



# Northeastern University

## ASSIGNMENT FRONT SHEET

**Course Name:** ALY6040 Data Mining Applications

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**Student Class:** Fall 2019 CPS

**Term:** Winter 2021

### Module 1: Introduction to tm Package in R

**Completion Date:** Jan 24<sup>th</sup>

**Due Time:** 12:00am

### Statement of Authorship

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In this paper, we will analyze the Trump's twitter in order to understand more about the person.

To start with, we will install the necessary packages, download the files and set the right directory for the system.

### **Start the analysis:**

We create an empty corpus with VCorpus. Text corpus is defined as a language resource consisting of a large and structured set of texts to perform statistical analysis, hypothesis testing, occurrences, checking or validating linguistic rules ("NLP - Linguistic Resources," 2018)

	Length	Class	Mode
Trump Black History Month Speech.txt	2	PlainTextDocument	list
Trump CIA Speech.txt	2	PlainTextDocument	list
Trump Congressional Address.txt	2	PlainTextDocument	list
Trump CPAC Speech.txt	2	PlainTextDocument	list
Trump Florida Rally 2-18-17.txt	2	PlainTextDocument	list
Trump Immigration Speech 8-31-16.txt	2	PlainTextDocument	list
Trump Inauguration Speech.txt	2	PlainTextDocument	list
Trump National Prayer Breakfast.txt	2	PlainTextDocument	list
Trump Nomination Speech.txt	2	PlainTextDocument	list
Trump Police Chiefs Speech.txt	2	PlainTextDocument	list
Trump Response to Healthcare Bill Failure.txt	2	PlainTextDocument	list

Next we loaded the details of any documents in the corpus. Looking at the first and second document, we can see that both documents have the same Meta data at 7 but the second one contains 3 times more characters compared to the first one, 12747 and 4068 respectively

<<PlainTextDocument>>	<<PlainTextDocument>>
Metadata: 7	Metadata: 7
Content: chars: 4068	Content: chars: 12747

## **Preprocessing**

We remove anything that hinders our analysis process. This process includes numbers, capitalization, unnecessary figures (\\, @, etc.) common words – stop words in the English language (the, a, etc.) and punctuation. However that is not enough. Since Trump tends to repeat his messages multiple times in a speech and make vague assumption, we need to also use `tm_map(docs, removeWords, c("syllogism", "tautology"))` to eliminate any words with the same meaning (ex: “ATM machine”, because “M” stands for “machine”). Another thing to remember while analyzing someone’s speech, especially Trump is his frequent use of words that are often associate with each other to have a specific meaning. “Fake” and “news”, if separated is totally misconstrued because they are always put together for “fake news” to be established as a contemporary phenomenon

Lastly, we move on to the stemming step and clean the white spaces. Stemming is to reduce inflected words to their word stem, base or root form—generally a written word form. So “Consulting”, “Consultant”, “Consultative” turns into “consult”.

## **Stage your data**

A document-term matrix or term-document matrix is a mathematical matrix that describes the frequency of terms that occur in a collection of documents. (Yangchang Zhao, 2012) The spare entries / non spare entries ratio is 3/1. The longest words have 19 characters in them. Keeping in mind Trump’s preference of sound bites and short words to complicated ones, those long words could be the combination of 2 separate words like “politically-correct” (19) that we created above.

```
> dtm
<<DocumentTermMatrix (documents: 11, terms: 3698)>>
Non-/sparse entries: 8443/32235
Sparsity           : 79%
Maximal term length: 19
weighting          : term frequency (tf)
```

Then we transpose the matrix and organize terms by frequency. Next, we start having a look at the most and least frequently occurring words. The resulting output is two rows of numbers. The top row reflects the frequency with which words appear while the bottom row indicates how many words appears that frequently. For example, here we are examining 20 least frequent words and we can see that 1655 terms appear once, 631 words appears twice, etc.

```
freq
 1   2   3   4   5   6   7   8   9  10  11  12  13  14  15  16
1655 631 329 214 124 107  82  60  59  45  38  33  31  25  25  16
 17  18  19  20
  8  13  16  11
```

Here are the 20 most frequent words

```
freq
79 83 88 89 98 100 101 102 105 107 111 122 127 139 140 163 174 265 278 428
 2  2  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1
```

Then we create the vocabulary table with the frequency of appearances for each word. For example, “also” appears 54 times similarly to “years”

```

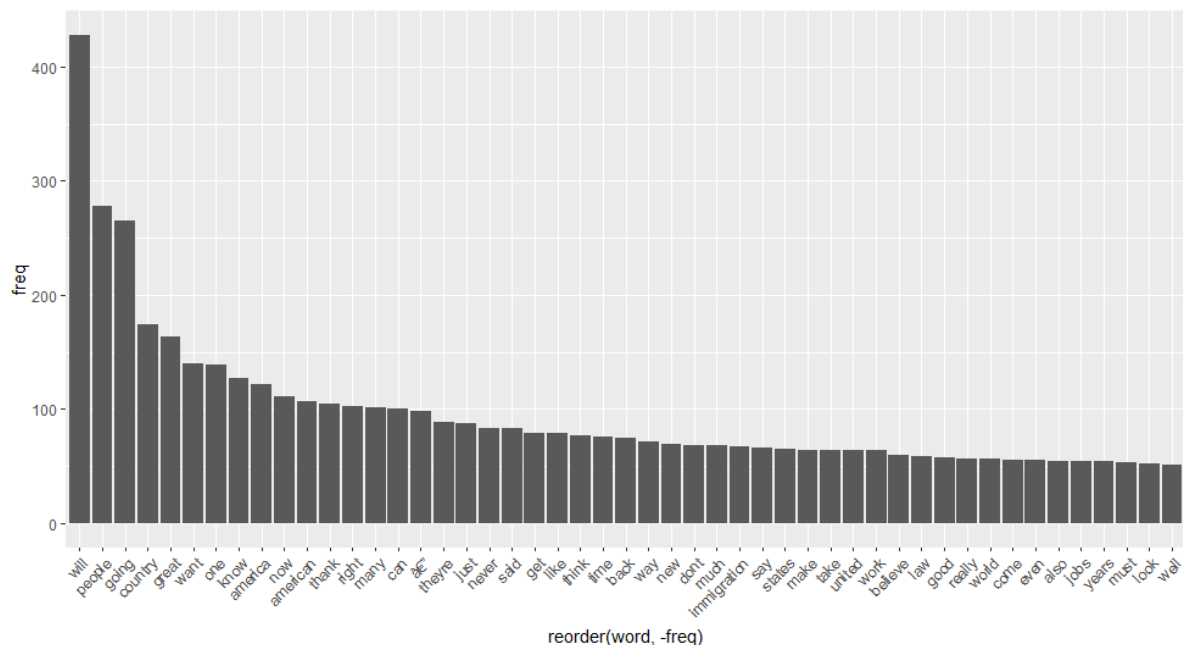
also      always    america    american    another      back      bad
54        24        122        107         22         75        35
believe  big            came        can          care        come      country
60        45        20         100         37         55        174
day       different   done        enforcement  even        ever      every
36        16        24         43          55         42        49
get       getting      give        going        good        great     group
79        23        25         265         58         163       20
happen    job          just        know         last        law       let
36        38        88         127         44         59        40
life      like        little      long         look        lot       love
27        79        24         36          52         44        45
made      many        much        must         nation      need      never
32        101       68         53          48         32        83
new       now         office      one          people      president put
69        111       24         139         278        44        35
really    remember    right       safe         said        say       see
57        27        102        35          83         66        48
seen      something    special     states       take        tell      thank
34        25        26         65          64         50        105
things    think       time        today        together    totally   truly
40        77        76         33          34         18        16
understand united      want        way          well        will      work
29        64        140        71          51         428      64
world     year        years
56        47        54
```

Next we sort the words according to the frequency of appearances in decreasing order and create a data frame from our next step. Here is the final outcome

```
word freq
will 428
people 278
going 265
country 174
great 163
want 140
```

### **Plot Word Frequency , Calculate terms correlations , Create word clouds**

To plot the word frequency histogram, we will use the ggplot2 package. In order for the histogram to not get too clustered or all over the place , we will make sure to only include words that appear more than 50 times in the corpus and get some alignment parameters for our code. As we can see that Trump’s most favorite words are “will”, “people”, “going”, “country”, “great”, “one” indicating the fact that he likes to make a lot of promises that target the common folks to make them feel united for the country or something great.



The findings leads us to a question to what words often get associated to the words “American” and ”Country” as we can see they are one of the few words Trump likes to use constantly. If the words always appear together then the correlation is 1. In this case we are specifying the correlation limit of 0.85 but we can change that in the future. Looking into this allows us to see whether or not we need to update “Combining words” section that we established above.

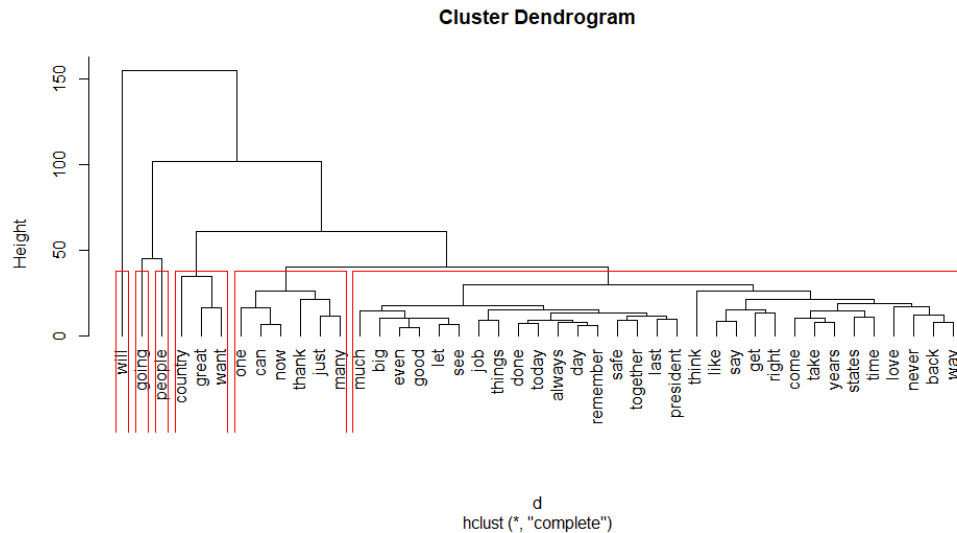
\$country								
nothing	cities	countries	jobs	come	biggest	donors	second	
0.95	0.94	0.94	0.92	0.91	0.90	0.90	0.90	
begin	border	plan	crimes	globe	meant	thousands	means	
0.88	0.88	0.88	0.87	0.87	0.87	0.87	0.86	
workers	also	despite	take					
0.86	0.85	0.85	0.85					
\$american								
restore	task	fair	budget	cycle	new promises	dollars	finally	
0.97	0.93	0.92	0.91	0.89	0.89	0.89	0.88	0.88
millions	national	tens	foreign	middle	justice	program	break	joining
0.88	0.88	0.88	0.87	0.87	0.86	0.86	0.85	0.85
united								
0.85								

From the result, we can deduct that Trump likes to use the “country” with “nothing” as the base and then it is the “American” to “restore” the country as his answer.

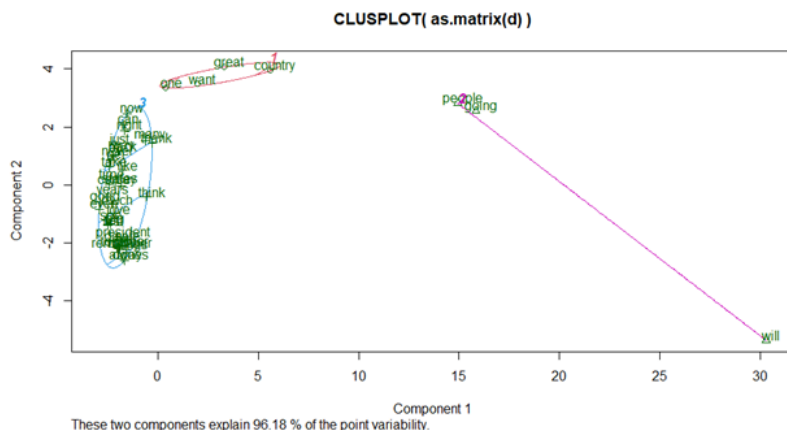
Wordcloud library was created to specifying in creating word cloud. After preparing the data max 15% and getting colored according to the frequencies. We can see that “will” is the most used words (1<sup>st</sup> in yellow) followed by “people” and “going” (2<sup>nd</sup> and 3<sup>rd</sup> in pink). Then we have “country” and “great” (4<sup>th</sup> and 5<sup>th</sup> in purple) the next top ten in orange and the rest in green. The clear and concise visualization allows the readers to digest information faster



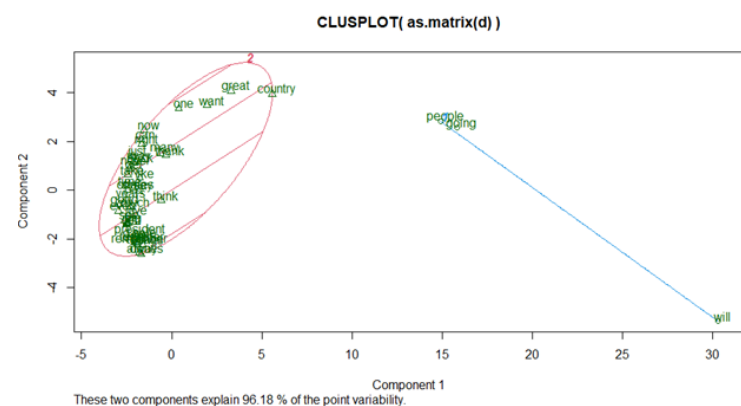
clusters is paired by the splitting of a vertical line into the vertical line. We can give an example like “like” and “right” are equally distant from “just”.



We do the same with K-means clustering where we prepare the data max 15% empty space and use the Euclidian distance. From what we have seen above, there are actually two groups of clusters due to one having a significant number of words and thus decide to assign k as 2 or 3 for this. After running the code, we can see that k=3 is the much better choice compared to 2 due to the fact that the first 2 clusters contain words that appear too frequently compared to the second cluster’s ones. “Will” seems to be the outlier, worthy of having its own cluster but it is best to group them with the other popular words that are “people“, “going”



**K= 3**



**K= 2**



## **References**

- NLP - Linguistic Resources. (2018). Retrieved January 24, 2021, from [https://www.tutorialspoint.com/natural\\_language\\_processing/natural\\_language\\_processing\\_linguistic\\_resources.htm](https://www.tutorialspoint.com/natural_language_processing/natural_language_processing_linguistic_resources.htm)
- Valentina Alto. (2019, July 8). Unsupervised Learning: K-means vs Hierarchical Clustering. Retrieved January 24, 2021, from <https://towardsdatascience.com/unsupervised-learning-k-means-vs-hierarchical-clustering-5fe2da7c9554>
- Yangchang Zhao. (2012). Document Matrix - an overview. Retrieved January 24, 2021, from <https://www.sciencedirect.com/topics/mathematics/document-matrix>