Softmax Regression - BoW_L1

May 13, 2024

1 Initialization

[ ]:
```
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_L1
X_test = X_test_bow_L1
```

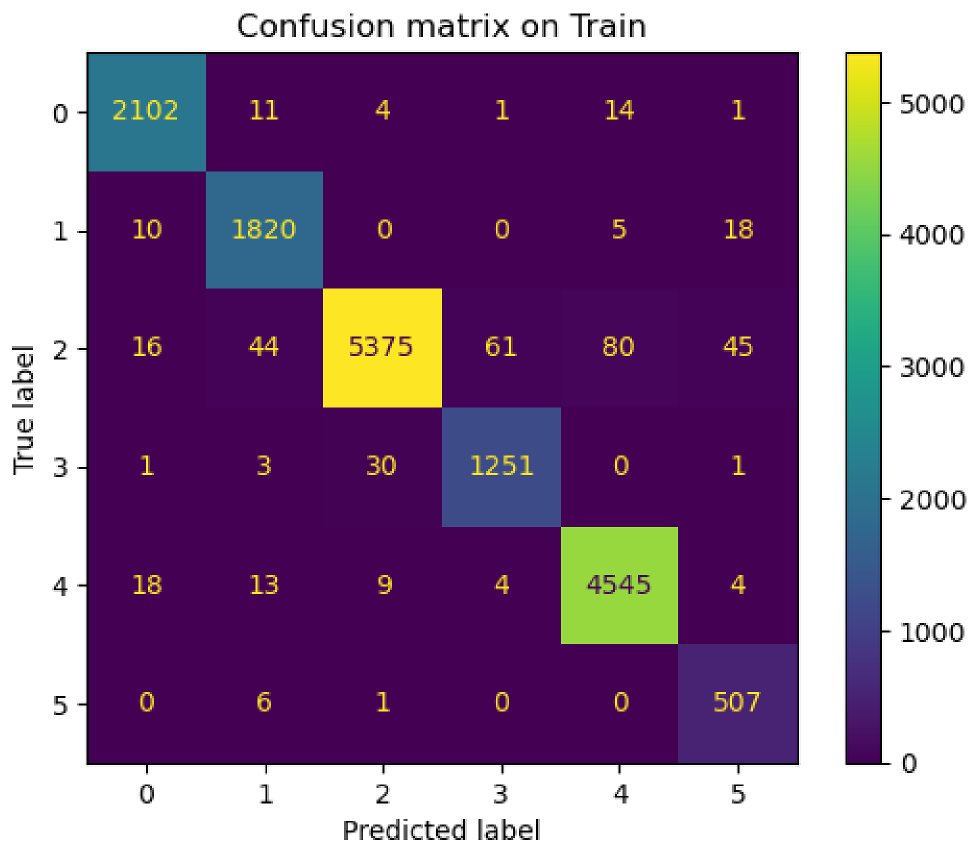
2 Basic training

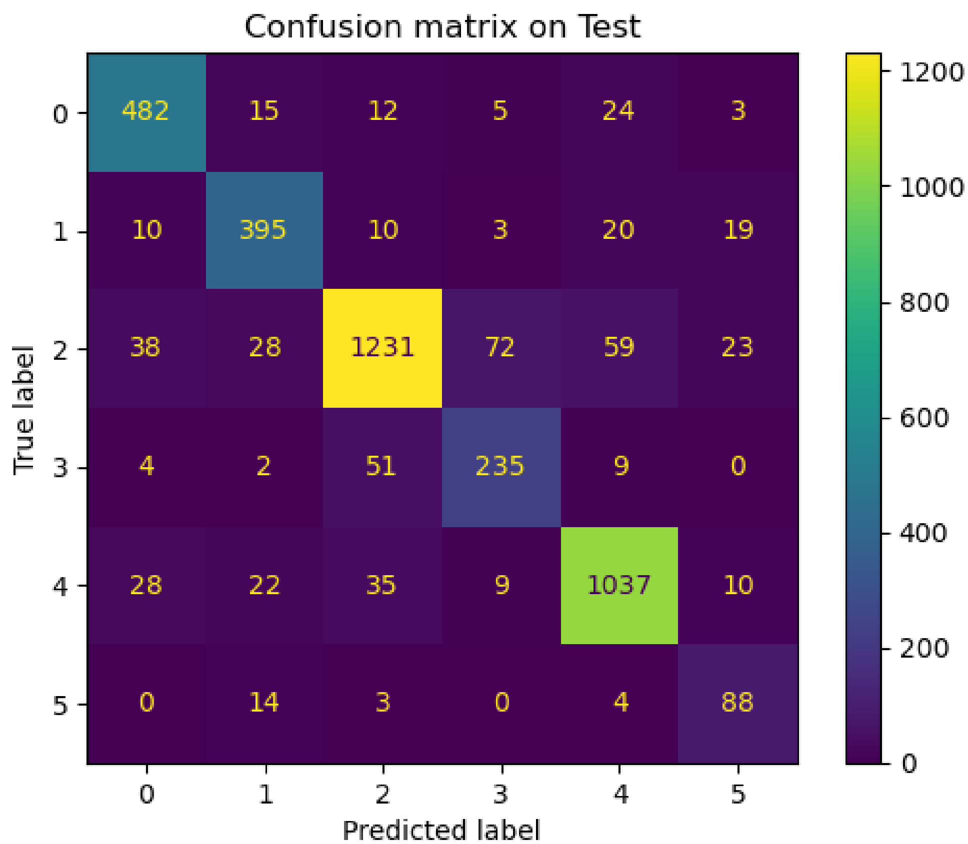
[ ]:
```
softmax_model = LogisticRegression(multi_class='multinomial')
softmax_model.fit(X_train, y_train)
```

[ ]:
```
LogisticRegression(multi_class='multinomial')
```

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

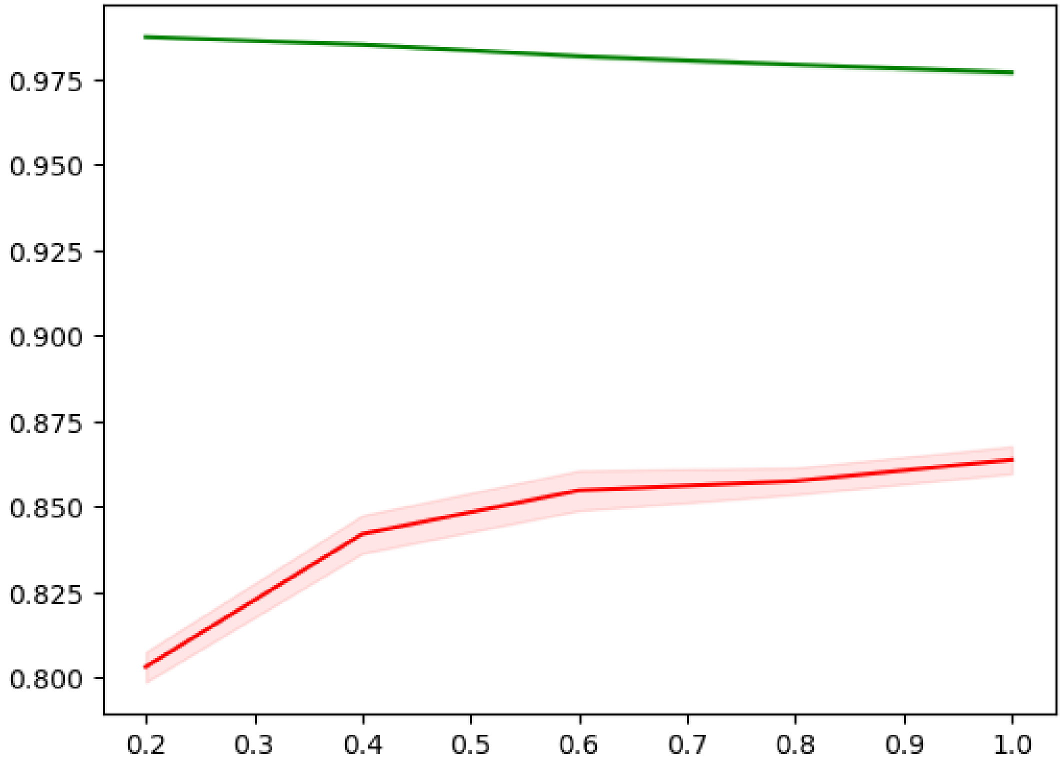
```
Score of on train are:
        - Accuracy score: 0.9750
        - Micro F1 score: 0.9750
        - Macro F1 score: 0.9670
Score of on test are:
        - Accuracy score: 0.8670
        - Micro F1 score: 0.8670
        - Macro F1 score: 0.8261
```





[ ]:

```
draw_learning_curve(softmax_model, X_train, y_train)
```



3 Multiple tuning

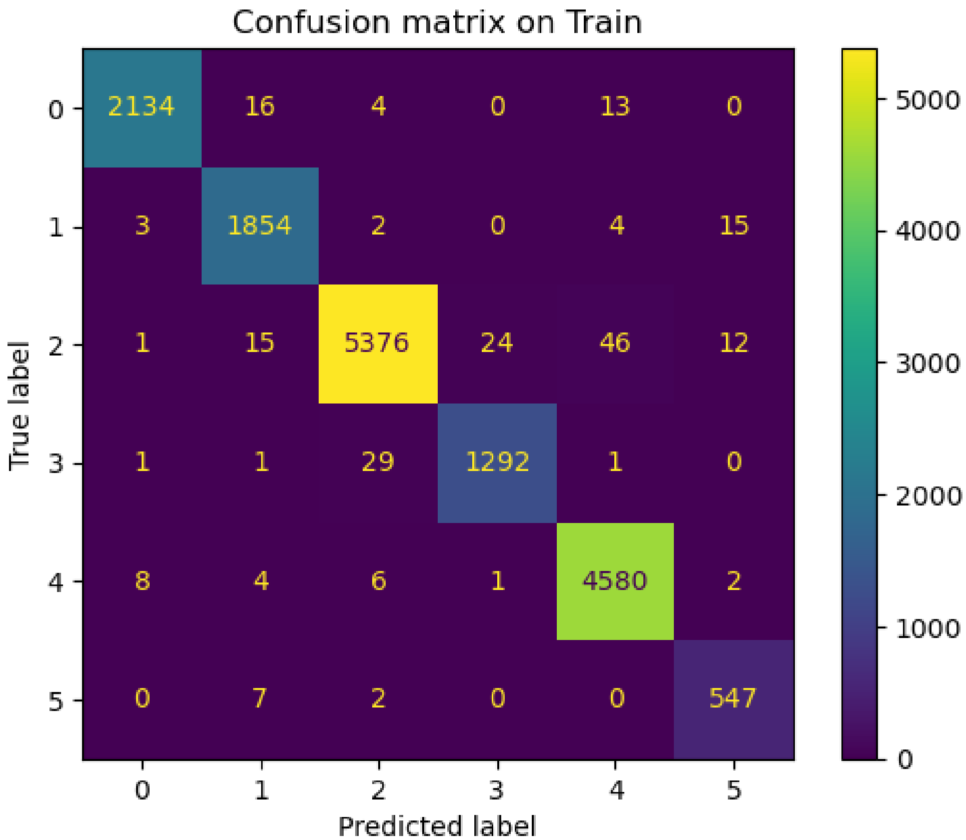
3.1 No regularization

[ ]:
```
softmax_model = LogisticRegression(penalty=None, solver='lbfgs',␣
 ↪multi_class='multinomial')
softmax_model.fit(X_train, y_train)
```

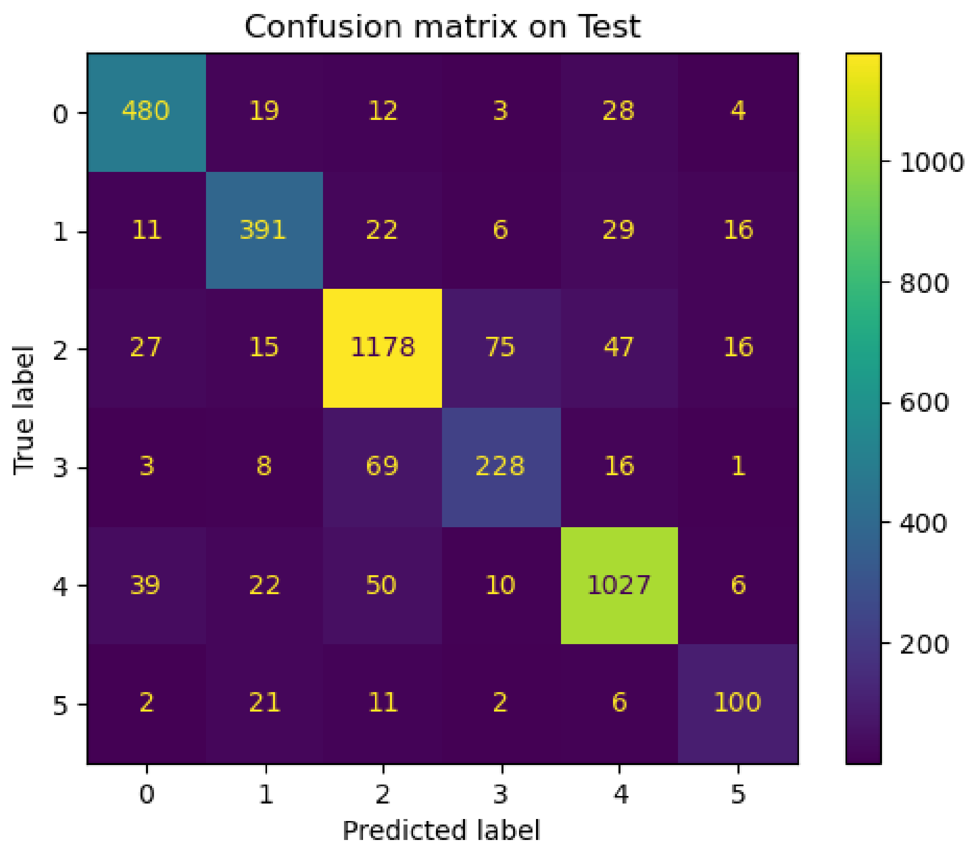
[ ]:
```
LogisticRegression(multi_class='multinomial', penalty=None)
```

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

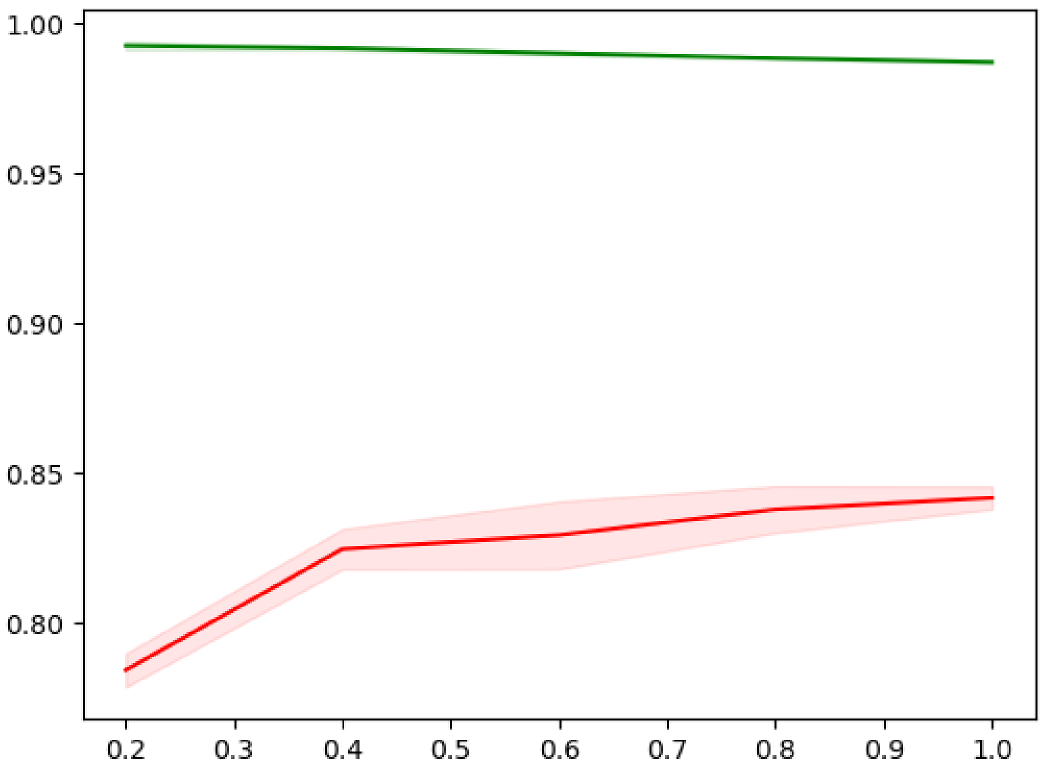
```
Score of on train are:
        - Accuracy score: 0.9864
        - Micro F1 score: 0.9864
        - Macro F1 score: 0.9824
Score of on test are:
        - Accuracy score: 0.8510
        - Micro F1 score: 0.8510
        - Macro F1 score: 0.8093
```



Confusion matrix on Train
True label
Predicted label
2134
16
4
0
13
0
3
1854
2
0
4
15
1
15
5376
24
46
12
1
1
29
1292
1
0
8
4
6
1
4580
2
0
7
2
0
0
547
0
1
2
3
4
5
5000
4000
3000
2000
1000



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



3.2 L1 regularization

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

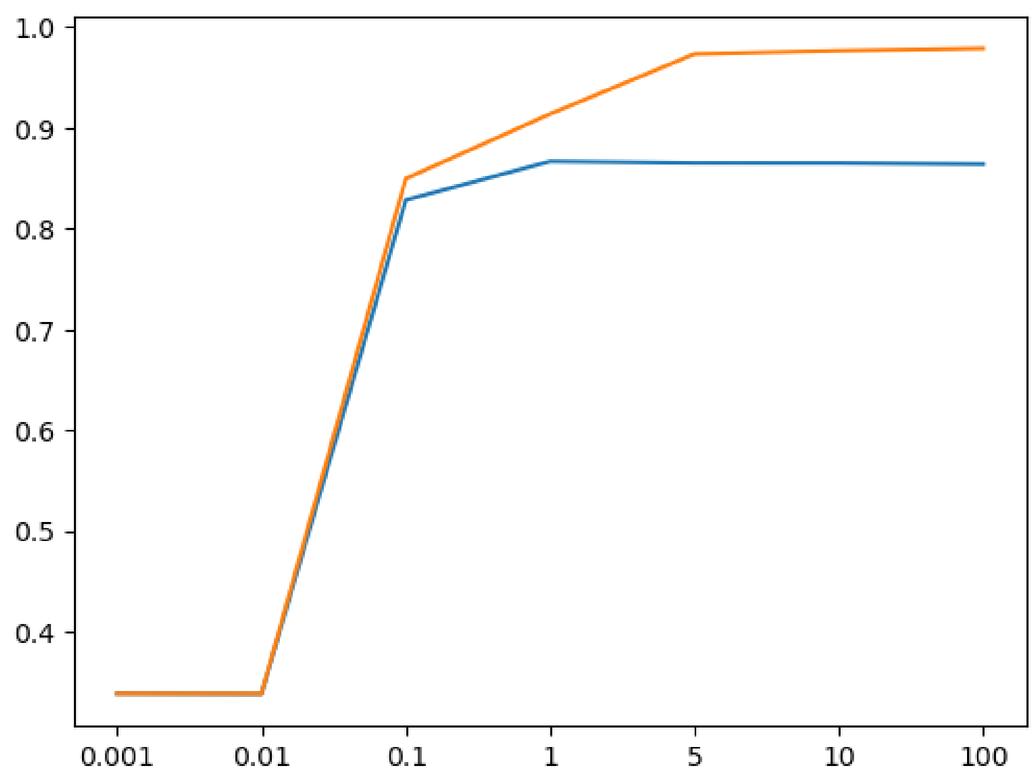
[ ]:
```
C_list = [0.001, 0.01, 0.1, 1, 5, 10, 100]

# 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
    softmax_model = LogisticRegression(C=c, penalty='l1', solver='saga',␣
 ↪multi_class='multinomial')
    softmax_model.fit(X_train, y_train)

    # Calculate score of cross validation
    train_score = accuracy_score(y_train, softmax_model.predict(X_train))
    cv_score = np.mean(cross_val_score(softmax_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]
[0.3386875, 0.338625, 0.849625, 0.9138125, 0.97325, 0.9765, 0.978875]
[0.3386875000000001, 0.33831249999999996, 0.828375, 0.86675, 0.8651875,
0.8651249999999999, 0.8640625]
```

[ ]:
```
[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 $C = 1$:

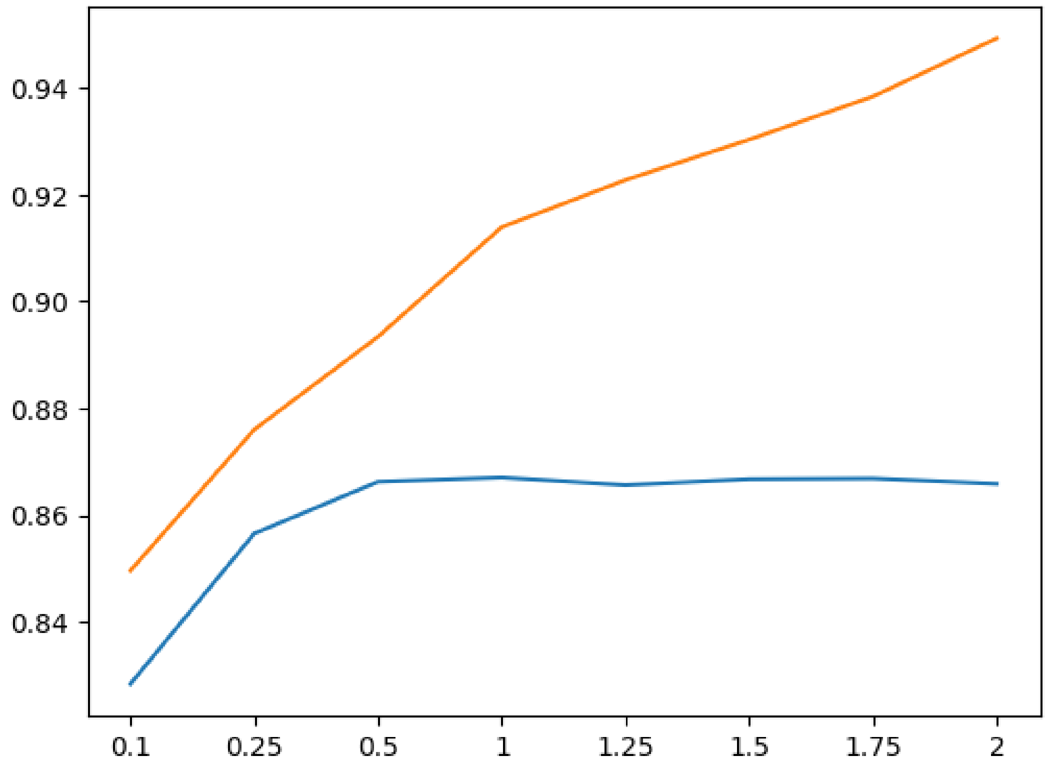
[ ]:
```
C_list = [0.1, 0.25, 0.5, 1, 1.25, 1.5, 1.75, 2]

# 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
    softmax_model = LogisticRegression(C=c, penalty='l1', solver='saga',␣
 ↪multi_class='multinomial')
    softmax_model.fit(X_train, y_train)

    # Calculate score of cross validation
    train_score = accuracy_score(y_train, softmax_model.predict(X_train))
    cv_score = np.mean(cross_val_score(softmax_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)
```

```
[0.1, 0.25, 0.5, 1, 1.25, 1.5, 1.75, 2]
[0.849625, 0.876, 0.893375, 0.913875, 0.9226875, 0.93025, 0.9383125, 0.9491875]
[0.8284375, 0.8565625000000001, 0.86625, 0.8670625, 0.865625, 0.86675, 0.866875,
0.865875]
```

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

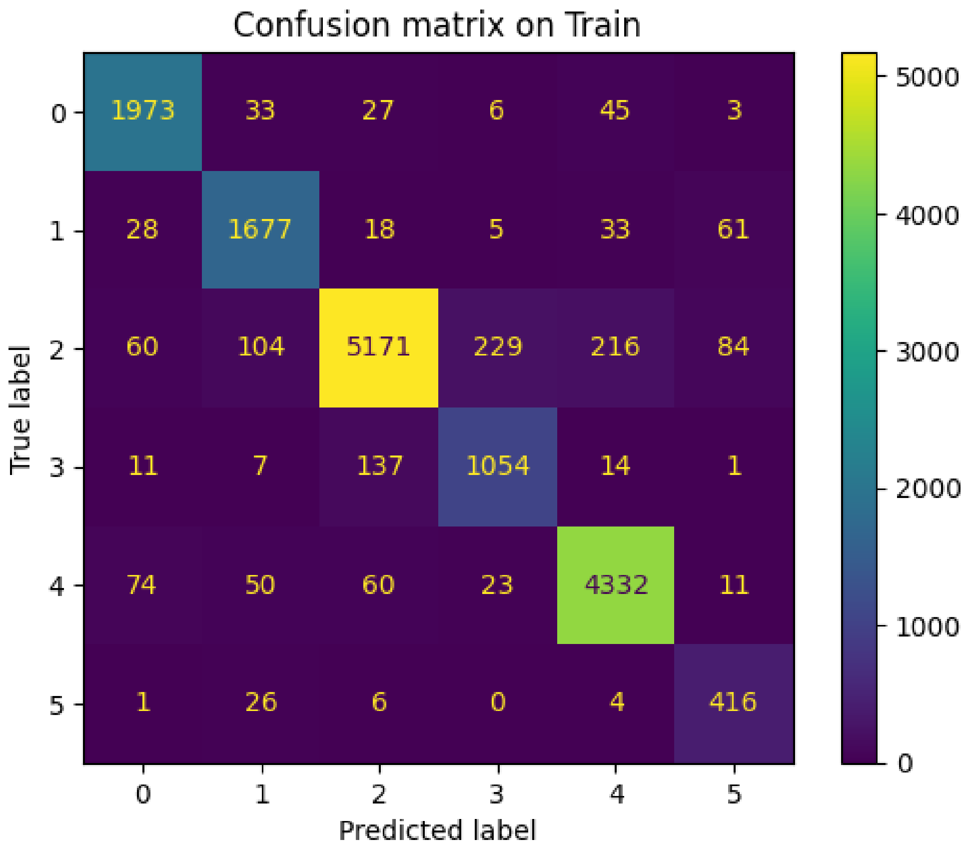


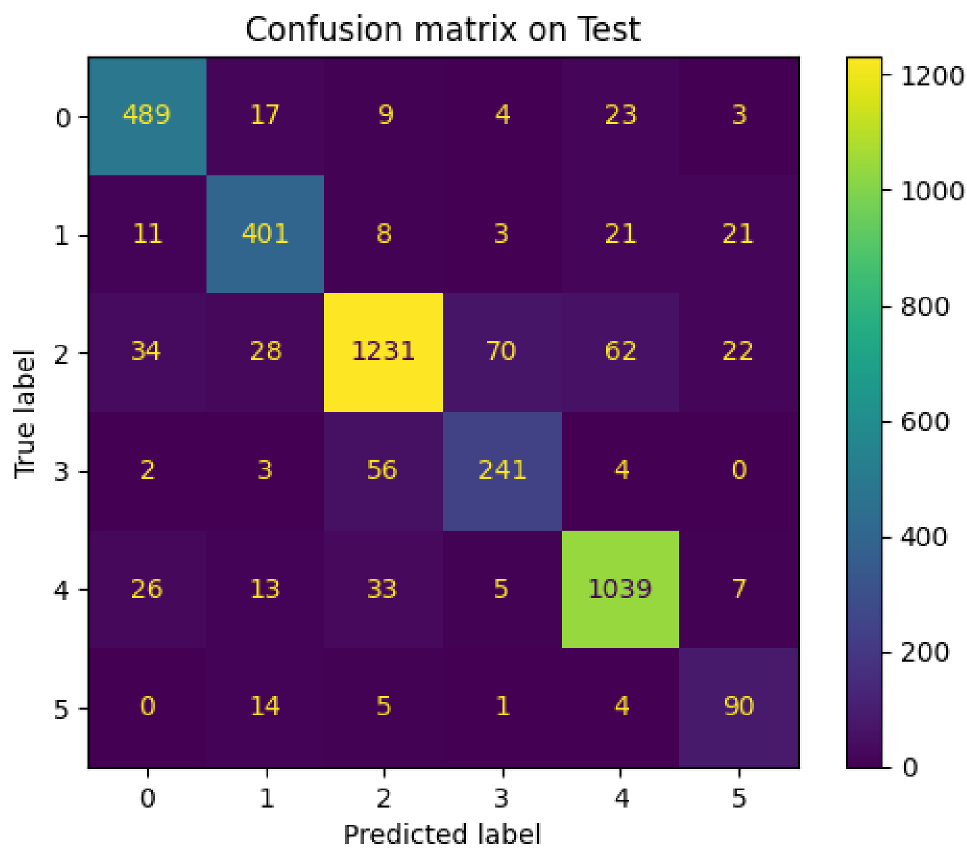
We choose $C = 1$ to be the best model.

[ ]:
```
best_l1_softmax_model = LogisticRegression(C=1, penalty='l1', solver='saga',
    multi_class='multinomial')
```

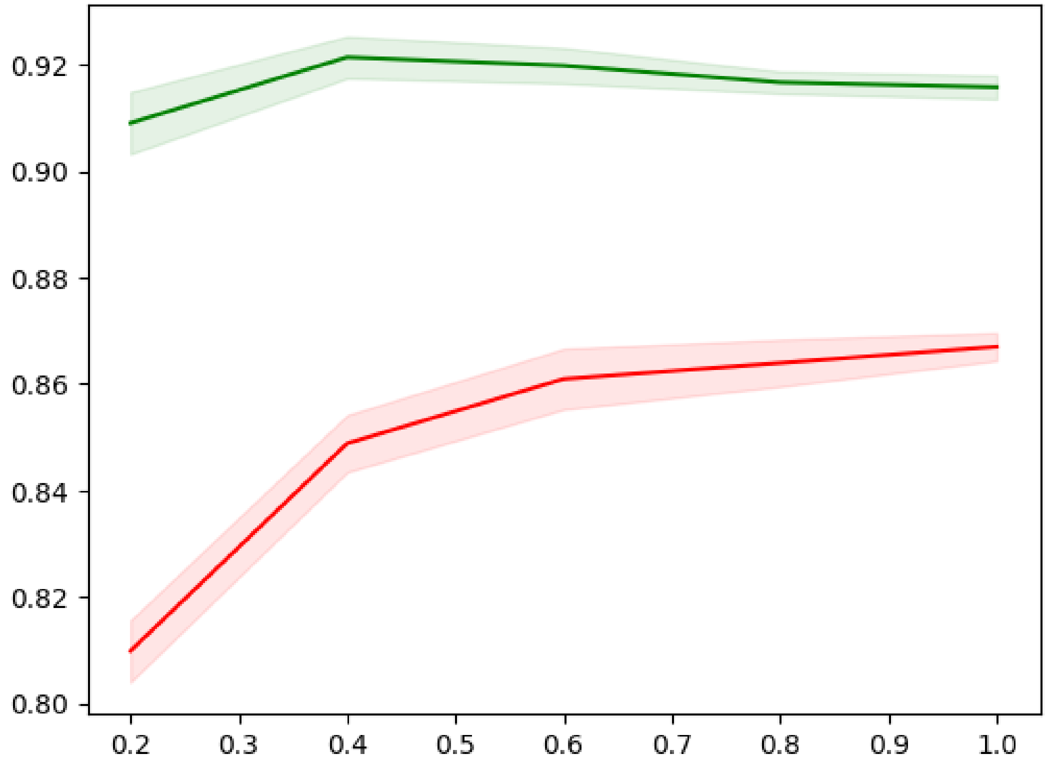
[ ]:
```
best_l1_softmax_model.fit(X_train, y_train)
evaluate_model(best_l1_softmax_model, X_train, X_test, y_train, y_test,
    include_training=True)
```

```
Score of on train are:
        - Accuracy score: 0.9139
        - Micro F1 score: 0.9139
        - Macro F1 score: 0.8885
Score of on test are:
        - Accuracy score: 0.8728
        - Micro F1 score: 0.8728
        - Macro F1 score: 0.8328
```


Confusion matrix on Train
True label
Predicted label
0
1
2
3
4
5
1973
33
27
6
45
3
28
1677
18
5
33
61
60
104
5171
229
216
84
11
7
137
1054
14
1
74
50
60
23
4332
11
1
26
6
0
4
416
5000
4000
3000
2000
1000
0



[ ]:
```
draw_learning_curve(best_l1_softmax_model, X_train, y_train)
```



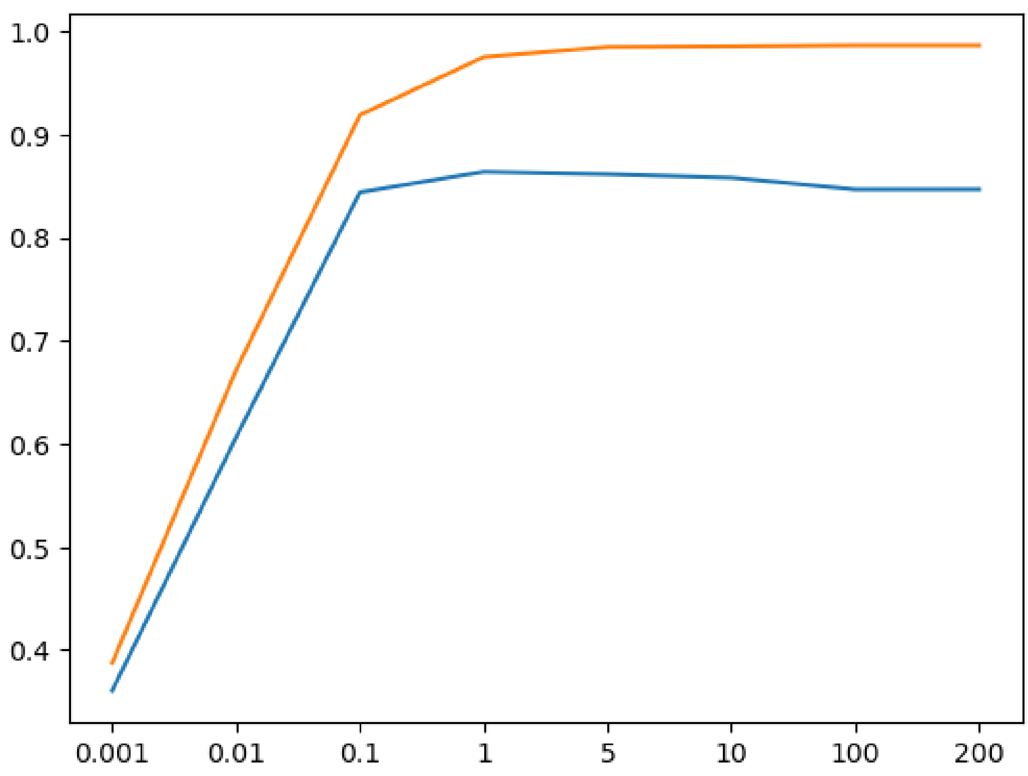
3.3 L2 regularization

[ ]:
```
C_list = [0.001, 0.01, 0.1, 1, 5, 10, 100, 200]

# 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
    softmax_model = LogisticRegression(C=c, penalty='l2', solver='lbfgs',␣
 ↪multi_class='multinomial')
    softmax_model.fit(X_train, y_train)

    # Calculate score of cross validation
    train_score = accuracy_score(y_train, softmax_model.predict(X_train))
    cv_score = np.mean(cross_val_score(softmax_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, 200]
[0.3876875, 0.6714375, 0.91875, 0.975, 0.98475, 0.985375, 0.9863125, 0.9863125]
[0.36081250000000004, 0.6063125, 0.8438749999999999, 0.8637500000000001,
0.8614375000000001, 0.8579375, 0.8466250000000001, 0.8466875]
```

```
[ ]: [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'),
 Text(7, 0, '200')]
```



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

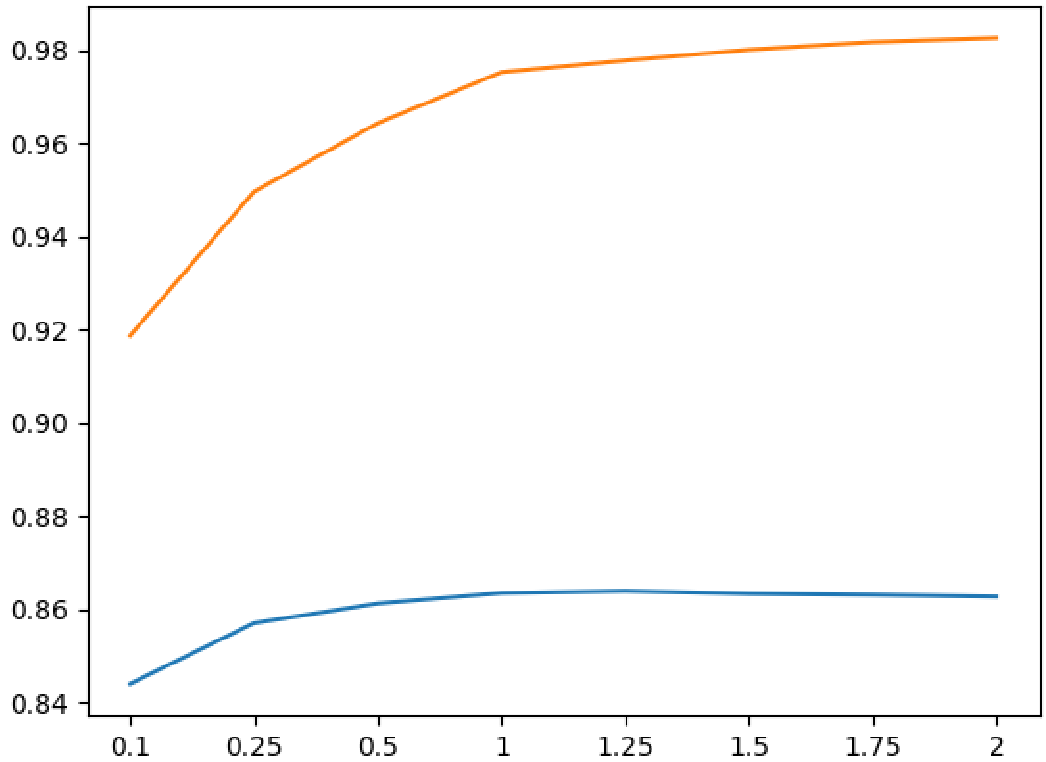
[ ]:
```
C_list = [0.1, 0.25, 0.5, 1, 1.25, 1.5, 1.75, 2]

# 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
    softmax_model = LogisticRegression(C=c, penalty='l2', solver='lbfgs',␣
 ↪multi_class='multinomial')
    softmax_model.fit(X_train, y_train)

    # Calculate score of cross validation
    train_score = accuracy_score(y_train, softmax_model.predict(X_train))
    cv_score = np.mean(cross_val_score(softmax_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)
```

```
[0.1, 0.25, 0.5, 1, 1.25, 1.5, 1.75, 2]
[0.9186875, 0.9495625, 0.96425, 0.9751875, 0.9776875, 0.98, 0.981625, 0.9825]
[0.844, 0.857, 0.8611875000000001, 0.8634375000000001, 0.863875,
0.8633124999999999, 0.8630625000000001, 0.8626875]
```

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



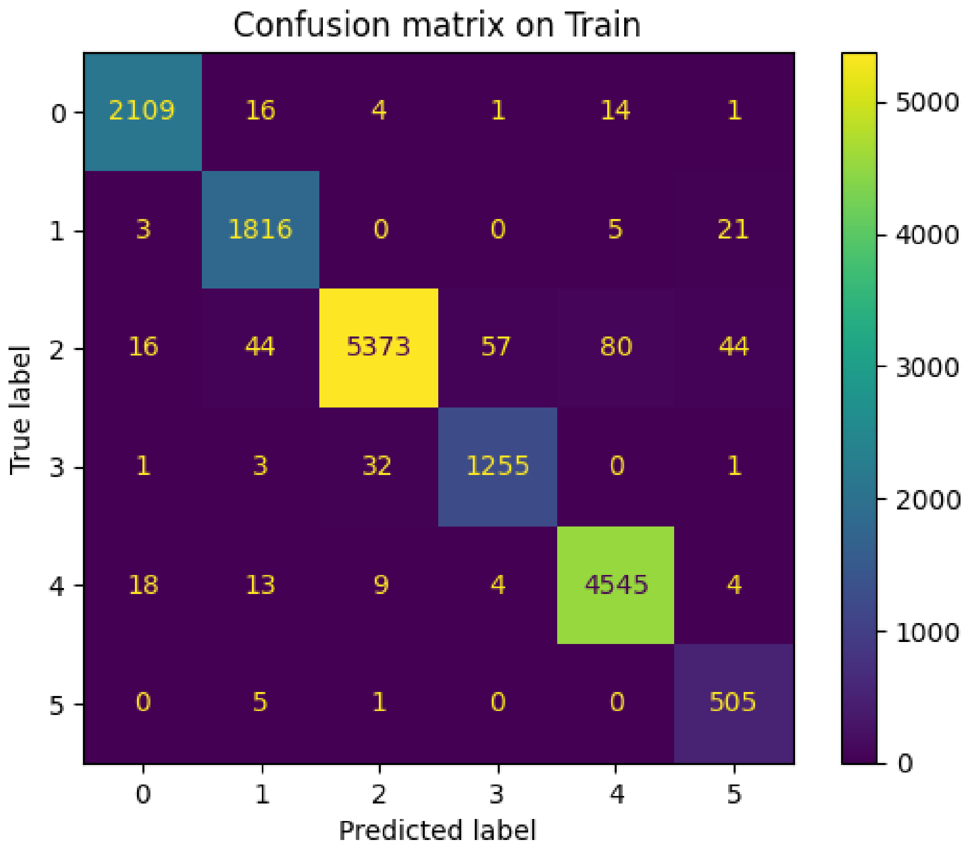
The valid scores are almost the same at every value, but we will choose value with lowest train score for generalization.

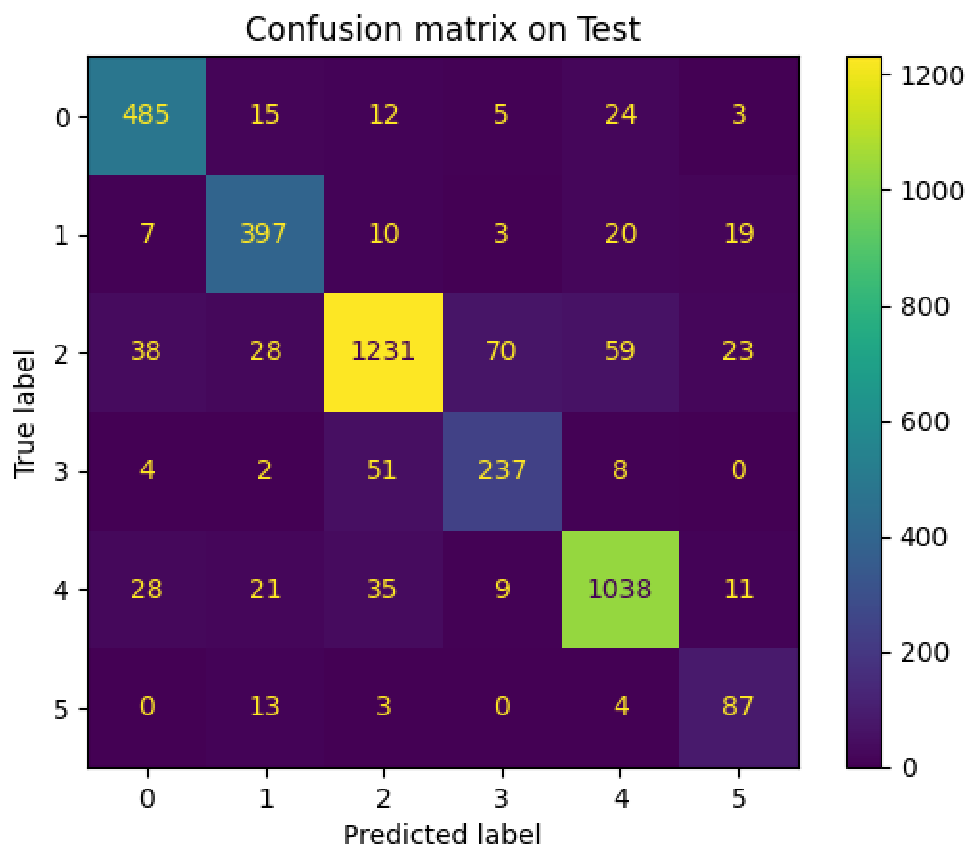
We choose $C = 1$ to be the best model.

```
[ ]: best_l2_softmax_model = LogisticRegression(C=1, penalty='l2', solver='lbfgs',␣
      ↪multi_class='multinomial')
```

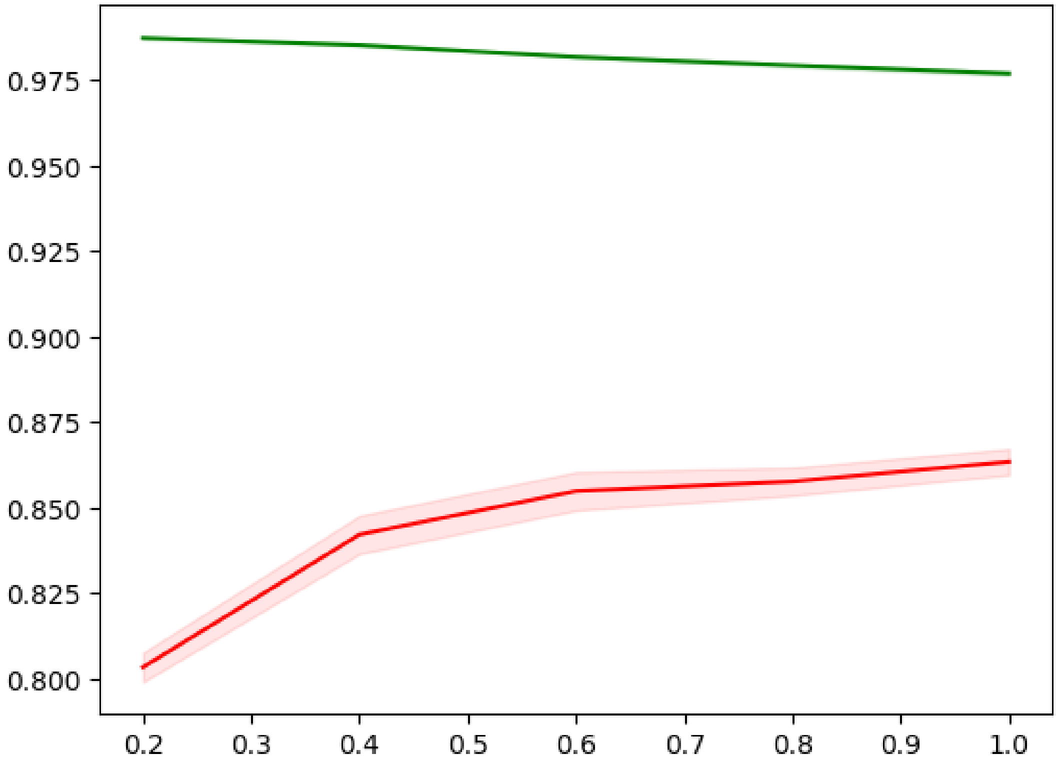
```
[ ]: best_l2_softmax_model.fit(X_train, y_train)
     evaluate_model(best_l2_softmax_model, X_train, X_test, y_train, y_test,␣
      ↪include_training=True)
```

```
Score of on train are:
        - Accuracy score: 0.9752
        - Micro F1 score: 0.9752
        - Macro F1 score: 0.9671
Score of on test are:
        - Accuracy score: 0.8688
        - Micro F1 score: 0.8688
        - Macro F1 score: 0.8281
```


Confusion matrix on Train
True label
Predicted label
0
1
2
3
4
5
2109
16
4
1
14
1
3
1816
0
0
5
21
16
44
5373
57
80
44
1
3
32
1255
0
1
18
13
9
4
4545
4
0
5
1
0
0
505
5000
4000
3000
2000
1000
0



[ ]:
```
draw_learning_curve(best_l2_softmax_model, X_train, y_train)
```



3.4 Elastic regularization

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

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

[ ]:
```
GridSearchCV(cv=5,
             estimator=LogisticRegression(multi_class='multinomial',
                                          penalty='elasticnet', solver='saga'),
             n_jobs=5,
             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)
}

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

[ ]:
```
GridSearchCV(cv=5,
             estimator=LogisticRegression(multi_class='multinomial',
                                          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  0.864875
1    1.000000       0.3  0.864625
2    1.000000       0.5  0.865875
3    1.000000       0.7  0.865437
4    1.000000       0.9  0.866437
5    3.162278       0.1  0.864125
6    3.162278       0.3  0.864500
7    3.162278       0.5  0.865500
8    3.162278       0.7  0.865625
9    3.162278       0.9  0.866062
10  10.000000       0.1  0.864688
11  10.000000       0.3  0.863875
12  10.000000       0.5  0.864188
13  10.000000       0.7  0.864312
14  10.000000       0.9  0.864125
15  31.622777       0.1  0.864375
16  31.622777       0.3  0.863687
17  31.622777       0.5  0.863937
18  31.622777       0.7  0.863750
19  31.622777       0.9  0.863875
20 100.000000       0.1  0.864125
21 100.000000       0.3  0.864062
22 100.000000       0.5  0.864000
23 100.000000       0.7  0.864125
24 100.000000       0.9  0.863875
```

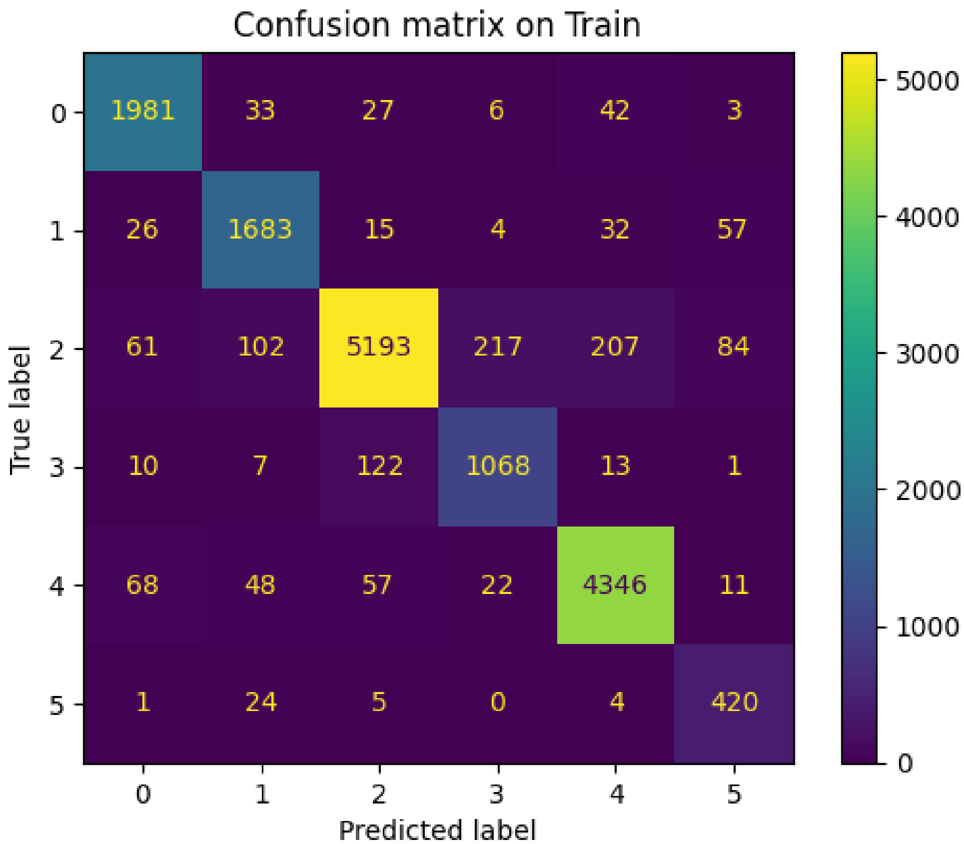
[ ]:
```
print(grid_search.best_estimator_, grid_search.best_score_)
```

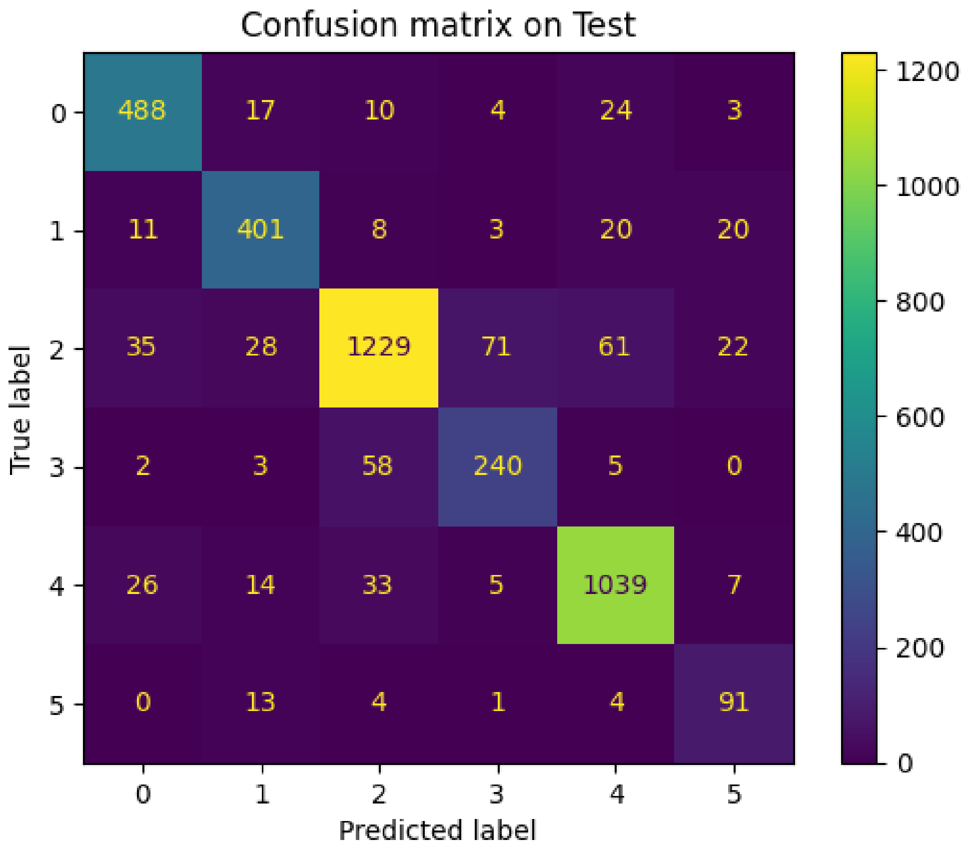
```
LogisticRegression(l1_ratio=0.9, multi_class='multinomial',
                   penalty='elasticnet', solver='saga') 0.8664375
```

[ ]:
```
best_en_softmax_model = LogisticRegression(C=1, l1_ratio=0.9,
                    multi_class='multinomial', penalty='elasticnet',
                    solver='saga')
```

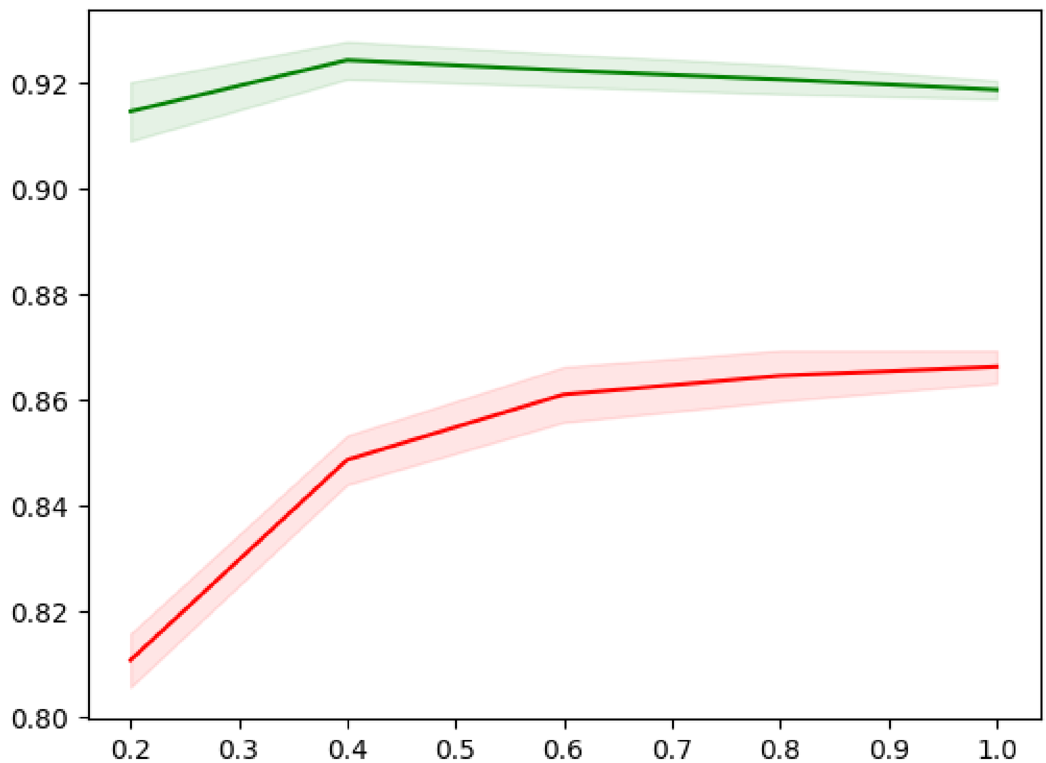
[ ]:
```
best_en_softmax_model.fit(X_train, y_train)
evaluate_model(best_en_softmax_model, X_train, X_test, y_train, y_test,␣
 ↪include_training=True)
```

```
Score of on train are:
        - Accuracy score: 0.9182
        - Micro F1 score: 0.9182
        - Macro F1 score: 0.8940
Score of on test are:
        - Accuracy score: 0.8720
        - Micro F1 score: 0.8720
        - Macro F1 score: 0.8333
```


Confusion matrix on Train
1981
33
27
6
42
3
26
1683
15
4
32
57
61
102
5193
217
207
84
10
7
122
1068
13
1
68
48
57
22
4346
11
1
24
5
0
4
420
True label
Predicted label
0
1
2
3
4
5
5000
4000
3000
2000
1000
0



[ ]:
```
draw_learning_curve(best_en_softmax_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_softmax_model = best_l1_softmax_model
```

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

dump(best_softmax_model, directory + "best_softmax_bow_l1_model.joblib")
```

[ ]:
```
['data/models/softmax/best_softmax_bow_l1_model.joblib']
```