Anomaly Detection in Transactions using 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. If you want to learn how to detect anomalies in transactions,
this is for you.
```

```
Anomaly Detection in Transactions: Process We Can Follow
Anomaly detection plays a crucial role in various businesses, especially those dealing
with financial transactions, online activities, and security-sensitive operations.

We can follow a systematic process to address the challenge of anomaly detection. We
can begin by collecting and preparing transaction data, ensuring its accuracy and
consistency. Then, we can find patterns in the data to find anomalies and use
specialized anomaly detection algorithms like isolation forest to detect anomalies.

So the process starts with data collection. I have found an ideal dataset that can be
used for detecting anomalies in transactions.
```

In [1]:

```
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

data = pd.read_csv("C:\\Users\\kourg\\Downloads\\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       06:00   36    Male  1436074   
1                           22      Friday       01:00   41  Female   627069   
2                           12     Tuesday       21:00   61    Male   786232   
3                           28      Sunday       14:00   61    Male   619030   
4                            7      Friday       08:00   56  Female   649457   

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

In [2]:
```
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
```

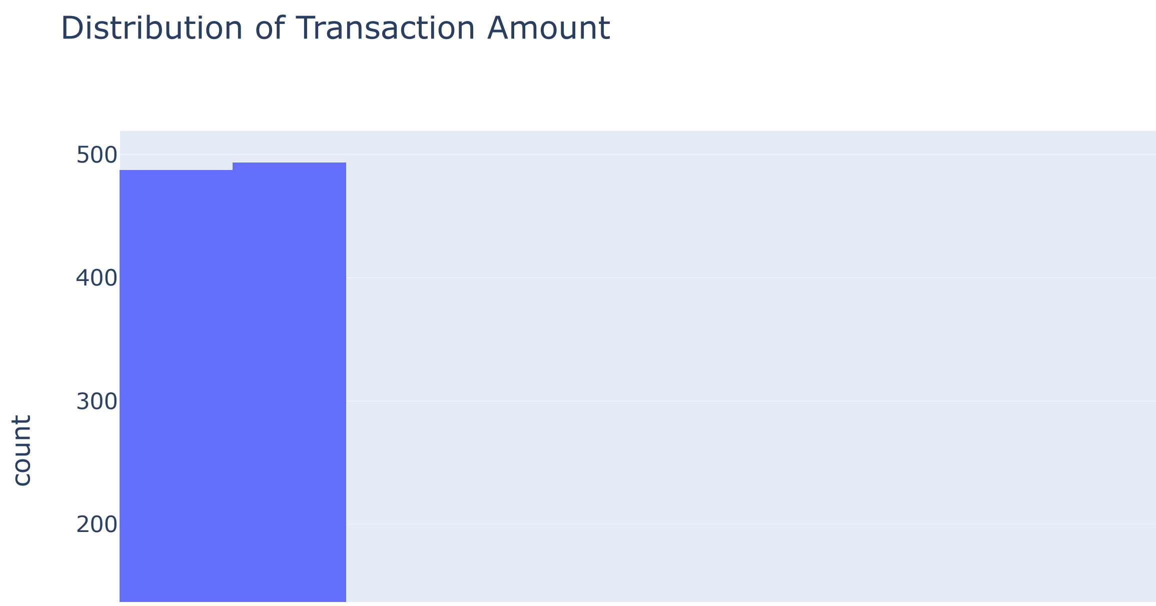
In [3]:
```
print(data.info())
```

```
<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   object
 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(2), int64(5), object(5)
memory usage: 93.9+ KB
None
```

In [4]:
```
print(data.describe())
```

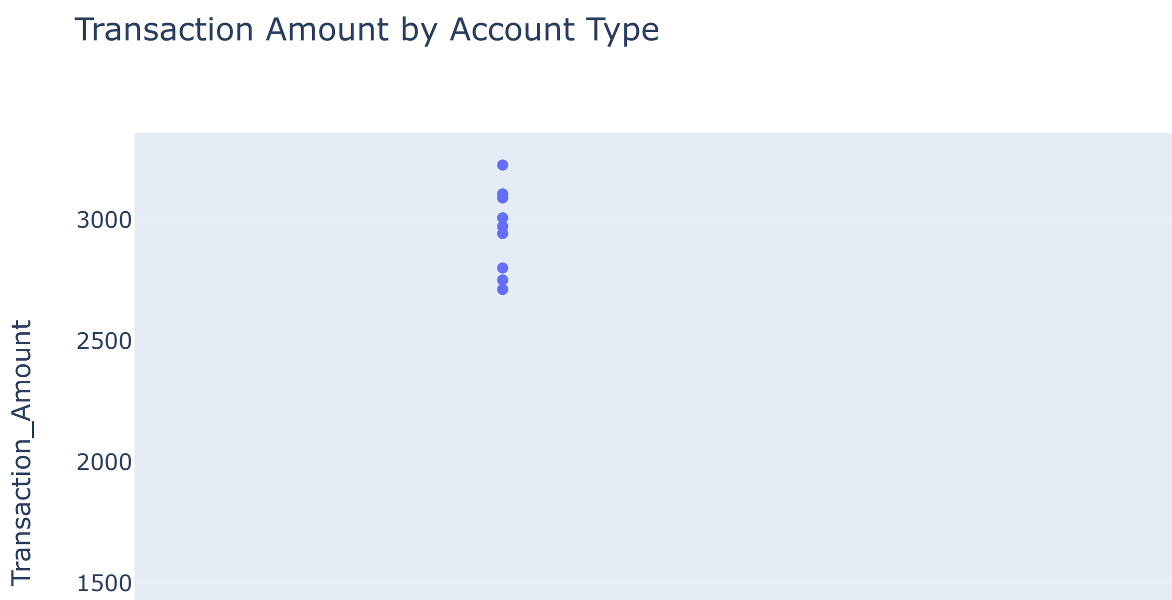
```
       Transaction_Amount  Transaction_Volume  Average_Transaction_Amount  \
count         1000.000000         1000.000000                 1000.000000   
mean          1038.122511            2.498000                 1000.682506   
std            283.580055            1.115006                   20.632334   
min            849.024392            1.000000                  939.081423   
25%            966.028796            1.000000                  986.800556   
50%           1002.118678            3.000000                 1000.501902   
75%           1033.143657            3.000000                 1015.155595   
max           3227.459108            4.000000                 1073.154036   

       Frequency_of_Transactions  Time_Since_Last_Transaction          Age  \
count                1000.000000                  1000.000000  1000.000000   
mean                   12.078000                    15.341000    40.641000   
std                     4.245225                     8.361258    13.819953   
min                     5.000000                     1.000000    18.000000   
25%                     8.000000                     8.000000    29.000000   
50%                    12.000000                    16.000000    41.000000   
75%                    16.000000                    22.000000    53.000000   
max                    19.000000                    29.000000    64.000000   

             Income  
count  1.000000e+03  
mean   8.948238e+05  
std    3.453562e+05  
min    3.001590e+05  
25%    5.917308e+05  
50%    8.876645e+05  
75%    1.178102e+06  
max    1.499670e+06  
```

In [5]:
```
# Distribution of Transaction Amount
fig_amount = px.histogram(data, x='Transaction_Amount',
                          nbins=20,
                          title='Distribution of Transaction Amount')
fig_amount.show()
```

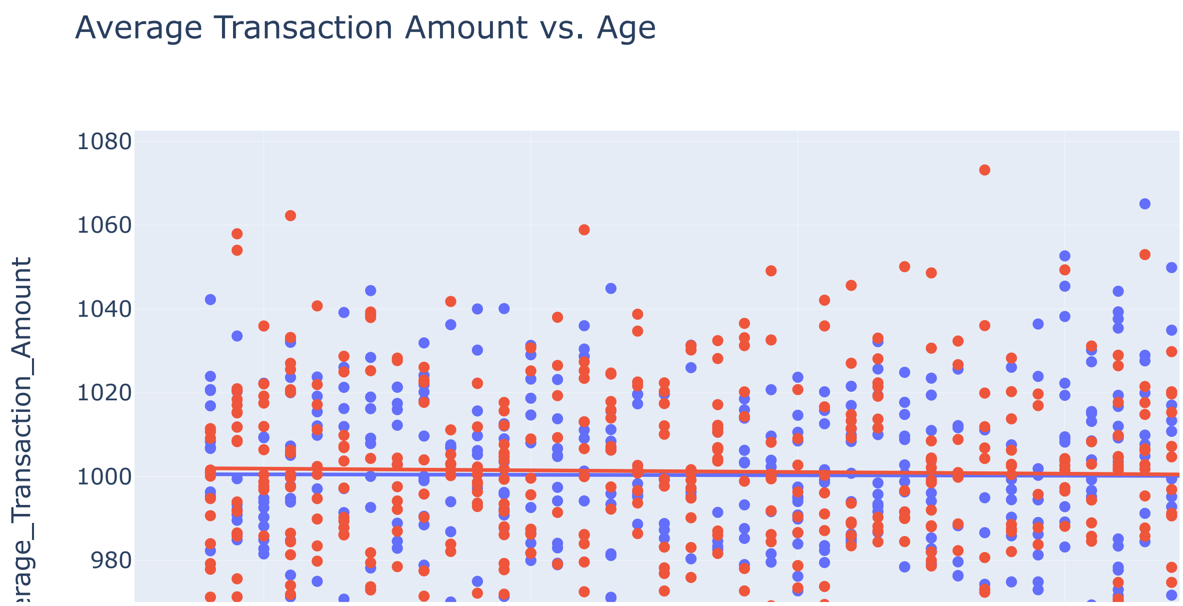


In [6]:

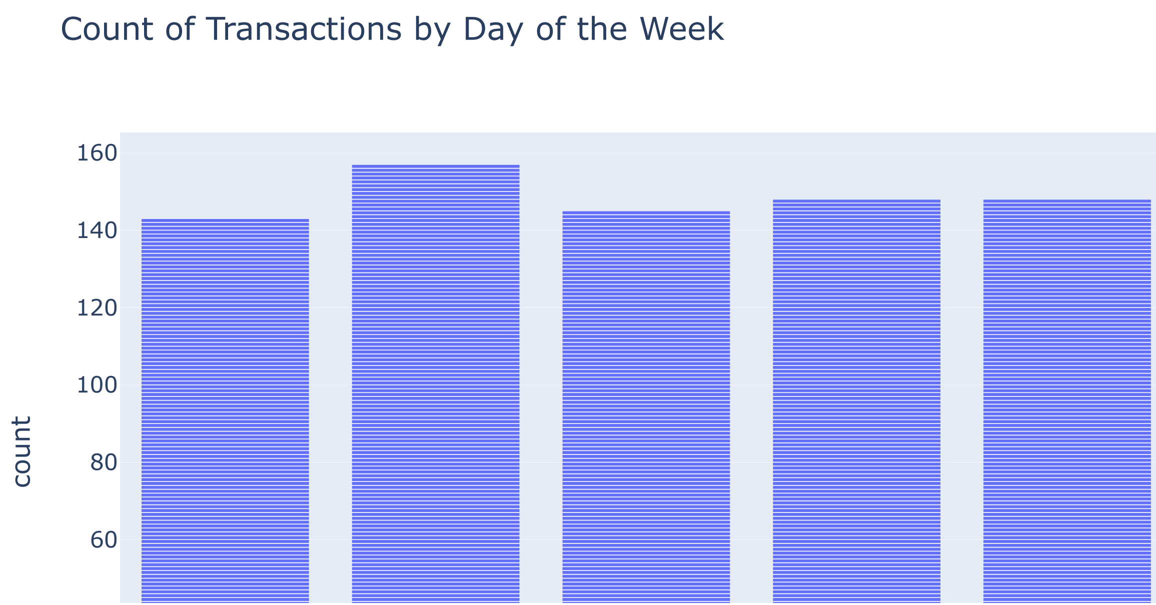
```
# Transaction Amount by Account Type
fig_box_amount = px.box(data,
                        x='Account_Type',
                        y='Transaction_Amount',
                        title='Transaction Amount by Account Type')
fig_box_amount.show()
```



In [7]:
```
# Average Transaction Amount vs. Age
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()
```

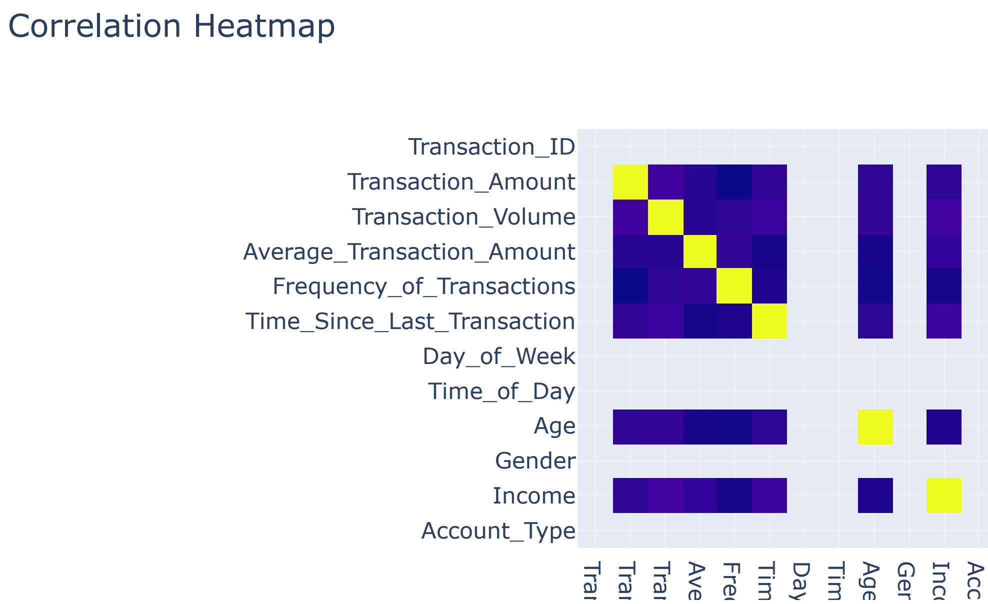


In [8]:
```
# Count of Transactions by Day of the Week
fig_day_of_week = px.bar(data, x='Day_of_Week',
                         title='Count of Transactions by Day of the Week')
fig_day_of_week.show()
```



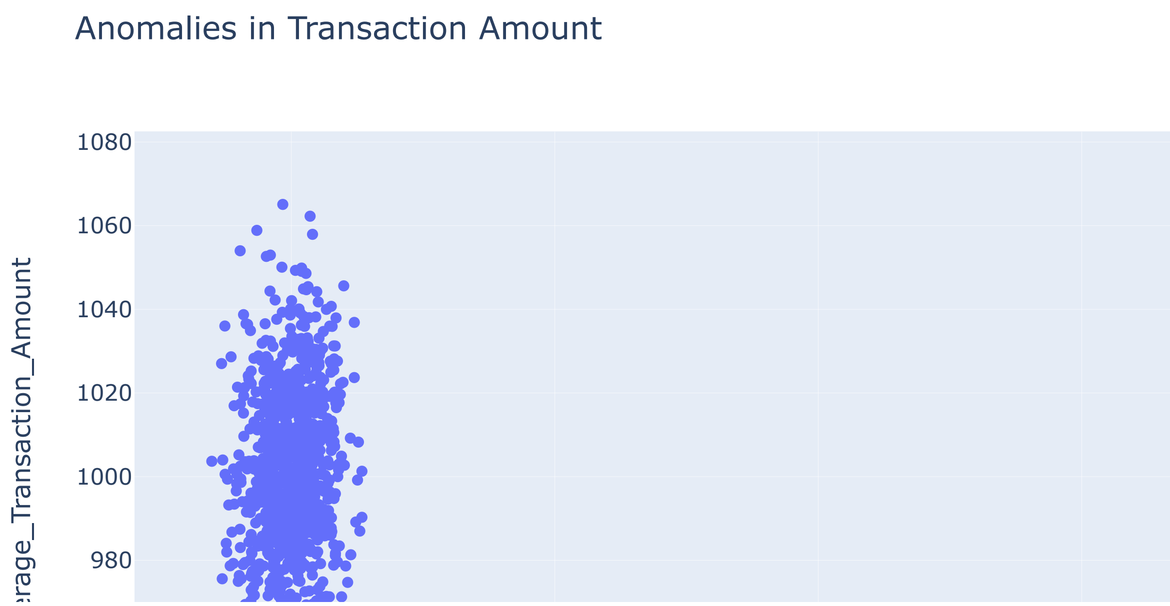
In [10]:

```
import pandas as pd

# Assuming 'data' is your DataFrame
data_numeric = data.apply(pd.to_numeric, errors='coerce')

# Correlation Heatmap
correlation_matrix = data_numeric.corr()
fig_corr_heatmap = px.imshow(correlation_matrix, title='Correlation Heatmap')
fig_corr_heatmap.show()
```



In [11]:

```
# Calculate mean and standard deviation of Transaction Amount
mean_amount = data['Transaction_Amount'].mean()
std_amount = data['Transaction_Amount'].std()

# Define the anomaly threshold (2 standard deviations from the mean)
anomaly_threshold = mean_amount + 2 * std_amount

# Flag anomalies
data['Is_Anomaly'] = data['Transaction_Amount'] > anomaly_threshold

# Scatter plot of Transaction Amount with anomalies highlighted
fig_anomalies = px.scatter(data, x='Transaction_Amount', y='Average_Transaction_Amour
                           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()
```



In [12]:

```
# Calculate the number of anomalies
num_anomalies = data['Is_Anomaly'].sum()

# Calculate the total number of instances in the dataset
total_instances = data.shape[0]

# Calculate the ratio of anomalies
anomaly_ratio = num_anomalies / total_instances
print(anomaly_ratio)
```

```
0.02
```

In [14]:

```
relevant_features = ['Transaction_Amount',
                     'Average_Transaction_Amount',
                     'Frequency_of_Transactions']

# Split data into features (X) and target variable (y)
X = data[relevant_features]
y = data['Is_Anomaly']

# Split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state

# Train the Isolation Forest model
model = IsolationForest(contamination=0.02, random_state=42)
model.fit(X_train)
```

Out[14]:

```
▸ IsolationForest
```

Here we are training an anomaly detection model using the Isolation Forest algorithm. First, we selected the relevant features for detection, namely Transaction_Amount, Average_Transaction_Amount, and Frequency_of_Transactions.

We split the dataset into features (X) and the target variable (y), where X contains the selected features and y contains the binary labels indicating whether an instance is an anomaly or not. Then, we further split the data into training and testing sets using an 80-20 split ratio. Next, we created an Isolation Forest model with a specified contamination parameter of 0.02 (indicating the expected ratio of anomalies) and a random seed for reproducibility. The model is then trained on the training set (X_train).

Now let’s have a look at the performance of this anomaly detection model:

In [15]:

```
# Predict anomalies on the test set
y_pred = model.predict(X_test)

# Convert predictions to binary values (0: normal, 1: anomaly)
y_pred_binary = [1 if pred == -1 else 0 for pred in y_pred]

# Evaluate the model's performance
report = classification_report(y_test, y_pred_binary, target_names=['Normal', 'Anomal
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
```

In [16]:

```
# Relevant features used during training
relevant_features = ['Transaction_Amount', 'Average_Transaction_Amount', 'Frequency_o

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

# Create a DataFrame from user inputs
user_df = pd.DataFrame([user_inputs], columns=relevant_features)

# Predict anomalies using the model
user_anomaly_pred = model.predict(user_df)

# Convert the prediction to binary value (0: normal, 1: anomaly)
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': 5889
Enter the value for 'Average_Transaction_Amount': 3000
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.