ALMA MATER STUDIORUM
UNIVERSITÀ DI BOLOGNA
CAMPUS DI FORLÌ

91258 / B0385
Natural Language Processing

Lesson 7. From Word Counts to Meaning

Alberto Barrón-Cedeño
a.barron@unibo.it

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Previously

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

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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)

Topic Vectors

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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

d_1	Una macchina rossa
d_2	Le macchine blu

Topic Vectors

Limitation of word vectors

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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)

Common-Sense Topic Modeling

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topic	high	medium	low
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Cityness	NYC	apple	cat, dog

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Let us see

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

Common-Sense Topic Modeling

We have a 3×6 matrix: 3 topic vectors

	cat	dog	apple	lion	NYC	love
petness	[.3	.3	0	0	-.2	.2]
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The relationships between words and topics can be "flipped": transposing the 3×6 matrix to produce topic weights for each word

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NYC	[	-.2	.1	.5	]
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Given:

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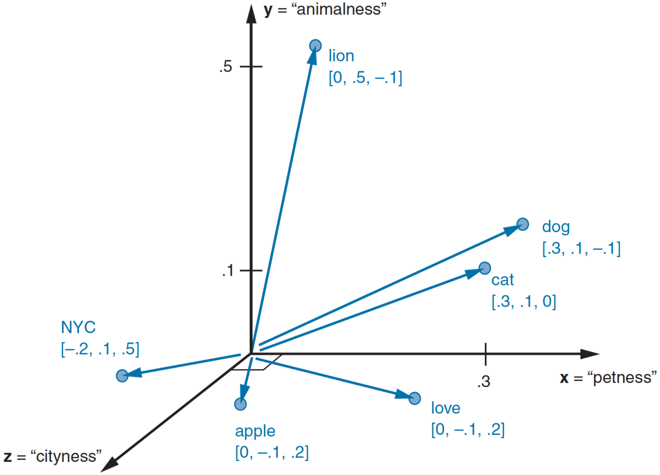
Let us see

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)

In summary...

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

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

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How can we learn the "transformation" matrix?

Towards a Topic Space

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J. R. Firth (1957)

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

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

Latent Semantic Analysis

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- It (somehow) captures the meaning of words
- It is a dimension reduction technique (sparse $\rightarrow$ dense vectors)

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AKA

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

A supervised algorithm (it requires labeled data)

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Algorithm

```
1. Compute the centroid of the vectors in the class
2. Compute the centroid of the vectors not in the
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Centroid: average in a vector space

Basic algebra!

Let us see

- We are not relying on individual words
- 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

Lane, H., C. Howard, and H. Hapkem
2019. *Natural Language Processing in Action*. Shelter Island, NY: Manning Publication Co.