# Multinomial Naive Bayes - tfidf

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_tfidf
X_test = X_test_tfidf
```

## 2 Basic training

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

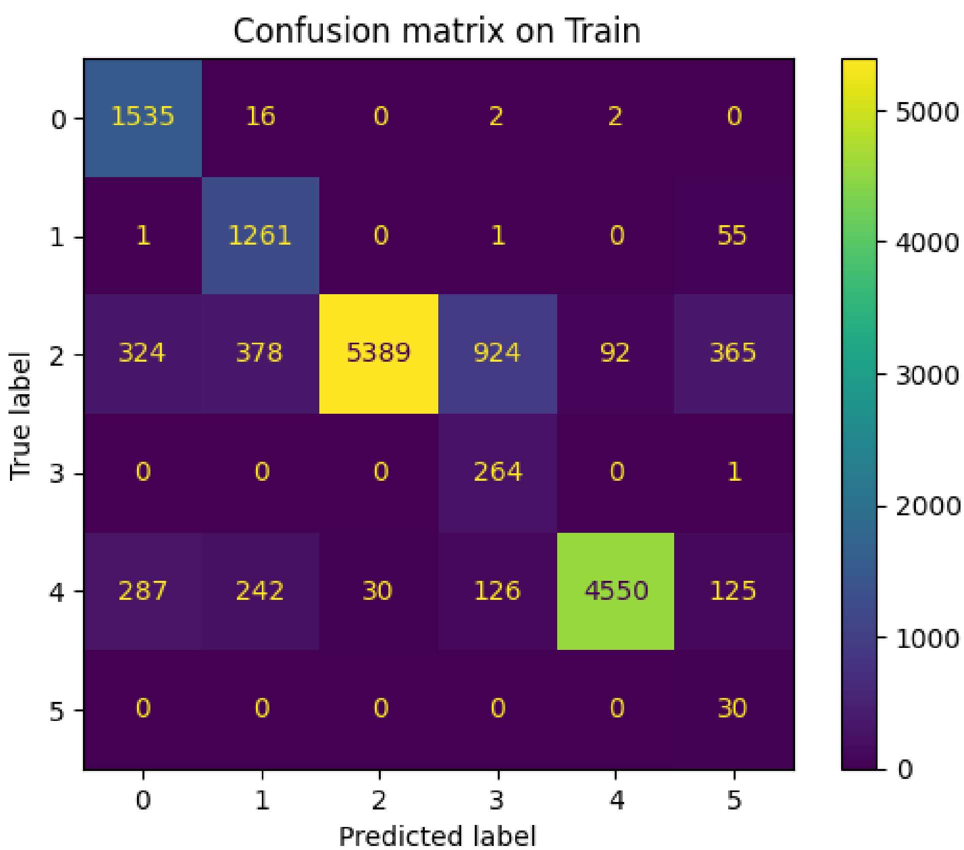
[ ]:
```
nb_model = MultinomialNB()
nb_model.fit(X_train, y_train)
```

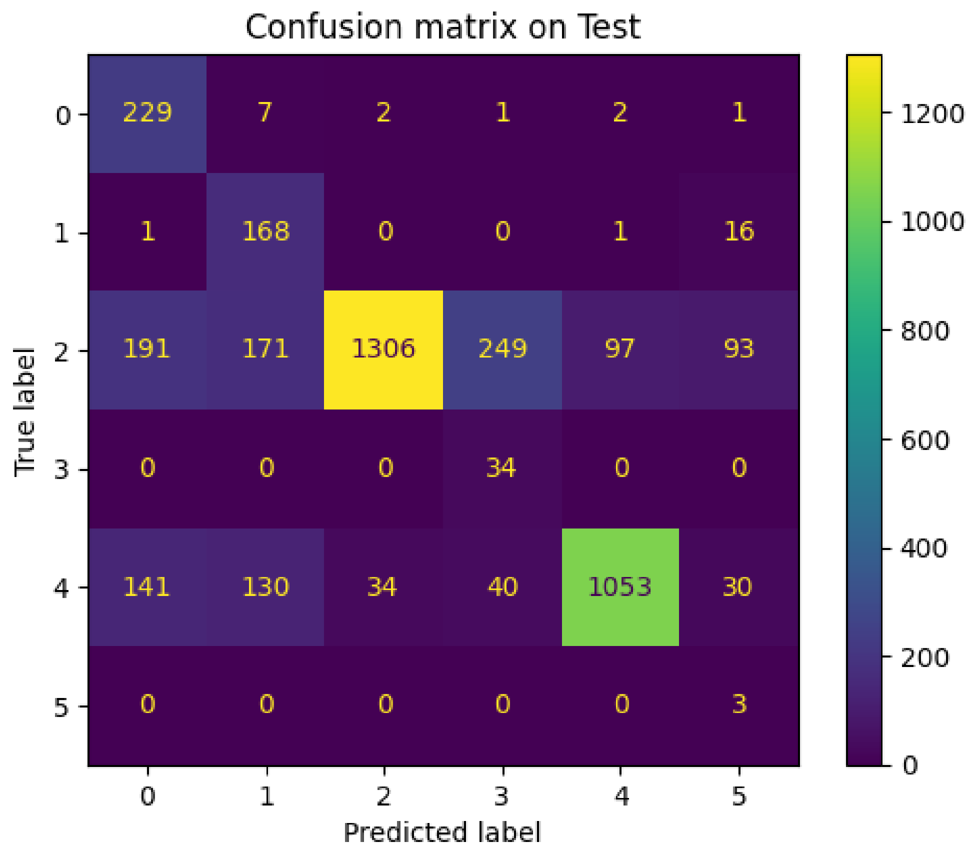
[ ]:
```
MultinomialNB()
```

Evaluate model using preset function:

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

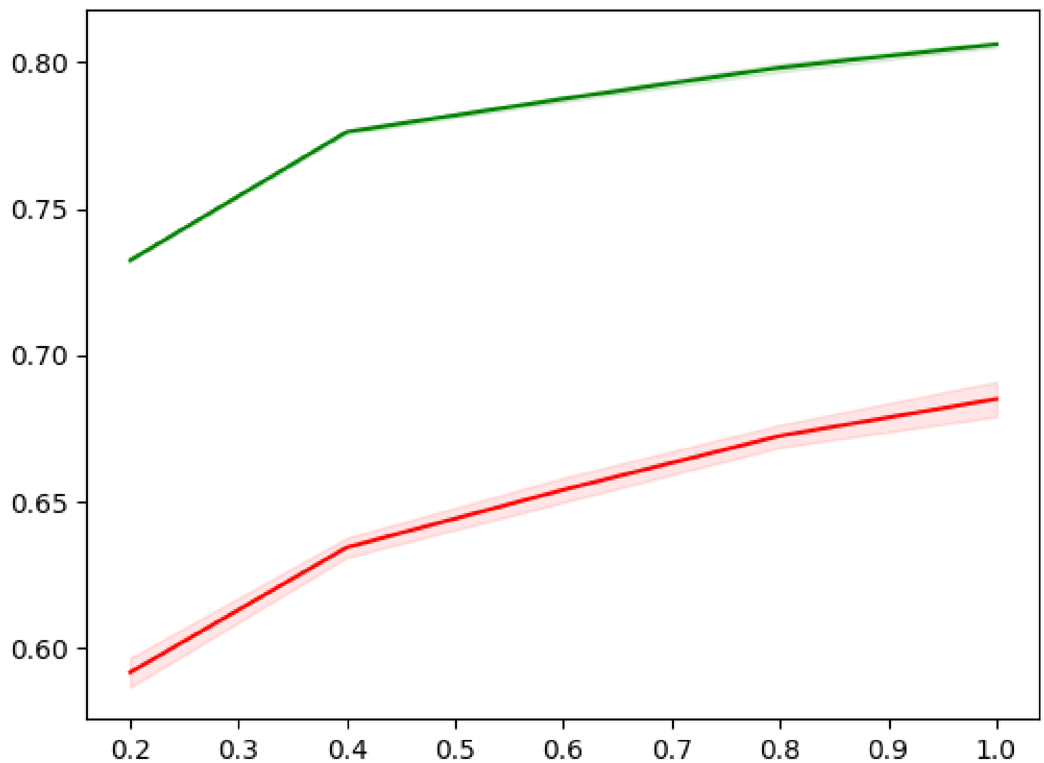
```
Score of on train are:
        - Accuracy score: 0.81
        - Micro F1 score: 0.81
        - Macro F1 score: 0.63
Score of on test are:
        - Accuracy score: 0.70
        - Micro F1 score: 0.70
        - Macro F1 score: 0.48
```






Draw the learning curve using preset function:

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




# 3 Model selection

## 3.1 $\alpha$ parameter

First we try a hyperparameter range:

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

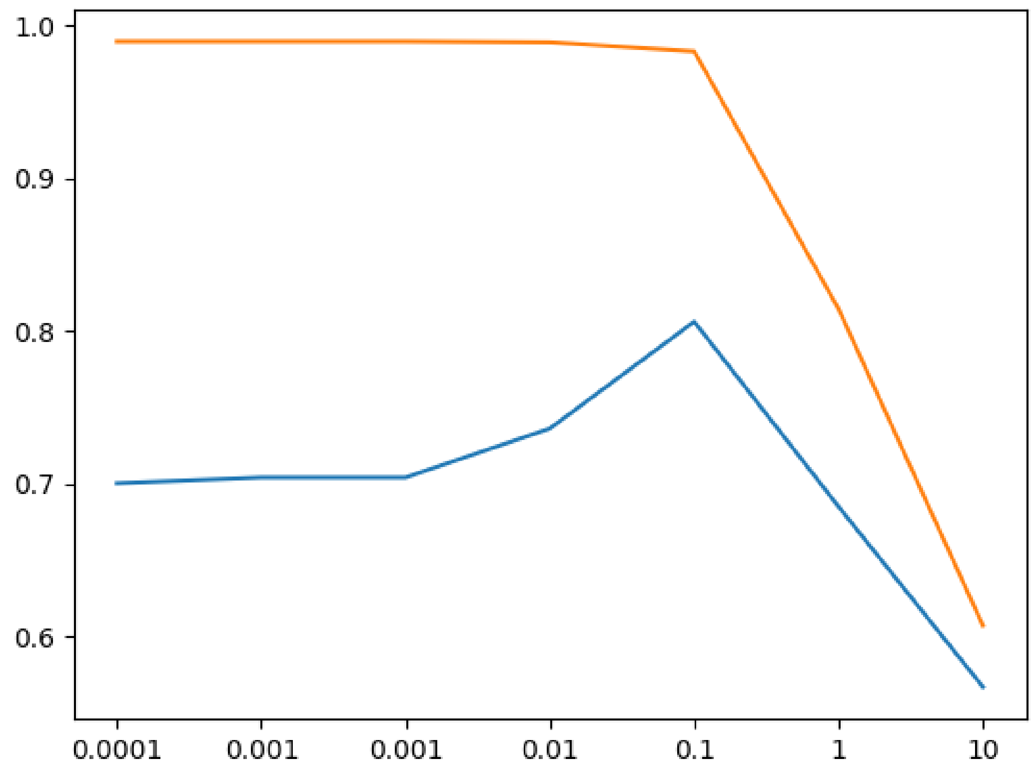
[ ]:
```
# Define a list in order to store accuracy points
cvs_list = list()
trs_list = list()

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]
[0.9895, 0.9895, 0.9895, 0.9889375, 0.9829375, 0.8143125, 0.6070625]
[0.7001875, 0.7039375000000001, 0.7039375000000001, 0.736, 0.806,
0.6848750000000001, 0.5668124999999999]
```

[ ]:
```
[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')]
```




Iteration 1: From the result of above section, we can see the good value of $\alpha$ is near the value 0.1.

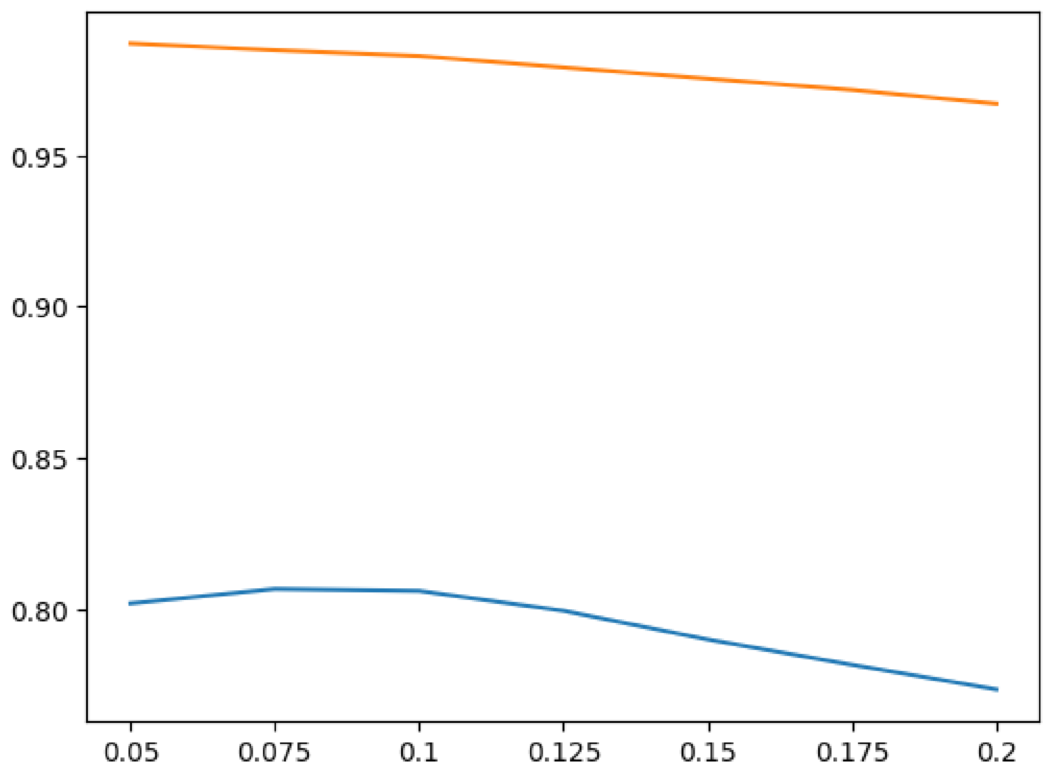
[ ]:
```
# Setting the hyperparameter range
K = [0.05, 0.075, 0.1, 0.125, 0.15, 0.175, 0.2]
```

[ ]:
```
# 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)
```

```
[0.05, 0.075, 0.1, 0.125, 0.15, 0.175, 0.2]
[0.987125, 0.984875, 0.9829375, 0.9791875, 0.9754375, 0.97175, 0.9671875]
[0.8018749999999999, 0.806625, 0.806, 0.7994374999999999, 0.7899375, 0.7815625,
0.7734375]
```

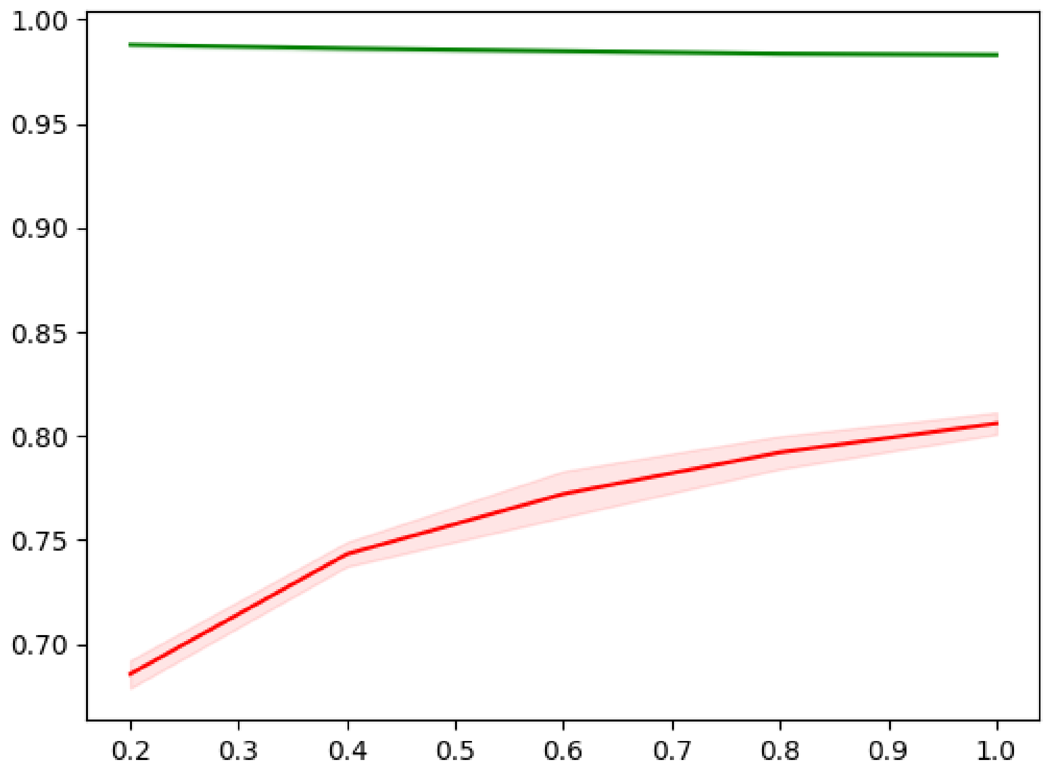
[ ]:
```
[Text(0, 0, '0.05'),
 Text(1, 0, '0.075'),
 Text(2, 0, '0.1'),
 Text(3, 0, '0.125'),
 Text(4, 0, '0.15'),
 Text(5, 0, '0.175'),
 Text(6, 0, '0.2')]
```



As the result, we can claim that $\alpha = 0.1$ give a model with good accuracy and avoid overfitting. We will test the model again in test set.

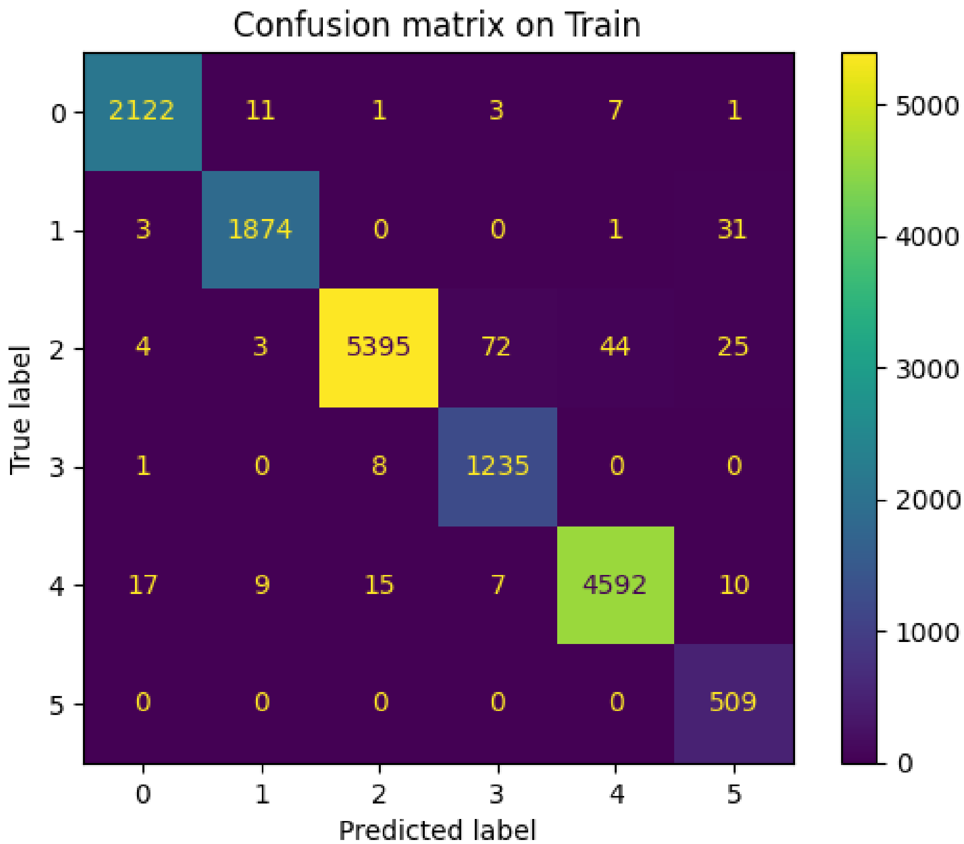
[ ]:
```
best_nb_model = MultinomialNB(alpha=0.1)
```

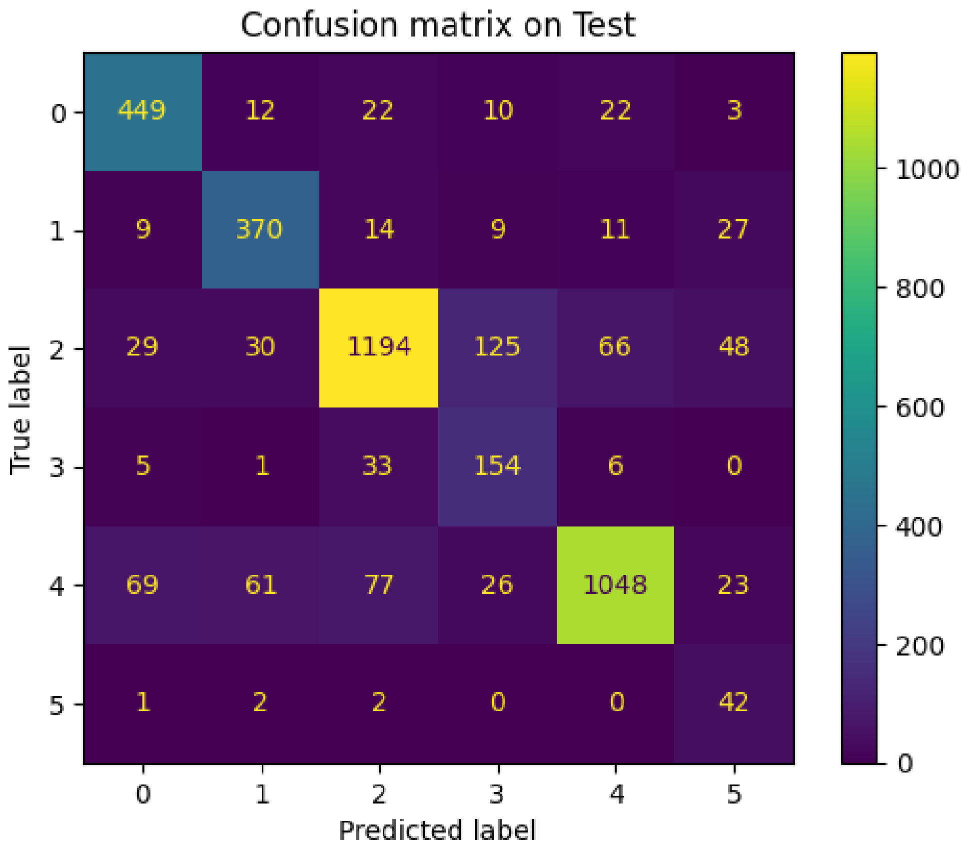
[ ]:
```
draw_learning_curve(best_nb_model, X_train, y_train)
```




[ ]:
```
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: 0.98
        - Micro F1 score: 0.98
        - Macro F1 score: 0.97
Score of on test are:
        - Accuracy score: 0.81
        - Micro F1 score: 0.81
        - Macro F1 score: 0.73
```


Confusion matrix on Train
True label
Predicted label
0
1
2
3
4
5
2122
11
1
3
7
1
3
1874
0
0
1
31
4
3
5395
72
44
25
1
0
8
1235
0
0
17
9
15
7
4592
10
0
0
0
0
0
509
5000
4000
3000
2000
1000
0




## 4 Export model

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

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

[ ]:
```
['data/models/nb/best_nb_tfidf_model.joblib']
```