Rev. 7 Dec 2023

MGT 667 ONA 2023
FINAL EXAM

ANSWER KEY

Important note: you will need access to the internet for this exam.

This is a take-home, open-book exam. You can consult all class materials including your notes. Please do not consult anyone else in the class about the exam. The completed exam is due midnight Wednesday Dec 13th. When done, upload this document to Canvas. Please include your name in the filename. If you spot any errors in the exam, please email me immediately (sborgatti@uky.edu). Good luck!

Q1. Your name: Vanessa

Q2. For this question, you will import a network and its associated attribute data. Then you will answer a few questions about the data. You can find the data in a Google Docs spreadsheet called Conco.

Q2a. The “information” tab contains the network of a consulting company (hence the name “conco”) in matrix form. The values indicate frequency of interaction, from 1= yearly, 2= quarterly, 3= monthly, 4= weekly, to 5 = daily. Import this into UCINET and call the dataset “conconet”. To check that it has been imported correctly, in the CLI type: ->dsp average(conconet). If the answer is not 0.926, something is wrong.

```
->dsp average(conco)
Diagonal included in calculations. To exclude, add diag:no to command.


                 1
               avg
             -----
      1 CONCO 0.926

1 rows, 1 columns, 1 levels.
```

Q2b. The “concoattr” tab contains attribute data. Import that into UCINET and call the dataset concoattr. Display the dataset and make sure the values match the Excel file. There are 11 women. The variables include:

- Hier. Hierarchical level. 1= Research Assistant ... 8= Vice president
- TimeCo. Months in the company
- TimeUn. Months in the current unit
- Gender. 1=male, 0=female
- Prac. "Practice" -- the type of work the person does
- Region. 1=Europe, 2=usa
- City. Where located. categorical variable

Input dataset: concoatt (C:\Users\vbe230\Documents\UCINET data\concoatt

		1 Hier	2 TimeCo	3 TimeUn	4 Gender	5 Prac	6 Region	7 City
1	AR1	3	45	6	1	3	1	5
2	BM2	4	57	57	1	7	2	2
3	BJ3	1	18	18	0	7	1	5
4	BS4	4	7	7	1	7	1	3
5	BR5	4	17	17	1	7	2	2
6	BS6	4	45	18	1	5	2	2
7	BW7	5	42	42	1	7	2	2
8	BS8	5	14	14	1	7	1	3
9	BP9	2	30	3	1	7	1	5
10	BD10	4	37	37	1	4	1	3
11	CR11	5	2	2	1	7	2	2
12	CD12	4	42	42	1	7	1	5
13	DI13	2	34	34	0	2	2	2
14	DB14	4	60	24	1	4	2	6
15	EE15	3	11	11	0	7	1	4
16	ER16	3	31	31	1	7	1	9
17	FK17	1	22	22	0	7	2	2
18	GS18	3	44	3	1	7	2	2
19	GM19	5	24	24	1	5	2	2
20	HA20	5	18	18	1	5	2	2
21	HK21	4	24	24	0	1	2	2
22	HB22	2	10	10	1	5	1	11
23	HS23	3	100	72	0	1	2	2
24	HR24	1	3	3	0	6	2	2
25	JE25	2	30	30	1	1	2	2
26	KR26	4	79	79	1	5	2	2
27	KA27	2	24	24	1	5	2	2
28	LR28	8	372	50	1	7	2	2
29	LK29	2	228	48	0	5	2	2
30	ME30	1	2	2	1	2	2	2
31	MG31	4	206	100	1	3	1	3
32	MJ32	2	36	36	1	7	1	5
33	NP33	4	55	55	1	5	1	4
34	OI34	4	115	100	1	3	1	10
35	PH35	2	9	9	0	7	2	2
36	PS36	4	20	20	1	5	2	2
37	RL37	7	180	24	0	6	1	3
38	SR38	8	72	72	1	7	2	8
39	SF39	3	11	11	1	1	2	2
40	TO40	4	46	46	1	7	1	4
41	TM41	7	63	63	1	4	1	7
42	VB42	5	100	20	1	5	1	10
43	VF43	8	230	170	1	5	1	1
44	WS44	4	150	21	1	5	2	2
45	WD45	5	103	103	1	5	2	2
46	WL46	2	26	5	0	2	1	5

46 rows, 7 columns, 1 levels.

Q2c. Dichotomize conconet at greater than 4 and save the result as a dataset called “daily”. In other words, create a network called “daily” in which there is a tie between two people only if they interact on a daily basis. Show the density of “daily” here.

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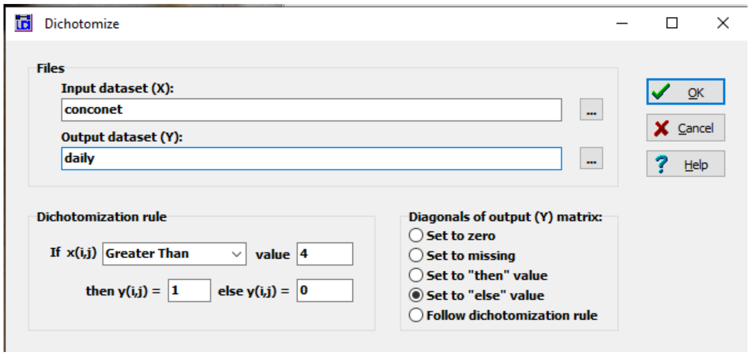
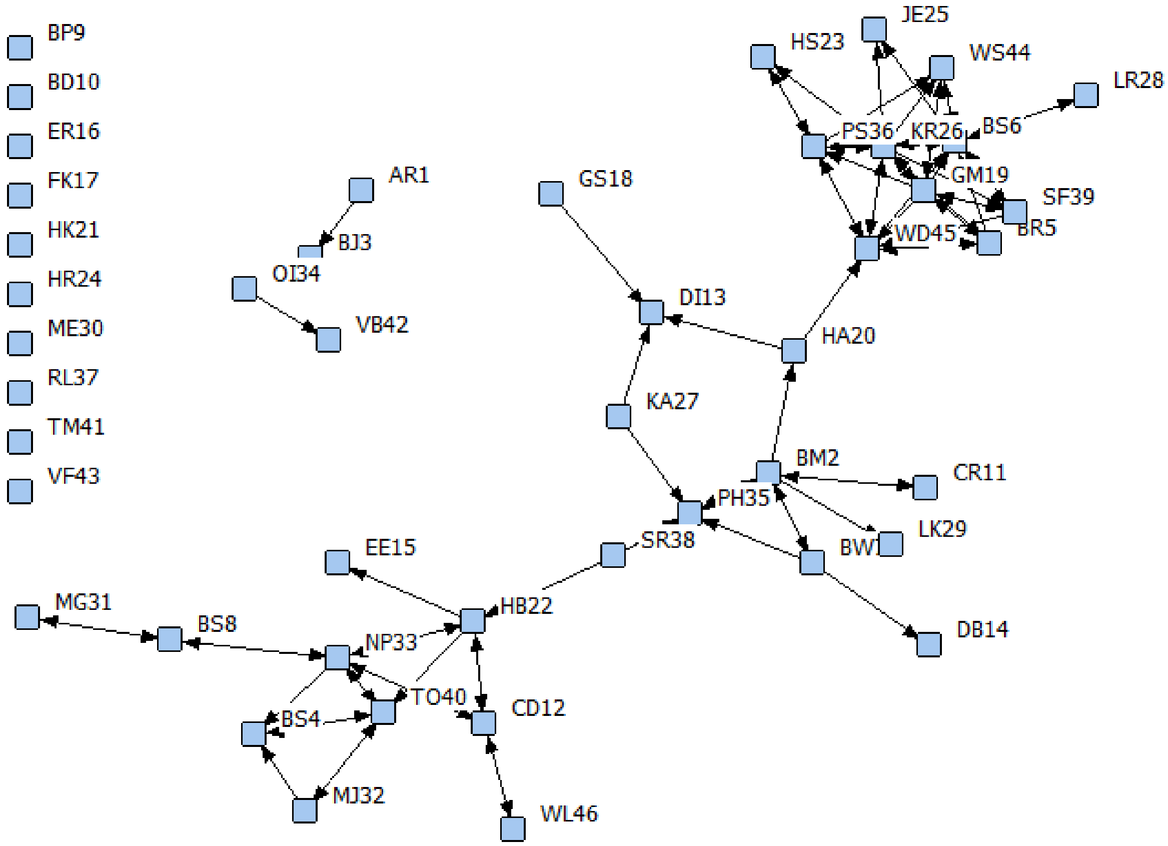
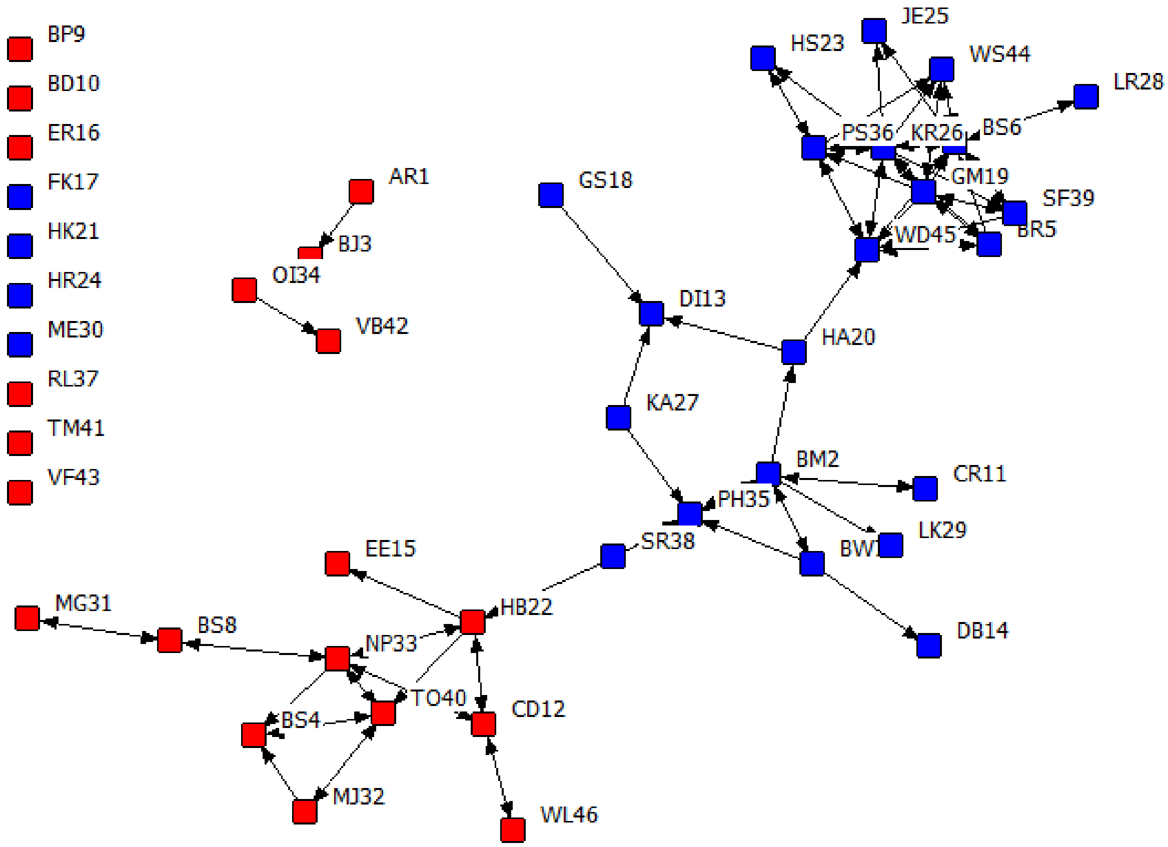



```
Number of 1s: 84
Number of cells: 2070
Density: 0.041
```

Q2d. Open “daily” in NetDraw. Press the layout button to clean up the drawing and paste the diagram here.



Q2e. While you have “daily” open in NetDraw, bring in the attribute file “concoattr”. Color the nodes by region and paste the diagram here. Does region affect who interacts with whom?



Yes, Region has a huge impact on who interacts with whom. Most ties are within-region. There is only one tie between regions.

Q3. What are the main takeaways from the Heidi Roizen case?

Take advantage of every opportunity to form ties throughout the organization and the industry. As editor of the company newsletter, Roizen had a reason to meet and get to know everyone in the company. As she notes: “It’s difficult to develop a professional relationship with anyone, let alone a senior-level executive, when you have no reason for interacting. So, it would be tough to start working at a company and say, “Gee, I think I’ll get to know the CEO.”. Later on, she served as company representative at trade shows and industry events. These are normally considered boring tasks that no one wants to do. She embraced them because it gave her opportunity to meet people before they became famous. As she says: “It’s easier to get to know people when they’re not famous; then when they do become famous, you already have a relationship with them.”

She went on to become a famous and successful venture capitalist and entrepreneur. She excelled at providing value by going through her Rolodex and pulling out the right names who could help the company she was working with.

Q4. Here are a few questions about core/periphery structures.

Q4a. What is the definition of a core/periphery structure?

In a core/periphery structure, we can divide the network into two classes: the core and periphery. The core nodes are characterized by having ties to each other and to the peripheral nodes. The periphery nodes are characterized by having ties only to the core, not to each other.

Q4b. What are the consequences of having a core/periphery structure, either for the network as a whole, or the nodes within it?

Nodes in a core/periphery structure tend to have a clear sense of identity: they identify with the group as a whole. In contrast, nodes in a clumpy structure may identify more with their subgroup than with the group as a whole.

Core/periphery structures are good at spreading best practices, creating a sense of consistency and commonality. They also support holding and enforcing of unitary (uncontested norms).

Core/periphery structures may benefit from innovations generated in the periphery, which may then be accepted and passed along by the core. But core/periphery structures may also suffer from groupthink, and be less good at radical innovation as, say, clumpy structures.

Q5. Using UCINET's Network|Core-periphery|Categorical function, calculate the core/peripheriness score of both the marriage and business networks in the Padgett dataset. Show the two measures here, and explain which network has a more core/periphery-type network.

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```
Matrix: PADGM
-------------

Core/Periphery fit (correlation) = 0.4243

Core/Periphery Class Memberships:

       Core:  ALBIZZI CASTELLANI GUADAGNI MEDICI PERUZZI STROZZI TORNABUONI
  Periphery:  ACCIAIUOLI BARBADORI BISCHERI GINORI LAMBERTESCHI PAZZI PUCCI RIDOLFI SALV


                       1 1     1       1   1 1 1
                   9 2 1 6 5 7 5   6 4 0 1 2 3 4 3 8
                   M A P T C G S   G B P A P R S B L
                  -----------------------------------
  9       MEDICI |   1   1       |       1   1 1 1   |
  2      ALBIZZI | 1         1   | 1                 |
 11      PERUZZI |         1   1 |   1               |
 16   TORNABUONI | 1         1   |           1       |
  5   CASTELLANI |     1       1 |               1   |
  7     GUADAGNI |   1   1       |   1             1 |
 15      STROZZI |     1   1     |   1       1       |
                 -------------------------------------
  6       GINORI |   1           |                   |
  4     BISCHERI |     1     1 1 |                   |
 10        PAZZI |               |             1     |
  1   ACCIAIUOLI | 1             |                   |
 12        PUCCI |               |                   |
 13      RIDOLFI | 1     1     1 |                   |
 14     SALVIATI | 1             |     1             |
  3    BARBADORI | 1       1     |                   |
  8 LAMBERTESCHI |           1   |                   |
                  ------------------------------------


Iterations:  3 1
```

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```
Matrix: PADGB
-------------

Core/Periphery fit (correlation) = 0.6794

Core/Periphery Class Memberships:

       Core:  BARBADORI BISCHERI CASTELLANI LAMBERTESCHI MEDICI PERUZZI
  Periphery:  ACCIAIUOLI ALBIZZI GINORI GUADAGNI PAZZI PUCCI RIDOLFI SALVIATI STROZZI TORNABUONI


                             1         1   1 1 1 1 1
                   9 4 3 8 5 1   2 6 1 0 7 2 3 4 5 6
                   M B B L C P   A G A P G P R S S T
                  -----------------------------------
  9       MEDICI |     1       |   1   1       1   1 |
  4     BISCHERI |       1   1 |         1           |
  3    BARBADORI | 1       1 1 |   1                 |
  8 LAMBERTESCHI |   1     1 1 |         1           |
  5   CASTELLANI |     1 1   1 |                     |
 11      PERUZZI |   1 1 1 1   |                     |
                 -------------------------------------
  2      ALBIZZI |             |                     |
  6       GINORI | 1   1       |                     |
  1   ACCIAIUOLI |             |                     |
 10        PAZZI | 1           |                     |
  7     GUADAGNI |   1   1     |                     |
 12        PUCCI |             |                     |
 13      RIDOLFI |             |                     |
 14     SALVIATI | 1           |                     |
 15      STROZZI |             |                     |
 16   TORNABUONI | 1           |                     |
                  -----------------------------------


Iterations:  1 5
```

The core/peripheriness scores for the two networks are:

Padgm: 0.4243

Padgb: 0.6794

Hence, the business network has a more clearly defined core/periphery structure.

Q6. What did the Bavelas-Leavitt experiments show?

The experiments investigated how different communication structures affected how well groups could solve problems that involved pooling of information. They showed that, for a variety of outcome measures (including speed, efficiency, and accuracy of solutions), more centralized structures were better less centralized structures. In particular, they argued that networks in which each person was a short distance from the ”natural integrator” or information, the better it was at solving puzzles.

Q7. Explain the concept of betweenness centrality. What advantages or disadvantages can you expect nodes with high betweenness to have?

Loosely speaking, betweenness centrality measures how often a given node falls along the shortest path between two other nodes.

Advantages: Betweenness is typically interpreted as the potential for controlling flows through the network, that is, playing a gatekeeping role. Nodes with high betweenness are in a position to filter or change information as they pass it along. This has been called “secretary power”, as an executive’s secretary controls who gets to see them.

Disadvantages: The node with extreme betweenness has a personal network that looks like a star, with them at the center. None of their friends are connected, and this may feel to the node like there is a lack of community in their lives.

Q8. Explain the concept of structural holes. What are the various benefits that structural holes are thought to provide?

A structural hole is the lack of a tie between two alters within an ego network. In certain contexts, especially work contexts, it is thought that a personal network with many structural holes has certain advantages, and so is thought of as coterminous with social capital.

One measure of structural holes is effective size: it is the number of alters a node has, minus the average degree each alter has within the ego network. Bigger numbers mean more structural holes / more social capital. Another measure of structural holes is constraint. It is an inverse measure in the sense that bigger numbers mean fewer holes, and lower social capital. Constraint essentially measures the extent to which a person is invested in just a few friends. A person has a high constraint score if they have few friends, and if their friends are connected to each other.

Structural holes are thought to provide a number of benefits including:

- Autonomy. Because your friends are NOT connected to each other, you can be very different with each one – essentially, have a different identity or life story. You can lie easily
- Control. Because your contacts are not connected to each other they can’t gang up on you, they cant coordinate with each other to hold you down. You can divide and conquer.
- Information. Because your contacts are not connected with each other, they don’t have an opportunity to come to consensus about things. So you can independent points of view from each of them. If they were all connected, it would be harder to get novel perspectives from them.
- Skill. Over time, having structural holes gives you practice managing people with different perspectives and ways of doing things. This makes it easier for you manage complex projects.

Q9. Symmetrize the campnet dataset and call the result csym. Now calculate structural holes on the csym dataset using Network|Ego Networks|Structural Holes. According to the constraint measure, which nodes have the most structural holes and therefore the most social capital?

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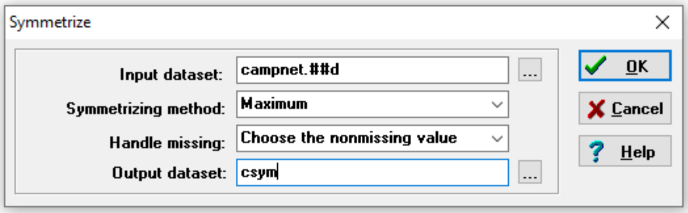
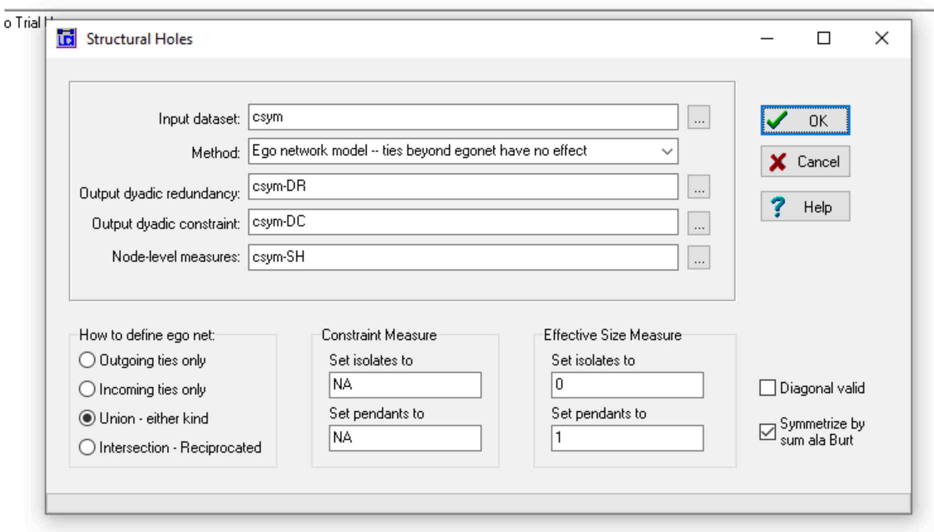




Structural Hole Measures

		1 Degree	2 EffSize	3 Efficiency	4 Constraint	5 Hierarchy	6 EgoBet	7 Ln(Constraint)	8 Indirects	9 Density	10 AvgDeg	11 Open Pairs
1	HOLLY	5	3.800	0.760	0.413	0.061	14	-0.884	0.400	0.300	1.200	14
2	BRAZEY	3	1	0.333	0.926	0	0	-0.077	0.667	1	2	0
3	CAROL	3	1.667	0.556	0.840	0.074	1	-0.175	0.556	0.667	1.333	2
4	PAM	5	3.800	0.760	0.451	0.056	12	-0.796	0.467	0.300	1.200	14
5	PAT	4	3.500	0.875	0.406	0.055	10	-0.901	0.250	0.167	0.500	10
6	JENNIE	3	2.333	0.778	0.611	0.052	4	-0.492	0.333	0.333	0.667	4
7	PAULINE	5	3.800	0.760	0.451	0.056	12	-0.796	0.467	0.300	1.200	14
8	ANN	3	1.667	0.556	0.840	0.074	1	-0.175	0.556	0.667	1.333	2
9	MICHAEL	5	3	0.600	0.514	0.052	8.667	-0.666	0.567	0.500	2	10
10	BILL	3	1	0.333	0.926	0	0	-0.077	0.667	1	2	0
11	LEE	3	1	0.333	0.926	0	0	-0.077	0.667	1	2	0
12	DON	4	1.500	0.375	0.740	0.021	0.667	-0.300	0.708	0.833	2.500	2
13	JOHN	3	2.333	0.778	0.611	0.052	4	-0.492	0.333	0.333	0.667	4
14	HARRY	4	1.500	0.375	0.740	0.021	0.667	-0.300	0.708	0.833	2.500	2
15	GERY	4	3	0.750	0.535	0.092	7	-0.626	0.417	0.333	1	8
16	STEVE	5	3	0.600	0.554	0.022	7	-0.590	0.650	0.500	2	10
17	BERT	4	2	0.500	0.704	0.057	2	-0.350	0.646	0.667	2	4
18	RUSS	4	2.500	0.625	0.642	0.035	4	-0.443	0.583	0.500	1.500	6

18 rows, 11 columns, 1 levels.

Small constraint means more structural holes, therefore more social capital. The nodes with the highest social capital are: Pat (0.406), Holly (0.413), Pam and Pauline (0.451). In this group, the women clearly have the most social capital.

Q10. I believe that people are more likely to see each other as work friends if they are at similar levels in the organization (the bigger the difference in level, the less likely a friendship is). You will test this idea using the kracknet/krackattr datasets.

Q10a. Unpack the kracknet dataset using the prefix "k-", which will create the k-friends dataset. (no output to show here)

Q10b. Next, use the "Data|Attribute to Matrix" menu option to create a matrix that indicates, for each pair of persons, how different in level they are (krackattr as the dataset and "absolute difference" as the method). This will create a new dataset "krackattr-absdifflevel". Paste this resulting matrix here.

```
CONVERT ATTRIBUTE TO MATRIX
--------------------------------------------------------------------------------

Input file:                          krackattr (C:\Users\vbe230\Documents\UCINET
Dimension:                           Column
Variable:                            Level



              1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21
             A0 A0 A0 A0 A0 A0 A0 A0 A1 A1 A1 A1 A1 A1 A1 A1 A1 A1 A1 A2 A2
              1  2  3  4  5  6  7  8  0  0  1  2  3  4  5  6  7  8  9  0  1
             -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- --
    1 A01     0  1  0  0  0  0  2  0  0  0  0  0  0  1  0  0  0  1  0  0  1
    2 A02     1  0  1  1  1  1  1  1  1  1  1  1  1  0  1  1  1  0  1  1  0
    3 A03     0  1  0  0  0  0  2  0  0  0  0  0  0  1  0  0  0  1  0  0  1
    4 A04     0  1  0  0  0  0  2  0  0  0  0  0  0  1  0  0  0  1  0  0  1
    5 A05     0  1  0  0  0  0  2  0  0  0  0  0  0  1  0  0  0  1  0  0  1
    6 A06     0  1  0  0  0  0  2  0  0  0  0  0  0  1  0  0  0  1  0  0  1
    7 A07     2  1  2  2  2  2  0  2  2  2  2  2  2  1  2  2  2  1  2  2  1
    8 A08     0  1  0  0  0  0  2  0  0  0  0  0  0  1  0  0  0  1  0  0  1
    9 A10     0  1  0  0  0  0  2  0  0  0  0  0  0  1  0  0  0  1  0  0  1
   10 A10     0  1  0  0  0  0  2  0  0  0  0  0  0  1  0  0  0  1  0  0  1
   11 A11     0  1  0  0  0  0  2  0  0  0  0  0  0  1  0  0  0  1  0  0  1
   12 A12     0  1  0  0  0  0  2  0  0  0  0  0  0  1  0  0  0  1  0  0  1
   13 A13     0  1  0  0  0  0  2  0  0  0  0  0  0  1  0  0  0  1  0  0  1
   14 A14     1  0  1  1  1  1  1  1  1  1  1  1  1  0  1  1  1  0  1  1  0
   15 A15     0  1  0  0  0  0  2  0  0  0  0  0  0  1  0  0  0  1  0  0  1
   16 A16     0  1  0  0  0  0  2  0  0  0  0  0  0  1  0  0  0  1  0  0  1
   17 A17     0  1  0  0  0  0  2  0  0  0  0  0  0  1  0  0  0  1  0  0  1
   18 A18     1  0  1  1  1  1  1  1  1  1  1  1  1  0  1  1  1  0  1  1  0
   19 A19     0  1  0  0  0  0  2  0  0  0  0  0  0  1  0  0  0  1  0  0  1
   20 A20     0  1  0  0  0  0  2  0  0  0  0  0  0  1  0  0  0  1  0  0  1
   21 A21     1  0  1  1  1  1  1  1  1  1  1  1  1  0  1  1  1  0  1  1  0

21 rows, 21 columns, 1 levels.
```

Q10c. Now use dyadic regression (Tools|Testing Hypotheses|Dyadic QAP|MR-QAP Linear Regression|Double Dekker Semi-Partialling MR-QAP) to predict “k-friends” (the dependent variable) from the difference in level (the independent variable, “krackattr-absdiffLevel”). Paste the results here.

```
P(r2) = :                          0.00600

MODEL FIT

              R-Square    Adj R-Sqr          Obs        Perms
          ------------ ------------ ------------ ------------
     Model     0.03247      0.03015    420.00000   2000.00000


REGRESSION COEFFICIENTS

                          Un-Stdized Stdized Coef      P-value     As Large     As Small   As Extreme     Perm Avg      Std Err
                        ------------ ------------ ------------ ------------ ------------ ------------ ------------ ------------
     krackattr-absdiffLevel    -0.12190     -0.18019      0.03098      0.99100      0.01000      0.03098     -0.00076      0.05676
                  Intercept     0.30090      0.00000      0.00000      0.00000      0.00000      0.00000      0.00000      0.00000


Note: At least one matrix was not symmetric, so all data treated as directed.
```

Q10d. Interpret the results. Am I right – are people more likely to be friends if they are at similar levels in the organization? What makes you think so?

Yes, people are more likely to be friends if they are at similar level in the organization. P-value is < 0.05 and the coefficient is negative, which means that the greater the difference in level between two people, the less likely they are to be friends.

Q11. There is a dataset called “Bank” that is available in Canvas as well on Google. The file contains two tabs, one for the network and one for the attribute data. Import both into ucinet. Call the network dataset “banknet” and the attribute dataset “bankattr”. In the network, there is a tie from A to B if person A sees person B as a leader. Obviously, a person’s indegree in this network is the number of people that see the person a leader. Let’s call this variable “leadership score”.

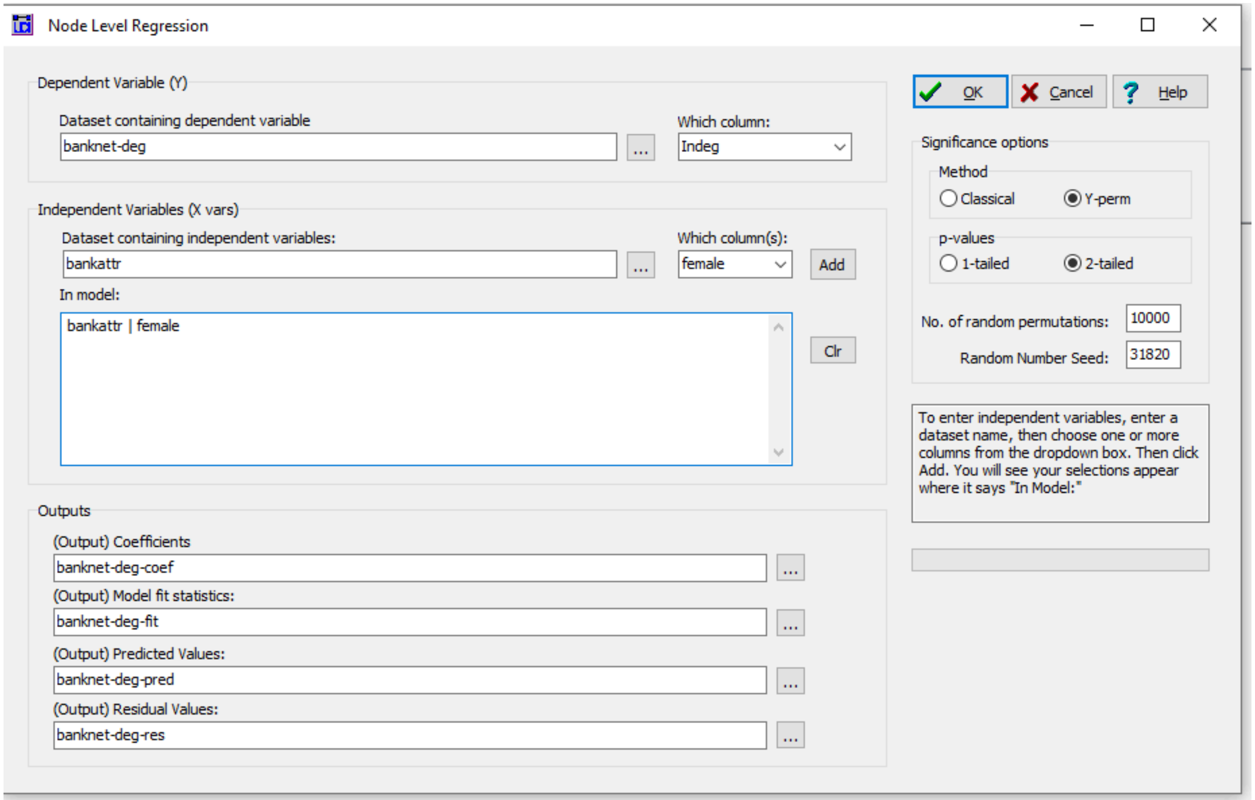
Q11a. Calculate each person’s leadership score and paste it here.

id	Outdeg	Indeg	nOutdeg	nIndeg
100215030	10	99	0.049019609	0.485294104
100215114	6	76	0.029411765	0.372549027
100215182	62	76	0.30392158	0.372549027
100215162	0	72	0	0.352941185
100215066	5	62	0.024509804	0.30392158
100215219	5	57	0.024509804	0.279411763
100215199	4	54	0.019607844	0.264705896
100215058	11	51	0.053921569	0.25
100215180	5	49	0.024509804	0.240196079
100215189	40	49	0.196078435	0.240196079
100215034	3	48	0.014705882	0.235294119
100215026	10	42	0.049019609	0.205882356
100215020	3	41	0.014705882	0.200980395
100215094	27	40	0.132352948	0.196078435
100215178	10	39	0.049019609	0.191176474
100215203	1	38	0.004901961	0.186274514
100215049	20	37	0.098039217	0.181372553
100215022	0	35	0	0.171568632
100215125	9	35	0.044117648	0.171568632
100215080	30	34	0.14705883	0.166666672
100215138	13	33	0.063725494	0.161764711
100215161	15	33	0.073529415	0.161764711
100215040	63	30	0.308823526	0.14705883
100215124	7	30	0.034313727	0.14705883
100215041	4	25	0.019607844	0.12254902
100215130	16	25	0.078431375	0.12254902
100215208	5	23	0.024509804	0.112745099
100215225	23	22	0.112745099	0.107843138
100215195	0	20	0	0.098039217
100215055	10	19	0.049019609	0.093137257
100215202	6	19	0.029411765	0.093137257
100215070	4	18	0.019607844	0.088235296
100215101	3	18	0.014705882	0.088235296
100215177	7	18	0.034313727	0.088235296
100215218	28	18	0.137254909	0.088235296
100215149	4	17	0.019607844	0.083333336
100215116	5	16	0.024509804	0.078431375

Q11b. Which person has the highest leadership score?

100215030

Q11c. Use node-level regression to predict leadership score as a function of gender. Are men or women more likely to be seen as leaders in this bank? Is the result significant?



```
Overall Regression Fit Statistics

                       Value
                     -------
              Nobs       205
          R-Square     0.035
      Adj R-square     0.030
          F(203,1)     7.313
   Sig (classical)     0.007
        Sig (perm)     0.007


Regression coefficients.

                       1       2       3       4       5       6
                    Coef    Beta      SE       T   c.Sig   p.sig
                 ------- ------- ------- ------- ------- -------
  1 Intercept     13.644       0   1.669
  2    female     -6.027  -0.186   2.229  -2.704   0.007   0.007

2 rows, 6 columns, 1 levels.
```

The coefficient for "female" is significant (p-value = 0.007 which is less than .05). The coefficient is also negative, which means that being female reduces your leadership score. Specifically, on average, women receive 6 votes less than men do on leadership.

Q11d. Interpret the coefficient for "female". What exactly does it mean?

In general, the coefficient -6.027 for any X variable means that if X increases by unit, on average, Y in increases by -6.027 units (i.e., leadership declines by 6.027). Since the X variable in this is "Female" with values 1 (=female) and 0 (=male). The coefficient -6.027 means that, on average, going from male to female loses you 6.027 leadership points. In other words, women are less likely to be seen as leaders.

Q12. Is job satisfaction contagious? In other words, if our friends are unhappy with their jobs, does this tend to reduce our own job satisfaction? Let's test this using the lexnet and lexattr datasets. The lexnet dataset contains several networks, including one called 'feeling,' which measures friendship.

Q12a. Your first task is to unpack lexnet. Use the prefix "l-" (that's the letter el, not the number 1) to create a dataset (among others) called "l-feeling". (no need to show anything here)

Q12b. The l-feeling dataset has values from 1 to 5, where 1 means "dislikes a lot", 2 means "dislikes", 3 means "neutral", 4 means "likes" and 5 means "likes a lot". We want to create a new network called "l-friends" in which there is a tie from node A to node B if the strength of l-feeling is greater than 3. We will call this new matrix "l-friends". Calculate indegree on this new matrix and show the results here.

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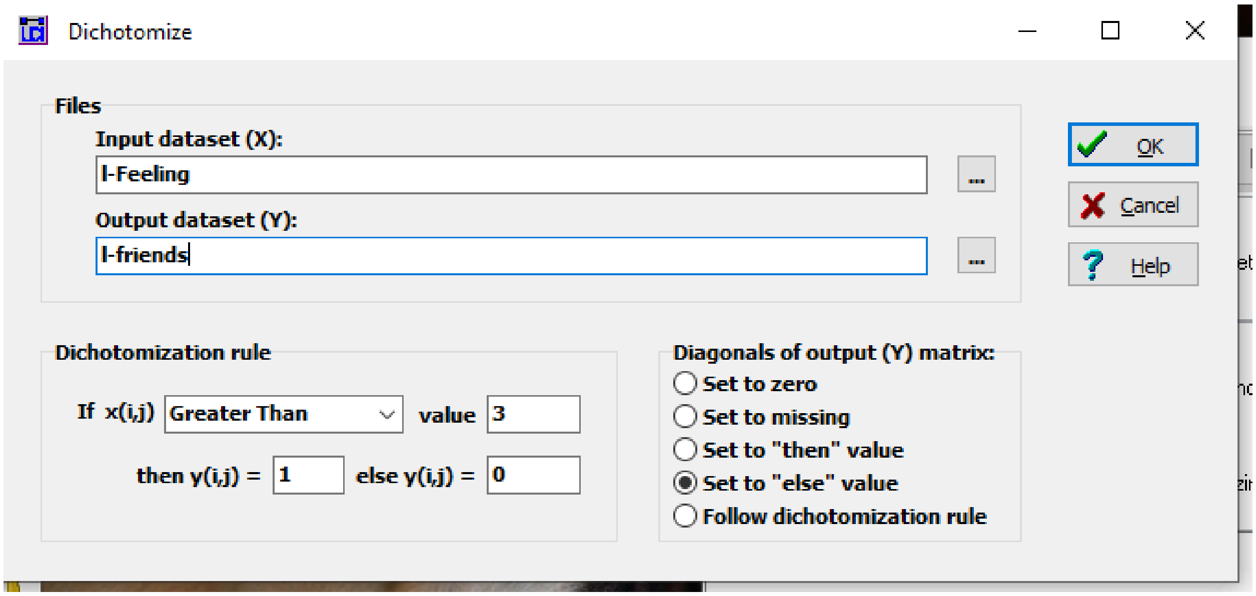


Degree Measures

		1 Outdeg	2 Indeg	3 nOutdeg	4 nIndeg
1	9	0.000	1.000	0.000	0.014
2	10	0.000	2.000	0.000	0.027
3	16	7.000	6.000	0.095	0.081
4	20	10.000	15.000	0.135	0.203
5	21	7.000	12.000	0.095	0.162
6	24	13.000	8.000	0.176	0.108
7	30	8.000	9.000	0.108	0.122
8	37	11.000	11.000	0.149	0.149
9	40	10.000	21.000	0.135	0.284
10	41	12.000	10.000	0.162	0.135
11	50	8.000	11.000	0.108	0.149
12	52	18.000	14.000	0.243	0.189
13	56	14.000	11.000	0.189	0.149
14	59	7.000	5.000	0.095	0.068
15	60	3.000	9.000	0.041	0.122
16	70	2.000	3.000	0.027	0.041
17	75	8.000	7.000	0.108	0.095
18	77	6.000	7.000	0.081	0.095
19	78	7.000	9.000	0.095	0.122
20	80	1.000	9.000	0.014	0.122
21	82	9.000	3.000	0.122	0.041
22	83	5.000	4.000	0.068	0.054
23	84	7.000	23.000	0.095	0.311
24	87	4.000	6.000	0.054	0.081
25	90	10.000	12.000	0.135	0.162
26	100	7.000	6.000	0.095	0.081
27	109	12.000	7.000	0.162	0.095
28	111	10.000	4.000	0.135	0.054
29	114	4.000	2.000	0.054	0.027
30	116	17.000	8.000	0.230	0.108
31	129	13.000	12.000	0.176	0.162
32	130	8.000	5.000	0.108	0.068
33	134	6.000	4.000	0.081	0.054
34	145	19.000	14.000	0.257	0.189
35	147	8.000	14.000	0.108	0.189
36	163	10.000	8.000	0.135	0.108
37	171	9.000	15.000	0.122	0.203
38	173	2.000	12.000	0.027	0.162
39	180	5.000	7.000	0.068	0.095
40	182	6.000	16.000	0.081	0.216
41	183	10.000	2.000	0.135	0.027
42	192	12.000	11.000	0.162	0.149
43	194	21.000	8.000	0.284	0.108
44	196	0.000	1.000	0.000	0.014
45	197	3.000	2.000	0.041	0.027
46	200	2.000	5.000	0.027	0.068
47	208	0.000	0.000	0.000	0.000
48	209	6.000	4.000	0.081	0.054
49	211	10.000	19.000	0.135	0.257
50	220	20.000	14.000	0.270	0.189
51	222	1.000	1.000	0.014	0.014
52	229	2.000	1.000	0.027	0.014
53	238	4.000	9.000	0.054	0.122
54	245	5.000	3.000	0.068	0.041
55	246	4.000	6.000	0.054	0.081
56	256	3.000	6.000	0.041	0.081
57	257	6.000	12.000	0.081	0.162
58	267	24.000	14.000	0.324	0.189
59	273	1.000	4.000	0.014	0.054
60	275	9.000	5.000	0.122	0.068
61	276	14.000	12.000	0.189	0.162
62	291	4.000	2.000	0.054	0.027
63	298	14.000	14.000	0.189	0.189
64	300	7.000	6.000	0.095	0.081
65	302	14.000	12.000	0.189	0.162

Q12c. Now use Network|Egonet|Egonet Alter Composition|Continuous to compute the average job satisfaction (“jobsat”) of each person’s friends. You will need both the “l-friends” dataset and the “lexattr” datasets for this. This will create a new dataset called “l-friends-compcont”.

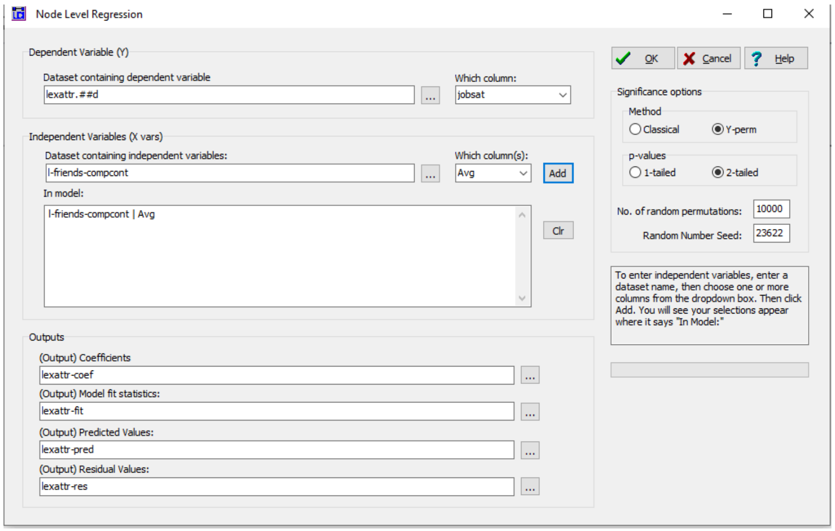
```
EGONET COMPOSITION: CONTINUOUS ATTRIBUTES
--------------------------------------------------------------------------------

Input Network:                          l-friends (C:\Users\vbe230\Documents\UCINET data\l-friends)
Input Attribute:                        jobsat (C:\Users\vbe230\Documents\UCINET data\lexattr Column 39:jobsat)
Ego Network Type:                       Both incoming and outgoing ties
Weighted Ties:                          Treat tie strengths as analytical weights
Filter alters above mean?               NO
Filter alters below mean?               NO
Combine criteria via                    OR
Output dataset:                         l-friends-compcont (C:\Users\vbe230\Documents\UCINET data\l-friends-compcont)

Ego Net Composition - Continuous Attribute measures
```

		1 Avg	2 Sum	3 Min	4 Max	5 StdDev	6 EstSD	7 CV	8 Num	9 WtdNum
1	9	1.330	1.330	1.330	1.330	0	0	0	1	1
2	10	1.165	2.330	1	1.330	0.165	0.233	0.142	2	2
3	16	3.875	31	2.670	4.670	0.643	0.688	0.166	8	8
4	20	4.018	72.330	2.670	5	0.550	0.565	0.137	18	18
5	21	4.042	64.670	1	5	0.897	0.927	0.222	16	16
6	24	3.896	62.340	1	5	0.919	0.949	0.236	16	16
7	30	3.871	50.320	2.670	5	0.606	0.631	0.157	13	13
8	37	4.102	53.320	3.330	5	0.442	0.460	0.108	13	13
9	40	3.879	85.340	2	5	0.686	0.702	0.177	22	22
10	41	3.524	49.330	1	5	1.118	1.161	0.317	14	14
11	50	4.077	53	2	5	0.868	0.904	0.213	13	13
12	52	3.864	85.010	1	5	1.038	1.063	0.269	22	22
13	56	3.926	70.660	1.330	5	0.879	0.905	0.224	18	18
14	59	4.221	37.990	3.330	5	0.445	0.472	0.105	9	9
15	60	3.600	36	1	5	1.030	1.086	0.286	10	10
16	70	2	6	1	3.670	1.189	1.456	0.594	3	3
17	75	4.200	42	2.670	5	0.599	0.632	0.143	10	10
18	77	3.791	30.330	3	4.330	0.406	0.434	0.107	8	8
19	78	3.242	35.660	1	4.330	1.065	1.117	0.328	11	11
20	80	4.297	38.670	4	5	0.367	0.390	0.085	9	9
21	82	4.111	37	3.330	5	0.446	0.473	0.108	9	9
22	83	3.832	30.660	1	5	1.118	1.195	0.292	8	8
23	84	4.102	94.340	1	5	0.860	0.879	0.210	23	23
24	87	3.612	21.670	1	4.670	1.254	1.374	0.347	6	6
25	90	4.027	48.320	2.670	5	0.686	0.716	0.170	12	12
26	100	3.953	27.670	2.670	5	0.722	0.780	0.183	7	7
27	109	3.933	59	1.330	5	0.991	1.026	0.252	15	15
28	111	4.168	50.010	2.670	5	0.660	0.689	0.158	12	12
29	114	4.668	23.340	4	5	0.365	0.408	0.078	5	5
30	116	3.650	73	1	4.670	0.946	0.971	0.259	20	20
31	129	3.963	71.340	2	5	0.785	0.808	0.198	18	18
32	130	3.584	28.670	1	5	1.187	1.269	0.331	8	8
33	134	3.945	23.670	2.670	5	0.677	0.742	0.172	6	6
34	145	3.847	92.330	1.330	5	0.788	0.805	0.205	24	24
35	147	4.021	64.330	2.670	5	0.651	0.672	0.162	16	16
36	163	4.127	53.650	3.330	5	0.445	0.463	0.108	13	13

Q12d. Finally, run node level regression (Tools|Testing Hypotheses|Node-level|Regression) to predict a person’s job satisfaction from the average job satisfaction of their friends.




```
NODE LEVEL REGRESSION
--------------------------------------------------------------------------------

Method:                                Y-perm
# of permutations:                     10000
Random seed:                           23622
Dependent variable:                    lexattr.##d | jobsat
Predicted values:                      lexattr-pred (C:\Users\vbe230\Documents\UCINET data\lexattr-pred
Residual values:                       lexattr-res (C:\Users\vbe230\Documents\UCINET data\lexattr-res
Model fit stats:                       lexattr-fit (C:\Users\vbe230\Documents\UCINET data\lexattr-fit
Model coefficients:                    lexattr-coef (C:\Users\vbe230\Documents\UCINET data\lexattr-coef
p-values are 2-tailed


Overall Regression Fit Statistics

                        Value
                       ------
                 Nobs     74
             R-Square  0.187
         Adj R-square  0.176
            F(72,1) 16.551
      Sig (classical)  0.000
           Sig (perm)  0.001


Regression coefficients - predicting jobsat

                     1     2     3     4     5     6
          jobsat  Coef  Beta    SE     T c.Sig p.sig
                 ----- ----- ----- ----- ----- -----
     1 Intercept 1.426     0 0.590
     2       Avg 0.626 0.432 0.154 4.068 0.000 0.001

2 rows, 6 columns, 1 levels.

c.Sig is classical significance test. p.Sig is permutation test

-------------------------------------
Running time: 00:00:01 seconds.
Output generated: 11 Dec 23 18:55:09
UCINET 6.775 Copyright (c) 2002-2023 Analytic Technologies
```

The results show that the average job satisfaction of your friends is indeed related to your own job satisfaction. The coefficient for “avg” is positive and significant. Of course, we don’t know the direction of causality. Maybe being friends with people who like their job tends rub off on us, and so we tend to like our job more as well. Or maybe it’s homophily – people tend to befriend others who have similar levels of job satisfaction.

Q13. That’s it, you’re done. Thank you for an excellent semester. I hope you learned a lot of about organizational network analysis, and also about analytics in general. In particular, we have often used regression to answer questions about how people work and perform. This is a fundamental approach in analytics that everyone needs to know. I hope being familiar with this perspective will serve you well in the future.