# Refurbished Cars Price Prediction

In [1]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

In [2]:

```
data=pd.read_csv(r"C:\Users\hrush\Downloads\Data_Train.csv")
data.head()
```

Out[2]:

| | Name | Location | Year | Kilometers_Driven | Fuel_Type | Transmission | Owner_Type | Mileage |
|---|---|---|---|---|---|---|---|---|
| **0** | Maruti Wagon R LXI CNG | Mumbai | 2010 | 72000 | CNG | Manual | First | 26.6 km/kg |
| **1** | Hyundai Creta 1.6 CRDi SX Option | Pune | 2015 | 41000 | Diesel | Manual | First | 19.67 kmpl |
| **2** | Honda Jazz V | Chennai | 2011 | 46000 | Petrol | Manual | First | 18.2 kmpl |
| **3** | Maruti Ertiga VDI | Chennai | 2012 | 87000 | Diesel | Manual | First | 20.77 kmpl |
| **4** | Audi A4 New 2.0 TDI Multitronic | Coimbatore | 2013 | 40670 | Diesel | Automatic | Second | 15.2 kmpl |

# Checking how many unique cars are there

In [3]:

```
uniqueCars = data.Name.unique()
```

In [4]:

```
plt.rcParams["figure.figsize"] = [20,8]
```

In [5]:

```
uniqueCars.size
```

Out[5]:

```
1876
```

In [6]:

```
# checking null values

data.isnull().sum()
```

Out[6]:

```
Name                  0
Location              0
Year                  0
Kilometers_Driven     0
Fuel_Type             0
Transmission          0
Owner_Type            0
Mileage               2
Engine               36
Power                36
Seats                42
Price                 0
dtype: int64
```

# Filled all null values of seats with number 4

In [7]:

```
data["Seats"].fillna(4, inplace = True)
```

# Checking null columns

In [8]:

```
data.isnull().sum()
```

Out[8]:

```
Name                  0
Location              0
Year                  0
Kilometers_Driven     0
Fuel_Type             0
Transmission          0
Owner_Type            0
Mileage               2
Engine               36
Power                36
Seats                 0
Price                 0
dtype: int64
```

# Removing CC from Engine column

In [9]:

```
data['Engine'] = data['Engine'].fillna('1197 CC')
cleanEngine = (data.Engine.str.split(' ').str[0])
```

In [10]:
```
cleanEngine
```

Out[10]:
```
0        998
1       1582
2       1199
3       1248
4       1968
        ...
6014    1248
6015    1120
6016    2498
6017     998
6018     936
Name: Engine, Length: 6019, dtype: object
```

# Adding a clean engine column in the dataset

In [11]:
```
data['cleanEngine'] = cleanEngine
```

In [12]:
```
data.head(5)
```

Out[12]:

| | Name | Location | Year | Kilometers_Driven | Fuel_Type | Transmission | Owner_Type | Mileage |
|---|---|---|---|---|---|---|---|---|
| **0** | Maruti Wagon R LXI CNG | Mumbai | 2010 | 72000 | CNG | Manual | First | 26.6 km/kg |
| **1** | Hyundai Creta 1.6 CRDi SX Option | Pune | 2015 | 41000 | Diesel | Manual | First | 19.67 kmpl |
| **2** | Honda Jazz V | Chennai | 2011 | 46000 | Petrol | Manual | First | 18.2 kmpl |
| **3** | Maruti Ertiga VDI | Chennai | 2012 | 87000 | Diesel | Manual | First | 20.77 kmpl |
| **4** | Audi A4 New 2.0 TDI Multitronic | Coimbatore | 2013 | 40670 | Diesel | Automatic | Second | 15.2 kmpl |

# Removing bhp from Power column

In [13]:
```
data['Power'] = data['Power'].fillna('74 bhp')

data['Power']=data['Power'].replace("null","74 bhp")
cleanPower = (data.Power.str.split(' ').str[0])
```

In [14]:
```
cleanPower
```

Out[14]:
```
0       58.16
1       126.2
2        88.7
3       88.76
4       140.8
        ...  
6014       74
6015       71
6016      112
6017     67.1
6018     57.6
Name: Power, Length: 6019, dtype: object
```

# Adding a clean power column in the dataset

In [15]:
```
data['cleanPower'] = cleanPower
```

In [16]:
```
data.head(5)
```

Out[16]:

| | Name | Location | Year | Kilometers_Driven | Fuel_Type | Transmission | Owner_Type | Mileage |
|---|---|---|---|---|---|---|---|---|
| **0** | Maruti Wagon R LXI CNG | Mumbai | 2010 | 72000 | CNG | Manual | First | 26.6 km/kg |
| **1** | Hyundai Creta 1.6 CRDi SX Option | Pune | 2015 | 41000 | Diesel | Manual | First | 19.67 kmpl |
| **2** | Honda Jazz V | Chennai | 2011 | 46000 | Petrol | Manual | First | 18.2 kmpl |
| **3** | Maruti Ertiga VDI | Chennai | 2012 | 87000 | Diesel | Manual | First | 20.77 kmpl |
| **4** | Audi A4 New 2.0 TDI Multitronic | Coimbatore | 2013 | 40670 | Diesel | Automatic | Second | 15.2 kmpl |

# Removing km/kg or kmpl from mileage column

In [17]:
```
data['Mileage'] = data['Mileage'].fillna('17.0 kmpl')

data['Mileage'] = data['Mileage'].replace("0.0 kmpl", "17.0 kmpl")
cleanMileage = (data.Mileage.str.split(' ').str[0])
```

```
In [18]: cleanMileage
```

```
Out[18]: 0        26.6
         1       19.67
         2        18.2
         3       20.77
         4        15.2
                 ...
         6014     28.4
         6015     24.4
         6016     14.0
         6017     18.9
         6018    25.44
         Name: Mileage, Length: 6019, dtype: object
```

# Adding a clean power mileage in the dataset

```
In [19]: data['cleanMileage'] = cleanMileage
```

```
In [20]: data.head(5)
```

Out[20]:

| | Name | Location | Year | Kilometers_Driven | Fuel_Type | Transmission | Owner_Type | Mileage |
|---|---|---|---|---|---|---|---|---|
| **0** | Maruti Wagon R LXI CNG | Mumbai | 2010 | 72000 | CNG | Manual | First | 26.6 km/kg |
| **1** | Hyundai Creta 1.6 CRDi SX Option | Pune | 2015 | 41000 | Diesel | Manual | First | 19.67 kmpl |
| **2** | Honda Jazz V | Chennai | 2011 | 46000 | Petrol | Manual | First | 18.2 kmpl |
| **3** | Maruti Ertiga VDI | Chennai | 2012 | 87000 | Diesel | Manual | First | 20.77 kmpl |
| **4** | Audi A4 New 2.0 TDI Multitronic | Coimbatore | 2013 | 40670 | Diesel | Automatic | Second | 15.2 kmpl |

# Checking data type of all columns

In [21]:
```
data.dtypes
```

Out[21]:
```
Name                  object
Location              object
Year                   int64
Kilometers_Driven      int64
Fuel_Type             object
Transmission          object
Owner_Type            object
Mileage               object
Engine                object
Power                 object
Seats                float64
Price                float64
cleanEngine           object
cleanPower            object
cleanMileage          object
dtype: object
```

# Changing data type of cleanMileage and cleanEngine column from object to numeric

In [22]:
```
data["cleanMileage"] = pd.to_numeric(data["cleanMileage"])

data["cleanEngine"] = pd.to_numeric(data["cleanEngine"])
```

In [23]:
```
data.dtypes
```

Out[23]:
```
Name                  object
Location              object
Year                   int64
Kilometers_Driven      int64
Fuel_Type             object
Transmission          object
Owner_Type            object
Mileage               object
Engine                object
Power                 object
Seats                float64
Price                float64
cleanEngine            int64
cleanPower            object
cleanMileage         float64
dtype: object
```

# Replacing "null" values in Power column with 0.0

In [24]:
```
data["cleanPower"].replace({"null": "0.0",}, inplace=True)
```

# Changing data type of cleanPower column from object to numeric

In [25]:
```
data["cleanPower"] = pd.to_numeric(data["cleanPower"])
```

In [26]:
```
data.head(10)
```

Out[26]:

| | Name | Location | Year | Kilometers_Driven | Fuel_Type | Transmission | Owner_Type | Mileag |
|---|---|---|---|---|---|---|---|---|
| **0** | Maruti Wagon R LXI CNG | Mumbai | 2010 | 72000 | CNG | Manual | First | 26. km/k |
| **1** | Hyundai Creta 1.6 CRDi SX Option | Pune | 2015 | 41000 | Diesel | Manual | First | 19.6 kmp |
| **2** | Honda Jazz V | Chennai | 2011 | 46000 | Petrol | Manual | First | 18. kmp |
| **3** | Maruti Ertiga VDI | Chennai | 2012 | 87000 | Diesel | Manual | First | 20.7 kmp |
| **4** | Audi A4 New 2.0 TDI Multitronic | Coimbatore | 2013 | 40670 | Diesel | Automatic | Second | 15. kmp |
| **5** | Hyundai EON LPG Era Plus Option | Hyderabad | 2012 | 75000 | LPG | Manual | First | 21. km/k |
| **6** | Nissan Micra Diesel XV | Jaipur | 2013 | 86999 | Diesel | Manual | First | 23.0 kmp |
| **7** | Toyota Innova Crysta 2.8 GX AT 8S | Mumbai | 2016 | 36000 | Diesel | Automatic | First | 11.3 kmp |
| **8** | Volkswagen Vento Diesel Comfortline | Pune | 2013 | 64430 | Diesel | Manual | First | 20.5 kmp |
| **9** | Tata Indica Vista Quadrajet LS | Chennai | 2012 | 65932 | Diesel | Manual | Second | 22. kmp |

# Getting average value of each column

```
In [27]: data.mean(axis=0)
```

```
Out[27]: Year                  2013.358199
         Kilometers_Driven    58738.380296
         Seats                    5.269812
         Price                    9.479468
         cleanEngine           1618.738827
         cleanPower             111.004971
         cleanMileage            18.326642
         dtype: float64
```

# Calculating number of null values in each column

```
In [28]: data.isnull().sum()
```

```
Out[28]: Name                 0
         Location             0
         Year                 0
         Kilometers_Driven    0
         Fuel_Type            0
         Transmission         0
         Owner_Type           0
         Mileage              0
         Engine               0
         Power                0
         Seats                0
         Price                0
         cleanEngine          0
         cleanPower           0
         cleanMileage         0
         dtype: int64
```

# Filling null values of cleanEngine column

```
In [29]: data["cleanEngine"].fillna(1621.276, inplace = True)
```

# Filling null values of cleanMileage column

```
In [30]: data["cleanMileage"].fillna(18.134, inplace = True)
```

# Filling null or zero values of cleanPower column

In [31]:

```
data["cleanPower"].replace({0.0: 111.227,}, inplace=True)
```

In [32]:

```
data["cleanPower"].fillna(111.227, inplace = True)
```

# Again checking number of null value in each column

In [33]:

```
data.isnull().sum()
```

Out[33]:

```
Name                 0
Location             0
Year                 0
Kilometers_Driven    0
Fuel_Type            0
Transmission         0
Owner_Type           0
Mileage              0
Engine               0
Power                0
Seats                0
Price                0
cleanEngine          0
cleanPower           0
cleanMileage         0
dtype: int64
```

# Cleaning name of cars

# 1. By car company

In [34]:

```
carCompany = (data.Name.str.split(' ').str[0])
```

# Adding Car Company column in the dataset

In [35]:

```

data['carCompany'] = carCompany
```

# Checking unique car companys in the dataset

In [36]:

```
uniqueCarCompany = data.carCompany.unique()
```

In [37]:
```
uniqueCarCompany.size
```

Out[37]:
```
31
```

In [38]:
```
data.head(10)
```

Out[38]:

|  | Name | Location | Year | Kilometers_Driven | Fuel_Type | Transmission | Owner_Type | Mileag |
|---|---|---|---|---|---|---|---|---|
| **0** | Maruti Wagon R LXI CNG | Mumbai | 2010 | 72000 | CNG | Manual | First | 26. km/k |
| **1** | Hyundai Creta 1.6 CRDi SX Option | Pune | 2015 | 41000 | Diesel | Manual | First | 19.6 kmp |
| **2** | Honda Jazz V | Chennai | 2011 | 46000 | Petrol | Manual | First | 18. kmp |
| **3** | Maruti Ertiga VDI | Chennai | 2012 | 87000 | Diesel | Manual | First | 20.7 kmp |
| **4** | Audi A4 New 2.0 TDI Multitronic | Coimbatore | 2013 | 40670 | Diesel | Automatic | Second | 15. kmp |
| **5** | Hyundai EON LPG Era Plus Option | Hyderabad | 2012 | 75000 | LPG | Manual | First | 21. km/k |
| **6** | Nissan Micra Diesel XV | Jaipur | 2013 | 86999 | Diesel | Manual | First | 23.0 kmp |
| **7** | Toyota Innova Crysta 2.8 GX AT 8S | Mumbai | 2016 | 36000 | Diesel | Automatic | First | 11.3 kmp |
| **8** | Volkswagen Vento Diesel Comfortline | Pune | 2013 | 64430 | Diesel | Manual | First | 20.5 kmp |
| **9** | Tata Indica Vista Quadrajet LS | Chennai | 2012 | 65932 | Diesel | Manual | Second | 22. kmp |

# 2. By car model

In [39]:
```
carModel = (data.Name.str.split(' ').str[1:])
```

In [40]:

```
carModel
```

Out[40]:

```
0                   [Wagon, R, LXI, CNG]
1         [Creta, 1.6, CRDi, SX, Option]
2                              [Jazz, V]
3                          [Ertiga, VDI]
4       [A4, New, 2.0, TDI, Multitronic]
                      ...
6014                        [Swift, VDI]
6015               [Xcent, 1.1, CRDi, S]
6016                    [Xylo, D4, BSIV]
6017                     [Wagon, R, VXI]
6018                      [Beat, Diesel]
Name: Name, Length: 6019, dtype: object
```

# Combining elements of each list to form the meaningful car model name

In [41]:

```
Model = []

for items in carModel:
    tempstr = ""
    for i in range(0,len(items)):
        if(i == 0):
                   tempstr = tempstr + items[i]
        else:
                   tempstr = tempstr + " " + items[i]

    Model.append(tempstr)
```

In [42]:

```
Model
```

```
 'i10 Sportz 1.2',
 'Grand i10 Sportz',
 'Santro Xing XO',
 'Amaze SX i-VTEC',
 'Fortuner 4x2 Manual',
 'A6 2011-2015 35 TDI Premium',
 'Ecosport 1.5 DV5 MT Titanium Optional',
 'XUV500 W8 2WD',
 'Amaze SX i-DTEC',
 'Polo Diesel Highline 1.2L',
 'Verna Transform SX VGT CRDi',
 'Wagon R VXI BS IV',
 'Polo Petrol Highline 1.6L',
 'i20 1.4 CRDi Sportz',
 'i20 Asta 1.2',
 'GO Plus T Petrol',
 'A4 3.0 TDI Quattro Premium',
 'i20 2015-2017 Asta',
 'Omni 5 Str STD',
 'Etios Liva 1.2 G',
```

# Entering car model name in dataset

In [43]:

```
data['Model'] = Model
```

```
In [44]: data.head(10)
```

```
Out[44]:
```

| | Name | Location | Year | Kilometers_Driven | Fuel_Type | Transmission | Owner_Type | Mileag |
|---|---|---|---|---|---|---|---|---|
| **0** | Maruti Wagon R LXI CNG | Mumbai | 2010 | 72000 | CNG | Manual | First | 26.<br>km/k |
| **1** | Hyundai Creta 1.6 CRDi SX Option | Pune | 2015 | 41000 | Diesel | Manual | First | 19.6<br>kmp |
| **2** | Honda Jazz V | Chennai | 2011 | 46000 | Petrol | Manual | First | 18.<br>kmp |
| **3** | Maruti Ertiga VDI | Chennai | 2012 | 87000 | Diesel | Manual | First | 20.7<br>kmp |
| **4** | Audi A4 New 2.0 TDI Multitronic | Coimbatore | 2013 | 40670 | Diesel | Automatic | Second | 15.<br>kmp |
| **5** | Hyundai EON LPG Era Plus Option | Hyderabad | 2012 | 75000 | LPG | Manual | First | 21.<br>km/k |
| **6** | Nissan Micra Diesel XV | Jaipur | 2013 | 86999 | Diesel | Manual | First | 23.0<br>kmp |
| **7** | Toyota Innova Crysta 2.8 GX AT 8S | Mumbai | 2016 | 36000 | Diesel | Automatic | First | 11.3<br>kmp |
| **8** | Volkswagen Vento Diesel Comfortline | Pune | 2013 | 64430 | Diesel | Manual | First | 20.5<br>kmp |
| **9** | Tata Indica Vista Quadrajet LS | Chennai | 2012 | 65932 | Diesel | Manual | Second | 22.<br>kmp |

# Dropping multiple useless columns like name, mileage, power and engine

In [45]:
```
data=data.drop(['Name', 'Mileage', 'Engine', 'Power','Model'], axis = 1)
data.head()
```

Out[45]:

| | Location | Year | Kilometers_Driven | Fuel_Type | Transmission | Owner_Type | Seats | Price | clear |
|---|---|---|---|---|---|---|---|---|---|
| **0** | Mumbai | 2010 | 72000 | CNG | Manual | First | 5.0 | 1.75 | |
| **1** | Pune | 2015 | 41000 | Diesel | Manual | First | 5.0 | 12.50 | |
| **2** | Chennai | 2011 | 46000 | Petrol | Manual | First | 5.0 | 4.50 | |
| **3** | Chennai | 2012 | 87000 | Diesel | Manual | First | 7.0 | 6.00 | |
| **4** | Coimbatore | 2013 | 40670 | Diesel | Automatic | Second | 5.0 | 17.74 | |

# Checking number of unique Locations

In [46]:
```
uniqueLocations = data.Location.unique()
```

In [47]:
```
uniqueLocations.size
```

Out[47]:
```
11
```

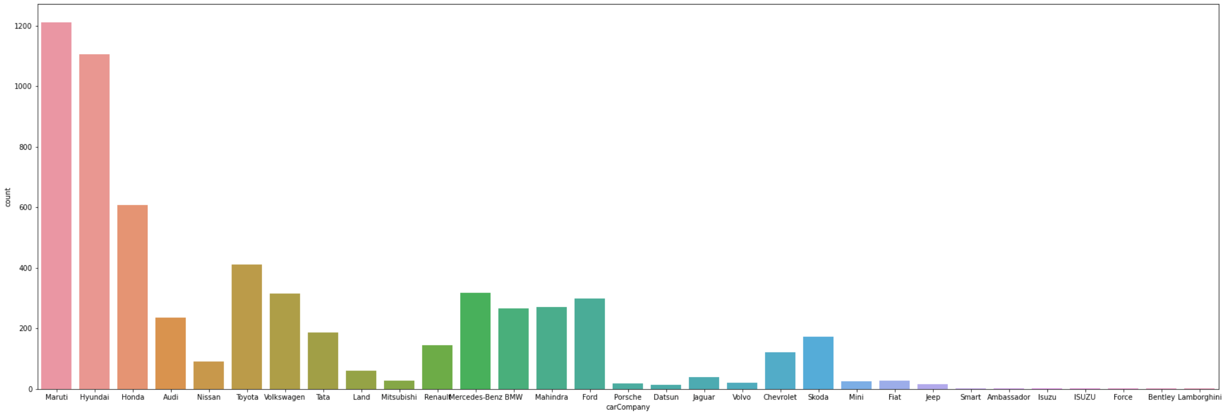
# Exploratory Data Analysis

In [48]:
```
plt.rcParams["figure.figsize"] = [30,10]
```

# 1. Which car company produces maximum cars

In [49]:
```
sns.countplot(x = "carCompany" , data = data)
```

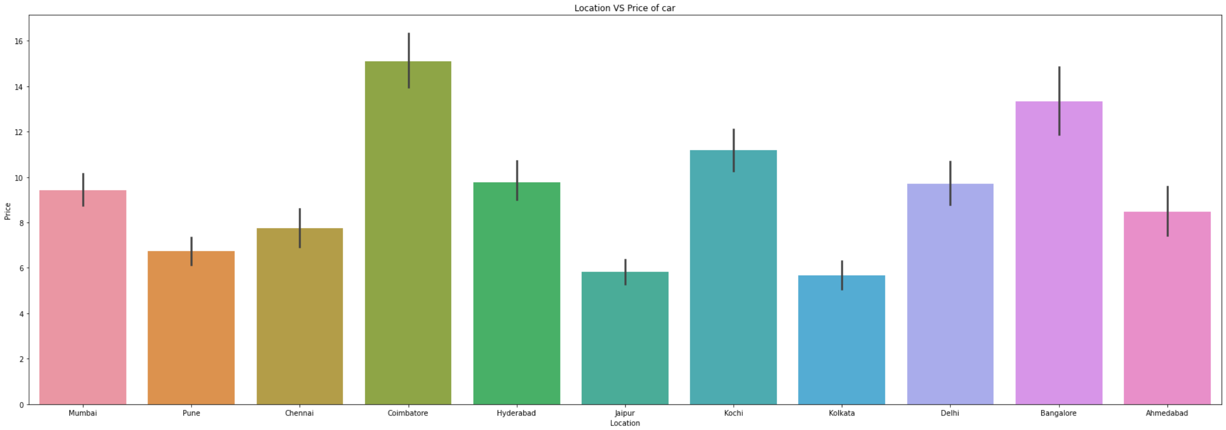
Out[49]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2ace6721280>
```



# 2. Which location gives maximum price of cars

In [50]:
```
plt.title('Location VS Price of car')
sns.barplot(data['Location'], data['Price'])
```

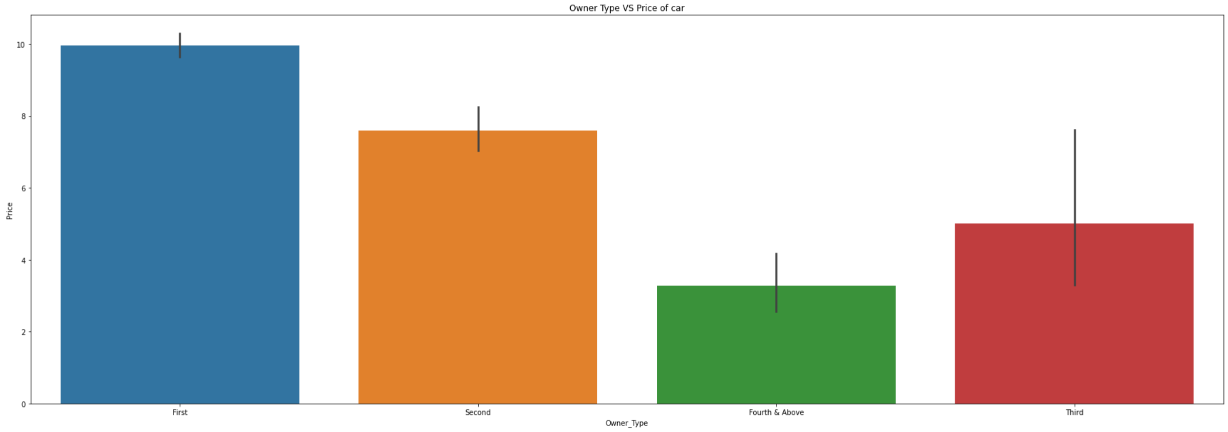
Out[50]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2ace7217760>
```



# 3. Price of cars according to owner type

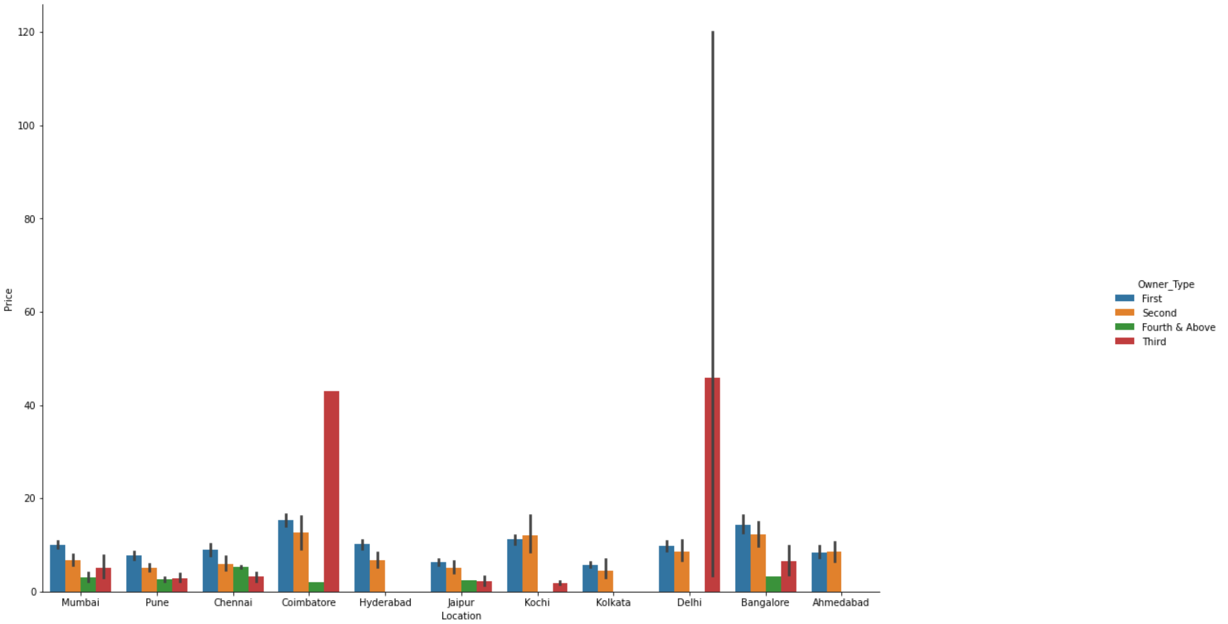
```
In [51]: plt.title('Owner Type VS Price of car')
         sns.barplot(data['Owner_Type'], data['Price'])
```

```
Out[51]: <matplotlib.axes._subplots.AxesSubplot at 0x2ace7c85370>
```



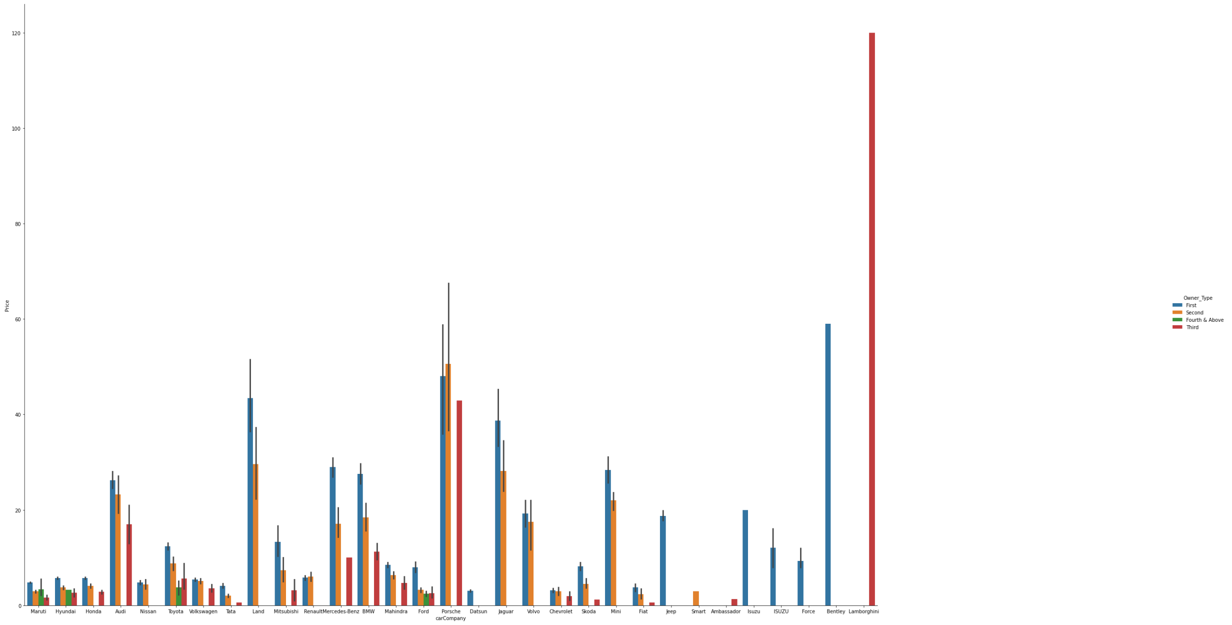
## 4. Location wise distribution of owner_type of cars

```
In [52]: g = sns.catplot(x="Location", y="Price", hue="Owner_Type", data=data,kind="bar")
         g.fig.set_figwidth(20)
         g.fig.set_figheight(10)
```



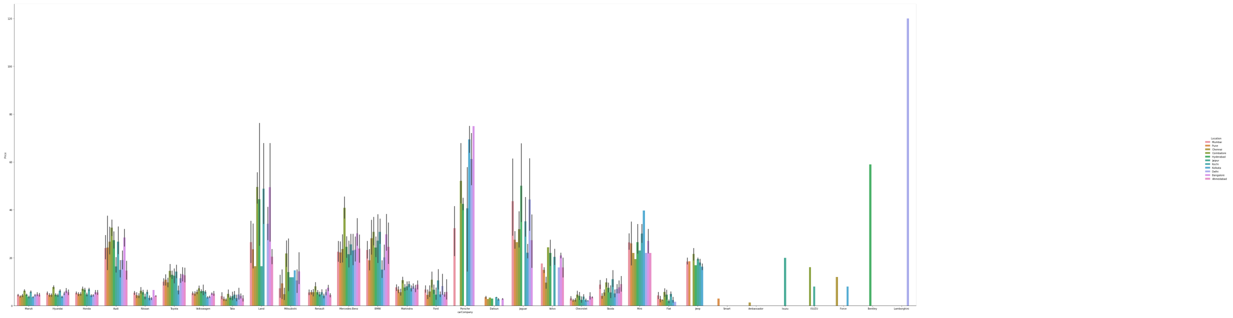
# 5. Car Company wise distribution of owner type of cars

```
In [53]: g = sns.catplot(x="carCompany", y="Price", hue="Owner_Type", data=data,kind="bar'
         g.fig.set_figwidth(40)
         g.fig.set_figheight(20)
```



# 6. Location wise variation in price of cars belonging to different compnay

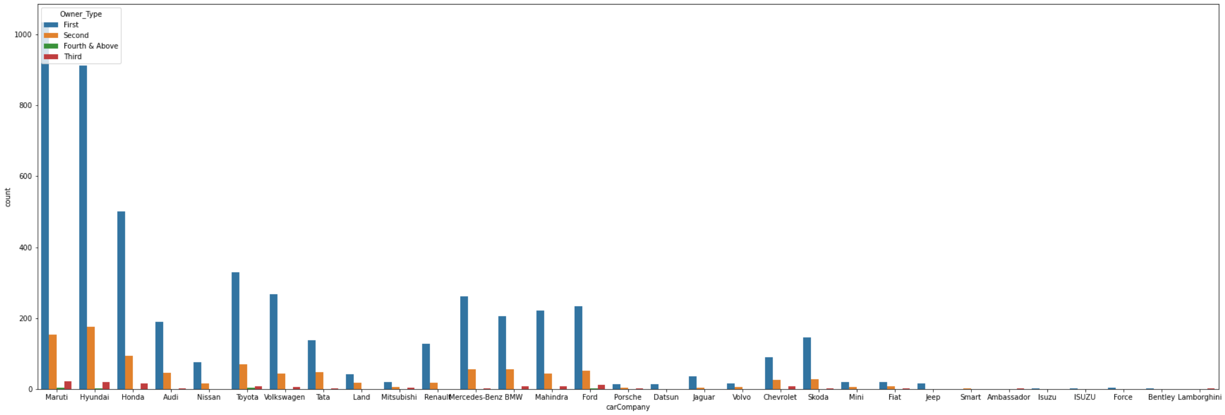
In [54]:
```
g = sns.catplot(x="carCompany", y="Price", hue="Location", data=data,kind="bar")
g.fig.set_figwidth(80)
g.fig.set_figheight(20)
```



For maruti maximum price is at: Coimbatore and kochi For Hyundai maximum price is at: Coimbatore, Kochi and Bangalore For Honda maximum price is at: Coimbatore, Hyderabad and Kochi For Audi maximum price is at: Coimbatore, Bangalore For Nissan maximum price is at: Coimabatore, Bangalore and Kochi For Toyota maximum price is at: Coimbatore and Kochi

# 7. Company wise distribution of owner_type of cars and thier count

In [55]:
```
plt.rcParams["figure.figsize"] = [30,10]
g = sns.countplot(x="carCompany", data = data, hue = 'Owner_Type')
```



# Number of unique values in each column

In [56]:
```
data.nunique(axis=0)
```

Out[56]:
```
Location                11
Year                    22
Kilometers_Driven     3093
Fuel_Type                5
Transmission             2
Owner_Type               4
Seats                    9
Price                 1373
cleanEngine            146
cleanPower             370
cleanMileage           429
carCompany              31
dtype: int64
```

Type *Markdown* and LaTeX: $\alpha^2$

In [57]:
```
from sklearn import preprocessing
```

# Feature extraction

In [58]:
```
data.head()
```

Out[58]:

| | Location | Year | Kilometers_Driven | Fuel_Type | Transmission | Owner_Type | Seats | Price | clear |
|---|---|---|---|---|---|---|---|---|---|
| **0** | Mumbai | 2010 | 72000 | CNG | Manual | First | 5.0 | 1.75 | |
| **1** | Pune | 2015 | 41000 | Diesel | Manual | First | 5.0 | 12.50 | |
| **2** | Chennai | 2011 | 46000 | Petrol | Manual | First | 5.0 | 4.50 | |
| **3** | Chennai | 2012 | 87000 | Diesel | Manual | First | 7.0 | 6.00 | |
| **4** | Coimbatore | 2013 | 40670 | Diesel | Automatic | Second | 5.0 | 17.74 | |

In [59]:
```
y = data['Price']
y=y.to_numpy()
```

In [60]:
```
b=pd.get_dummies(data['carCompany'],drop_first=True)
l=pd.get_dummies(data['Location'],drop_first=True)
f=pd.get_dummies(data['Fuel_Type'],drop_first=True)
t=pd.get_dummies(data['Transmission'],drop_first=True)
o=pd.get_dummies(data['Owner_Type'],drop_first=True)
data.drop(['carCompany','Location','Fuel_Type','Owner_Type','Transmission','Price
data=pd.concat([data,t,b,l,f,o],axis=1)
X=data.iloc[:,:].values
```

## Applying train-test-split

In [61]:
```
#applying train-test-split

from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.28, random_state
print ('Train set:', X_train.shape,  y_train.shape)
print ('Test set:', X_test.shape,  y_test.shape)
```

```
Train set: (4333, 54) (4333,)
Test set: (1686, 54) (1686,)
```

In [62]:
```
from sklearn.linear_model import LinearRegression
lr = LinearRegression().fit(X_train,y_train)
lr
```

Out[62]:
```
LinearRegression()
```

In [63]:
```
print(lr.intercept_)
print(lr.coef_)
```

```
-1817.6317450312063
[ 9.04941421e-01 -1.89753823e-05  1.93639997e-01  1.49288485e-03
  8.48359862e-02 -1.05982459e-01  4.28162875e-02  2.48324551e+00
  1.77000429e+00  6.20199312e+00 -6.85097535e+00 -8.03709658e+00
 -6.22851011e+00 -8.47039932e+00 -6.02357076e+00 -6.99733382e+00
 -6.17817033e+00 -8.31761701e+00  2.00284234e-13  8.66012929e+00
 -5.26636235e+00  6.41212067e+01  1.71330345e+01 -8.87124874e+00
 -5.17394331e+00  3.81839409e+00  8.04771099e+00 -5.88183300e+00
 -6.63156526e+00  1.59821068e+01 -6.85104097e+00 -6.68843335e+00
 -3.38932694e+00 -7.38203136e+00 -4.76140366e+00 -6.85835850e+00
 -3.35860466e+00  1.73956741e+00  9.55247679e-01  1.34114113e+00
 -1.06538800e+00  1.48659649e+00  5.27919659e-01 -4.89602984e-01
 -1.64192599e+00 -9.77047928e-01  2.29838486e-01  1.18373367e-01
  1.07282664e+01  9.50538568e-01 -1.10541534e+00  9.99974364e-01
 -7.09494351e-01  9.81366656e-01]
```

In [64]:
```
yhat = lr.predict(X_test)
yhat
```

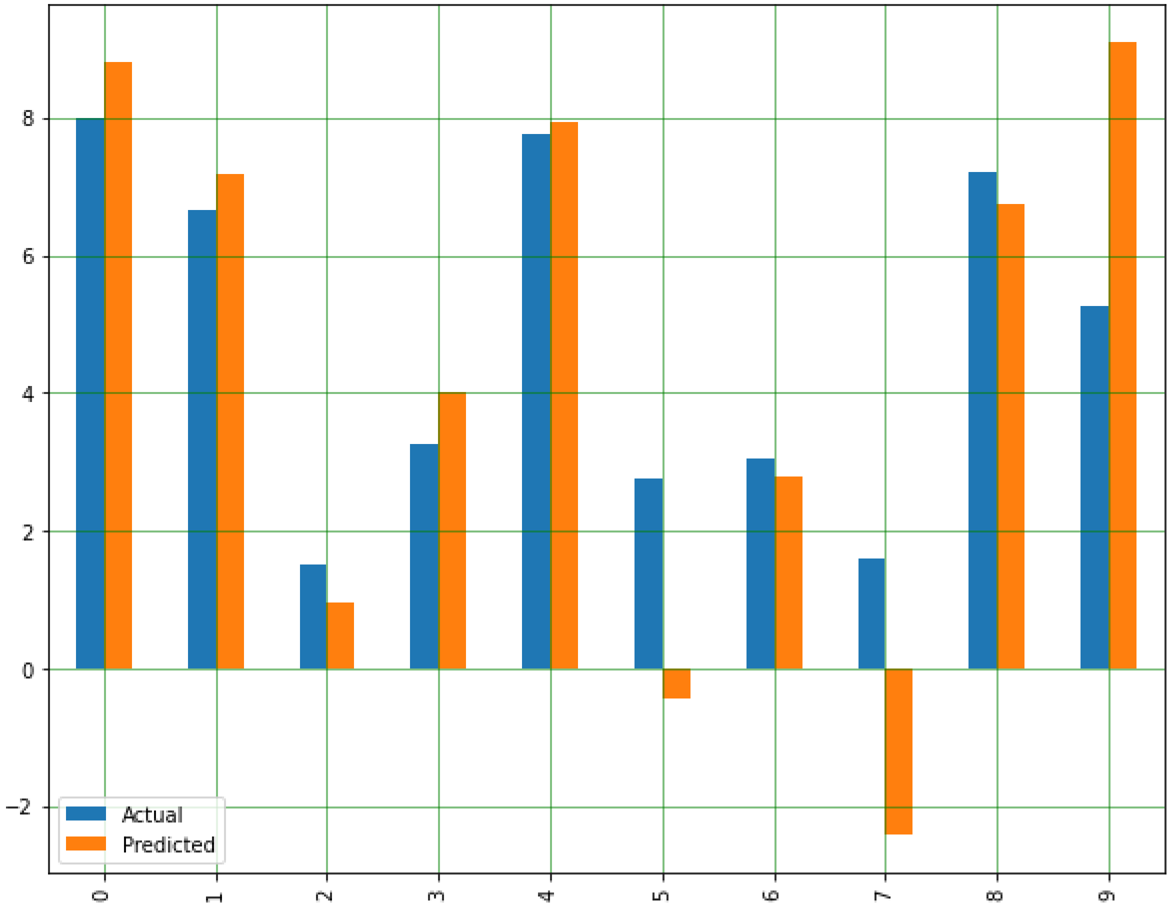
Out[64]:
```
array([ 8.82232587,  7.17176299,  0.94436903, ...,  9.85116063,
       10.30064229,  9.7185404 ])
```

In [65]:
```
from sklearn.metrics import r2_score
r2_score(y_test,yhat)
```

Out[65]:
```
0.6602507456871065
```

# Pridicted Price vs Actual Price With Linear Regression Model

In [66]:
```
df = pd.DataFrame({'Actual': y_test, 'Predicted': yhat})
df1=df.head(10)
df1.plot(kind='bar',figsize=(10,8))
plt.grid(which='major', linestyle='-', linewidth='0.5', color='green')
plt.grid(which='minor', linestyle=':', linewidth='0.5', color='black')
plt.show()
```



# Linear Regression Statisticals

In [67]:
```
from sklearn import metrics
from sklearn.metrics import r2_score

print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, yhat))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, yhat))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test, yhat
print('Accuracy:',lr.score(X_test,y_test))
```

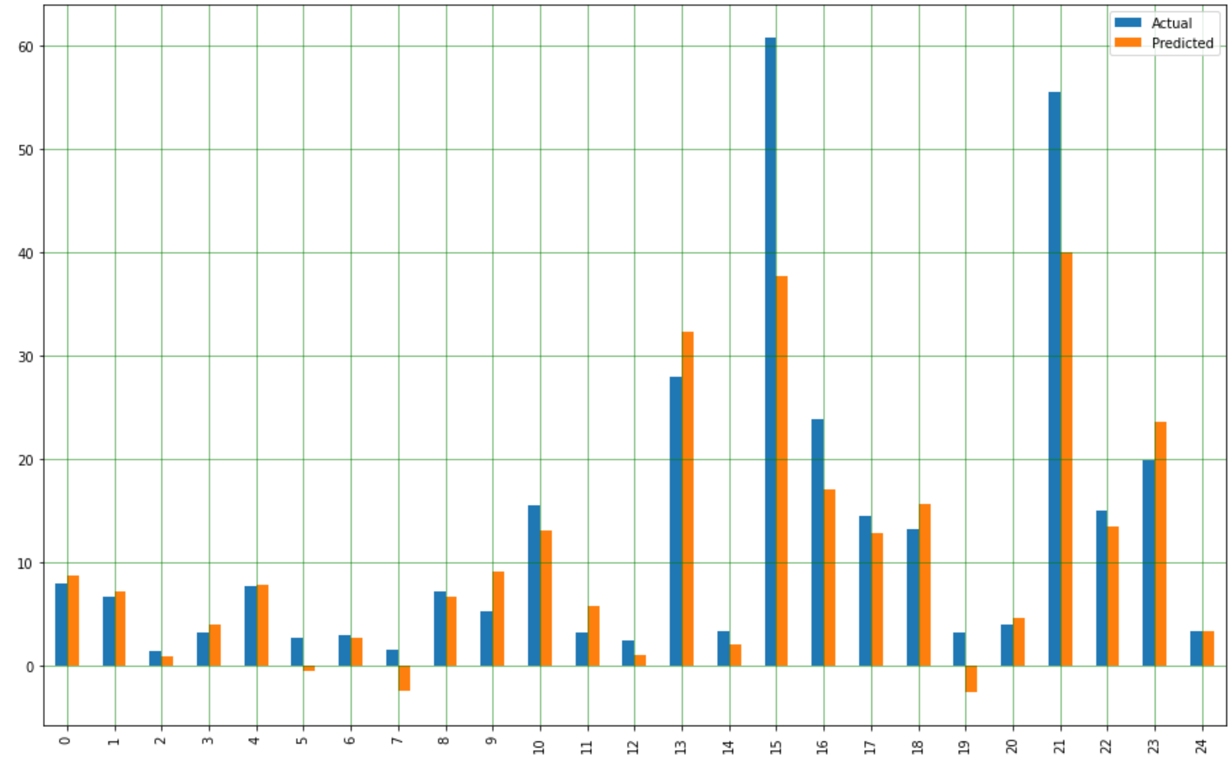
```
Mean Absolute Error: 2.986625348461073
Mean Squared Error: 41.029616137316495
Root Mean Squared Error: 6.405436451742886
Accuracy: 0.6602507456871065
```

In [68]:
```
df = pd.DataFrame({'Actual': y_test, 'Predicted': yhat})
df1=df.head(10)
df1
```

Out[68]:

| | Actual | Predicted |
|---|---|---|
| **0** | 8.00 | 8.822326 |
| **1** | 6.67 | 7.171763 |
| **2** | 1.50 | 0.944369 |
| **3** | 3.25 | 3.997811 |
| **4** | 7.75 | 7.931644 |
| **5** | 2.75 | -0.427004 |
| **6** | 3.04 | 2.783382 |
| **7** | 1.59 | -2.407397 |
| **8** | 7.20 | 6.750654 |
| **9** | 5.27 | 9.091296 |

In [69]:
```
df1 = df.head(25)
df1.plot(kind='bar',figsize=(16,10))
plt.grid(which='major', linestyle='-', linewidth='0.5', color='green')
plt.grid(which='minor', linestyle=':', linewidth='0.5', color='black')
plt.show()
```



In [70]:
```
print (f' Train Score is {lr.score(X_train, y_train)}')
```

```
 Train Score is 0.7834258271290557
```

# Accuracy Before Using XGBoost

In [71]:

```
print (f' Train Score is {lr.score(X_train, y_train)}')
print (f' Test Score is {lr.score(X_test, y_test)}')
```

```
 Train Score is 0.7834258271290557
 Test Score is 0.6602507456871065
```

# Accuracy After Using XGBoost

In [72]:

```
from xgboost import XGBRegressor
model=XGBRegressor(n_estimators=1000,learning_rate=0.05)
model.fit(X_train,y_train,early_stopping_rounds=5,eval_set=[(X_test,y_test)],verb
y_pred=model.predict(X_test)
r2_score(y_test,y_pred)
```

Out[72]:

```
0.9283908848528357
```

In [73]:

```
df = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})
df1=df.head(10)
```

In [74]:

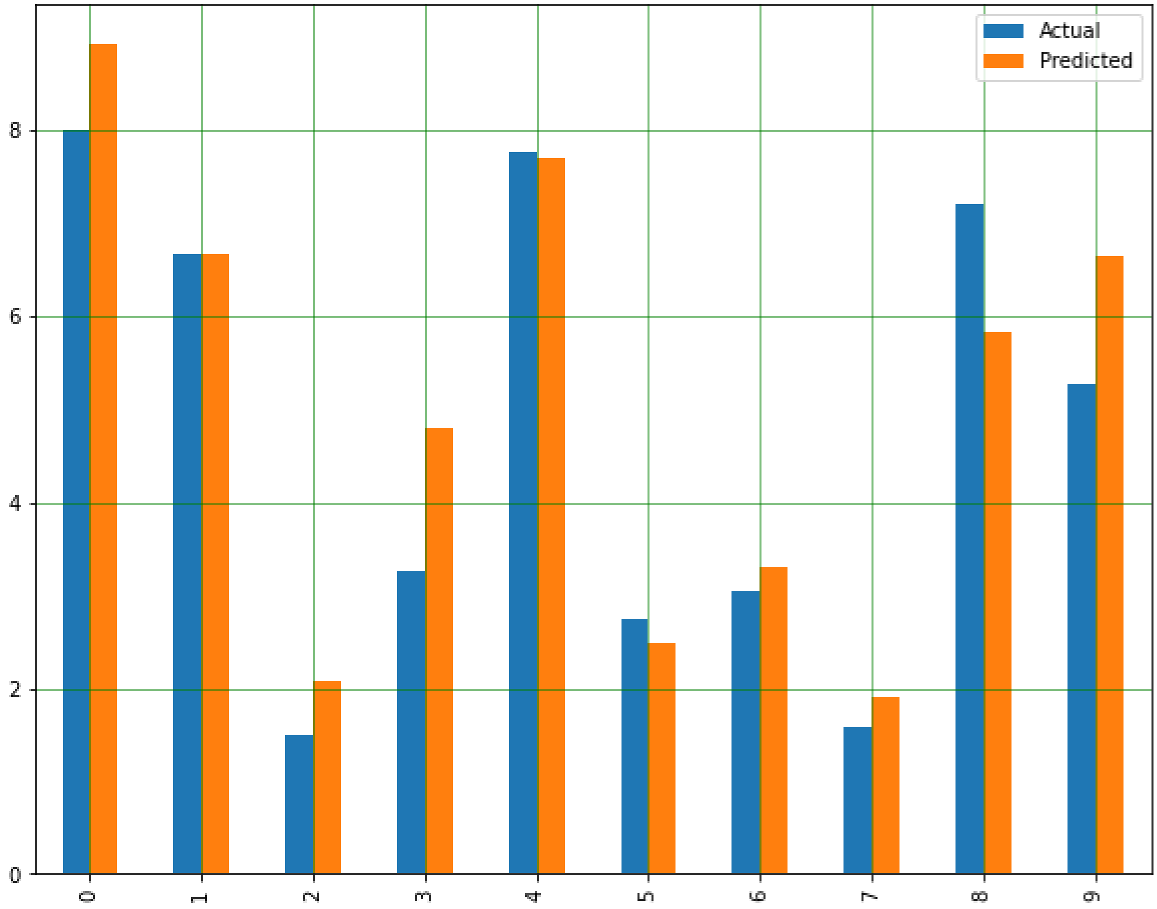
```
df1.head(10)
```

Out[74]:

| | Actual | Predicted |
|---|---|---|
| **0** | 8.00 | 8.915669 |
| **1** | 6.67 | 6.667004 |
| **2** | 1.50 | 2.066256 |
| **3** | 3.25 | 4.787928 |
| **4** | 7.75 | 7.686142 |
| **5** | 2.75 | 2.483622 |
| **6** | 3.04 | 3.306697 |
| **7** | 1.59 | 1.899079 |
| **8** | 7.20 | 5.827969 |
| **9** | 5.27 | 6.628943 |

# Pridicted Price vs Actual Price With XGBoost Model

```
In [75]: df1.plot(kind='bar',figsize=(10,8))
         plt.grid(which='major', linestyle='-', linewidth='0.5', color='green')
         plt.grid(which='minor', linestyle=':', linewidth='0.5', color='black')
         plt.show()
```



```
In [ ]:
```