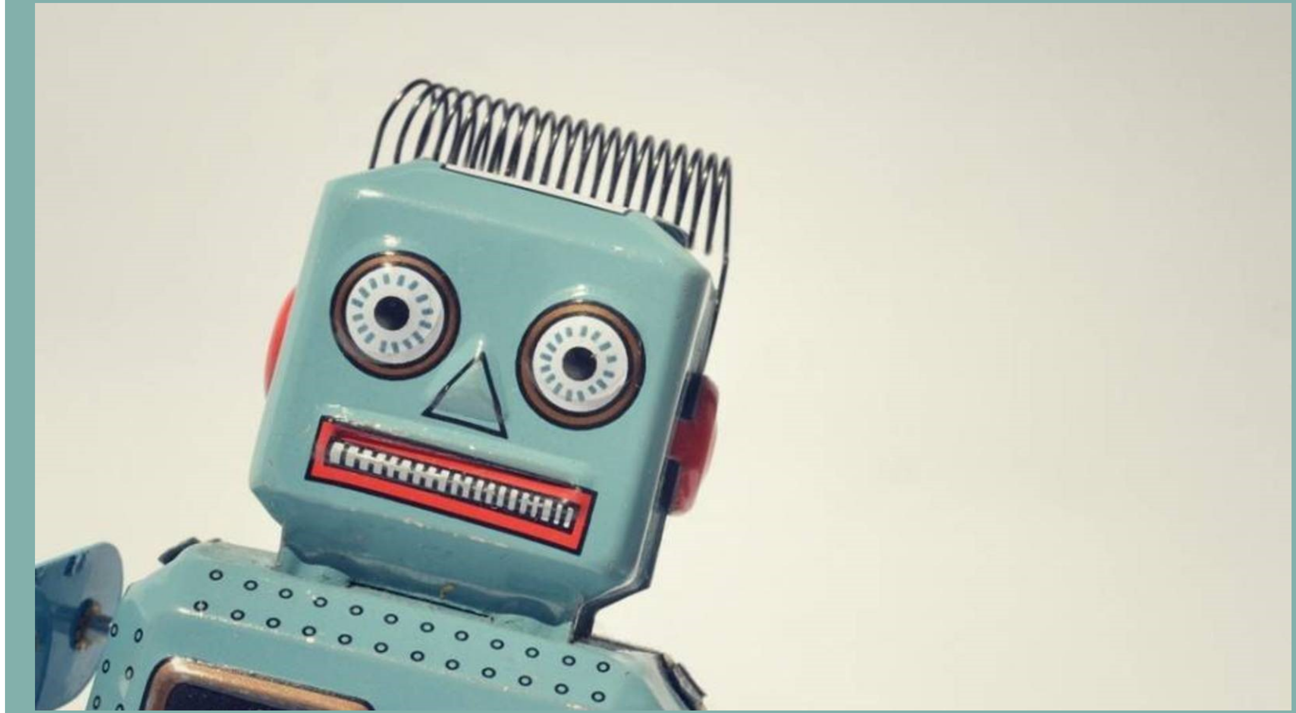
DIGITAL METHODS FOR ANALYSING TEXTS //

02_Analysing text



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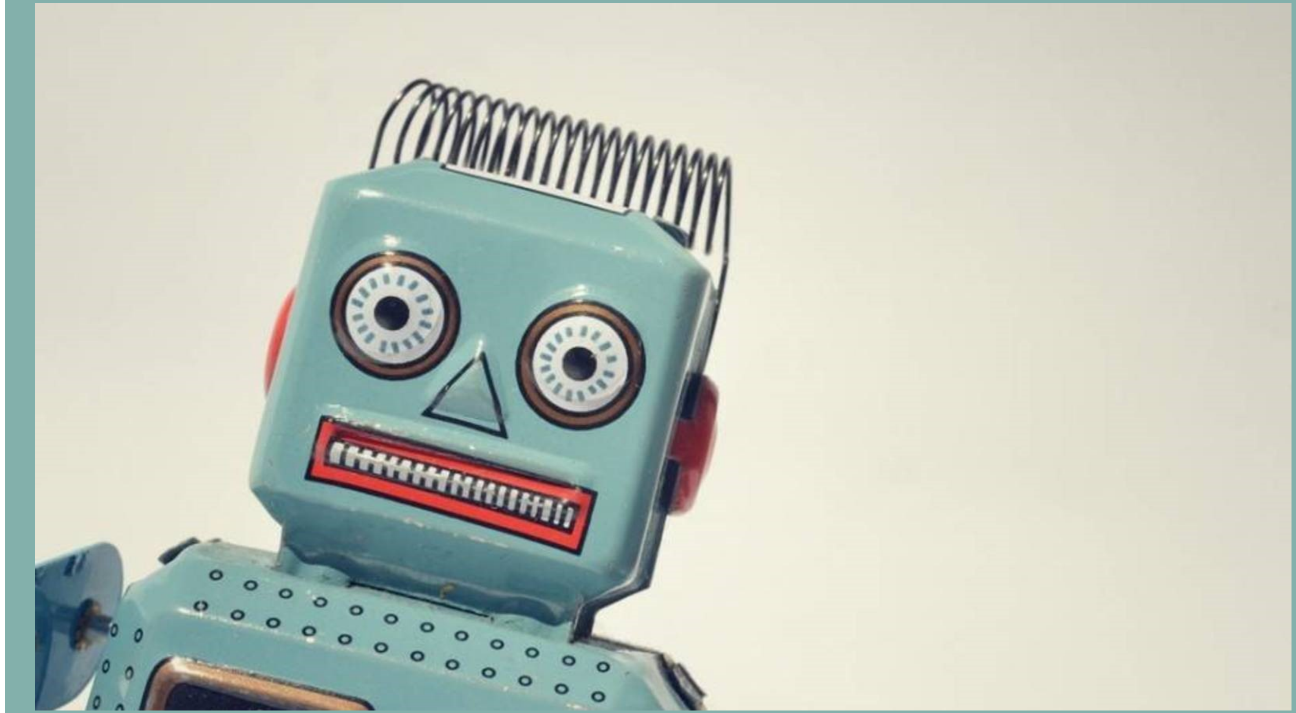
ROAD MAP//

1. Corpus Preprocessing

2. Representing text

2.1. Enter the matrix
2.2. Discrete Representations
2.3. Distributed Representations
5.4. Discrete versus Continuous

CORPUS PREPROCESSING //



CORPUS PREPROCESSING//

How would you manually represent a corpus?

CORPUS PREPROCESSING//

Think like a person would do it,
and translate it into code.

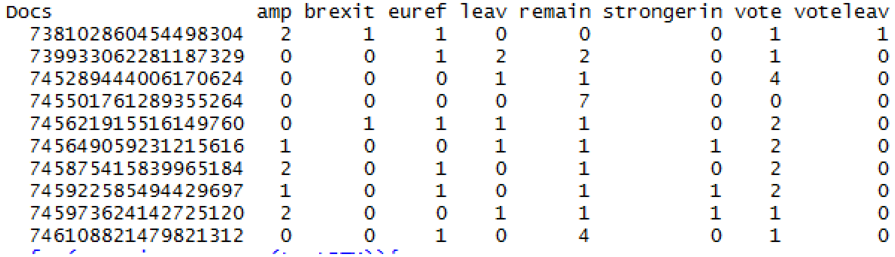
CORPUS PREPROCESSING//

Office documents

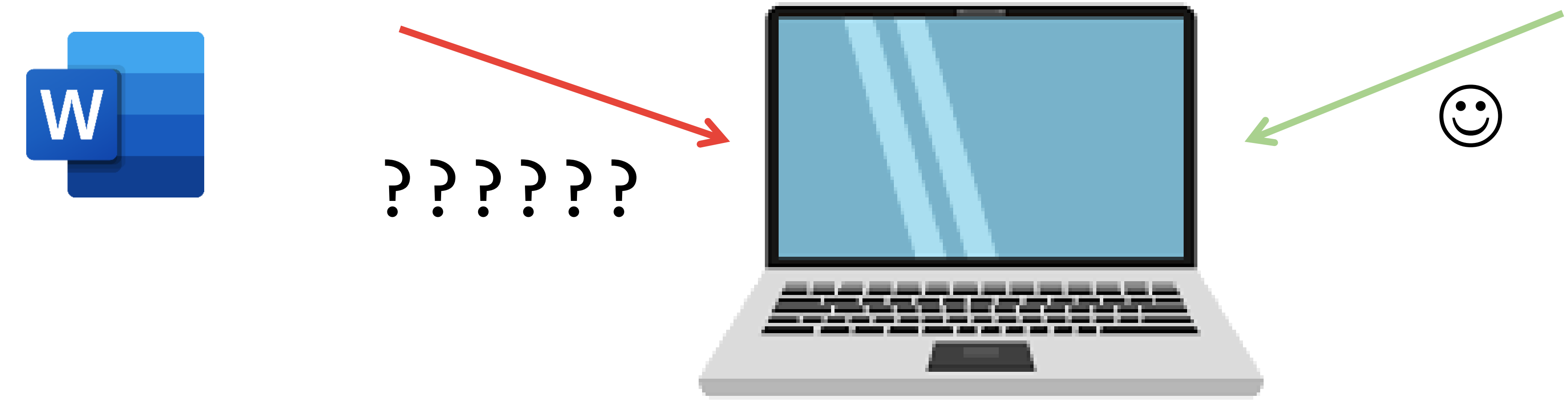
Features:

Term-matrix documents

Embeddings

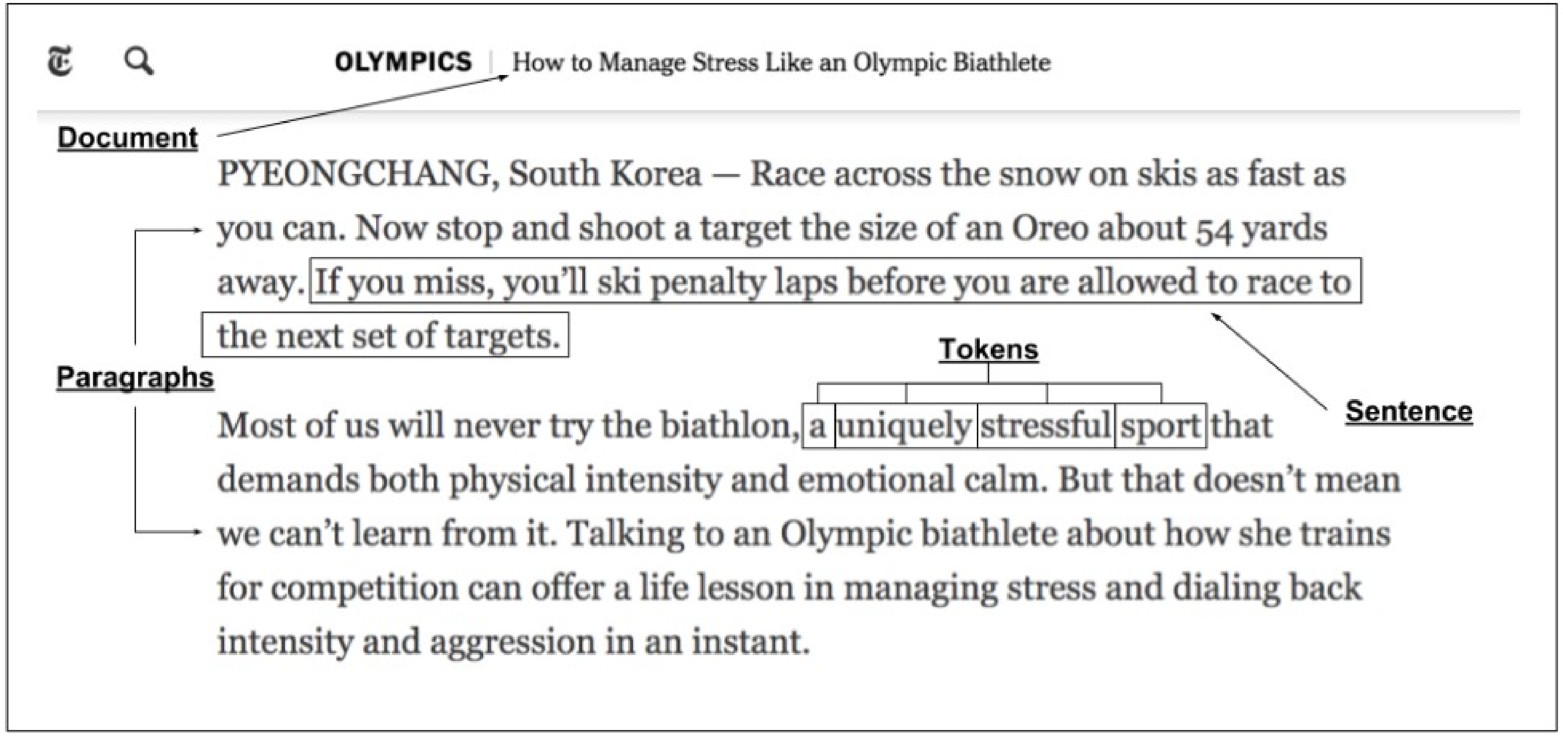


```
Docs                amp brexit euref leav remain strongerin vote voteleav
  738102860454498304  2      1     1    0      0          0    1        1
  739933062281187329  0      0     1    2      2          0    1        0
  745289444006170624  0      0     0    1      1          0    4        0
  745501761289355264  0      0     0    0      7          0    0        0
  745621915516149760  0      1     1    1      1          0    2        0
  745649059231215616  1      0     0    1      1          1    2        0
  745875415839965184  2      0     1    0      1          0    2        0
  745922585494429697  1      0     1    0      1          1    2        0
  745973624142725120  2      0     0    1      1          1    1        0
  746108821479821312  0      0     1    0      4          0    1        0
```



CORPUS PREPROCESSING//

Document decomposition



How to Manage Stress Like an Olympic Biathlete

PYEONGCHANG, South Korea — Race across the snow on skis as fast as you can. Now stop and shoot a target the size of an Oreo about 54 yards away. If you miss, you'll ski penalty laps before you are allowed to race to the next set of targets.

Most of us will never try the biathlon, a uniquely stressful sport that demands both physical intensity and emotional calm. But that doesn't mean we can't learn from it. Talking to an Olympic biathlete about how she trains for competition can offer a life lesson in managing stress and dialing back intensity and aggression in an instant.

Figure 3-2. Document decomposition illustrating the distribution of meaning across paragraphs, sentences, and individual tokens

Features

Discrete features

Represents a feature with a specific meaning.

Term-document matrix.

Continuous features

Do not *mean* anything anymore.
They can not be interpreted.

Word embeddings.

CORPUS PREPROCESSING//

Unicode

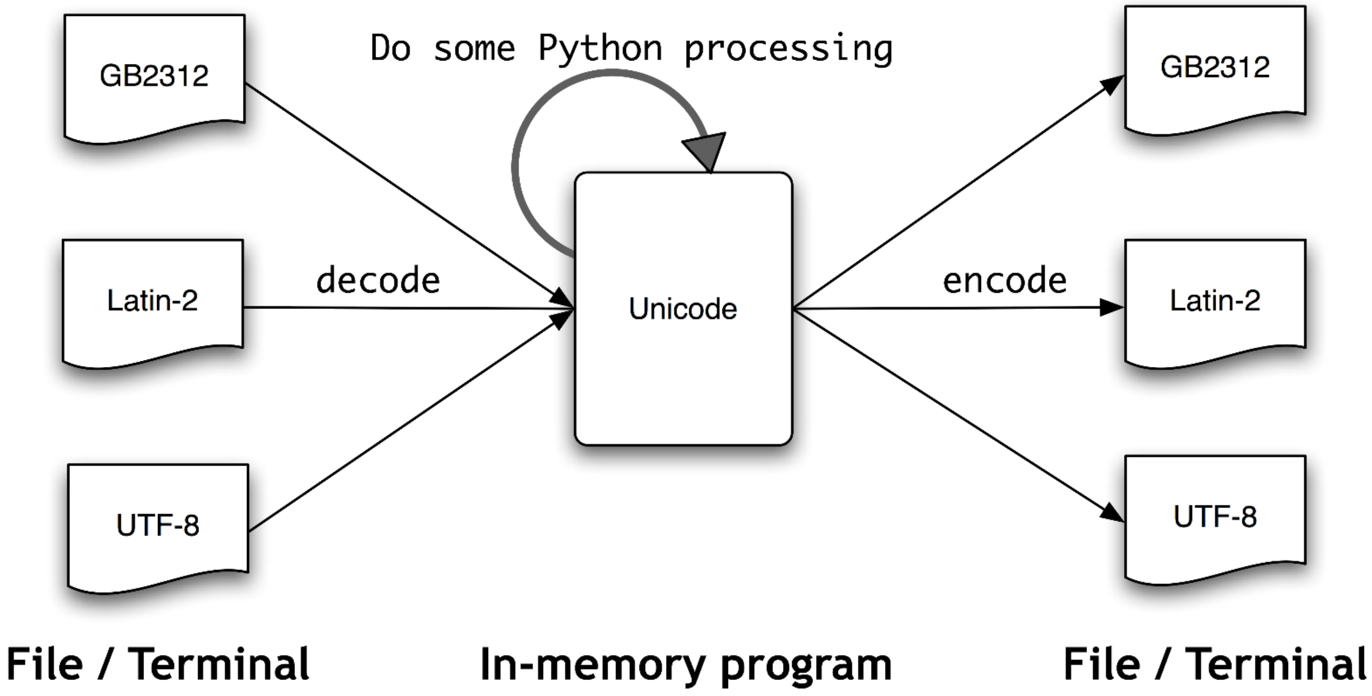
Our programs will often need to deal with different languages, and different character sets.

- If you live in the English-speaking world you probably use ASCIIT.
- If you live in Europe you might use one of the extended Latin character sets, containing such characters as:
    - “ø” for Danish and Norwegian,
    - “ő” for Hungarian,
    - “ñ” for Spanish and Breton, and
    - “ň” for Czech and Slovak.

Unicode

Unicode supports over a million characters. Each character is assigned a number, called a code point.

In Python, code points are written in the form \uXXXX, where XXXX is the number in four-digit hexadecimal form.



CORPUS PREPROCESSING//

Regular Expressions (regexpr)

Many linguistic processing tasks involve pattern matching. For example, we can find words ending with ed using endswith('ed').

Regular expressions give us a more powerful and flexible method for describing the character patterns we are interested in,

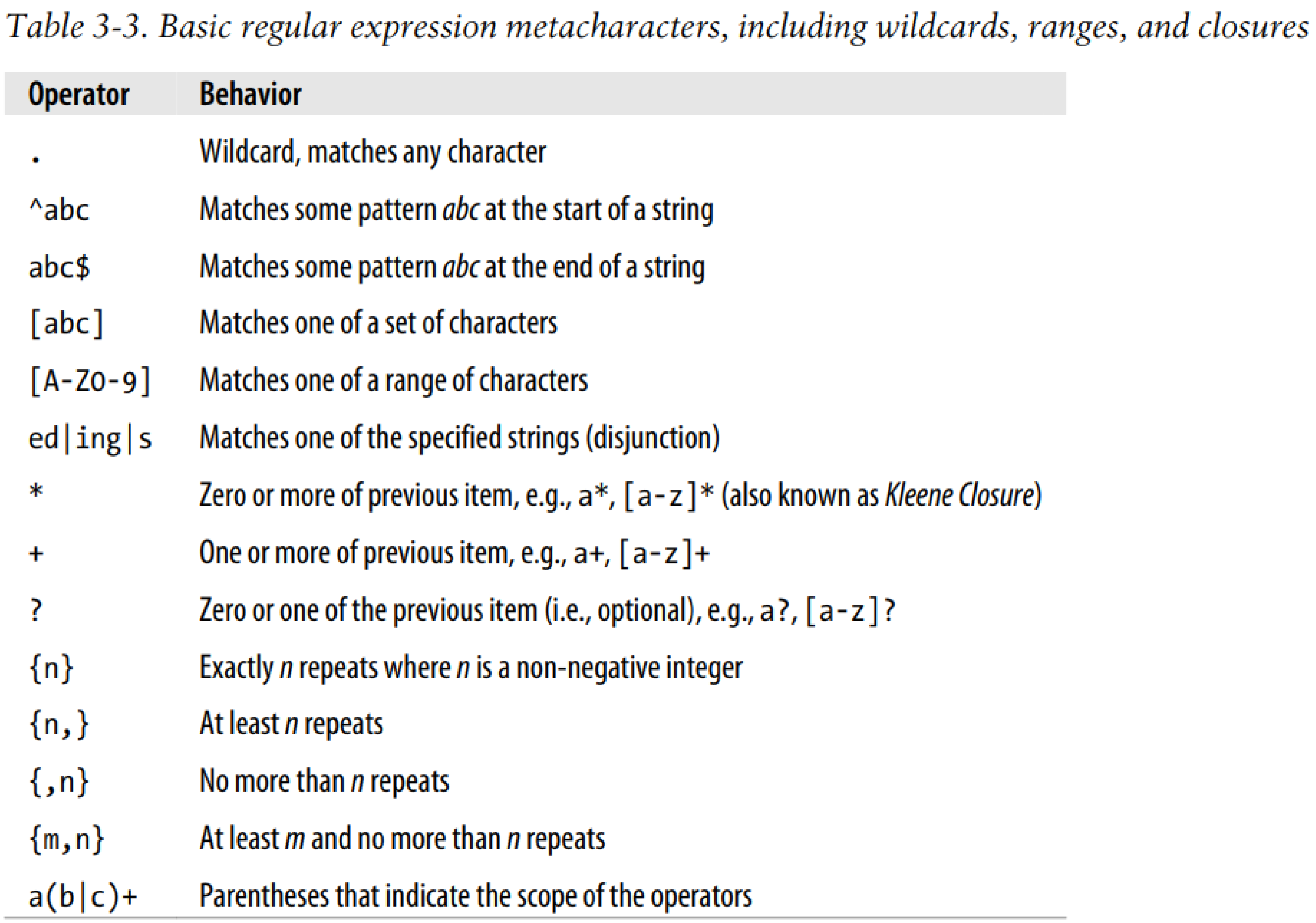
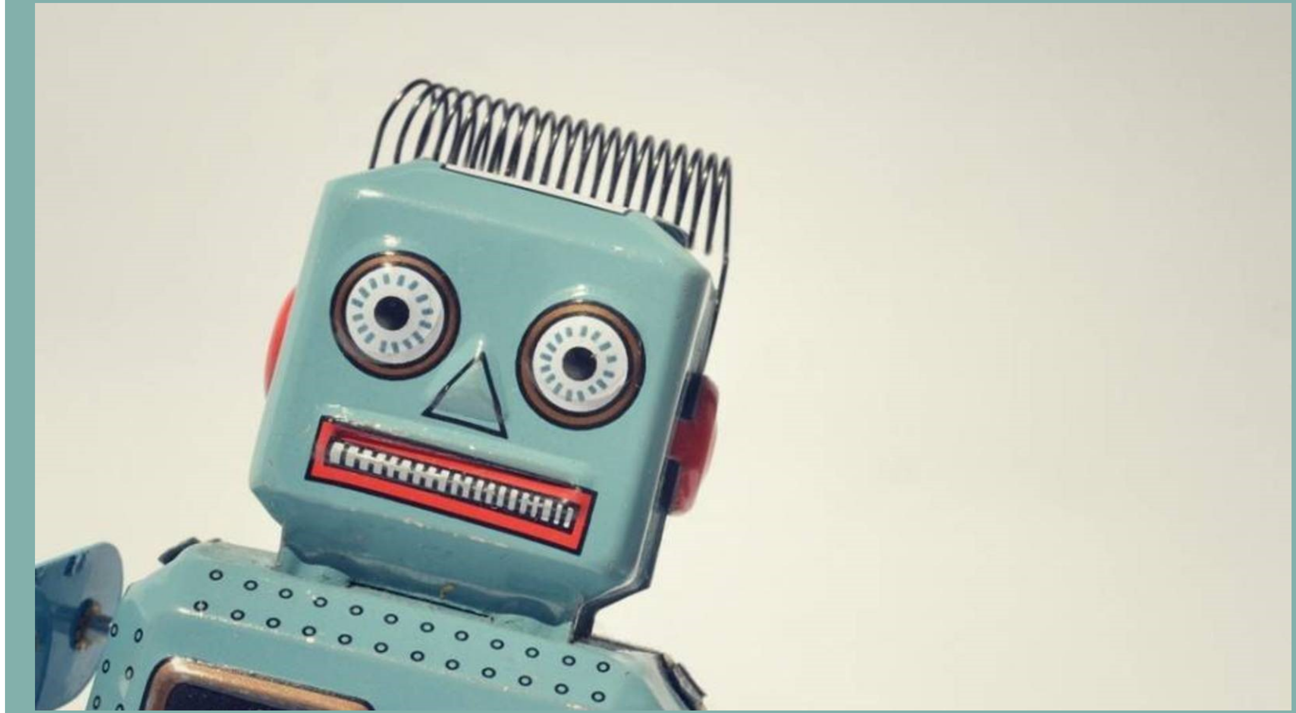


Table 3-3. Basic regular expression metacharacters, including wildcards, ranges, and closures

Operator	Behavior
.	Wildcard, matches any character
^abc	Matches some pattern *abc* at the start of a string
abc$	Matches some pattern *abc* at the end of a string
[abc]	Matches one of a set of characters
[A-Z0-9]	Matches one of a range of characters
ed|ing|s	Matches one of the specified strings (disjunction)
*	Zero or more of previous item, e.g., a*, [a-z]* (also known as *Kleene Closure*)
+	One or more of previous item, e.g., a+, [a-z]+
?	Zero or one of the previous item (i.e., optional), e.g., a?, [a-z]?
{n}	Exactly *n* repeats where *n* is a non-negative integer
{n,}	At least *n* repeats
{,n}	No more than *n* repeats
{m,n}	At least *m* and no more than *n* repeats
a(b|c)+	Parentheses that indicate the scope of the operators

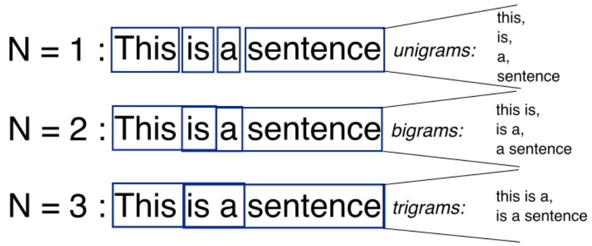
REPRESENTING TEXT //

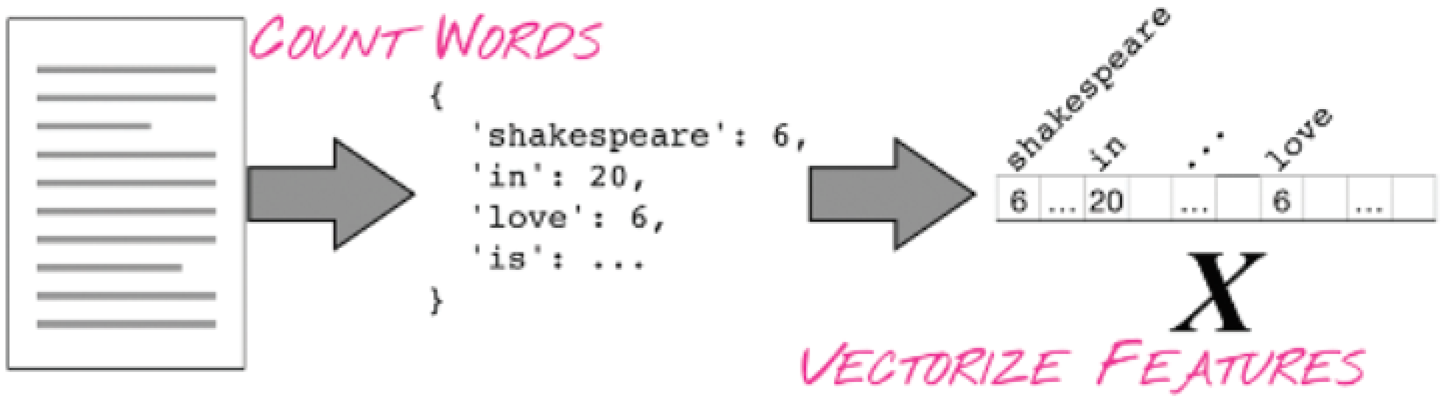


REPRESENTING TEXT//

Discrete features

N-gran features





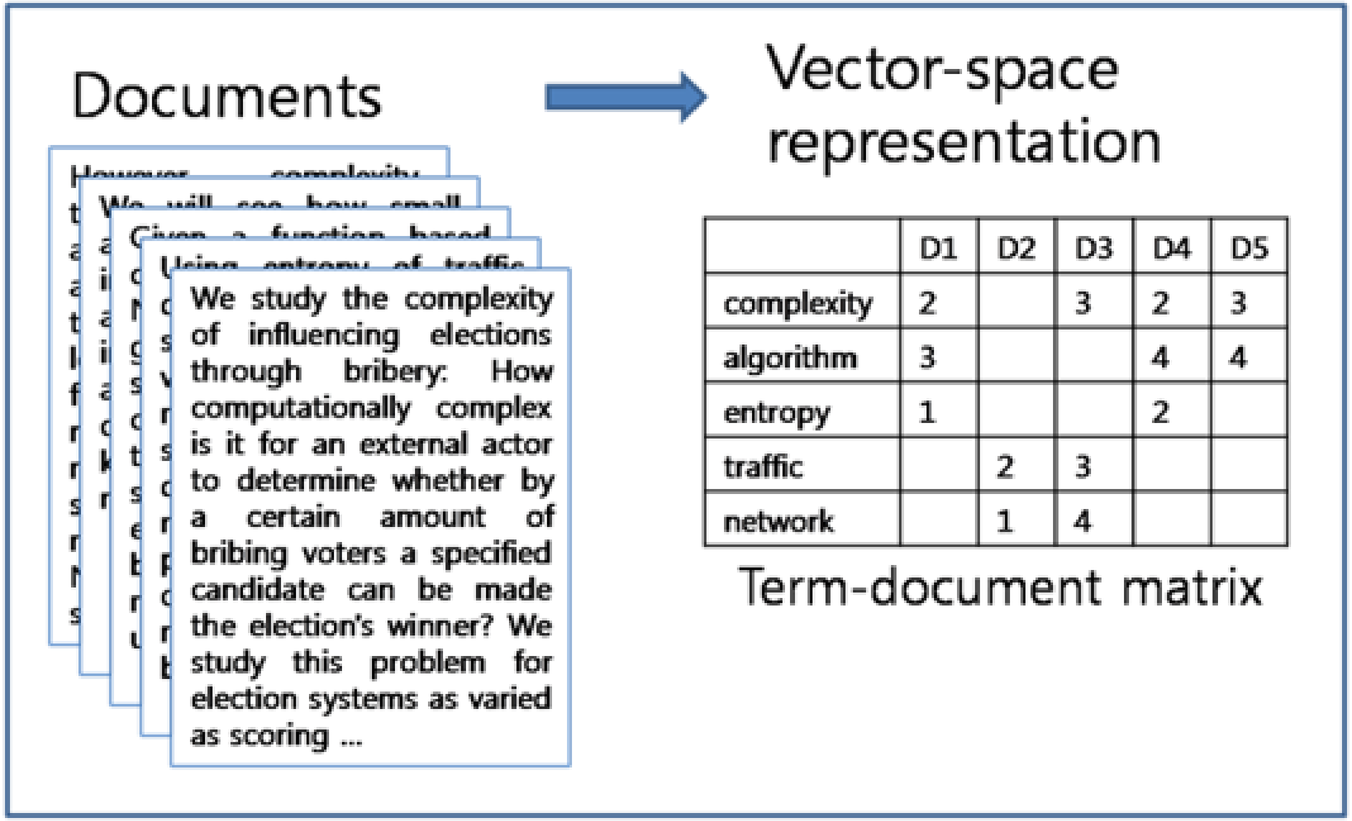
```
{
   'shakespeare': 6,
   'in': 20,
   'love': 6,
   'is': ...
}
```

Figure 4 Schematic of a bag-of-words representation.

REPRESENTING TEXT//

The Term-Document matrix

A **document-term matrix** is a mathematical matrix that describes the frequency of terms that occur in a collection of documents. In a document-term matrix, rows correspond to documents in the collection and columns correspond to terms.



We study the complexity of influencing elections through bribery: How computationally complex is it for an external actor to determine whether by a certain amount of bribing voters a specified candidate can be made the election's winner? We study this problem for election systems as varied as scoring ...

	D1	D2	D3	D4	D5
complexity	2		3	2	3
algorithm	3			4	4
entropy	1			2	
traffic		2	3		
network		1	4		

Term-document matrix

REPRESENTING TEXT//

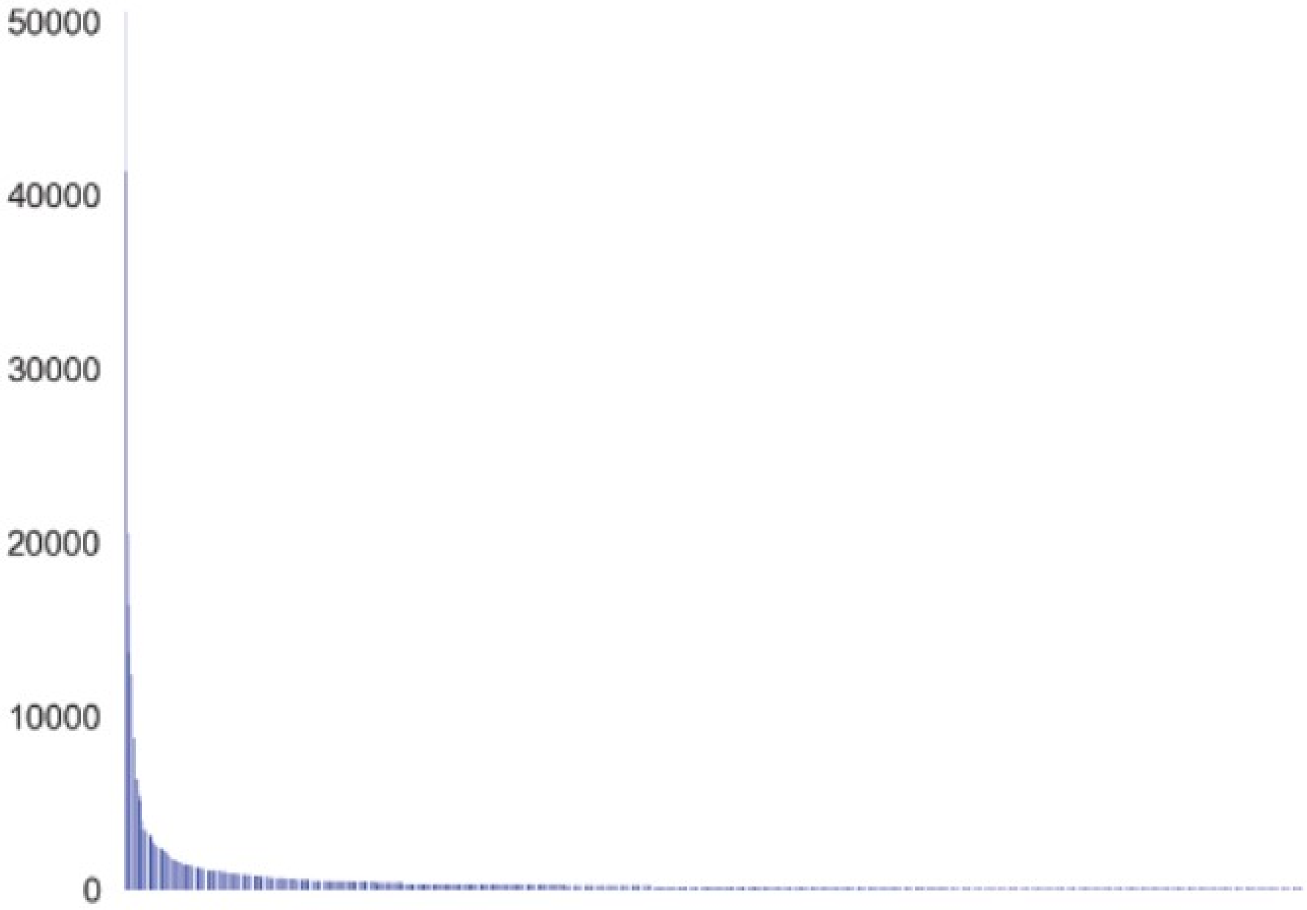
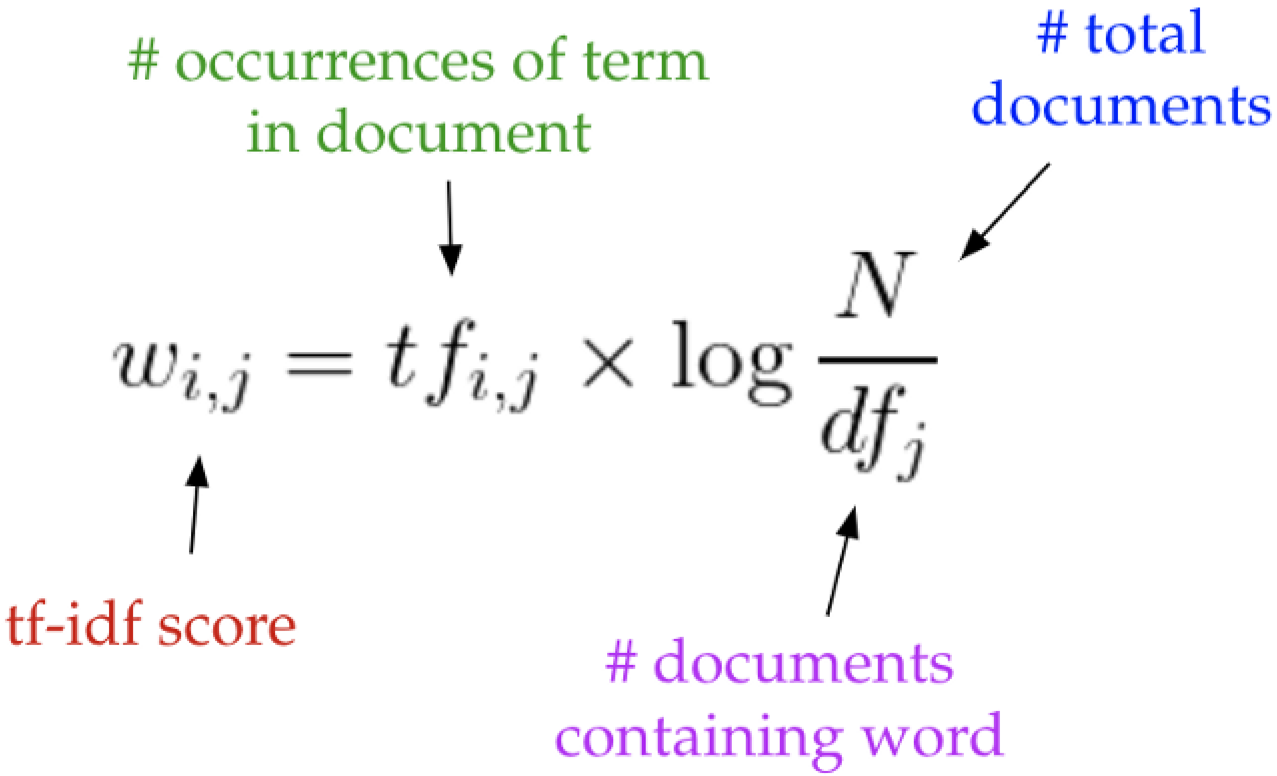


Figure 3 Frequency distribution of the top 1,000 words in a random sample of tweets, following Zipf's law.

REPRESENTING TEXT//

TF-IDF Counts

The **term frequency-inverse document frequency (tf-idf)**, is a numerical statistic that is intended to reflect how important a word is to a document in a collection or corpus.



occurrences of term in document

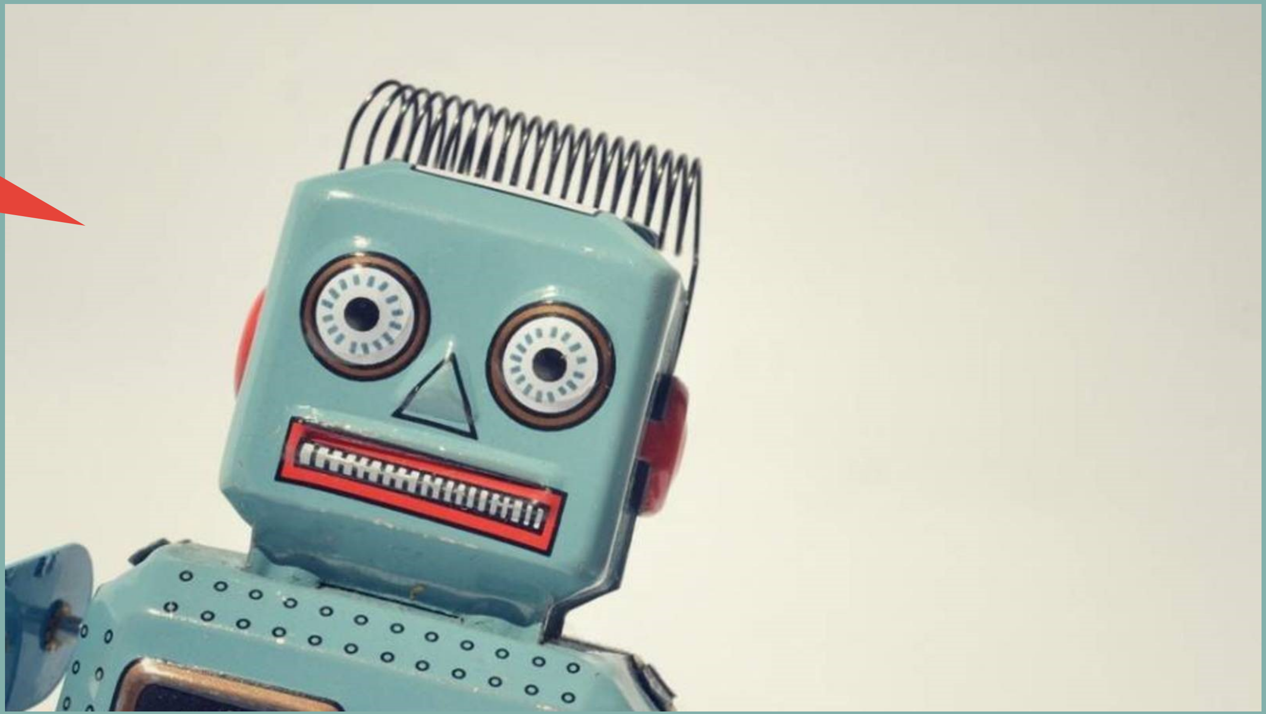
total documents

$$w_{i,j} = tf_{i,j} \times \log \frac{N}{df_j}$$

tf-idf score

documents containing word

LET’S CODE!



WE’LL BE BACK IN 15 MIN…