Data Mining [CSE-572]

Homework 2

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```
#import required modules

import string
import pandas as pd
import nltk
from nltk.corpus import stopwords
from nltk.stem.porter import *
from nltk.tokenize import word_tokenize
import numpy as np
import json
from math import log
from collections import Counter
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split, cross_val_score, cross_val_predict
```

```
# Load the train Dataset
train = pd.read_csv('news-train-1.csv')

# Load the test Dataset
test = pd.read_csv('news-test.csv')
```

Question 1:- Preprocess the raw Training Data and Testing Data

Preprocessing the raw data by using standard techniques of Lowercase,removing punctuations and removing stopwords.

```
# Initialize NLTK's Porter Stemmer and stopwords
# Download stopwords and punkt tokenizer data
nltk.download('punkt')
nltk.download('stopwords')

stemmer = PorterStemmer()
stop_words = set(stopwords.words('english'))

# Define the punctuation removal map
remove_punctuation_map = dict((ord(char), None) for char in string.punctuation)

# Read the words from the dictionary file
with open('dictionary.txt', 'r') as f:
    dictionary = set(f.read().splitlines())

# Define the get_tokens function
def getting_tokens(text, n=1):
    # Turn document into lowercase
    lower = text.lower()
    # Remove punctuations
    punc_no = lower.translate(remove_punctuation_map)
    # Tokenize document
    tok = word_tokenize(punc_no)
    # Remove stop words
    filtered = [w for w in tok if not w in stop_words]
    # Stemming process
    stemmed = [stemmer.stem(item) for item in filtered]

    # Generate n-grams
    ngrams = []
    for i in range(len(stemmed) - n + 1):
        ngrams.append(' '.join(stemmed[i:i+n]))

    return stemmed, ngrams
```

```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

Unigrams are individual words in a text or corpus, serving as the basic units of language analysis in NLP tasks

Bigrams are pairs of consecutive words in a text or corpus. They are used in natural language processing (NLP) to analyze the relationship between adjacent words.

```
# Apply the getting_tokens function to each row in the DataFrame
train['Unigrams'], train['Bigrams'] = zip(*train['Text'].apply(lambda x: getting_tokens(x, n=2)))

unigrams = []

for _, row in train.iterrows():
    unigrams.append([token for token in row['Unigrams'] if token in dictionary])

bigrams = []

for _, row in train.iterrows():
    bigrams.append([token for token in row['Bigrams'] if token in dictionary])
```

```
# Apply the getting_tokens function to each row in the test DataFrame
test['Unigrams'], test['Bigrams'] = zip(*test['Text'].apply(lambda x: getting_tokens(x, n=2)))

test_unigrams = []

for _, row in test.iterrows():
    test_unigrams.append([token for token in row['Unigrams'] if token in dictionary])

test_bigrams = []

for _, row in test.iterrows():
    test_bigrams.append([token for token in row['Bigrams'] if token in dictionary])
```

```
# Create a document-term matrix
num_doc = len(unigrams)
num_word = len(dictionary)
document_term_matrix = np.zeros((num_doc, num_word))

for i, doc_unigrams in enumerate(unigrams):
    for word in doc_unigrams:
        j = list(dictionary).index(word)
        document_term_matrix[i, j] += 1
```

```
# Create a document-term matrix for bigrams
num_doc_bigrams = len(bigrams)
document_term_matrix_bigrams = np.zeros((num_doc_bigrams, num_word))

for i, doc_bigrams in enumerate(bigrams):
    for word in doc_bigrams:
        j = list(dictionary).index(word)
        document_term_matrix_bigrams[i, j] += 1
```

```
# Concatenate the unigram and bigram matrices
document_term_matrix_combined = np.concatenate((document_term_matrix, document_term_matrix_bigrams), axis=1)

# Calculate term frequency
term_frequency = document_term_matrix_combined / np.max(document_term_matrix_combined, axis=1, keepdims=True)

# Calculate inverse document frequency
```

```
document_frequency = np.sum(document_term_matrix_combined > 0, axis=0)
inverse_document_frequency = np.log(num_doc / (1 + document_frequency))

# Calculate TFIDF matrix
tfidf_matrix = term_frequency * inverse_document_frequency
```

```
# Calculate top 3 most frequent words for each category
category_words_frequency = {}
for category in train['Category'].unique():
    category_data = train[train['Category'] == category]
    category_unigrams = [word for words in category_data['Unigrams'] for word in words]
    word_counts = Counter(category_unigrams)
    top_words = word_counts.most_common(3)
    category_words_frequency[category] = {word: count for word, count in top_words}

# Calculate top 3 highest average TFIDF words by category
category_words_tfidf = {}
for category in train['Category'].unique():
    category_data = train[train['Category'] == category]
    category_indices = category_data.index
    category_tfidf_scores = tfidf_matrix[category_indices].mean(axis=0)
    top_indices = category_tfidf_scores.argsort()[-3:][::-1]
    top_words = [list(dictionary)[i] for i in top_indices]
    category_words_tfidf[category] = {word: score for word, score in zip(top_words, category_tfidf_scores[top_indices])}
```

Keyword extraction is a process in natural language processing (NLP) that involves identifying and extracting the most relevant words or phrases from a piece of text.

```
# Function to extract keywords using TF-IDF
def extract_keywords(tfidf_matrix, dictionary, doc_index, num_keywords=3):
    doc_tfidf_scores = tfidf_matrix[doc_index]
    top_indices = doc_tfidf_scores.argsort()[-num_keywords:][::-1]
    top_keywords = [list(dictionary)[i] for i in top_indices]
    return top_keywords

# Define a list to store keywords for all documents
all_keywords = []

# Iterate over all document indices
for doc_index in range(tfidf_matrix.shape[0]):
    keywords = extract_keywords(tfidf_matrix, dictionary, doc_index)
    all_keywords.append(keywords)

# Print the keywords for all documents
for doc_index, keywords in enumerate(all_keywords):
    print(f"Top keywords for document {doc_index}: {keywords}")

all_keywords
```

```
 ['bt', 'broadband', 'custom'],
 ['front', 'parti', 'polit'],
 ['track', 'event', '2005'],
 ['hunt', 'polic', 'law'],
 ['court', 'lord', 'victim'],
 ['digit', 'design', 'technolog'],
 ['ceremoni', 'best', 'star'],
 ['liverpool', 'point', 'difficult'],
 ['tax', 'asylum', 'tori'],
 ['ukip', 'tori', 'elect'],
 ['film', 'festiv', 'award'],
 ['england', 'robinson', 'centr'],
 ['poll', 'mr', 'sunday'],
 ['role', 'actor', 'refus'],
 ['davi', 'actor', 'film'],
 ['spain', 'feder', 'comment'],
 ['technolog', 'data', 'use'],
 ['refere', 'comment', 'boss'],
 ['russia', 'rate', 'russian'],
 ['export', 'deficit', 'trade'],
 ['mini', 'car', 'produc'],
 ['mike', 'club', 'contract'],
 ['movi', 'weekend', 'version'],
 ['film', 'box', 'offic'],
 ['award', 'film', 'best'],
 ['arsen', 'game', 'footbal'],
 ['machin', 'user', 'viru'],
 ['arrest', 'commit', 'man'],
 ['album', 'magazin', 'grand'],
 ['eu', 'blair', 'talk'],
 ['song', 'singl', 'artist'],
 ['film', 'award', 'best'],
 ['liverpool', 'night', 'leagu'],
 ]
```

```
# Printing the train dataframe with applied pre-processing tasks.

train
```

	ArticleId	Text	Category	Unigrams	Bigrams
0	893	rangers seal old firm win goals from gregory v...	sport	[ranger, seal, old, firm, win, goal, gregori, ...	[ranger seal, seal old, old firm, firm win, wi...
1	1164	bt program to beat dialler scams bt is introdu...	tech	[bt, program, beat, dialler, scam, bt, introdu...	[bt program, program beat, beat dialler, diall...
2	1696	new yob targets to be unveiled fifty new are...	politics	[new, yob, target, unveil, fifti, new, area, g...	[new yob, yob target, target unveil, unveil fi...
3	396	holmes is hit by hamstring injury kelly holmes...	sport	[holm, hit, hamstr, injuri, kelli, holm, forc,...	[holm hit, hit hamstr, hamstr injuri, injuri k...
4	1862	capriati out of australian open jennifer capri...	sport	[capriati, australian, open, jennif, capriati,...	[capriati australian, australian open, open je...
...	...	...	...	...	...

```
# Printing the test dataframe with applied pre-processing tasks.

test
```

	ArticleId	Text	Unigrams	Bigrams
0	1018	qpr keeper day heads for preston queens park r...	[qpr, keeper, day, head, preston, queen, park,...	[qpr keeper, keeper day, day head, head presto...
1	1319	software watching while	[softwar, watch, work, softwar, monitor,	[softwar watch, watch work, work softwar,
		d arcy injury adds to	[arci, injur, add,	[arci injuri, injuri add,
		india s reliance family feud	[india, relianc, famili	[india relianc, relianc

1) a)

Run Neural Networks with the 2-hidden layers, each has 128 neurons, extracting features by CountVectorizer() as the original features.

```
import numpy as np
from sklearn.neural_network import MLPClassifier
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.model_selection import KFold
from sklearn.pipeline import make_pipeline

X = train['Unigrams'].apply(lambda x: ' '.join(x))  # Convert lists of words to space-separated strings
y = train['Category']

# Initialize the CountVectorizer
count_vectorizer = CountVectorizer()

# Initialize the Multi-Layer Perceptron (MLP) Classifier
mlp_classifier = MLPClassifier(hidden_layer_sizes=(128, 128), random_state=42)

# Create a pipeline with CountVectorizer and MLP Classifier
pipeline = make_pipeline(count_vectorizer, mlp_classifier)
```

5-fold cross-validation to evaluate the performance for Count Vectorizer()

```
# Initialize variables to store accuracies
train_accuracies = []
val_accuracies = []

# Perform 5-fold cross-validation manually
kf = KFold(n_splits=5, shuffle=True, random_state=42)
for train_index, val_index in kf.split(X):
    X_train, X_val = X.iloc[train_index], X.iloc[val_index]
    y_train, y_val = y.iloc[train_index], y.iloc[val_index]

    # Fit the pipeline on the training data
    pipeline.fit(X_train, y_train)

    # Calculate the accuracy on the training set
    train_accuracy = pipeline.score(X_train, y_train)
    train_accuracies.append(train_accuracy)

    # Calculate the accuracy on the validation set
    val_accuracy = pipeline.score(X_val, y_val)
    val_accuracies.append(val_accuracy)

# Print training and validation accuracies for each fold
for fold, (train_accuracy, val_accuracy) in enumerate(zip(train_accuracies, val_accuracies)):
    print(f'Fold {fold+1}: Training Accuracy = {train_accuracy:.4f}, Validation Accuracy = {val_accuracy:.4f}')

# Calculate and print the mean and standard deviation of the training accuracies
mean_train_accuracy_count = np.mean(train_accuracies)
std_train_accuracy_count = np.std(train_accuracies)

# Calculate and print the mean and standard deviation of the validation accuracies
mean_val_accuracy_count = np.mean(val_accuracies)
std_val_accuracy_count = np.std(val_accuracies)
```

```
Fold 1: Training Accuracy = 1.0000, Validation Accuracy = 0.9765
Fold 2: Training Accuracy = 1.0000, Validation Accuracy = 0.9718
Fold 3: Training Accuracy = 1.0000, Validation Accuracy = 0.9765
Fold 4: Training Accuracy = 1.0000, Validation Accuracy = 0.9623
Fold 5: Training Accuracy = 1.0000, Validation Accuracy = 0.9670
```

1)b)

Feature exploration. Used features like TFIDF and GloVe

```
import numpy as np
from sklearn.model_selection import cross_val_score
from sklearn.neural_network import MLPClassifier
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.pipeline import make_pipeline
from gensim.models import KeyedVectors
from sklearn.preprocessing import FunctionTransformer


# Load pre-trained GloVe embeddings
from gensim.models import KeyedVectors

# Load GloVe word vectors
def load_glove_embeddings(glove_file_path):
    word_to_vec = {}
    with open(glove_file_path, 'r', encoding='utf-8') as file:
        for line in file:
            values = line.split()
            word = values[0]
            vector = np.array(values[1:], dtype='float32')
            word_to_vec[word] = vector
    return word_to_vec

glove_file_path = 'glove.6B.50d.txt'
glove_model = load_glove_embeddings(glove_file_path)
```

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

Initialization: We initialized a TF-IDF vectorizer using scikit-learn's TfidfVectorizer. TF-IDF is a technique used to convert text data into numerical form, which can be used as features for machine learning models.

Transforming Text Data: We applied the TF-IDF vectorizer to the text data (X). This converts the text into a matrix where each row corresponds to a document and each column corresponds to a term (word) in the document. The values in the matrix represent the TF-IDF score of each term.

GloVe Embeddings:

Loading Pre-trained GloVe Embeddings: We loaded pre-trained word embeddings from the GloVe file using the gensim library. These embeddings represent words as high-dimensional vectors in a continuous vector space, where semantically similar words are located close to each other.

Converting Words to GloVe Embeddings: We defined a function sentence_to_embedding(sentence) that takes a sentence, splits it into words, and converts each word to its corresponding GloVe embedding. If a word is not found in the GloVe embeddings (which may happen for common English words), it returns a zero vector.

Creating GloVe Features: We applied this function to each sentence in the text data (X). This resulted in a matrix where each row represents a document and each column contains the average GloVe embedding vector for the terms in the document.

Combining Features:

We then combined the TF-IDF features and the GloVe features into a single feature matrix (X_combined). This was done by horizontally stacking the TF-IDF matrix and the GloVe matrix. These combined features were used as input for training the neural network model. This approach leveraged the strengths of both TF-IDF (capturing term importance in individual documents) and GloVe embeddings (capturing semantic relationships between words) to potentially improve the model's performance.

```
# Initialize the TF-IDF vectorizer
tfidf_vectorizer = TfidfVectorizer(max_features=1000)

# Transform the text data using TF-IDF
X_tfidf = tfidf_vectorizer.fit_transform(X)

# Convert words to GloVe embeddings
def sentence_to_embedding(sentence):
    words = sentence.split()
    embeddings = [glove_model[word] for word in words if word in glove_model]
    if len(embeddings) > 0:
```

```
        return np.mean(embeddings, axis=0)
    else:
        return np.zeros(300)  # Return zero vector if no embeddings are found

X_glove = np.array([sentence_to_embedding(sentence) for sentence in X])

# Combine TF-IDF and GloVe features
X_combined = np.hstack((X_tfidf.toarray(), X_glove))

# Initialize the Multi-Layer Perceptron (MLP) Classifier
mlp_classifier = MLPClassifier(hidden_layer_sizes=(128, 128), random_state=42)

# Create a pipeline with the combined features and MLP Classifier
pipeline = make_pipeline(mlp_classifier)
```

5-fold cross-validation to evaluate the performance of the Neural Network

```
# Initialize variables to store accuracies
train_accuracies = []
val_accuracies = []

# Perform 5-fold cross-validation manually
kf = KFold(n_splits=5, shuffle=True, random_state=42)
for train_index, val_index in kf.split(X_combined):
    X_train, X_val = X_combined[train_index], X_combined[val_index]
    y_train, y_val = y.iloc[train_index], y.iloc[val_index]

    # Fit the MLP Classifier on the training data
    mlp_classifier.fit(X_train, y_train)

    # Calculate the accuracy on the training set
    train_accuracy = mlp_classifier.score(X_train, y_train)
    train_accuracies.append(train_accuracy)

    # Calculate the accuracy on the validation set
    val_accuracy = mlp_classifier.score(X_val, y_val)
    val_accuracies.append(val_accuracy)

# Calculate and print the mean and standard deviation of the validation accuracies
mean_val_accuracy_combined = np.mean(val_accuracies)
std_val_accuracy_combined = np.std(val_accuracies)

# Calculate and print the mean and standard deviation of the training accuracies
mean_train_accuracy_combined = np.mean(train_accuracies)
std_train_accuracy_combined = np.std(train_accuracies)

# Print training and validation accuracies for each fold
for fold, (train_accuracy, val_accuracy) in enumerate(zip(train_accuracies, val_accuracies)):
    print(f'Fold {fold+1}: Training Accuracy = {train_accuracy:.4f}, Validation Accuracy = {val_accuracy:.4f}')
```

```
Fold 1: Training Accuracy = 1.0000, Validation Accuracy = 0.9718
Fold 2: Training Accuracy = 1.0000, Validation Accuracy = 0.9718
Fold 3: Training Accuracy = 1.0000, Validation Accuracy = 0.9812
Fold 4: Training Accuracy = 1.0000, Validation Accuracy = 0.9623
Fold 5: Training Accuracy = 1.0000, Validation Accuracy = 0.9764
```

```
# Initialize the TF-IDF vectorizer
tfidf_vectorizer = TfidfVectorizer(max_features=1000)

# Transform the text data using TF-IDF
X_tfidf = tfidf_vectorizer.fit_transform(X)

# Convert words to GloVe embeddings
def sentence_to_embedding(sentence):
    words = sentence.split()
    embeddings = [glove_model[word] for word in words if word in glove_model]
    if len(embeddings) > 0:
        return np.mean(embeddings, axis=0)
    else:
        return np.zeros(300)  # Return zero vector if no embeddings are found

X_glove = np.array([sentence_to_embedding(sentence) for sentence in X])

# Initialize the Multi-Layer Perceptron (MLP) Classifier
```

```
# Initialize the Multi-Layer Perceptron (MLP) Classifier
mlp_classifier = MLPClassifier(hidden_layer_sizes=(128, 128), random_state=42)

# Create a pipeline with only TF-IDF features and MLP Classifier
pipeline_tfidf = make_pipeline(TfidfVectorizer(max_features=1000), mlp_classifier)

# Create a pipeline with only GloVe embeddings and MLP Classifier
pipeline_glove = make_pipeline(FunctionTransformer(np.array), mlp_classifier)

# Initialize variables to store accuracies
train_accuracies_tfidf = []
val_accuracies_tfidf = []

train_accuracies_glove = []
val_accuracies_glove = []

# Perform 5-fold cross-validation manually for TF-IDF
kf = KFold(n_splits=5, shuffle=True, random_state=42)
for train_index, val_index in kf.split(X_tfidf):
    X_train, X_val = X_tfidf[train_index], X_tfidf[val_index]
    y_train, y_val = y.iloc[train_index], y.iloc[val_index]

    # Fit the MLP Classifier on the training data (TF-IDF)
    mlp_classifier.fit(X_train, y_train)

    # Calculate the accuracy on the training set (TF-IDF)
    train_accuracy = mlp_classifier.score(X_train, y_train)
    train_accuracies_tfidf.append(train_accuracy)

    # Calculate the accuracy on the validation set (TF-IDF)
    val_accuracy = mlp_classifier.score(X_val, y_val)
    val_accuracies_tfidf.append(val_accuracy)

# Perform 5-fold cross-validation manually for GloVe
kf = KFold(n_splits=5, shuffle=True, random_state=42)
for train_index, val_index in kf.split(X_glove):
    X_train, X_val = X_glove[train_index], X_glove[val_index]
    y_train, y_val = y.iloc[train_index], y.iloc[val_index]

    # Fit the MLP Classifier on the training data (GloVe)
    mlp_classifier.fit(X_train, y_train)

    # Calculate the accuracy on the training set (GloVe)
    train_accuracy = mlp_classifier.score(X_train, y_train)
    train_accuracies_glove.append(train_accuracy)

    # Calculate the accuracy on the validation set (GloVe)
    val_accuracy = mlp_classifier.score(X_val, y_val)
    val_accuracies_glove.append(val_accuracy)

# Print the mean and standard deviation of the training and validation accuracies for TF-IDF
mean_train_accuracy_tfidf = np.mean(train_accuracies_tfidf)
std_train_accuracy_tfidf = np.std(train_accuracies_tfidf)

mean_val_accuracy_tfidf = np.mean(val_accuracies_tfidf)
std_val_accuracy_tfidf = np.std(val_accuracies_tfidf)

print(f'TF-IDF Results:')
print(f'Mean Training Accuracy: {mean_train_accuracy_tfidf:.4f} (±{std_train_accuracy_tfidf:.4f})')
print(f'Mean Validation Accuracy: {mean_val_accuracy_tfidf:.4f} (±{std_val_accuracy_tfidf:.4f})')

# Print the mean and standard deviation of the training and validation accuracies for GloVe
mean_train_accuracy_glove = np.mean(train_accuracies_glove)
std_train_accuracy_glove = np.std(train_accuracies_glove)

mean_val_accuracy_glove = np.mean(val_accuracies_glove)
std_val_accuracy_glove = np.std(val_accuracies_glove)

print(f'\nGloVe Results:')
print(f'Mean Training Accuracy: {mean_train_accuracy_glove:.4f} (±{std_train_accuracy_glove:.4f})')
print(f'Mean Validation Accuracy: {mean_val_accuracy_glove:.4f} (±{std_val_accuracy_glove:.4f})')
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:686: ConvergenceWarning: Stochastic Optimizer:
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:686: ConvergenceWarning: Stochastic Optimizer:
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:686: ConvergenceWarning: Stochastic Optimizer:
```

```
  warnings.warn(
TF-IDF Results:
Mean Training Accuracy: 1.0000 (±0.0000)
Mean Validation Accuracy: 0.9652 (±0.0122)

GloVe Results:
Mean Training Accuracy: 1.0000 (±0.0000)
Mean Validation Accuracy: 0.9445 (±0.0158)
/usr/local/lib/python3.10/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:686: ConvergenceWarning: Stochastic Optimizer:
  warnings.warn(
```

1) d)

Report the average training and validation accuracy, and their standard deviation for different feature construction

```
import pandas as pd

# Sample Result Structure
# avg_train_accuracy_count, std_train_accuracy_count, avg_val_accuracy_count, std_val_accuracy_count
# avg_train_accuracy_tfidf, std_train_accuracy_tfidf, avg_val_accuracy_tfidf, std_val_accuracy_tfidf
# avg_train_accuracy_glove, std_train_accuracy_glove, avg_val_accuracy_glove, std_val_accuracy_glove
# avg_train_accuracy_combined, std_train_accuracy_combined, avg_val_accuracy_combined, std_val_accuracy_combined

# Create a DataFrame to store the results
results_df = pd.DataFrame({
    'Feature Method': ['CountVectorizer', 'GloVe+TFIDF', 'TFIDF', 'Glove'],
    'Avg Training Accuracy': [mean_train_accuracy_count, mean_train_accuracy_combined,mean_train_accuracy_tfidf,mean_train_accuracy_glove],
    'Std Training Accuracy': [std_train_accuracy_count, std_train_accuracy_combined,std_train_accuracy_tfidf,std_train_accuracy_glove],
    'Avg Validation Accuracy': [mean_val_accuracy_count, mean_val_accuracy_combined,mean_val_accuracy_tfidf,mean_val_accuracy_glove],
    'Std Validation Accuracy': [std_val_accuracy_count, std_val_accuracy_combined,std_val_accuracy_tfidf,std_val_accuracy_glove]
})

# Print the results
results_df
```

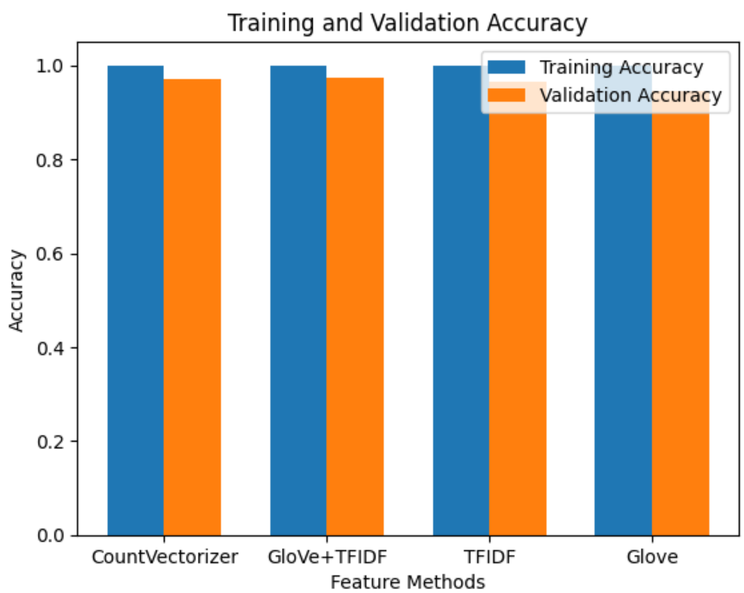
	Feature Method	Avg Training Accuracy	Std Training Accuracy	Avg Validation Accuracy	Std Validation Accuracy
0	CountVectorizer	1.0	0.0	0.970826	0.005551
1	GloVe+TFIDF	1.0	0.0	0.972712	0.006274
2	TFIDF	1.0	0.0	0.965170	0.012201
3	Glove	1.0	0.0	0.944499	0.015816

1) e)

A Bar figure showing the training and validation result, x-axis should be the parameter values, y-axis should be the training and validation accuracy.

```
import matplotlib.pyplot as plt

# Define the data
methods = ['CountVectorizer', 'GloVe+TFIDF','TFIDF','Glove']
train_accuracies = [mean_train_accuracy_count, mean_train_accuracy_combined,mean_train_accuracy_tfidf,mean_train_accuracy_glove]
val_accuracies = [mean_val_accuracy_count,mean_val_accuracy_combined ,mean_val_accuracy_tfidf, mean_val_accuracy_glove]

# Set up positions for bars on x-axis
x = range(len(methods))

# Set bar width
bar_width = 0.35

# Create the figure and axis objects
fig, ax = plt.subplots()

# Create bars for training accuracies
train_bars = plt.bar(x, train_accuracies, bar_width, label='Training Accuracy')

# Create bars for validation accuracies
val_bars = plt.bar([i + bar_width for i in x], val_accuracies, bar_width, label='Validation Accuracy')
```

```
# Set labels and title
plt.xlabel('Feature Methods')
plt.ylabel('Accuracy')
plt.title('Training and Validation Accuracy')
plt.xticks([i + bar_width/2 for i in x], methods)

# Add a legend
plt.legend()

# Show the plot
plt.show()
```



The training and Validation accuracies are almost similar in both the cases.

Question 2:-

2)b)

5-fold cross-validation to evaluate the performance w.r.t. the learning rates ()

```
import pandas as pd

# Define candidate learning rates
learning_rates = [0.0001, 0.0003, 0.001, 0.003, 0.01, 0.03, 0.1]

# Initialize lists to store results
results = []

for lr in learning_rates:
    # Initialize the MLP Classifier with the specified learning rate
    mlp_classifier = MLPClassifier(hidden_layer_sizes=(128, 128), max_iter=4000, learning_rate_init=lr, random_state=42)


    # Initialize variables to store accuracies
    train_accuracies = []
    val_accuracies = []

    # Perform 5-fold cross-validation manually
    kf = KFold(n_splits=5, shuffle=True, random_state=42)
    for train_index, val_index in kf.split(X_combined):
        X_train, X_val = X_combined[train_index], X_combined[val_index]
        y_train, y_val = y.iloc[train_index], y.iloc[val_index]

        # Fit the MLP Classifier on the training data
        mlp_classifier.fit(X_train, y_train)

        # Calculate the accuracy on the training set
```

```
        # Calculate the accuracy on the training set
        train_accuracy = mlp_classifier.score(X_train, y_train)
        train_accuracies.append(train_accuracy)

        # Calculate the accuracy on the validation set
        val_accuracy = mlp_classifier.score(X_val, y_val)
        val_accuracies.append(val_accuracy)

    # Calculate and store the mean and standard deviation of accuracies
    mean_train_accuracy = np.mean(train_accuracies)
    std_train_accuracy = np.std(train_accuracies)
    mean_val_accuracy = np.mean(val_accuracies)
    std_val_accuracy = np.std(val_accuracies)

    # Append results to the list
    results.append([lr, mean_train_accuracy, std_train_accuracy, mean_val_accuracy, std_val_accuracy])

# Create a DataFrame to store the results
results_df = pd.DataFrame(results, columns=['Learning Rate', 'Avg Training Accuracy', 'Std Training Accuracy', 'Avg Validation Accuracy', 'St
```

2)b)1)

Report the average training and validation accuracy, and their standard deviation for different parameter values

```
# Print the results

results_df
```

	Learning Rate	Avg Training Accuracy	Std Training Accuracy	Avg Validation Accuracy	Std Validation Accuracy
0	0.0001	1.0	0.0	0.974599	0.003765
1	0.0003	1.0	0.0	0.973660	0.004786
2	0.0010	1.0	0.0	0.972712	0.006274
3	0.0030	1.0	0.0	0.971769	0.005995
4	0.0100	1.0	0.0	0.974581	0.009736
5	0.0300	1.0	0.0	0.967074	0.007856
6	0.1000	1.0	0.0	0.965174	0.009763

```
for idx, (lr, train_accuracy, val_accuracy) in enumerate(zip(learning_rates, train_accuracies, val_accuracies)):
    print(f'Learning Rate: {lr}')
    print(f'Training Accuracy = {train_accuracy:.4f}, Validation Accuracy = {val_accuracy:.4f}')
```

```
Learning Rate: 0.0001
Training Accuracy = 1.0000, Validation Accuracy = 0.9718
Learning Rate: 0.0003
Training Accuracy = 1.0000, Validation Accuracy = 0.9671
Learning Rate: 0.001
Training Accuracy = 1.0000, Validation Accuracy = 0.9765
Learning Rate: 0.003
Training Accuracy = 1.0000, Validation Accuracy = 0.9481
Learning Rate: 0.01
Training Accuracy = 1.0000, Validation Accuracy = 0.9623
```

Report the average training and validation accuracy, and their standard deviation for different parameter values

```
# Calculate and store the mean and standard deviation of accuracies
mean_train_accuracy = np.mean(train_accuracies)
std_train_accuracy = np.std(train_accuracies)
mean_val_accuracy = np.mean(val_accuracies)
std_val_accuracy = np.std(val_accuracies)

# Append results to the list
results.append([lr, mean_train_accuracy, std_train_accuracy, mean_val_accuracy, std_val_accuracy])

# Create a DataFrame to store the results
```

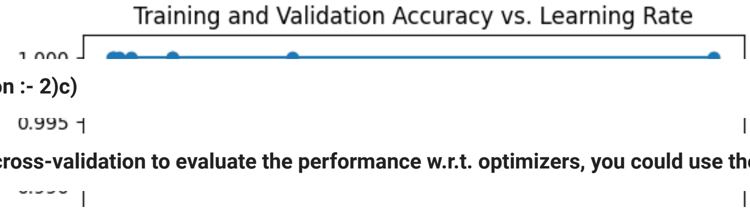
```
results_df = pd.DataFrame(results, columns=['Learning Rate', 'Avg Training Accuracy', 'Std Training Accuracy', 'Avg Validation Accuracy', 'St

# Print the results
results_df
```

	Learning Rate	Avg Training Accuracy	Std Training Accuracy	Avg Validation Accuracy	Std Validation Accuracy
0	0.0001	1.0	0.0	0.974599	0.003765
1	0.0003	1.0	0.0	0.973660	0.004786
2	0.0010	1.0	0.0	0.972712	0.006274
3	0.0030	1.0	0.0	0.971769	0.005995
4	0.0100	1.0	0.0	0.974581	0.009736
5	0.0300	1.0	0.0	0.967074	0.007856
6	0.1000	1.0	0.0	0.965174	0.009763
7	0.0100	1.0	0.0	0.965174	0.009763

2)b)2)

Draw a line figure showing the training and validation result

```
import matplotlib.pyplot as plt

# Extract parameter values and accuracies from the results DataFrame
learning_rates = results_df['Learning Rate']
train_accuracies = results_df['Avg Training Accuracy']
val_accuracies = results_df['Avg Validation Accuracy']

# Create a figure and axis objects
fig, ax = plt.subplots()

# Plot training accuracies
ax.plot(learning_rates, train_accuracies, label='Training Accuracy', marker='o')

# Plot validation accuracies
ax.plot(learning_rates, val_accuracies, label='Validation Accuracy', marker='o')

# Set labels and title
plt.xlabel('Learning Rate')
plt.ylabel('Accuracy')
plt.title('Training and Validation Accuracy vs. Learning Rate')

# Add a legend
plt.legend()

# Show the plot
plt.show()
```



Question :- 2)c)

5-fold cross-validation to evaluate the performance w.r.t. optimizers, you could use the feature engineering method

```
import torch
import torch.nn as nn
import torch.optim as optim
from sklearn.model_selection import KFold
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.preprocessing import LabelEncoder
import pandas as pd

# Define a simple neural network
class Net(nn.Module):
    def __init__(self, input_dim, output_dim):
        super(Net, self).__init__()
        self.fc = nn.Linear(input_dim, output_dim)

    def forward(self, x):
        x = self.fc(x)
        return x

X_text = train['Unigrams'].apply(lambda x: ' '.join(x))  # Convert lists of words to space-separated strings
y = train['Category']

# Convert text data to a bag-of-words representation
vectorizer = CountVectorizer()
X = vectorizer.fit_transform(X_text)

# Initialize lists to store results
results = []

# Define candidate optimizers
optimizers = ['SGD', 'Adam', 'RMSprop']

# Perform 5-fold cross-validation
kf = KFold(n_splits=5, shuffle=True, random_state=42)
for train_index, val_index in kf.split(X):
    X_train, X_val = X[train_index], X[val_index]
    y_train, y_val = y.iloc[train_index], y.iloc[val_index]

    # Convert data to PyTorch tensors
    X_train = torch.tensor(X_train.toarray(), dtype=torch.float32)
    X_val = torch.tensor(X_val.toarray(), dtype=torch.float32)

    # Encode categorical labels
    label_encoder = LabelEncoder()
    y_train = torch.tensor(label_encoder.fit_transform(y_train), dtype=torch.long)
    y_val = torch.tensor(label_encoder.transform(y_val), dtype=torch.long)

    # Define input and output dimensions based on your data
    input_dim = X_train.shape[1]
    output_dim = len(label_encoder.classes_)

    for optimizer_name in optimizers:
        # Initialize the neural network and optimizer
        net = Net(input_dim, output_dim)
        if optimizer_name == 'SGD':
            optimizer = optim.SGD(net.parameters(), lr=0.01)
        elif optimizer_name == 'Adam':
            optimizer = optim.Adam(net.parameters(), lr=0.001)
        elif optimizer_name == 'RMSprop':
            optimizer = optim.RMSprop(net.parameters(), lr=0.001)
        else:
            raise ValueError(f'Unsupported optimizer: {optimizer_name}')

        # Train the model
        criterion = nn.CrossEntropyLoss()
        for epoch in range(10):
            optimizer.zero_grad()
            outputs = net(X_train)
            loss = criterion(outputs, y_train)
```

```
            loss.backward()
            optimizer.step()

        # Calculate the accuracy on the training set
        train_accuracy = (net(X_train).argmax(dim=1) == y_train).float().mean().item()

        # Calculate the accuracy on the validation set
        val_accuracy = (net(X_val).argmax(dim=1) == y_val).float().mean().item()

        # Store the results
        results.append([optimizer_name, train_accuracy, val_accuracy])


# Create a DataFrame to store the results
results_df = pd.DataFrame(results, columns=['Optimizer', 'Training Accuracy', 'Validation Accuracy'])

# Print the results
results_df
```

	Optimizer	Training Accuracy	Validation Accuracy
0	SGD	0.897647	0.906103
1	Adam	0.997647	0.962441
2	RMSprop	1.000000	0.967136
3	SGD	0.877647	0.802817
4	Adam	0.996471	0.962441
5	RMSprop	1.000000	0.962441
6	SGD	0.891765	0.882629
7	Adam	0.998824	0.971831
8	RMSprop	1.000000	0.976526
9	SGD	0.888367	0.872642
10	Adam	0.996475	0.952830
11	RMSprop	1.000000	0.971698
12	SGD	0.894242	0.811321
13	Adam	0.996475	0.962264
14	RMSprop	1.000000	0.962264

2)c)1)

Report the average training and validation accuracy, and their standard deviation for different parameter values

```
import pandas as pd
results_df = pd.DataFrame(results, columns=['Optimizer', 'Training Accuracy', 'Validation Accuracy'])

# Calculate mean and standard deviation
mean_results = results_df.groupby('Optimizer').mean()
std_results = results_df.groupby('Optimizer').std()

print("Mean Results:")
mean_results
```

```
Mean Results:
```

Optimizer	Training Accuracy	Validation Accuracy
Adam	0.997178	0.962362
RMSprop	1.000000	0.968013
SGD	0.889934	0.855102

```
print("\nStandard Deviation:")
std_results
```

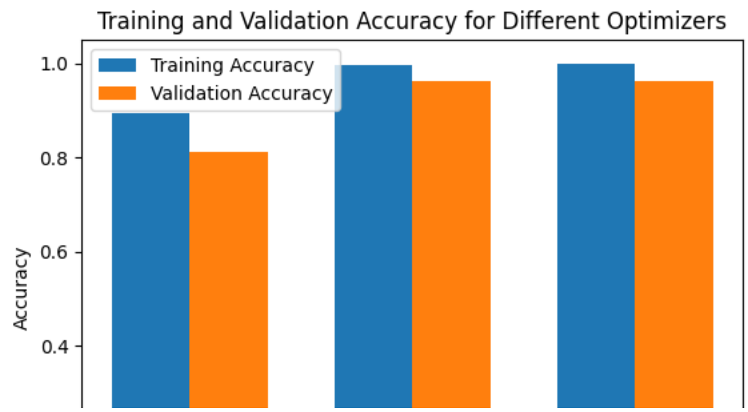
Standard Deviation:

Optimizer	Training Accuracy	Validation Accuracy
Adam	0.001051	0.006718
RMSprop	0.000000	0.006142
SGD	0.007662	0.045599

2)c)2)

Draw a bar figure showing the training and validation result, x-axis should be the parameter values, y-axis should be the training and validation accuracy.

```
import matplotlib.pyplot as plt
# results (list of [optimizer_name, train_accuracy, val_accuracy] lists)

# Separate the results for each optimizer
sgd_results = [result for result in results if result[0] == 'SGD']
adam_results = [result for result in results if result[0] == 'Adam']
rmsprop_results = [result for result in results if result[0] == 'RMSprop']

# Extract the accuracies
sgd_train_accuracies = [result[1] for result in sgd_results]
sgd_val_accuracies = [result[2] for result in sgd_results]

adam_train_accuracies = [result[1] for result in adam_results]
adam_val_accuracies = [result[2] for result in adam_results]

rmsprop_train_accuracies = [result[1] for result in rmsprop_results]
rmsprop_val_accuracies = [result[2] for result in rmsprop_results]

# Define labels and positions
labels = ['SGD', 'Adam', 'RMSprop']
x = range(len(labels))

# Set bar width
bar_width = 0.35

# Create the figure and axis objects
fig, ax = plt.subplots()

# Create bars for training accuracies
train_bars = plt.bar(x, [sgd_train_accuracies[-1], adam_train_accuracies[-1], rmsprop_train_accuracies[-1]], bar_width, label='Training Accur

# Create bars for validation accuracies
val_bars = plt.bar([i + bar_width for i in x], [sgd_val_accuracies[-1], adam_val_accuracies[-1], rmsprop_val_accuracies[-1]], bar_width, labe

# Set labels and title
plt.xlabel('Optimizers')
plt.ylabel('Accuracy')
plt.title('Training and Validation Accuracy for Different Optimizers')
plt.xticks([i + bar_width/2 for i in x], labels)

# Add a legend
plt.legend()

# Show the plot
plt.show()
```



Question 3:-

Predict the labels for the testing data

```
import torch
import torch.nn as nn
import torch.optim as optim
from sklearn.neural_network import MLPClassifier
from sklearn.feature_extraction.text import TfidfVectorizer
import numpy as np

# Define the MLP Classifier with Adam optimizer and learning rate of 0.0001
mlp_classifier = MLPClassifier(hidden_layer_sizes=(128, 128), activation='relu', solver='adam', learning_rate_init=0.0001, max_iter=1000)

# Pre-process the training data
X_train_tfidf = tfidf_vectorizer.fit_transform(train['Unigrams'].apply(lambda x: ' '.join(x)))

def sentence_to_embedding(sentence):
    words = sentence.split()
    embeddings = [glove_model[word] for word in words if word in glove_model]
    if len(embeddings) > 0:
        return np.mean(embeddings, axis=0)
    else:
        return np.zeros(300)

X_train_glove = np.array([sentence_to_embedding(' '.join(sentence)) for sentence in train['Unigrams']])
X_train_combined = np.hstack((X_train_tfidf.toarray(), X_train_glove))
X_train_torch = torch.tensor(X_train_combined, dtype=torch.float32)

# Fit the MLP Classifier with training data
mlp_classifier.fit(X_train_combined, train['Category'])

# Pre-process the test data
X_test_tfidf = tfidf_vectorizer.transform(test['Unigrams'].apply(lambda x: ' '.join(x)))

X_test_glove = np.array([sentence_to_embedding(' '.join(sentence)) for sentence in test['Unigrams']])
X_test_combined = np.hstack((X_test_tfidf.toarray(), X_test_glove))
X_test_torch = torch.tensor(X_test_combined, dtype=torch.float32)

# Predict labels for the test data using the trained MLP Classifier
test_predictions = mlp_classifier.predict(X_test_combined)

# Add the 'Predicted Category' column to the 'test' DataFrame
test['Predicted Category'] = test_predictions

# Print the updated DataFrame with predicted categories
test
```

	ArticleId	Text	Unigrams	Bigrams	Predicted Category
0	1018	qpr keeper day heads for preston queens park r...	[qpr, keeper, day, head, preston, queen, park,...	[qpr keeper, keeper day, day head, head presto...	sport
1	1319	software watching while you work software that...	[softwar, watch, work, softwar, monitor, everi...	[softwar watch, watch work, work softwar, soft...	tech
2	1138	d arcy injury adds to ireland woe gordon d arc...	[arci, injuri, add, ireland, woe, gordon, arci...	[arci injuri, injuri add, add ireland, ireland...	sport
3	459	india s reliance family feud heats up the ongo...	[india, relianc, famili, feud, heat, ongo, pub...	[india relianc, relianc famili, famili feud, f...	business
4	1020	boro suffer morrison injury blow middlesbrough...	[boro, suffer, morrison, injuri, blow, middles...	[boro suffer, suffer morrison, morrison injuri...	sport

```
# Save the DataFrame as a CSV file without header and with specific columns
test[['ArticleId', 'Predicted Category']].to_csv('labels.csv', index=False, header=False)
```

731	373	u2 to play at grammy awards show	[u2, play, grammi, award, show,	[u2 play, play grammi, grammi award,	entertainment

```
import torch
import torch.nn as nn
import torch.optim as optim
from sklearn.neural_network import MLPClassifier
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics import accuracy_score
import numpy as np

# Define the MLP Classifier with RMSprop optimizer and learning rate of 0.0001
mlp_classifier = MLPClassifier(hidden_layer_sizes=(128, 128), activation='relu', solver='adam', learning_rate_init=0.0001, max_iter=1000)

# Pre-process the training data
X_train_tfidf = tfidf_vectorizer.fit_transform(train['Unigrams'].apply(lambda x: ' '.join(x)))

def sentence_to_embedding(sentence):
    words = sentence.split()
    embeddings = [glove_model[word] for word in words if word in glove_model]
    if len(embeddings) > 0:
        return np.mean(embeddings, axis=0)
    else:
        return np.zeros(300)

X_train_glove = np.array([sentence_to_embedding(' '.join(sentence)) for sentence in train['Unigrams']])
X_train_combined = np.hstack((X_train_tfidf.toarray(), X_train_glove))
X_train_torch = torch.tensor(X_train_combined, dtype=torch.float32)

# Fit the MLP Classifier with training data
mlp_classifier.fit(X_train_combined, train['Category'])

# Predict labels for the training data using the trained MLP Classifier
train_predictions = mlp_classifier.predict(X_train_combined)

# Calculate the accuracy of training predictions compared to training labels
train_accuracy = accuracy_score(train['Category'], train_predictions)
print(f"Training Accuracy: {train_accuracy:.2f}")

# Add the 'Predicted Category' column to the 'train' DataFrame
train['Predicted Category'] = train_predictions

# Print the updated DataFrame with predicted categories
train
```

```
Training Accuracy: 1.00
```

	ArticleId	Text	Category	Unigrams	Bigrams	Predicted Category
0	893	rangers seal old firm win goals from gregory v...	sport	[ranger, seal, old, firm, win, goal, gregori, ...	[ranger seal, seal old, old firm, firm win, wi...	sport
1	1164	bt program to beat dialler scams bt is introdu...	tech	[bt, program, beat, dialler, scam, bt, introdu...	[bt program, program beat, beat dialler, diall...	tech
2	1696	new yob targets to be unveiled fifty new are...	politics	[new, yob, target, unveil, fifti, new, area, g...	[new yob, yob target, target unveil, unveil fi...	politics
3	396	holmes is hit by hamstring injury kelly holmes...	sport	[holm, hit, hamstr, injuri, kelli, holm, forc,...	[holm hit, hit hamstr, hamstr injuri, injuri k...	sport
4	1862	capriati out of australian open jennifer capri...	sport	[capriati, australian, open, jennif, capriati,...	[capriati australian, australian open, open je...	sport
...	...	...	...	...	...	...
[illegible]	[illegible]	housewives lift channel 4	entertainment	[housew, lift, channel, 4,	[housew lift, lift channel,	entertainment