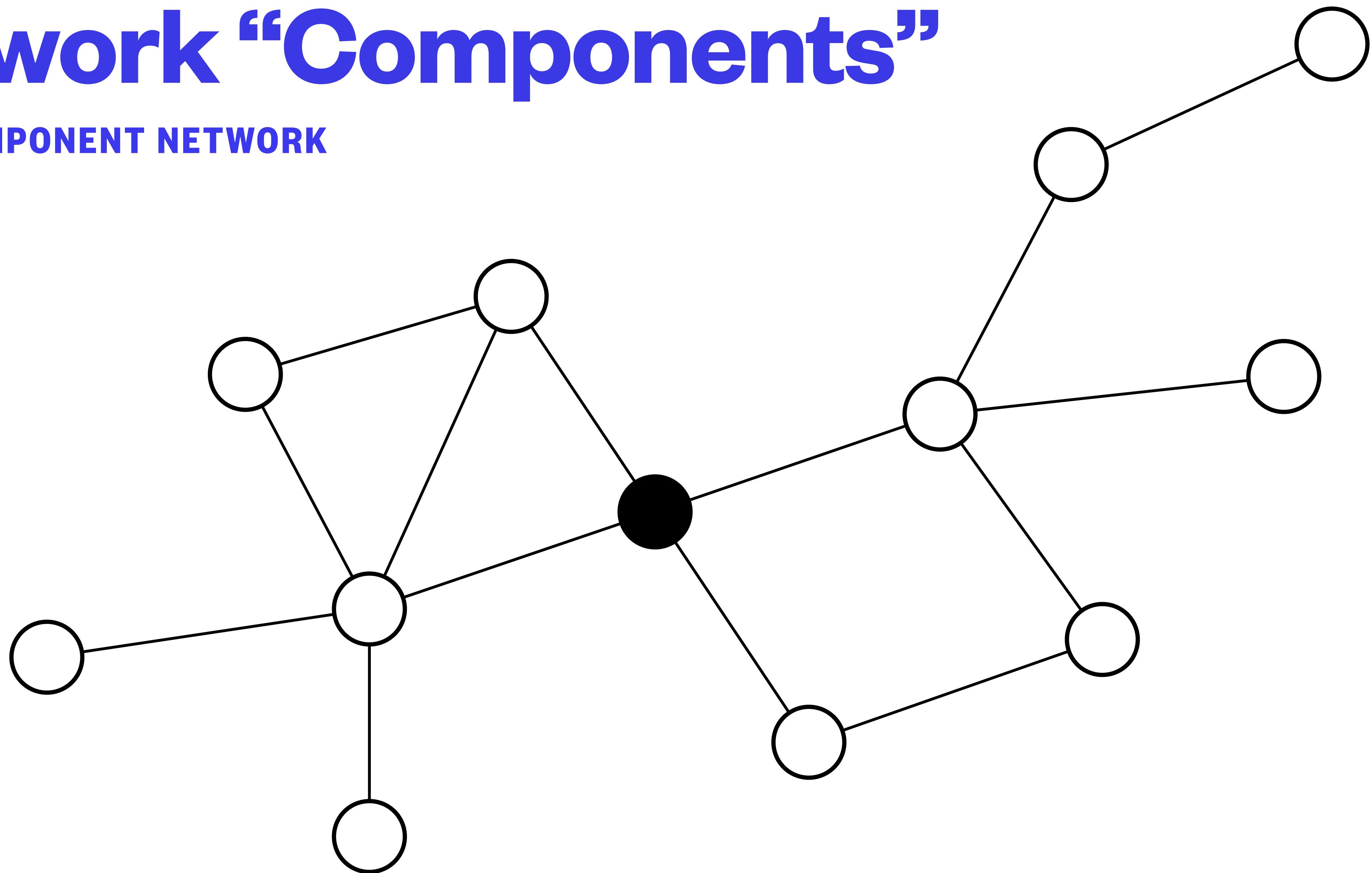
Network “Components”

A TWO-COMPONENT NETWORK



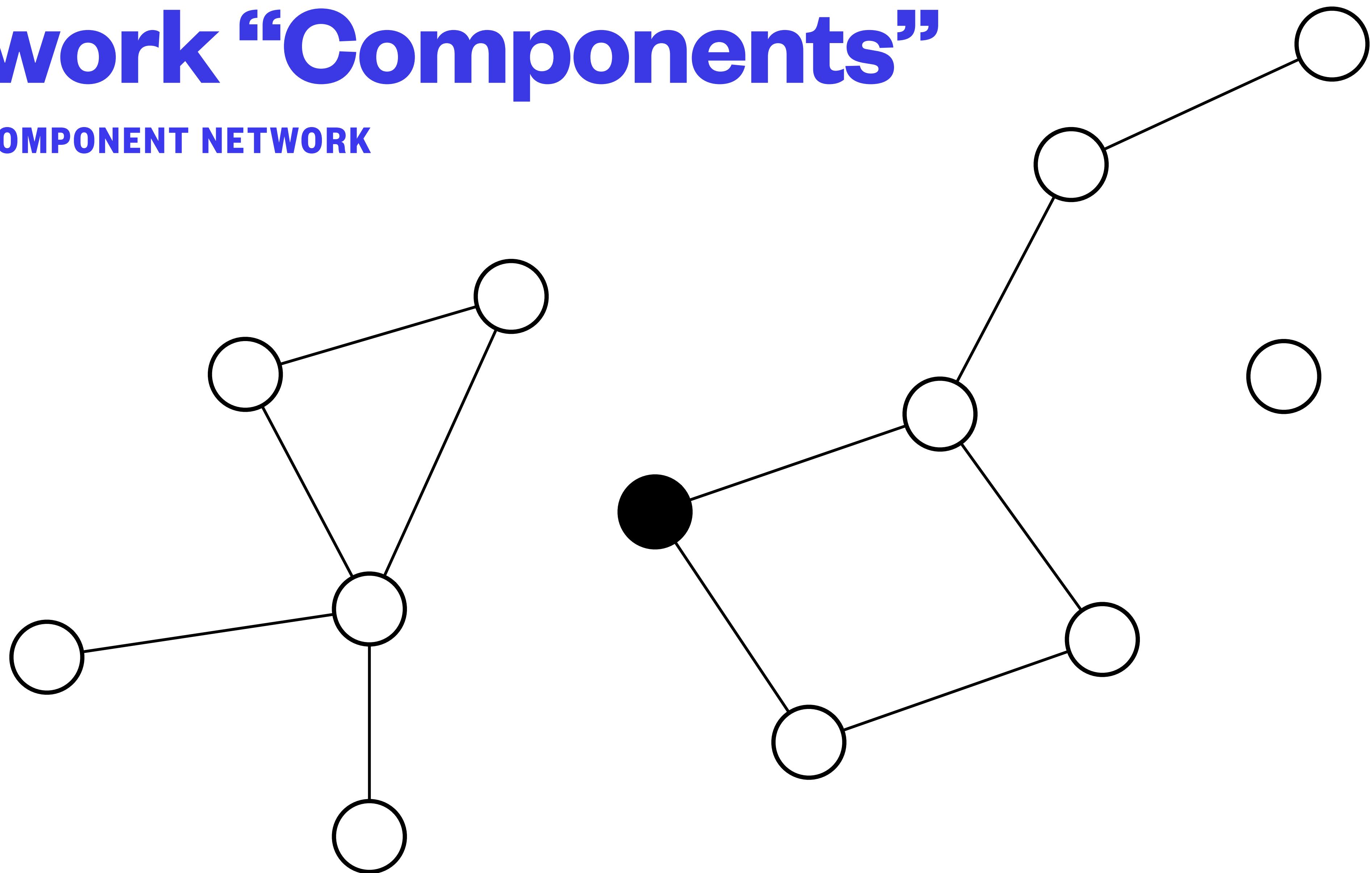
Network “Components”

A ONE-COMPONENT NETWORK



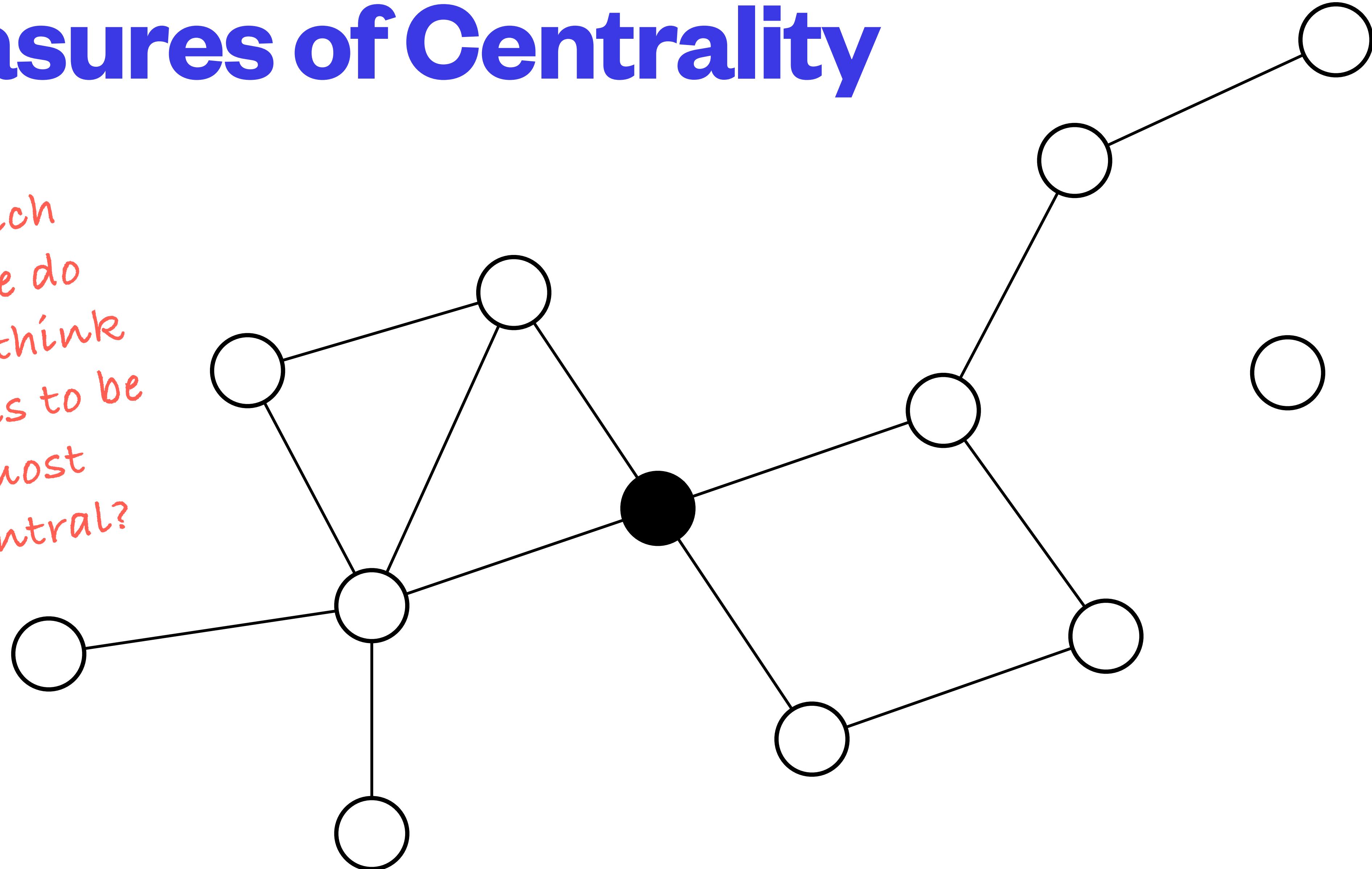
Network “Components”

A THREE-COMPONENT NETWORK



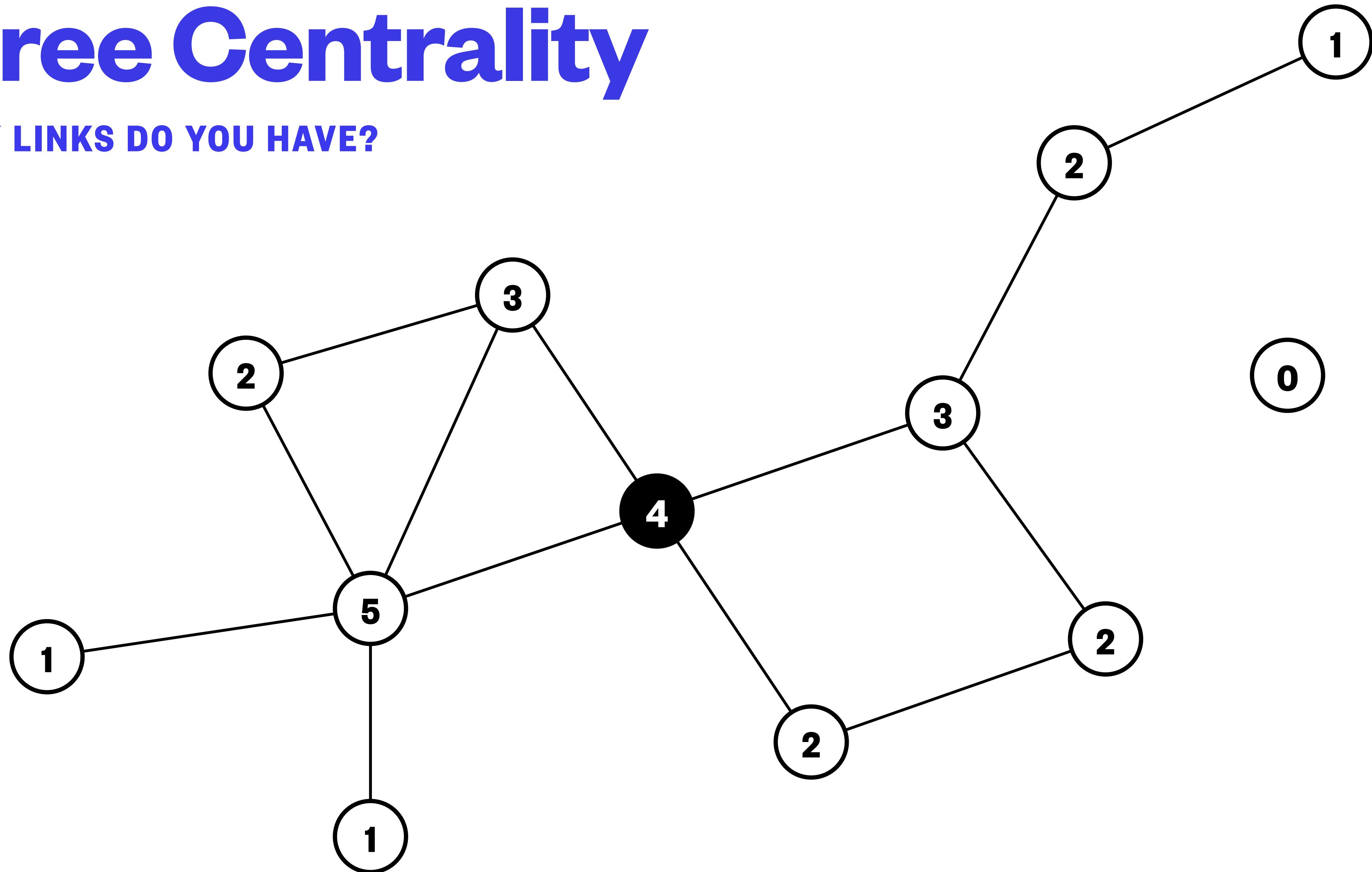
Measures of Centrality

which
node do
you think
seems to be
most
central?



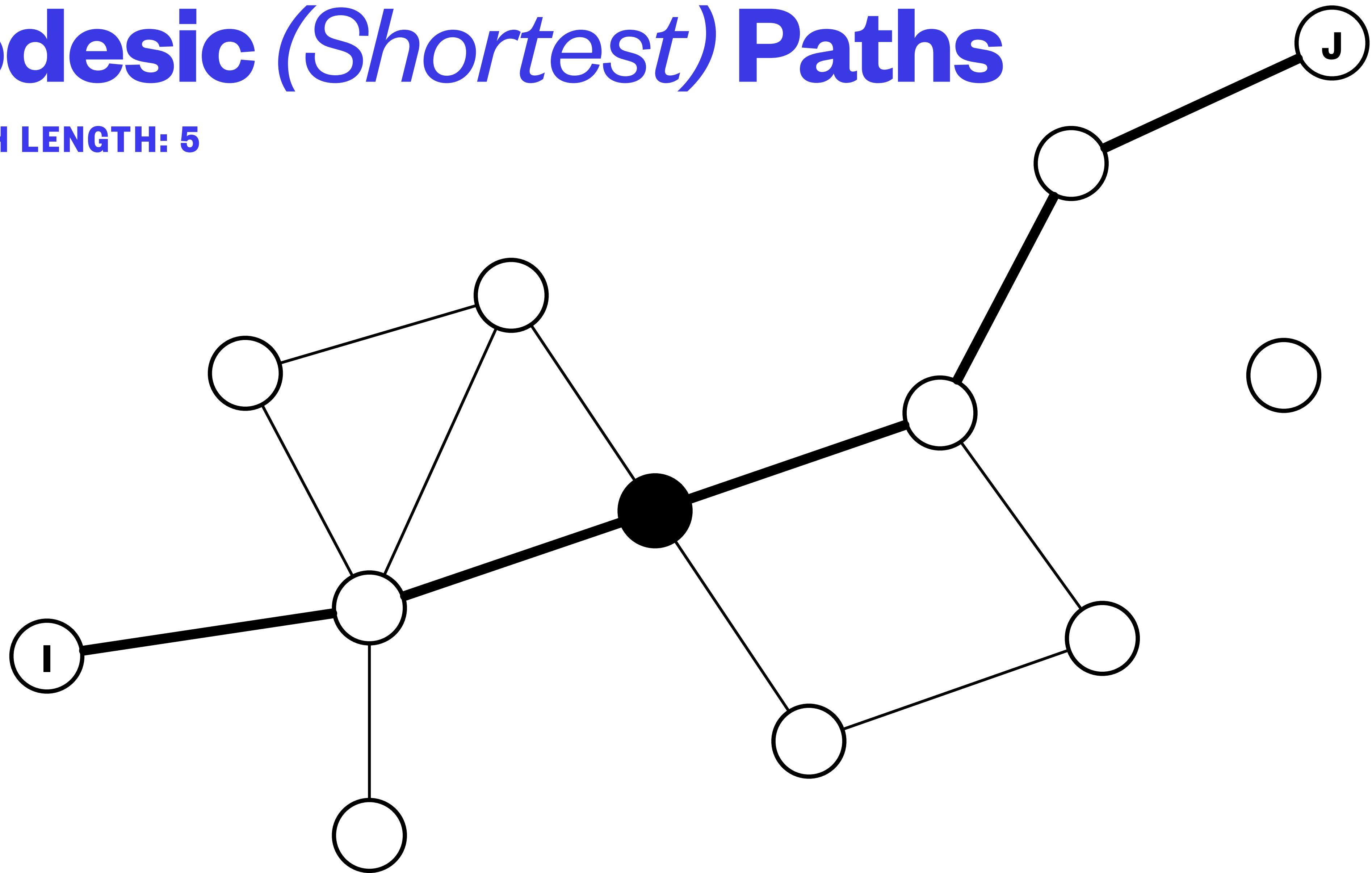
Degree Centrality

HOW MANY LINKS DO YOU HAVE?



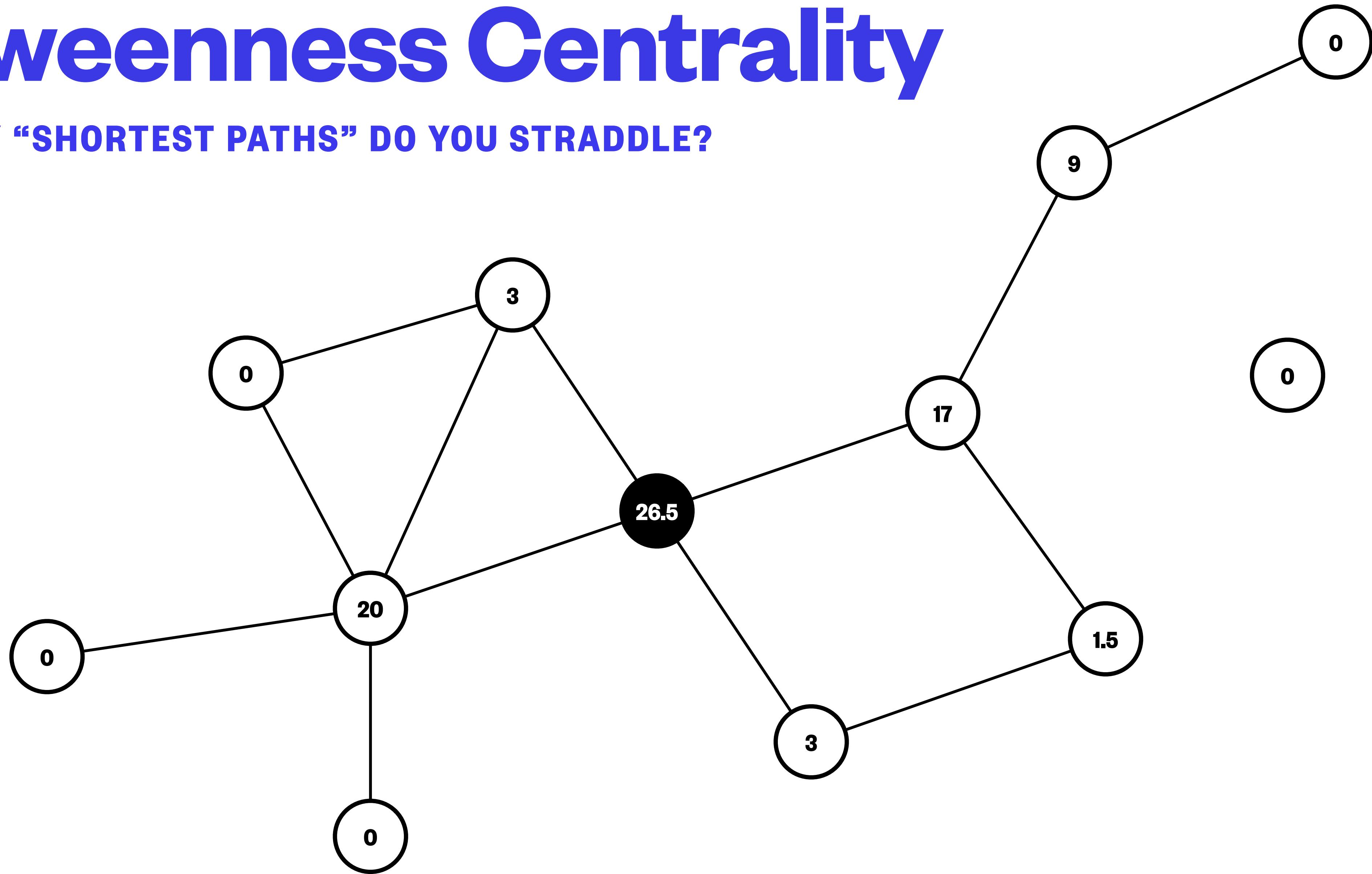
Geodesic (Shortest) Paths

I TO J PATH LENGTH: 5



Betweenness Centrality

HOW MANY “SHORTEST PATHS” DO YOU STRADDLE?



Measures of Centrality

OTHER MEASURES

- Closeness - how close is the given node to all other nodes?
- Eigenvector - are the other nodes that the chosen node is connected to also central nodes?
- Bespoke measures - power, influence, etc

Networks language

- We now know how to talk about networks
 - Main elements (nodes, edges)
 - Core variations (direction, weight)
 - Descriptors of components (dyads, triads)
 - Basic statistics (degree, centrality)
- We're ready

Part Three

How do we visualize networks?

Network Data

- The core element of a network is defining the **relationship(s) between the actors**
- Two main datasets to any network:
 - Data defining attributes of the **nodes**
 - Data defining attributes of the **edges**
- Let's motivate with a simple example: the network of agreement among members of the Supreme Court in the 2020-2021 term
 - <https://harvardlawreview.org/supreme-court-statistics/>

Node data: the node list

supreme_nodelist.csv

id	justice	abbrev	type	party	president	year	seniority
j01	Roberts	JR	Chief	Republican	Bush Jr	2005	16
j02	Thomas	CT	Associate	Republican	Bush Sr	1991	30
j03	Breyer	SB	Associate	Democrat	Clinton	1994	27
j04	Alito	SA	Associate	Republican	Bush Jr	2006	15
j05	Sotomayor	SS	Associate	Democrat	Obama	2009	12
j06	Kagan	EK	Associate	Democrat	Obama	2010	11
j07	Gorsuch	NG	Associate	Republican	Trump	2017	4
j08	Kavanaugh	BK	Associate	Republican	Trump	2018	3
j09	Barrett	ACB	Associate	Republican	Trump	2020	1

- A pretty ordinary looking dataset, similar to what we'd see in cross-sectional analysis
- Each row corresponds to a justice, each column corresponds to an attribute of the justice

Edge data: the edge list

`supreme_edgelist.csv`

from	to	type	weight
j01	j02	agreement	0.463
j01	j03	agreement	0.488
j01	j04	agreement	0.625
j01	j05	agreement	0.366
j01	j06	agreement	0.463
j01	j07	agreement	0.512
j01	j08	agreement	0.927
j01	j09	agreement	0.743
j02	j03	agreement	0.293
j02	j04	agreement	0.525
j02	j05	agreement	0.171
j02	j06	agreement	0.341

- Each row corresponds to an edge/link in the dataset
 - IDs link the node list and edge list
- Each column is an attribute of the edge
- This network is *undirected* (the agreement between j01 and j02 is the same as the agreement between j02 and j01)
 - Only a single row per relation
 - A *directed* network would have not just a j01-j02 row, but a j02-j01 row as well

More edge data: the adjacency matrix

`supreme_adjacency.csv`

	j01	j02	j03	j04	j05	j06	j07	j08	j09
j01	.	0.463	0.488	0.625	0.366	0.463	0.512	0.927	0.743
j02	.	.	0.293	0.525	0.171	0.341	0.707	0.488	0.600
j03	.	.	.	0.200	0.805	0.854	0.366	0.537	0.429
j04	0.125	0.175	0.600	0.600	0.588
j05	0.805	0.244	0.415	0.314
j06	0.415	0.512	0.486
j07	0.561	0.686
j08	0.800
j09

- Each cell corresponds to an edge/link in the dataset
 - The weight of each edge is given by the value of the cell
- This network is *undirected* (the agreement between j01 and j02 is the same as the agreement between j02 and j01)
 - Only a single cell per relation
 - A *directed* network would have not just a j01-j02 cell, but a j02-j01 cell as well
- Unlike an edge list, only one attribute per link

Using R (and iGraph) for Social Networks

- R's advantages:
 - Easily integrates with the rest of a data workflow
 - More programmatically flexible (for the programmatically inclined) than GUIs
 - Reproducible
 - Free!
- R's “disadvantages”:
 - Needs to be scripted/programmed
 - Network visualization not built in; must use additional libraries, which themselves have different strengths and weaknesses
- **iGraph** vs. **Statnet**; assorted others for interactive and dynamic networks

Loading the data

```
#Load library
library("igraph")

#Load nodelist and edgelist as objects
nodes <- read.csv("supreme_nodes.csv", header=T, as.is=T)
links <- read.csv("supreme_edgelist.csv", header=T, as.is=T)

#Convert to an iGraph network. "d" identifies the edgelist; "vertices" identifies the nodelist
net <- graph_from_data_frame(d=links, vertices=nodes, directed=F)

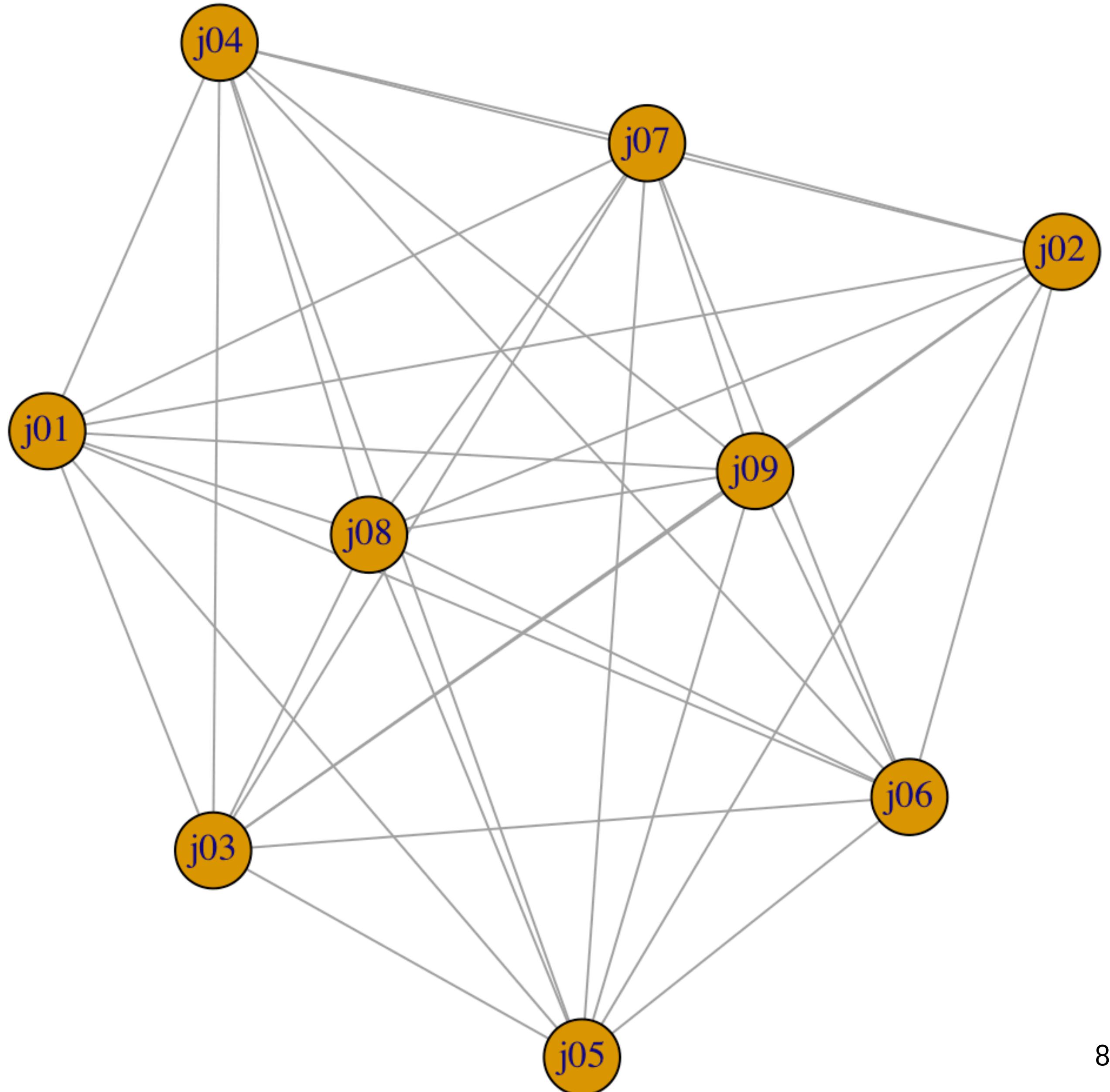
#If we want to output an adjacency matrix, we can
#(we just need to identify the attribute to encode)
adjacency<-as_adjacency_matrix(net, attr="weight")
```

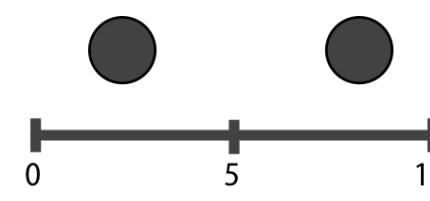
Working with the data

Command	Usage
E(net)	Access the edges of the network
V(net)	Access the nodes of the network
E(net)\$weight	Access a particular attribute (weight) of the edges of the network
V(net)\$seniority	Access a particular attribute (seniority) of the nodes of the network
V(net)[president=="Obama"]	Returns all vertices with appointing president "Obama"
E(net)[weight>.9]	Returns all edges with weight greater than .9
net[1,]	Returns first row of network matrix
net[5, 7]	Returns cell in the fifth row, seventh column
plot.igraph(net) or plot(net)	Plots the network (!)

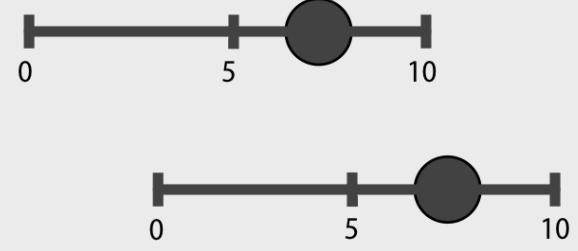
plot.igraph(net)

- And . . . ok, but, it's kind of . . .
 - uninspired
- What's wrong?
 - Links are overplotted
 - Links are undifferentiated
 - Node labels are uninspiring
 - Colors
- How should we fix it?





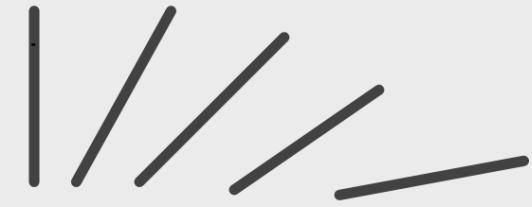
Position on
a common scale



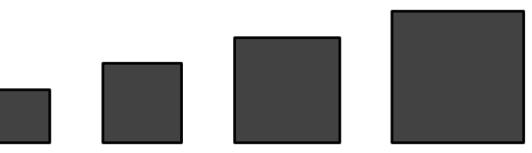
Position on
unaligned
scales



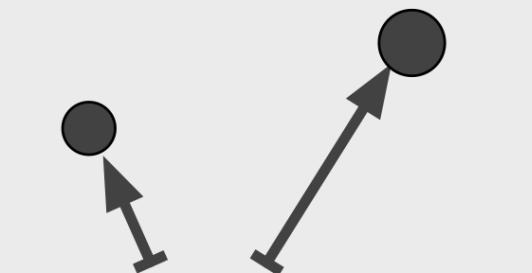
Length



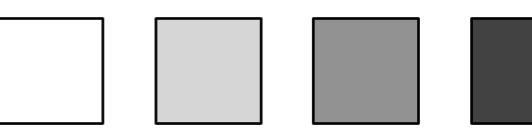
Tilt or Angle



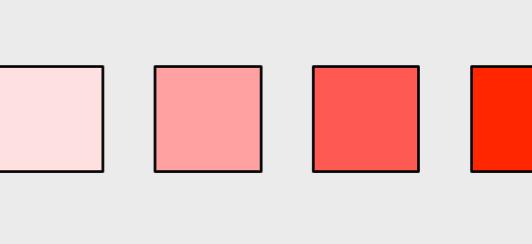
Area (2D as size)



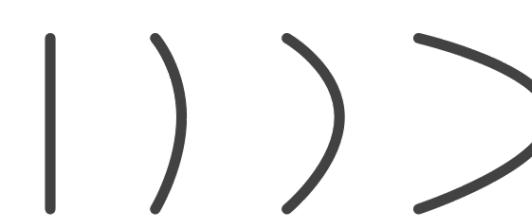
Depth
(3D as position)



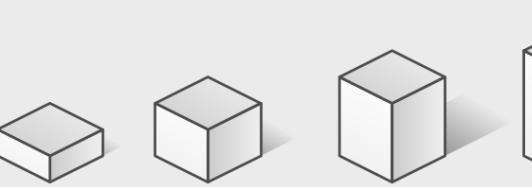
Color luminance
or brightness



Color saturation
or intensity



Curvature



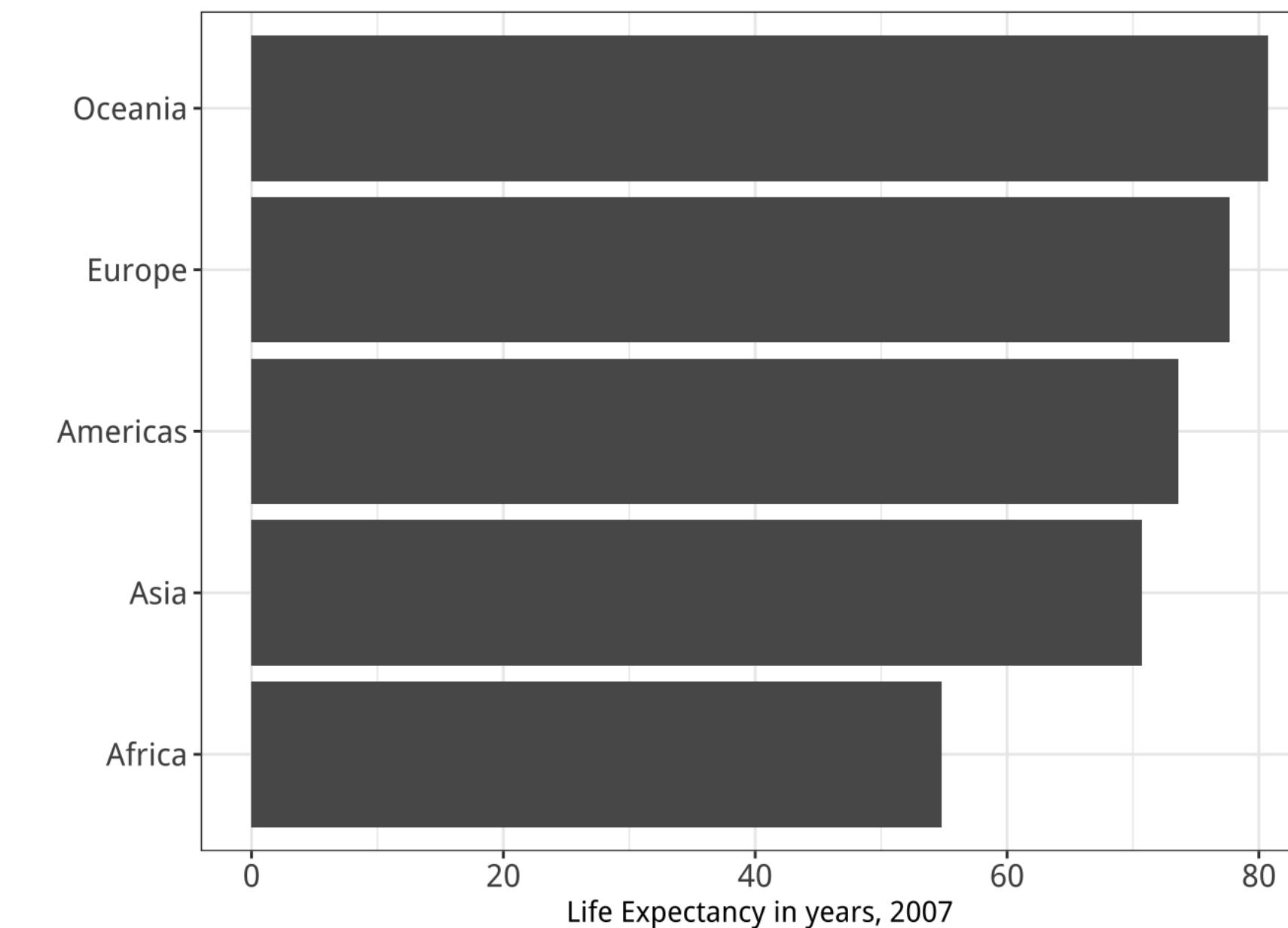
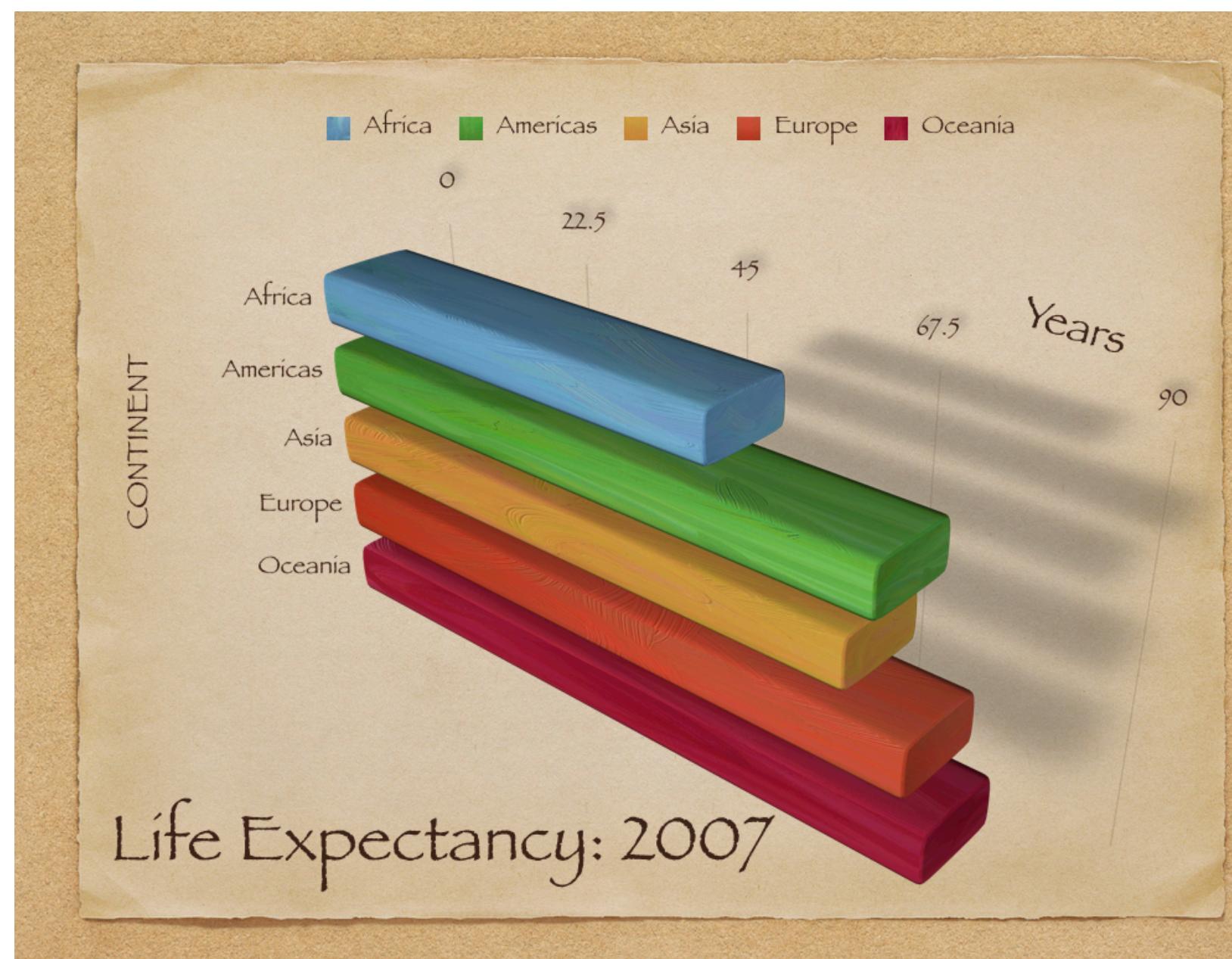
Volume
(3D as size)

Graphics guidelines

- Data does not speak for itself
- Like in regular graphics and visualization, plotting networks is a matter of **taste**, not (unfortunately) science
 - *Tastes can differ, but . . .*
- Healy (2020) identifies three common graphics challenges to focus on:
 - **Aesthetic** - inconsistent or displeasing design choices
 - **Substantive** - the data presented are mistaken, incorrect, or misleading
 - **Perceptual** - something about the presentation doesn't easily translate to information through human visual apparatus

Bad graphics

- Tufte (2001) suggests that **chartjunk** is often to blame, with too much detritus on the graphic getting in the way of the information being presented
- **Data-ink ratio** - the amount of “ink” used to achieve **data communication goals** vs the total amount of ink on the graphic

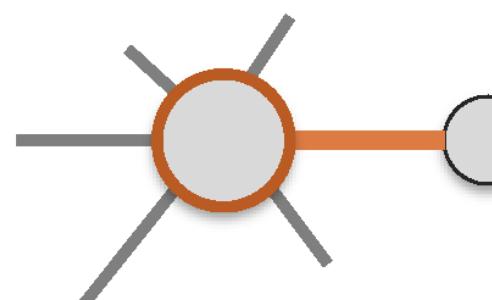


Visualization guidelines for networks

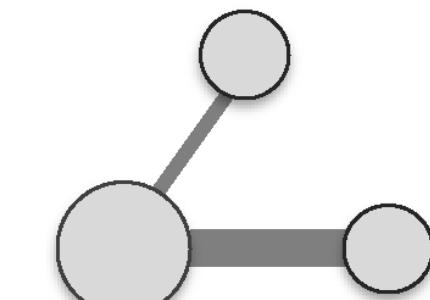
- Ognyanova (2021)
 - What visualization **goals** do you have? What is(are) the main relationship(s) you are trying to illustrate?
 - What **type** of network visualization do you want to use?
 - What **elements** do you want to utilize in your visualization to illustrate contrast in your network?
 - What **aesthetics** should you be aware of when plotting networks

Network visualization goals

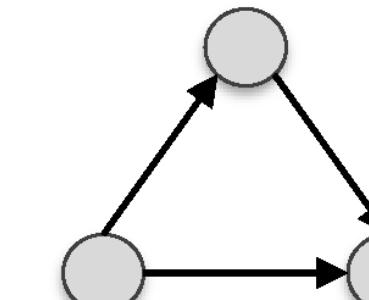
Key actors and links



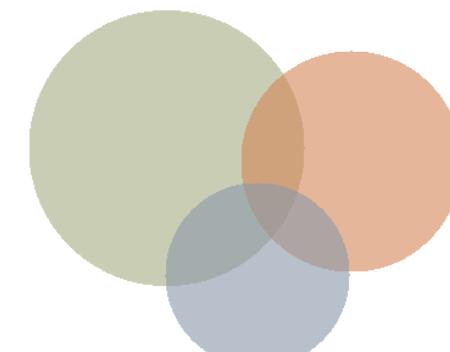
Relationship strength



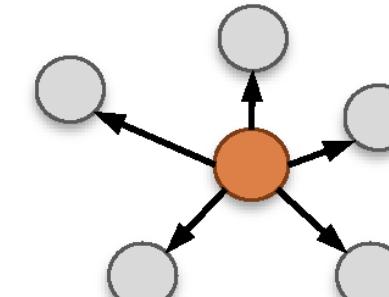
Structural properties



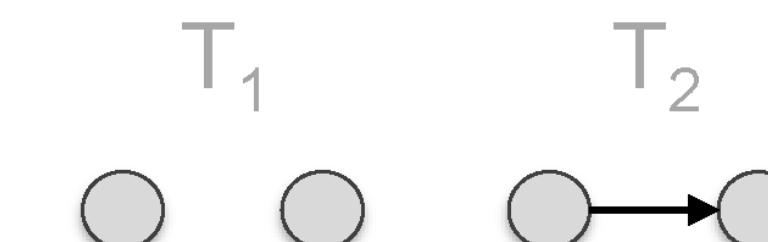
Communities



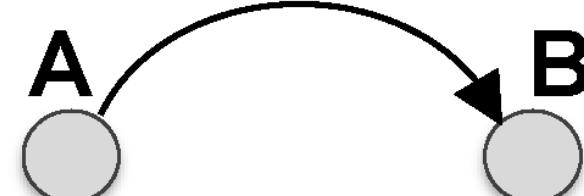
Diffusion patterns



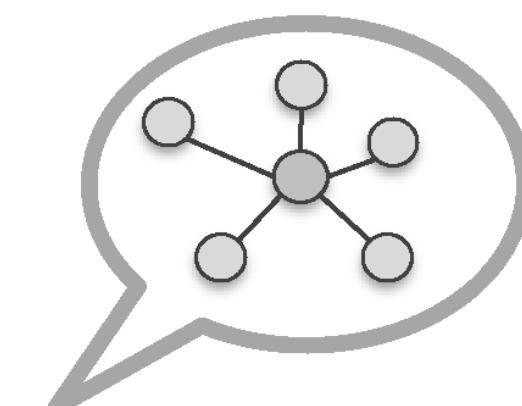
Network evolution



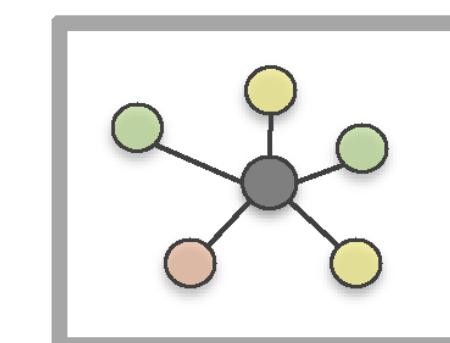
Networks as maps



Networks as persuasion

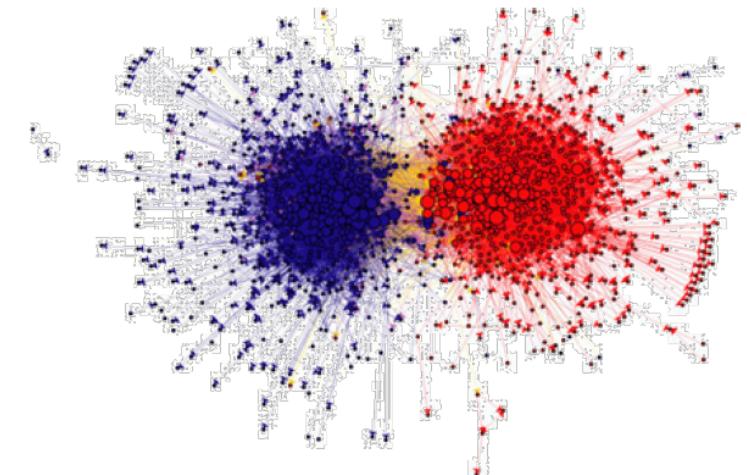


Networks as art

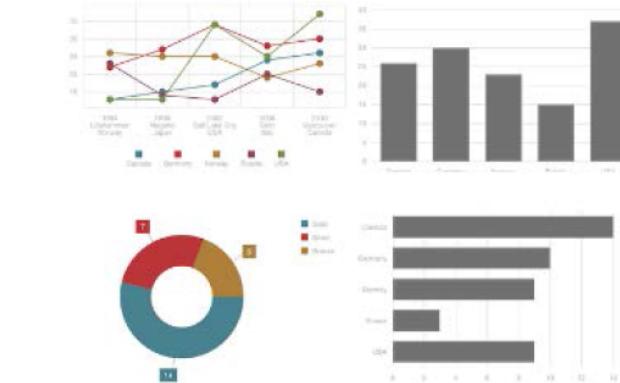


Some network visualization types

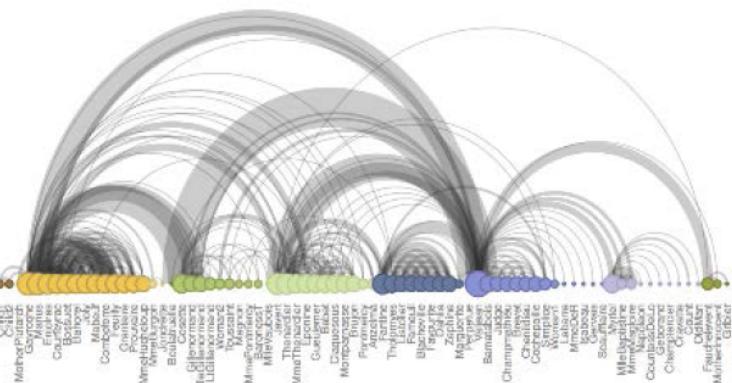
Network Maps



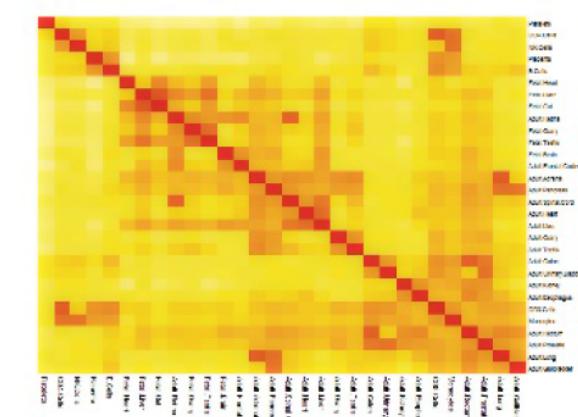
Statistical charts



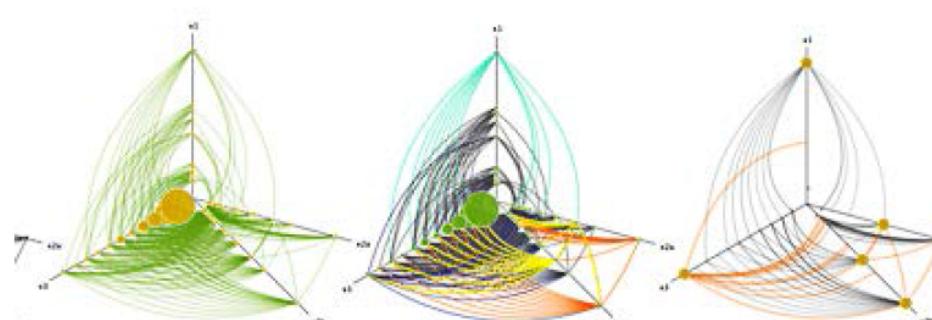
Arc diagrams



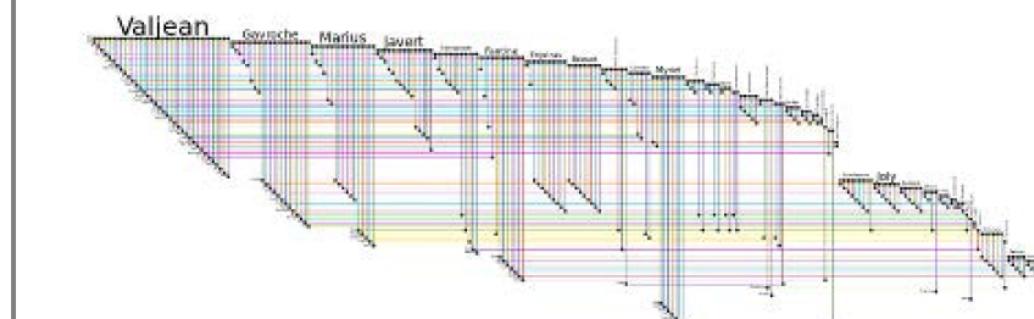
Heat maps



Hive plots

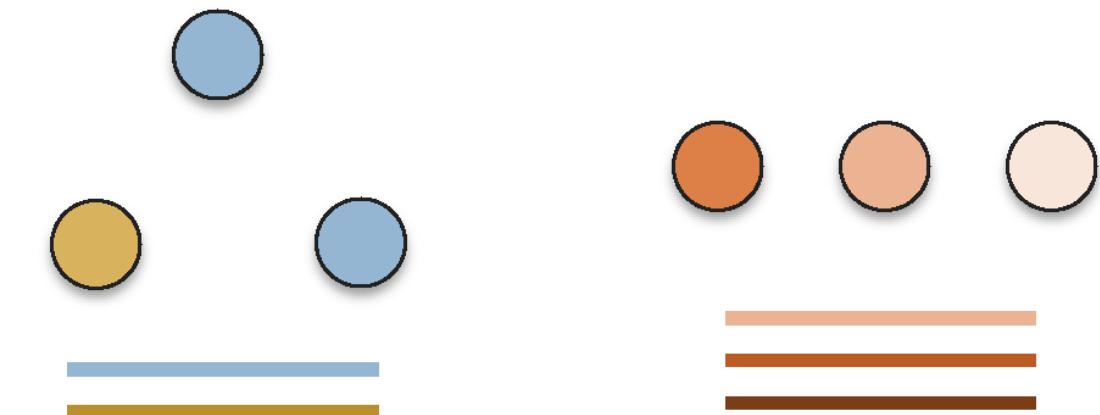


Biofabric



Network visualization controls

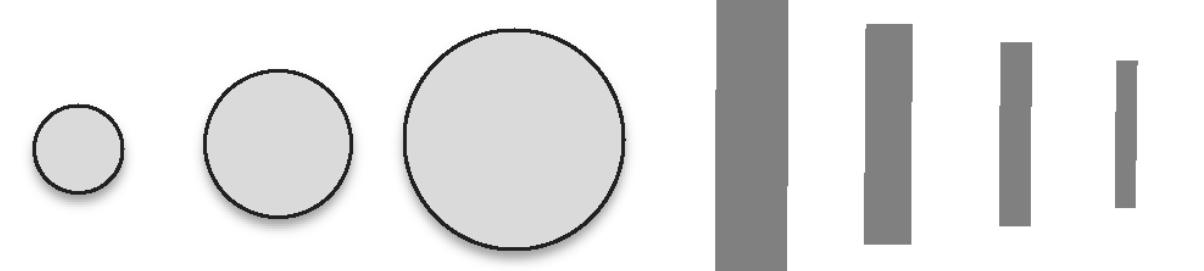
Color



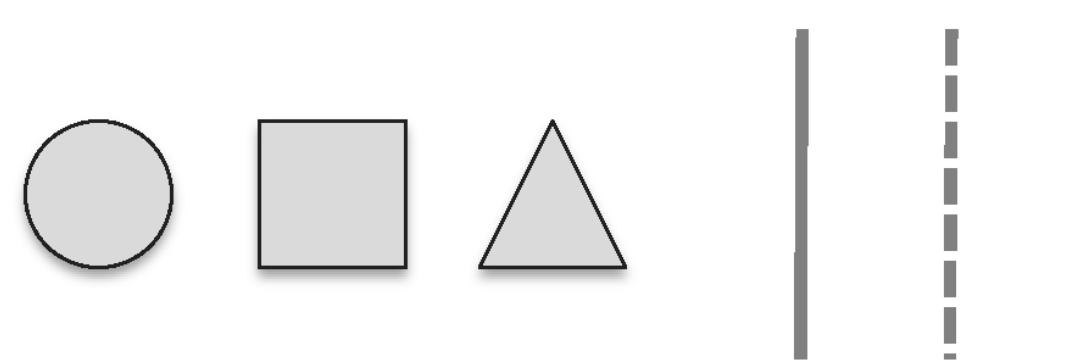
Position



Size



Shape

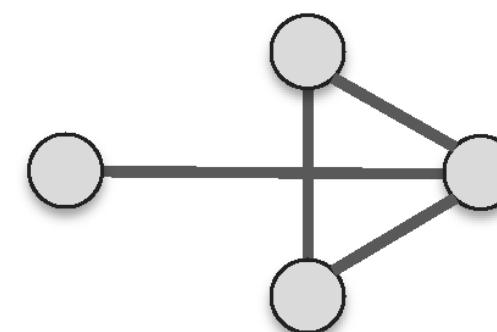


Honorable mention: arrows (direction) and labels (identification)

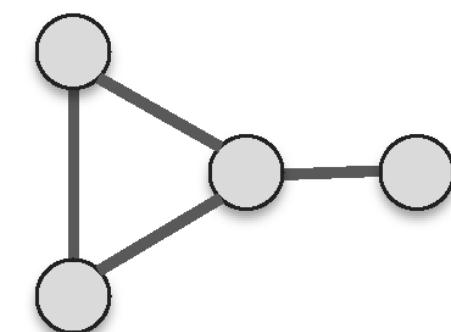
Layout aesthetics

Minimize edge crossing

No

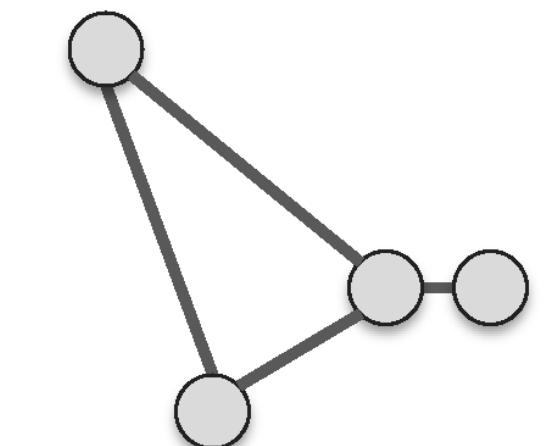


Yes

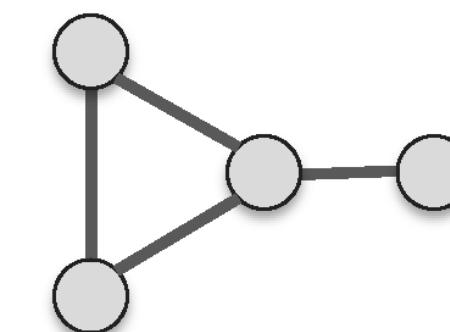


Uniform edge length

No

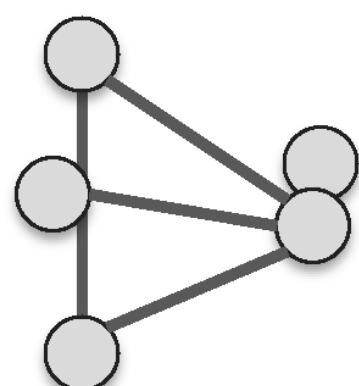


Yes

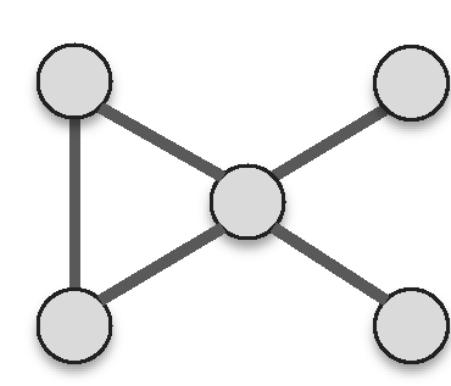


Prevent overlap

No

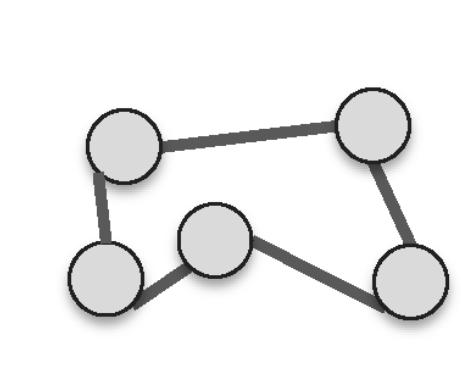


Yes

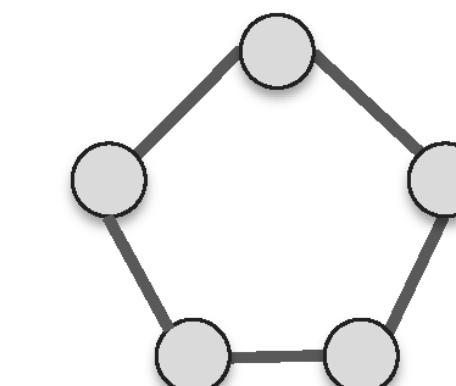


Symmetry

No

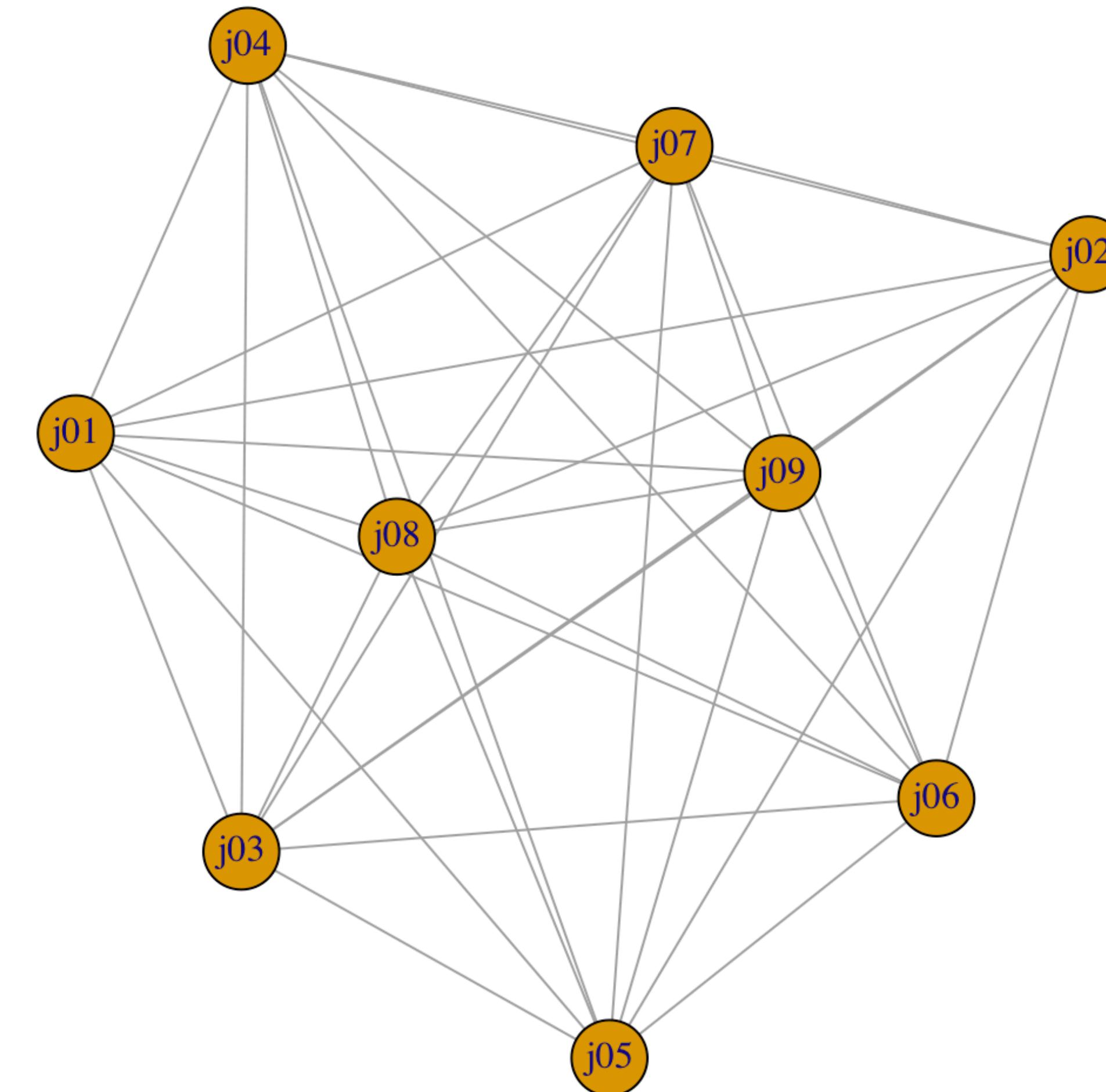


Yes



Goals in the Supreme Court network

- Identify **who** the justices are
- Illustrate external **political factors** relevant to the Supreme Court
- Show who the most **central** (likely “decisive”) justices are
- Show **agreement** and **disagreement** among the justices



Goals in the Supreme Court network

- Identify **who** the justices are → • *Label the nodes*
- Illustrate external **political factors** relevant to the Supreme Court → • *Color the nodes to show party of appointment*
- Show who the most **central** (likely “decisive”) justices are → • *Calculate centrality and illustrate it visually*
- Show **agreement** and **disagreement** among the justices → • *Do something with the ties/edges - thickness and/or color*

Along the way, don't forget about other aesthetics: color, tie overlap, etc.

Controlling iGraph graphic elements

- Two ways of editing network graphs
 - Use parameters of the `plot.igraph` command
 - Write information about graphical attributes to the network object itself (that `plot.igraph` will then read)
- Command order and priority
 - Parameters of the `plot.igraph` command itself will overwrite information written into the network object

Plotting parameters

NODES

vertex.color Node color

vertex.frame.color Node border color

vertex.shape One of “none”, “circle”, “square”, “csquare”, “rectangle”, “crectangle”, “vrectangle”, “pie”, “raster”, or “sphere”

vertex.size Size of the node (default is 15)

vertex.size2 The second size of the node (e.g. for a rectangle)

vertex.label Character vector used to label the nodes

vertex.label.family Font family of the label (e.g. “Times”, “Helvetica”)

vertex.label.font Font: 1 plain, 2 bold, 3, italic, 4 bold italic, 5 symbol

vertex.label.cex Font size (multiplication factor, device-dependent)

vertex.label.dist Distance between the label and the vertex

vertex.label.degree The position of the label in relation to the vertex, where 0 is right, “pi” is left, “pi/2” is below, and “-pi/2” is above

Plotting parameters

EDGES

edge.color Edge color

edge.width Edge width, defaults to 1

edge.arrow.size Arrow size, defaults to 1

edge.arrow.width Arrow width, defaults to 1

edge.lty Line type, could be 0 or “blank”, 1 or “solid”, 2 or “dashed”,
3 or “dotted”, 4 or “dotdash”, 5 or “longdash”, 6 or “twodash”

edge.label Character vector used to label edges

edge.label.family Font family of the label (e.g. “Times”, “Helvetica”)

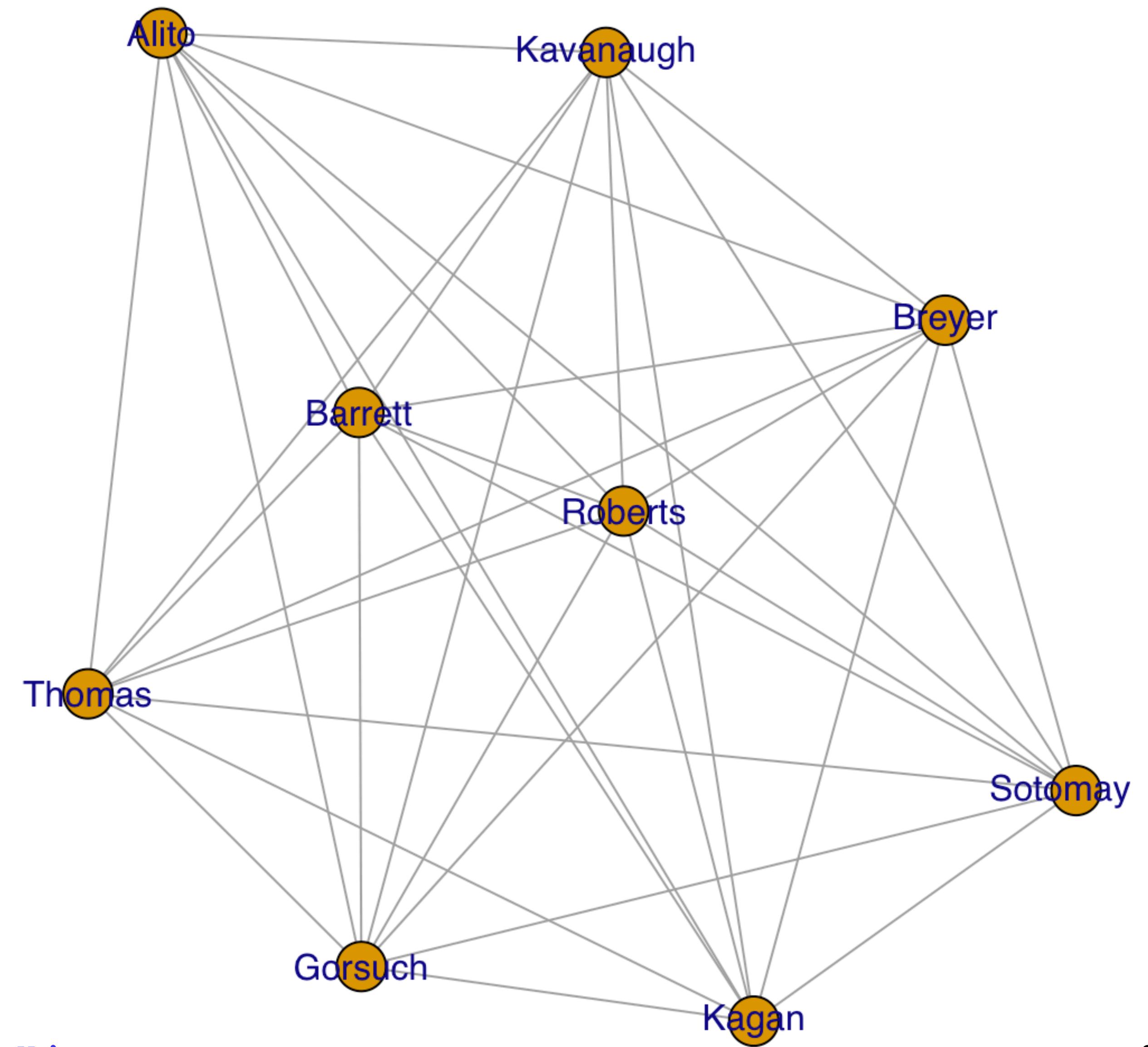
edge.label.font Font: 1 plain, 2 bold, 3, italic, 4 bold italic, 5 symbol

edge.label.cex Font size for edge labels

edge.curved Edge curvature, range 0-1 (FALSE sets it to 0, TRUE to 0.5)

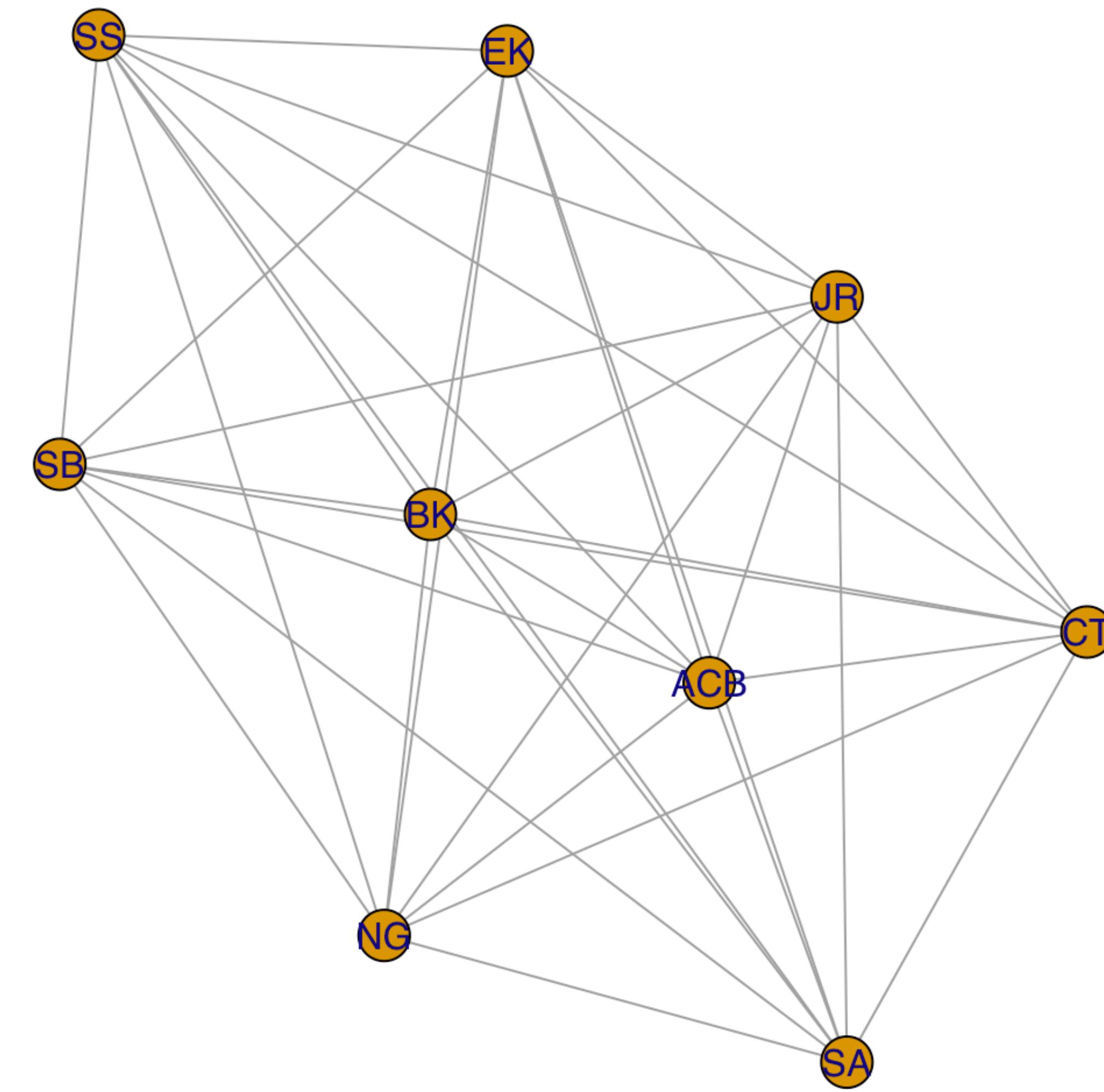
arrow.mode Vector specifying whether edges should have arrows,
possible values: 0 no arrow, 1 back, 2 forward, 3 both

Label nodes



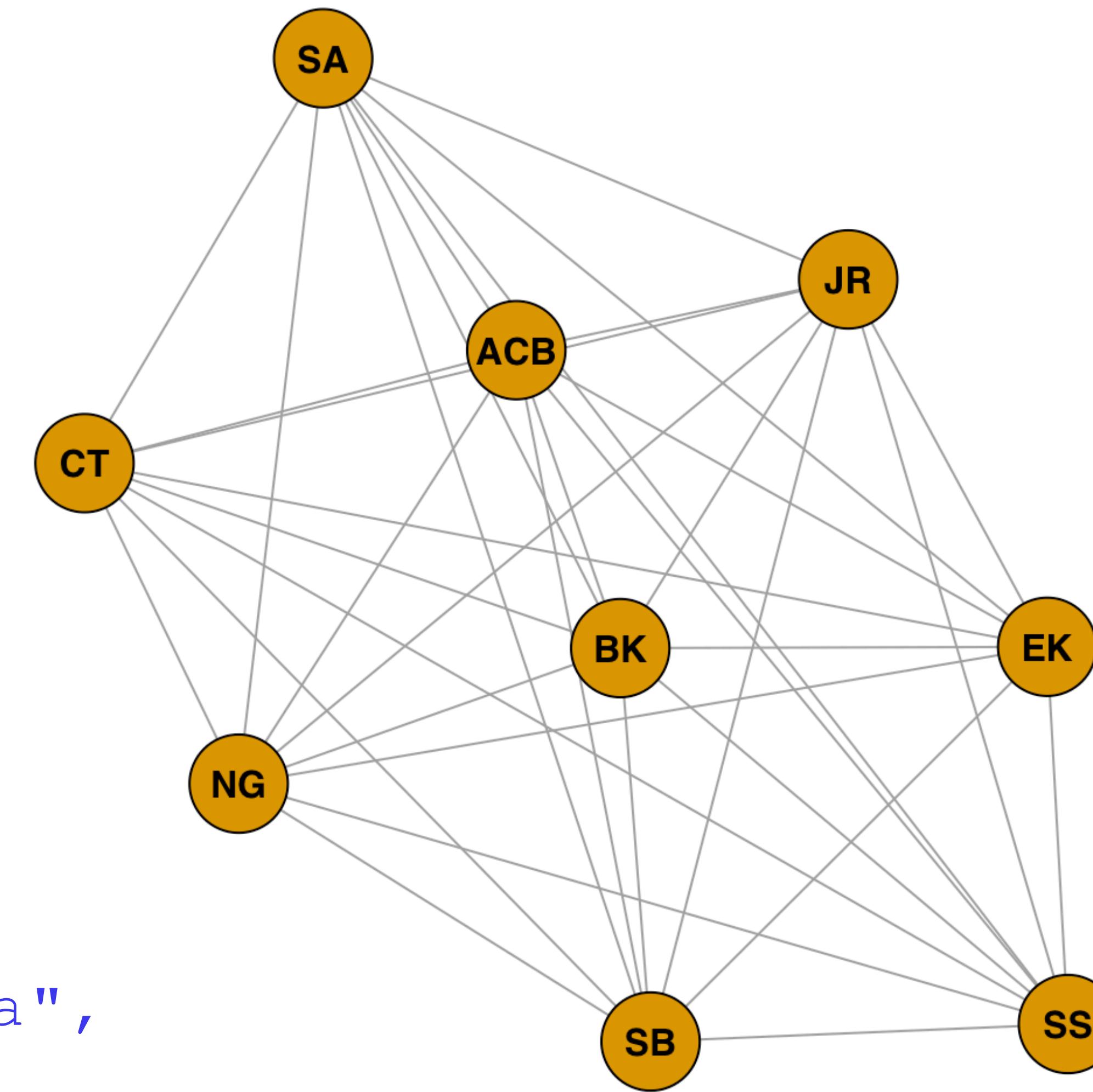
```
plot.igraph(net,  
vertex.label=v(net)$justice,  
vertex.label.family="Helvetica")
```

Label nodes



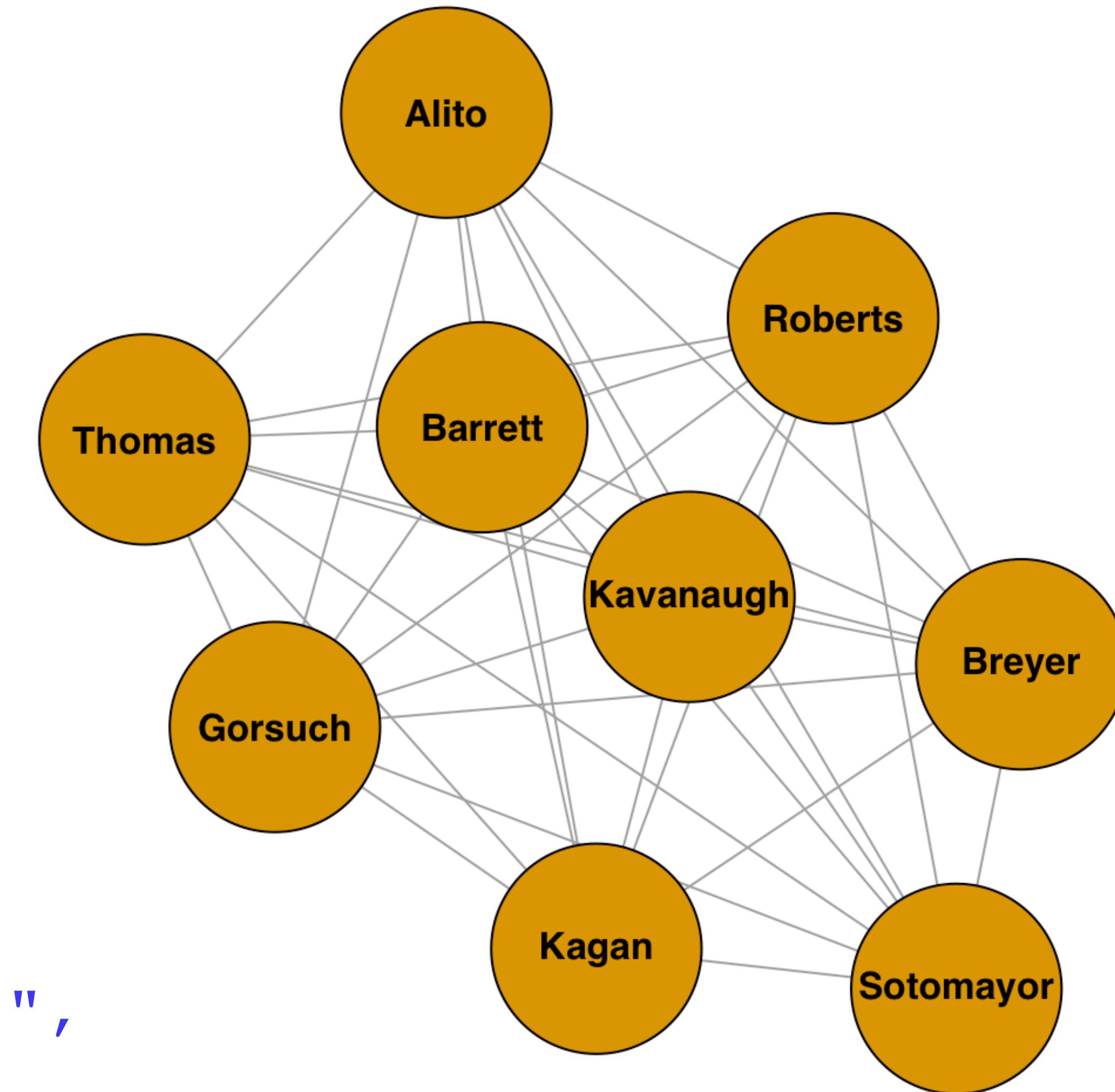
```
plot.igraph(net,  
vertex.label=V(net)$abbrev,  
vertex.label.family="Helvetica")
```

Label nodes



```
plot.igraph(net,  
vertex.label=v(net)$abbrev,  
vertex.label.family="Helvetica",  
vertex.label.font=2,  
vertex.label.color="black",  
vertex.size=20)
```

Label nodes



```
plot.igraph(net,  
vertex.label=v(net)$justice,  
vertex.label.family="Helvetica",  
vertex.label.font=2,  
vertex.label.color="black",  
vertex.size=48)
```

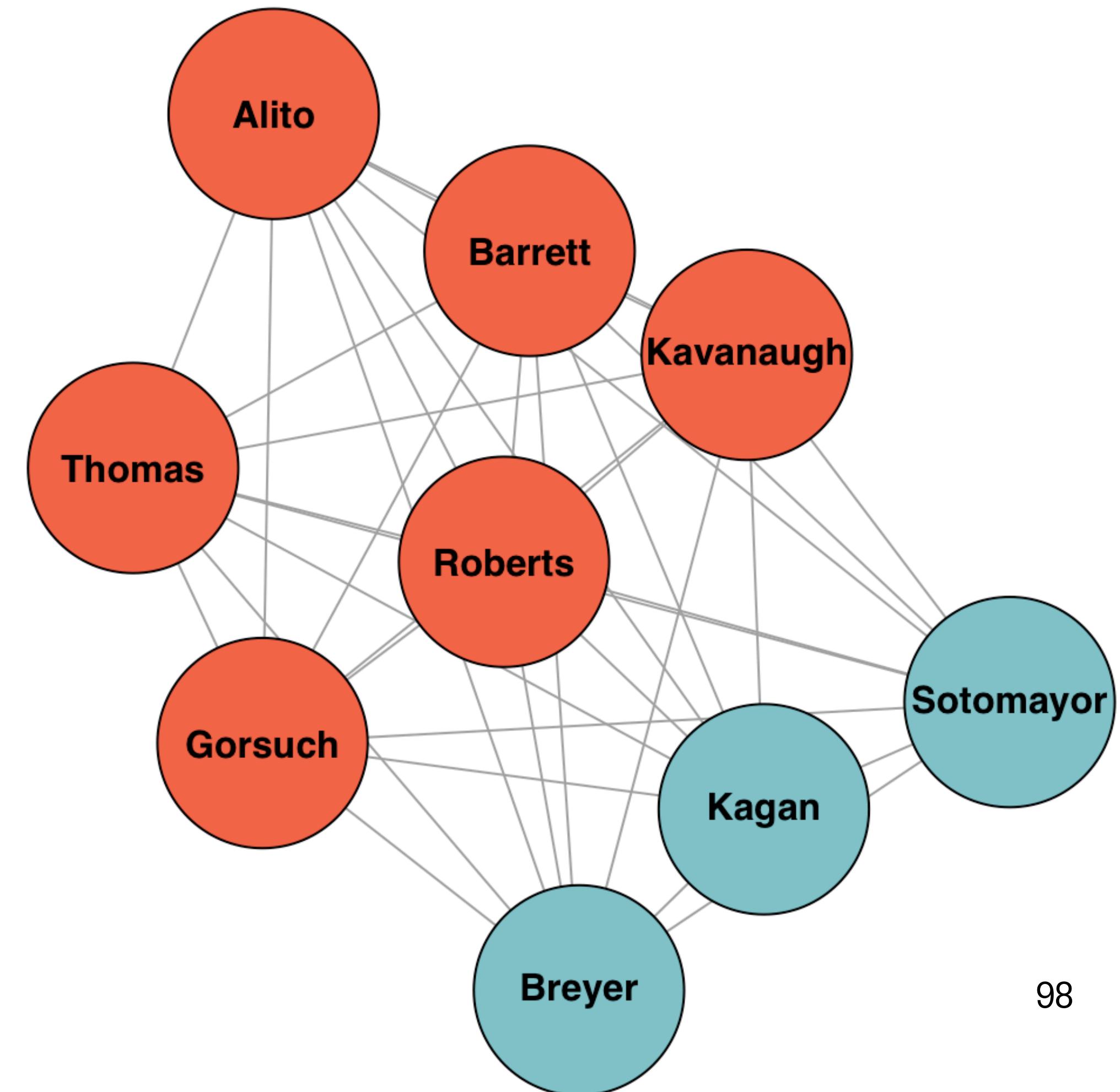
Color by appointment party

```
#Generate colors based on party and write into network:
```

```
v(net)$color <- ifelse(v(net)$party=="Republican","coral1","cadetblue3")
```

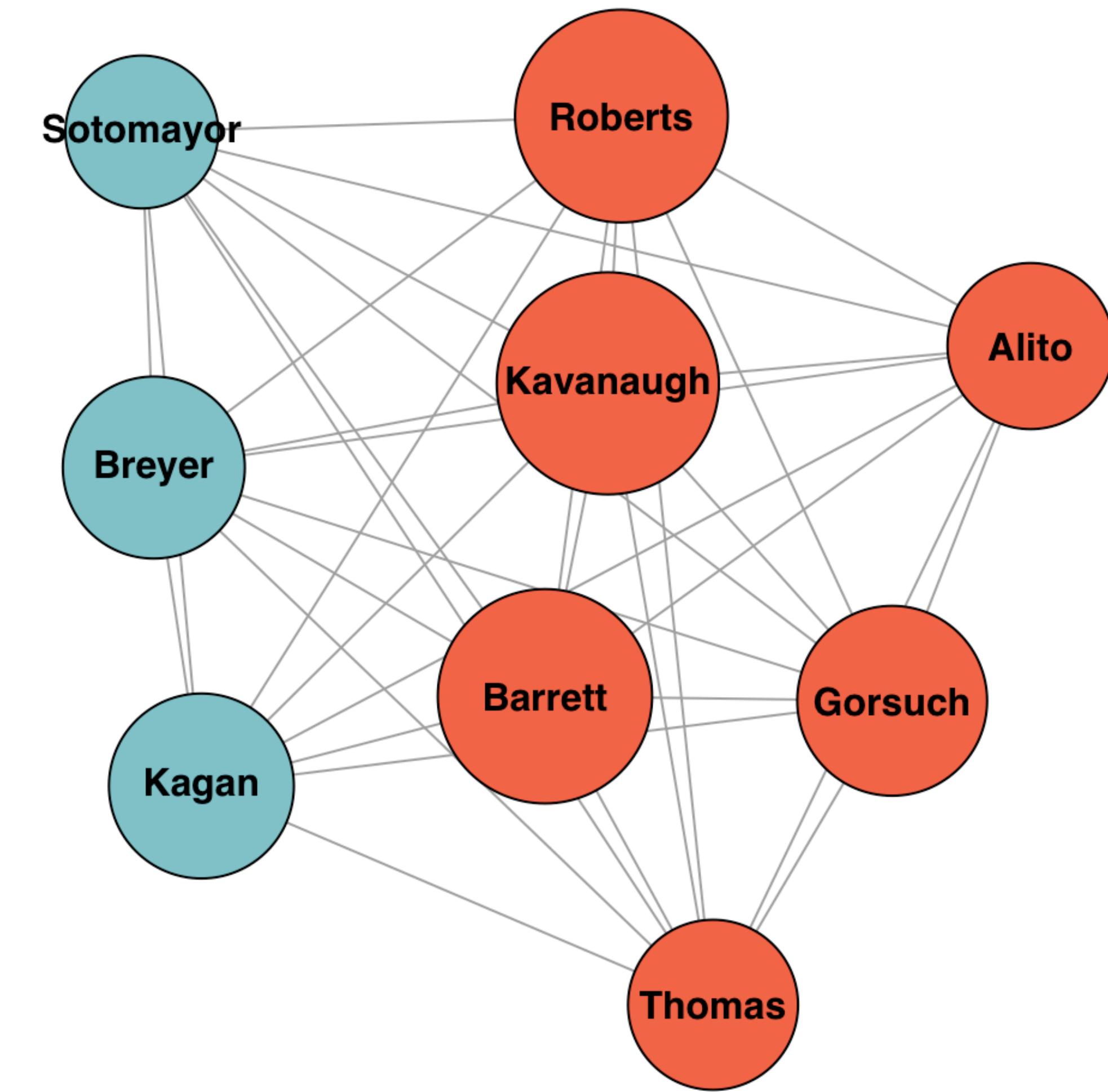
```
plot.igraph(net,  
           vertex.label=V(net)$justice,  
           vertex.label.family="Helvetica",  
           vertex.label.font=2,  
           vertex.label.color="black",  
           vertex.size=48)
```

- Note that we no longer have to “keep” color in the main line of graph code, it’s “written in” to the network object itself



Scale nodes by centrality

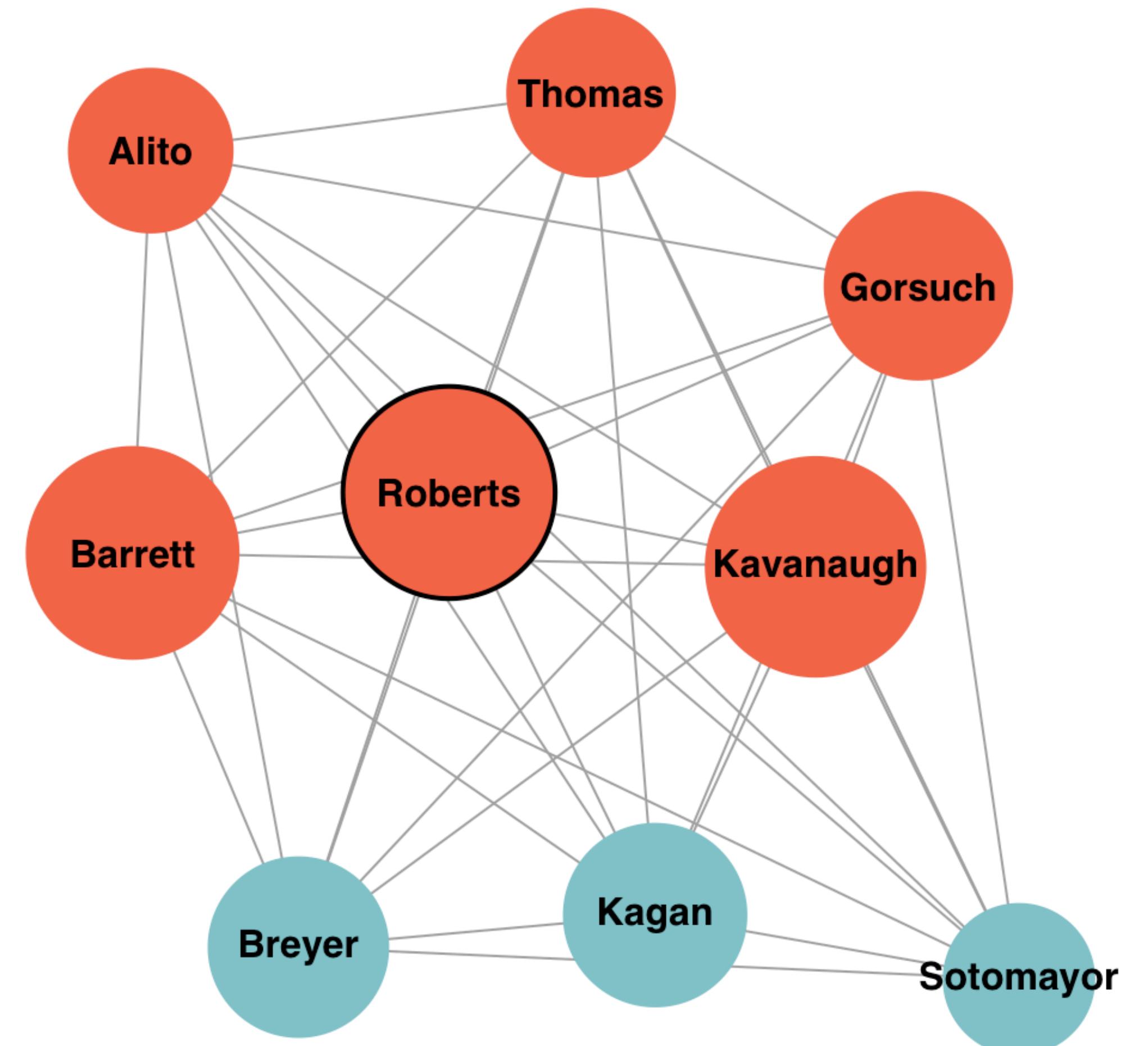
```
V(net)$eigen<-evcent(net)$vector  
  
plot.igraph(net,  
vertex.label=V(net)$justice,  
vertex.label.family="Helvetica",  
vertex.label.font=2,  
vertex.label.color="black",  
vertex.size=v(net)$eigen*50)
```



While we're at it

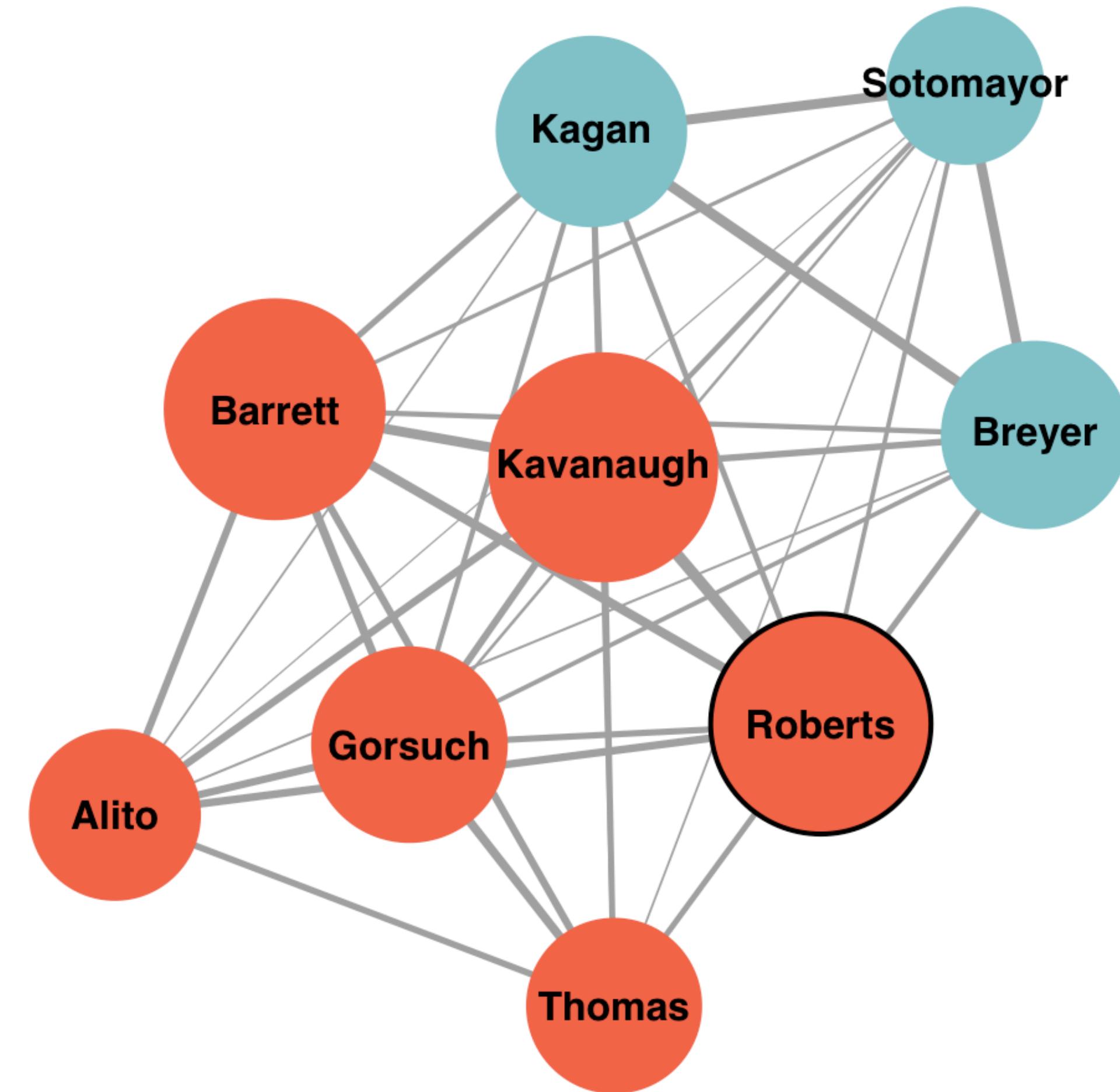
```
v(net)$width<-
  ifelse(V(net)$type=="Chief",2,1)

plot.igraph(net,
  vertex.label=V(net)$justice,
  vertex.label.family="Helvetica",
  vertex.label.font=2,
  vertex.label.color="black",
  vertex.size=V(net)$eigen*50,
  vertex.frame.width=V(net)$width)
```



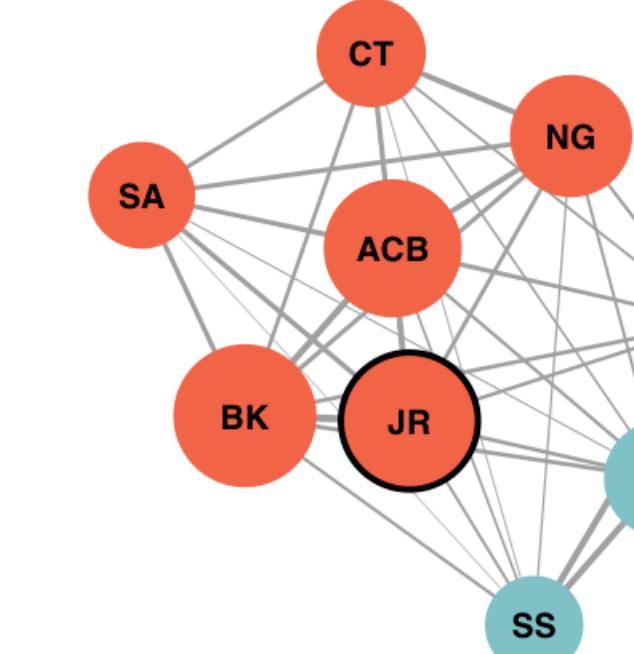
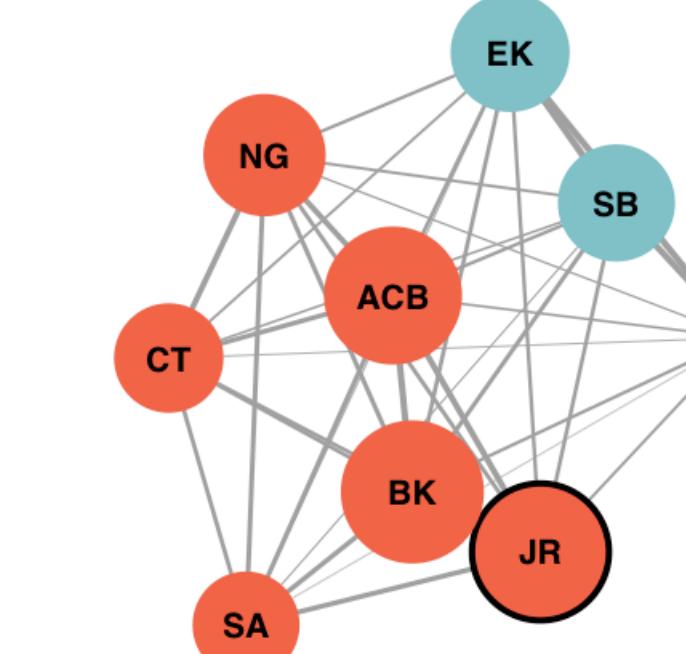
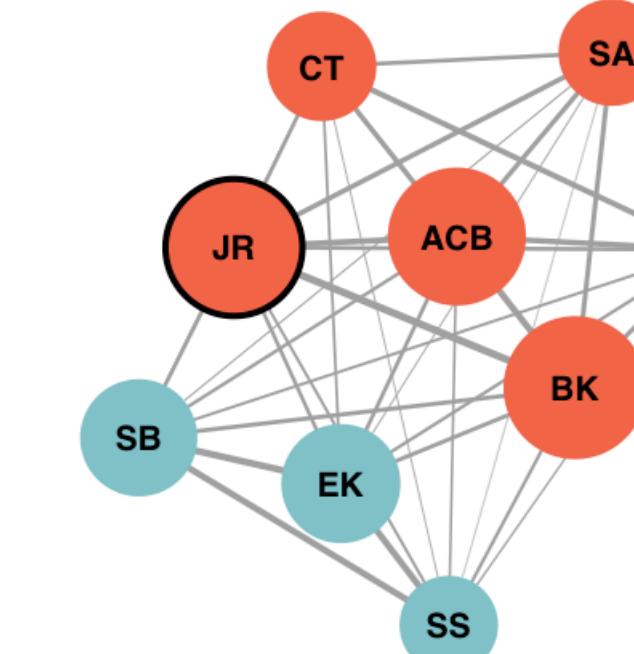
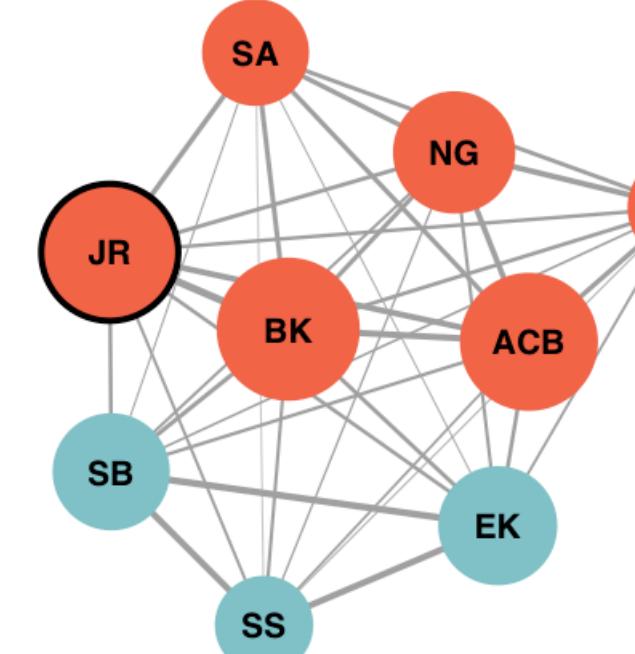
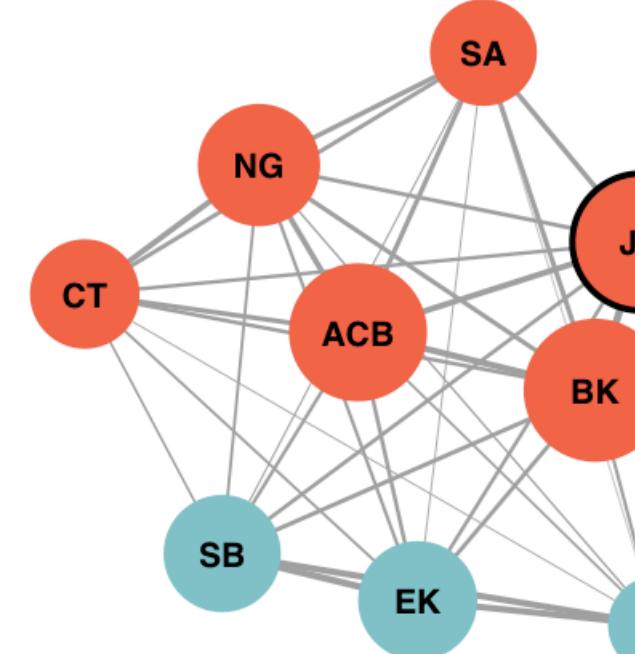
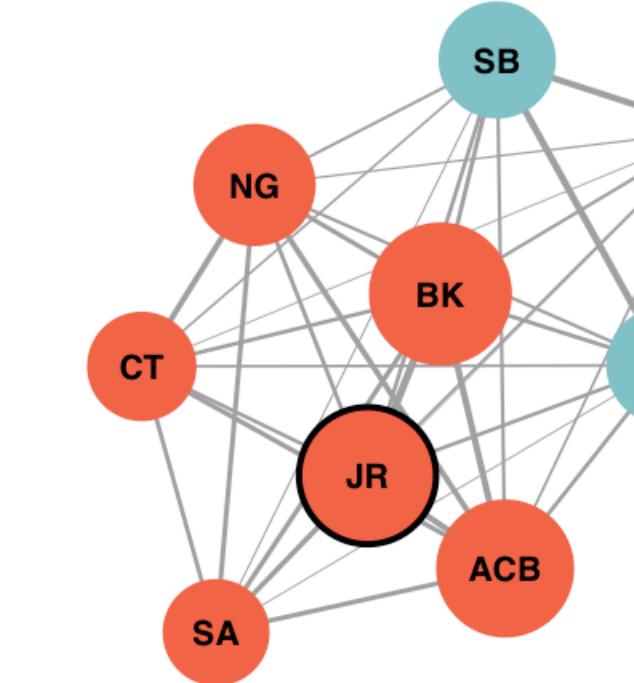
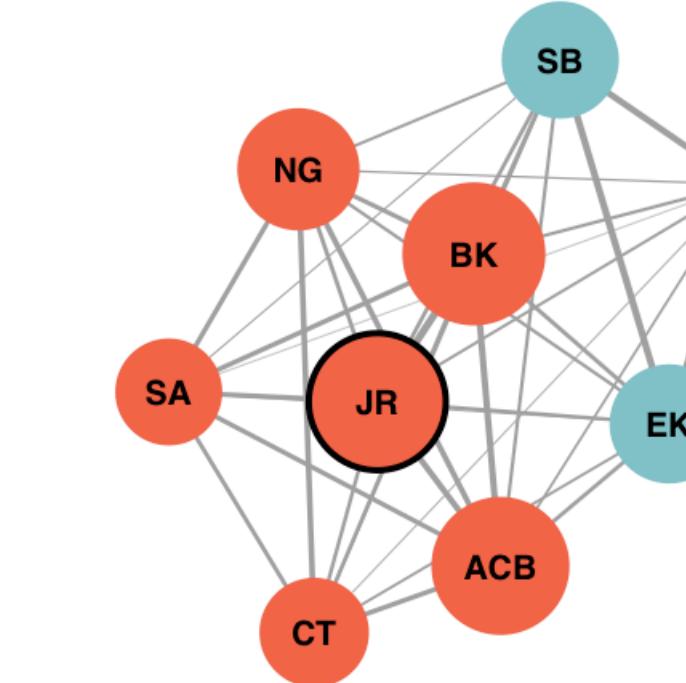
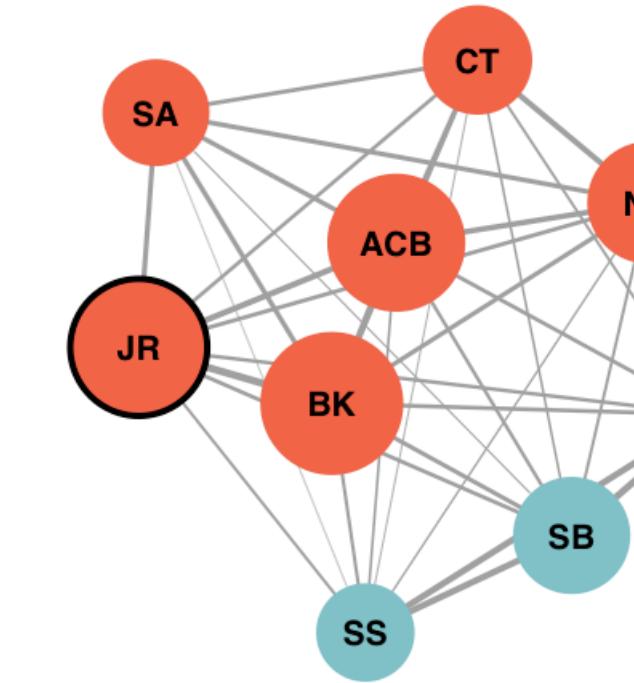
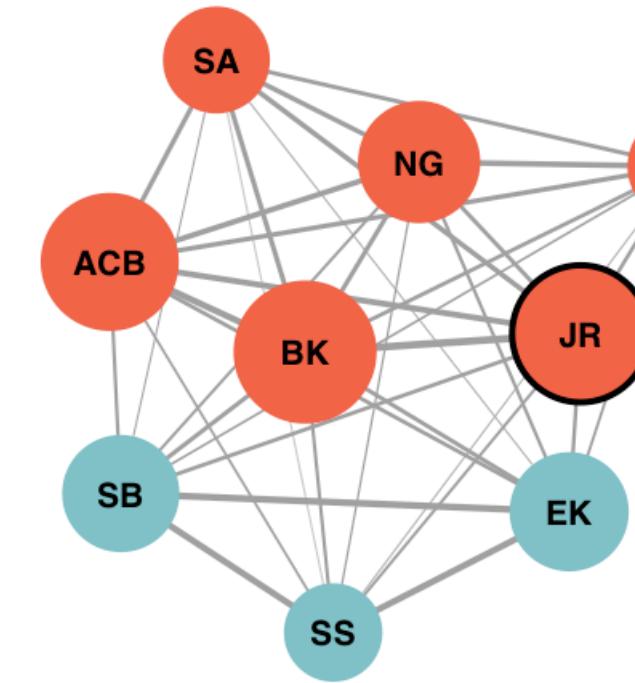
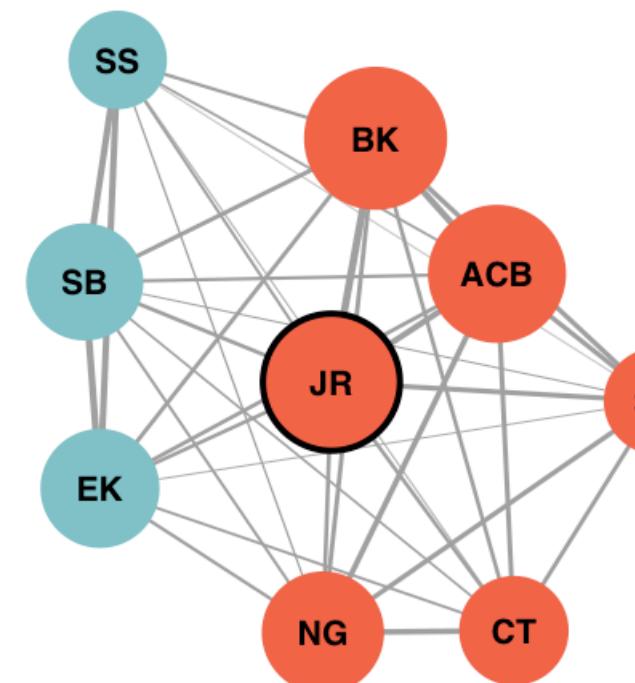
Finally: tie strength

```
plot.igraph(net,  
            edge.width=E(net)$weight*5,  
            vertex.label=V(net)$justice,  
            vertex.label.family="Helvetica",  
            vertex.label.font=2,  
            vertex.label.color="black",  
            vertex.size=V(net)$eigen*50,  
            vertex.frame.width=V(net)$width)
```



Graph layouts

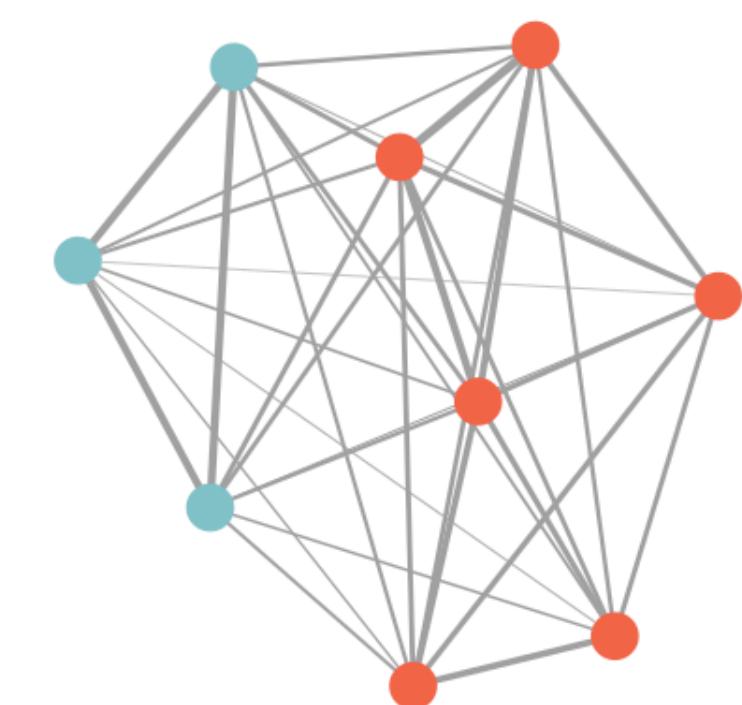
- iGraph generates layouts quasi-randomly within similar constraints; each time the network is drawn, the layout will look slightly different



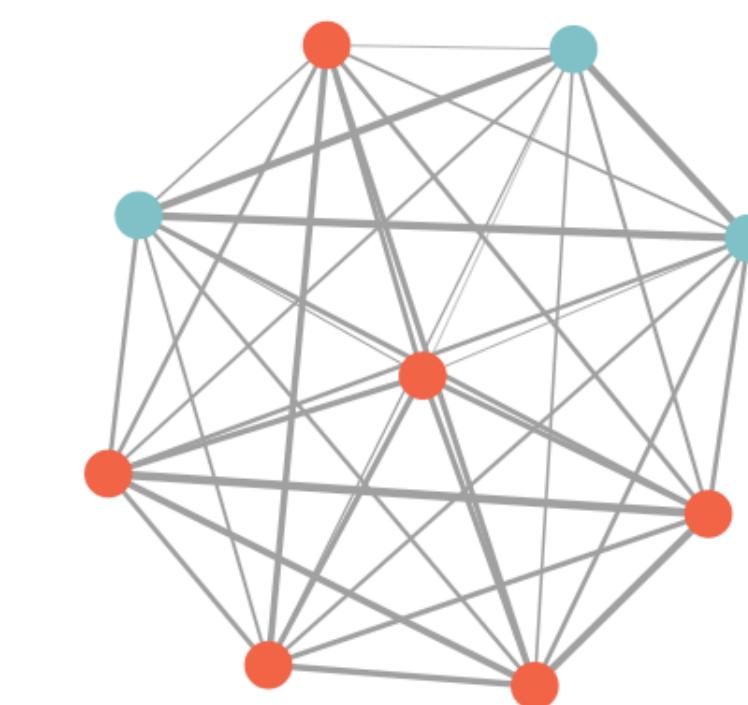
An assortment of network layouts

- We control with the `layout` option within `plot.igraph`

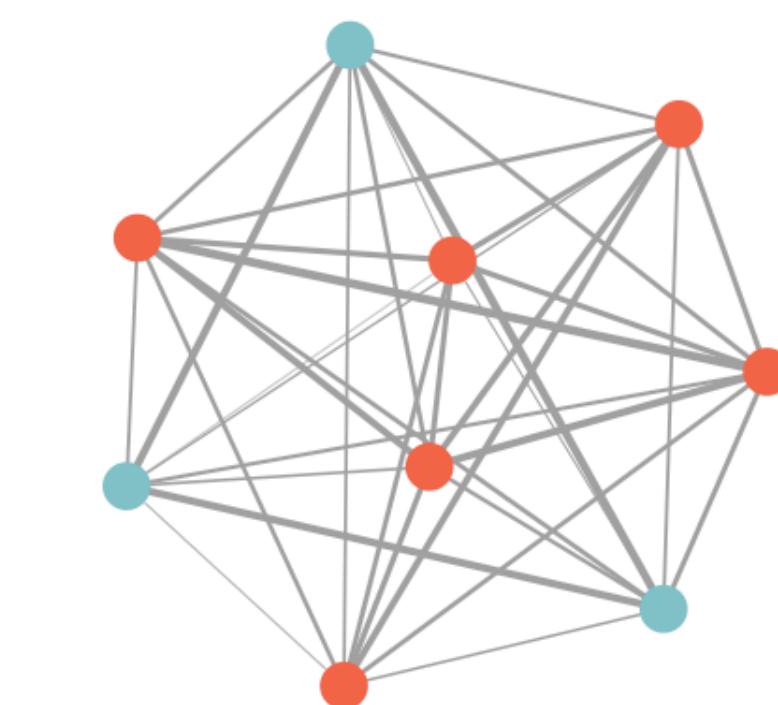
`layout_with_fr`



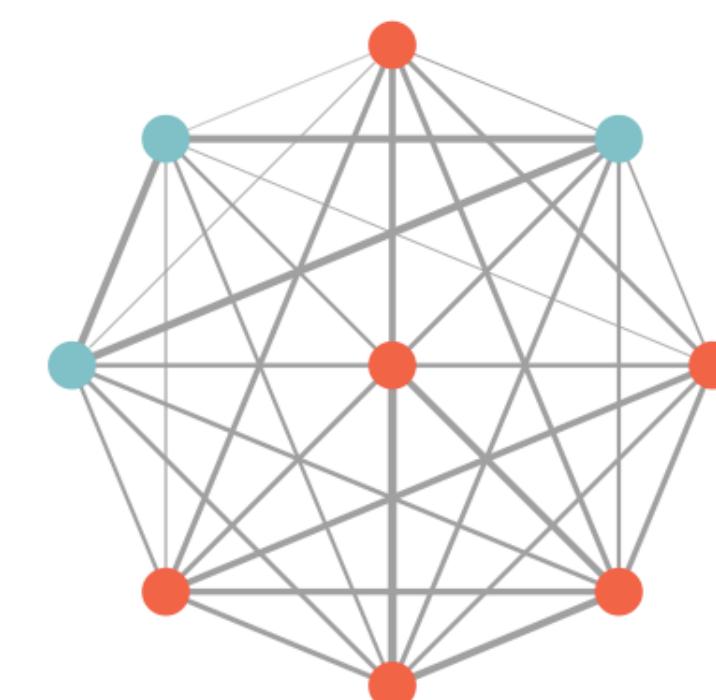
`layout_with_gem`



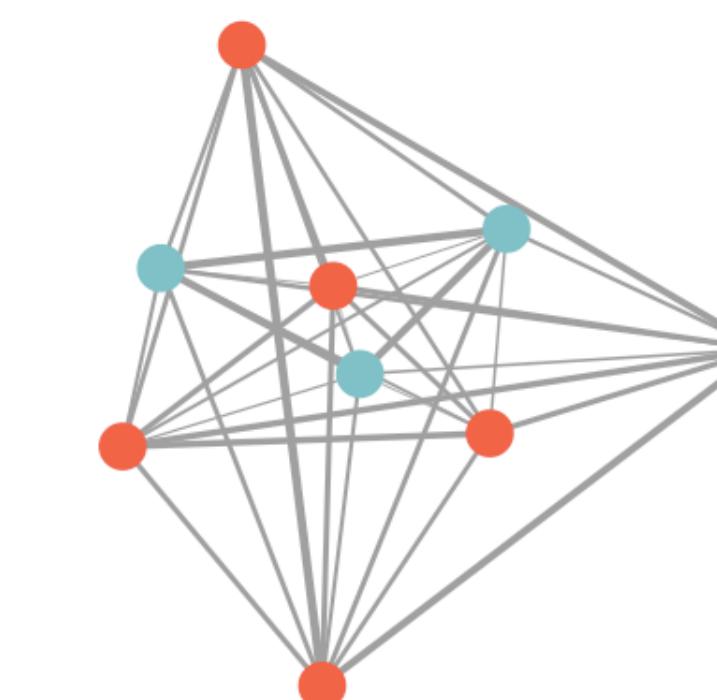
`layout_with_graphopt`



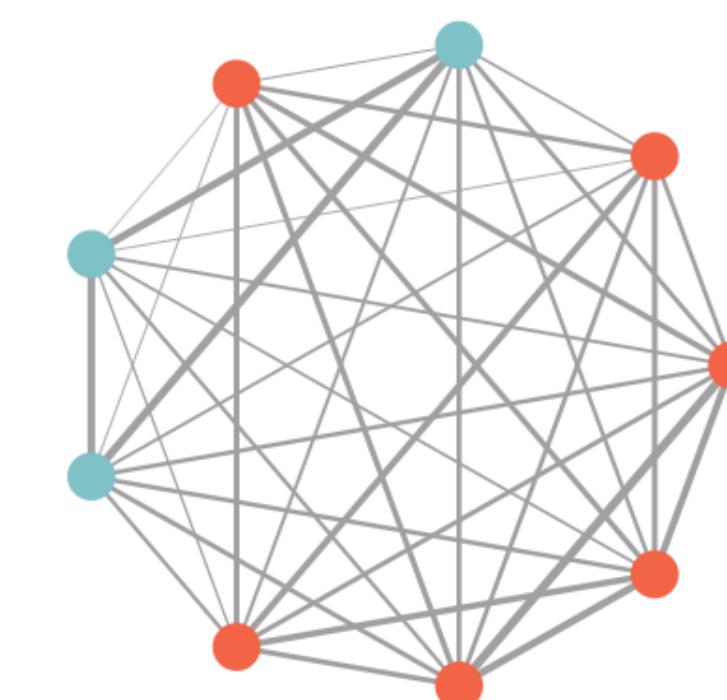
`layout_as_star`



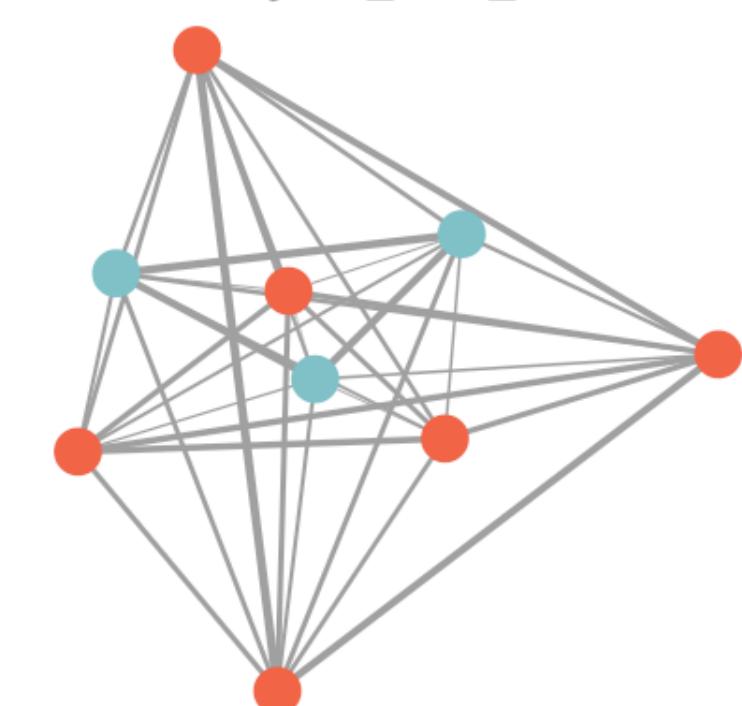
`layout_components`



`layout_in_circle`



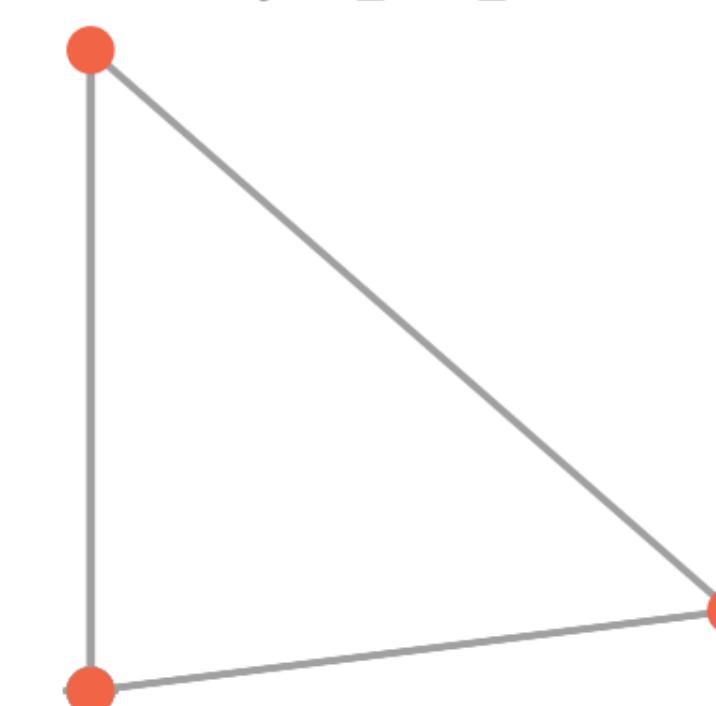
`layout_with_kk`



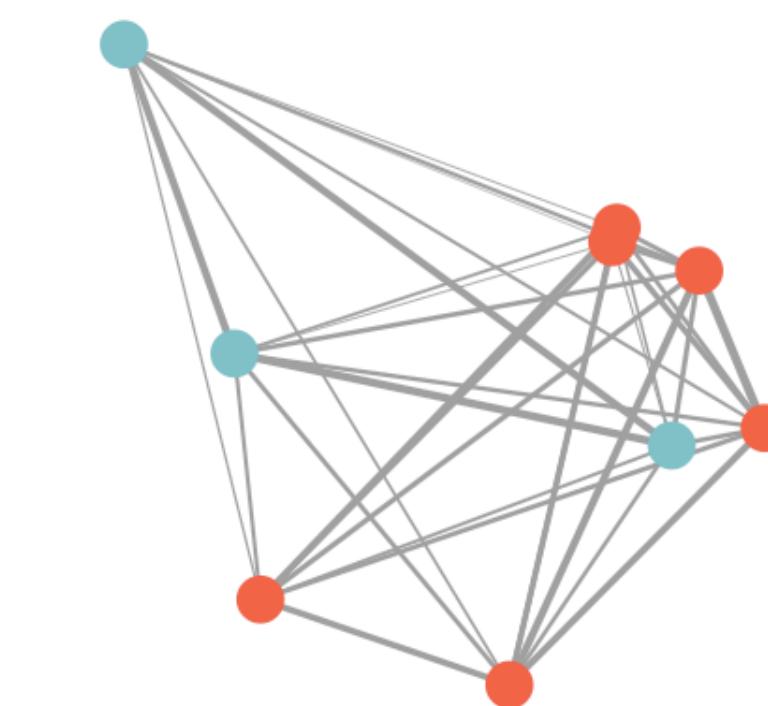
`layout_with_lgl`



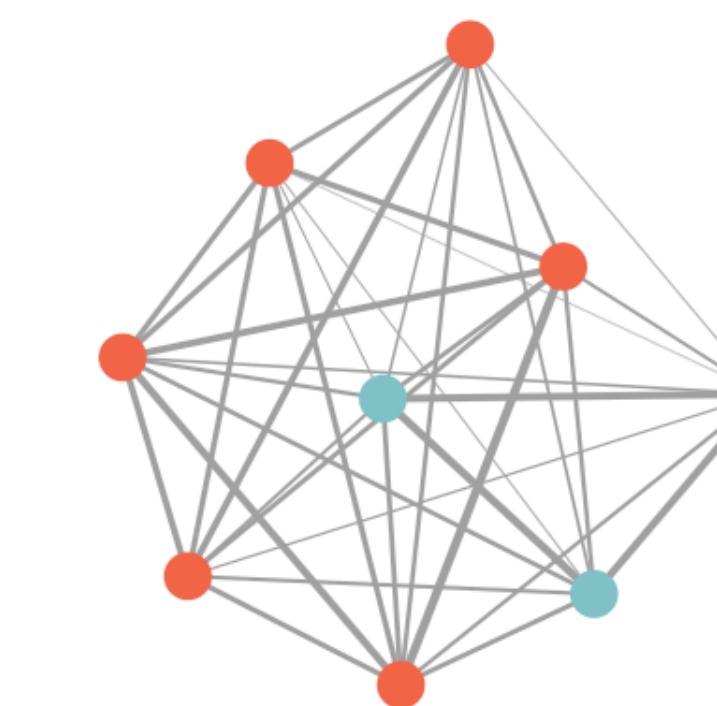
`layout_with_mds`



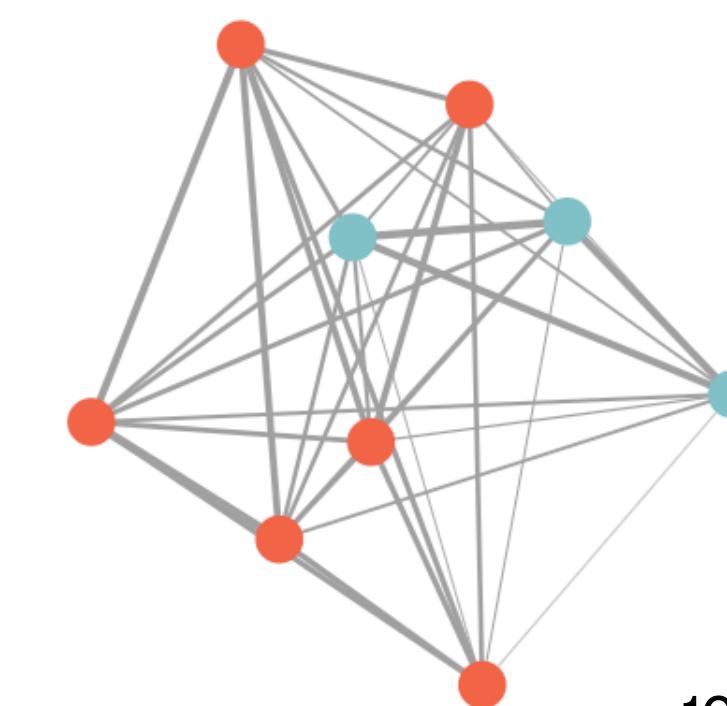
`layout_randomly`



`layout_with_dh`

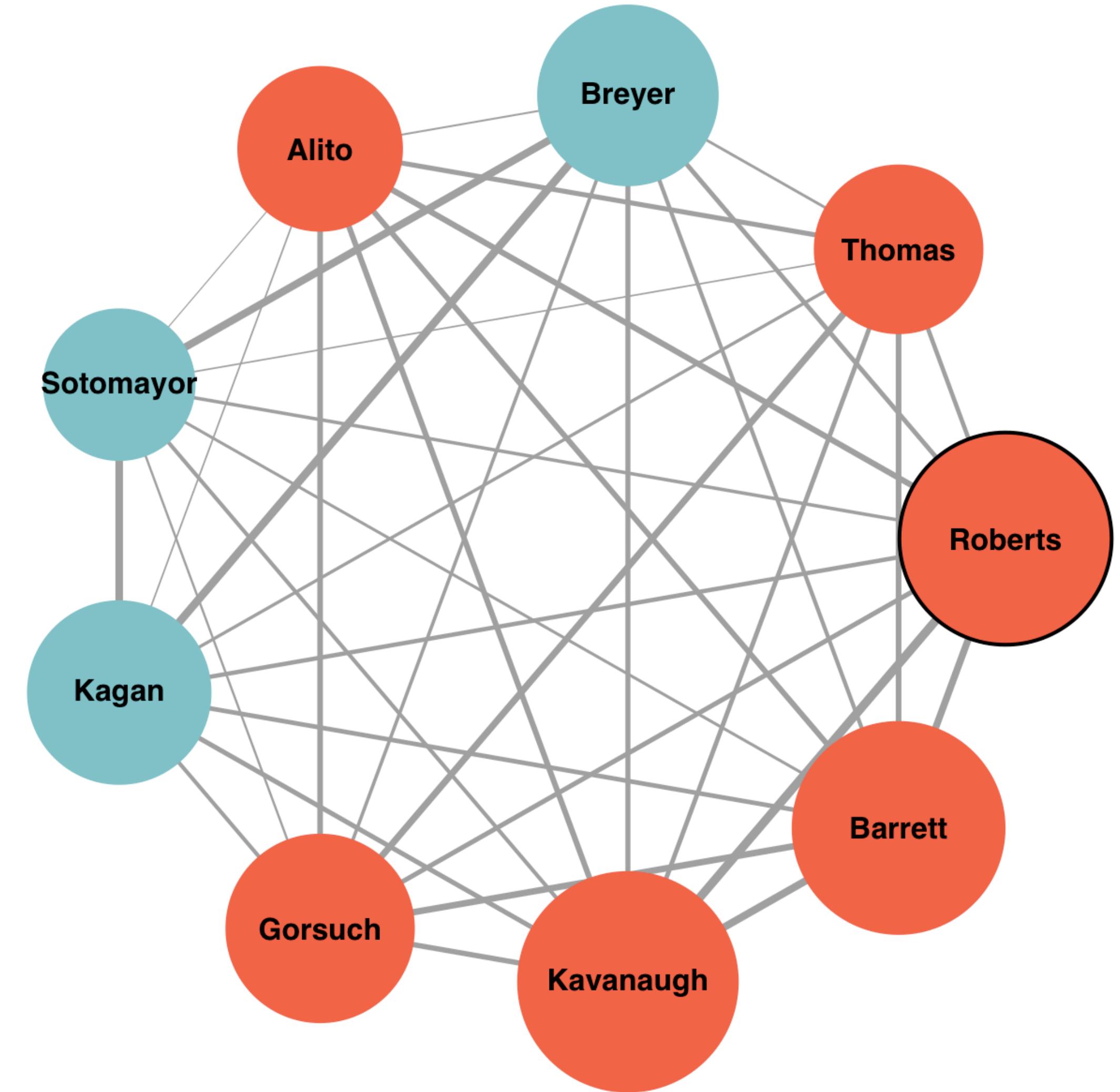


`layout_with_drl`



The circle layout

```
plot.igraph(net,
edge.width=E(net)$weight*5,
vertex.label=V(net)$justice,
vertex.label.family="Helvetica",
vertex.label.font=2,
vertex.label.color="black",
vertex.size=V(net)$eigen*50,
vertex.frame.width=V(net)$width,
layout=layout_in_circle)
```

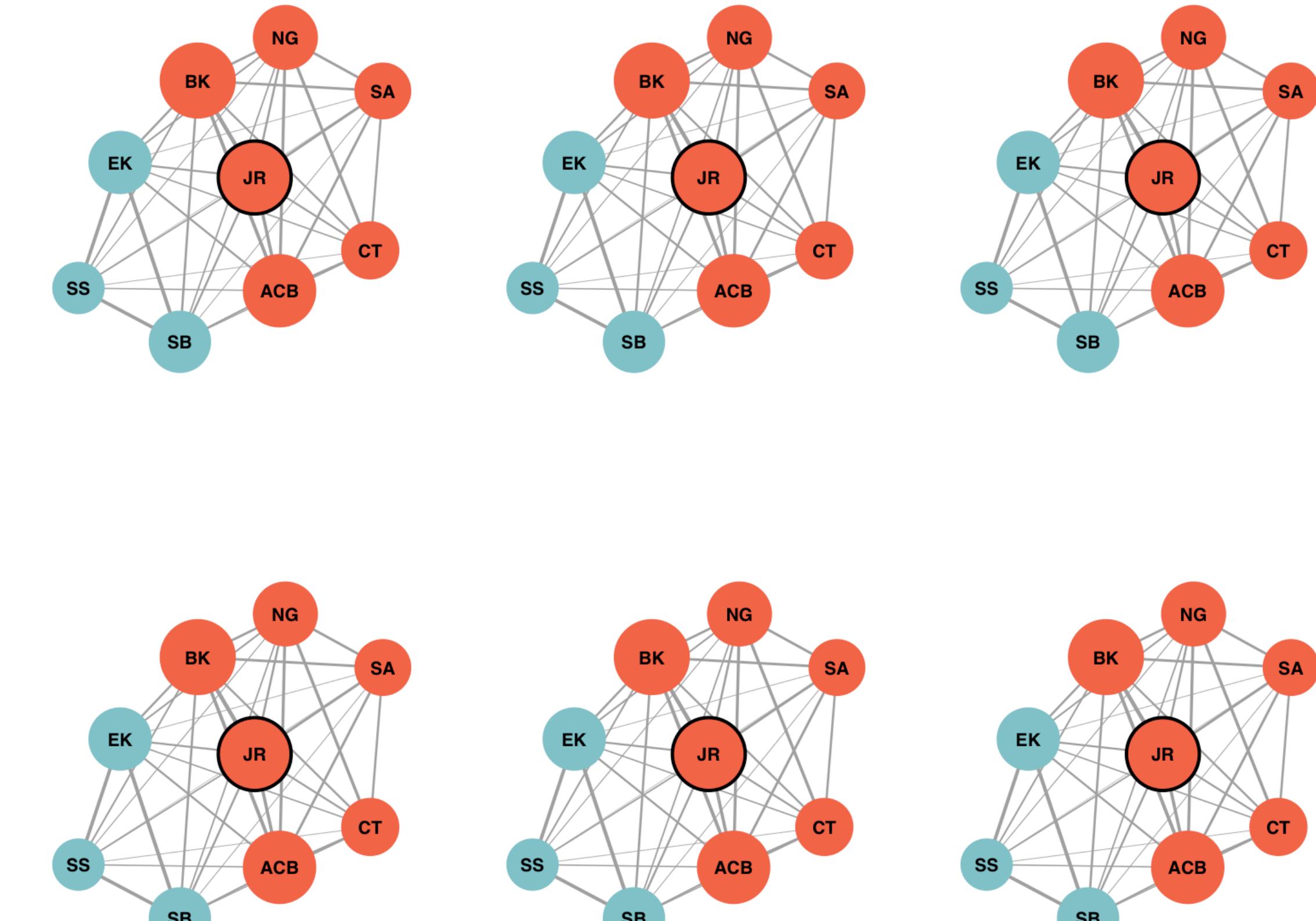


Locking in layouts

- We can create and store a particular layout to use if we wish (in this case, a layout linked to tie strength), so that the graph appears the same every time

```
nicelayout <- layout_with_fr(net,  
  weights=E(net)$weight)
```

```
plot.igraph(net,  
  edge.width=E(net)$weight*5,  
  vertex.label=V(net)$abbrev,  
  vertex.label.family="Helvetica",  
  vertex.label.font=2,  
  vertex.label.color="black",  
  vertex.size=V(net)$eigen*50,  
  vertex.frame.width=V(net)$width,  
  layout=nicelayout)
```



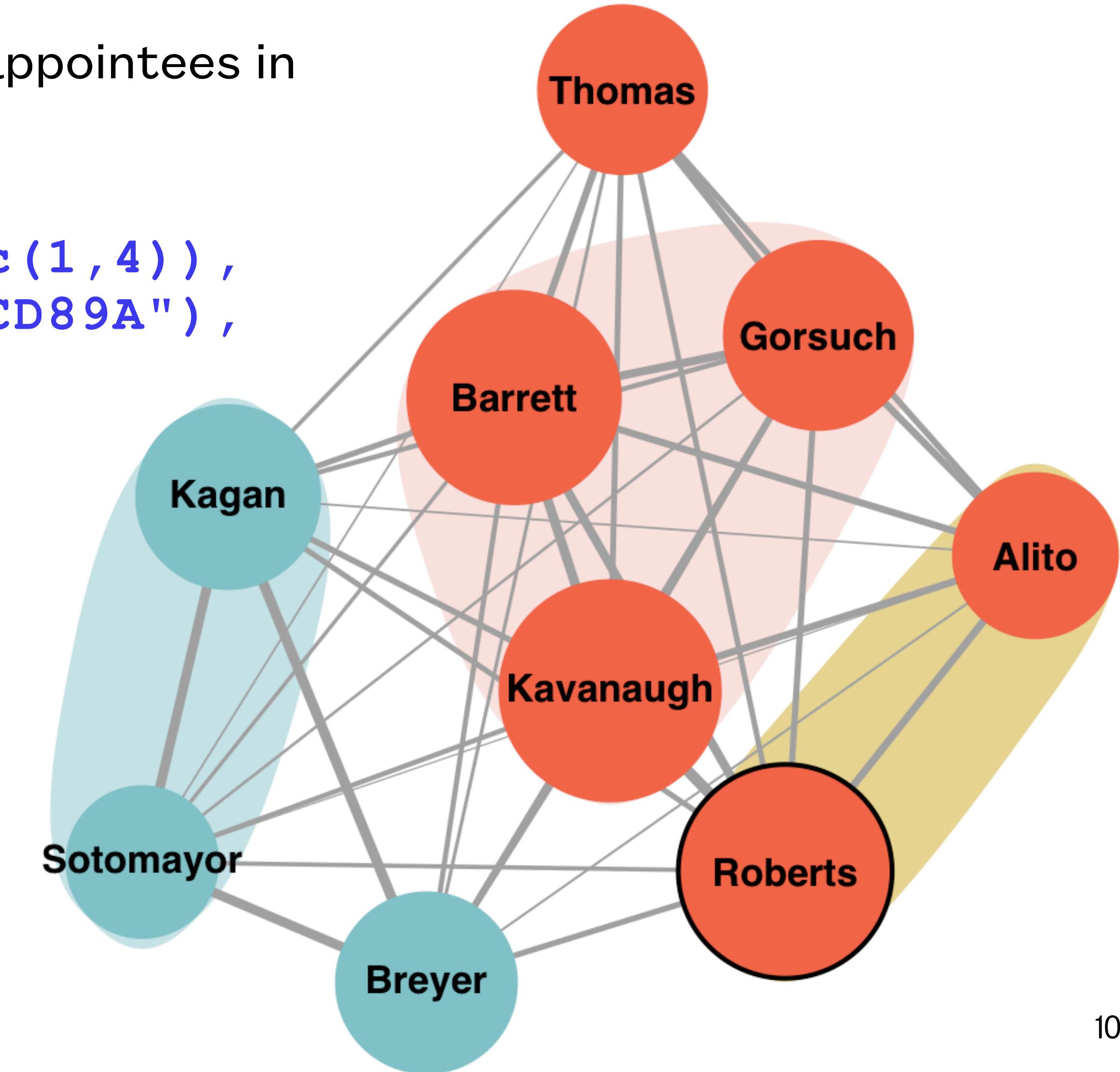
- And can store it to drive for next time

```
write.csv(nicelayout, "layout.csv")  
nicelayout <- as.matrix(read.csv("layout.csv"))
```

Highlighting nodes

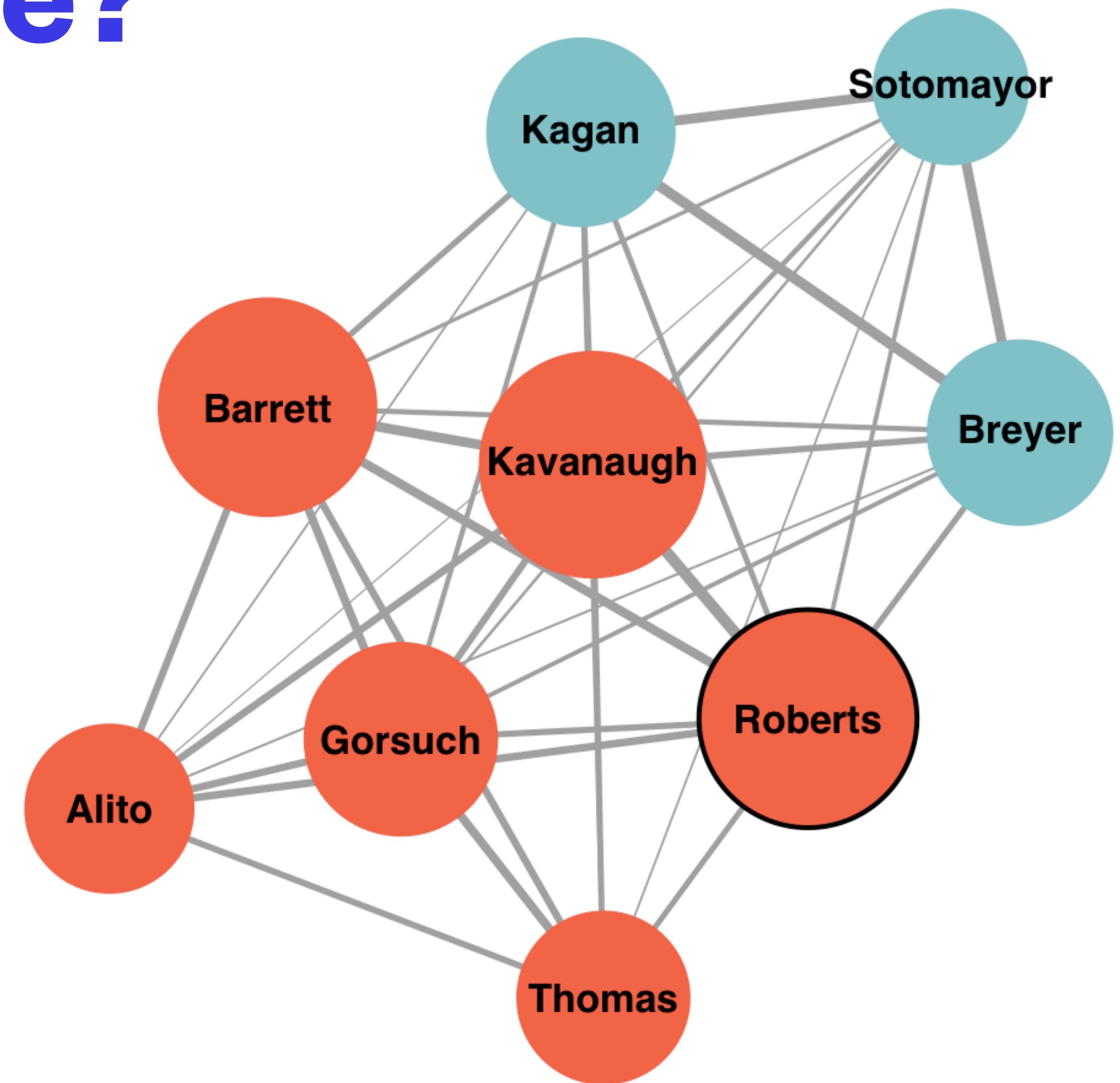
- Here, we highlight Trump, Obama, and Bush Jr. appointees in red, blue, and yellow, respectively.

```
plot.igraph(net,
mark.groups=list(c(7,8,9), c(5,6), c(1,4)),
mark.col=c("#FFE4E1", "#C5E5E7", "#ECD89A"),
mark.border=NA,
edge.width=E(net)$weight*5,
vertex.label=V(net)$justice,
vertex.label.family="Helvetica",
vertex.label.font=2,
vertex.label.color="black",
vertex.size=V(net)$eigen*50,
vertex.frame.width=V(net)$width)
```



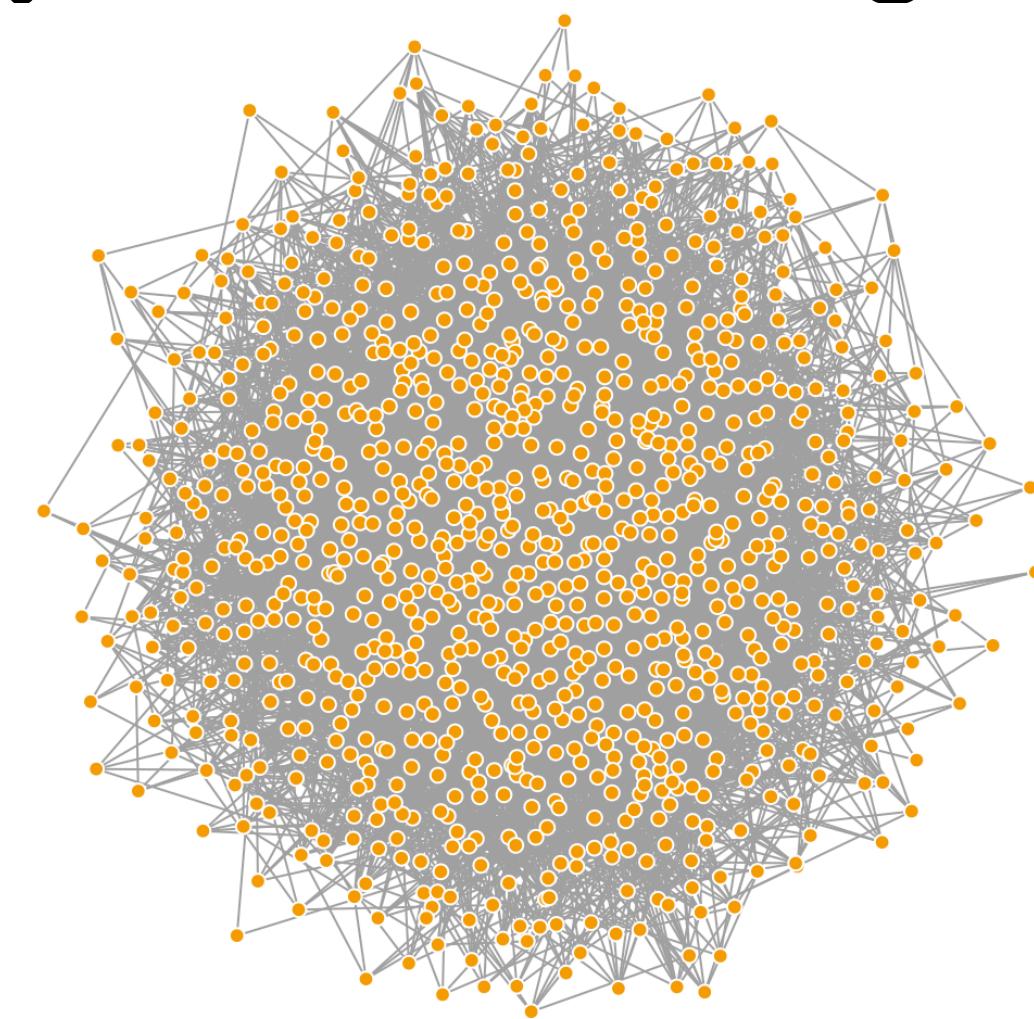
So what can we see?

- *Strong graphics present ready information quickly, at a glance*
 - *While rewarding further inspection with more detail*
- Centrality/importance (node size, graph position from layout tied to edge weights)
- Party (color)
- Tie strength (line width)
- Identities of justices



The example is just an example

- The Supreme Court is a nice (small, simple) network to begin with
- But the techniques here can be used for larger networks just as easily (albeit with things possibly slowing down as the scale and size of your network expands)
 - Larger networks bring different considerations:
 - Smaller (or no!) nodes between links
 - Focus on structure over individual elements
 - Easier to draw “hairballs”
 - Also, don’t let yourself be caught by thinking you *must* draw a network with network data

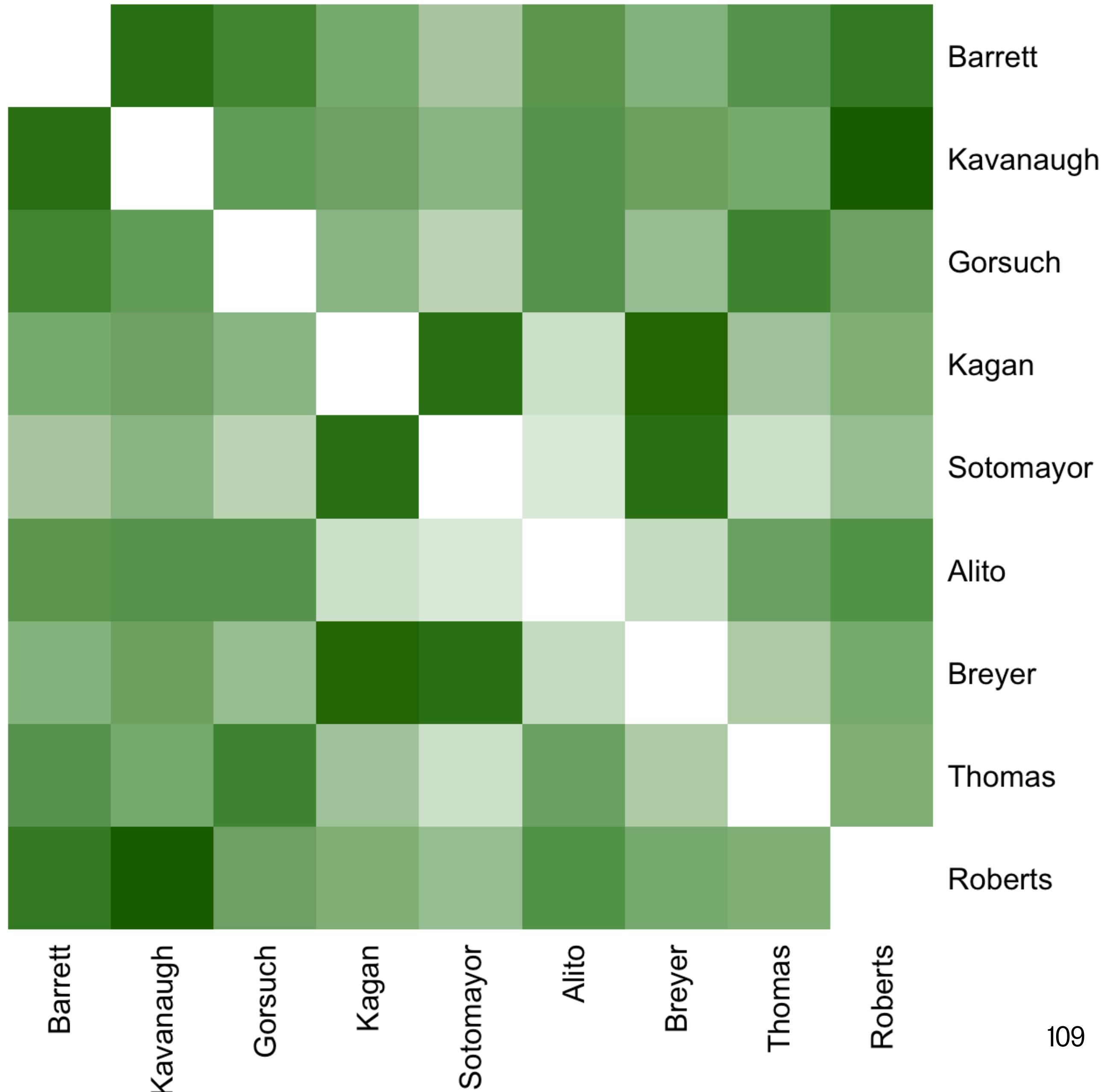


More than one

WAY TO VISUALIZE A NETWORK

- This is a heatmap of network agreement (note that it is symmetrical/undirected)

```
palf <-  
  colorRampPalette(  
    c("white", "darkgreen"))  
  
netm <- get.adjacency(net,  
  attr="weight", sparse=F)  
  
colnames(netm) <- V(net)$justice  
rownames(netm) <- V(net)$justice  
  
heatmap(netm, Rowv = NA,  
  Colv = NA, col = palf(100),  
  scale="none", margins=c(10,10) )
```



Part Four

Wrapping up: where do I go from here?

Alternatives to R

- Programmatic
 - Python's **NetworkX** library (and iGraph again)
 - Julia's **JuliaGraphs** library
- GUIs
 - UCI-NET
 - SocNetV
 - Gephi
 - Cytoscape
 - Pajek
 - GraphVis

Resources

- Materials from this lecture (slides, data, code): <https://jacklreilly.github.io/networkscrashcourse>
- Core references in these slides
 - Ognyanova, K. (2021) Network visualization with R. Retrieved from www.kateto.net/network-visualization.
 - Healy, K. (2018) Data Visualization: [A Practical Introduction](#). Princeton. (Also available: socviz.co.)
- Other books
 - The classic: Wasserman and Faust, 1994. *Social Network Analysis*.
 - The modern classic: Jackson, 2010. *Social and Economic Networks*.
 - For undergraduate courses: Scott, 2017. *Social Network Analysis*.
 - More formal: Menczer, Fortunato, and Davis, 2020. *A First Course in Network Analysis*.

Teaching in context

WHERE DOES THIS FIT?

- Not an exhaustive overview of networks, of course
- Placed in a course, this content would be different in a few ways
 - Interspersed with hands-on R workshops
 - In undergraduate classes, include active learning (with yarn!)
- Where would this fit in a class?
 - This is a more concentrated dose of presentations I do in my current advanced undergraduate course on social networks
 - Normally, it would be divided more (not covering data and visualization together, for one)

Teaching in context

- What would come around this?
 - Depends - social networks exists at the cross-section of methodology and substance
 - In a more substantive course, reading substantive applications goes hand-in-hand with learning core elements of network data, description, and visualization
 - In a more methodologically focused course, this would precede a deeper discussion of proper network analysis: network formation, blockmodels and community detection, contagion and influence, and eventually, models for inference (ERGMs)
 - It might be done with intro to R content at the beginning, as well

Thank you!

Materials: <https://jacklreilly.github.io/networkscrashcourse>

Contact: jreilly@ncf.edu

Questions?