# WEEK 3: TEXT MINING I

## SECU0057

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Applied Data Science

# WEEK 3: TEXT MINING 1

# TODAY

- text quantification
- numerical representations


every MINUTE of the DAY
UBER PASSENGERS TAKE 694 RIDES
Facebook USERS LIKE 4,166,667 POSTS
TWITTER USERS SEND 347,222 TWEETS
YOUTUBE USERS UPLOAD 300 HOURS OF NEW VIDEO
Instagram USERS LIKE 1,736,111 PHOTOS
PINTEREST USERS PIN 9,722 IMAGES
APPLE USERS DOWNLOAD 51,000 APPS
Netflix SUBSCRIBERS STREAM 77,160 HOURS OF VIDEO
reddit USERS CAST 18,327 VOTES
AMAZON RECEIVES 4,310 UNIQUE VISITORS
VINE USERS PLAY 1,041,666 VIDEOS
Tinder USERS SWIPE 590,278 TIMES
SNAPCHAT USERS SHARE 284,722 SNAPS
Buzzfeed USERS VIEW 34,150 VIDEOS
Skype USERS MAKE 110,040 CALLS

# TEXT IS EVERYWHERE ...

- Practically all websites
- Emails
- Messaging
- Government reports
- Laws
- Police reports
- Uni coursework
- Newspapers

# … AND EVERYTHING IS TEXT

- videos -> transcripts
- music -> lyrics
- conversations -> transcripts
- speeches -> transcripts

# CORE IDEA

Text is a unique documentation of human activity.

*We are obsessed with documenting.*

# TEXT EXAMPLE

How would you analyse the text?

# EXAMPLE

*All I ever wanted was to love women, and in turn to be loved by them back. Their behavior towards me has only earned my hatred, and rightfully so! I am the true victim in all of this. I am the good guy. Humanity struck at me first by condemning me to experience so much suffering. I didn't ask for this. I didn't want this. I didn't start this war. I wasn't the one who struck first. But I will finish it by striking back. I will punish everyone. And it will be beautiful. Finally, at long last, I can show the world my true worth.*

# CHALLENGE OF QUANTIFICATION

- text is not a numerical representation
- compare this to trading data, crime statistics, etc.
- text is just that, “a text”
- but: for quantitative analyses, we need numbers

Text –> numerical representation?

# FEATURES OF TEXT DATA

- meta dimension
- syntactic dimension
- semantic dimension
- text metrics

# META DIMENSION

- no. of words
- no. of sentences

# SYNTACTIC DIMENSION

- word frequencies
- verbs, nouns, persons, locations, ..
- structure of a sentence

## SEMANTIC DIMENSION

- sentiment
- psycholinguistic features

# TEXT METRICS

- readability
- lexical diversity

# THE `QUANTEDA` PACKAGE

```r
library(quanteda)
```

- quanteda: Quantitative Analysis of Textual Data
  - documentation
  - tutorials
  - examples

# LEVELS OF TEXT DATA

- characters `c('h', 'a', 't', 'r', 'e', 'd')`
- words `hatred`
- sentences `I didn’t ask for this.`
- documents: individual text files
- corpora: collection of documents

# COUNTING META FEATURES IN R

| text level | R function |
|---:|---:|
| characters | `nchar()` |
| words | `quanteda::ntoken()` |
| sentences | `quanteda::nsentence()` |

# R EXAMPLES

```
#sentences
no_of_sentences = nsentence(er)
no_of_sentences
```

```
## text1
##    13
```

```
#words 1
no_of_words_1 = ntoken(er)
no_of_words_1
```

```
## text1
##   123
```

```
#words 2
no_of_words_2 = ntype(er)
no_of_words_2
```

```
## text1
##    72
```

# TYPE-TOKE RATIO

Note: often used metric for “lexical diversity” is the TTR (type-token ratio).

```
string_a = "I didn’t ask for this. I didn’t want this."
string_b = "But I will finish it by striking back."
```

**What are the type-token ratios of each string?**

# TYPE-TOKEN RATIO

```r
ntype(string_a)/ntoken(string_a)
```

```
##     text1
## 0.6363636
```

```r
ntype(string_b)/ntoken(string_b)
```

```
## text1
##     1
```

# CHARACTERS PER WORD

```
nchar(er)/ntoken(er)
```

```
##    text1
## 4.317073
```

# WORDS PER SENTENCE

```
ntoken(er)/nsentence(er)
```

```
##    text1
## 9.461538
```

# TEXT REPRESENTATION

# AIM

- representing a text by its tokens (terms)
- each text consists of a frequency of its tokens

```
"I think I believe him"
```

# TEXT REPRESENTATION BY HAND

1. create a column for each token
2. count the frequency

| text_id | I | think | believe | him |
|---|---|---|---|---|
| text1 | 2 | 1 | 1 | 1 |

# TERM FREQUENCY

- frequency of each token in each document
- represented in a table (matrix)
- tokens are features of a document
- voilá: **Document Feature Matrix (= DFM)**

```
example_string_tok = tokens("I think I believe him")
```

# DFM IN `QUANTEDA`

- from ‘tokens’ object, create a DFM table

```
dfm(example_string_tok)
```

```
## Document-feature matrix of: 1 document, 4 features (0% sparse).
## 1 x 4 sparse Matrix of class "dfm"
##        features
## docs    i think believe him
##   text1 2     1       1   1
```

# SPARSITY

Sparsity = % of zero-cells

- Why is sparsity = 0% here?
- What would you expect if we take additional documents, and why?

# DFM WITH MULTIPLE DOCUMENTS

```
multiple_docs_tok = tokens(c("I think I believe him", "This is a cool fur
```

```
dfm(multiple_docs_tok)
```

```
## Document-feature matrix of: 2 documents, 9 features (50% sparse).
## 2 x 9 sparse Matrix of class "dfm"
##        features
## docs    i think believe him this is a cool function
##   text1 2     1       1   1    0  0 0    0        0
##   text2 0     0       0   0    1  1 1    1        1
```

# DFM WITH TWO LONE-ACTORS

*All I ever wanted was to love women, and in turn to be loved by them back. Their behavior towards me has only earned my hatred, and rightfully so! I am the true victim in all of this. I am the good guy. Humanity struck at me first by condemning me to experience so much suffering. I didn't ask for this. I didn't want this. I didn't start this war. I wasn't the one who struck first. But I will finish it by striking back. I will punish everyone. And it will be beautiful. Finally, at long last, I can show the world my true worth.*

# DFM WITH TWO TEXTS

*The Industrial Revolution and its consequences have been a disaster for the human race. They have greatly increased the life-expectancy of those of us who live in "advanced" countries, but they have destabilized society, have made life unfulfilling, have subjected human beings to indignities, have led to widespread psychological suffering (in the Third World to physical suffering as well) and have inflicted severe damage on the natural world. The continued development of technology will worsen the situation.*

# USING THE CORPUS METHOD

- Create a “mini corpus” for convenience
- makes using the quanteda pipeline easier

```
mini_corpus = corpus(c(er, ub))
summary(mini_corpus)
```

```
## Corpus consisting of 2 documents:
##
##    Text Types Tokens Sentences
##   text1    72    123        13
##   text2    63     88         3
##
## Source: /Users/bennettkleinberg/GitHub/UCL_SECU0057/lectures/week_3/*
## Created: Thu Jan 30 06:39:31 2020
## Notes:
```

# DFM REPRESENTATION

```
corpus_tokenised = tokens(mini_corpus)
corpus_dfm = dfm(corpus_tokenised)
```

| document | all | i | ever | wanted | was | to | love | women |
|---|---|---|---|---|---|---|---|---|
| text1 | 2 | 10 | 1 | 1 | 1 | 3 | 1 | 1 |
| text2 | 0 | 0 | 0 | 0 | 0 | 3 | 0 | 0 |

| document | am | the | true | victim | of | this | good | guy |
|---|---|---|---|---|---|---|---|---|
| text1 | 2 | 4 | 2 | 1 | 1 | 4 | 1 | 1 |
| text2 | 0 | 7 | 0 | 0 | 3 | 0 | 0 | 0 |

**Is this ideal?**

# WHAT ARE THE MOST FREQUENT “TERMS”?

```
topfeatures(corpus_dfm[1])
```

```
##       .       i       ,     the    this      to     and      by      me  didn't
##      12      10       4       4       4       3       3       3       3       3
```

```
topfeatures(corpus_dfm[2])
```

```
##         the      have           ,          to           .          of         and
##           7         7           4           3           3           3           2
##          in suffering       world
##           2         2           2
```

# ZIPF'S LAW


THE OF AND TO A IN IS I THAT IT FOR YOU WAS WITH ON AS HAVE BUT BE THEY
0:35 / 21:04
The Zipf Mystery
13,315,384 views
340K
3.7K
SHARE
SAVE

## WORD HIERARCHIES

- some words add more meaning than others
- stopwords = meaningless (?)
- in any case: too frequent words, don’t tell much about the documents
- ideally: we want to get an *importance score* for each word

# WORD IMPORTANCE

| document | and | in | turn | be | loved | by |
|---|---|---|---|---|---|---|
| text1 | 3 | 2 | 1 | 2 | 1 | 3 |
| text2 | 2 | 2 | 0 | 0 | 0 | 0 |

We want to “reward” words that are:

- important locally (for individual documents)
- but not ‘inflated’ globally (for the whole corpus)

# METRIC FOR WORD IMPORTANCE: TERM FREQUENCY

- $tf(t, d) = \frac{\#_{t,d}}{nwords_d}$ (proportion)
- $tf(t, d)$ = #_(t, d) (count)

# PROPORTIONS

| document | and | in | turn | be | loved | by |
|---|---|---|---|---|---|---|
| text1 | 0.024 | 0.016 | 0.008 | 0.016 | 0.008 | 0.024 |
| text2 | 0.023 | 0.023 | 0.000 | 0.000 | 0.000 | 0.000 |

# COUNTS

| document | and | in | turn | be | loved | by |
|---|---|---|---|---|---|---|
| text1 | 3 | 2 | 1 | 2 | 1 | 3 |
| text2 | 2 | 2 | 0 | 0 | 0 | 0 |

# DOUBLE-CHECK THE FORMULAE

- $tf(t,d) = \frac{\#_{t,d}}{nwords_d}$
- $tf(t,d)$ = #_(t, d)

```
3/ntoken(mini_corpus[1])
```

```
##       text1
## 0.02439024
```

Term frequency: *reward for words that occur often in a document*

# PROBLEM

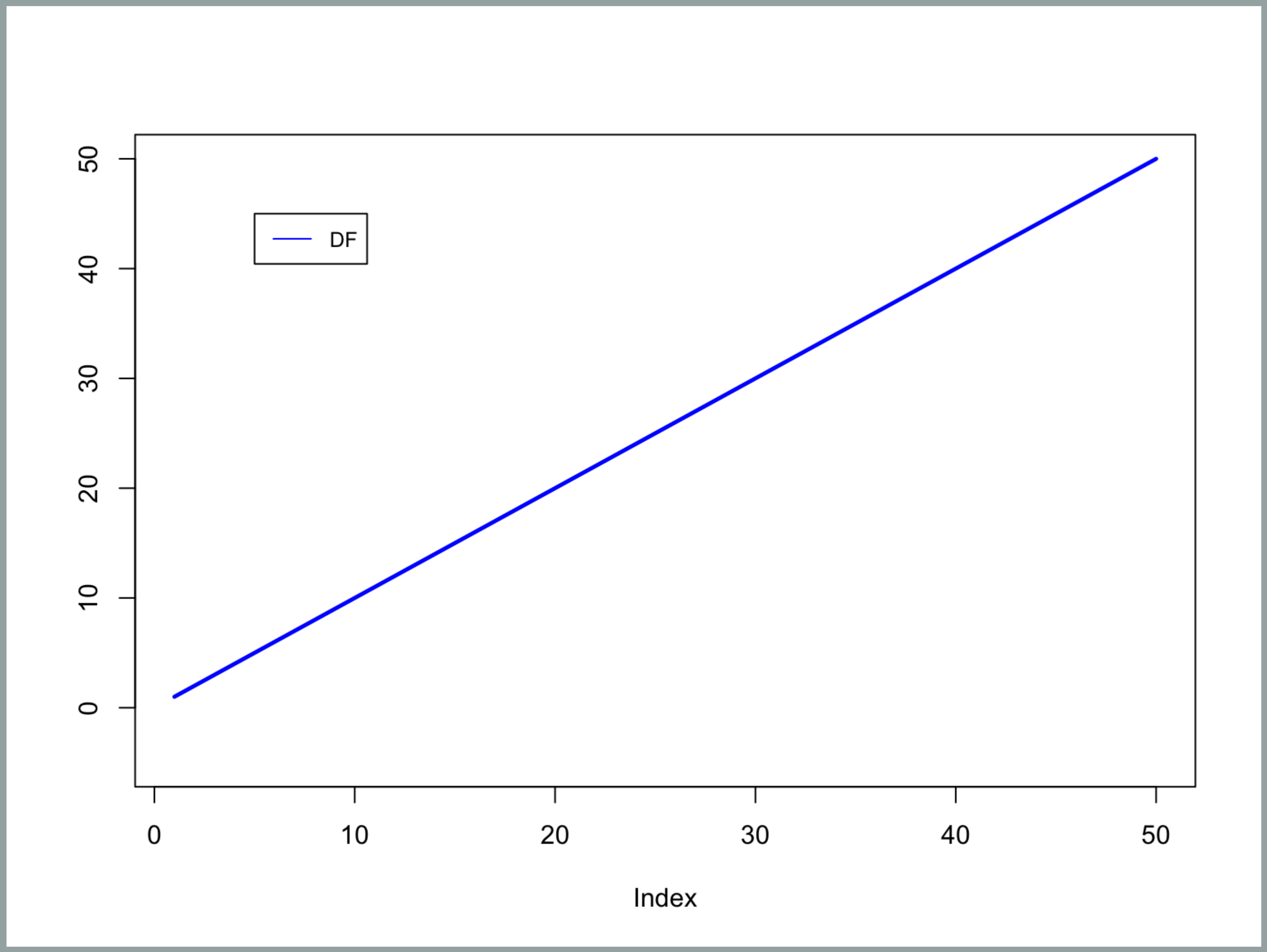
Some words just occur a lot anyway (e.g. “stop words”).

Global occurrence: document frequency

| | x |
|---|---|
| and | 2 |
| in | 2 |
| turn | 1 |
| be | 1 |
| loved | 1 |
| by | 1 |

$$df(t) = \text{\# of docs with t}$$

# DF



# CORRECTING FOR TERM INFLATION

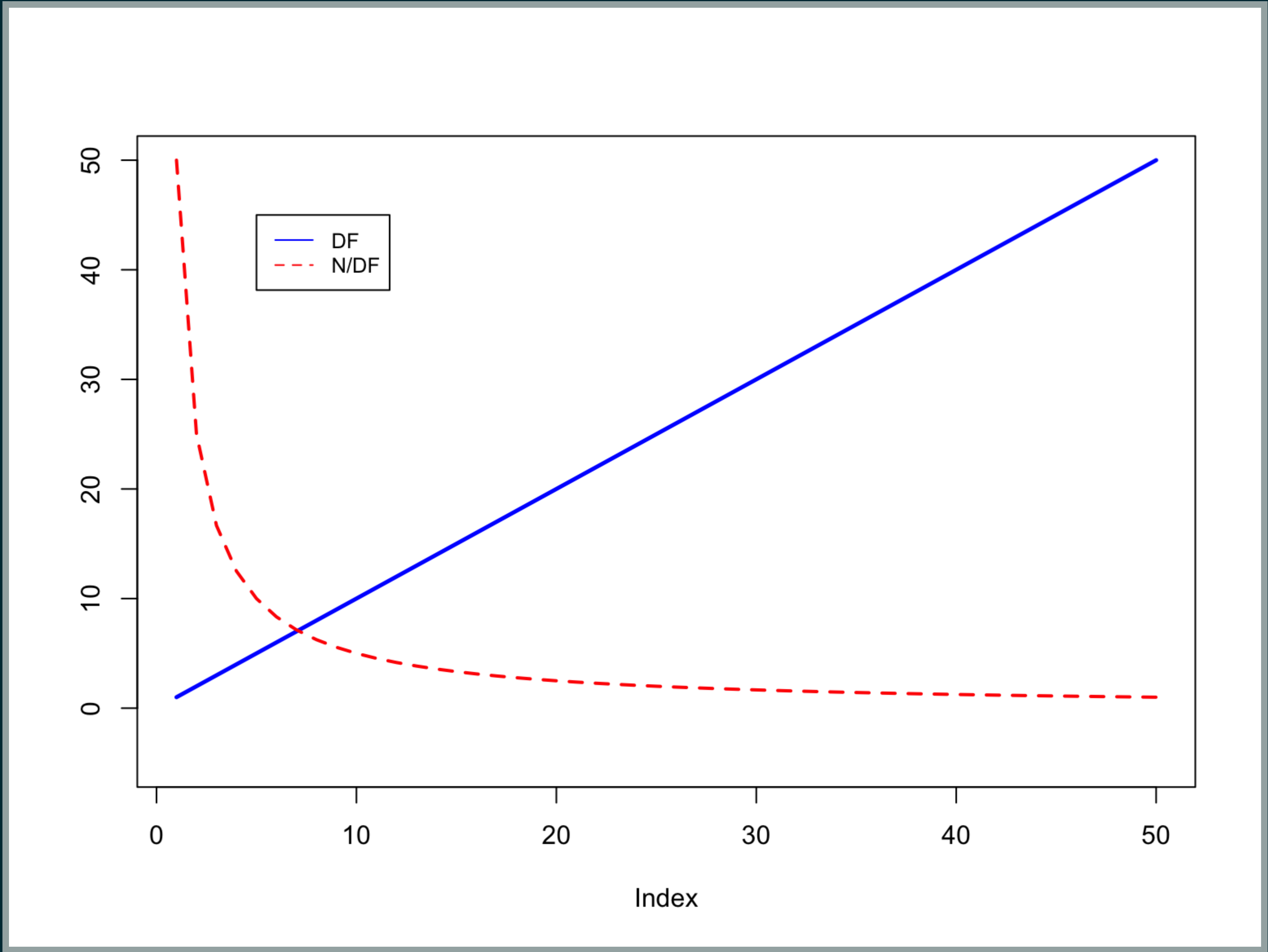
- we want: low values for common words
- and: higher values for *important* words

Trick: *inverse* document-frequency

# INVERSE DF (IDF)

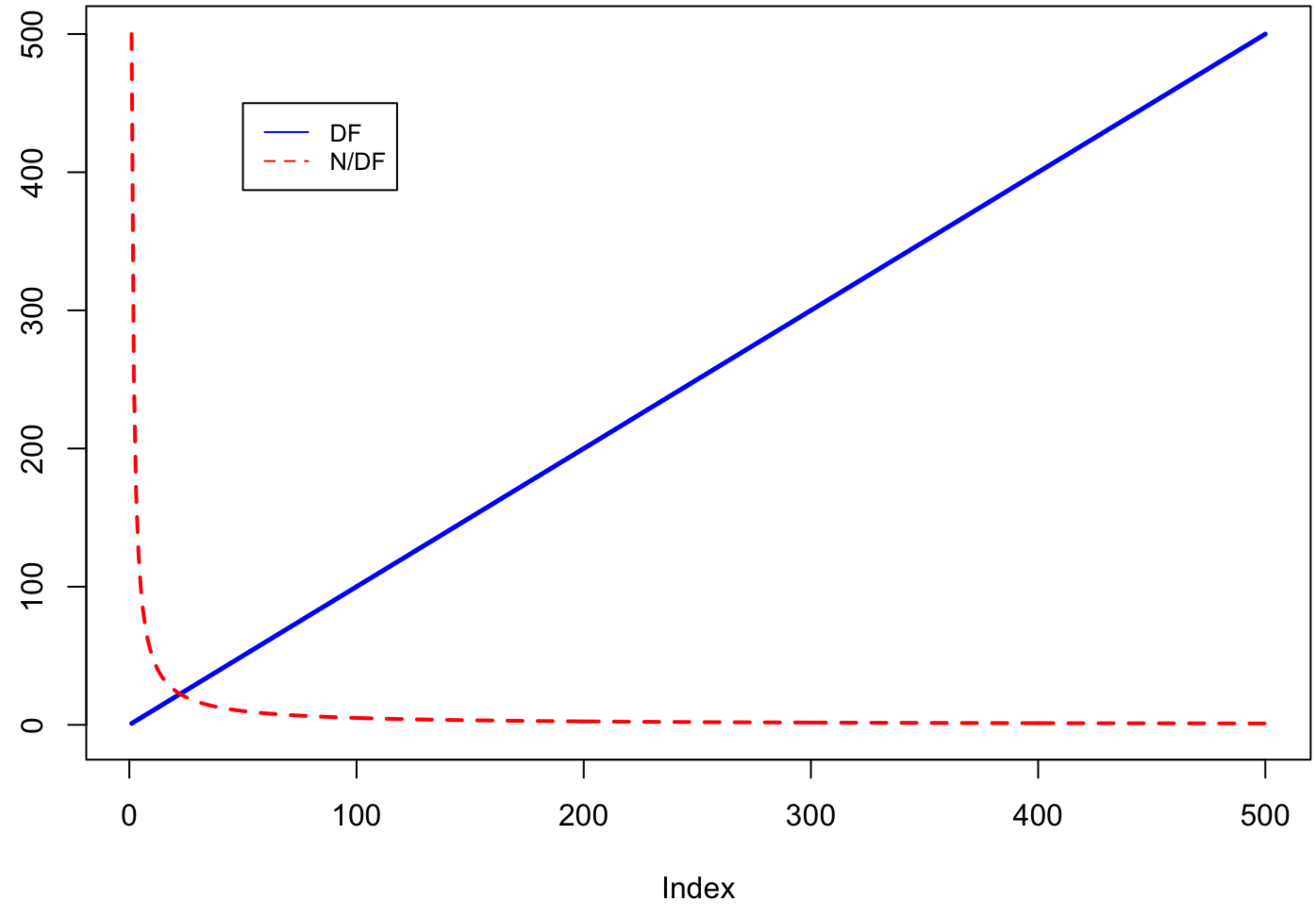
$$idf(t) = \frac{N}{df(t)}$$

# IDF



# PROBLEM?

- What happens if $N$ becomes really large?



DF
N/DF
0
100
200
300
400
500
Index

# LOG IDF

- to avoid extreme values, we use the logarithm
- simple transformation: $idf(t) = log(\frac{N}{df(t)+1})$

# ABOUT LOGARITHMS

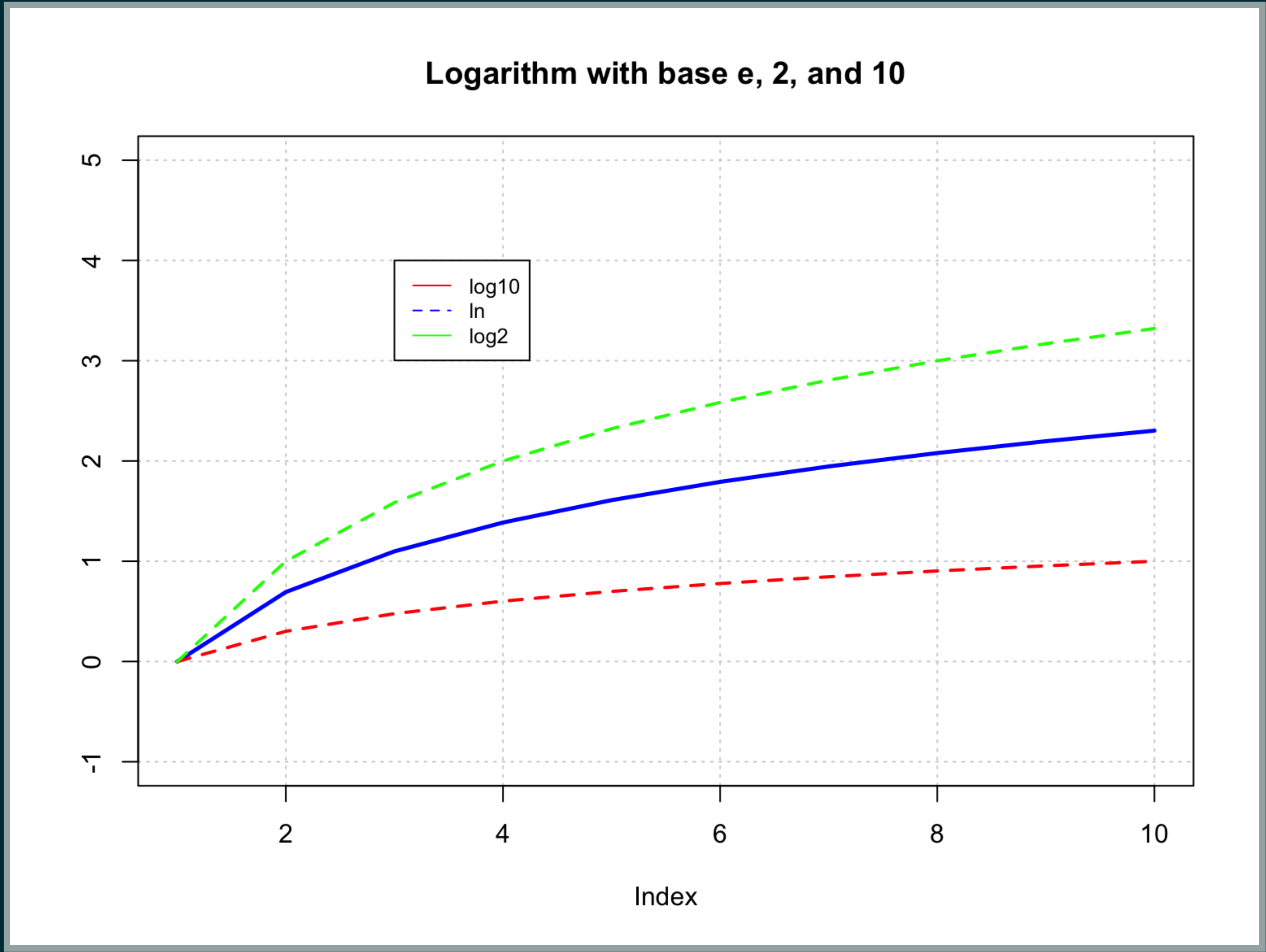
$$log_b(a) = c <=> b^c = a$$

“the power to which {base b} would have to be raised to equal a”

$$log_2(8) =? \text{->} 2^? = 8$$

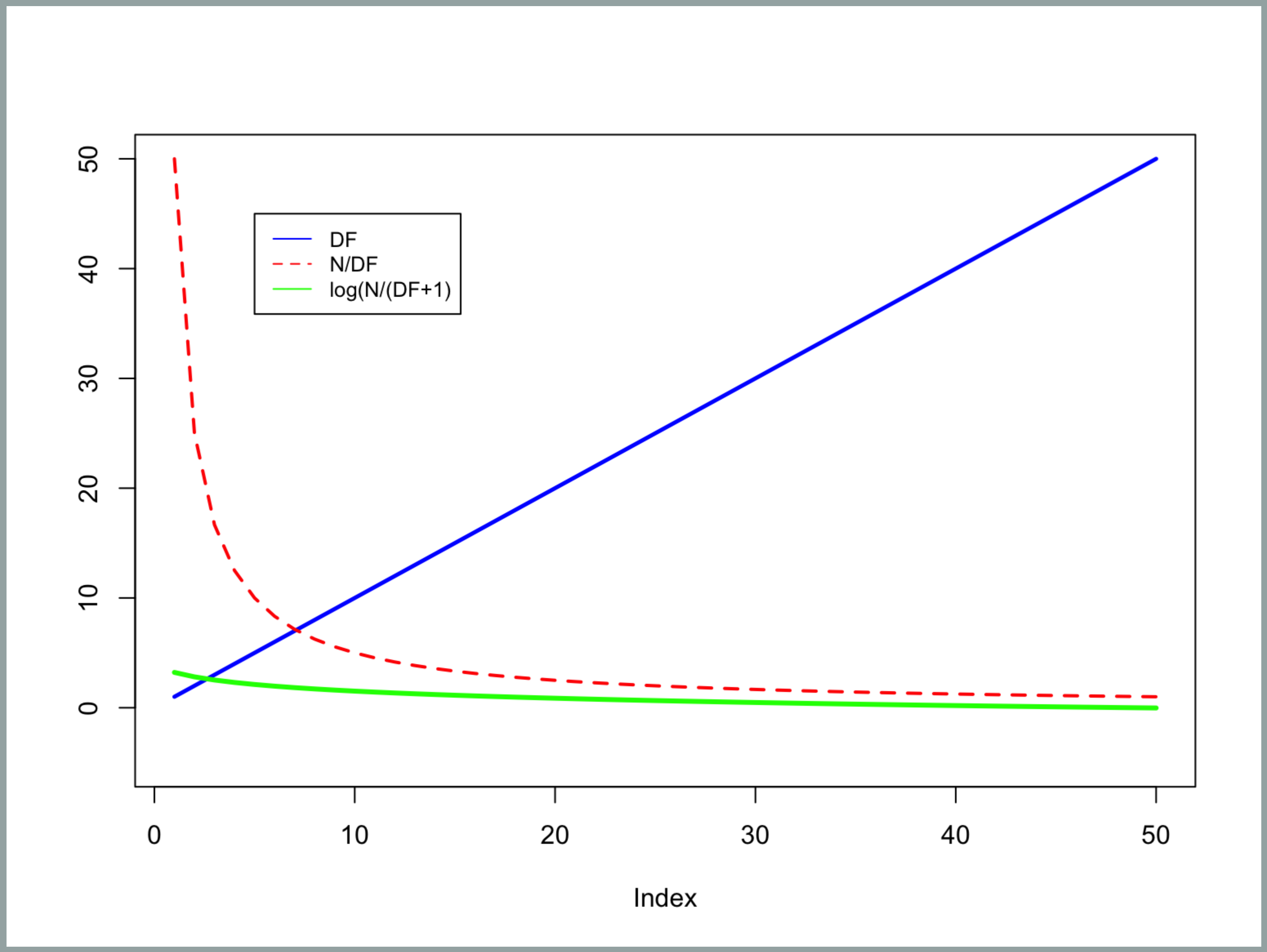
# LOGARITHM BASES

- natural logarithm: base $e = 2.718281\ldots$
- base 10 logarithm: $log_{10}(x)$



Logarithm with base e, 2, and 10
log10
ln
log2
Index
5
4
3
2
1
0
-1
2
4
6
8
10

# LOG IDF



# COMBINING TERM FREQUENCY AND DOCUMENT FREQUENCY

1. Local importance (TF)

| document | and | in | turn |
|---|---|---|---|
| text1 | 3 | 2 | 1 |
| text2 | 2 | 2 | 0 |

2. Correct for global occurrences (DF)

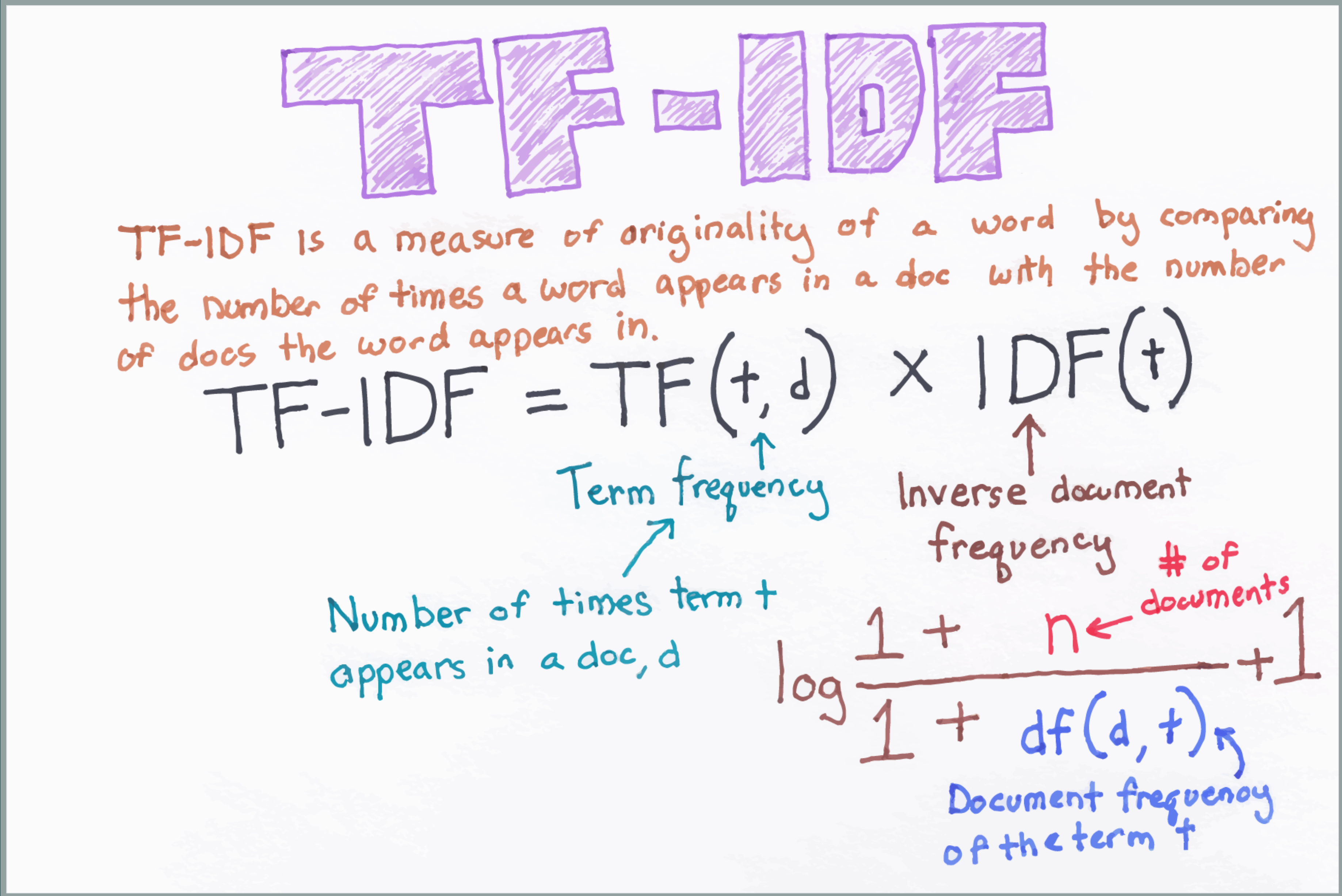
| | x |
|---|---|
| and | -0.1760913 |
| in | -0.1760913 |
| turn | 0.0000000 |

# TF/IDF

```
#text1: "and"
3/-0.1760913

#text2: "and"
2/-0.1760913
```

# TF-IDF


TF-IDF
TF-IDF is a measure of originality of a word by comparing the number of times a word appears in a doc with the number of docs the word appears in.
$$\text{TF-IDF} = \text{TF}(t, d) \times \text{IDF}(t)$$
Term frequency
Number of times term t appears in a doc, d
Inverse document frequency
$$\log \frac{1 + n}{1 + df(d, t)} + 1$$
# of documents
Document frequency of the term t

Img reference

# WORKING WITH TEXT AS DATA

## RESEARCHER’S DEGREES OF FREEDOM

- stop word removal
- stemming

# STOPWORD REMOVAL

- We know many words are “low in meaning”
- so-called stop words

| x |
|---|
| i |
| me |
| my |
| myself |
| we |
| hers |
| herself |
| it |
| its |
| itself |
| they |

# WITHOUT STOPWORD REMOVAL

| document | all | i | ever | wanted | was | to | love | women |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| text1 | 2 | 10 | 1 | 1 | 1 | 3 | 1 | 1 |
| text2 | 0 | 0 | 0 | 0 | 0 | 3 | 0 | 0 |

# WITH STOPWORD REMOVAL

| document | ever | wanted | love | women | , | turn | loved | back |
|---|---|---|---|---|---|---|---|---|
| text1 | 1 | 1 | 1 | 1 | 4 | 1 | 1 | 2 |
| text2 | 0 | 0 | 0 | 0 | 4 | 0 | 0 | 0 |

# STEMMING

- some words originate from the same “stem”
- e.g. “love”, “loved”, “loving”, “lovely”
- but you might want to reduce all these to the stem

# WORD STEMS

```
love_stem = c("love", "loved", "loving", "lovely")
```

| document | love | loved | loving | lovely |
|---|---|---|---|---|
| text1 | 1 | 0 | 0 | 0 |
| text2 | 0 | 1 | 0 | 0 |
| text3 | 0 | 0 | 1 | 0 |
| text4 | 0 | 0 | 0 | 1 |

# AFTER STEMMING

| document | love |
|---|---|
| text1 | 1 |
| text2 | 1 |
| text3 | 1 |
| text4 | 1 |

# OUR MINI CORPUS

Incl. stop words and without stemming:

| document | all | i | ever | wanted | was | to | love | women |
|---|---|---|---|---|---|---|---|---|
| text1 | 2 | 10 | 1 | 1 | 1 | 3 | 1 | 1 |
| text2 | 0 | 0 | 0 | 0 | 0 | 3 | 0 | 0 |

# ... TO

Without stop words and stemmed:

| document | ever | want | love | women | , | turn | back | . |
|---|---|---|---|---|---|---|---|---|
| text1 | 1 | 2 | 2 | 1 | 4 | 1 | 2 | 12 |
| text2 | 0 | 0 | 0 | 0 | 4 | 0 | 0 | 3 |

# CONSIDERATIONS WITH TEXT DATA

- a lot of assumptions
- text == behaviour?
- produced text == displayed text?
- many decisions in your hand
  - stemming
  - stopwords
  - custom dictionary

# WHAT'S NEXT?

- Today's tutorial: analysing speeches by US presidents, examining UK rap lyrics
- Homework: quanteda practice, text preprocessing

Next week: Text Mining 2