Project 1

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Dataset

Question 1 : Data Analysis

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
import math
import numpy as np
import random
import pandas as pd
from matplotlib import pyplot as plt
```

```
df = pd.read_csv('/content/drive/MyDrive/ECE ENGR 219/Project1-ClassificationDataset.csv')
```

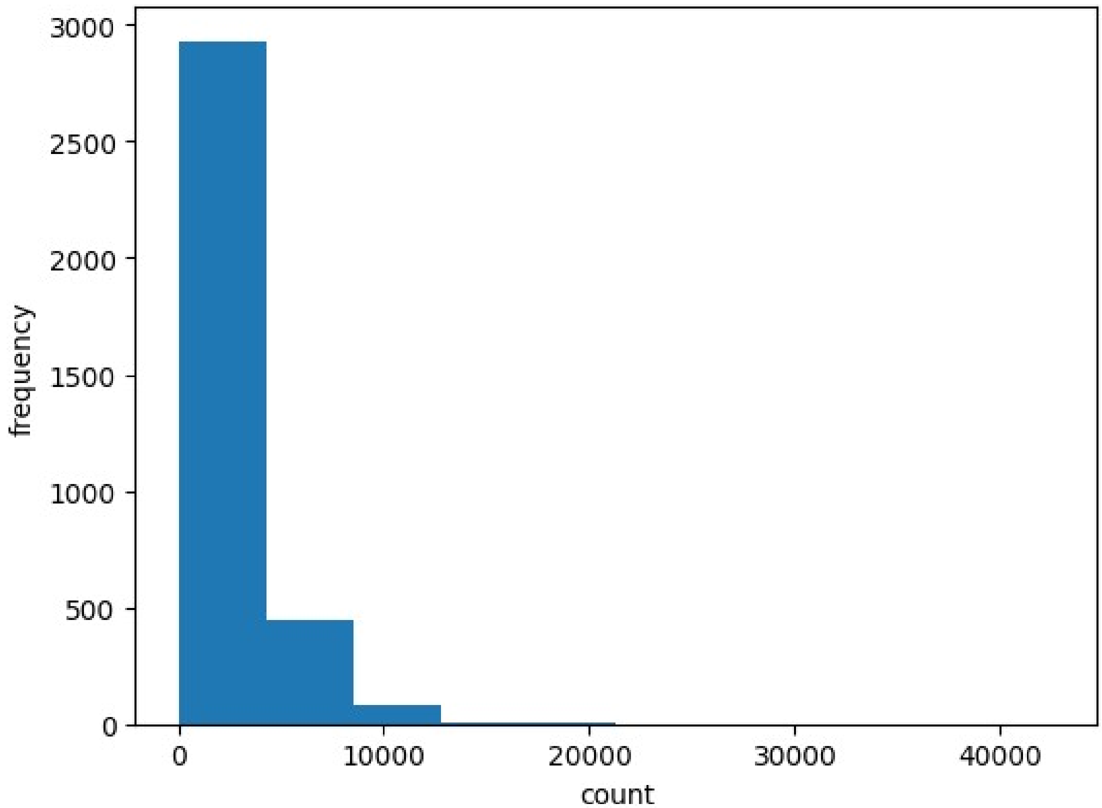
```
df.shape
```

```
(3476, 8)
```

(a) The total number of alpha-numeric characters per data point (row) in the feature full text: i.e count on the x-axis and frequency on the y-axis:

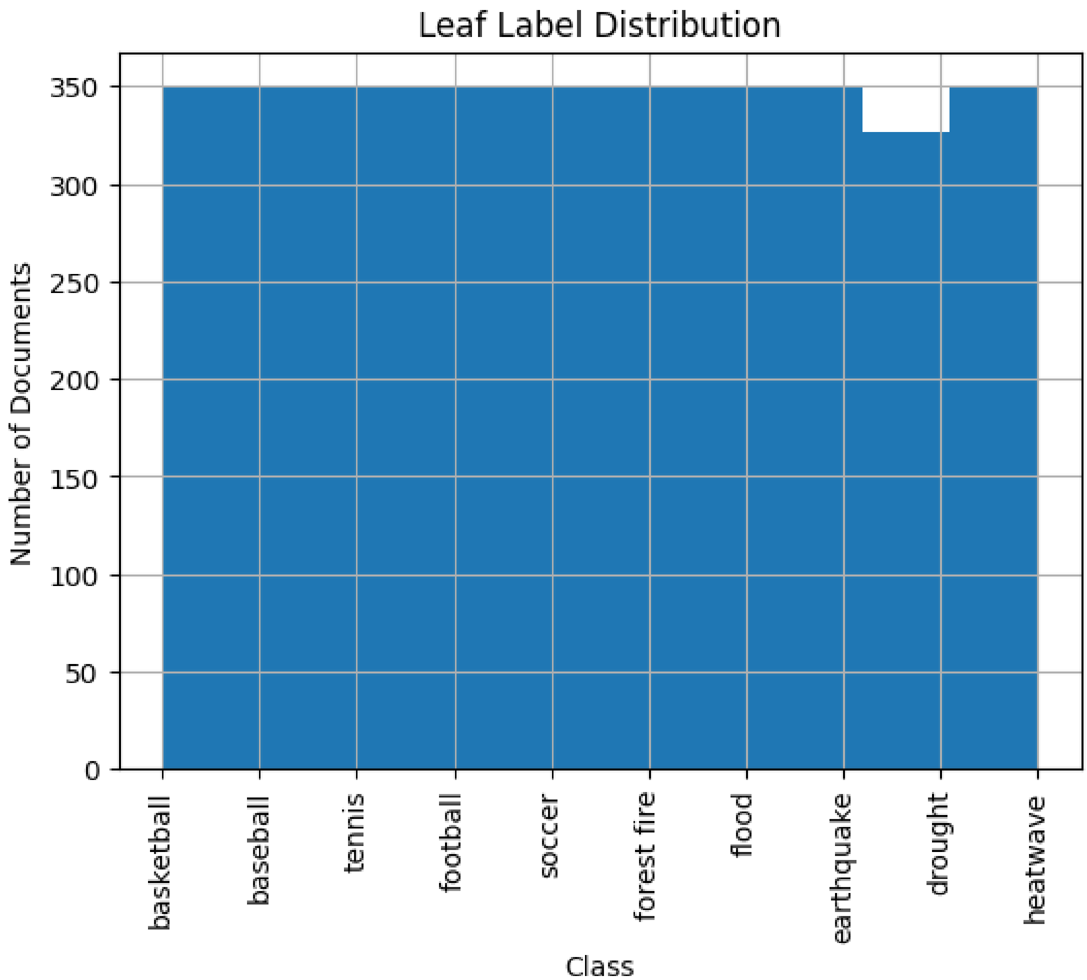
```
def get_alpha_numeric_count(s):
  sum = 0
  for i in s:
    if i.isnumeric():
      sum += 1
    elif i.isalpha():
      sum += 1
  return sum

plt.hist([get_alpha_numeric_count(sent) for sent in df['full_text']])
plt.xlabel('count')
```

```
plt.ylabel('frequency')
plt.show()
```



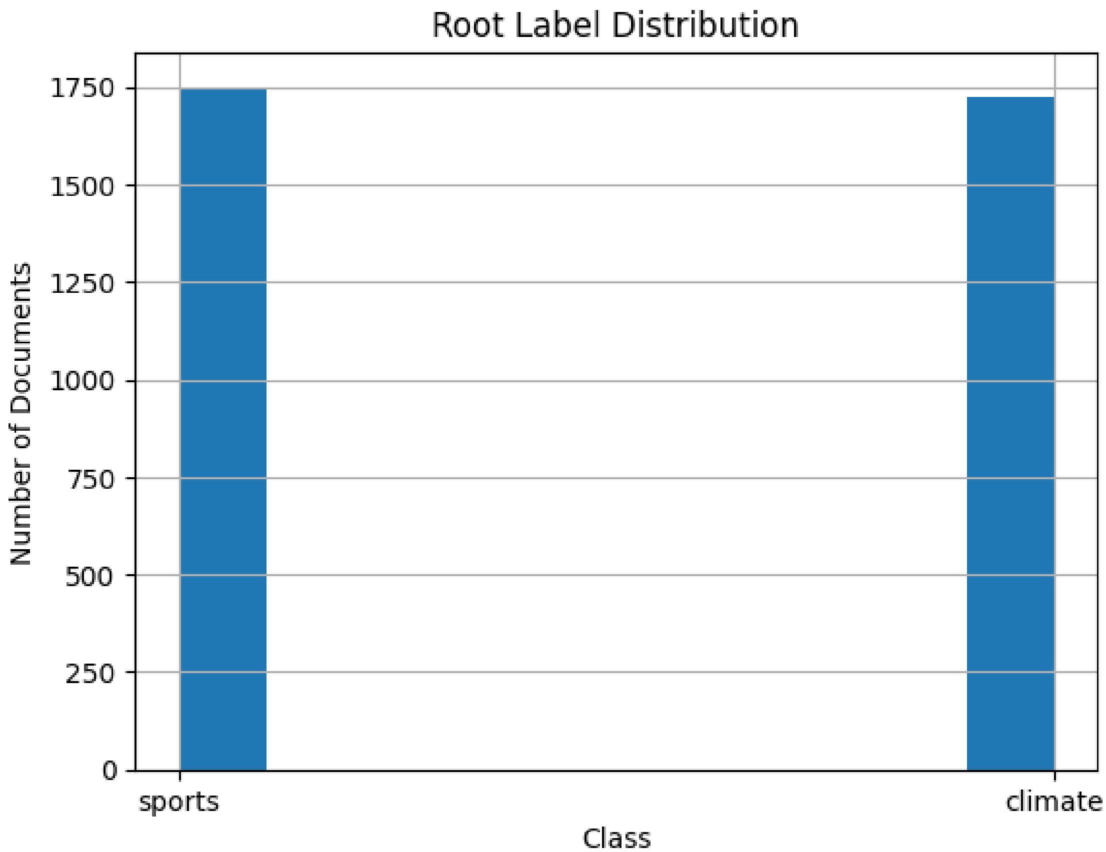
(b) The column leaf label – class on the x-axis:

```
df["leaf_label"].hist(xrot =90)
plt.ylabel('Number of Documents')
plt.xlabel('Class')
plt.title('Leaf Label Distribution')

Text(0.5, 1.0, 'Leaf Label Distribution')
```



(c) The column root label – class on the x-axis:

```
df["root_label"].hist()
plt.ylabel('Number of Documents')
plt.xlabel('Class')
plt.title('Root Label Distribution')

Text(0.5, 1.0, 'Root Label Distribution')
```



Question 1

How many rows (samples) and columns (features) are present in the dataset?

- rows = 3476
- columns = 8

Histograms: Plot 3 histograms on : all three given above

(a) The total number of alpha-numeric characters per data point (row) in the feature full text: i.e count on the x-axis and frequency on the y-axis:

(b) The column leaf label – class on the x-axis:

(c) The column root label – class on the x-axis:

Provide qualitative interpretations of the histograms.

- From the alpha numeric count for the full text feature, we can see that a majority of the rows have an alpha numeric count is less than 10k.
- From the histogram for leaf label, we can see that there is a pretty even distribution of leaf label topics among the entire dataset.

- For the historgram of root label, there is also an even distribution of labels between sports and climate with all the data.

Question 2 : Train & Test set

```
np.random.seed(42)
random.seed(42)

from sklearn.model_selection import train_test_split
train, test = train_test_split(df[["full_text","root_label"]],
test_size=0.2)
```

Question 2

Report the number of training and testing samples.

- training samples = 2780
- testing samples = 696

Question 3 : Data Processing

```
from sklearn.feature_extraction.text import CountVectorizer
import nltk
import re
from nltk.stem import WordNetLemmatizer as wl
from nltk.tag import pos_tag as pt
from nltk import pos_tag
import nltk
wnl = nltk.wordnet.WordNetLemmatizer()
nltk.download('wordnet')
```

```
[nltk_data] Downloading package wordnet to /root/nltk_data...
```

```
True
```

```
def clean(text):
  text = re.sub(r'^https?:\/\/.*[\r\n]*', '', text,
flags=re.MULTILINE)
  texter = re.sub(r"<br />", " ", text)
  texter = re.sub(r"&quot;", "\"",texter)
  texter = re.sub('&#39;', "\"", texter)
  texter = re.sub('\n', " ", texter)
  texter = re.sub(' u '," you ", texter)
  texter = re.sub('`',"", texter)
  texter = re.sub(' +', ' ', texter)
  texter = re.sub(r"(!)\1+", r"!", texter)
  texter = re.sub(r"(\?)\1+", r"?", texter)
  texter = re.sub('&amp;', 'and', texter)
  texter = re.sub('\r', ' ',texter)
  clean = re.compile('<.*?>')
  texter = texter.encode('ascii', 'ignore').decode('ascii')
```

```
  texter = re.sub(clean, '', texter)
  if texter == "":
    texter = ""
  return texter

def penn2morphy(penntag):
    """ Converts Penn Treebank tags to WordNet. """
    morphy_tag = {'NN':'n', 'JJ':'a',
                  'VB':'v', 'RB':'r'}
    try:
        return morphy_tag[penntag[:2]]
    except:
        return 'n'
# def lemmatize_sent_demo(text):
#     # Text input is string, returns array of lowercased
strings(words).
#     return [wnl.lemmatize(word.lower(), pos=penn2morphy(tag))
#             for word, tag in pos_tag(nltk.word_tokenize(text))]
def lemmatize_sent(list_word):
    # Text input is string, returns array of lowercased
strings(words).
    return [wnl.lemmatize(word.lower(), pos=penn2morphy(tag))
            for word, tag in pos_tag(list_word)]

train_clean = train
train_clean['full_text'] = train_clean["full_text"].map(clean)

test_clean = test
test_clean['full_text'] = test_clean["full_text"].map(clean)

from sklearn.feature_extraction import text
stop_words_skt = text.ENGLISH_STOP_WORDS
from nltk.corpus import stopwords
nltk.download('stopwords')
stop_words_en = stopwords.words('english')

from string import punctuation
combined_stopwords =
set.union(set(stop_words_en),set(punctuation),set(stop_words_skt))
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
```

```
nltk.download('averaged_perceptron_tagger')
analyzer = CountVectorizer().build_analyzer()
# def stemmed_words(doc):
#     return (stemmer.stem(w) for w in analyzer(doc))
def stem_rmv_punc(doc):
    return (word for word in lemmatize_sent(analyzer(doc)) if word not
in combined_stopwords and not word.isdigit())
```

```
[nltk_data] Downloading package averaged_perceptron_tagger to
[nltk_data]     /root/nltk_data...
[nltk_data]   Unzipping taggers/averaged_perceptron_tagger.zip.
```

```
from sklearn.feature_extraction.text import CountVectorizer
count_vect = CountVectorizer(min_df=3, analyzer=stem_rmv_punc)

X_train_counts = count_vect.fit_transform(train_clean['full_text'])
print(X_train_counts.shape)
```

```
(2780, 13287)
```

```
X_test_counts = count_vect.transform(test_clean['full_text'])
X_test_counts.shape
```

```
(696, 13287)
```

```
len(count_vect.get_feature_names_out())
```

```
13287
```

```
from sklearn.feature_extraction.text import TfidfTransformer
tfidf_transformer = TfidfTransformer()

# recall that X_train_counts =
count_vect.fit_transform(train_clean['full_text'])
X_train_tfidf = tfidf_transformer.fit_transform(X_train_counts)
X_test_tfidf = tfidf_transformer.fit_transform(X_test_counts)
```

Question 3

• What are the pros and cons of lemmatization versus stemming? How do these processes affect the dictionary size?

- Pros of Lemmatization: provides actual base or roote form of word, preferred for information retrieval tasks
  Cons of Lemmatization: lots of complexity and computational cost
  Pros of Stemming: A lot more simpler and computationally efficient
  Cons of Stemming: Stems produced are not the best and doesn't consider context of the word
- Lemmatization tends to result in a larger dictionary size because there are many grammatical variations for base forms. Stemming tends to result in a shorter size because it reduces words to basic stems, which isn't as large of a variety.

• min df means minimum document frequency. How does varying min df change the TF-IDF matrix?

- Higher min df is more selective which reduces the size of the TF-IDF matrix because it focuses on terms that are more common across documents. This can result in a sparse matrix with fewer entries. Lower min df is less selective and increases the size of the TF-IDF matrix because of the larger vocabulary. This can result in a denser matrix.

• Should I remove stopwords before or after lemmatizing? Should I remove punctuations before or after lemmatizing? Should I remove numbers before or after lemmatizing? Hint: Recall that the full sentence is input into the Lemmatizer and the lemmatizer is tagging the position of every word based on the sentence structure.

- The goal of lemmatization is to reduce a word to its root form and it considers the context of the given sentence to do this. Removing stopwords, numbers, and puctuations can destroy this context of the sentence. Therefore we should remove stopwords, punctuations, and numbers after lemmitization.

• Report the shape of the TF-IDF-processed train and test matrices. The number of rows should match the results of Question 2. The number of columns should roughly be in the order of kx10^3

- Test Matrix Shape: (696, 13447)
- Train Matrix Shape: (2780, 13447)

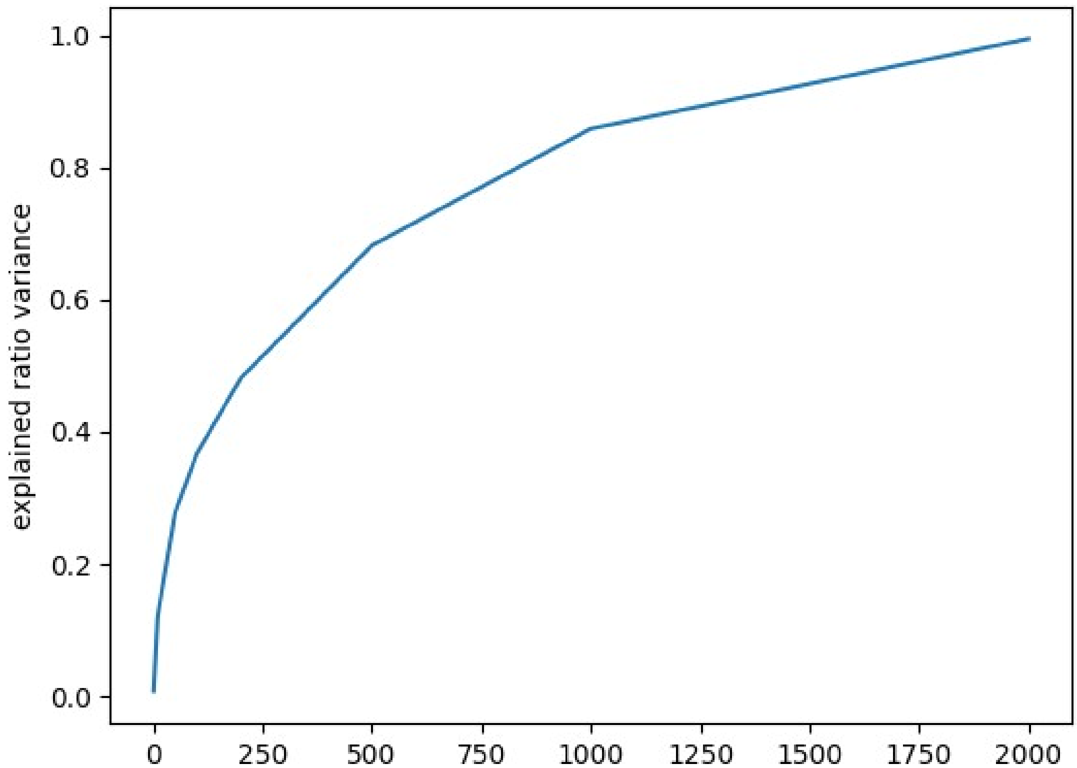
3 Dimensionality Reduction

Question 4 : Variance ration, LSI vs NMF

```
# SVD explained variance ratio
from sklearn.decomposition import TruncatedSVD

svd_evr = TruncatedSVD(n_components=2000, random_state=42)
X_train_reduced = svd_evr.fit_transform(X_train_tfidf)
X_test_reduced = svd_evr.transform(X_test_tfidf)

evr = svd_evr.explained_variance_ratio_.cumsum()
print(evr)
evr = [evr[0], evr[9], evr[49], evr[99], evr[199], evr[499], evr[999], evr[1999]]
print(evr)

[0.00662305 0.03175044 0.05072009 ... 0.99433506 0.99438054
0.99442597]
[0.006623049555206013, 0.11891044717685503, 0.2762839437404552,
0.3664451621024311, 0.48035018325651796, 0.6815508993223091,
0.8583092988811805, 0.9944259662780556]

#from matplotlib import pyplot as plt
x = [1, 10, 50, 100, 200, 500, 1000, 2000]
```

```
plt.plot(x, evr)
plt.ylabel('explained ratio variance')
```

```
Text(0, 0.5, 'explained ratio variance')
```




```
# LSI
from sklearn.decomposition import TruncatedSVD

svd = TruncatedSVD(n_components=50, random_state=42)
X_train_LSI = svd.fit_transform(X_train_tfidf)
X_test_LSI = svd.transform(X_test_tfidf)
print(X_train_LSI.shape)
print(X_test_LSI.shape)
```

```
(2780, 50)
(696, 50)
```

```
from sklearn.utils.extmath import randomized_svd
from sklearn.decomposition import NMF

U,S,V = randomized_svd(X_train_tfidf, n_components=50, random_state =
42)
error = np.sum(np.array(X_train_tfidf - U.dot(np.diag(S)).dot(V))**2)
print("LSI error:", error)
nmf = NMF(n_components=50, random_state = 42)
```

```
X_train_NMF = nmf.fit_transform(X_train_tfidf)
X_test_NMF = nmf.fit_transform(X_test_tfidf)
error = np.sum(np.array(X_train_tfidf -
X_train_NMF.dot(nmf.components_))**2)
print("NMF error:", error)
```

```
LSI error: 1947.5144800015685
NMF error: 3118.7340213205093
```

Question 4

• Plot the explained variance ratio across multiple different k = [1, 10, 50, 100, 200, 500, 1000, 2000] for LSI and for the next few sections choose k = 50. What does the explained variance ratio plot look like? What does the plot's concavity suggest?

- Explained variance ratio plotted above!
- The explained variance ratio plot looks like it is concave down. The reason for this is because the more principal components we add the more data can be explained but the rate at which each additional principal component contributes to the explained variance diminishes.

• With k = 50 found in the previous sections, calculate the reconstruction residual MSE error when using LSI and NMF they both should use the same k = 50. Which one is larger, the NMF or the LSI and why?

- NMF residual error: 3078.0556638139406
- LSI residual error: 1946.6620651321361
- The NMF error is larger than LSI's. Some reasons include: NMF enforces a non-negativity constraint on the factorized matrices, NMF tends to produce sparser representations compared to LSI, and NMF is sensitive to the initial values of the factorized matrice.

4 Classification Algorithmns

Question 5 : SVM

```
from sklearn.metrics import confusion_matrix, accuracy_score,
recall_score, precision_score, f1_score, roc_curve, auc
def plot_roc(fpr, tpr):
    fig, ax = plt.subplots()

    roc_auc = auc(fpr,tpr)
```

```
    ax.plot(fpr, tpr, lw=2, label= 'area under curve = %0.4f' %
roc_auc)

    ax.grid(color='0.7', linestyle='--', linewidth=1)

    ax.set_xlim([-0.1, 1.1])
    ax.set_ylim([0.0, 1.05])
    ax.set_xlabel('False Positive Rate',fontsize=15)
    ax.set_ylabel('True Positive Rate',fontsize=15)

    ax.legend(loc="lower right")

    for label in ax.get_xticklabels()+ax.get_yticklabels():
        label.set_fontsize(15)

def fit_predict_and_plot_roc(pipe, train_data, train_label, test_data,
test_label):
    pipe.fit(train_data, train_label)

    if hasattr(pipe, 'decision_function'):
        prob_score = pipe.decision_function(test_data)
        fpr, tpr, _ = roc_curve(test_label, prob_score)
    else:
        prob_score = pipe.predict_proba(test_data)
        fpr, tpr, _ = roc_curve(test_label, prob_score[:,1])

    plot_roc(fpr, tpr)

from sklearn.svm import LinearSVC, SVC

# fit on LSI data not tfidf data fixed issue
hard_svm = SVC(C=1000, kernel='linear', random_state=42,
probability=True)
hard_svm_predicted = hard_svm.fit(X_train_LSI,
train['root_label']).predict(X_test_LSI)
soft_svm = SVC(C=0.0001, kernel='linear', random_state=42,
probability=True)
soft_svm_predicted = soft_svm.fit(X_train_LSI,
train['root_label']).predict(X_test_LSI)
extra_svm = SVC(C=100000, kernel='linear', random_state=42,
probability=True)
extra_svm_predicted = extra_svm.fit(X_train_LSI,
train['root_label']).predict(X_test_LSI)

print(hard_svm_predicted.shape)
```

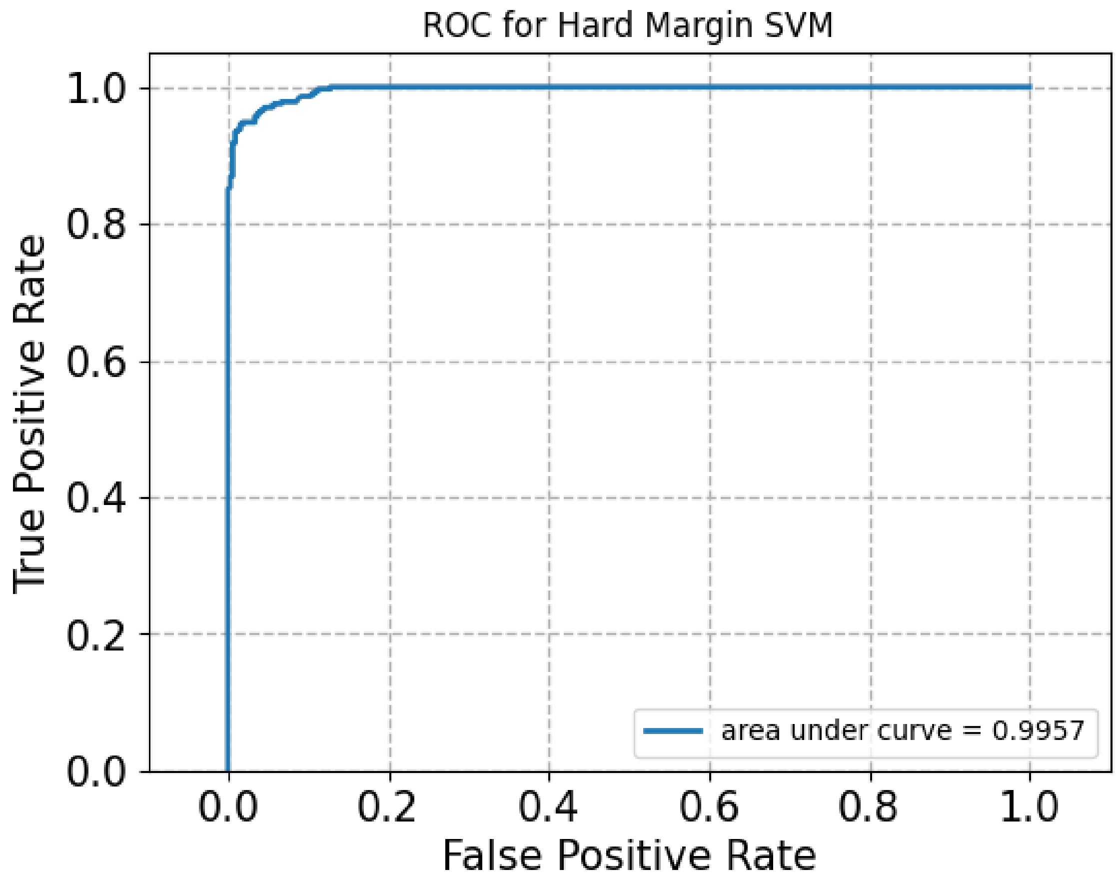
```
(696,)
```

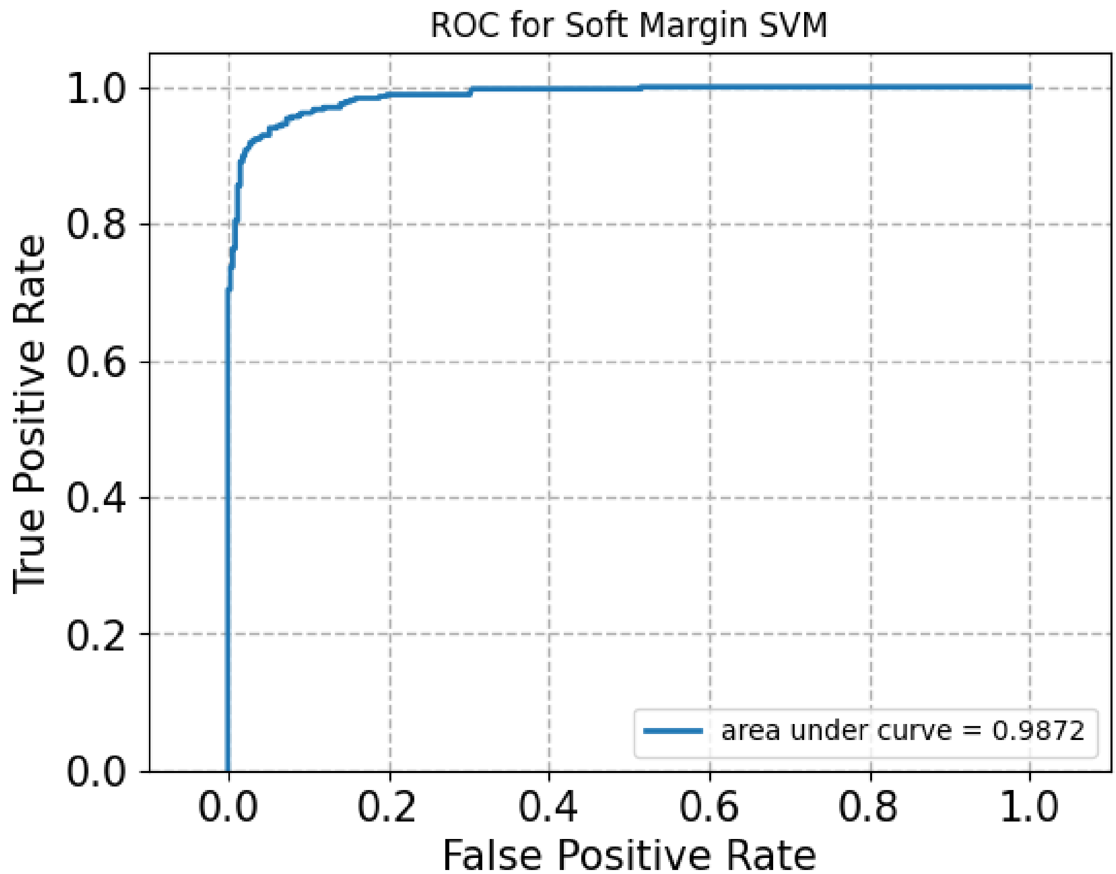
```
print(len(test['root_label']))
print(len(hard_svm_predicted))
```

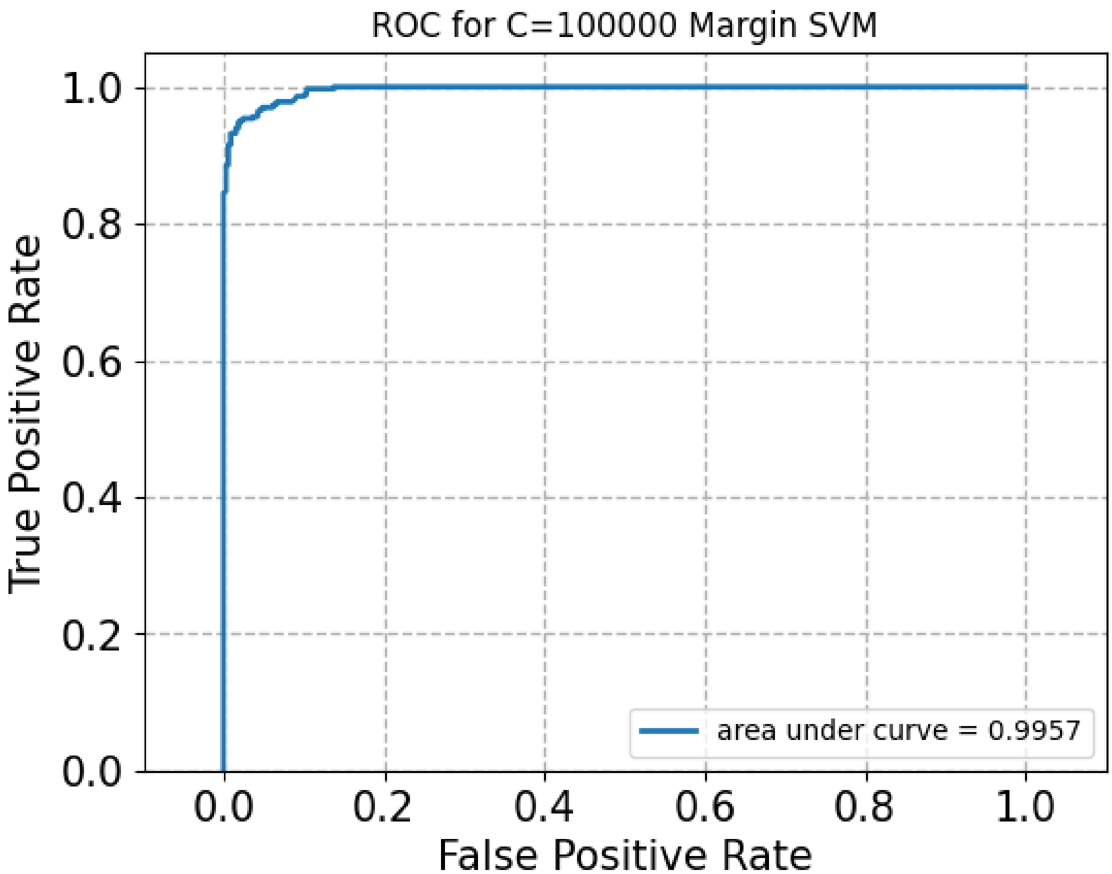
```
696
696
```

```python
import numpy as np
from sklearn import metrics
fpr_hard, tpr_hard, thresholds_hard =
metrics.roc_curve(test['root_label'],
hard_svm.decision_function(X_test_LSI), pos_label= 'sports')
fpr_soft, tpr_soft, thresholds_soft =
metrics.roc_curve(test['root_label'],
soft_svm.decision_function(X_test_LSI), pos_label= 'sports')
fpr_extra, tpr_extra, thresholds_extra =
metrics.roc_curve(test['root_label'],
extra_svm.decision_function(X_test_LSI), pos_label= 'sports')

plot_roc(fpr_hard, tpr_hard)
plt.title('ROC for Hard Margin SVM')

plot_roc(fpr_soft, tpr_soft)
plt.title('ROC for Soft Margin SVM')

plot_roc(fpr_extra, tpr_extra)
plt.title('ROC for C=100000 Margin SVM')
```

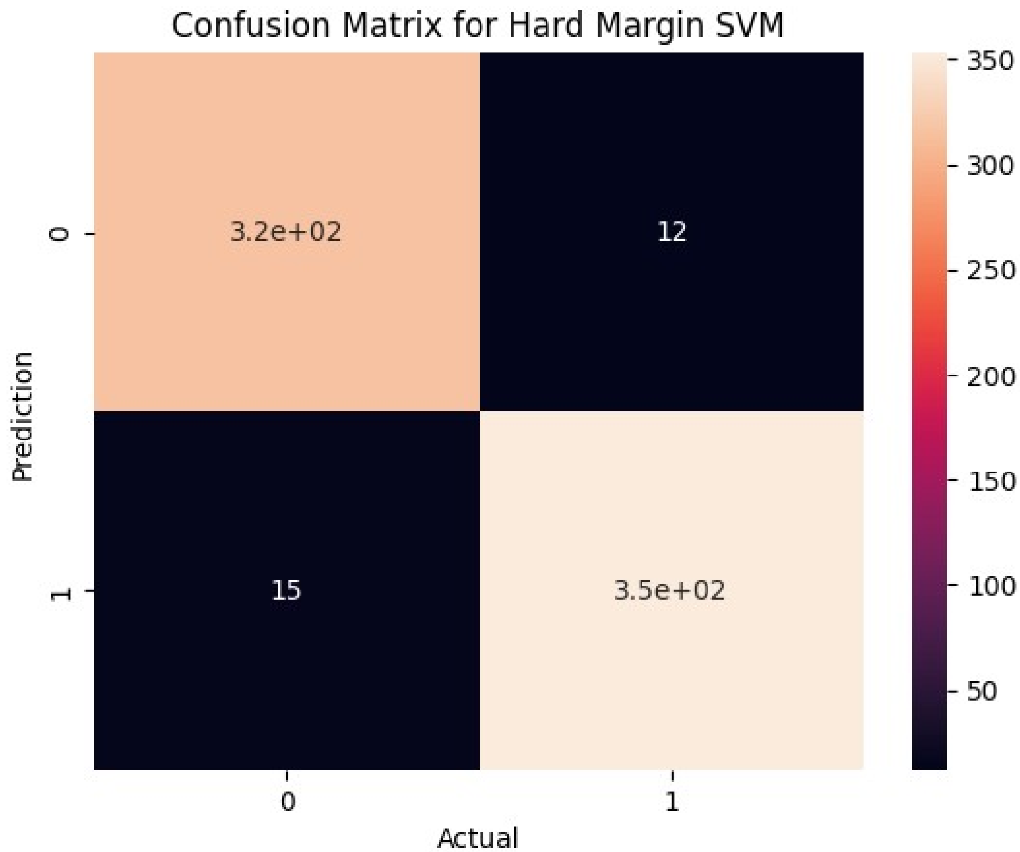
```
Text(0.5, 1.0, 'ROC for C=100000 Margin SVM')
```


ROC for Hard Margin SVM
True Positive Rate
False Positive Rate
area under curve = 0.9957
0.0
0.2
0.4
0.6
0.8
1.0

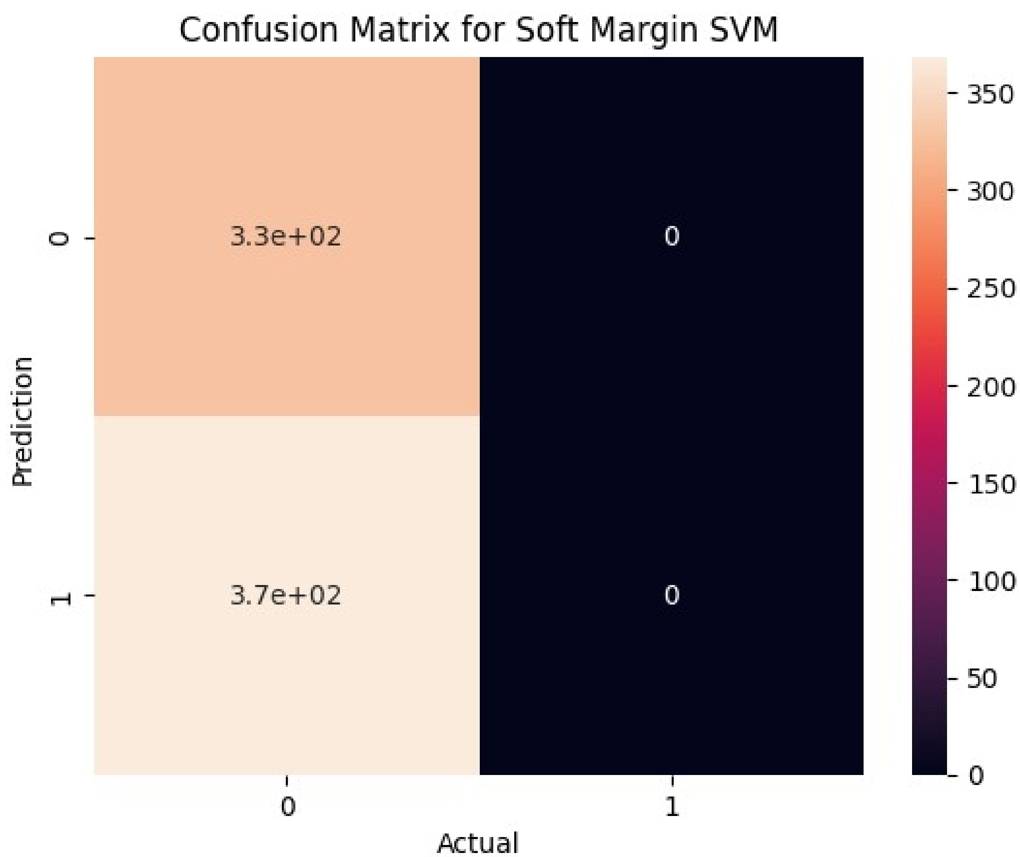

ROC for Soft Margin SVM
True Positive Rate
False Positive Rate
area under curve = 0.9872
0.0
0.2
0.4
0.6
0.8
1.0



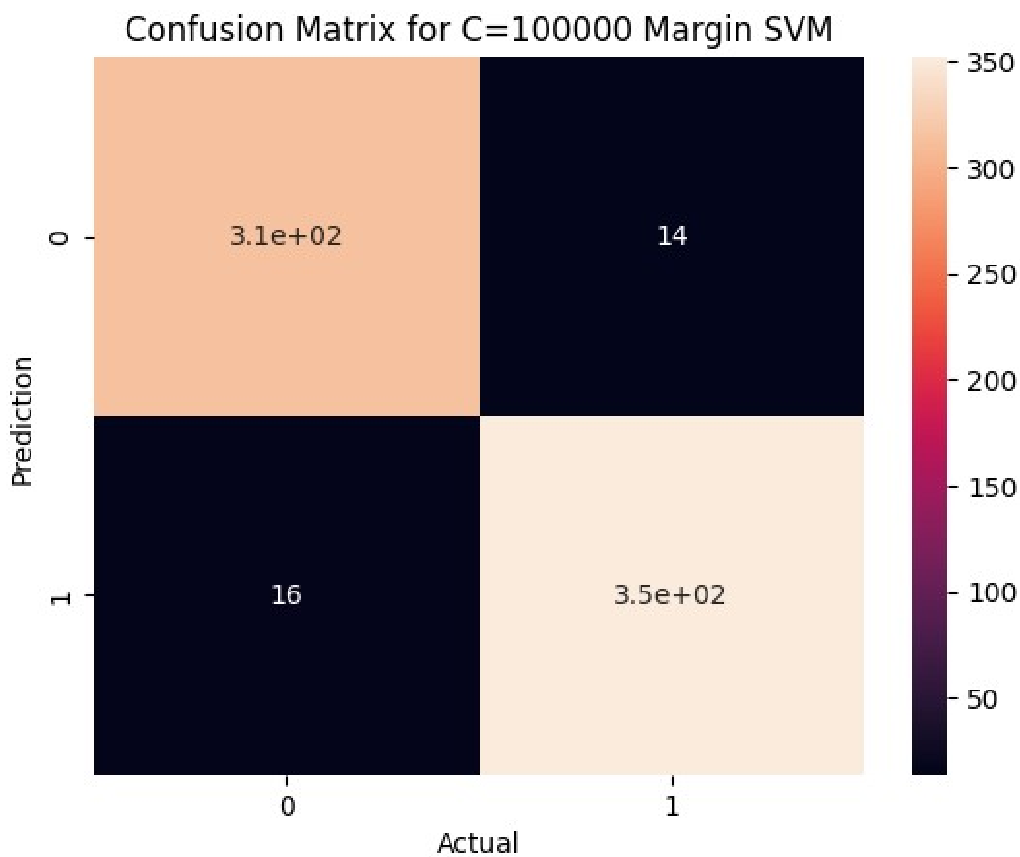

```
import seaborn as sns
cm = confusion_matrix(test['root_label'],hard_svm_predicted)
sns.heatmap(cm,annot=True)
plt.ylabel('Prediction')
plt.xlabel('Actual')
plt.title('Confusion Matrix for Hard Margin SVM')
plt.show()
```




```
cm = confusion_matrix(test['root_label'],soft_svm_predicted)
sns.heatmap(cm,annot=True)
plt.ylabel('Prediction')
plt.xlabel('Actual')
plt.title('Confusion Matrix for Soft Margin SVM')
plt.show()
```




```
cm = confusion_matrix(test['root_label'],extra_svm_predicted)
sns.heatmap(cm,annot=True)
plt.ylabel('Prediction')
plt.xlabel('Actual')
plt.title('Confusion Matrix for C=100000 Margin SVM')
plt.show()
```




```
print("Precision for Hard SVM:",
precision_score(test['root_label'],hard_svm_predicted, pos_label=
'sports'))
print("Precision for Soft SVM:",
precision_score(test['root_label'],soft_svm_predicted, pos_label=
'sports'))
print("Precision for C=100000 SVM:",
precision_score(test['root_label'],extra_svm_predicted, pos_label=
'sports'))


print("F1-Score for Hard SVM:",
f1_score(test['root_label'],hard_svm_predicted, pos_label= 'sports'))
print("F1-Score for Soft SVM:",
f1_score(test['root_label'],soft_svm_predicted, pos_label= 'sports'))
print("F1-Score for C=100000 SVM:",
f1_score(test['root_label'],extra_svm_predicted, pos_label= 'sports'))

print("Accuracy for Hard SVM:",
accuracy_score(test['root_label'],hard_svm_predicted))
print("Accuracy for Soft SVM:",
accuracy_score(test['root_label'],soft_svm_predicted))
print("Accuracy for C=100000 SVM:",
```

```
accuracy_score(test['root_label'],extra_svm_predicted))

print("Recall for Hard SVM:",
recall_score(test['root_label'],hard_svm_predicted, pos_label=
'sports'))
print("Recall for Soft SVM:",
recall_score(test['root_label'],soft_svm_predicted, pos_label=
'sports'))
print("Recall for C=100000 SVM:",
recall_score(test['root_label'],extra_svm_predicted, pos_label=
'sports'))
```

```
Precision for Hard SVM: 0.9671232876712329
Precision for Soft SVM: 0.0
Precision for C=100000 SVM: 0.9617486338797814
F1-Score for Hard SVM: 0.9631650750341064
F1-Score for Soft SVM: 0.0
F1-Score for C=100000 SVM: 0.9591280653950953
Accuracy for Hard SVM: 0.9612068965517241
Accuracy for Soft SVM: 0.47126436781609193
Accuracy for C=100000 SVM: 0.9568965517241379
Recall for Hard SVM: 0.9592391304347826
Recall for Soft SVM: 0.0
Recall for C=100000 SVM: 0.9565217391304348
```

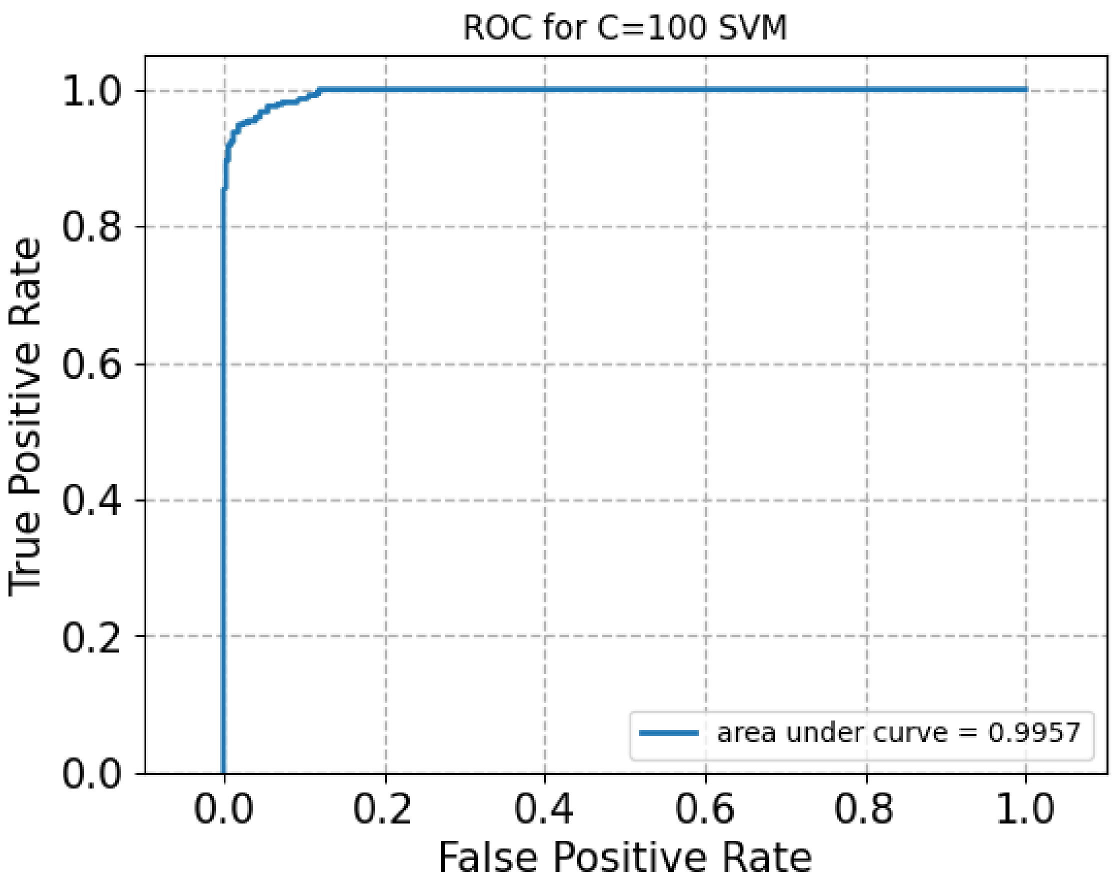
```
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/
_classification.py:1344: UndefinedMetricWarning: Precision is ill-
defined and being set to 0.0 due to no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

```
from sklearn.model_selection import GridSearchCV
svm_cv = SVC(kernel='linear', random_state=42)
params = {'C': [0.001,0.01,0.1,1,10,100,1000, 10000, 100000, 1000000]}
grid_search = GridSearchCV(svm_cv,params,cv=5,scoring='accuracy')
grid_search.fit(X_train_LSI,train['root_label'])
predictions_cv = grid_search.best_estimator_.predict(X_test_LSI)
print('Best Value of gamma:',grid_search.best_params_['C'])
```

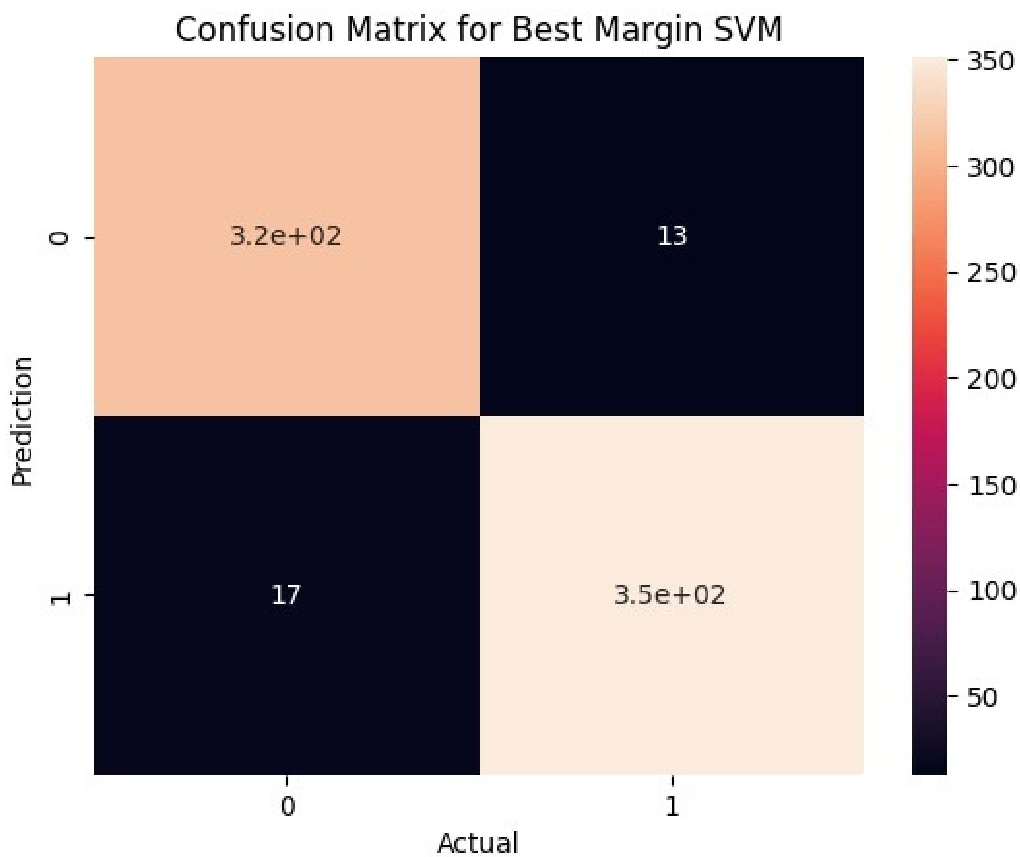
```
Best Value of gamma: 100
```

```
best_svm = SVC(C=100,kernel='linear', random_state=42,
probability=True)
best_svm_predicted = best_svm.fit(X_train_LSI,
train['root_label']).predict(X_test_LSI)
fpr_extra, tpr_extra, thresholds_extra =
metrics.roc_curve(test['root_label'],
best_svm.decision_function(X_test_LSI), pos_label= 'sports')
plot_roc(fpr_extra, tpr_extra)
plt.title('ROC for C=100 SVM')
```

```
Text(0.5, 1.0, 'ROC for C=100 SVM')
```




```
cm = confusion_matrix(test['root_label'],best_svm_predicted)
sns.heatmap(cm,annot=True)
plt.ylabel('Prediction')
plt.xlabel('Actual')
plt.title('Confusion Matrix for Best Margin SVM')
plt.show()
```




```
print("Precision for C=100 SVM:",
precision_score(test['root_label'],best_svm_predicted, pos_label=
'sports'))
print("F1-Score for C=100 SVM:",
f1_score(test['root_label'],best_svm_predicted, pos_label= 'sports'))
print("Accuracy for C=100 SVM:",
accuracy_score(test['root_label'],best_svm_predicted))
print("Recall for C=100 SVM:",
recall_score(test['root_label'],best_svm_predicted, pos_label=
'sports'))
```

```
Precision for C=100 SVM: 0.9642857142857143
F1-Score for C=100 SVM: 0.9590163934426229
Accuracy for C=100 SVM: 0.9568965517241379
Recall for C=100 SVM: 0.9538043478260869
```

Question 5

Compare and contrast hard-margin and soft-margin linear SVMs:

• Train two linear SVMs:
-Train one SVM with γ = 1000 (hard margin), another with γ = 0.0001 (soft margin).
-Plot the ROC curve, report the confusion matrix and calculate the accuracy, recall, precision and

F-1 score of both SVM classifiers on the testing set. Which one performs better? What about for γ = 100000?

- In 3 of the 4 metrics(recall, accuracy, f1-score), hard svm performed better, but in terms of precision soft svm performed better. When C=100000, it performed better than Soft SVM in all metrics except precision. However for C=100000, it performed worse on all metrics except recall

• What happens for the soft margin SVM? Why is the case? Analyze in terms of the confusion matrix.

- The soft margin SVM performs poorly and can be seen in the confusion matrix, especially when predicting correctly on class label 1. This is because when gamma is very small(0.0001) the first term in the objective function has a larger impact so there is a higher misclassification rate towards some of the points. This is reflected in the confusion matrix when there are predicitons being made and the model is not able to predict correctly for one class at all, based on both the 0s shown in the matrix.

• Does the ROC curve reflect the performance of the soft-margin SVM? Why?

- The ROC curve does not reflect the performance of the soft-margin SVM because even though the hard-margin SVM and soft-margin SVM have similar ROC curves, the confusion matrix shows how poorly soft-margin performs when predicting for class=1. The ROC curve for soft-margin SVM looks really good because its true positive rate or recall is very high and consistent even when the threshold changes.

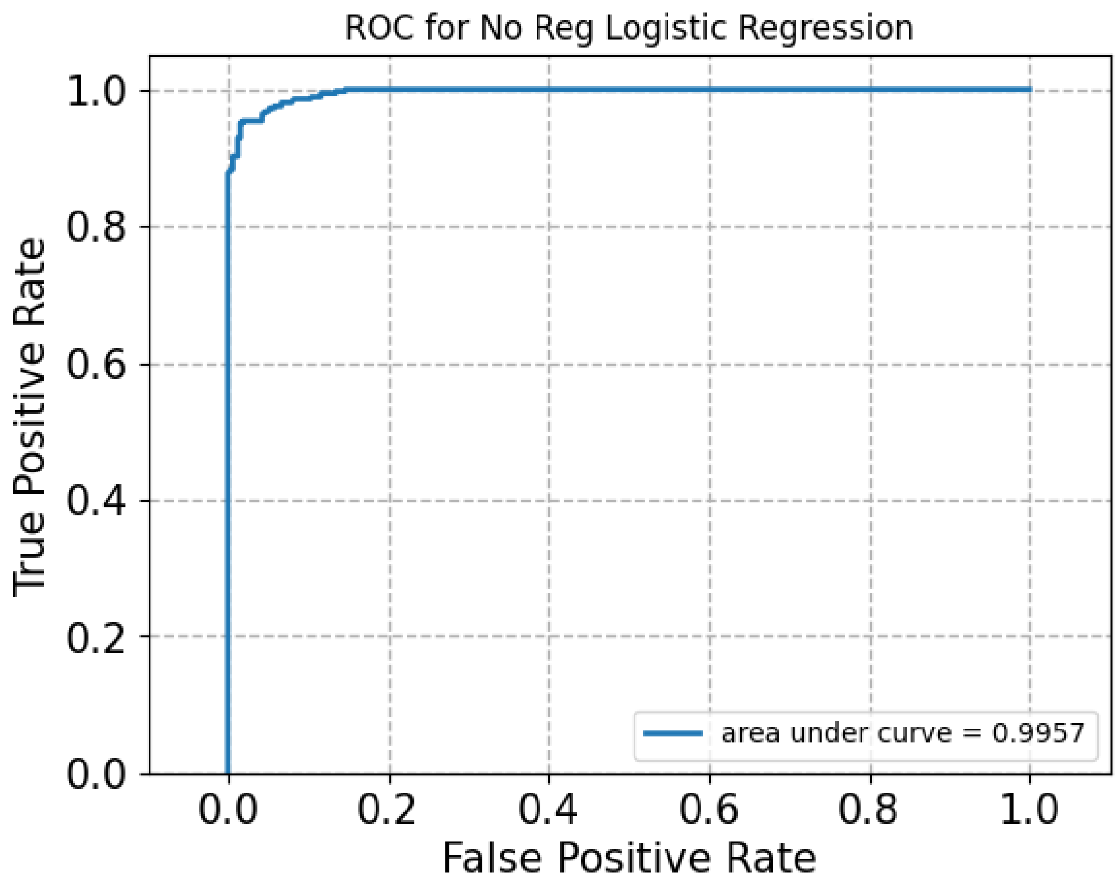
• Use cross-validation to choose γ (use average validation 3 accuracy to compare): Using a 5-fold cross-validation, find the best value of the parameter γ in the range {10k| − 3 ≤ k ≤ 6, k ∈ Z}. Again, plot the ROC curve and report the confusion matrix and calculate the accuracy, recall precision and F-1 score of this best SVM.

- The best parameter for γ is 100.

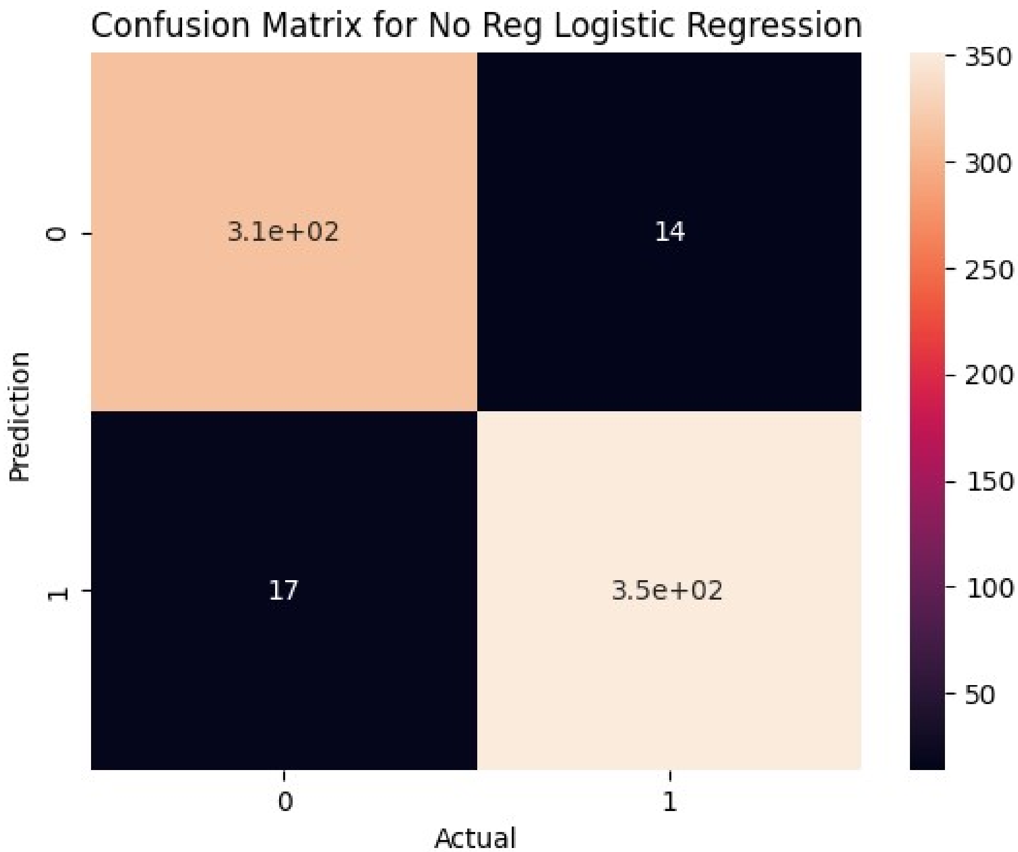
Question 6 : Logistic Regression

```
from sklearn.linear_model import LogisticRegression

lr_no_reg = LogisticRegression(C=1e10,random_state=42, max_iter=1000)
lr_no_reg_predicted =
lr_no_reg.fit(X_train_LSI,train['root_label']).predict(X_test_LSI)
fpr_extra, tpr_extra, thresholds_extra =
metrics.roc_curve(test['root_label'],
lr_no_reg.decision_function(X_test_LSI), pos_label= 'sports')
plot_roc(fpr_extra, tpr_extra)
plt.title('ROC for No Reg Logistic Regression')
```

```
Text(0.5, 1.0, 'ROC for No Reg Logistic Regression')
```




```
cm = confusion_matrix(test['root_label'],lr_no_reg_predicted)
sns.heatmap(cm,annot=True)
plt.ylabel('Prediction')
plt.xlabel('Actual')
plt.title('Confusion Matrix for No Reg Logistic Regression')
plt.show()
```




```
l1_lr_cv = LogisticRegression(penalty='l1', random_state=42,
max_iter=1000, solver='liblinear')
params = {'C': [0.00001,0.00001,0.001,0.01,0.1,1,10,100,1000, 10000,
100000]}
grid_search = GridSearchCV(l1_lr_cv,params,cv=5,scoring='accuracy')
grid_search.fit(X_train_LSI,train['root_label'])
predictions_cv = grid_search.best_estimator_.predict(X_test_LSI)
print('Best Value of gamma:',grid_search.best_params_['C'])
```

```
Best Value of gamma: 10
```

```
l2_lr_cv = LogisticRegression(penalty='l2', random_state=42,
max_iter=1000, solver='liblinear')
params = {'C': [0.00001,0.00001,0.001,0.01,0.1,1,10,100,1000, 10000,
100000]}
grid_search = GridSearchCV(l2_lr_cv,params,cv=5,scoring='accuracy')
grid_search.fit(X_train_LSI,train['root_label'])
predictions_cv = grid_search.best_estimator_.predict(X_test_LSI)
print('Best Value of gamma:',grid_search.best_params_['C'])
```

```
Best Value of gamma: 10
```

```
lr_l1_reg = LogisticRegression(penalty='l1', C=10,random_state=42,
max_iter=1000, solver='liblinear')
```

```
lr_l1_reg_predicted =
lr_l1_reg.fit(X_train_LSI,train['root_label']).predict(X_test_LSI)
lr_l2_reg = LogisticRegression(penalty='l2', C=10,random_state=42,
max_iter=1000)
lr_l2_reg_predicted =
lr_l2_reg.fit(X_train_LSI,train['root_label']).predict(X_test_LSI)

print("Precision for No Reg Logistic Regression:",
precision_score(test['root_label'],lr_no_reg_predicted, pos_label=
'sports'))
print("Precision for L1 Reg Logistic Regression",
precision_score(test['root_label'],lr_l1_reg_predicted, pos_label=
'sports'))
print("Precision for L2 Reg Logistic Regression",
precision_score(test['root_label'],lr_l2_reg_predicted, pos_label=
'sports'))


print("F1-Score for No Reg Logistic Regression:",
f1_score(test['root_label'],lr_no_reg_predicted, pos_label= 'sports'))
print("F1-Score for L1 Reg Logistic Regression:",
f1_score(test['root_label'],lr_l1_reg_predicted, pos_label= 'sports'))
print("F1-Score for L2 Reg Logistic Regression:",
f1_score(test['root_label'],lr_l2_reg_predicted, pos_label= 'sports'))

print("Accuracy for No Reg Logistic Regression:",
accuracy_score(test['root_label'],lr_no_reg_predicted))
print("Accuracy for L1 Reg Logistic Regression:",
accuracy_score(test['root_label'],lr_l1_reg_predicted))
print("Accuracy for L2 Reg Logistic Regression:",
accuracy_score(test['root_label'],lr_l2_reg_predicted))

print("Recall for No Reg Logistic Regression:",
recall_score(test['root_label'],lr_no_reg_predicted, pos_label=
'sports'))
print("Recall for L1 Reg Logistic Regression:",
recall_score(test['root_label'],lr_l1_reg_predicted, pos_label=
'sports'))
print("Recall for L2 Reg Logistic Regression:",
recall_score(test['root_label'],lr_l2_reg_predicted, pos_label=
'sports'))
```

```
Precision for No Reg Logistic Regression: 0.9616438356164384
Precision for L1 Reg Logistic Regression 0.967032967032967
Precision for L2 Reg Logistic Regression 0.9643835616438357
F1-Score for No Reg Logistic Regression: 0.9577080491132333
F1-Score for L1 Reg Logistic Regression: 0.9617486338797815
F1-Score for L2 Reg Logistic Regression: 0.9604365620736699
Accuracy for No Reg Logistic Regression: 0.9554597701149425
Accuracy for L1 Reg Logistic Regression: 0.9597701149425287
```

```
Accuracy for L2 Reg Logistic Regression: 0.9583333333333334
Recall for No Reg Logistic Regression: 0.9538043478260869
Recall for L1 Reg Logistic Regression: 0.9565217391304348
Recall for L2 Reg Logistic Regression: 0.9565217391304348
```

QUESTION 6

• Train a logistic classifier without regularization (you may need to come up with some way to approximate this if you use sklearn.linear model.LogisticRegression); plot the ROC curve and report the confusion matrix and calculate the accuracy, recall precision and F-1 score of this classifier on the testing set.

• Find the optimal regularization coefficient:

- Using 5-fold cross-validation on the dimension-reduced-by-SVD training data, find the optimal regularization strength in the range {10k|−5 ≤ k ≤ 5, k ∈ Z} for logistic regression with L1 regularization and logistic regression with L2 regularization, respectively.
  - shown above

- Compare the performance (accuracy, precision, recall and F-1 score) of 3 logistic classifiers: w/o regularization, w/ L1 regularization and w/ L2 regularization (with the best parameters you found from the part above), using test data.
  - L1 Regularization performed the best on Precision, F1-Score, Accuracy and tied with L2 Regularuzation on Recall.

- How does the regularization parameter affect the test error? How are the learnt coefficients affected? Why might one be interested in each type of regularization?
  - The regularization parameter in L1 and L2 regularization lowers the test error. In L1 Regularization the penalty term is the sum of the absolute values of the coefficients, whereas in L2 Regularization its the sum of the squares of coefficients. In L1 Regularization, some of the learned coefficients become exactly zero, which completely get rid of impact of some features. In L2 Regularization, more likely makes the learned coefficients very close to 0 but not exactly 0, reducing impact of some features. It's better to use L1 Regularization for feature elimination, when features are irrelevant or redundant. It's better to use L2 Regularization when you want to reduced impact of correlated predictors.

- Both logistic regression and linear SVM are trying to classify data points using a linear decision boundary. What is the difference between their ways to find this boundary? Why do their performances differ? Is this difference statistically significant?

- For logistic regression, the decision boundary comes from the logistic function and is chosen to maximize the liklihood of the observed data being correctly classified. However, for SVM, the decision boundary comes from the hyperplae that maximizes the margin, which support vectors influence a lot. Performance-wise, SVM are generally more sensitive to outliers, which affect the hyperplane chosen, and tend to perform well on clearly linearly separable data. Logistic regression performs better on cases when the data is not as linearly separable, and is not as sensitive to outliers compared to SVM. The difference in performance can be statistically determined based on important factors like: cross validation, perform t-test or paired test using performance metric, metric choice, quality of data, and outliers.

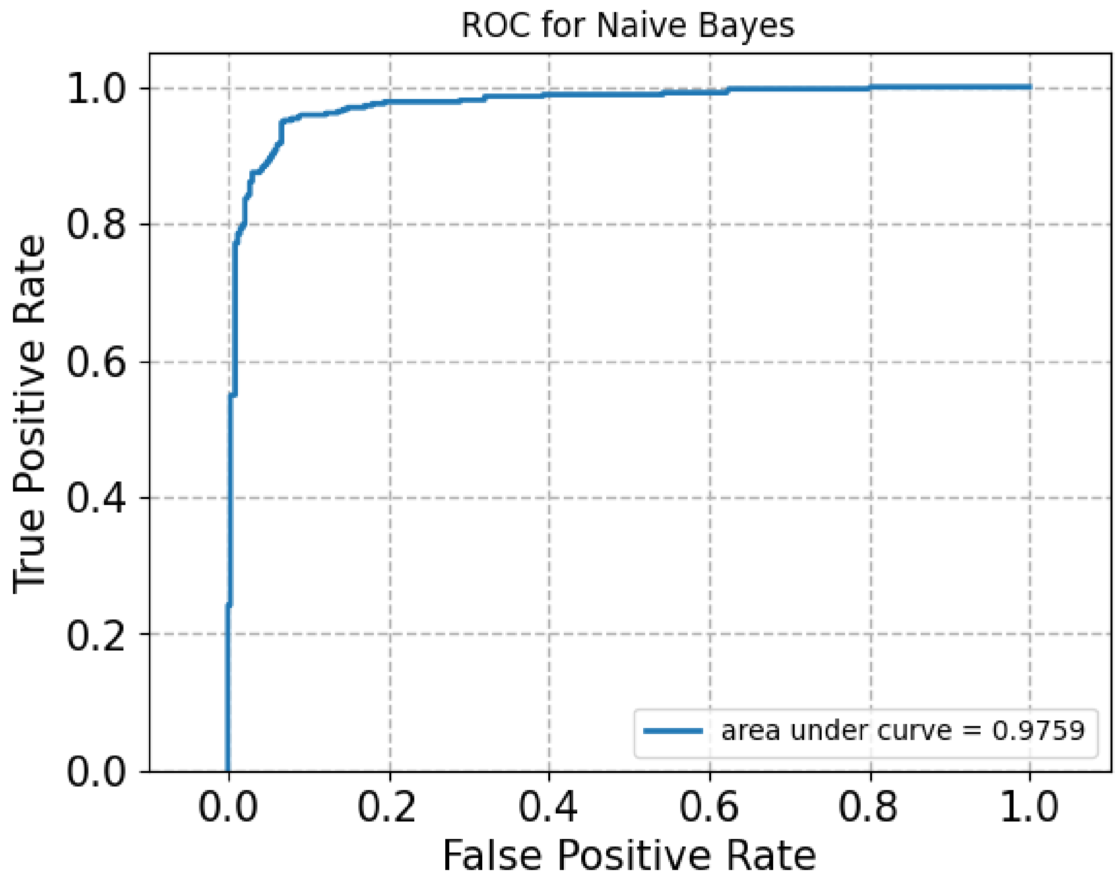
Question 7 : GaussianNB

QUESTION 7:

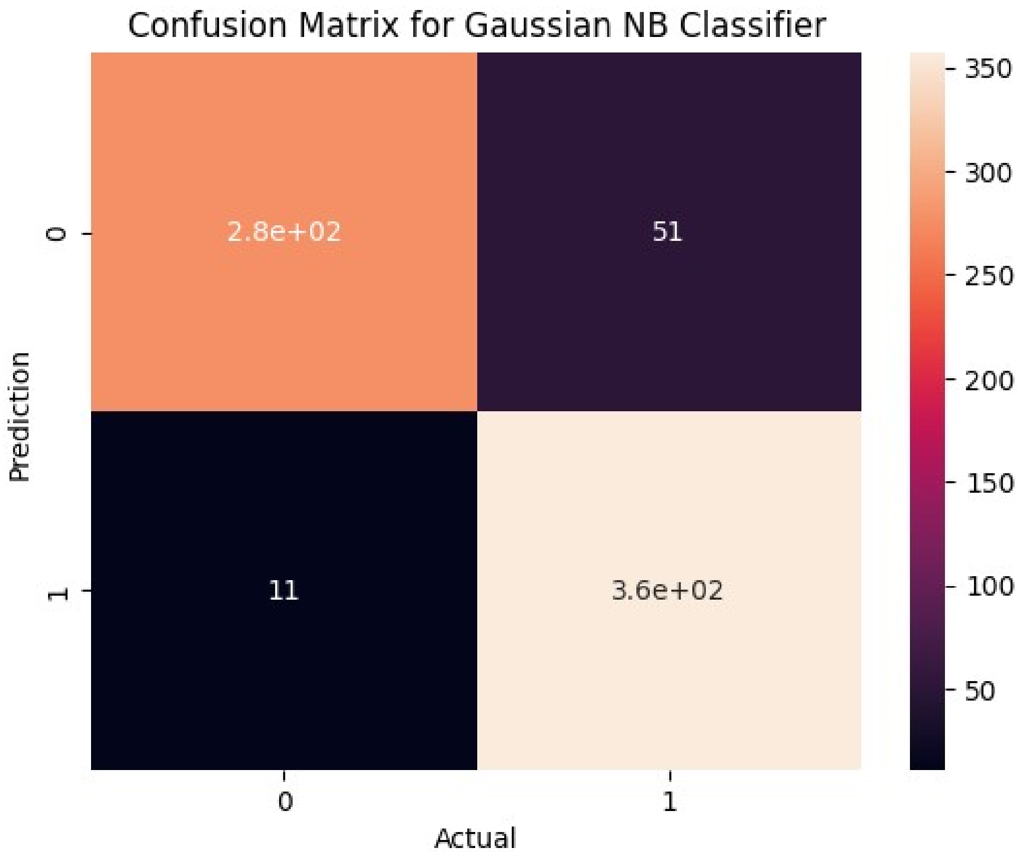
Evaluate and profile a Na¨ıve Bayes classifier: Train a GaussianNB classifier; plot the ROC curve and report the confusion matrix and calculate the accuracy, recall, precision and F-1 score of this classifier on the testing set.

```
from sklearn.naive_bayes import GaussianNB
nb = GaussianNB()
nb_predicted = nb.fit(X_train_LSI,
train['root_label']).predict(X_test_LSI)

fpr_nb, tpr_nb, thresholds_nb = metrics.roc_curve(test['root_label'],
nb.predict_proba(X_test_LSI)[:,1], pos_label= 'sports')
plot_roc(fpr_nb, tpr_nb)
plt.title('ROC for Naive Bayes')
```

```
Text(0.5, 1.0, 'ROC for Naive Bayes')
```




```
cm = confusion_matrix(test['root_label'],nb_predicted)
sns.heatmap(cm,annot=True)
plt.ylabel('Prediction')
plt.xlabel('Actual')
plt.title('Confusion Matrix for Gaussian NB Classifier')
plt.show()
```




```
print("Precision for Gaussian NB:",
precision_score(test['root_label'],nb_predicted, pos_label= 'sports'))
print("F1-Score for Gaussian NB:",
f1_score(test['root_label'],nb_predicted, pos_label= 'sports'))
print("Accuracy for Gaussian NB:",
accuracy_score(test['root_label'],nb_predicted))
print("Recall for Gaussian NB:",
recall_score(test['root_label'],nb_predicted, pos_label= 'sports'))

Precision for Gaussian NB: 0.875
F1-Score for Gaussian NB: 0.9201030927835052
Accuracy for Gaussian NB: 0.9109195402298851
Recall for Gaussian NB: 0.970108695652174
```

Grid Search

Question 8 : Find Best Model

- Construct a Pipeline that performs feature extraction, dimensionality reduction and classification;

• The evaluation of each combination is performed with 5-fold cross-validation (use the average validation set accuracy across folds)

• In addition to any other hyperparameters you choose, your gridsearch must at least include:

```
def lem_rmv_punc(doc):
    return ' '.join([word for word in lemmatize_sent(analyzer(doc)) if
word not in combined_stopwords and not word.isdigit()])
def lemmatize_sent(list_word):
    return [wnl.lemmatize(word.lower(), pos=penn2morphy(tag)) for
word, tag in pos_tag(list_word)]

lemmatized_train = [lem_rmv_punc(sent) for sent in
train_clean['full_text']]
lemmatized_test = [lem_rmv_punc(sent) for sent in
test_clean['full_text']]

sno = nltk.stem.SnowballStemmer('english')
def stem_sent(list_word):
    return [sno.stem(word.lower()) for word in list_word]
def stem_rmv_punc(doc):
    return ' '.join([word for word in stem_sent(analyzer(doc)) if word
not in combined_stopwords and not word.isdigit()])
stemmed_train = [stem_rmv_punc(sent) for sent in
train_clean['full_text']]
stemmed_test = [stem_rmv_punc(sent) for sent in
test_clean['full_text']]

#WHICH STEMMING TOOL TO USE???
import nltk
from sklearn.pipeline import Pipeline
pipeline = Pipeline([
    ('countVect', CountVectorizer(stop_words='english')),
    ('tfidf', TfidfTransformer()),
    ('reduce_dimension', None),
    ('classifiers', None),
]
)

param_grid = [
    {
        'countVect__min_df': (3,5),
        'reduce_dimension': (TruncatedSVD(n_components=5,
random_state=42),
                             TruncatedSVD(n_components=30, random_state=42),
                             TruncatedSVD(n_components=80, random_state=42),
                             NMF(n_components=5, random_state=42),
                             NMF(n_components=30, random_state=42),
                             NMF(n_components=80, random_state=42)),
        'classifiers': (SVC(C=100, kernel='linear', random_state=42,
```

```
probability=True),
                LogisticRegression(penalty='l1', C=10,random_state=42,
max_iter=1000, solver='liblinear'),
                LogisticRegression(penalty='l2', C=10,random_state=42,
max_iter=1000, solver='liblinear'),
                GaussianNB()),
    }
]

grid_lem =
GridSearchCV(pipeline,cv=5,param_grid=param_grid,scoring='accuracy')
grid_lem.fit(lemmatized_train, list(train['root_label']))
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/decomposition/
_nmf.py:1665: ConvergenceWarning: Maximum number of iterations 200
reached. Increase it to improve convergence.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/decomposition/_nmf.py:
1665: ConvergenceWarning: Maximum number of iterations 200 reached.
Increase it to improve convergence.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/decomposition/_nmf.py:
1665: ConvergenceWarning: Maximum number of iterations 200 reached.
Increase it to improve convergence.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/decomposition/_nmf.py:
1665: ConvergenceWarning: Maximum number of iterations 200 reached.
Increase it to improve convergence.
  warnings.warn(
```

```
GridSearchCV(cv=5,
             estimator=Pipeline(steps=[('countVect',

CountVectorizer(stop_words='english')),
                                       ('tfidf', TfidfTransformer()),
                                       ('reduce_dimension', None),
                                       ('classifiers', None)]),
             param_grid=[{'classifiers': (SVC(C=100, kernel='linear',
                                              probability=True,
                                              random_state=42),
                                          LogisticRegression(C=10,

max_iter=1000,

penalty='l1',

random_state=42,

solver='liblinear'),
                                          L...
```

```
random_state=42,

solver='liblinear'),
                                          GaussianNB()),
                          'countVect__min_df': (3, 5),
                          'reduce_dimension':
(TruncatedSVD(n_components=5,

random_state=42),

TruncatedSVD(n_components=30,

random_state=42),

TruncatedSVD(n_components=80,

random_state=42),
                                               NMF(n_components=5,
                                                   random_state=42),
                                               NMF(n_components=30,
                                                   random_state=42),
                                               NMF(n_components=80,

random_state=42))}],
             scoring='accuracy')

predictions_cv_lem = grid_lem.best_estimator_.predict(lemmatized_test)

results_l = pd.DataFrame(grid_lem.cv_results_)
results_l.sort_values(by='mean_test_score', inplace=True,
ascending=False)
results_l[:5]

    mean_fit_time  std_fit_time  mean_score_time  std_score_time  \
32       1.788852      0.536163         0.208929        0.048319
20       2.030368      0.545825         0.188403        0.057050
2        2.068463      0.382638         0.172185        0.051867
14       1.553022      0.054014         0.166561        0.049501
26       1.622470      0.299333         0.157869        0.010116

                                    param_classifiers
param_countVect__min_df  \
32  LogisticRegression(C=10, max_iter=1000, random...
5
20  LogisticRegression(C=10, max_iter=1000, penalt...
5
2   SVC(C=100, kernel='linear', probability=True, ...
3
14  LogisticRegression(C=10, max_iter=1000, penalt...
3
26  LogisticRegression(C=10, max_iter=1000, random...
```

```
3

                            param_reduce_dimension  \
32  TruncatedSVD(n_components=80, random_state=42)
20  TruncatedSVD(n_components=80, random_state=42)
2   TruncatedSVD(n_components=80, random_state=42)
14  TruncatedSVD(n_components=80, random_state=42)
26  TruncatedSVD(n_components=80, random_state=42)

                                               params
split0_test_score  \
32  {'classifiers': LogisticRegression(C=10, max_i...
0.958633
20  {'classifiers': LogisticRegression(C=10, max_i...
0.964029
2   {'classifiers': SVC(C=100, kernel='linear', pr...
0.960432
14  {'classifiers': LogisticRegression(C=10, max_i...
0.965827
26  {'classifiers': LogisticRegression(C=10, max_i...
0.956835

    split1_test_score  split2_test_score  split3_test_score  \
32           0.965827           0.960432           0.958633
20           0.962230           0.960432           0.955036
2            0.960432           0.962230           0.955036
14           0.962230           0.962230           0.953237
26           0.962230           0.958633           0.956835

    split4_test_score  mean_test_score  std_test_score
rank_test_score
32           0.962230         0.961151        0.002692
1
20           0.962230         0.960791        0.003094
2
2            0.960432         0.959712        0.002440
3
14           0.955036         0.959712        0.004772
4
26           0.962230         0.959353        0.002440
5
```

```
print(grid_lem.best_estimator_)
```

```
Pipeline(steps=[('countVect', CountVectorizer(min_df=5,
stop_words='english')),
                ('tfidf', TfidfTransformer()),
                ('reduce_dimension',
                 TruncatedSVD(n_components=80, random_state=42)),
                ('classifiers',
```

```
                 LogisticRegression(C=10, max_iter=1000,
random_state=42,
                                    solver='liblinear'))])

grid_stem =
GridSearchCV(pipeline,cv=5,param_grid=param_grid,scoring='accuracy')
grid_stem.fit(stemmed_train, list(train['root_label']))

/usr/local/lib/python3.10/dist-packages/sklearn/decomposition/
_nmf.py:1665: ConvergenceWarning: Maximum number of iterations 200
reached. Increase it to improve convergence.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/decomposition/_nmf.py:
1665: ConvergenceWarning: Maximum number of iterations 200 reached.
Increase it to improve convergence.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/decomposition/_nmf.py:
1665: ConvergenceWarning: Maximum number of iterations 200 reached.
Increase it to improve convergence.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/decomposition/_nmf.py:
1665: ConvergenceWarning: Maximum number of iterations 200 reached.
Increase it to improve convergence.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/decomposition/_nmf.py:
1665: ConvergenceWarning: Maximum number of iterations 200 reached.
Increase it to improve convergence.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/decomposition/_nmf.py:
1665: ConvergenceWarning: Maximum number of iterations 200 reached.
Increase it to improve convergence.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/decomposition/_nmf.py:
1665: ConvergenceWarning: Maximum number of iterations 200 reached.
Increase it to improve convergence.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/decomposition/_nmf.py:
1665: ConvergenceWarning: Maximum number of iterations 200 reached.
Increase it to improve convergence.
  warnings.warn(

GridSearchCV(cv=5,
             estimator=Pipeline(steps=[('countVect',

CountVectorizer(stop_words='english')),
                                       ('tfidf', TfidfTransformer()),
                                       ('reduce_dimension', None),
                                       ('classifiers', None)]),
             param_grid=[{'classifiers': (SVC(C=100, kernel='linear',
                                              probability=True,
```

```
                                                                      random_state=42),
                                                                LogisticRegression(C=10,

max_iter=1000,

penalty='l1',

random_state=42,

solver='liblinear'),
                                                                L...

random_state=42,

solver='liblinear'),
                                                                GaussianNB()),
                                        'countVect__min_df': (3, 5),
                                        'reduce_dimension':
(TruncatedSVD(n_components=5,

random_state=42),

TruncatedSVD(n_components=30,

random_state=42),

TruncatedSVD(n_components=80,

random_state=42),
                                                                        NMF(n_components=5,
                                                                            random_state=42),
                                                                        NMF(n_components=30,
                                                                            random_state=42),
                                                                        NMF(n_components=80,

random_state=42))}],
             scoring='accuracy')

predictions_cv_stem = grid_stem.best_estimator_.predict(stemmed_test)
results = pd.DataFrame(grid_stem.cv_results_)
results.sort_values(by='mean_test_score', inplace=True,
ascending=False)
results[:5]
```

```
    mean_fit_time  std_fit_time  mean_score_time  std_score_time  \
11      17.623265      3.334202         0.371102        0.118950
20       1.673228      0.373450         0.180086        0.056430
14       1.486003      0.025491         0.156491        0.019841
23      16.992734      3.243806         0.308662        0.009920
26       1.782027      0.533129         0.196666        0.040198
```

```
                                      param_classifiers
param_countVect__min_df  \
11  SVC(C=100, kernel='linear', probability=True, ...
5
20  LogisticRegression(C=10, max_iter=1000, penalt...
5
14  LogisticRegression(C=10, max_iter=1000, penalt...
3
23  LogisticRegression(C=10, max_iter=1000, penalt...
5
26  LogisticRegression(C=10, max_iter=1000, random...
3

                            param_reduce_dimension  \
11           NMF(n_components=80, random_state=42)
20  TruncatedSVD(n_components=80, random_state=42)
14  TruncatedSVD(n_components=80, random_state=42)
23           NMF(n_components=80, random_state=42)
26  TruncatedSVD(n_components=80, random_state=42)

                                             params
split0_test_score  \
11  {'classifiers': SVC(C=100, kernel='linear', pr...
0.962230
20  {'classifiers': LogisticRegression(C=10, max_i...
0.960432
14  {'classifiers': LogisticRegression(C=10, max_i...
0.962230
23  {'classifiers': LogisticRegression(C=10, max_i...
0.956835
26  {'classifiers': LogisticRegression(C=10, max_i...
0.958633

    split1_test_score  split2_test_score  split3_test_score  \
11           0.969424           0.958633           0.951439
20           0.960432           0.964029           0.962230
14           0.960432           0.962230           0.960432
23           0.962230           0.964029           0.956835
26           0.964029           0.958633           0.955036

    split4_test_score  mean_test_score  std_test_score
rank_test_score
11           0.965827         0.961511        0.006189
1
20           0.953237         0.960072        0.003668
2
14           0.955036         0.960072        0.002643
2
23           0.958633         0.959712        0.002922
4
```

```
26              0.956835         0.958633        0.003010
5
```

```python
print('Top 5 combinations:')
print()
print('1) Params: Stemming', results.iloc[0]['params'], " Mean Test Score:", results.iloc[0]['mean_test_score'])
print('2) Params: Lemmatize', results_l.iloc[0]['params'], " Mean Test Score:", results_l.iloc[0]['mean_test_score'])
print('3) Params: Lemmatize', results_l.iloc[1]['params'], " Mean Test Score:", results_l.iloc[0]['mean_test_score'])
print('4) Params: Stemming', results.iloc[1]['params'], " Mean Test Score:", results.iloc[0]['mean_test_score'])
print('5) Params: Stemming', results.iloc[2]['params'], " Mean Test Score:", results.iloc[0]['mean_test_score'])
```

```
Top 5 combinations:

1) Params: Stemming {'classifiers': SVC(C=100, kernel='linear',
probability=True, random_state=42), 'countVect__min_df': 5,
'reduce_dimension': NMF(n_components=80, random_state=42)}  Mean Test
Score: 0.9615107913669064
2) Params: Lemmatize {'classifiers': LogisticRegression(C=10,
max_iter=1000, random_state=42, solver='liblinear'),
'countVect__min_df': 5, 'reduce_dimension':
TruncatedSVD(n_components=80, random_state=42)}  Mean Test Score:
0.9611510791366907
3) Params: Lemmatize {'classifiers': LogisticRegression(C=10,
max_iter=1000, penalty='l1', random_state=42,
                   solver='liblinear'), 'countVect__min_df': 5,
'reduce_dimension': TruncatedSVD(n_components=80, random_state=42)}
Mean Test Score: 0.9611510791366907
4) Params: Stemming {'classifiers': LogisticRegression(C=10,
max_iter=1000, penalty='l1', random_state=42,
                   solver='liblinear'), 'countVect__min_df': 5,
'reduce_dimension': TruncatedSVD(n_components=80, random_state=42)}
Mean Test Score: 0.9615107913669064
5) Params: Stemming {'classifiers': LogisticRegression(C=10,
max_iter=1000, penalty='l1', random_state=42,
                   solver='liblinear'), 'countVect__min_df': 3,
'reduce_dimension': TruncatedSVD(n_components=80, random_state=42)}
Mean Test Score: 0.9615107913669064
```

Question 8

What are the 5 best combinations? Report their performances on the testing set.

- Top 5 combinations:

  1) Params: Stemming {'classifiers': SVC(C=100, kernel='linear', probability=True, random_state=42), 'countVect__min_df': 5, 'reduce_dimension':

NMF(n_components=80, random_state=42)} Mean Test Score: 0.9615107913669064

2) Params: Lemmatize {'classifiers': LogisticRegression(C=10, max_iter=1000, random_state=42, solver='liblinear'), 'countVect__min_df': 5, 'reduce_dimension': TruncatedSVD(n_components=80, random_state=42)} Mean Test Score: 0.9611510791366907

3) Params: Lemmatize {'classifiers': LogisticRegression(C=10, max_iter=1000, penalty='l1', random_state=42, solver='liblinear'), 'countVect__min_df': 5, 'reduce_dimension': TruncatedSVD(n_components=80, random_state=42)} Mean Test Score: 0.9611510791366907

4) Params: Stemming {'classifiers': LogisticRegression(C=10, max_iter=1000, penalty='l1', random_state=42, solver='liblinear'), 'countVect__min_df': 5, 'reduce_dimension': TruncatedSVD(n_components=80, random_state=42)} Mean Test Score: 0.9615107913669064

5) Params: Stemming {'classifiers': LogisticRegression(C=10, max_iter=1000, penalty='l1', random_state=42, solver='liblinear'), 'countVect__min_df': 3, 'reduce_dimension': TruncatedSVD(n_components=80, random_state=42)} Mean Test Score: 0.9615107913669064

Multiclass Classification

Question 9 : Leaf Label Classification

```
map_row_to_class = {0:"basketball", 1:"baseball", 2:"tennis",
3:"football", 4:"soccer", 5:"forest fire", 6:"flood",
7:"earthquake", 8:"drought", 9:"heatwave"}

classes = ['basketball', 'baseball', 'tennis', 'football',
          'soccer', 'forest fire', 'flood', 'earthquake',
          'drought', 'heatwave']

train_mc, test_mc = train_test_split(df[["full_text","leaf_label"]],
random_state=42, test_size=0.2)

# Clean data
train_mc['full_text'] = train_mc['full_text'].map(clean)
test_mc['full_text'] = test_mc["full_text"].map(clean)

# Count Vectorizer
X_train_mc_counts = count_vect.fit_transform(train_mc['full_text'])
X_test_mc_counts = count_vect.transform(test_mc['full_text'])

print(X_train_mc_counts.shape)
print(X_test_mc_counts.shape)
```

```
(2780, 13287)
(696, 13287)
```

```
# Tfidf
from sklearn.feature_extraction.text import TfidfTransformer
tfidf_transformer = TfidfTransformer()

X_train_mc_tfidf = tfidf_transformer.fit_transform(X_train_mc_counts)
X_test_mc_tfidf = tfidf_transformer.transform(X_test_mc_counts)

print(X_train_mc_tfidf.shape)
print(X_test_mc_tfidf.shape)
```

```
(2780, 13287)
(696, 13287)
```

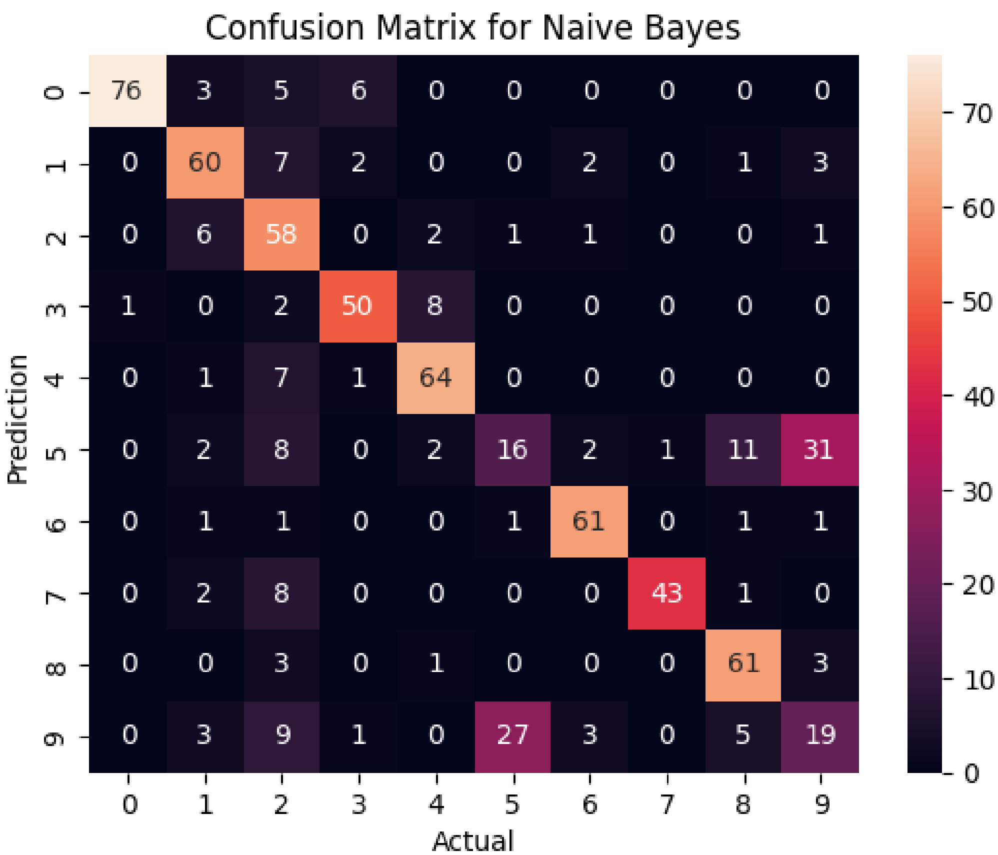
```
# LSI
from sklearn.decomposition import TruncatedSVD

svd = TruncatedSVD(n_components=50, random_state=42)
X_train_mc_LSI = svd.fit_transform(X_train_mc_tfidf)
X_test_mc_LSI = svd.transform(X_test_mc_tfidf)
print(X_train_mc_LSI.shape)
print(X_test_mc_LSI.shape)
```

```
(2780, 50)
(696, 50)
```

Naive Bayes

```
from sklearn.metrics import confusion_matrix
from sklearn.svm import SVC, LinearSVC
import seaborn as sns

from sklearn.naive_bayes import GaussianNB
nb = GaussianNB()
nb_predicted = nb.fit(X_train_mc_LSI,
train_mc['leaf_label']).predict(X_test_mc_LSI)
cm =
confusion_matrix(test_mc['leaf_label'],nb_predicted,labels=classes)
sns.heatmap(cm,annot=True)
plt.ylabel('Prediction')
plt.xlabel('Actual')
plt.title('Confusion Matrix for Naive Bayes')
plt.show()

print("Precision for NB:",
precision_score(test_mc['leaf_label'],nb_predicted, labels = classes,
average='macro'))
print("F1-Score for NB:", f1_score(test_mc['leaf_label'],nb_predicted,
```

```
labels = classes, average='macro'))
print("Accuracy for NB:",
accuracy_score(test_mc['leaf_label'],nb_predicted))
print("Recall for NB:",
recall_score(test_mc['leaf_label'],nb_predicted, labels = classes,
average='macro'))
```

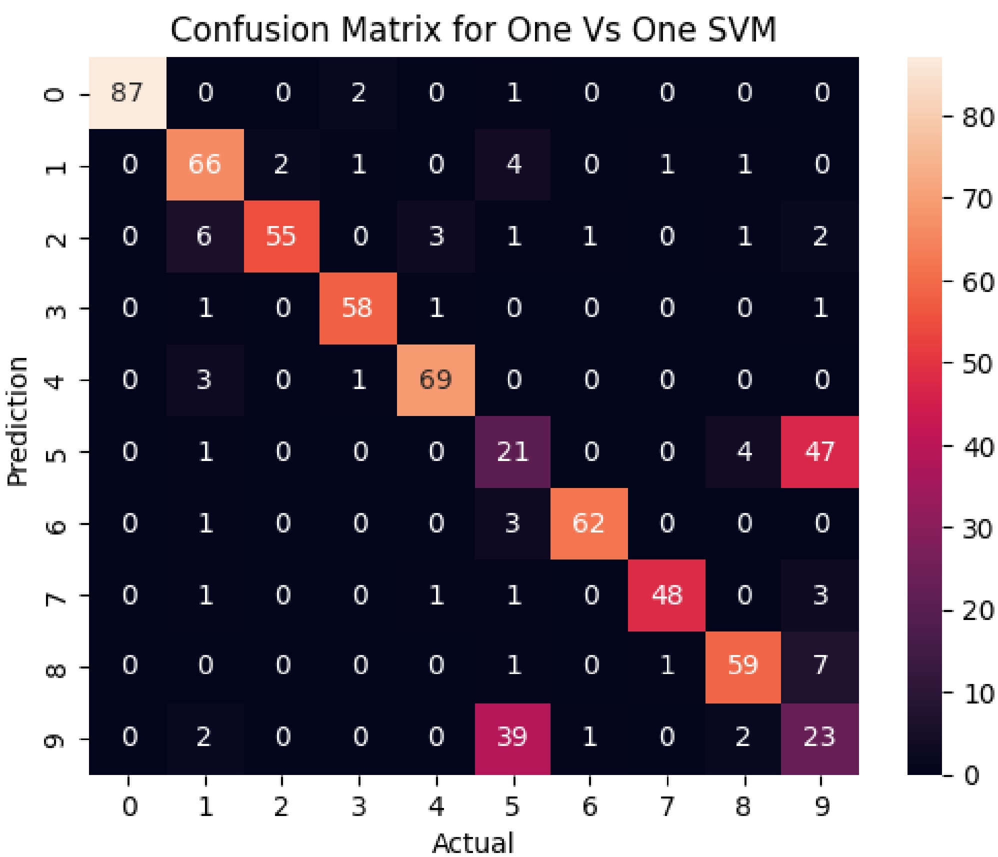



```
Precision for NB: 0.7264755418522285
F1-Score for NB: 0.7210405701286404
Accuracy for NB: 0.7298850574712644
Recall for NB: 0.7301766330316188
```

SVM (One Vs One)

```
# One vs One
ovo_svm = SVC(kernel = 'linear', C = 100, random_state = 42,
decision_function_shape = 'ovo')
ovo_svm_predicted = ovo_svm.fit(X_train_mc_LSI,
train_mc['leaf_label']).predict(X_test_mc_LSI)

cm =
confusion_matrix(test_mc['leaf_label'],ovo_svm_predicted,labels=classe
```

```
s)
sns.heatmap(cm,annot=True)
plt.ylabel('Prediction')
plt.xlabel('Actual')
plt.title('Confusion Matrix for One Vs One SVM')
plt.show()

print("Precision for OVO SVM:",
precision_score(test_mc['leaf_label'],ovo_svm_predicted, labels =
classes, average='macro'))
print("F1-Score for OVO SVM:",
f1_score(test_mc['leaf_label'],ovo_svm_predicted, labels = classes,
average='macro'))
print("Accuracy for OVO SVM:",
accuracy_score(test_mc['leaf_label'],ovo_svm_predicted))
print("Recall for OVO SVM:",
recall_score(test_mc['leaf_label'],ovo_svm_predicted, labels =
classes, average='macro'))
```



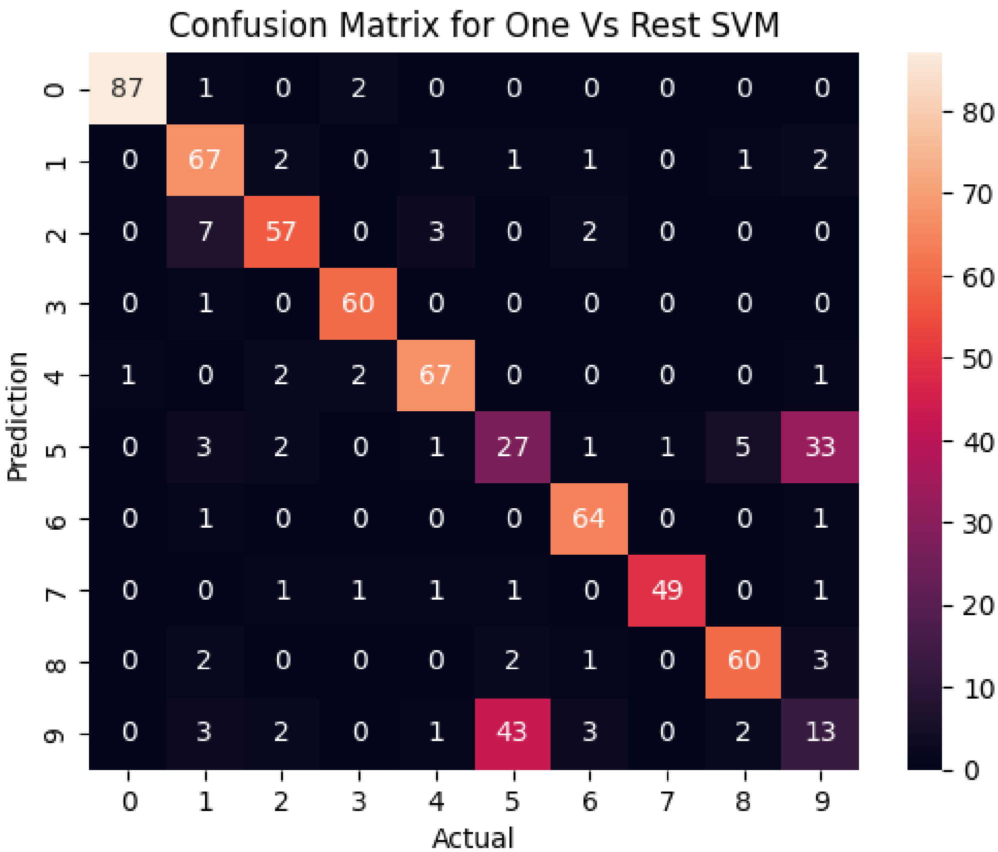

```
Precision for OVO SVM: 0.8029873495464381
F1-Score for OVO SVM: 0.7933415992056221
```

```
Accuracy for OVO SVM: 0.7873563218390804
Recall for OVO SVM: 0.7866677969597853
```

SVM (One vs Rest)

```
# One vs Rest
ovr_svm = LinearSVC(C = 100, random_state = 42)
ovr_svm_predicted = ovr_svm.fit(X_train_mc_LSI,
train_mc['leaf_label']).predict(X_test_mc_LSI)

cm =
confusion_matrix(test_mc['leaf_label'],ovr_svm_predicted,labels=classe
s)
sns.heatmap(cm,annot=True)
plt.ylabel('Prediction')
plt.xlabel('Actual')
plt.title('Confusion Matrix for One Vs Rest SVM')
plt.show()

print("Precision for OVR SVM:",
precision_score(test_mc['leaf_label'],ovr_svm_predicted, labels =
classes, average='macro'))
print("F1-Score for OVR SVM:",
f1_score(test_mc['leaf_label'],ovr_svm_predicted, labels = classes,
average='macro'))
print("Accuracy for OVR SVM:",
accuracy_score(test_mc['leaf_label'],ovr_svm_predicted))
print("Recall for OVR SVM:",
recall_score(test_mc['leaf_label'],ovr_svm_predicted, labels =
classes, average='macro'))
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/svm/_base.py:1244:
ConvergenceWarning: Liblinear failed to converge, increase the number
of iterations.
  warnings.warn(
```




```
Precision for OVR SVM: 0.7825837785543668
F1-Score for OVR SVM: 0.7857837949764959
Accuracy for OVR SVM: 0.7916666666666666
Recall for OVR SVM: 0.7910851915802617
```

```
print("Precision for OVR SVM:",
precision_score(test_mc['leaf_label'],ovr_svm_predicted, labels =
classes, average='macro'))
print("F1-Score for OVR SVM:",
f1_score(test_mc['leaf_label'],ovr_svm_predicted, labels = classes,
average='macro'))
print("Accuracy for OVR SVM:",
accuracy_score(test_mc['leaf_label'],ovr_svm_predicted))
print("Recall for OVR SVM:",
recall_score(test_mc['leaf_label'],ovr_svm_predicted, labels =
classes, average='macro'))
```

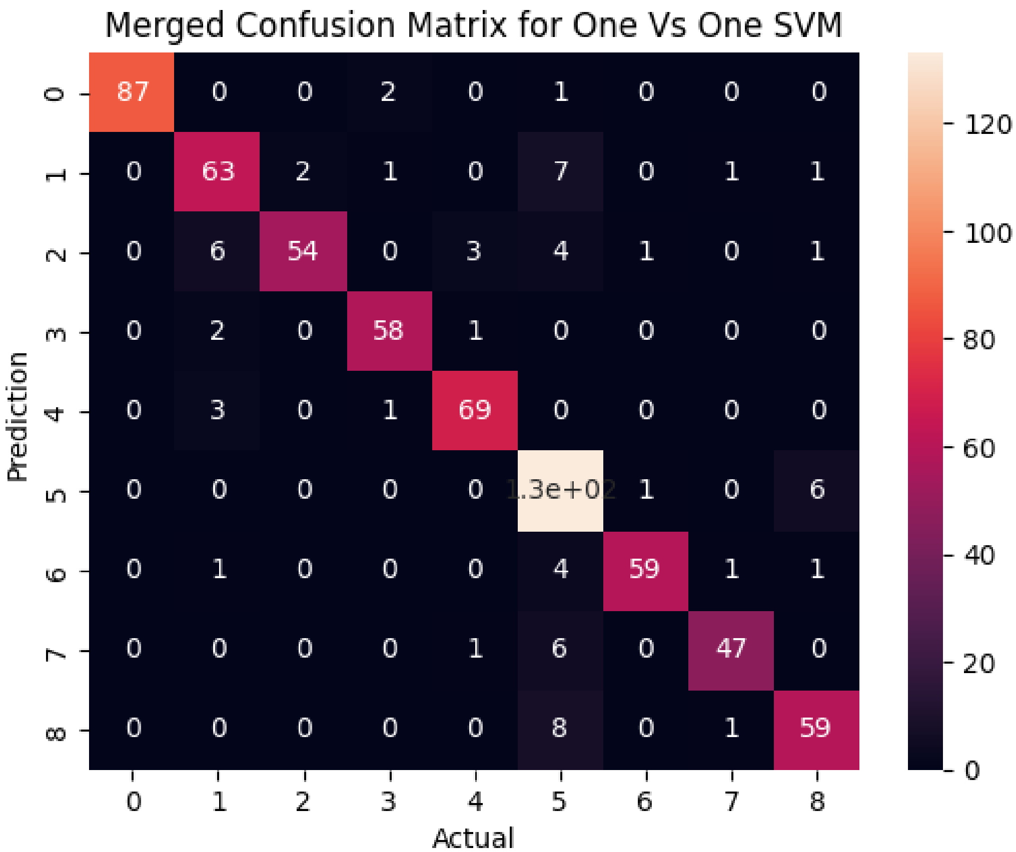

```
Precision for OVR SVM: 0.7825837785543668
F1-Score for OVR SVM: 0.7857837949764959
Accuracy for OVR SVM: 0.7916666666666666
Recall for OVR SVM: 0.7910851915802617
```

Merge Classes

```
# Merge 5: forest fire and 9: heatwave
train_merged = train_mc
train_merged['leaf_label'] =
train_mc['leaf_label'].replace('heatwave', 'fire')
train_merged['leaf_label']= train_mc['leaf_label'].replace('forest
fire', 'fire')

test_merged = test_mc
test_merged['leaf_label'] = test_mc['leaf_label'].replace('heatwave',
'fire')
test_merged['leaf_label'] = test_mc['leaf_label'].replace('forest
fire', 'fire')

# Put merged class at 5
classes_merged = ['basketball', 'baseball', 'tennis', 'football',
          'soccer', 'fire', 'flood', 'earthquake',
          'drought']
```

SVM (One vs One)

```
# One vs One
ovo_svm = SVC(kernel = 'linear', C = 100, random_state = 42,
decision_function_shape = 'ovo')
ovo_svm_predicted = ovo_svm.fit(X_train_mc_LSI,
train_merged['leaf_label']).predict(X_test_mc_LSI)

cm =
confusion_matrix(test_merged['leaf_label'],ovo_svm_predicted,labels=cl
asses_merged)
sns.heatmap(cm,annot=True)
plt.ylabel('Prediction')
plt.xlabel('Actual')
plt.title('Merged Confusion Matrix for One Vs One SVM')
plt.show()

print("Precision for Merged OVO SVM:",
precision_score(test_merged['leaf_label'],ovo_svm_predicted, labels =
classes_merged, average='macro'))
print("F1-Score for Merged OVO SVM:",
f1_score(test_merged['leaf_label'],ovo_svm_predicted, labels =
classes_merged, average='macro'))
print("Accuracy for Merged OVO SVM:",
accuracy_score(test_merged['leaf_label'],ovo_svm_predicted))
print("Recall for Merged OVO SVM:",
recall_score(test_merged['leaf_label'],ovo_svm_predicted, labels =
classes_merged, average='macro'))
```

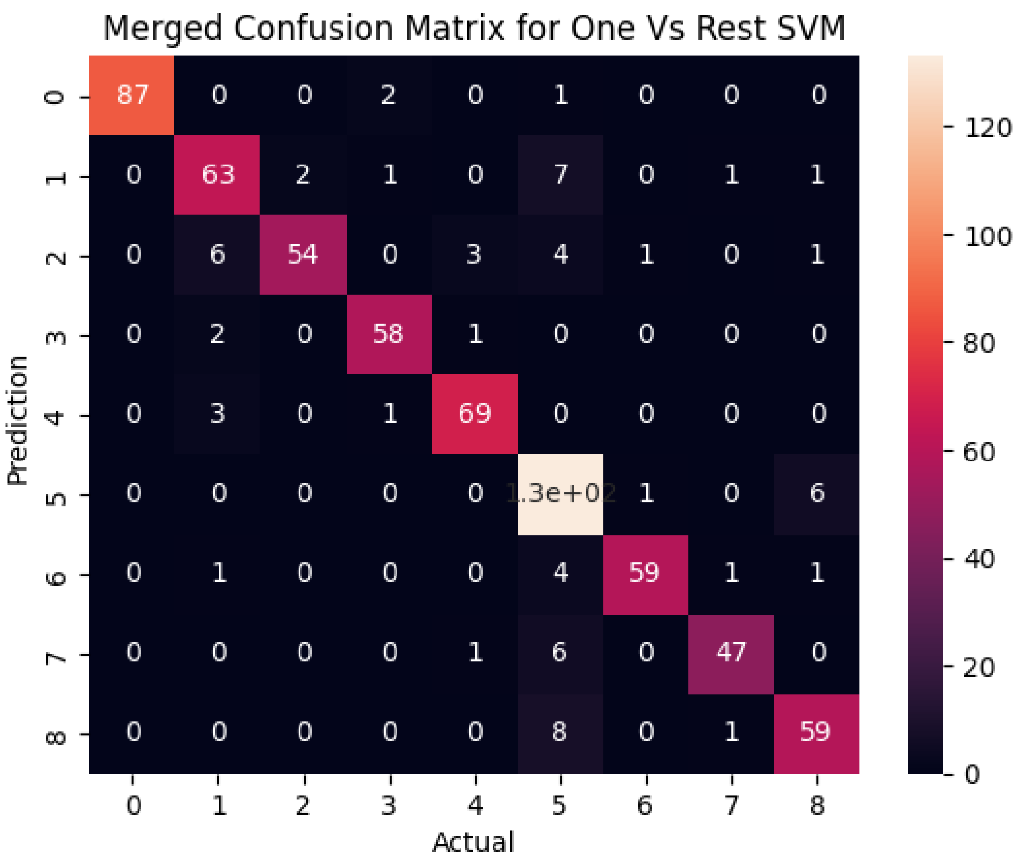



```
Precision for Merged OVO SVM: 0.9181125679454349
F1-Score for Merged OVO SVM: 0.9052700720302549
Accuracy for Merged OVO SVM: 0.9037356321839081
Recall for Merged OVO SVM: 0.8963619263372595
```

SVM (One vs Rest)

```
# One vs Rest
ovr_svm = SVC(kernel = 'linear', C = 100, random_state = 42,
decision_function_shape='ovr')
ovr_svm_predicted = ovr_svm.fit(X_train_mc_LSI,
train_merged['leaf_label']).predict(X_test_mc_LSI)

cm =
confusion_matrix(test_merged['leaf_label'],ovr_svm_predicted,labels=cl
asses_merged)
sns.heatmap(cm,annot=True)
plt.ylabel('Prediction')
plt.xlabel('Actual')
plt.title('Merged Confusion Matrix for One Vs Rest SVM')
plt.show()

print("Precision for Merged OVR SVM:",
```

```
precision_score(test_merged['leaf_label'],ovr_svm_predicted, labels =
classes_merged, average='macro'))
print("F1-Score for Merged OVR SVM:",
f1_score(test_merged['leaf_label'],ovr_svm_predicted, labels =
classes_merged, average='macro'))
print("Accuracy for Merged OVR SVM:",
accuracy_score(test_merged['leaf_label'],ovr_svm_predicted))
print("Recall for Merged OVR SVM:",
recall_score(test_merged['leaf_label'],ovr_svm_predicted, labels =
classes_merged, average='macro'))
```




```
Precision for Merged OVR SVM: 0.9181125679454349
F1-Score for Merged OVR SVM: 0.9052700720302549
Accuracy for Merged OVR SVM: 0.9037356321839081
Recall for Merged OVR SVM: 0.8963619263372595
```

Balance Data

```
# Get count of each class
print(train_merged.groupby("leaf_label").count())
print(test_merged.groupby("leaf_label").count())
```

```
train_sample = train_merged.groupby("leaf_label").sample(n=258,
random_state=42)
test_sample = test_merged.groupby("leaf_label").sample(n=54,
random_state=42)
```

```
            full_text
leaf_label
baseball          275
basketball        260
drought           258
earthquake        296
fire              560
flood             284
football          289
soccer            277
tennis            281
            full_text
leaf_label
baseball           75
basketball         90
drought            68
earthquake         54
fire              140
flood              66
football           61
soccer             73
tennis             69
```

```
print(train_sample.groupby("leaf_label").count())
print(test_sample.groupby("leaf_label").count())
```

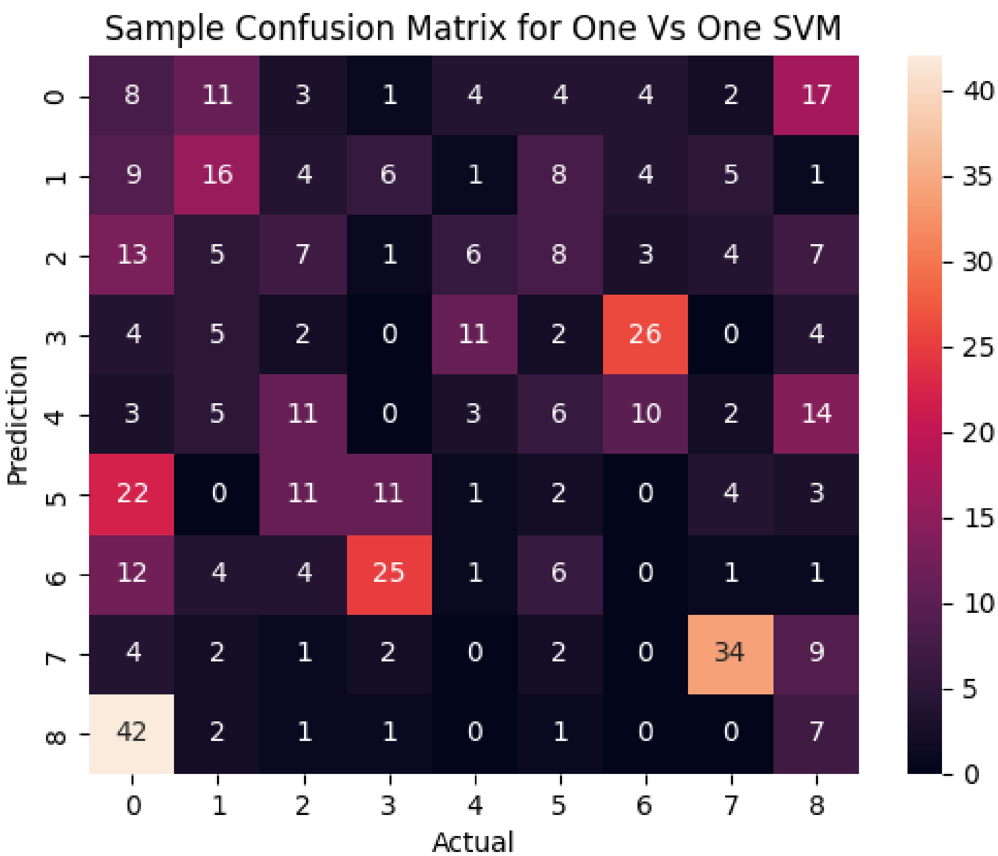
```
            full_text
leaf_label
baseball          258
basketball        258
drought           258
earthquake        258
fire              258
flood             258
football          258
soccer            258
tennis            258
            full_text
leaf_label
baseball           54
basketball         54
drought            54
earthquake         54
fire               54
flood              54
```

```
football            54
soccer              54
tennis              54

# Clean data
train_sample['full_text'] = train_sample['full_text'].map(clean)
test_sample['full_text'] = test_sample['full_text'].map(clean)

# Count Vectorizer
X_train_sample_counts =
count_vect.fit_transform(train_sample['full_text'])
X_test_sample_counts = count_vect.transform(test_sample['full_text'])

# Tfidf
from sklearn.feature_extraction.text import TfidfTransformer
tfidf_transformer = TfidfTransformer()

X_train_sample_tfidf =
tfidf_transformer.fit_transform(X_train_sample_counts)
X_test_sample_tfidf =
tfidf_transformer.fit_transform(X_test_sample_counts)

print(X_train_mc_tfidf.shape)

# LSI
from sklearn.decomposition import TruncatedSVD

svd = TruncatedSVD(n_components=50, random_state=42)
X_train_sample_LSI = svd.fit_transform(X_train_sample_tfidf)
X_test_sample_LSI = svd.fit_transform(X_test_sample_tfidf)

(2780, 13287)
```

SVM (One vs One)

```
ovo_svm = SVC(kernel = 'linear', C = 100, random_state = 42,
decision_function_shape='ovo')
ovo_svm_predicted = ovo_svm.fit(X_train_sample_LSI,
train_sample['leaf_label']).predict(X_test_sample_LSI)

cm =
confusion_matrix(test_sample['leaf_label'],ovo_svm_predicted,labels=cl
asses_merged)
sns.heatmap(cm,annot=True)
plt.ylabel('Prediction')
plt.xlabel('Actual')
plt.title('Sample Confusion Matrix for One Vs One SVM')
plt.show()

print("Precision for Sample OVO SVM:",
```

```
precision_score(test_sample['leaf_label'],ovo_svm_predicted, labels =
classes_merged, average='macro'))
print("F1-Score for Sample OVO SVM:",
f1_score(test_sample['leaf_label'],ovo_svm_predicted, labels =
classes_merged, average='macro'))
print("Accuracy for Sample OVO SVM:",
accuracy_score(test_sample['leaf_label'],ovo_svm_predicted))
print("Recall for Sample OVO SVM:",
recall_score(test_sample['leaf_label'],ovo_svm_predicted, labels =
classes_merged, average='macro'))
```

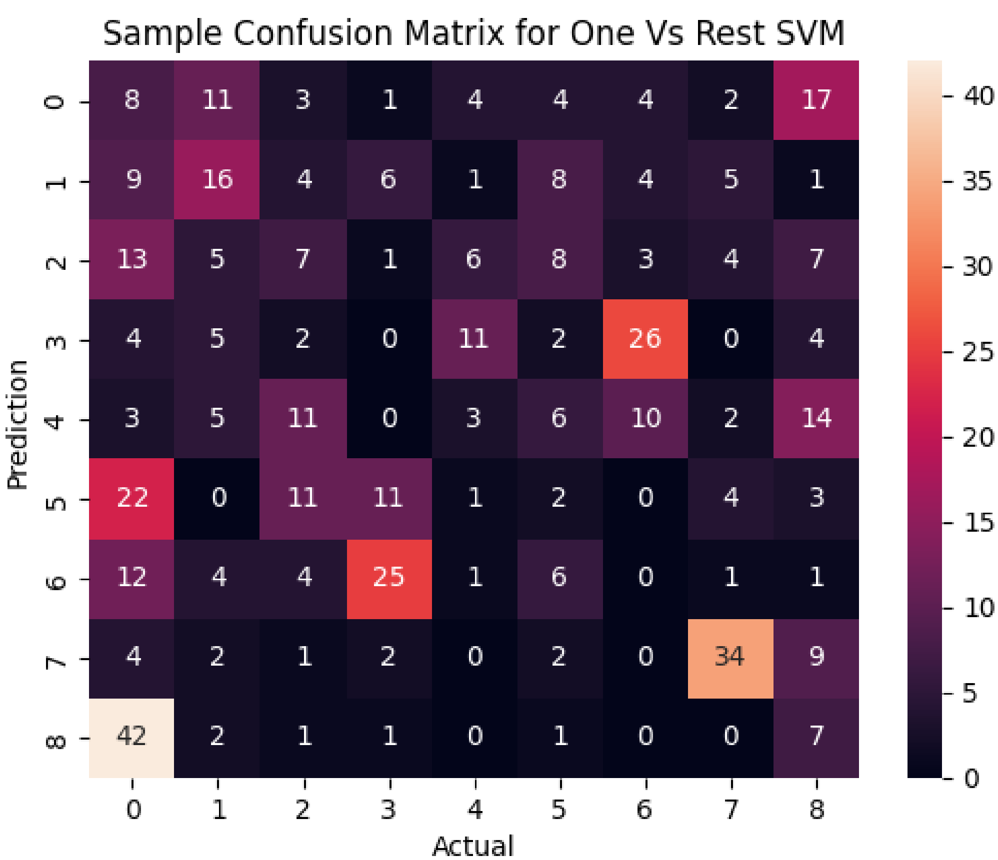



```
Precision for Sample OVO SVM: 0.1638686005352672
F1-Score for Sample OVO SVM: 0.15804100915489652
Accuracy for Sample OVO SVM: 0.15843621399176955
Recall for Sample OVO SVM: 0.15843621399176955
```

SVM (One vs Rest)

```
ovr_svm = SVC(kernel = 'linear', C = 100, random_state = 42,
decision_function_shape='ovr')
ovr_svm_predicted = ovr_svm.fit(X_train_sample_LSI,
train_sample['leaf_label']).predict(X_test_sample_LSI)
```

```
cm =
confusion_matrix(test_sample['leaf_label'],ovr_svm_predicted,labels=cl
asses_merged)
sns.heatmap(cm,annot=True)
plt.ylabel('Prediction')
plt.xlabel('Actual')
plt.title('Sample Confusion Matrix for One Vs Rest SVM')
plt.show()

print("Precision for Sample OVR SVM:",
precision_score(test_sample['leaf_label'],ovr_svm_predicted, labels =
classes_merged, average='macro'))
print("F1-Score for Sample OVR SVM:",
f1_score(test_sample['leaf_label'],ovr_svm_predicted, labels =
classes_merged, average='macro'))
print("Accuracy for Sample OVR SVM:",
accuracy_score(test_sample['leaf_label'],ovr_svm_predicted))
print("Recall for Sample OVR SVM:",
recall_score(test_sample['leaf_label'],ovr_svm_predicted, labels =
classes_merged, average='macro'))
```



```
Precision for Sample OVR SVM: 0.1638686005352672
F1-Score for Sample OVR SVM: 0.15804100915489652
Accuracy for Sample OVR SVM: 0.15843621399176955
Recall for Sample OVR SVM: 0.15843621399176955
```

#9

QUESTION 9:

• Perform Na¨ıve Bayes classification and multiclass SVM classification (with both One VS One and One VS the rest methods described above) and report the confusion matrix and calculate the accuracy, recall, precision and F-1 score of your classifiers. How did you resolve the class imbalance issue in the One VS the rest model?*

- To resolve the class imbalance issue, we can take a sample of the same size of data from each category so that the classes are balanced.

• Do you observe any structure in the confusion matrix? Are there distinct visible blocks on the major diagonal? What does this mean?*

- Yes there are distint blocks along the diagonal meaning that the most of the predicted labels match the actual labels. We can also see that for labels 5 and 9, the classifier mislabels the data between the two quite often.

• Based on your observation from the previous part, suggest a subset of labels that should be merged into a new larger label and recompute the accuracy and plot the confusion matrix. How did the accuracy change in One VS One and One VS the rest.*

- We should merge forest fire and heatwave into a larger label called 'fire'. We can see that accuracy for both OVO and OVR increased from around 10%.

• Does class imbalance impact the performance of the classification once some classes are merged? Provide a resolution for the class imbalance and recompute the accuracy and plot the confusion matrix in One VS One and One VS the rest.*

- Class imbalance can cause the classifier to be biased toward the majority class causing the accuraccy to be high even though overall performance might be poor.

GLoVE Embedding

Question 10 : GLoVE Paper Read

QUESTION 10:

Read the paper about GLoVE embeddings - found here and answer the following subquestions:

(a) Why are GLoVE embeddings trained on the ratio of co-occurrence probabilities rather than the probabilities themselves?

- Compared to the raw probabilities, the ratio is better able to distinguish relevant words from irrelevant words and it is also better able to discriminate between the two relevant words.

(b) In the two sentences: “James is running in the park.” and “James is running for the presidency.”, would GLoVE embeddings return the same vector for the word running in both cases? Why or why not?

- No, the GLoVE embedding return will not return the same vector. GLoVE embedding vectorizes the word by the ratio of co-occurence probabilities. The word "running" used with "park", and used with "presidency" would therefore result in a different vector.

(c) What do you expect for the values of, ||GLoVE["woman"] - GLoVE["man"]||2, ||GLoVE["wife"] - GLoVE["husband"]||2 and ||GLoVE["wife"] - GLoVE["orange"]||2 ? Compare these values.

- ||GLoVE["woman"] - GLoVE["man"]||_2 : 4.7539396
- ||GLoVE["wife"] - GLoVE["husband"]||_2 : 3.1520464
- ||GLoVE["wife"] - GLoVE["orange"]||_2 : 8.667715

(d) Given a word, would you rather stem or lemmatize the word before mapping it to its GLoVE embedding?

- I will choose lemmatize rather than stem. As GLoVE embedding relies on the relation between words, it is meaningful to consider the context of the words in a given sentence. Furthermore, stemming removes the last few characters from a word which could cause damage to the original word(making it spelled wrong or give incorrect meaning). Generally, lemitizing is a better than stemming because it converts the word to its meaningful base form.

Question 11

```
import os
from gensim.models import KeyedVectors
from gensim.scripts.glove2word2vec import glove2word2vec

embeddings_dict = {}
dimension_of_glove = 300
with open("/content/drive/MyDrive/ECE ENGR 219/glove/glove.6B.300d.txt", 'r') as f: # if 'r' fails with unicode error, please use 'rb'
```

```
  for line in f:
    values = line.split()
    word = values[0]
    vector = np.asarray(values[1:], "float32")
    embeddings_dict[word] = vector


root_folder='/content/drive/MyDrive/ECE ENGR 219'
glove_folder_name='glove'
glove_filename='glove.6B.300d.txt'
glove_path = os.path.abspath(os.path.join(root_folder,
glove_folder_name, glove_filename))
word2vec_output_file = glove_filename+'.word2vec'
glove2word2vec(glove_path, word2vec_output_file)
model = KeyedVectors.load_word2vec_format(word2vec_output_file,
binary=False)
```

```
<ipython-input-104-25c79b64e87e>:21: DeprecationWarning: Call to
deprecated `glove2word2vec` (KeyedVectors.load_word2vec_format(..,
binary=False, no_header=True) loads GLoVE text vectors.).
  glove2word2vec(glove_path, word2vec_output_file)
```

```
from numpy.linalg import norm

arr1 = [embeddings_dict["woman"] - embeddings_dict["man"]]
arr2 = [embeddings_dict["wife"] - embeddings_dict["husband"]]
arr3 = [embeddings_dict["wife"] - embeddings_dict["orange"]]
norm_l2_1 = norm(arr1)  # ||GLoVE["woman"] - GLoVE["man"]||_2
norm_l2_2 = norm(arr2)  # ||GLoVE["wife"] - GLoVE["husband"]||_2
norm_l2_3 = norm(arr3)  # ||GLoVE["wife"] - GLoVE["orange"]||_2

print("||GLoVE[woman] - GLoVE[man]||_2 : ", norm_l2_1)
print("||GLoVE[wife] - GLoVE[husband]||_2 : ", norm_l2_2)
print("||GLoVE[wife] - GLoVE[orange]||_2 : ", norm_l2_3)
```

```
||GLoVE[woman] - GLoVE[man]||_2 :  4.7539396
||GLoVE[wife] - GLoVE[husband]||_2 :  3.1520464
||GLoVE[wife] - GLoVE[orange]||_2 :  8.667715
```

Question 11 : GLoVE Embedding Binary Classification

QUESTION 11:

For the binary classification task distinguishing the “sports” class and “climate”class:

(a) Describe a feature engineering process that uses GLoVE word embeddings to represent each document. You have to abide by the following rules:

• A representation of a text segment needs to have a vector dimension that CANNOT exceed the dimension of the GLoVE embedding used per word of the segment.

• You cannot use TF-IDF scores (or any measure that requires looking at the complete dataset) as a pre-processing routine.

• Important: In this section, feel free to use raw features from any column in the original data file not just full text. The column keywords might be useful... or not. Make sure that your result achieves an accuracy of at least 92%.

• To aggregate these words into a single vector consider normalization the vectors, averaging across the vectors.

- Step1: Import data set and split them into train and test data set.
- Step2: Clean and and lemmatize the train set and test set.
- Step3: Open the pre-trained GLoVE model and convert the GLoVE embedding into a word2vec file.
- Step4: Transform the sentences in train and test set to GLoVE features using vectorizer. Each sentence has the same dimension with the GLoVE.

(b) Select a classifier model, train and evaluate it with your GLoVE-based feature. If you are doing any cross-validation, please make sure to use a limited set of options so that your code finishes running in a reasonable amount of time.

- given below

```
class Word2VecVectorizer:
    def __init__(self, model):
        print("Loading in word vectors...")
        self.word_vectors = model
        print("Finished loading in word vectors")

    def fit(self, data):
        pass

    def transform(self, data):
        v = self.word_vectors.get_vector('king')
        self.D = v.shape[0]

        X = np.zeros((len(data), self.D))
        n = 0
        emptycount = 0
        for sentence in data:
            tokens = sentence.split()
            vecs = []
            m = 0
            for word in tokens:
                try:
                    vec = self.word_vectors.get_vector(word)
                    vecs.append(vec)
                    m += 1
                except KeyError:
                    pass
            if len(vecs) > 0:
```

```
                vecs = np.array(vecs)
                X[n] = vecs.mean(axis=0)
            else:
                emptycount += 1
            n += 1
        print("Number of samples with no words found: %s / %s" %
(emptycount, len(data)))
        return X

vectorizer = Word2VecVectorizer(model)
```

```
Loading in word vectors...
Finished loading in word vectors
```

```
train_glove = vectorizer.transform(lemmatized_train)
test_glove = vectorizer.transform(lemmatized_test)
```

```
Number of samples with no words found: 0 / 2780
Number of samples with no words found: 0 / 696
```

```
print(train_glove)
```

```
[[-0.07284649 -0.01332922 -0.11297492 ... -0.0101648  -0.11148712
   0.09395094]
 [-0.10539048  0.22951683  0.02506633 ... -0.10446478 -0.0394552
  -0.01534163]
 [-0.08559454  0.01144987 -0.10544897 ... -0.1401062   0.05561281
   0.07804989]
 ...
 [-0.10538218  0.18105043  0.03132303 ... -0.11982799 -0.01270362
  -0.05126897]
 [-0.20333721  0.05042237 -0.0310696  ...  0.02129313 -0.06194102
   0.04510168]
 [-0.06115711 -0.10269144 -0.21807997 ... -0.0272742   0.03353392
   0.0140867 ]]
```

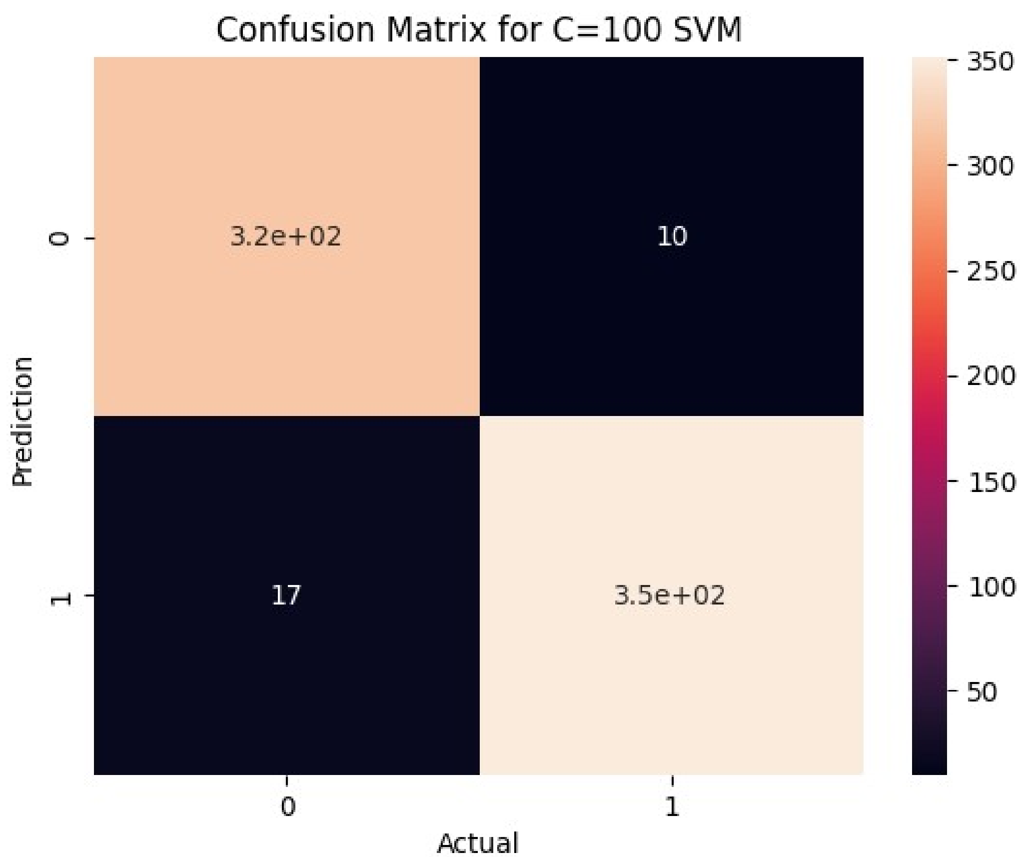
```
# just to test if this works

c_glove = SVC(C=10, kernel='linear', random_state=42)

y_pred =  c_glove.fit(train_glove,
train["root_label"]).predict(test_glove)


print("train score:", c_glove.score(train_glove, train["root_label"]))
print("test score:", c_glove.score(test_glove, test["root_label"]))
```

```
train score: 0.9852517985611511
test score: 0.9612068965517241
```

```
from sklearn import metrics
print(metrics.classification_report(test["root_label"], y_pred,
digits=5))
```

```
              precision    recall  f1-score   support

     climate    0.94925   0.96951   0.95928       328
      sports    0.97230   0.95380   0.96296       368

    accuracy                        0.96121       696
   macro avg    0.96078   0.96166   0.96112       696
weighted avg    0.96144   0.96121   0.96123       696
```

```
import seaborn as sns
cm = confusion_matrix(test['root_label'],y_pred)
sns.heatmap(cm,annot=True)
plt.ylabel('Prediction')
plt.xlabel('Actual')
plt.title('Confusion Matrix for C=100 SVM')
plt.show()
```



Question 12 : Dimension and Accuracy Relation

QUESTION 12:

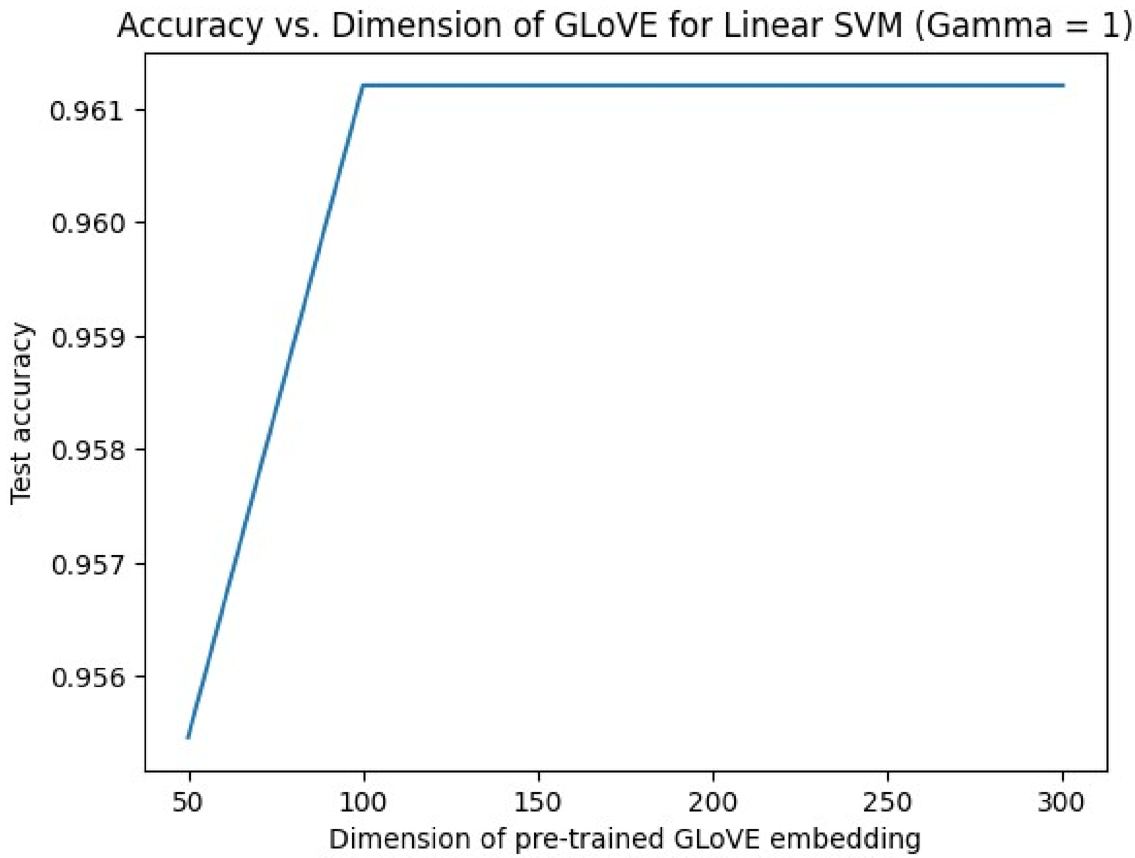
Plot the relationship between the dimension of the pre-trained GLoVE embedding and the resulting accuracy of the model in the classification task.

Describe the observed trend. Is this trend expected? Why or why not?

- The given result is partialy expected.
- The accuracy should increase as the dimension of the pre-trained GLoVE embedding increases, because it is better able to capture more semantics and learn more information. In the practice below, the accuracy got saturated with dimention of 100 and above.

```
filenames_glove =
['glove.6B.50d.txt','glove.6B.100d.txt','glove.6B.200d.txt','glove.6B.
300d.txt']
accu_list_glove = []
for filename in filenames_glove:
    print('Training for: ', filename)
    glove_filename=filename
    glove_path = os.path.abspath(os.path.join(root_folder,
glove_folder_name, glove_filename))
    word2vec_output_file = glove_filename+'.word2vec'
    glove2word2vec(glove_path, word2vec_output_file)
    model = KeyedVectors.load_word2vec_format(word2vec_output_file,
binary=False)
    vectorizer = Word2VecVectorizer(model)
    train_glove = vectorizer.transform(lemmatized_train)
    test_glove = vectorizer.transform(lemmatized_test)
    c_glove = SVC(C=10, kernel='linear', random_state=42)
    pred =  c_glove.fit(train_glove,
train["root_label"]).predict(test_glove)
    accu_list_glove.append(accuracy_score(test["root_label"],pred))


# In[55]:


dim_list = [50,100,200,300]
plt.plot(dim_list,accu_list_glove)
plt.title('Accuracy vs. Dimension of GLoVE for Linear SVM (Gamma =
10)')
plt.xlabel('Dimension of pre-trained GLoVE embedding')
plt.ylabel('Test accuracy')
plt.savefig('Q101.png',dpi=300,bbox_inches='tight')
plt.show()

Training for:  glove.6B.50d.txt
```

```
<ipython-input-119-13675637d975>:8: DeprecationWarning: Call to
deprecated `glove2word2vec` (KeyedVectors.load_word2vec_format(..,
binary=False, no_header=True) loads GLoVE text vectors.).
  glove2word2vec(glove_path, word2vec_output_file)

Loading in word vectors...
Finished loading in word vectors
Number of samples with no words found: 0 / 2780
Number of samples with no words found: 0 / 696
Training for:  glove.6B.100d.txt

<ipython-input-119-13675637d975>:8: DeprecationWarning: Call to
deprecated `glove2word2vec` (KeyedVectors.load_word2vec_format(..,
binary=False, no_header=True) loads GLoVE text vectors.).
  glove2word2vec(glove_path, word2vec_output_file)

Loading in word vectors...
Finished loading in word vectors
Number of samples with no words found: 0 / 2780
Number of samples with no words found: 0 / 696
Training for:  glove.6B.200d.txt

<ipython-input-119-13675637d975>:8: DeprecationWarning: Call to
deprecated `glove2word2vec` (KeyedVectors.load_word2vec_format(..,
binary=False, no_header=True) loads GLoVE text vectors.).
  glove2word2vec(glove_path, word2vec_output_file)

Loading in word vectors...
Finished loading in word vectors
Number of samples with no words found: 0 / 2780
Number of samples with no words found: 0 / 696
Training for:  glove.6B.300d.txt

<ipython-input-119-13675637d975>:8: DeprecationWarning: Call to
deprecated `glove2word2vec` (KeyedVectors.load_word2vec_format(..,
binary=False, no_header=True) loads GLoVE text vectors.).
  glove2word2vec(glove_path, word2vec_output_file)

Loading in word vectors...
Finished loading in word vectors
Number of samples with no words found: 0 / 2780
Number of samples with no words found: 0 / 696
```



Question 13 : UMAP Plot

QUESTION 13:

Visualize the set of normalized GLoVE-based embeddings of the documents with their binary labels in a 2D plane using the UMAP library.

Similarly generate a set of normalized random vectors of the same dimension as GLoVE

Compare and contrast the two visualizations. Are there clusters formed in either or both of the plots? We will pursue the clustering aspect further in the next project.

- The set of normalized GLoVE-based embeddings formed a cluster, but the normalized random vectors didn't.

```
!pip install umap-learn

!pip install umap-learn[plot]
!pip install holoviews
!pip install -U ipykernel

Collecting umap-learn
  Downloading umap-learn-0.5.5.tar.gz (90 kB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 90.9/90.9 kB 1.8 MB/s eta
```

```
0:00:00
etadata (setup.py) ... ent already satisfied: numpy>=1.17 in
/usr/local/lib/python3.10/dist-packages (from umap-learn) (1.23.5)
Requirement already satisfied: scipy>=1.3.1 in
/usr/local/lib/python3.10/dist-packages (from umap-learn) (1.11.4)
Requirement already satisfied: scikit-learn>=0.22 in
/usr/local/lib/python3.10/dist-packages (from umap-learn) (1.2.2)
Requirement already satisfied: numba>=0.51.2 in
/usr/local/lib/python3.10/dist-packages (from umap-learn) (0.58.1)
Collecting pynndescent>=0.5 (from umap-learn)
  Downloading pynndescent-0.5.11-py3-none-any.whl (55 kB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 55.8/55.8 kB 5.7 MB/s eta
0:00:00
ent already satisfied: tqdm in /usr/local/lib/python3.10/dist-packages
(from umap-learn) (4.66.1)
Requirement already satisfied: llvmlite<0.42,>=0.41.0dev0 in
/usr/local/lib/python3.10/dist-packages (from numba>=0.51.2->umap-
learn) (0.41.1)
Requirement already satisfied: joblib>=0.11 in
/usr/local/lib/python3.10/dist-packages (from pynndescent>=0.5->umap-
learn) (1.3.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.22-
>umap-learn) (3.2.0)
Building wheels for collected packages: umap-learn
  Building wheel for umap-learn (setup.py) ... ap-learn:
filename=umap_learn-0.5.5-py3-none-any.whl size=86832
sha256=60e2775d24c15862241e8153f5a9294dc1b128393c8048199467819709 37d8c
3
  Stored in directory:
/root/.cache/pip/wheels/3a/70/07/428d2b58660a1a3b431db59b806a10da73661
2ebbc66c1bcc5
Successfully built umap-learn
Installing collected packages: pynndescent, umap-learn
Successfully installed pynndescent-0.5.11 umap-learn-0.5.5
Requirement already satisfied: umap-learn[plot] in
/usr/local/lib/python3.10/dist-packages (0.5.5)
Requirement already satisfied: numpy>=1.17 in
/usr/local/lib/python3.10/dist-packages (from umap-learn[plot])
(1.23.5)
Requirement already satisfied: scipy>=1.3.1 in
/usr/local/lib/python3.10/dist-packages (from umap-learn[plot])
(1.11.4)
Requirement already satisfied: scikit-learn>=0.22 in
/usr/local/lib/python3.10/dist-packages (from umap-learn[plot])
(1.2.2)
Requirement already satisfied: numba>=0.51.2 in
/usr/local/lib/python3.10/dist-packages (from umap-learn[plot])
(0.58.1)
```

```
Requirement already satisfied: pynndescent>=0.5 in
/usr/local/lib/python3.10/dist-packages (from umap-learn[plot])
(0.5.11)
Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-
packages (from umap-learn[plot]) (4.66.1)
Requirement already satisfied: pandas in
/usr/local/lib/python3.10/dist-packages (from umap-learn[plot])
(1.5.3)
Requirement already satisfied: matplotlib in
/usr/local/lib/python3.10/dist-packages (from umap-learn[plot])
(3.7.1)
Collecting datashader (from umap-learn[plot])
  Downloading datashader-0.16.0-py2.py3-none-any.whl (18.3 MB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 18.3/18.3 MB 31.3 MB/s eta
0:00:00
ent already satisfied: bokeh in /usr/local/lib/python3.10/dist-
packages (from umap-learn[plot]) (3.3.3)
Requirement already satisfied: holoviews in
/usr/local/lib/python3.10/dist-packages (from umap-learn[plot])
(1.17.1)
Requirement already satisfied: colorcet in
/usr/local/lib/python3.10/dist-packages (from umap-learn[plot])
(3.0.1)
Requirement already satisfied: seaborn in
/usr/local/lib/python3.10/dist-packages (from umap-learn[plot])
(0.13.1)
Requirement already satisfied: scikit-image in
/usr/local/lib/python3.10/dist-packages (from umap-learn[plot])
(0.19.3)
Requirement already satisfied: llvmlite<0.42,>=0.41.0dev0 in
/usr/local/lib/python3.10/dist-packages (from numba>=0.51.2->umap-
learn[plot]) (0.41.1)
Requirement already satisfied: joblib>=0.11 in
/usr/local/lib/python3.10/dist-packages (from pynndescent>=0.5->umap-
learn[plot]) (1.3.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.22-
>umap-learn[plot]) (3.2.0)
Requirement already satisfied: Jinja2>=2.9 in
/usr/local/lib/python3.10/dist-packages (from bokeh->umap-learn[plot])
(3.1.3)
Requirement already satisfied: contourpy>=1 in
/usr/local/lib/python3.10/dist-packages (from bokeh->umap-learn[plot])
(1.2.0)
Requirement already satisfied: packaging>=16.8 in
/usr/local/lib/python3.10/dist-packages (from bokeh->umap-learn[plot])
(23.2)
Requirement already satisfied: pillow>=7.1.0 in
/usr/local/lib/python3.10/dist-packages (from bokeh->umap-learn[plot])
```

```
(9.4.0)
Requirement already satisfied: PyYAML>=3.10 in
/usr/local/lib/python3.10/dist-packages (from bokeh->umap-learn[plot])
(6.0.1)
Requirement already satisfied: tornado>=5.1 in
/usr/local/lib/python3.10/dist-packages (from bokeh->umap-learn[plot])
(6.3.2)
Requirement already satisfied: xyzservices>=2021.09.1 in
/usr/local/lib/python3.10/dist-packages (from bokeh->umap-learn[plot])
(2023.10.1)
Requirement already satisfied: python-dateutil>=2.8.1 in
/usr/local/lib/python3.10/dist-packages (from pandas->umap-
learn[plot]) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in
/usr/local/lib/python3.10/dist-packages (from pandas->umap-
learn[plot]) (2023.3.post1)
Requirement already satisfied: pyct>=0.4.4 in
/usr/local/lib/python3.10/dist-packages (from colorcet->umap-
learn[plot]) (0.5.0)
Requirement already satisfied: dask in /usr/local/lib/python3.10/dist-
packages (from datashader->umap-learn[plot]) (2023.8.1)
Requirement already satisfied: multipledispatch in
/usr/local/lib/python3.10/dist-packages (from datashader->umap-
learn[plot]) (1.0.0)
Requirement already satisfied: param in
/usr/local/lib/python3.10/dist-packages (from datashader->umap-
learn[plot]) (2.0.2)
Requirement already satisfied: requests in
/usr/local/lib/python3.10/dist-packages (from datashader->umap-
learn[plot]) (2.31.0)
Requirement already satisfied: toolz in
/usr/local/lib/python3.10/dist-packages (from datashader->umap-
learn[plot]) (0.12.0)
Requirement already satisfied: xarray in
/usr/local/lib/python3.10/dist-packages (from datashader->umap-
learn[plot]) (2023.7.0)
Requirement already satisfied: pyviz-comms>=0.7.4 in
/usr/local/lib/python3.10/dist-packages (from holoviews->umap-
learn[plot]) (3.0.1)
Requirement already satisfied: panel>=0.13.1 in
/usr/local/lib/python3.10/dist-packages (from holoviews->umap-
learn[plot]) (1.3.7)
Requirement already satisfied: cycler>=0.10 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->umap-
learn[plot]) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->umap-
learn[plot]) (4.47.2)
Requirement already satisfied: kiwisolver>=1.0.1 in
```

```
/usr/local/lib/python3.10/dist-packages (from matplotlib->umap-
learn[plot]) (1.4.5)
Requirement already satisfied: pyparsing>=2.3.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->umap-
learn[plot]) (3.1.1)
Requirement already satisfied: networkx>=2.2 in
/usr/local/lib/python3.10/dist-packages (from scikit-image->umap-
learn[plot]) (3.2.1)
Requirement already satisfied: imageio>=2.4.1 in
/usr/local/lib/python3.10/dist-packages (from scikit-image->umap-
learn[plot]) (2.31.6)
Requirement already satisfied: tifffile>=2019.7.26 in
/usr/local/lib/python3.10/dist-packages (from scikit-image->umap-
learn[plot]) (2023.12.9)
Requirement already satisfied: PyWavelets>=1.1.1 in
/usr/local/lib/python3.10/dist-packages (from scikit-image->umap-
learn[plot]) (1.5.0)
Requirement already satisfied: MarkupSafe>=2.0 in
/usr/local/lib/python3.10/dist-packages (from Jinja2>=2.9->bokeh-
>umap-learn[plot]) (2.1.4)
Requirement already satisfied: markdown in
/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
>holoviews->umap-learn[plot]) (3.5.2)
Requirement already satisfied: markdown-it-py in
/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
>holoviews->umap-learn[plot]) (3.0.0)
Requirement already satisfied: linkify-it-py in
/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
>holoviews->umap-learn[plot]) (2.0.2)
Requirement already satisfied: mdit-py-plugins in
/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
>holoviews->umap-learn[plot]) (0.4.0)
Requirement already satisfied: bleach in
/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
>holoviews->umap-learn[plot]) (6.1.0)
Requirement already satisfied: typing-extensions in
/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
>holoviews->umap-learn[plot]) (4.5.0)
Requirement already satisfied: six>=1.5 in
/usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.8.1-
>pandas->umap-learn[plot]) (1.16.0)
Requirement already satisfied: click>=8.0 in
/usr/local/lib/python3.10/dist-packages (from dask->datashader->umap-
learn[plot]) (8.1.7)
Requirement already satisfied: cloudpickle>=1.5.0 in
/usr/local/lib/python3.10/dist-packages (from dask->datashader->umap-
learn[plot]) (2.2.1)
Requirement already satisfied: fsspec>=2021.09.0 in
/usr/local/lib/python3.10/dist-packages (from dask->datashader->umap-
```

```
learn[plot]) (2023.6.0)
Requirement already satisfied: partd>=1.2.0 in
/usr/local/lib/python3.10/dist-packages (from dask->datashader->umap-
learn[plot]) (1.4.1)
Requirement already satisfied: importlib-metadata>=4.13.0 in
/usr/local/lib/python3.10/dist-packages (from dask->datashader->umap-
learn[plot]) (7.0.1)
Requirement already satisfied: charset-normalizer<4,>=2 in
/usr/local/lib/python3.10/dist-packages (from requests->datashader-
>umap-learn[plot]) (3.3.2)
Requirement already satisfied: idna<4,>=2.5 in
/usr/local/lib/python3.10/dist-packages (from requests->datashader-
>umap-learn[plot]) (3.6)
Requirement already satisfied: urllib3<3,>=1.21.1 in
/usr/local/lib/python3.10/dist-packages (from requests->datashader-
>umap-learn[plot]) (2.0.7)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.10/dist-packages (from requests->datashader-
>umap-learn[plot]) (2023.11.17)
Requirement already satisfied: zipp>=0.5 in
/usr/local/lib/python3.10/dist-packages (from importlib-
metadata>=4.13.0->dask->datashader->umap-learn[plot]) (3.17.0)
Requirement already satisfied: locket in
/usr/local/lib/python3.10/dist-packages (from partd>=1.2.0->dask-
>datashader->umap-learn[plot]) (1.0.0)
Requirement already satisfied: webencodings in
/usr/local/lib/python3.10/dist-packages (from bleach->panel>=0.13.1-
>holoviews->umap-learn[plot]) (0.5.1)
Requirement already satisfied: uc-micro-py in
/usr/local/lib/python3.10/dist-packages (from linkify-it-py-
>panel>=0.13.1->holoviews->umap-learn[plot]) (1.0.2)
Requirement already satisfied: mdurl~=0.1 in
/usr/local/lib/python3.10/dist-packages (from markdown-it-py-
>panel>=0.13.1->holoviews->umap-learn[plot]) (0.1.2)
Installing collected packages: datashader
Successfully installed datashader-0.16.0
Requirement already satisfied: holoviews in
/usr/local/lib/python3.10/dist-packages (1.17.1)
Requirement already satisfied: param<3.0,>=1.12.0 in
/usr/local/lib/python3.10/dist-packages (from holoviews) (2.0.2)
Requirement already satisfied: numpy>=1.0 in
/usr/local/lib/python3.10/dist-packages (from holoviews) (1.23.5)
Requirement already satisfied: pyviz-comms>=0.7.4 in
/usr/local/lib/python3.10/dist-packages (from holoviews) (3.0.1)
Requirement already satisfied: panel>=0.13.1 in
/usr/local/lib/python3.10/dist-packages (from holoviews) (1.3.7)
Requirement already satisfied: colorcet in
/usr/local/lib/python3.10/dist-packages (from holoviews) (3.0.1)
Requirement already satisfied: packaging in
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/usr/local/lib/python3.10/dist-packages (from holoviews) (23.2)
Requirement already satisfied: pandas>=0.20.0 in
/usr/local/lib/python3.10/dist-packages (from holoviews) (1.5.3)
Requirement already satisfied: python-dateutil>=2.8.1 in
/usr/local/lib/python3.10/dist-packages (from pandas>=0.20.0-
>holoviews) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in
/usr/local/lib/python3.10/dist-packages (from pandas>=0.20.0-
>holoviews) (2023.3.post1)
Requirement already satisfied: bokeh<3.4.0,>=3.2.0 in
/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
>holoviews) (3.3.3)
Requirement already satisfied: xyzservices>=2021.09.1 in
/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
>holoviews) (2023.10.1)
Requirement already satisfied: markdown in
/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
>holoviews) (3.5.2)
Requirement already satisfied: markdown-it-py in
/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
>holoviews) (3.0.0)
Requirement already satisfied: linkify-it-py in
/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
>holoviews) (2.0.2)
Requirement already satisfied: mdit-py-plugins in
/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
>holoviews) (0.4.0)
Requirement already satisfied: requests in
/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
>holoviews) (2.31.0)
Requirement already satisfied: tqdm>=4.48.0 in
/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
>holoviews) (4.66.1)
Requirement already satisfied: bleach in
/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
>holoviews) (6.1.0)
Requirement already satisfied: typing-extensions in
/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
>holoviews) (4.5.0)
Requirement already satisfied: pyct>=0.4.4 in
/usr/local/lib/python3.10/dist-packages (from colorcet->holoviews)
(0.5.0)
Requirement already satisfied: Jinja2>=2.9 in
/usr/local/lib/python3.10/dist-packages (from bokeh<3.4.0,>=3.2.0-
>panel>=0.13.1->holoviews) (3.1.3)
Requirement already satisfied: contourpy>=1 in
/usr/local/lib/python3.10/dist-packages (from bokeh<3.4.0,>=3.2.0-
>panel>=0.13.1->holoviews) (1.2.0)
Requirement already satisfied: pillow>=7.1.0 in
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/usr/local/lib/python3.10/dist-packages (from bokeh<3.4.0,>=3.2.0-
>panel>=0.13.1->holoviews) (9.4.0)
Requirement already satisfied: PyYAML>=3.10 in
/usr/local/lib/python3.10/dist-packages (from bokeh<3.4.0,>=3.2.0-
>panel>=0.13.1->holoviews) (6.0.1)
Requirement already satisfied: tornado>=5.1 in
/usr/local/lib/python3.10/dist-packages (from bokeh<3.4.0,>=3.2.0-
>panel>=0.13.1->holoviews) (6.3.2)
Requirement already satisfied: six>=1.5 in
/usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.8.1-
>pandas>=0.20.0->holoviews) (1.16.0)
Requirement already satisfied: webencodings in
/usr/local/lib/python3.10/dist-packages (from bleach->panel>=0.13.1-
>holoviews) (0.5.1)
Requirement already satisfied: uc-micro-py in
/usr/local/lib/python3.10/dist-packages (from linkify-it-py-
>panel>=0.13.1->holoviews) (1.0.2)
Requirement already satisfied: mdurl~=0.1 in
/usr/local/lib/python3.10/dist-packages (from markdown-it-py-
>panel>=0.13.1->holoviews) (0.1.2)
Requirement already satisfied: charset-normalizer<4,>=2 in
/usr/local/lib/python3.10/dist-packages (from requests->panel>=0.13.1-
>holoviews) (3.3.2)
Requirement already satisfied: idna<4,>=2.5 in
/usr/local/lib/python3.10/dist-packages (from requests->panel>=0.13.1-
>holoviews) (3.6)
Requirement already satisfied: urllib3<3,>=1.21.1 in
/usr/local/lib/python3.10/dist-packages (from requests->panel>=0.13.1-
>holoviews) (2.0.7)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.10/dist-packages (from requests->panel>=0.13.1-
>holoviews) (2023.11.17)
Requirement already satisfied: MarkupSafe>=2.0 in
/usr/local/lib/python3.10/dist-packages (from Jinja2>=2.9-
>bokeh<3.4.0,>=3.2.0->panel>=0.13.1->holoviews) (2.1.4)
Requirement already satisfied: ipykernel in
/usr/local/lib/python3.10/dist-packages (5.5.6)
Collecting ipykernel
  Downloading ipykernel-6.29.0-py3-none-any.whl (116 kB)
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m>=0.1.1 (from ipykernel)
  Downloading comm-0.2.1-py3-none-any.whl (7.2 kB)
Requirement already satisfied: debugpy>=1.6.5 in
/usr/local/lib/python3.10/dist-packages (from ipykernel) (1.6.6)
Requirement already satisfied: ipython>=7.23.1 in
/usr/local/lib/python3.10/dist-packages (from ipykernel) (7.34.0)
Requirement already satisfied: jupyter-client>=6.1.12 in
/usr/local/lib/python3.10/dist-packages (from ipykernel) (6.1.12)
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Requirement already satisfied: jupyter-core!=5.0.*,>=4.12 in
/usr/local/lib/python3.10/dist-packages (from ipykernel) (5.7.1)
Requirement already satisfied: matplotlib-inline>=0.1 in
/usr/local/lib/python3.10/dist-packages (from ipykernel) (0.1.6)
Requirement already satisfied: nest-asyncio in
/usr/local/lib/python3.10/dist-packages (from ipykernel) (1.6.0)
Requirement already satisfied: packaging in
/usr/local/lib/python3.10/dist-packages (from ipykernel) (23.2)
Requirement already satisfied: psutil in
/usr/local/lib/python3.10/dist-packages (from ipykernel) (5.9.5)
Collecting pyzmq>=24 (from ipykernel)
  Downloading pyzmq-25.1.2-cp310-cp310-manylinux_2_28_x86_64.whl (1.1
MB)
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ent already satisfied: tornado>=6.1 in /usr/local/lib/python3.10/dist-
packages (from ipykernel) (6.3.2)
Requirement already satisfied: traitlets>=5.4.0 in
/usr/local/lib/python3.10/dist-packages (from ipykernel) (5.7.1)
Requirement already satisfied: setuptools>=18.5 in
/usr/local/lib/python3.10/dist-packages (from ipython>=7.23.1-
>ipykernel) (67.7.2)
Collecting jedi>=0.16 (from ipython>=7.23.1->ipykernel)
  Downloading jedi-0.19.1-py2.py3-none-any.whl (1.6 MB)
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ent already satisfied: decorator in /usr/local/lib/python3.10/dist-
packages (from ipython>=7.23.1->ipykernel) (4.4.2)
Requirement already satisfied: pickleshare in
/usr/local/lib/python3.10/dist-packages (from ipython>=7.23.1-
>ipykernel) (0.7.5)
Requirement already satisfied: prompt-toolkit!=3.0.0,!
=3.0.1,<3.1.0,>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from
ipython>=7.23.1->ipykernel) (3.0.43)
Requirement already satisfied: pygments in
/usr/local/lib/python3.10/dist-packages (from ipython>=7.23.1-
>ipykernel) (2.16.1)
Requirement already satisfied: backcall in
/usr/local/lib/python3.10/dist-packages (from ipython>=7.23.1-
>ipykernel) (0.2.0)
Requirement already satisfied: pexpect>4.3 in
/usr/local/lib/python3.10/dist-packages (from ipython>=7.23.1-
>ipykernel) (4.9.0)
Requirement already satisfied: python-dateutil>=2.1 in
/usr/local/lib/python3.10/dist-packages (from jupyter-client>=6.1.12-
>ipykernel) (2.8.2)
Requirement already satisfied: platformdirs>=2.5 in
/usr/local/lib/python3.10/dist-packages (from jupyter-core!
=5.0.*,>=4.12->ipykernel) (4.1.0)
```

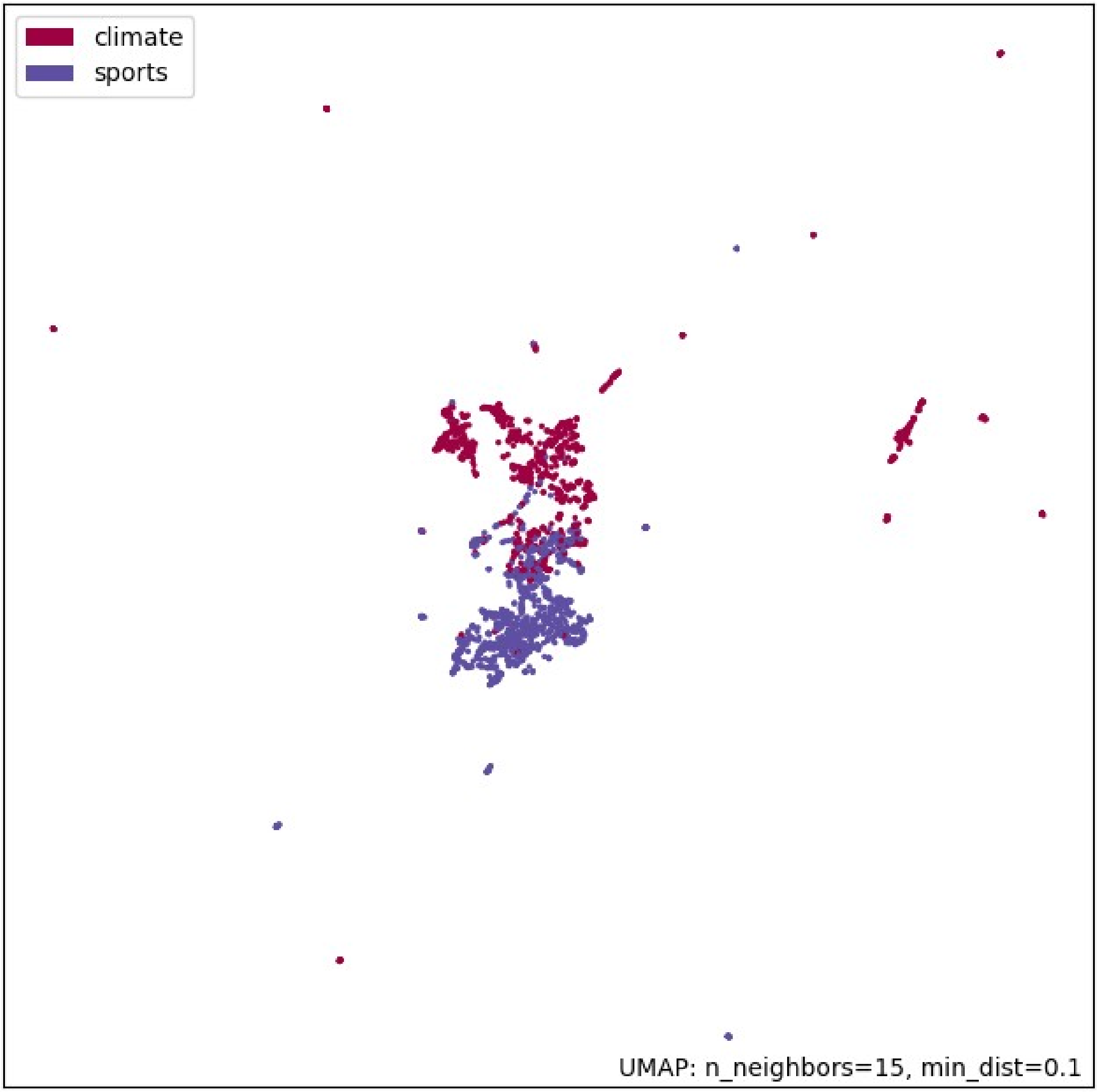
```
Requirement already satisfied: parso<0.9.0,>=0.8.3 in
/usr/local/lib/python3.10/dist-packages (from jedi>=0.16-
>ipython>=7.23.1->ipykernel) (0.8.3)
Requirement already satisfied: ptyprocess>=0.5 in
/usr/local/lib/python3.10/dist-packages (from pexpect>4.3-
>ipython>=7.23.1->ipykernel) (0.7.0)
Requirement already satisfied: wcwidth in
/usr/local/lib/python3.10/dist-packages (from prompt-toolkit!=3.0.0,!
=3.0.1,<3.1.0,>=2.0.0->ipython>=7.23.1->ipykernel) (0.2.13)
Requirement already satisfied: six>=1.5 in
/usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.1-
>jupyter-client>=6.1.12->ipykernel) (1.16.0)
Installing collected packages: pyzmq, jedi, comm, ipykernel
  Attempting uninstall: pyzmq
    Found existing installation: pyzmq 23.2.1
    Uninstalling pyzmq-23.2.1:
      Successfully uninstalled pyzmq-23.2.1
  Attempting uninstall: ipykernel
    Found existing installation: ipykernel 5.5.6
    Uninstalling ipykernel-5.5.6:
      Successfully uninstalled ipykernel-5.5.6
ERROR: pip's dependency resolver does not currently take into account
all the packages that are installed. This behaviour is the source of
the following dependency conflicts.
google-colab 1.0.0 requires ipykernel==5.5.6, but you have ipykernel
6.29.0 which is incompatible.
notebook 6.5.5 requires pyzmq<25,>=17, but you have pyzmq 25.1.2 which
is incompatible.
Successfully installed comm-0.2.1 ipykernel-6.29.0 jedi-0.19.1 pyzmq-
25.1.2
```

{"pip_warning":{"packages":["zmq"]}}

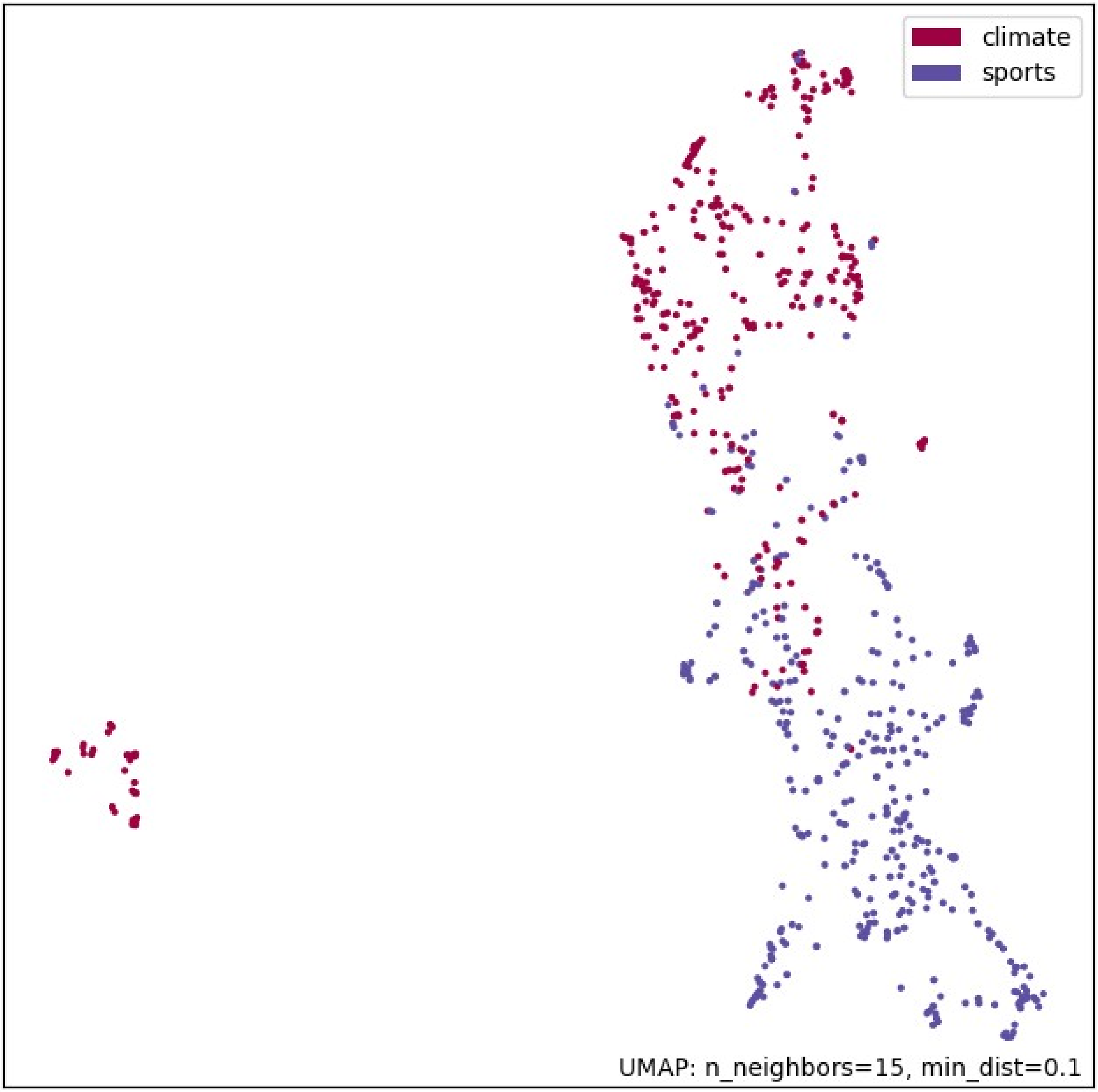
```python
import umap
import umap.plot
```

```
/usr/local/lib/python3.10/dist-packages/umap/plot.py:203:
NumbaDeprecationWarning: The keyword argument 'nopython=False' was
supplied. From Numba 0.59.0 the default is being changed to True and
use of 'nopython=False' will raise a warning as the argument will have
no effect. See
https://numba.readthedocs.io/en/stable/reference/deprecation.html#depr
ecation-of-object-mode-fall-back-behaviour-when-using-jit for details.
  @numba.jit(nopython=False)
```

```python
embedding = umap.UMAP(n_components=2).fit(train_glove)
embedding.embedding_.shape
f = umap.plot.points(embedding, labels=train["root_label"])
```




```
embedding = umap.UMAP(n_components=2).fit(test_glove)
embedding.embedding_.shape
f = umap.plot.points(embedding, labels=test["root_label"])
```




```
v = np.random.rand(300, 300)
v_hat = v / np.linalg.norm(v)

embedding = umap.UMAP(n_components=2).fit(v_hat)
embedding.embedding_.shape
f = umap.plot.points(embedding)

/usr/local/lib/python3.10/dist-packages/umap/plot.py:449: UserWarning:
*c* argument looks like a single numeric RGB or RGBA sequence, which
should be avoided as value-mapping will have precedence in case its
length matches with *x* & *y*.  Please use the *color* keyword-
argument or provide a 2D array with a single row if you intend to
```

```
specify the same RGB or RGBA value for all points.
  ax.scatter(points[:, 0], points[:, 1], s=point_size, c=color)
```