Assignment 2: Exploration and Preprocessing of Data

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```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# Load the dataset
data = pd.read_csv('C:\\Users\\ibpri\\Downloads\\default-of-credit-card-clients.csv', head
```

Question 1. Data Exploration

Task 1a: For each amount-of-bill-statement attribute (X12-X17), calculate its average, standard deviation, minimum, and maximum values.

```
# Task 1a: Calculate statistics for amount-of-bill-statement attributes
bill_attributes = data.iloc[:, 12:18]  # Columns 12-17
attribute_stats = bill_attributes.describe()
print("Statistics")
print("="*50,"\n")
print(attribute_stats)
```

```
Statistics
==================================================

          BILL_AMT1     BILL_AMT2     BILL_AMT3     BILL_AMT4
count   30000.000000  30000.000000  3.000000e+04  30000.000000  \
mean    51223.330900  49179.075167  4.701315e+04  43262.948967
```

```
std     73635.860576   71173.768783  6.934939e+04   64332.856134
min   -165580.000000  -69777.000000 -1.572640e+05 -170000.000000
25%      3558.750000    2984.750000  2.666250e+03    2326.750000
50%     22381.500000   21200.000000  2.008850e+04   19052.000000
75%     67091.000000   64006.250000  6.016475e+04   54506.000000
max    964511.000000  983931.000000  1.664089e+06  891586.000000

           BILL_AMT5      BILL_AMT6
count   30000.000000   30000.000000
mean    40311.400967   38871.760400
std     60797.155770   59554.107537
min    -81334.000000 -339603.000000
25%      1763.000000    1256.000000
50%     18104.500000   17071.000000
75%     50190.500000   49198.250000
max    927171.000000  961664.000000
```

Task 1b: Compute the covariance and correlation between those attribute pairs.

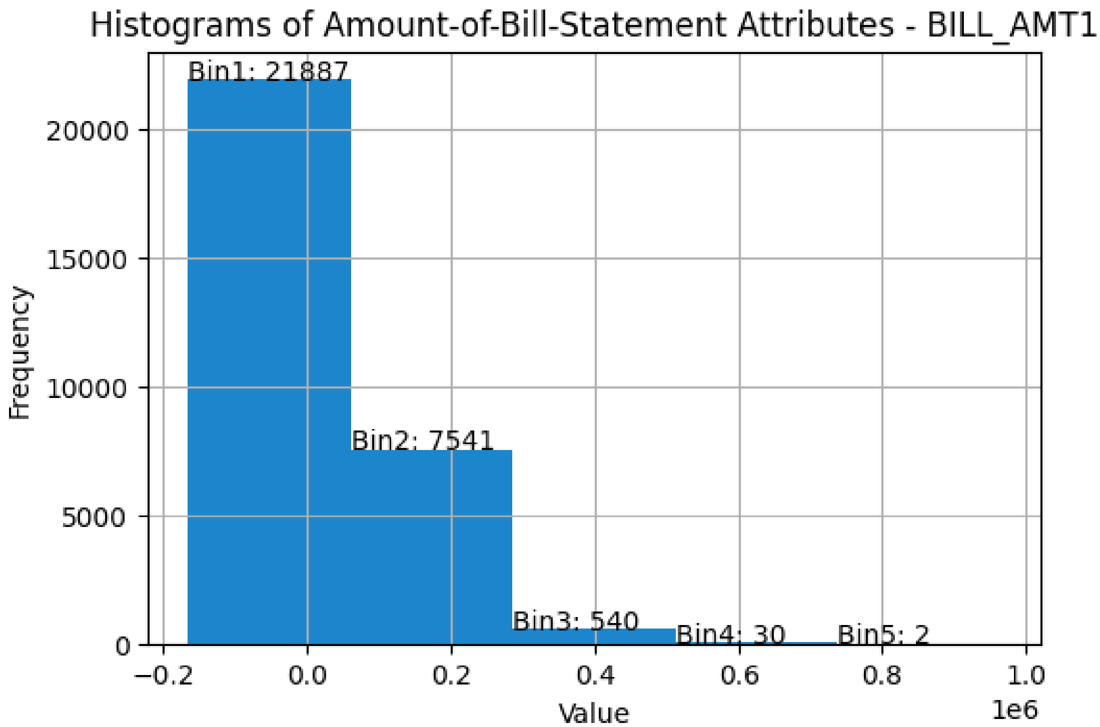
```python
# Task 1b: Compute covariance and correlation
covariance_matrix = bill_attributes.cov()
correlation_matrix = bill_attributes.corr()
print("\nCovariance Matrix\n","="*50,"\n",covariance_matrix)
print("\nCorrelation Matrix\n","="*50,"\n",correlation_matrix)
```

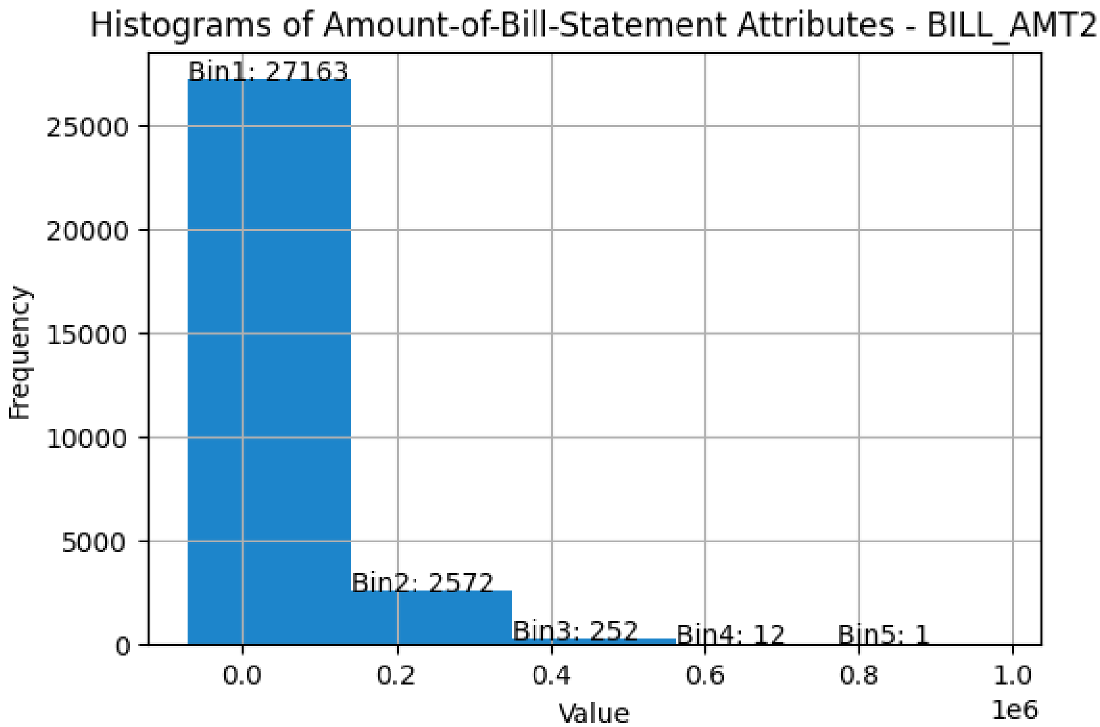
```
Covariance Matrix
 ==================================================
               BILL_AMT1     BILL_AMT2     BILL_AMT3     BILL_AMT4  \
BILL_AMT1  5.422240e+09  4.986670e+09  4.556511e+09  4.075286e+09
BILL_AMT2  4.986670e+09  5.065705e+09  4.582086e+09  4.086508e+09
BILL_AMT3  4.556511e+09  4.582086e+09  4.809338e+09  4.122238e+09
BILL_AMT4  4.075286e+09  4.086508e+09  4.122238e+09  4.138716e+09
BILL_AMT5  3.714795e+09  3.720401e+09  3.726780e+09  3.677105e+09
BILL_AMT6  3.519876e+09  3.524868e+09  3.524247e+09  3.451762e+09

              BILL_AMT5     BILL_AMT6
BILL_AMT1  3.714795e+09  3.519876e+09
BILL_AMT2  3.720401e+09  3.524868e+09
BILL_AMT3  3.726780e+09  3.524247e+09
BILL_AMT4  3.677105e+09  3.451762e+09
BILL_AMT5  3.696294e+09  3.425914e+09
```

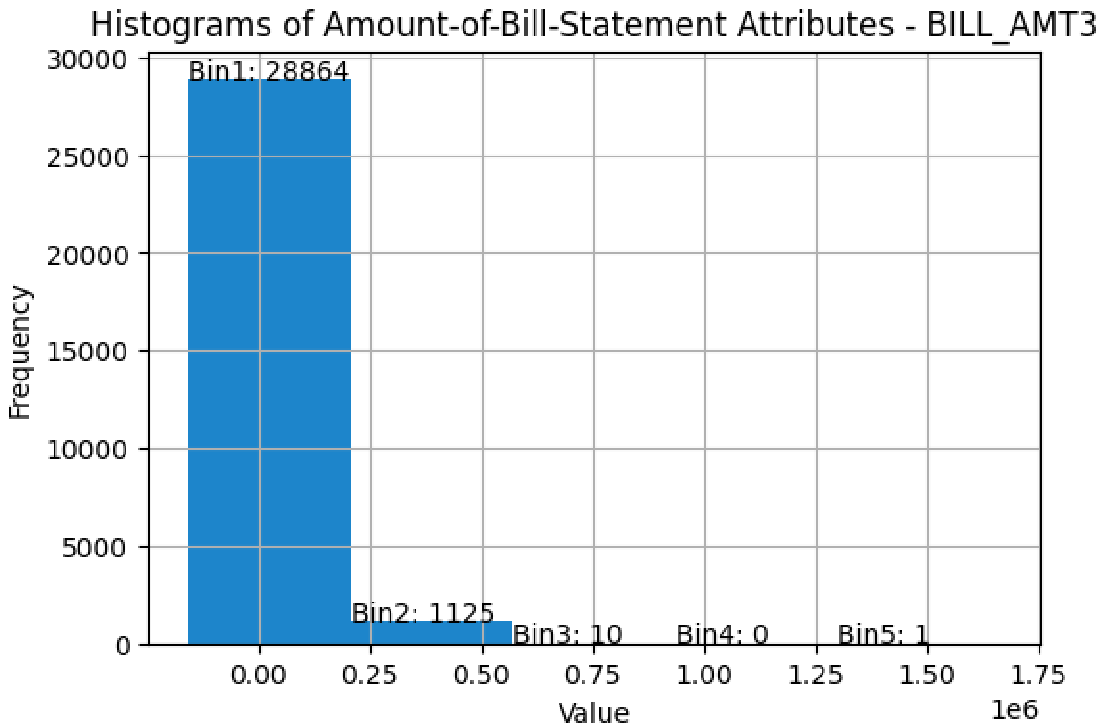
```
BILL_AMT6  3.425914e+09  3.546692e+09

Correlation Matrix
 ==================================================
            BILL_AMT1  BILL_AMT2  BILL_AMT3  BILL_AMT4  BILL_AMT5  BILL_AMT6
BILL_AMT1   1.000000   0.951484   0.892279   0.860272   0.829779   0.802650
BILL_AMT2   0.951484   1.000000   0.928326   0.892482   0.859778   0.831594
BILL_AMT3   0.892279   0.928326   1.000000   0.923969   0.883910   0.853320
BILL_AMT4   0.860272   0.892482   0.923969   1.000000   0.940134   0.900941
BILL_AMT5   0.829779   0.859778   0.883910   0.940134   1.000000   0.946197
BILL_AMT6   0.802650   0.831594   0.853320   0.900941   0.946197   1.000000
```

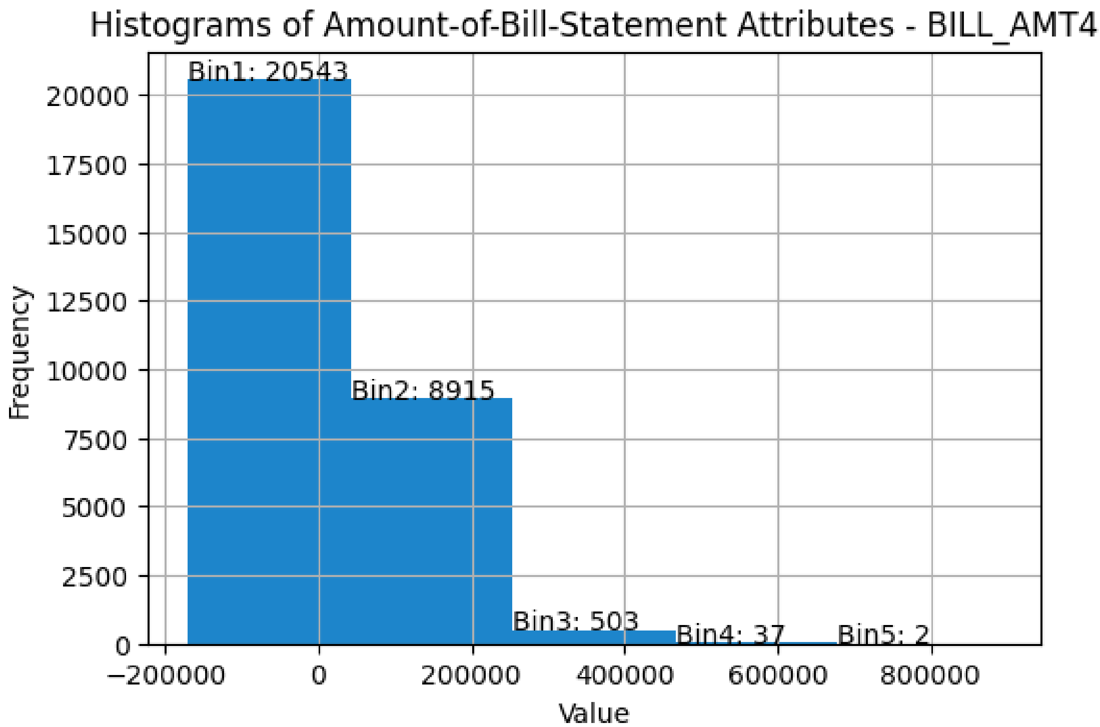
Task 1c: Display the histogram for each of those quantitative attributes by discretizing it into 5 separate bins and counting the frequency for each bin.

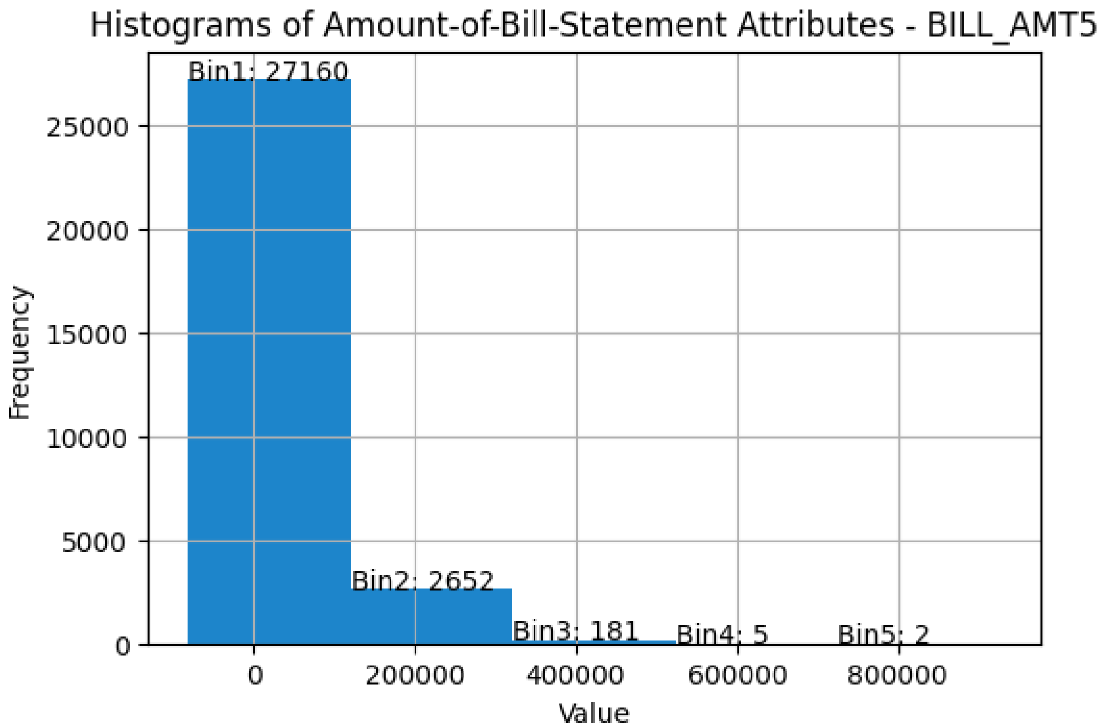
```
# Task 1c: Display histograms for each attribute
for num in range(1,7):
    plt.figure(figsize=(6, 4))
    bill_attributes["BILL_AMT"+str(num)].hist(bins=5, alpha=0.7)
    n, bins, _ = plt.hist(bill_attributes["BILL_AMT"+str(num)], bins=5, alpha=0.7, color='
    plt.title("Histograms of Amount-of-Bill-Statement Attributes - BILL_AMT"+str(num))
    plt.xlabel("Value")
    plt.ylabel("Frequency")
    for i in range(len(n)):
        plt.annotate(f'{"Bin"+ str(i+1) + ": "+ str(int(n[i]))}', (bins[i], n[i]))
    plt.show()
```

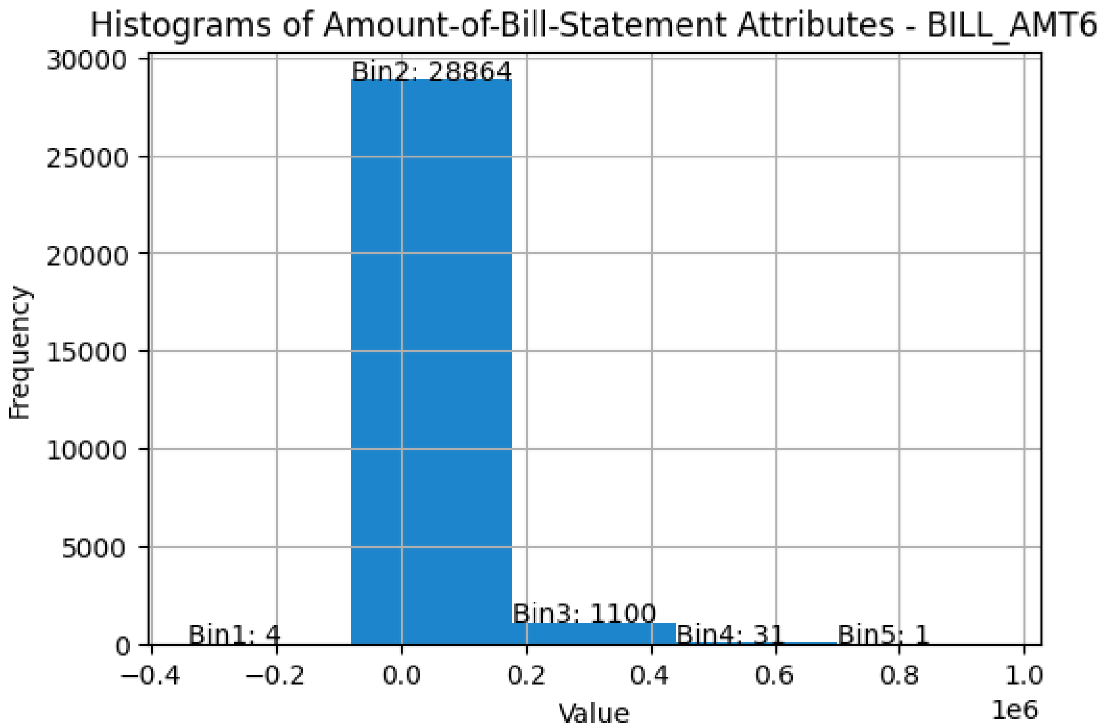

Histograms of Amount-of-Bill-Statement Attributes - BILL_AMT1
Bin1: 21887
Bin2: 7541
Bin3: 540
Bin4: 30
Bin5: 2
Frequency
Value
1e6
0
5000
10000
15000
20000
−0.2
0.0
0.2
0.4
0.6
0.8
1.0


Histograms of Amount-of-Bill-Statement Attributes - BILL_AMT2
Bin1: 27163
Bin2: 2572
Bin3: 252
Bin4: 12
Bin5: 1
Frequency
0
5000
10000
15000
20000
25000
0.0
0.2
0.4
0.6
0.8
1.0
1e6
Value


Histograms of Amount-of-Bill-Statement Attributes - BILL_AMT3
Bin1: 28864
Bin2: 1125
Bin3: 10
Bin4: 0
Bin5: 1
Frequency
Value
1e6
0
5000
10000
15000
20000
25000
30000
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75

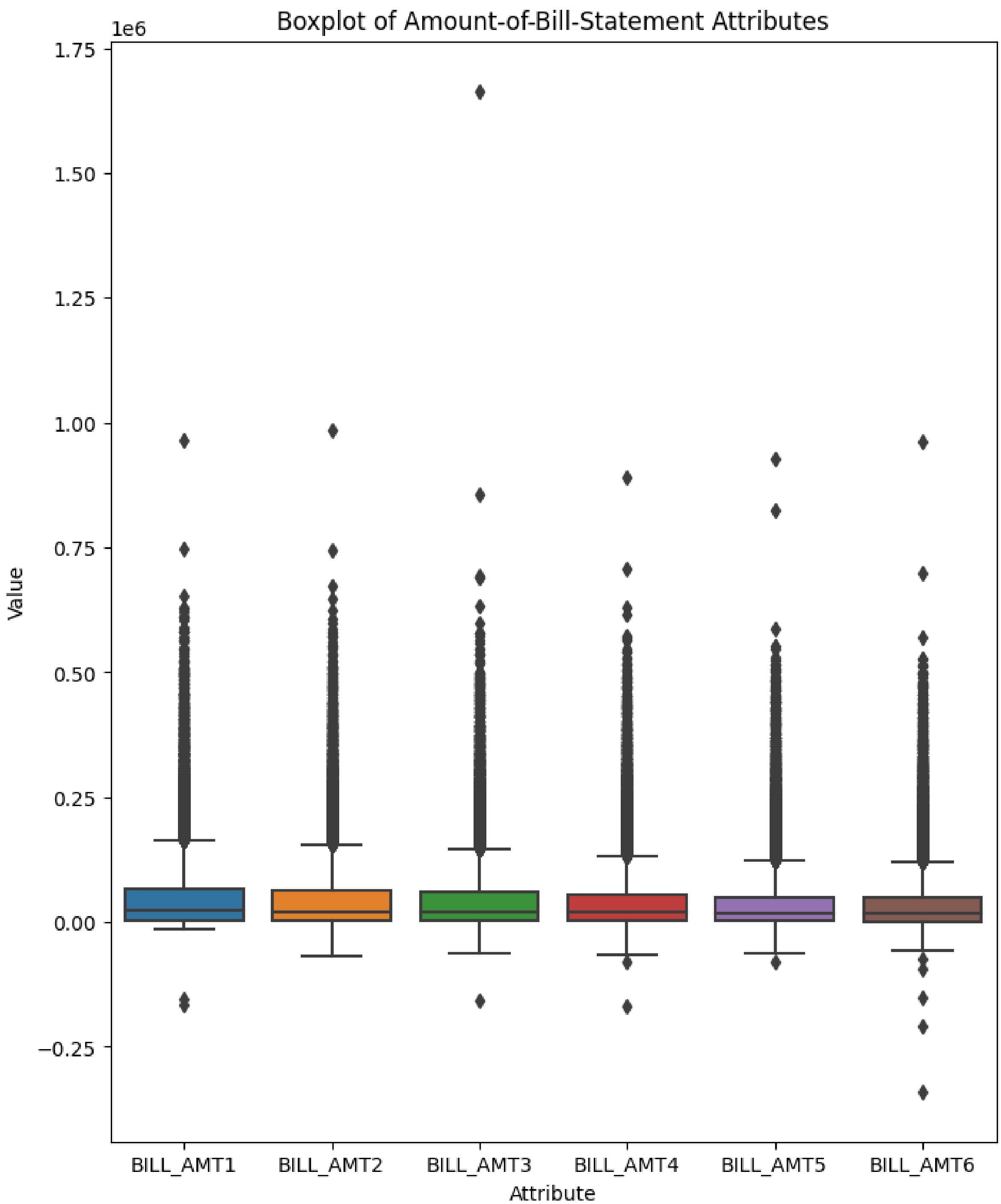

Histograms of Amount-of-Bill-Statement Attributes - BILL_AMT4
Bin1: 20543
Bin2: 8915
Bin3: 503
Bin4: 37
Bin5: 2
Frequency
0
2500
5000
7500
10000
12500
15000
17500
20000
−200000
0
200000
400000
600000
800000
Value


Histograms of Amount-of-Bill-Statement Attributes - BILL_AMT5
Bin1: 27160
Bin2: 2652
Bin3: 181
Bin4: 5
Bin5: 2
25000
20000
15000
10000
5000
0
Frequency
0
200000
400000
600000
800000
Value



Task 1d: Display a boxplot to show the distribution of values for each of those attributes and finding out outliers

```
# Task 1d: Display boxplots
plt.figure(figsize=(8, 10))
sns.boxplot(data=bill_attributes)
plt.title("Boxplot of Amount-of-Bill-Statement Attributes")
plt.xlabel("Attribute")
plt.ylabel("Value")
plt.show()
```



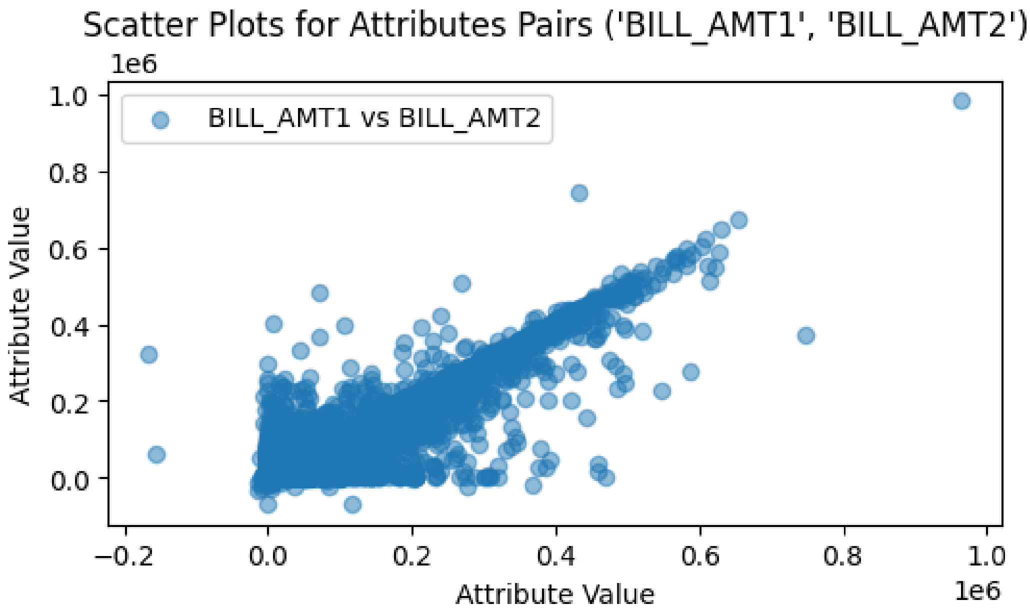
Suspected outliers are identified by the common rule of thumb of singling out values falling at least 1.5 x IQR above the third quartile or below the first quartile.

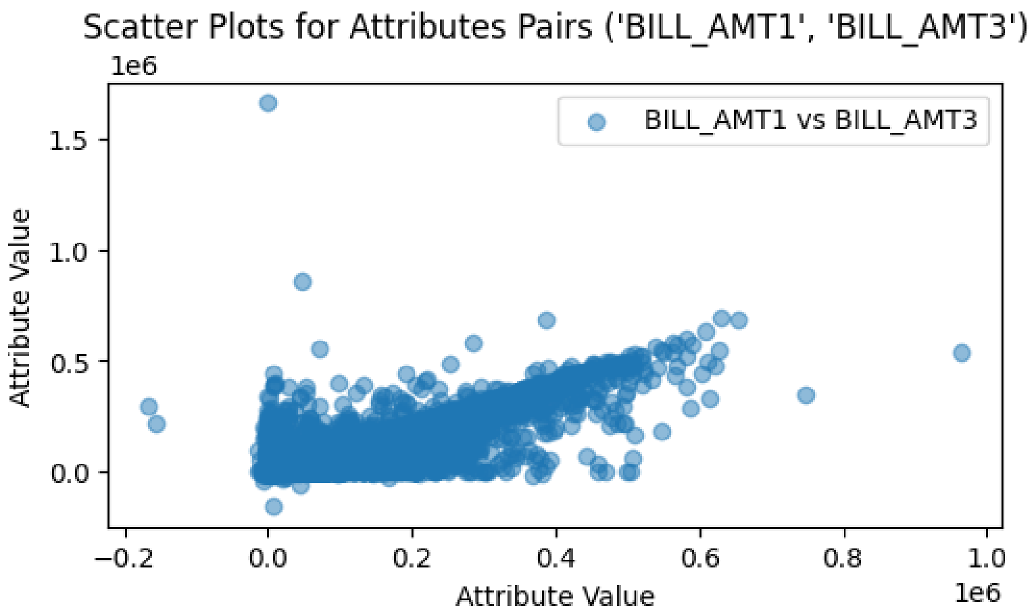
```
# Task 1d: Checking outliers
# Function to detect outliers using IQR
def find_outliers_iqr(data_column):
    Q1 = data_column.quantile(0.25)
    Q3 = data_column.quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    outliers = (data_column < lower_bound) | (data_column > upper_bound)
    return outliers

# Find outliers for each attribute
outliers_dict = {}
for col in bill_attributes.columns:
    outliers_dict[col] = find_outliers_iqr(bill_attributes[col])

for col, outliers in outliers_dict.items():
    print(f"Attribute {col}: {outliers.sum()} outliers")
```

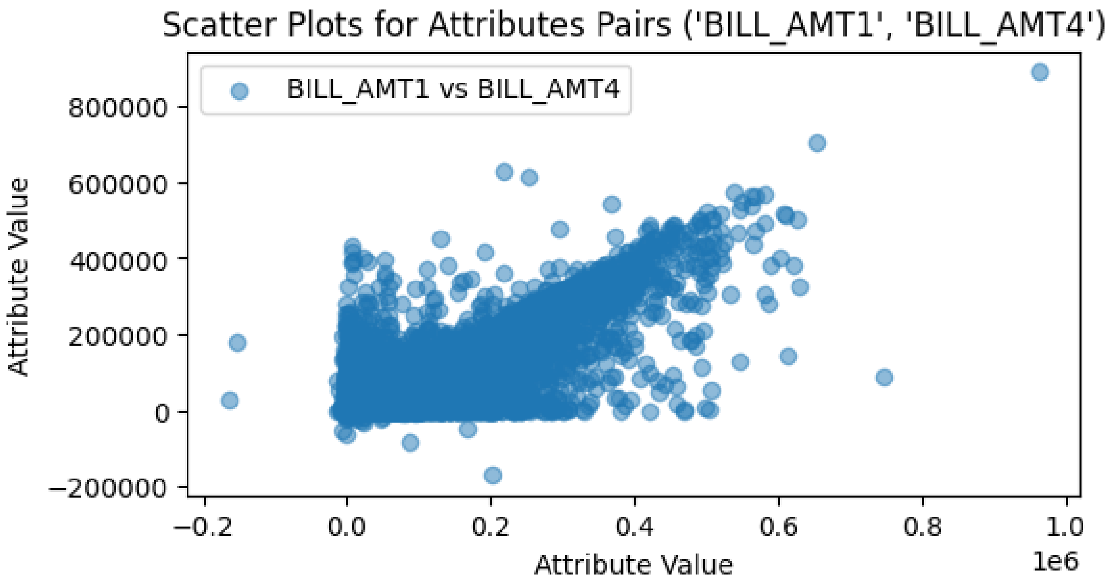
```
Attribute BILL_AMT1: 2400 outliers
Attribute BILL_AMT2: 2395 outliers
Attribute BILL_AMT3: 2469 outliers
Attribute BILL_AMT4: 2622 outliers
Attribute BILL_AMT5: 2725 outliers
Attribute BILL_AMT6: 2693 outliers
```

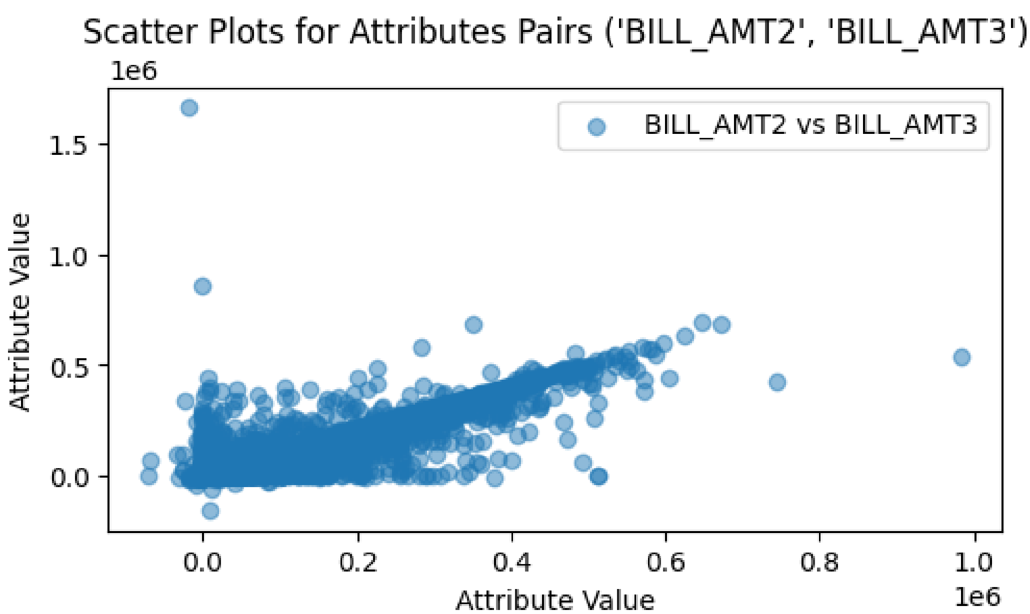
Task 1e: Consider the four attributes X12-X15. For each pair of those four attributes, use a scatter plot to visualize their joint distribution.

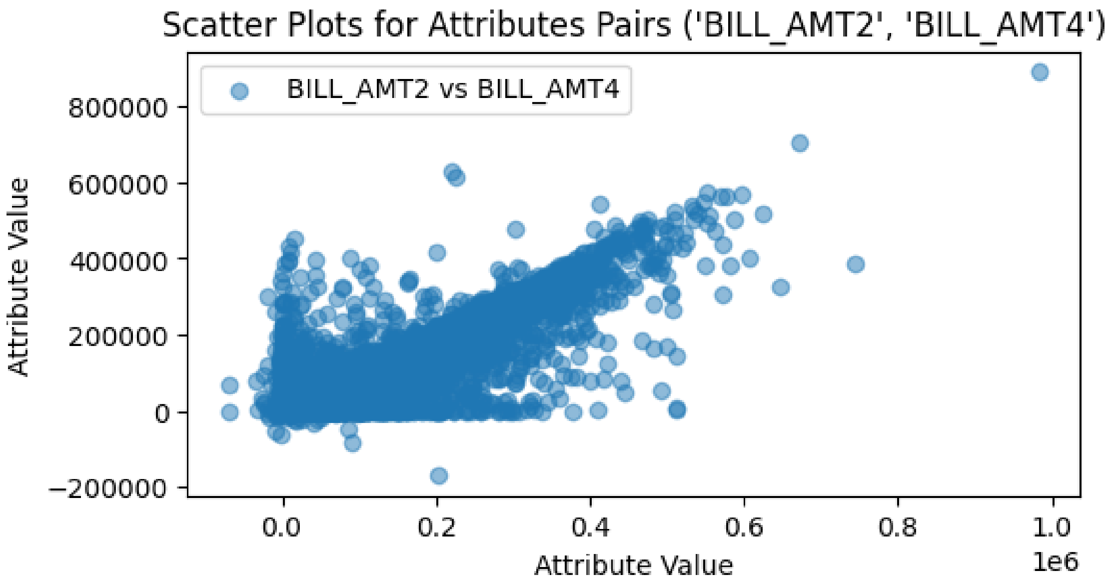
```
# Task 1e: Scatter plots for attribute pairs X12-X15
scatter_pairs = [('BILL_AMT1', 'BILL_AMT2'), ('BILL_AMT1', 'BILL_AMT3'), ('BILL_AMT1', 'BI
                 ('BILL_AMT2', 'BILL_AMT3'), ('BILL_AMT2', 'BILL_AMT4'), ('BILL_AMT3', 'BI

for pair in scatter_pairs:
    plt.figure(figsize=(6, 3))
    plt.scatter(data[pair[0]], data[pair[1]], alpha=0.5, label=f'{pair[0]} vs {pair[1]}')
    plt.title("Scatter Plots for Attributes Pairs " + str(pair))
    plt.xlabel("Attribute Value")
    plt.ylabel("Attribute Value")
    plt.legend()
    plt.show()
```

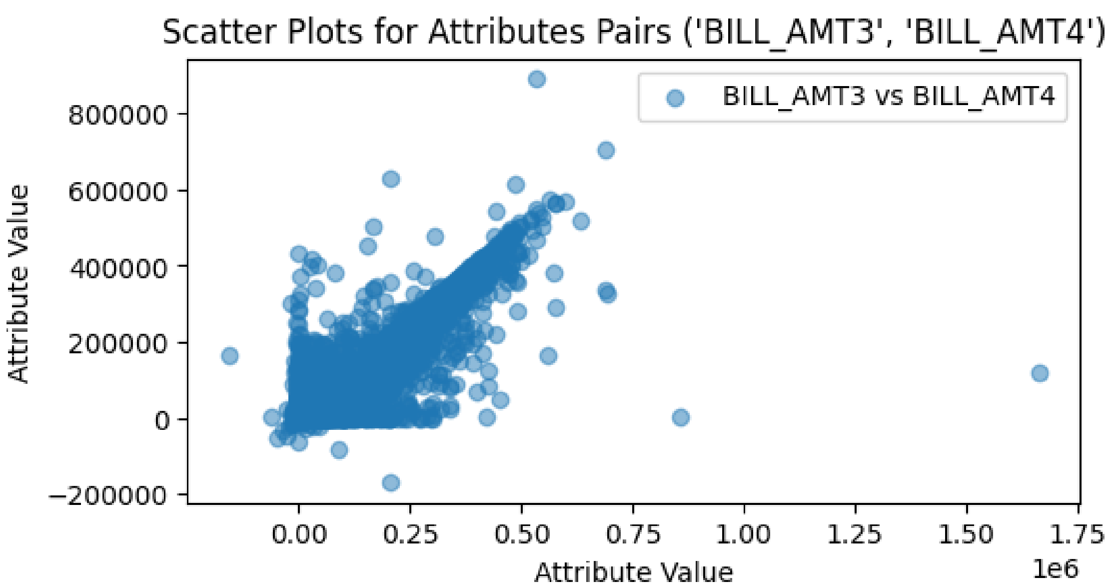

Scatter Plots for Attributes Pairs ('BILL_AMT1', 'BILL_AMT2')
1e6
BILL_AMT1 vs BILL_AMT2
Attribute Value
Attribute Value
1e6


Scatter Plots for Attributes Pairs ('BILL_AMT1', 'BILL_AMT3')
1e6
BILL_AMT1 vs BILL_AMT3
Attribute Value
Attribute Value
1e6


Scatter Plots for Attributes Pairs ('BILL_AMT1', 'BILL_AMT4')
BILL_AMT1 vs BILL_AMT4
800000
600000
400000
200000
0
−200000
Attribute Value
−0.2
0.0
0.2
0.4
0.6
0.8
1.0
1e6
Attribute Value


Scatter Plots for Attributes Pairs ('BILL_AMT2', 'BILL_AMT3')
1e6
BILL_AMT2 vs BILL_AMT3
1.5
1.0
0.5
0.0
Attribute Value
0.0
0.2
0.4
0.6
0.8
1.0
1e6
Attribute Value





Accordingto the scatter plots for attribute pairs X12-X15 ('BILL_AMT1', 'BILL_AMT2'), ('BILL_AMT1', 'BILL_AMT3'), ('BILL_AMT1', 'BILL_AMT4'), ('BILL_AMT2', 'BILL_AMT3'), ('BILL_AMT2', 'BILL_AMT4'), ('BILL_AMT3', 'BILL_AMT4'), we observe positive correlations. For all of the pairs, the values of X increase as the values of Y increase.

Question 2. Data Preprocessing

Task 2a: Standardize the attributes X1, X5, and X12-X23.

The attributes (Age, Limit Balance, Bill Amount 1-6, Pay Amount 1-6) are standardized using Standard Scalar.

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA

# Task 2a: Standardize the specified attributes
attributes_to_standardize = ['LIMIT_BAL', 'AGE'] + ['BILL_AMT1', 'BILL_AMT2','BILL_AMT3',
scaler = StandardScaler()
data[attributes_to_standardize] = scaler.fit_transform(data[attributes_to_standardize])
```

Task 2b: Create a data sample of size 1000 which is randomly selected (without replacement) from the original data.

```
# Task 2b: Create a random data sample of size 1000
random_sample = data.sample(n=1000, replace=False)
print(random_sample.head())
```

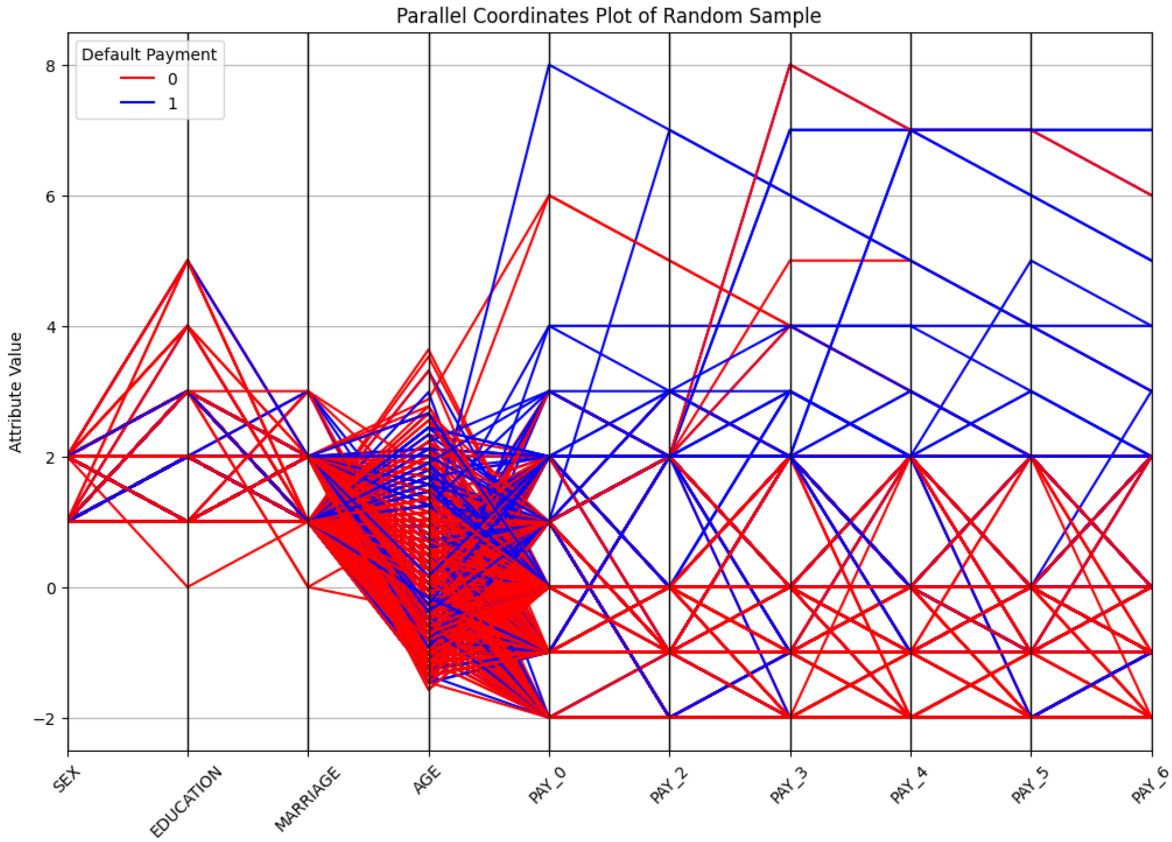
```
          ID  LIMIT_BAL  SEX  EDUCATION  MARRIAGE       AGE  PAY_0  PAY_2
24207  24208  -0.134759    1          2         2 -1.137534      0      0  \
11997  11998  -0.597202    1          2         2 -0.161156      1      2
24421  24422   0.558907    1          2         1 -0.161156      0      0
29431  29432  -0.905498    1          2         2 -0.595102     -1      0
2382    2383   0.867203    1          1         1  1.683111     -1     -1

       PAY_3  PAY_4  ...  BILL_AMT4  BILL_AMT5  BILL_AMT6  PAY_AMT1  PAY_AMT2  \
24207      0      0  ...   1.638304   1.570109   1.675970 -0.100440  3.084954
11997      0     -1  ...  -0.358935   0.546097   0.566154 -0.341942 -0.170186
24421      0      0  ...   3.101221   2.487141   2.259987  0.261814  0.220431
29431      0      2  ...  -0.605983  -0.587527  -0.652724 -0.263453 -0.159162
2382      -1     -1  ...  -0.667927  -0.659391  -0.423769 -0.315075 -0.239933

       PAY_AMT3  PAY_AMT4  PAY_AMT5  PAY_AMT6  default payment next month
24207  0.043979  0.011102  0.019676 -0.006497                           0
11997  0.848901  4.384423 -0.117776 -0.068374                           0
```

```
24421  0.228454  0.202920  0.209491  0.156633                           0
29431 -0.296801 -0.288083 -0.314136 -0.293382                           0
2382  -0.280103 -0.293828  0.578321  0.617449                           0

[5 rows x 25 columns]
```

Task 2c: Create a data sample of size 1000 which is randomly selected (without replacement) from the original data such that the default labels are represented equally (500 instances with default = 1 and 500 instances with default = 0) and use parallel coordinates to visualize this data sample based on attributes X2-X11.

```
from pandas.plotting import parallel_coordinates as parallel

# Task 2c: Create a balanced data sample of size 1000
default_0 = data[data['default payment next month'] == 0].sample(n=500, replace=False)
default_1 = data[data['default payment next month'] == 1].sample(n=500, replace=False)
balanced_sample = pd.concat([default_0, default_1])
print(balanced_sample['default payment next month'].value_counts())

# Create a parallel coordinates plot
attributes_to_visualize = random_sample.iloc[:, 2:12]
plt.figure(figsize=(12, 8))
parallel(random_sample[['default payment next month'] + list(attributes_to_visualize.colum
plt.title("Parallel Coordinates Plot of Random Sample")
plt.ylabel("Attribute Value")
plt.xticks(rotation=45)
plt.legend(title="Default Payment", loc="upper left")
plt.show()
```

```
default payment next month
0    500
1    500
Name: count, dtype: int64
```



Task 2d: Generate a random sample of size 1000 from the original data, then use Principal component analysis (PCA) to reduce the number of attributes by projecting the data sample from its original high-dimensional space into a lower-dimensional space. In this case, reduce the dimension from 23 to 2 for visualization using a scatterplot.

```
# Task 2d: PCA for dimensionality reduction and scatter plot
pca = PCA(n_components=2)
pca_result = pca.fit_transform(data.iloc[:, 1:24])
plt.figure(figsize=(10, 6))
# Scatter plot for default payment = 0
plt.scatter(
    pca_result[data['default payment next month'] == 0, 0],
    pca_result[data['default payment next month'] == 0, 1],
    c='blue', label='Default Payment = 0', alpha=0.5)

# Scatter plot for default payment = 1
plt.scatter(
```

```python
    pca_result[data['default payment next month'] == 1, 0],
    pca_result[data['default payment next month'] == 1, 1],
    c='red', label='Default Payment = 1', alpha=0.5)

plt.title("PCA Scatter Plot of Projected Data")
plt.xlabel("Principal Component 1")
plt.ylabel("Principal Component 2")
plt.legend(title="Default Payment", loc="upper left")
plt.show()
```