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Understanding TF-IDF (Term Frequency-Inverse Document Frequency)

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TF-IDF (Term Frequency-Inverse Document Frequency) is a statistical measure used in natural language processing and information retrieval **to evaluate the importance of a word in a document relative to a collection of documents (corpus).**

> *Unlike simple word frequency, TF-IDF balances common and rare words to highlight the most meaningful terms.*

How TF-IDF Works?

TF-IDF combines two components: Term Frequency (TF) and Inverse Document Frequency (IDF).

Term Frequency (TF): Measures how often a word appears in a document. A higher frequency suggests greater importance. If a term appears frequently in a document, it is likely relevant to the document's content. **Formula:**

$$\text{TF}(t, d) = \frac{\text{Number of times term } t \text{ appears in document } d}{\text{Total number of terms in document } d}$$

Term Frequency (TF)

Limitations of TF Alone:

- TF does not account for the global importance of a term across the entire corpus.
- Common words like **"the"** or **"and"** may have high TF scores but are not meaningful in distinguishing documents.

Inverse Document Frequency (IDF): Reduces the weight of common words across multiple documents while increasing the weight of rare words. If a term appears in fewer documents, it is more likely to be meaningful and specific.

Formula:

$$\text{IDF}(t, D) = \log \frac{\text{Total number of documents in corpus D}}{\text{Number of documents containing term t}}$$

Inverse Document Frequency (IDF)

- The logarithm is used to dampen the effect of very large or very small values, ensuring the IDF score scales appropriately.
- It also helps balance the impact of terms that appear in extremely few or extremely many documents.

Limitations of IDF Alone:

- IDF does not consider how often a term appears within a specific document.
- A term might be rare across the corpus (high IDF) but irrelevant in a specific document (low TF).

Converting Text into vectors with TF-IDF : Example

To better grasp how TF-IDF works, let's walk through a detailed example. Imagine we have a **corpus** (a collection of documents) with three documents:

1. **Document 1:** "The cat sat on the mat."
2. **Document 2:** "The dog played in the park."
3. **Document 3:** "Cats and dogs are great pets."

Our goal is to calculate the TF-IDF score for specific terms in these documents. Let's focus on the word **"cat"** and see how TF-IDF evaluates its importance.

Step 1: Calculate Term Frequency (TF)

For Document 1:

- The total number of terms in Document 1 is **6** (“the”, “cat”, “sat”, “on”, “the”, “mat”).
- So, TF(cat,Document 1) = 1/6

For Document 2:

- The word **“cat”** does **not appear**.
- So, TF(cat,Document 2)=0.

For Document 3:

- The word **“cat”** appears **1 time** (as “cats”).
- The total number of terms in Document 3 is **6** (“cats”, “and”, “dogs”, “are”, “great”, “pets”).
- So, TF(cat,Document 3)=1/6

  - *In Document 1 and Document 3, the word **“cat”** has the same TF score. This means it appears with the same relative frequency in both documents.*
  - *In Document 2, the TF score is 0 because the word **“cat”** does not appear.*

Step 2: Calculate Inverse Document Frequency (IDF)

- **Total number of documents in the corpus (D):** 3
- **Number of documents containing the term “cat”:** 2 (Document 1 and Document 3).

So, $IDF(cat, D) = log\frac{3}{2} \approx 0.176$

> *The IDF score for **“cat”** is relatively low. This indicates that the word **“cat”** is not very rare in the corpus—it appears in 2 out of 3 documents. If a term appeared in only 1 document, its IDF score would be higher, indicating greater uniqueness.*

The TF-IDF score for **“cat”** is 0.029 in Document 1 and Document 3, and 0 in Document 2 that **reflects both the frequency of the term in the document (TF) and its rarity across the corpus (IDF)**.

The TF-IDF score is the product of TF and IDF:

$$\text{TF-IDF}(t, d, D) = \text{TF}(t, d) \times \text{IDF}(t, D)$$

For Document 1:

$$\text{TF-IDF}(\text{cat}, \text{Document 1}, D) = 0.167 \times 0.176 \approx 0.029$$

For Document 2:

$$\text{TF-IDF}(\text{cat}, \text{Document 2}, D) = 0 \times 0.176 = 0$$

For Document 3:

$$\text{TF-IDF}(\text{cat}, \text{Document 3}, D) = 0.167 \times 0.176 \approx 0.029$$

TF-IDF

> *A higher TF-IDF score means the term is more important in that specific document.*

Why is TF-IDF Useful in This Example?

1. Identifying Important Terms: TF-IDF helps us understand that **“cat”** is somewhat important in Document 1 and Document 3 but irrelevant in Document 2.

> *If we were building a search engine, this score would help rank Document 1 and Document 3 higher for a query like **“cat”**.*

2. Filtering Common Words: Words like **“the”** or **“and”** would have high TF scores but very low IDF scores because they appear in almost all documents. Their TF-IDF scores would be close to 0, indicating they are not meaningful.

3. Highlighting Unique Terms: If a term like **“mat”** appeared only in Document 1, it would have a higher IDF score, making its TF-IDF score more significant in

Implementing TF-IDF in Sklearn with Python

In python tf-idf values can be computed using *TfidfVectorizer()* method in *sklearn* module.

Syntax:

> *sklearn.feature_extraction.text.TfidfVectorizer(input)*
>
> ***Parameters:***
>
> - ***input:*** *It refers to parameter document passed, it can be a filename, file or content itself.*
>
> ***Attributes:***
>
> - ***vocabulary_:*** *It returns a dictionary of terms as keys and values as feature indices.*
> - ***idf_:*** *It returns the inverse document frequency vector of the document passed as a parameter.*
>
> ***Returns:***
>
> - ***fit_transform():*** *It returns an array of terms along with tf-idf values.*
> - ***get_feature_names():*** *It returns a list of feature names.*

Step-by-step Approach:

- Import modules.

```
# import required module
from sklearn.feature_extraction.text import TfidfVectorizer
```

- Collect strings from documents and create a corpus having a collection of strings from the documents *d0, d1,* and *d2*.

```
d2 = 'r2j'

# merge documents into a single corpus
string = [d0, d1, d2]
```

- Get tf-idf values from *fit_transform()* method.

```
# create object
tfidf = TfidfVectorizer()

# get tf-df values
result = tfidf.fit_transform(string)
```

- Display idf values of the words present in the corpus.

```
# get idf values
print('\nidf values:')
for ele1, ele2 in zip(tfidf.get_feature_names(), tfidf.idf_):
    print(ele1, ':', ele2)
```

Output:

```
idf values:
for : 1.6931471805599454
geeks : 1.2876820724517808
r2j : 1.6931471805599454
```

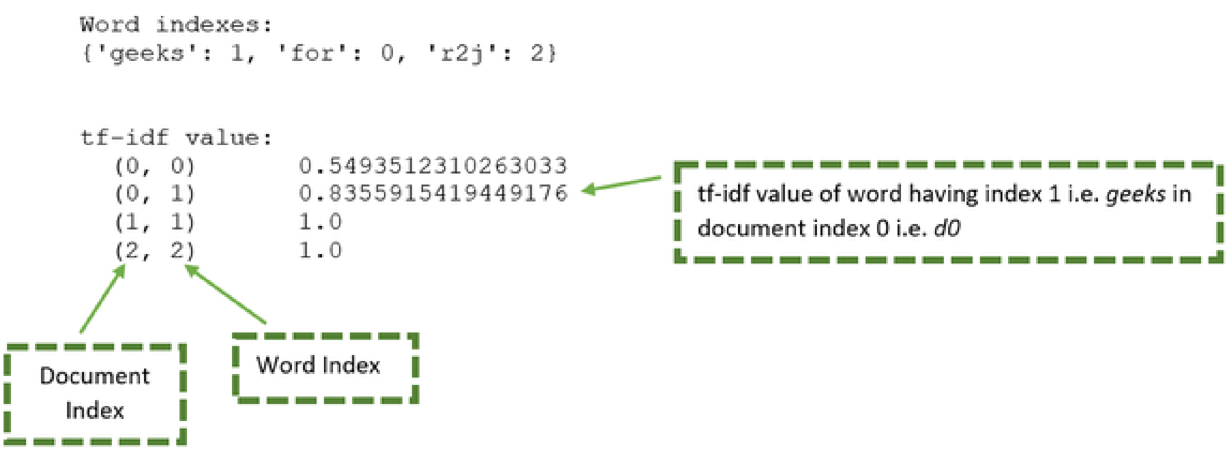
- Display tf-idf values along with indexing.

```
# get indexing
print('\nWord indexes:')
print(tfidf.vocabulary_)

# display tf-idf values
print('\ntf-idf value:')
print(result)

# in matrix form
print('\ntf-idf values in matrix form:')
print(result.toarray())
```

Output:

```
Word indexes:
{'geeks': 1, 'for': 0, 'r2j': 2}

tf-idf value:
  (0, 0)        0.5493512310263033
  (0, 1)        0.8355915419449176
  (1, 1)        1.0
  (2, 2)        1.0

tf-idf values in matrix form:
[[0.54935123 0.83559154 0.        ]
 [0.         1.         0.        ]
 [0.         0.         1.        ]]
```

The *result* variable consists of unique words as well as the tf-if values. It can be elaborated using the below image:



From the above image the below table can be generated:

Document	Word	Document Index	Word Index	tf-idf value
d0	for	0	0	0.549
d0	geeks	0	1	0.8355
d1	geeks	1	1	1.000
d2	r2j	2	2	1.000

Below are some examples which depict how to compute tf-idf values of words from a corpus:

Example 1: Below is the complete program based on the above approach:

```
# import required module
from sklearn.feature_extraction.text import TfidfVectorizer

# assign documents
d0 = 'Geeks for geeks'
d1 = 'Geeks'
d2 = 'r2j'

# merge documents into a single corpus
string = [d0, d1, d2]

# create object
tfidf = TfidfVectorizer()

# get tf-df values
result = tfidf.fit_transform(string)

# get idf values
print('\nidf values:')
for ele1, ele2 in zip(tfidf.get_feature_names(), tfidf.idf_):
    print(ele1, ':', ele2)

# get indexing
print('\nWord indexes:')
print(tfidf.vocabulary_)

# display tf-idf values
print('\ntf-idf value:')
print(result)

# in matrix form
print('\ntf-idf values in matrix form:')
print(result.toarray())
```

Output:

```
idf values:
for : 1.6931471805599454
geeks : 1.2876820724517808
r2j : 1.6931471805599454

Word indexes:
{'geeks': 1, 'for': 0, 'r2j': 2}

tf-idf value:
  (0, 0)        0.5493512310263033
  (0, 1)        0.8355915419449176
  (1, 1)        1.0
  (2, 2)        1.0

tf-idf values in matrix form:
[[0.54935123 0.83559154 0.        ]
 [0.         1.         0.        ]
 [0.         0.         1.        ]]
```

Example 2: Here, tf-idf values are computed from a corpus having unique values.

```python
# import required module
from sklearn.feature_extraction.text import TfidfVectorizer

# assign documents
d0 = 'geek1'
d1 = 'geek2'
d2 = 'geek3'
d3 = 'geek4'

# merge documents into a single corpus
string = [d0, d1, d2, d3]

# create object
tfidf = TfidfVectorizer()

# get tf-df values
result = tfidf.fit_transform(string)

# get indexing
print('\nWord indexes:')
print(tfidf.vocabulary_)

# display tf-idf values
print('\ntf-idf values:')
print(result)
```

Output:

```
Word indexes:
{'geek1': 0, 'geek2': 1, 'geek3': 2, 'geek4': 3}

tf-idf values:
  (0, 0)        1.0
  (1, 1)        1.0
  (2, 2)        1.0
  (3, 3)        1.0
```

Example 3: In this program, tf-idf values are computed from a corpus having similar documents.

```
# import required module
from sklearn.feature_extraction.text import TfidfVectorizer

# assign documents
d0 = 'Geeks for geeks!'
d1 = 'Geeks for geeks!'


# merge documents into a single corpus
string = [d0, d1]

# create object
tfidf = TfidfVectorizer()

# get tf-df values
result = tfidf.fit_transform(string)

# get indexing
print('\nWord indexes:')
print(tfidf.vocabulary_)

# display tf-idf values
print('\ntf-idf values:')
print(result)
```

Output:

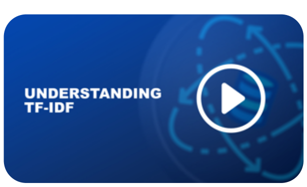
```
Word indexes:
{'geeks': 1, 'for': 0}

tf-idf values:
  (0, 0)        0.4472135954999579
  (0, 1)        0.8944271909999159
```

Example 4: Below is the program in which we try to calculate tf-idf value of a single word *geeks* is repeated multiple times in multiple documents.

```python
# import required module
from sklearn.feature_extraction.text import TfidfVectorizer

# assign corpus
string = ['Geeks geeks']*5

# create object
tfidf = TfidfVectorizer()

# get tf-df values
result = tfidf.fit_transform(string)

# get indexing
print('\nWord indexes:')
print(tfidf.vocabulary_)

# display tf-idf values
print('\ntf-idf values:')
print(result)
```

Output:

```
Word indexes:
{'geeks': 0}

tf-idf values:
  (0, 0)        1.0
  (1, 0)        1.0
  (2, 0)        1.0
  (3, 0)        1.0
  (4, 0)        1.0
```



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