credit_card_fraud

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1 Credit Card Fraud Transaction Classification

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1.1 Introduction

Transitioning from cash-based transactions to digital payments globally has amplified the challenge of credit card fraud in financial transactions, impacting consumers and institutions worldwide. The rapid evolution of information leaks and advancements in hacking techniques has led to increasingly sophisticated fraudulent activities, necessitating advanced detection methods to mitigate financial losses. Detecting fraudulent credit card transactions promptly is crucial for banks to protect customers from potential losses while ensuring seamless processing of legitimate transactions. While various other projects on this subject matter seek to investigate the performance of individual machine learning models from logistic regression to k-nearest neighbors to identify the likelihood of a transaction being fraudulent, this project aims to build on those discoveries and develop a robust credit card fraud detection model by analyzing key transaction features such as time, location, and amount. Leveraging machine learning algorithms and transaction data, we aim to identify patterns and anomalies indicative of fraudulent behavior, thereby enhancing fraud detection capabilities within the financial sector.

The dataset utilized for this project encompasses a comprehensive collection of credit card transactions, capturing crucial features including transaction timestamps, geographical locations, transaction amounts, and additional metadata associated with each transaction. This dataset serves as the cornerstone for training and testing machine learning models designed to differentiate between legitimate and fraudulent transactions. The dataset's richness in transactional details enables the development of predictive models capable of detecting suspicious patterns in real-time transactions, facilitating proactive measures to mitigate fraud risks and bolster overall transaction security.

1.2 Method

In our project, we explored various classification algorithms to develop and assess classification models tailored to our dataset. First, we tried to utilize the Random Forest algorithm because of its capability to handle large datasets with numerous features, which aligns well with the complexity of our transaction data. Moreover, Random Forest is also adept at managing imbalanced datasets, which is a common challenge in fraud detection where fraudulent transactions are relatively rare, as appeared in our training dataset. To further address the imbalance in class distribution, we implemented the Balanced Random Forest algorithm, combining the strengths of Random Forest with techniques to handle skewed class distributions effectively. In addition to that, we employed XGBoost, an ensemble learning technique known for its accuracy and scalability in classification tasks. Like random forest, it can also adjust its learning process to focus more on correctly classifying the minority class (fraudulent transactions), thus improving the model's ability to detect fraud while minimizing false positives. Gaussian Naive Bayes was considered due to its simplicity and efficiency, particularly suited for scenarios where features are assumed to be independent. Stochastic Gradient Descent (SGD) was chosen for its efficiency in handling large datasets and adaptability to different loss functions. Lastly, we explored Support Vector Machines (SVM) for their ability to capture complex data patterns using kernel functions, enabling robust generalization. By leveraging this diverse set of classification algorithms, we aimed to evaluate multiple modeling approaches and select the most effective models for credit card fraud detection based on the unique characteristics of our dataset and the challenges inherent in fraud detection tasks. After confirming the plausibility of each model, hyperparameter tuning through grid search is performed on each model. And lastly, ensembling is taken into consideration to further improve accuracy of the detection model.

[1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
```

First, we load in our predownloaded dataset from data folder. We will clean up the data by dropping duplicate rows. We also check for null rows, but there isn't any. Our dataset has customers' email address domains, customers' located states, zipcodes, two time features, 12 anonymized features, transaction amount, total transaction amount, and transaction types, which are marked "LEGIT" and "FRAUD."

[2]:
```python
DATA_CSV_PATH1 = './data/CC_FRAUD.csv'

# load csv data
df1 = pd.read_csv(DATA_CSV_PATH1)

# remove duplicate data
df1 = df1.drop_duplicates().reset_index(drop=True)
display(df1)
```

```
                     DOMAIN STATE  ZIPCODE  TIME1  TIME2  VIS1  VIS2  XRN1  \
0      CDRZLKAJIJVQHCN.COM    AO      675     12     12     1     0     0
1              NEKSXUK.NET    KK      680     18     18     1     0     0
2                XOSOP.COM    UO      432      3      3     1     0     0
3                  TMA.COM    KR      119     23     23     0     0     1
4              VUHZRNB.COM    PO      614      9      9     0     0     0
…                        …     …        …      …      …     …     …     …
89609            XOSOP.COM    MO      685     11     11     0     0     0
89610          RONHGNCN.COM    KR      108     16     16     0     0     1
```

```
89611            XOSOP.COM    VO      601     18      18      0      0      1
89612          VUHZRNB.COM    LO      398     23      23      0      0      0
89613          VUHZRNB.COM   ROK      655     11      11      0      0      0

       XRN2  XRN3  XRN4  XRN5  VAR1  VAR2    VAR3  VAR4  VAR5  TRN_AMT  \
0         1     1     0     1     2     1  16.680    34     0    12.95
1         0     0     0     1     3     0  37.880    23     0    38.85
2         1     1     0     1     3     1  -9.080    19     2    38.85
3         0     0     0     3     0     0  -6.392    18     0    11.01
4         1     0     0     1     3     0  42.512     7     0    12.95
…     …    …    …    …    …    …      …    …     …       …
89609     1     1     0     1     3     0   8.112    15     1    49.95
89610     0     0     1     1     4     0  11.248    10     4    12.95
89611     1     1     0     1     2     0  27.824    23     0    38.85
89612     0     0     0     1     3     0  31.904    20     0    12.95
89613     0     0     0     1     2     0  17.608    20     0    33.03

       TOTAL_TRN_AMT TRN_TYPE
0              12.95    LEGIT
1              38.85    LEGIT
2              38.85    LEGIT
3              11.01    LEGIT
4              12.95    LEGIT
…                …       …
89609          49.95    LEGIT
89610          12.95    LEGIT
89611          38.85    LEGIT
89612          12.95    LEGIT
89613          33.03    LEGIT

[89614 rows x 20 columns]
```

[3]:
```
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 89614 entries, 0 to 89613
Data columns (total 20 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   DOMAIN         89614 non-null  object
 1   STATE          89614 non-null  object
 2   ZIPCODE        89614 non-null  int64
 3   TIME1          89614 non-null  int64
 4   TIME2          89614 non-null  int64
 5   VIS1           89614 non-null  int64
 6   VIS2           89614 non-null  int64
 7   XRN1           89614 non-null  int64
 8   XRN2           89614 non-null  int64
```

```
 9   XRN3          89614 non-null  int64
 10  XRN4          89614 non-null  int64
 11  XRN5          89614 non-null  int64
 12  VAR1          89614 non-null  int64
 13  VAR2          89614 non-null  int64
 14  VAR3          89614 non-null  float64
 15  VAR4          89614 non-null  int64
 16  VAR5          89614 non-null  int64
 17  TRN_AMT       89614 non-null  float64
 18  TOTAL_TRN_AMT 89614 non-null  float64
 19  TRN_TYPE      89614 non-null  object
dtypes: float64(3), int64(14), object(3)
memory usage: 13.7+ MB
```

[4]:
```
df1.isnull().sum()
```

[4]:
```
DOMAIN           0
STATE            0
ZIPCODE          0
TIME1            0
TIME2            0
VIS1             0
VIS2             0
XRN1             0
XRN2             0
XRN3             0
XRN4             0
XRN5             0
VAR1             0
VAR2             0
VAR3             0
VAR4             0
VAR5             0
TRN_AMT          0
TOTAL_TRN_AMT    0
TRN_TYPE         0
dtype: int64
```

[5]:
```
df1.groupby('TRN_TYPE')['TOTAL_TRN_AMT'].mean()
```

[5]:
```
TRN_TYPE
FRAUD    24.972315
LEGIT    26.343905
Name: TOTAL_TRN_AMT, dtype: float64
```

[6]:
```
df1['TRN_AMT']
```

[6]:
```
0        12.95
1        38.85
2        38.85
3        11.01
4        12.95
         …
89609    49.95
89610    12.95
89611    38.85
89612    12.95
89613    33.03
Name: TRN_AMT, Length: 89614, dtype: float64
```

[7]:
```python
df1['TRN_TYPE'].unique()
```

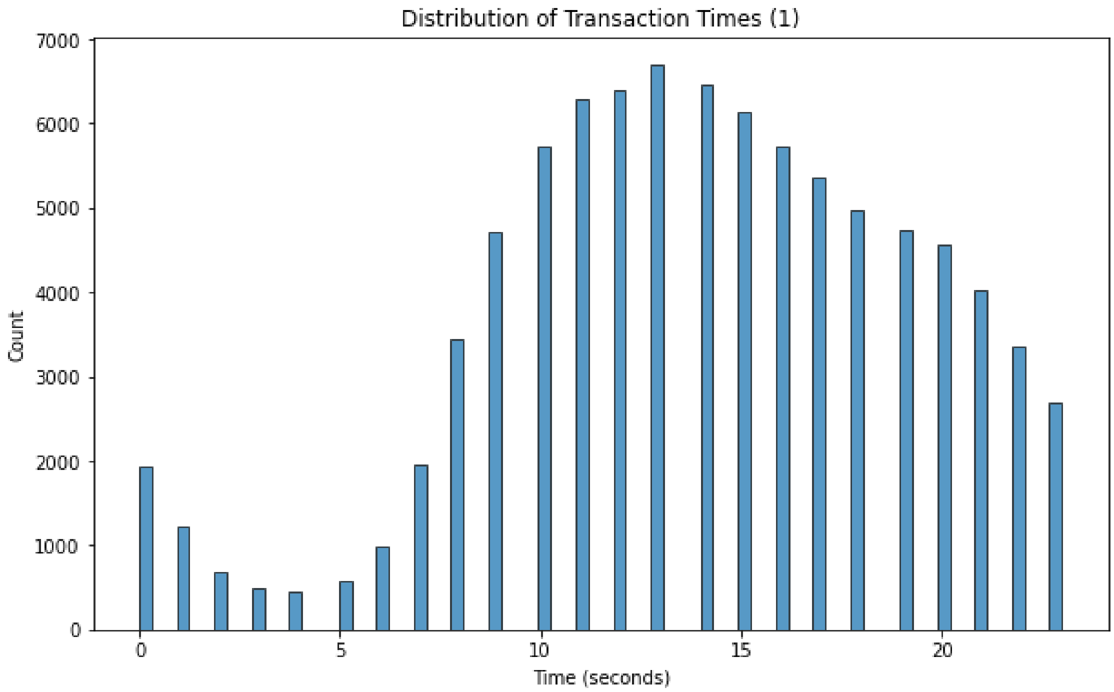
[7]:
```
array(['LEGIT', 'FRAUD'], dtype=object)
```

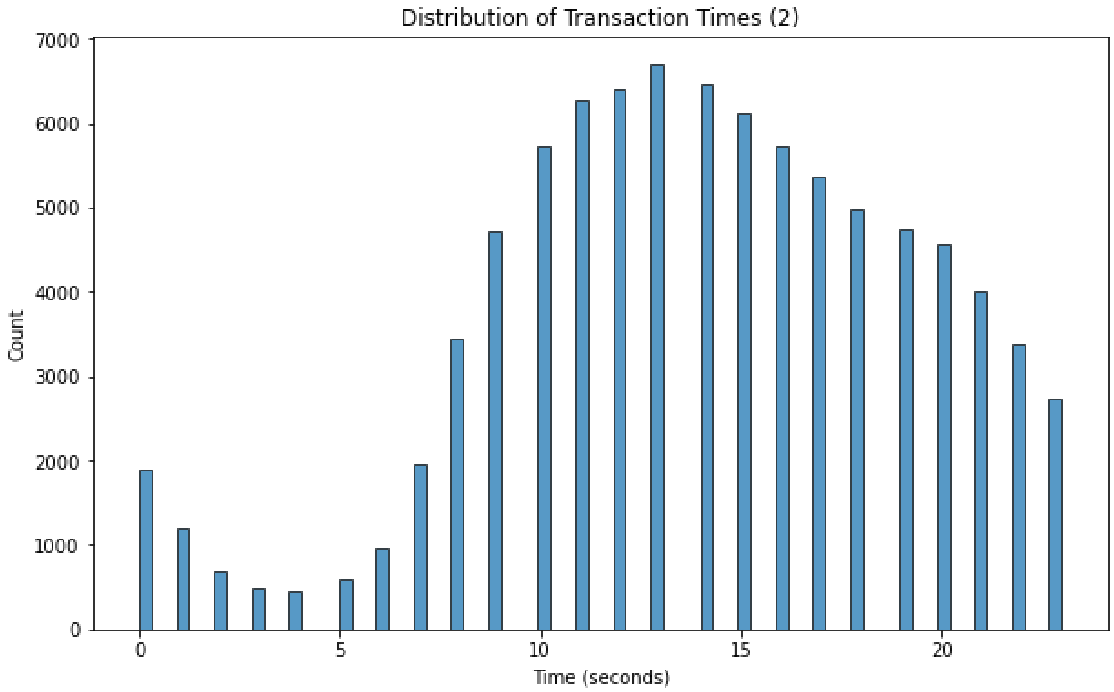
[8]:
```python
df1['TIME1']
```

[8]:
```
0        12
1        18
2         3
3        23
4         9
         ..
89609    11
89610    16
89611    18
89612    23
89613    11
Name: TIME1, Length: 89614, dtype: int64
```

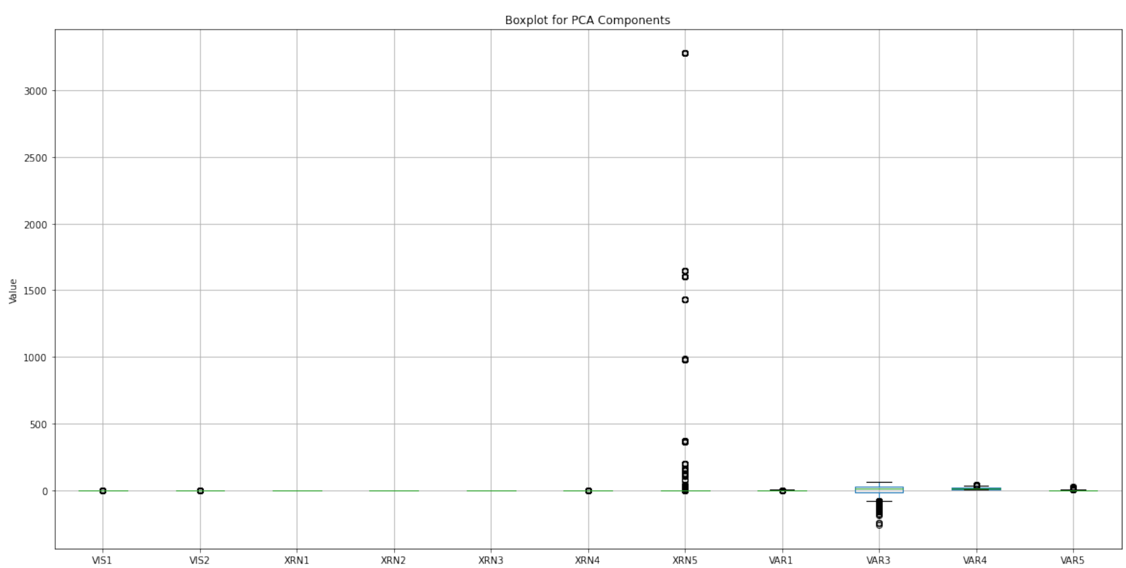
[9]:
```python
plt.figure(figsize=(10,6))
sns.histplot(data=df1, x='TIME1')
plt.title('Distribution of Transaction Times (1)')
plt.xlabel('Time (seconds)')
plt.ylabel('Count')
plt.show()

plt.figure(figsize=(10,6))
sns.histplot(data=df1, x='TIME2')
plt.title('Distribution of Transaction Times (2)')
plt.xlabel('Time (seconds)')
plt.ylabel('Count')
plt.show()

print(df1['TRN_TYPE'].value_counts(normalize=True))
```

```python
plt.figure(figsize=(20,10))
df1.boxplot(column=['VIS1', 'VIS2', 'XRN1', 'XRN2', 'XRN3', 'XRN4', 'XRN5',␣
↪'VAR1', 'VAR3', 'VAR4', 'VAR5'])
plt.title('Boxplot for PCA Components')
plt.xlabel('PCA Components')
plt.ylabel('Value')
plt.show()
```

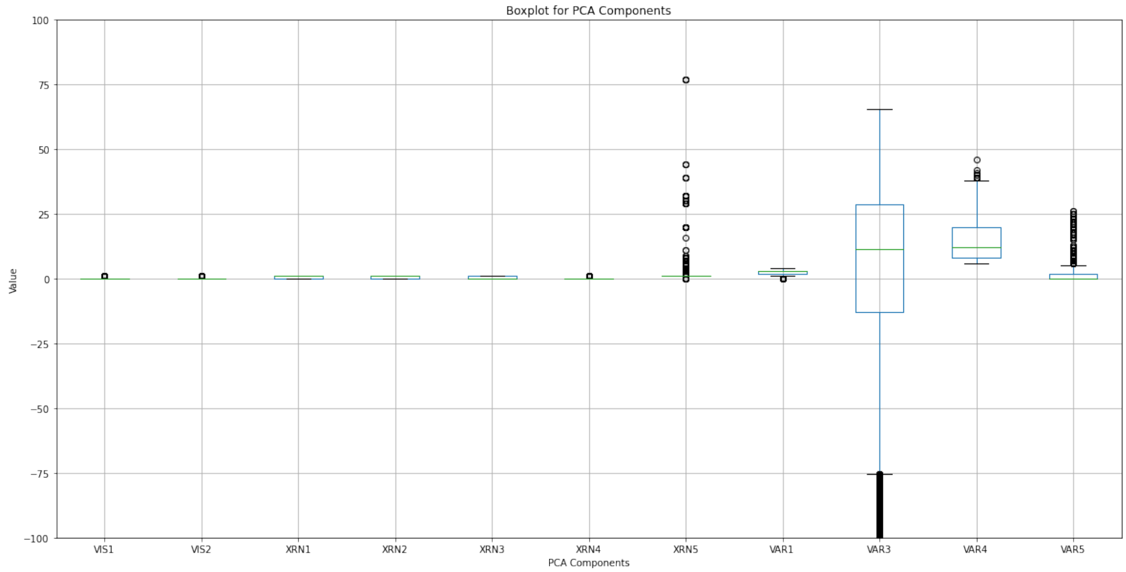




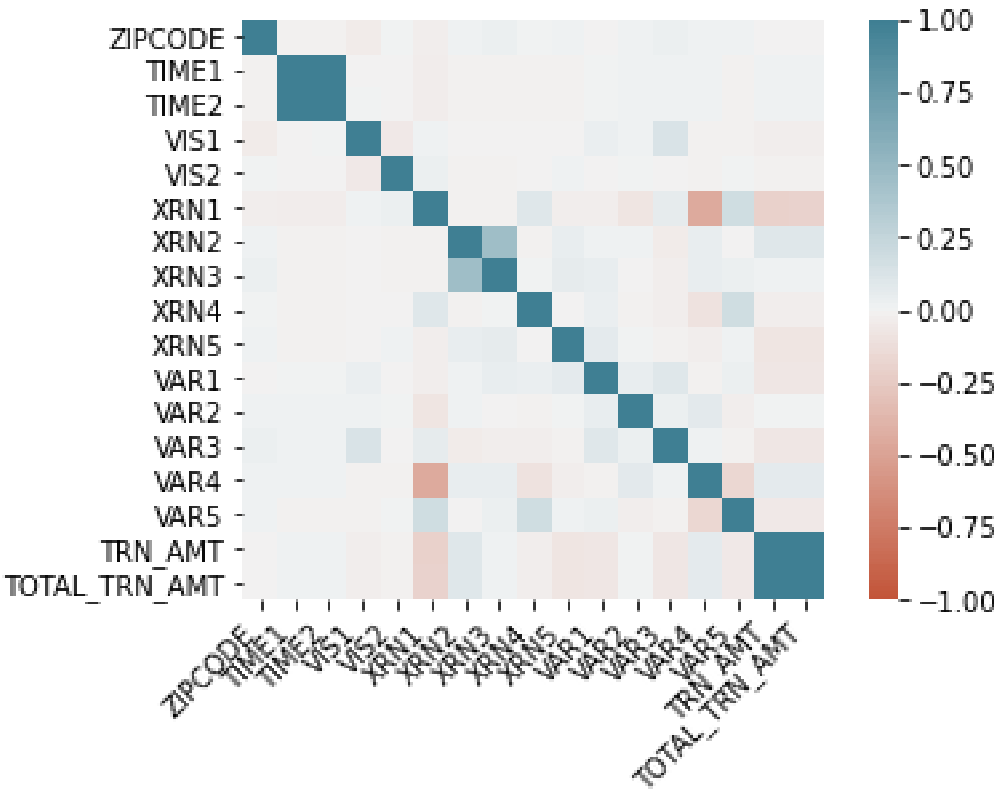

```
TRN_TYPE
LEGIT    0.977102
FRAUD    0.022898
Name: proportion, dtype: float64
```



[10]:
```
plt.figure(figsize=(20,10))
plt.ylim(-100, 100)
df1.boxplot(column=['VIS1', 'VIS2', 'XRN1', 'XRN2', 'XRN3', 'XRN4', 'XRN5',␣
↪'VAR1', 'VAR3', 'VAR4', 'VAR5'])
plt.title('Boxplot for PCA Components')
plt.xlabel('PCA Components')
plt.ylabel('Value')
plt.show()
```



[11]:
```
corr = df1.select_dtypes(include='number').corr()
ax = sns.heatmap(
    corr,
    vmin=-1, vmax=1, center=0,
    cmap=sns.diverging_palette(20, 220, n=200),
    square=True
)
ax.set_xticklabels(
    ax.get_xticklabels(),
    rotation=45,
    horizontalalignment='right'
);
```



[12]:
```python
X = df1.drop(['TRN_TYPE'], axis=1)
y = df1['TRN_TYPE']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
X_train
```

[12]:
```
                DOMAIN STATE  ZIPCODE  TIME1  TIME2  VIS1  VIS2  XRN1  XRN2  \
24993      VUHZRNB.COM    KR      119     15     15     0     0     0     1
5185      INCJOCBC.COM    KR      124     14     14     0     0     0     0
25177          TMA.COM    SO      693     17     17     0     0     0     1
55517      TGRXNMB.NET   NAO      166     14     14     0     0     0     0
78860      VUHZRNB.COM    TO      625     10     10     0     0     1     0
…                  …   …        …      …      …   …     …    …     …
73653  XOONBRQMIWLM.COM    MV      369     10     10     1     0     1     0
2120          XOSOP.COM    KR      121     12     12     0     0     1     1
19498         NUFKP.COM    CO      672     20     20     0     0     0     0
56137      VCWGQDR.NET    SP      192     20     20     0     0     1     0
68488          TMA.COM    MO      685     23     23     0     0     1     0

       XRN3  XRN4  XRN5  VAR1  VAR2    VAR3  VAR4  VAR5  TRN_AMT  \
24993     0     0     2     3     0 -51.960     8     0    12.95
5185      0     0     1     0     0  15.256     8     0    38.85
```

```
25177      1      0      1      2      1   6.496      8      0     38.85
55517      0      0      2      2      1   6.080      6      0     38.85
78860      0      0      1      2      1  41.656     10      3     49.95
…      …     …     …     …     …      …     …     …      …
73653      0      0      1      2      1  29.792      9      9     38.85
2120       1      0      1      3      0  -7.392      6      0     38.85
19498      1      0      1      3      0  11.808     21      0     12.95
56137      0      0      3      2      0  -9.816      9      0     12.95
68488      0      0      1      3      0  33.800      7      2     38.85

       TOTAL_TRN_AMT
24993          12.95
5185           38.85
25177          38.85
55517          38.85
78860          49.95
…              …
73653          38.85
2120           38.85
19498          12.95
56137          12.95
68488          38.85

[71691 rows x 19 columns]
```

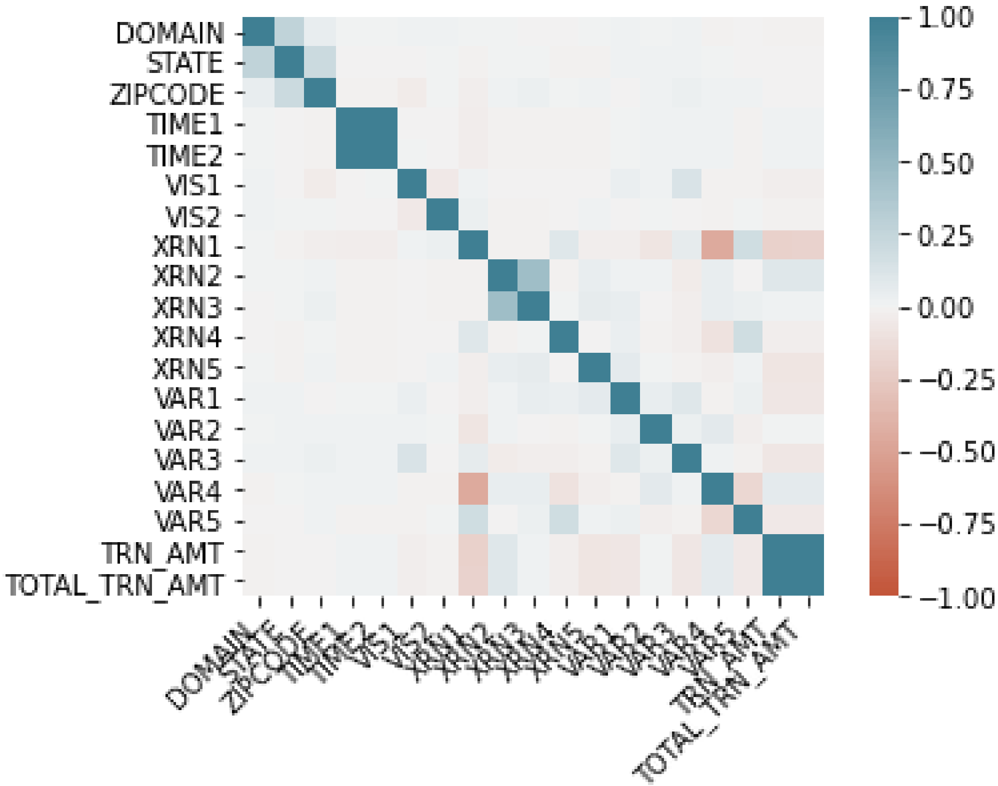
[13]:
```python
data = df1.copy()
data.TRN_TYPE = data.TRN_TYPE=='FRAUD'
```

[14]:
```python
# %pip install category_encoders
```

[15]:
```python
import category_encoders as ce

numeric_columns = ['ZIPCODE', 'TIME1', 'TIME2', 'VIS1', 'VIS2', 'XRN1', 'XRN2', 'XRN3', 'XRN4', 'XRN5', 'VAR1', 'VAR2', 'VAR3', 'VAR4', 'VAR5', 'TRN_AMT', 'TOTAL_TRN_AMT']
categorical_columns = ['DOMAIN', 'STATE']

# Assuming 'X_train' is your training data with categorical features
# Replace 'categorical_columns' with the names of your categorical columns
encoder = ce.TargetEncoder(cols=['DOMAIN', 'STATE'])
data_encoded = encoder.fit_transform(data.drop(columns=['TRN_TYPE']), data.TRN_TYPE)
```

[16]:
```python
corr = data_encoded.corr()
ax = sns.heatmap(
    corr,
    vmin=-1, vmax=1, center=0,
```

```
    cmap=sns.diverging_palette(20, 220, n=200),
    square=True
)
ax.set_xticklabels(
    ax.get_xticklabels(),
    rotation=45,
    horizontalalignment='right'
);
```



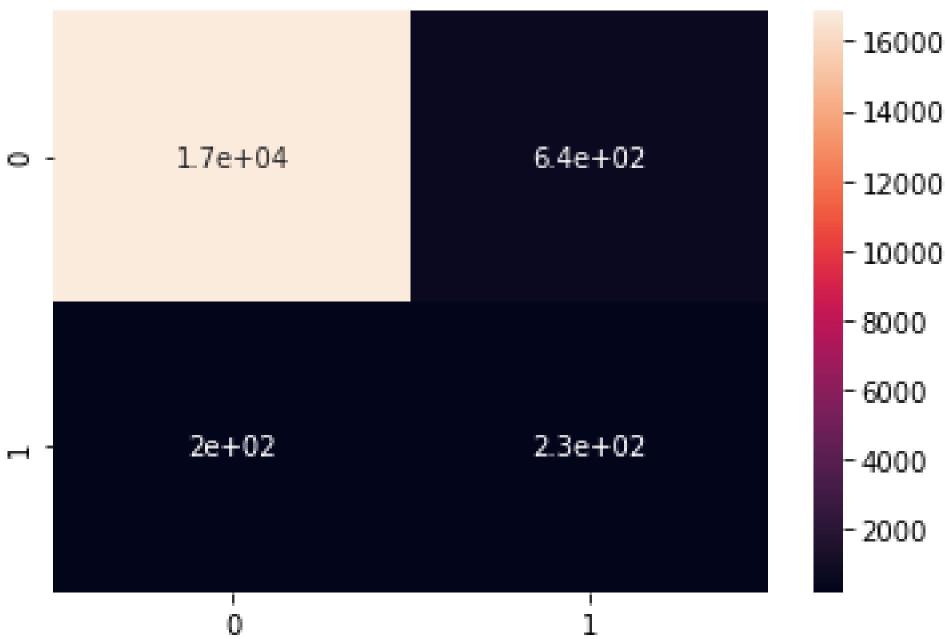
[17]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix

X_train, X_test, y_train, y_test = train_test_split(data_encoded, data.TRN_TYPE, test_size=0.2, random_state=42)
```

[18]:
```
RF_clf = RandomForestClassifier(n_estimators = 150, criterion = 'gini', max_depth=12,
                             class_weight='balanced', max_features=6)
RF_clf.fit(X_train, y_train)
```

```python
y_pred_RF = RF_clf.predict(X_test)
print(classification_report(y_test, y_pred_RF))
cm = confusion_matrix(y_test, y_pred_RF)
sns.heatmap(cm, annot=True)
```

```
              precision    recall  f1-score   support

       False       0.99      0.96      0.98     17490
        True       0.26      0.53      0.35       433

    accuracy                           0.95     17923
   macro avg       0.63      0.75      0.66     17923
weighted avg       0.97      0.95      0.96     17923
```

[18]: <AxesSubplot:>



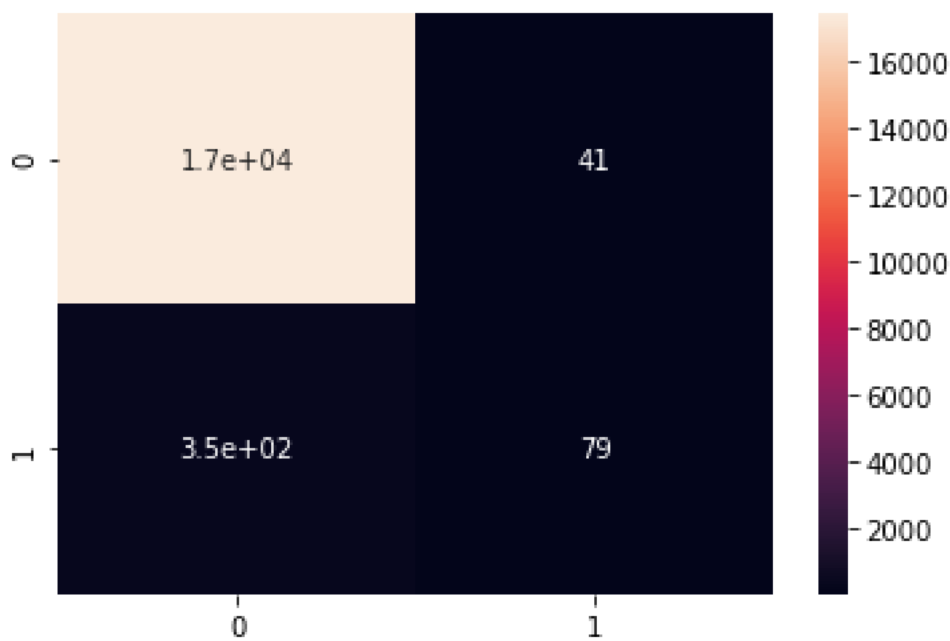
[19]:
```python
#%pip install xgboost
```

[20]:
```python
from xgboost import XGBClassifier

XGB_clf = XGBClassifier(n_estimators=10, max_depth=5, learning_rate=1,␣
 ↪objective='binary:logistic')
XGB_clf.fit(X_train, y_train)
y_pred = XGB_clf.predict(X_test)
```

```
print(classification_report(y_test, y_pred))
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True)
```

```
              precision    recall  f1-score   support

       False       0.98      1.00      0.99     17490
        True       0.66      0.18      0.29       433

    accuracy                           0.98     17923
   macro avg       0.82      0.59      0.64     17923
weighted avg       0.97      0.98      0.97     17923
```

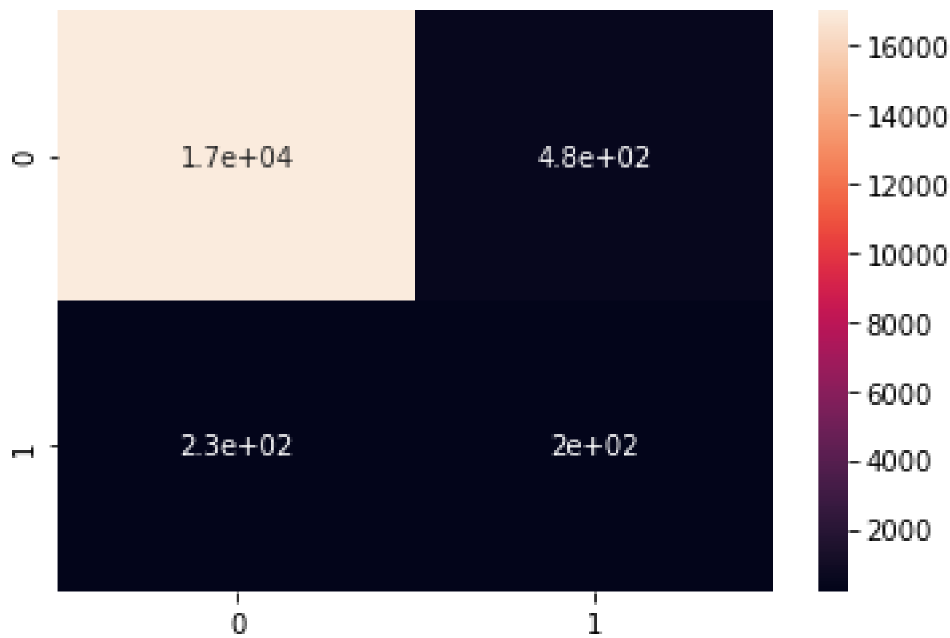
[20]: <AxesSubplot:>



[21]:
```
from sklearn.naive_bayes import GaussianNB

GNB_clf = GaussianNB()
GNB_clf.fit(X_train, y_train)
y_pred_GNB = GNB_clf.predict(X_test)

print(classification_report(y_test, y_pred))
cm = confusion_matrix(y_test, y_pred_GNB)
sns.heatmap(cm, annot=True)
```

```
              precision    recall  f1-score   support

       False       0.98      1.00      0.99     17490
        True       0.66      0.18      0.29       433

    accuracy                           0.98     17923
   macro avg       0.82      0.59      0.64     17923
weighted avg       0.97      0.98      0.97     17923
```

[21]: <AxesSubplot:>



[22]:
```
%pip install imblearn
```

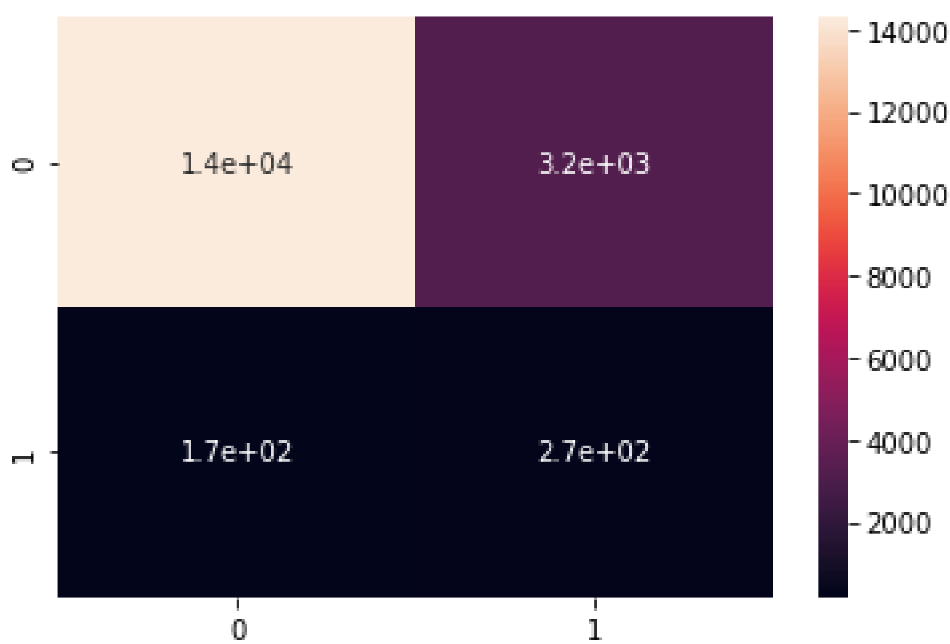
```
Defaulting to user installation because normal site-packages is not writeable
Requirement already satisfied: imblearn in
/home/wolee/.local/lib/python3.9/site-packages (0.0)
Requirement already satisfied: imbalanced-learn in
/home/wolee/.local/lib/python3.9/site-packages (from imblearn) (0.12.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/opt/conda/lib/python3.9/site-packages (from imbalanced-learn->imblearn) (2.2.0)
Requirement already satisfied: numpy>=1.17.3 in /opt/conda/lib/python3.9/site-
packages (from imbalanced-learn->imblearn) (1.22.4)
Requirement already satisfied: scikit-learn>=1.0.2 in
/home/wolee/.local/lib/python3.9/site-packages (from imbalanced-learn->imblearn)
(1.4.2)
```

```
Requirement already satisfied: scipy>=1.5.0 in /opt/conda/lib/python3.9/site-
packages (from imbalanced-learn->imblearn) (1.7.0)
Requirement already satisfied: joblib>=1.1.1 in
/home/wolee/.local/lib/python3.9/site-packages (from imbalanced-learn->imblearn)
(1.4.0)
Note: you may need to restart the kernel to use updated packages.
```

[23]:
```python
from imblearn.ensemble import BalancedRandomForestClassifier

bal_RF_clf = BalancedRandomForestClassifier(sampling_strategy="auto",␣
 ↪replacement=True, max_depth=2, bootstrap=True)
bal_RF_clf.fit(X_train, y_train)
y_pred = bal_RF_clf.predict(X_test)
print(classification_report(y_test, y_pred))
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True)
```

```
              precision    recall  f1-score   support

       False       0.99      0.82      0.89     17490
        True       0.08      0.62      0.14       433

    accuracy                           0.81     17923
   macro avg       0.53      0.72      0.52     17923
weighted avg       0.97      0.81      0.88     17923
```

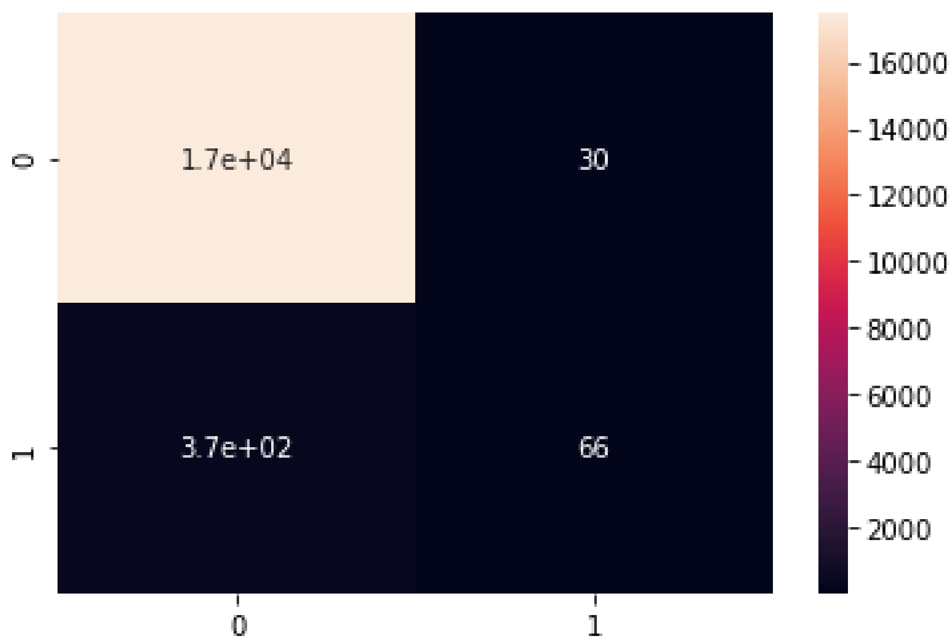
[23]: <AxesSubplot:>



[24]:
```python
from sklearn.linear_model import SGDClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import make_pipeline
from sklearn.pipeline import Pipeline

lin_clf = make_pipeline(StandardScaler(), SGDClassifier(max_iter=1000, tol=1e3))
lin_clf.fit(X_train, y_train)
Pipeline(steps=[('standardscaler', StandardScaler()),
                ('sgdclassifier', SGDClassifier())])
y_pred = lin_clf.predict(X_test)
print(classification_report(y_test, y_pred))
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True)
```

```
              precision    recall  f1-score   support

       False       0.98      1.00      0.99     17490
        True       0.69      0.15      0.25       433

    accuracy                           0.98     17923
   macro avg       0.83      0.58      0.62     17923
weighted avg       0.97      0.98      0.97     17923
```

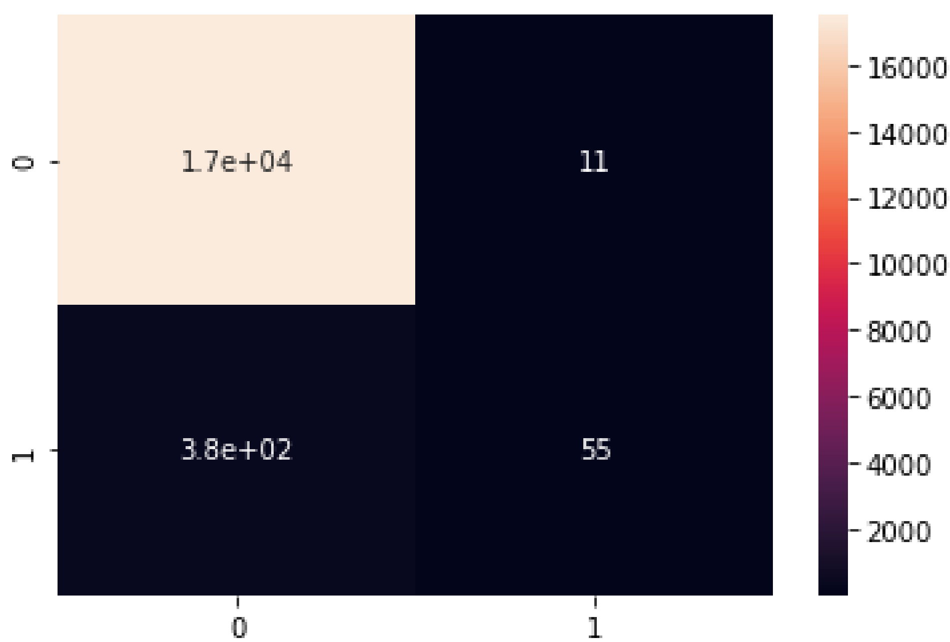
[24]: <AxesSubplot:>



[25]:
```
from sklearn.svm import SVC

SVM_clf = make_pipeline(StandardScaler(), SVC(gamma='auto'))
SVM_clf.fit(X_train, y_train)
Pipeline(steps=[('standardscaler', StandardScaler()),
                ('svc', SVC(gamma='auto'))])
y_pred = SVM_clf.predict(X_test)
print(classification_report(y_test, y_pred))
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True)
```

```
              precision    recall  f1-score   support

       False       0.98      1.00      0.99     17490
        True       0.83      0.13      0.22       433

    accuracy                           0.98     17923
   macro avg       0.91      0.56      0.60     17923
weighted avg       0.98      0.98      0.97     17923
```

[25]: <AxesSubplot:>

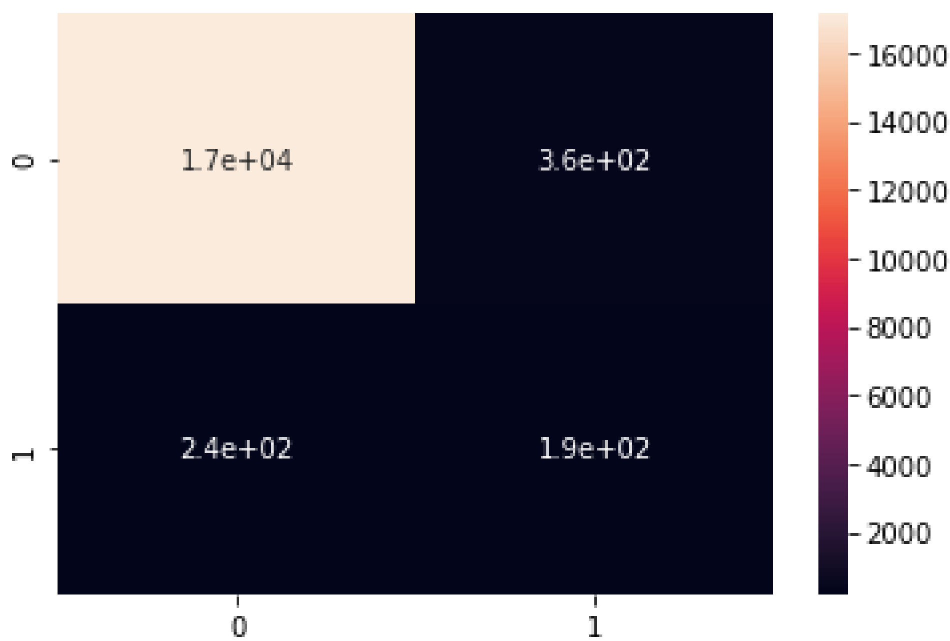


We will create an ensemble classifier with the three best performing classifiers so far: random forest, XGBoost, and bayes classifiers.

[26]:
```
from sklearn.ensemble import VotingClassifier

eclf = VotingClassifier(estimators=[('rf', RF_clf), ('gnb', GNB_clf), ('xgb',␣
↪XGB_clf)], voting='hard')
eclf.fit(X_train, y_train)
y_pred = eclf.predict(X_test)
print(classification_report(y_test, y_pred))
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True)
```

```
              precision    recall  f1-score   support

       False       0.99      0.98      0.98     17490
        True       0.34      0.44      0.39       433

    accuracy                           0.97     17923
   macro avg       0.67      0.71      0.68     17923
weighted avg       0.97      0.97      0.97     17923
```

[26]: <AxesSubplot:>



Because our custom ensemble classifier performs the best among the models we have tried, we will go ahead and find hyperparameters for our custom ensemble.

[27]:
```python
from sklearn.model_selection import GridSearchCV
```

[ ]:
```python
rf_params = {
    'rf__n_estimators': [100, 150, 200],
    'rf__max_depth': [10, 12, 14],
    'rf__max_features': [4, 6, 8]
}

xgb_params = {
    'xgb__n_estimators': [5, 10, 15],
    'xgb__max_depth': [3, 5, 7],
    'xgb__learning_rate': [0.1, 0.5, 1]
}

param_grid = {**rf_params, **xgb_params}

eclf = VotingClassifier(estimators=[('rf', RF_clf), ('gnb', GNB_clf), ('xgb',␣
 ↪XGB_clf)], voting='hard')

grid_search = GridSearchCV(estimator=eclf, param_grid=param_grid, cv=5,␣
 ↪scoring='accuracy')
grid_search.fit(X_train, y_train)
```

[28]:
```python
import pickle
```

[29]:
```python
# with open('best_model.pkl', 'wb') as f:
#     pickle.dump(best_model, f)
# with open('grid_search_results.pkl', 'wb') as f:
#     pickle.dump(grid_search, f)
```

[30]:
```python
with open('best_model.pkl', 'rb') as f:
    pkl = pickle.load(f)
with open('grid_search_results.pkl', 'rb') as f:
    loaded_grid_search = pickle.load(f)
```

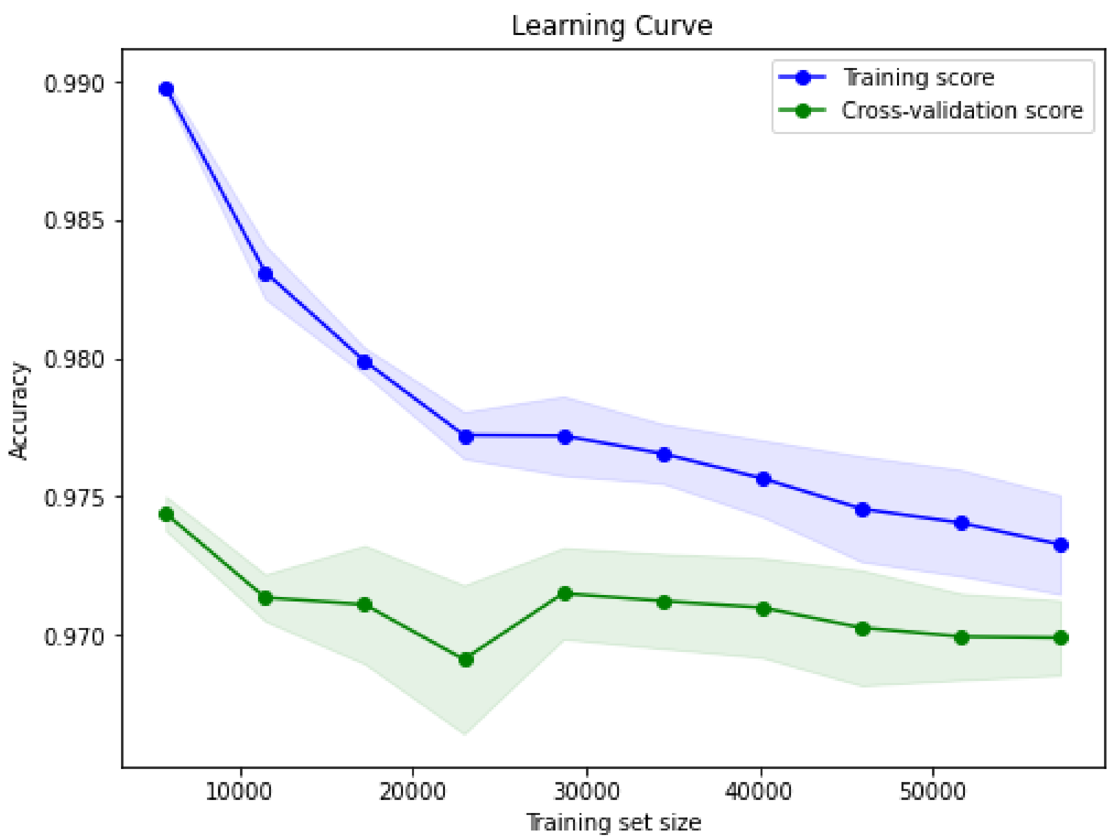
[32]:
```python
best_params = loaded_grid_search.best_params_
best_score = loaded_grid_search.best_score_

print("Best parameters: ", best_params)
print("Best score: ", best_score)
best_model = loaded_grid_search.best_estimator_
best_model
```

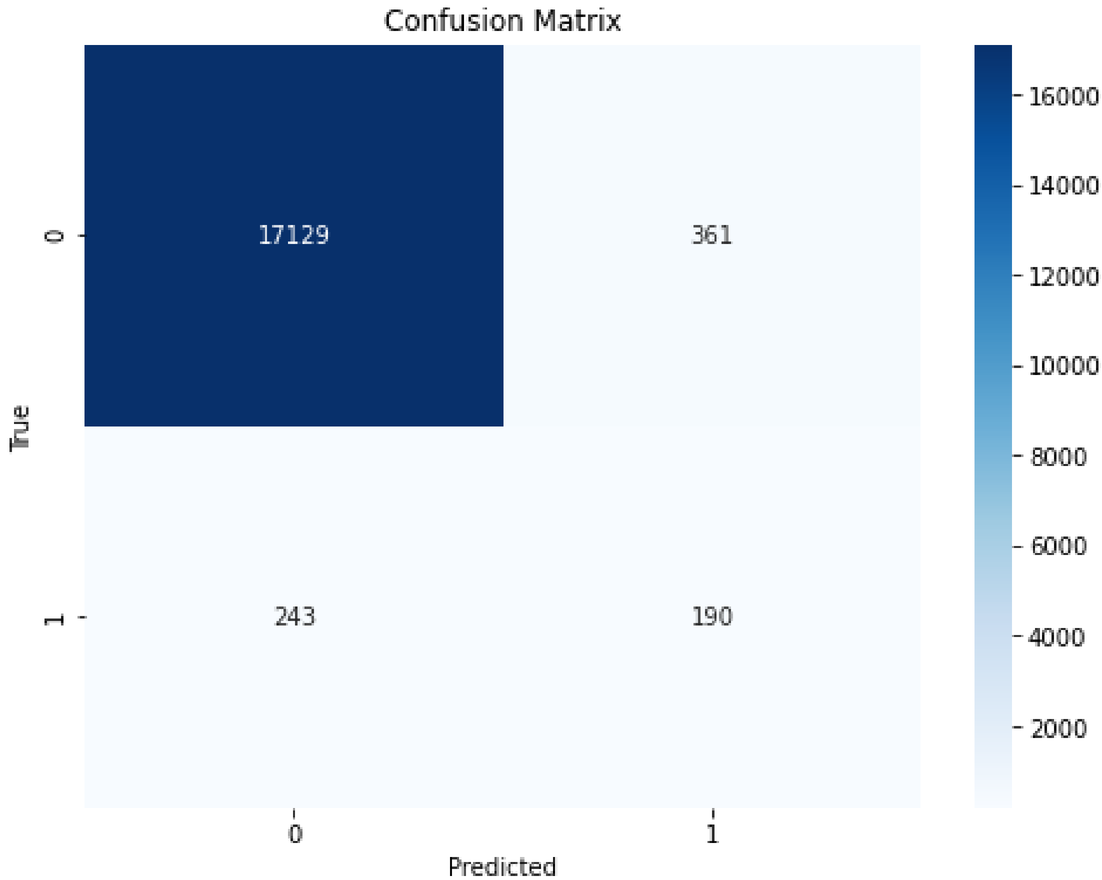
```
Best parameters:  {'rf__max_depth': 14, 'rf__max_features': 8,
'rf__n_estimators': 200, 'xgb__learning_rate': 0.1, 'xgb__max_depth': 7,
'xgb__n_estimators': 10}
Best score:  0.969954364404062
```

[32]:
```
VotingClassifier(estimators=[('rf',
                              RandomForestClassifier(class_weight='balanced',
                                                     max_depth=14,
                                                     max_features=8,
                                                     n_estimators=200)),
                             ('gnb', GaussianNB()),
                             ('xgb',
                              XGBClassifier(base_score=None, booster=None,
                                            callbacks=None,
                                            colsample_bylevel=None,
                                            colsample_bynode=None,
                                            colsample_bytree=None, device=None,
                                            early_stopping_rounds=None,
                                            enable_categorical=False,
                                            eval…
                                            feature_types=None, gamma=None,
                                            grow_policy=None,
                                            importance_type=None,
                                            interaction_constraints=None,
                                            learning_rate=0.1, max_bin=None,
                                            max_cat_threshold=None,
                                            max_cat_to_onehot=None,
                                            max_delta_step=None, max_depth=7,
                                            max_leaves=None,
                                            min_child_weight=None, missing=nan,
                                            monotone_constraints=None,
                                            multi_strategy=None,
                                            n_estimators=10, n_jobs=None,
                                            num_parallel_tree=None,
                                            random_state=None, …))])
```

[33]:
```python
from sklearn.model_selection import learning_curve

train_sizes, train_scores, val_scores = learning_curve(loaded_grid_search.
 ↪best_estimator_, X_train, y_train, cv=5, scoring='accuracy', n_jobs=-1,␣
 ↪train_sizes=np.linspace(0.1, 1.0, 10))

train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
val_scores_mean = np.mean(val_scores, axis=1)
val_scores_std = np.std(val_scores, axis=1)

plt.figure(figsize=(8, 6))
plt.plot(train_sizes, train_scores_mean, 'o-', color='blue', label='Training␣
 ↪score')
plt.plot(train_sizes, val_scores_mean, 'o-', color='green',␣
 ↪label='Cross-validation score')
```

```
plt.fill_between(train_sizes, train_scores_mean - train_scores_std,␣
↪train_scores_mean + train_scores_std, alpha=0.1, color='blue')
plt.fill_between(train_sizes, val_scores_mean - val_scores_std, val_scores_mean␣
↪+ val_scores_std, alpha=0.1, color='green')
plt.xlabel('Training set size')
plt.ylabel('Accuracy')
plt.title('Learning Curve')
plt.legend(loc='best')
plt.show()

plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, cmap='Blues', fmt='d')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()

y_pred = loaded_grid_search.predict(X_test)
print(classification_report(y_test, y_pred))
```





	precision	recall	f1-score	support
False	0.99	0.98	0.98	17490
True	0.35	0.41	0.38	433
accuracy			0.97	17923
macro avg	0.67	0.69	0.68	17923
weighted avg	0.97	0.97	0.97	17923

1.3 Result

The primary objective of this project was to develop a model capable of effectively detecting credit card fraud. Various classification algorithms were explored, including Random Forest, XGBoost, Gaussian Naive Bayes, Balanced Random Forest, Stochastic Gradient Descent, and Support Vector Machines. An ensemble model combining the Random Forest, XGBoost, and Gaussian Naive Bayes classifiers using hard voting demonstrated the best performance. Hyperparameter tuning was performed on this ensemble model using GridSearchCV. The optimal parameters identified were:

Random Forest: n_estimators: 200, max_depth: 14, max_features: 8

XGBoost: n_estimators: 10, max_depth: 7, learning_rate: 0.1

The confusion matrix reveals that out of 433 fraudulent transactions in the test set, the model correctly identified 177 of them, resulting in a recall of 41%. However, 256 fraudulent transactions remained undetected by the model. The model exhibited very high precision (0.99) and recall (0.98) for non-fraudulent transactions.

1.4 Conclusion

Developing an effective fraud detection model presents significant challenges due to the highly imbalanced nature of the data, with fraudulent transactions constituting a very small minority. The ensemble model developed in this project achieves a high overall accuracy of 97% but only detects 41% of fraudulent transactions. While the model succeeds in minimizing false positives, it allows a considerable number of fraudulent transactions to pass through undetected. In the context of a fraud detection system, recall holds greater importance than precision. The failure to detect a fraudulent transaction bears more severe consequences than flagging some legitimate transactions for additional manual review. There remains room for improvement in the model's ability to identify fraudulent transactions.

Potential avenues for future research and development include:

- Gathering a larger dataset, particularly with more examples of fraudulent transactions, to enhance the model's capacity to learn fraud patterns
- Conducting feature engineering to create new predictive features
- Exploring alternative resampling techniques to address the class imbalance
- Investigating anomaly detection algorithms that may be better suited for this highly imbalanced scenario

This project demonstrates the development of a machine learning pipeline for fraud detection, encompassing data preprocessing, model training, hyperparameter tuning, and evaluation. The results highlight the intricacies involved and emphasize the necessity for continuous iteration and refinement in constructing effective fraud detection systems.

```
[ ]:
```