# **Lesson 13 Intro to Text Mining**

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# **Bibliography**

- See on Github: Handling and Processing Strings
- Character Strings Chapter 2
- String Manipulation + stringr Chapter 3, 4
- RegEx Chapter 5

### **Intro Glossary**

- A token is a meaningful unit of text, such as a word, that we are interested in using for analysis, and tokenization is the process of splitting text into tokens.
- Semantics means the meaning and interpretation of words, signs, and sentence structure.
- In semantic analysis we will care about the place and order of the words

### **Intro Glossary**

- String manipulation series of functions used to extract information from text variables.
- Regex is set of commands used to match a family of text (alphanumeric, digits, words) to detect string sequences in a large text data.
- Regular expressions to do more complicated tasks such as extract email IDs or date from a set of text.
- String manipulation functions are not customized however we can customize regular expressions in any way we want.

### String Manipulation

- We can create strings with either single quotes or double quotes.
- Unlike other languages, there is no difference in behavior.
- To include a literal single or double quote in a string you can use \ to escape it.

```
(x <- "This is my first character!") # double quotes</pre>
## [1] "This is my first character!"
class(x) == typeof(x)
## [1] TRUE
(x <- 'This is my second string') # single quotes</pre>
## [1] "This is my second string"
(x <- "Why do we need the 'python'?")</pre>
## [1] "Why do we need the 'python'?"
```

(x <- 'Why do we need the "python"?')

# Working with strings

 If you try to include single quotes within single quotes, or double quotes within double quotes, it will not work

```
# Something went wrong
"Why call langauge "python" ? "
'Why call langauge 'python' ? '
## Error: <text>:2:21: unexpected symbol
## 1: # Something went wrong
## 2: "Why call langauge "python
##
  \ escaping character
(x <- 'Why do we need the \'python\'?')
## [1] "Why do we need the 'python'?"
is.character(x)
## [1] TRUE
```

- Paste() and its arguments
- Takes or more R objects, conver them to character and then concatenates them to character (one or more)

```
paste("Life of", pi)
## [1] "Life of 3.14159265358979"

    Element wise concatenation of two vectors.

x < -1:26
(a <- LETTERS[x[1:13]])
    [1] "A" "B" "C" "D" "E" "F" "G" "H" "I" "J" "K" "L" "M"
##
(b <- letters[x[14:26]])
```

[1] "n" "o" "p" "q" "r" "s" "t" "u" "v" "w" "x" "v" "z"

```
## [1] "1 A" "2 B" "3 C" "4 D" "5 E" "6 F" "7 G" "8 H" "9 I" "10 ## [11] "11 K" "12 L" "13 M" "14 n" "15 o" "16 p" "17 q" "18 r" "19 s" "20 ## [21] "21 u" "22 v" "23 w" "24 x" "25 y" "26 z"
```

# length(char1)

## [1] 26

##

 $(char1 \leftarrow paste(x, c(a, b)))$ 

- sep = The element which separates every term.
- collapse = The element which separates every result.

```
paste(x, c(a, b), sep = " - is - ") # optional - Define your own separator
```

[1] "1 - is - A" "2 - is - B" "3 - is - C" "4 - is - D" "5 - is - E

```
## [6] "6 - is - F" "7 - is - G" "8 - is - H" "9 - is - I" "10 - is - ## [11] "11 - is - K" "12 - is - L" "13 - is - M" "14 - is - n" "15 - is - ## [16] "16 - is - p" "17 - is - q" "18 - is - r" "19 - is - s" "20 - is - ## [21] "21 - is - u" "22 - is - v" "23 - is - w" "24 - is - x" "25 - is -
```

(char2 <- paste(x, c(a, b), sep = " - is - ", collapse = " , ")) # optional

## [26] "26 - is - z"

# **Basic Sting manipulations (Base)**

- nchar() counts the number of characters (including whitespaces)
- for single character

```
nchar("Here are 16 chars:)")
## [1] 19
char1
    [1] "1 A" "2 B" "3 C" "4 D" "5 E" "6 F" "7 G" "8 H" "9 I"
                                                                      "10
   [11] "11 K" "12 L" "13 M" "14 n" "15 o" "16 p" "17 q" "18 r" "19 s" "20
  [21] "21 u" "22 v" "23 w" "24 x" "25 v" "26 z"
length(char2)
## [1] 1
nchar(char1)
```

##

- We can convert all characters of our string to lower case with the tolower command
- and to upper case with toupper

```
toupper("Here are 16 chars:)")

## [1] "HERE ARE 16 CHARS:)"

tolower(toupper("Here are 16 chars:)"))

## [1] "here are 16 chars:)"

chartr(old = "is", new = "is not", char2) # the size should be equal
```

## [1] "1 - is - A , 2 - is - B , 3 - is - C , 4 - is - D , 5 - is - E , 6

# Substring + replacement based on the positions

substr() and substring()

x <- "Lusine Zilfimian"

These function can be used to overwrite or replace a part of character string.

```
substr(x, start = 8, stop = 7 + 5)
## [1] "Zilfi"
substring(x, first = 8) # last = 1000000L
## [1] "Zilfimian"
substr(x, start = 14, stop = 14) \leftarrow "y"
x
```

## [1] "Lusine Zilfimyan"

#### Replacement and detection

```
sub("Lusine Zilfimian", pattern = "i", replacement = "y") # find and replace
## [1] "Lusyne Zilfimian"
gsub("Lusine Zilfimian", pattern = "i", replacement = "y")
## [1] "Lusyne Zylfymyan"
grep(pattern = "Lusine", x = c("Lusine Zilfimian", "David", "Mar")) #detec
## [1] 1
grepl(pattern = "Lusine", x = c("Lusine Zilfimian", "David", "Mar"))
## [1] TRUE FALSE FALSE
```

#### **Abbreviations**

 Abbreviate strings to at least minlength characters, such that they remain unique (if they were), unless strict = TRUE.

```
x <- c("Lusin ", " Lusine ", "Lusine Zilfimian", "Lusine Zilfi", "Lus - ",
(abb1 <- abbreviate(x, minlength = 4))</pre>
                                Lusine Lusine Zilfimian
##
               Lusin
                                                               Lusine Zilfi
##
             "Lusin"
                              "Lusine"
                                               "I.sn7.1fm"
                                                                   "Lusn7.1f"
                           Lusine 1995
##
               Lus -
##
              "Lus-"
                                 "L199"
(abb2 <- abbreviate(x, minlength = 4, strict = T))</pre>
               Lusin
                                Lusine Lusine Zilfimian
                                                               Lusine Zilfi
##
##
              "Lusn"
                                 "Lusn"
                                                   "I.sn7."
                                                                      "Lsn7."
##
               Lus -
                           Lusine 1995
              "Lus-"
##
                                 "I.199"
```

#### Why is base not enough?

 The objects NULL and character(0) have zero length, yet when included inside paste() they are treated as an empty string:

```
paste("This", "is", NULL, character(0), "value")
## [1] "This is value"
length(NULL)
## [1] O
length(character(0))
## [1] 0
stringr::str_c("This", "is", NULL, character(0), "value", sep = " ")
## [1] "This is value"

    str_c() - zero argument are silently removed
```

### Stingr

- All functions start with str\_
- All functions take a vector of strings as the first argument
- str\_sub works the same way as substr() but allows for negative subsetting as well

```
library(stringr)
str_sub("Joe Satriani", start = 5)
## [1] "Satriani"
str_sub("Joe Satriani", start = 5, end = 5+4)
## [1] "Satri"
str sub("Joe Satriani", start = -8, end = -4)
## [1] "Satri"
```

- str\_detect() For detecting whether a pattern is present (or absent) in a string vector. You get a TRUE if a match is detected in a string, FALSE otherwise
- str\_subset() Keep strings matching a pattern
- str\_count() Count the number of matches in a string
- str\_split() Similar to strsplit() to separate a character vector into a number of pieces
- str\_replace() For replacing the first occurrence of a matched pattern in a string
- str\_exctact() For extracting a string containing a pattern

detect - bolean, extract - only pattern, subset - all the text.

### **Examples**

```
(geners <- c("Action, Adventure, Comedy", "Comedy",
  "Comedy, Drama, Drama, Romance", "Crime, Drama, History"))
## [1] "Action, Adventure, Comedy" "Comedy"
## [3] "Comedy, Drama, Drama, Romance" "Crime, Drama, History"
str_detect(string = geners, pattern = "Drama")
## [1] FALSE FALSE TRUE TRUE
str_subset(string = geners, pattern = "Action")
## [1] "Action, Adventure, Comedy"
str <-c("123abd", "lz@yahoo.com", "Name567cd", "abc5.00", "lusinezilfimian@
str_subset(str, pattern="@yahoo.com")
## [1] "lz@vahoo.com"
                                   "lusinezilfimian@yahoo.com"
str_count(string = geners, pattern = "Drama")
```

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### **Examples**

```
str_replace(string = geners, pattern = ",", replacement = " &")
## [1] "Action & Adventure, Comedy" "Comedy"
## [3] "Comedy & Drama, Drama, Romance" "Crime & Drama, History"
sub(x = geners, pattern = ",", replacement = " &") # from base
## [1] "Action & Adventure, Comedy" "Comedy"
## [3] "Comedy & Drama, Drama, Romance" "Crime & Drama, History"
gsub(x = geners, pattern = ",", replacement = " &") # from base
## [1] "Action & Adventure & Comedy" "Comedy"
## [3] "Comedy & Drama & Drama & Romance" "Crime & Drama & History"
str_replace_all(string = geners, pattern = ",", replacement = " &")
## [1] "Action & Adventure & Comedy" "Comedy"
```

## [3] "Comedy & Drama & Drama & Romance" "Crime & Drama & History"

# **Examples**

## [4,] "Drama"

### Let's consider the example

```
movies <- read.csv('movies3.csv', stringsAsFactors = F)

How many romcom movies are there?

movies$Comedy <- str_detect(string = movies$Genre, pattern = "Comedy")
movies$rom <- str_detect(string = movies$Genre, pattern = "Romance")
table(movies$Comedy,movies$rom)

##

## FALSE TRUE
## FALSE 1478 202
## TRUE 886 319</pre>
```

## **Split string into pieces**

```
(gen_m <- str_split(geners, ",", simplify = T))

## [,1] [,2] [,3] [,4]

## [1,] "Action" " Adventure" " Comedy" ""

## [2,] "Comedy" "" "" ""

## [3,] "Comedy" " Drama" " Prama" " Romance"

## [4,] "Crime" " Drama" " History" ""

trimws(" Lus ine ") # trim whitespaces</pre>

## [1] "Lus ine"
```

### **Regular Expressions**

- Sequance of characters that define a search pattern
- For instance, one could have the following pattern: 2 digits, 2 letters and 4 digits
- ?regex to see more

#### Form of Regular Expressions

- Literal characters which are characters that match themselves
- Metacharacters any character that is not a literal character . ^ \$ + \* ? | (), {}, [], -
- Sequences
- Character classes
- Quantifiers
- O POSIX character classes
- $\bullet$  If you want to match the metacharacter you need to use  $\backslash$  (escapes) before the metacharacter

#### Literal and Metacharacters

- Literal character the simplest form of regular expressions are those that match a single charact
- Metacharacters special characters that have a reserved status:

```
str <-c("Lusine1995^", "Say$1995-02(", "David.", "M*77", "M&95", "1995.27")
str_subset(string = str, pattern = "Lusine") # literal
## [1] "Lusine1995^"
str_subset(string = str, pattern = "Lusine|David|Say")
## [1] "Lusine1995^" "Say$1995-02(" "David."
str_subset(string = "money$", pattern = "money\\$")
## [1] "money$"
str_subset(string = "This is money1", pattern = "money$")
```

#### Metacharacters

```
str_subset(string = str, pattern = ".") # meta
## [1] "Lusine1995^" "Say$1995-02(" "David." "M*77"
## [5] "M&95" "1995.27"
str_subset(string = "\n", pattern = ".") # meta
## character(0)
str_subset(string = " ", pattern = ".") # meta
## [1] " "
str_subset(string = "", pattern = ".") # meta
## character(0)
str_subset(string = str, pattern = "\\.") # literal
```

## [1] "David." "1995.27"

#### Metacharacters

```
str_subset(string = str, pattern = "^M") # meta
## [1] "M*77" "M&95"
str_subset(string = str, pattern = "\\^") # literal
## [1] "Lusine1995^"
str_subset(string = str, pattern = "\\$") # literal
## [1] "Say$1995-02("
```

### **Sequences**

```
str_subset(string = c("123", "4L", "M"), pattern = "\\d") # [0-9]
## [1] "123" "4L"
str_subset(string = c("123", "4L", "M"), pattern = "\\D") # [^0-9]
## [1] "4L" "M"
str_subset(string = c(" ", "l ", "l"), pattern = "\\s")
## [1] " " "1 "
str_subset(string = c(" ", "1 ", "1"), pattern = "\\S")
## [1] "1 " "1"
str_subset(string = c(" ", "l ", "l"), pattern = "\\w") # word
## [1] "1 " "1"
str_subset(string = c(" ", "l ", "l"), pattern = "\\W") # non-word
```

#### **Character classes**

```
str_subset(string = str, pattern = "[0-9]")
## [1] "Lusine1995^" "Say$1995-02(" "M*77"
                                                  "M&95"
## [5] "1995.27"
str_subset(string = str, pattern = "[f-z]")
## [1] "Lusine1995^" "Say$1995-02(" "David."
str_subset(string = str, pattern = "[a-zA-Z]")
## [1] "Lusine1995^" "Say$1995-02(" "David."
                                                  "M*77"
## [5] "M&95"
str_subset(string = str, pattern = "[aeuio]")
## [1] "Lusine1995^" "Say$1995-02(" "David."
str_subset(string = c("AI", "ai"), pattern = "[AEIOU]")
## [1] "AI"
```

# Special meaning of ^

Not in specified character

```
str_subset(string = c("ou", "lk"), pattern = "[^aeuio]")
## [1] "lk"
str_subset(string = c("ou", "19", "-"), pattern = "[a-zA-Z0-9]")
## [1] "ou" "19"
str_subset(string = c("ou", "19", "-"), pattern = "[a-zA-Z]")
## [1] "ou"
str_subset(string = c("ou", "19", "-"), pattern = "[^0-9]")
## [1] "ou" "-"
str_subset(string = str, pattern = "[^1-9]")
```

Lusine Zilfimian

## [5] "M&95"

## [1] "Lusine1995^" "Say\$1995-02(" "David."

"1995.27"

"M\*77"

### Quantifiers

```
str_subset(string = c(" ", "l ", "l"), pattern = "\\s+")
## [1] " " "1 "
str_subset(string = c(" ", "l ", "l"), pattern = "\\s*")
## [1] " " "1 " "1"
str_subset(string = c(" ", "l ", "l"), pattern = "\\s?")
## [1] " " "1 " "1"
str_subset(string = c(" ", "l ", "l"), pattern = "\\s{3}")
## [1] "1 "
str_subset(string = c(" ", "l ", "l"), pattern = "\\s{2,}")
## [1] "1 "
str_subset(string = c(" ", "l ", "l"), pattern = "\\s{1,3}")
```

#### **POSIX** character classes

```
str_subset(string = str, pattern = "[:alnum:]") # [a-zA-ZO-9]
## [1] "Lusine1995^" "Say$1995-02(" "David." "M*77"
## [5] "M&95"
             "1995.27"
str_subset(string = str, pattern = "[:alpha:]") # [a-zA-Z]
## [1] "Lusine1995^" "Say$1995-02(" "David."
                                               "M*77"
## [5] "M&95"
str subset(string = str, pattern = "[:digit:]") # [0-9]
## [1] "Lusine1995^" "Say$1995-02(" "M*77" "M&95"
## [5] "1995.27"
str_subset(string = str, pattern = "[:lower:]") # [a-z]
```

## [1] "Lusine1995^" "Say\$1995-02(" "David."

#### **POSIX** character classes

```
str subset(string = str, pattern = "[:upper:]") # [A-Z]
## [1] "Lusine1995^" "Say$1995-02(" "David." "M*77"
## [5] "M&95"
str_subset(string = str, pattern = "[:space:]") # [\f\n\r\t\v]
## character(0)
str_subset(string = str, pattern = "[:punct:]")
## [1] "Say$1995-02(" "David." "M*77"
                                                  "M&95"
## [5] "1995.27"
str_subset(string = c("grey", "gray"), pattern = "gr(e|a)y")
## [1] "grey" "gray"
```

# How many wins and nominations are there?

```
movies$Awards[1:5]

## [1] "4 wins & 8 nominations." "7 wins & 17 nominations."

## [3] "1 win & 2 nominations." "9 wins & 28 nominations."

## [5] "2 wins & 67 nominations."

movies$awards_num <- str_replace_all(movies$Awards, pattern="[^0-9]", replacement = " ")

movies$awards_num <- str_replace_all(movies$awards_num, pattern="\\s+", replacement = " ")</pre>
```

# How many wins and nominations are there?

```
movies$awards_num <- trimws(movies$awards_num)</pre>
movies$awards_num[1:20]
    [1] "4 8" "7 17"
                                       "9 28" "2 67"
##
                           "1 2"
                                                            "1"
       "1 87 171" "2 3"
                          "2 4"
                                       "1 5 7" "1 1"
                                                            "1 3"
##
                                       "1 3 31" "2 2"
   [13] "1 1 3"
               "1 2"
                          "2 11 5"
                                                            "2 2"
## [19] "1 3" "1 5"
x1 <- str_split(movies$awards_num, pattern = " ", simplify = T)</pre>
x1 <- apply(x1, 2, as.numeric)</pre>
x1 <- rowSums(x1, na.rm=T)</pre>
x1[1:20]
    Г1]
                 3 37 69 1 259 5
                                        6 13
                                                           3 18
                                                                 35
        12
            24
```

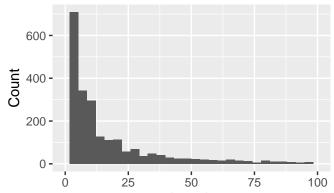
[18] 4 4

#### Visualization

```
movies$awards_num <- x1
ggplot(movies, aes(x = awards_num)) + geom_histogram() +
    xlim(c(0,100)) + labs(title = "Awards histogram (wins and nominations)",
    x = "Awards", y = "Count")</pre>
```

## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.

# Awards histogram (wins and nominati



# Wins only

```
m <- movies$Awards[1:20]
m1 <- str_extract_all(movies$Awards, pattern="[0-9]+\\swin", simplify = T)
m1 <- str_remove_all(m1, pattern="[a-zA-Z]")
m1 <- as.numeric(m1)
movies$Wins <- m1
head(m1)</pre>
```

```
## [1] 4 7 1 9 2 NA
```

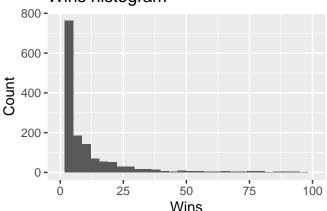
Possible strings are . . .

#### Visualization

```
ggplot(movies, aes(x = Wins)) + geom_histogram() +
  labs(title = "Wins histogram", x = "Wins", y = "Count")+
  xlim(c(0,100))
```

## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.

# Wins histogram



#### Task

- Read the file Text.txt without warnings. Use regular expressions to solve the problems:
- Show only the first line. Eliminate the periods before and after the words, but not periods inside the values and at the end of the statement.
- Show only the second line. Convert the GDP of Armenia into proper numbers, create a data frame with variables year and GDP.

### Solution

readLines("Text.txt", warn=FALSE)

```
## [1] "..The. ...economy. ...of ..Armenia ...grew ..by. 5.2% in ..2018. an
## [2] "The GDP of Armenia was ?4,000,722.0 millions in 2012, ?4,555,638.2
## [3] "Even in this small mountainous country, there are places where they
## [4] "Armenian cuisine is wonderful and varied, with only kharavts and sh
## [5] "The most popular tours in Armenia are tours to mountain lakes among
(text1 <- readLines("Text.txt", warn=FALSE)[1])</pre>
## [1] "..The. ...economy. ...of ..Armenia ...grew ..by. 5.2% in ..2018. an
words <- unlist(str_split(text1, pattern = " "))</pre>
words <- str_replace_all(string = words, pattern = "^\\.+", replacement = "</pre>
words <- str replace_all(string = words, pattern = "\\.+$", replacement = "
paste(words, sep = " ", collapse = " ")
```

## [1] "The economy of Armenia grew by 5.2% in 2018 and reached a nominal G

### Solution

```
(text2 <- readLines("Text.txt", warn=FALSE)[2])

## [1] "The GDP of Armenia was ?4,000,722.0 millions in 2012, ?4,555,638.2 mords2 <- unlist(str_split(text2, pattern = " "))
numbers <- str_subset(words2, pattern = "[0-9]")
numbers <- str_replace(numbers, pattern = "\\.[0-9]", replacement = "")
numbers <- str_replace_all(numbers, pattern = "^\\?[,$|\\.$|[,]", replacement
df = data.frame(matrix(numbers, ncol = 2, byrow = T))
colnames(df) = c("gdp", "year")
df</pre>
```

```
## gdp year
## 1 4000722 2012
## 2 4555638 2013
## 3 4828626 2014
## 4 5032089 2015
```

## **Text Mining**

We will use the tm text mining package.

```
library(tm)
```

- Load the data into a Corpus (a collection of documents) which is the main data structure used by tm
- In order to create a VCorpus using tm, we need to pass a "Source" object as a paramter to the 'VCorpus
- First you need to create a VectorSource A vector source interprets each element of the vector x as a document
- VectorSource is for only character vectors.

```
text <- c("The best guitar models are Gibson and Fender!",
    "My guitars are the best guitars.",
    "Are these guitars yours?")
vs <- VectorSource(text)
corpus <- VCorpus(vs)</pre>
```

• use [[ ]] to access single element in the corpus

```
inspect(corpus[[3]]) # like print
```

```
## <<PlainTextDocument>>
## Metadata: 7
## Content: chars: 24
##
## Are these guitars yours?
```

Access content directly for the second document

```
corpus[[2]][1]
```

```
## $content
## [1] "My guitars are the best guitars."
```

## corpus[[2]][2]

```
## $meta
    author : character(0)
##
    datetimestamp: 2020-05-20 19:41:38
##
    description : character(0)
##
##
    heading : character(0)
    id
          : 2
##
##
    language
                : en
    origin
                : character(0)
##
```

 Metadata is used to annotate text documents or whole corpora with additional information. The easiest way to accomplish this with tm is to use the meta() function

```
meta(corpus, tag = 'language')
## $`1`
## [1] "en"
##
## $`2`
```

## [1] "en"

##

- Create new metadata tag class for the first document and assign Guitar to it
- Same for IDs

```
meta(corpus[[1]], tag="class") <- "Guitar"</pre>
corpus[[1]][2]
## $meta
            : character(0)
##
    author
##
    datetimestamp: 2020-05-20 19:41:38
##
    description : character(0)
    heading : character(0)
##
##
    id
    language : en
##
    origin : character(0)
##
    class : Guitar
##
meta(corpus, tag = "ids") <- c("DOC1", "DOC2", "DOC3")</pre>
meta(corpus, "ids")
```

ids

##

### Document-term matrix or term-document matrix

tdm <- TermDocumentMatrix(corpus)</pre>

- A matrix that describes the frequency of terms that occur in a collection of documents.
- In a document-term matrix, rows correspond to documents in the collection and columns correspond to

```
inspect(tdm)
## <<TermDocumentMatrix (terms: 12, documents: 3)>>
## Non-/sparse entries: 17/19
## Sparsity
                    : 53%
## Maximal term length: 8
## Weighting : term frequency (tf)
## Sample
##
           Docs
## Terms 1 2 3
##
    and 1 0 0
##
    are 1 1 1
## best 110
    fender! 1 0 0
##
##
    gibson
             1 0 0
```

• Document term matrix is the transposed Term document matrix

```
dtm <- DocumentTermMatrix(corpus, control = list(weightTfIdf))</pre>
inspect(dtm)
## <<DocumentTermMatrix (documents: 3, terms: 12)>>
## Non-/sparse entries: 17/19
                      : 53%
## Sparsity
## Maximal term length: 8
## Weighting
                      : term frequency (tf)
## Sample
##
       Terms
## Docs and are best fender! gibson guitar guitars guitars. models the
##
##
      3
##
                                          0
                                                                      0
```

 Sparsity is defined as a percentage of element with value 0 in total number of elements in document term matrix

```
mm <- as.matrix(dtm)
# Sparsity
sum(mm == 0)/(3*12)</pre>
```

## [1] 0.5277778

#### **Problems**

- Guitar; Guitars, Guitar.
- One way would be to remove all punctuations before creating corpus, using regex

```
text2 <- str_remove_all(text, pattern = "[:punct:]")
text2</pre>
```

```
## [1] "The best guitar models are Gibson and Fender"
## [2] "My guitars are the best guitars"
## [3] "Are these guitars yours"
```

- Or alternatively use tm\_map().
- tm\_map() takes corpus and applies on it a function, in this case removePunctuation

```
corpus <- VCorpus(VectorSource(text))</pre>
corpus <- tm map(corpus, removePunctuation)
dtm <- DocumentTermMatrix(corpus)</pre>
inspect(dtm)
## <<DocumentTermMatrix (documents: 3, terms: 11)>>
## Non-/sparse entries: 16/17
## Sparsity
                     : 52%
## Maximal term length: 7
## Weighting : term frequency (tf)
## Sample
##
      Terms
## Docs and are best fender gibson guitar guitars models the these
##
      1
                                                                0
##
                                 0
                                                                0
##
                         0
                                 0
                                                                1
```

## TF-IDF

- Term frequency—inverse document frequency numerical statistic that is intended to reflect how important a word is to a document tin a collection or corpus
- The tf-idf value increases proportionally to the number of times a word appears in the document and is offset by the frequency of the word in the corpus, which helps to adjust for the fact that some words appear more frequently in general.
- TF Term Frequency, which measures how frequently a term occurs in a document
- $TF(t) = \frac{Number\ of\ times\ term\ t\ appears\ in\ adocument}{Total\ number\ of\ terms\ in\ the\ document}$
- Since every document is different in length, it is possible that a term would appear
  much more times in long documents than shorter ones. Thus, the term frequency is
  often divided by the document length (the total number of terms in the document)
  as a way of normalization.

### TF-IDF

- Tf the importance of the term in the separate document.
- Inverse Document Frequency measures how important a term is.
- While computing TF, all terms are considered equally important. However it is known that certain terms, such as "is", "of", and "that", may appear a lot of times but have little importance. Thus we need to weigh down the frequent terms while scale up the rare ones, by computing the following:
- $IDF(t) = log_2(\frac{Total\ number\ of\ documents}{Number\ of\ documents\ with\ term\ in\ it})$
- IDF decrease the weight of frequent words.
- Could you say which words have the high tf-idf weight?
- The smaller the weight, the more common the term.

```
dtm1 <- DocumentTermMatrix(corpus, control = list(weighting = weightTfIdf))
as.matrix(dtm1)
## Terms</pre>
```

```
## Docs
         and are
                  best
                        fender gibson guitar guitars
##
    ##
   2 0.0000000 0 0.11699250 0.0000000 0.0000000 0.0000000 0.2339850
##
   ##
    Terms
## Docs
       models the
                      these
                             vours
##
    1 0.1981203 0.07312031 0.0000000 0.0000000
   2 0.0000000 0.11699250 0.0000000 0.0000000
##
##
   3 0.0000000 0.00000000 0.3962406 0.3962406
```

for guitar

```
(1/8)*log(3/1, base=2)
```

```
## [1] 0.1981203
```

# 300,000 songs and their lyrics

• Let's consider the example from the file lyrics.csv

```
lyrics <- read.csv("lyrics.csv", stringsAsFactors = F)
summary(lyrics$year)</pre>
```

```
## Min. 1st Qu. Median Mean 3rd Qu. Max.
## 67 2006 2008 2009 2014 2038
```

```
lyrics %>%
  group_by(year) %>%
  summarise(count = n()) %>%
  arrange(desc(year))
## # A tibble: 52 x 2
##
       year count
      <int> <int>
##
##
    1
       2038
            10
##
      2016 35042
##
    3 2015 27159
       2014 26393
##
##
    5 2013 16245
      2012 14581
##
##
       2011 11387
    8 2010 11374
##
##
      2009 11333
   10
       2008 20375
##
```

## # ... with 42 more rows

```
lyrics %>%
  group_by(year) %>%
  summarise(count = n()) %>%
  arrange(year)
## # A tibble: 52 x 2
##
      year count
      <int> <int>
##
##
        67
##
      112
##
     702
      1968
##
##
   5
      1970
            421
      1971
            480
##
##
    7
      1972
            496
      1973
            504
##
##
   9
      1974
            395
   10
      1975
            321
##
## # ... with 42 more rows
```

```
lyrics %>%
  group_by(artist) %>%
  summarise(n_songs=n()) %>%
  arrange(desc(n_songs))
## # A tibble: 17,088 x 2
##
      artist
                       n_songs
##
      <chr>>
                          <int>
##
    1 dolly-parton
                            755
    2 american-idol
##
                            700
                            680
##
    3 elton-john
    4 b-b-king
                            667
##
    5 chris-brown
                            655
##
                            628
##
    6 eddy-arnold
                            624
##
    7 barbra-streisand
    8 ella-fitzgerald
                            623
##
##
    9 bob-dylan
                            614
   10 bee-gees
                            599
##
## # ... with 17,078 more rows
```

```
lyrics$char_num <- nchar(lyrics$lyrics)</pre>
summary(lyrics$char_num)
##
      Min. 1st Qu. Median
                               Mean 3rd Qu.
                                                Max.
       0.0
               0.0
                      744.0
                              844.1 1212.0 42155.0
##
table(lyrics$genre)
##
##
         Country
                     Electronic
                                          Folk
                                                      Hip-Hop
                                                                       Indie
           16449
                          15446
                                          3095
                                                        30644
                                                                        5373
##
                          Metal Not Available
##
            Jazz
                                                        Other
                                                                         Pop
           15659
                          26900
                                         27984
                                                        22394
                                                                       46371
##
                           Rock
##
             R&B
                         123402
##
            5560
sum(lyrics$char_num==0)
```

```
lyrics <- lyrics %>%
  filter(char_num>100 & genre != "Not Available" & year > 1968 & year <= 20
dim(lyrics)
## [1] 221669
table(lyrics$genre)
##
##
      Country Electronic
                               Folk
                                       Hip-Hop
                                                    Indie
                                                                 Jazz
        13710
                    7027
                                         22168
##
                               2006
                                                     2888
                                                                 6915
##
        Metal
                   Other
                                Pop
                                           R&B
                                                     Rock
##
        21250
                  4838
                              37770
                                          3198
                                                    99899
summary(lyrics$char_num)
```

```
##
     Min. 1st Qu. Median
                            Mean 3rd Qu.
                                           Max.
##
      101
             681
                     986
                            1184
                                   1419
                                          42155
```

```
b <- "[Intro: BeyoncÃfî]"
iconv(b, to="ASCII", sub="")

## [1] "[Intro: Beyonc]"

lyrics$lyrics <- iconv(lyrics$lyrics, to="ASCII", sub="")

Let's analyze lyrics of Beyonce

beyonce <- lyrics[lyrics$artist =='beyonce-knowles',]
beyonce_vs <- VectorSource(beyonce$lyrics)
beyonce corpus <- VCorpus(beyonce vs)</pre>
```

## **Stopwords**

## stopwords("english")

```
##
      [1]
         "i"
                          "me"
                                         "my"
                                                        "myself"
                                                                        "we"
##
      [6]
                                         "ourselves"
          "our"
                          "ours"
                                                        "you"
                                                                        "your"
     [11]
##
         "yours"
                          "yourself"
                                         "yourselves"
                                                        "he"
                                                                        "him"
##
     Г167
          "his"
                          "himself"
                                         "she"
                                                        "her"
                                                                        "hers"
     [21]
                          "it"
                                                                        "they"
##
          "herself"
                                         "its"
                                                        "itself"
     [26]
##
          "them"
                          "their"
                                         "theirs"
                                                        "themselves"
                                                                        "what"
     Γ317
                          "who"
                                                        "this"
                                                                        "that"
##
          "which"
                                         "whom"
##
     [36]
          "these"
                          "those"
                                         "am"
                                                        "is"
                                                                        "are"
##
     Γ417
          "was"
                          "were"
                                         "be"
                                                        "been"
                                                                        "being"
     [46]
##
          "have"
                          "has"
                                         "had"
                                                        "having"
                                                                        "do"
     [51]
                                                        "would"
##
          "does"
                          "did"
                                         "doing"
                                                                        "should"
     [56]
##
          "could"
                          "ought"
                                         "i'm"
                                                        "you're"
                                                                        "he's"
     [61]
##
          "she's"
                          "it's"
                                         "we're"
                                                        "they're"
                                                                        "i've"
##
     [66]
          "you've"
                          "we've"
                                         "they've"
                                                        "i'd"
                                                                        "you'd"
     [71]
##
          "he'd"
                          "she'd"
                                         "we'd"
                                                        "they'd"
                                                                        "i'll"
     [76]
         "you'11"
                          "he'll"
                                         "she'11"
                                                                        "they'11"
##
                                                        "we'll"
     [81]
##
          "isn't"
                          "aren't"
                                         "wasn't"
                                                        "weren't"
                                                                        "hasn't"
     [86] "haven't"
                          "hadn't"
                                                        "don't"
##
                                         "doesn't"
                                                                        "didn't"
        Lusine Zilfimian
                                  Lesson 13 Intro to Text Mining
                                                                  May 11 (Monday), 2020
```

# Stemming

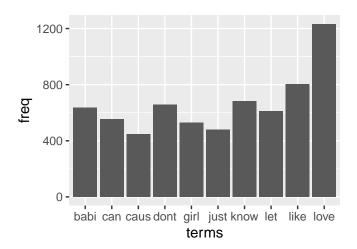
```
## [1] "love" "love" "love" "love" "love" "love" "love" "game" ## [9] "game" "game"
```

## **Analysis**

## love love 1233
## like like 803
## know know 684
## dont dont 659
## babi babi 638
## let let 610

# **Analysis**

```
df_top10 <- df_freq[1:10,]
ggplot(df_top10, aes(x=terms, y=freq)) + geom_bar(stat = 'identity')</pre>
```



## Wordcloud

```
set.seed(1)
wordcloud(words = df_freq$terms, freq = df_freq$freq, min.freq = 10,
max.words = 200, random.order = FALSE, colors=brewer.pal(8, "Dark2"))
```

#### Tf-Idf

##

```
beyonce_tdm <- TermDocumentMatrix(beyonce_corpus,</pre>
               control = list(removeNumbers = T, removePunctuation = T,
               stopwords = T, stemming = T, weighting = weightTfIdf))
tdm_mat <- as.matrix(beyonce_tdm)</pre>
freqs <- rowSums(tdm mat)</pre>
df_freq <- data.frame(terms=rownames(tdm_mat),</pre>
                        freq = freqs)
df_freq <- df_freq[order(df_freq$freq, decreasing = T),]</pre>
head(df_freq)
```

```
terms
                 frea
## halo halo 5.295742
## love love 4.083825
## girl girl 3.326538
## run run 3.293408
## let let 3.269829
## babi babi 2.828966
```

## Tf-Idf

```
set.seed(27)
wordcloud(words = df_freq$terms, freq = df_freq$freq, min.freq = 1,
    max.words = 90, random.order = FALSE, colors = brewer.pal(8, "Dark2"))
```



### **Task**

- Extract the phone numbers in one column and the names in another:
- Combine them in the data frame

```
phones <- c("Joe 027-789663",
   "Jimi 99656565",
   "Adri2 099-65-1995 GUITARIS")</pre>
```