Importing Libraries

In [97]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import pickle
```

Importing Dataset

In [2]:
```
df=pd.read_csv(r"Cardekho Data.csv")
```

Basic Information about the Dataset

In [3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20026 entries, 0 to 20025
Data columns (total 16 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   Source.Name            20026 non-null  object 
 1   web-scraper-order      20026 non-null  object 
 2   web-scraper-start-url  20026 non-null  object 
 3   full_name              19980 non-null  object 
 4   selling_price          19980 non-null  object 
 5   new-price              9566 non-null   object 
 6   year                   19980 non-null  float64
 7   seller_type            19980 non-null  object 
 8   km_driven              19980 non-null  object 
 9   owner_type             19980 non-null  object 
 10  fuel_type              19980 non-null  object 
 11  transmission_type      19980 non-null  object 
 12  mileage                19980 non-null  object 
 13  engine                 19921 non-null  object 
 14  max_power              19921 non-null  object 
 15  seats                  19853 non-null  object 
dtypes: float64(1), object(15)
memory usage: 2.4+ MB
```

The dataset consists of 16 features (columns) and 20026 rows. All the columns except 'year' column are of object datatype and the 'year' column is of float datatype.

Feature 'new price' has the highest number of null values i.e 9566 non-null values out of 20026. All the other features has less than 5% null values.

In [4]:
```
df.head()
```

Out[4]:

	Source.Name	web-scraper-order	web-scraper-start-url	full_name	selling_price	ne pri
0	cardekho_extract(0-2000).csv	1611917819-1662	https://www.cardekho.com/used-car-details/used...	Maruti Alto Std	1.2 Lakh*	N:
1	cardekho_extract(0-2000).csv	1611918361-1902	https://www.cardekho.com/used-car-details/used...	Hyundai Grand i10 Asta	5.5 Lakh*	New C (C Ro Price Rs.7.' 7. Lak
2	cardekho_extract(0-2000).csv	1611917012-1306	https://www.cardekho.com/used-car-details/used...	Hyundai i20 Asta	2.15 Lakh*	N:
3	cardekho_extract(0-2000).csv	1611917695-1607	https://www.cardekho.com/used-car-details/used...	Maruti Alto K10 2010-2014 VXI	2.26 Lakh*	N:
4	cardekho_extract(0-2000).csv	1611914861-367	https://www.cardekho.com/used-car-details/used...	Ford Ecosport 2015-2021 1.5 TDCi Titanium BSIV	5.7 Lakh*	New C (C Ro Price Rs.10.1 13. Lak

It can be observed that the columns 'Source.Name','web-scraper-order' and 'web-scraper-start-url' does not provide any valuable insights about the car features in particular. Hence removing the three columns.

In [5]:
```
df.drop('Source.Name', inplace=True, axis=1)
df.drop('web-scraper-start-url', inplace=True, axis=1)
df.drop('web-scraper-order', inplace=True, axis=1)
```

Data Cleaning and Exploratory Data Analysis

There is 3292 unique cars in the dataset with the same model having different names. This increases the complexity of the names column, therefore creating a new column as "Company" and "Model". This creates uniformity for the name column.

Also since Company and Model name columns are created, now removing the full name column as it would create redundancy.

In [6]:
```
df["full_name"]=df["full_name"].str.upper()
df["Company"]=df["full_name"].str.split(" ", n = 2, expand = True)[0]
df['Model']=df["full_name"].str.split(" ", n = 2, expand = True)[1]

df.drop('full_name', inplace=True, axis=1)
```

There are 42 unique company names in the dataset. Below are the diffrent company names in the dataset

In [7]:
```

print('There are {} unique company names in the dataset.'.format(len(df.Compan
print(df.Company.unique())
```

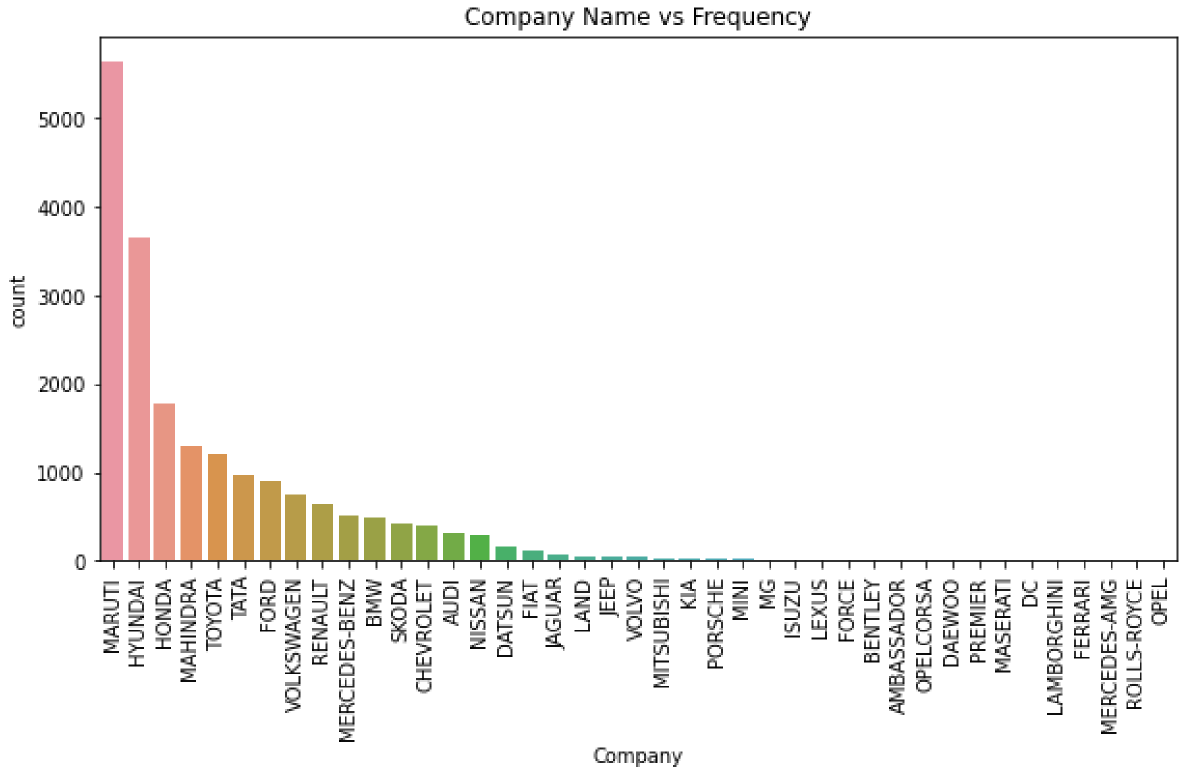
```
There are 42 unique company names in the dataset.
['MARUTI' 'HYUNDAI' 'FORD' 'MAHINDRA' 'TATA' 'RENAULT' 'NISSAN' 'MINI'
 'MERCEDES-BENZ' 'TOYOTA' 'FIAT' 'VOLKSWAGEN' 'HONDA' 'CHEVROLET'
 'AMBASSADOR' 'DATSUN' 'KIA' 'BMW' 'MITSUBISHI' 'AUDI' 'SKODA' nan 'LAND'
 'JAGUAR' 'DAEWOO' 'BENTLEY' 'MG' 'ISUZU' 'PORSCHE' 'VOLVO' 'LEXUS' 'JEEP'
 'PREMIER' 'MASERATI' 'FORCE' 'LAMBORGHINI' 'FERRARI' 'OPELCORSA'
 'MERCEDES-AMG' 'DC' 'ROLLS-ROYCE' 'OPEL']
```

The below plot represents the word cloud for Company names in the dataset.

Hyundai, Honda, Maruti, Skoda and Mahindra are most common car companies in the dataset.

In [8]:
```
from wordcloud import WordCloud
word_cloud = WordCloud(background_color = 'white').generate(str(df['Company'].
plt.imshow(word_cloud)
plt.axis("off")
plt.show()
```

In [9]:
```
plt.figure(figsize=(10,5))
sns.countplot(x='Company' , data=df,order = df['Company'].value_counts().index
plt.xticks(rotation=90);
plt.title("Company Name vs Frequency");
```



There are 274 unique car model names in the dataset. Below are the diffrent car names in the dataset

In [10]:
```
print('There are {} unique car model names in the dataset.'.format(len(df.Mode
print(df.Model.unique())
```

```
There are 274 unique car model names in the dataset.
['ALTO' 'GRAND' 'I20' 'ECOSPORT' 'WAGON' 'I10' 'VENUE' 'TUV' 'INDIGO'
 'CAPTUR' 'SWIFT' 'MICRA' 'VERNA' 'DUSTER' 'COOPER' 'CIAZ' 'C-CLASS'
 'INNOVA' 'BALENO' 'GRANDE' 'VENTO' 'CRETA' 'XYLO' 'CITY' 'BOLERO'
 'FORTUNER' 'KWID' 'AMAZE' 'SANTRO' 'XUV500' 'SAIL' 'XCENT' '800' 'AVIGO'
 'NANO' 'KUV100' 'ETIOS' 'IGNIS' 'COROLLA' 'REDIGO' 'VISTA' 'OMNI'
 'SCORPIO' 'MARAZZO' 'ASPIRE' 'FIGO' 'SUPRO' 'VITARA' 'TIAGO' 'POLO'
 'SELTOS' 'BEAT' 'CELERIO' 'TERRANO' 'SANTA' 'GO' '5' 'CR-V' 'ENDEAVOUR'
 'KUV' 'AVEO' 'JAZZ' 'PAJERO' 'INDICA' '3' 'RITZ' 'S-CROSS' 'SUMO' 'NEW'
 'Q5' 'A4' 'TIGOR' 'MANZA' 'BRIO' 'SX4' 'Q3' 'ERTIGA' 'SAFARI' 'SUNNY'
 'GLA' 'THAR' 'HEXA' 'ZEN' 'LAURA' 'AVVENTURA' nan 'ROVER' 'BRV' 'EECO'
 'A6' 'E-CLASS' 'QUANTO' 'Q7' 'NUVOSPORT' 'Z4' 'KOLEOS' 'A3' '6' 'LAND'
 'SCALA' 'XF' 'X5' 'ZEST' 'CLA' 'MATIZ' 'MULSANNE' 'HECTOR' 'EON' 'AMEO'
 'SPARK' 'GLE' 'CIVIC' 'KIZASHI' 'D-MAX' 'CAYENNE' 'FABIA' 'X1' 'RAPID'
 'FREESTYLE' 'BOLT' 'SUPERB' 'CAPTIVA' '1' 'PLATINUM' 'NEXON' 'XUV300' 'A'
 'DZIRE' 'S90' 'S60' 'WR-V' 'XL6' 'XENON' 'LINEA' 'PULSE' 'A5' 'TRIBER'
 'CROSSPOLO' 'IKON' 'ACCENT' 'ES' 'WRANGLER' 'CAMRY' 'MOBILIO' 'ELANTRA'
 'YARIS' 'LODGY' 'GL-CLASS' '1000' 'RIO' 'CLASSIC' 'ESTILO' 'PUNTO' '7'
 'S-PRESSO' 'YETI' 'MUSTANG' 'AURA' 'XC' 'GHIBLI' 'PALIO' 'CRUZE'
 'INGENIO' 'ACCORD' 'ABARTH' 'CONTINENTAL' 'CR' 'X3' 'JETTA' 'FIESTA'
 'KICKS' 'S-CLASS' 'SONATA' 'ONE' 'TUCSON' 'HARRIER' 'VERSA' 'OCTAVIA'
 'SSANGYONG' 'ENJOY' 'VERITO' 'GETZ' 'COMPASS' 'CLS' 'XJ' 'REDI-GO' 'BR-V'
 'B-CLASS' 'TAVERA' 'JEEP' 'E' 'OUTLANDER' 'BEETLE' 'M-CLASS' 'FLUENCE'
 'QUALIS' 'GLANZA' 'MACAN' 'X4' 'SLK' 'PASSAT' 'TRAILBLAZER' 'LOGAN' 'GLC'
 'B' 'VENTURE' '500' 'XC90' 'GALLARDO' 'F-PACE' 'OPTRA' 'KODIAQ' 'A-CLASS'
 'A8' 'M' 'CLUBMAN' 'MUX' 'TIGUAN' 'PRADO' 'RENAULT' 'X6' 'GTC4LUSSO'
 'GLS' 'GYPSY' 'LANCER' 'V40' 'S4' 'ARIA' 'X-TRAIL' 'ESTEEM' 'XE'
 'TERRACAN' 'EVALIA' '1.4GSI' 'XC60' 'PANAMERA' 'GTI' 'TT' 'MU' 'F-TYPE'
 'MONTERO' 'ESCORT' 'CLK' 'SONET' 'ALTURAS' 'BOXSTER' 'CEDIA' 'TEANA'
 'CAYMAN' 'S' 'CLS-CLASS' 'ALTROZ' 'NX' 'E2OPLUS' 'CARNIVAL' 'PRIUS'
 'SIERRA' 'C' 'CL-CLASS' 'AVANTI' 'RX' 'S5' 'GHOST' 'QUATTROPORTE' 'SLC'
 'R8' 'A-STAR' 'E20' 'CORSA' 'S40' 'WINGER' 'GURKHA' 'INFINITI' 'KONA']
```

In [11]:
```
from wordcloud import WordCloud
word_cloud = WordCloud(background_color = 'white').generate(str(df['Model'].va
plt.imshow(word_cloud)
plt.axis("off")
plt.show()
```

Selling Price column has entries in Thousands, Lakhs and Crores with the text. Therefore removing the units and multiplying the respective units with the numerical values.

In [12]:
```
df["SP"]=df["selling_price"].str.split(" ", n = 2, expand = True)[0]
df["SP_range"]=df["selling_price"].str.split(" ", n = 2, expand = True)[1]
df["SP"]=df['SP'].str.replace('*','')
df['SP']=df['SP'].str.replace(',','')
df['SP']=pd.to_numeric(df['SP'])
df['SP'] = np.where(df['SP_range'] == 'Lakh*',df['SP'] * 100000,df['SP'])
df['SP'] = np.where(df['SP_range'] == 'Cr*',df['SP'] * 10000000,df['SP'])
df.drop('SP_range', inplace=True, axis=1)
df.drop('selling_price', inplace=True, axis=1)
df['selling_price']=df['SP']
df.drop('SP', inplace=True, axis=1)
```

```
C:\Users\DHRUV~1.BHA\AppData\Local\Temp/ipykernel_3596/3764464627.py:3: Futur
eWarning: The default value of regex will change from True to False in a futu
re version. In addition, single character regular expressions will *not* be t
reated as literal strings when regex=True.
  df["SP"]=df['SP'].str.replace('*','')
```

In [13]:
```
df['selling_price'].describe()
```

Out[13]:
```
count    1.998000e+04
mean     7.392066e+05
std      9.103088e+05
min      2.500000e+04
25%      3.400000e+05
50%      5.200000e+05
75%      7.850000e+05
max      3.950000e+07
Name: selling_price, dtype: float64
```

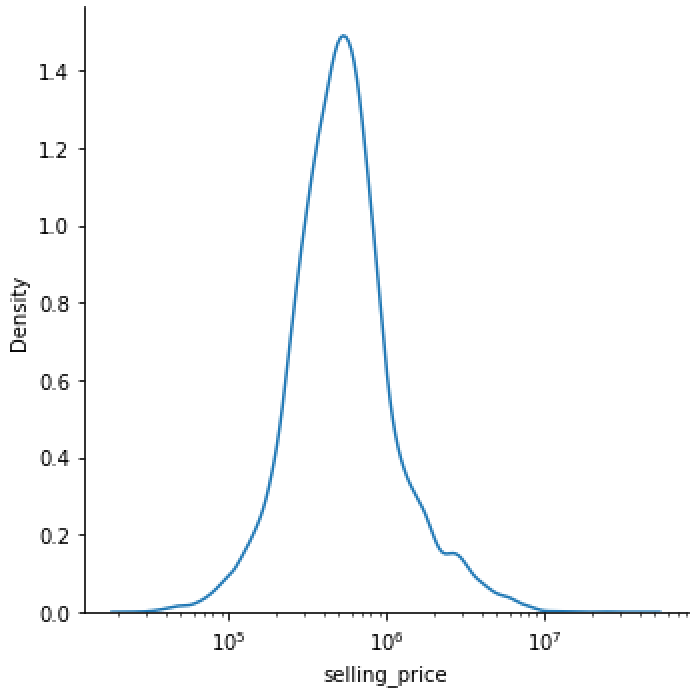
Univariate Analysis: Plotting distribution plot for selling price column. The selling price data is rightly skewed with outliers. Hence the plot with normal scale did not provide any useful insights. Therefor to reduce the effect of such outliers in the plot only, log scale is used.

Observations

- **The minimum selling price amount is 25,000 and max is 3.95 crore.**
- **The major distribution falls between 1 lakh to 1 crore.**

In [14]:
```
sns.displot(data=df,x="selling_price",kind="kde",log_scale=10)
```

Out[14]: <seaborn.axisgrid.FacetGrid at 0x1c32c649550>



Kilometeres driven column (km_driven) has all numerical values but with text 'kms' with the numerical number. Therefore removing the text from the column.

In [15]:
```
df["km_driven"]=df["km_driven"].str.split(" ", n = 1, expand = True)[0].str.re
df["km_driven"]=pd.to_numeric(df["km_driven"])
```

In [16]:
```
df['km_driven'].describe()
```

Out[16]:
```
count    1.998000e+04
mean     5.824488e+04
std      5.172509e+04
min      1.000000e+02
25%      3.116425e+04
50%      5.200000e+04
75%      7.400000e+04
max      3.800000e+06
Name: km_driven, dtype: float64
```

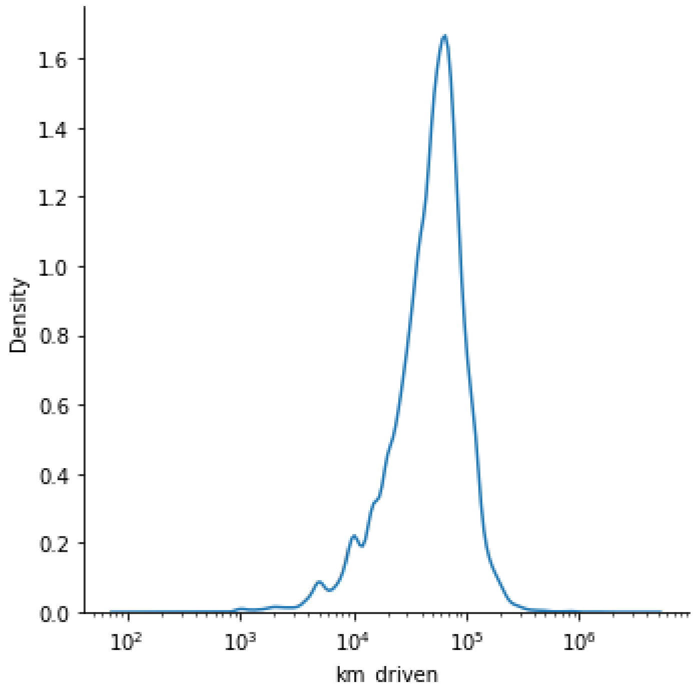
Univariate Analysis: Plotting distribution plot for kilometer driven column. The data is rightly skewed with outliers. Hence the plot with normal scale did not provide any useful insights. Therefore to reduce the effect of such outliers in the plot only, log scale is used.

Observations

- **The minimum km driven is 100 kms and max is 3800000 kms.**
- **The majority of cars have driven between 10,000 to 1,00,000 kms**

In [17]:
```
sns.displot(data=df,x="km_driven",kind="kde",log_scale=10)
```

Out[17]: <seaborn.axisgrid.FacetGrid at 0x1c330a63820>



Mileage column has units such as 'kmpl', 'km/kg' and 'km/hr'. Out of these clearly km/hr does not represent mileage but speed hence removing these values. Also removing text from the column and few values of more than 100 were observed which is not correct for mileage, hence removing those values also.

In [18]:
```
df['mileage']=df["mileage"].str.split(" ", n = 2, expand = True)[0].str[7:]
df["mileage"]=pd.to_numeric(df["mileage"])

# It is observed that some values of mileage were greater than 100 (110 and 12

df[df['mileage'] > 100] = np.NaN
```

In [19]:
```
df['mileage'].describe()
```

Out[19]:
```
count    19976.000000
mean        19.327565
std          4.406338
min          0.000000
25%         16.800000
50%         19.160000
75%         22.320000
max         33.540000
Name: mileage, dtype: float64
```

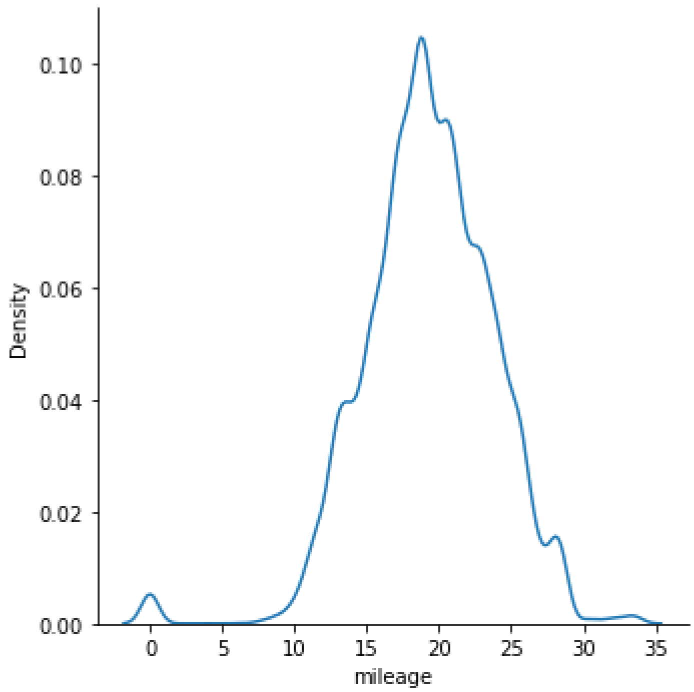
Univariate Analysis: Plotting distribution plot for mileage column. The data is left skewed without outliers. Hence the plot is with normal scale.

Observations

- **The mean mileage is 19.3 kmpl.**
- **The data is normally distributed.**

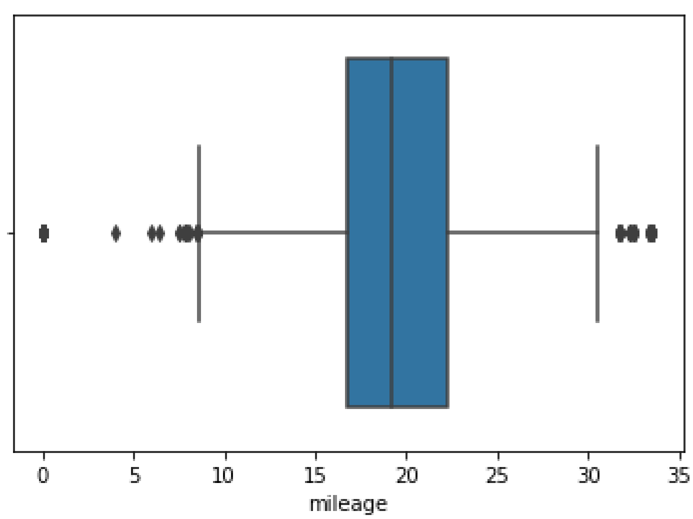
In [20]:
```
sns.displot(data=df,x="mileage",kind="kde")
```

Out[20]: <seaborn.axisgrid.FacetGrid at 0x1c3309d2250>



In [21]:
```
sns.boxplot(x=df["mileage"])
```

Out[21]: <AxesSubplot:xlabel='mileage'>



The engine column describes the engine capacity of the cars in unit CC. After analysing the column, it had text data which is removed and also some rows had entries like 'wheel size' which is clearly a data entry error, hence that also had to be removed.

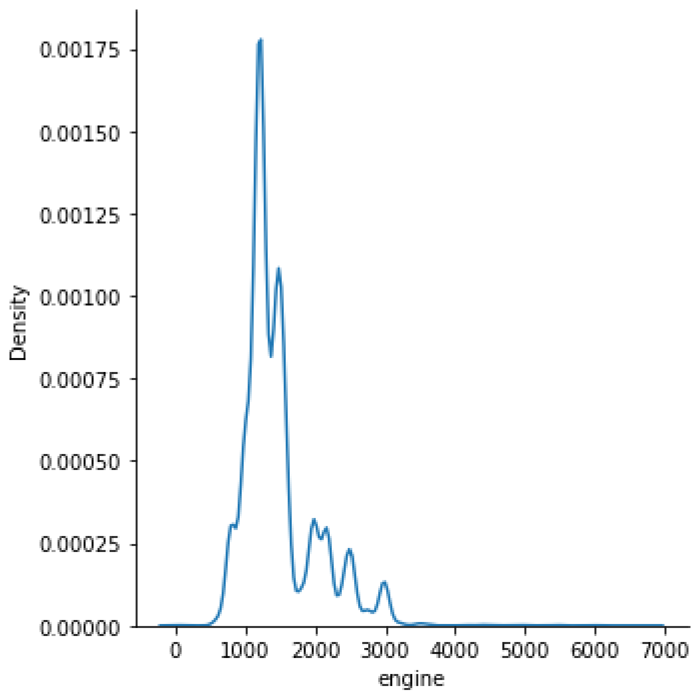
In [22]:
```
df['engine']=df['engine'].str.split(" ", n = 2, expand = True)[0].str[6:]
df['engine']=pd.to_numeric(df['engine'])
```

In [23]:
```
df['engine'].describe()
```

Out[23]:
```
count    19872.000000
mean      1477.651822
std        520.001300
min          0.000000
25%       1197.000000
50%       1248.000000
75%       1582.000000
max       6752.000000
Name: engine, dtype: float64
```

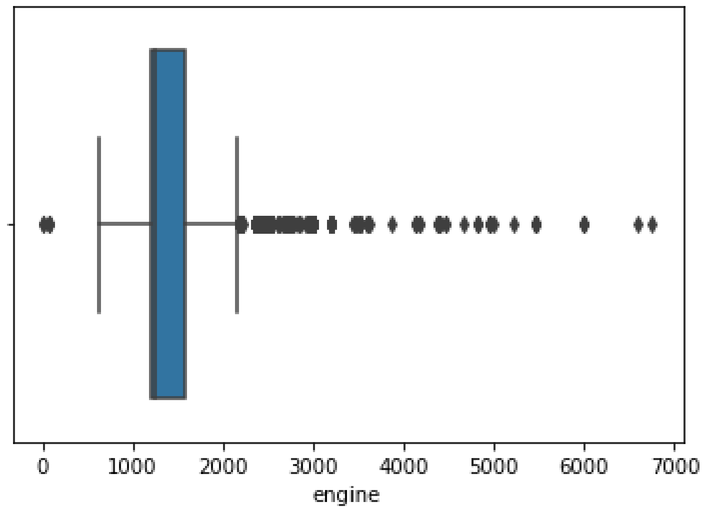
In [24]:
```
sns.displot(data=df,x="engine",kind="kde")
```

Out[24]: <seaborn.axisgrid.FacetGrid at 0x1c32ff94730>



In [25]:
```
sns.boxplot(x=df["engine"])
```

Out[25]: <AxesSubplot:xlabel='engine'>



The maximum power column also had entries in Brake horsepower (bhp) with the text. The text is removed and few data entry errors are also removed and the column is also converted to numerical feature.

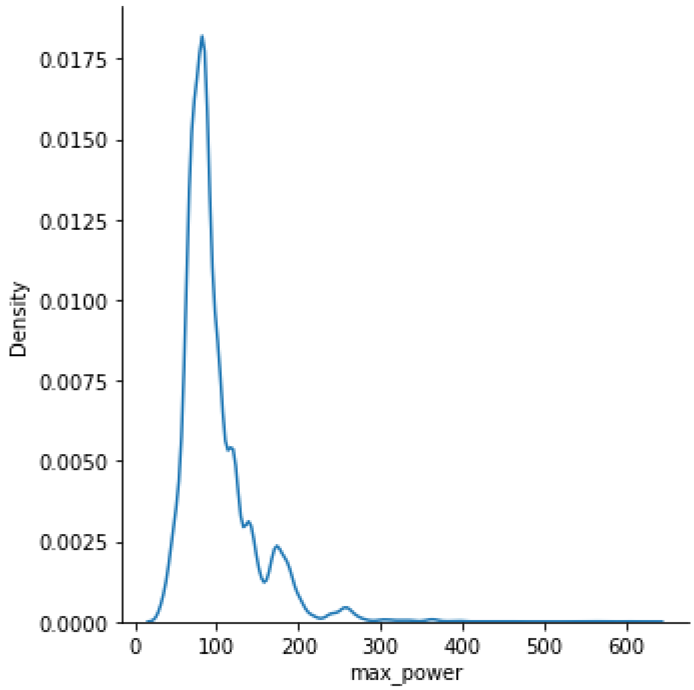
In [26]:
```
df['max_power']=df['max_power'].str.split(" ", n = 2, expand = True)[1].str[5:
df[df['max_power'] =='null'] = np.NaN ##After splitting a few values with stri
df['max_power']=pd.to_numeric(df['max_power'])
```

In [27]:
```
df['max_power'].describe()
```

Out[27]:
```
count    19639.000000
mean        99.462084
std         43.772478
min         34.200000
25%         73.940000
50%         86.800000
75%        114.000000
max        626.000000
Name: max_power, dtype: float64
```

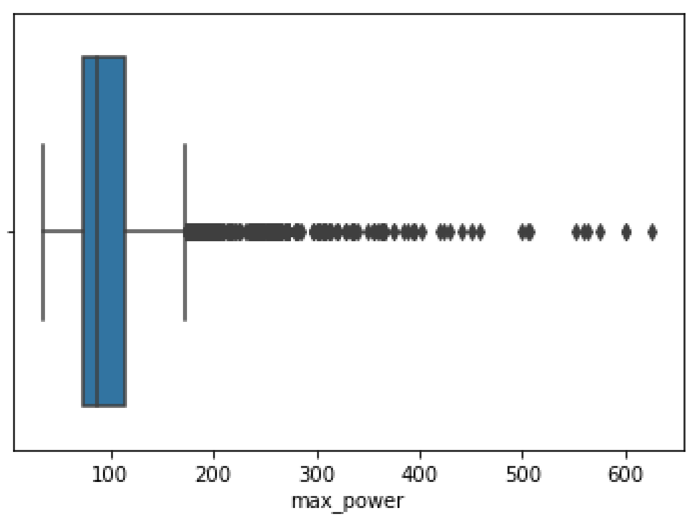
In [28]:
```
sns.displot(data=df,x="max_power",kind="kde")
```

Out[28]: <seaborn.axisgrid.FacetGrid at 0x1c32f943e20>



In [29]:
```
sns.boxplot(x=df["max_power"])
```

Out[29]: <AxesSubplot:xlabel='max_power'>



Seats column is a categorical variable which describes the number of seats in a car. The column contains number of seats which text "SEATS" so this text has to be removed. Apart from text removal, few rows had N/A and Null values which also had to be converted to NaN.

In [30]:
```
df['seats']=df['seats'].str[5:]
df[df['seats'] =='null'] = np.NaN ##After splitting a few values with string 'n
df[df['seats'] =='N/A'] = np.NaN  ##After splitting a few values with string 'N
df['seats']=pd.to_numeric(df['seats'])
```

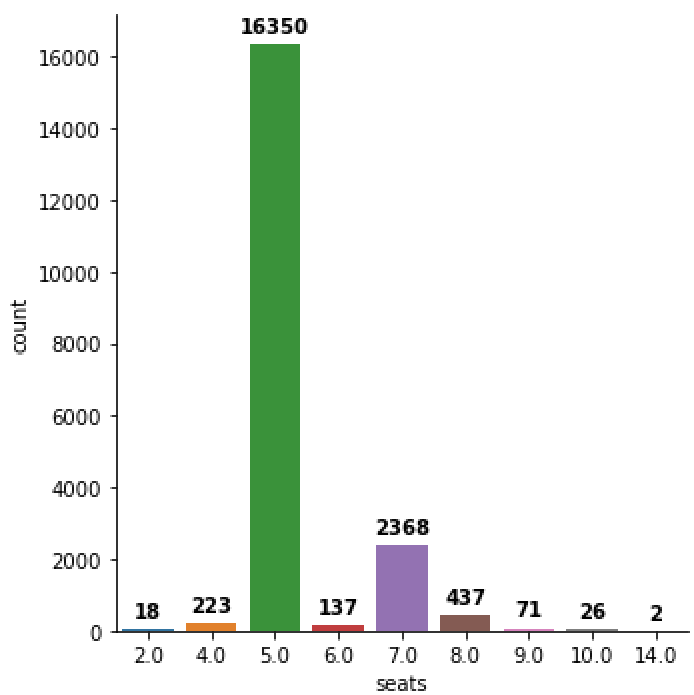
Frequency plot for seats columns

Observations

* **There are cars from 2 seats to 14 seats in the dataset.**
* **The highest number of cars has 5 seats with 16350 cars**
* **There are also a high frequency of 7 seater cars**

In [31]:
```
plt.figure(figsize=(4, 3))
plot = sns.catplot(x='seats', kind='count', data=df)

for i, bar in enumerate(plot.ax.patches):
    h = bar.get_height()
    plot.ax.text(
        i, # bar index (x coordinate of text)
        h+500, # y coordinate of text
        '{}'.format(int(h)),  # y label
        ha='center',
        va='center',
        fontweight='bold',
        size=10)
```

```
<Figure size 288x216 with 0 Axes>
```



Replacing Values with string 'null' in the dataset.

In [32]:
```
df[df =='null'] = np.NaN
```

Dropping Duplicate Rows

In [33]:
```
df.drop_duplicates()
```

Out[33]:

	new-price	year	seller_type	km_driven	owner_type	fuel_type	transmission_type	milea
0	NaN	2012.0	Individual	120000.0	First Owner	Petrol	Manual	19.
1	New Car (On-Road Price) : Rs.7.11-7.48 Lakh*	2016.0	Individual	20000.0	First Owner	Petrol	Manual	18.
2	NaN	2010.0	Individual	60000.0	First Owner	Petrol	Manual	17.
3	NaN	2012.0	Individual	37000.0	First Owner	Petrol	Manual	20.
4	New Car (On-Road Price) : Rs.10.14-13.79 Lakh*	2015.0	Dealer	30000.0	First Owner	Diesel	Manual	22.
...	...	...	...	...	...	...	...	
20021	NaN	2017.0	Dealer	69480.0	First Owner	Diesel	Manual	23.
20022	NaN	2019.0	Dealer	18000.0	First Owner	Petrol	Manual	17.
20023	NaN	2015.0	Dealer	67000.0	First Owner	Diesel	Manual	21.
20024	New Car (On-Road Price) : Rs.17.83-24.91 Lakh*	2016.0	Dealer	3800000.0	First Owner	Diesel	Manual	16.
20025	NaN	2019.0	Dealer	13000.0	First Owner	Petrol	Automatic	18.

19603 rows × 14 columns

Since 83% of the cars in the dataset has 5 seats, hence replacing the null values in the setas column with mode i.e 5 seats.

In [34]:
```
df['seats'].fillna(df['seats'].mode()[0], inplace=True)
```

Intuitionally the maximum power and engine capacity of a car would be directly dependent on the number of seats. For example all 5 seater cars would have similar max power and engine capacity and all 10 seater cars will have a similar higher max power

and engine capacity. Therefore, replacing the null values in max power and engine column with average values based on the groupby seats columns

In [35]:
```
mp=df.groupby(['seats'])['max_power'].mean().to_dict()
df.max_power = df.max_power.fillna(df.seats.map(mp))
```

In [36]:
```
en=df.groupby(['seats'])['engine'].mean().to_dict()
df.engine = df.engine.fillna(df.seats.map(en))
```

Dropping Rows with Null in all columns

In [37]:
```
df.dropna(subset=['Company'], inplace=True)
```

Since both Company Name and Full Name have large categorical values hence removing both from final analysis

In [38]:
```
df.drop('Company', inplace=True, axis=1)
df.drop('Model', inplace=True, axis=1)
```

Dropping new-price column since it has more than 50% null values and does not provide any valuable information in the dataset.

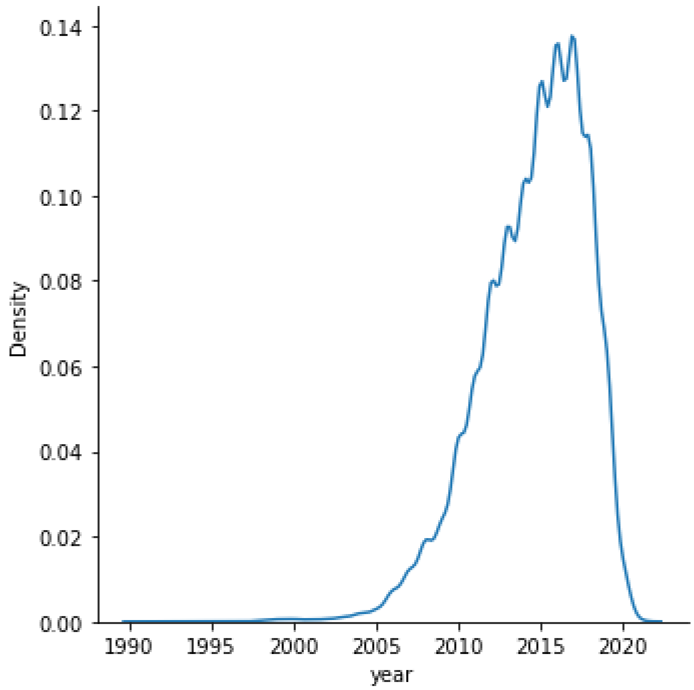
In [39]:
```
df.drop('new-price', inplace=True, axis=1)
```

Year Column

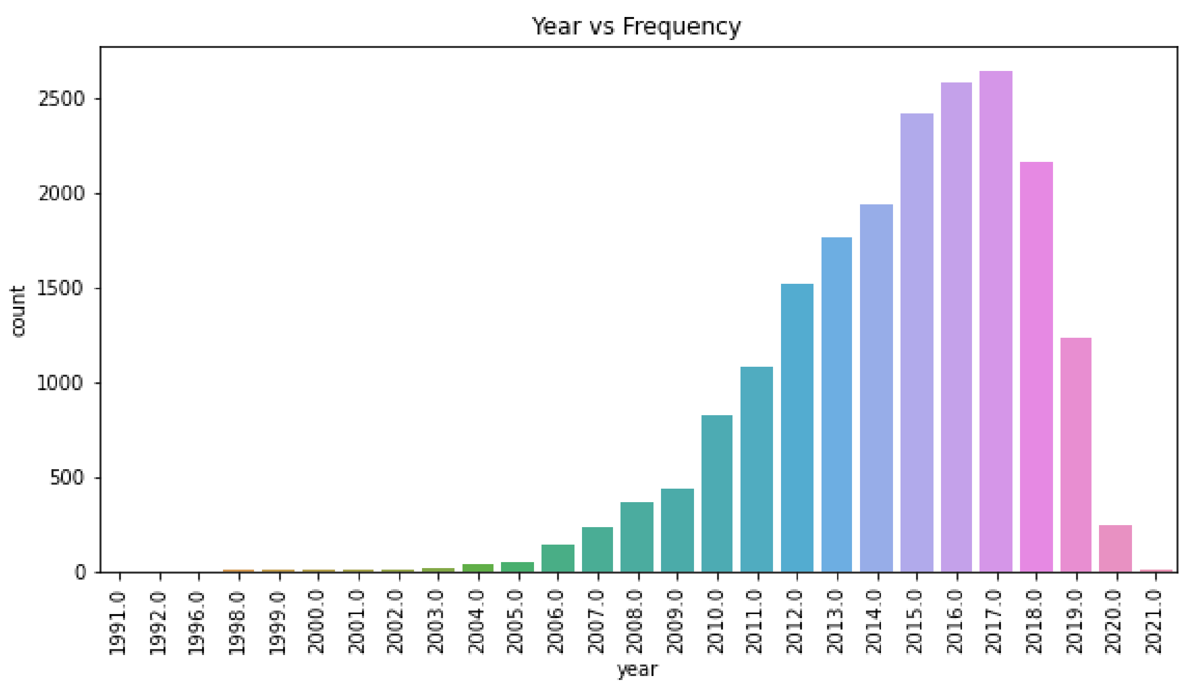
Year column consists of the year the cars were manufactured in. This can also describe the age of the car if it is substracted from the current year.

In [40]:
```
sns.displot(data=df,x="year",kind="kde")
```

Out[40]: <seaborn.axisgrid.FacetGrid at 0x1c3322cf820>



In [41]:
```
plt.figure(figsize=(10,5))
sns.countplot(x='year' , data=df,)
plt.xticks(rotation=90);
plt.title("Year vs Frequency");
```



Univariate Analysis on Categorical Features

In [42]:
```
df.describe(include='O')
```

Out[42]:

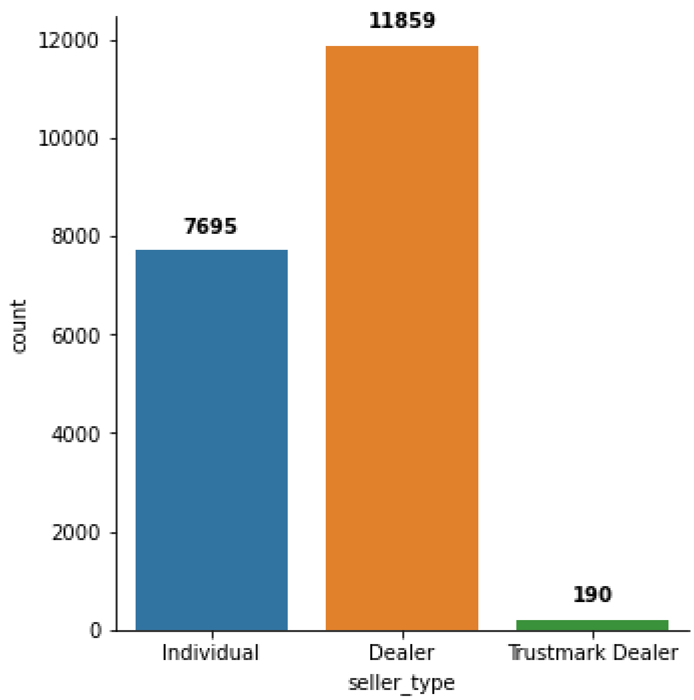
	seller_type	owner_type	fuel_type	transmission_type
count	19744	19744	19744	19744
unique	3	3	5	2
top	Dealer	First Owner	Diesel	Manual
freq	11859	19738	9722	15809

Seller Type Column

The seller type column has 2 major entries with 'individual' and 'dealer' based cars. The third category 'trustmark dealer' has only 190 entries which is negligible.

In [43]:
```
plt.figure(figsize=(4, 3))
plot = sns.catplot(x='seller_type', kind='count', data=df)

for i, bar in enumerate(plot.ax.patches):
    h = bar.get_height()
    plot.ax.text(
        i, # bar index (x coordinate of text)
        h+500, # y coordinate of text
        '{}'.format(int(h)),  # y label
        ha='center',
        va='center',
        fontweight='bold',
        size=10)
```

```
<Figure size 288x216 with 0 Axes>
```

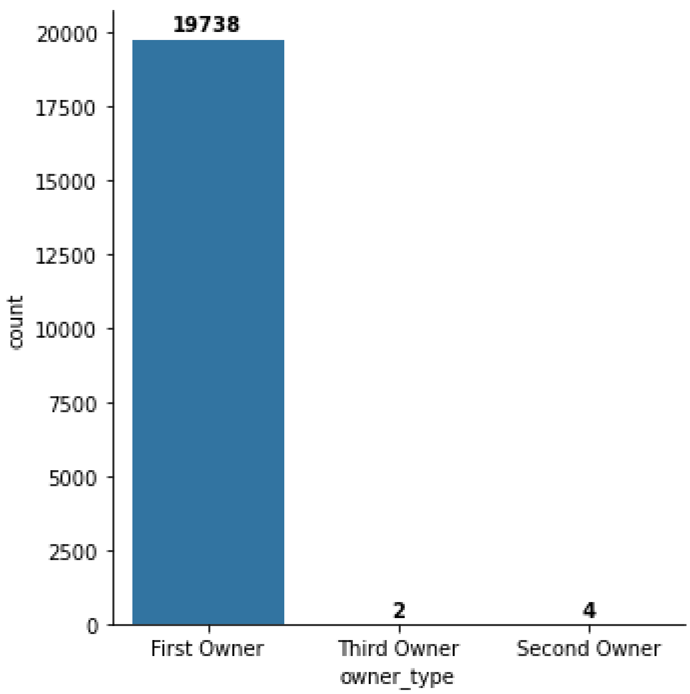


Owner Type

Owner type column describes the owner of the car whether it is first owner, second owner or third owner. More than 99% of the data has first owner seller type. Only 6 rown has second owner or third owner entries. Hence this can be considered as outliers. Therefore dropping the owner type column.

In [44]:
```
plt.figure(figsize=(4, 3))
plot = sns.catplot(x='owner_type', kind='count', data=df)

for i, bar in enumerate(plot.ax.patches):
    h = bar.get_height()
    plot.ax.text(
        i, # bar index (x coordinate of text)
        h+500, # y coordinate of text
        '{}'.format(int(h)),  # y label
        ha='center',
        va='center',
        fontweight='bold',
        size=10)
```

```
<Figure size 288x216 with 0 Axes>
```



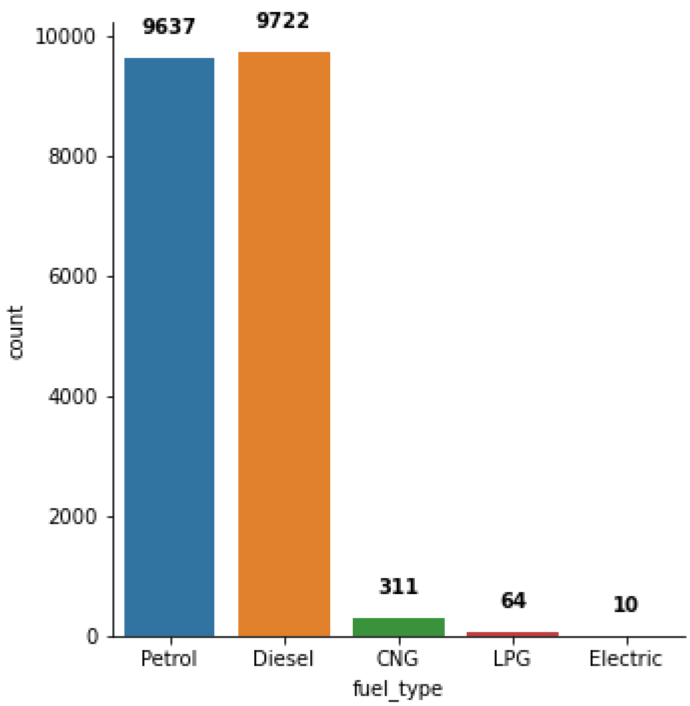
In [45]:
```
df.drop('owner_type', inplace=True, axis=1)
```

Fuel Type Column

Fuel type column has 5 entries types i.e Petrol, Diesel, CNG, Electric and LPG type cars. Here majority of cars are of Petrol and Diesel full category. With a marginal number of entries for CNG, LPG and Electric cars.

In [46]:
```
plt.figure(figsize=(4, 3))
plot = sns.catplot(x='fuel_type', kind='count', data=df)

for i, bar in enumerate(plot.ax.patches):
    h = bar.get_height()
    plot.ax.text(
        i, # bar index (x coordinate of text)
        h+500, # y coordinate of text
        '{}'.format(int(h)),  # y label
        ha='center',
        va='center',
        fontweight='bold',
        size=10)
```

```
<Figure size 288x216 with 0 Axes>
```

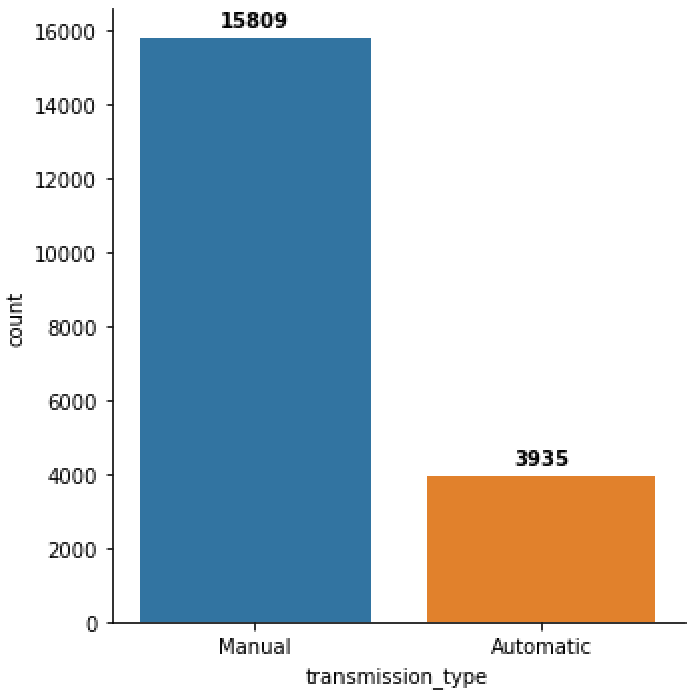


Transmission Type Column

Transmission type column has 2 entries with manual or automatic cars.

In [47]:
```
plt.figure(figsize=(4, 3))
plot = sns.catplot(x='transmission_type', kind='count', data=df)

for i, bar in enumerate(plot.ax.patches):
    h = bar.get_height()
    plot.ax.text(
        i, # bar index (x coordinate of text)
        h+500, # y coordinate of text
        '{}'.format(int(h)),  # y label
        ha='center',
        va='center',
        fontweight='bold',
        size=10)
```

```
<Figure size 288x216 with 0 Axes>
```



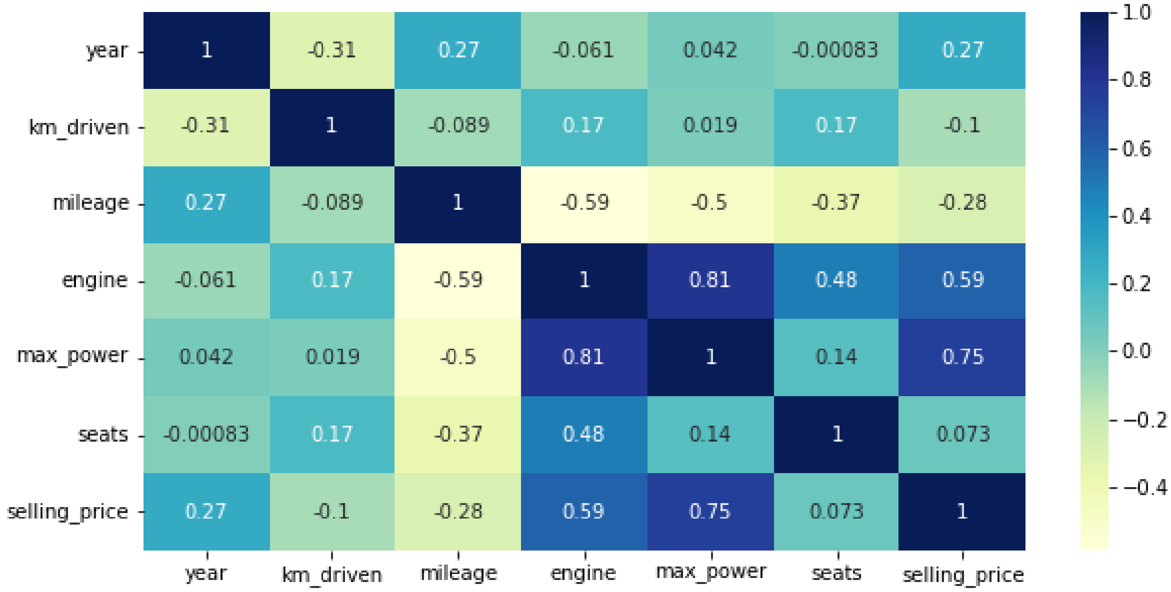
Bivariate Analysis

The following observations can be made from the above matrix:

- **The variable mileage has negative coefficient of correlation with every other variable except year column.**
- **Maximum power and engine columns are highly positively correlated i.e. when one variable increases the other variable also increases.**
- **Maximum power and selling price variable are also highly correlated i.e. higher the maximum power higher will be the selling price of the car.**

In [48]:
```
plt.figure(figsize=(10,5))
sns.heatmap(df.corr() ,  cmap="YlGnBu" , annot=True)
```

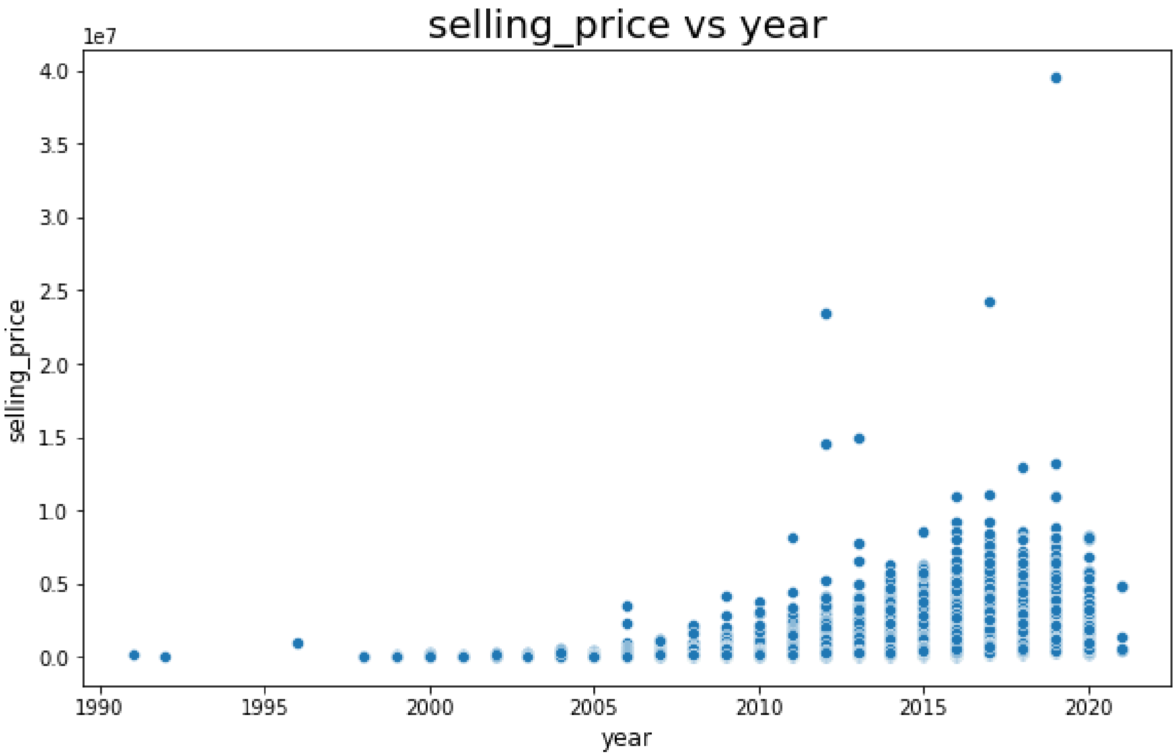
Out[48]: <AxesSubplot:>



Observation: It is observed that the cars manufactured in recent years have a higher selling price than the older cars. Here selling price is of continuous type and year is of discrete type that is why we are using scatter plot for the visualization.

In [49]:
```
fig,ax = plt.subplots(figsize=(10,6))
ax.set_title('selling_price vs year',fontsize=20)
ax.set_xlabel('year',fontsize=12)
ax.set_ylabel('selling_price',fontsize=12)
sns.scatterplot(x='year',y='selling_price',data=df)
```

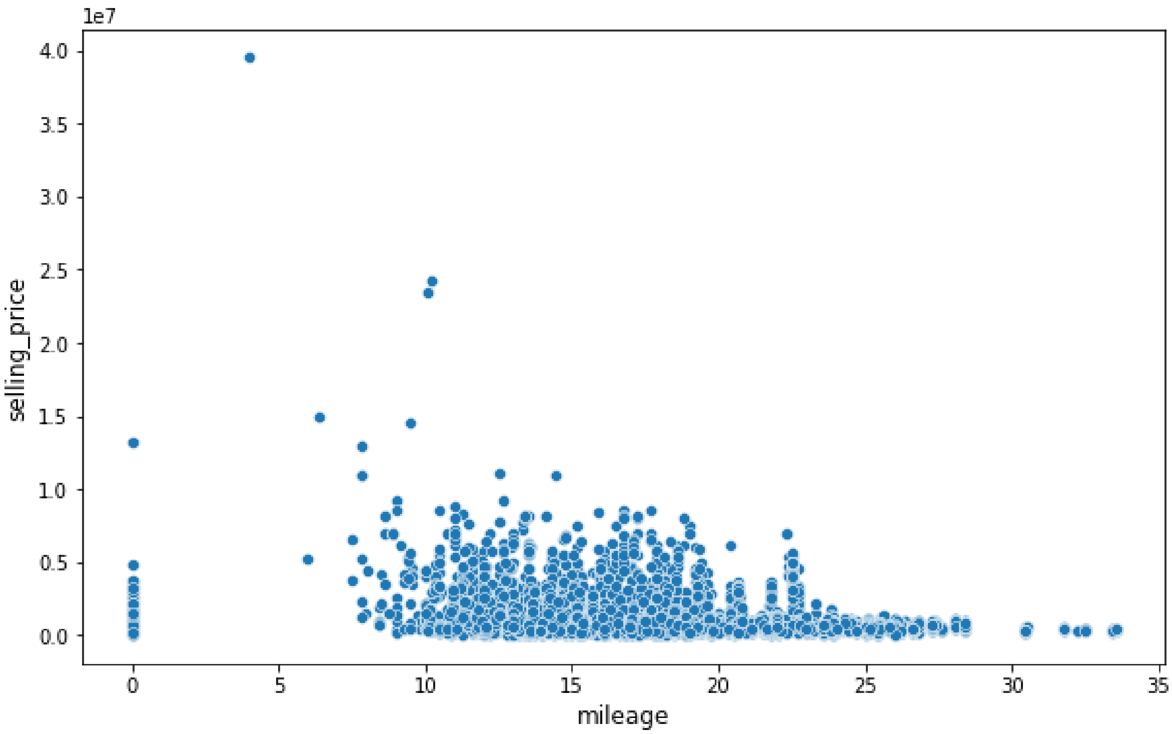
Out[49]:
```
<AxesSubplot:title={'center':'selling_price vs year'}, xlabel='year', ylabel
='selling_price'>
```



Observation: Higher the mileage lower is the selling price. It can be seen from the plot that mileage with 20 kmpl and greater has lower selling price as compared to mileage with less than 20 kmpl. This can also be seen from the negative coefficient of correlation in the heat map matrix above.

In [50]:
```
fig,ax = plt.subplots(figsize=(10,6))

ax.set_xlabel('mileage',fontsize=12)
ax.set_ylabel('selling_price',fontsize=12)
sns.scatterplot(x='mileage',y='selling_price',data=df)
```

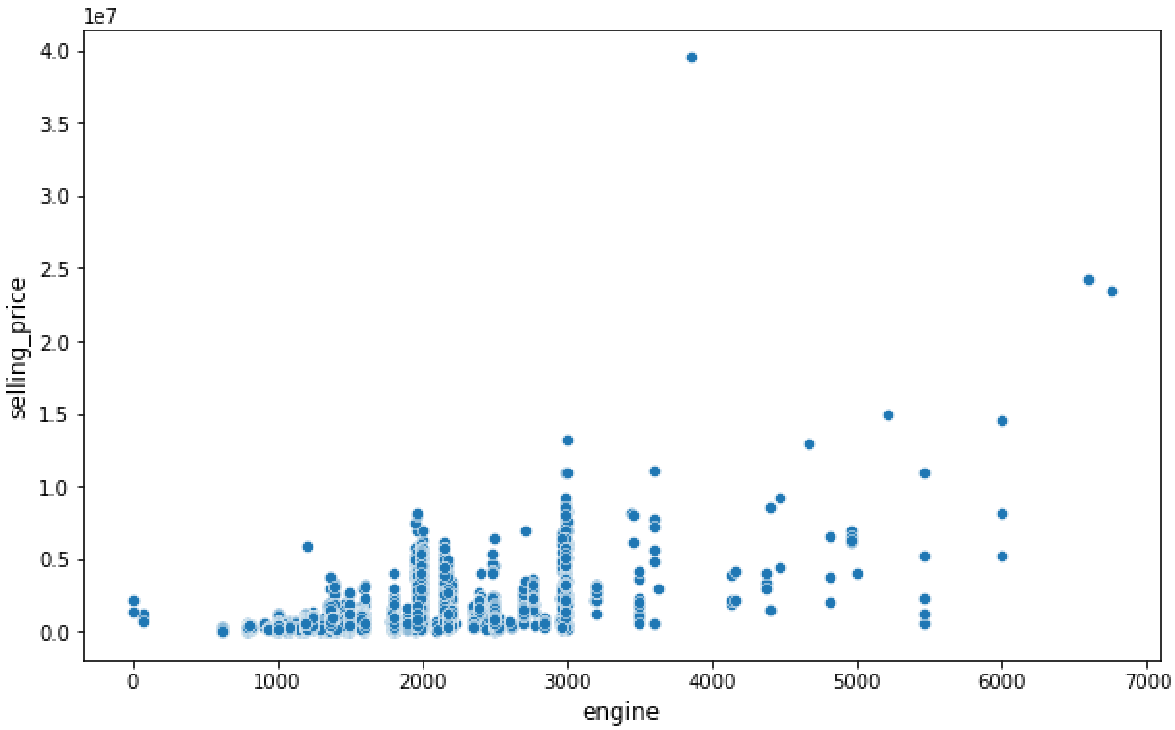
Out[50]: <AxesSubplot:xlabel='mileage', ylabel='selling_price'>



Observation: It can be observed that higher the engine capacity higher would be the selling price. It can also be validated with a correlation coefficient of 0.59.

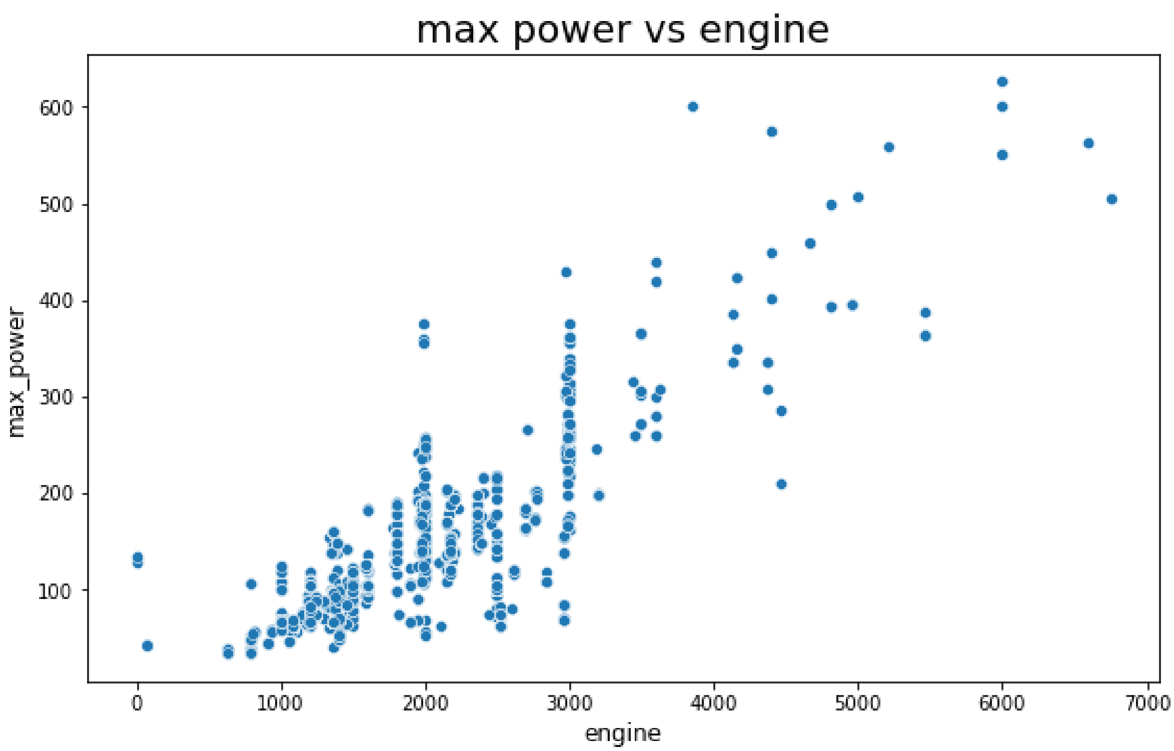
In [51]:
```
fig,ax = plt.subplots(figsize=(10,6))

ax.set_xlabel('engine',fontsize=12)
ax.set_ylabel('selling_price',fontsize=12)
sns.scatterplot(x='engine',y='selling_price',data=df)
```

Out[51]: <AxesSubplot:xlabel='engine', ylabel='selling_price'>



In [52]:
```
fig,ax = plt.subplots(figsize=(10,6))
ax.set_title('max power vs engine',fontsize=20)
ax.set_xlabel('engine',fontsize=12)
ax.set_ylabel('max_power',fontsize=12)
sns.scatterplot(x='engine',y='max_power',data=df)
```

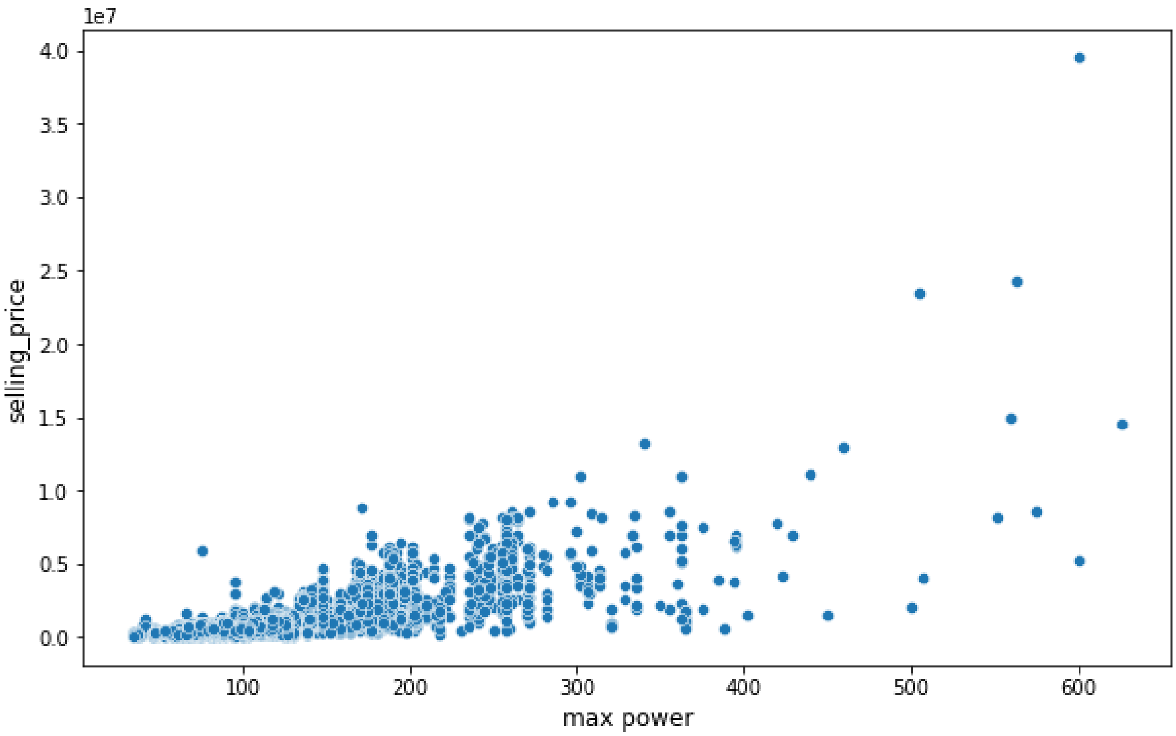
Out[52]:
```
<AxesSubplot:title={'center':'max power vs engine'}, xlabel='engine', ylabel
='max_power'>
```



Observation: With a high correlation of 0.75 there is also a positive relation between the above two variables.

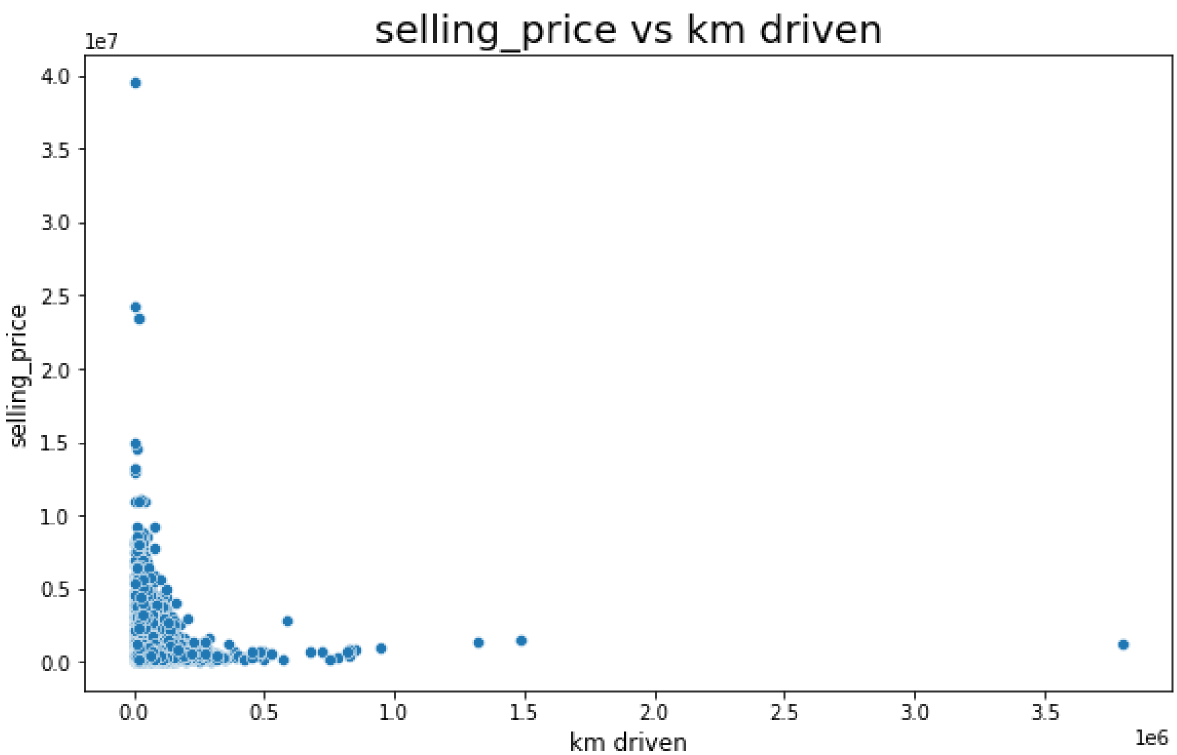
In [53]:
```
fig,ax = plt.subplots(figsize=(10,6))

ax.set_xlabel('max power',fontsize=12)
ax.set_ylabel('selling_price',fontsize=12)
sns.scatterplot(x='max_power',y='selling_price',data=df)
```

Out[53]: <AxesSubplot:xlabel='max power', ylabel='selling_price'>



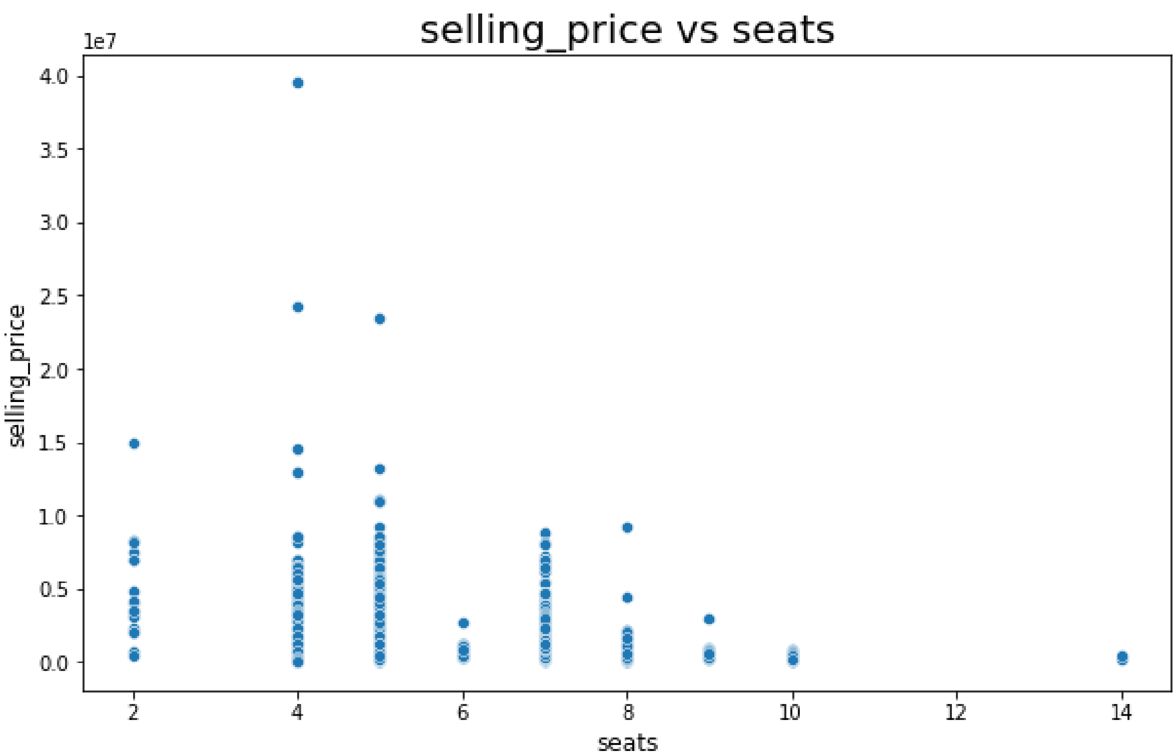
In [54]:
```
fig,ax = plt.subplots(figsize=(10,6))
ax.set_title('selling_price vs km driven',fontsize=20)
ax.set_xlabel('km driven',fontsize=12)
ax.set_ylabel('selling_price',fontsize=12)
sns.scatterplot(x='km_driven',y='selling_price',data=df)
```

Out[54]:
```
<AxesSubplot:title={'center':'selling_price vs km driven'}, xlabel='km drive
n', ylabel='selling_price'>
```



In [55]:
```
fig,ax = plt.subplots(figsize=(10,6))
ax.set_title('selling_price vs seats',fontsize=20)
ax.set_xlabel('seats',fontsize=12)
ax.set_ylabel('selling_price',fontsize=12)
sns.scatterplot(x='seats',y='selling_price',data=df)
```

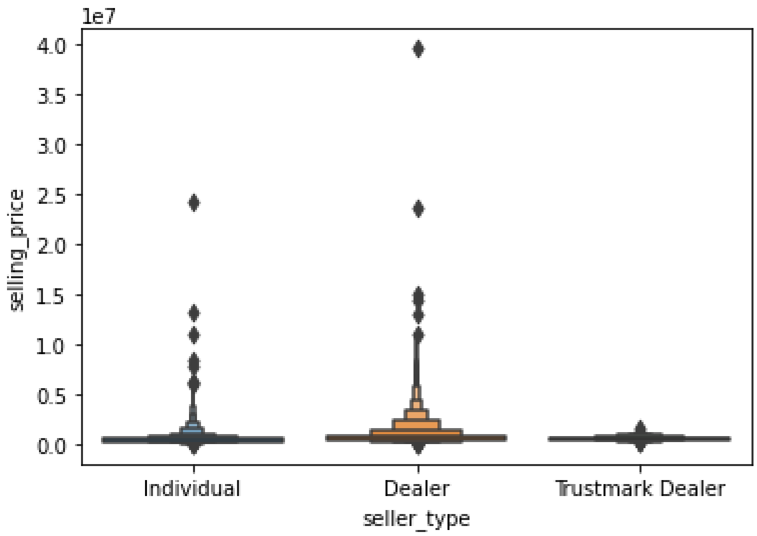
Out[55]:
```
<AxesSubplot:title={'center':'selling_price vs seats'}, xlabel='seats', ylabe
l='selling_price'>
```



Here we are using box plot method since one variable is categorical and one is continuous and it can be clearly observed that Dealer seller type have a higher aggregate selling price from Individual and Trustmark Dealers seller types.

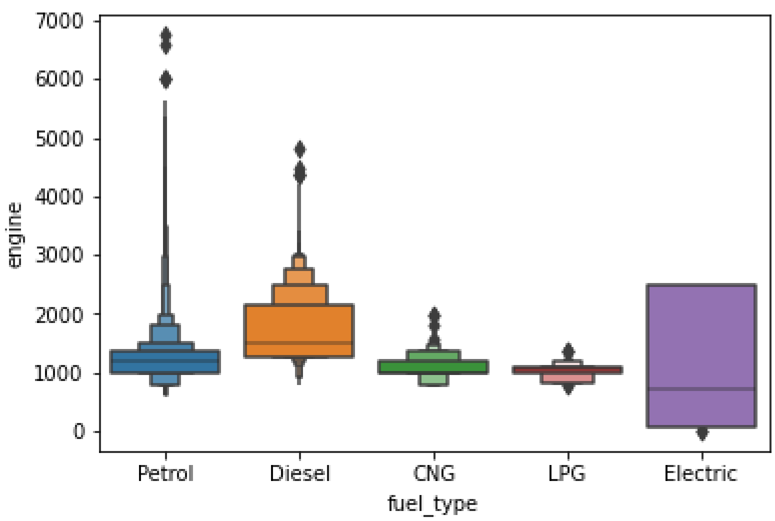
In [56]:
```
sns.boxenplot(x = 'seller_type', y = 'selling_price', data = df)
```

Out[56]: <AxesSubplot:xlabel='seller_type', ylabel='selling_price'>



In [57]:
```
sns.boxenplot(x = 'fuel_type', y = 'engine', data = df)
```

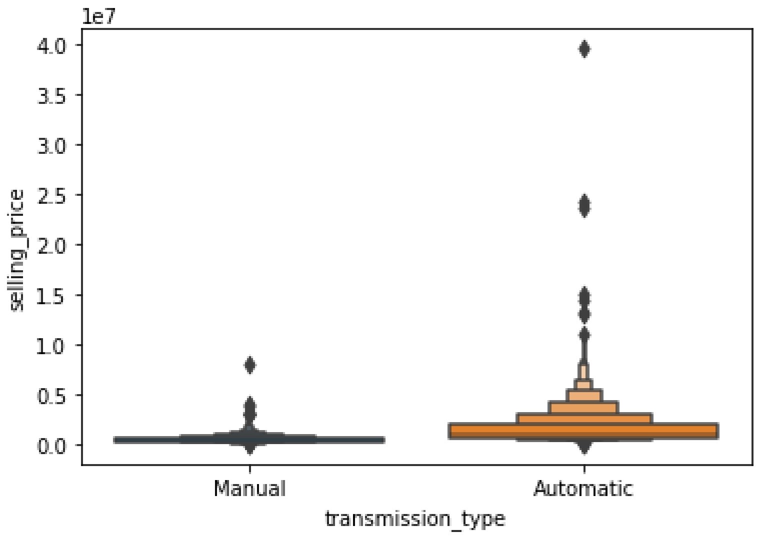
Out[57]: <AxesSubplot:xlabel='fuel_type', ylabel='engine'>



Observation: Automatic type cars have a higher selling price than Manual type cars.

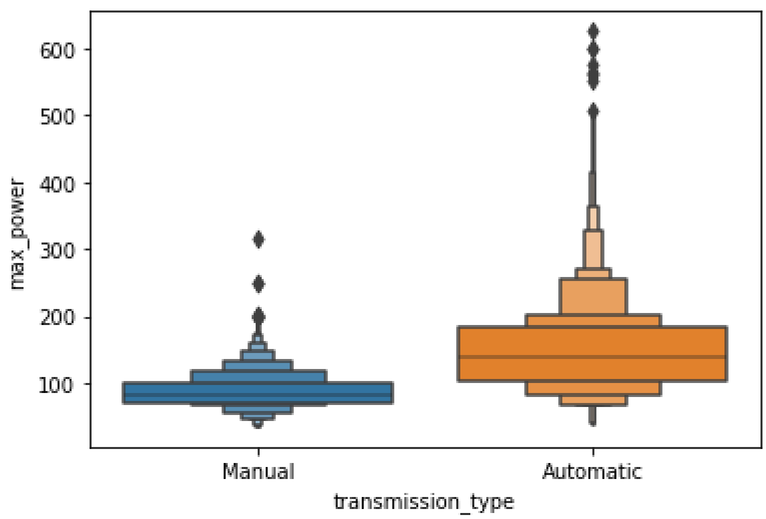
In [58]:
```
sns.boxenplot(x = 'transmission_type', y = 'selling_price', data = df)
```

Out[58]: <AxesSubplot:xlabel='transmission_type', ylabel='selling_price'>



In [59]:
```
sns.boxenplot(x = 'transmission_type', y = 'max_power', data = df)
```

Out[59]: <AxesSubplot:xlabel='transmission_type', ylabel='max_power'>



Creating Copy of Original Analysed dataset. All the encoding techniques will be applied on the copied dataframe.

In [60]:
```
df1=df.copy()
```

Encoding of Categorical Features

One Hot Encoding on seller_type

In [61]:
```
one_hot_st = pd.get_dummies(df1['seller_type'],drop_first=True)
df1 = df1.drop('seller_type',axis = 1)
df1 = df1.join(one_hot_st)
```

One Hot Encoding on transmission_type

In [62]:
```
one_hot_tt = pd.get_dummies(df1['transmission_type'],drop_first=True)
df1 = df1.drop('transmission_type',axis = 1)
df1 = df1.join(one_hot_tt)
```

One Hot Encoding on fuel_type

In [63]:
```
one_hot_ft = pd.get_dummies(df1['fuel_type'],drop_first=True)
df1 = df1.drop('fuel_type',axis = 1)
df1 = df1.join(one_hot_ft)
```

In [64]:
```
df1.head()
```

Out[64]:

	year	km_driven	mileage	engine	max_power	seats	selling_price	Individual	Trustmark Dealer	M
0	2012.0	120000.0	19.70	796.0	46.30	5.0	120000.0	1	0	
1	2016.0	20000.0	18.90	1197.0	82.00	5.0	550000.0	1	0	
2	2010.0	60000.0	17.00	1197.0	80.00	5.0	215000.0	1	0	
3	2012.0	37000.0	20.92	998.0	67.10	5.0	226000.0	1	0	
4	2015.0	30000.0	22.77	1498.0	98.59	5.0	570000.0	0	0	

In [65]:
```
df2=df1.copy()
```

In [66]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()

cols_to_scale = ['year','km_driven','mileage','engine','max_power','seats']
scaler.fit(df1[cols_to_scale])
df1[cols_to_scale] = scaler.transform(df1[cols_to_scale])
```

In [67]:
```
y = df1['selling_price']
X = df1.drop(['selling_price'], axis = 1)
```

In [68]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, rand
```

R2 Performance Metric from Scratch

In [69]:
```
def r2_value(y,y_pred):
  y_mean=np.mean(y)
  ss_reg=np.sum(np.square(np.subtract(y,y_pred)))
  ss_tot=np.sum(np.square(np.subtract(y,y_mean)))
  R_square=1-(ss_reg/ss_tot)
  return R_square
```

Linear Regression - 4-Fold Cross Validation

In [71]:
```
%%time
from sklearn.model_selection import KFold
from sklearn.linear_model import LinearRegression
lr = LinearRegression()
from sklearn.metrics import r2_score
from sklearn import metrics
from sklearn.model_selection import cross_val_score
LR=cross_val_score(lr,X_train,y_train,scoring='r2',cv=4)
lr.fit(X_train,y_train)
predict_lr=lr.predict(X_test)
print("R2 CV Scores : ",LR)
print("Mean r2 CV Score : ",np.mean(LR))
print("R2 value on test dataset : ",r2_value(y_test,predict_lr))
```

```
R2 CV Scores :  [0.54676366 0.67695906 0.66055764 0.60045648]
Mean r2 CV Score :  0.6211842102173946
R2 value on test dataset :  0.668316285144045
Wall time: 64.8 ms
```

Lasso Regression - 4-Fold Cross Validation

In [72]:
```
%%time
from sklearn.linear_model import Lasso
lasso = Lasso()
LASSO=cross_val_score(lasso,X_train,y_train,scoring='r2',cv=4)
lasso.fit(X_train,y_train)
predict_lasso=lasso.predict(X_test)

print("CV Scores : ",LASSO)
print("Mean CV Score : ",np.mean(LASSO))
print("R2 value on test dataset : ",r2_value(y_test,predict_lasso))
```

```
CV Scores :  [0.5467643  0.67696186 0.66055833 0.60045498]
Mean CV Score :  0.6211848692456259
R2 value on test dataset :  0.6683158582855311
Wall time: 179 ms
```

K-NN Regressor - 4-Fold Cross Validation

In [73]:
```
%%time
from sklearn.neighbors import KNeighborsRegressor
neigh = KNeighborsRegressor()
KNN=cross_val_score(neigh,X_train,y_train,scoring='r2',cv=4)
neigh.fit(X_train,y_train)
predict_knn=neigh.predict(X_test)
print("CV Scores : ",KNN)
print("Mean CV Score : ",np.mean(KNN))
print("R2 value on test dataset : ",r2_value(y_test,predict_knn))
```

```
CV Scores :  [0.68112351 0.86886798 0.86986352 0.79113903]
Mean CV Score :  0.8027485093455222
R2 value on test dataset :  0.8432506776202495
Wall time: 1.34 s
```

Decision Tree - 4-Fold Cross Validation

In [74]:
```
y1 = df2['selling_price']
X1 = df2.drop(['selling_price'], axis = 1)
X_train1, X_test1, y_train1, y_test1 = train_test_split(X1, y1, test_size=0.20
```

In [105]:
```
%%time
from sklearn.tree import DecisionTreeRegressor
dt = DecisionTreeRegressor()
DT=cross_val_score(dt,X_train1,y_train1,scoring='r2',cv=10)
dt.fit(X_train1,y_train1)
predict_dt=dt.predict(X_test1)
print("CV Scores : ",DT)
print("Mean CV Score : ",np.mean(DT))
print("R2 value on test dataset : ",r2_value(y_test1,predict_dt))
```

```
CV Scores :  [ 0.64761075  0.85480365  0.90815049  0.84328319  0.86339547  0.
83520879
 -0.3947663   0.59680718  0.87439694  0.91061541]
Mean CV Score :  0.6939505579078403
R2 value on test dataset :  0.8647602494494132
Wall time: 668 ms
```

Random Forest - 4-Fold Cross Validation

In [76]:
```
%%time
from sklearn.ensemble import RandomForestRegressor
rf_random = RandomForestRegressor()
RF=cross_val_score(rf_random,X_train1,y_train1,scoring='r2',cv=4)
rf_random.fit(X_train1,y_train1)
predict_rf=rf_random.predict(X_test1)
print("CV Scores : ",RF)
print("Mean CV Score : ",np.mean(RF))
print("R2 value on test dataset : ",r2_value(y_test1,predict_rf))
```

```
CV Scores :  [0.7523259  0.9193331  0.72323148 0.82025198]
Mean CV Score :  0.8037856144526561
R2 value on test dataset :  0.8825773513475873
Wall time: 23.1 s
```

XGBoost - 4-Fold Cross Validation

In [77]:
```
%%time
import xgboost as xgb
xg_reg = xgb.XGBRegressor()
XGB=cross_val_score(xg_reg,X_train1,y_train1,scoring='r2',cv=4)
xg_reg.fit(X_train1,y_train1)
predict_xgb=xg_reg.predict(X_test1)
print("CV Scores : ",XGB)
print("Mean CV Score : ",np.mean(XGB))
print("R2 value on test dataset : ",r2_value(y_test1,predict_xgb))
```

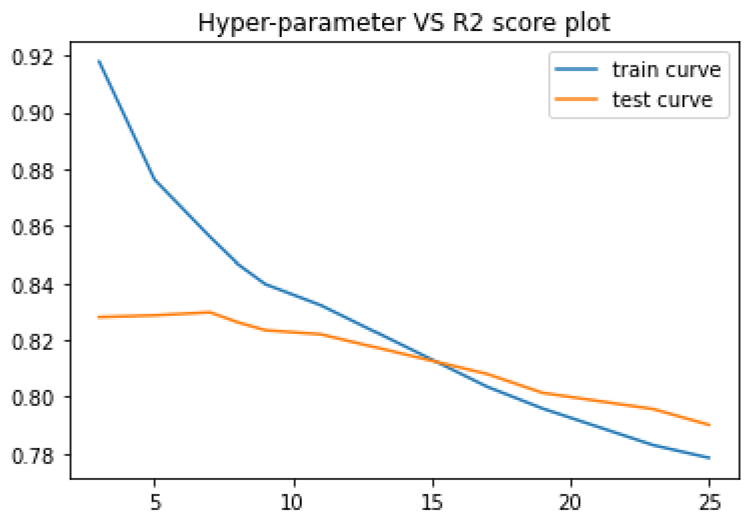
```
CV Scores :  [0.77519274 0.9270123  0.65826142 0.78350358]
Mean CV Score :  0.7859925068789624
R2 value on test dataset :  0.9110439619012481
Wall time: 2.15 s
```

Random Search CV with K-Fold CV from Scratch

In [78]:
```
import warnings
warnings.filterwarnings("ignore")
```

In [79]:
```
%%time
import random
from random import sample
def RandomSearchCV(X_train,Y_train,regressor, param_range, folds):

    train_scores=[]
    cv_scores=[]

    #Creating 10 random integers from the range give in variable 'param_range'
    para=[]
    r1=param_range[0]
    r2=param_range[1]
    while(r1<r2+1):
        para.append(r1)
        r1+=1
    params=sample(para,10)
    params.sort()

    for k in params:

        #Splitting x-train and y-train into subarrays according to the fold va
        x_t=[]
        y_t=[]
        for i in range (0,folds):
            j=0
            if i>=1:
                j=j+1
            x_t.append(X_train[(int((len(X_train)/folds)*i)+j):(int(len(X_trai
            y_t.append(Y_train[(int((len(Y_train)/folds)*i)+j):(int(len(Y_trai
        train_scores_fold=[]
        cv_scores_fold=[]
        for i in range (0,folds):


            x_cv=x_t[i]
            y_cv=y_t[i]
            x_train=np.zeros((1,13))
            y_train=np.zeros((1))
            for m in range (0,folds):
                if i!=m:
                    x_train=np.concatenate((x_train,x_t[m]))
                    y_train=np.concatenate((y_train,y_t[m]))

            #Calculating r2 scores for test and cv datasets.
            x_train=np.delete(x_train,0,0)
            y_train=np.delete(y_train,0,0)

            regressor.n_neighbors=k
            regressor.fit(x_train,y_train)

            Y_predicted=regressor.predict(x_cv)
            cv_scores_fold.append(r2_score(y_cv,Y_predicted))

            Y_predicted=regressor.predict(x_train)
            train_scores_fold.append(r2_score(y_train,Y_predicted))
        train_scores.append(np.mean(np.array(train_scores_fold)))
        cv_scores.append(np.mean(np.array(cv_scores_fold)))
```

```
    return train_scores,cv_scores,params
param_range=(1,25)
folds=10
neigh = KNeighborsRegressor()
trainscores,testscores,params=RandomSearchCV(X_train,y_train,neigh,param_range
plt.plot(params,trainscores, label='train curve')
plt.plot(params,testscores, label='test curve')
plt.title('Hyper-parameter VS R2 score plot')
plt.legend()
plt.show()
```




```
Wall time: 1min 36s
```

k=15 is the best value of hyperparameter

Grid Search CV for Lasso Regression

In [80]:
```
%%time
from sklearn.linear_model import Lasso
from sklearn.model_selection import GridSearchCV
lasso = Lasso()
lasso_alphas = np.logspace(-3,3,num=14)
lasso_gscv = GridSearchCV(lasso, param_grid=dict(alpha=lasso_alphas), cv = 4, 
lasso_gscv.fit(X_train, y_train)
print(lasso_gscv.best_params_)
print(lasso_gscv.best_score_)
```

```
{'alpha': 119.37766417144383}
0.6212043756318263
Wall time: 1.86 s
```

In [81]:
```
predict_lasso_hpt=lasso_gscv.predict(X_test)
print("R2 value on test dataset : ",r2_value(y_test,predict_lasso_hpt))
```

```
R2 value on test dataset :  0.66823565687871
```

Grid Search CV for Decision Tree

In [82]:
```
%%time
dt_params = [{'max_depth': list(range(1, 15)), 'max_leaf_nodes':list(range(0,1(
dt_gscv = GridSearchCV(dt, dt_params, cv = 4, scoring='r2')
dt_gscv.fit(X_train1, y_train1)
print(dt_gscv.best_params_)
print(dt_gscv.best_score_)
```

```
{'max_depth': 9, 'max_leaf_nodes': 99}
0.7274753136879395
Wall time: 2min 12s
```

In [83]:
```
predict_dt_hpt=dt_gscv.predict(X_test1)
print("R2 value on test dataset : ",r2_value(y_test1,predict_dt_hpt))
```

```
R2 value on test dataset :  0.8626804931982136
```

Grid Search CV for XGBoost

In [84]:
```
%%time
import warnings
warnings.filterwarnings("ignore")
xgb_params = [{'max_depth': list(range(1, 10)), 'learning_rate': list(np.linspa
xgb_gscv = GridSearchCV(xg_reg, xgb_params, cv = 4, scoring='r2')
xgb_gscv.fit(X_train1, y_train1)
print(xgb_gscv.best_params_)
print(xgb_gscv.best_score_)
```

```
{'learning_rate': 0.5555555555555556, 'max_depth': 8, 'n_estimators': 9}
0.7663237282643942
Wall time: 1min 54s
```

In [85]:
```
predict_xgb_hpt=xgb_gscv.predict(X_test1)
print("R2 value on test dataset : ",r2_value(y_test1,predict_xgb_hpt))
```

```
R2 value on test dataset :  0.9039448955950413
```

Grid Search CV for Random Forest

In [87]:
```
from pprint import pprint
print('Parameters used in default setting:\n')
pprint(rf_random.get_params())
```

```
Parameters used in default setting:

{'bootstrap': True,
 'ccp_alpha': 0.0,
 'criterion': 'squared_error',
 'max_depth': None,
 'max_features': 1.0,
 'max_leaf_nodes': None,
 'max_samples': None,
 'min_impurity_decrease': 0.0,
 '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': None,
 'verbose': 0,
 'warm_start': False}
```

In [88]:
```
%%time
from sklearn.model_selection import RandomizedSearchCV
# Number of trees in random forest
n_estimators = [int(x) for x in np.linspace(start = 500, stop = 2000, num = 10
random_grid = {'n_estimators': n_estimators}
rf_rscv = RandomizedSearchCV(estimator = rf_random, param_distributions = rand
rf_rscv.fit(X_train1, y_train1)
rf_rscv.best_params_
```

```
Wall time: 1h 48min 11s
```

Out[88]:
```
{'n_estimators': 1000}
```

In [106]:
```
rf_rscv.best_score_
```

Out[106]:
```
0.8544879083283694
```

In [89]:
```
predict_rf_rscv=rf_rscv.predict(X_test1)
print("R2 value on test dataset : ",r2_value(y_test1,predict_rf_rscv))
```

```
R2 value on test dataset :  0.8712697080220759
```

In [90]:
```
df3=df1.copy()
```

In [91]:
```
df3 = df3.rename(columns={'Trustmark Dealer': 'Trustmark_Dealer'})
```

In [92]:
```
df3.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 19744 entries, 0 to 20025
Data columns (total 14 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   year              19744 non-null  float64
 1   km_driven         19744 non-null  float64
 2   mileage           19744 non-null  float64
 3   engine            19744 non-null  float64
 4   max_power         19744 non-null  float64
 5   seats             19744 non-null  float64
 6   selling_price     19744 non-null  float64
 7   Individual        19744 non-null  uint8  
 8   Trustmark_Dealer  19744 non-null  uint8  
 9   Manual            19744 non-null  uint8  
 10  Diesel            19744 non-null  uint8  
 11  Electric          19744 non-null  uint8  
 12  LPG               19744 non-null  uint8  
 13  Petrol            19744 non-null  uint8  
dtypes: float64(7), uint8(7)
memory usage: 1.8 MB
```

In [93]:
```
y_final = df3['selling_price']
X_final = df3.drop(['selling_price'], axis = 1)
```

In [94]:
```

X_train_final, X_test_final, y_train_final, y_test_final = train_test_split(X_
```

In [95]:
```
%%time
import xgboost as xgb
xg_reg_final = xgb.XGBRegressor()
XGB_final=cross_val_score(xg_reg_final,X_train_final,y_train_final,scoring='r2
xg_reg_final.fit(X_train_final,y_train_final)
predict_xgb_final=xg_reg.predict(X_test_final)
print("CV Scores : ",XGB_final)
print("Mean CV Score : ",np.mean(XGB_final))
print("R2 value on test dataset : ",r2_value(y_test_final,predict_xgb_final))
```

```
CV Scores :  [0.71846814 0.94172205 0.91057739 0.92310967 0.9439498  0.541090
52
 0.40859015 0.68569053 0.93511365 0.94397881]
Mean CV Score :  0.7952290701390704
R2 value on test dataset :  -0.768888363659975
Wall time: 4.23 s
```

In [98]:
```
filename = 'rfrm.pkl'
with open(filename, 'wb') as f:
    classification_dict = pickle.dump(rf_random,f)
```