

WZB



Wissenschaftszentrum Berlin
für Sozialforschung

R Tutorial at the WZB

09 - Text mining II

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Today's schedule

1. Short recap
2. Practical text mining with the `tm` package (II)
3. Document similarity

Short recap

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 ARGS>)
```

- **<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`, ...

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 $\neq 0$ 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
```

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
## ep-00-01-17.en 0.000000e+00 0.000000000 0.000000000 0.000000e+00
## ep-00-01-18.en 8.929568e-05 0.000000000 0.000000000 2.655956e-04
## ep-00-01-19.en 0.000000e+00 0.000000000 0.000000000 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 0.000000000 0.000000000 0.000000e+00
## ep-00-02-03.en 8.155637e-03 0.000000000 0.000000000 0.000000e+00
## ep-00-02-14.en 7.293414e-05 0.000000000 0.000000000 0.000000e+00
## ep-00-02-15.en 0.000000e+00 0.000000000 0.000000000 2.907957e-05
## ep-00-02-16.en 0.000000e+00 0.000000000 0.000000000 0.000000e+00
## ep-00-02-17.en 0.000000e+00 0.000000000 0.000000000 2.181760e-04
##
##           Terms
## Docs
##           keenness      madrid      murderers      planted
## ep-00-01-17.en 0.000000000 0.00000000000 0.000000e+00 0.000000000
## ep-00-01-18.en 0.000000000 0.00000000000 0.000000e+00 0.000000000
## ep-00-01-19.en 0.000000000 0.0001884217 0.000000e+00 0.000000000
## ep-00-01-21.en 0.06920684 0.0361867832 4.837350e-02 0.06920684
## ep-00-02-02.en 0.000000000 0.00000000000 0.000000e+00 0.000000000
## ep-00-02-03.en 0.000000000 0.00000000000 0.000000e+00 0.000000000
## ep-00-02-14.en 0.000000000 0.00000000000 0.000000e+00 0.000000000
## ep-00-02-15.en 0.000000000 0.0000382095 0.000000e+00 0.000000000
## ep-00-02-16.en 0.000000000 0.00000000000 0.000000e+00 0.000000000
## ep-00-02-17.en 0.000000000 0.00000000000 7.664394e-05 0.000000000
##
##           Terms
```

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"
```

Working with a DTM

`findMostFreqTerms()` returns the $\backslash(N\backslash)$ 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:

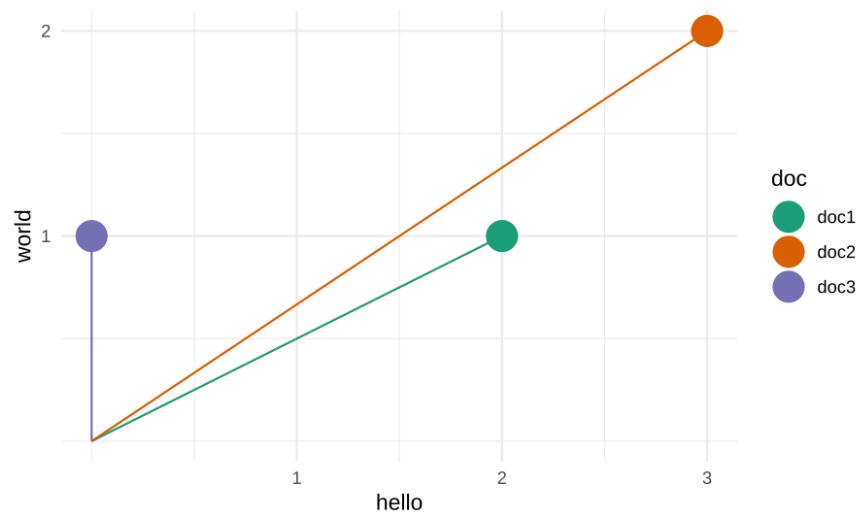
##		hello	world
##	doc1	2	1
##	doc2	3	2
##	doc3	0	1

→ each document is a two-dimensional feature vector, e.g.:

$\text{doc1} = \begin{pmatrix} 2 \\ 1 \end{pmatrix}$.

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

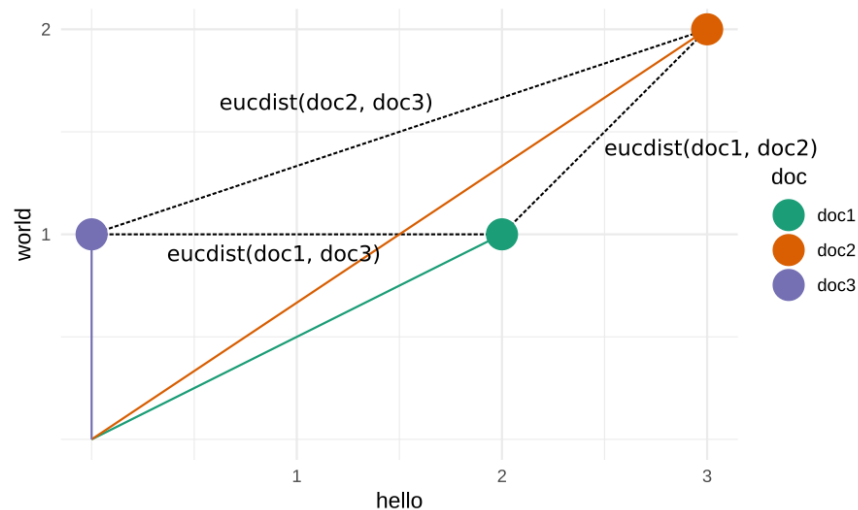
We can use **similarity and distance measures** to measure a degree of closeness (or distance) between two feature vectors (i.e. documents).

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. $d(x, y) \geq 0$: 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. $d(x, z) \leq d(x, y) + d(y, z)$: satisfies triangle inequality.

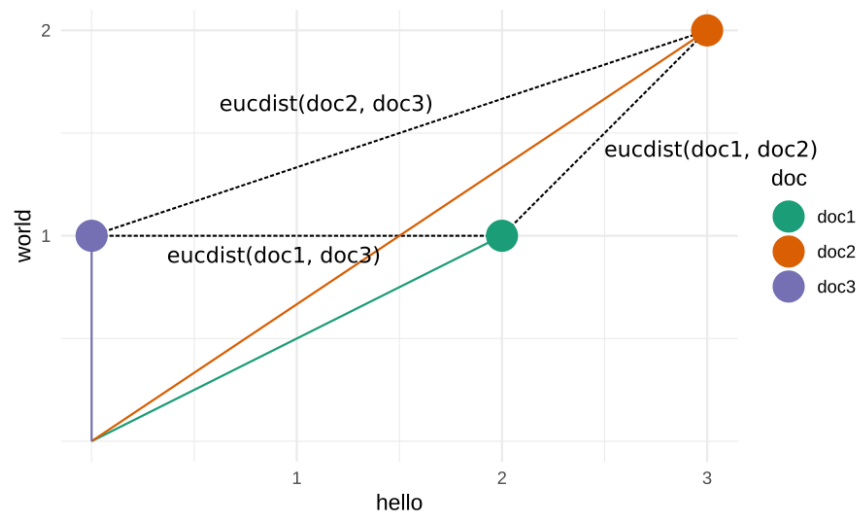
Euclidian distance

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



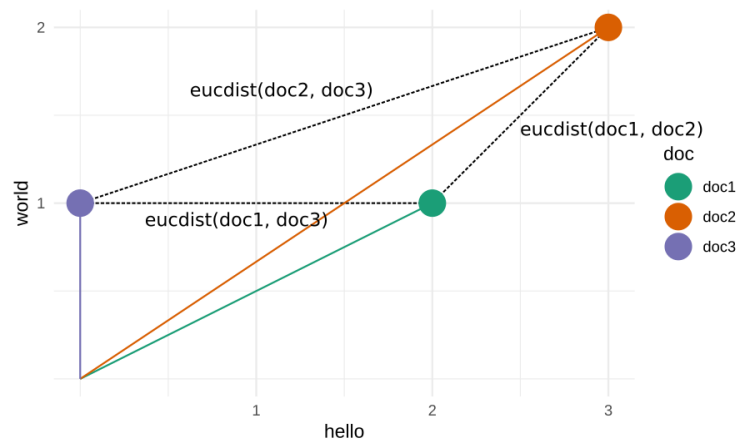
In 2D, it's an application of the Pythagorean theorem $(c = \sqrt{a^2 + b^2})$. For doc2 and doc3 this means: $(\sqrt{(3-0)^2 + (2-1)^2})$.

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:

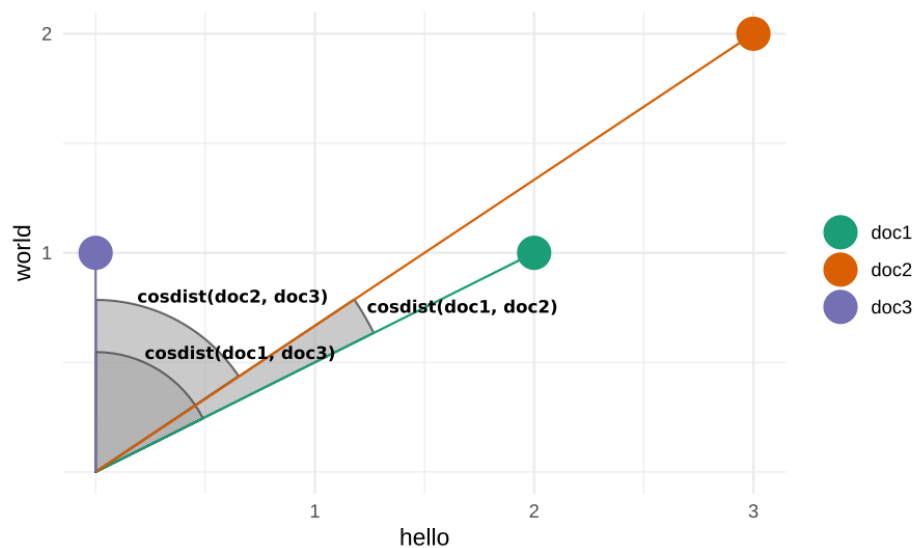
```
docs_normed <- docs / rowSums(docs)  # word proportions
dist(docs_normed)
```

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

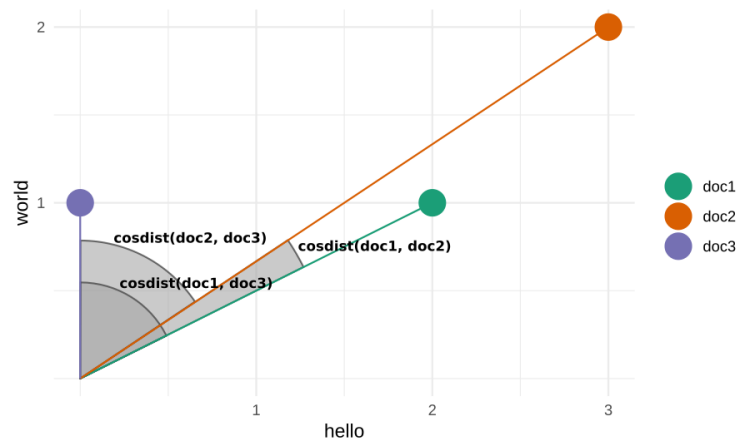
You can use `as.matrix()` to convert to a distance to a proper matrix.

Cosine distance

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



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(sqrt(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"

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](#).