In-class Exercise 10: Text Visual Analytics with R

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Overview

In this hands-on exercise, you will learn how to visualise and analyse text data using R.

By the end of this hands-on exercise, you will be able to:

- understand tidytext framework for processing, analysing and visualising text data,
- write function for importing multiple files into R,
- combine multiple files into a single data frame,
- clean and wrangle text data by using tidyverse approach,
- visualise words with Word Cloud,
- compute term frequency–inverse document frequency (TF-IDF) using tidytext method, and
- visualising texts and terms relationship.

Getting Started

Installing and launching R packages

In this hands-on exercise, the following R packages for handling, processing, wrangling, analysing and visualising text data will be used:

- tidytext, tidyverse (mainly readr, purrr, stringr, ggplot2)
- widyr,
- wordcloud and ggwordcloud,
- textplot (required igraph, tidygraph and ggraph,)
- DT,
- lubridate and hms.

The code chunk:

```r
packages = c('tidytext',
             'widyr', 'wordcloud',
             'DT', 'ggwordcloud',
             'textplot', 'lubridate',
             'hms','tidyverse',
             'tidygraph', 'ggraph',
             'igraph')

for(p in packages){
  if(!require(p, character.only = T)){
    install.packages(p)
  }
  library(p, character.only = T)
}
```

Importing Multiple Text Files from Multiple Folders

Step 1: Creating a folder list

```
news20 <- "data/20news/"
```

Step 2: Define a function to read all files from a folder into a data frame

```
read_folder <- function(infolder) {
  tibble(file = dir(infolder,
                    full.names = TRUE)) %>%
    mutate(text = map(file,
                      read_lines)) %>%
    transmute(id = basename(file),
              text) %>%
    unnest(text)
}
```

Importing Multiple Text Files from Multiple Folders

Step 3: Reading in all the messages from the 20news folder

```
raw_text <- tibble(folder =
                     dir(news20,
                         full.names = TRUE)) %>%
  mutate(folder_out = map(folder,
                          read_folder)) %>%
  unnest(cols = c(folder_out)) %>%
  transmute(newsgroup = basename(folder),
            id, text)
write_rds(raw_text, "data/rds/news20.rds")
```

Things to learn from the code chunk above:

- *read_lines()* of **readr** package is used to read up to n_max lines from a file.
- *map()* of **purrr** package is used to transform their input by applying a function to each element of a list and returning an object of the same length as the input.
- *unnest()* of **dplyr** package is used to flatten a list-column of data frames back out into regular columns.
- mutate() of **dplyr** is used to add new variables and preserves existing ones;
- transmute() of **dplyr** is used to add new variables and drops existing ones.
- read_rds() is used to save the extracted and combined data frame as rds file for future use.

Initial EDA

Figure below shows the frequency of messages by newsgroup.

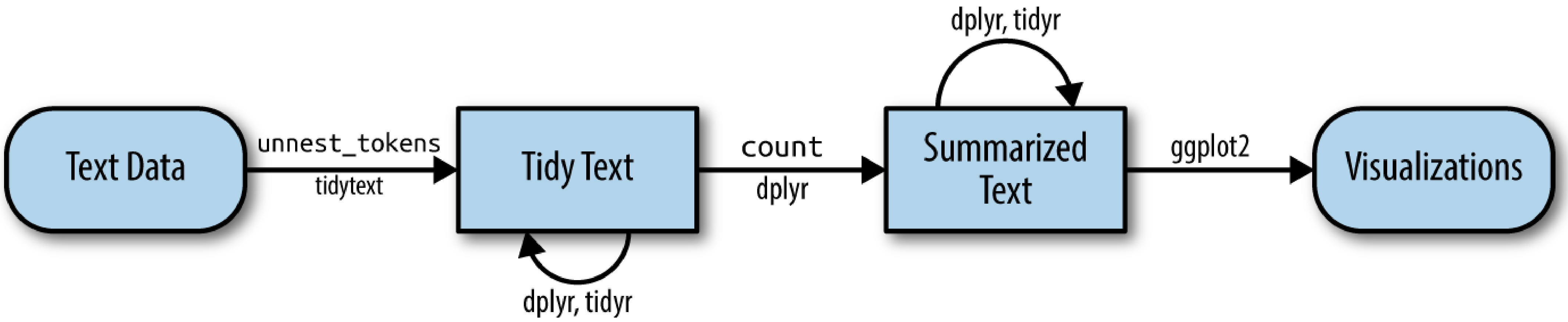
The code chunk:

```
raw_text <- news20
raw_text %>%
  group_by(newsgroup) %>%
  summarize(messages = n_distinct(id)) %>%
  ggplot(aes(messages, newsgroup)) +
  geom_col(fill = "lightblue") +
  labs(y = NULL)
```

Introducing tidytext

- Using tidy data principles in processing, analysing and visualising text data.
- Much of the infrastructure needed for text mining with tidy data frames already exists in packages like 'dplyr', 'broom', 'tidyr', and 'ggplot2'.

Figure below shows the workflow using tidytext approach for processing and visualising text data.



Cleaning Text Data

Step 1: Removing header and automated email signitures

Notice that each message has some structure and extra text that we don’t want to include in our analysis. For example, every message has a header, containing field such as “from:” or “in_reply_to:” that describe the message. Some also have automated email signatures, which occur after a line like "--".

```
cleaned_text <- raw_text %>%
  group_by(newsgroup, id) %>%
  filter(cumsum(text == "") > 0,
         cumsum(str_detect(
           text, "^--")) == 0) %>%
  ungroup()
```

Things to learn from the code chunk:

- *cumsum()* of base R is used to return a vector whose elements are the cumulative sums of the elements of the argument.
- *str_detect()* from **stringr** is used to detect the presence or absence of a pattern in a string.

Cleaning Text Data

Step 2: Removing lines with nested text representing quotes from other users.

In this code chunk below, regular expressions are used to remove with nested text representing quotes from other users.

```
cleaned_text <- cleaned_text %>%
  filter(str_detect(text, "^[^>]+[A-Za-z\\d]")
         | text == "",
         !str_detect(text,
                     "writes(:|\\.\\.\\.)$"),
         !str_detect(text,
                     "^In article <")
  )
```

Things to learn from the code chunk:

- *str_detect()* from **stringr** is used to detect the presence or absence of a pattern in a string.
- *filter()* of **dplyr** package is used to subset a data frame, retaining all rows that satisfy the specified conditions.

Text Data Processing

In this code chunk below, *unnest_tokens()* of **tidytext** package is used to split the dataset into tokens, while *stop_words()* is used to remove stop-words.

```
usenet_words <- cleaned_text %>%
  unnest_tokens(word, text) %>%
  filter(str_detect(word, "[a-z']$"),
         !word %in% stop_words$word)
```

Text Data Processing

Now that we've removed the headers, signatures, and formatting, we can start exploring common words. For starters, we could find the most common words in the entire dataset, or within particular newsgroups.

```
usenet_words %>%
  count(word, sort = TRUE)
```

```
## # A tibble: 5,542 x 2
##    word          n
##    <chr>     <int>
##  1 people       57
##  2 time         50
##  3 jesus        47
##  4 god          44
##  5 message      40
##  6 br           27
##  7 bible        23
##  8 drive        23
##  9 homosexual   23
## 10 read         22
## # ... with 5,532 more rows
```

Instead of counting individual word, you can also count words within by newsgroup by using the code chunk below.

```
words_by_newsgroup <- usenet_words %>%
  count(newsgroup, word, sort = TRUE) %>%
  ungroup()
```

Visualising Words in newsgroups

In this code chunk below, *wordcloud()* of **wordcloud** package is used to plot a static wordcloud.

```
wordcloud(words_by_newsgroup$word,
          words_by_newsgroup$n,
          max.words = 300)
```

A DT table can be used to complement the visual discovery.

Show 10 entries Search:

	newsgroup	word	n
	All	All	All
1	alt.atheism	jesus	39
2	sci.crypt	message	31
3	alt.atheism	br	27
4	alt.atheism	rh	21
5	sci.crypt	pad	20
6	talk.politics.misc	homosexual	20
7	talk.politics.misc	homosexuals	19
8	comp.windows.x	widget	18
9	misc.forsale	comics	17
10	rec.sport.hockey	pts	17

Showing 1 to 10 of 8,124 entries

Previous 1 2 3 4 5 … 813 Next

Visualising Words in newsgroups

The wordcloud below is plotted by using **ggwordcloud** package.

The code chunk used:

```
set.seed(1234)

words_by_newsgroup %>%
  filter(n > 0) %>%
ggplot(aes(label = word,
           size = n)) +
  geom_text_wordcloud() +
  theme_minimal() +
  facet_wrap(~newsgroup)
```

Basic Concept of TF-IDF

- tf–idf, short for term frequency–inverse document frequency, is a numerical statistic that is intended to reflect how important a word is to a document in a collection of corpus.

$$idf(\text{term}) = \ln\left(\frac{n_{\text{documents}}}{n_{\text{documents containing term}}}\right)$$

Computing tf-idf within newsgroups

The code chunk below uses *bind_tf_idf()* of tidytext to compute and bind the term frequency, inverse document frequency and ti-idf of a tidy text dataset to the dataset.

```
tf_idf <- words_by_newsgroup %>%
  bind_tf_idf(word, newsgroup, n) %>%
  arrange(desc(tf_idf))
```

Visualising tf-idf as interactive table

Table below is an interactive table created by using *datatable()*.

Show 10 entries Search:

	newsgroup	word	n	tf	idf	tf_idf
	All	All	All	All	All	All
1	rec.autos	car	11	0.042	2.303	0.096
2	sci.crypt	pad	20	0.031	2.996	0.093
3	comp.sys.ibm.pc.hardware	cpu	11	0.030	2.996	0.090
4	rec.sport.hockey	pts	17	0.027	2.996	0.081
5	talk.politics.misc	homosexuals	19	0.026	2.996	0.078
6	comp.windows.x	widget	18	0.026	2.996	0.078
7	sci.crypt	message	31	0.048	1.609	0.078
8	comp.sys.mac.hardware	vv	12	0.023	2.996	0.070
9	talk.politics.guns	charles	13	0.023	2.996	0.068
10	comp.windows.x	static	15	0.022	2.996	0.065

Showing 1 to 10 of 8,124 entries

Previous 1 2 3 4 5 … 813 Next

Visualising tf-idf as interactive table

The code chunk below uses *datatable()* of DT package to create a html table that allows pagination of rows and columns.

```
DT::datatable(tf_idf, filter = 'top') %>%
  formatRound(columns = c('tf', 'idf',
                          'tf_idf'),
              digits = 3) %>%
  formatStyle(0,
              target = 'row',
              lineHeight='25%')
```

Things to learn from the code chunk:

- *filter* argument is used to turn control the filter UI.
- *formatRound()* is used to customise the values format. The argument *digits* define the number of decimal places.
- *formatStyle()* is used to customise the output table. In this example, the arguments *target* and *lineHeight* are used to reduce the line height by 25%.

To learn more about customising DT's table, visit this link.

Visualising tf-idf within newsgroups

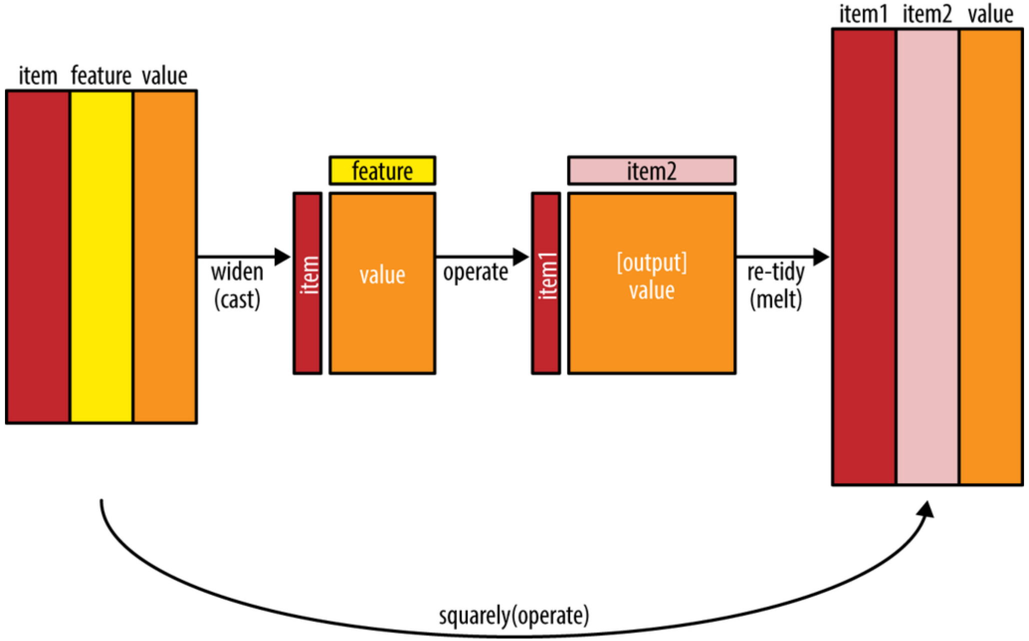
Facet bar charts technique is used to visualise the tf-idf values of science related newsgroup.

The code chunk used to prepare the plot.

```
tf_idf %>%
  filter(str_detect(newsgroup, "^sci\\.")) %>%
  group_by(newsgroup) %>%
  slice_max(tf_idf,
            n = 12) %>%
  ungroup() %>%
  mutate(word = reorder(word,
                        tf_idf)) %>%
  ggplot(aes(tf_idf,
             word,
             fill = newsgroup)) +
  geom_col(show.legend = FALSE) +
  facet_wrap(~ newsgroup,
             scales = "free") +
  labs(x = "tf-idf",
       y = NULL)
```

Counting and correlating pairs of words with the widyr package

- To count the number of times that two words appear within the same document, or to see how correlated they are.
- Most operations for finding pairwise counts or correlations need to turn the data into a wide matrix first.
- **widyr** package first 'casts' a tidy dataset into a wide matrix, performs an operation such as a correlation on it, then re-tidies the result.



In this code chunk below, *pairwise_cor()* of **widyr** package is used to compute the correlation between newsgroup based on the common words found.

```
newsgroup_cors <- words_by_newsgroup %>%
  pairwise_cor(newsgroup,
               word,
               n,
               sort = TRUE)
```

Visualising correlation as a network

Now, we can visualise the relationship between newgroups in network graph as shown below.

The code chunk:

```
set.seed(2017)

newsgroup_cors %>%
  filter(correlation > .025) %>%
  graph_from_data_frame() %>%
  ggraph(layout = "fr") +
  geom_edge_link(aes(alpha = correlation,
                     width = correlation)) +
  geom_node_point(size = 6,
                  color = "lightblue") +
  geom_node_text(aes(label = name),
                 color = "red",
                 repel = TRUE) +
  theme_void()
```

Bigram

In this code chunk below, a bigram data frame is created by using unnest_tokens() of tidytext.

```
bigrams <- cleaned_text %>%
  unnest_tokens(bigram,
                text,
                token = "ngrams",
                n = 2)
```

```
bigrams
```

```
## # A tibble: 28,824 x 3
##    newsgroup   id    bigram
##    <chr>       <chr> <chr>
##  1 alt.atheism 54256 <NA>
##  2 alt.atheism 54256 <NA>
##  3 alt.atheism 54256 as i
##  4 alt.atheism 54256 i don't
##  5 alt.atheism 54256 don't know
##  6 alt.atheism 54256 know this
##  7 alt.atheism 54256 this book
##  8 alt.atheism 54256 book i
##  9 alt.atheism 54256 i will
## 10 alt.atheism 54256 will use
## # ... with 28,814 more rows
```

Counting bigrams

The code chunk is used to count and sort the bigram data frame ascendingly.

```
bigrams_count <- bigrams %>%
  filter(bigram != 'NA') %>%
  count(bigram, sort = TRUE)
```

.pull-right

```
bigrams_count
```

```
## # A tibble: 19,885 x 2
##    bigram        n
##    <chr>     <int>
##  1 of the      169
##  2 in the      113
##  3 to the       74
##  4 to be        59
##  5 for the      52
##  6 i have       48
##  7 that the     47
##  8 if you       40
##  9 on the       39
## 10 it is        38
## # ... with 19,875 more rows
```

Cleaning bigram

The code chunk below is used to seperate the bigram into two words.

```
bigrams_separated <- bigrams %>%
  filter(bigram != 'NA') %>%
  separate(bigram, c("word1", "word2"),
           sep = " ")

bigrams_filtered <- bigrams_separated %>%
  filter(!word1 %in% stop_words$word) %>%
  filter(!word2 %in% stop_words$word)
```

```
bigrams_filtered
```

```
## # A tibble: 4,604 x 4
##    newsgroup   id    word1        word2
##    <chr>       <chr> <chr>        <chr>
##  1 alt.atheism 54256 defines      god
##  2 alt.atheism 54256 term         preclues
##  3 alt.atheism 54256 science      ideas
##  4 alt.atheism 54256 ideas        drawn
##  5 alt.atheism 54256 supernatural precludes
##  6 alt.atheism 54256 scientific   assertions
##  7 alt.atheism 54256 religious    dogma
##  8 alt.atheism 54256 religion     involves
##  9 alt.atheism 54256 involves     circumventing
## 10 alt.atheism 54256 gain         absolute
## # ... with 4,594 more rows
```

Counting the bigram again

```
bigram_counts <- bigrams_filtered %>%
  count(word1, word2, sort = TRUE)
```

Create a network graph from bigram data frame

In the code chunk below, a network graph is created by using *graph_from_data_frame()* of igraph.

```
bigram_graph <- bigram_counts %>%
  filter(n > 3) %>%
  graph_from_data_frame()
bigram_graph
```

```
## IGRAPH afa88a6 DN-- 40 24 --
## + attr: name (v/c), n (e/n)
## + edges from afa88a6 (vertex names):
##  [1] 1          ->2          1          ->3           static     ->void
##  [4] time       ->pad        1          ->4           infield    ->fly
##  [7] mat        ->28         vv         ->vv          1          ->5
## [10] cock       ->crow       noticeshell->widget      27         ->1993
## [13] 3          ->4          child      ->molestation cock       ->crew
## [16] gun        ->violence   heat       ->sink        homosexual ->male
## [19] homosexual ->women      include    ->xol         mary       ->magdalene
## [22] read       ->write      rev        ->20          tt         ->ee
```

Visualizing a network of bigrams with ggraph

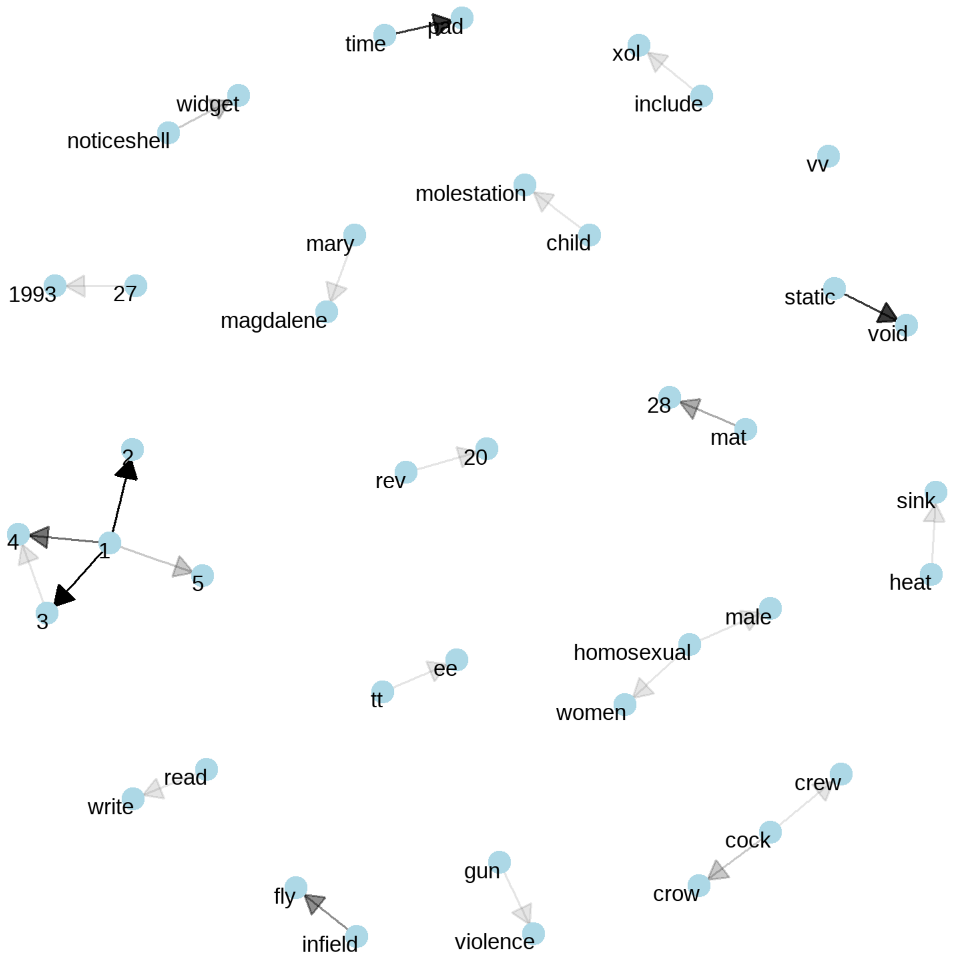
In this code chunk below, ggraph package is used to plot the bigram.

The code chunk used to plot the network graph:

```
set.seed(1234)

ggraph(bigram_graph, layout = "fr") +
  geom_edge_link() +
  geom_node_point() +
  geom_node_text(aes(label = name),
                 vjust = 1,
                 hjust = 1)
```

Revised version



The code chunl used to plot the network graph.

```
set.seed(1234)

a <- grid::arrow(type = "closed",
                 length = unit(.15,
                          "inches"))

ggraph(bigram_graph,
       layout = "fr") +
  geom_edge_link(aes(edge_alpha = n),
                 show.legend = FALSE,
                 arrow = a,
                 end_cap = circle(.07,
                           'inches')) +
  geom_node_point(color = "lightblue",
                  size = 5) +
  geom_node_text(aes(label = name),
                 vjust = 1,
                 hjust = 1) +
  theme_void()
```

References

widyr

- Reference guide
  - widyr: Widen, process, and re-tidy a dataset
  - United Nations Voting Correlations