Unsupervised Learning Project: Trade & Ahead

Context

The stock market has consistently proven to be a good place to invest in and save for the future. There are a lot of compelling reasons to invest in stocks. It can help in fighting inflation, create wealth, and also provides some tax benefits. Good steady returns on investments over a long period of time can also grow a lot more than seems possible. Also, thanks to the power of compound interest, the earlier one starts investing, the larger the corpus one can have for retirement. Overall, investing in stocks can help meet life's financial aspirations.

It is important to maintain a diversified portfolio when investing in stocks in order to maximise earnings under any market condition. Having a diversified portfolio tends to yield higher returns and face lower risk by tempering potential losses when the market is down. It is often easy to get lost in a sea of financial metrics to analyze while determining the worth of a stock, and doing the same for a multitude of stocks to identify the right picks for an individual can be a tedious task. By doing a cluster analysis, one can identify stocks that exhibit similar characteristics and ones which exhibit minimum correlation. This will help investors better analyze stocks across different market segments and help protect against risks that could make the portfolio vulnerable to losses.

Objective

Trade&Ahead is a financial consultancy firm who provide their customers with personalized investment strategies. They have hired you as a Data Scientist and provided you with data comprising stock price and some financial indicators for a few companies listed under the New York Stock Exchange. They have assigned you the tasks of analyzing the data, grouping the stocks based on the attributes provided, and sharing insights about the characteristics of each group.

Data Dictionary

- Ticker Symbol: An abbreviation used to uniquely identify publicly traded shares of a particular stock on a particular stock market
- Company: Name of the company
- GICS Sector: The specific economic sector assigned to a company by the Global Industry Classification Standard (GICS) that best defines its business operations
- GICS Sub Industry: The specific sub-industry group assigned to a company by the Global Industry Classification Standard (GICS) that best defines its business operations

- Current Price: Current stock price in dollars
- Price Change: Percentage change in the stock price in 13 weeks
- Volatility: Standard deviation of the stock price over the past 13 weeks
- ROE: A measure of financial performance calculated by dividing net income by shareholders' equity (shareholders' equity is equal to a company's assets minus its debt)
- Cash Ratio: The ratio of a company's total reserves of cash and cash equivalents to its total current liabilities
- Net Cash Flow: The difference between a company's cash inflows and outflows (in dollars)
- Net Income: Revenues minus expenses, interest, and taxes (in dollars)
- Earnings Per Share: Company's net profit divided by the number of common shares it has outstanding (in dollars)
- Estimated Shares Outstanding: Company's stock currently held by all its shareholders
- P/E Ratio: Ratio of the company's current stock price to the earnings per share
- P/B Ratio: Ratio of the company's stock price per share by its book value per share (book value of a company is the net difference between that company's total assets and total liabilities)

Importing necessary libraries, data, and creating functions

```
from google.colab import drive
drive.mount('/content/drive')
```

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

```
# Libraries to help with reading and manipulating data
import numpy as np
import pandas as pd

# Libraries to help with data visualization
import matplotlib.pyplot as plt
import seaborn as sns

# to scale the data using z-score
from sklearn.preprocessing import StandardScaler

# to compute distances
from scipy.spatial.distance import cdist, pdist

# to perform k-means clustering and compute silhouette scores
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score

# to perform hierarchical clustering, compute cophenetic correlation, and crea
```

```
from sklearn.cluster import AgglomerativeClustering
from scipy.cluster.hierarchy import dendrogram, linkage, cophenet

# to perform PCA
from sklearn.decomposition import PCA

# to visualize the elbow curve and silhouette scores
from yellowbrick.cluster import KElbowVisualizer, SilhouetteVisualizer

#format numeric data for easier readability
pd.set_option(
    "display.float_format", lambda x: "%.2f" % x
)  # to display numbers rounded off to 2 decimal places

# Removes the limit for the number of displayed columns
pd.set_option("display.max_columns", None)
# Sets the limit for the number of displayed rows
pd.set_option("display.max_rows", 200)

# To supress warnings
import warnings
warnings.filterwarnings("ignore")
```

```
# function to create labeled barplots


def labeled_barplot(data, feature, perc=False, n=None):
    """
    Barplot with percentage at the top

    data: dataframe
    feature: dataframe column
    perc: whether to display percentages instead of count (default is False)
    n: displays the top n category levels (default is None, i.e., display all levels)
    """

    total = len(data[feature])  # length of the column
    count = data[feature].nunique()
    if n is None:
        plt.figure(figsize=(count + 1, 5))
    else:
        plt.figure(figsize=(n + 1, 5))

    plt.xticks(rotation=90, fontsize=12)
    ax = sns.countplot(
        data=data,
        x=feature,
        palette="viridis",
        order=data[feature].value_counts().index[:n].sort_values(),
    )

    for p in ax.patches:
        if perc == True:
            label = "{:.1f}%".format(
                100 * p.get_height() / total
            )  # percentage of each class of the category
        else:
            label = p.get_height()  # count of each level of the category

        x = p.get_x() + p.get_width() / 2  # width of the plot
        y = p.get_height()  # height of the plot

        ax.annotate(
            label,
            (x, y),
            ha="center",
            va="center",
            size=12,
            xytext=(0, 5),
            textcoords="offset points",
        )  # annotate the percentage

    plt.show()  # show the plot
```

```
# function to plot a boxplot and a histogram along the same scale

def histogram_boxplot(data, feature, figsize=(16, 6), kde=False, bins=None, hue=None):
    """
    Combines boxplot and histogram

    data: dataframe
    feature: dataframe column
    figsize: size of figure (default (16,6))
    kde: whether to show the density curve (default False)
    bins: number of bins for histogram (default None)
    """
    f2, (ax_box2, ax_hist2) = plt.subplots(
        nrows=2,  # Number of rows of the subplot grid= 2
        sharex=True,  # x-axis will be shared among all subplots
        gridspec_kw={"height_ratios": (0.25, 0.75)},
        figsize=figsize,
    )  # creating the 2 subplots
    sns.boxplot(
        data=data, x=feature, ax=ax_box2, showmeans=True,
    )  # boxplot will be created and a star will indicate the mean value of the column
    sns.histplot(
        data=data, x=feature, kde=kde, ax=ax_hist2, bins=bins, palette="winter",
    ) if bins else sns.histplot(
        data=data, x=feature, kde=kde, ax=ax_hist2
    )  # For histogram
    ax_hist2.axvline(
        data[feature].mean(), color="green", linestyle="--"
    )  # Add mean to the histogram
    ax_hist2.axvline(
        data[feature].median(), color="black", linestyle="-"
    )  # Add median to the histogram
```

```
#reading csv file into a pandas Dataframe
ta = pd.read_csv('/content/drive/MyDrive/Unsupervised Learning/stock_data.csv')
# copying data to another varaible to preserve original data
df = ta.copy()
```

Data Overview

```
# print a sample of five rows randomly selected from the training data
df.sample(n=5)
```

	Ticker Symbol	Security	GICS Sector	GICS Sub Industry	Current Price	Price Change	Volatility	ROE	Cash Ratio
75	COF	Capital One Financial	Financials	Consumer Finance	72.18	-0.62	1.36	9	99
199	MAS	Masco Corp.	Industrials	Building Products	28.30	11.64	1.43	263	61
214	MPC	Marathon Petroleum	Energy	Oil & Gas Refining & Marketing & Transportation	51.84	11.51	1.99	22	18
235	OKE	ONEOK	Energy	Oil & Gas Exploration & Production	24.66	-24.12	3.56	73	6
334	XYL	Xylem Inc.	Industrials	Industrial Conglomerates	36.50	11.01	1.17	16	83

```
1 df.shape
```

```
(340, 15)
```

- Dataset has 340 rows and 15 columns

```
1 # print the data types of the columns within the datset
2 df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 340 entries, 0 to 339
Data columns (total 15 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   Ticker Symbol                340 non-null    object
 1   Security                     340 non-null    object
 2   GICS Sector                  340 non-null    object
 3   GICS Sub Industry            340 non-null    object
 4   Current Price                340 non-null    float64
 5   Price Change                 340 non-null    float64
 6   Volatility                   340 non-null    float64
 7   ROE                          340 non-null    int64
 8   Cash Ratio                   340 non-null    int64
 9   Net Cash Flow                340 non-null    int64
 10  Net Income                   340 non-null    int64
 11  Earnings Per Share           340 non-null    float64
 12  Estimated Shares Outstanding 340 non-null    float64
 13  P/E Ratio                    340 non-null    float64
```

```
 14  P/B Ratio                     340 non-null    float64
dtypes: float64(7), int64(4), object(4)
memory usage: 40.0+ KB
```

```
# checking for duplicate values
df.duplicated().sum()
```

```
0
```

- Dataset has no missing or duplicate values
- All columns with dtype object should be dtype category in order to conserve memory

```
# convert all columns with dtype object into category
for col in df.columns[df.dtypes=='object']:
    df[col] = df[col].astype('category')
```

```
# dropping the ticker symbol column, as it does not provide any information
df.drop("Ticker Symbol", axis=1, inplace=True)
```

```
# confirm new dataset
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 340 entries, 0 to 339
Data columns (total 14 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   Security                      340 non-null    category
 1   GICS Sector                   340 non-null    category
 2   GICS Sub Industry             340 non-null    category
 3   Current Price                 340 non-null    float64
 4   Price Change                  340 non-null    float64
 5   Volatility                    340 non-null    float64
 6   ROE                           340 non-null    int64
 7   Cash Ratio                    340 non-null    int64
 8   Net Cash Flow                 340 non-null    int64
 9   Net Income                    340 non-null    int64
 10  Earnings Per Share            340 non-null    float64
 11  Estimated Shares Outstanding  340 non-null    float64
 12  P/E Ratio                     340 non-null    float64
 13  P/B Ratio                     340 non-null    float64
dtypes: category(3), float64(7), int64(4)
memory usage: 46.7 KB
```

- The 14 columns have three different dtypes: category(3), float64(7), int64(4)
- All of these dtypes are appropriate for their respective columns

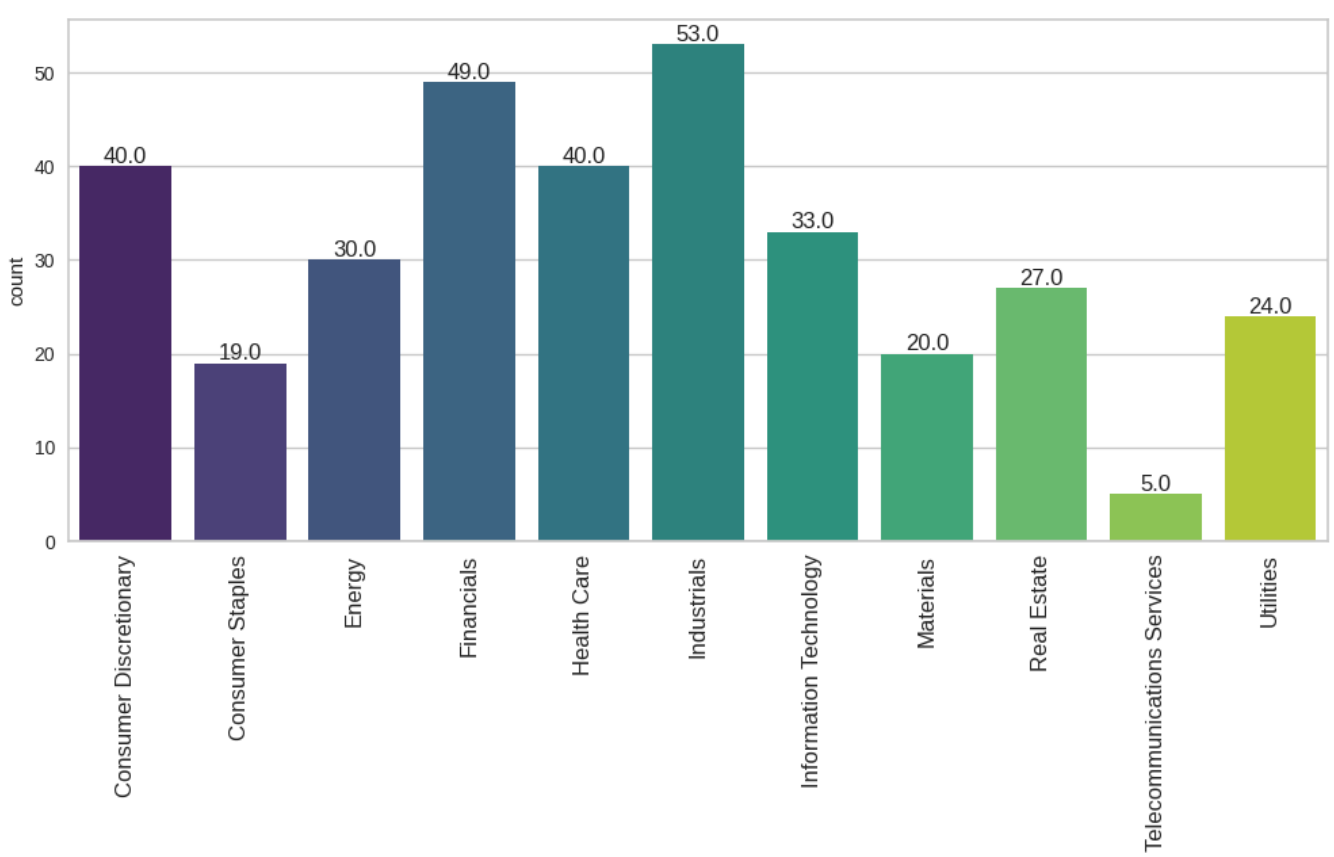
Exploratory Data Analysis (EDA)

```
1 #provide statistical summary of all categorical columns
2 df.describe(include='category').T
```

	count	unique	top	freq
Security	340	340	3M Company	1
GICS Sector	340	11	Industrials	53
GICS Sub Industry	340	104	Oil & Gas Exploration & Production	16

GICS Sector

```
1 #create labeled barplot of stocks by sector
2 labeled_barplot(df, 'GICS Sector')
```




```
1 #display the five sectors with the most number of stocks
2 df["GICS Sector"].value_counts().head(n=5)
```

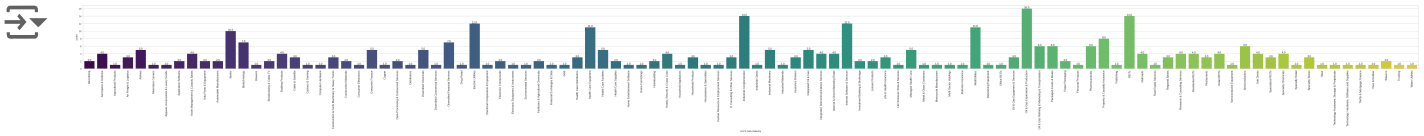
```
Industrials              53
Financials               49
Consumer Discretionary   40
```

```
Health Care               40
Information Technology    33
Name: GICS Sector, dtype: int64
```

- The stocks are drawn from 11 different industrial sectors, with no one sector comprising more than 16% of the dataset
- The top 4 of the 11 sectors (industrials, financials, consumer discretionary, and health care) comprise over half of the total number of stocks

GICS Sub Industry

```
1 #create labeled barplot of stocks by sub industry
2 labeled_barplot(df, 'GICS Sub Industry')
```



```
1 #display the five sub industries with the most number of stocks
2 df['GICS Sub Industry'].value_counts().head(n=5)
```

```
Oil & Gas Exploration & Production    16
REITs                                 14
Industrial Conglomerates              14
Internet Software & Services          12
Electric Utilities                    12
Name: GICS Sub Industry, dtype: int64
```

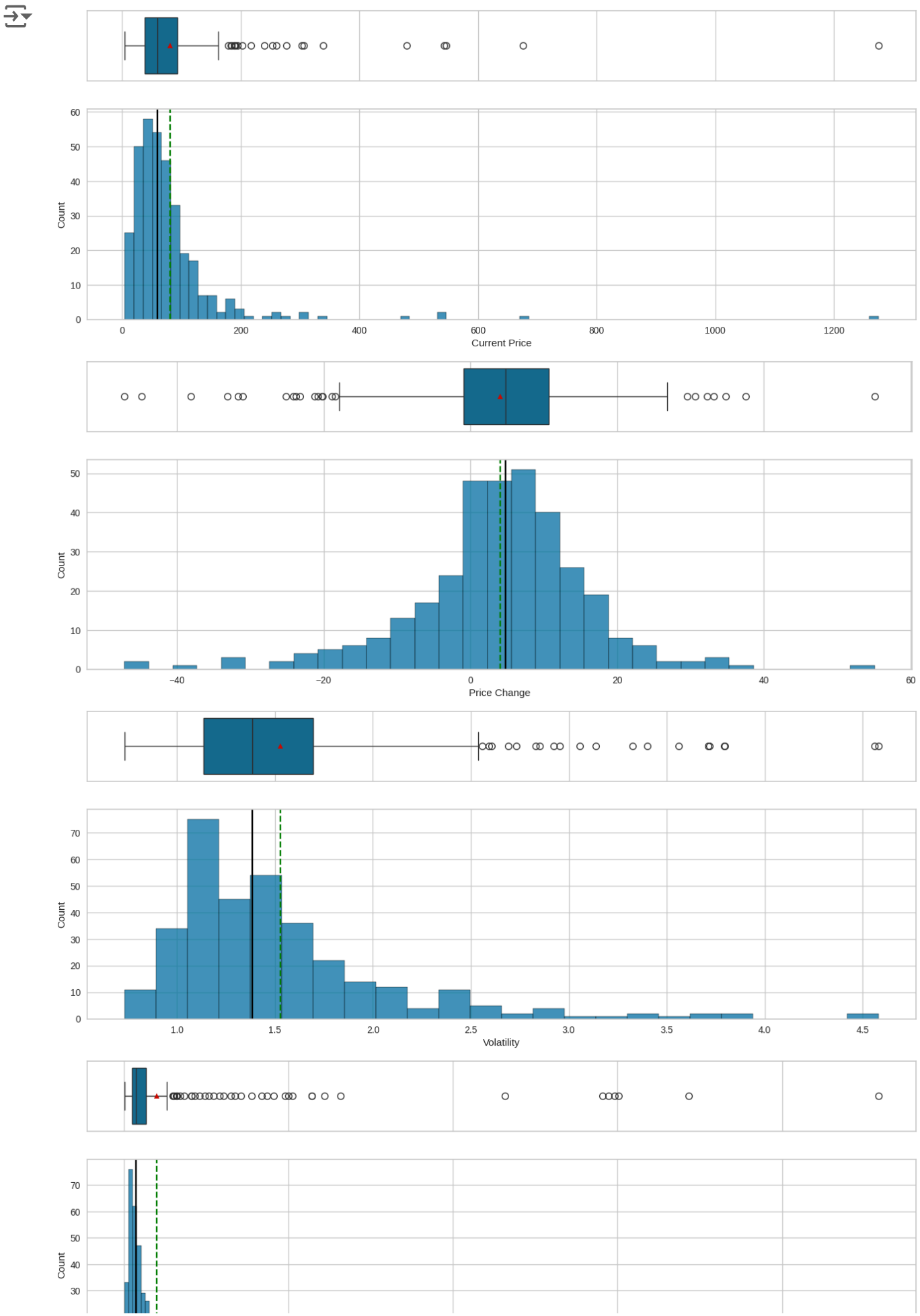
- The dataset is comprised of stocks from 104 different subindustries, with no subindustry having more than 16 stocks in the dataset
- These observations indicate that the 340 stocks held within the dataset are highly diversified across sectors and subindustries

```
1 #provide statistical summary of all numerical columns
2 df.describe().T
```

	count	mean	std	min	25%	
Current Price	340.00	80.86	98.06	4.50	38.55	5
Price Change	340.00	4.08	12.01	-47.13	-0.94	
Volatility	340.00	1.53	0.59	0.73	1.13	
ROE	340.00	39.60	96.55	1.00	9.75	1
Cash Ratio	340.00	70.02	90.42	0.00	18.00	4
Net Cash Flow	340.00	55537620.59	1946365312.18	-11208000000.00	-193906500.00	209800
Net Income	340.00	1494384602.94	3940150279.33	-23528000000.00	352301250.00	70733600
Earnings Per Share	340.00	2.78	6.59	-61.20	1.56	
Estimated Shares Outstanding	340.00	577028337.75	845849595.42	27672156.86	158848216.10	30967513
P/E Ratio	340.00	32.61	44.35	2.94	15.04	2
P/B Ratio	340.00	-1.72	13.97	-76.12	-4.35	

Numerical Columns

```
#create list of columns with numerical variables
num_col = df.select_dtypes(include=np.number).columns.tolist()

#display histograms and boxplots for all numerical columns
for col in num_col:
    histogram_boxplot(df, col)
```


Count
Current Price
Count
Price Change
Count
Volatility
Count

Current price

- The distribution is heavily right skewed, with 49 of the 340 stocks having twice the median value of all stocks
- As expected, no stock is listed at less of less than 0 dollars

Price change

- The distribution is biased towards lower volatilities, but long tails do exist both for positive and negative price changes
- The most volatile stocks show as low as a 47% decrease to as high as a 55% increase over 13 weeks

Volatility

- As expected, the distribution of standard deviations is right skewed and not normal

Cash Ratio / ROE

- As expected, both distributions are heavily right skewed and no stock is listed with either metric with a value of less than 0
    - For example, 24 stocks are listed with returns on equity of less than 5 and 25 stocks are listed with returns of over 100 percent

Net Income / EPS

- As expected, net income is shown to be right skewed with both long positive and negative tails
    - I.e., most companies generate meager profits, but some are failing and some are highly successful
- 32 companies within the dataset are showing a net income of less than 0 dollars
- EPS, as a derivative of Net Income, shows a similar distribution, with most showing low positive values and a few stocks (34) showing negative values

Estimated shares outstanding

- The distribution is highly right skewed, but no stock has a value of outstanding shares that is unrealistic

P/E and P/B Ratio

- The distribution of P/E ratios is highly right skewed
    - Interestingly, no stock shows a negative ratio, even though several stocks have a negative EPS and no stock stock has a price listed of less than 0

- The distribution for P/B ratios is mostly centered around 0 but with long positive and negative
    - For example, 175 of the 340 total stocks are shown to below the 25th percentile and above the 75th percentile and
    - Additionally, 31 of the stocks are outliers

Conclusions

- As expected, stocks offer uncertain returns with high upsides, mostly modest returns, and the omnipresent possibility that the value of the stock may become worthless (i.e., the company goes bankrupt)
- All of these variables contain a few or several outliers; however, none of these values appear to be unrealistic given the nature of stock prices and historical expectations

The stocks of which economic sector have seen the maximum price increase on average?

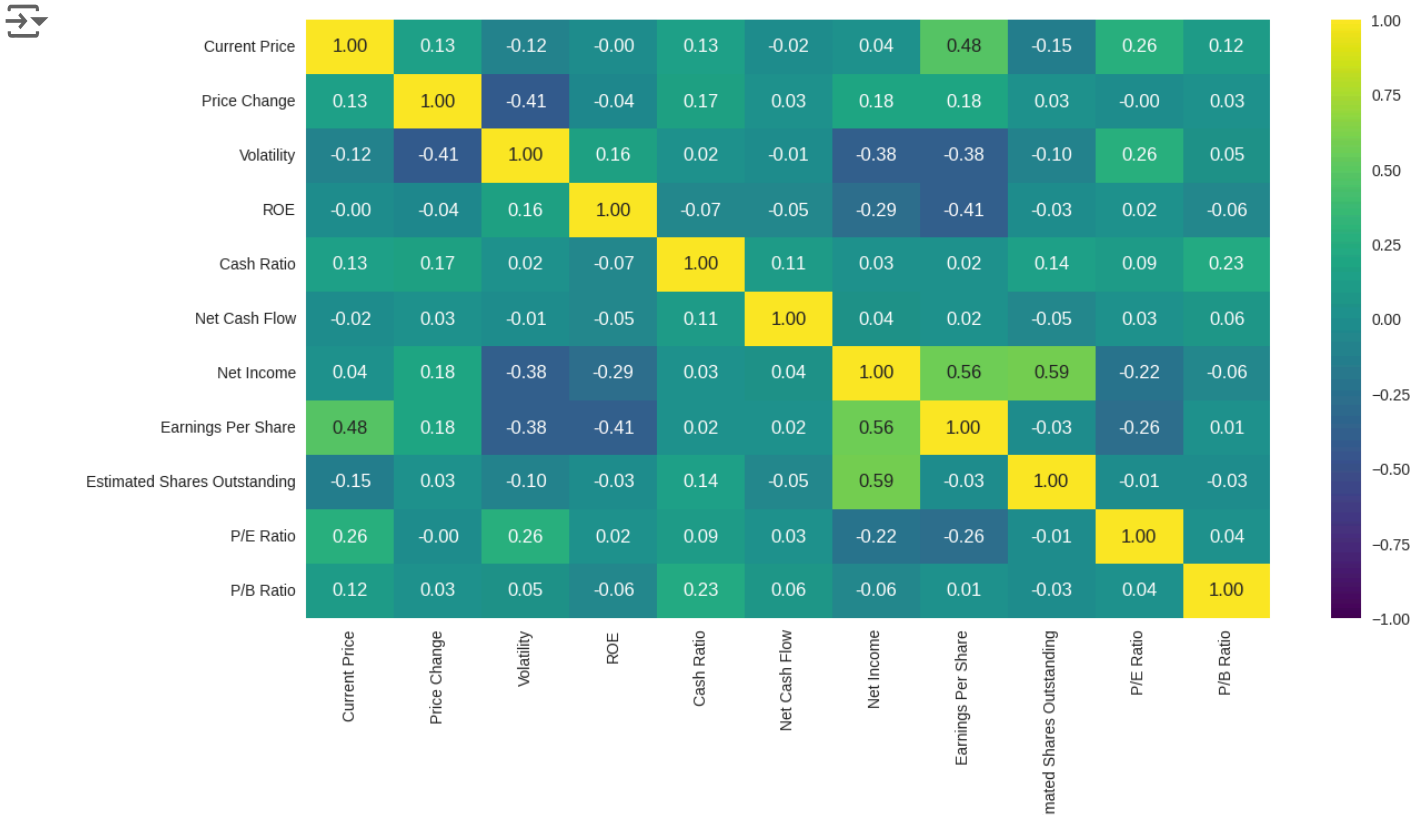

```
1 df.groupby('GICS Sector')['Price Change'].mean().sort_values()
```

```
GICS Sector
Energy                        -10.23
Utilities                       0.80
Industrials                     2.83
Financials                      3.87
Materials                       5.59
Consumer Discretionary          5.85
Real Estate                     6.21
Telecommunications Services     6.96
Information Technology          7.22
Consumer Staples                8.68
Health Care                     9.59
Name: Price Change, dtype: float64
```

- Stocks within the health care sectors have shown the highest average price increase over the preeceding period

How are the different variables correlated with each other?

```
#create correlation heat map for numerical variables
plt.figure(figsize=(14, 7))
sns.heatmap(
    df[num_col].corr(),
    annot=True,
    vmin=-1,
    vmax=1,
    fmt=".2f",
    cmap='viridis'
)
plt.show()
```



- Several variables are moderately correlated (+/- .40) with one another
    - Volatility is negatively correlated with price change, i.e., as a stock becomes more volatile, its price is likely dropping
    - Net income is negatively correlayed with volatility, i.e. as a company generates higher net income its price is likely less volatile
    - Net income is also positively correlated with earnings per share (EPS) and estimated shares outstanding
    - EPS is positively correlated with current price, i.e. as a company's EPS rises, its prices is also highly likely to increase
    - EPS is also negatively correlated with ROE, i.e. as a company generates more equity for shareholders, an equivalent amount of net income the following periods will generate a

lower return

Cash ratio provides a measure of a company's ability to cover its short-term obligations using only cash and cash equivalents. How does the average cash ratio vary across economic sectors?

```
df.groupby('GICS Sector')['Cash Ratio'].mean().sort_values(ascending=False)
```

```
GICS Sector
Information Technology        149.82
Telecommunications Services   117.00
Health Care                   103.78
Financials                     98.59
Consumer Staples               70.95
Energy                         51.13
Real Estate                    50.11
Consumer Discretionary         49.58
Materials                      41.70
Industrials                    36.19
Utilities                      13.62
Name: Cash Ratio, dtype: float64
```

- IT and Telecommunications sectors, both relatively newer and unregulated industries, are able to generate significantly higher average cash ratios than their peer sectors
- Utilities, a highly regulated industry, generates the lowest average cash ratios of all sectors

P/E ratios can help determine the relative value of a company's shares as they signify the amount of money an investor is willing to invest in a single share of a company per dollar of its earnings. How does the P/E ratio vary, on average, across economic sectors?

```
df.groupby('GICS Sector')['P/E Ratio'].mean().sort_values(ascending=False)
```

```
GICS Sector
Energy                        72.90
Information Technology        43.78
Real Estate                   43.07
Health Care                   41.14
Consumer Discretionary        35.21
Consumer Staples              25.52
Materials                     24.59
Utilities                     18.72
Industrials                   18.26
Financials                    16.02
Telecommunications Services   12.22
Name: P/E Ratio, dtype: float64
```

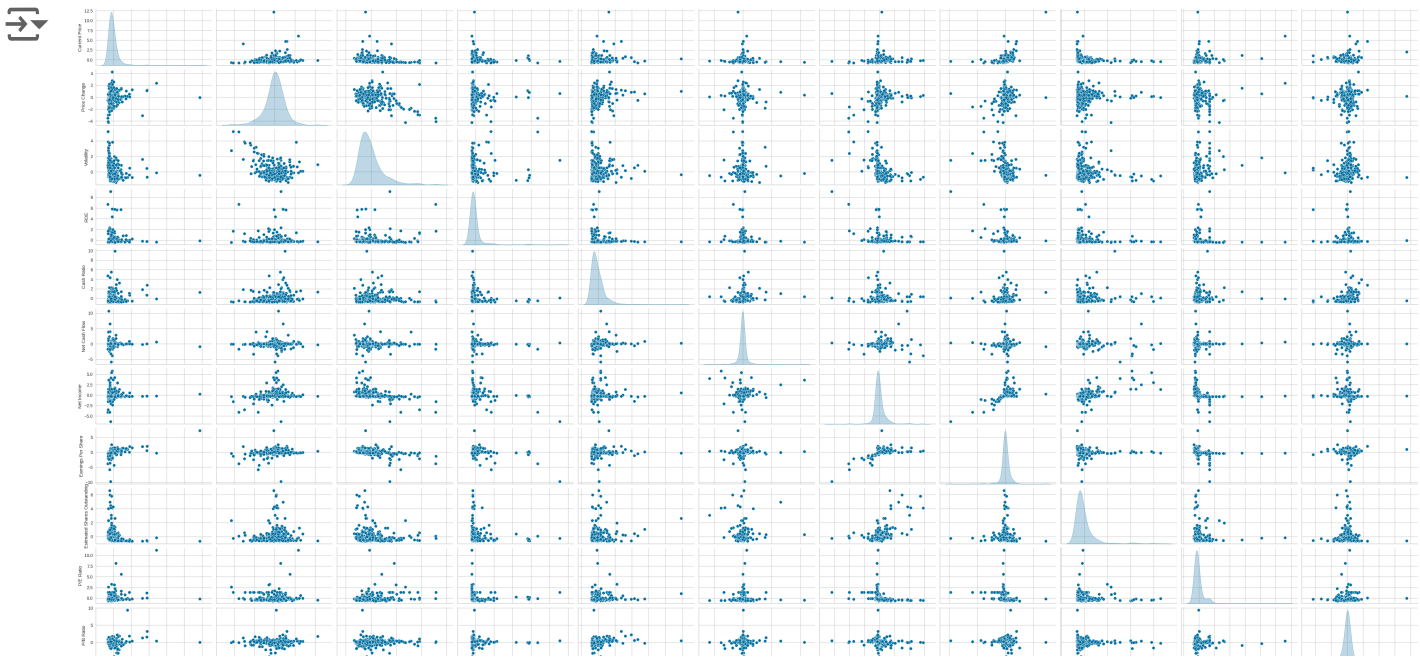
- Energy companies have the highest average P/E ratios of all sectors by a considerable margin, with telecoms having the lowest average P/E ratios

K-means Clustering

```
1 #scale the data set before clustering
2 scaler = StandardScaler()
3 subset = df[num_col].copy()
4 subset_scaled = scaler.fit_transform(subset)
```

```
1 #create a dataframe from the scaled data
2 subset_scaled_df = pd.DataFrame(subset_scaled, columns=subset.columns)
```

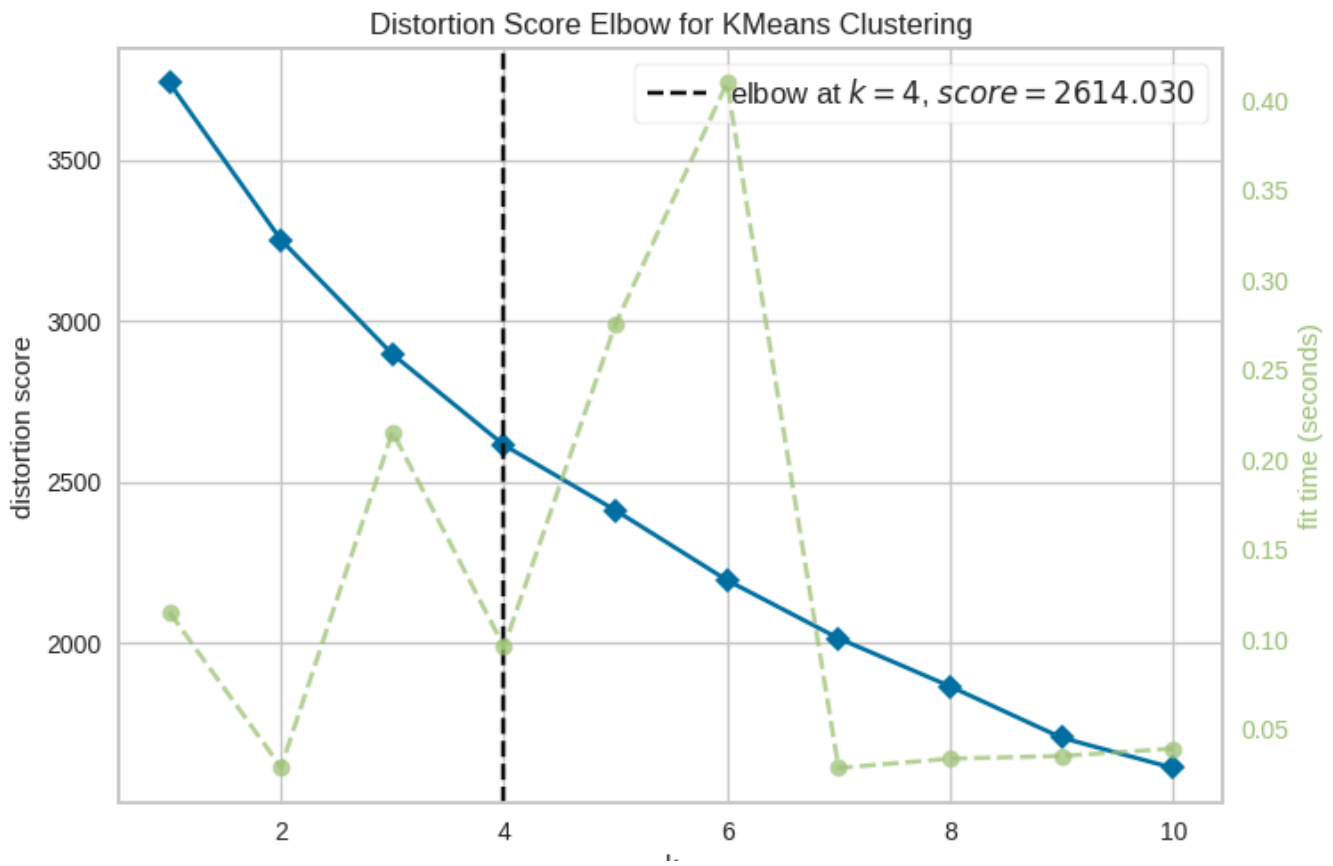
```
1 #create pairplot for scaled dataframe
2 sns.pairplot(subset_scaled_df, height=2,aspect=2 , diag_kind='kde')
3 plt.show()
```



```
#print average distortions for range of kmeans models fitted to scaled dataset
clusters = range(1, 11)
meanDistortions = []

for k in clusters:
    model = KMeans(n_clusters=k)
    model.fit(subset_scaled_df)
    prediction = model.predict(subset_scaled_df)
    distortion = (
        sum(
            np.min(cdist(subset_scaled_df, model.cluster_centers_, "euclidean"), axis=1)
        )
        / subset_scaled_df.shape[0]
    )

    meanDistortions.append(distortion)

    print("Number of Clusters:", k, "\tAverage Distortion:", distortion)
```

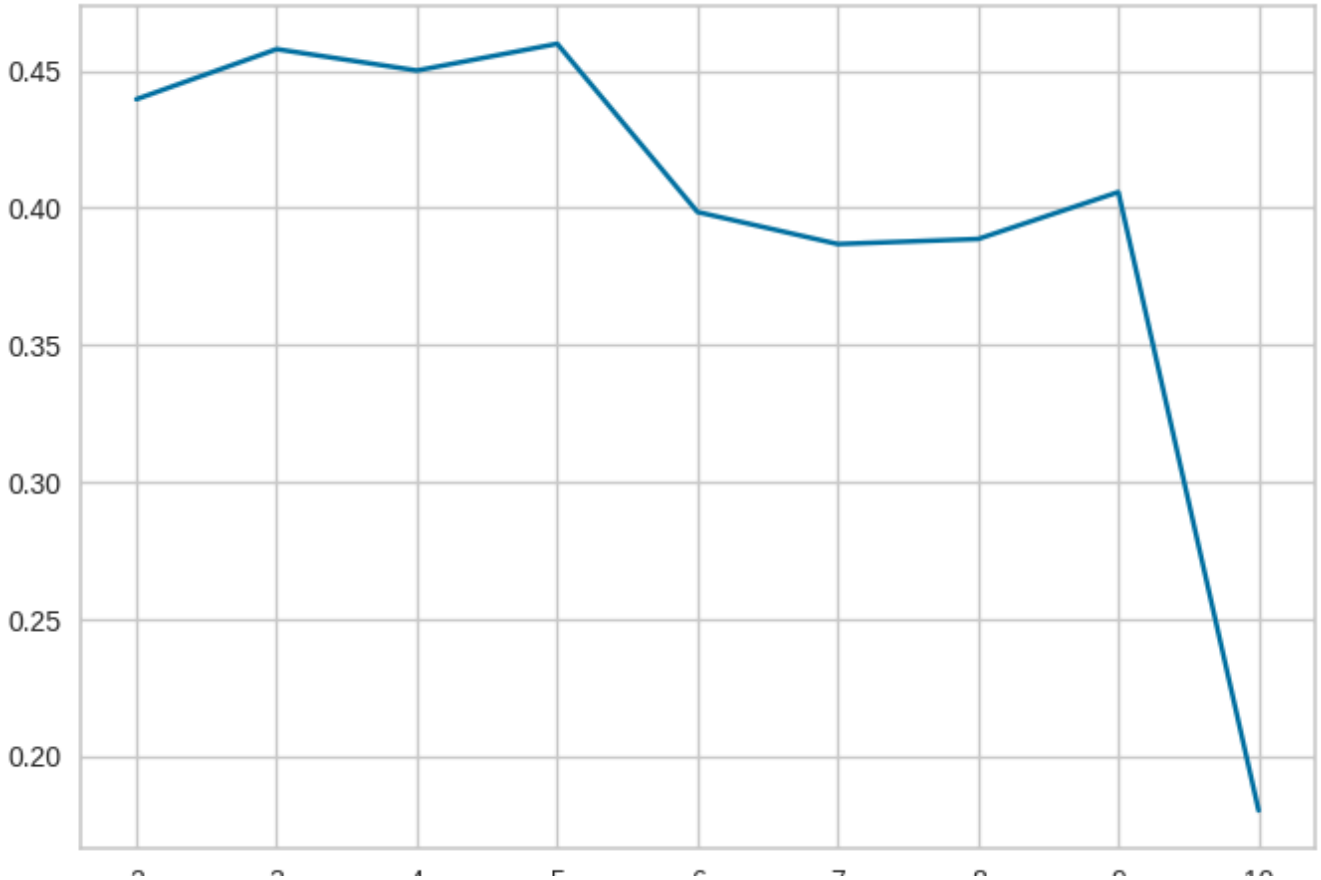
```
Number of Clusters: 1   Average Distortion: 2.5425069919221697
Number of Clusters: 2   Average Distortion: 2.382318498894466
Number of Clusters: 3   Average Distortion: 2.2659465936501304
Number of Clusters: 4   Average Distortion: 2.2106334639099248
Number of Clusters: 5   Average Distortion: 2.128338996505974
Number of Clusters: 6   Average Distortion: 2.0598763618226803
Number of Clusters: 7   Average Distortion: 2.0246699618696655
Number of Clusters: 8   Average Distortion: 1.9887592433275094
Number of Clusters: 9   Average Distortion: 1.8929684909747697
Number of Clusters: 10  Average Distortion: 1.8540958566681758
```

```
#fit KMeans model and use visualizaer to indicate optimal K value
model = KMeans(random_state=42)
visualizer = KElbowVisualizer(model, k=(1, 11), timings=True)
visualizer.fit(subset_scaled_df)  # fit the data to the visualizer
visualizer.show()  # finalize and render figure
plt.show()
```

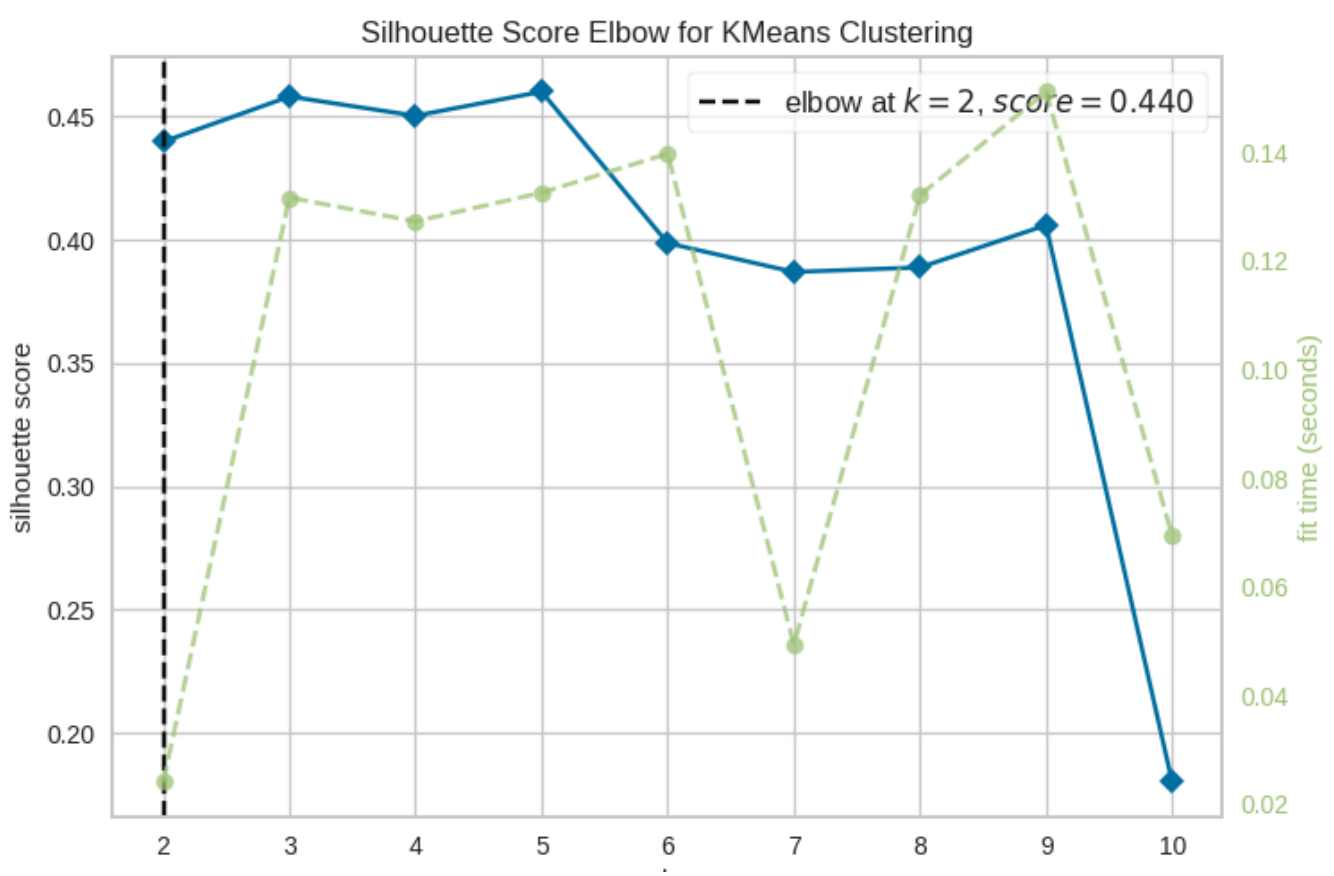



```
#fit KMeans model and provide silhouette scores for range of k clusters
sil_score = []
cluster_list = range(2, 11)
for n_clusters in cluster_list:
    clusterer = KMeans(n_clusters=n_clusters, random_state=42)
    preds = clusterer.fit_predict((subset_scaled_df))
    score = silhouette_score(subset_scaled_df, preds)
    sil_score.append(score)
    print("For n_clusters = {}, the silhouette score is {})".format(n_clusters, score))

#show scores in line graph
plt.plot(cluster_list, sil_score)
plt.show()
```

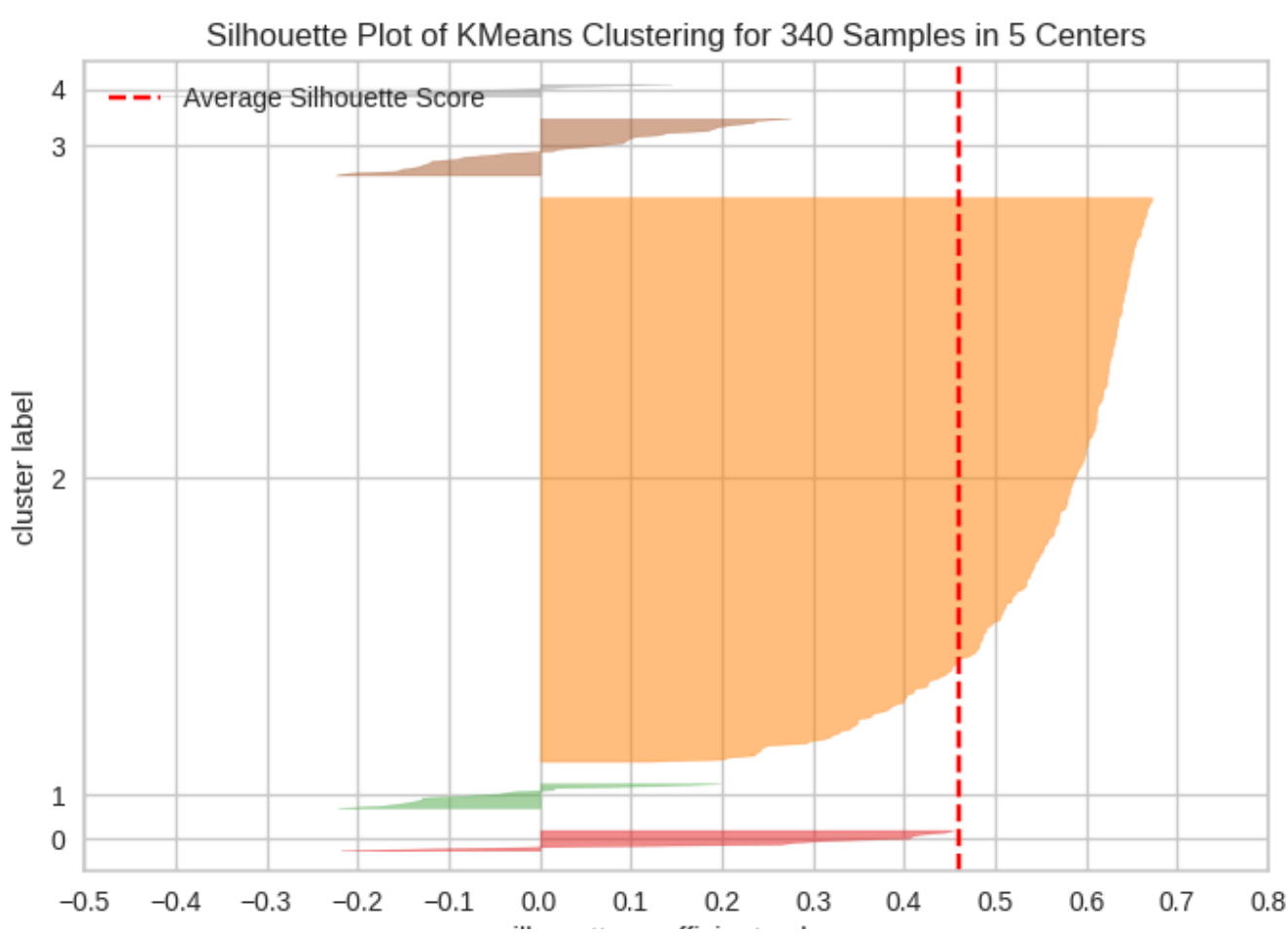
```
For n_clusters = 2, the silhouette score is 0.43969639509980457)
For n_clusters = 3, the silhouette score is 0.45797710447228496)
For n_clusters = 4, the silhouette score is 0.45017906939331087)
For n_clusters = 5, the silhouette score is 0.4599352800740646)
For n_clusters = 6, the silhouette score is 0.3985379248608659)
For n_clusters = 7, the silhouette score is 0.3868475076242907)
For n_clusters = 8, the silhouette score is 0.3886929719130642)
For n_clusters = 9, the silhouette score is 0.40581042332267614)
For n_clusters = 10, the silhouette score is 0.18011528994705786)
```




```
#fit KMeans model and use visualizaer to indicate optimal K value
model = KMeans(random_state=42)
visualizer = KElbowVisualizer(model, k=(2, 11), metric="silhouette", timings=True)
visualizer.fit(subset_scaled_df)  # fit the data to the visualizer
visualizer.show()  # finalize and render figure
plt.show()
```




```
1 #find optimal no. of clusters with silhouette coefficients
2 visualizer = SilhouetteVisualizer(KMeans(5, random_state=42))
3 visualizer.fit(subset_scaled_df)
4 visualizer.show()
5 plt.show()
```



- Between the Elbow and Silhouette plots, the number of clusters with the best performance appears to be 5

```
#create kmeans cluster model
kmeans = KMeans(n_clusters=5, random_state=42)

#fit model to scaled dataset
kmeans.fit(subset_scaled_df)
```

```
KMeans
KMeans(n_clusters=5, random_state=42)
```

Cluster Profiling

```
# adding kmeans cluster labels to the original dataframe
df["KMeans_clusters"] = kmeans.labels_
```

```
#group dataset by kmeans cluster labels
cluster_profile = df.groupby("KMeans_clusters").mean()

#add counts for number of stocks in each cluster
cluster_profile["Count"] = (
    df.groupby("KMeans_clusters")["Current Price"].count().values
)
```

```
cluster_profile.style.highlight_max(color="lightblue", axis=0)
```

KMeans_clusters	Current Price	Price Change	Volatility	ROE	Cash Ratio	Net Cash
0	50.477272	5.588148	1.141171	31.545455	64.181818	-2581727272.72
1	81.418719	10.536341	1.578634	17.000000	367.538462	3857062692.30
2	73.769121	5.466467	1.392827	34.632143	55.710714	4183132.14
3	38.808966	-13.680395	2.938240	106.034483	55.551724	-189825655.17
4	585.527134	7.752090	1.508020	17.571429	159.142857	210520428.57

```
# print the names of the companies in each cluster
for cl in df["KMeans_clusters"].unique():
    print("In cluster {}, the following companies are present:".format(cl))
    print(df[df["KMeans_clusters"] == cl]["Security"].unique().to_list())
    print()
```

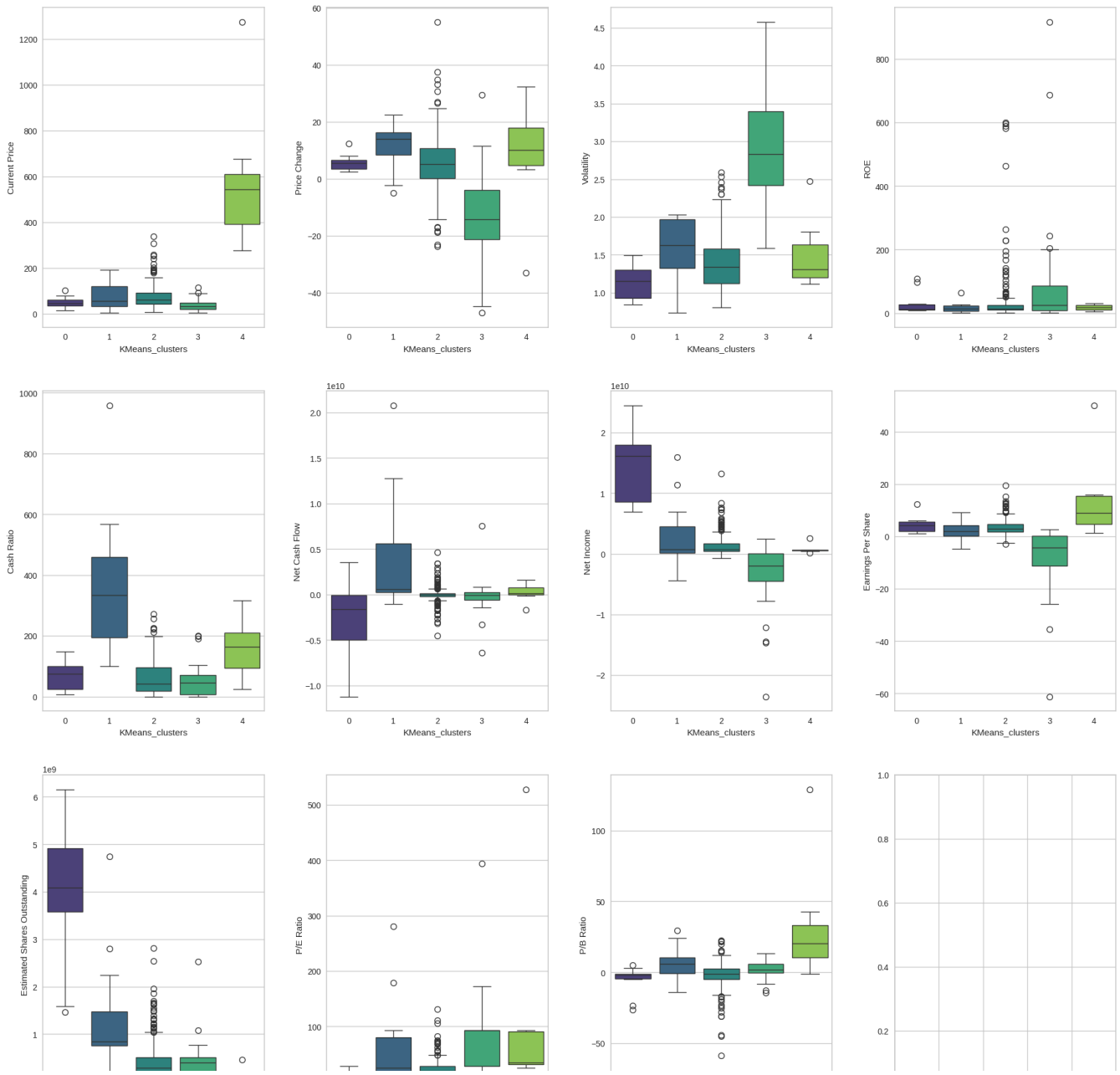
```
In cluster 2, the following companies are present:
['American Airlines Group', 'AbbVie', 'Abbott Laboratories', 'Adobe Systems Inc', 'Arche

In cluster 1, the following companies are present:
['Analog Devices, Inc.', 'Alexion Pharmaceuticals', 'Amgen Inc', 'Bank of America Corp',

In cluster 4, the following companies are present:
['Alliance Data Systems', 'Amazon.com Inc', 'Chipotle Mexican Grill', 'Equinix', 'Intuit

In cluster 3, the following companies are present:
['Apache Corporation', 'Anadarko Petroleum Corp', 'Baker Hughes Inc', 'Chesapeake Energy

In cluster 0, the following companies are present:
['Citigroup Inc.', 'Ford Motor', 'Gilead Sciences', 'General Motors', 'JPMorgan Chase &
```

```
#print number of stocks within each sector for all of the clusters
for k in range(0,df['KMeans_clusters'].nunique()):
    print('The number of stocks within each GICS Sector for Cluster '+str(k)+' are:')
    print(df[df['KMeans_clusters']==k]['GICS Sector'].value_counts())
    print("   ")
```

```
The number of stocks within each GICS Sector for Cluster 0 are:
Financials                     3
Consumer Discretionary         2
Health Care                    2
Telecommunications Services    2
Consumer Staples               1
Energy                         1
Industrials                    0
Information Technology         0
Materials                      0
Real Estate                    0
Utilities                      0
Name: GICS Sector, dtype: int64

The number of stocks within each GICS Sector for Cluster 1 are:
Health Care                    4
Information Technology         4
Consumer Discretionary         1
Consumer Staples               1
Energy                         1
Financials                     1
Telecommunications Services    1
Industrials                    0
Materials                      0
Real Estate                    0
Utilities                      0
Name: GICS Sector, dtype: int64

The number of stocks within each GICS Sector for Cluster 2 are:
Industrials                   52
Financials                    45
Consumer Discretionary        33
Health Care                   32
Real Estate                   26
Information Technology        25
Utilities                     24
Materials                     18
Consumer Staples              17
Energy                         6
Telecommunications Services    2
Name: GICS Sector, dtype: int64

The number of stocks within each GICS Sector for Cluster 3 are:
Energy                        22
Information Technology         3
Materials                      2
Consumer Discretionary         1
Industrials                    1
Consumer Staples               0
Financials                     0
```

```
Health Care                     0
Real Estate                     0
Telecommunications Services     0
Utilities                       0
Name: GICS Sector, dtype: int64

The number of stocks within each GICS Sector for Cluster 4 are:
Consumer Discretionary         3
```

```
# show boxplots of numerical variables for each K-Means cluster
fig, axes = plt.subplots(3, 4, figsize=(20, 20))
counter = 0

for ii in range(3):
    for jj in range(4):
        if counter < 11:
            sns.boxplot(
                ax=axes[ii][jj],
                data=df,
                y=df.columns[3+counter],
                x="KMeans_clusters",
                palette="viridis"
            )
            counter = counter + 1

fig.tight_layout(pad=3.0)
```



KMeans Clusters

Cluster 0 - Large Market Capitalization / Dow Jones Industrial Average

- 11 stocks, comprised mostly of stocks within the Financials, Health Care, Information Technology (IT), and Consumer Discretionary sectors
- Companies within this cluster have:
    - Low volatility
    - Most of the companies with the highest outflows of cash
    - The highest net incomes
    - The highest number of shares outstanding

Cluster 1 - "Cash is King"

- 13 stocks, comprised mostly of stocks within the Healthcare and IT sectors
- Companies within this cluster have:
    - Moderate volatility
    - Mostly profitable
    - Most of the highest cash ratios and cash inflows

Cluster 2 - S&P 500 / Diversification

- 280 stocks (~84% of all stocks in the dataset) drawn from all sectors present in the dataset
- Companies within this cluster have:
    - Low P/E ratios
    - Most of the outliers on negative P/B ratios

Cluster 3 - "Ride the Energy Rollercoaster" portfolio / Growth mindset

- 29 stocks, a vast majority of which are from the Energy sector
- Companies within this cluster have:
    - Low stock prices, but high ROE
    - High beta
    - Most of the most volatile stocks, especially those with outliers in price decreases
    - Mostly negative net incomes and earnings per share

Cluster 4 - High Earnings for a High Price

- 7 stocks, comprised mostly of stocks from the Health Care and Consumer Discretionary sectors
- Companies within this cluster have:
    - Most of stocks with the highest prices
    - Favorable cash ratios
    - The most favorable P/B ratios
    - Most of the highest earnings-per-share

Hierarchical Clustering

```
# list of distance metrics
distance_metrics = ["euclidean", "chebyshev", "mahalanobis", "cityblock"]

# list of linkage methods
linkage_methods = ["single", "complete", "average", "weighted"]

high_cophenet_corr = 0
high_dm_lm = [0, 0]

for dm in distance_metrics:
    for lm in linkage_methods:
        Z = linkage(subset_scaled_df, metric=dm, method=lm)
        c, coph_dists = cophenet(Z, pdist(subset_scaled_df))
        print(
            "Cophenetic correlation for {} distance and {} linkage is {}.".format(
                dm.capitalize(), lm, round(c,4)
            )
        )
        print(" ")
        if high_cophenet_corr < c:
            high_cophenet_corr = c
            high_dm_lm[0] = dm
            high_dm_lm[1] = lm
```

```
Cophenetic correlation for Euclidean distance and single linkage is 0.9232.

Cophenetic correlation for Euclidean distance and complete linkage is 0.7873.

Cophenetic correlation for Euclidean distance and average linkage is 0.9423.

Cophenetic correlation for Euclidean distance and weighted linkage is 0.8694.

Cophenetic correlation for Chebyshev distance and single linkage is 0.9063.

Cophenetic correlation for Chebyshev distance and complete linkage is 0.5989.

Cophenetic correlation for Chebyshev distance and average linkage is 0.9338.

Cophenetic correlation for Chebyshev distance and weighted linkage is 0.9127.

Cophenetic correlation for Mahalanobis distance and single linkage is 0.9259.

Cophenetic correlation for Mahalanobis distance and complete linkage is 0.7925.

Cophenetic correlation for Mahalanobis distance and average linkage is 0.9247.

Cophenetic correlation for Mahalanobis distance and weighted linkage is 0.8708.

Cophenetic correlation for Cityblock distance and single linkage is 0.9334.

Cophenetic correlation for Cityblock distance and complete linkage is 0.7375.

Cophenetic correlation for Cityblock distance and average linkage is 0.9302.
```

```
Cophenetic correlation for Cityblock distance and weighted linkage is 0.731.
```

```
# printing the combination of distance metric and linkage method with the highest cophene
print(
    "Highest cophenetic correlation is {}, which is obtained with {} distance and {} link
        round(high_cophenet_corr,4), high_dm_lm[0].capitalize(), high_dm_lm[1]
    )
)
```

```
Highest cophenetic correlation is 0.9423, which is obtained with Euclidean distance and
```

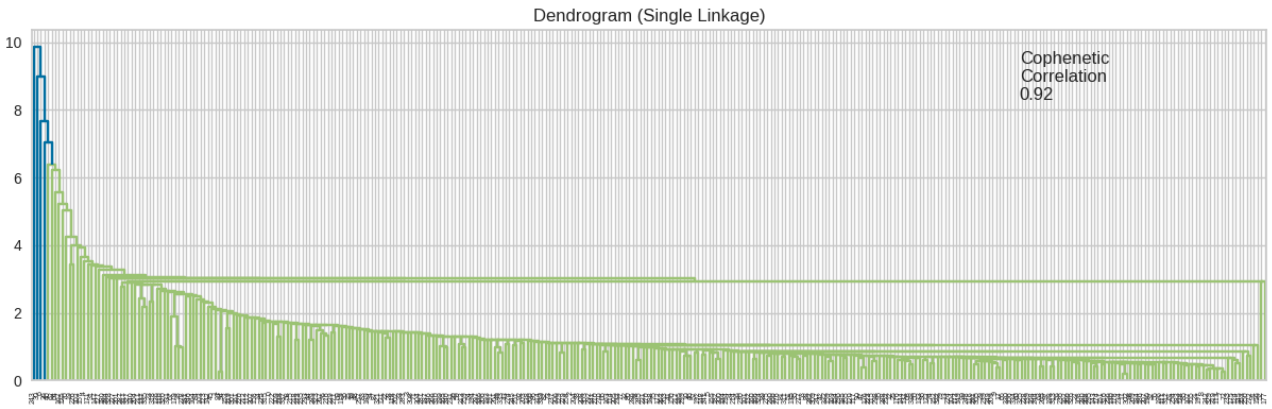
```
# list of linkage methods for euclidean distance metric
linkage_methods = ["single", "complete", "average", "centroid", "ward", "weighted"]

high_cophenet_corr = 0
high_dm_lm = [0, 0]

for lm in linkage_methods:
    Z = linkage(subset_scaled_df, metric="euclidean", method=lm)
    c, coph_dists = cophenet(Z, pdist(subset_scaled_df))
    print(
            "Cophenetic correlation for Euclidean distance and {} linkage is {}.".format(
                lm, round(c,4)
            )
        )
    print(" ")
    if high_cophenet_corr < c:
        high_cophenet_corr = c
        high_dm_lm[0] = "euclidean"
        high_dm_lm[1] = lm
```

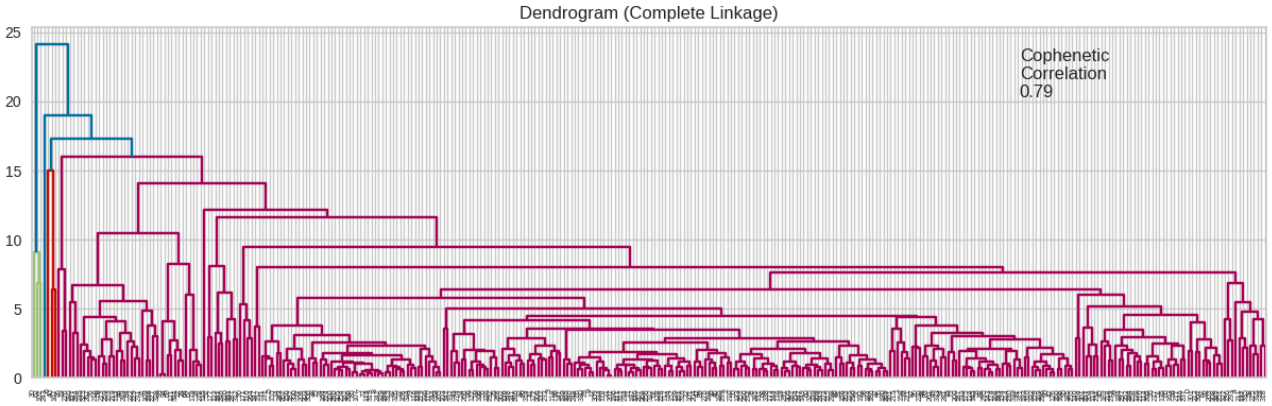
```
Cophenetic correlation for Euclidean distance and single linkage is 0.9232.

Cophenetic correlation for Euclidean distance and complete linkage is 0.7873.

Cophenetic correlation for Euclidean distance and average linkage is 0.9423.

Cophenetic correlation for Euclidean distance and centroid linkage is 0.9314.

Cophenetic correlation for Euclidean distance and ward linkage is 0.7101.

Cophenetic correlation for Euclidean distance and weighted linkage is 0.8694.
```

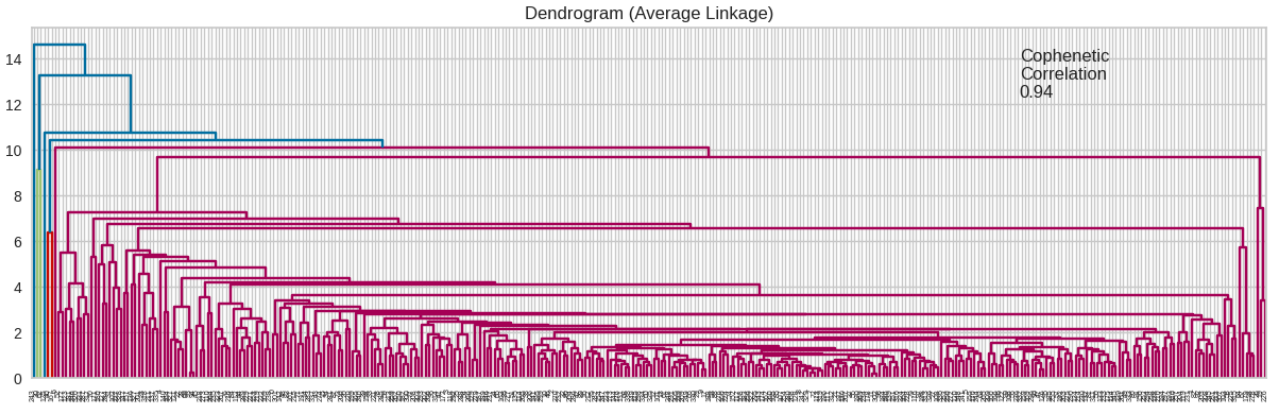
```
# printing the combination of distance metric and linkage method with the highest cophene
print(
    "Highest cophenetic correlation is {}, which is obtained with {} linkage.".format(
        round(high_cophenet_corr,4), high_dm_lm[1]
    )
)
```

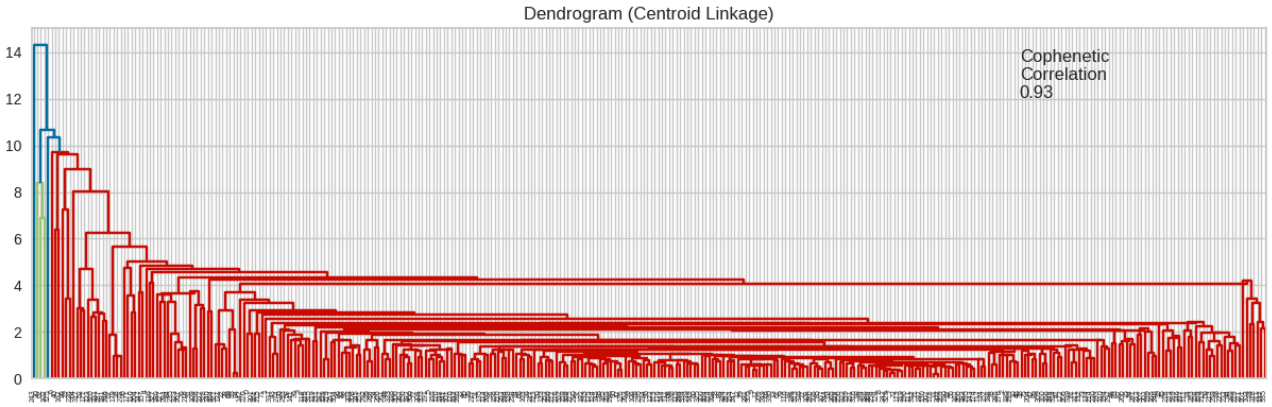
```
Highest cophenetic correlation is 0.9423, which is obtained with average linkage.
```

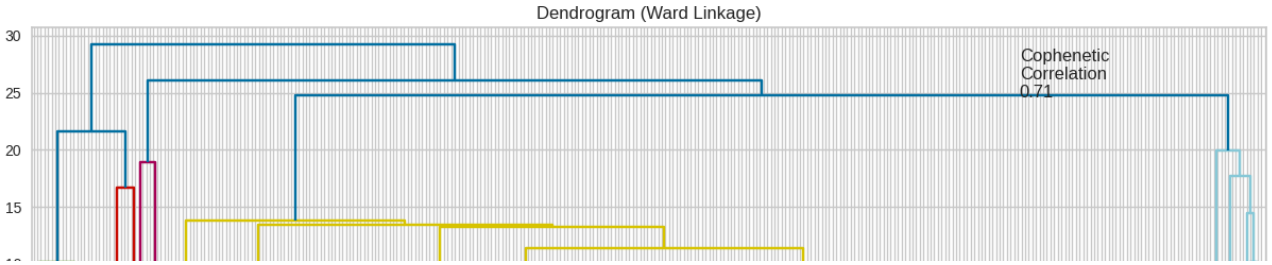
```
# list of linkage methods
linkage_methods = ["single", "complete", "average", "centroid", "ward", "weighted"]

# lists to save results of cophenetic correlation calculation
compare_cols = ["Linkage", "Cophenetic Coefficient"]

# to create a subplot image
fig, axs = plt.subplots(len(linkage_methods), 1, figsize=(15, 30))

# We will enumerate through the list of linkage methods above
# For each linkage method, we will plot the dendrogram and calculate the cophenetic corre
for i, method in enumerate(linkage_methods):
    Z = linkage(subset_scaled_df, metric="euclidean", method=method)

    dendrogram(Z, ax=axs[i])
    axs[i].set_title(f"Dendrogram ({method.capitalize()} Linkage)")

    coph_corr, coph_dist = cophenet(Z, pdist(subset_scaled_df))
    axs[i].annotate(
        f"Cophenetic\nCorrelation\n{coph_corr:0.2f}",
        (0.80, 0.80),
        xycoords="axes fraction",
    )
```


Dendrogram (Single Linkage)
Cophenetic Correlation 0.92


Dendrogram (Complete Linkage)
Cophenetic Correlation 0.79


Dendrogram (Average Linkage)
Cophenetic Correlation 0.94


Dendrogram (Centroid Linkage)
Cophenetic Correlation 0.93


Dendrogram (Ward Linkage)
Cophenetic Correlation 0.71

- The cophenetic correlation is highest for average and centroid linkage methods, but the dendrogram for average appears to provide better clusters
- 5 appears to be the appropriate number of clusters for the average linkage method

```
Z = linkage(subset_scaled_df, metric='euclidean', method='average')
c, coph_dists = cophenet(Z , pdist(subset_scaled_df))
```

```
hierarchy = AgglomerativeClustering(n_clusters=5, affinity='euclidean',  linkage='average
hierarchy.fit(subset_scaled_df)
```

```
AgglomerativeClustering(affinity='euclidean', linkage='average', n_clusters=5)
```

Cluster Profiling

```
df_hierarchy = df.copy()
df_hierarchy.drop("KMeans_clusters", axis=1, inplace=True)
df_hierarchy['HC_clusters'] = hierarchy.labels_
```

```
#group dataset by Hierarchical clusters
cluster_profile_h = df_hierarchy.groupby("HC_clusters").mean()

#add counts for number of stocks in each cluster
cluster_profile_h["Count"] = (
    df_hierarchy.groupby("HC_clusters")["Current Price"].count().values
)

#show dataframe with maximum values for each metric highlighted
cluster_profile_h.style.highlight_max(color="lightblue", axis=0)
```

HC_clusters	Current Price	Price Change	Volatility	ROE	Cash Ratio	Net Cash Fl
0	77.884243	4.105986	1.516865	35.320359	66.775449	-32825817.3652
1	25.640000	11.237908	1.322355	12.500000	130.500000	16755500000.0000
2	24.485001	-13.351992	3.482611	802.000000	51.000000	-1292500000.0000
3	104.660004	16.224320	1.320606	8.000000	958.000000	592000000.0000
4	1274.949951	3.190527	1.268340	29.000000	184.000000	-1671386000.0000

- There are 2 clusters of one company, 2 clusters of two companies, and a single cluster of the remaining 334 companies
- The clustering of these companies does not solve the business problem at hand, because the clusters do not have enough variability

In contrasts, the dendrogram for Ward linkage appears to provide better clustering, with 5 appearing to be the appropriate number of clusters

```
HCmodel = AgglomerativeClustering(n_clusters=5, affinity="euclidean", linkage="ward")
HCmodel.fit(subset_scaled_df)
```

```
AgglomerativeClustering(affinity='euclidean', n_clusters=5)
```

Cluster Profiling

```
subset_scaled_df["HC_clusters"] = HCmodel.labels_
df_hierarchy["HC_clusters"] = HCmodel.labels_
```

```
#group dataset by Hierarchical clusters
cluster_profile_h = df_hierarchy.groupby("HC_clusters").mean()

#add counts for number of stocks in each cluster
cluster_profile_h["Count"] = (
    df_hierarchy.groupby("HC_clusters")["Current Price"].count().values
)

#show dataframe with maximum values for each metric highlighted
cluster_profile_h.style.highlight_max(color="lightblue", axis=0)
```

HC_clusters	Current Price	Price Change	Volatility	ROE	Cash Ratio	Net Cash Flow
0	326.198218	10.563242	1.642560	14.400000	309.466667	288850666.666667
1	84.355716	3.854981	1.827670	633.571429	33.571429	-568400000.000000
2	42.848182	6.270446	1.123547	22.727273	71.454545	558636363.636364
3	72.760400	5.213307	1.427078	25.603509	60.392982	79951512.280702
4	36.440455	-16.073408	2.832884	57.500000	42.409091	-472834090.909091

```
# print the names of the companies in each cluster
for cl in df_hierarchy["HC_clusters"].unique():
    print("In cluster {}, the following companies are present:".format(cl))
    print(df_hierarchy[df_hierarchy["HC_clusters"] == cl]["Security"].unique().to_list())
    print()
```

```
In cluster 3, the following companies are present:
['American Airlines Group', 'AbbVie', 'Abbott Laboratories', 'Adobe Systems Inc', 'Analo

In cluster 0, the following companies are present:
['Alliance Data Systems', 'Alexion Pharmaceuticals', 'Amgen Inc', 'Amazon.com Inc', 'Chi

In cluster 1, the following companies are present:
['Allegion', 'Apache Corporation', 'Chesapeake Energy', 'Charter Communications', 'Colga

In cluster 4, the following companies are present:
['Anadarko Petroleum Corp', 'Baker Hughes Inc', 'Cabot Oil & Gas', 'Concho Resources', '

In cluster 2, the following companies are present:
['Bank of America Corp', 'Citigroup Inc.', 'Ford Motor', 'Intel Corp.', 'JPMorgan Chase
```

```
# print the number of stocks in each GICS sector for each cluster
for k in range(0,df_hierarchy['HC_clusters'].nunique()):
    print('The number of stocks within each GICS Sector for Cluster '+str(k)+' are:')
    print(df_hierarchy[df_hierarchy['HC_clusters']==k]['GICS Sector'].value_counts())
    print("   ")
```

```
The number of stocks within each GICS Sector for Cluster 0 are:
Health Care                    5
Information Technology         4
Consumer Discretionary         3
Consumer Staples               1
Real Estate                    1
Telecommunications Services    1
Energy                         0
```

```
Financials                    0
```