

DS745 Network Analysis

Telling a Network Story: Global Online Course Social Interactions

Analysis using Exponential Random Graph Modelling (ERGM) and Network Visualization

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Dataset: Explanation

After reviewing the publically available datasets, I found the CMOOC dataset interesting since it captured social interactions between 3 teachers and 764 students of an distributed massive open online course offered in 2011. A link was added whenever party A referenced part B in their Tweet.

To perform the Exponential random graph model (ERGM) analysis, common elements of the object definition are extracted and added as node level attributes. Here is a table detailing the network's vertex attributes.

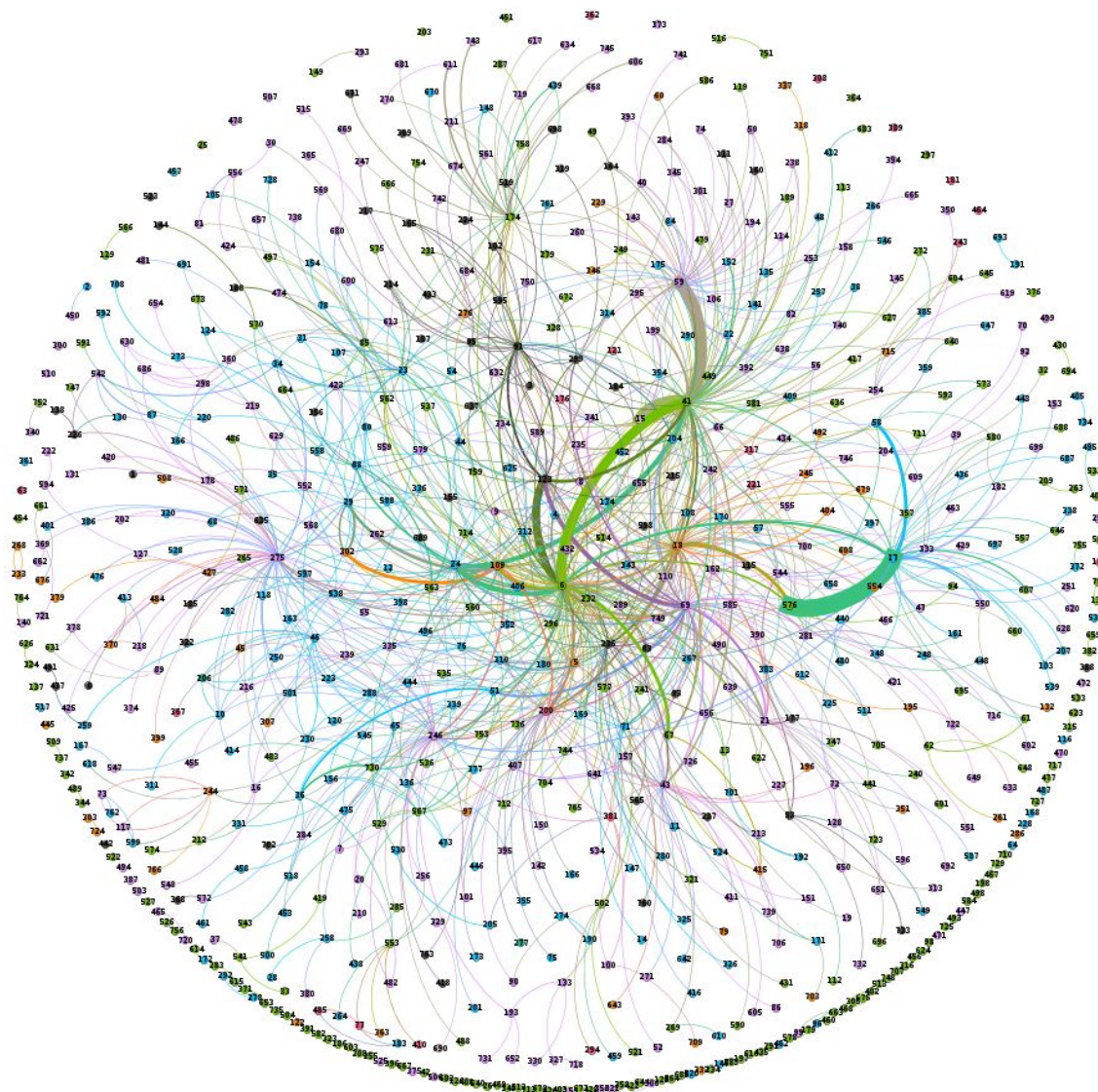
Attribute Name	Example	Description
id	123	Subject ID, range 1-767
domain	Undergraduate, Community	Social cluster, group
gender	M, F, unk/other, Org	Reported gender or organization or unk
role	Instr, Student	Role in network
continent	Intl, Asia, Europe	Reported continent
socio_tech	Social, Technical, Unk	Category Social or Techincal, or Unknown
work_type	Mixed, Practice, Research	Employment role or Unknown



Visualization and Network Summary

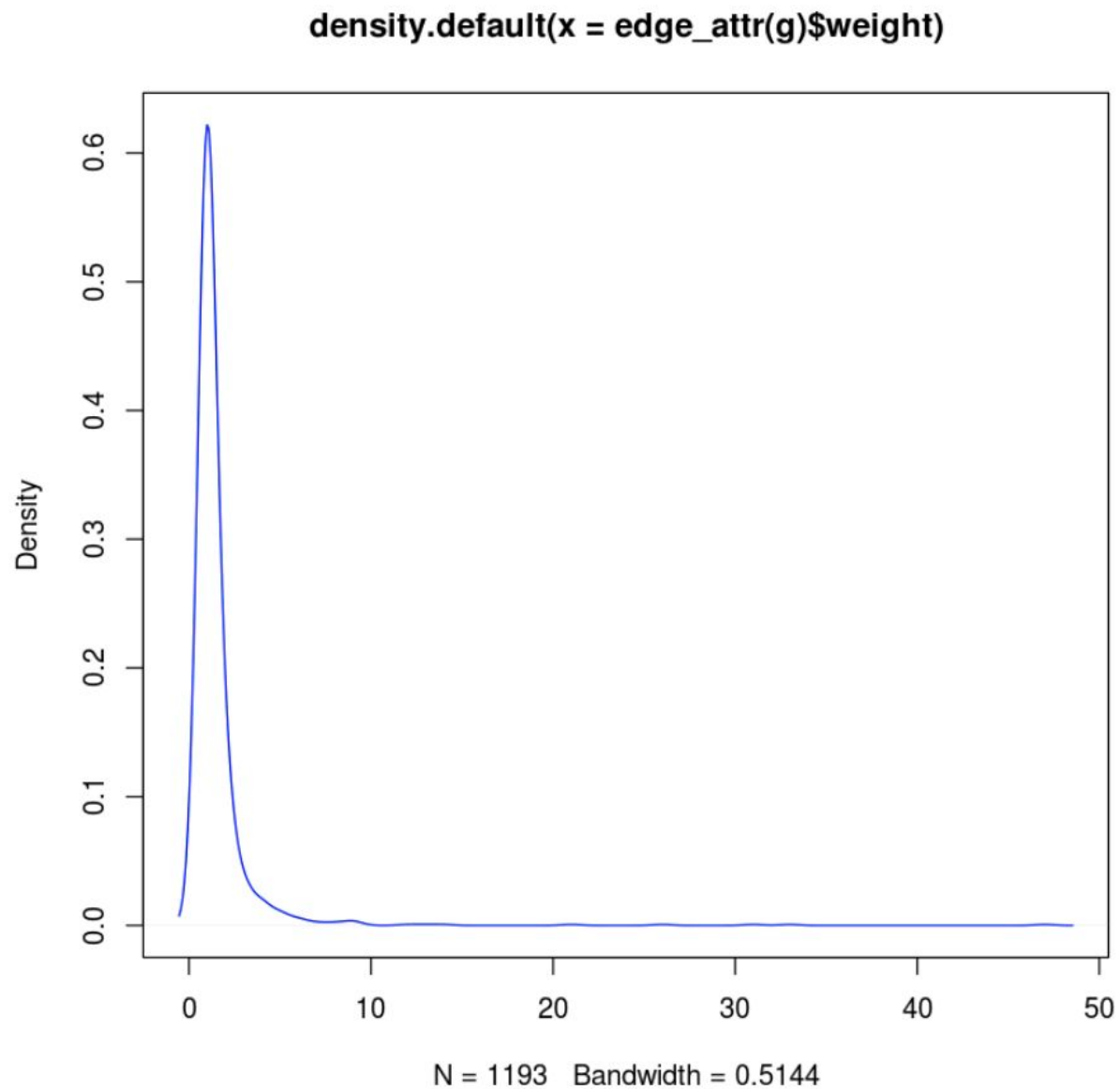
We start by looking at the overall color-coded structure of the entire network. Then analysis is shown for the network's structural properties. These will help build up ideas about the features we may want to include in models created in later sections of this paper.

The network consists of 1193 interactions (edges) and has a small density value of 0.002.



The above Fruchterman Reingold visualization colors the links between persons according to geographical region. Other categories were used for this coloring, but less visual correlation was represented. We expect that regional association will be a large factor in our model.

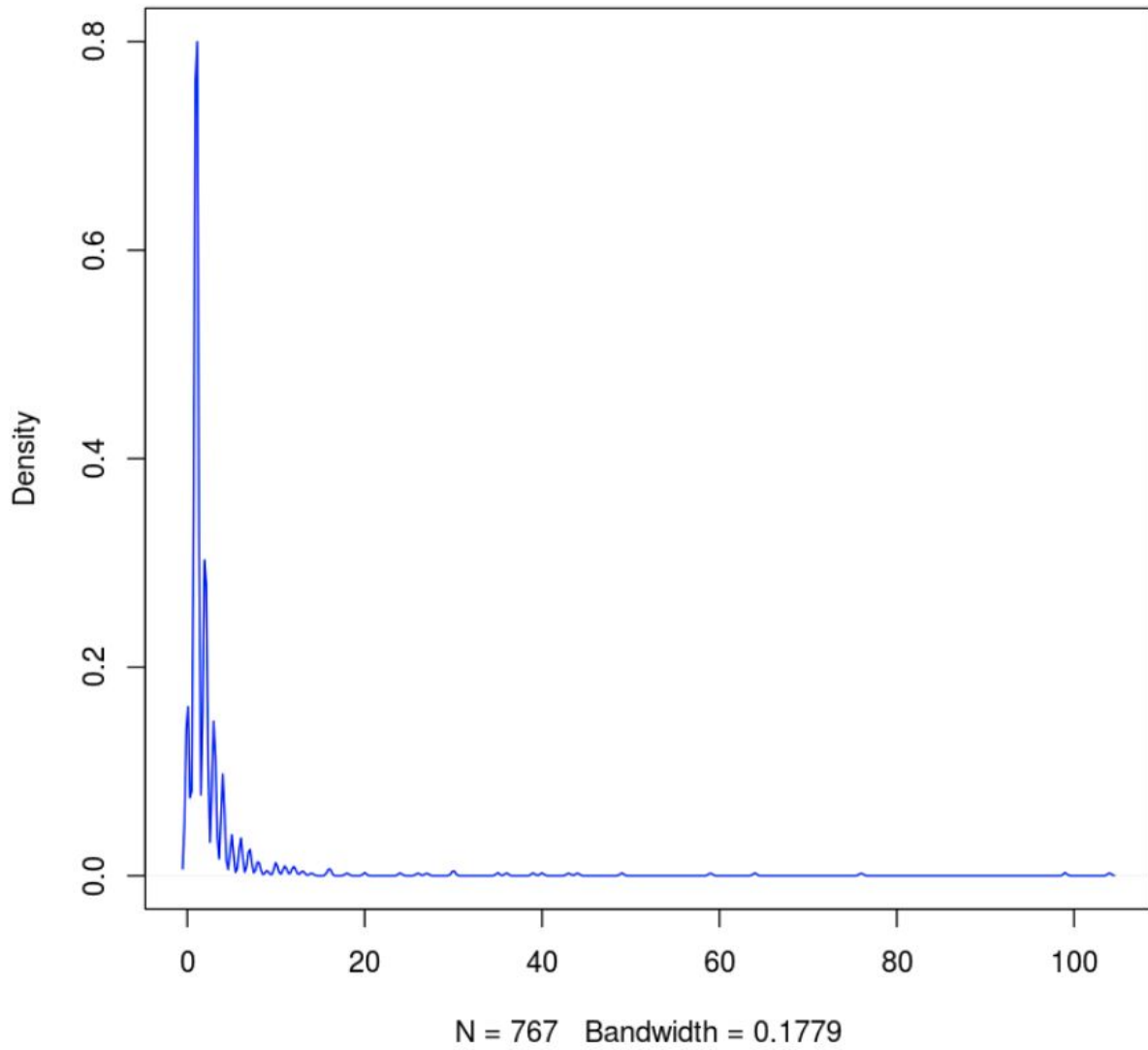
Next, we can look at the distribution of the edge weights (where parties mention each other in their messages). The the below plot, we can see that the distribution is skewed. Most of the values are less than five, and the maximum is 47.



Next, we can consider the degree distribution. This tells us the probability distribution (fraction of the nodes in the network with degree k) based on the number of connection the node has to other nodes. Most nodes have less than five connections, but some have over 100!

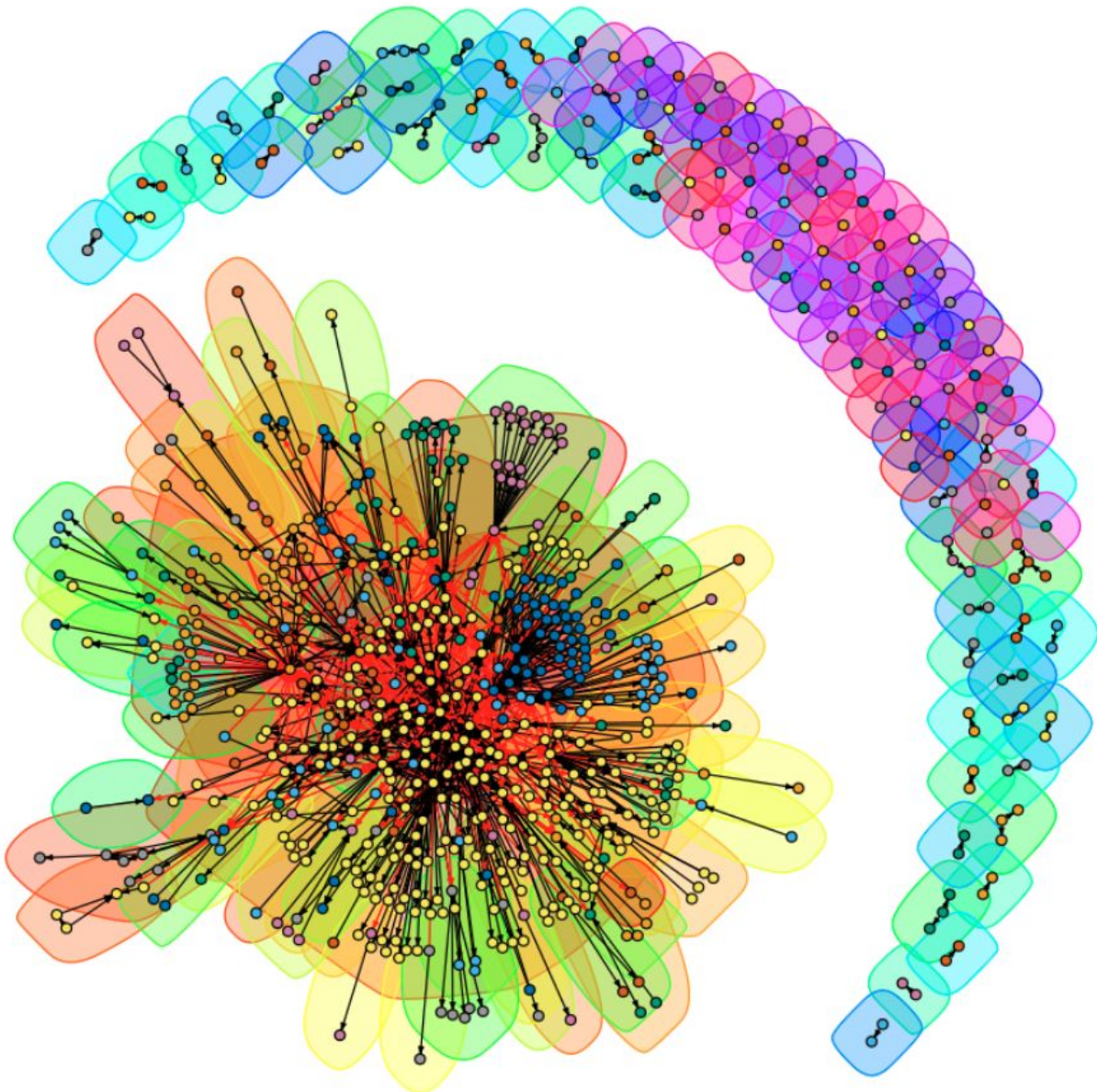


Density, Degree Distribution, N=767



Community Detection

The below community detection algorithm represented the strongest of a variety of algorithms. 'Walktrap' was better than 'fast greedy', 'edge betweenness', 'spinglass', 'leading eigenvector', and 'propagation'.



This provides an interesting perspective as it shows what one may intuit about the distributions of active, public communications in an online course. Here we see that many students mention just

one or two others. But a few dominant nodes, seemingly sharing a common geography, have many social mentions.

We can build two hypothesis based on community clustering. One is that many students pair up in small groups. These small communities are physically separate from the main network (on the upper right arc above). Recalling that node color is based on geographic region, we concluded a second hypothesis, based on many clusters (e.g. the blue, purple, and yellow in the center) that have obvious groupings in the main, central network.

Finally, we use mixing matrices to view the actual numerical relationships between our attributes discussed above.

```
mixingmatrix(net, "Continent")
```

From	To	Africa	Asia	Australia and NZ	Europe	International
Africa		0	1	0	1	0
Asia		0	3	2	3	0
Australia and NZ		1	3	17	52	1
Europe		2	13	20	99	3
International		0	0	0	0	0
North America		1	6	13	51	3
South America		0	2	0	20	0
Unknown		0	3	14	50	3
Total		4	31	66	276	10

From	To	North America	South America	Unknown	Total
Africa		0	0	0	2
Asia		4	1	11	24
Australia and NZ		46	11	26	157
Europe		110	17	79	343
International		0	0	1	1
North America		141	15	81	311
South America		29	34	18	103
Unknown		73	19	90	252
Total		403	97	306	1193

These relationships are seemingly not as clear cut as the images portray. Additionally, over 25% of the nodes are unknown. Next, we look at the next 4 attributes:


```
mixingmatrix(net, "SocioTech")
```

From	To			
	Social	Technical	Unknown	Total
Social	1078	2	49	1129
Technical	0	0	0	0
Unknown	21	0	43	64
Total	1099	2	92	1193

```
mixingmatrix(net, "WorkType")
```

From	To					
	Mixed	Other	Practice	Research	Unknown	Total
Mixed	51	0	60	21	11	143
Other	1	0	1	0	2	4
Practice	137	0	471	80	98	786
Research	43	0	45	30	15	133
Unknown	17	0	50	4	56	127
Total	249	0	627	135	182	1193

```
# next explore the mixing matrix of the network  
mixingmatrix(net, 'Role')
```

From	To			
	Course	Instructor	Student	Total
Course			1	9
Instructor				10
Student			98	1085
Total			99	1094
				1193

```
mixingmatrix(net, "Gender")
```

From	To				
	F	M	Org	Unknown	Total
F	143	244	67	30	484
M	149	240	59	31	479
Org	47	69	20	20	156
Unknown	9	17	3	45	74
Total	348	570	149	126	1193

Under the role above, it stands out that there is little public instructor interaction, and little instructor mentioning of students. Student's mainly mention students and about 8% of the time, instructors. In also looking at gender above, it appears as though male interaction is likely a factor we want want to consider.

Finally, we need to consider factors associated with the network's structural features. In the below summary table, we observe high two-path and intransitive properties.

```
# use ergm counts for elected structural features
summary(net ~ edges + mutual + triangles + simmelianties + intransitive + transitive + cyclicalities + twopath)
```

edges	1193
mutual	55
triangle	1020
simmeliainties	18
intransitive	7415
transitive	964
cyclicalities	108
twopath	8379

Network Modeling

From the course notes we recall that goodness of fit is generated by the Monte Carlo Markov Chain algorithm in that it is used to approximate the Maximum Likelihood Estimation function.

Network modeling with ERGM starts with a null model that is used as a benchmark for other models to assess goodness of fit. Typically the null model isn't very good, since it only considers network density in relation to a randomly generated network. As we build in both network structural elements and certain edge and node attributes, the AIC coefficients tell us how the model is doing.

```

: ## part III, modeling
null_model <- ergm(net ~ edges)

Evaluating log-likelihood at the estimate.

: summary(null_model)

=====
Summary of model fit
=====

Formula:    net ~ edges

Iterations:  8 out of 20

Monte Carlo MLE Results:
      Estimate Std. Error MCMC % p-value
edges -6.19741    0.02898     0  <1e-04 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

      Null Deviance: 814478 on 587522 degrees of freedom
      Residual Deviance: 17175 on 587521 degrees of freedom

AIC: 17177    BIC: 17189    (Smaller is better.)

: # find the z density
gden(net)

0.00203056225979623

```

Here we see that the network density is less than 50% which is not unusual. We also see that the zDensity is 0.00203. This means that the probability of creating an additional edge by adding one more node is very low.

```
summary(model_v1)

=====
Summary of model fit
=====

Formula:   net ~ edges + mutual + idegree(1) + odegree(1)

Iterations: 2 out of 20

Monte Carlo MLE Results:
      Estimate Std. Error MCMC % p-value
edges      -6.31164    0.03340    0 < 1e-04 ***
mutual       4.00271    0.14179    1 < 1e-04 ***
idegree1     0.04523    0.08071    0 0.57521
odegree1    -0.23137    0.08277    0 0.00519 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

      Null Deviance: 814478 on 587522 degrees of freedom
Residual Deviance: 16858 on 587518 degrees of freedom

AIC: 16866    BIC: 16911    (Smaller is better.)
```

For my first of three non-baseline (null) models, I look at first order and mutual interactions. In the above summary, we can see that the mutual connections and out degree one, offer the strongest improvements over the null model (BIC improves from 17,189 to 16,911).

```
summary(model_v2)

=====
Summary of model fit
=====

Formula:   net ~ edges + mutual + gwidegree(0.6, fixed = T)

Iterations: 7 out of 20

Monte Carlo MLE Results:
      Estimate Std. Error MCMC % p-value
edges      -5.16274    0.03373     0 <1e-04 ***
mutual       4.03486    0.14796     1 <1e-04 ***
gwidegree  -3.07379    0.09579     0 <1e-04 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

      Null Deviance: 814478 on 587522 degrees of freedom
Residual Deviance:  15961 on 587519 degrees of freedom

AIC: 15967    BIC: 16001    (Smaller is better.)
```

For the second non-baseline model, I keep mutual and add gwidegree to control for degree and closure. According to the above summary, this offers further improvement from BIC 16,911 to 15,994.

So, for the third model, what did we explore earlier that may help our model's performance? Domain and gender both looked interesting. In the below summary, we can see how these new additions impacted our model:


```
summary(model_v3)
```

```
=====
Summary of model fit
=====
```

```
Formula: net ~ edges + mutual + gwidegree(0.6, fixed = T) + nodematch("Gender",
diff = T) + nodefactor("Domain")
```

```
Iterations: 16 out of 20
```

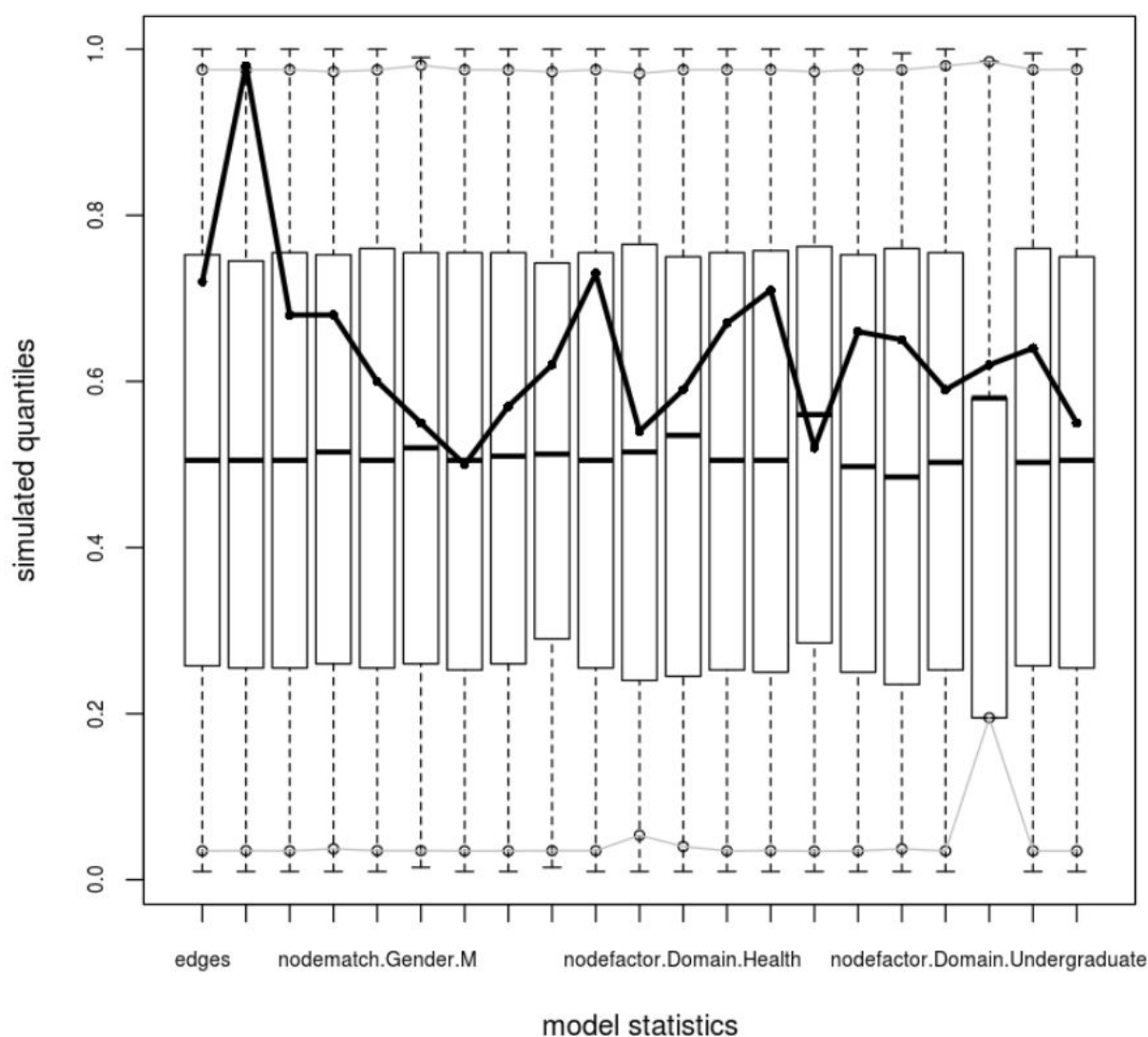
```
Monte Carlo MLE Results:
```

	Estimate	Std. Error	MCMC %
edges	-5.54253	0.12950	0
mutual	3.71491	0.16767	1
gwidegree	-2.75169	0.09909	0
nodematch.Gender.F	0.17227	0.08619	0
nodematch.Gender.M	0.19783	0.07221	0
nodematch.Gender.Org	-0.26117	0.23549	0
nodematch.Gender.Unknown	1.58809	0.18826	0
nodefactor.Domain.Community	1.25815	0.15294	0
nodefactor.Domain.Elementary and primary education	-0.14047	0.20760	0
nodefactor.Domain.Entrepreneurship	0.34182	0.07483	0
nodefactor.Domain.Government	-0.26587	0.34408	0
nodefactor.Domain.Health	0.37759	0.12246	0
nodefactor.Domain.Higher Education	0.23750	0.06679	0
nodefactor.Domain.Languages	0.38243	0.07967	0
nodefactor.Domain.Library	-0.10912	0.24161	0
nodefactor.Domain.Organization	0.32405	0.08448	0
nodefactor.Domain.Other	-0.32783	0.26564	0
nodefactor.Domain.Secondary education	-0.01437	0.08275	0
nodefactor.Domain.Undergraduate	-1.82696	0.94976	0
nodefactor.Domain.Unknown	-0.39930	0.08818	0
nodefactor.Domain.Various	0.22400	0.09915	0
	p-value		
edges	< 1e-04	***	
mutual	< 1e-04	***	
gwidegree	< 1e-04	***	
nodematch.Gender.F	0.045651	*	
nodematch.Gender.M	0.006149	**	
nodematch.Gender.Org	0.267420		
nodematch.Gender.Unknown	< 1e-04	***	
nodefactor.Domain.Community	< 1e-04	***	
nodefactor.Domain.Elementary and primary education	0.498621		
nodefactor.Domain.Entrepreneurship	< 1e-04	***	
nodefactor.Domain.Government	0.439698		
nodefactor.Domain.Health	0.002047	**	
nodefactor.Domain.Higher Education	0.000377	***	
nodefactor.Domain.Languages	< 1e-04	***	
nodefactor.Domain.Library	0.651526		
nodefactor.Domain.Organization	0.000125	***	
nodefactor.Domain.Other	0.217172		
nodefactor.Domain.Secondary education	0.862105		
nodefactor.Domain.Undergraduate	0.054404	.	
nodefactor.Domain.Unknown	< 1e-04	***	
nodefactor.Domain.Various	0.023872	*	

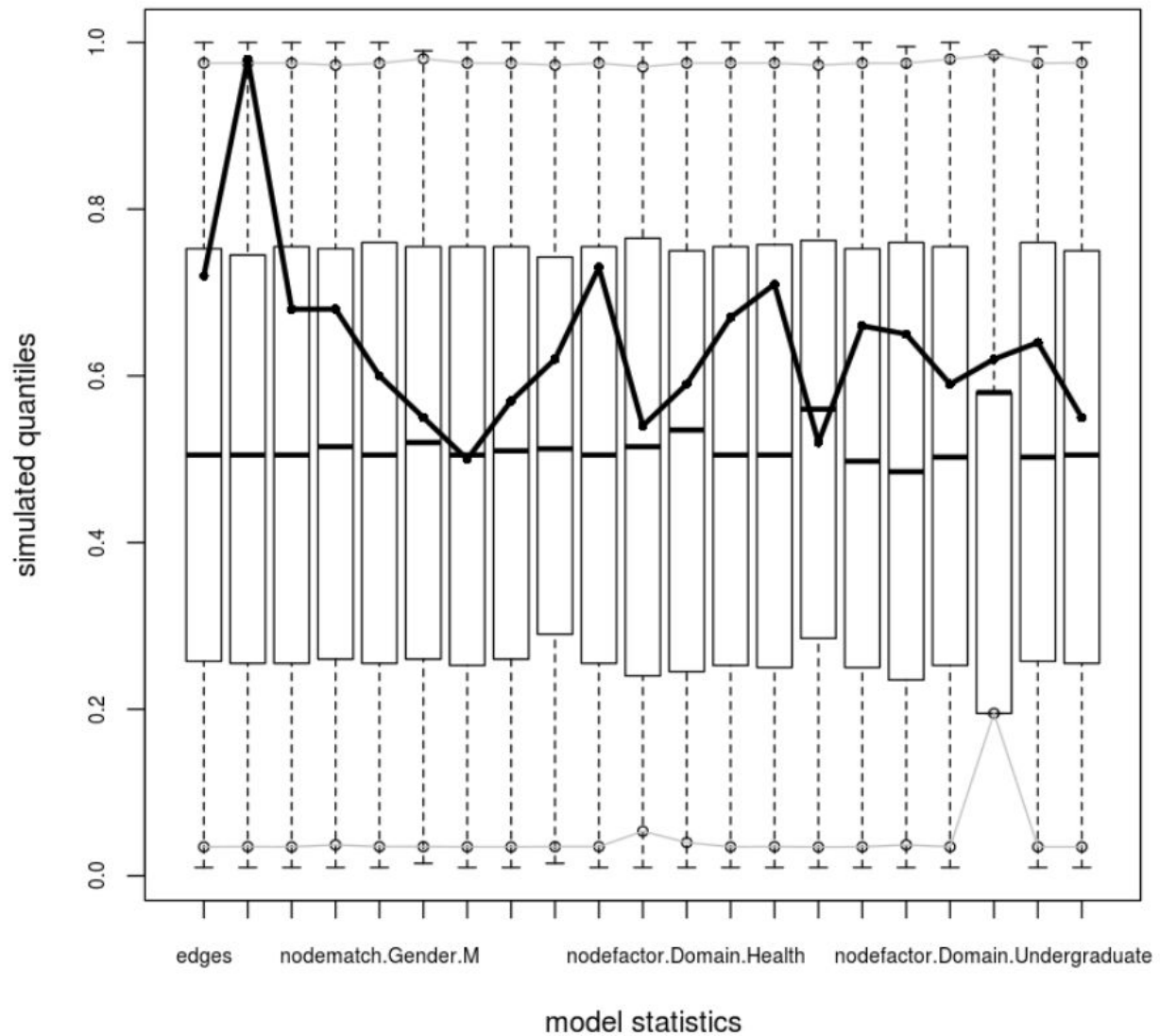
The BIC took a nice improvement (from 15,994 to 15,891).

The next plots are helpful in reviewing the model's goodness of fit, that is modelled versus observed performance. Here we run simulations and see that the model still struggles for some categories (while considering it is trying to capture edges, gender, and different domains):

Goodness-of-fit diagnostics



Goodness-of-fit diagnostics



Finally, we can observe the odds of the external and internal factors based on our initial thoughts and later findings:

```
# check the odds of the data  
lapply(model_v3[1], exp)
```

Scoef =

edges

0.00391661826485624

mutual

41.0547372320082

gwidegree

0.063819727764621

nodematch.Gender.F

1.18799674927322

nodematch.Gender.M

1.21875251802766

nodematch.Gender.Org

0.770151522368293

nodematch.Gender.Unknown

4.89437985237417

nodefactor.Domain.Community

3.51890637065117

nodefactor.Domain.Elementary and primary education

0.868945447973084

nodefactor.Domain.Entrepreneurship

1.40750648049384

nodefactor.Domain.Government

0.766535273380976

nodefactor.Domain.Health

1.45876545194954

nodefactor.Domain.Higher Education

1.26808114702961


nodefactor.Domain.Languages

1.4658360717404

nodefactor.Domain.Library

0.896620272033604

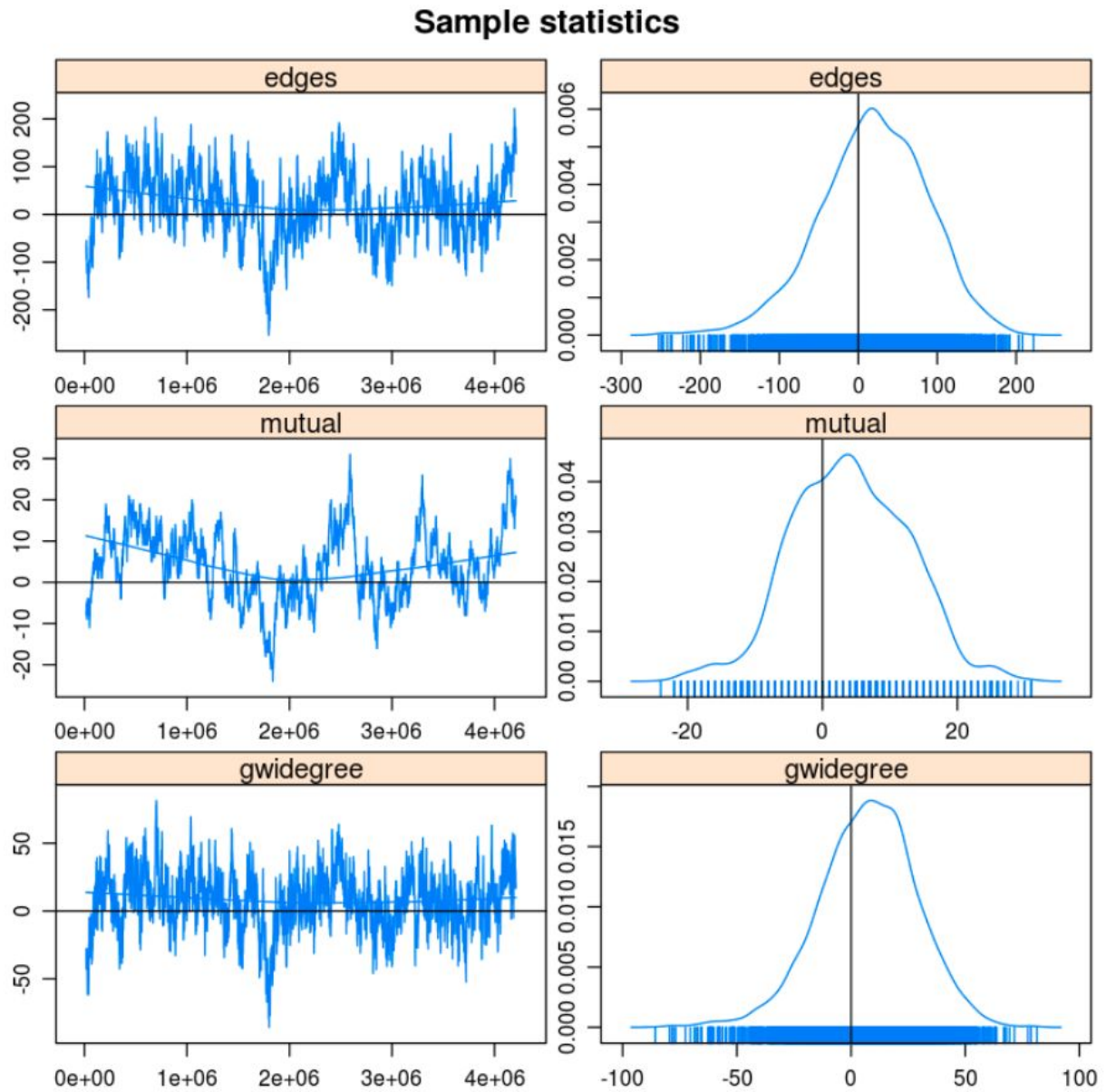
nodefactor.Domain.Organization



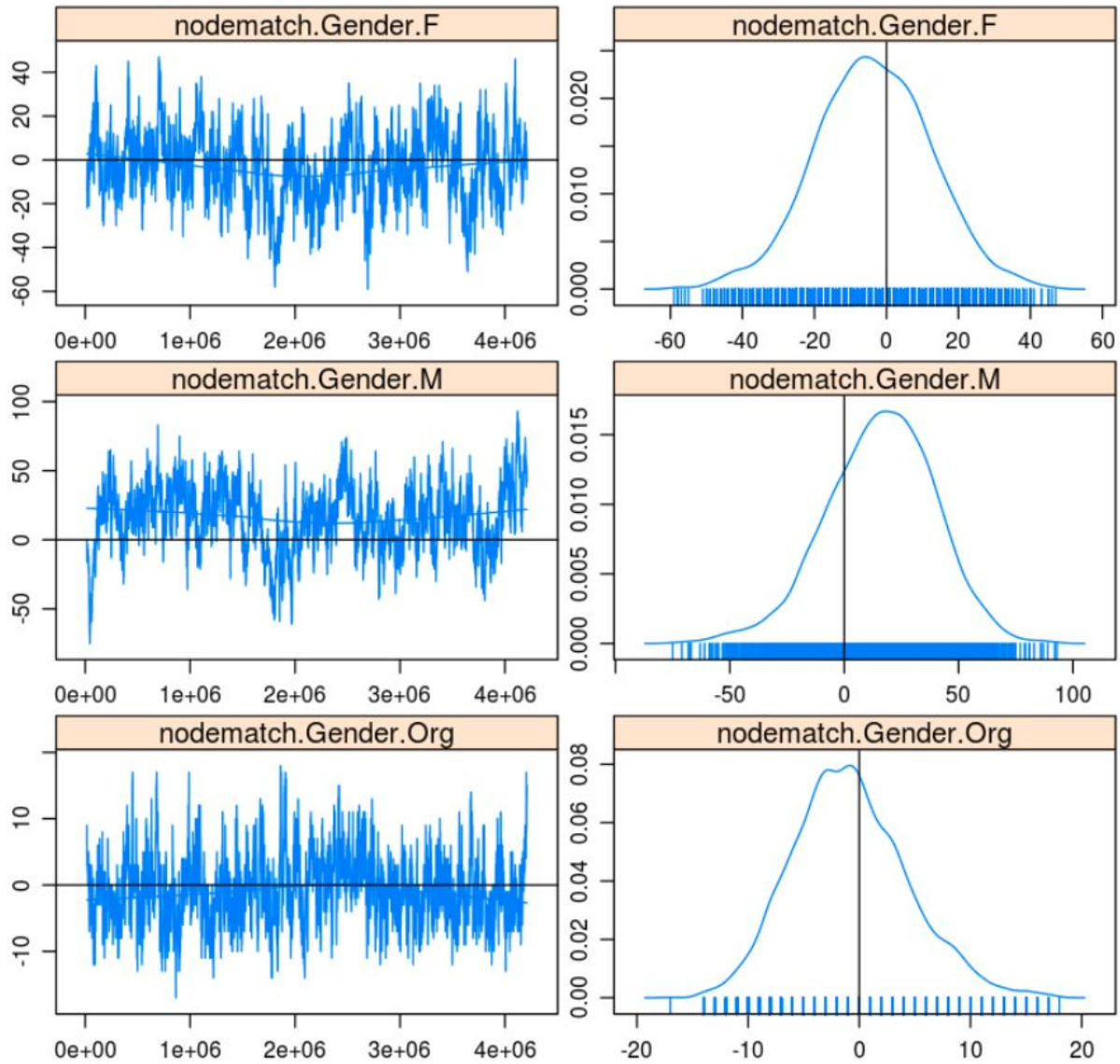
Based on the above, we can observe some homophily between males, higher education, institution accounts, community members, and entrepreneurs. These subgroups were factors of the information network's flow and structural reciprocity.

This analysis is publically available on my [GitHub](#) account under the creative commons license as it may be helpful for others studying social information exchanges or comparison between large online program behaviors.

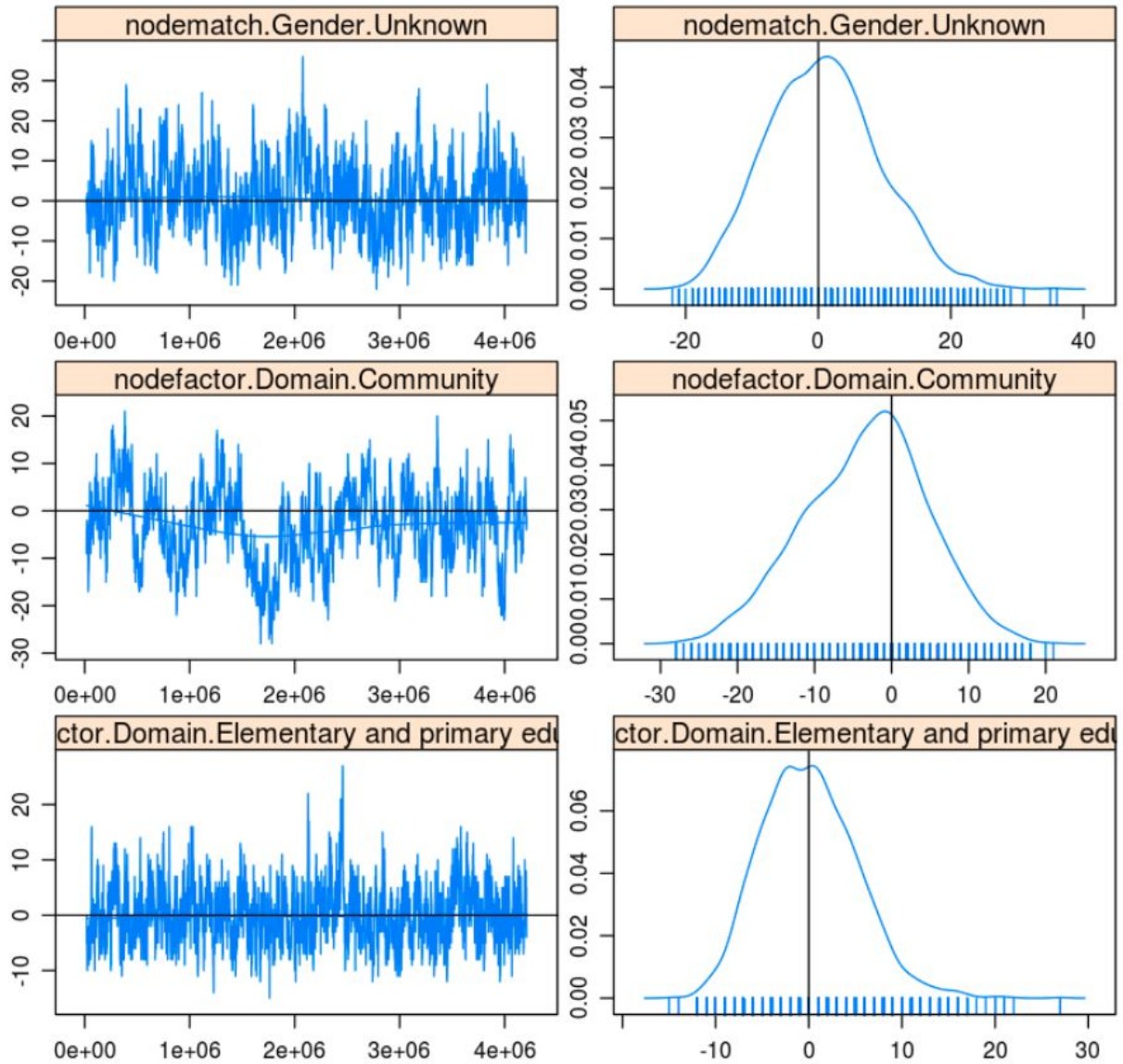
Appendix A : Model III Sample Statistics Plots



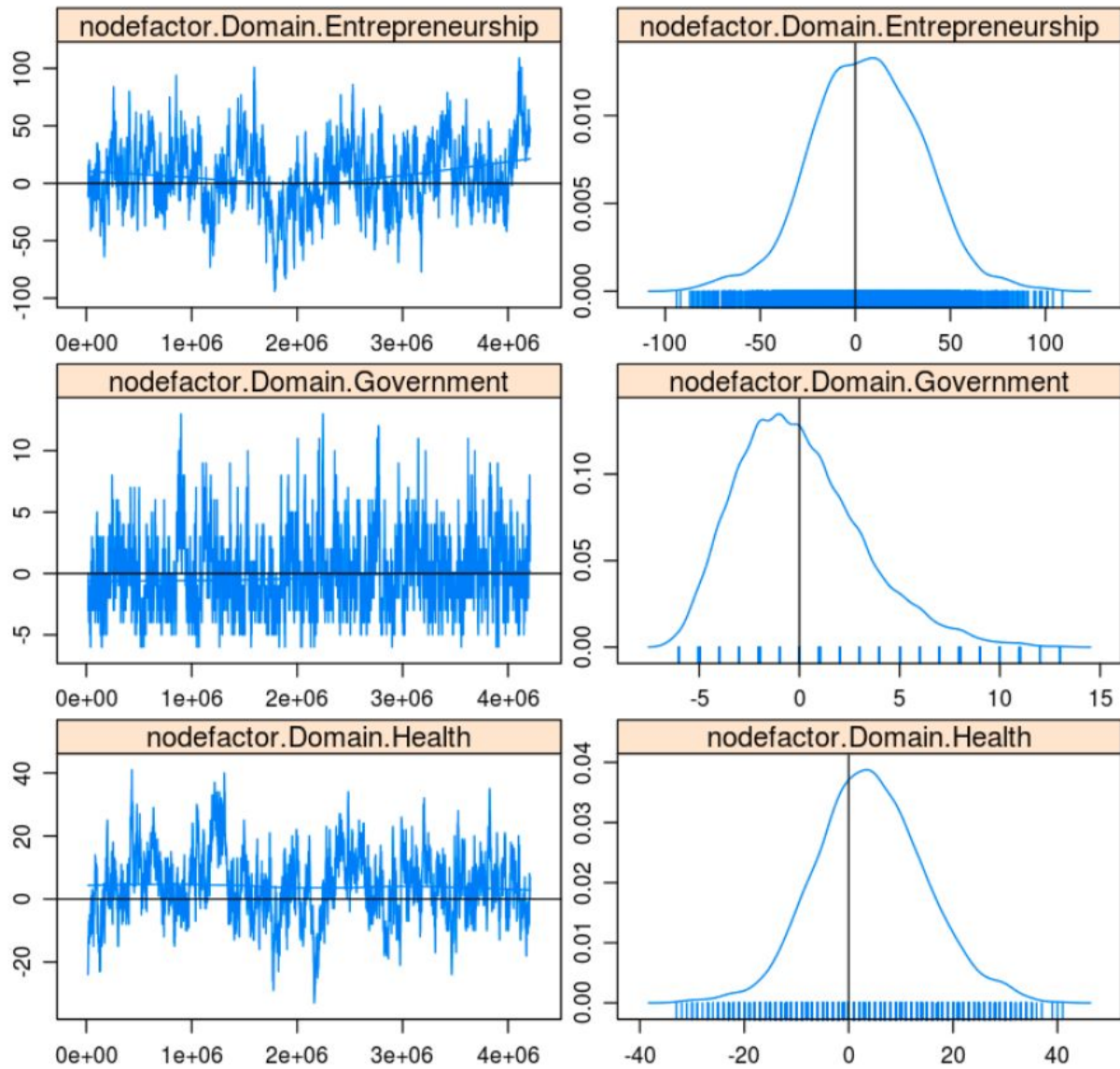
Sample statistics



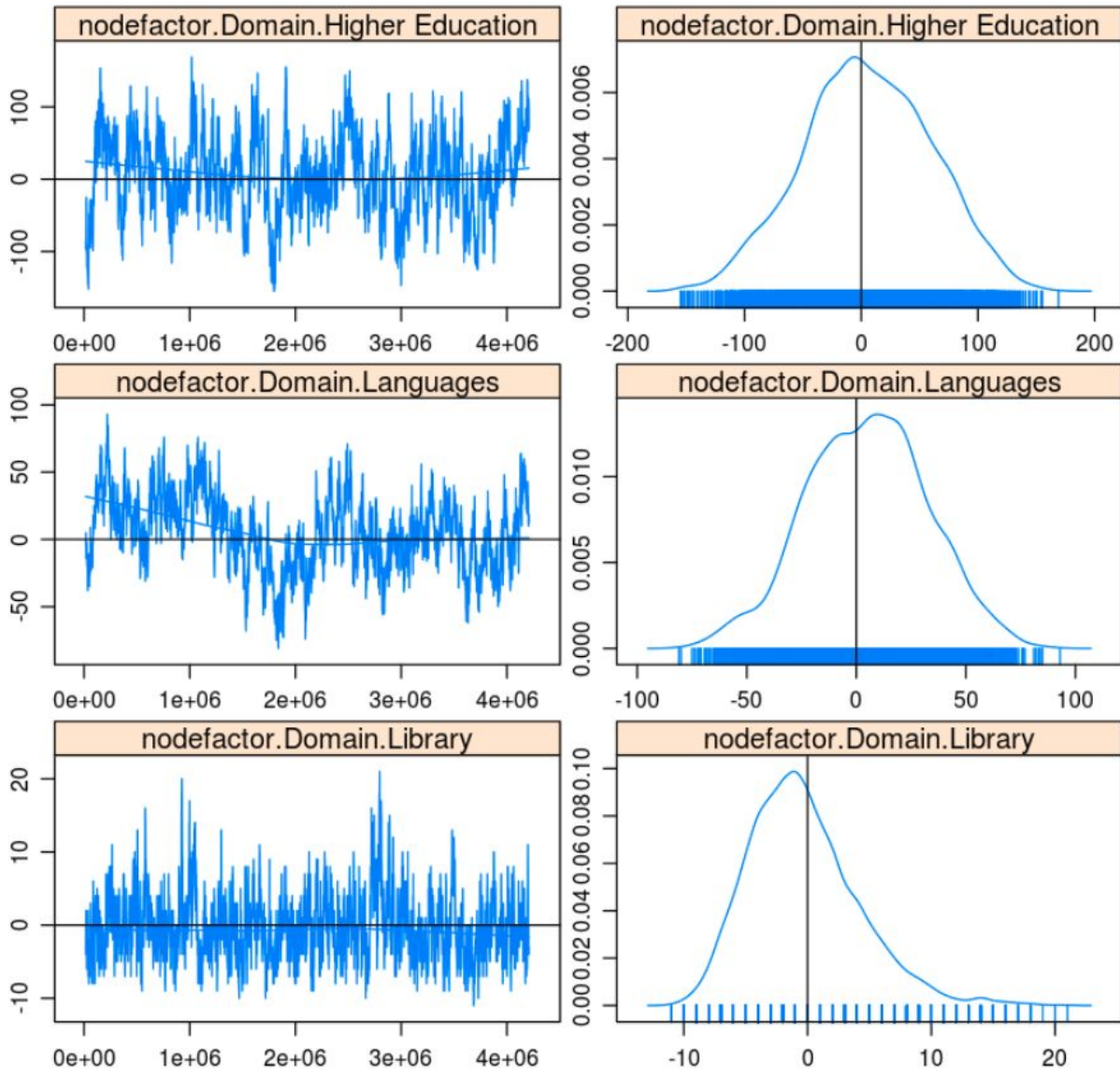
Sample statistics



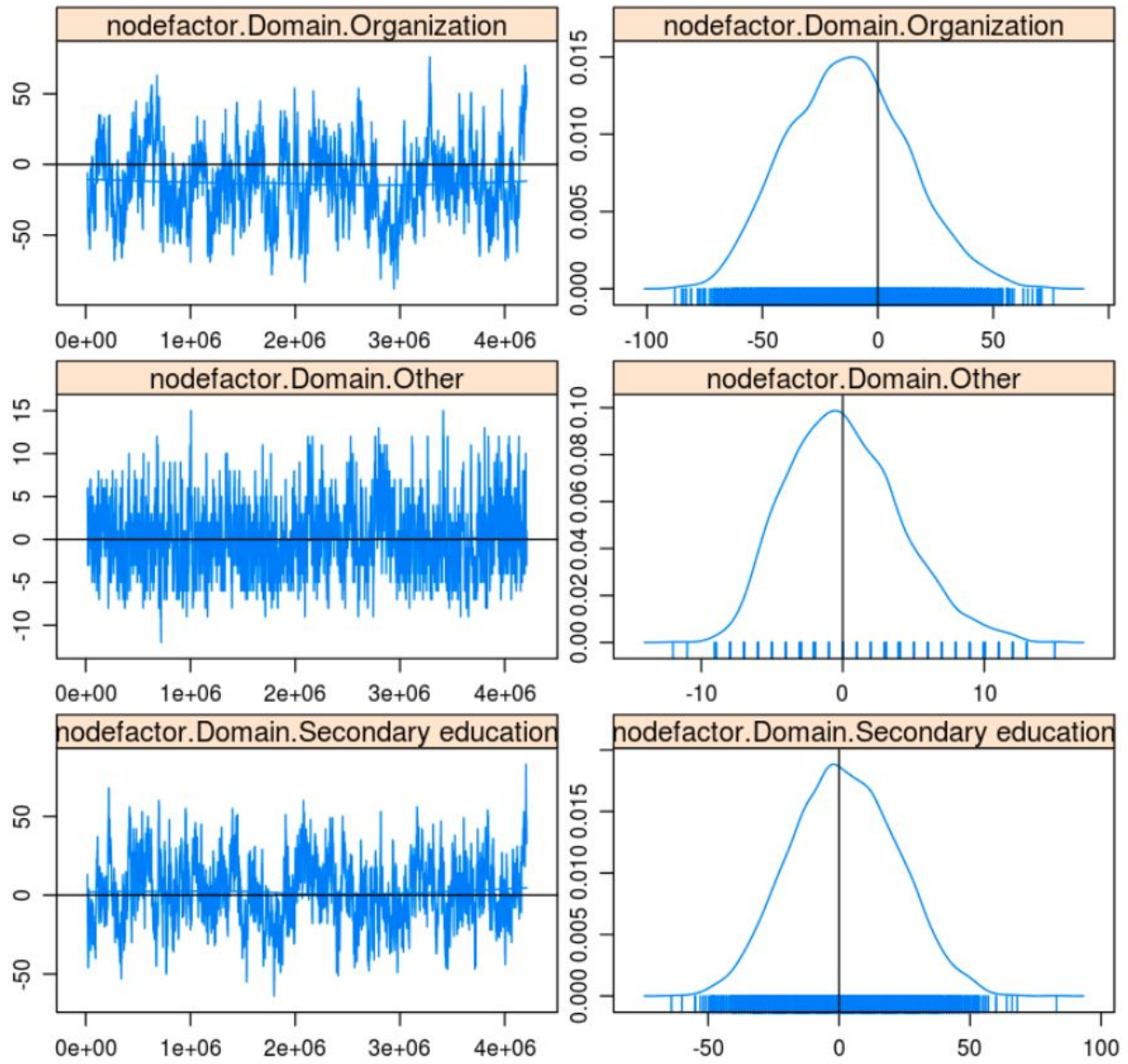
Sample statistics



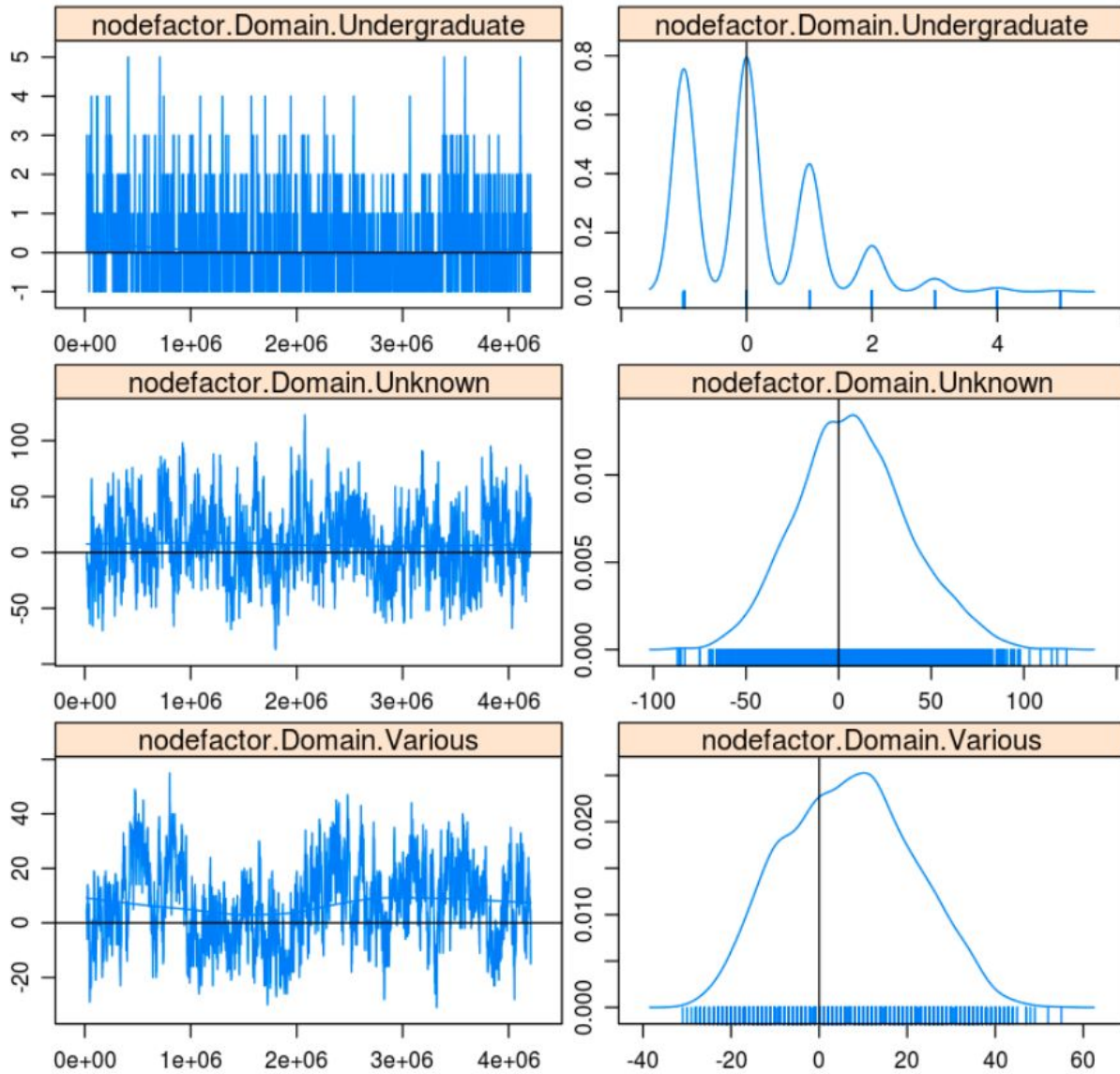
Sample statistics



Sample statistics



Sample statistics





R Code


```

library(igraph)

Attaching package: 'igraph'

The following objects are masked from 'package:stats':

    decompose, spectrum

The following object is masked from 'package:base':

    union

setwd('/home/cbios/github/swib_data_quality_analysis/EOMTechnicalTasks/application_analysis/week10')

g <- read_graph("cck11_dataset.gml", format=c("gml"))

summary(g)

IGRAPH 68db74a DNW- 767 1193 --
+ attr: id (v/n), name (v/c), Role (v/c), SocioTech (v/c), Gender
| (v/c), Domain (v/c), WorkType (v/c), Continent (v/c), weight (e/n)

# extract the dataframes with node and edge information
g_net.v.df <- as_data_frame(g, what='vertices')
g_net.e.df <- as_data_frame(g, what='edges')

# write the split network to csv
write.csv(g_net.v.df, file="cmooc_v.csv")
write.csv(g_net.e.df, file="cmooc_e.csv")

# also export to gexf for networks analysis using python
graph_gexf <- igraph.to.gexf(g, position=NULL)

Error in igraph.to.gexf(g, position = NULL): could not find function "igraph.to.gexf"
Traceback:

# take a look at the communities:
wc <- walktrap.community(g)
modularity(wc)
#wc <- fastgreedy.community(g)
#modularity(wc)
#wc <- edge.betweenness.community(g)
#modularity(wc)
#wc <- springlass.community(g)
#modularity(wc)
#wc <- leading.eigenvector.community(g)
#modularity(wc)
#wc <- label.propagation.community(g)
#modularity(wc)

# Plot
par(mfrow=c(1,1), mar=rep(1,4))
layout <- layout_fruchterman_reingold(g)
plot(wc, g, layout=layout, vertex.label=NA, vertex.size=2, edge.arrow.size=.2)

```

0.502232670783997



—

```
table(V(g)$Gender)
```

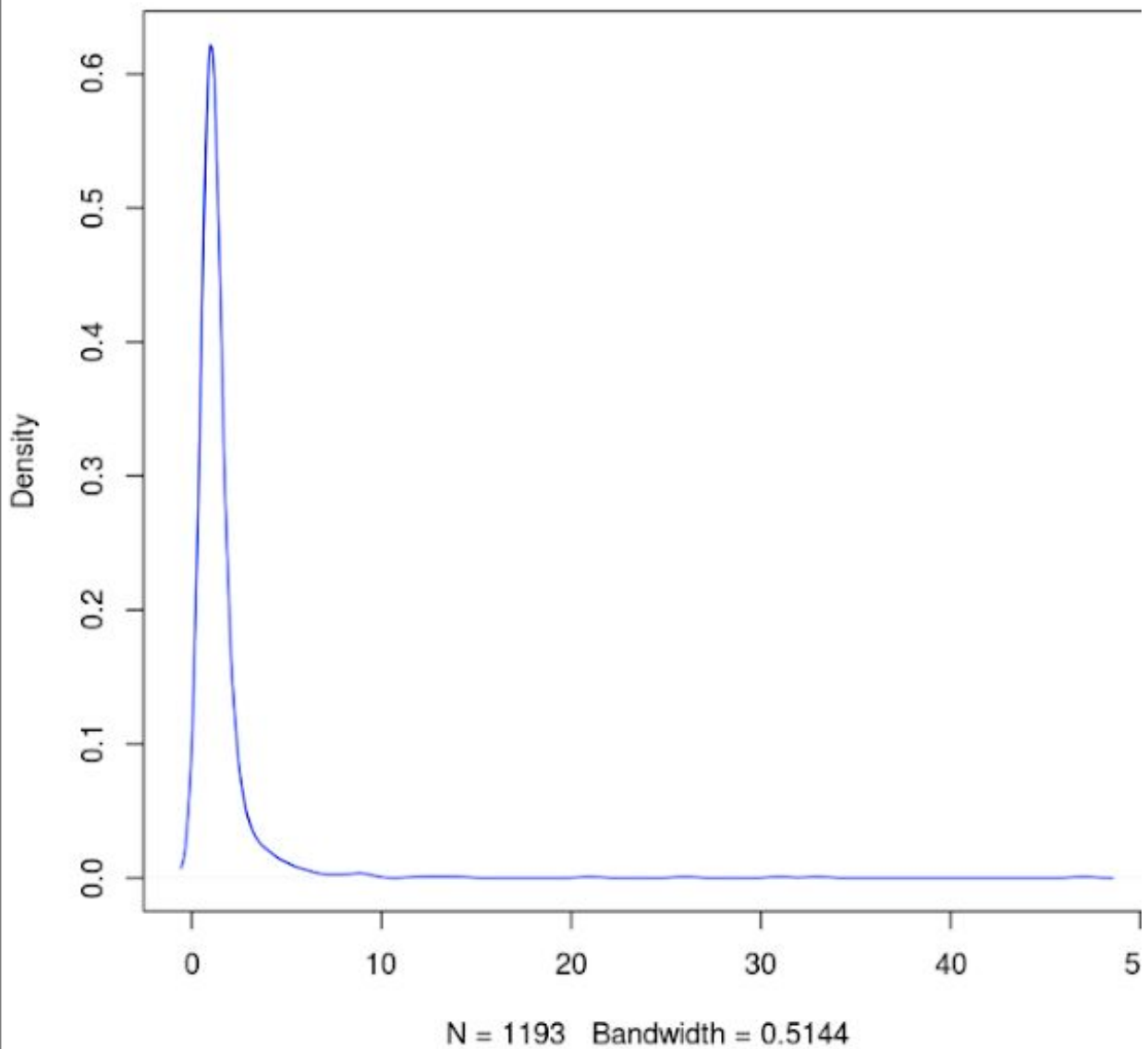
F	M	Org	Unknown
237	285	100	145

```
table(V(g)$WorkType)
```

Mixed	Other	Practice	Research	Unknown
66	2	400	107	192

```
plot(density(edge_attr(g)$weight), col='blue')
```

density.default(x = edge_attr(g)\$weight)



```
summary(E(g)$weight)
```

—

```
# ergm needs iGraph, convert
net <- asNetwork(g)
```

```
net
```

Network attributes:

```
vertices = 767
directed = TRUE
hyper = FALSE
loops = FALSE
multiple = FALSE
bipartite = FALSE
total edges= 1193
  missing edges= 0
  non-missing edges= 1193
```

Vertex attribute names:

```
Continent Domain Gender id Role SocioTech vertex.names WorkType
```

Edge attribute names not shown

```
list.vertex.attributes(net)
```

1. 'Continent'
2. 'Domain'
3. 'Gender'
4. 'id'
5. 'na'
6. 'Role'
7. 'SocioTech'
8. 'vertex.names'
9. 'WorkType'

```
mixingmatrix(net, "SocioTech")
```

From	To			
	Social	Technical	Unknown	Total
Social	1078	2	49	1129
Technical	0	0	0	0
Unknown	21	0	43	64
Total	1099	2	92	1193

```
mixingmatrix(net, "WorkType")
```

From	To					
	Mixed	Other	Practice	Research	Unknown	Total
Mixed	51	0	60	21	11	143
Other	1	0	1	0	2	4
Practice	137	0	471	80	98	786
Research	43	0	45	30	15	133
Unknown	17	0	50	4	56	127
Total	249	0	627	135	182	1193

```
# next explore the mixing matrix of the network
```

```
mixingmatrix(net, 'Role')
```

From	To			
	Course	Instructor	Student	Total
Course Instructor		1	9	10
Student		98	1085	1183
Total		99	1094	1193

—

From	To			
	Higher Education	Languages	Library	
Business	18	8	2	
Community	19	3	0	
Elementary and primary education	2	0	0	
Entrepreneurship	55	8	0	
Government	0	0	0	
Health	8	1	0	
Higher Education	164	20	1	
Languages	28	26	1	
Library	5	0	0	
Organization	39	4	1	
Other	1	0	0	
Secondary education	19	16	0	
Undergraduate	0	1	0	
Unknown	30	11	1	
Various	17	2	0	
Total	405	100	6	

From	To		
	Organization	Other	Secondary education
Business	10	0	4
Community	5	2	3
Elementary and primary education	3	0	5
Entrepreneurship	16	1	16
Government	0	0	0
Health	2	0	0
Higher Education	28	3	8
Languages	2	0	4
Library	0	0	0
Organization	17	1	11
Other	0	0	0
Secondary education	18	2	15
Undergraduate	0	0	0
Unknown	16	0	2
Various	1	0	2
Total	118	9	70

From	To			
	Undergraduate	Unknown	Various	Total
Business	0	10	3	67
Community	0	10	2	57
Elementary and primary education	0	0	0	12
Entrepreneurship	0	21	5	164
Government	0	0	0	1
Health	0	2	1	20
Higher Education	0	39	17	338
Languages	0	12	3	100
Library	0	0	0	5
Organization	0	30	3	131
Other	0	1	0	3
Secondary education	0	11	1	109
Undergraduate	0	0	0	1
Unknown	0	58	8	151
Various	0	4	1	34
Total	0	198	44	1193

```
mixingmatrix(net, "Continent")
```

From	To				
	Africa	Asia	Australia and NZ	Europe	International
Africa	0	1	0	1	0
Asia	0	3	2	3	0
Australia and NZ	1	3	17	52	1
Europe	2	13	20	99	3
International	0	0	0	0	0
North America	1	6	13	51	3
South America	0	2	0	20	0
Unknown	0	3	14	50	3
Total	4	31	66	276	10

From	To			
	North America	South America	Unknown	Total
Africa	0	0	0	2
Asia	4	1	11	24
Australia and NZ	46	11	26	157
Europe	110	17	79	343
International	0	0	1	1

```

nodefactor.Continent.Asia
55
nodefactor.Continent.Australia and NZ
223
nodefactor.Continent.Europe
619
nodefactor.Continent.International
11
nodefactor.Continent.North America
714
nodefactor.Continent.South America
200
nodefactor.Continent.Unknown
558
nodematch.Continent.Africa
0
nodematch.Continent.Asia
3
nodematch.Continent.Australia and NZ
17
nodematch.Continent.Europe
99
nodematch.Continent.International
0
nodematch.Continent.North America
141
nodematch.Continent.South America
34
nodematch.Continent.Unknown
90
mix.Continent.Africa.Africa
0
mix.Continent.Asia.Africa
0
mix.Continent.Australia and NZ.Africa
1
mix.Continent.Europe.Africa
2
mix.Continent.International.Africa
0
mix.Continent.North America.Africa
1
mix.Continent.South America.Africa
0
mix.Continent.Unknown.Africa
0
mix.Continent.Africa.Asia
1
mix.Continent.Asia.Asia
3

```

—

```

mix.Continent.Africa.North America
0
mix.Continent.Asia.North America
4
mix.Continent.Australia and NZ.North America
46
mix.Continent.Europe.North America
110
mix.Continent.International.North America
0
mix.Continent.North America.North America
141
mix.Continent.South America.North America
29
mix.Continent.Unknown.North America
73
mix.Continent.Africa.South America
0
mix.Continent.Asia.South America
1
mix.Continent.Australia and NZ.South America
11
mix.Continent.Europe.South America
17
mix.Continent.International.South America
0
mix.Continent.North America.South America
15
mix.Continent.South America.South America
34
mix.Continent.Unknown.South America
19
mix.Continent.Africa.Unknown
0
mix.Continent.Asia.Unknown
11
mix.Continent.Australia and NZ.Unknown
26
mix.Continent.Europe.Unknown
79
mix.Continent.International.Unknown
1
mix.Continent.North America.Unknown
81
mix.Continent.South America.Unknown
18
mix.Continent.Unknown.Unknown
90

```

```

## part III, modeling
null_model <- ergm(net ~ edges)

```

```
Evaluating log-likelihood at the estimate.
```

```
summary(null_model)
```

```

=====
Summary of model fit
=====

```

—

```
summary(model_v2)

=====
Summary of model fit
=====

Formula: net ~ edges + mutual + gwidegree(0.6, fixed = T)

Iterations: 7 out of 20

Monte Carlo MLE Results:
      Estimate Std. Error MCMC % p-value
edges      -5.16442    0.03377      0 <1e-04 ***
mutual       4.04740    0.16913      1 <1e-04 ***
gwidegree  -3.07472    0.09431      0 <1e-04 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Null Deviance: 814478 on 587522 degrees of freedom
Residual Deviance: 15954 on 587519 degrees of freedom

AIC: 15960 BIC: 15994 (Smaller is better.)

## not much improvement via structural components, lets look at attributes

model_v3 <- ergm( net ~ edges + mutual + gwidegree(0.6, fixed=T) + nodematch("Gender", diff=T) + nodefactor("Domain") )

summary(model_v3)

=====
Summary of model fit
=====

Formula: net ~ edges + mutual + gwidegree(0.6, fixed = T) + nodematch("Gender",
diff = T) + nodefactor("Domain")

Iterations: 16 out of 20

Monte Carlo MLE Results:
      Estimate Std. Error MCMC %
edges      -5.54253    0.12950      0
mutual       3.71491    0.16767      1
gwidegree  -2.75169    0.09909      0
nodematch.Gender.F      0.17227    0.08619      0
nodematch.Gender.M      0.19783    0.07221      0
nodematch.Gender.Org    -0.26117    0.23549      0
nodematch.Gender.Unknown 1.58809    0.18826      0
nodefactor.Domain.Community 1.25815    0.15294      0
nodefactor.Domain.Elementary and primary education -0.14047    0.20760      0
nodefactor.Domain.Entrepreneurship 0.34182    0.07483      0
nodefactor.Domain.Government -0.26587    0.34408      0
nodefactor.Domain.Health 0.37759    0.12246      0
nodefactor.Domain.Higher Education 0.23750    0.06679      0
nodefactor.Domain.Languages 0.38243    0.07967      0
nodefactor.Domain.Library -0.10912    0.24161      0
nodefactor.Domain.Organization 0.32405    0.08448      0
nodefactor.Domain.Other -0.32783    0.26564      0
nodefactor.Domain.Secondary education -0.01437    0.08275      0
nodefactor.Domain.Undergraduate -1.82696    0.94976      0
nodefactor.Domain.Unknown -0.39930    0.08818      0
nodefactor.Domain.Various 0.22400    0.09915      0
p-value
edges      < 1e-04 ***
mutual      < 1e-04 ***
gwidegree  < 1e-04 ***
nodematch.Gender.F 0.045651 *
nodematch.Gender.M 0.006149 **
nodematch.Gender.Org 0.267420
nodematch.Gender.Unknown < 1e-04 ***
nodefactor.Domain.Community < 1e-04 ***
nodefactor.Domain.Elementary and primary education 0.498621
nodefactor.Domain.Entrepreneurship < 1e-04 ***
nodefactor.Domain.Government 0.439698
nodefactor.Domain.Health 0.002047 **
nodefactor.Domain.Higher Education 0.000377 ***
nodefactor.Domain.Languages < 1e-04 ***
nodefactor.Domain.Library 0.651526
nodefactor.Domain.Organization 0.000125 ***
nodefactor.Domain.Other 0.217172
```


—

```
mcmc.diagnostics(model_v3)
```

Sample statistics summary:

Iterations = 16384:4209664

Thinning interval = 1024

Number of chains = 1

Sample size per chain = 4096

1. Empirical mean and standard deviation for each variable,
plus standard error of the mean:

	Mean	SD	Naive SE
edges	19.266846	68.417	1.06901
mutual	4.069824	8.574	0.13397
gwidegree	7.252364	21.571	0.33705
nodematch.Gender.F	-3.675781	16.091	0.25142
nodematch.Gender.M	15.806885	23.821	0.37221
nodematch.Gender.Org	-0.817871	5.196	0.08119
nodematch.Gender.Unknown	0.860596	8.484	0.13257
nodefactor.Domain.Community	-3.378418	7.961	0.12439
nodefactor.Domain.Elementary and primary education	0.063232	5.141	0.08033
nodefactor.Domain.Entrepreneurship	6.082031	28.929	0.45202
nodefactor.Domain.Government	-0.008057	3.079	0.04810
nodefactor.Domain.Health	4.220703	10.528	0.16450
nodefactor.Domain.Higher Education	5.509521	54.677	0.85433
nodefactor.Domain.Languages	4.876709	27.713	0.43301
nodefactor.Domain.Library	-0.335449	4.450	0.06953
nodefactor.Domain.Organization	-12.954834	25.722	0.40191
nodefactor.Domain.Other	0.088623	3.958	0.06184
nodefactor.Domain.Secondary education	1.992676	20.216	0.31587
nodefactor.Domain.Undergraduate	0.086182	1.062	0.01659
nodefactor.Domain.Unknown	7.899414	30.145	0.47101
nodefactor.Domain.Various	6.755859	14.572	0.22769

Time-series SE

edges	7.58354
mutual	1.68879
gwidegree	2.15759
nodematch.Gender.F	1.42752
nodematch.Gender.M	2.57811
nodematch.Gender.Org	0.33354
nodematch.Gender.Unknown	0.68204
nodefactor.Domain.Community	0.92044
nodefactor.Domain.Elementary and primary education	0.27190
nodefactor.Domain.Entrepreneurship	2.90808
nodefactor.Domain.Government	0.16688
nodefactor.Domain.Health	0.98073
nodefactor.Domain.Higher Education	5.74094
nodefactor.Domain.Languages	3.54856
nodefactor.Domain.Library	0.30089
nodefactor.Domain.Organization	2.37463
nodefactor.Domain.Other	0.17827
nodefactor.Domain.Secondary education	1.65031
nodefactor.Domain.Undergraduate	0.03619
nodefactor.Domain.Unknown	2.16518
nodefactor.Domain.Various	1.40319

2. Quantiles for each variable:

	2.5%	25%	50%
edges	-124.62	-24.000	21.000
mutual	-13.00	-2.000	4.000
gwidegree	-38.67	-6.095	8.025
nodematch.Gender.F	-36.00	-14.250	-4.000
nodematch.Gender.M	-34.00	0.000	17.000

—

```

edges gwidegree
mutual 0.86008538
gwidegree 0.51651260
1.00000000
nodematch.Gender.F 0.45301735
nodematch.Gender.M 0.55507574
nodematch.Gender.Org 0.17871492
nodematch.Gender.Unknown 0.20313068
nodefactor.Domain.Community 0.17706779
nodefactor.Domain.Elementary and primary education 0.10590116
nodefactor.Domain.Entrepreneurship 0.41618427
nodefactor.Domain.Government 0.09402141
nodefactor.Domain.Health 0.24132331
nodefactor.Domain.Higher Education 0.67717052
nodefactor.Domain.Languages 0.48205690
nodefactor.Domain.Library 0.17034845
nodefactor.Domain.Organization 0.41154703
nodefactor.Domain.Other 0.13379807
nodefactor.Domain.Secondary education 0.51759758
nodefactor.Domain.Undergraduate 0.02488983
nodefactor.Domain.Unknown 0.53980556
nodefactor.Domain.Variou 0.27038192
nodematch.Gender.F
edges 0.528354614
mutual 0.385362502
gwidegree 0.453017353
nodematch.Gender.F 1.000000000
nodematch.Gender.M 0.194959927
nodematch.Gender.Org -0.032426972
nodematch.Gender.Unknown 0.069254999
nodefactor.Domain.Community 0.216467501
nodefactor.Domain.Elementary and primary education 0.027882659
nodefactor.Domain.Entrepreneurship 0.370144093
nodefactor.Domain.Government 0.060540386
nodefactor.Domain.Health 0.217866345
nodefactor.Domain.Higher Education 0.471294761
nodefactor.Domain.Languages 0.422718606
nodefactor.Domain.Library 0.130870933
nodefactor.Domain.Organization 0.059427560
nodefactor.Domain.Other 0.090263623
nodefactor.Domain.Secondary education 0.276771427
nodefactor.Domain.Undergraduate 0.097284831
nodefactor.Domain.Unknown 0.249892747
nodefactor.Domain.Variou 0.088739908
nodematch.Gender.M
edges 0.68153433
mutual 0.48315349
gwidegree 0.55507574
nodematch.Gender.F 0.19495993
nodematch.Gender.M 1.00000000
nodematch.Gender.Org 0.02691665
nodematch.Gender.Unknown -0.06224170
nodefactor.Domain.Community 0.21886666
nodefactor.Domain.Elementary and primary education 0.14333064
nodefactor.Domain.Entrepreneurship 0.49555856
nodefactor.Domain.Government 0.10231918
nodefactor.Domain.Health 0.16632984
nodefactor.Domain.Higher Education 0.57067780
nodefactor.Domain.Languages 0.42854958
nodefactor.Domain.Library 0.09293787
nodefactor.Domain.Organization 0.18268736
nodefactor.Domain.Other 0.08270728
nodefactor.Domain.Secondary education 0.35579405
nodefactor.Domain.Undergraduate 0.04906837
nodefactor.Domain.Unknown 0.15820592
nodefactor.Domain.Variou 0.34371169

```

—

	nodefactor.Domain.Elementary and primary education	
edges	0.141113769	
mutual	0.102150121	
gwidegree	0.105901161	
nodematch.Gender.F	0.027882659	
nodematch.Gender.M	0.143330641	
nodematch.Gender.Org	0.000473779	
nodematch.Gender.Unknown	-0.019639454	
nodefactor.Domain.Community	0.136339281	
nodefactor.Domain.Elementary and primary education	1.000000000	
nodefactor.Domain.Entrepreneurship	0.033433750	
nodefactor.Domain.Government	0.055039018	
nodefactor.Domain.Health	0.059992529	
nodefactor.Domain.Higher Education	0.058865493	
nodefactor.Domain.Languages	0.086276039	
nodefactor.Domain.Library	0.026556163	
nodefactor.Domain.Organization	0.032762692	
nodefactor.Domain.Other	-0.024988687	
nodefactor.Domain.Secondary education	0.064805246	
nodefactor.Domain.Undergraduate	0.083976340	
nodefactor.Domain.Unknown	0.048084921	
nodefactor.Domain.Variou	0.062141859	
	nodefactor.Domain.Entrepreneurship	
edges	0.57091147	
mutual	0.42213042	
gwidegree	0.41618427	
nodematch.Gender.F	0.37014409	
nodematch.Gender.M	0.49555856	
nodematch.Gender.Org	0.08978220	
nodematch.Gender.Unknown	-0.03036702	
nodefactor.Domain.Community	0.16718569	
nodefactor.Domain.Elementary and primary education	0.03343375	
nodefactor.Domain.Entrepreneurship	1.00000000	
nodefactor.Domain.Government	-0.01662256	
nodefactor.Domain.Health	0.14728925	
nodefactor.Domain.Higher Education	0.29598120	
nodefactor.Domain.Languages	0.26953581	
nodefactor.Domain.Library	0.09568942	
nodefactor.Domain.Organization	0.18112091	
nodefactor.Domain.Other	0.10556981	
nodefactor.Domain.Secondary education	0.19929528	
nodefactor.Domain.Undergraduate	0.01749452	
nodefactor.Domain.Unknown	0.18156115	
nodefactor.Domain.Variou	0.22135090	
	nodefactor.Domain.Government	
edges	0.1060584973	
mutual	-0.0248457125	
gwidegree	0.0940214063	
nodematch.Gender.F	0.0605403864	
nodematch.Gender.M	0.1023191830	
nodematch.Gender.Org	-0.0139978644	
nodematch.Gender.Unknown	0.1072483065	
nodefactor.Domain.Community	0.1270138740	
nodefactor.Domain.Elementary and primary education	0.0550390183	
nodefactor.Domain.Entrepreneurship	-0.0166225618	
nodefactor.Domain.Government	1.0000000000	
nodefactor.Domain.Health	0.0306891265	
nodefactor.Domain.Higher Education	0.0505915646	
nodefactor.Domain.Languages	0.0260785379	
nodefactor.Domain.Library	-0.0449377846	
nodefactor.Domain.Organization	0.0119265399	
nodefactor.Domain.Other	-0.0357382492	
nodefactor.Domain.Secondary education	0.0729310217	
nodefactor.Domain.Undergraduate	-0.0003852756	
nodefactor.Domain.Unknown	0.1303084330	
nodefactor.Domain.Variou	0.0271954551	
	nodefactor.Domain.Health	
edges	0.32096407	
mutual	0.30198295	
gwidegree	0.24132331	
nodematch.Gender.F	0.21786634	
nodematch.Gender.M	0.16632984	
nodematch.Gender.Org	0.01455511	

—

```

edges nodefactor.Domain.Secondary education 0.50150216
mutual 0.25919743
gwidegree 0.51759758
nodematch.Gender.F 0.27677143
nodematch.Gender.M 0.35579405
nodematch.Gender.Org 0.04130083
nodematch.Gender.Unknown 0.10264946
nodefactor.Domain.Community 0.05689256
nodefactor.Domain.Elementary and primary education 0.06480525
nodefactor.Domain.Entrepreneurship 0.19929528
nodefactor.Domain.Government 0.07293102
nodefactor.Domain.Health 0.04996144
nodefactor.Domain.Higher Education 0.31222629
nodefactor.Domain.Languages 0.22668423
nodefactor.Domain.Library 0.07738162
nodefactor.Domain.Organization 0.21449632
nodefactor.Domain.Other 0.04483081
nodefactor.Domain.Secondary education 1.00000000
nodefactor.Domain.Undergraduate 0.02832994
nodefactor.Domain.Unknown 0.21770626
nodefactor.Domain.Various 0.14405499

edges nodefactor.Domain.Undergraduate 0.0286332105
mutual 0.0359871415
gwidegree 0.0248898312
nodematch.Gender.F 0.0072848314
nodematch.Gender.M 0.0490683749
nodematch.Gender.Org -0.0265304955
nodematch.Gender.Unknown 0.0142673342
nodefactor.Domain.Community 0.0215442219
nodefactor.Domain.Elementary and primary education 0.0839763396
nodefactor.Domain.Entrepreneurship 0.0174945243
nodefactor.Domain.Government -0.0003852756
nodefactor.Domain.Health -0.0184393271
nodefactor.Domain.Higher Education -0.0038743172
nodefactor.Domain.Languages 0.0432110346
nodefactor.Domain.Library -0.0032870108
nodefactor.Domain.Organization -0.0146574750
nodefactor.Domain.Other 0.0264891384
nodefactor.Domain.Secondary education 0.0283299379
nodefactor.Domain.Undergraduate 1.0000000000
nodefactor.Domain.Unknown 0.0200435383
nodefactor.Domain.Various 0.0233196842

edges nodefactor.Domain.Unknown 0.506680892
mutual 0.206628708
gwidegree 0.539805563
nodematch.Gender.F 0.249892747
nodematch.Gender.M 0.158205920
nodematch.Gender.Org 0.024801558
nodematch.Gender.Unknown 0.721435915
nodefactor.Domain.Community 0.027932339
nodefactor.Domain.Elementary and primary education 0.048084921
nodefactor.Domain.Entrepreneurship 0.181561150
nodefactor.Domain.Government 0.130308433
nodefactor.Domain.Health 0.200517365
nodefactor.Domain.Higher Education 0.266326684
nodefactor.Domain.Languages 0.227681230
nodefactor.Domain.Library 0.050136822
nodefactor.Domain.Organization 0.092549319
nodefactor.Domain.Other -0.006395582
nodefactor.Domain.Secondary education 0.217706263
nodefactor.Domain.Undergraduate 0.020043538
nodefactor.Domain.Unknown 1.000000000
nodefactor.Domain.Various 0.092764740

```

```

nodefactor.Domain.Organization nodefactor.Domain.Other
Lag 0 1.0000000 1.0000000
Lag 1024 0.9255489 0.7845069
Lag 2048 0.8606799 0.6127741
Lag 3072 0.8023264 0.4634444
Lag 4096 0.7565444 0.3577600
Lag 5120 0.7191442 0.2861780

nodefactor.Domain.Secondary education nodefactor.Domain.Undergraduate
Lag 0 1.0000000 1.0000000
Lag 1024 0.8939031 0.6684404
Lag 2048 0.8035353 0.4314014
Lag 3072 0.7293580 0.2795459
Lag 4096 0.6684204 0.1972900
Lag 5120 0.6165003 0.1314849

nodefactor.Domain.Unknown nodefactor.Domain.Various
Lag 0 1.0000000 1.0000000
Lag 1024 0.8716120 0.9303217
Lag 2048 0.7714445 0.8724157
Lag 3072 0.6887132 0.8193043
Lag 4096 0.6261163 0.7723890
Lag 5120 0.5727898 0.7318261

```

Sample statistics burn-in diagnostic (Geweke):

Chain 1

Fraction in 1st window = 0.1

Fraction in 2nd window = 0.5

```

edges
0.05044
mutual
0.28372
gwidegree
-0.51463
nodematch.Gender.F
1.05342
nodematch.Gender.M
-0.77085
nodematch.Gender.Org
-0.99103
nodematch.Gender.Unknown
-0.06608
nodefactor.Domain.Community
2.60822
nodefactor.Domain.Elementary and primary education
-0.77229
nodefactor.Domain.Entrepreneurship
-0.78821
nodefactor.Domain.Government
-1.20365
nodefactor.Domain.Health
-1.12079
nodefactor.Domain.Higher Education
0.22530
nodefactor.Domain.Languages
2.21018
nodefactor.Domain.Library
-0.77069
nodefactor.Domain.Organization
-0.52960
nodefactor.Domain.Other
-0.42884
nodefactor.Domain.Secondary education
-0.71109
nodefactor.Domain.Undergraduate
2.38083
nodefactor.Domain.Unknown
-0.46930
nodefactor.Domain.Various
-2.66171


```

Individual P-values (lower = worse):

```

edges
0.959769054
mutual
0.776626526

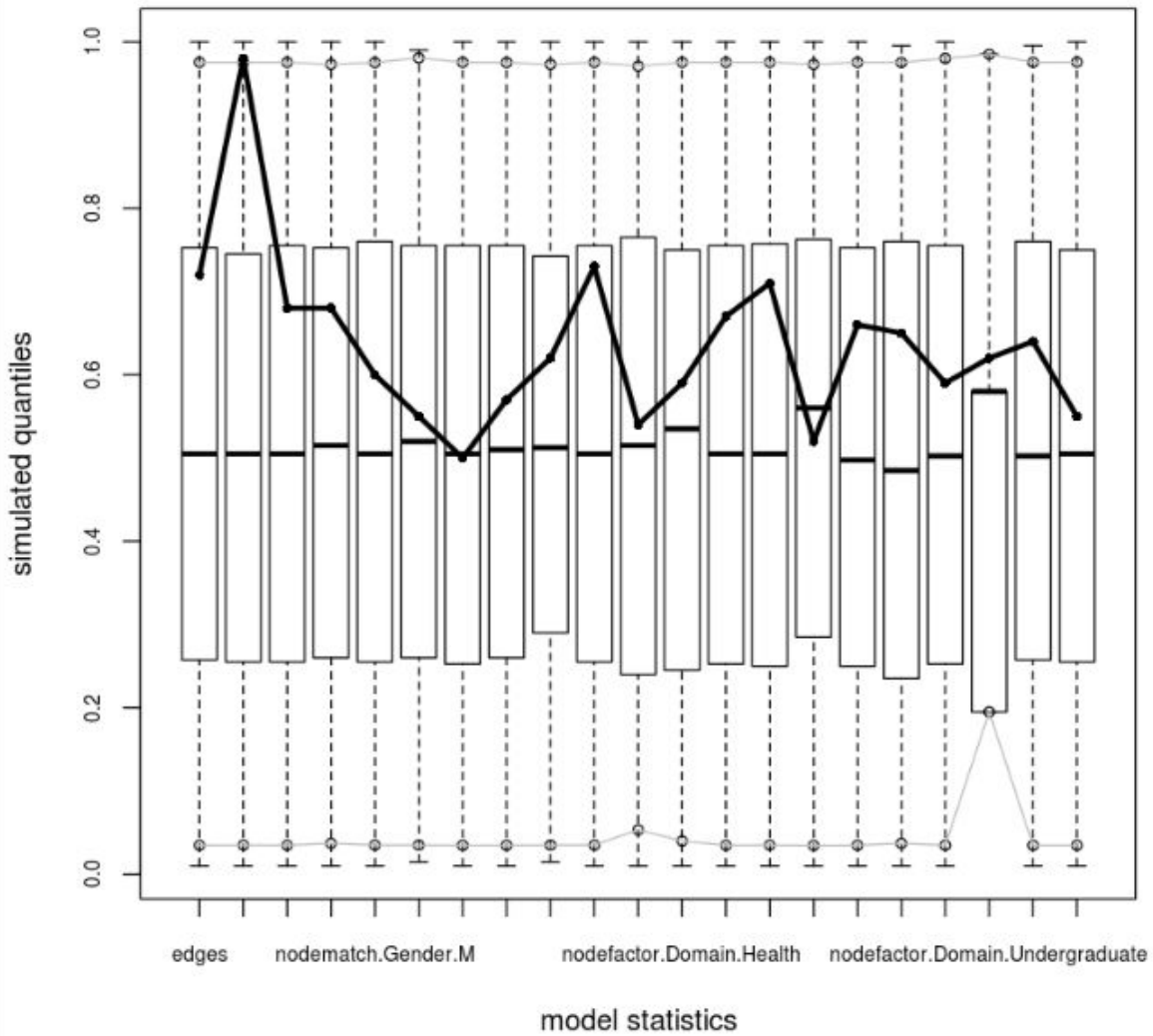
```



***sample stats show in first appendix, removed for brevity ***

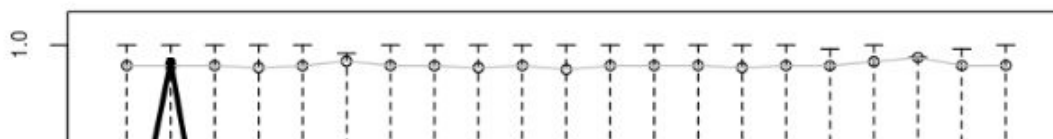
```
# generate compare plot for goodness of fit
mgof <- gof(model_v3, GOF=-model)
plot(mgof)
```

Goodness-of-fit diagnostics



```
# look at degree
mgof.degree <- gof(model_v3, GOF=-idegree)
plot(mgof)
```

Goodness-of-fit diagnostics



—


```
# check the odds of the data  
lapply(model_v3[1], exp)
```

Scoef =

edges

0.00391661826485624

mutual

41.0547372320082

gwidegree

0.063819727764621

nodematch.Gender.F

1.18799674927322

nodematch.Gender.M

1.21875251802766

nodematch.Gender.Org

0.770151522368293

nodematch.Gender.Unknown

4.89437985237417

nodefactor.Domain.Community

3.51890637065117

nodefactor.Domain.Elementary and primary education

0.868945447973084

nodefactor.Domain.Entrepreneurship

1.40750648049384

nodefactor.Domain.Government

0.766535273380976

nodefactor.Domain.Health

1.45876545194954

nodefactor.Domain.Higher Education

1.26808114702961

nodefactor.Domain.Languages

1.4658360717404

nodefactor.Domain.Library

0.896620272033604

nodefactor.Domain.Organization

1.38271530297064

nodefactor.Domain.Other

0.720486811932691

nodefactor.Domain.Secondary education

0.985729682828447

nodefactor.Domain.Undergraduate

0.160901322073474

nodefactor.Domain.Unknown

0.670788002542859

nodefactor.Domain.Various

1.25107529122044



References

CCK11 Dataset part of Gephi <https://gephi.org/users/download/>

Douglas A Luke, A User's Guide to Network Analysis in R

J. K. Harris, An Introduction to Exponential Random Graph Modeling

ERGM tutorial <http://www.irrodl.org/index.php/irrodl/article/view/2170/3388>

