92586 Computational Linguistics

Lesson 7. Latent Semantic Analysis

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Previously

- BoW representation
- Rule-based vs Naïve Bayes classifiers (sentiment)
- *tf-idf* (+ Zipf's law)

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- Word Model $\rightarrow$ Topic Model
- Linear Discriminant Analysis

Table of Contents

Section 4.2 of Lane et al. (2019)

Introduction

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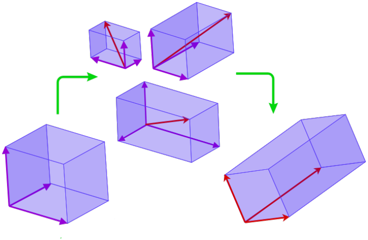
Latent semantic analysis (Lane et al., 2019, p. 112)

- A mathematical technique for finding the "best" way to linearly transform —**rotate and stretch**— any set of NLP vectors (e.g., TF-IDF, BoW)

Intuition (1)

1. Line up the axes (dimensions) in the new vectors with the greatest "spread" or variance in the word frequencies
2. Rotate the vectors so that the new dimensions (basis vectors) align with the maximum variance directions
3. Eliminate the dimensions in the new vector space that contribute the least to the variance in the vectors from document to document.

Intuition (2)



From Wikipedia: “Change of basis”

a Depart from a matrix (left)

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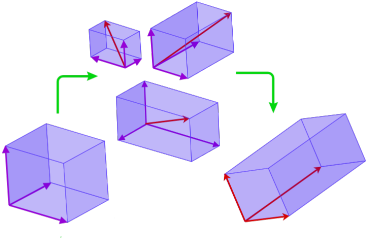

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a Depart from a matrix (left)

b Decompose it into 3 simpler matrices

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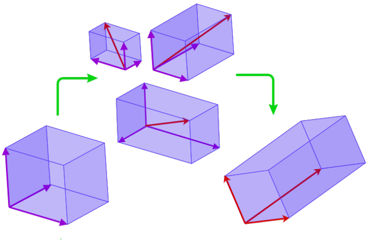

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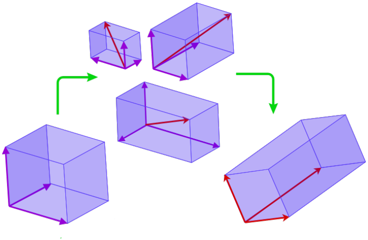


From Wikipedia: "Change of basis"

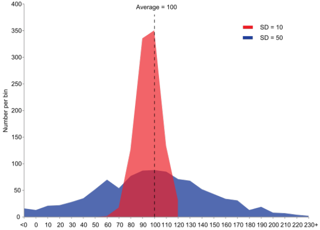
a Depart from a matrix (left)

b Decompose it into 3 simpler matrices

c Truncate the matrices

d Multiply them and produce a lower-dimensional matrix

Intuition (3)



https://en.wikipedia.org/wiki/Variance

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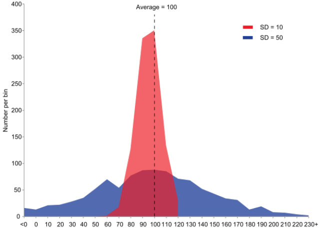

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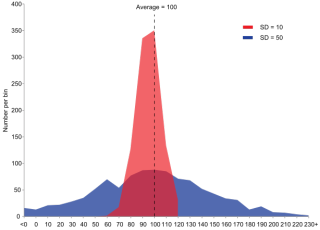

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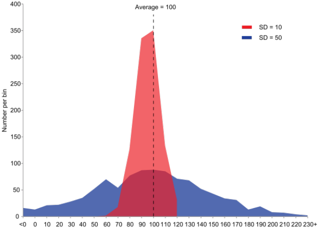

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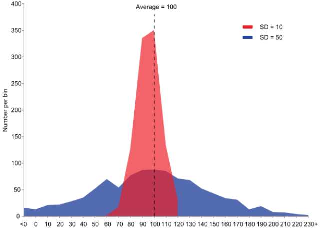

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- Each dimension (axis) becomes a **combination of word frequencies** rather than a single word frequency.
- They are weighted combinations of words that make up various "topics" in the corpus

Singular Value Decomposition

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- SVD finds co-occurring words by calculating the correlation between the terms of the term-document matrix
- SVD simultaneously finds the correlation of term use between documents and the correlation of documents with each other

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These linear combinations of term frequencies will become topics

Considerations

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- A human has to look at the words with a high weight to name the topic
- **They can be used, even without a name**
- We can be add, subtract, compute similarities. . .

Behind SVD for NLP

Mathematical Formulation

$$W_{m\times n} \Rightarrow U_{m\times p} S_{p\times p} V^T_{p\times n}$$

where

- m is the size of the vocabulary

Behind SVD for NLP

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We know what is W: BoW or TF-IDF matrix

Behind SVD for NLP

U–left singular vectors

$$W_{m \times n} \Rightarrow U_{m \times p} S_{p \times p} V^T_{p \times n}$$

- The **term-topic matrix**: "the company a word keeps"
- The cross-correlation between words and topics based on word co-occurrence in the same document.
- It is a square matrix

Behind SVD for NLP

S—singular vectors

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- The **Sigma matrix**: the topic "singular values"

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$$\begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \end{bmatrix} \rightarrow \begin{bmatrix} 0.6 & 0 & 0 \\ 0 & 0.2 & 0 \\ 0 & 0 & 0.05 \end{bmatrix}$$

- It tells you how much information is captured by each dimension in the new topic vector space.

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- The first dimension contains the most information (“explained variance”)

Behind SVD for NLP

V^T—right singular vectors

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- The **document-document matrix**: the shared meaning between documents
- It measures how often documents use the same topics in the new model

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V^T—right singular vectors

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- A square matrix

SVD in Action

Let us see

Some Extra Pointers

Gensim Topic Modelling for Humans[1]

[1] https://radimrehurek.com/gensim/

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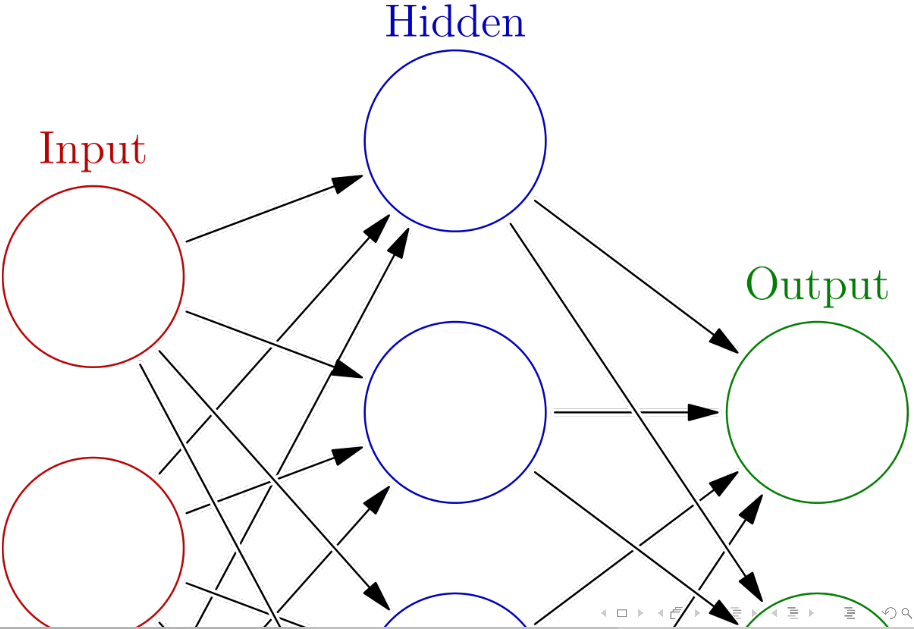
(Literally) some random papers:

- Godin, et al. (2013). **Using Topic Models for Twitter Hashtag Recommendation**. WWW 2013 Companion.
- Rodriguez and Storer (2019). **A computational social science perspective on qualitative data exploration: Using topic models for the descriptive analysis of social media data** JTHS.
- Seroussi, et al. (2014). **Authorship Attribution with Topic Models**. COLI

[1] `https://radimrehurek.com/gensim/`

Coming soon



References

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