Multinomial Naive Bayes - tfidf_l1

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_L1
X_test = X_test_tfidf_L1
```

2 Basic training

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

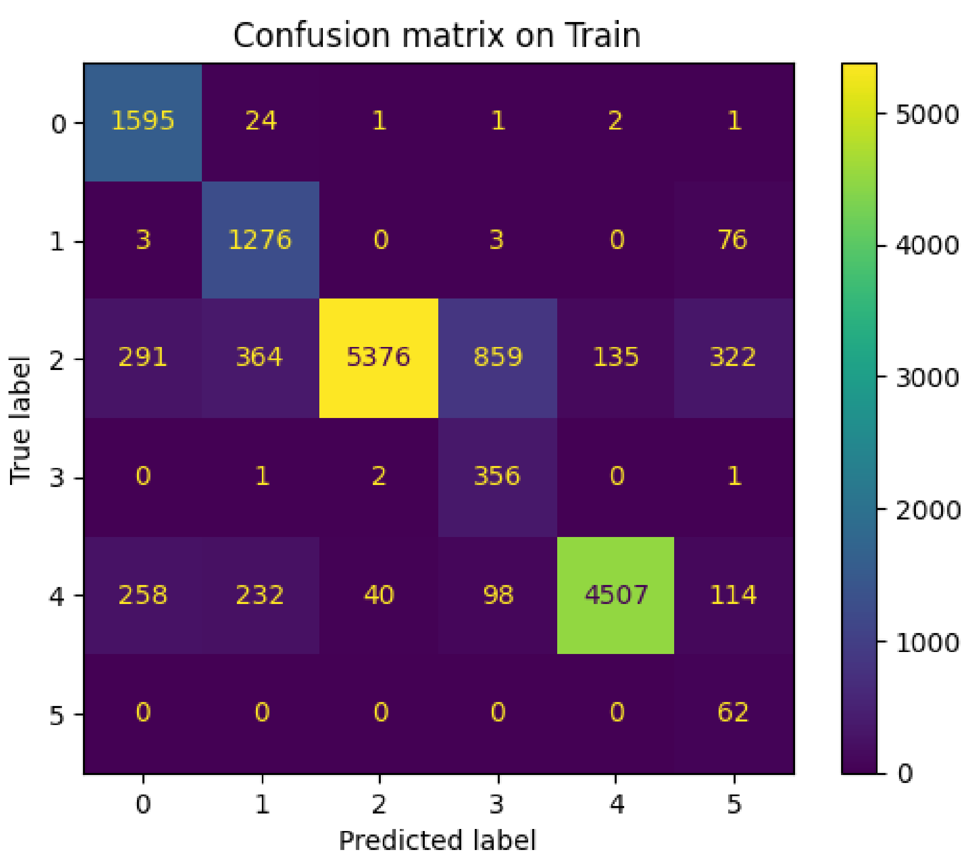
[ ]:
```
nb_model = MultinomialNB()
nb_model.fit(X_train, y_train)
```

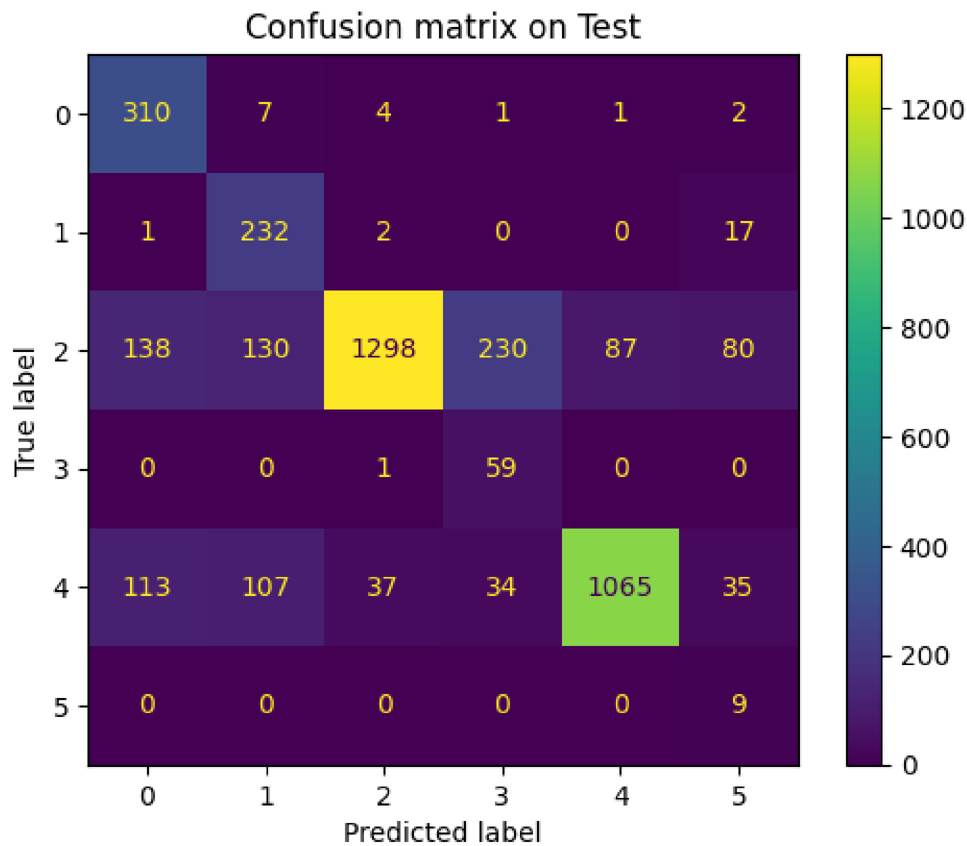
[ ]:
```
MultinomialNB()
```

Evaluate model using preset function:

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

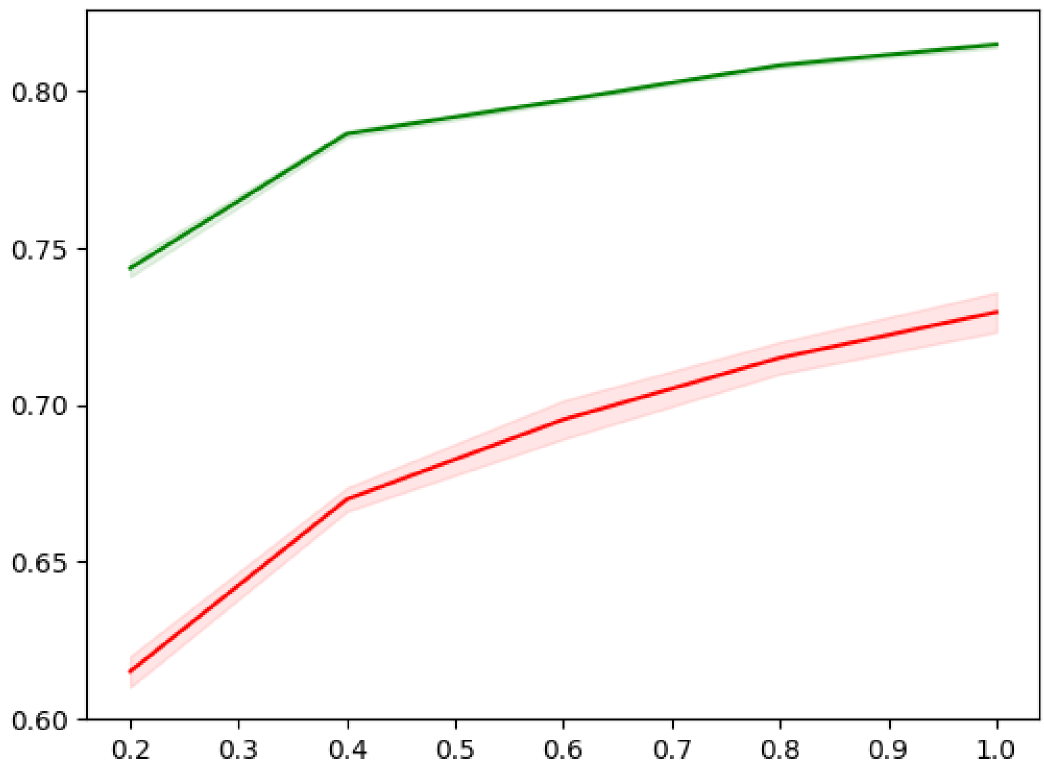
```
Score of on train are:
        - Accuracy score: 0.8233
        - Micro F1 score: 0.8233
        - Macro F1 score: 0.6670
Score of on test are:
        - Accuracy score: 0.7432
        - Micro F1 score: 0.7432
        - Macro F1 score: 0.5641
```





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]
```

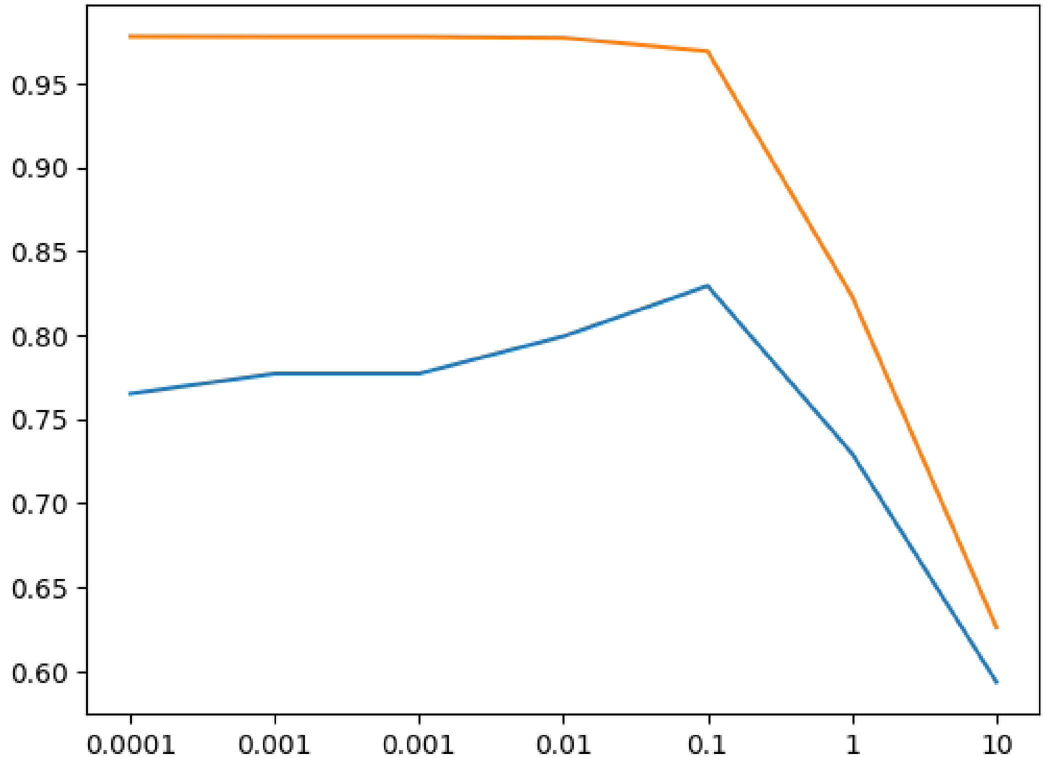
[ ]:
```
# Define a list in order to store accuracy points
cvs_list = list()
trs_list = list()

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]
[0.9780625, 0.9779375, 0.9779375, 0.97725, 0.9691875, 0.82325, 0.6259375]
[0.7651249999999999, 0.7770625, 0.7770625, 0.7993125, 0.829375, 0.7295,
0.593375]
```

[ ]:
```
[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 0.1.

Scope to $\alpha = 0.1$.

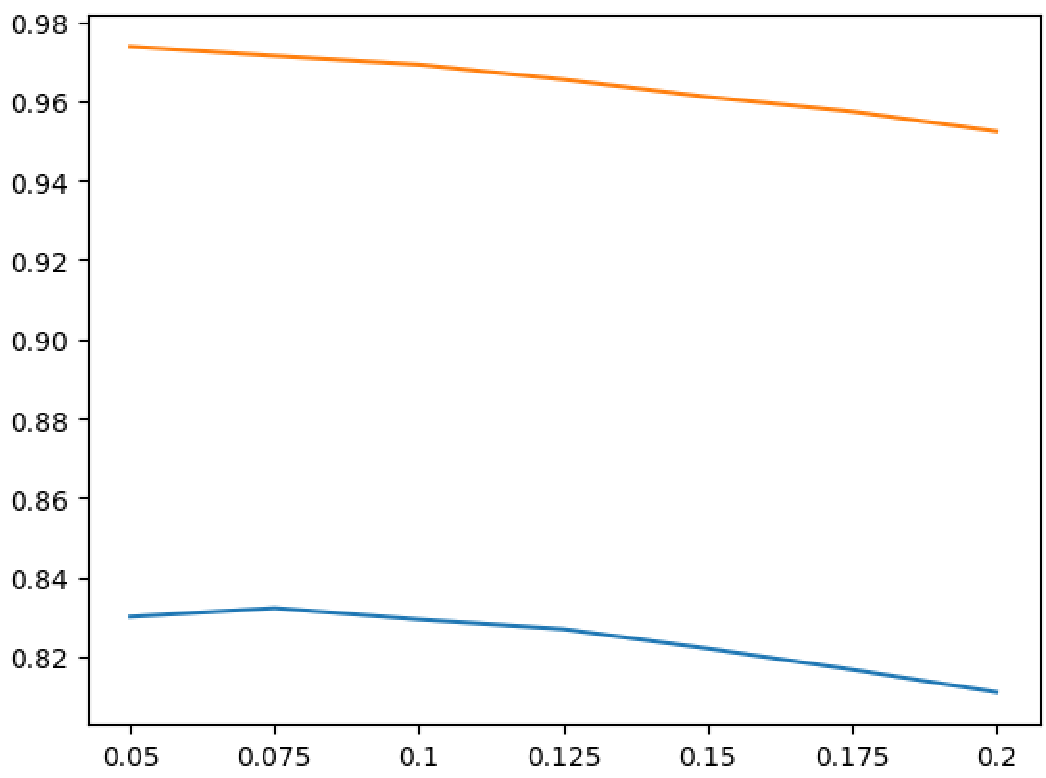
[ ]:
```
# Setting the hyperparameter range
K = [0.05, 0.075, 0.1, 0.125, 0.15, 0.175, 0.2]
```

[ ]:
```
# 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)
```

[ ]:
```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)
```

```
[0.05, 0.075, 0.1, 0.125, 0.15, 0.175, 0.2]
[0.97375, 0.971375, 0.9691875, 0.9654375, 0.9610625, 0.957375, 0.952375]
[0.8300625, 0.8322499999999999, 0.829375, 0.8269375, 0.8220625,
0.8167500000000001, 0.8110625]
```

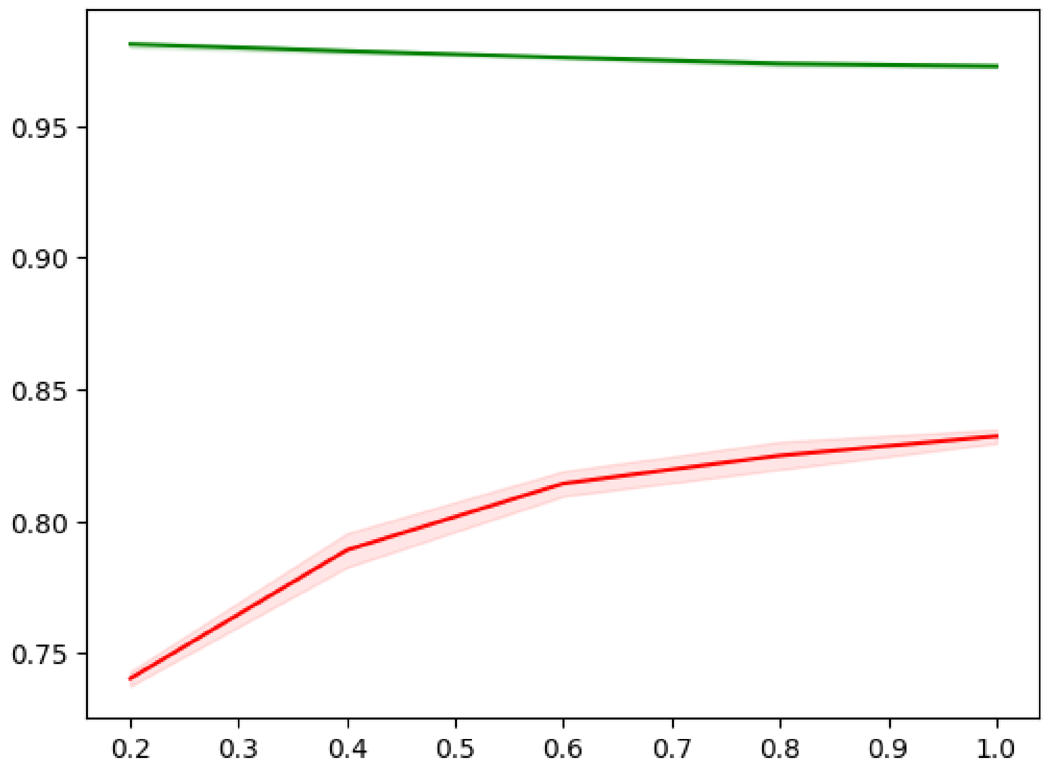
[ ]:
```
[Text(0, 0, '0.05'),
 Text(1, 0, '0.075'),
 Text(2, 0, '0.1'),
 Text(3, 0, '0.125'),
 Text(4, 0, '0.15'),
 Text(5, 0, '0.175'),
 Text(6, 0, '0.2')]
```



As the result, we can claim that $\alpha = 0.075$ give a model with good accuracy and avoid overfitting. We will test the model again in test set.

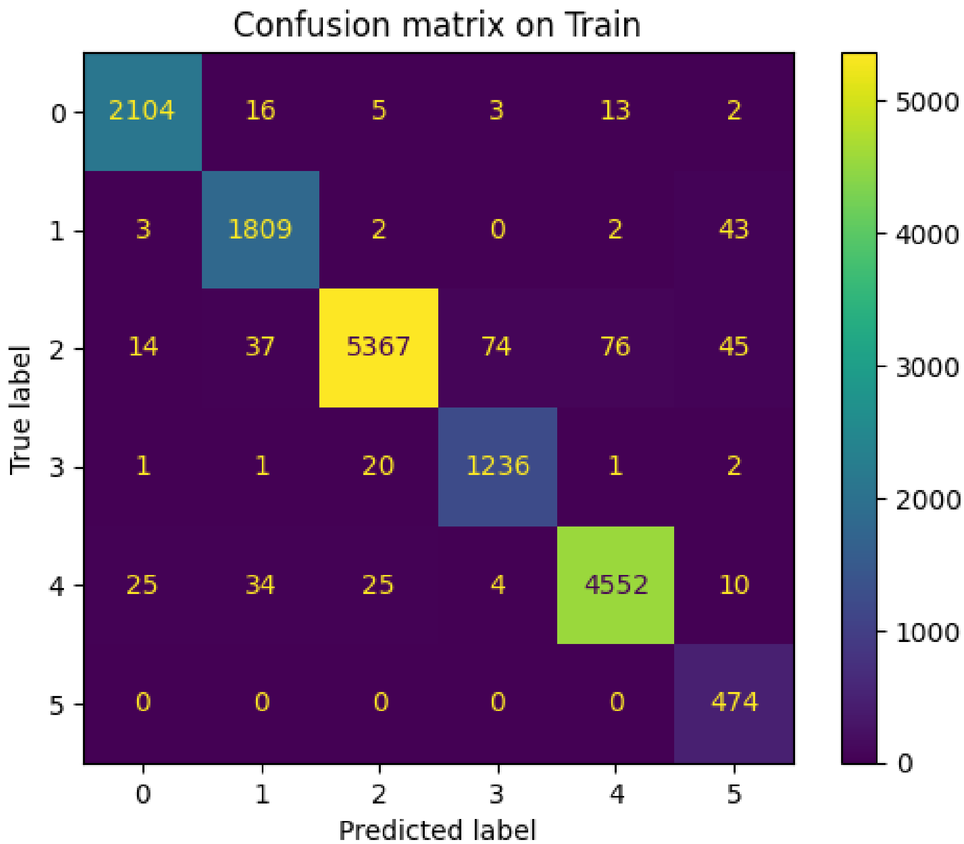
[ ]:
```
best_nb_model = MultinomialNB(alpha=0.075)
```

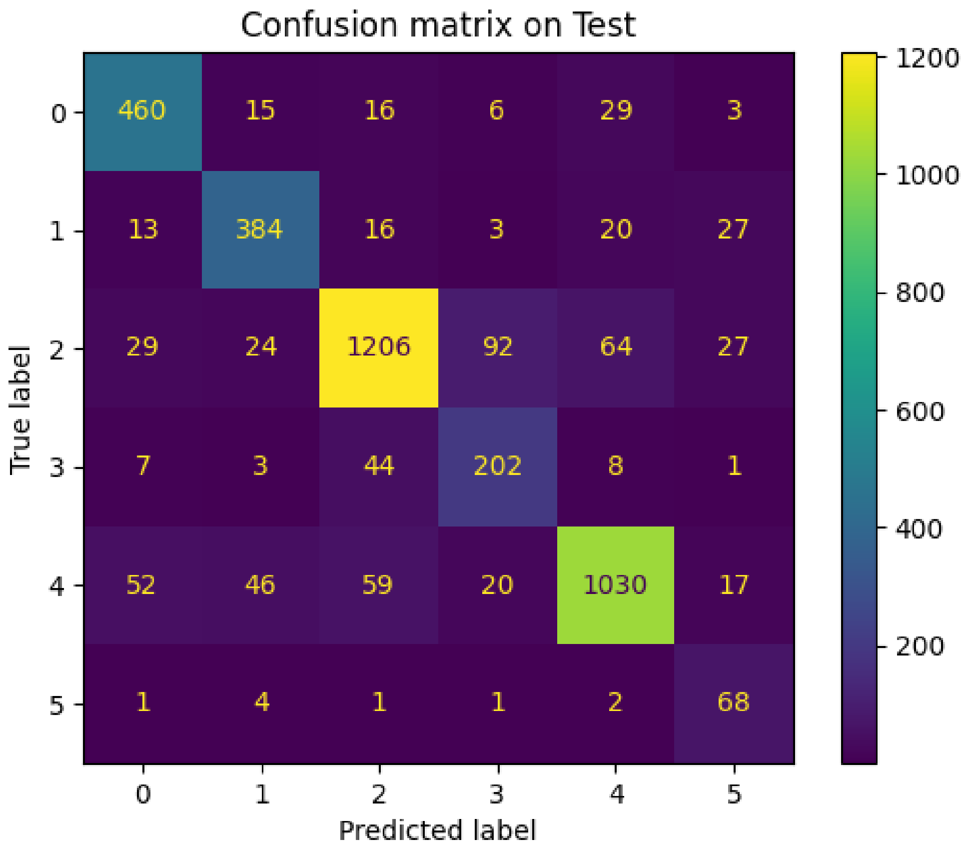
[ ]:
```
draw_learning_curve(best_nb_model, X_train, y_train)
```



[ ]:
```
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: 0.9714
        - Micro F1 score: 0.9714
        - Macro F1 score: 0.9597
Score of on test are:
        - Accuracy score: 0.8375
        - Micro F1 score: 0.8375
        - Macro F1 score: 0.7830
```


Confusion matrix on Train
True label
Predicted label
0
1
2
3
4
5
2104
16
5
3
13
2
3
1809
2
0
2
43
14
37
5367
74
76
45
1
1
20
1236
1
2
25
34
25
4
4552
10
0
0
0
0
0
474
5000
4000
3000
2000
1000
0



4 Export model

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

dump(best_nb_model, directory + "best_nb_tfidf_l1_model.joblib")
```

[ ]: ['data/models/nb/best_nb_tfidf_l1_model.joblib']