XGBoost Model

April 8, 2024

0.1 XGBoost Model

[ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import gc
pd.options.mode.chained_assignment = None

import xgboost as xgb
root = './data/'

from sklearn.model_selection import train_test_split, GridSearchCV,␣
 ↪cross_val_score
from sklearn.metrics import confusion_matrix, accuracy_score,␣
 ↪classification_report
from sklearn.metrics import roc_auc_score, roc_curve, precision_score,␣
 ↪recall_score, f1_score
```

[ ]:
```
df = pd.read_pickle(root + 'Finaldata.pkl')
df.head()
```

[ ]:

	user_id	product_id	total_product_orders_by_user	total_product_reorders_by_user	user_product_reorder_percentage	avg_add_to_cart_by_user	avg_days_since_last_bought	last_ordered_in
0	1	196	10.0	9.0	0.900000	1.400000	17.600000	10.0
1	1	10258	9.0	8.0	0.888889			
2	1	10326	1.0	0.0	0.000000			
3	1	12427	10.0	9.0	0.900000			
4	1	13032	3.0	2.0	0.666667			

```
1                3.333333                   19.555555             10.0
2                5.000000                   28.000000              5.0
3                3.300000                   17.600000             10.0
4                6.333333                   21.666666             10.0

   is_reorder_3  is_reorder_2  …  total_reorders_by_user  \
0           1.0           1.0  …                      41
1           1.0           1.0  …                      41
2           0.0           0.0  …                      41
3           1.0           1.0  …                      41
4           1.0           0.0  …                      41

   reorder_propotion_by_user  average_order_size  reorder_in_order  orders_3  \
0                   0.694915                 5.9          0.705833         6
1                   0.694915                 5.9          0.705833         6
2                   0.694915                 5.9          0.705833         6
3                   0.694915                 5.9          0.705833         6
4                   0.694915                 5.9          0.705833         6

   orders_2  orders_1  reorder_3  reorder_2  reorder_1
0         6         9   0.666667        1.0   0.666667
1         6         9   0.666667        1.0   0.666667
2         6         9   0.666667        1.0   0.666667
3         6         9   0.666667        1.0   0.666667
4         6         9   0.666667        1.0   0.666667

[5 rows x 69 columns]
```

[ ]:
```python
def reduce_memory(df):

    """
    This function reduce the dataframe memory usage by converting it's type for easier handling.

    Parameters: Dataframe
    Return: Dataframe
    """

    start_mem_usg = df.memory_usage().sum() / 1024**2
    print("Memory usage of properties dataframe is :",start_mem_usg," MB")

    for col in df.columns:
        if df[col].dtypes in ["int64", "int32", "int16"]:

            cmin = df[col].min()
            cmax = df[col].max()
```

```
            if cmin > np.iinfo(np.int8).min and cmax < np.iinfo(np.int8).max:
                df[col] = df[col].astype(np.int8)

            elif cmin > np.iinfo(np.int16).min and cmax < np.iinfo(np.int16).
↪max:
                df[col] = df[col].astype(np.int16)

            elif cmin > np.iinfo(np.int32).min and cmax < np.iinfo(np.int32).
↪max:
                df[col] = df[col].astype(np.int32)

        if df[col].dtypes in ["float64", "float32"]:

            cmin = df[col].min()
            cmax = df[col].max()

            if cmin > np.finfo(np.float16).min and cmax < np.finfo(np.float16).
↪max:
                df[col] = df[col].astype(np.float16)

            elif cmin > np.finfo(np.float32).min and cmax < np.finfo(np.
↪float32).max:
                df[col] = df[col].astype(np.float32)

    print("")
    print("___MEMORY USAGE AFTER COMPLETION:___")
    mem_usg = df.memory_usage().sum() / 1024**2
    print("Memory usage is: ",mem_usg," MB")
    print("This is ",100*mem_usg/start_mem_usg,"% of the initial size")

    return df
```

[ ]:
```
df = reduce_memory(df)
```

```
Memory usage of properties dataframe is : 4315.823656082153  MB

___MEMORY USAGE AFTER COMPLETION:___
Memory usage is:  1163.8177070617676  MB
This is  26.96629426509668 % of the initial size
```

[ ]:
```
df['order_diff'] = df.order_number - df.last_ordered_in
df.drop(['user_id', 'product_id'], axis = 1, inplace = True)
```

[ ]:
```
df.head()
```

[ ]:
```
   total_product_orders_by_user  total_product_reorders_by_user  \
0                          10.0                             9.0
```

```
1                          9.0                             8.0
2                          1.0                             0.0
3                         10.0                             9.0
4                          3.0                             2.0

   user_product_reorder_percentage  avg_add_to_cart_by_user  \
0                         0.899902                 1.400391
1                         0.888672                 3.333984
2                         0.000000                 5.000000
3                         0.899902                 3.300781
4                         0.666504                 6.332031

   avg_days_since_last_bought  last_ordered_in  is_reorder_3  is_reorder_2  \
0                   17.593750            10.0           1.0           1.0
1                   19.562500            10.0           1.0           1.0
2                   28.000000             5.0           0.0           0.0
3                   17.593750            10.0           1.0           1.0
4                   21.671875            10.0           1.0           0.0

   is_reorder_1  order_number  …  reorder_propotion_by_user  \
0           1.0          11.0  …                   0.694824
1           1.0          11.0  …                   0.694824
2           0.0          11.0  …                   0.694824
3           1.0          11.0  …                   0.694824
4           0.0          11.0  …                   0.694824

   average_order_size  reorder_in_order  orders_3  orders_2  orders_1  \
0            5.898438          0.706055         6         6         9
1            5.898438          0.706055         6         6         9
2            5.898438          0.706055         6         6         9
3            5.898438          0.706055         6         6         9
4            5.898438          0.706055         6         6         9

   reorder_3  reorder_2  reorder_1  order_diff
0   0.666504        1.0   0.666504         1.0
1   0.666504        1.0   0.666504         1.0
2   0.666504        1.0   0.666504         6.0
3   0.666504        1.0   0.666504         1.0
4   0.666504        1.0   0.666504         1.0

[5 rows x 68 columns]
```

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

[ ]:
```
(8474661, 68)
```

[ ]:
```
label = 'reordered'
x_cols = df.columns.drop('reordered')
```

[ ]:
```
X = df[x_cols]
y = df[label]
```

[ ]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, stratify = y,␣
 ↪test_size = 0.25)

print(X_train.shape, y_train.shape)
print(X_test.shape, y_test.shape)
```

```
(6355995, 67) (6355995,)
(2118666, 67) (2118666,)
```

[ ]:
```
y_train.value_counts()
```

[ ]:
```
reordered
0.0    5734377
1.0     621618
Name: count, dtype: int64
```

[ ]:
```
np.ceil(y_train.value_counts()[0]/y_train.value_counts()[1])
```

[ ]:
```
10.0
```

[ ]:
```
y_test.value_counts()
```

[ ]:
```
reordered
0.0    1911460
1.0     207206
Name: count, dtype: int64
```

0.1.1 XGBoost Model

[ ]:
```
D_train = xgb.DMatrix(X_train, label=y_train)
D_test = xgb.DMatrix(X_test, label=y_test)
```

[ ]:
```
xgb_params = {
    "objective"        :"reg:logistic",
    "eval_metric"      :"logloss",
    "eta"              :0.1,
    "max_depth"        :6,
    "min_child_weight" :10,
    "gamma"            :0.70,
    "subsample"        :0.76,
    "colsample_bytree" :0.95,
    "alpha"            :2e-05,
```

```
    "scale_pos_weight" :10,
    "lambda"           :10
}
```

[ ]:
```
watchlist= [(D_train, "train")]
model = xgb.train(params=xgb_params, dtrain=D_train, num_boost_round = 80,␣
 ↪evals = watchlist, verbose_eval = 10)
```

```
[0]     train-logloss:0.69455
[10]    train-logloss:0.56348
[20]    train-logloss:0.53676
[30]    train-logloss:0.52884
[40]    train-logloss:0.52548
[50]    train-logloss:0.52364
[60]    train-logloss:0.52255
[70]    train-logloss:0.52192
[79]    train-logloss:0.52134
```

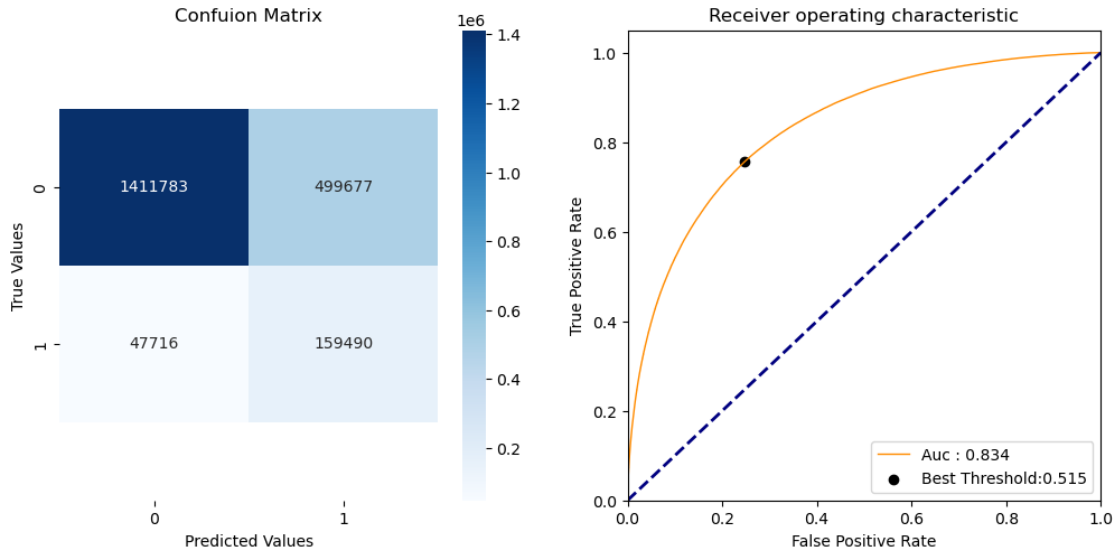
[ ]:
```
probability = model.predict(D_test)
```

[ ]:
```
predictions = [1 if i > 0.5 else 0 for i in probability]
```

[ ]:
```
print ("\n Classification report : \n",classification_report(y_test,␣
 ↪predictions))
print ("Accuracy   Score : ",accuracy_score(y_test, predictions))

#confusion matrix
conf_matrix = confusion_matrix(y_test,predictions)
plt.figure(figsize=(12,12))
plt.subplot(221)
sns.heatmap(conf_matrix, fmt = "d",annot=True, cmap='Blues')
b, t = plt.ylim()
plt.ylim(b + 0.5, t - 0.5)
plt.title('Confuion Matrix')
plt.ylabel('True Values')
plt.xlabel('Predicted Values')

#f1-score
f1 = f1_score(y_test, predictions)
print("F1 Score: ", f1)

#roc_auc_score
model_roc_auc = roc_auc_score(y_test,probability)
print ("Area under curve : ",model_roc_auc,"\n")
fpr,tpr,thresholds = roc_curve(y_test,probability)
gmeans = np.sqrt(tpr * (1-fpr))
ix = np.argmax(gmeans)
threshold = np.round(thresholds[ix],3)
```

```
plt.subplot(222)
plt.plot(fpr, tpr, color='darkorange', lw=1, label = "Auc : %.3f"␣
 ↪%model_roc_auc)
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.scatter(fpr[ix], tpr[ix], marker='o', color='black', label='Best Threshold:
 ↪' + str(threshold))
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic')
plt.legend(loc="lower right")

plt.show()
```

```
 Classification report :
              precision    recall  f1-score   support

         0.0       0.97      0.74      0.84   1911460
         1.0       0.24      0.77      0.37    207206

    accuracy                           0.74   2118666
   macro avg       0.60      0.75      0.60   2118666
weighted avg       0.90      0.74      0.79   2118666

Accuracy   Score :  0.741633178613335
F1 Score:  0.36817860205708164
Area under curve :  0.833847909809814
```



[ ]:
```
fig, ax = plt.subplots(figsize = (10,15))
xgb.plot_importance(model, ax = ax)
fig.savefig('XGBoost Feature Importance Plot.png')
```