Anomaly Detection in Transactions using Machine Learning

Importing Data Set

In [1]:

```
import pandas as pd
data=pd.read_csv("/content/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  
```

Checking for if the data has any null values

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
```

Column insights

In [3]:

```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   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
```

The descriptive statistics of the data

In [4]:

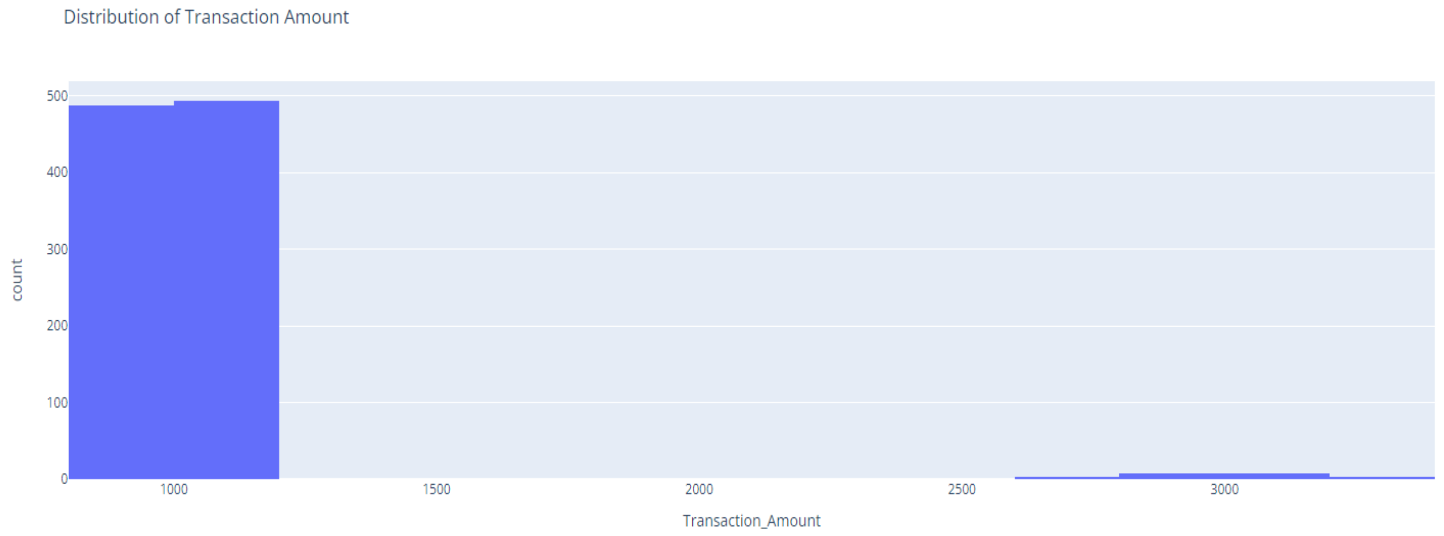
```python
print(data.describe())
```

```
       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                 1000.501902   
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  
```

Have a look at the distribution of transactions amount in the data

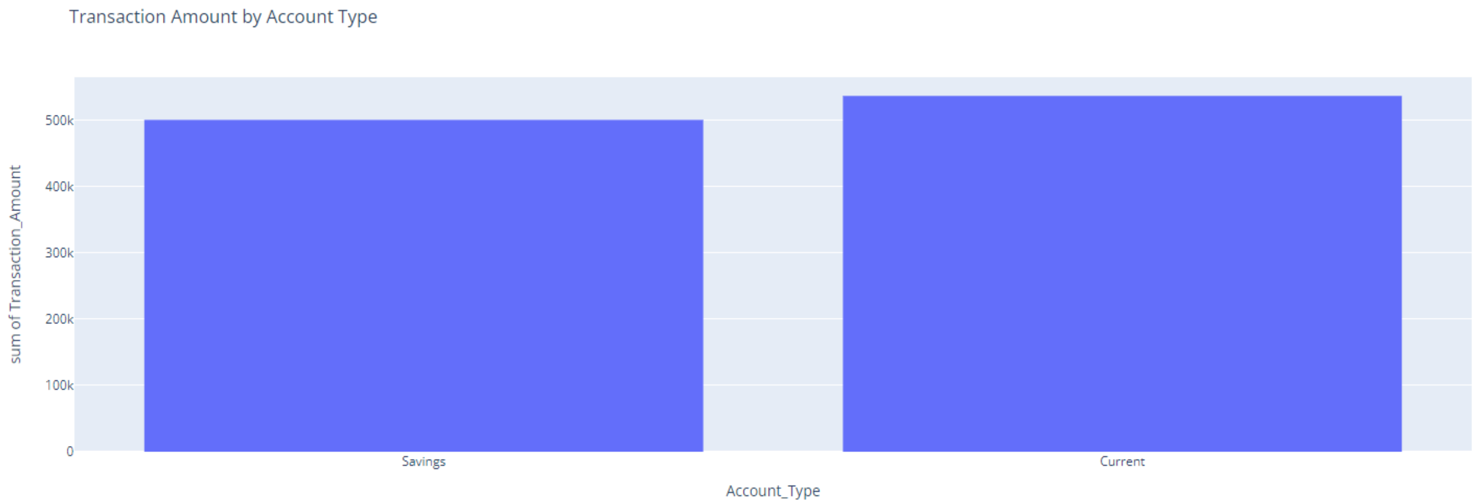
In [5]:

```python
import plotly.express as px
# Distribution of Transaction Amount
fig_amount = px.histogram(data, x='Transaction_Amount',
                          nbins=20,
                          title='Distribution of Transaction Amount')
fig_amount.show()
```



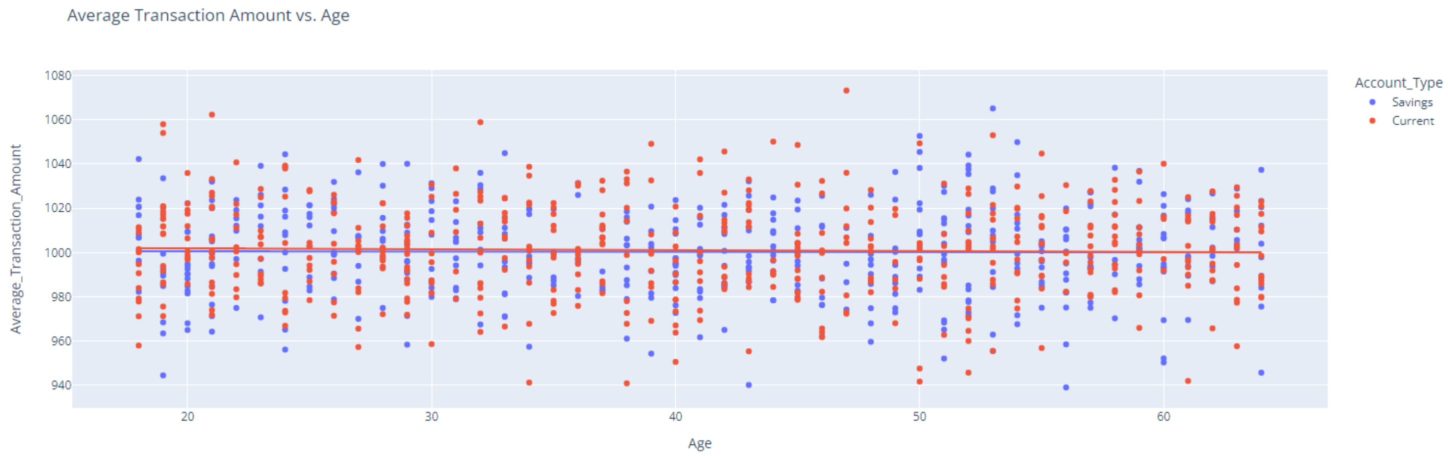
Have a look at the distribution of transactions amount by account type

In [6]:
```
# Transaction Amount by Account Type
fig_box_amount = px.histogram(data,
                              x='Account_Type',
                              y='Transaction_Amount',
                              title='Transaction Amount by Account Type')
fig_box_amount.show()
```



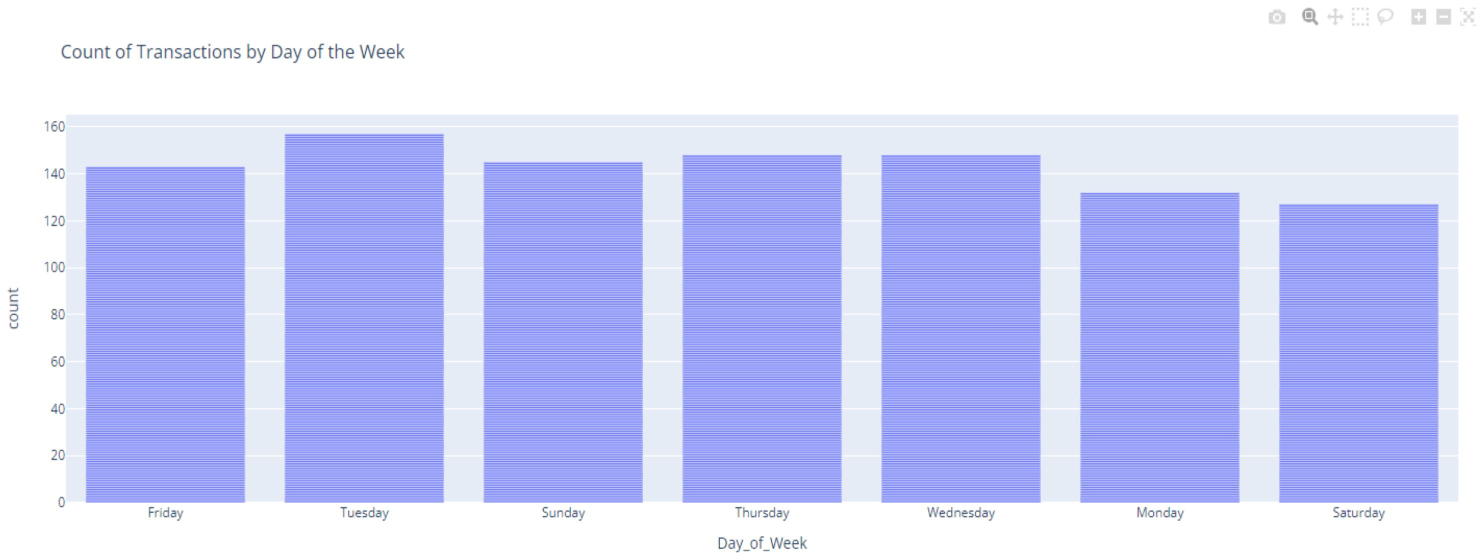
Have a look at the average transaction amount by age

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()
```



Now let's have a look at the count of transactions by day of the week

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()
```

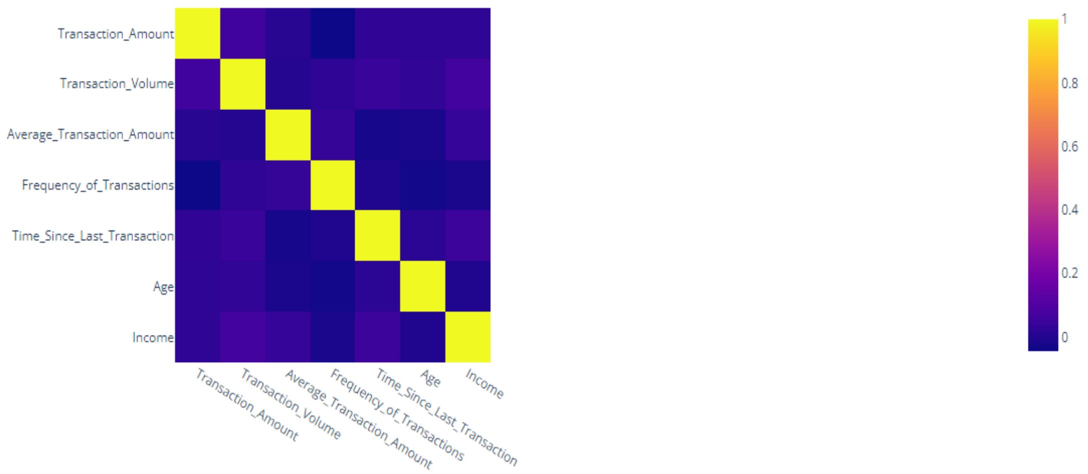


Have a look at the correlation between all the columns in the data

In [9]:
```
# Correlation Heatmap
correlation_matrix = data.corr()
fig_corr_heatmap = px.imshow(correlation_matrix,
                             title='Correlation Heatmap')
fig_corr_heatmap.show()
```

```
<ipython-input-9-5299ddece13e>:2: 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.
```

Correlation Heatmap



Visualizing anomalies in the data

In [10]:

```python
# 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_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()
```

Anomalies in Transaction Amount

Calculate the number of anomalies in the data to find the ratio of anomalies in the data, which will be useful while using anomaly detection algorithms like isolation forest

In [11]:

```python
# 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(num_anomalies)
print(anomaly_ratio)
```

```
20
0.02
```

Train Machine Learning model for detecting anomalies

In [12]:

```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import IsolationForest
from sklearn.metrics import classification_report

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=42)

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

```
IsolationForest
IsolationForest(contamination=0.02, random_state=42)
```

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).

look at the performance of this anomaly detection model

In [13]:

```
# 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', '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
```

In [14]:

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

# 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': 10000
Enter the value for 'Average_Transaction_Amount': 690
Enter the value for 'Frequency_of_Transactions': 6
Anomaly detected: This transaction is flagged as an anomaly.
```

Summary

Anomaly detection model using Machine Learning and Python 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.