222112058_Feza Raffa Arnanda_Penugasan Praktikum 4

September 18, 2023

1 Praktikum 4

 $Referensi: https://github.com/peermohtaram/Vector_Space_Model.ipynbulker/Vector_Space_Model.ip$

1.0.1 Raw Term Frequency

```
[]: def termFrequencyInDoc(vocab, doc_dict):
    tf_docs = {}
    for doc_id in doc_dict.keys():
        tf_docs[doc_id] = {}
    for word in vocab:
        for doc_id,doc in doc_dict.items():
            tf_docs[doc_id][word] = doc.count(word)
    return tf_docs
```

```
[]: doc1_term = ["pengembangan", "sistem", "informasi", "penjadwalan"]
     doc2_term = ["pengembangan", "model", "analisis", "sentimen", "berita"]
     doc3_term = ["analisis", "sistem", "input", "output"]
     corpus_term = [doc1_term, doc2_term, doc3_term]
     from Sastrawi.Stemmer.StemmerFactory import StemmerFactory
     stemmer_factory = StemmerFactory()
     stemmer = stemmer_factory.create_stemmer()
     inverted_index = {}
     for i in range(len(corpus_term)):
         for item in corpus_term[i]:
             item = stemmer.stem(item)
             if item not in inverted_index:
                 inverted_index[item] = []
             if (item in inverted_index) and ((i+1) not in inverted_index[item]):
                 inverted_index[item].append(i+1)
     print("--- Inverted Index ---")
     print(inverted_index)
     print("\n")
```

```
vocab = list(inverted_index.keys())
doc_dict = {}
#clean after stemming
doc_dict['doc1'] = "kembang sistem informasi jadwal"
doc_dict['doc2'] = "kembang model analisis sentimen berita"
doc_dict['doc3'] = "analisis sistem input output"

print("--- Term Frequency -- ")
print(termFrequencyInDoc(vocab, doc_dict))
```

```
[2], 'analisis': [2, 3], 'sentimen': [2], 'berita': [2], 'input': [3], 'output': [3]}

--- Term Frequency --
{'doc1': {'kembang': 1, 'sistem': 1, 'informasi': 1, 'jadwal': 1, 'model': 0, 'analisis': 0, 'sentimen': 0, 'berita': 0, 'input': 0, 'output': 0}, 'doc2': {'kembang': 1, 'sistem': 0, 'informasi': 0, 'jadwal': 0, 'model': 1, 'analisis': 1, 'sentimen': 1, 'berita': 1, 'input': 0, 'output': 0}, 'doc3': {'kembang': 0, 'sistem': 1, 'informasi': 0, 'jadwal': 0, 'model': 0, 'analisis': 1, 'sentimen': 0, 'berita': 0, 'input': 1}
```

{'kembang': [1, 2], 'sistem': [1, 3], 'informasi': [1], 'jadwal': [1], 'model':

Inverted index untuk list apa saja kata yang mau dicari di suatu document

Nah, term frequencynya itu biar kita cari setiap kata yang ada di inverted index di suatu document tuh muncul berapa kalii. Gitu bro.

1.0.2 Document Frequency

Penjelasan kode di atas :

1.0.3 Inverse Document Frequency

Formula : IDF = log (N/Df)

```
[]: import numpy as np
def inverseDocFre(vocab,doc_fre,length):
   idf= {}
   for word in vocab:
      idf[word] = idf[word] = 1 + np.log((length + 1) / (doc_fre[word]+1))
   return idf
```

```
[]: print(inverseDocFre(vocab, wordDocFre(vocab, doc_dict),len(doc_dict)))
```

```
{'kembang': 1.2876820724517808, 'sistem': 1.2876820724517808, 'informasi': 1.6931471805599454, 'jadwal': 1.6931471805599454, 'model': 1.6931471805599454, 'analisis': 1.2876820724517808, 'sentimen': 1.6931471805599454, 'berita': 1.6931471805599454, 'input': 1.6931471805599454, 'output': 1.6931471805599454}
```

1.0.4 Vector Space Model

Function dibawah ini menghasilkan w = TF*IDF

```
[]: def tfidf(vocab,tf,idf_scr,doc_dict):
    tf_idf_scr = {}
    for doc_id in doc_dict.keys():
        tf_idf_scr[doc_id] = {}
    for word in vocab:
        for doc_id,doc in doc_dict.items():
            tf_idf_scr[doc_id][word] = tf[doc_id][word] * idf_scr[word]
    return tf_idf_scr
```

Term-Document Matrix doc1 doc2 doc3 t1 |w11 w12 w13| t2 |w21 w22 w23| t3 |w31 w32 w33|

```
[[1.28768207 1.28768207 0.
                        1.28768207]
[1.28768207 0.
[1.69314718 0.
                        0.
                                   ٦
[1.69314718 0.
                        0.
[0.
             1.69314718 0.
             1.28768207 1.28768207]
ГО.
             1.69314718 0.
[0.
ГО.
             1.69314718 0.
ГО.
             0.
                        1.693147187
```

[0. 0. 1.69314718]]

1.0.5 Text Similarity

Edit Distace Ref : https://www.w3resource.com/python-exercises/challenges/1/python-challenges-1-exercise-52.php

```
[]: def edit_distance(string1, string2):
    if len(string1) > len(string2):
        difference = len(string1) - len(string2)
        string1[:difference]
        n = len(string2)
    elif len(string2) > len(string1):
        difference = len(string2) - len(string1)
        string2[:difference]
        n = len(string1)
    for i in range(n):
        if string1[i] != string2[i]:
            difference += 1
```

```
[]: print(edit_distance(doc_dict['doc1'], doc_dict['doc2']))
print(edit_distance(doc_dict['doc1'], doc_dict['doc3']))
```

30

31

Jaccard Similarity Ref: https://www.w3resource.com/python-exercises/extended-data-types/python-extended-data-types-index-counter-exercise-9.php

```
[]: def jaccard_sim(list1, list2):
   intersection = len(list(set(list1).intersection(list2)))
   union = (len(list1) + len(list2)) - intersection
   return float(intersection) / union
```

```
[]: print(jaccard_sim(doc_dict['doc1'].split(" "), doc_dict['doc2'].split(" ")))
print(jaccard_sim(doc_dict['doc1'].split(" "), doc_dict['doc3'].split(" ")))
```

- 0.125
- 0.14285714285714285

1.0.6 Euclidian Distance

```
[]: def euclidian_dist(vec1, vec2):
    # subtracting vector
    temp = vec1 - vec2
    # doing dot product
```

```
# for finding
# sum of the squares
sum_sq = np.dot(temp.T, temp)
# Doing squareroot and
# printing Euclidean distance
return np.sqrt(sum_sq)
```

```
[]: print(euclidian_dist(TD[:, 0], TD[:, 1])) #doc1 & doc2 print(euclidian_dist(TD[:, 0], TD[:, 2])) #doc1 & doc3
```

- 4.201188773980275
- 3.844897884155026

1.0.7 Cosine Similarity

Ref: https://algoritmaonline.com/kemiripan-teks/

```
import math
def cosine_sim(vec1, vec2):
    vec1 = list(vec1)
    vec2 = list(vec2)
    dot_prod = 0
    for i, v in enumerate(vec1):
        dot_prod += v * vec2[i]
    mag_1 = math.sqrt(sum([x**2 for x in vec1]))
    mag_2 = math.sqrt(sum([x**2 for x in vec2]))

return dot_prod / (mag_1 * mag_2)
```

```
[]: print(cosine_sim(TD[:, 0], TD[:, 1])) #doc1 & doc2 print(cosine_sim(TD[:, 0], TD[:, 2])) #doc1 & doc3
```

- 0.15967058203849993
- 0.1832234081332565

1.0.8 Penugasan

1. Buat vector space model dengan menggunakan sekumpulan dokumen pada folder "berita"

```
def read_text_file(file_path):
         with open(file_path, 'r') as f:
             content = f.read()
         return content
     def preprocess_text(text):
         stemmer = StemmerFactory().create_stemmer()
         stemmed_text = stemmer.stem(text)
         doc = nlp(stemmed_text)
         tokens = [token.text for token in doc if token.text.lower() not in_
      →STOP_WORDS]
         return tokens
     inverted_index = {}
     doc_dict = {}
     for file in os.listdir(path):
         if os.path.isfile(os.path.join(path, file)) and file.endswith(".txt"):
             file_path = os.path.join(path, file)
             text = read_text_file(file_path)
             cleaned_tokens = preprocess_text(text)
             doc_dict[file] = cleaned_tokens
             # Ini utk inverted index nya
             for token in set(cleaned_tokens): # Menghindari duplikat
                 inverted_index.setdefault(token, []).append(file)
             vocab=list(inverted_index.keys())
[]: tf_idf = tfidf(vocab, termFrequencyInDoc(vocab, doc_dict), inverseDocFre(vocab,
     →wordDocFre(vocab, doc_dict), len(doc_dict)), doc_dict)
     # Term - Document Matrix
     TD = np.zeros((len(inverted_index), len(doc_dict)))
     for word in vocab:
         for doc_id, doc in tf_idf.items():
             ind1 = list(vocab).index(word)
             ind2 = list(tf_idf.keys()).index(doc_id)
             TD[ind1][ind2] = tf_idf[doc_id][word]
```

[]: print(TD)

11	2.09861229	0.	0.	0.	0.
	4.19722458	0.	0.	0.	
L	2.09861229		0.		_
L	4.19722458	0.		0.	0.]
L		0.	0.	0.	0.]
L	1.40546511	1.40546511	1.40546511	0.	0.]
L	2.09861229	0.	0.	0.	0.]
L	2.09861229	0.	0.	0.	0.]
L	2.09861229	0.	0.	0.	0.]
L	2.09861229	0.	0.	0.	0.]
	1.69314718	1.69314718	0.	0.	0.
	2.09861229	0.	0.	0.	0.]
	1.	1.	1.	1.	1.]
	1.69314718	1.69314718	0.	0.	0.]
	2.09861229	0.	0.	0.	0.]
	2.09861229	0.	0.	0.	0.]
[4.19722458	0.	0.	0.	0.]
Ε	2.09861229	0.	0.	0.	0.]
Γ	6.29583687	0.	0.	0.	0.]
[2.09861229	0.	0.	0.	0.]
Ε	1.69314718	0.	0.	1.69314718	0.]
Ε	1.	1.	1.	1.	1.]
Γ	2.09861229	0.	0.	0.	0.]
Γ	2.81093022	0.	2.81093022	1.40546511	0.]
Ī	3.	7.	4.	2.	3.]
Ĺ	2.09861229	0.	0.	0.	0.]
Γ	2.09861229	0.	0.	0.	0.]
Γ	6.29583687	0.	0.	0.	0.]
Г	6.29583687	0.	0.	0.	0.]
L	2.09861229	0.	0.	0.	0.]
Г	1.	1.	1.	1.	1.
Г	2.09861229	0.	0.	0.	0.]
Г	2.09861229	0.	0.	0.	
L	1.69314718				_
L		0.	0.	3.38629436	0.]
L	1.69314718	0.	3.38629436	0.	0.
L	1.	1.	1.	1.	1.
L	2.09861229	0.	0.	0.	0.]
Ĺ	2.09861229	0.	0.	0.	0.]
L	2.09861229	0.	0.	0.	0.]
L	1.	1.	1.	1.	1.
L	1.	1.	1.	4.	1.
	2.09861229	0.	0.	0.	0.
	2.09861229	0.	0.	0.	0.]
[2.09861229	0.	0.	0.	0.]
[2.09861229	0.	0.	0.	0.]
[3.38629436	0.	0.	0.	1.69314718]
[2.09861229	0.	0.	0.	0.]

[1.	1.	1.	1.	1.
[3.38629436	0.	0.	0.	1.69314718]
[1.69314718	0.	0.	1.69314718	0.]
[4.19722458	0.	0.	0.	0.]
[1.	1.	1.	1.	1.
[4.19722458	0.	0.	0.	0.
[16.	18.	19.	12.	16.
[2.09861229	0.	0.	0.	0.]
[2.09861229	0.	0.	0.	0.]
[4.19722458	0.	0.	0.	0.]
[2.09861229	0.	0.	0.	0.
[1.69314718	0.	0.	0.	1.69314718]
[3.	7.	4.	2.	3.
[4.19722458	0.	0.	0.	0.
[1.69314718	1.69314718	0.	0.	0.]
[2.09861229	0.	0.	0.	0.]
[0.	1.69314718	5.07944154	0.	0.]
[0.	1.69314718	1.69314718	0.	0.]
[0.	6.29583687	0.	0.	0.]
[0.	2.09861229	0.	0.	0.]
[0.	1.69314718	1.69314718	0.	0.]
[0.	1.69314718	1.69314718	0.	0.]
[0.	4.19722458	0.	0.	0.]
[0.	1.69314718	1.69314718	0.	0.]
[0.	1.69314718	1.69314718	0.	0.]
[0.	1.69314718	5.07944154	0.	0.]
[0.	2.09861229	0.	0.	0.]
[0.	2.09861229	0.	0.	0.]
[0.	1.69314718	1.69314718	0.	0.]
[0.	3.38629436	5.07944154	0.	0.]
[0.	2.81093022	2.81093022	1.40546511	0.]
[0.	2.09861229	0.	0.	0.]
[0.	2.09861229	0.	0.	0.]
[0.	1.69314718	1.69314718	0.	0.]
[0.	2.09861229	0.	0.	0.]
[0.	6.77258872	8.4657359	0.	0.]
[0.	1.69314718	1.69314718	0.	0.]
[0.	1.69314718	1.69314718	0.	0.]
[0.	0.	2.09861229	0.	0.
[0.	0.	3.38629436	0.	1.69314718]
[0.	0.	1.69314718	0.	3.38629436]
[0.	0.	2.09861229	0.	0.]
[0.	0.	2.09861229	0.	0.]
[0.	0.	2.09861229	0.	0.]
[0.	0.	2.09861229	0.	0.
[0.	0.	5.62186043	7.02732554	5.62186043]
[0.	0.	7.02732554	9.83825576	2.81093022]
[0.	0.	4.19722458	0.	0.
L U.	.	1.10,22400	.	٠. ا

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[0.	0.	2.09861229	0.	0.
[0.	0.	2.09861229	0.	0.]
[0.	0.	4.19722458	0.	0.]
[0.	0.	2.09861229	0.	0.]
[0.	0.	4.19722458	0.	0.]
[0.	0.	3.38629436	1.69314718	0.]
ΓΟ.	0.	6.29583687	0.	0.]
[0.	0.	6.29583687	0.	0.]
[0.	0.	2.09861229	0.	0.]
[0.	0.	2.09861229	0.	0.]
[0.		2.09861229	0.	_
_	0.			
[0.	0.	1.69314718	1.69314718	0.]
[0.	0.	2.09861229	0.	0.]
[0.	0.	2.09861229	0.	0.]
[0.	0.	0.	2.09861229	0.
[0.	0.	0.	2.09861229	0.
[0.	0.	0.	4.19722458	0.
[0.	0.	0.	2.09861229	0.]
[0.	0.	0.	1.69314718	1.69314718]
[0.	0.	0.	2.09861229	0.]
[0.	0.	0.	2.09861229	0.]
[0.	0.	0.	10.49306144	0.]
[0.	0.	0.	2.09861229	0.]
[0.	0.	0.	2.09861229	0.]
[0.	0.	0.	2.09861229	0.]
[0.	0.	0.	2.09861229	0.]
[0.	0.	0.	2.09861229	0.]
[0.	0.	0.	2.09861229	0.]
[0.	0.	0.	2.09861229	0.]
ΓΟ.	0.	0.	2.09861229	0.]
[0.	0.	0.	2.09861229	0.]
[0.	0.	0.	4.19722458	0.]
[0.	0.	0.	2.09861229	0.]
[0.	0.	0.	0.	2.09861229]
[0.	0.	0.	0.	2.09861229]
[0.	0.	0.	0.	2.09861229]
[0.		0.	0.	2.09861229]
	0.			
_	0.	0.	0.	2.09861229]
[0.	0.	0.	0.	2.09861229]
[0.	0.	0.	0.	2.09861229]
[0.	0.	0.	0.	2.09861229]
[0.	0.	0.	0.	4.19722458]
[0.	0.	0.	0.	2.09861229]
[0.	0.	0.	0.	2.09861229]
[0.	0.	0.	0.	4.19722458]
[0.	0.	0.	0.	2.09861229]
[0.	0.	0.	0.	6.29583687]
[0.	0.	0.	0.	4.19722458]

```
Γο.
                                    0.
                      0.
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                                                                2.098612297
      Γο.
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                                                                2.09861229]
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                                                                2.09861229]
      Γ0.
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                                                                2.09861229]
      Γ0.
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                                                                2.098612297
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      Γ0.
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                                                                2.09861229]
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      ΓО.
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      Γ0.
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                                                                4.197224587
      Γο.
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                                                                2.09861229]
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                                                                2.09861229]
      Γ0.
                      0.
                                    0.
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                                                                2.09861229]
      ΓО.
                      0.
                                    0.
                                                  0.
                                                                2.09861229]]
[]:
```

2. Dari 5 file pada folder "berita", hitung skor kemiripan antara berita yang satu dan lainnya masing-masing dengan edit distance, jaccard similarity, euclidian distance, dan cosine similarity

```
[]: import os
  import numpy as np
  from spacy.lang.id import Indonesian
  from Sastrawi.Stemmer.StemmerFactory import StemmerFactory
  from spacy.lang.id.stop_words import STOP_WORDS
  from scipy.spatial import distance
  import math
```

Pada kode dibawah kita melakukan beberapa revisi pada function edit_distance, dimana nantinya akan terdapat seluruh operasi yang ada di edit distance seperti insert, substitusi, dan delete. Penggunaan library scipy digunakan untuk mempermudah penggunaan operasi perbedaan antar dokumen pada beberap fungsi dibawah sepertin distance.

```
[]: def read_text_file(file_path):
    with open(file_path, 'r', encoding='utf-8') as f:
        content = f.read()
    return content

def preprocess_text(text):
    stemmer = StemmerFactory().create_stemmer()
    stemmed_text = stemmer.stem(text)
```

```
doc = nlp(stemmed_text)
   tokens = [token.text for token in doc if token.text.lower() not in_
 →STOP_WORDS]
   return tokens
def edit_distance(string1, string2):
    # Implementasi edit distance
   if len(string1) > len(string2):
        string1, string2 = string1[:len(string2)], string2
   elif len(string2) > len(string1):
        string1, string2 = string1, string2[:len(string1)]
   distance_matrix = [[0] * (len(string2) + 1) for _ in range(len(string1) +__
 1)]
   for i in range(len(string1) + 1):
        distance_matrix[i][0] = i
   for j in range(len(string2) + 1):
        distance_matrix[0][j] = j
   for i in range(1, len(string1) + 1):
        for j in range(1, len(string2) + 1):
            cost = 0 if string1[i - 1] == string2[j - 1] else 1
            distance_matrix[i][j] = min(
                distance_matrix[i - 1][j] + 1,
                distance_matrix[i][j - 1] + 1,
                                                    # Insert
                distance_matrix[i - 1][j - 1] + cost # Substitusi
            )
   return distance_matrix[len(string1)][len(string2)]
def jaccard_sim(list1, list2):
    intersection = len(set(list1).intersection(list2))
   union = len(set(list1).union(list2))
   return intersection / union
def euclidean_dist(vec1, vec2):
   return distance.euclidean(vec1, vec2)
def cosine_sim(vec1, vec2):
   return 1 - distance.cosine(vec1, vec2)
```

Kemudian, kita lakukan double iterasi untuk membandingkan setiap dokumen satu dengan keseluruhan dokumen yang ada di folder berita. Total ada 10 kombinasi yang akan didapatkan dari

```
iterasi berikut dan menghitung skor kesamaan dan perbedaan setiap dokumen.
[]: #perhitungan untuk setiap dokumen di berita
     for i, (file1, tokens1) in enumerate(doc_dict.items()):
         for file2, tokens2 in list(doc_dict.items())[i+1:]:
             edit_dist = edit_distance(' '.join(tokens1), ' '.join(tokens2))
             jaccard_similarity = jaccard_sim(tokens1, tokens2)
             # Ubah tokens menjadi vektor biner
             vec1 = [1 if token in tokens1 else 0 for token in vocab]
             vec2 = [1 if token in tokens2 else 0 for token in vocab]
             euclidean_distance = euclidean_dist(vec1, vec2)
             cosine_similarity = cosine_sim(vec1, vec2)
             print(f"Kesamaan antara {file1} and {file2}:")
             print(f"Edit Distance: {edit_dist}")
             print(f"Jaccard Similarity: {jaccard_similarity}")
             print(f"Euclidean Distance: {euclidean_distance}")
             print(f"Cosine Similarity: {cosine_similarity}")
             print()
    Kesamaan antara berita1.txt and berita2.txt:
    Edit Distance: 331
    Jaccard Similarity: 0.17857142857142858
    Euclidean Distance: 8.306623862918075
    Cosine Similarity: 0.31318038399724624
    Kesamaan antara berita1.txt and berita3.txt:
    Edit Distance: 396
    Jaccard Similarity: 0.14
    Euclidean Distance: 9.273618495495704
    Cosine Similarity: 0.24656448378672147
    Kesamaan antara berita1.txt and berita4.txt:
    Edit Distance: 313
    Jaccard Similarity: 0.1744186046511628
    Euclidean Distance: 8.426149773176359
    Cosine Similarity: 0.3050444380432815
    Kesamaan antara berita1.txt and berita5.txt:
    Edit Distance: 338
    Jaccard Similarity: 0.13725490196078433
    Euclidean Distance: 9.38083151964686
```

Cosine Similarity: 0.2419553954370992

Edit Distance: 264

Kesamaan antara berita2.txt and berita3.txt:

Jaccard Similarity: 0.4126984126984127 Euclidean Distance: 6.082762530298219 Cosine Similarity: 0.5927489783638191

Kesamaan antara berita2.txt and berita4.txt:

Edit Distance: 260

Jaccard Similarity: 0.1875

Euclidean Distance: 7.211102550927978 Cosine Similarity: 0.31589887589559384

Kesamaan antara berita2.txt and berita5.txt:

Edit Distance: 285

Jaccard Similarity: 0.1375

Euclidean Distance: 8.306623862918075 Cosine Similarity: 0.24609055357847565

Kesamaan antara berita3.txt and berita4.txt:

Edit Distance: 312

Jaccard Similarity: 0.22972972972974 Euclidean Distance: 7.54983443527075 Cosine Similarity: 0.3774982529316784

Kesamaan antara berita3.txt and berita5.txt:

Edit Distance: 343

Jaccard Similarity: 0.16483516483516483 Euclidean Distance: 8.717797887081348 Cosine Similarity: 0.28306925853614895

Kesamaan antara berita4.txt and berita5.txt:

Edit Distance: 284

Jaccard Similarity: 0.17721518987341772 Euclidean Distance: 8.06225774829855 Cosine Similarity: 0.3050695435482862