FIT3152 Data analytics. Tutorial 11: Network Analysis – Solutions (by many contributors)

Download and install package functions using:

```
install.packages(c("igraph", "igraphdata"))
library(igraph)
library(igraphdata)
```

Formulas from lecture slides

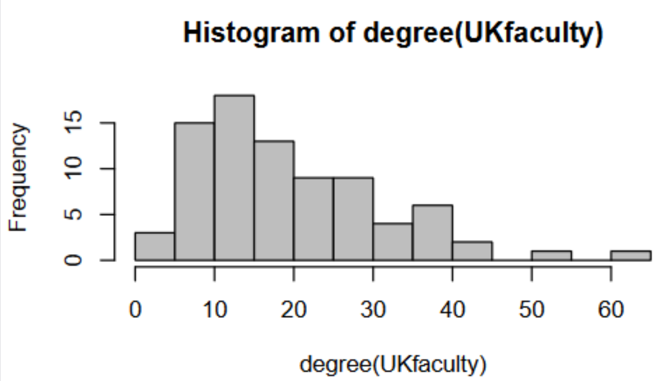
Density	**Clustering/transitivity coefficient**
$$den(g) = \frac{\lvert E_g \rvert}{\lvert V_g \rvert(\lvert V_g \rvert - 1)/2}$$ where $\lvert E_g \rvert$ is number of edges, $\lvert V_g \rvert$ is number of vertices	$$clt(g) = \frac{3\tau_{\Delta}(g)}{\tau 3(g)}$$ where $3\tau_{\Delta}(g)$ is number of triangles, $\tau 3(g)$ is number of connected triples
Closeness Centrality	**Betweenness Centrality**
$$c_{Cl}(v) = \frac{1}{\sum_{u \in V} \quad dist(u,v)}$$	$$c_B(v) = \sum_{s \neq t \neq v \in V} \frac{\sigma(s,t\vert v)}{\sigma(s,t)}$$ $\sigma(s,t)\sigma(s,t)$ is the number of shortest paths between *s* and *t*, $\sigma(s,t\vert v)\sigma(s,t\vert v)$ is the number of shortest paths between *s* and *t* passing through *v*

Pre-tutorial Activity

The dataset "UKfaculty" from the igraphdata package depicts the personal friendship network of a faculty at a UK university. The network is given as a directed, weighted graph.

1. Explore the degree distribution of nodes in the network

```
data("UKfaculty")
hist(degree(UKfaculty), breaks = 14, col = "grey")
```

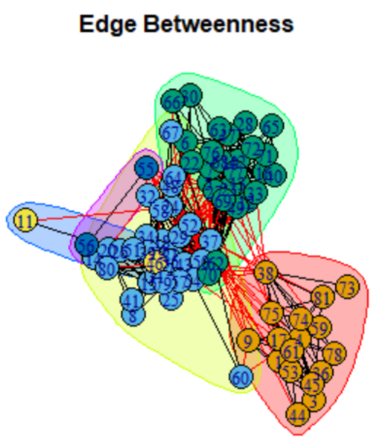


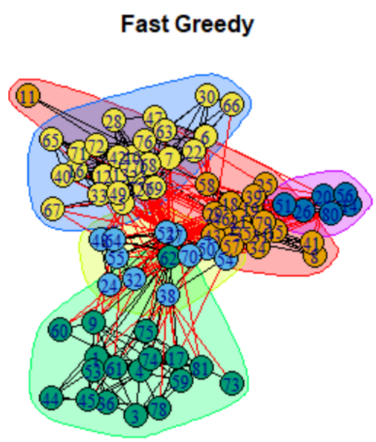
2. Calculate network statistics to identify key players in the network. For example which node/player has the most hub potential in the network.

```
#calculate network centrality measures and combine in a dataframe
d = as.table(degree(UKfaculty))
b = as.table(betweenness(UKfaculty))
c = as.table(closeness(UKfaculty))
e = as.table(evcent(UKfaculty)$vector)
stats = as.data.frame(rbind(d,b,c,e))
stats = as.data.frame(t(stats))
colnames(stats) = c("degree", "betweenness", "closeness", "eigenvector")

#sort and explore key nodes
head(stats)
stats[order(-stats$betweenness),]
stats[order(-stats$closeness),]
stats[order(-stats$eigenvector),]
stats[order(-stats$degree),]
```

3. Identify and plot community groups in the network considering edge betweenness and greedy modularity optimization. Hint: Treat the graph as undirected.

```
#identify community groups/clusters using cluster_edge_betweenness()
ceb = cluster_edge_betweenness(as.undirected(UKfaculty))

#identify community groups/clusters using cluster_fast_greedy()
cfg = cluster_fast_greedy(as.undirected(UKfaculty))

#create plots
par(mfrow = c(2,2)) #set plot parameters as 2x2 grid
g_ceb = plot(ceb,
as.undirected(UKfaculty),vertex.label=V(UKfaculty)$role,main="Edge
Betweenness")
g_cfg = plot(cfg,
as.undirected(UKfaculty),vertex.label=V(UKfaculty)$role,main="Fast
Greedy")
```

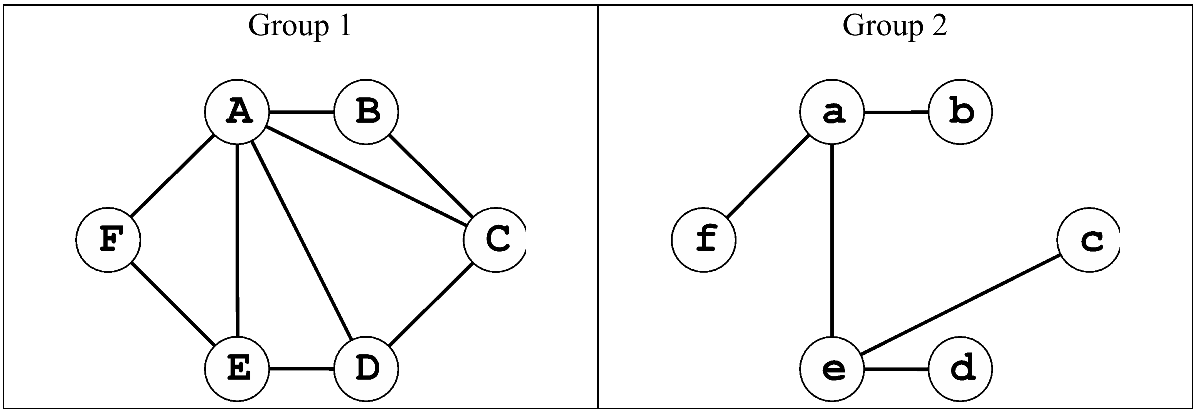




Tutorial Activities

4 Work through the analysis on the lecture slides. In particular the Research Collaborators and the Karate networks.

5 Two student groups are based on the friendship networks below.



(a) Calculate the following graph and vertex measures by hand for each group:
<u>Degree Distribution</u>

Group 1

Degree	N
0	0
1	0
2	2 - F, B
3	3 – C, D, E
4	0
5	1 – A

Group 2

Degree	N
0	0
1	4 – b,c,d,f
2	0
3	2 – a, e
4	0
5	0

<u>Betweenness</u>
Group 1

Node	betweenness
A	FAB, FAD/FED, FAC, EAB, EAC/EDC, DAB/DCB 1+1/2+1+1+1/2+1/2 = 4.5
B	0
C	DCB/DAB ½ = 0.5
D	EDC/EAC ½ = 0.5

E	FED/FAD ½ = 0.5
F	0

Group 2

Node	betweenness
a	fab, fae, faec, faed, bae, baed, baec 1+1+1+1+1+1+1 = 7
b	0
c	0
d	0
e	dec, dea, deab, deaf, cea, ceab, ceaf, 1+1+1+1+1+1+1 = 7
f	0

<u>Closeness</u>

Group 1

Node	closeness
A	AF, AE, AD, AC, AB 1/5
B	BA, BC, BCD or BAD, BAE, BAF 1/(1+1+2+2+2) = 1/8
C	CA, CB, CD, CDE or CAE, CAF 1/(1+1+1+2+2) = 1/7
D	DA, DAB or DCB, DC, DE, DEF or DAF 1/(1+2+1+1+2) = 1/7
E	EA,EAB, EDC, ED, EF 1/(1+2+2+1+1) = 1/7
F	FA, FAB, FAC, FAD or FED, FE 1/(1+2+2+2+1) = 1/8

Group 2

Node	closeness
a	ab, aec, aed, ae, af 1/(1+2+2+1+1) = 1/7
b	ba, baec, baed, bae, baf 1/(1+3+3+2+2) = 1/11
c	cea, ceab, ced, ce, ceaf 1/(2+3+2+1+3) = 1/11
d	dea, deab, dec, de, deaf 1/(2+3+2+1+3) = 1/11
e	ea, eab, ec, ed, eaf 1/(1+2+1+1+2) = 1/7
f	fa, fab, face, faed, fae 1/(1+2+3+3+2) = 1/11

Diameter

Distance matrix

Group 1: diameter = 2

	A	B	C	D	E	F
A		1	1	1	1	1
B			1	2	2	2
C				1	2	2
D					1	2
E						1
F						

Group 2: diameter = 3

	a	b	c	d	e	f
a		1	2	2	1	1
b			3	3	2	2
c				2	1	3
d					1	3
e						2
f						

Draw the distance matrix and calculate Average Path Length

Group 1: 21/15 = 1.4
Group 2: 29/15 = 1.93

Draw the Adjacency Matrix

Group 1

	A	**B**	**C**	**D**	**E**	**F**
A	0	1	1	1	1	1
B	1	0	1	0	0	0
C	1	1	0	1	0	0
D	1	0	1	0	1	0
E	1	0	0	1	0	1
F	1	0	0	0	1	0

Group 2

	a	**b**	**e**	**d**	**c**	**f**
a	0	1	1	0	0	1
b	1	0	0	0	0	0
e	1	0	0	1	1	0
d	0	0	1	0	0	0
c	0	0	1	0	0	0
f	1	0	0	0	0	0

(b) Create each graph using the igraph package in R and check your answers.

```
> G1 = graph.formula(A-B, B-C, C-D, D-E, E-F, F-A, A-C, A-D, A-E)
>
> degree(G1)
A B C D E F
5 2 3 3 3 2
>
> betweenness(G1)
  A   B   C   D   E   F
4.5 0.0 0.5 0.5 0.5 0.0
>
> format(closeness(G1), digits = 2)
     A      B      C      D      E      F
"0.20" "0.12" "0.14" "0.14" "0.14" "0.12"
>
> diameter(G1)
[1] 2
>
> average.path.length(G1)
[1] 1.4
>
> get.adjacency(G1)
6 x 6 sparse Matrix of class "dgCMatrix"
  A B C D E F
A . 1 1 1 1 1
B 1 . 1 . . .
C 1 1 . 1 . .
D 1 . 1 . 1 .
E 1 . . 1 . 1
F 1 . . . 1 .
>
> G2 = graph.formula(a-b, a-e, e-d, e-c, a-f)
>
> degree(G2)
a b e d c f
3 1 3 1 1 1
>
> betweenness(G2)
a b e d c f
7 0 7 0 0 0
>
> format(closeness(G2), digits = 2)
      a       b       e       d       c       f
"0.143" "0.091" "0.143" "0.091" "0.091" "0.091"
>
> diameter(G2)
[1] 3
>
> average.path.length(G2)
[1] 1.933333
>
 get.adjacency(G2)
6 x 6 sparse Matrix of class "dgCMatrix"
  a b e d c f
a . 1 1 . . 1
b 1 . . . . .
e 1 . . 1 1 .
d . . 1 . . .
c . . 1 . . .
f 1 . . . . .
```

(c) Using any of the network measures covered in the lecture describe the difference between the two networks. Identify the most powerful individual in each of the networks with respect to their ability to control information flow. Can you describe either of the graphs in terms of the network topologies given in Slide 64 of the lecture notes?

A is the most important vertex for Group 1 (is max on most measures), a and e are equally important in Group 2. Group 2 is a tree.

6 A group of friends have the following network (data on Moodle as Friends.csv)

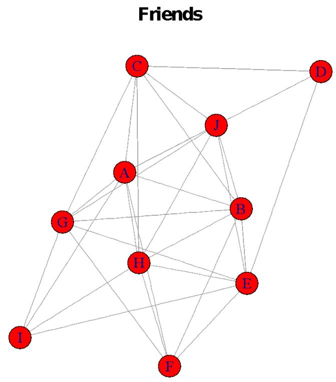
	A	B	C	D	E	F	G	H	I	J
A	0	1	1	1	0	1	1	1	1	1
B	1	0	1	0	1	1	1	1	0	1
C	1	1	0	1	0	0	1	1	0	1
D	1	0	1	0	1	0	0	0	0	0
E	0	1	0	1	0	1	1	1	1	1
F	1	1	0	0	1	0	1	1	0	0
G	1	1	1	0	1	1	0	0	1	1
H	1	1	1	0	1	1	0	0	1	1
I	1	0	0	0	1	0	1	1	0	0
J	1	1	1	0	1	0	1	1	0	0

Describe the network. Who is the most dominant member of the group?

```
> # This solution by Dilpreet

library(igraph)
library(igraphdata)

> adjFriends = read.csv("~/Desktop/Lecture 05 Friends.csv", header = TRUE,
      row.names = 1)
> adjMatrix = as.matrix(adjFriends)
> g1 = graph_from_adjacency_matrix(adjMatrix, mode = "undirected")
>
> plot(g1, vertex.color = "red", main = "Friends")
>
> degree = as.table(degree(g1))
> betweenness = as.table(betweenness(g1))
> closeness = as.table(closeness(g1))
> eig = as.table(evcent(g1)$vector)
>
> averagePath = average.path.length(g1)
> diameter = diameter(g1)
>
> tabularised = as.data.frame(rbind(degree, betweenness, closeness, eig))
> tabularised = t(tabularised)
>
> cat("Average Path Length: ", averagePath)
Average Path Length:  1.333333
>
> cat("\nDiameter: ", diameter, "\n\n")

Diameter:  2

> print(tabularised, digits = 3)
  degree betweenness closeness   eig
A      8       4.010    0.1000 1.000
B      7       0.936    0.0909 0.980
C      6       1.476    0.0833 0.817
D      3       0.343    0.0667 0.426
E      7       3.426    0.0909 0.871
F      5       0.286    0.0769 0.748
G      7       1.876    0.0909 0.933
H      7       1.876    0.0909 0.933
```

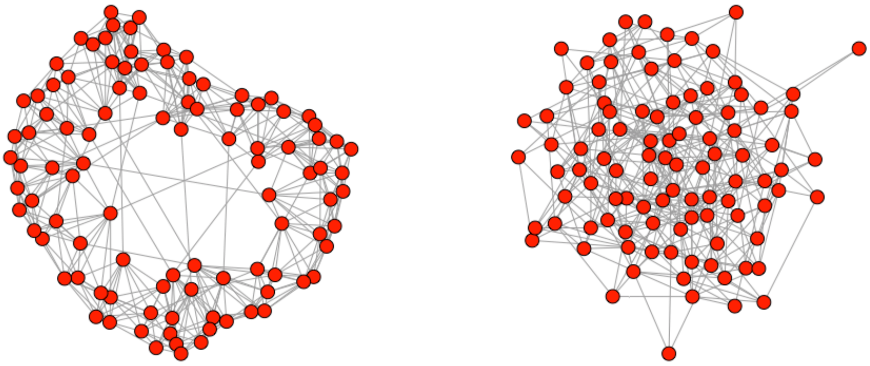
```
I      4       0.286    0.0714 0.593
J      6       0.486    0.0833 0.877
>
> # Print properties ordered by degree
> cat("\nOrder by Degree\n")

Order by Degree
> print(head(tabularised[order(-degree),]), digits = 3)
  degree betweenness closeness   eig
A      8       4.010    0.1000 1.000
B      7       0.936    0.0909 0.980
E      7       3.426    0.0909 0.871
G      7       1.876    0.0909 0.933
H      7       1.876    0.0909 0.933
C      6       1.476    0.0833 0.817
>
> # Print properties ordered by betweenness
> cat("\nOrder by Betweenness\n")

Order by Betweenness
> print(head(tabularised[order(-betweenness),]), digits = 3)
  degree betweenness closeness   eig
A      8       4.010    0.1000 1.000
E      7       3.426    0.0909 0.871
G      7       1.876    0.0909 0.933
H      7       1.876    0.0909 0.933
C      6       1.476    0.0833 0.817
B      7       0.936    0.0909 0.980
>
> # Print properties ordered by closeness
> cat("\nOrder by Closeness\n")

Order by Closeness
> print(head(tabularised[order(-closeness),]), digits = 3)
  degree betweenness closeness   eig
A      8       4.010    0.1000 1.000
B      7       0.936    0.0909 0.980
E      7       3.426    0.0909 0.871
G      7       1.876    0.0909 0.933
H      7       1.876    0.0909 0.933
C      6       1.476    0.0833 0.817
>
> # Print properties ordered by eigenvector centrality
> cat("\nOrder by Eigenvector Centrality\n")

Order by Eigenvector Centrality
> print(head(tabularised[order(-eig),]), digits = 3)
  degree betweenness closeness   eig
A      8       4.010    0.1000 1.000
B      7       0.936    0.0909 0.980
H      7       1.876    0.0909 0.933
G      7       1.876    0.0909 0.933
J      6       0.486    0.0833 0.877
E      7       3.426    0.0909 0.871
```

Based on the analysis above, Friends A, followed by B, are the most important players in the network. A is first ranked in all measures, B is second ranked in most.



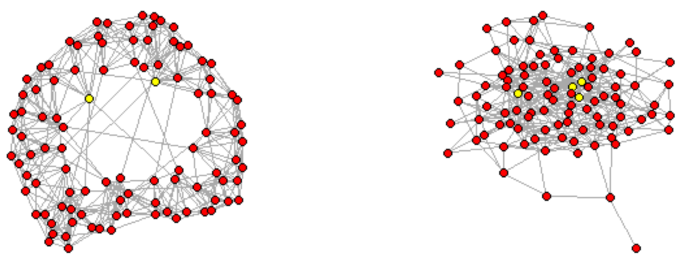
7 The two networks were generated with the following script. By using an appropriate choice of network statistics and vertex importance/centrality measures comment on (a) how the two networks are different, and (b) which node/nodes are the most important in each network.

(a) (b)



```
library(igraph)
set.seed(999)
# Generate a graph with 100 vertex
g <- sample_smallworld(1, 100, 5, 0.03)
# Modify some properties of the vertex
V(g)$label <- NA
V(g)$size <- 8
V(g)$color <- "red"
# Generate a graph with 100 vertex and edge with a prob. of 1/15 between
any 2 vertex
h <- erdos.renyi.game(100, 1/15)

# Modify some properties of the vertex
V(h)$label <- NA
V(h)$size <- 8
V(h)$color <- "red"
# Create a grid of 1 row 2 columns for plotting
par(mfrow=c(1,2))
plot(g, layout =  layout.fruchterman.reingold)
plot(h, layout =  layout.fruchterman.reingold)
```

```
# Compare densities of graphs
graph.density(g)
graph.density(h)
# Compare diameter of graphs
diameter(g)
diameter(h)
# Compare clustering coefficient of graphs
transitivity(g)
transitivity(h)

# Compare individual vertex based on closeness centrality
closeness(g)
closeness(h)
# Compare individual vertex based on betweenness centrality
betweenness(g)
betweenness(h)

# Seems like vertex 70 and 47 are the one with highest closeness, betweennes and
      degree.
# So that ones are the most important.
order(closeness(g), decreasing = T)
order(betweenness(g), decreasing = T)
order(degree(g), decreasing = T)

# Let's colour those important nodes and see where they are in the network
V(g)[70]$color = "yellow"
V(g)[47]$color = "yellow"
plot(g)

#91  14  31  37 appears in the top for all measures. Hence, those vertex are the
      most important
order(closeness(h), decreasing = T)
order(betweenness(h), decreasing = T)
order(degree(h), decreasing = T)

# Lets colour those important nodes and see where they are in the network
V(h)[91]$color = "yellow"
V(h)[14]$color = "yellow"
V(h)[31]$color = "yellow"
V(h)[37]$color = "yellow"
plot(h)
```



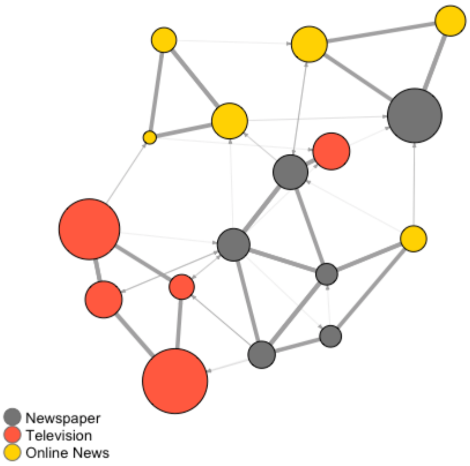
8 Create a <u>Complete</u>, <u>Ring</u>, <u>Tree</u> and <u>Star</u> graph each of 8 vertices (using the code in the lecture notes). Calculate the network and vertex statistics and explain, with reasons, which network structure is most robust (that is a failure in any node will have least effect on information flow through the network) and by contrast, which structure is most fragile.

```
library(igraph)

g.full <- graph.full(8)
g.ring <- graph.ring(8)
g.tree <- graph.tree(8, children=4, mode="undirected")
g.star <- graph.star(8, mode="undirected")

par(mfrow=c(2, 2))
plot(g.full)
plot(g.ring)
plot(g.tree)
plot(g.star)

degree = as.table(degree(g.full))
betweenness = as.table(betweenness(g.full))
closeness = as.table(closeness(g.full))
eig = as.table(evcent(g.full)$vector)
f.averagePath = average.path.length(g.full)
f.diameter = diameter(g.full)
T.full = as.data.frame(rbind(degree, betweenness, closeness, eig))
T.full = t(T.full)

degree = as.table(degree(g.ring))
betweenness = as.table(betweenness(g.ring))
closeness = as.table(closeness(g.ring))
eig = as.table(evcent(g.ring)$vector)
r.averagePath = average.path.length(g.ring)
r.diameter = diameter(g.ring)
T.ring = as.data.frame(rbind(degree, betweenness, closeness, eig))
T.ring = t(T.ring)

degree = as.table(degree(g.tree))
betweenness = as.table(betweenness(g.tree))
closeness = as.table(closeness(g.tree))
eig = as.table(evcent(g.tree)$vector)
t.averagePath = average.path.length(g.tree)
t.diameter = diameter(g.tree)
T.tree = as.data.frame(rbind(degree, betweenness, closeness, eig))
T.tree = t(T.tree)

degree = as.table(degree(g.star))
betweenness = as.table(betweenness(g.star))
closeness = as.table(closeness(g.star))
eig = as.table(evcent(g.star)$vector)
s.averagePath = average.path.length(g.star)
s.diameter = diameter(g.star)
T.star = as.data.frame(rbind(degree, betweenness, closeness, eig))
T.star = t(T.star)
```

9 Use the following data and code to generate a basic graph.

```
library("igraph")
nodes <- read.csv("Dataset1-Media-Example-NODES.csv", header=T, as.is=T)
links <- read.csv("Dataset1-Media-Example-EDGES.csv",header=T, as.is=T)
# Create Igraph object
net <- graph_from_data_frame(d=links, vertices=nodes, directed=T)
plot(net)
```

Using the example in https://kateto.net/wp-content/uploads/2018/06/Polnet%202018%20R%20Network%20Visualization%20Workshop.pdf
try and improve the plot, along the lines of the example given.




```
nodes <- read.csv("Dataset1-Media-Example-NODES.csv", header=T, as.is=T)
links <- read.csv("Dataset1-Media-Example-EDGES.csv",header=T, as.is=T)

# Create Igraph object
net <- graph_from_data_frame(d=links, vertices=nodes, directed=T)

plot(net)

# Run the codes below and see properties of Edges and Vertex
# assigned from nodes and links dataframes
E(net) # The edges of the "net" object
V(net) # The vertices of the "net" object
E(net)$type # Edge attribute "type"
V(net)$media # Vertex attribute "media"

# Previous plot looked so complicated so remove loops -- arraw from and to same
      vertex --
net <- simplify(net, remove.multiple = F, remove.loops = T)

## Design and create a network visualisation

#Generate colors based on media type:
colrs <- c("gray50", "tomato", "gold")
V(net)$color <- colrs[V(net)$media.type]

# Compute node degrees (#links) and use that to set node size:
deg <- degree(net, mode="all")
V(net)$size <- deg*3

# We could also use the audience size value:
V(net)$size <- V(net)$audience.size*0.6
```

```
# The labels are currently node IDs.
# Setting them to NA will render no labels:
V(net)$label <- NA

# Set edge width based on weight:
E(net)$width <- E(net)$weight/6

#change arrow size and edge color:
E(net)$arrow.size <- .2
E(net)$edge.color <- "gray80"

# We can even set the network layout:
graph_attr(net, "layout") <- layout_with_lgl
plot(net)

# Add a legend
legend(x=-1.5, y=-1.1, c("Newspaper","Television", "Online News"), pch=21,
       col="#777777", pt.bg=colrs, pt.cex=2, cex=.8, bty="n", ncol=1)
```

10 Create a random graph based on the scale-free Barabási-Albert model using the code below.

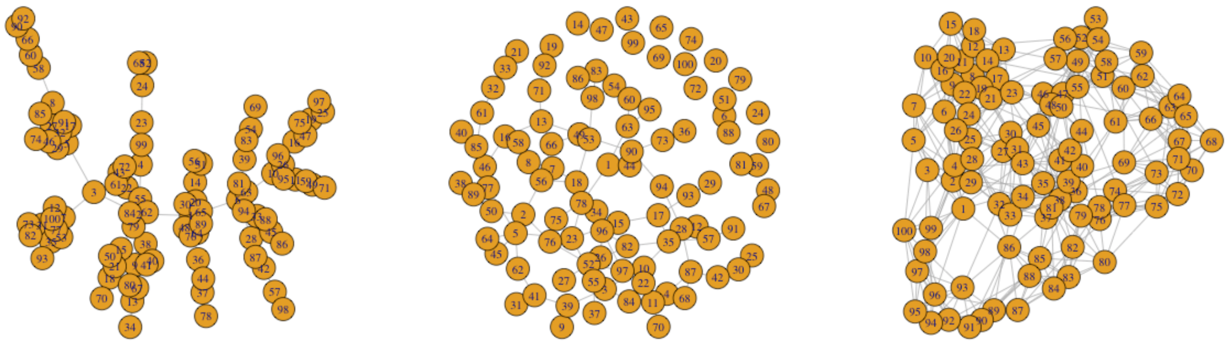
```
      > set.seed(9999)
> BA <- sample_pa(100)
```

Now create another graph according to Erdós-Rényi random graph model.

```
> set.seed(9999)
> ER <- sample_gnm(100, 100)
```

Now create a Small World graph according to the Watts and Strogatz model.

```
> set.seed(9999)
SW <- sample_smallworld(1, 100, 5, 0.05)

set.seed(9999)
BA <- sample_pa(100)

BA <- as.undirected(BA)

set.seed(9999)
ER <- sample_gnm(100, 100)

set.seed(9999)
SW <- sample_smallworld(1, 100, 5, 0.05)


par(mfrow=c(1, 3))
plot(BA)
plot(ER)
plot(SW)
```



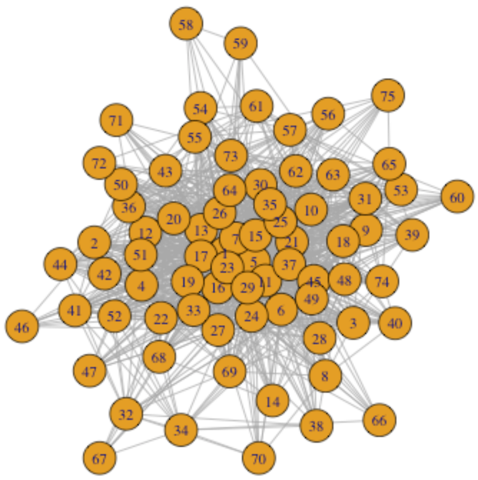
```
degree = as.table(degree(BA))
betweenness = as.table(betweenness(BA))
closeness = as.table(closeness(BA))
eig = as.table(evcent(BA)$vector)
averagePath = average.path.length(BA)
diameter = diameter(BA)
T.BA = as.data.frame(rbind(degree, betweenness, closeness, eig))
T.BA = t(T.BA)

degree = as.table(degree(ER))
betweenness = as.table(betweenness(ER))
closeness = as.table(closeness(ER))
eig = as.table(evcent(ER)$vector)
averagePath = average.path.length(ER)
diameter = diameter(ER)
T.ER = as.data.frame(rbind(degree, betweenness, closeness, eig))
T.ER = t(T.ER)

degree = as.table(degree(SW))
betweenness = as.table(betweenness(SW))
closeness = as.table(closeness(SW))
eig = as.table(evcent(SW)$vector)
averagePath = average.path.length(SW)
diameter = diameter(SW)
T.SW = as.data.frame(rbind(degree, betweenness, closeness, eig))
T.SW = t(T.SW)

#order using degree/betweenness/closeness as needed
print(T.BA[order(-betweenness),])
print(T.ER[order(-betweenness),])
print(T.SW[order(-betweenness),])
```

(a) Using any of the techniques covered in the lecture, such as degree distribution, cliques and the closeness measures comment on the main differences between the graphs.

(b) Which type of network has more powerful individuals with respect to their ability to control information flow in the network?

11 The file “rfid” contains encounter network data for staff in a hospital. Looking at the simplified network, describe the network and calculate summary statistics. Using the results of your analysis, identify the most important people in the network. Use the following code to create the data

```
> library(igraph)
> library(igraphdata)
> data(rfid)
> nrfid <- rfid
> nrfid <- simplify(nrfid, remove.multiple = TRUE, remove.loops = TRUE,
+                  edge.attr.comb = getIgraphOpt("edge.attr.comb"))
> plot(nrfid)

degree = as.table(degree(nrfid))
betweenness = as.table(betweenness(nrfid))
closeness = as.table(closeness(nrfid))
eig = as.table(evcent(nrfid)$vector)
averagePath = average.path.length(nrfid)
diameter = diameter(nrfid)
T.nrfid = as.data.frame(rbind(degree, betweenness, closeness, eig))
T.nrfid = t(T.nrfid)

print(T.nrfid[order(-betweenness),])
```



```
> print(T.nrfid[order(-betweenness),])
   degree  betweenness   closeness       eig
A      61 109.14283032 0.011494253 1.0000000
W      58  94.95749118 0.011111111 0.9470520
Q      57  84.45036602 0.010989011 0.9590789
G      57  77.48865860 0.010989011 0.9508491
...
```

12 The following data records the attendance 18 women at social functions over a 9 month period during the 1930s. The data was recorded by Davis, and reported in Davis, A., Gardner, B. B. and M. R. Gardner (1941) *Deep South, Chicago*: The University of Chicago Press.

Names of Participants of Group I	Code Numbers and Dates of Social Events Reported in *Old City Herald*													
	(1) 6/27	(2) 3/2	(3) 4/12	(4) 9/26	(5) 2/25	(6) 5/19	(7) 3/15	(8) 9/16	(9) 4/8	(10) 6/10	(11) 2/23	(12) 4/7	(13) 11/21	(14) 8/3
1. Mrs. Evelyn Jefferson	X	X	X	X	X	X		X	X					
2. Miss Laura Mandeville	X	X	X		X	X	X	X						
3. Miss Theresa Anderson		X	X	X	X	X	X	X	X					
4. Miss Brenda Rogers	X		X	X	X	X	X	X						
5. Miss Charlotte McDowd			X	X	X		X							
6. Miss Frances Anderson			X		X	X		X						
7. Miss Eleanor Nye					X	X	X	X						
8. Miss Pearl Oglethorpe						X		X	X					
9. Miss Ruth DeSand					X		X	X	X					
10. Miss Verne Sanderson							X	X	X			X		
11. Miss Myra Liddell								X	X	X		X		
12. Miss Katherine Rogers								X	X	X		X	X	X
13. Mrs. Sylvia Avondale							X	X	X	X		X	X	X
14. Mrs. Nora Fayette						X	X		X	X	X	X	X	X
15. Mrs. Helen Lloyd							X	X		X	X	X		
16. Mrs. Dorothy Murchison								X	X					
17. Mrs. Olivia Carleton									X		X			
18. Mrs. Flora Price									X		X			

In the table above, an X indicates the attendance by a woman at an event. By treating each pair of women who attended the same event as being 'connected' and aggregating this over the 14 meetings construct a social network for the women using the following methods:

(a) Create a bipartite graph of this social network. Note: to do this first create a suitable data structure using the example in Lecture 12. Make a suitable network plot.

(b) Create a graph of the connections between the women. Treat the graph as unweighted. That is, the number of meetings each pair of women attended is not counted (1 if the pair were present at any meeting and 0 otherwise). Make a suitable network plot.

(c) Extension. Adapt Part (b) treating the graph as weighted. That is, each pair of women attending each meeting is counted. For example, the first pair of women (Jefferson and Mandeville) would have a weight of 6 since they both attended 6 meetings where the other was in attendance. Make a suitable network plot.

You may want to create csv files for this problem.

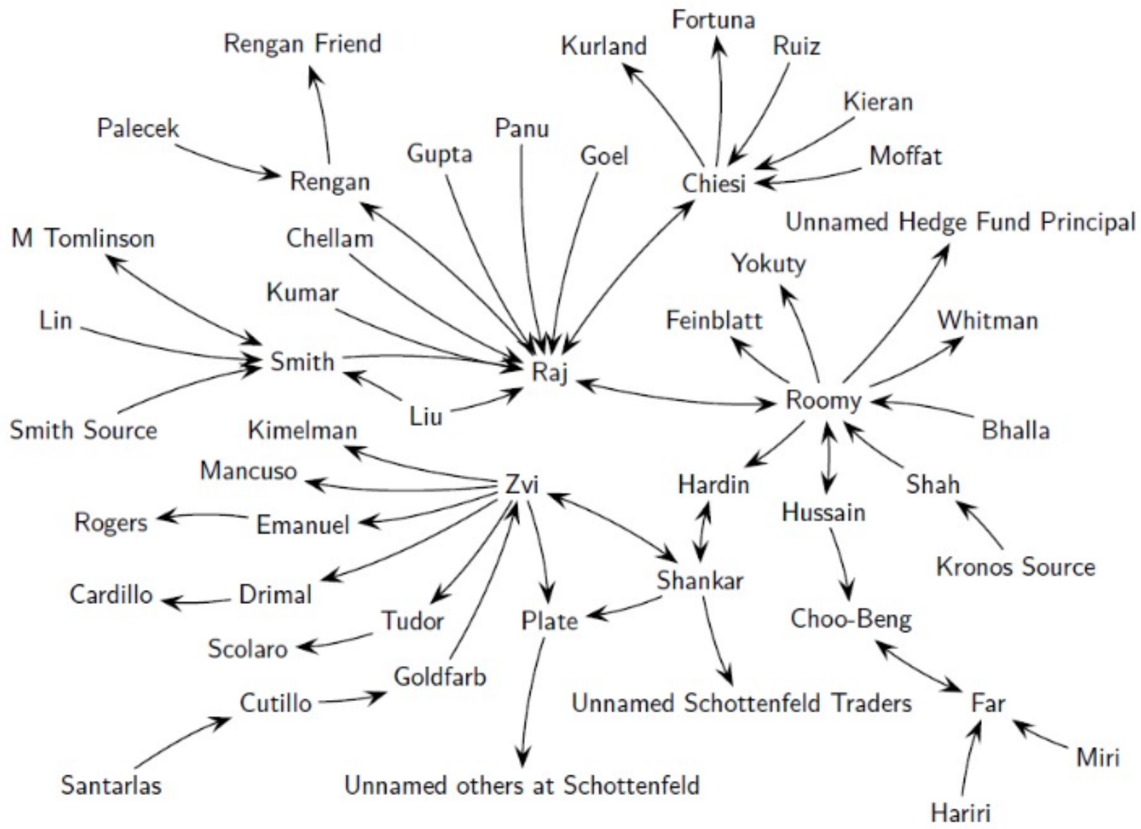
Analyse the data and describe the social network formed using both methods. Are there differences in your analysis for part (b) that become apparent using weighted edges.

For more information on the data see:
http://svitsrv25.epfl.ch/R-doc/library/latentnet/html/davis.html

Solutions to come.

13 The following graph shows an alleged insider trading network. Construct the directed graph in igraph and using your analysis identify who, in addition to Raj Rajaratnam, was an important player in the network. (You might want to enter your data into R as a directed graph formula (Slides 64, 65), using a two letter abbreviation for each person)

For more information on the data see:
https://www.valuewalk.com/2015/03/information-networks-evidence-from-illegal-insider-trading-tips/



Solutions to come.