Stock Correlation Analysis

May 16, 2022

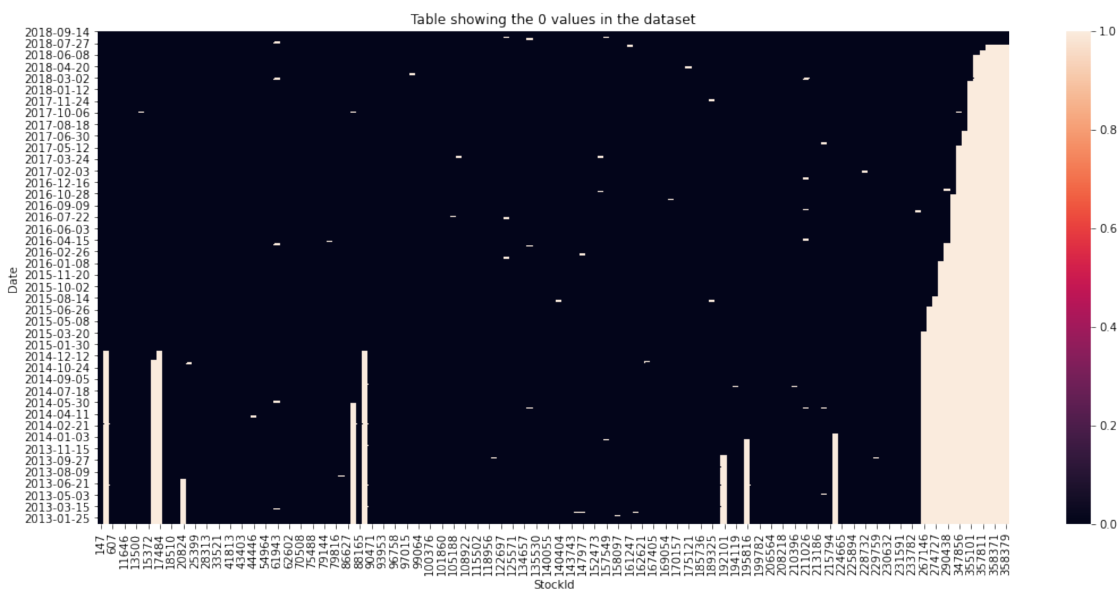
0.1 Cleaning Data

[2]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

[4]:
```
df = pd.read_csv("OrbQuantData.csv")

def cleanTheData(df):
    # function checks for NA values and replaces them with 0s
    # returns the cleanedData


    # reshape the data from lonng format to wide - https://pandas.pydata.org/
↪pandas-docs/stable/user_guide/reshaping.html
    fullTable = df.pivot(index ="Date", columns ="StockId", values = "Value")

    # check NA values
    naTable = fullTable.isnull().sum()
    pctNas = 100* fullTable.isnull().sum().sum()/ (fullTable.shape[0]*fullTable.
↪shape[1])

    print('Number of NA values in related to each stock:')
    print(naTable)
    print('\n{0}% of the data contains NA values'.format(pctNas))

    fullTable = fullTable.fillna(0)
    fullTable = fullTable.iloc[::-1]      # reverse table so dates in␣
↪descending order

    # Plot graph
    f, ax = plt.subplots(figsize=(18, 8))
    sns.heatmap(fullTable == 0)
    ax.set_title('Table showing the 0 values in the dataset')
    plt.show()

    return fullTable
```

```
fullTable = cleanTheData(df)
```

```
Number of NA values in related to each stock:
StockId
147         0
452       104
607         0
2582        0
11646       0
         …
357811    286
358368    289
358371    289
358376    289
358379    289
Length: 155, dtype: int64

8.711842390127734% of the data contains NA values
```



1 QS 1: 5yr data set

[3]:
```python
# 5 year data set consists of 52*5 = 260 weeks
fiveYrReturns = fullTable.iloc[0:52*5,:]

def computeCumulativeReturns(df):
    # this method computes the cumulative returns each of the stocks and prints the best
```

```
    # worst performers

    # Add 1 to each weekly return and compute the product of all the returns of␣
↪each stock
    #https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.
↪DataFrame.product.html
    cumuReturns = df.add(1).product(axis = 0)

    # sort cumulative returns
    cumuReturns.sort_values(ascending = False)

    print('Best performing Stock ID: {0} \n Return multiple: {1}'.
↪format(cumuReturns.idxmax(), cumuReturns.max()))

    print('\nWorst performing Stock ID: {0} \n Return multiple: {1}'.
↪format(cumuReturns.idxmin(), cumuReturns.min()))


computeCumulativeReturns(fiveYrReturns)
```

```
Best performing Stock ID: 206469
 Return multiple: 3.711696288149029

Worst performing Stock ID: 100376
 Return multiple: 0.003179589341807984
```

2 QS 2a

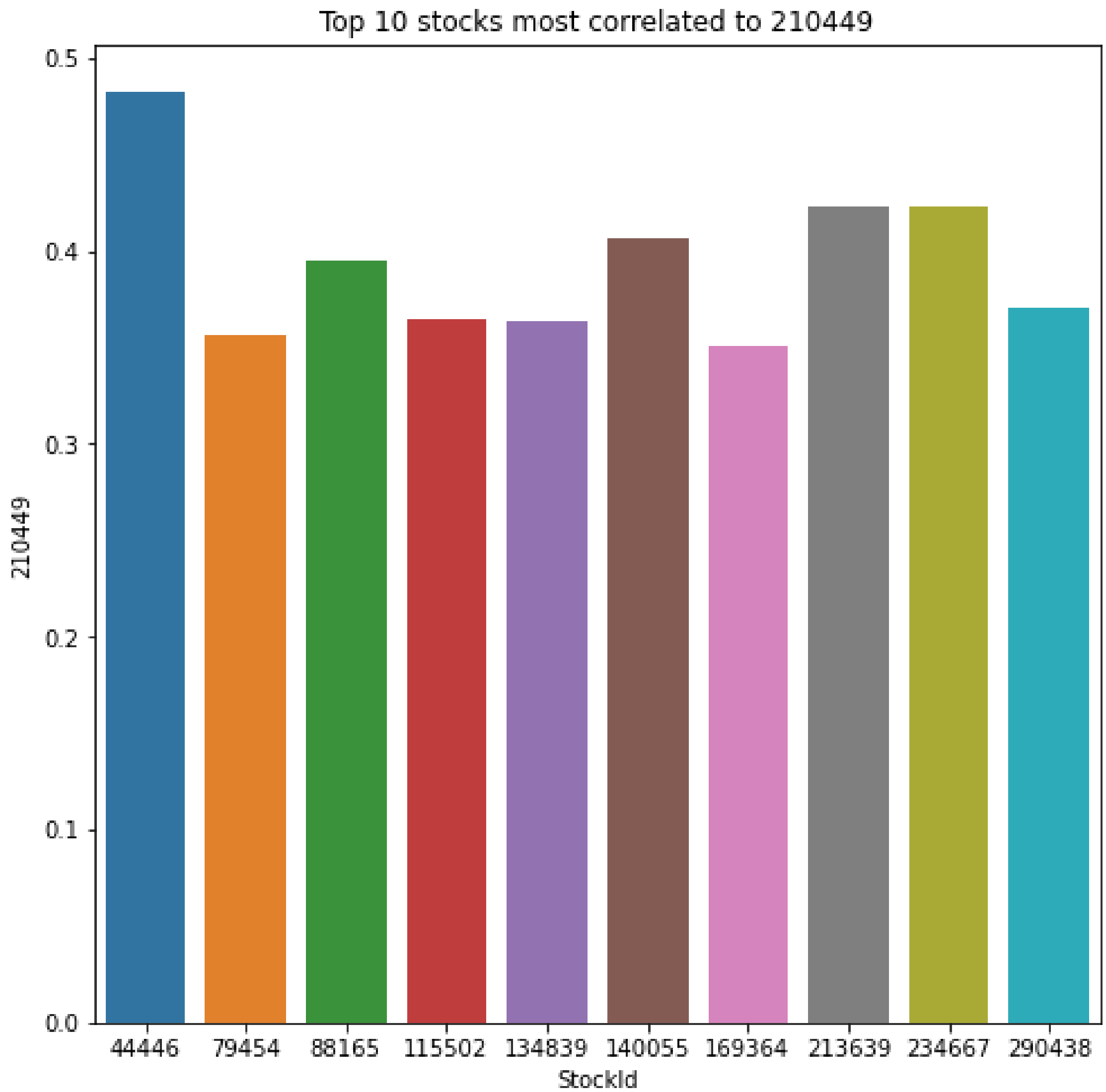
2.0.1 Part i) Stock 210449

[4]:
```
# 3 year data set consists of 52*3 = 156 weeks

lastThreeYearsReturns = fullTable.iloc[0:52*3,:]
```

[5]:
```
def computeCorrelations(df):
    # This method computes the correlations across the data set, removes rows␣
↪and
    # columns that are entirely populated with NA values
    # from the correlation matrix and then returns the result

    ## drop columns and rows containing only NA values
    correlDroppedNas = df.corr().dropna(axis = 0, how='all')
    correlDroppedNas = correlDroppedNas.dropna(axis = 1, how='all')

    return correlDroppedNas
```

```
[6]: def getTopCorrelationsOfStockOfInterest(df, StockId):
         # this method takes the correlations table, stock ID of interest and number␣
      ↪of
         # most correlated stocks one wants to view as inputs
         # it prints a bar chart of correlated stocks
         # and outputs the raw tabular data

         # sort values and remove first element, which is necessarily the StockId
         #(which will always have correlation of 1)
         correlationsSet = df[StockId].sort_values(ascending = False)[1:]

         f, ax = plt.subplots(figsize=(8, 8))
         sns.barplot(x = correlationsSet.head(10).index, y = correlationsSet.
      ↪head(10))
         ax.set_title('Top 10 stocks most correlated to {0}'.format(StockId))

         plt.show()

         print('Top 10 stocks most correlated to {0}'.format(StockId))
         print(correlationsSet.head(10))

         print('\n Stocks most correlated to {0} by StockID'.format(StockId))
         print(list(correlationsSet.head(10).index.values))
         return correlationsSet.head(10)
```

```
[119]: lastThreeYearsCorrelations = computeCorrelations(lastThreeYearsReturns)

       correlatedSet210449 =␣
        ↪getTopCorrelationsOfStockOfInterest(lastThreeYearsCorrelations, 210449)
```



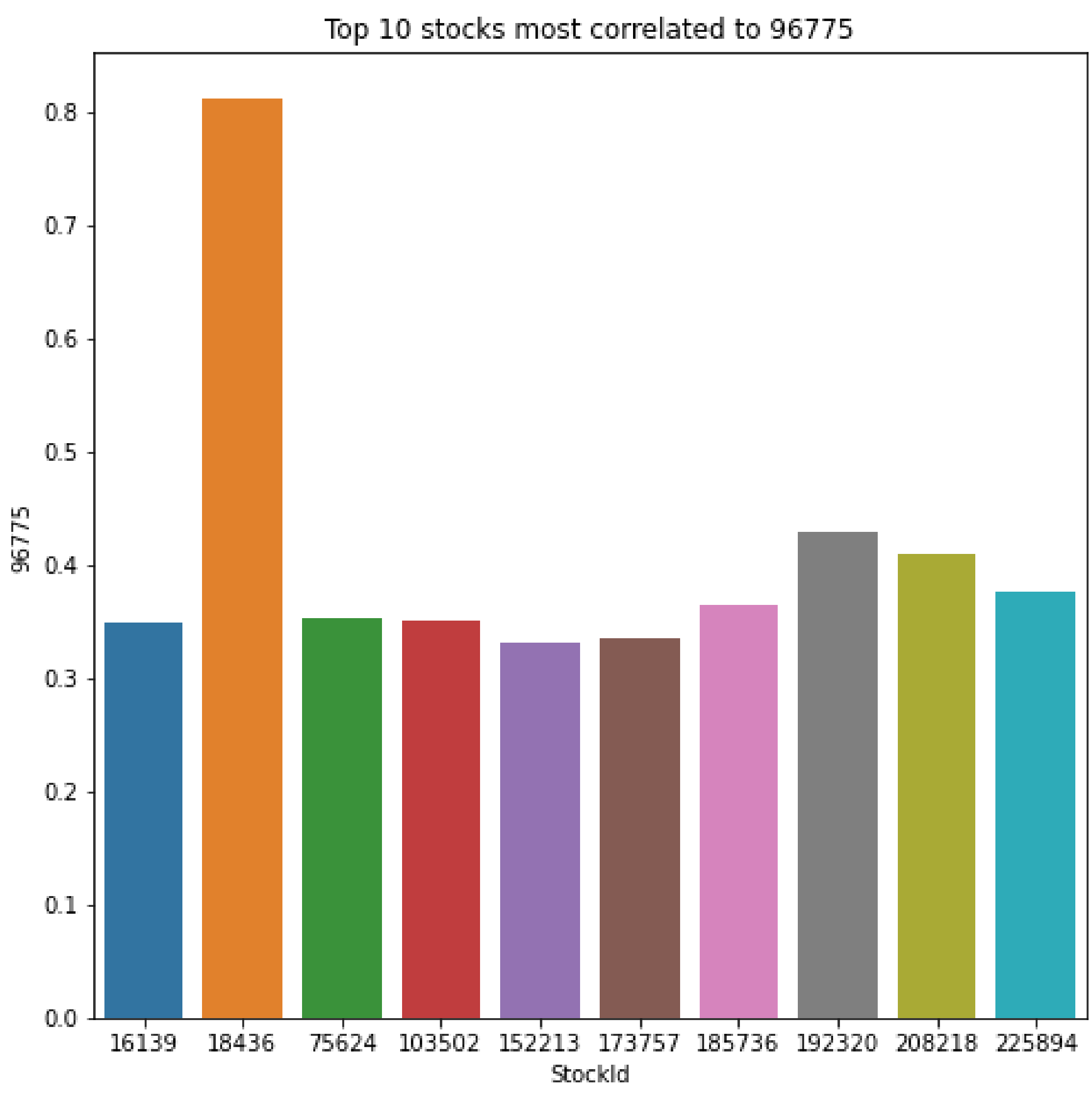

```
Top 10 stocks most correlated to 210449
StockId
44446     0.482828
213639    0.423521
234667    0.422793
140055    0.406538
88165     0.395443
290438    0.370108
115502    0.364522
134839    0.363199
79454     0.356205
169364    0.350195
Name: 210449, dtype: float64
```

```
Stocks most correlated to 210449 by StockID
[44446, 213639, 234667, 140055, 88165, 290438, 115502, 134839, 79454, 169364]
```

2.1 Part ii) Stock 96775

[120]:
```
# 3 yrs ending 01-03-2017
# 3 yrs == 3*52 = 156 wks

threeYrsEndingMarch17 = fullTable.iloc[fullTable.index <= '2017-03-01',:]
threeYrsEndingMarch17 = threeYrsEndingMarch17.head(156)
```

[121]:
```
threeYearsEnding2017Correlations = computeCorrelations(lastThreeYearsReturns)

correlatedSet96775 =␣
↪getTopCorrelationsOfStockOfInterest(threeYearsEnding2017Correlations, 96775)
```



```
Top 10 stocks most correlated to 96775
StockId
18436     0.812427
192320    0.429964
208218    0.410276
225894    0.376059
185736    0.364736
75624     0.352845
103502    0.350985
16139     0.349340
173757    0.334303
152213    0.331907
Name: 96775, dtype: float64

 Stocks most correlated to 96775 by StockID
[18436, 192320, 208218, 225894, 185736, 75624, 103502, 16139, 173757, 152213]
```

3 Qs 2b

Inspecting the graphs visually, we can see that Stock 210449's group of correlated stocks appears to be more homogeneous than Stock 96775's.

- We compute 1/(variance of correlations) as our dispersion measure to quantify the degree of homogeneity

[150]:

```python
if  1/correlatedSet210449.var() == 1/correlatedSet96775.var():
    print('Same degree of homogeneity across both sets of correlated stocks')
elif 1/correlatedSet210449.var() < 1/correlatedSet96775.var():
    print('Variance score implies Stock 96775s set of correlated stocks is more homoegenous')
    print('\nHomogeneity scores\n')
    print('210449: ' + str(1/correlatedSet210449.var()))
    print('96775: ' + str(1/correlatedSet96775.var()))
else:
    print('Homogeneity score implies Stock 210449s set of correlated stocks is more homoegenous')
    print('\nHomogeneity scores\n')
    print('210449: ' + str(1/correlatedSet210449.var()))
    print('96775: ' + str(1/correlatedSet96775.var()))
```

```
Homogeneity score implies Stock 210449s set of correlated stocks is more
homoegenous

Homogeneity scores
```

```
210449: 581.2497849738794
96775: 47.92632551451869
```