September 11, 2024

0.1 Introduction

What is Exploratory Data Analysis ?

Exploratory Data Analysis or (EDA) is understanding the data sets by summarizing their main characteristics often plotting them visually. This step is very important especially when we arrive at modeling the data in order to apply Machine learning. Plotting in EDA consists of Histograms, Box plot, Scatter plot and many more. It often takes much time to explore the data. Through the process of EDA, we can ask to define the problem statement or definition on our data set which is very important.

How to perform Exploratory Data Analysis ?

This is one such question that everyone is keen on knowing the answer. Well, the answer is it depends on the data set that you are working. There is no one method or common methods in order to perform EDA, whereas in this tutorial you can understand some common methods and plots that would be used in the EDA process.

What data are we exploring today ?

Since I am a huge fan of cars, I got a very beautiful data-set of cars from Kaggle. The data-set can be downloaded from here. To give a piece of brief information about the data set this data contains more of 10, 000 rows and more than 10 columns which contains features of the car such as Engine Fuel Type, Engine HP, Transmission Type, highway MPG, city MPG and many more. So in this tutorial, we will explore the data and make it ready for modeling.

0.2 1. Importing the required libraries for EDA

Below are the libraries that are used in order to perform EDA (Exploratory data analysis) in this tutorial.

[1]:
```
import pandas as pd
import numpy as np
import seaborn as sns                   #visualisation
import matplotlib.pyplot as plt         #visualisation
%matplotlib inline
sns.set(color_codes=True)
```

0.3 2. Loading the data into the data frame.

Loading the data into the pandas data frame is certainly one of the most important steps in EDA, as we can see that the value from the data set is comma-separated. So all we have to do is to just read the CSV into a data frame and pandas data frame does the job for us.

To get or load the dataset into the notebook, all I did was one trivial step. In Google Colab at the left-hand side of the notebook, you will find a > (greater than symbol). When you click that you will find a tab with three options, you just have to select Files. Then you can easily upload your file with the help of the Upload option. No need to mount to the google drive or use any specific libraries just upload the data set and your job is done. One thing to remember in this step is that uploaded files will get deleted when this runtime is recycled. This is how I got the data set into the notebook.

[2]:
```
df = pd.read_csv("../input/cardataset/data.csv")
# To display the top 5 rows
df.head(5)
```

[2]:
```
  Make       Model  Year             Engine Fuel Type  Engine HP  \
0  BMW  1 Series M  2011  premium unleaded (required)      335.0
1  BMW    1 Series  2011  premium unleaded (required)      300.0
2  BMW    1 Series  2011  premium unleaded (required)      300.0
3  BMW    1 Series  2011  premium unleaded (required)      230.0
4  BMW    1 Series  2011  premium unleaded (required)      230.0

   Engine Cylinders Transmission Type     Driven_Wheels  Number of Doors  \
0               6.0            MANUAL  rear wheel drive              2.0
1               6.0            MANUAL  rear wheel drive              2.0
2               6.0            MANUAL  rear wheel drive              2.0
3               6.0            MANUAL  rear wheel drive              2.0
4               6.0            MANUAL  rear wheel drive              2.0

                         Market Category Vehicle Size Vehicle Style  \
0  Factory Tuner,Luxury,High-Performance      Compact         Coupe
1                     Luxury,Performance      Compact   Convertible
2                Luxury,High-Performance      Compact         Coupe
3                     Luxury,Performance      Compact         Coupe
4                                 Luxury      Compact   Convertible

   highway MPG  city mpg  Popularity   MSRP
0           26        19        3916  46135
1           28        19        3916  40650
2           28        20        3916  36350
3           28        18        3916  29450
4           28        18        3916  34500
```

[3]:
```
df.tail(5)                          # To display the botton 5 rows
```

[3]:
```
            Make   Model  Year             Engine Fuel Type  Engine HP  \
11909    Acura     ZDX  2012     premium unleaded (required)      300.0
11910    Acura     ZDX  2012     premium unleaded (required)      300.0
11911    Acura     ZDX  2012     premium unleaded (required)      300.0
11912    Acura     ZDX  2013  premium unleaded (recommended)      300.0
11913  Lincoln  Zephyr  2006                regular unleaded      221.0

       Engine Cylinders Transmission Type     Driven_Wheels  Number of Doors  \
11909               6.0         AUTOMATIC    all wheel drive              4.0
11910               6.0         AUTOMATIC    all wheel drive              4.0
11911               6.0         AUTOMATIC    all wheel drive              4.0
11912               6.0         AUTOMATIC    all wheel drive              4.0
11913               6.0         AUTOMATIC  front wheel drive              4.0

                  Market Category Vehicle Size  Vehicle Style  highway MPG  \
11909  Crossover,Hatchback,Luxury      Midsize  4dr Hatchback           23
11910  Crossover,Hatchback,Luxury      Midsize  4dr Hatchback           23
11911  Crossover,Hatchback,Luxury      Midsize  4dr Hatchback           23
11912  Crossover,Hatchback,Luxury      Midsize  4dr Hatchback           23
11913                      Luxury      Midsize          Sedan           26

       city mpg  Popularity   MSRP
11909        16         204  46120
11910        16         204  56670
11911        16         204  50620
11912        16         204  50920
11913        17          61  28995
```

0.4 3. Checking the types of data

Here we check for the datatypes because sometimes the MSRP or the price of the car would be stored as a string, if in that case, we have to convert that string to the integer data only then we can plot the data via a graph. Here, in this case, the data is already in integer format so nothing to worry.

[4]:
```python
df.dtypes
```

[4]:
```
Make                  object
Model                 object
Year                   int64
Engine Fuel Type      object
Engine HP            float64
Engine Cylinders     float64
Transmission Type     object
Driven_Wheels         object
Number of Doors      float64
```

```
Market Category       object
Vehicle Size          object
Vehicle Style         object
highway MPG            int64
city mpg               int64
Popularity             int64
MSRP                   int64
dtype: object
```

0.5 4. Dropping irrelevant columns

This step is certainly needed in every EDA because sometimes there would be many columns that we never use in such cases dropping is the only solution. In this case, the columns such as Engine Fuel Type, Market Category, Vehicle style, Popularity, Number of doors, Vehicle Size doesn't make any sense to me so I just dropped for this instance.

[5]:
```
df = df.drop(['Engine Fuel Type', 'Market Category', 'Vehicle Style',␣
 ↪'Popularity', 'Number of Doors', 'Vehicle Size'], axis=1)
df.head(5)
```

[5]:
```
  Make       Model  Year  Engine HP  Engine Cylinders Transmission Type  \
0  BMW  1 Series M  2011      335.0               6.0            MANUAL
1  BMW    1 Series  2011      300.0               6.0            MANUAL
2  BMW    1 Series  2011      300.0               6.0            MANUAL
3  BMW    1 Series  2011      230.0               6.0            MANUAL
4  BMW    1 Series  2011      230.0               6.0            MANUAL

     Driven_Wheels  highway MPG  city mpg   MSRP
0  rear wheel drive           26        19  46135
1  rear wheel drive           28        19  40650
2  rear wheel drive           28        20  36350
3  rear wheel drive           28        18  29450
4  rear wheel drive           28        18  34500
```

0.6 5. Renaming the columns

In this instance, most of the column names are very confusing to read, so I just tweaked their column names. This is a good approach it improves the readability of the data set.

[6]:
```
df = df.rename(columns={"Engine HP": "HP", "Engine Cylinders": "Cylinders",␣
 ↪"Transmission Type": "Transmission", "Driven_Wheels": "Drive Mode","highway␣
 ↪MPG": "MPG-H", "city mpg": "MPG-C", "MSRP": "Price" })
df.head(5)
```

[6]:
```
  Make       Model  Year     HP  Cylinders Transmission        Drive Mode  \
0  BMW  1 Series M  2011  335.0        6.0       MANUAL  rear wheel drive
1  BMW    1 Series  2011  300.0        6.0       MANUAL  rear wheel drive
2  BMW    1 Series  2011  300.0        6.0       MANUAL  rear wheel drive
3  BMW    1 Series  2011  230.0        6.0       MANUAL  rear wheel drive
4  BMW    1 Series  2011  230.0        6.0       MANUAL  rear wheel drive

   MPG-H  MPG-C  Price
0     26     19  46135
1     28     19  40650
2     28     20  36350
3     28     18  29450
4     28     18  34500
```

0.7 6. Dropping the duplicate rows

This is often a handy thing to do because a huge data set as in this case contains more than 10, 000 rows often have some duplicate data which might be disturbing, so here I remove all the duplicate value from the data-set. For example prior to removing I had 11914 rows of data but after removing the duplicates 10925 data meaning that I had 989 of duplicate data.

[7]:
```
df.shape
```

[7]:
```
(11914, 10)
```

[8]:
```
duplicate_rows_df = df[df.duplicated()]
print("number of duplicate rows: ", duplicate_rows_df.shape)
```

```
number of duplicate rows:  (989, 10)
```

Now let us remove the duplicate data because it's ok to remove them.

[9]:
```
df.count()      # Used to count the number of rows
```

[9]:
```
Make            11914
Model           11914
Year            11914
HP              11845
Cylinders       11884
Transmission    11914
Drive Mode      11914
MPG-H           11914
MPG-C           11914
Price           11914
dtype: int64
```

So seen above there are 11914 rows and we are removing 989 rows of duplicate data.

[10]:
```
df = df.drop_duplicates()
df.head(5)
```

[10]:
```
  Make       Model  Year     HP  Cylinders Transmission        Drive Mode  \
0  BMW  1 Series M  2011  335.0        6.0       MANUAL  rear wheel drive
1  BMW    1 Series  2011  300.0        6.0       MANUAL  rear wheel drive
2  BMW    1 Series  2011  300.0        6.0       MANUAL  rear wheel drive
3  BMW    1 Series  2011  230.0        6.0       MANUAL  rear wheel drive
4  BMW    1 Series  2011  230.0        6.0       MANUAL  rear wheel drive

   MPG-H  MPG-C  Price
0     26     19  46135
1     28     19  40650
2     28     20  36350
3     28     18  29450
4     28     18  34500
```

[11]:
```
df.count()
```

[11]:
```
Make            10925
Model           10925
Year            10925
HP              10856
Cylinders       10895
Transmission    10925
Drive Mode      10925
MPG-H           10925
MPG-C           10925
Price           10925
dtype: int64
```

0.8 7. Dropping the missing or null values.

This is mostly similar to the previous step but in here all the missing values are detected and are dropped later. Now, this is not a good approach to do so, because many people just replace the missing values with the mean or the average of that column, but in this case, I just dropped that missing values. This is because there is nearly 100 missing value compared to 10, 000 values this is a small number and this is negligible so I just dropped those values.

[12]:
```
print(df.isnull().sum())
```

```
Make             0
Model            0
Year             0
HP              69
Cylinders       30
```

```
Transmission     0
Drive Mode       0
MPG-H            0
MPG-C            0
Price            0
dtype: int64
```

This is the reason in the above step while counting both Cylinders and Horsepower (HP) had 10856 and 10895 over 10925 rows.

[13]:
```python
df = df.dropna()    # Dropping the missing values.
df.count()
```

[13]:
```
Make            10827
Model           10827
Year            10827
HP              10827
Cylinders       10827
Transmission    10827
Drive Mode      10827
MPG-H           10827
MPG-C           10827
Price           10827
dtype: int64
```

Now we have removed all the rows which contain the Null or N/A values (Cylinders and Horsepower (HP)).

[14]:
```python
print(df.isnull().sum())   # After dropping the values
```

```
Make            0
Model           0
Year            0
HP              0
Cylinders       0
Transmission    0
Drive Mode      0
MPG-H           0
MPG-C           0
Price           0
dtype: int64
```

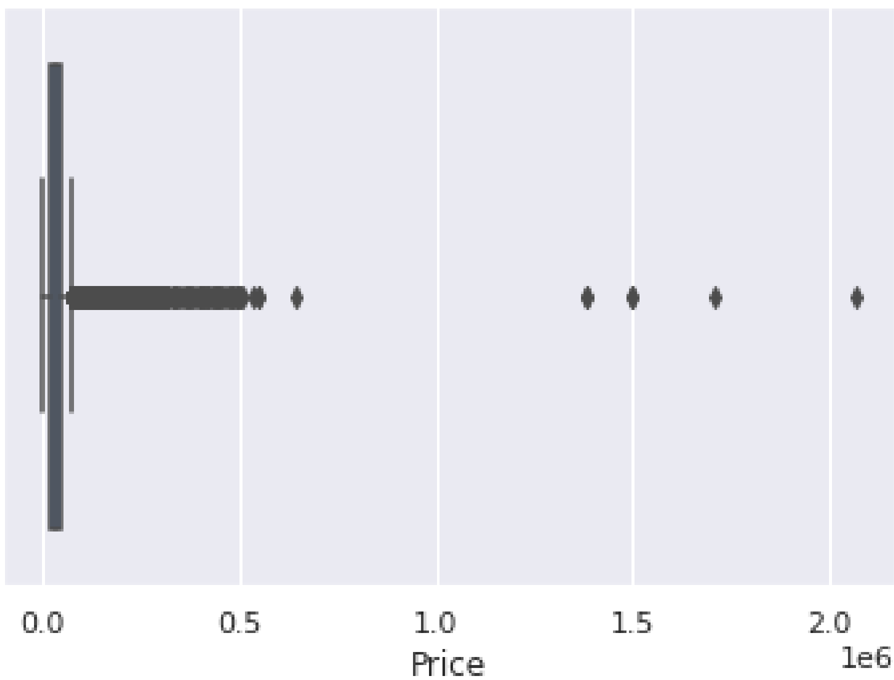
0.9 8. Detecting Outliers

An outlier is a point or set of points that are different from other points. Sometimes they can be very high or very low. It's often a good idea to detect and remove the outliers. Because outliers are one of the primary reasons for resulting in a less accurate model. Hence it's a good idea to remove them. The outlier detection and removing that I am going to perform is called IQR score technique.

Often outliers can be seen with visualizations using a box plot. Shown below are the box plot of MSRP, Cylinders, Horsepower and EngineSize. Herein all the plots, you can find some points are outside the box they are none other than outliers. The technique of finding and removing outlier that I am performing in this assignment is taken help of a tutorial fromtowards data science.

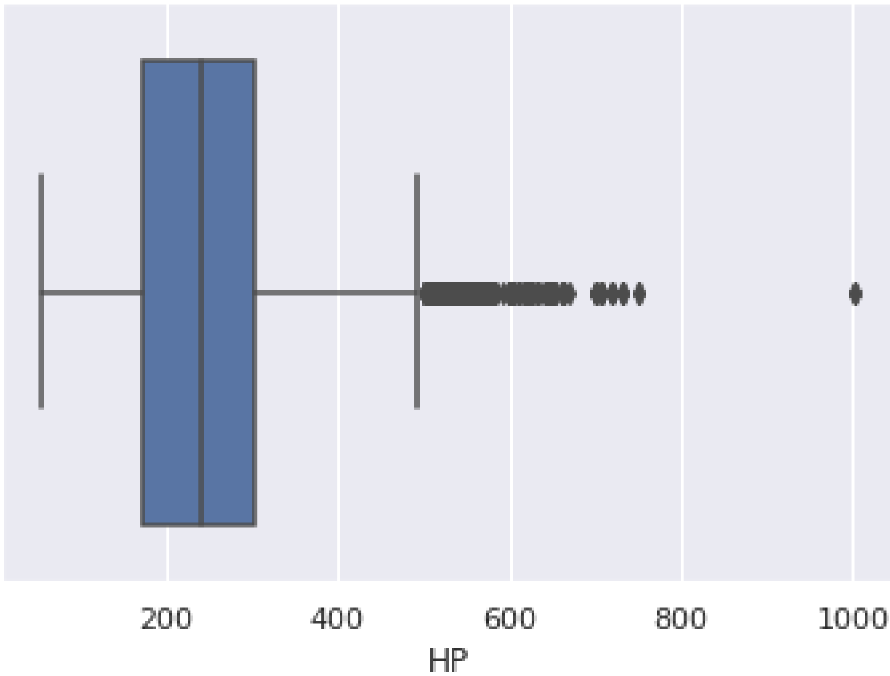
[15]:
```
sns.boxplot(x=df['Price'])
```

[15]: <matplotlib.axes._subplots.AxesSubplot at 0x7f89e9c87a90>



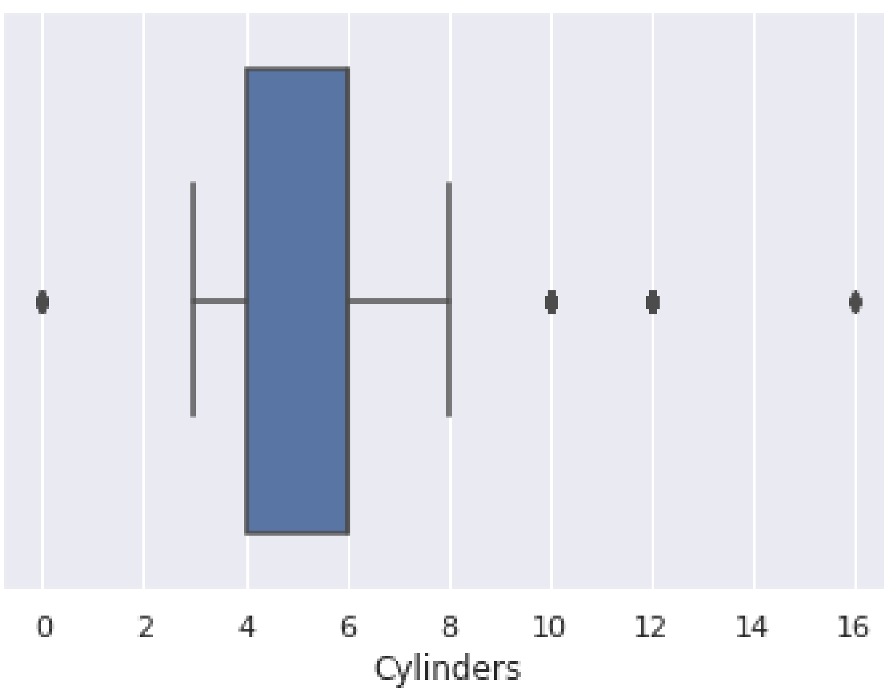
[16]:
```
sns.boxplot(x=df['HP'])
```

[16]: <matplotlib.axes._subplots.AxesSubplot at 0x7f89e79e2990>




```
[17]: sns.boxplot(x=df['Cylinders'])
```

[17]: <matplotlib.axes._subplots.AxesSubplot at 0x7f89e79e2250>



[18]:
```
Q1 = df.quantile(0.25)
Q3 = df.quantile(0.75)
IQR = Q3 - Q1
print(IQR)
```

```
Year             9.0
HP             130.0
Cylinders        2.0
MPG-H            8.0
MPG-C            6.0
Price        21327.5
dtype: float64
```

Don't worry about the above values because it's not important to know each and every one of them because it's just important to know how to use this technique in order to remove the outliers.

[19]:
```
df = df[~((df < (Q1 - 1.5 * IQR)) |(df > (Q3 + 1.5 * IQR))).any(axis=1)]
df.shape
```

[19]:
```
(9191, 10)
```

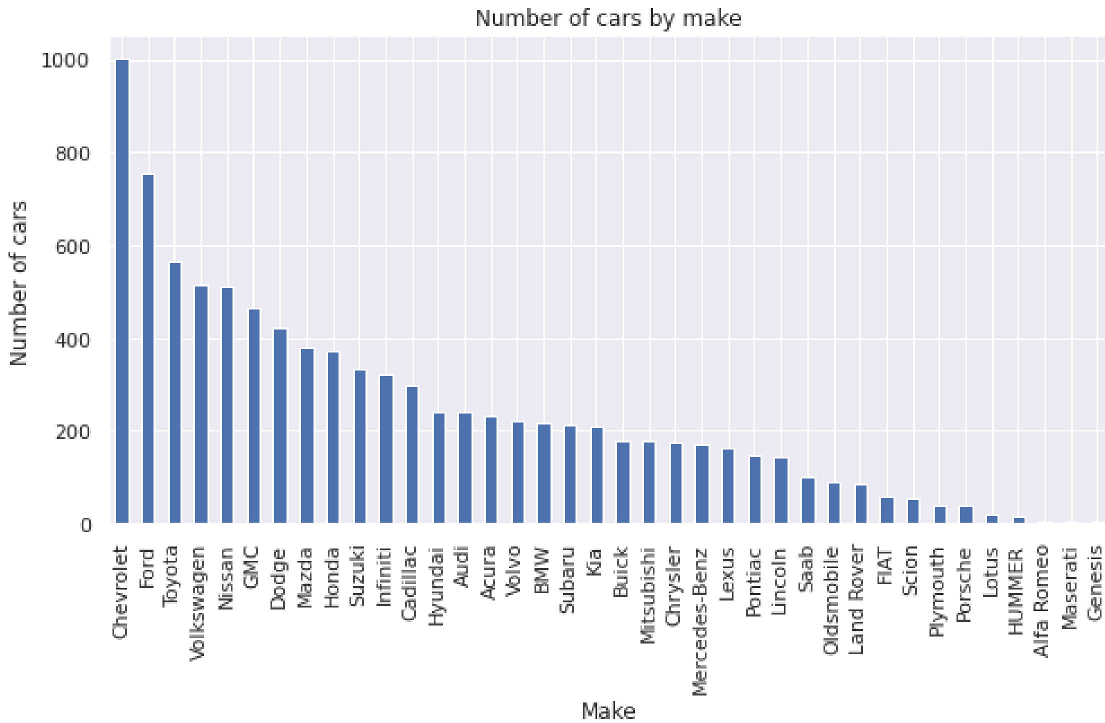
As seen above there were around 1600 rows were outliers. But you cannot completely remove the outliers because even after you use the above technique there maybe 1–2 outlier unremoved but that ok because there were more than 100 outliers. Something is better than nothing.

0.10 9. Plot different features against one another (scatter), against frequency (histogram)

0.10.1 Histogram

Histogram refers to the frequency of occurrence of variables in an interval. In this case, there are mainly 10 different types of car manufacturing companies, but it is often important to know who has the most number of cars. To do this histogram is one of the trivial solutions which lets us know the total number of car manufactured by a different company.

[20]:
```
df.Make.value_counts().nlargest(40).plot(kind='bar', figsize=(10,5))
plt.title("Number of cars by make")
plt.ylabel('Number of cars')
plt.xlabel('Make');
```



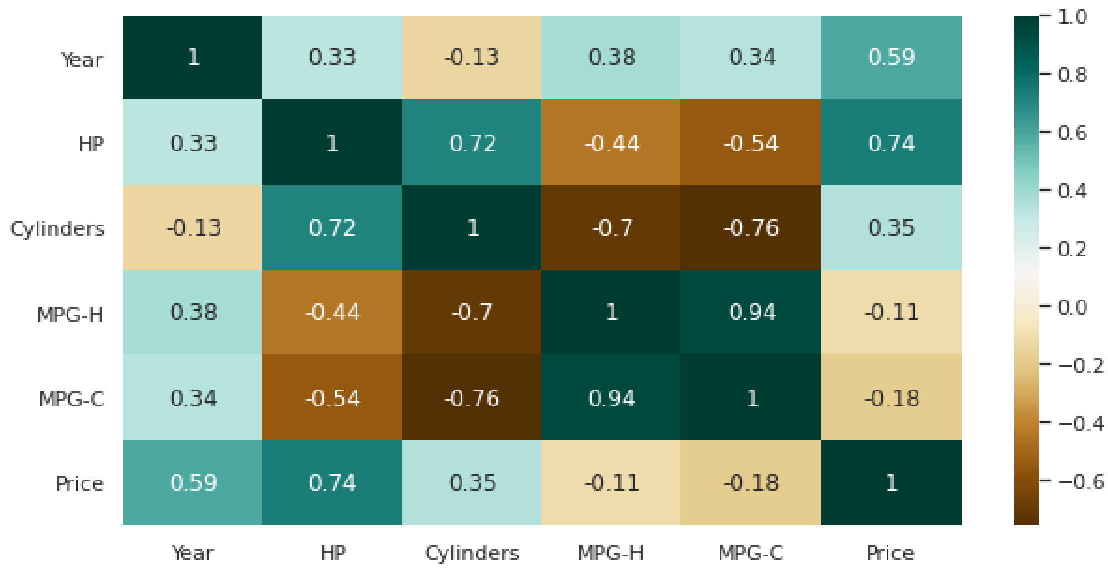
0.10.2 Heat Maps

Heat Maps is a type of plot which is necessary when we need to find the dependent variables. One of the best way to find the relationship between the features can be done using heat maps. In the below heat map we know that the price feature depends mainly on the Engine Size, Horsepower, and Cylinders.

[21]:
```
plt.figure(figsize=(10,5))
c= df.corr()
sns.heatmap(c,cmap="BrBG",annot=True)
c
```

[21]:

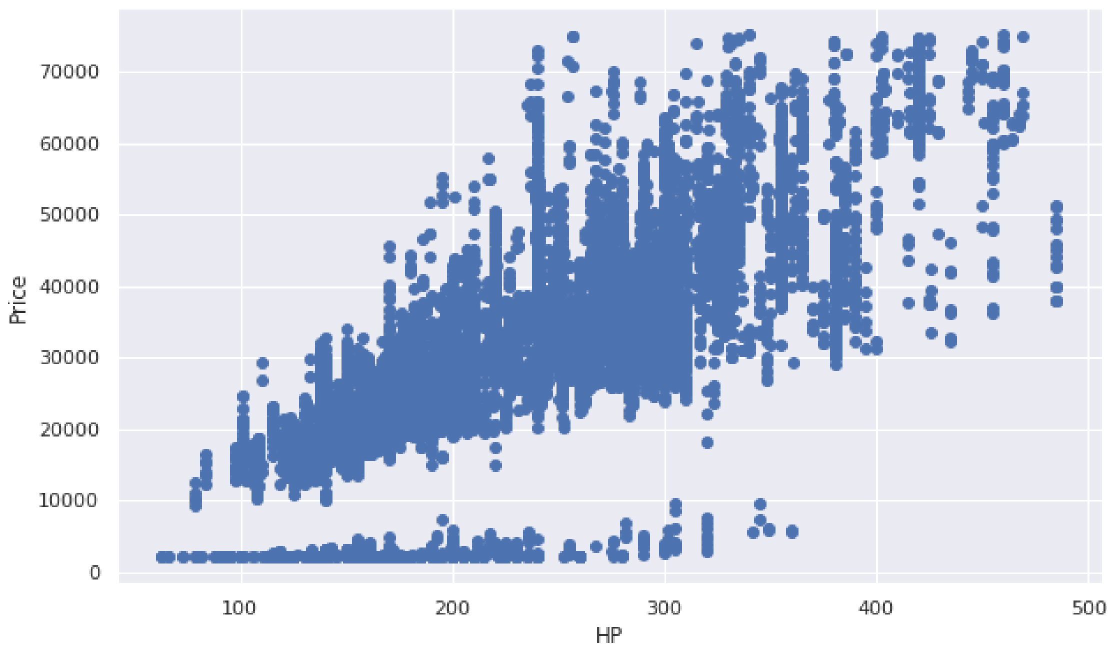
	Year	HP	Cylinders	MPG-H	MPG-C	Price
Year	1.000000	0.326726	-0.133920	0.378479	0.338145	0.592983
HP	0.326726	1.000000	0.715237	-0.443807	-0.544551	0.739042
Cylinders	-0.133920	0.715237	1.000000	-0.703856	-0.755540	0.354013
MPG-H	0.378479	-0.443807	-0.703856	1.000000	0.939141	-0.106320
MPG-C	0.338145	-0.544551	-0.755540	0.939141	1.000000	-0.180515
Price	0.592983	0.739042	0.354013	-0.106320	-0.180515	1.000000



0.10.3 Scatterplot

We generally use scatter plots to find the correlation between two variables. Here the scatter plots are plotted between Horsepower and Price and we can see the plot below. With the plot given below, we can easily draw a trend line. These features provide a good scattering of points.

[22]:
```
fig, ax = plt.subplots(figsize=(10,6))
ax.scatter(df['HP'], df['Price'])
ax.set_xlabel('HP')
ax.set_ylabel('Price')
plt.show()
```



Hence the above are some of the steps involved in Exploratory data analysis, these are some general steps that you must follow in order to perform EDA. There are many more yet to come but for now, this is more than enough idea as to how to perform a good EDA given any data sets. Stay tuned for more updates.

Thank you.