Model

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0.1 Baseline Model

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[ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing  import LabelEncoder, StandardScaler
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split, StratifiedKFold,␣
↪cross_val_score
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, ConfusionMatrixDisplay,␣
↪classification_report, confusion_matrix, precision_recall_curve
from imblearn.over_sampling import SMOTE
from imblearn.pipeline import Pipeline
from xgboost import XGBClassifier
```

[ ]:
```
# loading dataset assuming you have downloaded the dataset from kaggle
# using the link below and have it in a /data folder
df = pd.read_csv("../data/LI-Small_Trans.csv")
```

0.2 Dataset Highlights and Attributes

Link to Dataset: https://www.kaggle.com/datasets/ealtman2019/ibm-transactions-for-anti-money-laundering-aml?select=LI-Small_Trans.csv

Dataset Description

[ ]:
```
df.describe
```

[ ]:
```
<bound method NDFrame.describe of                 Timestamp  From Bank
Account  To Bank  Account.1  \
0        2022/09/01 00:08        11  8000ECA90       11  8000ECA90
1        2022/09/01 00:21      3402  80021DAD0     3402  80021DAD0
2        2022/09/01 00:00        11  8000ECA90     1120  8006AA910
3        2022/09/01 00:16      3814  8006AD080     3814  8006AD080
4        2022/09/01 00:00        20  8006AD530       20  8006AD530
```

```
…                       …           …          …         …          …
6924044  2022/09/10 23:39      71696  81B2518F1    71528  81C0482E1
6924045  2022/09/10 23:48     271241  81B567481   173457  81C0DA751
6924046  2022/09/10 23:50     271241  81B567481   173457  81C0DA751
6924047  2022/09/10 23:57     170558  81A2206B1   275798  81C1D5CA1
6924048  2022/09/10 23:31     170558  81A2206B1   275798  81C1D5CA1

         Amount Received Receiving Currency   Amount Paid Payment Currency  \
0           3.195403e+06          US Dollar  3.195403e+06        US Dollar
1           1.858960e+03          US Dollar  1.858960e+03        US Dollar
2           5.925710e+05          US Dollar  5.925710e+05        US Dollar
3           1.232000e+01          US Dollar  1.232000e+01        US Dollar
4           2.941560e+03          US Dollar  2.941560e+03        US Dollar
…                    …                  …            …                …
6924044     3.346900e-02            Bitcoin  3.346900e-02          Bitcoin
6924045     1.313000e-03            Bitcoin  1.313000e-03          Bitcoin
6924046     1.305800e-02            Bitcoin  1.305800e-02          Bitcoin
6924047     4.145370e-01            Bitcoin  4.145370e-01          Bitcoin
6924048     3.427700e-02            Bitcoin  3.427700e-02          Bitcoin

        Payment Format  Is Laundering
0         Reinvestment              0
1         Reinvestment              0
2               Cheque              0
3         Reinvestment              0
4         Reinvestment              0
…                  …              …
6924044        Bitcoin              0
6924045        Bitcoin              0
6924046        Bitcoin              0
6924047        Bitcoin              0
6924048        Bitcoin              0

[6924049 rows x 11 columns]>
```

Shape of the dataset

[ ]:
```python
print("Number of Instances: " + str(df.shape[0]))
print("Number of Attributes: " + str(df.shape[1]))

df.shape
```

```
Number of Instances: 6924049
Number of Attributes: 11
```

[ ]:
```
(6924049, 11)
```

Dataset Information

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6924049 entries, 0 to 6924048
Data columns (total 11 columns):
 #   Column              Dtype
---  ------              -----
 0   Timestamp           object
 1   From Bank           int64
 2   Account             object
 3   To Bank             int64
 4   Account.1           object
 5   Amount Received     float64
 6   Receiving Currency  object
 7   Amount Paid         float64
 8   Payment Currency    object
 9   Payment Format      object
 10  Is Laundering       int64
dtypes: float64(2), int64(3), object(6)
memory usage: 581.1+ MB
```

Attributes and types:

[ ]:
```
df.dtypes.to_frame("Data Type")
```

[ ]:
```
                   Data Type
Timestamp             object
From Bank              int64
Account               object
To Bank                int64
Account.1             object
Amount Received      float64
Receiving Currency    object
Amount Paid          float64
Payment Currency      object
Payment Format        object
Is Laundering          int64
```

Random Sample of the data:

[ ]:
```
df.sample(5)
```

[ ]:

	Timestamp	From Bank	Account	To Bank	Account.1	\
4720616	2022/09/07 10:23	3597	803616010	115481	805E8BA10	
2017814	2022/09/02 11:13	3100	805534530	3100	805534530	
51292	2022/09/01 00:19	18081	807A11330	18081	807A11330	
6691891	2022/09/10 02:59	27425	801CF93A0	210858	805201B30	
371103	2022/09/01 00:03	44474	8105089E0	44474	8105089E0	

```
         Amount Received Receiving Currency  Amount Paid   Payment Currency  \
4720616           365.22          US Dollar       365.22          US Dollar
2017814          3618.57               Euro      4240.18          US Dollar
51292           11470.11          US Dollar     11470.11          US Dollar
6691891          1528.17               Yuan      1528.17               Yuan
371103            799.11  Australian Dollar       799.11  Australian Dollar

        Payment Format  Is Laundering
4720616         Cheque              0
2017814            ACH              0
51292     Reinvestment              0
6691891         Cheque              0
371103    Reinvestment              0
```

Number of missing values:

[ ]:
```python
# Create a new DataFrame with missing values summary
missing_values = pd.DataFrame({
    "Column Name": df.columns,
    "Missing Count": df.isnull().sum(),
    "Missing Percentage": (df.isnull().sum() / len(df)) * 100
})

missing_values.head(10)
```

[ ]:
```
                           Column Name  Missing Count  Missing Percentage
Timestamp                    Timestamp              0                 0.0
From Bank                    From Bank              0                 0.0
Account                        Account              0                 0.0
To Bank                        To Bank              0                 0.0
Account.1                    Account.1              0                 0.0
Amount Received        Amount Received              0                 0.0
Receiving Currency  Receiving Currency              0                 0.0
Amount Paid                Amount Paid              0                 0.0
Payment Currency      Payment Currency              0                 0.0
Payment Format          Payment Format              0                 0.0
```

Droppng Missing Values if any

[ ]:
```python
# drop rows with missing values
df = df.dropna()
```

Encoding categorical features in copied dataframe for possible use later for logistic regression

[ ]:
```python
# encode categorical features
categorical_cols = ['Receiving Currency', 'Payment Currency', 'Payment Format']
label_encoders = {}

df_encoded = df.copy()
```

```
for col in categorical_cols:
    le = LabelEncoder()
    df_encoded[col] = le.fit_transform(df_encoded[col])
    label_encoders[col] = le
```

Splitting Features and Target

Splitting into our Training and Testing Sets

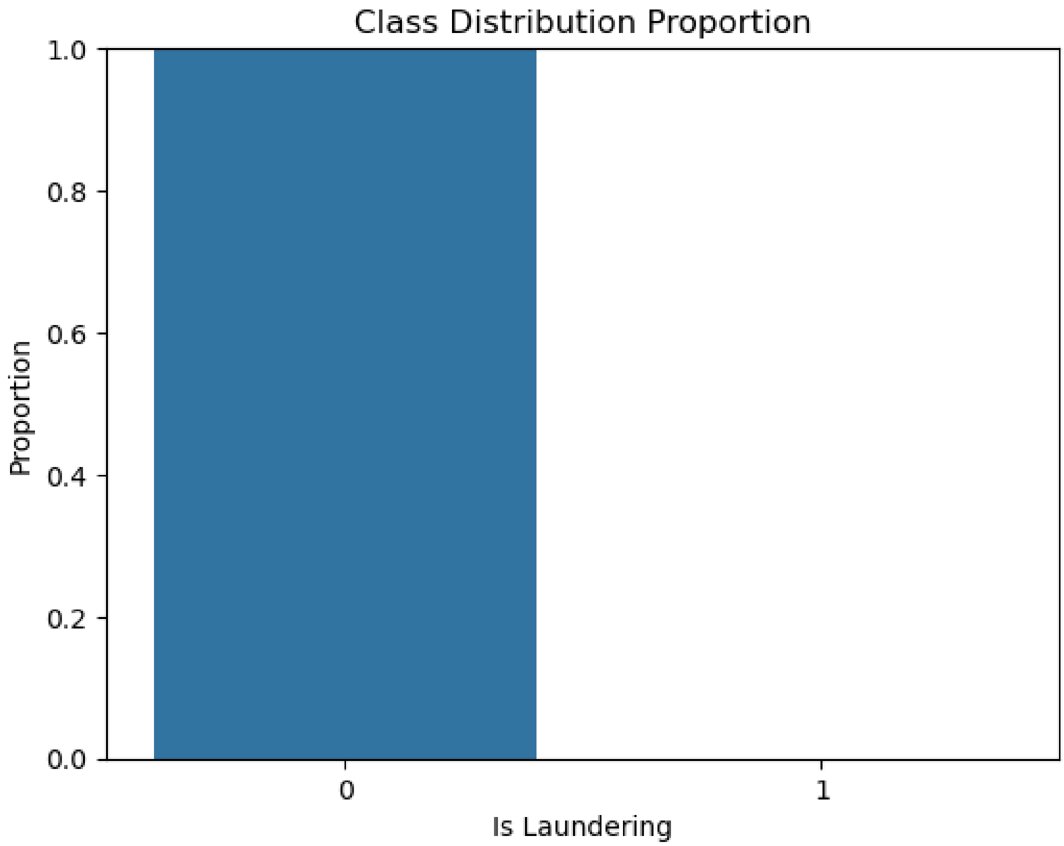
[ ]:
```
# seperating features and target variable
X = df_encoded.drop(columns=['Account', 'Account.1', 'Timestamp', 'Is␣
↪Laundering'])
y = df_encoded['Is Laundering']
```

0.3 EDA Graphs

Visualized class imbalance

Extreme class imbalance represented as proportions with bar plot, class 0 has +99.95%.

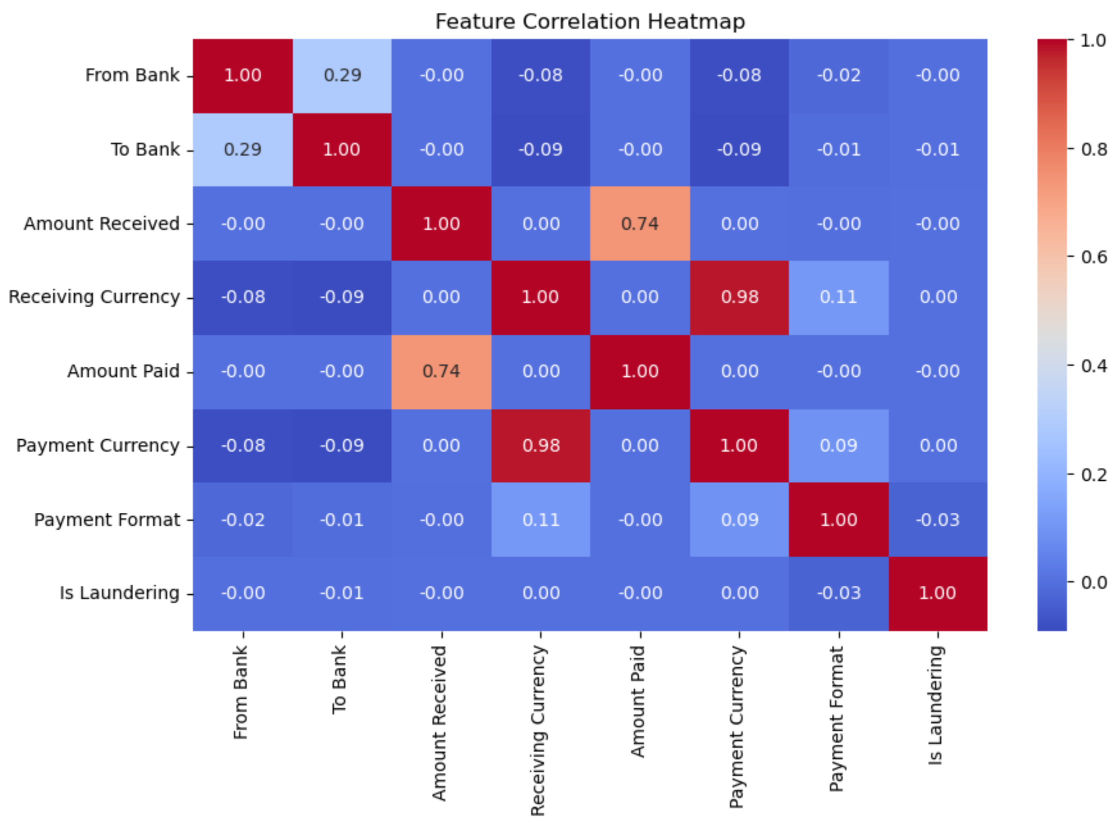
[ ]:
```
class_counts = df["Is Laundering"].value_counts(normalize=True)



sns.barplot(x=class_counts.index, y=class_counts.values)
plt.title("Class Distribution Proportion")
plt.ylabel("Proportion")
plt.xlabel("Is Laundering")
plt.ylim(0, 1)
plt.show()
```



Feature Correlation Heatmap

Visualize relationships between features and the target of Is Laundering

[ ]:
```
numeric_df = df_encoded.select_dtypes(include=["number"])
corr_matrix = numeric_df.corr()
plt.figure(figsize=(10, 6))

sns.heatmap(corr_matrix, annot=True, fmt=".2f", cmap="coolwarm")
plt.title("Feature Correlation Heatmap")
plt.show()
```



Normalizing Numeric Features

[ ]:
```
# normalize feature values
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# split dataset into training and testing set 80/20 respectively
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2,␣
↪random_state=42)
```

Training the Logistic Regression Model over 1000 iterations

[ ]:
```
# training logistic regression model
lr_model = LogisticRegression(max_iter=1000, class_weight='balanced')
lr_model.fit(X_train, y_train)
```

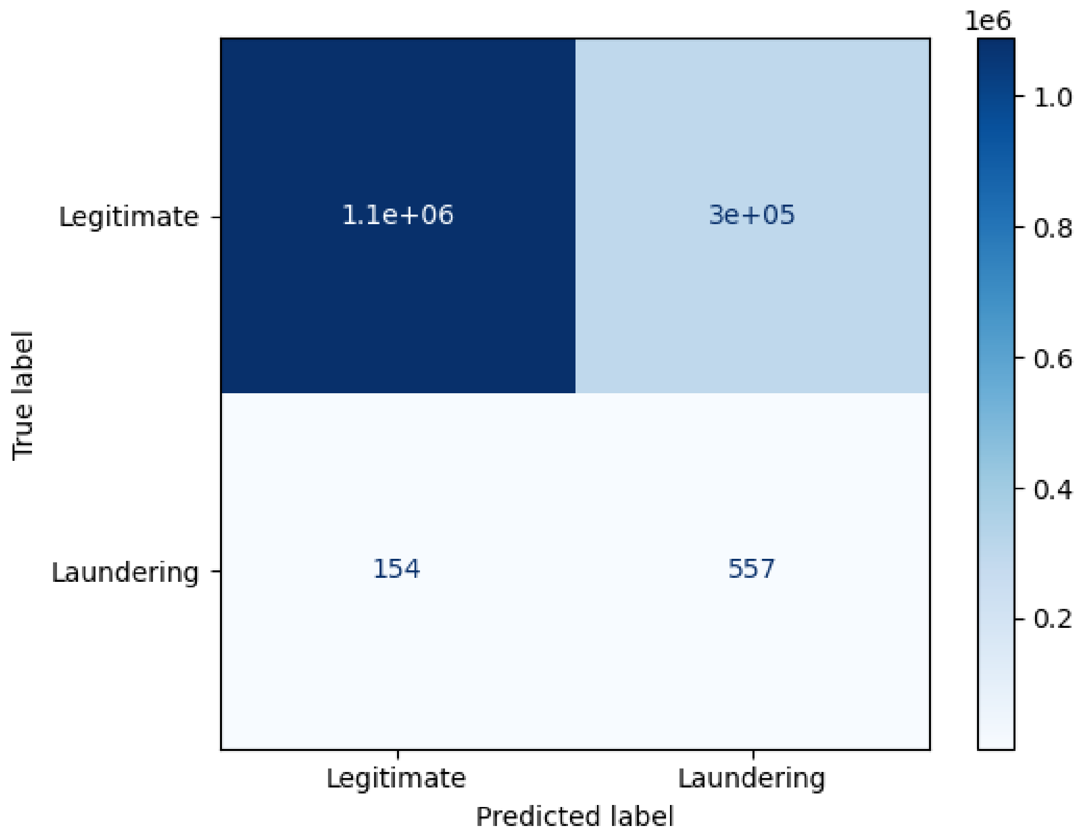
[ ]:
```
LogisticRegression(class_weight='balanced', max_iter=1000)
```

Using Evaluation Metrics and a Confusion Matrix to evaluate base model

[ ]:
```
y_pred = lr_model.predict(X_test)
```

```python
print("Accuracy:", accuracy_score(y_test, y_pred))
print("\nClassifcation Report:\n", classification_report(y_test, y_pred,␣
↪target_names=["Legitimate", "Laundering"]))
ConfusionMatrixDisplay.from_estimator(lr_model, X_test, y_test,␣
↪display_labels=['Legitimate', "Laundering"], cmap="Blues")
print(confusion_matrix(y_test, y_pred))
```

```
Accuracy: 0.7867165892793957

Classifcation Report:
               precision    recall  f1-score   support

  Legitimate       1.00      0.79      0.88   1384099
  Laundering       0.00      0.78      0.00       711

    accuracy                           0.79   1384810
   macro avg       0.50      0.79      0.44   1384810
weighted avg       1.00      0.79      0.88   1384810

[[1088896  295203]
 [    154     557]]
```



0.4 Model Improvement using SMOTE

Using SMOTE to synthetically increase dataset size increasing instances of laundering

Using normalized variables from previous preprocessing and applying SMOTE

[ ]:
```
smote = SMOTE(random_state=42)
X_resampled, y_resampled = smote.fit_resample(X_scaled, y)

#y.value_counts()
y_resampled.value_counts()
```

[ ]:
```
Is Laundering
0    6920484
1    6920484
Name: count, dtype: int64
```

Train/Test split on Resampled Data and fit new Logistic Regression Model

[ ]:
```
X_train_sm, X_test_sm, y_train_sm, y_test_sm = train_test_split(X_resampled,␣
 ↪y_resampled, test_size=0.2, random_state=42)

lr_smote = LogisticRegression(max_iter=10000, class_weight="balanced")
lr_smote.fit(X_train_sm, y_train_sm)
```

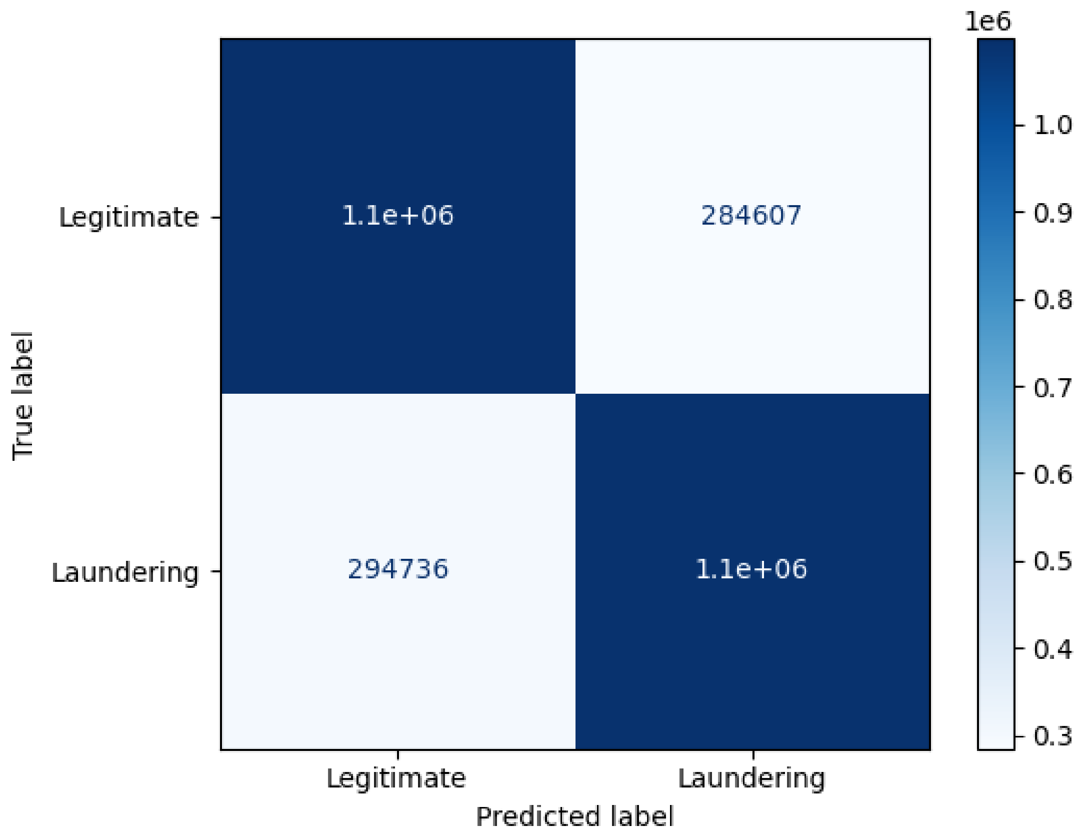
[ ]:
```
LogisticRegression(class_weight='balanced', max_iter=10000)
```

New SMOTE Model Evaluation

[ ]:
```
y_pred_sm = lr_smote.predict(X_test_sm)

print("Accuracy (SMOTE)", accuracy_score(y_test_sm, y_pred_sm))
print("\nClassification Report (SMOTE):\n", classification_report(y_test_sm,␣
 ↪y_pred_sm, target_names=["Legitimate", "Laundering"]))

ConfusionMatrixDisplay.from_estimator(lr_smote, X_test_sm, y_test_sm,␣
 ↪display_labels=["Legitimate", "Laundering"], cmap="Blues")
print(confusion_matrix(y_test_sm, y_pred_sm))
```

```
Accuracy (SMOTE) 0.7907144513715441

Classification Report (SMOTE):
               precision    recall  f1-score   support

  Legitimate       0.79      0.79      0.79   1382957
  Laundering       0.79      0.79      0.79   1385237

    accuracy                           0.79   2768194
```

```
   macro avg       0.79      0.79      0.79   2768194
weighted avg       0.79      0.79      0.79   2768194

[[1098350  284607]
 [ 294736 1090501]]
```



Better Precision and F1-score since there is not still such a huge class imbalance due to synthetic increasing

0.5 Using Random Forest Classifier

Non-SMOTE

Training Random Forest

[ ]:
```
# training random forest model, can take 2~ minutes
rf_model = RandomForestClassifier(class_weight='balanced_subsample',␣
 ↪n_estimators=100, random_state=42, max_depth=15, n_jobs=-1,␣
 ↪min_samples_leaf=1)
rf_model.fit(X_train, y_train)
```

[ ]: RandomForestClassifier(class_weight='balanced_subsample', max_depth=15,
                       n_jobs=-1, random_state=42)

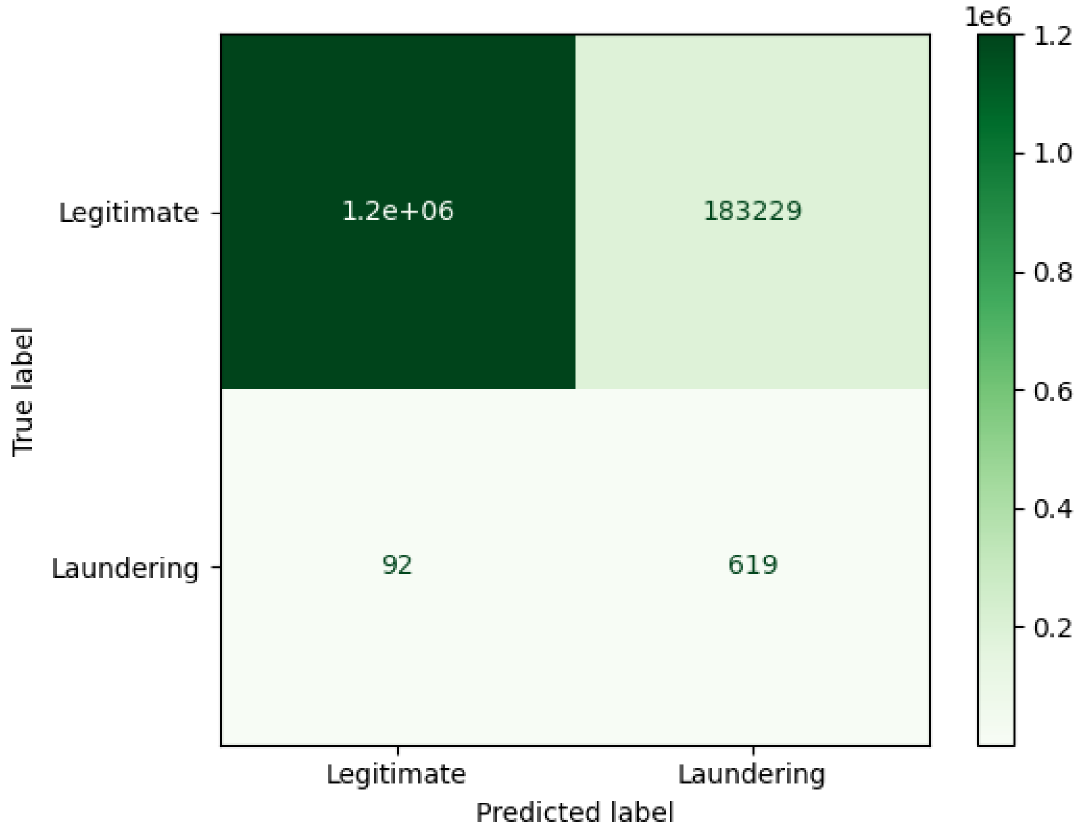
Predicting and Evaluating

Predicting the probabilities for each class. Also setting a custom threshold for the laundering class.

```
[ ]: #y_pred_rf = rf_model.predict(X_test)
y_proba = rf_model.predict_proba(X_test)

custom_threshold = 0.3
y_pred_thresh = (y_proba[:, 1] >= custom_threshold).astype(int)

print(accuracy_score(y_test, y_pred_thresh))
print("\nClassification Report:\n".format(custom_threshold),␣
 ↪classification_report(y_test, y_pred_thresh, target_names=["Legitimate",␣
 ↪"Laundering"]))

ConfusionMatrixDisplay.from_predictions(y_test, y_pred_thresh,␣
 ↪display_labels=["Legitimate", "Laundering"], cmap="Greens")
```

```
0.867620106729443

Classification Report:
               precision    recall  f1-score   support

  Legitimate       1.00      0.87      0.93   1384099
  Laundering       0.00      0.87      0.01       711

    accuracy                           0.87   1384810
   macro avg       0.50      0.87      0.47   1384810
weighted avg       1.00      0.87      0.93   1384810
```

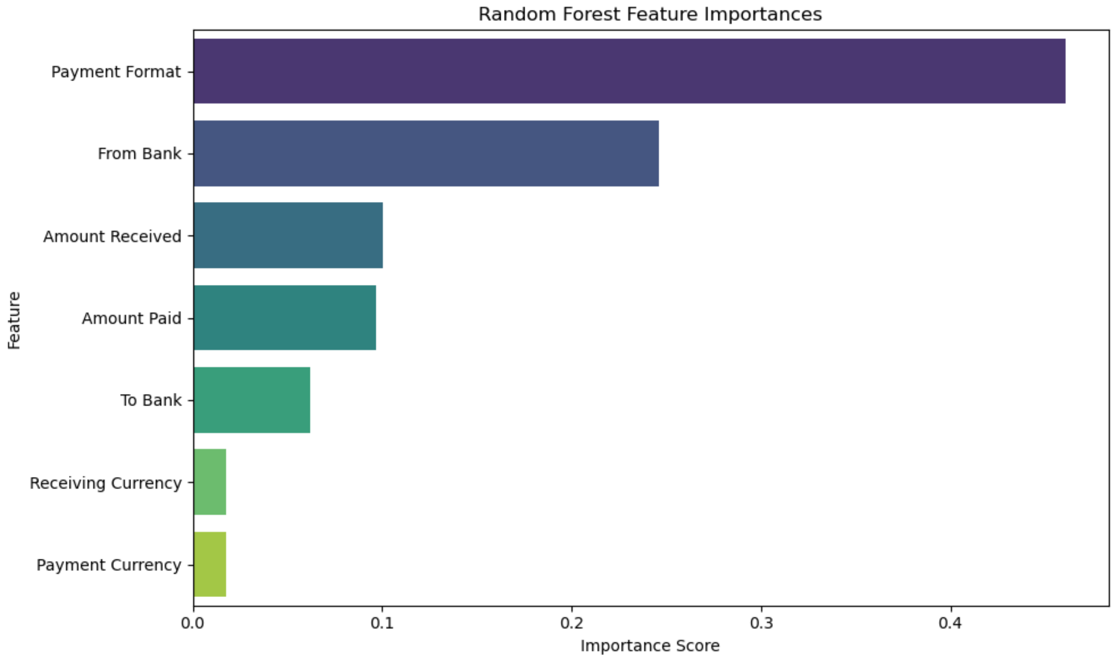
```
[ ]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x3030fecf0>
```



Random Forest Feature Importance Plot

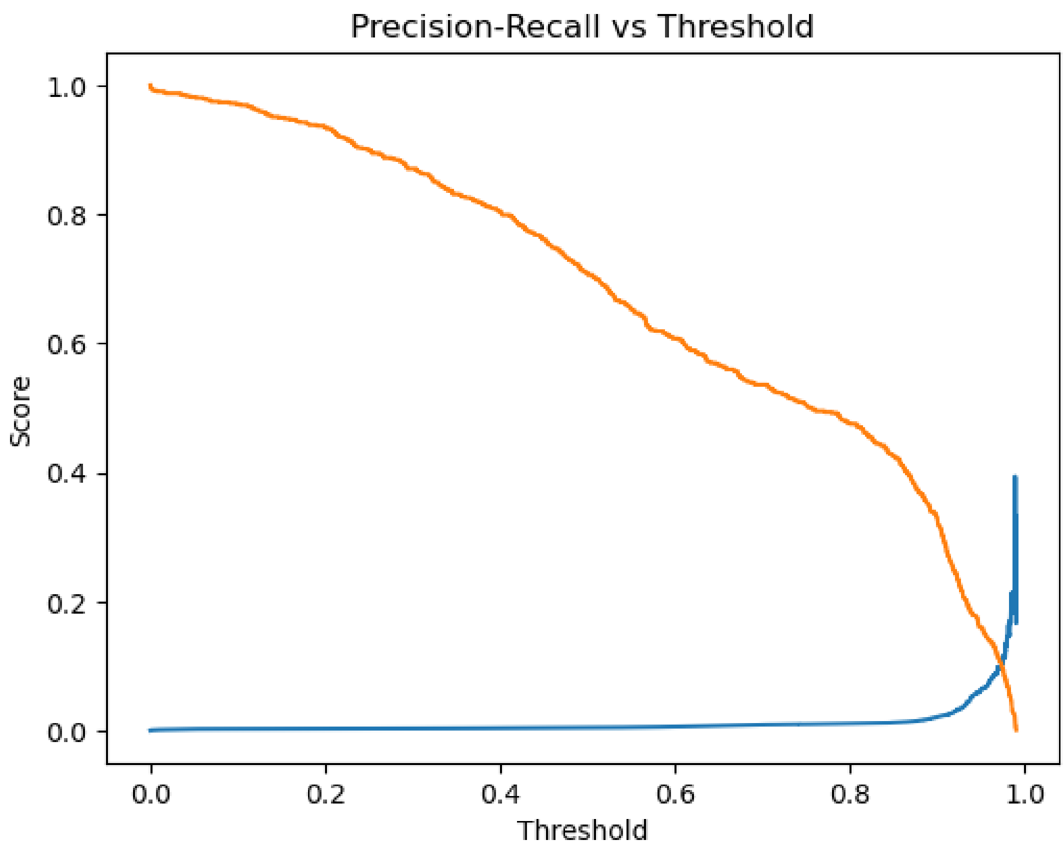
The features at the top contribute the most to the model's decision making.

[ ]:
```
importances = rf_model.feature_importances_
feature_names = X.columns

indices = np.argsort(importances)[::-1]
sorted_features = feature_names[indices]
sorted_importances = importances[indices]

plt.figure(figsize=(10, 6))
sns.barplot(x=sorted_importances, y=sorted_features, hue=sorted_features,␣
 ↪palette="viridis", legend=False)
plt.title("Random Forest Feature Importances")
plt.xlabel("Importance Score")
plt.ylabel("Feature")
plt.tight_layout()
plt.show()
```



Threshold Tuning Curve Visualization of precision-recall tradeoffs from custom threshold

[ ]:
```
probs = rf_model.predict_proba(X_test)[:, 1]
precision, recall, thresholds = precision_recall_curve(y_test, probs)

plt.plot(thresholds, precision[:-1], label = 'Precision')
plt.plot(thresholds, recall[:-1], label='Recall')
plt.xlabel("Threshold")
plt.ylabel("Score")
plt.title("Precision-Recall vs Threshold")
plt.show()
```



0.6 Using XGBoost Classifier

Continuing with 80/20 train test split

```
[ ]: X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2,␣
      ↪random_state=42, stratify=y)
```

Attempting to handle class imbalance Given the large class imbalance we are trying to have the model give more importance to the minority/laundering class

```
[ ]: imbalance_ratio = (y_train == 0).sum() / (y_train == 1).sum()
```

Train and fit model

```
[ ]: # training XGBoost model
     xgb_model = XGBClassifier(scale_pos_weight =imbalance_ratio,␣
      ↪eval_metric='logloss', random_state=42)

     _ = xgb_model.fit(X_train, y_train) # Supressing .fit output, possible scikit␣
      ↪and xgboost incompatability causing error
```

Generating predicted probabilities and then applying same custom threshold for comparison

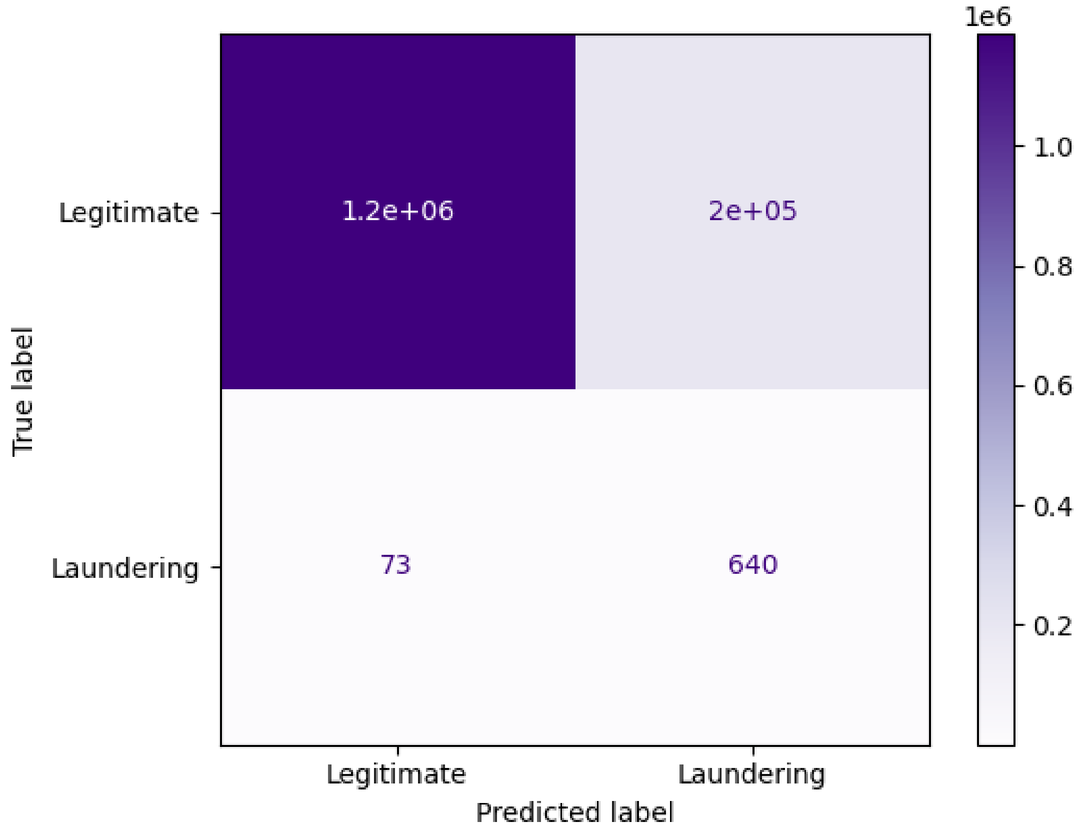
[ ]:
```python
# applying custom threshold to predictions
y_proba_xgb = xgb_model.predict_proba(X_test)[:, 1]
y_pred_xgb = (y_proba_xgb >= 0.3).astype(int)
```

Model Evaluation

[ ]:
```python
# showing classification metrics / confusion matrix
print("Classification Report (XGBoost, threshold of 0.3):")
print(classification_report(y_test, y_pred_xgb, target_names=["Legitimate",␣
↪"Laundering"]))

ConfusionMatrixDisplay.from_predictions(y_test, y_pred_xgb,␣
↪display_labels=["Legitimate", "Laundering"], cmap="Purples")
```

```
Classification Report (XGBoost, threshold of 0.3):
              precision    recall  f1-score   support

  Legitimate       1.00      0.86      0.92   1384097
  Laundering       0.00      0.90      0.01       713

    accuracy                           0.86   1384810
   macro avg       0.50      0.88      0.46   1384810
weighted avg       1.00      0.86      0.92   1384810
```

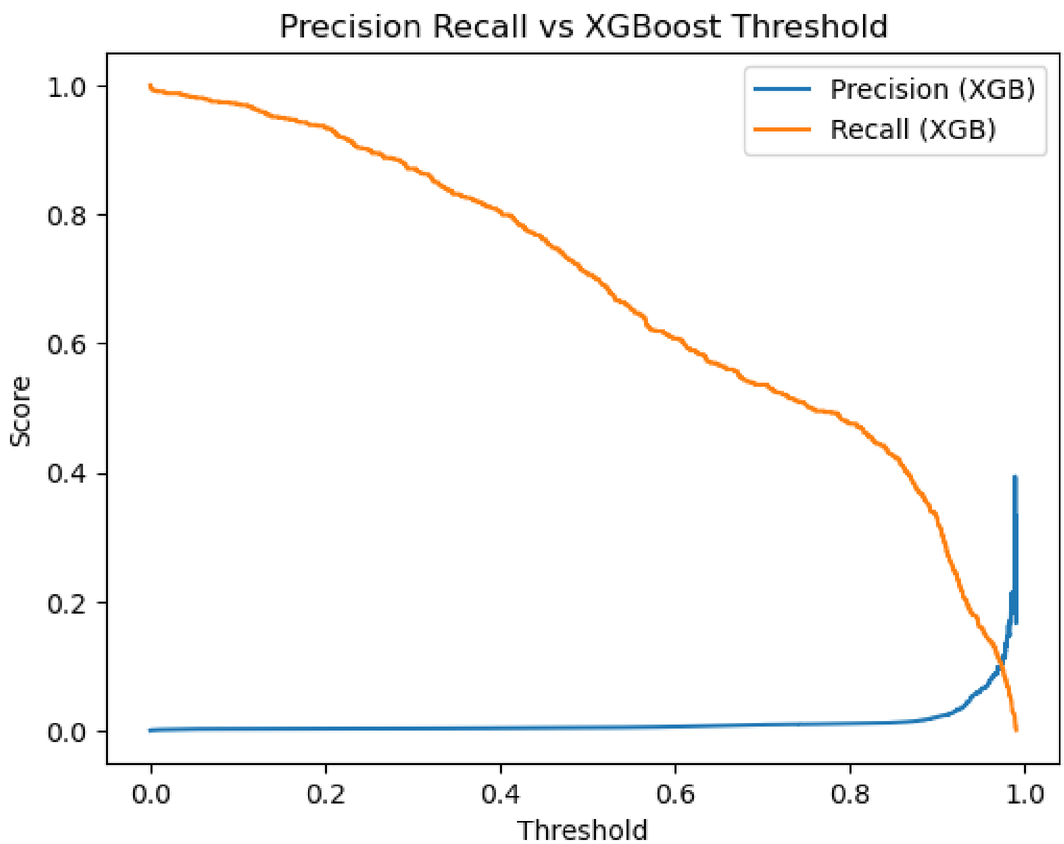
[ ]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x37865e450>
```



Precision Recall Curve for XGBoost

[ ]:
```
precision, recall, thresholds, precision_recall_curve(y_test, y_proba_xgb)

plt.plot(thresholds, precision[:-1], label='Precision (XGB)')
plt.plot(thresholds, recall[:-1], label='Recall (XGB)')
plt.xlabel("Threshold")
plt.ylabel("Score")
plt.title("Precision Recall vs XGBoost Threshold")
plt.legend()
plt.show
```

[ ]:
```
<function matplotlib.pyplot.show(close=None, block=None)>
```


Precision Recall vs XGBoost Threshold
Precision (XGB)
Recall (XGB)
Score
Threshold
0.0
0.2
0.4
0.6
0.8
1.0