Car Price Prediction Data Visualizing and Data Modeling

Imports

In [6]:

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from matplotlib.pyplot import xticks
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import KFold
```

Reading Dataset

In [7]:

```
cardf = pd.read_csv("CarPrice_Assignment.csv")
cardf.head()
```

Out[7]:

	car_ID	symboling	CarName	fueltype	aspiration	doornumber	carbody	drivewheel	enginelocation	wheelbase	...	enginesize
0	1	3	alfa-romero giulia	gas	std	two	convertible	rwd	front	88.6	...	130
1	2	3	alfa-romero stelvio	gas	std	two	convertible	rwd	front	88.6	...	130
2	3	1	alfa-romero Quadrifoglio	gas	std	two	hatchback	rwd	front	94.5	...	152
3	4	2	audi 100 ls	gas	std	four	sedan	fwd	front	99.8	...	109
4	5	2	audi 100ls	gas	std	four	sedan	4wd	front	99.4	...	136

5 rows × 26 columns

Data Cleansing

Checking Dublicates

In [8]:

```
if sum(cardf.duplicated(subset = 'car_ID')) == 0:
    print("No Duplicates data is clean")
else:
    print("Duplicates")
```

```
No Duplicates data is clean
```

Checking Null Values

In [9]:

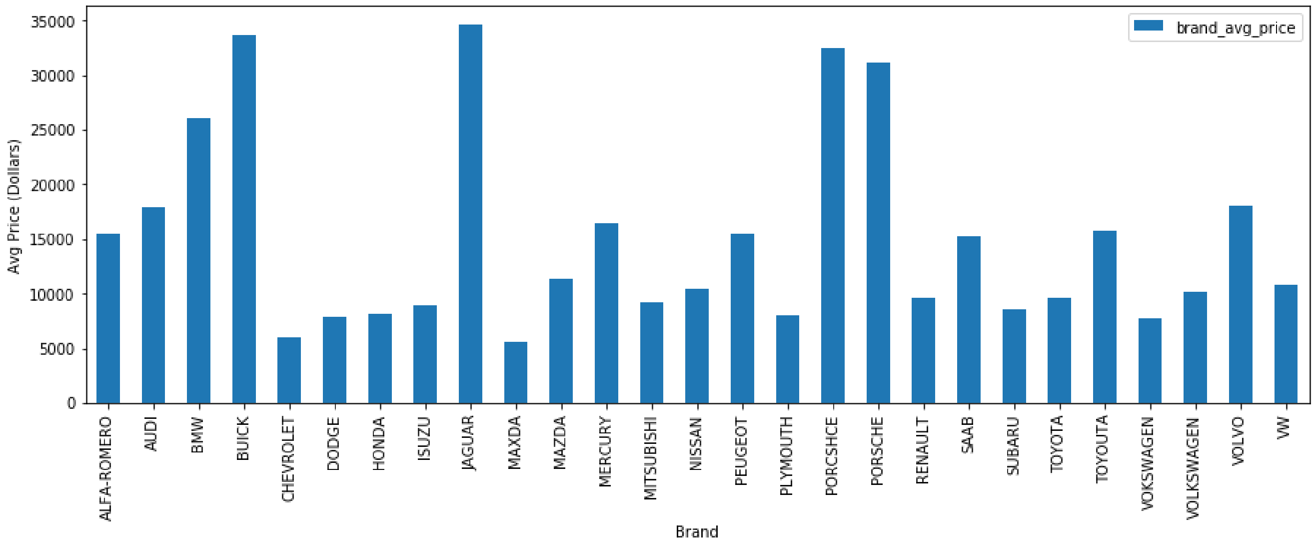
```
if any(cardf.isnull().sum()):
    print("Null values exist")
else:
    print("No Null values Data is clean")
```

```
No Null values Data is clean
```

Univariate Analysis

In [10]:

```
cardf['brand'] = cardf.CarName.str.split(' ').str.get(0).str.upper()
cardf['mileage'] = cardf['citympg']*0.55 + cardf['highwaympg']*0.45
df_comp_avg_price = cardf[['brand','price']].groupby("brand", as_index =
False).mean().rename(columns={'price':'brand_avg_price'})
cardf = cardf.merge(df_comp_avg_price, on = 'brand')
cardf['brand_category'] = cardf['brand_avg_price'].apply(lambda x : "Budget" if x < 10000 else ("Mi
d_Range" if 10000 <= x < 20000 else "Luxury"))



df_comp_avg_price = cardf[['brand','price']].groupby("brand", as_index =
False).mean().rename(columns={'price':'brand_avg_price'})
plt1 = df_comp_avg_price.plot(x = 'brand', kind='bar',legend = True, sort_columns = True, figsize =
(15,5))
plt1.set_xlabel("Brand")
plt1.set_ylabel("Avg Price (Dollars)")
xticks(rotation = 90)
plt.show()

print("Above graph shows Avg Price of each company")
```

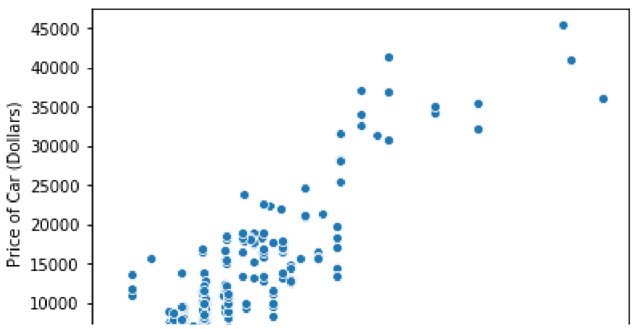


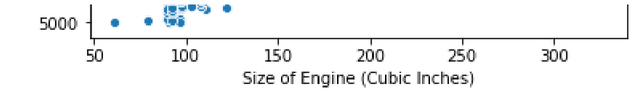

```
Above graph shows Avg Price of each company
```

engine size VS price

In [11]:

```
plt1 = sns.scatterplot(x = 'enginesize', y = 'price', data = cardf)
plt1.set_xlabel('Size of Engine (Cubic Inches)')
plt1.set_ylabel('Price of Car (Dollars)')
plt.show()
```

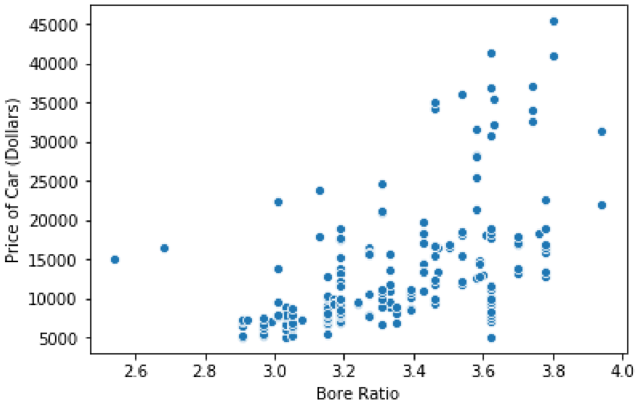




Bore ratio VS price

In [12]:

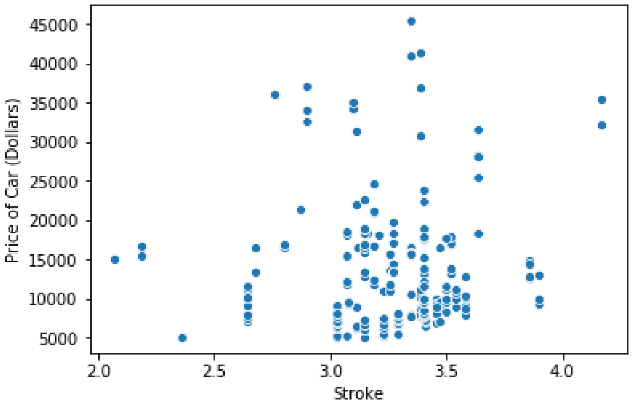
```
plt2 = sns.scatterplot(x = 'boreratio', y = 'price', data = cardf)
plt2.set_xlabel('Bore Ratio')
plt2.set_ylabel('Price of Car (Dollars)')
plt.show()
```



Stroke vs price

In [8]:

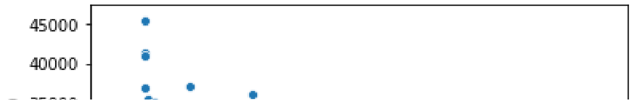
```
plt3 = sns.scatterplot(x = 'stroke', y = 'price', data = cardf)
plt3.set_xlabel('Stroke')
plt3.set_ylabel('Price of Car (Dollars)')
plt.show()
```

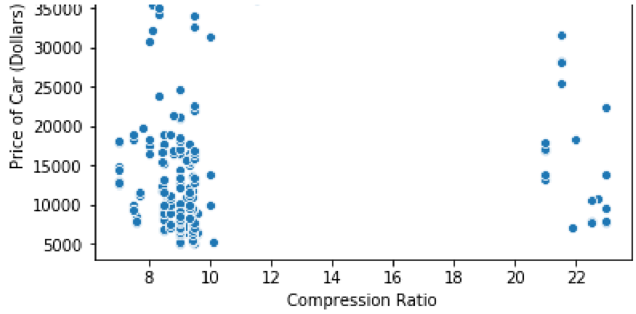


Compression Ratio

In [9]:

```
plt4 = sns.scatterplot(x = 'compressionratio', y = 'price', data = cardf)
plt4.set_xlabel('Compression Ratio')
plt4.set_ylabel('Price of Car (Dollars)')
plt.show()
```

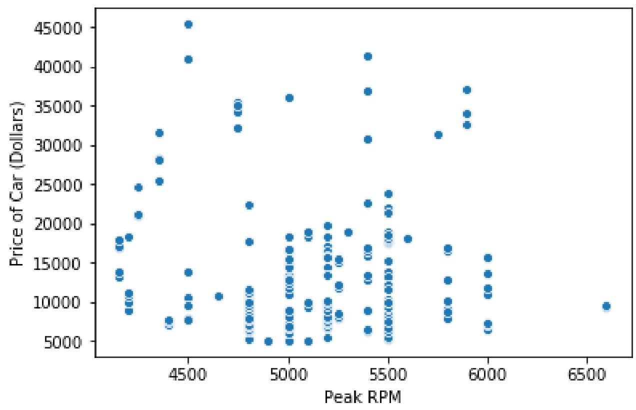




peakRpm vs price

In [10]:

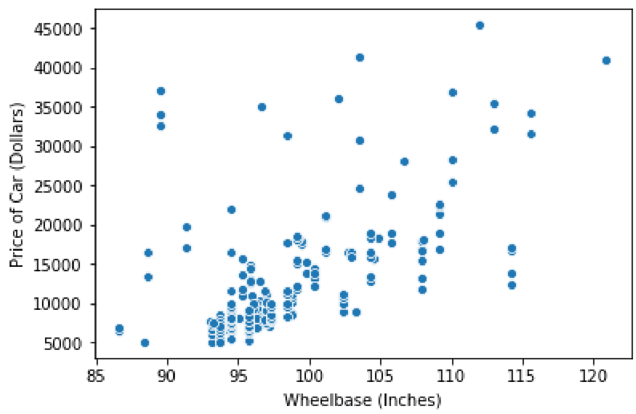
```
plt5 = sns.scatterplot(x = 'peakrpm', y = 'price', data = cardf)
plt5.set_xlabel('Peak RPM')
plt5.set_ylabel('Price of Car (Dollars)')
plt.show()
```



Wheelbase VS price

In [12]:

```
plt9 = sns.scatterplot(x = 'wheelbase', y = 'price', data = cardf)
plt9.set_xlabel('Wheelbase (Inches)')
plt9.set_ylabel('Price of Car (Dollars)')
plt.show()
```

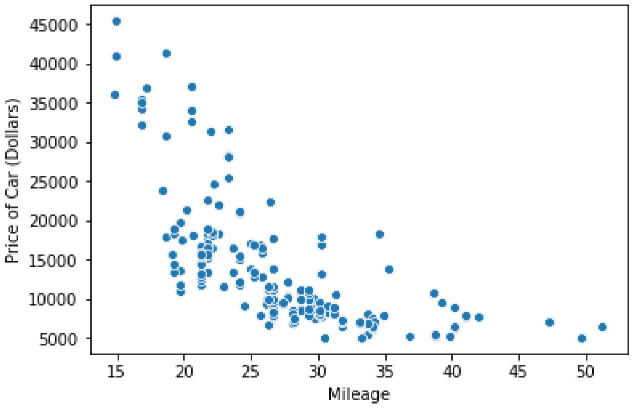


Mileage VS price

In [17]:

```
plt6 = sns.scatterplot(x = 'mileage', y = 'price', data = cardf)
plt6.set_xlabel('Mileage')
```

```
plt6.set_xlabel('Mileage')
plt6.set_ylabel('Price of Car (Dollars)')
plt.show()
print("Size of Engine, bore ratio,wheelbase has positive correlation with price")
```

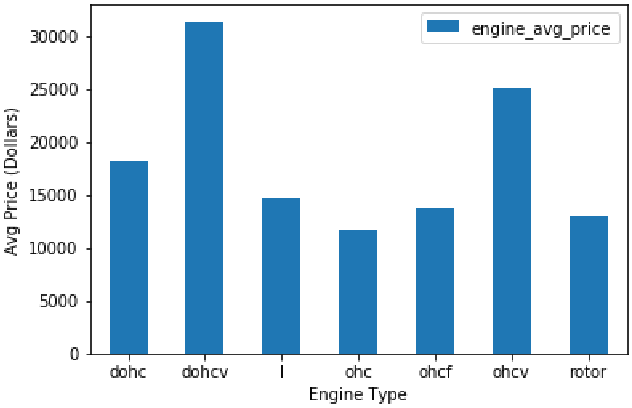



```
Size of Engine, bore ratio,wheelbase has positive correlation with price
```

Engine Type VS price

In [14]:

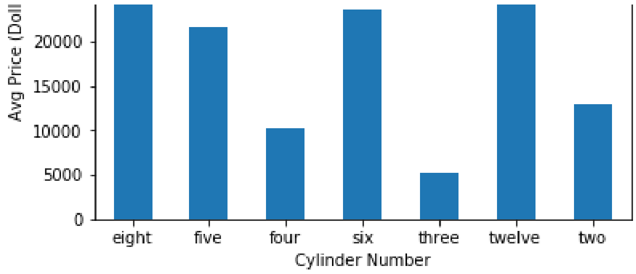
```
df_engine_avg_price = cardf[['enginetype','price']].groupby("enginetype", as_index = False).mean()
.rename(columns={'price':'engine_avg_price'})
plt1 = df_engine_avg_price.plot(x = 'enginetype', kind='bar', sort_columns = True, legend = True)
plt1.set_xlabel("Engine Type")
plt1.set_ylabel("Avg Price (Dollars)")
xticks(rotation = 0)
plt.show()
```



Num of Cylinder VS price

In [15]:

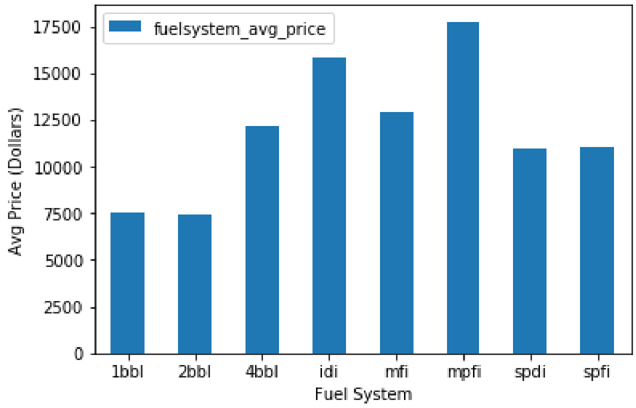
```
df_cylindernumber_avg_price = cardf[['cylindernumber','price']].groupby("cylindernumber", as_index
= False).mean().rename(columns={'price':'cylindernumber_avg_price'})
plt1 = df_cylindernumber_avg_price.plot(x = 'cylindernumber', kind='bar', sort_columns = True,legen
d = True)
plt1.set_xlabel("Cylinder Number")
plt1.set_ylabel("Avg Price (Dollars)")
xticks(rotation = 0)
plt.show()
```



Fuel system VS price

In [18]:

```
df_fuelsystem_avg_price = cardf[['fuelsystem','price']].groupby("fuelsystem", as_index =
False).mean().rename(columns={'price':'fuelsystem_avg_price'})
plt1 = df_fuelsystem_avg_price.plot(x = 'fuelsystem', kind='bar', sort_columns = True,legend = True
)
plt1.set_xlabel("Fuel System")
plt1.set_ylabel("Avg Price (Dollars)")
xticks(rotation = 0)
plt.show()


print("DOHCV and OHCV engine types are priced high, Eight and twelve cylinder cars have higher pri
ce, IDI and MPFI fuel system have higher price.")
```

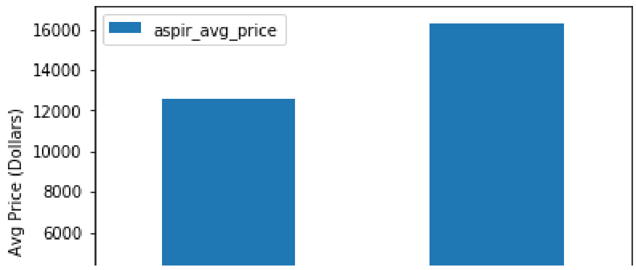


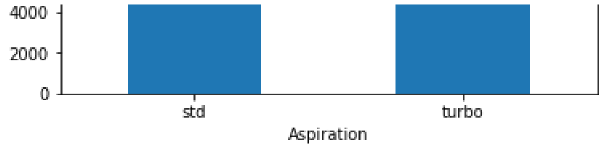

```
DOHCV and OHCV engine types are priced high, Eight and twelve cylinder cars have higher price, IDI
and MPFI fuel system have higher price.
```

aspiration VS price

In [20]:

```
df_aspir_avg_price = cardf[['aspiration','price']].groupby("aspiration", as_index = False).mean().
rename(columns={'price':'aspir_avg_price'})
plt1 = df_aspir_avg_price.plot(x = 'aspiration', kind='bar',legend = True, sort_columns = True)
plt1.set_xlabel("Aspiration")
plt1.set_ylabel("Avg Price (Dollars)")
xticks(rotation = 0)
plt.show()
print("It can be seen that turbo aspiration have more Avg price than std")
```



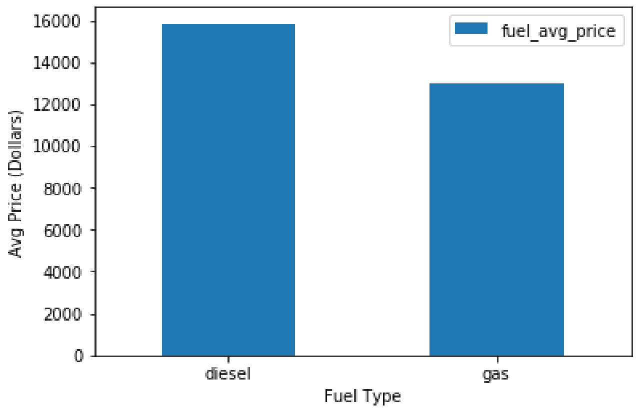



```
It can be seen that turbo aspiration have more Avg price than std
```

Fuel type VS price

In [21]:

```python
df_fuel_avg_price = cardf[['fueltype','price']].groupby("fueltype", as_index =
False).mean().rename(columns={'price':'fuel_avg_price'})
plt1 = df_fuel_avg_price.plot(x = 'fueltype', kind='bar',legend = True, sort_columns = True)
plt1.set_xlabel("Fuel Type")
plt1.set_ylabel("Avg Price (Dollars)")
xticks(rotation = 0)
plt.show()

print("It can be seen that that diesel cars are more expensive than gas cars")
```

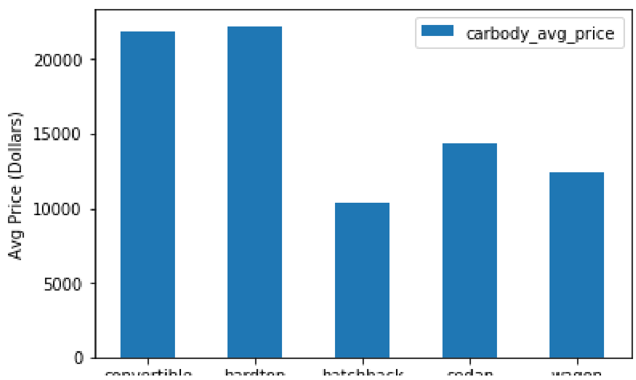


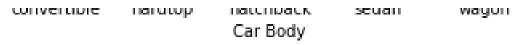

```
It can be seen that that diesel cars are more expensive than gas cars
```

Car Body VS price

In [22]:

```python
df_body_avg_price = cardf[['carbody','price']].groupby("carbody", as_index = False).mean().rename(
columns={'price':'carbody_avg_price'})
plt1 = df_body_avg_price.plot(x = 'carbody', kind='bar',legend = True, sort_columns = True)
plt1.set_xlabel("Car Body")
plt1.set_ylabel("Avg Price (Dollars)")
xticks(rotation = 0)
plt.show()


print("Hardtop and convertible are the most expensive so Price is depended on car body")
```



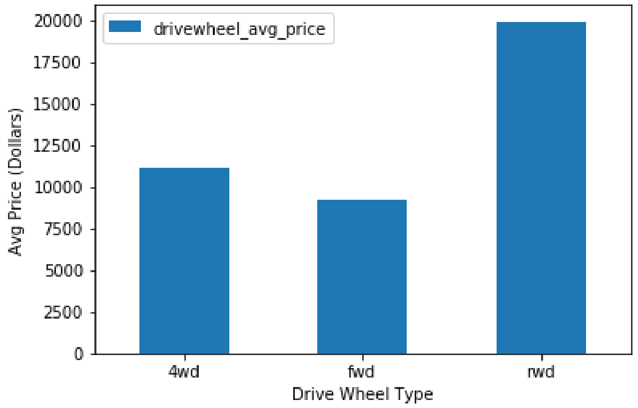


Hardtop and convertible are the most expensive so Price is depended on car body

Drive wheel VS price

In [23]:

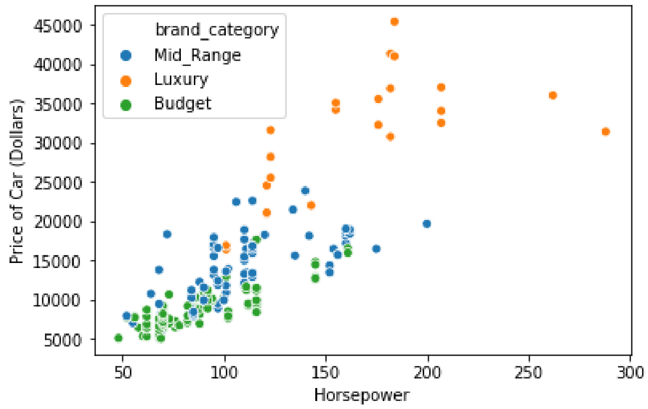
```
df_drivewheel_avg_price = cardf[['drivewheel','price']].groupby("drivewheel", as_index = 
False).mean().rename(columns={'price':'drivewheel_avg_price'})
plt1 = df_drivewheel_avg_price.plot(x = 'drivewheel', kind='bar', sort_columns = True,legend = True
,)
plt1.set_xlabel("Drive Wheel Type")
plt1.set_ylabel("Avg Price (Dollars)")
xticks(rotation = 0)
plt.show()
```



Horse power VS price

In [24]:

```
plt8 = sns.scatterplot(x = 'horsepower', y = 'price', hue = 'brand_category', data = cardf)
plt8.set_xlabel('Horsepower')
plt8.set_ylabel('Price of Car (Dollars)')
plt.show()
```



Car Dimensions VS price

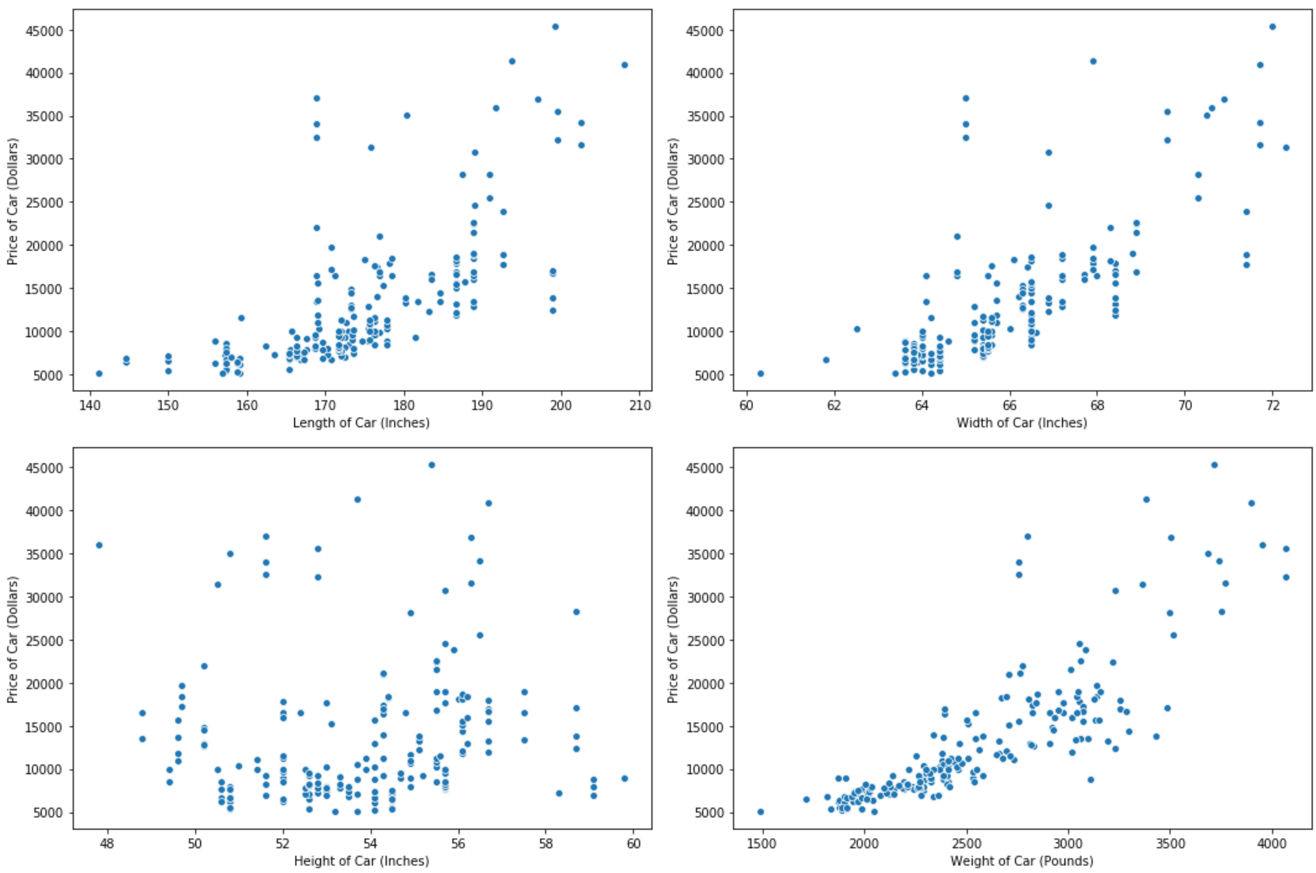
length, height , width , Weight

In [26]:

```
fig, axs = plt.subplots(2,2,figsize=(15,10))
plt1 = sns.scatterplot(x = 'carlength', y = 'price', data = cardf, ax = axs[0,0])
```

```
plt1.set_xlabel('Length of Car (Inches)')
plt1.set_ylabel('Price of Car (Dollars)')



plt2 = sns.scatterplot(x = 'carwidth', y = 'price', data = cardf, ax = axs[0,1])
plt2.set_xlabel('Width of Car (Inches)')
plt2.set_ylabel('Price of Car (Dollars)')



plt3 = sns.scatterplot(x = 'carheight', y = 'price', data = cardf, ax = axs[1,0])
plt3.set_xlabel('Height of Car (Inches)')
plt3.set_ylabel('Price of Car (Dollars)')



plt4 = sns.scatterplot(x = 'curbweight', y = 'price', data = cardf, ax = axs[1,1])
plt4.set_xlabel('Weight of Car (Pounds)')
plt4.set_ylabel('Price of Car (Dollars)')
plt.tight_layout()

print("Length width and weight of the car is positively related with the price.")
```

```
Length width and weight of the car is positively related with the price.
```



Data Attribute selection on basis of Dependency shown above

In [13]:

```
print("Dependent Variables finalized")

auto = cardf[['fueltype', 'aspiration', 'carbody', 'drivewheel', 'wheelbase', 'carlength', 'carwidt
h', 'curbweight', 'enginetype',
       'cylindernumber', 'enginesize',  'boreratio', 'horsepower', 'price', 'brand_category', 'mile
age']]
```

```
Dependent Variables finalized
```

Changing Categorical in Numerical using Dummy variables

In [14]:

```
cyl_no = pd.get_dummies(auto['cylindernumber'], drop_first = True)
auto = pd.concat([auto, cyl_no], axis = 1)

brand_cat = pd.get_dummies(auto['brand_category'], drop_first = True)
auto = pd.concat([auto, brand_cat], axis = 1)

eng_typ = pd.get_dummies(auto['enginetype'], drop_first = True)
auto = pd.concat([auto, eng_typ], axis = 1)


drwh = pd.get_dummies(auto['drivewheel'], drop_first = True)
auto = pd.concat([auto, drwh], axis = 1)

carb = pd.get_dummies(auto['carbody'], drop_first = True)
auto = pd.concat([auto, carb], axis = 1)

asp = pd.get_dummies(auto['aspiration'], drop_first = True)
auto = pd.concat([auto, asp], axis = 1)

fuelt = pd.get_dummies(auto['fueltype'], drop_first = True)
auto = pd.concat([auto, fuelt], axis = 1)

auto.head()
```

Out[14]:

	fueltype	aspiration	carbody	drivewheel	wheelbase	carlength	carwidth	curbweight	enginetype	cylindernumber	...	ohcv	roto
0	gas	std	convertible	rwd	88.6	168.8	64.1	2548	dohc	four	...	0	
1	gas	std	convertible	rwd	88.6	168.8	64.1	2548	dohc	four	...	0	
2	gas	std	hatchback	rwd	94.5	171.2	65.5	2823	ohcv	six	...	1	
3	gas	std	sedan	fwd	99.8	176.6	66.2	2337	ohc	four	...	0	
4	gas	std	sedan	4wd	99.4	176.6	66.4	2824	ohc	five	...	0	

5 rows × 38 columns

Droping useless attributes

In [15]:

```
auto.drop(['fueltype', 'aspiration', 'carbody', 'drivewheel', 'enginetype',
'cylindernumber','brand_category'], axis = 1, inplace = True)
auto.head()
```

Out[15]:

	wheelbase	carlength	carwidth	curbweight	enginesize	boreratio	horsepower	price	mileage	five	...	ohcv	rotor	fwd	rwd
0	88.6	168.8	64.1	2548	130	3.47	111	13495.0	23.70	0	...	0	0	0	1
1	88.6	168.8	64.1	2548	130	3.47	111	16500.0	23.70	0	...	0	0	0	1
2	94.5	171.2	65.5	2823	152	2.68	154	16500.0	22.15	0	...	1	0	0	1
3	99.8	176.6	66.2	2337	109	3.19	102	13950.0	26.70	0	...	0	0	1	0
4	99.4	176.6	66.4	2824	136	3.19	115	17450.0	19.80	1	...	0	0	0	0

5 rows × 31 columns

Split Data and Set role

In [16]:

```
x = auto.drop(['price'],axis=1)
y = auto['price']
X_train,X_test,Y_train,Y_test = train_test_split(x,y, test_size = 0.35)
```

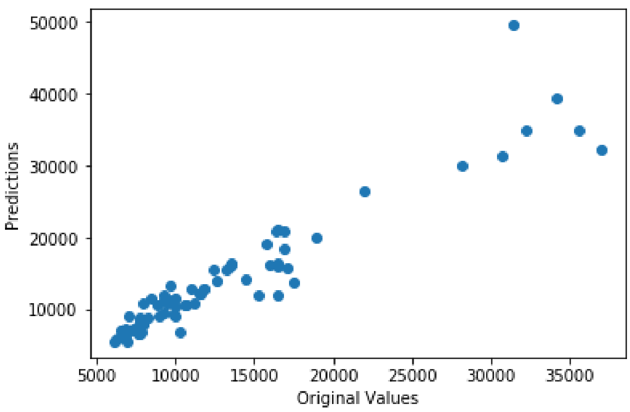
Linear Regression

In [18]:

```
lm = LinearRegression()
lm.fit(X_train,Y_train)
predictions = lm.predict(X_test)


plt.scatter(Y_test, predictions)
plt.xlabel("Original Values")
plt.ylabel("Predictions")
```

Out[18]:

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



In [19]:

```
tscore = lm.score(X_test,Y_test)
print("Score : ",tscore)
```

```
Score :  0.8332819325564096
```

In [20]:

```
taccuracy = tscore * 100
print("Accuracy : ",taccuracy)
```

```
Accuracy :  83.32819325564095
```

Random Forest

In [36]:

```
regr = RandomForestRegressor(max_depth=7,random_state=10,n_estimators=100)
regr.fit(X_train,Y_train)
```

Out[36]:

```
RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=7,
           max_features='auto', max_leaf_nodes=None,
           min_impurity_decrease=0.0, min_impurity_split=None,
           min_samples_leaf=1, min_samples_split=2,
           min_weight_fraction_leaf=0.0, n_estimators=100, n_jobs=None,
           oob_score=False, random_state=10, verbose=0, warm_start=False)
```

In [37]:

```
tscore = regr.score(X_test,Y_test)
print("Score : ",tscore)
```

```
Score :  0.9292148705994201
```

In [38]:

```
taccuracy = tscore * 100
print("Accuracy : ",taccuracy)
```

```
Accuracy :  92.92148705994201
```

In [ ]:

```
```