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CS 6120: Natural Language Processing - Prof. Ahmad Uzair

Assignment 3: n-gram Language Models, Word Sense disambiguation(LSA using SVD), LSTM

Total points: 100

Q1. Latent Semantic Analysis (35 Points)

- A. Singular Value Decomposition (SVD) based distributed representation of text and documents. You can use python libraries for matrix decomposition (scipy). To demonstrate your work, use the example dataset (Table 2) of "R. A. Harshman (1990). Indexing by latent semantic analysis. Journal of the American society for information science". (10 Points)

- B. Visualize (2-D) the documents and terms using library of your choice. (10 Points)

- C. Implement a function that converts a query string to distributed representation and retrieves relevent documents. Visualize the the results as shown in Fig 1 of the paper. (10 Points)

Task-1 (10 Points)

Input data

```
#Dataset
c1 = 'Computer vision is a field of artificial intelligence that
focuses on enabling computers to interpret and understand visual
information from the world.'
c2 = 'One of the most prominent applications of computer vision is in
autonomous vehicles, where it helps the vehicle "see" and make
decisions based on its surroundings.'
c3 = 'Computer vision is also used in facial recognition technology,
which has become controversial due to concerns over privacy and
potential misuse.'
c4 = 'In the medical field, computer vision is used to assist doctors
in diagnosing diseases and analyzing medical images such as x-rays and
MRIs.'
c5 = 'Computer vision is also used in security and surveillance
systems, where it can detect and recognize suspicious activities or
individuals.'
m1 = 'Cybersecurity refers to the practices and technologies used to
protect computer systems, networks, and data from unauthorized access,
use, disclosure, disruption, modification, or destruction.'
m2 = 'One of the most important applications of cybersecurity is in
safeguarding sensitive data and personal information, such as
financial data or healthcare records.'
```

```
m3 = 'Cybersecurity is also essential in protecting critical
infrastructure, such as power grids and transportation systems, from
cyber attacks that could cause significant disruptions.'
m4 = 'In the healthcare industry, cybersecurity is used to protect
medical devices and prevent unauthorized access to patient data.'
documents = [c1, c2, c3, c4, c5, m1, m2, m3, m4]
```

Perform preprocessing of documents

In the below cell remove punctuations and lowercase the message

```
# TASK CELL
import re

def preprocess(message):
    '''
    Input:
        message: a string containing a message.
    Output:
        preprocessed_message_list: a list of words containing the
processed message.
    '''

    # Remove punctuation
    message = re.sub('[^A-Za-z0-9]+', " ", message)

    # Remove multiple spaces
    message = re.sub(' +', " ", message)

    # Lower Case
    message = message.lower()

    # Convert to List
    preprocessed_message_list = message.split(" ")

    # Remove spaces
    preprocessed_message_list = list(filter(None,
preprocessed_message_list))

    # Return list
    return preprocessed_message_list

preprocess(c2)
```

```
['one',
 'of',
 'the',
 'most',
 'prominent',
 'applications',
 'of',
```

```
 'computer',
 'vision',
 'is',
 'in',
 'autonomous',
 'vehicles',
 'where',
 'it',
 'helps',
 'the',
 'vehicle',
 'see',
 'and',
 'make',
 'decisions',
 'based',
 'on',
 'its',
 'surroundings']
```

Verify preprocessed data

```
for sent in documents:
    print(preprocess(sent))
```

```
['computer', 'vision', 'is', 'a', 'field', 'of', 'artificial',
'intelligence', 'that', 'focuses', 'on', 'enabling', 'computers',
'to', 'interpret', 'and', 'understand', 'visual', 'information',
'from', 'the', 'world']
['one', 'of', 'the', 'most', 'prominent', 'applications', 'of',
'computer', 'vision', 'is', 'in', 'autonomous', 'vehicles', 'where',
'it', 'helps', 'the', 'vehicle', 'see', 'and', 'make', 'decisions',
'based', 'on', 'its', 'surroundings']
['computer', 'vision', 'is', 'also', 'used', 'in', 'facial',
'recognition', 'technology', 'which', 'has', 'become',
'controversial', 'due', 'to', 'concerns', 'over', 'privacy', 'and',
'potential', 'misuse']
['in', 'the', 'medical', 'field', 'computer', 'vision', 'is', 'used',
'to', 'assist', 'doctors', 'in', 'diagnosing', 'diseases', 'and',
'analyzing', 'medical', 'images', 'such', 'as', 'x', 'rays', 'and',
'mris']
['computer', 'vision', 'is', 'also', 'used', 'in', 'security', 'and',
'surveillance', 'systems', 'where', 'it', 'can', 'detect', 'and',
'recognize', 'suspicious', 'activities', 'or', 'individuals']
['cybersecurity', 'refers', 'to', 'the', 'practices', 'and',
'technologies', 'used', 'to', 'protect', 'computer', 'systems',
'networks', 'and', 'data', 'from', 'unauthorized', 'access', 'use',
'disclosure', 'disruption', 'modification', 'or', 'destruction']
['one', 'of', 'the', 'most', 'important', 'applications', 'of',
'cybersecurity', 'is', 'in', 'safeguarding', 'sensitive', 'data',
'and', 'personal', 'information', 'such', 'as', 'financial', 'data',
```

```
'or', 'healthcare', 'records']
['cybersecurity', 'is', 'also', 'essential', 'in', 'protecting',
'critical', 'infrastructure', 'such', 'as', 'power', 'grids', 'and',
'transportation', 'systems', 'from', 'cyber', 'attacks', 'that',
'could', 'cause', 'significant', 'disruptions']
['in', 'the', 'healthcare', 'industry', 'cybersecurity', 'is', 'used',
'to', 'protect', 'medical', 'devices', 'and', 'prevent',
'unauthorized', 'access', 'to', 'patient', 'data']
```

Expected Output

```
['computer', 'vision', 'is', 'a', 'field', 'of', 'artificial',
'intelligence', 'that', 'focuses', 'on', 'enabling', 'computers',
'to', 'interpret', 'and', 'understand', 'visual', 'information',
'from', 'the', 'world']
['one', 'of', 'the', 'most', 'prominent', 'applications', 'of',
'computer', 'vision', 'is', 'in', 'autonomous', 'vehicles', 'where',
'it', 'helps', 'the', 'vehicle', '"see"', 'and', 'make', 'decisions',
'based', 'on', 'its', 'surroundings']
['computer', 'vision', 'is', 'also', 'used', 'in', 'facial',
'recognition', 'technology', 'which', 'has', 'become',
'controversial', 'due', 'to', 'concerns', 'over', 'privacy', 'and',
'potential', 'misuse']
['in', 'the', 'medical', 'field', 'computer', 'vision', 'is', 'used',
'to', 'assist', 'doctors', 'in', 'diagnosing', 'diseases', 'and',
'analyzing', 'medical', 'images', 'such', 'as', 'x', 'rays', 'and',
'MRIs']
['computer', 'vision', 'is', 'also', 'used', 'in', 'security', 'and',
'surveillance', 'systems', 'where', 'it', 'can', 'detect', 'and',
'recognize', 'suspicious', 'activities', 'or', 'individuals']
['Cybersecurity', 'refers', 'to', 'the', 'practices', 'and',
'technologies', 'used', 'to', 'protect', 'computer', 'systems',
'networks', 'and', 'data', 'from', 'unauthorized', 'access', 'use',
'disclosure', 'disruption', 'modification', 'or', 'destruction']
['one', 'of', 'the', 'most', 'important', 'applications', 'of',
'cybersecurity', 'is', 'in', 'safeguarding', 'sensitive', 'data',
'and', 'personal', 'information', 'such', 'as', 'financial', 'data',
'or', 'healthcare', 'records']
['Cybersecurity', 'is', 'also', 'essential', 'in', 'protecting',
'critical', 'infrastructure', 'such', 'as', 'power', 'grids', 'and',
'transportation', 'systems', 'from', 'cyber', 'attacks', 'that',
'could', 'cause', 'significant', 'disruptions']
['in', 'the', 'healthcare', 'industry', 'cybersecurity', 'is', 'used',
'to', 'protect', 'medical', 'devices', 'and', 'prevent',
'unauthorized', 'access', 'to', 'patient', 'data']
```

Assign names to document names

In the below cell create a list of document names. It will be later used to visualize documents

```
def createDocName(documents):
    '''
    Input:
        documents: list of documents.
    Output:
        doc_names: a list of document names.

    '''
    doc_names = ['c1', 'c2', 'c3', 'c4', 'c5', 'm1', 'm2', 'm3', 'm4']

    return doc_names

docName = createDocName(documents)
print(docName)
```

```
['c1', 'c2', 'c3', 'c4', 'c5', 'm1', 'm2', 'm3', 'm4']
```

Expected Output

```
['c1', 'c2', 'c3', 'c4', 'c5', 'm1', 'm2', 'm3', 'm4']
```

Words to Index mapping

Retrieve words from documents and create map of word and associate index to it

```
from nltk.corpus import stopwords
stop_words = stopwords.words('english')

def build_word_to_ix(documents, stopwords=None):
    '''
    Input:
        documents: list of documents
        stopwords: list of stopwords
    Output:
        doc_names: map of words and assoicated index. Make sure to
remove words which occur in less than 2 documents

    '''
    # Instantiate dicts
    word_to_ix = {}
    doc_count = {}

    # Iterate over documents
    for i, doc in enumerate(documents):

        # Preprocess document using previous script
        words = preprocess(doc)

        # Get unique words from the list
        unique_words = set(words)

        # Iterate over the words
```

```python
        for word in unique_words:
            # Stop word conditional
            if stopwords and word in stopwords:
                continue

            # Conditional to add
            if word not in doc_count:
                doc_count[word] = set()
            doc_count[word].add(i)

    # Remove words that occur in less than 2 documents
    doc_count = {k: v for k, v in doc_count.items() if len(v) > 1}

    for i, word in enumerate(doc_count.keys()):
        word_to_ix[word] = i

    return word_to_ix

word_to_ix = build_word_to_ix(documents, stop_words)
print(word_to_ix)
```

```
{'field': 0, 'information': 1, 'computer': 2, 'vision': 3,
'applications': 4, 'one': 5, 'used': 6, 'also': 7, 'medical': 8,
'systems': 9, 'unauthorized': 10, 'access': 11, 'protect': 12,
'cybersecurity': 13, 'data': 14, 'healthcare': 15}
```

Expected Output

Note: the index value for each token could be different in your implementation

```
{'field': 0, 'vision': 1, 'information': 2, 'computer': 3, 'one': 4,
'applications': 5, 'also': 6, 'used': 7, 'medical': 8, 'systems': 9,
'data': 10, 'unauthorized': 11, 'access': 12, 'cybersecurity': 13,
'protect': 14, 'healthcare': 15}
```

Document-Terms count matrix

```python
import numpy as np

def build_td_matrix(documents, word_to_ix):
    '''
    Input:
        documents: list of documents.
        word_to_ix: {word, index} map
    Output:
        td_matrix: matrix of count of words in documents, each row
            represent a word and each column represent a document

    '''

    # Instantiate zeros matrix
    td_matrix = np.zeros((len(word_to_ix), len(documents)))
```

```python
    # Iterate over the documents
    for idx, sentence in enumerate(documents):

        # Preprocess and split words
        sentence = preprocess(sentence)

        # for each word, check if its in word_to_ix
        for word in sentence:
            if word in word_to_ix:
                # Increment if included
                td_matrix[word_to_ix[word], idx] = 
td_matrix[word_to_ix[word], idx]+1

    return td_matrix

X = build_td_matrix(documents, word_to_ix)
print(X)
```

```
[[1. 0. 0. 1. 0. 0. 0. 0. 0.]
 [1. 0. 0. 0. 0. 0. 1. 0. 0.]
 [1. 1. 1. 1. 1. 1. 0. 0. 0.]
 [1. 1. 1. 1. 1. 0. 0. 0. 0.]
 [0. 1. 0. 0. 0. 0. 1. 0. 0.]
 [0. 1. 0. 0. 0. 0. 1. 0. 0.]
 [0. 0. 1. 1. 1. 1. 0. 0. 1.]
 [0. 0. 1. 0. 1. 0. 0. 1. 0.]
 [0. 0. 0. 2. 0. 0. 0. 0. 1.]
 [0. 0. 0. 0. 1. 1. 0. 1. 0.]
 [0. 0. 0. 0. 0. 1. 0. 0. 1.]
 [0. 0. 0. 0. 0. 1. 0. 0. 1.]
 [0. 0. 0. 0. 0. 1. 0. 0. 1.]
 [0. 0. 0. 0. 0. 1. 1. 1. 1.]
 [0. 0. 0. 0. 0. 1. 2. 0. 1.]
 [0. 0. 0. 0. 0. 0. 1. 0. 1.]]
```

Expected Output

Note: the order of rows could be different in your implementation as it is based on the indexing of the tokens done in build_word_to_ix

```
[[1. 0. 0. 1. 0. 0. 0. 0. 0.]
 [1. 1. 1. 1. 1. 0. 0. 0. 0.]
 [1. 0. 0. 0. 0. 0. 1. 0. 0.]
 [1. 1. 1. 1. 1. 1. 0. 0. 0.]
 [0. 1. 0. 0. 0. 0. 1. 0. 0.]
 [0. 1. 0. 0. 0. 0. 1. 0. 0.]
 [0. 0. 1. 0. 1. 0. 0. 1. 0.]
 [0. 0. 1. 1. 1. 1. 0. 0. 1.]
 [0. 0. 0. 2. 0. 0. 0. 0. 1.]
 [0. 0. 0. 0. 1. 1. 0. 1. 0.]
```

```
 [0. 0. 0. 0. 0. 1. 2. 0. 1.]
 [0. 0. 0. 0. 0. 1. 0. 0. 1.]
 [0. 0. 0. 0. 0. 1. 0. 0. 1.]
 [0. 0. 0. 0. 0. 1. 1. 1. 1.]
 [0. 0. 0. 0. 0. 1. 0. 0. 1.]
 [0. 0. 0. 0. 0. 0. 1. 0. 1.]]
```

Singular Value Decomposition

Perform singular value decomposition of count matrix into term singular vector matrix, singular value matrix and document singular vector matrix

- To perform the singular value decompostion please check tutorial: https://numpy.org/doc/stable/reference/generated/numpy.linalg.svd.html

```
def svd(documents, word_to_ix, rank):
    '''
    Input:
        documents: list of documents.
        word_to_ix: {word, index} map
        rank: number of colums/rows to retain in decomposed matrix
    Output:
        Uk: term singular vector matrix
        Sk: singular value matrix
        Vk_t: transpose of document singular vector matrix
    '''

    # Insantiate Matrix using previous function
    X = build_td_matrix(documents, word_to_ix)

    # Apply SVD based on documentation
    u, s, vh = np.linalg.svd(X)

    # Reshape outputs to fit required shape
    Uk, Sk, Vk_t = u[:,:rank], np.diag(s[:rank]),
np.dstack((vh[0],vh[1]))[0]

    return Uk, Sk, Vk_t

Uk, Sk, Vk_t = svd(documents, word_to_ix, 2)
print(Uk)
print(Sk)
print(Vk_t)
```

```
[[-0.12717294  0.20278638]
 [-0.11470385 -0.06974269]
 [-0.40776071  0.39028813]
 [-0.30025142  0.45516076]
 [-0.11406442 -0.09695837]
 [-0.11406442 -0.09695837]
 [-0.41909101  0.14444841]
 [-0.1610913   0.18784146]
```

```
 [-0.26503675  0.13251736]
 [-0.20868502  0.02493571]
 [-0.20656126 -0.17503165]
 [-0.20656126 -0.17503165]
 [-0.20656126 -0.17503165]
 [-0.3086385  -0.33652293]
 [-0.34760786 -0.47741341]
 [-0.16957527 -0.26134991]]
[[4.63682644 0.        ]
 [0.         3.4660758 ]]
[[-0.20485755  0.28230559]
 [-0.2018926   0.18797401]
 [-0.27781813  0.33979025]
 [-0.3848213   0.42056737]
 [-0.32282413  0.34698447]
 [-0.49850192 -0.22485343]
 [-0.3270043  -0.52403905]
 [-0.14631016 -0.03570198]
 [-0.4592868  -0.38181953]]
```

Expected Output

Note: the order of rows could be different in your implementation as it is based on the indexing of the tokens done in build_word_to_ix

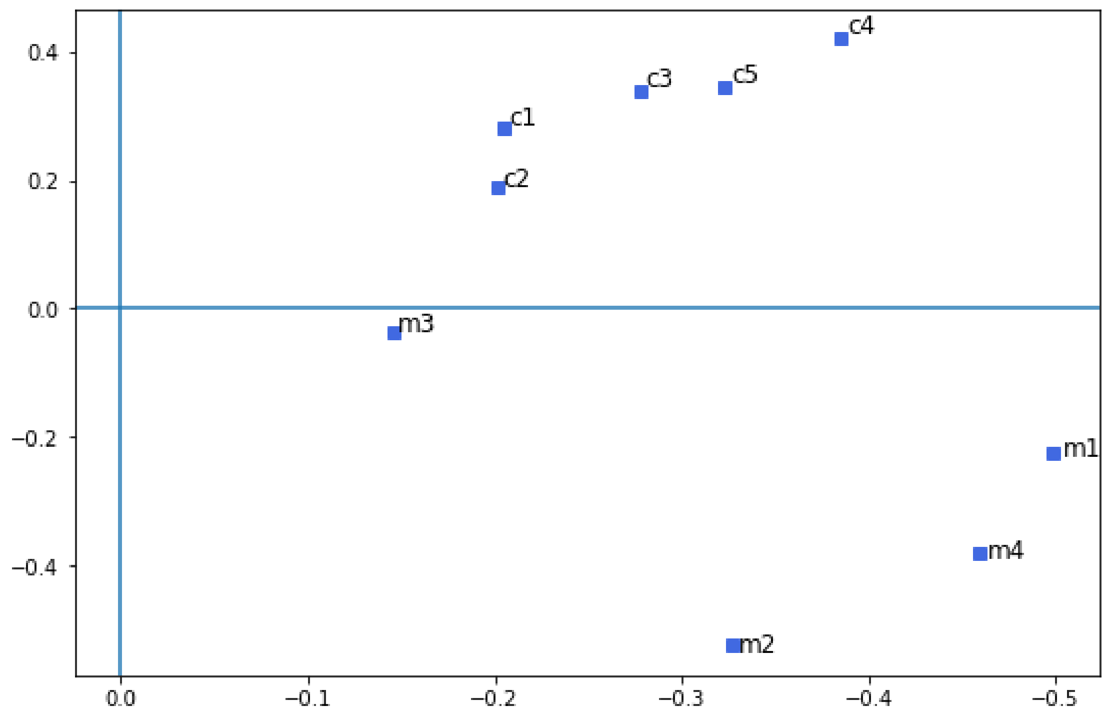
```
[[-0.12717294  0.20278638]
 [-0.30025142  0.45516076]
 [-0.11470385 -0.06974269]
 [-0.40776071  0.39028813]
 [-0.11406442 -0.09695837]
 [-0.11406442 -0.09695837]
 [-0.1610913   0.18784146]
 [-0.41909101  0.14444841]
 [-0.26503675  0.13251736]
 [-0.20868502  0.02493571]
 [-0.34760786 -0.47741341]
 [-0.20656126 -0.17503165]
 [-0.20656126 -0.17503165]
 [-0.3086385  -0.33652293]
 [-0.20656126 -0.17503165]
 [-0.16957527 -0.26134991]]
[[4.63682644 0.        ]
 [0.         3.4660758 ]]
[[-0.20485755  0.28230559]
 [-0.2018926   0.18797401]
 [-0.27781813  0.33979025]
 [-0.3848213   0.42056737]
 [-0.32282413  0.34698447]
 [-0.49850192 -0.22485343]
 [-0.3270043  -0.52403905]
```

```
 [-0.14631016 -0.03570198]
 [-0.4592868  -0.38181953]]
```

Task-2 (10 Points)

Visualize documents in 2D space

```
#Visualize documents and print coordinates

print(Vk_t[:,1])

[ 0.28230559  0.18797401  0.33979025  0.42056737  0.34698447 -
0.22485343
 -0.52403905 -0.03570198 -0.38181953]

print(list(Vk_t[:,1]))

[0.2823055896544668, 0.1879740062511464, 0.3397902468946739,
0.42056737349036843, 0.34698446576097886, -0.22485343260914267, -
0.5240390546984037, -0.035701979310270214, -0.38181952763444904]

list(Vk_t[:,0])

[-0.20485755174016054,
 -0.20189260174249035,
 -0.27781812630383496,
 -0.384821296267465,
 -0.3228241278377758,
 -0.49850191940256217,
 -0.32700429857251795,
 -0.14631016162914728,
 -0.45928679890632584]

import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(9,6))
plt.gca().invert_xaxis()
plt.axhline(0)
plt.axvline(0)

for i in range (0, len(Vk_t)):
    x = Vk_t[i][0]
    y = Vk_t[i][1]
    plt.plot(x, y, 's', color='royalblue')
    plt.text(x * 1.01, y*1.02, docName[i], fontsize=12)
```




```
Vk_t
```

```
array([[-0.20485755,  0.28230559],
       [-0.2018926 ,  0.18797401],
       [-0.27781813,  0.33979025],
       [-0.3848213 ,  0.42056737],
       [-0.32282413,  0.34698447],
       [-0.49850192, -0.22485343],
       [-0.3270043 , -0.52403905],
       [-0.14631016, -0.03570198],
       [-0.4592868 , -0.38181953]])
```

Expected

```
[[-0.94988891  0.97849257]
 [-0.93614095  0.65153215]
 [-1.28819443  1.17773875]
 [-1.78434956  1.4577184 ]
 [-1.49687945  1.20267446]
 [-2.31146688 -0.77935904]
 [-1.51626218 -1.81635909]
 [-0.67841483 -0.12374577]
 [-2.12963317 -1.32341543]]
```

images/image.png

images/image.png

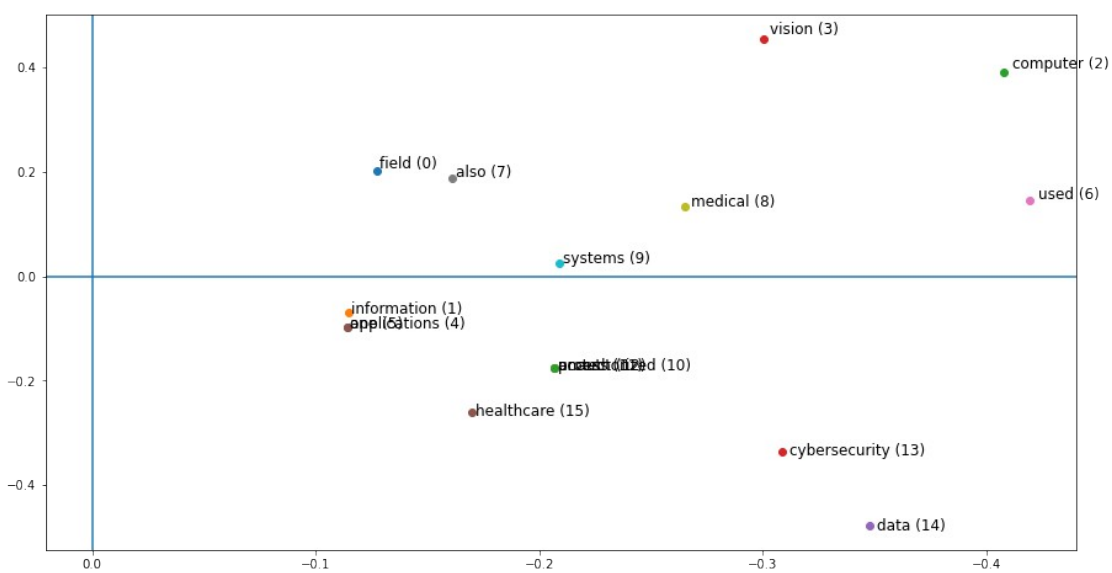
Visualize terms in 2D space

```
#Visualize terms and print coordinates
```

```
word_to_ix
```

```
{'field': 0,
 'information': 1,
 'computer': 2,
 'vision': 3,
 'applications': 4,
 'one': 5,
 'used': 6,
 'also': 7,
 'medical': 8,
 'systems': 9,
 'unauthorized': 10,
 'access': 11,
 'protect': 12,
 'cybersecurity': 13,
 'data': 14,
 'healthcare': 15}
```

```python
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(15,8))
plt.gca().invert_xaxis()
plt.axhline(0)
plt.axvline(0)

for i in range (0, len(Uk)):
    x = Uk[i][0]
    y = Uk[i][1]
    label = [key for key, value in word_to_ix.items() if value == i]
    plt.plot(x, y, 'o')
    plt.text(x * 1.01, y*1.02, f'{label[0]} ({i})', fontsize=12)
```



```
print(Uk)
```

```
[[-0.12717294  0.20278638]
 [-0.11470385 -0.06974269]
 [-0.40776071  0.39028813]
 [-0.30025142  0.45516076]
 [-0.11406442 -0.09695837]
 [-0.11406442 -0.09695837]
 [-0.41909101  0.14444841]
 [-0.1610913   0.18784146]
 [-0.26503675  0.13251736]
 [-0.20868502  0.02493571]
 [-0.20656126 -0.17503165]
 [-0.20656126 -0.17503165]
 [-0.20656126 -0.17503165]
 [-0.3086385  -0.33652293]
 [-0.34760786 -0.47741341]
 [-0.16957527 -0.26134991]]
```

Expected

Note: the order of rows could be different in your implementation as it is based on the indexing of the tokens done in build_word_to_ix

```
[[-0.58967885  0.70287296]
 [-1.3922137   1.57762168]
 [-0.53186185 -0.24173347]
 [-1.89071562  1.35276825]
 [-0.5288969  -0.33606505]
 [-0.5288969  -0.33606505]
 [-0.74695242  0.65107273]
 [-1.94325227  0.50066913]
 [-1.22892939  0.45931522]
 [-0.96763621  0.08642905]
 [-1.61179732 -1.65475107]
 [-0.95778872 -0.60667296]
 [-0.95778872 -0.60667296]
 [-1.43110318 -1.16641399]
 [-0.95778872 -0.60667296]
 [-0.7862911  -0.90585858]]
```

term.png

images/term.png

Task-3 (10 Points)

Find matching documents for given document

```
# Hint create query vector for input document. Calculate its cosine distance from other documents
```

```
def query(s, Uk, Sk, Vk_t, word_to_ix, documents, min_score=0.9):
    '''
    Input:
        s:query document.
        Uk:Term matrix
        Sk:singular value matrix
        Vk_t:Document matrix
        word_to_ix: {word, index} map
        documents:list of document
        min_score:min score beyond which documents are considerd
matching
    Output:
        q_hat: coordinates of query vector
        matches: list of tuples containing matching document and its
score
    '''
    # Add space for the matches found
    matches = []

    # tokenize the input document using processing script
    query_words = preprocess(s)

    # instantiate zeros matrix
    query_mtx = np.zeros(len(word_to_ix))

    # iterate over the query's words
    for word in query_words:

        # add word if found, increment
        if word in word_to_ix:
            query_mtx[word_to_ix[word]] += 1

    # Vector for the query s
    q_hat = np.matmul(query_mtx, Uk[:, :2])

    # Iterate over the documents
    for idx, document in enumerate(documents):

        # Check Current Document:
#         print(f"({idx})-{document}")

        # Preprocess each document
        d_tokens = preprocess(document)

        # Create zeros array
        doc_mtx = np.zeros(len(word_to_ix))

        # Iterate over the words
        for word in d_tokens:
```

```
            # If matches, increment
            if word in word_to_ix:
                doc_mtx[word_to_ix[word]] += 1
        doc_vec = np.matmul(doc_mtx, Uk[:, :2])

        # Calcualte cosine as dot prod
        cos_sim = np.dot(q_hat, doc_vec) / (np.linalg.norm(q_hat) *
np.linalg.norm(doc_vec))

        # If greater than score, add to list
        if cos_sim >= min_score:
            matches.append((document, cos_sim))

    return q_hat, matches

q_hat, matches = query('E-commerce companies use cybersecurity to
protect online transactions and prevent fraud.', Uk, Sk, Vk_t,
word_to_ix, documents, 0.9)

q_hat, matches = query('E-commerce companies use cybersecurity to
protect online transactions and prevent fraud.', Uk, Sk, Vk_t,
word_to_ix, documents, 0.9)
print(q_hat)
if matches is not None:
    print(matches)
else:
    print("No matches found")
```

```
[-0.51519977 -0.51155458]
[('One of the most important applications of cybersecurity is in
safeguarding sensitive data and personal information, such as
financial data or healthcare records.', 0.9956454663736863), ('In the
healthcare industry, cybersecurity is used to protect medical devices
and prevent unauthorized access to patient data.', 0.974610647387395)]
```

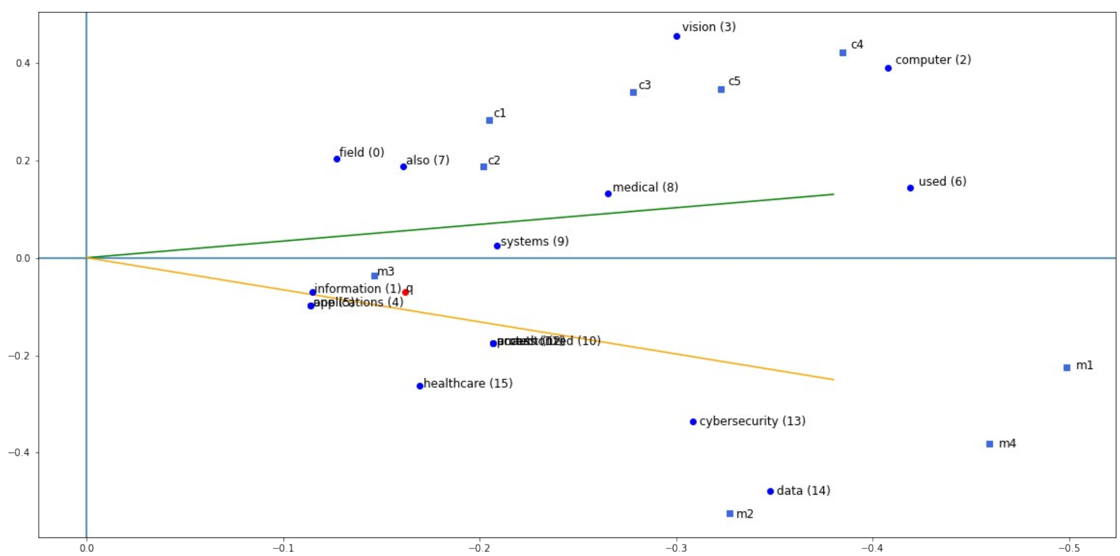
Expected

```
[-0.51519977 -0.51155458]
[('One of the most important applications of cybersecurity is in
safeguarding sensitive data and personal information, such as
financial data or healthcare records.', 0.9956454663736864), ('In the
healthcare industry, cybersecurity is used to protect medical devices
and prevent unauthorized access to patient data.',
0.9746106473873951)]
```

Visual representation of query/document

```
# Plot terms, documents and query documents along with lines
representing its cosine angle

px1, px2, py1, py2 = get_cosine_points_pos()

nx1, nx2, ny1, ny2 = get_cosine_points_neg()
```

```python
qx, qy = get_query_coords()

import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(20,10))
plt.gca().invert_xaxis()
plt.axhline(0)
plt.axvline(0)
plt.plot(qx, qy, 'o', color='red')
plt.text(qx, qy, 'q', fontsize=12)

plt.plot([px1, px2], [py1, py2], 'k-', color='green')
plt.plot([nx1, nx2], [ny1, ny2], 'k-', color='orange')

for i in range (0, len(Uk)):
    x = Uk[i][0]
    y = Uk[i][1]
    label = [key for key, value in word_to_ix.items() if value == i]
    plt.plot(x, y, 'o', color="blue")
    plt.text(x * 1.01, y*1.02, f'{label[0]} ({i})', fontsize=12)

for i in range (0, len(Vk_t)):
    x = Vk_t[i][0]
    y = Vk_t[i][1]
    plt.plot(x, y, 's', color='royalblue')
    plt.text(x * 1.01, y*1.02, docName[i], fontsize=12)
```



Expected

Cosine angle.png

images/Cosineangle.png

Theory questions: (5 points)

- A) Give short description of Left-eigen vectors, right-eigen vectors and eigen-values matrix retured by Singular Value Decompostion of document-terms count matrix.

    - We can define SVD as singular value decomposition as a technique that can be used to decompose a given matrix into three separate matrices which we represent above as Uk, Sk and Vk_t.
    - Uk represets the left-singular vectors or left-eigen vectors. These vectors represent a set of orthogonal vectors for the distribution of terms across the set of documents, in the form of a reduced dimensionality.
    - Sk represents the singular values, or the eigen values. These are a set of diagonal values that show the variationin the data, account for by the left and right vectors, generally used to determine important dimensions on the document term count.
    - Vk represents the right singular vectors, or right eigen vectors. These are orthogonal vectors representing distribution of documents, and are used to identify important temrs in the collection.
- B) Visually represent the document "Graph and tree generation" in 2D space along with words and documents as given in previous question.

```
q_hat, matches = query('Graph and tree generation', Uk, Sk, Vk_t,
word_to_ix, documents, 0.9)
print(q_hat)
if matches is not None:
    print(matches)
else:
    print("No matches found")
    print("This will not yield any meaningful results since the
coordinates are 0,0 and therefore graphing this in the graph above
would not be useful")
```

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

```
<ipython-input-53-c2bad76552b7>:57: RuntimeWarning: invalid value
encountered in double_scalars
  cos_sim = np.dot(q_hat, doc_vec) / (np.linalg.norm(q_hat) *
np.linalg.norm(doc_vec))
```

We could add a few more relevant keywords to the query document, in order to graph it using our corpus above:

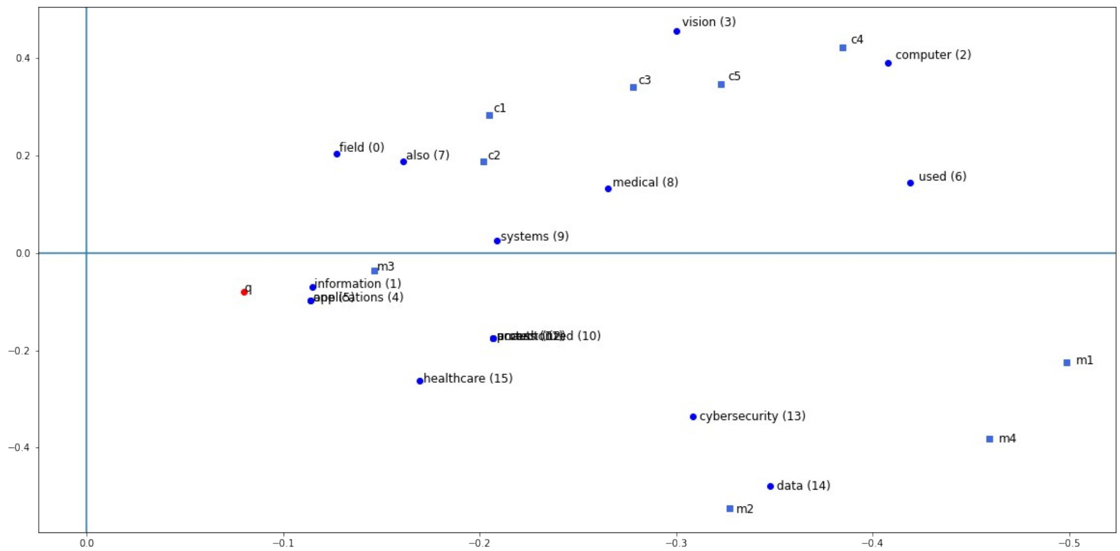
```
q_hat, matches = query('Graph and tree generation in cybersecurity',
Uk, Sk, Vk_t, word_to_ix, documents, 0.9)
print(q_hat)
if matches is not None:
    print(matches)
else:
    print("No matches found")
```

```
    print("This will not yield any results and therefore graphing this
in the graph above would not be useful")
```

```
[-0.3086385  -0.33652293]
[('One of the most important applications of cybersecurity is in
safeguarding sensitive data and personal information, such as
financial data or healthcare records.', 0.9989138516575635), ('In the
healthcare industry, cybersecurity is used to protect medical devices
and prevent unauthorized access to patient data.',
0.9630835650829891)]
```

```
qx, qy = get_query_coords()
```

```
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(20,10))
plt.gca().invert_xaxis()
plt.axhline(0)
plt.axvline(0)
plt.plot(qx, qy, 'o', color='red')
plt.text(qx, qy, 'q', fontsize=12)

# plt.plot([px1, px2], [py1, py2], 'k-', color='green')
# plt.plot([nx1, nx2], [ny1, ny2], 'k-', color='orange')

for i in range (0, len(Uk)):
    x = Uk[i][0]
    y = Uk[i][1]
    label = [key for key, value in word_to_ix.items() if value == i]
    plt.plot(x, y, 'o', color="blue")
    plt.text(x * 1.01, y*1.02, f'{label[0]} ({i})', fontsize=12)

for i in range (0, len(Vk_t)):
    x = Vk_t[i][0]
    y = Vk_t[i][1]
    plt.plot(x, y, 's', color='royalblue')
    plt.text(x * 1.01, y*1.02, docName[i], fontsize=12)
```



Q2. n-Gram Language Models (35 points)

Your task is to train n-gram language models. [Ref SLP Chapter 3]

- Task 1: You will train unigram, bigram, and trigram models on given training files. Then you will score on given test files for unigram, bigram, and trigram. you will generate sentences from the trained model and compute perplexity.
- Task 2: You will create training data for n > 3. and Repeat the above task from training model. Part-A = (55 Points)

```
'''
Your imports go here
You are encouraged to implement your own functions and not use from
library.
'''
import sys
from collections import Counter
import numpy as np

# constants to define pseudo-word tokens
# access via UNK, for instance
# for this assignemnt we will follow <s> tag for beginning of sentence
and
# </s> for end of senetence as suggested in SLP Book. Check sample
training files for reference.
UNK = "<UNK>"
SENT_BEGIN = "<s>"
SENT_END = "</s>"
```

We need to initialise global variables for model

```
"""Initializes Parameters:
```

```
  n_gram (int): the n-gram order.
  is_laplace_smoothing (bool): whether or not to use Laplace smoothing
  threshold: words with frequency  below threshold will be converted
to token
"""
# Initializing different object attributes
n_gram = None
is_laplace_smoothing = True
vocab = []
n_gram_counts = {}
n_minus_1_gram_counts = None
threshold = 1
```

Implement training function (10 points)

```
def make_ngrams(tokens: list, n: int) -> list:
    """Creates n-grams for the given token sequence.
    Args:
    tokens (list): a list of tokens as strings
    n (int): the length of n-grams to create

    Returns:
    list: list of tuples of strings, each tuple being one of the
individual n-grams
    """
    n_grams = []
    for i in range(len(tokens)-n+1):
        n_gram = tuple(tokens[i:i+n])
        n_grams.append(n_gram)
    return n_grams
```

```
make_ngrams("My name is Saleh and I lead a data science team".split("
"), 1)
```

```
[('My',),
 ('name',),
 ('is',),
 ('Saleh',),
 ('and',),
 ('I',),
 ('lead',),
 ('a',),
 ('data',),
 ('science',),
 ('team',)]
```

```
make_ngrams("My name is Saleh and I lead a data science team".split("
"), 2)
```

```
[('My', 'name'),
 ('name', 'is'),
 ('is', 'Saleh'),
```

```
 ('Saleh', 'and'),
 ('and', 'I'),
 ('I', 'lead'),
 ('lead', 'a'),
 ('a', 'data'),
 ('data', 'science'),
 ('science', 'team')]
```

```
make_ngrams("My name is Saleh and I lead a data science team".split("
"), 3)
```

```
[('My', 'name', 'is'),
 ('name', 'is', 'Saleh'),
 ('is', 'Saleh', 'and'),
 ('Saleh', 'and', 'I'),
 ('and', 'I', 'lead'),
 ('I', 'lead', 'a'),
 ('lead', 'a', 'data'),
 ('a', 'data', 'science'),
 ('data', 'science', 'team')]
```

```
from collections import Counter

def train(training_file_path, n):
    """Trains the language model on the given data. Input file that
    has tokens that are white-space separated, has one sentence per
line, and
    that the sentences begin with <s> and end with </s>
    Parameters:
      training_file_path (str): the location of the training data to
read

    Returns:
    N Gram Counts, Vocab, N Minus 1 Gram Counts
    """
    n_gram_counts = Counter()
    vocab = set()
    n_minus_1_gram_counts = Counter()

    # Read in the training file and tokenize
    with open(training_file_path, 'r') as f:
        for line in f:
            # Tokenize the line by splitting on whitespace
            tokens = line.strip().split()
            # Add <s> and </s> to the beginning and end of the
sentence respectively
#             tokens = ['<s>'] + tokens + ['</s>']
            # Update the vocabulary
            vocab.update(tokens)
            # Create n-grams for the sentence
```

```
            n_grams = make_ngrams(tokens, n)
            # Update the counts
            n_gram_counts.update(n_grams)
            n_minus_1_grams = make_ngrams(tokens, n-1)
            n_minus_1_gram_counts.update(n_minus_1_grams)
    return n_gram_counts, vocab, n_minus_1_gram_counts
```

Unigram Training :

```
import itertools

n_gram_counts, vocab, n_minus_1_gram_counts =
train("./train_data/berp-training_uni.txt", 1)

print("Examples of n_gram_counts")
print(dict(itertools.islice(n_gram_counts.items(), 5)))

print("Examples of n_gram_counts")
print(set(itertools.islice(vocab, 5)))

print("Examples of n_minus_1_gram_counts")
print(set(itertools.islice(n_minus_1_gram_counts, 5))) # Will be empty
since its unigram
```

```
Examples of n_gram_counts
{('<s>',): 6756, ("let's",): 236, ('start',): 438, ('over',): 414,
('</s>',): 6756}
Examples of n_gram_counts
{"giovanni's", 'fondue', 'triple', 'wanna', 'portuguese'}
Examples of n_minus_1_gram_counts
{()}
```

Bigram Training:

Output your Trained Data Parameters:

```
n_gram_counts, vocab, n_minus_1_gram_counts =
train("./train_data/berp-training_bi.txt", 2)

print("Examples of n_gram_counts")
print(dict(itertools.islice(n_gram_counts.items(), 5)))

print("Examples of n_gram_counts")
print(set(itertools.islice(vocab, 5)))

print("Examples of n_minus_1_gram_counts")
print(set(itertools.islice(n_minus_1_gram_counts, 5)))
```

```
Examples of n_gram_counts
{('<s>', "let's"): 196, ("let's", 'start'): 170, ('start', 'over'):
403, ('over', '</s>'): 367, ('<s>', 'my'): 6}
Examples of n_gram_counts
```

```
{"giovanni's", 'fondue', 'triple', 'wanna', 'portuguese'}
Examples of n_minus_1_gram_counts
{('start',), ("let's",), ('over',), ('</s>',), ('<s>',)}
```

Trigram Training:

```
n_gram_counts, vocab, n_minus_1_gram_counts =
train("./train_data/berp-training-tri.txt", 3)

print("Examples of n_gram_counts")
print(dict(itertools.islice(n_gram_counts.items(), 5)))

print("Examples of n_gram_counts")
print(set(itertools.islice(vocab, 5)))

print("Examples of n_minus_1_gram_counts")
print(set(itertools.islice(n_minus_1_gram_counts, 5)))

Examples of n_gram_counts
{('<s>', '<s>', "let's"): 196, ('<s>', "let's", 'start'): 163,
("let's", 'start', 'over'): 136, ('start', 'over', '</s>'): 366,
('over', '</s>', '</s>'): 367}
Examples of n_gram_counts
{"giovanni's", 'fondue', 'triple', 'wanna', 'portuguese'}
Examples of n_minus_1_gram_counts
{('<s>', "let's"), ('over', '</s>'), ("let's", 'start'), ('<s>',
'<s>'), ('start', 'over')}
```

Scoring function (points 5):

Implement Score function that will take input sentence and output probability of given string representing a single sentence.

```
def score(sentence, vocab, n, n_gram_counts, n_minus_1_gram_counts,
k=0.1, debug=True):
    """Calculates the probability score for a given string
representing a single sentence.
    Parameters:
      sentence (str): a sentence with tokens separated by whitespace
to calculate the score of

    Returns:
      float: the probability value of the given string for this model
    """
    tokens = sentence.split()
    log_prob = 0
    for i in range(n-1, len(tokens)):
        n_gram = tuple(tokens[i-n+1:i+1])
        n_gram_count = n_gram_counts[n_gram] + k
        n_minus_1_gram = tuple(tokens[i-n+1:i])
        n_minus_1_gram_count = n_minus_1_gram_counts[n_minus_1_gram] +
k
```

```
        if n_minus_1_gram_count == k:
            # If the count of (n-1)-gram is k, it means we have not
seen this context before
            # In this case, we use the count of the unigram
            unigram_count = sum(n_gram_counts[uni] for uni in
n_gram_counts if uni[0] == n_gram[-1]) + k*len(vocab)
            log_prob += math.log(n_gram_count + 1 / unigram_count +
len(vocab))
        else:
            log_prob += math.log((n_gram_count +1) /
(n_minus_1_gram_count + len(vocab)))
    return math.exp(log_prob)
```

```
import math
```

```
score("<s> a vegetarian meal </s>", vocab, 2, n_gram_counts,
n_minus_1_gram_counts, k=0.1, debug=False)
```

```
1.5048726304983363e-09
```

```
score("Saleh works at Amgen as a data scientist", vocab, 2,
n_gram_counts, n_minus_1_gram_counts, k=0.1, debug=False)
```

```
0.0005579225084999843
```

```
score("I am going to work", vocab, 2, n_gram_counts,
n_minus_1_gram_counts, k=0.1, debug=False)
```

```
1.2024373757362843e-06
```

Unigram Scoring:

```
with open("test_data/hw2-test_uni.txt", 'r') as fh:
    test_content = fh.read().split("\n")
num_sentences_1 = len(test_content)
ten_sentences_1 = test_content[:10]
print("# of test sentences: ", num_sentences_1)
probablities = []
```

```
# of test sentences:  100
```

```
# print probabilities/score of sentences in test content
for sentence in test_content:
    probablities.append(score(sentence, vocab, 1, n_gram_counts,
n_minus_1_gram_counts, k=0.1, debug=False))
probablities = np.array(probablities)
mean = np.mean(probablities)
std_dev = np.std(probablities)

print(mean)
print(std_dev)
```

```
9.970361046407934e-07
6.388290374629924e-06
```

```
probablities
```

```
array([1.92756193e-10, 1.17531654e-09, 1.71931755e-20, 6.85744227e-18,
       2.49898987e-23, 2.07631737e-18, 1.06672468e-15, 5.82554535e-31,
       1.58886722e-25, 3.51534421e-07, 5.68125863e-11, 6.08330367e-15,
       2.72973073e-18, 4.06727784e-08, 1.23418250e-12, 5.82441550e-08,
       1.91000369e-05, 6.54230358e-08, 5.51463293e-21, 1.04753240e-24,
       8.86828045e-43, 8.55831996e-44, 9.00210999e-28, 2.44672134e-21,
       9.01615173e-23, 1.34598068e-13, 6.18115302e-09, 1.98181931e-11,
       2.39476247e-26, 1.80355184e-17, 1.21381855e-15, 3.51659596e-22,
       6.36266453e-24, 6.79322278e-16, 4.79485101e-22, 2.90546467e-25,
       6.82064764e-15, 2.09514997e-16, 1.95197559e-21, 5.16048698e-14,
       7.74621987e-18, 1.15634442e-19, 3.21657439e-18, 3.83727604e-21,
       8.81341652e-23, 1.85205664e-23, 3.20002984e-11, 8.27443593e-11,
       5.96951757e-23, 9.22037723e-23, 2.93887666e-24, 7.57854165e-21,
       5.72254404e-10, 1.72007823e-09, 1.72007823e-09, 4.88346204e-16,
       4.62954536e-17, 2.52769988e-06, 3.87377486e-14, 2.85205684e-18,
       4.70479482e-07, 5.88196828e-20, 3.70837594e-20, 4.05728844e-14,
       5.16437833e-32, 9.14776067e-22, 5.52649144e-08, 8.72140159e-06,
       6.04304409e-06, 6.86634027e-28, 1.70350238e-23, 1.77439942e-27,
       8.93764357e-17, 8.81691503e-16, 5.00270824e-33, 1.20814597e-13,
       3.48669481e-11, 3.50016088e-16, 1.34659129e-12, 1.18551777e-16,
       4.01935102e-13, 5.86522455e-08, 1.35591848e-06, 1.99064078e-10,
       1.54103595e-35, 4.88954994e-11, 2.67165364e-61, 1.18532754e-23,
       6.07819754e-05, 9.46859556e-22, 5.81869844e-15, 1.54813513e-15,
       6.12233957e-08, 7.99112114e-16, 1.26923869e-18, 5.52273783e-18,
       2.13250372e-13, 3.21958091e-21, 6.06806336e-23, 2.94986918e-
13])
```

Bigram Scoring:

```
with open("test_data/hw2-test_bi.txt", 'r') as fh:
    test_content = fh.read().split("\n")
num_sentences_1 = len(test_content)
ten_sentences_1 = test_content[:10]
print("# of test sentences: ", num_sentences_1)
probablities = []
```

```
# of test sentences:  100
```

```
# print probabilities/score of sentences in test content
for sentence in test_content:
    probablities.append(score(sentence, vocab, 2, n_gram_counts,
n_minus_1_gram_counts, k=0.1, debug=False))
probablities = np.array(probablities)
mean = np.mean(probablities)
std_dev = np.std(probablities)
```

```
print(mean)
print(std_dev)
```

```
2.49021841924635e-05
0.0001559681357600102
```

```
probablities
```

```
array([1.50487263e-09, 3.93725789e-08, 5.33532327e-17, 1.25711631e-14,
       6.40215880e-20, 1.35214587e-13, 7.22556292e-13, 1.73514405e-20,
       2.28297148e-17, 1.05884818e-07, 1.29361926e-09, 3.30461782e-11,
       1.09327845e-14, 1.00880188e-05, 5.99453573e-12, 5.21004683e-06,
       1.82246246e-05, 2.89645958e-06, 1.95809477e-13, 1.12147721e-21,
       3.25026870e-35, 4.36172012e-24, 4.05058028e-20, 5.27987858e-19,
       4.40606311e-17, 2.00582274e-10, 3.57607780e-06, 6.09945013e-10,
       1.06133799e-21, 1.29819804e-12, 1.09575220e-09, 4.49262884e-16,
       2.01917131e-14, 1.32947220e-11, 4.83304850e-18, 2.12504516e-16,
       2.51899329e-08, 1.22468499e-08, 1.74452035e-14, 1.43473659e-10,
       8.48823863e-14, 1.11506001e-12, 4.99859244e-12, 1.52418880e-17,
       1.65100569e-16, 1.73926721e-16, 4.38072565e-11, 2.23150686e-10,
       6.64978942e-18, 3.97439387e-20, 2.96464567e-23, 5.51174569e-15,
       3.30486212e-06, 1.12737541e-04, 1.12737541e-04, 4.25966297e-13,
       1.02948407e-12, 2.02106187e-06, 1.12393032e-08, 1.21114639e-14,
       1.30227038e-03, 3.66845928e-15, 1.88350107e-16, 2.75036443e-12,
       5.67281617e-23, 8.80470422e-17, 1.01947293e-06, 2.56866806e-05,
       8.09153897e-06, 8.65369803e-20, 6.20474242e-19, 1.03000026e-20,
       6.64597706e-11, 9.98974793e-08, 1.79055701e-22, 1.38405319e-12,
       4.57216943e-09, 8.92901348e-13, 5.51993134e-11, 1.53068671e-17,
       3.00195180e-10, 7.24132931e-08, 5.84675661e-07, 7.30908240e-11,
       1.99453665e-21, 3.54925333e-11, 1.88736363e-52, 2.34181176e-20,
       8.78668916e-04, 8.25020318e-18, 4.53451109e-08, 8.37781969e-12,
       2.67847768e-06, 1.71217999e-14, 1.49443830e-13, 2.09224711e-13,
       1.13009111e-10, 3.88192487e-15, 1.26560591e-16, 4.66904442e-
11])
```

Trigram Scoring

```
with open("test_data/hw2-test-tri.txt", 'r') as fh:
    test_content = fh.read().split("\n")
num_sentences_1 = len(test_content)
ten_sentences_1 = test_content[:10]
print("# of test sentences: ", num_sentences_1)
probablities = []
```

```
# of test sentences:  102
```

```
# print probabilities/score of sentences in test content
for sentence in test_content:
    probablities.append(score(sentence, vocab, 3, n_gram_counts,
n_minus_1_gram_counts, k=0.1, debug=False))
probablities = np.array(probablities)
mean = np.mean(probablities)
```

```python
std_dev = np.std(probablities)


print(mean)
print(std_dev)
```

```
66.09319253493008
618.0515625366791
```

```python
probablities
```

```
array([8.65415895e-13, 4.35116532e-11, 1.16948477e-15, 4.66094509e-18,
       1.66162627e-25, 9.52261497e-17, 4.22341862e-17, 3.15672817e-06,
       3.83276905e-16, 2.64382488e+02, 1.81249460e-06, 2.88261459e-08,
       1.79006756e-17, 9.42607089e-08, 2.77292625e-16, 2.92079130e-08,
       5.57976122e-08, 7.90611241e-09, 1.84113726e-17, 6.83699156e-07,
       7.78718314e-13, 5.80627873e-12, 7.64020361e-20, 1.59125701e-05,
       5.61251085e-15, 2.83548048e-14, 1.74335155e-08, 2.42533838e-13,
       8.84514196e-21, 2.52476513e-17, 7.50697436e-13, 1.82895727e-22,
       5.41221432e-18, 1.00480798e-15, 1.64590392e-23, 1.37570389e-21,
       7.98962782e-11, 4.22685836e-11, 1.54129195e-11, 6.65154018e-14,
       7.41673477e-18, 2.88152224e-16, 2.44306559e-15, 7.76679428e-16,
       3.84720127e-14, 1.95866785e-13, 6.12026944e-08, 2.45396653e-14,
       4.04967981e-16, 1.97651262e-25, 7.90391834e-15, 2.39418491e-19,
       7.86869876e-08, 9.20093513e-06, 9.20093513e-06, 1.46979354e-17,
       5.47339710e-17, 3.03780562e-09, 2.24311101e-10, 3.60759134e-20,
       1.80065413e-04, 1.32337104e-18, 2.98059360e-10, 5.05571399e-15,
       1.69218884e-29, 3.40836423e-21, 8.66137497e-10, 1.49929092e-07,
       1.22211994e-08, 6.22902958e-26, 1.20449015e-12, 7.45024499e-26,
       5.46942999e-14, 2.05365455e+02, 3.98217580e-03, 6.26867139e+03,
       1.59043187e-11, 3.16931209e-17, 1.45343492e-08, 6.26003810e-10,
       9.23602456e-14, 3.47353901e-11, 8.19773765e-04, 2.32678078e-01,
       3.90456627e-01, 2.97471820e-14, 2.46370573e-17, 4.79722389e-25,
       2.75824159e-05, 1.57268222e-23, 6.82828166e-06, 2.06401313e-02,
       6.60372092e-09, 9.00265815e-13, 8.31457447e-18, 8.86158019e-12,
       4.37471549e-01, 7.58304480e-18, 1.19648507e-22, 1.14367283e-15,
       1.00000000e+00, 1.00000000e+00])
```

Sentence generation (10 points)

Generate sentence from the above trained model

- To generate next word from a set of probable n-grams and their probabilities check below tutorial: https://numpy.org/doc/stable/reference/random/generated/numpy.random.choice.html

```python
def generate_sentence(n):
    """Generates a single sentence from a trained language model using
the Shannon technique.

    Returns:
```

```
      str: the generated sentence
    """
    # Start with <s> and randomly generate words until we encounter
sentence end
    # Append sentence begin markers for n>2
    # Keep track of previous word for stop condition

    sentence = ""
    prev_word = "<s>"
    sentence += "<s> " * max(n - 1, 1)

    if n > 1:
        while prev_word != "</s>":

            # Construct the (n-1) gram so far

            gram = sentence.split()[-(n - 1):]
#             print(sentence)
#             print(gram)

            # Get the counts of all available choices based on n-1
gram
            avail_choice = {}
            for key in n_gram_counts:
#                 print(key[:-1])
                if key[:-1] == tuple(gram):
#                     print(key)

                    avail_choice[key[-1]] = n_gram_counts[key]
#             print(avail_choice)

            # Convert the counts into probability for random.choice()
function
            values = np.array(list(avail_choice.values())) /
np.sum(np.array(list(avail_choice.values())))
#             print(values)
#             print(avail_choice.keys())
            probs = np.random.choice(list(avail_choice.keys()),
p=values)



            # If <s> is generated, ignore and generate another word
            if probs == "<s>":
                continue

            sentence += (" " + probs)

            prev_word = probs
#             print("gram", gram)
```

```
#             print("############################################")
    else:
      # In case of unigram model, n-1 gram is just the previous word
and possible choice is whole vocabulary
        while prev_word != "</s>":
#             continue
            avail_choice = n_gram_counts
            values = np.array(list(avail_choice.values())) /
np.sum(np.array(list(avail_choice.values())))

            probs = np.random.choice(list(avail_choice.keys()),
p=values)

            if probs == "<s>":
                continue

            sentence += (" " + probs)

            prev_word = probs

        # Convert the counts into probability for random.choice()
function
        # If <s> is generated, ignore and generate another word

    # Append sentence end markers for n>2

    sentence += "</s> " * max(n - 2, 0)

    return sentence

x = generate_sentence(2)

x

"<s>  i'd like to go there a french food </s>"

def generate(n, m):
    """Generates n sentences from a trained language model using the
Shannon technique.
    Parameters:
      n (int): the number of sentences to generate
      m (int): gram of generator

    Returns:
      list: a list containing strings, one per generated sentence
    """
    # Generate sentences one by one and store
    sentences = []

    for i in range(n):
#         temp_sent = generate_sentence(m)
```

```
        sentences.append(generate_sentence(m))

    return sentences
```

```
sentence = ""
sentence += "<s> " * max(2 - 1, 1)

sentence.split()
```

```
['<s>']
```

Unigram Sentence Generation:

```
sentences = generate(50, 1)
print("Sentences:")
for sentence in sentences:
    print(sentence)
```

```
Sentences:
<s>  not plearn's </s>
<s>  one hour </s>
<s>  i see the list </s>
<s>  it </s>
<s>  okay shows me about taqueria de la-paz </s>
<s>  i do you show me a soup kitchen heike </s>
<s>  i could you have lunch and i'm looking for </s>
<s>  the information about the price range may i would like to go for
finding a cheap and the list ethiopian restaurants please </s>
<s>  okay three dollars </s>
<s>  not cost </s>
<s>  i'd like to have to have within a half an american food </s>
<s>  what about the list of time </s>
<s>  less than fifteen minutes' walk three minutes from icsi </s>
<s>  german restaurant is best chinese food </s>
<s>  what it's possible </s>
<s>  close to travel further than twenty dollars </s>
<s>  i would like to have lunch </s>
<s>  looking for a pretty close to go for fat apple's </s>
<s>  i want to bike </s>
<s>  it i'd like to travel any kind of food and i'd like it doesn't
matter </s>
<s>  this </s>
<s>  tell me about cafe located ten minutes </s>
<s>  it metropole </s>
<s>  she went there a tuesday </s>
<s>  i would like to go to have to spend one you give me about kip's
like to that serves </s>
<s>  well what is the weekend </s>
<s>  hunan </s>
<s>  do you start over </s>
<s>  is about kip's </s>
<s>  uh a restaurant called uh between the spanish food </s>
```

```
<s>  i don't know the meal </s>
<s>  i would like to a mile </s>
<s>  five blocks of restaurants serving american food </s>
<s>  what kinds of course the cheapest cheapest cheapest japanese food
</s>
<s>  show me something uh actually i'm looking for la tour eiffel </s>
<s>  what kind of food this one billion steps </s>
<s>  start again </s>
<s>  i'm looking for pizza for dinner on saturday night </s>
<s>  i will be close to eat today </s>
<s>  i'd like to a list again </s>
<s>  um within twenty five dollars or seven bucks </s>
<s>  i would like to have cambodian restaurants </s>
<s>  do you know the restaurant </s>
<s>  let's start over </s>
<s>  do they also about taiwan restaurant in berkeley thai cuisine
</s>
<s>  any vegetarian </s>
<s>  are there is okay let's say i've got very much money uh ten to
have a lunch there any amount of mexican food on telegraph avenue </s>
<s>  mediterranean food </s>
<s>  what's the other italian food </s>
<s>  i want a good </s>
```

Bigram Sentence Generation:

```python
sentences = generate(50, 2)
print("Sentences:")
for sentence in sentences:
    print(sentence)
```

```
Sentences:
<s>  okay show italian </s>
<s>  is wednesday </s>
<s>  uh breakfast today </s>
<s>  the great china </s>
<s>  tell me back to go to have lunch during the cost doesn't matter
</s>
<s>  tell me information about guerrero's </s>
<s>  i would like food </s>
<s>  indian food doesn't matter </s>
<s>  do you have indian food at somewhere a nice </s>
<s>  what's caffe giovanni </s>
<s>  not really matter </s>
<s>  i want to go there any of dishes </s>
<s>  tell me more than ten dollars there is same case are available
</s>
<s>  which are they serve </s>
<s>  what is the list of distance from icsi </s>
<s>  cafe </s>
```

```
<s>  not chinese restaurant </s>
<s>  does chez-panisse </s>
<s>  uh icsi </s>
<s>  not matter </s>
<s>  to spend less expensive restaurant </s>
<s>  i don't wanna have chinese food please </s>
<s>  sunday </s>
<s>  tell me a german restaurants serving bad </s>
<s>  tell me about sun-hong-kong serve there any day of a restaurant
in the list the price of the united states </s>
<s>  i would like some chinese is the first one mile </s>
<s>  okay let's start over </s>
<s>  the list vegi house </s>
<s>  a cheap would like to twenty dollars </s>
<s>  six blocks away say ten dollars </s>
<s>  uh vegetarian restaurants on the meal ticket </s>
<s>  where can i would like to see the stuffed inn </s>
<s>  i only about bette's bakeshop </s>
<s>  uh can i want to have to spend not french or the indian food </s>
<s>  not much money is open during the bart station </s>
<s>  tell me la tour eiffel </s>
<s>  i like to sizzler </s>
<s>  does viva taqueria cancun </s>
<s>  i find a hamburger </s>
<s>  i'd like to drive so maybe if we should be whether or less than
five blocks away </s>
<s>  i would like to go there a restaurant </s>
<s>  how about mexican food </s>
<s>  where i don't care how about five kilometers </s>
<s>  cafe vin </s>
<s>  it should cost more about mexican restaurant </s>
<s>  can i want to eat a full bar and then </s>
<s>  does cafe </s>
<s>  i want a saturday please start over </s>
<s>  it is unimportant </s>
<s>  can i want pancakes </s>
```

Trigram Sentence Generation:

```
sentences = generate(50, 3)
print("Sentences:")
for sentence in sentences:
    print(sentence)
```

```
Sentences:
<s>  how about the available in california food </s>
<s>  no more information on the area </s>
<s>  let's start over </s>
<s>  uh start over </s>
<s>  and chips zachary's pizza </s>
<s>  could be on the type of restaurants now </s>
```

<s> i prefer is okay as close </s>
<s> i don't know of any area </s>
<s> indonesian restaurants in berkeley </s>
<s> i would like to have lunch </s>
<s> the price </s>
<s> not much for sushi </s>
<s> i am interested in berkeley </s>
<s> i would be not much you've been really don't want to icsi </s>
<s> uh i'd like to go to have dinner </s>
<s> to spend ten dollars </s>
<s> tell me the distance to go to go for dinner not very fast food to spend more information on north african food is the first restaurant </s>
<s> actually it walking distance doesn't matter </s>
<s> tell me more than fifty dollars </s>
<s> i have about the indian restaurants serving a restaurant </s>
<s> i want to eat tuesday </s>
<s> what i have inexpensive </s>
<s> i'd like not matter </s>
<s> i would like </s>
<s> start over </s>
<s> i like to eat indian cuisine or dinner </s>
<s> when is there is jupiter </s>
<s> i'd like to the area </s>
<s> this cafe christopher's cafe claremont seafood coffee </s>
<s> dinner on saturday </s>
<s> i would like to pay ten miles of water water </s>
<s> what's the great wall restaurant </s>
<s> i have a reservation at maximum </s>
<s> great china restaurant could be lunch </s>
<s> i can you have a cake </s>
<s> and i'm looking for a distance to eat today and fifteen miles </s>
<s> are you have breakfast today </s>
<s> can pay thirteen and very little bit more information about caffe giovanni's for lunch near icksee </s>
<s> can you have skates soup kitchen heike </s>
<s> i want to thirty dollars </s>
<s> oh i i'm looking for lunch </s>
<s> i don't want mexican food </s>
<s> polish food </s>
<s> oliveto's </s>
<s> monday </s>
<s> eight a__m </s>
<s> change it has a lot of these restaurants that cost up to um serving ethiopian food </s>
<s> i am willing to the distance doesn't matter but i would like that </s>
<s> let's start over </s>
<s> indian food </s>

Evaluate model perplexity (5 points)

Measures the perplexity for the test sequence with your trained model. you may assume that this sequence may consist of many sentences "glued together"

The perplexity of the given sequence is the inverse probability of the test set, normalized by the number of words.

```
# Since this sequence will cross many sentence boundaries, we need to
include
# the begin- and end-sentence markers <s> and </s> in the probability
computation.
# We also need to include the end-of-sentence marker </s>
# but not the beginning-of-sentence marker <s>) in the total count of
word tokens N

def perplexity(test_sequence, vocab, n, n_gram_counts,
n_minus_1_gram_counts, k=0.1, debug=True):
    """.
    Parameters:
      test_sequence (string): a sequence of space-separated tokens to
measure the perplexity of

    Returns:
      float: the perplexity of the given sequence
    """

    # Replace out of vocab words with <UNK>, already done in score
function
    # test_sequence = [token if token in vocab else UNK for token in
test_sequence.split()]
    # Remove sentence begin markers from data for computing N
    sentences = test_sequence.strip().split('</s> <s>')
    N = sum(len(sentence.split()) - 1 for sentence in sentences)

    # Get the probability for the sequence
    log_prob_sum = 0
    for sentence in sentences:
        sentence = '<s> ' + sentence.strip() + ' </s>'
        log_prob_sum += math.log(score(sentence, vocab, n,
n_gram_counts, n_minus_1_gram_counts, k, debug))


    perplexity = 2 ** (-1 / N * log_prob_sum)

    return perplexity
```

Unigram:

```
print(perplexity(" ".join(sentences[0:10]), vocab, 1, n_gram_counts,
n_minus_1_gram_counts, k=0.1, debug=True))
```

```
135.71256259824693
```

Bigram:

```
print(perplexity(" ".join(sentences[0:10]), vocab, 2, n_gram_counts,
n_minus_1_gram_counts, k=0.1, debug=True))
```

```
87.96717929361927
```

Trigram:

```
print(perplexity(" ".join(sentences[0:10]), vocab, 3, n_gram_counts,
n_minus_1_gram_counts, k=0.1, debug=True))
```

```
76.76909551297624
```

```
#print(perplexity(" ".join(sentences[0:10])))
```

78.4934782125397

Explore and explain: (5 points)

- Experiment n_gram model for n = [1,2,3..7] of your choice. Explain the best choice of n that generates more meaninful sentences.
    - I tested code on models with n = 1, 2, 3, 4, 5, 6, 7
    - Best performance, based on the most meaningful sentences was n=2 or n=3
    - Based on observed perplexity alone, unigram seems to have the highest whereas trigram is lowest
    - This observation in perplexity seems reasonable given that the corpus is limited and the average sentence is about 10 or so words
    - Larger n-gram models appear to have memorized the sentences more than others
    - Smaller n-gram models did not have enough history to 'remember'
    - In summary, n=2 or n=3 was sufficient for this corpus

```
n_gram_counts, vocab, n_minus_1_gram_counts =
train("./train_data/berp-training_bi.txt", 2)

print("Examples of n_gram_counts")
print(dict(itertools.islice(n_gram_counts.items(), 5)))

print("Examples of n_gram_counts")
print(set(itertools.islice(vocab, 5)))

print("Examples of n_minus_1_gram_counts")
print(set(itertools.islice(n_minus_1_gram_counts, 5)))
```

```
Examples of n_gram_counts
{('<s>', "let's"): 196, ("let's", 'start'): 170, ('start', 'over'):
403, ('over', '</s>'): 367, ('<s>', 'my'): 6}
Examples of n_gram_counts
{"giovanni's", 'fondue', 'triple', 'wanna', 'portuguese'}
Examples of n_minus_1_gram_counts
{('start',), ("let's",), ('over',), ('</s>',), ('<s>',)}
```

```
with open("test_data/hw2-test_bi.txt", 'r') as fh:
    test_content = fh.read().split("\n")
num_sentences_1 = len(test_content)
ten_sentences_1 = test_content[:10]
print("# of test sentences: ", num_sentences_1)
probablities = []
```

```
# of test sentences:  100
```

```
# print probabilities/score of sentences in test content
for sentence in test_content:
    probablities.append(score(sentence, vocab, 2, n_gram_counts,
n_minus_1_gram_counts, k=0.1, debug=False))
probablities = np.array(probablities)
mean = np.mean(probablities)
std_dev = np.std(probablities)


print(mean)
print(std_dev)
```

```
2.49021841924635e-05
0.0001559681357600102
```

```
sentences = generate(5, 2)
print("Sentences:")
for sentence in sentences:
    print(sentence)
```

```
Sentences:
<s>  start again </s>
<s>  i'm willing to eat a cuban food </s>
<s>  i would like a sunday </s>
<s>  i wanna know about um french food does not to go for lunch </s>
<s>  i don't eat american breakfast in dinner on oriental </s>
```

Q3. Classification using LSTM - using Tensorflow (30 Points)

In this part, we will be building a bidirectional LSTM network to train and inference sentiment analysis on IMDB dataset.

If you need a refresher or have never worked with Neural Networks before, here are a few resources:

- https://web.stanford.edu/~jurafsky/slp3/7.pdf
- https://web.stanford.edu/~jurafsky/slp3/9.pdf
- https://colah.github.io/posts/2015-08-Understanding-LSTMs/

Training a neural network model will take time.

- You can use Google Colab / Kaggle notebooks. You get a free GPU for a limited time to tweak your hyperparameters.
- Without a GPU, You might have to wait longer to experiment.

Library Imports

```
import tensorflow as tf
import pandas as pd
import numpy as np
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
import seaborn as sns
# import tensorflow_datasets as tfds

# from tensorflow.keras.preprocessing.sequence import pad_sequences
# from tensorflow.keras.preprocessing.text import Tokenizer
```

```
C:\Users\Saleh Alkhalifa\anaconda3\lib\site-packages\numpy\
_distributor_init.py:30: UserWarning: loaded more than 1 DLL
from .libs:
C:\Users\Saleh Alkhalifa\anaconda3\lib\site-packages\numpy\.libs\
libopenblas.GK7GX5KEQ4F6UYO3P26ULGBQYHGQO7J4.gfortran-win_amd64.dll
C:\Users\Saleh Alkhalifa\anaconda3\lib\site-packages\numpy\.libs\
libopenblas.PYQHXLVVQ7VESDPUVUADXEVJOBGHJPAY.gfortran-win_amd64.dll
  warnings.warn("loaded more than 1 DLL from .libs:"
```

```
!pip show tensorflow
```

```
Name: tensorflow
Version: 2.10.0
Summary: TensorFlow is an open source machine learning framework for
everyone.
Home-page: https://www.tensorflow.org/
Author: Google Inc.
Author-email: packages@tensorflow.org
License: Apache 2.0
Location: c:\users\saleh alkhalifa\appdata\roaming\python\python38\
site-packages
Requires: absl-py, astunparse, flatbuffers, gast, google-pasta,
grpcio, h5py, keras, keras-preprocessing, libclang, numpy, opt-einsum,
```

```
packaging, protobuf, setuptools, six, tensorboard, tensorflow-
estimator, tensorflow-io-gcs-filesystem, termcolor, typing-extensions,
wrapt
Required-by: autokeras

WARNING: Ignoring invalid distribution -rotobuf (c:\users\saleh
alkhalifa\anaconda3\lib\site-packages)
WARNING: Ignoring invalid distribution -illow (c:\users\saleh
alkhalifa\anaconda3\lib\site-packages)
```

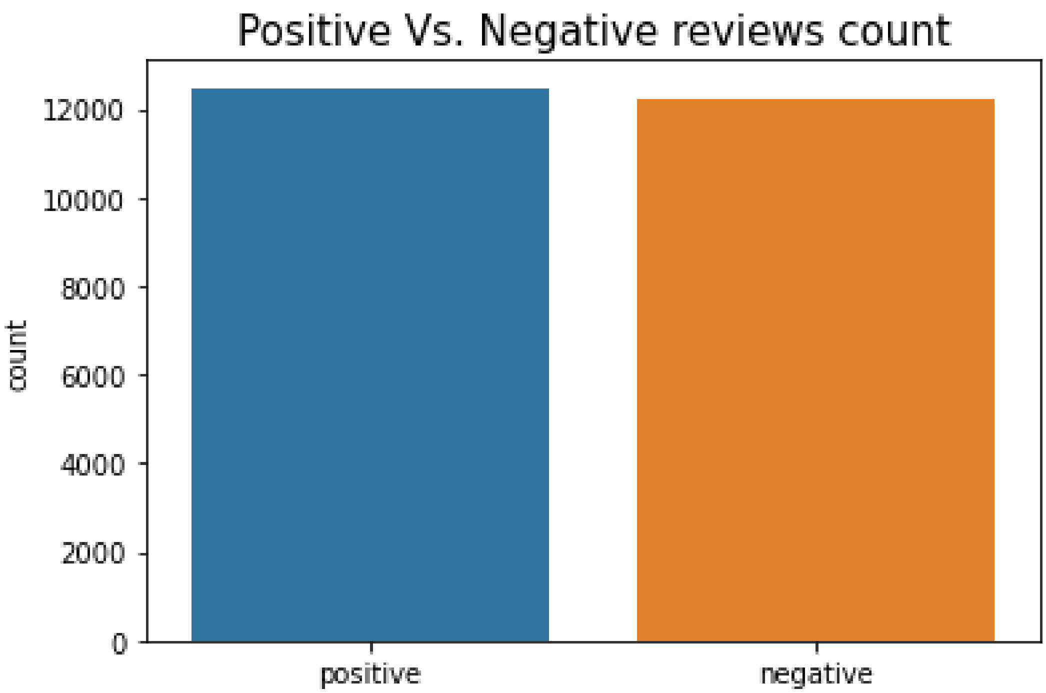
Visualizing data distribution (1 Point)

```
## Reading the data and removing columns that are not important.
dataset = pd.read_csv("data/movie_reviews-2.csv", sep = ',', encoding
= 'latin-1', usecols = lambda col: col not in ["Unnamed: 2", "Unnamed:
3", "Unnamed: 4"])

#######################################################
# print head of data frame with help of head function #
#######################################################

dataset.head()
```

```
                                              review sentiment
0  One of the other reviewers has mentioned that ...  positive
1  A wonderful little production. <br /><br />The...  positive
2  I thought this was a wonderful way to spend ti...  positive
3  Petter Mattei's "Love in the Time of Money" is...  positive
4  Probably my all-time favorite movie, a story o...  positive
```

```
#######################################################
# plot Positive Vs. Negative reviews count            #
#######################################################

sns.countplot(dataset["sentiment"].values)

plt.title("Positive Vs. Negative reviews count", fontsize = 15)
plt.show()
```

```
C:\Users\Saleh Alkhalifa\anaconda3\lib\site-packages\seaborn\
_decorators.py:36: FutureWarning: Pass the following variable as a
keyword arg: x. From version 0.12, the only valid positional argument
will be `data`, and passing other arguments without an explicit
keyword will result in an error or misinterpretation.
  warnings.warn(
```



Cleaning the Reviews (2 Points)

```python
import nltk
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.tokenize import word_tokenize
import string
import pandas as pd
import re
import nltk
nltk.download('omw-1.4')
nltk.download('stopwords')
nltk.download('wordnet')
nltk.download('words')

stopword = nltk.corpus.stopwords.words('english')
wn = nltk.WordNetLemmatizer()
ps = nltk.PorterStemmer()
words = set(nltk.corpus.words.words())

# From the first assignment
def clean_text(text):
    text = text.lower()
    text = re.sub(r"http\S+", "", text)
    text = re.sub(r"www.\S+", "", text)
    text_links_removed = "".join([char for char in text if char not in
string.punctuation])
    text_cleaned = " ".join([word for word in re.split('\W+',
text_links_removed)
```

```
        if word not in stopword])
    text = " ".join([wn.lemmatize(word) for word in re.split('\W+',
text_cleaned)])
    return text
```

```
[nltk_data] Downloading package omw-1.4 to C:\Users\Saleh
[nltk_data]     Alkhalifa\AppData\Roaming\nltk_data...
[nltk_data]   Package omw-1.4 is already up-to-date!
[nltk_data] Downloading package stopwords to C:\Users\Saleh
[nltk_data]     Alkhalifa\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package wordnet to C:\Users\Saleh
[nltk_data]     Alkhalifa\AppData\Roaming\nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
[nltk_data] Downloading package words to C:\Users\Saleh
[nltk_data]     Alkhalifa\AppData\Roaming\nltk_data...
[nltk_data]   Package words is already up-to-date!
```

```
######################################################################
#######################
# Clean all the reviews in the dataset using the clean_text function
provided above         #
######################################################################
#######################

dataset["cleaned_review"] = dataset["review"].apply(clean_text)

#####################################################################
# print head of the "CLEANED" data frame with help of head function #
#####################################################################

dataset.head()
```

```
                                              review sentiment  \
0  One of the other reviewers has mentioned that ...  positive
1  A wonderful little production. <br /><br />The...  positive
2  I thought this was a wonderful way to spend ti...  positive
3  Petter Mattei's "Love in the Time of Money" is...  positive
4  Probably my all-time favorite movie, a story o...  positive

                                      cleaned_review
0  one reviewer mentioned watching 1 oz episode y...
1  wonderful little production br br filming tech...
2  thought wonderful way spend time hot summer we...
3  petter matteis love time money visually stunni...
4  probably alltime favorite movie story selfless...
```

Splitting the dataset and Encoding Labels (2 Points)

Spliting data: 80% for the training and the remaining 20% for validation.

Encoding Labels: Encode labels as negative and positive as 0 and 1 respectively

```
dataset.shape
```

```
(24699, 3)
```

```
# dataset = dataset.sample(5000)
```

```
dataset.shape
```

```
(24699, 3)
```

```
######################################################################
###########
# Split the data using the sklearn module
#
# 80% for the training and the remaining 20% for validation
#
######################################################################
###########
from sklearn.model_selection import train_test_split

X = dataset["cleaned_review"].values
y = dataset["sentiment"]

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.20)

print(X_train.shape)
print(X_test.shape)
```

```
(19759,)
(4940,)
```

```
######################################################################
###########
# Initialize label encoder from sklearn module
#
# fit on train labels and transform both train and validation labels
#
######################################################################
###########
from sklearn.preprocessing import LabelEncoder

encoder = LabelEncoder()
encoder.fit(y_train)
y_train = encoder.transform(y_train)

print(y_test[:5])
y_test = encoder.transform(y_test)
```

```
print(y_test[:5])
```

```
14908    positive
16995    positive
11010    negative
2588     positive
8266     negative
Name: sentiment, dtype: object
[1 1 0 1 0]
```

Pre-Processing The Text (5 Points)

```
# You can use the modules given below
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.preprocessing.text import Tokenizer

######################################################################
#########
# Fit your tokenizer on the training reviews
#
######################################################################
#########

num_words = 10000
tokenizer = Tokenizer(num_words=num_words)

tokenizer.fit_on_texts(X_train)
# train_sequences = tokenizer.texts_to_sequences(X_train)
# val_sequences = tokenizer.texts_to_sequences(X_test)

######################################################################
###########################
# The word_index dictionary assigns a unique index to each unique word
present in the training  #
# reviews.
#
#
#
# Create the word_index dictionary using the tokenizer
#
# Find the vocabulary of your training reviews
#
######################################################################
###########################

# word_index = {}
word_index = tokenizer.word_index

word_counts = dict(tokenizer.word_counts)
vocabulary = set(word_counts.keys())
```

```python
##########################################################################################
# Convert the reviews in the dataset to their index form by using a function available          #
# with the tokenizer                                                                            #
# HINT : convert training and validation reviews into sequences                                 #
##########################################################################################

train_sequences = tokenizer.texts_to_sequences(X_train)
val_sequences = tokenizer.texts_to_sequences(X_test)

##########################################################################################
# Pad the the training and validation sequences so all of them have the same length            #
# set maxlen = 200                                                                              #
##########################################################################################

# maxlen which is the maximum length of one review we will use for our training

maxlen = 200

train_sequences = pad_sequences(train_sequences, maxlen=maxlen)
val_sequences = pad_sequences(val_sequences, maxlen=maxlen)


print('Vocabulary : {}'.format(len(vocabulary))) #Using len() instead to avoid flooding the page
```

```
Vocabulary : 100159
```

Using glove vectors for embedding (5 Points)

GloVe vectors capture both global statistics and local statistics of a corpus. We use GloVe to convert words to embeddings in the vector space based on their semantics.

We will be using the 200-dimensional GloVe vectors for the task at hand.

To learn more about GloVe please read the following resource:

- https://nlp.stanford.edu/pubs/glove.pdf

```python
glove_dictionary = {}
with open('glove.6B.200d.txt', encoding="utf8") as file:
    for each_line in file:
        words_in_line, coeff_cients = each_line.split(maxsplit=1)
        coeff_cients = np.array(coeff_cients.split(),dtype = float)
        glove_dictionary[words_in_line] = coeff_cients

 # All the words which are not in the GloVe dictionary will be
assigned a zero vector.

# embedding_matrix = np.zeros((vocabulary, 200))

######################################################################
# The glove_dictionary contains words vs their respective embeddings #
#                                                                    #
# Create the embedding matrix using the glove_dictionary             #
######################################################################

embedding_matrix = np.zeros((num_words, 200))

for word, i in word_index.items():
    if i >= num_words:
        continue
    embedding_vector = glove_dictionary.get(word)
    if embedding_vector is not None:
        # words not found in embedding index will be all-zeros.
        embedding_matrix[i] = embedding_vector
    else:
        embedding_matrix[i] = np.random.randn(200)

embedding_matrix.shape
```

```
(10000, 200)
```

Sample output : (99987, 200)

Creating The Model (10)

If you need a refresher or have never worked with Neural Networks before, here are a few resources:

- https://web.stanford.edu/~jurafsky/slp3/7.pdf
- https://web.stanford.edu/~jurafsky/slp3/9.pdf
- https://colah.github.io/posts/2015-08-Understanding-LSTMs/

Training a neural network model will take time.

- You can use Google Colab / Kaggle notebooks. You get a free GPU for a limited time.
- Without a GPU, You might have to wait longer to experiment.

Useful resources : https://www.tensorflow.org/api_docs/python/tf/keras/Sequential
https://www.tensorflow.org/api_docs/python/tf/keras/layers/Dense
https://www.tensorflow.org/api_docs/python/tf/keras/layers/Dropout

```
import tensorflow as tf

tf.random.set_seed(42)

######################################################
# Complete this linear model in tensorflow           #
######################################################

def build_model(embedding_matrix):

    '''
    Arguments:
    embedding_matrix : a matrix with the corresponding embeddings
    of all words.

    Returns:
    The LSTM model that you created.
    '''

    model = tf.keras.Sequential()

    # TO DO: layer 1 : add embedding layer
    # The embedding layer maps the words to their embedding vectors
from the embedding matrix

model.add(tf.keras.layers.Embedding(input_dim=embedding_matrix.shape[0
],

output_dim=embedding_matrix.shape[1],
                                        weights=[embedding_matrix],
                                        trainable=False))

    # TO DO: layer 2 : add Bidirectional LSTM Layer

model.add(tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(units=128
)))


    # TO DO Add more layers : you can add more dense layers and
dropout
    # NOTE : You should be able to achieve an validation accuracy
greater than 85%
    #       within 10 epochs
    model.add(tf.keras.layers.Dropout(0.2))
    model.add(tf.keras.layers.Dense(units=64, activation='relu'))
```

```
    model.add(tf.keras.layers.Dropout(0.2))


    # TO DO Final layer : add output layer and activation
    model.add(tf.keras.layers.Dense(units=1, activation='sigmoid'))

    # TO DO : use a loss function, optimizer as adam to compile
    # and evaluate model on auc,precision,recall,accuracy
    # HINT : choose your loss function based on the task (binary
classification)
    model.compile(loss='binary_crossentropy', optimizer='adam',
                  metrics=[tf.keras.metrics.AUC(name="auc"),
tf.keras.metrics.Precision(name="precision"),
                           tf.keras.metrics.Recall(name="recall"),
'accuracy'])

    return model

# y_train = y_train.reshape((-1,1))
# y_test = y_test.reshape((-1,1))

# NOTE : You should be able to achieve an validation accuracy greater
than 85%
#        within 10 epochs

#################################################################
# Call the build_model function and initialize the model        #
#################################################################

model = build_model(embedding_matrix)
model.summary()

######################################################################
#################################
# train and validate the model on the padded sequences of text which
we have created initially        #
######################################################################
#################################

history = model.fit(train_sequences, y_train, epochs=10,
                    validation_data=(val_sequences, y_test))
# history = model.fit(train_sequences, y_train, epochs=10)

Model: "sequential_23"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_23 (Embedding)    (None, None, 200)         2000000

 bidirectional_23 (Bidirecti  (None, 256)              336896
```

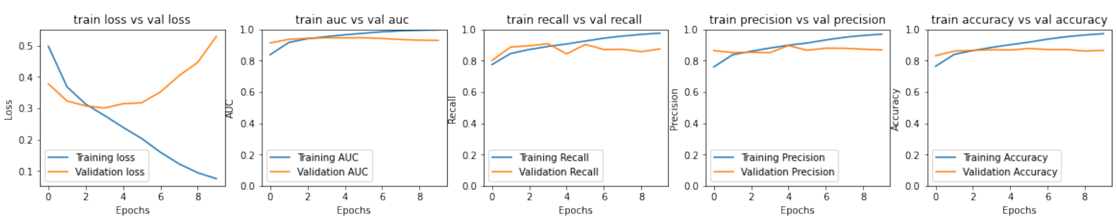
```
 onal)

 dropout_46 (Dropout)       (None, 256)              0

 dense_46 (Dense)           (None, 64)               16448

 dropout_47 (Dropout)       (None, 64)               0

 dense_47 (Dense)           (None, 1)                65

=================================================================
Total params: 2,353,409
Trainable params: 353,409
Non-trainable params: 2,000,000
_________________________________________________________________
Epoch 1/10
618/618 [==============================] - 307s 493ms/step - loss:
0.4979 - auc: 0.8379 - precision: 0.7591 - recall: 0.7745 - accuracy:
0.7637 - val_loss: 0.3778 - val_auc: 0.9130 - val_precision: 0.8642 -
val_recall: 0.8009 - val_accuracy: 0.8312
Epoch 2/10
618/618 [==============================] - 293s 475ms/step - loss:
0.3682 - auc: 0.9161 - precision: 0.8368 - recall: 0.8453 - accuracy:
0.8398 - val_loss: 0.3230 - val_auc: 0.9360 - val_precision: 0.8517 -
val_recall: 0.8866 - val_accuracy: 0.8609
Epoch 3/10
618/618 [==============================] - 292s 473ms/step - loss:
0.3130 - auc: 0.9400 - precision: 0.8599 - recall: 0.8708 - accuracy:
0.8641 - val_loss: 0.3074 - val_auc: 0.9425 - val_precision: 0.8532 -
val_recall: 0.8948 - val_accuracy: 0.8654
Epoch 4/10
618/618 [==============================] - 293s 475ms/step - loss:
0.2769 - auc: 0.9531 - precision: 0.8799 - recall: 0.8905 - accuracy:
0.8842 - val_loss: 0.3006 - val_auc: 0.9461 - val_precision: 0.8507 -
val_recall: 0.9080 - val_accuracy: 0.8694
Epoch 5/10
618/618 [==============================] - 294s 475ms/step - loss:
0.2388 - auc: 0.9650 - precision: 0.8983 - recall: 0.9063 - accuracy:
0.9016 - val_loss: 0.3142 - val_auc: 0.9452 - val_precision: 0.8960 -
val_recall: 0.8429 - val_accuracy: 0.8676
Epoch 6/10
618/618 [==============================] - 290s 470ms/step - loss:
0.2030 - auc: 0.9746 - precision: 0.9124 - recall: 0.9250 - accuracy:
0.9179 - val_loss: 0.3173 - val_auc: 0.9463 - val_precision: 0.8659 -
val_recall: 0.9034 - val_accuracy: 0.8771
Epoch 7/10
618/618 [==============================] - 289s 467ms/step - loss:
0.1594 - auc: 0.9841 - precision: 0.9321 - recall: 0.9434 - accuracy:
0.9371 - val_loss: 0.3518 - val_auc: 0.9414 - val_precision: 0.8792 -
val_recall: 0.8710 - val_accuracy: 0.8709
```

```
Epoch 8/10
618/618 [==============================] - 289s 468ms/step - loss:
0.1222 - auc: 0.9905 - precision: 0.9490 - recall: 0.9569 - accuracy:
0.9526 - val_loss: 0.4037 - val_auc: 0.9352 - val_precision: 0.8787 -
val_recall: 0.8722 - val_accuracy: 0.8711
Epoch 9/10
618/618 [==============================] - 287s 464ms/step - loss:
0.0939 - auc: 0.9941 - precision: 0.9607 - recall: 0.9675 - accuracy:
0.9639 - val_loss: 0.4464 - val_auc: 0.9307 - val_precision: 0.8727 -
val_recall: 0.8574 - val_accuracy: 0.8609
Epoch 10/10
618/618 [==============================] - 287s 465ms/step - loss:
0.0747 - auc: 0.9962 - precision: 0.9688 - recall: 0.9753 - accuracy:
0.9719 - val_loss: 0.5292 - val_auc: 0.9292 - val_precision: 0.8684 -
val_recall: 0.8745 - val_accuracy: 0.8660
```

Plotting Accuracy and Losses (5 Points)

```
####################################
# PLOT :                           #
# train loss vs val loss           #
# train auc vs val auc             #
# train recall vs val recall       #
# train precision vs val precision #
# train accuracy vs val accuracy   #
####################################

plt.figure(figsize=(20,3))

# Plot subplot 1 with loss
plt.subplot(1, 5, 1)
plt.title("train loss vs val loss")
plt.plot(history.history['loss'], label = 'Training loss')
plt.plot(history.history['val_loss'], label = 'Validation loss')
plt.legend()
plt.xlabel("Epochs")
plt.ylabel("Loss")

# Plot subplot 2 with auc
plt.subplot(1, 5, 2)
plt.ylim(0, 1)
plt.title("train auc vs val auc ")
plt.plot(history.history['auc'], label = 'Training AUC')
plt.plot(history.history['val_auc'], label = 'Validation AUC')
plt.legend()
plt.xlabel("Epochs")
plt.ylabel("AUC")

# Plot subplot 3 with recall
plt.subplot(1, 5, 3)
plt.ylim(0, 1)
```

```
plt.title("train recall vs val recall ")
plt.plot(history.history['recall'], label = 'Training Recall')
plt.plot(history.history['val_recall'], label = 'Validation Recall')
plt.legend()
plt.xlabel("Epochs")
plt.ylabel("Recall")

# Plot subplot 4 with recall
plt.subplot(1, 5, 4)
plt.ylim(0, 1)
plt.title("train precision vs val precision")
plt.plot(history.history['precision'], label = 'Training Precision')
plt.plot(history.history['val_precision'], label = 'Validation
Precision')
plt.legend()
plt.xlabel("Epochs")
plt.ylabel("Precision")

# Plot subplot 5 with recall
plt.subplot(1, 5, 5)
plt.ylim(0, 1)
plt.title("train accuracy vs val accuracy")
plt.plot(history.history['accuracy'], label = 'Training Accuracy')
plt.plot(history.history['val_accuracy'], label = 'Validation
Accuracy')
plt.legend()
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.show()
```




```
# You will need to include the pickled model along with the other
submission files
# The saved model will be used to verify your lstm's predictions on
hidden reviews

######################################################################
############
# Save your trained model as a pickle file named "lstm_classifier"
#
# You will be using this saved model to make predictions in the next
module      #
######################################################################
############
```

```python
# import pickle

# with open("lstm_classifier.pkl", "wb") as f:
#     pickle.dump(model, f)

path = './lstm_classifier.h5'
model.save(path)
```

Prediction (5 Points)

```python
######################################################################
# Load your saved model                                              #
# Use the saved model to make predictions                            #
######################################################################

# with open("lstm_classifier.pkl", "rb") as f:
#     saved_model = pickle.load(f)

saved_model= tf.keras.models.load_model(path)

# use the saved model to predict the reviews
def predict_review(review):
    '''
    Arguments:
    review : A single review for which you want to predict the
sentiment for.
    example: "This movie was amazing! I would defenitely watch it
again."

    Returns:
    The predicted sentiment for the review : either 1 or 0
    '''


######################################################################
#######
    # Predict the sentiment for the given review using the model
#
    # that you trained and return the sentiment
#
    #
#
    # HINT : Remember that the review needs to be "preprocessed"
before you use #
    # it for prediction
#

######################################################################
#######
```

```
    clean_review = clean_text(review)
    new_review_sequence = tokenizer.texts_to_sequences([clean_review])
    new_review_sequence_padded = pad_sequences(new_review_sequence, 
maxlen=200)

    y_pred = saved_model.predict(new_review_sequence_padded)

#     print(y_pred)

    y_pred_labels = int(np.round(y_pred).astype(int))

    return y_pred_labels
```

```
# Do not edit this cell

for review in ["If you like original gut wrenching laughter you will 
like this movie. If you are young or old then you will love this 
movie, hell even my mom liked it.<br /><br />Great Camp!!!",
                "What a waste of talent. A very poor, semi-coherent, 
script cripples this film. Rather unimaginative direction, too. Some 
VERY faint echoes of Fargo here, but it just doesn't come off.",
                "I have seen this film at least 100 times and I am 
still excited by it, the acting is perfect and the romance between Joe 
and Jean keeps me on the edge of my seat, plus I still think Bryan 
Brown is the tops. Brilliant Film.",
                "Cheap, amateurish, unimaginative, exploitative... but 
don't think it'll have redeeming amusement value. About as 
unentertaining, uninstructive and just plain dull as a film can be."]:
    p = predict_review(review)
    print(f'{review[:100]} -> {p}')
```

```
1/1 [==============================] - 0s 24ms/step
If you like original gut wrenching laughter you will like this movie. 
If you are young or old then y -> 1
1/1 [==============================] - 0s 23ms/step
What a waste of talent. A very poor, semi-coherent, script cripples 
this film. Rather unimaginative  -> 0
1/1 [==============================] - 0s 22ms/step
I have seen this film at least 100 times and I am still excited by it,
the acting is perfect and the -> 1
1/1 [==============================] - 0s 22ms/step
Cheap, amateurish, unimaginative, exploitative... but don't think 
it'll have redeeming amusement val -> 0
```

Expected Output:

If you like original gut wrenching laughter you will like this movie. If you are young or old then y -> 1 What a waste of talent. A very poor, semi-coherent, script cripples this film. Rather unimaginative -> 0 I have seen this film at least 100 times and I am still excited by it, the acting is perfect and the -> 1 Cheap, amateurish, unimaginative, exploitative... but don't think it'll have redeeming amusement val -> 0