Network

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In this example we use following libraries. Install the libraries in case you have not before. We also collect Twitter data using `rtweet`. So make sure you have your twitter token in your system.

```
library(rtweet)
library(dplyr)
library(plotly)
library(igraph)
library(RColorBrewer)

# Create twitter token
source("0_token.R")
```

```
# In case you don't have above packages..
install.packages("package.name")
```

In this exampel we tweets containing two keywords “rigged” and “election”. This will take about an hour. Q. Why?

```
# Data collection
rigged <- search_tweets(q = "rigged election",
                        n = 72000,
                        retryonratelimit = TRUE,
                        since = "2020-12-03",
                        until = "2020-12-05")
```

Check collected data.

```
dim(rigged)
```

```
## [1] 59790    90
```

```
head(rigged)[,1:5]
```

```
## # A tibble: 6 x 5
##   user_id    status_id    created_at          screen_name  text
##   <chr>      <chr>        <dttm>              <chr>        <chr>
## 1 796568442  13349298819… 2020-12-04 18:37:40 MartinRoyHi… "@realDonaldTrump Ye
…
## 2 127132210… 13349298767… 2020-12-04 18:37:39 anthonygyam… "Mitt Romney on CNN:
…
## 3 122108652… 13349298761… 2020-12-04 18:37:38 susanlovesb… "Not statistically p
…
## 4 122108652… 13349285749… 2020-12-04 18:32:28 susanlovesb… "Rigged Election. Sh
…
## 5 122108652… 13349273000… 2020-12-04 18:27:24 susanlovesb… "RIGGED ELECTION!"
## 6 16260533   13349298652… 2020-12-04 18:37:36 decamom      "Proud to Chair the
…
```

```
min(rigged$created_at)
```

```
## [1] "2020-12-02 23:54:26 UTC"
```

```
max(rigged$created_at)
```

```
## [1] "2020-12-04 18:37:40 UTC"
```

Now let's create a graph object using the data.

```
# Create graph object -----------------------------
t_rt <- rigged %>%
  filter(is_retweet == 'TRUE') %>%
  select(user_id,retweet_user_id,screen_name, retweet_screen_name, verified, retwe
et_verified)


t_rt <- as.matrix(t_rt)

# edges
edges <- t_rt[,c(1,2)]
head(edges)
```

```
##      user_id               retweet_user_id
## [1,] "1271322107767480322" "32871086"
## [2,] "1221086524000870410" "25073877"
## [3,] "1221086524000870410" "25073877"
## [4,] "1221086524000870410" "25073877"
## [5,] "16260533"            "74303349"
## [6,] "813898161500528640"  "25073877"
```

```
# actors
actors <- rbind(t_rt[,c(1,3,5)], t_rt[,c(2,4,6)])
head(actors)
```

```
##      user_id               screen_name       verified
## [1,] "1271322107767480322" "anthonygyamfi11" "FALSE"
## [2,] "1221086524000870410" "susanlovesbrad2" "FALSE"
## [3,] "1221086524000870410" "susanlovesbrad2" "FALSE"
## [4,] "1221086524000870410" "susanlovesbrad2" "FALSE"
## [5,] "16260533"            "decamom"         "FALSE"
## [6,] "813898161500528640"  "lovescienceart"  "FALSE"
```

```
# Check if there are duplicated user_ids
table(duplicated(actors[,1]))
```

```
##
## FALSE  TRUE
## 41132 47372
```

```
length(unique(actors[,1]))
```

```
## [1] 41132
```

```
# Remove duplicated ones
dup <- duplicated(actors[,1])
actors <- actors[!dup,] # ! is negation.
```

```
# Create a graph object using igraph function
g <- graph_from_data_frame(edges, directed=TRUE, vertices = actors)
```

```
# Check graph object
summary(g)
```

```
## IGRAPH 8945a35 DN-- 41132 44252 --
## + attr: name (v/c), screen_name (v/c), verified (v/c), degree (v/n),
## | indegree (v/n), color (v/c), color2 (v/c), label_fg (v/c), outdegree
## | (v/n), closeness (v/n), between (v/n)
```

```
# Check Edges and nodes
V(g)
```

```
## + 41132/41132 vertices, named, from 8945a35:
##     [1] 1271322107767480322 1221086524000870410 16260533
##     [4] 813898161500528640  765386574880137216  824705339383840768
##     [7] 477414516           312606173           839540301207318528
##    [10] 2169506769          821173258842042369  2575780104
##    [13] 859722686           1080409535880351744 1371234511
##    [16] 1140183143468736512 1330005307368501249 1227021286968365057
##    [19] 1309967277073330176 1165748373476917248 574427567
##    [22] 1135234412          1140962418002190336 570058505
##    [25] 843908050847186944  98222944            1103992284
##    [28] 1260647419          521826631           2229667098
## + ... omitted several vertices
```

```
E(g)
```

```
## + 44252/44252 edges from 8945a35 (vertex names):
##  [1] 1271322107767480322->32871086
##  [2] 1221086524000870410->25073877
##  [3] 1221086524000870410->25073877
##  [4] 1221086524000870410->25073877
##  [5] 16260533           ->74303349
##  [6] 813898161500528640 ->25073877
##  [7] 765386574880137216 ->216776631
##  [8] 824705339383840768 ->25073877
##  [9] 477414516          ->216776631
## [10] 312606173          ->25073877
## + ... omitted several edges
```

```
head(V(g)$screen_name)
```

```
## [1] "anthonygyamfi11" "susanlovesbrad2" "decamom"         "lovescienceart"
## [5] "savizzlemynizzl" "ke6byr"
```

```
head(V(g)$verified)
```

```
## [1] "FALSE" "FALSE" "FALSE" "FALSE" "FALSE" "FALSE"
```

Let's check if Donald Trump's node is existed in our network.

```
# Finding Donald Trump
trump_v <- which(V(g)$screen_name == "realDonaldTrump")
trump_v
```

```
## [1] 40084
```

```
# Trump degree
degree(g, v = trump_v)
```

```
## 25073877
##    19540
```

```
# Trump indegree
degree(g, v = trump_v, mode = "in")
```

```
## 25073877
##    19540
```

```
# Trump outdegree
degree(g, v = trump_v, mode = "out")
```

```
## 25073877
##        0
```

Centrality

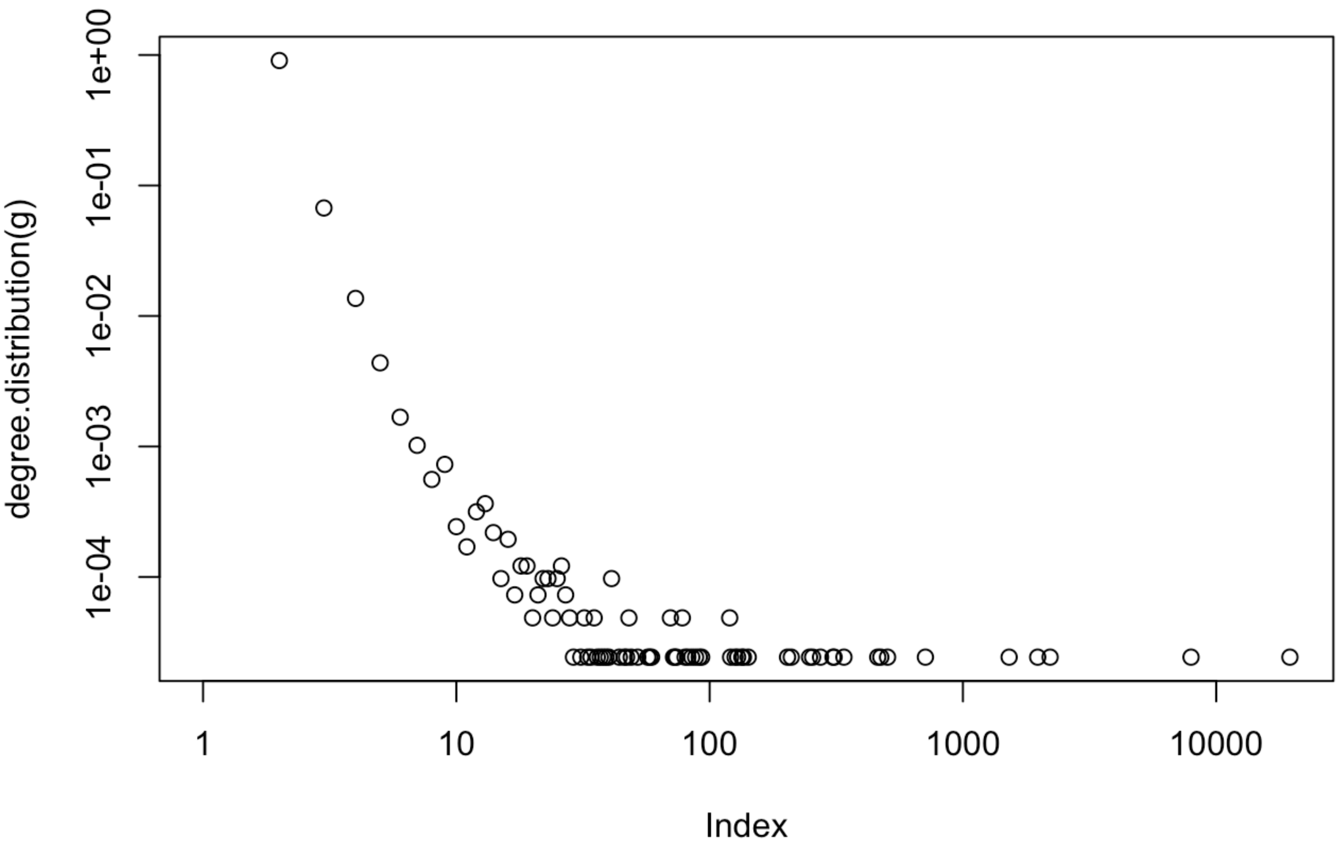
Here we calculate three centrality measures: degree, betweenness, closeness. Other centrality can be measured using igraph function. For more detail, check its documentation.

```
# degree
head(degree(g))
```

```
## 1271322107767480322 1221086524000870410            16260533  813898161500528640
##                   1                   3                   1                   1
##  765386574880137216  824705339383840768
##                   1                   1
```

```
# Plot the degree distribution in a log-log plot
plot(degree.distribution(g), log = "xy")
```

```
## Warning in xy.coords(x, y, xlabel, ylabel, log): 19458 y values <= 0 omitted
## from logarithmic plot
```




```
# Let's write the degree as a node attribute:
V(g)$degree <- degree(g)
V(g)$indegree <- degree(g, mode="in") # The same can be done for in-degree:
V(g)$outdegree <- degree(g, mode="out") # and out-degree


# Chek top 10 nodes by its degree
V(g)[order(-degree)]$degree[1:10]
```

```
##  [1] 19540  7953  2208  1972  1521   710   503   473   460   338
```

```
V(g)[order(-degree)]$screen_name[1:10]
```

```
##  [1] "realDonaldTrump" "BernieSanders"   "justinbaragona"  "kylegriffin1"
##  [5] "MarkFinchem"     "tuckahoetommy"   "mkraju"          "weijia"
##  [9] "ericswalwell"    "TeaPainUSA"
```

```
# Also check is those accounts are verified one or not
V(g)[order(-degree)][1:10]$verified
```

```
##  [1] "TRUE"  "TRUE"  "TRUE"  "TRUE"  "FALSE" "FALSE" "TRUE"  "TRUE"  "TRUE"
## [10] "FALSE"
```

```
# Also indegree
V(g)[order(-indegree)][1:10]$screen_name
```

```
##  [1] "realDonaldTrump" "BernieSanders"   "justinbaragona"  "kylegriffin1"
##  [5] "MarkFinchem"     "tuckahoetommy"   "mkraju"          "weijia"
##  [9] "ericswalwell"    "TeaPainUSA"
```

```
V(g)[order(-indegree)][1:10]$verified
```

```
##  [1] "TRUE"  "TRUE"  "TRUE"  "TRUE"  "FALSE" "FALSE" "TRUE"  "TRUE"  "TRUE"
## [10] "FALSE"
```

```
# Closeness and Betweenness
# It can take couple of minutes!
V(g)$closeness <- closeness(g, mode = "all") # "all" uses undirected pass.
V(g)$between <- betweenness(g, directed = FALSE)
```

```
# Check top 10 nodes by two centrarity measures
V(g)[order(-closeness)]$screen_name[1:10]
```

```
##  [1] "realDonaldTrump" "SmithSeigel"     "sangersprings"   "SiegelGeorge6"
##  [5] "FanFDC"          "tthornton1969"   "MAGAGirlDiva"    "hypnoticOMG"
##  [9] "bayiskendr"      "monty723"
```

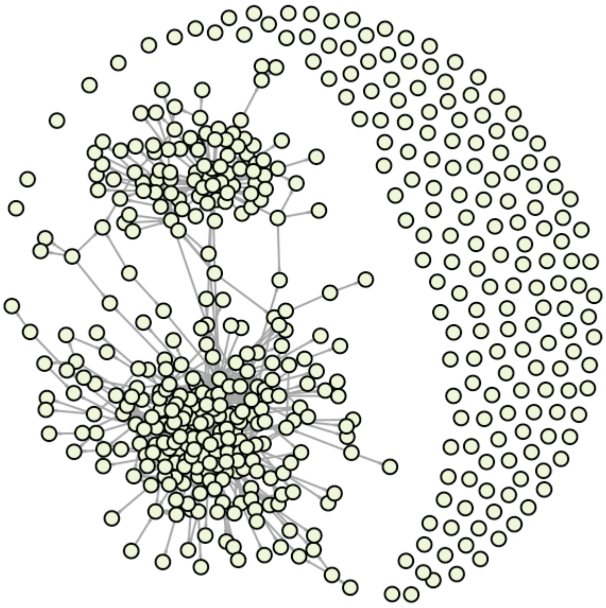
```
V(g)[order(-between)]$screen_name[1:10]
```

```
##  [1] "realDonaldTrump" "BernieSanders"   "justinbaragona"  "kylegriffin1"
##  [5] "SmithSeigel"     "MarkFinchem"     "tuckahoetommy"   "weijia"
##  [9] "ericswalwell"    "sangersprings"
```

Plot graph

Lets plot our retweet network. igraph does not plot well when it has more than 1,000 of nodes. So in this example, we plot a small subset of the graph.

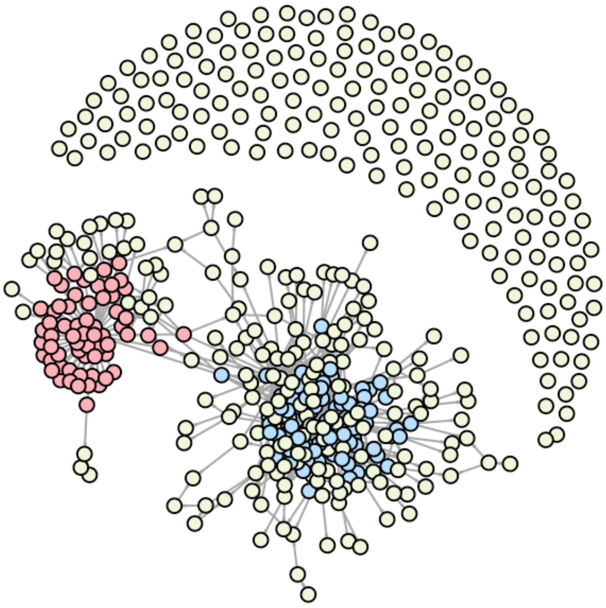
```
# simple plot

# Set node color
V(g)$color <- rgb(239, 249, 222, maxColorValue = 255) # light green

# Get top nodes
top_nodes <- V(g)[order(-degree)][1:500]

# Create a small graph
small.g <- delete.vertices(g, which(!V(g) %in% top_nodes)) # delete nodes if those are not included in 'top_nodes'

# Layout setting. We use Fruchterman Rheingold algorithm for network layout.
lay <- layout_with_fr(small.g)

small.g <- simplify(small.g)
plot(small.g,
     vertex.label = NA,
     vertex.size = 5,
     edge.arrow.size = 0.1,
     edge.arrow.width = 0.3,
     vertex.color = V(small.g)$color,
     layout = lay)
```



```
# Plot: Set color ----------------------

# add color

# base color2 # light green
V(g)$color2 <- rgb(239, 249, 222, maxColorValue = 255)



# Add red color to @realDonaldTrump and nodes who retweeted realDonaldTrump
ok <- V(g)$screen_name == "realDonaldTrump"
V(g)$color2[ok] <- (rgb(255,179,186, maxColorValue = 255)) # red
ok2 <- neighbors(g, ok, mode = "in")
V(g)$color2[ok2] <- (rgb(255,179,186, maxColorValue = 255))

# Add blue color to @BernieSanders and nodes who retweeted BernieSanders
ok <- V(g)$screen_name == "BernieSanders"
V(g)$color2[ok] <- rgb(186,225,255, maxColorValue = 255) # blue
ok2 <- neighbors(g, ok, mode = "in")
V(g)$color2[ok2] <- rgb(186,225,255, maxColorValue = 255)


# check
table(V(g)$color2)
```

```
##
## #BAE1FF #EFF9DE #FFB3BA
##    7953   13878   19301
```

```
# Lets plot again.

top_nodes <- V(g)[order(-degree)][1:500]
small.g <- delete.vertices(g, which(!V(g) %in% top_nodes))
lay <- layout_with_fr(small.g)


small.g <- simplify(small.g)
plot(small.g,
     vertex.size = 5,
     edge.arrow.size = 0.1,
     edge.arrow.width = 0.3,
     vertex.label = NA,
     vertex.color = V(small.g)$color2,
     layout = lay
     )

mtext("Top 500 users by degree", side = 1)
```



Top 500 users by degree

Clustering

It looks like this network has some clusters. Lets figure out clusters using fast greedy algorithm here. Note that it might take couple of minitues to get the results.

```
un_g <- as.undirected(g) # it should be undirected graph
un_g <- simplify(un_g) # remove redundent edges

# Fast greedy algorithm
fg <- cluster_fast_greedy(un_g)
```

```
# Check how many clusters are detected
length(fg)
```

```
## [1] 793
```

```
# Check sizes of the clusters
head(sizes(fg), 30)
```

```
## Community sizes
##     1     2     3     4     5     6     7     8     9    10    11    12    13
##  2643  1767  7298  1027  2790   229   487  1076   556   284   181 18205   412
##    14    15    16    17    18    19    20    21    22    23    24    25    26
##   229   516   118   302   101   135    98    36    32    31    29    20    20
##    27    28    29    30
##    41    28    29    21
```

```
# Check modularity
modularity(fg)
```

```
## [1] 0.7026744
```

```
# Check which nodes belongs to which clusters
head(membership(fg))
```

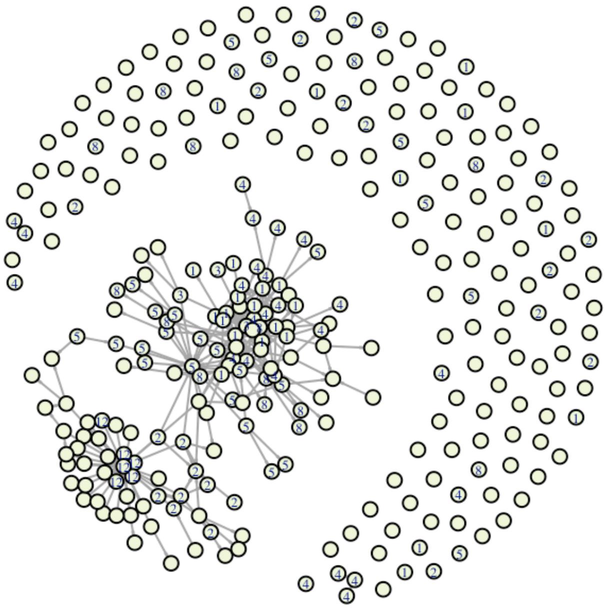
```
## 1271322107767480322 1221086524000870410            16260533  813898161500528640
##                   1                  12                   2                  12
##  765386574880137216  824705339383840768
##                   3                  12
```

The algorithm detects about 700 clusters. But lets look into large clusters which consists more than 1000 nodes.

```
# We use community, 1,2,3,4,5,8,12
# check plot
V(g)$label_fg <- NA

for (i in c(1,2,3,4,5,8,12)){
  ok <- membership(fg) == i
  str_i <- as.character(i)
  V(g)$label_fg[ok] <- str_i
}

table(V(g)$label_fg)
```

```
##
##     1    12     2     3     4     5     8
##  2643 18205  1767  7298  1027  2790  1076
```

```
# Plot graph with cluster label
top_nodes <- V(g)[order(-degree)][1:300]
small.g <- delete.vertices(g, which(!V(g) %in% top_nodes))
lay <- layout_with_fr(small.g)

small.g <- simplify(small.g)

plot(small.g,
     vertex.size = 5,
     edge.arrow.size = 0.1,
     edge.arrow.width = 0.3,
     vertex.label = V(small.g)$label_fg,
     vertex.label.cex = 0.4,
     vertex.color = V(small.g)$color,
     layout = lay)

mtext("Top 300 verticies by degree", side = 1)
```



Top 300 verticies by degree

Now I am interested in the discourse of those groups. More concretely, lets look into tweets published by each group members. To do that, lets save user_id of the groups.

```
# Group 1: 12, 2 -> red
# Group 2: 1, 4, 5, 8, 3 -> blue

# Store users id
# red part
ok <- (V(g)$label_fg == "12" | V(g)$label_fg == "2")
red <- V(g)$name[ok]
red <- red[!is.na(red)]
length(red)
```

```
## [1] 19972
```

```
# blue part
ok <- (V(g)$label_fg == "1" |
         V(g)$label_fg == "4"|
         V(g)$label_fg == "5"|
         V(g)$label_fg == "8"|
         V(g)$label_fg == "3")
table(ok)
```

```
## ok
## FALSE  TRUE
## 19972 14834
```

```
blue <- V(g)$name[ok]
blue <- blue[!is.na(blue)]
length(blue)
```

```
## [1] 14834
```

Let's save R objects for next part, creating a word cloud using Tweets.

```
save(rigged, g, fg, red, blue, file = "rigged_election.RData")
```

Exercise

Create a **reply network** of the rigged election data.

1. Create graph object containing reply network.
2. Find out top 10 users by indegree.
3. Find out top 10 users by outdegree.
4. Plot a reply network.