K-nearest neighbors (KNN)

May 7, 2024

1 Initialization

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

from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import GridSearchCV
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
```

2 Basic training

We define the model and train it first

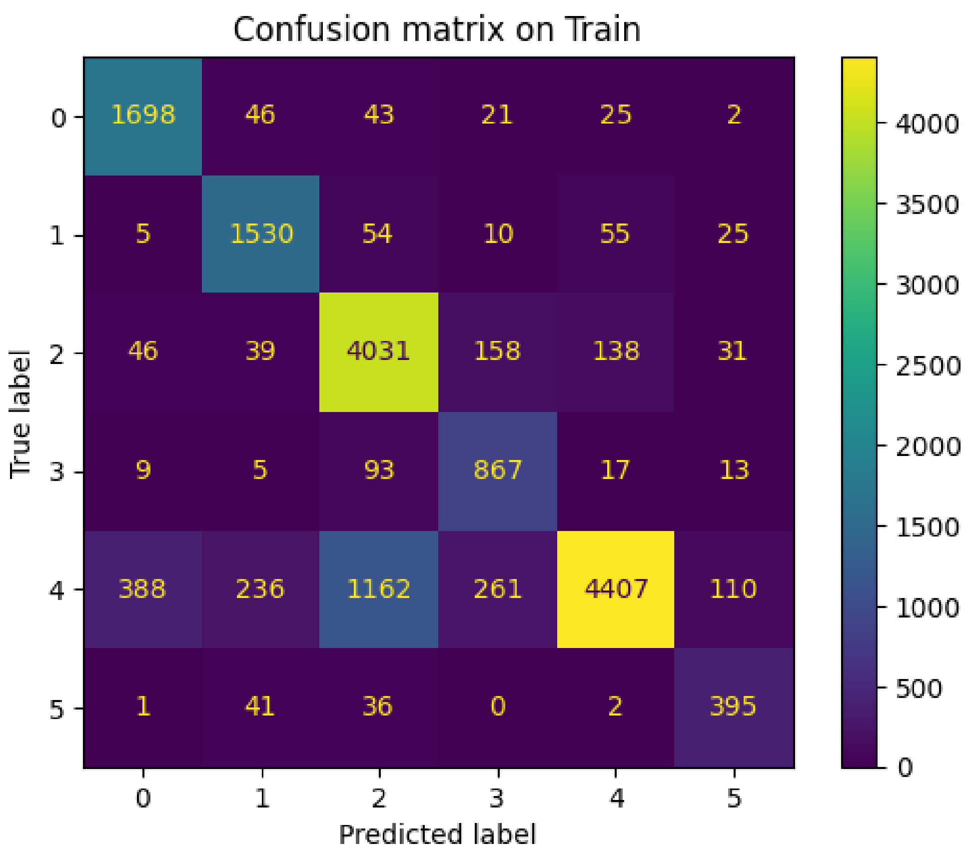
[ ]:
```
knn_model = KNeighborsClassifier(n_neighbors = 3)
knn_model.fit(X_train_bow, y_train)
```

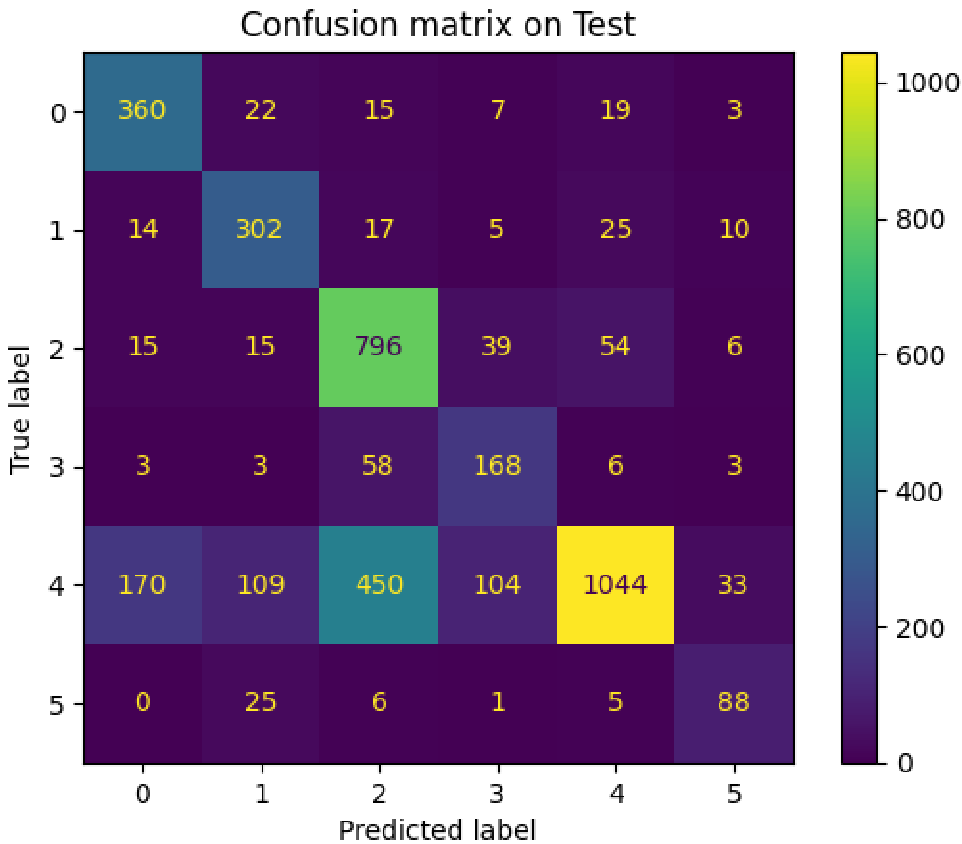
[ ]:
```
KNeighborsClassifier(n_neighbors=3)
```

Getting prediction on training set (without cross validation) then evaluate it!

```
[ ]: evaluate_model(knn_model, X_train_bow, X_test_bow, y_train, y_test,␣
     ↪include_training = True)
```

```
Score of on train are:
        - Accuracy score: 0.8080
        - Micro F1 score: 0.8080
        - Macro F1 score: 0.8019
Score of on test are:
        - Accuracy score: 0.6895
        - Micro F1 score: 0.6895
        - Macro F1 score: 0.6793
```

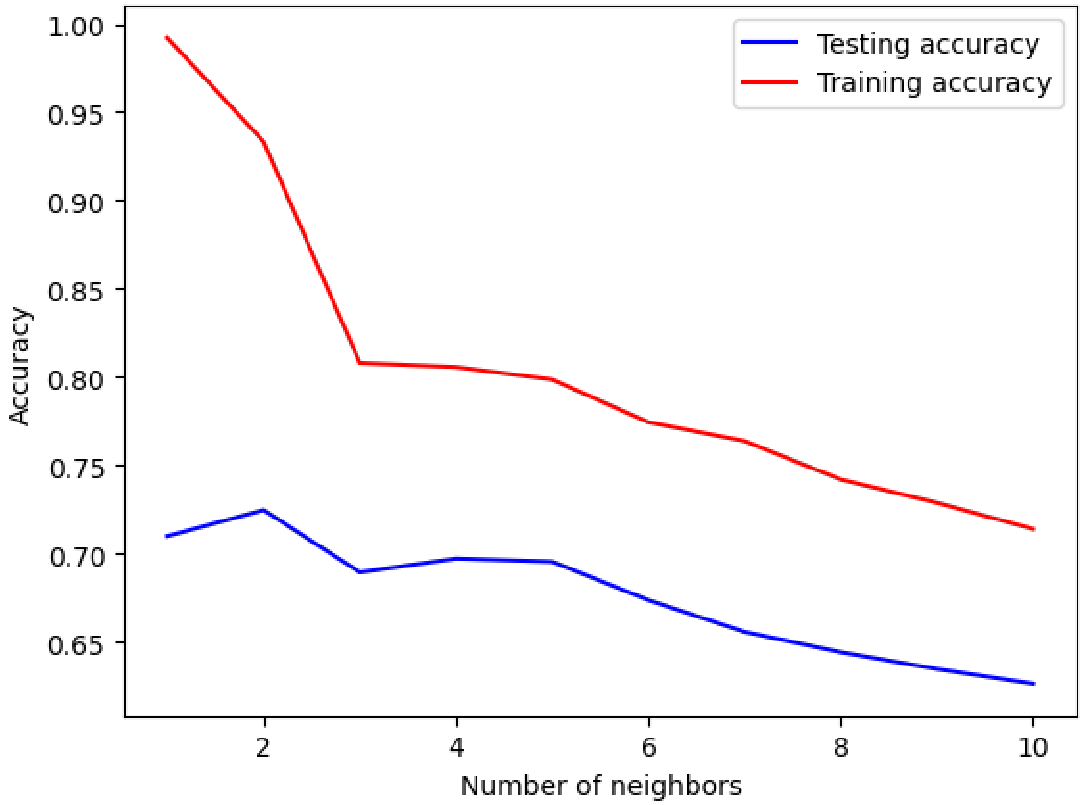




Now we draw the plot for a range of k-neighbors

[ ]:
```
# Setting the hyperparameter range
K = [1, 2, 3, 4, 5, 6, 7, 8, 9, 10]
accuracy_list = list()
valid_accuracy_list = list()

for k in K:
  knn_model = KNeighborsClassifier(n_neighbors = k)
  knn_model.fit(X_train_bow, y_train)

  data_pred_y = knn_model.predict(X_test_bow)
  data_valid_y = knn_model.predict(X_train_bow)

  accuracy_list.append([k, accuracy_score(y_test, data_pred_y)])
  valid_accuracy_list.append([k, accuracy_score(y_train, data_valid_y)])

accuracy_list = np.asarray(accuracy_list)
valid_accuracy_list = np.asarray(valid_accuracy_list)
```

```
plt.plot(accuracy_list[:, 0], accuracy_list[:, 1], label = "Testing accuracy",␣
↪color = 'b')
plt.plot(valid_accuracy_list[:, 0], valid_accuracy_list[:, 1], label =␣
↪"Training accuracy", color = 'r')
plt.xlabel('Number of neighbors')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```



2.0.1 Model evaluation

We'll evaluate models based on different datasets

1. BoW - Normal Dataset

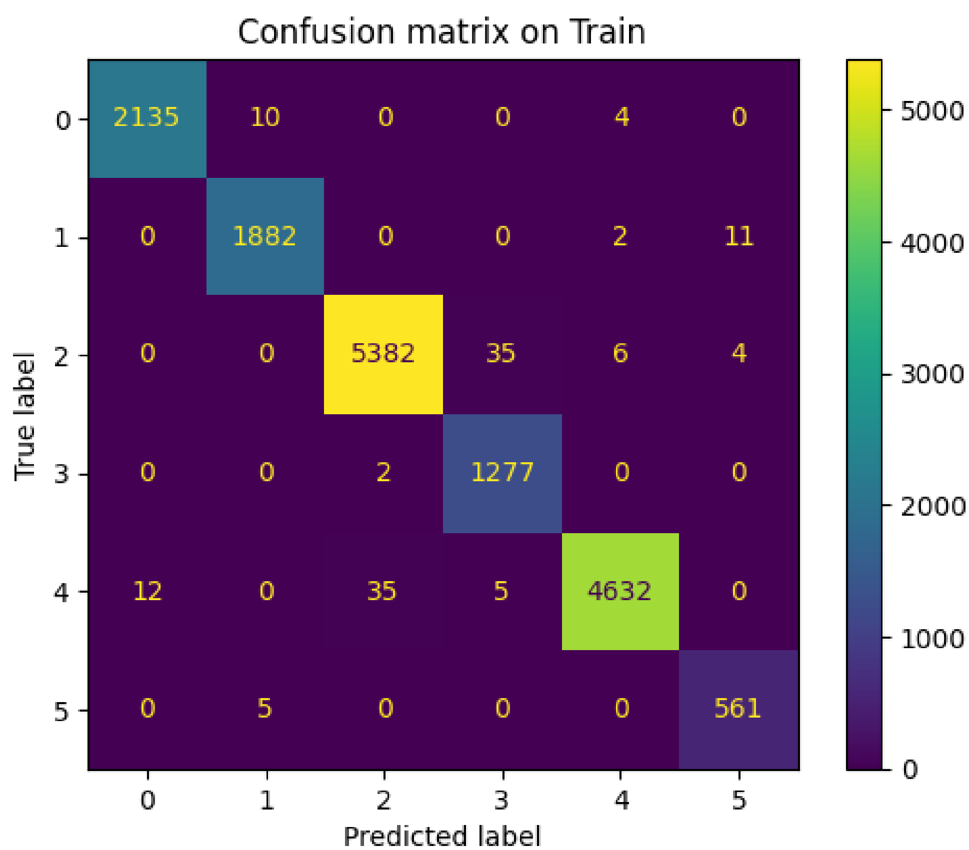
[ ]:
```
dict_param = {'n_neighbors': np.arange(1, 51),
              'p': np.arange(1, 3),
              'weights': ['uniform', 'distance']}
best_knn_model_bow_normal = GridSearchCV(KNeighborsClassifier(), param_grid =␣
↪dict_param, n_jobs = 8, cv = 10, scoring = 'accuracy')
```

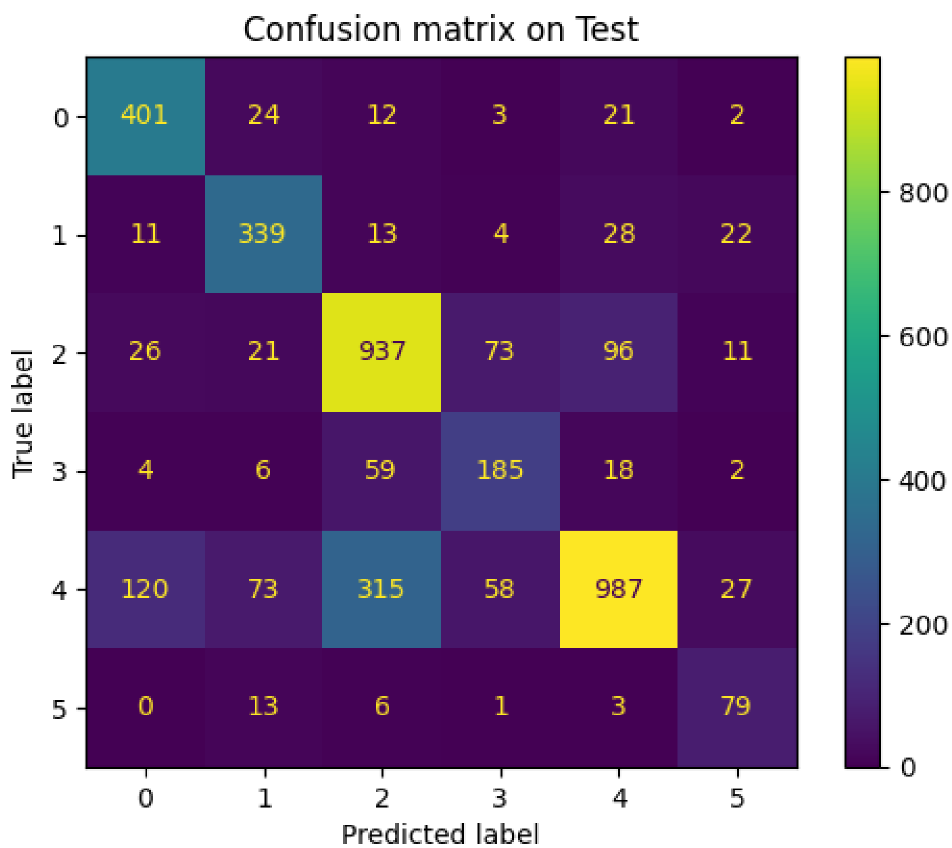
```
best_knn_model_bow_normal.fit(X_train_bow, y_train)

print("Best parameters for k_NN on BoW - Normal Dataset:",␣
 ↪best_knn_model_bow_normal.best_params_)
```

```
Best parameters for k_NN on BoW - Normal Dataset: {'n_neighbors': 2, 'p': 1,
'weights': 'distance'}
```

[ ]:
```
evaluate_model(best_knn_model_bow_normal, X_train_bow, X_test_bow, y_train,␣
 ↪y_test, include_training=True)
```

```
Score of on train are:
        - Accuracy score: 0.9918
        - Micro F1 score: 0.9918
        - Macro F1 score: 0.9897
Score of on test are:
        - Accuracy score: 0.7320
        - Micro F1 score: 0.7320
        - Macro F1 score: 0.7126
```





2. TF-IDF - Normal Dataset

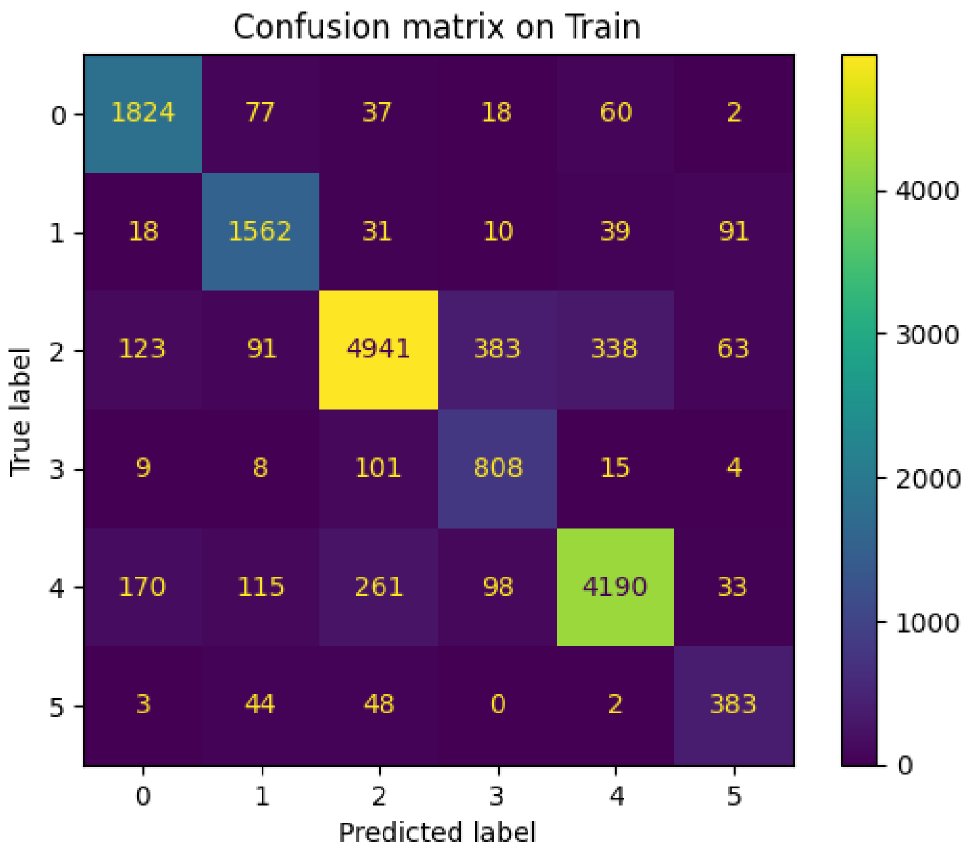
[ ]:
```
dict_param = {'n_neighbors': np.arange(1, 51),
              'p': np.arange(1, 3),
              'weights': ['uniform', 'distance']}
best_knn_model_tfidf_normal = GridSearchCV(KNeighborsClassifier(), param_grid =␣
 ↪dict_param, n_jobs = 8, cv = 10, scoring = 'accuracy')

best_knn_model_tfidf_normal.fit(X_train_tfidf, y_train)

print("Best parameters for k_NN on TF-IDF - Normal Dataset:",␣
 ↪best_knn_model_tfidf_normal.best_params_)
```

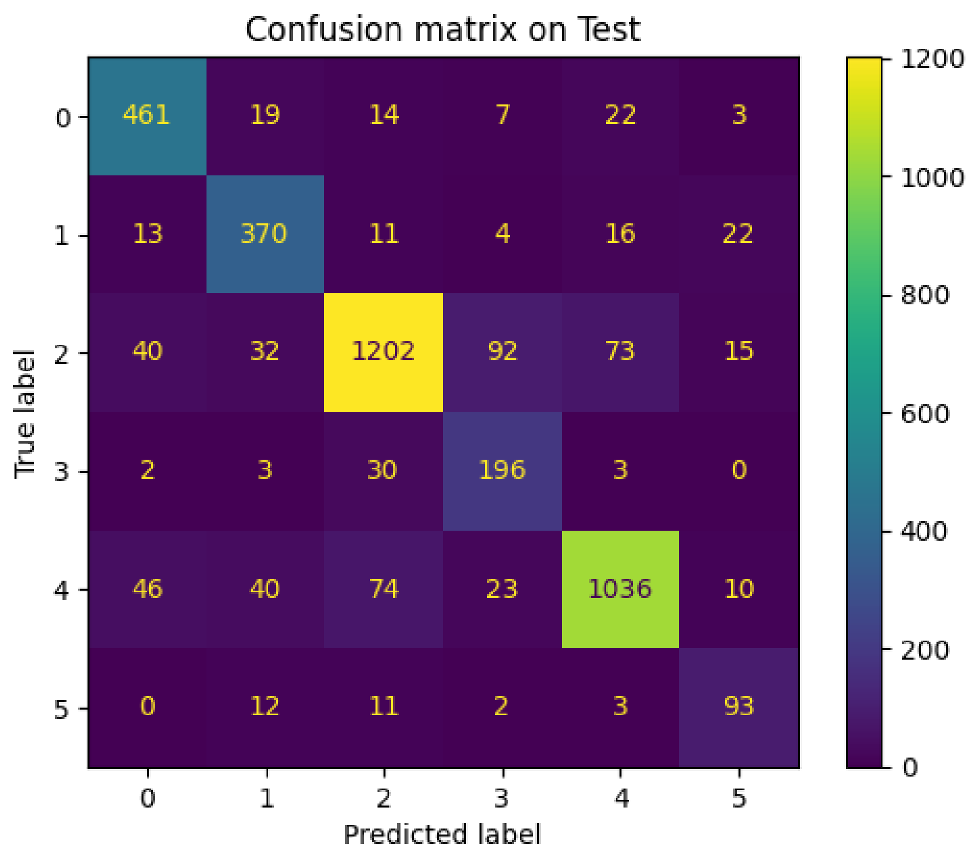
```
Best parameters for k_NN on TF-IDF - Normal Dataset: {'n_neighbors': 24, 'p': 2,
'weights': 'uniform'}
```

[ ]:
```
evaluate_model(best_knn_model_tfidf_normal, X_train_tfidf, X_test_tfidf,␣
 ↪y_train, y_test, include_training=True)
```

```
Score of on train are:
        - Accuracy score: 0.8568
```

```
        - Micro F1 score: 0.8568
        - Macro F1 score: 0.8205
Score of on test are:
        - Accuracy score: 0.8395
        - Micro F1 score: 0.8395
        - Macro F1 score: 0.7993
```





3. BoW - L1-altered dataset

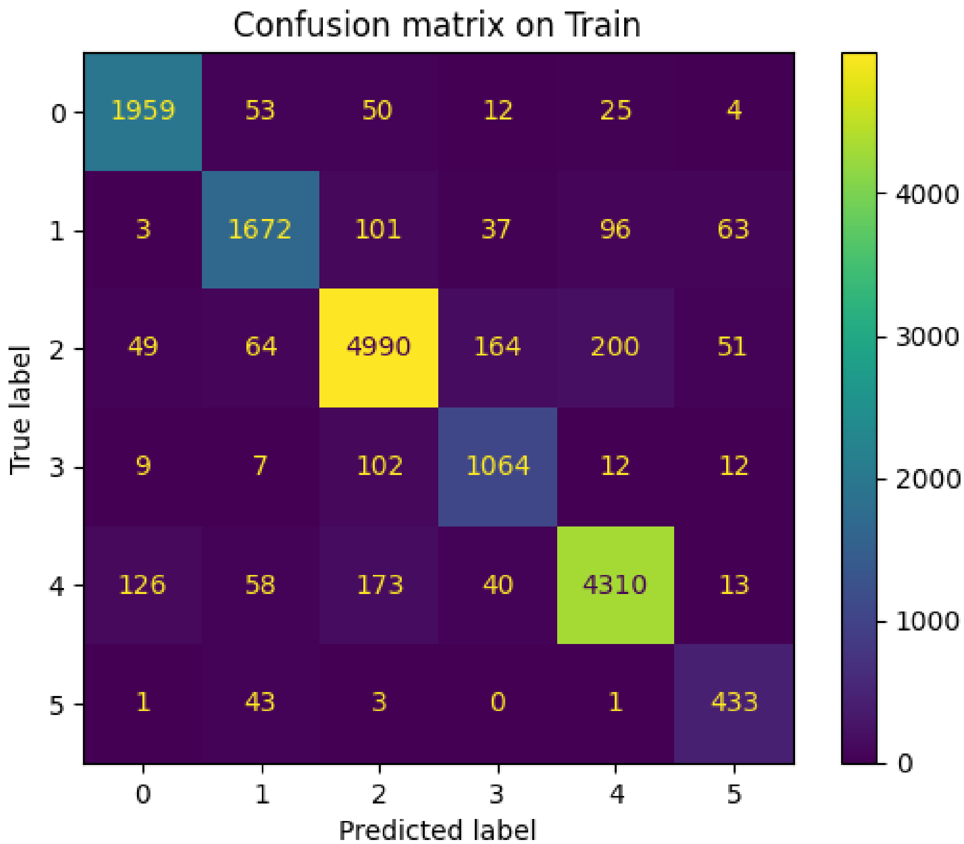
[ ]:
```
dict_param = {'n_neighbors': np.arange(1, 51),
              'p': np.arange(1, 3),
              'weights': ['uniform', 'distance']}
best_knn_model_bow_L1 = GridSearchCV(KNeighborsClassifier(), param_grid =␣
 ↪dict_param, n_jobs = 8, cv = 10, scoring = 'accuracy')

best_knn_model_bow_L1.fit(X_train_bow_L1, y_train)

print("Best parameters for k_NN on BoW - L1-altered Dataset:",␣
 ↪best_knn_model_bow_L1.best_params_)
```

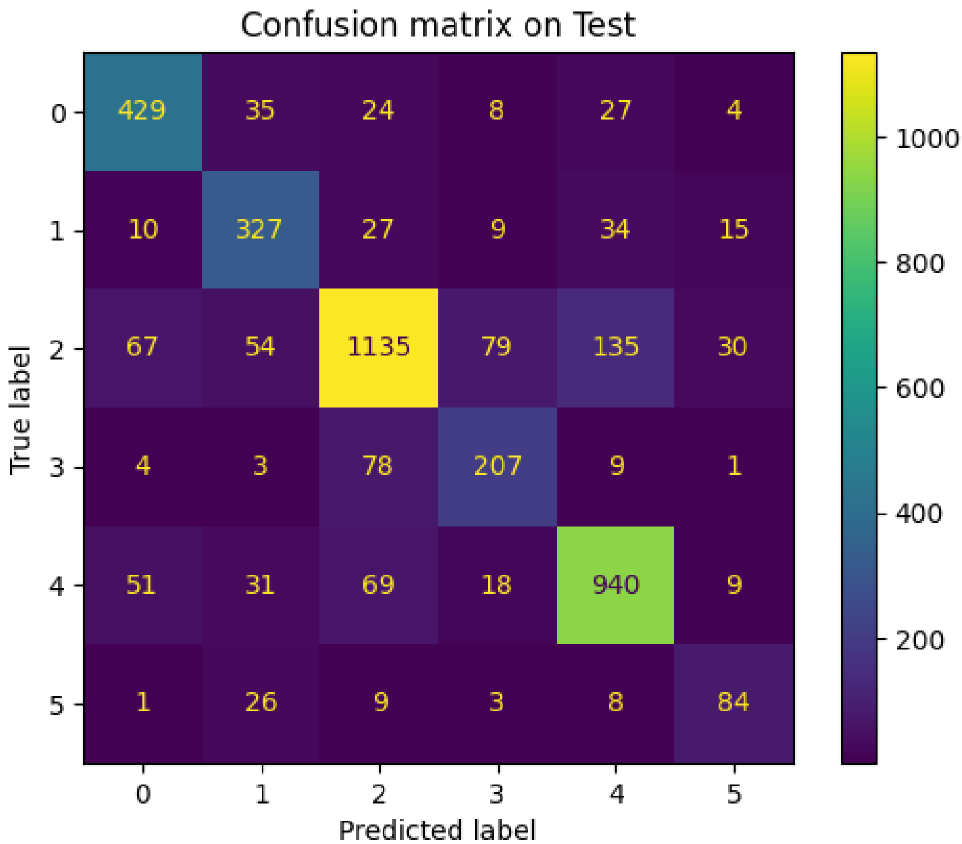
```
Best parameters for k_NN on BoW - L1-altered Dataset: {'n_neighbors': 3, 'p': 1,
'weights': 'uniform'}
```

[ ]:
```
evaluate_model(best_knn_model_bow_L1, X_train_bow_L1, X_test_bow_L1, y_train,␣
 ↪y_test, include_training=True)
```

```
Score of on train are:
        - Accuracy score: 0.9018
```

```
        - Micro F1 score: 0.9018
        - Macro F1 score: 0.8803
Score of on test are:
        - Accuracy score: 0.7805
        - Micro F1 score: 0.7805
        - Macro F1 score: 0.7362
```





4. TF-IDF - L1-altered dataset

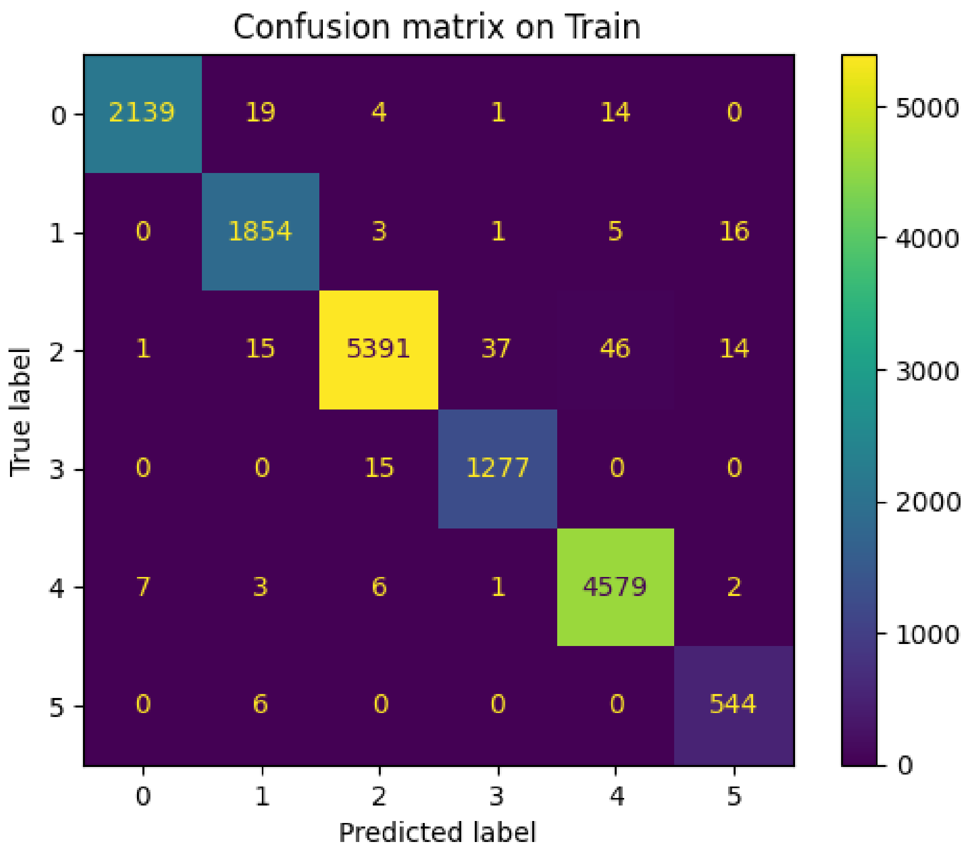
[ ]:
```
dict_param = {'n_neighbors': np.arange(1, 51),
              'p': np.arange(1, 3),
              'weights': ['uniform', 'distance']}
best_knn_model_tfidf_L1 = GridSearchCV(KNeighborsClassifier(), param_grid =␣
 ↪dict_param, n_jobs = 8, cv = 10, scoring = 'accuracy')

best_knn_model_tfidf_L1.fit(X_train_tfidf_L1, y_train)

print("Best parameters for k_NN on TF-IDF - L1-altered Dataset:",␣
 ↪best_knn_model_tfidf_L1.best_params_)
```

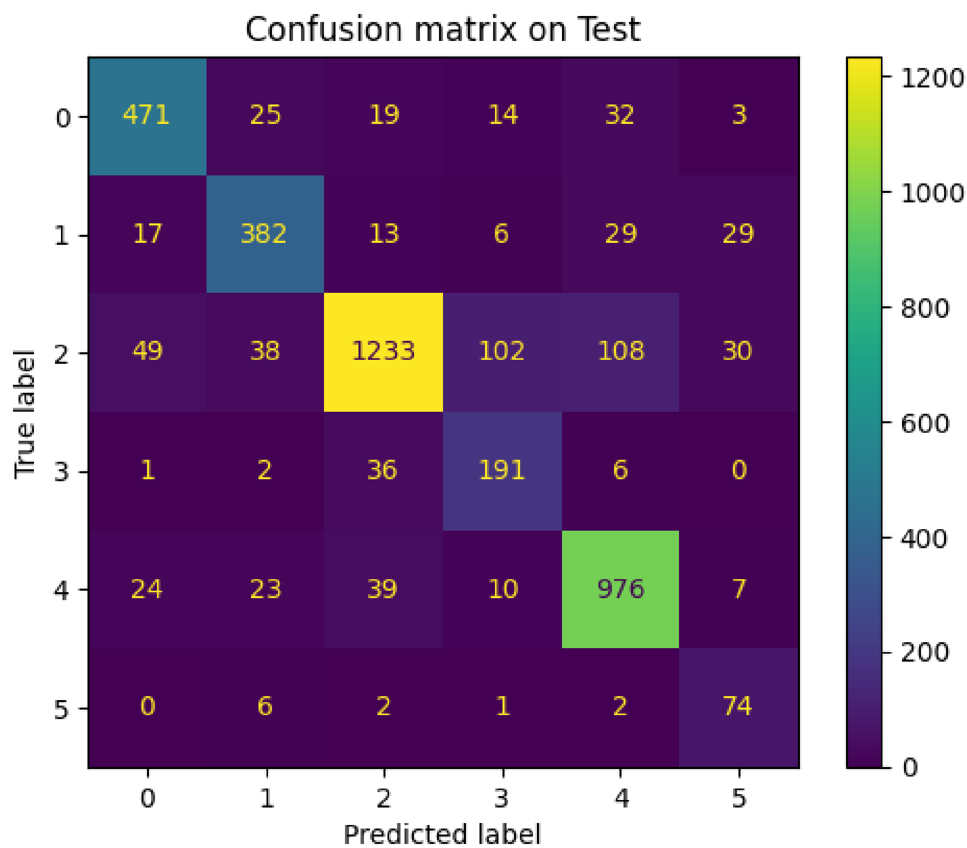
```
Best parameters for k_NN on TF-IDF - L1-altered Dataset: {'n_neighbors': 40,
'p': 2, 'weights': 'distance'}
```

[ ]:
```
evaluate_model(best_knn_model_tfidf_L1, X_train_tfidf_L1, X_test_tfidf_L1,␣
 ↪y_train, y_test, include_training=True)
```

```
Score of on train are:
        - Accuracy score: 0.9865
```

```
        - Micro F1 score: 0.9865
        - Macro F1 score: 0.9824
Score of on test are:
        - Accuracy score: 0.8317
        - Micro F1 score: 0.8317
        - Macro F1 score: 0.7824
```





2.1 Conclusion

From the above observations, it can be easily seen that:

- Comparing to BoW datasets, models running on TF-IDF datasets tend to cost less time and have significantly better performance
- Comparing to originally-filtered datasets, L1-altered datasets tend to have less execution time, with the difference between accuracy being negatable.
- TF-IDF datasets tends to product "strange" best kNN parameters, which will be delved deeper as a part of our project.

Here, we choose the models working on TF-IDF Original Dataset.

3 Export models

Only the Untrimmed TF-IDF Dataset got imported here

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

dump(best_knn_model_bow_normal, directory + "best_knn_model_bow_normal.joblib")
```

```
dump(best_knn_model_bow_L1, directory + "best_knn_model_bow_L1.joblib")
dump(best_knn_model_tfidf_normal, directory + "best_knn_model_tfidf_normal.
 ↪joblib")
dump(best_knn_model_tfidf_L1, directory + "best_knn_model_tfidf_L1.joblib")
```

[ ]: ['data/models/best_knn_model_tfidf_L1.joblib']