DATA 3300

ICE - Clustering Analysis

Name: Chance Wiese

Q1

Load the required packages and then import the dataset

```
# install a new library called kneed using pip installer
!pip install kneed
```

```
Collecting kneed
  Downloading kneed-0.8.5-py3-none-any.whl (10 kB)
Requirement already satisfied: numpy>=1.14.2 in /usr/local/lib/python3.10/dist-packages (from kneed) (1.23.5
Requirement already satisfied: scipy>=1.0.0 in /usr/local/lib/python3.10/dist-packages (from kneed) (1.11.4)
Installing collected packages: kneed
Successfully installed kneed-0.8.5
```

```
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
from kneed import KneeLocator
import sklearn.cluster
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
from sklearn.preprocessing import StandardScaler
```

```
# read in the dataframe
df = pd.read_csv("/content/sandp500.csv")
# display a heading
df.head()
```

	Symbol	Name	Sector	Price	Dividend Yield	Price/Earnings	Earnings/Share
0	A	Agilent Technologies Inc	Health Care	51.21	1.02	32.85	1.56
1	AAL	American Airlines Group	Industrials	44.84	0.85	9.32	4.81
2	AAP	Advance Auto Parts	Consumer Discretionary	151.99	0.15	24.51	6.20
3	AAPL	Apple Inc.	Information Technology	139.52	1.63	16.75	8.33
4	ABBV	AbbVie	Health Care	63.69	4.04	17.55	3.63

1A

Before running the actual clustering analysis, you're going to exclude the Symbol and Name variables. Explain why this is important to do:

These are both primary keys, and therefore won't contribute meaningful information to our analysis.

1B

Also there would be a problem with keeping all three of Price, 52 Week High, and 52 Week Low involved when the clustering analysis is run. Explain why this is the case.

```
df.columns
```

```
Index(['Symbol', 'Name', 'Sector', 'Price', 'Dividend Yield', 'Price/Earnings',
       'Earnings/Share', 'Book Value', '52 week low', '52 week high',
       'Market Cap', 'EBITDA', 'Price/Sales', 'Price/Book'],
      dtype='object')
```

```
df = df.drop(['Symbol', 'Name', '52 week low', '52 week high', 'Sector'], axis=1) #drop out redundant columns and
# drop missing values
df = df.dropna()

df.head()
```

	Price	Dividend Yield	Price/Earnings	Earnings/Share	Book Value	Market Cap	EBITDA	Price/S
0	51.21	1.02	32.85	1.56	13.35	16.49	0.942	
1	44.84	0.85	9.32	4.81	7.46	22.61	7.830	
2	151.99	0.15	24.51	6.20	39.66	11.18	1.120	
3	139.52	1.63	16.75	8.33	25.19	732.00	69.750	
4	63.69	4.04	17.55	3.63	2.91	101.52	10.950	

```
# switch sector to dummy variables
# df = pd.get_dummies(data = df, drop_first = False)

# df.head()
```

Because it would be redundant and would overwieght this variable as it counts the same thing three different ways.

Q2

Run a clustering analysis in Python to find three groups of similar stocks.

Your analysis should address each of the following considerations (pre-processing)

1. **It should remove variables not to be included in the analysis**
2. **It should normalize all variables using the Z-transformation method**
3. **It should utilize the K-means clustering method**

```
# use the standard scaler function
scaler = StandardScaler()
# normalize features
scaled_features = scaler.fit_transform(df)
scaled_features
```

```
# add comments to explain the kmeans parameters
```

```
kmeans = KMeans(
    init="random",      # init does
    n_clusters=3,       # n_clusters does
    n_init=10,          # n_init does
    max_iter=300,       # max_iter does
    random_state=42     # random_state does
)


kmeans.fit(scaled_features)
# find SSE value or inertia value of the model
kmeans.inertia_
```

```
2858.255995389018
```

Q3

Use the Elbow rule to determine the optimal number of clusters between 1-11 by:

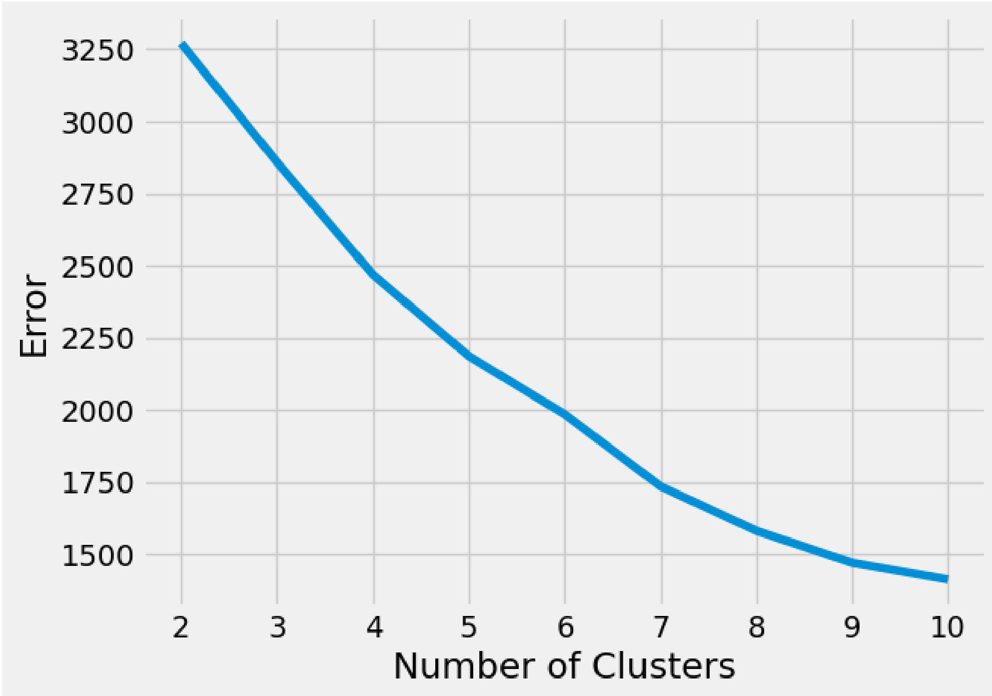
1. **Running k-means iteratively on k of size 1-11**
2. **Plotting the SSE curve by k size**
3. **Using the Knee Locator method**

```
kmeans_kwargs = {
    "init": "random",
    "n_init": 10,
    "max_iter": 300,
    "random_state": 42,
}

sse = []
# create empty list for SSE values
for k in range(2,11):       # replace a and b with the range of values for the number of clusters
    kmeans = KMeans(n_clusters=k, **kmeans_kwargs)
    kmeans.fit(scaled_features)
    sse.append(kmeans.inertia_)

sse


plt.style.use("fivethirtyeight")
plt.plot(range(2,11), sse)
plt.xticks(range(2,11))
plt.xlabel("Number of Clusters")
plt.ylabel("Error")
plt.show()
```




```
kl = KneeLocator(
    range(2,11), sse, curve="convex", direction="decreasing"                     # replace a and b with the appı
)

# locate knee/elbow in the plot
kl.elbow
```

    7

Q4

Rerun kmeans with the optimal number of clusters and report its SSE value. Is it less than when k was set to 3? Why would this occur?

```
# copy down the initial kmeans parameters, what do we need to change to make 5 clusters instead of 3?
kmeans = KMeans(
    init="random",      # init does
    n_clusters=7,       # n_clusters does
    n_init=10,          # n_init does
    max_iter=300,       # max_iter does
    random_state=42     # random_state does
)


kmeans.fit(scaled_features)
kmeans.inertia_
```

    1735.1124862672036

The inertia did decrease by including more clusters. Generally by adding in more clusters leads to having more similar stocks grouped together

Q5

Generate a centroid table using the cluster_centers_ feature from kmeans, convert the array into a dataframe. Which cluster of stocks are the highest price on average, how do you know?

```
# save cluster centroids to an object called 'centroids'
centroids = kmeans.cluster_centers_
centroid_table = pd.DataFrame(centroids,
                              columns = df.columns,
                              index =['cl_0','cl_1','cl_2','cl_3','cl_4','cl_5','cl_6'])

# display table
centroid_table
```

Cluster 6 has the highest average stock prices. We know this because its centroid for price is almost 5x above the average. (4.65)

Q6

Now create a new centroid table after de-normalizing the centroid values. Why is it important to de-normalize your centroids after the fact?

```
# de-normalize centroid values from centroids object, called unscaled
unscaled = scaler.inverse_transform(centroids)
unscaled_centroid_table = pd.DataFrame(unscaled,
                              columns = df.columns,
                              index =['Cluster_0', 'Cluster_1', 'Cluster_2', 'Cluster_3', 'Cluster_4', 'Cluster_

unscaled_centroid_table #produce a non-scaled centroid table
```

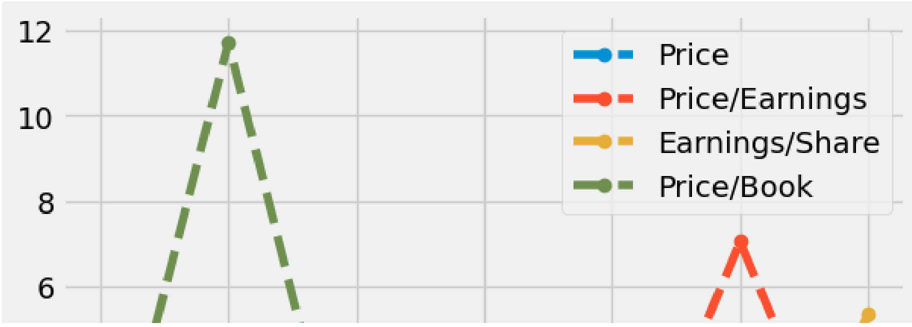
It's easier to communicate about findings and interpret your clusters when they are in tersm of their natural units (USD)

Q7

Explore plotting the centroid values to examine differences between clusters across the different variables of interest. Then come up with a brief descriptive title for each of the 5 clusters of stocks:

1. **Cluser_0:** Average Joe Performers
2. **Cluster_1:** Low Book Values
3. **Cluster_6:** High Risk, High Reward

```
centroid_table.plot(kind = 'line', y = ['Price', 'Price/Earnings', 'Earnings/Share', 'Price/Book'], style = '--
plt.show()
```



Q8

Based on your plot and centroid tables, describe which cluster of stocks you'd recommend and why. Create a visualization that supports your recommendation (pull from the data understanding module!). Briefly describe what the viz is showing and why it's relevant.

```
unscaled_centroid_table.plot(kind = 'bar', y = ['Price','Market Cap'])
plt.title("Stock Cluster Price & Market Cap")
plt.ylabel("USD")
plt.show()
```