In [1]:
```python
import pandas as pd

df = pd.read_csv('personal_transactions.csv')
df
```

Out[1]:

	Date	Description	Amount	Transaction Type	Category	Account Name
0	01/01/2018	Amazon	11.11	debit	Shopping	Platinum Card
1	01/02/2018	Mortgage Payment	1247.44	debit	Mortgage & Rent	Checking
2	01/02/2018	Thai Restaurant	24.22	debit	Restaurants	Silver Card
3	01/03/2018	Credit Card Payment	2298.09	credit	Credit Card Payment	Platinum Card
4	01/04/2018	Netflix	11.76	debit	Movies & DVDs	Platinum Card
...	...	...	...	...	...	...
801	09/27/2019	Biweekly Paycheck	2250.00	credit	Paycheck	Checking
802	09/28/2019	BP	33.46	debit	Gas & Fuel	Platinum Card
803	09/28/2019	Sheetz	4.27	debit	Gas & Fuel	Platinum Card
804	09/30/2019	Starbucks	1.75	debit	Coffee Shops	Platinum Card
805	09/30/2019	Internet Service Provider	75.00	debit	Internet	Checking

806 rows × 6 columns

In [2]:
```python
print(df.isnull().sum())
```

```
Date                0
Description         0
Amount              0
Transaction Type    0
Category            0
Account Name        0
dtype: int64
```

In [5]:
```python
df.describe()
```

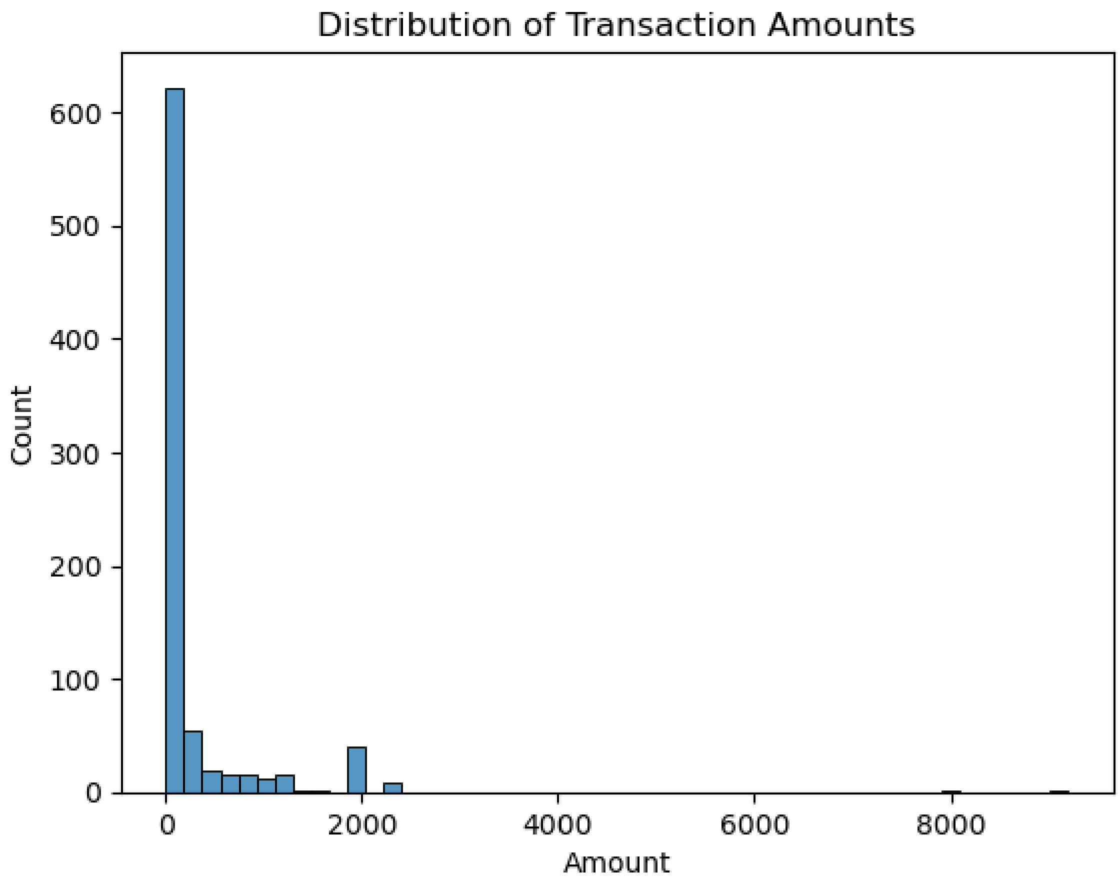
Out[5]:

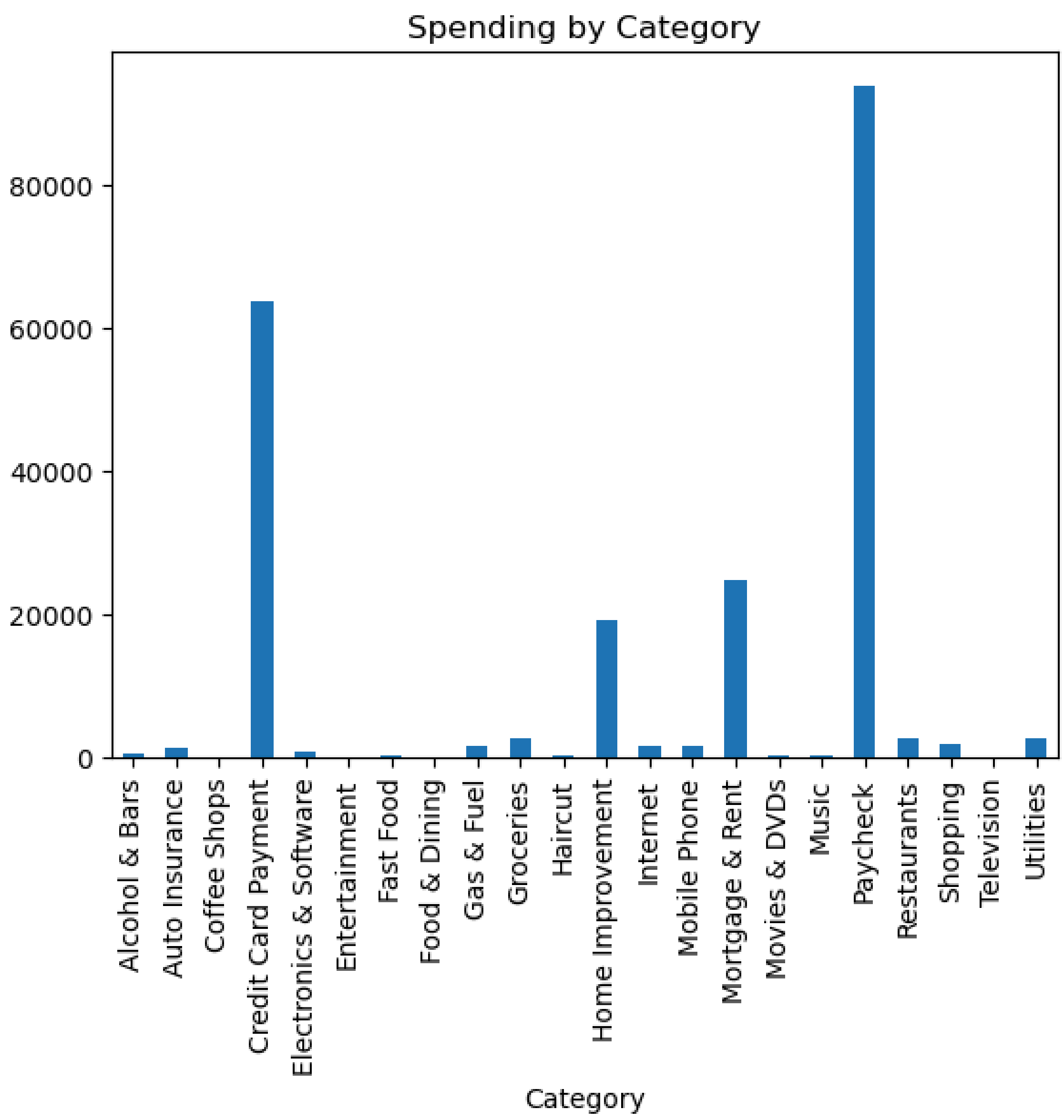
	Amount
count	806.000000
mean	273.391489
std	667.630374
min	1.750000
25%	15.687500
50%	37.480000
75%	117.680000
max	9200.000000

Exploratory Data Analysis

In [4]:

```
import seaborn as sns
import matplotlib.pyplot as plt

sns.histplot(df['Amount'], bins=50)
plt.title('Distribution of Transaction Amounts')
plt.show()

df.groupby('Category')['Amount'].sum().plot(kind='bar')
plt.title('Spending by Category')
plt.show()
```





Feature Engineering

In [6]:
```
# Convert 'Date' to datetime
df['Date'] = pd.to_datetime(df['Date'])
df['Year'] = df['Date'].dt.year
df['Month'] = df['Date'].dt.month

# Feature from 'Description'
df['Description_length'] = df['Description'].apply(len)

df = pd.get_dummies(df, columns=['Transaction Type', 'Account Name'], drop_first=True)
```

Building the Machine Learning Model

In [8]:
```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score

X = df[['Amount', 'Description_length', 'Year', 'Month']]
y = df['Category']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
```

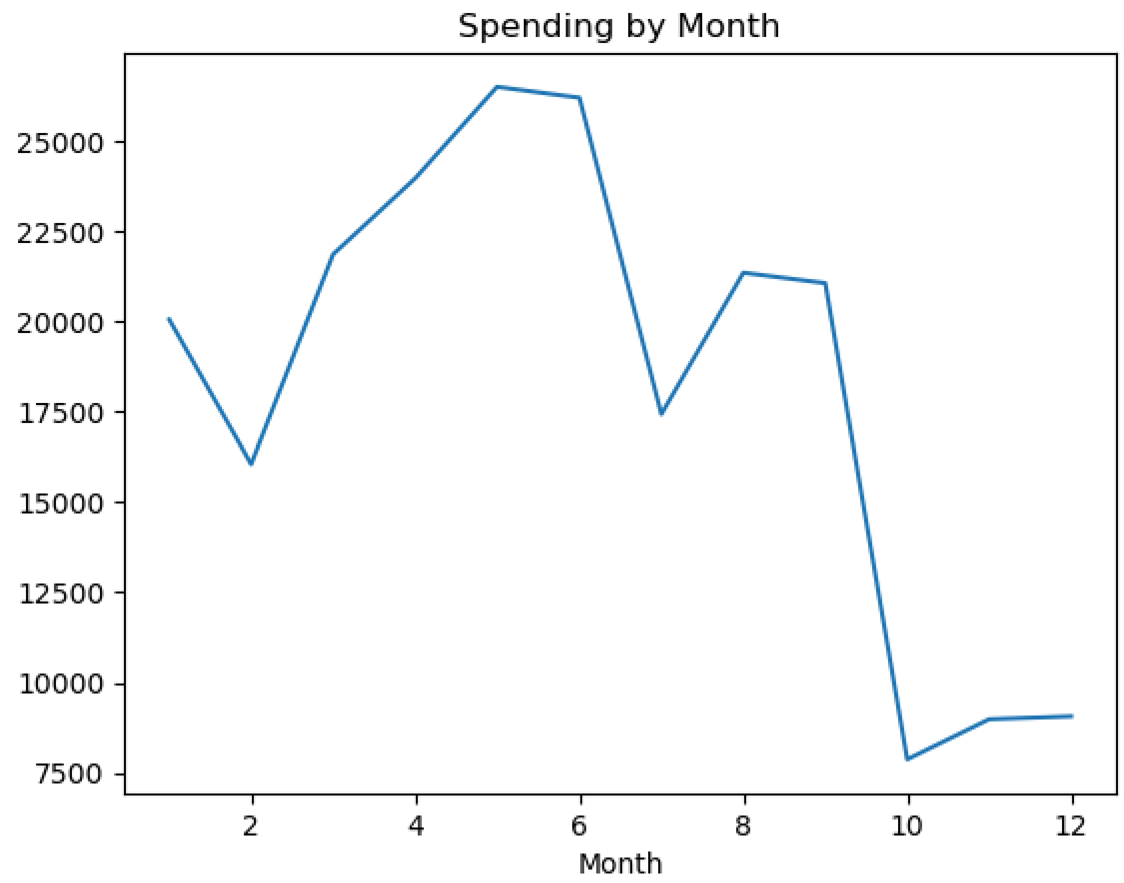
```
Train the model
```

In [9]:
```
model = RandomForestClassifier(n_estimators=100)
model.fit(X_train, y_train)

y_pred = model.predict(X_test)
print('Accuracy:', accuracy_score(y_test, y_pred))
```

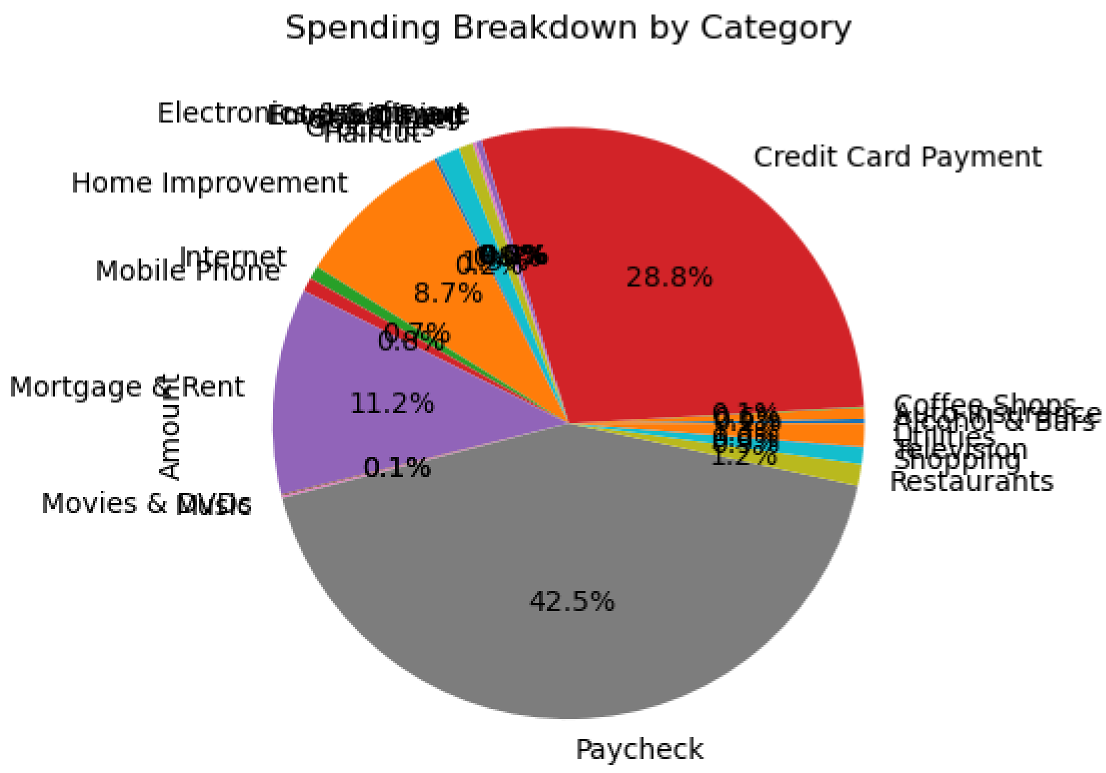
```
Accuracy: 0.9008264462809917
```

Visualizing Spending Patterns (Data Visualization)

In [10]:
```
# Visualize spending by month
df.groupby('Month')['Amount'].sum().plot(kind='line')
plt.title('Spending by Month')
plt.show()
```



In [31]:
```
#Spending Breakdown by Category

df.groupby('Category')['Amount'].sum().plot(kind='pie', autopct='%1.1f%%')
plt.title('Spending Breakdown by Category')
plt.show()
```



Advanced Features (Optional)

Budget Alerts:

Implement a function to check if the total spending exceeds a set budget:

In [13]:
```
def check_budget(df, budget):
    total_spent = df['Amount'].sum()
    if total_spent > budget:
        print(f"Alert: You have exceeded your budget by {total_spent - budget}")
    else:
        print(f"Budget is on track. Total spent: {total_spent}")
```

In [15]:
```
import pandas as pd

df = pd.read_csv('personal_transactions.csv')
df['Date'] = pd.to_datetime(df['Date'])
df.set_index('Date', inplace=True)
```

In [20]:
```
# Resample data by month and sum amounts
monthly_data = df.resample('M').sum(numeric_only=True)
print("Columns in monthly_data:", monthly_data.columns)
```

```
Columns in monthly_data: Index(['Amount'], dtype='object')
```

In [21]:
```
print("Missing values in monthly_data:")
print(monthly_data.isnull().sum())
```

```
Missing values in monthly_data:
Amount    0
dtype: int64
```

In [22]:
```
monthly_data = monthly_data.fillna(0)

monthly_data['Amount'] = pd.to_numeric(monthly_data['Amount'], errors='coerce')
data = monthly_data['Amount']
print(data.head())
```

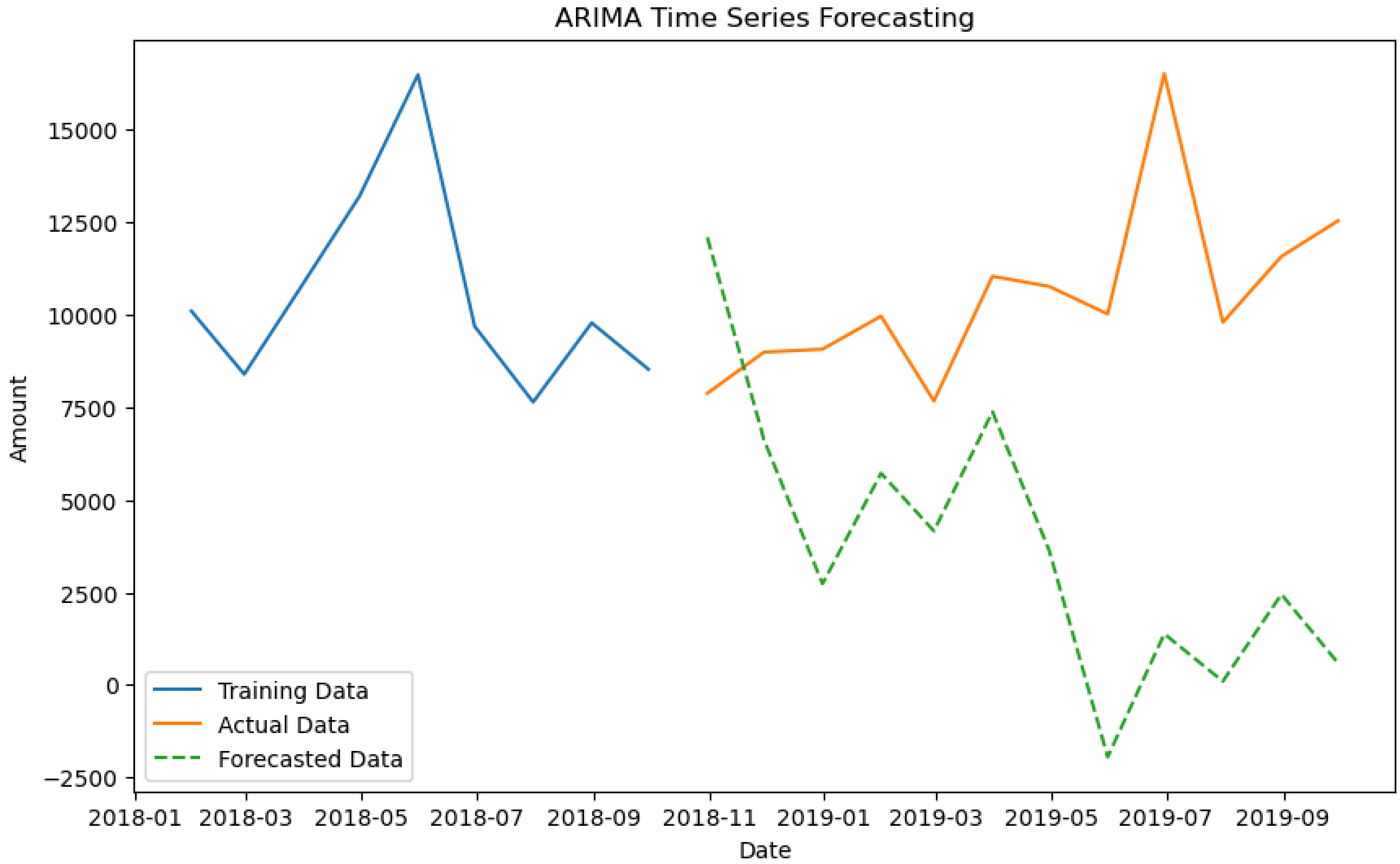
```
Date
2018-01-31    10094.34
2018-02-28     8385.80
2018-03-31    10821.66
2018-04-30    13196.42
2018-05-31    16483.58
Freq: M, Name: Amount, dtype: float64
```

Time-Series Forecasting with ARIMA

In [26]:
```
import pmdarima
print(pmdarima.__version__)
```

```
2.0.4
```

In [54]:
```python
import pandas as pd
import matplotlib.pyplot as plt
from statsmodels.tsa.arima.model import ARIMA
from sklearn.metrics import mean_squared_error

df['Date'] = pd.to_datetime(df['Date'])
df.set_index('Date', inplace=True)
df['Amount'] = pd.to_numeric(df['Amount'], errors='coerce')
df.dropna(subset=['Amount'], inplace=True)
monthly_data = df.resample('M').sum()

train = monthly_data[:-12]
test = monthly_data[-12:]

model = ARIMA(train['Amount'], order=(5,1,0))  # Adjust (p,d,q) parameters # Build and fit the ARIMA model
model_fit = model.fit()

forecast = model_fit.forecast(steps=12)            # Forecast for the test period

plt.figure(figsize=(10,6))                         # Plot actual vs forecasted data
plt.plot(train.index, train['Amount'], label='Training Data')
plt.plot(test.index, test['Amount'], label='Actual Data')
plt.plot(test.index, forecast, label='Forecasted Data', linestyle='--')
plt.title('ARIMA Time Series Forecasting')
plt.xlabel('Date')
plt.ylabel('Amount')
plt.legend()
plt.show()

mse = mean_squared_error(test['Amount'], forecast)
print(f'Mean Squared Error: {mse}')
```




```
Mean Squared Error: 70812305.2179404
```

Blue Line (Training Data): This represents the actual historical data used to train the ARIMA model up to a certain point in time (before 2018-09). The training data shows the trend and seasonal patterns up to the cutoff date.

Orange Line (Actual Data): This is the actual data after the training period, used to compare against the forecasted data. It shows the true values beyond the training window.

Green Dashed Line (Forecasted Data): This line represents the forecasted values by the ARIMA model for the period after the training data. It projects the expected trend based on historical data patterns.

The forecasted data deviates from the actual data, indicating that while the model captures general trends, there are differences between what was predicted and what actually occurred during that time frame.

Key Observations:
The ARIMA model reasonably forecasts the general trend but with notable inaccuracies at certain points compared to actual data.
The forecast begins around late 2018, and the orange line (actual data) shows fluctuations that the green dashed line doesn't fully capture.

Clustering (Unsupervised Learning)

Goal: Group similar transactions together based on features

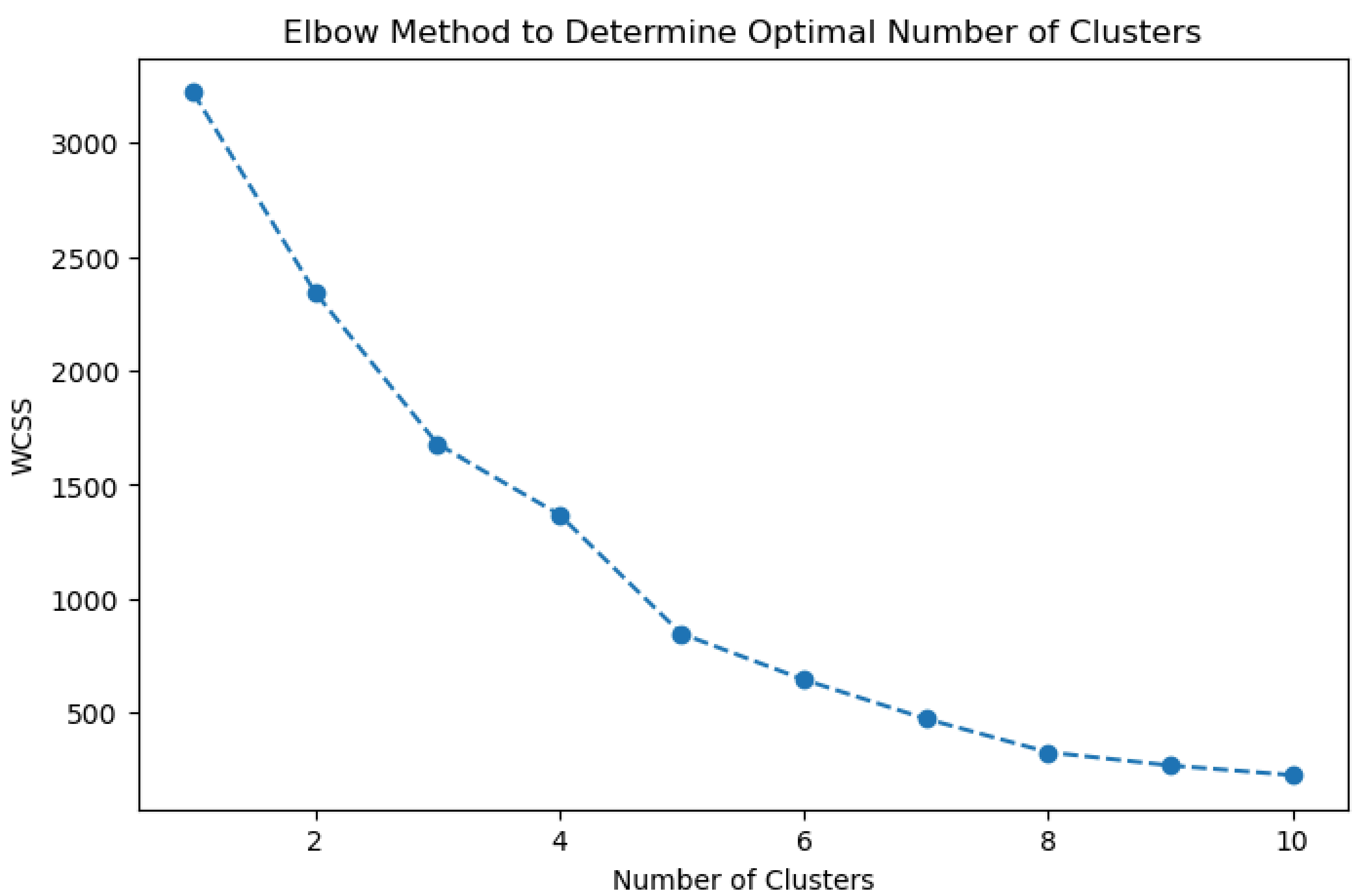
In [49]:

```
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
import seaborn as sns

df['Transaction Type'] = df['Transaction Type'].astype('category').cat.codes       # Convert categorical variable
df['Category'] = df['Category'].astype('category').cat.codes
df['Account Name'] = df['Account Name'].astype('category').cat.codes

X = df[['Amount', 'Category', 'Transaction Type', 'Account Name']]             # Select the relevant columns f

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

wcss = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, init='k-means++', random_state=42)
    kmeans.fit(X_scaled)
    wcss.append(kmeans.inertia_)
```

```
         Date          Description   Amount Transaction Type  \
0  01/01/2018               Amazon    11.11            debit
1  01/02/2018     Mortgage Payment  1247.44            debit
2  01/02/2018      Thai Restaurant    24.22            debit
3  01/03/2018  Credit Card Payment  2298.09           credit
4  01/04/2018              Netflix    11.76            debit

              Category   Account Name
0             Shopping  Platinum Card
1      Mortgage & Rent       Checking
2          Restaurants    Silver Card
3  Credit Card Payment  Platinum Card
4        Movies & DVDs  Platinum Card
```

In [50]:

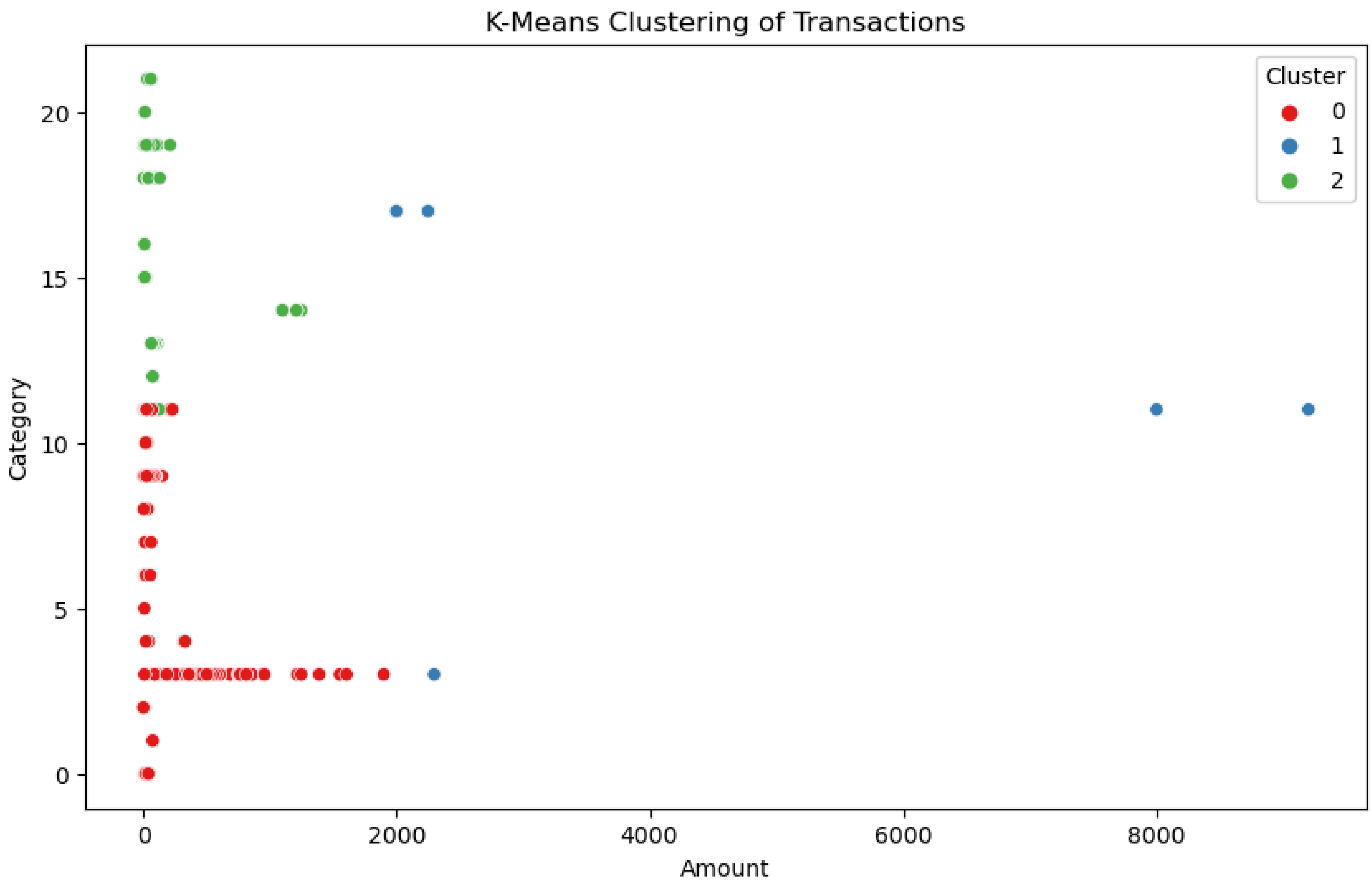
```
plt.figure(figsize=(8, 5))                          # Plotting the Elbow Curve
plt.plot(range(1, 11), wcss, marker='o', linestyle='--')
plt.title('Elbow Method to Determine Optimal Number of Clusters')
plt.xlabel('Number of Clusters')
plt.ylabel('WCSS')  # Within-cluster sum of squares
plt.show()
```



In [51]:

```
optimal_clusters = 3

kmeans = KMeans(n_clusters=optimal_clusters, init='k-means++', random_state=42)
df['Cluster'] = kmeans.fit_predict(X_scaled)
print(df['Cluster'].value_counts())

# Visualize the clusters (Amount vs Category as an example)
plt.figure(figsize=(10, 6))
sns.scatterplot(x=df['Amount'], y=df['Category'], hue=df['Cluster'], palette='Set1')
plt.title('K-Means Clustering of Transactions')
plt.show()

df.to_csv('clustered_transactions.csv', index=False)
```

```
0    440
2    315
1     51
Name: Cluster, dtype: int64
```



Anomaly Detection

Isolation Forest / LOF: identify unusual or fraudulent transactions. They are effective for detecting outliers in transactional data.

In [53]:

```
from sklearn.ensemble import IsolationForest

features = df[['Amount']]  # Add more features if available

# Initialize and fit the Isolation Forest model
iso_forest = IsolationForest(contamination=0.01)
df['anomaly'] = iso_forest.fit_predict(features)

# -1 indicates an anomaly
print(df[df['anomaly'] == -1])
```

```
           Date              Description   Amount Transaction Type  \
3    01/03/2018       Credit Card Payment  2298.09           credit
172  05/11/2018  Mike's Construction Co.  8000.00            debit
676  06/20/2019  Mike's Construction Co.  9200.00            debit

                Category  Account Name  anomaly
3    Credit Card Payment  Platinum Card       -1
172     Home Improvement       Checking       -1
676     Home Improvement       Checking       -1
```

Local Outlier Factor (LOF)

In [54]:
```python
from sklearn.neighbors import LocalOutlierFactor

lof = LocalOutlierFactor(n_neighbors=20)
df['anomaly'] = lof.fit_predict(features)
print(df[df['anomaly'] == -1])
```

```
           Date               Description   Amount Transaction Type  \
0    01/01/2018                    Amazon    11.11            debit
3    01/03/2018        Credit Card Payment  2298.09           credit
11   01/11/2018                     Shell    34.87            debit
28   01/25/2018  Internet Service Provider    69.99            debit
29   01/29/2018                     Shell    30.42            debit
..          ...                       ...      ...              ...
793  09/18/2019        Credit Card Payment  1606.46            debit
796  09/20/2019        Credit Card Payment     9.43           credit
798  09/23/2019        Credit Card Payment     9.43            debit
801  09/27/2019          Biweekly Paycheck  2250.00           credit
804  09/30/2019                  Starbucks     1.75            debit

                Category  Account Name  anomaly
0               Shopping  Platinum Card       -1
3    Credit Card Payment  Platinum Card       -1
11            Gas & Fuel  Platinum Card       -1
28              Internet       Checking       -1
29            Gas & Fuel    Silver Card       -1
..                   ...            ...      ...
793  Credit Card Payment       Checking       -1
796  Credit Card Payment    Silver Card       -1
798  Credit Card Payment       Checking       -1
801             Paycheck       Checking       -1
804         Coffee Shops  Platinum Card       -1

[134 rows x 7 columns]
```

Sentiment Analysis on Descriptions

In [58]:
```python
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer

analyzer = SentimentIntensityAnalyzer()
df['sentiment'] = df['Description'].apply(lambda x: analyzer.polarity_scores(x)['compound'])
print(df[['Description', 'sentiment']])
```

```
                   Description  sentiment
0                       Amazon     0.1779
1             Mortgage Payment     0.0000
2              Thai Restaurant     0.0000
3          Credit Card Payment     0.3818
4                      Netflix     0.0000
..                         ...        ...
801          Biweekly Paycheck     0.0000
802                         BP     0.0000
803                     Sheetz     0.0000
804                  Starbucks     0.0000
805  Internet Service Provider     0.0000

[806 rows x 2 columns]
```