WQU_MScFE600FINANCIALDATA_Task 4.ipynb

File Edit View Insert Runtime Tools Help

```
from google.colab import drive

# Mount Google Drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

[12]
```
import os
import pandas as pd
import numpy as np

# Define the path to the dataset
data_dir = '/content/drive/MyDrive/WQU_Task4/individual_stocks_5yr/individual_stocks_5yr'

# Initialize an empty dictionary to store closing prices
all_data = {}

# Loop through all files in the directory
for filename in os.listdir(data_dir):
    if filename.endswith('_data.csv'):  # Only process stock data files
        ticker = filename.split('_')[0]  # Extract ticker symbol (e.g., 'AAPL')
        file_path = os.path.join(data_dir, filename)
        try:
            # Load the stock data
            data = pd.read_csv(file_path)

            # Ensure the 'date' column is parsed as datetime
            data['date'] = pd.to_datetime(data['date'])

            # Use the 'close' column as a proxy for adjusted closing prices
            if 'close' in data.columns:
                adj_close = data.set_index('date')['close']
                all_data[ticker] = adj_close
            else:
                raise ValueError("Closing price column not found")

        except Exception as e:
            print(f"Error processing {filename}: {e}")

# Combine all data into a single DataFrame
prices_df = pd.DataFrame(all_data).dropna()

# Print the resulting DataFrame shape
print(f"Prices DataFrame Shape: {prices_df.shape}")
```

```
Prices DataFrame Shape: (44, 505)
```

[13]
```
# Inspect the structure of CL_data.csv
file_path = os.path.join(data_dir, 'CL_data.csv')
data = pd.read_csv(file_path)
print("Column Names:")
print(data.columns)
```

```
Column Names:
Index(['date', 'open', 'high', 'low', 'close', 'volume', 'Name'], dtype='object')
```

[14]
```
# Compute daily returns
returns_df = prices_df.pct_change().dropna()

# Print the first few rows of the returns DataFrame
print("\nDaily Returns Preview:")
print(returns_df.head())
```

```
Daily Returns Preview:
                DWDP      CTAS       COG       BXP      COST       AES  \
date
2017-12-06 -0.006430  0.001408 -0.009884 -0.000638 -0.003195  0.010261
2017-12-07  0.004080  0.009585 -0.009626 -0.011642 -0.005448 -0.012004
2017-12-08 -0.008967  0.007468 -0.001080  0.005728  0.010043  0.005607
2017-12-11  0.001131 -0.005340  0.020901  0.003129  0.004201  0.009294
2017-12-12 -0.000282 -0.007200 -0.025768  0.009036 -0.002965 -0.012891

                 COP      CINF       ETN       AXP  ...       XRX       VMC  \
date                                                ...
2017-12-06 -0.016592  0.001076  0.011207 -0.005065  ...  0.006793 -0.013039
2017-12-07  0.003176 -0.004029  0.019396  0.003767  ... -0.001687  0.031129
2017-12-08  0.020380  0.003236  0.000388 -0.000304  ...  0.000000  0.008008
2017-12-11  0.002327  0.002151  0.006210  0.004566  ...  0.000000 -0.023514
2017-12-12  0.005223 -0.000536 -0.000129  0.003737  ...  0.005069 -0.011471

                 WMB      XLNX       WBA       VFC       VTR      WYNN  \
date
2017-12-06 -0.013072 -0.000438  0.012397  0.018326  0.004145 -0.010034
2017-12-07 -0.007668  0.008919 -0.020267  0.003209  0.008573  0.006779
2017-12-08  0.002810 -0.006667  0.027870  0.020025 -0.003463  0.003901
2017-12-11  0.012259 -0.002334  0.004612 -0.010225  0.000158  0.029585
2017-12-12  0.006228 -0.010237  0.001809 -0.000964  0.007896 -0.011871

                 XOM       XEL
date
2017-12-06 -0.007359  0.005709
2017-12-07  0.003281 -0.004893
2017-12-08  0.001333  0.007081
2017-12-11  0.004476  0.004687
2017-12-12 -0.003252 -0.017496

[5 rows x 505 columns]
```

```
# Step 4: Compute Covariance Matrix
```

```python
cov_matrix = returns_df.cov()

# Print the covariance matrix
print("\nCovariance Matrix:")
print(cov_matrix)
```

```

Covariance Matrix:
              DWDP      CTAS       COG       BXP      COST       AES  \
DWDP  2.490529e-04  0.000096  0.000178  0.000074  0.000090  0.000110
CTAS  9.551310e-05  0.000104  0.000064  0.000063  0.000060  0.000061
COG   1.777956e-04  0.000064  0.000361  0.000048  0.000095  0.000091
BXP   7.418323e-05  0.000063  0.000048  0.000177  0.000060  0.000052
COST  9.011380e-05  0.000060  0.000095  0.000060  0.000147  0.000108
...            ...       ...       ...       ...       ...       ...
VFC   3.735924e-05  0.000044  0.000029  0.000020  0.000055  0.000068
VTR   5.750155e-05  0.000051  0.000023  0.000130  0.000058  0.000051
WYNN -3.883925e-05  0.000019  0.000009 -0.000019  0.000017 -0.000145
XOM   1.034506e-04  0.000083  0.000169  0.000043  0.000098  0.000104
XEL  -7.506973e-07  0.000038  0.000019  0.000053  0.000036  0.000029

           COP      CINF       ETN       AXP  ...       XRX       VMC  \
DWDP  0.000091  0.000049  0.000087  0.000128  ...  0.000076  0.000118
CTAS  0.000060  0.000051  0.000048  0.000060  ...  0.000092  0.000078
COG   0.000166  0.000073  0.000137  0.000090  ...  0.000067  0.000144
BXP   0.000024  0.000064  0.000009  0.000053  ...  0.000088  0.000022
COST  0.000056  0.000071  0.000093  0.000077  ...  0.000061  0.000116
...        ...       ...       ...       ...  ...       ...       ...
VFC   0.000053  0.000038  0.000024  0.000020  ...  0.000053  0.000052
VTR  -0.000022  0.000048  0.000022  0.000041  ...  0.000043  0.000064
WYNN  0.000021  0.000088  0.000002  0.000009  ... -0.000022 -0.000005
XOM   0.000148  0.000082  0.000155  0.000109  ...  0.000071  0.000119
XEL  -0.000018  0.000044  0.000007  0.000009  ...  0.000020  0.000033

           WMB      XLNX           WBA       VFC       VTR      WYNN  \
DWDP  0.000135  0.000192  8.814572e-05  0.000037  0.000058 -0.000039
CTAS  0.000059  0.000086  4.244215e-05  0.000044  0.000051  0.000019
COG   0.000170  0.000174  1.281764e-04  0.000029  0.000023  0.000009
BXP   0.000047  0.000080  8.001417e-05  0.000020  0.000130 -0.000019
COST  0.000073  0.000048  1.383163e-04  0.000055  0.000058  0.000017
...        ...       ...           ...       ...       ...       ...
VFC   0.000035  0.000051  6.087456e-05  0.000108  0.000017  0.000006
VTR   0.000020  0.000033  5.247087e-05  0.000017  0.000174 -0.000043
WYNN  0.000033 -0.000162 -8.763984e-05  0.000006 -0.000043  0.001070
XOM   0.000138  0.000126  1.355359e-04  0.000038  0.000030  0.000037
XEL  -0.000012 -0.000003 -6.491973e-07  0.000013  0.000067  0.000060

           XOM           XEL
DWDP  0.000103 -7.506973e-07
CTAS  0.000083  3.803561e-05
COG   0.000169  1.933293e-05
BXP   0.000043  5.285115e-05
COST  0.000098  3.606966e-05
...        ...           ...
VFC   0.000038  1.304749e-05
VTR   0.000030  6.687788e-05
WYNN  0.000037  6.034601e-05
XOM   0.000210  3.218190e-05
XEL   0.000032  8.527323e-05

[505 rows x 505 columns]
```

[18]

```python
from sklearn.decomposition import PCA
# Step 5: Perform PCA
pca = PCA()
principal_components = pca.fit_transform(returns_df)
explained_variance = pca.explained_variance_ratio_

# Print explained variance ratio
print("\nExplained Variance Ratio (PCA):")
print(explained_variance)
```

```

Explained Variance Ratio (PCA):
[3.17449626e-01 6.25541078e-02 4.81491888e-02 3.99602164e-02
 3.72209475e-02 3.35148205e-02 3.02986704e-02 2.76202654e-02
 2.49953077e-02 2.40067125e-02 2.20018266e-02 2.10962344e-02
 1.89976536e-02 1.75864572e-02 1.72324476e-02 1.66352073e-02
 1.60704359e-02 1.53185136e-02 1.50225471e-02 1.46946848e-02
 1.40154830e-02 1.28167575e-02 1.26505508e-02 1.20192354e-02
 1.16142627e-02 1.09308114e-02 1.01139439e-02 9.84301438e-03
 9.02898135e-03 8.56451611e-03 8.29440878e-03 7.73843638e-03
 7.59545988e-03 6.99678737e-03 6.94571582e-03 6.27899887e-03
 5.55020627e-03 4.74799835e-03 4.41418094e-03 3.86191474e-03
 2.99658108e-03 2.55588370e-03 6.26058999e-32]
```

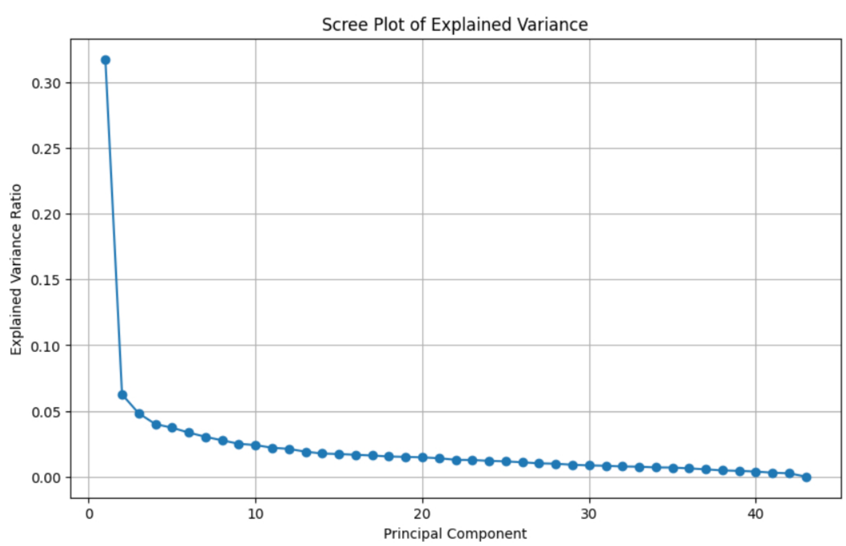
[19]

```python

# Step 6: Perform SVD
U, S, Vt = np.linalg.svd(cov_matrix)

# Print singular values
print("\nSingular Values (SVD):")
print(S)
```

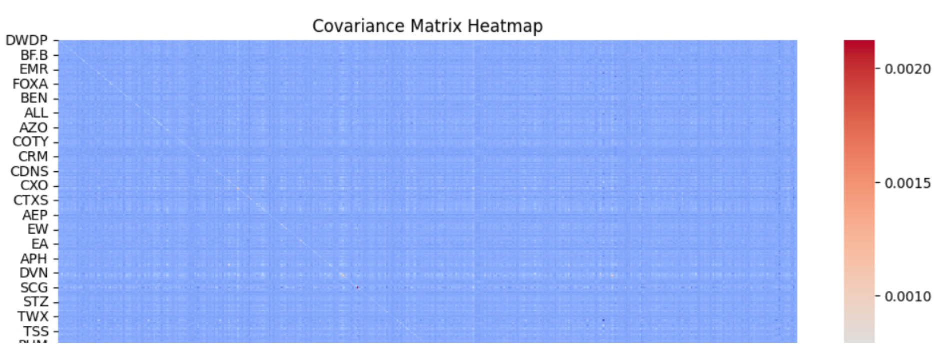
```
 4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
 4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
 4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
 4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
 4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
 4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
 4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
 4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
 4.08755153c 18 4.08755153c 18 4.08755153c 18 4.08755153c 18
 4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
 4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
 4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
 4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
 4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
 4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
 4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
```

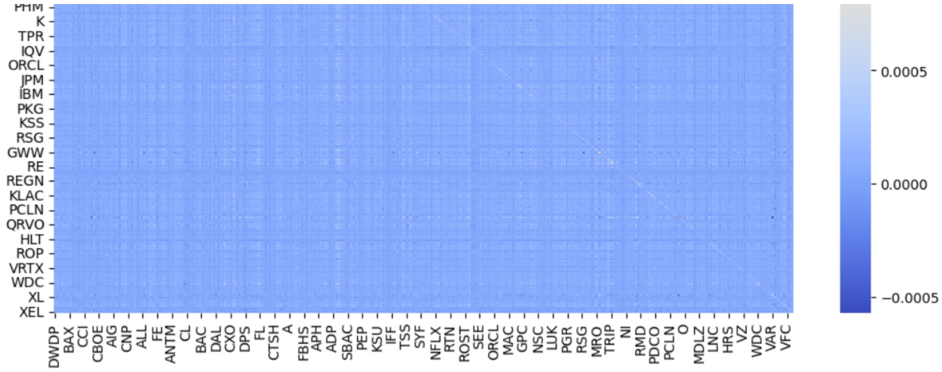
```
4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
4.08755153e-18 4.08755153e-18 4.08755153e-18 4.08755153e-18
4.08755153e-18 4.08755153e-18 4.08755153e-18 2.78518903e-18
9.75074605e-19]
```

[21]
```
import matplotlib.pyplot as plt
# Step 7: Visualizations
# Scree Plot (Explained Variance Ratio)
plt.figure(figsize=(10, 6))
plt.plot(range(1, len(explained_variance) + 1), explained_variance, marker='o')
plt.title('Scree Plot of Explained Variance')
plt.xlabel('Principal Component')
plt.ylabel('Explained Variance Ratio')
plt.grid(True)
plt.show()
```



[23]
```
import seaborn as sns
# Heatmap of Covariance Matrix
plt.figure(figsize=(12, 8))
sns.heatmap(cov_matrix, cmap='coolwarm', annot=False)
plt.title('Covariance Matrix Heatmap')
plt.show()
```





[24]

```python
# Step 8: Interpretation (Print Key Results)
print("\nTop 5 Eigenvectors (PCA):")
print(pca.components_[:5])

# Additional Interpretation
print("\nKey Insights:")
print("1. The first principal component explains the largest proportion of variance.")
print("2. Singular values indicate the importance of each dimension in the data.")
```

```
Top 5 Eigenvectors (PCA):
[[ 0.05811365  0.03214686  0.06091315 ... -0.00281216  0.05437171
   0.00346748]
 [ 0.01275586  0.04263893 -0.04366108 ...  0.0058134   0.00794854
   0.06810065]
 [ 0.05101396  0.01053209  0.05228765 ... -0.10484237 -0.02186964
   0.02040563]
 [-0.02854154  0.02051434  0.02599461 ...  0.15131361  0.01156248
   0.05452788]
 [-0.02828475 -0.00320748 -0.05707429 ...  0.10273525 -0.04540468
   0.00468335]]

Key Insights:
1. The first principal component explains the largest proportion of variance.
2. Singular values indicate the importance of each dimension in the data.
```