In [1]:
```python
import pandas as pd
import plotly.express as px
from sklearn.model_selection import train_test_split
from sklearn.ensemble import IsolationForest
from sklearn.metrics import classification_report
```

In [3]:
```python
data = pd.read_csv("C://Users//DHANUSHA//Desktop//PROJECTS//transaction_anomalies_dataset.csv")
print(data.head())
```

```
  Transaction_ID  Transaction_Amount  Transaction_Volume  \
0            TX0         1024.835708                   3
1            TX1         1013.952065                   4
2            TX2          970.956093                   1
3            TX3         1040.822254                   2
4            TX4          998.777241                   1

   Average_Transaction_Amount  Frequency_of_Transactions  \
0                  997.234714                         12
1                 1020.210306                          7
2                  989.496604                          5
3                  969.522480                         16
4                 1007.111026                          7

   Time_Since_Last_Transaction Day_of_Week  Time_of_Day  Age  Gender   Income  \
0                           29      Friday          6.0   36    Male  1436074
1                           22      Friday          1.0   41  Female   627069
2                           12     Tuesday         21.0   61    Male   786232
3                           28      Sunday         14.0   61    Male   619030
4                            7      Friday          8.0   56  Female   649457

  Account_Type
0      Savings
1      Savings
2      Savings
3      Savings
4      Savings
```

In [4]:
```python
print(data.isnull().sum())
```

```
Transaction_ID                 0
Transaction_Amount             0
Transaction_Volume             0
Average_Transaction_Amount     0
Frequency_of_Transactions      0
Time_Since_Last_Transaction    0
Day_of_Week                    0
Time_of_Day                    0
Age                            0
Gender                         0
Income                         0
Account_Type                   0
dtype: int64
```

In [5]:
```python
print(data.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 12 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   Transaction_ID               1000 non-null   object
 1   Transaction_Amount           1000 non-null   float64
 2   Transaction_Volume           1000 non-null   int64
 3   Average_Transaction_Amount   1000 non-null   float64
 4   Frequency_of_Transactions    1000 non-null   int64
 5   Time_Since_Last_Transaction  1000 non-null   int64
 6   Day_of_Week                  1000 non-null   object
 7   Time_of_Day                  1000 non-null   float64
 8   Age                          1000 non-null   int64
 9   Gender                       1000 non-null   object
 10  Income                       1000 non-null   int64
 11  Account_Type                 1000 non-null   object
dtypes: float64(3), int64(5), object(4)
memory usage: 93.9+ KB
None
```

In [6]:
```python
print(data.describe())
```

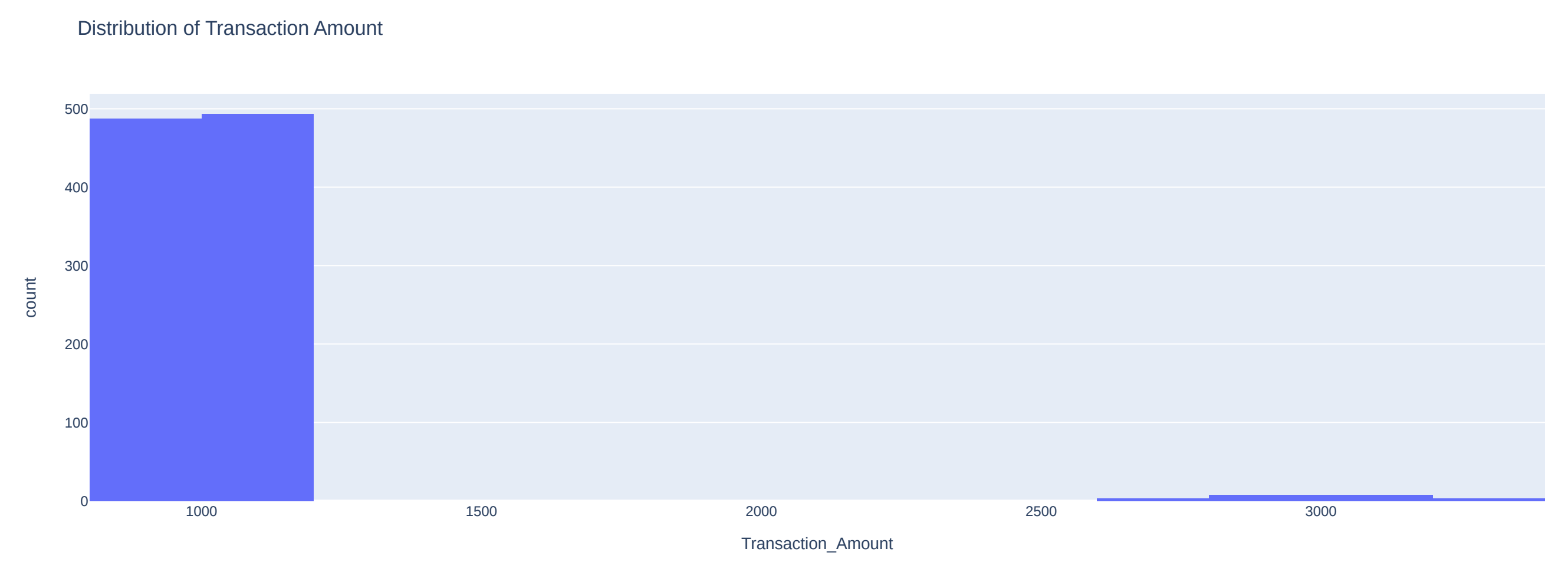
```
       Transaction_Amount  Transaction_Volume  Average_Transaction_Amount  \
count         1000.000000         1000.000000                 1000.000000
mean          1038.122511            2.498000                 1000.682506
std            283.580055            1.115006                   20.632334
min            849.024392            1.000000                  939.081423
25%            966.028796            1.000000                  986.800556
50%           1002.118678            3.000000                 1000.501903
75%           1033.143657            3.000000                 1015.155595
max           3227.459108            4.000000                 1073.154036

       Frequency_of_Transactions  Time_Since_Last_Transaction  Time_of_Day  \
count                1000.000000                  1000.000000  1000.000000
mean                   12.078000                    15.341000    11.796000
std                     4.245225                     8.361258     6.983778
min                     5.000000                     1.000000     0.000000
25%                     8.000000                     8.000000     5.750000
50%                    12.000000                    16.000000    12.000000
75%                    16.000000                    22.000000    18.000000
max                    19.000000                    29.000000    23.000000

               Age        Income
count  1000.000000  1.000000e+03
mean     40.641000  8.948238e+05
std      13.819953  3.453562e+05
min      18.000000  3.001590e+05
25%      29.000000  5.917308e+05
50%      41.000000  8.876645e+05
75%      53.000000  1.178102e+06
max      64.000000  1.499670e+06
```

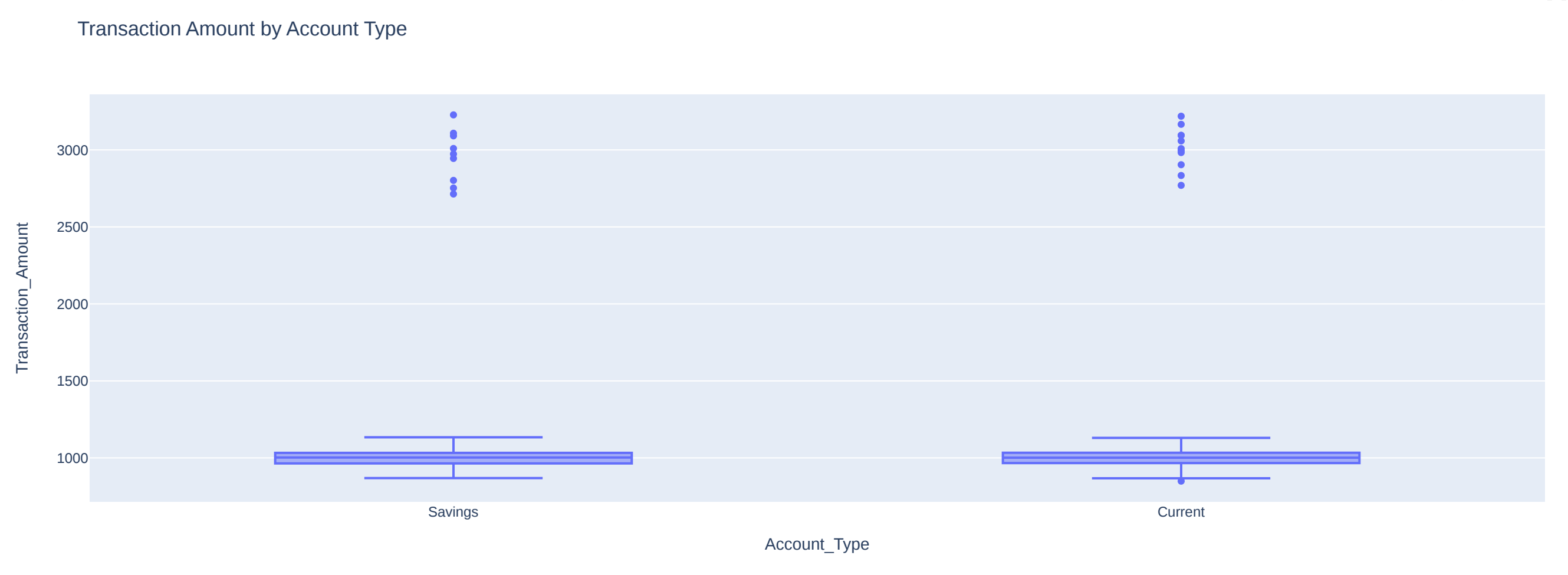
Distribution of Transaction Amount

In [7]:
```python
fig_amount = px.histogram(data, x='Transaction_Amount',
                          nbins=20,
                          title='Distribution of Transaction Amount')
fig_amount.show()
```



Distribution of transactions amount by account type

In [8]:
```python
fig_box_amount = px.box(data,
                        x='Account_Type',
                        y='Transaction_Amount',
                        title='Transaction Amount by Account Type')
fig_box_amount.show()
```

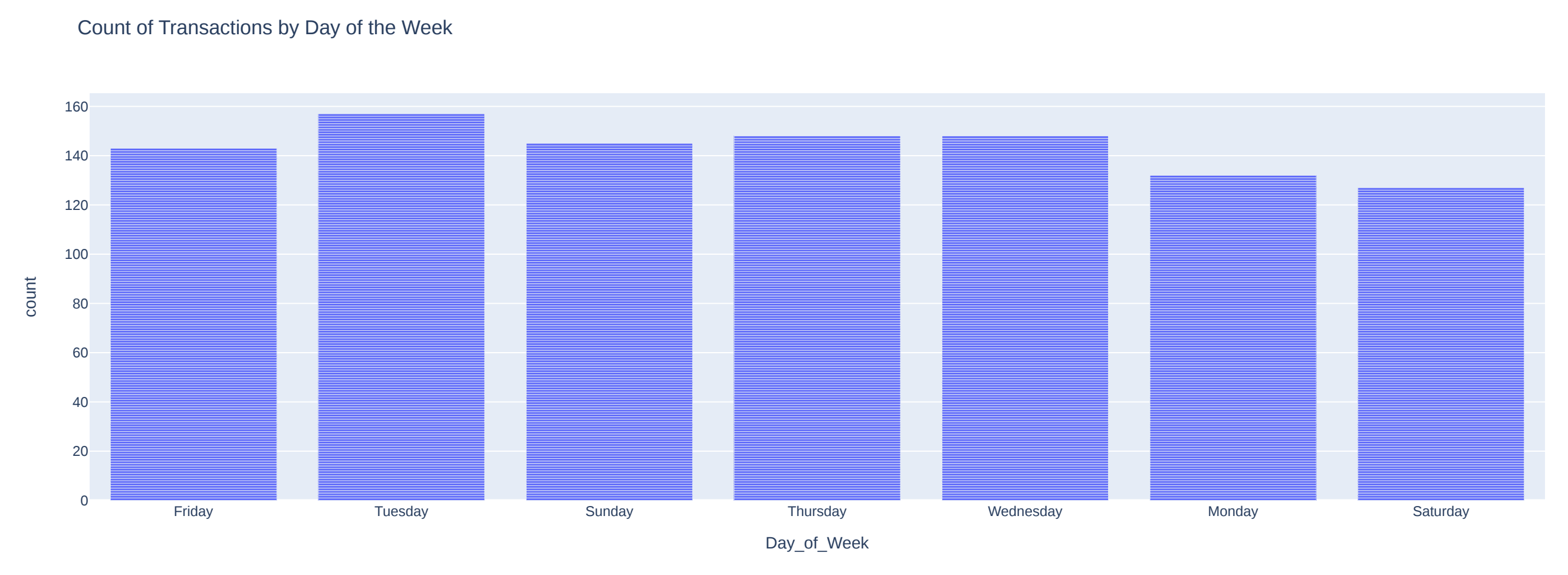


Average Transaction Amount vs. Age

In [9]:
```python
fig_scatter_avg_amount_age = px.scatter(data, x='Age',
                                        y='Average_Transaction_Amount',
                                        color='Account_Type',
                                        title='Average Transaction Amount vs. Age',
                                        trendline='ols')
fig_scatter_avg_amount_age.show()
```

Count of Transactions by Day of the Week

In [10]:
```python
fig_day_of_week = px.bar(data, x='Day_of_Week',
                         title='Count of Transactions by Day of the Week')
fig_day_of_week.show()
```

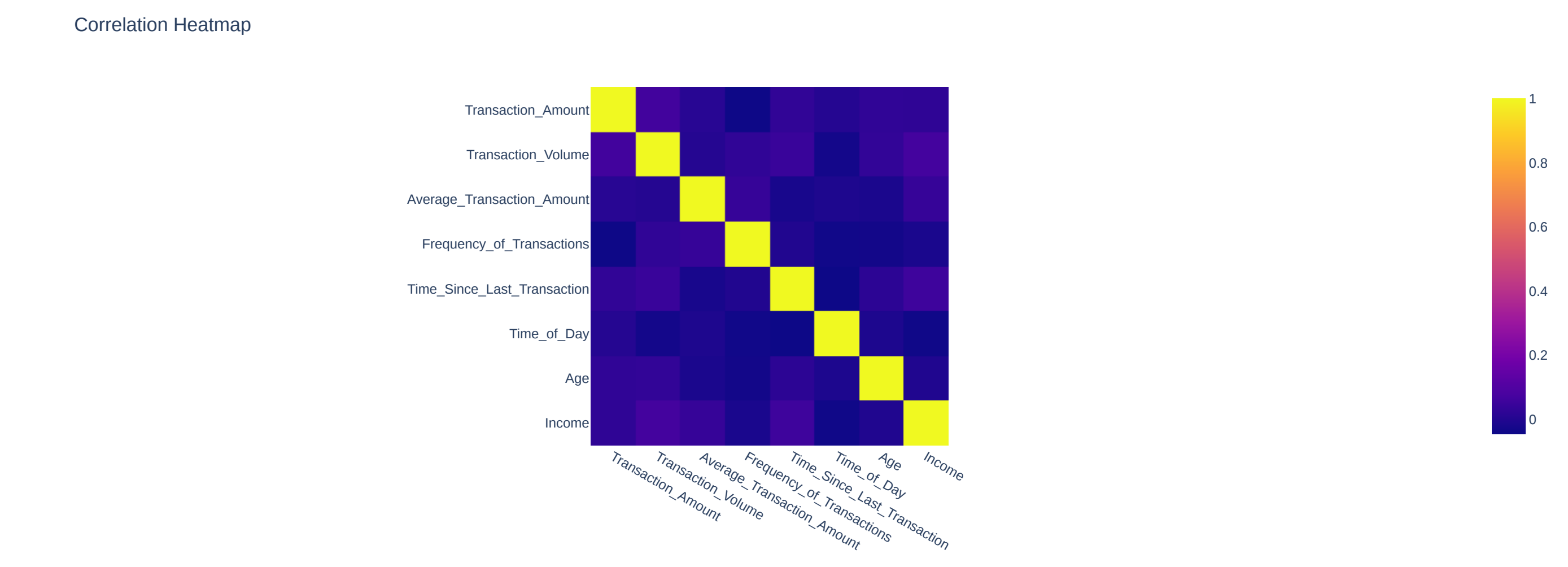


Correlation Heatmap

In [11]:
```python
correlation_matrix = data.corr()
fig_corr_heatmap = px.imshow(correlation_matrix,
                             title='Correlation Heatmap')
fig_corr_heatmap.show()
```

```
C:\Users\DHANUSHA\AppData\Local\Temp\ipykernel_11624\1665080487.py:1: FutureWarning:

The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric_only to silence this warning.
```



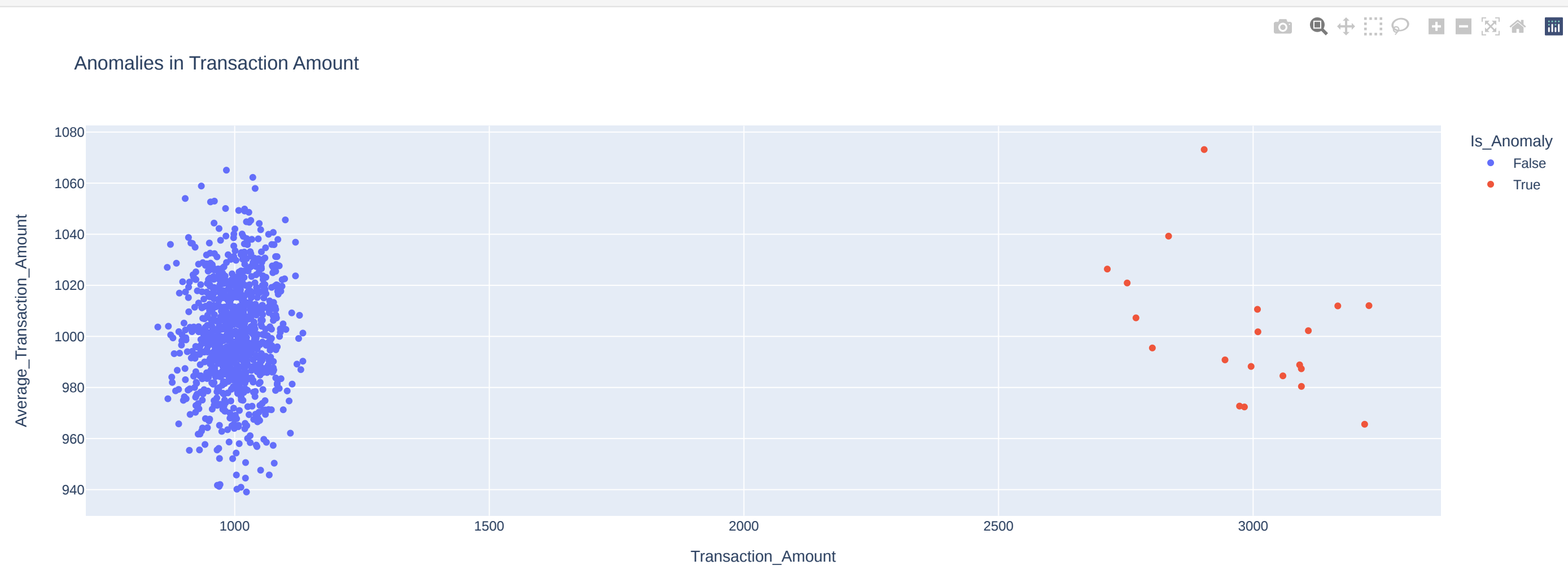
Anomalies in Transaction Amount

In [12]:
```python
mean_amount = data['Transaction_Amount'].mean()
std_amount = data['Transaction_Amount'].std()

anomaly_threshold = mean_amount + 2 * std_amount

data['Is_Anomaly'] = data['Transaction_Amount'] > anomaly_threshold

fig_anomalies = px.scatter(data, x='Transaction_Amount', y='Average_Transaction_Amount',
                           color='Is_Anomaly', title='Anomalies in Transaction Amount')
fig_anomalies.update_traces(marker=dict(size=12),
                            selector=dict(mode='markers', marker_size=1))
fig_anomalies.show()
```



Calculate the number of Anomalies in the data to find the ratio of anomalies in the data

In [13]:
```python
num_anomalies = data['Is_Anomaly'].sum()
total_instances = data.shape[0]
anomaly_ratio = num_anomalies / total_instances
print(anomaly_ratio)
```

```
0.02
```

Machine Learning Model

In [14]:
```python
relevant_features = ['Transaction_Amount',
                     'Average_Transaction_Amount',
                     'Frequency_of_Transactions']

X = data[relevant_features]
y = data['Is_Anomaly']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

model = IsolationForest(contamination=0.02, random_state=42)
model.fit(X_train)
```

Out[14]:
```
IsolationForest
IsolationForest(contamination=0.02, random_state=42)
```

Performance of this anomaly detection

In [15]:
```python
y_pred = model.predict(X_test)
y_pred_binary = [1 if pred == -1 else 0 for pred in y_pred]
report = classification_report(y_test, y_pred_binary, target_names=['Normal', 'Anomaly'])
print(report)
```

```
              precision    recall  f1-score   support

      Normal       1.00      1.00      1.00       196
     Anomaly       1.00      1.00      1.00         4

    accuracy                           1.00       200
   macro avg       1.00      1.00      1.00       200
weighted avg       1.00      1.00      1.00       200
```

How we can use our trained model to detect anomalies

In [17]:
```python
relevant_features = ['Transaction_Amount', 'Average_Transaction_Amount', 'Frequency_of_Transactions']

user_inputs = []
for feature in relevant_features:
    user_input = float(input(f"Enter the value for '{feature}': "))
    user_inputs.append(user_input)

user_df = pd.DataFrame([user_inputs], columns=relevant_features)

user_anomaly_pred = model.predict(user_df)

user_anomaly_pred_binary = 1 if user_anomaly_pred == -1 else 0

if user_anomaly_pred_binary == 1:
    print("Anomaly detected: This transaction is flagged as an anomaly.")
else:
    print("No anomaly detected: This transaction is normal.")
```

```
Enter the value for 'Transaction_Amount': 20000
Enter the value for 'Average_Transaction_Amount': 600
Enter the value for 'Frequency_of_Transactions': 5
Anomaly detected: This transaction is flagged as an anomaly.
```

SUMMARY

So this is how you can perform anomaly detection in transactions using Machine Learning and Python. Anomaly detection in transactions means identifying unusual or unexpected patterns within transactions or related activities. These patterns, known as anomalies or outliers, deviate significantly from the expected norm and could indicate irregular or fraudulent behaviour. I hope you liked this article on Anomaly Detection in transactions using Python. Feel free to ask valuable questions in the comments section below.