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.

I got a very beautiful data-set of cars from Kaggle. 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 Size, HP, Transmission Type, highway MPG, city MPG and many more.

1. Importing the required libraries for EDA

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

In [1]:
```
# Importing Required Libraries

import pandas as pd
import numpy as np
import seaborn as sns # Data Visualisation
import matplotlib.pyplot as plt # Data Visualisation
%matplotlib inline
sns.set(color_codes=True)
```

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.

In [2]:
```
df = pd.read_csv("cars_data.csv")
df.head(5) #to display top 5 rows
```

Out[2]:

	Make	Model	Year	Engine Fuel Type	Engine HP	Engine Cylinders	Transmission Type	Driven_Wheels	Number of Doors	Market Category	Vehicle Size	Vehicle Style	highway MPG	city mpg
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	Coupe	26	19
1	BMW	1 Series	2011	premium unleaded (required)	300.0	6.0	MANUAL	rear wheel drive	2.0	Luxury,Performance	Compact	Convertible	28	19
2	BMW	1 Series	2011	premium unleaded (required)	300.0	6.0	MANUAL	rear wheel drive	2.0	Luxury,High-Performance	Compact	Coupe	28	20
3	BMW	1 Series	2011	premium unleaded (required)	230.0	6.0	MANUAL	rear wheel drive	2.0	Luxury,Performance	Compact	Coupe	28	18
4	BMW	1 Series	2011	premium unleaded (required)	230.0	6.0	MANUAL	rear wheel drive	2.0	Luxury	Compact	Convertible	28	18

In [3]:
```
# To display bottom 5 rows
df.tail(5)
```

Out[3]:

	Make	Model	Year	Engine Fuel Type	Engine HP	Engine Cylinders	Transmission Type	Driven_Wheels	Number of Doors	Market Category	Vehicle Size	Vehicl Styl
11909	Acura	ZDX	2012	premium unleaded (required)	300.0	6.0	AUTOMATIC	all wheel drive	4.0	Crossover,Hatchback,Luxury	Midsize	4c Hatchbac
11910	Acura	ZDX	2012	premium unleaded (required)	300.0	6.0	AUTOMATIC	all wheel drive	4.0	Crossover,Hatchback,Luxury	Midsize	4c Hatchbac
11911	Acura	ZDX	2012	premium unleaded (required)	300.0	6.0	AUTOMATIC	all wheel drive	4.0	Crossover,Hatchback,Luxury	Midsize	4c Hatchbac
11912	Acura	ZDX	2013	premium unleaded (recommended)	300.0	6.0	AUTOMATIC	all wheel drive	4.0	Crossover,Hatchback,Luxury	Midsize	4c Hatchbac
11913	Lincoln	Zephyr	2006	regular unleaded	221.0	6.0	AUTOMATIC	front wheel drive	4.0	Luxury	Midsize	Seda

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 or object, 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.

In [4]:
```
# checking data types
df.dtypes
```

Out[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
```

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 Market Category, Number of doors, Vehicle Size doesn't make any sense to me so I just dropped for this instance.

In [5]:
```
# Dropping unnecessary columns
df = df.drop(["Market Category","Number of Doors","Vehicle Size"],axis=1)
df.head()
```

Out[5]:

	Make	Model	Year	Engine Fuel Type	Engine HP	Engine Cylinders	Transmission Type	Driven_Wheels	Vehicle Style	highway MPG	city mpg	Popularity	MSRP
0	BMW	1 Series M	2011	premium unleaded (required)	335.0	6.0	MANUAL	rear wheel drive	Coupe	26	19	3916	46135
1	BMW	1 Series	2011	premium unleaded (required)	300.0	6.0	MANUAL	rear wheel drive	Convertible	28	19	3916	40650
2	BMW	1 Series	2011	premium unleaded (required)	300.0	6.0	MANUAL	rear wheel drive	Coupe	28	20	3916	36350
3	BMW	1 Series	2011	premium unleaded (required)	230.0	6.0	MANUAL	rear wheel drive	Coupe	28	18	3916	29450
4	BMW	1 Series	2011	premium unleaded (required)	230.0	6.0	MANUAL	rear wheel drive	Convertible	28	18	3916	34500

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.

In [6]:
```
ssion","Driven_Wheels":"Drive Mode","highway MPG":"MPG-H","city mpg":"MPG-C","MSRP":"Price","Engine Fuel Type":"Fuel"})
```

Out[6]:

	Make	Model	Year	Fuel	HP	Engine Cylinders	Transmission	Drive Mode	Vehicle Style	MPG-H	MPG-C	Popularity	Price
0	BMW	1 Series M	2011	premium unleaded (required)	335.0	6.0	MANUAL	rear wheel drive	Coupe	26	19	3916	46135
1	BMW	1 Series	2011	premium unleaded (required)	300.0	6.0	MANUAL	rear wheel drive	Convertible	28	19	3916	40650
2	BMW	1 Series	2011	premium unleaded (required)	300.0	6.0	MANUAL	rear wheel drive	Coupe	28	20	3916	36350
3	BMW	1 Series	2011	premium unleaded (required)	230.0	6.0	MANUAL	rear wheel drive	Coupe	28	18	3916	29450
4	BMW	1 Series	2011	premium unleaded (required)	230.0	6.0	MANUAL	rear wheel drive	Convertible	28	18	3916	34500

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.

In [7]:
```
# total number of rows and columns
df.shape
```

Out[7]:
```
(11914, 13)
```

In [8]:
```
# checking duplicate entries

duplicate_df = df[df.duplicated()]
print("Number of Duplicate rows : ",duplicate_df.shape)
```

```
Number of Duplicate rows :  (732, 13)
```

In [9]:
```
# use count the number of rows before removing the data
df.count()
```

Out[9]:
```
Make               11914
Model              11914
Year               11914
Fuel               11911
HP                 11845
Engine Cylinders   11884
Transmission       11914
Drive Mode         11914
Vehicle Style      11914
MPG-H              11914
MPG-C              11914
Popularity         11914
Price              11914
dtype: int64
```

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

In [10]:
```
# Dropping the duplicates
df = df.drop_duplicates()
df.head()
```

Out[10]:

	Make	Model	Year	Fuel	HP	Engine Cylinders	Transmission	Drive Mode	Vehicle Style	MPG-H	MPG-C	Popularity	Price
0	BMW	1 Series M	2011	premium unleaded (required)	335.0	6.0	MANUAL	rear wheel drive	Coupe	26	19	3916	46135
1	BMW	1 Series	2011	premium unleaded (required)	300.0	6.0	MANUAL	rear wheel drive	Convertible	28	19	3916	40650
2	BMW	1 Series	2011	premium unleaded (required)	300.0	6.0	MANUAL	rear wheel drive	Coupe	28	20	3916	36350
3	BMW	1 Series	2011	premium unleaded (required)	230.0	6.0	MANUAL	rear wheel drive	Coupe	28	18	3916	29450
4	BMW	1 Series	2011	premium unleaded (required)	230.0	6.0	MANUAL	rear wheel drive	Convertible	28	18	3916	34500

In [11]:
```
# counting the number of rows after removing dupicates
df.count()
```

Out[11]:
```
Make               11182
Model              11182
Year               11182
Fuel               11179
HP                 11113
Engine Cylinders   11152
Transmission       11182
Drive Mode         11182
Vehicle Style      11182
MPG-H              11182
MPG-C              11182
Popularity         11182
Price              11182
dtype: int64
```

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.

In [12]:
```
#finding the null values

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

```
Make                0
Model               0
Year                0
Fuel                3
HP                 69
Engine Cylinders   30
Transmission        0
Drive Mode          0
Vehicle Style       0
MPG-H               0
MPG-C               0
Popularity          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.

In [13]:
```
# dropping the missing values

df= df.dropna()
df.count()
```

Out[13]:
```
Make               11081
Model              11081
Year               11081
Fuel               11081
HP                 11081
Engine Cylinders   11081
Transmission       11081
Drive Mode         11081
Vehicle Style      11081
MPG-H              11081
MPG-C              11081
Popularity         11081
Price              11081
dtype: int64
```

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

In [14]:
```
# after dropping the null values
print(df.isnull().sum())
```

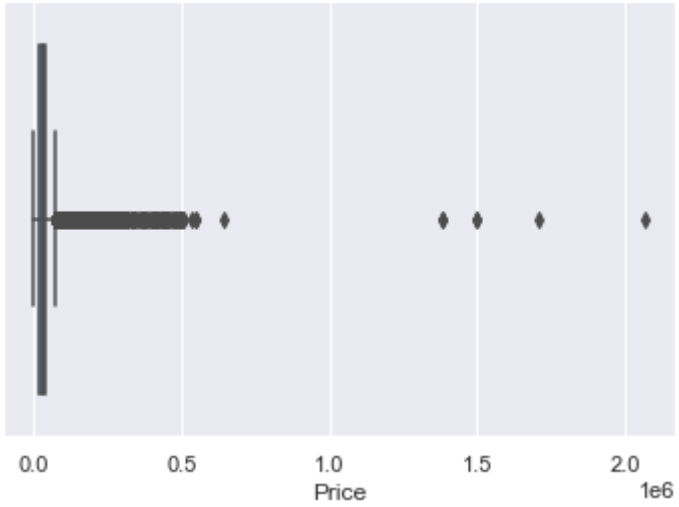
```
Make               0
Model              0
Year               0
Fuel               0
HP                 0
Engine Cylinders   0
Transmission       0
Drive Mode         0
Vehicle Style      0
MPG-H              0
MPG-C              0
Popularity         0
Price              0
dtype: int64
```

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 from towards data science.

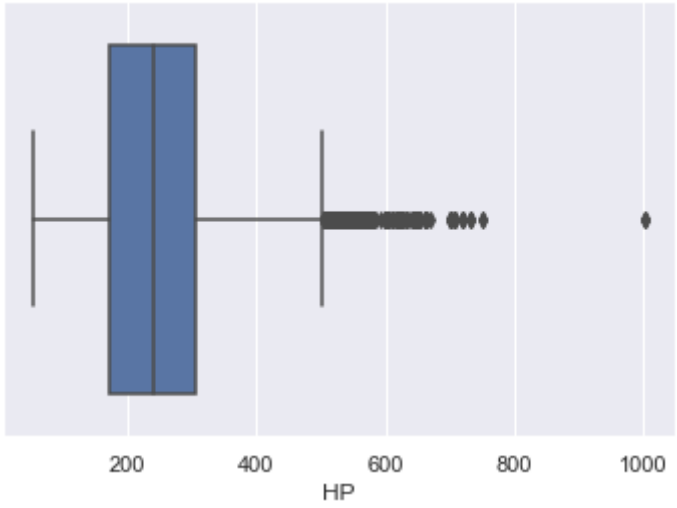
In [15]:
```
1 sns.boxplot(x=df["Price"])
```

Out[15]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2b2697bca30>
```



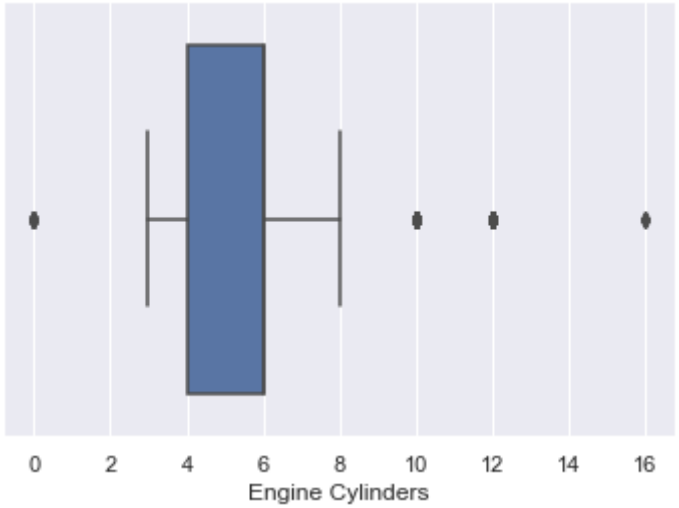
In [16]:
```
1 sns.boxplot(x=df["HP"])
```

Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0x2b269f0baf0>



In [17]:
```
1 sns.boxplot(x=df["Engine Cylinders"])
```

Out[17]: <matplotlib.axes._subplots.AxesSubplot at 0x2b269f4b130>



In [18]:
```
Q1 = df.quantile(0.25)
Q3 = df.quantile(0.75)

IQR = Q3 - Q1
print(IQR)
```

```
Year                   9.0
HP                   132.0
Engine Cylinders       2.0
MPG-H                  8.0
MPG-C                  6.0
Popularity          1460.0
Price              21460.0
dtype: float64
```

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

In [20]:
```
df.shape
```

Out[20]: (8601, 13)

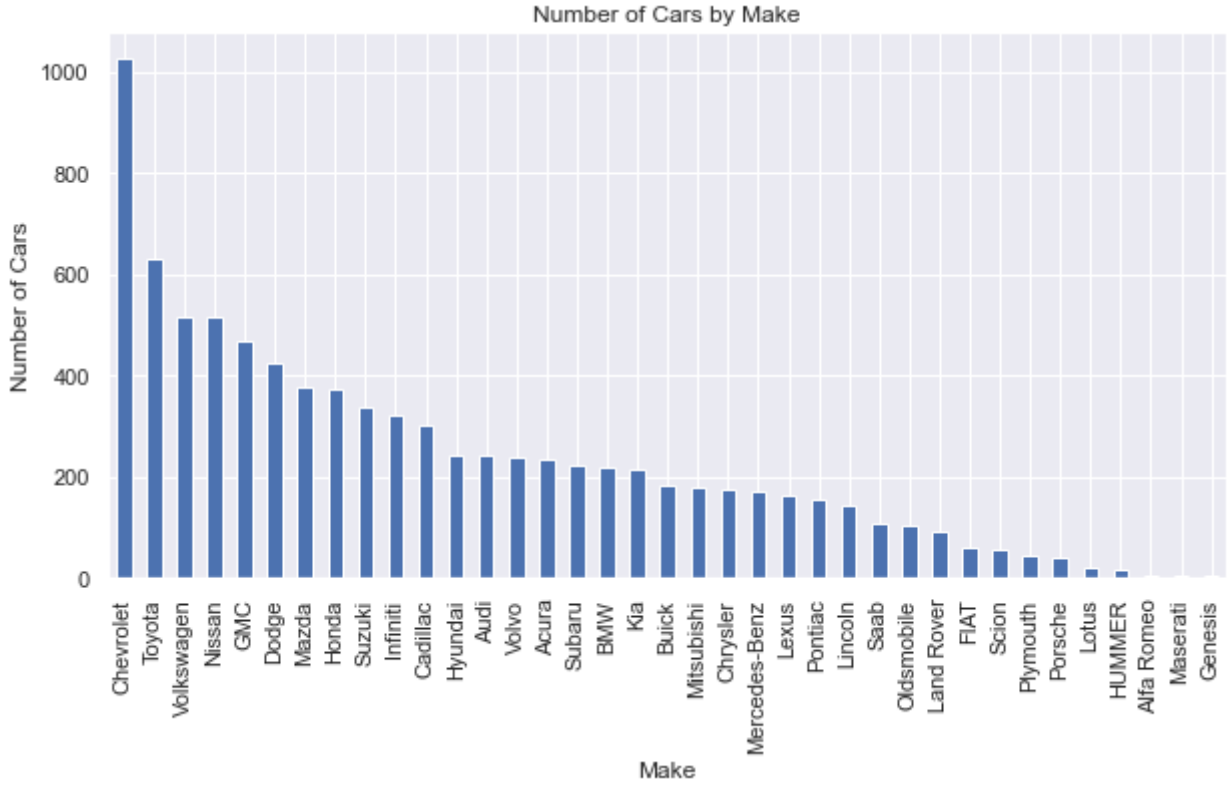
As seen above there were around 1600 rows were outliers. But you cannot completely remove the outliers because even after you use the above technique there maybe 1–2 outlier unremoved but that ok because there were more than 100 outliers. Something is better than nothing.

9. Data Visualization

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.

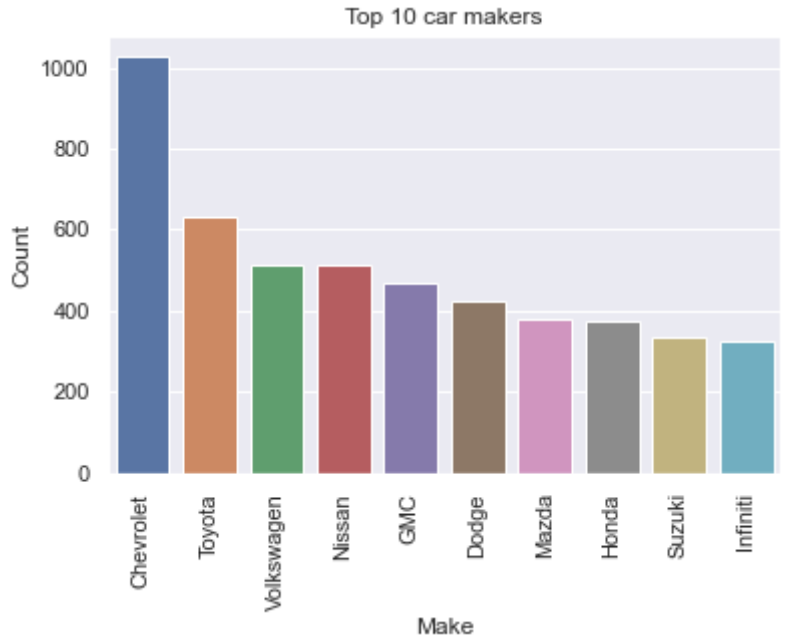
In [21]:
```
# histogram plotting

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");
```



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.

Top 10 manufacturers (number of cars produced)

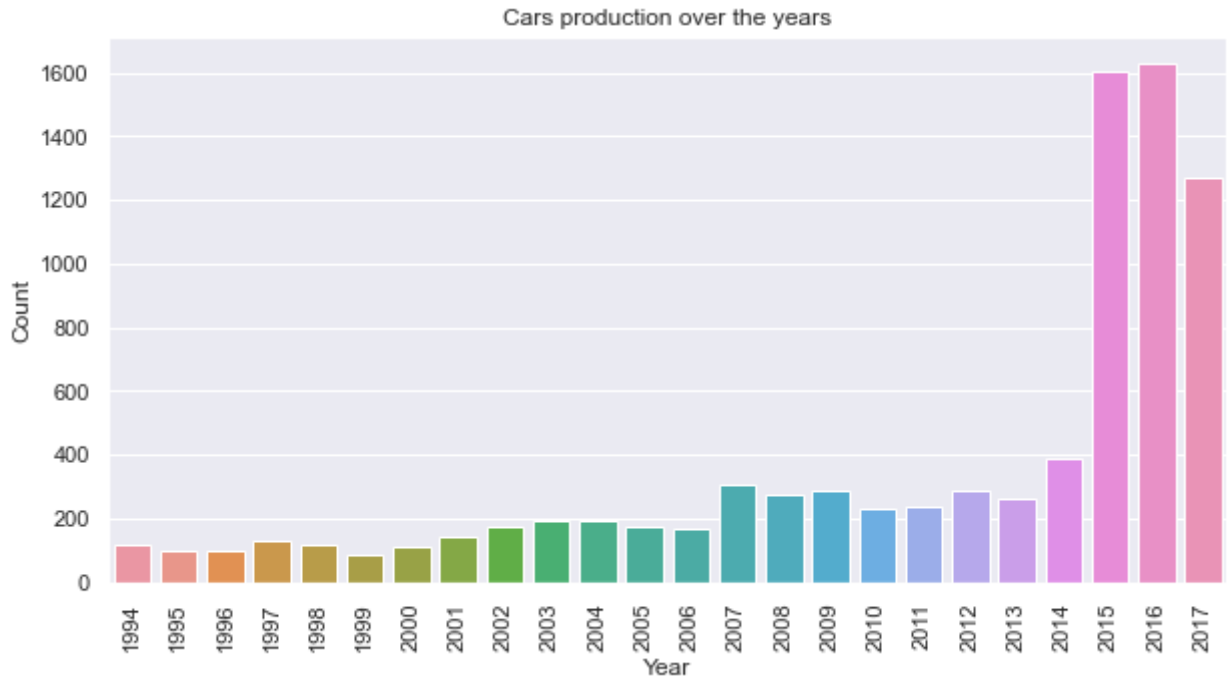
In [22]:
```
#plt.figure(figsize=(7,3))
top_ten = df.groupby("Make").size().sort_values(ascending=False).head(10)
top_ten_df = pd.DataFrame(top_ten.reset_index(name="Count"))
plt.title('Top 10 car makers')
plt.ylabel('Number of cars')
plt.xticks(rotation=90)
sns.barplot(x='Make', y='Count', data=top_ten_df);
```



From the above bar plot we can infer that most of the people buy cars from Chevrolet, Ford, Toyota and Volkswagen as they produce more economical cars which can afford by more people.

Cars produced over the years

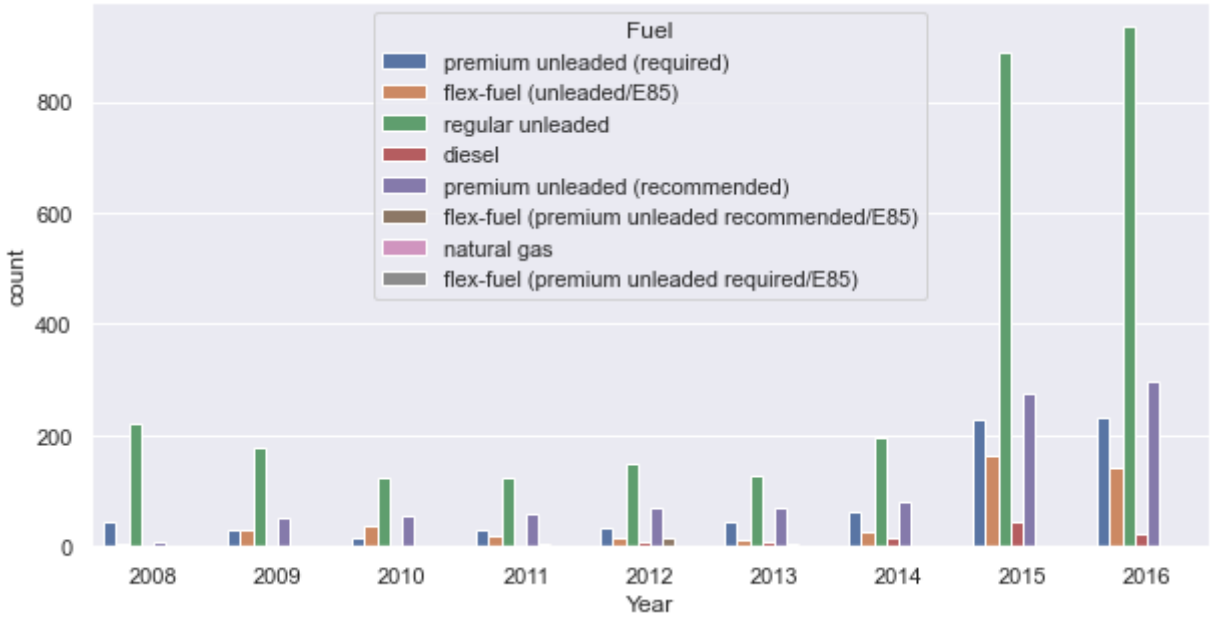
In [23]:
```
plt.figure(figsize=(10,5))
cars_prod_df = pd.DataFrame(
    df.groupby("Year")
    .size()
    .reset_index(name="Count")
)
plt.title('Cars production over the years')
plt.xticks(rotation=90)
sns.barplot(x="Year", y="Count", data=cars_prod_df);
```



rom the above chart we can see that cars production has increased over the years. In year 2017 though, we see a dip in the number of cars produced. It could also be because of incomplete data for 2017.

Fuel types per Year

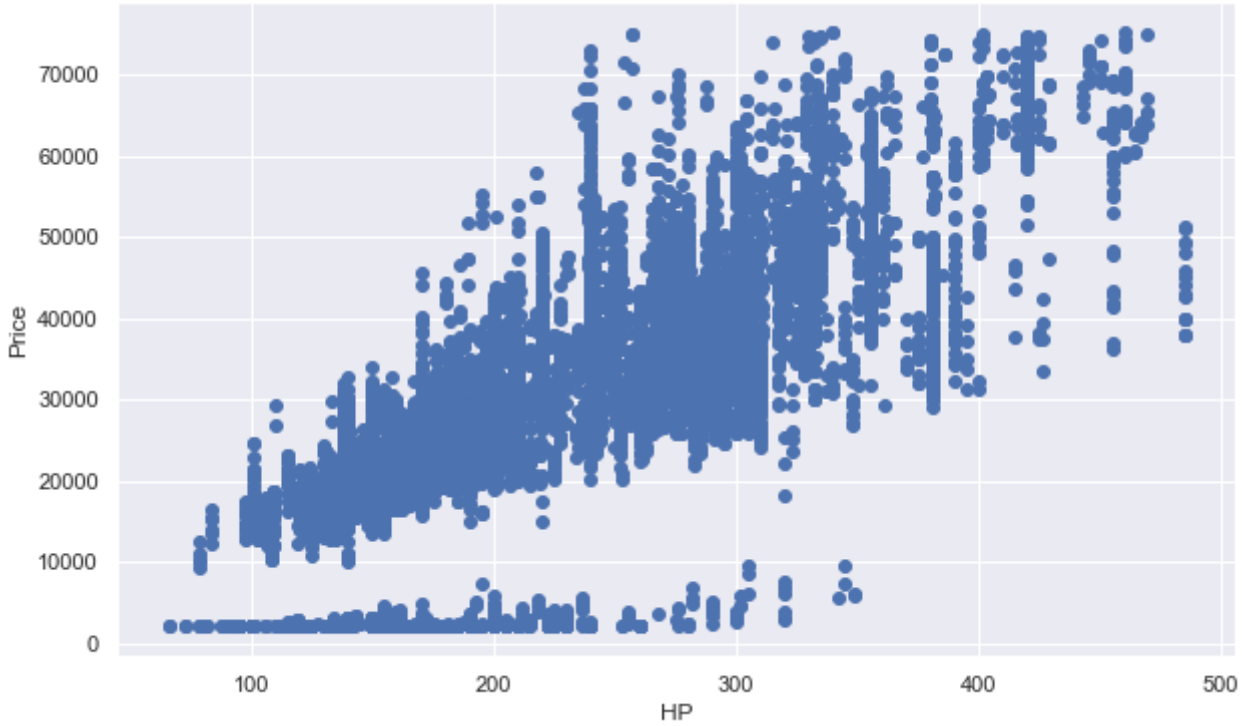
In [24]:
```
plt.figure(figsize=(10,5))
fueldf = df[(df['Year'] > 2007) & (df['Year'] < 2017)].copy()
ax = sns.countplot(x="Year", hue="Fuel", data=fueldf)
#plt.setp(ax.get_legend().get_title(), fontsize='32')
#plt.setp(ax.get_legend().get_texts(), fontsize='28')
plt.show()
```



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.

In [25]:
```
# Plotting a scatter plot
fig, ax = plt.subplots(figsize=(10,6))
ax.scatter(df['HP'], df['Price'])
ax.set_xlabel('HP')
ax.set_ylabel('Price')
plt.show()
```



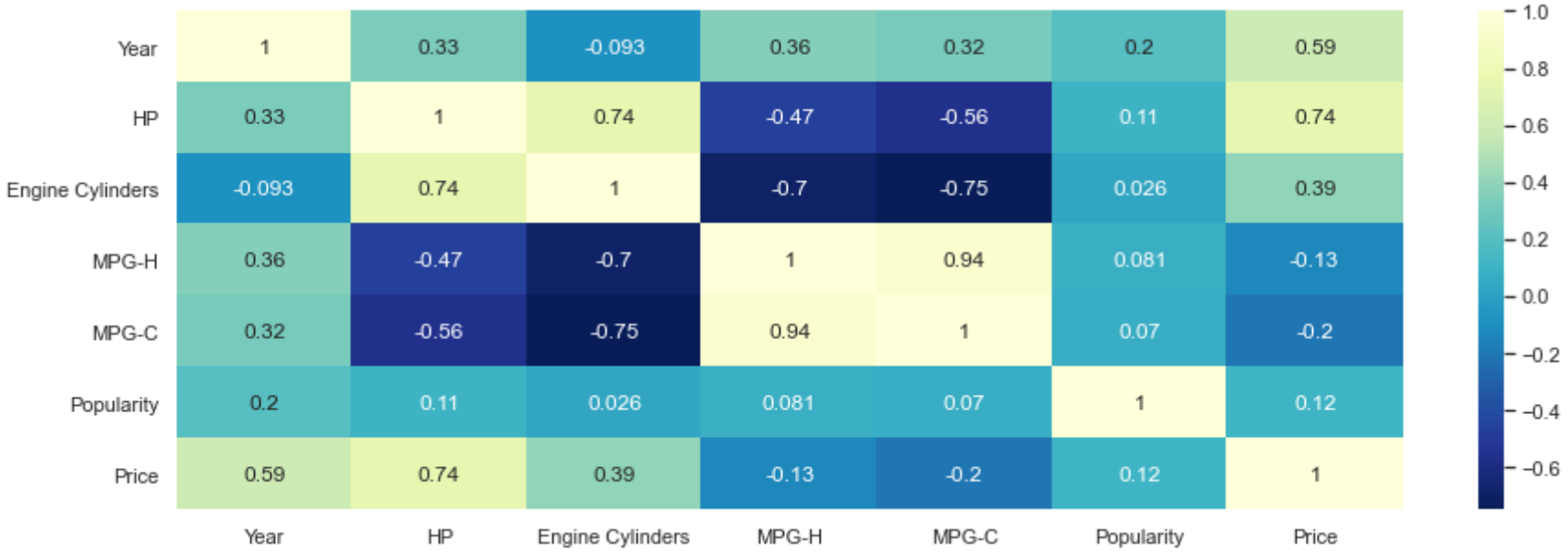
Heat Maps

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.

In [26]:
```
# find relation betweeb the variables
plt.figure(figsize=(15,5))
c = df.corr()
sns.heatmap(c,cmap="YlGnBu_r",annot=True)
c
```

Out[26]:

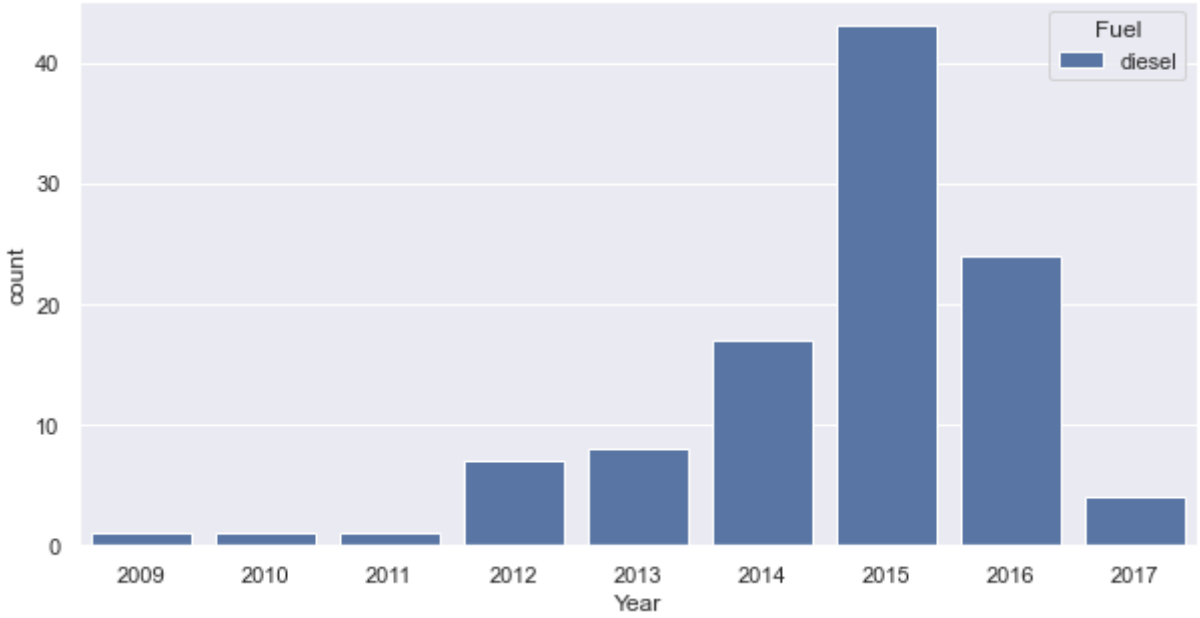
	Year	HP	Engine Cylinders	MPG-H	MPG-C	Popularity	Price
Year	1.000000	0.330139	-0.092862	0.358082	0.321957	0.204183	0.590127
HP	0.330139	1.000000	0.741905	-0.466543	-0.564547	0.105459	0.743740
Engine Cylinders	-0.092862	0.741905	1.000000	-0.697714	-0.750664	0.026059	0.394267
MPG-H	0.358082	-0.466543	-0.697714	1.000000	0.937859	0.080608	-0.130348
MPG-C	0.321957	-0.564547	-0.750664	0.937859	1.000000	0.070032	-0.204918
Popularity	0.204183	0.105459	0.026059	0.080608	0.070032	1.000000	0.116246
Price	0.590127	0.743740	0.394267	-0.130348	-0.204918	0.116246	1.000000



Asking and Answering Questions

Q1: Has use of diesel cars increased or decresed over the years?

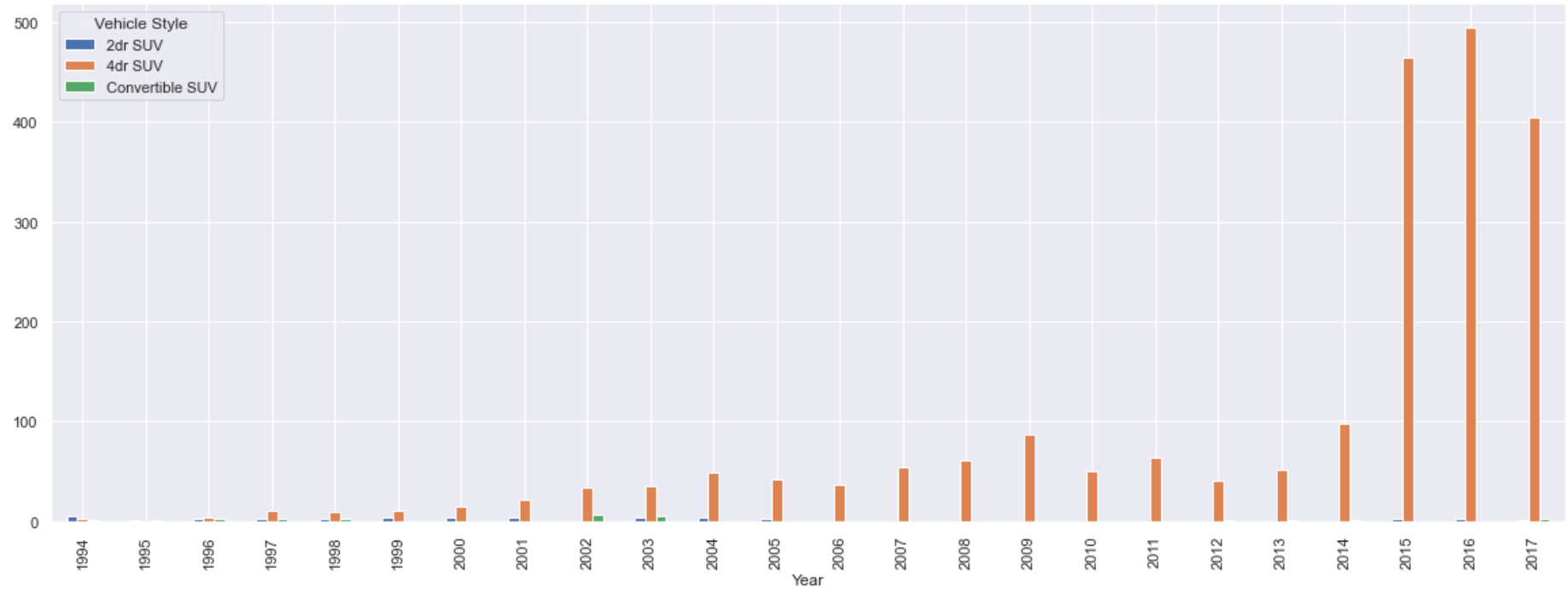
In [27]:
```
plt.figure(figsize=(10,5))
diesel_df = df[df['Fuel'].str.contains('diesel')].copy()
ax = sns.countplot(x="Year", hue="Fuel", data=diesel_df)
plt.show()
```



Use of diesel cars increased steadily from 2010 to 2015. Thereafter, the usage has gone down drastically which could be attributed to the stricter pollution laws coming in.

Q2: Has production of SUVs increased over the years?

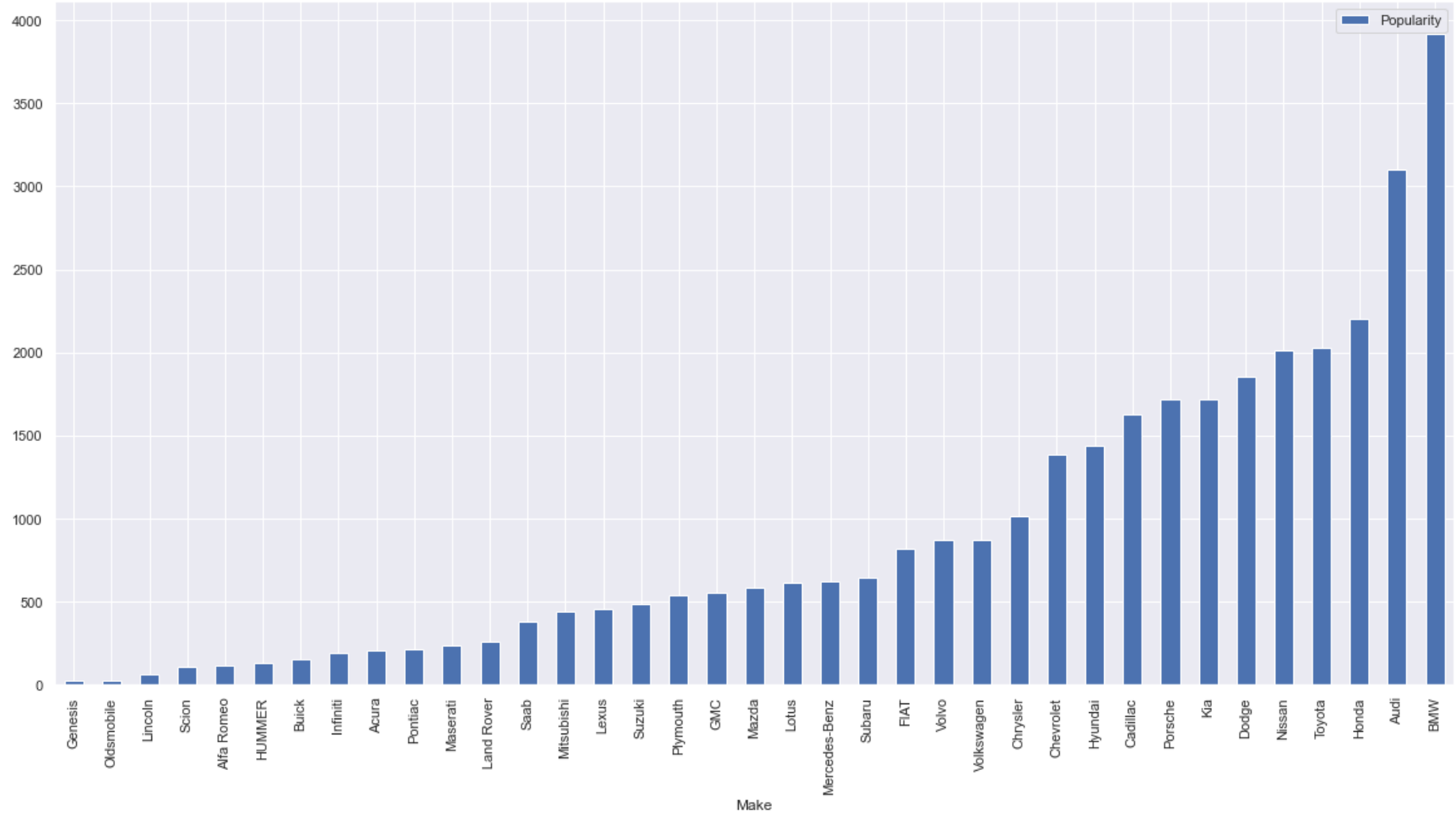
In [28]:
```
vs_df = df[df['Vehicle Style'].str.contains('SUV')].groupby(['Year', 'Vehicle Style']).size().reset_index(name="Coun
df_pivot =  pd.pivot_table(
    vs_df,
    values="Count",
    index="Year",
    columns="Vehicle Style",
    aggfunc=np.mean
)

df_pivot.plot(kind="bar", figsize=(20, 7));
```



From the graph we can cleary see that SUV production has gone up significantly as compared to previous decades.

Q3: Which brand is least popular and which one is most popular?

In [29]:
```
# Popular Cars
popcars_df = df[['Make', 'Popularity']].sort_values('Popularity')
popcars_df = popcars_df.drop_duplicates()
popcars_df.plot(kind="bar", x="Make", figsize=(20,10));
```



Spyker is least popular and Ford is most popular brand.

Inferences and Conclusion

- Our analysis shows that Price of the car positively correlates with higher Engine specifications like more horsepower.
- Using the above conclusion we can also form a linear relationship between the variables to predict price of the car based on engine specifications.
- The use of E85 fuel has gone up over the years as green initiatives have picked up the pace. More people prefer greener alternatives now.
- Production of SUVs increased rapidly in last few years.
- Ford is the most popular brand in the world but Chevrolet produced most cars.