

PGR 210 - Natural Language Processing Part

Kristiania University College

By Huamin Ren

Huamin.ren@kristiania.no



Outline of week 43

- Text classification
- Topic models
 - LSA
 - SVD
 - LDiA

LSA

- Latent semantic analysis is based on the oldest and most commonly used technique for dimension reduction, singular value decomposition.
- A similar but simpler algorithm: Linear discriminant analysis (LDA)
- A similar but can break down documents into many topics: Latent Dirichlet allocation (LDiA)

Take one step further on LDA

- Re-think on the process

- Compute the average position (centroid) of all the TF-IDF vectors within the class (such as spam SMS messages).
- Compute the average position (centroid) of all the TF-IDF vectors not in the class (such as nonspam SMS messages).
- Compute the vector difference between the centroids (the line that connects them).

Why it works?

When it fails to work?

How to evaluate?

How to show performance?

- Framework: tf-idf + LDA
- Enlarge the vocabulary

LSA

- The algebra behind LSA called singular value decomposition.
- LSA uses SVD to find the combinations of words that are responsible, together, for the biggest variation in the data.
 - ✓ Line up the axes (dimensions) in your new vectors with the greatest “spread” or variance in the word frequencies
- New basis vectors are generated; each dimension (axes) becomes a combination of word frequencies rather than a single word frequency.

SVD is an algorithm for decomposing any matrix into three “factors,” three matrices that can be multiplied together to recreate the original matrix.

- SVD was in widespread use long before the term “machine learning” even existed
- SVD decomposes a matrix into three square matrices, one of which is diagonal.

Application of SVD

- Matrix inversion

A matrix can be inverted by ***decomposing*** it into three simpler ***square matrices, transposing matrices***, and then multiplying them back together.



Using SVD, LSA can break down your TF-IDF term-document matrix into three simpler matrices. And they can be multiplied back together to produce the original matrix, without any changes.

Even truncate!

- Truncate those matrices
 - Ignore some rows and columns before multiplying them back together, which reduces the number of dimensions in vector space model

The heart of LSA: SVD

$$W_{m \times n} \Rightarrow U_{m \times p} S_{p \times p} V_{p \times n}^T$$

m: number of terms in vocabulary

n: number of documents

p: number of topics (same as the number of words)

Truncating the topics

- Hint:

```
from sklearn.decomposition import TruncatedSVD
```

```
svd = TruncatedSVD(n_components=16, n_iter=100)  
print(tfidf_docs.shape)  
svd_topic_vectors = svd.fit_transform(tfidf_docs)
```

Implement LSA using the same dataset (sms-spam.csv)