NLP CS5803 IITH Notes

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Contents

1	Introduction	2
2	Input Representation 2.1 TF-IDF scheme	2
	2.1.1 Formulation 2.1.2 Limitation 2.2 SVD - text representation 2.2.1 Formulation	2 2 3
3	Results	3
4	Conclusion	3

1 Introduction

The starting question is how to make computers understand human language. We need to find smart ways of representing the language.

2 Input Representation

Consider text modality, where the input is a document, it consists of words (also called tokens). The document is represented by the set of words/tokens it contains.

Lets see some methods for text representation

2.1 TF-IDF scheme

2.1.1 Formulation

The TF-IDF (Term Frequency-Inverse Document Frequency) scheme is a popular technique used to represent the importance of words in a document corpus.

It combines two factors: term frequency (TF) and inverse document frequency (IDF).

TF measures the frequency of a term in a document. It is calculated by counting the number of occurrences of a term in a document as a raw or by taking a log of it.

$$tf(t,d) = \begin{cases} 0 & \text{if } c(t,d) = 0\\ 1 + \log(c(t,d)) & \text{if } c(t,d) \neq 0 \end{cases}$$

where c(t, d) is the count of term t in document d.

IDF de-emphasizes the frequent words across the corpus (all documents combined is usually called corpus) and emphasizes the on words differentiating the documents.

$$idf(t) = \log_{10} \left(\frac{N}{df_t} \right)$$

where N is the total number of documents in the corpus and df_t is the number of documents containing the term t.

The TF-IDF score for a term in a document is obtained by multiplying its TF value with its IDF value. Mathematically, it can be represented as:

$$tf\text{-}idf(t,d) = tf(t,d) \times idf(t)$$

Now we get a table with TF-IDF values.

This way, each document is represented by a vector from the column of the table and each word is presented by a vector from the row of the table.

2.1.2 Limitation

- Words are considered at their lexical appearance
- Synonymy is not considered
- Polysemy(word with multiple meanings) is not considered

- long sparse vectors
- context is not considered

2.2 SVD - text representation

2.2.1 Formulation

Consider the term-document matrix and apply SVD to it to do dimensionality reduction, so that we can get dense representations.

Let A be the term-document matrix (matrix with freq. of words in docs), where each row represents a term and each column represents a document, by SVD we have

$$A = U\Sigma V^T$$

U, V are orthonormal matrices and Σ is a diagonal matrix of singular values of A in decreasing order.

By keep only the first k singular values, we have

$$A_k = U_k \Sigma_k V_k^T$$

The k here is much smaller than the original dimension of A. Terms can be represented by the rows of U_k and documents can be represented by the columns of V_k .

3 Results

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4 Conclusion

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