LondonR Webinar

Intro to NLP with R

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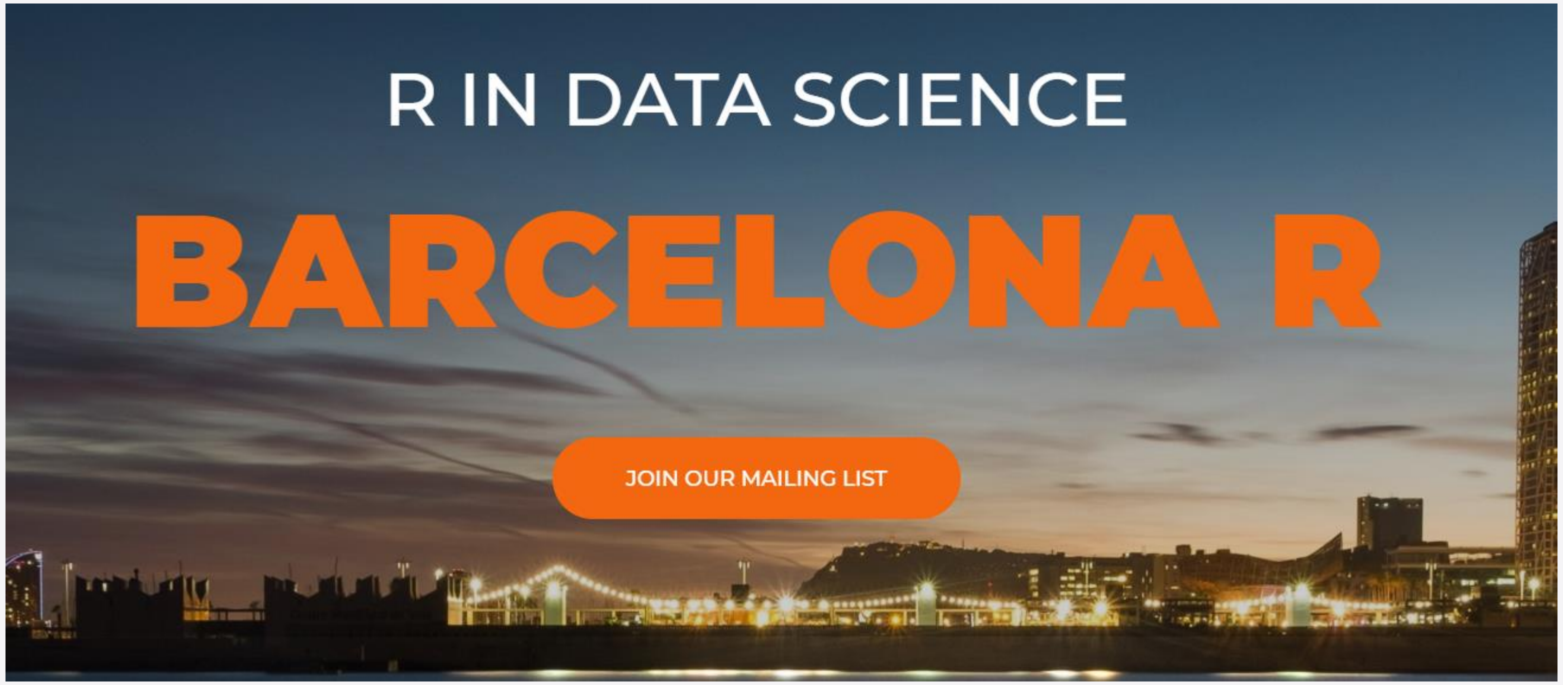
Big thanks to Barcelona R



- https://www.barcelonar.org/

Workshop Setup

- Resources
- R (recommended: version 3.6.3)
- RStudio (recommended: version 1.2.5003)

- Packages
- tidytext, widyr, textstem, irlba, wordcloud2

- Data
- https://github.com/kmeteyard/NLP_workshop/tree/master/data

What is NLP?

Natural language processing (NLP) is a field within linguistics and artificial intelligence that enables computers to understand and interact with human language.

Some examples where NLP can be found are:

- virtual assistants (Siri or Alexa)
- automatic spell checking
- word autocompletion
- machine translation (Google Translate)

Workshop aims

Workshop aim:

Learn the basics of how to do text mining and sentiment analysis as well as some background theory on NLP.

Topics:

- Tokenization, stop words and stemming/lemmatisation
- Sentiment analysis
- Term Frequency - Inverse Document Frequency (TF-IDF)
- Word Embeddings

Key piece of NLP terminology

As a test of your Latin, the following is used to refer to texts

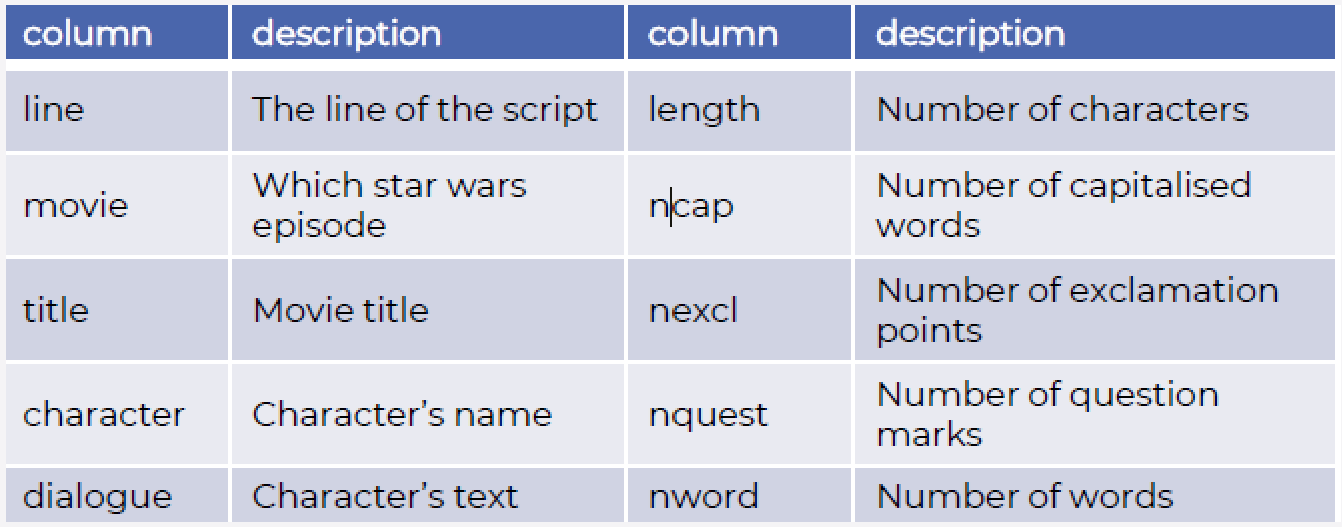
Corpus (s) $\longrightarrow$ Corpora (pl)

A body/collection of texts

Highlights some of the challenges in analysing languages

Live Coding Example 1

1. Load the star_wars_scripts.rds dataset
2. Which movie has the most lines?
3. Which movie has the most characters?
4. Summarise the lines, exclamations, questions, words per character per movie and sort by words (descending).



column	description	column	description
line	The line of the script	length	Number of characters
movie	Which star wars episode	ncap	Number of capitalised words
title	Movie title	nexcl	Number of exclamation points
character	Character's name	nquest	Number of question marks
dialogue	Character's text	nword	Number of words

Live Coding Example 1

```r
library(dplyr)
library(magrittr)

# Load the star_wars_scripts.rds dataset
df <- readRDS("data/star_wars_scripts.rds")

# Which movie has the most lines?
df %>%
  group_by(movie) %>%
  summarise(line_count = n())
```

Live Coding Example 1

```r
# Which movie has the most characters?
df %>%
  group_by(movie) %>%
  summarise(character_count = n_distinct(character))

# Summarise the lines, exclamations, questions, words per character per movie
res <- df %>%
  group_by(movie, character) %>%
  summarise(line_count = n(),
            total_excl = sum(nexcl),
            total_quest = sum(nquest),
            total_words = sum(nword)) %>%
  arrange(desc(total_words))
```

Tokenisation

This is the process of breaking up a text into individual tokens.

A token is a unit of text that we use for text analysis.

Most commonly tokens are single words.

We will follow Hadley Wickham's tidy data structure and use the {tidytext} package to process our data into a table with one token per row format where a token is a single word.

N-grams

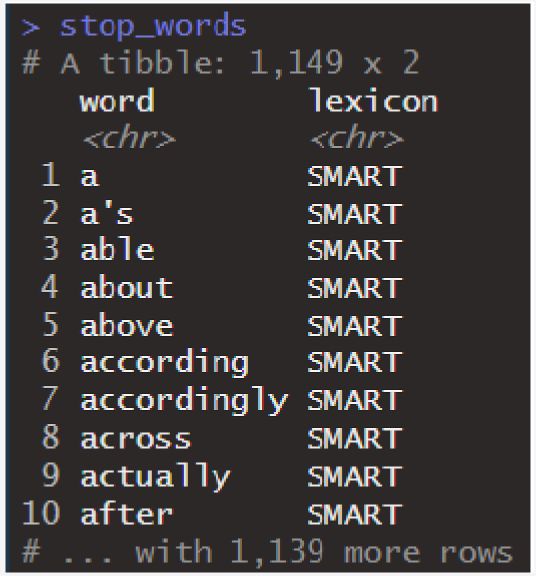
An n-gram is a successive sequence of n items from a text, e.g.

- A single word is a unigram
- A pair of words is a bigram (“red house”)
- Three words are a trigram

https://books.google.com/ngrams

Stop Words

When analysing text we will come across words that are not very meaningful. For example, in English, particularly common words such as “the”, “a”, “of”, “to” etc. are not useful for analysis. We can remove them by using a list of words called “stop words”. The {tidytext} package contains a dataset of stop words from three lexicons.



```
> stop_words
# A tibble: 1,149 x 2
   word        lexicon
   <chr>       <chr>
 1 a           SMART
 2 a's         SMART
 3 able        SMART
 4 about       SMART
 5 above       SMART
 6 according   SMART
 7 accordingly SMART
 8 across      SMART
 9 actually    SMART
10 after       SMART
# ... with 1,139 more rows
```

Live Coding Example 2

1. Use {tidytext} to tokenize the star wars scripts, where a token is a single word to create a one token per row data frame (also remove the summary columns).
2. Remove the stop words from the data frame and create “tidy_script ”
3. Find the top 5 words for all movies and create a bar chart visualisation.
4. Find the most common word used for all the characters. What do you think is Yoda’s?
5. Create a word cloud!

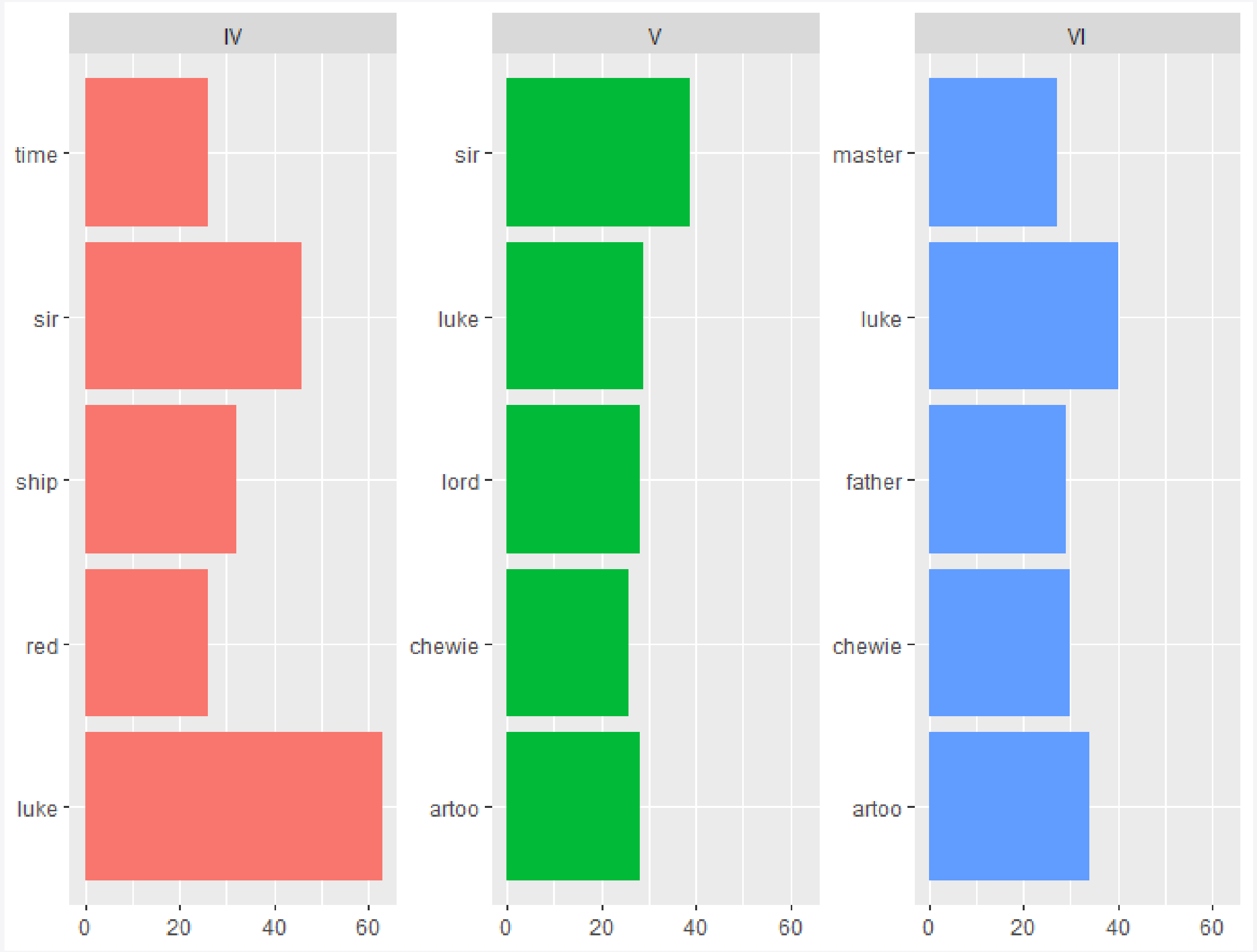
Live Coding Example 2

```
library(tidytext)

# Load the star_wars_scripts.rds dataset
df <- readRDS("data/star_wars_scripts.rds")

# Use {tidytext} to tokenize the star wars scripts, where a token is a single
# word to create a one-token-per-row data frame (also remove summary columns)
tidy_script <- df %>%
  select(-length, -ncap, -nexcl, -nquest, -nword) %>%
  unnest_tokens(output = word, input = dialogue)

# Remove the stop words from the data frame and create “tidy_script” object
tidy_script <- tidy_script %>%
  anti_join(stop_words, by = "word")
```

Live Coding Example 2

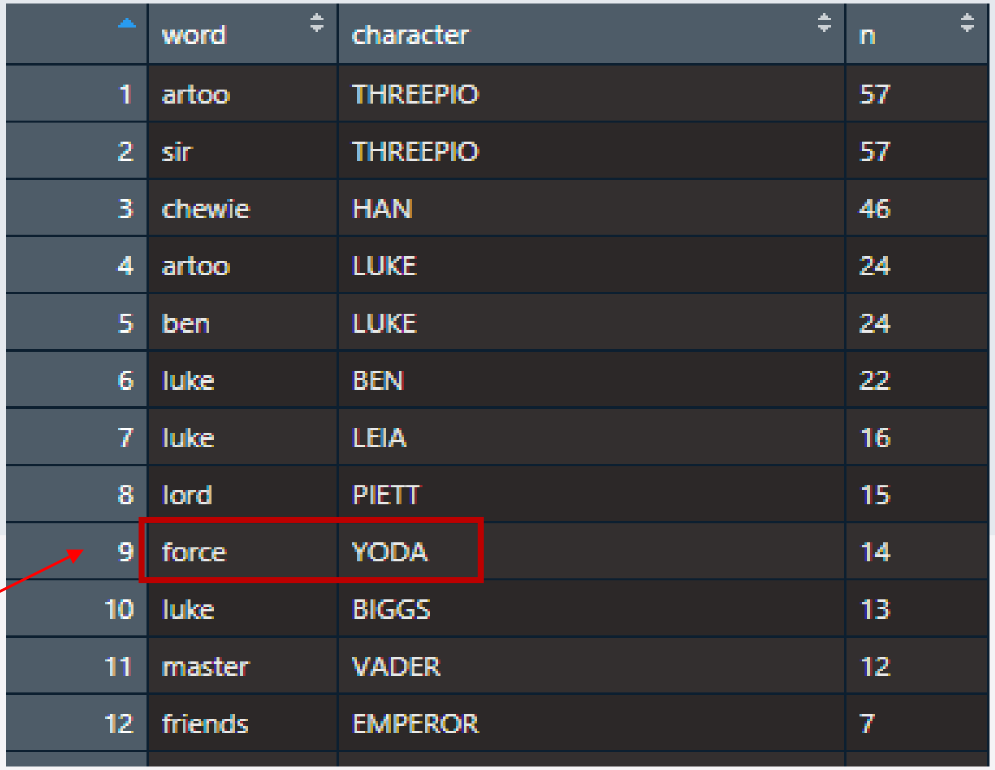
```r
# Find the top 5 words for all movies and create a bar chart visualisation.
library(ggplot2)

tidy_script %>%
  count(word, movie) %>%
  ungroup() %>%
  group_by(movie) %>%
  top_n(5) %>%
  ungroup() %>%
  ggplot(aes(word, n, fill = movie)) +
  geom_col(show.legend = FALSE) +
  labs(y = NULL, x = NULL) +
  facet_wrap(~movie, ncol = 3, scales = "free_y") +
  coord_flip()
```

Live Coding Example 2



Live Coding Example 2

```
# Find the most common word used for all the characters.
# What do you think is Yoda's?
res <- tidy_script %>%
  count(word, character) %>%
  ungroup() %>%
  group_by(character) %>%
  top_n(1) %>%
  ungroup() %>%
  arrange(desc(n))
```



	word	character	n
1	artoo	THREEPIO	57
2	sir	THREEPIO	57
3	chewie	HAN	46
4	artoo	LUKE	24
5	ben	LUKE	24
6	luke	BEN	22
7	luke	LEIA	16
8	lord	PIETT	15
9	force	YODA	14
10	luke	BIGGS	13
11	master	VADER	12
12	friends	EMPEROR	7

Live Coding Example 2

```r
# Create an awesome word cloud!
# devtools::install_github("lchiffon/wordcloud2")
# Might require some package installation steps
library(wordcloud2)

plot_data <- tidy_script %>%
  count(word) %>%
  ungroup() %>%
  mutate(word = factor(word),
         freq = as.numeric(n)) %>%
  arrange(desc(freq))

wordcloud2(plot_data, size = 1, figPath="data/vader.png")

wordcloud2(plot_data, size = 1, figPath="data/yoda.png")
```

Live Coding Example 2

Further Text Preprocessing

There are two common methods to condense words into their root forms:

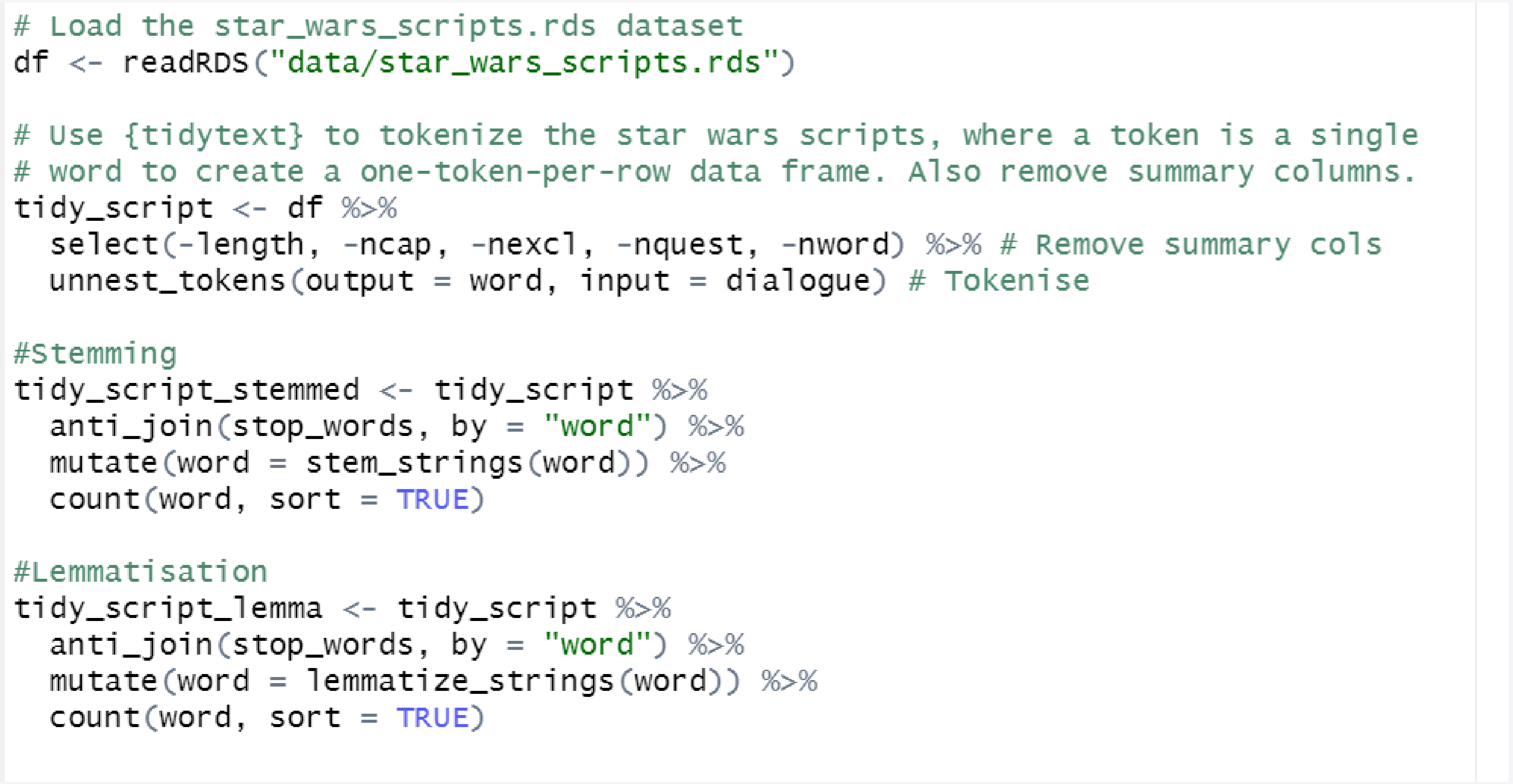
- **Stemming** is the process of reducing words to their written word stem:

  Runs, Ran -> Run

- **Lemmatisation** returns a word to its morphological route and thus better takes into account meaning:

  Better -> Good

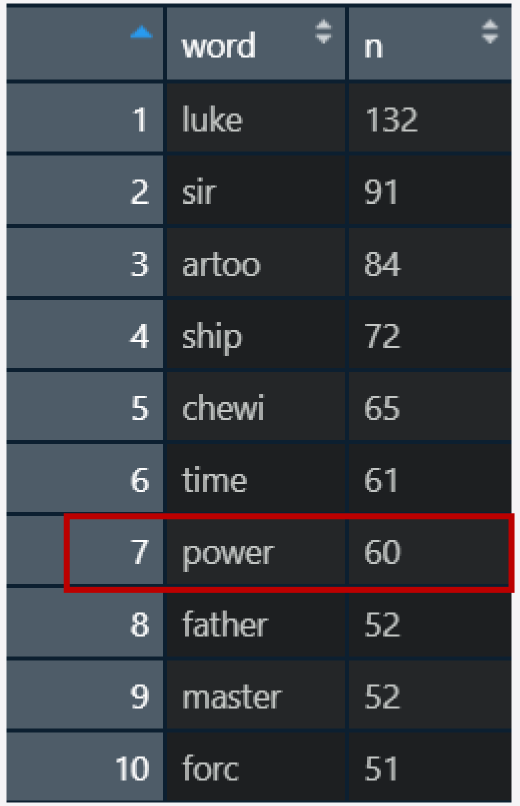
Live Coding Example 3



```
# Load the star_wars_scripts.rds dataset
df <- readRDS("data/star_wars_scripts.rds")

# Use {tidytext} to tokenize the star wars scripts, where a token is a single
# word to create a one-token-per-row data frame. Also remove summary columns.
tidy_script <- df %>%
  select(-length, -ncap, -nexcl, -nquest, -nword) %>% # Remove summary cols
  unnest_tokens(output = word, input = dialogue) # Tokenise

#Stemming
tidy_script_stemmed <- tidy_script %>%
  anti_join(stop_words, by = "word") %>%
  mutate(word = stem_strings(word)) %>%
  count(word, sort = TRUE)

#Lemmatisation
tidy_script_lemma <- tidy_script %>%
  anti_join(stop_words, by = "word") %>%
  mutate(word = lemmatize_strings(word)) %>%
  count(word, sort = TRUE)
```

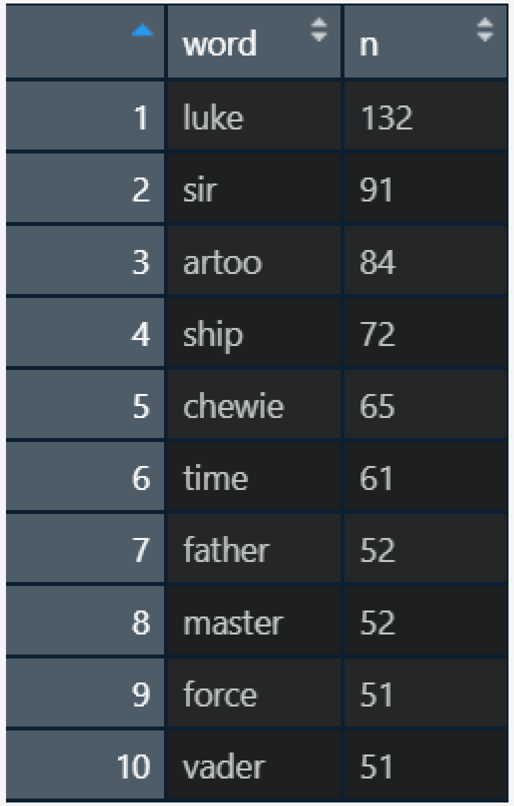
Live Coding Example 3

Stemming



	word	n
1	luke	132
2	sir	91
3	artoo	84
4	ship	72
5	chewi	65
6	time	61
7	power	60
8	father	52
9	master	52
10	forc	51

Lemmatisation



	word	n
1	luke	132
2	sir	91
3	artoo	84
4	ship	72
5	chewie	65
6	time	61
7	father	52
8	master	52
9	force	51
10	vader	51

Sentiment Analysis

It is easy for humans to understand the emotional content of a piece of text and interpret it as something positive or negative. We can even describe some text as expressing anger, disgust or surprise.

Sentiment analysis, which is also known as opinion mining, is the process where we aim to attach emotional content to a piece of text in a programmatic way.

The most common method to analyse the sentiment of a piece of text is to add up the individual sentiment content of each of the words that make up the text.

We will use one of the three general purpose sentiment lexicons of the {tidytext} package, namely the AFINN

Live Coding Example 4

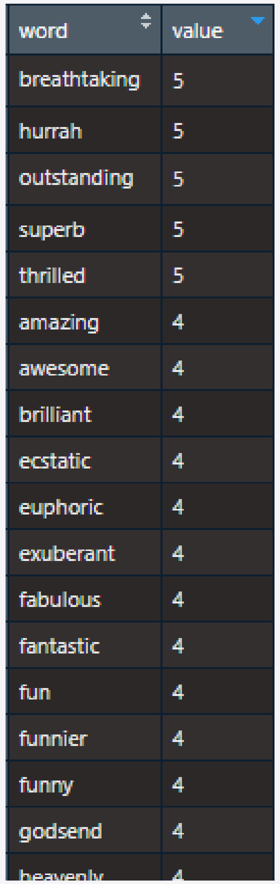
1. Use {tidytext} and create the data frame “ afinn ” of the AFINN sentiment lexicon and inspect it.
2. Inner join the AFINN sentiment lexicon to tidy_script ” from Example 2 and calculate the total sentiment score per movie per line.
3. Attach the sentiment scores to the original starwars script dataset. What do you think is the most negative script line from all movies?
4. Who is the most negative character of all movies?
5. Visualise the sentiment score changes line by line for each movie.

Live Coding Example 4

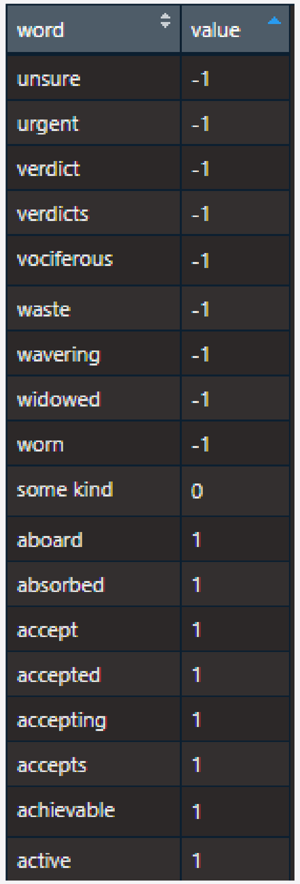
```r
# Use {tidytext} and create the data frame “afinn” of the AFINN sentiment
# lexicon and inspect it.
afinn <- get_sentiments("afinn")

# Inner join the AFINN sentiment lexicon to tidy_script from Example 2
# and calculate the total sentiment per movie per line
sentiment_script <- tidy_script %>%
  inner_join(afinn) %>%
  group_by(movie, line) %>%
  mutate(sentiment = sum(value)) %>%
  ungroup() %>%
  select(-word, -value) %>%
  distinct()
```

Live Coding Example 4

Some sample extracts from AFINN

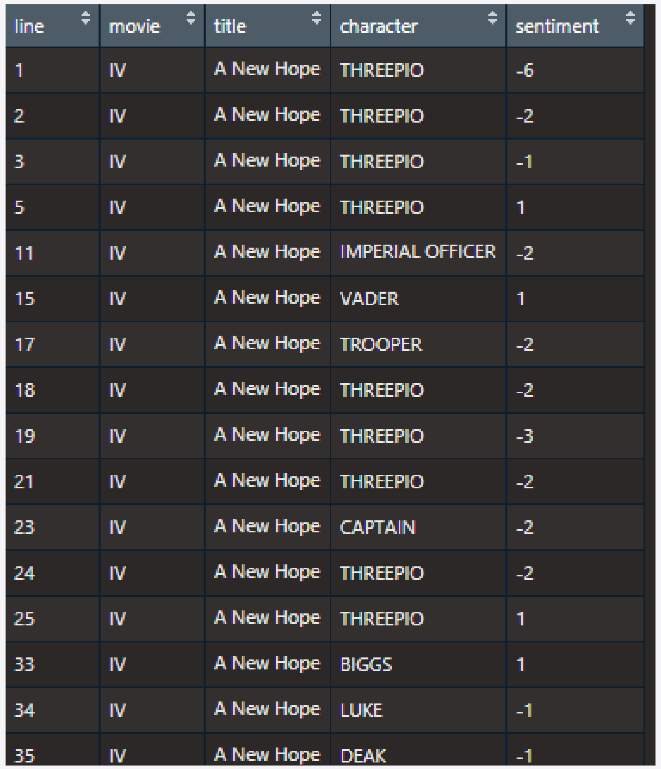


word	value
breathtaking	5
hurrah	5
outstanding	5
superb	5
thrilled	5
amazing	4
awesome	4
brilliant	4
ecstatic	4
euphoric	4
exuberant	4
fabulous	4
fantastic	4
fun	4
funnier	4
funny	4
godsend	4
heavenly	4



word	value
unsure	-1
urgent	-1
verdict	-1
verdicts	-1
vociferous	-1
waste	-1
wavering	-1
widowed	-1
worn	-1
some kind	0
aboard	1
absorbed	1
accept	1
accepted	1
accepting	1
accepts	1
achievable	1
active	1

Total sentiment per movie per line



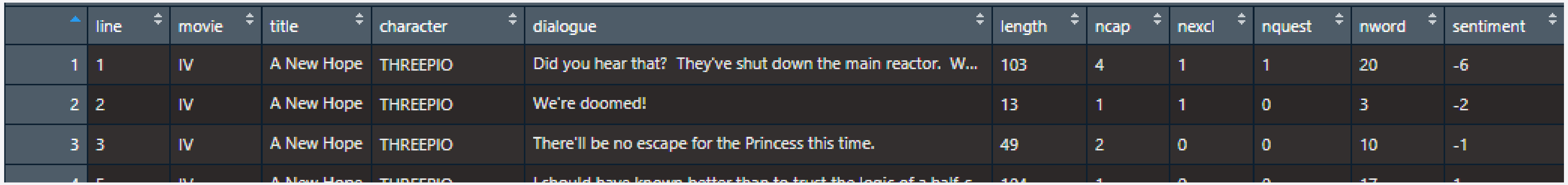
line	movie	title	character	sentiment
1	IV	A New Hope	THREEPIO	-6
2	IV	A New Hope	THREEPIO	-2
3	IV	A New Hope	THREEPIO	-1
5	IV	A New Hope	THREEPIO	1
11	IV	A New Hope	IMPERIAL OFFICER	-2
15	IV	A New Hope	VADER	1
17	IV	A New Hope	TROOPER	-2
18	IV	A New Hope	THREEPIO	-2
19	IV	A New Hope	THREEPIO	-3
21	IV	A New Hope	THREEPIO	-2
23	IV	A New Hope	CAPTAIN	-2
24	IV	A New Hope	THREEPIO	-2
25	IV	A New Hope	THREEPIO	1
33	IV	A New Hope	BIGGS	1
34	IV	A New Hope	LUKE	-1
35	IV	A New Hope	DEAK	-1

Live Coding Example 4

```
# Attach the sentiment scores to the original star wars script dataset.
# What do you think is the most negative script line from all movies?
df <- df %>%
  inner_join(sentiment_script)

# Who is the most negative character of all movies?
res <- df %>%
  group_by(character) %>%
  summarise(total_sentiment = sum(sentiment)) %>%
  ungroup() %>%
  arrange(total_sentiment)
```

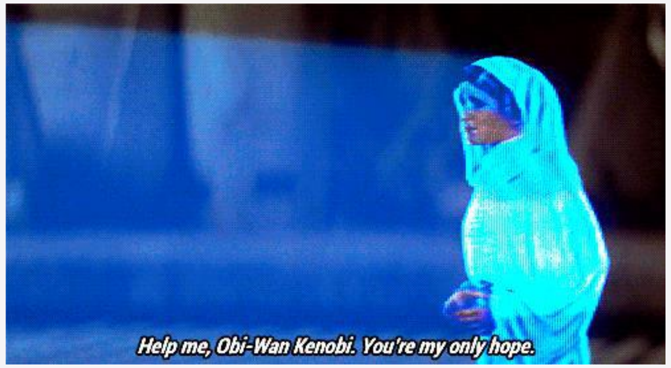
Live Coding Example 4

Sentiment score per script line per movie



	line	movie	title	character	dialogue	length	ncap	nexcl	nquest	nword	sentiment
1	1	IV	A New Hope	THREEPIO	Did you hear that? They've shut down the main reactor. W...	103	4	1	1	20	-6
2	2	IV	A New Hope	THREEPIO	We're doomed!	13	1	1	0	3	-2
3	3	IV	A New Hope	THREEPIO	There'll be no escape for the Princess this time.	49	2	0	0	10	-1
4	5	IV	A New Hope	THREEPIO	I should have known better than to trust the logic of a half-s...	104	1	0	0	17	-1

And the award for the most negative script line from all movies goes to...

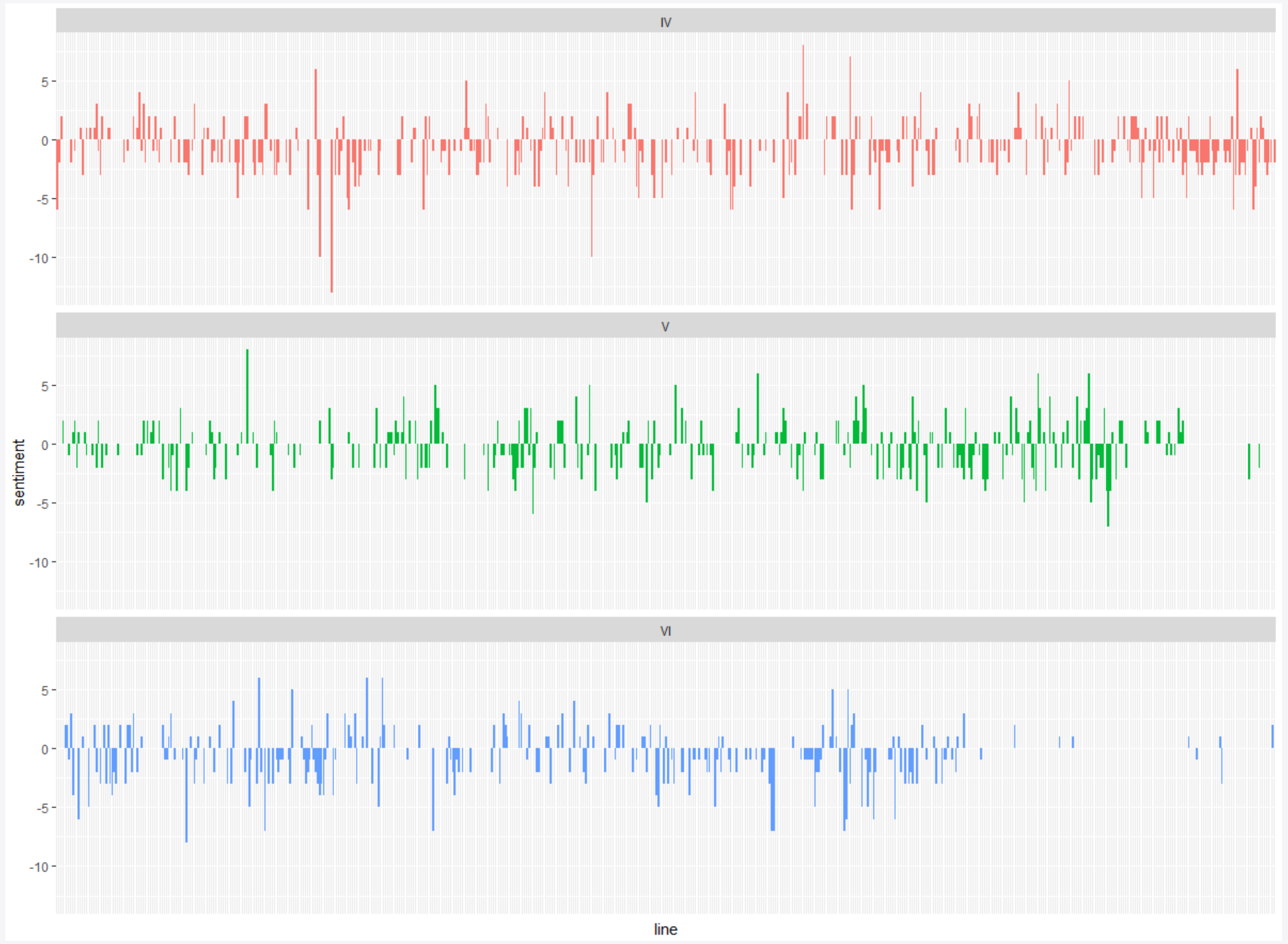


And the award for the most negative character goes to...

Live Coding Example 4

```r
# Visualise the sentiment score changes line by line for each movie
df %>%
  ggplot(aes(line, sentiment, fill = movie)) +
  geom_col(show.legend = FALSE) +
  theme(axis.text.x=element_blank(),
        axis.ticks.x=element_blank()) +
  facet_wrap(~movie, ncol = 1)
```

Live Coding Example 4



Term Frequency – Inverse Document Frequency

Q: Lets say we have a document, how could we quantify what it is about?
A: Look at and analyse the words that make up the document!

Term Frequency (TF) how frequently does a term appear in the document
Inverse Document Frequency (IDF) adjust the weight of commonly used terms (such as “the”) by decreasing the word’s importance

Combining the two measures by multiplying them results in a TF–IDF score which reflects the frequency of a term adjusted for how rarely it is used.

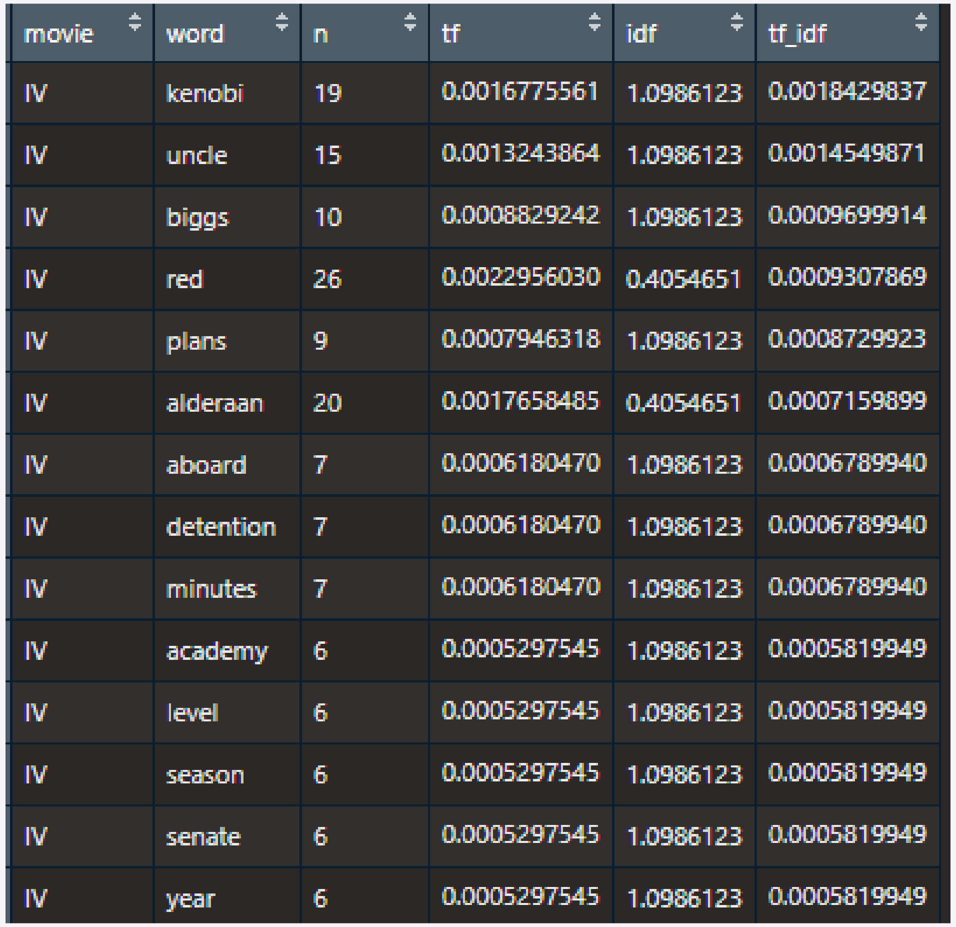
Live Coding Example 5

1. Use {tidytext} to tokenize the star wars scripts, where a token is a single word to create a one token per row data frame. Also remove summary columns. Then count the frequency of each word for each move and apply the TF IDF function of {tidytext} and extract the top 10 words per movie.

Live Coding Example 5

```r
# Use {tidytext} to tokenize the star wars scripts, where a token is a single
# word to create a one-token-per-row data frame. Also remove summary columns.
# Then count the frequency of each word for each move and apply the
# TF-IDF function of {tidytext} and extract the top 10 words per movie
tf_idf_script <- df %>%
  select(-length, -ncap, -nexcl, -nquest, -nword) %>%
  unnest_tokens(output = word, input = dialogue) %>%
  count(movie, word, sort = TRUE) %>%
  bind_tf_idf(word, movie, n) %>%
  ungroup() %>%
  group_by(movie) %>%
  top_n(10) %>%
  arrange(movie, desc(tf_idf))
```

Live Coding Example 5



movie	word	n	tf	idf	tf_idf
IV	kenobi	19	0.0016775561	1.0986123	0.0018429837
IV	uncle	15	0.0013243864	1.0986123	0.0014549871
IV	biggs	10	0.0008829242	1.0986123	0.0009699914
IV	red	26	0.0022956030	0.4054651	0.0009307869
IV	plans	9	0.0007946318	1.0986123	0.0008729923
IV	alderaan	20	0.0017658485	0.4054651	0.0007159899
IV	aboard	7	0.0006180470	1.0986123	0.0006789940
IV	detention	7	0.0006180470	1.0986123	0.0006789940
IV	minutes	7	0.0006180470	1.0986123	0.0006789940
IV	academy	6	0.0005297545	1.0986123	0.0005819949
IV	level	6	0.0005297545	1.0986123	0.0005819949
IV	season	6	0.0005297545	1.0986123	0.0005819949
IV	senate	6	0.0005297545	1.0986123	0.0005819949
IV	year	6	0.0005297545	1.0986123	0.0005819949

Word embeddings

A way to represent words numerically (as vectors) and thus identify similarities between them. We do this by investigating the surrounding words in a text.

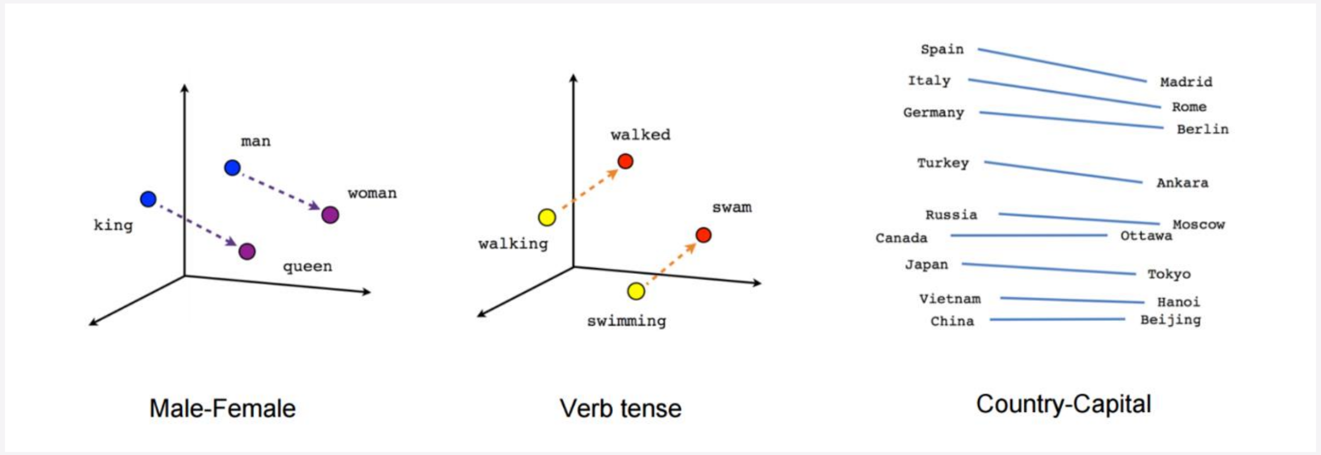
...government debt problems turning into	banking	crises as happened in 2009...
...saying that Europe needs unified	banking	regulation to replace the hodgepodge...
...India has just given its	banking	system a shot in the arm...

A key idea is that a words meaning is contained within the words that surround it.

Word embeddings

We map words to a vector space and the distance between them works to encode their meaning.

$$\textit{banking} = \begin{pmatrix} 0.286 \\ 0.792 \\ -0.177 \\ -0.107 \\ 0.109 \\ -0.542 \\ 0.349 \\ 0.271 \end{pmatrix}$$



There are a variety of methods to do this. Most commonly, people use neural networks (e.g. word2vec, GloVe).

Worked example 6

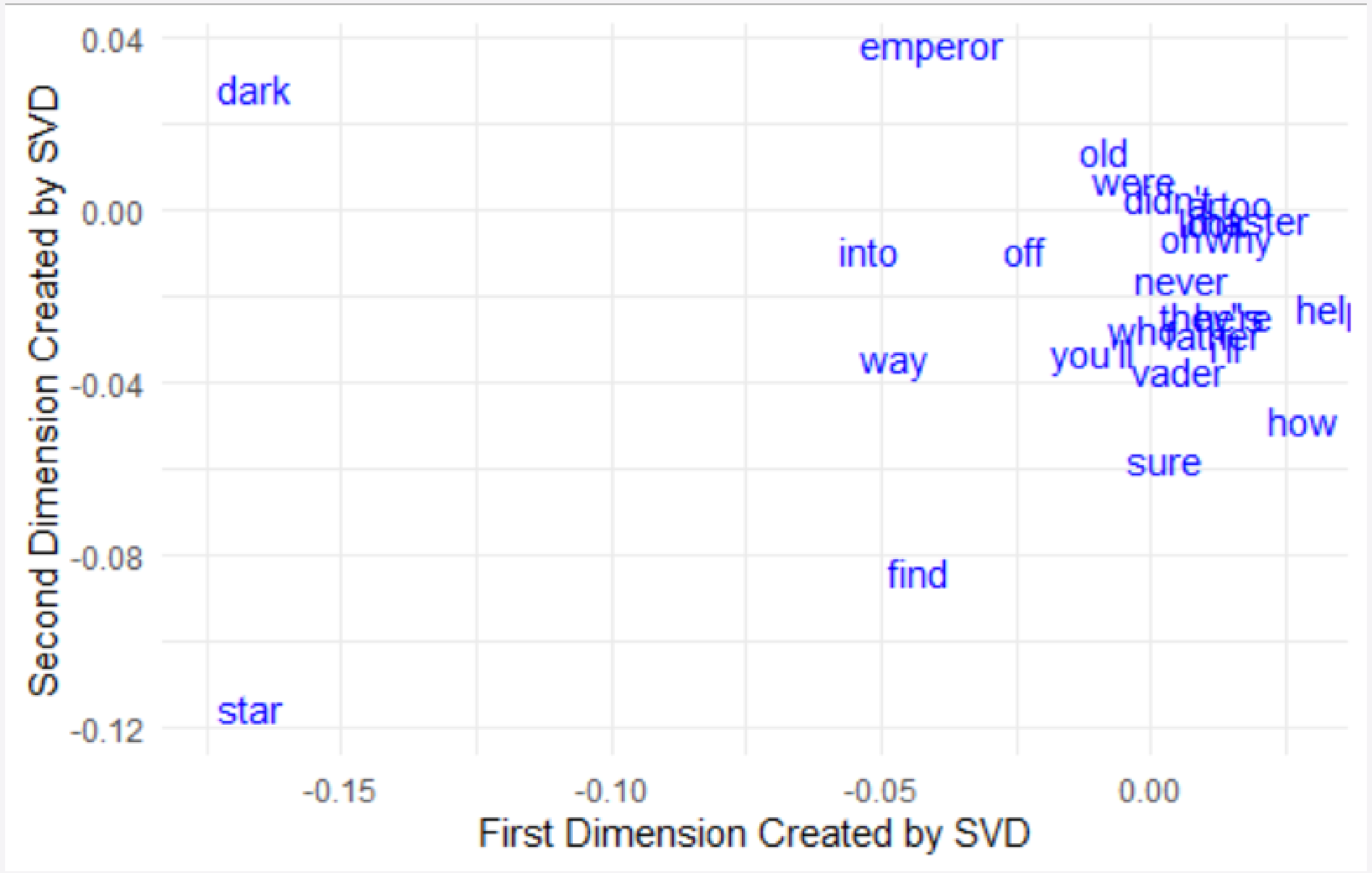
1. Create word embeddings using the Star Wars scripts.
   - Create unigram and skipgram probabilities
   - Normalise these and perform matrix operations

2. Examine some synonyms for key words in the film scripts

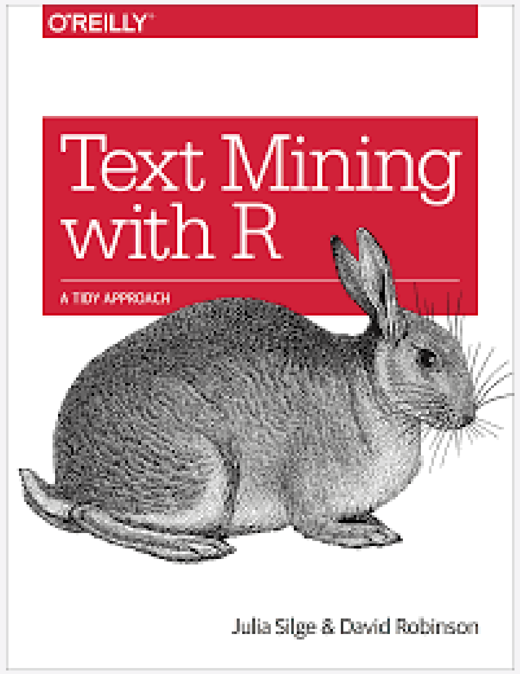
3. Visualise a set of words from the data in two dimensional space

Credit to Julia Silge for her fantastic example that motivated this one

Worked example 6



Other Resources



- Get the book online at: https://www.tidytextmining.com/