In [1]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
```

In [2]:

```
data = pd.read_csv("car data.csv")
data.head(10)
```

Out[2]:

	Car_Name	Year	Selling_Price	Present_Price	Kms_Driven	Fuel_Type
0	ritz	2014	3.35	5.59	27000	Petrol
1	sx4	2013	4.75	9.54	43000	Diesel
2	ciaz	2017	7.25	9.85	6900	Petrol
3	wagon r	2011	2.85	4.15	5200	Petrol
4	swift	2014	4.60	6.87	42450	Diesel
5	vitara brezza	2018	9.25	9.83	2071	Diesel
6	ciaz	2015	6.75	8.12	18796	Petrol
7	s cross	2015	6.50	8.61	33429	Diesel
8	ciaz	2016	8.75	8.89	20273	Diesel
9	ciaz	2015	7.45	8.92	42367	Diesel

In [3]:

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

Out[3]:

```
Car_Name         0
Year             0
Selling_Price    0
Present_Price    0
Kms_Driven       0
Fuel_Type        0
Seller_Type      0
Transmission     0
Owner            0
dtype: int64
```

In [4]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 301 entries, 0 to 300
Data columns (total 9 columns):
Car_Name         301 non-null object
Year             301 non-null int64
Selling_Price    301 non-null float64
Present_Price    301 non-null float64
Kms_Driven       301 non-null int64
Fuel_Type        301 non-null object
Seller_Type      301 non-null object
Transmission     301 non-null object
Owner            301 non-null int64
dtypes: float64(2), int64(3), object(4)
memory usage: 21.2+ KB
```

In [5]:

```
data.describe(include = 'all')
```

Out[5]:

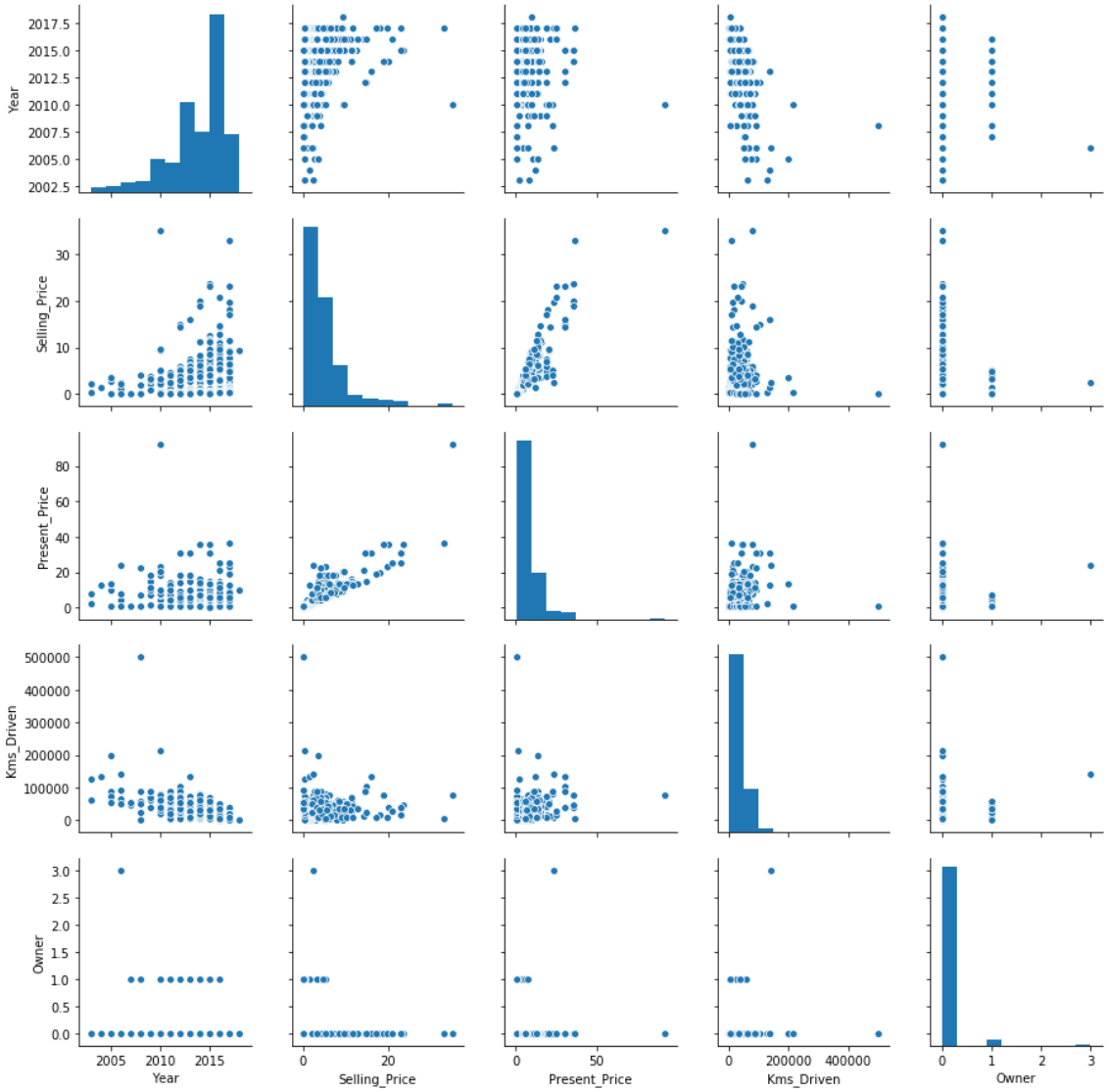
	Car_Name	Year	Selling_Price	Present_Price	Kms_Drive
count	301	301.000000	301.000000	301.000000	301.00000
unique	98	NaN	NaN	NaN	Nal
top	city	NaN	NaN	NaN	Nal
freq	26	NaN	NaN	NaN	Nal
mean	NaN	2013.627907	4.661296	7.628472	36947.20598
std	NaN	2.891554	5.082812	8.644115	38886.88388
min	NaN	2003.000000	0.100000	0.320000	500.00000
25%	NaN	2012.000000	0.900000	1.200000	15000.00000
50%	NaN	2014.000000	3.600000	6.400000	32000.00000
75%	NaN	2016.000000	6.000000	9.900000	48767.00000
max	NaN	2018.000000	35.000000	92.600000	500000.00000

In [6]:

```
sns.pairplot(data)
```

Out[6]:

```
<seaborn.axisgrid.PairGrid at 0x7f7c5543ae50>
```



Now Lets Check few Hypothesis

Hypothesis - 1 :Less Driven cars have high selling price

Hypothesis - 2 :Latest Cars will have high selling price

Hypothesis - 3 :Automatic Transmission Cars have high selling price

Lets check our hypothesis

Hypothesis - 1

In [7]:

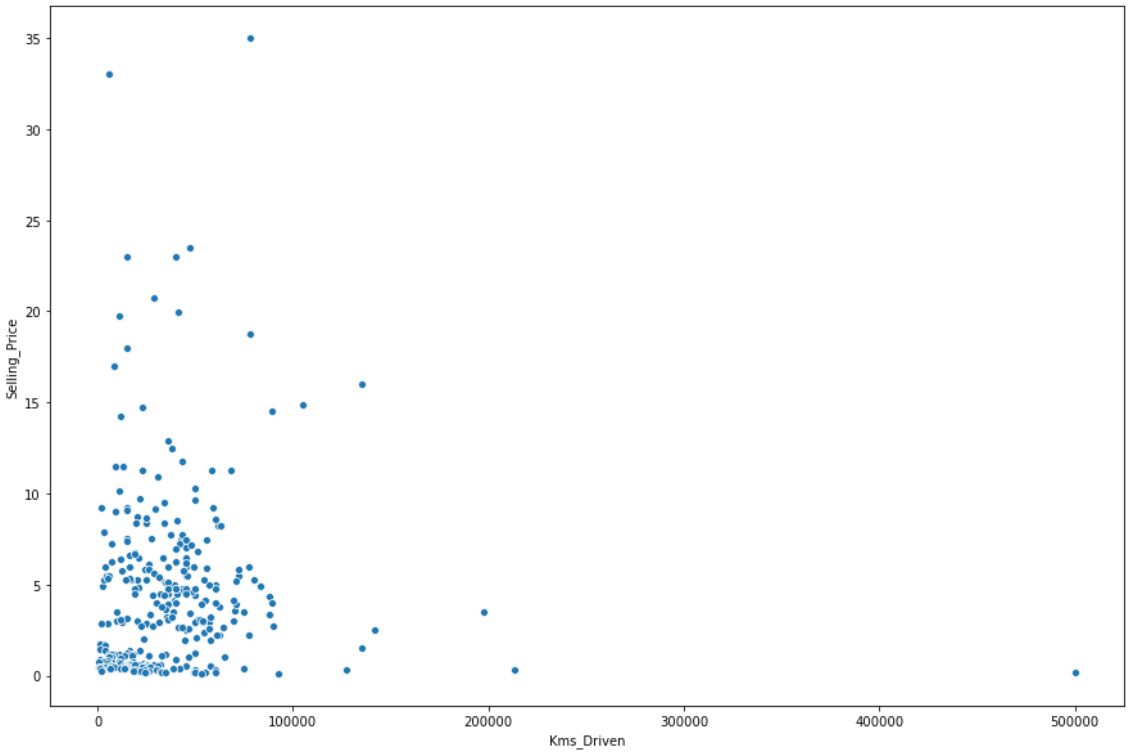
```
# Less Drive Cars have high selling price
```

In [8]:

```
fig,ax1 = plt.subplots(figsize = (15,10))
sns.scatterplot(x='Kms_Driven' , y ="Selling_Price",data = data , ax = ax
1)
```

Out[8]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f7c3c7e0990>
```



Hypothesis - 2

In [9]:

```
#Latest Cars will have high selling price
```

In [10]:

```
data['latest_car_year'] = 2020 - data.Year
data.head()
```

Out[10]:

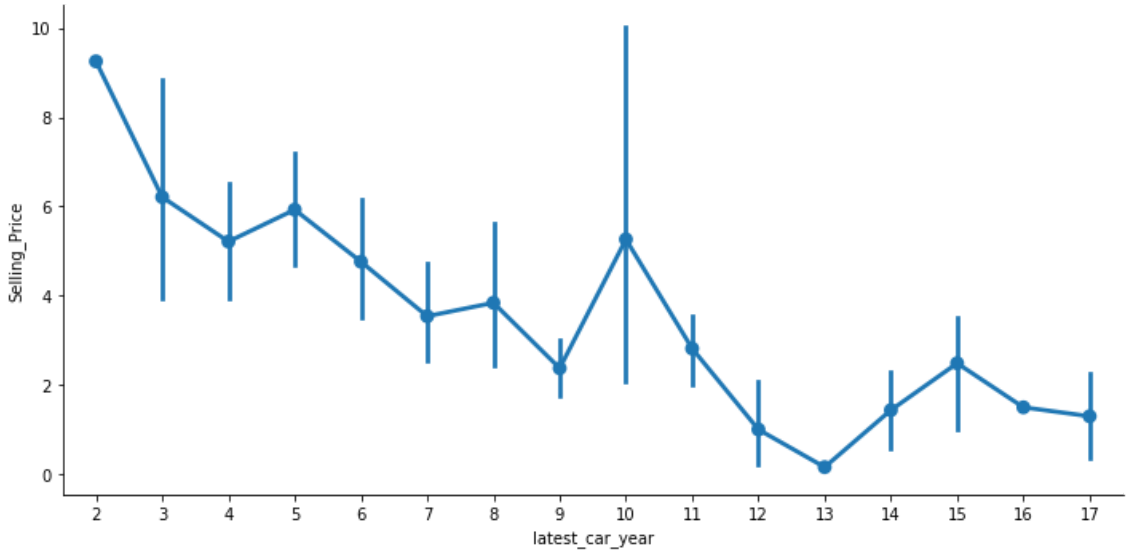
	Car_Name	Year	Selling_Price	Present_Price	Kms_Driven	Fuel_Type
0	ritz	2014	3.35	5.59	27000	Petrol
1	sx4	2013	4.75	9.54	43000	Diesel
2	ciaz	2017	7.25	9.85	6900	Petrol
3	wagon r	2011	2.85	4.15	5200	Petrol
4	swift	2014	4.60	6.87	42450	Diesel

In [11]:

```
sns.catplot(x='latest_car_year',y='Selling_Price',data=data,kind= 'point'
,height = 5,aspect = 2)
```

Out[11]:

```
<seaborn.axisgrid.FacetGrid at 0x7f7c3c385750>
```



In [12]:

```
#Second hypothesis is also true
```

Hypothesis - 3

In [13]:

```
data.Transmission.value_counts()
```

Out[13]:

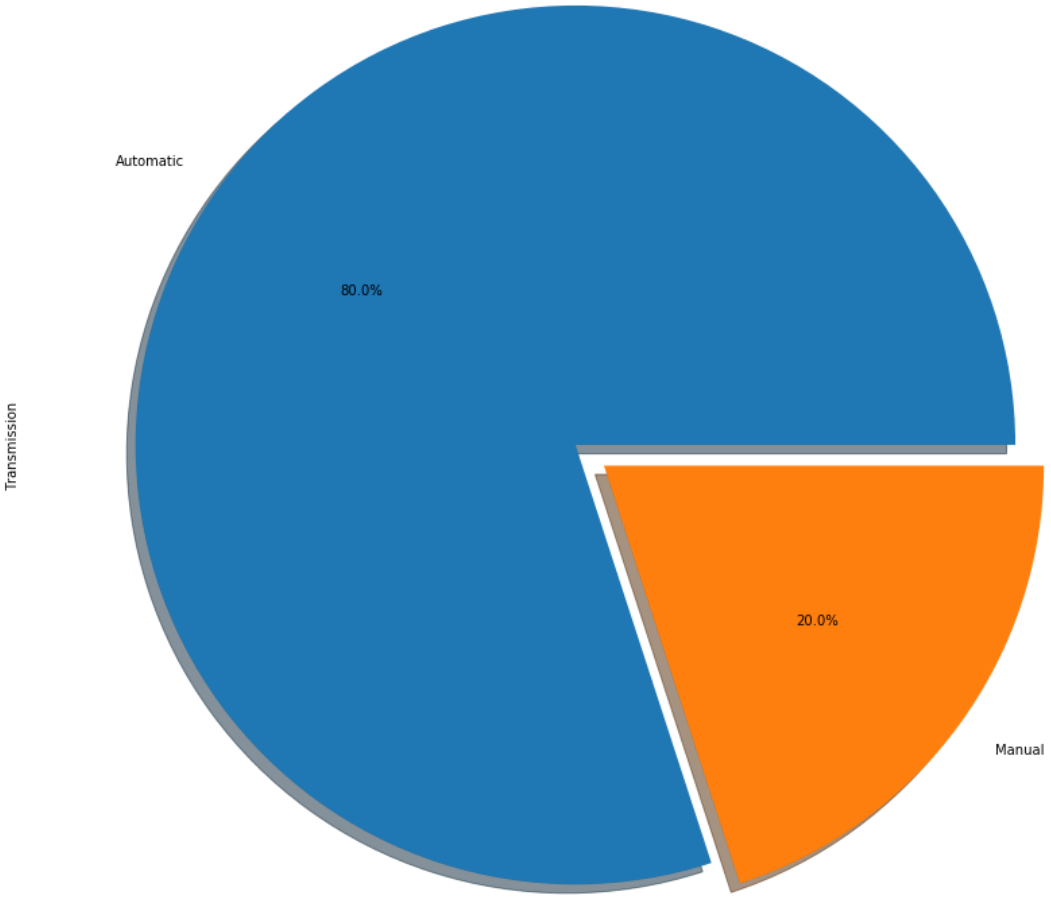
```
Manual       261
Automatic     40
Name: Transmission, dtype: int64
```

In [14]:

```
data.loc[:,['Transmission','Selling_Price']].sort_values(by=['Selling_Price'],ascending = False)['Transmission'].head(15).value_counts().plot.pie(figsize=(15,15),subplots = True , autopct = '%.1f%%',explode=[0,.08],shadow=True)
```

Out[14]:

```
array([<matplotlib.axes._subplots.AxesSubplot object at 0x7f
7c3c2bd710>],
      dtype=object)
```


Automatic
80.0%
Transmission
20.0%
Manual

In [15]:

```
#Top 15 cars with high sale price have Automatic transmission.That proves our 3rd hypothesis

#Now Lets get in to prediction
```

In [16]:

```
label = LabelEncoder()
data1 = pd.get_dummies(data['Fuel_Type'],prefix = 'FT' , drop_first = True)
data1.head()
```

Out[16]:

	FT_Diesel	FT_Petrol
0	0	1
1	1	0
2	0	1
3	0	1
4	1	0

In [17]:

```
data['Seller_Type'] = label.fit_transform(data['Seller_Type'])
data['Transmission'] = label.fit_transform(data['Transmission'])
```

In [18]:

```
data = pd.concat([data,data1],axis = 1)
data.drop(['Fuel_Type'],axis=1,inplace=True)
data.head()
```

Out[18]:

	Car_Name	Year	Selling_Price	Present_Price	Kms_Driven	Seller_Type
0	ritz	2014	3.35	5.59	27000	0
1	sx4	2013	4.75	9.54	43000	0
2	ciaz	2017	7.25	9.85	6900	0
3	wagon r	2011	2.85	4.15	5200	0
4	swift	2014	4.60	6.87	42450	0

In [19]:

```
data.info()
```

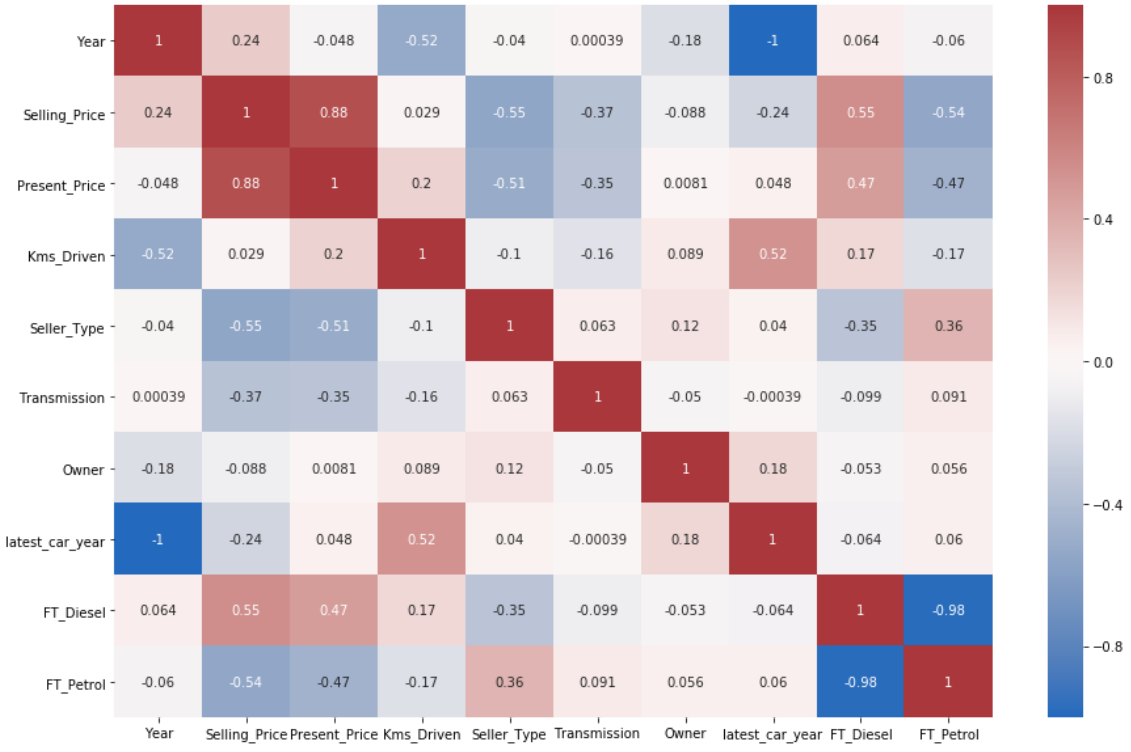
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 301 entries, 0 to 300
Data columns (total 11 columns):
Car_Name            301 non-null object
Year                301 non-null int64
Selling_Price       301 non-null float64
Present_Price       301 non-null float64
Kms_Driven          301 non-null int64
Seller_Type         301 non-null int64
Transmission        301 non-null int64
Owner               301 non-null int64
latest_car_year     301 non-null int64
FT_Diesel           301 non-null uint8
FT_Petrol           301 non-null uint8
dtypes: float64(2), int64(6), object(1), uint8(2)
memory usage: 21.8+ KB
```

In [20]:

```
fig , ax2 = plt.subplots(figsize = (15,10))
sns.heatmap(data.corr() , annot= True , ax =ax2 , cmap = sns.cm.vlag)
```

Out[20]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f7c3c233d90>
```



In [21]:

```
#The Selling Price has Strong Correlation with Year and Present Price , D
iesel Fuel Type of the car

#I am gonna create 2 models

#Model with all features
#Model with Strong Correlated features
```

In [52]:

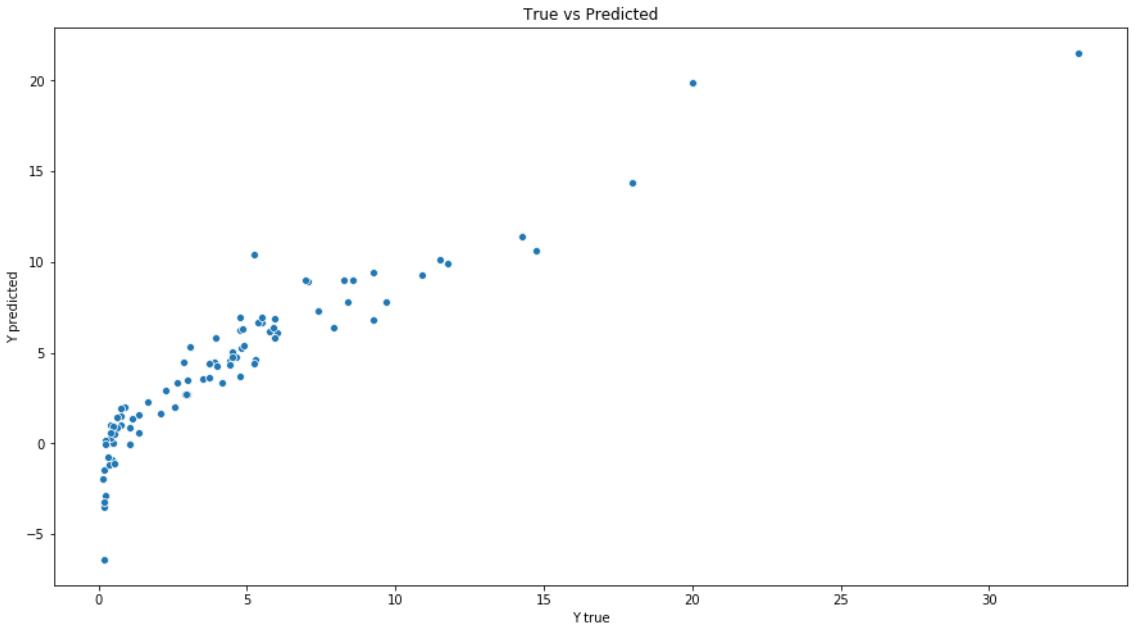
```
def model(x,y):
    training_x ,testing_x ,training_y ,testing_y = train_test_split(x,y,t
est_size=0.30,random_state =10)
    li_model = LinearRegression()
    li_model.fit(training_x,training_y)
    print("Training Sucessfully Done !!!!!!")
    y_pred = li_model.predict(testing_x)


    fig,ax1 = plt.subplots(figsize=(15,8))
    fig = sns.scatterplot(testing_y,y_pred,ax=ax1)
    plt.xlabel('Y true')
    plt.ylabel('Y predicted')
    plt.title('True vs Predicted')
    plt.show(fig)
```

Model 1

In [53]:

```
x = data.drop(['Car_Name','Selling_Price'] ,axis = 1)
y= data['Selling_Price']
model(x,y)
```

```
Training Sucessfully Done !!!!!!
```

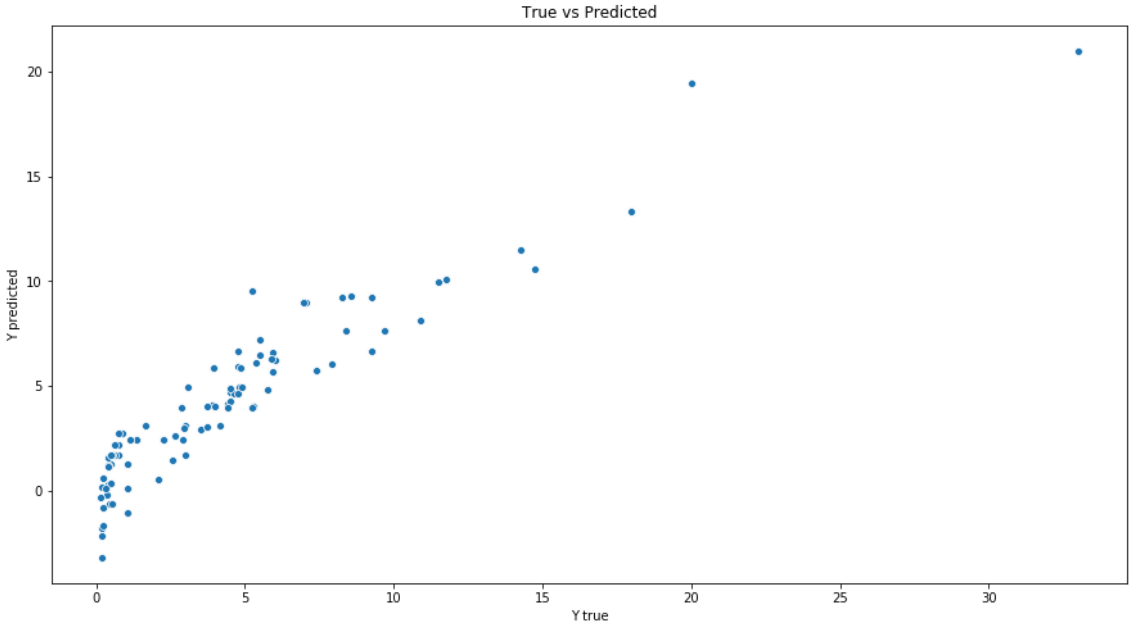


Model 2

In [54]:

```
x = data.drop(['Car_Name','Selling_Price','Kms_Driven','Seller_Type','Transmission','Owner', 'latest_car_year','FT_Petrol'],axis = 1)
y = data['Selling_Price']
model(x,y)
```

```
Training Sucessfully Done !!!!!!
```



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