

Data Science Capstone Milestone Report

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Synopsis

Here i am performing exploratory data analysis for few text file using NLP and data mining with libraries like “tm”, and “RWeka”. From this analysis we can understanding the distribution of words and relationship between the word sand later can used latter to develop next word predicting app.

Setting a Seed

To make sure this notebook is reproducible:

```
#set seed  
set.seed(1000)
```

Library's

```
library(tm)  
library(RWeka)  
library(ggplot2)  
library(knitr)  
library(dplyr)  
library(plyr)  
library(data.table)
```

Function's

```
# words without contraction form  
word_contraction <- function(w){  
  rows <- nrow(contr_wo_ls)  
  for(i in 1 : rows ){  
    w <- gsub(contr_wo_ls[i,1], contr_wo_ls[i,2], w, perl=T)  
  }  
  return(w)  
}  
  
# function to determine file size  
Size_MB <- function(x){round(file.info(x)$size/1024^2)}  
  
# function to determine word count  
Word_Count <- function(x){sum(sapply(strsplit(x, " "), length))}  
  
# function to determine line count  
Line_Count <- function(x){length(x)}
```

```

# function to Plot
PT <- function(x, y, z, z1, z2 = 0){
  gg <- ggplot(x, aes(File, x[,y], fill = File))+ geom_bar(stat =
    "identity",width = 0.4)+ theme(legend.position="none")+
    ggtitle(z1)+ xlab("Files")+
    ylab(z)+ theme(plot.title = element_text(color="steelblue"))
  if (z2 == 1){
    gg <- gg + facet_wrap(as.factor(x[,5]))
  }
  return(gg)
}

PT1 <- function(z, z1){
  gg <- ggplot(head(z,20), aes(x = reorder(word,-freq), y = freq))+ geom_bar(stat =
    "identity",width = 0.4,fill="steelblue")+ theme(legend.position="none")+
    ggtitle(z1)+ xlab("Words")+ ylab("Frequency")+
    theme(axis.text.x = element_text(angle = 90, hjust = 1),
    plot.title = element_text(color="steelblue"))
  return(gg)
}

# function to crate a sample
Text_Sample <- function(x,y){sample(x, length(x) * y)}

# function to write to txt
Text_Out <- function(x,y){writeLines(x, y)}

# function to corpora file
Text_corp <- function(x){VCorpus(VectorSource(x))}

# Replacement function
Repl_func <- content_transformer(function(x,pattern){return(gsub(pattern, "",x))})

# function for Tokenization
Text_t <- function(x){
  Text_c <- tm_map(x, Repl_func, '')
  Text_c <- tm_map(Text_c, Repl_func, '')
  Text_c <- tm_map(Text_c, Repl_func, '-')
  Text_c <- tm_map(Text_c, Repl_func, '- ')
  Text_c <- tm_map(Text_c, Repl_func, "@[^\s]+" )
  Text_c <- tm_map(Text_c, removePunctuation)
  Text_c <- tm_map(Text_c, removeNumbers)
  Text_c <- tm_map(Text_c, removeWords, "profanity_word")
  Text_c <- tm_map(Text_c, content_transformer(tolower))
  Text_c <- tm_map(Text_c, stripWhitespace)
}

# Function to write Tokenized Text
Text_wt <- function (x,y) {
  text_t <- data.frame(text=unlist(sapply(x, `[`, "content")),
    stringsAsFactors=F)
write.csv(text_t,y, row.names=FALSE)
}

```

```

# Function to determine the frequency of Words

Freq_fun <- function(tdm){ freq <- sort(rowSums(as.matrix(tdm),na.rm = TRUE),
                                             decreasing = TRUE)
  return(data.frame(word = names(freq), freq = freq))
}

## Using the functions described bellow, we generated bigrams, trigrams .. etc from each sample source

unigram <- function(x) NGramTokenizer(x, Weka_control(min = 1, max = 1))
bigram <- function(x) NGramTokenizer(x, Weka_control(min = 2, max = 2))
trigram <- function(x) NGramTokenizer(x, Weka_control(min = 3, max = 3))
quadgram <- function(x) NGramTokenizer(x, Weka_control(min = 4, max = 4))
pentagram <- function(x) NGramTokenizer(x, Weka_control(min = 5, max = 5))
hexagram <- function(x) NGramTokenizer(x, Weka_control(min = 6, max = 6))

Wordcoverage <- function(x,wordcover){
  nwords <- 0
  coverage <- wordcover*sum(x$freq)
  for (i in 1:nrow(x)) {
    if (nwords >= coverage) {
      return (i)
    }
    nwords<-nwords+x$freq[i]
  }
}

```

Task 1 - Getting and cleaning the data

Loading and Reading Data

```

# Working Directory
work_dir <- "F:/DS/ASS/Text_mining"

# Input files
in_dir = "F:/DS/ASS/Text_mining/Input/en_US"

# Read each file in Input Folder
file_list <- "File list"
file_name <- dir(in_dir)
for (i in 1:3){
  file_seq <- paste(in_dir,file_name[i],sep = "/")
  con <- file(file_seq, "r")
  file_temp <- readLines(con,encoding="UTF-8")
  file_name_temp1 <- unlist(strsplit(file_name[i], ".txt"))
  file_name_temp1 <- strsplit(file_name_temp1, "\\.")[[1]]
  file_name_temp1 <- unique(tolower(file_name_temp1))[2]
  do.call("<- ",list(file_name_temp1,file_temp))
  file_list <- c(file_list,file_name_temp1)
  close(con)
}

```

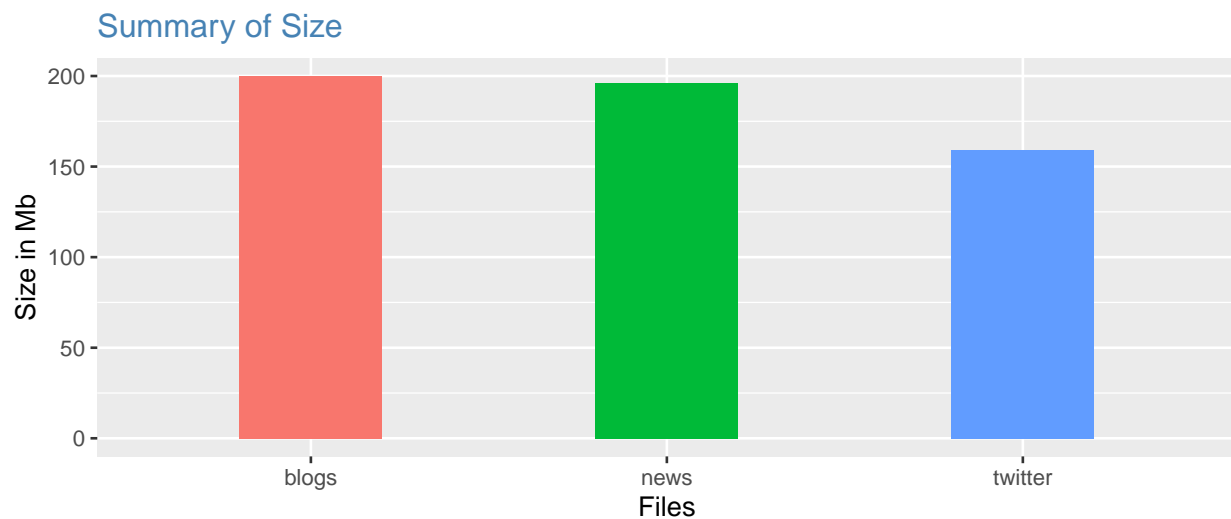
```

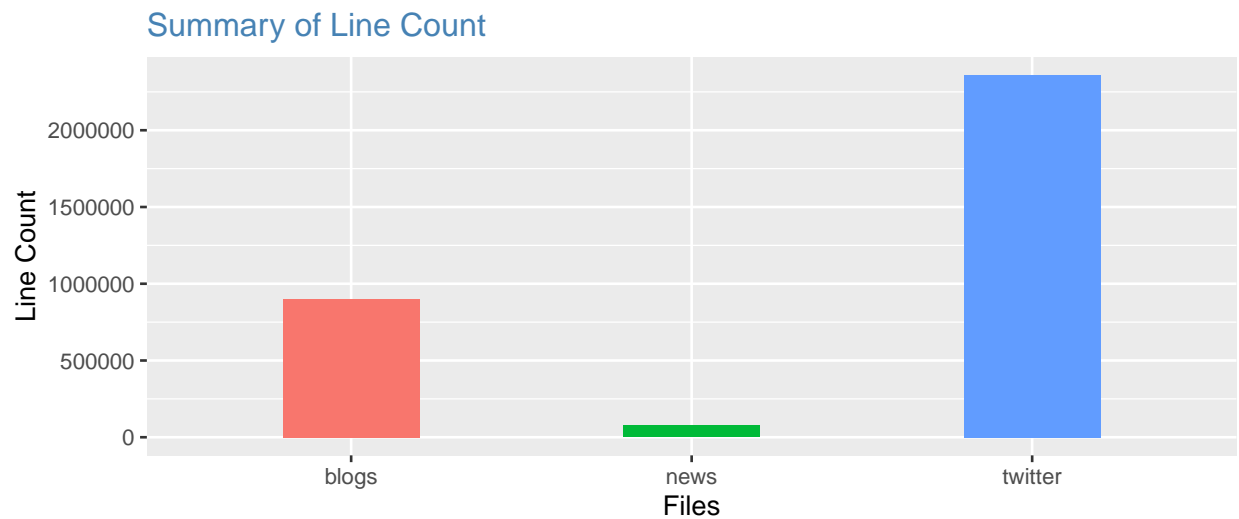
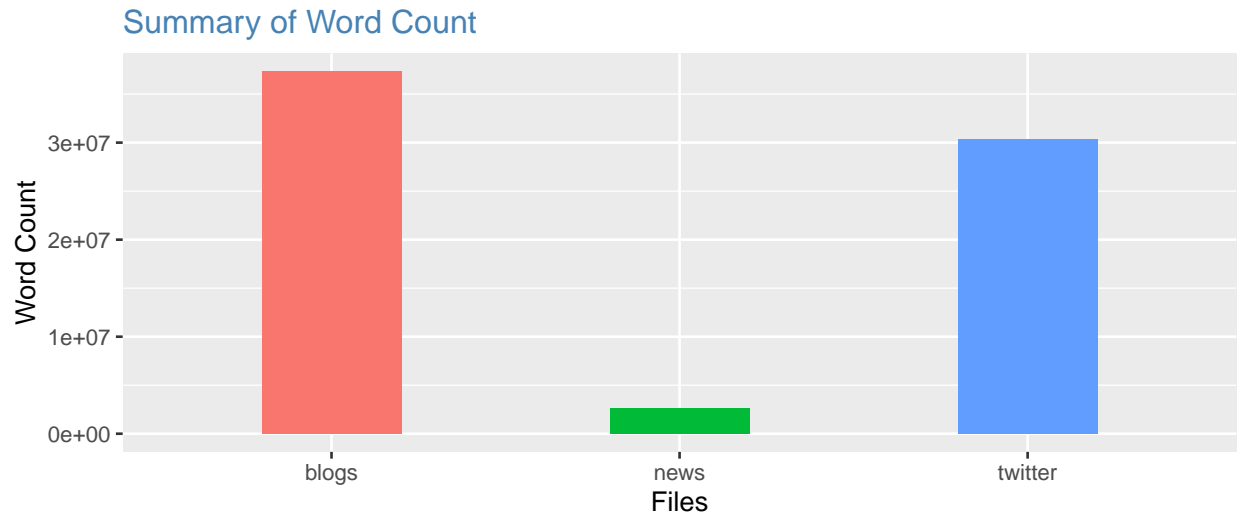
Text_summary <- as.data.frame(file_list[2:4])
Text_summary <- cbind(Text_summary,as.data.frame(Size_MB(c(paste(in_dir,file_name[1],
sep = "/"),paste(in_dir,file_name[2],sep = "/"),
paste(in_dir,file_name[3],sep = "/")))))
Text_summary <- cbind(Text_summary,as.data.frame(c(Word_Count(blogs),
Word_Count(news),Word_Count(twitter))))
Text_summary <- cbind(Text_summary,as.data.frame(c(Line_Count(blogs),
Line_Count(news),Line_Count(twitter))))
File_type <- rep("Orginal file",nrow(Text_summary))
Text_summary <- cbind(Text_summary,File_type)
names(Text_summary) <- c("File","Size MB","Word Count","Line count", "File type")

```

Table 1: Text File Summary

File	Size MB	Word Count	Line count	File type
blogs	200	37334131	899288	Orginal file
news	196	2643969	77259	Orginal file
twitter	159	30373543	2360148	Orginal file





1.Sampling

We have three different data files from sources folder. Due to limitations in processing power, a sample of the data is taken. A approx 1800000 consecutive words are considered from the given each data set.

```
blogs_s <- Text_Sample(blogs,0.018) #0.025
news_s <- Text_Sample(news,0.26) #0.35
twitter_s <- Text_Sample(twitter,0.022) #0.03

# words without contraction

contr_wo_ls <- as.data.frame(read.csv("Contraction_en.csv",
                                     sep = ',',header = TRUE,))
blogs_s <- word_contraction(blogs_s)
news_s <- word_contraction(news_s)
twitter_s <- word_contraction(twitter_s)
rm(contr_wo_ls)

Text_Out(blogs_s,"blogs_s.txt")
Text_Out(news_s,"news_s.txt")
```

```

Text_Out(twitter_s,"twitter_s.txt")

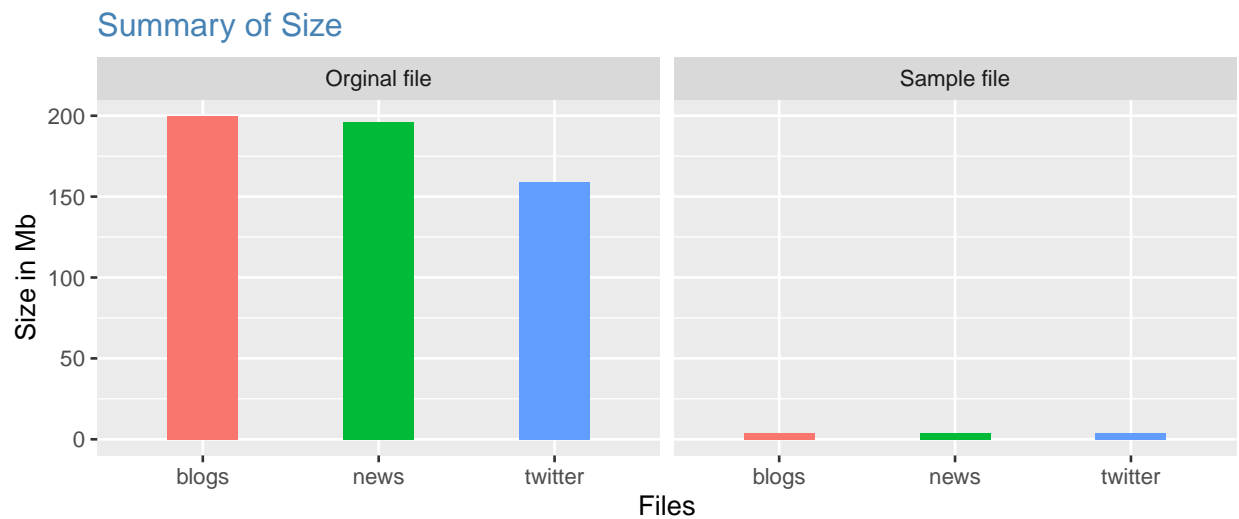
Text_summary1 <- as.data.frame(file_list[2:4])
Text_summary1 <- cbind(Text_summary1,as.data.frame(Size_MB(c(paste(work_dir,"blogs_s.txt",
  sep = "/"),paste(work_dir,"news_s.txt",sep = "/"),
  paste(work_dir,"twitter_s.txt",sep = "/")))))
Text_summary1 <- cbind(Text_summary1,as.data.frame(c(Word_Count(blogs_s),
  Word_Count(news_s),Word_Count(twitter_s))))
Text_summary1 <- cbind(Text_summary1,as.data.frame(c(Line_Count(blogs_s),
  Line_Count(news_s),Line_Count(twitter_s))))
File_type <- rep("Sample file",nrow(Text_summary1))
Text_summary1 <- cbind(Text_summary1,File_type)
names(Text_summary1) <- c("File","Size MB","Word Count","Line count", "File type")

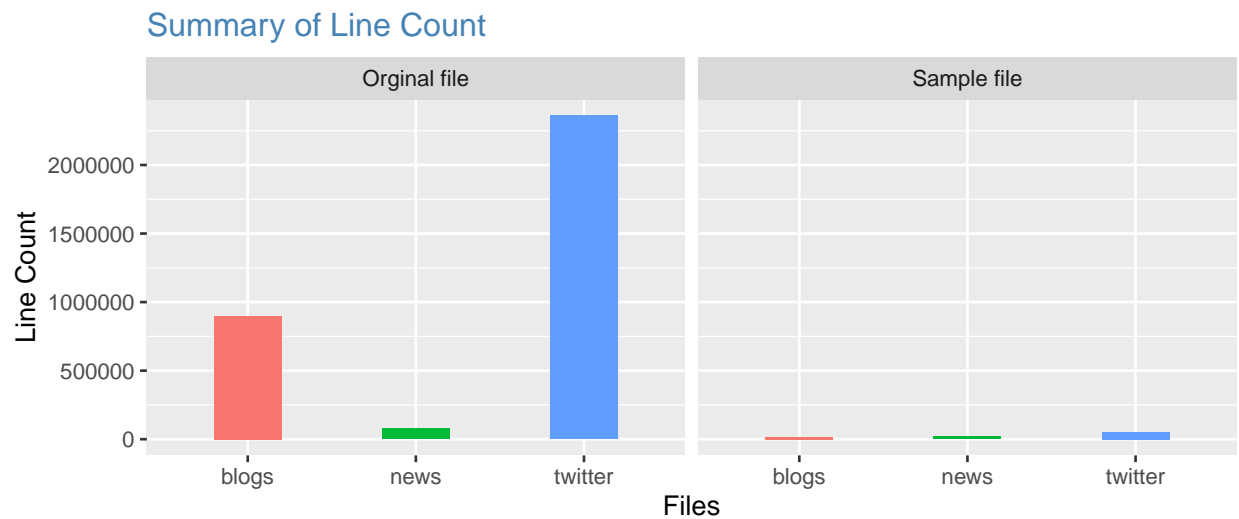
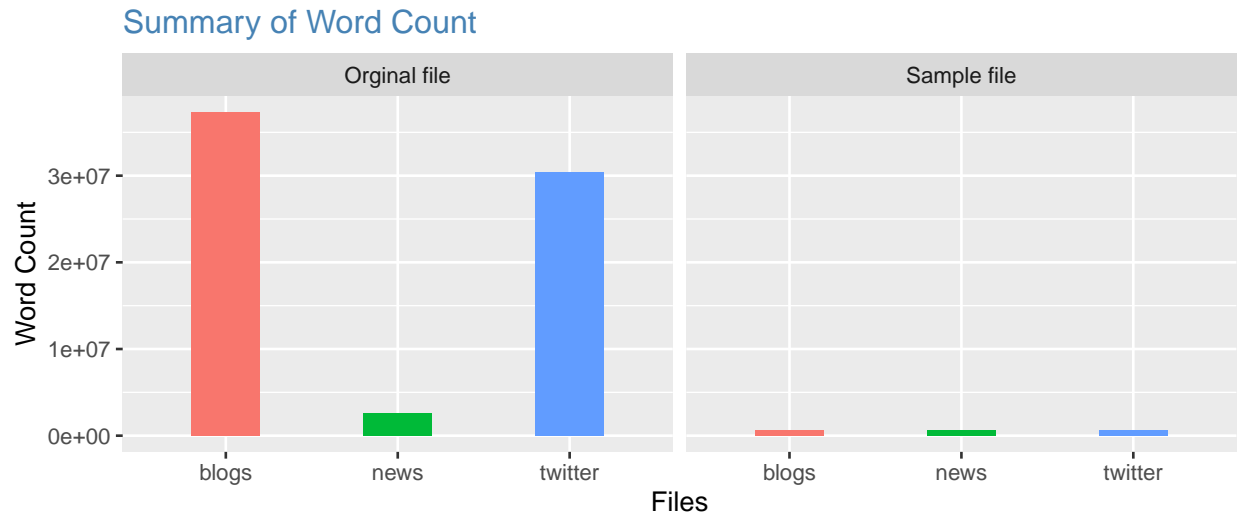
Text_summary <- rbind(Text_summary,Text_summary1)
rm(Text_summary1)

```

Table 2: Text File Summary

File	Size MB	Word Count	Line count	File type
blogs	200	37334131	899288	Orginal file
news	196	2643969	77259	Orginal file
twitter	159	30373543	2360148	Orginal file
blogs	4	679897	16187	Sample file
news	4	688779	20087	Sample file
twitter	4	679320	51923	Sample file





From the figure it can be seen the sample data extracted from the original files have very similar in size and Total Word count. hence with sample data we could further clean and Tokenize the data for unnecessary arguments.

2.Tokenization

Now we can token all words associated with text by creating a corpus and then removing bad words, punctuation and numbers. For profanity filtering, we downloaded a “badwords” list (source: <https://github.com/shutterstock/List-of-Dirty-Naughty-Obscene-and-Otherwise-Bad-Words/blob/master/en>) and removed the words accordingly.

```
# Corpora file Creation
blogs_s_c <- Text_corp(blogs_s)
news_s_c <- Text_corp(news_s)
twitter_s_c <- Text_corp(twitter_s)

# Remove double forward and backward quotes

profanity_word <- read.csv("profanity_words.csv")

blogs_t <- Text_t(blogs_s_c)
```

	word	freq		word	freq		word	freq
	the	33923	the	the	39349	the	the	20700
	and	19752	and	and	17662	you	you	12741
	that	8320	that	that	7065	and	and	9441
	for	6452	for	for	7019	for	for	8549
	you	5660	with	with	5127	that	that	5708
	with	5205	said	said	4943	not	not	5585
	was	5113	was	was	4576	are	are	4554
	this	4752	not	not	3943	have	have	4423
	have	4268	have	have	3213	your	your	3846
	not	4252	are	are	3162	with	with	3707
	are	3733	his	his	3126	this	this	3610
	but	3703	from	from	3015	just	just	3377
	from	2683	but	but	3004	will	will	3062
	all	2645	will	will	2504	but	but	2650
	they	2511	has	has	2486	was	was	2632
	will	2397	they	they	2446	like	like	2621
	one	2320	this	this	2446	what	what	2614
	had	2213	who	who	2236	get	get	2585
	about	2156	you	you	2180	all	all	2583
	his	2022	about	about	1820	out	out	2532

x

Word Frequency in Blogs,News and Twitter text File

```
news_t <- Text_t(news_s_c)
twitter_t <-Text_t(twitter_s_c)

Text_wt(blogs_t,"blogs_t.txt")
Text_wt(news_t,"news_t.txt")
Text_wt(twitter_t,"twitter_t.txt")
```

Task 1 - Exploratory Data Analysis

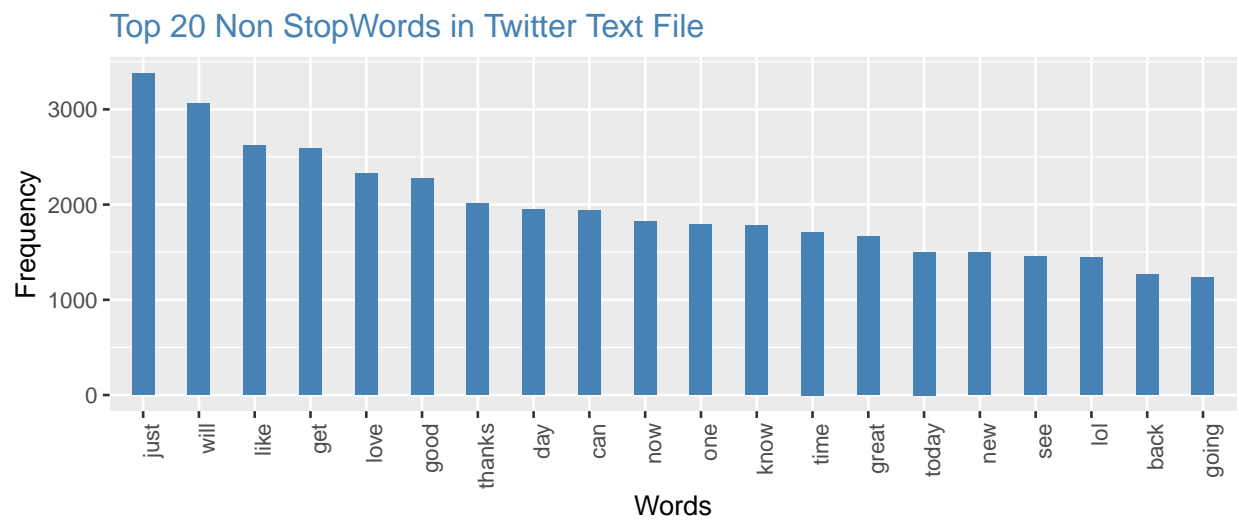
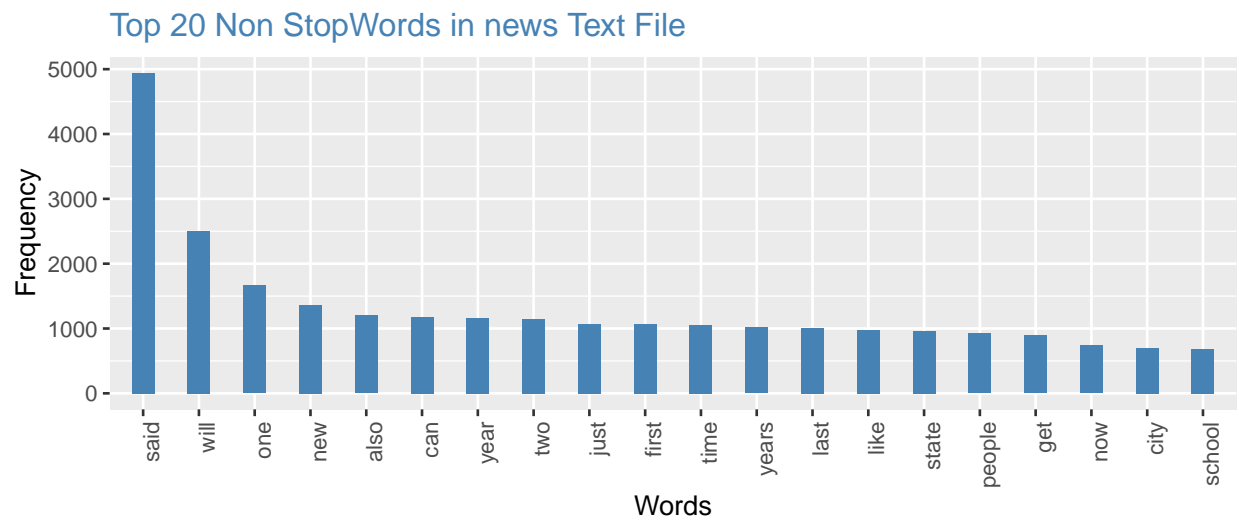
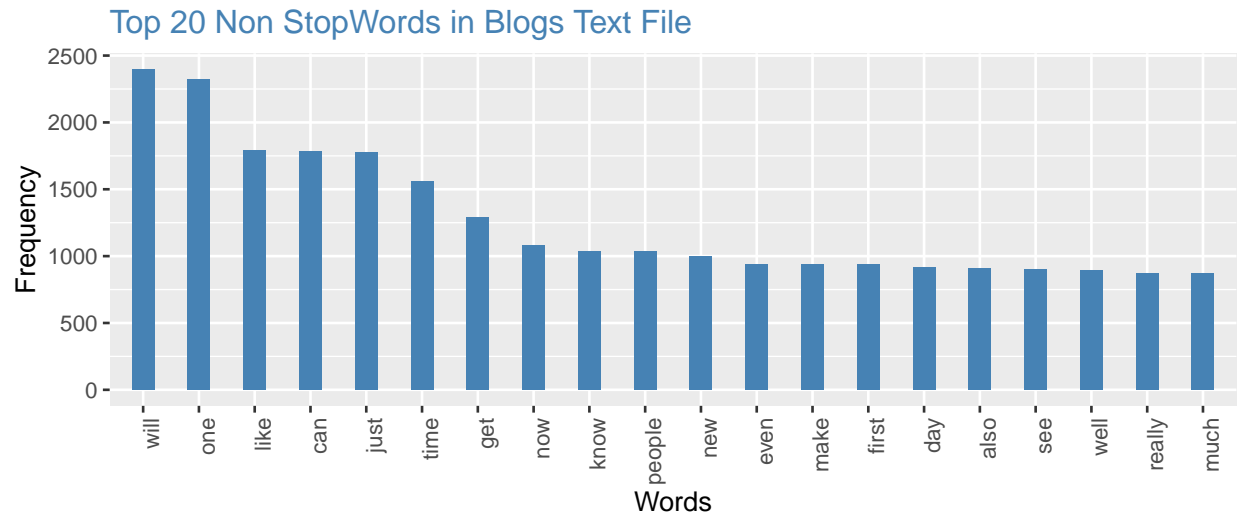
To understanding the distribution of words and relationship between the words in the corpora, we will use TermDocumentMatrix

```
blogs_tdm <- TermDocumentMatrix(blogs_t)
news_tdm <- TermDocumentMatrix(news_t)
twitter_tdm <- TermDocumentMatrix(twitter_t)

# Word frequencies

blogs_wf <- Freq_fun(removeSparseTerms(blogs_tdm, 0.999))
news_wf <- Freq_fun(removeSparseTerms(news_tdm, 0.999))
twitter_wf <- Freq_fun(removeSparseTerms(twitter_tdm, 0.999))
```

From the Table 3 its clear that most frequent words are Stop words of English. let see what are the other words other than Stop words



The figure show the frequencies of words other than Stop words.

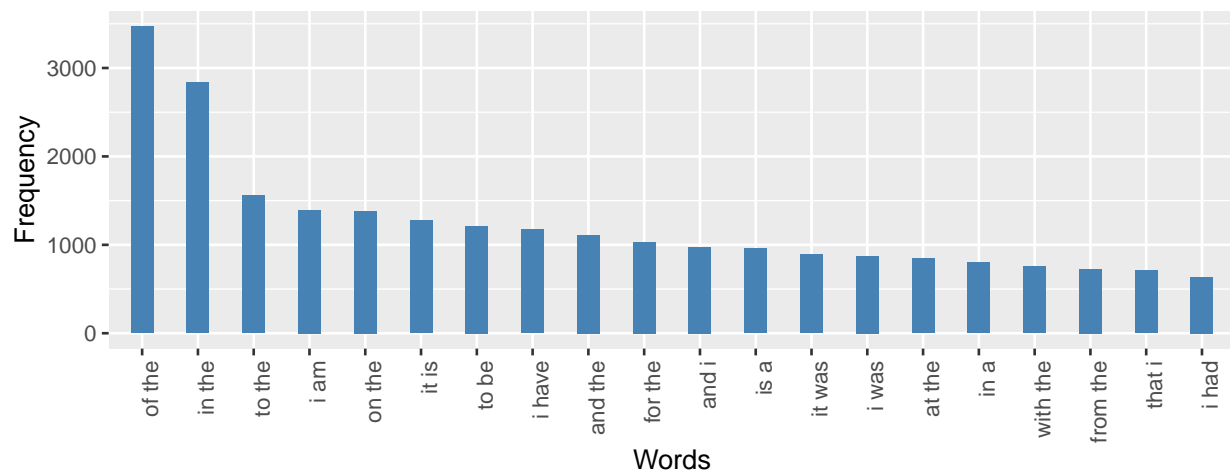
Understand frequencies of words and word pairs

Frequencies of 2-Grams

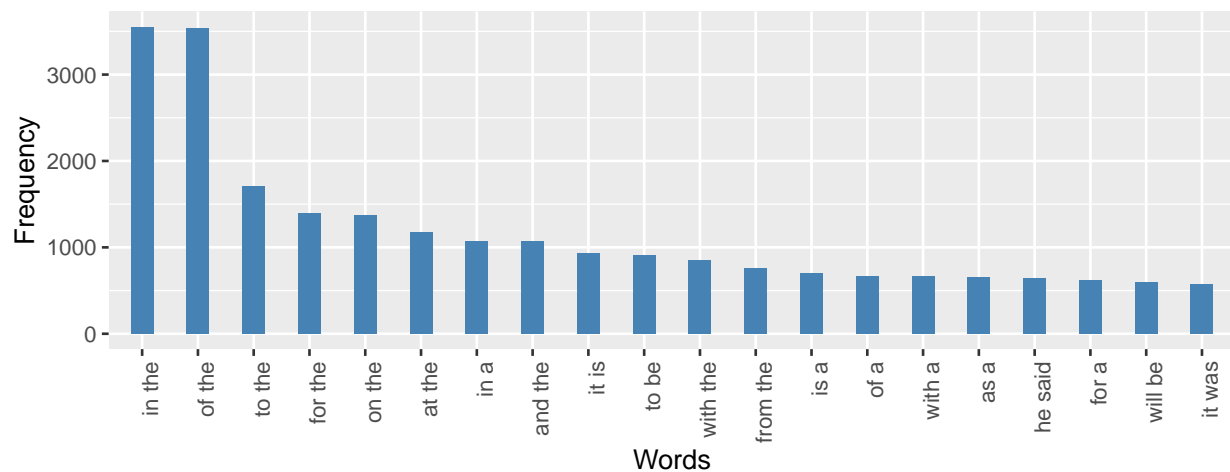
```
# 2 - grams
blogs_2gram <- Freq_fun(TermDocumentMatrix(blogs_t,
  control = list(tokenize = bigram, bounds = list(global = c(50, Inf)))))
news_2gram <- Freq_fun(TermDocumentMatrix(news_t,
  control = list(tokenize = bigram, bounds = list(global = c(50, Inf)))))
twitter_2gram <- Freq_fun(TermDocumentMatrix(twitter_t,
  control = list(tokenize = bigram, bounds = list(global = c(50, Inf)))))
```

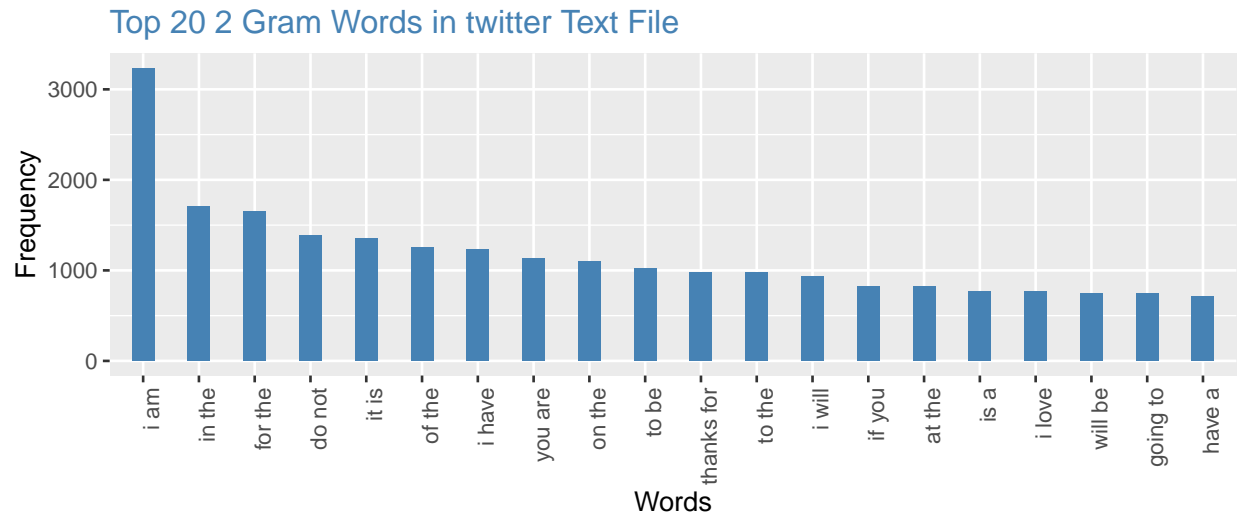
2- Gram Words Frequency

Top 20 2 Gram Words in Blogs Text File



Top 20 2 Gram Words in News Text File



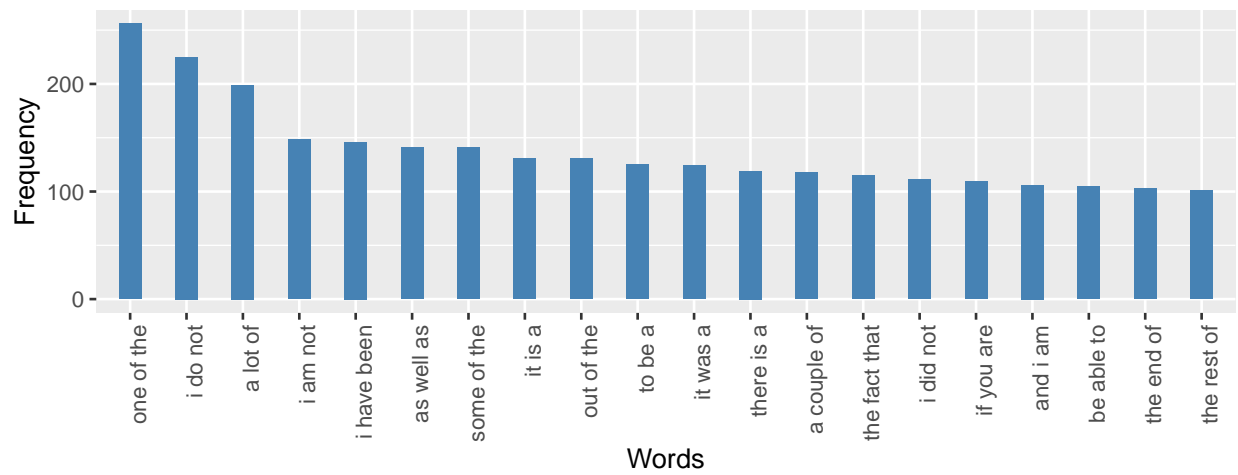


Frequencies of 3-Grams

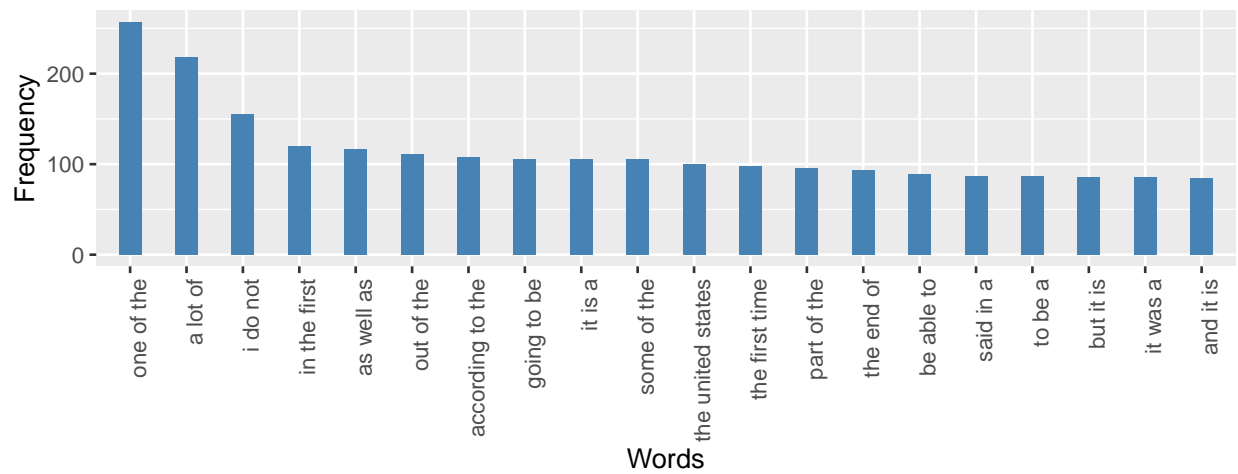
```
blogs_3gram <- Freq_fun(TermDocumentMatrix(blogs_t,
  control = list(tokenize = trigram, bounds = list(global = c(30, Inf))))
news_3gram <- Freq_fun(TermDocumentMatrix(news_t,
  control = list(tokenize = trigram, bounds = list(global = c(30, Inf))))
twitter_3gram <- Freq_fun(TermDocumentMatrix(twitter_t,
  control = list(tokenize = trigram, bounds = list(global = c(30, Inf))))
```

3- Gram Words Frequency

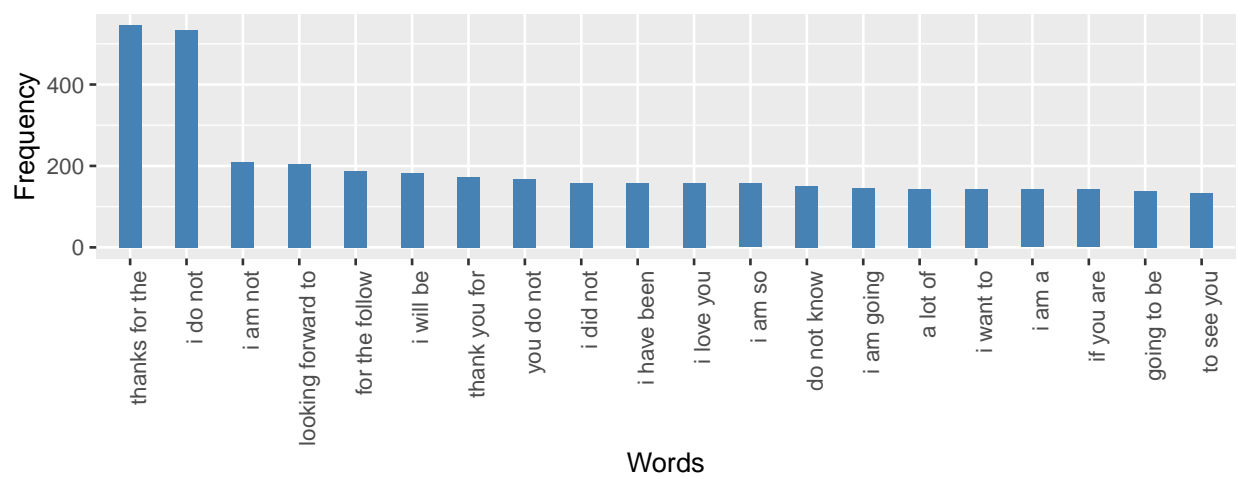
Top 20 3 Gram Words in Blogs Text File



Top 20 3 Gram Words in News Text File



Top 20 3 Gram Words in Twitter Text File



Unique Word Coverage

Unique words needed in a frequency sorted dictionary to cover 50% of all word instances in the language? and 90%?

```
# Merge the Text Files

All_Text <- c(blogs_t,news_t,twitter_t)
All_Text_tdm <- TermDocumentMatrix(All_Text)
All_Text_1gram <- Freq_fun(removeSparseTerms(All_Text_tdm, 0.999))

# 50% Word Coverage
Wordcoverage(All_Text_1gram,0.5)

## [1] 94

# 50% Word Coverage
Wordcoverage(All_Text_1gram,0.9)

## [1] 1144
```

Unsurprisingly, the number of words increases exponentially when we increase our desired percent coverage of the language. This is because the frequency of unique words appearing in the corpora also drop exponentially. Hence, for a higher word coverage of the language or dictionary, it will require an exponential increase in number words.

Foreign Language Evaluation

The code developed in this exploratory analysis is not discriminating of languages. When it is necessary to evaluate words from foreign languages, one can make use of the “tm_map” function to “removeWords” based on a language dictionary. The difference in word count will provide insight into the number of words from that particular language in the corpora.

Increasing Coverage

There are several ways that could be used to increase the coverage. One is to reduce the number of low-frequency unique words by stemming or by substitution using a thesaurus library. Additionally, increasing the coverage is possible via context-clustering - with the introduction of a context to the corpora, it will be possible to cluster certain word groups together. For example, if the snapshot of the twitter corpora is taken during a major sporting event, there are many terms, lingos and slangs that could be clustered within the context.

Task 3 - Modeling

- To Build model predicting the next word based on the previous 1, 2, or 3 words we can use N-gram models.
- To handle unseen n-grams in N-gram we can use Katz Backoff Mode.
- And finally Markov chain is used to store the model effeciently.

Building N-gram Frequencies

```
corpus_without_curse_words <- All_Text
# N-grams of different sizes Function
```

```

grams1 <- Freq_fun(TermDocumentMatrix(All_Text,
  control = list(tokenize = unigram, bounds = list(global = c(50, Inf))))
grams2 <- Freq_fun(TermDocumentMatrix(All_Text,
  control = list(tokenize = bigram, bounds = list(global = c(40, Inf))))
grams3 <- Freq_fun(TermDocumentMatrix(All_Text,
  control = list(tokenize = trigram, bounds = list(global = c(15, Inf))))
grams4 <- Freq_fun(TermDocumentMatrix(All_Text,
  control = list(tokenize = quadgram, bounds = list(global = c(5, Inf))))
grams5 <- Freq_fun(TermDocumentMatrix(All_Text,
  control = list(tokenize = pentagram, bounds = list(global = c(3, Inf))))

ngrams <- rbind(grams1,grams2,grams3,grams4,grams5) %>%
  arrange((word))
frequencies_dt <- ngrams
colnames(frequencies_dt) <- c("ngram","frequency")

```

Table 3: N-gram Frequencies

ngram	frequency
i do not have any	5
theres a lot of	9
of what i	20
concert	150
was the same	15
of passes for yards	5
look forward to a	7
morning i	46
said i do not want	3
produced	87
will find	55
have so many	21

The Table Show the 12 random N-grams and its frequencies.

An history column is created in the table

```

# function to calculate words history
extract_history <- function(ngram){
  ifelse(length(ngram) > 1,
    paste(ngram[1:(length(ngram)-1)], collapse = " "),
    ""
  )
}

extract_word <- function(ngram) paste(ngram[length(ngram)], collapse = " ")

build_processed_ngram_frequencies <- function(frequencies_dt) {
  data <- as.data.frame(frequencies_dt)
  data$ngram <- strsplit(data$ngram, split = " |")
  data$ngram_length <- sapply(data$ngram, length)
  data$history <- sapply(data$ngram, extract_history)
  data$word <- sapply(data$ngram, extract_word)
  data$ngram <- sapply(data$ngram, paste, collapse = " ")
}

```

```

data.table(data)
}
# Extract the history word
ngram_frequencies_dt <- build_processed_ngram_frequencies(frequencies_dt)

```

Table 4: N-gram Frequencies with its word history

ngram	frequency	ngram_length	history	word
of the	8263	2	of	the
in the	8100	2	in	the
i am	5068	2	i	am
to the	4238	2	to	the
for the	4076	2	for	the
on the	3851	2	on	the
it is	3564	2	it	is
to be	3145	2	to	be
at the	2836	2	at	the
i have	2683	2	i	have
and the	2519	2	and	the
do not	2482	2	do	not
is a	2434	2	is	a
in a	2351	2	in	a
with the	1944	2	with	the
it was	1942	2	it	was
will be	1915	2	will	be
for a	1902	2	for	a
and i	1836	2	and	i
you are	1771	2	you	are
from the	1737	2	from	the
is the	1713	2	is	the
if you	1673	2	if	you
i was	1657	2	i	was
going to	1583	2	going	to
with a	1575	2	with	a
of a	1519	2	of	a
i will	1517	2	i	will
that is	1464	2	that	is
to get	1428	2	to	get
have a	1422	2	have	a
as a	1394	2	as	a
one of	1376	2	one	of
is not	1337	2	is	not
did not	1284	2	did	not
i do	1254	2	i	do
have been	1244	2	have	been
want to	1244	2	want	to
i had	1241	2	i	had
have to	1215	2	have	to
by the	1206	2	by	the
this is	1200	2	this	is
but i	1182	2	but	i
to do	1178	2	to	do
the first	1152	2	the	first

ngram	frequency	ngram_length	history	word
we are	1152	2	we	are
that the	1149	2	that	the
i think	1138	2	i	think
that i	1136	2	that	i
and a	1106	2	and	a

To computing probabilities for the model will require counts for histories as well, so let's create a data table specifically for this purpose

```
history_frequencies_dt <-
  ngram_frequencies_dt[, c("history", "frequency")][, lapply(.SD, sum), by = list(history)]
```

Table 5: Frequency of History Words

history	frequency
	1245903
the	38544
to	34405
i	31524
in	19484
and	19400
of	19128
a	17409
is	15850
it	13050
you	12860
for	12567
that	10852
on	9891
with	7364
not	7232
have	7172
at	6341
as	5842
but	5582
we	5557
do	5268
was	4989
he	4934
are	4817
this	4681
will	4442
if	4328
be	3979
so	3969
what	3902
they	3742
my	3623
out	3546
when	3493
me	3455
all	3371

history	frequency
from	3289
in the	3143
up	3103
i am	3029
there	2838
like	2827
about	2820
am	2723
said	2635
one	2621
get	2596
had	2416
has	2374

```
frequencies_of_frequencies <- table(ngram_frequencies_dt$frequency)
frequencies_of_frequencies
```

```
##
##      3      4      5      6      7      8      9     10     11     12     13     14     15
## 1412  478 1677  913  605  369  278  186  143  119  89   77  401
##   16   17   18   19   20   21   22   23   24   25   26   27   28
##  369  315  268  226  182  223  180  147  133  117  119  113  84
##   29   30   31   32   33   34   35   36   37   38   39   40   41
##   75   76   89   81   60   60   49   43   34   42   33   98  125
##   42   43   44   45   46   47   48   49   50   51   52   53   54
##  109  117  135  126  124  101   95  103  108   99   88  121  116
##   55   56   57   58   59   60   61   62   63   64   65   66   67
##  108  121  129  102  126   92  113  112   90   84   86   86   74
##   68   69   70   71   72   73   74   75   76   77   78   79   80
##   72   81   66   63   67   60   62   79   66   64   50   58   59
##   81   82   83   84   85   86   87   88   89   90   91   92   93
##   74   50   49   57   50   44   41   49   44   43   45   41   40
##   94   95   96   97   98   99  100  101  102  103  104  105  106
##   44   50   38   35   37   44   41   38   36   35   35   21   30
##  107  108  109  110  111  112  113  114  115  116  117  118  119
##   32   29   40   26   30   27   28   31   24   30   28   31   21
##  120  121  122  123  124  125  126  127  128  129  130  131  132
##   23   21   26   16   29   25   27   23   21   21   25   24   18
##  133  134  135  136  137  138  139  140  141  142  143  144  145
##   23   22   26   20   14   22   20   21   19   15   17   24   23
##  146  147  148  149  150  151  152  153  154  155  156  157  158
##   21   15   19   16   15   10   13   16   17   15   8   15   19
##  159  160  161  162  163  164  165  166  167  168  169  170  171
##    5   10   11   10   14   18   10   15   12   12   16   11   20
##  172  173  174  175  176  177  178  179  180  181  182  183  184
##   19    9    7   13    4   14    8   13    6   13   11    8   17
##  185  186  187  188  189  190  191  192  193  194  195  196  197
##    9   12   12   10   10    8   15   15   18   12   12    9   10
##  198  199  200  201  202  203  204  205  206  207  208  209  210
##    6    3    5    9   10   12   12    6   13    8    4   15   13
##  211  212  213  214  215  216  217  218  219  220  221  222  223
##    9    6   10    8    8    9   12   12    8    8    8    5    7
```

##	224	225	226	227	228	229	230	231	232	233	234	235	236
##	12	8	7	6	10	5	4	4	3	8	8	6	8
##	237	238	239	240	241	242	243	244	245	246	247	248	249
##	17	8	7	6	2	8	2	10	2	8	10	3	7
##	250	251	252	253	254	255	256	257	258	259	260	261	262
##	5	9	6	7	3	8	4	6	7	4	9	6	6
##	263	264	265	266	267	268	269	270	271	272	273	274	275
##	7	4	5	3	4	1	5	4	5	4	2	5	3
##	276	277	278	279	280	281	282	283	284	285	286	287	288
##	3	3	5	7	6	4	9	6	5	6	2	1	4
##	289	290	291	292	293	294	295	296	297	298	299	300	301
##	3	4	5	2	8	5	1	5	2	7	3	2	2
##	302	303	304	305	306	307	308	309	310	311	312	313	314
##	2	3	3	2	3	2	4	4	1	4	4	6	6
##	315	316	317	318	319	320	321	322	323	324	325	326	327
##	4	3	2	3	2	3	6	2	2	1	8	5	3
##	328	329	330	331	332	333	334	335	336	337	338	339	340
##	5	5	3	4	1	5	4	3	2	4	2	2	3
##	341	343	344	345	346	347	348	349	350	351	352	353	354
##	3	3	3	2	1	5	2	1	5	4	4	3	4
##	355	356	357	359	360	361	362	363	364	366	367	368	369
##	3	3	3	2	3	2	3	2	4	5	2	1	5
##	370	371	372	373	375	376	377	378	379	380	381	382	383
##	4	3	1	2	2	1	1	2	2	4	1	1	3
##	384	385	386	387	388	389	390	391	392	393	394	395	396
##	2	2	1	1	3	2	2	3	1	6	1	3	2
##	397	398	400	401	403	404	405	406	407	409	411	412	413
##	3	6	1	2	1	3	3	1	3	3	2	4	1
##	414	415	416	417	418	419	420	421	422	423	424	425	426
##	5	2	2	2	1	2	2	1	1	5	3	2	2
##	427	428	429	430	433	434	435	436	438	442	443	444	445
##	3	3	1	6	2	3	4	1	2	1	2	2	2
##	446	448	449	450	451	453	454	455	456	457	458	460	461
##	2	1	2	2	4	2	1	1	2	1	1	1	1
##	462	464	466	467	468	469	470	471	472	473	475	476	477
##	2	2	1	3	1	1	3	1	3	1	5	1	1
##	480	481	482	484	485	486	487	490	491	492	493	494	495
##	2	1	1	1	1	4	3	4	1	1	1	2	1
##	497	499	500	502	503	504	505	506	508	509	511	512	515
##	1	2	2	1	3	1	2	2	2	2	3	2	3
##	516	519	520	521	522	525	526	528	529	530	531	532	534
##	4	2	2	1	1	1	1	4	2	2	1	4	1
##	538	539	541	542	543	547	548	549	550	551	552	553	554
##	2	1	1	3	2	1	3	1	1	2	1	1	2
##	555	556	558	559	560	561	562	565	566	569	572	575	576
##	1	1	1	2	1	2	1	1	1	1	1	1	1
##	577	579	580	581	582	584	585	586	587	589	590	591	592
##	1	2	1	2	1	1	1	1	1	1	1	3	1
##	594	596	598	599	600	602	603	604	606	607	610	614	615
##	1	1	1	1	2	2	1	2	2	2	1	1	2
##	616	617	620	621	622	623	624	625	626	628	630	635	636
##	1	2	1	2	1	1	2	1	1	2	2	1	1
##	637	638	639	641	646	647	648	651	653	654	658	660	661
##	1	1	2	3	1	2	1	1	1	2	1	1	1

##	662	663	664	665	666	670	671	675	678	679	680	683	684
##	2	1	2	1	2	1	1	1	1	2	1	1	1
##	687	688	690	693	696	698	699	701	702	704	706	707	713
##	1	1	1	1	1	2	1	1	3	2	1	1	2
##	716	717	718	719	723	724	727	733	734	735	737	739	742
##	1	1	1	2	1	1	1	2	1	1	1	1	1
##	743	744	746	747	748	752	753	754	757	762	767	772	773
##	2	1	1	1	1	1	1	1	1	1	1	1	1
##	774	781	782	784	792	796	799	800	804	810	813	815	819
##	1	1	1	1	1	1	3	1	1	1	1	2	1
##	820	823	827	829	832	833	838	839	840	841	843	845	847
##	2	1	1	1	1	2	1	1	2	1	2	2	1
##	851	852	856	857	859	864	865	868	873	876	878	881	882
##	2	1	1	1	2	2	2	1	1	1	1	1	1
##	887	889	891	892	894	895	906	910	912	914	917	919	920
##	1	1	1	1	1	1	1	1	2	3	1	1	1
##	925	956	967	982	985	993	1002	1005	1008	1011	1014	1015	1016
##	1	1	2	1	1	1	1	1	2	1	2	1	1
##	1023	1024	1032	1033	1036	1039	1043	1056	1058	1060	1070	1073	1074
##	1	1	1	1	1	1	1	1	1	1	1	1	1
##	1075	1078	1083	1095	1100	1102	1103	1106	1113	1121	1126	1129	1132
##	1	1	1	1	1	2	1	1	1	1	1	1	1
##	1133	1136	1138	1141	1149	1152	1155	1177	1178	1182	1183	1188	1200
##	1	1	1	1	1	2	1	1	1	2	1	1	1
##	1202	1206	1212	1215	1226	1241	1244	1246	1254	1268	1269	1284	1289
##	1	1	1	1	1	1	2	1	1	1	1	1	1
##	1290	1293	1295	1304	1322	1326	1327	1337	1343	1353	1359	1376	1394
##	1	1	1	1	1	1	1	1	1	1	1	1	1
##	1422	1428	1450	1453	1464	1471	1488	1491	1517	1519	1531	1538	1544
##	1	1	1	1	1	1	1	1	2	1	1	1	1
##	1547	1575	1578	1579	1583	1587	1605	1633	1643	1657	1667	1670	1673
##	1	1	1	1	1	1	1	1	1	1	1	1	1
##	1694	1696	1701	1709	1713	1723	1736	1737	1749	1765	1770	1771	1809
##	1	1	1	1	1	1	1	1	1	1	1	1	1
##	1820	1836	1860	1871	1891	1902	1910	1915	1918	1940	1942	1944	1973
##	1	1	1	1	1	1	1	1	1	1	1	1	1
##	2048	2070	2101	2148	2151	2168	2187	2213	2220	2232	2243	2259	2335
##	1	1	1	1	1	1	1	1	1	1	1	1	1
##	2345	2351	2380	2394	2413	2434	2455	2461	2466	2469	2482	2499	2505
##	1	1	1	1	1	1	1	1	1	1	1	2	1
##	2513	2519	2533	2569	2587	2593	2633	2683	2697	2773	2779	2826	2836
##	1	1	1	1	1	1	1	1	2	1	1	1	1
##	3066	3131	3145	3153	3219	3352	3399	3564	3584	3647	3687	3689	3712
##	1	1	1	1	1	1	1	1	1	1	1	1	1
##	3851	3857	3907	3977	3984	3986	4076	4179	4211	4224	4238	4320	4572
##	1	1	1	1	1	1	1	1	1	1	1	1	1
##	4697	4765	4892	5068	5150	5195	5272	5293	5393	5722	5772	5850	5875
##	1	1	1	1	1	1	1	1	1	1	1	1	1
##	5949	5963	6228	6293	6605	6633	7501	7963	8100	8263	9357	10806	11449
##	1	1	1	1	1	1	1	1	1	1	1	1	1
##	11904	12321	13780	14038	20580	21093	22020	46855	93972				
##	1	1	1	1	1	1	1	1	1				

Good-Turing discount Function

```
frequency_of_frequency <- function(frequency, frequencies_of_frequencies)
  try_default(frequencies_of_frequencies[[toString(frequency)]], 1, quiet = TRUE)

discount <- function(count, frequencies_of_frequencies) {
  good_turing_count <- (count + 1) *
    frequency_of_frequency(count + 1, frequencies_of_frequencies) /
    frequency_of_frequency(count, frequencies_of_frequencies)
  computed_discount <- good_turing_count / count
  ifelse(computed_discount < 1, computed_discount, 1)
}
```

Testing Good- turing for 1 counts is 1

Katz's probability calculation

```
count_ngram <- function(word_value, history_value, ngram_frequencies_dt) {
  count <- ngram_frequencies_dt[word == word_value & history == history_value, ]$frequency
  ifelse(length(count) > 0, count, 1)
}

count_history <- function(history_value, history_frequencies_dt) {
  count <- history_frequencies_dt[history == history_value, ]$frequency
  ifelse(length(count) > 0, count, 1)
}
```

Count of word “the” after word “in” in a sentence is 8100

Frequency of word “in” as precedence word is 1.9484×10^4

Function to remove the first word in a sentences

```
backoff_history <- function(history) {
  history_words <- strsplit(history, split = " |'")
  ifelse(
    length(history_words[[1]]) > 1,
    trimws(paste(backoff_history_words <- history_words[[1]][2:length(history_words[[1]])], collapse = ""))
  )
}
```

Testing backoff_history Function

In a sentences “bird is the word” the function will remove each word from left 1 step ...1st word... is the word 2 step ...2 words... is the word

function to calculate Beta probability

```
katz_beta <- function(history_value, k,
  ngram_frequencies_dt,
  history_frequencies_dt,
  frequencies_of_frequencies) {

  counts <- ngram_frequencies_dt[history == history_value & frequency > k, ]$frequency
  history_count <- count_history(history_value, history_frequencies_dt)
```

```

1 - ifelse(length(counts) > 0,
          sum(
            sapply(counts,
                    function(x) discount(x, frequencies_of_frequencies) * x / history_count
            ),
          0
        )
}

```

```

#memoized_katz_beta <- addMemoization(katz_beta)

```

Testing Katz's beta probability for the word "the" is 0.1401981

```

total_words <- sum(ngram_frequencies_dt[ngram_length == 1, ]$frequency)

```

```

katz_alpha_summation <- function(history_value, k,
                                ngram_frequencies_dt,
                                history_frequencies_dt,
                                frequencies_of_frequencies) {
  words <- ngram_frequencies_dt[history == history_value & frequency <= k, ]$word
  ifelse(length(words) > 0,
        sum(
          sapply(words,
                  katz_probability,
                  history = backoff_history(history_value),
                  k = k,
                  ngram_frequencies_dt = ngram_frequencies_dt,
                  history_frequencies_dt = history_frequencies_dt,
                  frequencies_of_frequencies = frequencies_of_frequencies
          ),
        0
      )
}

```

```

#memoized_katz_alpha_summation <- addMemoization(katz_alpha_summation)

```

```

katz_alpha <- function(history, k,
                      ngram_frequencies_dt,
                      history_frequencies_dt,
                      frequencies_of_frequencies) {

  computed_katz_alpha_summation <- katz_alpha_summation(history,
                                                         k, ngram_frequencies_dt,
                                                         history_frequencies_dt,
                                                         frequencies_of_frequencies)

  computed_katz_beta <- katz_beta(history, k,
                                  ngram_frequencies_dt,
                                  history_frequencies_dt,
                                  frequencies_of_frequencies)

  computed_katz_alpha <- ifelse(computed_katz_alpha_summation != 0,

```

computed,

```

        computed_katz_alpha_summation, 1)
  ifelse(computed_katz_alpha < 1, computed_katz_alpha, 1)
}

#memoized_katz_alpha <- addMemoization(katz_alpha)

katz_probability <- function(word, history, k,
                             ngram_frequencies_dt,
                             history_frequencies_dt,
                             frequencies_of_frequencies,
                             verbose = FALSE) {
  if(verbose) print(paste0("katz_probability(word: [", word, "], history: [",
                           history, "])..."))

  word_with_history <- trimws(paste(history, word))
  count <- count_ngram(word, history, ngram_frequencies_dt)

  probability <- ifelse(history == "", discount(count,
                                                frequencies_of_frequencies) * count /
                                                total_words,
                        ifelse(count > k, discount(count, frequencies_of_frequencies) * count /
                                ngram_frequencies_dt, history_frequencies_dt, frequencies_of_frequencies) * katz_probability(word, history, k,
                                ngram_frequencies_dt, history_frequencies_dt, frequencies_of_frequencies,
                                verbose = verbose)
                        )
  )

  if(verbose) print(paste0("katz_probability(word: [", word, "], history: [", history, "]) = ", probability))
}

```

Testing Katz's alpha simulation probability for the word "the" is 0

Testing Katz's alpha probability for the word "the" is 1

Testing Katz's probability for the word "did" before the word "i" is 1.7205882

Computing a Markov Chain Transition Matrix

With Katz's alpha and Beta probability we can now store the Ngrams in more efficient way representing Markov Chain

```

create_transition_matrix <- function(k,
                                     ngram_frequencies_dt,
                                     history_frequencies_dt,
                                     frequencies_of_frequencies,
                                     min_count = 3, verbose = FALSE) {

  prediction_data <- ngram_frequencies_dt[ngram_length > 1 & frequency > min_count, ]

  histories <- unique(c("", prediction_data$history))
  print(paste0("history size: ", length(histories)))
}

```

```

words <- unique(prediction_data$word)
print(paste0("word size: ", length(words)))

transition_matrix <- matrix(NA, length(histories), length(words))
rownames(transition_matrix) <- histories
colnames(transition_matrix) <- words

percentage_complete <- 0
percentage_counter <- 0
for(i in 1:length(histories)){
  for(j in 1:length(words)){
    transition_matrix[i, j] <- katz_probability(words[[j]],
                                                histories[[i]],
                                                k,
                                                ngram_frequencies_dt,
                                                history_frequencies_dt,
                                                frequencies_of_frequencies,
                                                verbose = verbose)
  }
  percentage_complete <- round((i * length(words) + j + 1) / (length(histories) * length(words)) * 100)
  if(percentage_complete > percentage_counter & percentage_complete < 100) {
    percentage_counter <- percentage_complete
    print(paste0("percentage counter: ", percentage_counter, "% complete."))
  }
}
print("complete.")
transition_matrix
}

```