R Tutorial at the WZB

08 - Text mining I

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Today's schedule

1. Review of last week's tasks
2. Text as data
3. Text mining methods for the Social Sciences
4. Matrices and lists in R
5. Bag-of-words model
6. Practical text mining with the `tm` package
7. Document similarity
8. The `tidytext` package

Review of last week's tasks

Solution for tasks #7

now online on
https://wzbsocialsciencecenter.github.io/wzb_r_tutorial/

Text as data

Text as data

Natural language is context-dependent, loosely structured and often ambigious. This makes extracting structured information hard.

Text mining (TM) or text analytics tries to uncover structured key information from natural language text.

Other important fields:

- **Natural language processing (NLP)**: deals with understanding and generating natural language (Amazon Echo, Apple Siri, etc.)
- **Quantitative text analysis (QTA):** "[…] extracting quantitative information from […] text for social scientific purposes […]"
  (Ken Benoit)

Key terms in TM: Text corpus

Text material is compiled to a **corpus**. This is the data base for TM contains a set of **documents**. Each document has:

1. A unique name
2. Its raw text (machine-readable but unprocessed text)
3. Additional variables used during analysis, e.g. author, date, etc.
4. Meta data (variables not used during analysis, e.g. source)

Documents can be anything: news articles, scientific papers, twitter posts, books, paragraphs of books, speeches, etc.

Usually, you don't mix different sorts of text within a corpus.

Key terms in TM: Tokens/terms

A **token** is the lexical unit you work with during your analysis. This can be phrases, **words**, symbols, characters, etc.

→ ~ unit of measurement in your TM project.

Even if you initially use words as lexical unit, a tokenized and processed word might not be a lexicographically correct word anymore.

Example that employs stemming and lower-case transformation:
"I argued with him" → `["i", "argu", "with", "he"]`

Tokens are also called **terms**.

Text mining applications

What can you find out with text mining? A few key methods often employed in the Soc. Sciences:

1. Simple & weighted word frequency comparisons

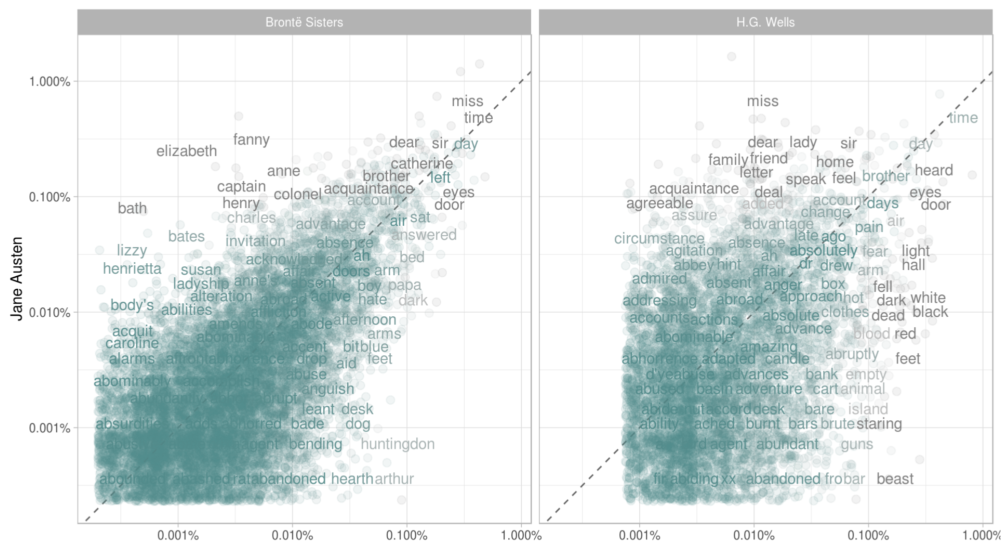
Count the words that occur in each document, calculate proportions, compare.

Weighted frequencies: Increase importance of document-specific words, reduce importance of very common words
→ key concept: term frequency - inverse document frequency
(tf-idf).

Text mining applications

What can you find out with text mining? A few key methods often employed in the Soc. Sciences:

1. Simple & weighted word frequency comparisons



source: [Silge & Robinson 2018: Text Mining with R]()

Text mining applications

2. Document classification

Approach:

1. Train a machine learning model with labelled documents
2. Evaluate model performance (estimate accuracy using held-out labelled data)
3. Classify unlabelled documents (prediction)

Examples:

- binary classification (spam / not spam, hate-speech / not hate-speech, …)
- multiclass classification (predefined political categories, style categories, …)

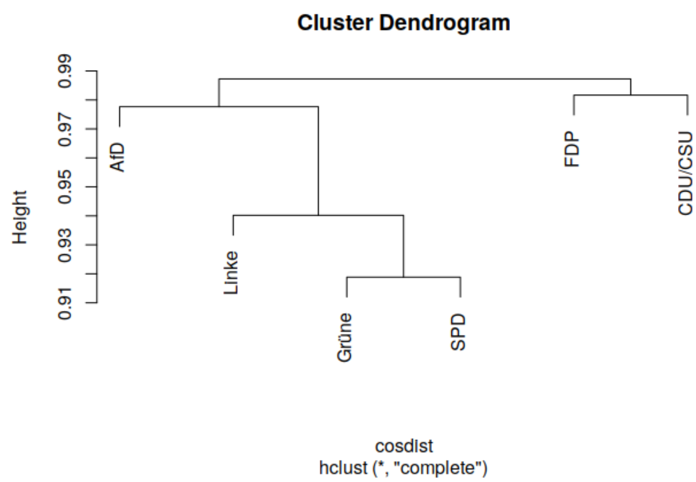
Text mining applications

3. Document similarity and clustering

How similar is document A as compared to document B?

Mostly used with word frequencies → compare (weighted) word usage between documents.

Once you have similarity scores for documents, you can cluster them.



Hierarchical clusters of party manifestos for Bundestag election 2017

Text mining applications

4. Term similarity and edit-distances

Term similarity work on the level of terms and their (phonetic, lexicographic, etc.) similarity. Edit-distances are often used to measure the editing difference between two terms or two documents A, B (how many editing steps to you need to come from A to B?).

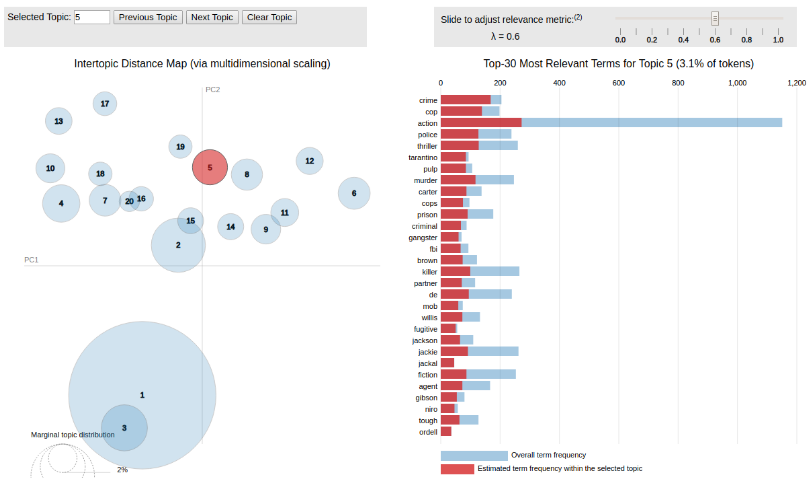
Example: Levenshtein distance between "**k**itt**e**n" and "sittin**g**" is 3 edits.

Pratical example: Measure how much drafts for a law changed over time.

Text mining applications

5. Topic modeling

Unsupervised machine learning approach to find latent topics in text corpora. Topics are distributions across words. Each document can be represented as a mixture of topics.



Practical example: Measure how the presence of certain topics changed over time in parliamentary debates; differences between parties, etc.

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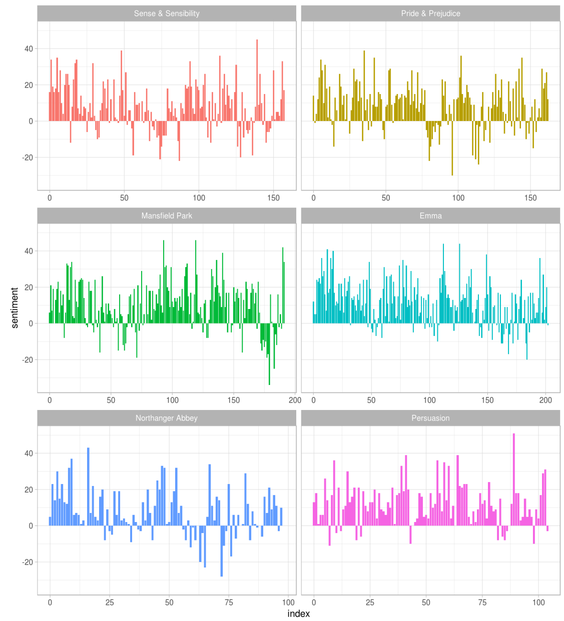
Text mining applications

6. Sentiment analysis

Also known as opinion mining. In it's basic form, it tries to find out if the sentiment in a document is positive, neutral or negative by assigning a sentiment score.

This score can be estimated by using supervised machine learning approaches (using training data of already scored documents) or in a lexicon-based manner (adding up the individual sentiment scores for each word in the text).



source: Silge & Robinson 2018: Text Mining with R

Text mining applications

Named entity recognition: Find out company names, people's names, etc. in texts.

Gender (from name) prediction: Estimate the gender of a person (for example from a name).

... and much more

Text mining steps

TM consists of several steps, each of them applying a variety of methods:

1. Collection of text material into a corpus
2. Text processing (tokenization and normalization of the corpus)
3. Feature extraction (extracting structured information)
4. Modeling

Which steps and methods you apply depends on your material and the modeling approach.

Packages for TM in the R world

- tm, Feinerer et al.
  - extensive set of tools for text mining
  - developed since 2008
- tidytext, Silge & Robinson 2018
  - text preprocessing, topic modeling, sentiment analysis in the "tidyverse"
  - designed for English language text
- quanteda, Benoit et al.
  - newly developed, extensive framework
  - also non-English texts

Specific methods:

- Topic modeling: topicmodels, lda, stm
- Text classification: RTextTools
- Word embeddings and similarities: text2vec

Matrices and lists in R

Matrices

The `matrix` data structure stores two-dimensional matrices with \(m\) rows and \(n\) columns. Each value must be of the same data type (type coercion rules apply).

To create a matrix, specify the data and its dimensions:

```
matrix(1:6, nrow = 2, ncol = 3)
```

```
##      [,1] [,2] [,3]
## [1,]    1    3    5
## [2,]    2    4    6
```

Matrices

The `matrix` data structure stores two-dimensional matrices with \(m\) rows and \(n\) columns. Each value must be of the same data type (type coercion rules apply).

To create a matrix, specify the data and its dimensions:

```
matrix(1:6, nrow = 3, ncol = 2)
```

```
##      [,1] [,2]
## [1,]    1    4
## [2,]    2    5
## [3,]    3    6
```

Matrices

The `matrix` data structure stores two-dimensional matrices with \(m\) rows and \(n\) columns. Each value must be of the same data type (type coercion rules apply).

To create a matrix, specify the data and its dimensions:

```
# fill data in rowwise order
matrix(1:6, nrow = 2, ncol = 3, byrow = TRUE)
```

```
##      [,1] [,2] [,3]
## [1,]    1    2    3
## [2,]    4    5    6
```

Indexing matrices

```
(A <- matrix(1:6, nrow = 2, ncol = 3, byrow = TRUE))
```

```
##      [,1] [,2] [,3]
## [1,]    1    2    3
## [2,]    4    5    6
```

The same indexing rules as for data frames apply. Individual cells are selected by `[row index, column index]`:

```
A[2, 3]
```

```
## [1] 6
```

Rows are selected by `[row index,]`:

```
A[2,]
```

```
## [1] 4 5 6
```

Columns are selected by `[, column index]`:

```
A[,3]
```

```
## [1] 3 6
```

Matrix operations

```
A
```

```
##      [,1] [,2] [,3]
## [1,]    1    2    3
## [2,]    4    5    6
```

Matrix `B` with dimensions 3x3:

```
(B <- matrix(rep(1:3, 3), nrow = 3, ncol = 3, byrow = TRUE))
```

```
##      [,1] [,2] [,3]
## [1,]    1    2    3
## [2,]    1    2    3
## [3,]    1    2    3
```

Matrix multiplication:

```
A %*% B
```

```
##      [,1] [,2] [,3]
## [1,]    6   12   18
## [2,]   15   30   45
```

Matrix operations

```
A
```

```
##      [,1] [,2] [,3]
## [1,]    1    2    3
## [2,]    4    5    6
```

Matrix `C` with same dimensions as `A`:

```
(C <- matrix(6:1, nrow = 2, ncol = 3, byrow = TRUE))
```

```
##      [,1] [,2] [,3]
## [1,]    6    5    4
## [2,]    3    2    1
```

Matrix addition:

```
A + C
```

```
##      [,1] [,2] [,3]
## [1,]    7    7    7
## [2,]    7    7    7
```

Matrix operations

```
A
```

```
##      [,1] [,2] [,3]
## [1,]    1    2    3
## [2,]    4    5    6
```

Matrix `C` with same dimensions as `A`:

```
(C <- matrix(6:1, nrow = 2, ncol = 3, byrow = TRUE))
```

```
##      [,1] [,2] [,3]
## [1,]    6    5    4
## [2,]    3    2    1
```

Element-wise multiplication:

```
A * C
```

```
##      [,1] [,2] [,3]
## [1,]    6   10   12
## [2,]   12   10    6
```

Matrix operations

```
A
```

```
##      [,1] [,2] [,3]
## [1,]    1    2    3
## [2,]    4    5    6
```

Rowwise normalization of A:

```
rowSums(A)
```

```
## [1]  6 15
```

```
A / rowSums(A)
```

```
##           [,1]      [,2] [,3]
## [1,] 0.1666667 0.3333333  0.5
## [2,] 0.2666667 0.3333333  0.4
```

Transpose:

```
t(A)
```

```
##      [,1] [,2]
## [1,]    1    4
## [2,]    2    5
## [3,]    3    6
```

Row and column names for matrix

As with data frames, row names and column names can optionally be set via `rownames()` and `colnames()`:

```
A
```

```
##      [,1] [,2] [,3]
## [1,]    1    2    3
## [2,]    4    5    6
```

```
rownames(A) <- c('row1', 'row2')
colnames(A) <- c('col1', 'col2', 'col3')
A
```

```
##      col1 col2 col3
## row1    1    2    3
## row2    4    5    6
```

```
A['row2',]
```

```
## col1 col2 col3
##    4    5    6
```

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Lists

In contrast vectors, lists can contain elements of different types:

```
list(1:3, 'abc', 3.1415, c(FALSE, TRUE, TRUE, FALSE))
```

```
## [[1]]
## [1] 1 2 3
##
## [[2]]
## [1] "abc"
##
## [[3]]
## [1] 3.1415
##
## [[4]]
## [1] FALSE  TRUE  TRUE FALSE
```

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Lists

You can think of a list as arbitrary "key-value" data structure. For each unique "key" (i.e. index), a list can hold a value of arbitrary type, even another list.

```
l <- list(a = 1:3, b = 'abc', c = 3.1415,
          d = c(FALSE, TRUE, TRUE, FALSE),
          e = list(1, 2, 3))
str(l)
```

```
## List of 5
##  $ a: int [1:3] 1 2 3
##  $ b: chr "abc"
##  $ c: num 3.14
##  $ d: logi [1:4] FALSE TRUE TRUE FALSE
##  $ e:List of 3
##   ..$ : num 1
##   ..$ : num 2
##   ..$ : num 3
```

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Indexing a list

If no key is given, the default keys are set as 1 to N:

```
(l <- list(1:3, 'abc', 3.1415, c(FALSE, TRUE, TRUE, FALSE)))
```

```
## [[1]]
## [1] 1 2 3
##
## [[2]]
## [1] "abc"
##
## [[3]]
## [1] 3.1415
##
## [[4]]
## [1] FALSE  TRUE  TRUE FALSE
```

Indexing with single square brackets **always results in a new list** (here, containing only a single element):

```
l[4]
```

```
## [[1]]
## [1] FALSE  TRUE  TRUE FALSE
```

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Indexing a list

If no key is given, the default keys are set as 1 to N:

```
(l <- list(1:3, 'abc', 3.1415, c(FALSE, TRUE, TRUE, FALSE)))
```

```
## [[1]]
## [1] 1 2 3
##
## [[2]]
## [1] "abc"
##
## [[3]]
## [1] 3.1415
##
## [[4]]
## [1] FALSE  TRUE  TRUE FALSE
```

Use double square brackets to get the actual element as vector:

```
l[[4]]
```

```
## [1] FALSE  TRUE  TRUE FALSE
```

Indexing a list

We can explicitly define keys for a list:

```
l <- list(a = 1:3, b = 'abc', c = 3.1415,
          d = c(FALSE, TRUE, TRUE, FALSE),
          e = list(1, 2, 3))
str(l)
```

```
## List of 5
##  $ a: int [1:3] 1 2 3
##  $ b: chr "abc"
##  $ c: num 3.14
##  $ d: logi [1:4] FALSE TRUE TRUE FALSE
##  $ e:List of 3
##   ..$ : num 1
##   ..$ : num 2
##   ..$ : num 3
```

The same rules for single and double square brackets apply:

```
l['d']
```

```
## $d
## [1] FALSE  TRUE  TRUE FALSE
```

Indexing a list

We can explicitly define keys for a list:

```
l <- list(a = 1:3, b = 'abc', c = 3.1415,
          d = c(FALSE, TRUE, TRUE, FALSE),
          e = list(1, 2, 3))
str(l)
```

```
## List of 5
##  $ a: int [1:3] 1 2 3
##  $ b: chr "abc"
##  $ c: num 3.14
##  $ d: logi [1:4] FALSE TRUE TRUE FALSE
##  $ e:List of 3
##   ..$ : num 1
##   ..$ : num 2
##   ..$ : num 3
```

The same rules for single and double square brackets apply:

```
l[['d']]
```

```
## [1] FALSE  TRUE  TRUE FALSE
```

Indexing a list

We can explicitly define keys for a list:

```
l <- list(a = 1:3, b = 'abc', c = 3.1415,
          d = c(FALSE, TRUE, TRUE, FALSE),
          e = list(1, 2, 3))
str(l)
```

```
## List of 5
##  $ a: int [1:3] 1 2 3
##  $ b: chr "abc"
##  $ c: num 3.14
##  $ d: logi [1:4] FALSE TRUE TRUE FALSE
##  $ e:List of 3
##   ..$ : num 1
##   ..$ : num 2
##   ..$ : num 3
```

A shortcut to access elements in a list by key is the dollar symbol:

```
l$d    # same as l[['d']]
```

```
## [1] FALSE  TRUE  TRUE FALSE
```

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Bag-of-words model

Bag-of-words model

Bag-of-words is a simple, but powerful representation of a text corpus.

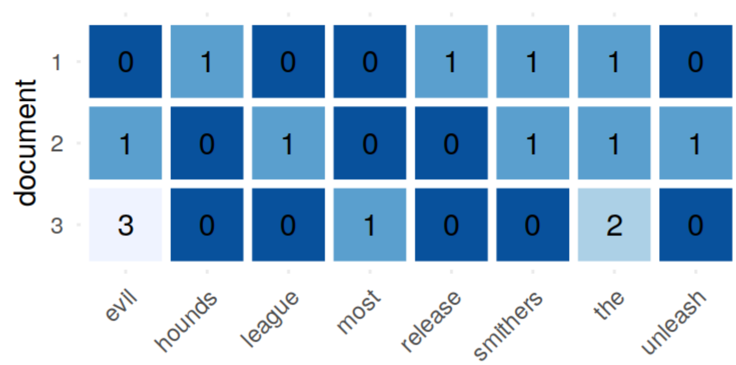
- each document in a corpus is "bag of its words"
  → store which words occur and how often do they occur
  → disregard grammar, word order
- basis for:
  - word frequency comparisons
  - document similarity and clustering
  - topic modeling
  - text classification, etc.
- result is a document term matrix (DTM) (also: document feature matrix)

Bag-of-words model – example

Three documents:

doc_id	text
1	Smithers, release the hounds.
2	Smithers, unleash the League of Evil!
3	The evil Evil of the most Evil.

The resulting DTM with **normalized** words:



- rows are N_{docs} documents, columns are words, elements are counts
- unique words (terms) of all documents make up vocabulary of size N_{terms}
- column sums: overall occurences per word; row sums: document length

Bag of words with n-grams

So far, we've used unigrams. Each word ("term") is counted individually.

We can also count **subsequent word combinations (n-grams)**. This counts \(n\) subsequent words for each word:

"Smithers, release the hounds."

→ as bigrams (2-grams):

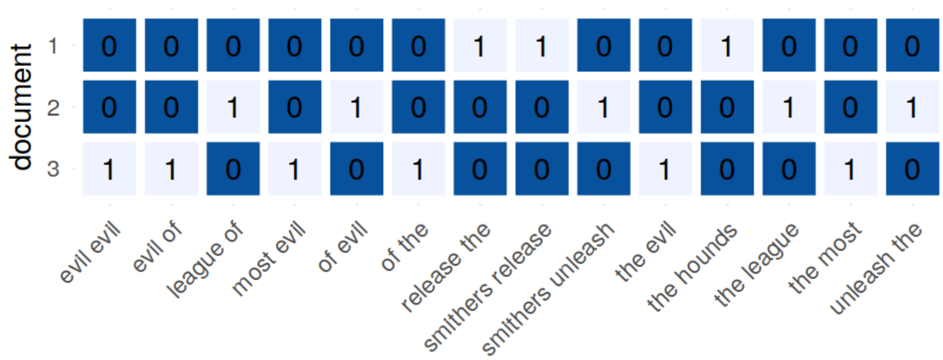
```
["smithers release", "release the", "the hounds"]
```

Bag of words with n-grams

Again, our example data:

doc_id	text
1	Smithers, release the hounds.
2	Smithers, unleash the League of Evil!
3	The evil Evil of the most Evil.

Bigrams:



- advantage: captures more "context"
- disadvantage: captures lots of very rare word combinations

Tf-idf weighting

Problem with BoW: common (uninformative) words (e.g. "the, a, and, or, …") that occur often in many documents overshadow more specific (potentially more interesting) words.

Solutions:

- use **stopword lists** → manual effort
- use a **weighting factor** that decreases the weight of uninformative words / increases the weight of specific words

Tf-idf weighting

Tf-idf (term frequency – inverse document frequency) is such a weighting factor.

For each term t in each document d in a corpus of all documents D, the tfidf weighting factor is calculated as product of two factors:

$$\text{tfidf}(t, d, D) = \text{tf}(t, d) \cdot \text{idf}(t, D)$$

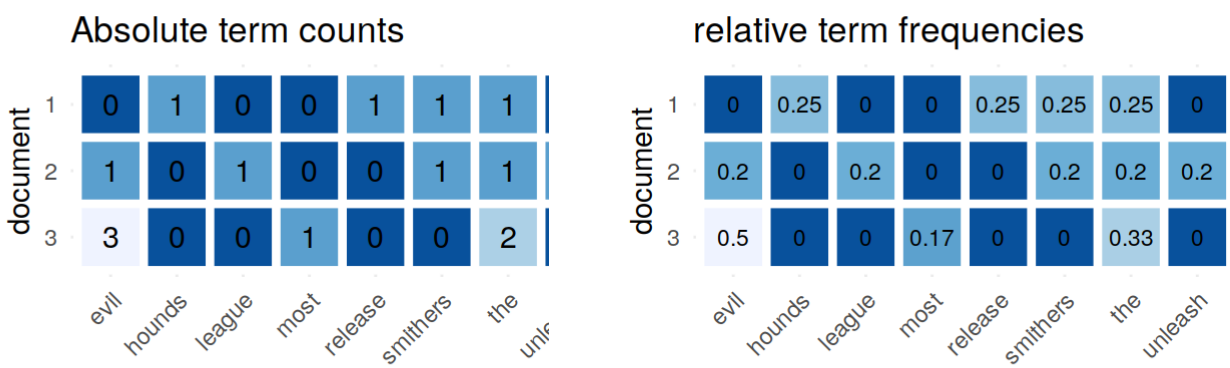
- $tf(t, d)$: term frequency – measures how often a word t occurs in document d
- $idf(t, D)$: inverse document frequency – inverse of how common a word t is across all documents D in a corpus

There are different weighting variants for both factors.

Term frequency \(\text{tf}\)

Common variants:

- absolute word count of term \(t\): \(\text{tf(t, d)} = N_{d,t}\)
- relative word frequency of \(t\) in a document \(d\): \(\text{tf(t, d)} = N_{d,t}/N_d\)
    - prevents that documents with many words get higher weights than those with few words



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Inverse document frequency idf

Again, many variants. We'll use this one:

$$\text{idf}(t, D) = log_2 (1 + \frac{|D|}{|d \in D: t \in d|})$$

- t: a term from our vocabulary of corpus D
- $|D|$: the number of documents in corpus D
- $|d \in D: t \in d|$: number of documents d in which t appears
- we assume that each t occurs at least once in D (otherwise a division by zero would be possible)
- we add 1 inside log in order to avoid an idf value of 0

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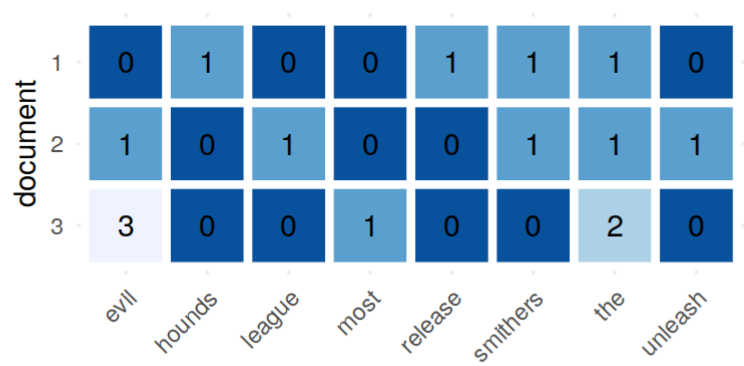
Inverse document frequency idf

Again, many variants. We'll use this one:

$$\text{idf}(t, D) = log_2 (1 + \frac{|D|}{|d \in D: t \in d|})$$



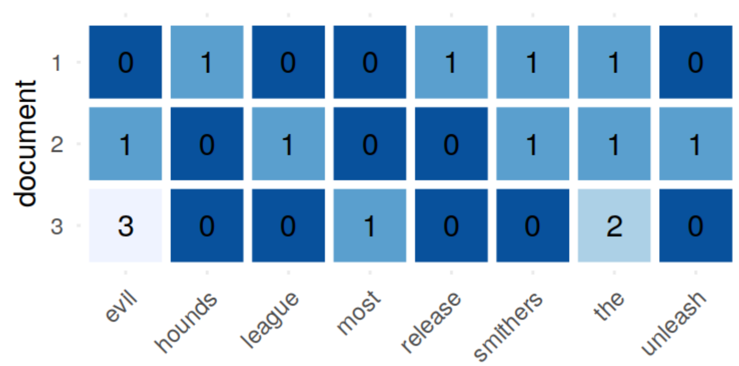
Calculate $|d \in D: t \in d|$ (number of doc. d in which t appears) for all terms:

```
##      evil    hounds    league      most   release smithers       the   unleash
##         2         1         1         1         1        2         3         1
```

Inverse document frequency idf

Again, many variants. We'll use this one:

$$\text{idf}(t, D) = \log_2 (1 + \frac{|D|}{|d \in D: t \in d|})$$



Plug-in to above formula and you get the idf for all terms:

```
##     evil    hounds    league      most   release smithers       the   unleash
##     1.32      2.00      2.00      2.00      2.00      1.32      1.00      2.00
```

This factor is multiplied to each term frequency
→ the more common the word in the corpus, the lower its idf value

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Why is \(\text{idf}\) logarithmically scaled?

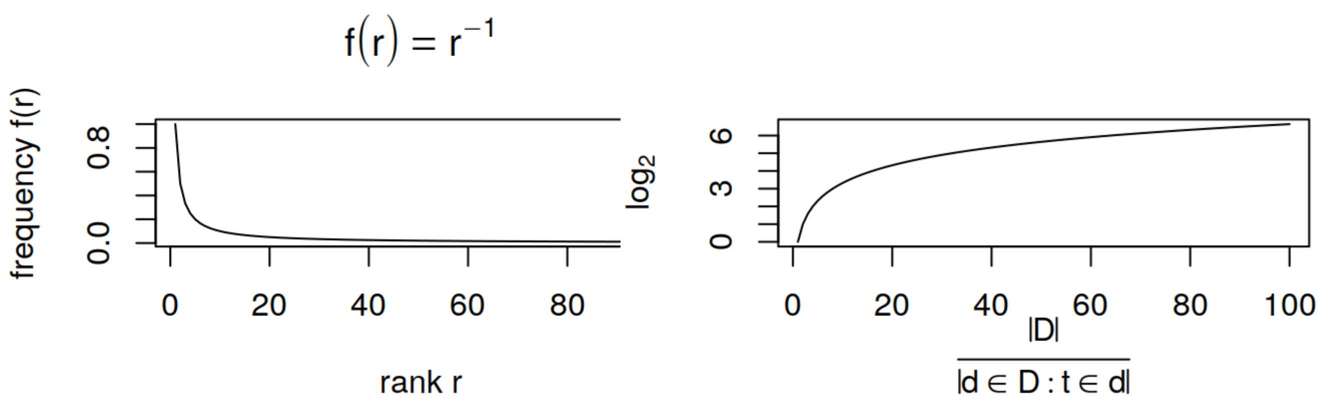
The distribution of words in a natural language text usually follows the "Zipfian distribution", which relates to Zipf's law:

> Zipf’s law states that the frequency that a word appears is inversely proportional to its rank. – Silge & Robinson 2017

\[\text{frequency} \propto r^{-1}\]

→ second most frequent word occurs half as often as the most frequent word; third most frequent word occurs a third of the time of the most frequent word, etc.

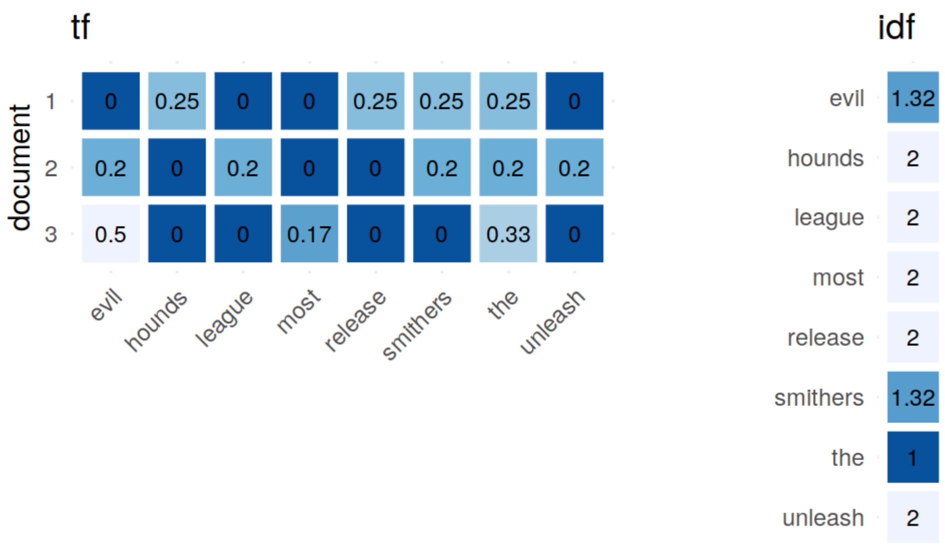
To account for that, we use logarithmical values:



Tf-idf weighting

Back to the initial formula:

\[\text{tfidf}(t, d, D) = \text{tf}(t, d) \cdot \text{idf}(t, D) \]

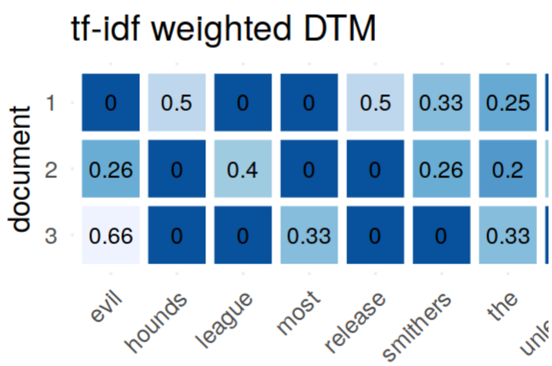


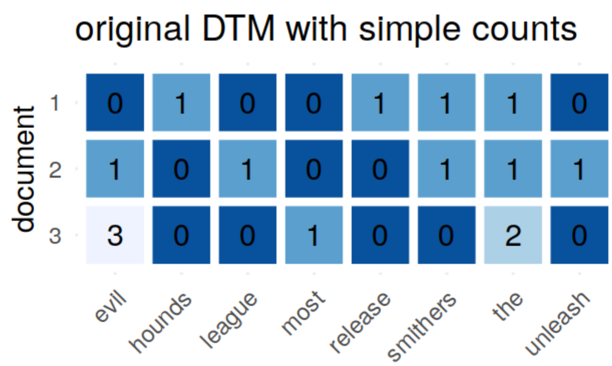
Tf-idf weighting

Back to the initial formula:

\[\text{tfidf}(t, d, D) = \text{tf}(t, d) \cdot \text{idf}(t, D) \]

Result after matrix multiplication between \(\text{tf}\) and diagonal of \(\text{idf}\):





→ uncommon (i.e. more specific) words get higher weight (e.g. "hounds" or "league")

Feature vectors

Once we have a DTM, we can consider each document as a **vector across terms** (each row in a DTM is a vector of size \(N_{terms}\)).

E.g. document #3 has the following term count vector:

```
##          [,1]
## evil        3
## hounds      0
## league      0
## most        1
## release     0
## smithers    0
## the         2
## unleash     0
```

In machine learning terminology this is a **feature vector**. We can use these features for example for document classification, **document similarity**, document clustering, etc.

Non-English text

Most packages, tutorials, etc. are designed for English language texts. When you work with other languages, you may need to apply other methods for text preprocessing. For example, working with German texts might require proper lemmatization to bring words from their inflected form to their base form (e.g. "geschlossen" → "schließen").

Practical text mining with the `tm` package

The `tm` package

- extensive set of tools for text mining in R
- developed since 2008 by Feinerer et al.

Resources to start:

- [package overview on CRAN]
- [Introduction to the tm Package]

I will demonstrate how to use the package to investigate word frequency and document similarity.

Creating a corpus

A corpus contains the raw text for each document (identified by a document ID).

The base class is `VCorpus` which can be initialized with a data source.

Read plain text files from a directory:

```
corpus <- VCorpus(DirSource('path/to/documents', encoding = 'UTF-8'),
                  readerControl = list(language = 'de'))  # default language
```

- `encoding` specifies the text format → important for special characters (like German umlauts)
- many file formats supported (Word documents, PDF documents, etc.)

Creating a corpus

A data frame can be converted to a corpus, too. It must contain at least the columns `doc_id`, `text`:

```
df_texts
##  doc_id  text                                              date
##  <chr>   <chr>                                             <chr>
## 1 Grüne   "A. EINLEITUNG\nLiebe Bürgerinnen und Bürger,… 2017…
## 2 Linke   "Die Zukunft, für die wir kämpfen: SOZIAL. GE… 2017…
## 3 SPD     "Es ist Zeit für mehr Gerechtigkeit!\n2017 is… 2017…
```

```
corpus <- VCorpus(DataframeSource(df_texts))
```

The English Europarl corpus

We load a sample of the European Parliament Proceedings Parallel Corpus with English texts. If you want to follow along, download "08textmining-resource.zip" from the tutorial website.

```
library(tm)

europarl <- VCorpus(DirSource('08textmining-resources/nltk_europarl'))
europarl
```

```
## <<VCorpus>>
## Metadata:  corpus specific: 0, document level (indexed): 0
## Content:  documents: 10
```

Inspecting a corpus

`inspect` returns information on corpora and documents:

```
inspect(europarl)
```

```
## <<VCorpus>>
## Metadata:  corpus specific: 0, document level (indexed): 0
## Content:  documents: 10
##
## [[1]]
## <<PlainTextDocument>>
## Metadata:  7
## Content:  chars: 145780
##
## [[2]]
## <<PlainTextDocument>>
## Metadata:  7
## Content:  chars: 554441
##
## [[3]]
## <<PlainTextDocument>>
## Metadata:  7
## Content:  chars: 228141
##
## [[4]]
## <<PlainTextDocument>>
## Metadata:  7
## Content:  chars: 559
##
## [[5]]
## <<PlainTextDocument>>
## Metadata:  7
## Content:  chars: 314931
##
## [[6]]
## <<PlainTextDocument>>
## Metadata:  7
## Content:  chars: 147766
##
## [[7]]
## <<PlainTextDocument>>
## Metadata:  7
## Content:  chars: 170580
```

Inspecting a corpus

Information for the fourth document:

```
inspect(europarl[[4]])
```

```
## <<PlainTextDocument>>
## Metadata:  7
## Content:  chars: 559
##
##
## Adoption of the Minutes of the previous sitting Mr President , I simply w
## There was a terrorist attack this morning in Madrid .
## Someone planted a car bomb and one person has died .
## On behalf of my Group , I once again condemn these terrorist acts .
## Thank you , Mrs Fraga Estévez .
## We had heard about this regrettable incident .
## Unfortunately , the terrorist murderers are once again punishing Spanish
## I note your comments with particular keenness , as you may expect , given
## ( The Minutes were approved )
```

Inspecting a corpus

Get the raw text of a document with `content()`:

```
head(content(europarl[[1]]))
```

```
## [1] " "
## [2] "Resumption of the session I declare resumed the session of the Europ
## [3] "Although , as you will have seen , the dreaded ' millennium bug ' fa
## [4] "You have requested a debate on this subject in the course of the nex
## [5] "In the meantime , I should like to observe a minute ' s silence , as
## [6] "Please rise , then , for this minute ' s silence ."
```

Text processing

We want to investigate word frequencies in our corpus. To count words, we need to transform raw text into a normalized sequence of tokens.

Why normalize text? Consider these documents:

1. "We can't explain what we don't know."
2. "We cannot do that. We do not want that."

- instances of "We" and "we" shouldn't be counted separately → transform to lower case
- instances of contracted and expanded words ("can't" and "cannot") shouldn't be counted separately → expand all contractions

Text processing

Text processing includes many steps and hence many decisions that have **big effect** on your results. Several possibilities will be shown here. If and how to apply them depends heavily on your data and your later analysis.

Can you think of an example, where unconditional lower case transformation is bad?

Text normalization

Normalization might involve some of the following steps:

- replace contractions ("shouldn't" → "should not")
- remove punctuation and special characters
- case conversion (usually to lower case)
- remove stopwords (extremely common words like
"the, a, to, …")
- correct spelling
- stemming / lemmatization

The order is important!

Text normalization with `tm`

Text normalization can be employed with "transformations" in `tm`.

Concept:

```
tm_map(<CORPUS>, content_transformer(<FUNCTION>), <OPTIONAL AR
```

- `<FUNCTION>` can be any function that takes a character vector, transforms it, and returns the result as character vector
- `<OPTIONAL ARGS>` are fixed arguments passed to `<FUNCTION>`
- `tm` comes with many predefined transformation functions like `removeWords`, `removePunctuation`, `stemDocuments`, …

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Text normalization with `tm`

A transformation pipeline applied to our corpus (only showing the first three documents):

Original documents:

```
##   name                                                    text
## 1    1 Resumption of the session I declare resumed the se...
## 2    2 Adoption of the Minutes of the previous sitting Th...
## 3    3 Middle East peace process ( continuation ) The nex...
```

```
europarl <- tm_map(europarl, content_transformer(textclean::replace_contract
  tm_map(content_transformer(tolower)) %>%
  tm_map(removeNumbers) %>%
  tm_map(removeWords, stopwords('en')) %>%
  tm_map(removePunctuation) %>%
  tm_map(stripWhitespace)
```

After text normalization:

```
##   name                                                    text
## 1    1 resumption session declare resumed session europea...
## 2    2 adoption minutes previous sitting minutes yesterda...
## 3    3 middle east peace process continuation next item c...
```

Creating a DTM

- `DocumentTermMatrix()` takes a corpus, tokenizes it, generates document term matrix (DTM)
- parameter `control`: adjust the transformation from corpus to DTM
  - here: allow words that are at least 2 characters long
  - by default, words with less than 3 characters would be removed

```
dtm <- DocumentTermMatrix(europarl,
                          control = list(wordLengths = c(2, Inf)))
inspect(dtm)
```

```
## <<DocumentTermMatrix (documents: 10, terms: 14118)>>
## Non-/sparse entries: 42920/98260
## Sparsity           : 70%
## Maximal term length: 24
## Weighting          : term frequency (tf)
## Sample             :
##                  Terms
## Docs              also can commission european  mr must parliament
##   ep-00-01-17.en    82  46        130       93 128   53         79
##   ep-00-01-18.en   306 200        692      477 356  316        258
##   ep-00-01-19.en   132 107        104      187 157   99        104
##   ep-00-01-21.en     0   0          0        0   1    0          0
##   ep-00-02-02.en   188 118        194      298 220  157        191
##   ep-00-02-03.en    69  59         36      146  73   68        101
##   ep-00-02-14.en    80  63        126      132  86   75         91
##   ep-00-02-15.en   312 255        562      449 365  375        216
##   ep-00-02-16.en   293 183        260      556 360  179        212
##   ep-00-02-17.en   185 142        184      336 307  215        116
##                  Terms
## Docs              president union will
##   ep-00-01-17.en         89    56   94
##   ep-00-01-18.en        203   169  575
##   ep-00-01-19.en         89   114  284
##   ep-00-01-21.en          1     0    0
##   ep-00-02-02.en        183   199  297
##   ep-00-02-03.en         47    50  113
##   ep-00-02-14.en         90    61  123
```

Creating a DTM

- a `tm` DTM is a **sparse matrix** → only values \(\ne 0\) are stored → saves a lot of memory
- many values in a DTM are 0 for natural language texts → can you explain why?
- some functions in R can't work with sparse matrices → convert to an ordinary matrix then:

```
as.matrix(dtm)[,1:8]   # cast to an ordinary matrix and see first 8 terms
```

```
##                  Terms
## Docs              aan abandon abandoned abandoning abandonment abattoirs
##   ep-00-01-17.en    0       0         0          0           0         0
##   ep-00-01-18.en    0       1         4          0           0         0
##   ep-00-01-19.en    0       1         1          1           0         0
##   ep-00-01-21.en    0       0         0          0           0         0
##   ep-00-02-02.en    0       0         0          0           0         0
##   ep-00-02-03.en    0       1         6          0           0         0
##   ep-00-02-14.en    0       0         1          0           0         0
##   ep-00-02-15.en    1       0         1          0           0         1
##   ep-00-02-16.en    0       0         0          0           0         0
##   ep-00-02-17.en    0       1         6          0           1         0
##                  Terms
## Docs              abb abbalsthom
##   ep-00-01-17.en    0          0
##   ep-00-01-18.en    3          0
##   ep-00-01-19.en    0          0
##   ep-00-01-21.en    0          0
##   ep-00-02-02.en    0          0
##   ep-00-02-03.en    0          0
##   ep-00-02-14.en    0          0
##   ep-00-02-15.en    0          0
##   ep-00-02-16.en    0          0
##   ep-00-02-17.en    0          7
```

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Creating a \(\text{tfidf}\)-weighted DTM

You can create a \(\text{tfidf}\)-weighted matrix by passing `weightTfIdf` as a weighting function:

```
tfidf_dtm <- DocumentTermMatrix(europarl,
                                control = list(weighting = weightTfIdf))
inspect(tfidf_dtm)
```

```
## <<DocumentTermMatrix (documents: 10, terms: 14058)>>
## Non-/sparse entries: 42518/98062
## Sparsity           : 70%
## Maximal term length: 24
## Weighting          : term frequency - inverse document frequency (normali
## Sample             :
##                  Terms
## Docs                       car    estévez      fraga     incident
##   ep-00-01-17.en 0.000000e+00 0.00000000 0.00000000 0.000000e+00
##   ep-00-01-18.en 8.929568e-05 0.00000000 0.00000000 2.655956e-04
##   ep-00-01-19.en 0.000000e+00 0.00000000 0.00000000 0.000000e+00
##   ep-00-01-21.en 2.083333e-02 0.06920684 0.06920684 2.754017e-02
##   ep-00-02-02.en 4.004806e-05 0.00000000 0.00000000 0.000000e+00
##   ep-00-02-03.en 8.155637e-03 0.00000000 0.00000000 0.000000e+00
##   ep-00-02-14.en 7.293414e-05 0.00000000 0.00000000 0.000000e+00
##   ep-00-02-15.en 0.000000e+00 0.00000000 0.00000000 2.907957e-05
##   ep-00-02-16.en 0.000000e+00 0.00000000 0.00000000 0.000000e+00
##   ep-00-02-17.en 0.000000e+00 0.00000000 0.00000000 2.181760e-04
##                  Terms
## Docs               keenness       madrid    murderers    planted
##   ep-00-01-17.en 0.00000000 0.0000000000 0.000000e+00 0.00000000
##   ep-00-01-18.en 0.00000000 0.0000000000 0.000000e+00 0.00000000
##   ep-00-01-19.en 0.00000000 0.0001884217 0.000000e+00 0.00000000
##   ep-00-01-21.en 0.06920684 0.0361867832 4.837350e-02 0.06920684
##   ep-00-02-02.en 0.00000000 0.0000000000 0.000000e+00 0.00000000
##   ep-00-02-03.en 0.00000000 0.0000000000 0.000000e+00 0.00000000
##   ep-00-02-14.en 0.00000000 0.0000000000 0.000000e+00 0.00000000
##   ep-00-02-15.en 0.00000000 0.0000382095 0.000000e+00 0.00000000
##   ep-00-02-16.en 0.00000000 0.0000000000 0.000000e+00 0.00000000
##   ep-00-02-17.en 0.00000000 0.0000000000 7.664394e-05 0.00000000
##                  Terms
```

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Working with a DTM

`Terms()` returns the vocabulary of a DTM as a character string vector. We can see how many unique words we have:

```
length(Terms(dtm))
```

```
## [1] 14118
```

```
range(dtm)
```

```
## [1]   0 692
```

`findFreqTerms()` returns the terms that occur above a certain threshold (here at least 500 occurrences):

```
findFreqTerms(dtm, 500)
```

```
##  [1] "also"         "can"          "commission"   "commissioner"
##  [5] "committee"    "community"    "council"      "countries"
##  [9] "development"  "europe"       "european"     "fact"
## [13] "first"        "however"      "important"    "just"
## [17] "like"         "made"         "make"         "member"
## [21] "mr"           "must"         "need"         "new"
## [25] "now"          "one"          "parliament"   "people"
## [29] "policy"       "political"    "president"    "question"
## [33] "report"       "rights"       "say"          "social"
## [37] "states"       "support"      "take"         "therefore"
## [41] "time"         "union"        "us"           "way"
## [45] "will"         "within"       "work"
```

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Working with a DTM

`findMostFreqTerms()` returns the \(N\) most frequent terms per document:

```
findMostFreqTerms(dtm, 5)
```

```
## $`ep-00-01-17.en`
## commission         mr    regions       like     report
##        130        128        103         98         98
##
## $`ep-00-01-18.en`
## commission       will   european         mr       must
##        692        575        477        356        316
##
## $`ep-00-01-19.en`
##     will  council european       mr     also
##      284      218      187      157      132
##
## $`ep-00-01-21.en`
## terrorist   minutes   spanish      acts  adoption
##         3         2         2         1         1
##
## $`ep-00-02-02.en`
##   european       will         mr      union commission
##        298        297        220        199        194
##
## $`ep-00-02-03.en`
##   european       will parliament        car       cars
##        146        113        101         96         93
##
## $`ep-00-02-14.en`
##   european commission       will      areas      urban
##        132        126        123        101         99
##
## $`ep-00-02-15.en`
##       will commission   european       must         mr
##        565        562        449        375        365
##
## $`ep-00-02-16.en`
## european     will    union       mr   council
##      556      484      391      360      325
##
```

Working with a DTM

With a tf-idf weighted DTM, we get a better sense of which terms are central to each document:

```
findMostFreqTerms(tfidf_dtm, 5)
```

```
## $`ep-00-01-17.en`
##      berend  schroedter        koch  structural         cen
## 0.002601040 0.002506025 0.002095435 0.001830871 0.001800720
##
## $`ep-00-01-18.en`
##      hulten  commission        will    forestry   discharge
## 0.002521388 0.002348167 0.001951150 0.001853961 0.001829658
##
## $`ep-00-01-19.en`
##       tobin      israel     anchovy     israeli        will
## 0.005667232 0.004407847 0.002702659 0.002518770 0.002341426
##
## $`ep-00-01-21.en`
##    estévez      fraga   keenness    planted  terrorist
## 0.06920684 0.06920684 0.06920684 0.06920684 0.06250000
##
## $`ep-00-02-02.en`
## conciliation      altener     european         will         card
##  0.002488211  0.002045752  0.001814054  0.001807966  0.001535279
##
## $`ep-00-02-03.en`
##        cars   recycling         car    vehicles     endlife
## 0.013723371 0.010060176 0.008155637 0.007636659 0.006706784
##
## $`ep-00-02-14.en`
##    interreg      strand       urban       rural         iii
## 0.010768148 0.005757826 0.003715465 0.002476977 0.002121101
##
## $`ep-00-02-15.en`
##       water        will  commission   lienemann   additives
## 0.001954556 0.001889213 0.001879182 0.001685555 0.001604799
##
## $`ep-00-02-16.en`
##      cyprus         acp   macedonia    european     cypriot
## 0.003717818 0.002682789 0.002163648 0.001948263 0.001914479
##
```

Document similarity

Document similarity and distance

Feature vectors such as word counts per document in a DTM can be used to measure **similarity between documents**.

Imagine we had a very simple corpus with only three documents and two words in the vocabulary:

```
##      hello world
## doc1     2     1
## doc2     3     2
## doc3     0     1
```

→ each document is a two-dimensional feature vector, e.g.:
\(\text{doc1} = \begin{pmatrix}2 \\ 1 \end{pmatrix}\).

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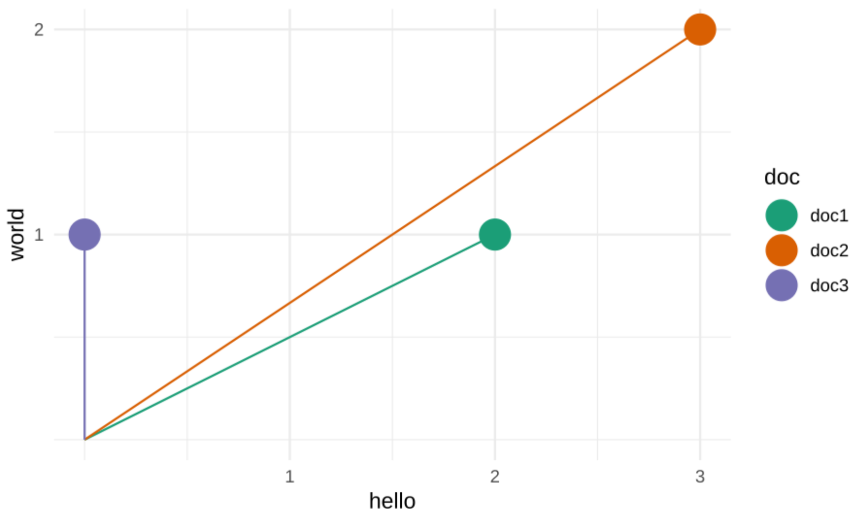
Document similarity and distance

Since we have two-dimensional feature vectors, we could visualize feature vectors in cartesian space:



How can we measure how close or far apart these vectors are?

Document similarity and distance

If normalized to a range of $[0, 1]$, similarity and distance are **complements**. You can then convert between both:

$\text{distance} = 1 - \text{similarity}$.

A distance of 0 means two vectors are identical (they have maximum similarity of 1).

Distance measures

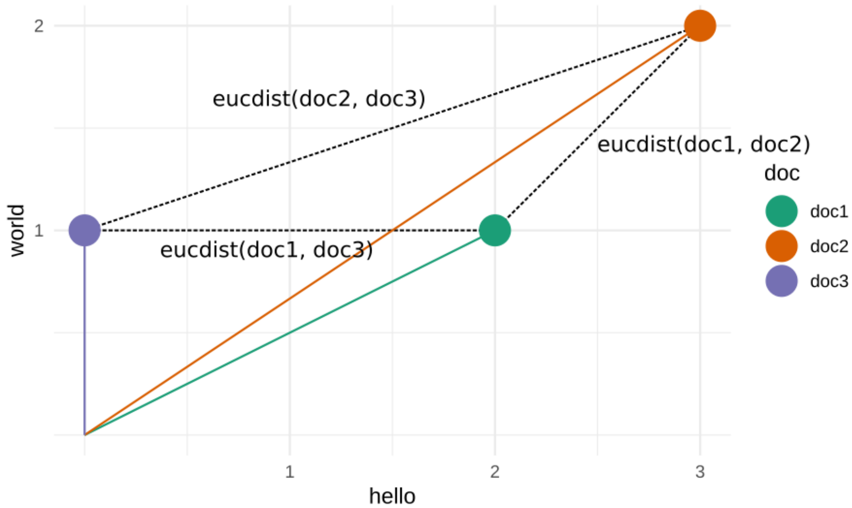
We can use **similarity and distance measures** to measure a degree of closeness (or distance) between two feature vectors (i.e. documents).

There are many different measures, but a proper distance metric must satisfy the following conditions for distance metric d and feature vectors x, y, z (A. Huang 2008):

1. $d(x, y) \ge 0$: the distance can never be negative.
2. $d(x, y) = 0$ if and only if $x = y$: (only) identical vectors have a distance of 0.
3. $d(x, y) = d(y, x)$: distances are symmetric.
4. $d(x, z) \le d(x, y) + d(y, z)$: satisfies triangle inequality.

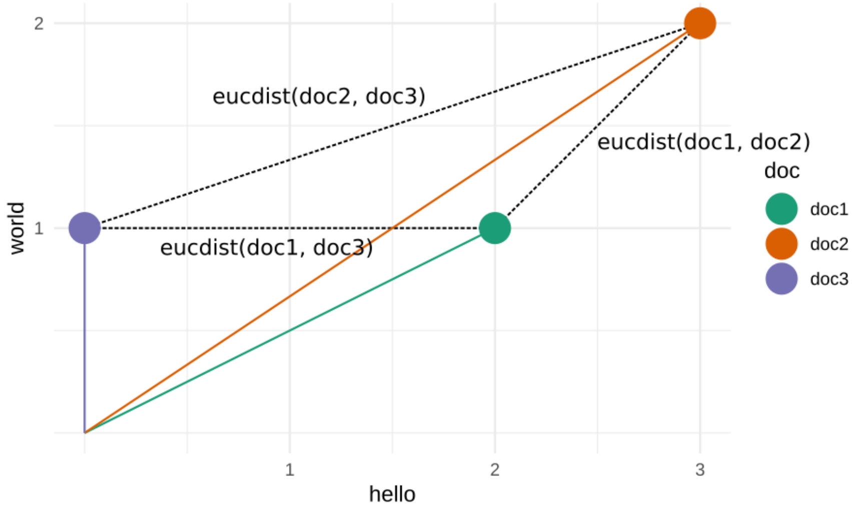
Euclidian distance

The Euclidian distance is the length of the straight line between two points in space.



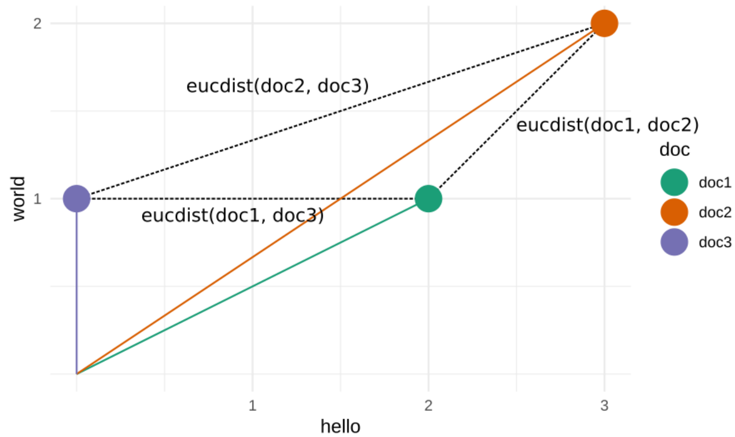
In 2D, it's an application of the Pythagorean theorem \(c = \sqrt{a^2 + b^2}\). For doc2 and doc3 this means: \(\sqrt{(3-0)^2 + (2-1)^2}\).

Euclidian distance



General formular: \(d(x, y) = \sqrt{\sum_{i=1}^{n}(x_i-y_i)^2}\) for vectors \(x\), \(y\) in \(n\)-dimensional space. This distance is also called the L2-norm.

Euclidian distance



The Euclidian distance satisfies all conditions for distance metrics.

Beware: The euclidian distance takes the length of the vectors into account (not only their direction!). → in a DTM, the total count of words determines the distance.

How can you make sure that only the proportion of words is taken into account?

Euclidian distance

In R, the function `dist` provides several distance measures. The default is the Euclidian distance. The distances between each row are calculated and returned as `dist` type ("triangular matrix"):

```
dist(docs)
```

```
##          doc1     doc2
## doc2 1.414214
## doc3 2.000000 3.162278
```

Using a normalized DTM:

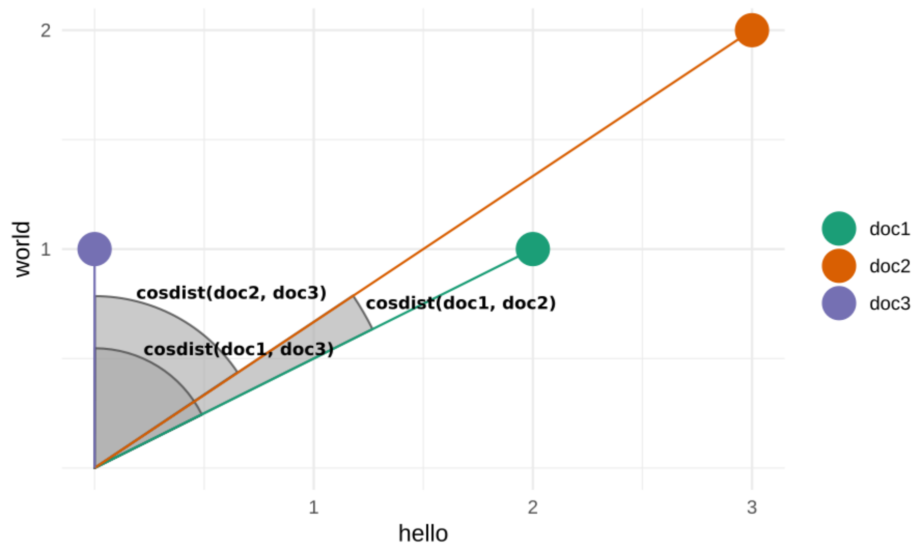
```
docs_normed <- docs / rowSums(docs)   # word proportions
dist(docs_normed)
```

```
##           doc1      doc2
## doc2 0.0942809
## doc3 0.9428090 0.8485281
```

You can use `as.matrix()` to convert to a distance to a proper matrix.

Cosine distance

The cosine distance uses the angle between two vectors as distance metric:



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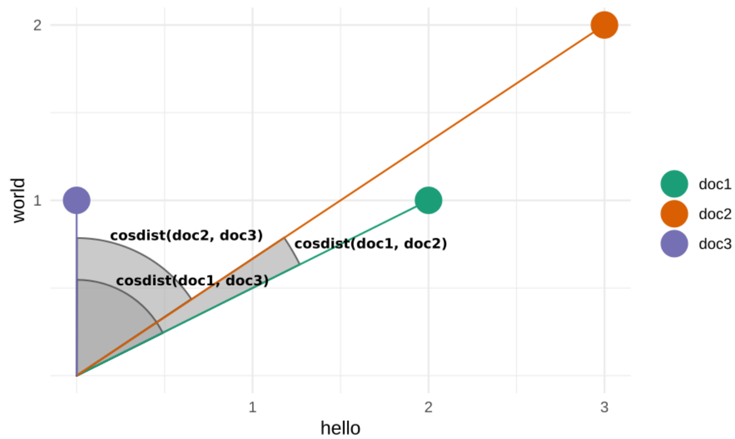
Cosine distance



The angle \(\cos(\theta)\) between vectors \(x\), \(y\) can be calculated with:

\[\cos(\theta) = \frac{x \cdot y}{\|x\| \|y\|} \] → calculate dot product of \(x\) and \(y\) and divide by product of their magnitudes (their "length").

Cosine distance

Example in R for angle between doc1 and doc2:

```
doc1 <- docs['doc1',]
doc2 <- docs['doc2',]
cos_theta <- (doc1 %*% doc2) / (sqrt(sum(doc1^2)) * sqrt(sum(doc2^2)))
rad2deg(acos(cos_theta))   # cos^-1 (arc-cosine) converted to degrees
```

```
##          [,1]
## [1,] 7.125016
```

A function to calculate the cosine distance between \(n\)-dimensional feature vectors in a matrix `x`:

```
cosineDist <- function(x) {
  cos_theta <- x %*% t(x) / (sqrt(rowSums(x^2) %*% t(rowSums(x^2))))
  as.dist(2 * acos(cos_theta) / pi)   # normalize to range [0, 1]
}

cosineDist(docs)
```

```
##            doc1       doc2
## doc2 0.07916685
## doc3 0.70483276 0.62566592
```

Cosine distance

The cosine distance only takes the direction of the vectors into account, not their length. This means it is invariant to scaling the vectors.

$$ x = \begin{pmatrix}2 \\ 1 \end{pmatrix},\\ y = \begin{pmatrix}4 \\ 2 \end{pmatrix} $$

What is the angle between these vectors?

It is 0 because $y = 2x$. Both vectors point in the same direction, hence their angle is the same. Only their magnitude is different.

In practical terms this means the cosine distance only takes word proportions into account.

The cosine distance does not adhere to the second condition of distance metrics (only identical vectors have a distance of 0).

Closing words on document similarity

For illustrative purposes, we've used vectors in 2D space, i.e. with only two words ("hello" and "world"). Most text corpora contain thousands of words. **Distances can be calculated in the same way in this \(n\)-dimensional space.**

There are much more distance metrics, but Euclidian and cosine distance are among the most popular.

Once you have a distance matrix, you can use it for **clustering documents**.

Remember that **we only compare word usage in documents**, not meaning, intent or sentiment. Two documents may have similar word usage but different meaning:

doc1 = "not all cats are beautiful"
doc2 = "all cats are not beautiful"

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The `tidytext` package

`tm` and `tidytext`

The tidytext package integrates Text Mining into the tidyverse framework. Similar things as with tm can be done, but it uses data frames in long table format instead of matrices.

The following slides are just for reference, so that you can see how you can use tidytext in conjuction with a tm corpus. Check out Julia Silge, David Robinson 2018: Text mining with R (free online book) if you want to do more with this package.

tm and tidytext

It's possible to convert a `tm` matrix to a data frame which can be used with the tidytext package Silge & Robinson 2017. You can then use all the data transformations on this data frame that you already know.

```
library(tidytext)

docs_subset <- paste0('ep-00-01-', c(17:19, 21), '.en')

# convert tf-idf matrix to data frame and filter for a subset of documents
df <- tidy(tfidf_dtm) %>% filter(document %in% docs_subset)
head(df)
```

```
## # A tibble: 6 x 3
##   document       term        count
##   <chr>          <chr>       <dbl>
## 1 ep-00-01-17.en abc     0.000286
## 2 ep-00-01-17.en abide   0.000114
## 3 ep-00-01-17.en ability 0.0000277
## 4 ep-00-01-17.en able    0.000223
## 5 ep-00-01-17.en abreast 0.000286
## 6 ep-00-01-17.en abroad  0.000114
```

tm and tidytext

Identify the top words per document by tf-idf value:

```
top_per_doc <- df %>%
  group_by(document) %>%
  top_n(10, count) %>%
  ungroup() %>%
  arrange(document, count) %>%
  mutate(order = row_number())  # necessary for plot on next slide

top_per_doc
```

```
## # A tibble: 40 x 4
##    document       term          count order
##    <chr>          <chr>         <dbl> <int>
##  1 ep-00-01-17.en rural      0.00137     1
##  2 ep-00-01-17.en tunnel     0.00143     2
##  3 ep-00-01-17.en advisers   0.00150     3
##  4 ep-00-01-17.en guidelines 0.00150     4
##  5 ep-00-01-17.en commission 0.00170     5
##  6 ep-00-01-17.en cen        0.00180     6
##  7 ep-00-01-17.en structural 0.00183     7
##  8 ep-00-01-17.en koch       0.00210     8
##  9 ep-00-01-17.en schroedter 0.00251     9
## 10 ep-00-01-17.en berend     0.00260    10
## # ... with 30 more rows
```

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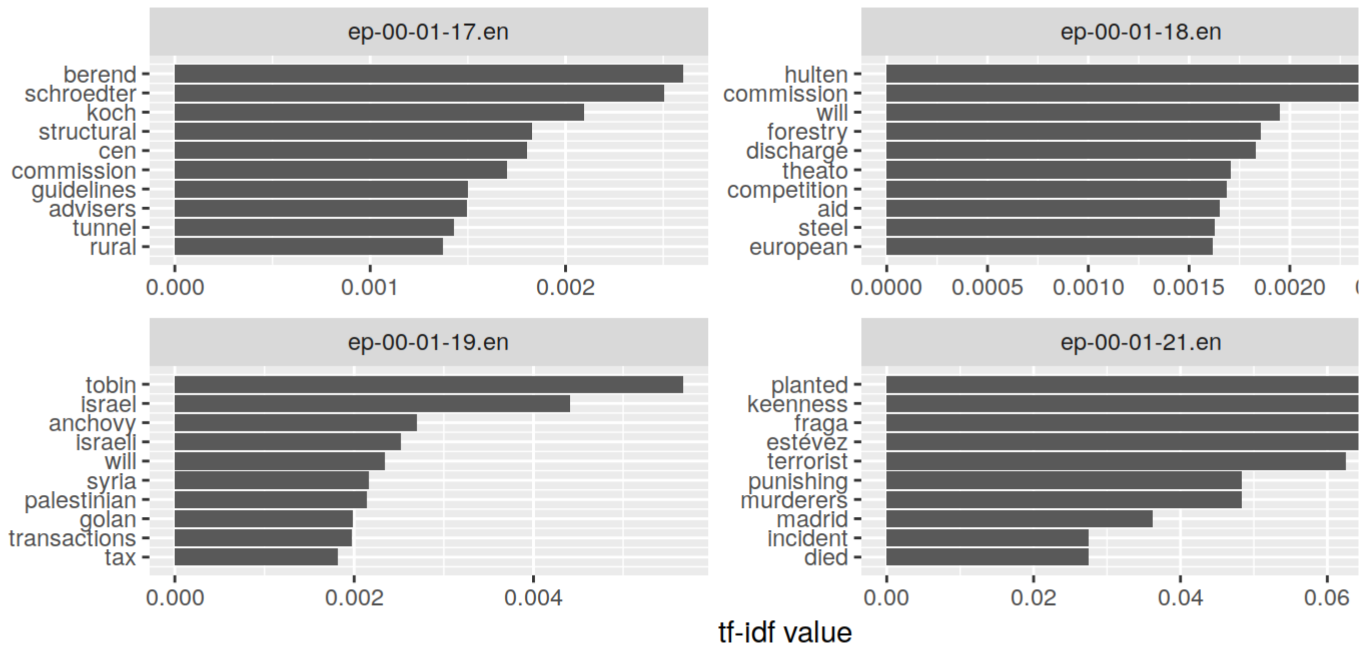
tm and tidytext

```
# use "order" on x-axis so that we order per tfidf value
ggplot(top_per_doc, aes(order, count)) +
  geom_col() +
  # add words as labels
  scale_x_continuous(breaks = top_per_doc$order, labels = top_per_doc$term)
  xlab(NULL) + ylab('tf-idf value') + coord_flip() +
  # every facet can have different x and y scales
  facet_wrap(~document, ncol = 2, scales = 'free')
```



Literature

- Feinerer et al 2008: Text Mining Infrastructure in R
- Julia Silge, David Robinson 2018: Text mining with R – available online for free
- Kwartler 2017: Text Mining in Practice with R
- Ken Benoit, Paul Nulty (in progress): Quantitative Text Analysis Using R (with quanteda package)

Tasks

See dedicated tasks sheet on the tutorial website.