Exploratory Data Analysis

Problem Statement:

We have used Cars dataset from kaggle with features including make, model, year, engine, and other properties of the car used to predict its price.

Importing the necessary libraries

In [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)
from scipy import stats
import warnings
warnings.filterwarnings("ignore")
```

Load the dataset into dataframe

In [2]:

```
## load the csv file
df = pd.read_csv('/content/Cars_data.csv')
```

In [3]:

```
## print the head of the dataframe
df.head()
```

Out[3]:

	Make	Model	Year	Engine Fuel Type	Engine HP	Engine Cylinders	Transmission Type	Driven_Wheels	Number of Doors	Market Category	Vehicle Size
0	BMW	1 Series M	2011	premium unleaded (required)	335.0	6.0	MANUAL	rear wheel drive	2.0	Factory Tuner,Luxury,High-Performance	Compact
1	BMW	1 Series	2011	premium unleaded (required)	300.0	6.0	MANUAL	rear wheel drive	2.0	Luxury,Performance	Compact
2	BMW	1 Series	2011	premium unleaded (required)	300.0	6.0	MANUAL	rear wheel drive	2.0	Luxury,High-Performance	Compact
3	BMW	1 Series	2011	premium unleaded (required)	230.0	6.0	MANUAL	rear wheel drive	2.0	Luxury,Performance	Compact
4	BMW	1 Series	2011	premium unleaded (required)	230.0	6.0	MANUAL	rear wheel drive	2.0	Luxury	Compact

Now we observe the each features present in the dataset.

`Make:` **The Make feature is the company name of the Car.**
`Model:` **The Model feature is the model or different version of Car models.**
`Year:` **The year describes the model has been launched.**
`Engine Fuel Type:` **It defines the Fuel type of the car model.**
`Engine HP:` **It's say the Horsepower that refers to the power an engine produces.**
`Engine Cylinders:` **It define the nos of cylinders in present in the engine.**
`Transmission Type:` **It is the type of feature that describe about the car transmission type i.e Mannual or automatic.**
`Driven_Wheels:` **The type of wheel drive.**
`No of doors:` **It defined nos of doors present in the car.**
`Market Category:` **This features tells about the type of car or which category the car belongs.**
`Vehicle Size:` **It's say about the about car size.**
`Vehicle Style:` **The feature is all about the style that belongs to car.**
`highway MPG:` **The average a car will get while driving on an open stretch of road without stopping or starting, typically at a higher speed.**
`city mpg:` **City MPG refers to driving with occasional stopping and braking.**
`Popularity:` **It can refered to rating of that car or popularity of car.**
`MSRP:` **The price of that car.**

`Check the datatypes`

In [4]:

```
# Get the datatypes of each columns number of records in each column.

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11914 entries, 0 to 11913
Data columns (total 16 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Make               11914 non-null  object 
 1   Model              11914 non-null  object 
 2   Year               11914 non-null  int64  
 3   Engine Fuel Type   11911 non-null  object 
 4   Engine HP          11845 non-null  float64
 5   Engine Cylinders   11884 non-null  float64
 6   Transmission Type  11914 non-null  object 
 7   Driven_Wheels      11914 non-null  object 
 8   Number of Doors    11908 non-null  float64
 9   Market Category    8172 non-null   object 
 10  Vehicle Size       11914 non-null  object 
 11  Vehicle Style      11914 non-null  object 
 12  highway MPG        11914 non-null  int64  
 13  city mpg           11914 non-null  int64  
 14  Popularity         11914 non-null  int64  
 15  MSRP               11914 non-null  int64  
dtypes: float64(3), int64(5), object(8)
memory usage: 1.5+ MB
```

`Dropping irrevalent columns`

If we consider all columns present in the dataset then unneccessary columns will impact on the model's accuracy.
Not all the columns are important to us in the given dataframe, and hence we would drop the columns that are irrevalent to us. It would reflect our model's accucary so we need to drop them. Otherwise it will affect our model.

The list cols_to_drop contains the names of the cols that are irrevalent, drop all these cols from the dataframe.

`cols_to_drop = ["Engine Fuel Type", "Market Category", "Vehicle Style", "Popularity", "Number of Doors", "Vehicle Size"]`

These features are not neccessary to obtain the model's accucary. It does not contain any relevant information in the dataset.

In [5]:

```
# initialise cols_to_drop
cols_to_drop = ["Engine Fuel Type", "Market Category", "Vehicle Style", "Popularity", "N
umber of Doors", "Vehicle Size"]
```

In [6]:

```
# drop the irrevalent cols and print the head of the dataframe
df = df.drop(cols_to_drop,axis=1)

# print df head
df.head()
```

Out[6]:

	Make	Model	Year	Engine HP	Engine Cylinders	Transmission Type	Driven_Wheels	highway MPG	city mpg	MSRP
0	BMW	1 Series M	2011	335.0	6.0	MANUAL	rear wheel drive	26	19	46135
1	BMW	1 Series	2011	300.0	6.0	MANUAL	rear wheel drive	28	19	40650
2	BMW	1 Series	2011	300.0	6.0	MANUAL	rear wheel drive	28	20	36350
3	BMW	1 Series	2011	230.0	6.0	MANUAL	rear wheel drive	28	18	29450
4	BMW	1 Series	2011	230.0	6.0	MANUAL	rear wheel drive	28	18	34500

Renaming the columns

Now, Its time for renaming the feature to useful feature name. It will help to use them in model training purpose.

We have already dropped the unneccesary columns, and now we are left with useful columns. One extra thing that we would do is to rename the columns such that the name clearly represents the essence of the column.

The given dict represents (in key value pair) the previous name, and the new name for the dataframe columns

In [7]:

```
# rename cols
rename_cols = {'Make':'Company_Name','Engine HP':'HP','Engine Cylinders':'Cylinders','MS
RP':'Price'}
```

In [8]:

```
# use a pandas function to rename the current columns -
df = df.rename(columns=rename_cols)
```

In [9]:

```
# Print the head of the dataframe

df.head()
```

Out[9]:

	Company_Name	Model	Year	HP	Cylinders	Transmission Type	Driven_Wheels	highway MPG	city mpg	Price
0	BMW	1 Series M	2011	335.0	6.0	MANUAL	rear wheel drive	26	19	46135
1	BMW	1 Series	2011	300.0	6.0	MANUAL	rear wheel drive	28	19	40650

	Company_Name	Model	Year	HP	Cylinders	Transmission Type	Driven_Wheels	highway MPG	city mpg	Price
2	BMW	1 Series	2011	300.0	6.0	MANUAL	rear wheel drive	28	20	36350
~~3~~	~~BMW~~	~~1 Series~~	~~2011~~	~~230.0~~	~~6.0~~	~~MANUAL~~	~~rear wheel drive~~	~~28~~	~~18~~	~~29450~~
4	BMW	1 Series	2011	230.0	6.0	MANUAL	rear wheel drive	28	18	34500

Dropping the duplicate rows

There are many rows in the dataframe which are duplicate, and hence they are just repeating the information. Its better if we remove these rows as they don't add any value to the dataframe.

For given data, we would like to see how many rows were duplicates. For this, we will count the number of rows, remove the dublicated rows, and again count the number of rows.

In [10]:

```
# number of rows before removing duplicated rows

df.shape
#no. of rows=11914.
```

Out[10]:

```
(11914, 10)
```

In [11]:

```
# drop the duplicated rows
df = df.drop_duplicates()

# print head of df
df.head()
```

Out[11]:

	Company_Name	Model	Year	HP	Cylinders	Transmission Type	Driven_Wheels	highway MPG	city mpg	Price
0	BMW	1 Series M	2011	335.0	6.0	MANUAL	rear wheel drive	26	19	46135
1	BMW	1 Series	2011	300.0	6.0	MANUAL	rear wheel drive	28	19	40650
2	BMW	1 Series	2011	300.0	6.0	MANUAL	rear wheel drive	28	20	36350
3	BMW	1 Series	2011	230.0	6.0	MANUAL	rear wheel drive	28	18	29450
4	BMW	1 Series	2011	230.0	6.0	MANUAL	rear wheel drive	28	18	34500

In [12]:

```
# Count Number of rows after deleting duplicated rows

df.shape    #now no. of rows=10925.
```

Out[12]:

```
(10925, 10)
```

In [13]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10925 entries, 0 to 11913
Data columns (total 10 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Company_Name       10925 non-null  object
 1   Model              10925 non-null  object
 2   Year               10925 non-null  int64
 3   HP                 10856 non-null  float64
```

```
 4   Cylinders           10895 non-null   float64
 5   Transmission Type   10925 non-null   object
 6   Driven_Wheels       10925 non-null   object
 7   highway MPG         10925 non-null   int64
 8   city mpg            10925 non-null   int64
 9   Price               10925 non-null   int64
dtypes: float64(2), int64(4), object(4)
memory usage: 938.9+ KB
```

Dropping the null or missing values

Missing values are usually represented in the form of Nan or null or None in the dataset.

Finding whether we have null values in the data is by using the isnull() function.

There are many values which are missing, in pandas dataframe these values are reffered to as np.nan. We want to deal with these values beause we can't use nan values to train models. Either we can remove them to apply some strategy to replace them with other values.

To keep things simple we will be dropping nan values

In [14]:

```
# check for nan values in each columns

df.isnull().sum()
```

Out[14]:

```
Company_Name         0
Model                0
Year                 0
HP                  69
Cylinders           30
Transmission Type    0
Driven_Wheels        0
highway MPG          0
city mpg             0
Price                0
dtype: int64
```

As we can see that the HP and Cylinders have null values of 69 and 30. As these null values will impact on models' accuracy. So to avoid the impact we will drop the these values. As these values are small camparing with dataset that will not impact any major affect on model accuracy so we will drop the values.

In [15]:

```
# drop missing values
df = df.dropna(how='any')
```

In [16]:

```
# Make sure that missing values are removed
# check number of nan values in each col again

df.isnull().sum()
```

Out[16]:

```
Company_Name        0
Model               0
Year                0
HP                  0
Cylinders           0
Transmission Type   0
Driven_Wheels       0
highway MPG         0
city mpg            0
Price               0
```

dtype: int64

In [17]:

```
#Describe statistics of df
df.describe()
```

Out[17]:

	Year	HP	Cylinders	highway MPG	city mpg	Price
count	10827.000000	10827.000000	10827.000000	10827.000000	10827.000000	1.082700e+04
mean	2010.896370	254.553062	5.691604	26.308119	19.327607	4.249325e+04
std	7.029534	109.841537	1.768551	7.504652	6.643567	6.229451e+04
min	1990.000000	55.000000	0.000000	12.000000	7.000000	2.000000e+03
25%	2007.000000	173.000000	4.000000	22.000000	16.000000	2.197250e+04
50%	2015.000000	240.000000	6.000000	25.000000	18.000000	3.084500e+04
75%	2016.000000	303.000000	6.000000	30.000000	22.000000	4.330000e+04
max	2017.000000	1001.000000	16.000000	354.000000	137.000000	2.065902e+06

Removing outliers

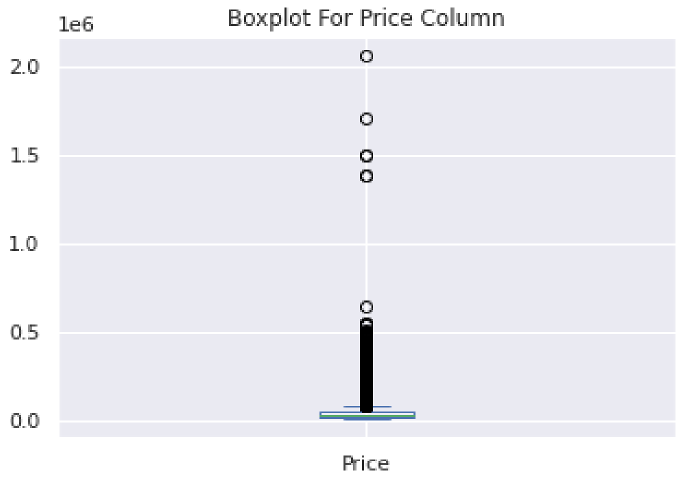
Sometimes a dataset can contain extreme values that are outside the range of what is expected and unlike the other data. These are called outliers and often machine learning modeling and model skill in general can be improved by understanding and even removing these outlier values.

In [18]:

```
## Plot a boxplot for 'Price' column in dataset.
df['Price'].plot(kind='box',title='Boxplot For Price Column')
#sns.boxplot(df['Price'])
```

Out[18]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f22757eb5e0>

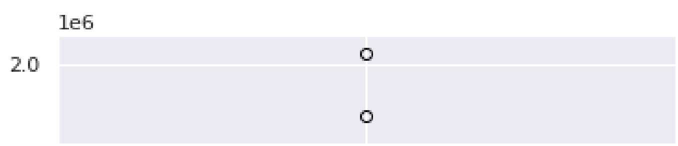


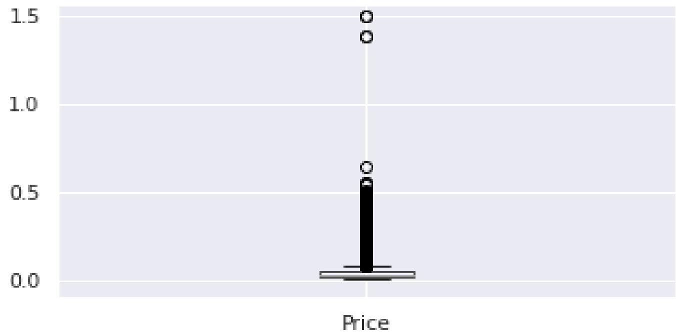
In [19]:

```
df.boxplot('Price')
```

Out[19]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f2275885280>



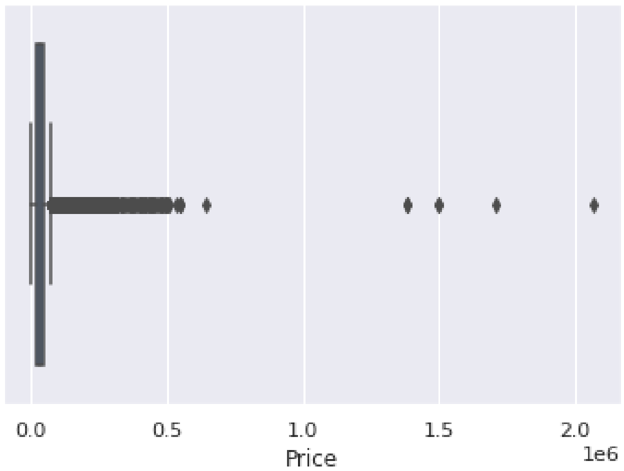


In [20]:

```
sns.boxplot(df['Price'])
```

Out[20]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f22752a1d60>



`Observation:`

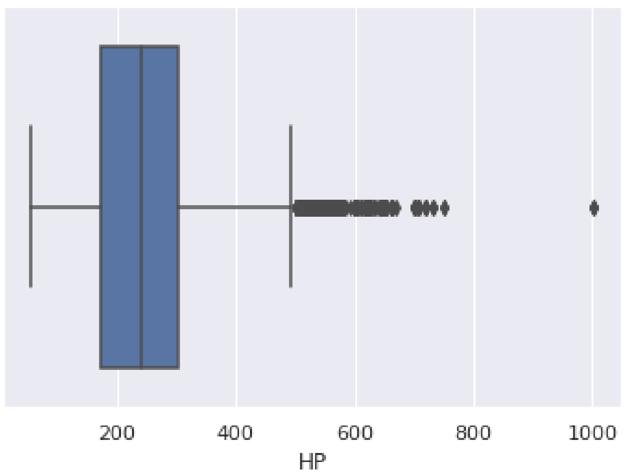
Here as you see that we got some values near to 1.5 and 2.0 . So these values are called outliers. Because there are away from the normal values. Now we have detect the outliers of the feature of Price. Similarly we will checking of anothers features.

In [21]:

```
## PLot a boxplot for 'HP' columns in dataset
sns.boxplot(df['HP'])
```

Out[21]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f227524d610>



`Observation:`

Here boxplots show the proper distribution of of 25 percentile and 75 percentile of the feature of HP.

In [22]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10827 entries, 0 to 11913
Data columns (total 10 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Company_Name       10827 non-null  object 
 1   Model              10827 non-null  object 
 2   Year               10827 non-null  int64  
 3   HP                 10827 non-null  float64
 4   Cylinders          10827 non-null  float64
 5   Transmission Type  10827 non-null  object 
 6   Driven_Wheels      10827 non-null  object 
 7   highway MPG        10827 non-null  int64  
 8   city mpg           10827 non-null  int64  
 9   Price              10827 non-null  int64  
dtypes: float64(2), int64(4), object(4)
memory usage: 930.4+ KB
```

print all the columns which are of int or float datatype in df.

Hint: Use loc with condition

In [23]:

```
# print all the columns which are of int or float datatype in df.

int_or_float_columns=df.select_dtypes(include=['int64','float64']).columns
```

In [24]:

```
int_or_float_columns
```

Out[24]:

```
Index(['Year', 'HP', 'Cylinders', 'highway MPG', 'city mpg', 'Price'], dtype='object')
```

`Save the column names of the above output in variable list named 'l'`

In [25]:

```
# save column names of the above output in variable list
l=list(int_or_float_columns)
l
```

Out[25]:

```
['Year', 'HP', 'Cylinders', 'highway MPG', 'city mpg', 'Price']
```

`Outliers removal techniques - IQR Method`

Here comes cool Fact for you!

IQR is the first quartile subtracted from the third quartile; these quartiles can be clearly seen on a box plot on the data.

- **Calculate IQR and give a suitable threshold to remove the outliers and save this new dataframe into df2.**

Let us help you to decide threshold: Outliers in this case are defined as the observations that are below (Q1 − 1.5x IQR) or above (Q3 + 1.5x IQR)

In [26]:

```
## define Q1 and Q2
Q1 = np.percentile(df[l],25,interpolation='midpoint')
Q3 = np.percentile(df[l],75,interpolation='midpoint')

# # define IQR (interquantile range)
IQR = Q3-Q1

#upper bound
upper=np.where(df[l]>=(Q3+1.5*IQR))
#lower bound
lower=np.where(df[l]<=(Q1-1.5*IQR))

# # define df2 after removing outliers
# df2=df
# df2=df2.drop(lower[0],inplace=True)
# df2=df2.drop(upper[0],inplace=True)
# df[l]
# df[lower[0]]
def remove_outlier_IQR(df):
    Q1=df.quantile(0.25)
    Q3=df.quantile(0.75)
    IQR=Q3-Q1
    df2=df[~((df<(Q1-1.5*IQR)) | (df>(Q3+1.5*IQR)))]
    return df2
df2=remove_outlier_IQR(df)
# df_outlier_removed=remove_outlier_IQR(df['Price'])
# df_outlier_removed=pd.DataFrame(df_outlier_removed)
# ind_diff=df.index.difference(df_outlier_removed.index)
```

In [27]:

```
# len(ind_diff)
```

In [28]:

```
df['Price'].shape,df2['Price'].shape
```

Out[28]:

```
((10827,), (10827,))
```

In [29]:

```
# find the shape of df & df2
print(df.shape,df2.shape)
```

```
(10827, 10) (10827, 10)
```

In [30]:

```
sns.boxplot(df['Price'])
```

Out[30]:

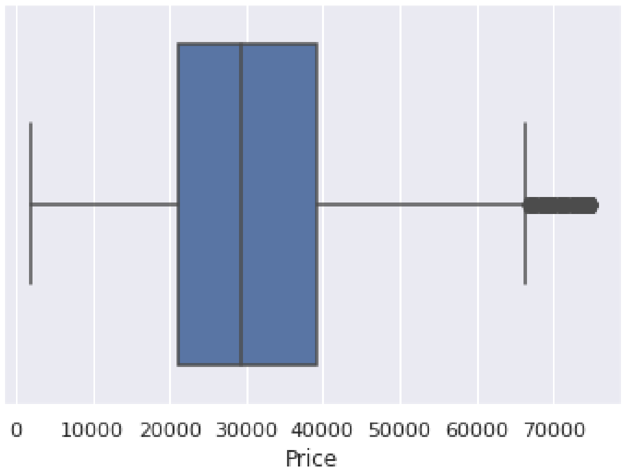
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f2284a15340>
```

In [31]:

```
sns.boxplot(df2['Price'])
```

Out[31]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f22751929a0>

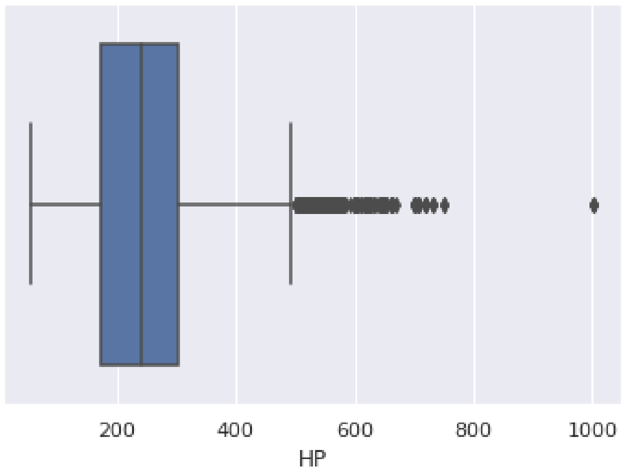


In [32]:

```
sns.boxplot(df['HP'])
```

Out[32]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f22750e34c0>

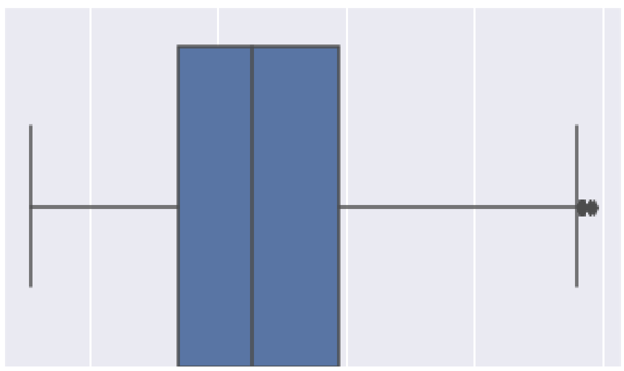


In [33]:

```
sns.boxplot(df2['HP'])
```

Out[33]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f227509fe20>



In [34]:

```
# find unique values and there counts in each column in df using value counts function.

for i in df.columns:
  print ("---------------- %s -----------------" % i)
  print(df[(i)].value_counts())
```

```
--------------- Company_Name ----------------
Chevrolet        1043
Ford              798
Toyota            651
Volkswagen        563
Nissan            540
Dodge             513
GMC               475
Honda             429
Cadillac          396
Mazda             392
Mercedes-Benz     340
Suzuki            338
Infiniti          326
BMW               324
Audi              320
Hyundai           254
Acura             246
Volvo             241
Subaru            229
Kia               219
Mitsubishi        202
Lexus             201
Chrysler          185
Buick             184
Pontiac           163
Lincoln           152
Porsche           134
Land Rover        126
Oldsmobile        111
Saab              101
Aston Martin       91
Bentley            74
Ferrari            69
Plymouth           62
Scion              60
FIAT               58
Maserati           55
Lamborghini        52
Rolls-Royce        31
Lotus              28
HUMMER             17
Maybach            16
McLaren             5
Alfa Romeo          5
Genesis             3
Bugatti             3
Spyker              2
Name: Company_Name, dtype: int64
--------------- Model ----------------
Silverado 1500    156
F-150             126
Sierra 1500        90
Tundra             78
Frontier           76
                 ...
M4 GTS              1
LFA                 1
Horizon             1
```

```
GS F                   1
Zephyr                 1
Name: Model, Length: 904, dtype: int64
--------------- Year ----------------
2015    2029
2016    2022
2017    1580
2014     530
2012     350
2009     349
2007     332
2013     320
2008     316
2011     278
2010     272
2003     233
2004     230
2005     205
2002     203
2006     194
2001     168
1997     148
1998     143
1993     135
2000     114
1999     111
1994     109
1992     104
1995     103
1996      98
1991      84
1990      67
Name: Year, dtype: int64
--------------- HP ----------------
200.0    373
170.0    255
240.0    248
285.0    246
210.0    243
        ...
557.0      1
361.0      1
456.0      1
661.0      1
151.0      1
Name: HP, Length: 355, dtype: int64
--------------- Cylinders ----------------
4.0     4227
6.0     4215
8.0     1889
12.0     228
5.0      159
10.0      65
3.0       28
0.0       13
16.0       3
Name: Cylinders, dtype: int64
--------------- Transmission Type ----------------
AUTOMATIC           7750
MANUAL              2498
AUTOMATED_MANUAL     553
DIRECT_DRIVE          15
UNKNOWN               11
Name: Transmission Type, dtype: int64
--------------- Driven_Wheels ----------------
front wheel drive    4168
rear wheel drive     3120
all wheel drive      2281
four wheel drive     1258
Name: Driven_Wheels, dtype: int64
--------------- highway MPG ----------------
24     822
```

```
23      758
26      725
22      686
25      685
28      651
27      555
30      499
21      488
19      488
31      488
20      469
29      425
18      345
17      340
33      329
32      292
34      270
16      199
35      199
36      191
37      166
38      130
15      116
40      109
39      107
41       65
42       46
14       37
43       21
46       21
44       21
48       16
45       14
13       13
50       10
47        7
109       6
12        5
53        5
82        3
111       3
354       1
106       1
Name: highway MPG, dtype: int64
--------------- city mpg ----------------
17      1154
16      1014
15       949
18       938
19       793
20       742
14       603
22       571
21       551
13       537
23       425
25       392
24       372
12       282
27       243
26       207
11       187
28       160
30       127
31       116
29        98
10        76
9         33
32        21
34        20
36        20
40        19
```

```
44        18
42        17
41        17
35        15
33        13
53        13
43        13
54        10
8          9
37         8
39         6
51         6
50         6
128        6
49         4
137        3
85         3
55         3
47         2
58         2
129        1
7          1
38         1
Name: city mpg, dtype: int64
--------------- Price ----------------
2000     599
29995     18
25995     16
20995     15
27995     15
        ...
66347      1
62860      1
48936      1
68996      1
50920      1
Name: Price, Length: 6014, dtype: int64
```

Visualising Univariate Distributions

We will use seaborn library to visualize eye catchy univariate plots.

Do you know? you have just now already explored one univariate plot. guess which one? Yeah its box plot.

Histogram & Density Plots

Histograms and density plots show the frequency of a numeric variable along the y-axis, and the value along the x-axis. The `sns.distplot()` function plots a density curve. Notice that this is aesthetically better than vanilla `matplotlib`.

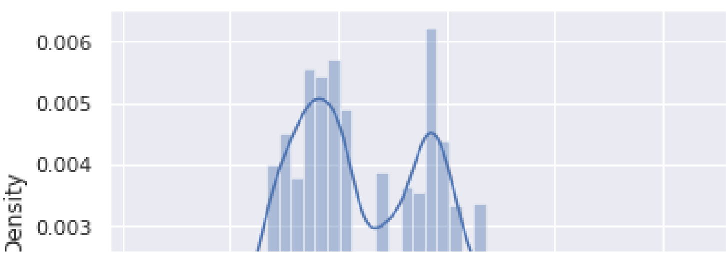
In [35]:

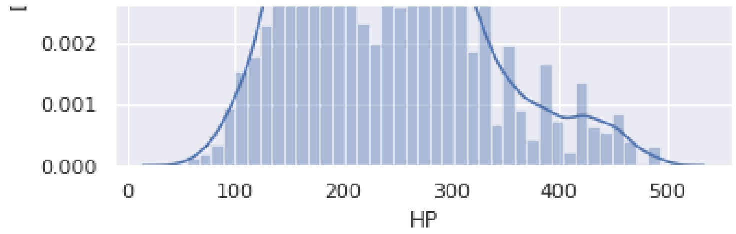
```
#ploting distplot for variable HP

sns.distplot(df2['HP'])
```

Out[35]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f2275079f40>
```



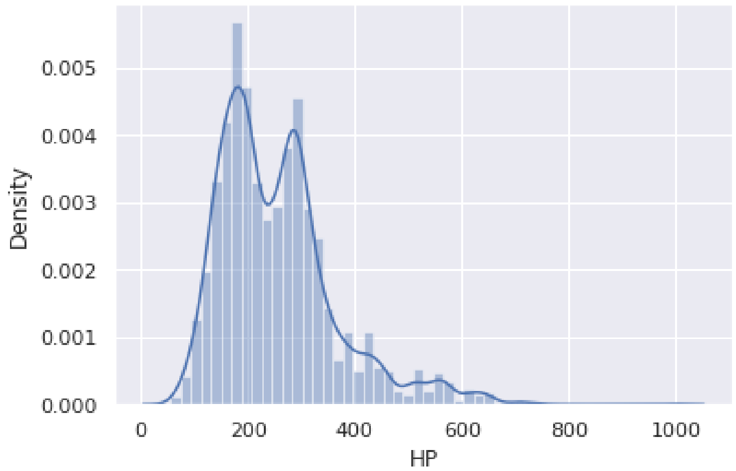


In [36]:

```
sns.distplot(df['HP']) #df contains outliers.
```

Out[36]:

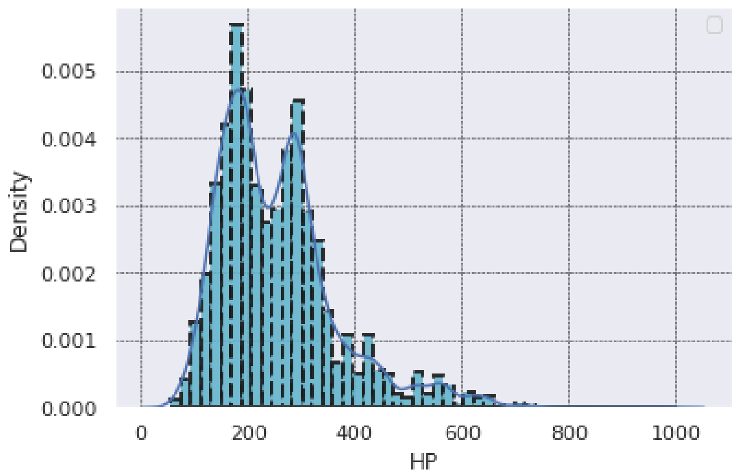
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f22707585e0>
```



In [37]:

```
sns.distplot(df['HP'],kde='False',hist_kws={'color':'c','edgecolor':'k','linewidth':2,'linestyle':'--','alpha':0.9})
plt.grid(color='k',linestyle='--',linewidth=0.5)
plt.legend()
plt.show()
```

```
WARNING:matplotlib.legend:No handles with labels found to put in legend.
```



`Observation:`

We plot the Histogram of feature HP with help of distplot in seaborn.
In this graph we can see that there is max values near at 200. similary we have also the 2nd highest value near 400 and so on.
It represents the overall distribution of continuous data variables.

Since seaborn uses matplotlib behind the scenes, the usual matplotlib functions work well with seaborn. For example, you can use subplots to plot multiple univariate distributions.

- **Hint: use matplotlib subplot function**

In [38]:

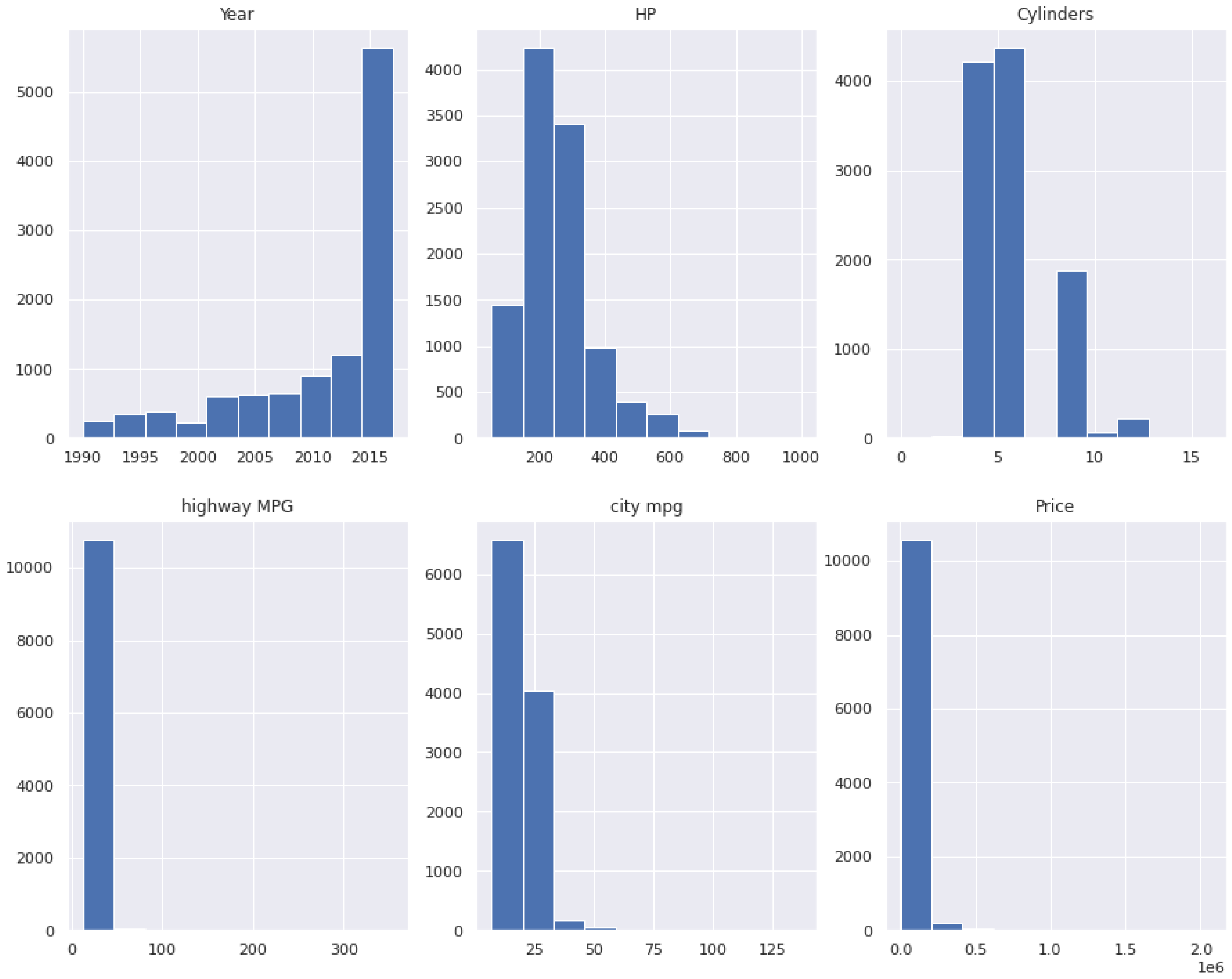
```
l=list(int_or_float_columns)
l
```

Out[38]:

```
['Year', 'HP', 'Cylinders', 'highway MPG', 'city mpg', 'Price']
```

In [39]:

```
fig, axs = plt.subplots(nrows=2, ncols=3, figsize=(15, 12))
axs=axs.ravel()
plt.figure(figsize=(15,12))
for i,column in enumerate(l):
  axs[i].hist(df[column])
  axs[i].set_title(column)
plt.show()
```




```
<Figure size 1080x864 with 0 Axes>
```

In [40]:

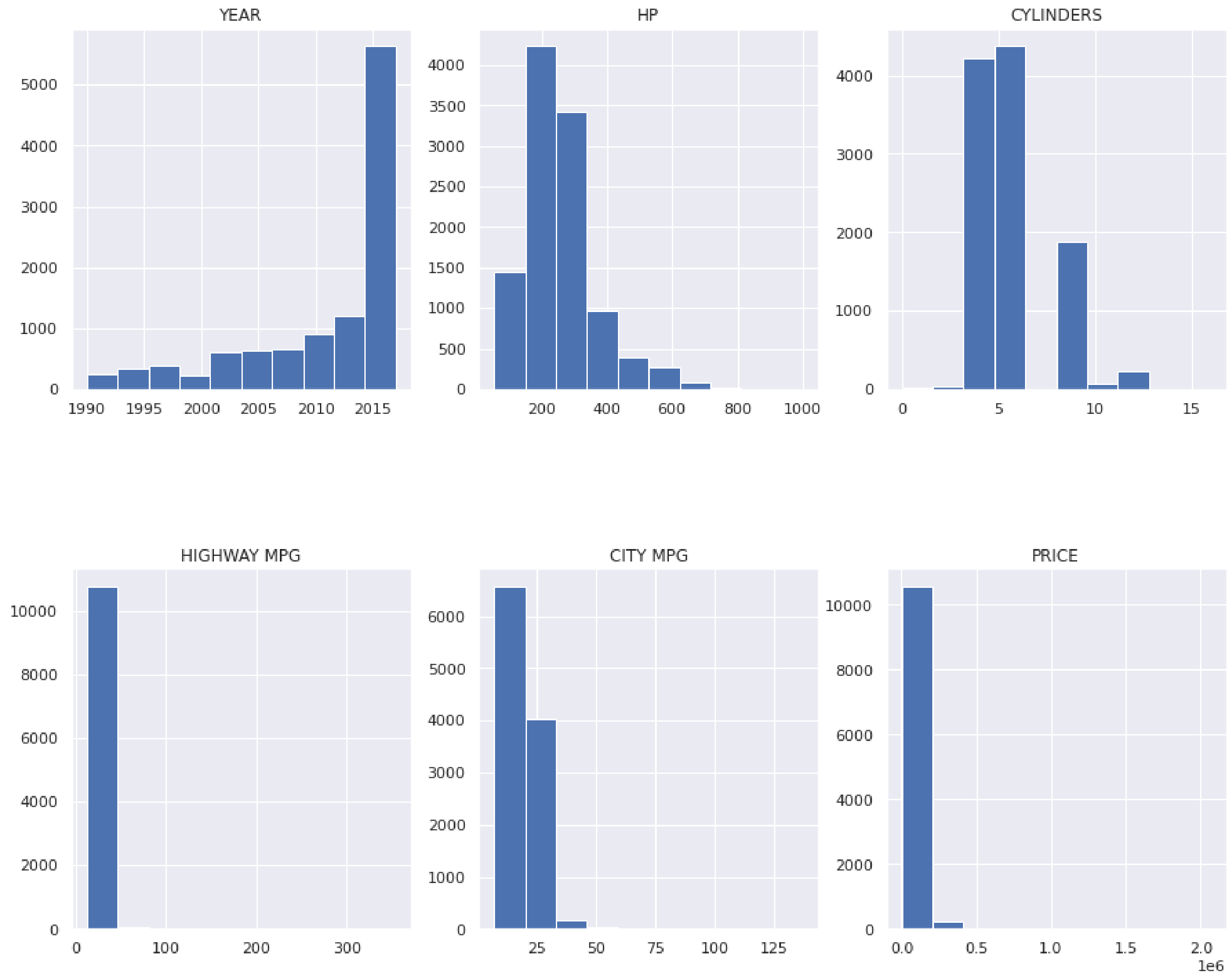
```
# plot all the columns present in list l together using subplot of dimention (2,3).
# sns.pairplot(df2[l])
fig, axs = plt.subplots(nrows=2, ncols=3, figsize=(15, 12))
plt.subplots_adjust(hspace=0.5)

# loop through tickers and axes
for i, ax in zip(l, axs.ravel()):
    # filter df for ticker and plot on specified axes
```

```
    df[i].hist(ax=ax)

    # chart formatting
    ax.set_title(i.upper())
    # ax.get_legend().remove()
    ax.set_xlabel("")

plt.show()
```

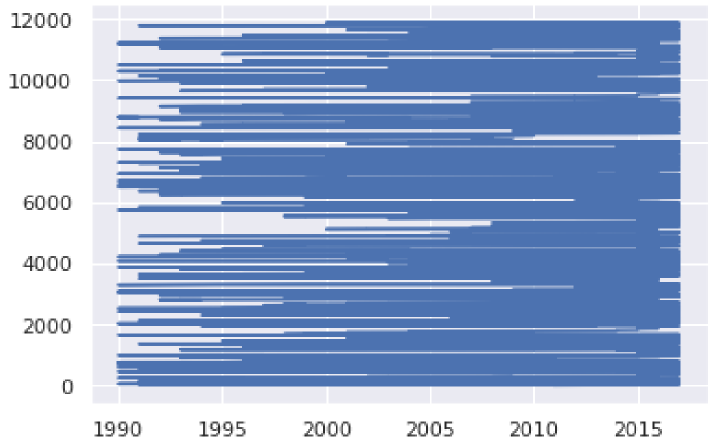


In [41]:

```
plt.plot(df['Year'],df['Year'].index)
```

Out[41]:

```
[<matplotlib.lines.Line2D at 0x7f2270200460>]
```

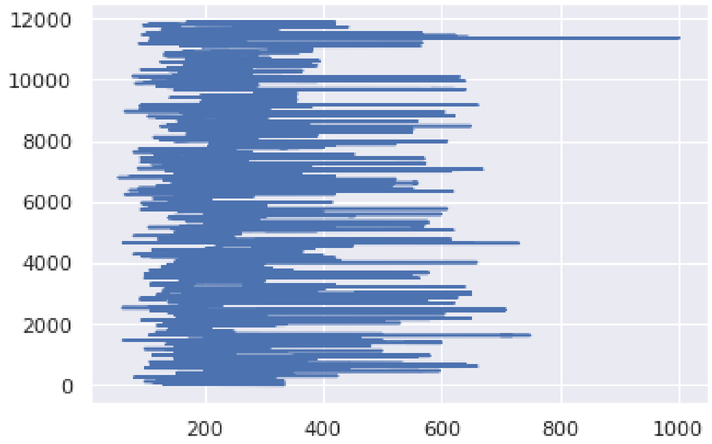


In [42]:

```
plt.plot(df['HP'],df['HP'].index)
```

Out[42]:

```
[<matplotlib.lines.Line2D at 0x7f22701d1760>]
```

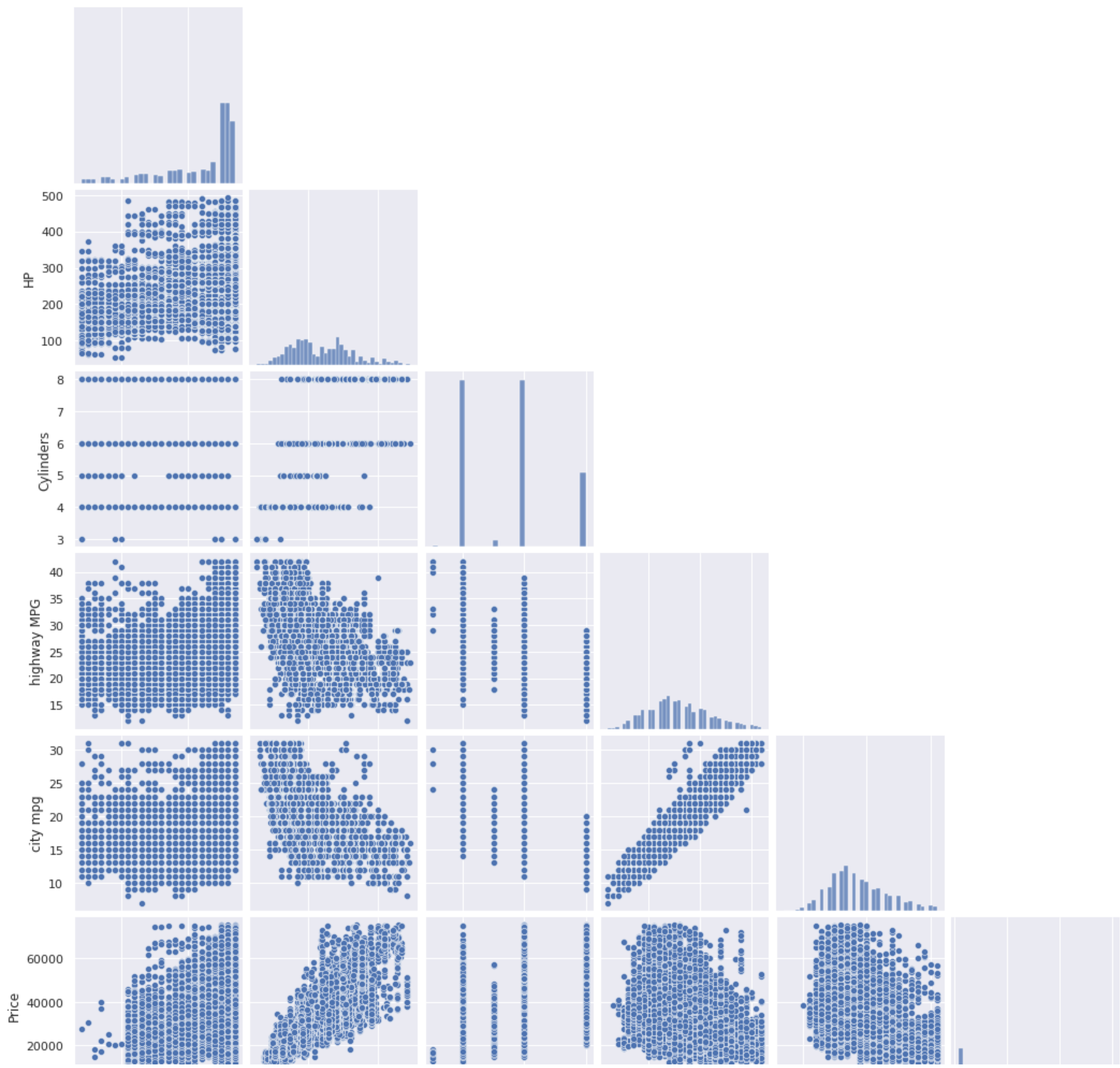


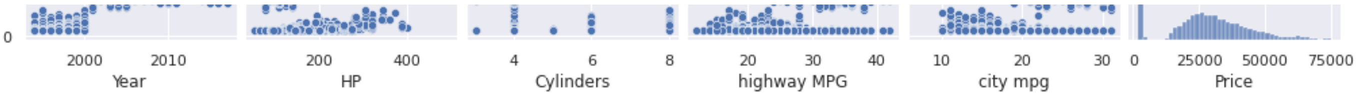
In [43]:

```
sns.pairplot(df2[l],corner=True)
```

Out[43]:

```
<seaborn.axisgrid.PairGrid at 0x7f227586fdc0>
```





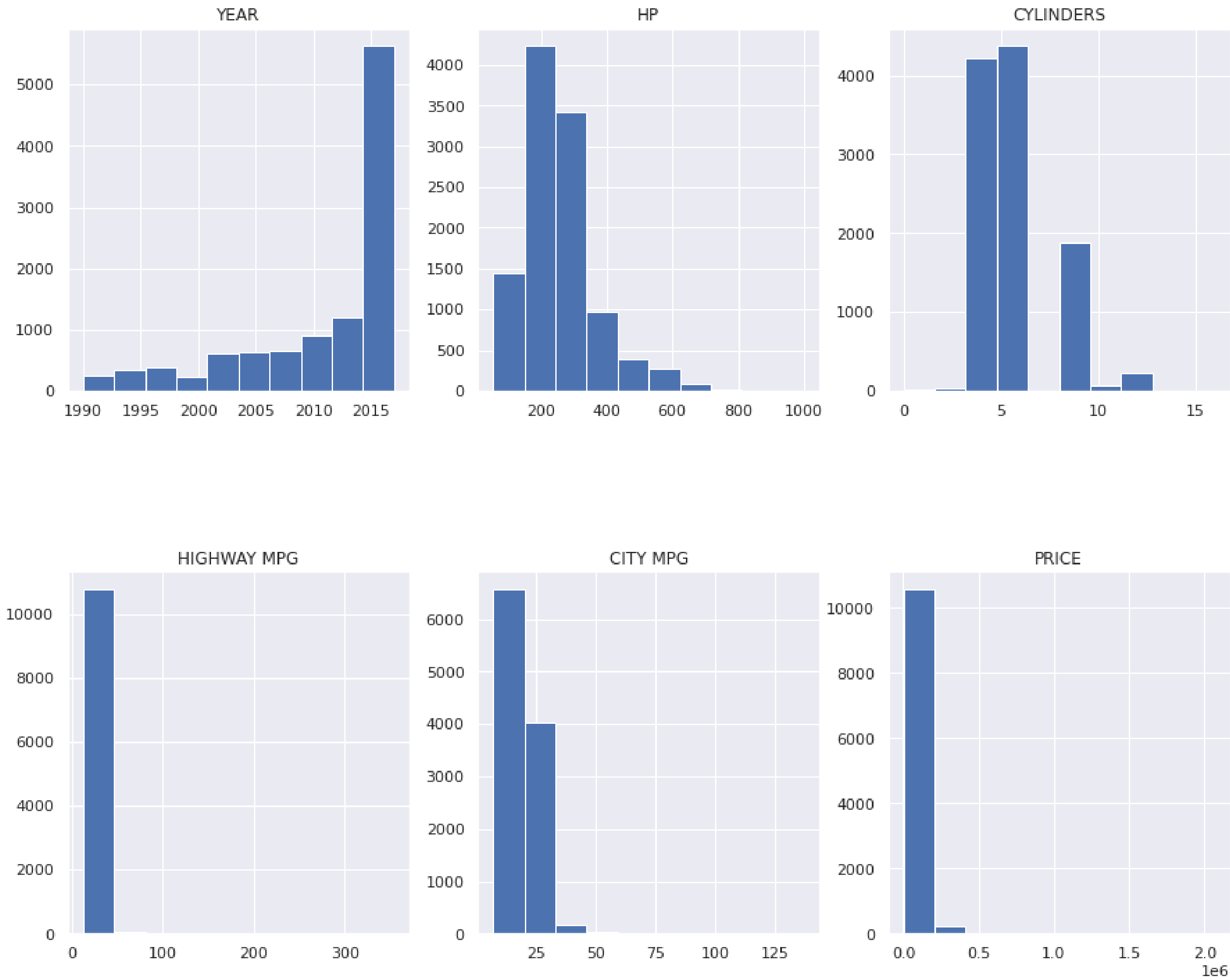
In [44]:

```
plt.figure(figsize=(15, 12))
plt.subplots_adjust(hspace=0.5)

# loop through the length of tickers and keep track of index
for n, ticker in enumerate(l):
    # add a new subplot iteratively
    ax = plt.subplot(2, 3, n + 1)

    # filter df and plot ticker on the new subplot axis
    df[ticker].hist(ax=ax)

    # chart formatting
    ax.set_title(ticker.upper())
    # ax.get_legend().remove()
    ax.set_xlabel("")
```



Bar Chart Plots

Count Plot

A count plot can be thought of as a histogram across a categorical, instead of quantitative, variable.

Plot a countplot for a variable Transmission vertically with hue as Drive mode

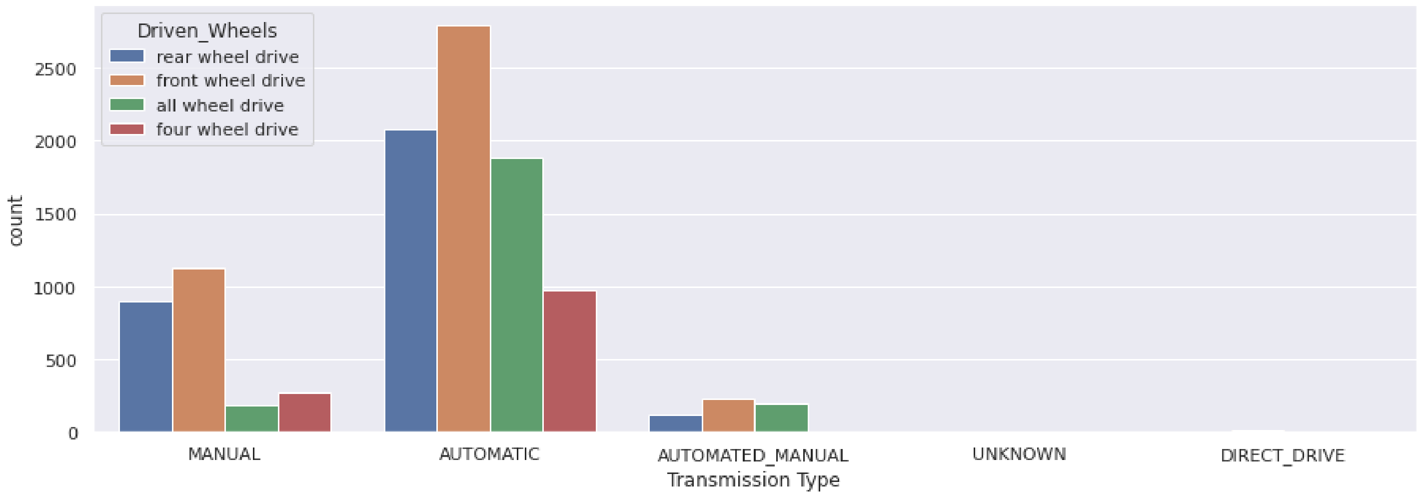
In [46]:

```
plt.figure(figsize=(15,5))

# plot countplot on transmission and drive mode
# plt.xticks(rotation=90)
sns.countplot(x=df['Transmission Type'],hue='Driven_Wheels',data=df2)
# df.columns
```

Out[46]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f226ffa3e20>
```



Observation:

In this count plot, We have plot the feature of Transmission with help of hue.
We can see that the the nos of count and the transmission type and automated manual is plotted. Drive mode as been given with help of hue.

Visualising Bivariate Distributions

Bivariate distributions are simply two univariate distributions plotted on x and y axes respectively. They help you observe the relationship between the two variables.

Scatter Plots

Scatterplots are used to find the correlation between two continuos variables.

Using scatterplot find the correlation between 'HP' and 'Price' column of the data.

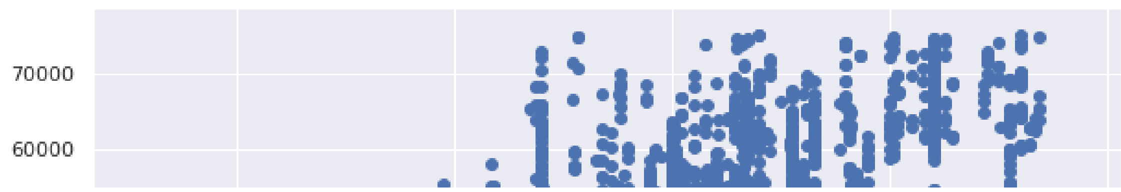
In [47]:

```
## Your code here -
fig, ax = plt.subplots(figsize=(10,6))

# plot scatterplot on hp and price
plt.scatter(df2['HP'],df2['Price'])
plt.xlabel('HP')
plt.ylabel('Price')
```

Out[47]:

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



Observation:

It is a type of plot or mathematical diagram using Cartesian coordinates to display values for typically two variables for a set of data.
We have plot the scatter plot with x axis as HP and y axis as Price.
The data points between the features should be same either wise it give errors.

Plotting Aggregated Values across Categories

Bar Plots - Mean, Median and Count Plots

Bar plots are used to display aggregated values of a variable, rather than entire distributions. This is especially useful when you have a lot of data which is difficult to visualise in a single figure.

For example, say you want to visualise and *compare the Price across Cylinders*. The `sns.barplot()` function can be used to do that.

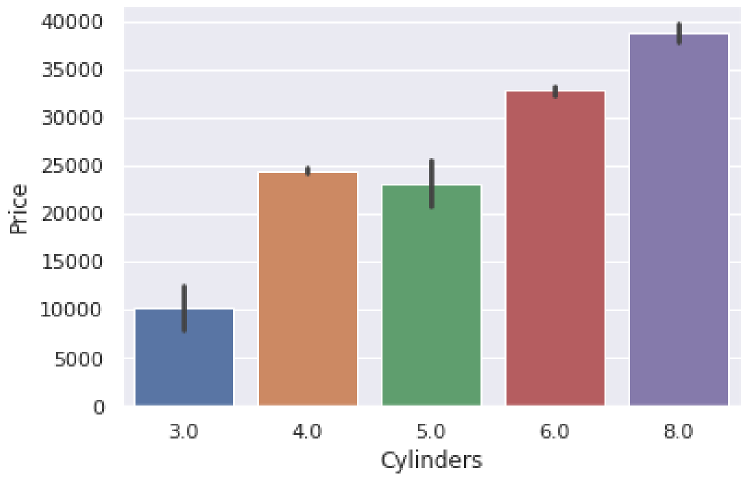
In [48]:

```
# bar plot with default statistic=mean between Cylinder and Price

# sns.barplot(x=df['Price'],y=df['Cylinders'],data=df)
# df.columns
sns.barplot(x='Cylinders',y='Price',data=df2,estimator=np.mean)
```

Out[48]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f226dc24cd0>
```



Observation:

By default, seaborn plots the mean value across categories, though you can plot the count, median, sum etc.

Also, barplot computes and shows the confidence interval of the mean as well.

When you want to visualise having a large number of categories, it is helpful to plot the categories across the y-axis.

Let's now drill down into Transmission sub categories.

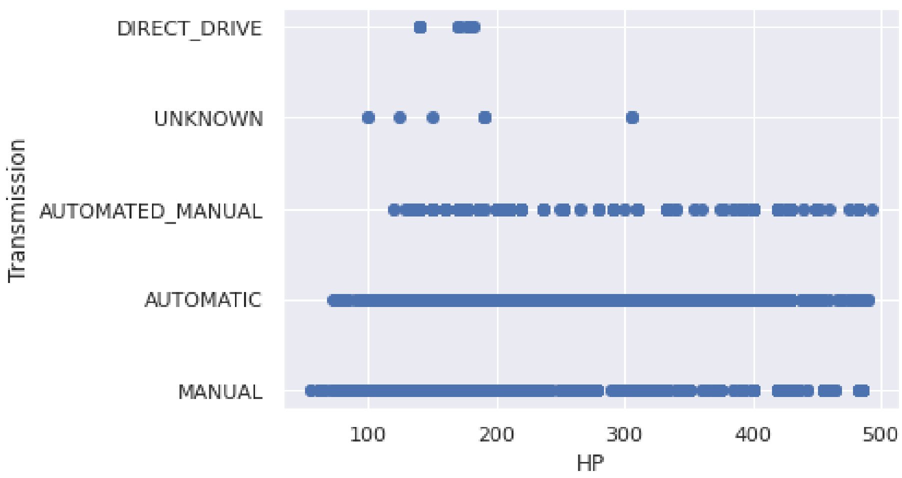
In [49]:

```
# Plotting categorical variable Transmission across the y-axis

plt.scatter(df2['HP'],df2['Transmission Type'])
plt.xlabel('HP')
plt.ylabel('Transmission')
# df.columns
```

Out[49]:

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



These plots looks beutiful isn't it? In Data Analyst life such charts are there unavoidable friend.:)

Multivariate Plots

Heatmaps

A heat map is a two-dimensional representation of information with the help of colors. Heat maps can help the user visualize simple or complex information

Using heatmaps plot the correlation between the features present in the dataset.

In [50]:

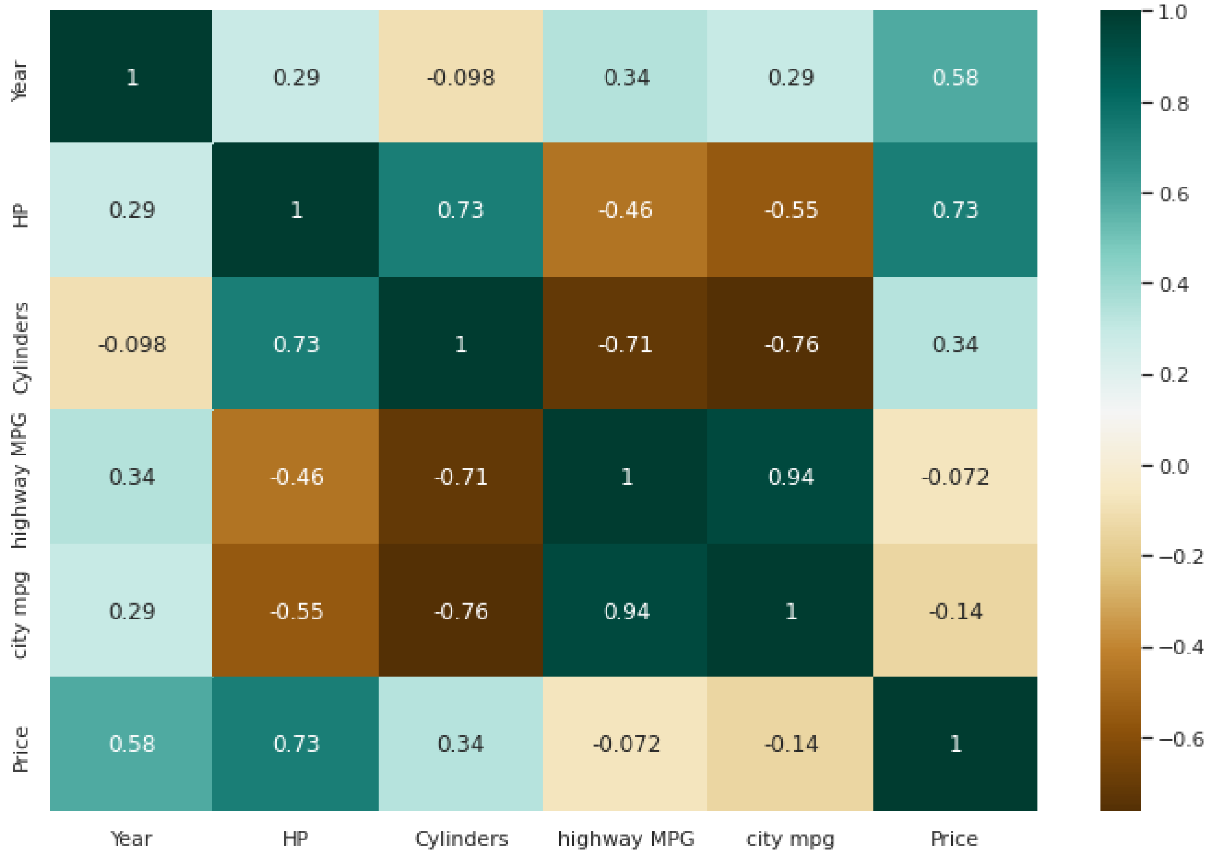
```
#find the correlation of features of the data
corr = df2.corr()

print(corr)
```

```
                 Year        HP  Cylinders  highway MPG  city mpg     Price
Year         1.000000  0.285214  -0.098451     0.344425  0.292570  0.583586
HP           0.285214  1.000000   0.732369    -0.456375 -0.550897  0.732342
Cylinders   -0.098451  0.732369   1.000000    -0.710149 -0.763844  0.336879
highway MPG  0.344425 -0.456375  -0.710149     1.000000  0.942015 -0.072042
city mpg     0.292570 -0.550897  -0.763844     0.942015  1.000000 -0.142005
Price        0.583586  0.732342   0.336879    -0.072042 -0.142005  1.000000
```

In [51]:

```
# Using the correlated df, plot the heatmap
# set cmap = 'BrBG', annot = True - to get the same graph as shown below
# set size of graph = (12,8)
plt.figure(figsize=(12,8))
sns.heatmap(corr,cmap = 'BrBG', annot = True)
plt.show()
```



`Observation:`

A heatmap contains values representing various shades of the same colour for each value to be plotted. Usually the darker shades of the chart represent higher values than the lighter shade. For a very different value a completely different colour can also be used.

The above heatmap plot shows correlation between various variables in the colored scale of -1 to 1.

In [51]: