04_fraud_detection

October 23, 2025

1 Task 4: Fraud Detection in Financial Transactions

1.1 Task Overview

Objective: Identify fraudulent transactions from synthetic financial data.

Deliverables:

- Data preprocessing and visualization
- Class balancing (SMOTE or undersampling)
- Random Forest / Gradient Boosting model
- Confusion matrix, Precision/Recall analysis

[ ]:
```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 imblearn.over_sampling import SMOTE
from imblearn.under_sampling import RandomUnderSampler
from imblearn.pipeline import Pipeline
```

[ ]:
```python
n = 50000
data = pd.DataFrame({
    'TransactionID': np.arange(n),
    'Amount': np.round(np.random.exponential(scale=100, size=n), 2),
    'Time': np.random.randint(0, 86400, size=n),  # seconds in a day
    'Location': np.random.choice(['NY', 'CA', 'TX', 'FL'], size=n),
    'Device': np.random.choice(['Mobile', 'Web', 'ATM'], size=n),
    'IsFraud': np.random.choice([0, 1], size=n, p=[0.98, 0.02])
})
```

[103]:
```python
data.sample(5)
```

[103]:
```
       TransactionID  Amount   Time Location  Device  IsFraud
5548            5548  229.46  19688       FL  Mobile        0
37543          37543   12.16  24901       TX     Web        0
22735          22735  143.40  16649       TX  Mobile        0
3494            3494   59.95  61208       NY     ATM        0
```

```
42802          42802  294.04  83431       TX     Web        0
```

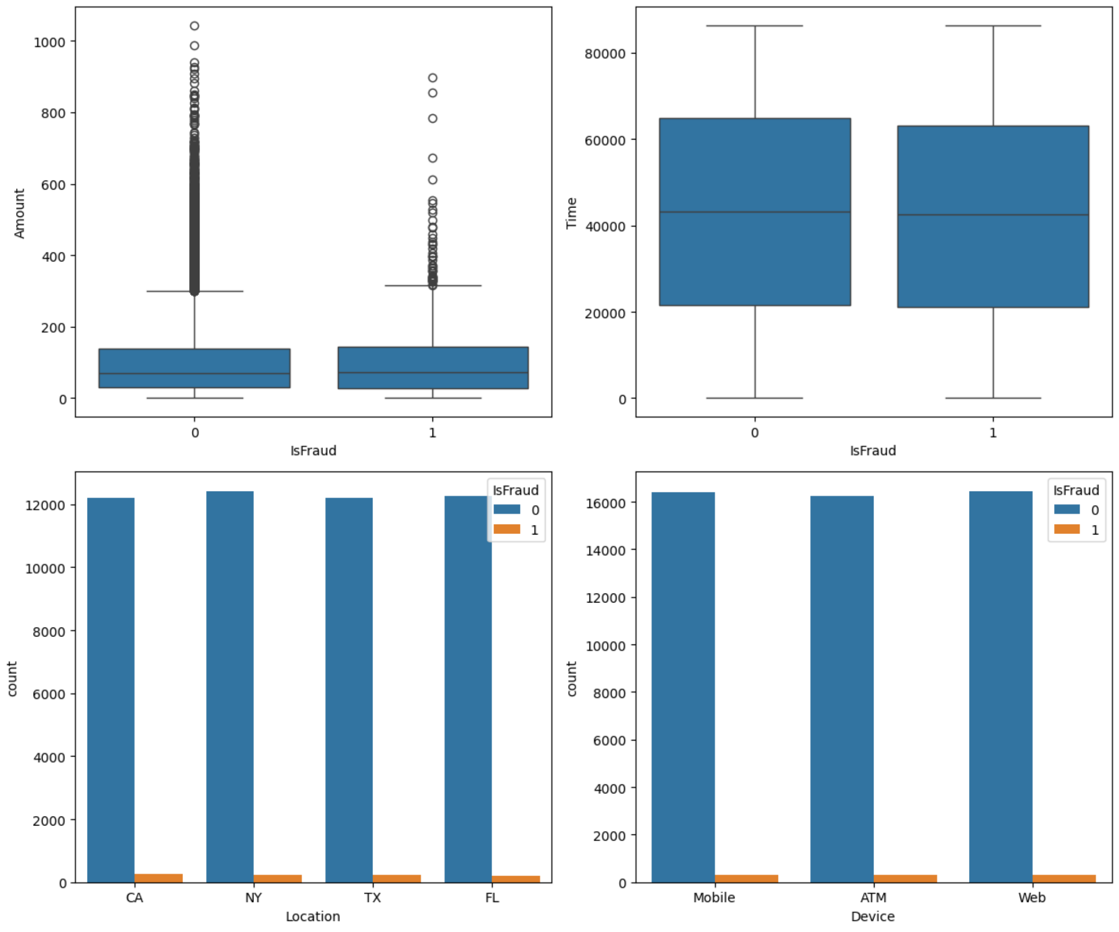
[104]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50000 entries, 0 to 49999
Data columns (total 6 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   TransactionID  50000 non-null  int64
 1   Amount         50000 non-null  float64
 2   Time           50000 non-null  int64
 3   Location       50000 non-null  object
 4   Device         50000 non-null  object
 5   IsFraud        50000 non-null  int64
dtypes: float64(1), int64(3), object(2)
memory usage: 2.3+ MB
```

[105]:
```
data.describe()
```

[105]:
```
       TransactionID        Amount          Time       IsFraud
count   50000.000000  50000.000000  50000.000000  50000.000000
mean    24999.500000    100.478261  43233.109520      0.018500
std     14433.901067    100.564985  24910.786162      0.134752
min         0.000000      0.000000      0.000000      0.000000
25%     12499.750000     29.305000  21647.750000      0.000000
50%     24999.500000     70.280000  43265.500000      0.000000
75%     37499.250000    138.110000  64926.250000      0.000000
max     49999.000000   1043.960000  86399.000000      1.000000
```

[106]:
```
fig, axs = plt.subplots(2, 2, figsize=(12, 10))
sns.boxplot(x='IsFraud', y='Amount', data=data, ax=axs[0, 0])
sns.boxplot(x='IsFraud', y='Time', data=data, ax=axs[0, 1])
sns.countplot(x='Location', hue='IsFraud', data=data, ax=axs[1, 0])
sns.countplot(x='Device', hue='IsFraud', data=data, ax=axs[1, 1])
plt.tight_layout()
plt.show()
```



```
[107]: data.columns
```

```
[107]: Index(['TransactionID', 'Amount', 'Time', 'Location', 'Device', 'IsFraud'],
       dtype='object')
```

```
[108]: X = data[['Amount', 'Time', 'Location', 'Device']]
       y = data['IsFraud']
```

```
[109]: print("Original class distribution:")
       print(data['IsFraud'].value_counts())
```

```
Original class distribution:
IsFraud
0    49075
1      925
Name: count, dtype: int64
```

[112]:
```python
# Preprocess data
from sklearn.preprocessing import LabelEncoder, MinMaxScaler

le = LabelEncoder()
X.loc[:, 'Location'] = le.fit_transform(X['Location'])
X.loc[:, 'Device'] = le.fit_transform(X['Device'])

# preprocess the data
scalar = MinMaxScaler()
X.loc[:, ['Amount', 'Time']] = scalar.fit_transform(X[['Amount', 'Time']])
```

```
/tmp/ipykernel_514198/2501154083.py:10: FutureWarning: Setting an item of
incompatible dtype is deprecated and will raise in a future error of pandas.
Value '[0.88507969 0.94760356 0.444982   … 0.7705992  0.69556361 0.48238984]'
has dtype incompatible with int64, please explicitly cast to a compatible dtype
first.
  X.loc[:, ['Amount', 'Time']] = scalar.fit_transform(X[['Amount', 'Time']])
```

[113]:
```python
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, stratify=y, random_state=42
)
```

[114]:
```python
# --- Balancing with SMOTE + Undersampling ---
over = SMOTE(sampling_strategy=0.1, random_state=42)
under = RandomUnderSampler(sampling_strategy=0.5, random_state=42)

balancing_pipeline = Pipeline(steps=[
    ('smote', over),
    ('under', under)
])
```

[115]:
```python
# Apply balancing
X_train_res, y_train_res = balancing_pipeline.fit_resample(X_train, y_train)
```

[116]:
```python
len(X_train_res), y_train_res.value_counts()
```

[116]:
```
(11778,
 IsFraud
 0    7852
 1    3926
 Name: count, dtype: int64)
```

[ ]:
```python
from sklearn.ensemble import RandomForestClassifier

model = RandomForestClassifier(random_state=42,
                                  n_estimators=100,
                               #   min_samples_leaf=0.05
```

```
                                   )
model.fit(X_train_res, y_train_res)
```

[ ]:

```
RandomForestClassifier(random_state=42)
```

[118]:

```
y_pred = model.predict(X_test)
```

[119]:

```
from sklearn.metrics import accuracy_score, confusion_matrix,␣
 ↪classification_report

#evaluate the model
print('accuracy score: ', accuracy_score(y_test, y_pred))
print('confusion matrix:\n', confusion_matrix(y_test, y_pred))
print('classification report:\n', classification_report(y_test, y_pred))
```

```
accuracy score:  0.8498
confusion matrix:
 [[8477 1338]
 [ 164   21]]
classification report:
               precision    recall  f1-score   support

           0       0.98      0.86      0.92      9815
           1       0.02      0.11      0.03       185

    accuracy                           0.85     10000
   macro avg       0.50      0.49      0.47     10000
weighted avg       0.96      0.85      0.90     10000
```

1.2 REPORT:

The model is evaluated on a dataset of 10000 samples. The results are as follows:

- Our model is predicting 85% accurately.
- The model performs well on `Class 0`, achieving high recall (0.86), meaning it correctly identifies most of the `Class 0` samples.
- For `Class 1`, performance is poor, with recall only 0.11. This shows the model is failing to detect most of `Class 1` cases.

The model is biased toward `Class 0` and struggles with detecting `Class 1`