ECE 20875

Python for Data Science

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(Adapted from material developed by Profs. Milind Kulkarni, Stanley Chan, Chris Brinton, David Inouye)

n-grams and basic natural language processing

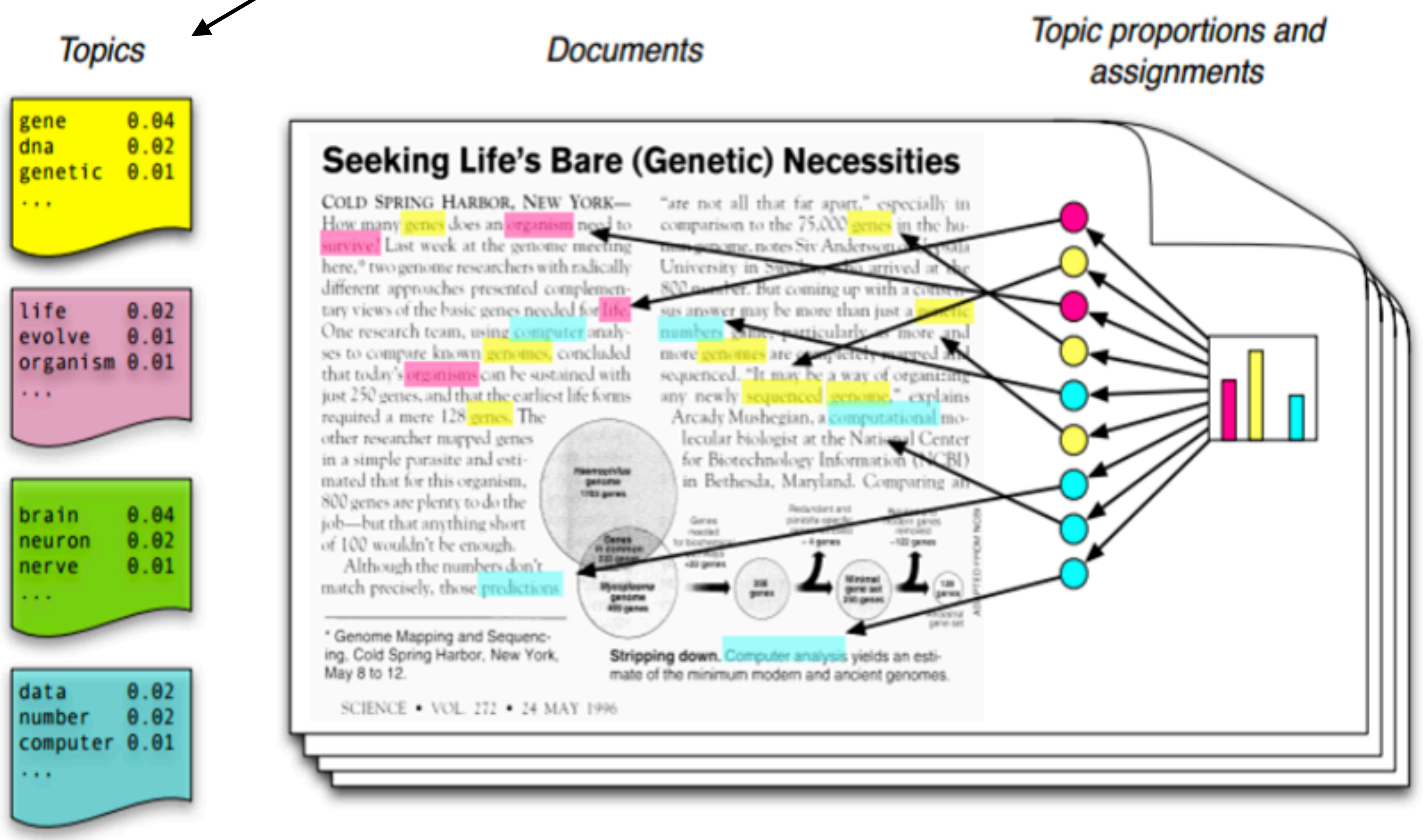
text data analysis

- Written text is often treated as a form of data for analysis
- Some types of analyses:
    - Measuring similarity between **documents**
    - Extracting **topics** from documents
    - Finding the most frequently occurring words
    - Quantifying the importance of **phrases**
- Most of these involve breaking up documents into words or “*n*-grams”

Popular example: Latent Dirichlet Allocation (LDA)

documents: combinations of *topics*

topics: combinations of *words*



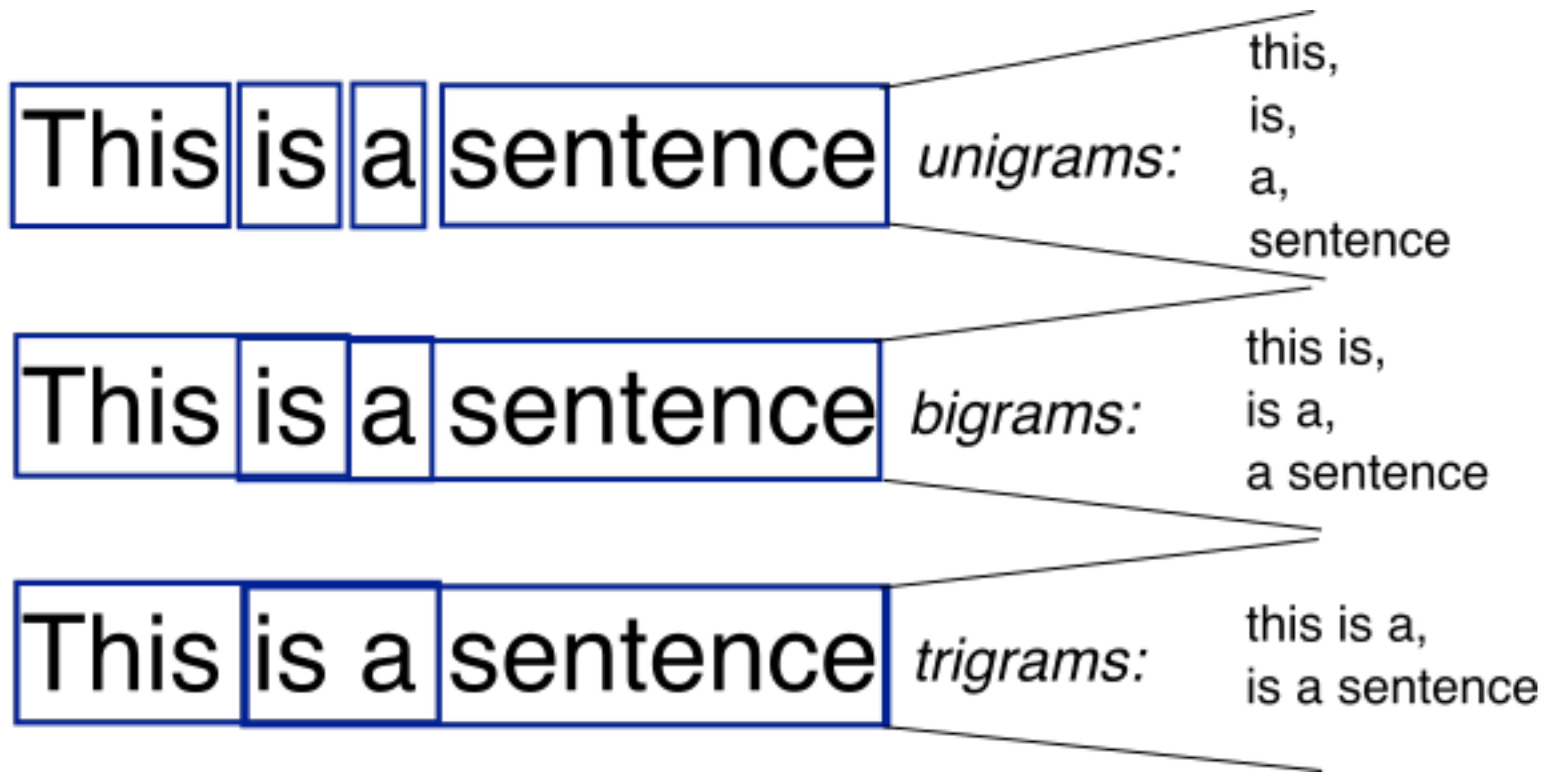
n-grams

- ***n*-grams** break up a sentence into overlapping **subsequences** of length *n*
  - *n* typically refers to words or characters (though it could also be e.g., syllables)
  - Unigrams (*n*=1), bigrams (*n*=2), trigrams (*n*=3), …
- Consider the string: `“I saw a cat”`
  - Word-based 3-grams:

    `“I saw a”, “saw a cat”`
  - Character-based 3-grams:

    `“I␣s”, “␣sa”, “saw”, “aw␣”, “w␣a”, “␣a␣”, “a␣c”, “␣ca”, “cat”`

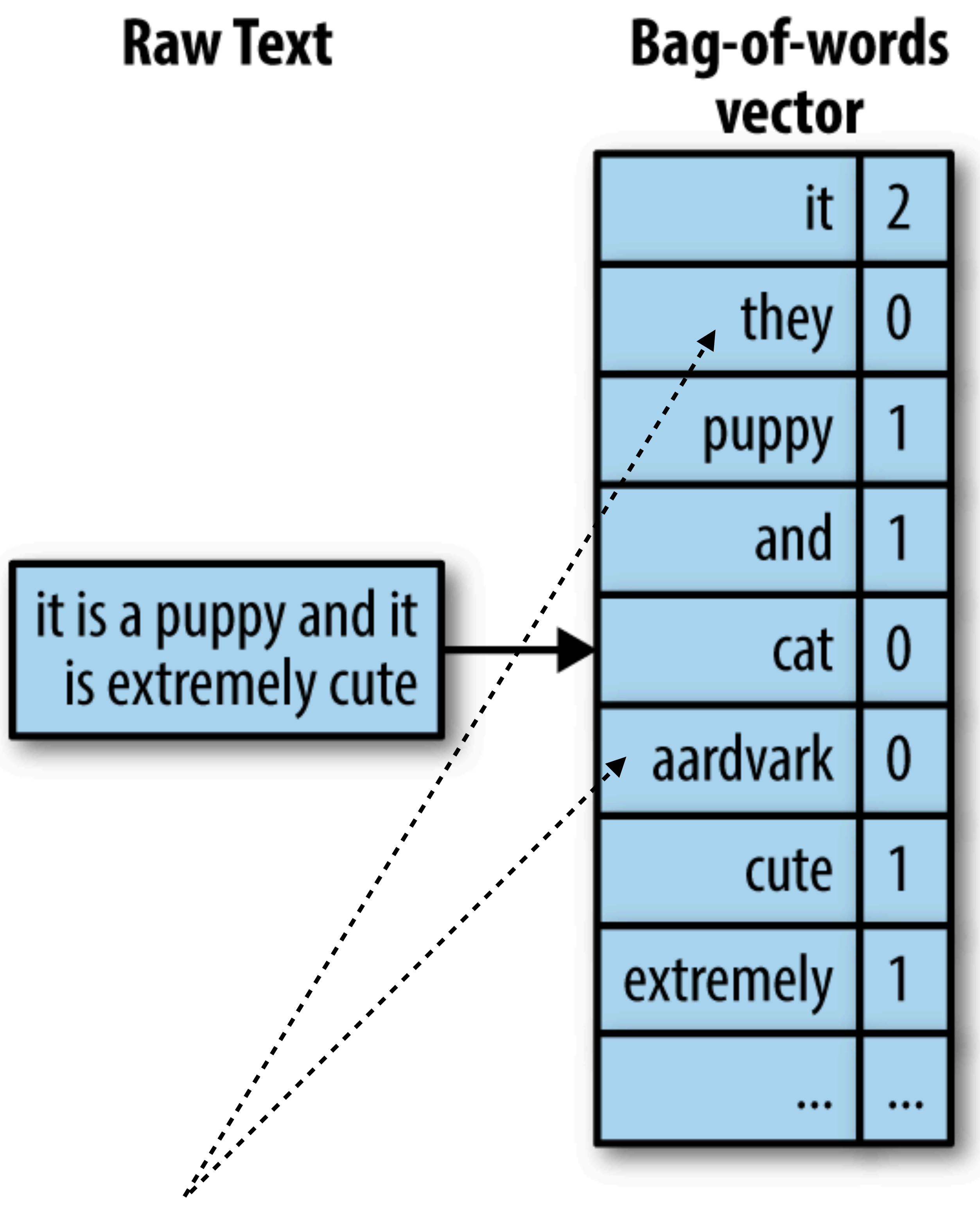
word-based n-gram extraction



bag-of-words

- The same *n*-gram can appear multiple times in a string
  - This indicates a higher frequency
- Generally we only care about order *within* an n-gram, not *between* n-grams
- **Bag-of-words** model: Order between words (more generally, between *n*-grams) in a document is not considered
  - We call it "bag-of-words," but it's really "bag-of-*n*-grams"
- For example, consider this string: "`wan can cup`"
  - bag-of-words of character-based 3-grams:

```
wan : 1    an␣ : 2    n␣c : 2
␣ca : 1    can : 1    ␣cu : 1    cup : 1
```



- Where would the 0s come from?
- We often compare documents by their bag-of-words representations

language classification

- Consider the commonly encountered **language classification** problem, i.e., identifying the language in which a document is written

- We could consider the *n*-grams of characters contained in the document

  - Documents written in a particular language will tend to have similar *n*-gram frequencies (e.g., “the” in English vs. “el” in Spanish)

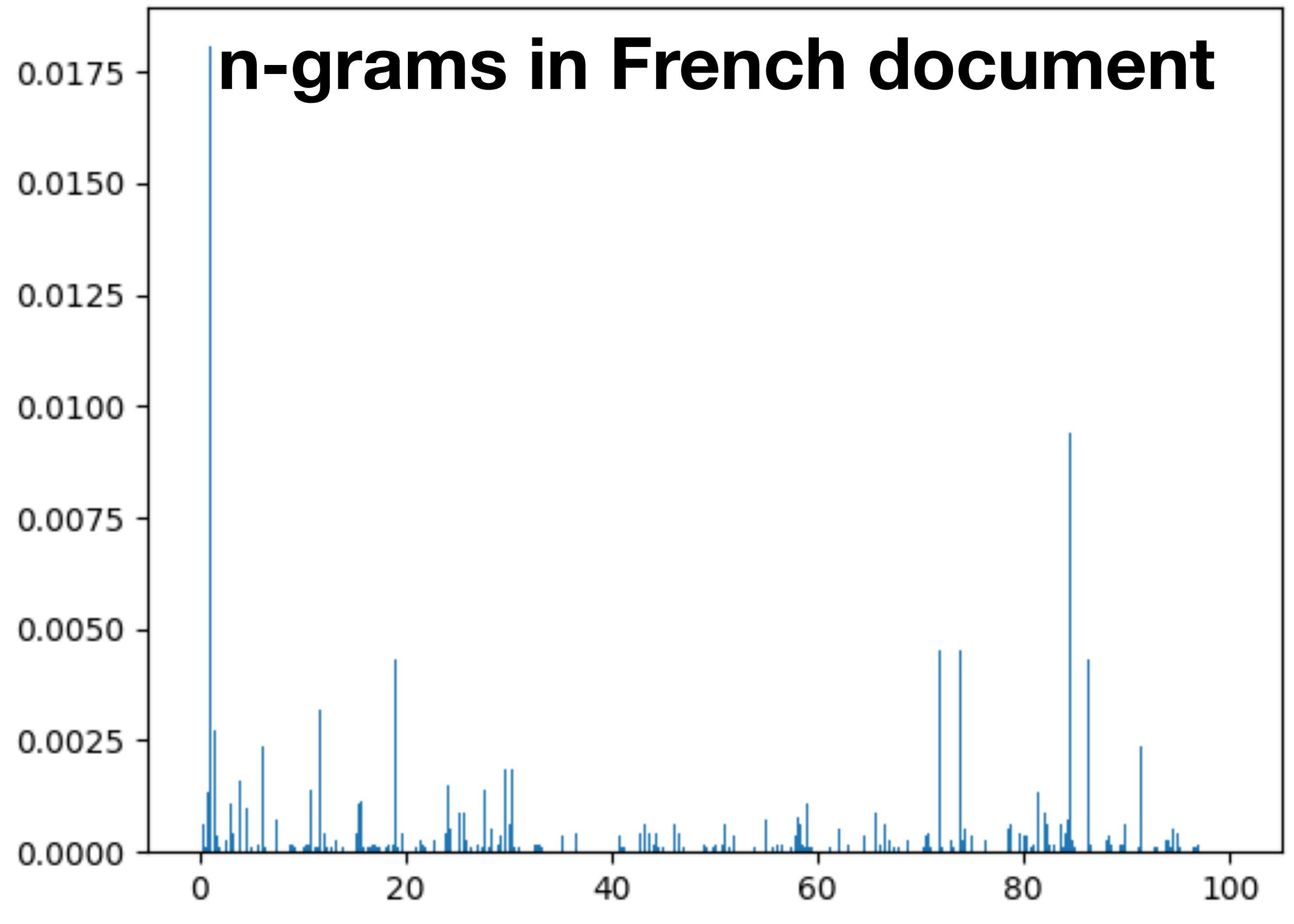
  - We can compare a document of interest to known *n*-gram language frequencies

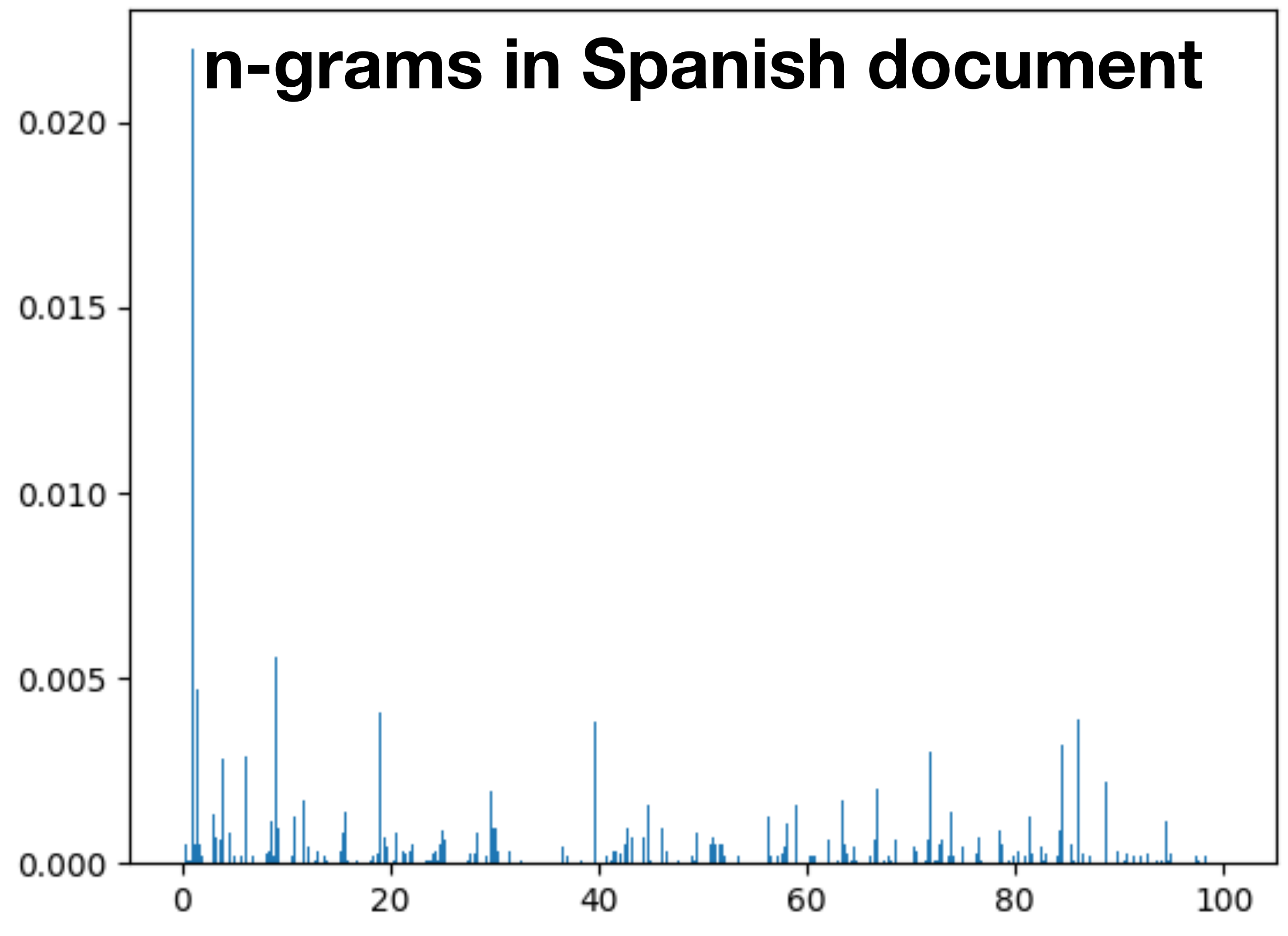
unigram		**bigram**		**trigram**	
e	12.6%	th	3.9%	the	3.5%
t	9.1%	he	3.7%	and	1.6%
a	8.0%	in	2.3%	ing	1.1%
o	7.6%	er	2.2%	her	0.8%
i	6.9%	an	2.1%	hat	0.7%
n	6.9%	re	1.7%	his	0.6%
s	6.3%	nd	1.6%	tha	0.6%
h	6.2%	on	1.4%	ere	0.6%
...		...		...	

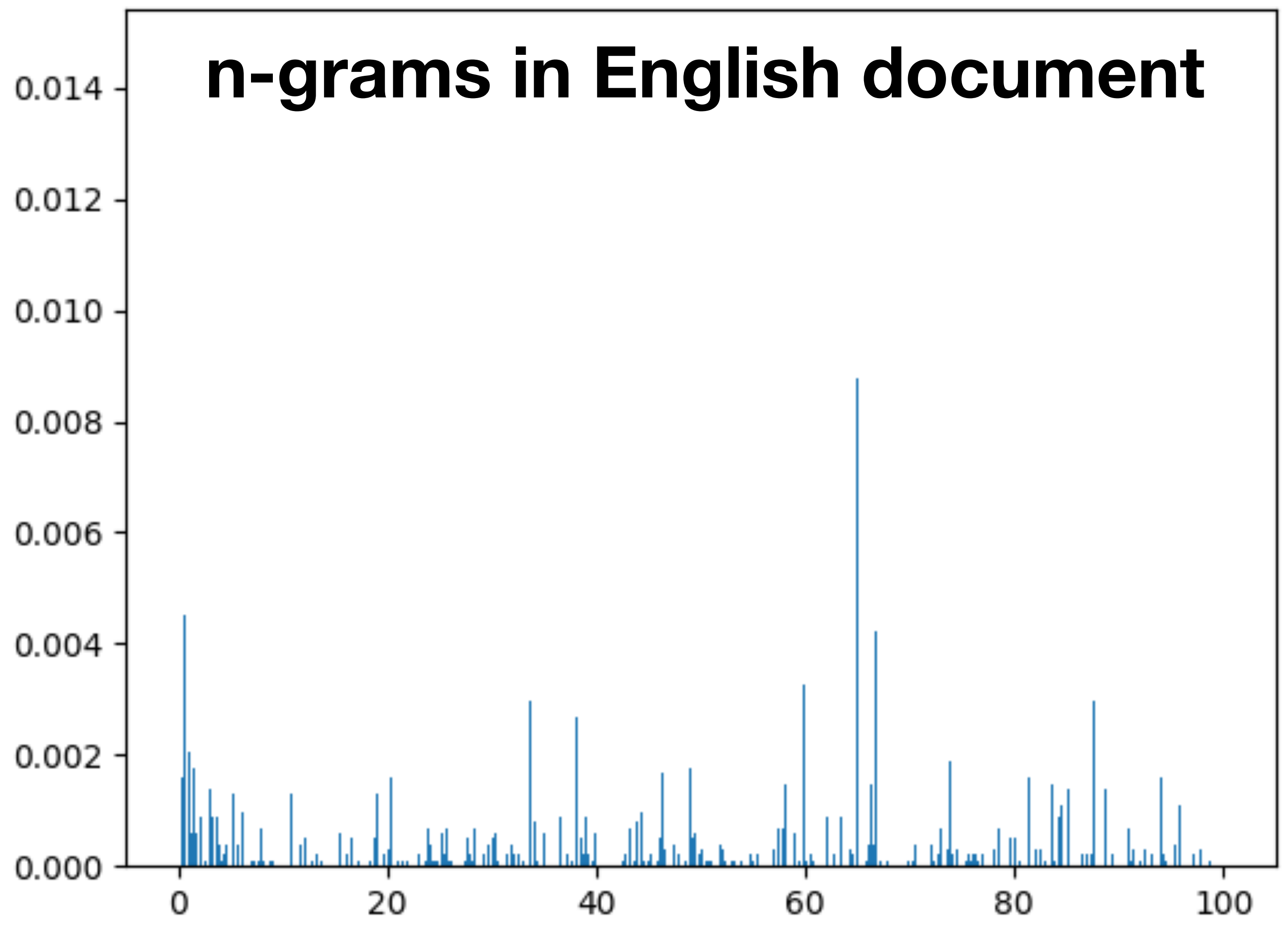
- Can visualize this by building a histogram of the *n*-grams

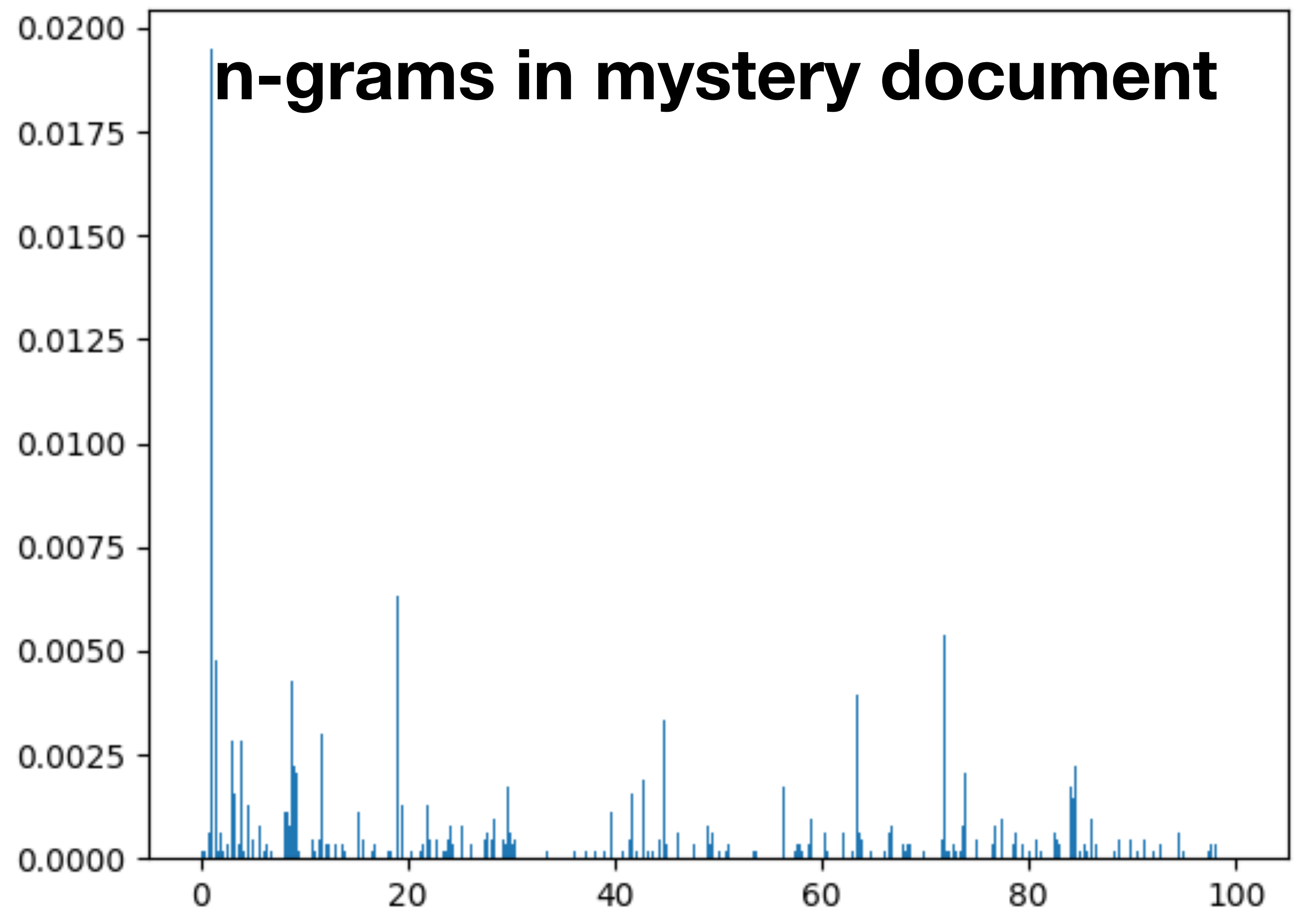
  - Treat each *n*-gram across the documents as a separate (categorical) bucket

n-gram histogram examples









- How would we quantify which language is "closest" to the mystery document?
- We could use the MSE between the *n*-gram vectors

n-gram importance

- How do we quantify the *importance* of an *n*-gram in a document?

- One possibility: Count the number of times it occurs, i.e., its **frequency**

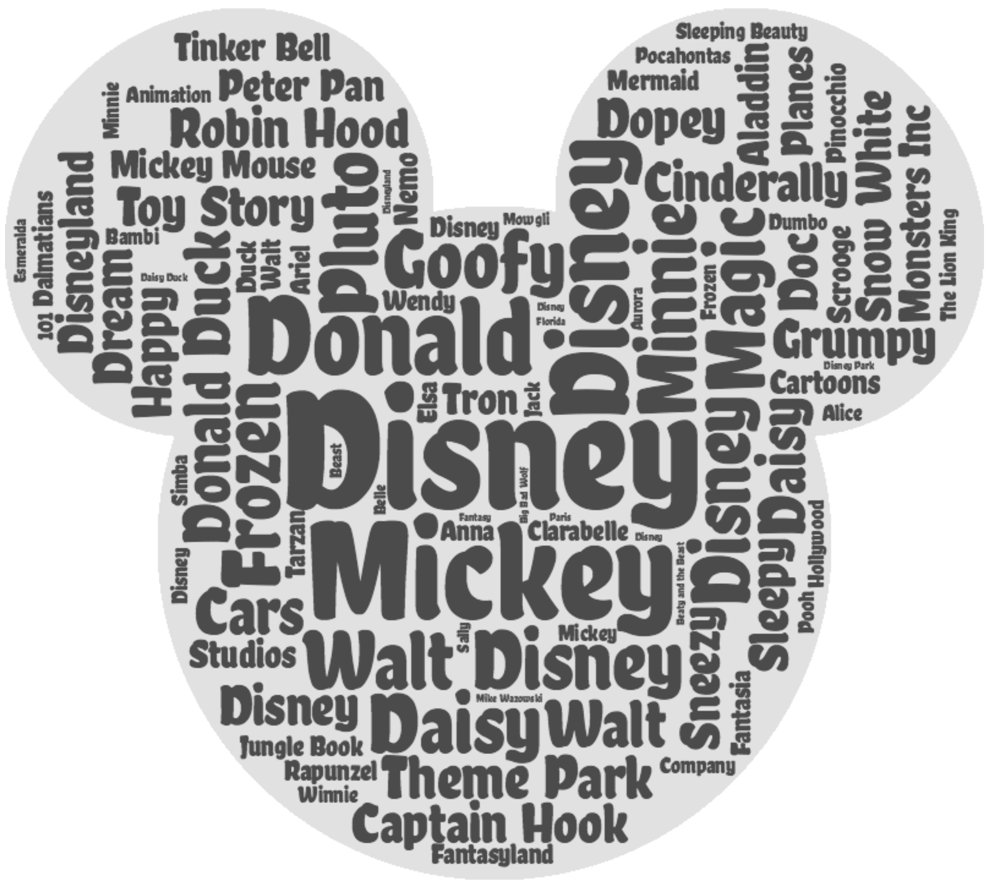
    - More frequently occurring should be more important

- But what about common words like “a”, “as”, “is”, …?

    - These specific examples are **stopwords**, which we should probably remove from the analysis of “importance” anyway

    - But many high frequency non-stopwords will not provide much information in a given context (e.g., “`Disney`” in a collection of documents about “`Disney World`”)

- Need to somehow measure how “unique” the *n*-gram is across documents



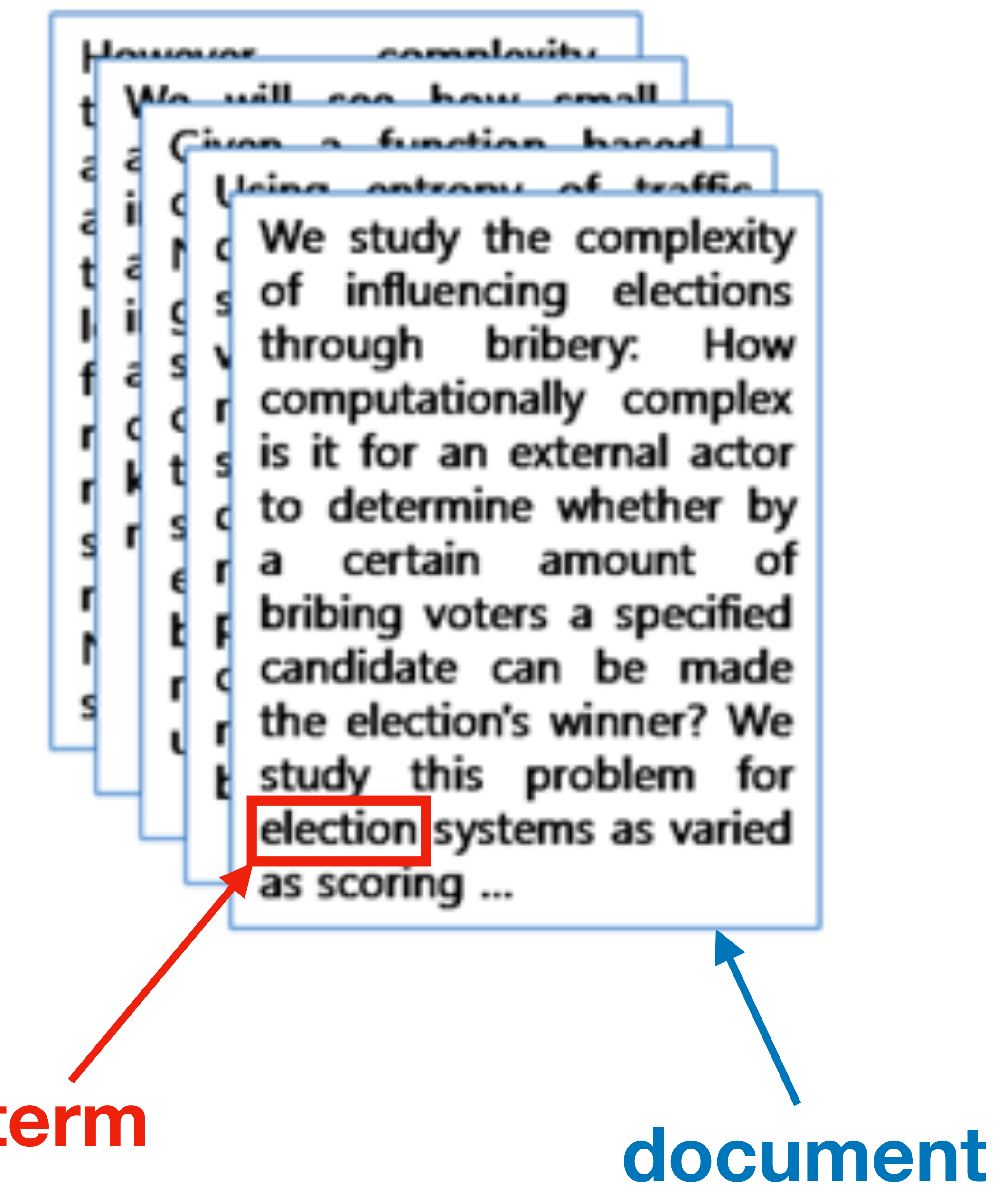
tf-idf score

- A statistic that quantifies this intuition is the **term frequency-inverse document frequency** or **tf-idf** score
  - One of the most popular schemes used today
  - Let t be a term (n-gram), d be a document, and D be a **corpus** (collection of documents) under consideration
  - The tf-idf score of term t in document d with respect to corpus D is

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

- Many different methods for quantifying `tf` and `idf`

Corpus



Here we we will assume terms are words, but more generally they can be n-grams

tf-idf score

- Term frequency $\texttt{tf}(t, d)$: Typically the fraction of terms in document d which are term t
    - Letting $f_{t,d}$ be the number of occurrences of t in d,

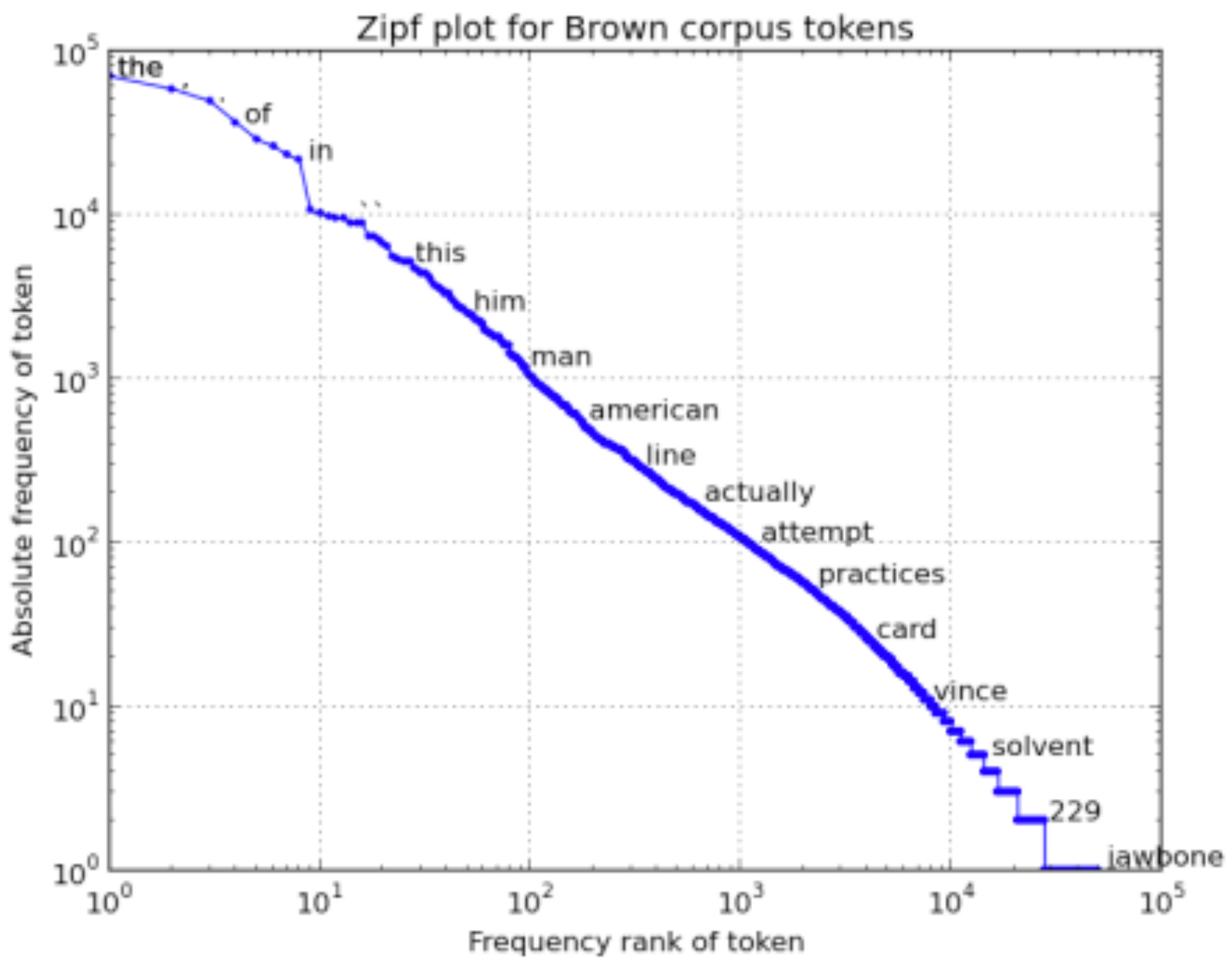
$$\texttt{tf}(t, d) = \frac{f_{t,d}}{\sum_{t'} f_{t',d}}$$

Word	TF A	TF B	IDF	TF*IDF A	TF*IDF B
The	1/7	1/7	log(2/2) = 0	0	0
Car	1/7	0	log(2/1) = 0.3	0.043	0
Truck	0	1/7	log(2/1) = 0.3	0	0.043
Is	1/7	1/7	log(2/2) = 0	0	0
Driven	1/7	1/7	log(2/2) = 0	0	0
On	1/7	1/7	log(2/2) = 0	0	0
The	1/7	1/7	log(2/2) = 0	0	0
Road	1/7	0	log(2/1) = 0.3	0.043	0
Highway	0	1/7	log(2/1) = 0.3	0	0.043

- Inverse document frequency $\texttt{idf}(t, D)$: A measure of how rare term t is across the corpus D (i.e., how much information it provides about a document it appears in)
    - Letting $N = |D|$ be the number of documents in the corpus and n_t be the number of documents where t occurs, it is typically quantified as

$$\texttt{idf}(t, D) = \log_{10}\left(\frac{n_t}{N}\right)^{-1} = \log_{10}\frac{N}{n_t}$$

Why log?



example

Dataset: Take the following four strings to be (very small) documents comprising a (very small) corpus:

1. “The sky is blue.”
2. “The sun is bright today.”
3. “The sun in the sky is bright.”
4. “We can see the shining sun, the bright sun.”

Task: Filter out obvious stopwords, and determine the tf-idf scores of each term in each document.

solution

- After stopword filtering: (1) “`sky blue`”, (2) “`sun bright today`”, (3) “`sun sky bright`”, (4) “`can see shining sun bright sun`”

- TF: Find doc-word matrix, then normalize rows to sum to 1

$$f_{t,d}$$

$$\mathtt{tf}(t,d) = \frac{f_{t,d}}{\sum_{t'} f_{t',d}}$$

	blue	bright	can	see	shining	sky	sun	today
1	1	0	0	0	0	1	0	0
2	0	1	0	0	0	0	1	1
3	0	1	0	0	0	1	1	0
4	0	1	1	1	1	0	2	0

	blue	bright	can	see	shining	sky	sun	today
1	1/2	0	0	0	0	1/2	0	0
2	0	1/3	0	0	0	0	1/3	1/3
3	0	1/3	0	0	0	1/3	1/3	0
4	0	1/6	1/6	1/6	1/6	0	1/3	0

solution

- IDF: Find number of documents each word occurs in, then compute formula

$f_{t,d}$

	blue	bright	can	see	shining	sky	sun	today
1	1	0	0	0	0	1	0	0
2	0	1	0	0	0	0	1	1
3	0	1	0	0	0	1	1	0
4	0	1	1	1	1	0	2	0
n_t	**1**	**3**	**1**	**1**	**1**	**2**	**3**	**1**

$N = 4$

$$\texttt{idf}(t, D) = \log_{10} \frac{N}{n_t}$$

	blue	bright	can	see	shining	sky	sun	today
	0.602	0.125	0.602	0.602	0.602	0.301	0.125	0.602

$$\log_{10} \frac{4}{1} = 0.602$$

$$\log_{10} \frac{4}{3} = 0.125$$

solution

$$\mathtt{tf}(t,d)$$

	blue	bright	can	see	shining	sky	sun	today
1	1/2	0	0	0	0	1/2	0	0
2	0	1/3	0	0	0	0	1/3	1/3
3	0	1/3	0	0	0	1/3	1/3	0
4	0	1/6	1/6	1/6	1/6	0	1/3	0

x

$$\mathtt{idf}(t,D)$$

	blue	bright	can	see	shining	sky	sun	today
	0.602	0.125	0.602	0.602	0.602	0.301	0.125	0.602

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

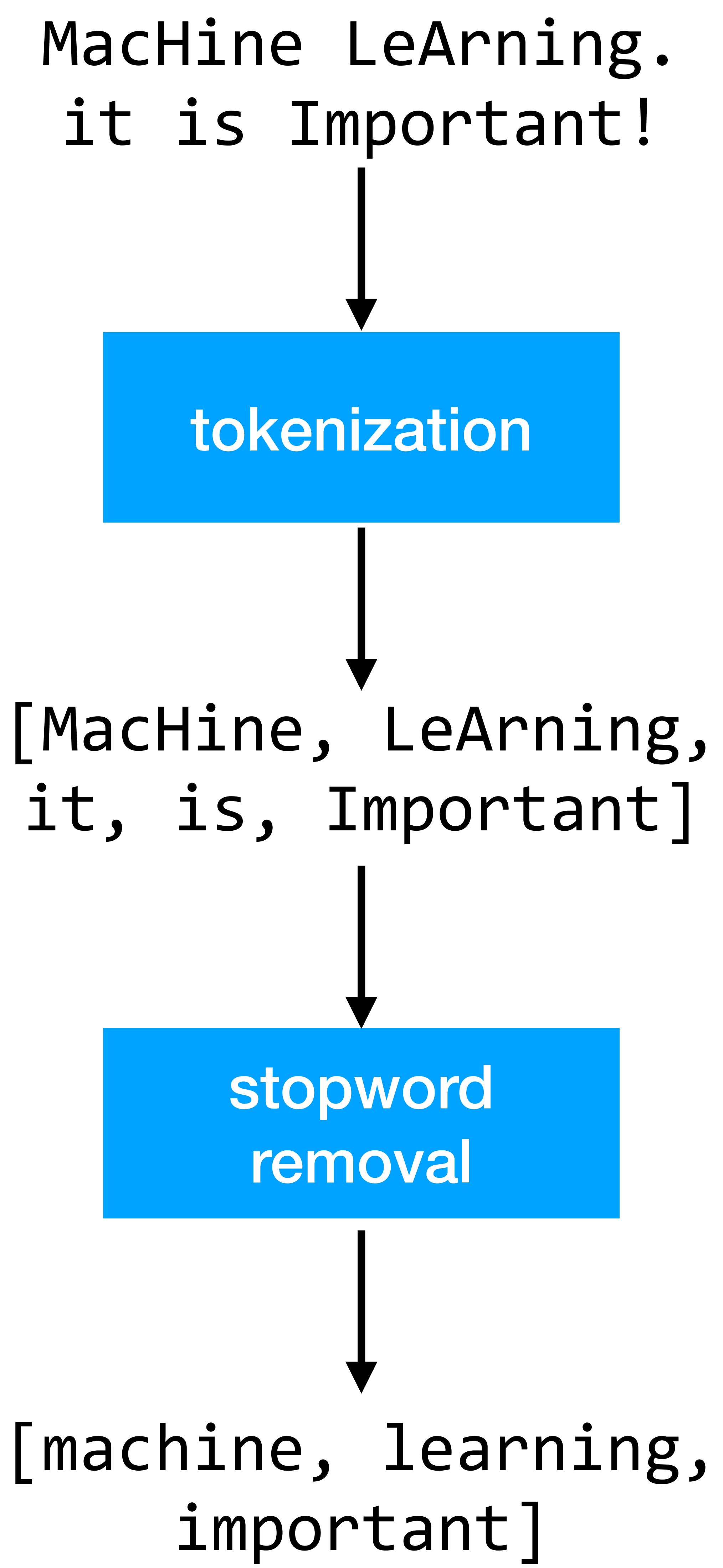
	blue	bright	can	see	shining	sky	sun	today
1	**0.301**	0	0	0	0	0.151	0	0
2	0	0.0417	0	0	0	0	0.0417	**0.201**
3	0	0.0417	0	0	0	**0.100**	0.0417	0
4	0	0.0209	**0.100**	**0.100**	**0.100**	0	0.0417	0

- TF-IDF: Multiply TF and IDF scores, use to rank importance of words within documents
  - Most important word for each document is highlighted

text preprocessing

- Typically apply a series of preprocessing steps prior to analysis
  - Mostly using Python's `nltk` (natural language processing toolkit) library

1. **Tokenization**
   - Break text into tokens, e.g., n-grams of words (`nltk.word_tokenize(string)` or `string.split()`)
   - Remove non-word characters, e.g., punctuation
2. **Stopword removal**
   - Make words lowercase (`s.lower()`)
   - Remove common word tokens (`stopwords.words('english')`)



text preprocessing

3. **Stemming / Lemmatizing**

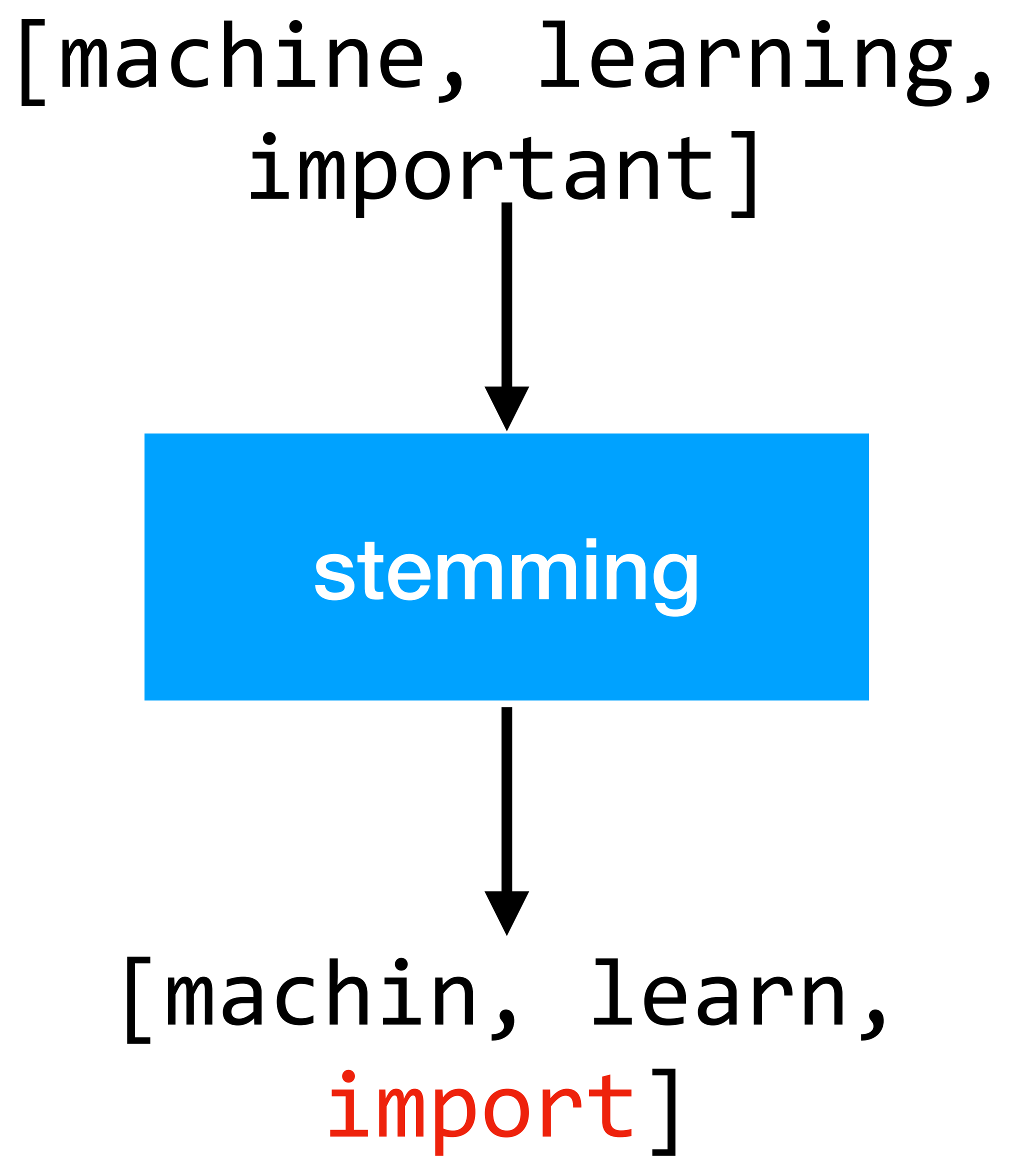
   - **Stemming** reduces inflected words to their word stem (e.g., `studies, studying -> studi`)

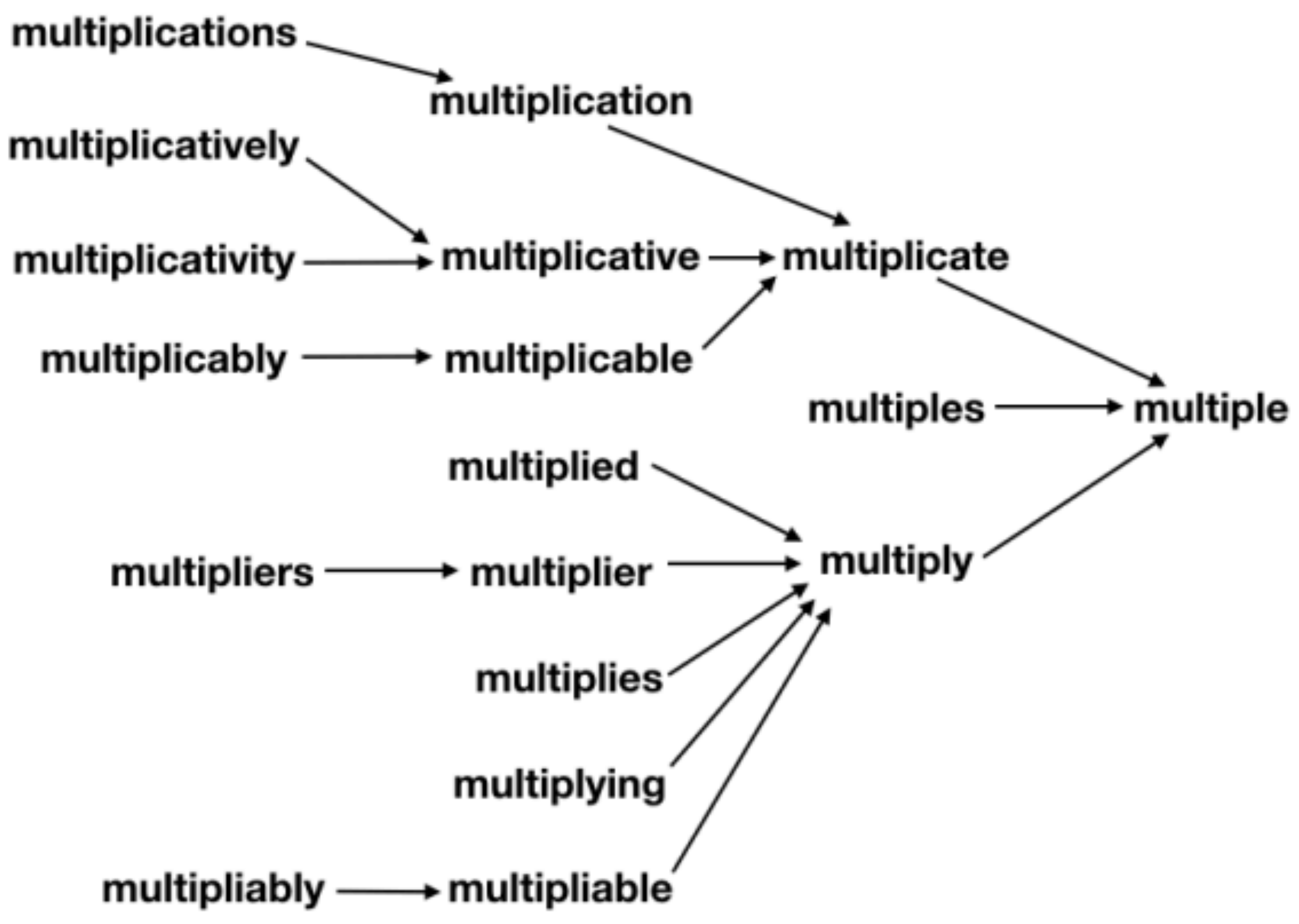
   - **Lemmatization** maps words to their dictionary form, representing them as words (e.g., `studies, studying –> study`)

     - Requires part-of-speech (POS) specification

   - Lemmatization is more complex (we need to tag a words POS to get the right result), but preferred when possible (e.g., on the right, the stemmed version of `important` is `import`)

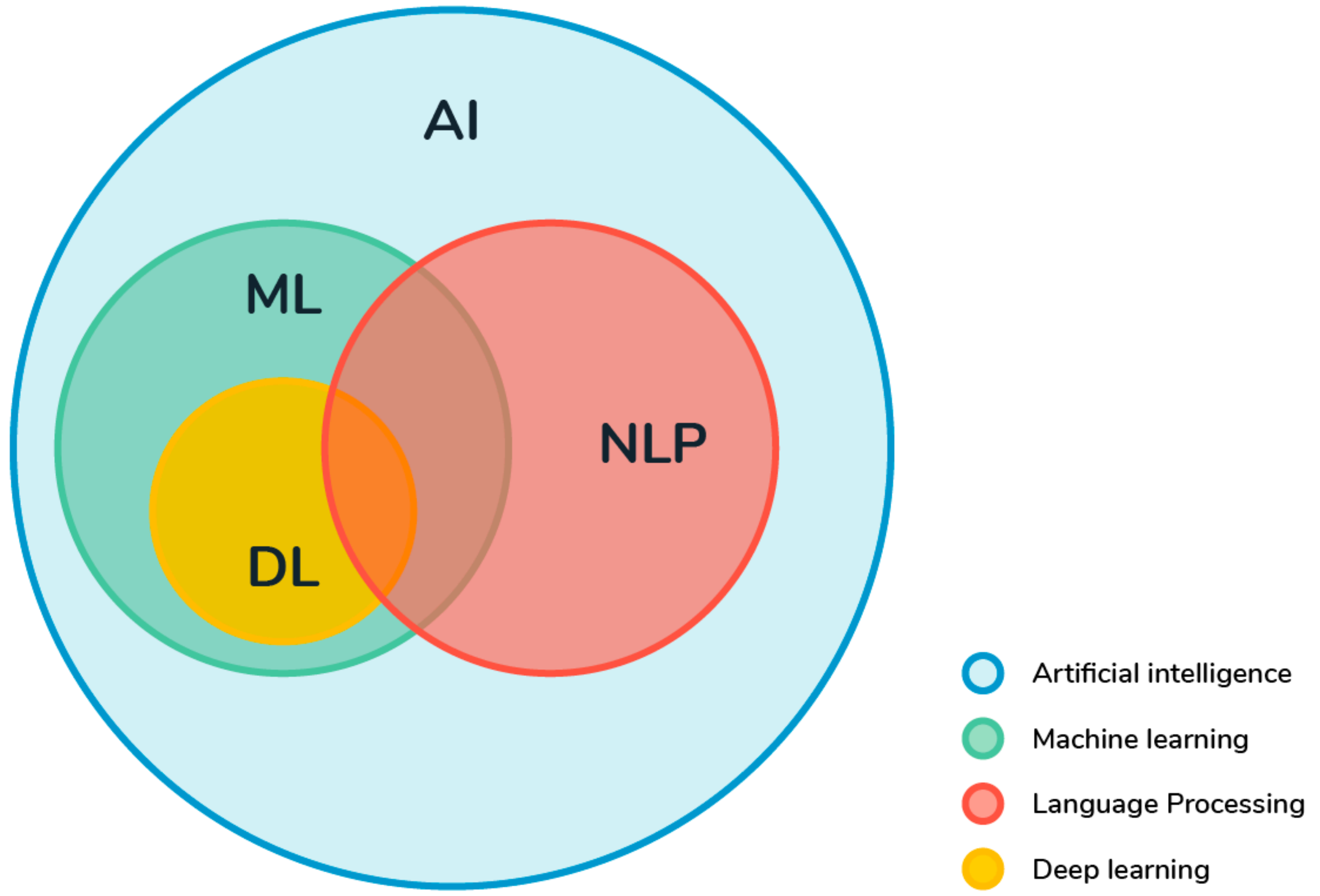
   - `from nltk.stem import PorterStemmer, WordNetLemmatizer`





natural language processing

- What we have been studying are specific methods in **natural language processing**, or **NLP**
    - NLP is concerned with how to automatically analyze large corpuses of text
- Two main classes of NLP: rules-based and statistical
    - tf-idf is a simple (yet widely used) statistical technique
    - Today's innovations are largely in the statistical category, leveraging *machine learning*
- Key is building **knowledge representations**



natural language processing

- Some common functions of NLP
  - **Machine translation**: Translating between languages (e.g., Google translate)
  - **Speech recognition**: Determine the textual representation of an audio track (e.g., Siri)
  - **Document summarization**: Determine an effective summary of a document (e.g., Watson)
- All of these are constantly being innovated with new NLP algorithms