LIGHT-GBM

March 8, 2020

Telcom Customer Churn Each row represents a customer, each column contains customer's attributes described on the column Metadata.

The raw data contains 7032 rows (customers) and 21 columns (features).

The "Churn" column is our target.

[11]:
```
import pandas as pd
import numpy as np
import matplotlib
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
%matplotlib inline
import plusmodules as pm
import warnings
warnings.filterwarnings('ignore')
```

[6]:
```
df=pd.read_csv('telco_chrun_encoded (1).csv')
```

[7]:
```
df.shape
```

[7]:
```
(7032, 25)
```

[9]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7032 entries, 0 to 7031
Data columns (total 25 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   gender                      7032 non-null   int64
 1   senior                      7032 non-null   int64
 2   partner                     7032 non-null   int64
 3   dependents                  7032 non-null   int64
 4   tenure                      7032 non-null   int64
 5   phone_service               7032 non-null   int64
 6   multiple_lines              7032 non-null   int64
 7   online_security             7032 non-null   int64
```

```
 8   online_backup                    7032 non-null   int64
 9   device_protection                7032 non-null   int64
 10  tech_support                     7032 non-null   int64
 11  streaming_tv                     7032 non-null   int64
 12  streaming_movies                 7032 non-null   int64
 13  paperless_billing                7032 non-null   int64
 14  monthly_charges                  7032 non-null   float64
 15  total_charges                    7032 non-null   float64
 16  churn                            7032 non-null   int64
 17  avg_monthly_charges              7032 non-null   float64
 18  internet_service-fiber_optic     7032 non-null   int64
 19  internet_service-no              7032 non-null   int64
 20  contract-one_year                7032 non-null   int64
 21  contract-two_year                7032 non-null   int64
 22  payment_method-credit_card_auto  7032 non-null   int64
 23  payment_method-electronic_check  7032 non-null   int64
 24  payment_method-mailed_check      7032 non-null   int64
dtypes: float64(3), int64(22)
memory usage: 1.3 MB
```

[10]:
```
df.isnull().sum()
```

[10]:
```
gender                             0
senior                             0
partner                            0
dependents                         0
tenure                             0
phone_service                      0
multiple_lines                     0
online_security                    0
online_backup                      0
device_protection                  0
tech_support                       0
streaming_tv                       0
streaming_movies                   0
paperless_billing                  0
monthly_charges                    0
total_charges                      0
churn                              0
avg_monthly_charges                0
internet_service-fiber_optic       0
internet_service-no                0
contract-one_year                  0
contract-two_year                  0
payment_method-credit_card_auto    0
payment_method-electronic_check    0
payment_method-mailed_check        0
```

```
dtype: int64
```

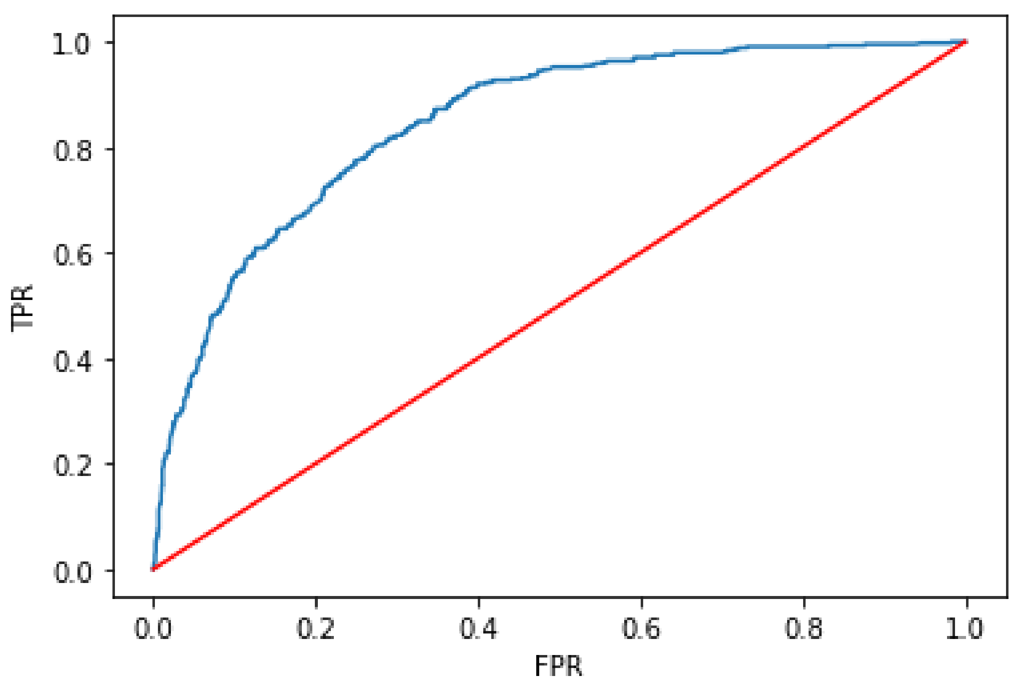
[4]:
```
y=df['churn']
x=df.drop('churn', axis=1)
```

[5]:
```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, random_state=3)
```

[11]:
```
from sklearn.ensemble import AdaBoostClassifier
from sklearn.metrics import confusion_matrix, roc_auc_score, accuracy_score,␣
 ↪roc_curve, classification_report
ada = AdaBoostClassifier(random_state=3)

ada.fit(x_train, y_train)

y_train_pred=ada.predict(x_train)

y_train_prob=ada.predict_proba(x_train)[:,1]

print('Confusion Matrix - Train: ', '\n' ,confusion_matrix(y_train,␣
 ↪y_train_pred))

print('Overall Accuracy - Train: ', accuracy_score(y_train, y_train_pred))


print('AUC- Train:' , roc_auc_score(y_train, y_train_prob))



y_test_pred= ada.predict(x_test)

y_test_prob=ada.predict_proba(x_test)[:,1]

print('Confusion Matrix - Test: ', '\n' ,confusion_matrix(y_test, y_test_pred))

print('Overall Accuracy - Test: ', accuracy_score(y_test, y_test_pred))

print('AUC- Test:' , roc_auc_score(y_test, y_test_prob))

print('Classification Report - Test', classification_report(y_test,␣
 ↪y_test_pred))

fpr, tpr, thresholds =roc_curve(y_test, y_test_prob)
plt.plot(fpr, tpr)
plt.plot(fpr, fpr, 'red')
plt.xlabel('FPR')
plt.ylabel('TPR')
```

```
Confusion Matrix - Train:
 [[3442  403]
 [ 615  814]]
Overall Accuracy - Train:  0.806977626090254
AUC- Train: 0.8590076813106913
Confusion Matrix - Test:
 [[1181  137]
 [ 192  248]]
Overall Accuracy - Test:  0.8128555176336746
AUC- Test: 0.8466952338253553
Classification Report - Test               precision    recall  f1-score
support

           0       0.86      0.90      0.88      1318
           1       0.64      0.56      0.60       440

    accuracy                           0.81      1758
   macro avg       0.75      0.73      0.74      1758
weighted avg       0.81      0.81      0.81      1758
```

[11]: Text(0, 0.5, 'TPR')



1 light gbm classifier

Light GBM is a fast, distributed, high-performance gradient boosting framework based on decision tree algorithm, used for ranking, classification and many other machine learning tasks.

Since it is based on decision tree algorithms, it splits the tree leaf wise with the best fit whereas other boosting algorithms split the tree depth wise or level wise rather than leaf-wise. So when growing on the same leaf in Light GBM, the leaf-wise algorithm can reduce more loss than the level-wise algorithm and hence results in much better accuracy which can rarely be achieved by any of the existing boosting algorithms. Also, it is surprisingly very fast, hence the word 'Light'.

2 Advantages of Light GBM

1. Faster training speed and higher efficiency: Light GBM use histogram based algorithm i.e it buckets continuous feature values into discrete bins which fasten the training procedure.
2. Lower memory usage: Replaces continuous values to discrete bins which result in lower memory usage.
3. Better accuracy than any other boosting algorithm: It produces much more complex trees by following leaf wise split approach rather than a level-wise approach which is the main factor in achieving higher accuracy. However, it can sometimes lead to 4. 4. 4. overfitting which can be avoided by setting the max_depth parameter.
4. Compatibility with Large Datasets: It is capable of performing equally good with large datasets with a significant reduction in training time as compared to XGBOOST.
5. Parallel learning supported.

[13]:
```python
import lightgbm as lgb
lgbm = lgb.LGBMClassifier()
```

[17]:
```python
from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import randint as sp_randint
from scipy.stats import uniform as sp_uniform

params = {'n_estimators': sp_randint(50,200),
         'max_depth': sp_randint(2,15),
         'learning_rate': sp_uniform(0.001, 0.5),
         'num_leaves': sp_randint(20,50)}

rsearch = RandomizedSearchCV( lgbm, param_distributions = params, cv=3,␣
 ↪n_iter=100, random_state=3, n_jobs=-1)

rsearch.fit(x,y)
```

[17]:
```
RandomizedSearchCV(cv=3, error_score=nan,
                   estimator=LGBMClassifier(boosting_type='gbdt',
                                            class_weight=None,
                                            colsample_bytree=1.0,
                                            importance_type='split',
                                            learning_rate=0.1, max_depth=-1,
```

```
                                        min_child_samples=20,
                                        min_child_weight=0.001,
                                        min_split_gain=0.0,
                                        n_estimators=100, n_jobs=-1,
                                        num_leaves=31, objective=None,
                                        random_state=None, reg_alpha=0.0,
                                        reg_lambda=0.0, sile…
                                    'max_depth':
<scipy.stats._distn_infrastructure.rv_frozen object at 0x0000023BFE00B240>,
                                    'n_estimators':
<scipy.stats._distn_infrastructure.rv_frozen object at 0x0000023BFE00B0B8>,
                                    'num_leaves':
<scipy.stats._distn_infrastructure.rv_frozen object at 0x0000023BFE00BBA8>},
                   pre_dispatch='2*n_jobs', random_state=3, refit=True,
                   return_train_score=False, scoring=None, verbose=0)
```

[18]:
```
rsearch.best_params_
```

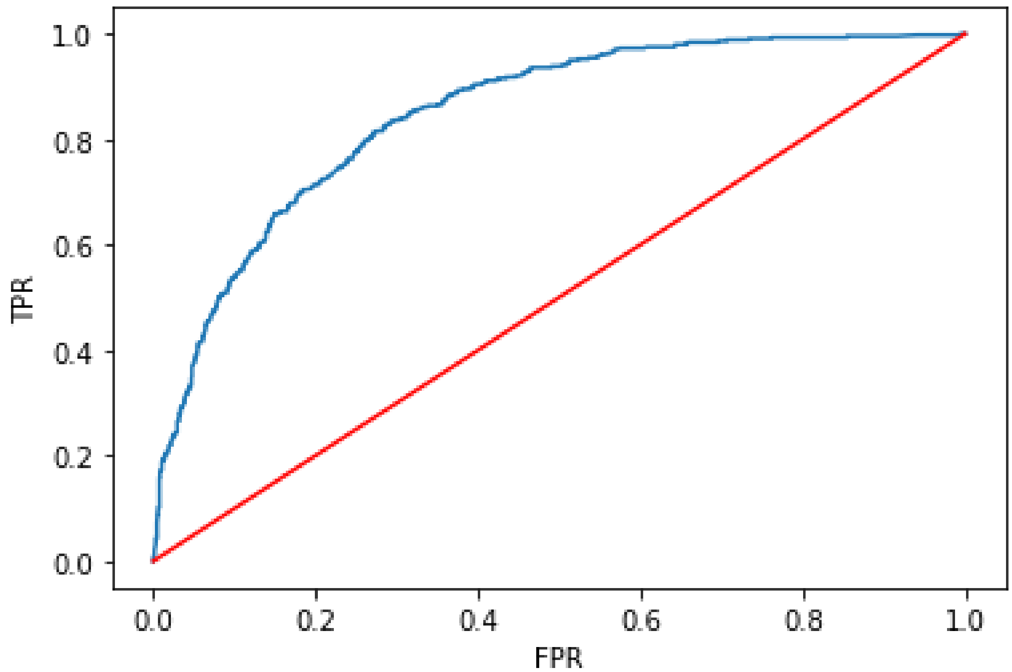
[18]:
```
{'learning_rate': 0.16390357903243724,
 'max_depth': 2,
 'n_estimators': 59,
 'num_leaves': 21}
```

[21]:
```
lgbm=lgb.LGBMClassifier(**rsearch.best_params_)

lgbm.fit(x_train, y_train)

y_train_pred=lgbm.predict(x_train)

y_train_prob=lgbm.predict_proba(x_train)[:,1]

print('Confusion Matrix - Train: ', '\n' ,confusion_matrix(y_train,␣
 ↪y_train_pred))

print('Overall Accuracy - Train: ', accuracy_score(y_train, y_train_pred))

print('AUC- Train:' , roc_auc_score(y_train, y_train_prob))



y_test_pred= lgbm.predict(x_test)

y_test_prob=lgbm.predict_proba(x_test)[:,1]

print('Confusion Matrix - Test: ', '\n' ,confusion_matrix(y_test, y_test_pred))

print('Overall Accuracy - Test: ', accuracy_score(y_test, y_test_pred))
```

```python
print('AUC- Test:' , roc_auc_score(y_test, y_test_prob))

print('Classification Report - Test', classification_report(y_test,␣
 ↪y_test_pred))

fpr, tpr, thresholds =roc_curve(y_test, y_test_prob)
plt.plot(fpr, tpr)
plt.plot(fpr, fpr, 'red')
plt.xlabel('FPR')
plt.ylabel('TPR')
```

```
Confusion Matrix - Train:
 [[3504  341]
 [ 637  792]]
Overall Accuracy - Train:  0.8145620022753128
AUC- Train: 0.8629819246683732
Confusion Matrix - Test:
 [[1187  131]
 [ 204  236]]
Overall Accuracy - Test:  0.8094425483503982
AUC- Test: 0.8478359084011587
Classification Report - Test               precision    recall  f1-score
support

           0       0.85      0.90      0.88      1318
           1       0.64      0.54      0.58       440

    accuracy                           0.81      1758
   macro avg       0.75      0.72      0.73      1758
weighted avg       0.80      0.81      0.80      1758
```

[21]:
```
Text(0, 0.5, 'TPR')
```


1.0
0.8
0.6
0.4
0.2
0.0
TPR
0.0
0.2
0.4
0.6
0.8
1.0
FPR

```
[ ]:
```