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Practical No. 9

Aim: Load the demotext2.txt text file into a variable , Do vectorization using TFID Vectorizer for Comprehension Feature Extraction

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AIM: Load the demotext2.txt text file into a variable , Do vectorization using TFID Vectorizer for Comprehension Feature Extraction

OBJECTIVE/EXPECTED LEARNING OUTCOME:

- Understanding Vectorization.
- Understanding TFID

HARDWARE AND SOFTWARE REQUIRMENTS:

Hardware Requirement:

Moniter, CPU, Keyboard

Software Requirement:

Google Colab

THEORY:

In Natural language Processing (NLP), we have to convert text into numerical representation to apply machine learning techniques to process the text. This is called Vectorization. TF-IDF is a popular vectorization technique used in NLP. One way to convert words (in a document)in to numbers is by calculating how many times a term (t) appears in document(D). This is called Term Frequency(TF).

$$TF(t) = (\text{count}(t) \text{ in } D / \text{Total words in } D)$$

TF gives a measure of important words in a single document.

The problem with Term Frequency is that, it considers all words equally, stop words like ‘a’, ‘the’ etc will occur more in any document but are not significant. To solve this issue, we discuss IDF.

Inverse Document Frequency(IDF):

Before discussing IDF, let's see what is Document Frequency(DF). Also remember now we are going to talk about a set of documents as in a document similarity, or search ranking application.

Document Frequency (DF) : *says how many documents in a set of documents contain a particular term.*

This will decide the informativeness of a word. If a term ‘t’ is present in all documents of the set, chances are less that the word is informative. Eg: *stop words*. So, we can say informativeness is inversely proportional to Document Frequency(DF).

And that is why **Inverse Document Frequency(IDF)** is significant. It is defined as

$$IDF(w) = \log(\text{Total no. of Docs} / \text{No. of docs containing the term } 't')$$

Let's see with an example,

If there are 1000 documents and a word appears in all 1000,

$$\log(1000/1000) = 0$$

(I take base 10 to keep it simple).

This means it is not an important word (can be a stop word).

But if only 10 documents have this word,

$$\log(1000/10) = 2$$

This means word may be an important word and that document can be relevant in case of ranking/information retrieval.

TF-IDF

Now we use both TF and IDF to create a meaningful numerical representation of text.

$$\text{TF-IDF} = \text{TF}(t) * \text{IDF}(t)$$

This product will be high if both TF and IDF are high for a term. A term, 't' that repeats many times in a document, say **D1** and it occurs only in a few documents in the corpus will have a high TF-IDF value for **D1**. So if this is a search for 't' (like Google search) **D1** will appear first.

TF-IDF is frequencies weighted by uniqueness.

CODE:

```
from sklearn.feature_extraction.text import TfidfVectorizer
try:
    with open('/content/demotext2.txt', 'r') as file:
        text_content = file.read()
        print("File loaded successfully.")
    if text_content:
        tfidf_vectorizer = TfidfVectorizer()
        tfidf_features = tfidf_vectorizer.fit_transform([text_content])
        print("TF-IDF vectorization complete.")
        print("\nTF-IDF Feature Vectors:")
        # print(tfidf_features)
        # Get the feature names (words)
        feature_names = tfidf_vectorizer.get_feature_names_out()
        # Convert the sparse matrix to a dense array for easier iteration
        dense_features = tfidf_features.todense()
        # Print the words and their TF-IDF scores
        print("\nWords and their TF-IDF Scores:")
        for doc_index, doc_features in enumerate(dense_features):
            print(f"Document {doc_index + 1}:")
```

```
for word_index, score in enumerate(doc_features.tolist()[0]):  
    if score > 0: # Only print words with a score greater than 0  
        print(f" {feature_names[word_index]}: {score}")  
  
else:  
    print("Text content is empty. Cannot perform TF-IDF vectorization.")  
  
except FileNotFoundError:  
    text_content = None  
    print("Error: demotext2.txt not found. Please upload the file.")  
  
except Exception as e:  
    print(f"An error occurred: {e}")
```

OUTPUT (SCREENSHOT):

```
→ File loaded successfully.  
TF-IDF vectorization complete.  
  
TF-IDF Feature Vectors:  
  
Words and their TF-IDF Scores:  
Document 1:  
16j7: 0.028629916715693413  
9th: 0.028629916715693413  
admirable: 0.028629916715693413  
admirer: 0.028629916715693413  
after: 0.057259833431386825  
alike: 0.028629916715693413  
also: 0.028629916715693413  
an: 0.028629916715693413  
and: 0.486708584166788  
any: 0.057259833431386825  
arabic: 0.028629916715693413  
arts: 0.028629916715693413  
as: 0.028629916715693413  
at: 0.028629916715693413  
attended: 0.028629916715693413  
beer: 0.028629916715693413  
bra: 0.028629916715693413  
brought: 0.028629916715693413  
but: 0.028629916715693413  
by: 0.057259833431386825
```

The screenshot shows a web-based NLP simulation titled "Chunking". At the top right, there are five yellow stars, a "Rate Me" button, and a "Report a Bug" button. Below the title, a blue bar contains the text "Instructions ▾". The main interface is divided into two sections: "Language Selection" on the left and "Result" on the right.

Language Selection:

- Select the language for chunking analysis: English

Sentence Selection:

- Choose a sentence to analyze for chunking: Close the door.

Result:

Lexicon	POS	Chunk	Result	Answer
Close	RB	B-VP	✓	
the	DT	B-NP	✓	
door	NN	I-NP	✓	

Below the table, there is a green button labeled "Submit your chunking answers for evaluation" and a blue "Submit" button. A message at the bottom right says "Perfect! All answers are correct!"

CONCLUSION:

Thus, successfully perform load the demotext2.txt text file into a variable , Do vectorization using TFID Vectorizer for Comprehension Feature Extraction.

DISCUSSION AND VIVA VOCE:

- What is TFIDF?
- Why we need TFIDF?

REFERENCE:

- <https://nlp-iiith.vlabs.ac.in/exp/chunking/simulation.html>
- <https://www.geeksforgeeks.org/data-analysis/how-to-chunk-text-data-a-comparative-analysis/>