Code AXA

October 23, 2024

[1]:
```python
# Importing libraries

import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

[2]:
```python
# Load the dataset

file_path = 'depression_data.csv'
depression_data = pd.read_csv(file_path)
```

[3]:
```python
# Display the first few rows of the dataset to understand its structure
depression_data.head()
```

[3]:
```
                Name  Age Marital Status    Education Level  \
0  Christine Barker   31        Married  Bachelor's Degree
1  Jacqueline Lewis   55        Married        High School
2    Shannon Church   78        Widowed    Master's Degree
3    Charles Jordan   58       Divorced    Master's Degree
4      Michael Rich   18         Single        High School

   Number of Children Smoking Status Physical Activity Level  \
0                   2     Non-smoker                  Active
1                   1     Non-smoker               Sedentary
2                   1     Non-smoker               Sedentary
3                   3     Non-smoker                Moderate
4                   0     Non-smoker               Sedentary

  Employment Status     Income Alcohol Consumption Dietary Habits  \
0        Unemployed   26265.67            Moderate       Moderate
1          Employed   42710.36                High      Unhealthy
2          Employed  125332.79                 Low      Unhealthy
3        Unemployed    9992.78            Moderate       Moderate
4        Unemployed    8595.08                 Low       Moderate

  Sleep Patterns History of Mental Illness History of Substance Abuse  \
```

```
0          Fair                        Yes                         No
1          Fair                        Yes                         No
2          Good                         No                         No
3          Poor                         No                         No
4          Fair                        Yes                         No

  Family History of Depression Chronic Medical Conditions
0                          Yes                        Yes
1                           No                        Yes
2                          Yes                         No
3                           No                         No
4                          Yes                        Yes
```

[4]:

```python
# Basic statistics and missing values check
summary_stats = depression_data.describe(include='all')
print(summary_stats)
```

```
                 Name            Age Marital Status    Education Level  \
count          413768  413768.000000         413768             413768
unique         196851            NaN              4                  5
top     Michael Smith            NaN        Married  Bachelor's Degree
freq              198            NaN         240444             124329
mean              NaN      49.000713            NaN                NaN
std               NaN      18.158759            NaN                NaN
min               NaN      18.000000            NaN                NaN
25%               NaN      33.000000            NaN                NaN
50%               NaN      49.000000            NaN                NaN
75%               NaN      65.000000            NaN                NaN
max               NaN      80.000000            NaN                NaN

        Number of Children Smoking Status Physical Activity Level  \
count        413768.000000         413768                  413768
unique                 NaN              3                       3
top                    NaN     Non-smoker               Sedentary
freq                   NaN         247416                  176850
mean              1.298972            NaN                     NaN
std               1.237054            NaN                     NaN
min               0.000000            NaN                     NaN
25%               0.000000            NaN                     NaN
50%               1.000000            NaN                     NaN
75%               2.000000            NaN                     NaN
max               4.000000            NaN                     NaN

       Employment Status         Income Alcohol Consumption Dietary Habits  \
count             413768  413768.000000              413768         413768
unique                 2            NaN                   3              3
top             Employed            NaN            Moderate      Unhealthy
freq              265659            NaN              173440         170817
```

```
mean                NaN    50661.707971                NaN              NaN
std                 NaN    40624.100565                NaN              NaN
min                 NaN        0.410000                NaN              NaN
25%                 NaN    21001.030000                NaN              NaN
50%                 NaN    37520.135000                NaN              NaN
75%                 NaN    76616.300000                NaN              NaN
max                 NaN   209995.220000                NaN              NaN

       Sleep Patterns History of Mental Illness History of Substance Abuse  \
count          413768                    413768                     413768
unique              3                         2                          2
top              Fair                        No                         No
freq           196789                    287943                     284880
mean              NaN                       NaN                        NaN
std               NaN                       NaN                        NaN
min               NaN                       NaN                        NaN
25%               NaN                       NaN                        NaN
50%               NaN                       NaN                        NaN
75%               NaN                       NaN                        NaN
max               NaN                       NaN                        NaN

       Family History of Depression Chronic Medical Conditions
count                        413768                     413768
unique                            2                          2
top                              No                         No
freq                         302515                     277561
mean                            NaN                        NaN
std                             NaN                        NaN
min                             NaN                        NaN
25%                             NaN                        NaN
50%                             NaN                        NaN
75%                             NaN                        NaN
max                             NaN                        NaN
```

[5]:

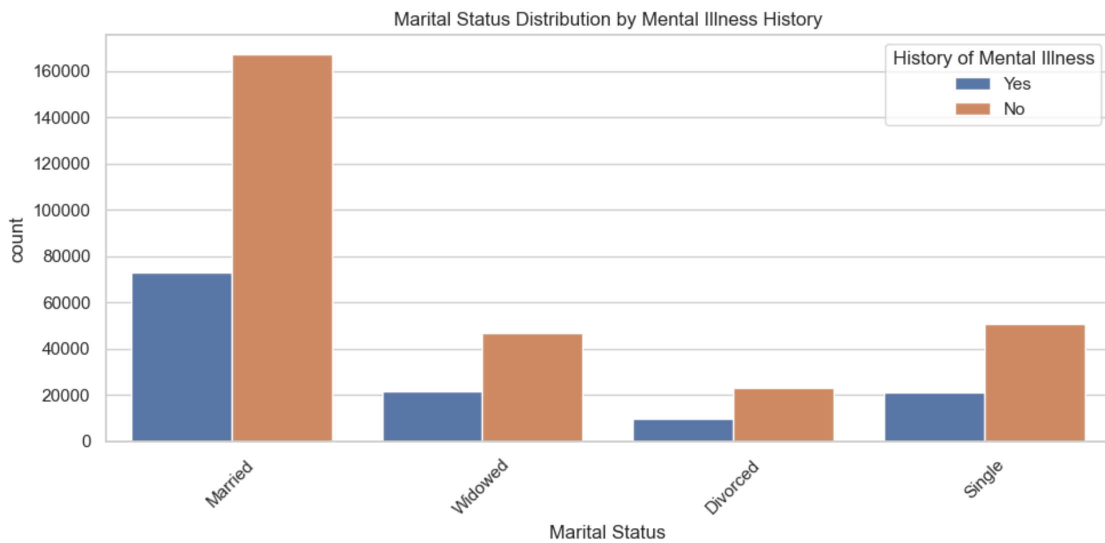
```python
# Check for missing values
missing_values = depression_data.isnull().sum()
print(missing_values)
```

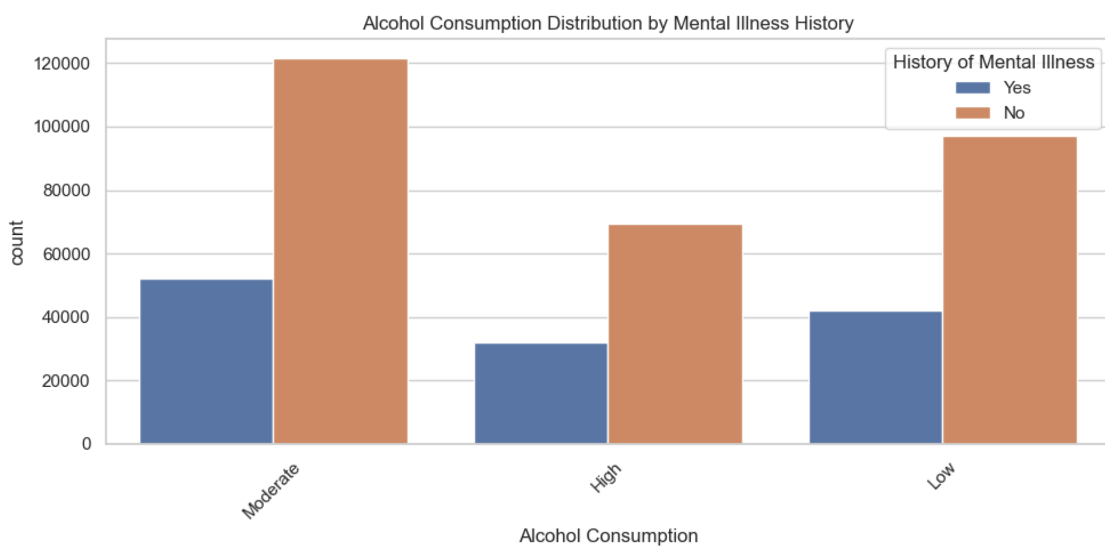
```
Name                            0
Age                             0
Marital Status                  0
Education Level                 0
Number of Children              0
Smoking Status                  0
Physical Activity Level         0
Employment Status               0
Income                          0
Alcohol Consumption             0
```

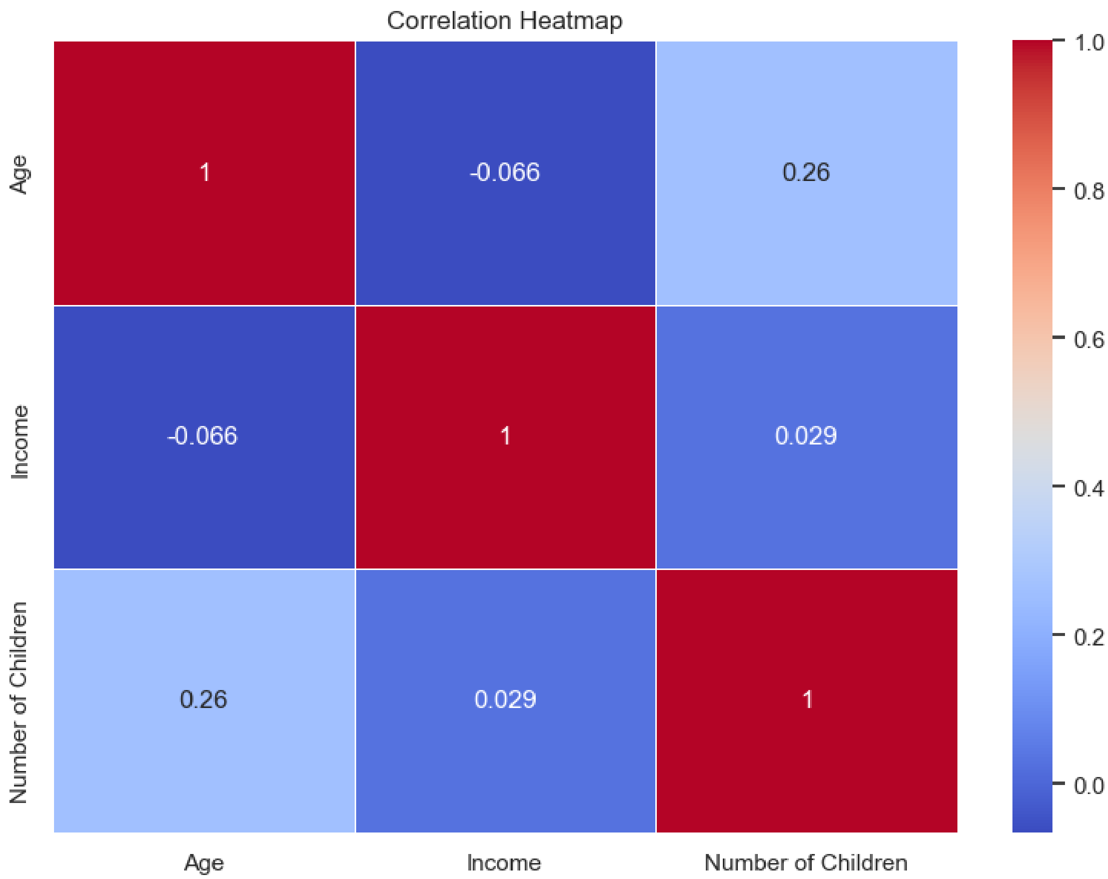
```
Dietary Habits                  0
Sleep Patterns                  0
History of Mental Illness       0
History of Substance Abuse      0
Family History of Depression    0
Chronic Medical Conditions      0
dtype: int64
```

[6]:

```python
# Set plot style
sns.set(style="whitegrid")

# Distribution of Marital Status
plt.figure(figsize=(10, 5))
sns.countplot(x='Marital Status', hue='History of Mental Illness',␣
 ↪data=depression_data)
plt.title('Marital Status Distribution by Mental Illness History')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

# Alcohol consumption comparison based on mental illness history
plt.figure(figsize=(10, 5))
sns.countplot(x='Alcohol Consumption', hue='History of Mental Illness',␣
 ↪data=depression_data)
plt.title('Alcohol Consumption Distribution by Mental Illness History')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

# Correlation heatmap for numerical data
numerical_data = depression_data[['Age', 'Income', 'Number of Children']]
correlation = numerical_data.corr()

plt.figure(figsize=(8, 6))
sns.heatmap(correlation, annot=True, cmap="coolwarm", linewidths=0.5)
plt.title('Correlation Heatmap')
plt.tight_layout()
plt.show()
```


Marital Status Distribution by Mental Illness History
History of Mental Illness
Yes
No
count
0
20000
40000
60000
80000
100000
120000
140000
160000
Married
Widowed
Divorced
Single
Marital Status


Alcohol Consumption Distribution by Mental Illness History
History of Mental Illness
Yes
No
count
0
20000
40000
60000
80000
100000
120000
Moderate
High
Low
Alcohol Consumption



Key Insights from Exploratory Data Analysis: Marital Status:

Individuals who are married seem to have a slightly lower prevalence of mental illness history compared to those who are widowed, divorced, or single. Alcohol Consumption:

Moderate alcohol consumption appears more common among individuals without a history of mental illness, whereas individuals with a history of mental illness are more spread out across low and moderate consumption categories. Correlation Heatmap:

The correlation between numerical variables such as age, income, and number of children is weak, suggesting these features may not strongly interact with each other. However, these may still be useful for predicting mental illness when combined with other factors.

[7]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder

# Convert categorical variables to numerical using Label Encoding
label_encoders = {}
for column in depression_data.select_dtypes(include=['object']).columns:
    label_encoders[column] = LabelEncoder()
```

```
    depression_data[column] = label_encoders[column].
 ↪fit_transform(depression_data[column])

# Split the data into features and target variable
X = depression_data.drop('History of Mental Illness', axis=1)
y = depression_data['History of Mental Illness']

# Split the data into training and testing sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)

# We'll start by trying a Random Forest Classifier and a Logistic Regression␣
 ↪model to compare their performance
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report

# Random Forest Classifier
rf_model = RandomForestClassifier(random_state=42)
rf_model.fit(X_train, y_train)
rf_predictions = rf_model.predict(X_test)

# Logistic Regression
lr_model = LogisticRegression(max_iter=1000, random_state=42)
lr_model.fit(X_train, y_train)
lr_predictions = lr_model.predict(X_test)

# Performance report for both models
rf_report = classification_report(y_test, rf_predictions)
lr_report = classification_report(y_test, lr_predictions)

rf_report, lr_report
```

[7]:
```
('              precision    recall  f1-score   support\n\n           0
0.70      0.95      0.80     57471\n           1       0.38      0.07      0.12
25283\n\n    accuracy                           0.68     82754\n   macro avg
0.54      0.51      0.46     82754\nweighted avg       0.60      0.68      0.60
82754\n',
 '              precision    recall  f1-score   support\n\n           0
0.69      1.00      0.82     57471\n           1       0.00      0.00      0.00
25283\n\n    accuracy                           0.69     82754\n   macro avg
0.35      0.50      0.41     82754\nweighted avg       0.48      0.69      0.57
82754\n')
```

[8]:
```
from imblearn.over_sampling import SMOTE
```

[9]:
```python
# Apply SMOTE to the training data to handle class imbalance
smote = SMOTE(random_state=42)
X_train_smote, y_train_smote = smote.fit_resample(X_train, y_train)
```

[10]:
```python
# Train the Random Forest model again on the balanced dataset
random_forest_smote = RandomForestClassifier(n_estimators=100, random_state=42)
random_forest_smote.fit(X_train_smote, y_train_smote)
```

[10]:
```
RandomForestClassifier(random_state=42)
```

[11]:
```python
# Make predictions on the test set
rf_preds_smote = random_forest_smote.predict(X_test)
```

[12]:
```python
# Evaluate the Random Forest model on the test data after SMOTE
from sklearn.metrics import classification_report, roc_auc_score
rf_report_smote = classification_report(y_test, rf_preds_smote)
rf_auc_smote = roc_auc_score(y_test, rf_preds_smote)

rf_report_smote, rf_auc_smote
```

[12]:
```
('              precision    recall  f1-score   support\n\n           0
0.71      0.78      0.74     57471\n           1       0.34      0.27      0.30
25283\n\n    accuracy                           0.62     82754\n   macro avg
0.53      0.52      0.52     82754\nweighted avg       0.60      0.62      0.61
82754\n',
 0.5215343051290768)
```

0.1 Hyperparameter Tuning

[13]:
```python
from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import randint

# Define the parameter distribution
param_dist = {
    'n_estimators': randint(100, 500),
    'max_depth': [10, 20, 30, None],
    'min_samples_split': randint(2, 10),
    'min_samples_leaf': randint(1, 5)
}

# Initialize the Random Forest model
random_forest = RandomForestClassifier(random_state=42)

# Set up RandomizedSearchCV
random_search = RandomizedSearchCV(estimator=random_forest,␣
 ↪param_distributions=param_dist,
```

```
                                   n_iter=10, cv=2, n_jobs=-1, verbose=2,␣
↪random_state=42, scoring='roc_auc')

# Fit the random search to the data (using SMOTE-balanced data)
random_search.fit(X_train_smote, y_train_smote)

# Get the best parameters from the search
best_params = random_search.best_params_
print(f"Best parameters found: {best_params}")

# Evaluate the tuned model on the test set
best_rf_model = random_search.best_estimator_
rf_preds_tuned = best_rf_model.predict(X_test)

# Get the evaluation report
rf_report_tuned = classification_report(y_test, rf_preds_tuned)
rf_auc_tuned = roc_auc_score(y_test, rf_preds_tuned)

print(rf_report_tuned)
print(f"ROC-AUC score after tuning: {rf_auc_tuned}")
```

```
Fitting 2 folds for each of 10 candidates, totalling 20 fits
[CV] END max_depth=30, min_samples_leaf=3, min_samples_split=9,
n_estimators=472; total time= 2.3min
[CV] END max_depth=None, min_samples_leaf=1, min_samples_split=2,
n_estimators=158; total time=  47.7s
[CV] END max_depth=30, min_samples_leaf=4, min_samples_split=6,
n_estimators=370; total time= 1.8min
[CV] END max_depth=None, min_samples_leaf=4, min_samples_split=6,
n_estimators=260; total time= 1.3min
[CV] END max_depth=30, min_samples_leaf=3, min_samples_split=9,
n_estimators=472; total time= 2.5min
[CV] END max_depth=None, min_samples_leaf=1, min_samples_split=2,
n_estimators=158; total time=  49.6s
[CV] END max_depth=None, min_samples_leaf=4, min_samples_split=9,
n_estimators=230; total time= 1.1min
[CV] END max_depth=None, min_samples_leaf=2, min_samples_split=7,
n_estimators=485; total time= 2.3min
[CV] END max_depth=30, min_samples_leaf=2, min_samples_split=4,
n_estimators=314; total time= 1.8min
[CV] END max_depth=None, min_samples_leaf=2, min_samples_split=7,
n_estimators=352; total time= 1.6min
[CV] END max_depth=None, min_samples_leaf=4, min_samples_split=9,
n_estimators=230; total time= 1.2min
[CV] END max_depth=None, min_samples_leaf=2, min_samples_split=7,
n_estimators=485; total time= 2.4min
[CV] END max_depth=30, min_samples_leaf=4, min_samples_split=6,
n_estimators=370; total time= 2.0min
```

```
[CV] END max_depth=None, min_samples_leaf=2, min_samples_split=7,
n_estimators=352; total time= 1.7min
Best parameters found: {'max_depth': 20, 'min_samples_leaf': 1,
'min_samples_split': 3, 'n_estimators': 443}
              precision    recall  f1-score   support

           0       0.71      0.79      0.74     57471
           1       0.35      0.25      0.29     25283

    accuracy                           0.63     82754
   macro avg       0.53      0.52      0.52     82754
weighted avg       0.60      0.63      0.61     82754

ROC-AUC score after tuning: 0.5209567051260741
```

1 Ensemble Techniques

1.1 XGBoost

[14]:
```
import xgboost as xgb
from sklearn.metrics import classification_report, roc_auc_score
from xgboost import XGBClassifier

# Initialize the XGBoost model
xgb_model = XGBClassifier(
    objective='binary:logistic',
    scale_pos_weight=len(y_train_smote[y_train_smote == 0]) /
 ↪len(y_train_smote[y_train_smote == 1]),  # Handling class imbalance
    use_label_encoder=False,
    eval_metric='logloss',  # A common evaluation metric for binary
 ↪classification
    random_state=42
)

# Fit the model
xgb_model.fit(X_train_smote, y_train_smote)

# Make predictions on the test data
xgb_preds = xgb_model.predict(X_test)

# Evaluate the model
xgb_report = classification_report(y_test, xgb_preds)
xgb_auc = roc_auc_score(y_test, xgb_preds)

# Display the report and AUC
print("XGBoost Classification Report:")
print(xgb_report)
```

```
print(f"ROC-AUC Score: {xgb_auc}")
```

```
XGBoost Classification Report:
              precision    recall  f1-score   support

           0       0.70      0.82      0.76     57471
           1       0.35      0.22      0.27     25283

    accuracy                           0.64     82754
   macro avg       0.53      0.52      0.51     82754
weighted avg       0.60      0.64      0.61     82754

ROC-AUC Score: 0.5198005567630579
```

1.2 LightGBM

[15]:
```
import lightgbm as lgb
from sklearn.metrics import classification_report, roc_auc_score
from lightgbm import LGBMClassifier

# Initialize the LightGBM model
lgb_model = LGBMClassifier(
    objective='binary',
    is_unbalance=True,  # Automatically balances classes
    random_state=42,
    n_estimators=1000,  # Number of boosting rounds
    learning_rate=0.05,  # Learning rate to control the size of a step during␣
 ↪optimization
    max_depth=20,  # Maximum depth of the trees
)

# Train the model
lgb_model.fit(X_train_smote, y_train_smote)

# Make predictions on the test set
lgb_preds = lgb_model.predict(X_test)

# Evaluate the model
lgb_report = classification_report(y_test, lgb_preds)
lgb_auc = roc_auc_score(y_test, lgb_preds)

# Print the classification report and ROC-AUC score
print("LightGBM Classification Report:")
print(lgb_report)
print(f"ROC-AUC Score: {lgb_auc}")
```

```
[LightGBM] [Warning] Accuracy may be bad since you didn't explicitly set
num_leaves OR 2^max_depth > num_leaves. (num_leaves=31).
```

```
[LightGBM] [Warning] Found whitespace in feature_names, replace with underlines
[LightGBM] [Warning] Accuracy may be bad since you didn't explicitly set
num_leaves OR 2^max_depth > num_leaves. (num_leaves=31).
[LightGBM] [Info] Number of positive: 230472, number of negative: 230472
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of
testing was 0.007958 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 611
[LightGBM] [Info] Number of data points in the train set: 460944, number of used
features: 15
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Warning] Accuracy may be bad since you didn't explicitly set
num_leaves OR 2^max_depth > num_leaves. (num_leaves=31).
LightGBM Classification Report:
              precision    recall  f1-score   support

           0       0.70      0.84      0.77     57471
           1       0.35      0.19      0.25     25283

    accuracy                           0.64     82754
   macro avg       0.53      0.52      0.51     82754
weighted avg       0.60      0.64      0.61     82754

ROC-AUC Score: 0.5182308621161287
```

1.3 Stacking Model

[16]:
```python
from sklearn.ensemble import StackingClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
import xgboost as xgb
from lightgbm import LGBMClassifier
from sklearn.metrics import classification_report, roc_auc_score

# Define the base models
base_models = [
    ('random_forest', RandomForestClassifier(n_estimators=200,␣
 ↪random_state=42)),
    ('xgboost', xgb.XGBClassifier(use_label_encoder=False,␣
 ↪eval_metric='logloss', random_state=42)),
    ('lightgbm', LGBMClassifier(random_state=42))
]

# Define the meta-model
meta_model = LogisticRegression()
```

```python
# Create the Stacking Classifier
stacking_model = StackingClassifier(estimators=base_models,␣
 ↪final_estimator=meta_model, cv=5, n_jobs=-1)

# Train the Stacking model using the SMOTE balanced data
stacking_model.fit(X_train_smote, y_train_smote)

# Make predictions on the test set
stacking_preds = stacking_model.predict(X_test)

# Evaluate the Stacking model
stacking_report = classification_report(y_test, stacking_preds)
stacking_auc = roc_auc_score(y_test, stacking_preds)

# Display the report and ROC-AUC score
print("Stacking Classifier Report:")
print(stacking_report)
print(f"ROC-AUC Score: {stacking_auc}")
```

```
[CV] END max_depth=30, min_samples_leaf=2, min_samples_split=4,
n_estimators=314; total time= 1.6min
[CV] END max_depth=None, min_samples_leaf=4, min_samples_split=6,
n_estimators=260; total time= 1.3min
[CV] END max_depth=30, min_samples_leaf=4, min_samples_split=6,
n_estimators=120; total time=  38.7s
[CV] END max_depth=20, min_samples_leaf=1, min_samples_split=3,
n_estimators=443; total time= 2.4min
[LightGBM] [Warning] Found whitespace in feature_names, replace with underlines
[LightGBM] [Warning] Found whitespace in feature_names, replace with underlines
[LightGBM] [Info] Number of positive: 184378, number of negative: 184377
[LightGBM] [Warning] Found whitespace in feature_names, replace with underlines
[LightGBM] [Info] Number of positive: 184378, number of negative: 184378
[LightGBM] [Info] Number of positive: 184378, number of negative: 184377
[LightGBM] [Warning] Found whitespace in feature_names, replace with underlines
[LightGBM] [Warning] Found whitespace in feature_names, replace with underlines
[LightGBM] [Info] Number of positive: 184377, number of negative: 184378
[LightGBM] [Info] Number of positive: 184377, number of negative: 184378
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of
testing was 0.105127 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 611
[LightGBM] [Info] Number of data points in the train set: 368755, number of used
features: 15
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500001 -> initscore=0.000005
[LightGBM] [Info] Start training from score 0.000005
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.152572 seconds.
```

```
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 611
[LightGBM] [Info] Number of data points in the train set: 368756, number of used
features: 15
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of
testing was 0.124604 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 611
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of data points in the train set: 368755, number of used
features: 15
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of
testing was 0.171513 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 611
[LightGBM] [Info] Number of data points in the train set: 368755, number of used
features: 15
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500001 -> initscore=0.000005
[LightGBM] [Info] Start training from score 0.000005
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499999 -> initscore=-0.000005
[LightGBM] [Info] Start training from score -0.000005
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of
testing was 0.184576 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 611
[LightGBM] [Info] Number of data points in the train set: 368755, number of used
features: 15
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499999 -> initscore=-0.000005
[LightGBM] [Info] Start training from score -0.000005
Stacking Classifier Report:
              precision    recall  f1-score   support

           0       0.71      0.79      0.75     57471
           1       0.35      0.26      0.30     25283

    accuracy                           0.63     82754
   macro avg       0.53      0.52      0.52     82754
weighted avg       0.60      0.63      0.61     82754

ROC-AUC Score: 0.5232308511288138
```

1.4 Adjsuting Class Weights in the Stacking Classifier

[17]:
```
from sklearn.utils.class_weight import compute_class_weight
import numpy as np

# Calculate class weights
class_weights = compute_class_weight(class_weight='balanced', classes=np.
 ↪unique(y_train_smote), y=y_train_smote)
class_weights_dict = {0: class_weights[0], 1: class_weights[1]}

# Update the base models with class weights
base_models_weighted = [
    ('random_forest', RandomForestClassifier(n_estimators=200, random_state=42,␣
 ↪class_weight=class_weights_dict)),
    ('xgboost', xgb.XGBClassifier(use_label_encoder=False,␣
 ↪eval_metric='logloss', random_state=42,␣
 ↪scale_pos_weight=class_weights_dict[1])),
    ('lightgbm', LGBMClassifier(random_state=42,␣
 ↪class_weight=class_weights_dict))
]

# Create the Stacking Classifier with class weights
stacking_model_weighted = StackingClassifier(estimators=base_models_weighted,␣
 ↪final_estimator=LogisticRegression(class_weight=class_weights_dict), cv=5,␣
 ↪n_jobs=-1)

# Train the model
stacking_model_weighted.fit(X_train_smote, y_train_smote)

# Make predictions on the test set
stacking_preds_weighted = stacking_model_weighted.predict(X_test)

# Evaluate the model
stacking_report_weighted = classification_report(y_test,␣
 ↪stacking_preds_weighted)
stacking_auc_weighted = roc_auc_score(y_test, stacking_preds_weighted)

# Display the updated report and ROC-AUC score
print("Stacking Classifier with Class Weights Report:")
print(stacking_report_weighted)
print(f"ROC-AUC Score: {stacking_auc_weighted}")
```

```
[LightGBM] [Warning] Found whitespace in feature_names, replace with underlines
[LightGBM] [Warning] Found whitespace in feature_names, replace with underlines
[LightGBM] [Info] Number of positive: 184378, number of negative: 184377
[LightGBM] [Warning] Found whitespace in feature_names, replace with underlines
[LightGBM] [Warning] Found whitespace in feature_names, replace with underlines
[LightGBM] [Info] Number of positive: 184377, number of negative: 184378
```

```
[LightGBM] [Info] Number of positive: 184377, number of negative: 184378
[LightGBM] [Info] Number of positive: 184378, number of negative: 184377
[LightGBM] [Warning] Found whitespace in feature_names, replace with underlines
[LightGBM] [Info] Number of positive: 184378, number of negative: 184378
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of
testing was 0.058180 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 611
[LightGBM] [Info] Number of data points in the train set: 368755, number of used
features: 15
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.085135 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 611
[LightGBM] [Info] Number of data points in the train set: 368755, number of used
features: 15
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of
testing was 0.063318 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 611
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500001 -> initscore=0.000005
[LightGBM] [Info] Start training from score 0.000005
[LightGBM] [Info] Number of data points in the train set: 368755, number of used
features: 15
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of
testing was 0.072224 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 611
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499999 -> initscore=-0.000005
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500001 -> initscore=0.000005
[LightGBM] [Info] Start training from score -0.000005
[LightGBM] [Info] Number of data points in the train set: 368755, number of used
features: 15
[LightGBM] [Info] Start training from score 0.000005
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499999 -> initscore=-0.000005
[LightGBM] [Info] Start training from score -0.000005
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.086936 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 611
[LightGBM] [Info] Number of data points in the train set: 368756, number of used
features: 15
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
Stacking Classifier with Class Weights Report:
              precision    recall  f1-score   support
```

```
           0       0.71      0.79      0.75     57471
           1       0.35      0.26      0.30     25283

    accuracy                           0.63     82754
   macro avg       0.53      0.52      0.52     82754
weighted avg       0.60      0.63      0.61     82754

ROC-AUC Score: 0.5232308511288138
[LightGBM] [Warning] Found whitespace in feature_names, replace with underlines
[LightGBM] [Info] Number of positive: 230472, number of negative: 230472
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of
testing was 0.014339 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 611
[LightGBM] [Info] Number of data points in the train set: 460944, number of used
features: 15
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[CV] END max_depth=30, min_samples_leaf=4, min_samples_split=6,
n_estimators=120; total time=  35.4s
[CV] END max_depth=20, min_samples_leaf=1, min_samples_split=3,
n_estimators=443; total time= 2.2min
[LightGBM] [Warning] Found whitespace in feature_names, replace with underlines
[LightGBM] [Info] Number of positive: 230472, number of negative: 230472
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of
testing was 0.023533 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 611
[LightGBM] [Info] Number of data points in the train set: 460944, number of used
features: 15
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
```

[ ]: