20230910_assignment2

September 10, 2023

[1]:
```
!pip install -U pandas numpy matplotlib seaborn scikit-learn
```

```
Requirement already satisfied: pandas in
/home/ziad/angelsshit/lib/python3.8/site-packages (2.0.3)
Requirement already satisfied: numpy in
/home/ziad/angelsshit/lib/python3.8/site-packages (1.24.4)
Requirement already satisfied: matplotlib in
/home/ziad/angelsshit/lib/python3.8/site-packages (3.7.2)
Requirement already satisfied: seaborn in
/home/ziad/angelsshit/lib/python3.8/site-packages (0.12.2)
Requirement already satisfied: scikit-learn in
/home/ziad/angelsshit/lib/python3.8/site-packages (1.3.0)
Requirement already satisfied: python-dateutil>=2.8.2 in
/home/ziad/angelsshit/lib/python3.8/site-packages (from pandas) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in
/home/ziad/angelsshit/lib/python3.8/site-packages (from pandas) (2021.1)
Requirement already satisfied: tzdata>=2022.1 in
/home/ziad/angelsshit/lib/python3.8/site-packages (from pandas) (2023.3)
Requirement already satisfied: contourpy>=1.0.1 in
/home/ziad/angelsshit/lib/python3.8/site-packages (from matplotlib) (1.1.0)
Requirement already satisfied: cycler>=0.10 in
/home/ziad/angelsshit/lib/python3.8/site-packages (from matplotlib) (0.10.0)
Requirement already satisfied: fonttools>=4.22.0 in
/home/ziad/angelsshit/lib/python3.8/site-packages (from matplotlib) (4.42.1)
Requirement already satisfied: kiwisolver>=1.0.1 in
/home/ziad/angelsshit/lib/python3.8/site-packages (from matplotlib) (1.3.2)
Requirement already satisfied: packaging>=20.0 in
/home/ziad/angelsshit/lib/python3.8/site-packages (from matplotlib) (21.0)
Requirement already satisfied: pillow>=6.2.0 in
/home/ziad/angelsshit/lib/python3.8/site-packages (from matplotlib) (9.1.0)
Requirement already satisfied: pyparsing<3.1,>=2.3.1 in
/home/ziad/angelsshit/lib/python3.8/site-packages (from matplotlib) (2.4.7)
Requirement already satisfied: importlib-resources>=3.2.0 in
/home/ziad/angelsshit/lib/python3.8/site-packages (from matplotlib) (6.0.1)
Requirement already satisfied: scipy>=1.5.0 in
/home/ziad/angelsshit/lib/python3.8/site-packages (from scikit-learn) (1.10.1)
Requirement already satisfied: joblib>=1.1.1 in
/home/ziad/angelsshit/lib/python3.8/site-packages (from scikit-learn) (1.3.2)
```

```
Requirement already satisfied: threadpoolctl>=2.0.0 in
/home/ziad/angelsshit/lib/python3.8/site-packages (from scikit-learn) (3.1.0)
Requirement already satisfied: six in /home/ziad/angelsshit/lib/python3.8/site-
packages (from cycler>=0.10->matplotlib) (1.16.0)
Requirement already satisfied: zipp>=3.1.0 in
/home/ziad/angelsshit/lib/python3.8/site-packages (from importlib-
resources>=3.2.0->matplotlib) (3.8.1)
```

[2]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

1 Assignment 2

1.1 Ziad Arafat

1.1.1 Reading in the data

1. We read in the CSV using the pandas library and store it in a dataframe.
2. We print the data in the first two rows using the `head()` method

[3]:
```python
df_default_credit = pd.read_csv("Default-of-Credit-Card-Clients.csv")
print(df_default_credit.head(n=2))
```

```
   ID  LIMIT_BAL  SEX  EDUCATION  MARRIAGE  AGE  PAY_0  PAY_2  PAY_3  PAY_4  \
0   1      20000    2          2         1   24      2      2     -1     -1
1   2     120000    2          2         2   26     -1      2      0      0

   …  BILL_AMT4  BILL_AMT5  BILL_AMT6  PAY_AMT1  PAY_AMT2  PAY_AMT3  \
0  …          0          0          0         0       689         0
1  …       3272       3455       3261         0      1000      1000

   PAY_AMT4  PAY_AMT5  PAY_AMT6  default payment next month
0         0         0         0                           1
1      1000         0      2000                           1

[2 rows x 25 columns]
```

1.1.2 1.

1. We want to obtain information about the “BILL_AMTN” columns so first lets see how to select those.
2. We can get a list of all the columns labels and then select only the columns that we need.
3. Now we can get the information we need from each column.

[4]:
```python
bill_amt_col_labels = df_default_credit.columns[12:18]
```

1a.

1. We print the mean, std, min, and max of each column
2. The `describe()` method has a useful property that allows us to select specific parts of the output instead of printing all the values.
3. This allows us to easily display it in a nice table of elements.

[5]:
```python
stats = df_default_credit[bill_amt_col_labels].describe()
selected_stats = stats.loc[['mean', 'std', 'min', 'max']]
selected_stats
```

[5]:
```
          BILL_AMT1      BILL_AMT2     BILL_AMT3      BILL_AMT4  \
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
max   964511.000000  983931.000000  1.664089e+06  891586.000000

          BILL_AMT5      BILL_AMT6
mean   40311.400967   38871.760400
std    60797.155770   59554.107537
min   -81334.000000 -339603.000000
max   927171.000000  961664.000000
```

1b.

1. Now we need to calculate the covariance and correlation between all the pairs of attributes.
2. We can do this using a covariance/correlation matrix to display it nicely.

[6]:
```python
covariance_matrix = df_default_credit[bill_amt_col_labels].cov()
print("Covariance matrix:\n", covariance_matrix)

correlation_matrix = df_default_credit[bill_amt_col_labels].corr()
print("\nCorrelation matrix:\n", correlation_matrix)
```

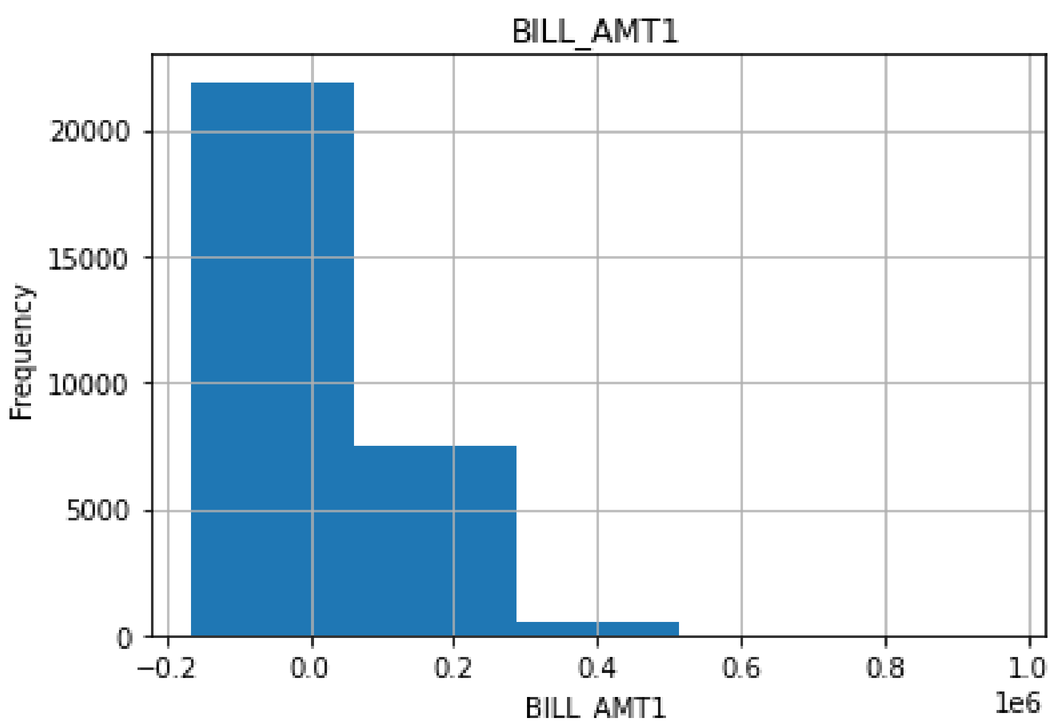
```
Covariance matrix:
               BILL_AMT1     BILL_AMT2     BILL_AMT3     BILL_AMT4  \
BILL_AMT1  5.422240e+09  4.986670e+09  4.556511e+09  4.075286e+09
BILL_AMT2  4.986670e+09  5.065705e+09  4.582086e+09  4.086508e+09
BILL_AMT3  4.556511e+09  4.582086e+09  4.809338e+09  4.122238e+09
BILL_AMT4  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
```

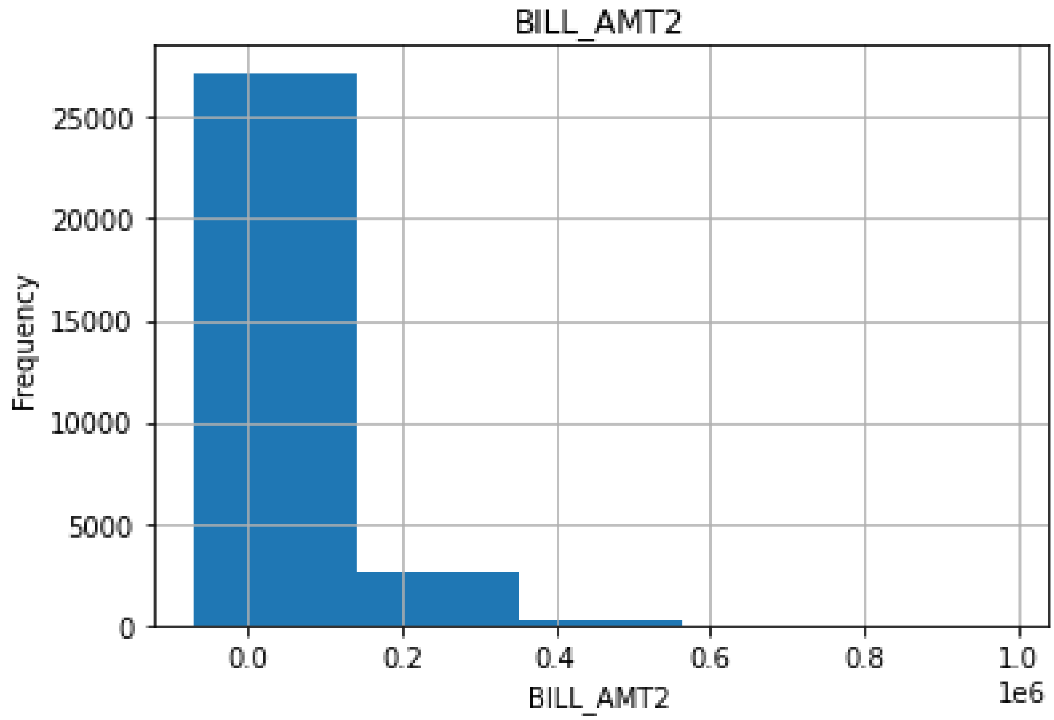
```
Correlation matrix:
           BILL_AMT1  BILL_AMT2  BILL_AMT3  BILL_AMT4  BILL_AMT5  BILL_AMT6
BILL_AMT1  1.000000   0.951484   0.892279   0.860272   0.829779   0.802650
BILL_AMT2  0.951484   1.000000   0.928326   0.892482   0.859778   0.831594
BILL_AMT3  0.892279   0.928326   1.000000   0.923969   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
```

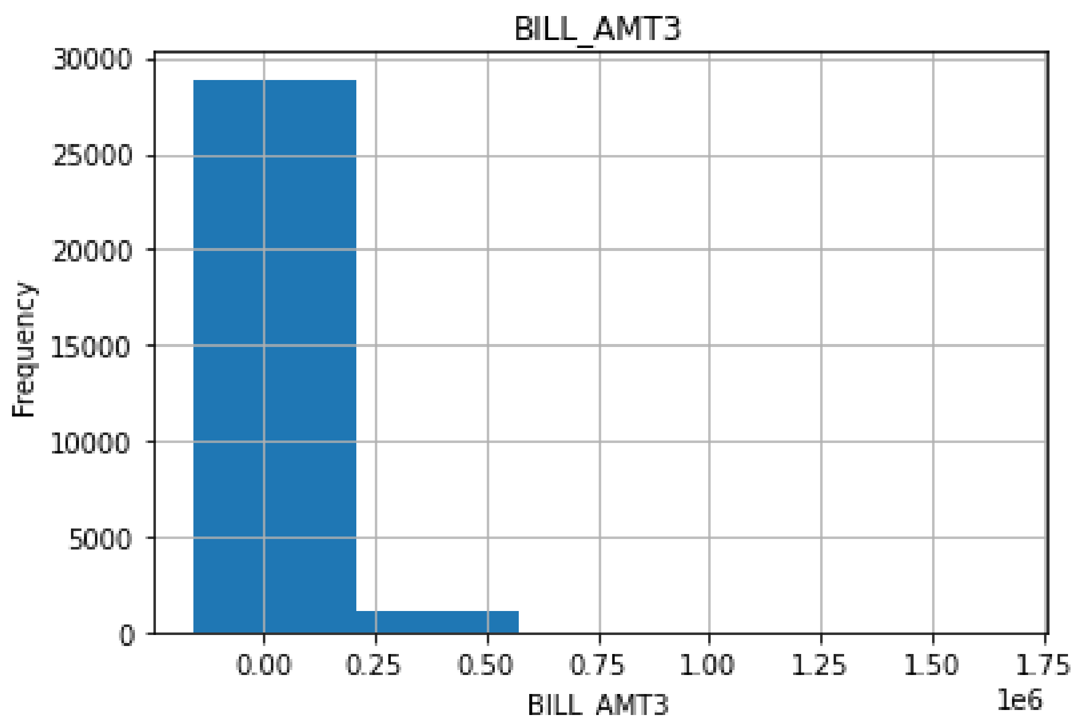
1c.

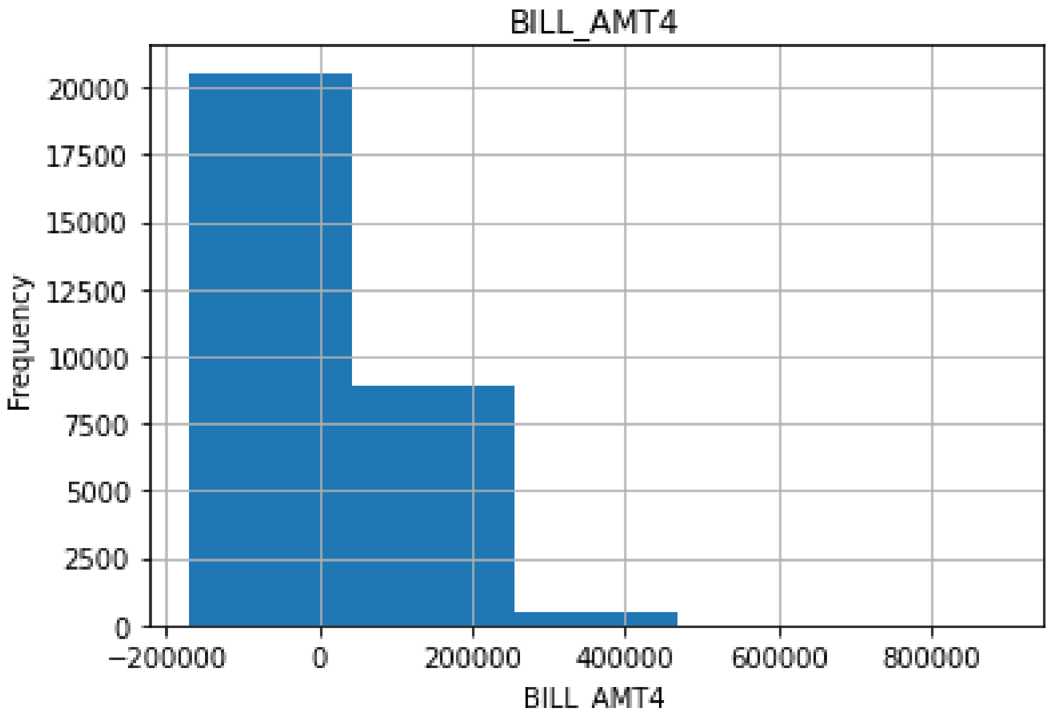
1. Let's create a histogram for each column
2. Matplotlib decided to use a different scale label for some them not sure why.

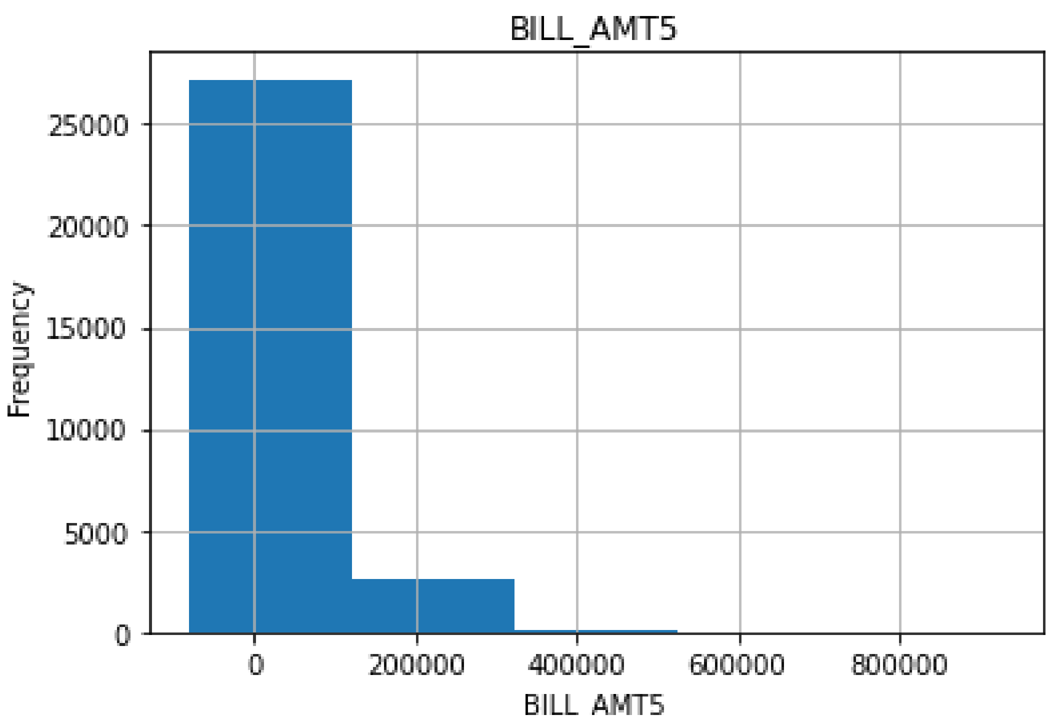
[7]:
```
for label in bill_amt_col_labels:
    df_default_credit[label].hist(bins=5)
    plt.title(label)
    plt.xlabel(label)
    plt.ylabel('Frequency')
    plt.show()
```

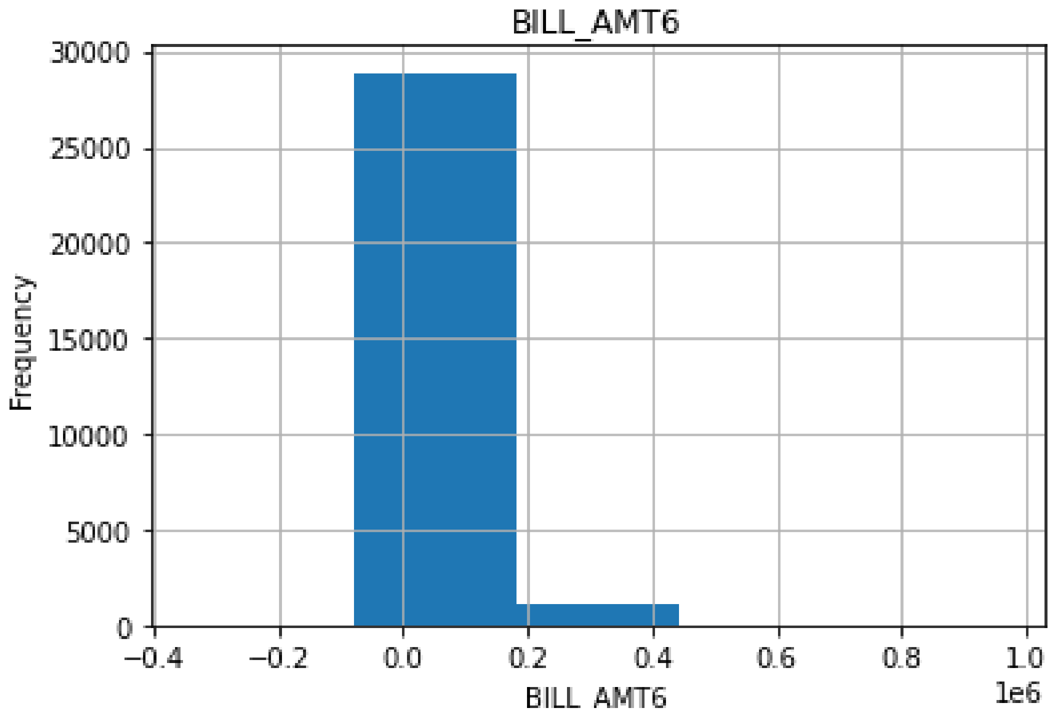



BILL_AMT2
Frequency
25000
20000
15000
10000
5000
0
0.0
0.2
0.4
0.6
0.8
1.0
1e6
BILL_AMT2


BILL_AMT3
Frequency
30000
25000
20000
15000
10000
5000
0
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
1e6
BILL_AMT3


BILL_AMT4
Frequency
20000
17500
15000
12500
10000
7500
5000
2500
0
−200000
0
200000
400000
600000
800000
BILL_AMT4

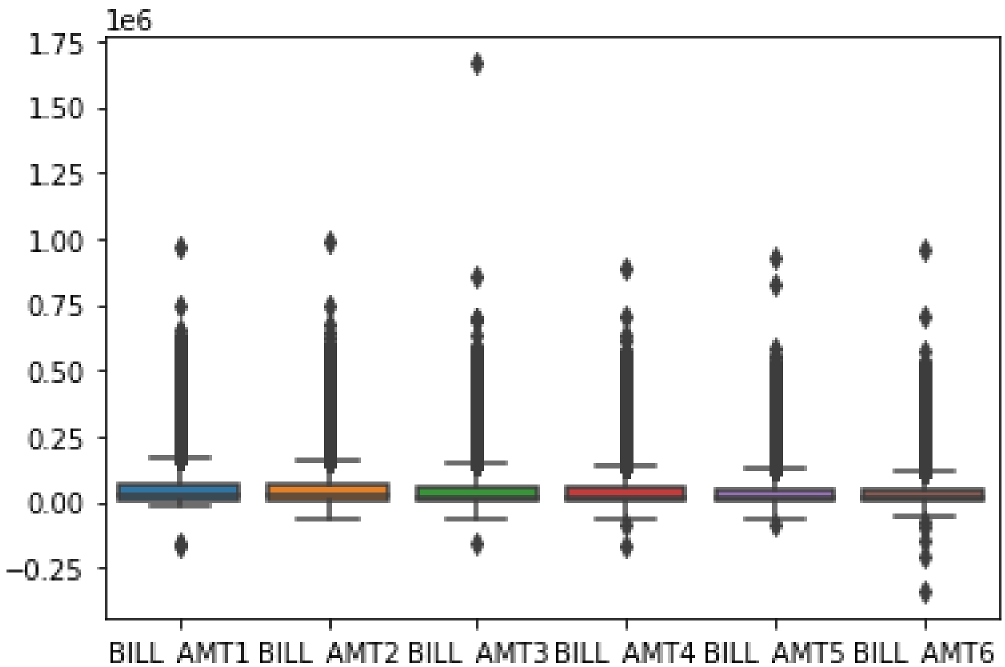

BILL_AMT5
Frequency
25000
20000
15000
10000
5000
0
0
200000
400000
600000
800000
BILL_AMT5



1d.

1. We create a boxplot to show a whisker for each column.
2. We used the seaborn library because it makes nicer boxplots.
3. The boxplot shows that all the columns have several outliers indicated by the dots on either sides of the whiskers.

[8]:
```
import seaborn as sns

sns.boxplot(data=df_default_credit[bill_amt_col_labels])
plt.show()
```

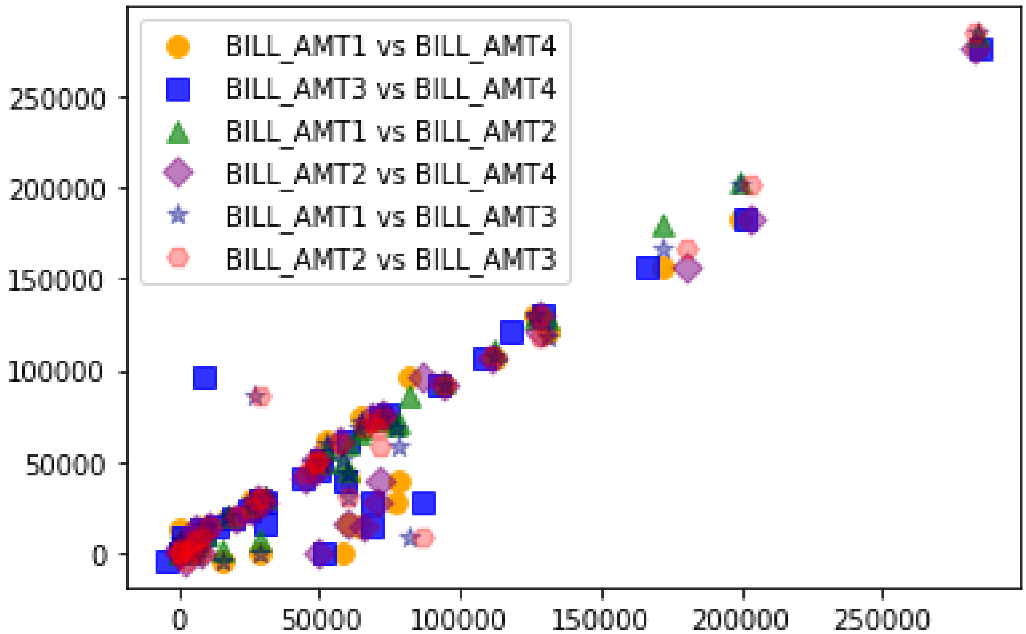


1e.

1. We can create a pretty scatter plot using matplotlib
2. We use some interesting logic to create a list of unique pairs.
    1. First we iterate through all combinations
    2. For each of them we create a sorted tuple of the pair
    3. Then we turn it into a set which eliminates duplicates.
3. To make the graph more readable
    1. we can take a random sample of 35 from each column.
    2. Vary the color of the markers and add transparency
    3. Vary the shape of the markers
    4. add a legend
    5. For each layer I decreased the transparency by 20 percent so that the top layer doesn't completely oversaturate the others.
4. We can see from this graph that there is a great deal of correlation between the pairs.
    1. This may indicate that the Bill amount does not vary significantly between months.
    2. The implication of this may be that we can merge all these columns into 1 column to reduce our problem size.

[9]:
```
list_of_pairs = []

for labelx in bill_amt_col_labels[:4]:
    for labely in bill_amt_col_labels[:4]:
        if labelx != labely:
            list_of_pairs.append(tuple(sorted((labelx, labely))))
```

```python
colors = ['orange', 'blue', 'green', 'purple', 'darkblue', 'red']
markers = ['o', 's', '^', 'D', '*', 'H']
alpha_value = 1
colors_markers_pairs = zip(colors, markers, list(set(list_of_pairs)))

for color, marker, labels in colors_markers_pairs:
    x_col = df_default_credit[labels[0]].sample(n=35, random_state=2)
    y_col = df_default_credit[labels[1]].sample(n=35, random_state=2)

    plt.scatter(x_col, y_col,
                c=color, alpha=alpha_value, marker=marker, s=60,
                label=f'{labels[0]} vs {labels[1]}')
    plt.legend()
    alpha_value *= 0.80
plt.show()
```



1.1.3 2.

2a.

1. first we need to select the columns we want to work on.
2. then we can standardize them using scikit learn's StandardScaler class

[10]:
```python
from sklearn.preprocessing import StandardScaler
```

```python
selected_cols = [df_default_credit.columns[i] for i in [1, 5] + list(range(12,
 ↪24))]

scaler = StandardScaler()
df_default_credit[selected_cols] = scaler.
 ↪fit_transform(df_default_credit[selected_cols])

df_default_credit[selected_cols].head(10)
```

[10]:

	LIMIT_BAL	AGE	BILL_AMT1	BILL_AMT2	BILL_AMT3	BILL_AMT4	BILL_AMT5
0	-1.136720	-1.246020	-0.642501	-0.647399	-0.667993	-0.672497	-0.663059
1	-0.365981	-1.029047	-0.659219	-0.666747	-0.639254	-0.621636	-0.606229
2	-0.597202	-0.161156	-0.298560	-0.493899	-0.482408	-0.449730	-0.417188
3	-0.905498	0.164303	-0.057491	-0.013293	0.032846	-0.232373	-0.186729
4	-0.905498	2.334029	-0.578618	-0.611318	-0.161189	-0.346997	-0.348137
5	-0.905498	0.164303	0.178947	0.110856	0.152777	-0.371029	-0.340357
6	2.562830	-0.703588	4.301531	5.098086	5.739063	7.762727	7.281574
7	-0.520128	-1.354506	-0.534359	-0.685644	-0.669262	-0.669062	-0.665674
8	-0.211833	-0.812074	-0.542385	-0.492930	-0.503332	-0.482684	-0.469082
9	-1.136720	-0.052670	-0.695642	-0.690983	-0.677929	-0.672497	-0.449114

	BILL_AMT6	PAY_AMT1	PAY_AMT2	PAY_AMT3	PAY_AMT4	PAY_AMT5	PAY_AMT6
0	-0.652724	-0.341942	-0.227086	-0.296801	-0.308063	-0.314136	-0.293382
1	-0.597966	-0.341942	-0.213588	-0.240005	-0.244230	-0.314136	-0.180878
2	-0.391630	-0.250292	-0.191887	-0.240005	-0.244230	-0.248683	-0.012122
3	-0.156579	-0.221191	-0.169361	-0.228645	-0.237846	-0.244166	-0.237130
4	-0.331482	-0.221191	1.335034	0.271165	0.266434	-0.269039	-0.255187
5	-0.316487	-0.191003	-0.178215	-0.259486	-0.244230	-0.248683	-0.248381
6	7.305617	2.978712	1.479085	1.861472	0.983852	0.585848	0.481207
7	-0.643203	-0.318999	-0.230905	-0.296801	-0.270976	-0.203716	-0.206642
8	-0.590276	-0.140952	-0.256990	-0.272265	-0.244230	-0.248683	-0.237130
9	-0.419118	-0.341942	-0.256990	-0.296801	0.522212	-0.240697	-0.293382

2b.

1. We can easily make a random sample of 1000 using `.sample()`

[11]:
```python
sample_of_1000 = df_default_credit.sample(n=1000, random_state=2)
sample_of_1000.head(n=10)
```

[11]:

	ID	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	\
7945	7946	-1.136720	2	2	1	0.164303	0	0	
16536	16537	2.562830	1	2	2	-1.029047	0	0	
26726	26727	-0.134759	1	1	2	-1.029047	-2	-1	
16333	16334	-0.828424	2	2	1	0.055816	0	0	
20629	20630	0.404759	1	1	2	-0.703588	0	0	
321	322	1.329647	2	1	2	-0.920561	0	0	

```
9579     9580  -0.905498     1           3          1  1.574625      0       0
27004   27005  -0.828424     1           1          2 -0.486615      0       0
2360     2361  -1.136720     2           2          1  0.598248     -1       2
6593     6594  -0.905498     1           2          2  2.225543      0       0

       PAY_3  PAY_4  …  BILL_AMT4  BILL_AMT5  BILL_AMT6  PAY_AMT1  PAY_AMT2  \
7945       2      0  …  -0.367578  -0.346788  -0.318938 -0.148740 -0.256990
16536      0      0  …   1.350391   1.437387   1.439912  0.020613  0.003639
26726      0      0  …  -0.635812  -0.661907  -0.645672 -0.320206 -0.211808
16333      0      0  …  -0.031430  -0.177271  -0.160777 -0.221191 -0.124961
20629      0      0  …  -0.299975  -0.270517  -0.255314 -0.256812 -0.195489
321        0      0  …   1.746649   1.732570   1.081240  0.932284 -0.019972
9579       0      2  …  -0.449388  -0.398075  -0.353294 -0.172890 -0.083382
27004      0      0  …  -0.672497  -0.663059  -0.652724 -0.160815 -0.126784
2360      -1     -1  …  -0.536561  -0.575619  -0.584583 -0.341942 -0.191887
6593       0      0  …   0.025944  -0.341344  -0.336049 -0.228194 -0.170316

       PAY_AMT3  PAY_AMT4  PAY_AMT5  PAY_AMT6  default payment next month
7945  -0.249660 -0.260188 -0.248683 -0.277519                           1
16536  0.049318 -0.042454  0.014505 -0.048686                           0
26726 -0.240005 -0.303594 -0.270937 -0.293382                           0
16333 -0.215412 -0.243464 -0.246785 -0.232967                           1
20629 -0.221091 -0.261401 -0.247439 -0.234599                           0
321   -0.012818  0.065296 -0.135317  2.519214                           0
9579  -0.296801 -0.180397 -0.183229 -0.237130                           0
27004 -0.296801 -0.308063 -0.314136 -0.293382                           0
2360   0.199886 -0.308063 -0.314136 -0.199779                           0
6593  -0.186445 -0.263826 -0.269431 -0.255131                           0

[10 rows x 25 columns]
```

2c.

1. First lets split our dataset into two sets based on the label value.
2. Then we can take a sample from each of size 500
3. Finally we merge those samples and we have the results we need.
4. We also shuffle the new dataset we merged by sampling itself

[12]:
```
df_default_credit_0 = df_default_credit[df_default_credit['default payment next␣
↪month'] == 0]
df_default_credit_1 = df_default_credit[df_default_credit['default payment next␣
↪month'] == 1]

sampled_0 = df_default_credit_0.sample(n=500, random_state=2)
sampled_1 = df_default_credit_1.sample(n=500, random_state=2)
```

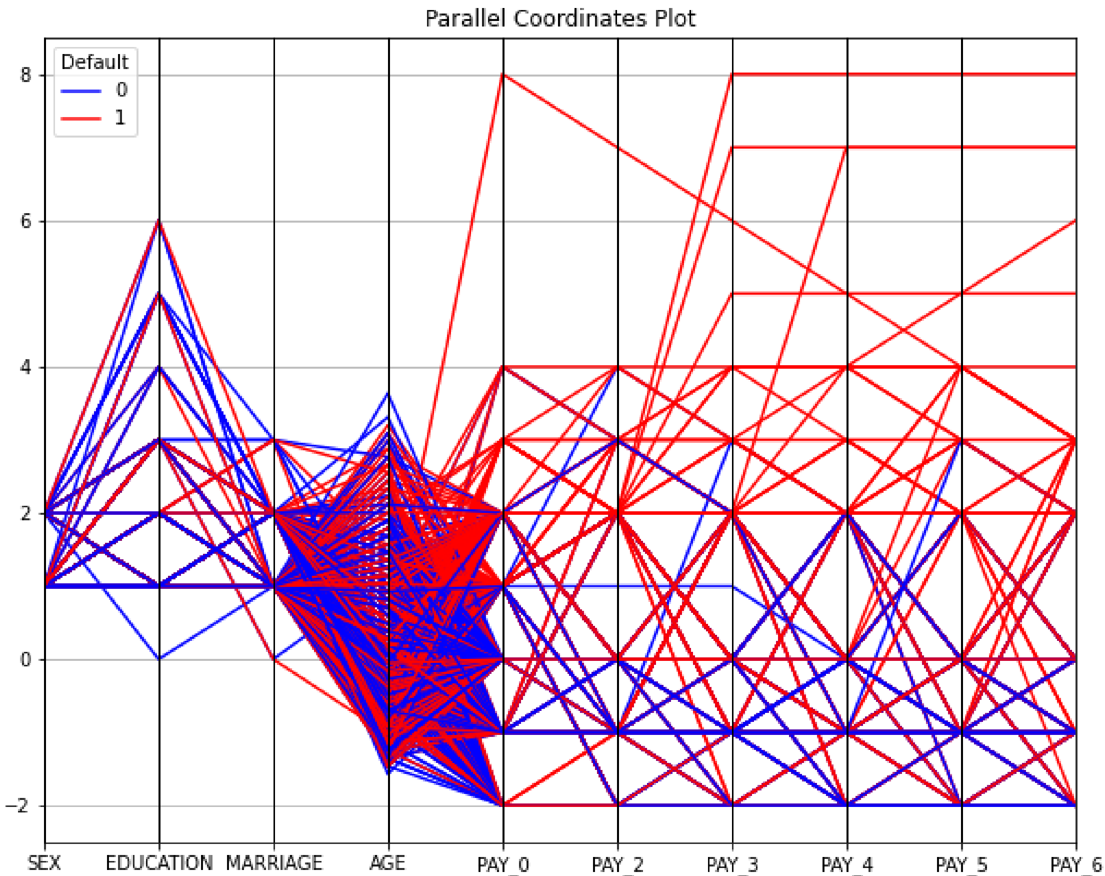
```
balanced_sample_1000 = pd.concat([sampled_0, sampled_1], axis=0).sample(frac=1,␣
↪random_state=2)

balanced_sample_1000.head()
```

[12]:
```
        ID  LIMIT_BAL  SEX  EDUCATION  MARRIAGE       AGE  PAY_0  PAY_2  \
304    305   0.250611    2          1         2 -0.920561     -1     -1
3941  3942   1.869164    2          1         2 -0.161156      1     -1
1830  1831  -1.136720    1          3         1  0.272789      0      0
2420  2421   0.096463    2          1         2 -0.052670     -1      3
6034  6035   0.250611    2          2         1  0.055816     -1     -1

      PAY_3  PAY_4  …  BILL_AMT4  BILL_AMT5  BILL_AMT6  PAY_AMT1  PAY_AMT2  \
304      -1      0  …  -0.606558  -0.595883  -0.528230 -0.301792 -0.215324
3941     -1     -2  …  -0.672497  -0.663059  -0.641541  0.480433 -0.256990
1830     -1     -1  …  -0.666435  -0.663059  -0.639627 -0.281566 -0.240063
2420      2      0  …  -0.658974  -0.613253  -0.610611 -0.341942 -0.256990
6034     -1      0  …  -0.642403  -0.633928  -0.652724 -0.068561 -0.034685

      PAY_AMT3  PAY_AMT4  PAY_AMT5  PAY_AMT6  default payment next month
304  -0.074840 -0.243336 -0.085049 -0.131377                           0
3941 -0.296801 -0.308063 -0.270544 -0.293382                           1
1830 -0.274651 -0.308063 -0.263082 -0.293382                           1
2420 -0.296801 -0.114776 -0.314136 -0.275044                           0
6034 -0.296801 -0.195014 -0.314136 -0.259406                           1

[5 rows x 25 columns]
```

2c - Visualization

1. Pandas has a built in plotting library with a parallel_coordinates library that works with matplotlib.
2. First we select the columns we want to work with
3. Then we can create the plot and customize it

[13]:
```
from pandas.plotting import parallel_coordinates

selected_cols = [balanced_sample_1000.columns[i] for i in list(range(2,␣
↪12))+[24]]
plt.figure(figsize=(10, 8))
parallel_coordinates(balanced_sample_1000[selected_cols],
                     'default payment next month',
                     color=['blue', 'red'])
plt.title('Parallel Coordinates Plot')
plt.legend(title='Default')
plt.show()
```



2d.

1. We already have a balanced sample of 1000
2. Now we can use scikit learn's PCA class to perform pincipal component analysis
3. At the end we combine the projected dataset with the labels and store it in a new variable.
4. now we can begin plotting it.

[14]:
```
from sklearn.decomposition import PCA

attributes = balanced_sample_1000.drop(columns=["default payment next month",␣
 ↪"ID"])
labels = balanced_sample_1000["default payment next month"]

pca = PCA(n_components=2)
principal_components = pca.fit_transform(attributes)

df_principal = pd.DataFrame(data=principal_components,
                            columns=['PC 1', 'PC 2'])
```

```
df_principal_labeled = pd.concat([df_principal, labels.reset_index(drop=True)],
                                 axis=1)

df_principal_labeled
```

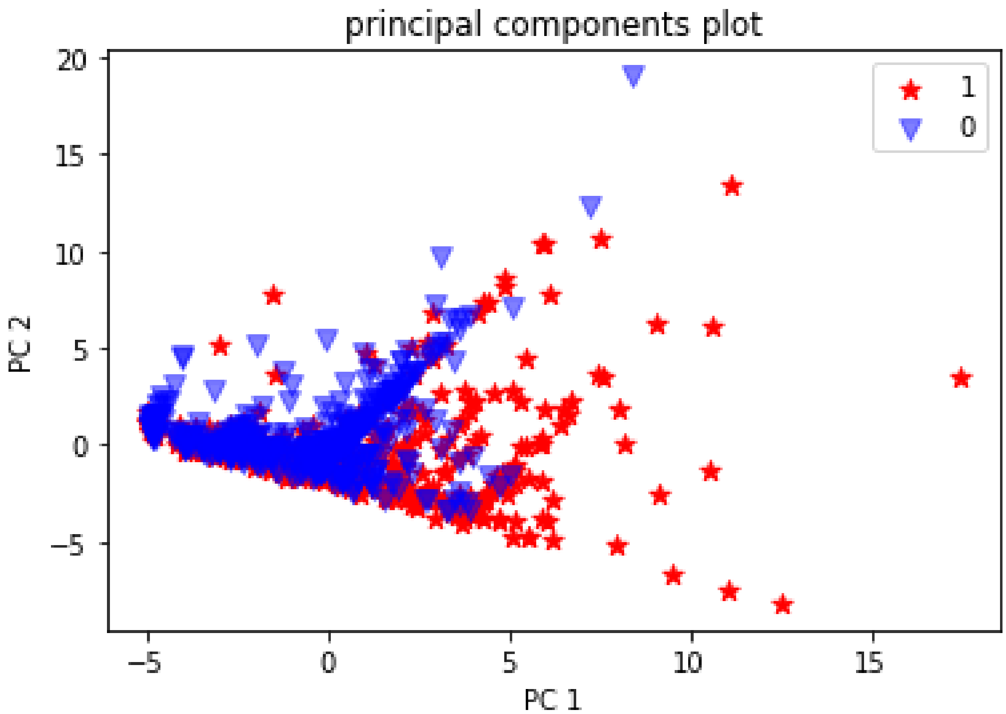
[14]:
```
          PC 1      PC 2  default payment next month
0   -1.603675 -0.766889                           0
1   -2.912391  0.313129                           1
2   -1.879191 -0.880717                           1
3    1.292375 -2.304832                           0
4   -2.315521 -0.405323                           1
..        …         …                           …
995  4.304769 -2.798802                           1
996  0.966453 -0.466210                           1
997 -1.011304 -0.578056                           0
998  1.050118 -0.486183                           1
999 -2.780543  0.146420                           0

[1000 rows x 3 columns]
```

2d - Visualization

1. For the visualization we can split our data based on the label
2. Then we can scatter plot each one in a different color.
3. Since the scatter plot is so dense we can take a sample of 35 and plot it again to better interpret the data.
    1. We then doubled the sample size to improve the saturation.
4. From the looks of it there is no clear separation of labels in the new dataset so we may need to rethink our approach to reduce the attributes.
    1. One possible thing to do is increase the output dimensionality on the PCA because going from 23 to 2 might be a bit ambitious with this complex dataset.
    2. Another possible approach is to eliminate some features that might not be useful.

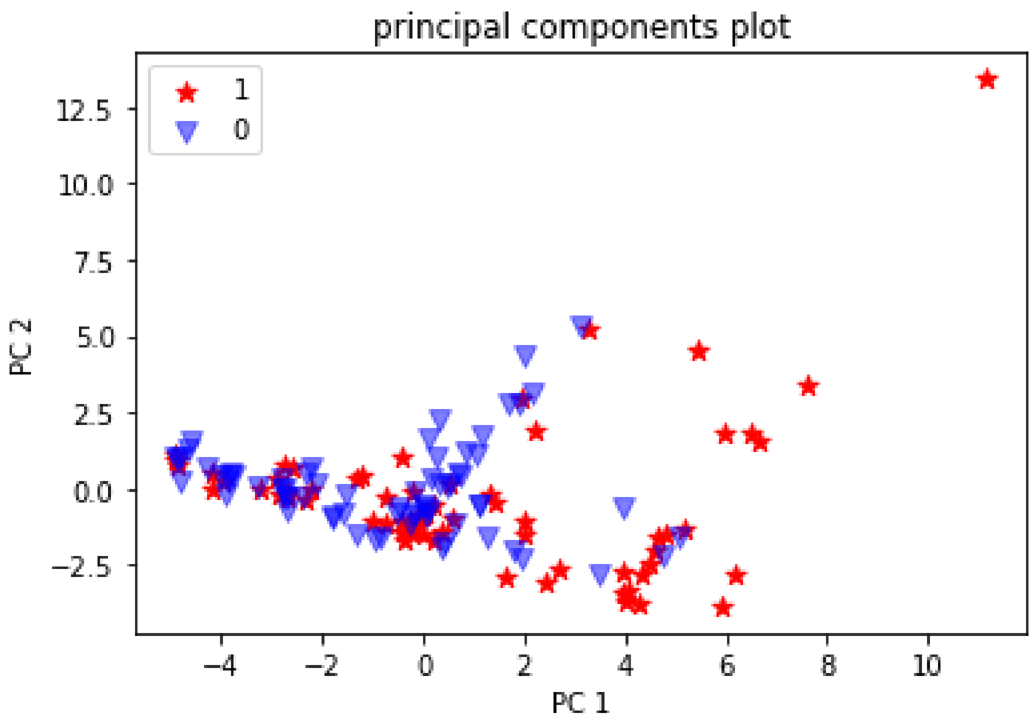
[15]:
```
df_principal_labeled_0 = df_principal_labeled[df_principal_labeled['default␣
 ↪payment next month'] == 0]
df_principal_labeled_1 = df_principal_labeled[df_principal_labeled['default␣
 ↪payment next month'] == 1]

x_col_0 = df_principal_labeled_0['PC 1']
y_col_0 = df_principal_labeled_0['PC 2']

x_col_1 = df_principal_labeled_1['PC 1']
y_col_1 = df_principal_labeled_1['PC 2']

plt.scatter(x_col_1, y_col_1,
        c='red', alpha=1, marker="*", s=60,
        label='1')
```

```
plt.scatter(x_col_0, y_col_0,
        c='blue', alpha=0.5, marker="v", s=60,
        label='0')
plt.legend()
plt.title('principal components plot')
plt.xlabel('PC 1')
plt.ylabel('PC 2')
plt.show()
```



[16]:
```
df_principal_labeled_0 = df_principal_labeled[df_principal_labeled['default␣
 ↪payment next month'] == 0]
df_principal_labeled_1 = df_principal_labeled[df_principal_labeled['default␣
 ↪payment next month'] == 1]

df_principal_labeled_0 = df_principal_labeled_0.sample(n=35*2, random_state=42)
df_principal_labeled_1 = df_principal_labeled_1.sample(n=35*2, random_state=42)

x_col_0 = df_principal_labeled_0['PC 1']
y_col_0 = df_principal_labeled_0['PC 2']

x_col_1 = df_principal_labeled_1['PC 1']
y_col_1 = df_principal_labeled_1['PC 2']
```

```python
plt.scatter(x_col_1, y_col_1,
        c='red', alpha=1, marker="*", s=60,
        label='1')

plt.scatter(x_col_0, y_col_0,
        c='blue', alpha=0.5, marker="v", s=60,
        label='0')
plt.legend()
plt.title('principal components plot')
plt.xlabel('PC 1')
plt.ylabel('PC 2')
plt.show()
```



[ ]:

```python

```