Cancel or Not

Import tools

```
import pandas as pd                                # basic data tools
import numpy as np
from sklearn.preprocessing import LabelEncoder     # reprocessing tools
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import GridSearchCV   # model selection
from sklearn import model_selection
from sklearn import metrics
import joblib                                      # model saving
import datetime
from sklearn.linear_model import LogisticRegression #Models:# # LogisticRegression
from sklearn.ensemble import RandomForestClassifier         # # Random Forest
import lightgbm as lgbm                                     # # LightGBM
from xgboost import XGBClassifier                           # # XGBoost
import seaborn as sns                              # plotting
from matplotlib.pyplot import savefig
from matplotlib.pyplot import axes
from matplotlib import pyplot as plt
```

Accessing data:

```
# df = pd.read_csv('../data/hotel_bookings.csv')
train = pd.read_csv('../data/train.csv') # pre-splited dataset in previous work
test = pd.read_csv('../data/test.csv')

# Extra features spreadsheet for hepling understanding
features = pd.read_csv('../data/feature_description.csv', header=None)
features.columns = ['feature', 'description']
```

Cleaning, Exploration and Basic Feature Engineering

Task alread done, see `part1.ipynb` if needed.

Preparation

Check features:

```
# show features
pd.set_option("display.max_colwidth", 200)
pd.merge(features, train.describe().T, left_on='feature', right_index=True, how="right")
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	feature	description	count	mean	std	min	25%	50%	75
1	is_canceled	order canceled (1) or not (0)	95512.0	0.370414	0.482918	0.00	0.0000	0.0	1.0
2	lead_time	Number of days that elapsed between the entering date of the booking into the PMS and the arrival date	95512.0	104.151583	106.821437	0.00	18.0000	69.0	160.
5	arrival_date_week_number	Week number of year for arrival date	95512.0	27.171047	13.593740	1.00	16.0000	28.0	38.0
6	arrival_date_day_of_month	Day of arrival date	95512.0	15.797041	8.785365	1.00	8.0000	16.0	23.0
7	stays_in_weekend_nights	Number of weekend nights (Saturday or Sunday) the guest stayed or booked to stay at the hotel	95512.0	0.927852	0.997446	0.00	0.0000	1.0	2.0
8	stays_in_week_nights	Number of week nights (Monday to Friday) the guest stayed or booked to stay at the hotel	95512.0	2.500806	1.905649	0.00	1.0000	2.0	3.0
9	adults	Number of adults	95512.0	1.856866	0.594198	0.00	2.0000	2.0	2.0
10	children	Number of children	95512.0	0.104175	0.399210	0.00	0.0000	0.0	0.0
11	babies	Number of babies	95512.0	0.008020	0.094440	0.00	0.0000	0.0	0.0
16	is_repeated_guest	Value indicating if the booking name was from a repeated guest (1) or not (0)	95512.0	0.031640	0.175041	0.00	0.0000	0.0	0.0
17	previous_cancellations	Number of previous bookings that were cancelled by the customer prior to the current booking	95512.0	0.086617	0.830586	0.00	0.0000	0.0	0.0
18	previous_bookings_not_canceled	Number of previous bookings not cancelled by the customer prior to the current booking	95512.0	0.139899	1.546800	0.00	0.0000	0.0	0.0
21	booking_changes	Number of changes/amendments made to the booking from the moment the booking was entered on the PMS until the moment of check-in or cancellation	95512.0	0.219972	0.649299	0.00	0.0000	0.0	0.0
23	agent	ID of the travel agency that made the booking	82419.0	86.795436	110.798087	1.00	9.0000	14.0	229.
24	company	ID of the company/entity that made the booking or responsible for paying the booking. ID is presented instead of designation for anonymity reasons	5454.0	189.881371	132.301220	6.00	62.0000	179.0	270.
25	days_in_waiting_list	Number of days the booking was in the waiting list before it was confirmed to the customer	95512.0	2.307710	17.414238	0.00	0.0000	0.0	0.0

	feature	description	count	mean	std	min	25%	50%	75
27	adr	Average Daily Rate as defined by dividing the sum of all lodging transactions by the total number of staying nights	95512.0	101.871490	51.137746	-6.38	69.0075	95.0	126.
28	required_car_parking_spaces	Number of car parking spaces required by the customer	95512.0	0.062149	0.245172	0.00	0.0000	0.0	0.0
29	total_of_special_requests	Number of special requests made by the customer (e.g. twin bed or high floor)	95512.0	0.572525	0.793103	0.00	0.0000	0.0	1.0

Use plain integer to encode categrical features according to official documentation and explicit explanation in sector Parameters.

Preprocessing

Encoding categorical features:

```
categoricals = [
    'hotel',
    'arrival_date_month',
    'meal',
    'country',
    'market_segment',
    'distribution_channel',
    'reserved_room_type',
    'assigned_room_type',
    'deposit_type',
    'agent',
    'company',
    'customer_type',
]

df = train.append(test) # construct a full dataframe for consistent encoding
df = df.fillna('0')
df['children'] = df['children'].astype(int) # type convertting
df_cat_tmp = df[categoricals].astype(str).apply(LabelEncoder().fit_transform) # encode cat columns
# df_encoded = pd.merge(df.drop(categoricals, axis=1), df_cat_tmp, left_index=True, right_index=True) # merge numeric and encoded cat columns
df[categoricals] = df_cat_tmp[categoricals].astype(int) # merge numeric and encoded cat columns
train_encoded = df.iloc[:len(train)]
test_encoded = df.iloc[len(train):]
```

Splitting encoded dataset:

```
target = 'is_canceled' # splitting features and target

X_train, X_test = train_encoded.drop(target, axis=1), test_encoded.drop(target, axis=1)
y_train, y_test = train_encoded[target], test_encoded[target]
```

Standarzation (note that categorical features ignored due to model requirements):

```
X_num_train, X_num_test = X_train.drop(categoricals, axis=1),  X_test.drop(categoricals, axis=1) # extracting numerical features

# scaling
scaler = StandardScaler()
scaler.fit(X_num_train)
scaled_features_train = scaler.transform(X_num_train)
scaled_features_test = scaler.transform(X_num_test)

# merge numeric & categorical features
scaled_features_df_train = pd.DataFrame(scaled_features_train, index=X_num_train.index, columns=X_num_train.columns)
scaled_features_df_test = pd.DataFrame(scaled_features_test, index=X_num_test.index, columns=X_num_test.columns)

# create standerized dataframes
X_train_std = pd.merge(X_train[categoricals], scaled_features_df_train, left_index=True, right_index=True)
X_test_std = pd.merge(X_test[categoricals], scaled_features_df_test, left_index=True, right_index=True)
```

Modelling

Define a cutomized DridSearchCV function for convinience:

```
def algorithm_pipeline(model, \
```

```
                      param_grid, \
                      X_train_data = X_train_std, \
                      X_test_data = X_test_std, \
                      y_train_data = y_train, \
                      y_test_data = y_test, \
                      cv=10, \
                      scoring_fit='accuracy',
                      do_probabilities = False):

    gs = GridSearchCV(
        estimator=model,
        param_grid=param_grid,
        cv=cv,
        n_jobs=-1,
        scoring=scoring_fit,
        verbose=2,
        refit=True # return the best refitted model
    )

    fitted_model = gs.fit(X_train_data, y_train_data)

    if do_probabilities:
      y_pred = fitted_model.predict_proba(X_test_data)
    else:
      y_pred = fitted_model.predict(X_test_data)

    return fitted_model, y_pred
```

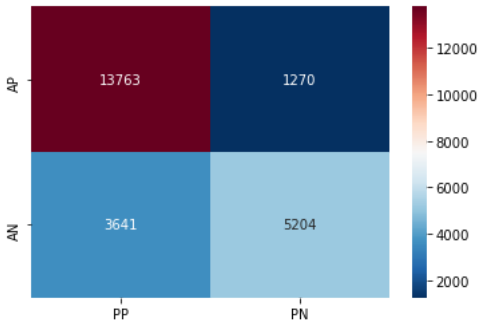
1. Logistic Regrssion (baseline)

```
lr = LogisticRegression(penalty='l2', max_iter=7600)
lr = lr.fit(X_train, y_train)
```

```
y_pred = lr.predict(X_test)
print(f'Train(accuracy): {lr.score(X_train, y_train).round(5)}')
print(f'Test(accuracy): {lr.score(X_test, y_test).round(5)}\n')
print(metrics.classification_report(y_test, y_pred))

cm_matrix = pd.DataFrame(data=metrics.confusion_matrix(y_test, y_pred), columns=['PP', 'PN'], index=['AP', 'AN'])
cm_plot = sns.heatmap(cm_matrix, annot=True, fmt='d', cmap='RdBu_r') # visualize confusion matrix with seaborn heatmap
cm_plot
```

```
Train(accuracy): 0.79377
Test(accuracy): 0.79433

              precision    recall  f1-score   support

           0       0.79      0.92      0.85     15033
           1       0.80      0.59      0.68      8845

    accuracy                           0.79     23878
   macro avg       0.80      0.75      0.76     23878
weighted avg       0.80      0.79      0.79     23878
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x1ac18372448>
```




```
clf = lr
now = datetime.datetime.now()
file_name = "../models/LogisticRegression_" + now.strftime("%m%d%H%M")

# save parameters
with open(f"{file_name}_{gs.best_score_.round(4)*100}%.txt", "w") as para_file:
```

```
    para_file.write(str(gs.best_params_))
    print(gs.best_params_)

# save figure
cm_plot.get_figure().savefig(file_name + ".png")

# save model
joblib.dump(clf, file_name + ".model")

# use this to load a saved model
# lgbm_loded = joblib.load('.model')
```

```
{'boosting': 'dart', 'feature_fraction': 0.7, 'lambda_l2': 0.1, 'max_depth': 25, 'min_split_gain': 0.1, 'n_estimators': 3000,
'num_leaves': 100, 'objective': 'binary'}
```

```
['../models/LogisticRegression_04161442.model']
```

2. Random Forest (baseline)

Fit the training set:

```
# feat_labels = X_train.columns
# X_train = X_train[feat_labels]
forest = RandomForestClassifier(n_estimators = 100, max_depth = 25, n_jobs = -1,
                                random_state = 0, bootstrap = True)
forest.fit(X_train, y_train)
```

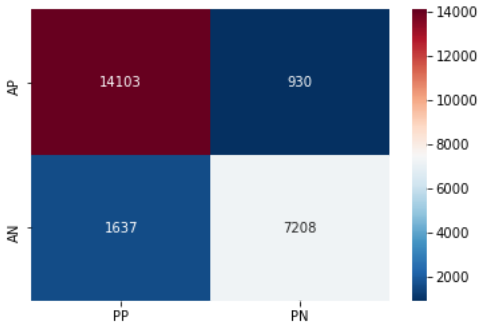
```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None,
                       criterion='gini', max_depth=25, max_features='auto',
                       max_leaf_nodes=None, max_samples=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=100,
                       n_jobs=-1, oob_score=False, random_state=0, verbose=0,
                       warm_start=False)
```

Prediction and result:

```
y_pred = forest.predict(X_test)
print(f'Train(accuracy): {forest.score(X_train, y_train).round(5)}')
print(f'Test(accuracy): {forest.score(X_test, y_test).round(5)}\n')
print(metrics.classification_report(y_test, y_pred))

cm_matrix = pd.DataFrame(data=metrics.confusion_matrix(y_test, y_pred), columns=['PP', 'PN'], index=['AP', 'AN'])
cm_plot = sns.heatmap(cm_matrix, annot=True, fmt='d', cmap='RdBu_r') # visualize confusion matrix with seaborn heatmap
cm_plot
```

```
Train(accuracy): 0.97796
Test(accuracy): 0.8925

              precision    recall  f1-score   support

           0       0.90      0.94      0.92     15033
           1       0.89      0.81      0.85      8845

    accuracy                           0.89     23878
   macro avg       0.89      0.88      0.88     23878
weighted avg       0.89      0.89      0.89     23878
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x1405cbe3188>
```



Feature importance:

```
importances = forest.feature_importances_
feat_labels = X_train.columns
indices = np.argsort(importances)[::-1]
for f in range(X_train.shape[1]):
     print("%2d) %-*s %f" % (f + 1, 30,
                             feat_labels[f],
                             importances[indices[f]]))
```

```
 1) hotel                          0.146114
 2) lead_time                      0.120920
 3) arrival_date_month             0.115639
 4) arrival_date_week_number       0.068819
 5) arrival_date_day_of_month      0.062851
 6) stays_in_weekend_nights        0.059945
 7) stays_in_week_nights           0.046318
 8) adults                         0.045873
 9) children                       0.044790
10) babies                         0.035386
11) meal                           0.030336
12) country                        0.026822
13) market_segment                 0.026390
14) distribution_channel           0.025442
15) is_repeated_guest              0.024904
16) previous_cancellations         0.022886
17) previous_bookings_not_canceled 0.019146
18) reserved_room_type             0.014447
19) assigned_room_type             0.011666
20) booking_changes                0.011630
21) deposit_type                   0.010561
22) agent                          0.009580
23) company                        0.005719
24) days_in_waiting_list           0.004627
25) customer_type                  0.004015
26) adr                            0.002204
27) required_car_parking_spaces    0.002110
28) total_of_special_requests      0.000859
```

Save:

```
clf = forest
now = datetime.datetime.now()
file_name = "../models/RandomForest_" + now.strftime("%m%d%H%M")

# save parameters
with open(f"{file_name}_{gs.best_score_.round(4)*100}%.txt", "w") as para_file:
    para_file.write(str(gs.best_params_))
    print(gs.best_params_)

# save figure
cm_plot.get_figure().savefig(file_name + ".png")

# save model
joblib.dump(clf, file_name + ".model")

# use this to load a saved model
# lgbm_loded = joblib.load('.model')
```

```
{'colsample_bytree': 0.7, 'max_depth': 50, 'n_estimators': 100, 'reg_alpha': 1.3, 'reg_lambda': 1.1, 'subsample': 0.9}
```

```
['../models/RandomForest_04160226.model']
```

3. LightGBM

A fast, distributed, high performance gradient boosting (GBT, GBDT, GBRT, GBM or MART) framework based on decision tree algorithms, used for ranking, classification and many other machine learning tasks.

GitHub | Documentation | Parameter Tuning (official tutorial)

```
# !pip install lightgbm # if not installed
lgbmclf = lgbm.LGBMClassifier()
param_grid = {
#     'objective':['binary','cross_entropy'],
    'objective':['binary'],
    'boosting':['gbdt', 'dart'],
#     'boosting':['dart'],
    'n_estimators': [3000],
    'num_leaves': [25, 50, 100],
#     'min_data_in_leaf':[]
    'max_depth': [10, 25],
#     'reg_alpha': [1.1, 1.3],
#     'reg_lambda': [1.1, 1.3],
    'lambda_l2': [0.1, 0.3],
    'min_split_gain': [0.1, 0.3],
    'feature_fraction': [0.5, 0.7],
#     'subsample': [0.7, 0.9],
#     'subsample_freq': [20]
#     'max_bin': [100, 150]
}
gs, pred = algorithm_pipeline(lgbmclf, param_grid, cv=3) # some parameters already define above, see function algorithm_pipeline()
print(gs.best_score_)
print(gs.best_params_)
```

```
Fitting 3 folds for each of 96 candidates, totalling 288 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 6 concurrent workers.
[Parallel(n_jobs=-1)]: Done  29 tasks      | elapsed:  1.1min
[Parallel(n_jobs=-1)]: Done 150 tasks      | elapsed: 14.9min
[Parallel(n_jobs=-1)]: Done 288 out of 288 | elapsed: 205.9min finished
```

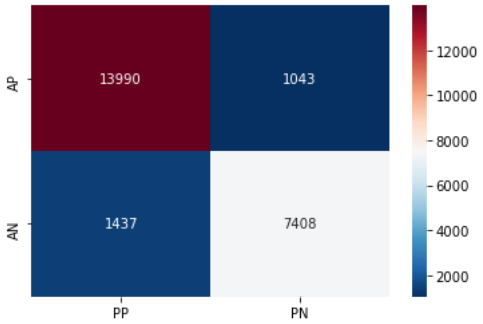
```
0.8903593200853003
{'boosting': 'dart', 'feature_fraction': 0.7, 'lambda_l2': 0.1, 'max_depth': 25, 'min_split_gain': 0.1, 'n_estimators': 3000,
'num_leaves': 100, 'objective': 'binary'}
```

Prediction and result:

```
clf = gs.best_estimator_
clf.fit(X_train, y_train)
print(f'Train(accuracy): {clf.score(X_train, y_train).round(5)}') # Python >= 3.7
print(f'Test(accuracy): {clf.score(X_test, y_test).round(5)}\n')
y_pred = clf.predict(X_test)
print(metrics.classification_report(y_test, y_pred))

cm_matrix = pd.DataFrame(data=metrics.confusion_matrix(y_test, y_pred), columns=['PP', 'PN'], index=['AP', 'AN'])
cm_plot = sns.heatmap(cm_matrix, annot=True, fmt='d', cmap='RdBu_r') # visualize confusion matrix with seaborn heatmap
cm_plot
```

```
Train(accuracy): 0.98896
Test(accuracy): 0.89614

              precision    recall  f1-score   support

           0       0.91      0.93      0.92     15033
           1       0.88      0.84      0.86      8845

    accuracy                           0.90     23878
   macro avg       0.89      0.88      0.89     23878
weighted avg       0.90      0.90      0.90     23878
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x1ac5f715f48>
```



Dump the model to file for persistence:

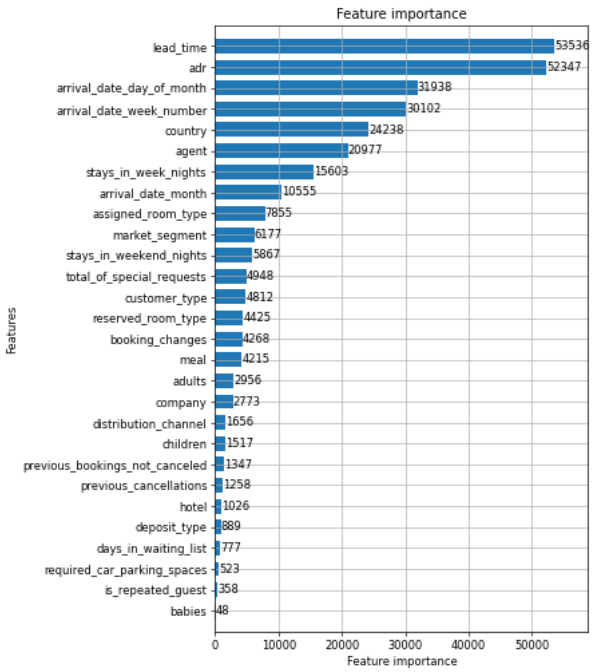
```
now = datetime.datetime.now()
file_name = "../models/LightGBM_" + now.strftime("%m%d%H%M")

# save parameters
with open(f"{file_name}_{gs.best_score_.round(4)*100}%.txt", "w") as para_file:
    para_file.write(str(gs.best_params_))
    print(gs.best_params_)

# save figure
cm_plot.get_figure().savefig(file_name + ".png")

# save model
joblib.dump(clf, file_name + ".model")

# use this to load a saved model
# lgbm_loded = joblib.load('.model')
```

```
{'boosting': 'dart', 'feature_fraction': 0.7, 'lambda_l2': 0.1, 'max_depth': 25, 'min_split_gain': 0.1, 'n_estimators': 3000,
'num_leaves': 100, 'objective': 'binary'}
```

```
['../models/LightGBM_04161347.model']
```

```
lgbm.plot_importance(clf, height = 0.7, figsize = (6, 10), dpi = 60)
```

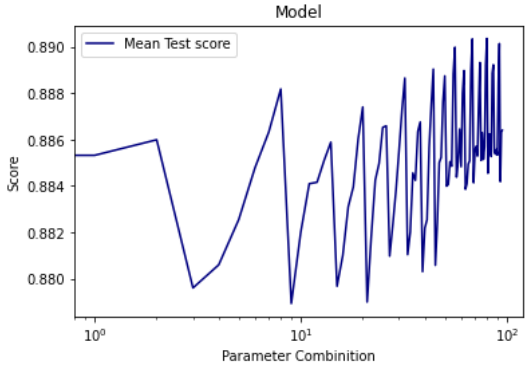
```
<matplotlib.axes._subplots.AxesSubplot at 0x1ac71de8c88>
```



```
# !pip install graphviz
# lgbm.plot_tree(clf, figsize = (6, 10), dpi = 60)
```

```
Collecting graphviz
  Downloading graphviz-0.13.2-py2.py3-none-any.whl (17 kB)
Installing collected packages: graphviz
Successfully installed graphviz-0.13.2
```

```
# train_scores_mean = gs.cv_results_["mean_train_score"]
# train_scores_std = gs.cv_results_["std_train_score"]
test_scores_mean = gs.cv_results_["mean_test_score"]
test_scores_std = gs.cv_results_["std_test_score"]
params = range(len(gs.cv_results_["params"]))

plt_cv = plt.figure()
plt.title('Model')
plt.xlabel('Parameter Combinition')
plt.ylabel('Score')
# plot train scores
plt.semilogx(params, test_scores_mean, label='Mean Test score',
             color='navy')
plt.legend(loc='best')
plt.show()
plt_cv.savefig(file_name + "_cvresult.png")
```



4. XGBoost

XGBoost - Extreme Gradient Boosting, which is an efficient implementation of the gradient boosting framework from Chen & Guestrin (2016) doi:10.1145/2939672.2939785.

Github | Documentation | Parameter Tuning (official tutorial)

Parameter tuning using GS

```
xgb = XGBClassifier()
param_grid = {
    'n_estimators': [50, 100, 500],
    'colsample_bytree': [0.7, 0.8],
    'max_depth': [5, 15, 25, 50],
    'reg_alpha': [1.1, 1.3],
    'reg_lambda': [1.1, 1.3],
    'subsample': [0.7, 0.9],
#      'tree_method':['gpu_hist'],
#      'gpu_id':[1]
}
gs, pred = algorithm_pipeline(xgb, param_grid, cv=3)
print(gs.best_score_)
print(gs.best_params_)
```

```
Fitting 3 folds for each of 192 candidates, totalling 576 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 6 concurrent workers.
[Parallel(n_jobs=-1)]: Done  29 tasks      | elapsed:   31.0s
[Parallel(n_jobs=-1)]: Done 150 tasks      | elapsed: 16.3min
[Parallel(n_jobs=-1)]: Done 353 tasks      | elapsed: 47.1min
[Parallel(n_jobs=-1)]: Done 576 out of 576 | elapsed: 91.7min finished
```

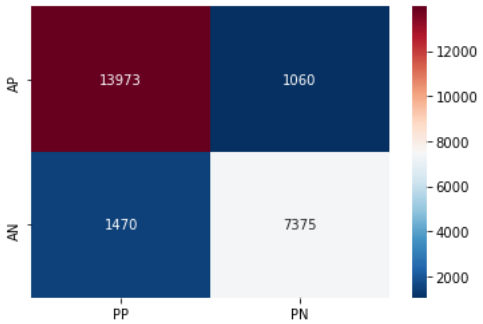
```
0.8873858846569945
{'colsample_bytree': 0.7, 'max_depth': 50, 'n_estimators': 100, 'reg_alpha': 1.3, 'reg_lambda': 1.1, 'subsample': 0.9}
```

Prediction and result:

```
clf = gs.best_estimator_
clf.fit(X_train, y_train)
print(f'Train(accuracy): {clf.score(X_train, y_train).round(5)}') # Python >= 3.7
print(f'Test(accuracy): {clf.score(X_test, y_test).round(5)}\n')
y_pred = clf.predict(X_test)
print(metrics.classification_report(y_test, y_pred))

cm_matrix = pd.DataFrame(data=metrics.confusion_matrix(y_test, y_pred), columns=['PP', 'PN'], index=['AP', 'AN'])
cm_plot = sns.heatmap(cm_matrix, annot=True, fmt='d', cmap='RdBu_r') # visualize confusion matrix with seaborn heatmap
cm_plot
```

```
Train(accuracy): 0.99574
Test(accuracy): 0.89404

              precision    recall  f1-score   support

           0       0.90      0.93      0.92     15033
           1       0.87      0.83      0.85      8845

    accuracy                           0.89     23878
   macro avg       0.89      0.88      0.89     23878
weighted avg       0.89      0.89      0.89     23878
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x1405e6b0248>
```



Dumping to file:

```
now = datetime.datetime.now()
file_name = "../models/XGBoost_" + now.strftime("%m%d%H%M")

# save parameters
with open(f"{file_name}_{gs.best_score_.round(4)*100}%.txt", "w") as para_file:
    para_file.write(str(gs.best_params_))
    print(gs.best_params_)

# save figure
cm_plot.get_figure().savefig(file_name + ".png")

# save model
joblib.dump(clf, file_name + ".model")

# use this to load a saved model
# lgbm_loded = joblib.load('.model')
```

```
{'colsample_bytree': 0.7, 'max_depth': 50, 'n_estimators': 100, 'reg_alpha': 1.3, 'reg_lambda': 1.1, 'subsample': 0.9}
```

```
['../models/XGBoost_04160226.model']
```