Social Media Analytics for Canadian Banks (Sprint#2 Report)

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Abstract This is for the fulfillment of the York University's Advanced Analytics Course Capstone Project. The aim of this project is to uncover insights from the social media space through programmatic means.

Project Scope

Here are the boundaries of the project:

1. Social media channel: Twitter (to include Facebook if time permits)
2. Social media scope: Major Canadian Financial Institutions (FI) like BMO, CIBC, RBC, Scotiabank, TD (to include digital banks like Simplii, Tangerine, EQ if time permits)
3. Comparison of the following insights across the above FIs: Sentiment Analysis (polarity and categorical); Word Cloud (conversation drivers); Key-word dendrogram (blend of sentiment and conversation drivers); Network Analysis (demographics and product segmentation). Paraphrases of these insights are given in the "Research Questions" section below

Research Questions

Here are the research questions for this project:

1. Which bank has the most favourable / unfavourable trending opinion?

2. What are the current financial products being discussed?

3. What are the current emotions (anger, fear, anticipation, trust, surprise, sadness, joy, and disgust) towards each bank?

4. What are the current sentiments towards trending financial product segments / categories (and the general network of terms being tweeted)?

Research Questions (revised)

Based on the exploratory data analysis (EDA) from Sprint #1, the research questions are revised as follows:

1. Which bank has the most favourable / unfavourable trending opinion?
Comments: About 1,623 tweets have been collected since July 7th, 2019, with close 5,500 terms. The collection will increase in the next several weeks. It should be feasible to answer this research question. The main drawback is for the low count of CIBC tweets (40 tweets) versus that of Scotia Bank (661 tweets). The wide difference will skew the analysis, especially that of CIBC's

2. What are the current financial products being discussed?
Comments: The EDA shows that frequent terms related to banking products are generic ones, for example, stock, charges, account. Unless we have a much more collection of tweets, it will be difficult to objectively address this research question

3. What are the current emotions (anger, fear, anticipation, trust, surprise, sadness, joy, and disgust) towards each bank?
Comments: Not shown in this Sprint#1 report as the codes are still experimental, the author managed to "see" these emotional terms at the AllBanks level. Again, due to the low tweet count for CIBC, it may be difficult to pin down the sentiments, especially for these 8 sentiment categories.

4. What are the current sentiments towards trending financial product segments / categories (and the general network of terms being tweeted)?
Comments: As stated above, frequent terms related to banking products are generic ones, hence it will be difficult to assess sentiments towards product segments. Network of terms is certainly a possibility

Introduction and overall approach

Here is the general approach I adopted for this project:

Sprint #1:

1. Data Preparation
   1.1 1.1 Preliminaries - Load libraries and set seed / working directory
   1.2 Data Access
   1.3 Data extraction using twitteR
   1.4 Data Storage

2. Exploratory Data Analysis
   2.1 Create the term-document matrix
   2.2 Remove terms which have at least 99% of sparse elements
   2.3 Visualise term counts (or frequency)
   2.4 Data processing and normalisation
      2.4.1 Remove stop words
      2.4.2 Remove terms which have at least 99% of sparse elements
      2.4.3 Visualise term counts (or frequency)
   2.5 Additional data processing and normalisation
   2.6 Explore clustering of terms/tweets using k-means method
   2.7 Plot the hierarchical clusters
   2.8 Find the pair of terms that appears frequently together
      2.8.1 Pair of terms that appears frequently together
      2.8.2 Find the network of terms
   2.9 Wordcloud
   2.10 Sentiment analysis
   2.11 Observations

Sprint #2:

3. Social Media Analytics for Canadian Banks
   3.1 Create and compact the term-document matrix (TDM) for each bank
   3.2 Further compact the term-document matrix
   3.3 Clustering of terms/tweets k-means method
   3.4 Plot the hierarchical clusters
   3.5 Find the pair of terms that appears frequently together
      3.5.1 Find the network of terms
      3.5.2 Find optimal term count for optimal (neither too busy nor sparse) visualisation of network diagram

Steps employed in Social Media (Twitter) Analytics using R

1. Data Preparation

1.1 Preliminaries - Load libraries and set seed / working directory

```{r}
options(warn=-1) # Suppress warnings to make output more readable
# This is tweets data extraction and other utilities specific to Twitter
suppressMessages(library(twitteR))

# Core data analytics packages like ggplot2, dplyr, tidyr, readr, purrr, tibble, stringr, forcats
suppressMessages(library(tidyverse))

# Primary text mining package
suppressMessages(library(tm))

suppressMessages(library(wordcloud))

suppressMessages(library(syuzhet)) # Extracts Sentiment and Sentiment-Derived Plot Arcs from Text
suppressMessages(library(lubridate)) # For ease of analysis on date fields

# Graphical scales map data to aesthetics, and provide methods for automatically determining breaks and labels for axes and legends
suppressMessages(library(scales))

suppressMessages(library(reshape2)) # Flexibly restructure and aggregate data using just two functions: melt and 'dcast'

suppressMessages(library(igraph)) # Network Analysis and Visualization

set.seed(123)

setwd("/Users/sgchr/Documents/CSDA1050/Data/")
```

1.2 Data Access

Because the four keys and tokens below are confidential, I have commented the code. Uncomment the codes, enter your own tokens and keys before running the codes

```{r}
### set the credentials
#CONSUMER_SECRET <- 'Your CONSUMER_SECRET'
#CONSUMER_KEY <- 'Your CONSUMER_KEY'
#ACCESS_TOKEN <- 'Your ACCESS_TOKEN'
#ACCESS_TOKEN_SECRET <- 'Your ACCESS_TOKEN_SECRET'

### Connect to twitter app. Select 2 in the console
#setup_twitter_oauth(CONSUMER_KEY, CONSUMER_SECRET, ACCESS_TOKEN, ACCESS_TOKEN_SECRET)
```

1.3 Data extraction using twitteR

Like above, uncomment codes below before running them

```{r}
# Get tweets separately for each bank for two reasons (1) Twitter's free developer account has limits to search terms (2) Easier to do analysis by individual banks later

### Get Cibc tweets
#Cibc <- searchTwitter("CIBC", n=4000, lang="en", since='2019-07-07', until='2019-08-10')

### Get Rbc tweets
#Rbc <- searchTwitter("rbc", n=4000, lang="en", since='2019-07-07', until='2019-08-10')

### Get Td tweets
#Td <- searchTwitter("TD bank", n=4000, lang="en", since='2019-07-07', until='2019-08-10')

### Get Bmo tweets
#Bmo <- searchTwitter("bmo", n=4000, lang="en", since='2019-07-07', until='2019-08-10')

### Get Bns tweets
#Bns <- searchTwitter("scotiabank", n=4000, lang="en", since='2019-07-07', until='2019-08-10')

### Check remaining rate limits to avoid penalty from Twitter
#RL <- getCurRateLimitInfo()
```

Notes:

1. I found that searchTwitter using multiple terms does not seem to work, even when the syntax is correct (see example below)

```
terms <- c("cibc","Canadian Imperial Bank of Commerce", "CanadianImperialBankofCommerce", "CIBCForTheFans")
terms_search <- paste(terms, collapse = " OR ") # Insert "OR between each term
Cibc <- searchTwitter(terms_search, n=4000, since='2019-07-07')
```

2. The above only gives a small handful of tweets, and mainly discussion on stocks

3. But using one search term gives many more tweets. It is the same situation the other four banks. Hence, I restrict the search terms to just one

4. Multiple search terms used for other banks (and method discarded) are:

```
terms <- c("rbc", "royal bank of canada", "royalbankofcanada")
terms <- c("toronto dominion bank", "td bank", "TD bank", "TD Bank", "#tdbank", "#TDBank")
terms <- c("bmo", "bank of montreal", "bankofmontreal", "bmoharris")
terms <- c("scotiabank", "scotia bank")
```

5. Must remember to run code below periodically to make sure you don't go over the rate limit

```
RL <- getCurRateLimitInfo()
```

1.4 Data storage

Uncomment below before running the codes. For first time run, use col.names=T. The collected csv files are uploaded to github.com/chrissgtan/CSDA-1050F18S1

```{r}
### Convert into dataframe for easier analysis later
```

```
#Cibc_df <- twListToDF(Cibc)
#Rbc_df <- twListToDF(Rbc)
#Td_df <- twListToDF(Td)
#Bmo_df <- twListToDF(Bmo)
#Bns_df <- twListToDF(Bns)

### Store the dataframed tweets
#write.table(Cibc_df,"/Users/sgchr/Documents/CSDA1050/Data/Cibc.csv", append=T,
row.names=F, col.names=F,  sep=",")
#write.table(Cibc_df,"/Users/sgchr/Documents/CSDA1050/Data/AllBanks.csv", append=T,
row.names=F, col.names=F,  sep=",")

#write.table(Rbc_df,"/Users/sgchr/Documents/CSDA1050/Data/Rbc.csv", append=T,
row.names=F, col.names=F,  sep=",")
#write.table(Rbc_df,"/Users/sgchr/Documents/CSDA1050/Data/AllBanks.csv", append=T,
row.names=F, col.names=F,  sep=",")

#write.table(Td_df,"/Users/sgchr/Documents/CSDA1050/Data/Td.csv", append=T, row.names=F,
col.names=F,  sep=",")
#write.table(Td_df,"/Users/sgchr/Documents/CSDA1050/Data/AllBanks.csv", append=T,
row.names=F, col.names=F,  sep=",")

#write.table(Bmo_df,"/Users/sgchr/Documents/CSDA1050/Data/Bmo.csv", append=T,
row.names=F, col.names=F,  sep=",")
#write.table(Bmo_df,"/Users/sgchr/Documents/CSDA1050/Data/AllBanks.csv", append=T,
row.names=F, col.names=F,  sep=",")

#write.table(Bns_df,"/Users/sgchr/Documents/CSDA1050/Data/Bns.csv", append=T,
row.names=F, col.names=F,  sep=",")
#write.table(Bns_df,"/Users/sgchr/Documents/CSDA1050/Data/AllBanks.csv", append=T,
row.names=F, col.names=F,  sep=",")
```

2. Exploratory Data Analysis

Unlike spreasheets and typical databases, tweet contents are unstructured data. To aid in the analysis of unstructured data, I employ a technique to transform the tweets into structured data. In Data Science jargon, this is called the term-document matrix (or document-term matrix if we want the document to be displayed in rows). "Documents" are the tweets; and "terms" are the words in the tweets. Each element in the matrix represents the number of times a particular term appears in a particular document (the tweets).

2.1 Create the term-document matrix

```{r}
# Load the archived tweets
AllBanks_csv <- read.csv("/Users/sgchr/Documents/CSDA1050/Data/AllBanks.csv", header =
TRUE)

# Build the term-document matrix Corpus
AllBankstext <- iconv(AllBanks_csv$text, to = 'UTF-8')
corp <- Corpus(VectorSource(AllBankstext))

# Create term document matrix. Inf or infinity means to ingest everything
tdmat <- TermDocumentMatrix(corp, control = list(minWordLength=c(1,Inf)))
inspect(tdmat)
```

```
<<TermDocumentMatrix (terms: 46775, documents: 29310)>>
Non-/sparse entries: 357528/1370617722
Sparsity           : 100%
Maximal term length: 439
Weighting          : term frequency (tf)
Sample             :
                    Docs
Terms                2079 2139 2152 344 483 5247 540 6328 6508 6512
  @arilennox:           0    0    0   0   0    0   0    0    0    0
  <u+0001f60d>          0    0    0   0   0    0   0    0    0    0
  bank                  0    0    0   0   0    0   0    0    0    0
  bmo                   0    0    0   1   1    1   1    1    0    1
  https://t.co/ao4jqjtgwp    0    0    0   0   0    0   0    0    0    0
  https://t.co/lfcs1xlaqn    0    0    0   0   0    0   0    0    0    0
  now!!!                0    0    0   0   0    0   0    0    0    0
  out                   0    0    0   1   1    0   0    0    0    0
  the                   0    2    0   3   3    2   4    0    0    3
  video                 0    1    0   0   0    0   0    0    0    0
```

There are 46,775 terms in 29,310 documents (tweets). 100% sparsity means there are lots of terms occuring zero times in a document.

2.2 Remove terms which have at least 99% of sparse elements

```{r}
tdm <- removeSparseTerms(tdmat, sparse=0.99)

# Check sparsity
inspect(tdm)
```

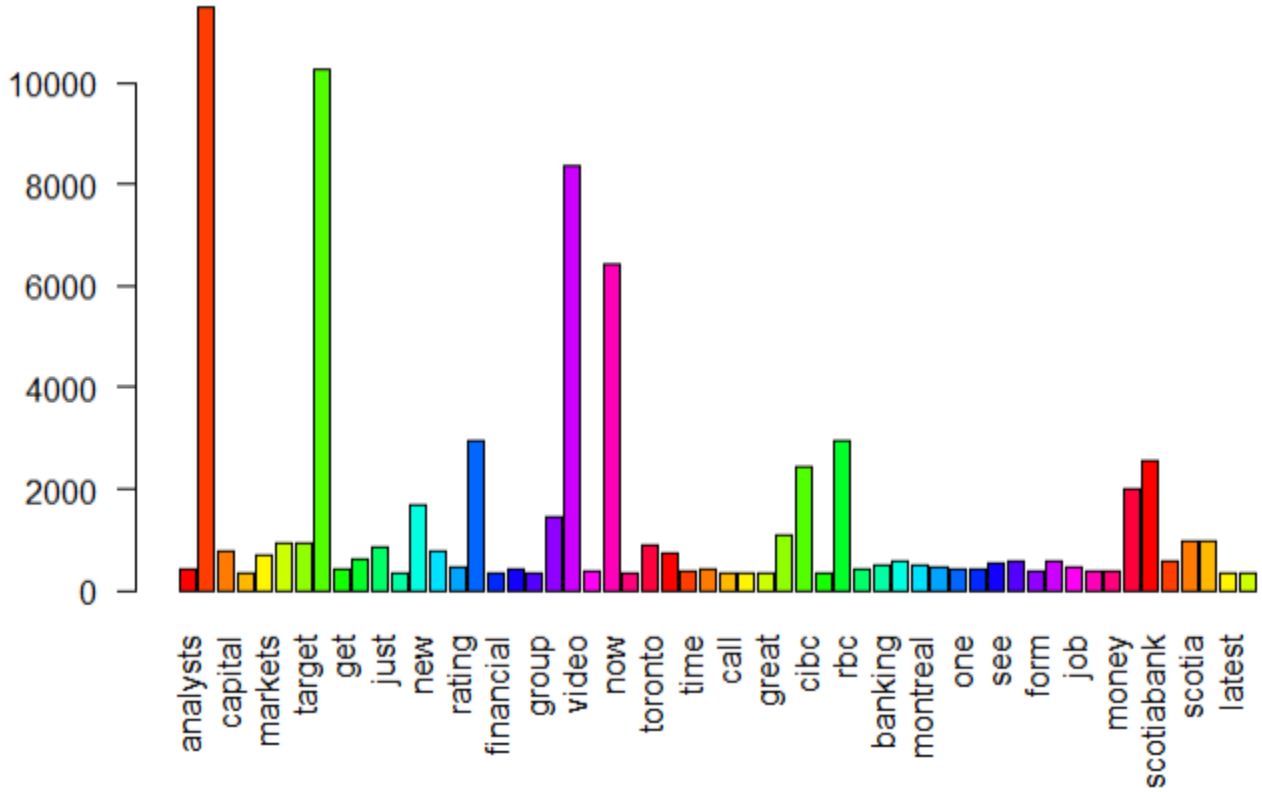
```
<<TermDocumentMatrix (terms: 107, documents: 29310)>>
Non-/sparse entries: 139832/2996338
Sparsity           : 96%
Maximal term length: 23
Weighting          : term frequency (tf)
Sample             :
                    Docs
Terms                19577 23669 24237 344 3902 4223 483 487 556 869
  @arilennox:            0     0     0   0    0    0   0   0   0   0
  <u+0001f60d>           0     0     0   0    0    0   0   0   0   0
  bank                   0     1     0   0    0    0   0   0   0   0
  bmo                    0     0     0   1    1    1   1   1   1   1
  https://t.co/ao4jqjtgwp     0     0     0   0    0    0   0   0   0   0
  https://t.co/lfcs1xlaqn     0     0     0   0    0    0   0   0   0   0
  now!!!                 0     0     0   0    0    0   0   0   0   0
  out                    0     0     0   1    0    1   1   0   0   0
  the                    1     0     2   3    3    3   3   1   1   1
  video                  0     0     0   0    1    2   0   0   0   0
```

Number of terms has dropped to 107 and sparsity has dropped to 96%. We can experiment with sparse=0.xx values to make sure we have sufficient term counts for analysis. sparse=0.98 reduced the term count to 51 with 92% sparsity. To make sure terms are not unduly deleted, and there is enough terms for analysis, I opted for sparse=0.99. Not surprisingly, the term "bank" appeared at least twice in majority of the document sample

2.3 Visualise term counts (or frequency)

```{r}
# Convert into matrix for further analysis
mat <- as.matrix(tdm)

# Plot frequent terms
```

```
freq <- rowSums(mat) # Count number of times each of the 107 terms appears

# It will be a very busy chart if we plot all 107 terms, so we restrict any terms that
appears more > 320 times. You can experiment with freq > ?? to make sure you can see all
the text in the bar plot. This is so that you could determine what "junk" terms (eg.,
"&amp:") you could eliminate
freq <- subset(freq, freq>320)

# Visualise
barplot(freq,
        las=2, # list all words in rows and display text vertically
        col = rainbow(25))
```



There are many stop words that can be removed

2.4 Data processing and normalisation

2.4.1 Remove stop words

```{r}
corp <- tm_map(corp, removeWords, stopwords(kind="en"))
tdmat <- TermDocumentMatrix(corp, control = list(minWordLength=c(1,Inf)))
inspect(tdmat)
```

```
transformation drops documents<<TermDocumentMatrix (terms: 46316, documents: 29310)>>
Non-/sparse entries: 308769/1357213191
Sparsity           : 100%
Maximal term length: 436
Weighting          : term frequency (tf)
Sample             :
                    Docs
Terms                11461 15479 15509 15516 16749 2079 2152 6328 6344 6508
  @arilennox:            0     0     0     0     0    0    0    0    0    0
  <u+0001f60d>           0     0     0     0     0    0    0    0    0    0
  bank                   0     0     0     0     0    0    0    0    0    0
  bmo                    0     0     0     0     0    0    0    1    0    0
  canada                 0     0     0     0     0    0    0    0    0    0
  https://t.co/ao4jqjtgwp    0     0     0     0     0    0    0    0    0    0
  https://t.co/lfcs1xlaqn    0     0     0     0     0    0    0    0    0    0
  now!!!                 0     0     0     0     0    0    0    0    0    0
  royal                  0     0     0     0     0    0    0    0    0    0
  video                  0     0     0     0     0    0    0    0    0    0
```

Term count reduced from 46,775 to 46,316 (459 stop words have been removed). But sparsity is still 100%

2.4.2 Remove terms which have at least 99% of sparse elements

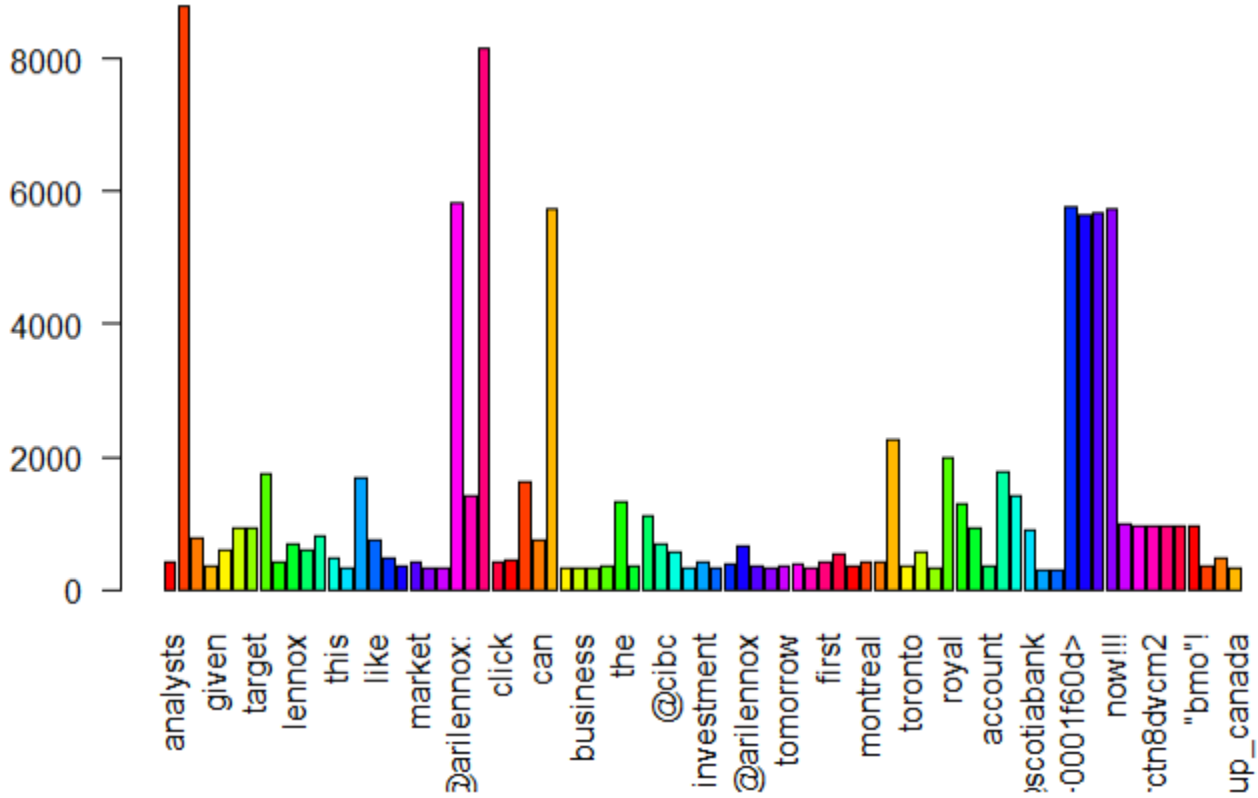
```
```{r}
tdm <- removeSparseTerms(tdmat, sparse=0.99)

# Check sparsity
inspect(tdm)
```
```

```
<<TermDocumentMatrix (terms: 79, documents: 29310)>>
Non-/sparse entries: 98971/2216519
Sparsity           : 96%
Maximal term length: 23
Weighting          : term frequency (tf)
Sample             :
                    Docs
Terms                2365 2373 2375 2377 2383 2394 2424 2431 2444 6328
  @arilennox:           0    0    0    0    0    0    0    0    0    0
  <u+0001f60d>          0    0    0    0    0    0    0    0    0    0
  bank                  0    0    0    0    0    0    0    0    0    0
  bmo                   0    0    0    0    0    0    0    0    0    1
  canada                0    0    0    0    0    0    0    0    0    0
  https://t.co/ao4jqjtgwp    0    0    0    0    0    0    0    0    0    0
  https://t.co/lfcs1xlaqn    0    0    0    0    0    0    0    0    0    0
  now!!!                0    0    0    0    0    0    0    0    0    0
  royal                 0    0    0    0    0    0    0    0    0    0
  video                 1    1    1    1    1    1    1    1    1    0
```

Term count has reduced to 79 (and with stop words also removed via the preceding code)

2.4.3 Visualise term counts (or frequency)

```
```{r}
# Convert into matrix for further analysis
mat <- as.matrix(tdm)

# Plot frequent terms
freq <- rowSums(mat) # Count number of times each of the 79 terms appears

# It will be a very busy chart if we plot all 79 terms, so we restrict any terms that
appears more > 70 times. Can experiment with freq>?? to make sure you can see all the
```
```

```
text in the bar plot. This is so that you could determine what "junk" terms (eg.,
"@amp:") you could eliminate
freq <- subset(freq, freq>70)

# Visualise
barplot(freq,
        las=2, # list all words vertically
        col = rainbow(25))
```



It is evident that more text cleaning are still needed. We will iterate steps 2.5 and 2.6 to buid the stop and replacement words

2.5 Additional data processing and normalisation

```{r}
corp <- tm_map(corp, tolower) # Not crucial for text analytics but good practice to do so
corp <- tm_map(corp, removePunctuation) # Remove punctuations
corp <- tm_map(corp, removeNumbers) # Remove numbers

# Remove URL
removeURL <- function(x) gsub('http[[:alnum:]]*', '', x)
corp <- tm_map(corp, content_transformer(removeURL))

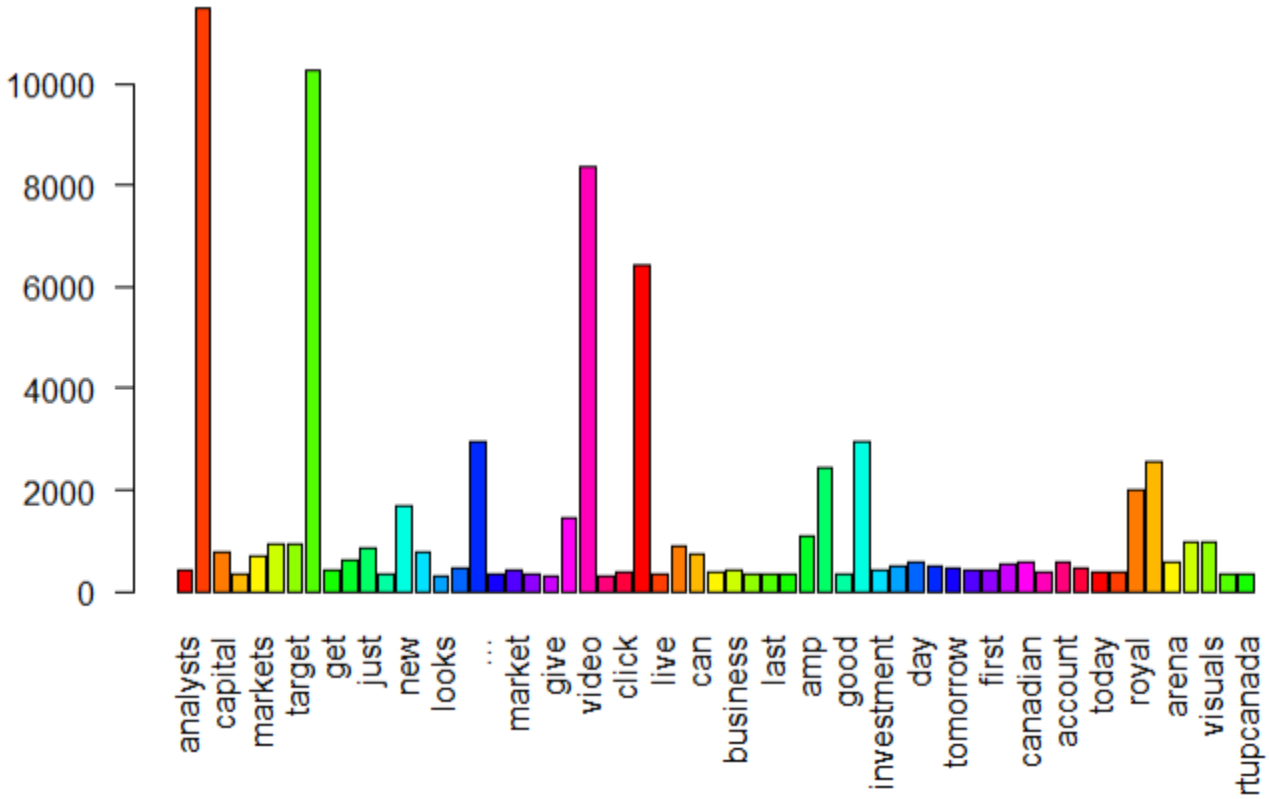
# Remove words. Since we are analysing "banks" in "Canada", words like "bank" and
"canada" do not add value to our analysis
MyStopwords <- c(stopwords(kind="en"), "bank", "canada", "…", "’s", "ufd", "via",
"mefeater")
corp <- tm_map(corp, removeWords, MyStopwords)

# Replace words
corp <- tm_map(corp, gsub, pattern = 'lennox', replacement = 'arilennox')
corp <- tm_map(corp, gsub, pattern = '“bmo”', replacement = 'bmo')
corp <- tm_map(corp, gsub, pattern = 'lennox’s', replacement = 'arilennox')
corp <- tm_map(corp, gsub, pattern = 'ariarilennox', replacement = 'arilennox')
corp <- tm_map(corp, gsub, pattern = 'ari', replacement = 'arilennox')
```

```
corp <- tm_map(corp, gsub, pattern = 'arilennoxlennox', replacement = 'arilennox')

corp <- tm_map(corp, stripWhitespace) # remove leftover from the preceding removal

# Repeat the preceding codes
tdmat <- TermDocumentMatrix(corp, control = list(minWordLength=c(1,Inf)))
tdm <- removeSparseTerms(tdmat, sparse=0.99)
mat <- as.matrix(tdm)
freq <- rowSums(mat)
freq <- subset(freq, freq>=60)
barplot(freq,
        las=2, # list all words vertically
        col = rainbow(25))
```



The text is mostly cleaned up, and the barplot is evidently cleaner

2.6 Explore clustering of terms/tweets using k-means method

This analysis will uncover the following two insights:

1. Within cluster sum of squares by cluster: We want this to be low, which means the elements within each cluster are close to each other

2. Between_SS / total_SS: We want this to be high, that is, distances between clusters are further apart

I experimented with k = 9 to 18 to find best mix of distance within and between clusters and deemed the best is k=17

In section 2.7, we will use k=17 to visualise the term-clusters using a cluster dendrogram plot

```
```{r}
set.seed(123)
```
```

```
m1 <- t(mat) # Transpose
k <- 17 # I experimented with k = 9 to 18 to find best mix of distance within and between clusters and deemed the best is k=17
kc <- kmeans(m1, k)
kc
```

```
K-means clustering with 17 clusters of sizes 6290, 2243, 6523, 898, 236, 1630, 1121, 440, 401, 2015, 235, 490, 2048, 1636, 2530, 238, 336

Cluster means:
      analysts          bmo      capital        given     markets        price       target
arilennox         get         will        just       stocks         new         like       looks
rating          …
1  0.000000000 0.9993640700 0.0000000000 0.0000000000 0.000000000 0.0000000000 0.0000000000
1.000317965 0.000317965 0.0001589825 0.006995231 0.0000000000 0.000317965 0.0004769475 0.003338633
0.0000000000 0.016375199
2  0.008916630 0.0584039233 0.0414623272 0.0008916630 0.023183237 0.0013374944 0.0013374944
0.000000000 0.010254124 0.0022291574 0.020062416 0.0040124833 0.027641551 0.0133749443 0.001337494
0.0022291574 0.007133304
3  0.002146252 0.0000000000 0.0045991108 0.0024528591 0.002912770 0.0027594665 0.0003066074
0.002912770 0.022229036 0.0000000000 0.038019316 0.0056722367 0.027134754 0.0406254791 0.002146252
0.0016863406 0.000000000
4  0.357461024 0.3184855234 0.3229398664 0.3151447661 0.308463252 1.0077951002 1.0044543430
0.000000000 0.000000000 0.0000000000 0.001113586 0.1714922049 0.065701559 0.0000000000 0.002227171
0.0022271715 0.007795100
5  0.000000000 0.0042372881 0.0000000000 0.0000000000 0.000000000 0.0000000000 0.0000000000
0.000000000 0.008474576 0.0000000000 0.008474576 0.0000000000 0.004237288 0.5805084746 0.000000000
0.0000000000 0.021186441
6  0.007975460 0.0055214724 0.0263803681 0.0030674847 0.022699387 0.0042944785 0.0042944785
0.000000000 0.031901840 0.0276073620 0.022699387 0.0134969325 0.021472393 0.0263803681 0.003067485
0.0693251534 0.010429448
7  0.018733274 0.0000000000 0.0017841213 0.0223015165 0.008920607 0.0044603033 0.0000000000
0.000000000 0.010704728 0.0000000000 0.005352364 0.0713648528 0.016057092 0.0062444246 0.000000000
0.2256913470 0.003568243


 [ reached getOption("max.print") -- omitted 28310 entries ]

Within cluster sum of squares by cluster:
 [1]  813.0590 2207.6416 5773.9703 1817.4276  402.7754 1600.9620  821.6753  682.0909  449.0324
2589.6754  216.1277  783.1878 3185.4604 1364.4756 3335.7700  370.5924  552.9702
 (between_SS / total_SS =  61.4 %)

Available components:

[1] "cluster"      "centers"      "totss"        "withinss"     "tot.withinss" "betweenss"    "size"
"iter"         "ifault"
```

Observations:

1. There are 17 clusters of sizes 6290, 2243, 6523, etc

2. "Cluster means" shows the average of each term being analysed. High average means that word has appeared in the particular cluster with higher frequency.

3. "Clustering vector" shows which cluster each term has gone to.

4. "Within cluster sum of squares by cluster" shows the distance between terms within each cluster. We want this to be low.

5. "between_SS / total_SS" shows the distance between clusters. We want this to be high

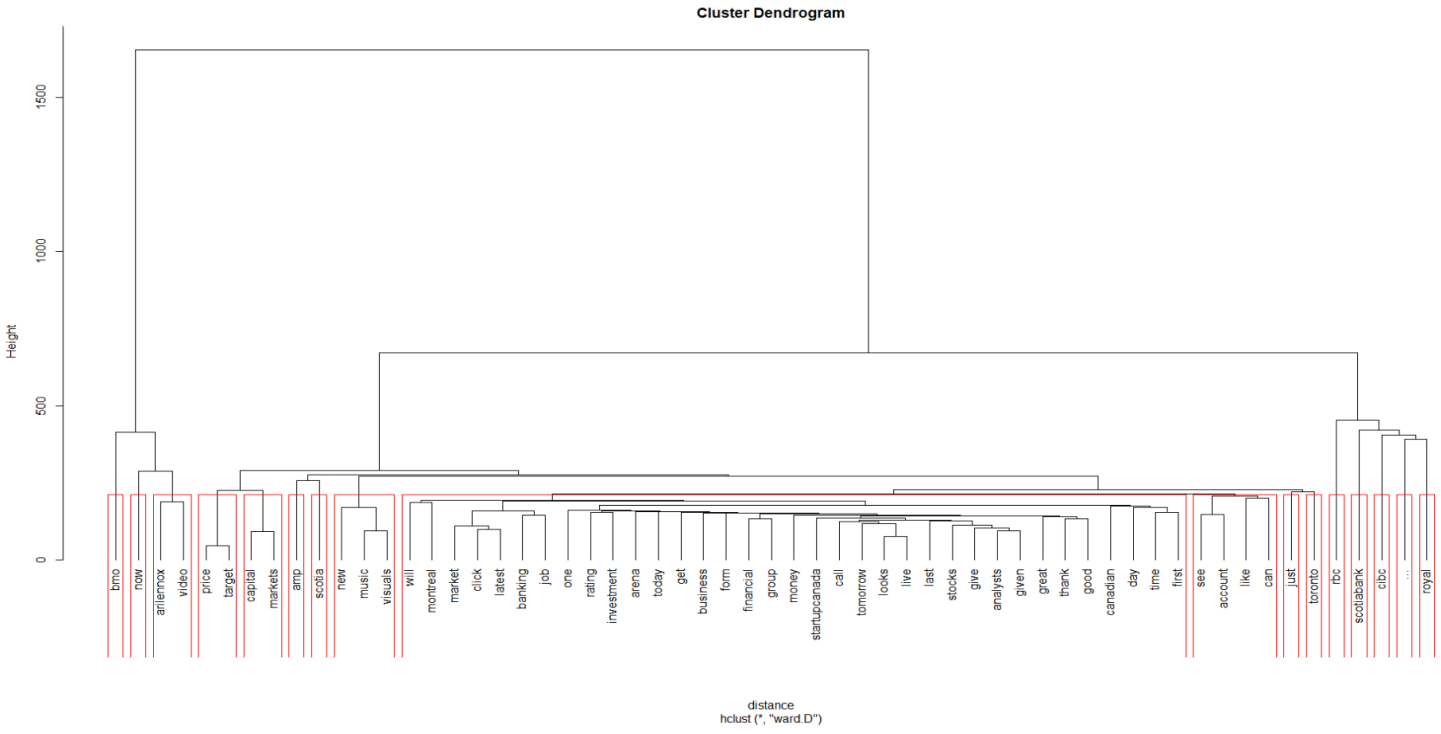
I have experimented with k = 9 to 18 and deemed the best mix of distance within and between clusters is k=17

```
k   Within clusters   Between clusters
```

```
=    ==============    ================
9    3,844             50.5
10   3,590             48.6
11   2,997             52.8
12   2,802             51.9
13   2,529             53.0
14   2,390             52.1
15   2,127             54.3
16   1,991             54.4
17   1,586 <-          61.4 <-
18   1,791             53.9
```

2.7 Plot the hierarchical clusters

```{r}
# Utilise dendrogram for hierarchical clustering of terms in tweets
# Find the distance, use scale to normalise the matrix
distance <- dist(scale(mat))

# Print the terms, and calculate the distance between the words in each document (tweets)
print(distance, digits = 2)

hc <- hclust(distance, method = "ward.D")
plot(hc, hang=-1)
rect.hclust(hc, k=17) # 17 clusters per findings in step 2.6
```



Observations:

1. Notice the banks are clustered together, which is logical. But there is a single cluster "scotia". This can be easily corrected by replacing "scotia" with "scotiabank"

2. Price and target are clustered together due to discussions about stock prices

2.8 Find the pair of terms that appears frequently together

```{r}
# Term document matrix to convert unstructure text into structured for easier analysis
tdmat <- TermDocumentMatrix(corp)
```

```
tdmat <- as.matrix(tdmat)
tdmat[1:30,1:30] # See the first 30 terms in the first 30 documents (tweets)
```

	Docs																													
Terms	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
analysts	1	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	1	1
arcc	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ares	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
bmo	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
capital	2	0	0	1	0	1	1	1	0	1	0	0	0	1	1	0	1	1	1	0	1	0	0	1	1	1	1	1	1	1
given	1	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
markets	1	0	0	1	0	2	1	1	0	1	0	0	0	0	1	0	1	1	1	0	1	0	0	1	1	1	1	1	1	1
price	1	0	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	1	1	1
target	1	0	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	1	1	1
arilennox	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
get	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
hype	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
never	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
will	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
amiller	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
another	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
city	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
fan	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
field	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
just	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
manofbird	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
owned	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
share	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
tfc	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
toro…	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
upset	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
aks	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
reiterates	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
steel	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
bygoneboatmen	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Above show how many times each term appears in each tweet. Example "city" appears twice in tweet 3

```{r}
# Network of terms
tdmat[tdmat>1] <- 1 # Convert matrix into binary, that is whether a term appears (1) or not (0)

tdmat[1:25,1:25]
```

2.8.1 Pair of terms that appears frequently together

```{r}
# Create term-term matrix
termM <- tdmat %*% t(tdmat) # Multiply tdmat and transpose of tdmat
termM[1:25,1:25]
```

Terms	analysts	arcc	ares	bmo	capital	given	markets	price	target	arilennox	get	hype	never	will	amiller	another	city	fan	field	just	manofbird	owned	share	tfc	toro…
analysts	425	3	3	133	117	124	121	322	322	0	3	0	1	2	0	0	0	0	0	1	0	0	0	0	0
arcc	3	5	5	5	5	2	5	4	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ares	3	5	5	5	5	2	5	4	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
bmo	133	5	5	11369	555	127	512	286	287	8428	62	3	19	48	3	24	9	16	158	387	4	2	7	6	1
capital	117	5	5	555	773	113	588	283	287	0	0	0	0	6	0	3	0	0	0	4	0	0	2	0	0
given	124	2	2	127	113	353	117	283	283	8	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
markets	121	5	5	512	588	117	699	273	275	0	0	0	0	26	0	2	0	0	0	3	0	0	1	0	0
price	322	4	4	286	283	283	273	940	898	4	2	0	0	0	0	0	0	0	0	1	0	0	5	0	0
target	322	4	4	287	287	283	275	898	927	0	0	0	0	2	0	0	0	0	0	3	0	0	2	0	0
arilennox	0	0	0	8428	0	8	0	4	0	8544	9	3	4	2	0	0	0	4	0	253	0	0	0	0	0
get	3	0	0	62	0	0	0	2	0	9	412	1	5	20	1	2	1	1	6	16	12	1	0	2	0
hype	0	0	0	3	0	0	0	0	0	3	1	6	1	1	0	0	0	0	0	0	0	0	0	0	0
never	1	0	0	19	0	0	0	0	0	4	5	1	218	17	0	0	1	0	1	8	0	0	0	1	0
will	2	0	0	48	6	0	26	0	2	2	20	1	17	572	1	9	11	1	5	6	1	0	24	1	0
amiller	0	0	0	3	0	0	0	0	0	0	1	0	0	1	4	1	3	1	3	2	4	2	1	2	1
another	0	0	0	24	3	0	2	0	0	0	2	0	0	9	1	166	1	1	1	5	1	1	1	1	1
city	0	0	0	9	0	0	0	0	0	0	1	0	1	11	3	1	73	1	5	2	3	2	2	2	1
fan	0	0	0	16	0	0	0	0	0	4	1	0	0	1	1	1	1	77	3	4	1	1	1	1	1
field	0	0	0	158	0	0	0	0	0	0	6	0	1	5	3	1	5	3	182	62	3	2	1	2	1
just	1	0	0	387	4	1	3	1	3	253	16	0	8	6	2	5	2	4	62	860	2	1	1	1	1
manofbird	0	0	0	4	0	0	0	0	0	0	12	0	0	1	4	1	3	1	3	2	17	2	1	2	1
owned	0	0	0	2	0	0	0	0	0	0	1	0	0	0	2	1	2	1	2	1	2	5	1	2	1
share	0	0	0	7	2	0	1	5	2	0	0	0	0	24	1	1	2	1	1	1	1	1	78	1	1
tfc	0	0	0	6	0	0	0	0	0	0	2	0	1	1	2	1	2	1	2	1	2	2	1	12	1
toro…	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	7

The above shows pair of terms that appears frequently together. For example: tfc and bmo appear together in 6 tweets. This is not surprising, since bmo is a major sponsor of the Toronto Football Club (tfc)

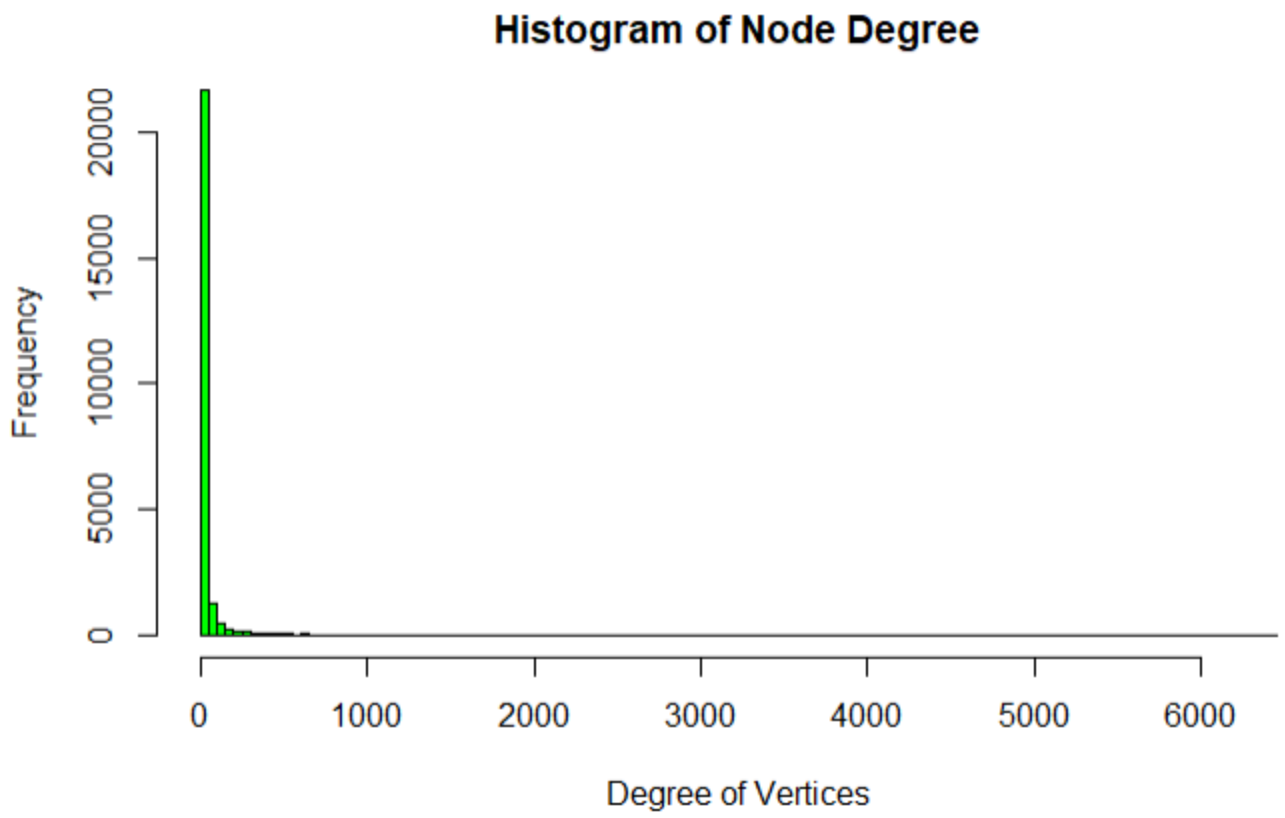
2.8.2 Find the network of terms

```{r}
g <- graph.adjacency(termM, weighted = T, mode = 'undirected')
g
```

```
IGRAPH 9f0c209 UNW- 24277 411973 --
+ attr: name (v/c), weight (e/n)
+ edges from 9f0c209 (vertex names):
 [1] analysts--analysts      analysts--arcc          analysts--ares          analysts--bmo           analysts--capital       analysts--given         analysts--markets       analysts--price
 [9] analysts--target        analysts--get           analysts--never         analysts--will          analysts--just          analysts--aks           analysts--steel         analysts--well
[17] analysts--primo         analysts--prmw          analysts--water         analysts--stocks        analysts--coverage      analysts--new           analysts--okta          analysts--receives
[25] analysts--earnings      analysts--level         analysts--right         analysts--like          analysts--fuel          analysts--growth        analysts--rating        analysts--realty
[33] analysts--stock         analysts--trust         analysts--…             analysts--financial     analysts--initiated     analysts--zscaler       analysts--t…            analysts--can't
[41] analysts--market        analysts--mastercard    analysts--gild          analysts--gilead        analysts--sciences      analysts--set           analysts--group         analysts--international
[49] analysts--connections   analysts--give          analysts--waste         analysts--wcn           analysts--now           analysts--increased     analysts--mcd           analysts--mcdonald
[57] analysts--amgen         analysts--amgn          analysts--street        analysts--know          analysts--near          analysts--won't         analysts--actually      analysts--national
+ ... omitted several edges
```

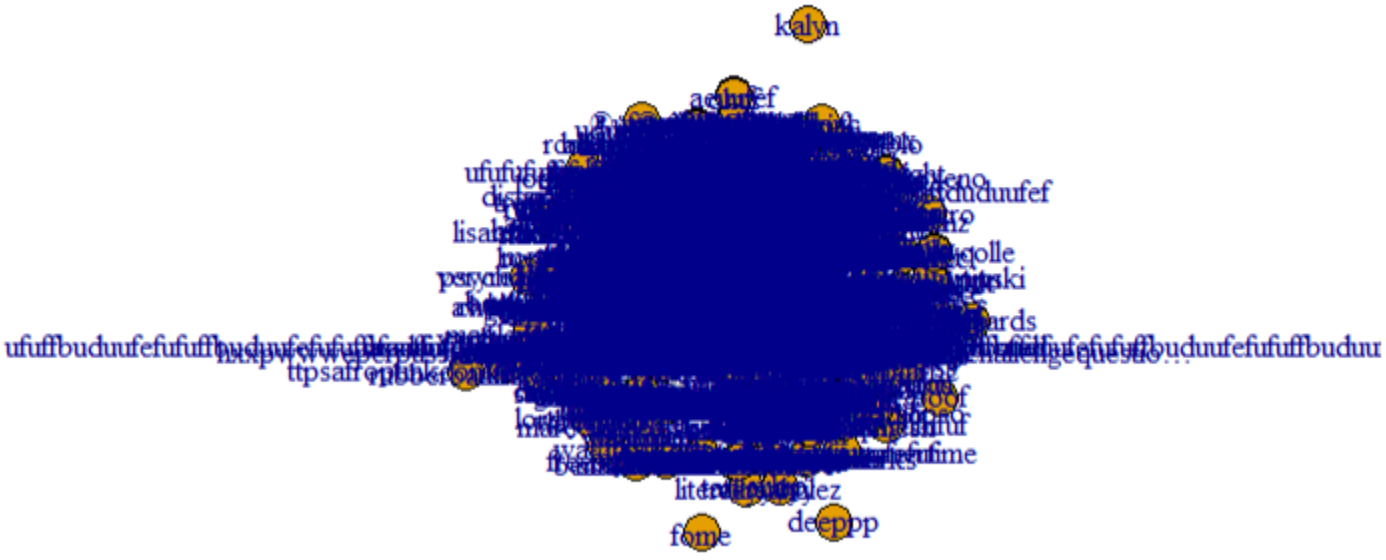
```{r}
g <- simplify(g) # To prevent looping of same terms, example, pairing of same terms like "analysts--analysts"
V(g)$label <- V(g)$name # Labels for the terms
V(g)$degree <- degree(g) # How often each term appears
```

```{r}
# Histogram of node degree
hist(V(g)$degree,
     breaks = 100, # how many bars
     col = 'green',
     main = 'Histogram of Node Degree',
     ylab = 'Frequency',
     xlab = 'Degree of Vertices')
```



Above is a right skewed histogram and most terms appears less than 400 times

```{r}
# Network diagram
plot(g)
```



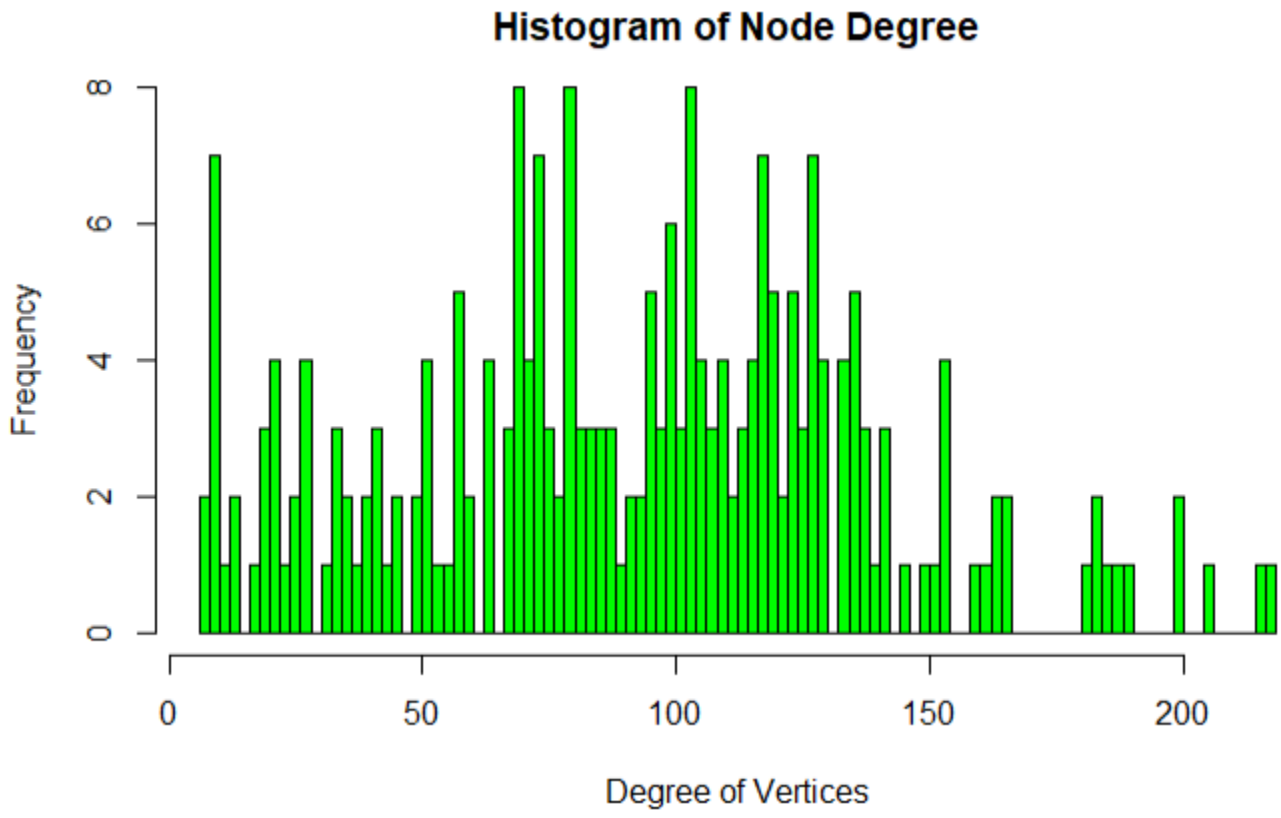
Above graph is too busy. One method is to reduce the size of the matrix

```{r}
tdmat <- tdmat[rowSums(tdmat)>120,] # rowSums counts the total frequency; that is, keep terms that appear > 120 times

# Re-run earlier code
```

```
tdmat[tdmat>1] <- 1
termM <- tdmat %*% t(tdmat)
termM[1:10,1:10]
g <- graph.adjacency(termM, weighted = T, mode = 'undirected')
g
g <- simplify(g) # To prevent looping of same terms
V(g)$label <- V(g)$name
V(g)$degree <- degree(g)
```

```
          Terms
Terms      analysts   bmo capital given markets price target arilennox get never
  analysts       425   133     117   124     121   322    322         0   3     1
  bmo            133 11369     555   127     512   286    287      8428  62    19
  capital        117   555     773   113     588   283    287         0   0     0
  given          124   127     113   353     117   283    283         8   0     0
  markets        121   512     588   117     699   273    275         0   0     0
  price          322   286     283   283     273   940    898         4   2     0
  target         322   287     287   283     275   898    927         0   0     0
  arilennox        0  8428       0     8       0     4      0      8544   9     4
  get              3    62       0     0       0     2      0         9 412     5
  never            1    19       0     0       0     0      0         4   5   218
IGRAPH ab08a1d UNW- 231 10884 --
+ attr: name (v/c), weight (e/n)
+ edges from ab08a1d (vertex names):
 [1] analysts--analysts     analysts--bmo          analysts--capital      analysts--given        analysts--markets      analysts--price        analysts--target       analysts--get
 [9] analysts--never        analysts--will         analysts--just         analysts--well         analysts--stocks       analysts--new          analysts--earnings     analysts--right
[17] analysts--like         analysts--growth       analysts--rating       analysts--stock        analysts--…            analysts--financial    analysts--t…           analysts--market
[25] analysts--set          analysts--group        analysts--international analysts--give        analysts--now          analysts--know         analysts--week         analysts--last
[33] analysts--great        analysts--watch        analysts--amp          analysts--banks        analysts--best         analysts--cibc         analysts--rbc          analysts--report
[41] analysts--investment   analysts--banking      analysts--apha         analysts--montreal     analysts---            analysts--way          analysts--perform      analysts--'m
[49] analysts--don't        analysts--life         analysts--still        analysts--cut          analysts--much         analysts--buy          analysts--global       analysts--first
[57] analysts--say          analysts--see          analysts--research     analysts--canadian     analysts--downgraded   analysts--th…          analysts--million      analysts--energy
+ ... omitted several edges
```

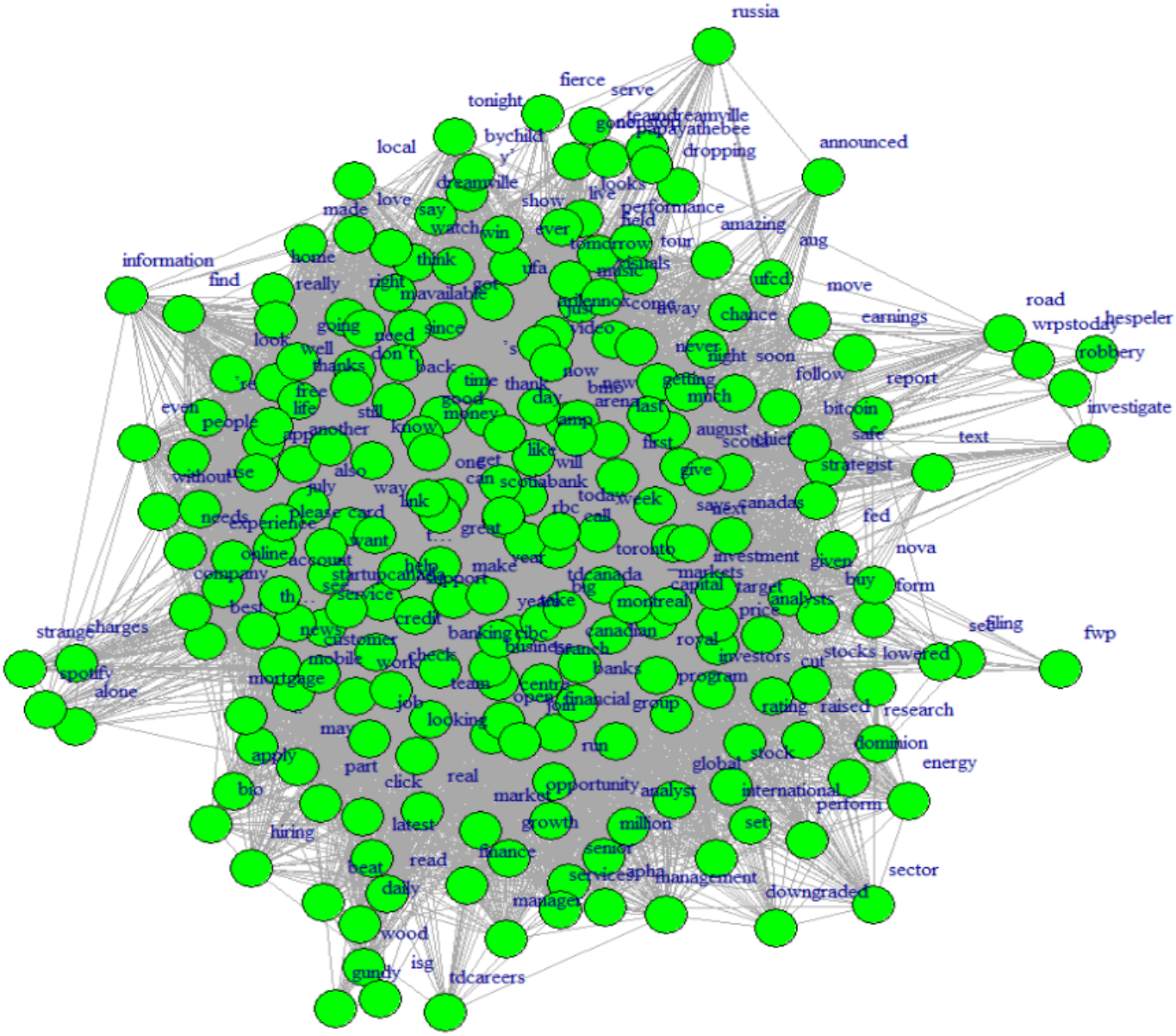
```{r}
# Histogram of node degree
hist(V(g)$degree,
     breaks = 100, # how many bars
     col = 'green',
     main = 'Histogram of Node Degree',
     ylab = 'Frequency',
     xlab = 'Degree of Vertices')
```



Note the histogram is less busy and more evenly spreadout

```{r}
```

```
# Network diagram
plot(g)
plot(g,
     vertex.color='green',
     vertex.size = 8, # can experiment with this
     vertex.label.dist = 1.5)
```



Much less busy than earlier. There are obvious discussions around branch robbery, russia, CIBC Wood Gundy and careers at TD Bank

2.9 Word cloud

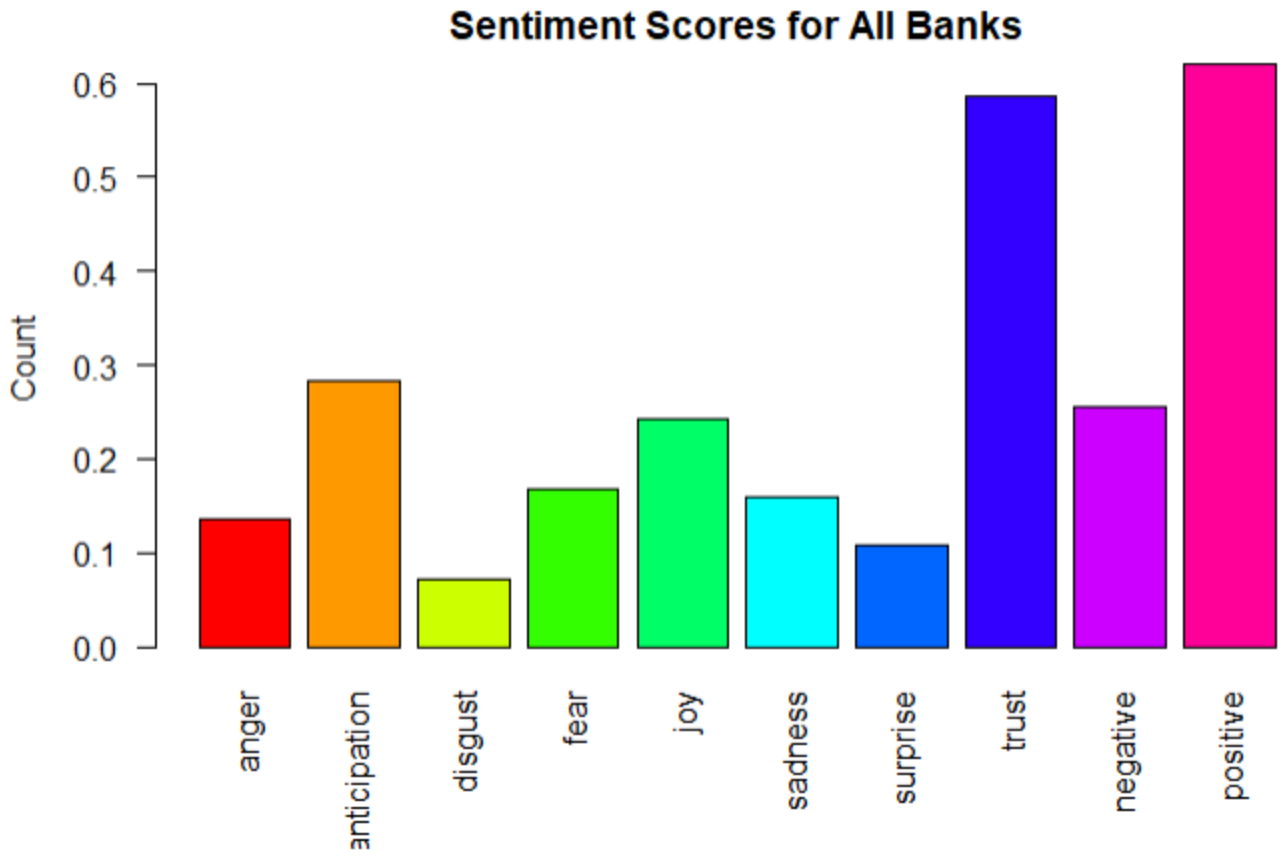
```{r}
w <- sort(rowSums(tdmat), decreasing = TRUE)
wordcloud(words = names(w),
          freq = w,
          max.words = 150,
          random.order = F,
          min.freq = 5,
          colors = brewer.pal(8, 'Dark2'),
          scale = c(5, 0.3),
```

```
          rot.per = 0.7)
```

If Ari Lennox indeed is the professional singer and songwriter, there is an odd discussion about this artiste in banking tweets. Maybe this artiste performed at the Scotiabank arena

2.10 Sentiment analysis

```{r}
sen <- get_nrc_sentiment(AllBankstext)

# Archive the sentiment scores for further analysis later
Allbanks_sen_df <- t(as.data.frame(colMeans(sen)))
write.table(Allbanks_sen_df,"/Users/sgchr/Documents/CSDA1050/Data/Allbanks_sen_df.csv",
append=T, row.names=F, col.names=T,  sep=",")

# So that we could compare with the individual banks, we will normalise the data by
applying the statistical mean
barplot(colMeans(sen),
        las = 2,
        col = rainbow(10),
        ylab = 'Count',
        main = 'Sentiment Scores for All Banks')
```



Observations:

1. The sentiment is generally positive for all banks

2. There is also a lot of trust in the banks

3. "Disgust" is the lowest sentiment

3. Social Media Analytics for Canadian Banks

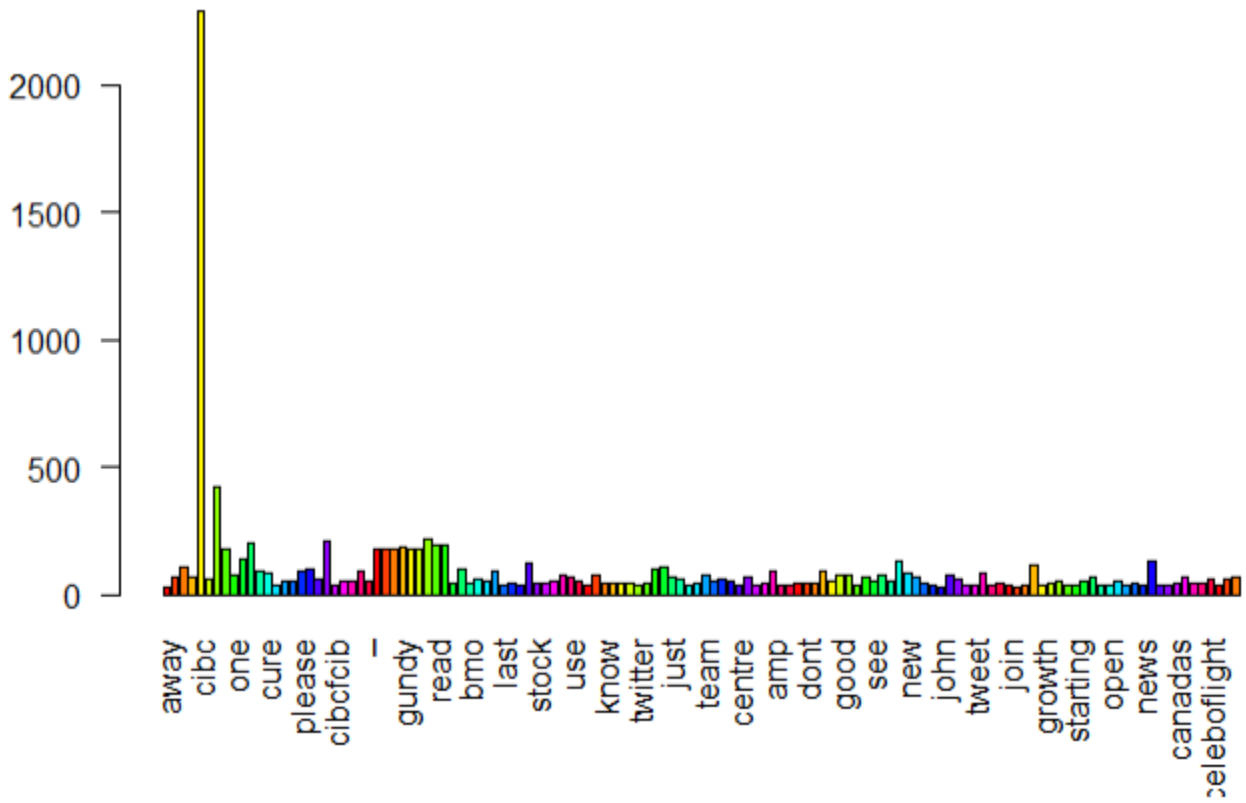
Based on the exploratory data analysis for all banks in the preceding sections, we are now ready to do the social media analytics for each of the five Canadian Banks. The outline is given below

3.1 Create and compact the term-document matrix (TDM) for each bank
3.2 Further compact the term-document matrix
3.3 Clustering of terms/tweets k-means method
3.4 Plot the hierarchical clusters
3.5 Find the pair of terms that appears frequently together
    3.5.1 Find the network of terms
    3.5.2 Find optimal term count for optimal (neither too busy nor sparse) visualisation of network diagram
    3.5.3 Plot the network of terms diagram
3.6 Word cloud
3.7 Sentiment analysis

CIBC

3.1a Create and compact the term-document matrix (TDM) for each bank

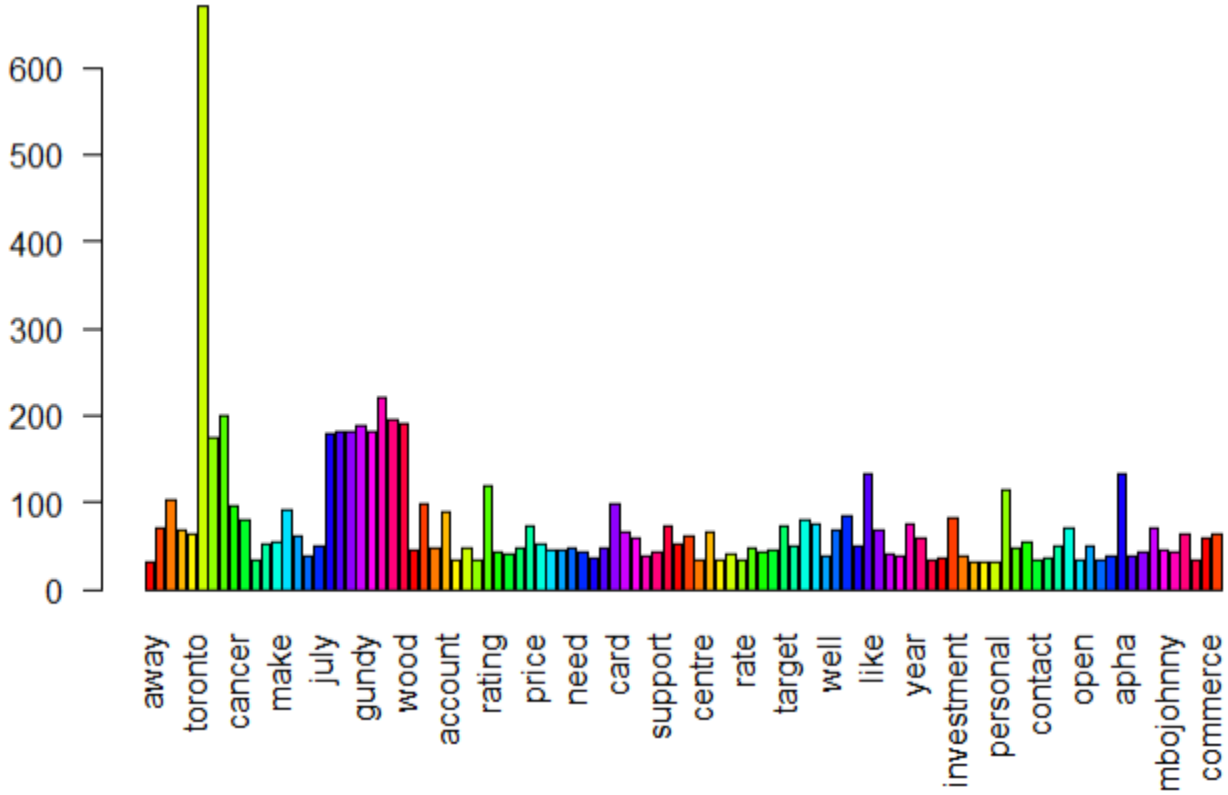
```{r}
# Load the archived tweets
CIBC_csv <- read.csv("/Users/sgchr/Documents/CSDA1050/Data/Cibc.csv", header = TRUE)

# Build the initial term-document matrix Corpus
CIBCtext <- iconv(CIBC_csv$text, to = 'UTF-8')
CIBCcorp <- Corpus(VectorSource(CIBCtext))

# Compact the Corpus
CIBCcorp <- tm_map(CIBCcorp, tolower) # Not crucial for text analytics but good practice
to do so
CIBCcorp <- tm_map(CIBCcorp, removePunctuation) # Remove punctuations
CIBCcorp <- tm_map(CIBCcorp, removeNumbers) # Remove numbers

# Remove URL
removeURL <- function(x) gsub('http[[:alnum:]]*', '', x)
CIBCcorp <- tm_map(CIBCcorp, content_transformer(removeURL))

CIBCcorp <- tm_map(CIBCcorp, removeWords, stopwords(kind="en")) # Remove "standard" stop
words

CIBCcorp <- tm_map(CIBCcorp, stripWhitespace) # remove leftover from the preceding
removal

# Create the term document matrix
CIBCtdmat <- TermDocumentMatrix(CIBCcorp, control = list(minWordLength=c(1,Inf)))
CIBCtdm <- removeSparseTerms(CIBCtdmat, sparse=0.99)
CIBCmat <- as.matrix(CIBCtdm)
CIBCfreq <- rowSums(CIBCmat)
CIBCfreq <- subset(CIBCfreq, CIBCfreq>=30) # Experiment with CIBCfreq=? to find the
optimal of of terms in the barplot
barplot(CIBCfreq,
        las=2, # list all words vertically
        col = rainbow(25))
```



The above plot shows we need remove and replace some terms. For example, since we are analysing banks, therefore term = "bank" is redundant. Likewise, this analysis is speacifically about CIBC, therefore "cibc" is redundant. Also, otherwise, "cibc" will unduly skew the wordcloud, network of terms analysis

3.2a Further compact the term-document matrix

```{r}
MyStopwords <- c("'s", "...", "bank", "b…", "cibc", "cibcs")
CIBCcorp <- tm_map(CIBCcorp, removeWords, MyStopwords)

CIBCcorp <- tm_map(CIBCcorp, gsub, pattern = 'aphria', replacement = 'aphriainc') # Replace words

CIBCcorp <- tm_map(CIBCcorp, stripWhitespace) # remove leftover from the preceding removal

# Repeat the preceding codes
CIBCtdmat <- TermDocumentMatrix(CIBCcorp, control = list(minWordLength=c(1,Inf)))
CIBCtdm <- removeSparseTerms(CIBCtdmat, sparse=0.99)
CIBCmat <- as.matrix(CIBCtdm)
CIBCfreq <- rowSums(CIBCmat)
CIBCfreq <- subset(CIBCfreq, CIBCfreq>=30) # Experiment with CIBCfreq=? to find the optimal of of terms in the barplot
barplot(CIBCfreq,
        las=2, # list all words vertically
        col = rainbow(25))
```



The text is mostly cleaned up

3.3a Clustering of terms/tweets k-means method

This analysis will uncover the following two insights:

1. **Within cluster sum of squares by cluster**: We want this to be low, which means the elements within each cluster are close to each other

2. **Between_SS / total_SS**: We want this to be high, that is, distances between clusters are further apart

I experimented with k = 10-22 to find best mix of distance within and between clusters and deemed the best is k=20

In section 3.4a, we will use k=20 to visualise the term-clusters using a cluster dendrogram plot

```{r}
set.seed(123)

CIBCm1 <- t(CIBCmat) # Transpose CIBCmat
CIBCk <- 20
CIBCkc <- kmeans(CIBCm1, CIBCk)
CIBCkc
```

```
 within cluster sum of squares by cluster:
  [1]   59.69231  721.75636   71.96429  233.39806  108.00000  114.61111  121.79592   53.18519
 20.76923   38.60000  121.78082   91.01587   77.13043    0.00000  104.51282   60.44444 2148.51050
 32.88889  104.68000
 [20]   38.43478
  (between_SS / total_SS =  44.3 %)
```

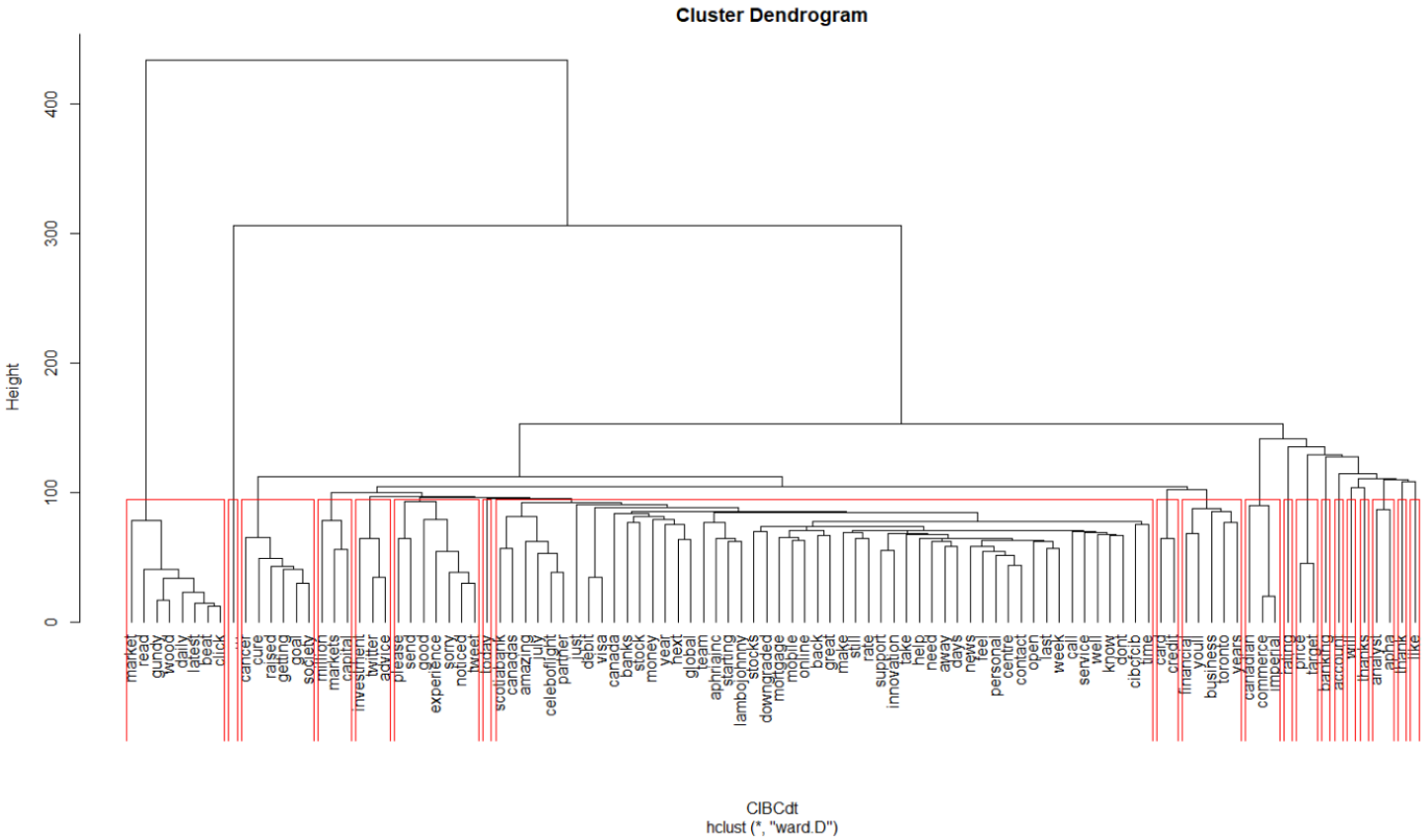
Observations:

Experimentation for k = 10 to 22 implied the best mix of distance within and between clusters for the current CIBC dataset is k=21

k	Within clusters	Between clusters
=	==========	==========
10	488	21.6
11	558	20.0
12	507	23.9
13	366	24.4
14	324	40.3
15	377	24.6
16	285	25.6
17	340	25.7
18	240	27.6
19	229	43.6
20	209	44.3 <-
21	195	29.2
22	190	30.7

3.4a Plot the hierarchical clusters

```{r}
# Find the distance, use scale to normalise the matrix
CIBCdt <- dist(scale(CIBCmat))

CIBChc <- hclust(CIBCdt, method = "ward.D")
plot(CIBChc, hang=-1)
rect.hclust(CIBChc, k=20) # 20 clusters based on analysis in section 3.3a
```



Not surprisingly, the terms "cancer", "cure", "raised", "goal" are clustered together since CIBC is a majore sponsor for "Run For The Cure" charity

3.5a Find the pair of terms that appears frequently together

```{r}
# Term document matrix to convert unstructure text into structured for easier analysis
CIBCtdmat <- TermDocumentMatrix(CIBCcorp)
CIBCtdmat <- as.matrix(CIBCtdmat)

# Convert matrix into binary, that is whether a term appears (1) or not (0)
CIBCtdmat[CIBCtdmat>1] <- 1

# Create term-term matrix
CIBCttm <- CIBCtdmat %*% t(CIBCtdmat) # Multiply CIBCtdmat and transpose of CIBCtdmat
```

3.5.1a Find the network of terms

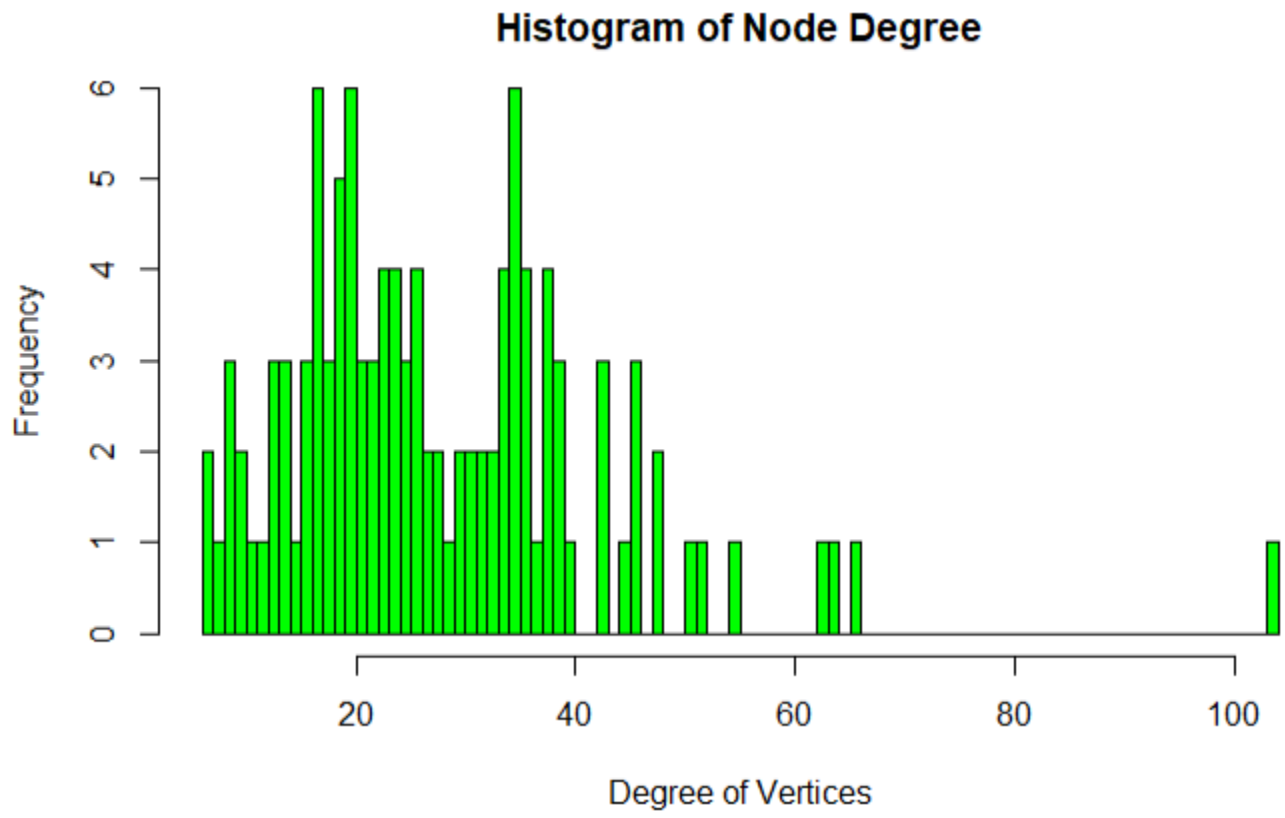
```{r}
CIBCg <- graph.adjacency(CIBCttm, weighted = T, mode = 'undirected')
CIBCg <- simplify(CIBCg) # To prevent looping of same terms
V(CIBCg)$label <- V(CIBCg)$name # Labels for the terms
V(CIBCg)$degree <- degree(CIBCg) # How often each term appears, or number of connections between terms
CIBCg
```

```
IGRAPH ded7853 UNW- 5749 56458 --
+ attr: name (v/c), label (v/c), degree (v/n), weight (e/n)
+ edges from ded7853 (vertex names):
 [1] awardwinning--away          awardwinning--broadway      awardwinning--broadwaychicago awardwinning--b…            awardwinning--chicago       awardwinning--director      awardwinning--honor
 [8] awardwinning--passed        awardwinning--producer      awardwinning--today           awardwinning--tony          awardwinning--will          awardwinning--today…        away        --broadway
[15] away        --broadwaychicago away        --b…          away        --chicago         away        --director      away        --honor         away        --passed        away        --producer
[22] away        --today           away        --tony        away        --will            away        --food          away        --today…        away        --gundy         away        --wood
[29] away        --thing           away        --goes        away        --thank           away        --house         away        --difficult     away        --need          away        --canada
[36] away        --card            away        --just        away        --rewarding       away        --stopped       away        --times         away        --working…      away        --month
[43] away        --right           away        --much        away        --builders        away        --cant          away        --create…       away        --enough        away        --helped
[50] away        --sponsors        away        --thecx       away        --money           away        --youre         away        --like          away        --bootsotground away        --days
+ … omitted several edges
```

3.5.2a Find optimal term count for optimal (neither too busy nor sparse) visualisation of network diagram

```{r}
```

```
# Reset CIBCtdmat if needed to experiment with optimal rowSums(CIBCtdmat)>?
# The larger ? is, the more visible the network of terms is, but less granular
CIBCtdmat <- TermDocumentMatrix(CIBCcorp)
CIBCtdmat <- as.matrix(CIBCtdmat)

# rowSums counts the total frequency; that is, keep terms that appear > 30 times
CIBCtdmat <- CIBCtdmat[rowSums(CIBCtdmat)>30,]

# Re-run earlier code
CIBCtdmat[CIBCtdmat>1] <- 1 # Whenvevr CIBCtdmat is > 1, assign value of 1
CIBCtermM <- CIBCtdmat %*% t(CIBCtdmat)
#CIBCtermM[1:10,1:10]
CIBCg <- graph.adjacency(CIBCtermM, weighted = T, mode = 'undirected')
CIBCg <- simplify(CIBCg) # To prevent looping of same terms
V(CIBCg)$label <- V(CIBCg)$name
V(CIBCg)$degree <- degree(CIBCg)

# Histogram of node degree
hist(V(CIBCg)$degree,
     breaks = 100, # how many bars
     col = 'green',
     main = 'Histogram of Node Degree',
     ylab = 'Frequency',
     xlab = 'Degree of Vertices')
```

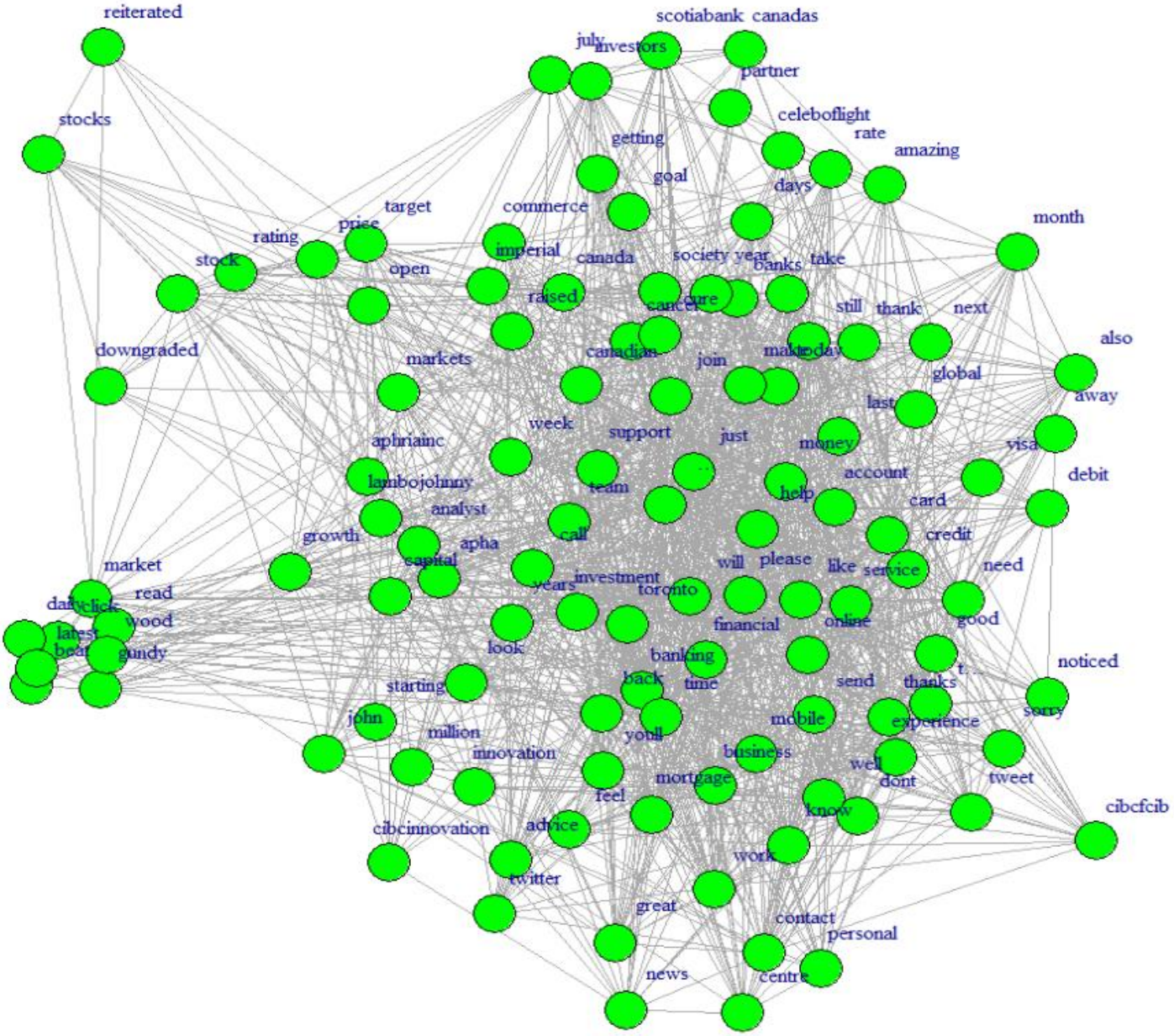


Most terms appears less than 70 times

3.5.3a Plot the network of terms diagram

```{r}
# To experiment with rowSums(CIBCtdmat)>? in 3.5.2 if there is no apparent clusters or if diagram is too busy / sparse
plot(CIBCg)
plot(CIBCg,
```

```
     vertex.color='green',
     vertex.size = 8, # can experiment with this
     vertex.label.dist = 1.5)
```



An apparent network appears surrounding "Wood Gundy", "Growth" and "Innovation"

3.6a Word cloud

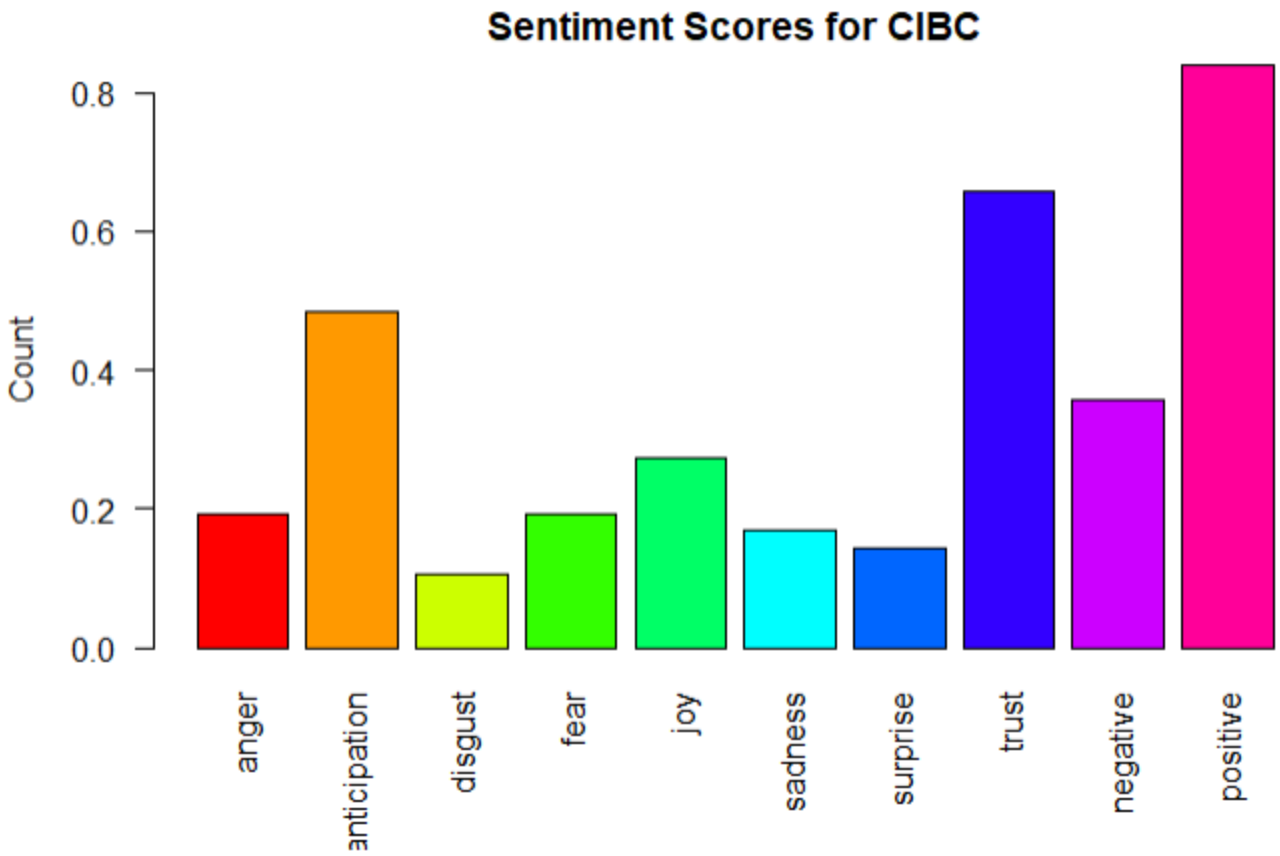
```{r}
CIBCtdmat <- TermDocumentMatrix(CIBCcorp)
CIBCtdmat <- as.matrix(CIBCtdmat)

CIBCw <- sort(rowSums(CIBCtdmat), decreasing = TRUE)
wordcloud(words = names(CIBCw),
          freq = CIBCw,
          max.words = 150,
          random.order = F,
          min.freq = 5,
          colors = brewer.pal(8, 'Dark2'),
          scale = c(5, 0.3),
```

```
        rot.per = 0.7)
```

Consistent with previous analysis, lots of discussion about stock investments, some postive words are obvious: "like", "thank"

3.7a Sentiment analysis

```{r}
CIBCsen <- get_nrc_sentiment(CIBCtext)

# Archive the sentiment scores for further analysis later
CIBC_sen_df <- t(as.data.frame(colMeans(CIBCsen)))
write.table(CIBC_sen_df,"/Users/sgchr/Documents/CSDA1050/Data/Allbanks_sen_df.csv",
append=T, row.names=F, col.names=F,  sep=",")

# So that we could compare with the individual banks, we will normalise the data by
applying the statistical mean
barplot(colMeans(CIBCsen),
        las = 2,
        col = rainbow(10),
        ylab = 'Count',
        main = 'Sentiment Scores for CIBC')
```

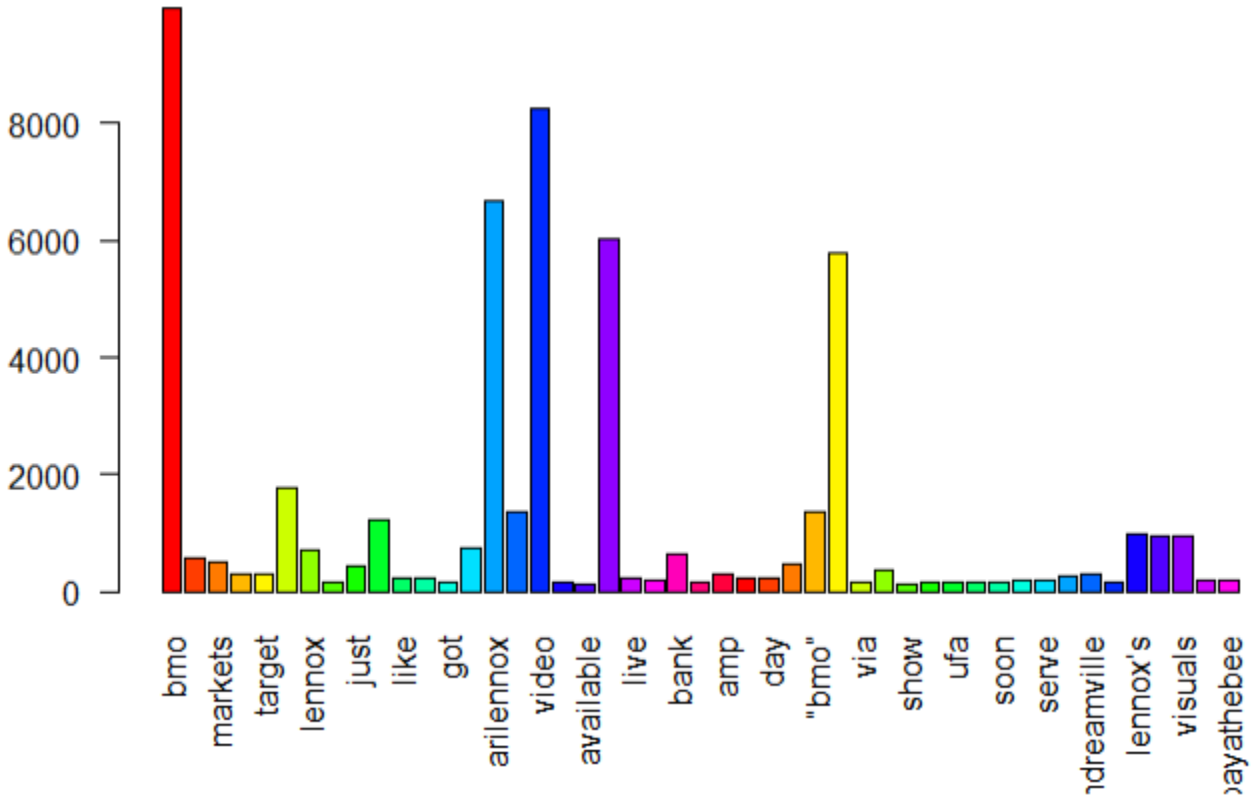


BMO

3.1b Create and compact the term-document matrix (TDM) for each bank

```{r}
# Load the archived tweets
BMO_csv <- read.csv("/Users/sgchr/Documents/CSDA1050/Data/Bmo.csv", header = TRUE)

# Build the initial term-document matrix Corpus
BMOtext <- iconv(BMO_csv$text, to = 'UTF-8')
BMOcorp <- Corpus(VectorSource(BMOtext))

# Compact the Corpus
BMOcorp <- tm_map(BMOcorp, tolower) # Not crucial for text analytics but good practice to do so
BMOcorp <- tm_map(BMOcorp, removePunctuation) # Remove punctuations
BMOcorp <- tm_map(BMOcorp, removeNumbers) # Remove numbers

# Remove URL
removeURL <- function(x) gsub('http[[:alnum:]]*', '', x)
BMOcorp <- tm_map(BMOcorp, content_transformer(removeURL))

BMOcorp <- tm_map(BMOcorp, removeWords, stopwords(kind="en")) # Remove "standard" stop words

BMOcorp <- tm_map(BMOcorp, stripWhitespace) # remove leftover from the preceding removal

# Create the term document matrix
BMOtdmat <- TermDocumentMatrix(BMOcorp, control = list(minWordLength=c(1,Inf)))
BMOtdm <- removeSparseTerms(BMOtdmat, sparse=0.99)
BMOmat <- as.matrix(BMOtdm)
BMOfreq <- rowSums(BMOmat)
```

```
BMOfreq <- subset(BMOfreq, BMOfreq>=50) # Experiment with BMOfreq=? to find the optimal
of of terms in the barplot
barplot(BMOfreq,
        las=2, # list all words vertically
        col = rainbow(25))
```



The above plot shows we need remove and replace some terms. For example, since we are analysing banks, therefore term = "bank" is redundant. Likewise, this analysis is speacifically about BMO, therefore "bmo" is redundant. Also, otherwise, "bmo" will unduly skew the wordcloud, network of terms analysis

3.2b Further compact the term-document matrix

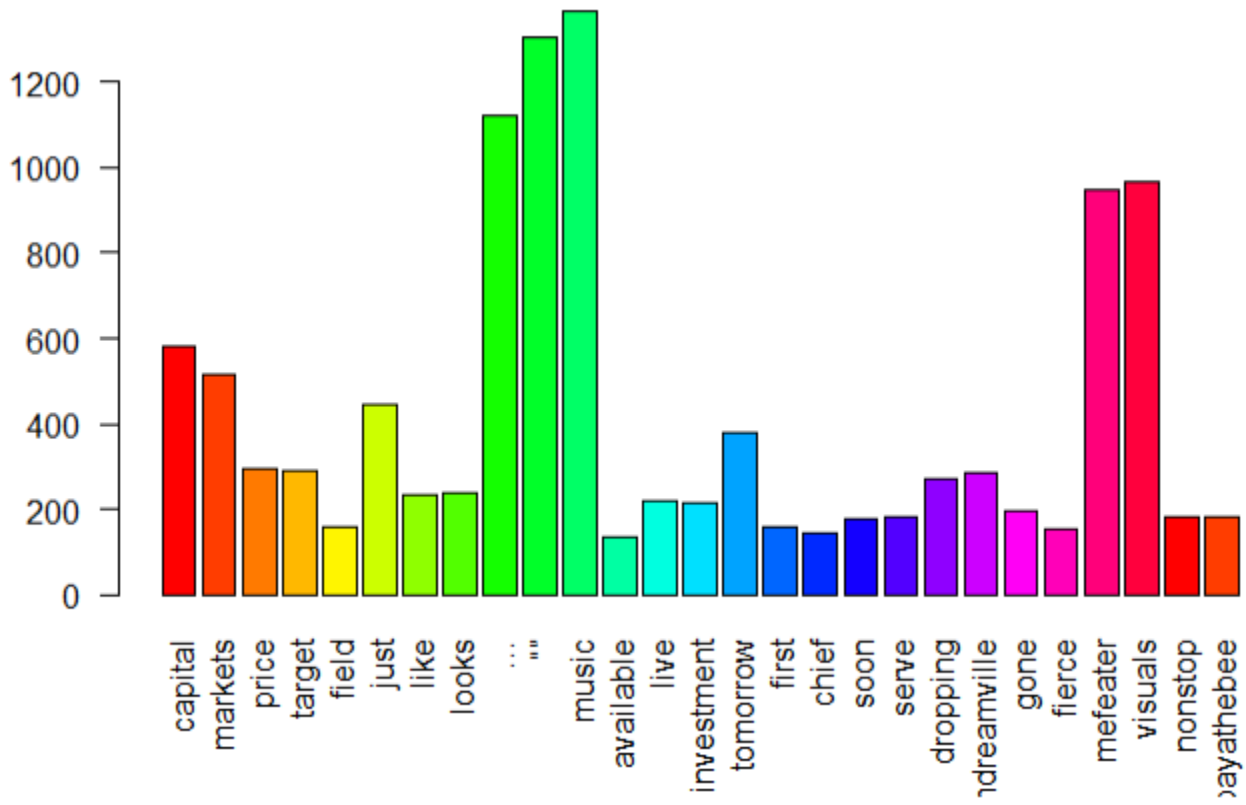
```{r}
MyStopwords <- c("...", "bank", "bmo", "href", "montreal", "“bmo”", "arilennox", "ari",
"lennox", "video", "lennox's", "“”")
BMOcorp <- tm_map(BMOcorp, removeWords, MyStopwords)

BMOcorp <- tm_map(BMOcorp, gsub, pattern = 'wages”', replacement = 'wages') # Replace
words
BMOcorp <- tm_map(BMOcorp, gsub, pattern = '“perhaps', replacement = 'perhaps')
BMOcorp <- tm_map(BMOcorp, gsub, pattern = '"hold”', replacement = 'hold')

BMOcorp <- tm_map(BMOcorp, stripWhitespace) # remove leftover from the preceding removal

# Repeat the preceding codes
BMOtdmat <- TermDocumentMatrix(BMOcorp, control = list(minWordLength=c(1,Inf)))
BMOtdm <- removeSparseTerms(BMOtdmat, sparse=0.99)
BMOmat <- as.matrix(BMOtdm)
BMOfreq <- rowSums(BMOmat)
BMOfreq <- subset(BMOfreq, BMOfreq>=30) # Experiment with BMOfreq=? to find the optimal
of of terms in the barplot
barplot(BMOfreq,
        las=2, # list all words vertically
        col = rainbow(25))
```

```




The text is mostly cleaned up

*3.3b Clustering of terms/tweets k-means method*
This analysis will uncover the following two insights:

1. Within cluster sum of squares by cluster: We want this to be low, which means the elements within each cluster are close to each other

2. Between_SS / total_SS: We want this to be high, that is, distances between clusters are further apart

I experimented with k = 10-12 to find best mix of distance within and between clusters and deemed the best is k=11

In section 3.4b, we will use k=11 to visualise the term-clusters using a cluster dendrogram plot

```{r}
set.seed(123)

BMOm1 <- t(BMOmat) # Transpose BMOmat
BMOk <- 11
BMOkc <- kmeans(BMOm1, BMOk)
BMOkc
```

```
within cluster sum of squares by cluster:
 [1]   46.918919    0.000000    7.989474   13.984375    0.000000   28.411765  318.951983  559.523005   68.058394    2.980916 1082.091026
 (between_SS / total_SS =  80.7 %)
```

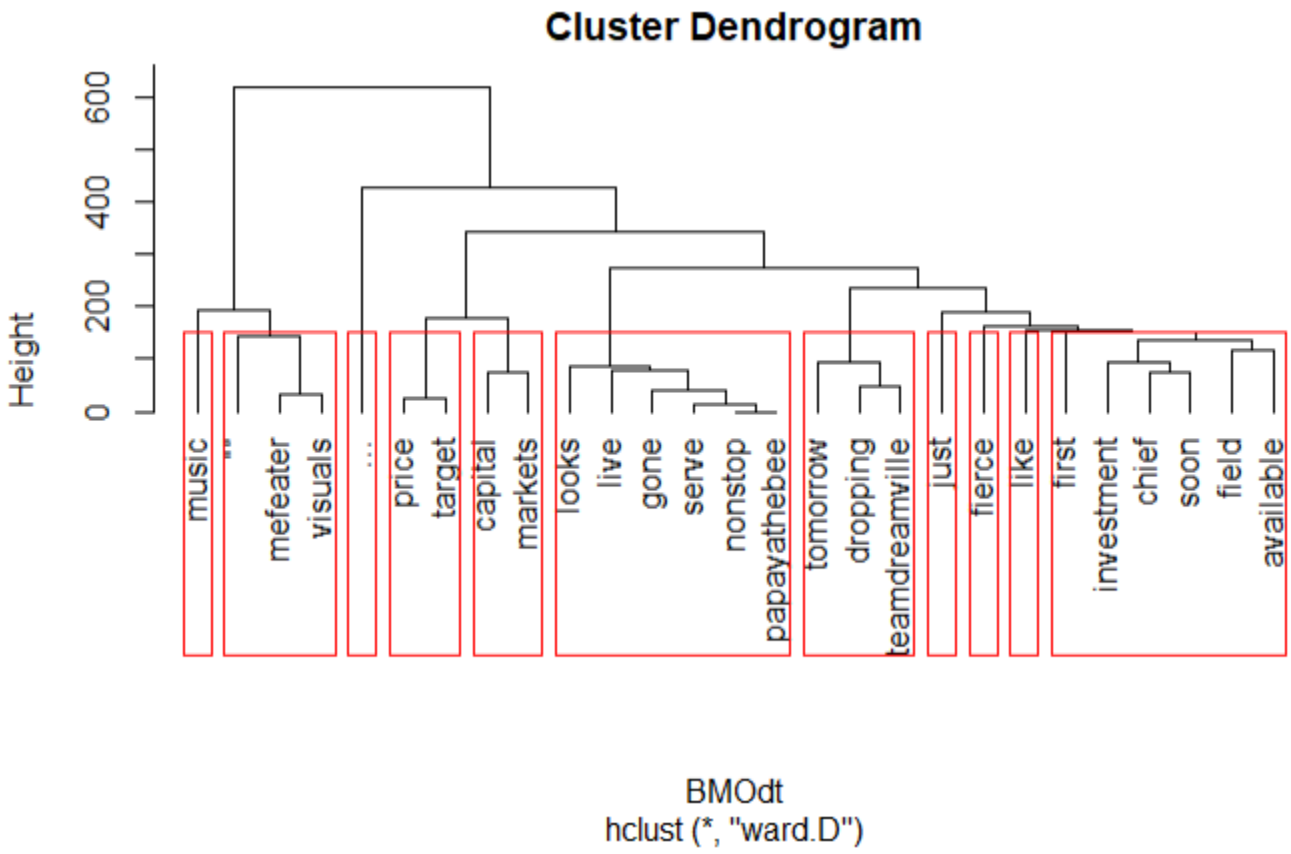
Observations:
```

Experimentation for k = 10 to 12 implied the best mix of distance within and between clusters for the current CIBC dataset is k=11

```
k   Within clusters  Between clusters
=   ===============  ================
10  627              67.4
11  424              80.7 <-
12  711              55.6
```

3.4b Plot the hierarchical clusters

```{r}
# Find the distance, use scale to normalise the matrix
BMOdt <- dist(scale(BMOmat))

BMOhc <- hclust(BMOdt, method = "ward.D")
plot(BMOhc, hang=-1)
rect.hclust(BMOhc, k=11) # 11 clusters
```



3.5b Find the pair of terms that appears frequently together

```{r}
# Term document matrix to convert unstructure text into structured for easier analysis
BMOtdmat <- TermDocumentMatrix(BMOcorp)
BMOtdmat <- as.matrix(BMOtdmat)

# Convert matrix into binary, that is whether a term appears (1) or not (0)
BMOtdmat[BMOtdmat>1] <- 1

# Create term-term matrix
BMOttm <- BMOtdmat %*% t(BMOtdmat) # Multiply BMOtdmat and transpose of BMOtdmat
```

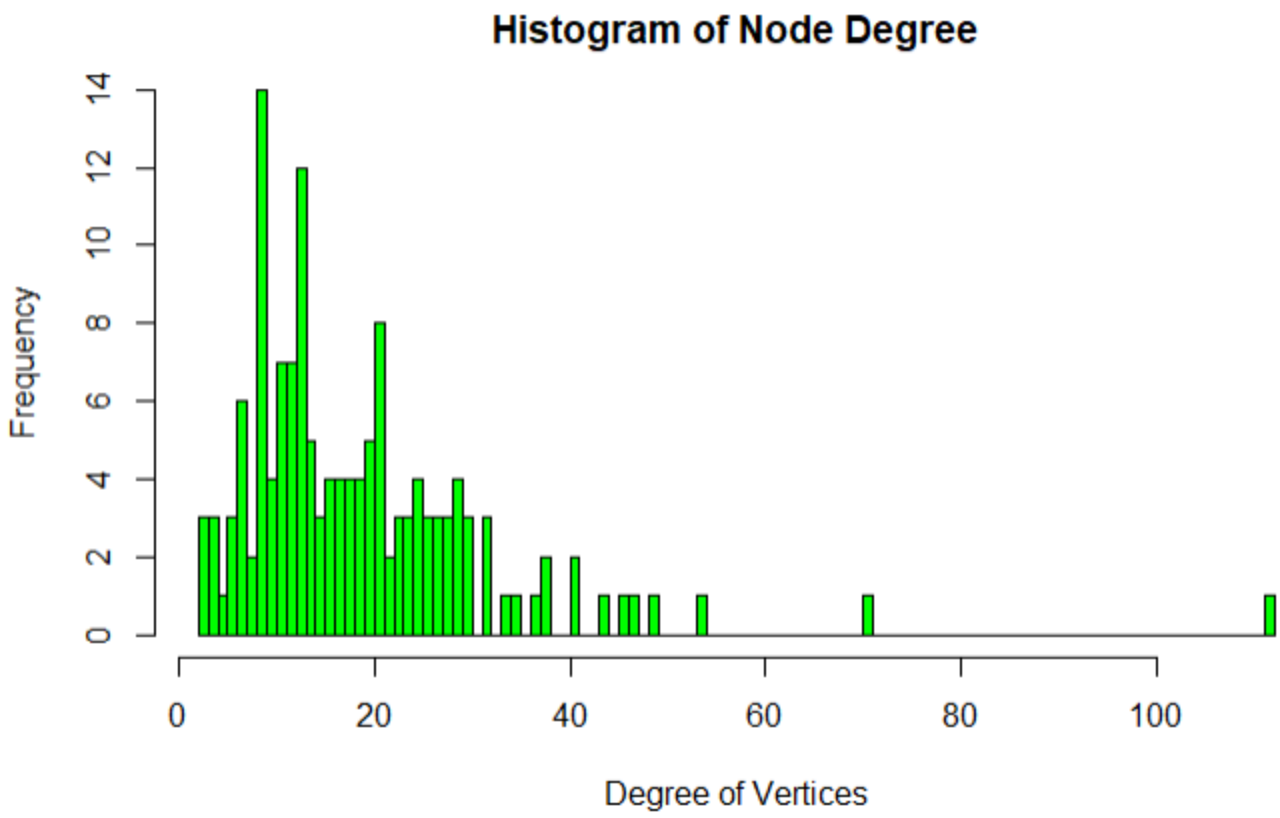
3.5.1b Find the network of terms

```{r}
BMOg <- graph.adjacency(BMOttm, weighted = T, mode = 'undirected')
BMOg <- simplify(BMOg) # To prevent looping of same terms
V(BMOg)$label <- V(BMOg)$name # Labels for the terms
V(BMOg)$degree <- degree(BMOg) # How often each term appears, or number of connections between terms
BMOg
```

```
IGRAPH 62b8aab UNW- 9131 76282 --
+ attr: name (v/c), label (v/c), degree (v/n), weight (e/n)
+ edges from 62b8aab (vertex names):
 [1] analysts--arcc          analysts--ares          analysts--capital       analysts--given         analysts--markets       analysts--price         analysts--target        analysts--steel
 [9] analysts--primo         analysts--prmw          analysts--water         analysts--stocks        analysts--coverage      analysts--okta          analysts--receives      analysts--earnings
[17] analysts--rating        analysts--trust         analysts--initiated     analysts--zscaler       analysts--market        analysts--mastercard    analysts--gild          analysts--gilead
[25] analysts--sciences      analysts--group         analysts--international analysts--connections analysts--give          analysts--waste         analysts--increased     analysts--mcdonald
[33] analysts--amgen         analysts--amgn          analysts--national      analysts--dean          analysts--investment    analysts--terex         analysts--perform       analysts--hudbay
[41] analysts--minerals      analysts--average       analysts--earns         analysts--"hold"        analysts--foods         analysts--energy        analysts--brands        analysts--management
[49] analysts--onemain       analysts--nutrien       analysts--medical       analysts--match         analysts--covered       analysts--equities      analysts--consensus     analysts--brewing
[57] analysts--coors         analysts--molson        analysts--offer         analysts--services      analysts--mednax        analysts--nexa          analysts--resources     analysts--restaurant
+ ... omitted several edges
```

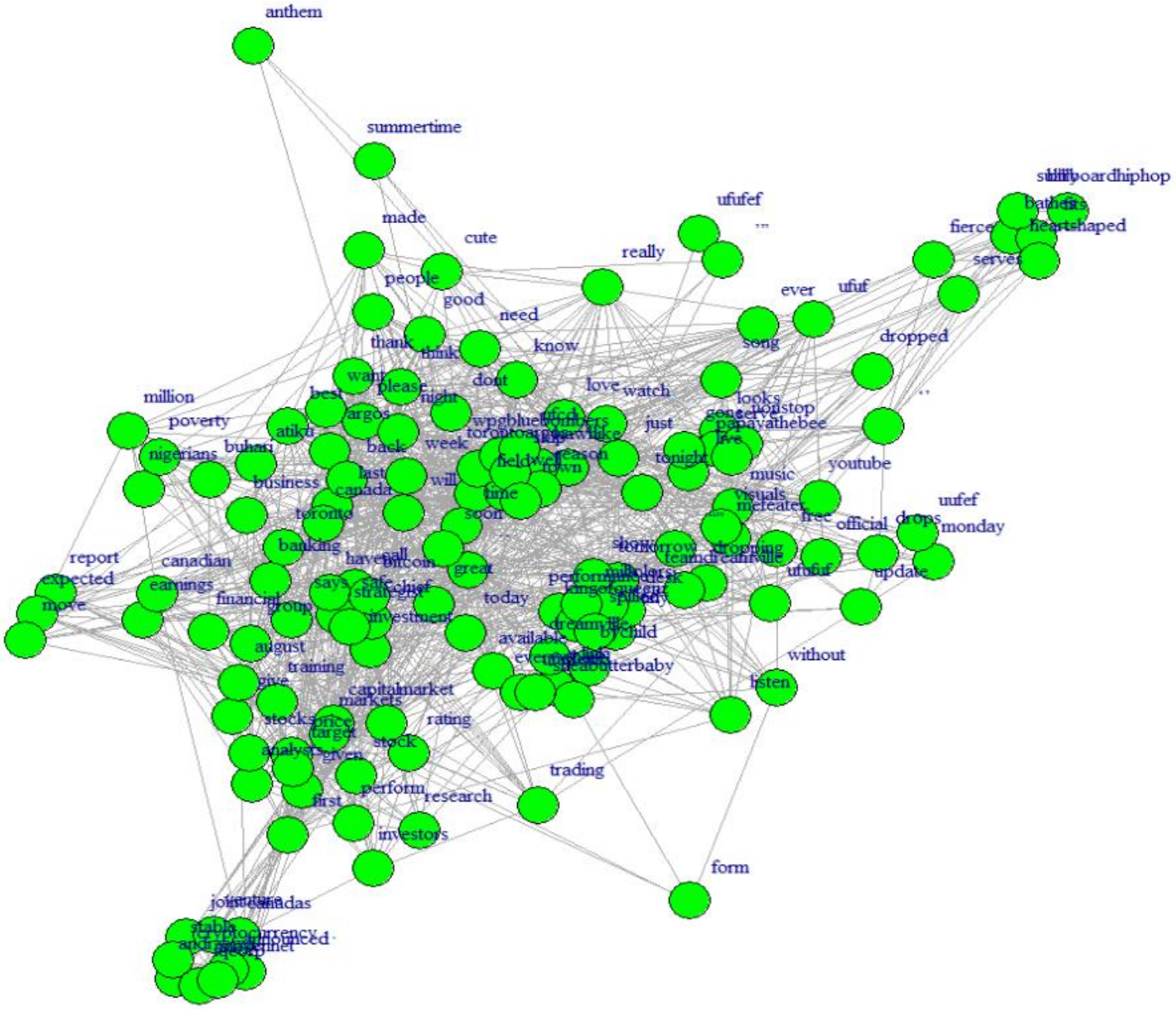
3.5.2b Find optimal term count for optimal (neither too busy nor sparse) visualisation of network diagram

```{r}
# Reset BMOtdmat if needed to experiment with optimal rowSums(BMOtdmat)>?
# The larger ? is, the more visible the network of terms is, but less granular
BMOtdmat <- TermDocumentMatrix(BMOcorp)
BMOtdmat <- as.matrix(BMOtdmat)

# rowSums counts the total frequency; that is, keep terms that appear > 25 times
BMOtdmat <- BMOtdmat[rowSums(BMOtdmat)>50,]

# Re-run earlier code
BMOtdmat[BMOtdmat>1] <- 1 # Whenvevr BMOtdmat is > 1, assign value of 1
BMOtermM <- BMOtdmat %*% t(BMOtdmat)
BMOg <- graph.adjacency(BMOtermM, weighted = T, mode = 'undirected')
BMOg <- simplify(BMOg) # To prevent looping of same terms
V(BMOg)$label <- V(BMOg)$name
V(BMOg)$degree <- degree(BMOg)

# Histogram of node degree
hist(V(BMOg)$degree,
     breaks = 100, # how many bars
     col = 'green',
     main = 'Histogram of Node Degree',
     ylab = 'Frequency',
     xlab = 'Degree of Vertices')
```



3.5.3b Plot the network of terms diagram

```{r}
# Network diagram
plot(BMOg)
plot(BMOg,
     vertex.color='green',
     vertex.size = 8, # can experiment with this
     vertex.label.dist = 1.5)
```



Obvious cluster of discussion on cryptocurrency for bmo

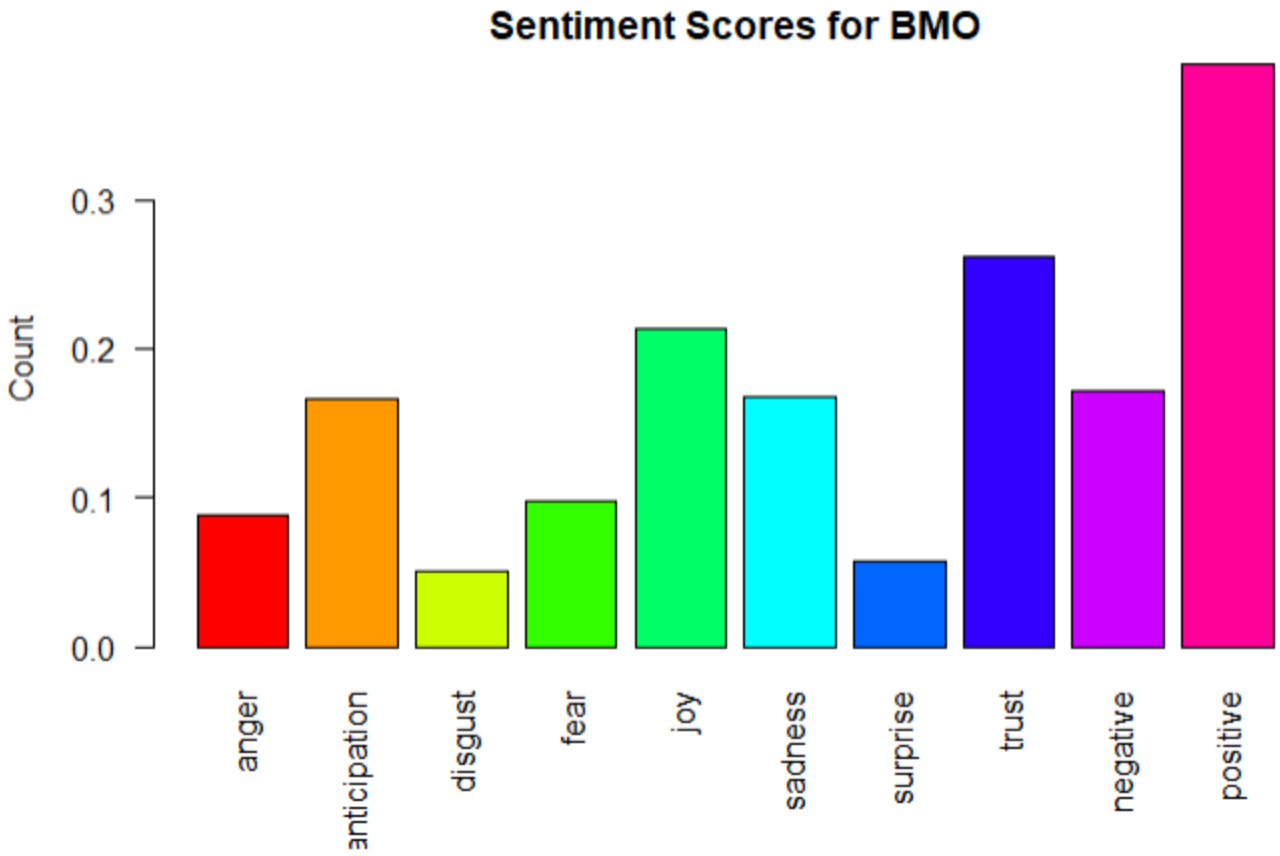
3.6b Word cloud

```{r}
BMOtdmat <- TermDocumentMatrix(BMOcorp)
BMOtdmat <- as.matrix(BMOtdmat)

BMOw <- sort(rowSums(BMOtdmat), decreasing = TRUE)
wordcloud(words = names(BMOw),
          freq = BMOw,
          max.words = 150,
          random.order = F,
          min.freq = 5,
          colors = brewer.pal(8, 'Dark2'),
          scale = c(5, 0.3),
          rot.per = 0.7)
```

Lots of discussion about (possibly the artiste) Ari Lennox, instead of banking stuff. Can include this into the stopword distionary. Afternote: "Ari Lennox" was included in stopword dictionary but "music" was not. Apparently there is a Ari Lennox music video about BMO, hence the enormous volume of tweets about this subject

3.7b Sentiment analysis

```{r}
BMOsen <- get_nrc_sentiment(BMOtext)

BMO_sen_df <- t(as.data.frame(colMeans(BMOsen)))
write.table(BMO_sen_df,"/Users/sgchr/Documents/CSDA1050/Data/Allbanks_sen_df.csv",
append=T, row.names=F, col.names=F,  sep=",")

barplot(colMeans(BMOsen),
        las = 2,
        col = rainbow(10),
        ylab = 'Count',
        main = 'Sentiment Scores for BMO')
```

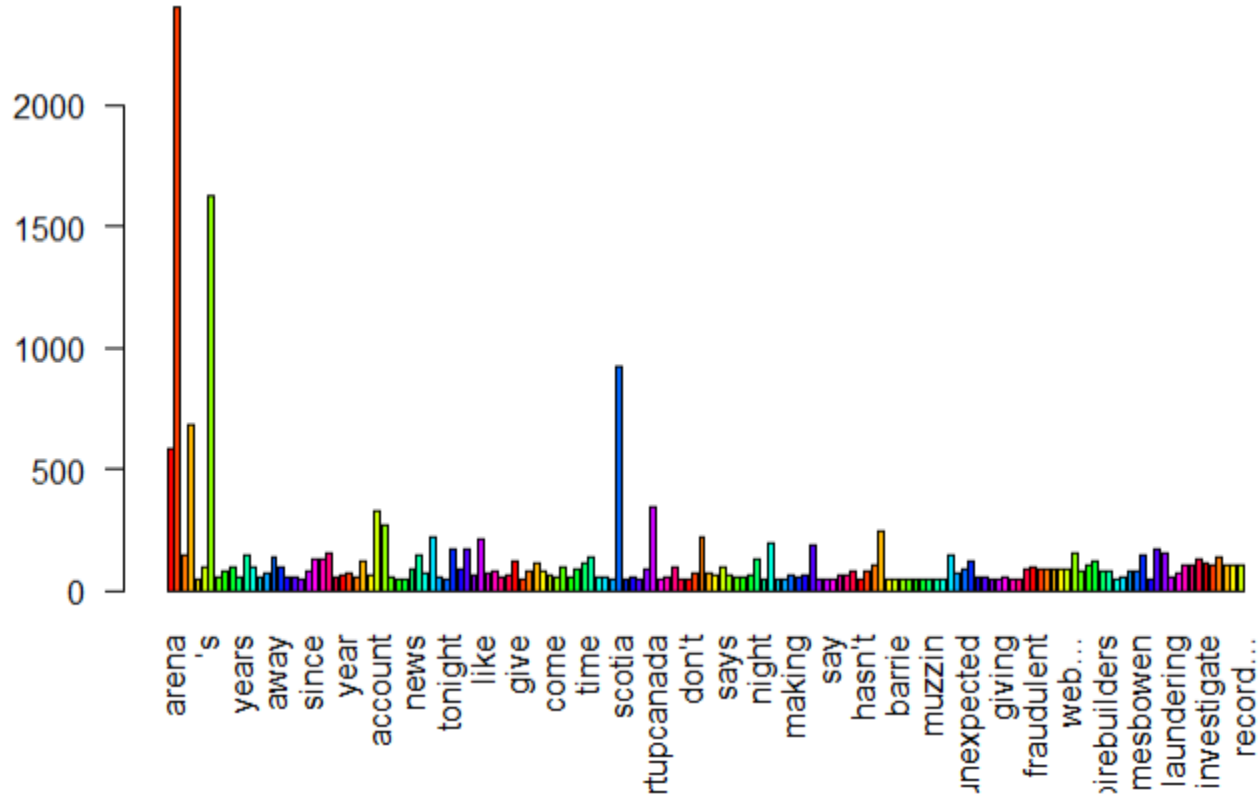


BNS

3.1c Create and compact the term-document matrix (TDM) for each bank

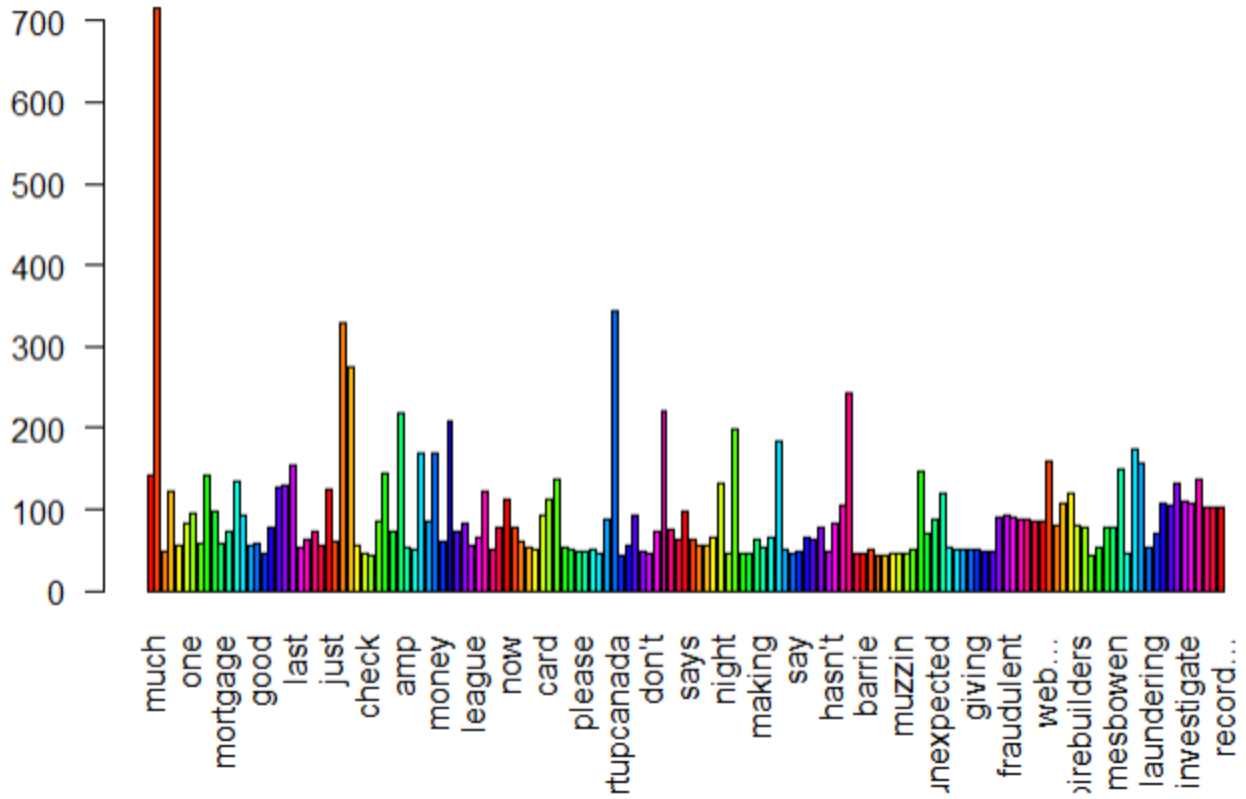
```{r}
# Load the archived tweets
BNS_csv <- read.csv("/Users/sgchr/Documents/CSDA1050/Data/Bns.csv", header = TRUE)

# Build the initial term-document matrix Corpus
BNStext <- iconv(BNS_csv$text, to = 'UTF-8')
BNScorp <- Corpus(VectorSource(BNStext))

# Compact the Corpus
BNScorp <- tm_map(BNScorp, tolower) # Not crucial for text analytics but good practice to do so
BNScorp <- tm_map(BNScorp, removePunctuation) # Remove punctuations
BNScorp <- tm_map(BNScorp, removeNumbers) # Remove numbers

# Remove URL
removeURL <- function(x) gsub('http[[:alnum:]]*', '', x)
BNScorp <- tm_map(BNScorp, content_transformer(removeURL))

BNScorp <- tm_map(BNScorp, removeWords, stopwords(kind="en")) # Remove "standard" stop words

BNScorp <- tm_map(BNScorp, stripWhitespace) # remove leftover from the preceding removal

# Create the term document matrix
BNStdmat <- TermDocumentMatrix(BNScorp, control = list(minWordLength=c(1,Inf)))
BNStdm <- removeSparseTerms(BNStdmat, sparse=0.99)
BNSmat <- as.matrix(BNStdm)
BNSfreq <- rowSums(BNSmat)
```

```
BNSfreq <- subset(BNSfreq, BNSfreq>=30) # Experiment with BNSfreq=? to find the optimal
of of terms in the barplot
barplot(BNSfreq,
        las=2, # list all words vertically
        col = rainbow(25))
```



3.2c Further compact the term-document matrix

```{r}
MyStopwords <- c("scotiabank", "scotia", "bank", "bns", "arena", "'m", "…","t…")
BNScorp <- tm_map(BNScorp, removeWords, MyStopwords)

BNScorp <- tm_map(BNScorp, gsub, pattern = 'aphria', replacement = 'aphriainc') # Replace
words

BNScorp <- tm_map(BNScorp, stripWhitespace) # remove leftover from the preceding removal

# Repeat the preceding codes
BNStdmat <- TermDocumentMatrix(BNScorp, control = list(minWordLength=c(1,Inf)))
BNStdm <- removeSparseTerms(BNStdmat, sparse=0.99)
BNSmat <- as.matrix(BNStdm)
BNSfreq <- rowSums(BNSmat)
BNSfreq <- subset(BNSfreq, BNSfreq>=30) # Experiment with BNSfreq=? to find the optimal
of of terms in the barplot
barplot(BNSfreq,
        las=2, # list all words vertically
        col = rainbow(25))
```



3.3c Clustering of terms/tweets k-means method

```{r}
set.seed(123)

BNSm1 <- t(BNSmat) # Transpose BNSmat
BNSk <- 21
BNSkc <- kmeans(BNSm1, BNSk)
BNSkc
```

```
 within cluster sum of squares by cluster:
  [1]  132.573643  107.938462  340.560510   25.818182  186.347826   77.450980  104.285714   73.859155
 140.275862  181.200000 4121.691330  131.000000  274.682927    3.954023  349.466667   56.122449
 13.695238
 [18]   98.604651  750.947531   94.000000    2.937500    3.911111
  (between_SS / total_SS =  49.1 %)
```

Observations:

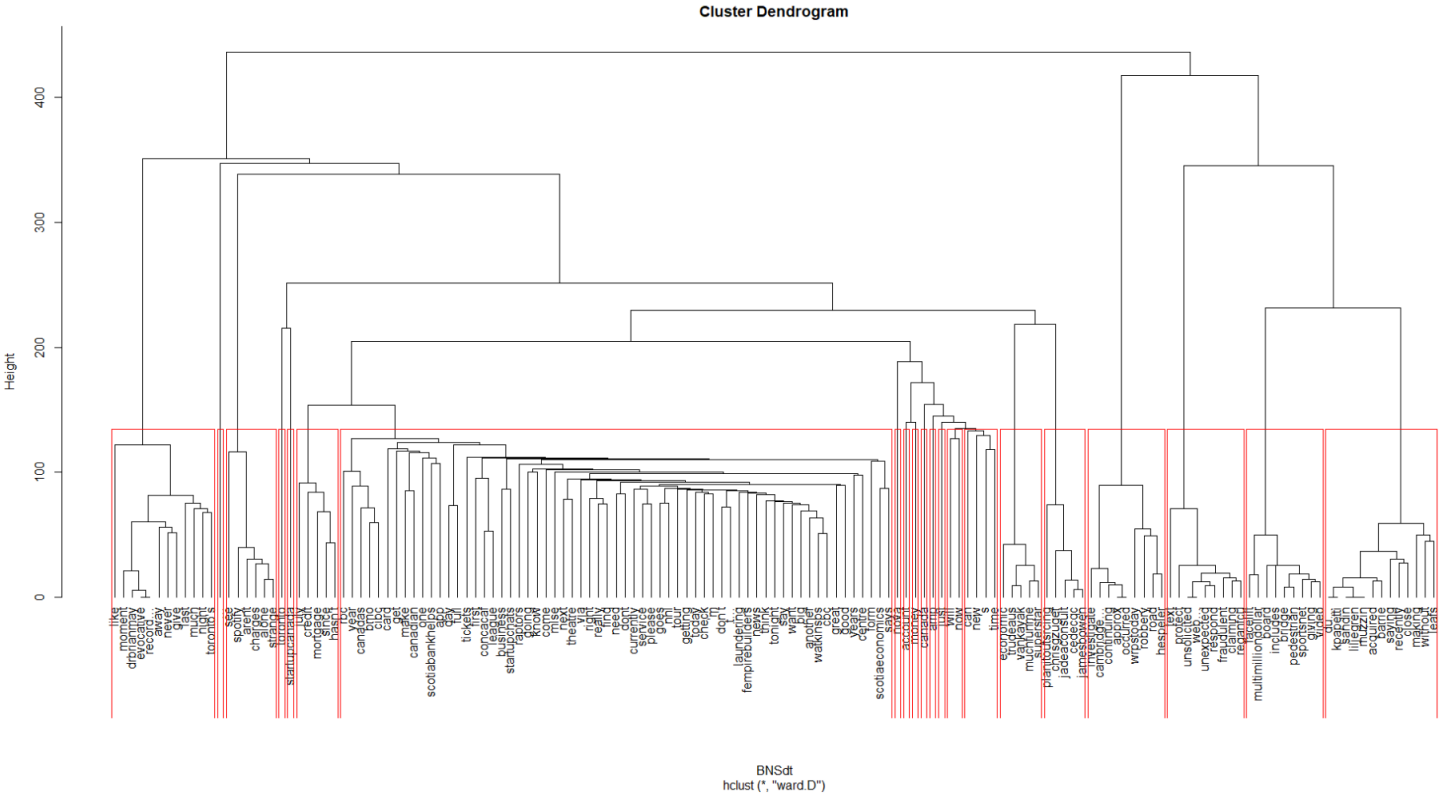
Experimentation for k = 10 to 22 implied the best mix of distance within and between clusters for the current CIBC dataset is k=21

k =	Within clusters	Between clusters
10	1066	25.4
11	958	26.2
12	781	34.4
13	852	22.4
14	646	36.7
15	619	35.0
16	585	34.4
17	484	42.5
18	535	32.7
19	502	33.2
20	521	27.0

```
21   311              49.1 <-
22   403              37.8
```

3.4c Plot the hierarchical clusters

```{r}
# Find the distance, use scale to normalise the matrix
BNSdt <- dist(scale(BNSmat))

BNShc <- hclust(BNSdt, method = "ward.D")
plot(BNShc, hang=-1)
rect.hclust(BNShc, k=21) # 21 clusters
```



3.5c Find the pair of terms that appears frequently together

```{r}
# Term document matrix to convert unstructure text into structured for easier analysis
BNStdmat <- TermDocumentMatrix(BNScorp)
BNStdmat <- as.matrix(BNStdmat)

# Convert matrix into binary, that is whether a term appears (1) or not (0)
BNStdmat[BNStdmat>1] <- 1

# Create term-term matrix
BNSttm <- BNStdmat %*% t(BNStdmat) # Multiply BNStdmat and transpose of BNStdmat
```

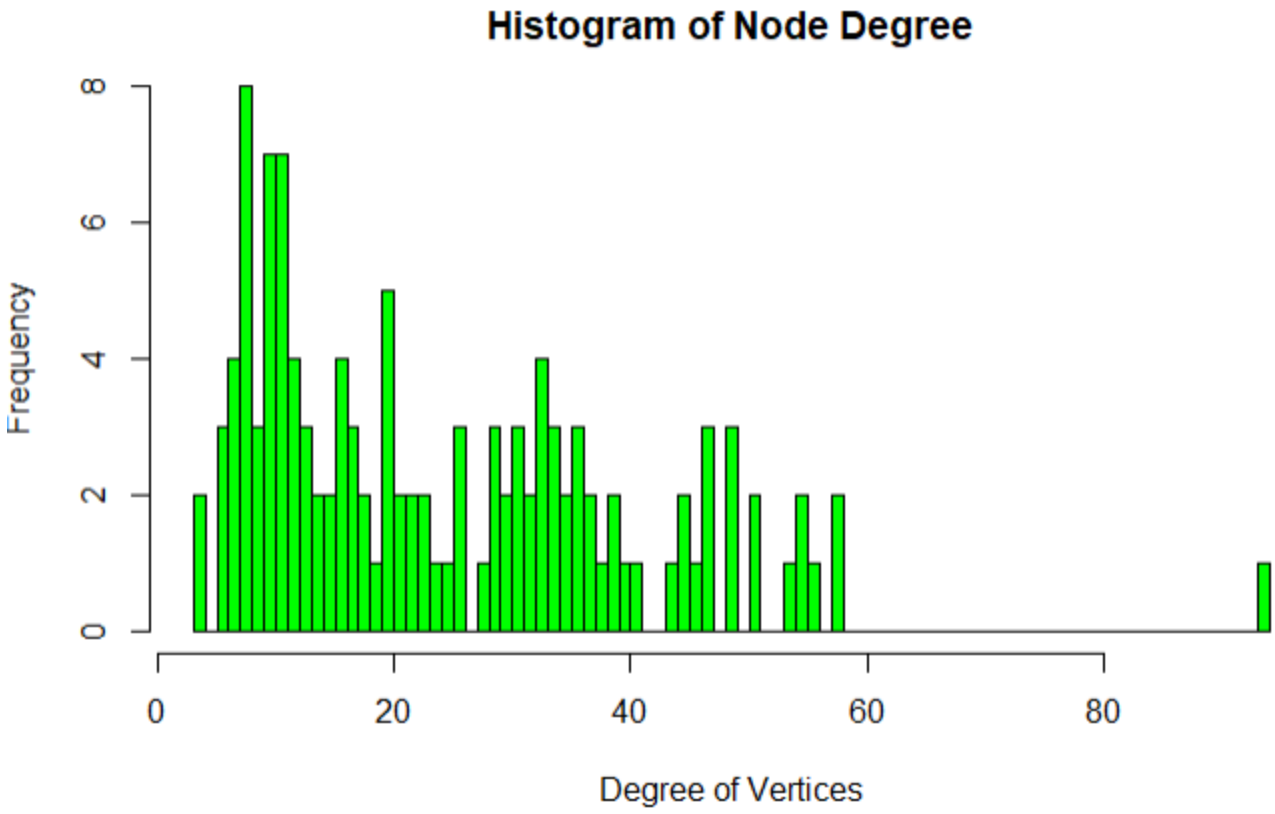
3.5.1c Find the network of terms

```{r}
BNSg <- graph.adjacency(BNSttm, weighted = T, mode = 'undirected')
BNSg <- simplify(BNSg) # To prevent looping of same terms
V(BNSg)$label <- V(BNSg)$name # Labels for the terms
V(BNSg)$degree <- degree(BNSg) # How often each term appears, or number of connections
between terms
BNSg
```

```
IGRAPH 5fa5a5d UNW- 6705 73864 --
+ attr: name (v/c), label (v/c), degree (v/n), weight (e/n)
+ edges from 5fa5a5d (vertex names):
 [1] chrestontalks--reno           chrestontalks--underway       reno         --underway
underway     --…                  underway     --year           underway     --toronto
 [7] underway     --raptors        underway     --mapleleafs     underway     --old
underway     --parts              underway     --play…          underway     --renovations
[13] underway     --scotiabankarena underway     --urbantoronto   underway     --venue
underway     --mapleleafs…        underway     --via            underway     --designed
[19] underway     --torontos       underway     --pictures       underway     --dollar
underway     --multimillion       underway     --renovation     underway     --cre
[25] underway     --urban          bloody       --enough         bloody       --fees
bloody       --hell               bloody       --jumping        bloody       --mean
[31] bloody       --much           bloody       --ridiculous     bloody       --work
bloody       --…                  enough       --fees           enough       --hell
[37] enough       --jumping        enough       --mean           enough       --much
enough       --ridiculous         enough       --work           enough       --…
[43] enough       --good           enough       --never          enough       --going
enough       --take               enough       --team           enough       --big
+ ... omitted several edges
```

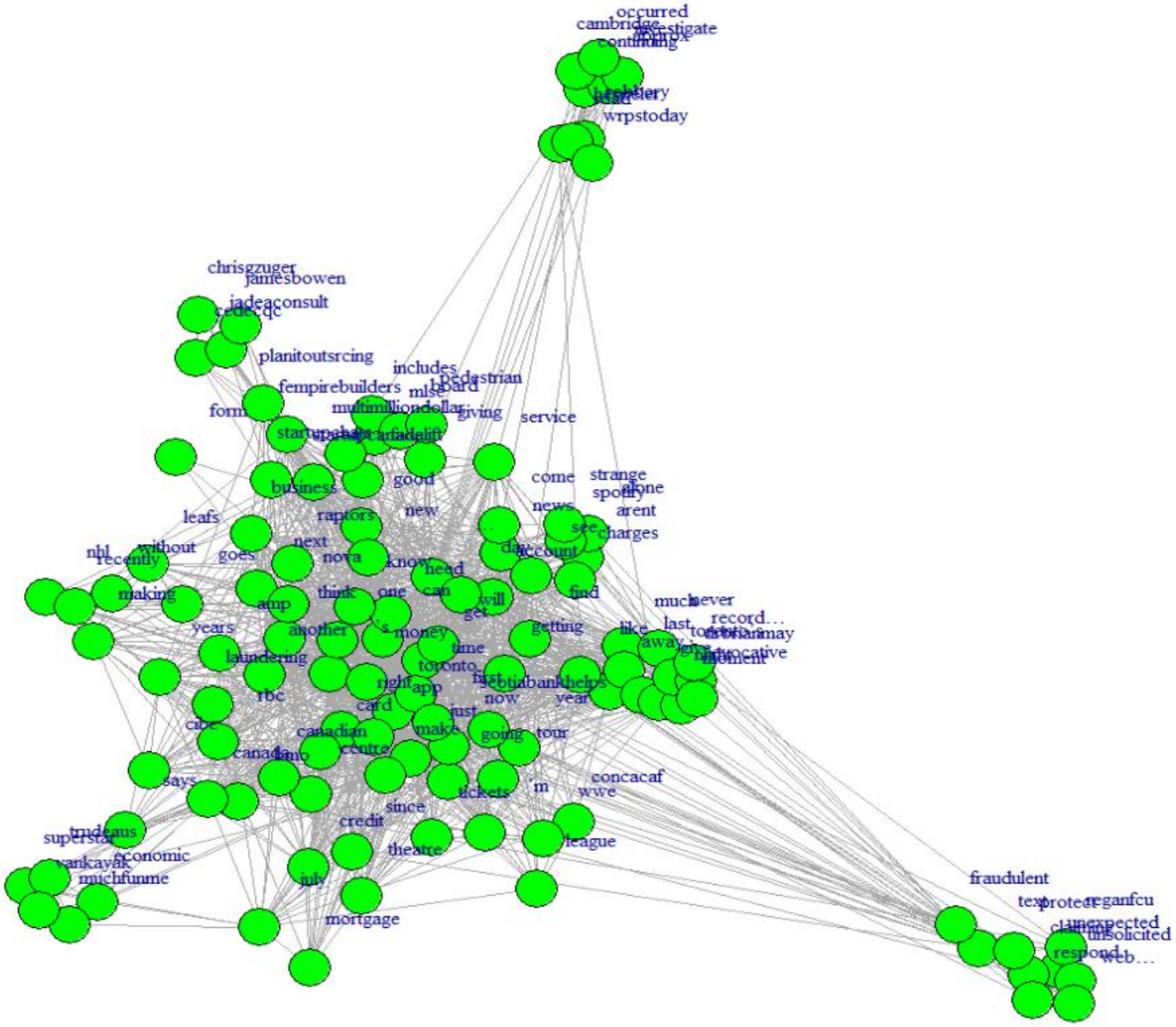
3.5.2c Find optimal term count for optimal (neither too busy nor sparse) visualisation of network diagram

```{r}
# Reset BNStdmat if needed to experiment with optimal rowSums(BNStdmat)>?
# The larger ? is, the more visible the network of terms is, but less granular
BNStdmat <- TermDocumentMatrix(BNScorp)
BNStdmat <- as.matrix(BNStdmat)

# rowSums counts the total frequency; that is, keep terms that appear > 25 times
BNStdmat <- BNStdmat[rowSums(BNStdmat)>50,]

# Re-run earlier code
BNStdmat[BNStdmat>1] <- 1 # Whenvevr BNStdmat is > 1, assign value of 1
BNStermM <- BNStdmat %*% t(BNStdmat)
BNSg <- graph.adjacency(BNStermM, weighted = T, mode = 'undirected')
BNSg <- simplify(BNSg) # To prevent looping of same terms
V(BNSg)$label <- V(BNSg)$name
V(BNSg)$degree <- degree(BNSg)

# Histogram of node degree
hist(V(BNSg)$degree,
     breaks = 100, # how many bars
     col = 'green',
     main = 'Histogram of Node Degree',
     ylab = 'Frequency',
     xlab = 'Degree of Vertices')
```



3.5.3c Plot the network of terms diagram

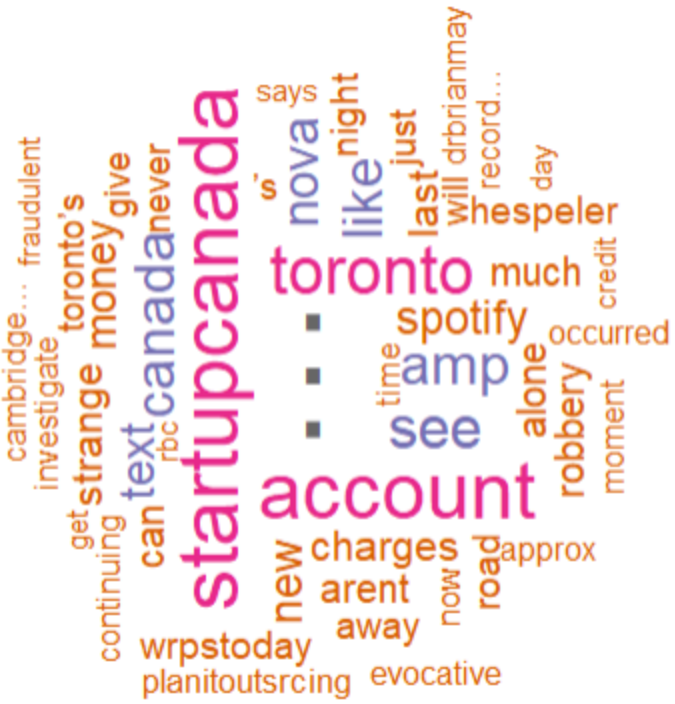
```{r}
# Network diagram
plot(BNSg)
plot(BNSg,
     vertex.color='green',
     vertex.size = 8, # can experiment with this
     vertex.label.dist = 2)
```



Discussions about "trudeaus"-economic"; "fraudulent-web-response"; "occured-cambridge-investigate-continuing"

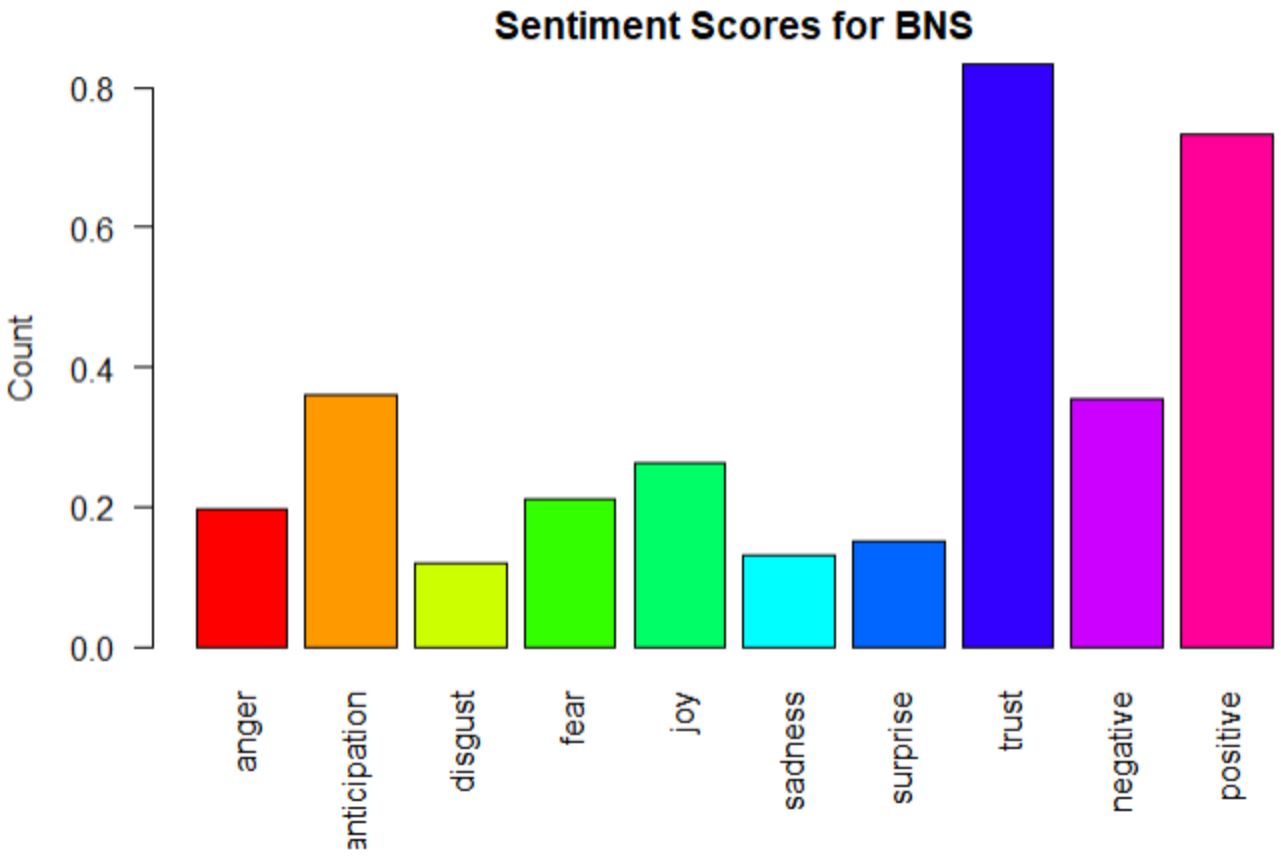
3.6c Word cloud

```{r}
BNStdmat <- TermDocumentMatrix(BNScorp)
BNStdmat <- as.matrix(BNStdmat)

BNSw <- sort(rowSums(BNStdmat), decreasing = TRUE)
wordcloud(words = names(BNSw),
          freq = BNSw,
          max.words = 50,
          random.order = F,
          min.freq = 5,
          colors = brewer.pal(8, 'Dark2'),
          scale = c(5, 0.3),
          rot.per = 0.7)
```



3.7c Sentiment analysis

```{r}
BNSsen <- get_nrc_sentiment(BNStext)

BNS_sen_df <- t(as.data.frame(colMeans(BNSsen)))
write.table(BNS_sen_df,"/Users/sgchr/Documents/CSDA1050/Data/Allbanks_sen_df.csv",
append=T, row.names=F, col.names=F,  sep=",")

barplot(colMeans(BNSsen),
        las = 2,
        col = rainbow(10),
        ylab = 'Count',
        main = 'Sentiment Scores for BNS')
```

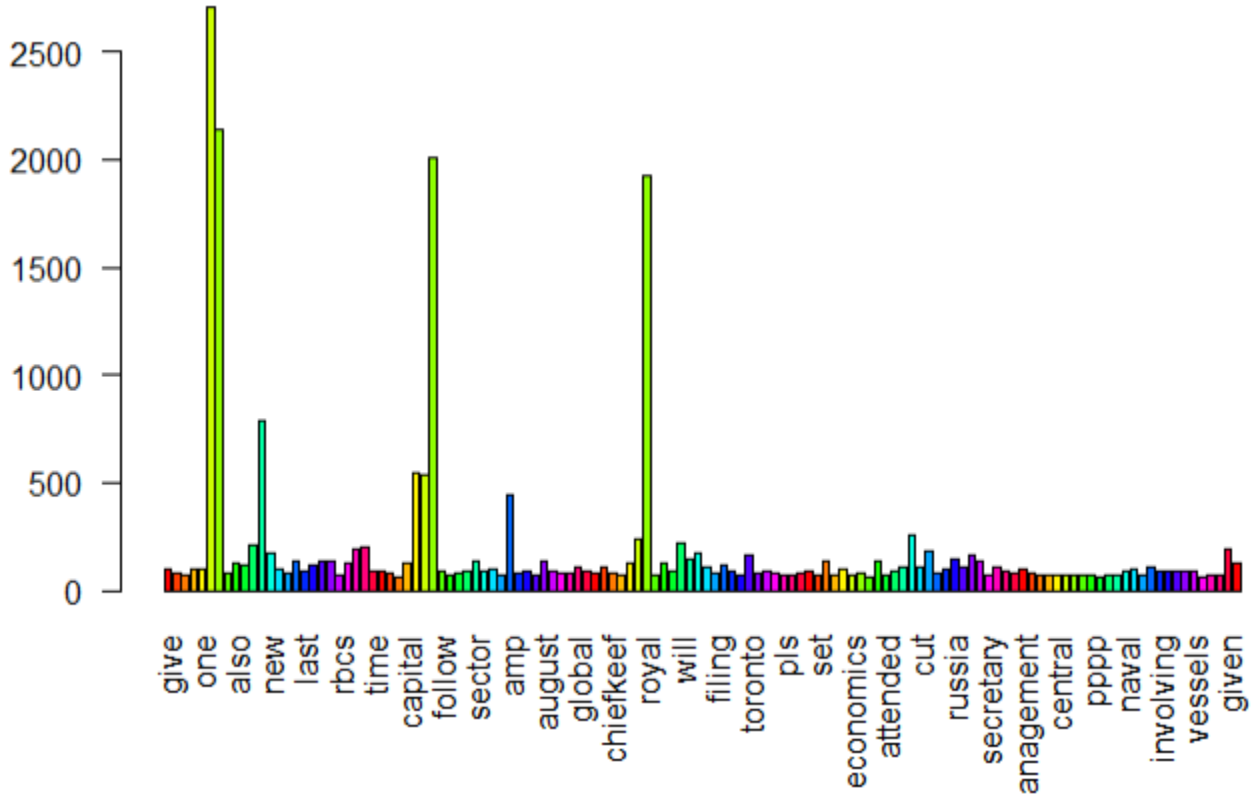


RBC

3.1d Create and compact the term-document matrix (TDM) for each bank

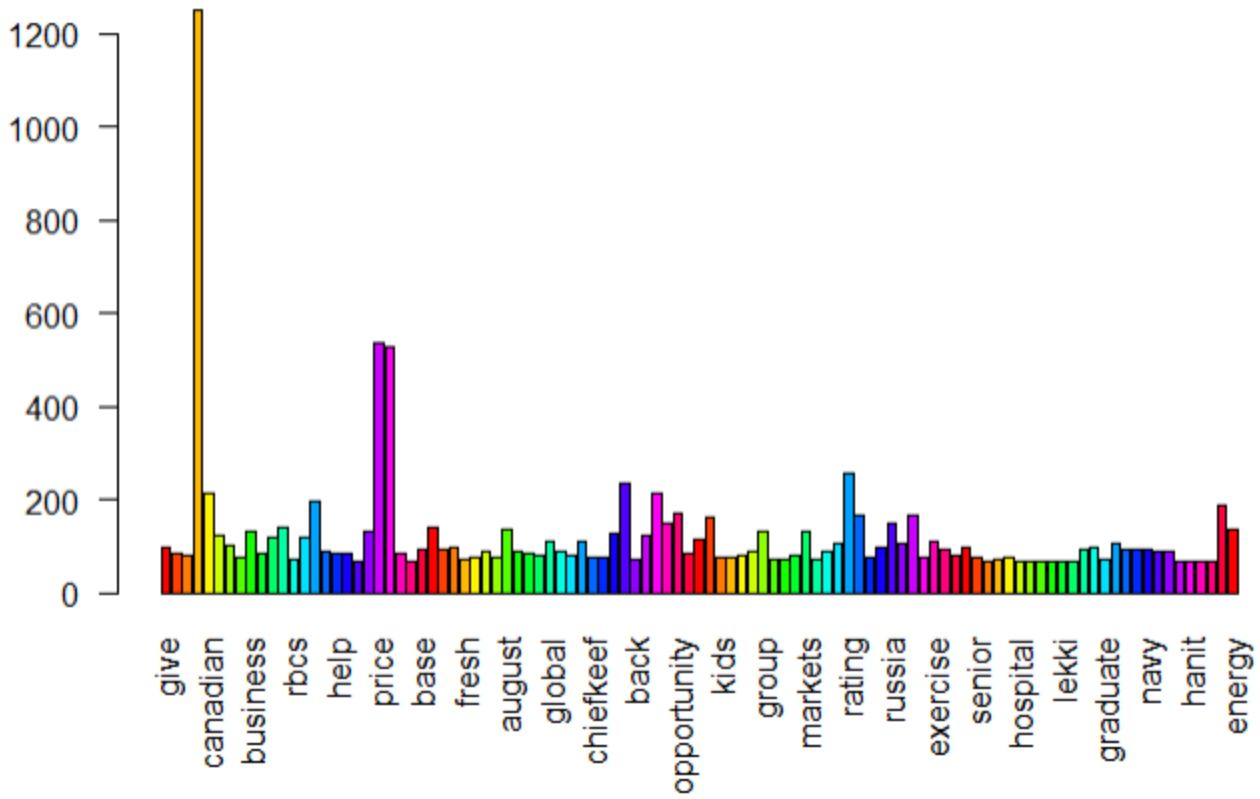
```{r}
# Load the archived tweets
RBC_csv <- read.csv("/Users/sgchr/Documents/CSDA1050/Data/Rbc.csv", header = TRUE)

# Build the initial term-document matrix Corpus
RBCtext <- iconv(RBC_csv$text, to = 'UTF-8')
RBCcorp <- Corpus(VectorSource(RBCtext))

# Compact the Corpus
RBCcorp <- tm_map(RBCcorp, tolower) # Not crucial for text analytics but good practice to do so
RBCcorp <- tm_map(RBCcorp, removePunctuation) # Remove punctuations
RBCcorp <- tm_map(RBCcorp, removeNumbers) # Remove numbers

# Remove URL
removeURL <- function(x) gsub('http[[:alnum:]]*', '', x)
RBCcorp <- tm_map(RBCcorp, content_transformer(removeURL))

RBCcorp <- tm_map(RBCcorp, removeWords, stopwords(kind="en")) # Remove "standard" stop words

RBCcorp <- tm_map(RBCcorp, stripWhitespace) # remove leftover from the preceding removal

# Create the term document matrix
RBCtdmat <- TermDocumentMatrix(RBCcorp, control = list(minWordLength=c(1,Inf)))
RBCtdm <- removeSparseTerms(RBCtdmat, sparse=0.99)
RBCmat <- as.matrix(RBCtdm)
RBCfreq <- rowSums(RBCmat)
RBCfreq <- subset(RBCfreq, RBCfreq>=40) # Experiment with RBCfreq=? to find the optimal of of terms in the barplot
```

```
barplot(RBCfreq,
        las=2, # list all words vertically
        col = rainbow(25))
```



3.2d Further compact the term-document matrix

```{r}
MyStopwords <- c("...", "bank", "royal", "canada", "jbgasajohn", "\"")
RBCcorp <- tm_map(RBCcorp, removeWords, MyStopwords)

RBCcorp <- tm_map(RBCcorp, gsub, pattern = '"buy"', replacement = 'buy') # Replace words
RBCcorp <- tm_map(RBCcorp, gsub, pattern = '"hold"', replacement = 'hold') # Replace
words

RBCcorp <- tm_map(RBCcorp, stripWhitespace) # remove leftover from the preceding removal

# Repeat the preceding codes
RBCtdmat <- TermDocumentMatrix(RBCcorp, control = list(minWordLength=c(1,Inf)))
RBCtdm <- removeSparseTerms(RBCtdmat, sparse=0.99)
RBCmat <- as.matrix(RBCtdm)
RBCfreq <- rowSums(RBCmat)
RBCfreq <- subset(RBCfreq, RBCfreq>=30) # Experiment with RBCfreq=? to find the optimal
of of terms in the barplot
barplot(RBCfreq,
        las=2, # list all words vertically
        col = rainbow(25))
```



3.3d Clustering of terms/tweets k-means method

```{r}
set.seed(123)

RBCm1 <- t(RBCmat) # Transpose RBCmat
RBCk <- 21
RBCkc <- kmeans(RBCm1, RBCk)
RBCkc
```

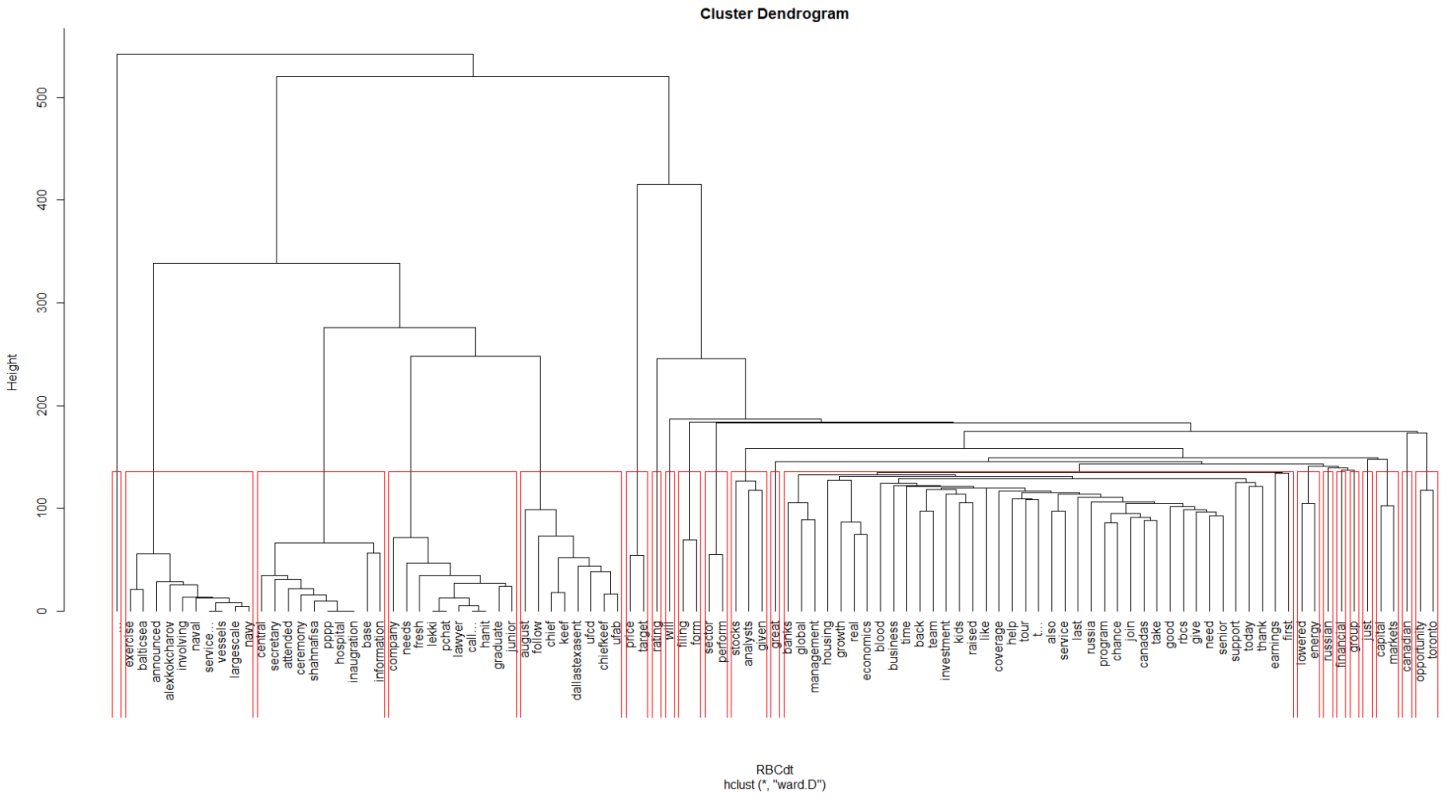
```
 within cluster sum of squares by cluster:
  [1]  127.167883   10.428571 2535.446373    0.000000    2.967391  154.930233  108.835366   76.591837
134.075949   42.958333  173.795620  275.739583 1406.043887  341.412088  175.295775   92.701031
1.970149
[18]   82.509804   82.028169  209.623037   22.952381
  (between_SS / total_SS =  51.5 %)
```

k	Within clusters	Between clusters
=	==========	==========
16	441	43.4
17	368	49.9
18	379	45.4
19	347	47.2
20	320	48.7
21	284	51.5 <-
22	277	51.1

3.4d Plot the hierarchical clusters

```{r}
# Find the distance, use scale to normalise the matrix
RBCdt <- dist(scale(RBCmat))

RBChc <- hclust(RBCdt, method = "ward.D")
plot(RBChc, hang=-1)
rect.hclust(RBChc, k=21) # 21 clusters
```

```
```



3.5d Find the pair of terms that appears frequently together

```{r}
# Term document matrix to convert unstructure text into structured for easier analysis
RBCtdmat <- TermDocumentMatrix(RBCcorp)
RBCtdmat <- as.matrix(RBCtdmat)

# Convert matrix into binary, that is whether a term appears (1) or not (0)
RBCtdmat[RBCtdmat>1] <- 1

# Create term-term matrix
RBCttm <- RBCtdmat %*% t(RBCtdmat) # Multiply RBCtdmat and transpose of RBCtdmat
```

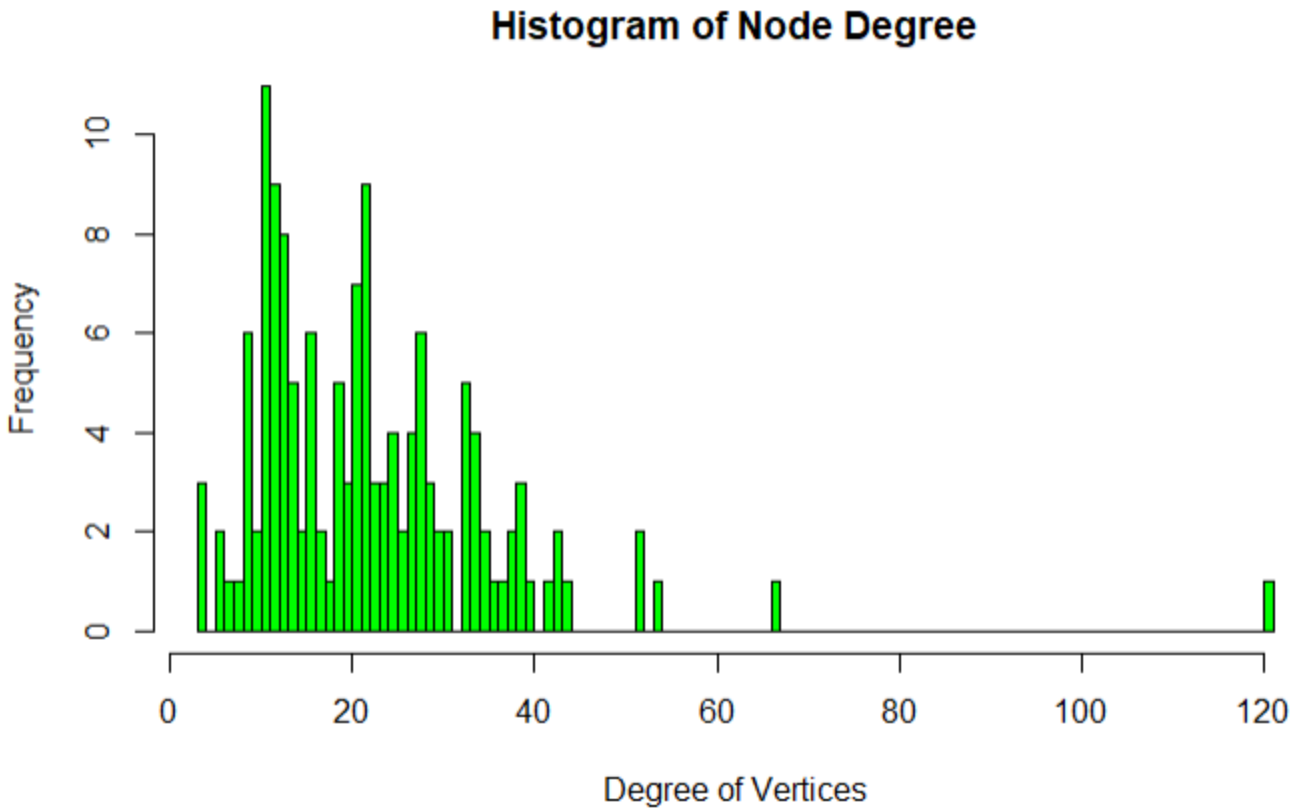
3.5.1d Find the network of terms

```{r}
RBCg <- graph.adjacency(RBCttm, weighted = T, mode = 'undirected')
RBCg <- simplify(RBCg) # To prevent looping of same terms
V(RBCg)$label <- V(RBCg)$name # Labels for the terms
V(RBCg)$degree <- degree(RBCg) # How often each term appears, or number of connections between terms
RBCg
```

```
IGRAPH 4aa6568 UNW- 9873 90923 --
+ attr: name (v/c), label (v/c), degree (v/n), weight (e/n)
+ edges from 4aa6568 (vertex names):
 [1] consider--ever          consider--firstwork     consider--give          consider--industry
consider--like          consider--look          consider--many          consider--unique
 [9] consider--windsor      consider--work          consider--year          consider--youth
consider--yout…         consider--ythaspire     consider--investment    consider--september
[17] consider--taking       consider--m…            consider--canadians     consider--think
consider--russia        consider--russians      consider--miracle       consider--forget
[25] consider--adding       consider--airlines      consider--allenthird    consider--american
consider--otherwise     consider--section       consider--'stuc…        consider--switch
[33] consider--ottawa       consider--kyruer        consider--laws          consider--prosecuti…
consider--protect       consider--spurious      consider--unsafe        consider--cardiac
[41] consider--cardiologists consider--drugholy     consider--grail         consider--manetteness
consider--pedsicu       consider--surgeons      consider--transfusions  consider--ucufef
[49] ever    --firstwork    ever    --give          ever    --industry      ever    --like
ever    --look          ever    --many          ever    --unique        ever    --windsor
[57] ever    --work         ever    --year          ever    --youth         ever    --yout…
ever    --ythaspire     ever    --…             ever    --canadian      ever    --read
+ ... omitted several edges
```

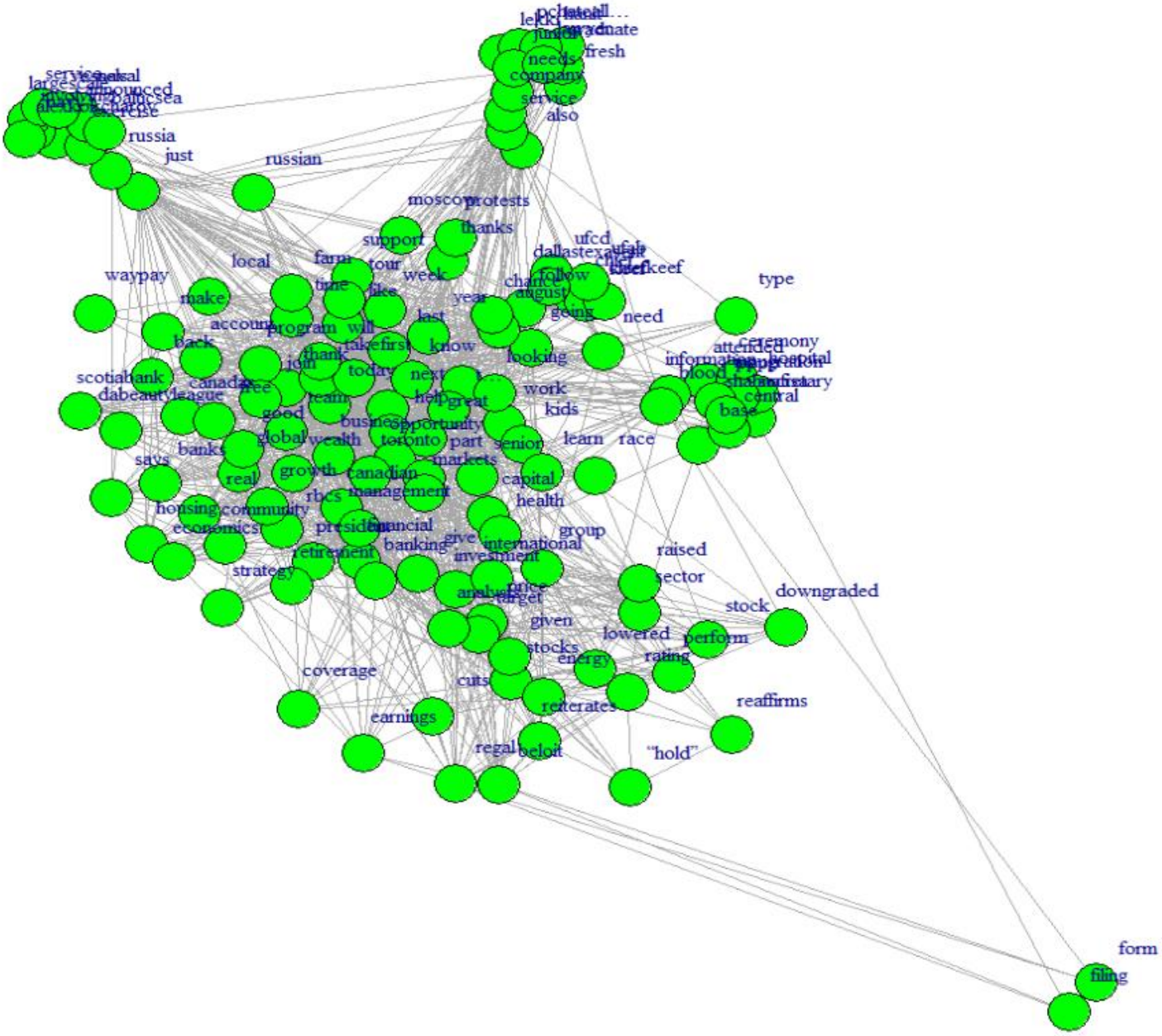
3.5.2d Find optimal term count for optimal (neither too busy nor sparse) visualisation of network diagram

```{r}
# Reset RBCtdmat if needed to experiment with optimal rowSums(RBCtdmat)>?
# The larger ? is, the more visible the network of terms is, but less granular
RBCtdmat <- TermDocumentMatrix(RBCcorp)
RBCtdmat <- as.matrix(RBCtdmat)

# rowSums counts the total frequency; that is, keep terms that appear > 25 times
RBCtdmat <- RBCtdmat[rowSums(RBCtdmat)>50,]

# Re-run earlier code
RBCtdmat[RBCtdmat>1] <- 1 # Whenvevr RBCtdmat is > 1, assign value of 1
RBCtermM <- RBCtdmat %*% t(RBCtdmat)

RBCg <- graph.adjacency(RBCtermM, weighted = T, mode = 'undirected')
RBCg <- simplify(RBCg) # To prevent looping of same terms

V(RBCg)$label <- V(RBCg)$name
V(RBCg)$degree <- degree(RBCg)

# Histogram of node degree
hist(V(RBCg)$degree,
     breaks = 100, # how many bars
     col = 'green',
     main = 'Histogram of Node Degree',
     ylab = 'Frequency',
     xlab = 'Degree of Vertices')
```



3.5.3d Plot the network of terms diagram

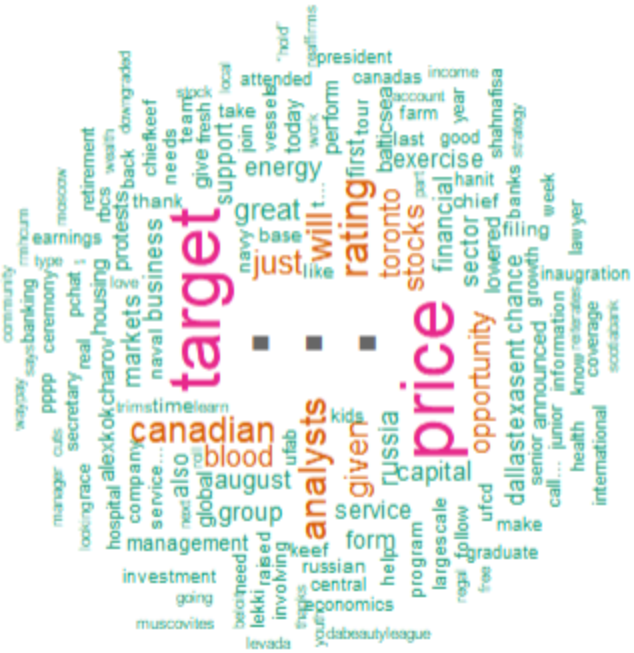
```{r}
# Network diagram
plot(RBCg)
plot(RBCg,
     vertex.color='green',
     vertex.size = 8, # can experiment with this
     vertex.label.dist = 1.5)
```



Some discussions about russia and protest; "largest-service-announced"; "central-base-information"

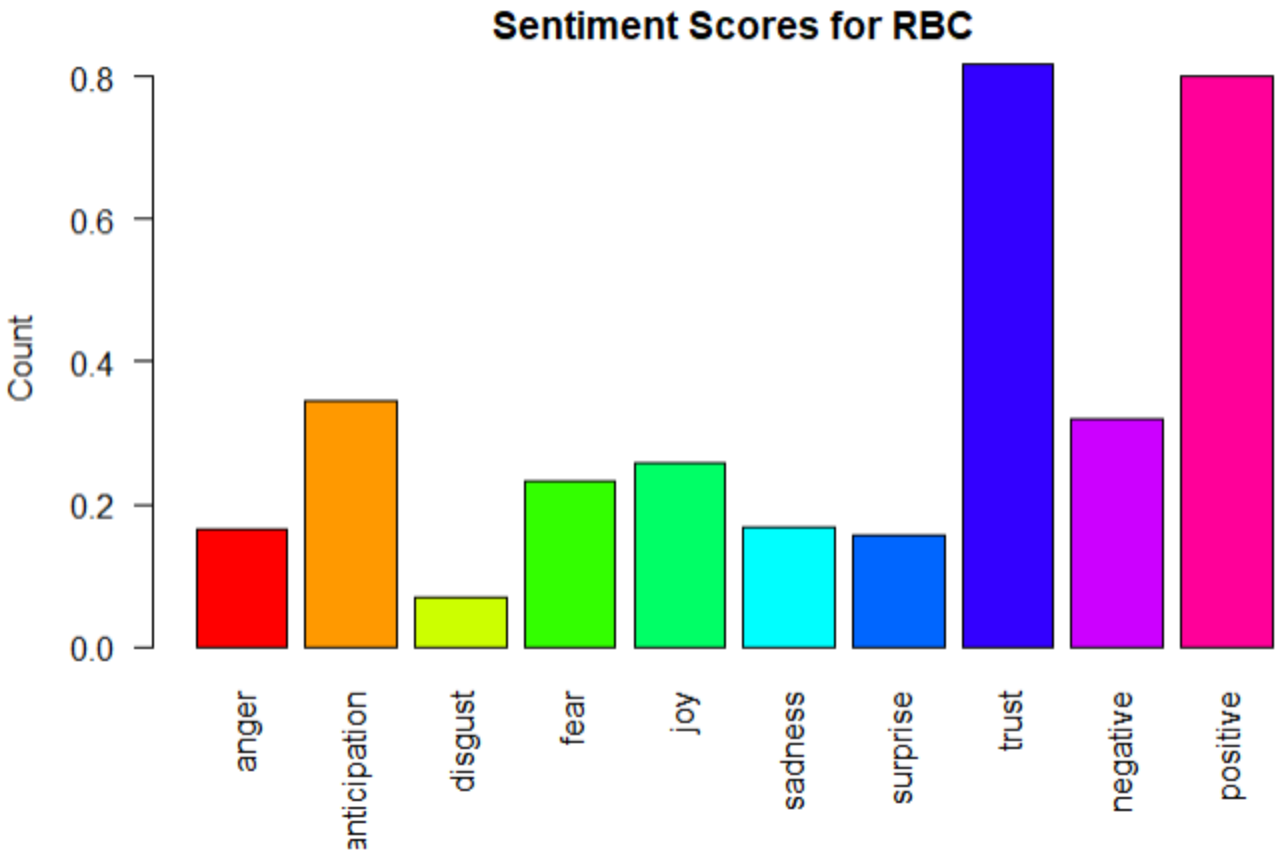
3.6d Word cloud

```{r}
RBCtdmat <- TermDocumentMatrix(RBCcorp)
RBCtdmat <- as.matrix(RBCtdmat)

RBCw <- sort(rowSums(RBCtdmat), decreasing = TRUE)
wordcloud(words = names(RBCw),
          freq = RBCw,
          max.words = 150,
          random.order = F,
          min.freq = 5,
          colors = brewer.pal(8, 'Dark2'),
          scale = c(5, 0.3),
          rot.per = 0.7)
```



3.7d Sentiment analysis

```{r}
RBCsen <- get_nrc_sentiment(RBCtext)

RBC_sen_df <- t(as.data.frame(colMeans(RBCsen)))
write.table(RBC_sen_df,"/Users/sgchr/Documents/CSDA1050/Data/Allbanks_sen_df.csv",
append=T, row.names=F, col.names=F,  sep=",")

barplot(colMeans(RBCsen),
        las = 2,
        col = rainbow(10),
        ylab = 'Count',
        main = 'Sentiment Scores for RBC')
```

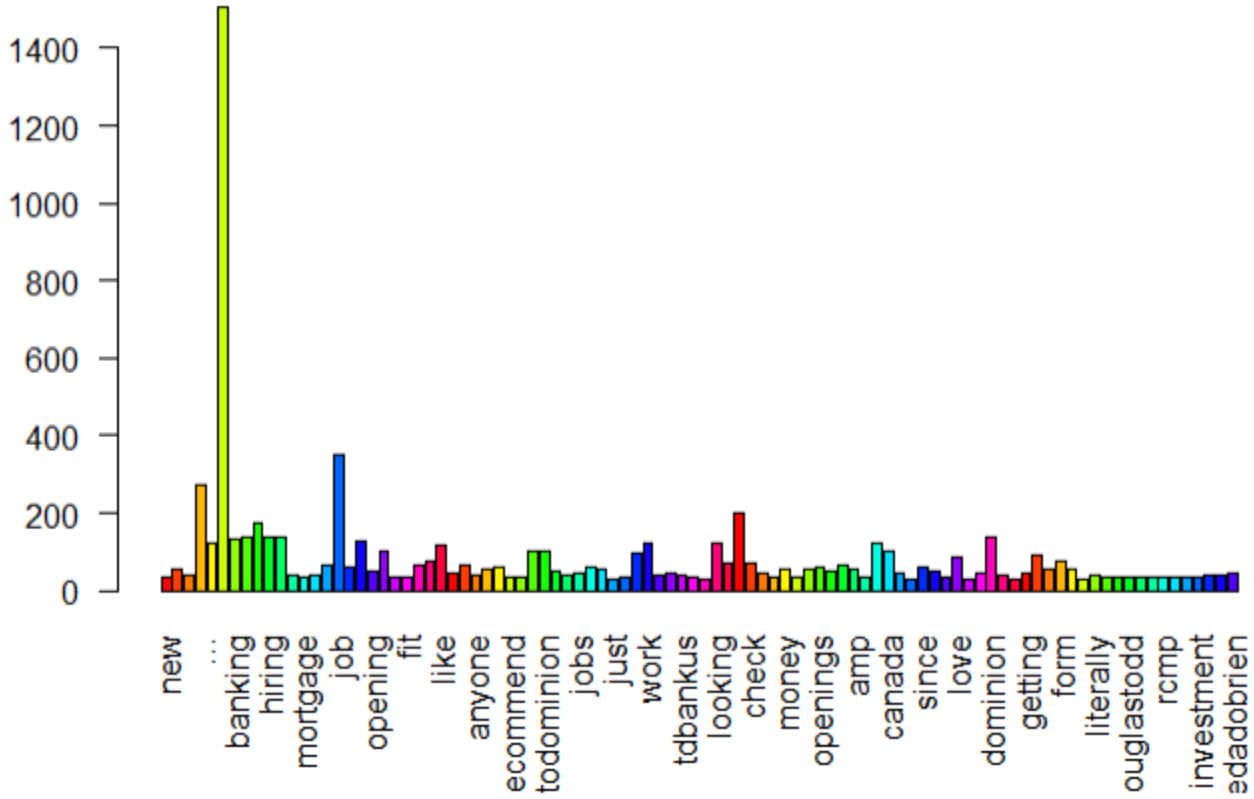


TD

3.1e Create and compact the term-document matrix (TDM) for each bank

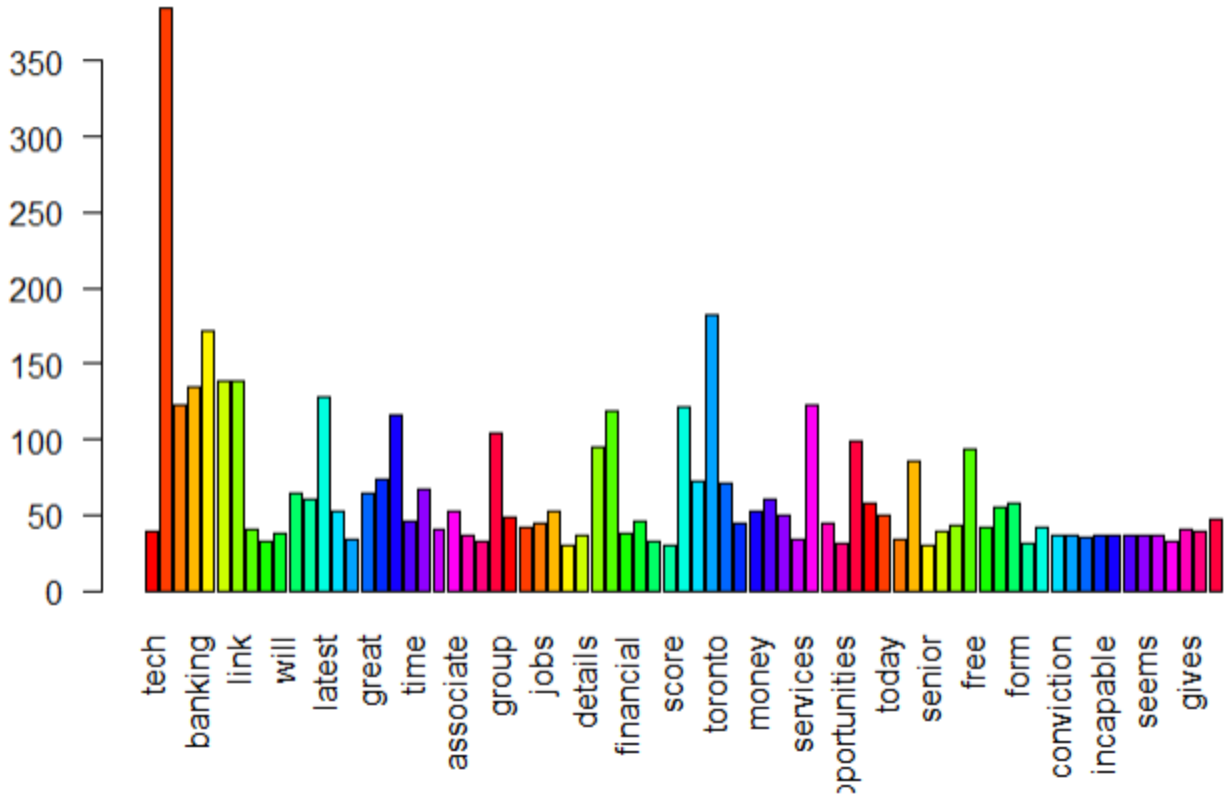
```{r}
# Load the archived tweets
TD_csv <- read.csv("/Users/sgchr/Documents/CSDA1050/Data/Td.csv", header = TRUE)

# Build the initial term-document matrix Corpus
TDtext <- iconv(TD_csv$text, to = 'UTF-8')
TDcorp <- Corpus(VectorSource(TDtext))

# Compact the Corpus
TDcorp <- tm_map(TDcorp, tolower) # Not crucial for text analytics but good practice to do so
TDcorp <- tm_map(TDcorp, removePunctuation) # Remove punctuations
TDcorp <- tm_map(TDcorp, removeNumbers) # Remove numbers

# Remove URL
removeURL <- function(x) gsub('http[[:alnum:]]*', '', x)
TDcorp <- tm_map(TDcorp, content_transformer(removeURL))

TDcorp <- tm_map(TDcorp, removeWords, stopwords(kind="en")) # Remove "standard" stop words

TDcorp <- tm_map(TDcorp, stripWhitespace) # remove leftover from the preceding removal

# Create the term document matrix
TDtdmat <- TermDocumentMatrix(TDcorp, control = list(minWordLength=c(1,Inf)))
TDtdm <- removeSparseTerms(TDtdmat, sparse=0.99)
TDmat <- as.matrix(TDtdm)
TDfreq <- rowSums(TDmat)
```

```
TDfreq <- subset(TDfreq, TDfreq>=30) # Experiment with TDfreq=? to find the optimal of of terms in the barplot
barplot(TDfreq,
        las=2, # list all words vertically
        col = rainbow(25))
```



3.2e Further compact the term-document matrix

```{r}
MyStopwords <- c("tdcanada", "...", "bank", "todominion", "tdbankus", "banks", "dominion", "torontodominion", "p…", "n…", "ugordonhoekstrau")
TDcorp <- tm_map(TDcorp, removeWords, MyStopwords)

#TDcorp <- tm_map(TDcorp, gsub, pattern = 'aphria', replacement = 'aphriainc') # Replace words

TDcorp <- tm_map(TDcorp, stripWhitespace) # remove leftover from the preceding removal

# Repeat the preceding codes
TDtdmat <- TermDocumentMatrix(TDcorp, control = list(minWordLength=c(1,Inf)))
TDtdm <- removeSparseTerms(TDtdmat, sparse=0.99)
TDmat <- as.matrix(TDtdm)
TDfreq <- rowSums(TDmat)
TDfreq <- subset(TDfreq, TDfreq>=30) # Experiment with TDfreq=? to find the optimal of of terms in the barplot
barplot(TDfreq,
        las=2, # list all words vertically
        col = rainbow(25))
```



3.3e Clustering of terms/tweets k-means method

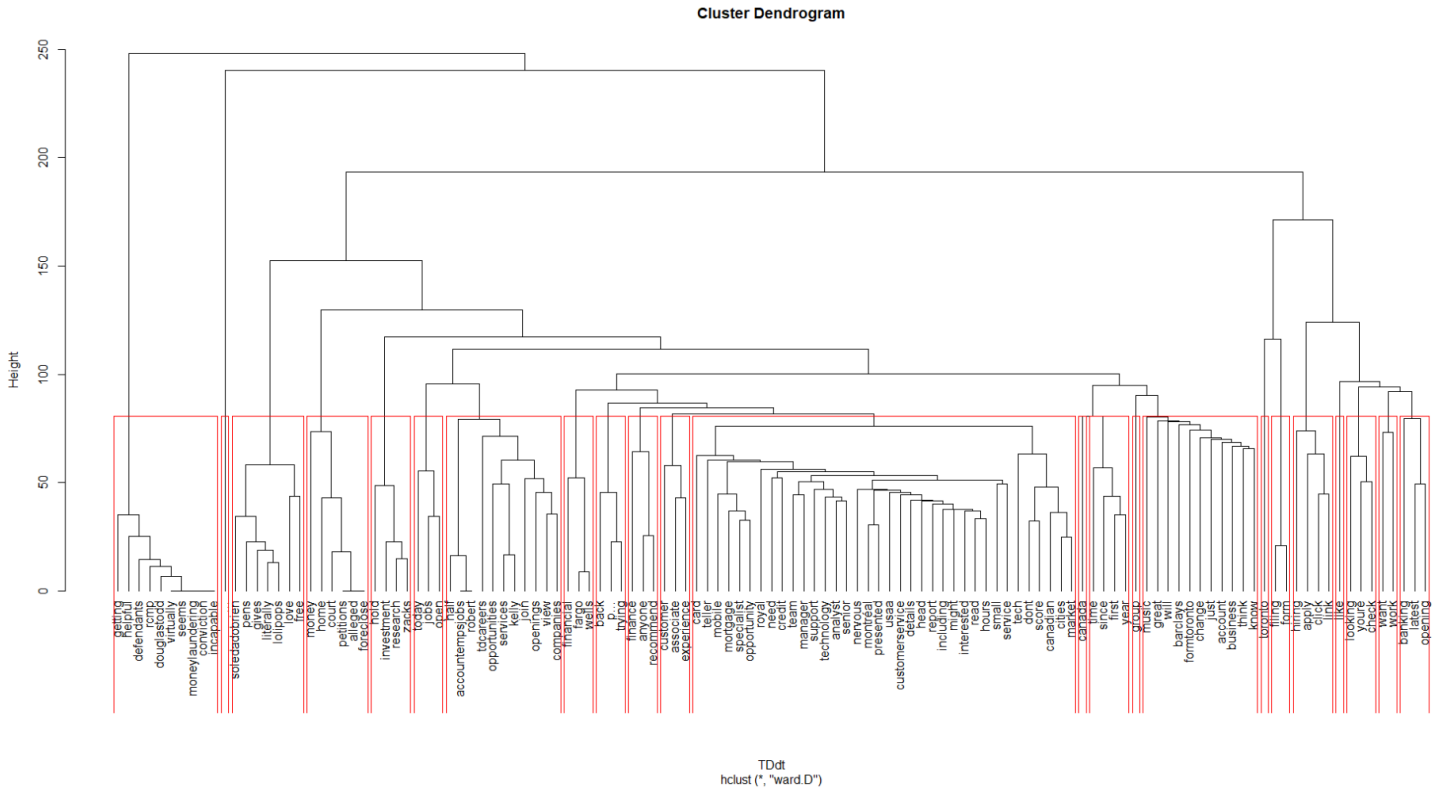
```{r}
set.seed(123)

TDm1 <- t(TDmat) # Transpose TDmat
TDk <- 23
TDkc <- kmeans(TDm1, TDk)
TDkc
```

```
 within cluster sum of squares by cluster:
  [1]   21.076923 1090.292560   44.411765   39.379310  178.861538   88.727273   51.772727  609.794393
 152.854167    0.974359  161.716667   97.181818  133.980000   53.379310  107.380000   66.114286
 26.689655
 [18]   73.500000   37.500000  123.152542   58.714286  106.300000   23.750000
  (between_SS / total_SS =  44.7 %)
```

k	Within clusters	Between clusters
19	200	37.3
20	194	35.7
21	166	42.5
22	176	36.1
23	138	44.7 <-
24	143	43.4

3.4e Plot the hierarchical clusters

```{r}
# Find the distance, use scale to normalise the matrix
TDdt <- dist(scale(TDmat))

TDhc <- hclust(TDdt, method = "ward.D")
plot(TDhc, hang=-1)
rect.hclust(TDhc, k=23) # 23 clusters
```



3.5e Find the pair of terms that appears frequently together

```{r}
# Term document matrix to convert unstructure text into structured for easier analysis
TDtdmat <- TermDocumentMatrix(TDcorp)
TDtdmat <- as.matrix(TDtdmat)

# Convert matrix into binary, that is whether a term appears (1) or not (0)
TDtdmat[TDtdmat>1] <- 1

# Create term-term matrix
TDttm <- TDtdmat %*% t(TDtdmat) # Multiply TDtdmat and transpose of TDtdmat
```

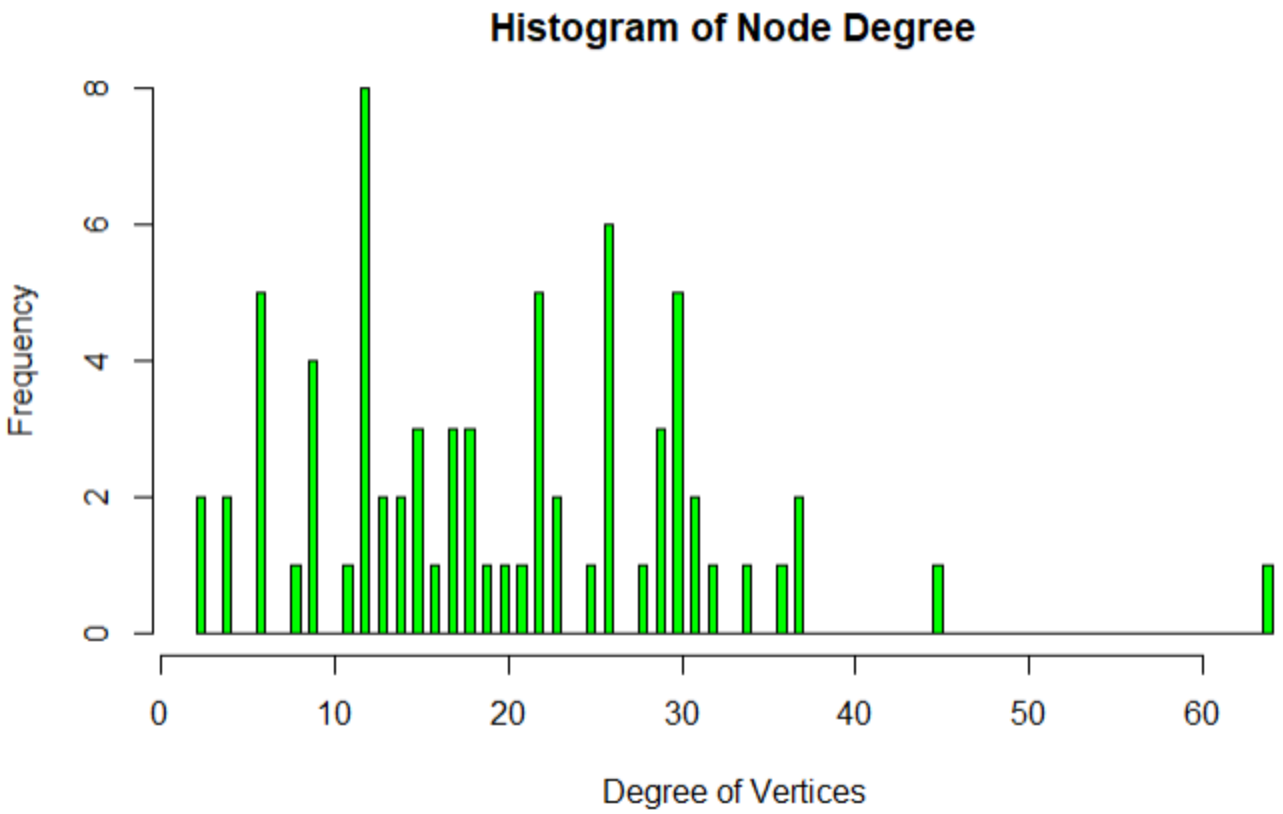
3.5.1e Find the network of terms

```{r}
TDg <- graph.adjacency(TDttm, weighted = T, mode = 'undirected')
TDg <- simplify(TDg) # To prevent looping of same terms
V(TDg)$label <- V(TDg)$name # Labels for the terms
V(TDg)$degree <- degree(TDg) # How often each term appears, or number of connections between terms
TDg
```

```
IGRAPH 8f5dfc4 UNW- 3526 28101 --
+ attr: name (v/c), label (v/c), degree (v/n), weight (e/n)
+ edges from 8f5dfc4 (vertex names):
 [1] calls--city           calls--four           calls--reasons        calls--report         calls-
-rising          calls--superstar      calls--tech           calls--waterloo       calls--
waterlooedc
[10] calls--…              calls--help           calls--call           calls--like           calls-
-dont            calls--today          calls--number         calls--friday         calls--
havenreceived
[19] calls--'made          calls--received       calls--careful        calls--ignore         calls-
-stephkleid      calls--users-         calls--usually        calls--'…             calls--concerned
[28] city --four           city --reasons        city --report         city --rising         city -
-superstar       city --tech           city --waterloo       city --waterlooedc    city --…
[37] city --banking        city --join           city --latest         city --great          city -
-like            city --teller         city --jobs           city --open           city --asking
[46] city --dont           city --referrals      city --score          city --looking        city -
-check           city --challenge      city --drops          city --growth         city --real
[55] city --sector         city --wages          city --warns          city --windsor        city -
-windsorpoli     city --never          city --openings       city --tdcareers      city --worst
[64] city --today          city --accountempsjobs city --half          city --robert         city -
-million         city --national       city --atlantic       city --cvshealthjobs  city --health
+ ... omitted several edges
```

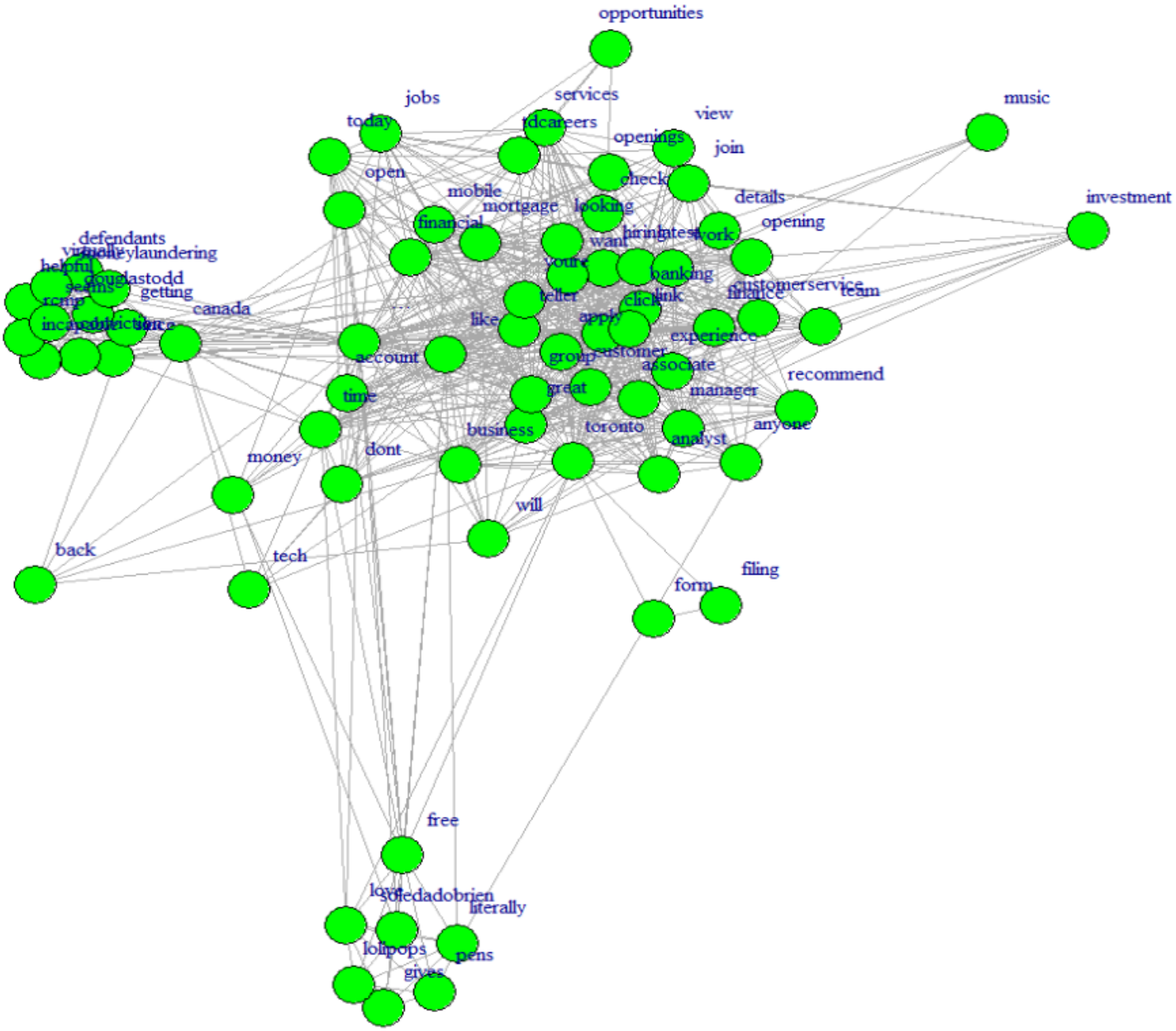
3.5.2e Find optimal term count for optimal (neither too busy nor sparse) visualisation of network diagram

```{r}
# Reset TDtdmat if needed to experiment with optimal rowSums(TDtdmat)>?
# The larger ? is, the more visible the network of terms is, but less granular
TDtdmat <- TermDocumentMatrix(TDcorp)
TDtdmat <- as.matrix(TDtdmat)

# rowSums counts the total frequency; that is, keep terms that appear > 30 times
TDtdmat <- TDtdmat[rowSums(TDtdmat)>30,]

# Re-run earlier code
TDtdmat[TDtdmat>1] <- 1 # Whenvevr TDtdmat is > 1, assign value of 1
TDtermM <- TDtdmat %*% t(TDtdmat)

TDg <- graph.adjacency(TDtermM, weighted = T, mode = 'undirected')
TDg <- simplify(TDg) # To prevent looping of same terms

V(TDg)$label <- V(TDg)$name
V(TDg)$degree <- degree(TDg)

# Histogram of node degree
hist(V(TDg)$degree,
     breaks = 100, # how many bars
     col = 'green',
     main = 'Histogram of Node Degree',
     ylab = 'Frequency',
     xlab = 'Degree of Vertices')
```



3.5.3e Plot the network of terms diagram

```{r}
# Network diagram
plot(TDg)
plot(TDg,
     vertex.color='green',
     vertex.size = 8, # can experiment with this
     vertex.label.dist = 1.5)
```



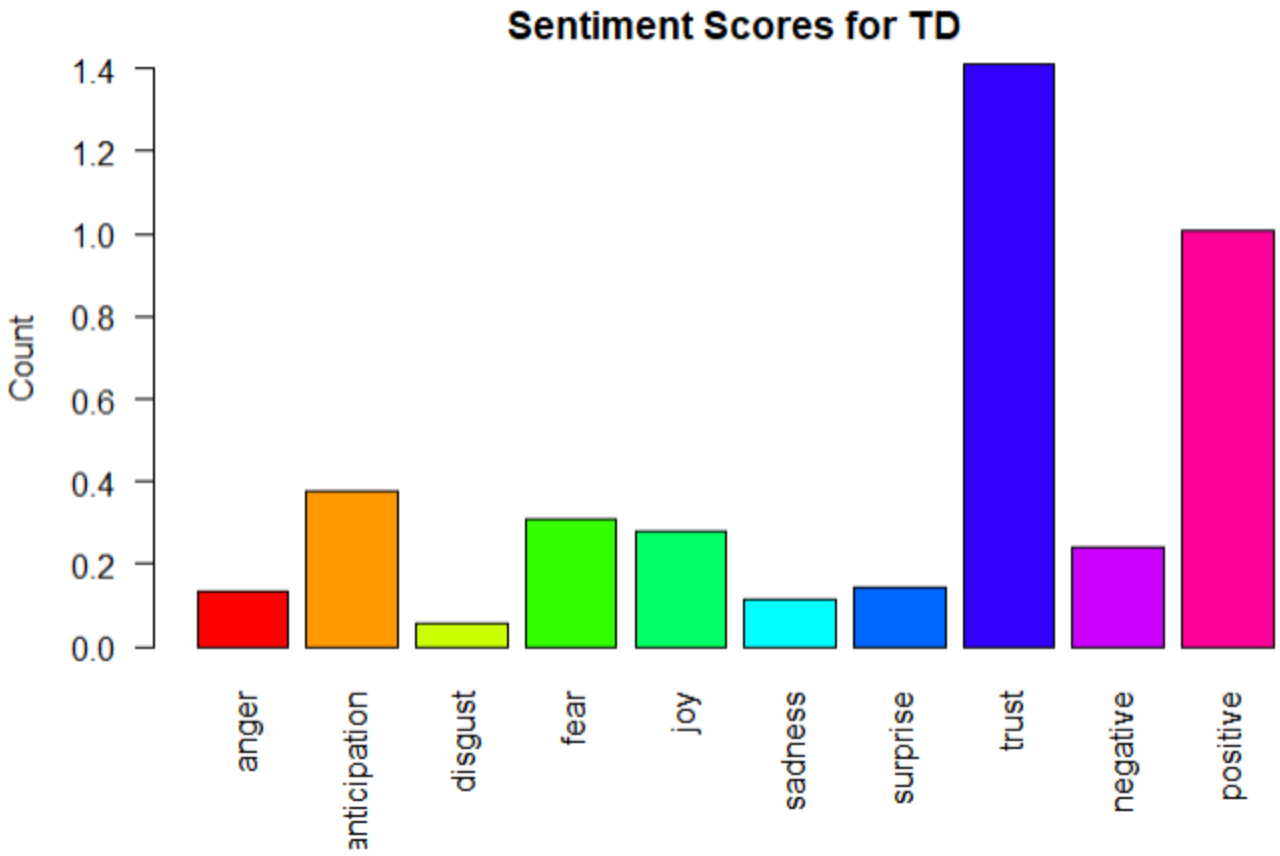
Discussions about "defendants-laundering-rcmp-douglastodd"; "lollipos-gives-pens-literally-free" (maybe there is a promotional event going on)

3.6e Word cloud

```{r}
TDtdmat <- TermDocumentMatrix(TDcorp)
TDtdmat <- as.matrix(TDtdmat)

TDw <- sort(rowSums(TDtdmat), decreasing = TRUE)
wordcloud(words = names(TDw),
          freq = TDw,
          max.words = 150,
          random.order = F,
          min.freq = 5,
          colors = brewer.pal(8, 'Dark2'),
          scale = c(5, 0.3),
          rot.per = 0.7)
```

3.7e Sentiment analysis

```{r}
TDsen <- get_nrc_sentiment(TDtext)

TD_sen_df <- t(as.data.frame(colMeans(TDsen)))
write.table(TD_sen_df,"/Users/sgchr/Documents/CSDA1050/Data/Allbanks_sen_df.csv",
append=T, row.names=F, col.names=F,  sep=",")

barplot(colMeans(TDsen),
        las = 2,
        col = rainbow(10),
        ylab = 'Count',
        main = 'Sentiment Scores for TD')
```



3.8 Observations

Additional analysis and commentaries will be provided in the next (final) report