Lab report 2

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Describe the social network(s) to me, in terms of how it was collected, what it represents and so forth. Also give me basic topography of the network: the nature of the ties; direction of ties; overall density; and if attributes are with the network, the distribution of the categories and variables of those attributes.

I have downloaded the publicly available dataset of Hillary's emails. It is a SQL file containing more than 41K emails. Each row, is an email containing the body of email in addition to meta data such as sender, recipents, classification (image 1).

body			
From:	H <pre>chrodi7gclintonenail.com >\nSent:</pre>	Sunday, September 20, 2009 7:30 PM/nTo:	,
From: Verweer, Melanne S		2009/nSubject: FW: Daily Star Article about Prime Minister Hasina	's Speech\n\nThe ongoing s
Fron:	On Sehalf Of Dr. Huha	mmad Yunus 86\nSent: Thursday, September 17, 20	09 9:54 AfinTo: Verveer, A
From:	H <pre>chrod17@clintonemail.com >\nSent;</pre>	Monday, September 21, 2009 4:24 PMI/rTo:	•
From: Verweer, Melanne S	«VerveerMS@state.govo\nTo: H\nSent: Hon Sep 21 16:22:52	2009\nSubject: Re: Oaily Star Article about Prime Minister Hasina	's Speech\n\nI will ask bu
From: H <+DR22@clintoner	uil.com>\nTo: Verveer, Melanne S\nSent: Mon Sep 21 16:21	:18 2009/nSubject: Re: Ouily Star Article about Prime Minister Has	ina's Speech\n\nkould he w
From: Verweer, Melanne S	«VerveerMS@state.govo\n?s: HinSent: Mon Sep 21 15:26:28	2009\nSubject: Fw: Caily Star Article about Prime Minister Hasina	's Speech\n\nI talked to Y
From: Verweer, Melanne S	TynTo: "N" eHER22@c1Entonemail.com>\nSent: Sun Sep 30 20:	84:38 2009\nSubject: 85: Oaily Star Article about Prime Minister H	lasina's Speech\n\nI'm seet
From: H [mailto:HDR22@c]	intonemail.com)\nSent: Sunday, September 20, 2009 7:30 R	Mynyn UNCLASSIFIED U.S. Department of State Case No. F-2014-2	0439 Doc No. C05759785 Dat
From: Verweer, Melanne S	«VerveerMS@state.govo\nTo: H\nSent: Fri Sep 18 00:30:12	2009\nSubject: FW: Daily Star Article about Prime Minister Hasina	's Speech\n\nThe ongoing s
From:	On Sehalf Of Dr. Huha	nnad Yunus\nSent: Thursday, September 17, 2009 9:54 AV\nTo: Vervee	r, Melanne S\nSubject: Awd
Front	H chrodi?@clintonemail.com/\nient:	Thursday, September 17, 2000 7:55 AMI/nTo:	*******
From:	H <hrodi7@clintonemail.com>\nSent:</hrodi7@clintonemail.com>	Sunday, September 20, 2009 8:22 PMynTo:	"wer
From: Verweer, Melanne S	-cVerveerMS@state.govo\nTo: H\nSent: Sun Sep 20:20:84:30	2009\nSubject: RS: Daily Star Article about Prime Minister Hasina	's Speech\n\nI'm seeing Yu
From: H [mailto:HDR22@cl	intonemail.com](nSent: Sunday, September 20, 2009 7:30 P	KinTo: Verveer, Helanne SinSubject: Re: Daily Star Article about P	rine Minister Hasina's Spe
From: Verweer, Melanne S	-(VerveerHightate.govo\nfo: H\ndent: Fr1 Sep 18 00:30:12	2009\nSubject: FW: Cally Star Article about Prime Minister Hasina	's Speech\n\nThe ongoing a
From:	H <pre>chrodi7@clintonensil.com>\nSent:</pre>	Friday, September 18, 2009 9:42 AM\nTo:	'sullivan@j@state.go
Fronc	H <pre>chrodi7@clintonenail.com >\nSent:</pre>	Tuesday, September 1, 2009 4:36 PM/nTo:	*abe
From: Abedin, Huma cAbed	tinë@vtate.govo\nTo: H\nSent: Tue Sep @1 16:20:51 2009\nS	ubject: Re:\n\n\n\n\n\ Original Message\n	
From: H <=0832gc11ntones	mil.com/nTo: Abedin, Huma\nSent: Tue Sep #1 16:18:21 20	89\nSubject: Re:\n\nAny word from\n\n Original Ressage\n	
From: Abedin, Huma cAbed	Enrightate.gov>\nTo: WinSent: Tue Sep @E 16:00:15 2000\nS	ubject: Re:\n\nile was at the house an hour ago. He may have gone t	o get food.\n\n Grigina
From: H <4DR22@clintonen	mil.com/nTo: Abedin, Humm/nSent: Tue Sep 01 16:06:41 20	89\nSubject: Re:\n\nls Occar at the househe didn't answer my ema	s and we're headed there n
From: Abedin, Huma cAbed	tini@state.govo\nTo: H\nSent: Tue Sep @1 15:58:58 2009\nS	ubject: Re:\n\nYes we have asked wh for a time\n\n\n UNCLASSIF	IED U.S. Department of Sta
From: H <= CREATER CONTRACTOR	mil.com/\nTo: Abedin, Humm\nSent: Tue Sep #1 15:56:#2 2#	89\nSubject: He:\n\nSo Lone will include in daily schedule for fue	eday?\n\n Original Ness
From: Abedin, Numa cAbed	Enightate.gov>\nTo: WinSent: Tue Sep 80 15:55:11 2000\nS	ubject: Re:\n\nTuesday we think.\nin Original Hessage\n	
From: H <4DR22@clintoner	mil.com/\nTo: Abedin, Humm\nSent: Tue Sep 01 15:54:00 20	89\nSubject: Re:\n\n]'ll wait to see him in person next week. Do w	e know when that would be?
From: Abedin, Huma cAbed	tink@state.gov>\nTo: W\nSent: Tue Sep @1 15:40:40 2009\nS	ubject: Re:\n\nTha\nFew other notes:\n- wh is asking if w want to	speak with potus tomorrow
From: H <=00022@clintoner	wil.com/nTo: Abedin, Huma/nSent: Tue Sep 01 15:37:20 30	89\nSubject: Re:\n\nOk. Thx. Enjoy the Mar. See you in DC.\n\n	Original Message\n
From: Abedin, Huma sAbed	Enrightate, govo\nTo: H\nSent: Tue Sep 85 14:38:23 2000\nS	ubject:\n\nianted to let you know I decided to go to do for the wh	Ofter tonote and big unga
Fron:	H <+OR22gclintonenail.com >\nSent:	Saturday, August 29, 2009 1:51 PW\nTo:	'yerye
From: Verweer, Melanne S	«VerveerHS@state.govo\nTo: H\nSent: Fri Aug 28 18:34:55	2009	9
Displayed 1000 rows of 40,75	37 (39,737 omitted)		

image 1- Initial data

For the purpose of this lab, I wanted to construct the Hillary's correspondence network. To do so, I extracted senders and receivers to use as a directed edge list using patterns in the data set and regular expressions. After having a dataframe with two columns of "sender" and "receivers", I cleaned the data more by removing special characters, white spaces, etc.

An interesting challenge of this process was entity resolution as not only there were a lot of typos in email addresses (for example 'Jake Sullivan' was typed 'Lake Sullivan') and there were variation of one name (like 'Human Abedin' and 'Abedin Huma'), but also single persons had different names (for example H, HRD, HClinton, etc for Hillary). To address that, I carried entity resolution using Levenshtein distance for similarity between words, and also decision trees for a higher resolution.

After cleaning up the data frame, there were more than 20,000 names. Therefore, I decided to construct the network based on the top 100 names with the highest number of emails (aggregated by both sent and received). Also in the case the more than one person was in the recipients field, I picked only the first one assuming that the first one in the list is more important in the communication.

Finally, I subset the data based on if the email was classified or not to create two seperate networks calling them 'classified' and 'unclassified' graphs. Ties in both networks are directed and denote if node A has sent an email to node B.

Basic topography of both networks are shown below.

Network	Number of Nodes	Number of Edges	Density
Classified	1236	1947	0.001274468
Unclassified	195	292	0.007679158

table 1. basic topography of networks

2. Calculate degree centrality; closeness centrality; betweenness centrality; and eigenvector centrality. Correlate those measures of centrality. Highlight which nodes are most central and least central, along different dimensions.

a summary of all centrality measures is shown in the table below.

##		inDegreeC o	utDegreeC	totalDeg	greeC	${\tt inClosenessC}$	$\verb"outClosenessC"$
##	h	64	604		668	7.062780e-07	1.185508e-05
##	cherylmills	64	266		330	7.062556e-07	1.179579e-05
##	humaabedin	50	150		200	7.063025e-07	1.166875e-05
##	${\tt sullivanjacob}$	56	104		160	7.063005e-07	1.177315e-05
##	${\tt opsnewsticker}$	0	44		44	6.551105e-07	6.787871e-07
##	${\tt mchalejuditha}$	8	30		38	7.062870e-07	1.154748e-05
##		totalClosen	essC betwe	eennessC		vector	
##	h	1.185508	e-05 55	5138.428	1.000	0000e+00	
##	cherylmills	1.179579	e-05 26	819.782	5.013	1265e-01	
##	humaabedin	1.166875	e-05 30	0551.407	6.258	3795e-01	
##	${\tt sullivanjacob}$	1.177315	e-05 29	9365.378	5.334	1829e-01	
##	${\tt opsnewsticker}$	6.787871	e-07	0.000	3.683	3675e-08	
##	${\tt mchalejuditha}$	1.154748	e-05 5	5000.559	5.370	0628e-02	

As expected, **Hillary** has the highest degree centrality. She also has the highest betweeness and eignevector centrality. These are all intuitive as it is her email network and every single email has her either as the sender or recipients. Huma Abedin(Hillary's aide), Cheryil Mills (Cheif of staff), and Jacob Sullivan (Policy advisor) who have the highest degree after hillary also have other highest centrality measures.

correlation between measures of centrality for the classified network.

```
outDegreeC totalDegreeC
##
                    inDegreeC
                                                          inClosenessC
## inDegreeC
                   1.00000000
                               0.8168445365
                                             0.865819706
                                                          0.0289936334
## outDegreeC
                               1.0000000000
                   0.81684454
                                             0.995874457 -0.0006531362
## totalDegreeC
                              0.9958744568 1.000000000 0.0039942812
                   0.86581971
```

```
## inClosenessC
                0.02899363 -0.0006531362 0.003994281
                                                1.000000000
## outClosenessC
                ## betweennessC
               0.866571088
                                                0.0197498369
## vector
                0.90203863 0.9132646369 0.934043095
                                                0.0124298811
                outClosenessC totalClosenessC betweennessC
##
                                                       vector
## inDegreeC
                  0.42574328
                               0.42574328
                                          0.85405218 0.90203863
## outDegreeC
                               0.28616684
                  0.28616684
                                          0.84417907 0.91326464
## totalDegreeC
                  0.31518686
                               0.31518686
                                          0.86657109 0.93404310
## inClosenessC
                 -0.04263097
                               -0.04263097
                                          0.01974984 0.01242988
## outClosenessC
                  1.0000000
                               1.00000000
                                          0.37945055 0.29677608
## totalClosenessC
                  1.00000000
                               1.00000000
                                          0.37945055 0.29677608
## betweennessC
                  0.37945055
                               0.37945055
                                          1.00000000 0.87151240
                  0.29677608
                               0.29677608
## vector
                                          0.87151240 1.00000000
```

3b. If you don't have a network with attribute data, then pick another network to compare your first network against. Calculate all of the same measures as above for Network #2. Consider if normalization is appropriate for any of these measures. Then state some hypothesis about why some (or all of the) measures of centrality in one network will be the same or different from the second network. Explain why you think these two networks should be similar or different.

As explained earlier, the other network I picked is the correspondence network for unclassified emails. a summary of all centrality measures is shown in the table below.

##		inDegreeU outI	DegreeU totalDeg	reeU inCl	Losene	essU
##	h	16	64	80 3.49	96137€	e-05
##	cherylmills	23	22	45 3.50)5943e	e-05
##	sullivanjacob	23	21	44 3.50)5328e	e-05
##	burnswilliam	8	13	21 3.49	99195e	e-05
##	humaabedin	6	14	20 3.47	75239e	e-05
##	${\tt feltmanjeffreyd}$	4	15	19 3.50)1768e	e-05
##		$\verb"outCloseness" U$	totalClosenessU	betweenr	nessU	vector
## ##	h	outClosenessU 0.0001541782	totalClosenessU 0.0001541782			vector 1.0000000
##	h cherylmills			3990	.8333	
## ##		0.0001541782	0.0001541782	3990. 3591.	.8333 .1667	1.0000000
## ## ##	cherylmills	0.0001541782 0.0001514463	0.0001541782 0.0001514463	3990 3591 5231	. 8333 . 1667 . 3333	1.0000000 0.3315094
## ## ## ##	cherylmills sullivanjacob	0.0001541782 0.0001514463 0.0001538935	0.0001541782 0.0001514463 0.0001538935	3990 3591 5231 890	.8333 .1667 .3333 .1667	1.0000000 0.3315094 0.7750269

Again Hillary has the highest degree followed by the same people in the classified network. correlation between measures of centrality for the classified network.

```
##
                   inDegreeU outDegreeU totalDegreeU inClosenessU
## inDegreeU
                   1.0000000 0.75041889
                                                        0.17529604
                                            0.8794767
## outDegreeU
                   0.7504189 1.00000000
                                           0.9745557
                                                        0.01613123
## totalDegreeU
                   0.8794767 0.97455572
                                            1.0000000
                                                        0.07106200
## inClosenessU
                   0.1752960 0.01613123
                                           0.0710620
                                                        1.00000000
## outClosenessU
                   0.2843117 0.45899250
                                            0.4269242 -0.35748351
## totalClosenessU 0.2843117 0.45899250
                                           0.4269242 -0.35748351
```

##	betweennessU	0.8477590 0.78	3593752 0.8534	1248 0.08448	3205
##	vector	0.8250938 0.88	3866129 0.9197	7073 0.07221	1896
##		$\verb"outCloseness" U$	${\tt totalClosenessU}$	${\tt betweennessU}$	vector
##	inDegreeU	0.2843117	0.2843117	0.84775897	0.82509378
##	${\tt outDegreeU}$	0.4589925	0.4589925	0.78593752	0.88866129
##	totalDegreeU	0.4269242	0.4269242	0.85342484	0.91970734
##	inClosenessU	-0.3574835	-0.3574835	0.08448205	0.07221896
##	${\tt outClosenessU}$	1.0000000	1.0000000	0.37802132	0.32182815
##	${\tt totalClosenessU}$	1.0000000	1.0000000	0.37802132	0.32182815
##	betweennessU	0.3780213	0.3780213	1.00000000	0.77001411
##	vector	0.3218282	0.3218282	0.77001411	1.00000000

4. In either case, when you are done above, then considers alternate specifications of your variables and codings and decisions and models. What would you want to consider changing and why. If you can, report on what are the consequences of those changes?

One observation from the previous tables is that because the number of emails to/from hillary is much more than the others, it skews the result for the less frequent nodes. Therefore, an alternative can be removing her from the network and calculating same centrality network measures for the remaining network.

doing so, the basic network topography comparing to the previous ones will be:

Network	Number of Nodes	Number of Edges	Density
Classified	1236	1947	0.001274468
${\bf Unclassified}$	195	292	0.007679158
Hillary-less	732	1280	0.002388844

centrality measures will also look like

##		inDegreeH ou	utDegreeH	totalDegreeH	inClosene	essH
##	cherylmills	63	265	328	2.106194	e-06
##	humaabedin	49	149	198	2.106580	e-06
##	sullivanjacob	55	103	158	2.106545	e-06
##	opsnewsticker	0	44	44	1.8688386	e-06
##	mchalejuditha	7	29	36	2.106483	e-06
##	${\tt reinesphilippei}$	12	23	35	2.106336	e-06
##		outCloseness	sH totalCl	osenessH bet	weennessH	vector
##	cherylmills	1.546360e-0	05 1.54	6360e-05	20748.806	5.776256e-06
##	humaabedin	1.536594e-0	05 1.53	86594e-05	19706.066	1.024929e-06
##	sullivanjacob	1.542353e-0	05 1.54	2353e-05	19634.194	1.217215e-06
##	opsnewsticker	1.984033e-0	06 1.98	34033e-06	0.000	1.000000e+00
##	mchalejuditha	1.528071e-0	05 1.52	28071e-05	4894.021	8.687026e-08
##	reinesphilippei	1.529450e-0	05 1.52	9450e-05	4320.300	2.700383e-07

Another interesting measure in this context is number and size of cliques. with Hillary in the network, it will be a large clique with 1236 nodes in it. However, removing her from the network, there is 732 clique with 6 nodes as the largest and ofcourse all of them include Cheryl Mills, Huma Abedin, and Jake Sullivan. It worth exploring more who are the members of each clique and what is their association.