Car_Price_Prediction

August 29, 2024

[177]:
```
import pandas as pd
import numpy as np
from scipy import stats
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
pd.options.display.float_format='{:,.2f}'.format # to round all number to 0.2
```

0.0.1 About Dataset

The price of a car depends on a lot of factors like the goodwill of the brand of the car, features of the car, horsepower and the mileage it gives, and many more. Car price prediction is one of the major research areas in machine learning. This dataset can be used to train a car price prediction model.

0.0.2 Dataset Columns

Column Name	Description
Year	The year the car was manufactured.
Selling_Price	The price at which the car is being sold.
Present_Price	The current ex-showroom price of the car.
Driven_kms	The total kilometers the car has been driven.
Fuel_Type	The type of fuel the car uses (e.g., Petrol, Diesel).
Selling_type	The type of seller (e.g., Dealer, Individual).
Transmission	The type of transmission (e.g., Manual, Automatic).
Owner	The number of previous owners the car has had.
No_of_Years	The number of years since the car was manufactured.

[178]:
```
data=pd.read_csv('Car_Price.csv',)
data
```

[178]:
```
     Car_Name  Year  Selling_Price  Present_Price  Driven_kms 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
```

```
..       …    …            …            …         …       …
296     city  2016         9.50         11.60     33988   Diesel
297     brio  2015         4.00          5.90     60000   Petrol
298     city  2009         3.35         11.00     87934   Petrol
299     city  2017        11.50         12.50      9000   Diesel
300     brio  2016         5.30          5.90      5464   Petrol

    Selling_type Transmission  Owner
0         Dealer       Manual      0
1         Dealer       Manual      0
2         Dealer       Manual      0
3         Dealer       Manual      0
4         Dealer       Manual      0
..           …          …     …
296       Dealer       Manual      0
297       Dealer       Manual      0
298       Dealer       Manual      0
299       Dealer       Manual      0
300       Dealer       Manual      0

[301 rows x 9 columns]
```

1 Data_Size

[179]:
```python
print('The Size Of Data Frame is :',data.shape)
```

```
The Size Of Data Frame is : (301, 9)
```

[180]:
```python
data.columns
```

[180]:
```
Index(['Car_Name', 'Year', 'Selling_Price', 'Present_Price', 'Driven_kms',
       'Fuel_Type', 'Selling_type', 'Transmission', 'Owner'],
      dtype='object')
```

2 Data_Types

[181]:
```python
data.dtypes
```

[181]:
```
Car_Name          object
Year               int64
Selling_Price    float64
Present_Price    float64
Driven_kms         int64
Fuel_Type         object
Selling_type      object
Transmission      object
```

```
Owner               int64
dtype: object
```

[182]:
```python
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 301 entries, 0 to 300
Data columns (total 9 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Car_Name       301 non-null    object
 1   Year           301 non-null    int64
 2   Selling_Price  301 non-null    float64
 3   Present_Price  301 non-null    float64
 4   Driven_kms     301 non-null    int64
 5   Fuel_Type      301 non-null    object
 6   Selling_type   301 non-null    object
 7   Transmission   301 non-null    object
 8   Owner          301 non-null    int64
dtypes: float64(2), int64(3), object(4)
memory usage: 21.3+ KB
```

3 Missing_Values

[183]:
```python
data.isna().sum()
```

[183]:
```
Car_Name         0
Year             0
Selling_Price    0
Present_Price    0
Driven_kms       0
Fuel_Type        0
Selling_type     0
Transmission     0
Owner            0
dtype: int64
```

[184]:
```python
data.isnull().mean()*100
```

[184]:
```
Car_Name        0.00
Year            0.00
Selling_Price   0.00
Present_Price   0.00
Driven_kms      0.00
Fuel_Type       0.00
Selling_type    0.00
Transmission    0.00
```

```
Owner            0.00
dtype: float64
```

4 Duplicated_Values

[185]:
```python
data.duplicated().sum()
```

[185]: 2

[186]:
```python
data.drop_duplicates(inplace=True)
data.duplicated().sum()
```

[186]: 0

[187]:
```python
print('The Size Of Data Frame after clean :',data.shape)
```

```
The Size Of Data Frame after clean : (299, 9)
```

5 Unique Values

[188]:
```python
for col in data.columns:
    print(f'{col}  number of unique values is :  {data[col].nunique()} \n␣
↪{data[col].unique()}')
    print('***************************************************')
```

```
Car_Name  number of unique values is :  98
 ['ritz' 'sx4' 'ciaz' 'wagon r' 'swift' 'vitara brezza' 's cross'
 'alto 800' 'ertiga' 'dzire' 'alto k10' 'ignis' '800' 'baleno' 'omni'
 'fortuner' 'innova' 'corolla altis' 'etios cross' 'etios g' 'etios liva'
 'corolla' 'etios gd' 'camry' 'land cruiser' 'Royal Enfield Thunder 500'
 'UM Renegade Mojave' 'KTM RC200' 'Bajaj Dominar 400'
 'Royal Enfield Classic 350' 'KTM RC390' 'Hyosung GT250R'
 'Royal Enfield Thunder 350' 'KTM 390 Duke ' 'Mahindra Mojo XT300'
 'Bajaj Pulsar RS200' 'Royal Enfield Bullet 350'
 'Royal Enfield Classic 500' 'Bajaj Avenger 220' 'Bajaj Avenger 150'
 'Honda CB Hornet 160R' 'Yamaha FZ S V 2.0' 'Yamaha FZ 16'
 'TVS Apache RTR 160' 'Bajaj Pulsar 150' 'Honda CBR 150' 'Hero Extreme'
 'Bajaj Avenger 220 dtsi' 'Bajaj Avenger 150 street' 'Yamaha FZ  v 2.0'
 'Bajaj Pulsar  NS 200' 'Bajaj Pulsar 220 F' 'TVS Apache RTR 180'
 'Hero Passion X pro' 'Bajaj Pulsar NS 200' 'Yamaha Fazer '
 'Honda Activa 4G' 'TVS Sport ' 'Honda Dream Yuga '
 'Bajaj Avenger Street 220' 'Hero Splender iSmart' 'Activa 3g'
 'Hero Passion Pro' 'Honda CB Trigger' 'Yamaha FZ S '
 'Bajaj Pulsar 135 LS' 'Activa 4g' 'Honda CB Unicorn'
 'Hero Honda CBZ extreme' 'Honda Karizma' 'Honda Activa 125' 'TVS Jupyter'
 'Hero Honda Passion Pro' 'Hero Splender Plus' 'Honda CB Shine'
 'Bajaj Discover 100' 'Suzuki Access 125' 'TVS Wego' 'Honda CB twister'
```

```
 'Hero Glamour' 'Hero Super Splendor' 'Bajaj Discover 125' 'Hero Hunk'
 'Hero  Ignitor Disc' 'Hero  CBZ Xtreme' 'Bajaj  ct 100' 'i20' 'grand i10'
 'i10' 'eon' 'xcent' 'elantra' 'creta' 'verna' 'city' 'brio' 'amaze'
 'jazz']
**************************************************
Year  number of unique values is :  16
 [2014 2013 2017 2011 2018 2015 2016 2009 2010 2012 2003 2008 2006 2005
 2004 2007]
**************************************************
Selling_Price  number of unique values is :  156
 [ 3.35  4.75  7.25  2.85  4.6   9.25  6.75  6.5   8.75  7.45  6.85  7.5
  6.1   2.25  7.75  3.25  2.65  4.9   4.4   2.5   2.9   3.    4.15  6.
  1.95  3.1   2.35  4.95  5.5   2.95  4.65  0.35  5.85  2.55  1.25  1.05
  5.8  14.9  23.   18.   16.    2.75  3.6   4.5   4.1  19.99  6.95 18.75
 23.5  33.   19.75  4.35 14.25  3.95  1.5   5.25 14.5  14.73 12.5   3.49
 35.    5.9   3.45  3.8  11.25  3.51  4.   20.75 17.    7.05  9.65  1.75
  1.7   1.65  1.45  1.35  1.2   1.15  1.11  1.1   1.    0.95  0.9   0.75
  0.8   0.78  0.72  0.65  0.6   0.55  0.52  0.51  0.5   0.48  0.45  0.42
  0.4   0.38  0.31  0.3   0.27  0.25  0.2   0.18  0.17  0.16  0.15  0.12
  0.1   5.75  5.15  7.9   4.85 11.75  3.15  6.45  3.5   8.25  5.11  2.7
  6.15 11.45  3.9   9.1   4.8   2.    5.35  6.25  5.95  5.2   3.75 12.9
  5.    5.4   7.2  10.25  8.5   8.4   9.15  6.6   3.65  8.35  6.7   5.3
 10.9   8.65  9.7   2.1   8.99  7.4   5.65 10.11  6.4   8.55  9.5  11.5 ]
**************************************************
Present_Price  number of unique values is :  148
 [ 5.59   9.54   9.85   4.15   6.87   9.83   8.12   8.61   8.89   8.92
  3.6   10.38   9.94   7.71   7.21  10.79   5.09   7.98   3.95   5.71
  8.01   3.46   4.41   4.99   5.87   6.49   5.98   4.89   7.49   9.95
  8.06   7.74   7.2    2.28   3.76   7.87   3.98   7.15   2.69  12.04
  9.29  30.61  19.77  10.21  15.04   7.27  18.54   6.8   35.96  18.61
  7.7   36.23   6.95  23.15  20.45  13.74  20.91   6.76  12.48   8.93
 14.68  12.35  22.83  14.89   7.85  25.39  13.46  23.73  92.6    6.05
 16.09  13.7   22.78  18.64   1.9    1.82   1.78   1.6    1.47   2.37
  3.45   1.5    2.4    1.4    1.26   1.17   1.75   0.95   0.8    0.87
  0.84   0.82   0.81   0.74   1.2    0.787  0.99   0.94   0.826  0.55
  0.88   0.51   0.52   0.54   0.73   0.83   0.64   0.72   1.05   0.57
  0.48   0.58   0.47   0.75   0.65   0.32   6.79   5.7    4.6    4.43
  7.13   8.1   14.79  13.6    9.4    8.4    5.43   7.6    9.9    6.82
  5.35   7.     5.97   5.8    8.7   10.     7.5    5.9   14.    11.8
  8.5    7.9    6.4    6.1   13.09  11.6   11.    12.5  ]
**************************************************
Driven_kms  number of unique values is :  206
 [ 27000  43000   6900   5200  42450   2071  18796  33429  20273  42367
   2135  51000  15000  26000  77427  41678  35500  41442  25000   2400
  50000  45280  56879  20000  55138  16200  44542  45000  51439  54200
  39000  49998  48767 127000  10079  62000  24524  46706  58000  45780
  64532  65000  25870  37000 104707  40000 135000  90000  70000  40534
  39485  41000  40001  40588  78000  47000   6000  11000  59000  88000
```

```
  12000  71000  56001  83000  36000  72000 135154  80000  89000  23000
  38000 197176 142000  56000  58242  75000  29000   8700  50024   3000
   1400   4000   1200   4100  21700  16500  18000   7000  35000  17000
  17500  33000  14000   5400   5700  46500  11500   1300   5000   3500
    500  11800  23500  16000  16600  32000  19000  24000  31000  13000
   8000   4300   8600  14500   1000  42000   5500   6700  13700  38600
  30000 213000  60000  21000   1900  22000  55000  49000 500000  53000
  92233  28200  53460  28282   3493  12479  34797   3435  21125  35775
  43535  22671  31604  20114  36100  12500  45078  38488  77632  61381
  36198  22517  24678  57000  52132  15001  12900   4492  15141  11849
  68000  60241  23709  32322  35866  34000  35934  56701  31427  48000
  54242  53675  49562  40324  36054  29223   5600  40023  16002  40026
  21200  19434  18828  69341  69562  27600  61203  30753  24800  21780
  40126  14465  50456  63000   9010   9800  15059  28569  44000  10980
  33019  60076  33988  87934   9000   5464]
*************************************************
Fuel_Type  number of unique values is :  3
 ['Petrol' 'Diesel' 'CNG']
*************************************************
Selling_type  number of unique values is :  2
 ['Dealer' 'Individual']
*************************************************
Transmission  number of unique values is :  2
 ['Manual' 'Automatic']
*************************************************
Owner  number of unique values is :  3
 [0 1 3]
*************************************************
```

[ ]:
```python
data.columns.str.strip()
```

[189]:
```python
data['Owner'] = data['Owner'].replace(to_replace=3, value=2)
print("'Owner' variable has {} unique categories: {}".format(data['Owner'].
 ↪nunique(), data['Owner'].unique()))
```

```
'Owner' variable has 3 unique categories: [0 1 2]
```

[190]:
```python
data['Current_Year'] = 2024
data['No_of_Years'] = data['Current_Year'] - data['Year']
data.head()
```

[190]:

	Car_Name	Year	Selling_Price	Present_Price	Driven_kms	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	

```
  Selling_type Transmission  Owner  Current_Year  No_of_Years
0       Dealer       Manual      0          2024           10
1       Dealer       Manual      0          2024           11
2       Dealer       Manual      0          2024            7
3       Dealer       Manual      0          2024           13
4       Dealer       Manual      0          2024           10
```

[191]:
```python
data.drop(['Current_Year','Car_Name'],inplace=True,axis=1)
```

6 Data_Preview

[192]:
```python
data.sample(2)
```

[192]:
```
     Year  Selling_Price  Present_Price  Driven_kms Fuel_Type Selling_type  \
125  2009           0.90           1.75       40000    Petrol   Individual
80   2016          14.73          14.89       23000    Diesel       Dealer

    Transmission  Owner  No_of_Years
125       Manual      0           15
80        Manual      0            8
```

[193]:
```python
data.head()
```

[193]:
```
   Year  Selling_Price  Present_Price  Driven_kms Fuel_Type Selling_type  \
0  2014           3.35           5.59       27000    Petrol       Dealer
1  2013           4.75           9.54       43000    Diesel       Dealer
2  2017           7.25           9.85        6900    Petrol       Dealer
3  2011           2.85           4.15        5200    Petrol       Dealer
4  2014           4.60           6.87       42450    Diesel       Dealer

  Transmission  Owner  No_of_Years
0       Manual      0           10
1       Manual      0           11
2       Manual      0            7
3       Manual      0           13
4       Manual      0           10
```

[194]:
```python
data.tail()
```

[194]:
```
     Year  Selling_Price  Present_Price  Driven_kms Fuel_Type Selling_type  \
296  2016           9.50          11.60       33988    Diesel       Dealer
297  2015           4.00           5.90       60000    Petrol       Dealer
298  2009           3.35          11.00       87934    Petrol       Dealer
299  2017          11.50          12.50        9000    Diesel       Dealer
300  2016           5.30           5.90        5464    Petrol       Dealer

    Transmission  Owner  No_of_Years
```

```
296        Manual      0           8
297        Manual      0           9
298        Manual      0          15
299        Manual      0           7
300        Manual      0           8
```

7 Statistical_OverView

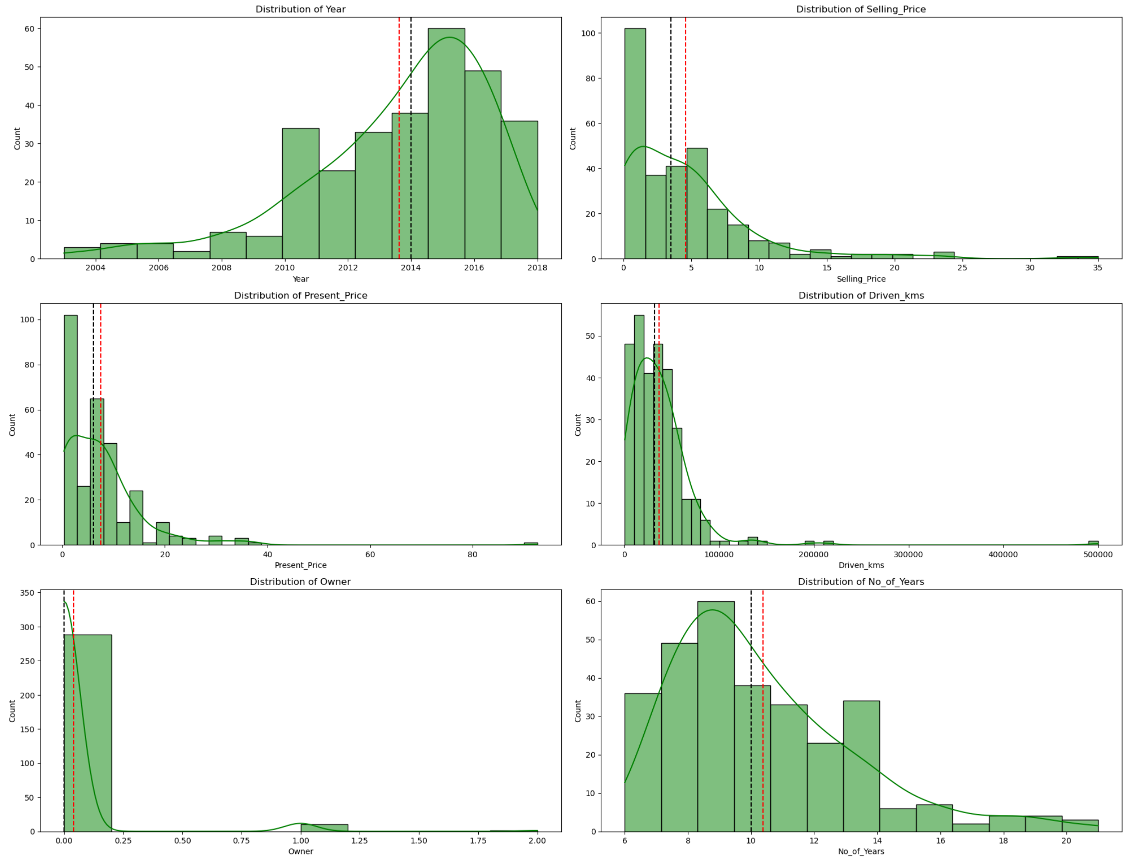
[195]:
```
data.describe().T
```

[195]:
```
               count      mean       std      min       25%       50%  \
Year          299.00  2,013.62      2.90 2,003.00  2,012.00  2,014.00
Selling_Price 299.00      4.59      4.98     0.10      0.85      3.51
Present_Price 299.00      7.54      8.57     0.32      1.20      6.10
Driven_kms    299.00 36,916.75 39,015.17   500.00 15,000.00 32,000.00
Owner         299.00      0.04      0.21     0.00      0.00      0.00
No_of_Years   299.00     10.38      2.90     6.00      8.00     10.00

                    75%        max
Year           2,016.00   2,018.00
Selling_Price      6.00      35.00
Present_Price      9.84      92.60
Driven_kms    48,883.50 500,000.00
Owner              0.00       2.00
No_of_Years       12.00      21.00
```

8 Univariate analysis

1-Numerical Data (Histogram/Distplot - Box Plot - Summary Statistics)

[196]:
```
numeric_columns =data.select_dtypes('number')
plt.figure(figsize=(20,20))
for i ,e in enumerate(numeric_columns):
    plt.subplot(4,2,i+1)
    sns.histplot(data[e],kde=True,color='g')
    plt.axvline(data[e].mean(), color='r', linestyle='--')
    plt.axvline(data[e].median(), color='black', linestyle='--')
    plt.title('Distribution of '+e)
    plt.tight_layout()
```



mean > median (right-skewed)

[197]:
```python
data.select_dtypes('number').describe()
```

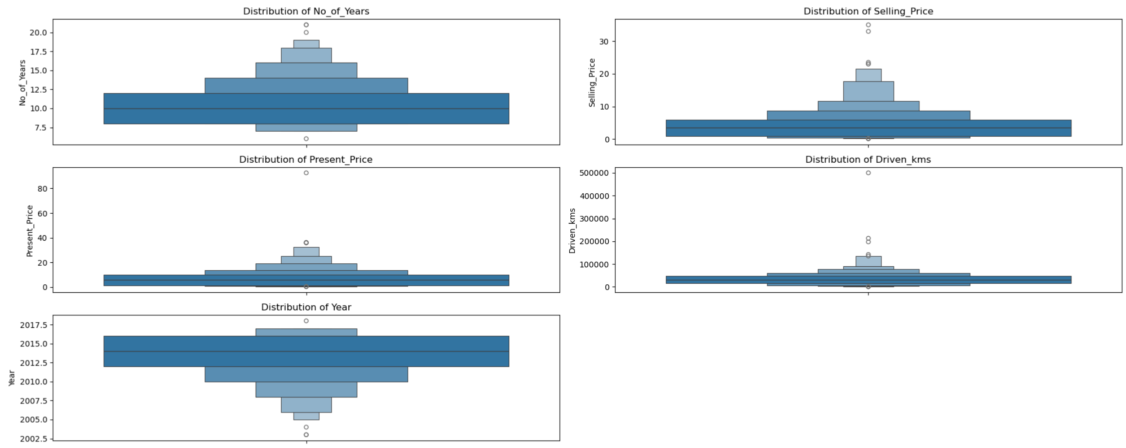
[197]:

	Year	Selling_Price	Present_Price	Driven_kms	Owner	No_of_Years
count	299.00	299.00	299.00	299.00	299.00	299.00
mean	2,013.62	4.59	7.54	36,916.75	0.04	10.38
std	2.90	4.98	8.57	39,015.17	0.21	2.90
min	2,003.00	0.10	0.32	500.00	0.00	6.00
25%	2,012.00	0.85	1.20	15,000.00	0.00	8.00
50%	2,014.00	3.51	6.10	32,000.00	0.00	10.00
75%	2,016.00	6.00	9.84	48,883.50	0.00	12.00
max	2,018.00	35.00	92.60	500,000.00	2.00	21.00

note that mean > median in table and graph

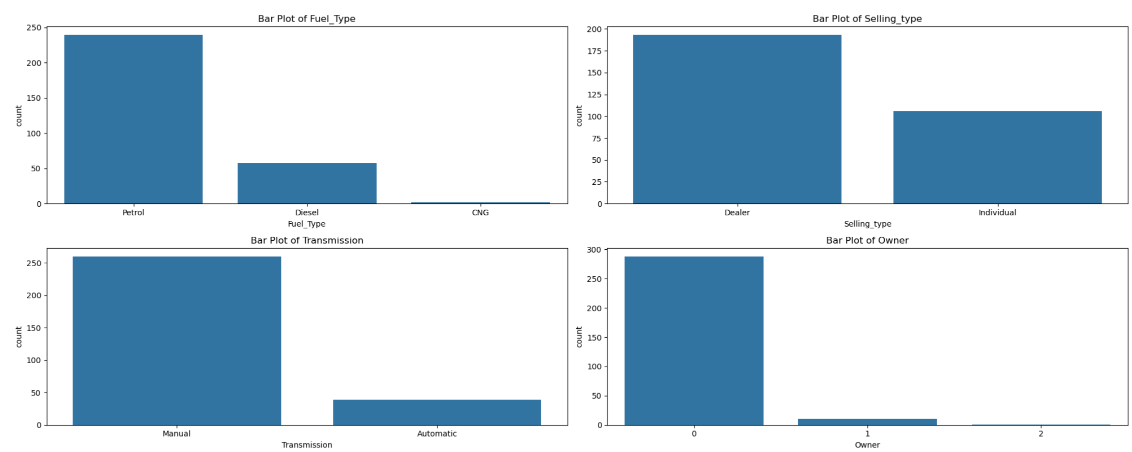
[198]:
```python
columns_to_plot =  ['No_of_Years', 'Selling_Price',␣
↪'Present_Price','Driven_kms','Year']
plt.figure(figsize=(20,8))
for i ,col in enumerate(columns_to_plot):
    plt.subplot(3,2,i+1)
```

```
    sns.boxenplot(data[col])
    plt.title('Distribution of '+col)
    plt.tight_layout()
```



2- Categorical Data (Bar Plot - Pie Chart)

[201]:
```
categorical_columns = ['Fuel_Type', 'Selling_type', 'Transmission', 'Owner']
plt.figure(figsize=(20,8))
for i ,col in enumerate(categorical_columns):
    plt.subplot(2,2,i+1)
    sns.countplot(x=data[col])
    plt.title(f'Bar Plot of {col}')
    plt.tight_layout()
```



[ ]:
```
categorical_columns = ['Fuel_Type', 'Selling_type', 'Transmission', 'Owner']
plt.figure(figsize=(20,8))
for i ,col in enumerate(categorical_columns):
    plt.subplot(2,2,i+1)
    v_c=data[col].value_counts()
    plt.pie(v_c,autopct='%1.1f%%', startangle=90)
    plt.title(f'Pie Chart of {col}')
    plt.tight_layout()
```

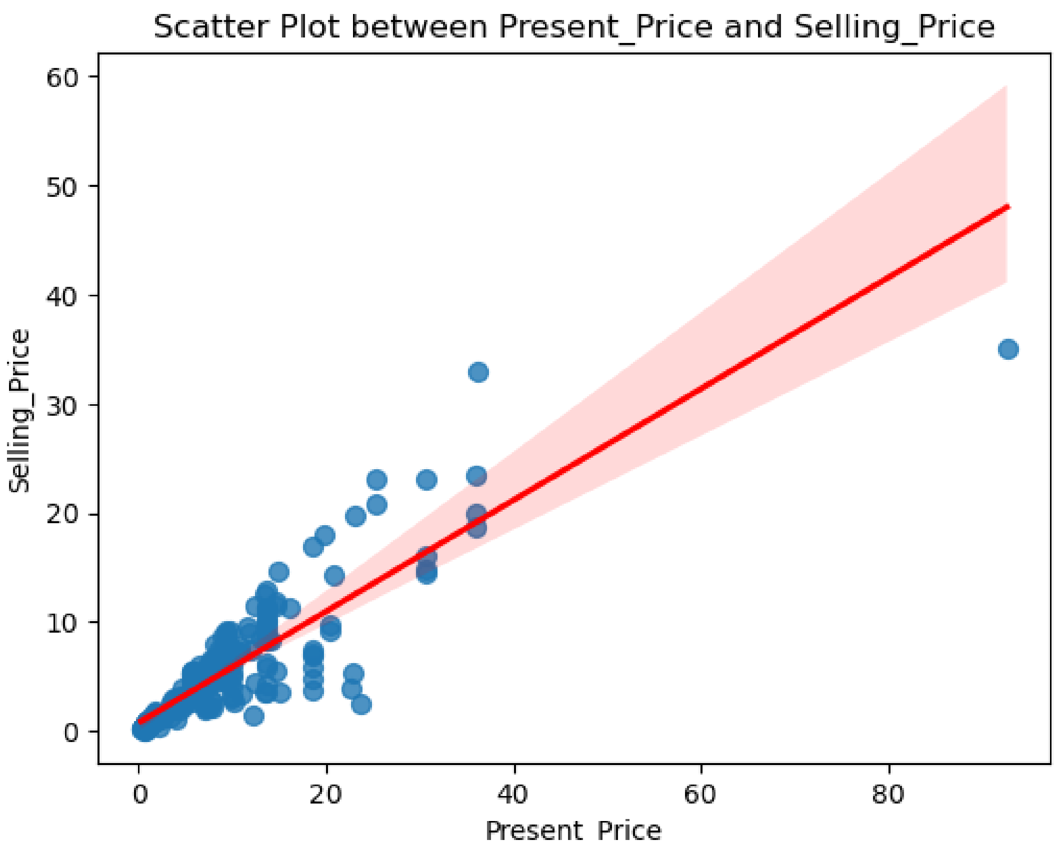
9 Bivariate Analysis

1- Numerical vs. Numerical (Correlation Matrix - Scatter Plot - Scatter Plot With a Trend Line)

[202]:
```
correlation_matrix=numeric_columns.corr()
correlation_matrix
```

[202]:
```
               Year  Selling_Price  Present_Price  Driven_kms  Owner  \
Year           1.00           0.23          -0.05       -0.53  -0.17
Selling_Price  0.23           1.00           0.88        0.03  -0.10
Present_Price -0.05           0.88           1.00        0.21  -0.02
Driven_kms    -0.53           0.03           0.21        1.00   0.06
Owner         -0.17          -0.10          -0.02        0.06   1.00
No_of_Years   -1.00          -0.23           0.05        0.53   0.17

               No_of_Years
Year                 -1.00
Selling_Price        -0.23
Present_Price         0.05
Driven_kms            0.53
Owner                 0.17
No_of_Years           1.00
```

[203]:
```
#regplot as scatter but with line
sns.regplot(x='Present_Price', y='Selling_Price', data=data,scatter_kws={'s':
 ↪50}, line_kws={'color':'red'})
plt.title('Scatter Plot between Present_Price and Selling_Price')
plt.xlabel('Present_Price')
plt.ylabel('Selling_Price')
plt.show()
```



Strong Correlation

[204]:
```
# grouped_data = data.groupby('No_of_Years', as_index=False)['Selling_Price'].
↪mean().round(2)
# fig = px.scatter(grouped_data, x='No_of_Years', y='Selling_Price',
#                  title='Scatter plot of No of Years vs Selling Price with␣
↪Trend Line')
# fig.add_traces(px.line(grouped_data, x='No_of_Years', y='Selling_Price').data)
# fig.show()
```

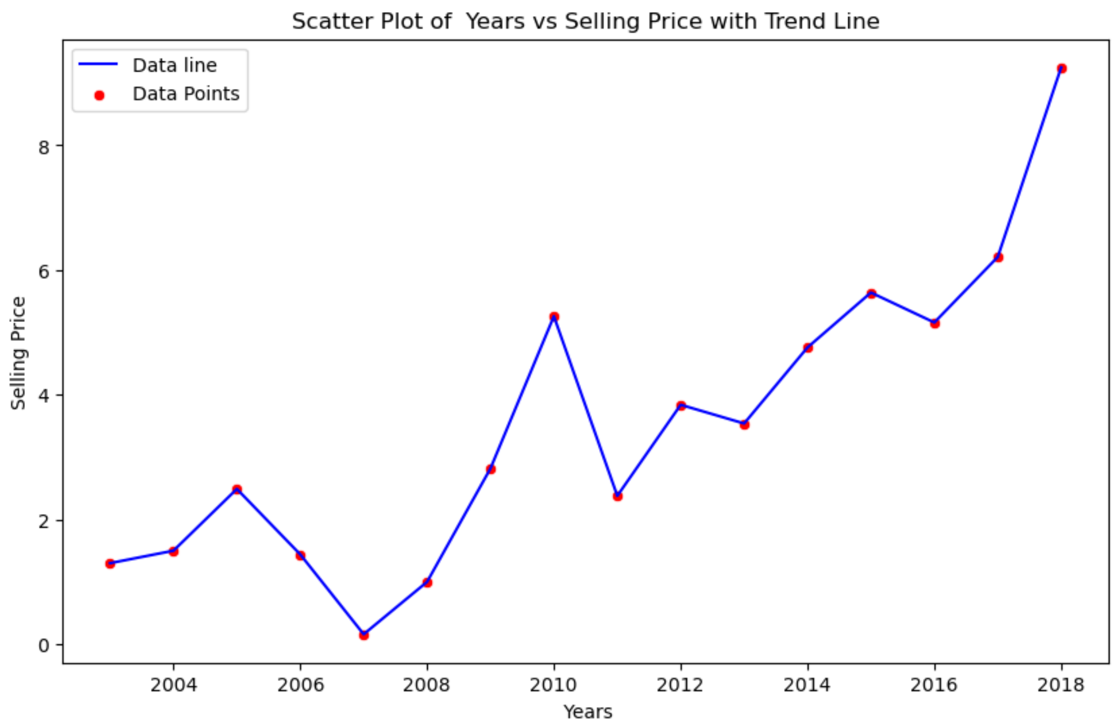
[205]:
```
grouped_data = data.groupby('No_of_Years', as_index=False)['Selling_Price'].
↪mean().round(2)
plt.figure(figsize=(10, 6))
sns.lineplot(data=grouped_data, x='No_of_Years', y='Selling_Price',␣
↪color='blue', label='Data line')
sns.scatterplot(data=grouped_data, x='No_of_Years', y='Selling_Price',␣
↪color='red', label='Data Points')

plt.title('Scatter Plot of No of Years vs Selling Price with Trend Line')
plt.xlabel('No of Years')
```

```
plt.ylabel('Selling Price')
plt.legend()
plt.show()
```

[206]:
```
# grouped_data = data.groupby('Year', as_index=False)['Selling_Price'].mean().
↪round(2)
# fig = px.scatter(grouped_data, x='Year', y='Selling_Price',
#                  title='Scatter plot of  Years vs Selling Price with Trend␣
↪Line')
# fig.add_traces(px.line(grouped_data, x='Year', y='Selling_Price').data)

# fig.show()
```

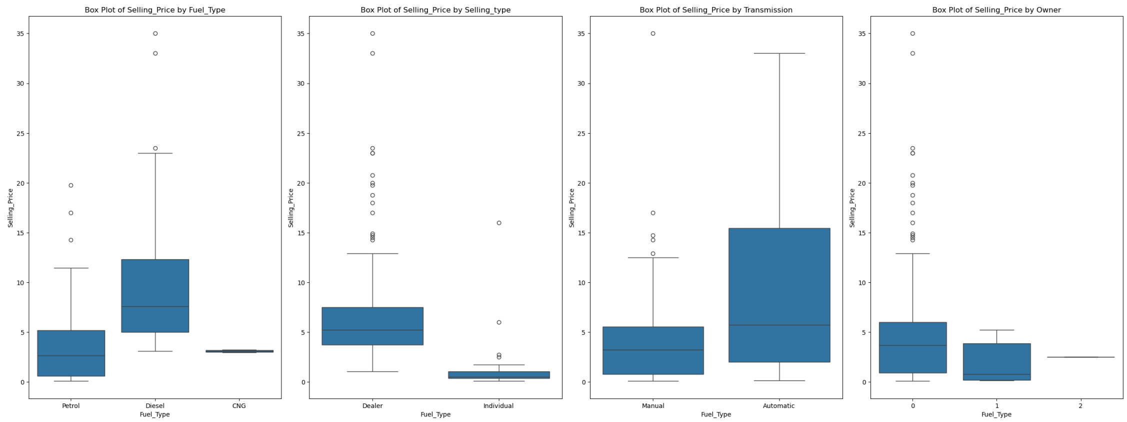
[207]:
```
grouped_data = data.groupby('Year', as_index=False)['Selling_Price'].mean().
↪round(2)
plt.figure(figsize=(10, 6))
sns.lineplot(data=grouped_data, x='Year', y='Selling_Price', color='blue',␣
↪label='Data line')
sns.scatterplot(data=grouped_data, x='Year', y='Selling_Price', color='red',␣
↪label='Data Points')

plt.title('Scatter Plot of  Years vs Selling Price with Trend Line')
plt.xlabel(' Years')
```

```
plt.ylabel('Selling Price')
plt.legend()
plt.show()
```



2- Numerical vs. Categorical (Box Plot)

[208]:
```
# Distribution of Selling_Price across different Fuel_Types
plt.figure(figsize=(25, 18))
for i ,col in enumerate(categorical_columns):
    plt.subplot(2,len(categorical_columns),i+1)
    sns.boxplot(x=data[col], y='Selling_Price', data=data)
    plt.title(f'Box Plot of Selling_Price by {col}')
    plt.xlabel('Fuel_Type')
    plt.tight_layout()
```



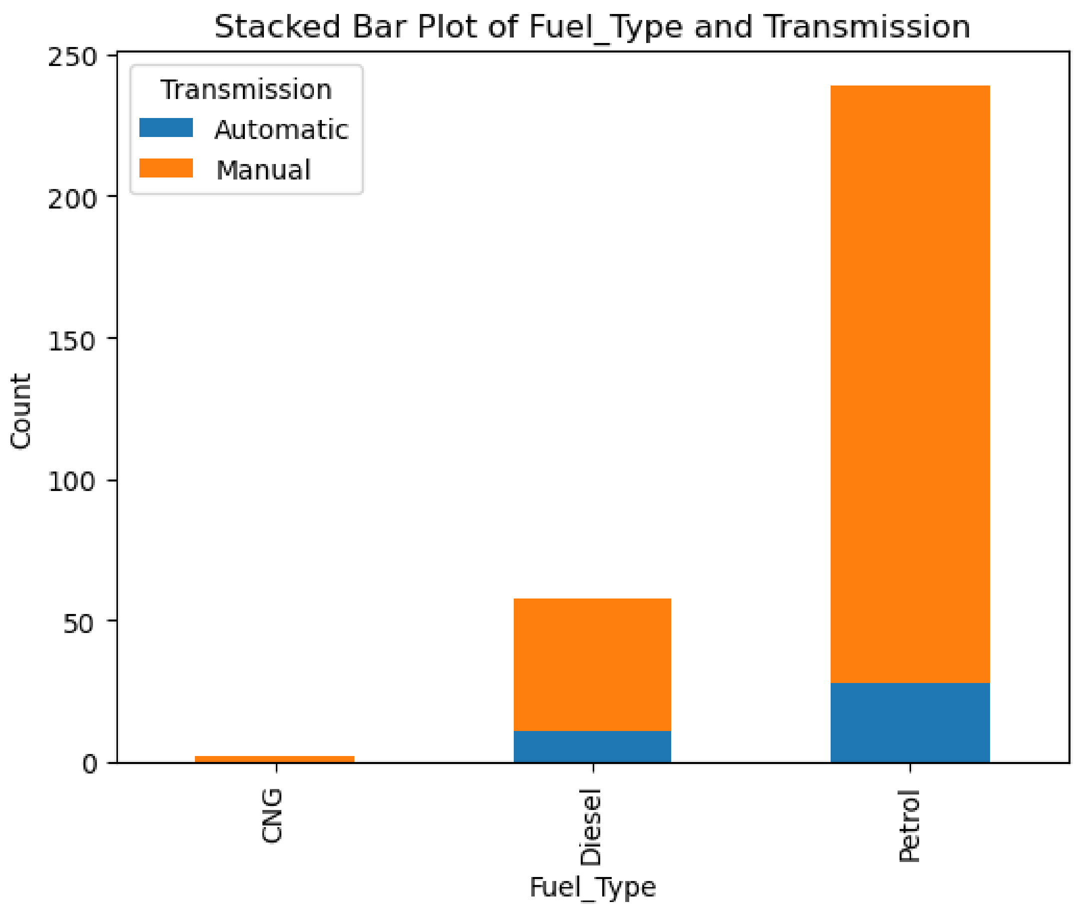
3- Categorical vs. Categorical (Cross-tabulation - Stacked Bar Plot)

[209]:
```
pd.crosstab(data['Fuel_Type'], data['Transmission'])
```

[209]:
```
Transmission  Automatic  Manual
Fuel_Type
CNG                   0       2
Diesel               11      47
Petrol               28     211
```

displays the frequency distribution of the variables Fuel_Type and Transmission

[210]:
```
pd.crosstab(data['Fuel_Type'], data['Transmission']).plot(kind='bar',␣
 ↪stacked=True)
plt.title('Stacked Bar Plot of Fuel_Type and Transmission')
plt.xlabel('Fuel_Type')
plt.ylabel('Count')
plt.show()
```

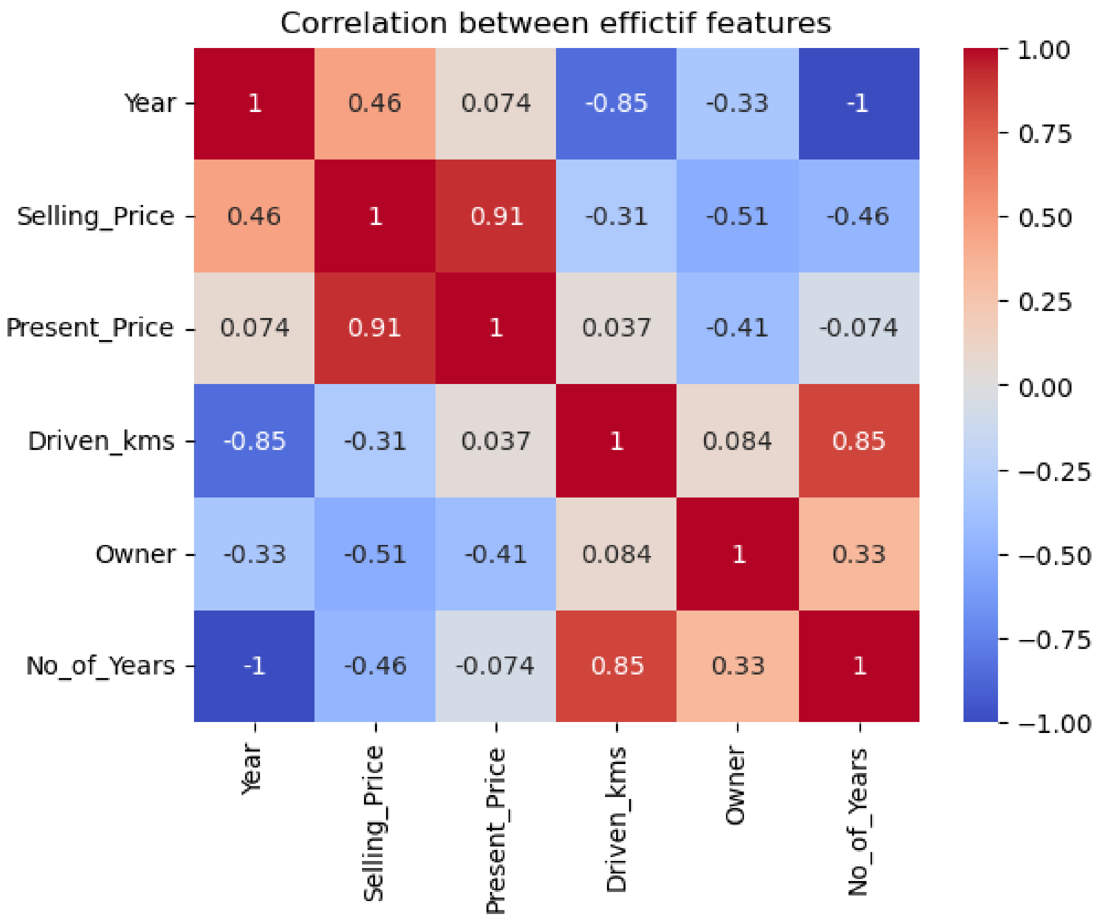


10 Multivariate Analysis

(Pair Plot - Heatmap)

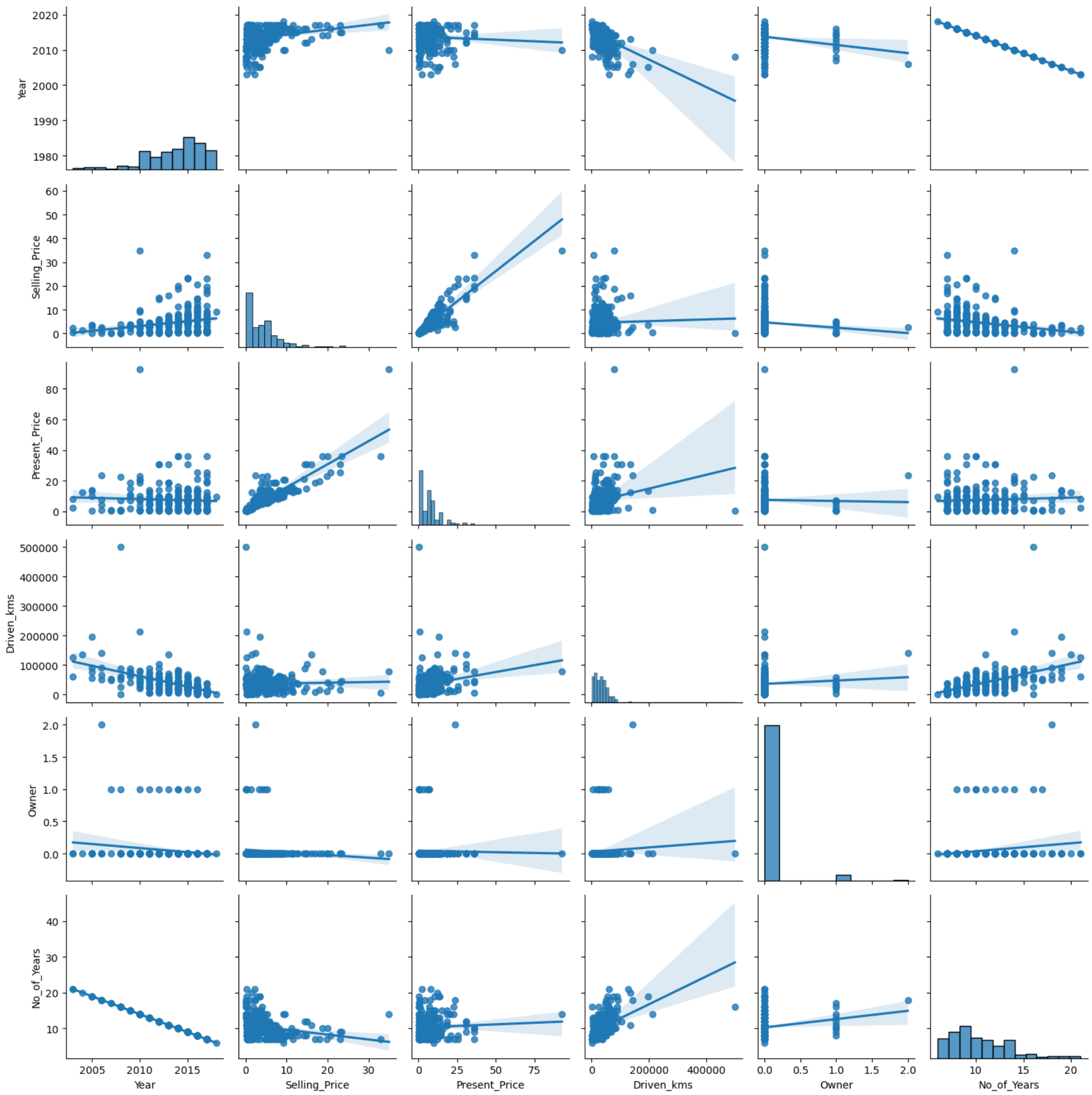
[211]:
```
sns.heatmap(correlation_matrix.corr(),annot=True,cmap='coolwarm')
plt.title('Correlation between effictif features')
```

[211]:
```
Text(0.5, 1.0, 'Correlation between effictif features')
```



Strong correlation between Selling_price & Present_price

[34]:
```
sns.pairplot(data.select_dtypes('number'),kind='reg')
plt.tight_layout()
```



11 Outliers

[212]:
```
Q1 = data['Present_Price'].quantile(0.25)
Q3 = data['Present_Price'].quantile(0.75)
IQR = Q3 - Q1

lower_bound = Q1 - IQR*1.5
upper_bound = Q3 + IQR*1.5

# outliers = New_data[(New_data['Present_Price'] > upper_bound) | (New_data['Present_Price'] < lower_bound)]
outliers = data[data.Present_Price > 25.39]
```

```
outliers_count = outliers.count()
outliers_count
```

[212]:
```
Year             9
Selling_Price    9
Present_Price    9
Driven_kms       9
Fuel_Type        9
Selling_type     9
Transmission     9
Owner            9
No_of_Years      9
dtype: int64
```

[213]:
```
outliers = data[data.Present_Price > 25.39]
data_clean =data[~(data.Present_Price > 25.39)]
data_clean
```

[213]:
```
     Year  Selling_Price  Present_Price  Driven_kms Fuel_Type Selling_type  \
0    2014           3.35           5.59       27000    Petrol       Dealer
1    2013           4.75           9.54       43000    Diesel       Dealer
2    2017           7.25           9.85        6900    Petrol       Dealer
3    2011           2.85           4.15        5200    Petrol       Dealer
4    2014           4.60           6.87       42450    Diesel       Dealer
..    …             …              …          …         …          …
296  2016           9.50          11.60       33988    Diesel       Dealer
297  2015           4.00           5.90       60000    Petrol       Dealer
298  2009           3.35          11.00       87934    Petrol       Dealer
299  2017          11.50          12.50        9000    Diesel       Dealer
300  2016           5.30           5.90        5464    Petrol       Dealer

    Transmission  Owner  No_of_Years
0         Manual      0           10
1         Manual      0           11
2         Manual      0            7
3         Manual      0           13
4         Manual      0           10
..           …    …          …
296       Manual      0            8
297       Manual      0            9
298       Manual      0           15
299       Manual      0            7
300       Manual      0            8

[290 rows x 9 columns]
```

[214]:
```
outliers.info()
```

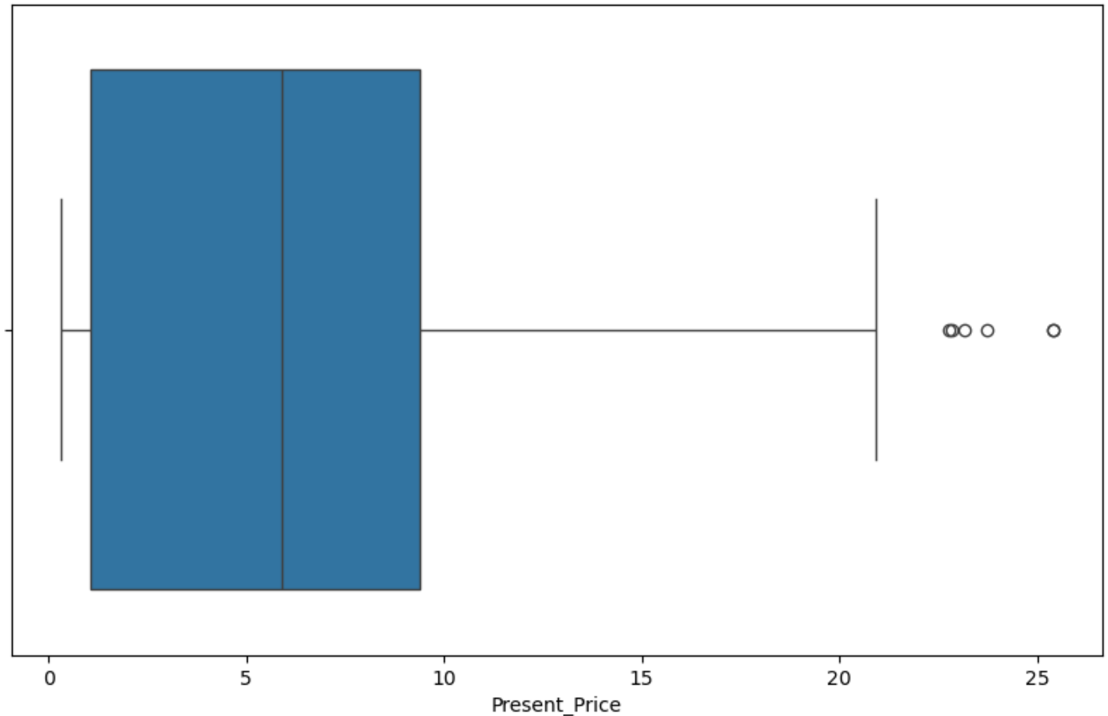
```
<class 'pandas.core.frame.DataFrame'>
Index: 9 entries, 50 to 86
Data columns (total 9 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Year           9 non-null      int64
 1   Selling_Price  9 non-null      float64
 2   Present_Price  9 non-null      float64
 3   Driven_kms     9 non-null      int64
 4   Fuel_Type      9 non-null      object
 5   Selling_type   9 non-null      object
 6   Transmission   9 non-null      object
 7   Owner          9 non-null      int64
 8   No_of_Years    9 non-null      int64
dtypes: float64(2), int64(4), object(3)
memory usage: 720.0+ bytes
```

[215]:
```
data_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 290 entries, 0 to 300
Data columns (total 9 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Year           290 non-null    int64
 1   Selling_Price  290 non-null    float64
 2   Present_Price  290 non-null    float64
 3   Driven_kms     290 non-null    int64
 4   Fuel_Type      290 non-null    object
 5   Selling_type   290 non-null    object
 6   Transmission   290 non-null    object
 7   Owner          290 non-null    int64
 8   No_of_Years    290 non-null    int64
dtypes: float64(2), int64(4), object(3)
memory usage: 22.7+ KB
```

[216]:
```
# px.box(data_frame=data_clean,x='Present_Price')
plt.figure(figsize=(10, 6))
sns.boxplot(data=data_clean,x='Present_Price')
```

[216]: <Axes: xlabel='Present_Price'>



12 Normality

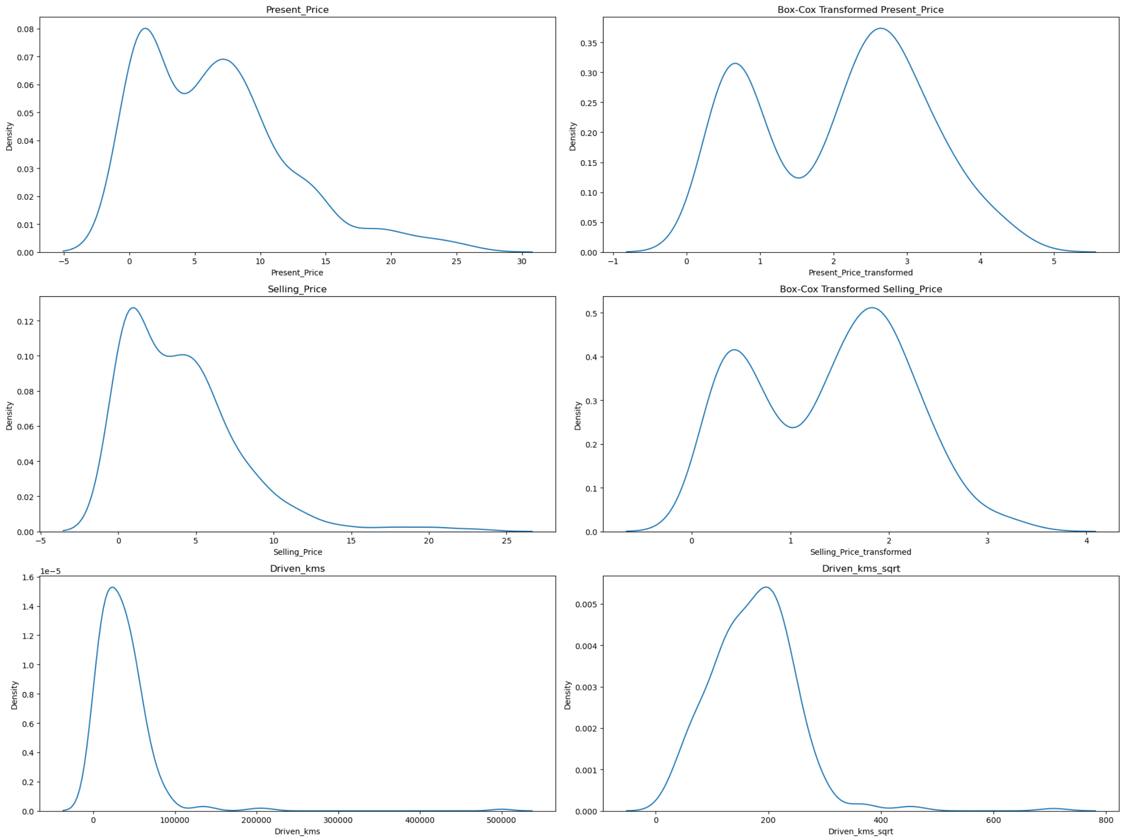
- **Box-Cox Transformation**:
  - **Purpose**: Normalize data, reduce skewness, and stabilize variance.
  - **Use**: When data is highly skewed and positive. Ideal for preparing data for models that assume normality.
- **Square Root Transformation**:
  - **Purpose**: Reduce moderate skewness and stabilize variance.
  - **Use**: For non-negative data, especially count data, where a simpler transformation is sufficient.

Both transformations are used to make data more suitable for modeling by addressing issues like skewness and variance instability.

[218]:
```
from scipy.stats import boxcox

#  Box-Cox transformation to both 'Present_Price' and 'Selling_Price'
data_clean.loc[:, 'Present_Price_transformed'], _ =␣
↪boxcox(data_clean['Present_Price'] + 1)
data_clean.loc[:, 'Selling_Price_transformed'], _ =␣
↪boxcox(data_clean['Selling_Price'] + 1)
#square root for Driven-kms
data_clean.loc[:, 'Driven_kms_sqrt'] = np.sqrt(data_clean['Driven_kms'])
```

Plot the original and transformed columns using kdeplot

[219]:
```
plt.figure(figsize=(20, 15))

plt.subplot(3, 2, 1)
sns.kdeplot(data=data_clean, x='Present_Price')
plt.title('Present_Price')

plt.subplot(3, 2, 2)
sns.kdeplot(data=data_clean, x='Present_Price_transformed')
plt.title('Box-Cox Transformed Present_Price')

plt.subplot(3, 2, 3)
sns.kdeplot(data=data_clean, x='Selling_Price')
plt.title('Selling_Price')

plt.subplot(3, 2, 4)
sns.kdeplot(data=data_clean, x='Selling_Price_transformed')
plt.title('Box-Cox Transformed Selling_Price')

plt.subplot(3, 2, 5)
sns.kdeplot(data=data_clean, x='Driven_kms')
plt.title('Driven_kms')

plt.subplot(3, 2, 6)
sns.kdeplot(data=data_clean, x='Driven_kms_sqrt')
plt.title('Driven_kms_sqrt')

plt.tight_layout()
plt.show()
```



13 Kurtosis

Kurtosis measures how much the tails of a data distribution differ from a normal distribution.

- **High Kurtosis**: Tails are heavy, meaning there are more extreme values (outliers) than usual.
- **Low Kurtosis**: Tails are light, meaning there are fewer extreme values than usual.
- **Normal Kurtosis**: Tails are similar to those of a normal distribution, with a balanced number of outliers.

[220]:
```
from scipy.stats import kurtosis
kurtosis_present_price = kurtosis(data_clean['Present_Price'])
kurtosis_selling_price = kurtosis(data_clean['Selling_Price'])
kurtosis_Driven_kms = kurtosis(data_clean['Driven_kms'])

print(f"Kurtosis of Present_Price: {kurtosis_present_price}")
print(f"Kurtosis of Selling_Price: {kurtosis_selling_price}")
print(f"Kurtosis of Driven_kms: {kurtosis_Driven_kms}")
```

```
Kurtosis of Present_Price: 0.7768684598078957
Kurtosis of Selling_Price: 4.182781604796288
```

```
Kurtosis of Driven_kms: 72.34036114182679
```

Before Transformation:

1. **Present_Price:**
   - **Kurtosis**: 0.7769
   - **Interpretation**: **Mesokurtic**. The distribution is close to normal with moderate peak and tails.
2. **Selling_Price:**
   - **Kurtosis**: 4.1828
   - **Interpretation**: **Leptokurtic**. This indicates a distribution with a higher peak and heavier tails, suggesting a greater presence of extreme values.
3. **Driven_kms:**
   - **Kurtosis**: 72.3404
   - **Interpretation**: **Highly Leptokurtic**. This extreme kurtosis shows a distribution with a very sharp peak and extremely heavy tails, indicating many extreme values and outliers.

[221]:

```
kurtosis_present_price_transformed =␣
 ↪kurtosis(data_clean['Present_Price_transformed'])
kurtosis_selling_price_transformed =␣
 ↪kurtosis(data_clean['Selling_Price_transformed'])
kurtosis_Driven_kms_sqrt = kurtosis(data_clean['Driven_kms_sqrt'])

print(f"Kurtosis of Present_Price_transformed:␣
 ↪{kurtosis_present_price_transformed}")
print(f"Kurtosis of Selling_Price_transformed:␣
 ↪{kurtosis_selling_price_transformed}")
print(f"Kurtosis of Driven_kms_sqrt: {kurtosis_Driven_kms_sqrt}")
```

```
Kurtosis of Present_Price_transformed: -1.1828042960228728
Kurtosis of Selling_Price_transformed: -1.035266774316057
Kurtosis of Driven_kms_sqrt: 7.824823450468216
```

After Transformation:

1. **Present_Price_transformed:**
   - **Kurtosis**: -1.1828
   - **Interpretation**: **Platykurtic**. The transformed distribution is flatter than normal, with fewer extreme values compared to the original Present_Price.
2. **Selling_Price_transformed:**
   - **Kurtosis**: -1.0353
   - **Interpretation**: **Platykurtic**. The transformed Selling_Price also shows a flatter distribution with fewer extreme values, improving the normality of the data.
3. **Driven_kms_sqrt:**
   - **Kurtosis**: 7.8248
   - **Interpretation**: **Leptokurtic**. Although the transformation made the distribution less extreme compared to the original, it still has heavy tails and a higher peak, indicating a significant presence of extreme values.

Conclusion: After Transformation: The transformed data generally shows improvements in terms of reducing extreme values, making it closer to normal distribution. This is usually beneficial for model performance

[222]:
```
data_clean.drop(columns=['Driven_kms','Selling_Price','Present_Price'],␣
    ↪inplace=True)
```

```
C:\Users\lenovo\AppData\Local\Temp\ipykernel_24308\361000944.py:1:
SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

[223]:
```
data_clean.columns
```

[223]:
```
Index(['Year', 'Fuel_Type', 'Selling_type', 'Transmission', 'Owner',
       'No_of_Years', 'Present_Price_transformed', 'Selling_Price_transformed',
       'Driven_kms_sqrt'],
      dtype='object')
```

[224]:
```
from sklearn.preprocessing import LabelEncoder

data_clean = data_clean.copy()
le = LabelEncoder()

#  LabelEncoder to each column
data_clean['Fuel_Type'] = le.fit_transform(data_clean['Fuel_Type'])
data_clean['Selling_type'] = le.fit_transform(data_clean['Selling_type'])
data_clean['Transmission'] = le.fit_transform(data_clean['Transmission'])

data_clean.head()
```

[224]:
```
   Year  Fuel_Type  Selling_type  Transmission  Owner  No_of_Years  \
0  2014          2             0             1      0           10
1  2013          1             0             1      0           11
2  2017          2             0             1      0            7
3  2011          2             0             1      0           13
4  2014          1             0             1      0           10

   Present_Price_transformed  Selling_Price_transformed  Driven_kms_sqrt
0                       2.25                       1.50           164.32
1                       2.94                       1.80           207.36
2                       2.98                       2.18            83.07
3                       1.91                       1.38            72.11
```

```
4                        2.50                       1.77          206.03
```

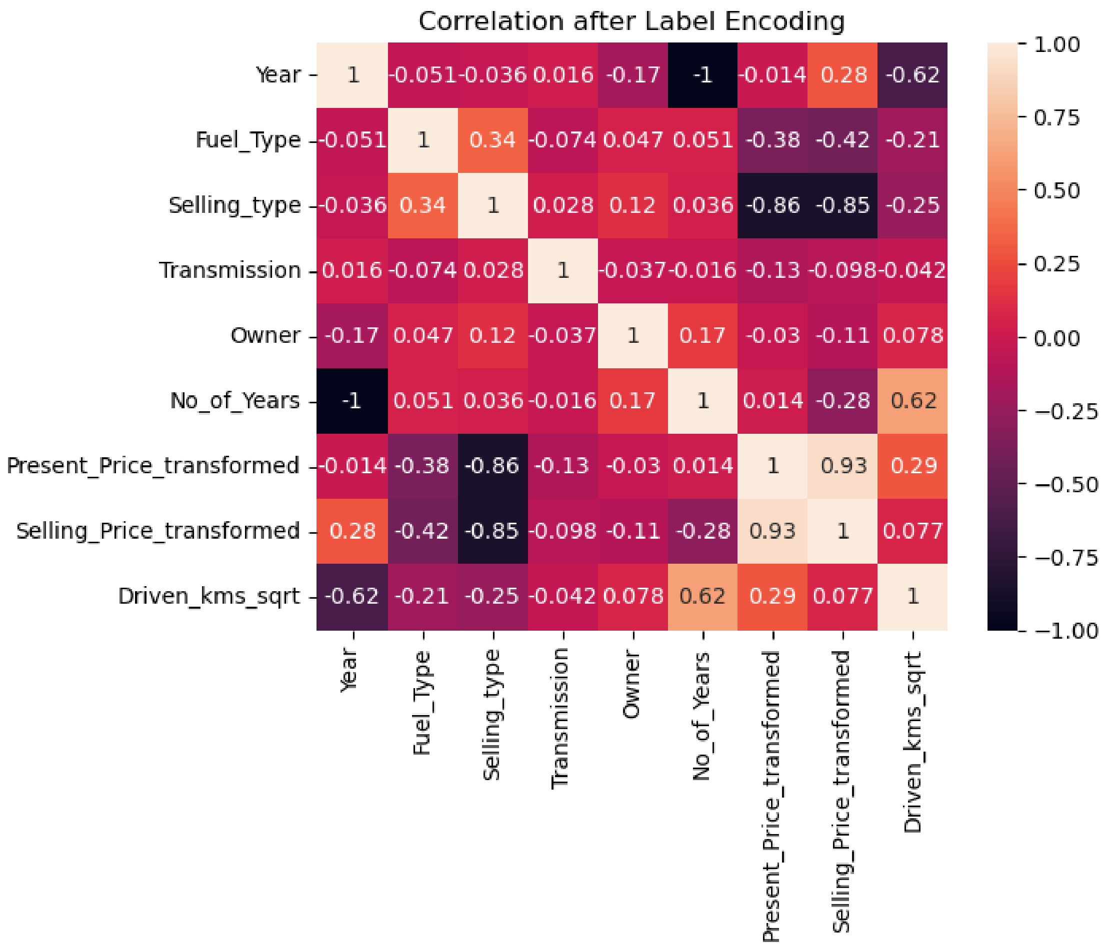
[225]:
```
data_clean.dtypes
```

[225]:
```
Year                          int64
Fuel_Type                     int32
Selling_type                  int32
Transmission                  int32
Owner                         int64
No_of_Years                   int64
Present_Price_transformed   float64
Selling_Price_transformed   float64
Driven_kms_sqrt             float64
dtype: object
```

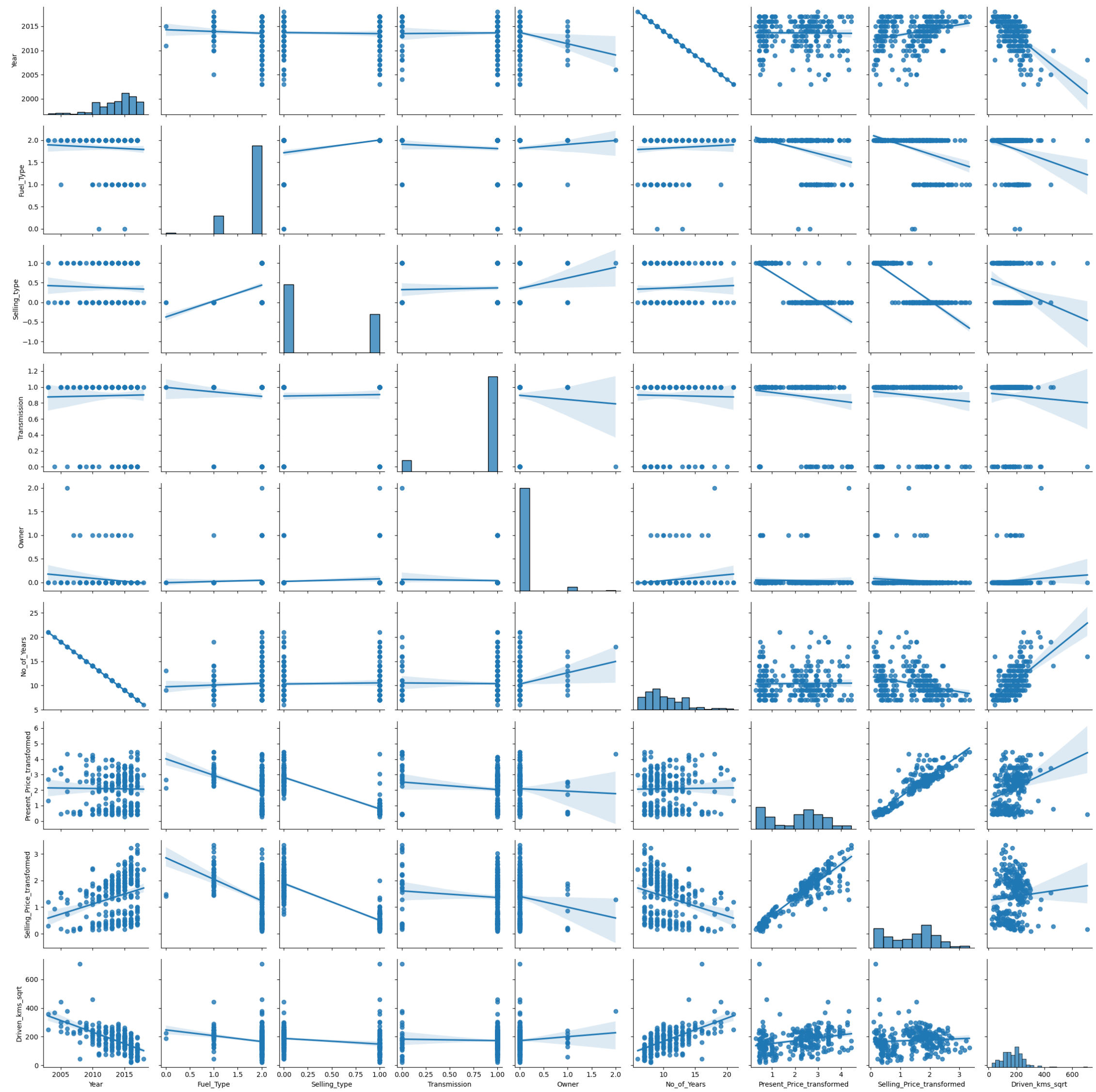
14 Correlations_After_Encoding

[226]:
```
sns.heatmap(data_clean.corr(),annot=True)
plt.title('Correlation after Label Encoding')
```

[226]:
```
Text(0.5, 1.0, 'Correlation after Label Encoding')
```



[227]:
```
sns.pairplot(data_clean,kind='reg')
plt.tight_layout()
```



15 Multivariate Regression Analysis

Multivariate Regression: Analyze the relationship between one dependent variable and multiple independent variables.

[228]:
```
import statsmodels.api as sm
x = data_clean.drop(['Selling_Price_transformed'],axis=1)
y = data_clean['Selling_Price_transformed']
```

[229]:
```
x = sm.add_constant(x)
```

[230]:
```
model = sm.OLS(y, x).fit()
```

[231]:
```
x.columns
```

[231]:
```
Index(['const', 'Year', 'Fuel_Type', 'Selling_type', 'Transmission', 'Owner',
       'No_of_Years', 'Present_Price_transformed', 'Driven_kms_sqrt'],
      dtype='object')
```

16 Assumptions in Ordinary Least Squares (OLS) regression

`1- Normality of Residuals`

[232]:
```
residuals = model.resid
```

- Anderson-Darling

[233]:
```
#  Anderson-Darling test on residuals
from scipy.stats import anderson

result_residuals = anderson(residuals, dist='norm')
print("Results for OLS Residuals:")
print(f"Anderson-Darling Test Statistic: {round(result_residuals.statistic,␣
↪4)}")
print(f"Critical Values: {result_residuals.critical_values}")
print(f"Significance Levels: {result_residuals.significance_level}")
```

```
Results for OLS Residuals:
Anderson-Darling Test Statistic: 0.5968
Critical Values: [0.568 0.647 0.777 0.906 1.077]
Significance Levels: [15.  10.   5.   2.5  1. ]
```

The Anderson-Darling test statistic for the OLS residuals is 0.5968.

- **At the 15% significance level**: The test statistic (0.5968) is slightly above the critical value (0.568). This indicates a minor deviation from normality, but it's minimal.
- **At the 10% significance level**: The test statistic (0.5968) is below the critical value (0.647). Thus, we do not reject the null hypothesis, suggesting the residuals are consistent with normality at this level.
- **At the 5%, 2.5%, and 1% significance levels**: The test statistic is below the critical values (0.777, 0.906, and 1.077, respectively). Therefore, we do not reject the null hypothesis at these levels, meaning the residuals are close to a normal distribution.

- Shapiro-Wilk

[234]:
```
from scipy.stats import shapiro
# Perform Shapiro-Wilk test on residuals
stat, p_value = shapiro(residuals)
print("Results for OLS Residuals:")
print(f"Shapiro-Wilk Test Statistic: {round(stat, 4)}")
print(f"p-value: {round(p_value, 4)}")
```

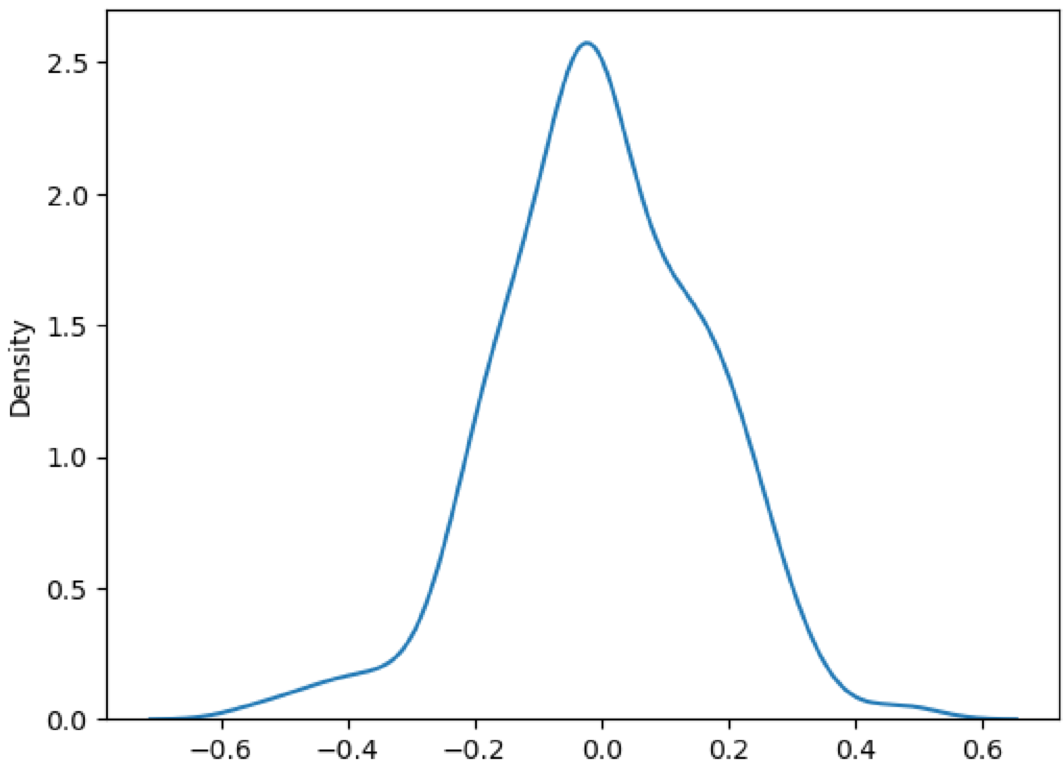
```
# Interpretation
if p_value > 0.05:
    print("Conclusion: The residuals are likely normally distributed (fail to␣
↪reject the null hypothesis)")
else:
    print("Conclusion: The residuals are not normally distributed (reject the␣
↪null hypothesis)")
```

```
Results for OLS Residuals:
Shapiro-Wilk Test Statistic: 0.9908
p-value: 0.0672
Conclusion: The residuals are likely normally distributed (fail to reject the
null hypothesis)
```

- Histogram of Residuals

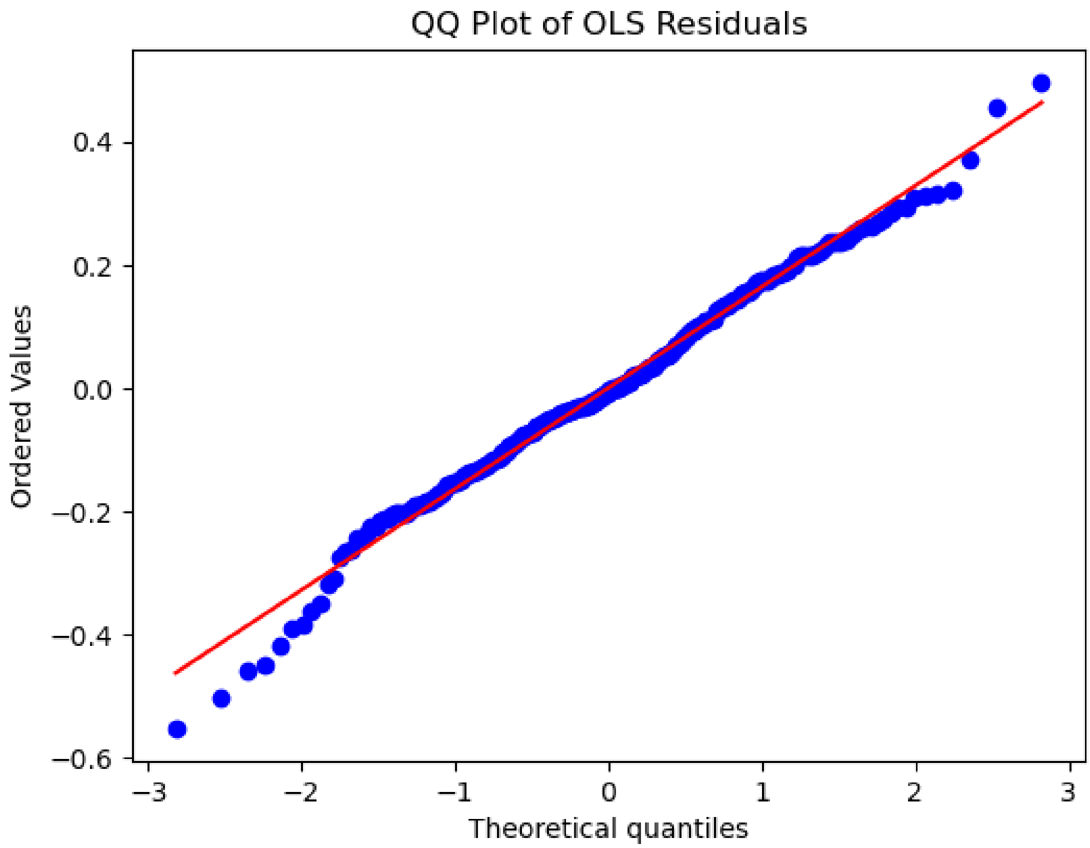
[235]:
```
sns.kdeplot(residuals)
```

[235]:
```
<Axes: ylabel='Density'>
```



- QQ Plot

[236]:
```
stats.probplot(residuals, dist="norm", plot=plt)
plt.title("QQ Plot of OLS Residuals")
plt.show()
```



2-Independence

The Durbin-Watson Statistic (DW) ranges from 0 to 4:

- **A value of 2** indicates no autocorrelation in the residuals.
- **Values closer to 0** suggest positive autocorrelation, meaning the residuals are positively correlated.
- **Values closer to 4** indicate negative autocorrelation, meaning the residuals are negatively correlated.

[237]:
```
dw = sm.stats.durbin_watson(residuals)
dw
```

[237]: 1.7698085280996163

1.7698, it is close to 2, suggesting that there is no strong evidence of autocorrelation in the residuals of your regression model.This is generally a good sign, indicating that your residuals are approximately uncorrelated

[238]:
```
model.summary()
```

[238]:

Dep. Variable:	Selling_Price_transformed	**R-squared:**	0.956
Model:	OLS	**Adj. R-squared:**	0.955
Method:	Least Squares	**F-statistic:**	878.6
Date:	Thu, 29 Aug 2024	**Prob (F-statistic):**	2.12e-187
Time:	23:04:28	**Log-Likelihood:**	113.29
No. Observations:	290	**AIC:**	-210.6
Df Residuals:	282	**BIC:**	-181.2
Df Model:	7		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	-3.214e-05	2.21e-06	-14.553	0.000	-3.65e-05	-2.78e-05
Year	0.0007	4.5e-05	15.228	0.000	0.001	0.001
Fuel_Type	-0.1268	0.027	-4.713	0.000	-0.180	-0.074
Selling_type	-0.2638	0.041	-6.419	0.000	-0.345	-0.183
Transmission	-0.0042	0.033	-0.130	0.897	-0.068	0.060
Owner	-0.0691	0.047	-1.482	0.139	-0.161	0.023
No_of_Years	-0.0657	0.004	-14.682	0.000	-0.075	-0.057
Present_Price_transformed	0.5361	0.018	30.085	0.000	0.501	0.571
Driven_kms_sqrt	-0.0005	0.000	-3.017	0.003	-0.001	-0.000

Omnibus:	4.910	**Durbin-Watson:**	1.770
Prob(Omnibus):	0.086	**Jarque-Bera (JB):**	5.136
Skew:	-0.201	**Prob(JB):**	0.0767
Kurtosis:	3.513	**Cond. No.**	7.31e+18

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 2.22e-29. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

R-squared = 0.95 that means i can dependent on these features to determine car price bec squared_correlation is high

17 Remove Insignificant Predictors

p-value > 0.05 (Transmission - Owner)

[239]:
```
x=x.drop(['Transmission'],axis=1)
model=sm.OLS(y,x).fit()
model.summary()
```

[239]:

Dep. Variable:	Selling_Price_transformed	**R-squared:**	0.956
Model:	OLS	**Adj. R-squared:**	0.955
Method:	Least Squares	**F-statistic:**	1029.
Date:	Thu, 29 Aug 2024	**Prob (F-statistic):**	6.38e-189
Time:	23:04:30	**Log-Likelihood:**	113.28
No. Observations:	290	**AIC:**	-212.6
Df Residuals:	283	**BIC:**	-186.9
Df Model:	6		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
const	-3.216e-05	2.2e-06	-14.594	0.000	-3.65e-05	-2.78e-05
Year	0.0007	3.87e-05	17.624	0.000	0.001	0.001
Fuel_Type	-0.1264	0.027	-4.747	0.000	-0.179	-0.074
Selling_type	-0.2629	0.040	-6.497	0.000	-0.343	-0.183
Owner	-0.0690	0.047	-1.484	0.139	-0.161	0.023
No_of_Years	-0.0658	0.004	-14.720	0.000	-0.075	-0.057
Present_Price_transformed	0.5367	0.017	30.964	0.000	0.503	0.571
Driven_kms_sqrt	-0.0005	0.000	-3.019	0.003	-0.001	-0.000

Omnibus:	4.619	**Durbin-Watson:**	1.769
Prob(Omnibus):	0.099	**Jarque-Bera (JB):**	4.786
Skew:	-0.192	**Prob(JB):**	0.0914
Kurtosis:	3.498	**Cond. No.**	7.31e+18

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 2.22e-29. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

[240]:
```
x=x.drop(['Owner'],axis=1)
model=sm.OLS(y,x).fit()
model.summary()
```

[240]:

Dep. Variable:	Selling_Price_transformed	**R-squared:**	0.956
Model:	OLS	**Adj. R-squared:**	0.955
Method:	Least Squares	**F-statistic:**	1229.
Date:	Thu, 29 Aug 2024	**Prob (F-statistic):**	5.18e-190
Time:	23:04:31	**Log-Likelihood:**	112.16
No. Observations:	290	**AIC:**	-212.3
Df Residuals:	284	**BIC:**	-190.3
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P> |t|	[0.025	0.975]
const	-3.256e-05	2.19e-06	-14.862	0.000	-3.69e-05	-2.82e-05
Year	0.0007	3.83e-05	18.030	0.000	0.001	0.001
Fuel_Type	-0.1272	0.027	-4.770	0.000	-0.180	-0.075
Selling_type	-0.2732	0.040	-6.840	0.000	-0.352	-0.195
No_of_Years	-0.0666	0.004	-14.992	0.000	-0.075	-0.058
Present_Price_transformed	0.5332	0.017	30.985	0.000	0.499	0.567
Driven_kms_sqrt	-0.0005	0.000	-2.997	0.003	-0.001	-0.000

Omnibus:	5.102	**Durbin-Watson:**	1.791
Prob(Omnibus):	0.078	**Jarque-Bera (JB):**	5.571
Skew:	-0.189	**Prob(JB):**	0.0617
Kurtosis:	3.564	**Cond. No.**	7.31e+18

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 2.22e-29. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

18 OLS_Parameters

[241]:
```
print("R-squared value:")
print(model.rsquared)

print("\nMSE value:")
print(model.mse_resid)

print("\nRSE value:")
rse = np.sqrt(model.mse_resid)
print(rse)

print("\nFitted Values:")
print(model.fittedvalues.head())

print("\nResiduals:")
print(model.resid.head())
```

```
R-squared value:
0.9558122939762361

MSE value:
0.027585261819877797

RSE value:
0.1660881146255745

Fitted Values:
0   1.58
```

```
1    1.99
2    2.22
3    1.25
4    1.82
dtype: float64

Residuals:
0   -0.08
1   -0.19
2   -0.04
3    0.13
4   -0.05
dtype: float64
```

[242]:
```python
x.columns
```

[242]:
```
Index(['const', 'Year', 'Fuel_Type', 'Selling_type', 'No_of_Years',
       'Present_Price_transformed', 'Driven_kms_sqrt'],
      dtype='object')
```

19 Car Price Prediction

[243]:
```python
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_squared_error,r2_score
```

[244]:
```python
y = data_clean['Selling_Price_transformed']
X = data_clean[['Year', 'Fuel_Type', 'Selling_type', 'No_of_Years',
       'Present_Price_transformed', 'Driven_kms_sqrt']]
```

[245]:
```python
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.
 ↪2,random_state=100)
```

** Scaling Data

[246]:
```python
scaler=StandardScaler()
x_train_scaled=scaler.fit_transform(X_train)
x_test_scaled=scaler.transform(X_test)
```

1- Gradient Boosting

[247]:
```python
from sklearn.ensemble import GradientBoostingRegressor
model=GradientBoostingRegressor(n_estimators=100, learning_rate=0.1,␣
 ↪max_depth=3, random_state=100)
```

[248]:
```python
model.fit(x_train_scaled,y_train)
```

[248]:
```
GradientBoostingRegressor(random_state=100)
```

[249]:
```python
y_pred=model.predict(x_test_scaled)
```

[250]:
```python
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
print(f"Mean Squared Error: {mse}")
print(f"R-squared: {r2}")
```

```
Mean Squared Error: 0.01275779694321093
R-squared: 0.9746054223909847
```

[251]:
```python
gradient_data=pd.DataFrame({'Actual':y_test ,'Predicted':y_pred})
gradient_data.reset_index(inplace=True,drop=True)
gradient_data.head()
```

[251]:

	Actual	Predicted
0	2.41	2.35
1	0.93	1.40
2	0.47	0.37
3	0.22	0.28
4	1.72	1.84

2- Decision Tree

[252]:
```python
from sklearn.tree import DecisionTreeRegressor
model = DecisionTreeRegressor(max_depth=None, random_state=100)
```

[253]:
```python
model.fit(x_train_scaled, y_train)
```

[253]:
```
DecisionTreeRegressor(random_state=100)
```

[254]:
```python
y_pred=model.predict(x_test_scaled)
```

[255]:
```python
mse=mean_squared_error(y_pred,y_test)
r2=r2_score(y_pred,y_test)
print(f'Mean Squared Error is : {mse}')
print(f'R-squared is :  {r2}')
```

```
Mean Squared Error is : 0.023709525712562646
R-squared is :  0.9564019812412028
```

[256]:
```python
desicion_data=pd.DataFrame({'Actaul':y_test ,'Predicted':y_pred})
desicion_data.reset_index(inplace=True,drop=True)
desicion_data.head()
```

[256]:

	Actaul	Predicted
0	2.41	2.45
1	0.93	1.54
2	0.47	0.34
3	0.22	0.18

```
4    1.72      1.67
```

3- Lasso

[257]:
```python
from sklearn.linear_model import Lasso
lasso = Lasso(alpha=0.1)  # You can adjust the alpha parameter for␣
 ↪regularization strength
```

[258]:
```python
lasso.fit(x_train_scaled, y_train)
```

[258]:
```
Lasso(alpha=0.1)
```

[259]:
```python
y_pred = model.predict(x_test_scaled)

# Evaluate model
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print(f"Mean Squared Error: {mse}")
print(f"R-squared: {r2}")
```

```
Mean Squared Error: 0.023709525712562646
R-squared: 0.9528058493593581
```

[260]:
```python
lasso_data=pd.DataFrame({'Actaul':y_test ,'Predicted':y_pred})
lasso_data.reset_index(inplace=True,drop=True)
lasso_data.head()
```

[260]:

	Actaul	Predicted
0	2.41	2.45
1	0.93	1.54
2	0.47	0.34
3	0.22	0.18
4	1.72	1.67

20 Feature selection using Lasso

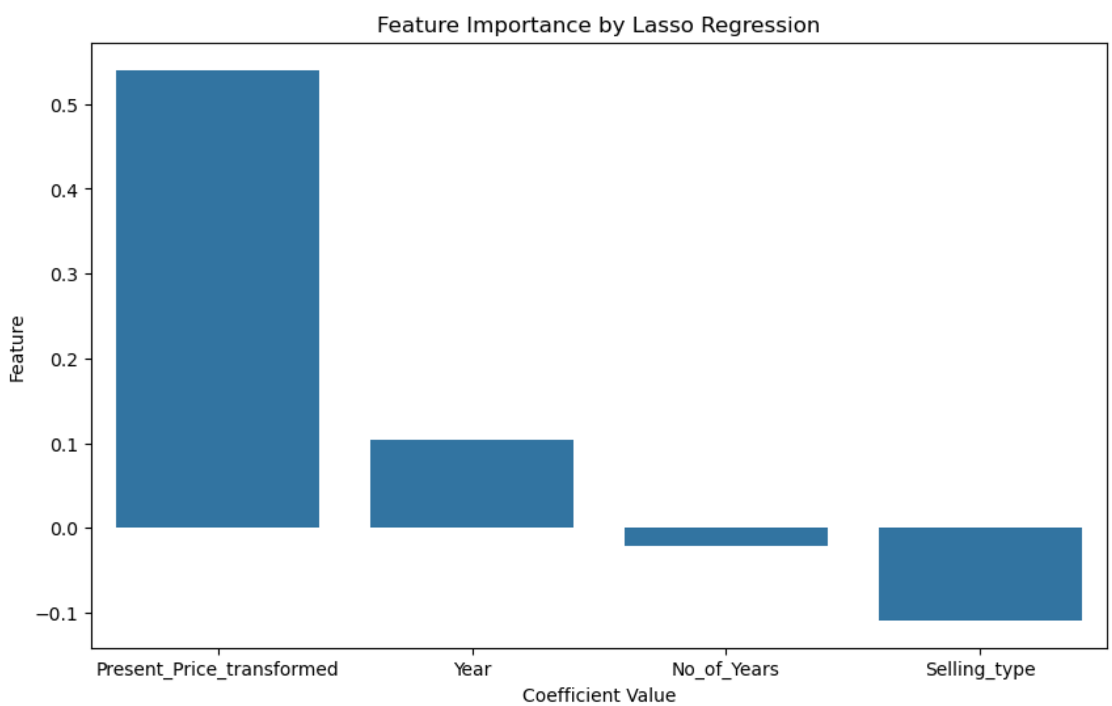
[261]:
```python
lasso_coefficients = pd.DataFrame({
    'Feature': X.columns,
    'Coefficient': lasso.coef_
})

# Select important features (non-zero coefficients)
important_features = lasso_coefficients[lasso_coefficients['Coefficient'] != 0]

print("Important features selected by Lasso:")
print(important_features)
```

```
Important features selected by Lasso:
                     Feature  Coefficient
0                       Year         0.10
2               Selling_type        -0.11
3                No_of_Years        -0.02
4   Present_Price_transformed         0.54
```

Year - Present_Price_transformed is the most important

- **Selected Features**: Those with non-zero coefficients after applying Lasso.
- **Excluded Features**: Those with zero or less coefficients

[262]:
```python
import matplotlib.pyplot as plt
import seaborn as sns

# Plot the important features selected by Lasso
plt.figure(figsize=(10, 6))
sns.barplot(y='Coefficient', x='Feature', data=important_features.
 ↪sort_values(by='Coefficient', ascending=False))

plt.title('Feature Importance by Lasso Regression')
plt.xlabel('Coefficient Value')
plt.ylabel('Feature')
plt.show()
```



4- Linear Regression

[263]:
```
from sklearn.linear_model import LinearRegression
model=LinearRegression()
```

[264]:
```
model.fit(X_train,y_train)
```

[264]: LinearRegression()

[ ]:
```
y_pred=model.predict(X_test)
```

[265]:
```
mse=mean_squared_error(y_pred,y_test)
r2=r2_score(y_pred,y_test)
print(f'Mean Squared Error is : {mse}')
print(f'R-squared is :  {r2}')
```

```
Mean Squared Error is : 0.023709525712562646
R-squared is :  0.9564019812412028
```

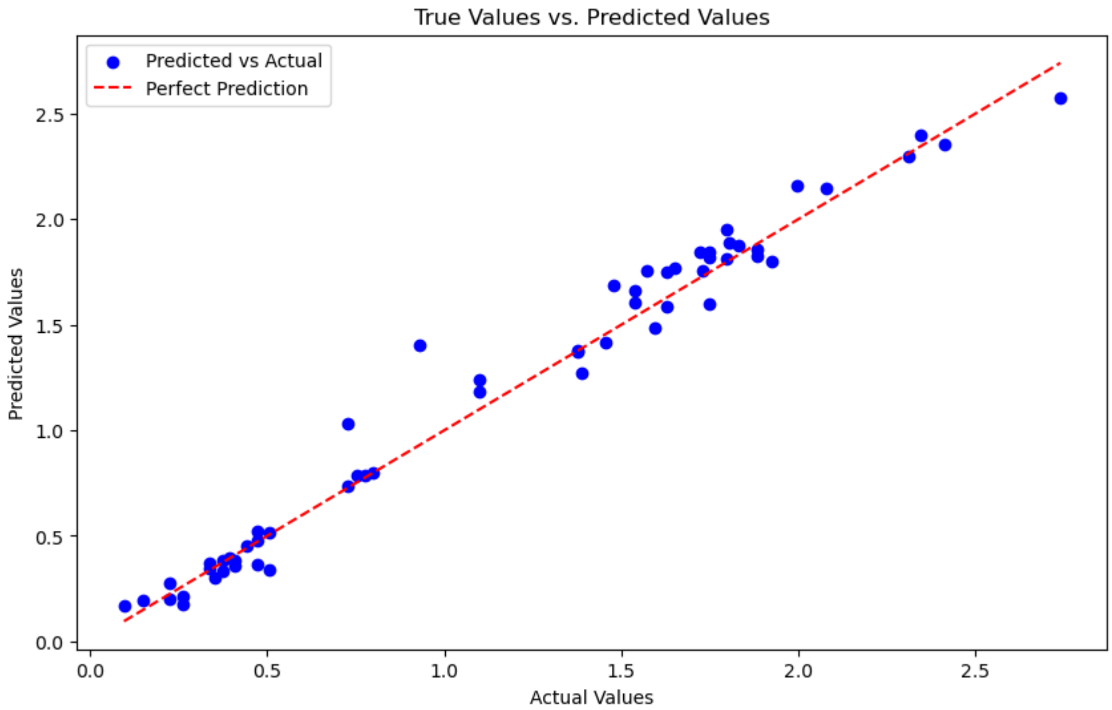
[266]:
```
linear_data=pd.DataFrame({'Actaul':y_test ,'Predicted':y_pred})
linear_data.reset_index(inplace=True,drop=True)
linear_data.head()
```

[266]:

	Actaul	Predicted
0	2.41	2.45
1	0.93	1.54
2	0.47	0.34
3	0.22	0.18
4	1.72	1.67

21 Plot True Values vs. Predicted Values

[267]:
```
plt.figure(figsize=(10, 6))
plt.scatter(gradient_data['Actual'], gradient_data['Predicted'], color='blue',␣
↪label='Predicted vs Actual')

# Line for perfect prediction
min_value = gradient_data['Actual'].min()
max_value = gradient_data['Actual'].max()
plt.plot([min_value, max_value], [min_value, max_value], color='red',␣
↪linestyle='--', label='Perfect Prediction')

plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.title('True Values vs. Predicted Values')
plt.legend()

plt.show()
```



[268]:
```
results=pd.DataFrame({
    'Model':['Gradient Boosting','Decision Tree','Lasso','LinearRegression'],
    'Score':[0.97,0.956,0.952,0.96]
})
result_pd=results.sort_values(by='Score',ascending=False)
result_pd=result_pd.set_index('Score')
result_pd
```

[268]:

Score	Model
0.97	Gradient Boosting
0.96	LinearRegression
0.96	Decision Tree
0.95	Lasso

[ ]:

[ ]: