Steps for building a machine learning model:

- Gaining the understanding of the project and what it is about
- Import libraries (atleast initial ones)
- Import the data / Get the data
- Data cleaning and understanding EDA: Exploratory data analysis:

  Univariate analysis

  - to look at the distribution in order to understand if there is an outlier present in the data Bi-variate analysis
  - When we look at the relationship between two variables (Typically between the target variable (Selling price in this case and all the other variables)

  Multivariate analysis

  - to check correlation between all the combination of features

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error
data = pd.read_csv("Cardekho.csv")
data.head(5)
```

```
   Unnamed: 0        car_name    brand     model  vehicle_age
km_driven  \
0           0     Maruti Alto   Maruti      Alto            9
120000
1           1   Hyundai Grand  Hyundai     Grand            5
20000
2           2     Hyundai i20  Hyundai       i20           11
60000
3           3     Maruti Alto   Maruti      Alto            9
37000
4           4   Ford Ecosport     Ford  Ecosport            6
30000

  seller_type fuel_type transmission_type  mileage  engine  max_power
seats  \
0  Individual    Petrol            Manual    19.70     796      46.30
5
1  Individual    Petrol            Manual    18.90    1197      82.00
5
```

```
2  Individual    Petrol            Manual    17.00    1197       80.00
5
3  Individual    Petrol            Manual    20.92     998       67.10
5
4      Dealer    Diesel            Manual    22.77    1498       98.59
5

   selling_price
0         120000
1         550000
2         215000
3         226000
4         570000
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15411 entries, 0 to 15410
Data columns (total 14 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Unnamed: 0         15411 non-null  int64
 1   car_name           15411 non-null  object
 2   brand              15411 non-null  object
 3   model              15411 non-null  object
 4   vehicle_age        15411 non-null  int64
 5   km_driven          15411 non-null  int64
 6   seller_type        15411 non-null  object
 7   fuel_type          15411 non-null  object
 8   transmission_type  15411 non-null  object
 9   mileage            15411 non-null  float64
 10  engine             15411 non-null  int64
 11  max_power          15411 non-null  float64
 12  seats              15411 non-null  int64
 13  selling_price      15411 non-null  int64
dtypes: float64(2), int64(6), object(6)
memory usage: 1.6+ MB
```

```
data.shape
```

```
(15411, 14)
```

```
# summary statistics
data.describe()
```

```
         Unnamed: 0   vehicle_age     km_driven       mileage
engine  \
count  15411.000000  15411.000000  1.541100e+04  15411.000000
15411.000000
mean    9811.857699      6.036338  5.561648e+04     19.701151
1486.057751
```

```
std      5643.418542      3.013291  5.161855e+04      4.171265
521.106696
min         0.000000      0.000000  1.000000e+02      4.000000
793.000000
25%      4906.500000      4.000000  3.000000e+04     17.000000
1197.000000
50%      9872.000000      6.000000  5.000000e+04     19.670000
1248.000000
75%     14668.500000      8.000000  7.000000e+04     22.700000
1582.000000
max     19543.000000     29.000000  3.800000e+06     33.540000
6592.000000

          max_power         seats  selling_price
count  15411.000000  15411.000000   1.541100e+04
mean     100.588254      5.325482   7.749711e+05
std       42.972979      0.807628   8.941284e+05
min       38.400000      0.000000   4.000000e+04
25%       74.000000      5.000000   3.850000e+05
50%       88.500000      5.000000   5.560000e+05
75%      117.300000      5.000000   8.250000e+05
max      626.000000      9.000000   3.950000e+07
```

```
data['car_name'].value_counts()
```

```
car_name
Hyundai i20            906
Maruti Swift Dzire     890
Maruti Swift           781
Maruti Alto            778
Honda City             757
                      ...
Mercedes-AMG C           1
Tata Altroz              1
Ferrari GTC4Lusso        1
Hyundai Aura             1
Force Gurkha             1
Name: count, Length: 121, dtype: int64
```

```
data['fuel_type'].value_counts()
```

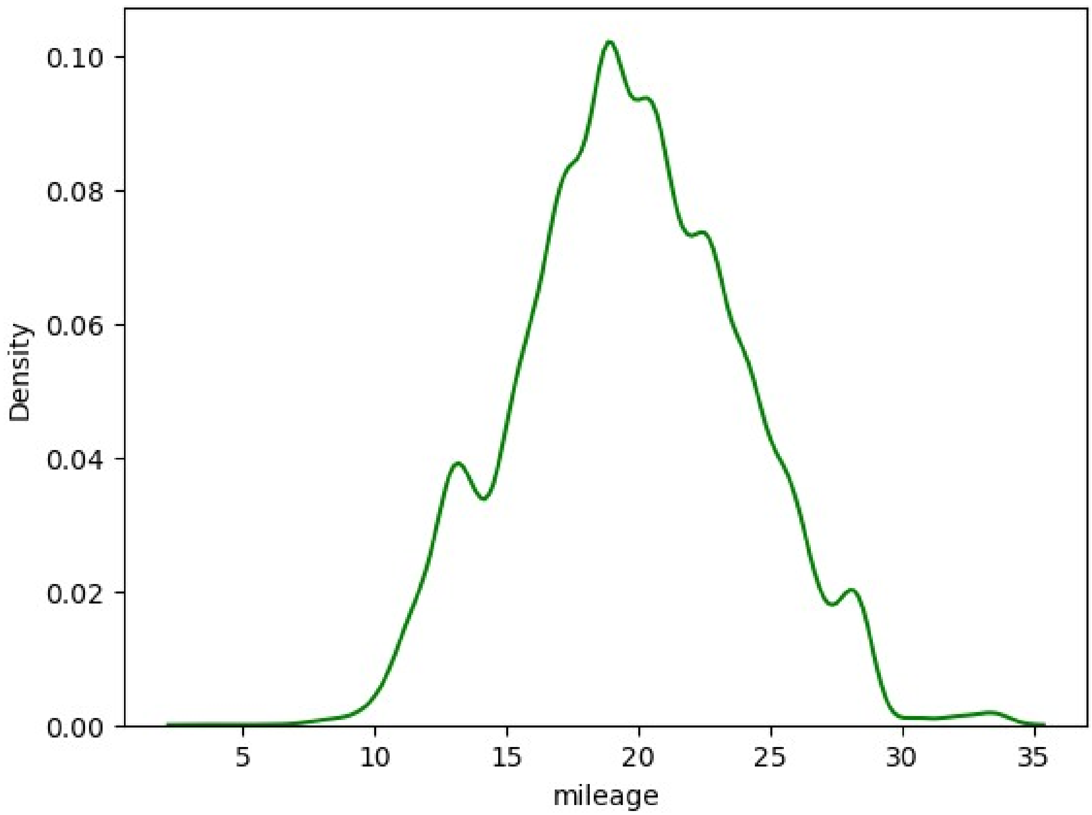
```
fuel_type
Petrol      7643
Diesel      7419
CNG          301
LPG           44
Electric       4
Name: count, dtype: int64
```

```
data['mileage'].mean()
```

```
19.70115112581922
```

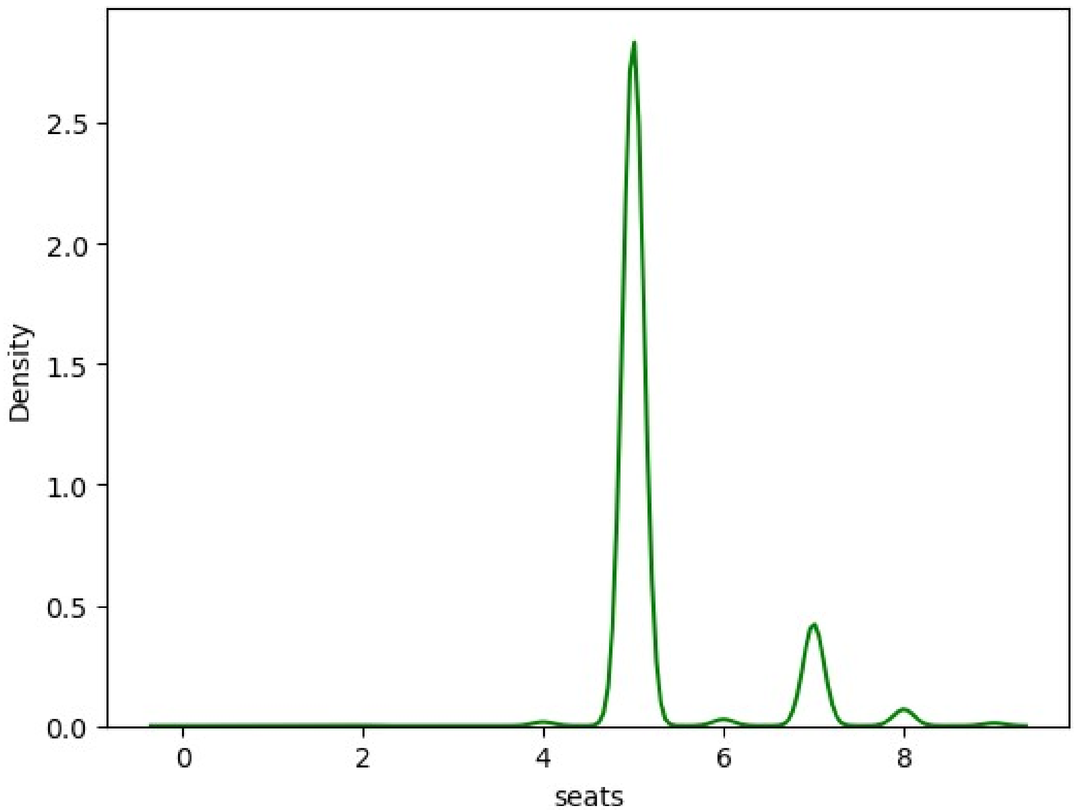
```
sns.kdeplot(x = data['mileage'],color = 'g')
```

```
<Axes: xlabel='mileage', ylabel='Density'>
```



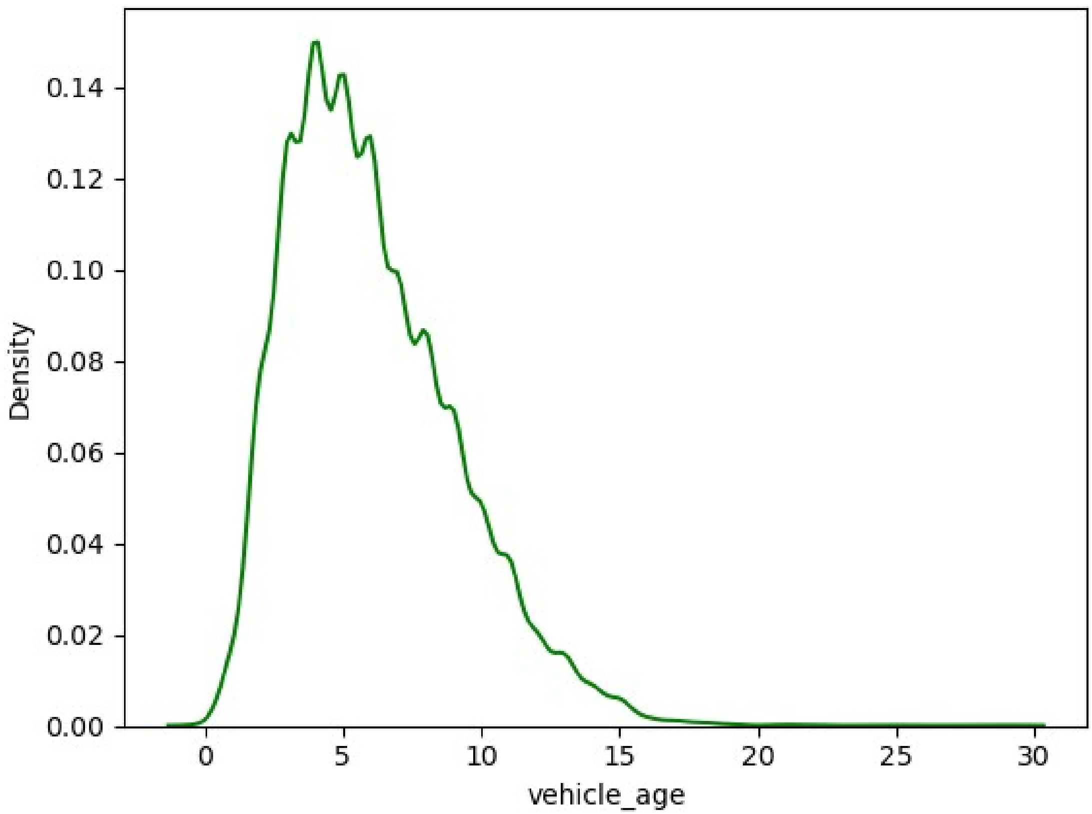

```
sns.kdeplot(x = data['seats'],color = 'g')
```

```
<Axes: xlabel='seats', ylabel='Density'>
```



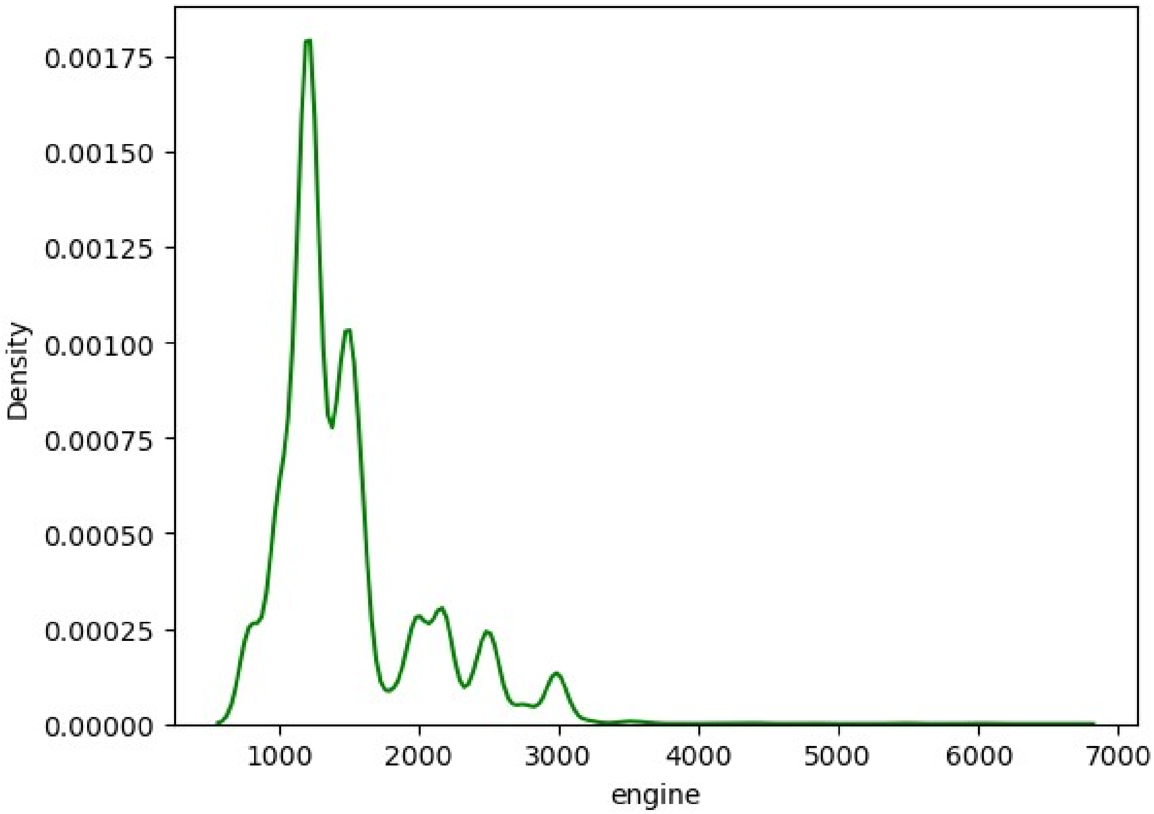

```
sns.kdeplot(x = data['vehicle_age'],color = 'g')
```

```
<Axes: xlabel='vehicle_age', ylabel='Density'>
```



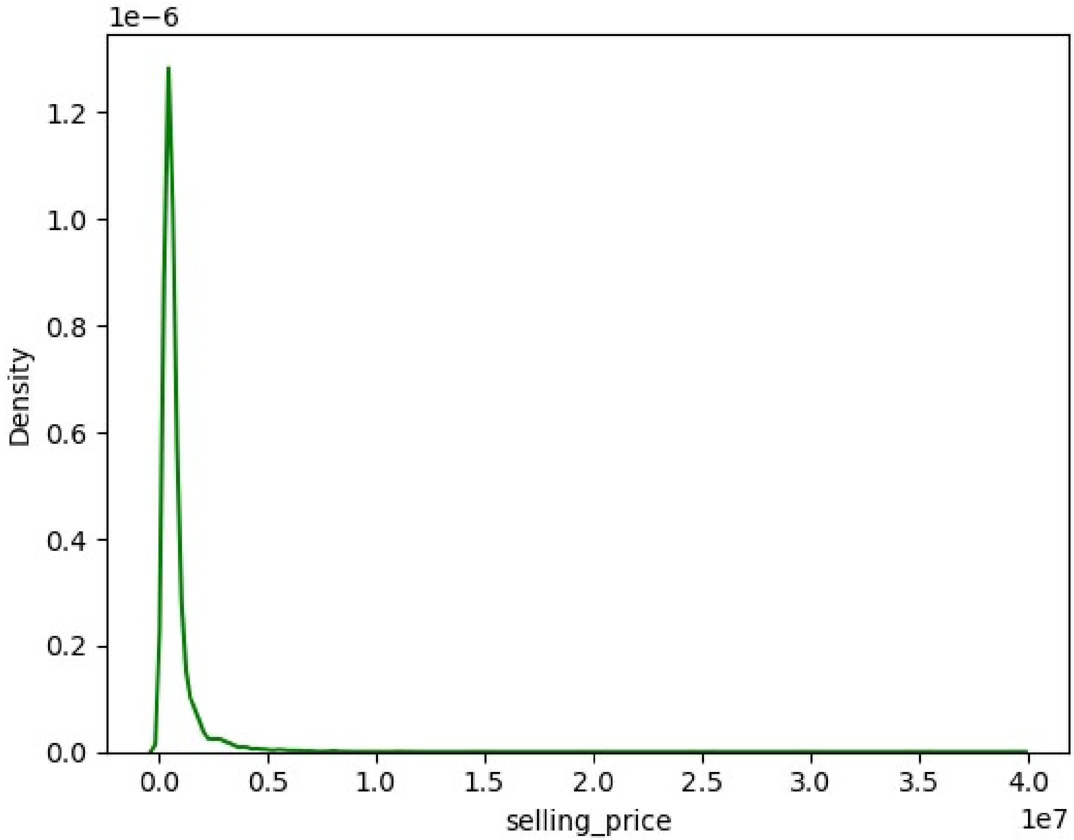

```
sns.kdeplot(x = data['engine'],color = 'g')
```

```
<Axes: xlabel='engine', ylabel='Density'>
```



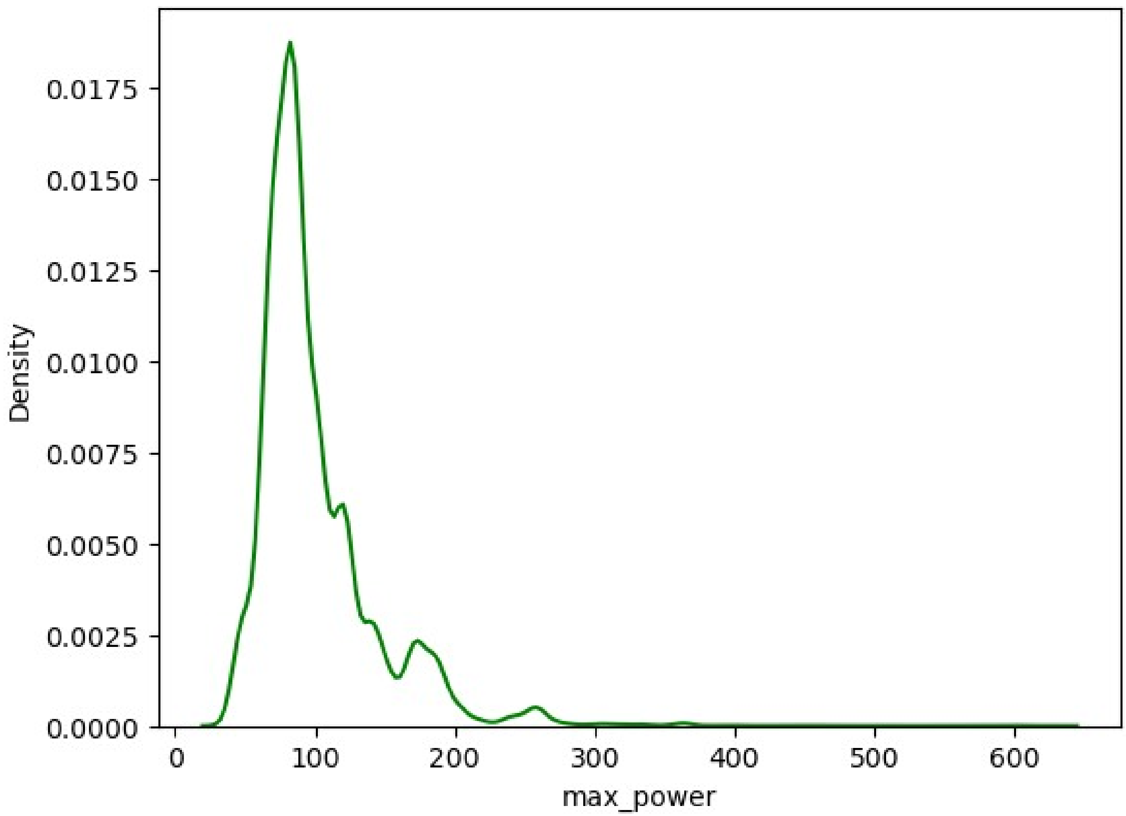

```
sns.kdeplot(x =data['selling_price'],color = 'g')
```

```
<Axes: xlabel='selling_price', ylabel='Density'>
```



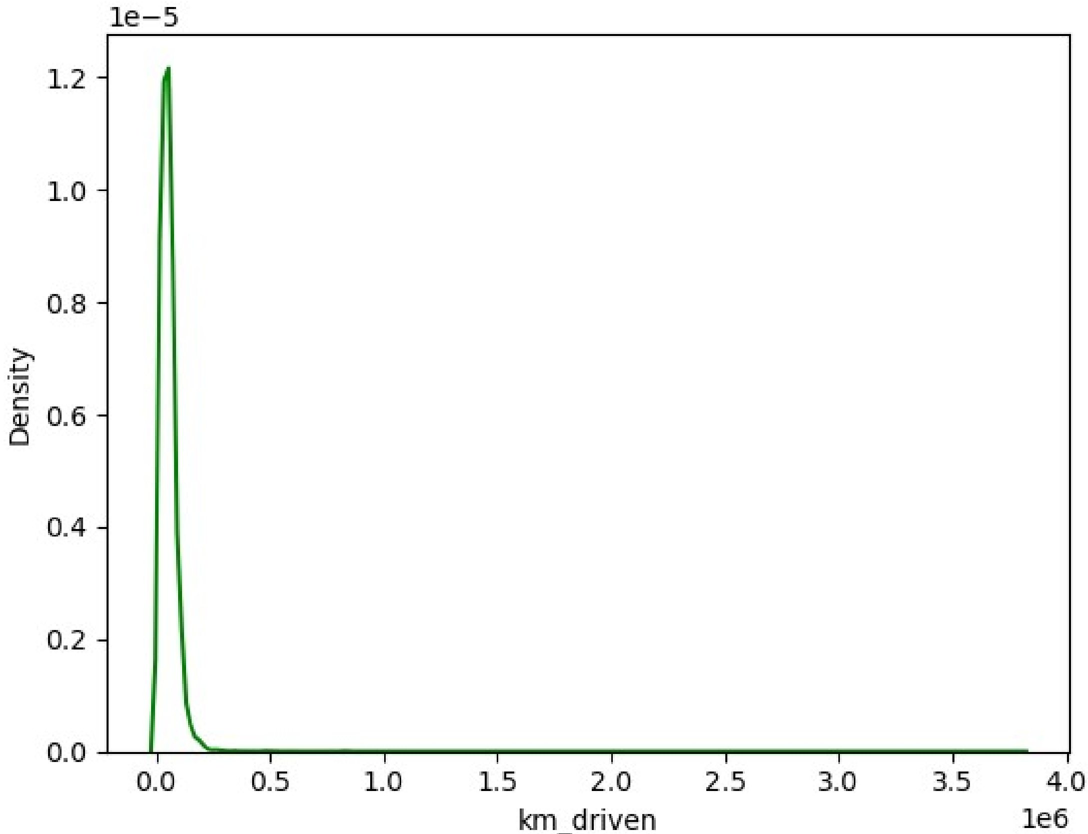

```
sns.kdeplot(x =data['max_power'],color = 'g')
```

```
<Axes: xlabel='max_power', ylabel='Density'>
```




```
sns.kdeplot(x =data['km_driven'],color = 'g')
```

```
<Axes: xlabel='km_driven', ylabel='Density'>
```



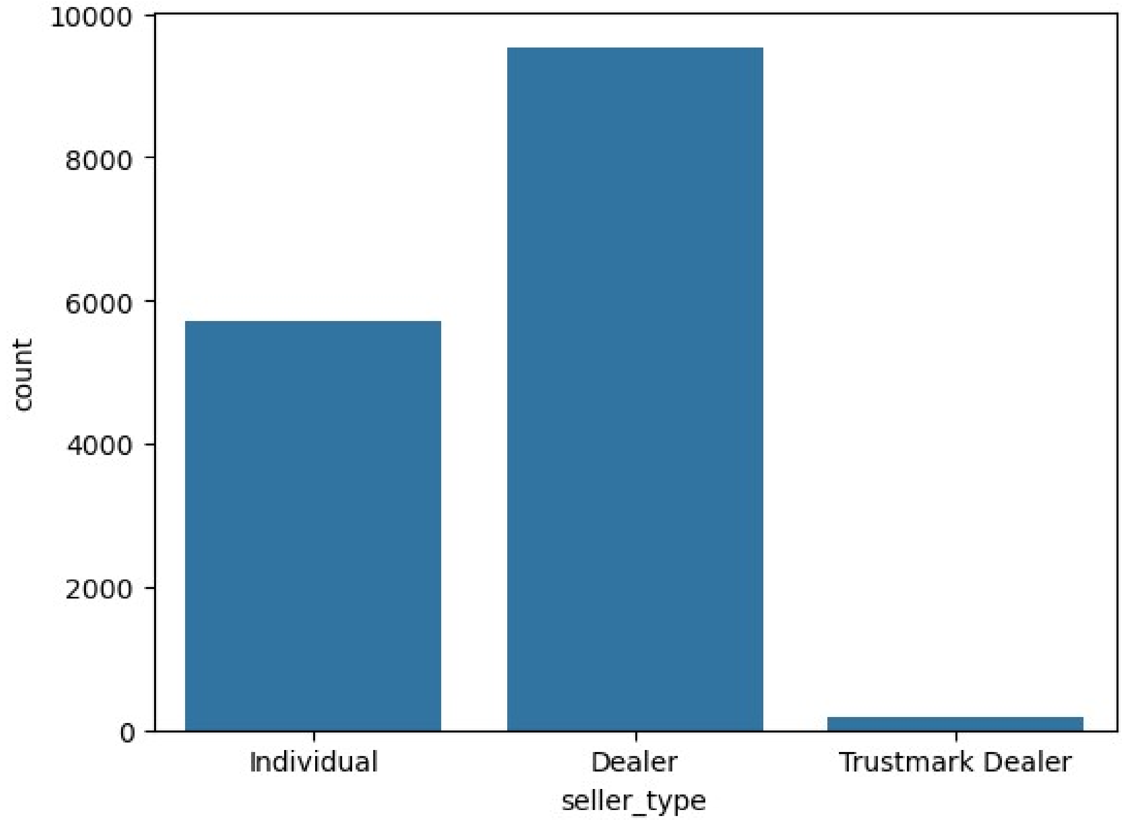

```
data[data['max_power'] >= 400]
```

```
      Unnamed: 0               car_name          brand
model  \
1172         1508    Bentley Continental        Bentley  Continental

1209         1556        Porsche Cayenne        Porsche      Cayenne

3799         4845      Ferrari GTC4Lusso        Ferrari    GTC4Lusso

9190        11816        Porsche Cayenne        Porsche      Cayenne

9364        12023        Porsche Cayenne        Porsche      Cayenne

9450        12131                  BMW 6            BMW            6

9722        12456  Mercedes-Benz S-Class  Mercedes-Benz      S-Class

10040       12839    Bentley Continental        Bentley  Continental

10969       13944      Rolls-Royce Ghost    Rolls-Royce        Ghost

12067       15307                  BMW 7            BMW            7
```

```
12997       16498    Bentley Continental        Bentley  Continental


       vehicle_age  km_driven seller_type fuel_type transmission_type
\
1172             9       9000      Dealer    Petrol         Automatic

1209             4      36000      Dealer    Petrol         Automatic

3799             2       3800      Dealer    Petrol         Automatic

9190            12     126000  Individual    Petrol         Automatic

9364             4      24000      Dealer    Petrol         Automatic

9450            12      65000      Dealer    Petrol         Automatic

9722             3       4000      Dealer    Petrol         Automatic

10040            9      37500      Dealer    Petrol         Automatic

10969            4       5000  Individual    Petrol         Automatic

12067           11      64000      Dealer    Petrol         Automatic

12997           10      30000      Dealer    Petrol         Automatic


       mileage  engine  max_power  seats  selling_price
1172      9.50    5998      626.0      4       14500000
1209     12.50    3604      420.0      5        7800000
3799      4.00    3855      601.0      4       39500000
9190      8.50    4806      500.0      5        2000000
9364     12.50    3604      440.0      5       11100000
9450      7.94    4395      450.0      4        1500000
9722      7.81    4663      459.0      4       13000000
10040     6.00    5998      600.0      5        5200000
10969    10.20    6592      563.0      4       24200000
12067     8.77    4395      402.0      5        1499000
12997     8.60    5998      552.0      4        8100000
```

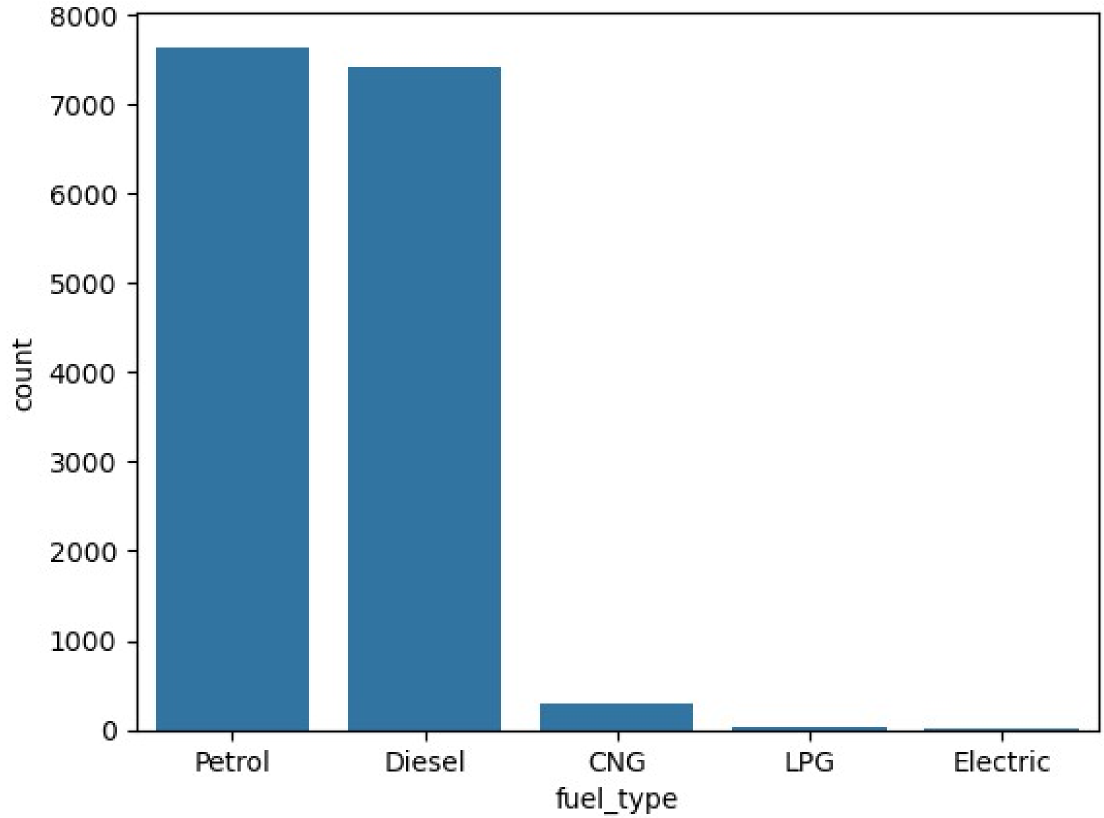
```python
sns.countplot(x = data['seller_type'])
```

```
<Axes: xlabel='seller_type', ylabel='count'>
```



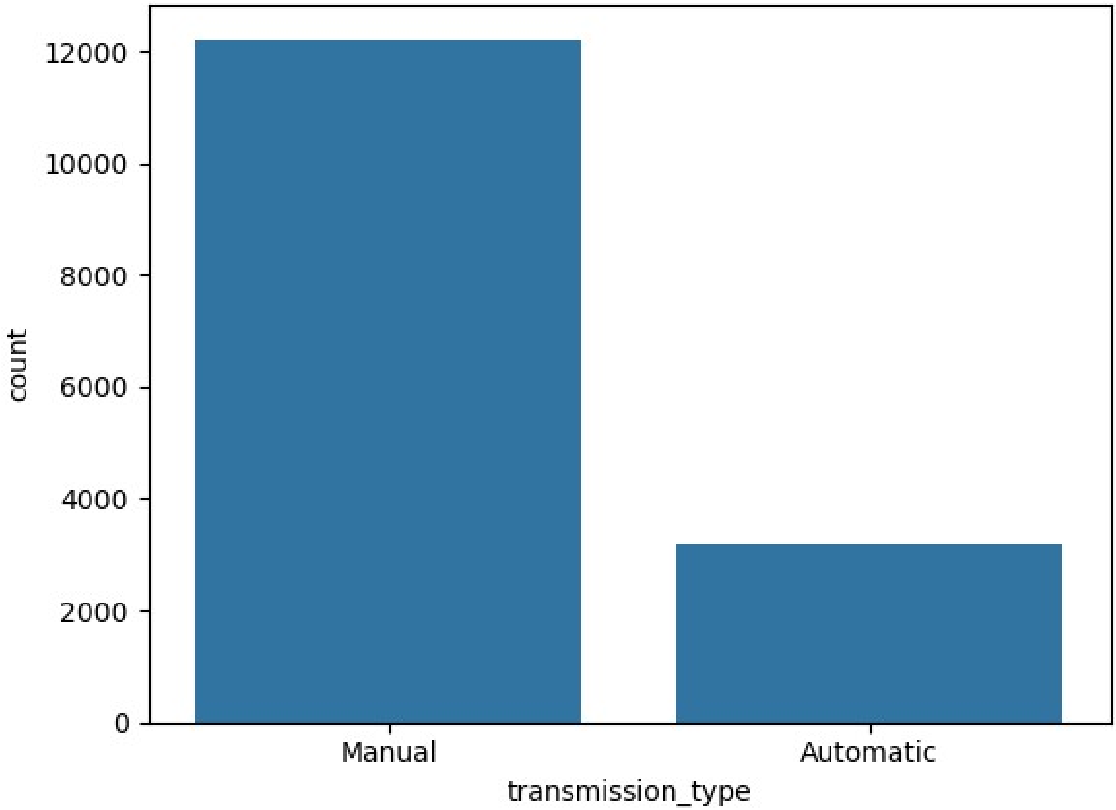

```
sns.countplot(x =data['fuel_type'])
```

```
<Axes: xlabel='fuel_type', ylabel='count'>
```

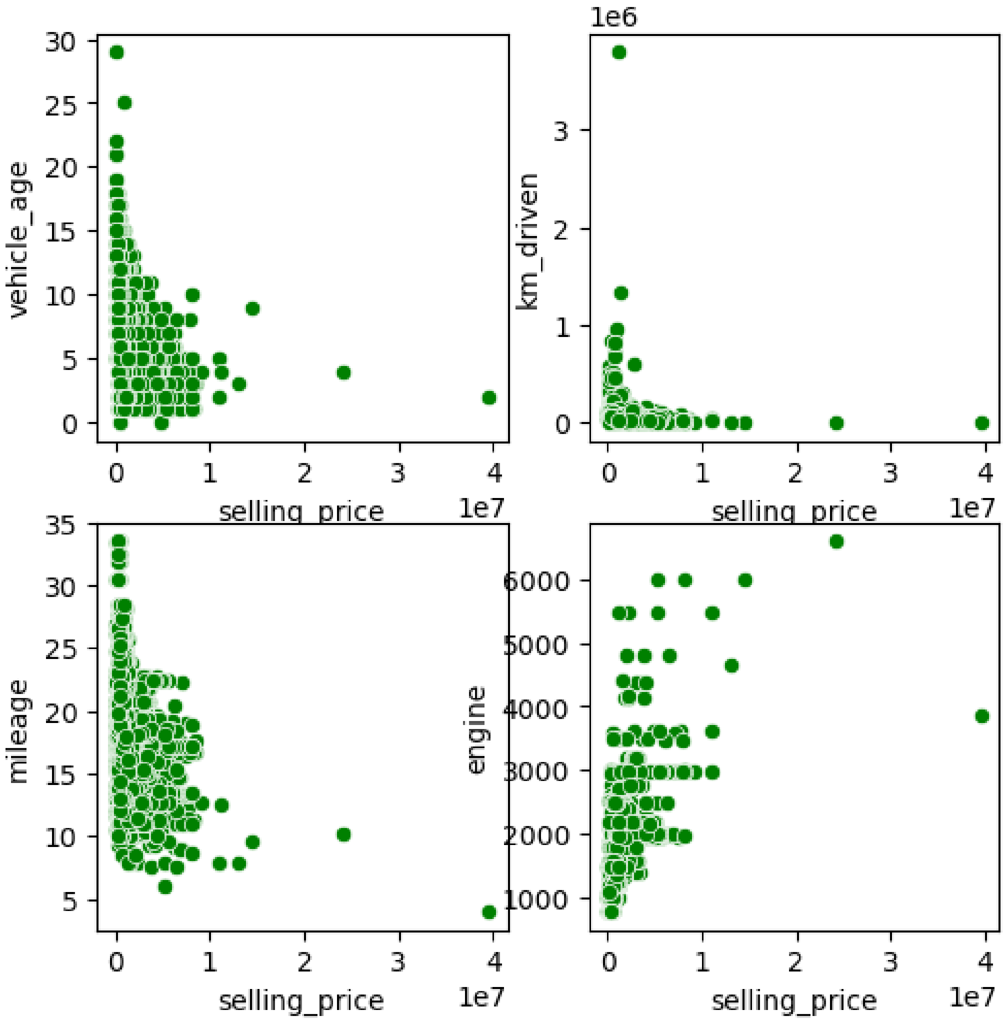



```
sns.countplot(x = data['transmission_type'])
```

```
<Axes: xlabel='transmission_type', ylabel='count'>
```

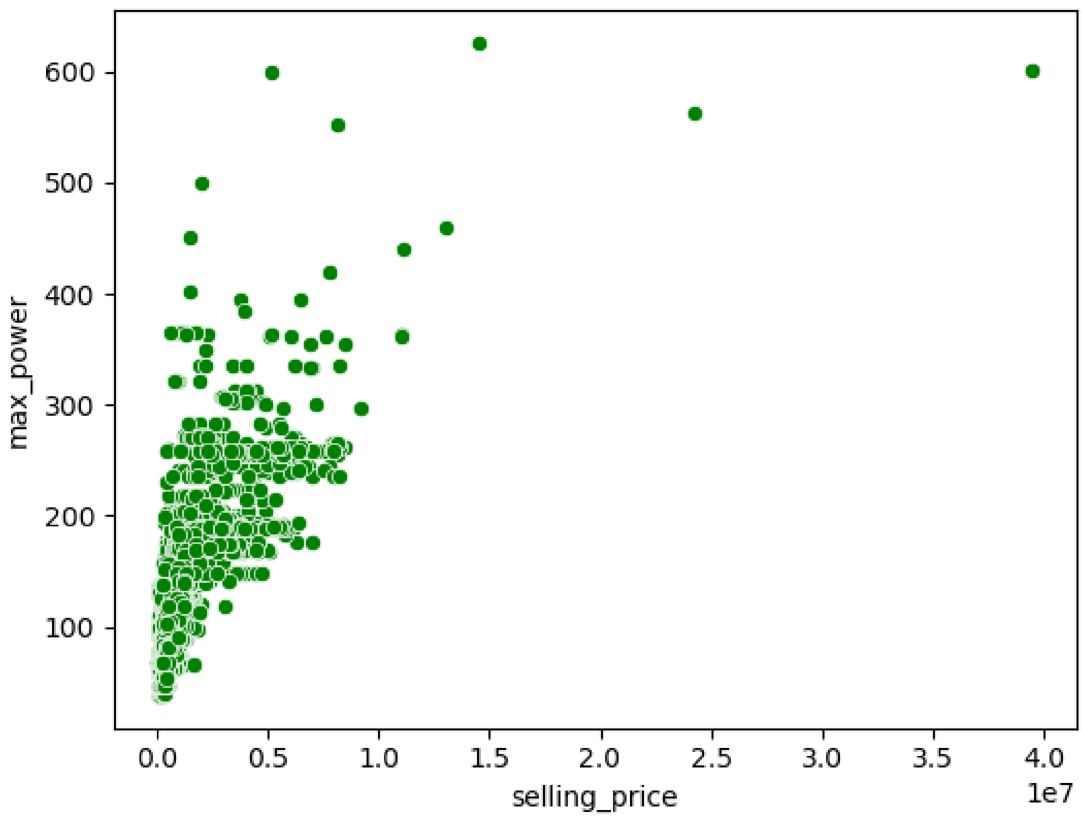



```
#Lets look at the relationship of each variable with the selling price
(Target variable)

fig = plt.figure(figsize = (6,6))

features = ['vehicle_age','km_driven','mileage','engine']

for i in range(len(features)):
    plt.subplot(2,2,i+1)
    sns.scatterplot(data = data, x = 'selling_price',y =
features[i],color = 'g')
```



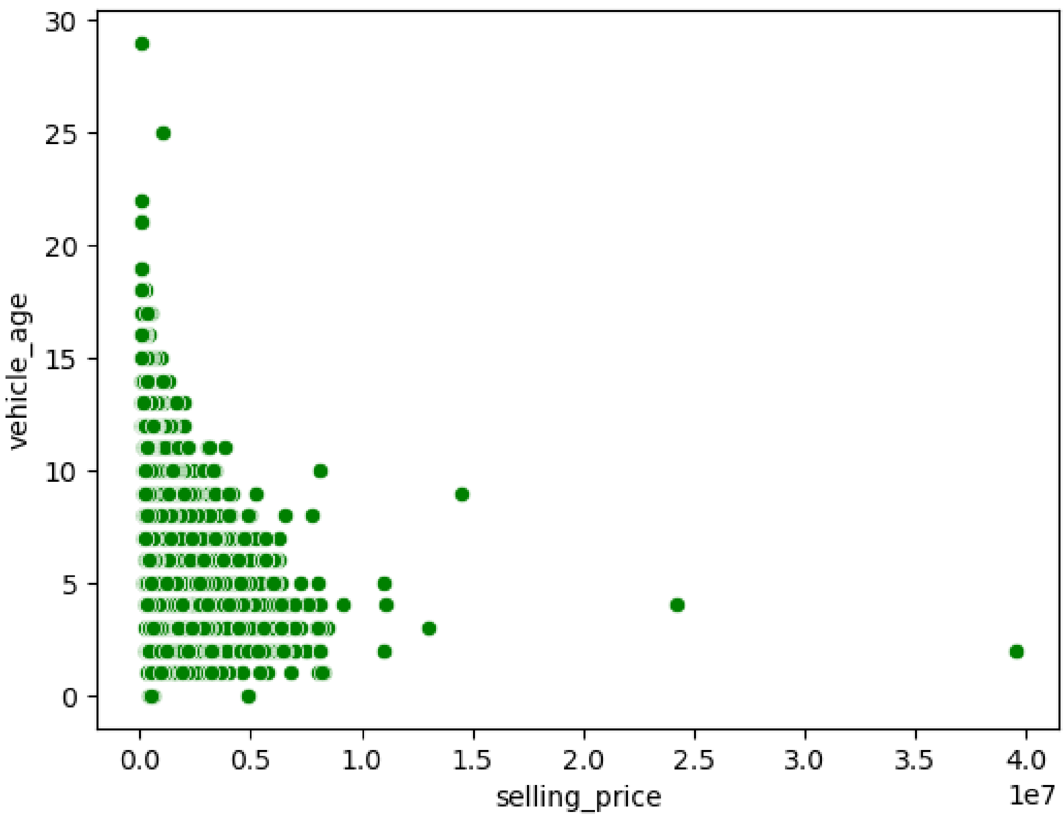

```
sns.scatterplot(data = data, x = 'selling_price', y =
'max_power',color  = 'g')
```

```
<Axes: xlabel='selling_price', ylabel='max_power'>
```



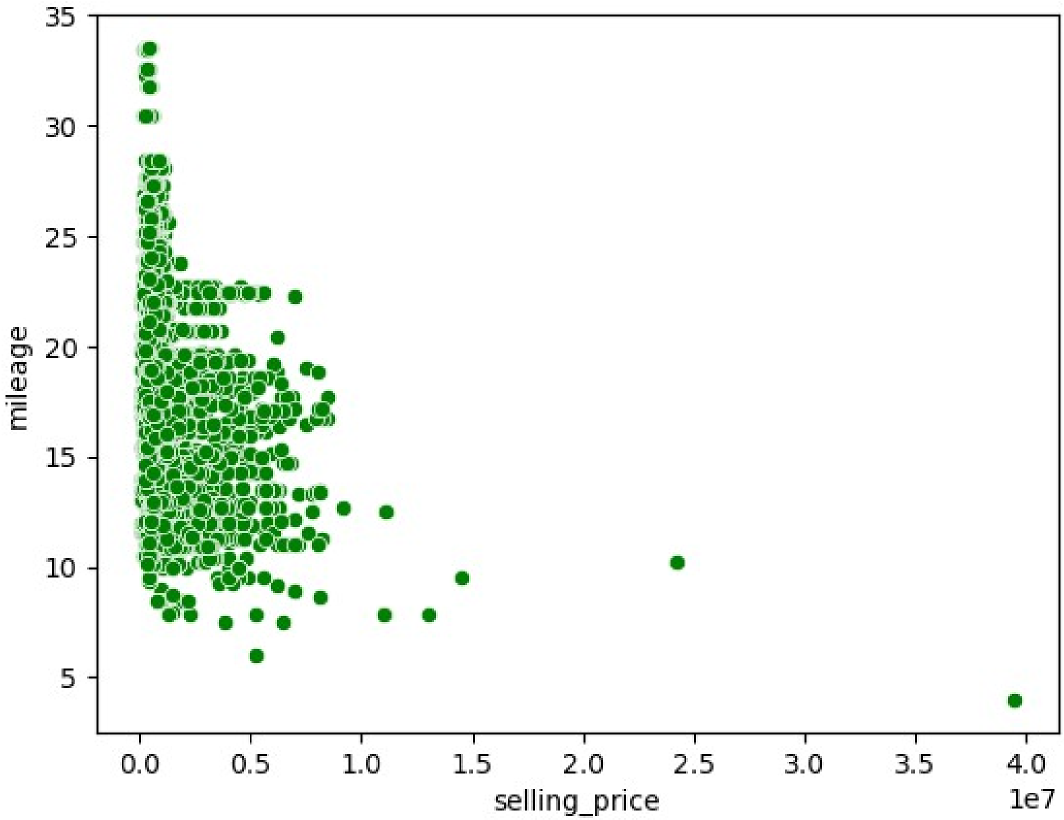

```
sns.scatterplot(data = data, x = 'selling_price', y =
'vehicle_age',color  = 'g')
```

```
<Axes: xlabel='selling_price', ylabel='vehicle_age'>
```



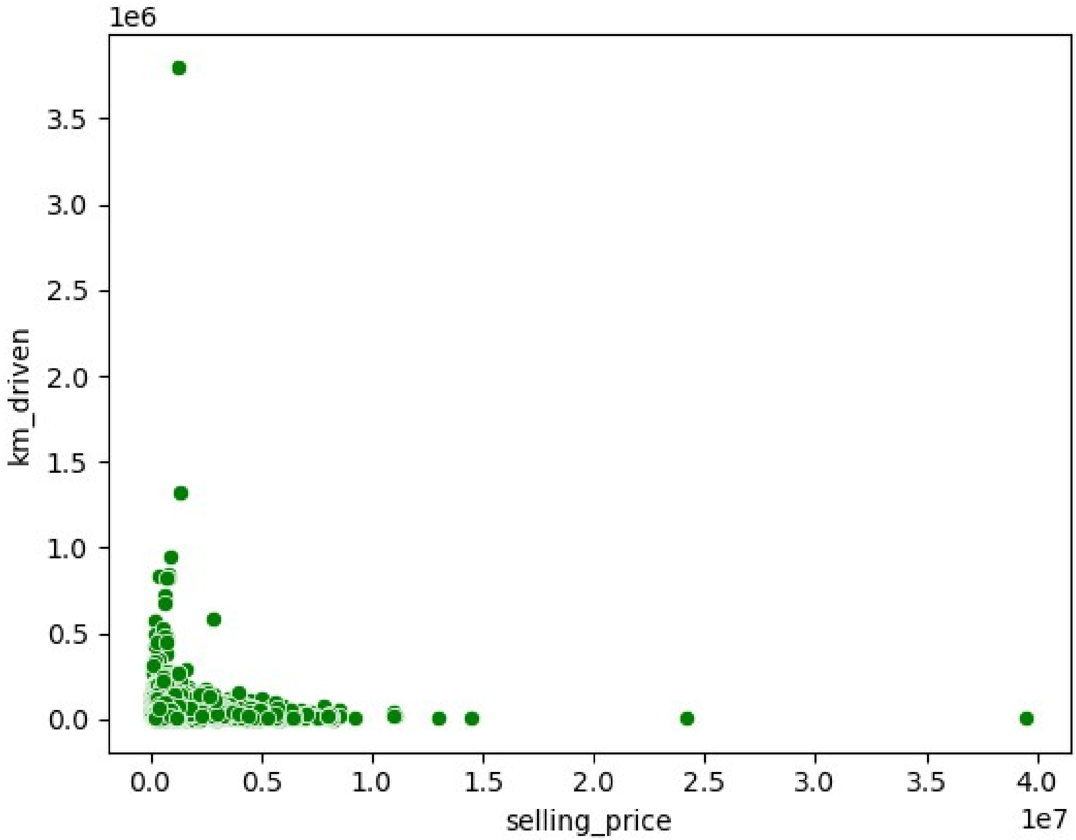

```
sns.scatterplot(data = data, x = 'selling_price', y =  'mileage',color
= 'g')
```

```
<Axes: xlabel='selling_price', ylabel='mileage'>
```



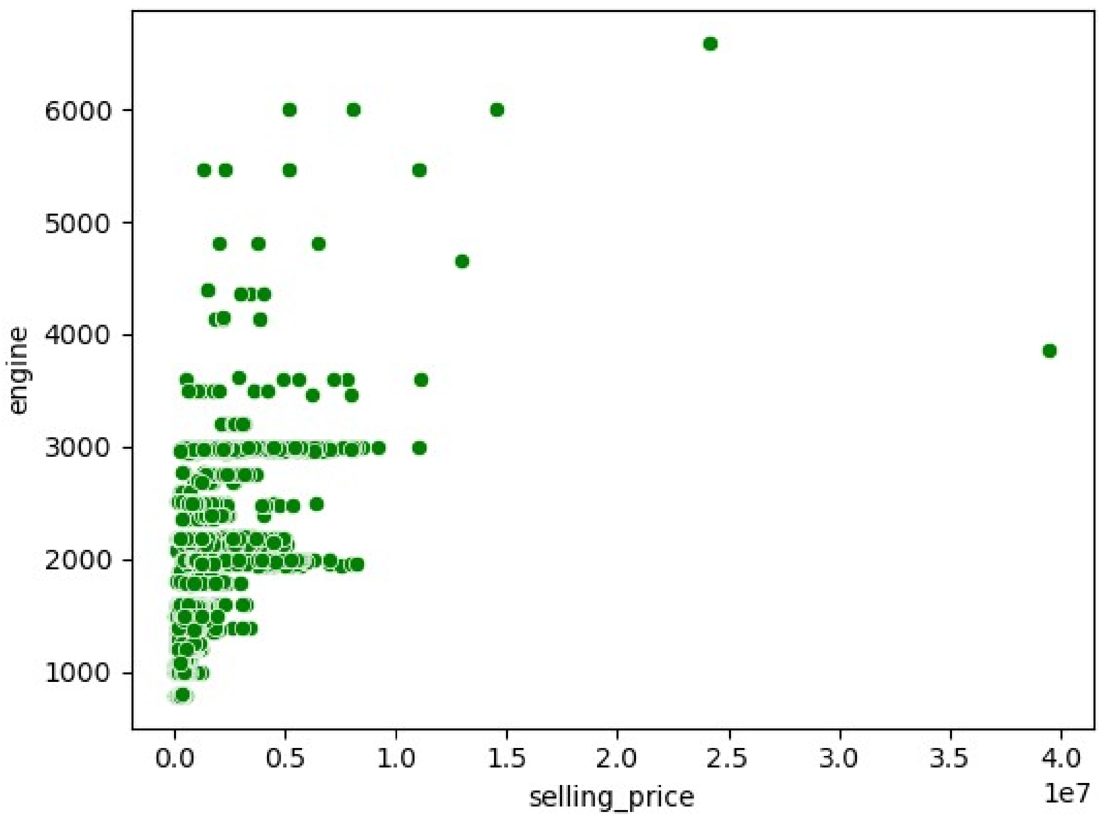

```
sns.scatterplot(data = data, x = 'selling_price', y =
'km_driven',color  = 'g')
```

```
<Axes: xlabel='selling_price', ylabel='km_driven'>
```



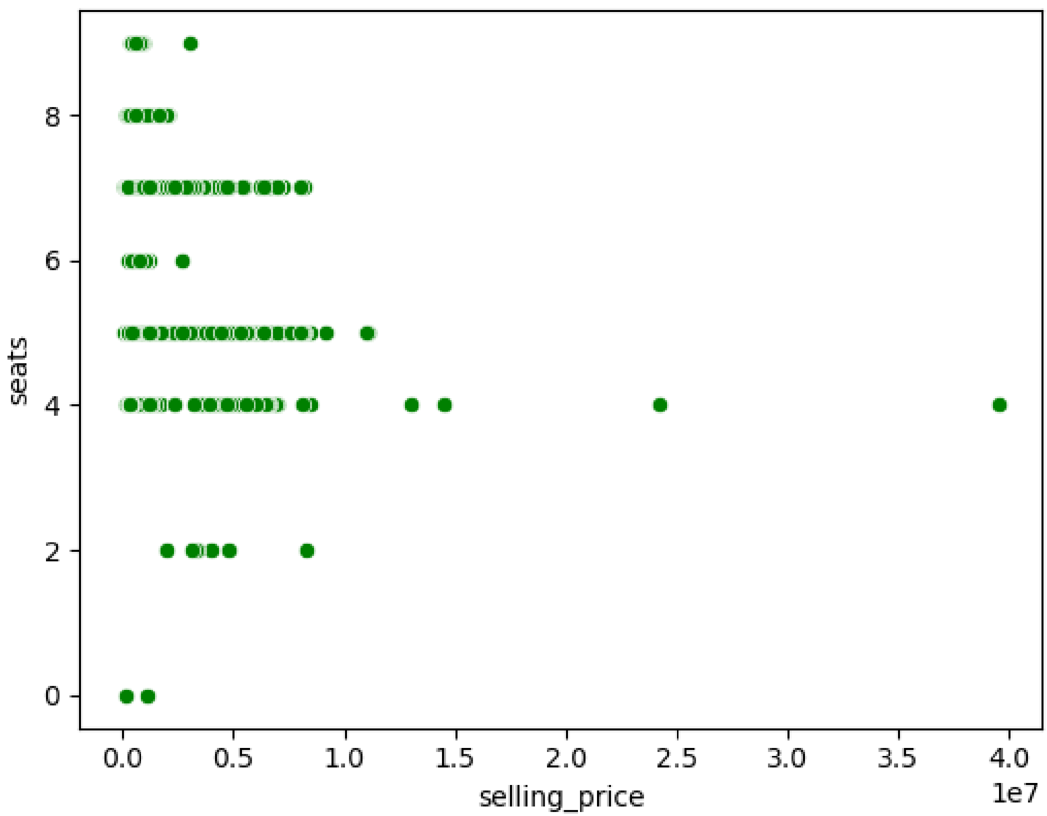

```
sns.scatterplot(data = data, x = 'selling_price', y =  'engine',color
= 'g')
```

```
<Axes: xlabel='selling_price', ylabel='engine'>
```




```
sns.scatterplot(data = data, x = 'selling_price', y =  'seats',color
= 'g')
```

```
<Axes: xlabel='selling_price', ylabel='seats'>
```




```
#Multi-variate analysis - to check correlation between all the combination of numerical features
features =
['vehicle_age','km_driven','mileage','engine','max_power','seats','selling_price']
data[features].corr()
```

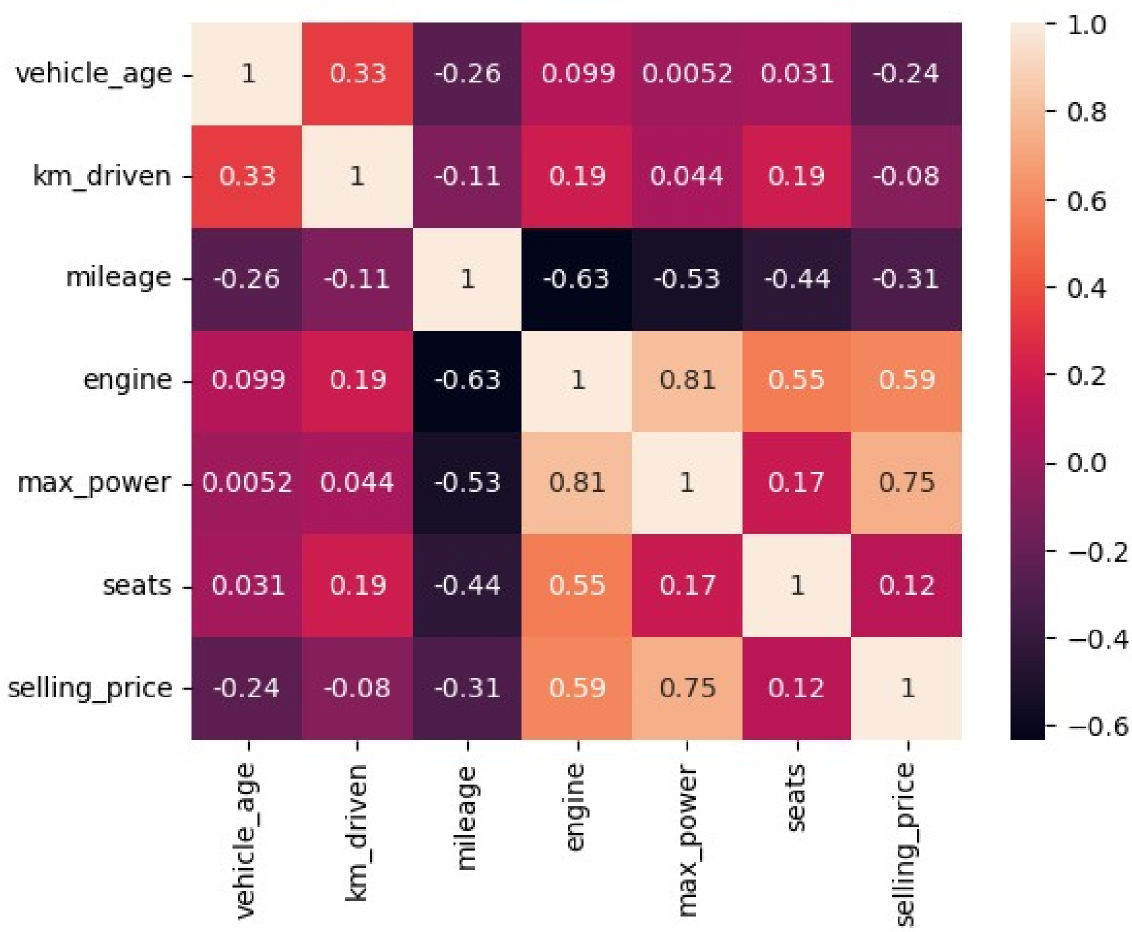
	vehicle_age	km_driven	mileage	engine	max_power
vehicle_age	1.000000	0.333891	-0.257394	0.098965	0.005208
km_driven	0.333891	1.000000	-0.105239	0.192885	0.044421
mileage	-0.257394	-0.105239	1.000000	-0.632987	-0.533128
engine	0.098965	0.192885	-0.632987	1.000000	0.807368
max_power	0.005208	0.044421	-0.533128	0.807368	1.000000
seats	0.030791	0.192830	-0.440280	0.551236	0.172257
selling_price	-0.241851	-0.080030	-0.305549	0.585844	0.750236

	seats	selling_price

```
vehicle_age    0.030791      -0.241851
km_driven      0.192830      -0.080030
mileage       -0.440280      -0.305549
engine         0.551236       0.585844
max_power      0.172257       0.750236
seats          1.000000       0.115033
selling_price  0.115033       1.000000
```

```python
sns.heatmap(data = data[features].corr(),annot = True)
```

```
<Axes: >
```




```python
data.head()
```

```
   Unnamed: 0       car_name    brand     model  vehicle_age
km_driven  \
0           0    Maruti Alto   Maruti      Alto            9
120000
1           1  Hyundai Grand  Hyundai     Grand            5
20000
2           2    Hyundai i20  Hyundai       i20           11
```

```
60000
3           3    Maruti Alto   Maruti      Alto            9
37000
4           4  Ford Ecosport     Ford  Ecosport            6
30000

  seller_type fuel_type transmission_type  mileage  engine  max_power
seats  \
0  Individual    Petrol            Manual    19.70     796      46.30
5
1  Individual    Petrol            Manual    18.90    1197      82.00
5
2  Individual    Petrol            Manual    17.00    1197      80.00
5
3  Individual    Petrol            Manual    20.92     998      67.10
5
4      Dealer    Diesel            Manual    22.77    1498      98.59
5

   selling_price
0         120000
1         550000
2         215000
3         226000
4         570000
```

```
model_data = data.copy()
model_data.head()
```

```
   Unnamed: 0       car_name    brand     model  vehicle_age
km_driven  \
0           0    Maruti Alto   Maruti      Alto            9
120000
1           1  Hyundai Grand  Hyundai     Grand            5
20000
2           2    Hyundai i20  Hyundai       i20           11
60000
3           3    Maruti Alto   Maruti      Alto            9
37000
4           4  Ford Ecosport     Ford  Ecosport            6
30000

  seller_type fuel_type transmission_type  mileage  engine  max_power
seats  \
0  Individual    Petrol            Manual    19.70     796      46.30
5
1  Individual    Petrol            Manual    18.90    1197      82.00
5
2  Individual    Petrol            Manual    17.00    1197      80.00
5
```

```
3  Individual    Petrol             Manual    20.92     998      67.10
5
4      Dealer    Diesel             Manual    22.77    1498      98.59
5

   selling_price
0         120000
1         550000
2         215000
3         226000
4         570000
```

```
model_data.drop(labels =
['car_name','brand','model','seller_type'],axis = 1, inplace = True)
model_data
```

```
       Unnamed: 0  vehicle_age  km_driven fuel_type transmission_type
\
0               0            9     120000    Petrol            Manual

1               1            5      20000    Petrol            Manual

2               2           11      60000    Petrol            Manual

3               3            9      37000    Petrol            Manual

4               4            6      30000    Diesel            Manual

...           ...          ...        ...       ...               ...

15406       19537            9      10723    Petrol            Manual

15407       19540            2      18000    Petrol            Manual

15408       19541            6      67000    Diesel            Manual

15409       19542            5    3800000    Diesel            Manual

15410       19543            2      13000    Petrol         Automatic


       mileage  engine  max_power  seats  selling_price
0        19.70     796      46.30      5         120000
1        18.90    1197      82.00      5         550000
2        17.00    1197      80.00      5         215000
3        20.92     998      67.10      5         226000
4        22.77    1498      98.59      5         570000
...        ...     ...        ...    ...            ...
15406    19.81    1086      68.05      5         250000
15407    17.50    1373      91.10      7         925000
15408    21.14    1498     103.52      5         425000
```

```
15409    16.00    2179     140.00      7        1225000
15410    18.00    1497     117.60      5        1200000

[15411 rows x 10 columns]
```

```python
model_data = pd.get_dummies(model_data,dtype = float)
model_data
```

```
       Unnamed: 0  vehicle_age  km_driven  mileage  engine  max_power  
seats  \
0               0            9     120000    19.70     796      46.30      
5
1               1            5      20000    18.90    1197      82.00      
5
2               2           11      60000    17.00    1197      80.00      
5
3               3            9      37000    20.92     998      67.10      
5
4               4            6      30000    22.77    1498      98.59      
5
...           ...          ...        ...      ...     ...        ...    
...
15406       19537            9      10723    19.81    1086      68.05      
5
15407       19540            2      18000    17.50    1373      91.10      
7
15408       19541            6      67000    21.14    1498     103.52      
5
15409       19542            5    3800000    16.00    2179     140.00      
7
15410       19543            2      13000    18.00    1497     117.60      
5

       selling_price  fuel_type_CNG  fuel_type_Diesel  
fuel_type_Electric  \
0             120000            0.0               0.0                 
0.0
1             550000            0.0               0.0                 
0.0
2             215000            0.0               0.0                 
0.0
3             226000            0.0               0.0                 
0.0
4             570000            0.0               1.0                 
0.0
...              ...            ...               ...                 
...
15406         250000            0.0               0.0                 
0.0
15407         925000            0.0               0.0
```

```
0.0
15408         425000            0.0                 1.0
0.0
15409        1225000            0.0                 1.0
0.0
15410        1200000            0.0                 0.0
0.0

       fuel_type_LPG  fuel_type_Petrol  transmission_type_Automatic  \
0                0.0               1.0                          0.0
1                0.0               1.0                          0.0
2                0.0               1.0                          0.0
3                0.0               1.0                          0.0
4                0.0               0.0                          0.0
...              ...               ...                          ...
15406            0.0               1.0                          0.0
15407            0.0               1.0                          0.0
15408            0.0               0.0                          0.0
15409            0.0               0.0                          0.0
15410            0.0               1.0                          1.0

       transmission_type_Manual
0                           1.0
1                           1.0
2                           1.0
3                           1.0
4                           1.0
...                         ...
15406                       1.0
15407                       1.0
15408                       1.0
15409                       1.0
15410                       0.0

[15411 rows x 15 columns]

"""Linear regression - Modelling
Y (Target variable) = m1x1 + m2x2 + m3x3 ............
We will drop selling_price from independent variable"""
X = model_data.drop('selling_price', axis = 1)
# For getting the target variable we will just have selling_price
Y = model_data['selling_price']
Y

0         120000
1         550000
2         215000
3         226000
4         570000
          ...
```

```
15406     250000
15407     925000
15408     425000
15409    1225000
15410    1200000
Name: selling_price, Length: 15411, dtype: int64
```

```python
# To divide the data into Train and Test
train_X, test_X,train_Y,test_Y = train_test_split(X,Y,test_size = 0.2)
train_X
# 80% of the data goes to training and 20% of the data goes to testing
```

```
       Unnamed: 0  vehicle_age  km_driven  mileage  engine  max_power
seats  \
1181         1520           17      80000    19.70     796      46.30
5
6240         7983            6      44842    28.40    1248      74.02
5
10514       13401            8      54000    20.50    1598     103.50
5
14593       18501            4      44771    28.09    1373      91.10
5
12547       15903           10     100000    17.80    1248      75.00
5
...           ...          ...        ...      ...     ...        ...
...
9098        11704            2      11000    23.84    1199      84.00
5
12695       16100            8     127000    11.50    2982     171.00
7
7517         9610           10     100000    20.54    1598     103.60
5
991          1276            7      61251    20.45    1461      83.80
5
11251       14289            6      51000    26.20     998      58.20
5

       fuel_type_CNG  fuel_type_Diesel  fuel_type_Electric
fuel_type_LPG  \
1181             0.0               0.0                 0.0
0.0
6240             0.0               1.0                 0.0
0.0
10514            0.0               1.0                 0.0
0.0
14593            0.0               0.0                 0.0
0.0
12547            0.0               1.0                 0.0
0.0
...              ...               ...                 ...
```

```
...
9098             0.0                 0.0                   0.0
0.0
12695            0.0                 1.0                   0.0
0.0
7517             0.0                 1.0                   0.0
0.0
991              0.0                 1.0                   0.0
0.0
11251            1.0                 0.0                   0.0
0.0

       fuel_type_Petrol  transmission_type_Automatic
transmission_type_Manual
1181                1.0                          0.0
1.0
6240                0.0                          0.0
1.0
10514               0.0                          0.0
1.0
14593               1.0                          0.0
1.0
12547               0.0                          0.0
1.0
...                 ...                          ...
...
9098                1.0                          0.0
1.0
12695               0.0                          0.0
1.0
7517                0.0                          0.0
1.0
991                 0.0                          0.0
1.0
11251               0.0                          0.0
1.0

[12328 rows x 14 columns]
```

```python
# Applying regression for training the model
Regressor = LinearRegression().fit(train_X,train_Y)
Regressor
LinearRegression()
# Getting the predictions
prediction = Regressor.predict(test_X)
print(prediction)
print(test_Y)
```

```
[ 298764.80863926  561655.76228784  405226.04293342 ...
87698.49988432
```

```
 3303625.82548873   86586.84118008]
275       390000
13673     450000
1263      320000
3566     1400000
6791      565000
          ...
15277     400000
4351      620000
9423      235000
14820    2250000
13059     425000
Name: selling_price, Length: 3083, dtype: int64
```

```
test_X['predicted_sales_price'] = prediction
test_X['Actual_price'] = test_Y
test_X['difference'] = test_X['predicted_sales_price'] -
test_X['Actual_price']
test_X
```

```
       Unnamed: 0  vehicle_age  km_driven  mileage  engine  max_power
seats  \
275           354            7      61500    23.40    1248      74.00
5
13673       17344            7      58100    22.70    1498      89.84
5
1263         1623            7      40000    20.40    1197      81.80
5
3566         4550            3      40000    17.60    2179     153.86
7
6791         8665            8      74000    22.70    1498      89.84
5
...           ...          ...        ...      ...     ...        ...
...
15277       19369            6      31200    20.40    1197      81.80
5
4351         5525            8      50000    22.32    1582     126.32
5
9423        12097            5      36000    22.70     799      53.64
5
14820       18788            9     110000    14.74    2993     270.90
5
13059       16577           11      80000    18.60    1197      81.83
5

       fuel_type_CNG  fuel_type_Diesel  fuel_type_Electric
fuel_type_LPG  \
275              0.0               1.0                 0.0
0.0
13673            0.0               1.0                 0.0
```

```
0.0
1263             0.0               0.0                 0.0
0.0
3566             0.0               1.0                 0.0
0.0
6791             0.0               1.0                 0.0
0.0
...              ...               ...                 ...
...
15277            0.0               0.0                 0.0
0.0
4351             0.0               1.0                 0.0
0.0
9423             0.0               0.0                 0.0
0.0
14820            0.0               1.0                 0.0
0.0
13059            0.0               0.0                 0.0
0.0

       fuel_type_Petrol  transmission_type_Automatic  \
275                 0.0                          0.0
13673               0.0                          0.0
1263                1.0                          0.0
3566                0.0                          1.0
6791                0.0                          0.0
...                 ...                          ...
15277               1.0                          0.0
4351                0.0                          0.0
9423                1.0                          0.0
14820               0.0                          1.0
13059               1.0                          0.0

       transmission_type_Manual  predicted_sales_price
Actual_price  \
275                         1.0           2.987648e+05        390000

13673                       1.0           5.616558e+05        450000

1263                        1.0           4.052260e+05        320000

3566                        0.0           1.900448e+06       1400000

6791                        1.0           4.896784e+05        565000

...                         ...                    ...           ...

15277                       1.0           4.700867e+05        400000

4351                        1.0           1.055601e+06        620000
```

```
9423                        1.0        8.769850e+04     235000
14820                       0.0        3.303626e+06    2250000
13059                       1.0        8.658684e+04     425000

         difference
275   -9.123519e+04
13673  1.116558e+05
1263   8.522604e+04
3566   5.004485e+05
6791  -7.532163e+04
...             ...
15277  7.008667e+04
4351   4.356011e+05
9423  -1.473015e+05
14820  1.053626e+06
13059 -3.384132e+05

[3083 rows x 17 columns]
```

```
mse = []
mse.append(mean_squared_error(y_true = test_Y,y_pred = prediction))
rmse = []
rmse.append(np.sqrt(mse))
rmse
```

```
[array([473172.14025473])]
```