Logistic regression (OvR) - BoW

May 7, 2024

1 Initialization

This notebook will train the Logistic Regression in **One vs Rest** decision function. The Multinomial Logistic Regression is in the Softmax Regression notebook

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
import warnings
warnings.filterwarnings('ignore')

from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV, cross_val_score
from sklearn.metrics import accuracy_score
from sklearn.preprocessing import StandardScaler
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
```

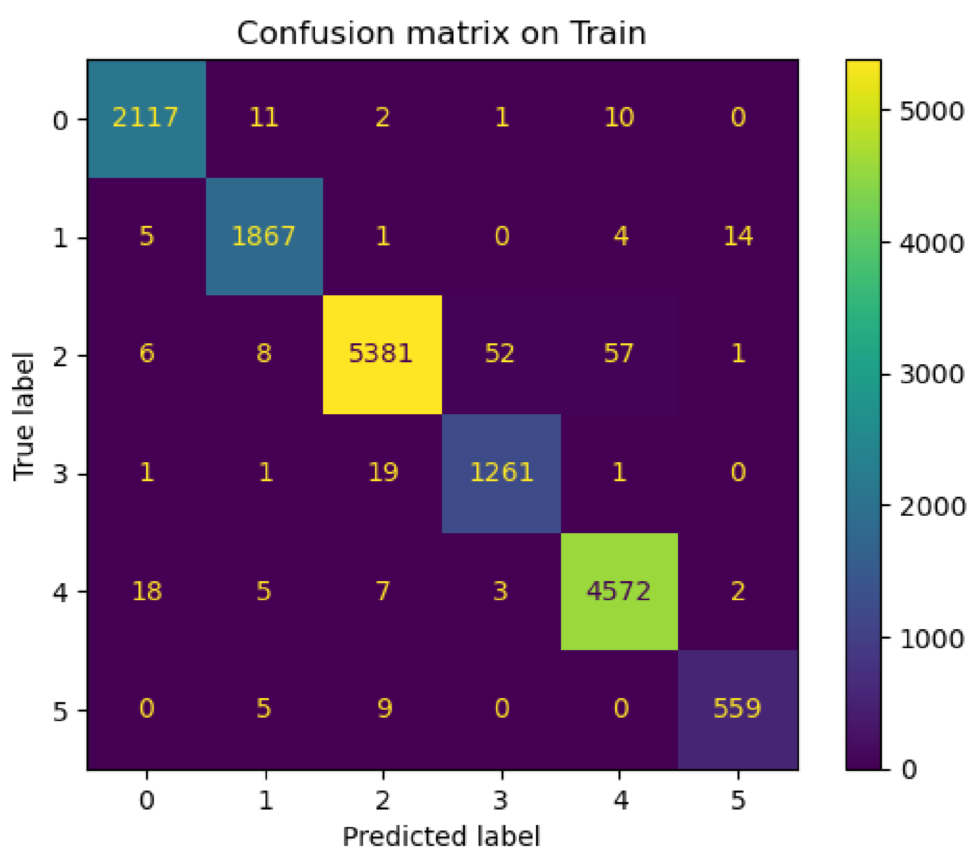
2 Basic training

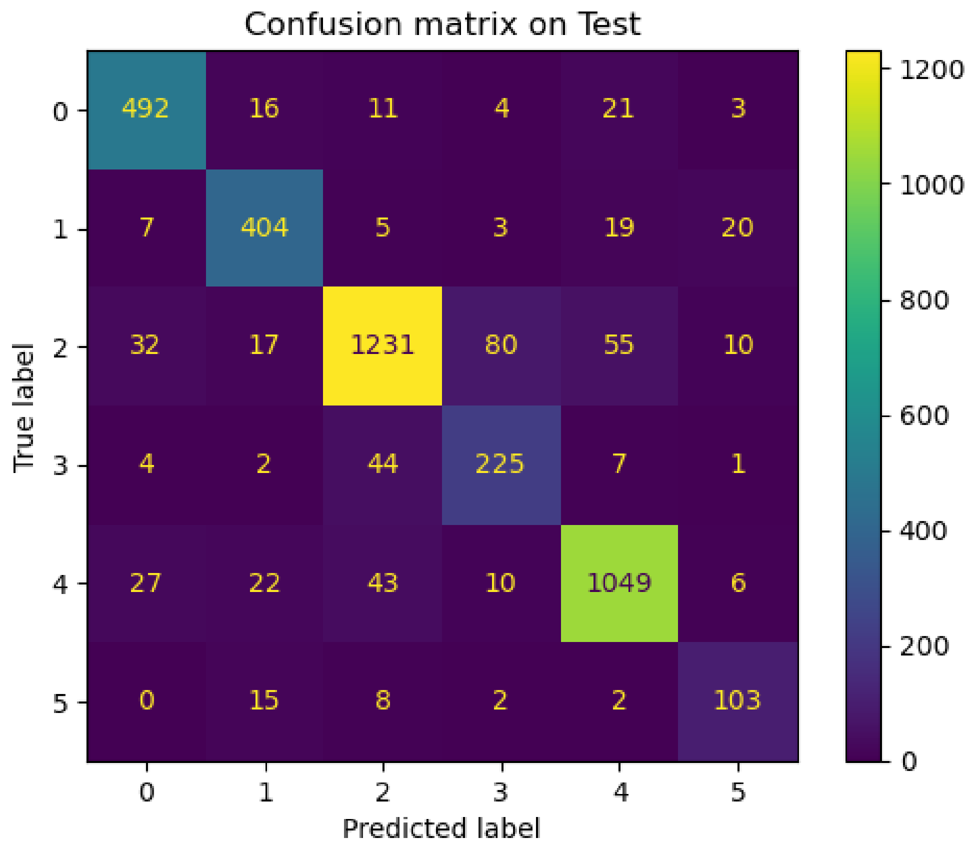
[ ]:
```
lr_model = LogisticRegression(multi_class='ovr')
lr_model.fit(X_train, y_train)
```

[ ]: LogisticRegression(multi_class='ovr')

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

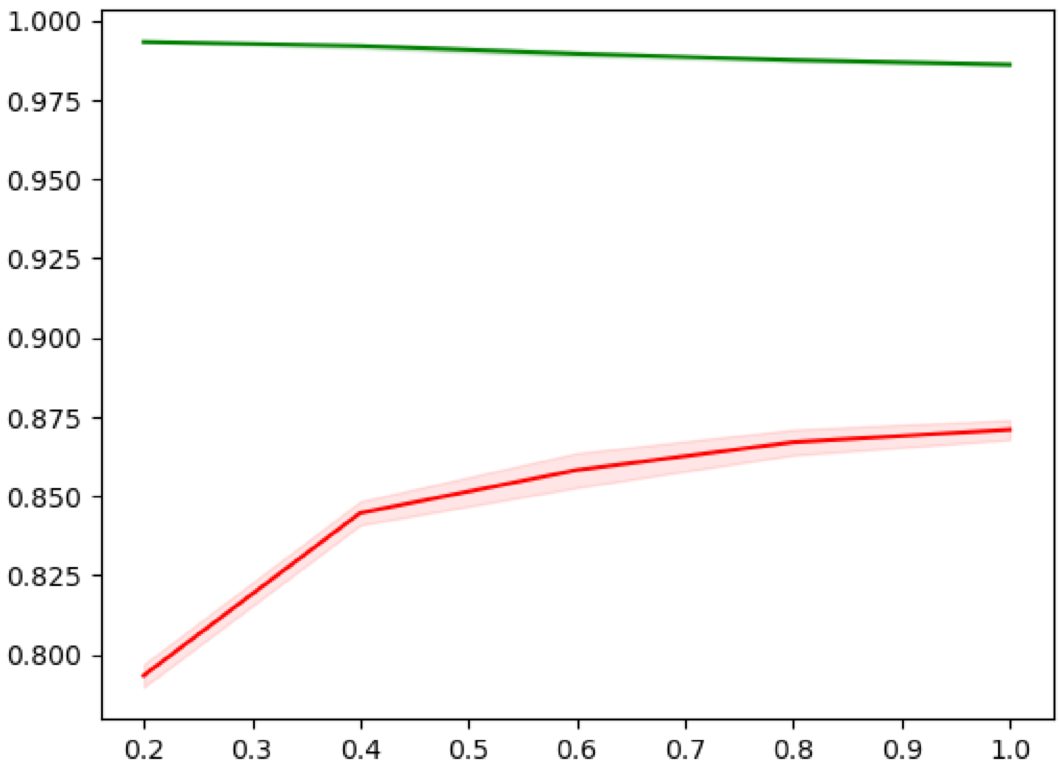
```
Score of on train are:
        - Accuracy score: 0.9848
        - Micro F1 score: 0.9848
        - Macro F1 score: 0.9816
Score of on test are:
        - Accuracy score: 0.8760
        - Micro F1 score: 0.8760
        - Macro F1 score: 0.8411
```





[ ]:

```
draw_learning_curve(lr_model, X_train, y_train)
```



3 Multiple tuning

3.1 L1 regularization

First, we try to plot the validation score through a list of C from 0.001 to 100

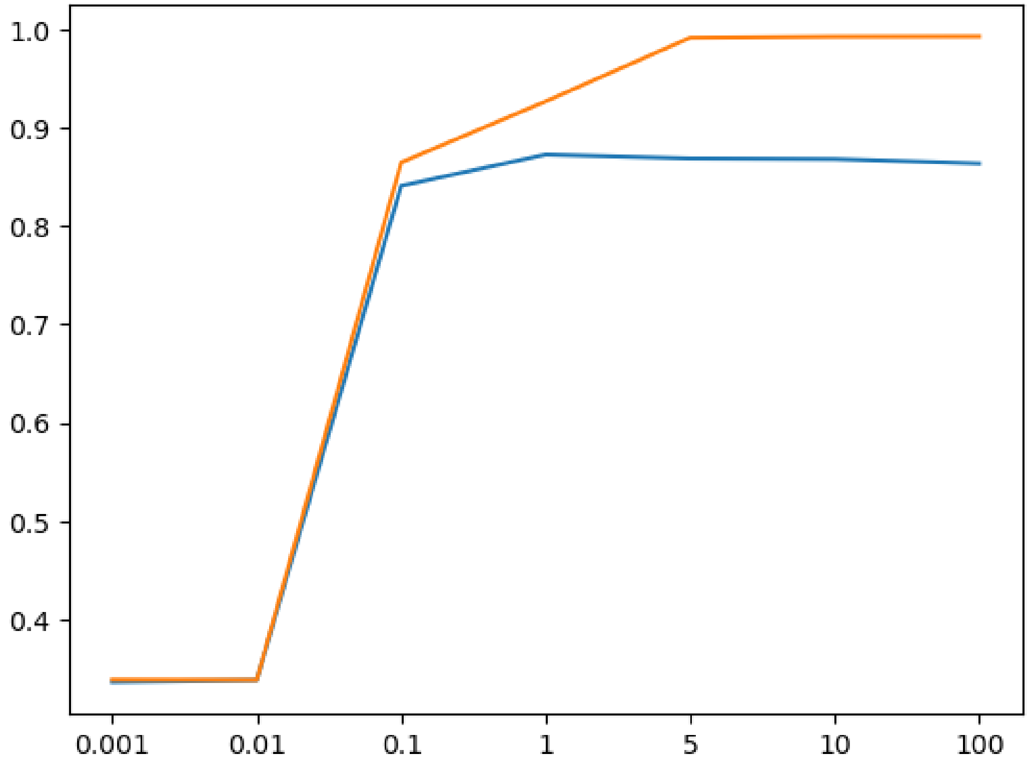
[ ]:
```
C_list = [0.001, 0.01, 0.1, 1, 5, 10, 100]

# Define a list in order to store accuracy points
cvs_list = list()
trs_list = list()

for c in C_list:
    # Define model for each C
    lr_model = LogisticRegression(C=c, penalty='l1', solver='liblinear',␣
 ↪multi_class='ovr')
    lr_model.fit(X_train, y_train)

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

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

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

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

```
[0.001, 0.01, 0.1, 1, 5, 10, 100]
[0.3390625, 0.3388125, 0.864625, 0.926625, 0.991375, 0.9924375, 0.9926875]
[0.3368125, 0.3386875, 0.8408749999999999, 0.8725624999999999,
0.8686875000000001, 0.8680625, 0.8635624999999999]
```

[ ]:
```
[Text(0, 0, '0.001'),
 Text(1, 0, '0.01'),
 Text(2, 0, '0.1'),
 Text(3, 0, '1'),
 Text(4, 0, '5'),
 Text(5, 0, '10'),
 Text(6, 0, '100')]
```



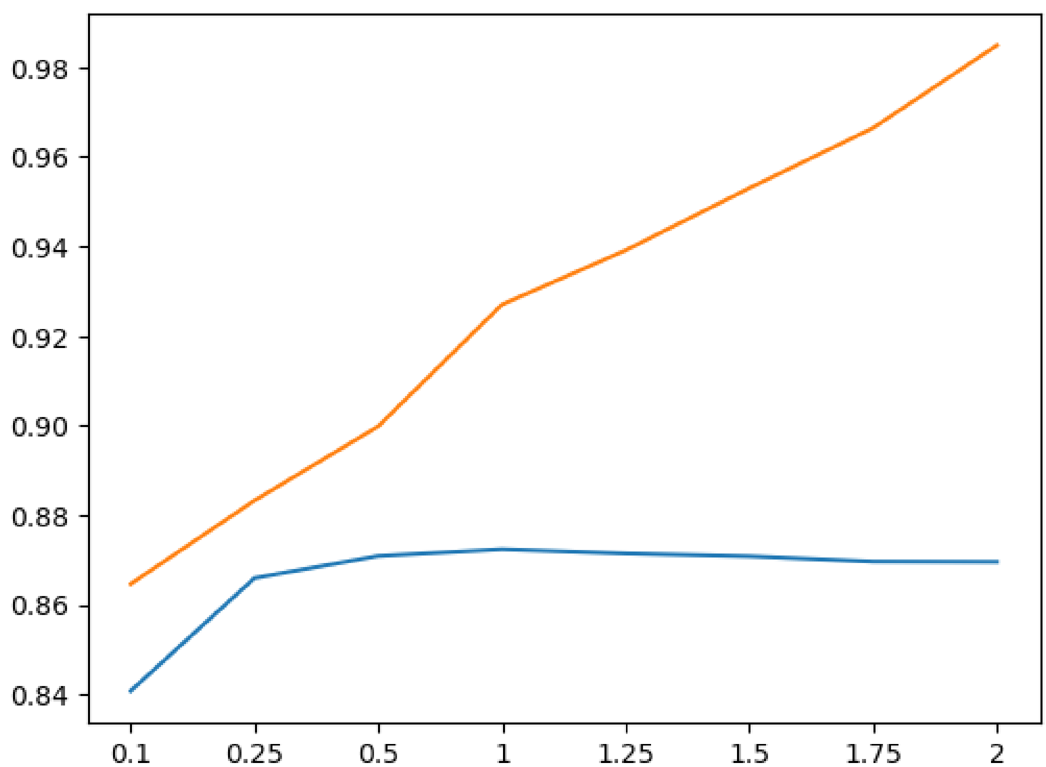
We can see the good value of C is near $C = 1$, then we scope to $C = 1$:

[ ]:
```
C_list = [0.1, 0.25, 0.5, 1, 1.25, 1.5, 1.75, 2]

# Define a list in order to store accuracy points
cvs_list = list()
trs_list = list()

for c in C_list:
    # Define model for each C
    lr_model = LogisticRegression(C=c, penalty='l1', solver='liblinear',␣
 ↪multi_class='ovr')
    lr_model.fit(X_train, y_train)

    # Calculate score of cross validation
    train_score = accuracy_score(y_train, lr_model.predict(X_train))
    cv_score = np.mean(cross_val_score(lr_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(C_list)
print(trs_list)
print(cvs_list)

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

```
[0.1, 0.25, 0.5, 1, 1.25, 1.5, 1.75, 2]
[0.864625, 0.88325, 0.8998125, 0.927, 0.939125, 0.953, 0.9664375, 0.984875]
[0.8407500000000001, 0.8659375, 0.8708750000000001, 0.8723749999999999,
0.8714375000000001, 0.8708125000000001, 0.8696249999999999, 0.8695625]
```

[ ]:
```
[Text(0, 0, '0.1'),
 Text(1, 0, '0.25'),
 Text(2, 0, '0.5'),
 Text(3, 0, '1'),
 Text(4, 0, '1.25'),
 Text(5, 0, '1.5'),
 Text(6, 0, '1.75'),
 Text(7, 0, '2')]
```

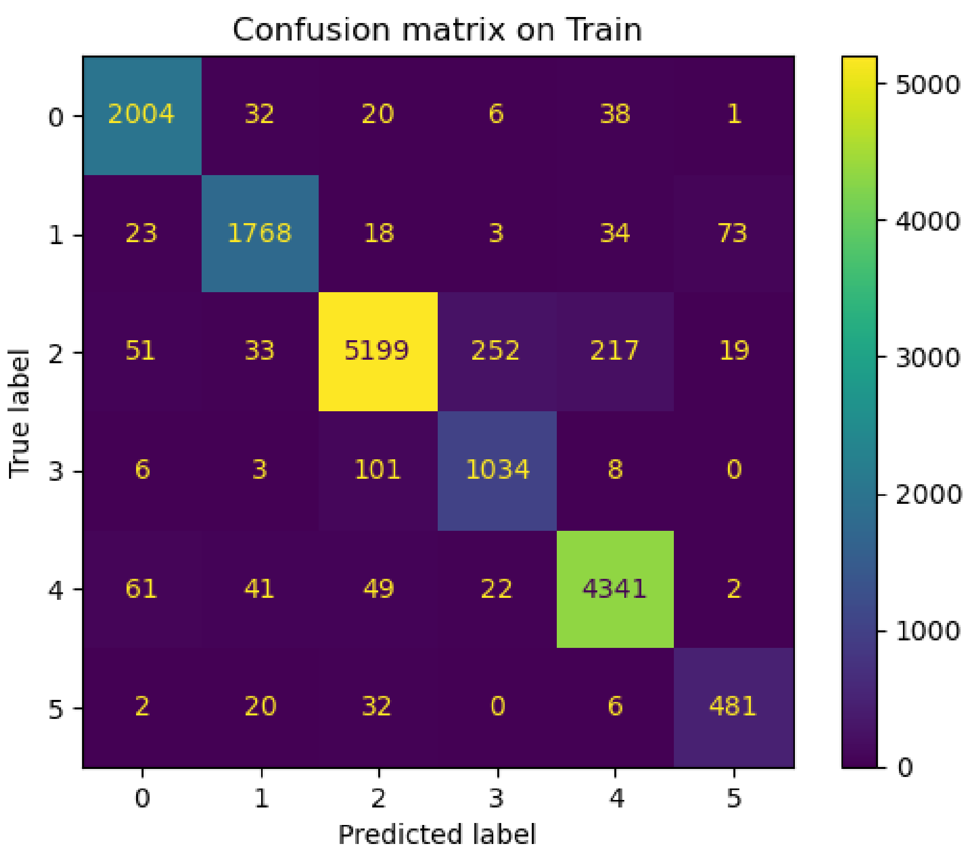


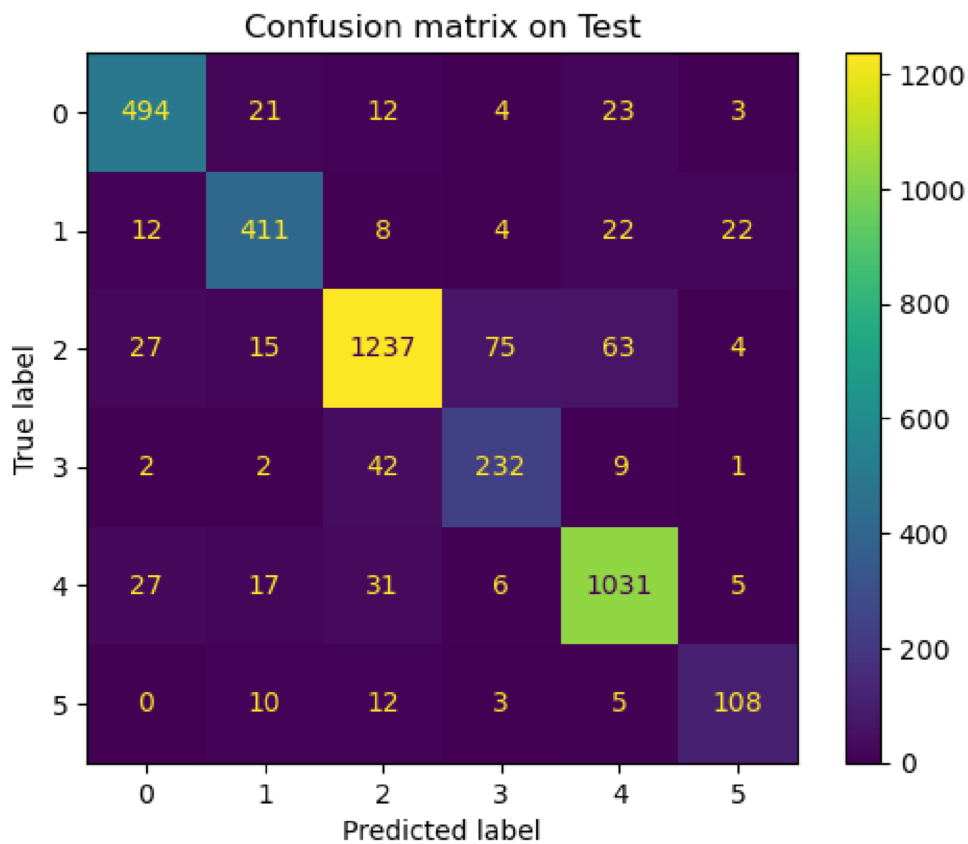
We choose $C = 1$ to be the best one

```
[ ]: best_l1_lr_model = LogisticRegression(C=1, penalty='l1', solver='liblinear',␣
     ↪multi_class='ovr')
```

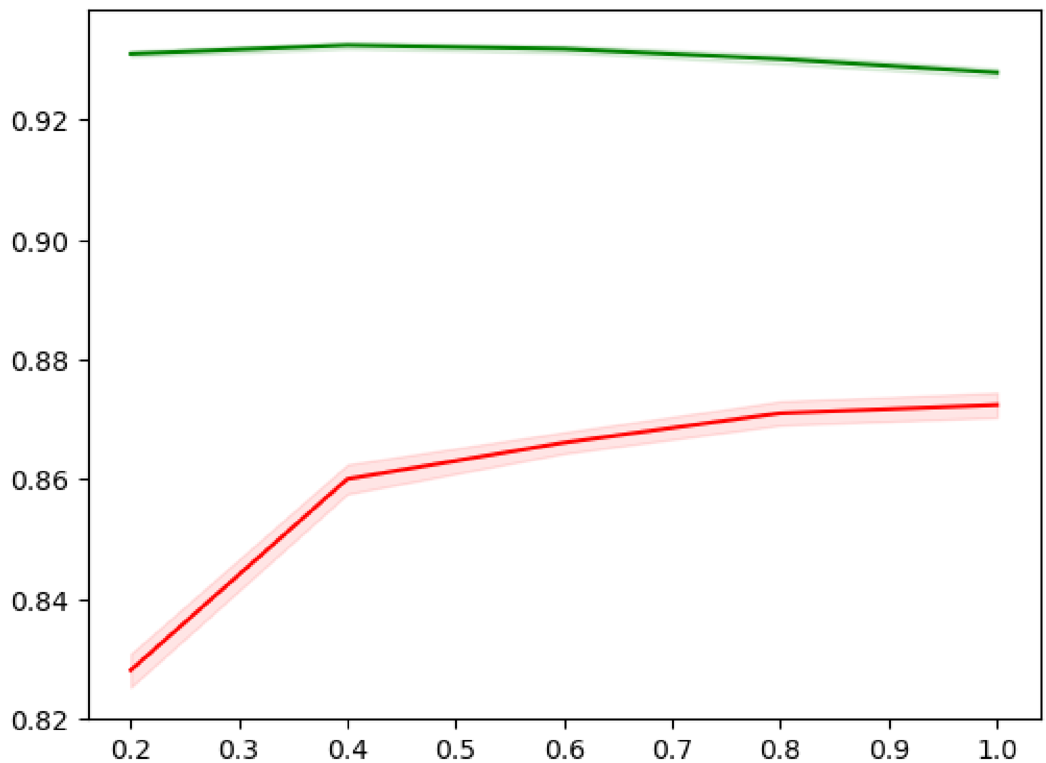
```
[ ]: best_l1_lr_model.fit(X_train, y_train)
     evaluate_model(best_l1_lr_model, X_train, X_test, y_train, y_test,␣
     ↪include_training=True)
```

```
Score of on train are:
        - Accuracy score: 0.9267
        - Micro F1 score: 0.9267
        - Macro F1 score: 0.9077
Score of on test are:
        - Accuracy score: 0.8782
        - Micro F1 score: 0.8782
        - Macro F1 score: 0.8457
```





[ ]:
```
draw_learning_curve(best_l1_lr_model, X_train, y_train)
```



3.2 L2 regularization

We do the same things from here

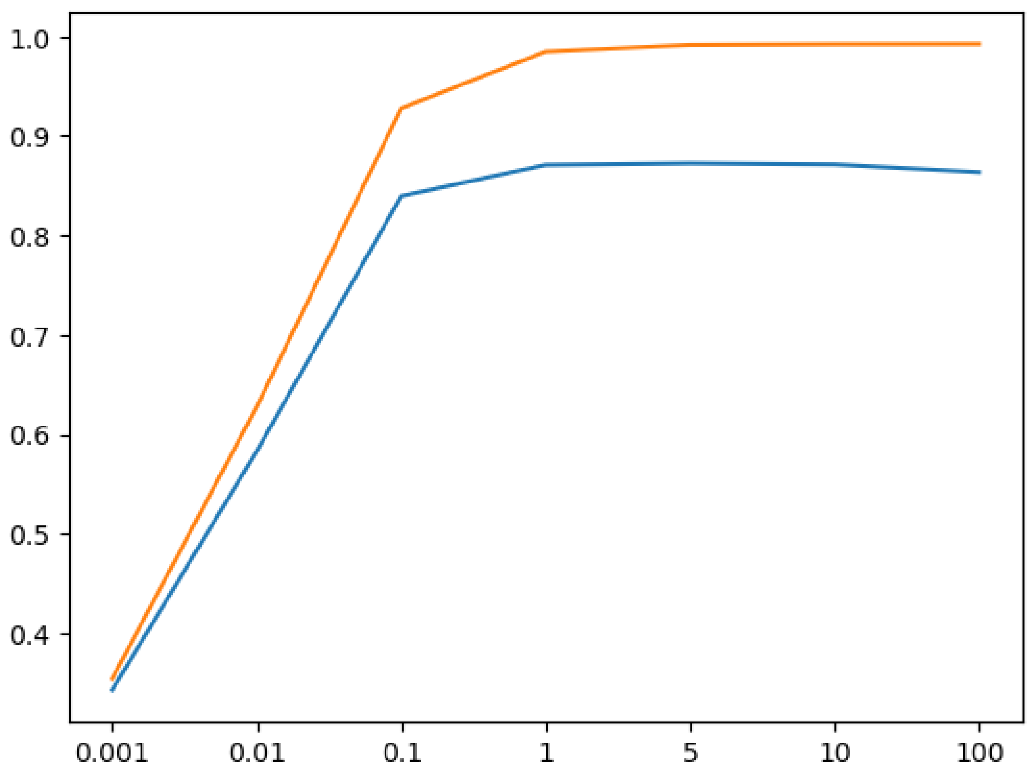
```
[ ]: C_list = [0.001, 0.01, 0.1, 1, 5, 10, 100]

# Define a list in order to store accuracy points
cvs_list = list()
trs_list = list()

for c in C_list:
    # Define model for each C
    lr_model = LogisticRegression(C=c, penalty='l2', solver='lbfgs',␣
 ↪multi_class='ovr')
    lr_model.fit(X_train, y_train)

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

    trs_list.append(train_score)
```

```
    cvs_list.append(cv_score)
```

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

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

```
[0.001, 0.01, 0.1, 1, 5, 10, 100]
[0.3545, 0.6278125, 0.928, 0.9848125, 0.9916875, 0.9924375, 0.9926875]
[0.3431875, 0.5831875, 0.8396250000000001, 0.8709374999999999,
0.8725625000000001, 0.8714375000000001, 0.8636250000000001]
```

[ ]:
```
[Text(0, 0, '0.001'),
 Text(1, 0, '0.01'),
 Text(2, 0, '0.1'),
 Text(3, 0, '1'),
 Text(4, 0, '5'),
 Text(5, 0, '10'),
 Text(6, 0, '100')]
```



It looks like good C is still near 1

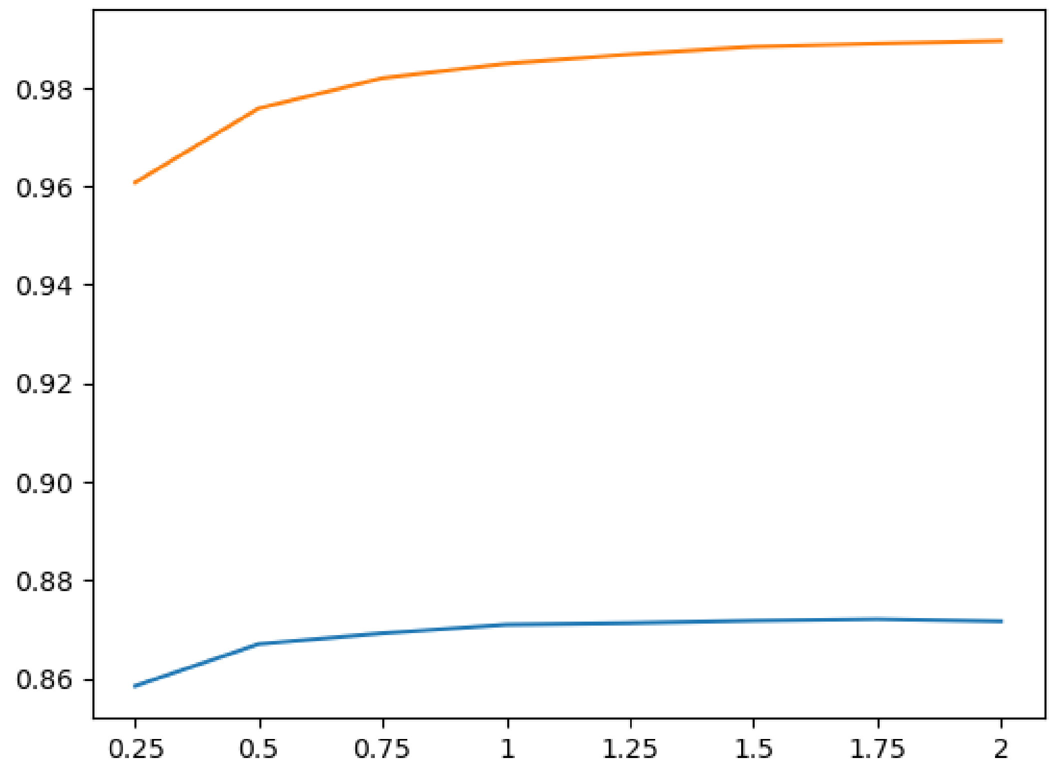
```
[ ]: C_list = [0.25, 0.5, 0.75, 1, 1.25, 1.5, 1.75, 2]

     # Define a list in order to store accuracy points
     cvs_list = list()
     trs_list = list()

     for c in C_list:
         # Define model for each C
         lr_model = LogisticRegression(C=c, penalty='l2', solver='lbfgs',␣
      ↪multi_class='ovr')
         lr_model.fit(X_train, y_train)

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

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

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

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

```
[0.25, 0.5, 0.75, 1, 1.25, 1.5, 1.75, 2]
[0.9606875, 0.97575, 0.981875, 0.9848125, 0.9866875, 0.98825, 0.988875,
0.9894375]
[0.8585, 0.8670000000000002, 0.8691875, 0.8709374999999999, 0.8712499999999999,
0.8717500000000001, 0.8720625, 0.8716250000000001]
```

```
[ ]: [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'),
 Text(7, 0, '2')]
```

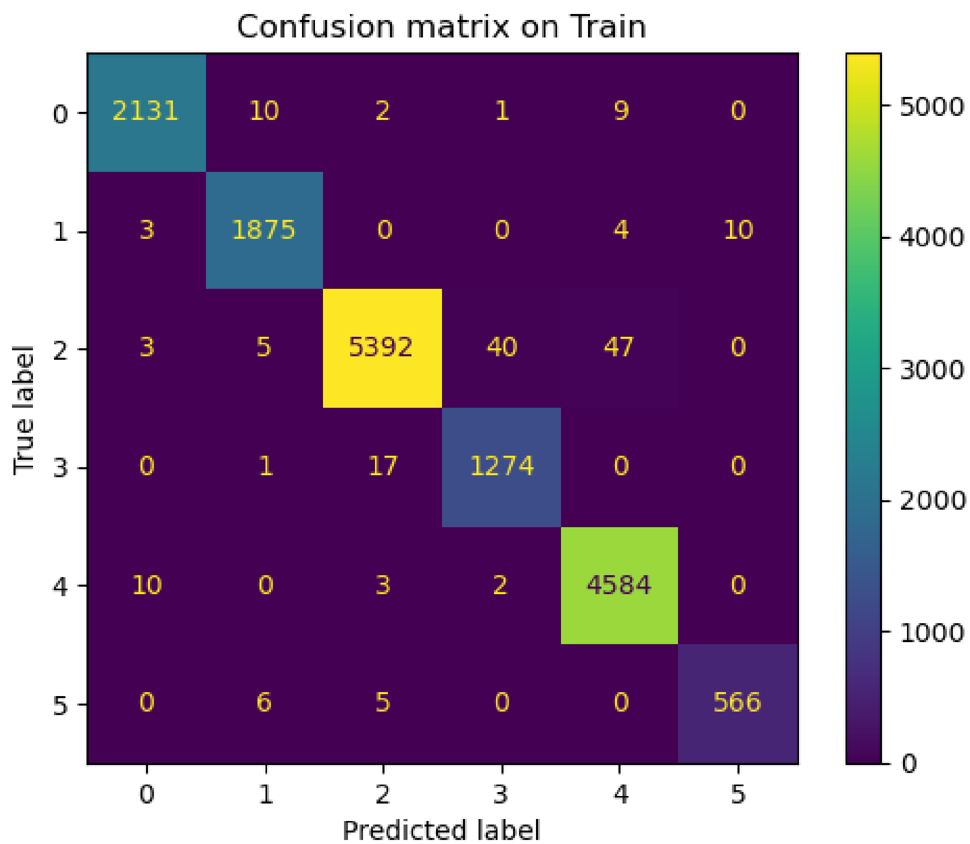


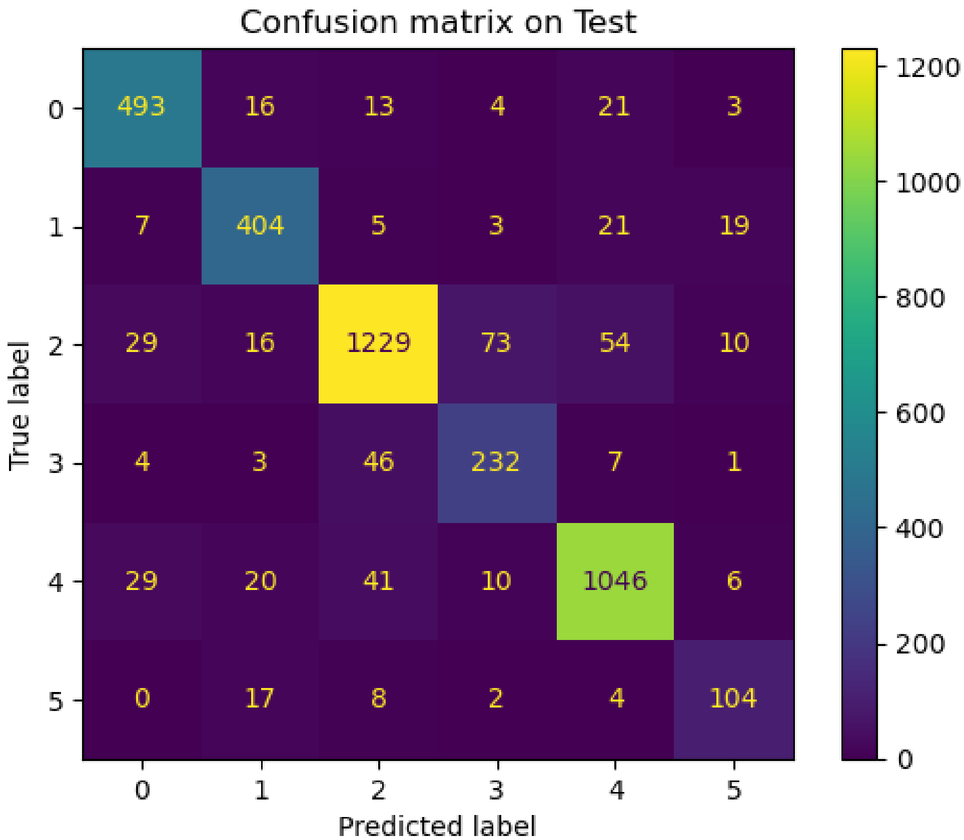
We choose $C = 1.75$

```
[ ]: best_l2_lr_model = LogisticRegression(C=1.75, penalty='l2', solver='lbfgs',␣
      ↪multi_class='ovr')
```

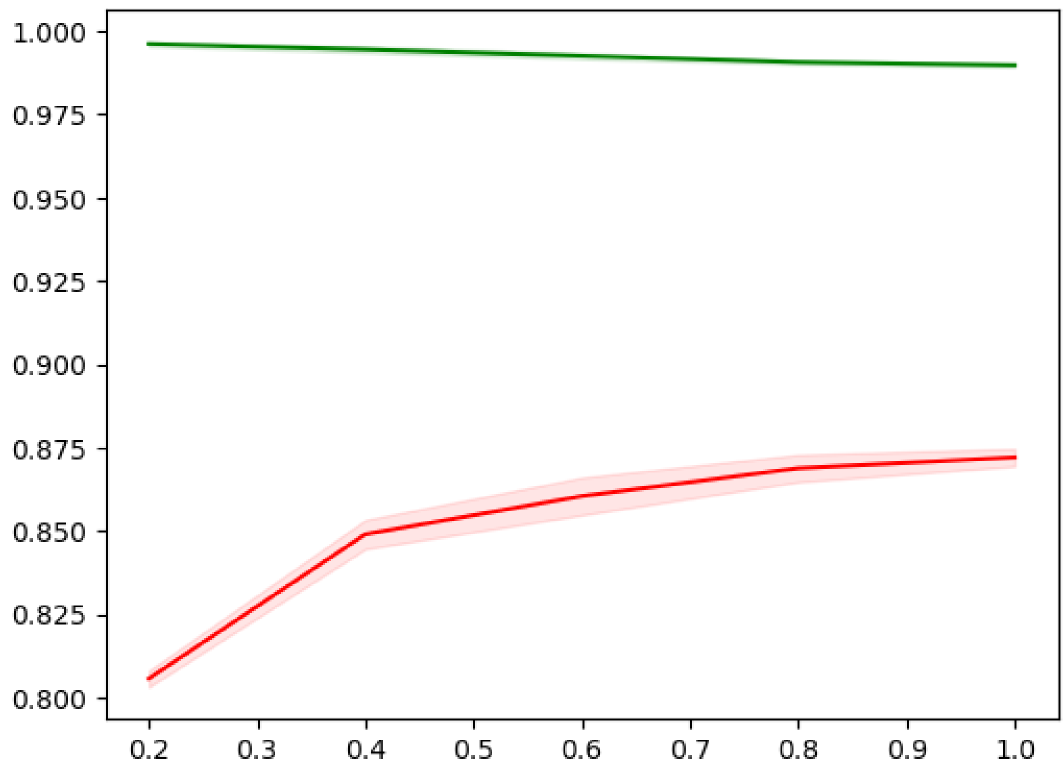
```
[ ]: best_l2_lr_model.fit(X_train, y_train)
     evaluate_model(best_l2_lr_model, X_train, X_test, y_train, y_test,␣
      ↪include_training=True)
```

```
Score of on train are:
        - Accuracy score: 0.9889
        - Micro F1 score: 0.9889
        - Macro F1 score: 0.9867
Score of on test are:
        - Accuracy score: 0.8770
        - Micro F1 score: 0.8770
        - Macro F1 score: 0.8419
```


Confusion matrix on Train
True label
Predicted label
0 1 2 3 4 5
2131 10 2 1 9 0
3 1875 0 0 4 10
3 5 5392 40 47 0
0 1 17 1274 0 0
10 0 3 2 4584 0
0 6 5 0 0 566
5000
4000
3000
2000
1000
0



[ ]:
```
draw_learning_curve(best_l2_lr_model, X_train, y_train)
```



3.3 Elastic regularization

[ ]:
```
dict_param = {
    'C' : [0.001, 0.01, 0.1, 1, 5, 10, 100],
    'l1_ratio' : np.linspace(0.1, 0.9, 5)
}

lr_model = LogisticRegression(penalty='elasticnet', solver='saga',␣
 ↪multi_class='ovr')
grid_search = GridSearchCV(lr_model, dict_param, scoring='accuracy', cv=5,␣
 ↪n_jobs=-1)
grid_search.fit(X_train, y_train)
```

[ ]:
```
GridSearchCV(cv=5,
             estimator=LogisticRegression(multi_class='ovr',
                                          penalty='elasticnet', solver='saga'),
             n_jobs=-1,
             param_grid={'C': [0.001, 0.01, 0.1, 1, 5, 10, 100],
                         'l1_ratio': array([0.1, 0.3, 0.5, 0.7, 0.9])},
             scoring='accuracy')
```

[ ]:
```
df = pd.DataFrame(
  dict(
    C = [val['C'] for val in grid_search.cv_results_['params']],
    l1_ratio = [val['l1_ratio'] for val in grid_search.cv_results_['params']],
    score = grid_search.cv_results_['mean_test_score']
  )
)
df = df[df['score'] < 0.8]
print("Bad hyperparameter:")
for param in dict_param:
  for value in dict_param[param]:
    if len(df[df[param] == value]) == 35 // len(dict_param[param]):
      print(param, value)
```

```
Bad hyperparameter:
C 0.001
C 0.01
```

[ ]:
```
dict_param = {
    'C' : np.logspace(0, 2, 5),
    'l1_ratio' : np.linspace(0.1, 0.9, 5)
}

lr_model = LogisticRegression(penalty='elasticnet', solver='saga',␣
 ↪multi_class='ovr')
grid_search = GridSearchCV(lr_model, dict_param, scoring='accuracy', cv=5,␣
 ↪n_jobs=-1)
grid_search.fit(X_train, y_train)
```

[ ]:
```
GridSearchCV(cv=5,
             estimator=LogisticRegression(multi_class='ovr',
                                          penalty='elasticnet', solver='saga'),
             n_jobs=-1,
             param_grid={'C': array([  1.        ,   3.16227766,  10.        ,
31.6227766 ,
       100.        ]),
                         'l1_ratio': array([0.1, 0.3, 0.5, 0.7, 0.9])},
             scoring='accuracy')
```

[ ]:
```
df = pd.DataFrame(
  dict(
    C = [val['C'] for val in grid_search.cv_results_['params']],
    l1_ratio = [val['l1_ratio'] for val in grid_search.cv_results_['params']],
    score = grid_search.cv_results_['mean_test_score']
  )
)
print(df)
```

```
            C  l1_ratio     score
0    1.000000       0.1  0.871063
1    1.000000       0.3  0.872437
2    1.000000       0.5  0.873688
3    1.000000       0.7  0.873250
4    1.000000       0.9  0.873937
5    3.162278       0.1  0.872125
6    3.162278       0.3  0.873375
7    3.162278       0.5  0.874188
8    3.162278       0.7  0.874313
9    3.162278       0.9  0.874375
10  10.000000       0.1  0.871813
11  10.000000       0.3  0.872750
12  10.000000       0.5  0.873625
13  10.000000       0.7  0.873625
14  10.000000       0.9  0.873562
15  31.622777       0.1  0.872500
16  31.622777       0.3  0.872437
17  31.622777       0.5  0.872375
18  31.622777       0.7  0.872188
19  31.622777       0.9  0.872687
20 100.000000       0.1  0.872062
21 100.000000       0.3  0.871937
22 100.000000       0.5  0.872375
23 100.000000       0.7  0.871687
24 100.000000       0.9  0.872125
```

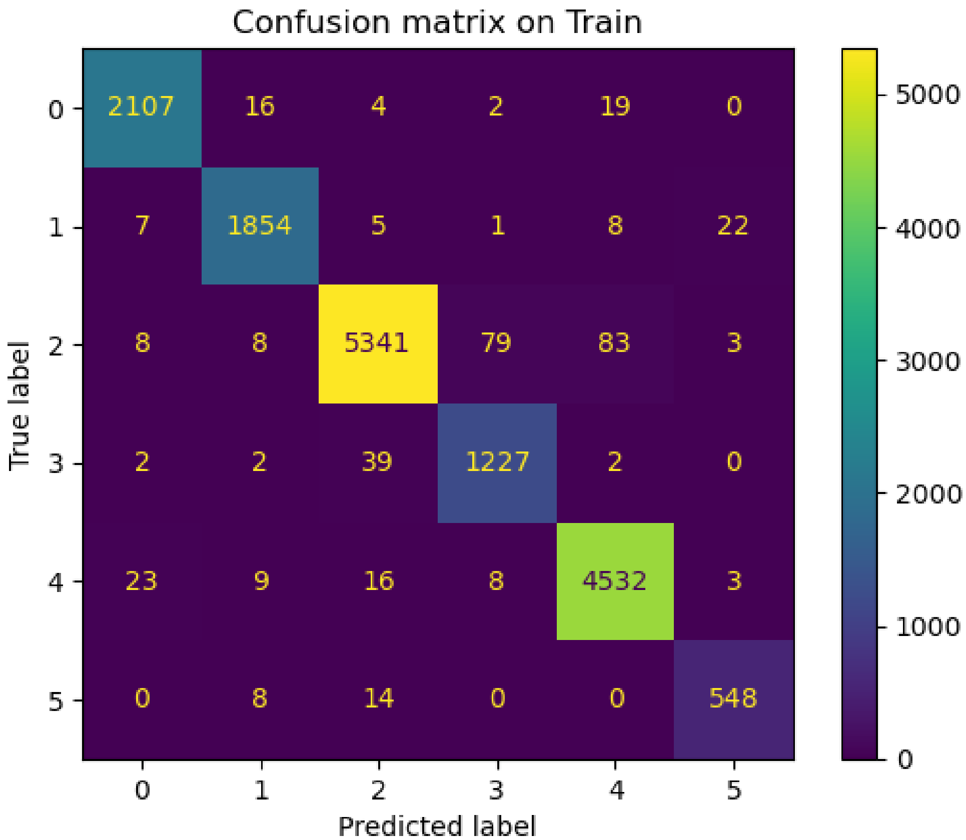
[ ]:
```
print(grid_search.best_estimator_, grid_search.best_score_)
```

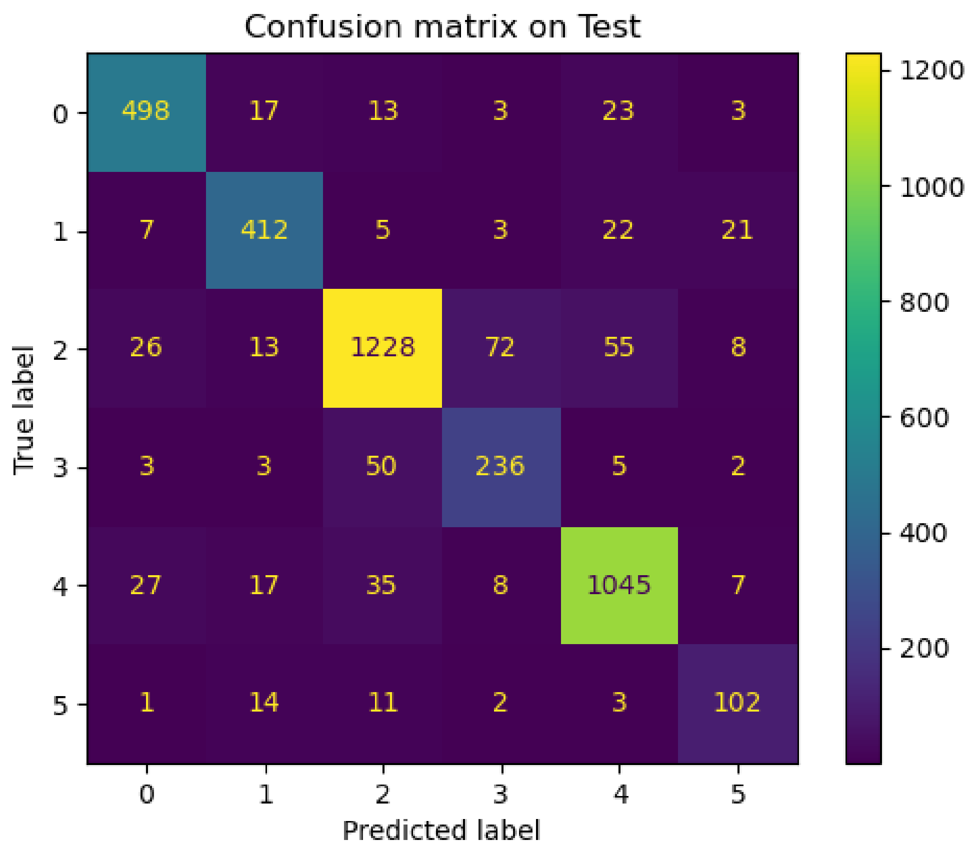
```
LogisticRegression(C=3.1622776601683795, l1_ratio=0.9, multi_class='ovr',
                   penalty='elasticnet', solver='saga') 0.874375
```

[ ]:
```
best_en_lr_model = LogisticRegression(C=3.1622776601683795, l1_ratio=0.9,␣
 ↪multi_class='ovr',
                   penalty='elasticnet', solver='saga')
```

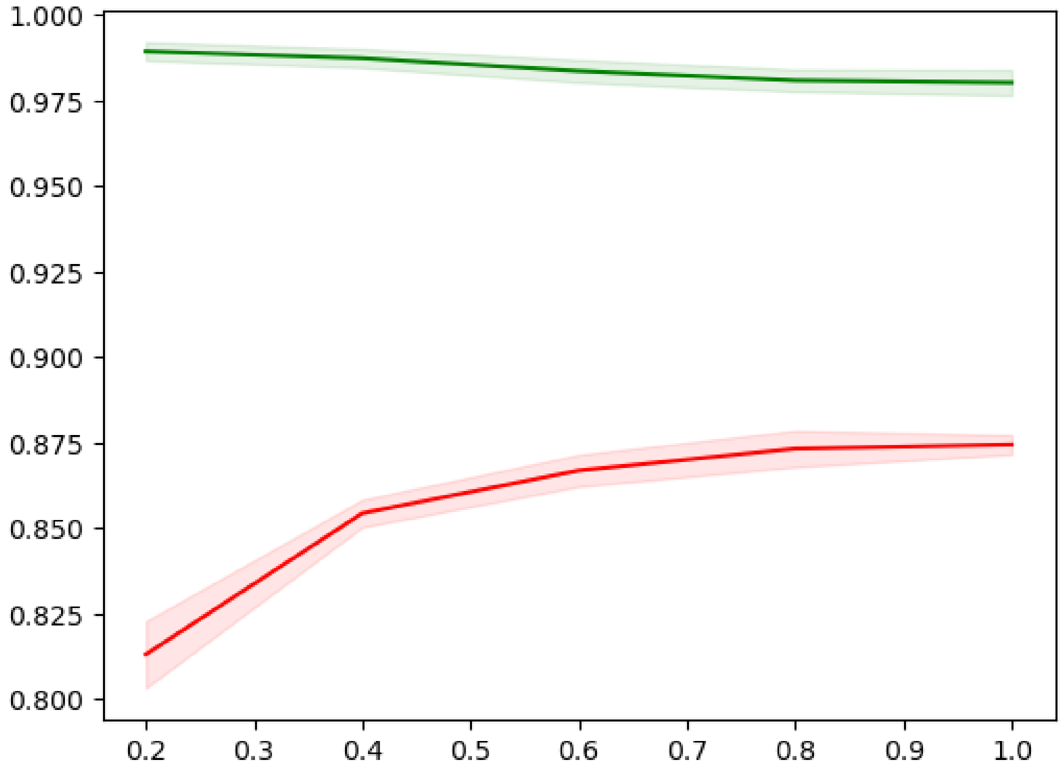
[ ]:
```
best_en_lr_model.fit(X_train, y_train)
evaluate_model(best_en_lr_model, X_train, X_test, y_train, y_test,␣
 ↪include_training=True)
```

```
Score of on train are:
        - Accuracy score: 0.9756
        - Micro F1 score: 0.9756
        - Macro F1 score: 0.9701
Score of on test are:
        - Accuracy score: 0.8802
        - Micro F1 score: 0.8802
        - Macro F1 score: 0.8441
```


Confusion matrix on Train
True label
Predicted label
0
1
2
3
4
5
2107 16 4 2 19 0
7 1854 5 1 8 22
8 8 5341 79 83 3
2 2 39 1227 2 0
23 9 16 8 4532 3
0 8 14 0 0 548
5000
4000
3000
2000
1000
0



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



4 Conclusion

There are a few difference among the accuracy of these 3 regularization. However, Elastic-net regularization gives the best performance then I will choose it to be the best model in this notebook.

[ ]:
```
best_lr_model = best_en_lr_model
```

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

dump(best_lr_model, directory + "best_lr_bow_model.joblib")
```

[ ]:
```
['data/models/lr/best_lr_bow_model.joblib']
```