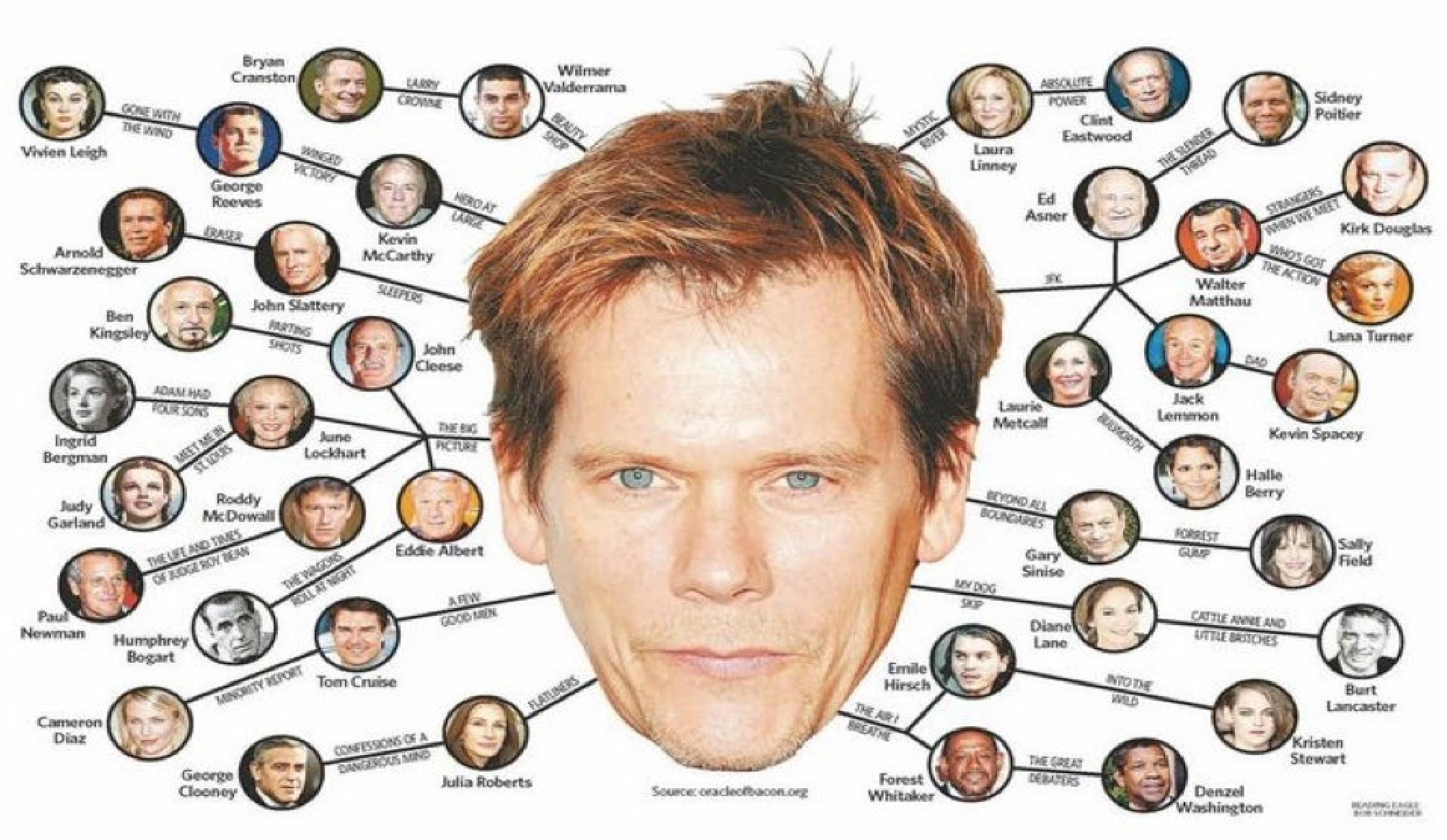
Social Network Analysis



[Six (or fewer) degrees of separation]

Lab 8

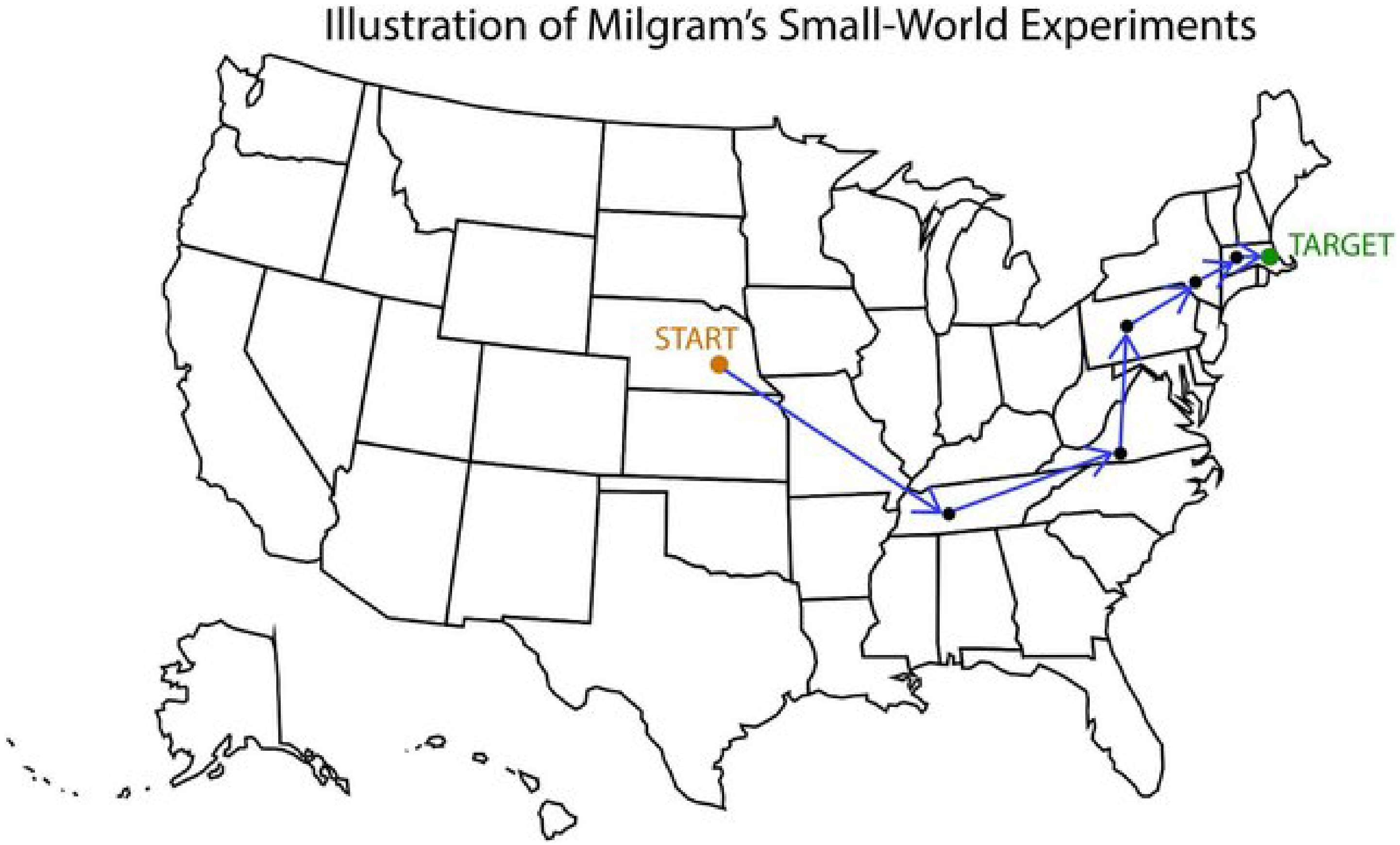
[Try for yourself!]

Agenda

- Network vocabulary
- Applications for justice

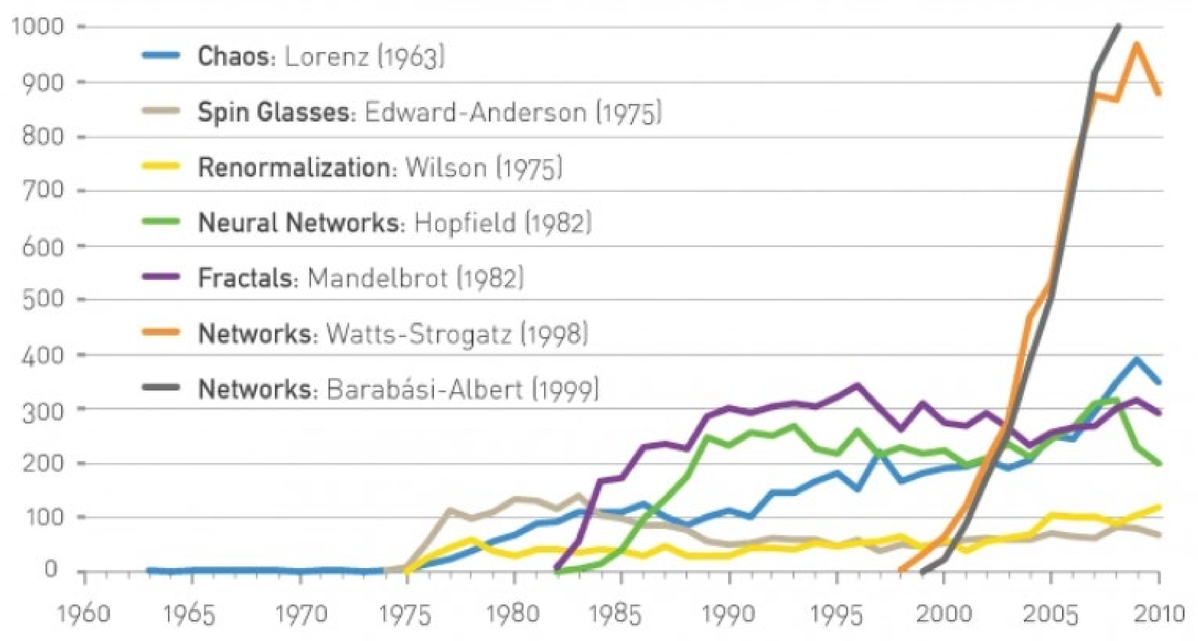
- Network analyses in R

“Small world”



Stanley Milgram

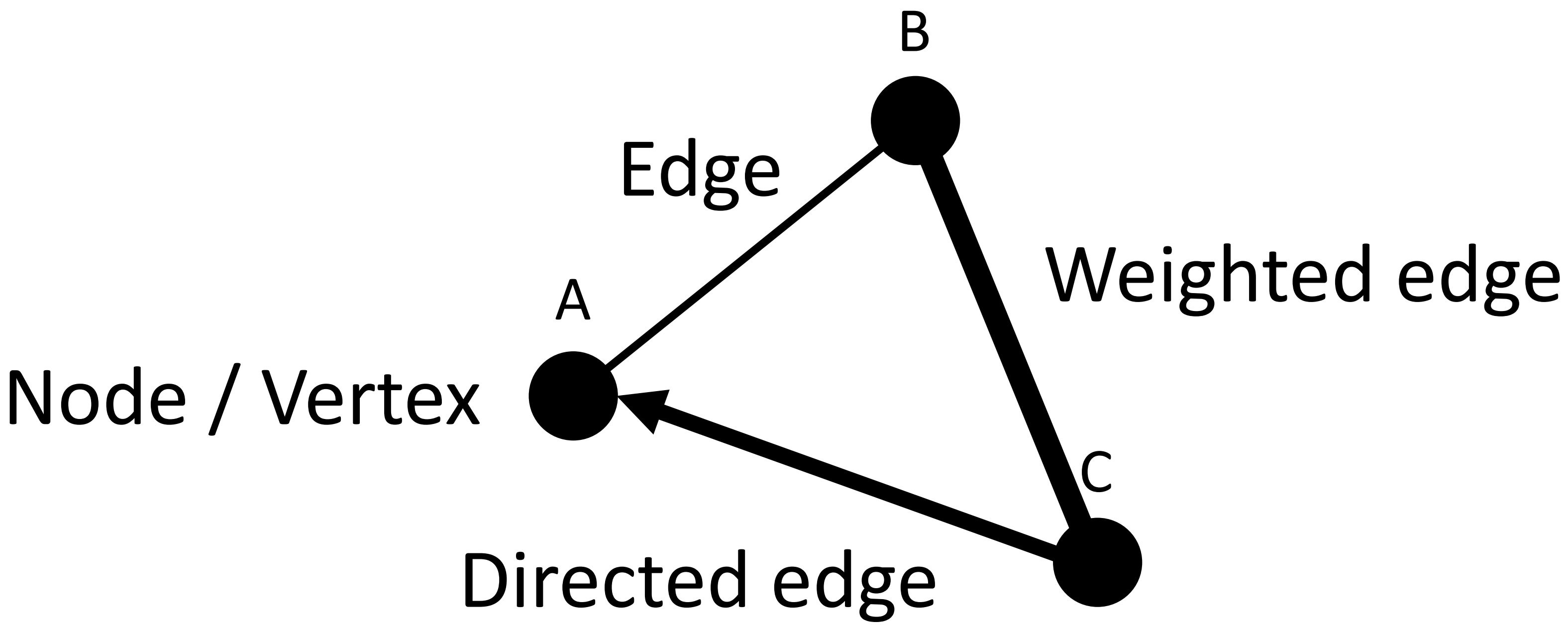
Network science is young but increasingly popular



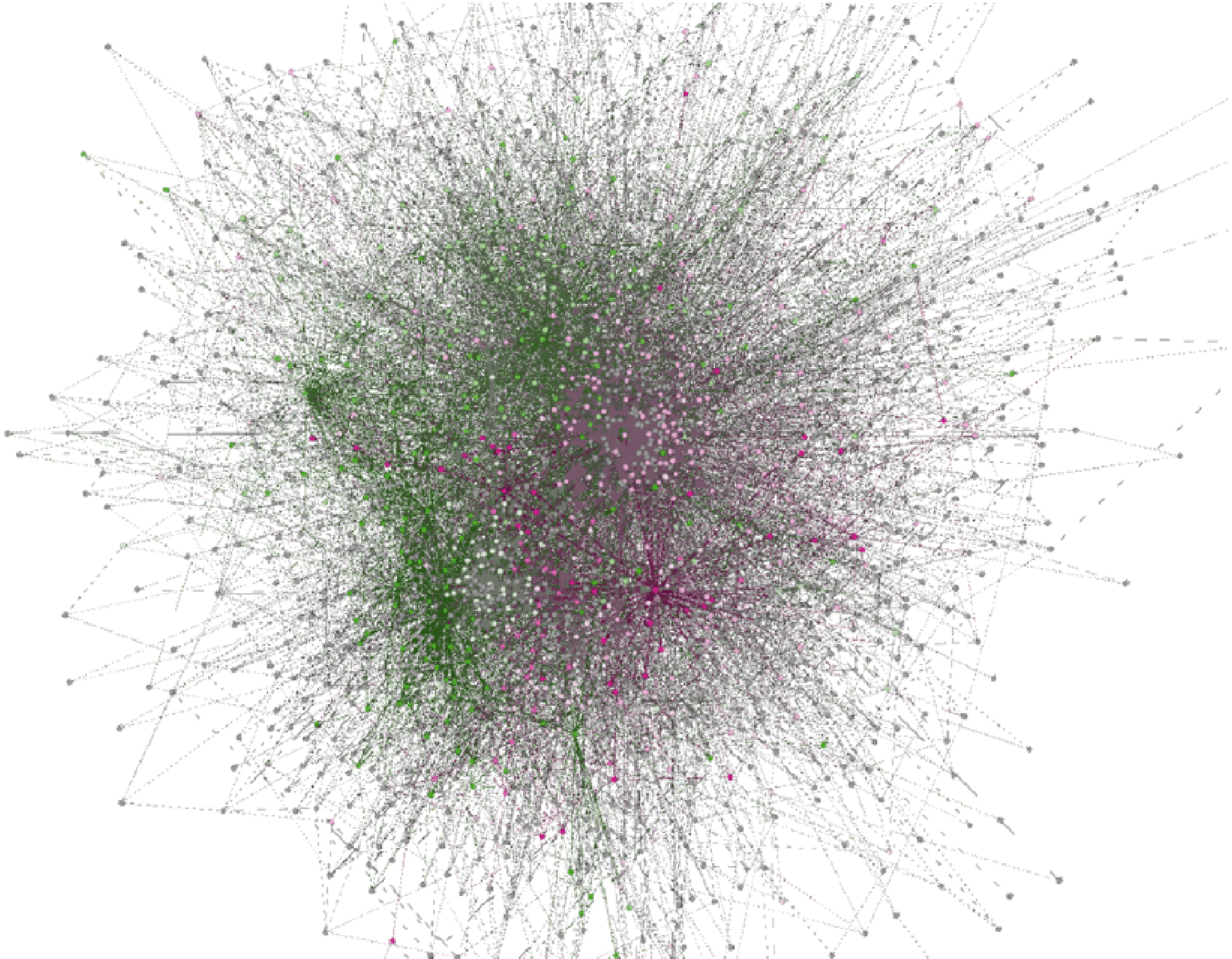
suggests that the field is on the cusp of a fifth stage in which network methodology becomes part of the standard toolkit in crime research (much as spatial modeling already has) and that network perspectives on understanding criminological outcomes will be better articulated and more widely adopted. As a consequence, future researchers will be fluent in the network perspective and able to turn their attention to developing fully articulated network theories of crime.

(Faust & Tita 2019)

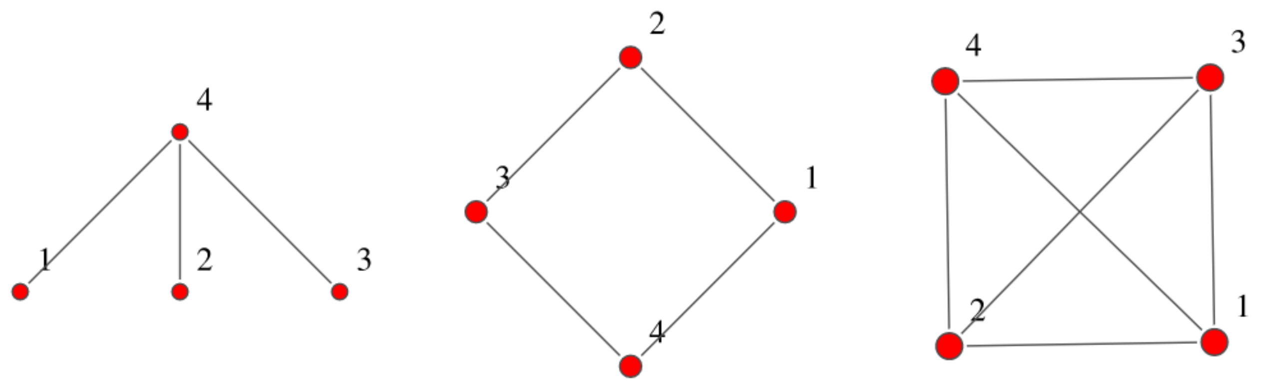
Networks = Graphs

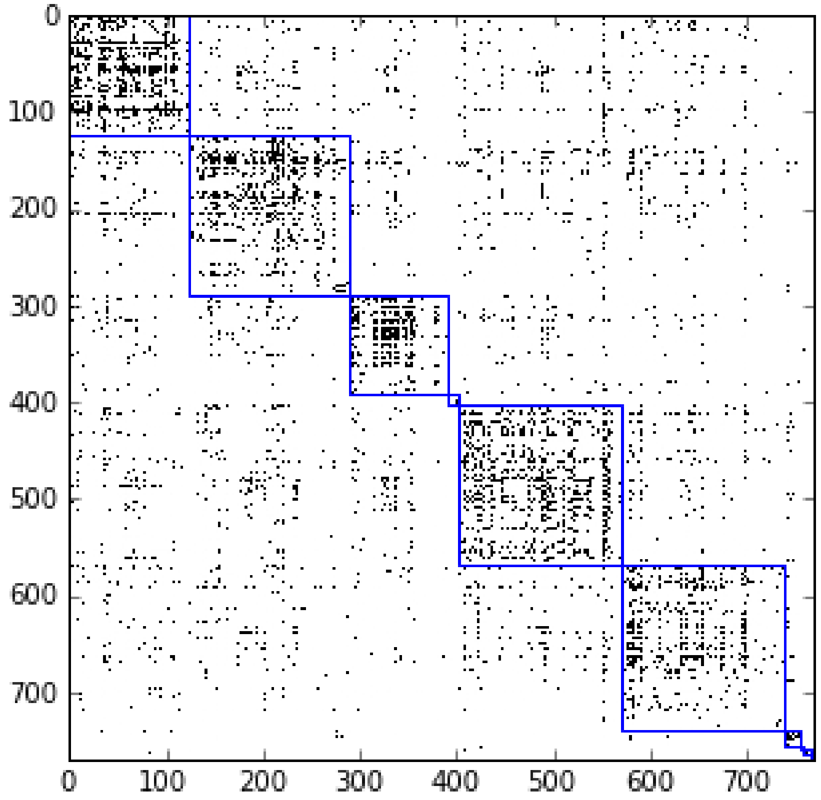


Networks can get big



How to represent a network/graph





$$\begin{array}{c|cccc} & 1 & 2 & 3 & 4 \\ \hline 1 & 0 & 0 & 0 & 1 \\ 2 & 0 & 0 & 0 & 1 \\ 3 & 0 & 0 & 0 & 1 \\ 4 & 1 & 1 & 1 & 0 \end{array} \qquad \begin{pmatrix} 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 \end{pmatrix} \qquad \begin{pmatrix} 0 & 1 & 1 & 1 \\ 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 1 \\ 1 & 1 & 1 & 0 \end{pmatrix}$$

Adjacency matrix

How to represent a network/graph

Node list

	A	B	C
1	id	gang	hierarchy
2	96	0	0
3	121	19	3
4	123	0	0
5	140	22	3
6	149	0	0
7	164	0	0
8	190	13	3
9	191	6	2
10	232	0	0
11	243	0	0
12	244	0	0
13	245	0	0
14	258	7	3
15	266	8	3

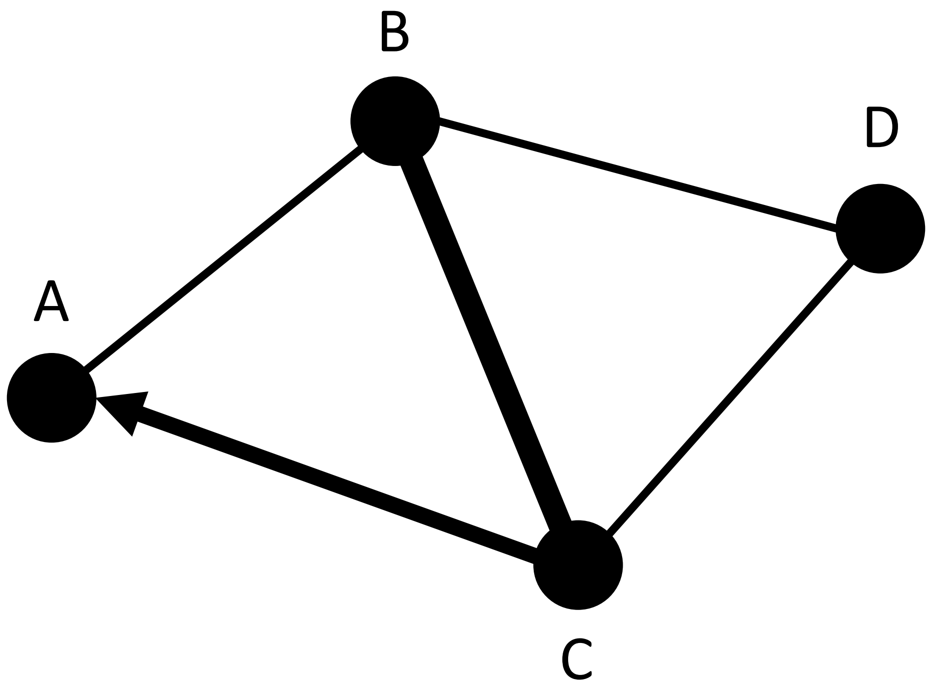
Edge list

	A	B	C
1	to	from	weight
2	2	4	2
3	2	8	2
4	2	33	2
5	2	41	2
6	2	44	2
7	2	45	2
8	2	55	2
9	2	59	2
10	3	8	3
11	3	44	1
12	4	8	2
13	4	31	2
14	4	32	1
15	4	33	4

Descriptive Statistics

- Node level

- Graph level

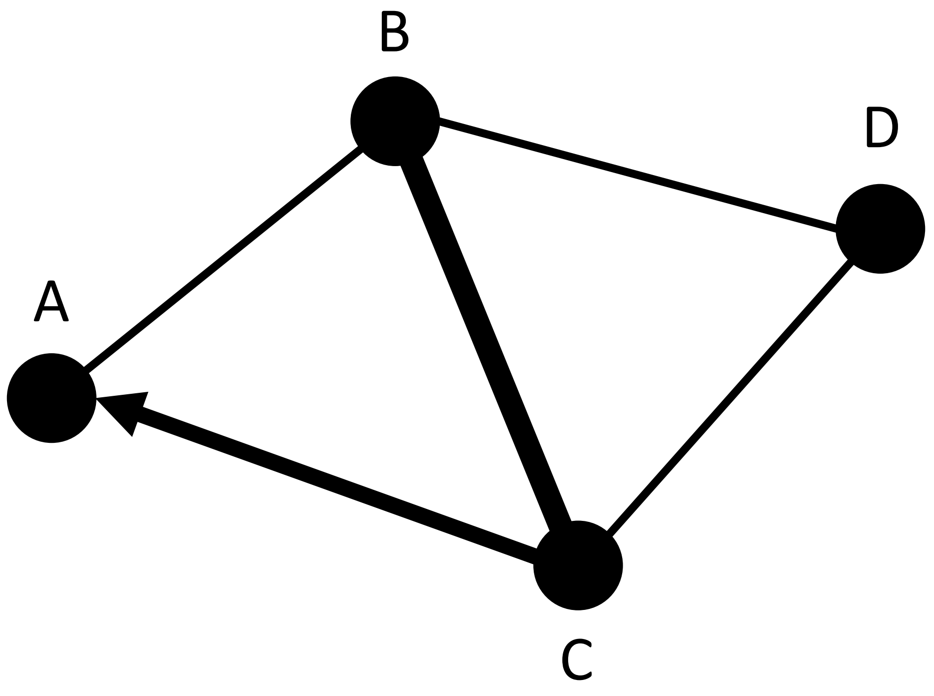


Node **centrality**

Numbers/rankings assigned to nodes that measure position in the network

E.g.

- Influential people in social network
- Key infrastructure nodes in internet or urban networks
- Super-spreaders of disease



Node **centrality**

<u>Degree centrality</u>

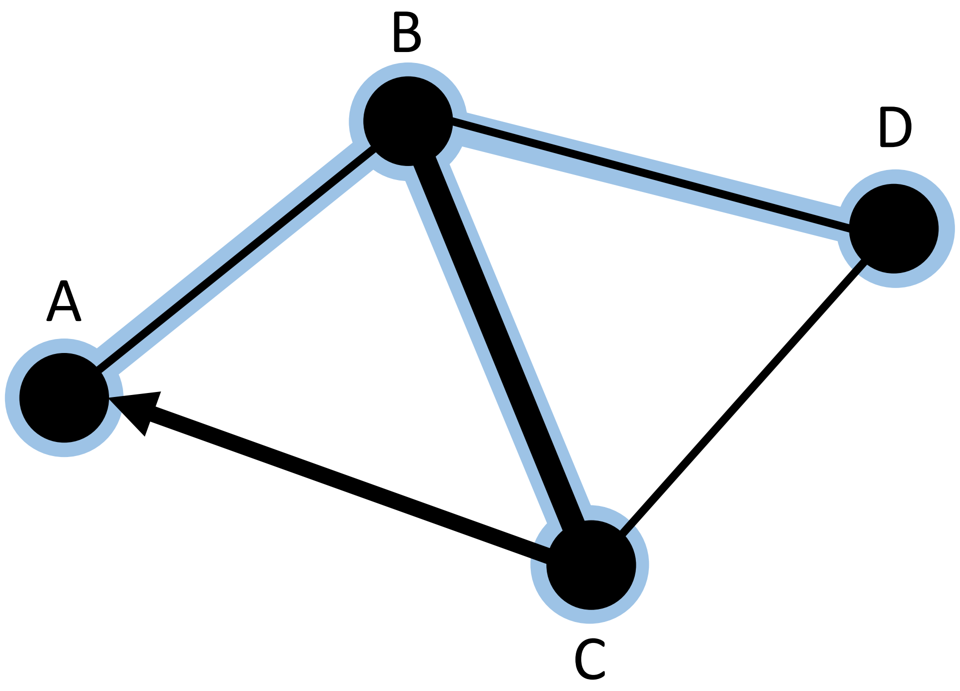
- How many edges in or out

In-degree(A) = 2; *Out-degree*(A) = 1

<u>Closeness centrality</u>

- Avg. shortest path between nodes

Closeness(A) = 1+2+2/3 = 1.7



Node **centrality**

<u>Degree centrality</u>

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In-degree(A) = 2; *Out-degree*(A) = 1

<u>Closeness centrality</u>

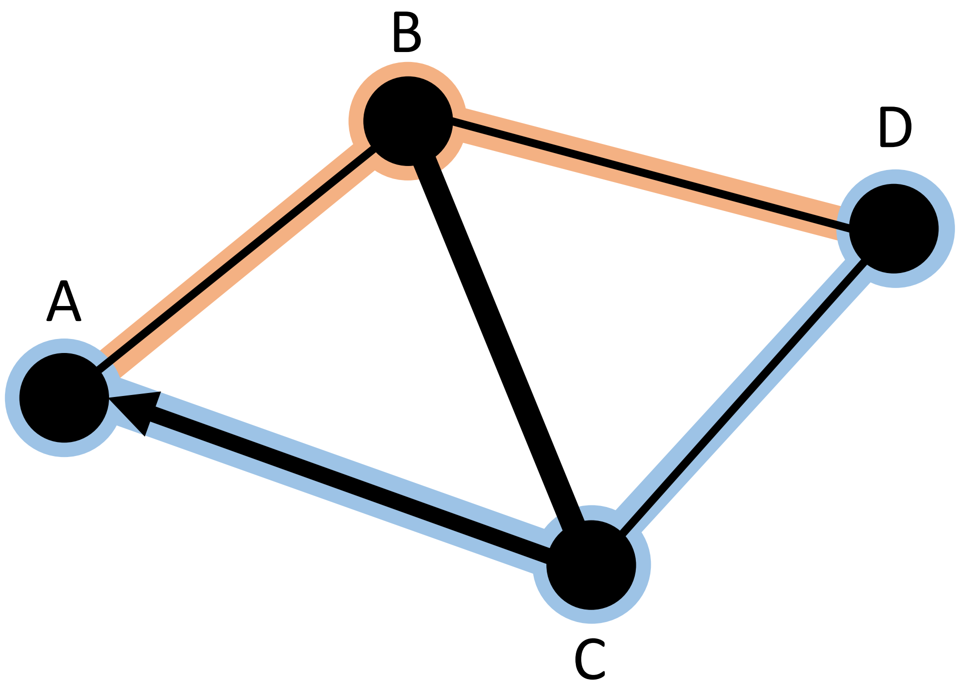
- Avg. shortest path between nodes

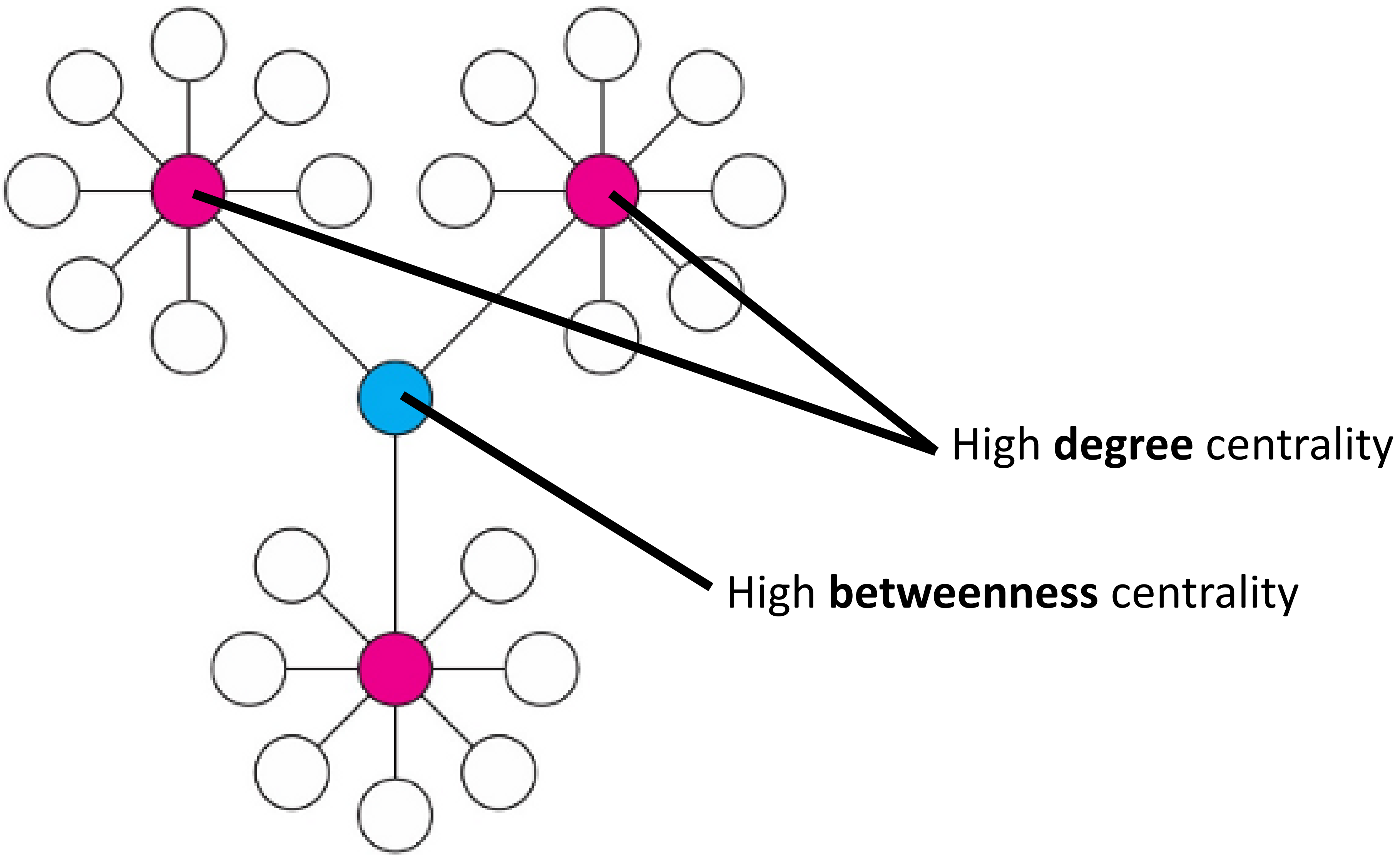
Closeness(A) = 1+2+2/3 = 1.7

<u>Betweenness centrality</u>

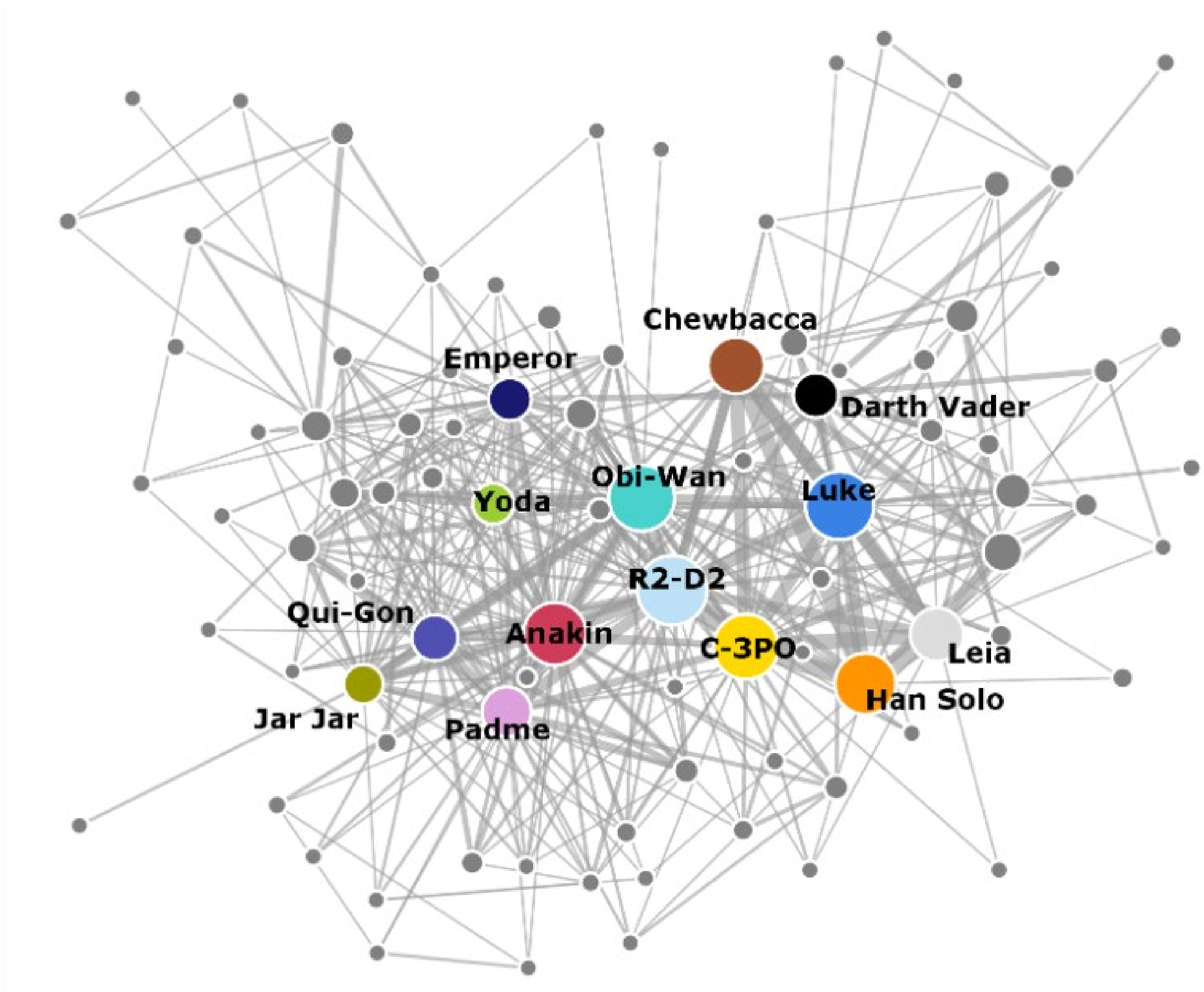
- How many times a node bridges other nodes

Betweenness(C) = 1/2 = 0.5

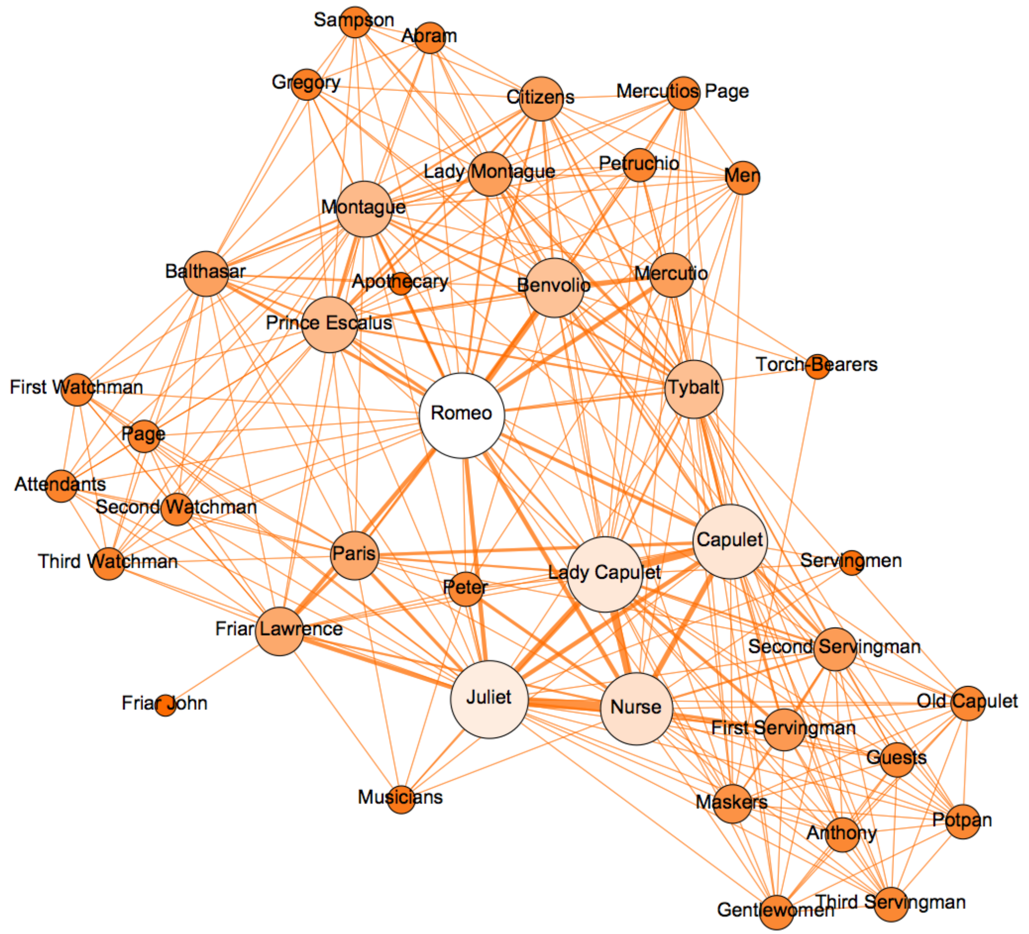



High **degree** centrality
High **betweenness** centrality

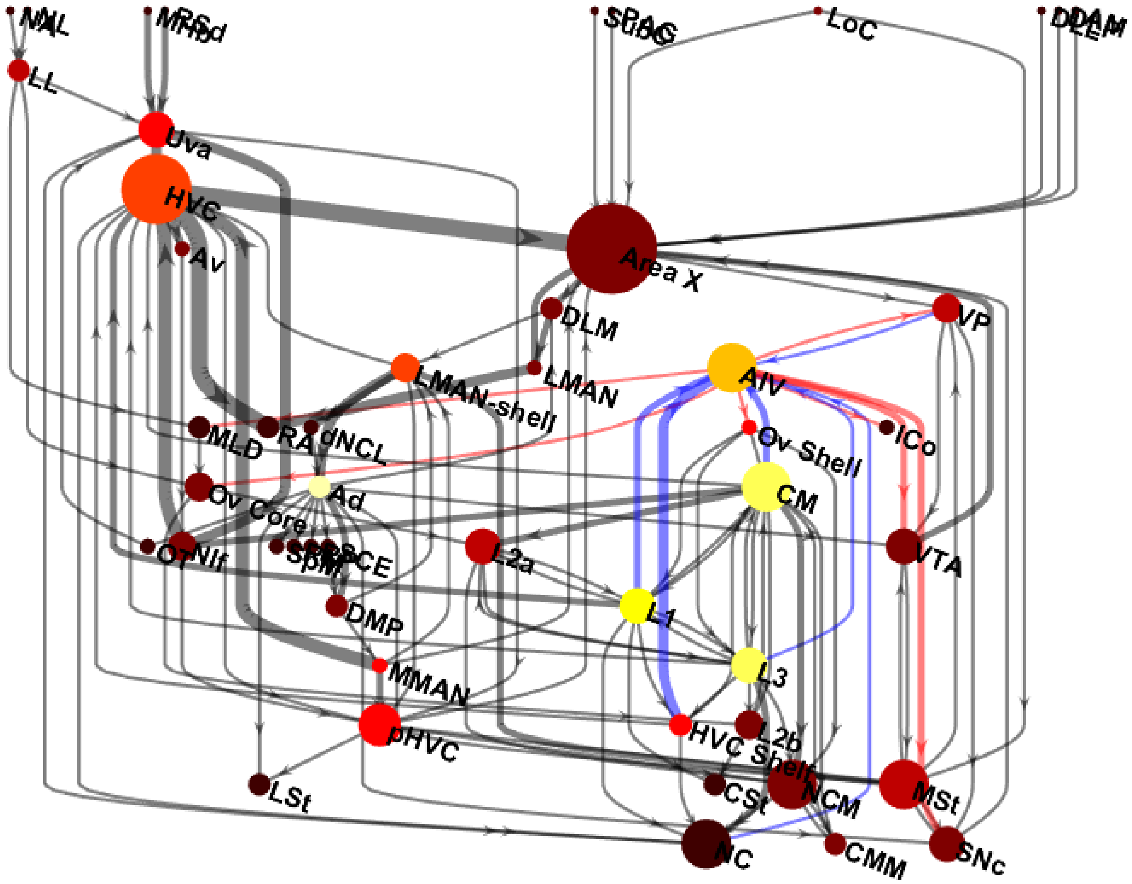
Star Wars (ep. 1-6)



Romeo & Juliet



Songbird brain ☺



Network **cohesion**

<u>Connected components</u>

- Subgraphs

<u>Clusters</u>

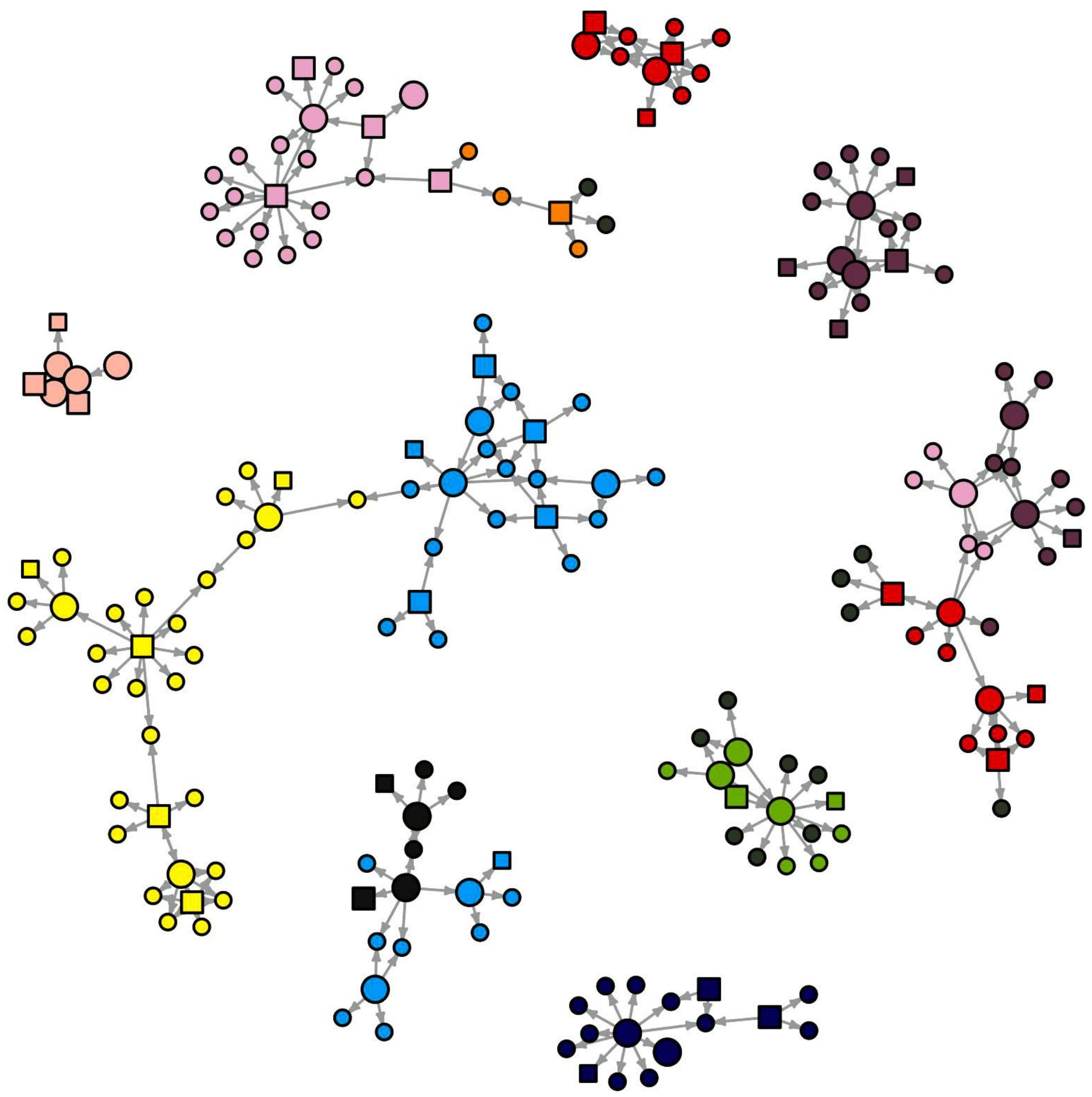
- Within-component subgroups

<u>Reciprocity</u>

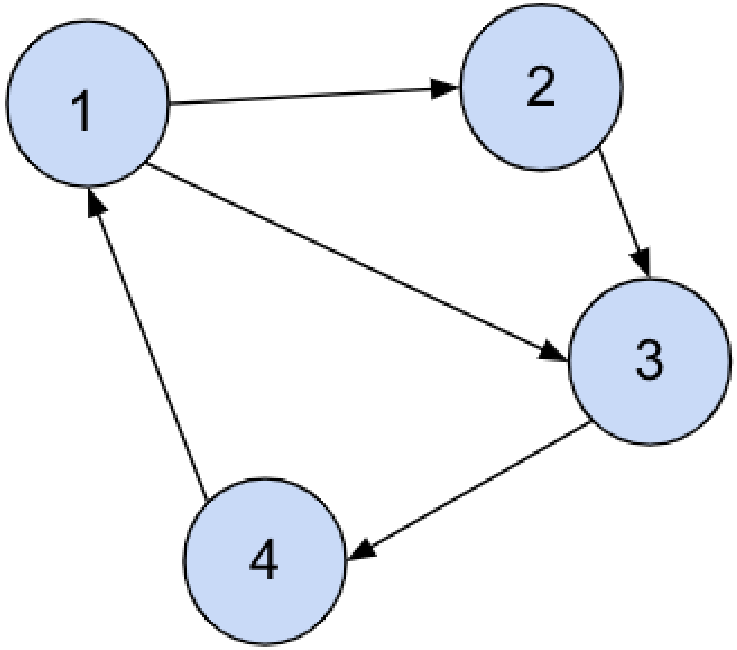
- Proportion of bi-directional edges (for directed graphs)

<u>Path lengths</u>

- Average paths among all nodes (degrees of separation)



Paths describe *flows*



Shortest path:
P(1,2) = 1
P(1,3) = 1
P(1,4) = (1,3) + (3,4) = 2
P(2,1) = (2,3) + (3,4) + (4,1) = 3
P(2,3) = 1
.....

Average path length:
(1 + 1 + 2 + 3 + 1 + ...) / (number of all shortest path)

E.g. average path length = 6
means 6 degrees of separation

Network analyses in justice data

JAMA Internal Medicine | Original Investigation | FIREARM VIOLENCE

Modeling Contagion Through Social Networks to Explain and Predict Gunshot Violence in Chicago, 2006 to 2014

Ben Green, MSc; Thibaut Horel, MSc; Andrew V. Papachristos, PhD

- Gun violence as an “epidemic”
- Due to demographics, geography, *social network*?

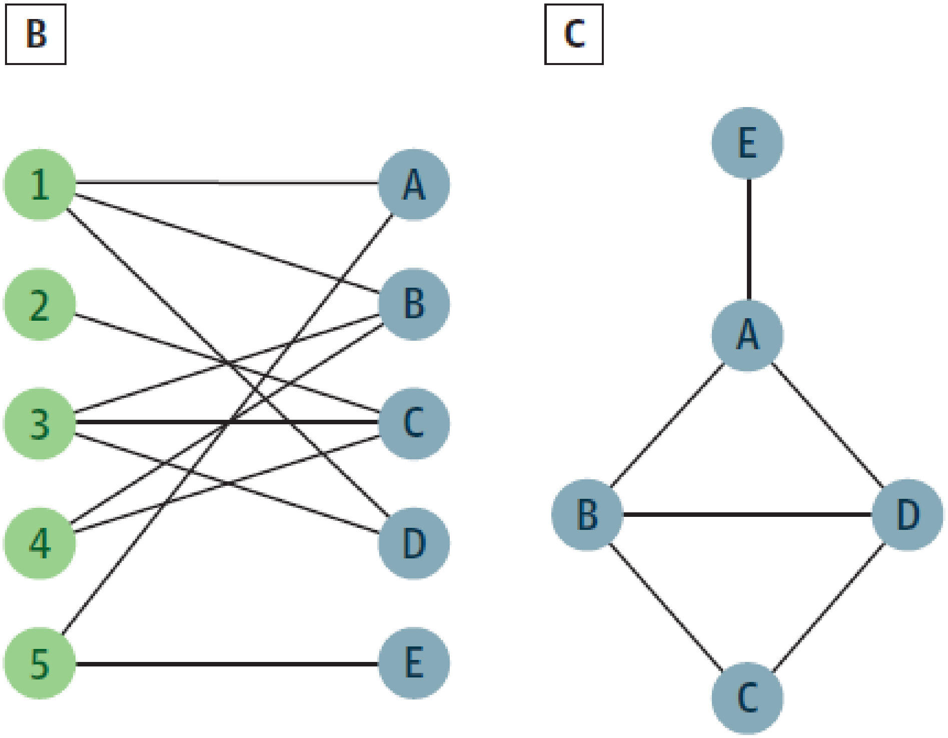
link to paper

Co-offending network data

Figure 1. Co-offending Network Generation Process

A

Event Code	Identity Code
1	A
1	B
1	D
2	C
3	B
3	C
3	D
4	B
4	C
5	A
5	E



Violence victims are non-randomly dispersed among non-victims

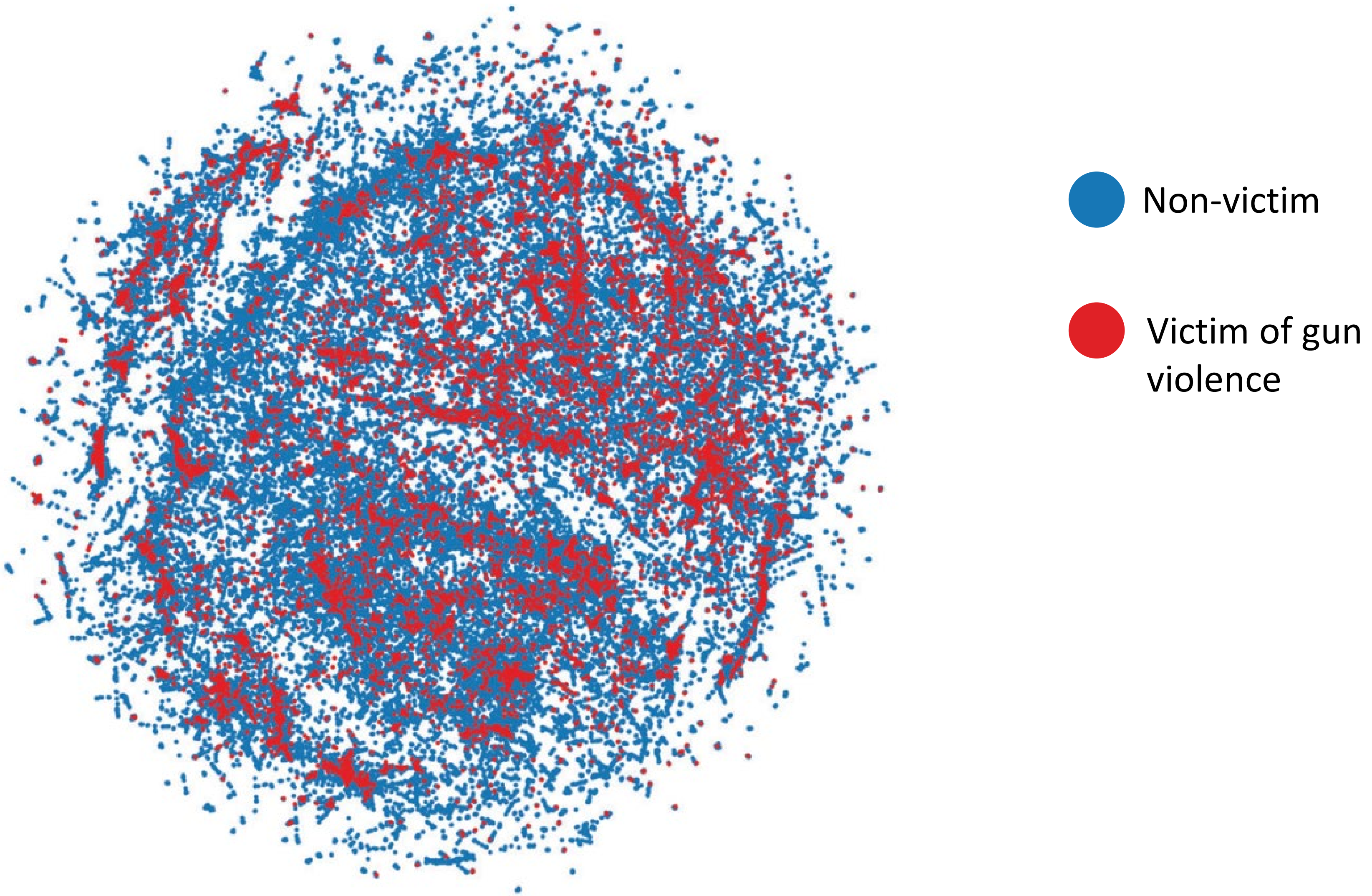
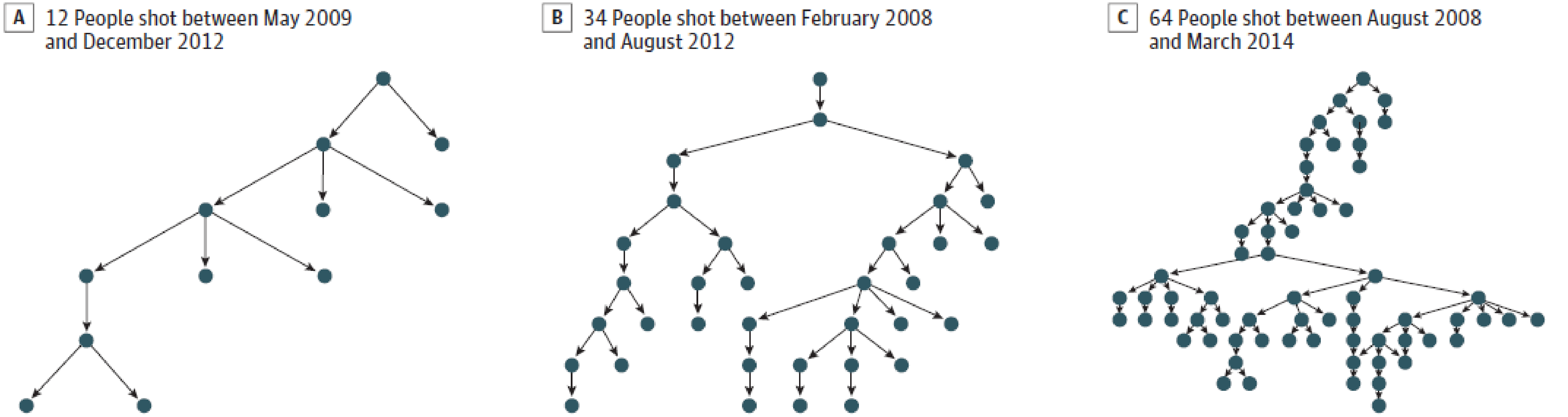


Table. Characteristics of the 138 163 Individuals Arrested in Chicago Between 2006 and 2014 and in the Largest Connected Component of the Network[a]

Variable	Largest Connected Component	Subjects of Gun Violence	Not Subjects of Gun Violence
Demographics			
No. of people	138 163	9773	128 390
Age at study midpoint, y	27.5	23.2	27.0
Male, %	82.0	97.0	80.9
Black race/ethnicity, %	75.6	79.8	75.3
White Hispanic race/ethnicity, %	23.3	19.5	23.6
Gang member, %	26.2	52.3	24.3
Network Characteristics			
No. of co-offenders (degree centrality)	6.1	10.2	5.7
Neighbors who are subjects of gun violence (first degree), %	10.4	17.9	9.8
Neighbors who are subjects of gun violence (first and second degree), %	11.1	15.9	10.7
Neighbors who are subjects of gun violence (first, second, and third degree), %	11.8	14.9	11.6

4,107 cascades of gun violence

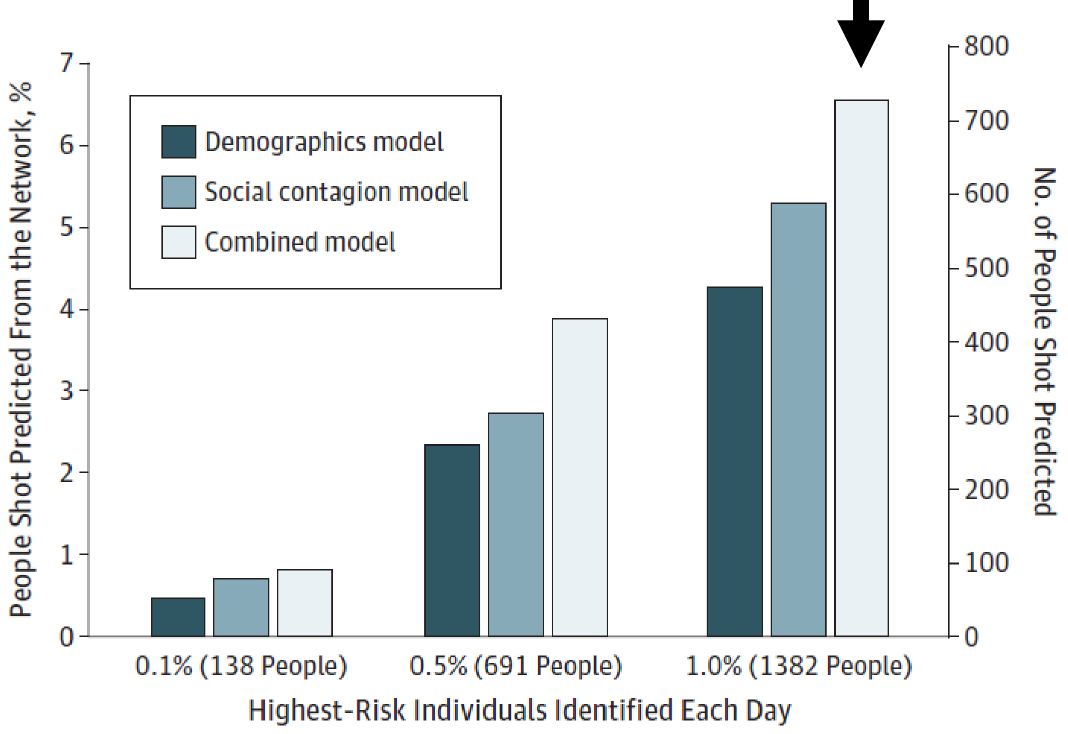
Figure 3. Three Cascades of Gunshot Violence Episodes Inferred From the Study Period



Each edge (a line with an arrow showing the direction) represents the transmission of gunshot violence from one individual to another. The originators of each cascade are on top.

Social contagion accounts for 63% of 11,123 gunshot violence episodes

Figure 4. Predictions of Gunshot Violence Among High-Risk Populations



Comparison of the ability of the 3 models to identify subjects of gun violence as one of the highest-risk individuals in the network on the day that the individual was shot; predictions for the 0.1%, 0.5%, and 1.0% of individuals at highest risk are shown.

Extended reading

Deeper reading into general network science

- Network Science by Albert-László Barabási

Network analyses applied to justice problems

- Social Networks and Crime: Pitfalls and Promises for Advancing the Field (Faust & Tita 2019)

Dealing with network data in R

- Statistical Analysis of Network Data with R
- Applied Network Science with R e-book