US Financial Performance during Pandemic Using Clustering

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link to Github

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OUTLINE

1 - Introduction of Financial Performance during Pandemic

- ⊡ Potential Impact of Covid-19
- ⊡ General overview of S&P 500

2 - Data Collection

- ⊡ Webscraping from Wiki for stocks
- ⊡ Webscraping from Yahoo Finance for time-series data

3 - 3 Ways to Cluster Companies and Industries

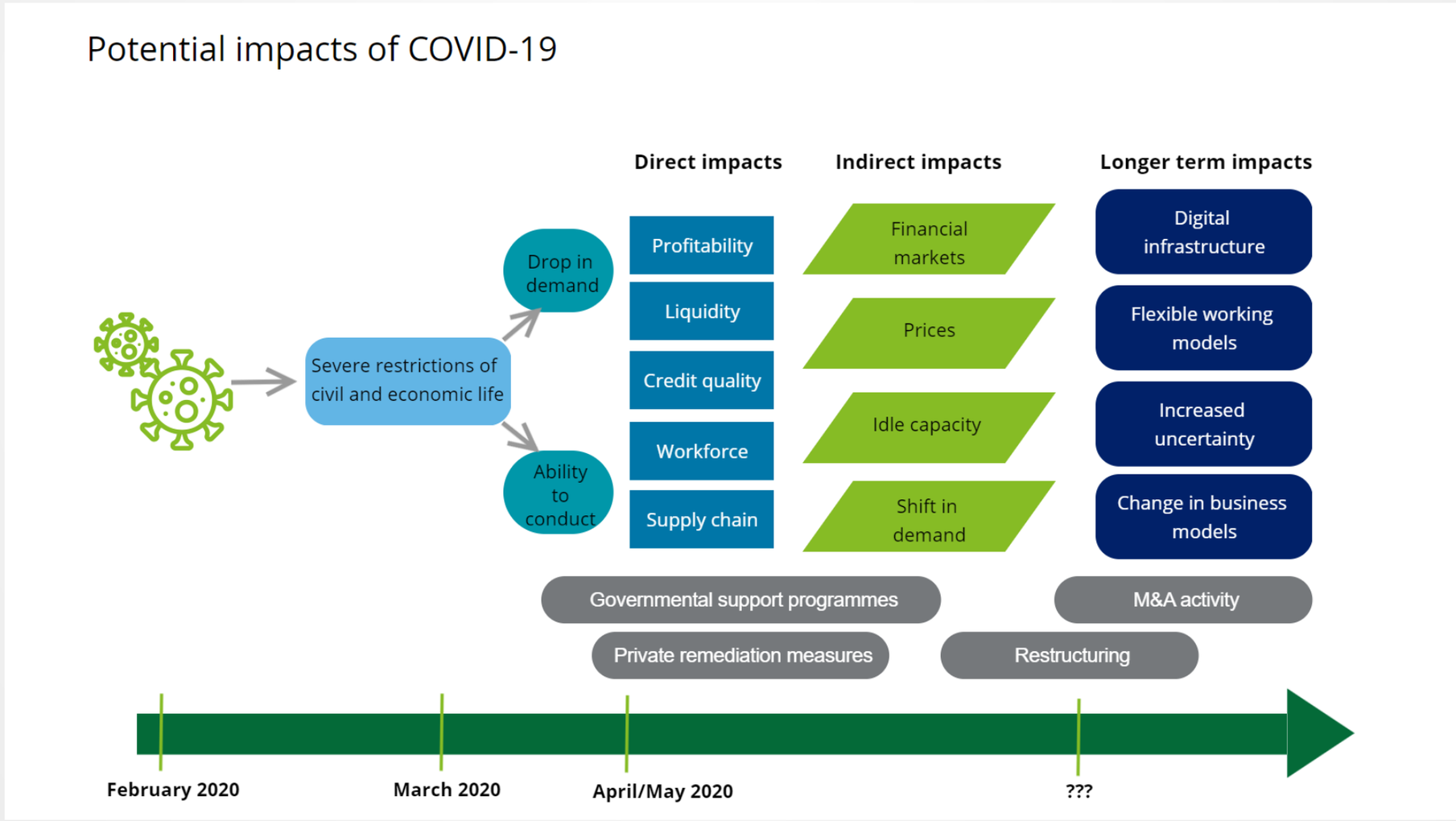
- ⊡ Set-up
- ⊡ Hierarchical Clustering based on industries
- ⊡ Agglomerative Clustering based on all 500 observations and on industries
- ⊡ K-means Clustering

5 - Conclusion

- ⊡ Analysis of results

Introduction

The COVID-19 pandemic is a major event with no precedence in recent history, which will have significant effects on many businesses all over the globe for an undetermined period of time.



Source:https://www2.deloitte.com/ch/en/pages/audit/articles/financial-reporting-survey-q1-2020.html

Introduction

Stock Prices, could be a good indicator for how pandemic affects global society. In our study, we choose the US market and S&P 500 stocks as the targets. The study period is from the first case in the US reported until recent date.

Source:https://edition.cnn.com/business/markets/coronavirus

Data Collecting

The S&P 500 includes 505 stocks from different industries. First, we need to collect the stock names and their industries from Wiki.

```
def save_sp500_tickers():
    resp = requests.get('
    soup = bs.BeautifulSoup(resp.text, 'lxml')
    table = soup.find('table', {'class': 'wikitable sortable'})
    tickers = []
sectors = []
for row in table.findAll('tr')[1:]:
    ticker = row.findAll('td')[0].text
    ticker = ticker[:-1]
    if "." in ticker:
        ticker = ticker.replace('.','-')
        print('ticker replaced to', ticker)
    tickers.append(ticker)
    sector = row.findAll('td')[3].text
    sectors.append(sector)
with open("sp500tickers.pickle","wb") as f:
    pickle.dump(tickers,f)

return tickers, sectors
```

Data Collecting

Second, use the company names as index to collect price data from Yahoo Finance.

```
def get_data_from_yahoo(reload_sp500=False):
    if reload_sp500:
        tickers = save_sp500_tickers()
    else:
        with open("sp500tickers.pickle", "rb") as f:
            tickers = pickle.load(f)
    if not os.path.exists('stock_dfs'):
        os.makedirs('stock_dfs')

start = datetime(2020, 1, 20)
end = dt.datetime.now()

for ticker in tickers:
    # just in case your connection breaks, we'd like to save our progress!
    if not os.path.exists('stock_dfs/{}.csv'.format(ticker)):
        df = web.DataReader(ticker, 'yahoo', start, end)
        df.reset_index(inplace=True)
        df.set_index("Date", inplace=True)
        #df = df.drop("Symbol", axis=1)
        df.to_csv('stock_dfs/{}.csv'.format(ticker))
    else:
        print('Already have {}'.format(ticker))
```

3 Ways to Cluster Companies and Industries

- ⊡ Set-up
- ⊡ Hierarchical Clustering based on industries
- ⊡ Clustering based on all 500 observations and on industries
- ⊡ K-Means Clustering

1. Set up

We have 500 observations, each of which belongs to a specific industry.

First, we use the group.by method to find the mean return and mean variance of all observations in an industry so that we can create hierarchical clustering.

Second, we consider 500 observations and divide them into 4 clusters to see which companies have the closest performances.

We drop ‘CARR’, ‘LUMN’, ‘OTIS’, ‘VNT’, since they do not include any stock prices. We also exclude ‘TSLA’ and ‘VIAC’ for having extreme annual return and kurtosis values respectively.

Python codes for Set-up

```
pdf=pd.read_csv('sp500_dataset.csv')
industry= pdf.groupby(['sector'])['annual_return_log', 'Std' ].mean()
industry = industry.reset_index()

featureset = industry[['annual_return_log']]
feature_mtx = featureset.values

feature500=pdf[['annual_return_log','Std']]
feature500_mtx=feature500.values
```

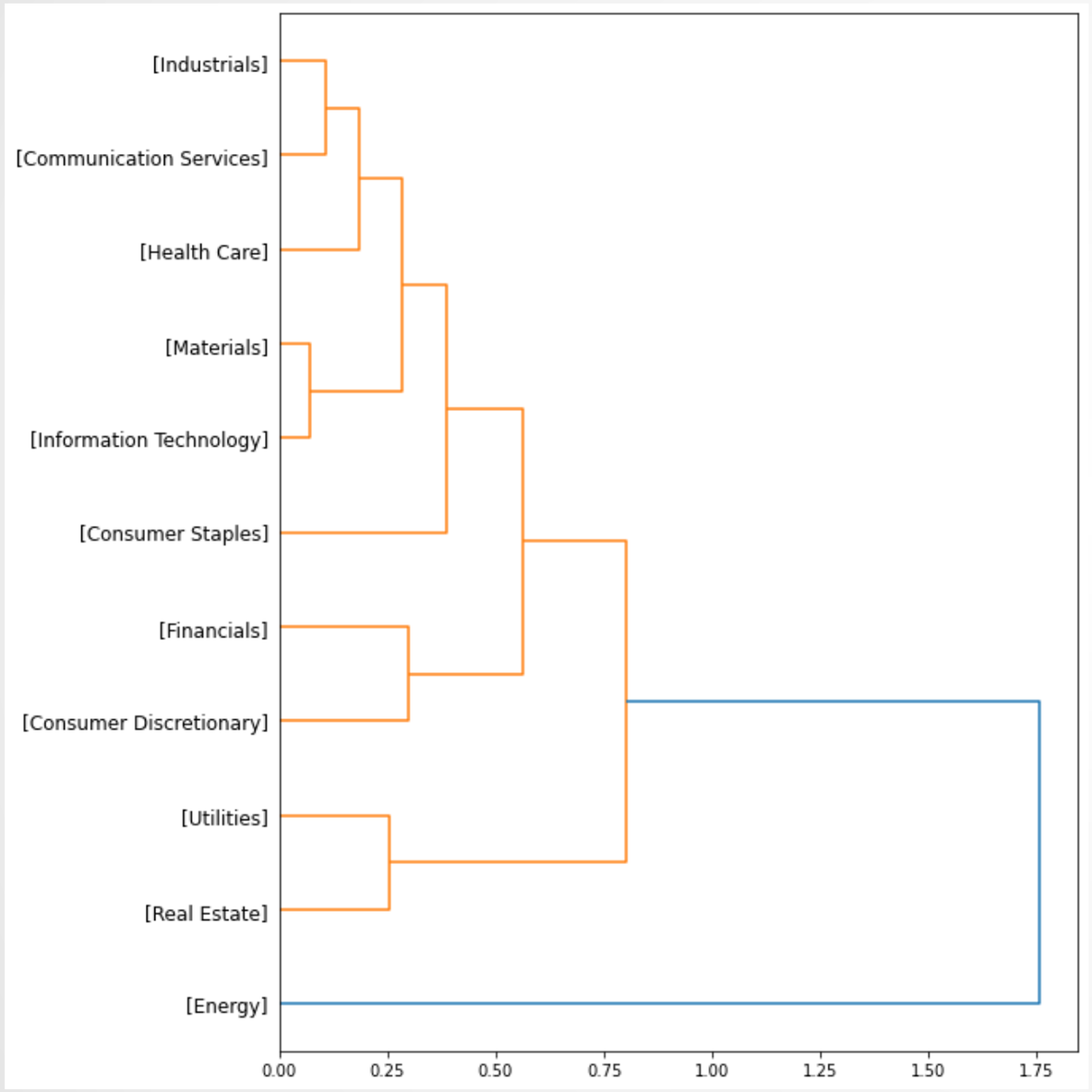
2. Hierarchical Clustering - Concept

What kind of hierarchical clustering is used?

We use agglomerative clustering, which is a down-to-top approach. For example,

- There are n observations. We find the closest pair and group them together as a single observation.
- Now, there are n-1 observations. We repeat the process as in the first step.
- We finish when all points are connected.

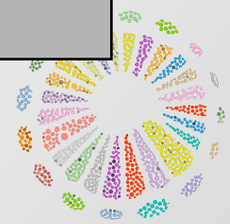
2. Hierarchical Clustering



- ‘Industrials’ is closest to ‘Communication Services’ and they are therefore grouped together.
- Next, ‘Health care’ and the pair mentioned above are the closest and are therefore put together.
- We continue until all categories are connected.

Python codes for clustering based on observations

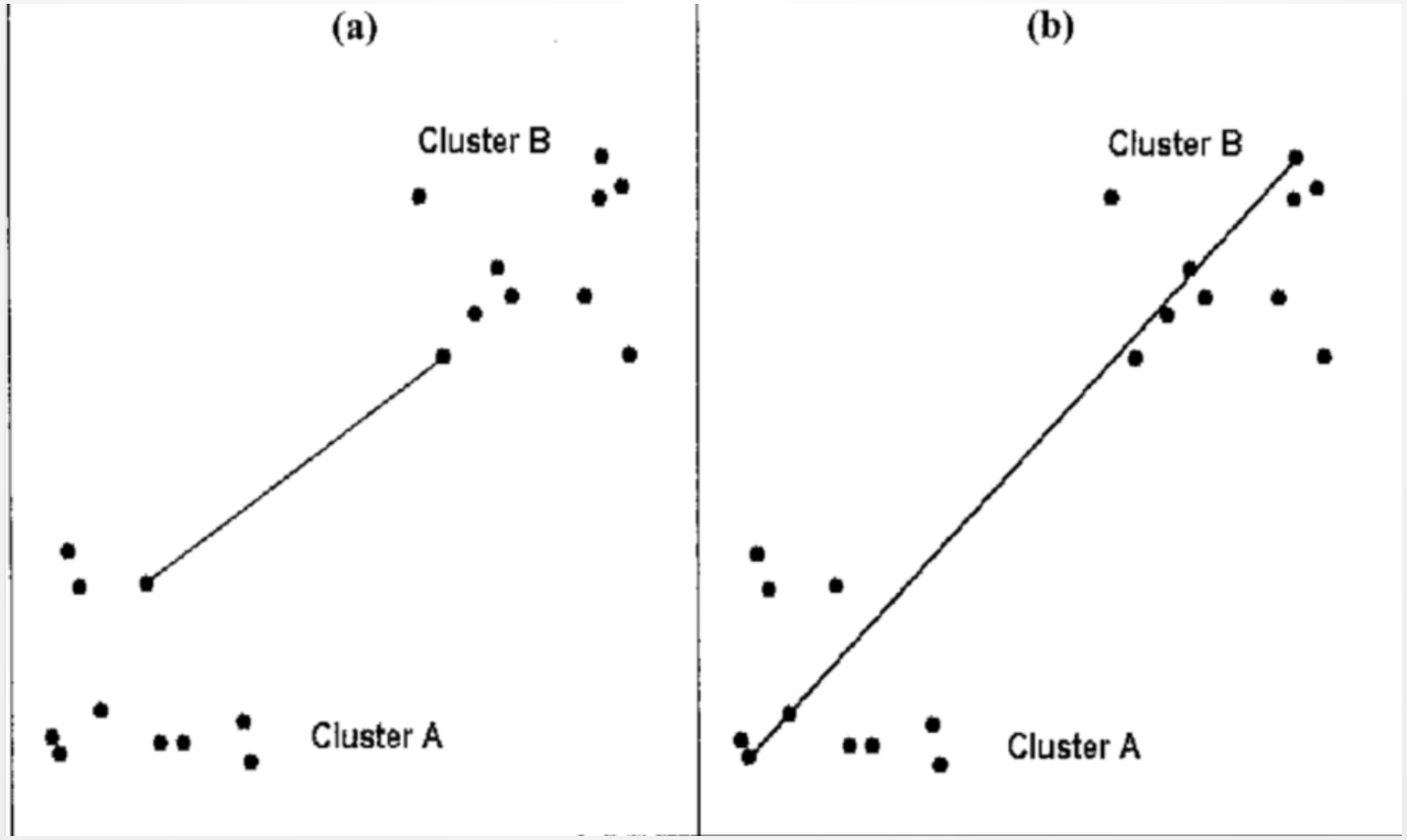
```
import scipy
leng = feature_mtx.shape[0]

D = scipy.zeros([leng,leng])
for i in range(leng):
    for j in range(leng):
        D[i,j] = scipy.spatial.distance.euclidean(feature_mtx[i], feature_mtx[j])
import pylab
import scipy.cluster.hierarchy
Z = hierarchy.linkage(D, 'complete')

from scipy.cluster.hierarchy import fcluster
max_d = 3
clusters = fcluster(Z, max_d, criterion='distance')
clusters

#plot the denrogram
fig = pylab.figure(figsize=(4, 12))
def llf(id):
    return '[%s]' % ( (str(industry['sector'][id])) )
dendro = hierarchy.dendrogram(Z,  leaf_label_func=llf, leaf_rotation=0, leaf_font_size =12,
orientation = 'right')
```



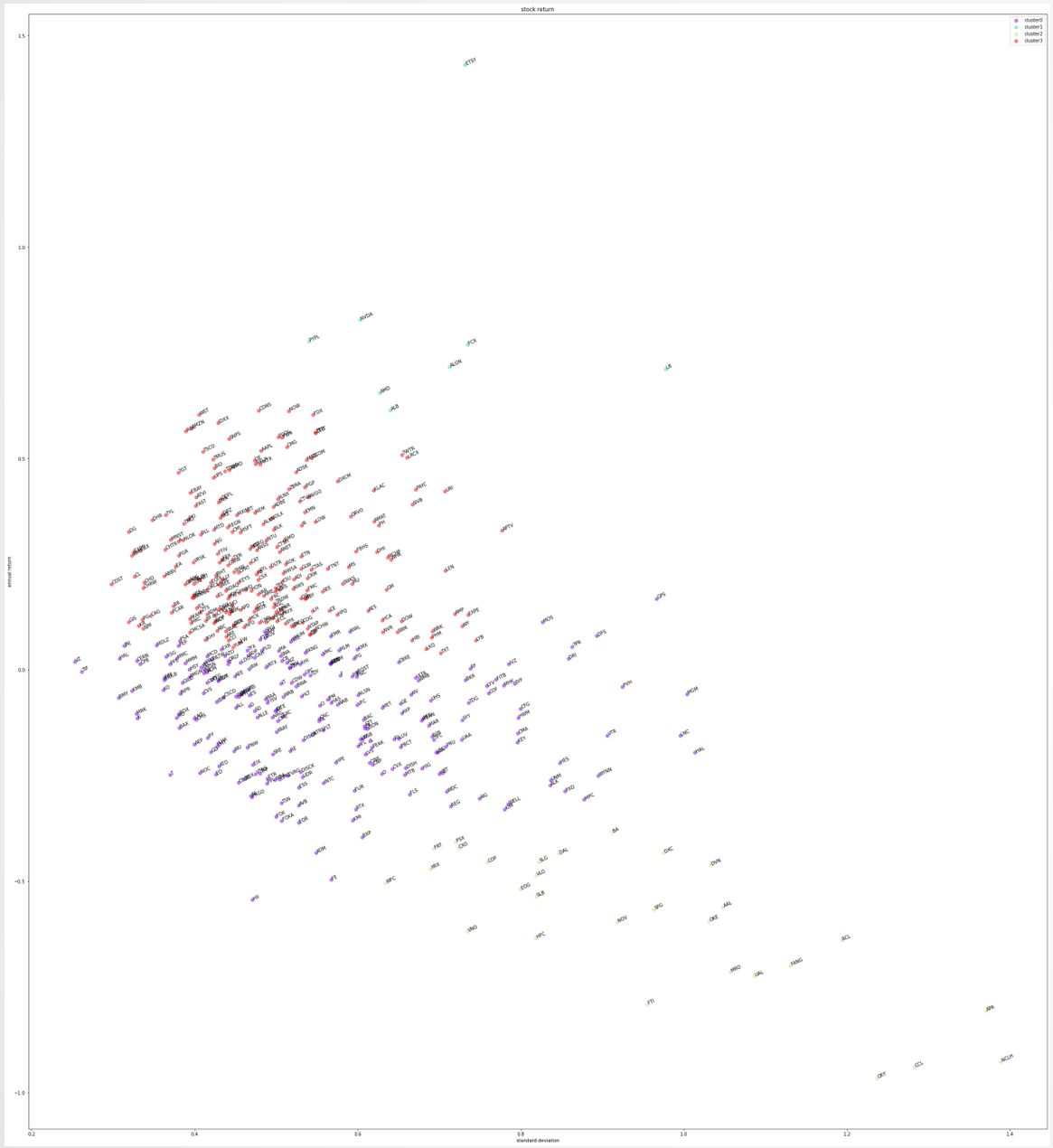
3. Clustering by complete distance - Concept

In our sample, we use the ‘complete’ distance method to group data. So the distance is based on a observation in a cluster which is the furtherest away from the one in another cluster.

The graph below compares two kinds of linkage: (a) Single linkage (b) Complete linkage.



3. Clustering by complete distance



Variables used to calculated the distance matrix:

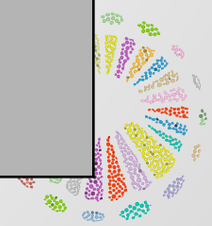
- Stock return
- Stock variance

We set the number of clusters as 4.

We can see that two clusters are in the centre (red and purple) and two are in SE and NW (light green and blue, which is represented by green, brown and yellow)

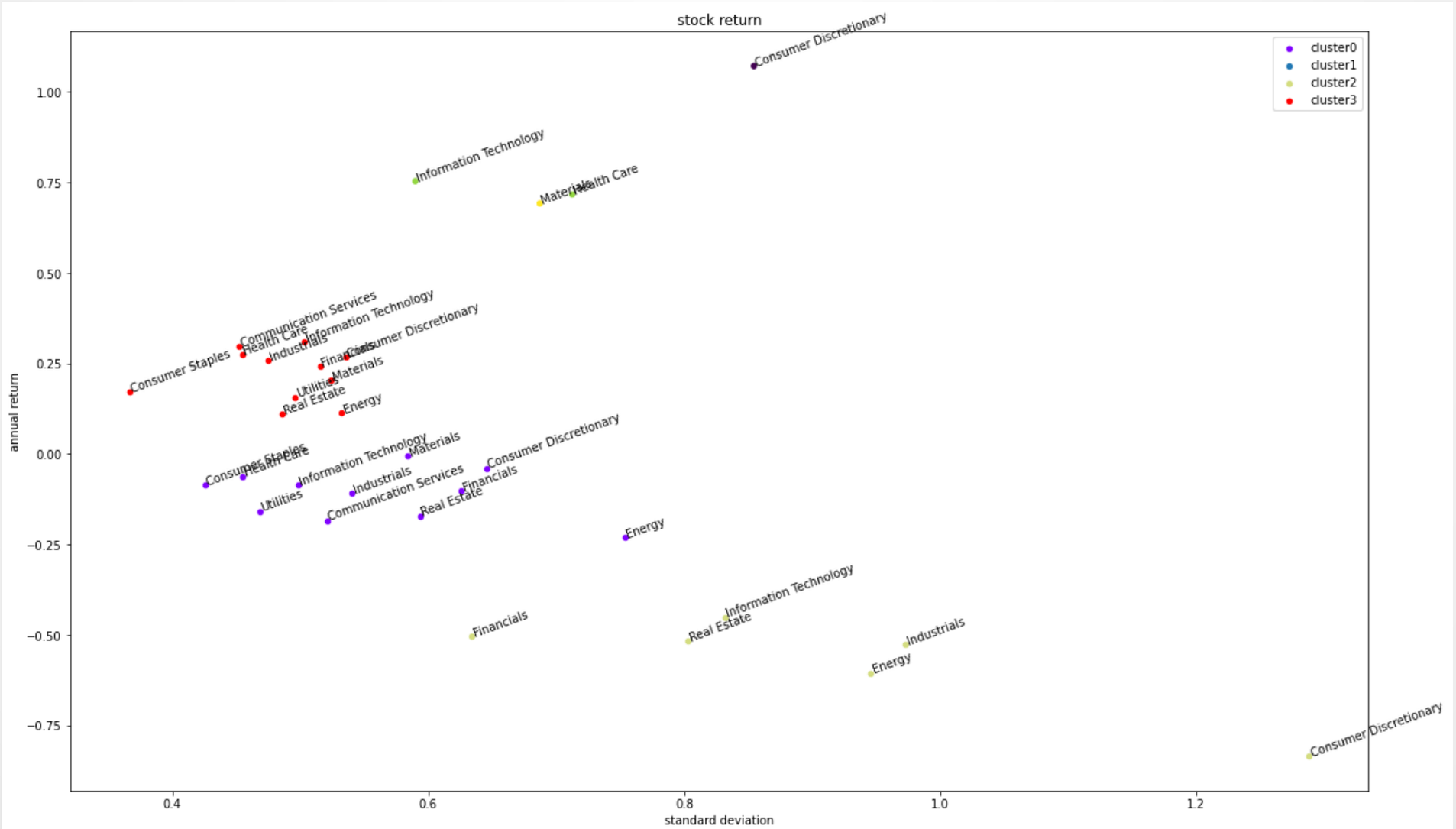
Python code for clustering based on observations

```
dist_matrix = distance_matrix(feature500_mtx,feature500_mtx)
agglom = AgglomerativeClustering(n_clusters = 4, linkage = 'complete')
agglom.fit(feature500_mtx)
agglom.labels_
pdf['cluster_'] = agglom.labels_
pdf.head()

import matplotlib.cm as cm
n_clusters = max(agglom.labels_)+1
colors = cm.rainbow(np.linspace(0, 1, n_clusters))
cluster_labels = list(range(0, n_clusters))
plt.figure(figsize=(40,45))

for color, label in zip(colors, cluster_labels):
    subset = pdf[pdf.cluster_ == label]
    for i in subset.index:
            plt.text(subset.Std[i], subset.annual_return_log[i], str(subset['Company'][i]), rotation=25)
    plt.scatter(subset.Std, subset.annual_return_log, s= 50, c=color,
label='cluster'+str(label),alpha=0.5)

plt.legend()
plt.title('stock return')
plt.xlabel('standard deviation')
plt.ylabel('annual return')
```



3. Clustering by complete distance (industry modified)

The result here is similar to the previous one.
We only identify the industries that each observation belongs to.



Python code for clustering based on observations (modified by industries)

```
df2= pdf.groupby(['cluster_', 'sector'])['annual_return_log', 'Std' ].mean()

plt.figure(figsize=(20,12))
for color, label in zip(colors, cluster_labels):
    subset = df2.loc[(label,),]
    for i in subset.index:
        plt.text(subset.loc[i][1], subset.loc[i][0], str(i), rotation=20)
    plt.scatter(subset.Std, subset.annual_return_log, s=20, c=color, label='cluster'+str(label))
plt.legend()
plt.title('stock return')
plt.xlabel('standard deviation')
plt.ylabel('annual return')
```

4. K-mean Clustering - Concept

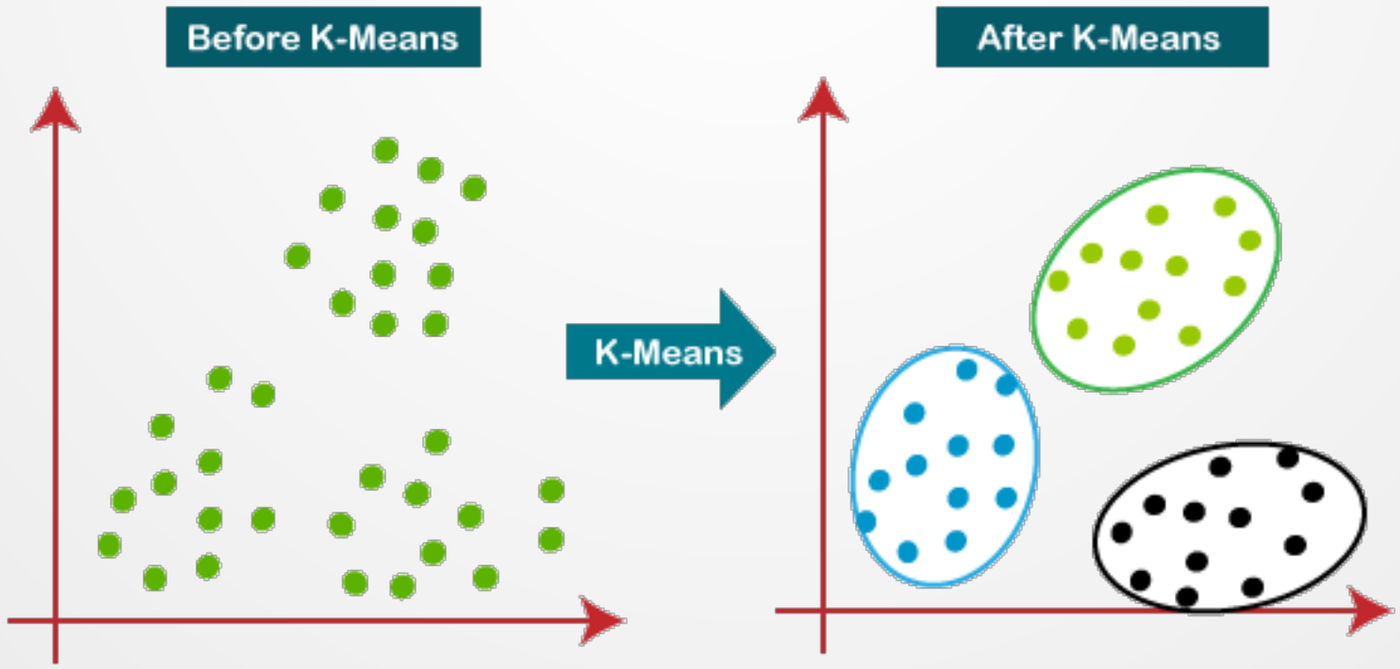
K-means Clustering follow the steps below:

1. Self-determine the number of centroids and randomly place them on a graph.

2. Calculate the distance of each point from each centroid and assign the points to its closest centroids.

3. Recalculate the position of the k centroids.

4. Repeat the above steps until the centroids no longer move.

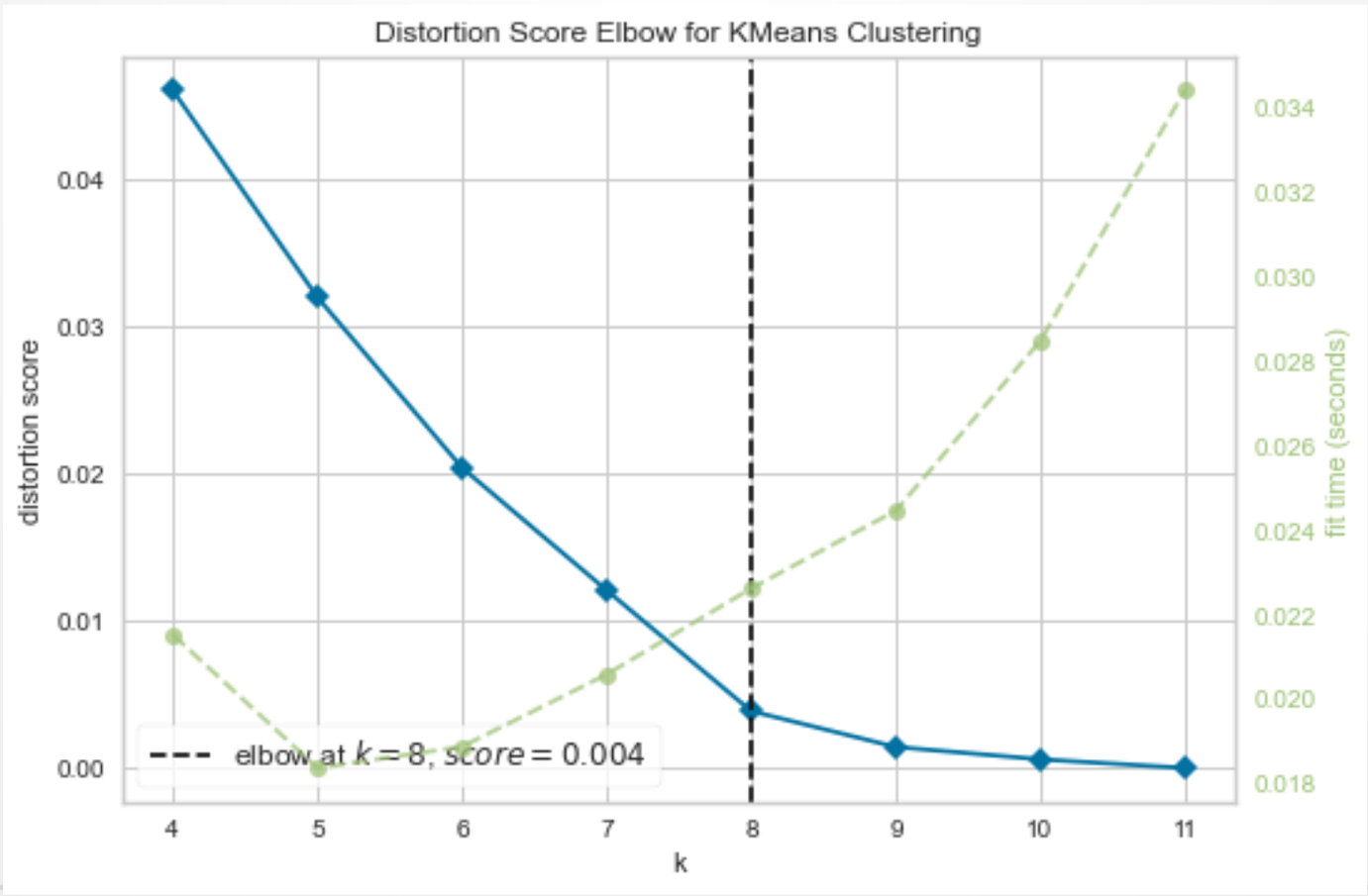


4. K-Means Clustering: Choosing the optimal k

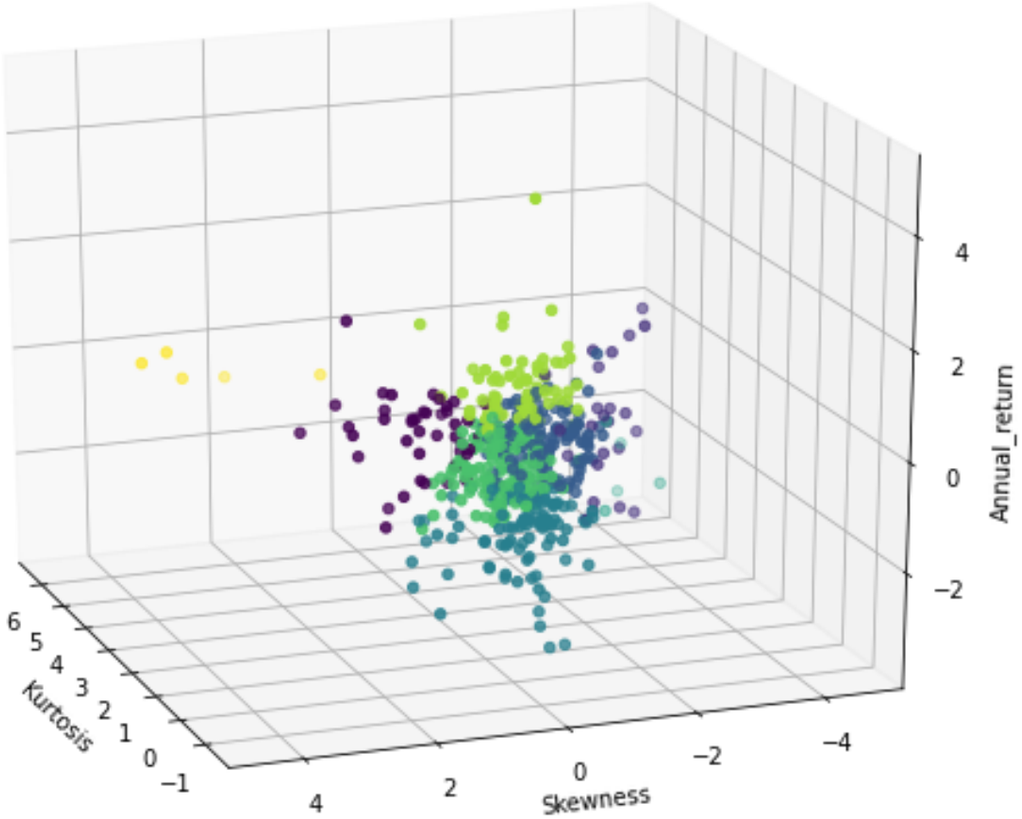
We apply the **Elbow point** method:

- **Distance score**: it is the distance between points and centroids, always goes down as k increases.
- **Optimal k**: it is determined by the point where decline in the score slows down hugely. In our case, the optimal k is 8.
-

Set up: we normalise the data since it helps algorithms to interpret features with different magnitudes and distributions equally. If not, too much weight would be given to kurtosis in our case.



4. K-Means Clustering: Skewness



Cluster group:

by adapting k=8, we see a pattern when looking from the skewness angle.

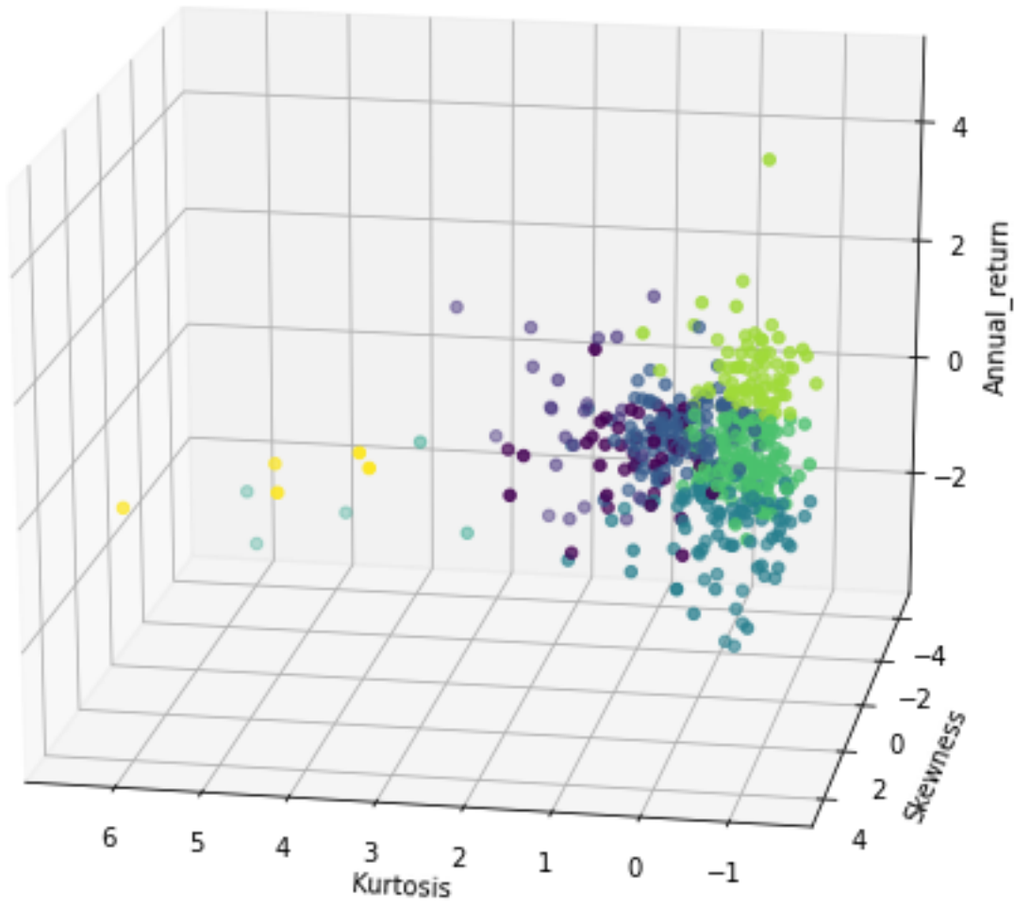
Skewness:

most observations have negative skewness, meaning the median is larger than the mean and the mode is to the right side of the distribution.

Sum:

Even though almost each observation has a negative average annual return, its daily returns are mostly positive. Short-term trades could be more profitable than long-term investments.

4. K-Means Clustering: Kurtosis



Cluster group:

it is evident that kurtosis and annual return influence the cluster groups.

Kurtosis:

although many observations have a value of zero, positive kurtosis values are common. So the distributions of daily returns of each observations are thin and tight.

Sum:

volatility of the daily returns is not high. Stocks with high returns and low volatility are typically attractive to investors.

Python code for K-Means Clustering set-up and choosing the optimal k

```
#Import files and select variables
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from mpl_toolkits.mplot3d import Axes3D
feature=pdf[['annual_return_log','Skewness','Kurtosis']]
feature_mtx2=feature.values

#Normalisation
from sklearn.preprocessing import StandardScaler
feature_mtx2 = StandardScaler().fit_transform(feature_mtx2)

#Elbow point method. (This part needs to be done separately as it eliminates the colours of the
cluster points)
from sklearn.cluster import KMeans
from yellowbrick.cluster import KElbowVisualizer
model = KMeans()
visualizer = KElbowVisualizer(model, k=(4,12))

visualizer.fit(feature_mtx)        # Fit the data to the visualizer
visualizer.show()
```

Python code for K-Means Clustering in a 3D graph

```
#K-Means calculation
clusterNum = 6
k_means = KMeans(init = "k-means++", n_clusters = clusterNum, n_init = 12)
k_means.fit(feature_mtx2)
labels = k_means.labels_

#Visualisation
fig = plt.figure(1, figsize=(8, 6))
plt.clf()
ax = Axes3D(fig, rect=[0, 0, .95, 1], elev=20, azim=160)    #azim allows us to change the angle
horizontally
plt.cla()
ax.set_xlabel(‘Kurtosis')
ax.set_ylabel('Skewness')
ax.set_zlabel('Annual_return')

ax.scatter(feature_mtx2[:, 2], feature_mtx2[:, 1], feature_mtx2[:, 0], c= labels.astype(np.float))
```

Conclusion

Based on stock returns and volatility during pandemic, stocks are distributed to 4 clusters, which have different performance.

There could be big variance among industries, though they have similar feature at most time.

Companies from IT, Industrial, Energy, Consumer Discretionary are more likely to have divergent performance.