Import Package and Read Data

```
# First, we'll import pandas, a data processing and CSV file I/O library
import pandas as pd
import numpy as np   #Linear algera Library
import matplotlib.pyplot as plt  #to plot graphs
import seaborn as sns  #to plot graphs
from sklearn.linear_model import LinearRegression   #for linear regression model  #setting seaborn as default
import math
sns.set(style="white", color_codes=True)
import warnings
warnings.filterwarnings('ignore')
# Next, we'll load the dataset, which is in the "../input/" directory
dior = pd.read_excel("DIOR stock prices.xlsx")
dior.head()
```

	Date	Symbol	Adj Close	Close	High	Low	Open	Volume	Unnamed: 8	Unı
0	1999-12-31	CDI.PA	32.674278	61.500000	61.500000	61.500000	61.500000	0	NaN	hi:
1	2000-01-03	CDI.PA	32.844299	61.820000	63.950001	61.750000	62.200001	424416	NaN	

```
# Let's see how many examples we have of each Symbol
dior["Symbol"].value_counts()
```

```
CDI.PA    5729
Name: Symbol, dtype: int64
```

Data Preprocessing

```
dior.isnull().sum()
```

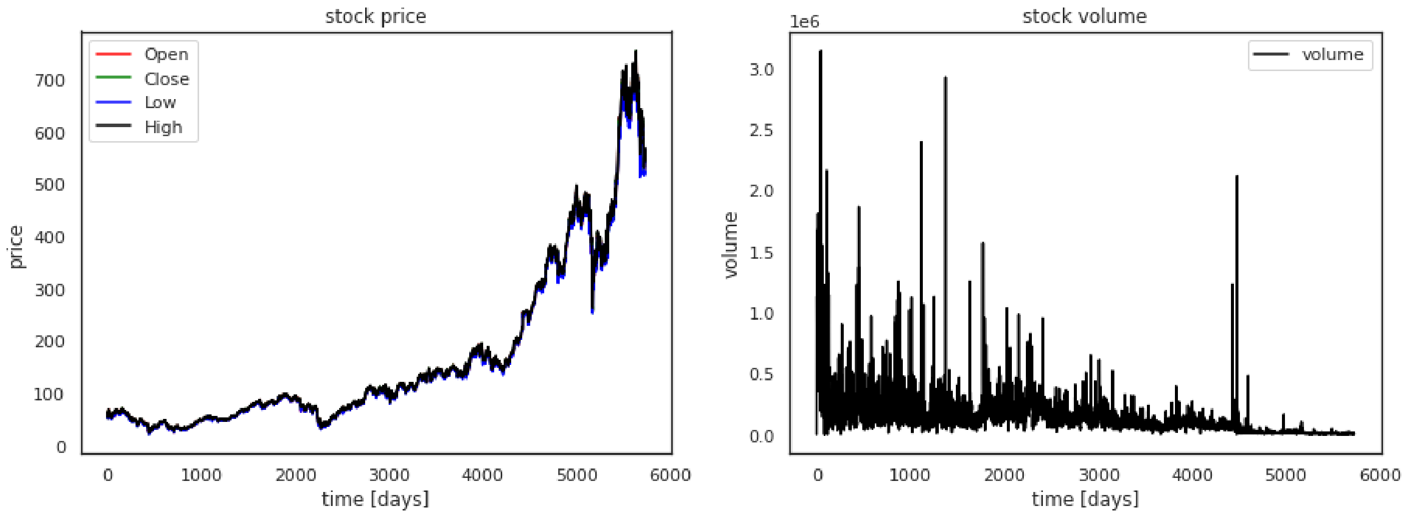
```
Date              0
Symbol            0
Adj Close         0
Close             0
High              0
Low               0
Open              0
Volume            0
Unnamed: 8     5729
Unnamed: 9     5727
dtype: int64
```

there are two coulmns have zero values which we are not consider for calculation

```
df=dior.copy()
```

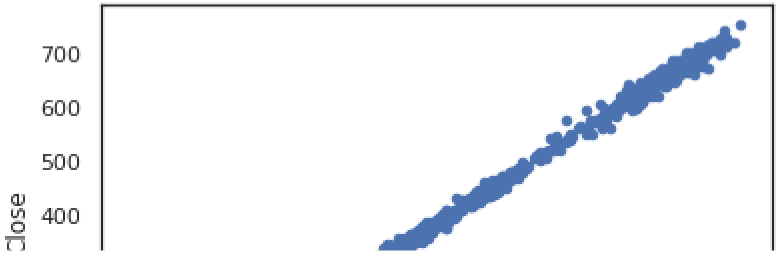
```
plt.figure(figsize=(15, 5));
plt.subplot(1,2,1);
plt.plot(df[df.Symbol == 'CDI.PA'].Open.values, color='red', label='Open')
plt.plot(df[df.Symbol == 'CDI.PA'].Close.values, color='green', label='Close')
plt.plot(df[df.Symbol == 'CDI.PA'].Low.values, color='blue', label='Low')
plt.plot(df[df.Symbol == 'CDI.PA'].High.values, color='black', label='High')
plt.title('stock price')
plt.xlabel('time [days]')
plt.ylabel('price')
plt.legend(loc='best')
#plt.show()

plt.subplot(1,2,2);
```

```
plt.plot(df[df.Symbol == 'CDI.PA'].Volume.values, color='black', label='volume')
plt.title('stock volume')
plt.xlabel('time [days]')
plt.ylabel('volume')
plt.legend(loc='best');
```




```
# The first way we can plot things is using the .plot extension from Pandas dataframes
# We'll use this to make a scatterplot of the dior stock features.
dior.plot(kind="scatter", x="Open", y="Close")
```

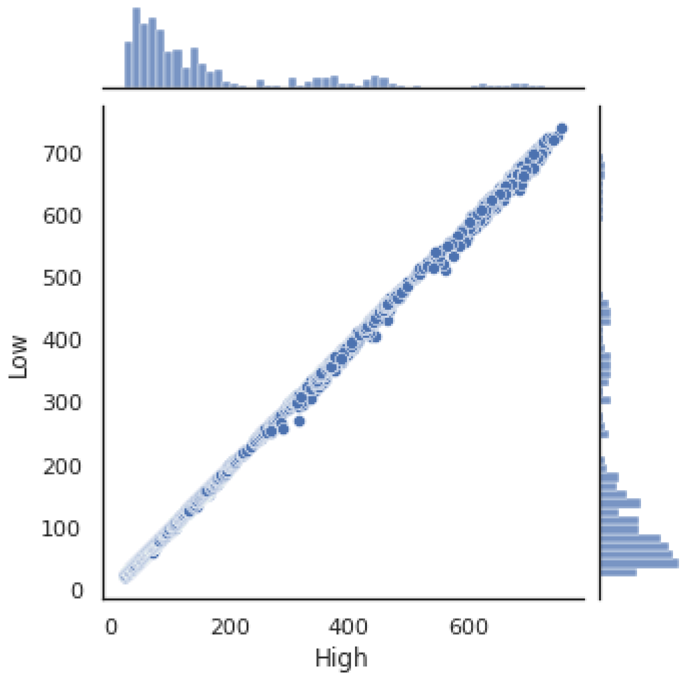
```
WARNING:matplotlib.axes._axes:*c* argument looks like a single numeric RGB or RGBA sequence,
<matplotlib.axes._subplots.AxesSubplot at 0x7f7375f37700>
```



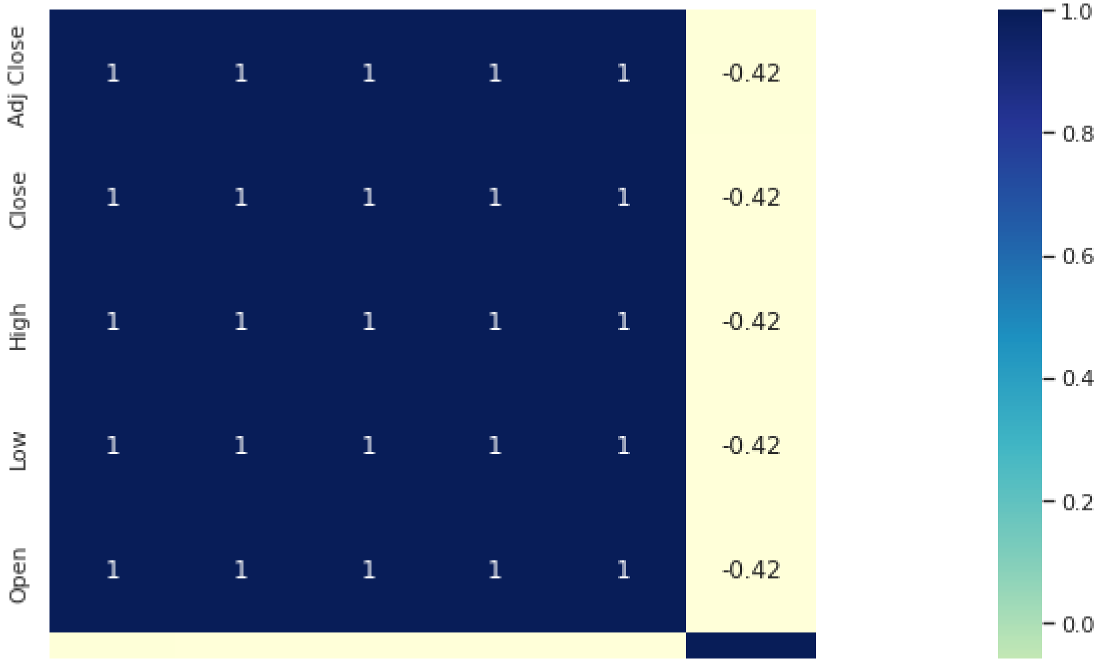

```
plt.figure(figsize=(15, 5));
plt.plot(df.Open.values, color='red', label='open')
plt.plot(df.Close.values, color='green', label='low')
plt.plot(df.Low.values, color='blue', label='low')
plt.plot(df.High.values, color='black', label='high')
#plt.plot(df_stock_norm.volume.values, color='gray', label='volume')
plt.title('stock')
plt.xlabel('time [days]')
plt.ylabel('normalized price/volume')
plt.legend(loc='best')
plt.show()
```


```
# We can also use the seaborn library to make a similar plot
# A seaborn jointplot shows bivariate scatterplots and univariate histograms in the same figure
sns.jointplot(x="High", y="Low", data=dior, size=5)
```

<seaborn.axisgrid.JointGrid at 0x7f7376163eb0>

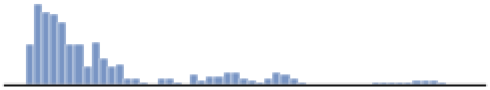



```
fig, ax = plt.subplots(figsize=(10,8))
sns.heatmap(dior.corr(),cmap="YlGnBu", annot=True)
plt.show()
```

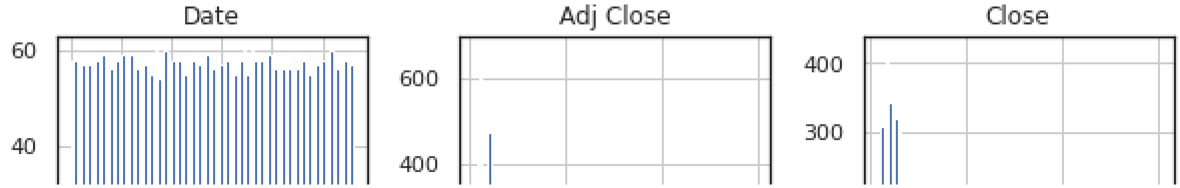



```
# We can also use the seaborn library to make a similar plot
# A seaborn jointplot shows bivariate scatterplots and univariate histograms in the same figure
sns.jointplot(x="Open", y="Close", data=dior, size=5)
```

```
<seaborn.axisgrid.JointGrid at 0x7f735d76ce80>
```

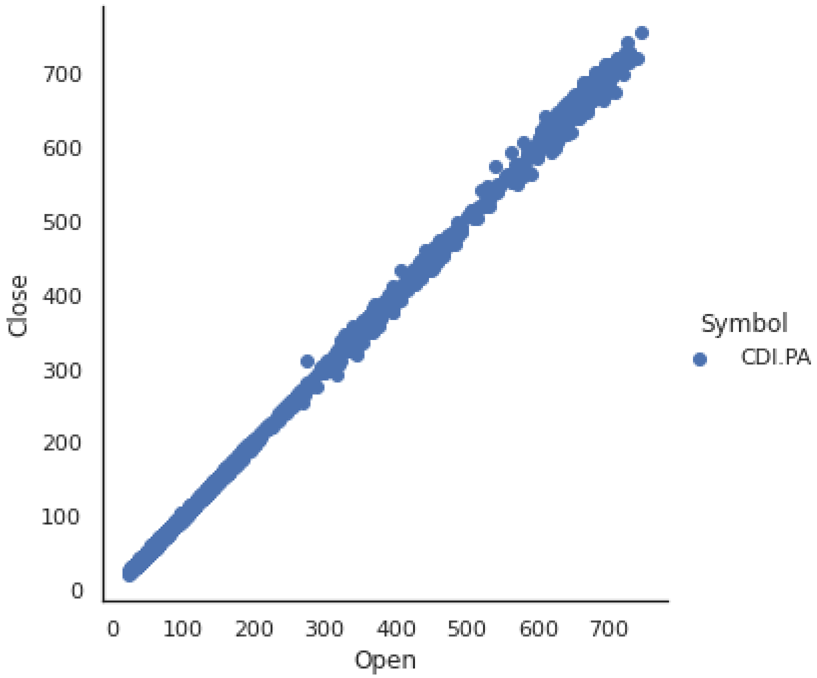


```
fig, (ax1, ax2) = plt.subplots(2, 1, figsize=(10, 10))
df.hist(bins=100, ax=ax1)
ax1.set_ylabel('Open')
ax1.set_xlabel('Close')

plt.show()
```



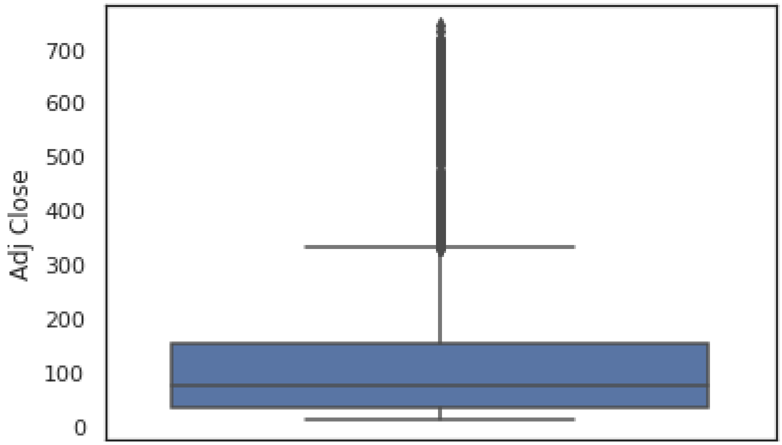

```
# We'll use seaborn's FacetGrid to color the scatterplot by Symbol
sns.FacetGrid(dior, hue="Symbol", size=5) \
   .map(plt.scatter, "Open", "Close") \
   .add_legend()
```

<seaborn.axisgrid.FacetGrid at 0x7f7374e90ee0>



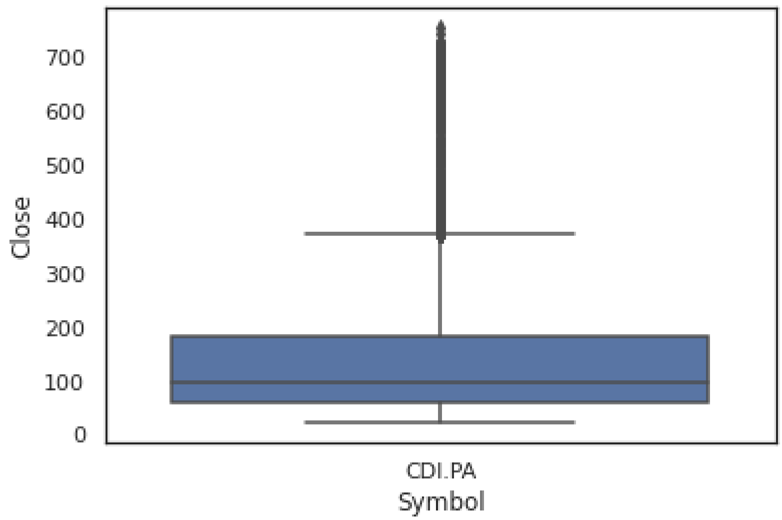
```
# We can look at an individual feature in Seaborn through a boxplot
sns.boxplot(x="Symbol", y="Adj Close", data=dior)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f7374b410d0>
```



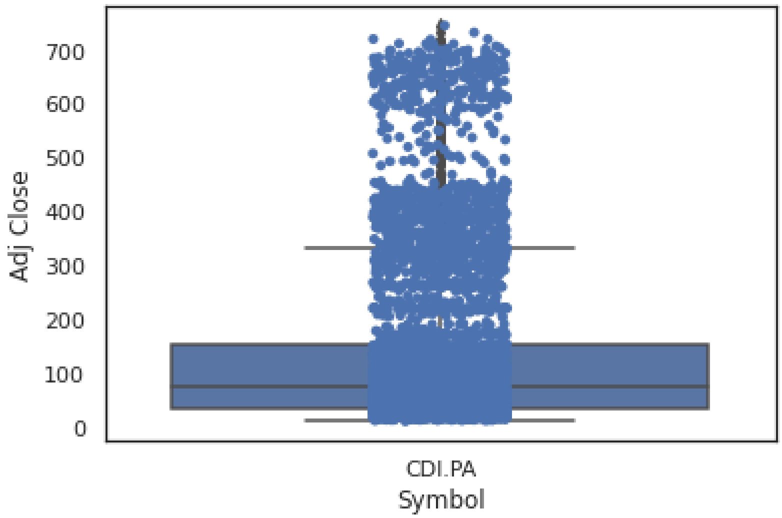

```
# We can look at an individual feature in Seaborn through a boxplot
sns.boxplot(x="Symbol", y="Close", data=dior)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f73749ac640>
```




```
# One way we can extend this plot is adding a layer of individual points on top of
# it through Seaborn's striplot
#
# We'll use jitter=True so that all the points don't fall in single vertical lines
#
```

```
# Saving the resulting axes as ax each time causes the resulting plot to be shown
# on top of the previous axes
ax = sns.boxplot(x="Symbol", y="Adj Close", data=dior)
ax = sns.stripplot(x="Symbol", y="Adj Close", data=dior, jitter=True, edgecolor="gray")
```

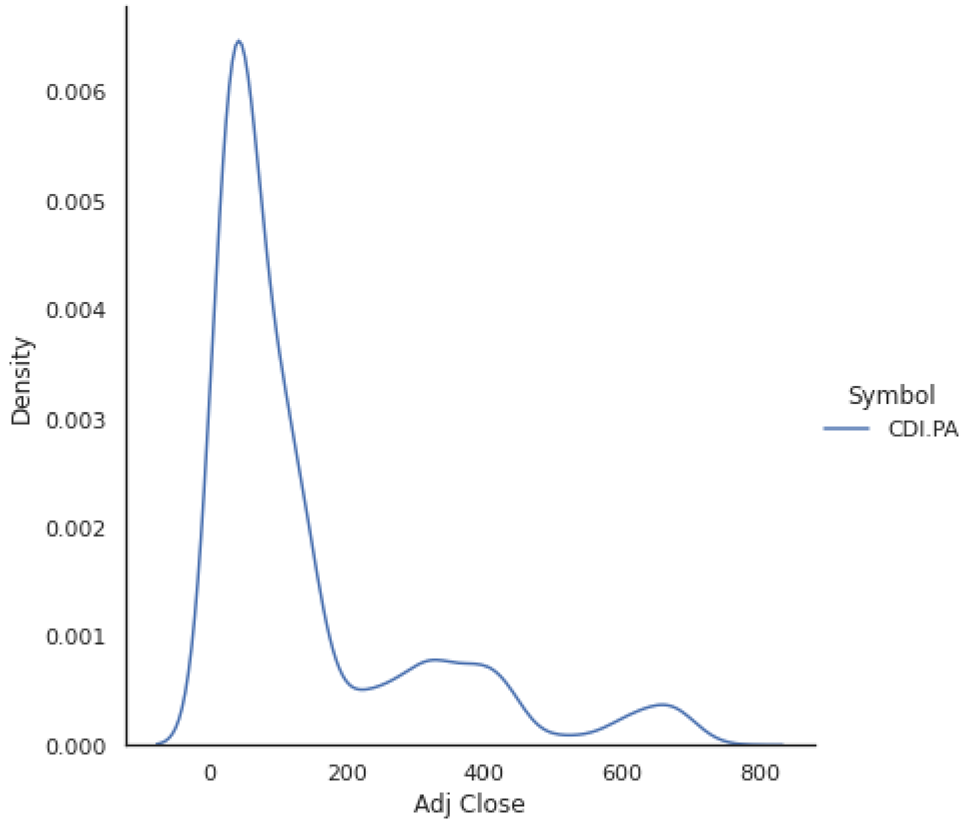



```
# A violin plot combines the benefits of the previous two plots and simplifies them
# Denser regions of the data are fatter, and sparser thiner in a violin plot
sns.violinplot(x="Symbol", y="Adj Close", data=dior, size=6)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f7374aa5af0>
```

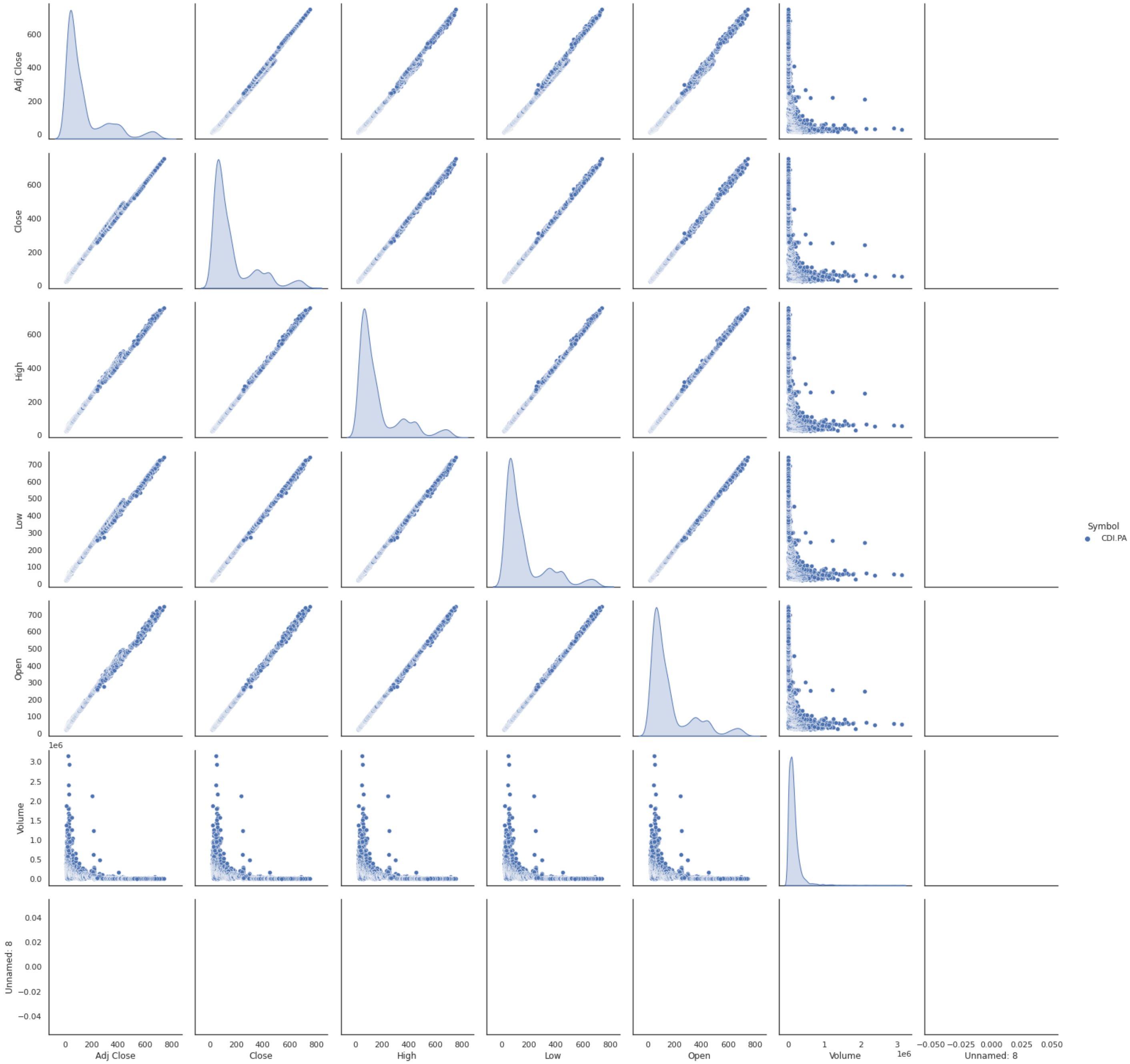
```
# A final seaborn plot useful for looking at univariate relations is the kdeplot,
# which creates and visualizes a kernel density estimate of the underlying feature
sns.FacetGrid(dior, hue="Symbol", size=6) \
   .map(sns.kdeplot, "Adj Close") \
   .add_legend()
```

```
<seaborn.axisgrid.FacetGrid at 0x7f7374a5d070>
```



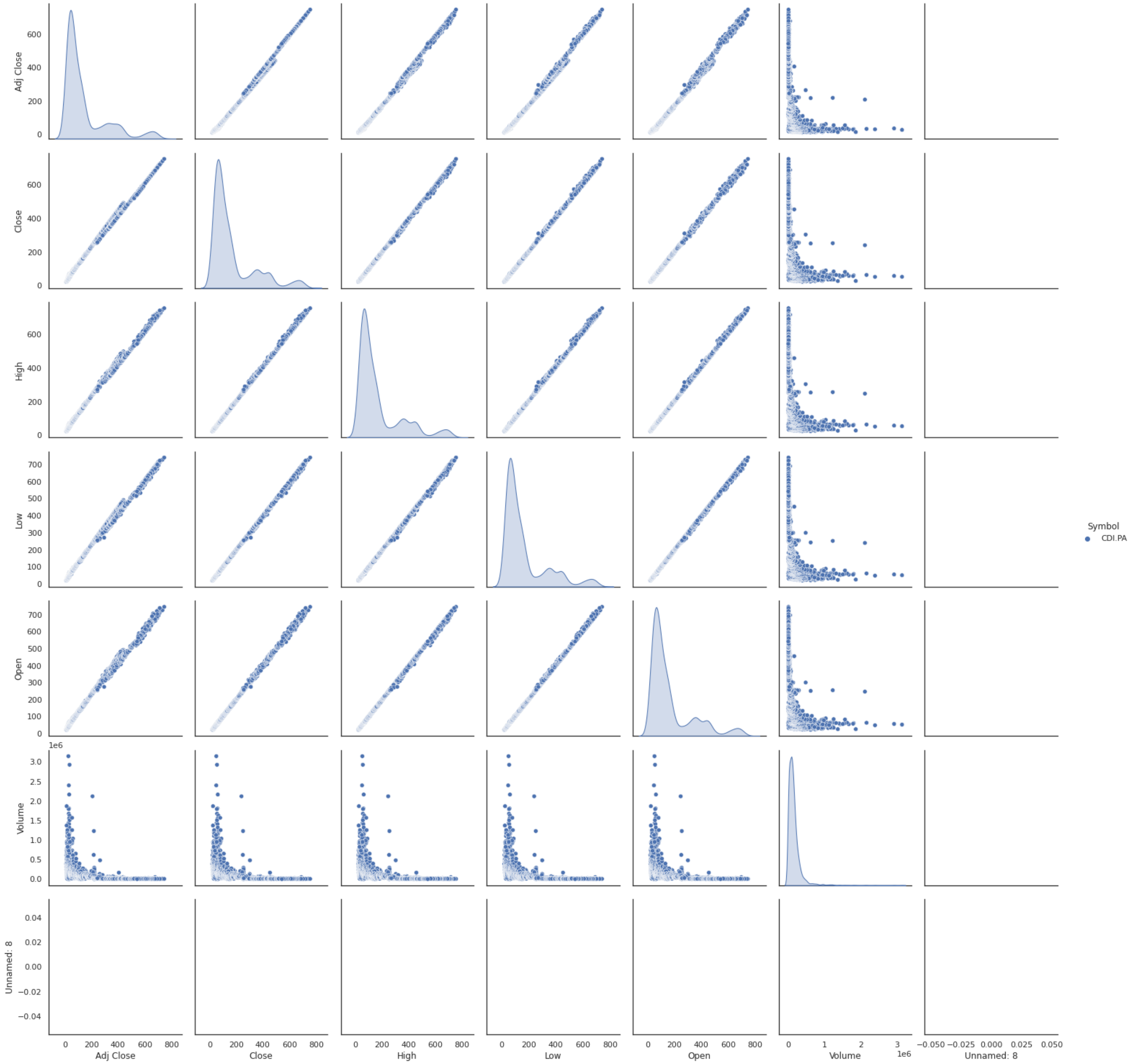

```
# Another useful seaborn plot is the pairplot, which shows the bivariate relation
# between each pair of features

sns.pairplot(dior.drop("Date", axis=1), hue="Symbol", size=3)
```

<seaborn.axisgrid.PairGrid at 0x7f73749f5730>

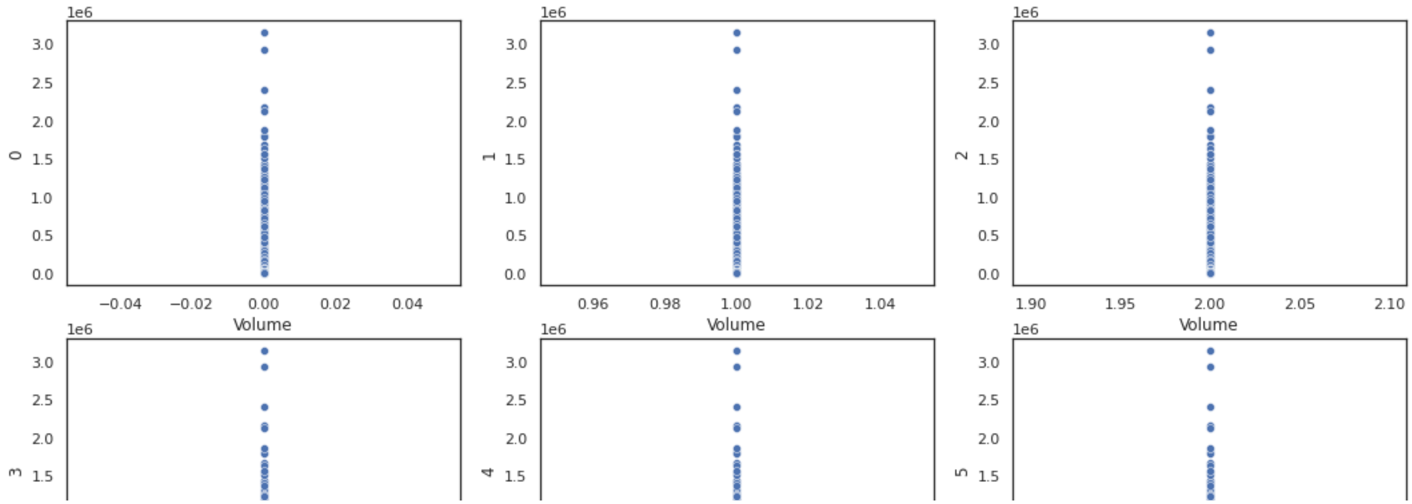


```
# The diagonal elements in a pairplot show the histogram by default
# We can update these elements to show other things, such as a kde
sns.pairplot(dior.drop("Date", axis=1), hue="Symbol", size=3, diag_kind="kde")
```

<seaborn.axisgrid.PairGrid at 0x7f7373bb22e0>



```
fig, axs = plt.subplots(2, 3, figsize=(18, 8))

axs = axs.flatten()
for i, col in enumerate(list(dior.index[:6])):
    sns.scatterplot(y='Volume', x=col, ax=axs[i], data=dior)
    axs[i].set_xlabel('Volume')
    axs[i].set_ylabel(col)
plt.show()
```




```
# Now that we've covered seaborn, let's go back to some of the ones we can make with Pandas
# We can quickly make a boxplot with Pandas on each feature split out by Symbol
dior.drop("Date", axis=1).boxplot(by="Symbol", figsize=(12, 6))
```

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7f73719d2070>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f73719d8d60>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f7371999e50>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7f73710921c0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f737103e4c0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f73710687c0>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7f7371076760>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f7371023a60>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f7370f7a4c0>]],
      dtype=object)
```

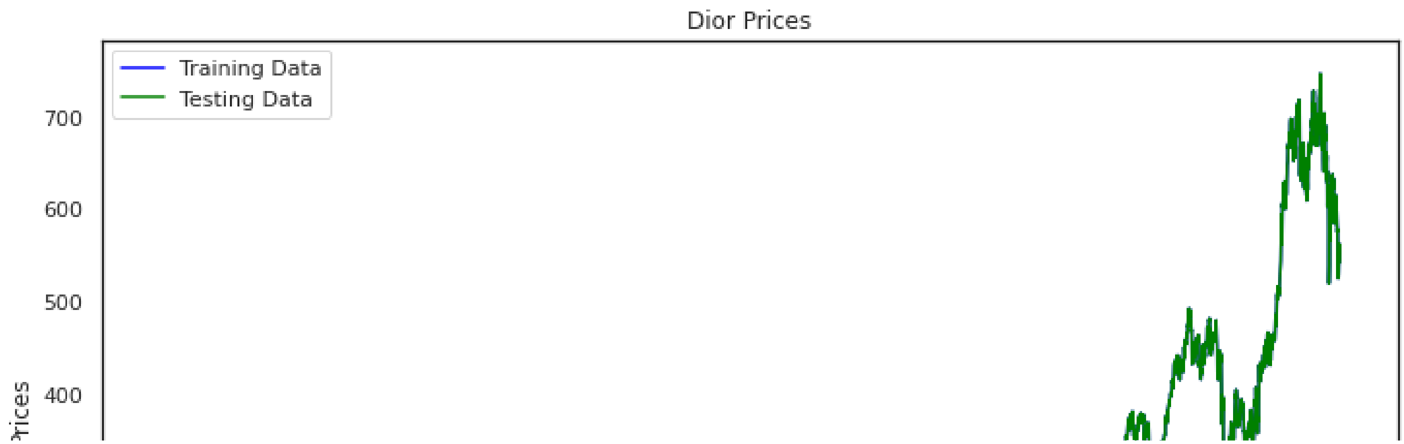
Boxplot grouped by Symbol

Adj Close Close High

Time Series Prediction

```
train_data, test_data = dior[0:int(len(dior)*0.8)], dior[int(len(dior)*0.8):]
plt.figure(figsize=(12,7))
plt.title('Dior Prices')
plt.xlabel('Dates')
plt.ylabel('Prices')
plt.plot(dior['Open'], 'blue', label='Training Data')
plt.plot(test_data['Open'], 'green', label='Testing Data')
plt.xticks(np.arange(0,5000, 400), dior['Date'][0:5000:400])
plt.legend()
```

```
<matplotlib.legend.Legend at 0x7f7370df9490>
```



Feature Selection (Consider Column for Regression)

```
#  we use open,high,low,Adj Close to predict  close price
x=dior[['High','Low','Adj Close','Open']].values   #input
y=dior[['Close']].values   #output
```

Data Split

```
from sklearn.model_selection import train_test_split
#split to train and test data
x_train, x_test, y_train, y_test = train_test_split(x,y, test_size=0.2,random_state=0)
```

```
print('x_train.shape = ',x_train.shape)
print('y_train.shape = ', y_train.shape)
print('x_test.shape = ', x_test.shape)
print('y_test.shape = ',y_test.shape)
```

```
x_train.shape =  (4583, 4)
y_train.shape =  (4583, 1)
```

```
x_test.shape =  (1146, 4)
y_test.shape =  (1146, 1)
```

linear regression

```
lm=LinearRegression()
lm.fit(x_train,y_train)
```

```
LinearRegression()
```

```
lm.coef_
```

```
array([[ 0.63918616,  0.84015144,  0.03882131, -0.51592858]])
```

```
#values from 0 to 1
#0 model explain None of the variability
#1 model explain Entire of the variability
lm.score(x_train,y_train)
```

```
0.9999075709692843
```

Model Prediction using test data

```
#predict the output(predictions) using the test data
predictions = lm.predict(x_test)
from sklearn.metrics import r2_score
r2_score(y_test, predictions)
```

```
0.9998638489031773
```

Compare the actual and predicted values

```
#load actual and predecited values side by side
dframe=pd.DataFrame({'actual':y_test.flatten(),'Predicted':predictions.flatten()})
#flatten toget single axis of data (1 dimension only)
dframe.head(10)
```

	actual	Predicted
0	99.889999	99.443762
1	83.599998	83.060797
2	55.500000	55.853165
3	67.050003	67.019461
4	33.900002	33.970030
5	77.500000	77.980660
6	64.900002	65.183197
7	50.000000	50.229588
8	505.500000	505.117539
9	362.799988	362.749614

```
#metrics to find accuracy of continous variables
import math
from sklearn import metrics
print('Mean Abs value:' ,metrics.mean_absolute_error(y_test,predictions))
print('Mean squared value:',metrics.mean_squared_error(y_test,predictions))
print('root mean squared error value:',math.sqrt(metrics.mean_squared_error(y_test,predictions)))
```

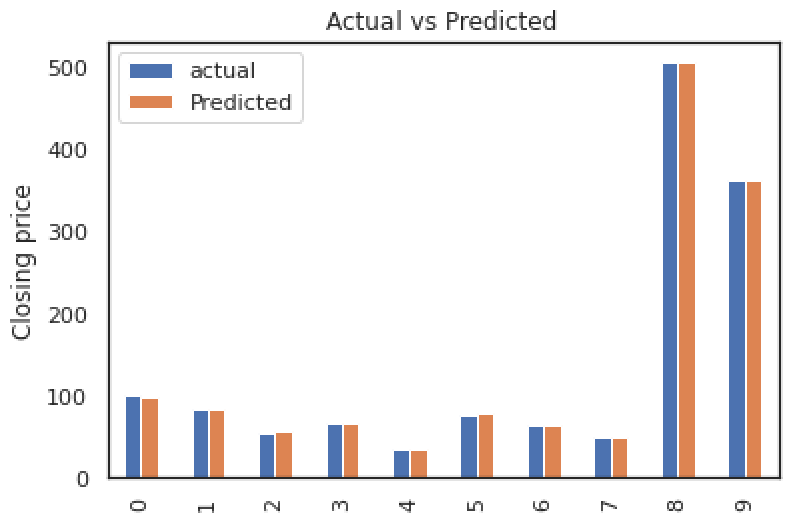
```
Mean Abs value: 0.9626937349022824
Mean squared value: 3.5955516992104
```

```
root mean squared error value: 1.8961940035793807
```

Result Analysis

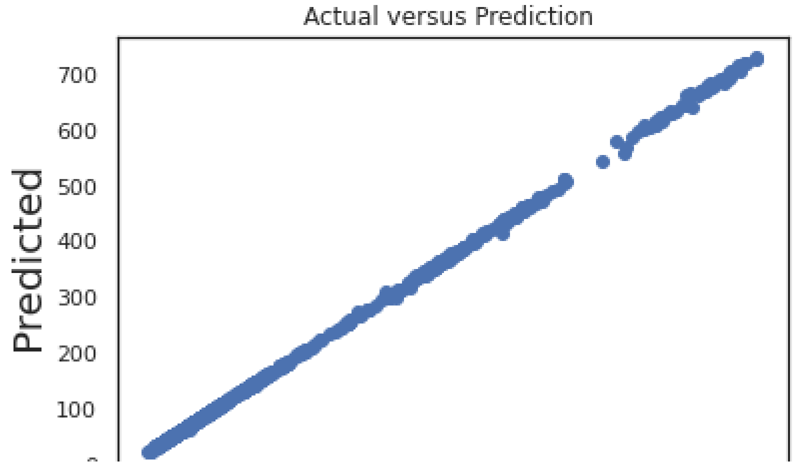
```
graph =dframe.head(10)
graph.plot(kind='bar')
plt.title('Actual vs Predicted')
plt.ylabel('Closing price')
```

```
Text(0, 0.5, 'Closing price')
```




```
#using scatter plot compare the actual and predicted data
fig = plt.figure()
plt.scatter(y_test,predictions)
plt.title('Actual versus Prediction ')
plt.xlabel('Actual', fontsize=20)
plt.ylabel('Predicted', fontsize=20)
```

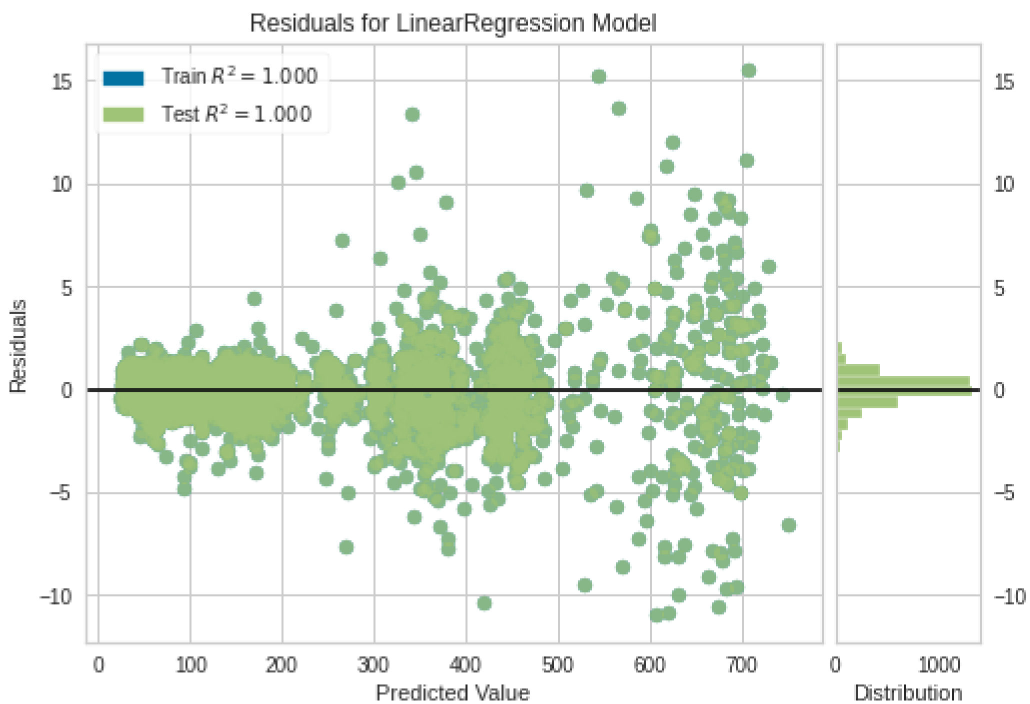
```
Text(0, 0.5, 'Predicted')
```




```
# Repeated K-fold cross validation
from sklearn.model_selection import KFold
import time
# Start counting time
from yellowbrick.regressor import ResidualsPlot
from sklearn.metrics import mean_squared_error

SEED = 42
kfolds = KFold(n_splits=10, shuffle=True, random_state=SEED)

# Return root mean square error of model prediction (Used for test prediction)
def rmse(y, y_pred):
    return np.sqrt(mean_squared_error(y, y_pred))

# Return root mean square error applied cross validation (Used for training prediction)
def evaluate_model_cv(model, X, y):
    rmse = np.sqrt(-cross_val_score(model, X, y, scoring="neg_mean_squared_error", cv=kfolds))
    return (rmse)


start = time.perf_counter()
visualizer = ResidualsPlot(lm)
visualizer.fit(x_train, y_train)
visualizer.score(x_train, y_train)
model = lm.fit(x_train,y_train)
```

```
rmse_result = rmse(y_test, model.predict(x_test))
print(f'Linear Regression rmse after training: {rmse_result}')
# Compute time for executing each algo
run = time.perf_counter() - start
print(f'Computational runtime of this algo: {round(run, 2)} seconds\n')
visualizer.show()
```

```
Linear Regression rmse after training: 1.8961940035793807
Computational runtime of this algo: 0.1 seconds
```



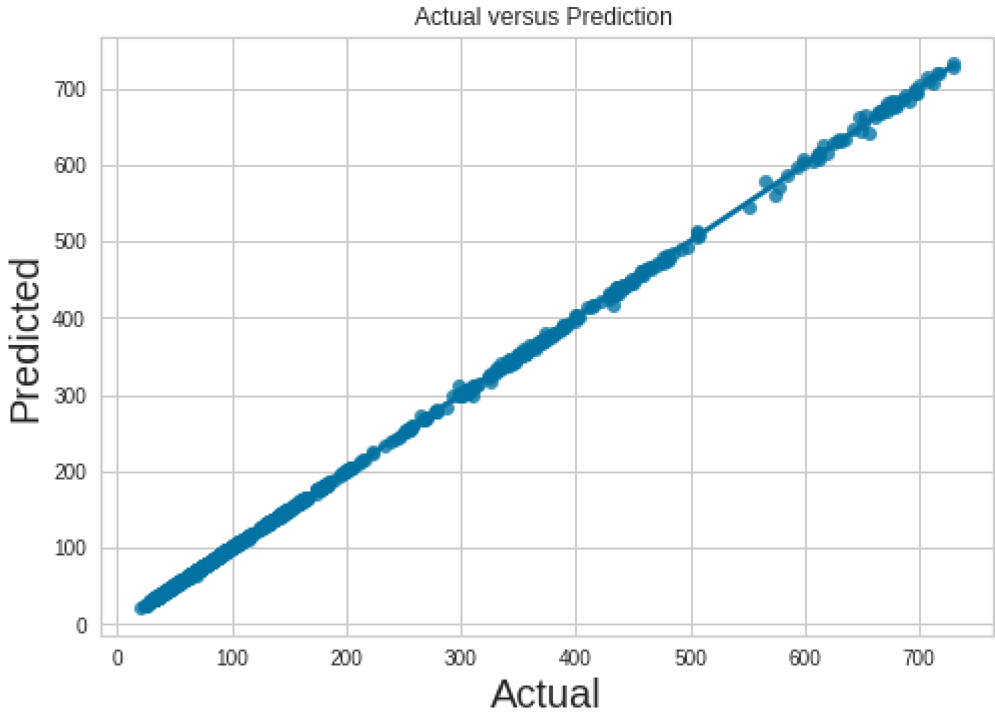

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f73707f9a30>
```

reg plot

```
#trying the same with a reg plot(optonal)
sns.regplot(y_test,predictions)
```

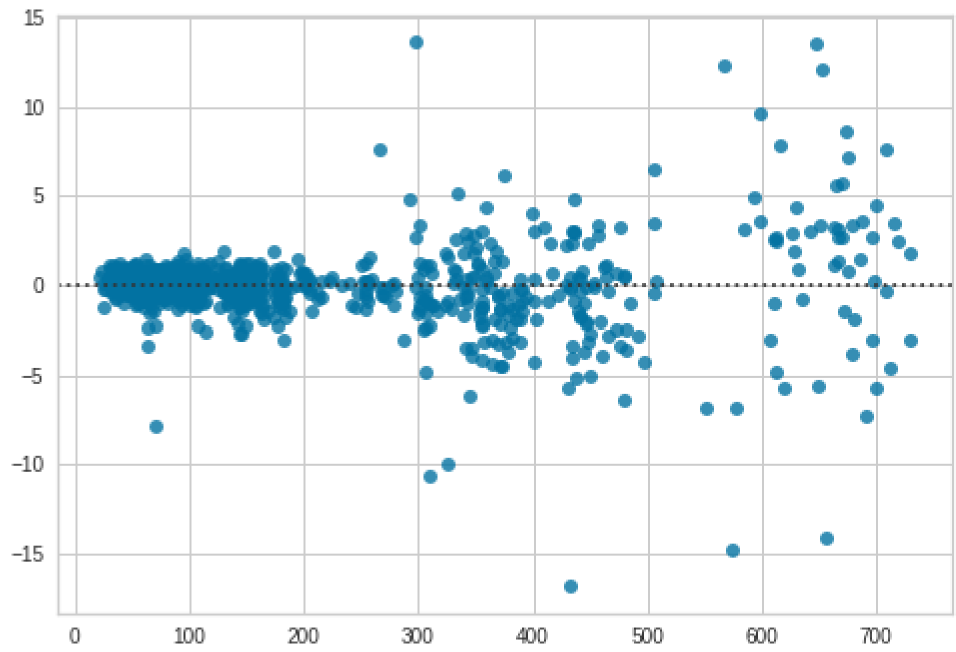
```
plt.title('Actual versus Prediction ')
plt.xlabel('Actual', fontsize=20)
plt.ylabel('Predicted', fontsize=20)
```

```
Text(0, 0.5, 'Predicted')
```



residplot

```
sns.residplot(y_test,predictions)
plt.savefig("out.png")
```



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