

Assignment-4**Q-1 A)**

- a) Read in the files and visualize the network (try using ggplot2 or networkD3 libraries).

Ans:

Code:

```
#Read the subs file over here
```

```
edges<-read.table(file.choose(),sep="\t")
```

```
colnames(edges)<-c("idsrc","iddest")
```

```
#Read the keys file over here
```

```
nodes<-read.table(file.choose(),sep="\t")
```

```
colnames(nodes)<-c("id","item")
```

```
require(sqldf)
```

```
#for changing the name of ids(Source ID, Destination id) to the Item Name
```

```
sourcenodenames<-sqldf("select item from edges,nodes where id=idsrc")
```

```
destinationnodenames<-sqldf("select item from edges,nodes where id=iddest")
```

```
#Created a frame called total which has item names for source and destination
```

```
total <- cbind(sourcenodenames,destinationnodenames)
```

```
colnames(total)<-c("itemsrc","itemdest")
```

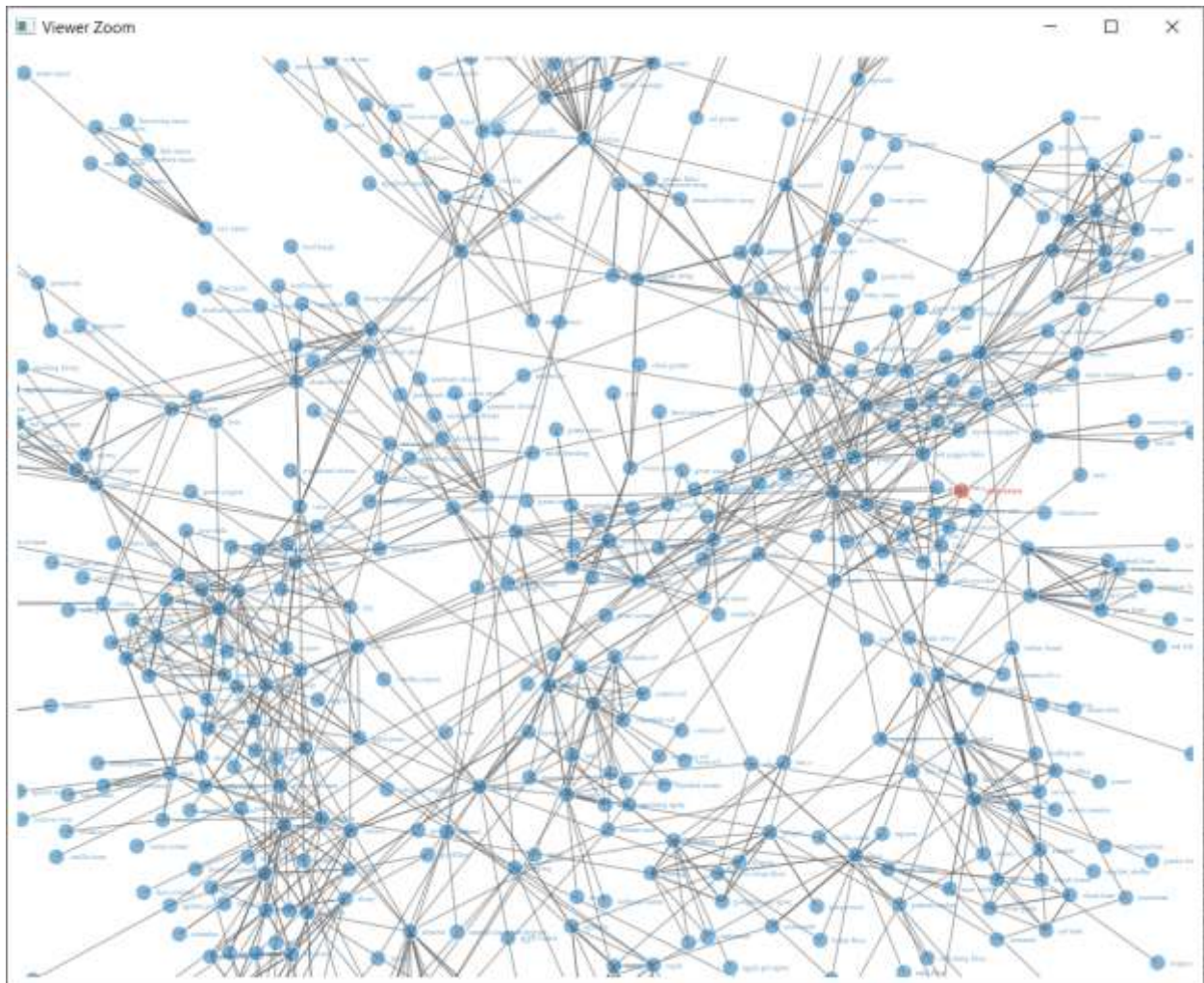
```
#plotted graph using networkD3
```

```
networkdata<-data.frame(total$itemsrc,total$itemdest)
```

```
library(networkD3)
```

```
simpleNetwork(networkdata)
```

Output:



Conclusion:

For visualization I've used networkD3 library

Q-1 B)

Calculate the degree centrality of each node.

Ans.

Code:

```
install.packages("igraph")
```

```
library(igraph)

net <- graph.data.frame(edges, nodes, directed=T)

#plot(net, edge.arrow.size=.4)

#net <- simplify(net, remove.multiple = F, remove.loops = T)

#calculating centrality for each node in graph

degrecentrality<-centralization.degree(net)

#Calculating count of indegree+outdegree

degcentdf<-data.frame(degrecentrality$res)

View(degcentdf)
```

Output:

	degrecentrality.res
1	3
2	33
3	4
4	8
5	1
6	19
7	1
8	5
9	5
10	5
11	5
12	29
13	5
14	19
15	22
16	7
17	13
18	9

Showing 1 to 18 of 562 entries

Conclusion:

Created the degree centrality(indegree+outdegree) for each node using `centralization.degree()` function.

Node 1's total(indegree+outdegree) is 3

Node 2's total(indegree+outdegree) is 33 e.t.c

Q-1D) Which are the most "connected" node(s).

Ans:

Code:

```
net <- graph.data.frame(edges, nodes, directed=T)
```

```
#calculating centrality for each node in graph
```

```
degreecentrality<-centralization.degree(net)
```

```
#Calculating count of indegree+outdegree
```

```
degcentdf<-data.frame(degreecentrality$res)
```

```
View(degcentdf)
```

#As we can see from data frame that node no with ID 2(degree-33),12(degree-29),79(degree-29) are the most three connected nodes

Conclusion:

We can see from data frame(degcentdf) that node no with ID 2(degree-33),12(degree-29),79(degree-29) are the most three connected nodes(Here I have taken only top 3 most connected nodes)

Q-1C)Visually determine what are the furthest ingredients from cocoa powder?

Ans.

Code:

```
#tmp2 = get.shortest.paths(net, from='408', to='142')
#fromcoca<-shortest_paths(net, from=408)

#Created distMatrix that showa the distance to all other nodes from node cocoa powder(408)
distMatrix <- shortest.paths(net, v=408)
max<-0
coll<-c()
cnt<-0
#for(i in 1:562){
# if(distMatrix[i][1]==1 && !is.na(distMatrix[i][1]))
# {
# cnt<-cnt+1
# }
#}

#Pls empty the coll first and then run the for loop to get required output

#Visually we can see that the nodes which are furthest from node cocoa powder are that nodes which
are not connected to it

#Created a simple for loop to verify the results which I got from visualization for the query
for(i in 1:562){
  if(distMatrix[i][1]==Inf && !is.na(distMatrix[i][1]))
  {
    cnt<-cnt+1
  }
}
```

```
coll<-union(coll,c(i))
}
}
coll
require(sqldf)
collnames<-sqldf("select item from nodes where id in
(93,94,107,108,109,110,111,113,114,256,353,431,432,459,460,463,464,480,481)")
```

Output:

#These no of nodes are furthest from node cocoa powder

```
#[1] 93 94 107 108 109 110 111 113 114 256 353 431 432 459 460 463 464 480 481
```

```
#      item
#1    marshmallow
#2  marshmallow creme
#3   yellow mustard
#4   honey mustard
#5      mustard
#6   dijon mustard
#7 spicy brown mustard
#8      mussel
#9      clam
#10  mustard powder
#11  mustard seed
#12   pound cake
#13  angel food cake
#14   toothpick
#15     skewer
#16   baking mix
```

#17 pancake mix
 #18 avocado
 #19 guacamole

Conclusion:

The nodes which are not connected to the node no 408(cocoa powder) are the furthest node from node no-408.We are getting 19 such nodes in our graph.

Q-2A)

Download 100 users ids that have tweeted about this, and their friends/followers. Note that due to rate limits you may need to include a pause in order to be able to download data on this many users

Code:

setup credentials: note you need to change to your own credentials

```
```{r}
require(twitterR)
require(RCurl)
consumer_key <-'x3DkrJTjJ1PjMAJx3HfCgJQya'
consumer_secret <-'XD3tQ5eODm7ICW9bhn2Ptg4oJEBLWrCW6ShDzrVIRde5urbXw'
access_token <-'1154193151-Fq8xxFjr90ODVEj2La9kTshvpUUd5OGLbl5Fmhp'
access_secret <-'DDgYIEuEUvTBd576VFCFe4RnNKOstpFv39rapLHIKhiwS'
setup_twitter_oauth(consumer_key, consumer_secret, access_token, access_secret)
```
```

search using keywords:

I use 10 here for simplicity, large number of n will cause the program running slow or reaching the twitter request limit, result in throwing a following error: In twInterfaceObj\$doAPICall("account/verify_credentials", ...) : Rate limit encountered & retry limit reached - returning partial results

Change 10 to at least 200, so we would most likely get at least 100 unique users.

searchTwitter returns List

```
``{r, echo=FALSE}  
myTweets <- searchTwitter("#SXSW2016", n=200, lang="en")  
myTweet  
``
```

Extract the usernames:

Change k = 100, if you want to process 100 users

```
``{r}  
k = 100  
tweetsDF <- twListToDF(myTweets)  
nameDF <- tweetsDF[, c("screenName")]  
uniqueNameDF <- unique(nameDF)  
hundredNamesDF <- head(uniqueNameDF, k)  
hundredNamesDF  
``
```

use networkD3 to plot the graph, igraph to assess the degree distribution of the graph

```
{r}  
# Load package  
require(networkD3)  
require(igraph)  
  
network_tw <- data.frame(src=character(), target=character(), stringsAsFactors=FALSE)
```



```

for(i in 1:100)
{
start <- getUser(uniqueNameDF[i],retryOnRateLimit=900)

#I used retryOnRateLimit=900 when it reached to it's maximum allowed rate limit to get User,Friends
and followers.

friends.object<-lookupUsers(start$getFriendIDs(retryOnRateLimit=900))
follower.object<-lookupUsers(start$getFollowerIDs(retryOnRateLimit=900))

n<- length(friends.object)
m<- length(follower.object)

friends <- sapply(friends.object[1:n],screenName)
followers <- sapply(follower.object[1:m],screenName)

networkData <- data.frame(src=uniqueNameDF[i], target=friends)
network_tw <- merge(network_tw, networkData, all=T)
networkData <- data.frame(src=followers, target=uniqueNameDF[i])
network_tw <- merge(network_tw, networkData, all=T)
}

```

Output:

Note---Here I have taken **retryOnRateLimit=900** argument for getting User,Friends and their Followers.If rate limit crosses the threshold it would repeat the same function(900 times—for ensuring that we get enough data).

Then after I build a network of friends and followers and feed them into a dataframe called network_tw

| | src | target |
|-----|-----------------|-----------------|
| 491 | WolfeNamedCruze | wyyU_LK |
| 492 | GDidDy210 | WolfeNamedCruze |
| 493 | GDidDy210 | wosahhelly |
| 494 | GDidDy210 | WxLLxM |
| 495 | GDidDy210 | x_MisJassy_ |
| 496 | GDidDy210 | XXL |
| 497 | GDidDy210 | YeahReG |
| 498 | GDidDy210 | Yequlz |
| 499 | GDidDy210 | yng_kani |
| 500 | GDidDy210 | YoShowtime |
| 501 | GDidDy210 | YoungRicans |
| 502 | GDidDy210 | YoungZillaGTM |
| 503 | GDidDy210 | YouOttoknow |
| 504 | GDidDy210 | YSF_Mel |
| 505 | GDidDy210 | YSFSean |
| 506 | GDidDy210 | YungSarnes |
| 507 | GDidDy210 | yungdiddy_ |
| 508 | GDidDy210 | YungHandsome19 |

Showing 491 to 500 of 27,623 entries

I got **27,623** for 100 users that I have taken from tweetsDF.

Q-2B) Assess and plot the degree distribution of your network (choose either in-degree or out-degree and motivate why you chose the metric).

Code:

```
# degree assess
```

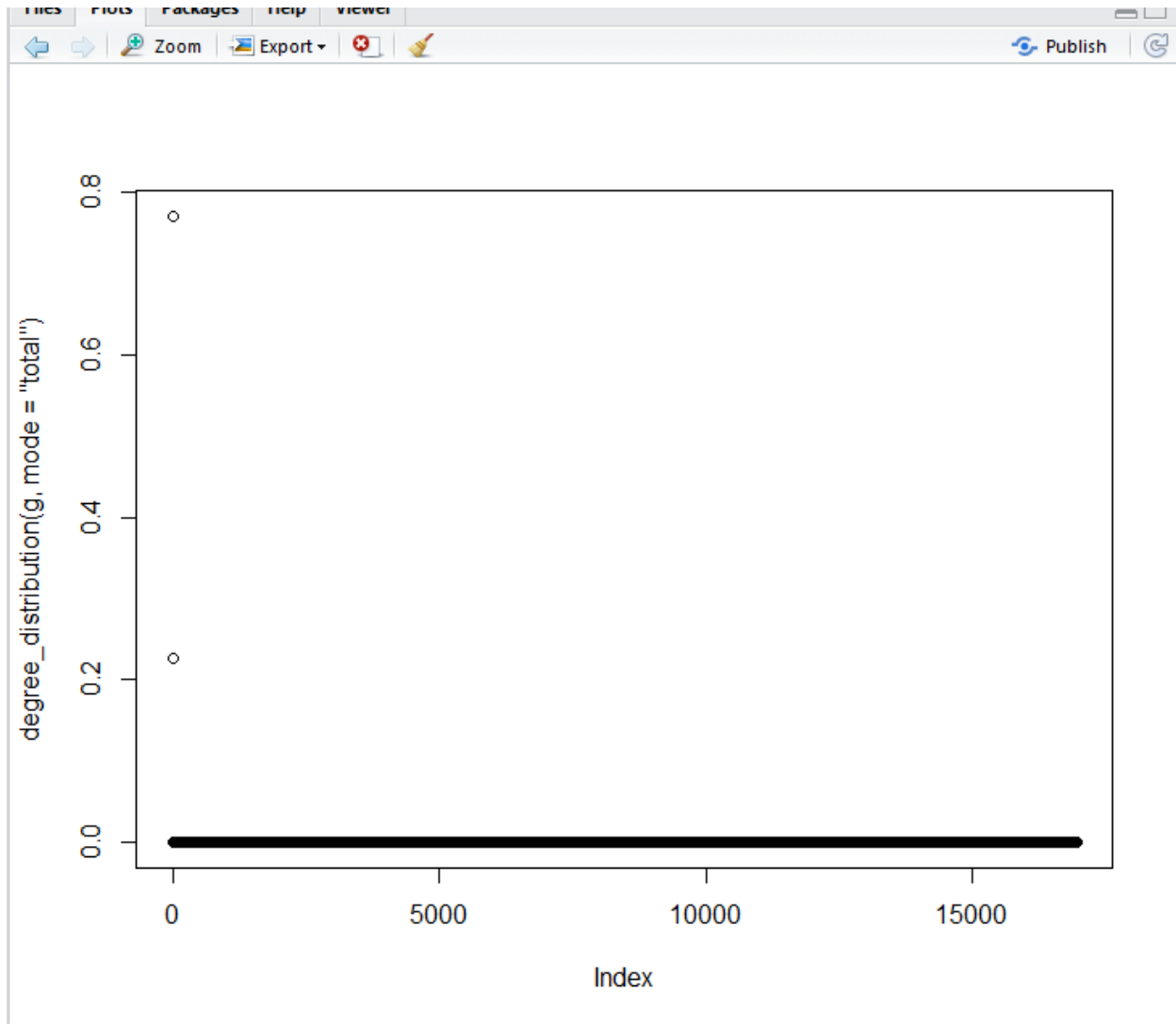
```
g <- graph.data.frame(network_tw, directed = F)
```

```
degree(g, mode = "total")
```

```
degree_distribution(g)
```

```
plot(degree_distribution(g, mode="total"))
```

Output:



Conclusion:

I have taken mode=total(indegree+outdegree).The reason for choosing total degree is that we can get Complete visualization of each user's friends and followers.If I only choose indegree than I can only be able to get distribution details of each users followers and If I only choose outdegree than I can only be able to get details of each users friends.

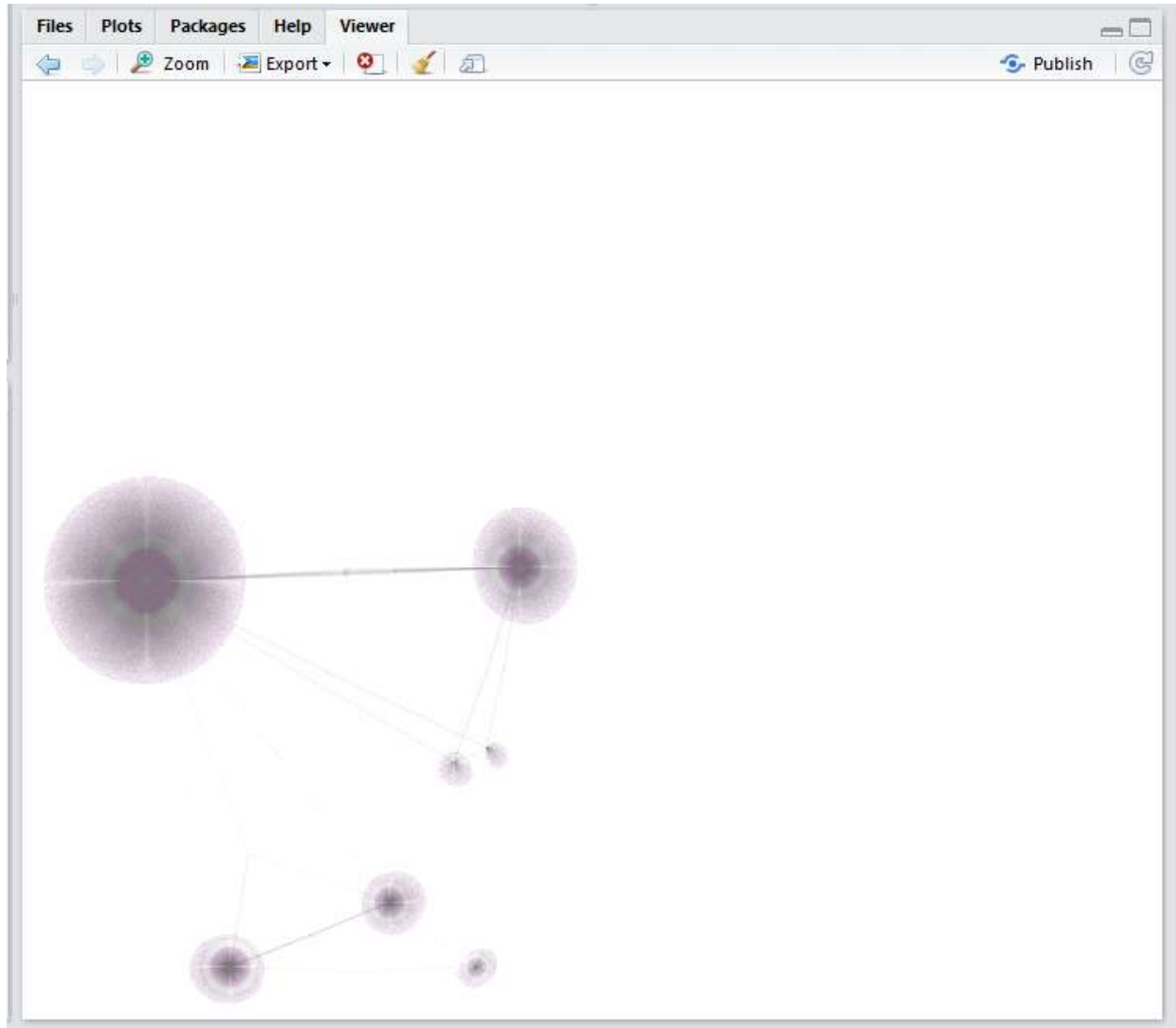
Q-2C) Visualize the network (try using ggplot2 or networkD3 libraries).

Plot

```
simpleNetwork(network_tw, zoom = T, linkDistance = 60, opacity = 0.5, linkColour = "grey", nodeColour = "purple",
```

```
nodeClickColour = "red", textColour = "blue")
```

Output:



Conclusion

Note---Request to wait for approximately 10-15 minutes to load complete graph after running the script.

I have pasted the zoom out version of the graph so that we can able to see the overall picture of user, friends and their followers(it is for 100 users).

Q-3A)Download Tweets from each user above that mention the hashtag you selected (over an appropriate time period)?

Code:

```
From <- "from:"
```

```
sxsw <- "+#SXSW2016"
```

```
tweets_list <- data.frame(src=character(), target=character(), stringsAsFactors=FALSE)
```

#looping to get the tweets from specific user by getting the hundredNamedDF[j](unique usernames) and searching tweets that they've put in recent times

```
for(j in 1:100)
```

```
{
```

```
  if(j %% 5 == 0){Sys.sleep(600)}
```

#Pausing the R execution if the rate limit reached to the specific threshold

```
  tweets_object<-do.call("rbind",lapply(searchTwitter(paste(From,hundredNamesDF[j],sxsw,sep =
  "")),resultType = "recent",lang="en"), as.data.frame))
```

```
  tweets_list <- merge(tweets_list, tweets_object, all=T)
```

```
}
```

```
tweetsDF<-tweets_list
```

Conclusion:

For this problem I've used following function

```
tweets_object<-do.call("rbind",lapply(searchTwitter(paste(From,hundredNamesDF[j],sxsw,sep =
  "")),resultType = "recent",lang="en"), as.data.frame))
```

This line of code will get the tweets from specific user that he/she has posted in recent times and then after I merge all user's tweets in the recent times into the data frame called tweets_object

Output:

| text | favorited | favoriteCount | replyToSN | created | truncated | replyToID | id | replyToID |
|--|-----------|---------------|-----------|---------------------|-----------|-----------|--------------------|-----------|
| 1 #Austin, TX #Engineering #Job: Power Electronics En... | FALSE | 0 | NA | 2016-04-11 22:08:48 | FALSE | NA | 710648421003419648 | NA |
| 2 #Austin, TX #Engineering #Job: Power Electronics En... | FALSE | 1 | NA | 2016-04-11 22:08:48 | FALSE | NA | 710648421003419648 | NA |
| 3 #Clerical alert: Legal Intern SunPower #Austin, TX ... | FALSE | 0 | NA | 2016-04-11 20:43:36 | FALSE | NA | 71062080509040053 | NA |
| 4 #Clerical in #Milpitas, CA: Mechantronics Intern at Su... | FALSE | 0 | NA | 2016-04-12 04:23:30 | FALSE | NA | 719742717991919616 | NA |
| 5 #Finance #Job alert: General Ledger Accountant Su... | FALSE | 1 | NA | 2016-04-11 08:20:39 | FALSE | NA | 719440010303307776 | NA |
| 6 #IT #Job in #SanRamonHQSP55: Q2C Business Proces... | FALSE | 1 | NA | 2016-04-11 23:31:50 | FALSE | NA | 710699314521923584 | NA |
| 7 #Sales in #SanRamonHQSP55: Partner Support Repres... | FALSE | 0 | NA | 2016-04-12 04:47:46 | FALSE | NA | 719748825431183360 | NA |
| 8 #Sanjose, CA #Construction - Sales Instructional Des... | FALSE | 1 | NA | 2016-04-11 15:13:50 | FALSE | NA | 71954308621059168 | NA |
| 9 #Sanjose, CA #HR #Job: Senior Director, Talent Mana... | FALSE | 0 | NA | 2016-04-11 16:27:27 | FALSE | NA | 719582515634458624 | NA |
| 10 Austin was LTTT with @khofmoscrl Channel K: #SX... | FALSE | 7 | NA | 2016-04-11 21:11:03 | FALSE | NA | 71063885362065408 | NA |
| 11 Austin was LTTT with @khofmoscrl Channel K: #SX... | FALSE | 5 | NA | 2016-04-11 21:52:15 | FALSE | NA | 710644254452141312 | NA |
| 12 Can you recommend anyone for this #Construction ... | FALSE | 1 | NA | 2016-04-12 01:33:20 | FALSE | NA | 710699801056597504 | NA |
| 13 Can you recommend anyone for this #Construction ... | FALSE | 1 | NA | 2016-04-11 15:38:21 | FALSE | NA | 719550162016731136 | NA |
| 14 Can you recommend anyone for this #Construction ... | FALSE | 2 | NA | 2016-04-11 12:47:51 | FALSE | NA | 719507252348077152 | NA |
| 15 Can you recommend anyone for this #Engineering #J... | FALSE | 0 | NA | 2016-04-11 20:57:12 | FALSE | NA | 710630403754004481 | NA |
| 16 Can you recommend anyone for this #Engineering #J... | FALSE | 1 | NA | 2016-04-12 03:52:11 | FALSE | NA | 719734835774787584 | NA |
| 17 Can you recommend anyone for this #Finance #Job? | FALSE | 1 | NA | 2016-04-12 04:11:20 | FALSE | NA | 71973955438919264 | NA |

| replyToID | statusSource | screenName | retweetCount | isRetweet | retweeted | longitude | latitude | src | target |
|--------------|---|----------------|--------------|-----------|-----------|--------------|------------|-----|--------|
| 21005419648 | Sa... | SunPowerTalent | 0 | FALSE | FALSE | -97.7036561 | 30.3870688 | NA | NA |
| 21005419648 | Sa... | SunPowerTalent | 0 | FALSE | FALSE | -97.7036561 | 30.3870688 | NA | NA |
| 10509949953 | Sa... | SunPowerTalent | 0 | FALSE | FALSE | -97.7036561 | 30.3870688 | NA | NA |
| 17991919616 | Sa... | SunPowerTalent | 0 | FALSE | FALSE | -121.8095741 | 37.4323341 | NA | NA |
| 110303307776 | Sa... | SunPowerTalent | 0 | FALSE | FALSE | 102.1821816 | 2.4472596 | NA | NA |
| 14521923584 | Sa... | SunPowerTalent | 0 | FALSE | FALSE | 121.774017 | 12.879721 | NA | NA |
| 125431183360 | Sa... | SunPowerTalent | 0 | FALSE | FALSE | 121.774017 | 12.879721 | NA | NA |
| 88621059168 | Sa... | SunPowerTalent | 0 | FALSE | FALSE | -121.8854337 | 37.3904943 | NA | NA |
| 15034458624 | Sa... | SunPowerTalent | 0 | FALSE | FALSE | -121.9529992 | 37.4308503 | NA | NA |
| 185362065408 | <a href="http://twitter.com/download/iphone" rel="... | TaylorGang | 1 | FALSE | FALSE | NA | NA | NA | NA |
| 154432141312 | <a href="http://twitter.com/download/iphone" rel="... | TaylorGang | 1 | FALSE | FALSE | NA | NA | NA | NA |
| 91050597504 | Sa... | SunPowerTalent | 0 | FALSE | FALSE | -97.7036561 | 30.3870688 | NA | NA |
| 62016731136 | Sa... | SunPowerTalent | 0 | FALSE | FALSE | -97.7036561 | 30.3870688 | NA | NA |
| 12348077152 | Sa... | SunPowerTalent | 1 | FALSE | FALSE | NA | NA | NA | NA |
| 93754004481 | <a href="http://www.tweetyjobs.com" rel="nofollow... | HydeCareers | 0 | FALSE | FALSE | 78.486671 | 17.385044 | NA | NA |
| 135774787584 | <a href="http://www.tweetyjobs.com" rel="nofollow... | HydeCareers | 0 | FALSE | FALSE | -8.0304975 | 52.6680204 | NA | NA |
| 155435999264 | Sa... | SunPowerTalent | 0 | FALSE | FALSE | -121.9529992 | 37.4308503 | NA | NA |

Q-3B) For $n = 1$, $n = 2$ and $n = 3$, submit the list of the 10 most frequent sequences

Ans:

Code:

```
myTweets <- searchTwitter("#SXSW2016", n=200, lang="en")
```

```
tweetsDF <- twListToDF(myTweets)
```

```
install.packages("tm")
```

```
library(tm)
```

```
tweets_source <- VectorSource(tweetsDF$text)
```

```
corpus <- Corpus(tweets_source)
```

```
corpus <- tm_map(corpus, removePunctuation)
```

```
corpus <- tm_map(corpus, stripWhitespace)
```

```
corpus <- tm_map(corpus, removeWords, stopwords("english"))
```

```
dtm <- DocumentTermMatrix(corpus)
```

```
dtm2 <- as.matrix(dtm)
```

```
#For n=1(unigram)
```

```
frequency <- colSums(dtm2)
```

```
frequency <- sort(frequency, decreasing=TRUE)
```

```
#Output
```

```
frequency[1:10]
```

```
#For n=2(Bigram)
```

```
BigramTokenizer <-
```

```
function(x)
```

```
  unlist(lapply(ngrams(words(x), 2), paste, collapse = " "), use.names = FALSE)
```

```
tdm <- TermDocumentMatrix(corpus, control = list(tokenize = BigramTokenizer))
```

```
tdm2 <- as.matrix(tdm)
```

```
frequency_2 <- rowSums(tdm2)
```

```
frequency_2 <- sort(frequency_2, decreasing=TRUE)
```

```
#Output
```

```
frequency_2[1:10]
```

```
#For Trigram
```

```
trigramTokenizer <-
```

```
function(x)
```

```
  unlist(lapply(ngrams(words(x), 3), paste, collapse = " "), use.names = FALSE)
```

```
tdm_3 <- TermDocumentMatrix(corpus, control = list(tokenize = trigramTokenizer))
```

```
tdm2_3 <- as.matrix(tdm_3)
```

```
frequency_3 <- rowSums(tdm2_3)
```

```
frequency_3 <- sort(frequency_3, decreasing=TRUE)
```

```
#Output
```

```
frequency_3[1:10]
```

```
Output:
```

```
For n=1
```

| | | | | |
|----------|--------------|---------|----------|------|
| sxsw2016 | austin | sxsweco | job | sxsw |
| 192 | 49 | 41 | 36 | 26 |
| channel | khofmoscrill | littt | sunpower | work |
| 23 | 23 | 23 | 20 | 20 |

```
For n=2
```

| | | | | | | | |
|--------------|----------|----------|--------------------|---------|----|--------------------|----------|
| sxsweco | sxsw2016 | austin | littt | channel | k | k | sxsw2016 |
| 41 | | | 23 | 23 | | | 23 |
| khofmoscrill | channel | littt | khofmoscrill | austin | rt | httpstcozvp3uu09aw | tgod |
| 23 | | 23 | | 15 | | 15 | |
| rt | ganggang | sxsw2016 | httpstcozvp3uu09aw | | | | |
| 15 | | | 15 | | | | |

```
For n=3
```

| | | | | | | | | |
|--------|-------|--------------|---------|---|----------|--------------|---------|---|
| austin | littt | khofmoscrill | channel | k | sxsw2016 | khofmoscrill | channel | k |
| 23 | | | 23 | | | 23 | | |

| | | |
|-------|--------------|---------|
| littt | khofmoscrill | channel |
| 23 | | |


```
austin rt ganggang httpstcozvp3uu09aw tgod Austin k sxsw2016 httpstcozvp3uu09
15                      15                      15
```

```
sxsw2016 httpstcozvp3uu09aw tgod
15
```

```
tgod austin rt      realtaylorlorgang austin littt
15                  14
```

Q-3C)

c) For $n = 1$, $n = 2$ and $n = 3$, submit the sum of all frequencies of all sequences for that n .

Code:

```
sum(frequency_3)
sum(frequency_2)
sum(frequency)
```

Output:

```
sum(frequency_3)
[1] 1967
> sum(frequency_2)
[1] 2167
> sum(frequency)
[1] 2057
```

Conclusion:

As we can see that for $n=1$ sum of all frequencies is 2057(as we have removed stopwords("English) and punctuation we got less count for $n=1$)

For $n=2$ we got 2167 frequency sum count

And For $n=3$ we got 1967 frequency sum count

Q-3D)

Using these frequencies, generate a distance measure for individuals (e.g. they share the X most common frequency 3-gram terms, or 2-gram terms, or 1-gram term). How does this network look compared to the network generated in question 2?

Ans:

Code:

```
myTweets <- searchTwitter("#SXSW2016", n=200, lang="en")
k = 100
tweetsSDF <- twListToDF(myTweets)
namedDF <- tweetsSDF[, c("screenName")]
```

```
uniqueNameDF <- unique(namedDF)
hundredNamesDF <- head(uniqueNameDF, k)
networkdata1 <- data.frame(src=character(), target=character(),distance=numeric(),stringsAsFactors=FALSE)

for(i in 1:100)
{
  for(j in 1:100)
  {
    networkdata2<-data.frame(src=uniqueNameDF[i],target=uniqueNameDF[j],stringsAsFactors=FALSE)
    networkdata1<-merge(networkdata1, networkdata2, all=T)
  }
}

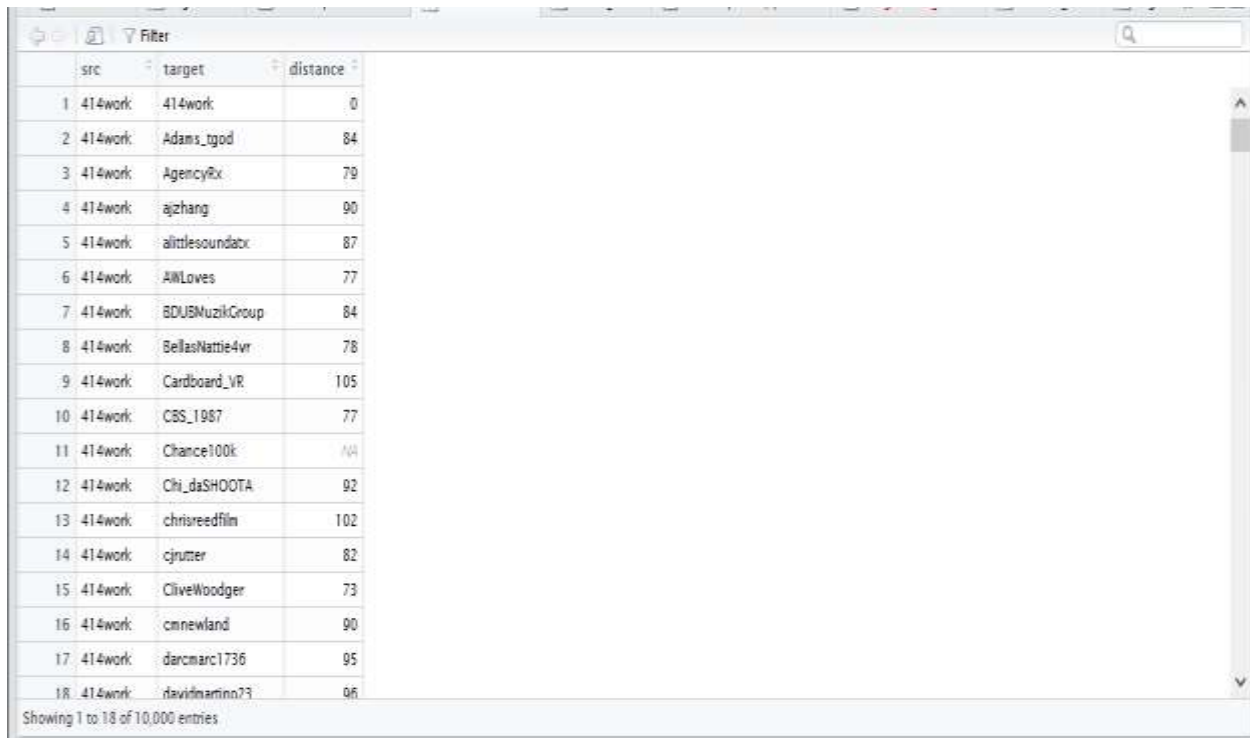
tweets_frame1<-data.frame(screenname=tweetsDF$screenName,tweets=tweetsDF$text,stringsAsFactors=FALSE)

tweets_frame1$tweets<-iconv(tweets_frame1$tweets,"UTF-8")

for (k in 1:length(networkdata1$src))
{
  networkdata1$distance[k]<-stringdist(as.character(tweets_frame1$tweets[tweets_frame1$screenname==networkdata1$src[k]]),as.character(tweets_frame1$tweets[tweets_frame1$screenname == networkdata1$target[k]]), method = "qgram", q = 1)
}

view(networkdata1)
```

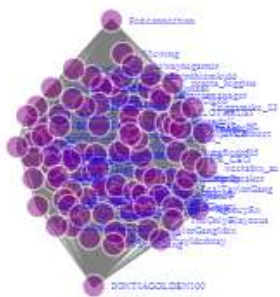
Output:

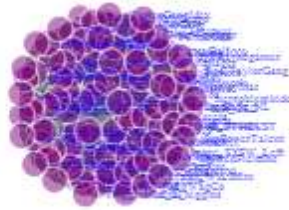


The screenshot shows a window titled "Filter" with a search bar in the top right corner. Below the search bar is a table with three columns: "src", "target", and "distance". The table contains 18 rows of data, each representing a connection between a source node (all starting with "414work:") and a target node, with a numerical distance value. The status bar at the bottom indicates "Showing 1 to 18 of 10,000 entries".

| | src | target | distance |
|----|----------|-----------------|----------|
| 1 | 414work: | 414work: | 0 |
| 2 | 414work: | Adams_tgod | 84 |
| 3 | 414work: | Agency8x | 79 |
| 4 | 414work: | ajzhang | 90 |
| 5 | 414work: | alittlesoundbox | 87 |
| 6 | 414work: | AWLoves | 77 |
| 7 | 414work: | BDUSMuzikGroup | 84 |
| 8 | 414work: | BellasNattie4vr | 78 |
| 9 | 414work: | Cardboard_VR | 105 |
| 10 | 414work: | CBS_1987 | 77 |
| 11 | 414work: | Chance100k | NA |
| 12 | 414work: | Chi_daSHOOTA | 92 |
| 13 | 414work: | chrisreedfilm | 102 |
| 14 | 414work: | cjrutter | 82 |
| 15 | 414work: | CliveWoodger | 73 |
| 16 | 414work: | cmnewland | 90 |
| 17 | 414work: | darcmarc1736 | 95 |
| 18 | 414work: | davidmartino23 | 96 |

Showing 1 to 18 of 10,000 entries





Conclusion:

We have chosen $n=1$ for this analysis and I've generated 100 graphs to compute the distance measure of each user. Here, I have shown just two graphs.

From these pictures we can say that

1) The distance measure between tweets from user's screen name="414work" to user's screen name="Adams_tgod" is 84, which means that 84 characters are different in their tweets.