Exploratory Data Analysis (EDA)

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Definition

Data Analysis is the use of statistics and probability to figure out trends in the data set.

Exploratory Data Analysis is the first step in the Data Analysis process. In statistics, EDA is an approach to analyze data sets to summarize their main characteristics, often with visual methods.

Need for EDA

When you are trying to build a machine learning model, you need to be pretty sure whether your data is making sense or not. The main aim of EDA is to obtain confidence in your data to an extent where you are ready to engage a machine learning algorithm.

Questions you will answer during the process of EDA:

1. Whether the selected features are good enough to the model
2. Are all the features required?
3. Are their any correlations based on which we can either go back to the Data Pre-processing step or move on to modelling

By completing the EDA process you will have many plots, heat-maps, frequency distribution, graphs, correlation matrix along with the hypothesis by which any individual can understand what your data is all about and what insights you got from exploring the data set

Through the process of EDA, we can ask to define the **problem statement** or definition on our data set which is normally very important.

Steps for EDA

There are many steps for conducting EDA. This highly depends on the data set being used. There is no one method for performing EDA. the ones i will use in the class are as below:

1. Import the required libraries for EDA
2. Loading the data into the data frame
3. Description of the data
    A. Checking the types of data
    B. Get and understand some statistics from the dataset e.g. central tendancy, count, mean, standard deviation, miimum values, maximum values, quartiles and the median e.t.c
4. Dropping irrelevant columns
5. Renaming the columns
6. Dropping the duplicate rows
7. Dropping the missing or null values
8. Detecting Outliers
9. Plot different features against one another (scatter plot)
10. Plot different features against their frequency (histogram)
11. Plotting Heat-maps
12. Deriving Insights and Conclusions that would guide the approach you take for training your machine learning algorithm as you build your machine learning model

The data we shall use

We will use a car dataset retrieved from [here (https://www.kaggle.com/CooperUnion/cardataset)](https://www.kaggle.com/CooperUnion/cardataset). This data contains more than 10 columns, which contains features of the car such as engine fuel types, engine size, horse power, transmission type, highway miles per gallon (MPG), city miles per gallon and so much more.

The Objective

The objective is to explore the data and make it ready for modelling.

Workbench

Import the required libraries for EDA

In [1]:

```
# Importing required libraries.
import pandas as pd
import numpy as np
import seaborn as sns           #This is for visualisation
import matplotlib.pyplot as plt     #This is for visualisation
```

In [2]:

```
# configuration settings
%matplotlib inline
sns.set(color_codes=True)
```

Loading the data into the dataframe

In [4]:

```
# load the data into a dataframe called cars_df
cars_df = pd.read_csv("../data/cardataset.csv")
```

In [5]:

```
# view the top five records
cars_df.head(5)
```

Out[5]:

	Make	Model	Year	Engine Fuel Type	Engine HP	Engine Cylinders	Transmission Type	Driven_Wheels	Number of Doors
0	BMW	1 Series M	2011	premium unleaded (required)	335.0	6.0	MANUAL	rear wheel drive	2.0
1	BMW	1 Series	2011	premium unleaded (required)	300.0	6.0	MANUAL	rear wheel drive	2.0
2	BMW	1 Series	2011	premium unleaded (required)	300.0	6.0	MANUAL	rear wheel drive	2.0
3	BMW	1 Series	2011	premium unleaded (required)	230.0	6.0	MANUAL	rear wheel drive	2.0
4	BMW	1 Series	2011	premium unleaded (required)	230.0	6.0	MANUAL	rear wheel drive	2.0

In [6]:

```
# view the last five records
cars_df.tail(5)
```

Out[6]:

	Make	Model	Year	Engine Fuel Type	Engine HP	Engine Cylinders	Transmission Type	Driven_Wheels
11909	Acura	ZDX	2012	premium unleaded (required)	300.0	6.0	AUTOMATIC	all wheel drive
11910	Acura	ZDX	2012	premium unleaded (required)	300.0	6.0	AUTOMATIC	all wheel drive
11911	Acura	ZDX	2012	premium unleaded (required)	300.0	6.0	AUTOMATIC	all wheel drive
11912	Acura	ZDX	2013	premium unleaded (recommended)	300.0	6.0	AUTOMATIC	all wheel drive
11913	Lincoln	Zephyr	2006	regular unleaded	221.0	6.0	AUTOMATIC	front wheel drive

In [8]:

```
# view sampled records
cars_df.sample(5)
```

Out[8]:

	Make	Model	Year	Engine Fuel Type	Engine HP	Engine Cylinders	Transmission Type	Driven_Wl
1150	GMC	Acadia	2016	regular unleaded	281.0	6.0	AUTOMATIC	all wheel
10290	Ford	Taurus	2016	flex-fuel (unleaded/E85)	288.0	6.0	AUTOMATIC	front w
3872	Hyundai	Elantra	2017	regular unleaded	147.0	4.0	AUTOMATIC	front w
9623	Chevrolet	Silverado 1500	2017	flex-fuel (unleaded/E85)	285.0	6.0	AUTOMATIC	rear wheel
8476	Suzuki	Reno	2006	regular unleaded	126.0	4.0	AUTOMATIC	front w

Checking the Types of Data

It is important to check the types of data becuse we may have situations where significant fields like dates or prices are stored as strings.

In such cases we must convert the strings to date or float to be able to use these fields to plot the data

In [9]:

```
# Checking the data type
cars_df.dtypes
```

Out[9]:

```
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
```

Dropping Irrelevant Columns

This is normally necessary especially if we have several columns that we may not need to use depending on our problem statement or objective. 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.

In [10]:

```
# Dropping irrelevant columns
cars_df = cars_df.drop(["Engine Fuel Type", "Market Category", "Vehicle Style", "Popula
rity", "Number of Doors", "Vehicle Size"], axis=1)
```

In [12]:

```
# show the remaining columns in the dataframe
cars_df.sample(5)
```

Out[12]:

	Make	Model	Year	Engine HP	Engine Cylinders	Transmission Type	Driven_Wheels	highway MPG
1262	Honda	Accord	2017	185.0	4.0	MANUAL	front wheel drive	32
9512	Chevrolet	Silverado 1500	2015	285.0	6.0	AUTOMATIC	rear wheel drive	24
8573	Nissan	Rogue	2015	170.0	4.0	AUTOMATIC	all wheel drive	32
4359	Ford	Explorer Sport Trac	2009	292.0	8.0	AUTOMATIC	four wheel drive	19
8926	Volvo	S70	2000	190.0	5.0	AUTOMATIC	front wheel drive	24

Renaming the columns

This at times helps with improving the readability of the columns as well as consistency when making reference to the columns in subsequent cells within your notebook.

In [13]:

```
# Renaming the column names
cars_df = cars_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" })
```

In [14]:

```
# view the dataframe with the new column names
cars_df.head(5)
```

Out[14]:

	Make	Model	Year	HP	Cylinders	Transmission	Drive Mode	MPG-H	MPG-C	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

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.

In [15]:

```
# check the shape of the records to know how many records are in the dataset
cars_df.shape
```

Out[15]:

```
(11914, 10)
```

In [17]:

```
# Rows containing duplicate data
duplicate_rows_df = cars_df[cars_df.duplicated()]
print("number of duplicate rows: ", duplicate_rows_df.shape)
```

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

In [18]:

```
# Used to count the number of rows before removing the data
cars_df.count()
```

Out[18]:

```
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
```

In [19]:

```
# Dropping the duplicates
cars_df = cars_df.drop_duplicates()
cars_df.head(5)
```

Out[19]:

	Make	Model	Year	HP	Cylinders	Transmission	Drive Mode	MPG-H	MPG-C	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 [20]:

```
# Counting the number of rows after removing duplicates.
cars_df.count()
```

Out[20]:

```
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
```

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.

In [21]:

```
# Finding the null values.
print(cars_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
```

In [22]:

```
# Dropping the missing values.
cars_df = cars_df.dropna()
cars_df.count()
```

Out[22]:

```
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
```

In [23]:

```
# After dropping the values
print(cars_df.isnull().sum())
```

```
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
```

Detecting Outliers

An outlier is a point or set of points that are different from other points. In statistics, an outlier is an observation point that is distant from other observations. 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.

There are several ways of detecting outliers:

1. Box plot - visual
2. Scatter plot - visual
3. Z-score (this is the signed number of standard deviations by which the value of an observation or data point is above the mean value of what is being observed or measured). The intuition behind Z-score is to describe any data point by finding their relationship with the Standard Deviation and Mean of the group of data points. Z-score is finding the distribution of data where mean is 0 and standard deviation is 1 i.e. normal distribution. It is mathematical. While calculating the Z-score we re-scale and center the data and look for data points which are too far from zero. These data points which are way too far from zero will be treated as the outliers. In most of the cases a threshold of 3 or -3 is used i.e if the Z-score value is greater than or less than 3 or -3 respectively, that data point will be identified as outliers.
4. IQR Score

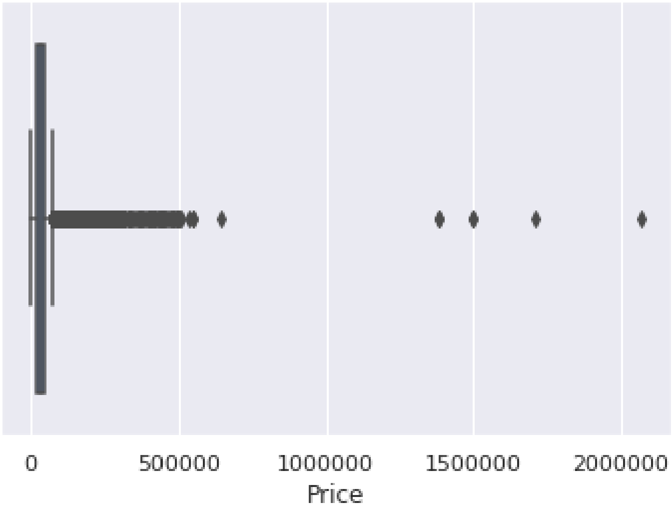
For this, i have opted to use IQR Score techniqueto remove the outliers. An assignment will be to identify outliers using the z-score.

In [25]:

```
sns.boxplot(x=cars_df["Price"])
```

Out[25]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa6ea04b110>
```

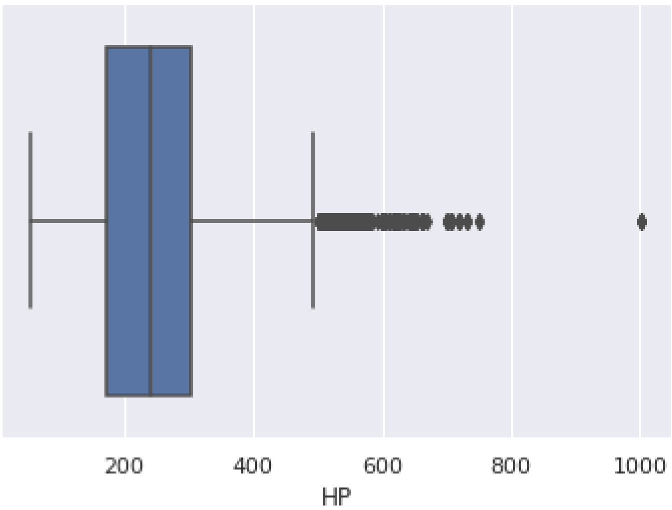


In [26]:

```
sns.boxplot(x=cars_df["HP"])
```

Out[26]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa6e9d54f50>
```

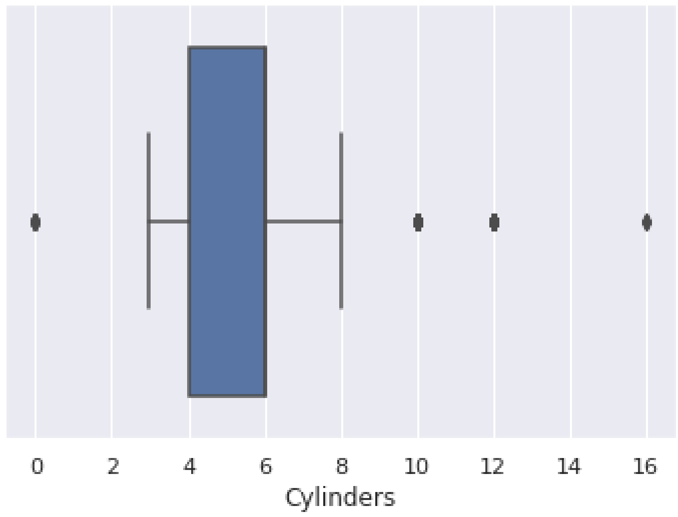


In [27]:

```
sns.boxplot(x=cars_df['Cylinders'])
```

Out[27]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa6e9c860d0>
```



In [30]:

```
# Print the Inter-Quartile Range
Q1 = cars_df.quantile(0.25)
Q3 = cars_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
```

In [31]:

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

Out[31]:

```
(9191, 10)
```

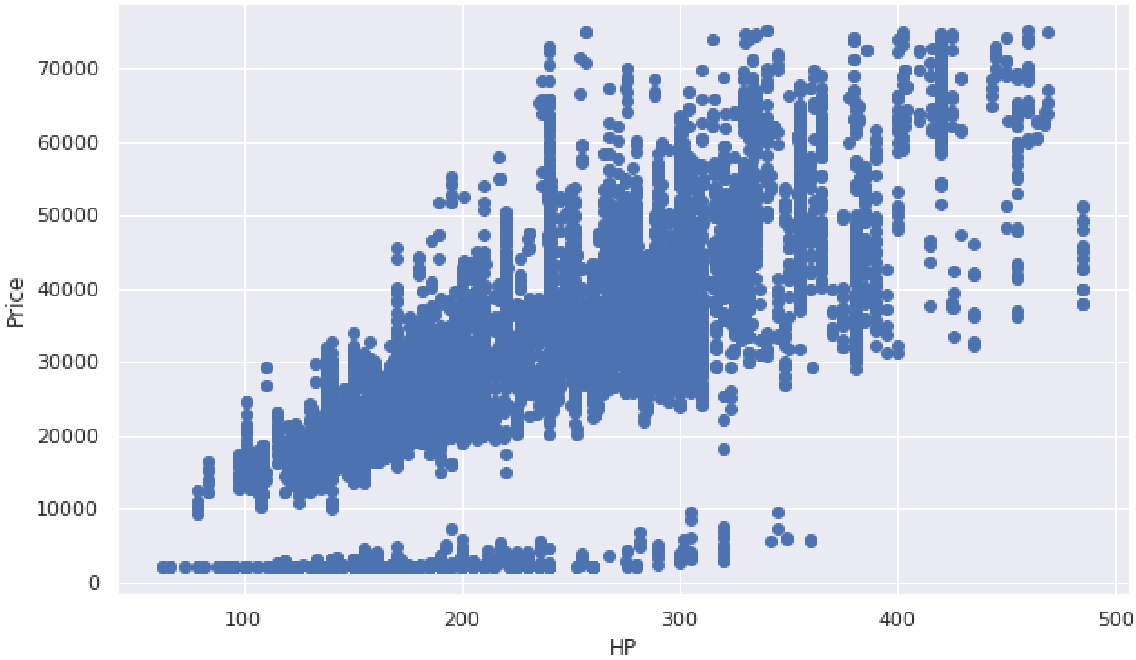
As seen above there were around 1600 rows were outliers. But you cannot completely remove the outliers because even after you use the above technique there maybe 1–2 outlier unremoved but that ok because there were more than 100 outliers.

Plot scatter plots

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.

In [32]:

```
# Plotting a scatter plot
fig, ax = plt.subplots(figsize=(10,6))
ax.scatter(cars_df["HP"], cars_df["Price"])
ax.set_xlabel("HP")
ax.set_ylabel("Price")
plt.show()
```

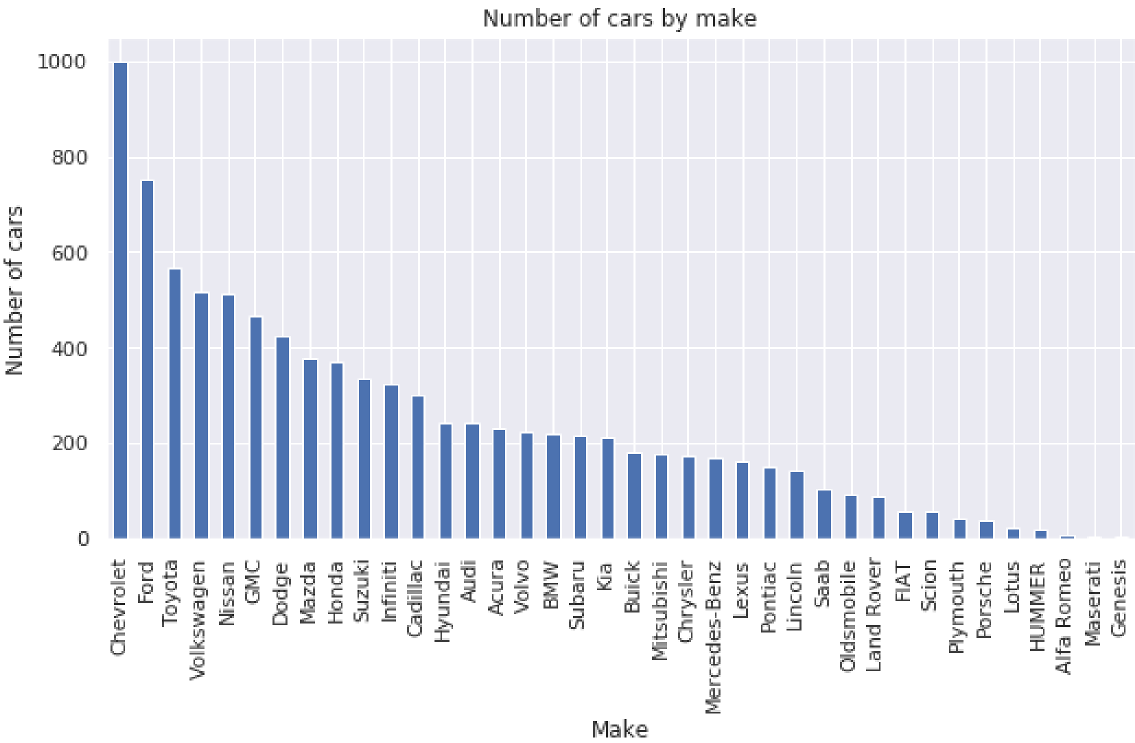


Plot Histograms

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.

In [33]:

```
# Plotting a Histogram
cars_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");
```



Plot Heatmaps

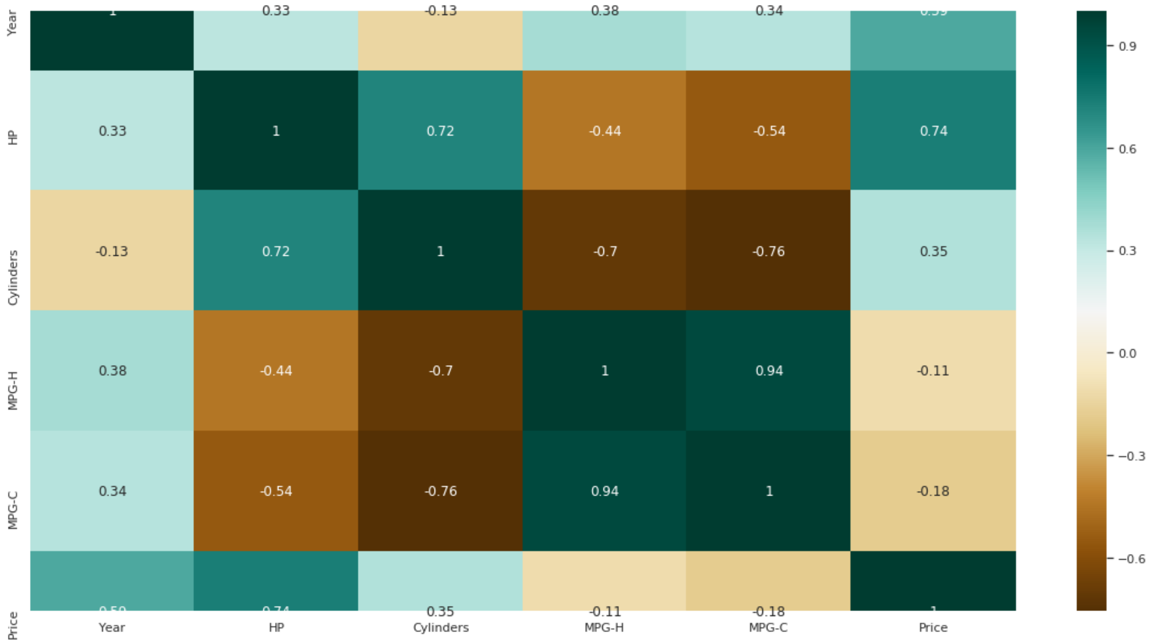
Heat Maps is a type of plot which is necessary when we need to find the dependent variables. One of the best way to find the relationship between the features can be done using heat maps. In the below heat map we know that the price feature depends mainly on the Engine Size, Horsepower, and Cylinders.

In [34]:

```
# Finding the relations between the variables.
plt.figure(figsize=(20,10))
c= cars_df.corr()
sns.heatmap(c,cmap="BrBG",annot=True)
c
```

Out[34]:

	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



Conclusions

Using the scatter plot and heatmap, we can choose to build a model that could be able to predict the price of a car since we are able to identify the dependent variable as well as the target variable.