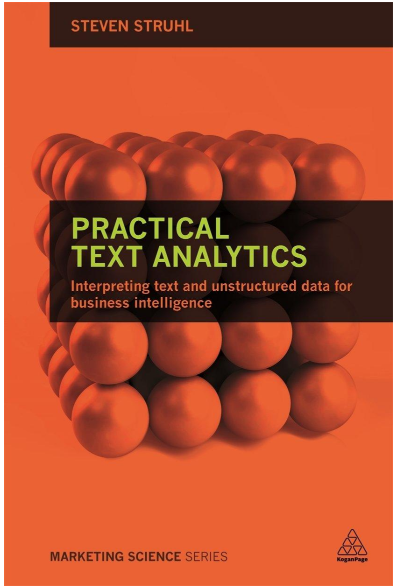
TOKENIZING TEXT

R, stringr & tidr

CONTENT

- Filter or Sample Data
- Clean and Normalize Text
- Split Text into Tokens
- Remove Stop Words
- Enrich Tokens (Stemming, Lemmatization, Part-of-Speech Tagging)

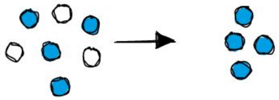


Struhl, Steven M. (2015): *Practical Text Analytics: Interpreting text and unstructured data for business intelligence*. London, UK, Philadelphia, PA: Kogan Page (Marketing science series).

Tokenization

Five steps to impose a structure on text

1. Filter or sample data



2. Clean and normalize text

"@all: This is the best course ever!!"

becomes

"this is the best course ever"

3. Split text into tokens

["this","is","the","best","course","ever"]

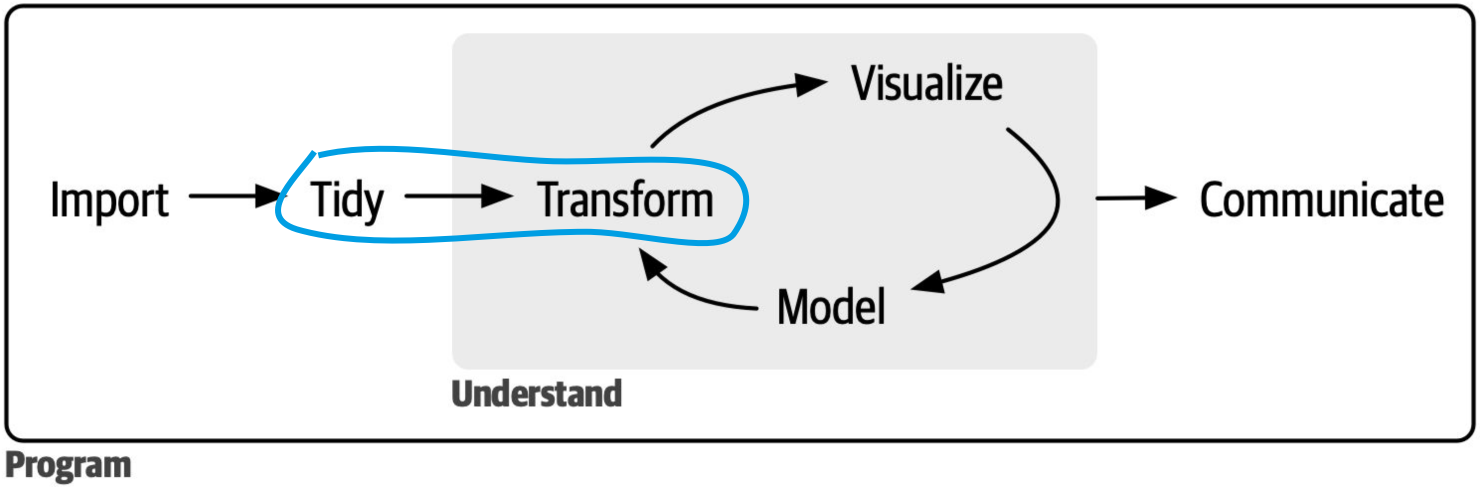
4. Remove stop words

["is","best","course","ever"]

5. Enrich tokens (lemmatization, stemming, part-of-speech)

```
["be" : [verb],
 "best": [adj],
 "course": [noun, obj],
 "ever": [temporal] ]
```

WHERE ARE WE?



Source: Wickham, Hadley, and Garrett Grolemund. R for Data Science: Import, Tidy, Transform, Visualize, and Model Data. First edition, O'Reilly, 2016. URL: https://r4ds.hadley.nz/diagrams/data-science/base.png

FILTER OR SAMPLE DATA

`filter, slice_sample`

DATA IS TOO LARGE?

WHAT OPTIONS DO WE HAVE?

With analyzing data on our laptop, we are limited in RAM and CPU.

What if the data is just too big?

- Reduce the data by filtering out irrelevant records (`filter`)
- Reduce the data through sampling and proceeding with a smaller portion (`slice_sample`)
- Pay for more compute resources, e.g., using a Spark cluster on Databricks
- Logon to the high performance compute (HPC) cluster from the university

Created with Bing Image Creator 2023

Reduce the data set before further analysis with `filter`:

```
tweets_filtered <-
  tweets |>
  filter(year(created_at) == 2023) |>
  filter(lang == "de") |>
  select(id, created_at, screen_name, text, is_retweet)
```

SAMPLE

When filtering is not possible, we can still use sampling with `slice_sample` from `{dplyr}`:

```
tweets |>
  slice_sample(n = 1000)
```

```
tweets |>
  slice_sample(prop = 0.1)
```

CLEAN AND NORMALIZE TEXT

ONLY WORDS

Text often contains irrelevant characters or character sequences that are of no value for analysis.

Cleaning text means to remove them from text. This can include:

- Punctuation
- Special characters, e.g., `@%&#/`
- Invisible characters, e.g, `\n`, `\r`, `\t`, or multiple spaces
- Specific character sequences, e.g., URLs, user mentions, hashtags

Normalization involves converting all characters to lowercase for better comparison.

```
"@all This is the best course ever! #bigdata #nlp 👌"
```

```
"this is the best course ever"
```

Remove character sequences from tweets with `str_remove_all`, `str_replace_all`, and `str_trim`:

```
tweets_clean <-
    tweets_filtered |>
    mutate(text = str_remove_all(text, "@\\w+")) |>
    mutate(text = str_remove_all(text, "#\\w+")) |>
    mutate(text = str_remove_all(text, "https?://\\S+")) |>
    mutate(text = str_remove_all(text, "[[:punct:]]")) |>
    mutate(text = str_replace_all(text, "\\s{2,}", " ")) |>
    mutate(text = str_trim(text))
```

With regular expressions, we can remove all kinds of characters:

```
emojis <- "[\U0001F600-\U0001F64F\U0001F300-\U0001F5FF+"

tweets |>
  mutate(text = str_remove_all(text, emojis))
```

NORMALIZE

Convert the text to lowercase with `str_to_lower`:

```
tweets |>
 mutate(text = str_to_lower(text))
```

SPLIT TEXT INTO TOKENS

IMPOSING STRUCTURE

Tokenization is one way to impose structure on otherwise unstructured text data.

- The assumption is that text is made of words (or tokens) separated by a space
- By splitting text into words (or tokens), we create a column with:
  - Atomic values → one word per column
  - A discrete range of values → the vocabulary used in the text data
- Methods like `filter`, `group_by`, `count` and the like can be applied → **Analysis is possible**
- Beware of the limits!

SPLIT TEXT

EXAMPLE

```
"this is the best course ever"
```

↓

```
"this"
"is"
"the"
"best"
"course"
"ever"
```

SPLIT TEXT

We can split text based on a separator and expand the result into rows with `separate_longer_delim`:

```
tweets_tokenized <-
  tweets_clean |>
  tidyr::separate_longer_delim(text, " ") |>
  rename(word = text)
```

REMOVE STOP WORDS

REMOVE STOP WORDS

Many words appear frequently in text but have very little meaning for analysis.

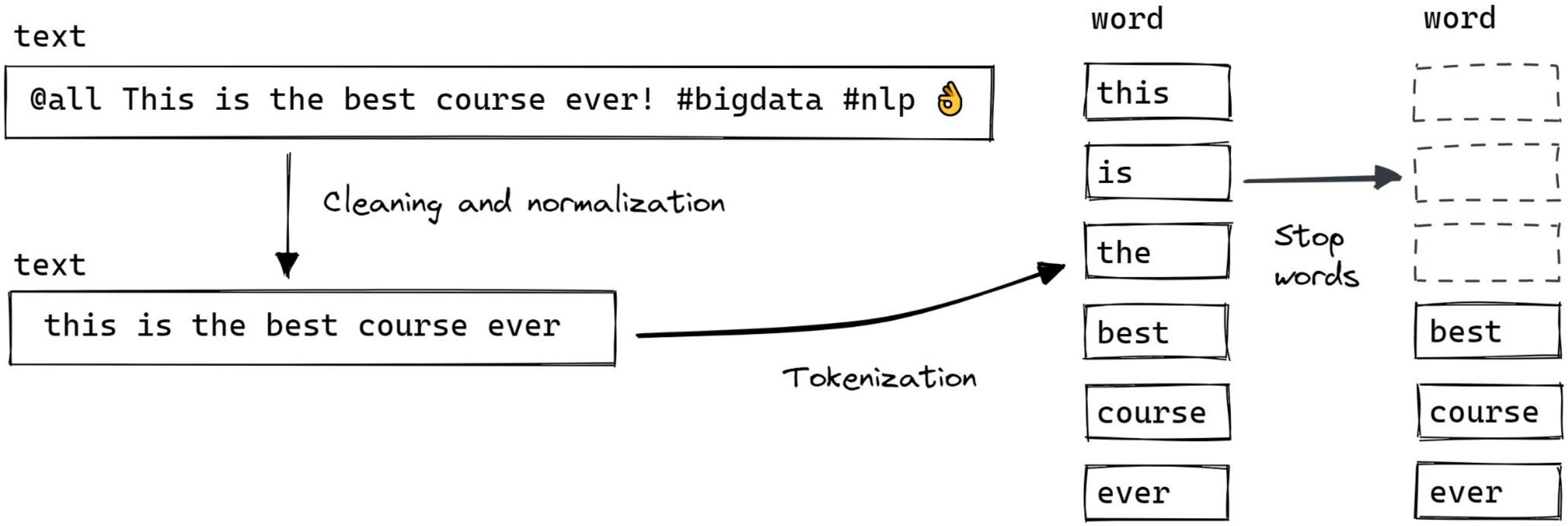
- Filter out words with little contribution to content, sentiment, meaning etc.
- Only then can we uncover the interesting words and their usage
- We can filter stop words based on a simple list and the `anti_join` function
  - List with English stop words (~670)
  - List with German stop words (~620)

REMOVE STOP WORDS

The `anti_join` is the opposite of a join and removes any rows with a match:

```
stop <- read_csv("data/stopwords_german.csv")

tweets_tokenized |>
  anti_join(stop, by = "word") |>
  count(word, sort = TRUE)
```


text
@all This is the best course ever! #bigdata #nlp 👌
Cleaning and normalization
text
this is the best course ever
Tokenization
word
this
is
the
best
course
ever
Stop words
word
best
course
ever

ENRICH TOKENS

Stemming, Lemmatization, Part-of-Speech

ENRICH TOKENS

STEMMING, LEMMATIZATION, POS

Now that we have a column with word, we can add more metadata, such as:

- What is the word's stem? (eats → eat, sitting → sit) (stemming)
- What is the base form of the word (is → be, mice → mouse, best → good) (lemmatization)
- What type of word is it (noun, verb, adjective…) (part-of-speech tagging)
- What role does the word play in its context? (contextual dependencies)

We could do the first three with the same rule-based approach as for the stop words (the last won't work that way). We'll see that probabilistic models from machine learning are much better at this.