Master Degree in Computer Science
Master Degree in Data Science and Economics

Information Retrieval

Scoring, term weighting and the vector space model

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sed noli modo

Text transformation

In order to process queries and other IR tasks on text, we need to transform it into a model that can be computed by a machine

Such a model should be

- suitable for any kind of text
- capable of modeling interesting properties of text, such as the semantics
- suitable for matching texts and supporting the notion of *text similarity* in a quantitative framework

The vector space model (intuition)

Doc 1

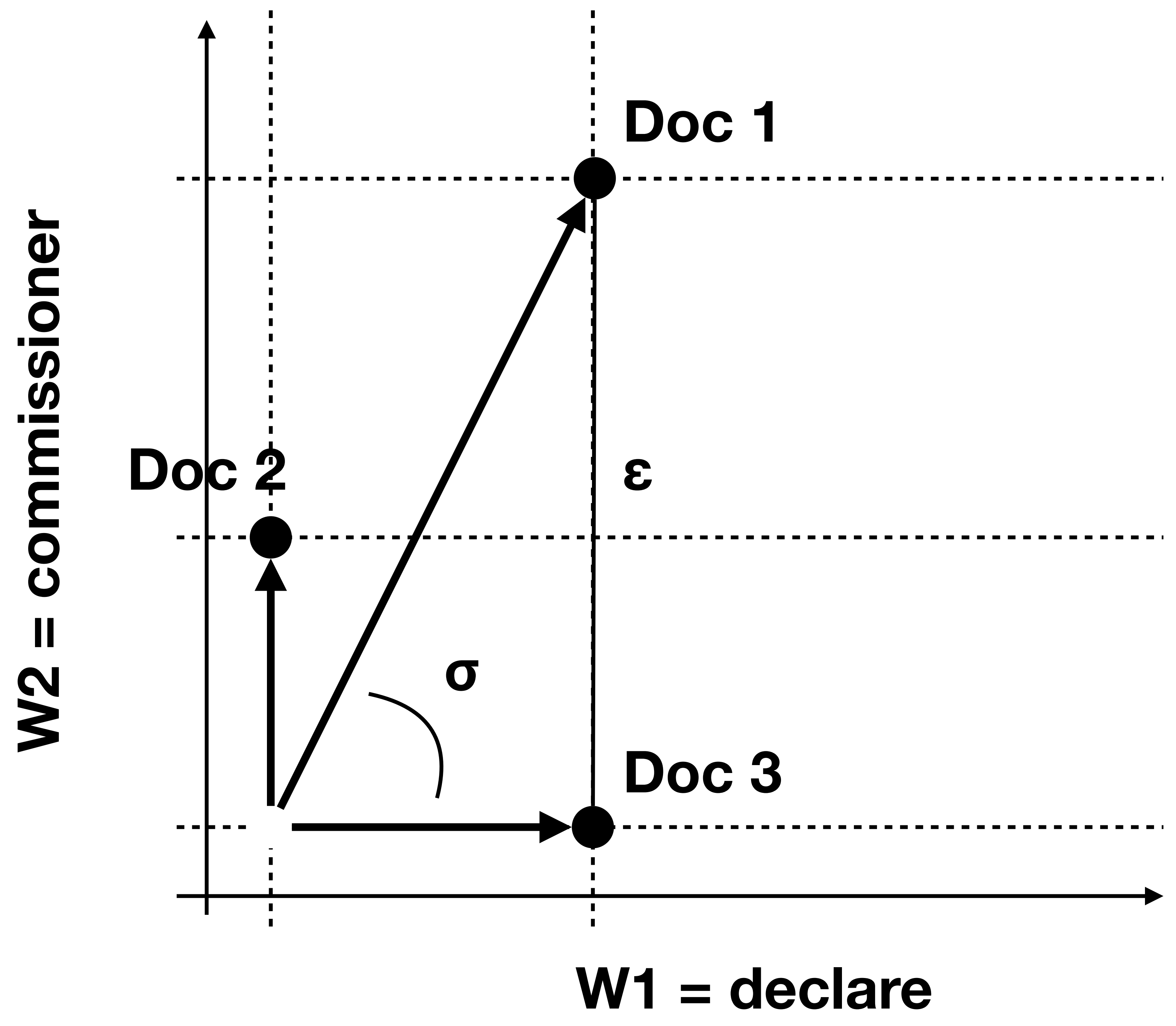
TO REVISE THE CHARTER; Governor Soon to Announce His Choice of Commissioners. [...] The Commissioners declared that [...]

Doc 2

JAMES McCARTNEY DEAD.; The Commissioner of Street Cleaning Passes Away at His Home After a Long Illness.

Doc 3

DENY COLGAN LOST JOB OVER 'AL' SMITH; Hylan Declares Cry of Politics Shows Attempt to Split Democratic Party.



Doc	W1	W2	...
Doc1	1	2	...
Doc 2	0	1	...
Doc 3	1	0	...

Mapping documents into the vector space

Doc 1

TO REVISE THE CHARTER; Governor Soon to Announce His Choice of Commissioners. [...] The Commissioners declared that [...]

TOKENIZE

```
['TO', 'REVISE', 'THE', 'CHARTER', ';', 'Governor', 'Soon', 'to', 'Announce', 'His', 'Choice',
'of', 'Commissioners', '.', 'The', 'Commissioners', 'declared', 'that']
```

NORMALIZE

```
['to', 'revis', 'the', 'charter', ';', 'governor', 'soon', 'to', 'announc', 'hi', 'choic', 'of',
'commission', '.', 'the', 'commission', 'declar', 'that']
```

WEIGHT

```
{'to': 2, 'the': 2, 'commission': 2, 'revis': 1, 'charter': 1, ';': 1, 'governor': 1, 'soon': 1,
'announc': 1, 'hi': 1, 'choic': 1, 'of': 1, '.': 1, 'declar': 1, 'that': 1}
```

INDEXING

	to	the	commission	revis	charter	;	governor	soon	announc	hi	choic	of	.	declar	that
Doc1	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1

Tokenize

REGEX	https://www.nltk.org/_modules/nltk/tokenize/regexp.html
CORPUS-BASED	https://www.nltk.org/api/nltk.tokenize.html
ML MODELS & RULE-BASED	https://spacy.io/usage/linguistic-features#tokenization

Normalize

STEMMING

"The Porter stemming algorithm (or 'Porter stemmer') is a process for removing the commoner morphological and inflexional endings from words in English. Its main use is as part of a term normalisation process that is usually done when setting up Information Retrieval systems."

M.F. Porter, 1980, An algorithm for suffix stripping, Program, 14(3) pp 130−137.

DICTIONARY-BASED LEMMATIZATION

WordNet: https://wordnet.princeton.edu

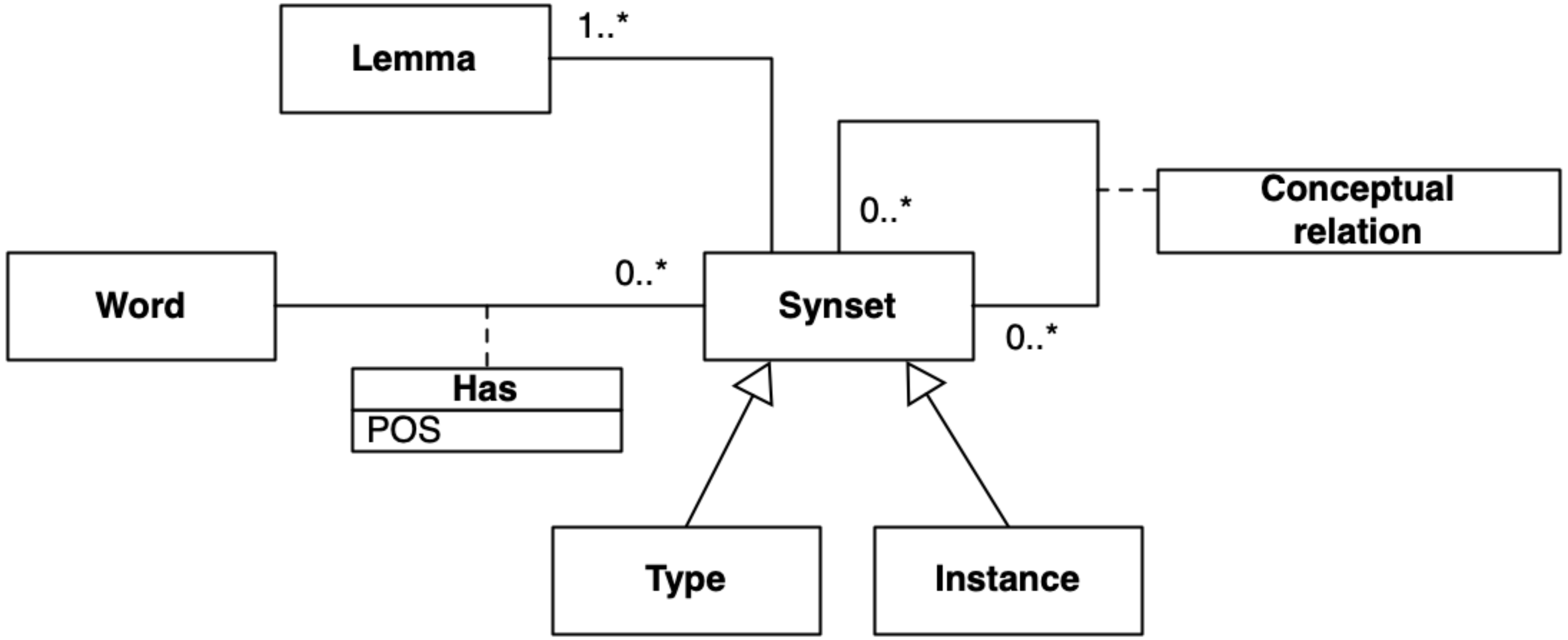
ML-MODELS

https://spacy.io/usage/linguistic-features#lemmatization

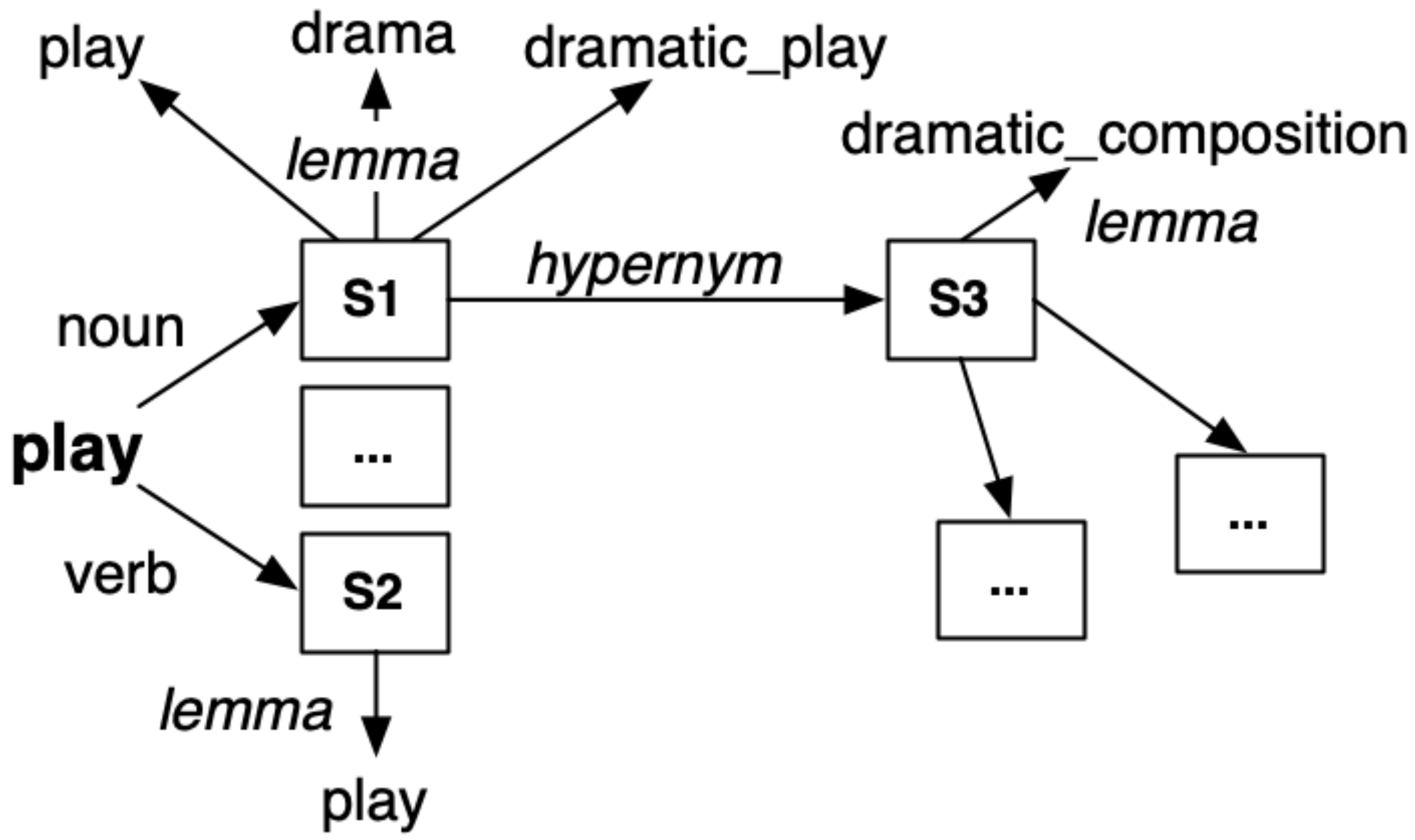
WordNet

WordNet® is a large lexical database of English. Nouns, verbs, adjectives and adverbs are grouped into sets of cognitive synonyms (synsets), each expressing a distinct concept. Synsets are interlinked by means of conceptual-semantic and lexical relations.

MODEL



EXAMPLE



Weight: Term Frequency (TF)

BOOLEAN $1 \ if \ tf_{t,d} > 0, \ 0 \ otherwise$

AUGMENTED $0.5 + \frac{0.5tf_{t,d}}{max_{t'}(tf_{t'd})}$

NATURAL $tf_{t,d} = count(t) \in d$

LOG AVG $\frac{1 + \log(tf_{t,d})}{1 + \log(avg_{t \in d}(tf_{t,d}))}$

LOG $1 + \log(tf_{t,d})$

MAX TF NORM $k + (1 - k)\frac{tf_{t,d}}{tf_{max}(d)}$

Weight: Inverse Document Frequency (IDF)

Besides term frequency, another important measure for weighting terms is the **document frequency**. The document frequency $df(t)$ of a term t is given by the number of documents d_i where $tf_{t,d_i} > 0$.

In many applications, we are interested in terms that are specific of a small subset of documents and, thus, have a low document frequency. To this end, we define the inverse document frequency idf_t as

$$idf_t = \log \frac{N}{df_t}$$

Weight: Inverse Document Frequency (IDF)

IDF $$\log \frac{N}{df_t} = -\log \frac{df_t}{N}$$

MAX $$\log \left(\frac{\max_{t' \in d} df_{t'}}{1 + df_t} \right) + 1$$

SMOOTH $$\log \left(\frac{N}{1 + df_t} \right) + 1$$

PROBABILISTIC $$\log \frac{N - df_t}{df_t}$$

Weight: TfIdf

By combining term frequency and inverse document frequency we obtain a measure that takes into account the specific relevance of a terms with respect to a document

$$TfIdf(t, d) = tf_{t,d} idf_t = tf_{t,d} \log \frac{N}{df_t}$$

TfIdf is:
- high when t appears in a small number of documents (high discriminating)
- low when t appears a few times in *d* or when it appears in many documents (irrelevant or generic)

Exploit vectors to measure document distances

Distance	Definition	Interpretation	Distance	Definition	Interpretation
Cosine Distance	$\frac{\sum_{i=1}^{n} a_i b_i}{\sqrt{\sum_{i=1}^{n} a_1^2}\sqrt{\sum_{i=1}^{n} b_1^2}}$	Cosine of the angle between the vectors	Canberra distance	$\sum_{i=1}^{n} \frac{\mid a_i - b_i \mid}{\mid a_i \mid \mid b_i \mid}$	Normalized version of Manhattan distance
Euclidean Distance	$\sqrt{\sum_{i=1}^{n} \mid a_i - b_i \mid^2}$	Vector points distance	Bray-Curtis distance	$\frac{\sum_{i=1}^{n} \mid a_i - b_i \mid}{\sum_{i=1}^{n} \mid a_i + b_i \mid}$	Variant of Manhattan distance
Chebyshev distance	$\max_{i=1}^{n}(\mid a_i - b_i \mid)$	The greatest different along any dimension	Correlation distance	$\frac{\sum_{i=1}^{n} (a_i - avg\ a)(b_i - avg\ b)}{\sqrt{\left\lvert \sum_{i=1}^{n} (a_i - avg\ a) \right\rvert^2} \sqrt{\left\lvert \sum_{i=1}^{n} (b_i - avg\ b) \right\rvert^2}}$	Equivalent to Cosine Distance of vectors shifted by their means
Manhattan distance	$\sum_{i=1}^{n} \mid a_i - b_i \mid$	Distance in a grid	Minkowski distance	$\left(\sum_{i=1}^{n} \mid a_i - b_i \mid^p \right)^{\frac{1}{p}}$	Generalization of Manhattan (p=1) and Euclidean (p=2) distances