Centrality

For the first part of the lab we will use 3 datasets:

WIRING:

This is a stacked dataset that includes many different files. We will be working with RDGAM. This is a dichotomous adjacency matrix of 14 employees of the bank wiring room of Western Electric. Ties are symmetric and represent participation in games during work breaks.

PRISON:

This is a dichotomous adjacency matrix of 67 prisoners. Ties are directed and represent each ego's friends. Each was free to choose as few or as many "friends" as he desired.

DRUGNET:

This is a dichotomous adjacency matrix of drug users in Hartford. Ties are directed and represent the lending of drug needles. We will also work with the attribute file **DRUGATTR**.

EXERCISES:

1) Centrality using UCINET and NetDraw with **RDGAM**

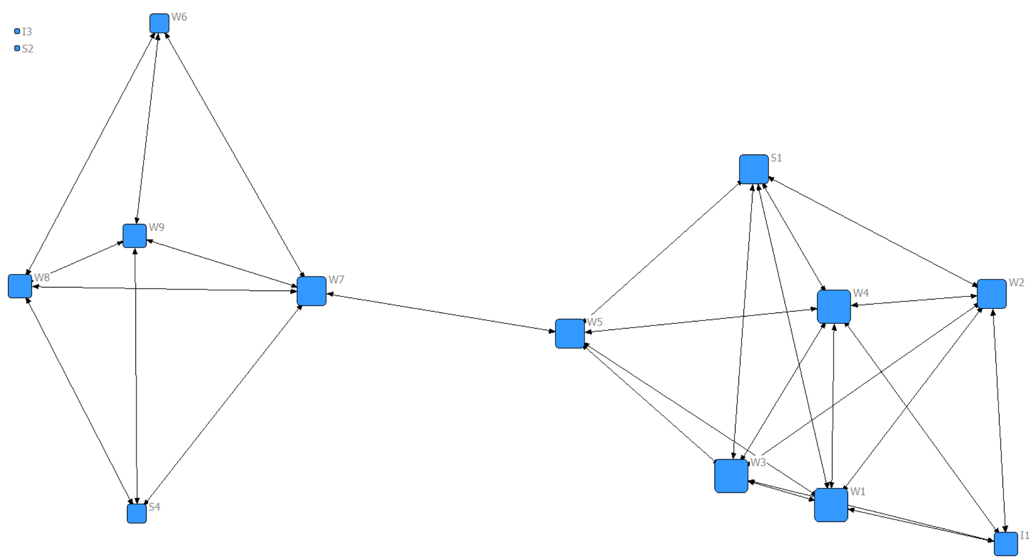
   If you have not done so already use UCINET to unpack **WIRING** (Data | Unpack). Be sure to eliminate the prefix so you filenames match what I have here.

   a) Open **RDGAM** in Netdraw to familiarize yourself with the data
      In UCINET calculate the following measures of centrality using
      Network | Centrality |
      - Degree
      - Freeman Betweenness | Node Betweenness
      - Closeness measures
      - Eigenvector centrality

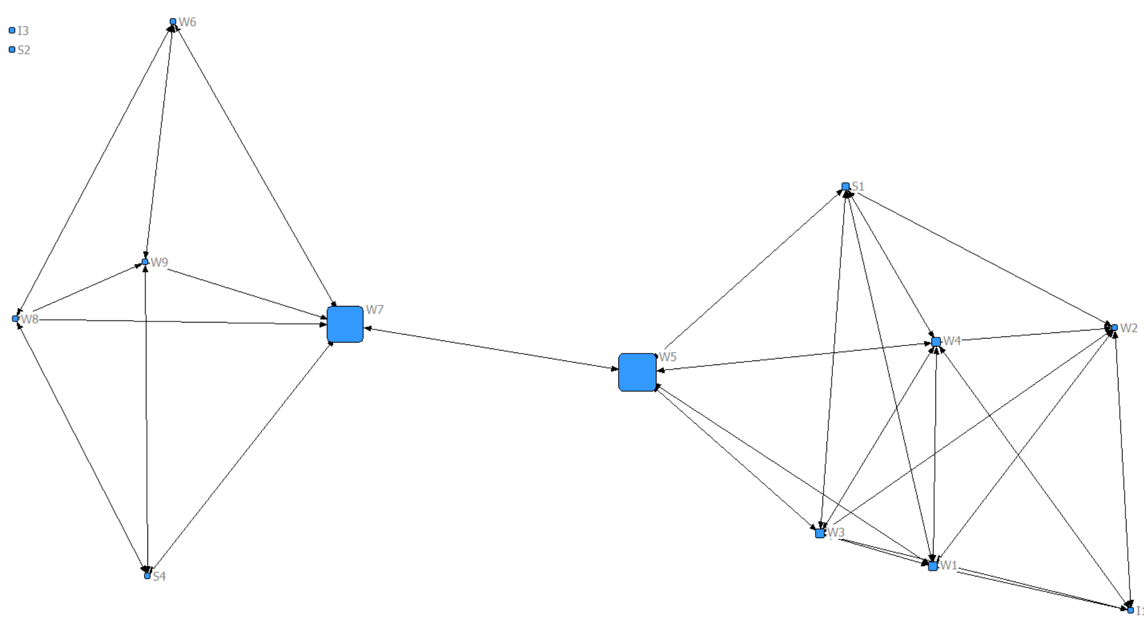
b) Using your Netdraw visualization, compare your calculations of various Centrality measures

In below diagrams, the size of square indicates the degree to which a specific node is central in the network. Thus, the bigger square nodes are more central than smaller square nodes.

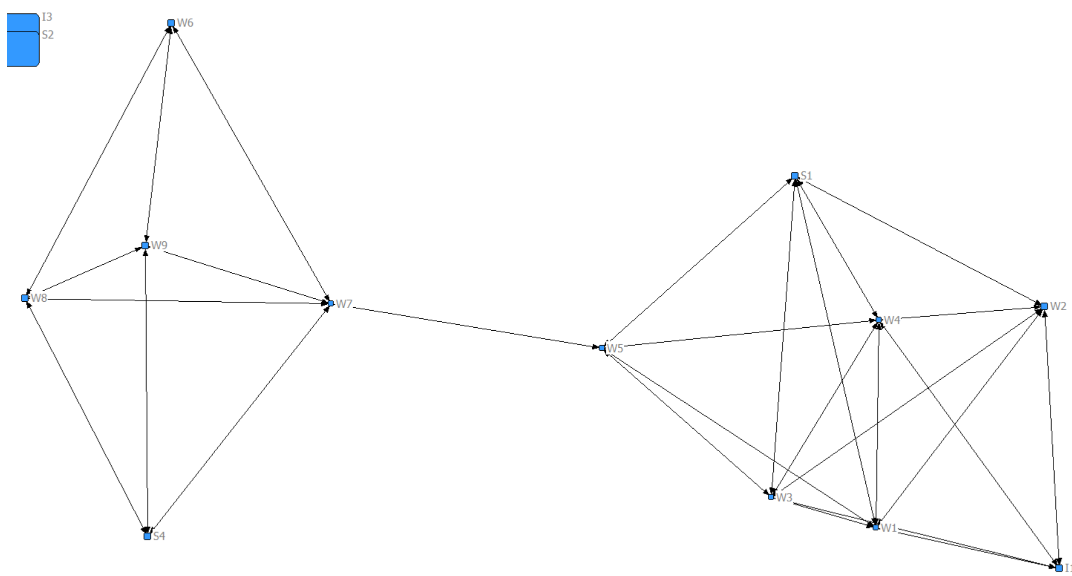
Degree centrality



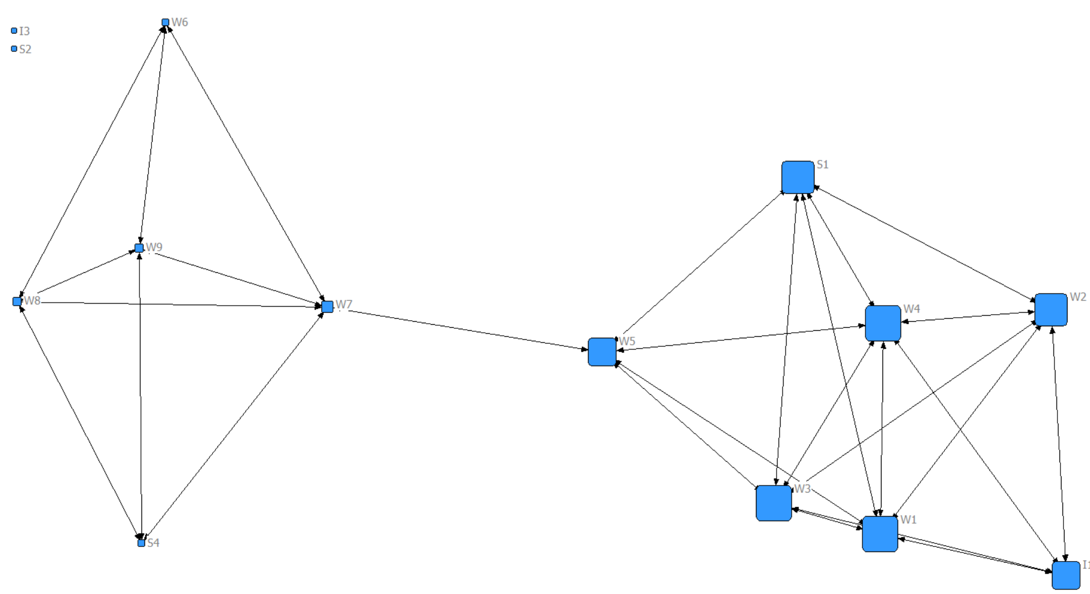
Betweenness centrality



Closeness centrality



Eigenvector centrality



c) Now run Centrality multiple measures in UCINET using Network | Centrality | Multiple Measures. Be sure to indicate you want "Raw" scores.

MULTIPLE CENTRALITY MEASURES

Input dataset: WIRING-RDGAM (C:\Users\Paulo Serodio\Documents\UCINET data\WIRING-RDGAM)

Output dataset: WIRING-RDGAM-cent (C:\Users\Paulo Serodio\Documents\UCINET data\WIRING-RDGAM-cent)

Treat data as: Auto-detect

Type of scores to output: Raw scores

Undefined dist in closeness: replace with max dist + 1

Network RDGAM is directed? NO

Value of Beta was: 0.188805369194129

Centrality Measures

	1 Degree	2 2local	3 BonPwr	4 2Step	5 ARD	6 Closenes	7 Eigenvec	8 Between	9 2StepBet
1 I1	4.000	23.000	911.060	6.000	6.333	37.000	0.307	0.000	0.000
2 I3	0.000	0.000	0.000	0.000	0.000	65.000	0.000	0.000	0.000
3 W1	6.000	31.000	1239.520	7.000	7.833	30.000	0.417	3.750	0.833
4 W2	5.000	27.000	1085.647	6.000	6.833	36.000	0.365	0.250	0.250
5 W3	6.000	31.000	1239.520	7.000	7.833	30.000	0.417	3.750	0.833
6 W4	6.000	31.000	1239.520	7.000	7.833	30.000	0.417	3.750	0.833
7 W5	5.000	28.000	963.556	11.000	8.000	27.000	0.323	30.000	4.000
8 W6	3.000	13.000	94.662	5.000	5.833	37.000	0.029	0.000	0.000
9 W7	5.000	19.000	264.410	9.000	7.667	29.000	0.085	28.333	4.333
10 W8	4.000	15.000	110.538	5.000	6.333	36.000	0.033	0.333	0.333
11 W9	4.000	15.000	110.538	5.000	6.333	36.000	0.033	0.333	0.333
12 S1	5.000	28.000	1093.985	7.000	7.333	31.000	0.368	1.500	0.250
13 S2	0.000	0.000	0.000	0.000	0.000	65.000	0.000	0.000	0.000
14 S4	3.000	13.000	94.662	5.000	5.833	37.000	0.029	0.000	0.000

Based on diagrams and UCINET output, we can tell as follows:

First of all, with respect to degree centrality, W1, W3, and W4 have the greatest degree, which means that they might be regarded as the most influential. Second, regarding betweenness centrality, W5 and W7 are in a favored position to the extent that the actor falls on the geodesic paths between other pairs of actors in the network. In other words, the more people depend on a specific node to make connections with other nodes, the more power that node has. We can check this by looking at diagram. Third, according to definition of Freeman, large numbers of closeness indicate that a node is highly peripheral (I3, S2), while small numbers indicate that a node is more central. We can check this through looking at diagram. Finally, eigenvector centrality scores show that W1, W3, and W4 are connected to other nodes that are themselves well connected.

d) Compare the profile of W1 with W5 across all measures. Note that W1 is stronger in eigenvector while W5 is stronger on betweenness. Interpret this result

	Degree	2local	BonPwr	2Step	ARD	Closenes	Eigenvec	Between	2StepBet
1 I1	4.000	23.000	911.060	6.000	6.333	37.000	0.307	0.000	0.000
2 I3	0.000	0.000	0.000	0.000	0.000	65.000	0.000	0.000	0.000
3 W1	6.000	31.000	1239.520	7.000	7.833	30.000	**0.417**	3.750	0.833
4 W2	5.000	27.000	1085.647	6.000	6.833	36.000	0.365	0.250	0.250
5 W3	6.000	31.000	1239.520	7.000	7.833	30.000	0.417	3.750	0.833
6 W4	6.000	31.000	1239.520	7.000	7.833	30.000	0.417	3.750	0.833
7 W5	5.000	28.000	963.556	11.000	8.000	27.000	0.323	**30.000**	4.000
8 W6	3.000	13.000	94.662	5.000	5.833	37.000	0.029	0.000	0.000
9 W7	5.000	19.000	264.410	9.000	7.667	29.000	0.085	28.333	4.333
10 W8	4.000	15.000	110.538	5.000	6.333	36.000	0.033	0.333	0.333
11 W9	4.000	15.000	110.538	5.000	6.333	36.000	0.033	0.333	0.333
12 S1	5.000	28.000	1093.985	7.000	7.333	31.000	0.368	1.500	0.250
13 S2	0.000	0.000	0.000	0.000	0.000	65.000	0.000	0.000	0.000
14 S4	3.000	13.000	94.662	5.000	5.833	37.000	0.029	0.000	0.000

Betweennes centrality is a measure of how often a given node falls along the shortest path between two other nodes. In other words, it is, loosely, the extent to which a given node is along the shortest paths of between all pairs of nodes. It is often interpreted as control over flows. Therefore, we can interpret W5 is the most influential node in terms of control over flows of information or something valuable. With respect to eigenvector, a node has high eigenvector score to the extent it is connected to many nodes who themselves have high scores. It is often interpreted as popularity or status – have ties not just to many others but many well-connected others. Therefore, we might interpret that W1 is the most famous or popular node in this network.

e) Compare W5 with W7. They have same degree yet differ on eigenvector centrality. Why is W7 so much weaker on eigenvector centrality?

	Degree	2local	BonPwr	2Step	ARD	Closenes	Eigenvec	Between	2StepBet
	--------	--------	--------	--------	--------	--------	--------	--------	--------
1 I1	4.000	23.000	911.060	6.000	6.333	37.000	0.307	0.000	0.000
2 I3	0.000	0.000	0.000	0.000	0.000	65.000	0.000	0.000	0.000
3 W1	6.000	31.000	1239.520	7.000	7.833	30.000	0.417	3.750	0.833
4 W2	5.000	27.000	1085.647	6.000	6.833	36.000	0.365	0.250	0.250
5 W3	6.000	31.000	1239.520	7.000	7.833	30.000	0.417	3.750	0.833
6 W4	6.000	31.000	1239.520	7.000	7.833	30.000	0.417	3.750	0.833
7 W5	5.000	28.000	963.556	11.000	8.000	27.000	**0.323**	30.000	4.000
8 W6	3.000	13.000	94.662	5.000	5.833	37.000	0.029	0.000	0.000
9 W7	5.000	19.000	264.410	9.000	7.667	29.000	0.085	28.333	4.333
10 W8	4.000	15.000	110.538	5.000	6.333	36.000	0.033	0.333	0.333
11 W9	4.000	15.000	110.538	5.000	6.333	36.000	0.033	0.333	0.333
12 S1	5.000	28.000	1093.985	7.000	7.333	31.000	0.368	1.500	0.250
13 S2	0.000	0.000	0.000	0.000	0.000	65.000	0.000	0.000	0.000
14 S4	3.000	13.000	94.662	5.000	5.833	37.000	**0.029**	0.000	0.000

A node with high eigenvector centrality is connected to nodes that are well connected to other nodes in network. Comparing W5 with W7, W5 is connected to nodes that have more connections to others than W7. According to netdraw diagram, we can also find the nodes that W5 is connected to are relatively well connected to others in the network.

f) Remove isolates using Data | Remove | Remove Isolates on **RDGAM** and recalculate centrality measures on the resultant data set, making sure to use whatever you specify as an Output dataset when removing isolates as the input dataset for calculating centrality. (That is, when you remove isolates, it creates a NEW dataset, and RDGAM will still have the isolates. Run it on the new file.)

Centrality output before removing isolates

		Degree	2local	BonPwr	2Step	ARD	**Closenes**	Eigenvec	Between	2StepBet
1	I1	4.000	23.000	911.060	6.000	6.333	37.000	0.307	0.000	0.000
2	*I3*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*65.000*	*0.000*	*0.000*	*0.000*
3	W1	6.000	31.000	1239.520	7.000	7.833	30.000	0.417	3.750	0.833
4	W2	5.000	27.000	1085.647	6.000	6.833	36.000	0.365	0.250	0.250
5	W3	6.000	31.000	1239.520	7.000	7.833	30.000	0.417	3.750	0.833
6	W4	6.000	31.000	1239.520	7.000	7.833	30.000	0.417	3.750	0.833
7	W5	5.000	28.000	963.556	11.000	8.000	27.000	0.323	30.000	4.000
8	W6	3.000	13.000	94.662	5.000	5.833	37.000	0.029	0.000	0.000
9	W7	5.000	19.000	264.410	9.000	7.667	29.000	0.085	28.333	4.333
10	W8	4.000	15.000	110.538	5.000	6.333	36.000	0.033	0.333	0.333
11	W9	4.000	15.000	110.538	5.000	6.333	36.000	0.033	0.333	0.333
12	S1	5.000	28.000	1093.985	7.000	7.333	31.000	0.368	1.500	0.250
13	*S2*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*65.000*	*0.000*	*0.000*	*0.000*
14	S4	3.000	13.000	94.662	5.000	5.833	37.000	0.029	0.000	0.000

Centrality output after removing isolates

		Degree	BonPwr	2Step	ARD	**Closenes**	Eigenvec	Between	2StepBet
1	I1	4.000	911.060	6.000	6.333	27.000	0.307	0.000	0.000
2	W1	6.000	1239.520	7.000	7.833	20.000	0.417	3.750	0.833
3	W2	5.000	1085.647	6.000	6.833	26.000	0.365	0.250	0.250
4	W3	6.000	1239.520	7.000	7.833	20.000	0.417	3.750	0.833
5	W4	6.000	1239.520	7.000	7.833	20.000	0.417	3.750	0.833
6	W5	5.000	963.556	11.000	8.000	17.000	0.323	30.000	4.000
7	W6	3.000	94.662	5.000	5.833	27.000	0.029	0.000	0.000
8	W7	5.000	264.410	9.000	7.667	19.000	0.085	28.333	4.333
9	W8	4.000	110.538	5.000	6.333	26.000	0.033	0.333	0.333
10	W9	4.000	110.538	5.000	6.333	26.000	0.033	0.333	0.333
11	S1	5.000	1093.985	7.000	7.333	21.000	0.368	1.500	0.250
12	S4	3.000	94.662	5.000	5.833	27.000	0.029	0.000	0.000

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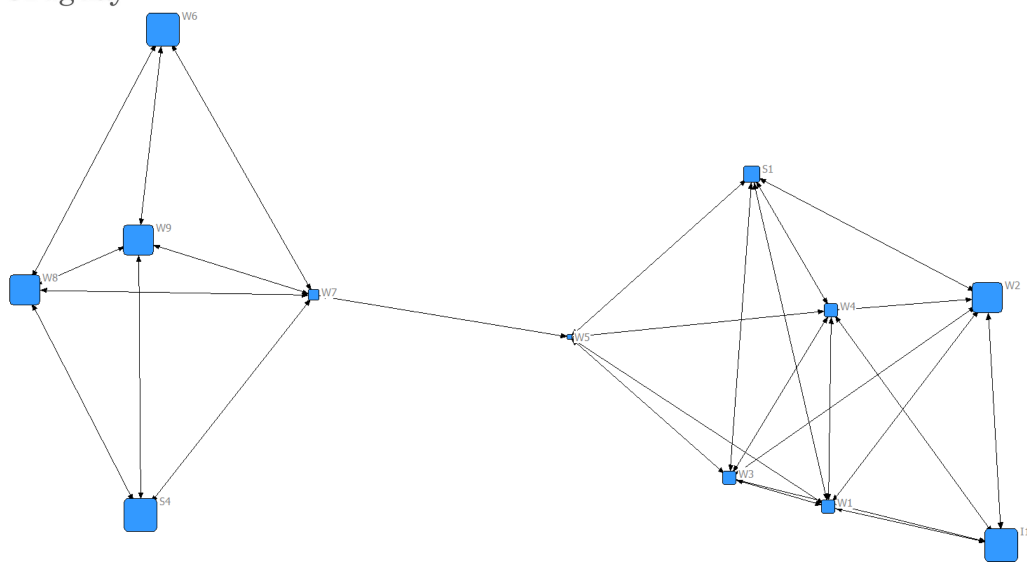


g) Compare the results for closeness centrality with those from the previous run. (Use File | View Previous Output to see prior output). What happened and why?

The mean farness went from 51 on the unconnected network with isolates to 23 on the connected network with isolates removed. You can also see the changes in individual measures for the network when you tell UCINET to substitute N for the missing distances. The values in the previous two tables, however, used Diameter Plus+1, which is 5, so the numbers when down by 10 (because the diameter is 4, so it used 5 for the values for the two isolates).

2) Directed Centrality using UCINET with **PRISON**

a) Open **PRISON** in Netdraw to familiarize yourself with the data

b) Using UCINET calculate Centrality measures, remembering that these are directed data.

MULTIPLE CENTRALITY MEASURES

Input dataset:	PRISON (C:\Users\Paulo Serodio\Documents\UCINET data\PRISON)
Output dataset:	PRISON-cent (C:\Users\Paulo Serodio\Documents\UCINET data\PRISON-cent)
Treat data as:	Directed
Type of scores to output:	Raw scores
Undefined dist in closeness:	replace with max dist + 1

Value of Beta was: 0.298764280458922

Principal eigenvalue was: 0

Centrality Measures

	1	2	3	4	5	6	7	8	9
	OutDeg	Indeg	OutBonPw	InBonPwr	OutClose	InClose	OutEigen	InEigen	Between
1	2.000	0.000	4.805	0.000	724.000	792.000	1.000	0.198	0.000
2	3.000	1.000	454.749	6.180	426.000	501.000	0.000	0.126	83.198
3	3.000	1.000	509.908	110.925	477.000	380.000	0.000	0.000	115.500
4	1.000	4.000	2.930	589.367	735.000	325.000	0.000	-0.324	0.000
5	3.000	4.000	6.459	589.367	730.000	325.000	0.000	-0.324	50.700
6	1.000	2.000	3.002	395.344	737.000	366.000	0.000	0.188	2.000
7	1.000	4.000	1.945	246.499	771.000	273.000	0.000	0.232	38.167
8	8.000	5.000	362.353	54.783	390.000	395.000	0.000	0.126	627.050
9	3.000	3.000	6.702	1315.144	732.000	312.000	0.000	0.000	130.233
10	2.000	1.000	249.752	1.426	445.000	781.000	0.000	0.000	48.000
11	1.000	1.000	75.617	1.426	493.000	781.000	0.000	0.000	0.000
12	4.000	4.000	515.432	49.911	382.000	402.000	0.000	0.000	276.583
13	2.000	2.000	291.855	17.338	401.000	453.000	0.000	0.000	116.532
14	2.000	1.000	62.084	1.426	447.000	771.000	0.000	0.117	47.897
15	3.000	3.000	117.504	13.177	500.000	464.000	0.000	0.014	0.500
16	2.000	7.000	176.051	43.342	458.000	365.000	0.000	-0.126	368.667
17	2.000	3.000	89.704	13.177	501.000	464.000	0.000	0.014	0.000
18	4.000	3.000	794.907	19.619	415.000	447.000	0.000	0.000	106.867
19	0.000	1.000	0.000	1.000	792.000	781.000	0.000	0.019	0.000
20	3.000	3.000	753.639	9.288	420.000	495.000	0.000	0.271	97.783
21	2.000	6.000	320.059	367.933	458.000	327.000	0.000	0.000	256.000
22	3.000	2.000	767.192	2051.740	524.000	379.000	0.000	-0.006	0.000
23	3.000	2.000	648.496	30.074	436.000	420.000	0.000	0.023	3.333
24	3.000	3.000	648.496	93.966	436.000	368.000	0.000	0.139	55.333
25	0.000	2.000	0.000	3.846	792.000	538.000	0.000	-0.680	0.000
26	0.000	2.000	0.000	2.426	792.000	751.000	0.000	0.141	0.000
27	3.000	0.000	456.051	0.000	426.000	792.000	0.000	-0.117	0.000
28	3.000	4.000	236.662	32.430	491.000	413.000	0.000	0.207	141.100
29	1.000	2.000	109.258	18.793	436.000	442.000	0.000	0.045	64.500
30	5.000	5.000	592.551	481.974	403.000	296.000	0.000	0.009	883.229
31	4.000	0.000	153.610	0.000	489.000	792.000	0.000	0.112	0.000
32	3.000	1.000	325.334	80.124	398.000	383.000	0.000	-0.126	576.383
33	2.000	4.000	201.108	264.836	422.000	330.000	0.000	0.000	617.864
34	2.000	3.000	116.002	29.747	437.000	442.000	0.000	0.207	164.083
35	0.000	1.000	0.000	11.200	792.000	475.000	0.000	1.000	0.000
36	3.000	0.000	767.138	0.000	421.000	792.000	0.000	0.000	0.000
37	6.000	6.000	957.383	274.399	406.000	318.000	0.000	0.117	615.692
38	1.000	1.000	53.747	1.426	468.000	781.000	0.000	0.000	0.000
39	4.000	1.000	329.102	8.415	492.000	500.000	0.000	-0.005	0.000
40	2.000	2.000	3.162	135.095	770.000	280.000	0.000	-0.009	32.033
41	5.000	5.000	1009.115	46.340	393.000	398.000	0.000	-0.271	371.216

42	2.000	2.000	144.915	16.375	424.000	493.000	0.000	0.081	56.000
43	2.000	2.000	582.506	83.981	428.000	365.000	0.000	-0.276	291.430
44	3.000	1.000	176.551	1.426	418.000	781.000	0.000	0.000	50.000
45	4.000	3.000	708.456	25.481	397.000	447.000	0.000	0.005	175.683
46	3.000	4.000	117.504	20.886	500.000	414.000	0.000	-0.126	125.500
47	2.000	6.000	235.445	32.181	494.000	423.000	0.000	-0.203	126.517
48	2.000	6.000	465.065	260.690	434.000	309.000	0.000	-0.302	355.821
49	4.000	4.000	807.855	3407.193	481.000	337.000	0.000	0.136	183.567
50	3.000	1.000	233.174	1.426	404.000	771.000	0.000	-0.126	90.500
51	1.000	4.000	71.343	21.967	539.000	411.000	0.000	-0.063	81.517
52	3.000	8.000	554.674	993.122	420.000	293.000	0.000	0.392	762.046
53	3.000	0.000	108.449	0.000	453.000	792.000	0.000	0.000	0.000
54	5.000	3.000	544.706	24.817	452.000	447.000	0.000	0.000	267.167
55	4.000	7.000	933.909	2478.430	449.000	298.000	0.000	0.006	609.834
56	4.000	7.000	982.796	3453.533	486.000	327.000	0.000	-0.136	132.908
57	1.000	4.000	1.945	198.984	771.000	259.000	0.000	-0.232	51.867
58	3.000	2.000	257.986	18.367	396.000	444.000	0.000	-0.207	94.667
59	2.000	1.000	79.534	1.426	425.000	781.000	0.000	0.000	46.000
60	2.000	1.000	26.343	1.426	468.000	781.000	0.000	0.000	2.500
61	4.000	1.000	393.828	34.141	474.000	432.000	0.000	0.000	59.000
62	5.000	1.000	432.140	1.426	363.000	781.000	0.000	0.000	15.000
63	5.000	0.000	681.152	0.000	392.000	792.000	0.000	-0.139	0.000
64	3.000	4.000	767.192	3407.193	524.000	337.000	0.000	0.136	19.792
65	2.000	0.000	79.077	0.000	426.000	792.000	0.000	-0.126	0.000
66	3.000	1.000	307.415	1.426	390.000	781.000	0.000	0.000	3.333
67	2.000	4.000	341.102	309.527	434.000	322.000	0.000	0.000	149.907

c) Identify which individuals have the most friends in this dataset. (What measure(s) did you use to identity them, and why?)

For directed data, the adjacency matrix is not always symmetric. Therefore, the row and column sums may be different. Generally, outdegree counts the number of outgoing ties whereas indegree counts the number of incoming ties. In this case, interpretation of this asymmetric data depends on what kind of social relation we explore. For example, you might interpret outdegree of friendship ties as the 'gregariousness' of the node, whereas the indegree as the 'popularity' of the node. Therefore, if you use 'indegree' of ties to identify which individuals have the most friends, you interpret 'friendship' as 'popularity of individuals.'

3) Directed Centrality using NetDraw with **PRISON**

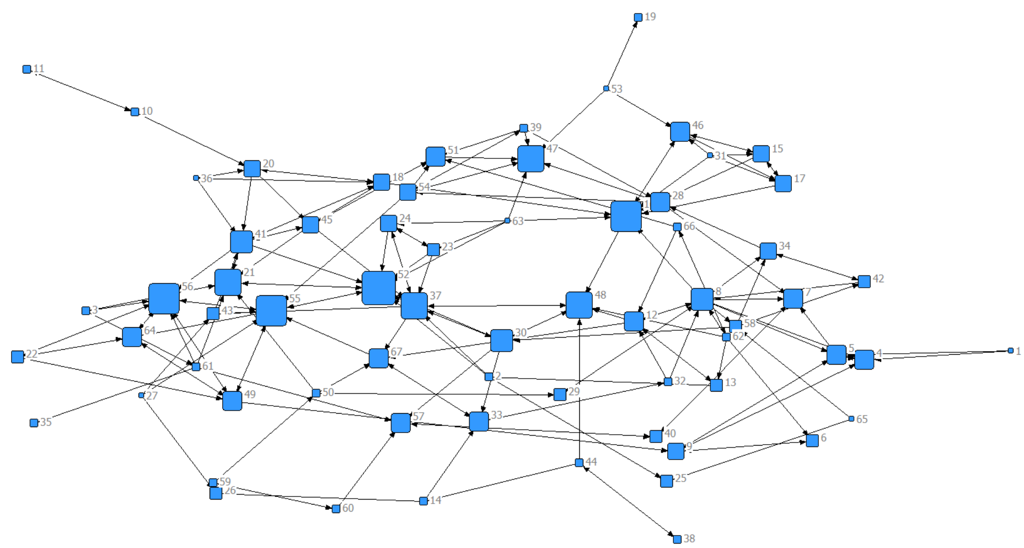
a) Open **PRISON** in Netdraw

b) Using NetDraw calculate Centrality measures under Analysis | Centrality measures. Tell the routine you have directed data.

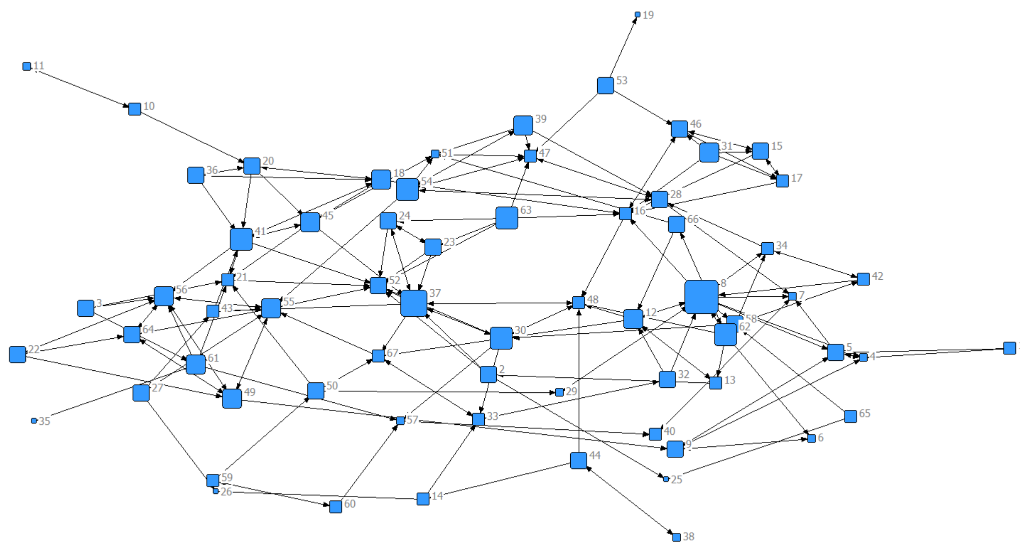
c) Resize the nodes based on various Centrality measures. (don't worry about measures we didn't talk about).

After you run the centrality measures you should be able to click the "Size" box on the "Nodes" tab then click through the different types of centrality.

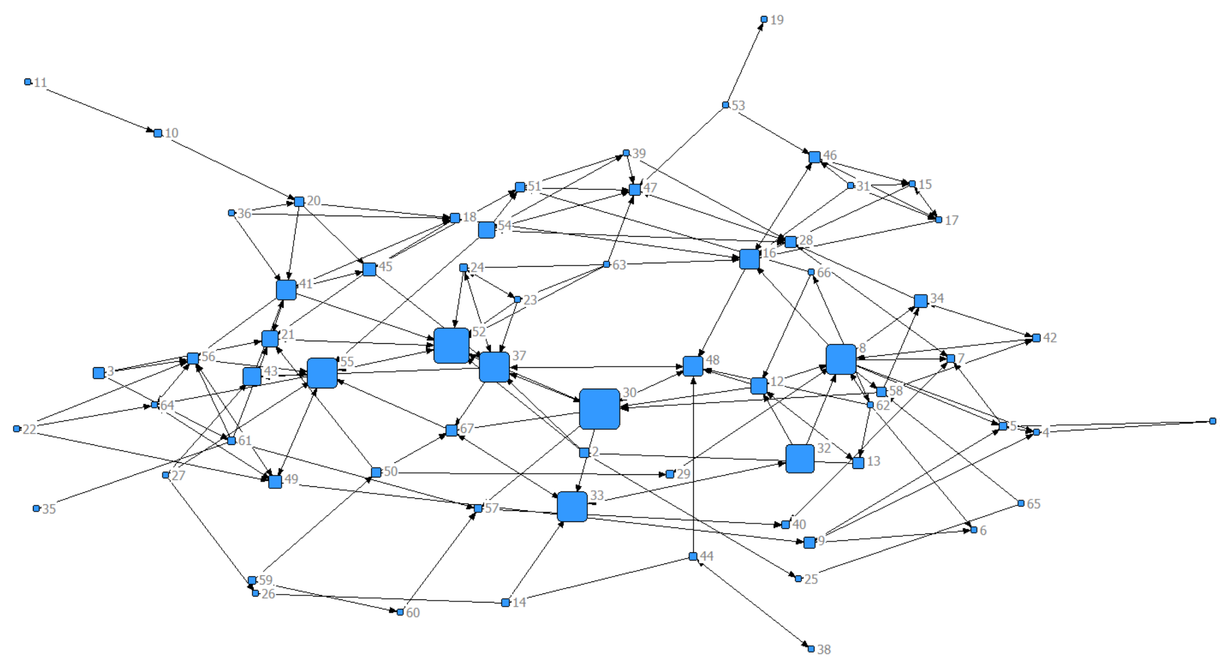
InDegree centrality



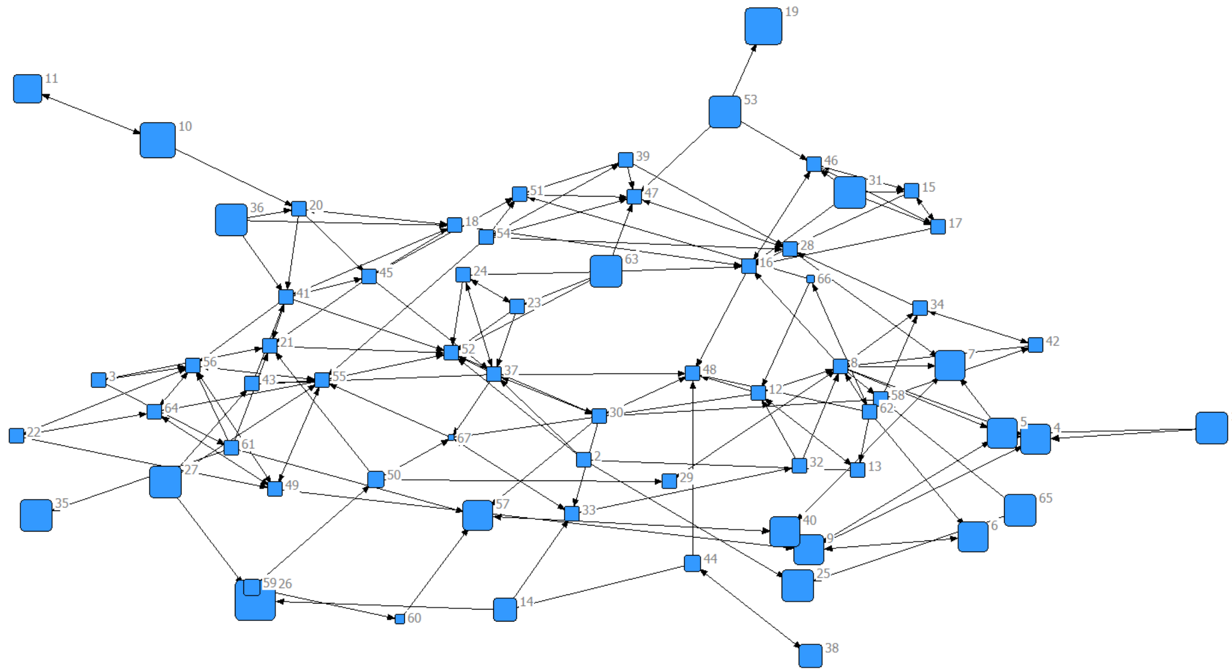
OutDegree centrality



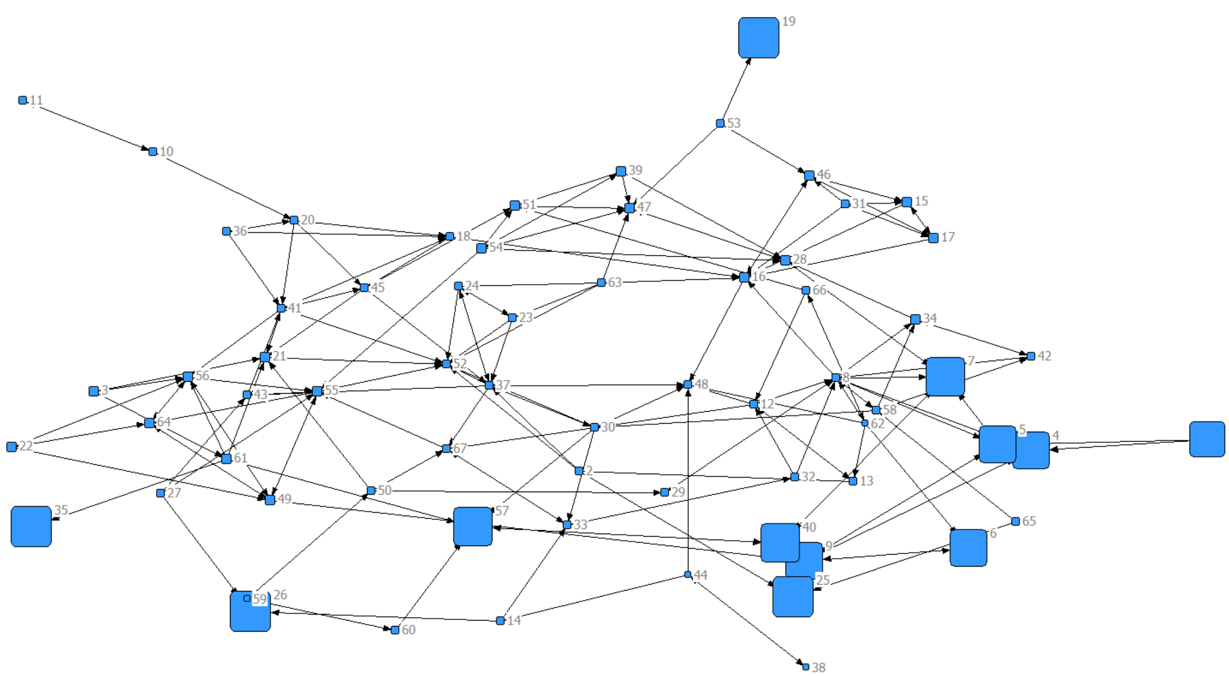
Betweenness centrality



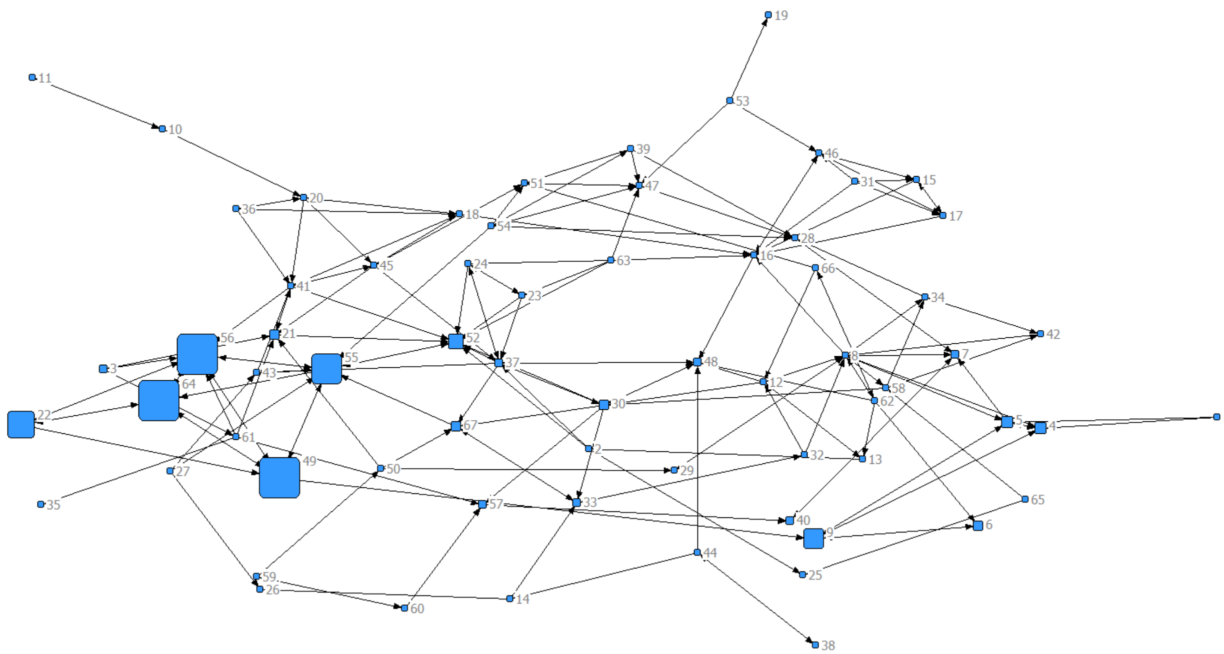
InCloseness centrality



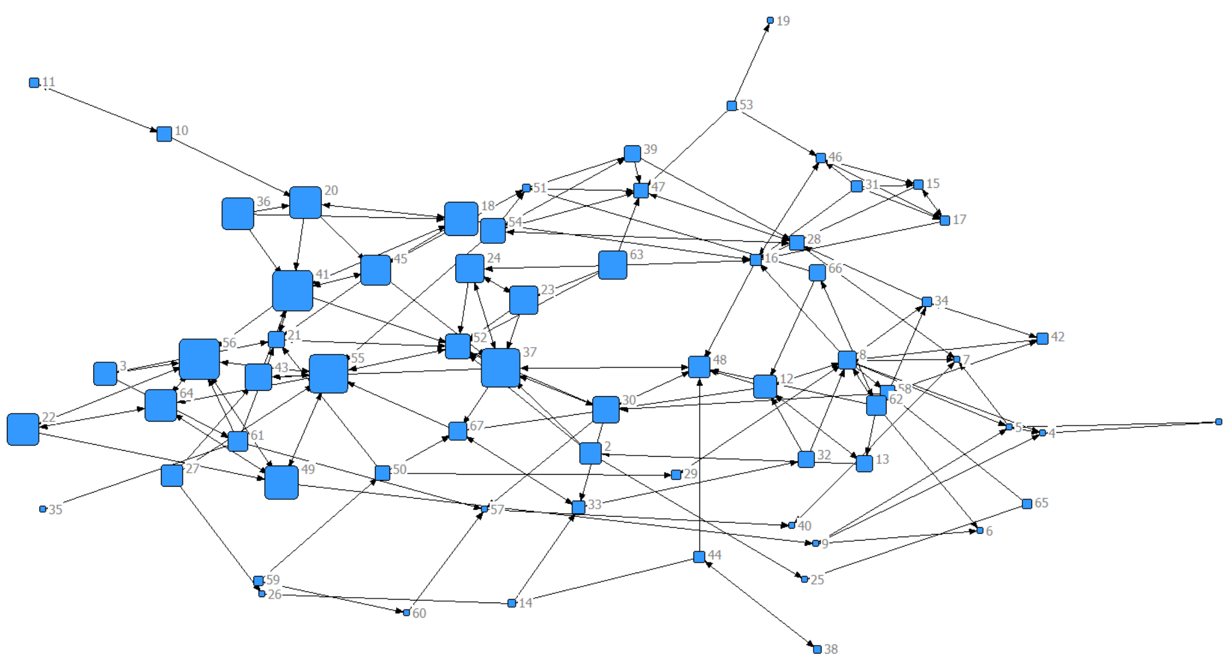
OutCloseness centrality



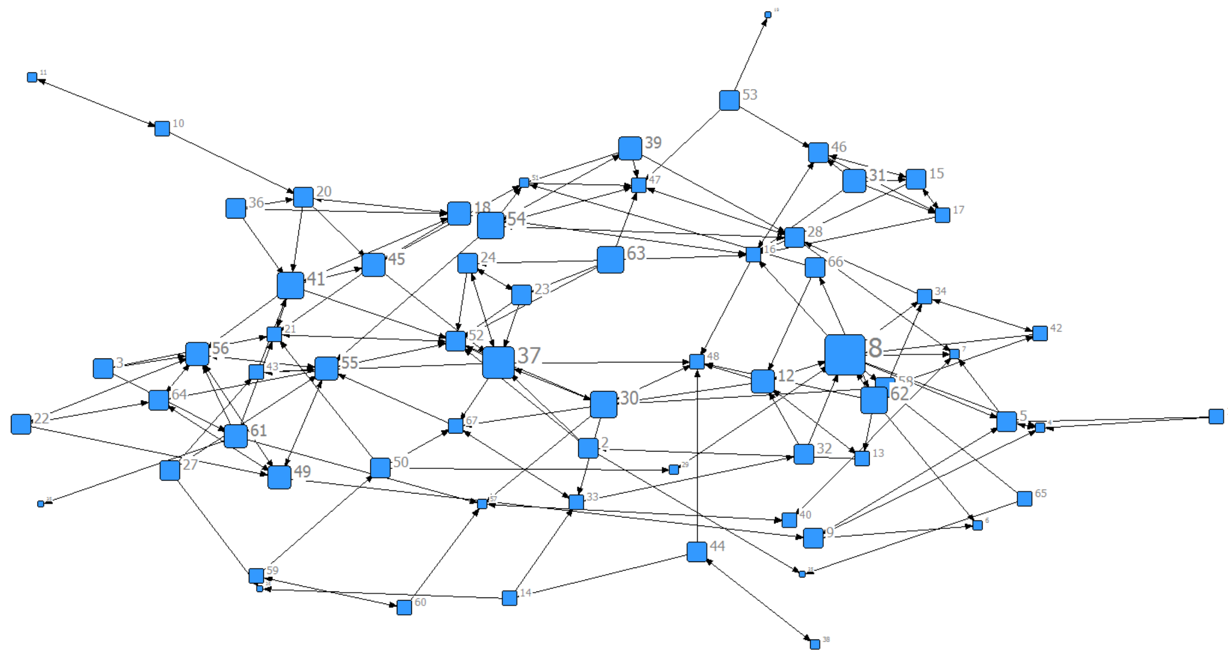
InEigenvector centrality



OutEigenvector centrality

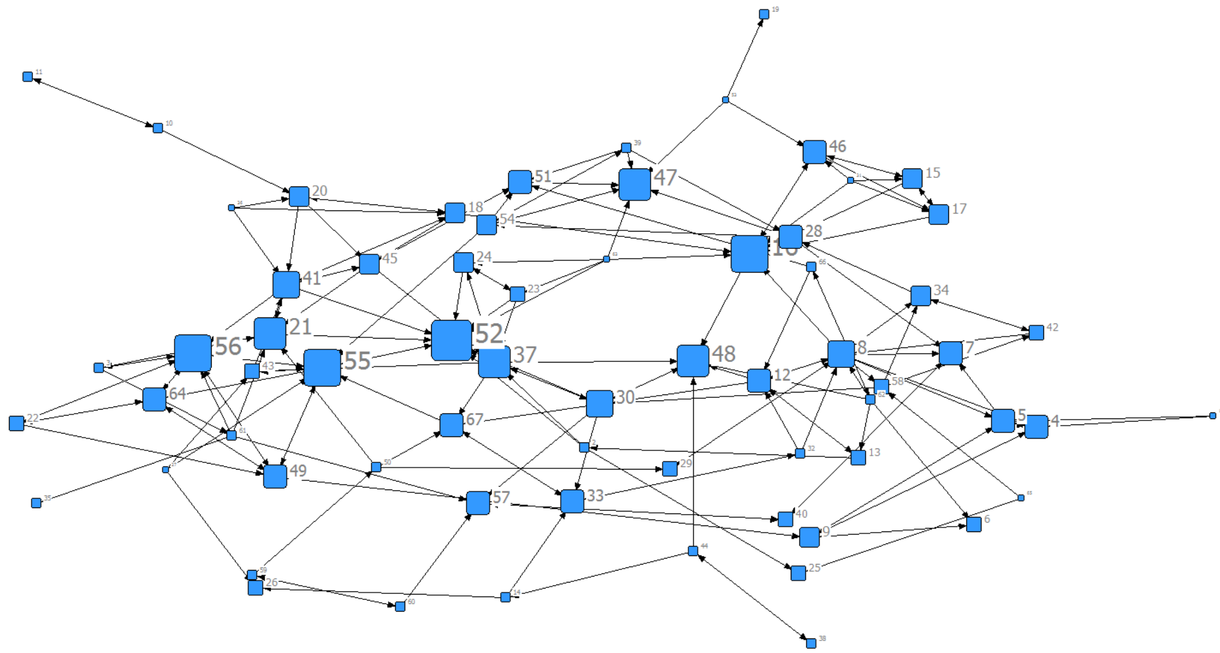


d) Identify which individuals **list** the most number of friends



Outdegree centrality would be the correct centrality measure to choose. It is based on who nominated the most other people. You can tell by sizing your network by outdegree that node 8 has the highest outdegree. To get a more refined idea of who the nodes are with most outdegree you can also uncheck the boxes in the nodes tab to only show individuals with the 5 or greater outdegree.

e) Identify which individuals **are listed as friends** by the most number of others



Indegree would be the type of centrality that identified who received the most nominations by others. Repeat what you did for step D with indegree. You should find node 52 has the highest indegree (8) followed by 16,55, and 56 (all with 7).

FREEMAN DEGREE CENTRALITY

	1	2	3	4
	Outded	Indeg	nOutdeg	nIndeg
	-----	-----	-----	-----
1	2.000	0.000	0.030	0.000
2	3.000	1.000	0.045	0.015
3	3.000	1.000	0.045	0.015
4	1.000	4.000	0.015	0.061
5	3.000	4.000	0.045	0.061
6	1.000	2.000	0.015	0.030
7	1.000	4.000	0.015	0.061
8	**8.000**	5.000	0.121	0.076
9	3.000	3.000	0.045	0.045
10	2.000	1.000	0.030	0.015
11	1.000	1.000	0.015	0.015
12	4.000	4.000	0.061	0.061
13	2.000	2.000	0.030	0.030
14	2.000	1.000	0.030	0.015
15	3.000	3.000	0.045	0.045
16	2.000	7.000	0.030	0.106
17	2.000	3.000	0.030	0.045
18	4.000	3.000	0.061	0.045
19	0.000	1.000	0.000	0.015
20	3.000	3.000	0.045	0.045

21	2.000	6.000	0.030	0.091
22	3.000	2.000	0.045	0.030
23	3.000	2.000	0.045	0.030
24	3.000	3.000	0.045	0.045
25	0.000	2.000	0.000	0.030
26	0.000	2.000	0.000	0.030
27	3.000	0.000	0.045	0.000
28	3.000	4.000	0.045	0.061
29	1.000	2.000	0.015	0.030
30	5.000	5.000	0.076	0.076
31	4.000	0.000	0.061	0.000
32	3.000	1.000	0.045	0.015
33	2.000	4.000	0.030	0.061
34	2.000	3.000	0.030	0.045
35	0.000	1.000	0.000	0.015
36	3.000	0.000	0.045	0.000
37	**6.000**	6.000	0.091	0.091
38	1.000	1.000	0.015	0.015
39	4.000	1.000	0.061	0.015
40	2.000	2.000	0.030	0.030
41	5.000	5.000	0.076	0.076
42	2.000	2.000	0.030	0.030
43	2.000	2.000	0.030	0.030
44	3.000	1.000	0.045	0.015
45	4.000	3.000	0.061	0.045
46	3.000	4.000	0.045	0.061
47	2.000	6.000	0.030	0.091
48	2.000	6.000	0.030	0.091
49	4.000	4.000	0.061	0.061
50	3.000	1.000	0.045	0.015
51	1.000	4.000	0.015	0.061
52	3.000	**8.000**	0.045	0.121
53	3.000	0.000	0.045	0.000
54	5.000	3.000	0.076	0.045
55	4.000	7.000	0.061	0.106
56	4.000	7.000	0.061	0.106
57	1.000	4.000	0.015	0.061
58	3.000	2.000	0.045	0.030
59	2.000	1.000	0.030	0.015
60	2.000	1.000	0.030	0.015
61	4.000	1.000	0.061	0.015
62	5.000	1.000	0.076	0.015
63	5.000	0.000	0.076	0.000
64	3.000	4.000	0.045	0.061
65	2.000	0.000	0.030	0.000
66	3.000	1.000	0.045	0.015
67	2.000	4.000	0.030	0.061

4) Directed Centrality using UCINET with **DRUGNET**

a) Open **DRUGNET** in NetDraw to familiarize yourself with the data

b) Using UCINET identify which individuals are at highest risk of contracting a disease based on their needle sharing habits.

Drugnet is a needle sharing network taking from a US city. Needles are either given (out-arrows), received (in arrows), or traded (bi-directional arrows).

First, consider what measures of Centrality to use based on the data and problem. We can use eigenvector centrality to identify individuals at higher risk of contracting a disease. In the case of directed network, we could interpret left eigenvector (columns) is popularity, whereas right eigenvector (rows) is influence. Therefore, we can interpret eigenvector centrality as a measure of popularity. In addition, we could also view eigenvector centrality as a measure of risk. Therefore, by looking at eigenvector centrality score, we could identify individuals who are at highest risk of contracting a disease. However, we should remember it is better to use beta centrality as a substitute for eigenvector centrality. Therefore, we could identify that node 150, 171, 173 are at highest risk of contracting a disease by looking at beta centrality score and eigenvector centrality. We could also identify those individuals through two diagrams.

On the other hand, indegree centrality shows the individuals who are receiving the most needles from other and at the most immediate risk of contracting a pathogen that travels by needles. Betweenness centrality also shows the individuals who are most necessary for flows through the network, such as disease, to pass through to get to others. These individuals may not be at high risk themselves but if you wanted to prevent a disease from traveling through the network they would be important to intervene with.

FREEMAN'S DEGREE CENTRALITY MEASURES

Diagonal valid? NO
Model: ASYMMETRIC
Input dataset: drugnet (C:\Users\Paulo Serodio\Documents\UCINET data\drugnet)

		1 OutDegree	2 InDegree	3 NrmOutDeg	4 NrmInDeg
55	55	5.00	3.00	1.71	1.03
31	31	5.00	4.00	1.71	1.37
50	50	5.00	10.00	1.71	3.42
58	58	5.00	2.00	1.71	0.68
82	83	5.00	1.00	1.71	0.34
49	49	5.00	1.00	1.71	0.34
148	150	4.00	4.00	1.37	1.37
190	192	4.00	0.00	1.37	0.00
66	66	4.00	0.00	1.37	0.00
170	172	4.00	1.00	1.37	0.34
146	148	4.00	1.00	1.37	0.34
64	64	4.00	8.00	1.37	2.74
214	216	4.00	1.00	1.37	0.34
191	193	4.00	0.00	1.37	0.00
7	7	3.00	3.00	1.03	1.03
38	38	3.00	10.00	1.03	3.42
94	95	3.00	1.00	1.03	0.34
149	151	3.00	2.00	1.03	0.68
169	171	3.00	3.00	1.03	1.03
198	200	3.00	2.00	1.03	0.68
171	173	3.00	5.00	1.03	1.71
83	84	3.00	1.00	1.03	0.34
23	23	3.00	1.00	1.03	0.34
104	105	3.00	2.00	1.03	0.68
74	74	3.00	1.00	1.03	0.34
111	113	3.00	2.00	1.03	0.68
18	18	3.00	2.00	1.03	0.68
67	67	3.00	1.00	1.03	0.34
24	24	3.00	2.00	1.03	0.68
107	108	3.00	2.00	1.03	0.68
22	22	3.00	5.00	1.03	1.71
207	209	3.00	2.00	1.03	0.68
43	43	3.00	3.00	1.03	1.03
9	9	3.00	1.00	1.03	0.34
92	93	3.00	0.00	1.03	0.00
37	37	3.00	3.00	1.03	1.03
17	17	2.00	0.00	0.68	0.00
208	210	2.00	0.00	0.68	0.00
138	140	2.00	1.00	0.68	0.34
11	11	2.00	0.00	0.68	0.00
141	143	2.00	1.00	0.68	0.34
20	20	2.00	4.00	0.68	1.37
35	35	2.00	4.00	0.68	1.37
234	236	2.00	0.00	0.68	0.00
78	79	2.00	1.00	0.68	0.34
42	42	2.00	1.00	0.68	0.34
84	85	2.00	1.00	0.68	0.34
36	36	2.00	0.00	0.68	0.00
280	285	2.00	0.00	0.68	0.00
187	189	2.00	1.00	0.68	0.34
10	10	2.00	4.00	0.68	1.37
8	8	2.00	2.00	0.68	0.68
4	4	2.00	3.00	0.68	1.03
54	54	2.00	1.00	0.68	0.34
197	199	2.00	0.00	0.68	0.00

[Remaining rows deleted]

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BETA CENTRALITY / BONACICH POWER

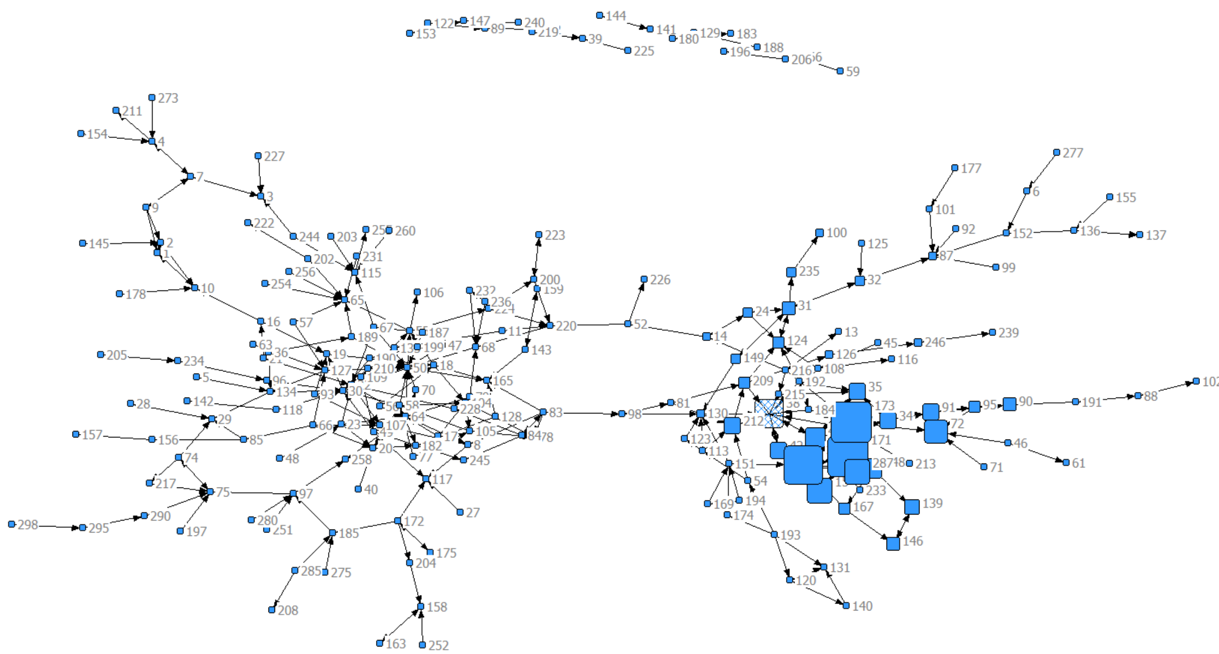
Beta value is 0.426837418476662

Bonacich Power

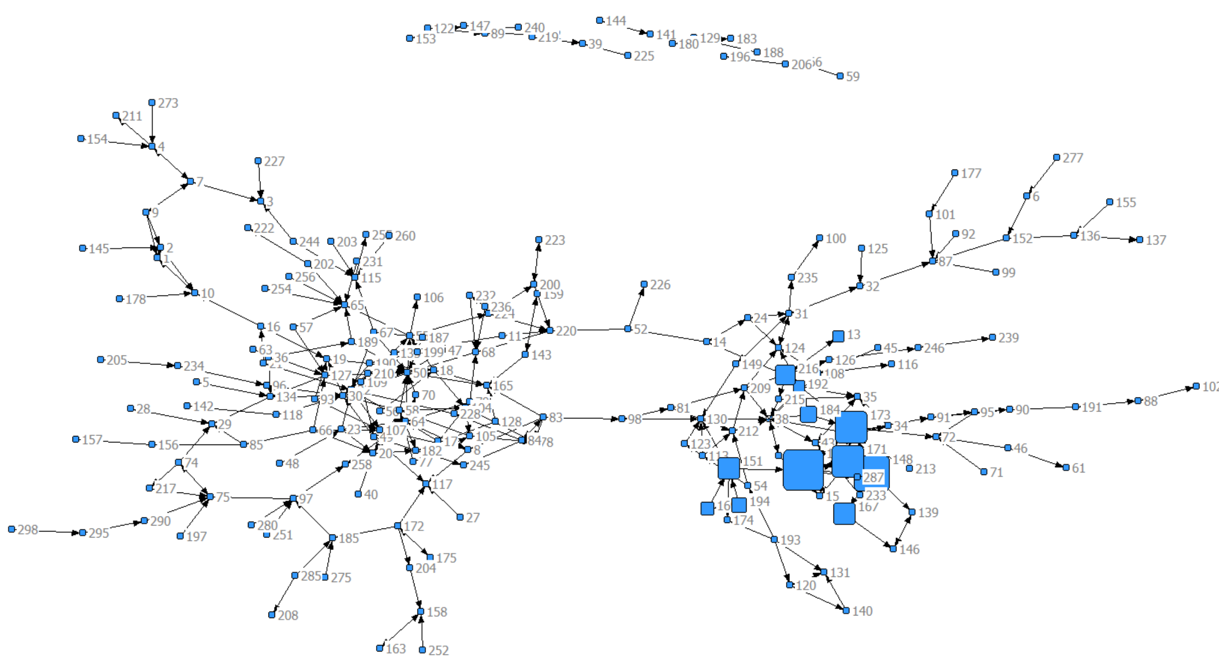
		1	2
		Beta Ce	Normali
		-------	-------
1	1	44.598	0.320
2	2	45.299	0.325
3	3	8.637	0.062
4	4	8.637	0.062
5	5	0.000	0.000
6	6	1.000	0.007
7	7	13.206	0.095
8	8	19.451	0.139
9	9	6.637	0.048
10	10	45.521	0.326
11	11	0.000	0.000
12	12	0.000	0.000
13	13	1.745	0.013
14	14	69.854	0.501
15	15	548.401	3.929
16	16	7.379	0.053
17	17	0.000	0.000
18	18	14.293	0.102
19	19	28.800	0.206
20	20	7.935	0.057
21	21	14.944	0.107
22	22	32.669	0.234
23	23	1.000	0.007
24	24	157.225	1.127
25	25	0.000	0.000
26	26	0.000	0.000
27	27	0.000	0.000
28	28	8.802	0.063
29	29	18.279	0.131
30	30	53.066	0.380
31	31	293.809	2.105
32	32	127.409	0.913
33	33	0.000	0.000
34	34	395.064	2.831
35	35	396.988	2.845
36	36	0.000	0.000

[Remaining rows deleted]

InEigenvector centrality



OutEigenvector centrality

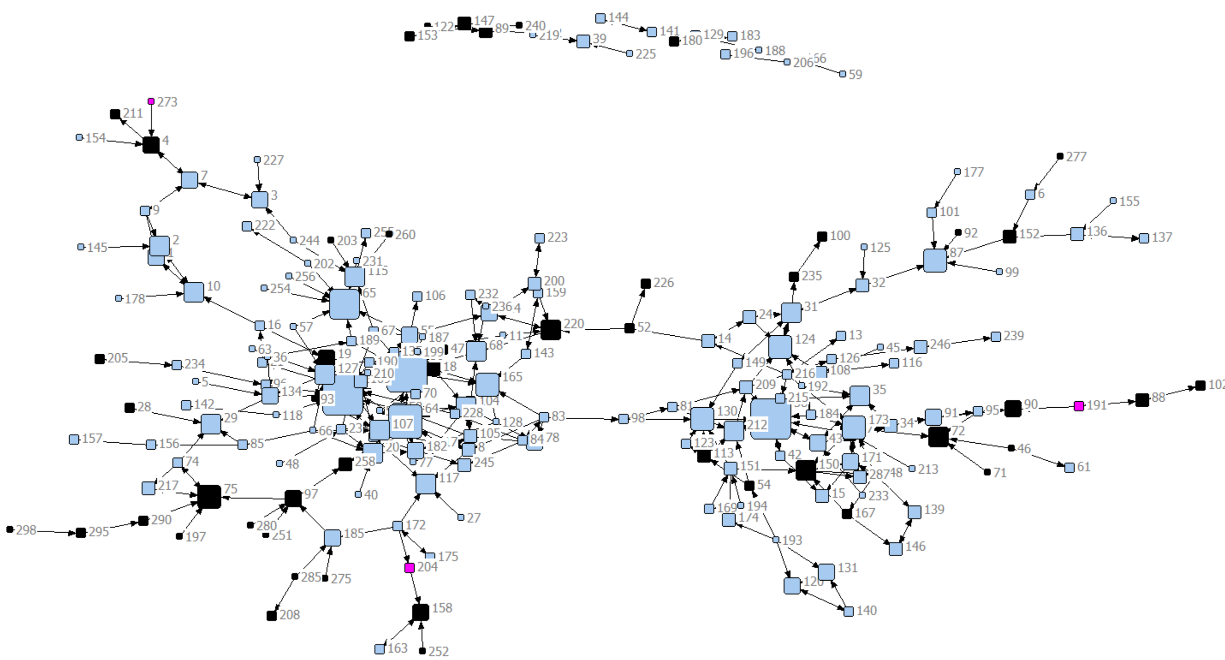


c) In NetDraw, with **DRUGNET** already open, load the attribute file, **DRUGATTR,** by clicking on the folder with the A

d) Calculate Centrality measures in NetDraw (remember that this is directed data)

e) Using NetDraw color the nodes based on different attributes (e.g., gender, race) and size the nodes based on different Centrality measures. Do you see any patterns?

Indegree by gender



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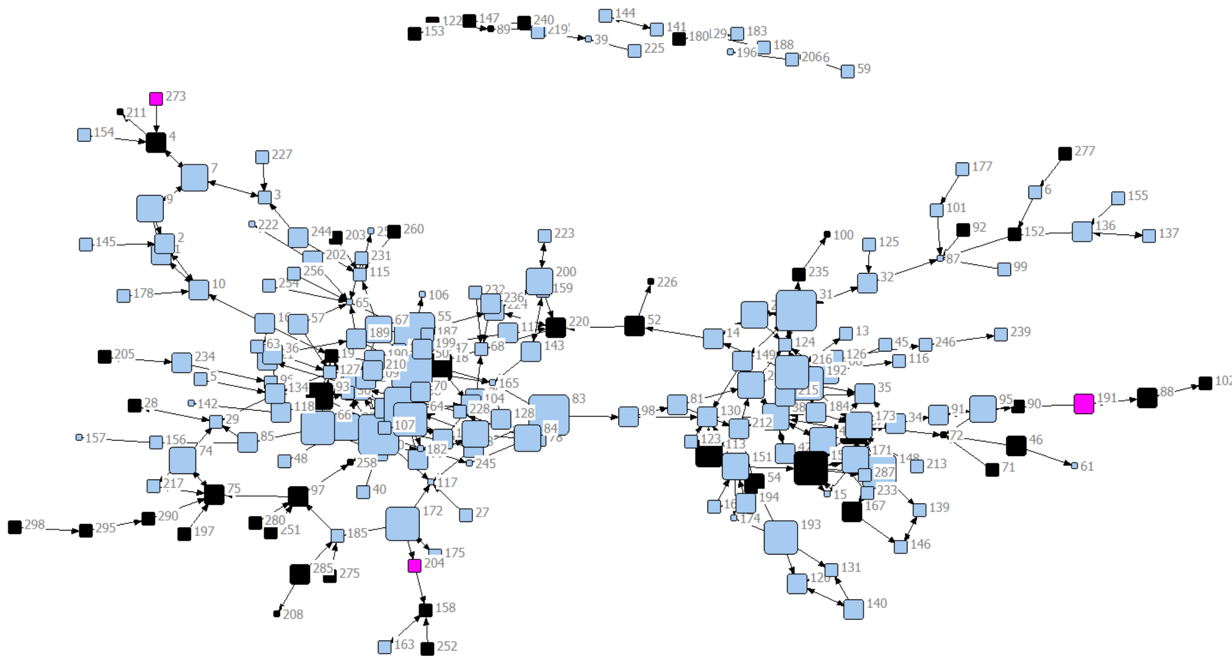
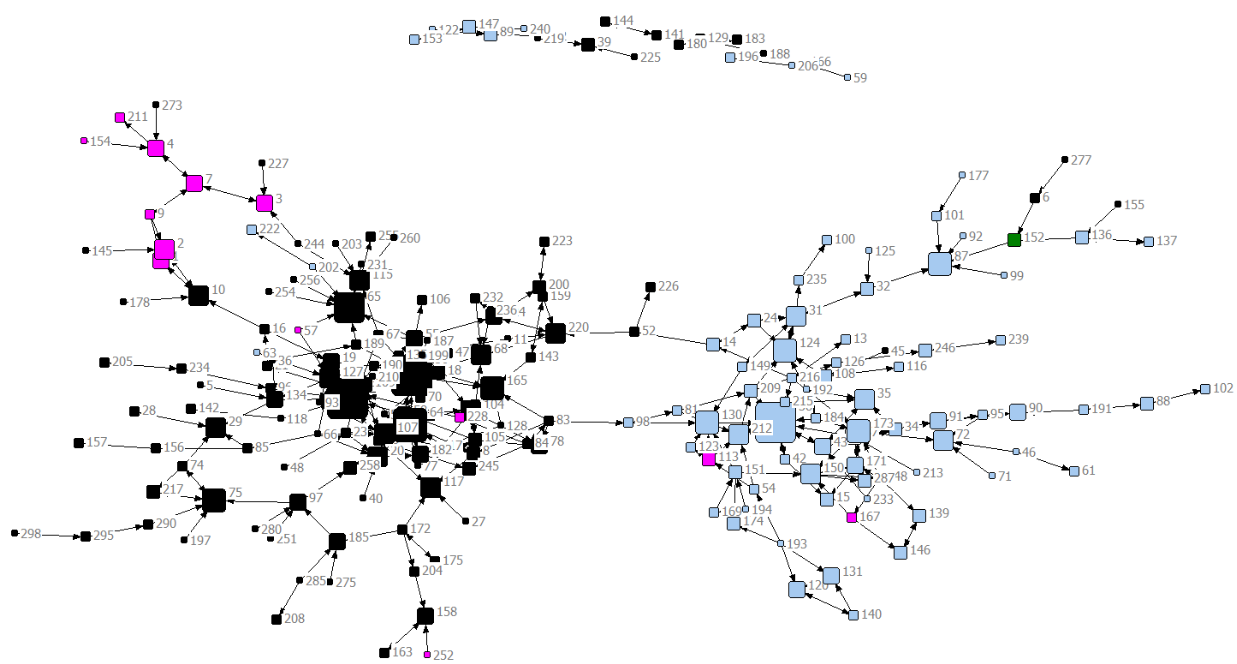
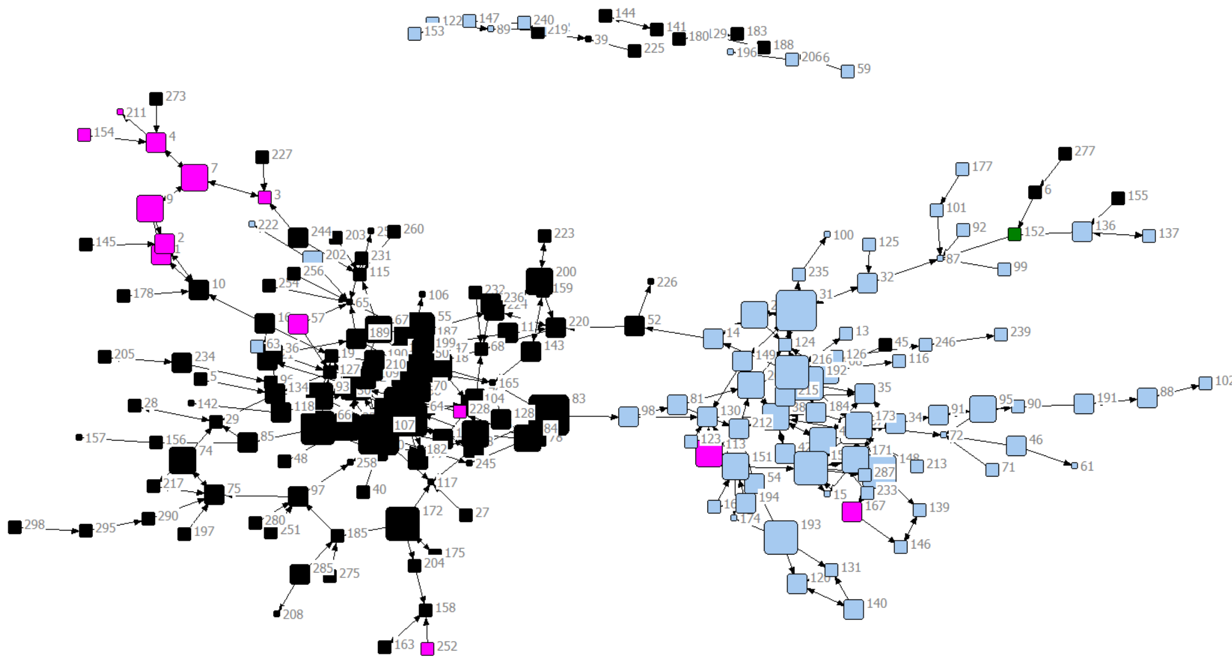
Outdegree by gender



Indegree by ethnicity



Outdegree by ethnicity



Interpretation: according two diagrams, people tend to share needles with people of same ethnicity (Homophily), and across genders, with a preponderance of one gender (indicated by squares)