Decision Tree bow

May 6, 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:

[ ]:
```
import numpy as np
import pandas as pd
import seaborn as sns

from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import GridSearchCV, cross_val_score
from sklearn.metrics import accuracy_score
from joblib import dump

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
```

1.1 Select dataset

At first, we choose the dataset to be used for training and testing the model.

[ ]:
```
X_train = X_train_bow
X_test = X_test_bow
```

2 Basic training

We define the model with the default parameters and train it.

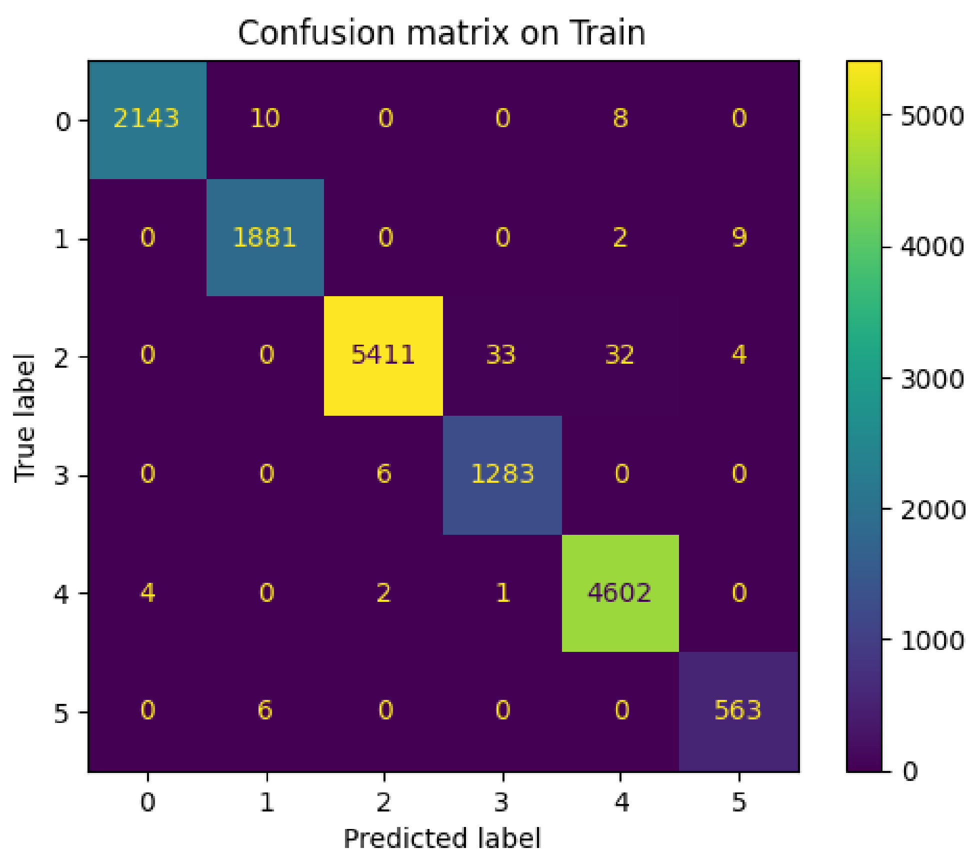
[ ]:
```
DT = DecisionTreeClassifier()
DT.fit(X_train, y_train)
```

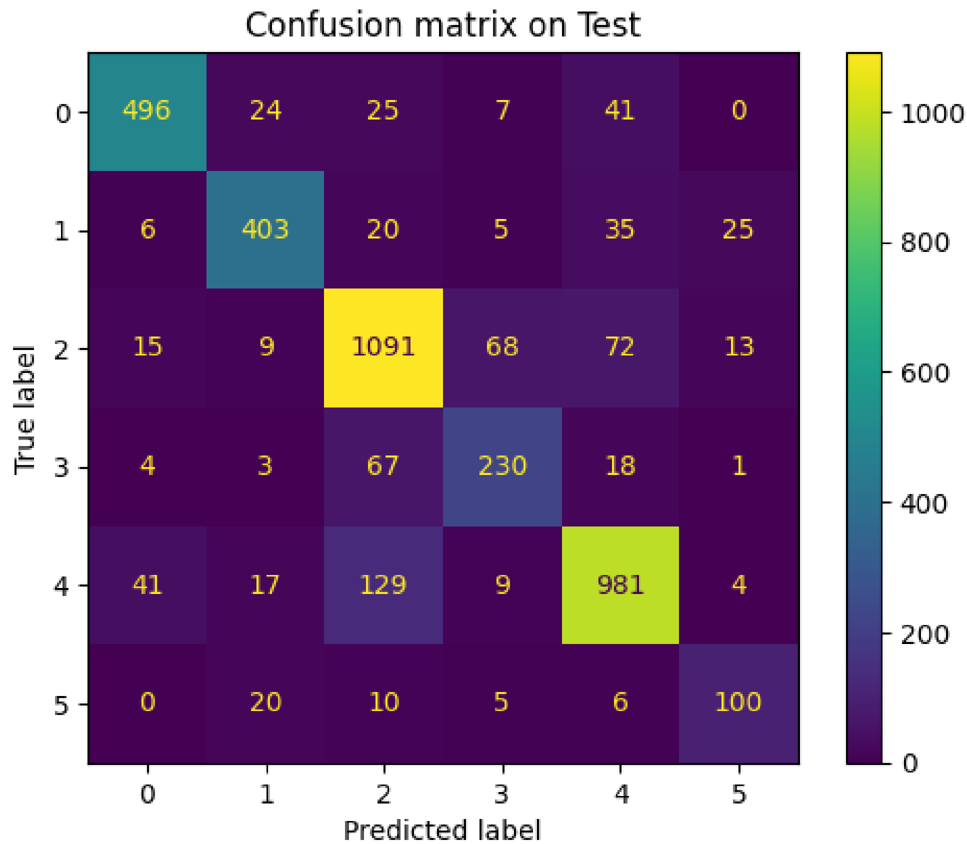
[ ]:
```
DecisionTreeClassifier()
```

Evaluate this model using a preset function:

[ ]:
```
evaluate_model(DT, X_train, X_test, y_train, y_test, include_training=True)
```

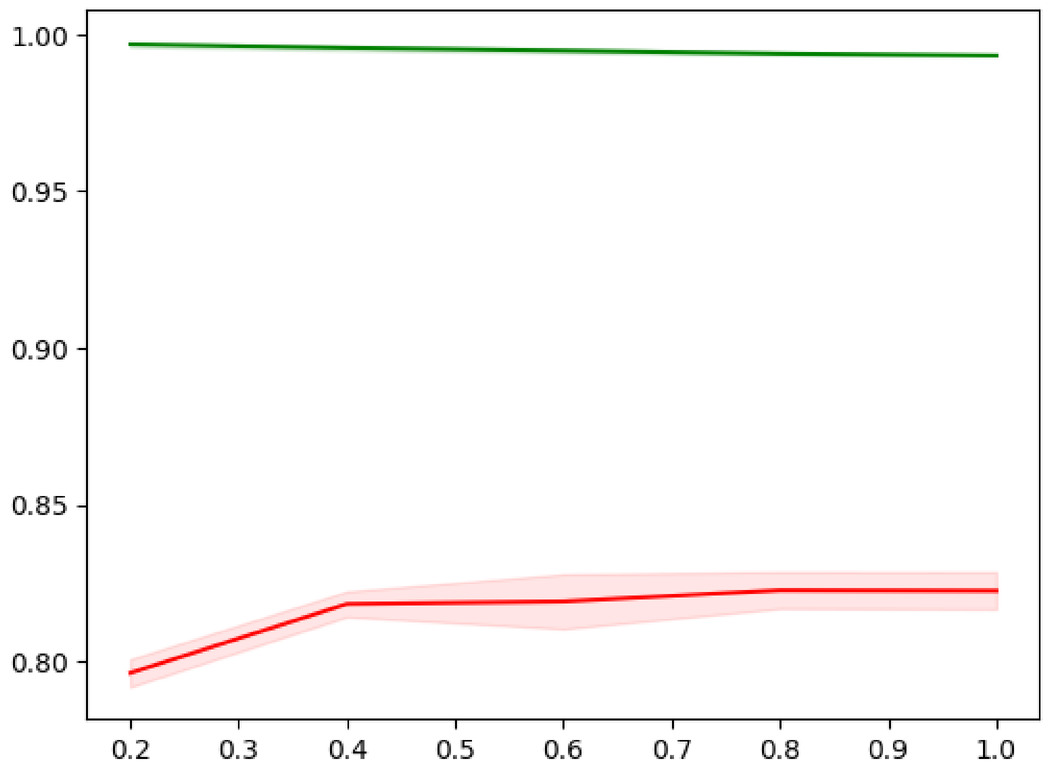
```
Score of on train are:
        - Accuracy score: 0.9927
        - Micro F1 score: 0.9927
        - Macro F1 score: 0.9906
Score of on test are:
        - Accuracy score: 0.8253
        - Micro F1 score: 0.8253
        - Macro F1 score: 0.7969
```





Draw learning curve using a preset function:

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



3 Single tuning

This section examines the best range for each parameters by plotting the performance of the model with a range of value for each parameters.

3.1 Max_depth

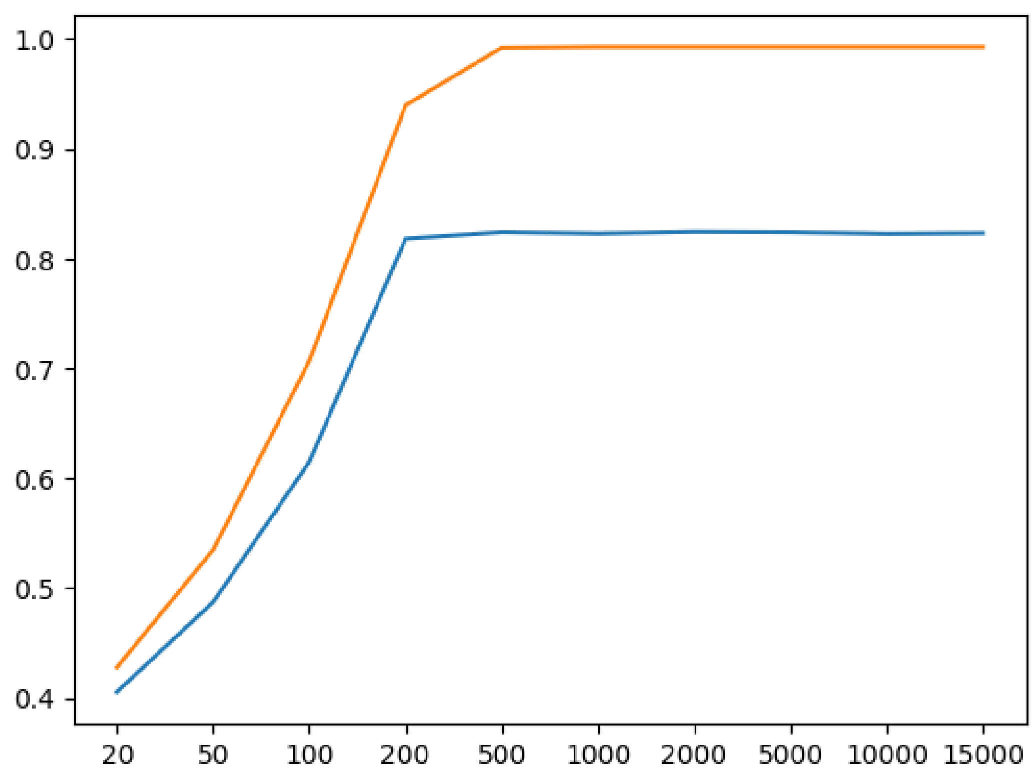
max_depth is the maximum depth of the tree.

[ ]:
```
# Setting the possible value for max depth
max_depth_list = [20, 50, 100, 200, 500, 1000, 2000, 5000, 10000, 15000]

trs_list = list()
cvs_list = list()

for max_depth in max_depth_list:
    # Define model for each max_depth
    dt_model = DecisionTreeClassifier(max_depth=max_depth)
    dt_model.fit(X_train_bow, y_train)

    # Calculate the cross validation score
    train_score = accuracy_score(y_train, dt_model.predict(X_train_bow))
```

```
    cvs_score = np.mean(cross_val_score(dt_model, X_train_bow, y_train, cv=5,␣
↪n_jobs=-1))

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

[ ]:
```
# Draw the plot for max depth
fig = sns.lineplot(x=list(range(len(max_depth_list))), y=cvs_list)
fig = sns.lineplot(x=list(range(len(max_depth_list))), y=trs_list)
fig.set_xticks(range(len(max_depth_list)))
fig.set_xticklabels(max_depth_list)
```

[ ]:
```
[Text(0, 0, '20'),
 Text(1, 0, '50'),
 Text(2, 0, '100'),
 Text(3, 0, '200'),
 Text(4, 0, '500'),
 Text(5, 0, '1000'),
 Text(6, 0, '2000'),
 Text(7, 0, '5000'),
 Text(8, 0, '10000'),
 Text(9, 0, '15000')]
```



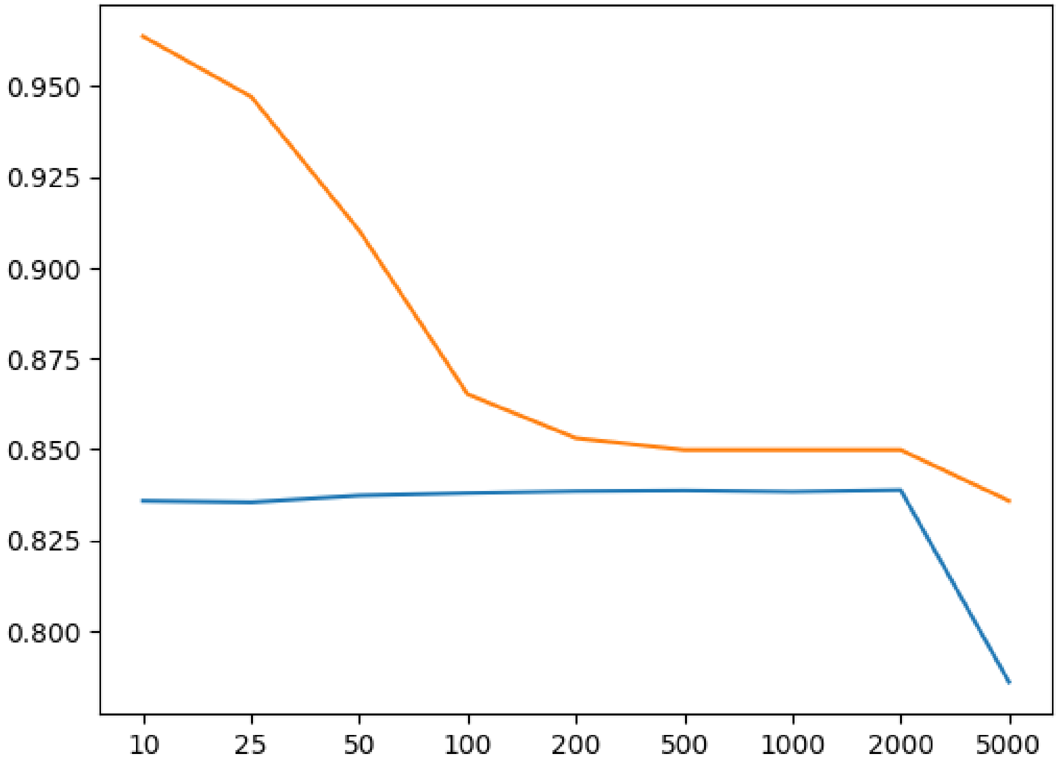
3.2 Min_samples_split

min_samples_split is the minimum number of samples required to split an internal node.

[ ]:
```
# Setting the possible value for max depth
min_samples_split_list = [10, 25, 50, 100, 200, 500, 1000, 2000, 5000]

trs_list = list()
cvs_list = list()

for min_samples_split in min_samples_split_list:
    # Define model for each max_depth
    dt_model = DecisionTreeClassifier(max_depth=276,
 ↪min_samples_split=min_samples_split)
    dt_model.fit(X_train_bow, y_train)

    # Calculate the cross validation score
    train_score = accuracy_score(y_train, dt_model.predict(X_train_bow))
    cvs_score = np.mean(cross_val_score(dt_model, X_train_bow, y_train, cv=5,
 ↪n_jobs=-1))

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

[ ]:
```
# Draw the plot for max depth
fig = sns.lineplot(x=list(range(len(min_samples_split_list))), y=cvs_list)
fig = sns.lineplot(x=list(range(len(min_samples_split_list))), y=trs_list)
fig.set_xticks(range(len(min_samples_split_list)))
fig.set_xticklabels(min_samples_split_list)
```

[ ]:
```
[Text(0, 0, '10'),
 Text(1, 0, '25'),
 Text(2, 0, '50'),
 Text(3, 0, '100'),
 Text(4, 0, '200'),
 Text(5, 0, '500'),
 Text(6, 0, '1000'),
 Text(7, 0, '2000'),
 Text(8, 0, '5000')]
```



3.3 Min_samples_leaf

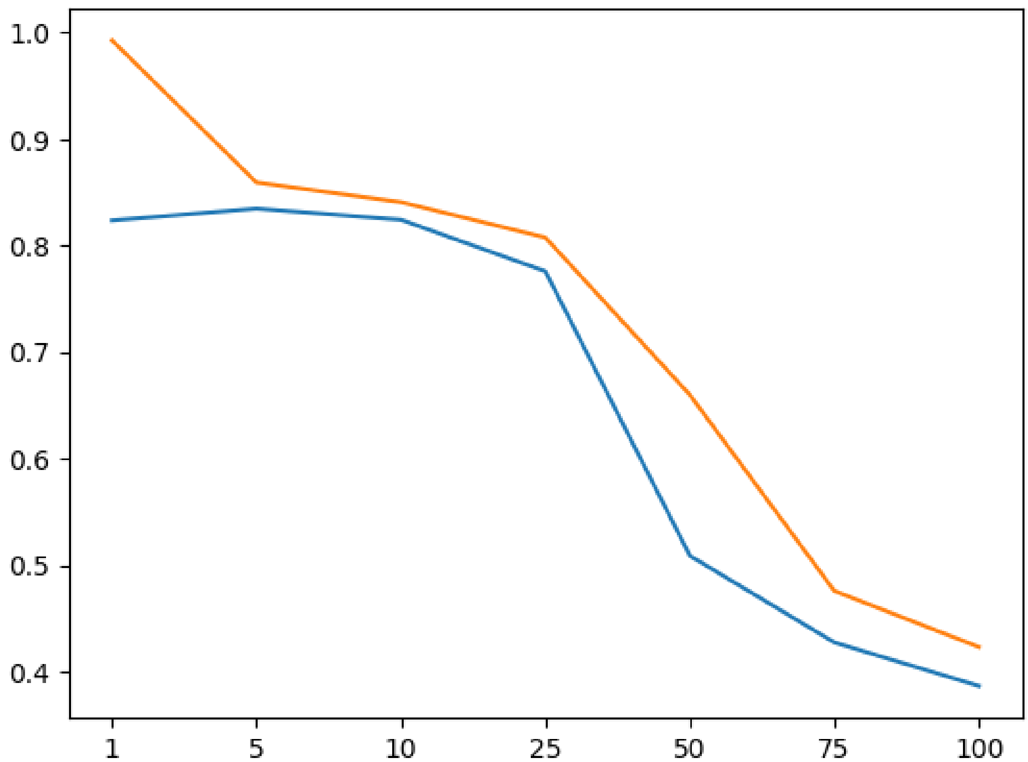
min_samples_leaf is the minimum number of samples required to be at a leaf node. A split point at any depth will only be considered if it leaves at least ***min_samples_leaf*** training samples in each of the left and right branches.

[ ]:
```
# Setting the min sample leaf range
min_samples_leaf_list = [1, 5, 10, 25, 50, 75, 100]
trs_list = list()
cvs_list = list()

for min_samples_leaf in min_samples_leaf_list:
  # Define model for each k
  dt_model = DecisionTreeClassifier(min_samples_leaf=min_samples_leaf)
  dt_model.fit(X_train_bow, y_train)

  # Calculate the cross validation score
  train_score = accuracy_score(y_train, dt_model.predict(X_train_bow))
  cv_score = np.mean(cross_val_score(dt_model, X_train_bow, y_train, cv=5,␣
 ↪n_jobs=-1))

  trs_list.append(train_score)
```

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

[ ]:
```
# Draw the plot for min_samples_leaf
fig = sns.lineplot(x=list(range(len(min_samples_leaf_list))), y=cvs_list)
fig = sns.lineplot(x=list(range(len(min_samples_leaf_list))), y=trs_list)
fig.set_xticks(range(len(min_samples_leaf_list)))
fig.set_xticklabels(min_samples_leaf_list)
```

[ ]:
```
[Text(0, 0, '1'),
 Text(1, 0, '5'),
 Text(2, 0, '10'),
 Text(3, 0, '25'),
 Text(4, 0, '50'),
 Text(5, 0, '75'),
 Text(6, 0, '100')]
```



From the plot, we can see that the higher this parameter is, the lower the accuracy for both training and testing are.

4 Multiple tuning

First, we use grid search to help tuning this model.

[ ]:
```
dict_param = {
    'max_depth' : np.asarray([100, 1000, 5000]),
    'min_samples_split': np.asarray([10, 100, 1000, 5000]),
    'min_samples_leaf': np.asarray([5, 25, 100]),
}

grid_search = GridSearchCV(DecisionTreeClassifier(), dict_param, cv = 5,␣
 ↪n_jobs=8)
grid_search.fit(X_train, y_train)
```

[ ]:
```
GridSearchCV(cv=5, estimator=DecisionTreeClassifier(), n_jobs=8,
             param_grid={'max_depth': array([ 100, 1000, 5000]),
                         'min_samples_leaf': array([  5,  25, 100]),
                         'min_samples_split': array([  10,  100, 1000, 5000])})
```

We elminate all parameters that appear in models with the validation accuracy < 0.83

[ ]:
```
df = pd.DataFrame(
  dict(
    max_depth = [val['max_depth'] for val in grid_search.cv_results_['params']],
    min_samples_split = [val['min_samples_split'] for val in grid_search.
 ↪cv_results_['params']],
    min_samples_leaf = [val['min_samples_leaf'] for val in grid_search.
 ↪cv_results_['params']],
    score = grid_search.cv_results_['mean_test_score']
  )
)

df = df[df['score'] <= 0.83]

for param in dict_param:
  for value in dict_param[param]:
    if len(df[df[param] == value]) == 36 // len(dict_param[param]) :
      print(param, value)
```

```
max_depth 100
min_samples_split 5000
min_samples_leaf 25
min_samples_leaf 100
```

Find the best combination of parameters for the model:

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

```
DecisionTreeClassifier(max_depth=2500, min_samples_leaf=2,
                       min_samples_split=1000) 0.8385624999999999
```

5 Max_leaf_nodes

This parameter is tuned separately after finding the best combination of other parameters because it is very time-consuming.

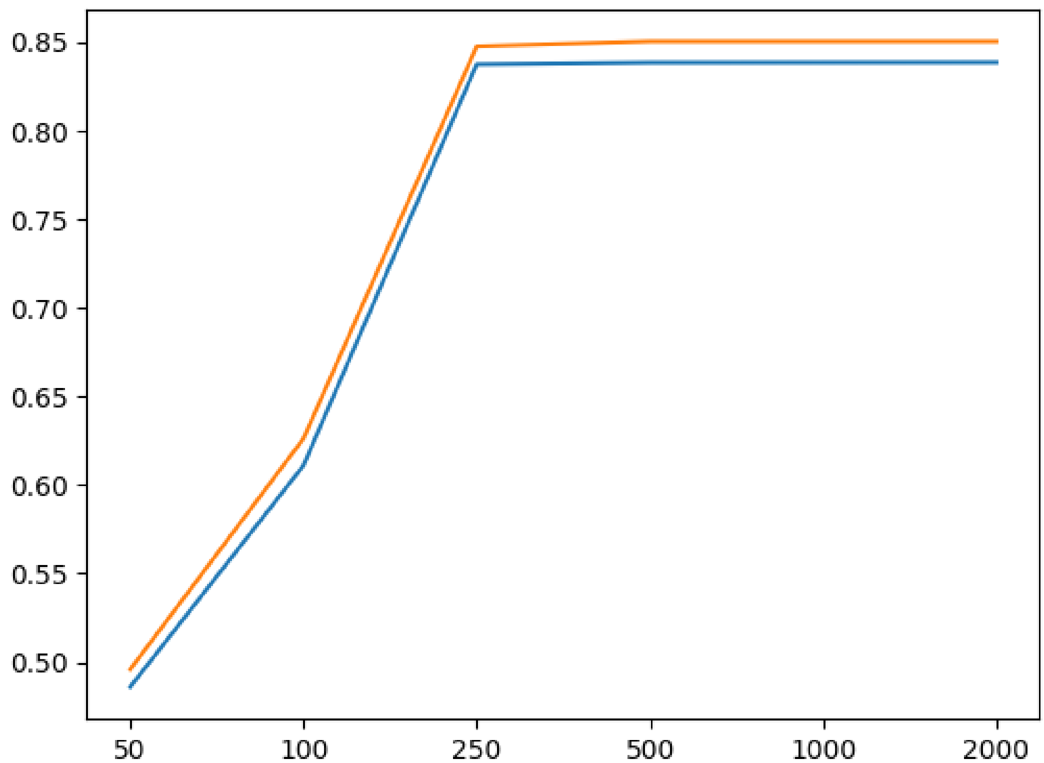
First, we examine this parameter in a wide range of value.

```
[ ]: # Setting the max_leaf_nodes range
max_leaf_nodes_list = [50, 100, 250, 500, 1000, 2000]
trs_list = list()
cvs_list = list()

for max_leaf_nodes in max_leaf_nodes_list:
  # Define model for each k
  dt_model = DecisionTreeClassifier(max_depth=2500, min_samples_leaf=2,
                      min_samples_split=1000, max_leaf_nodes=max_leaf_nodes)
  dt_model.fit(X_train_bow, y_train)

  # Calculate the cross validation score
  train_score = accuracy_score(y_train, dt_model.predict(X_train_bow))
  cv_score = np.mean(cross_val_score(dt_model, X_train_bow, y_train, cv=5,
 ↪n_jobs=8))

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

Then, we plot the result.

```
[ ]: # Draw the plot for max_leaf_nodes
fig = sns.lineplot(x=list(range(len(max_leaf_nodes_list))), y=cvs_list)
fig = sns.lineplot(x=list(range(len(max_leaf_nodes_list))), y=trs_list)
fig.set_xticks(range(len(max_leaf_nodes_list)))
fig.set_xticklabels(max_leaf_nodes_list)
```

```
[ ]: [Text(0, 0, '50'),
 Text(1, 0, '100'),
 Text(2, 0, '250'),
 Text(3, 0, '500'),
 Text(4, 0, '1000'),
 Text(5, 0, '2000')]
```



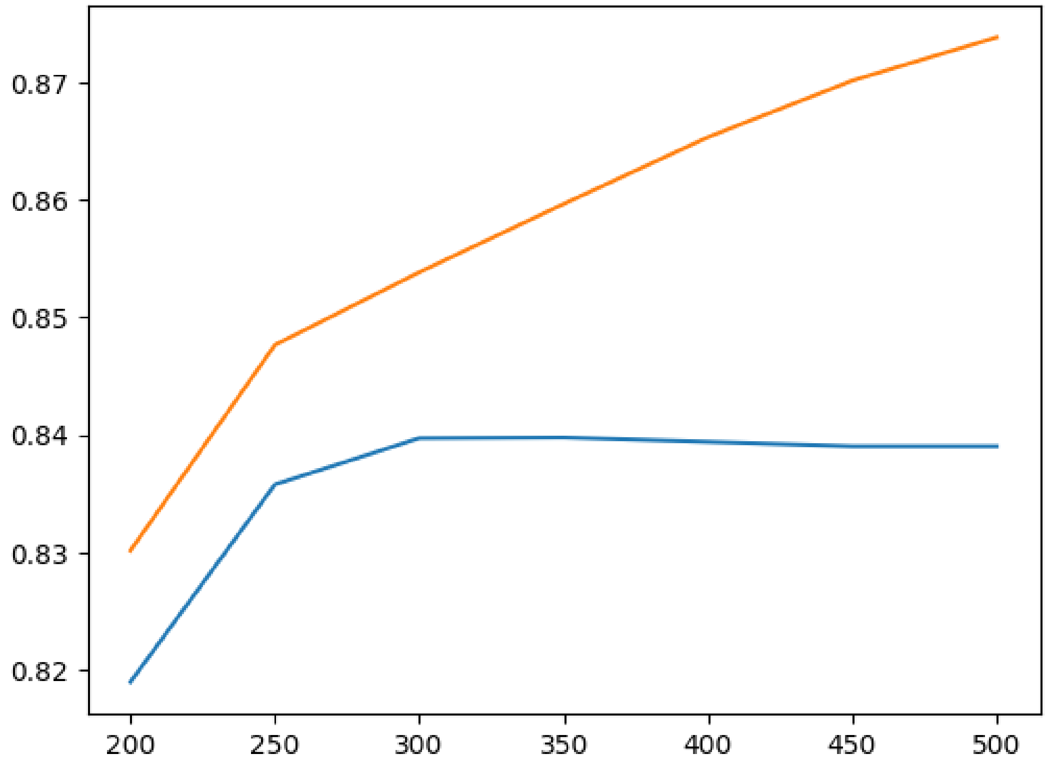
The plot shows that it would be the most ideal for this parameter to be in the range $(200, 500)$.

We further examine this range by plotting the performance of this model in the above range.

[ ]:
```
# Setting the max_leaf_nodes range
max_leaf_nodes_list = [i for i in range(200, 501, 50)]
trs_list = list()
cvs_list = list()

for max_leaf_nodes in max_leaf_nodes_list:
  # Define model for each k
  dt_model = DecisionTreeClassifier(max_leaf_nodes=max_leaf_nodes)
  dt_model.fit(X_train_bow, y_train)

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

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

```
[ ]: # Draw the plot for max_leaf_nodes
fig = sns.lineplot(x=list(range(len(max_leaf_nodes_list))), y=cvs_list)
fig = sns.lineplot(x=list(range(len(max_leaf_nodes_list))), y=trs_list)
fig.set_xticks(range(len(max_leaf_nodes_list)))
fig.set_xticklabels(max_leaf_nodes_list)
```

```
[ ]: [Text(0, 0, '200'),
 Text(1, 0, '250'),
 Text(2, 0, '300'),
 Text(3, 0, '350'),
 Text(4, 0, '400'),
 Text(5, 0, '450'),
 Text(6, 0, '500')]
```



It is illustrated from the plot that this parameter should be near 300.

After all the plotting, we use GridSearchCV to find the best value for it.

```
[ ]: dict_param = {'max_leaf_nodes': [i for i in range(285, 316, 5)]}
best_max_leaf_nodes = GridSearchCV(DecisionTreeClassifier(max_depth=2500,␣
 ↪min_samples_leaf=2, min_samples_split=1000), param_grid = dict_param, n_jobs␣
 ↪= -1, cv = 10, scoring = 'accuracy')
```

```
best_max_leaf_nodes.fit(X_train_bow, y_train)

print("Best max leaf nodes parameter for decision tree:", best_max_leaf_nodes.
 ↪best_params_)
data_best_max_leaf_nodes_y = best_max_leaf_nodes.predict(X_test_bow)
print("Accuracy of that model:", accuracy_score(data_best_max_leaf_nodes_y,␣
 ↪y_test))
```

```
Best max leaf nodes parameter for decision tree: {'max_leaf_nodes': 310}
Accuracy of that model: 0.83675
```

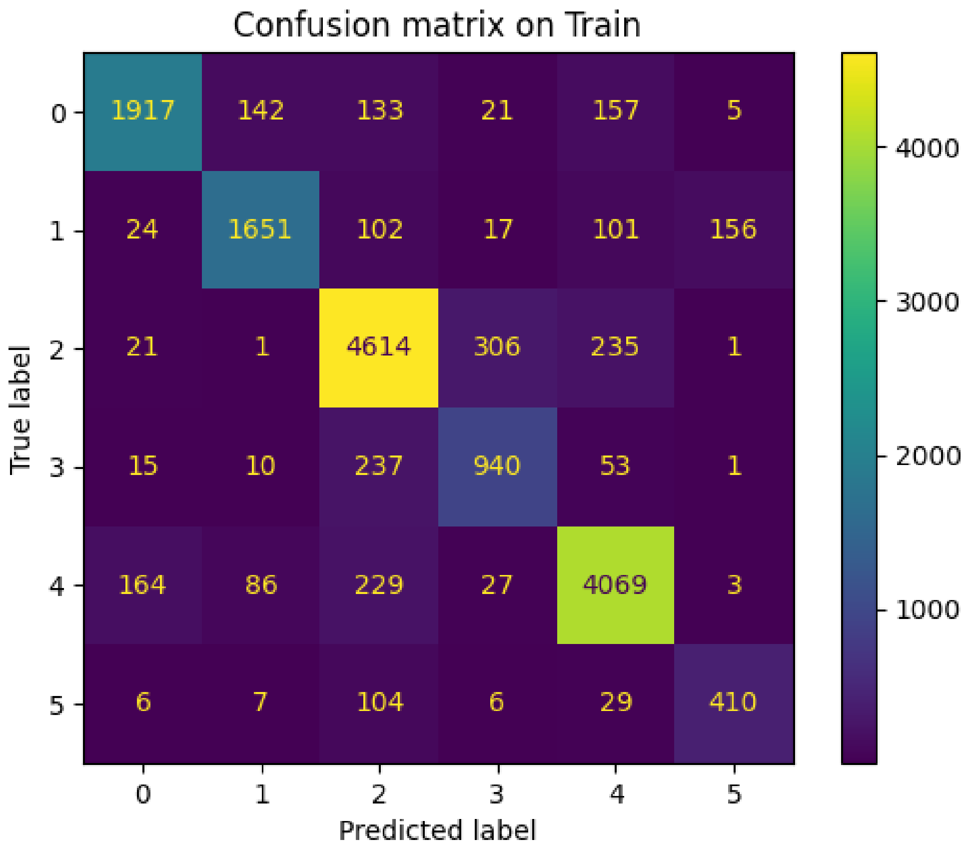
So, the best ***max_leaf_nodes*** parameter is 310.

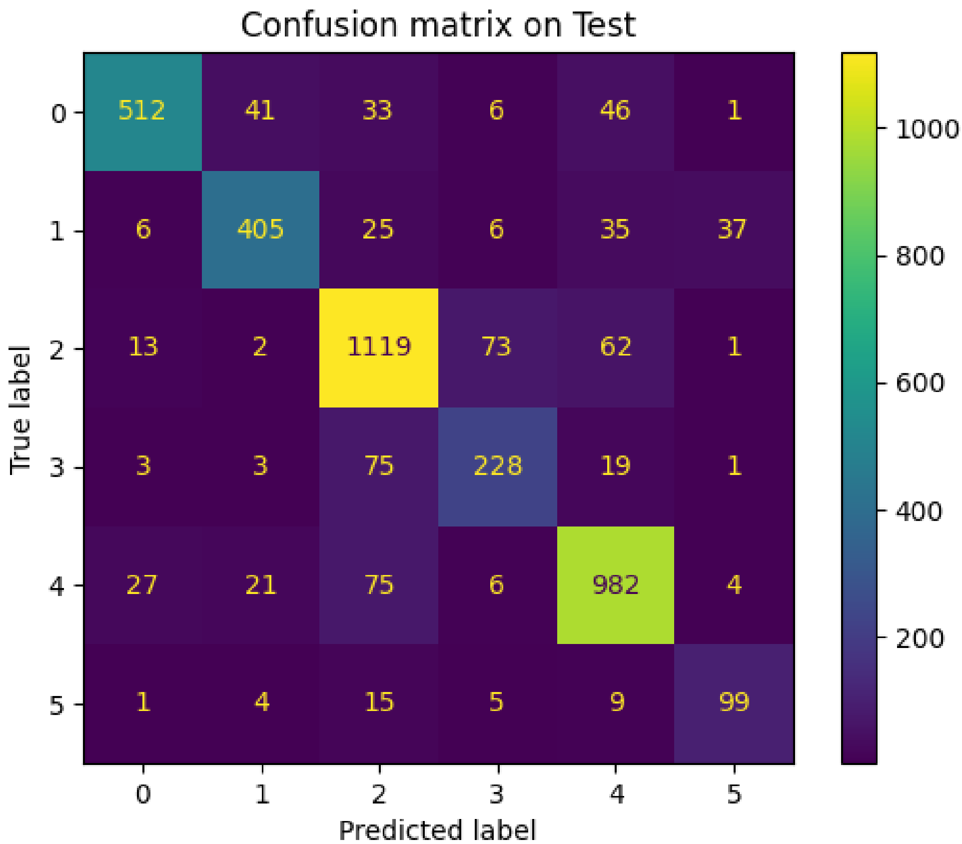
6 Conclusion

We use all the parameters from the last section to define the best model and then evaluate it using the preset functions.

[ ]:
```
best_dt_model = DecisionTreeClassifier(max_depth=2500, min_samples_leaf=2,␣
 ↪min_samples_split=1000, max_leaf_nodes=310)
best_dt_model.fit(X_train, y_train)

evaluate_model(best_dt_model, X_train, X_test, y_train, y_test,␣
 ↪include_training=True)
```

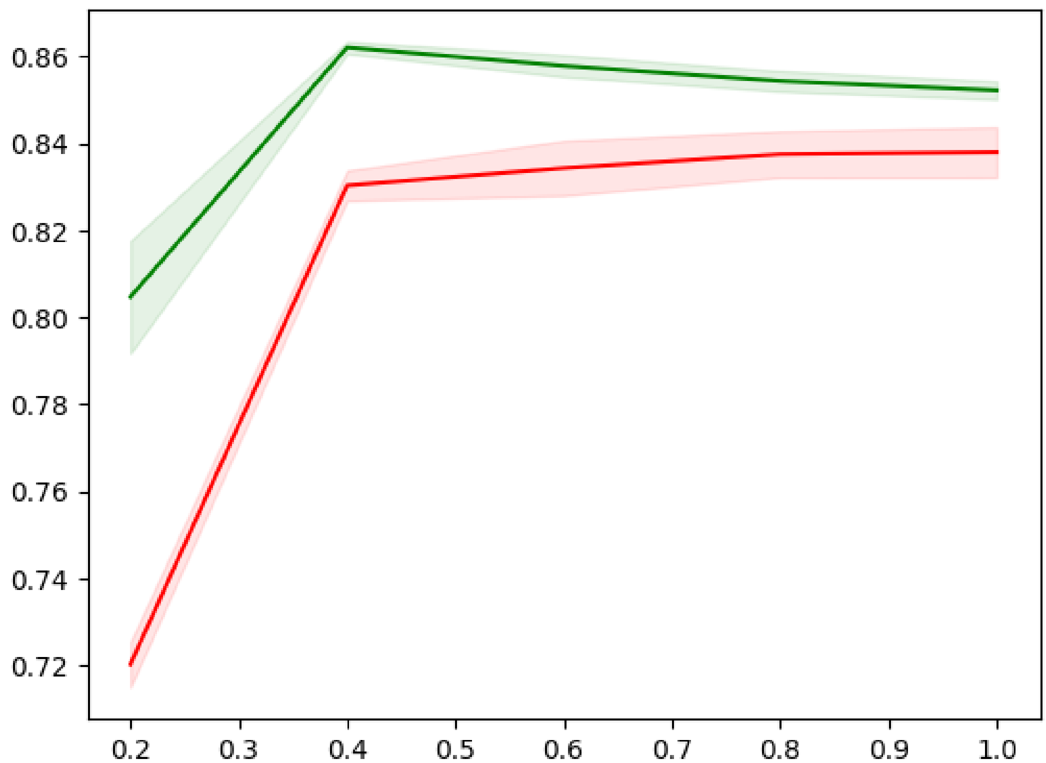
```
Score of on train are:
        - Accuracy score: 0.8501
        - Micro F1 score: 0.8501
        - Macro F1 score: 0.8148
Score of on test are:
        - Accuracy score: 0.8363
        - Micro F1 score: 0.8363
        - Macro F1 score: 0.8015
```


Confusion matrix on Train
True label
Predicted label
0
1
2
3
4
5
1917 142 133 21 157 5
24 1651 102 17 101 156
21 1 4614 306 235 1
15 10 237 940 53 1
164 86 229 27 4069 3
6 7 104 6 29 410
4000
3000
2000
1000



After that, we draw the learning curve of this Decision Tree model.

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



Finally, we export the model.

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

dump(best_dt_model, directory + "best_dt_model_bow.joblib")
```