Project 1a

(a)

First, I imported some necessary packages like NumPy, pandas and matplotlib, and read stockprice (2021).csv, selecting the data from the second column to the 31st column as the Dow Jones prices, and also checking the shape of the DJdata.

```
import numpy as np
import scipy.linalg as lina
import pandas as pd
import matplotlib.pyplot as plt
import math
data = pd.read_csv('C:\\Users\\60474\\Desktop\\stockprices(2021).csv')
DJdata = data.iloc[:,1:31]
print(DJdata.columns)
DJdata.shape
```

```
Index(['MMM', 'AXP', 'AMGN', 'AAPL', 'BA', 'CAT', 'CVX', 'CSCO', 'KO', 'DIS',
       'DOW', 'GS', 'HD', 'HON', 'IBM', 'INTC', 'JNJ', 'JPM', 'MCD', 'MRK',
       'MSFT', 'NKE', 'PG', 'CRM', 'TRV', 'UNH', 'VZ', 'V', 'WBA', 'WMT'],
      dtype='object')

(252, 30)
```

Convert the close prices to return (R), which will reduce one line of DJdata. Normalize the return to get the standard return (SR).

```
#(a)
R = np.zeros([251,30])
for i in range(0,251):
    for j in range(0,30):
        R[i,j]=(DJdata.iloc[i+1,j]-DJdata.iloc[i,j])/DJdata.iloc[i,j]
SR = np.zeros([251,30])
for n in range(0,251):
    for j in range(0,30):
        SR[n,j] = (R[n,j]-np.mean(R[:,j]))/np.std(R[:,j])
```

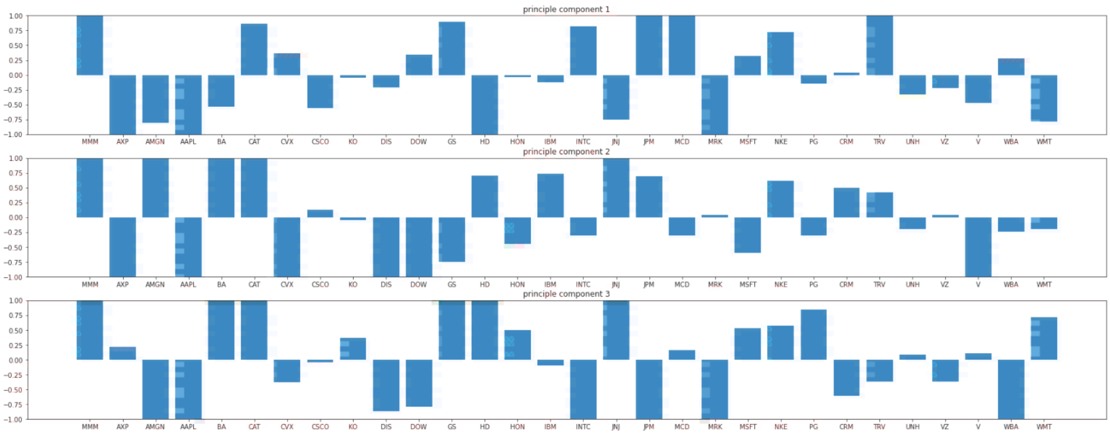
Then I calculate the auto covariance matrix, decompose the eigenvalues and eigenvectors, sort them according to the eigenvalues, and recalculate the transformed eigenvectors (w).

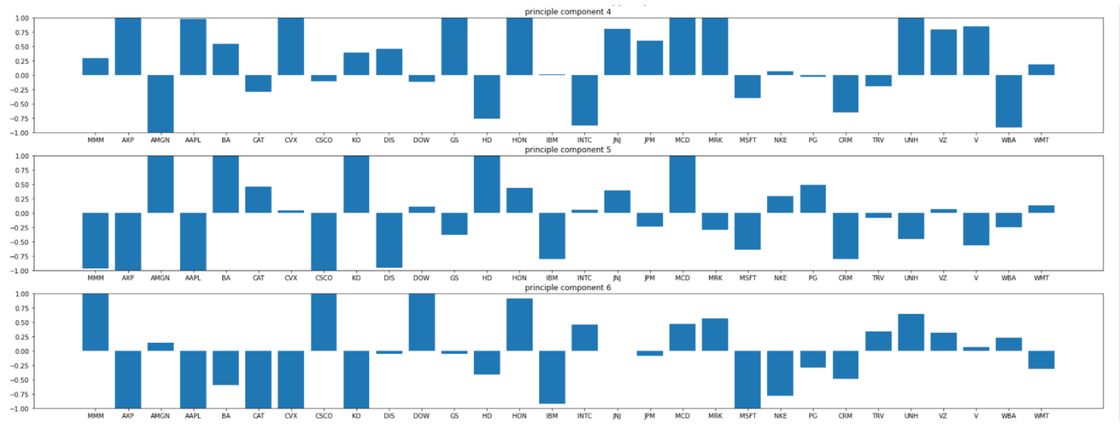
```
x = SR
C = x.T.dot(x)
lam,v= lina.eig(C)
new_index = np.argsort(lam)[::-1]
A = -v[:,new_index]
w = x.dot(A)
```

Finally, the histogram of the first ten principal components is obtained through Matplotlib.

```
ticker=["MMM",'AXP','AMGN','AAPL','BA','CAT','CVX','CSCO','KO','DIS','DOW','GS','HD','HON','IBM','INTC','JNJ','JPM','MCD','MRK',
plt.subplot(10, 1, 1)
plt.ylim(-1, 1)
plt.rcParams['figure.figsize'] = (20, 40.0)
plt.bar(ticker,w[0,:])
plt.title("principle component 1")
plt.subplot(10, 1, 2)
plt.ylim(-1, 1)
plt.bar(ticker,w[1,:])
plt.title("principle component 2")
plt.subplot(10, 1, 3)
plt.ylim(-1, 1)
plt.bar(ticker,w[2,:])
plt.title("principle component 3")
```

Here are the plots:





(b)

First, I selected the data from column 2 to 505 for K-means operation, r and sigma are calculated and written into the data set of RSdata.

```
#(b)
KMdata=data.iloc[:,1:504]
p = np.zeros([252,503])
r=np.zeros(503)
sigma=np.zeros(503)
for i in range (0,251):
    for j in range (0,503):
        p[i,j]=(KMdata.iloc[i+1,j]-KMdata.iloc[i,j])/KMdata.iloc[i,j]
        r[j] = np.mean(p[:,j])*252
        sigma[j] = np.std(p[:,j])*math.sqrt(252)
RSdata=np.zeros([503,2])
RSdata[:,0]=r
RSdata[:,1]=sigma
RSdata[0,0]
```

```
0.05036159792842661
```

Second, I defined a function kmeans_xufive(ds,k):

```
def kmeans_xufive(ds, k):
    m, n = ds.shape #m:the number of samples, n: the number of attribute values of each sample
    result = np.empty(m, dtype=np.int) # clustering results of M samples
    cores = ds[np.random.choice(np.arange(m), k, replace=False)]
    # From m data samples, k samples are randomly selected as the centroid without repetition

    while True: # Iterative calculation
        d = np.square(np.repeat(ds, k, axis=0).reshape(m, k, n) - cores)
        distance = np.sqrt(np.sum(d, axis=2))
        # Ndarray (m, k), the distance between each sample and k centroids, with m rows in total
        index_min = np.argmin(distance, axis=1) # The nearest centroid index sequence number of each sample

        if (index_min == result).all(): # If the sample clustering does not change
            return result, cores # Then the clustering result and centroid data are returned

        result[:] = index_min # Reclassification
        for i in range(k): # Ergodic centroid set
            items = ds[result==i] # Find the sub sample set corresponding to the current centroid
            cores[i] = np.mean(items, axis=0)
            # Take the mean value of the sub sample set as the position of the current centroid
```

In the end, I did a total of 600 operations, 200 times each when k = 6, 8 and 10, so as to ensure the accuracy of the results.

```
var1=np.zeros(600)
for j in range(200):
    var=[]
    K=[6,8,10]
    for k in K:
        result, cores=kmeans_xufive(RSdata, k)
        sigma2=[]
        for i in range(k):
            a=sum(sum((RSdata[np.where(result==i),0]-cores[(i,0)])**2+(RSdata[np.where(result==i),1]-cores[(i,1)])**2))
            sigma2.append(a)
        a=sum(sigma2)
        var.append(a)
    var1[j]=var[0]
    var1[j+200]=var[1]
    var1[j+400]=var[2]

print(np.mean(var1[0:200]))
print(np.mean(var1[200:400]))
print(np.mean(var1[400:600]))
```

At the same time, I also made a DataFrame to visualize the results I got. It can be seen that when K is 6, 8 and 10, the variance I calculated is 5.05, 3.74 and 3.02 respectively, indicating that the larger the value of K, the smaller the variance of the sample.

```
incluvariance=[np.mean(var1[0:200]),np.mean(var1[200:400]),np.mean(var1[400:600])]
df=pd.DataFrame(index=[6,8,10],columns=["Variance"])
df.iloc[:,0]=incluvariance
df
```

	Variance
6	5.052269
8	3.744921
10	3.017540

Here is my computer programme:

```
import numpy as np
import scipy.linalg as lina
import pandas as pd
import matplotlib.pyplot as plt
import math
data = pd.read_csv('C:\\Users\\60474\\Desktop\\stockprices(2021).csv')
DJdata = data.iloc[:,1:31]
print(DJdata.columns)
DJdata.shape

#(a)
R = np.zeros([251,30])
for i in range(0,251):
    for j in range(0,30):
        R[i,j]=(DJdata.iloc[i+1,j]-DJdata.iloc[i,j])/DJdata.iloc[i,j]
SR = np.zeros([251,30])
for n in range(0,251):
    for j in range(0,30):
        SR[n,j] = (R[n,j]-np.mean(R[:,j]))/np.std(R[:,j])
x = SR
C = x.T.dot(x)
lam,v= lina.eig(C)
new_index = np.argsort(lam)[::-1]
A = -v[:,new_index]
w = x.dot(A)

ticker=["MMM",'AXP','AMGN','AAPL','BA','CAT','CVX','CSCO','KO','DIS','DOW','GS','HD','HON','IBM','INTC','JNJ','JPM','MCD','MRK','MSFT','NKE','PG','CRM','TRV','UNH','VZ','V','WBA','WMT']
plt.subplot(10, 1, 1)
plt.ylim(-1, 1)
plt.rcParams['figure.figsize'] = (20, 40.0)
plt.bar(ticker,w[0,:])
plt.title("principle component 1")
```

```
plt.subplot(10, 1, 2)
plt.ylim(-1, 1)
plt.bar(ticker,w[1,:])
plt.title("principle component 2")
plt.subplot(10, 1, 3)
plt.ylim(-1, 1)
plt.bar(ticker,w[2,:])
plt.title("principle component 3")
plt.subplot(10, 1, 4)
plt.ylim(-1, 1)
plt.bar(ticker,w[3,:])
plt.title("principle component 4")
plt.subplot(10, 1, 5)
plt.ylim(-1, 1)
plt.bar(ticker,w[4,:])
plt.title("principle component 5")
plt.subplot(10, 1, 6)
plt.ylim(-1, 1)
plt.bar(ticker,w[5,:])
plt.title("principle component 6")
plt.subplot(10, 1, 7)
plt.ylim(-1, 1)
plt.bar(ticker,w[6,:])
plt.title("principle component 7")
plt.subplot(10, 1, 8)
plt.ylim(-1, 1)
plt.bar(ticker,w[7,:])
plt.title("principle component 8")
plt.subplot(10, 1, 9)
plt.ylim(-1, 1)
plt.bar(ticker,w[8,:])
plt.title("principle component 9")
plt.subplot(10, 1, 10)
plt.ylim(-1, 1)
plt.bar(ticker,w[9,:])
plt.title("principle component 10")

#(b)
KMdata=data.iloc[:,1:504]
p = np.zeros([252,503])
r=np.zeros(503)
sigma=np.zeros(503)
for i in range (0,251):
    for j in range (0,503):
```

```
            p[i,j]=(KMdata.iloc[i+1,j]-KMdata.iloc[i,j])/KMdata.iloc[i,j]
            r[j] = np.mean(p[:,j])*252
            sigma[j] = np.std(p[:,j])*math.sqrt(252)
RSdata=np.zeros([503,2])
RSdata[:,0]=r
RSdata[:,1]=sigma
RSdata[0,0]

def kmeans_xufive(ds, k):
      m, n = ds.shape #m:the number of samples, n: the number of attribute values of each sample
      result = np.empty(m, dtype=np.int) # clustering results of M samples
      cores = ds[np.random.choice(np.arange(m), k, replace=False)]
      # From m data samples, k samples are randomly selected as the centroid without repetition

      while True: # Iterative calculation
            d = np.square(np.repeat(ds, k, axis=0).reshape(m, k, n) - cores)
            distance = np.sqrt(np.sum(d, axis=2))
            # Ndarray (m, k), the distance between each sample and k centroids, with m rows in total
            index_min = np.argmin(distance, axis=1) # The nearest centroid index sequence number of each sample

            if (index_min == result).all(): # If the sample clustering does not change
                  return result, cores # Then the clustering result and centroid data are returned

            result[:] = index_min # Reclassification
            for i in range(k): # Ergodic centroid set
                  items = ds[result==i] # Find the sub sample set corresponding to the current centroid
                  cores[i] = np.mean(items, axis=0)
                  # Take the mean value of the sub sample set as the position of the current centroid

var1=np.zeros(600)
for j in range(200):
      var=[]
      K=[6,8,10]
      for k in K:
            result, cores=kmeans_xufive(RSdata, k)
            sigma2=[]
            for i in range(k):
```

```
            a=sum(sum((RSdata[np.where(result==i),0]-
cores[(i,0)])**2+(RSdata[np.where(result==i),1]-cores[(i,1)])**2))
            sigma2.append(a)
        a=sum(sigma2)
        var.append(a)
    var1[j]=var[0]
    var1[j+200]=var[1]
    var1[j+400]=var[2]

print(np.mean(var1[0:200]))
print(np.mean(var1[200:400]))
print(np.mean(var1[400:600]))
incluvariance=[np.mean(var1[0:200]),np.mean(var1[200:400]),np.mean(var1[400:600])]
df=pd.DataFrame(index=[6,8,10],columns=["Variance"])
df.iloc[:,0]=incluvariance
df
```