Network

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In this example we use following libraries.

```
library(rtweet)
library(dplyr)
```

```
## Warning: package 'dplyr' was built under R version 4.0.5
```

```
library(plotly)
library(igraph)
library(RColorBrewer)
```

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

The data used in this example collected in the following way.

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

Check the size of the data.

```
dim(rigged)
```

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

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

```
## # A tibble: 6 × 5
##   user_id             status_id           created_at          screen_name  text
##   <chr>               <chr>               <dttm>              <chr>        <chr>
## 1 796568442           1334929881935712256 2020-12-04 18:37:40 MartinRoyHi… "@re…
## 2 1271322107767480322 1334929876705562626 2020-12-04 18:37:39 anthonygyam… "Mit…
## 3 1221086524000870410 1334929876143525894 2020-12-04 18:37:38 susanlovesb… "Not…
## 4 1221086524000870410 1334928574994898944 2020-12-04 18:32:28 susanlovesb… "Rig…
## 5 1221086524000870410 1334927300039675908 2020-12-04 18:27:24 susanlovesb… "RIG…
## 6 16260533            1334929865292861441 2020-12-04 18:37:36 decamom      "Pro…
```

```
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 retweet network. To create a graph object, we need to provide two information: edges and nodes. In the following code, we first create a smaller data frame which only contains the information we need here. `user_id` and `retweet_user_id` will consists edge information, and we store user's screen name and varification status as node information.

```
t_rt <- rigged %>%
  filter(is_retweet == 'TRUE') %>% # remove tweets which are not retweets.
  select(user_id,retweet_user_id,screen_name, retweet_screen_name, verified, retweet_verified)
```

```
t_rt <- as.matrix(t_rt) # change data frame to matrix.

# edges
edges <- t_rt[,c(1,2)] # Store edge information
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"
```

User information comes from two different souces: (1) users who were retweeted others' tweet (column 1,3,5), (2) users who published original tweets (column 2,4,6). Thus, first we integrate two sources.

```
# actors
actors <- rbind(t_rt[,c(1,3,5)], t_rt[,c(2,4,6)]) # integrate user information
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.
```

Now let's create a graph object using the function `graph_from_data_frame()` from `igraph` package.

```
# 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
```

The node index `40084` is the Donald Trump's node. We can check it's degree. `in` degree means the sum of retweet counts of Donald Trump's posts. `out' degree means the other way around. Donald Trump's post retweeted a lot (19,540 times) but he did not retweet any other user's posts.

```
# 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
```

```
# 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 (retweeted by others)
V(g)$outdegree <- degree(g, mode="out") # and out-degree (retweeting other user's post)


# 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"
```

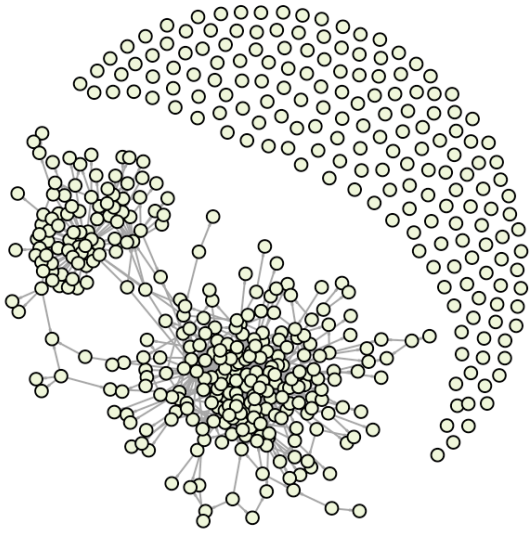
```
V(g)[order(-between)]$screen_name[1:10]
```

```
##  [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) # Create a `color` variable to nodes. rgb(
239, 249, 222) is light green. You can set up rgb color. rgb(r, g, b, maxColorValue=255, alpha=2
55). 255 is commonly used scale.

# Get top 500 nodes (based on degree)
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 inclu
ded in 'top_nodes'

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

small.g <- simplify(small.g) # Create a simple graph which do not contain loop and multiple edge
s.

plot(small.g, # graph object
     vertex.label = NA, # do not show vertex label
     vertex.size = 5, # size of vertex
     edge.arrow.size = 0.1, # size of edge arrow size
     edge.arrow.width = 0.3, # width of edge arrow
     vertex.color = V(small.g)$color, # set color
     layout = lay) # layout
```

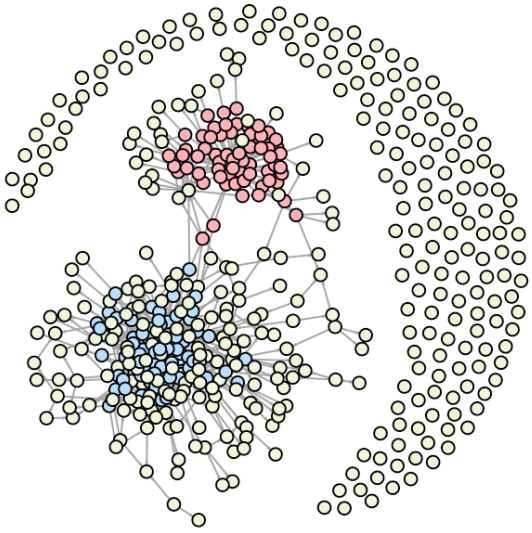


Above, we see two large clusters. Given the centurality results, it seems that `realDonaldTrump` and `BernieSanders` are at the center of the clusters (they are the top nodes in degree and betweenness centurality). To visualize it, let's color those nodes and nodes which retweeted them in red and blue, respectively.

```
# 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)$screen_name == "realDonaldTrump" # find realDonaldTrump node
V(g)$color2[ok] <- (rgb(255,179,186, maxColorValue = 255)) # Create a `color2` variable and set
realDonaldTrump node red.
ok2 <- neighbors(g, ok, mode = "in") # Find nodes who retweeting realDonaldTrump's tweet

V(g)$color2[ok2] <- (rgb(255,179,186, maxColorValue = 255)) # Assign red color as well.

# 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. Let’s detect 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
```

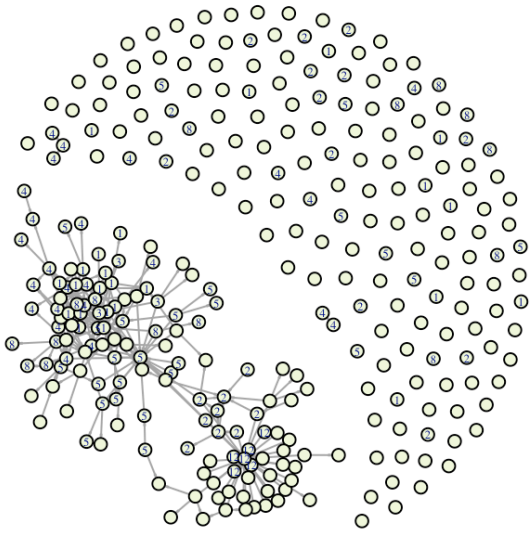
The algorithm detects about 700 clusters. But let's consider large clusters which consist more than 1000 nodes, i.e., cluster number 1,2,3,4,5,8, and 12. First, we create a label containing community number.

```
# We use community, 1,2,3,4,5,8,12
# Create a label, label_fg, containing community number.

V(g)$label_fg <- NA

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

# check the label_fg.
table(V(g)$label_fg)
```

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

Now we can plot the same graph as above but adding vertex label (cluster community number). By visual inspection, it looks like cluster 12,2 consists the same group; cluster 1,4,5,8,3 consists the other group.

```
# 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)$label_fg, # We use community number as vertex label.
     vertex.label.cex = 0.4,
     vertex.color = V(small.g)$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 two groups. Let's look into twitter posts published by each group members in the next session, `wordcloud`. To do that, let's save `user_id` associated with each group.

```
# 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)] # remove NA (those were assigned no label_fg value)
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 the next session.

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

Exercise

Exercise

1. 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.
5. Plot a **friend network** of three different twitter accounts.