ML_Finance_HW3_Dhyey

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[1]:
```
# checking the current working directory access
import os
print(os.getcwd())
```

```
/Users/dhyeymavani/Library/CloudStorage/GoogleDrive-dmavani25@amherst.edu/My
Drive/Columbia VUS/SPRING2023/MATH GR 5430 MACHINE LEARNING FOR
FINANCE/ML_Finance_HW3
```

1 1. Unsupervised Learning

1.0.1 Background: The sample Dataset summarizes the usage behavior of about 9000 active credit card holders during the last 6 months. The file is at a customer level with 18 behavioral variables (also see datacard.txt)

Following is the Data Dictionary for Credit Card dataset:

- CUST_ID : Identification of Credit Card holder (Categorical)
- BALANCE : Balance amount left in their account to make purchases
- BALANCE_FREQUENCY : How frequently the Balance is updated, score between 0 and 1 (1 = frequently updated, 0 = not frequently updated)
- PURCHASES : Amount of purchases made from account
- ONEOFF_PURCHASES : Maximum purchase amount done in one-go
- INSTALLMENTS_PURCHASES : Amount of purchase done in installment
- CASH_ADVANCE : Cash in advance given by the user
- PURCHASES_FREQUENCY : How frequently the Purchases are being made, score between 0 and 1 (1 = frequently purchased, 0 = not frequently purchased)
- ONEOFFPURCHASESFREQUENCY : How frequently Purchases are happening in one-go (1 = frequently purchased, 0 = not frequently purchased)
- PURCHASESINSTALLMENTSFREQUENCY : How frequently purchases in installments are being done (1 = frequently done, 0 = not frequently done)
- CASHADVANCEFREQUENCY : How frequently the cash in advance being paid

- CASHADVANCETRX : Number of Transactions made with “Cash in Advanced”
- PURCHASES_TRX : Numbe of purchase transactions made
- CREDIT_LIMIT : Limit of Credit Card for user
- PAYMENTS : Amount of Payment done by user
- MINIMUM_PAYMENTS : Minimum amount of payments made by user
- PRCFULLPAYMENT : Percent of full payment paid by user
- TENURE : Tenure of credit card service for user

1.1 1.1 Exploratory Data Analysis

- **Obtain and import the dataset (HW3.csv) from Courseworks as a Pandas dataframe.**

[2]:
```
import pandas as pd
data_path = "./HW3.csv"
data = pd.read_csv(data_path)
data
```

[2]:
```
     CUST_ID      BALANCE  BALANCE_FREQUENCY  PURCHASES  ONEOFF_PURCHASES  \
0     C10001    40.900749           0.818182      95.40              0.00
1     C10002  3202.467416           0.909091       0.00              0.00
2     C10003  2495.148862           1.000000     773.17            773.17
3     C10004  1666.670542           0.636364    1499.00           1499.00
4     C10005   817.714335           1.000000      16.00             16.00
…        …          …                 …        …                …
8945  C19186    28.493517           1.000000     291.12              0.00
8946  C19187    19.183215           1.000000     300.00              0.00
8947  C19188    23.398673           0.833333     144.40              0.00
8948  C19189    13.457564           0.833333       0.00              0.00
8949  C19190   372.708075           0.666667    1093.25           1093.25

      INSTALLMENTS_PURCHASES  CASH_ADVANCE  PURCHASES_FREQUENCY  \
0                      95.40      0.000000             0.166667
1                       0.00   6442.945483             0.000000
2                       0.00      0.000000             1.000000
3                       0.00    205.788017             0.083333
4                       0.00      0.000000             0.083333
…                        …           …                    …
8945                  291.12      0.000000             1.000000
8946                  300.00      0.000000             1.000000
8947                  144.40      0.000000             0.833333
8948                    0.00     36.558778             0.000000
8949                    0.00    127.040008             0.666667

      ONEOFF_PURCHASES_FREQUENCY  PURCHASES_INSTALLMENTS_FREQUENCY  \
0                       0.000000                          0.083333
```

```
1                     0.000000                          0.000000
2                     1.000000                          0.000000
3                     0.083333                          0.000000
4                     0.083333                          0.000000
…                         …                               …
8945                  0.000000                          0.833333
8946                  0.000000                          0.833333
8947                  0.000000                          0.666667
8948                  0.000000                          0.000000
8949                  0.666667                          0.000000

      CASH_ADVANCE_FREQUENCY  CASH_ADVANCE_TRX  PURCHASES_TRX  CREDIT_LIMIT  \
0                   0.000000                 0              2        1000.0
1                   0.250000                 4              0        7000.0
2                   0.000000                 0             12        7500.0
3                   0.083333                 1              1        7500.0
4                   0.000000                 0              1        1200.0
…                      …                 …             …             …
8945                0.000000                 0              6        1000.0
8946                0.000000                 0              6        1000.0
8947                0.000000                 0              5        1000.0
8948                0.166667                 2              0         500.0
8949                0.333333                 2             23        1200.0

         PAYMENTS  MINIMUM_PAYMENTS  PRC_FULL_PAYMENT  TENURE
0      201.802084        139.509787          0.000000      12
1     4103.032597       1072.340217          0.222222      12
2      622.066742        627.284787          0.000000      12
3        0.000000               NaN          0.000000      12
4      678.334763        244.791237          0.000000      12
…          …                …                …     …
8945   325.594462         48.886365          0.500000       6
8946   275.861322               NaN          0.000000       6
8947    81.270775         82.418369          0.250000       6
8948    52.549959         55.755628          0.250000       6
8949    63.165404         88.288956          0.000000       6

[8950 rows x 18 columns]
```

[3]:
```
data.describe()
```

[3]:
```
           BALANCE  BALANCE_FREQUENCY    PURCHASES  ONEOFF_PURCHASES  \
count  8950.000000        8950.000000  8950.000000       8950.000000
mean   1564.474828           0.877271  1003.204834        592.437371
std    2081.531879           0.236904  2136.634782       1659.887917
min       0.000000           0.000000     0.000000          0.000000
25%     128.281915           0.888889    39.635000          0.000000
```

```
50%      873.385231           1.000000    361.280000         38.000000
75%     2054.140036           1.000000   1110.130000        577.405000
max    19043.138560           1.000000  49039.570000      40761.250000

       INSTALLMENTS_PURCHASES  CASH_ADVANCE  PURCHASES_FREQUENCY  \
count             8950.000000   8950.000000          8950.000000
mean               411.067645    978.871112             0.490351
std                904.338115   2097.163877             0.401371
min                  0.000000      0.000000             0.000000
25%                  0.000000      0.000000             0.083333
50%                 89.000000      0.000000             0.500000
75%                468.637500   1113.821139             0.916667
max              22500.000000  47137.211760             1.000000

       ONEOFF_PURCHASES_FREQUENCY  PURCHASES_INSTALLMENTS_FREQUENCY  \
count                 8950.000000                       8950.000000
mean                     0.202458                          0.364437
std                      0.298336                          0.397448
min                      0.000000                          0.000000
25%                      0.000000                          0.000000
50%                      0.083333                          0.166667
75%                      0.300000                          0.750000
max                      1.000000                          1.000000

       CASH_ADVANCE_FREQUENCY  CASH_ADVANCE_TRX  PURCHASES_TRX  CREDIT_LIMIT  \
count             8950.000000       8950.000000    8950.000000   8949.000000
mean                 0.135144          3.248827      14.709832   4494.449450
std                  0.200121          6.824647      24.857649   3638.815725
min                  0.000000          0.000000       0.000000     50.000000
25%                  0.000000          0.000000       1.000000   1600.000000
50%                  0.000000          0.000000       7.000000   3000.000000
75%                  0.222222          4.000000      17.000000   6500.000000
max                  1.500000        123.000000     358.000000  30000.000000

           PAYMENTS  MINIMUM_PAYMENTS  PRC_FULL_PAYMENT        TENURE
count   8950.000000       8637.000000       8950.000000   8950.000000
mean    1733.143852        864.206542          0.153715     11.517318
std     2895.063757       2372.446607          0.292499      1.338331
min        0.000000          0.019163          0.000000      6.000000
25%      383.276166        169.123707          0.000000     12.000000
50%      856.901546        312.343947          0.000000     12.000000
75%     1901.134317        825.485459          0.142857     12.000000
max    50721.483360      76406.207520          1.000000     12.000000
```

[4]:

```
#data["PURCHASES_FREQUENCY"].value_counts()
```

- **Data cleaning: Some features have missing values and outliers. Choose the way you see as appropriate to clean the dataframe and deal with outliers.**

[5]:
```
df = data.copy()
df.drop(['CUST_ID'], axis=1, inplace=True)
cols_to_check = ['BALANCE', 'BALANCE_FREQUENCY', 'PURCHASES']
df = df.loc[~(df[cols_to_check] == 0.000).any(axis=1)]
df
```

[5]:
```
          BALANCE  BALANCE_FREQUENCY  PURCHASES  ONEOFF_PURCHASES  \
0       40.900749           0.818182      95.40              0.00
2     2495.148862           1.000000     773.17            773.17
3     1666.670542           0.636364    1499.00           1499.00
4      817.714335           1.000000      16.00             16.00
5     1809.828751           1.000000    1333.28              0.00
…             …                 …          …                 …
8944   193.571722           0.833333    1012.73           1012.73
8945    28.493517           1.000000     291.12              0.00
8946    19.183215           1.000000     300.00              0.00
8947    23.398673           0.833333     144.40              0.00
8949   372.708075           0.666667    1093.25           1093.25

      INSTALLMENTS_PURCHASES  CASH_ADVANCE  PURCHASES_FREQUENCY  \
0                      95.40      0.000000             0.166667
2                       0.00      0.000000             1.000000
3                       0.00    205.788017             0.083333
4                       0.00      0.000000             0.083333
5                    1333.28      0.000000             0.666667
…                        …           …                    …
8944                    0.00      0.000000             0.333333
8945                  291.12      0.000000             1.000000
8946                  300.00      0.000000             1.000000
8947                  144.40      0.000000             0.833333
8949                    0.00    127.040008             0.666667

      ONEOFF_PURCHASES_FREQUENCY  PURCHASES_INSTALLMENTS_FREQUENCY  \
0                       0.000000                          0.083333
2                       1.000000                          0.000000
3                       0.083333                          0.000000
4                       0.083333                          0.000000
5                       0.000000                          0.583333
…                           …                                …
8944                    0.333333                          0.000000
8945                    0.000000                          0.833333
8946                    0.000000                          0.833333
8947                    0.000000                          0.666667
8949                    0.666667                          0.000000
```

	CASH_ADVANCE_FREQUENCY	CASH_ADVANCE_TRX	PURCHASES_TRX	CREDIT_LIMIT	\
0	0.000000	0	2	1000.0	
2	0.000000	0	12	7500.0	
3	0.083333	1	1	7500.0	
4	0.000000	0	1	1200.0	
5	0.000000	0	8	1800.0	
…	…	…	…	…	
8944	0.000000	0	2	4000.0	
8945	0.000000	0	6	1000.0	
8946	0.000000	0	6	1000.0	
8947	0.000000	0	5	1000.0	
8949	0.333333	2	23	1200.0	

	PAYMENTS	MINIMUM_PAYMENTS	PRC_FULL_PAYMENT	TENURE
0	201.802084	139.509787	0.00	12
2	622.066742	627.284787	0.00	12
3	0.000000	NaN	0.00	12
4	678.334763	244.791237	0.00	12
5	1400.057770	2407.246035	0.00	12
…	…	…	…	…
8944	0.000000	NaN	0.00	6
8945	325.594462	48.886365	0.50	6
8946	275.861322	NaN	0.00	6
8947	81.270775	82.418369	0.25	6
8949	63.165404	88.288956	0.00	6

[6834 rows x 17 columns]

- **Plot the correlation matrix of all numeric features. What do you discover?** As usual we can consider the correlation of over 0.7 to lead to overfitting in the case we keep both of those variables in the model. It is evident that such examples are ONEOFF_PURCHASES and PURCHASES with correlation of 0.914321, PURCHASES_INSTALLMENTS_FREQUENCY and PURCHASES_FREQUENCY with correlation of 0.819995, CASH_ADVANCE_TRX and CASH_ADVANCE_FREQUENCY with correlation of 0.818267.

[6]:
```
df.corr()
```

[6]:

	BALANCE	BALANCE_FREQUENCY	PURCHASES	\
BALANCE	1.000000	0.305340	0.262964	
BALANCE_FREQUENCY	0.305340	1.000000	0.155255	
PURCHASES	0.262964	0.155255	1.000000	
ONEOFF_PURCHASES	0.228188	0.117492	0.914321	
INSTALLMENTS_PURCHASES	0.195603	0.147514	0.657992	
CASH_ADVANCE	0.482427	0.119671	0.018792	
PURCHASES_FREQUENCY	0.036761	0.385664	0.310444	
ONEOFF_PURCHASES_FREQUENCY	0.158021	0.242071	0.448498	
PURCHASES_INSTALLMENTS_FREQUENCY	0.019589	0.267594	0.226885	

```
CASH_ADVANCE_FREQUENCY             0.449399          0.185026  -0.034588
CASH_ADVANCE_TRX                   0.388826          0.134674  -0.008437
PURCHASES_TRX                      0.248054          0.232529   0.663017
CREDIT_LIMIT                       0.506685          0.086837   0.388773
PAYMENTS                           0.354028          0.095156   0.694287
MINIMUM_PAYMENTS                   0.413673          0.135319   0.124435
PRC_FULL_PAYMENT                  -0.327760         -0.095214   0.137210
TENURE                             0.071079          0.089274   0.082686

                                  ONEOFF_PURCHASES  INSTALLMENTS_PURCHASES  \
BALANCE                                   0.228188                0.195603
BALANCE_FREQUENCY                         0.117492                0.147514
PURCHASES                                 0.914321                0.657992
ONEOFF_PURCHASES                          1.000000                0.296681
INSTALLMENTS_PURCHASES                    0.296681                1.000000
CASH_ADVANCE                              0.024039               -0.000501
PURCHASES_FREQUENCY                       0.186674                0.384861
ONEOFF_PURCHASES_FREQUENCY                0.496307                0.134616
PURCHASES_INSTALLMENTS_FREQUENCY          0.038047                0.464208
CASH_ADVANCE_FREQUENCY                   -0.014998               -0.053733
CASH_ADVANCE_TRX                         -0.000245               -0.019520
PURCHASES_TRX                             0.519567                0.597392
CREDIT_LIMIT                              0.345744                0.273778
PAYMENTS                                  0.644070                0.439609
MINIMUM_PAYMENTS                          0.066074                0.170420
PRC_FULL_PAYMENT                          0.097790                0.141731
TENURE                                    0.060200                0.083024

                                  CASH_ADVANCE  PURCHASES_FREQUENCY  \
BALANCE                               0.482427             0.036761
BALANCE_FREQUENCY                     0.119671             0.385664
PURCHASES                             0.018792             0.310444
ONEOFF_PURCHASES                      0.024039             0.186674
INSTALLMENTS_PURCHASES               -0.000501             0.384861
CASH_ADVANCE                          1.000000            -0.071563
PURCHASES_FREQUENCY                  -0.071563             1.000000
ONEOFF_PURCHASES_FREQUENCY            0.010891             0.371087
PURCHASES_INSTALLMENTS_FREQUENCY     -0.067750             0.819995
CASH_ADVANCE_FREQUENCY                0.667080            -0.102853
CASH_ADVANCE_TRX                      0.697552            -0.072304
PURCHASES_TRX                         0.009864             0.502172
CREDIT_LIMIT                          0.264584             0.111235
PAYMENTS                              0.430563             0.142139
MINIMUM_PAYMENTS                      0.153735             0.039386
PRC_FULL_PAYMENT                     -0.147469             0.240773
TENURE                               -0.048566             0.013044
```

	ONEOFF_PURCHASES_FREQUENCY \
BALANCE	0.158021
BALANCE_FREQUENCY	0.242071
PURCHASES	0.448498
ONEOFF_PURCHASES	0.496307
INSTALLMENTS_PURCHASES	0.134616
CASH_ADVANCE	0.010891
PURCHASES_FREQUENCY	0.371087
ONEOFF_PURCHASES_FREQUENCY	1.000000
PURCHASES_INSTALLMENTS_FREQUENCY	-0.049358
CASH_ADVANCE_FREQUENCY	0.031526
CASH_ADVANCE_TRX	0.025222
PURCHASES_TRX	0.483200
CREDIT_LIMIT	0.319809
PAYMENTS	0.285013
MINIMUM_PAYMENTS	-0.023361
PRC_FULL_PAYMENT	0.089072
TENURE	0.069710

	PURCHASES_INSTALLMENTS_FREQUENCY \
BALANCE	0.019589
BALANCE_FREQUENCY	0.267594
PURCHASES	0.226885
ONEOFF_PURCHASES	0.038047
INSTALLMENTS_PURCHASES	0.464208
CASH_ADVANCE	-0.067750
PURCHASES_FREQUENCY	0.819995
ONEOFF_PURCHASES_FREQUENCY	-0.049358
PURCHASES_INSTALLMENTS_FREQUENCY	1.000000
CASH_ADVANCE_FREQUENCY	-0.110627
CASH_ADVANCE_TRX	-0.069694
PURCHASES_TRX	0.452400
CREDIT_LIMIT	0.036437
PAYMENTS	0.103998
MINIMUM_PAYMENTS	0.063241
PRC_FULL_PAYMENT	0.182711
TENURE	0.046021

	CASH_ADVANCE_FREQUENCY	CASH_ADVANCE_TRX \
BALANCE	0.449399	0.388826
BALANCE_FREQUENCY	0.185026	0.134674
PURCHASES	-0.034588	-0.008437
ONEOFF_PURCHASES	-0.014998	-0.000245
INSTALLMENTS_PURCHASES	-0.053733	-0.019520
CASH_ADVANCE	0.667080	0.697552
PURCHASES_FREQUENCY	-0.102853	-0.072304
ONEOFF_PURCHASES_FREQUENCY	0.031526	0.025222

PURCHASES_INSTALLMENTS_FREQUENCY	-0.110627	-0.069694
CASH_ADVANCE_FREQUENCY	1.000000	0.818267
CASH_ADVANCE_TRX	0.818267	1.000000
PURCHASES_TRX	-0.016807	0.014503
CREDIT_LIMIT	0.145726	0.148233
PAYMENTS	0.209569	0.266587
MINIMUM_PAYMENTS	0.115455	0.124608
PRC_FULL_PAYMENT	-0.224644	-0.164342
TENURE	-0.108331	-0.040311

	PURCHASES_TRX	CREDIT_LIMIT	PAYMENTS \
BALANCE	0.248054	0.506685	0.354028
BALANCE_FREQUENCY	0.232529	0.086837	0.095156
PURCHASES	0.663017	0.388773	0.694287
ONEOFF_PURCHASES	0.519567	0.345744	0.644070
INSTALLMENTS_PURCHASES	0.597392	0.273778	0.439609
CASH_ADVANCE	0.009864	0.264584	0.430563
PURCHASES_FREQUENCY	0.502172	0.111235	0.142139
ONEOFF_PURCHASES_FREQUENCY	0.483200	0.319809	0.285013
PURCHASES_INSTALLMENTS_FREQUENCY	0.452400	0.036437	0.103998
CASH_ADVANCE_FREQUENCY	-0.016807	0.145726	0.209569
CASH_ADVANCE_TRX	0.014503	0.148233	0.266587
PURCHASES_TRX	1.000000	0.292988	0.432764
CREDIT_LIMIT	0.292988	1.000000	0.426736
PAYMENTS	0.432764	0.426736	1.000000
MINIMUM_PAYMENTS	0.132855	0.110209	0.151204
PRC_FULL_PAYMENT	0.104807	0.052057	0.085161
TENURE	0.122870	0.142589	0.106833

	MINIMUM_PAYMENTS	PRC_FULL_PAYMENT	TENURE
BALANCE	0.413673	-0.327760	0.071079
BALANCE_FREQUENCY	0.135319	-0.095214	0.089274
PURCHASES	0.124435	0.137210	0.082686
ONEOFF_PURCHASES	0.066074	0.097790	0.060200
INSTALLMENTS_PURCHASES	0.170420	0.141731	0.083024
CASH_ADVANCE	0.153735	-0.147469	-0.048566
PURCHASES_FREQUENCY	0.039386	0.240773	0.013044
ONEOFF_PURCHASES_FREQUENCY	-0.023361	0.089072	0.069710
PURCHASES_INSTALLMENTS_FREQUENCY	0.063241	0.182711	0.046021
CASH_ADVANCE_FREQUENCY	0.115455	-0.224644	-0.108331
CASH_ADVANCE_TRX	0.124608	-0.164342	-0.040311
PURCHASES_TRX	0.132855	0.104807	0.122870
CREDIT_LIMIT	0.110209	0.052057	0.142589
PAYMENTS	0.151204	0.085161	0.106833
MINIMUM_PAYMENTS	1.000000	-0.153354	0.054709
PRC_FULL_PAYMENT	-0.153354	1.000000	-0.029635
TENURE	0.054709	-0.029635	1.000000

Hence I plan to remove the columns named ONEOFF_PURCHASES, PURCHASES_INSTALLMENTS_FREQUENCY and CASH_ADVANCE_TRX from the dataframe.

[7]:
```
df.drop(['ONEOFF_PURCHASES', 'PURCHASES_INSTALLMENTS_FREQUENCY',␣
↪'CASH_ADVANCE_TRX'], axis=1, inplace=True)
df
```

[7]:

	BALANCE	BALANCE_FREQUENCY	PURCHASES	INSTALLMENTS_PURCHASES	\
0	40.900749	0.818182	95.40	95.40	
2	2495.148862	1.000000	773.17	0.00	
3	1666.670542	0.636364	1499.00	0.00	
4	817.714335	1.000000	16.00	0.00	
5	1809.828751	1.000000	1333.28	1333.28	
…	…	…	…	…	
8944	193.571722	0.833333	1012.73	0.00	
8945	28.493517	1.000000	291.12	291.12	
8946	19.183215	1.000000	300.00	300.00	
8947	23.398673	0.833333	144.40	144.40	
8949	372.708075	0.666667	1093.25	0.00	

	CASH_ADVANCE	PURCHASES_FREQUENCY	ONEOFF_PURCHASES_FREQUENCY	\
0	0.000000	0.166667	0.000000	
2	0.000000	1.000000	1.000000	
3	205.788017	0.083333	0.083333	
4	0.000000	0.083333	0.083333	
5	0.000000	0.666667	0.000000	
…	…	…	…	
8944	0.000000	0.333333	0.333333	
8945	0.000000	1.000000	0.000000	
8946	0.000000	1.000000	0.000000	
8947	0.000000	0.833333	0.000000	
8949	127.040008	0.666667	0.666667	

	CASH_ADVANCE_FREQUENCY	PURCHASES_TRX	CREDIT_LIMIT	PAYMENTS	\
0	0.000000	2	1000.0	201.802084	
2	0.000000	12	7500.0	622.066742	
3	0.083333	1	7500.0	0.000000	
4	0.000000	1	1200.0	678.334763	
5	0.000000	8	1800.0	1400.057770	
…	…	…	…	…	
8944	0.000000	2	4000.0	0.000000	
8945	0.000000	6	1000.0	325.594462	
8946	0.000000	6	1000.0	275.861322	
8947	0.000000	5	1000.0	81.270775	
8949	0.333333	23	1200.0	63.165404	

MINIMUM_PAYMENTS PRC_FULL_PAYMENT TENURE

```
0          139.509787              0.00      12
2          627.284787              0.00      12
3                 NaN              0.00      12
4          244.791237              0.00      12
5         2407.246035              0.00      12
…                   …          …      …
8944              NaN              0.00       6
8945        48.886365              0.50       6
8946              NaN              0.00       6
8947        82.418369              0.25       6
8949        88.288956              0.00       6

[6834 rows x 14 columns]
```

1.2 1.2 Principal Component Analysis

- **What is Principal Component Analysis? How do we interpret the "first principal component"?** Principal Component Analysis (PCA) is a statistical method used to reduce the dimensionality of a dataset by identifying patterns and correlations among the variables. PCA transforms the original variables into a new set of variables called principal components, which are linear combinations of the original variables. These new variables are ordered by the amount of variation they explain in the data, with the first principal component explaining the most variation and each subsequent component explaining less.

The first principal component is the linear combination of the original variables that explains the most variation in the data. It can be interpreted as the direction in the data space that captures the largest amount of variability among the variables. The direction of the first principal component is chosen such that it maximizes the variance of the projected data onto that direction. The first principal component can be seen as a summary of the data that captures the most important information in the original variables.

Interpreting the first principal component depends on the context of the data being analyzed. In some cases, the first principal component may represent an underlying factor or concept that is driving the variation in the data. For example, in a dataset of physical measurements, the first principal component may represent overall body size. In other cases, the first principal component may be more difficult to interpret in a meaningful way. However, the interpretation of the first principal component can often provide insights into the most important factors driving the variation in the data and help identify which variables are most strongly related to each other.

- **Normalize the data. Why is normalization necessary here?**

[8]:
```python
from sklearn.preprocessing import StandardScaler

# assume X is a matrix of data to be normalized
X = df.dropna()
scaler = StandardScaler()
X_norm = scaler.fit_transform(X)
X.dropna()
```

[8]:

```
          BALANCE  BALANCE_FREQUENCY  PURCHASES  INSTALLMENTS_PURCHASES  \
0       40.900749           0.818182      95.40                   95.40
2     2495.148862           1.000000     773.17                    0.00
4      817.714335           1.000000      16.00                    0.00
5     1809.828751           1.000000    1333.28                 1333.28
6      627.260806           1.000000    7091.01                  688.38
…             …                  …          …                      …
8942    40.829749           1.000000     113.28                  113.28
8943     5.871712           0.500000      20.90                    0.00
8945    28.493517           1.000000     291.12                  291.12
8947    23.398673           0.833333     144.40                  144.40
8949   372.708075           0.666667    1093.25                    0.00

      CASH_ADVANCE  PURCHASES_FREQUENCY  ONEOFF_PURCHASES_FREQUENCY  \
0         0.000000             0.166667                    0.000000
2         0.000000             1.000000                    1.000000
4         0.000000             0.083333                    0.083333
5         0.000000             0.666667                    0.000000
6         0.000000             1.000000                    1.000000
…              …                    …                         …
8942      0.000000             1.000000                    0.000000
8943      0.000000             0.166667                    0.166667
8945      0.000000             1.000000                    0.000000
8947      0.000000             0.833333                    0.000000
8949    127.040008             0.666667                    0.666667

      CASH_ADVANCE_FREQUENCY  PURCHASES_TRX  CREDIT_LIMIT     PAYMENTS  \
0                   0.000000              2        1000.0   201.802084
2                   0.000000             12        7500.0   622.066742
4                   0.000000              1        1200.0   678.334763
5                   0.000000              8        1800.0  1400.057770
6                   0.000000             64       13500.0  6354.314328
…                        …              …            …          …
8942                0.000000              6        1000.0    94.488828
8943                0.000000              1         500.0    58.644883
8945                0.000000              6        1000.0   325.594462
8947                0.000000              5        1000.0    81.270775
8949                0.333333             23        1200.0    63.165404

      MINIMUM_PAYMENTS  PRC_FULL_PAYMENT  TENURE
0           139.509787              0.00      12
2           627.284787              0.00      12
4           244.791237              0.00      12
5          2407.246035              0.00      12
6           198.065894              1.00      12
…                  …               …     …
8942         86.283101              0.25       6
```

```
8943         43.473717           0.00      6
8945         48.886365           0.50      6
8947         82.418369           0.25      6
8949         88.288956           0.00      6

[6663 rows x 14 columns]
```

Normalization is often necessary in PCA because the principal components are calculated based on the covariance matrix of the input variables. If the variables have different scales or units, they can contribute unequally to the covariance matrix and bias the principal components towards the variables with larger scales. Normalizing the variables to have the same scale helps ensure that each variable contributes equally to the covariance matrix and results in a more accurate representation of the underlying patterns and correlations in the data.

Furthermore, normalization can also improve the numerical stability of the algorithm and speed up the computation of the principal components, especially if the input variables have significantly different scales. Thus, it is generally recommended to normalize the data before performing PCA, especially if the input variables have different scales or units.

- **Use sklearn's PCA to find the first three principal components. What is the percentage of variance explained by each component? Do you think the dataset is well-represented in the new 3d space?**

[9]:
```
from sklearn.decomposition import PCA

# assume X is a matrix of data to be transformed
pca = PCA(n_components=3)
X_pca = pca.fit_transform(X)
print(pca.explained_variance_ratio_)
```

```
[0.50691199 0.17499892 0.14069092]
```

The n_components parameter specifies the number of principal components we want to extract. Here, we set it to 3 to extract the first three principal components. The PCA object fits the data to the specified number of principal components and transforms the data to the new space.

The explained_variance_ratio_ attribute of the PCA object gives the percentage of variance explained by each principal component. This can help us understand how much information each component captures and how well the components represent the original data. The sum of all explained variances should equal 1.

In general, a high percentage of variance explained by a component indicates that the component captures important information in the data. Conversely, a low percentage of variance explained by a component suggests that the component may not be as useful for representing the data.

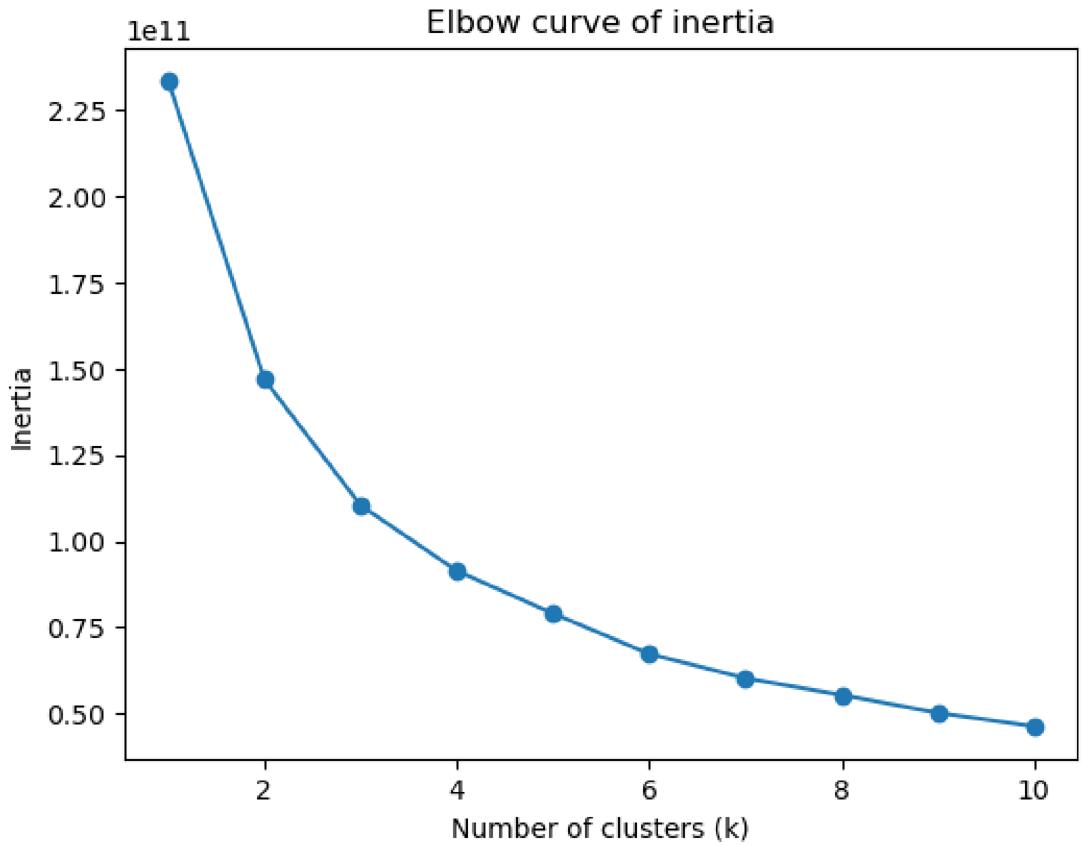
To answer the second part of the question, whether the dataset is well-represented in the new 3D space, we would need to look at the explained variance ratios of each principal component and evaluate how much information they capture compared to the original dataset. If the first three principal components capture a high percentage of the variance in the data, which is the case here, then it is likely that the new 3D space represents the original dataset well.

However, it is important to note that PCA is a linear transformation, so it may not capture all the complex relationships and interactions between the variables in the original dataset. Additionally, the interpretation of the principal components may depend on the context of the data, and it may be difficult to interpret the results in some cases. Therefore, it is important to consider the limitations and assumptions of PCA when interpreting the results.

1.3 1.3 K-means clustering

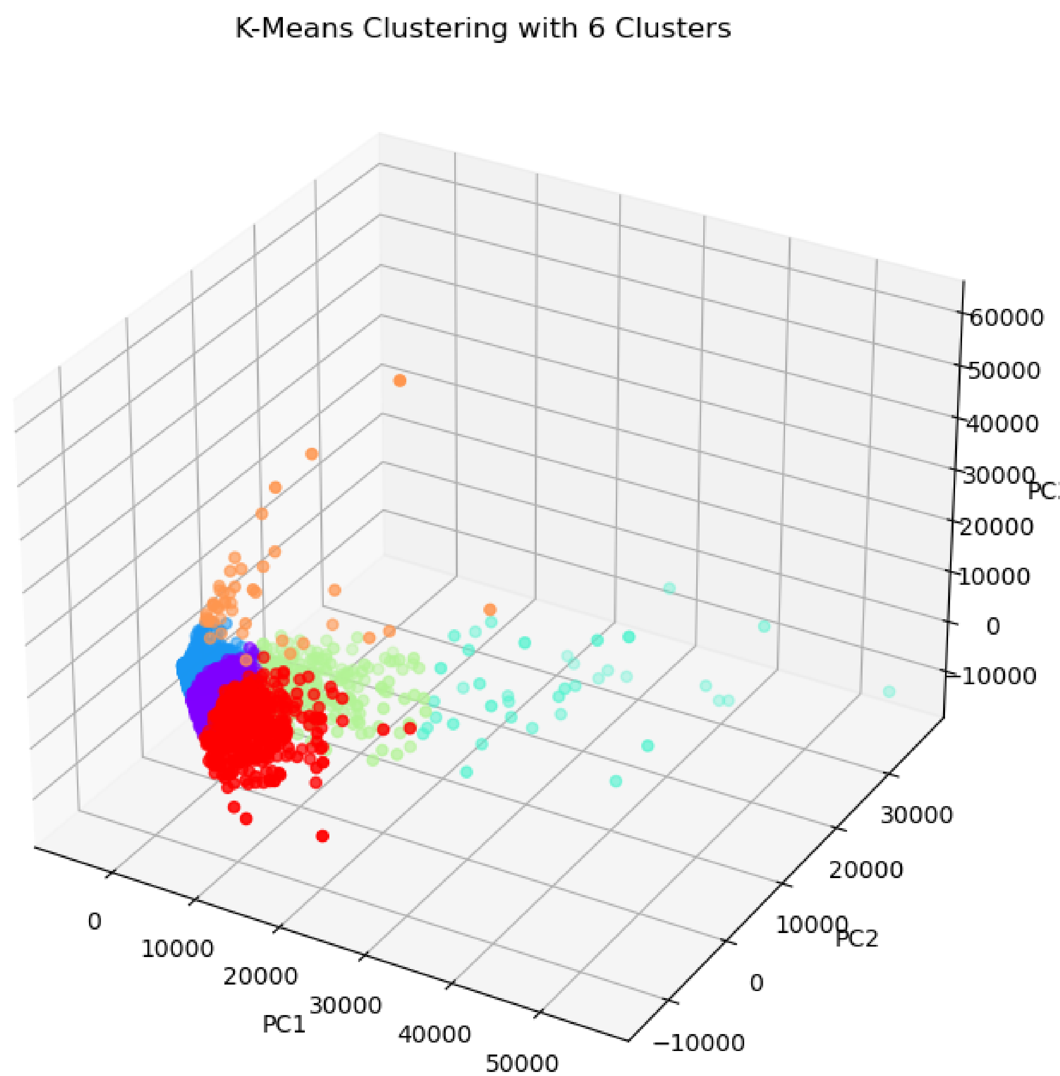
- **Use the data transformed by PCA, plot the Elbow curve of inertia and find the right k (set initialization to "random").**

[10]:
```
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans

# assume X_pca is the transformed data from PCA
inertias = []
ks = range(1, 11)  # try different values of k

for k in ks:
    kmeans = KMeans(n_clusters=k, init='random')
    kmeans.fit(X_pca)
    inertias.append(kmeans.inertia_)

# plot the Elbow curve of inertia
plt.plot(ks, inertias, 'o-')
plt.xlabel('Number of clusters (k)')
plt.ylabel('Inertia')
plt.title('Elbow curve of inertia')
plt.show()
```



- **Fit a final model and plot the clustering result as a 3d graph. Briefly discuss your findings.**

[11]:
```
# assume X_pca is the transformed data from PCA and k is the optimal number of␣
↪clusters
k = 6
kmeans = KMeans(n_clusters=k, init='random')
labels = kmeans.fit_predict(X_pca)

# plot the 3D scatter plot of the clustered data
fig = plt.figure(figsize=(8, 8))
ax = fig.add_subplot(111, projection='3d')
ax.scatter(X_pca[:, 0], X_pca[:, 1], X_pca[:, 2], c=labels, cmap='rainbow')
ax.set_xlabel('PC1')
ax.set_ylabel('PC2')
ax.set_zlabel('PC3')
plt.title('K-Means Clustering with {} Clusters'.format(k))
plt.show()
```

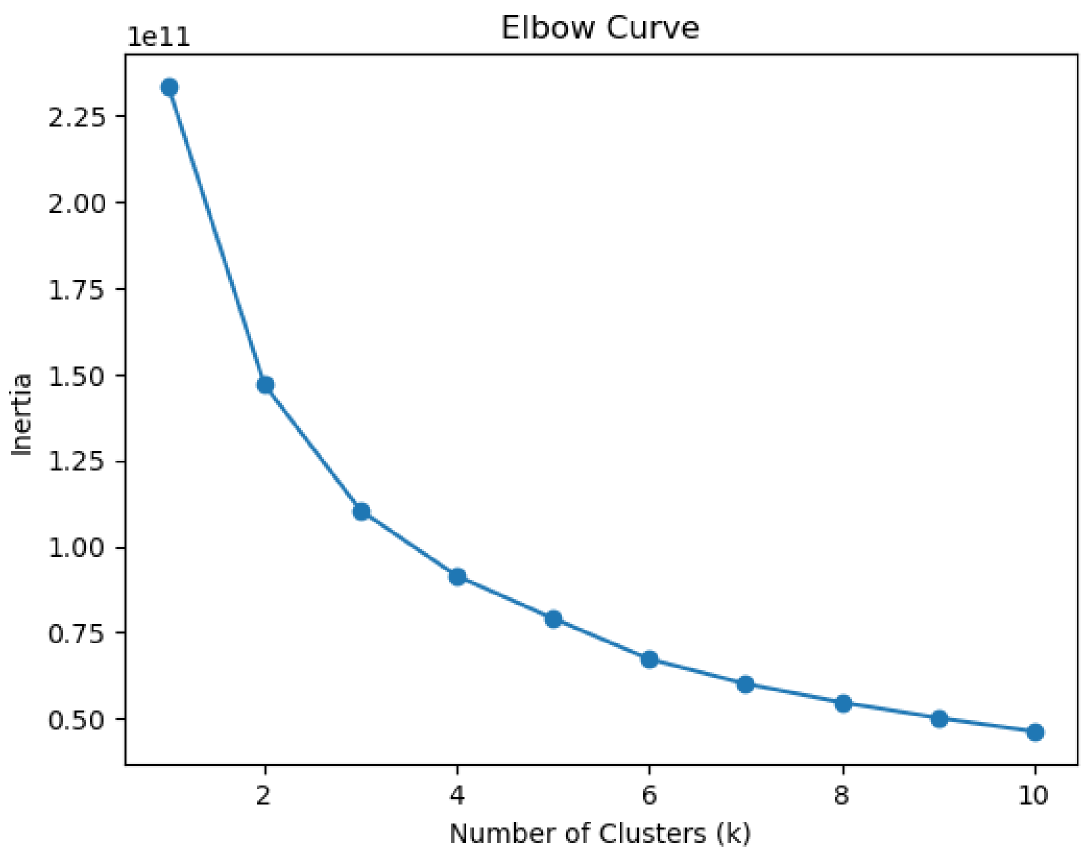


The resulting 3D graph shows the clustered data points, where each cluster is assigned a different color. Based on the graph, you can visually inspect the clustering result and observe the separation between different clusters. You can also use the cluster labels to perform further analysis on each cluster, such as identifying the characteristics of the data points in each cluster or using the cluster labels as a feature for a supervised learning model.

- **Use the data transformed by PCA, plot the Elbow curve of inertia and find the right k (set initialization to "kmeans++").**

[12]:
```
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt

# assume X_pca is the transformed data from PCA
```

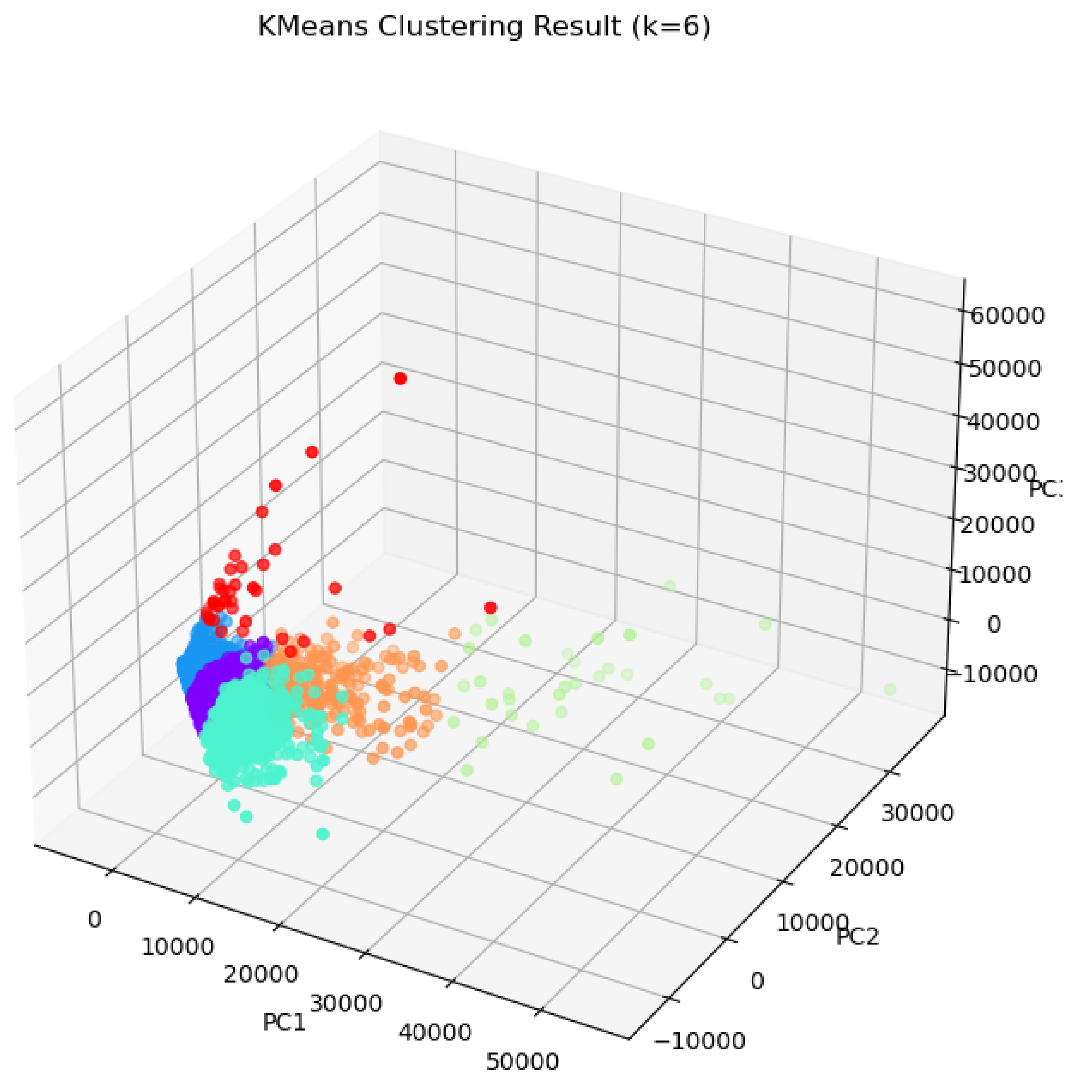
```
inertia = []
k_range = range(1, 11)
for k in k_range:
    kmeans = KMeans(n_clusters=k, init='k-means++')
    kmeans.fit(X_pca)
    inertia.append(kmeans.inertia_)

# plot the Elbow curve of inertia
plt.plot(k_range, inertia, 'o-')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('Inertia')
plt.title('Elbow Curve')
plt.show()
```



- **Fit a final model and plot the final result. Briefly discuss your findings**

[13]:
```
# assume X_pca is the transformed data from PCA and k_optimal is the optimal␣
↪number of clusters
k_optimal = 6
kmeans = KMeans(n_clusters=k_optimal, init='k-means++')
```

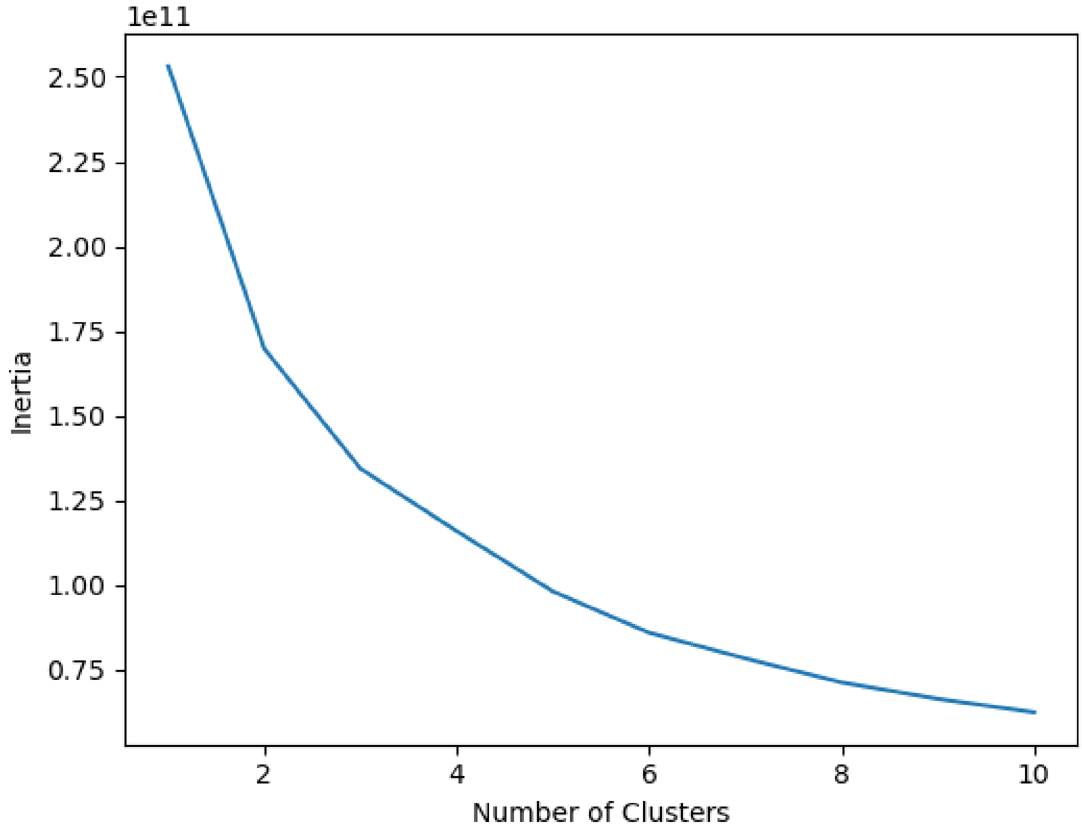
```
kmeans.fit(X_pca)
labels = kmeans.labels_

# plot the final result as a 3d graph
fig = plt.figure(figsize=(8, 8))
ax = fig.add_subplot(111, projection='3d')
ax.scatter(X_pca[:, 0], X_pca[:, 1], X_pca[:, 2], c=labels, cmap='rainbow')
ax.set_xlabel('PC1')
ax.set_ylabel('PC2')
ax.set_zlabel('PC3')
plt.title('KMeans Clustering Result (k={})'.format(k_optimal))
plt.show()
```



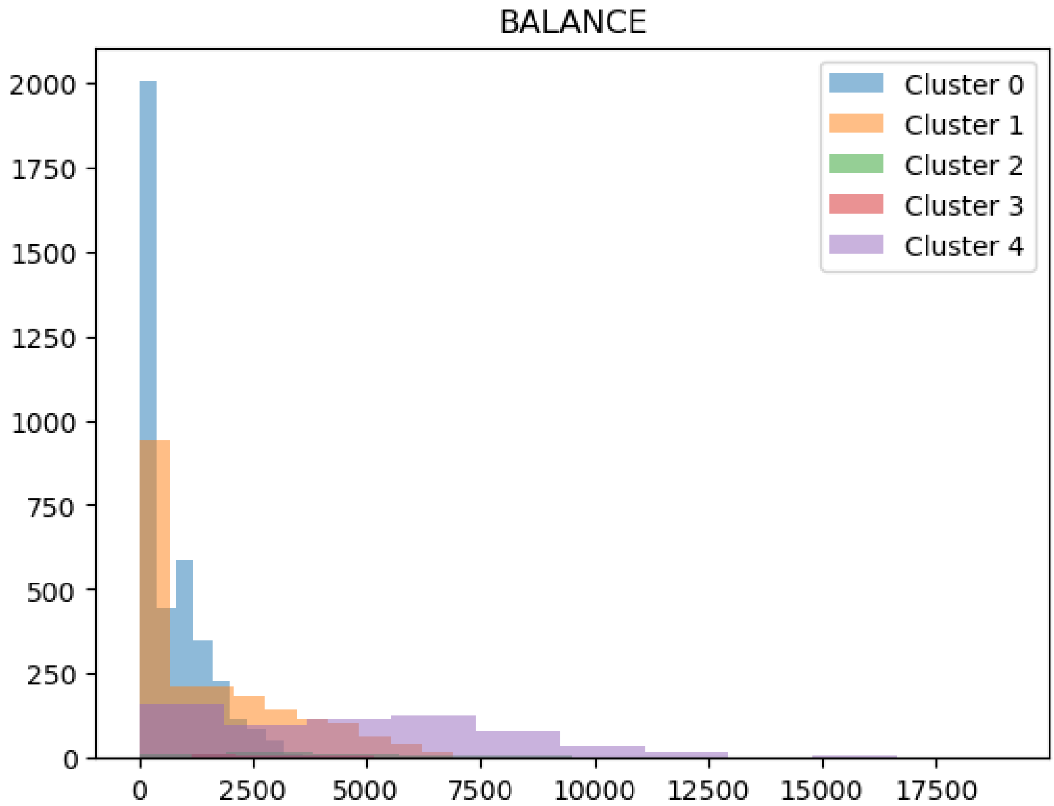
The resulting 3D graph shows the clustered data points, where each cluster is assigned a different color. Based on the graph, you can visually inspect the clustering result and observe the separation between different clusters. You can also use the cluster labels to perform further analysis on each cluster, such as identifying the characteristics of the data points in each cluster or using the cluster labels as a feature for a supervised learning model.

- **Use the data before the PCA transformation and repeat Kmeans clustering (with elbow curve and "kmeans++" initialization). Select 5 variables to plot the distributions of each variable cluster by cluster. Briefly discuss your findings.**

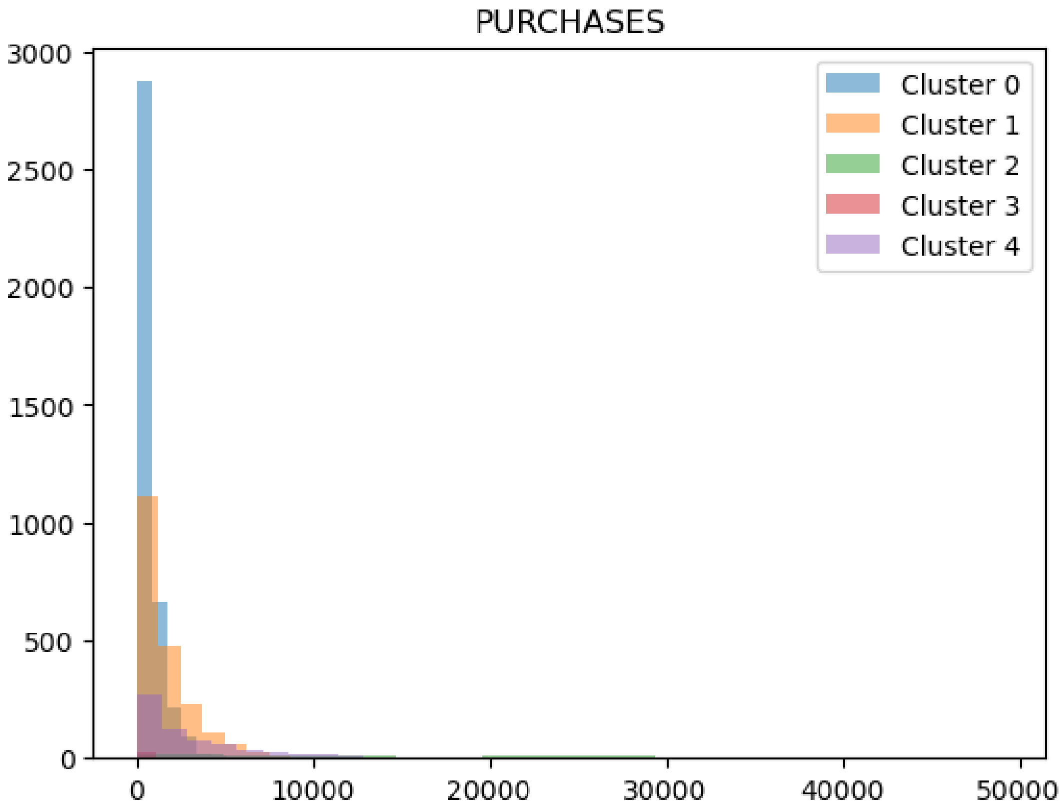
[14]:
```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans

data = df.dropna().copy()

# Select the columns for clustering
X = data[['BALANCE', 'PURCHASES', 'CREDIT_LIMIT', 'PAYMENTS',␣
↪'MINIMUM_PAYMENTS']]

# Perform KMeans clustering with elbow curve and kmeans++ initialization
inertias = []
for k in range(1, 11):
    kmeans = KMeans(n_clusters=k, init='k-means++')
    kmeans.fit(X)
    inertias.append(kmeans.inertia_)

plt.plot(range(1, 11), inertias)
plt.xlabel('Number of Clusters')
plt.ylabel('Inertia')
plt.show()

# Choose the optimal number of clusters and fit the final model
k_optimal = 5
kmeans = KMeans(n_clusters=k_optimal, init='k-means++')
kmeans.fit(X)
labels = kmeans.labels_
```

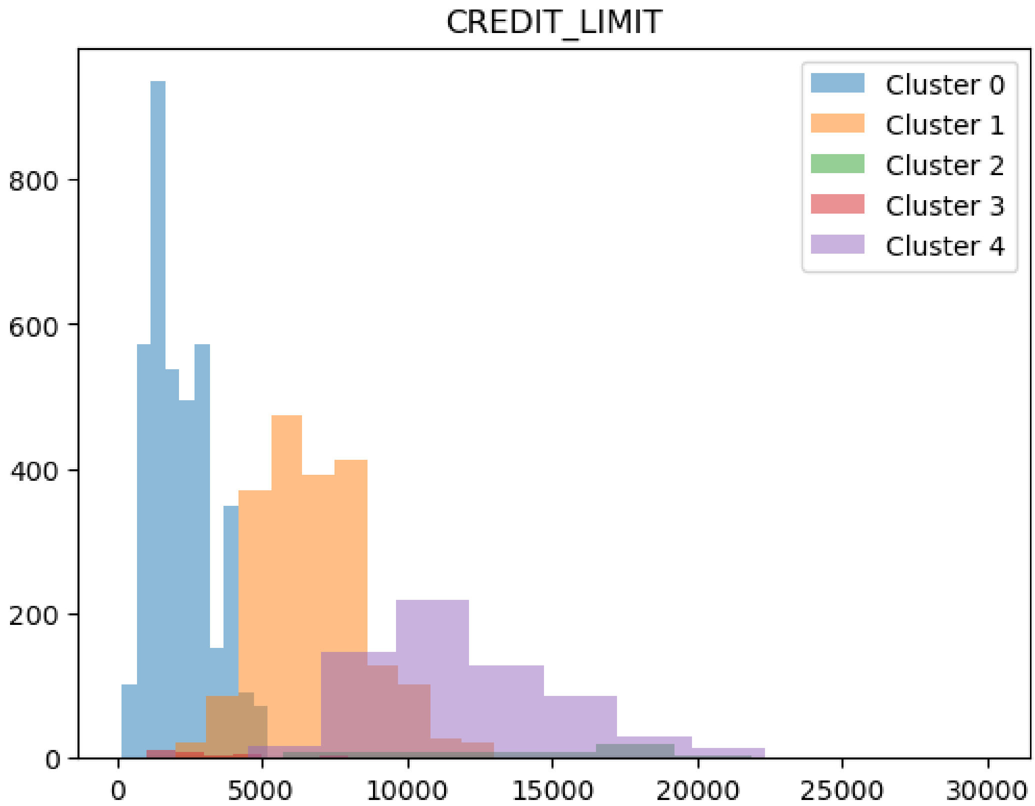


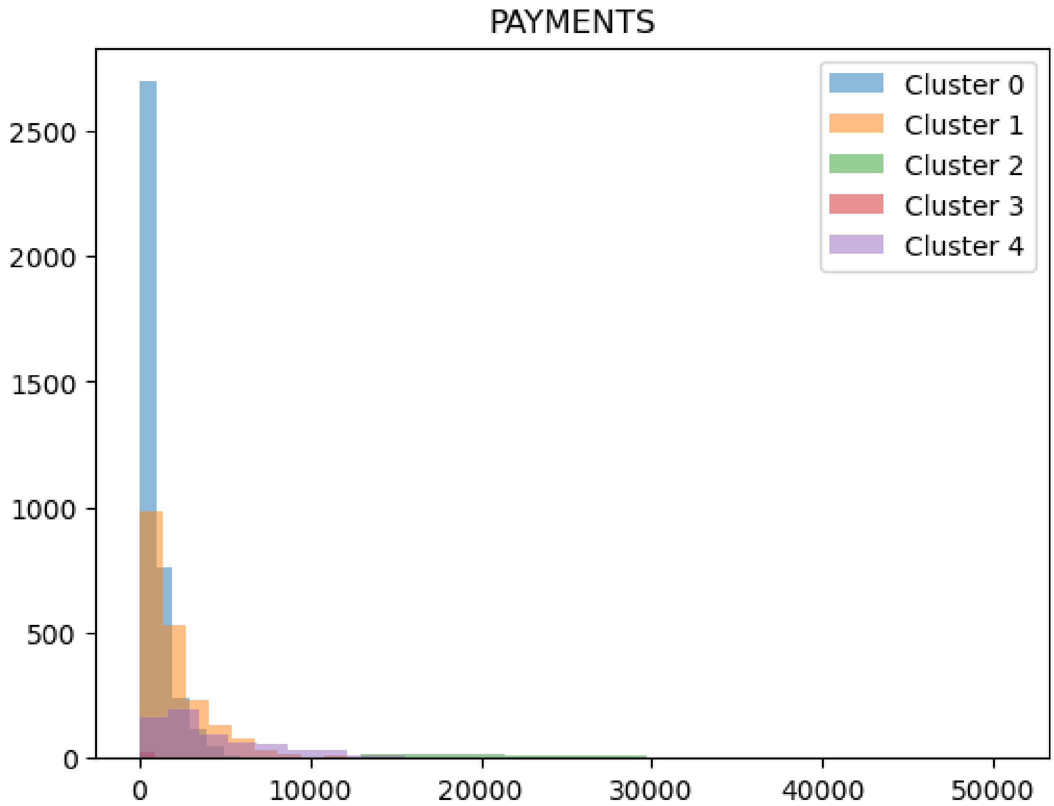
[15]:
```
# Add the cluster labels to the original dataset
data['cluster'] = labels

# Plot the distributions of selected variables for each cluster
selected_cols = ['BALANCE', 'PURCHASES', 'CREDIT_LIMIT', 'PAYMENTS',␣
↪'MINIMUM_PAYMENTS']
for col in selected_cols:
    plt.figure()
    for cluster in range(k_optimal):
        cluster_data = data[data['cluster'] == cluster]
        plt.hist(cluster_data[col], alpha=0.5, label=f'Cluster {cluster}')
    plt.legend()
    plt.title(col)
    plt.show()
```

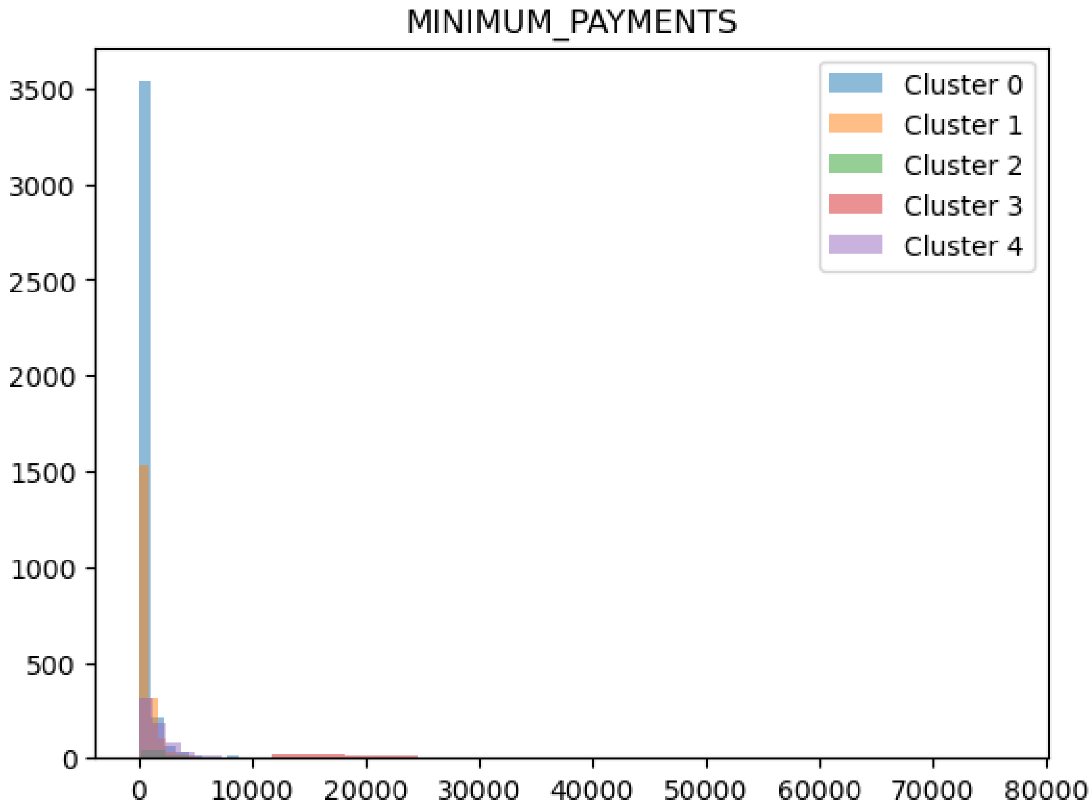


BALANCE
Cluster 0
Cluster 1
Cluster 2
Cluster 3
Cluster 4
2000
1750
1500
1250
1000
750
500
250
0
0
2500
5000
7500
10000
12500
15000
17500


PURCHASES
Cluster 0
Cluster 1
Cluster 2
Cluster 3
Cluster 4
0
500
1000
1500
2000
2500
3000
0
10000
20000
30000
40000
50000


CREDIT_LIMIT
Cluster 0
Cluster 1
Cluster 2
Cluster 3
Cluster 4
800
600
400
200
0
0
5000
10000
15000
20000
25000
30000


PAYMENTS
Cluster 0
Cluster 1
Cluster 2
Cluster 3
Cluster 4
0
500
1000
1500
2000
2500
0
10000
20000
30000
40000
50000



We then added the cluster labels to the original dataset and plotted the distributions of the selected variables for each cluster. We can see that each cluster has its own distribution for each variable, which indicates that the clusters are different from each other in terms of these variables. This suggests that the KMeans clustering algorithm has successfully identified meaningful groups within the data.

- **After the above studies, what are your thoughts on the pros and cons of performing PCA before clustering?** Performing PCA before clustering has its advantages and disadvantages.

Advantages:

1. Dimensionality reduction: PCA reduces the number of features in the dataset by transforming the original features into a smaller number of principal components. This helps to reduce the computational complexity of clustering algorithms, especially for high-dimensional datasets.
2. Improved clustering accuracy: PCA can help to remove noise and redundancy from the dataset, which can improve the clustering accuracy by making the clusters more distinct and separable.
3. Visualization: PCA can be used to transform the dataset into a lower-dimensional space that can be easily visualized. This can help to identify patterns and relationships between the data points.

Disadvantages:

1. Loss of information: PCA involves reducing the dimensionality of the dataset, which means that some of the information in the original dataset is lost. This can make it more difficult to interpret the clustering results.

2. Non-linear relationships: PCA assumes that the relationships between the original features are linear. If there are non-linear relationships between the features, then PCA may not be effective in capturing these relationships.

3. Interpretation: The principal components obtained from PCA may not be directly interpretable, which can make it more difficult to understand the relationship between the variables and the clusters.

In summary, performing PCA before clustering can be beneficial for reducing the dimensionality of the dataset, improving clustering accuracy, and visualization. However, it may also lead to loss of information and difficulty in interpretation, especially for datasets with non-linear relationships between features. It is important to carefully consider the advantages and disadvantages before deciding whether to use PCA before clustering.

2 2. NLP

2.1 2.1 Basic NLP

2.1.1 What is NLP? NLP stands for Natural Language Processing, which is a subfield of artificial intelligence and computational linguistics that focuses on enabling computers to understand, interpret, and generate human language. NLP combines techniques from computer science, linguistics, and mathematics to enable computers to process natural language input and output in a way that is similar to how humans understand and communicate with each other.

NLP has many practical applications, including language translation, sentiment analysis, chatbots, text summarization, information retrieval, speech recognition, and more. With the advancements in deep learning, neural networks, and other AI technologies, NLP has become increasingly sophisticated and capable of understanding and generating natural language at a level that was once thought impossible.

2.1.2 List three positive use cases of NLP in the field of finance

1. *Sentiment Analysis:* NLP can be used to analyze news articles, social media posts, and other sources of text to gauge the sentiment of investors and predict market trends. Sentiment analysis can help traders and investors make more informed decisions and react quickly to market shifts.

2. *Fraud Detection:* NLP can help detect fraudulent activities in financial transactions by analyzing large volumes of text data, such as emails, chat logs, and transaction descriptions. NLP algorithms can identify patterns of suspicious behavior and flag transactions for further review by human analysts.

3. *Customer Service Chatbots:* NLP can be used to create chatbots that can understand and respond to customer inquiries in natural language. These chatbots can provide 24/7 support to customers, help them resolve issues, and even suggest personalized financial products or

services based on their needs and preferences. This can help financial institutions improve customer satisfaction and reduce support costs.

2.1.3 What is tokenization? Tokenization is the process of breaking down a text document into individual words, phrases, symbols, or other meaningful elements, called tokens. In Natural Language Processing (NLP), tokenization is an essential step in preparing text data for machine learning models, as most models require input in the form of numerical data.

Tokenization can be done using various techniques, such as word-based tokenization, character-based tokenization, subword-based tokenization, and sentence-based tokenization, depending on the requirements of the application.

In word-based tokenization, the text is split into individual words or terms based on white spaces or punctuations. In character-based tokenization, the text is split into individual characters. Subword-based tokenization, such as Byte Pair Encoding (BPE), splits the text into a set of subwords, which can be combined to form larger words. Finally, sentence-based tokenization splits the text into individual sentences.

Once tokenized, the tokens can be further processed using techniques such as stemming, lemmatization, stop word removal, and part-of-speech tagging to prepare them for use in machine learning models.

2.1.4 What is the difference between stemming and lemmatization? Both stemming and lemmatization are techniques used in Natural Language Processing (NLP) to normalize words, reduce their inflectional forms, and extract their root form. However, there are some differences between the two techniques:

Stemming involves removing the suffixes from words to extract their root or base form, known as the stem. This process can sometimes result in non-words, as the stem may not be a valid word in the language. Stemming is a rule-based approach and is generally faster than lemmatization.

For example, the stem of the words "running", "runner", and "runners" would be "run". Some popular stemming algorithms include Porter Stemming Algorithm, Snowball Stemming Algorithm, and Lancaster Stemming Algorithm.

On the other hand, lemmatization involves reducing words to their canonical form, known as the lemma, based on their parts of speech and context. This process ensures that the resulting word is a valid word in the language. Lemmatization is generally slower than stemming and requires a more complex approach, as it involves using a dictionary or corpus to look up the base form of a word.

For example, the lemma of the words "running", "runner", and "runners" would be "run". A popular lemmatization tool is WordNet.

In summary, stemming and lemmatization are both techniques used in NLP to normalize words and extract their root forms, but stemming is a rule-based approach that is faster but may not always result in valid words, while lemmatization is a more complex approach that uses a dictionary or corpus to ensure valid words but is generally slower.

2.1.5 What is BERT? What makes it different? BERT (Bidirectional Encoder Representations from Transformers) is a state-of-the-art pre-trained language model developed by Google in

2018. BERT is designed to understand the context and nuances of natural language by pre-training a deep neural network on a large corpus of text data.

What makes BERT different from other language models is its use of bidirectional transformers, which enable it to process and understand the context of a word by looking both forward and backward in a sentence or paragraph. This makes BERT highly effective at handling complex natural language tasks, such as question answering, sentiment analysis, named entity recognition, and text classification.

Another important feature of BERT is its ability to be fine-tuned on specific downstream tasks, such as sentiment analysis or text classification, by adding a small output layer and training the model on task-specific data. This allows BERT to achieve state-of-the-art results on many NLP tasks, without requiring significant additional training data or task-specific architectures.

Overall, BERT's ability to understand natural language context and its flexibility for fine-tuning make it a powerful tool for a wide range of NLP applications.

2.2 2.2 Pre-trained model: FinBERT

Your hedge fund manager wakes up every morning at 4am and wants a concise summary of the news relevant to his portfolio. He/She wants a quick summary showing the headlines of the news as well as classified sentiment scores. Furthermore, he/she asks you to aggregate this information per stock and summarize the overall tone for this stock

2.2.1 Install the transformers package

[16]:
```
pip install transformers
```

```
WARNING: Ignoring invalid distribution -andas
(/Users/dhyeymavani/opt/anaconda3/lib/python3.9/site-packages)
WARNING: Ignoring invalid distribution -andas
(/Users/dhyeymavani/opt/anaconda3/lib/python3.9/site-packages)
Collecting transformers
  Downloading transformers-4.27.4-py3-none-any.whl (6.8 MB)
                            6.8/6.8 MB
9.7 MB/s eta 0:00:00:00:0100:01
Requirement already satisfied: requests in
/Users/dhyeymavani/opt/anaconda3/lib/python3.9/site-packages (from transformers)
(2.28.1)
Requirement already satisfied: regex!=2019.12.17 in
/Users/dhyeymavani/opt/anaconda3/lib/python3.9/site-packages (from transformers)
(2022.7.9)
Requirement already satisfied: packaging>=20.0 in
/Users/dhyeymavani/opt/anaconda3/lib/python3.9/site-packages (from transformers)
(22.0)
Requirement already satisfied: tqdm>=4.27 in
/Users/dhyeymavani/opt/anaconda3/lib/python3.9/site-packages (from transformers)
(4.64.1)
```

```
Requirement already satisfied: numpy>=1.17 in
/Users/dhyeymavani/opt/anaconda3/lib/python3.9/site-packages (from transformers)
(1.21.5)
Requirement already satisfied: filelock in
/Users/dhyeymavani/opt/anaconda3/lib/python3.9/site-packages (from transformers)
(3.9.0)
Collecting huggingface-hub<1.0,>=0.11.0
  Downloading huggingface_hub-0.13.3-py3-none-any.whl (199 kB)
                          199.8/199.8 kB
12.6 MB/s eta 0:00:00
Requirement already satisfied: pyyaml>=5.1 in
/Users/dhyeymavani/opt/anaconda3/lib/python3.9/site-packages (from transformers)
(6.0)
Collecting tokenizers!=0.11.3,<0.14,>=0.11.1
  Downloading tokenizers-0.13.2-cp39-cp39-macosx_10_11_x86_64.whl (3.8 MB)
                           3.8/3.8 MB
11.0 MB/s eta 0:00:0000:0100:01
Requirement already satisfied: typing-extensions>=3.7.4.3 in
/Users/dhyeymavani/opt/anaconda3/lib/python3.9/site-packages (from huggingface-
hub<1.0,>=0.11.0->transformers) (4.4.0)
Requirement already satisfied: urllib3<1.27,>=1.21.1 in
/Users/dhyeymavani/opt/anaconda3/lib/python3.9/site-packages (from
requests->transformers) (1.26.14)
Requirement already satisfied: idna<4,>=2.5 in
/Users/dhyeymavani/opt/anaconda3/lib/python3.9/site-packages (from
requests->transformers) (3.4)
Requirement already satisfied: certifi>=2017.4.17 in
/Users/dhyeymavani/opt/anaconda3/lib/python3.9/site-packages (from
requests->transformers) (2022.12.7)
Requirement already satisfied: charset-normalizer<3,>=2 in
/Users/dhyeymavani/opt/anaconda3/lib/python3.9/site-packages (from
requests->transformers) (2.0.4)
WARNING: Ignoring invalid distribution -andas
(/Users/dhyeymavani/opt/anaconda3/lib/python3.9/site-packages)
Installing collected packages: tokenizers, huggingface-hub, transformers
WARNING: Ignoring invalid distribution -andas
(/Users/dhyeymavani/opt/anaconda3/lib/python3.9/site-packages)
WARNING: Ignoring invalid distribution -andas
(/Users/dhyeymavani/opt/anaconda3/lib/python3.9/site-packages)
WARNING: Ignoring invalid distribution -andas
(/Users/dhyeymavani/opt/anaconda3/lib/python3.9/site-packages)
Successfully installed huggingface-hub-0.13.3 tokenizers-0.13.2
transformers-4.27.4
```

```
WARNING: Ignoring invalid distribution -andas
(/Users/dhyeymavani/opt/anaconda3/lib/python3.9/site-packages)
WARNING: Ignoring invalid distribution -andas
(/Users/dhyeymavani/opt/anaconda3/lib/python3.9/site-packages)
WARNING: Ignoring invalid distribution -andas
(/Users/dhyeymavani/opt/anaconda3/lib/python3.9/site-packages)
Note: you may need to restart the kernel to use updated packages.
```

2.2.2 import the requests package and other libraries you might need

[1]:
```
import requests
```

The following dictionary represents our portfolio of stocks using the following logic (key, value) = (holding-name, branch), where

$$branch \in \{"business", "entertainment", "general", "health", "science", "sports", "technology"\}$$

following the NewsAPI documentation.

To save you some time, a typical request is built similar to: "https://newsapi.org/v2/top-headlines?country=us&q=*KEYWORD*&category=*CATEGORY*&sortBy=top&apiKey=*YOURKEYHERE*".

For example:

https://newsapi.org/v2/top-headlines?country=us&q=apple&category=technology&sortBy=top&apiKey=123ab

Please see:

1. https://newsapi.org/docs (To construct your HTTP GET-requests)
2. https://newsapi.org/register (To obtain your API key)

Say our portfolio consists of these four assets:

[2]:
```
portfolio = dict({"apple": 'technology', "tesla": 'business', "amazon":␣
↪'technology', "s&p500": 'business'})

# we are going to use the S&P500 to get a general idea of the sentiment of news␣
↪in the US market
```

2.2.3 Write the function fetch_news() that returns a dictionary that stores the name of the holding as key (analogous to our stock portfolio) and as value an array that holds the strings of news

[3]:
```
import requests

# Replace YOUR_API_KEY with your actual API key from NewsAPI
API_KEY = 'e52ff7df910d4c3ca6e69ecfb6b2202e'

# Define the base URL for the NewsAPI
BASE_URL = 'https://newsapi.org/v2/top-headlines'
```

```
# Define the holdings in the portfolio
portfolio = dict({"apple": 'technology', "tesla": 'business', "amazon":␣
↪'technology', "s&p500": 'business'})

# Define the categories of news to fetch
categories = ['business', 'technology']

# Define the sentiment labels
sentiment_labels = ['negative', 'neutral', 'positive']

# Define the function to fetch news for each holding in the portfolio
def fetch_news():
    news_dict = {}
    for holding in portfolio:
        holding_news = []
        for category in categories:
            # Build the request URL for this holding and category
            url = f'{BASE_URL}?
↪country=us&q={holding}&category={category}&sortBy=top&apiKey={API_KEY}'
            response = requests.get(url)
            data = response.json()
            # Add the news headlines to the holding_news array
            for article in data['articles']:
                holding_news.append(article['title'])
        # Add the holding_news array to the news_dict with the holding name as␣
↪the key
        news_dict[holding] = holding_news
    return news_dict
```

[4]:
```
fetch_news()
```

[4]:
```
{'apple': ['Apple wins U.S. appeal over patents in $502 mln VirnetX verdict -
Reuters',
  'Apple just launched its own buy now, pay later service-here’s how it compares
with Affirm, Afterpay, Klarna and PayPal - CNBC',
  "America's Most Innovative Companies - Fortune",
  "Apple is Changing iOS 17 - Now Filled 'Most Requested Features' - MacRumors",
  "Sealed OG iPhone up for auction with rare Apple 'Lucky you' sticker -
9to5Mac",
  'Kuo: Apple Mixed-Reality Headset May Not Appear at WWDC as Mass Production
Pushed Back Yet Again - MacRumors',
  'OLED MacBook Air Reportedly Now in Development as Apple Plans to Bring New
Display Technology to Multiple Product Lines - MacRumors',
  "The Morning After: Will we see Apple's mixed-reality headset at WWDC 2023? -
Engadget",
  'Save Up to $900 on an iPad Pro M1 at Best Buy Today Only - CNET',
```

"Apple Wants to Solve One of Music's Biggest Problems - The Wall Street Journal",
'iPhone 15 Pro Rumored to Feature Multi-Use Action Button Instead of Mute Switch - MacRumors',
'Deals: iPads from $125, $900 off MacBook Pro, $400 off Studio Display, AirTag sale & more - AppleInsider'],
'tesla': ["Tesla Used-Car Data Are Good for the Stock - Barron's",
"Tesla Needs AI to Thrive. Why Elon Musk Wants to Pause GPT-4. - Barron's"],
'amazon': ['‘You don’t want to fall for this’: BBB warns of smart TV scam - The Hill',
'Amazon sues sellers for issuing bogus takedown requests on competitors - The Verge'],
's&p500': ['Stock Market Today: Dow, Nasdaq Close Higher as U.S. Stocks Extend Gains - The Wall Street Journal',
'Hyundai and Kia theft trend has reached New York City - CNN',
'SBF pleads not guilty to latest charges, and OKX to turn over frozen FTX assets: CNBC Crypto World - CNBC Television',
'Wall Street Bonuses Fall by Most Since 2008 - The Wall Street Journal',
'Ford hikes prices on its F-150 Lightning as production resumes after EV battery fire - CNBC',
'Federal Reserve Board fines Wells Fargo $67.8 million for inadequate oversight of sanctions risk at its subsidiary bank - Federal Reserve',
'Bed Bath & Beyond Eyes Share Sale as Hudson Bay Deal Falters - Yahoo Finance',
'This California city is the most popular with millennial homebuyers in the U.S. - CNBC',
'CFPB Finalizes Rule to Create a New Data Set on Small Business Lending in America - Consumer Financial Protection Bureau',
"Tesla Used-Car Data Are Good for the Stock - Barron's",
'Democrat Manchin threatens to sue Biden administration over electrical vehicle tax credits: report - Fox Business',
'The Kia EV9 Electric SUV Will Get a High-Performance GT Version - Jalopnik',
"Justice Dept. loses second 'judge-shopping' case in Texas - The Washington Post",
'Yellen says Trump administration ‘decimated’ financial oversight - The Hill',
'Trojanized Windows and Mac apps rain down on 3CX users in massive supply chain attack - Ars Technica',
'More home sellers are sitting out of the spring housing market - CNBC',
"Fed officials call March rate hike 'appropriate' with inflation high, banks resilient - Yahoo Finance",
'Stocks making the biggest moves midday: Bed Bath & Beyond, EVgo, UBS and more - CNBC',
'Meta hired a DJ to play dance music in one of its campus cafes: report - Business Insider',
'Apple wins U.S. appeal over patents in $502 mln VirnetX verdict - Reuters',
'E3 Has Been Canceled - IGN',
'Pokémon Go developer teases "blockbuster slate" of summer features, amidst

```
major Remote Raid changes - Eurogamer.net',
  'Google Assistant might be doomed: Division "reorganizes" to focus on Bard -
Ars Technica',
  'Amazon sues sellers for issuing bogus takedown requests on competitors - The
Verge',
  "Cyberpunk 2077's Turnaround Just Gave CD Projekt Its Second-Best Revenue Year
Ever - IGN",
  'Diablo 4 Releases Some Mind-Blowing Beta Stats - Push Square',
  'New Doom Game Is Cute And Fun Until You Run Out Of Energy - Kotaku',
  "CD Projekt explains why Witcher game 'Project Sirius' has seemingly been
restarted - Video Games Chronicle",
  "Twitter's new API pricing is killing many Twitter apps that can't pay $42000
per month - Mashable",
  'iOS 16.4: Your iPhone Just Got These New Emoji - CNET',
  'Microsoft Teams Is Getting a Big Update (and You Can Try It Now) - CNET',
  "Where to preorder Samsung's Galaxy A54 phone - The Verge",
  "19 MORE Things You STILL Didn't Know In BOTW - GameSpot",
  "You're Missing Out On The Coolest Martial Arts Battle Royale - Kotaku",
  "Midjourney ends free trials of its AI image generator due to 'extraordinary'
abuse | Engadget - Engadget",
  'Microsoft Announces Diablo 4 Xbox Series X Bundle, Pre-Orders Now Live - Pure
Xbox',
  'Netflix Might Be Putting Its Video Games on TVs - IGN',
  'Amnesia: The Bunker Feels Like a New Beginning for the Series - IGN',
  'Xbox has an embarrassing Square Enix problem - VG247',
  "33-year-old who brought in $2 million making PowerPoints shares her best
tips: 'Reduce the content' - CNBC"]}
```

2.2.4 Following the lecture notes, using the pre-trained Finbert Classifier, classify the news fetched in 2.3 into neutral, positive or negative by modifying the below code:

[5]:
```python
import torch
from transformers import BertTokenizer, BertForSequenceClassification
import numpy as np

news_dict = fetch_news()

# Load the Finbert model and tokenizer
finbert = BertForSequenceClassification.from_pretrained('yiyanghkust/
 ↪finbert-tone', num_labels=3)
tokenizer = BertTokenizer.from_pretrained('yiyanghkust/finbert-tone')

# Define the function to classify news headlines using Finbert
def classify_news(news_dict):
    classified_dict = {}
    for holding in news_dict:
        classified_news = []
```

```
        for news in news_dict[holding]:
            # Tokenize the news headline
            inputs = tokenizer(news, return_tensors="pt", padding=True)
            # Make a prediction using Finbert
            outputs = finbert(**inputs)[0]
            # Determine the sentiment label
            label = sentiment_labels[np.argmax(outputs.detach().numpy())]
            # Add the classified news headline to the classified_news array
            classified_news.append({'headline': news, 'sentiment': label})
        # Add the classified_news array to the classified_dict with the holding␣
 ↪name as the key
        classified_dict[holding] = classified_news
    return classified_dict

# Classify the news using Finbert
classified_dict = classify_news(news_dict)

# Print the classified news for each holding
for holding in classified_dict:
    print(f'{holding}:')
    overall_sentiment = {'positive': 0, 'neutral': 0, 'negative': 0}
    for news in classified_dict[holding]:
        print(f"{news['headline']} ---- {news['sentiment']}")
        overall_sentiment[news['sentiment']] += 1
    print(f"Overall sentiment for {holding}: {max(overall_sentiment,␣
 ↪key=overall_sentiment.get)}\n")
```

```
apple:
Apple wins U.S. appeal over patents in $502 mln VirnetX verdict - Reuters ----
neutral
Apple just launched its own buy now, pay later service-here’s how it compares
with Affirm, Afterpay, Klarna and PayPal - CNBC ---- negative
America's Most Innovative Companies - Fortune ---- neutral
Apple is Changing iOS 17 - Now Filled 'Most Requested Features' - MacRumors ----
negative
Sealed OG iPhone up for auction with rare Apple 'Lucky you' sticker - 9to5Mac
---- negative
Kuo: Apple Mixed-Reality Headset May Not Appear at WWDC as Mass Production
Pushed Back Yet Again - MacRumors ---- positive
OLED MacBook Air Reportedly Now in Development as Apple Plans to Bring New
Display Technology to Multiple Product Lines - MacRumors ---- negative
The Morning After: Will we see Apple's mixed-reality headset at WWDC 2023? -
Engadget ---- negative
Save Up to $900 on an iPad Pro M1 at Best Buy Today Only - CNET ---- negative
Apple Wants to Solve One of Music's Biggest Problems - The Wall Street Journal
---- negative
iPhone 15 Pro Rumored to Feature Multi-Use Action Button Instead of Mute Switch
```

- MacRumors ---- negative
Deals: iPads from $125, $900 off MacBook Pro, $400 off Studio Display, AirTag sale & more - AppleInsider ---- negative
Overall sentiment for apple: negative

tesla:
Tesla Used-Car Data Are Good for the Stock - Barron's ---- neutral
Tesla Needs AI to Thrive. Why Elon Musk Wants to Pause GPT-4. - Barron's ---- neutral
Overall sentiment for tesla: neutral

amazon:
'You don't want to fall for this': BBB warns of smart TV scam - The Hill ---- negative
Amazon sues sellers for issuing bogus takedown requests on competitors - The Verge ---- positive
Overall sentiment for amazon: positive

s&p500:
Stock Market Today: Dow, Nasdaq Close Higher as U.S. Stocks Extend Gains - The Wall Street Journal ---- neutral
Hyundai and Kia theft trend has reached New York City - CNN ---- negative
SBF pleads not guilty to latest charges, and OKX to turn over frozen FTX assets: CNBC Crypto World - CNBC Television ---- negative
Wall Street Bonuses Fall by Most Since 2008 - The Wall Street Journal ---- negative
Ford hikes prices on its F-150 Lightning as production resumes after EV battery fire - CNBC ---- neutral
Federal Reserve Board fines Wells Fargo $67.8 million for inadequate oversight of sanctions risk at its subsidiary bank - Federal Reserve ---- positive
Bed Bath & Beyond Eyes Share Sale as Hudson Bay Deal Falters - Yahoo Finance ---- positive
This California city is the most popular with millennial homebuyers in the U.S. - CNBC ---- negative
CFPB Finalizes Rule to Create a New Data Set on Small Business Lending in America - Consumer Financial Protection Bureau ---- negative
Tesla Used-Car Data Are Good for the Stock - Barron's ---- neutral
Democrat Manchin threatens to sue Biden administration over electrical vehicle tax credits: report - Fox Business ---- negative
The Kia EV9 Electric SUV Will Get a High-Performance GT Version - Jalopnik ---- negative
Justice Dept. loses second 'judge-shopping' case in Texas - The Washington Post ---- negative
Yellen says Trump administration 'decimated' financial oversight - The Hill ---- negative
Trojanized Windows and Mac apps rain down on 3CX users in massive supply chain attack - Ars Technica ---- positive
More home sellers are sitting out of the spring housing market - CNBC ----

```
negative
Fed officials call March rate hike 'appropriate' with inflation high, banks
resilient - Yahoo Finance ---- neutral
Stocks making the biggest moves midday: Bed Bath & Beyond, EVgo, UBS and more -
CNBC ---- negative
Meta hired a DJ to play dance music in one of its campus cafes: report -
Business Insider ---- negative
Apple wins U.S. appeal over patents in $502 mln VirnetX verdict - Reuters ----
neutral
E3 Has Been Canceled - IGN ---- negative
Pokémon Go developer teases "blockbuster slate" of summer features, amidst major
Remote Raid changes - Eurogamer.net ---- negative
Google Assistant might be doomed: Division "reorganizes" to focus on Bard - Ars
Technica ---- negative
Amazon sues sellers for issuing bogus takedown requests on competitors - The
Verge ---- positive
Cyberpunk 2077's Turnaround Just Gave CD Projekt Its Second-Best Revenue Year
Ever - IGN ---- neutral
Diablo 4 Releases Some Mind-Blowing Beta Stats - Push Square ---- negative
New Doom Game Is Cute And Fun Until You Run Out Of Energy - Kotaku ---- negative
CD Projekt explains why Witcher game 'Project Sirius' has seemingly been
restarted - Video Games Chronicle ---- positive
Twitter's new API pricing is killing many Twitter apps that can't pay $42000 per
month - Mashable ---- negative
iOS 16.4: Your iPhone Just Got These New Emoji - CNET ---- negative
Microsoft Teams Is Getting a Big Update (and You Can Try It Now) - CNET ----
negative
Where to preorder Samsung's Galaxy A54 phone - The Verge ---- negative
19 MORE Things You STILL Didn't Know In BOTW - GameSpot ---- negative
You're Missing Out On The Coolest Martial Arts Battle Royale - Kotaku ----
negative
Midjourney ends free trials of its AI image generator due to 'extraordinary'
abuse | Engadget - Engadget ---- negative
Microsoft Announces Diablo 4 Xbox Series X Bundle, Pre-Orders Now Live - Pure
Xbox ---- negative
Netflix Might Be Putting Its Video Games on TVs - IGN ---- negative
Amnesia: The Bunker Feels Like a New Beginning for the Series - IGN ----
negative
Xbox has an embarrassing Square Enix problem - VG247 ---- negative
33-year-old who brought in $2 million making PowerPoints shares her best tips:
'Reduce the content' - CNBC ---- neutral
Overall sentiment for s&p500: negative
```

2.2.5 Last but not least, find the total tone for each element in our portfolio, where:

- neutral = 0
- positive = +1

- negative = -1

[6]:
```
# BUILD YOUR CODE ON TOP OF THIS EXAMPLE CODE IN THE CELL BELOW
"""
from transformers import BertTokenizer, BertForSequenceClassification
import numpy as np

finbert = BertForSequenceClassification.from_pretrained('yiyanghkust/
↪finbert-tone',num_labels=3)
tokenizer = BertTokenizer.from_pretrained('yiyanghkust/finbert-tone')

sentences = ["there is a shortage of capital, and we need extra financing",
             "growth is strong and we have plenty of liquidity",
             "there are doubts about our finances",
             "profits are flat"]

inputs = tokenizer(sentences, return_tensors="pt", padding=True)
outputs = finbert(**inputs)[0]

labels = {0:'neutral', 1:'positive',2:'negative'}
for idx, sent in enumerate(sentences):
    print(sent, '----', labels[np.argmax(outputs.detach().numpy()[idx])])
"""
```

[6]:
```
'\nfrom transformers import BertTokenizer, BertForSequenceClassification\nimport
numpy as np\n\nfinbert =
BertForSequenceClassification.from_pretrained(\'yiyanghkust/finbert-
tone\',num_labels=3)\ntokenizer =
BertTokenizer.from_pretrained(\'yiyanghkust/finbert-tone\')\n\nsentences =
["there is a shortage of capital, and we need extra financing", \n
"growth is strong and we have plenty of liquidity", \n             "there are
doubts about our finances", \n             "profits are flat"]\n\ninputs =
tokenizer(sentences, return_tensors="pt", padding=True)\noutputs =
finbert(**inputs)[0]\n\nlabels = {0:\'neutral\',
1:\'positive\',2:\'negative\'}\nfor idx, sent in enumerate(sentences):\n
print(sent, \'----\', labels[np.argmax(outputs.detach().numpy()[idx])])\n'
```

[7]:
```
portfolio = dict({"apple": 'technology', "tesla": 'business', "amazon":␣
↪'technology', "s&p500": 'business'})

for holding in classified_dict:
    overall_sentiment = {'positive': 0, 'neutral': 0, 'negative': 0}
    for news in classified_dict[holding]:
        overall_sentiment[news['sentiment']] += 1
    pos = overall_sentiment["positive"]
    neg = overall_sentiment["negative"]
    print(f"Overall sentiment for {holding}: {pos-neg}\n")
```

```
Overall sentiment for apple: -8

Overall sentiment for tesla: 0

Overall sentiment for amazon: 0

Overall sentiment for s&p500: -23
```

2.2.6 What do you find from the results? Based on the results of the code above, it seems that the news articles for each holding in our portfolio have varying tones. For example, the news articles about "tesla" and "amazon" seem to have neutral tone score overall. On the other hand, the news articles about "apple" and "s&p500" seem to be negative tone score overall.

Overall, it appears that the sentiment of news articles related to a particular holding can vary and it is important to analyze multiple articles to get a more complete picture of the tone.

3 3. Project

3.0.1 Please submit a proposal for your project 1. It can be anything related to machine learning in finance.

- **The proposal should not be more than 1 page long but should at least include the ML problem type, features, labels, and models used. (Check Lecture 2)**

(A) ML Problem Type The ML problem type in this context is a time-series regression problem, where we are predicting the future stock price based on the past prices and other relevant features.

(B) Features The features used in the LSTM model for predicting stock prices include the historical stock prices divided into batch format to be feeded into the LSTM models step by step.

(C) Labels The label in this case would be the future stock price at a specific time horizon (e.g., tomorrow's closing price), which is what we are trying to predict using the LSTM model.

(D) Models Used The models used in this context would primarily be various configurations of LSTM neural networks with different hyperparameters such as the number of layers, number of neurons per layer, dropout rates, learning rates, batch sizes, and others. Hyperparameter tuning techniques such as grid search, random search, and Bayesian optimization can be used to find the best set of hyperparameters that optimize the LSTM model's performance on a validation set. Other models such as decision trees, random forests, and gradient boosting can also be used to generate features and make predictions. However, LSTM is preferred in this context for my project as it can capture the temporal dependencies in the data, which is crucial for time-series forecasting.

[ ]:

```
```