

#Class: Week 11
#Course: Big Data and Social Analysis
#Semester: Spring 2021
#Lesson: Text Mining
#Instructor: Chung-pei Pien
#Organization: ICI, NCCU

Student Information -----

#Chinese Name: 辛鐘成
#English First Name: Jongsung Shin
#UID: 110ZU1038
#E-mail: sjongsung97@gmail.com

Questions -----

#In the midterm, we used the data file fake_tweets_election.xlsx to analyze
#misinformation tweets collected during and after the first 2020 US presidential debate.

#Please read fake_tweets_election.xlsx and use the following code to delete
#the observation on the date before September 27, 2020.

```
library(dplyr) # bring all the library we might use for data cleaning
library(ggplot2)
library(readxl)
library(tidyr)
library(tidyverse)
library(zoo)
library(tidytext) # an efficient tool for text mining in R, merging with dplyr package
library(tm)
library(wordcloud2)
library(widyr)
```

```
setwd("C:/Users/sung/Desktop/Big data with R/BD EXCEL FILE")
```

```
fake_tweets <- read_xlsx("fake_tweets_election.xlsx")
fake_tweets <- fake_tweets %>%
  filter(date >= "2020-09-27")
```

#The column type records the text is a tweet or a retweet.
#In the midterm, we didn't delete retweet because we want to analyze misinformation's spread and size.

#Question 1: (2 points)

#In this week's homework, we attempt to apply text mining techniques to do word frequency, word association and sentiment analysis.

#Do you think you need to delete retweets? Please tell me your answer and provide me your reasons.

Yes, I think we need to delete retweets since it shows the tweets already used.

It will increase the word frequency and association and sentiment analysis,

which disturbs us to get an accurate analysis.

#If your answer is to delete retweets, please use filter() to delete them.

```
fake_tweets <- fake_tweets %>%
```

```
  filter(!type %in% ('retweet'))
```

```
unique(fake_tweets$type) # check if 'retweet' has been removed or not
```

#Question 2: (10 points)

#The column text records the content of tweets.

#Please remove words and symbols that we do not need for word frequency, and word association, and sentiment analysis.

#Remember, the cleaning process may do many times when you find the results of word frequency, and word association, and sentiment analysis involve many terms needed to eliminate.

I want to remove words and symbols that do not have any impact on the meaning to it

```
text <- fake_tweets$text
```

```
text[1:10] # I will check some text each time to see the change
```

Set the text to lowercase

```
text <- tolower(text)
```

```
text[1:10]
```

gsub(pattern, replacement, string) => replace all matches

Remove urls, emojis, etc.

```
text <- gsub("https?://.+", "", text)
```

```
text[1:10]
```

\d is a digit (a character in the range 0-9), and + means 1 or more times. So, \d+ is 1 or more digits.

^[\w*]\$ will match a string consisting of a single character, where that character is alphanumeric (letters, numbers) an underscore (_) or an asterisk (*).

Details: The " \w " means "any word character" which usually means alphanumeric (letters, numbers, regardless of case) plus underscore (_)

\d matches any decimal digit. The signification of a "decimal digit" depends on the options of the regex: Without RegexOptions.

```
text <- gsub("\\d+\\w*\\d*", "", text)
text[1:10]
```

```
text <- gsub("[^\\x01-\\x7F]", "", text) # this is for emoji
text[1:10]
```

```
# Remove references to other twitter users and hash tags
text <- gsub("@\\w+", "", text)
text[1:10]
```

```
# Remove hash tages
text <- gsub("#\\w+", "", text)
```

```
# Remove number and punctuation
text <- gsub("[[:digit:]]", "", text)
text <- gsub("[[:punct:]]", " ", text)
text[1:10]
```

```
# Remove spaces and newlines
text <- gsub("amp", "", text)
text <- gsub("\\n", " ", text)
text[1:10]
```

```
# There are spaces where the digits were, we need to remove it
text <- gsub("^\\s+", "", text)
text <- gsub("\\s+$", "", text)
text <- gsub("[ |\\t]+", " ", text)
text[1:10]
```

```
# Remove single alphabet
text <- gsub("\\W[a-zA-Z]\\W", "", text)
text[1:10]
```

```
fake_tweets$new_text <- text
```

```
colnames(fake_tweets)
```

```
fake_tweets_temp <- fake_tweets %>%
  select(content_id, new_text) # show me these columns only
```

#Question 3: (3 points)

#Please tokenize the tweets

```
fake_tokens <- fake_tweets_temp %>%  
  unnest_tokens(word, new_text) %>% # Tokenize fake_tweet_temp with stop word  
  anti_join(stop_words) %>%  
  filter(!word %in% stopwords('ENGLISH'))
```

#Question 4: (5 points)

#Please count tokenized terms' frequency

```
fake_frq <- fake_tokens %>% # Count word frequency  
  count(word, sort = TRUE)
```

#Question 5: (5 points)

#Please plot a word cloud with 200 top terms.

```
wordcloud2(fake_frq[1:201, ], shape = 'circle') # Use 201 to get 200 top terms
```

#Question 6: (5 points)

#Please use word association methods to tell me the top 5 high association terms with Biden.

Create tokenized tables so that we can easily calculate the word association.

```
fake_cors <- fake_tokens %>%  
  group_by(word) %>%  
  pairwise_cor(word, content_id, sort = TRUE)
```

Select a word I want to analyze

```
fake_biden <- fake_cors %>%  
  filter(item1 == 'biden') # biden is a criteria
```

top 5 high association terms with Biden: 1.debate / 2.joe / 3. wallace / 4. trump / 5. chris