Multinomial Naive Bayes - BoW

May 3, 2024

1 Initializtion

Connect to Google Drive:

```
[ ]: # from google.colab import drive
     # drive.mount('/content/drive')

     # %cd '/content/drive/MyDrive/GitHub/emotion-dectection-from-text'
```

Preparing necessary packages (may need to add more):

```
[ ]: import numpy as np
     import matplotlib.pyplot as plt
     import seaborn as sns
     import pandas as pd

     from sklearn.naive_bayes import MultinomialNB
     from sklearn.model_selection import GridSearchCV, cross_val_score
     from sklearn.metrics import accuracy_score
     from joblib import dump, load

     from preset_function import evaluate_model, draw_learning_curve,␣
      ↪load_processed_data

     X_train_bow, X_test_bow, X_train_tfidf, X_test_tfidf, \
         X_train_bow_L1, X_test_bow_L1, X_train_tfidf_L1, X_test_tfidf_L1 =␣
      ↪load_processed_data('input')

     y_train, y_test = load_processed_data('output')

     %matplotlib inline
```

Select dataset:

```
[ ]: X_train = X_train_bow
     X_test = X_test_bow
```

2 Basic training

We define and train a model with default hyperparameter, which is alpha = 1:

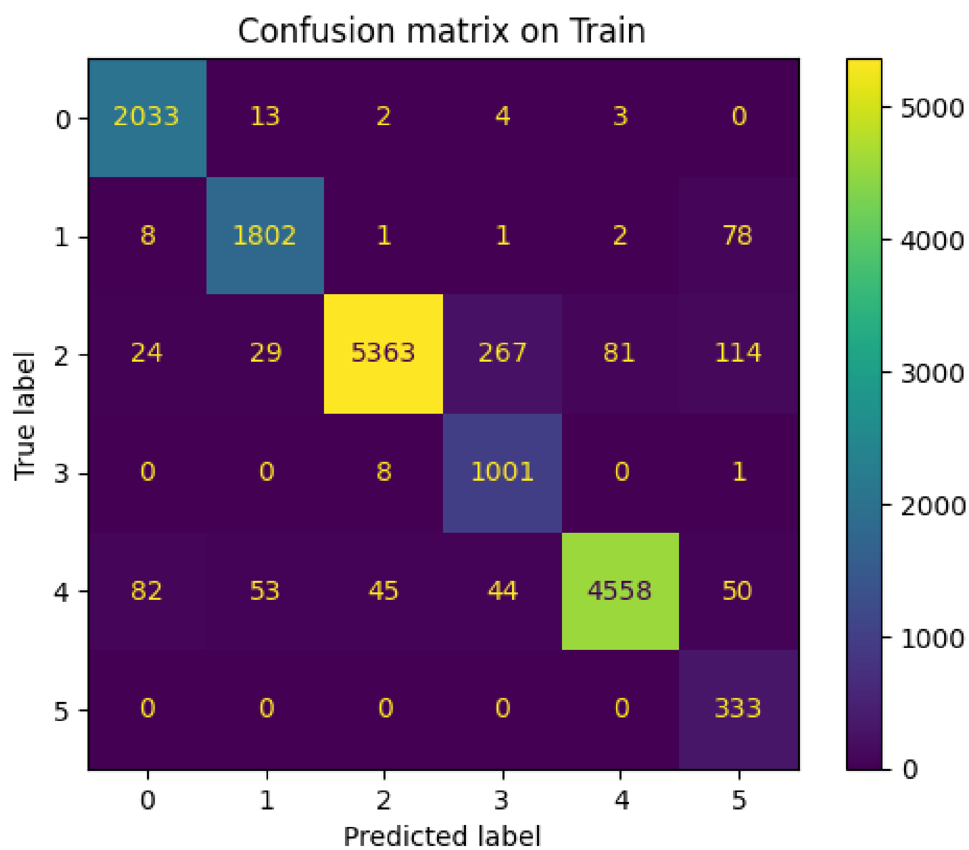
[ ]:
```
nb_model = MultinomialNB()
nb_model.fit(X_train, y_train)
```

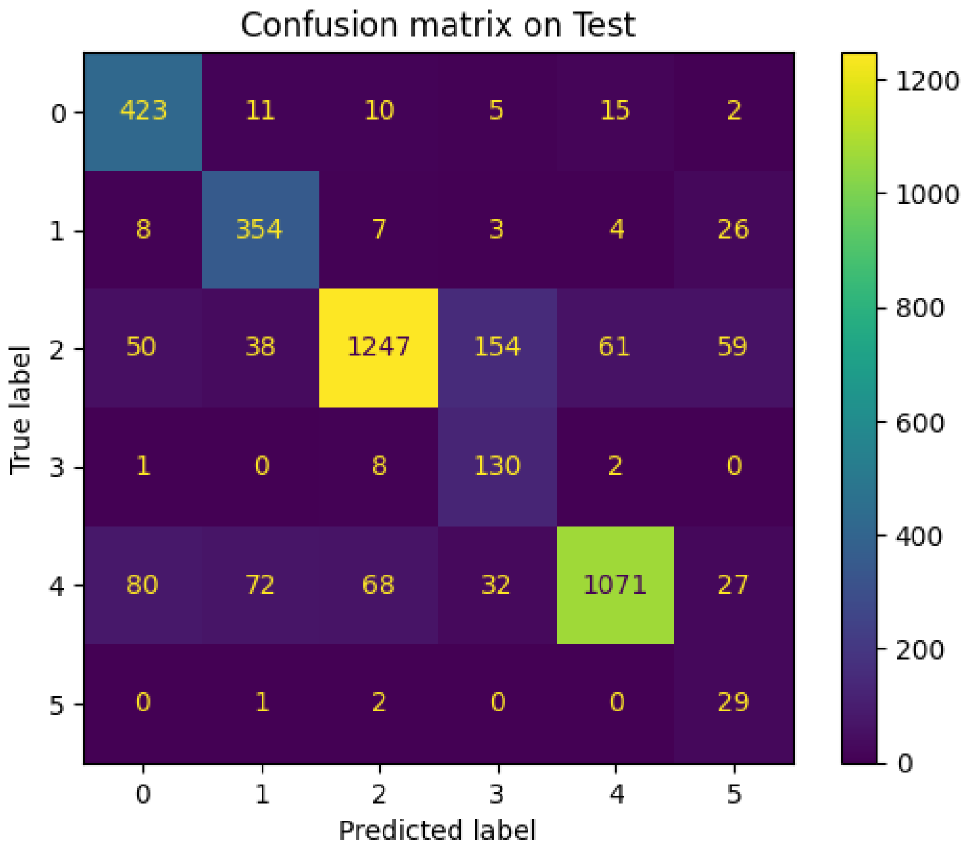
[ ]:
```
MultinomialNB()
```

Evaluate model using preset function:

[ ]:
```
evaluate_model(nb_model, X_train, X_test, y_train, y_test,␣
↪include_training=True)
```

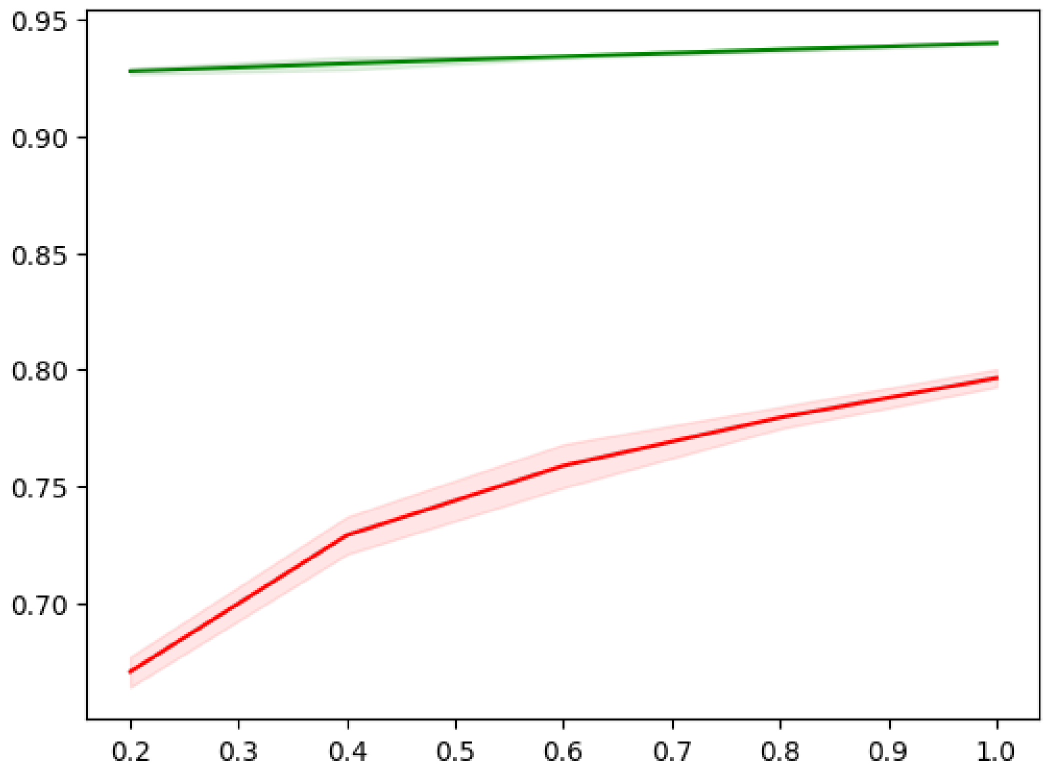
```
Score of on train are:
        - Accuracy score: 0.94
        - Micro F1 score: 0.94
        - Macro F1 score: 0.90
Score of on test are:
        - Accuracy score: 0.81
        - Micro F1 score: 0.81
        - Macro F1 score: 0.70
```





Draw the learning curve using preset function:

[ ]:
```
draw_learning_curve(nb_model, X_train, y_train)
```



3 Model selection

3.1 α parameter

First we try a hyperparameter range:

[ ]:
```
# Setting the hyperparameter range
K = [0.0001, 0.001, 0.001, 0.01, 0.1, 1, 10]
```

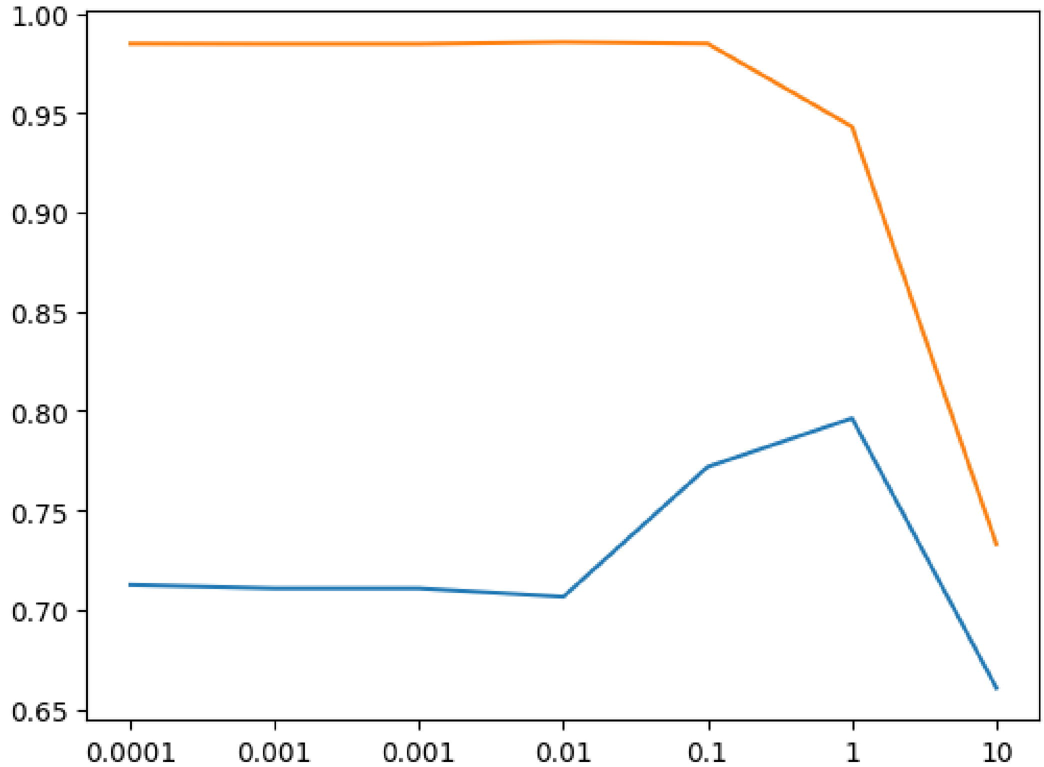
[ ]:
```
# Define a list in order to store accuracy points
cvs_list = list()
trs_list = list()

for k in K:
  # Define model for each K
  nb_model = MultinomialNB(alpha=k)
  nb_model.fit(X_train, y_train)

  # Calculate score of cross validation
  train_score = accuracy_score(y_train, nb_model.predict(X_train))
  cv_score = np.mean(cross_val_score(nb_model, X_train, y_train, cv=5,␣
↪n_jobs=8))
```

```
    trs_list.append(train_score)
    cvs_list.append(cv_score)
```

[ ]:
```
# Print the result
print(K)
print(trs_list)
print(cvs_list)

# Draw the plot
fig = sns.lineplot(x=list(range(len(K))), y=cvs_list)
fig = sns.lineplot(x=list(range(len(K))), y=trs_list)
fig.set_xticks(range(len(K)))
fig.set_xticklabels(K)
```

```
[0.0001, 0.001, 0.001, 0.01, 0.1, 1, 10]
[0.9848125, 0.9846875, 0.9846875, 0.985625, 0.984875, 0.943125, 0.733125]
[0.712625, 0.710875, 0.710875, 0.7066250000000001, 0.7719999999999999,
0.7964375, 0.6608124999999999]
```

[ ]:
```
[Text(0, 0, '0.0001'),
 Text(1, 0, '0.001'),
 Text(2, 0, '0.001'),
 Text(3, 0, '0.01'),
 Text(4, 0, '0.1'),
 Text(5, 0, '1'),
 Text(6, 0, '10')]
```



From the result of above section, we can see the good value of α is near the value 1.

Scope to $\alpha = 1$:

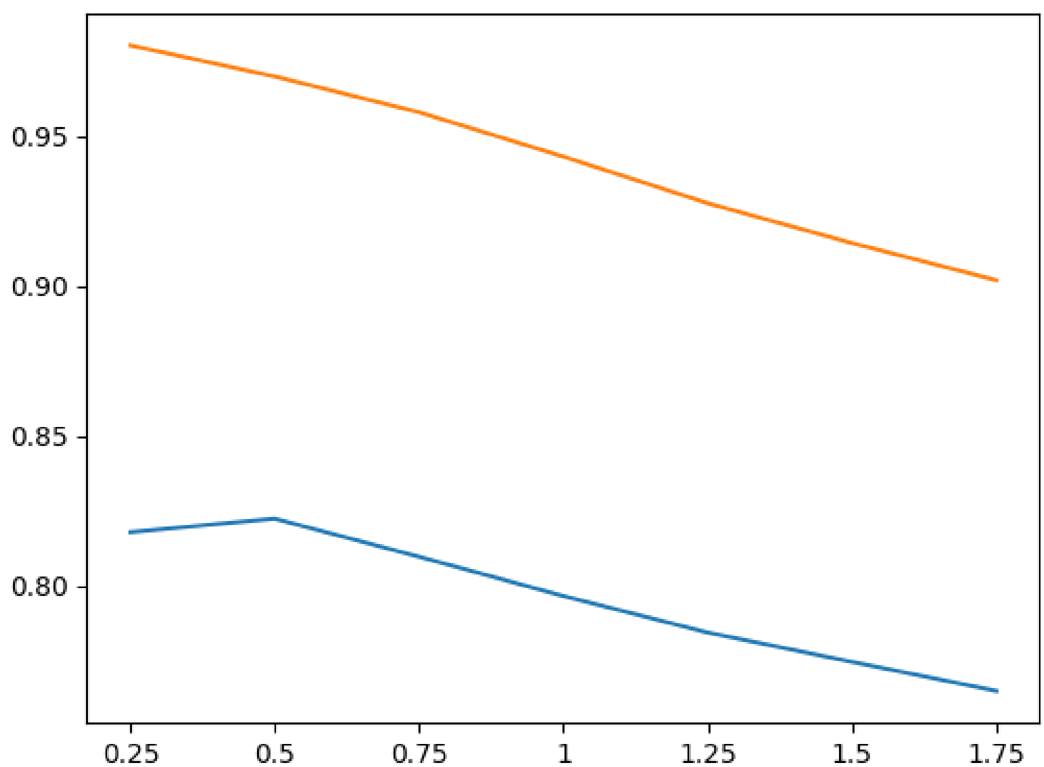
[ ]:
```
# Setting the hyperparameter range
K = [0.25, 0.5, 0.75, 1, 1.25, 1.5, 1.75 ]
```

[ ]:
```
# Define a list in order to store accuracy points
cvs_list = list()
trs_list = list()

for k in K:
  # Define model for each K
  nb_model = MultinomialNB(alpha=k)
  nb_model.fit(X_train, y_train)

  # Calculate score of cross validation
  train_score = accuracy_score(y_train, nb_model.predict(X_train))
  cv_score = np.mean(cross_val_score(nb_model, X_train, y_train, cv=5,
 ↪n_jobs=8))

  trs_list.append(train_score)
  cvs_list.append(cv_score)
```

[ ]:
```python
# Print the result
print(K)
print(trs_list)
print(cvs_list)

# Draw the plot
fig = sns.lineplot(x=list(range(len(K))), y=cvs_list)
fig = sns.lineplot(x=list(range(len(K))), y=trs_list)
fig.set_xticks(range(len(K)))
fig.set_xticklabels(K)
```

```
[0.25, 0.5, 0.75, 1, 1.25, 1.5, 1.75]
[0.98025, 0.969875, 0.9579375, 0.943125, 0.9275625, 0.91425, 0.901875]
[0.81775, 0.82225, 0.8095625, 0.7964375, 0.78425, 0.7744375, 0.76475]
```

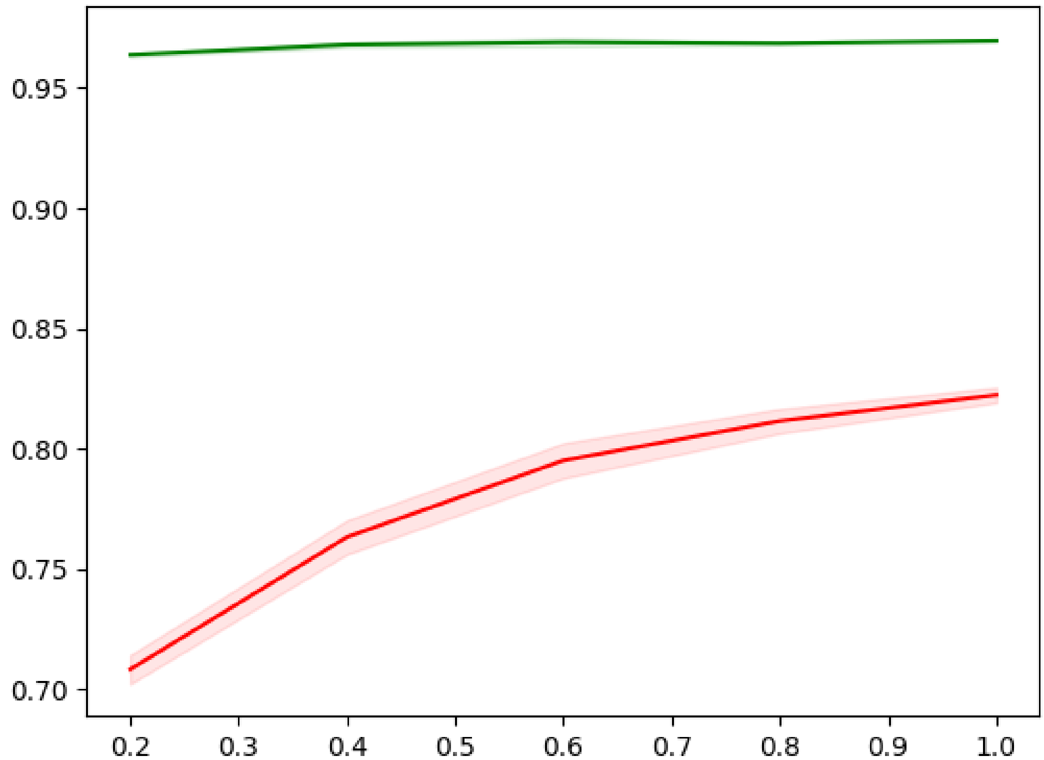
[ ]:
```
[Text(0, 0, '0.25'),
 Text(1, 0, '0.5'),
 Text(2, 0, '0.75'),
 Text(3, 0, '1'),
 Text(4, 0, '1.25'),
 Text(5, 0, '1.5'),
 Text(6, 0, '1.75')]
```



As the result, we can claim that $\alpha = 0.5$ give a model with good accuracy and avoid overfitting. We will test the model again in test set.

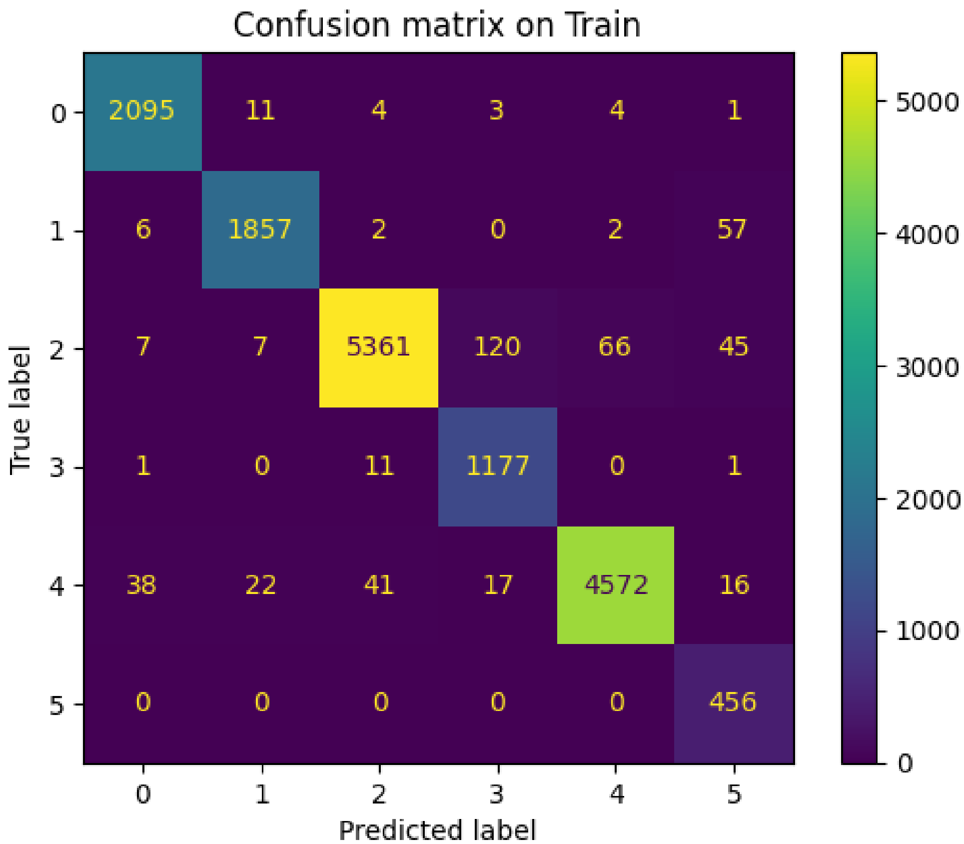
[ ]:
```
best_nb_model = MultinomialNB(alpha=0.5)
```

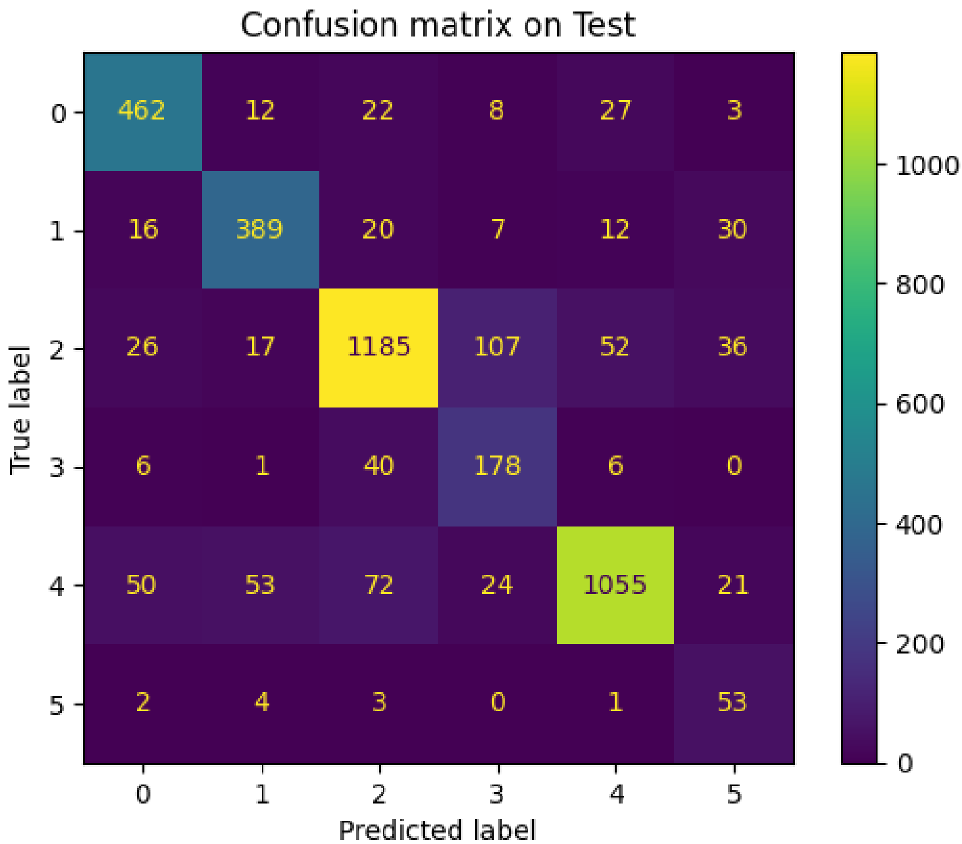
[ ]:
```
draw_learning_curve(best_nb_model, X_train, y_train)
```



[ ]:
```
best_nb_model.fit(X_train, y_train)
evaluate_model(best_nb_model, X_train, X_test, y_train, y_test,␣
 ↪include_training=True)
```

```
Score of on train are:
        - Accuracy score: 0.97
        - Micro F1 score: 0.97
        - Macro F1 score: 0.95
Score of on test are:
        - Accuracy score: 0.83
        - Micro F1 score: 0.83
        - Macro F1 score: 0.76
```


Confusion matrix on Train
True label
Predicted label
0
1
2
3
4
5
2095
11
4
3
4
1
6
1857
2
0
2
57
7
7
5361
120
66
45
1
0
11
1177
0
1
38
22
41
17
4572
16
0
0
0
0
0
456
5000
4000
3000
2000
1000
0



4 Export model

[ ]:
```
directory = "data/models/nb/"

dump(best_nb_model, directory + "best_nb_bow_model.joblib")
```

[ ]: ['data/models/nb/best_nb_bow_model.joblib']