Practical_Phase2

March 6, 2022

```
[]:  ## Practical Phase1
## Amir Pourmand
## Stu No: 99210259
```

```
Downloading Required Dataset
[1]: | gdown --id 15JJ6ZysFM57tlUjXo2nHVhkGwePbVMVV -O dataset_first.csv
    Downloading...
    From: https://drive.google.com/uc?id=15JJ6ZysFM57tlUjXo2nHVhkGwePbVMVV
    To: /content/dataset first.csv
    59.7MB [00:00, 96.0MB/s]
[2]: | gdown --id 1uykBJxWH5v5BsSuuwM0r9WLiKWQrDiDJ -0 dataset_tune.csv
    Downloading...
    From: https://drive.google.com/uc?id=1uykBJxWH5v5BsSuuwM0r9WLiKWQrDiDJ
    To: /content/dataset_tune.csv
    100% 211k/211k [00:00<00:00, 6.41MB/s]
[3]: import pandas as pd
     dataset = pd.read_csv('dataset_first.csv')
     dataset_tune = pd.read_csv('dataset_tune.csv')
[4]: # Load the Drive helper and mount
     from google.colab import drive
     drive.mount('/content/drive')
    Mounted at /content/drive
[5]: import scipy.sparse
     import numpy
     import pandas as pd
```

X_train_2_BOW=scipy.sparse.load_npz('/content/drive/MyDrive/DataForColob/

```
X_test_2_BOW=scipy.sparse.load_npz('/content/drive/MyDrive/DataForColob/
→ML Project/X test 2 BOW.npz')
X_train_w2v=pd.read_pickle('/content/drive/MyDrive/DataForColob/ML_Project/
X_test_w2v=pd.read_pickle('/content/drive/MyDrive/DataForColob/ML_Project/
y_train = numpy.load('/content/drive/MyDrive/DataForColob/ML_Project/y_train.
y_test = numpy.load('/content/drive/MyDrive/DataForColob/ML_Project/y_test.npy')
import pickle
svm_w2v = pickle.load(open('/content/drive/MyDrive/DataForColob/ML Project/SVM.
→pkl', 'rb'))
knn_w2v = pickle.load(open('/content/drive/MyDrive/DataForColob/ML_Project/KNN.
→pkl', 'rb'))
lr w2v = pickle.load(open('/content/drive/MyDrive/DataForColob/ML Project/LR.
→pkl', 'rb'))
mlp_best = pickle.load(open('/content/drive/MyDrive/DataForColob/ML_Project/
⇔best.pkl', 'rb'))
vectorizer_tfidf=pickle.load(open('/content/drive/MyDrive/DataForColob/
X_w2v = list(X_train_w2v)
X_w2v.extend(X_test_w2v )
len(X_w2v)
```

[5]: 45000

```
[6]: import numpy as np
     y_total = np.concatenate([y_train,y_test])
     X_bow = scipy.sparse.vstack([X_train_2_BOW, X_test_2_BOW])
```

```
[7]: lr_w2v.score(list(X_test_w2v),y_test)
```

[7]: 0.884888888888888

Imports

```
[8]: import numpy as np
     import matplotlib.pyplot as plt
```

3 Clustering

3.1 PCA

```
[9]: from sklearn.decomposition import PCA
    pca=PCA(n_components=2)
    pca_w2v=pca.fit_transform(X_w2v)
```

3.2 SVD

```
[10]: from sklearn.decomposition import TruncatedSVD
svd = TruncatedSVD(n_components=2, n_iter=7)
svd_bow=svd.fit_transform(X_bow)
svd_bow.shape
```

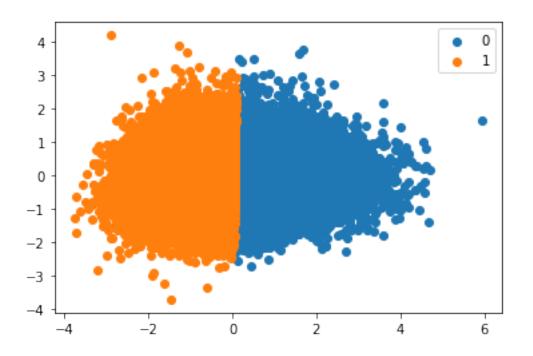
[10]: (45000, 2)

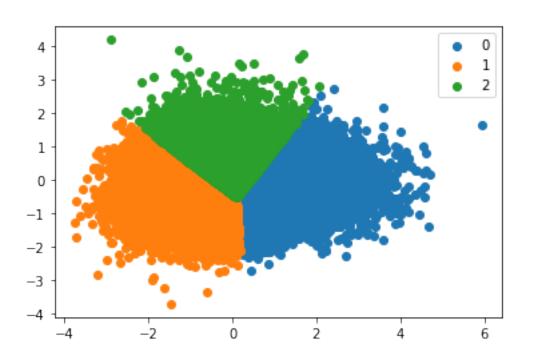
3.3 K-Means

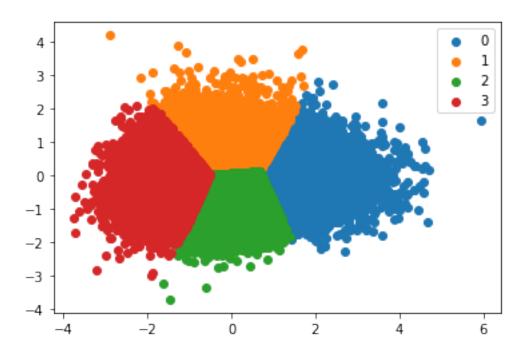
```
import matplotlib.pyplot as plt
def plot_scatter(X,pred):
    u_labels = np.unique(pred)
    for i in u_labels:
        plt.scatter(X[pred==i,0],X[pred==i,1],label=i)
    plt.legend()
    plt.show()
```

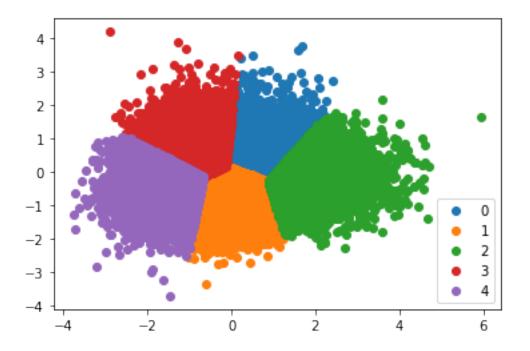
```
from sklearn.cluster import KMeans

for k in range(2,6):
    kmeans = KMeans(n_clusters=k)
    kmeans_label=kmeans.fit_predict(pca_w2v)
    plot_scatter(pca_w2v,kmeans_label)
```





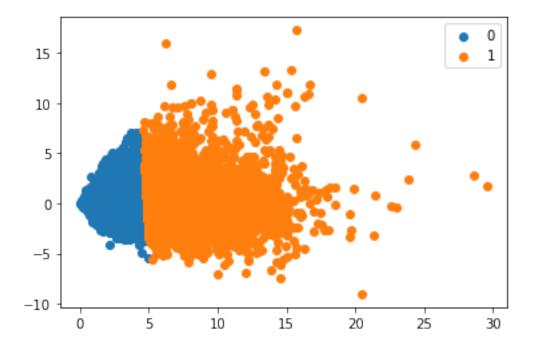


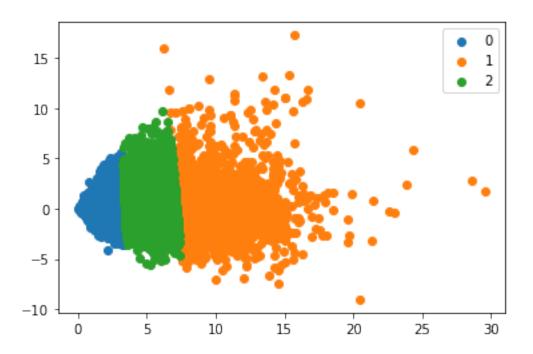


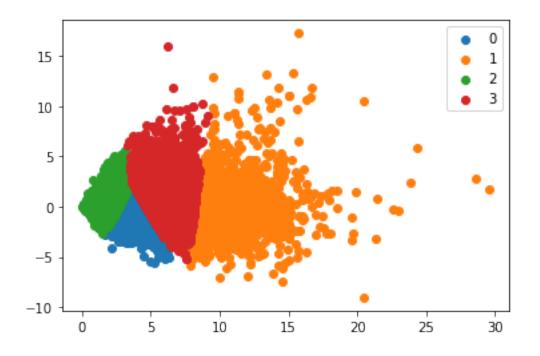
```
[13]: from sklearn.cluster import KMeans

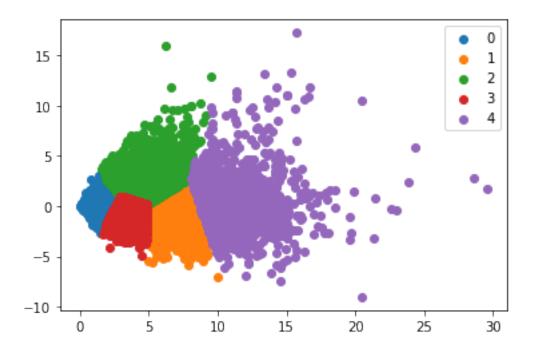
for k in range(2,6):
    kmeans = KMeans(n_clusters=k)
```

kmeans_label=kmeans.fit_predict(svd_bow)
plot_scatter(svd_bow,kmeans_label)





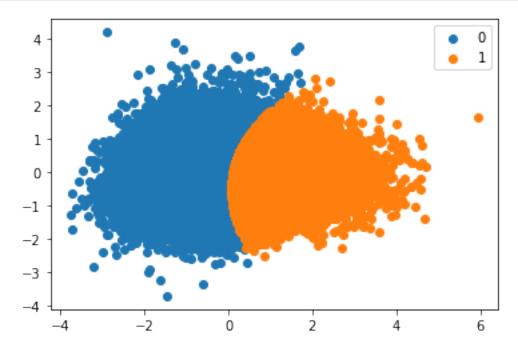


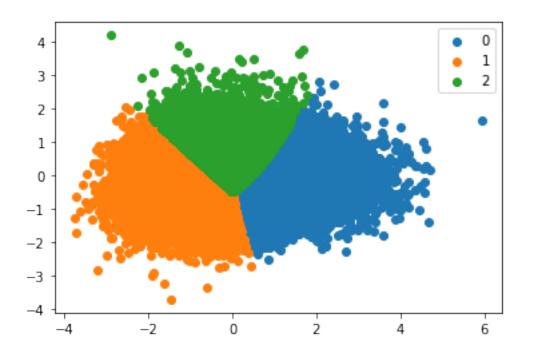


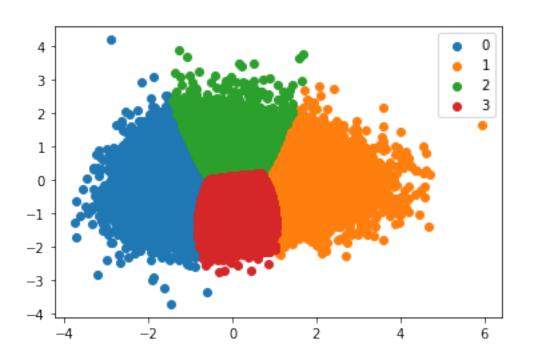
3.4 GMM

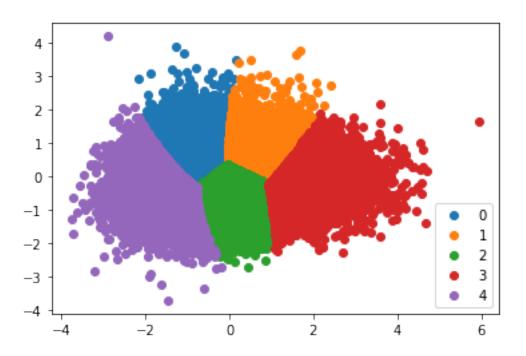
```
from sklearn.mixture import GaussianMixture

for k in range(2,6):
    gm = GaussianMixture(n_components=k)
    gm_pred=gm.fit_predict(pca_w2v)
    plot_scatter(pca_w2v,gm_pred)
```



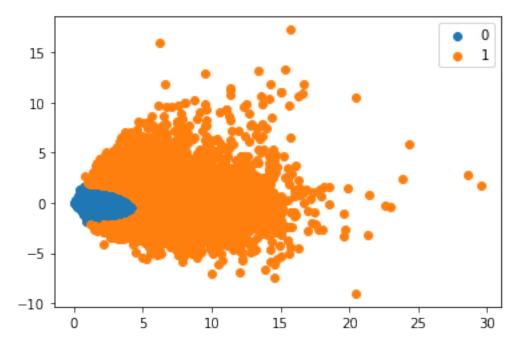


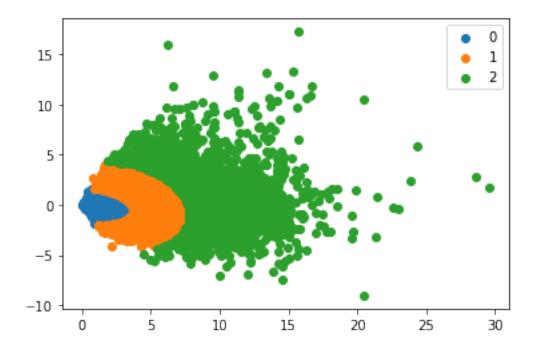


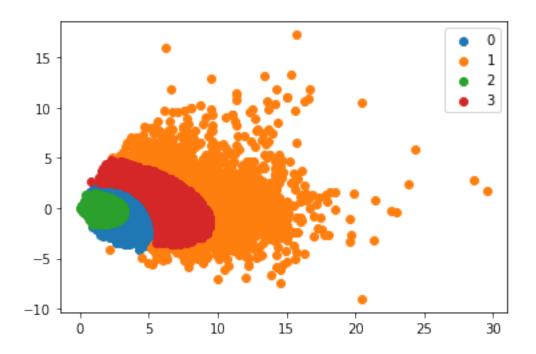


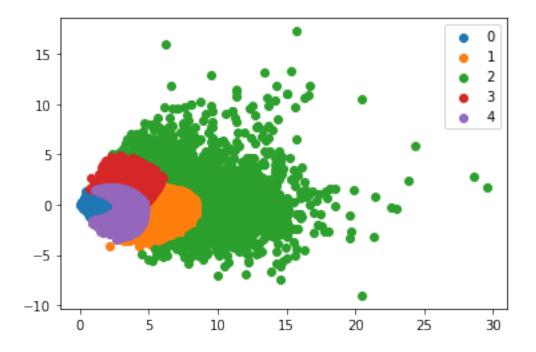
```
[14]: from sklearn.mixture import GaussianMixture

for k in range(2,6):
    gm = GaussianMixture(n_components=k)
    gm_pred=gm.fit_predict(svd_bow)
    plot_scatter(svd_bow,gm_pred)
```





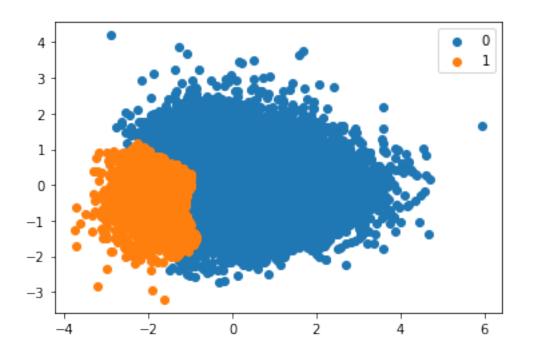


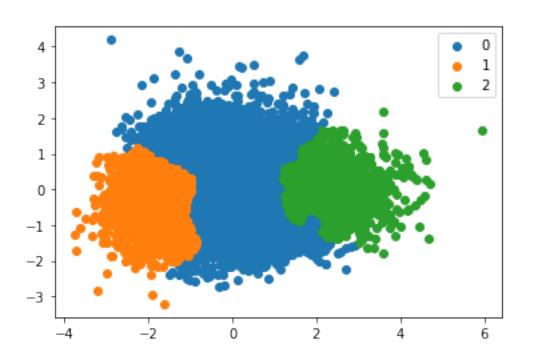


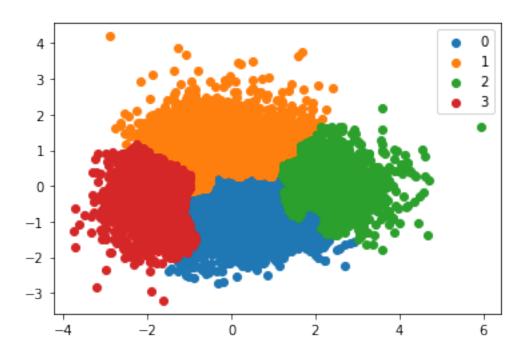
3.5 Agglomorative

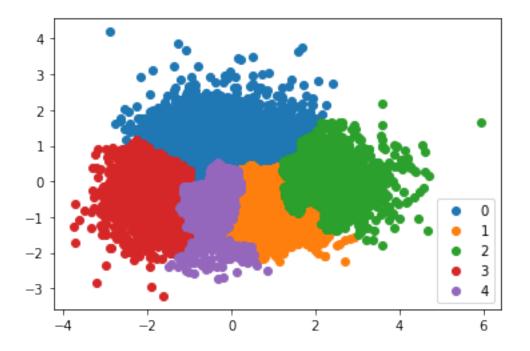
```
[]: from sklearn.cluster import AgglomerativeClustering

max_data= 30000
for k in range(2,6):
    agg = AgglomerativeClustering(n_clusters=k)
    agg_pred=agg.fit_predict(pca_w2v[:max_data])
    plot_scatter(pca_w2v[:max_data],agg_pred)
```





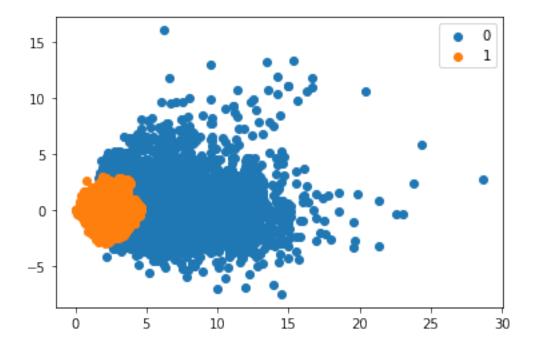


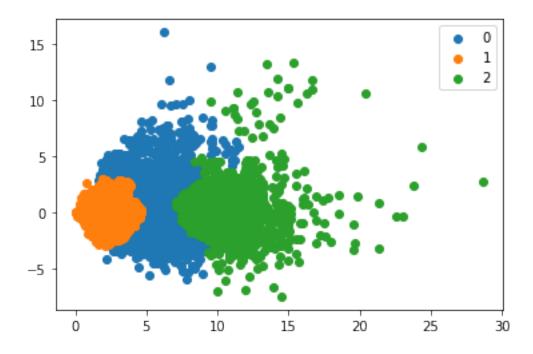


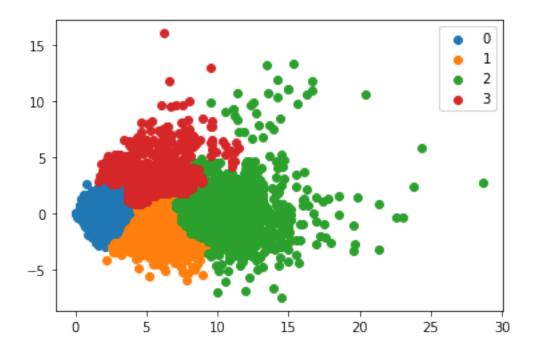
```
[18]: from sklearn.cluster import AgglomerativeClustering

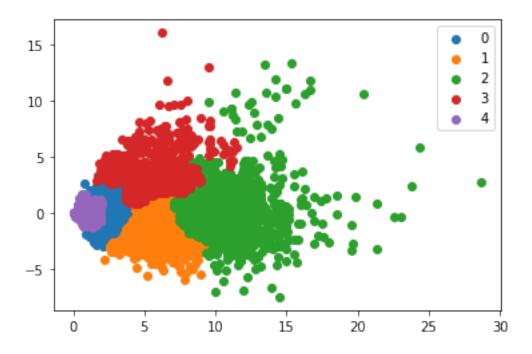
max_data= 30000
for k in range(2,6):
```

agg = AgglomerativeClustering(n_clusters=k)
agg_pred=agg.fit_predict(svd_bow[:max_data])
plot_scatter(svd_bow[:max_data],agg_pred)









3.6 Comparsion

```
[16]: from sklearn import metrics
      def get_analysis(name,true_label,predicted_label):
         print('V Measure ', name, ':', metrics.
       →v_measure_score(true_label,predicted_label))
          print('Adjusted RandScore Measure ', name, ':', metrics.
       →adjusted_rand_score(true_label,predicted_label))
          print('Adjusted Mutual Information ', name, ':', metrics.
       →adjusted_mutual_info_score(true_label,predicted_label))
         print('Homogenity', name, ':', metrics.
       →homogeneity_score(true_label,predicted_label))
         print('-'*30)
 []: from sklearn.cluster import KMeans
      from sklearn.mixture import GaussianMixture
      from sklearn.cluster import AgglomerativeClustering
      from sklearn import metrics
      kmeans = KMeans(n_clusters=2)
      kmeans_label=kmeans.fit_predict(pca_w2v)
      gm = GaussianMixture(n_components=2)
      gm_pred=gm.fit_predict(pca_w2v)
      max_data = 30000
      agg = AgglomerativeClustering(n_clusters=2)
      agg_pred=agg.fit_predict(pca_w2v[:max_data])
      get_analysis('kmeans',y_total,kmeans_label)
      get_analysis('gm', y_total,gm_pred)
      get_analysis('agg',y_total[:max_data],agg_pred)
     V Measure kmeans: 0.03865260111674556
     Adjusted RandScore Measure kmeans: 0.052532117323756226
     Adjusted Mutual Information kmeans: 0.038637148304102975
     Homogenity kmeans : 0.038548295065080805
     V Measure gm : 0.04585216408127864
     Adjusted RandScore Measure gm : 0.06102151128817464
     Adjusted Mutual Information gm : 0.045836750679784814
     Homogenity gm : 0.045502049103971876
     V Measure agg: 0.027294842860872137
     Adjusted RandScore Measure agg: 0.015243361512629535
     Adjusted Mutual Information agg: 0.02726576198577149
```

```
[17]: from sklearn.cluster import KMeans
      from sklearn.mixture import GaussianMixture
      from sklearn.cluster import AgglomerativeClustering
      from sklearn import metrics
      kmeans = KMeans(n clusters=2)
      kmeans_label=kmeans.fit_predict(svd_bow)
      gm = GaussianMixture(n_components=2)
      gm_pred=gm.fit_predict(svd_bow)
      max_data = 30000
      agg = AgglomerativeClustering(n_clusters=2)
      agg_pred=agg.fit_predict(svd_bow[:max_data])
      get_analysis('kmeans',y_total,kmeans_label)
      get_analysis('gm', y_total,gm_pred)
      get_analysis('agg',y_total[:max_data],agg_pred)
     V Measure kmeans: 4.4201352885522176e-06
     Adjusted RandScore Measure kmeans: -9.666372297861207e-06
     Adjusted Mutual Information kmeans: -1.4863700544218863e-05
     Homogenity kmeans : 3.6745964811703372e-06
     V Measure gm : 5.55823659046331e-05
     Adjusted RandScore Measure gm : 3.329568631687747e-05
     Adjusted Mutual Information gm: 3.765064848960804e-05
     Homogenity gm : 4.9688144512804354e-05
     V Measure agg: 0.0004589444711261654
     Adjusted RandScore Measure agg: 0.0003702319505944534
     Adjusted Mutual Information agg: 0.0004321287391475934
     Homogenity agg: 0.00041137599303339186
```

3.7 Semantic Comparison

```
[]: gm = GaussianMixture(n_components=3)
    gm_pred=gm.fit_predict(pca_w2v)
    for i in range(3):
        print(list(dataset[gm_pred==i][2:3]['sentiment']))
    for i in range(3):
        print(list(dataset[gm_pred==i][2:3]['comment']))
```

```
['negative']
['positive']
['positive']
```

["It's amazing that this no talent actor Chapa got all these well known stars to appear in this dismal, pathetic, cheesy and overlong film about a low life gangster who looks white but is half Mexican, much of the acting is bad and many of the well known stars in this trashy movie are given a script that seems made up by a 16 year old, i'm sure this movie is the career low point for actors such as Dunaway, Wagner, Keach, Tilly and Busey who i'm sure are very embarrassed that they ever appeared in this turkey of a film. I doubt many people have ever heard of Chapa and after this terrible movie i'm sure he will disappear into oblivion where he belongs."]

['I think this is a great, classic monster film for the family. The mole, what a machine! The tall creature with the beak, the flying green lizards, Ranthorincus/mayas or whatever they are and the ape men things the speak telepathically with them. The battle of the men in rubber suits fighting for a doll for breakfast umm! yummy! Class, what else can I say? How would they make a 2002 remake of this one?']

["I saw this film over Christmas, and what a great film it was! It tells the story of Custer (played by Errol Flynn) during and after his graduation from Westpoint. Although I've heard that the film isn't very historically accurate (Hollywood never is) I still enjoyed it as I knew little of the real events anyway.

| T thought Errol Flynn was brilliant as Custer and has since become my favourite actor! His acting alongside Olivia De Havilland was brilliant and the ending was fantastic! It brought me close to tears as he and Ned Sharp (Arthur Kennedy) rode to their deaths on little big horn.

| Ned Sharp (Arthur Kennedy) rode to their deaths on little big horn.

| T had always known that Errol Flynn was a brilliant actor as he was my dads favourite actor, and I grew up watching his films as a child. But it wasn't until I watched this film that I realised how great he actually was.

| Ned Sharp (Arthur Kennedy) rode to their deaths on little big horn.

| Ned Sharp (Arthur Kennedy) rode to their deaths on little big horn.

| Ned Sharp (Arthur Kennedy) rode to their deaths on little big horn.

| Ned Sharp (Arthur Kennedy) rode to their deaths on little big horn.

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| Ned Sharp (Arthur Kennedy) rode to their deaths on little big horn.

| Ned Sharp (Arthur Kennedy) rode to their deaths on little big horn.

| Ned Sharp (Arthur Kennedy) rode to their deaths on little big horn.

| Ned Sharp

```
[]: # first one - very negative
# second one: very positive
# third one: good but not very complimentary
```

4 Fine Tuning

4.1 Initial Run on MLP

```
[189]: !pip install contractions
!pip install unidecode
!pip install word2number

import pandas as pd
import numpy as np
```

```
import sklearn
from sklearn.model_selection import train_test_split
#for bag of words
from sklearn.feature_extraction.text import CountVectorizer
#these are all for preprocessing
import nltk
from nltk.tokenize import word tokenize
import re
from bs4 import BeautifulSoup
import spacy
import unidecode
from word2number import w2n
import contractions
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
# this is required for word_tokenize
nltk.download('punkt')
nltk.download('stopwords')
nltk.download('wordnet')
Requirement already satisfied: contractions in /usr/local/lib/python3.7/dist-
packages (0.0.52)
Requirement already satisfied: textsearch>=0.0.21 in
/usr/local/lib/python3.7/dist-packages (from contractions) (0.0.21)
Requirement already satisfied: anyascii in /usr/local/lib/python3.7/dist-
packages (from textsearch>=0.0.21->contractions) (0.2.0)
Requirement already satisfied: pyahocorasick in /usr/local/lib/python3.7/dist-
packages (from textsearch>=0.0.21->contractions) (1.4.2)
Requirement already satisfied: unidecode in /usr/local/lib/python3.7/dist-
packages (1.2.0)
Requirement already satisfied: word2number in /usr/local/lib/python3.7/dist-
packages (1.1)
[nltk_data] Downloading package punkt to /root/nltk_data...
             Package punkt is already up-to-date!
[nltk_data]
[nltk_data] Downloading package stopwords to /root/nltk_data...
             Package stopwords is already up-to-date!
[nltk_data]
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data] Package wordnet is already up-to-date!
```

[189]: True

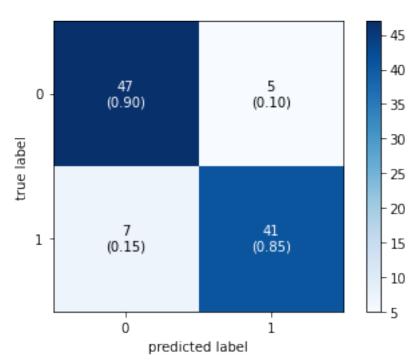
```
[190]: def remove_all_non_alphabetic(text):
         return re.sub('[^A-Za-z]',' ',text)
       def strip_html_tags(text):
           """remove html tags from text"""
           soup = BeautifulSoup(text, "html.parser")
           stripped_text = soup.get_text(separator=" ")
           return stripped_text
       def remove_accented_chars(text):
           """remove accented characters from text, e.g. café"""
           text = unidecode.unidecode(text)
           return text
       stop_words = set(stopwords.words('english'))
       def remove_stop_words(token):
         return [item for item in token if item not in stop_words]
       lemma = WordNetLemmatizer()
       def lemmatization(token):
         return [lemma.lemmatize(word=w,pos='v') for w in token]
       def clean_length(token):
        return [item for item in token if len(item)>2]
       def punctuation removal(text):
           return re.sub(r'[\.\?\!\,\:\;\"]', '', text)
       def text_merge(token):
        return ' '.join([i for i in token if not i.isdigit()])
[191]: def process_level1(data):
           return (data.apply(str.lower)
                       .apply(remove_all_non_alphabetic)
                       .apply(word_tokenize)
                       .apply(text_merge))
       def process_level2(data):
           return (data.apply(str.lower)
               .apply(contractions.fix)
               .apply(strip_html_tags)
               .apply(remove_accented_chars)
               .apply(remove_all_non_alphabetic)
               .apply(word_tokenize)
               .apply(remove_stop_words)
               .apply(lemmatization)
               .apply(clean_length)
```

```
.apply(text_merge))
[192]: X_train_small, X_test_small, y_train_small, y_test_small=train_test_split(dataset_tune['comment']
        →dataset_tune['sentiment'],test_size=0.2)
       X_train_small = process_level2(X_train_small)
       X_test_small = process_level2(X_test_small)
       from sklearn.feature_extraction.text import TfidfVectorizer
       vectorizer = TfidfVectorizer( min_df=0.01,max_df=0.5)
       X_train_small_tfidf=vectorizer.fit_transform(X_train_small)
       X_test_small_tfidf = vectorizer.transform(X_test_small)
[193]: from mlxtend.plotting import plot_confusion_matrix
       from sklearn.metrics import confusion_matrix as cm
       from sklearn.metrics import classification_report
       import matplotlib.pyplot as plt
       def print_confusion_matrix(y_test,y_prediction,title):
           print(classification_report(y_test,y_prediction))
           matrix = cm(y_test,y_prediction)
           fig, ax = plot_confusion_matrix(conf_mat=matrix,
                                           show_absolute=True,
                                           show_normed=True,
                                           colorbar=True)
           plt.title(title)
           plt.show()
[194]: from sklearn.neural_network import MLPClassifier
       from sklearn.model_selection import GridSearchCV
       grid_params = {
           'hidden_layer_sizes': [(250),(100),(90),(40,10),(50,10)]
       }
       mlp = MLPClassifier(learning rate='adaptive', solver='adam', max iter=1000)
       mlp_cv = GridSearchCV(estimator=mlp,param_grid=grid_params,cv=2)
       mlp_cv.fit(X_train_small_tfidf,y_train_small)
       mlp_prediction=mlp_cv.predict(X_test_small_tfidf)
       print_confusion_matrix(y_test_small,mlp_prediction,'TFIDF: MLP ')
       display(pd.DataFrame( mlp_cv.cv_results_))
```

precision recall f1-score support

0	0.87	0.90	0.89	52
1	0.89	0.85	0.87	48
accuracy			0.88	100
macro avg	0.88	0.88	0.88	100
weighted avg	0.88	0.88	0.88	100

TFIDF: MLP



	mean_fit_time	${ t std_fit_time}$	•••	std_test_score	rank_test_score
0	1.871995	0.039519	•••	0.0250	3
1	1.200242	0.023092		0.0225	5
2	1.142486	0.057154		0.0175	1
3	0.777441	0.026190		0.0000	4
4	0.785442	0.013229		0.0275	1

[5 rows x 11 columns]

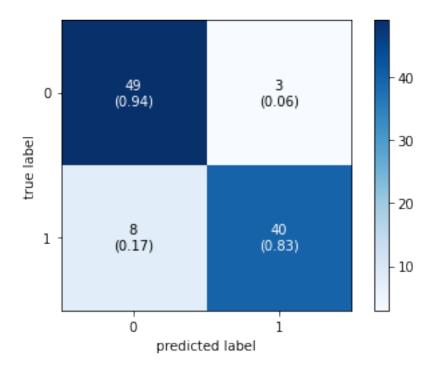
4.2 Fine tune based on previous model

```
[197]: X_train_small_tfidf_olddata=vectorizer_tfidf.transform(X_train_small)
X_test_small_tfidf_olddata = vectorizer_tfidf.transform(X_test_small)

mlp_best = MLPClassifier(warm_start=True)
mlp_best.fit(X_train_small_tfidf_olddata,y_train_small)
mlp_prediction=mlp_best.predict(X_test_small_tfidf_olddata)
print_confusion_matrix(y_test_small,mlp_prediction,'TFIDF: MLP ')
```

	precision	recall	f1-score	support
0 1	0.86 0.93	0.94 0.83	0.90 0.88	52 48
accuracy			0.89	100
macro avg	0.89	0.89	0.89	100
weighted avg	0.89	0.89	0.89	100

TFIDF: MLP



[]: