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91258 / B0385
Natural Language Processing
Lesson 7. From Word Counts to Meaning

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Previously

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

Table of Contents

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

$\downarrow$

stopwording + stemming

$\downarrow$

d_1' macchin ross
d_2' macchin blu

$\downarrow$

vectorisation

$\downarrow$

$\vec{d_1}$ $[\mathbf{1}, 1, 0]$
$\vec{d_2}$ $[\mathbf{1}, 0, 1]$

$$cos(\vec{d_1}, \vec{d_2}) > 0$$

Topic Vectors
Limitation of word vectors

d_1 Un'automobile rosso
d_2 Le macchine blu

$\downarrow$

d_1' automob ross
d_2' macchinn blu

$\downarrow$

$\vec{d_1}$ $[1, 1, 0, 0]$
$\vec{d_2}$ $[0, 0, 1, 1]$

$$cos(\vec{d_1}, \vec{d_2}) = 0$$

Topic Vectors

- We need to infer what $w \in d$ "means"
- Indeed, we need to infer what $\{w_k, w_{k+1}, \ldots\} \in d$ "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`

	score		
topic	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 3×6D matrix

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

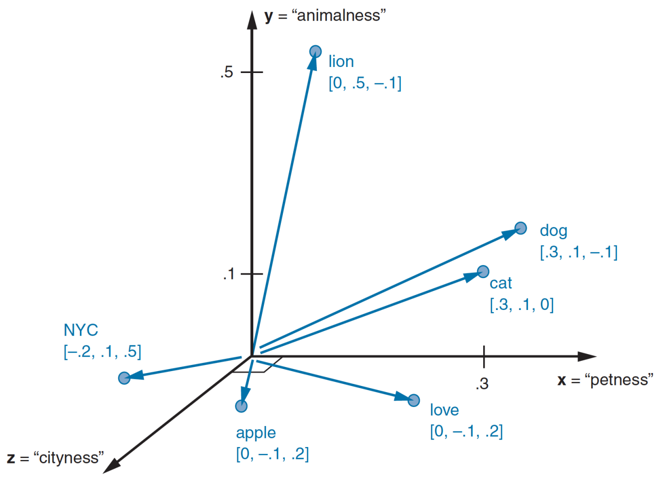
$\rightarrow$ 3D document vector

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

$\downarrow$

$\vec{d_t}$ 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 `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.