

TF-IDF calculation using Scikit-Learn

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POS Tag



❖ POS Tag

- A POS tag is a label assigned to each word in a text to indicate the part of speech.
Ex) subject, verb, object, etc.
- In general, main components of sentences are subject, verb, object, and complement, and these are usually verbs or nouns.
- In this assignment, we use only verbs and nouns tags.
 - Verb : (VB, VBD, VBG, VBN, VBP, VBZ)
 - Noun : (NN, NNS, NNP, NNPS)(Details in page 4)

POS Tag



❖ NLTK POS Tag

| Tag | Description | Example |
|------|---------------------------------------|----------------------|
| CC | coordinating conjunction | and |
| CD | cardinal number | 1, third |
| DT | determiner | the |
| EX | existential there | <i>there is</i> |
| FW | foreign word | d'hoevre |
| IN | preposition/subordinating conjunction | in, of, like |
| JJ | adjective | big |
| JJR | adjective, comparative | bigger |
| JJS | adjective, superlative | biggest |
| LS | list marker | 1) |
| MD | Modal | could, will |
| NN | noun, singular or mass | Door |
| NNS | noun plural | Doors |
| NNP | proper noun, singular | John |
| NNPS | proper noun, plural | Vikings |
| PDT | Predeterminer | <i>both</i> the boys |
| POS | possessive ending | friend's |

| | | |
|-------|---------------------------------|-----------------------------|
| PRP | personal pronoun | I, he, it |
| PRP\$ | possessive pronoun | my, his |
| RB | Adverb | however, usually |
| RBR | adverb, comparative | Better |
| RBS | adverb, superlative | Best |
| RP | Particle | give <i>up</i> |
| TO | To | <i>to</i> go, <i>to</i> him |
| UH | Interjection | Uhhuhhuhh |
| VB | verb, base form | Take |
| VBD | verb, past tense | Took |
| VBG | verb, gerund/present participle | Taking |
| VCN | verb, past participle | Taken |
| VBP | verb, sing. present, non-3d | Take |
| VBZ | verb, 3rd person sing. Present | Takes |
| WDT | wh-determiner | Which |
| WP | wh-pronoun | who, what |
| WP\$ | possessive wh-pronoun | Whose |
| WRB | wh-abverb | where, when |

Count based Word Representation

❖ Bag of Words(BoW)

- A method of numerical expression of text data that focuses only on the frequency of words **without considering the order of words**.

I love this movie! It's sweet, but with satirical humor. The dialogue is great and the adventure scenes are fun... It manages to be whimsical and romantic while laughing at the conventions of the fairy tale genre. I would recommend it to just about anyone. I've seen it several times, and I'm always happy to see it again whenever I have a friend who hasn't seen it yet!



| | |
|-----------|---|
| it | 6 |
| I | 5 |
| the | 4 |
| to | 3 |
| and | 3 |
| seen | 2 |
| yet | 1 |
| would | 1 |
| whimsical | 1 |
| times | 1 |
| sweet | 1 |
| satirical | 1 |
| adventure | 1 |
| genre | 1 |
| fairy | 1 |
| humor | 1 |
| have | 1 |
| great | 1 |

Count based Word Representation

❖ Bag of Words(BoW) based Document Features Extraction Method

- Doc0: I/PRP am/VBP a/DT boy/NN
- Doc1: I/PRP am/VBP a/DT girl/NN

1) Remove duplicates from all words in Doc0 and Doc1, and extract verbs and nouns. List each word in column form. (Sorted by alphabet)

- ['am/VBP', 'boy/NN', 'girl/NN']

2) Give each of the following words a unique number (index).

- { 'am/VBP' : 0, 'boy/NN' : 1, 'girl/NN' : 2 }

3) In each document, write the frequency in which the word appears in each number.

| | | | |
|-----------|------|----|-----|
| - Index : | 0 | 1 | 2 |
| - Doc0 : | [1, | 1, | 0] |
| - Doc1 : | [1, | 0, | 1] |

Count based Word Representation

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

- TF(Term Frequency)
: The number of times that term t occurs in document d ($tf_{t,d}$)
- DF(Document Frequency)
: The number of documents that contain the term t (df_t)
- IDF(Inverse Document Frequency)
: Inverse value of DF.

| Term frequency | | Document frequency | | Normalization | |
|----------------|---|--------------------|---|--------------------|--|
| n (natural) | $tf_{t,d}$ | n (no) | 1 | n (none) | 1 |
| l (logarithm) | $1 + \log(tf_{t,d})$ | t (idf) | $\log \frac{N}{df_t}$ | c (cosine) | $\frac{1}{\sqrt{w_1^2 + w_2^2 + \dots + w_M^2}}$ |
| a (augmented) | $0.5 + \frac{0.5 \times tf_{t,d}}{\max_t(tf_{t,d})}$ | p (prob idf) | $\max\{0, \log \frac{N - df_t}{df_t}\}$ | u (pivoted unique) | $1/u$ |
| b (boolean) | $\begin{cases} 1 & \text{if } tf_{t,d} > 0 \\ 0 & \text{otherwise} \end{cases}$ | | | b (byte size) | $1/CharLength^\alpha$, $\alpha < 1$ |
| L (log ave) | $\frac{1 + \log(tf_{t,d})}{1 + \log(\text{ave}_{t \in d}(tf_{t,d}))}$ | | | | |

Count based Word Representation

❖ TF (Term Frequency)

- Doc0 : I/PRP am/VBP a/DT boy/NN
- Doc1 : I/PRP am/VBP a/DT girl/NN
- Doc2 : who/WP is/VBZ a/DT boy/NN

- $tf_{t,d}$: The number of times that term t occurs in document d ($tf_{t,d}$)

| | am/VBP | is/VBZ | boy/NN | girl/NN |
|------|--------|--------|--------|---------|
| Doc0 | 1 | 0 | 1 | 0 |
| Doc1 | 1 | 0 | 0 | 1 |
| Doc2 | 0 | 1 | 1 | 0 |

Count based Word Representation

❖ IDF (Inverse Document Frequency)

- Doc0 : I/PRP am/VBP a/DT boy/NN
- Doc1 : I/PRP am/VBP a/DT girl/NN
- Doc2 : who/WP is/VBZ a/DT boy/NN

- $\log \frac{N}{df_t}$: Inverse value of DF.

- N : Total number of document

- df_t : The number of documents that contain the term t (df_t)

Ex) am/VBP = $\log \frac{3}{2} = 0.176$, girl/NN = $\log \frac{3}{1} = 0.477$

| | am/VBP | is/VBZ | boy/NN | girl/NN |
|-----|--------|--------|--------|---------|
| IDF | 0.176 | 0.477 | 0.176 | 0.477 |

Count based Word Representation

❖ TF-IDF(Term Frequency Inverse Document Frequency)

$$- tf_{t,d} \times \log \frac{N}{df_t}$$

Ex) am/VBP : $(1 \times 0.176) = 0.176$

| | am/VBP | is/VBZ | boy/NN | girl/NN |
|------|--------|--------|--------|---------|
| Doc0 | 0.176 | 0 | 0.176 | 0.477 |
| Doc1 | 0.176 | 0 | 0.176 | 0 |
| Doc2 | 0 | 0.477 | 0 | 0 |

❖ Install scikit-learn

- Google, 'Colab'
 - Packages installed by default
- Anaconda
 - If your virtual environment is activated,
\$ conda install scikit-learn
 - If your virtual environment is deactivated
\$ conda install --name [virtual_environment_name] scikit-learn
- Python environment
 - \$ pip install -U scikit-learn

❖ Scikit-Learn Package

- One of the most widely-used Python package for data science and machine learning.
 - Benchmark dataset
 - Preprocessing
 - Supervised learning
 - Unsupervised learning
 - Evaluation and selection

❖ Preprocessing with Scikit-Learn

- Subpackage `sklearn.feature_extraction` and `sklearn.feature_extraction.text` provide the following subsystems for document preprocessing:
- The following classes create vectors after automatically sorting each token.
 - `DictVectorizer`
 - Creates a BOW vector using a dictionary consisting of counts of each word.
 - `CountVectorizer`
 - Generates word tokens and then creates a BOW vector by counting the number of each token.
 - `TFidfVectorizer`
 - It is similar to `CountVectorizer` but creates a BOW vector using weights of words calculated by TF-IDF.

❖ DictVectorizer

- DictVectorizer is provided by the `feature_extraction` subpackage.
- Creates a BOW vector using a dictionary consisting of counts of each word.

```
1 from sklearn.feature_extraction import DictVectorizer
2
3 Bag_Of_Word = DictVectorizer(sparse=False)
4 Frequency = [{'am':1, 'boy':1}, {'am':1, 'girl':1}]
5 output = Bag_Of_Word.fit_transform(Frequency)
6
7 print(output)
```

```
[[1. 1. 0.]
 [1. 0. 1.]]
```

```
1 print(Bag_Of_Word.feature_names_)
```

```
['am', 'boy', 'girl']
```

```
1 print(Bag_Of_Word.transform({'girl':2, 'female':3}))
```

```
[[0. 0. 2.]]
```

❖ CountVectorizer

- CountVectorizer performs following tasks:
 1. Converting the document to a list of tokens.
 2. Counting the frequency of each token in each document.
 3. Converting each document to a BOW vector.

❖ CountVectorizer

```
1 from sklearn.feature_extraction.text import CountVectorizer
2 import nltk
3 from nltk.tokenize import word_tokenize
4
5 corpus = ['I am a boy',
6          'I am a girl',
7          'Who is a boy']
8
9 POS_corpus = list()
10
11 for sentence in corpus:
12     pos_token = nltk.pos_tag(word_tokenize(sentence))
13     POS_corpus.append(' '.join([t[0] for t in pos_token if t[1] in ['NN', 'NNS', 'NNP', 'NNPS', 'VB', 'VBD', 'VBG', 'VBN', 'VBP', 'VBZ']]))
14
15 print(POS_corpus)
```

```
['am boy', 'am girl', 'is boy']
```

```
1 vect = CountVectorizer()
2 vect.fit_transform(POS_corpus)
3 print(vect.vocabulary_)
```

```
{'am': 0, 'boy': 1, 'girl': 2, 'is': 3}
```

```
1 print(vect.transform(POS_corpus).toarray().tolist())
```

```
[[1 1 0 0]
 [1 0 1 0]
 [0 1 0 1]]
```


❖ TfidfVectorizer

- When TfidfVectorizer creates a vector from TF-IDF, the vector is normalized using L2 Norm.

- L2 Norm : $\|x\|_2 := \sqrt{x_1^2 + x_2^2 + \dots + x_n^2}$ where $x = (x_1, x_2, \dots, x_n)$

- TfidfVectorizer uses $idf = \log\left(\frac{N+1}{df_t+1}\right) + 1$ to calculate TF-IDF.

$$idf = \log\left(\frac{N + \textcolor{blue}{1}}{df_t + \textcolor{blue}{1}}\right) + \textcolor{red}{1}$$

- The constant **“1”** is added to the numerator and denominator of $\log\left(\frac{N}{df_t}\right)$ to prevent dividing by zero.
- The constant **“1”** is added to $\log\left(\frac{N+1}{df_t+1}\right)$ to prevent terms which occur in all documents in a training set from being entirely ignored.

❖ TfidfVectorizer

```
1 from sklearn.feature_extraction.text import TfidfVectorizer
2 import nltk
3 from nltk.tokenize import word_tokenize
4
5 corpus = ['I am a boy',
6           'I am a girl',
7           'Who is a boy']
8
9 POS_corpus = list()
10
11 for sentence in corpus:
12     pos_token = nltk.pos_tag(word_tokenize(sentence))
13     POS_corpus.append(' '.join([t[0] for t in pos_token if t[1] in ['NN', 'NNS', 'NNP', 'NNPS', 'VB', 'VBD', 'VBG', 'VBN', 'VBP', 'VBZ']]))
14
15 print(POS_corpus)
```

```
['am boy', 'am girl', 'is boy']
```

```
1 tfidfvect = TfidfVectorizer()
2 tfidfvect.fit_transform(POS_corpus)
3 print(tfidfvect.vocabulary_)
```

```
{'am': 0, 'boy': 1, 'girl': 2, 'is': 3}
```

```
1 print(tfidfvect.transform(POS_corpus).toarray().tolist())
```

```
[[0.70710678 0.70710678 0.         0.         ]
 [0.60534851 0.         0.79596054 0.         ]
 [0.         0.60534851 0.         0.79596054]]
```

Assignment



❖ Assignment

- 1) The attached JSON file in assignment 2 consists of 300 articles with multiple sentences.
 - See page 21 for JSON input file format.
- 2) Calculate TF-IDF vector of 300 articles using only nouns and verbs from given data.
 - Verbs (VB, VBD, VBG, VBN, VBP, VBZ) and nouns (NN, NNS, NNP, NNPS)
 - See page 4 for POS tags
- 3) You **MUST** create an output text file.
 - See page 22 for an example of output file.
- 4) You can use only Scikit-Learn for calculating TF-IDF and PyKomoran for morpheme analysis respectively.

Assignment



❖ Submit File

- 1) Python code file (.py) (python version 3.x)
 - Format: “Student Number_Name_TFIDF.py”.
 - Ex) “2020000000_홍길동.py”
- 2) TEXT file (.txt)
 - Format: “Student Number_Name_TFIDF.txt”.

JSON Input File

"business": [

"Ad sales boost Time Warner profit Quarterly profits at US media ...

"Dollar gains on Greenspan speech The dollar has hit ...

...

(중략)

...

"GM, Ford cut output as sales fall ...

"Ebbers denies WorldCom fraud ...

],

...

(중략)

...

"politics": [

"Labour plans maternity pay rise...

"Watchdog probes e-mail deletions...

...

(중략)

...

"Blair stresses prosperity goals...

"Guantanamo man 'suing government'...

]

Article Topic

Article

- JSON input file includes 300 articles on business, politics, and tech topics.

An Example of Output File

Student Number_Name_TFIDF.txt

Article

| | | | | | | | | | |
|---------------|--------|-----|--------|-----|--------|-----|--------|-----|------------|
| (business1) | 0.0 | 0.0 | 0.4311 | | 0.0 | 0.0 | 0.0 | 0.0 | ...(하락)... |
| (business2) | 0.0 | 0.0 | 0.0 | 0.0 | 0.1334 | 0.0 | 0.0 | ... | ...(하락)... |
| ... | | | | | | | | | |
| (중략) | | | | | | | | | |
| ... | | | | | | | | | |
| ... | | | | | | | | | |
| (중략) | | | | | | | | | |
| ... | | | | | | | | | |
| (politics1) | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.3311 | ... | ...(하락)... |
| ... | | | | | | | | | |
| (중략) | | | | | | | | | |
| ... | | | | | | | | | |
| (politics100) | 0.1176 | 0.0 | 0.3311 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | ...(하락)... |

- This is an example.
- This can be different with actual answers.