

91258 Natural Language Processing

Lesson 6. From Word Counts to *Meaning*

Alberto Barrón-Cedeño

Alma Mater Studiorum-Università di Bologna
a.barron@unibo.it @albarron_

17/10/2023



Previously

- ▶ Pre-processing
- ▶ BoW representation
- ▶ One rule-based sentiment model
- ▶ One statistical model (Naïve Bayes)
- ▶ *tf-idf* (+ Zipf's law)

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

Topic Vectors

Topic Vectors

What for?

“[...] using the correlation of normalized frequencies with each other to group words together in topics to define the dimensions of new topic vectors.” (Lane et al., 2019, p. 98)

What can we achieve with this?

- ▶ 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 macchina rossa
 d_2 Le macchine blu
↓
stopwording + stemming
↓
 d'_1 macchin ross
 d'_2 macchin blu
↓
vectorisation
↓
 \vec{d}_1 [1, 1, 0]
 \vec{d}_2 [1, 0, 1]

 $\cos(\vec{d}_1, \vec{d}_2) > 0$

Topic Vectors

Limitation of word vectors

d_1 Un'automobile rosso
 d_2 Le macchine blu
↓
 d'_1 automob ross
 d'_2 macchinn blu
↓
 \vec{d}_1 [1, 1, 0, 0]
 \vec{d}_2 [0, 0, 1, 1]

 $\cos(\vec{d}_1, \vec{d}_2) = 0$

Topic Vectors

- ▶ We need to infer what $w \in d$ “means”
- ▶ Indeed, we need to infer what $\{w_k, w_{k+1}, \dots\} \in d$ “mean”
- ▶ We need a *different* kind of vector

Word-topic vector One vector represents one word

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
- ▶ cat and dog should contribute similarly to petness
- ▶ NYC should contribute negatively to animalness
- ▶ apple should contribute mildly to cityness

| topic | score | | |
|----------|----------|--------|------------|
| | high | medium | low |
| Petness | cat, dog | | NYC, apple |
| Cityness | NYC | apple | cat, dog |

 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] |
| animalness | [| .1 | .1 | -.1 | .5 | .1 | -.1] |
| cityness | [| 0 | -.1 | .2 | -.1 | .5 | .1] |

The relationships between words and topics can be “flipped”: **transposing** the 3×6 matrix to produce topic weights for each word

| | petness | animalness | cityness |
|-------|---------|------------|----------|
| cat | [.3 | .1 | 0] |
| dog | [.3 | .1 | -.1] |
| apple | [0 | -.1 | .2] |
| lion | [0 | .5 | -.1] |
| NYC | [-.2 | .1 | .5] |
| love | [.2 | -.1 | .1] |


Common-Sense Topic Modeling

Given:

- ▶ A new 6D *tf-idf* vector
- ▶ Our 3×6 D matrix

Multiply: 6D vector \times $[3 \times 6]$ D matrix

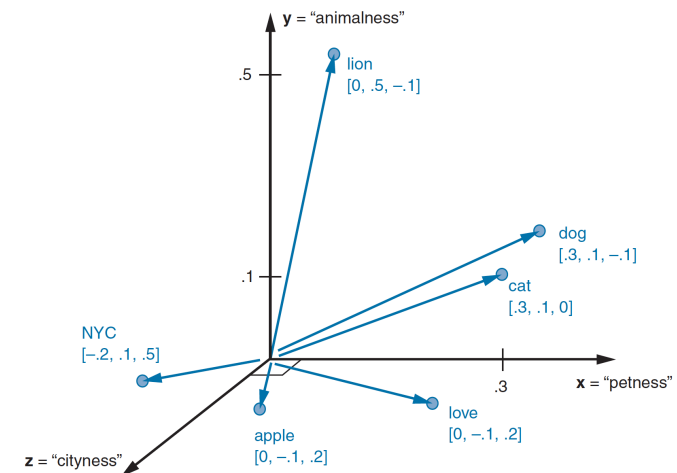
→ 3D document vector

 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} is a *tf-idf* vector of size $|V|$

M is a $3 \times V$ weight matrix

↓

\vec{d}_t becomes a topic vector of size 3

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)

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

We can count co-occurrences \rightarrow the company of a word

Latent Semantic Analysis

Latent Semantic Analysis

- ▶ An algorithm to gather words (*tf-idf* matrix) into topics
- ▶ It (somehow) captures the meaning of words
- ▶ It is a **dimension reduction** technique (sparse \rightarrow dense vectors)

AKA

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

Latent Semantic Analysis

Linear discriminant analysis (LDA)


A supervised algorithm (it requires labeled data)

Algorithm

1. Compute the centroid of the vectors in the class
2. Compute the centroid of the vectors not in the class
3. Compute the vector difference between the centroids

Centroid: average in a vector space

Basic algebra!

 Let us see

Latent Semantic Analysis

Linear discriminant analysis (LDA)

- ▶ We are not relying on individual words
- ▶ We are gathering up words with similar “semantics”

LDA has learned the *spami*ness 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.