92586 Computational Linguistics

Lesson 5. From Word Counts to *Meaning*

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- Pre-processing
- BoW representation
- One rule-based sentiment model
- One statistical model (Naïve Bayes)

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- One rule-based sentiment model
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- *tf-idf* (+ Zipf's law)

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Jumping from Chapter 3 to Chapter 4 of Lane et al. (2019)

tf-idf Tools

tf-idf Implementation

- We "hand-coded" the *tf-idf* implementation

[1] `http://scikit-learn.org/`. As usual, install it the first time; e.g., `pip install scipy; pip install sklearn`

tf-idf Implementation

- We "hand-coded" the *tf-idf* implementation
- Optimised and easy-to-use libraries exist

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tf-idf Implementation

- We "hand-coded" the *tf-idf* implementation
- Optimised and easy-to-use libraries exist
- `scikit-learn` is a good alternative[1]

Let us see

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tf-idf

Final Remarks

- *tf-idf*-like weighting is in the core of search engines and related technology

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BM	best matching
25	Combination of BM11 and BM15

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- Cosine similarity is a top choice distance for most text vector representations.
- Nothing prevents you from weighting n-grams, for $n = [1, 2, \ldots]$

Topic Vectors

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What for?

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- Compare texts on the basis of meaning (not keywords)
- Search based on meaning
- Represent the subject of a statement/document or corpus
- Extract keywords

Topic Vectors

Limitation of word vectors

d_1	Una macchinna rossa
d_2	Le macchinne blu

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$$
\begin{array}{ll}
d_1 & \text{Una macchinna rossa} \\
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 & \downarrow \\
d_1' & \text{macchinn ross} \\
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\vec{d_1} & [\mathbf{1}, 1, 0] \\
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$$cos(d_1, d_2) = 0$$

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Document-topic vector: One vector represents one document (by combining its word-topic vectors)

These models can deal with polysemy (e.g., homonyms) at some extent

Common-Sense Topic Modeling

Scenario

- We are processing sentences about pets, Central Park, and New York
- Three topics: `petness`, `animalness`, `cityness`

Example from (Lane et al., 2019, p. 101–102)

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topic	**high**	**medium**	**low**
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Cityness	NYC	apple	cat, dog

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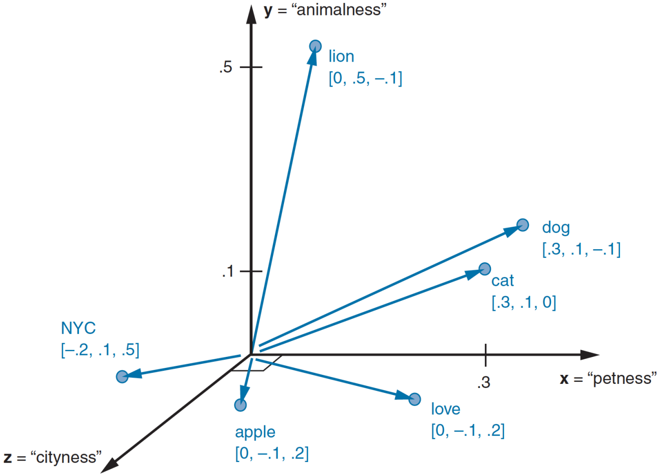
Let us see

Advantages

- We can visualise 3D vectors
- A 3D vector space is convenient for classification: it can be sliced with a hyperplane to divide it into classes

Common-Sense Topic Modeling



Borrowed from (Lane et al., 2019, p. 104)

Common-Sense Topic Modeling

In summary. . .

$\vec{d}$ a *tf-idf* vector of size $|V|$

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$\downarrow$

$\vec{d_t}$ a topic vector of size 3

From one vector space to another

high-dimensional *tf-idf* space $\rightarrow$ low-dimensional **topic** vector space

Common-Sense Topic Modeling

In summary. . .

$$\begin{array}{rl} \vec{d} & \text{a } \textit{tf-idf} \text{ vector of size } |V| \\ M & \text{a } 3 \times V \text{ weight matrix} \\ & \downarrow \\ \vec{d_t} & \text{a topic vector of size 3} \end{array}$$

From one vector space to another

high-dimensional *tf-idf* space $\rightarrow$ low-dimensional **topic** vector space

How can we **learn** the "transformation" matrix?

Towards a Topic Space

You shall know a word by the company it keeps

J. R. Firth (1957)

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- We have corpora
- We have pre-processors
- We can produce *tf-idf* matrices

Towards a Topic Space

You shall know a word by the company it keeps
J. R. Firth (1957)

- We have corpora
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- We can produce *tf-idf* matrices

We can count co-occurrences → the company of a word

Latent Semantic Analysis

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- An algorithm to gather words (*tf-idf* matrix) into topics
- It captures meaning of words
- It is a dimension reduction technique

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AKA

- Principal Component Analysis (PCA)
- Latent Semantic Indexing (LSI, in IR)

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Linear discriminant analysis (LDA)

A supervised algorithm (it needs labeled data!)

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1. Compute the centroid of the vectors in the class
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Centroid: average

Basic algebra!

Let us see

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- We are gathering up words with similar “semantics”

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LDA has learned the `spaminess` of words and documents

Coming Next

- Training and Evaluation in Machine Learning
- More LSA (from 4.2, p 111)

References

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