ECE 219: Large Scale Data Mining: Models and Algorithms Project 1

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1 Introduction

Throughout the project, the group gained experience in the classification analysis of textual data. Key ideas used throughout the project are data extraction, dimension reduction, classification and the creation of a pipeline that executed these tasks.The project expands these topics using key ideas of natural language processing which allowed different results to be attained and measured through key machine learning metrics, such as a confusion matrix, for a number of classifiers.

1.1 Question 1

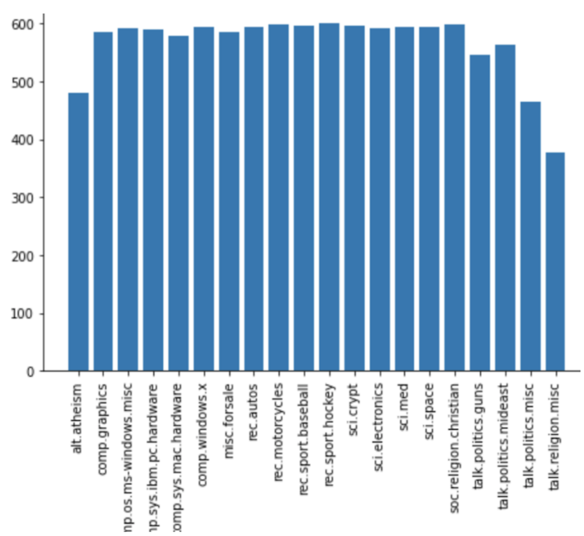


Figure 1: Histogram

The histogram above shows that the number of training documents for each of the 20 categories are overall evenly distributed, as expected.

2 Binary Classification

2.1 Question 2

Term-freq matrix shape train set: (4732, 16466) Term-freq matrix shape test set: (3150, 16466)

2.2 Question 3

$$\|X - WH\|_F^2$$

in NMF is smaller than

$$\left\|X - U_k \Sigma_k V_k^T\right\|_F^2$$

in LSI since NMF does not have any negative values, and therefore NMF has a greater sparcity than LSI when calculating the norms of each respective method.

2.3 Question 4

When training our classifier with both C = 1000 and C = 0.0001, in the case where C = 0.0001 we are seeing about 50 percent accuracy which is equivalent to randomly guessing our predictions. This makes sense as having a smaller C means we are being more lenient toward misclassifications and just want to reduce our w. In the case of the project this means that the priority is almost entirely on minimizing w with no penalty for the misclassifications giving us our low accuracy. The ROC curve of the soft margin case also shows us this visually with it being straight line.

After going through the cross validation, we found that C = 10 gave us the best accuracy of all 6 C values proposed.

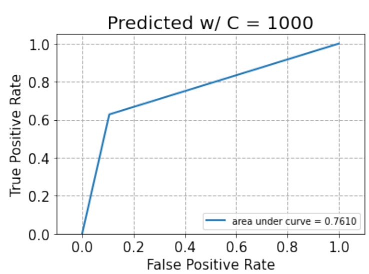


Figure 2: The ROC curve of SVM with C = 1000

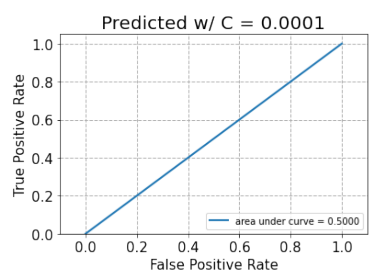


Figure 3: The ROC curve of SVM with C = 0.0001

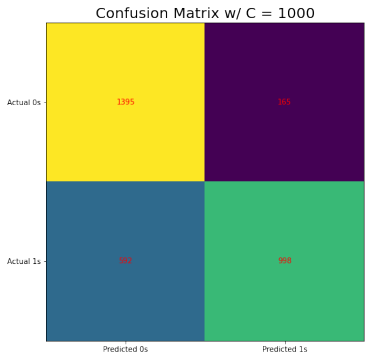


Figure 4: The confusion matrix of SVM with C = 1000

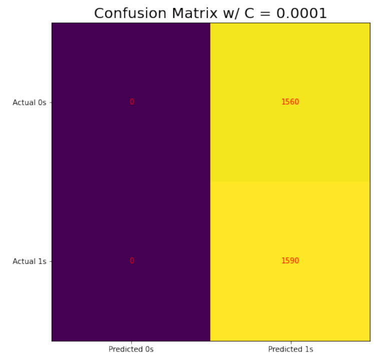


Figure 5: The confusion matrix of SVM with C = 0.0001

Performance Metrics of C = 1000 SVM

	Precision	Recall	F1 Score	Support
0	0.70	0.89	0.79	1560
1	0.86	0.63	0.73	1590
Accuracy			0.76	3150
Macro Avg.	0.78	0.76	0.76	3150
Weighted Avg.	0.78	0.76	0.76	3150

Performance Metrics of C = 0.0001 SVM

	Precision	Recall	F1 Score	Support
0	0.00	0.00	0.00	1560
1	0.50	1.00	0.67	1590
Accuracy			0.50	3150
Macro Avg.	0.25	0.50	0.34	3150
Weighted Avg.	0.25	0.50	0.34	3150

Performance Metrics of C = 10 SVM

	Precision	Recall	F1 Score	Support
0	0.71	0.92	0.80	1560
1	0.89	0.63	0.74	1590
Accuracy			0.77	3150
Macro Avg.	0.80	0.77	0.77	3150
Weighted Avg.	0.80	0.77	0.77	3150

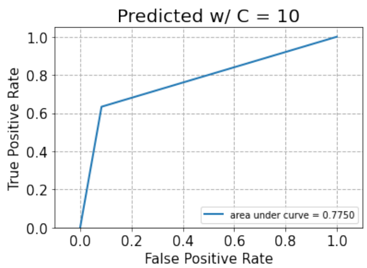


Figure 6: The ROC curve of SVM with C = 10

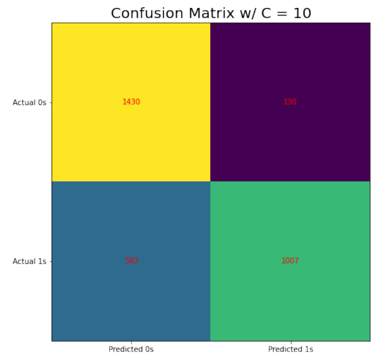


Figure 7: Confusion Matrix of SVM with C = 10

2.4 Question 5

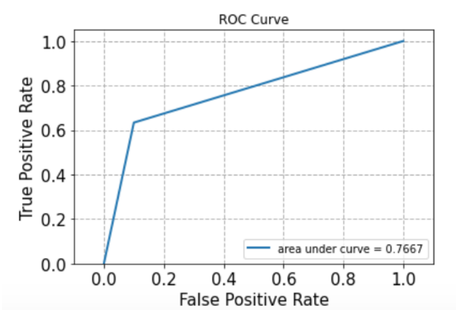


Figure 8: The ROC curve of logistic regression with no regularization

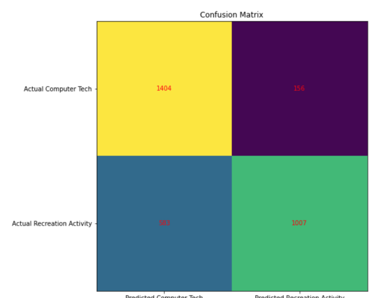


Figure 9: The Confusion Matrix of logistic regression with no regularization

Performance Metrics w/ No Regularization

	Precision	Recall	F1 Score
0	0.71	0.90	0.79
1	0.87	0.63	0.74
Accuracy			0.77

Performance Metrics of L1 Regularization at 0.01 strength

	Precision	Recall	F1 Score
0	0.71	0.90	0.79
1	0.87	0.64	0.73
Accuracy			0.77

Performance Metrics of L2 Regularization at 0.01 strength

	Precision	Recall	F1 Score
0	0.71	0.91	0.80
1	0.88	0.64	0.74
Accuracy			0.77

Using five-fold cross validation and varying the regularization strength, we found the best strength for l1 and l2 regularization was the same, at 0.01.

In our model, L1 and L2 regularization did not substantially effect the test error. Regularization penalizes large values in the weight matrix by adding a weight-based term to the loss function. L1 regularization penalizes the absolute values in the weight matrix, while L2 regularization penalizes the squared value of the weight matrix. L1 regularization pushes the model towards sparsity, by forcing the weights towards zero. In this way, L1 can be useful for feature reduction. L2 regularization evenly minimizes the weight values without forcing them to zero. Thus, L2 regularization is useful in situations where you want regularization without forcing sparcity.

Logistic regression uses the sigmoid function and maximum liklihood estimation to try to fit a boundary between each of the classes. SVM tries to find the boundary hyperplane that maximizes the margins between the two classes. Thus, SVM uses the geometric shape of the data to fit the boundary, while logistic regression uses statistical properties. In this way, the algorithms can find different boundary lines in the same data.

2.5 Question 6

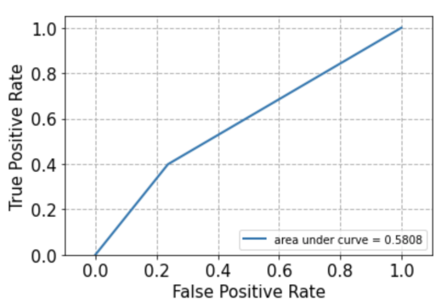


Figure 10: ROC of the Gaussian Naive Bayes classifier

Figure 11: Confusion Matrix of the Gaussian Naive Bayes classifier

Performance Metrics of the Gaussian Naive Bayes Classifier

	Precision	Recall	F1 Score	Support
0	0.55	0.76	0.64	1560
1	0.63	0.40	0.49	1590
Accuracy			0.58	3150
Macro Avg.	0.59	0.58	0.57	3150
Weighted Avg.	0.59	0.58	0.56	3150

2.6 Question 7

After performing the grid-search of hyperparameters and five-fold cross-validation, we found the best options were removing "headers" and "footers", with min-df = 3, no lemmatization, and LSI dimensionality reduction with Logistic Regression and L1 regularization at strength 0.01. This combination was able to achieve 85.8 percent test accuracy.

3 Word Embedding

3.1 Question 8

(a) The co-occurence probabilities are better able to distinguish relevant words from irrelevant words than the raw probabilities. This builds global word context into the embedding.

(b) The GloVe embedding would return the same vector for each instance of "running" despite having different contexts. This is because GloVe has no way to distinguish between the two versions of the word running; they are treated as the same word. Thus, the returned vector for the word running would include words similar to both contexts.

(c) We expect the value of

$$\|GloVe[\text{"}queen\text{"}] - GloVe[\text{"}king\text{"}] - GloVe[\text{"}wife\text{"}] + GloVe[\text{"}husband\text{"}]\|_2$$

to be close to zero since the relationship between "king" and "queen" is very similar to the relationship between "wife" and "husband". We expect the values of

$$\|GloVe[\text{"}queen\text{"}] - GloVe[\text{"}king\text{"}]\|_2$$

and

$$\|GloVe[\text{"}wife\text{"}] - GloVe[\text{"}husband\text{"}]\|_2$$

to be close to the value of

$$\|GloVe[\text{"}woman\text{"}]\|_2$$

because "wife" and "queen" are the feminine versions of "husband" and "king", respectively.

(d) Lemmatization is preferred over stemming when mapping words to their GloVe embedding. This is because lemmatization preserves the part-of-speech context of the word, whereas stemming reduces a word to its stem, ignoring context. For an example, the word "meeting" can be a verb or a noun and lemmatization would attempt to preserve the difference, while stemming would ad hoc remove the "-ing" in both cases. Because GloVe embeddings rely on co-occurrence probabilities of different words, it is important that the words retain their part-of-speech context.

3.2 Question 9

After creating an engineering process that uses GLoVE word embeddings to represent each document, the group chose the classifer as seen in the source code and attained an accuracy score of 0.784.

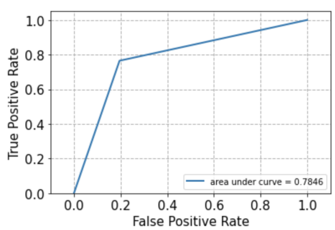


Figure 12: False positive rate for engineered features

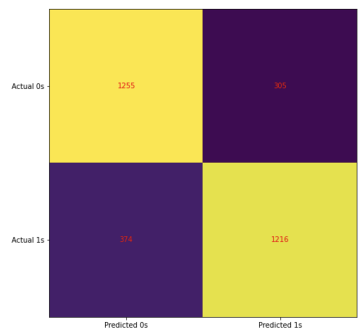


Figure 13: Confusion Matrix for engineered features

Performance Metrics using the features created

	Precision	Recall	F1 Score	Support
0	0.77	0.80	0.79	1560
1	0.80	0.76	0.78	1590
Accuracy			0.78	3150
Macro Avg.	0.78	0.78	0.78	3150
Weighted Avg.	0.79	0.78	0.78	3150

3.3 Question 10

As seen in the figure below, the trend line follows our expectations for dimensions 50 to 200. However, we do see our accuracy decrease as we go from 200 to 300 dimensions. One explanation for this change could be related to over-fitting where adding more dimensions decreases a classifiers accuracy on the test set.

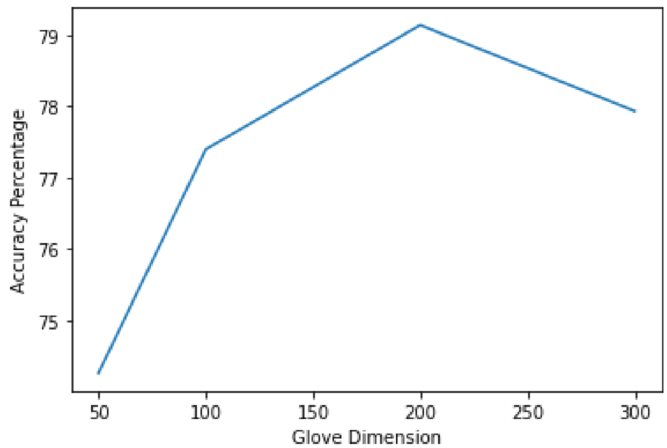


Figure 14: Accuracy of GloVe trained classifier over different GloVe dimensions

3.4 Question 11

As seen in the figures below, the normalized GLoVE-based embeddings of the documents with their labels in a 2D plan show a clustering that correlates to its accuracy.The randomized vector representation shows no measurable clustering as expected.

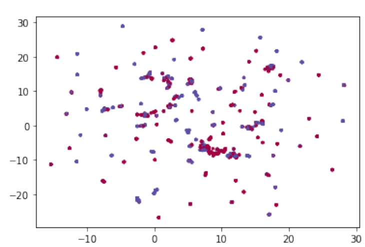


Figure 15: Normalized GLoVE-based embedding

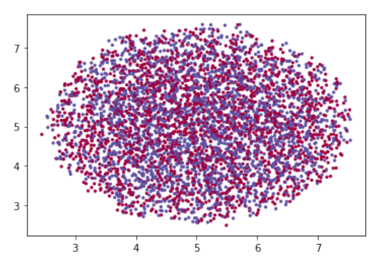


Figure 16: Randomized GLoVE-based embedding

4 Multiclass Classification

4.1 Question 12

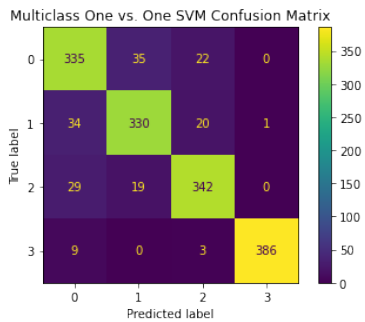


Figure 17: Multiclass One vs. One SVM

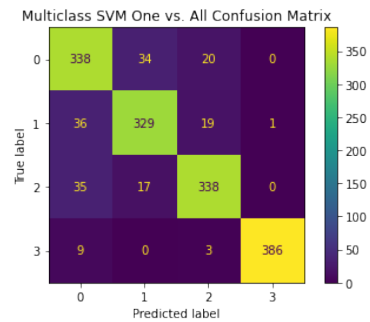


Figure 18: Multiclass One vs. All SVM

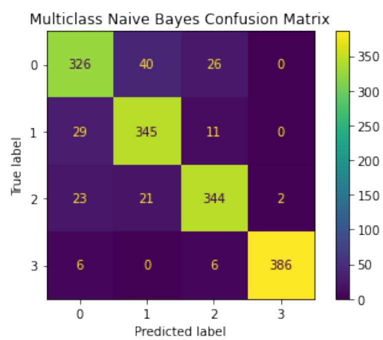


Figure 19: Multiclass Naive Bayes

Performance Metrics of Multiclass One vs. One SVM

	Precision	Recall	F1 Score	Support
0	0.82	0.85	0.84	392
1	0.86	0.86	0.86	385
2	0.88	0.88	0.88	390
3	1.00	0.97	0.98	398
Accuracy			0.89	1565

Performance Metrics of Multiclass One vs. All SVM

	Precision	Recall	F1 Score	Support
0	0.81	0.86	0.83	392
1	0.87	0.85	0.86	385
2	0.89	0.87	0.88	390
3	1.00	0.97	0.98	398
Accuracy			0.89	1565

Performance Metrics of Multiclass Naive Bayes

	Precision	Recall	F1 Score	Support
0	0.85	0.83	0.84	392
1	0.85	0.90	0.87	385
2	0.89	0.88	0.89	390
3	0.99	0.97	0.98	398
Accuracy			0.90	1565

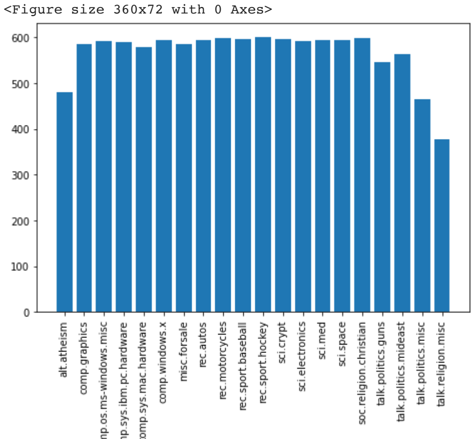
```
## Import General Libraries

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
np.random.seed(42)
import random
random.seed(42)
```

Intro

Question 1

```
from sklearn.datasets import fetch_20newsgroups


categories = ['alt.atheism', 'comp.graphics', 'comp.os.ms-windows.misc',
              'comp.sys.ibm.pc.hardware', 'comp.sys.mac.hardware', 'comp.windows.x',
              'misc.forsale', 'rec.autos', 'rec.motorcycles',
              'rec.sport.baseball', 'rec.sport.hockey', 'sci.crypt',
              'sci.electronics', 'sci.med', 'sci.space',
              'soc.religion.christian','talk.politics.guns', 'talk.politics.mideast',
              'talk.politics.misc', 'talk.religion.misc']
data = fetch_20newsgroups(categories=None)
print((data.target_names))
print(dir(data))

def counting(data, categories):
    count =0
    for x in data.filenames:
    #    print(x)
        if categories in x:
            count+=1
    return(count)
d={}
for x in categories:
    total=counting(data, x)
    d[x]=total

print(d)
d_x= list(d.keys())
d_y=list(d.values())
print(d_x)
print(d_y)
# df=pd.DataFrame(d)


fig = plt.figure(figsize=(5, 1))
fig, ax = plt.subplots()
ax = fig.add_axes([0,0,1,1])
ax.bar(d_x,d_y)
for tick in ax.get_xticklabels():
    tick.set_rotation(90)

plt.show()
```

```
Downloading 20news dataset. This may take a few minutes.
Downloading dataset from https://ndownloader.figshare.com/files/5975967 (14 MB)
['alt.atheism', 'comp.graphics', 'comp.os.ms-windows.misc', 'comp.sys.ibm.pc.hardware', 'comp.sys.mac.hardware', 'comp.windows.x', 'misc.forsale', 'rec.autos', 'rec.motc
['DESCR', 'data', 'filenames', 'target', 'target_names']
{'alt.atheism': 480, 'comp.graphics': 584, 'comp.os.ms-windows.misc': 591, 'comp.sys.ibm.pc.hardware': 590, 'comp.sys.mac.hardware': 578, 'comp.windows.x': 593, 'misc.fc
['alt.atheism', 'comp.graphics', 'comp.os.ms-windows.misc', 'comp.sys.ibm.pc.hardware', 'comp.sys.mac.hardware', 'comp.windows.x', 'misc.forsale', 'rec.autos', 'rec.motc
[480, 584, 591, 590, 578, 593, 585, 594, 598, 597, 600, 595, 591, 594, 593, 599, 546, 564, 465, 377]
<Figure size 360x72 with 0 Axes>
```



Binary Classification

Feature Extraction

Question 2

```
'''
Create training and testing sets
'''
from sklearn.datasets import fetch_20newsgroups


# Categories we are interested in
comp_categories = [ 'comp.graphics', 'comp.os.ms-windows.misc', 'comp.sys.ibm.pc.hardware', 'comp.sys.mac.hardware']
rec_categories = ['rec.autos', 'rec.motorcycles', 'rec.sport.baseball', 'rec.sport.hockey']
# Create train and test data sets
twenty_train = fetch_20newsgroups(subset='train',
                                  categories=comp_categories+rec_categories,
                                  shuffle=True, random_state=42,)
twenty_test = fetch_20newsgroups(subset='test',
                                 categories=comp_categories+rec_categories,
                                 shuffle=True, random_state=42,)


'''
Create stopwords
    exclude words that are too common, or too rare (words that tell us nothing
     specific about the document)
'''
import nltk
from sklearn.feature_extraction import text
from nltk.corpus import stopwords
nltk.download('stopwords')
from string import punctuation


# Use "english" stopwords of CountVectorizer
stop_words_en = stopwords.words('english')
stop_words_en.append('Re:')
stop_words_en.append('')
# Exclude terms that are numbers/symbols
combined_stopwords = set.union(set(stop_words_en), set(punctuation))
```

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

```
'''
Lemmatization w/ Part-of-Speach
'''
from nltk import pos_tag
nltk.download('wordnet')
nltk.download('punkt')
nltk.download('averaged_perceptron_tagger')


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'

wnl = nltk.wordnet.WordNetLemmatizer()
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)]
```

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

```
'''
Count Vectorization and TF-IDF Matrices
'''
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfTransformer


# overwrite analyzer with callable function:
analyzer = CountVectorizer().build_analyzer()

# performs lemmatization as function for analyzer
def stem_rmv_punc(doc):
    return (word for word in lemmatize_sent(analyzer(doc)) if word not in combined_stopwords and not word.isdigit())

# Apply CountVectorizer to train and test sets
count_vect = CountVectorizer(min_df=3, analyzer=stem_rmv_punc, stop_words='english')
train_rc_V = count_vect.fit_transform(twenty_train.data)
print("Term-freq matrix shape train set: ", train_rc_V.shape)                   # 4732 docs, 16466 terms
print()
test_rc_V = count_vect.transform(twenty_test.data)
print("Term-freq matrix shape test set: ", test_rc_V.shape)                     # 3150 docs, 16466 terms
print()

# get_feature_names gives us a list of words that each column of term-frequency
```

```
# matrix corresponds to
feat_names = count_vect.get_feature_names()
print("Number of terms: ", len((feat_names)))                                    # 16466 terms (matches above)
print(feat_names[1:10])
print()

# Compute the TF-IDF matrices of the train and test sets
tfidf_trans = TfidfTransformer()
X_train_tfidf = tfidf_trans.fit_transform(train_rc_V)
X_test_tfidf = tfidf_trans.transform(test_rc_V)
print("TF-IDF shape train set: ", X_train_tfidf.shape)
print()
print("TF-IDF shape test set: ", X_test_tfidf.shape)
print()
```

```
Term-freq matrix shape train set:  (4732, 16466)

Term-freq matrix shape test set:  (3150, 16466)

Number of terms:  16466
['0010580b', '002251w', '0096b0f0', '00bjgood', '00mbstultz', '00pm', '02uv', '03hz', '03k']

TF-IDF shape train set:  (4732, 16466)

TF-IDF shape test set:  (3150, 16466)
```

Dimensionality Reduction

Question 3

```
'''
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.fit_transform(X_test_tfidf)
print(X_train_LSI.shape)
```

```
(4732, 50)
```

```
np.sum(np.array(X_train_tfidf - X_train_LSI.dot(svd.components_))**2)
```

```
5062.75424563187
```

```
'''
NMF
'''
from sklearn.decomposition import NMF


model = NMF(n_components=50, init='random', random_state=42)
W_train = model.fit_transform(X_train_tfidf)
W_test = model.fit_transform(X_test_tfidf)

print(W_train.shape)
```

```
(4732, 50)
```

```
H = model.components_
# H.shape
```

```
np.sum(np.array(X_train_tfidf - W_train.dot(H))**2)
```

```
4143.541730848815
```

Classification Algorithms

Questions 4-7

```
from sklearn.datasets import fetch_20newsgroups

comp_categories = [ 'comp.graphics', 'comp.os.ms-windows.misc', 'comp.sys.ibm.pc.hardware', 'comp.sys.mac.hardware']
rec_categories = ['rec.autos', 'rec.motorcycles', 'rec.sport.baseball', 'rec.sport.hockey']

# Create train and test data sets
eight_train = fetch_20newsgroups(subset='train',
                                  categories=comp_categories+rec_categories,
                                  shuffle=True, random_state=42,)
eight_test = fetch_20newsgroups(subset='test',
                                 categories=comp_categories+rec_categories,
                                 shuffle=True, random_state=42,)


'''
Reassign labels to binary
    comp will get label '0' and rec will get label '1'
'''


for i in np.arange(eight_train.target.shape[0]):
    if eight_train.target[i] < 4:
        eight_train.target[i] = 0
    else:
```

```
        eight_train.target[i] = 1

for i in np.arange(eight_test.target.shape[0]):
    if eight_test.target[i] < 4:
        eight_test.target[i] = 0
    else:
        eight_test.target[i] = 1

print(np.unique(eight_train.target))
print(np.unique(eight_test.target))
```

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

SVM

Question 4

```
'''
Linear SVM
'''



comp_categories = [ 'comp.graphics', 'comp.os.ms-windows.misc', 'comp.sys.ibm.pc.hardware', 'comp.sys.mac.hardware']
rec_categories = ['rec.autos', 'rec.motorcycles', 'rec.sport.baseball', 'rec.sport.hockey']

# Create train and test data sets

eight_train = fetch_20newsgroups(subset='train',
                                  categories=comp_categories+rec_categories,
                                  shuffle=True, random_state=42,)
eight_test = fetch_20newsgroups(subset='test',
                                 categories=comp_categories+rec_categories,
                                 shuffle=True, random_state=42,)

eight_train_LSI = X_train_LSI
eight_test_LSI = X_test_LSI


'''
Reassign labels
    comp will get label '0' and rec will get label '1'
'''

for i in np.arange(X_train_tfidf.shape[0]):
    if eight_train.target[i] < 4:
        eight_train.target[i] = 0
    else:
        eight_train.target[i] = 1

for i in np.arange(X_test_tfidf.shape[0]):
    if eight_test.target[i] < 4:
        eight_test.target[i] = 0
    else:
        eight_test.target[i] = 1

print(np.unique(eight_train.target))
print(np.unique(eight_test.target))
```

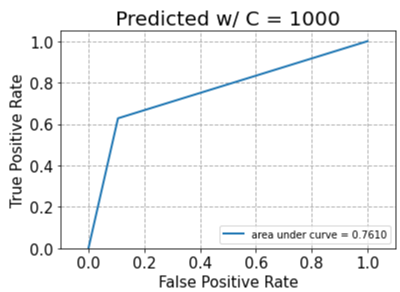
```
[0 1]
[0 1]
```

```
'''
Train Linear SVM w/ C = 1000, C = 0.0001
'''
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score

predicted_SVM_1000 = SVC(kernel='linear', C = 1000).fit(X_train_LSI, eight_train.target).predict(X_test_LSI)
acc1000 = accuracy_score(eight_test.target, predicted_SVM_1000)
print('Accuracy w/ C = 1000 = ')
print(acc1000)

predicted_SVM_0001 = SVC(kernel='linear', C = 0.0001).fit(X_train_LSI, eight_train.target).predict(X_test_LSI)
acc0001 = accuracy_score(eight_test.target, predicted_SVM_0001)
print('Accuracy w/ C = 0.0001 = ')
print(acc0001)
```

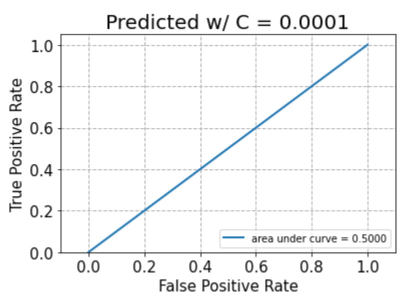
```
Accuracy w/ C = 1000 =
0.7596825396825397
Accuracy w/ C = 0.0001 =
0.5047619047619047
```

```
from sklearn.metrics import roc_curve
from sklearn.metrics import auc


fpr, tpr, thresholds = roc_curve(eight_test.target, predicted_SVM_1000)
roc_auc = auc(fpr,tpr)

fig, ax = plt.subplots()
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")
ax.set_title('Predicted w/ C = 1000',fontsize=20)
for label in ax.get_xticklabels()+ax.get_xticklabels():
```

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

plt.show()
```



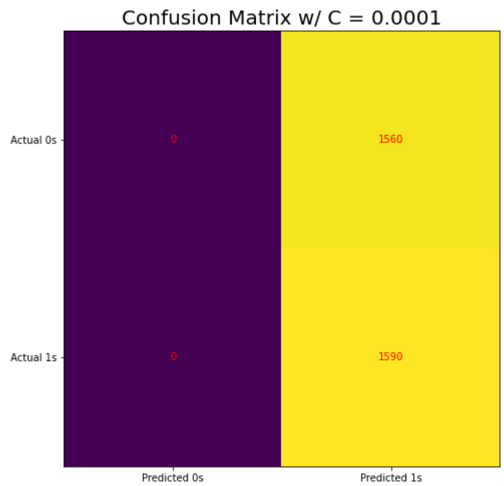

```
from sklearn.metrics import roc_curve
from sklearn.metrics import auc


fpr, tpr, thresholds = roc_curve(eight_test.target, predicted_SVM_0001)
roc_auc = auc(fpr,tpr)

fig, ax = plt.subplots()
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")
ax.set_title('Predicted w/ C = 0.0001',fontsize=20)
for label in ax.get_xticklabels()+ax.get_yticklabels():
    label.set_fontsize(15)

plt.show()
```




```
# Confusion matrix
from sklearn.metrics import confusion_matrix


cm = confusion_matrix(eight_test.target, predicted_SVM_1000)

fig, ax = plt.subplots(figsize=(8, 8))
ax.imshow(cm)
ax.grid(False)
ax.xaxis.set(ticks=(0, 1), ticklabels=('Predicted 0s', 'Predicted 1s'))
ax.yaxis.set(ticks=(0, 1), ticklabels=('Actual 0s', 'Actual 1s'))
ax.set_ylim(1.5, -0.5)
ax.set_title('Confusion Matrix w/ C = 1000',fontsize=20)
for i in range(2):
    for j in range(2):
        ax.text(j, i, cm[i, j], ha='center', va='center', color='red')
plt.show()
```

Confusion Matrix w/ C = 1000

```
# Confusion matrix
from sklearn.metrics import confusion_matrix


cm = confusion_matrix(eight_test.target, predicted_SVM_0001)

fig, ax = plt.subplots(figsize=(8, 8))
ax.imshow(cm)
ax.grid(False)
ax.xaxis.set(ticks=(0, 1), ticklabels=('Predicted 0s', 'Predicted 1s'))
ax.yaxis.set(ticks=(0, 1), ticklabels=('Actual 0s', 'Actual 1s'))
ax.set_ylim(1.5, -0.5)
ax.set_title('Confusion Matrix w/ C = 0.0001',fontsize=20)
for i in range(2):
    for j in range(2):
        ax.text(j, i, cm[i, j], ha='center', va='center', color='red')
plt.show()
```




```
from sklearn.metrics import classification_report

print("Performance Metrics of C = 1000 SVM")
print(classification_report(eight_test.target, predicted_SVM_1000))
print()

print("Performance Metrics of C = 0.0001 SVM")
print(classification_report(eight_test.target, predicted_SVM_0001))
print()
```

```
Performance Metrics of C = 1000 SVM
              precision    recall  f1-score   support

           0       0.70      0.89      0.79      1560
           1       0.86      0.63      0.73      1590

    accuracy                           0.76      3150
   macro avg       0.78      0.76      0.76      3150
weighted avg       0.78      0.76      0.76      3150


Performance Metrics of C = 0.0001 SVM
              precision    recall  f1-score   support

           0       0.00      0.00      0.00      1560
           1       0.50      1.00      0.67      1590

    accuracy                           0.50      3150
   macro avg       0.25      0.50      0.34      3150
weighted avg       0.25      0.50      0.34      3150


/usr/local/lib/python3.6/dist-packages/sklearn/metrics/_classification.py:1272: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in lab
  _warn_prf(average, modifier, msg_start, len(result))
```

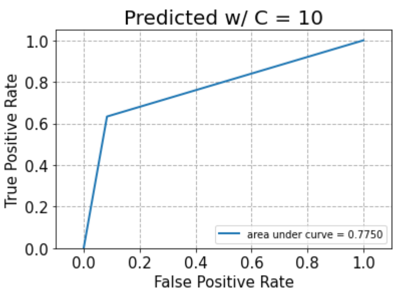
```
from sklearn.model_selection import cross_val_score

regularizers = [10e-3, 0.01, 0.1, 1, 10, 100, 10e3]
folds = 5
scores = []

for reg in regularizers:

    pred = SVC(kernel='linear', C = reg)
    score = cross_val_score(pred, X_train_LSI, eight_train.target, cv=folds)
    scores.append(score.mean())
print("Scores: ", scores)
best = scores.index(max(scores))
print("Best: ", best)
```

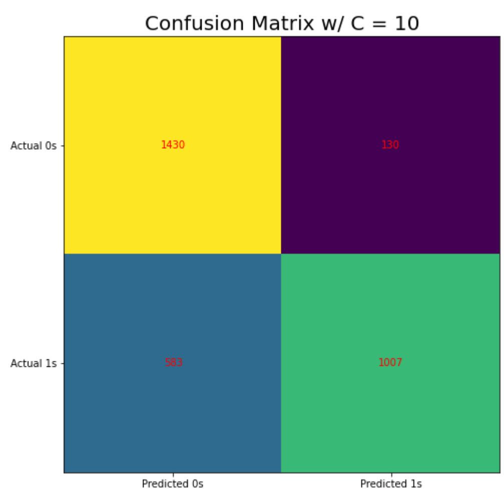
```
Scores:  [0.5052829565267865, 0.5052829565267865, 0.9678767488742686, 0.975484393801724, 0.9775985587065865, 0.9763316225043589, 0.9759076732800365]
Best:  4
```

```
bestreg = regularizers[best]
print("Best: ", bestreg)

predicted_SVM_best = SVC(kernel='linear', C = bestreg).fit(X_train_LSI, eight_train.target).predict(X_test_LSI)
```

```
from sklearn.metrics import roc_curve
from sklearn.metrics import auc


fpr, tpr, thresholds = roc_curve(eight_test.target, predicted_SVM_best)
roc_auc = auc(fpr,tpr)

fig, ax = plt.subplots()
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")
ax.set_title('Predicted w/ C = 10',fontsize=20)
for label in ax.get_xticklabels()+ax.get_yticklabels():
    label.set_fontsize(15)

plt.show()
# Confusion matrix
from sklearn.metrics import confusion_matrix


cm = confusion_matrix(eight_test.target, predicted_SVM_best)

fig, ax = plt.subplots(figsize=(8, 8))
ax.imshow(cm)
ax.grid(False)
ax.xaxis.set(ticks=(0, 1), ticklabels=('Predicted 0s', 'Predicted 1s'))
ax.yaxis.set(ticks=(0, 1), ticklabels=('Actual 0s', 'Actual 1s'))
ax.set_ylim(1.5, -0.5)
ax.set_title('Confusion Matrix w/ C = 10',fontsize=20)
for i in range(2):
    for j in range(2):
        ax.text(j, i, cm[i, j], ha='center', va='center', color='red')
plt.show()

print("Performance Metrics of C = 10 SVM")
print(classification_report(eight_test.target, predicted_SVM_best))
print()
```

```
Best:  10
```






```
Performance Metrics of C = 10 SVM
              precision    recall  f1-score   support

           0       0.71      0.92      0.80      1560
           1       0.89      0.63      0.74      1590

    accuracy                           0.77      3150
   macro avg       0.80      0.77      0.77      3150
weighted avg       0.80      0.77      0.77      3150
```

Logistic Regression

Question 5

[ ] ↳ 6 cells hidden

Naiive Bayes

Question 6

[ ] ↳ 1 cell hidden

Grid Search Of Parameters

Question 7

```
'''
All parameters but no lemmatization
'''

import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import GridSearchCV
from sklearn.pipeline import Pipeline
from sklearn.svm import LinearSVC
from sklearn.decomposition import TruncatedSVD, NMF

# used to cache results
from tempfile import mkdtemp
from shutil import rmtree
from sklearn.externals.joblib import Memory
# print(__doc__)
cachedir = mkdtemp()
memory = Memory(cachedir=cachedir, verbose=10)



N_FEATURES_OPTIONS = [50]
C_OPTIONS = [10]
REG_OPTIONS = ['l1', 'l2']
min_dfs = [3,5]
remove = ['none', ('headers', 'footer')]  # loading data options

for rem in remove:
    eight_train = fetch_20newsgroups(subset='train',
                                     categories=comp_categories+rec_categories,
                                     shuffle=True, random_state=42, remove=rem)
    eight_test = fetch_20newsgroups(subset='test',
                                   categories=comp_categories+rec_categories,
                                   shuffle=True, random_state=42, remove=rem)


    pipeline = Pipeline([
        ('vect', CountVectorizer(stop_words='english')),
        ('tfidf', TfidfTransformer()),
        ('reduce_dim', TruncatedSVD(random_state=42)),
        ('clf', GaussianNB()),
    ],
    memory=memory
    )


    param_grid = [
        {
        'vect__min_df': min_dfs,
        'reduce_dim': [TruncatedSVD(), NMF()], # 2 choices
        'reduce_dim__n_components': N_FEATURES_OPTIONS, # 2 choices
        'clf': [LinearSVC()], # 1 choice
        'clf__C': C_OPTIONS # 3 choices
        },
        {
        'vect__min_df': min_dfs,
        'reduce_dim': [TruncatedSVD(), NMF()],
        'reduce_dim__n_components': N_FEATURES_OPTIONS,
        'clf': [GaussianNB()],
        },
        {
        'vect__min_df': min_dfs,
        'reduce_dim': [TruncatedSVD(), NMF()],
        'reduce_dim__n_components': N_FEATURES_OPTIONS,
        'clf': [LogisticRegression(C=100, solver='liblinear')],
        'clf__penalty':REG_OPTIONS,
        }
        ]

    grid = GridSearchCV(pipeline, cv=5, n_jobs=-1, param_grid=param_grid, scoring='accuracy')
    grid.fit(eight_train.data, eight_train.target)

    results_df = pd.DataFrame.from_dict(grid.cv_results_)
    if rem is not 'none':
        results_df.to_csv('drive/My Drive/remove_hf_lem_false.csv')
    else:
        results_df.to_csv('drive/My Drive/remove_none_lem_false.csv')
    print(results_df)

    rmtree(cachedir)

'''
Lemmatization w/ Part-of-Speach
'''

import nltk
from nltk import pos_tag
nltk.download('wordnet')
nltk.download('punkt')
nltk.download('averaged_perceptron_tagger')
```

```
nltk.download('averaged_perceptron_tagger')

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'

wnl = nltk.wordnet.WordNetLemmatizer()
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)]


'''
All and w/ lemmatization
'''

import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import GridSearchCV
from sklearn.pipeline import Pipeline
from sklearn.svm import LinearSVC
from sklearn.decomposition import TruncatedSVD, NMF

# used to cache results
from tempfile import mkdtemp
from shutil import rmtree
from sklearn.externals.joblib import Memory
# print(__doc__)
cachedir = mkdtemp()
memory = Memory(cachedir=cachedir, verbose=10)

# overwrite COuntVect analyzer with callable function:
analyzer = CountVectorizer().build_analyzer()
# performs lemmatization as function for analyzer
def stem_rmv_punc(doc):
    return (word for word in lemmatize_sent(analyzer(doc)))



N_FEATURES_OPTIONS = [50]
C_OPTIONS = [10]
REG_OPTIONS = ['l1', 'l2']
min_dfs = [3,5]
remove = ['none', ('headers', 'footer')]  # loading data options

for rem in remove:
    eight_train = fetch_20newsgroups(subset='train',
                                     categories=comp_categories+rec_categories,
                                     shuffle=True, random_state=42, remove=rem)
    eight_test = fetch_20newsgroups(subset='test',
                                   categories=comp_categories+rec_categories,
                                   shuffle=True, random_state=42, remove=rem)

    for min_df in min_dfs:
        count_vect = CountVectorizer(min_df=min_df, analyzer=stem_rmv_punc, stop_words='english')
        X_train_counts = count_vect.fit_transform(eight_train.data)


        pipeline = Pipeline([
            ('tfidf', TfidfTransformer()),
            ('reduce_dim', TruncatedSVD(random_state=42)),
            ('clf', GaussianNB()),
        ],
        memory=memory
        )

        param_grid = [
            {
            'reduce_dim': [TruncatedSVD(), NMF()], # 2 choices
            'reduce_dim__n_components': N_FEATURES_OPTIONS, # 2 choices
            'clf': [LinearSVC()], # 1 choice
            'clf__C': C_OPTIONS # 3 choices
            },
            {
            'reduce_dim': [TruncatedSVD(), NMF()],
            'reduce_dim__n_components': N_FEATURES_OPTIONS,
            'clf': [GaussianNB()],
            },
            {
            'reduce_dim': [TruncatedSVD(), NMF()],
            'reduce_dim__n_components': N_FEATURES_OPTIONS,
            'clf': [LogisticRegression(C=100, solver='liblinear')],
            'clf__penalty':REG_OPTIONS,
            }
            ]

        grid = GridSearchCV(pipeline, cv=5, n_jobs=-1, param_grid=param_grid, scoring='accuracy')
        grid.fit(X_train_counts, eight_train.target)

        results_df = pd.DataFrame.from_dict(grid.cv_results_)
        if rem is not 'none':
            results_df.to_csv('drive/My Drive/df_'+str(min_df)+'remove_hf_lem_true.csv')
        else:
            results_df.to_csv('drive/My Drive/df_'+str(min_df)+'remove_none_lem_true.csv')
        print(results_df)

        rmtree(cachedir)
```

Multiclass Classification

Question 12

```
four_cat  = ('comp.sys.ibm.pc.hardware', 'comp.sys.mac.hardware',
'misc.forsale', 'soc.religion.christian')
four_train = fetch_20newsgroups(subset='train',
                                  categories=four_cat,
                                  shuffle=True, random_state=42,)
four_test = fetch_20newsgroups(subset='test',
                                 categories=four_cat,
                                 shuffle=True, random_state=42,)

analyzer = CountVectorizer().build_analyzer()

# performs lemmatization as function for analyzer
def stem_rmv_punc(doc):
    return (word for word in lemmatize_sent(analyzer(doc)) if word not in combined_stopwords and not word.isdigit())

# Apply CountVectorizer to train and test sets
count_vect = CountVectorizer(min_df=3, analyzer=stem_rmv_punc, stop_words='english')
four_train_rc_V = count_vect.fit_transform(four_train.data)


# get_feature_names gives us a list of words that each column of term-frequency
# matrix corresponds to
feat_names = count_vect.get_feature_names()
print("Number of terms: ", len((feat_names)))                                   # 16466 terms (matches above)
print(feat_names[1:10])
print()

# Compute the TF-IDF matrices of the train and test sets
tfidf_trans = TfidfTransformer()
four_train_tfidf = tfidf_trans.fit_transform(four_train_rc_V)
four_test_tfidf = tfidf_trans.transform(four_test_rc_V)
print("TF-IDF shape train set: ", four_train_tfidf.shape)
print()
print("TF-IDF shape test set: ", four_test_tfidf.shape)
print()


#print(four_train.target)
#print(four_test.shape)
```

```
Term-freq matrix shape train set:  (2352, 8567)

Term-freq matrix shape test set:  (1565, 8567)

Number of terms:  8567
['0a', '0b', '101e', '1024x768', '1024x768x16', '1024x768x256', '1024x768x65536', '105mb', '10base']

TF-IDF shape train set:  (2352, 8567)

TF-IDF shape test set:  (1565, 8567)
```

```
predicted_SVM_four_clf = SVC(kernel='linear', C = 1000).fit(four_train_tfidf, four_train.target)
predicted_SVM_four = predicted_SVM_four_clf.predict(four_test_tfidf)

acc = accuracy_score(four_test.target, predicted_SVM_four)
print('Accuracy = ')
print(acc)
```

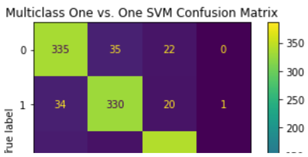
```
Accuracy =
0.888817891373802
```

```
from sklearn.svm import SVC
from sklearn.multiclass import OneVsOneClassifier
from sklearn.metrics import accuracy_score

clf = OneVsOneClassifier(SVC(kernel = 'linear', C = 1000, random_state=42)).fit(four_train_tfidf, four_train.target)
preds = clf.predict(four_test_tfidf)
acc = accuracy_score(four_test.target, preds)
print('Accuracy = ')
print(acc)
```

```
Accuracy =
0.8900958466453675
```

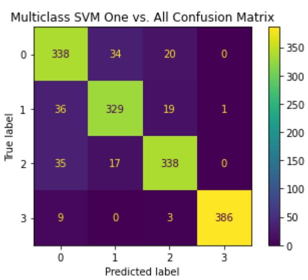
```
# Confusion matrix
from sklearn.metrics import confusion_matrix
from sklearn.metrics import plot_confusion_matrix

cm = confusion_matrix(four_test.target, preds)
disp = plot_confusion_matrix(clf, four_test_tfidf, four_test.target, values_format = 'd')
disp.ax_.set_title('Multiclass One vs. One SVM Confusion Matrix')
from sklearn.metrics import classification_report

print("Performance Metrics of One vs One Multiclass SVM")
print(classification_report(four_test.target, clf.predict(four_test_tfidf)))
print()
```

```
Performance Metrics of One vs One Multiclass SVM
              precision    recall  f1-score   support

           0       0.82      0.85      0.84       392
           1       0.86      0.86      0.86       385
           2       0.88      0.88      0.88       390
           3       1.00      0.97      0.98       398

    accuracy                           0.89      1565
   macro avg       0.89      0.89      0.89      1565
weighted avg       0.89      0.89      0.89      1565
```




```
# Confusion matrix
from sklearn.metrics import confusion_matrix
from sklearn.metrics import plot_confusion_matrix

cm = confusion_matrix(four_test.target, predicted_SVM_four)
disp = plot_confusion_matrix(predicted_SVM_four_clf, four_test_tfidf, four_test.target, values_format = 'd')
disp.ax_.set_title('Multiclass SVM One vs. All Confusion Matrix')
from sklearn.metrics import classification_report

print("Performance Metrics of One vs. All Multiclass SVM")
print(classification_report(four_test.target, predicted_SVM_four_clf.predict(four_test_tfidf)))
print()
```

```
Performance Metrics of One vs. All Multiclass SVM
              precision    recall  f1-score   support

           0       0.81      0.86      0.83       392
           1       0.87      0.85      0.86       385
           2       0.89      0.87      0.88       390
           3       1.00      0.97      0.98       398

    accuracy                           0.89      1565
   macro avg       0.89      0.89      0.89      1565
weighted avg       0.89      0.89      0.89      1565
```

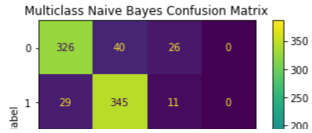



```
from sklearn.linear_model import LogisticRegression


logistic_model = LogisticRegression(penalty='none', random_state=0, max_iter=500)
# train
logistic_model.fit(four_train_tfidf, four_train.target)
# test
preds = logistic_model.predict(four_test_tfidf)


acc = accuracy_score(four_test.target, preds)
print('Accuracy = ')
print(acc)
```

```
Accuracy =
0.8952076677316294
```

```
# Confusion matrix
from sklearn.metrics import confusion_matrix
from sklearn.metrics import plot_confusion_matrix

cm = confusion_matrix(four_test.target, preds)
disp = plot_confusion_matrix(logistic_model, four_test_tfidf, four_test.target, values_format = 'd')
disp.ax_.set_title('Multiclass Naive Bayes Confusion Matrix')
from sklearn.metrics import classification_report

print("Performance Metrics of Multiclass Naive Bayes")
print(classification_report(four_test.target, preds))
print()
```

```
Performance Metrics of Multiclass Naive Bayes
              precision    recall  f1-score   support

           0       0.85      0.83      0.84       392
           1       0.85      0.90      0.87       385
           2       0.89      0.88      0.89       390
           3       0.99      0.97      0.98       398

    accuracy                           0.90      1565
   macro avg       0.90      0.89      0.90      1565
weighted avg       0.90      0.90      0.90      1565
```



GLOVE

```
from google.colab import files
import numpy as np
from google.colab import drive
drive.mount('/content/drive')
#!ls '/content/drive/My Drive/'
embeddings_dict = {}
dimension_of_glove = 300
with open('/content/drive/My Drive/glove.6B.300d.txt', 'r') as f:
  for line in f:
    values = line.split()
    word = values[0]
    vector = np.asarray(values[1:], "float32")
    embeddings_dict[word] = vector
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

```
from sklearn.datasets import fetch_20newsgroups

comp_categories = [ 'comp.graphics', 'comp.os.ms-windows.misc', 'comp.sys.ibm.pc.hardware', 'comp.sys.mac.hardware']
rec_categories = ['rec.autos', 'rec.motorcycles', 'rec.sport.baseball', 'rec.sport.hockey']

# Create train and test data sets
eight_train = fetch_20newsgroups(subset='train',
                                  categories=comp_categories+rec_categories,
                                  shuffle=True, random_state=42,)
eight_test = fetch_20newsgroups(subset='test',
                                 categories=comp_categories+rec_categories,
                                 shuffle=True, random_state=42,)


'''
Reassign labels to binary
    comp will get label '0' and rec will get label '1'
'''


for i in np.arange(eight_train.target.shape[0]):
    if eight_train.target[i] < 4:
        eight_train.target[i] = 0
    else:
        eight_train.target[i] = 1

for i in np.arange(eight_test.target.shape[0]):
    if eight_test.target[i] < 4:
        eight_test.target[i] = 0
    else:
        eight_test.target[i] = 1

print(np.unique(eight_train.target))
print(np.unique(eight_test.target))
```

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

```
import re

'''the goal of the function below is to pass a single document of form ('twenty_train.data[x]') and parse through it loooking for the
'Subject' and 'Keywords' text

The return variable from this list is a one-dimensional list of those words. Each entry into the list is a single word

'''


def per_document_keyword_parsing(doc):
  mystring = doc
  list_of_Sub_Keyword = [ ]
  d= [ ]
  final=[]
  one_l= []
  m = re.search('(?<=\Subject:)(.)+',mystring)
  list_of_Sub_Keyword.append(m.group(0))
  if 'Keywords:' in mystring:
    m1 = re.search('(?<=Keywords:)(.)+',mystring)
    if m1.group(0) is not None:
        list_of_Sub_Keyword.append((m1.group(0)))

   for x in list_of_Sub_Keyword:
```

```
        d.append(x.split(' '))
    for x in d:
        if x not in one_l:
          for x_x in x:
            one_l.append(x_x)
    for x in one_l:
        if x not in final:
          final.append(x)
    lists = [list_of_Sub_Keyword, d, one_l]
    for x in lists:
      x = None


    for i in combined_stopwords:
      if i in final:
          final.remove(i)
    final_L = []
    for i in final:
      tag = pos_tag(i)
      temp = wnl.lemmatize(i.lower(), pos=penn2morphy(tag))
      final_L.append(temp)

    '''print(final)
    print(final_L)'''

    return final_L





  #I am sending every single word extracted from a single document to glove and will create a vector of all the glove per that document


  '''The below will put all the glove entries per document into one glove_vector per docuemnt'''
  def glove_component(send_to_glove_embedding):
    final_glove_results_per_document = []
    for x in range(0,(len(send_to_glove_embedding))):
      flag = 0
      for word in send_to_glove_embedding[x]:
        try:
          var = embeddings_dict[word]
          #print(word)
          final_glove_results_per_document.append(var)
          flag = 1

        except KeyError:
          #print('Not recognized {}'.format(word))
          pass
      if flag == 0:
         final_glove_results_per_document.append(np.random.uniform(-1,1,dimension_of_glove))
         #print('No recognized words')

    ''' the below portion of the code does the division and normalizing'''


    final_glove_np=np.zeros(dimension_of_glove,)


    for x in final_glove_results_per_document:
      final_glove_np += x
      words_recognized = len(final_glove_results_per_document)
      #print(words_recognized)
      average_final = final_glove_np/words_recognized  #divided by number of words recognized
      final= average_final/np.max(average_final)      # divided by maximum value in the array
      send_to_glove_embedding = None


      #print(final)
      return (final)



  ''' Allows me to choose the document to send and extract from'''

  def initiate_process(doc_num):
      send_to_glove_embedding = []
      doc=eight_train.data[doc_num]
      document_info=per_document_keyword_parsing(doc)
      send_to_glove_embedding.append(document_info)
      x = glove_component(send_to_glove_embedding)
      return x


  def number_of_documents_to_extract_from(num):
    for x in range(0, num):
      #print(x)
      results = initiate_process(x)
      to_classifer.append(results)


  to_classifer =[]

  number_of_documents_to_extract_from(len(eight_train.data)) #will extract form 4 documents
  to_classifer= np.array(np.array([ y for y in to_classifer if y is not None]))
  ## to_classifer this is a np array where each entry is ideally a 300 entry. Ideally since for a document there can be the case where no words were recognize

  length_of_to_classifer = len(to_classifer)
  print(to_classifer.shape)
  #print(to_classifer[0])
  #print(eight_train)

       (4732, 300)
```

```
data = eight_train.target
print(data.shape)
print(eight_train.target)
```

```
(4732,)
[1 1 1 ... 1 1 0]
```

```
import re

'''the goal of the function below is to pass a single document of form ('twenty_train.data[x]') and parse through it loooking for the
'Subject' and 'Keywords' text

The return variable from this list is a one-dimensional list of those words. Each entry into the list is a single word

'''


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  d= [ ]
  final=[]
  one_l= []
  m = re.search('(?<=\Subject:)(.)+',mystring)
  list_of_Sub_Keyword.append(m.group(0))
  if 'Keywords:' in mystring:
    m1 = re.search('(?<=Keywords:)(.)+',mystring)
    if m1.group(0) is not None:
        list_of_Sub_Keyword.append((m1.group(0)))

  for x in list_of_Sub_Keyword:
      d.append(x.split(' '))
  for x in d:
      if x not in one_l:
        for x_x in x:
          one_l.append(x_x)
  for x in one_l:
      if x not in final:
        final.append(x)
  lists = [list_of_Sub_Keyword, d, one_l]
  for x in lists:
    x = None


  for i in combined_stopwords:
    if i in final:
        final.remove(i)
  final_L = []
  for i in final:
    tag = pos_tag(i)
    temp = wnl.lemmatize(i.lower(), pos=penn2morphy(tag))
    final_L.append(temp)

  '''print(final)
  print(final_L)'''

  return final_L




#I am sending every single word extracted from a single document to glove and will create a vector of all the glove per that document


'''The below will put all the glove entries per document into one glove_vector per docuemnt'''
def glove_component(send_to_glove_embedding):
  final_glove_results_per_document = []
  for x in range(0,(len(send_to_glove_embedding))):
    flag = 0
    for word in send_to_glove_embedding[x]:
      try:
        var = embeddings_dict[word]
        #print(word)
        final_glove_results_per_document.append(var)
        flag = 1

      except KeyError:
        #print('Not recognized {}'.format(word))
        pass
    if flag == 0:
       final_glove_results_per_document.append(np.random.uniform(-1,1,dimension_of_glove))
       #print('No recognized words')

  ''' the below portion of the code does the division and normalizing'''


  final_glove_np=np.zeros((dimension_of_glove,))


  for x in final_glove_results_per_document:
    final_glove_np += x
    words_recognized = len(final_glove_results_per_document)
    #print(words_recognized)
    average_final = final_glove_np/words_recognized  #divided by number of words recognized
    final= average_final/np.max(average_final)      # divided by maximum value in the array
    send_to_glove_embedding = None


    #print(final)
    return (final)
```

```
''' Allows me to choose the document to send and extract from'''

def initiate_process(doc_num):
    send_to_glove_embedding = []
    doc=eight_test.data[doc_num]
    document_info=per_document_keyword_parsing(doc)
    send_to_glove_embedding.append(document_info)
    x = glove_component(send_to_glove_embedding)
    return x


def number_of_documents_to_extract_from(num):
  for x in range(0, num):
    #print(x)
    results = initiate_process(x)
    to_classifer_test.append(results)


to_classifer_test =[]

number_of_documents_to_extract_from(len(eight_test.data)) #will extract form 4 documents
to_classifer_test = np.array(np.array([ y for y in to_classifer_test if y is not None]))
## to_classifer this is a np array where each entry is ideally a 300 entry. Ideally since for a document there can be the case where no words were recognize

length_of_to_classifer = len(to_classifer_test)
print(to_classifer_test.shape)
#print(to_classifer[0])
```

```
(3150, 300)
```

```
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
from sklearn.linear_model import LogisticRegression


logistic_model = LogisticRegression(penalty='none', random_state=0, max_iter=500)
# train
logistic_model.fit(to_classifer, eight_train.target)
# test
preds = logistic_model.predict(to_classifer_test)

#acc = []
'''
Run this only on first initialization and then comment out as we run the code again for different dimensions for the glove vector
'''
acc.append(accuracy_score(eight_test.target, preds))
print('Accuracy = ')
print(acc)
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-25-fd3d759b9341> in <module>()
     12 #acc = []
     13 #glove_SVM = SVC(kernel='linear', C = 1000).fit(to_classifer, eight_train.target).predict(to_classifer_test)
---> 14 acc.append(accuracy_score(eight_test.target, preds))
     15 print('Accuracy = ')
     16 print(acc)

NameError: name 'acc' is not defined
```

SEARCH STACK OVERFLOW

```
glove_dim = [50, 100, 200, 300]
perc = [x * 100 for x in acc]
#print(perc)
plt.plot(glove_dim, perc)
#plt.axis([0, 300, 50, 100])
plt.xlabel('Glove Dimension')
plt.ylabel('Accuracy Percentage')
plt.show()
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-26-a6d58a0198df> in <module>()
      1 glove_dim = [50, 100, 200, 300]
----> 2 perc = [x * 100 for x in acc]
      3 print(perc)
      4 plt.plot(glove_dim, perc)
      5 #plt.axis([0, 300, 50, 100])

NameError: name 'acc' is not defined
```

SEARCH STACK OVERFLOW

```
import umap
import numpy as np
from sklearn.datasets import load_digits
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
%matplotlib inline

reducer = umap.UMAP()
embedding = reducer.fit_transform(to_classifer)
print(embedding.shape)


plt.scatter(embedding[:, 0], embedding[:, 1], c=eight_train.target, cmap='Spectral', s=5)
```

```
plt.scatter(embedding[:, 0], embedding[:, 1], c=eight_train.target, cmap='Spectral', s=5)
```

```
3150
4732
```

```
random_glove = []
for i in range(0,len(eight_train.data)):
    random_glove.append(np.random.uniform(-1,1,300))
reducer = umap.UMAP()
embedding = reducer.fit_transform(random_glove)
print(embedding.shape)
plt.scatter(embedding[:, 0], embedding[:, 1], c=eight_train.target, cmap='Spectral', s=5)
```