```
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BESE -7B

184055

Natural Language Processing Project

Submitted to

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COMPARISON BETWEEN COSINE SIMILARITY & SOFT COSINE SIMILARITY

Installing packages and Importing Libraries

```
!pip install beautifulsoup4
```

```
Requirement already satisfied: beautifulsoup4 in /usr/local/lib/python3.6/dist-packages (4.6.3)
```

```
!pip install lxml
```

```
Requirement already satisfied: lxml in /usr/local/lib/python3.6/dist-packages (4.2.6)
```

```
import bs4 as bs
import urllib.request
import re
import nltk, string, numpy as np
```

```
nltk.download('wordnet') # first-time use only
nltk.download('punkt')
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfTransformer
import math
import pandas as pd
import networkx as nx
from networkx.generators.small import krackhardt_kite_graph
from string import ascii_lowercase
```

```
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data]   Unzipping corpora/wordnet.zip.
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
```

Extract Abstract from a webpage

```
def abstractExtracter(url_to_go):
  scraped_data = urllib.request.urlopen(url_to_go)
  article = scraped_data.read()

  parsed_article = bs.BeautifulSoup(article,'lxml')

  paragraphs = parsed_article.find_all(id='p-2')

  article_text = ""

  for p in paragraphs:
      article_text += p.text
  return article_text

# COVID-19 related
abstract1 = abstractExtracter('https://www.medrxiv.org/content/10.1101/2020.02.24.20027052v1')
abstract2 = abstractExtracter('https://www.medrxiv.org/content/10.1101/2020.03.07.20031575v1')
abstract3 = abstractExtracter('https://www.medrxiv.org/content/10.1101/2020.03.19.20034124v1')

# Movie Characters
```

```
# Movie characters
abstract4 = "Harry Potter is a series of fantasy novels written by British author J. K. Rowling. The novels chronicle the lives of a youn
abstract5 = "Cruise began acting in the early 1980s and made his breakthrough with leading roles in the comedy film Risky Business (1983)
abstract6 = "Spider-Man is a fictional superhero created by writer-editor Stan Lee and writer-artist Steve Ditko. He first appeared in th

# Sports related
abstract7 = "Cricket is a bat-and-ball game played between two teams of eleven players on a field at the centre of which is a 20-metre (2
abstract8 = "Roller hockey, also known as quad hockey, international-style ball hockey, rink hockey and Hoquei em Patins, is an overarchi
```

```
print('ABSTRACT # 1: ', abstract1)

print('\n-----------\n')

print('ABSTRACT # 2: ',abstract2)

print('\n-----------\n')

print('ABSTRACT # 3: ',abstract3)

print('\n-----------\n')

print('ABSTRACT # 4: ', abstract4)

print('\n-----------\n')

print('ABSTRACT # 5: ', abstract5)

print('\n-----------\n')

print('ABSTRACT # 6: ', abstract6)

print('\n-----------\n')

print('ABSTRACT # 7: ', abstract7)

print('\n-----------\n')
```

```
print('ABSTRACT # 8: ', abstract8)
```

```
ABSTRACT # 1:  Objective: To investigate the correlation between clinical characteristics and cardiac injury of COVID-2019 pneumonia
```

Creating Documents

```
def fileWriter(filename, content):
  abs_file = open(filename, mode='w+')
  abs_file.write(content)

fileWriter('doc3.txt', abstract3)
```

```
ABSTRACT # 3:  Background
```

```
d1 = abstract1
d2 = abstract2
d3 = abstract3
d4 = abstract4
d5 = abstract5
d6 = abstract6
d7 = abstract7
d8 = abstract8



documents = [d1, d2, d3, d4, d5, d6, d7, d8]
```

Data Preprocessing

```
lemmer = nltk.stem.WordNetLemmatizer()
def LemTokens(tokens):
    return [lemmer.lemmatize(token) for token in tokens]
remove_punct_dict = dict((ord(punct), None) for punct in string.punctuation)
def LemNormalize(text):
    return LemTokens(nltk.word_tokenize(text.lower().translate(remove_punct_dict)))
```

```
ABSTRACT # 8:  Roller hockey, also known as quad hockey, international-style ball hockey, rink hockey and Hoquei em Patins, is an ov
```

```
LemVectorizer = CountVectorizer(tokenizer=LemNormalize, stop_words='english')
LemVectorizer.fit_transform(documents)
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/feature_extraction/text.py:385: UserWarning: Your stop_words may be inconsistent with
  'stop_words.' % sorted(inconsistent))
<8x544 sparse matrix of type '<class 'numpy.int64'>'
	with 624 stored elements in Compressed Sparse Row format>
```

```
LemVectorizer.vocabulary_
```

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```

TF_IDF Calculations

```
tf_matrix = LemVectorizer.transform(documents).toarray()
print (tf_matrix)
```

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

```
tf_matrix.shape
```

```
(8, 544)
```

```
'weasley': 550,
```

```
tfidfTran = TfidfTransformer(norm="l2")
tfidfTran.fit(tf_matrix)
print (tfidfTran.idf_)
```

```
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```

```
def idf(n,df):
    result = math.log((n+1.0)/(df+1.0)) + 1
    return result
print( "The idf for terms that appear in one document: " + str(idf(4,1)))
print( "The idf for terms that appear in two documents: " + str(idf(4,2)))
```

```
The idf for terms that appear in one document: 1.916290731874155
The idf for terms that appear in two documents: 1.5108256237659907
```

```
tfidf_matrix = tfidfTran.transform(tf_matrix)
print (tfidf_matrix.toarray())
```

```
[[0.         0.         0.05690053 ... 0.         0.05690053 0.        ]
 [0.         0.         0.         ... 0.         0.         0.        ]
 [0.04549598 0.04549598 0.         ... 0.         0.         0.        ]
 ...
 [0.         0.         0.         ... 0.08517796 0.         0.        ]
 [0.         0.         0.         ... 0.         0.         0.        ]
 [0.         0.         0.         ... 0.         0.         0.        ]]
```

Cosine Similarity Matrix

```
cos_similarity_matrix = (tfidf_matrix * tfidf_matrix.T).toarray()
print (cos_similarity_matrix)
```

```
[[1.         0.31494383 0.22431601 0.         0.01490693 0.00194864
  0.00384484 0.00839603]
 [0.31494383 1.         0.27191561 0.00848904 0.         0.00338107
  0.00667113 0.01942379]
 [0.22431601 0.27191561 1.         0.         0.01260042 0.00816564
  0.00614843 0.01118869]
 [0.         0.00848904 0.         1.         0.0071785  0.05126799
  0.         0.01051885]
 [0.01490693 0.         0.01260042 0.0071785  1.         0.
  0.01692371 0.00717347]
 [0.00194864 0.00338107 0.00816564 0.05126799 0.         1.
  0.01726673 0.00837903]
 [0.00384484 0.00667113 0.00614843 0.         0.01692371 0.01726673
  1.         0.03306504]
 [0.00839603 0.01942379 0.01118869 0.01051885 0.00717347 0.00837903
  0.03306504 1.        ]]
```

```
df = pd.DataFrame(cos_similarity_matrix, index= ['doc1','doc2','doc3', 'doc4', 'doc5', 'doc6', 'doc7', 'doc8'], columns=['doc1','doc2','d
df
```

	doc1	doc2	doc3	doc4	doc5	doc6	doc7	doc8
doc1	1.000000	0.314944	0.224316	0.000000	0.014907	0.001949	0.003845	0.008396

```
df.to_csv('sim_matrix.csv')
```

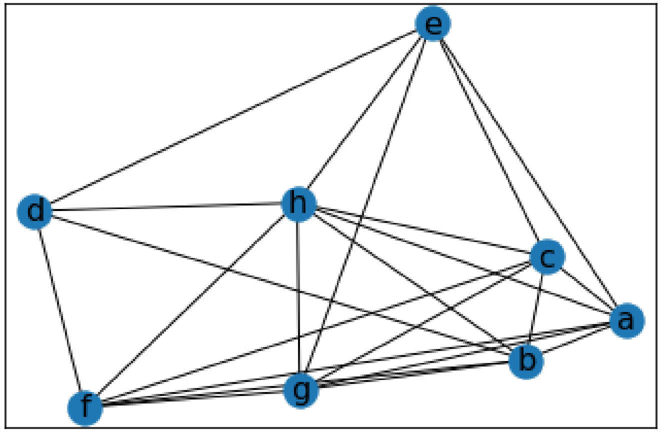
```
cos_similarity_matrix
```

```
array([[1.        , 0.31494383, 0.22431601, 0.        , 0.01490693,
        0.00194864, 0.00384484, 0.00839603],
       [0.31494383, 1.        , 0.27191561, 0.00848904, 0.        ,
        0.00338107, 0.00667113, 0.01942379],
       [0.22431601, 0.27191561, 1.        , 0.        , 0.01260042,
        0.00816564, 0.00614843, 0.01118869],
       [0.        , 0.00848904, 0.        , 1.        , 0.0071785 ,
        0.05126799, 0.        , 0.01051885],
       [0.01490693, 0.        , 0.01260042, 0.0071785 , 1.        ,
        0.        , 0.01692371, 0.00717347],
       [0.00194864, 0.00338107, 0.00816564, 0.05126799, 0.        ,
        1.        , 0.01726673, 0.00837903],
       [0.00384484, 0.00667113, 0.00614843, 0.        , 0.01692371,
        0.01726673, 1.        , 0.03306504],
       [0.00839603, 0.01942379, 0.01118869, 0.01051885, 0.00717347,
        0.00837903, 0.03306504, 1.        ]])
```

Similarity Network Graph

```
G = nx.from_numpy_matrix(np.array(cos_similarity_matrix))
pos=nx.spring_layout(G)
labels = {}
for idx, node in enumerate(G.nodes()):
    labels[node] = ascii_lowercase[idx]
nx.draw_networkx_nodes(G, pos)
nx.draw_networkx_edges(G, pos)
nx.draw_networkx_labels(G, pos, labels, font_size=16)
```

```
{0: Text(0.841745585842018, -0.1437313721044677, 'a'),
 1: Text(0.5297857290918704, -0.2615199885583736, 'b'),
 2: Text(0.5934057698571252, 0.044067664877l0522, 'c'),
 3: Text(-0.9999999999999999, 0.17826968106296096, 'd'),
 4: Text(0.2360313503960871, 0.7331077256377565, 'e'),
 5: Text(-0.8442270937553488, -0.40162029201579447, 'f'),
 6: Text(-0.17459786712837505, -0.3511607037451265, 'g'),
 7: Text(-0.18214347430337682, 0.20258728484593966, 'h')}
```



Soft Cosine Similarity

Importing Libraries and Downloading FastText pre-trained embeddings

```
#SOFT COSINE

import gensim
# upgrade gensim if you can't import softcossim
from gensim.matutils import softcossim
from gensim import corpora
import gensim.downloader as api
from gensim.utils import simple_preprocess
print(gensim.__version__)
#> '3.6.0'
```

```
# Download the FastText model
fasttext_model300 = api.load('fasttext-wiki-news-subwords-300')
```

Preparing Documents for Similarity Calculations

```
# Prepare a dictionary and a corpus.
dictionary = corpora.Dictionary([simple_preprocess(doc) for doc in documents])

# Prepare the similarity matrix
similarity_matrix = fasttext_model300.similarity_matrix(dictionary, tfidf=None, threshold=0.0, exponent=2.0, nonzero_limit=100)

# Convert the sentences into bag-of-words vectors.
sent_1 = dictionary.doc2bow(simple_preprocess(d1))
sent_2 = dictionary.doc2bow(simple_preprocess(d2))
sent_3 = dictionary.doc2bow(simple_preprocess(d3))
sent_4 = dictionary.doc2bow(simple_preprocess(d4))
sent_5 = dictionary.doc2bow(simple_preprocess(d5))
sent_6 = dictionary.doc2bow(simple_preprocess(d6))
sent_7 = dictionary.doc2bow(simple_preprocess(d7))
sent_8 = dictionary.doc2bow(simple_preprocess(d8))

sentences = [sent_1, sent_2, sent_3, sent_4, sent_5, sent_6, sent_7, sent_8]
```

```
/usr/local/lib/python3.6/dist-packages/gensim/matutils.py:737: FutureWarning: Conversion of the second argument of issubdtype from `
  if np.issubdtype(vec.dtype, np.int):
```

Soft Cosine Similarity Matrix

```
import numpy as np
import pandas as pd

def create_soft_cossim_matrix(sentences):
    len_array = np.arange(len(sentences))
    xx, yy = np.meshgrid(len_array, len_array)
```

```
    xx, yy = np.meshgrid(len_array, len_array)
    cossim_mat = pd.DataFrame([[round(softcossim(sentences[i],sentences[j], similarity_matrix) ,2) for i, j in zip(x,y)] for y, x in zip(
    return cossim_mat

soft = create_soft_cossim_matrix(sentences)
```

```
soft
```

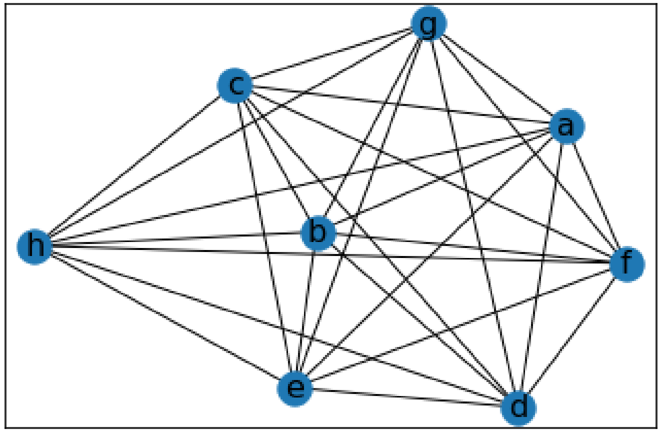
	0	1	2	3	4	5	6	7
0	1.00	0.86	0.86	0.65	0.75	0.73	0.69	0.40
1	0.86	1.00	0.78	0.57	0.68	0.65	0.65	0.40
2	0.86	0.78	1.00	0.65	0.71	0.72	0.69	0.42
3	0.65	0.57	0.65	1.00	0.65	0.70	0.64	0.34
4	0.75	0.68	0.71	0.65	1.00	0.78	0.75	0.38
5	0.73	0.65	0.72	0.70	0.78	1.00	0.74	0.43
6	0.69	0.65	0.69	0.64	0.75	0.74	1.00	0.46
7	0.40	0.40	0.42	0.34	0.38	0.43	0.46	1.00

Soft Cosine Similarity Network Graph

```
import networkx as nx
import numpy as np

from networkx.generators.small import krackhardt_kite_graph
from string import ascii_lowercase
G = nx.from_numpy_matrix(np.array(soft))
pos=nx.spring_layout(G)
labels = {}
for idx, node in enumerate(G.nodes()):
    labels[node] = ascii_lowercase[idx]
nx.draw_networkx_nodes(G, pos)
```

```
nx.draw_networkx_nodes(G, pos)
nx.draw_networkx_edges(G, pos)
nx.draw_networkx_labels(G, pos, labels, font_size=16)
```

```
{0: Text(0.5493962762436561, 0.35848933862869, 'a'),
 1: Text(-0.17672259010990607, -0.04027416548680531, 'b'),
 2: Text(-0.41582659408412376, 0.5109643940084911, 'c'),
 3: Text(0.4121130346081521, -0.6954231904792567, 'd'),
 4: Text(-0.24189609010584057, -0.6216772584907388, 'e'),
 5: Text(0.7260350879452805, -0.15844942825209118, 'f'),
 6: Text(0.14690087550278308, 0.7391572228312548, 'g'),
 7: Text(-1.0, -0.09278691275954416, 'h')}
```



Evaluations and Results

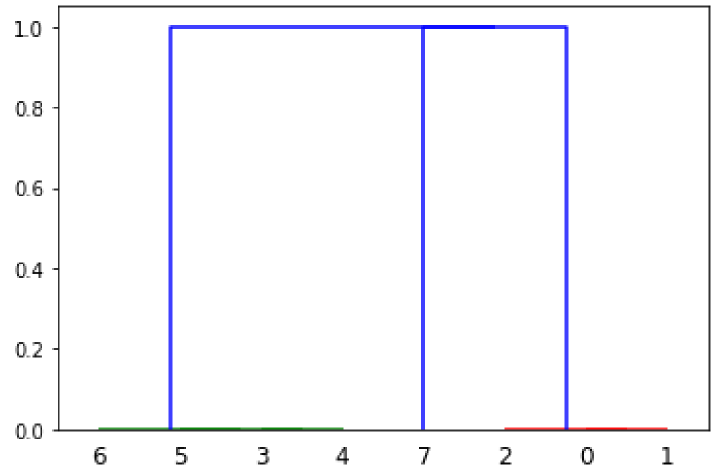
```
from sklearn.cluster import AgglomerativeClustering
import numpy as np
X = np.array(soft) # soft can be replaced with cos_similarity_matrix to generate its Dendogram and clusters
clustering = AgglomerativeClustering( n_clusters=3).fit(X)

AgglomerativeClustering(n_clusters=3)
clustering.labels_
```

```
array([2, 2, 2, 0, 0, 0, 0, 1])
```

```
from scipy.cluster.hierarchy import dendrogram, linkage
from matplotlib import pyplot as plt
X = [[i] for i in clustering.labels_]
X
```

```
[[2], [2], [2], [0], [0], [0], [0], [1]]
```

```
Z = linkage(X, 'single')
fig = plt.figure()
dn = dendrogram(Z)
```



Accuracy

```
Cos_Clusters_Predicted =  [[1], [1], [1], [2], [0], [2], [0], [1]]
Soft_Clusters_Predicted = [[2], [2], [2], [0], [0], [0], [0], [1]]

Cos_Clusters_Actual =  [[1], [1], [1], [2], [2], [2], [0], [0]]
Soft_Clusters_Actual = [[2], [2], [2], [0], [0], [0], [1], [1]]
```

Accuracy or Correct Rate

$$CR = \frac{C}{A}$$

CR – The correct rate;

C – The number of sample recognized correctly;

A – The number of all sample;

```
Soft_Accuracy = 7/8 * 100
Cos_Accuracy = 7/8 * 100
```

```
print("Soft Cosine Accuracy: ", Soft_Accuracy)

print("Cosine Accuracy: ", Cos_Accuracy)
```

```
Soft Cosine Accuracy:  87.5
Cosine Accuracy:  87.5
```

```
-- END ---
```