eXtreme Gradient Boosted Trees

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July 2020

In this project, xTreme gradient boosted trees algorithm is used to train the model. Among several parameters that can be manually chosen(eta, gamma, lambda, alpha, max_depth and more), only lambda is optimized in this project for simplicity.

Dataset : Breast Cancer Wisconsin

Source : https://www.kaggle.com/uciml/breast-cancer-wisconsin-data

Features : ID Number, Clump Thickness, Uniformity of Cell Size, Uniformity of Cell Shape, Marginal Adhesion, Single Epithelial Cell Size, Bare Nuclei, Bland Chromatin, Normal Nucleoli, Mitoses

Label : Class

0.1 Preliminary works

1. Import libraries

[ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import xgboost as xgb
from sklearn.metrics import classification_report, accuracy_score
from sklearn.model_selection import train_test_split
```

2. Get a dataset

[ ]:
```
from google.colab import files
data_to_load = files.upload()
```

```
<IPython.core.display.HTML object>
```

```
Saving breast-cancer-wisconsin.csv to breast-cancer-wisconsin.csv
```

[ ]:
```
data = pd.read_csv("breast-cancer-wisconsin.csv").dropna()
data.columns = ['ID Number', 'Clump Thickness', 'Uniformity of Cell Size',␣
 ↪'Uniformity of Cell Shape', 'Marginal Adhesion', 'Single Epithelial Cell Size'␣
 ↪, 'Bare Nuclei', 'Bland Chromatin', 'Normal Nucleoli', 'Mitoses', 'Class']
data['Class'] = data['Class'].replace(2,0).replace(4,1) #Replace 2(benign) and␣
 ↪4(malignant) into 0(benign) and 1(malignant)
```

3. Create train, test and validation sets

[ ]:
```python
X = data.iloc[:, 1:-1]
y = data.iloc[:, -1]

train_X, test_X, train_Y, test_Y = train_test_split(X, y, test_size=0.2,␣
↪random_state=1)
val_X, test_X, val_Y, test_Y = train_test_split(test_X, test_Y, test_size=0.5,␣
↪random_state=1)

print("Data length: %d, Training data length: %d, Validation data length: %d,␣
↪Testing data length: %d" %(len(X), len(train_X), len(val_X), len(test_X)))

# Create DMatrix
dtrain = xgb.DMatrix(train_X, label=train_Y)
dval = xgb.DMatrix(val_X, label=val_Y)
dtest = xgb.DMatrix(test_X, label=test_Y)
```

```
Data length: 682, Training data length: 545, Validation data length: 68, Testing
data length: 69
```

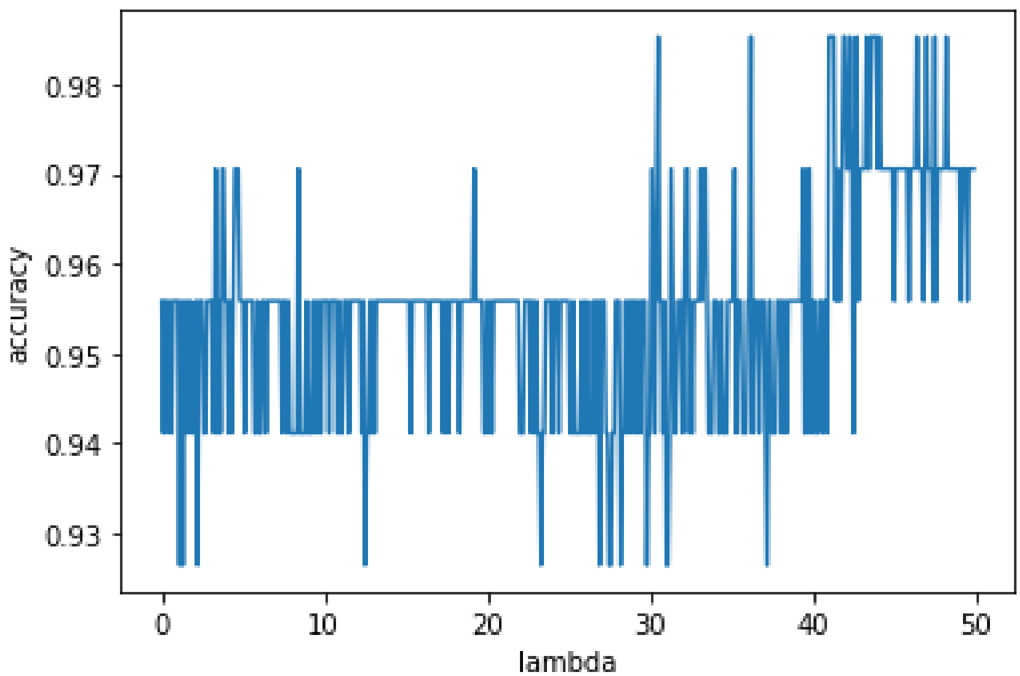
4. Define functions for optimal parameter selection

[ ]:
```python
# Chose best lambda
def val_accuracy_lamb(dtrain, dval, lamb, num_round):
  """
  Input:
    dtrain: training DMatrix
    dval: validation DMatrix
    eta: learning rate
    lamb: L2 penalizing tuning parameter
  Output:
    accuracy score between predicted and true label of validation dataset
  """
  param = {'booster':'gbtree', 'max_depth':2, 'lambda':lamb, 'objective':'binary:
↪hinge'}
  num = num_round
  bst = xgb.train(param, dtrain, num)
  preds = bst.predict(dval)
  return accuracy_score(val_Y, preds)
```

[ ]:
```python
lambs = np.arange(0, 50, 0.1)

num_round = 50

accuracy = []

#for eta in etas:
```

```
for lamb in lambs:
  accuracy.append(val_accuracy_lamb(dtrain, dval, lamb, num_round))
```

[ ]:
```
plt.xlabel('lambda')
plt.ylabel('accuracy')
plt.plot(lambs,np.asarray(accuracy))
plt.show()

print("Best lambda: %.2f with accuracy: %.2f%%" %(lambs[accuracy.
 ↪index(max(accuracy))],max(accuracy)*100))
```

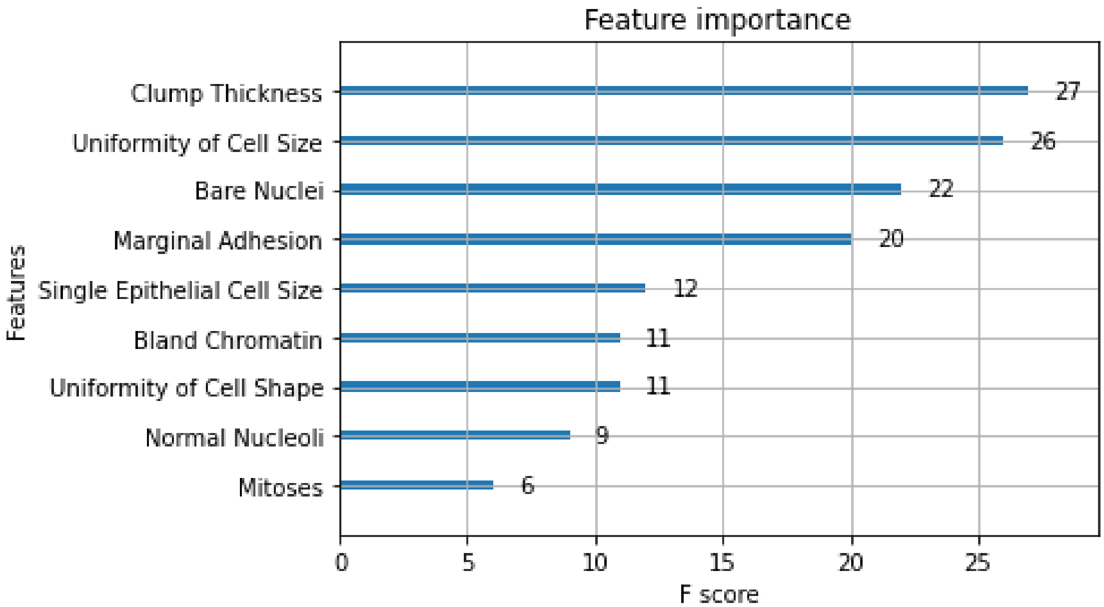



```
Best lambda: 30.50 with accuracy: 98.53%
```

0.2 XGBoost algorithm

[ ]:
```
# Train the algorithm with the optimal lambda value and plot the feature␣
 ↪importance
param = {'booster':'gbtree', 'max_depth':2, 'lambda':lambs[accuracy.
 ↪index(max(accuracy))], 'objective':'binary:hinge'}
num = 50
bst = xgb.train(param, dtrain, num)
xgb.plot_importance(bst)
```

[ ]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f21a468fcf8>
```



[ ]:
```
# Calculate the accuracy of this model using test dataset
preds = bst.predict(dtest)
accuracy = accuracy_score(test_Y, preds)
print("Accuracy: %.2f%%" % (accuracy * 100.0))
```

```
Accuracy: 94.20%
```