Business Problem

There's no need to buy new cars anymore! Second-hand vehicles are becoming more and more popular, with buyers getting great value for their money. But as opposed to showrooms or dealerships where you can walk away without much thought involved in the decision-making process, these second-hand car deals require careful consideration.

Before buying or selling an old car, knowing its value is essential. Unfortunately, dealers or owners can often ask for the wrong amount, hoping to gain an ill-gotten profit. However, if you know how to find the valuation, they won't be able to fool you.

This process can be made more accessible, with online tools that can help you calculate a car's value in minutes.

Business objective and constraints

- Interpretablity is partially important.
- No low latency requirement.
- Errors- deviation from the actual price should not be more than 50k to 1Lakh rupees.

Mapping to an ML problem

Data aquisation from kaggle

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
! pip install -q kaggle
```

```
! mkdir ~/.kaggle
```

```
! cp /content/drive/MyDrive/DS_DL_ML_AI_project/kaggle.json ~/.kaggle/
```

```
! chmod 600 ~/.kaggle/kaggle.json
```

```
! kaggle datasets download -d nehalbirla/vehicle-dataset-from-cardekho
```

```
Downloading vehicle-dataset-from-cardekho.zip to /content
100% 292k/292k [00:00<00:00, 861kB/s]
100% 292k/292k [00:00<00:00, 861kB/s]
```

```
! mkdir train
```

```
# All the data in the ZIP will be unzipped in train folder.
! unzip /content/vehicle-dataset-from-cardekho.zip -d train
```

```
Archive:  /content/vehicle-dataset-from-cardekho.zip
  inflating: train/CAR DETAILS FROM CAR DEKHO.csv
  inflating: train/Car details v3.csv
  inflating: train/car data.csv
  inflating: train/car details v4.csv
```

Data Files overview

There are 4 files in the kaggle API out of which we will concat 3 files by combining the rows of required features:

- Car details v3.csv file will be the primary dataset since it has just enough features required for modelling and highest number of rows compared to other files.
- Data contains 13 columns:

```
name: Name of the car barand and model.
year: Year of the car when it was bought.
selling_price: Price at which the car is being sold.
km_driven: Number of Kilometres the car is driven from the date of purchase.
fuel: Fuel type of car (petrol / diesel / CNG / LPG / electric)
seller_type: Tells if a Seller is Individual or a Dealer
transmission: Gear transmission of the car (Automatic/Manual)
owner: Number of previous owners of the car.
mileage: kmpl of the car.
engine: cc of the engine.
max_power: max power output of the engine.
torque: max torque output of the engine.
seats: Max seats in a car.
```

NOTE

- We will be using features of Car details v3.csv file but relevant data from other files will be added to this file.

ML Problem

- Regression problem.
- Need data featurizarion of continuous numerical feature into categories such as engine capacity.
- Encode categorical variables.

Performance Metric

- Mean Absolute Error(MAE)
- Root Mean Squared Error(RMSE)
- Root Mean Squared Log Error(RMSLE)
- R Squared (R2)
- Adjusted R Squared

Train Test Split

- Random split as there is no time stamps in the data and this problem doesn't depend completely on time unless affected by external factors.

Data Acquiring, Cleaning, Prepration and Feature engineering(basic)

Importing and downloading required libraries

```
! pip install lightgbm
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/
Requirement already satisfied: lightgbm in /usr/local/lib/python3.9/dist-packages (3
Requirement already satisfied: numpy in /usr/local/lib/python3.9/dist-packages (from
Requirement already satisfied: scikit-learn!=0.22.0 in /usr/local/lib/python3.9/dist
Requirement already satisfied: wheel in /usr/local/lib/python3.9/dist-packages (from
Requirement already satisfied: scipy in /usr/local/lib/python3.9/dist-packages (from
Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.9/dist-packag
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.9/dist
```

```
! pip install catboost
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/
Collecting catboost
  Downloading catboost-1.1.1-cp39-none-manylinux1_x86_64.whl (76.6 MB)
```

```
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 76.6/76.6 MB 12.8 MB/s eta 0:00:00
Requirement already satisfied: six in /usr/local/lib/python3.9/dist-packages (from c
Requirement already satisfied: pandas>=0.24.0 in /usr/local/lib/python3.9/dist-packa
Requirement already satisfied: scipy in /usr/local/lib/python3.9/dist-packages (from
Requirement already satisfied: matplotlib in /usr/local/lib/python3.9/dist-packages
Requirement already satisfied: graphviz in /usr/local/lib/python3.9/dist-packages (f
Requirement already satisfied: numpy>=1.16.0 in /usr/local/lib/python3.9/dist-packag
Requirement already satisfied: plotly in /usr/local/lib/python3.9/dist-packages (fro
Requirement already satisfied: python-dateutil>=2.8.1 in /usr/local/lib/python3.9/di
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.9/dist-package
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.9/dist-pa
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.9/dist-pac
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.9/dist-pac
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.9/dist-pack
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.9/dist-package
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.9/dist-packag
Requirement already satisfied: importlib-resources>=3.2.0 in /usr/local/lib/python3.
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.9/dist-pa
Requirement already satisfied: tenacity>=6.2.0 in /usr/local/lib/python3.9/dist-pack
Requirement already satisfied: zipp>=3.1.0 in /usr/local/lib/python3.9/dist-packages
Installing collected packages: catboost
Successfully installed catboost-1.1.1
```

```
# Import required libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.manifold import TSNE
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score
from catboost import CatBoostRegressor, Pool
import lightgbm as lgb
import math
import statistics
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import RandomizedSearchCV
import random
from sklearn.ensemble import RandomForestRegressor
from scipy import rand
from sklearn.svm import SVR
from sklearn.tree import DecisionTreeRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.neural_network import MLPRegressor
import tensorflow as tf
from tensorflow.keras import Model
from tensorflow.keras import Sequential
from tensorflow.keras.optimizers import Adam
from sklearn.preprocessing import StandardScaler
from tensorflow.keras.layers import Dense, Dropout
from sklearn.model_selection import train_test_split
from tensorflow.keras.losses import MeanSquaredError
```

```
from tensorflow.keras.metrics import RootMeanSquaredError
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import median_absolute_error
from prettytable import PrettyTable
import pickle
import datetime
```

Data reading

```
# 1) Getting data from 'Car details v3.csv' file
carsData_v3 = pd.read_csv('/content/train/Car details v3.csv') # Read CSV file
print("Shape of the data: ",carsData_v3.shape) # shape of the dataset
carsData_v3.head() # View first 5 rows by default
```

```
Shape of the data:  (8128, 13)
```

	name	year	selling_price	km_driven	fuel	seller_type	transmission	owner
0	Maruti Swift Dzire VDI	2014	450000	145500	Diesel	Individual	Manual	First Owner
1	Skoda Rapid 1.5 TDI Ambition	2014	370000	120000	Diesel	Individual	Manual	Second Owner
2	Honda City 2017-2020 EXi	2006	158000	140000	Petrol	Individual	Manual	Third Owner
	Hyundai							

```
# 2) Getting data from '/content/train/car details v4.csv' file
carsData_v4 = pd.read_csv('/content/train/car details v4.csv') # Read CSV file
print("Shape of the data: ",carsData_v4.shape) # shape of the dataset
carsData_v4.head() # View first 5 rows by default
```

```
Shape of the data:  (2059, 20)
```

	Make	Model	Price	Year	Kilometer	Fuel Type	Transmission	Location	Color
0	Honda	Amaze 1.2 VX i-VTEC	505000	2017	87150	Petrol	Manual	Pune	Grey
1	Maruti Suzuki	Swift DZire VDI	450000	2014	75000	Diesel	Manual	Ludhiana	White
2	Hyundai	i10 Magna 1.2 Kappa2	220000	2011	67000	Petrol	Manual	Lucknow	Maroon
3	Toyota	Glanza G	799000	2019	37500	Petrol	Manual	Mangalore	Red

```
# 3) Getting data from '/content/train/CAR DETAILS FROM CAR DEKHO.csv' file
carsData_CarDekho = pd.read_csv('/content/train/CAR DETAILS FROM CAR DEKHO.csv') # Read CS
print("Shape of the data: ",carsData_CarDekho.shape) # shape of the dataset
carsData_CarDekho.head() # View first 5 rows by default
```

```
Shape of the data:  (4340, 8)
```

	name	year	selling_price	km_driven	fuel	seller_type	transmission	owner
0	Maruti 800 AC	2007	60000	70000	Petrol	Individual	Manual	First Owner
1	Maruti Wagon R LXI Minor	2007	135000	50000	Petrol	Individual	Manual	First Owner
	Hyundai							

- Make and model are like index for cars.
- Hence modifying required features in each file to concat.

```
# Modifying 'name' feature from 'Car details v3.csv' file.


# we will split the name into 3 categories -> make,model and variant, hence we split first
# make -> car brand
# model -> car model
# Variant -> car variants in that model
carsData_v3[['make','model','variant']] = carsData_v3['name'].str.split(" ",2,expand=True)
```

```
carsData_v3 = carsData_v3.reindex(columns=['make','model','variant','year', 'selling_price
       'transmission', 'owner', 'mileage', 'engine', 'max_power', 'torque',
       'seats'])
carsData_v3.head()
```

	make	model	variant	year	selling_price	km_driven	fuel	seller_type	trans
0	Maruti	Swift	Dzire VDI	2014	450000	145500	Diesel	Individual	
1	Skoda	Rapid	1.5 TDI Ambition	2014	370000	120000	Diesel	Individual	
2	Honda	City	2017-2020 EXi	2006	158000	140000	Petrol	Individual	
3	Hyundai	i20	Sportz Diesel	2010	225000	127000	Diesel	Individual	
4	Maruti	Swift	VXI BSIII	2007	130000	120000	Petrol	Individual	

```
# Modifying 'model' feature from 'Car details v4.csv' file.
# Removing extra columns


# we will split the name into 3 categories -> make,model and variant, hence we split first
# make -> car brand
# model -> car model
# Variant -> car variants in that model

carsData_v4[['Model','variant']] = carsData_v4['Model'].str.split(" ",1,expand=True)

# Add milege value NaN in V4 file since it has no milege column and impute values later.
carsData_v4 = carsData_v4.reindex(columns=['Make', 'Model','variant','Year','Price','Kilom
                                           'Transmission','Owner', 'mileage','Engine','Max

carsData_v4.columns = carsData_v3.columns # To have same column names
carsData_v4.head()
```

	make	model	variant	year	selling_price	km_driven	fuel	seller_type	tran
0	Honda	Amaze	1.2 VX i-VTEC	2017	505000	87150	Petrol	Corporate	
1	Maruti Suzuki	Swift	DZire VDI	2014	450000	75000	Diesel	Individual	
2	Hyundai	i10	Magna 1.2 Kappa2	2011	220000	67000	Petrol	Individual	
3	Toyota	Glanza	G	2019	799000	37500	Petrol	Individual	

```
# Modifying 'name' feature from 'Car details v4.csv' file.
# adding extra columns to match primary file.


# we will split the name into 3 categories -> make,model and variant, hence we split first
# make -> car brand
# model -> car model
# Variant -> car variants in that model

carsData_CarDekho[['make','model','variant']] = carsData_CarDekho['name'].str.split(" ",2,

# Add extra columns with nan and impute values later if possible.
carsData_CarDekho = carsData_CarDekho.reindex(columns=['make','model','variant','year','se
                                        'transmission','owner', 'mileage','Engine','Max

carsData_CarDekho.columns = carsData_v3.columns # To have same column names
carsData_CarDekho.head()
```

	make	model	variant	year	selling_price	km_driven	fuel	seller_type	tra
0	Maruti	800	AC	2007	60000	70000	Petrol	Individual	
1	Maruti	Wagon	R LXI Minor	2007	135000	50000	Petrol	Individual	
2	Hyundai	Verna	1.6 SX	2012	600000	100000	Diesel	Individual	
3	Datsun	RediGO	T Option	2017	250000	46000	Petrol	Individual	
4	Honda	Amaze	VX i-DTEC	2014	450000	141000	Diesel	Individual	

```
# Concating all 3 data

carsData = pd.concat([carsData_v3, carsData_v4, carsData_CarDekho], ignore_index=True,sort

print("Shape of the final Cars Data data: ",carsData.shape) # shape of the dataset
carsData.head() # View first 5 rows by default
```

```
Shape of the final Cars Data data:  (14527, 15)
```

	make	model	variant	year	selling_price	km_driven	fuel	seller_type	trans
0	Maruti	Swift	Dzire VDI	2014	450000	145500	Diesel	Individual	
1	Skoda	Rapid	1.5 TDI Ambition	2014	370000	120000	Diesel	Individual	
2	Honda	City	2017-2020 EXi	2006	158000	140000	Petrol	Individual	
3	Hyundai	i20	Sportz Diesel	2010	225000	127000	Diesel	Individual	
4	Maruti	Swift	VXI BSIII	2007	130000	120000	Petrol	Individual	

```
# Check Dtype of the features
carsData.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14527 entries, 0 to 14526
Data columns (total 15 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   make           14527 non-null  object
 1   model          14527 non-null  object
 2   variant        14526 non-null  object
 3   year           14527 non-null  int64
 4   selling_price  14527 non-null  int64
 5   km_driven      14527 non-null  int64
 6   fuel           14527 non-null  object
 7   seller_type    14527 non-null  object
 8   transmission   14527 non-null  object
 9   owner          14527 non-null  object
 10  mileage        7907 non-null   object
 11  engine         9886 non-null   object
 12  max_power      9892 non-null   object
 13  torque         9885 non-null   object
 14  seats          9902 non-null   float64
dtypes: float64(1), int64(3), object(11)
memory usage: 1.7+ MB
```

Numerical features: year, selling_price , km_driven have int Dtype hence no non standard missing values.

mileage, engine, max_power, torque are numerical features but has UNIT hence displayed has object Dtype and has null values

preprocess to move units into new column for future analysis and ignore torque feature as it will be dropped since its not usefull from domain knowledge and data is complex.

Cleaning and Prepration

- Analyzing, cleaning and preparing each feature

```
# 1) cleaning 'Make'

carsData['make'].unique()
```

```
array(['Maruti', 'Skoda', 'Honda', 'Hyundai', 'Toyota', 'Ford', 'Renault',
       'Mahindra', 'Tata', 'Chevrolet', 'Fiat', 'Datsun', 'Jeep',
       'Mercedes-Benz', 'Mitsubishi', 'Audi', 'Volkswagen', 'BMW',
       'Nissan', 'Lexus', 'Jaguar', 'Land', 'MG', 'Volvo', 'Daewoo',
       'Kia', 'Force', 'Ambassador', 'Ashok', 'Isuzu', 'Opel', 'Peugeot',
       'Maruti Suzuki', 'Porsche', 'Land Rover', 'Maserati', 'MINI',
       'Ferrari', 'Lamborghini', 'Ssangyong', 'Rolls-Royce', 'OpelCorsa'],
      dtype=object)
```

- Clean duplicate name of car brands:

1) Maruti / Maruti Suzuki -> Maruti

2) Land Rover / Land -> Land Rover

3) Ssangyong -> Mahindra

```
# Cleaniing Maruti brand
indx_dup_maruti = carsData[(carsData['make'] == 'Maruti') | (carsData['make'] == 'Maruti S

#Replacing index values
carsData.loc[indx_dup_maruti,'make'] = 'Maruti'
```

```
# Cleaniing Land Rover brand
indx_dup_land = carsData[(carsData['make'] == 'Land') | (carsData['make'] == 'Land Rover')

#Replacing index values
carsData.loc[indx_dup_land,'make'] = 'Land Rover'
```

```
# Cleaniing Ssangyong brand
indx_dup_Mahindra = carsData[carsData['make'] == 'Ssangyong'].index
```

```
#Replacing index values
carsData.loc[indx_dup_Mahindra,'make'] = 'Mahindra'
carsData.loc[indx_dup_Mahindra,'model'] = 'Ssangyong'

carsData.loc[indx_dup_Mahindra,'variant'] = "Rexton "+carsData.loc[indx_dup_Mahindra,'vari
```

- Analyzing Car brands with counts <20 and drop them since there is no enough data to predict and high value luxary cars will be outliers.

```
carsData['make'].value_counts()
```

```
Maruti           4168
Hyundai          2585
Mahindra         1259
Tata             1152
Honda             877
Toyota            826
Ford              683
Chevrolet         425
Renault           417
Volkswagen        343
BMW               280
Mercedes-Benz     260
Audi              227
Skoda             213
Nissan            161
Datsun            110
Jaguar             94
Volvo              87
Fiat               86
Jeep               52
Land Rover         44
Lexus              40
Kia                28
Mitsubishi         24
MG                 22
Porsche            15
MINI               11
Ambassador          8
Isuzu               8
Force               7
Daewoo              4
Rolls-Royce         3
OpelCorsa           2
Maserati            1
Peugeot             1
Ferrari             1
Lamborghini         1
Ashok               1
Opel                1
Name: make, dtype: int64
```

```
makeLessThan20 = []
for make, count in carsData['make'].value_counts().iteritems():
```

```
    if count < 20:
      makeLessThan20.append(make)

print("Brands less than 20 counts: ",makeLessThan20)
```

```
Brands less than 20 counts:  ['Porsche', 'MINI', 'Ambassador', 'Isuzu', 'Force', 'Da
```

```
# Drop rows with the above brand name

# Getting index of rows to be dropped
minCountBrandsIndx = carsData.loc[carsData['make'].isin(makeLessThan20)].index

# Drop rows with above index
carsData.drop(axis = 0, index = minCountBrandsIndx, inplace=True)
```

```
# 2) cleaning 'Model'

carsData['model'].unique()
```

```
array(['Swift', 'Rapid', 'City', 'i20', 'Xcent', 'Wagon', '800', 'Etios',
       'Figo', 'Duster', 'Zen', 'KUV', 'Ertiga', 'Alto', 'Verito', 'WR-V',
       'SX4', 'Tigor', 'Baleno', 'Enjoy', 'Omni', 'Vitara', 'Palio',
       'Verna', 'GO', 'Safari', 'Compass', 'Fortuner', 'Innova', 'B',
       'Amaze', 'Pajero', 'Ciaz', 'Jazz', 'A6', 'Corolla', 'New', 'Manza',
       'i10', 'Ameo', 'Indica', 'Vento', 'EcoSport', 'X1', 'Celerio',
       'Polo', 'Eeco', 'Scorpio', 'Freestyle', 'Passat', 'XUV500',
       'Indigo', 'Terrano', 'Creta', 'KWID', 'Santro', 'Q5', 'ES', 'XF',
       'Wrangler', 'Rover', 'S-Class', '5', 'X4', 'Superb', 'E-Class',
       'Hector', 'XC40', 'Q7', 'Elantra', 'XE', 'Nexon', 'CLA', 'Glanza',
       '3', 'Camry', 'XC90', 'Ritz', 'Grand', 'Zest', 'Getz', 'Elite',
       'Brio', 'Hexa', 'Sunny', 'Micra', 'Ssangyong', 'Quanto', 'Accent',
       'Ignis', 'Marazzo', 'Tiago', 'Thar', 'Sumo', 'Bolero', 'GL-Class',
       'Beat', 'Willys', 'A-Star', 'XUV300', 'Nano', 'GTI', 'V40', 'CR-V',
       'EON', 'RediGO', 'Captiva', 'Fiesta', 'Seltos', 'Civic', 'Sail',
       'Venture', 'Estilo', 'Classic', 'BR-V', 'Ecosport', 'Aria', 'TUV',
       'Bolt', 'Accord', 'Xylo', 'Grande', 'S-Cross', 'Yaris', 'Tavera',
       'Linea', 'Endeavour', 'Aveo', 'Esteem', 'Triber', 'Fusion',
       'Octavia', 'A4', 'XL6', 'Santa', 'Spark', 'Aspire', 'Punto',
       'Optra', 'Mobilio', 'Qualis', 'BRV', 'X6', 'Cruze', 'GLA', '6',
       'NuvoSport', 'Scala', 'Jeep', 'Lodgy', 'Pulse', 'Supro', 'Ingenio',
       'Sonata', 'Renault', 'Kicks', 'Jetta', 'M-Class', 'Teana', 'Yeti',
       'Q3', 'Logan', 'A3', 'Dzire', 'Ikon', 'Fluence', 'Xenon', '7',
       'S60', 'Lancer', 'X7', 'Premio', 'Fabia', 'Platinum', 'Captur',
       'Gypsy', 'Estate', 'Koleos', 'Harrier', 'Multivan', 'Avventura',
       'Laura', 'Tucson', 'Winger', 'Spacio', 'Venue', 'CrossPolo',
       'Marshal', 'Kodiaq', 'X3', 'Land', 'X5', 'Trailblazer', 'GLC',
       'XC60', 'S90', 'S-Presso', 'Kwid', 'SLK-Class', '3-Series',
       'C-Class', 'DZire', 'Q2', '5-Series', 'Discovery', 'GLE', 'Astor',
       'Sonet', 'RS5', 'R-Class', 'Punch', 'F-Pace', 'Range', 'GLS',
       'Evoque', 'TT', 'Kiger', 'Eon', 'TUV300', 'Tiguan', 'Go',
       '7-Series', 'Gloster', 'Redigo', 'XUV700', 'A-Class', 'Alcazar',
       'Urban', 'XJ', '6-Series', 'Commuter', 'Magnite', 'A7', 'NX',
       'Taigun', 'Mustang', 'LX', '2', 'Vellfire', 'Q8', 'Kushaq', 'A8',
       'Alturas', 'Carnival', 'C-Coupe', 'Aura', 'CLS', 'V-Class',
```

```
       'B-class', 'ZS', 'Altroz', 'KUV100', 'Outlander', 'A5', 'redi-GO',
       'Evalia', '500', 'Montero', 'X-Trail', 'RS7', 'XC'], dtype=object)
```

```
carsData[carsData['model']=='Range']
```

	make	model	variant	year	selling_price	km_driven	fuel	seller_type	tr
8387	Land Rover	Range	Rover Sport SE 2.0 Petrol	2022	12500000	22010	Petrol	Individual	
8710	Land Rover	Range	Rover 3.0 V6 Diesel Vogue	2019	22000000	35000	Diesel	Individual	
8819	Land Rover	Range	Rover Sport SDV6 HSE	2014	5375000	80000	Diesel	Individual	
8921	Land Rover	Range	Rover Sport SDV6 SE	2016	7200000	45000	Diesel	Individual	
9066	Land Rover	Range	Rover Sport SDV6 S	2014	5900000	70000	Diesel	Corporate	
9433	Land Rover	Range	Rover 3.0 V6 Diesel Vogue LWB	2020	27500000	11000	Diesel	Individual	
9441	Land Rover	Range	Rover 3.0 V6 Diesel Vogue	2019	19300000	63000	Diesel	Individual	
10099	Land Rover	Range	Rover Sport SDV6 SE	2014	6000000	82000	Diesel	Individual	
10160	Land Rover	Range	Rover Velar 2.0 S Petrol 250	2020	8900000	88000	Petrol	Individual	

- analyzing unique model names and cleaning.

```
# clean model == 'B

# Before edit
model_b_Index_edit = carsData[carsData['model'] == 'B'].index
carsData.loc[model_b_Index_edit]
```

	make	model	variant	year	selling_price	km_driven	fuel	seller_type
49	Mercedes-Benz	B	Class B180	2014	1450000	27800	Diesel	Dealer
2932	Mercedes-Benz	B	Class B180 Sports	2014	1250000	42000	Petrol	Individual
7447	Mercedes-Benz	B	Class B200 CDI Sport	2016	1859000	40000	Diesel	Individual
7797	Mercedes-Benz	B	Class B200 CDI Sport	2015	2051000	35000	Diesel	Dealer
12537	Mercedes-Benz	B	Class B180 Sports	2013	1100000	40000	Petrol	Individual

```
# Edit both model and variant labels manually

#model edit
carsData.loc[model_b_Index_edit,'model']  = 'B-Class'

# variant edit
carsData.loc[model_b_Index_edit,'variant'] = carsData.loc[model_b_Index_edit,'variant'].st

# After edit
carsData.loc[model_b_Index_edit]
```

	make	model	variant	year	selling_price	km_driven	fuel	seller_type
49	Mercedes-Benz	B-Class	B180	2014	1450000	27800	Diesel	Dealer
2932	Mercedes-Benz	B-Class	B180 Sports	2014	1250000	42000	Petrol	Individual
7447	Mercedes-Benz	B-Class	B200 CDI Sport	2016	1859000	40000	Diesel	Individual

```
# clean model == 'New'

# Before edit
model_new_Index_edit = carsData[carsData['model'] == 'New'].index
carsData.loc[model_new_Index_edit]
```

	make	model	variant	year	selling_price	km_driven	fuel	seller_
60	Mercedes-Benz	New	C-Class 220 CDI AT	2013	1425000	59000	Diesel	D

```
# check for multiple make values

carsData.loc[model_new_Index_edit,'make'].unique()

# There is issue with 2 models
```

```
array(['Mercedes-Benz', 'Tata'], dtype=object)
```

```
# 'Mercedes-Benz'

new_merc_indx = carsData[(carsData['model'] == 'New') & (carsData['make']=='Mercedes-Benz'
# Before edit
carsData.loc[new_merc_indx]
```

	make	model	variant	year	selling_price	km_driven	fuel	seller_
60	Mercedes-Benz	New	C-Class 220 CDI AT	2013	1425000	59000	Diesel	D
158	Mercedes-Benz	New	C-Class C 200 AVANTGARDE	2017	2700000	16000	Petrol	D
362	Mercedes-Benz	New	C-Class 220 CDI AT	2013	1550000	25000	Diesel	Indi
1255	Mercedes-Benz	New	C-Class 220 CDI AT	2012	1400000	50000	Diesel	Indi
1990	Mercedes-Benz	New	C-Class C 220 CDI Elegance MT	2018	2950000	46000	Diesel	D
	[illegible]		C-Class C 200					

```
# Edit both model and variant labels manually

#model edit
carsData.loc[new_merc_indx,'model']  = "New C-Class"

# variant edit
carsData.loc[new_merc_indx,'variant'] = carsData.loc[new_merc_indx,'variant'].str.split("

# After edit
carsData.loc[new_merc_indx]
```

	make	model	variant	year	selling_price	km_driven	fuel	seller_
60	Mercedes-Benz	New C-Class	220 CDI AT	2013	1425000	59000	Diesel	D
158	Mercedes-Benz	New C-Class	C 200 AVANTGARDE	2017	2700000	16000	Petrol	D
362	Mercedes-Benz	New C-Class	220 CDI AT	2013	1550000	25000	Diesel	Indi
1255	Mercedes-Benz	New C-Class	220 CDI AT	2012	1400000	50000	Diesel	Indi
1990	Mercedes-Benz	New C-Class	C 220 CDI Elegance MT	2018	2950000	46000	Diesel	D
3107	Mercedes-Benz	New C-Class	C 200 Kompressor Elegance AT	2007	400000	42000	Petrol	D
4299	Mercedes-Benz	New C-Class	C 200 Kompressor Elegance MT	2006	650000	40000	Petrol	Indi
4789	Mercedes-Benz	New C-Class	C 200 AVANTGARDE	2017	2700000	16000	Petrol	D

```
# 'Tata'

new_tata_indx = carsData[(carsData['model'] == 'New') & (carsData['make']=='Tata')].index
# Before edit
carsData.loc[new_tata_indx]
```

	make	model	variant	year	selling_price	km_driven	fuel	seller_type	trai
285	Tata	New	Safari DICOR 2.2 EX 4x2	2011	450000	80000	Diesel	Individual	
506	Tata	New	Safari DICOR 2.2 VX 4x2	2009	250000	146000	Diesel	Individual	
941	Tata	New	Safari 3L Dicor LX 4x2	2007	280000	160000	Diesel	Individual	
1298	Tata	New	Safari DICOR 2.2 EX 4x2	2010	535000	96443	Diesel	Individual	
1354	Tata	New	Safari DICOR 2.2 EX 4x2	2008	150000	120000	Diesel	Individual	
...	...	...	...	...	...	...	...	...	
13953	Tata	New	Safari DICOR 2.2 GX 4x2 BS IV	2012	450000	97000	Diesel	Individual	
13980	Tata	New	Safari DICOR 2.2 EX 4x2	2012	320000	140000	Diesel	Individual	

```
# Edit both model and variant labels manually

#model edit
carsData.loc[new_tata_indx,'model']  = "New Safari"

# variant edit
carsData.loc[new_tata_indx,'variant'] = carsData.loc[new_tata_indx,'variant'].str.split("

# After edit
carsData.loc[new_tata_indx]
```

	make	model	variant	year	selling_price	km_driven	fuel	seller_type	tra
285	Tata	New Safari	DICOR 2.2 EX 4x2	2011	450000	80000	Diesel	Individual	
506	Tata	New Safari	DICOR 2.2 VX 4x2	2009	250000	146000	Diesel	Individual	
941	Tata	New Safari	3L Dicor LX 4x2	2007	280000	160000	Diesel	Individual	
1298	Tata	New Safari	DICOR 2.2 EX 4x2	2010	535000	96443	Diesel	Individual	
1354	Tata	New Safari	DICOR 2.2 EX 4x2	2008	150000	120000	Diesel	Individual	
...	...	...	...	...	...	...	...	...	
13953	Tata	New Safari	DICOR 2.2 GX 4x2 BS IV	2012	450000	97000	Diesel	Individual	
13980	Tata	New Safari	DICOR 2.2 EX 4x2	2012	320000	140000	Diesel	Individual	
14192	Tata	New Safari	4X2	2007	550000	80000	Petrol	Individual	
14300	Tata	New Safari	DICOR 2.2 GX 4x2 BS IV	2012	320000	80000	Diesel	Individual	

```
#'Rover'

new_rover_indx = carsData[carsData['model'] == 'Rover'].index
# Before edit
carsData.loc[new_rover_indx]
```

	make	model	variant	year	selling_price	km_driven	fuel	seller_type	t
135	Land Rover	Rover	Discovery Sport TD4 SE	2019	4500000	21000	Diesel	Dealer	
2137	Land Rover	Rover	Freelander 2 TD4 HSE	2013	1650000	64788	Diesel	Dealer	
3240	Land Rover	Rover	Discovery Sport TD4 SE	2019	4500000	21000	Diesel	Dealer	
5257	Land Rover	Rover	Discovery Sport TD4 SE	2019	4500000	21000	Diesel	Dealer	
6724	Land Rover	Rover	Range Rover Evoque 2.2L Pure	2013	2000000	77500	Diesel	Individual	
7711	Land Rover	Rover	Discovery Sport TD4 SE	2019	4500000	21000	Diesel	Dealer	
10918	Land Rover	Rover	Discovery Sport TD4 HSE 7S	2018	4000000	68000	Diesel	Individual	
11175	Land Rover	Rover	Discovery S 2.0 SD4	2018	4000000	68000	Petrol	Individual	
11275	Land Rover	Rover	Discovery Sport SD4 HSE Luxury	2016	3500000	53000	Diesel	Dealer	
13783	Land Rover	Rover	Range Rover Evoque	2012	2349000	149000	Diesel	Individual	

```
# Edit both model and variant labels manually

temp_rover_model = carsData.loc[new_rover_indx,'variant'].str.split(" ",2,expand=True)

#model edit
carsData.loc[new_rover_indx,'model']  = temp_rover_model.iloc[:,0]+ " " + temp_rover_model

# variant edit
carsData.loc[new_rover_indx,'variant'] = temp_rover_model.iloc[:,2]

# Edit evoque
carsData.loc[[6724,13783],'model'] = "Range Rover Evoque"

carsData.loc[[6724,13783],'variant'] = carsData.loc[[6724,13783],'variant'].str.split(" ",

# After edit
carsData.loc[new_rover_indx]
```

	make	model	variant	year	selling_price	km_driven	fuel	seller_type
135	Land Rover	Discovery Sport	TD4 SE	2019	4500000	21000	Diesel	Dealer
2137	Land	Freelander	TD4	2013	1650000	64788	Diesel	Dealer

```
# clean model == '3' ->'3-Series'

# Before edit
model_3_Index_edit = carsData[carsData['model'] == '3'].index
carsData.loc[model_3_Index_edit]
```

	make	model	variant	year	selling_price	km_driven	fuel	seller_type	tr
165	BMW	3	Series 320d Luxury Line	2016	2150000	30000	Diesel	Dealer	
1993	BMW	3	Series 320d	2017	3200000	13663	Diesel	Dealer	
2062	BMW	3	Series 320d Luxury Line	2012	1300000	140000	Diesel	Individual	
			Series						

```
# Edit both model and variant labels manually

#model edit
carsData.loc[model_3_Index_edit,'model']  = '3-Series'

# variant edit
carsData.loc[model_3_Index_edit,'variant'] = carsData.loc[model_3_Index_edit,'variant'].st

# After edit
carsData.loc[model_3_Index_edit]
```

	make	model	variant	year	selling_price	km_driven	fuel	seller_type	tr
165	BMW	3-Series	320d Luxury Line	2016	2150000	30000	Diesel	Dealer	
1993	BMW	3-Series	320d	2017	3200000	13663	Diesel	Dealer	
2062	BMW	3-Series	320d Luxury Line	2012	1300000	140000	Diesel	Individual	
2065	BMW	3-Series	320d Luxury Plus	2013	1300000	140000	Diesel	Individual	
2069	BMW	3-Series	320d Luxury Line	2012	1300000	140000	Diesel	Individual	
2072	BMW	3-Series	320d Luxury Plus	2013	1300000	140000	Diesel	Individual	
2708	BMW	3-Series	320d	2009	1100000	60000	Diesel	Individual	

```
# clean model == '5' ->'5-Series'

# Before edit
model_5_Index_edit = carsData[carsData['model'] == '5'].index
carsData.loc[model_5_Index_edit]
```

	make	model	variant	year	selling_price	km_driven	fuel	seller_type	tra
137	BMW	5	Series 520d Sport Line	2018	3790000	29500	Diesel	Dealer	
149	BMW	5	Series 523i	2010	975000	72200	Petrol	Dealer	
167	BMW	5	Series 520d Luxury Line	2016	2900000	12000	Diesel	Dealer	
2829	BMW	5	Series 520d Sport Line	2018	3900000	17100	Diesel	Dealer	
3241	BMW	5	Series 520d Sport Line	2018	3790000	29500	Diesel	Dealer	
4671	BMW	5	Series 520d Luxury Line	2019	5200000	10000	Diesel	Dealer	
4880	BMW	5	Series 525d	2010	1000000	60000	Diesel	Individual	
4901	BMW	5	Series 520d Line	2008	1100000	122000	Diesel	Individual	

```
# Edit both model and variant labels manually

#model edit
carsData.loc[model_5_Index_edit,'model']  = '5-Series'

# variant edit
carsData.loc[model_5_Index_edit,'variant'] = carsData.loc[model_5_Index_edit,'variant'].st

# After edit
carsData.loc[model_5_Index_edit]
```

	make	model	variant	year	selling_price	km_driven	fuel	seller_type	tra
137	BMW	5-Series	520d Sport Line	2018	3790000	29500	Diesel	Dealer	
149	BMW	5-Series	523i	2010	975000	72200	Petrol	Dealer	
167	BMW	5-Series	520d Luxury Line	2016	2900000	12000	Diesel	Dealer	
2829	BMW	5-Series	520d Sport Line	2018	3900000	17100	Diesel	Dealer	
3241	BMW	5-Series	520d Sport Line	2018	3790000	29500	Diesel	Dealer	
4671	BMW	5-Series	520d Luxury Line	2019	5200000	10000	Diesel	Dealer	
4880	BMW	5-Series	525d	2010	1000000	60000	Diesel	Individual	
4901	BMW	5-Series	520d	2008	1100000	122000	Diesel	Individual	
5188	BMW	5-Series	520d Luxury Line	2016	3200000	40000	Diesel	Individual	
5259	BMW	5-Series	520d Sport Line	2018	4000000	10000	Diesel	Dealer	
5985	BMW	5-Series	530d	2013	2000000	60000	Diesel	Individual	
6598	BMW	5-Series	520d Sedan	2008	890000	70000	Diesel	Individual	
7709	BMW	5-	Sport	2018	4000000	10000	Diesel	Dealer	

```
# clean model == '6' ->'6-Series'

# Before edit
model_6_Index_edit = carsData[carsData['model'] == '6'].index
carsData.loc[model_6_Index_edit]
```

	make	model	variant	year	selling_price	km_driven	fuel	seller_type	tran
1071	BMW	6	Series GT 630d Luxury Line	2018	6000000	28156	Diesel	Dealer	
4101	BMW	6	Series GT 630d Luxury Line	2018	6000000	28156	Diesel	Dealer	
4753	BMW	6	Series GT 630d Luxury Line	2018	5500000	22000	Diesel	Individual	
4766	BMW	6	Series GT 630d Luxury Line	2018	6000000	27000	Diesel	Dealer	
6258	BMW	6	Series GT 630d Luxury Line	2018	5830000	30000	Diesel	Individual	
7596	BMW	6	Series GT 630d Luxury Line	2018	5830000	30000	Diesel	Individual	

```
# Edit both model and variant labels manually

#model edit
carsData.loc[model_6_Index_edit,'model']  = '6-Series'

# variant edit
carsData.loc[model_6_Index_edit,'variant'] = carsData.loc[model_6_Index_edit,'variant'].st

# After edit
carsData.loc[model_6_Index_edit]
```

	make	model	variant	year	selling_price	km_driven	fuel	seller_type	tran
1071	BMW	6-Series	GT 630d Luxury Line	2018	6000000	28156	Diesel	Dealer	
4101	BMW	6-Series	GT 630d Luxury Line	2018	6000000	28156	Diesel	Dealer	
4753	BMW	6-Series	GT 630d Luxury Line	2018	5500000	22000	Diesel	Individual	
4766	BMW	6-Series	GT 630d Luxury Line	2018	6000000	27000	Diesel	Dealer	
6258	BMW	6-Series	GT 630d Luxury Line	2018	5830000	30000	Diesel	Individual	
7596	BMW	6-Series	GT 630d Luxury Line	2018	5830000	30000	Diesel	Individual	

```
# clean model == '7' ->'7-Series'

# Before edit
model_7_Index_edit = carsData[carsData['model'] == '7'].index
carsData.loc[model_7_Index_edit]
```

	make	model	variant	year	selling_price	km_driven	fuel	seller_type	tr
2722	BMW	7	Series 730Ld	2007	750000	60000	Diesel	Individual	
5710	BMW	7	Series 730Ld	2010	2000000	90000	Diesel	Individual	

```
# Edit both model and variant labels manually

#model edit
carsData.loc[model_7_Index_edit,'model']  = '7-Series'

# variant edit
carsData.loc[model_7_Index_edit,'variant'] = carsData.loc[model_7_Index_edit,'variant'].st

# After edit
carsData.loc[model_7_Index_edit]
```

	make	model	variant	year	selling_price	km_driven	fuel	seller_type	tr
2722	BMW	7-Series	730Ld	2007	750000	60000	Diesel	Individual	
5710	BMW	7-Series	730Ld	2010	2000000	90000	Diesel	Individual	
10292	BMW	7-Series	730Ld	2012	2500000	48000	Diesel	Dealer	
11155	BMW	7-Series	Signature 730Ld	2014	4000000	47000	Diesel	Individual	
12480	BMW	7-Series	730Ld	2006	1050000	30000	Diesel	Dealer	
12686	BMW	7-Series	730Ld	2011	1700000	100000	Diesel	Individual	
14489	BMW	7-Series	730Ld	2006	1050000	30000	Diesel	Dealer	

```
# clean model == 'Platinum' ->'Platinum Etios'

# Before edit
model_Platinum_Index_edit = carsData[carsData['model'] == 'Platinum'].index
carsData.loc[model_Platinum_Index_edit]
```

	make	model	variant	year	selling_price	km_driven	fuel	seller_type	t
3137	Toyota	Platinum	Etios 1.4 GXD	2018	730000	90000	Diesel	Individual	
3825	Toyota	Platinum	Etios 1.4 GD	2017	632000	150000	Diesel	Individual	
4565	Toyota	Platinum	Etios 1.4 GXD	2018	670000	150000	Diesel	Individual	
5935	Toyota	Platinum	Etios 1.4 GXD	2017	550000	40000	Diesel	Individual	
7428	Toyota	Platinum	Etios 1.4 GXD	2018	780000	116000	Diesel	Individual	
7588	Toyota	Platinum	Etios 1.4 GXD	2018	780000	116000	Diesel	Individual	

```
# Edit both model and variant labels manually

#model edit
carsData.loc[model_Platinum_Index_edit,'model']  = 'Platinum Etios'

# variant edit
carsData.loc[model_Platinum_Index_edit,'variant'] = carsData.loc[model_Platinum_Index_edit

# After edit
carsData.loc[model_Platinum_Index_edit]
```

	make	model	variant	year	selling_price	km_driven	fuel	seller_type	t
3137	Toyota	Platinum Etios	1.4 GXD	2018	730000	90000	Diesel	Individual	
3825	Toyota	Platinum Etios	1.4 GD	2017	632000	150000	Diesel	Individual	
4565	Toyota	Platinum Etios	1.4 GXD	2018	670000	150000	Diesel	Individual	
5935	Toyota	Platinum Etios	1.4 GXD	2017	550000	40000	Diesel	Individual	
		Platinum							

```
# clean model == 'DZire' ->'Dzire'

# Before edit
model_DZire_Index_edit = carsData[carsData['model'] == 'DZire'].index
carsData.loc[model_DZire_Index_edit]
```

	make	model	variant	year	selling_price	km_driven	fuel	seller_type	tra
8217	Maruti	DZire	VXi	2019	691000	16652	Petrol	Individual	
8481	Maruti	DZire	VDi	2018	590000	68500	Diesel	Individual	
8558	Maruti	DZire	VXi AMT	2019	825000	9644	Petrol	Individual	
8585	Maruti	DZire	ZDi Plus AMT	2018	685000	92000	Diesel	Individual	
8689	Maruti	DZire	VDi	2017	630000	36000	Diesel	Individual	
8700	Maruti	DZire	VDi AMT	2019	770000	72040	Diesel	Individual	

```
# Edit both model and variant labels manually

#model edit
carsData.loc[model_DZire_Index_edit,'model']  = 'Dzire'

# After edit
carsData.loc[model_DZire_Index_edit]
```

	make	model	variant	year	selling_price	km_driven	fuel	seller_type	tra
8217	Maruti	Dzire	VXi	2019	691000	16652	Petrol	Individual	
8481	Maruti	Dzire	VDi	2018	590000	68500	Diesel	Individual	
8558	Maruti	Dzire	VXi AMT	2019	825000	9644	Petrol	Individual	
8585	Maruti	Dzire	ZDi Plus AMT	2018	685000	92000	Diesel	Individual	
8689	Maruti	Dzire	VDi	2017	630000	36000	Diesel	Individual	
8700	Maruti	Dzire	VDi AMT	2019	770000	72040	Diesel	Individual	
8783	Maruti	Dzire	VDi AMT	2018	695000	55000	Diesel	Individual	
8880	Maruti	Dzire	ZXi	2018	695000	31000	Petrol	Individual	

```
# clean model == 'Swift' ->'Swift Dzire'

# Before edit
model_Swift_Index_edit = carsData[carsData['model'] == 'Swift'].index
carsData.loc[model_Swift_Index_edit]
```

	make	model	variant	year	selling_price	km_driven	fuel	seller_type	tra
0	Maruti	Swift	Dzire VDI	2014	450000	145500	Diesel	Individual	
4	Maruti	Swift	VXI BSIII	2007	130000	120000	Petrol	Individual	
12	Maruti	Swift	Dzire VDi	2009	280000	140000	Diesel	Individual	
13	Maruti	Swift	1.3 VXi	2007	200000	80000	Petrol	Individual	
22	Maruti	Swift	Dzire ZDI	2015	525000	40000	Diesel	Individual	
...	...	...	...	...	...	...	...	...	
14455	Maruti	Swift	VDI	2015	500000	100000	Diesel	Dealer	
14459	Maruti	Swift	VDI BSIV	2015	495000	105000	Diesel	Dealer	
14476	Maruti	Swift	Dzire VDI	2019	680000	40000	Diesel	Individual	
14501	Maruti	Swift	Dzire VDI	2015	470000	170000	Diesel	Individual	

```
# Get index of rows where 'variant' starts with Dzire within 'swift' index

temp_swf = carsData.loc[model_Swift_Index_edit,'variant'].str.split(" ",1, expand=True).re
swif_DZ_indx = temp_swf[temp_swf[0].isin(['Dzire','DZire'])]['index']
```

```
carsData.loc[swif_DZ_indx,]
```

	make	model	variant	year	selling_price	km_driven	fuel	seller_type	tra
0	Maruti	Swift	Dzire VDI	2014	450000	145500	Diesel	Individual	
12	Maruti	Swift	Dzire VDi	2009	280000	140000	Diesel	Individual	
22	Maruti	Swift	Dzire ZDI	2015	525000	40000	Diesel	Individual	
44	Maruti	Swift	Dzire VXi AT	2018	675000	23300	Petrol	Dealer	
64	Maruti	Swift	Dzire ZDI	2015	630000	147000	Diesel	Individual	
...	...	...	...	...	...	...	...	...	

```
# Edit both model and variant labels manually

#model edit
carsData.loc[swif_DZ_indx,'model']  = 'Swift Dzire'

# variant edit
carsData.loc[swif_DZ_indx,'variant'] = carsData.loc[swif_DZ_indx,'variant'].str.split(" ",

# After edit
carsData.loc[swif_DZ_indx]
```

	make	model	variant	year	selling_price	km_driven	fuel	seller_type	tra
0	Maruti	Swift Dzire	VDI	2014	450000	145500	Diesel	Individual	
12	Maruti	Swift Dzire	VDi	2009	280000	140000	Diesel	Individual	
		Swift							
		Swift							

```
# clean model == 'Evoque' ->'Range Rover Evoque'

# Before edit
model_Evoque_Index_edit = carsData[carsData['model'] == 'Evoque'].index
carsData.loc[model_Evoque_Index_edit]
```

	make	model	variant	year	selling_price	km_driven	fuel	seller_type	tra
8446	Land Rover	Evoque	HSE Dynamic	2015	2499000	50623	Diesel	Individual	
8511	Land	Evoque	SE R-	2021	5950000	35000	Diesel	Individual	

```
# Edit both model and variant labels manually

#model edit
carsData.loc[model_Evoque_Index_edit,'model']  = 'Range Rover Evoque'

# After edit
carsData.loc[model_Evoque_Index_edit]
```

	make	model	variant	year	selling_price	km_driven	fuel	seller_type	tra
8446	Land Rover	Range Rover Evoque	HSE Dynamic	2015	2499000	50623	Diesel	Individual	
		Range							

```
# clean model == 'Range'

# Before edit
model_Range_Index_edit = carsData[carsData['model'] == 'Range'].index
carsData.loc[model_Range_Index_edit]
```

	make	model	variant	year	selling_price	km_driven	fuel	seller_type	tr
8387	Land Rover	Range	Rover Sport SE 2.0 Petrol	2022	12500000	22010	Petrol	Individual	
8710	Land Rover	Range	Rover 3.0 V6 Diesel Vogue	2019	22000000	35000	Diesel	Individual	

```
#model edit
carsData.loc[model_Range_Index_edit,'model']  = 'Range Rover'

# variant edit
carsData.loc[model_Range_Index_edit,'variant'] = carsData.loc[model_Range_Index_edit,'vari
carsData.loc[model_Range_Index_edit]
```

	make	model	variant	year	selling_price	km_driven	fuel	seller_type	tr
8387	Land Rover	Range Rover	Sport SE 2.0 Petrol	2022	12500000	22010	Petrol	Individual	
8710	Land	Range	3.0 V6 Diesel	2019	22000000	35000	Diesel	Individual	

```
# Edit both model and variant labels manually

# Get index of rows where 'variant' starts with Sport/velar within 'Range rover' index

#getting split Data frame
temp_rover = carsData.loc[model_Range_Index_edit,'variant'].str.split(" ",1, expand=True).
sport_indx = temp_rover[temp_rover[0].isin(['Sport','Velar'])]['index']

#model edit
carsData.loc[sport_indx,'model']  = carsData.loc[sport_indx,'model'] + " " + carsData.loc[

# variant edit
carsData.loc[sport_indx,'variant'] = carsData.loc[sport_indx,'variant'].str.split(" ",1,ex

# After edit
carsData.loc[sport_indx]
```

	make	model	variant	year	selling_price	km_driven	fuel	seller_type	tr
	Land	Range	SE 2.0						

```
# clean model == 'Etios'

# Before edit
model_Etios_Index_edit = carsData[carsData['model'] == 'Etios'].index
carsData.loc[model_Etios_Index_edit]
```

	make	model	variant	year	selling_price	km_driven	fuel	seller_type	tr
8	Toyota	Etios	VXD	2011	350000	90000	Diesel	Individual	
200	Toyota	Etios	GD	2012	235000	120000	Diesel	Individual	
355	Toyota	Etios	Liva GD SP	2013	400000	70000	Diesel	Dealer	
381	Toyota	Etios	VX	2017	625000	25538	Petrol	Trustmark Dealer	
390	Toyota	Etios	Liva Diesel TRD Sportivo	2012	265000	162000	Diesel	Individual	
...	...	...	...	...	...	...	...	...	
13860	Toyota	Etios	VXD	2015	610000	55000	Diesel	Individual	
13882	Toyota	Etios	Liva VX	2012	269000	70000	Petrol	Individual	
14111	Toyota	Etios	GD	2014	500000	140000	Diesel	Individual	
14268	Toyota	Etios	Liva GD SP	2012	280000	120000	Diesel	Individual	
14367	Toyota	Etios	GD SP	2013	350000	75000	Diesel	Dealer	

172 rows × 15 columns

```
# Get index of rows where 'variant' starts with Dzire within 'swift' index

temp_eti = carsData.loc[model_Etios_Index_edit,'variant'].str.split(" ",1, expand=True).re
eti_liv_indx = temp_eti[temp_eti[0]=='Liva']['index']
```

```
# Edit both model and variant labels manually

#model edit
carsData.loc[eti_liv_indx,'model']  = 'Etios Liva'

# variant edit
carsData.loc[eti_liv_indx,'variant'] = carsData.loc[eti_liv_indx,'variant'].str.split(" ",

# After edit
carsData.loc[eti_liv_indx]
```

	make	model	variant	year	selling_price	km_driven	fuel	seller_type	tr
355	Toyota	Etios Liva	GD SP	2013	400000	70000	Diesel	Dealer	
390	Toyota	Etios Liva	Diesel TRD Sportivo	2012	265000	162000	Diesel	Individual	
433	Toyota	Etios Liva	Diesel	2013	450000	67000	Diesel	Individual	
496	Toyota	Etios	GD	2013	409999	45000	Diesel	Individual	
1185	Toyota	Etios	GD	2013	300000	80000	Diesel	Individual	

- Clean completed for most of the categories and ignored for category count <5
- Drop all the rows with 'model' category count < 5

```
modelLessThan = []
for make, count in carsData['model'].value_counts().iteritems():
    #if (count <= 10) & (count >3):
    if (count < 5):
      modelLessThan.append(make)

print("Models less than 5 counts: ",modelLessThan)
```

```
Models less than 5 counts:  ['A8', 'Fusion', 'Supro', 'Alcazar', 'Range Rover', 'Red
```

```
#carsData[carsData['model']=='Seltos']
```

```
# Drop rows with the above brand name

# Getting index of rows to be dropped
minCountModelIndx = carsData.loc[carsData['model'].isin(modelLessThan)].index

# Drop rows with above index
carsData.drop(axis = 0, index = minCountModelIndx, inplace=True)
```

- Cleaning variants

```
# Convert all the variant names to upper case to avoid duplicate due to alternate case.

carsData['variant'] = carsData['variant'].str.upper()
```

3793 Toyota Etios GD 2013 325000 120000 Diesel Individual

- Crating new Feature('Age') from year feature.
- current year is 2023 but this data was uploaded in 2022.
- Hence age is w.r.t 2022

```
# Creating car age column since price decrease as age increase
carsData['age'] = 2022 - carsData['year']
carsData.head()
```

	make	model	variant	year	selling_price	km_driven	fuel	seller_type	tra
0	Maruti	Swift Dzire	VDI	2014	450000	145500	Diesel	Individual	
1	Skoda	Rapid	1.5 TDI AMBITION	2014	370000	120000	Diesel	Individual	
2	Honda	City	2017-2020 EXI	2006	158000	140000	Petrol	Individual	
3	Hyundai	i20	SPORTZ DIESEL	2010	225000	127000	Diesel	Individual	
4	Maruti	Swift	VXI BSIII	2007	130000	120000	Petrol	Individual	

7086 Toyota Liva G 2012 200000 120000 Petrol Individual

```
# Convert Selling Price & KM driven -> in Lakhs
# with 2 digits after decimal point.

carsData['selling_price'] = round((carsData['selling_price']/100000),2)
carsData.head(3)
```

	make	model	variant	year	selling_price	km_driven	fuel	seller_type	trans
0	Maruti	Swift Dzire	VDI	2014	4.50	145500	Diesel	Individual	
1	Skoda	Rapid	1.5 TDI Ambition	2014	3.70	120000	Diesel	Individual	
2	Honda	City	1.3 DX	2006	1.58	140000	Petrol	Individual	
3	Hyundai	i10	Magna 1.2	2010	2.25	127000	Petrol	Individual	
4	Toyota	Etios	VX	2014	5.00	45000	Petrol	Individual	
5	Hyundai	Elite i20	Asta 1.2	2014	4.75	28200	Petrol	Individual	

```
# Converting Km_driver -> into categories
# Slight change in km wont change the price drastically(Domain knowledge) in real world ar

carsData['km_driven'].describe()
```

```
count    1.432900e+04
mean     6.675069e+04
std      5.425170e+04
min      1.000000e+00
25%      3.440000e+04
50%      6.000000e+04
75%      9.000000e+04
max      2.360457e+06
Name: km_driven, dtype: float64
```

- min km is 1 and max is 23 lakh.
- Both are impossible hence correcting the values

```
# Handling 1 km driven outlier - for unregistered vehicle

carsData.loc[(carsData['km_driven'] < 100) & (carsData['owner'] != 'UnRegistered Car' )]
```

	make	model	variant	year	selling_price	km_driven	fuel	seller_type
7913	Maruti	Eeco	5 STR WITH AC PLUS HTR CNG	2011	2.09	1	CNG	Individual
11499	Mahindra	Quanto	C6	2014	2.50	1	Diesel	Individual
12611	Toyota	Etios	1.2 V	2018	500000	10000	Petrol	Individual
12635	Toyota	Etios	1.4 VD	2017	425000	36000	Diesel	Dealer
13330	Toyota	Liva	1.4 VD	2017	425000	36000	Diesel	Dealer

```
# Handling missig values like 0 for km_driven.
# Using age to impute km because cars with more age tend to be driven more.
```

```
for indx in carsData.loc[(carsData['km_driven'] < 100) & (carsData['owner'] != 'UnRegister
    carAge = carsData.loc[indx,'age']

    # Fine the median km of the car by using age.
    mediankm = carsData.loc[carsData['age']==carAge,'km_driven'].median()

    # We might have car with not exact age, so we will take a range of age
    if mediankm < 100:
        mediankm = carsData.loc[(carsData['age'] > carAge-5) & (carsData['age'] < carAge+5
    elif mediankm < 100:
        mediankm = round((carsData['km_driven'].mean()),2) # Mean coz usually cars in this

    # Assigning the median value:
    carsData.loc[indx,'km_driven'] = mediankm

# For unregistered cars imputing km
for indx in carsData.loc[(carsData['km_driven'] < 100) & (carsData['owner'] == 'UnRegister
    carAge = carsData.loc[indx,'age']

    # Fine the median km of the car by using age.
    mediankm = carsData.loc[carsData['age']==carAge,'km_driven'].median() / 10

    # We might have car with not exact age, so we will take a range of age
    if mediankm < 100:
        mediankm = carsData.loc[(carsData['age'] > carAge-5) & (carsData['age'] < carAge+5
    elif mediankm < 100:
        mediankm = round((carsData['km_driven'].mean()),2) / 10 # Mean coz usually cars ir

    # Assigning the median value:
    carsData.loc[indx,'km_driven'] = mediankm
```

```
# Handling km driven > 6lakhs -> outlier
carsData.loc[carsData['km_driven'] > 500000]
```

	make	model	variant	year	selling_price	km_driven	fuel	seller_type
1810	Mahindra	XUV500	W6 2WD	2012	5.00	1500000	Diesel	Individual
3486	Hyundai	i20	ASTA 1.2	2007	5.50	2360457	Petrol	Individual
3508	Maruti	Wagon	R LXI MINOR	2010	1.94	577414	Petrol	Individual
9253	Renault	Duster	110 PS RXZ 4X2 MT DIESEL	2016	4.50	2000000	Diesel	Individual
			1.6					

- Impossible for very high km driven in a car hence assuming an extra zero, and correctig the values.

CROSS

```
carsData.loc[carsData['km_driven'] > 500000,'km_driven'] = carsData.loc[carsData['km_drive
```

DELTA

- converting km to catergorical variable with 10 km interval

BOM

```
for indx in carsData['km_driven'].index:
  km = carsData.loc[indx,'km_driven']

  if (km > 0) & (km <= 10000) :
      carsData.loc[indx,'km_driven'] = "0 - 10,000 Km"
      continue

  for i in range(1,51):
    if (km > i*10000) & (km <= (i+1)*10000):
      carsData.loc[indx,'km_driven'] = "{} - {} Km".format((i*10000),((i+1)*10000))
      break
```

```
# fuel

carsData['fuel'].unique()
```

```
array(['Diesel', 'Petrol', 'LPG', 'CNG', 'Electric', 'CNG + CNG',
       'Hybrid', 'Petrol + CNG', 'Petrol + LPG'], dtype=object)
```

```
# Modifying CNG+CNG category
pcng_indx = carsData[carsData['fuel']=='CNG + CNG'].index
carsData.loc[pcng_indx,'fuel'] = 'Petrol + CNG'
```

```
# Modifying CNG category
cng_indx = carsData[carsData['fuel']=='CNG'].index
```

```
carsData.loc[cng_indx,'fuel'] = 'Petrol + CNG'
```

```
# Modifying LPG category
lpg_indx = carsData[carsData['fuel']=='LPG'].index
carsData.loc[lpg_indx,'fuel'] = 'Petrol + LPG'
```

```
# Modifying electric
carsData[carsData['fuel']=='Electric']
```

	make	model	variant	year	selling_price	km_driven	fuel	seller_type	t
8255	Tata	Nexon	EV XZ PLUS	2021	13.75	10000 - 20000 Km	Electric	Individual	
8466	Tata	Nexon	EV XZ PLUS	2020	15.50	40000 - 50000 Km	Electric	Individual	
8767	Tata	Tigor	EV XZ PLUS	2021	12.75	10000 - 20000 Km	Electric	Individual	
9026	Tata	Tigor	EV XZ PLUS	2021	12.50	0 - 10,000 Km	Electric	Individual	
9037	Tata	Nexon	EV XZ PLUS	2022	14.50	0 - 10,000 Km	Electric	Individual	
9440	Tata	Nexon	EV XZ PLUS	2020	14.85	0 - 10,000 Km	Electric	Individual	
14332	Toyota	Camry	HYBRID	2006	3.10	60000 - 70000 Km	Electric	Dealer	

```
# Manual edit index 14332
carsData.loc[14332,'fuel'] = 'Hybrid'
```

```
# Seller type

carsData['seller_type'].value_counts()
```

```
Individual                11838
Dealer                     2102
Trustmark Dealer            338
Corporate                    46
Commercial Registration       5
Name: seller_type, dtype: int64
```

```
# transmission

carsData['transmission'].value_counts()
```

```
Manual       12026
Automatic     2303
Name: transmission, dtype: int64
```

```
#owner

carsData['owner'].value_counts()
```

```
First Owner             8065
Second Owner            3190
First                   1536
Third Owner              848
Second                   355
Fourth & Above Owner     252
Third                     38
Test Drive Car            22
UnRegistered Car          19
Fourth                     3
4 or More                  1
Name: owner, dtype: int64
```

```
# Combining duplicate labels

firsi_indx = carsData[(carsData['owner']=='First Owner') | (carsData['owner']=='First')].i
carsData.loc[firsi_indx,'owner'] = '1st owner'

second_indx = carsData[(carsData['owner']=='Second Owner') | (carsData['owner']=='Second')
carsData.loc[second_indx,'owner'] = '2nd owner'

Third_indx = carsData[(carsData['owner']=='Third Owner') | (carsData['owner']=='Third')].i
carsData.loc[Third_indx,'owner'] = '3rd owner'

Fourth_indx = carsData[(carsData['owner']=='Fourth') | (carsData['owner']=='4 or More')| (
carsData.loc[Fourth_indx,'owner'] = '4th & above owner'
```

```
# Split numerical value and unit and create new column.


carsData[['mileage','mileage_unit']] = carsData['mileage'].str.split(" ",1, expand=True)
carsData[['engine','engine_unit']] = carsData['engine'].str.split(" ",1, expand=True)
carsData[['max_power','max_power_unit']] = carsData['max_power'].str.split(" ",1, expand=T
carsData.head()
```

	make	model	variant	year	selling_price	km_driven	fuel	seller_type	tra
0	Maruti	Swift Dzire	VDI	2014	4.50	140000 - 150000 Km	Diesel	Individual	
1	Skoda	Rapid	1.5 TDI AMBITION	2014	3.70	110000 - 120000 Km	Diesel	Individual	
2	Honda	City	2017-2020 EXI	2006	1.58	130000 - 140000 Km	Petrol	Individual	
3	Hyundai	i20	SPORTZ DIESEL	2010	2.25	120000 - 130000 Km	Diesel	Individual	
4	Maruti	Swift	VXI BSIII	2007	1.30	110000 - 120000 Km	Petrol	Individual	

```
# Drop the irrelevant columns before analysis

# Drop parent feature from which new features are derived to avoid multi colinearity.
# Drop Torque since it has multiple values combination with different scale and will be co

carsData.drop(['year','torque'], axis = 1, inplace = True)
carsData.head()
```

	make	model	variant	selling_price	km_driven	fuel	seller_type	transmiss
0	Maruti	Swift Dzire	VDI	4.50	140000 - 150000 Km	Diesel	Individual	Mar
1	Skoda	Rapid	1.5 TDI AMBITION	3.70	110000 - 120000 Km	Diesel	Individual	Mar
2	Honda	City	2017-2020 EXI	1.58	130000 - 140000 Km	Petrol	Individual	Mar
3	Hyundai	i20	SPORTZ DIESEL	2.25	120000 - 130000 Km	Diesel	Individual	Mar
4	Maruti	Swift	VXI BSIII	1.30	110000 - 120000 Km	Petrol	Individual	Mar

- Seat clean

```
# Analyzing number of seats

carsData['seats'].unique()
```

```
array([ 5.,  4., nan,  7.,  8.,  6.,  9., 10.,  2.])
```

```
# Anylizing type of cars with seats >= 9 seats
noOfSeats = 9
print("Cars with {} and more seats : {}".format(noOfSeats,carsData[carsData['seats']>=noOf
```

```
Cars with 9 and more seats : ['Scorpio' 'Sumo' 'Bolero' 'Tavera' 'TUV' 'Qualis' 'Xyl
```

```
# Editing cars with 2 seats and replacing with the mode of the same car.

for indx in carsData[carsData['seats'] == 2].index:
  carName = carsData.loc[indx,'model']
  modeSeats = carsData.loc[carsData['model'] == carName,'seats'].mode()[0]

  if modeSeats == 0:
      modeSeats = 5

  carsData.loc[indx,'seats'] = modeSeats
```

```
# Check for non standard missing values eg: ?, <>, -- etc. and convert them to NaN.

# For non standard missing values in categorical features -> check using unique

catFeatList = ['mileage_unit','engine_unit','max_power_unit']

for feature in catFeatList:
  print('Unique values of {}: {}\n'.format(feature,carsData[feature].unique()))
```

```
Unique values of mileage_unit: ['kmpl' 'km/kg' nan]

Unique values of engine_unit: ['CC' nan 'cc']

Unique values of max_power_unit: ['bhp' nan None 'bhp @ 6000 rpm' 'bhp @ 4000 rpm' '
 'bhp @ 5500 rpm' 'bhp @ 5100 rpm' 'bhp @ 3750 rpm' 'bhp @ 5000 rpm'
 'bhp @ 6400 rpm' 'bhp @ 3000 rpm' 'bhp @ 4200 rpm' 'bhp @ 3800 rpm'
 'bhp @ 3600 rpm' 'bhp @ 6600 rpm' 'bhp @ 6300 rpm' 'bhp @ 3500 rpm'
 'bhp @ 5400 rpm' 'bhp @ 5250 rpm' 'bhp @ 5700 rpm' 'bhp @ 3900 rpm'
 'bhp @ 6200 rpm' 'bhp @ 2910 rpm' 'bhp @ 5600 rpm' 'bhp @ 4400 rpm'
 'bhp @ 5200 rpm' 'bhp @ 5678 rpm' 'bhp @ 6500 rpm' 'bhp @ 5800 rpm'
 'bhp @ 6250 rpm' 'bhp @ 3200 rpm' '@3600' 'bhp @ 4500 rpm'
```

```
 'bhp @ 4250 rpm' 'bhp @ 5150 rpm']
```

- Milege has 2 units needs to be converted and nan values needs be treated.
- engine and power has nan values to ve treated.
- No non standard missing values in categorical features.

```
# Overview of dtypes of features
carsData.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 14329 entries, 0 to 14526
Data columns (total 17 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   make            14329 non-null  object 
 1   model           14329 non-null  object 
 2   variant         14329 non-null  object 
 3   selling_price   14329 non-null  float64
 4   km_driven       14329 non-null  object 
 5   fuel            14329 non-null  object 
 6   seller_type     14329 non-null  object 
 7   transmission    14329 non-null  object 
 8   owner           14329 non-null  object 
 9   mileage         7859 non-null   object 
 10  engine          9738 non-null   object 
 11  max_power       9744 non-null   object 
 12  seats           9753 non-null   float64
 13  age             14329 non-null  int64  
 14  mileage_unit    7859 non-null   object 
 15  engine_unit     9738 non-null   object 
 16  max_power_unit  9612 non-null   object 
dtypes: float64(2), int64(1), object(14)
memory usage: 2.5+ MB
```

```
# null values noted
# Making nan values of numerical feature as 0 to impute later
carsData[['mileage','engine','max_power','seats']] = carsData[['mileage','engine','max_pov
```

```
# Summarizing Missing Values

carsData.isnull().sum()
```

```
make                0
model               0
variant             0
selling_price       0
km_driven           0
fuel                0
seller_type         0
```

```
transmission         0
owner                0
mileage              0
engine               0
max_power            0
seats                0
age                  0
mileage_unit      6470
engine_unit       4591
max_power_unit    4717
dtype: int64
```

```
carsData['max_power'].unique()
```

```
array(['74', '103.52', '78', '90', '88.2', '81.86', '57.5', '37', '67.1',
       '68.1', '108.45', '60', '73.9', 0, '67', '82', '88.5', '46.3',
       '88.73', '64.1', '98.6', '88.8', '83.81', '83.1', '47.3', '73.8',
       '34.2', '35', '81.83', '40.3', '121.3', '138.03', '160.77',
       '117.3', '116.3', '83.14', '67.05', '168.5', '100', '120.7',
       '98.63', '175.56', '103.25', '171.5', '100.6', '174.33', '187.74',
       '170', '78.9', '88.76', '86.8', '108.495', '108.62', '93.7',
       '103.6', '98.59', '189', '67.04', '68.05', '58.2', '82.85',
       '81.80', '73', '120', '94.68', '160', '65', '155', '69.01',
       '126.32', '138.1', '83.8', '126.2', '98.96', '62.1', '86.7', '188',
       '214.56', '177', '280', '148.31', '254.79', '190', '177.46', '204',
       '141', '117.6', '241.4', '282', '150', '147.5', '108.5', '103.5',
       '183', '181.04', '157.7', '164.7', '91.1', '68', '75', '85.8',
       '87.2', '118', '103.2', '83', '84', '58.16', '147.94', '74.02',
       '53.3', '80', '88.7', '97.7', '121.36', '162', '140', '94',
       '100.57', '82.9', '83.11', '70', '153.86', '121', '126.3', '73.97',
       '171', '69', '99.6', '102', '105', '63', '79.4', '97.9', '63.1',
       '66.1', '110', '174.5', '53.26', '73.75', '67.06', '64.08', '37.5',
       '158.8', '61.7', '55.2', '71.01', '73.74', '147.9', '71', '77',
       '121.4', '113.4', '47', '130', '57.6', '138', '52.8', '53.64',
       '53.5', '76.8', '82.4', '113.42', '76', '84.8', '0', '56.3', '218',
       '112', '92', '105.5', '169', '95', '72.4', '115', '152', '91.2',
       '156', '74.9', '62', '53', '105.3', '73.94', '85.80', '85',
       '118.3', '72', '147.51', '58', '64', '126.24', '76.9', '194.3',
       '99.23', '89.84', '123.7', '118.35', '99', '136', '261.4',
       '104.68', '37.48', '104', '88.50', '63.12', '91.7', '102.5',
       '177.6', '123.37', '147.8', '184', '84.48', '68.07', '74.96',
       '167.6', '152.87', '112.2', '83.83', '197', '110.4', '104.55',
       '103', '103.3', '66', '108.6', '165', '163.7', '116.9', '94.93',
       '127', '198.5', '120.69', '121.31', '187.7', '86.79', '93.87',
       '116.6', '143', '92.7', '88', '58.33', '78.8', '64.4', '125',
       '254.8', '181', '258', '55.23', '270.9', '157.75', '101', '186',
       '187.4', '224', '64.9', '89.75', '32.8', '91.72', '106', '98.97',
       '66.6', '86', '65.3', '98.82', '198.25', '38', '142', '132', '178',
       '163.2', '203.2', '177.5', '175', '57', '68.4', '167.67', '170.63',
       '149.5', '48.21', '148', '', '201.1', '100.5', '144', '194.4',
       '168.7', '104.5', '103.26', '116.4', '98.79', '35.5', '80.9',
       '58.3', '272', '235', '167.62', '139.46', '158', '110.5', '82.5',
       '141.1', '38.4', '194', '122.4', '134.10', '60.2', '203', '135.1',
       '87', '79', '91', '122', '89', '126', '124', '168', '117', '174',
       '179', '207@4200', '202', '108', '241', '118@6600', '63@5500',
       '81', '245', '116@3800', '248', '113', '192', '201', '453',
       '152@6000', '153', '134', '68@6200', '75@4000', '102@5600',
       '234@3800', '231@3800', '254', '109', '180', '172', '171@3600',
       '362', '296', '67@6200', '177@4000', '80@5200', '255', '90@4300',
```

```
       '47@6200', '95@3600', '262', '147', '87@6000', '90@6000', '119',
       '164', '120@4000', '136@5600', '114', '204@6100', '463', '59@6200',
       '154', '120@5500', '35@5250', '176', '55', '182', '326', '116',
       '122@4000', '368', '56@5500', '128', '335', '289', '142@4000',
       '150@4000', '170@3700', '231', '272@6000', '64@6200', '218@4000',
       '217', '265', '46', '132@6000', '100@5500', '195', '105@3800',
       '39', '237', '68@4000', '271', '260', '161', '90@4000', '69@4000',
       '67@5500', '225', '48', '98', '137', '102@5500', '240@4000', '187',
       '268', '227', '67.7', '215', '58@6000', '261', '78@5500', '236',
       '198@4000', '329'], dtype=object)
```

```
# Detecting non numerical in numerical features and converting them into Nan

numFeatList = ['mileage','engine','max_power','seats']
for features in numFeatList:
    cnt=0 # row_label
    for row in carsData[features]:
        try:
            int(float(row))
        except:
            index_no = carsData.columns.get_loc(features)
            carsData.iloc[cnt,index_no]=0 # Assigning 0 to impute later
        cnt+=1
```

```
# Summarizing Missing Values

carsData.isnull().sum()
```

```
make                0
model               0
variant             0
selling_price       0
km_driven           0
fuel                0
seller_type         0
transmission        0
owner               0
mileage             0
engine              0
max_power           0
seats               0
age                 0
mileage_unit     6470
engine_unit      4591
max_power_unit   4717
dtype: int64
```

- Unit features will be dropped in the end

Few numerical features are still in object Dtype post preprocessing, convert them to int.

```
carsData.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 14329 entries, 0 to 14526
Data columns (total 17 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   make            14329 non-null  object 
 1   model           14329 non-null  object 
 2   variant         14329 non-null  object 
 3   selling_price   14329 non-null  float64
 4   km_driven       14329 non-null  object 
 5   fuel            14329 non-null  object 
 6   seller_type     14329 non-null  object 
 7   transmission    14329 non-null  object 
 8   owner           14329 non-null  object 
 9   mileage         14329 non-null  object 
 10  engine          14329 non-null  object 
 11  max_power       14329 non-null  object 
 12  seats           14329 non-null  float64
 13  age             14329 non-null  int64  
 14  mileage_unit    7859 non-null   object 
 15  engine_unit     9738 non-null   object 
 16  max_power_unit  9612 non-null   object 
dtypes: float64(2), int64(1), object(14)
memory usage: 2.5+ MB
```

```
carsData = carsData.astype({'mileage':float, 'engine':float, 'max_power':float,'seats':int
carsData.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 14329 entries, 0 to 14526
Data columns (total 17 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   make            14329 non-null  object 
 1   model           14329 non-null  object 
 2   variant         14329 non-null  object 
 3   selling_price   14329 non-null  float64
 4   km_driven       14329 non-null  object 
 5   fuel            14329 non-null  object 
 6   seller_type     14329 non-null  object 
 7   transmission    14329 non-null  object 
 8   owner           14329 non-null  object 
 9   mileage         14329 non-null  float64
 10  engine          14329 non-null  float64
 11  max_power       14329 non-null  float64
 12  seats           14329 non-null  int64  
 13  age             14329 non-null  float64
 14  mileage_unit    7859 non-null   object 
 15  engine_unit     9738 non-null   object 
 16  max_power_unit  9612 non-null   object 
dtypes: float64(5), int64(1), object(11)
memory usage: 2.5+ MB
```

```

```

```

```

```
# Convert km in thousands.

carsData['engine'] = round((carsData['engine']/1000),2)
carsData['engine']
```

```
0        1.25
1        1.50
2        1.50
3        1.40
4        1.30
         ...
14522    0.00
14523    0.00
14524    0.00
14525    0.00
14526    0.00
Name: engine, Length: 14329, dtype: float64
```

Check new Unit value features for different unit measurement

```
catFeatList = ['mileage_unit','engine_unit','max_power_unit']

for feature in catFeatList:
  print('Unique values of {}: {}\n'.format(feature,carsData[feature].unique()))
```

```
Unique values of mileage_unit: ['kmpl' 'km/kg' nan]

Unique values of engine_unit: ['CC' nan 'cc']

Unique values of max_power_unit: ['bhp' nan None 'bhp @ 6000 rpm' 'bhp @ 4000 rpm' '
 'bhp @ 5500 rpm' 'bhp @ 5100 rpm' 'bhp @ 3750 rpm' 'bhp @ 5000 rpm'
 'bhp @ 6400 rpm' 'bhp @ 3000 rpm' 'bhp @ 4200 rpm' 'bhp @ 3800 rpm'
 'bhp @ 3600 rpm' 'bhp @ 6600 rpm' 'bhp @ 6300 rpm' 'bhp @ 3500 rpm'
 'bhp @ 5400 rpm' 'bhp @ 5250 rpm' 'bhp @ 5700 rpm' 'bhp @ 3900 rpm'
 'bhp @ 6200 rpm' 'bhp @ 2910 rpm' 'bhp @ 5600 rpm' 'bhp @ 4400 rpm'
 'bhp @ 5200 rpm' 'bhp @ 5678 rpm' 'bhp @ 6500 rpm' 'bhp @ 5800 rpm'
 'bhp @ 6250 rpm' 'bhp @ 3200 rpm' '@3600' 'bhp @ 4500 rpm'
 'bhp @ 4250 rpm' 'bhp @ 5150 rpm']
```

Observation

- Engine capacity and power has one type of unit measurement.
- Mileage has 2 different units, if possible should convert km/kg to kmpl.

```
# CNG-equipped car offers around one-and-a-half times the fuel efficiency in CNG mode thar
# So we will multiply CNG mileage by 1.5 times to match the scale.

carsData.loc[carsData['mileage_unit']=='km/kg','mileage'] = carsData.loc[carsData['mileage
```

```
# Remove Unit column as they are not useful now.
```

```
carsData.drop(['mileage_unit',  'engine_unit','max_power_unit'], axis=1, inplace=True)
carsData.head()
```

	make	model	variant	selling_price	km_driven	fuel	seller_type	transmiss
0	Maruti	Swift Dzire	VDI	4.50	140000 - 150000 Km	Diesel	Individual	Mar
1	Skoda	Rapid	1.5 TDI AMBITION	3.70	110000 - 120000 Km	Diesel	Individual	Mar
2	Honda	City	2017-2020 EXI	1.58	130000 - 140000 Km	Petrol	Individual	Mar
3	Hyundai	i20	SPORTZ	2.25	120000 - 130000	Diesel	Individual	Mar

```
# Handling missig or unappropriate values like 0 for numerical features.

numFeatList = ['mileage','engine','max_power','seats','age']
for i in numFeatList:
  print("Total records with ZERO value in {}: {}".format(i,(carsData[i] == 0).sum()))
```

```
Total records with ZERO value in mileage: 6486
Total records with ZERO value in engine: 4591
Total records with ZERO value in max_power: 4718
Total records with ZERO value in seats: 4576
Total records with ZERO value in age: 68
```

- Imputing 0[zero] values with related specification such as same car, fuel, engine etc

```
# Handling missig values like 0 for mileage

for indx in carsData.loc[carsData['mileage'] == 0].index:
    carMake,carModel,carFuel,carEngine = carsData.loc[indx,['make','model','fuel','engine'

    # Fine the median mileage of model and fue combination of specific car.
    medianMileage = carsData.loc[(carsData['model']==carModel) & (carsData['fuel']==carFue

    # We might have new car with no previous record we will replace
    if medianMileage == 0:
        medianMileage = carsData.loc[(carsData['fuel'] ==carFuel) & (carsData['engine']==c

    elif medianMileage == 0:
```

```
        medianMileage = carsData.loc[carsData['model'] ==carModel,'mileage'].median()

    elif medianMileage == 0:
        medianMileage = carsData.loc[carsData['make'] ==carMake,'mileage'].median()

    # Assigning the median value:
    carsData.loc[indx,'mileage'] = medianMileage
```

```
# Handling missig values like 0 for engine

for indx in carsData.loc[carsData['engine'] == 0].index:
    carMake,carModel,carFuel,carEngine = carsData.loc[indx,['make','model','fuel','engine'

    # Fine the median mileage of model and fue combination of specific car.
    medianEngine = carsData.loc[(carsData['model']==carModel) & (carsData['fuel']==carFuel

    # We might have new car with no previous record we will replace
    if medianEngine == 0:
        medianEngine = carsData.loc[(carsData['fuel'] ==carFuel) & (carsData['engine']==ca

    elif medianEngine == 0:
        medianEngine = carsData.loc[carsData['model'] ==carModel,'engine'].median()

    elif medianEngine == 0:
        medianEngine = carsData.loc[carsData['make'] ==carMake,'engine'].median()

    # Assigning the median value:
    carsData.loc[indx,'engine'] = medianEngine
```

```
# Handling missig values like 0 for max_power

for indx in carsData.loc[carsData['max_power'] == 0].index:
    carMake,carModel,carFuel,carEngine = carsData.loc[indx,['make','model','fuel','engine'

    # Fine the median mileage of model and fue combination of specific car.
    medianmax_power = carsData.loc[(carsData['model']==carModel) & (carsData['fuel']==carF

    # We might have new car with no previous record we will replace
    if medianmax_power == 0:
        medianmax_power = carsData.loc[(carsData['fuel'] ==carFuel) & (carsData['engine']=

    elif medianmax_power == 0:
        medianmax_power = carsData.loc[carsData['model'] ==carModel,'max_power'].median()

    elif medianmax_power == 0:
        medianmax_power = carsData.loc[carsData['make'] ==carMake,'max_power'].median()

    # Assigning the median value:
    carsData.loc[indx,'max_power'] = medianmax_power
```

```
# Handling missig values like 0 for seats

for indx in carsData.loc[carsData['seats'] == 0].index:
```

```
    carModel,carFuel,carEngine = carsData.loc[indx,['model','fuel','engine']]

    # Fine the median mileage of model and fue combination of specific car.
    medianSeats = carsData.loc[carsData['model']==carModel,'seats'].mode()[0]

    # We might have new car with no previous record we will replace
    if medianSeats == 0:
        medianSeats = carsData.loc[:,'seats'].mode()[0]

    # Assigning the median value:
    carsData.loc[indx,'seats'] = medianSeats
```

```
# Handling missig values like 0 for age

for indx in carsData.loc[carsData['mileage'] == 0].index:
    carMake,carModel,carFuel,carkm = carsData.loc[indx,['make','model','fuel','km_driven']

    # Fine the median mileage of model and fue combination of specific car.
    medianAge = carsData.loc[(carsData['model']==carModel) & (carsData['km_driven']==carkm

    # We might have new car with no previous record we will replace
    if medianAge == 0:
        medianAge = carsData.loc[carsData['fuel'] ==carFuel,'age'].median()

    elif medianAge == 0:
        medianAge = carsData.loc[carsData['model'] ==carModel,'age'].median()

    elif medianAge == 0:
        medianAge = carsData.loc[carsData['make'] ==carMake,'age'].median()

    # Assigning the median value:
    carsData.loc[indx,'age'] = medianAge
```

```
# convert remaining zero values to nan

carsData.loc[carsData['mileage'] == 0].index
```

```
Int64Index([   31,   138,   200,   336,   390,   535,   688,   725,   756,
                774,
            ...
            13581, 13651, 13664, 13669, 13910, 13960, 14188, 14263, 14332,
            14339],
           dtype='int64', length=955)
```

```
for i in numFeatList:
  ind = carsData.loc[carsData[i] == 0].index
  carsData.loc[ind,i] = np.nan
```

```
# Total % of missing records across whole dataset i.e zero value
```

```
totalMissRecord = round((carsData[carsData.isnull().any(axis=1)].shape[0]* 100 / len(carsD
print("Total percentage of missing records: {}%".format(totalMissRecord))
```

```
Total percentage of missing records: 8.42%
```

- After imputing missing values with related info by using their related features are are still 8% missing values and in more than 1 column.

```
# Drop missing values
print("Shape of Dataset before dropping missing values:",carsData.shape)
carsData.dropna(axis=0, inplace=True)
print("Shape of Dataset after dropping missing values:",carsData.shape)
```

```
Shape of Dataset before dropping missing values: (14329, 14)
Shape of Dataset after dropping missing values: (13122, 14)
```

```

```

Feature Engineerig (Advanced)

Reliability or Best resale

- Depends on the brand or make. (Domain Knowledge)

```
# create new best_resale feature.
# As of 2023 best resale brands are: Toyota,Maruti,Hyundai,Kia,Honda,Mahindra,Tata
bestResaleBrands = ['Toyota','Maruti','Hyundai','Kia','Honda','Mahindra','Tata']

bestResale = [] # New list to capture
for carBrand in carsData['make']:
  if carBrand in bestResaleBrands:
    bestResale.append('yes')
  else:
    bestResale.append('No')

carsData['best_resale'] = bestResale

carsData.head()
```

	make	model	variant	selling_price	km_driven	fuel	seller_type	transmiss
0	Maruti	Swift Dzire	VDI	4.50	140000 - 150000 Km	Diesel	Individual	Mai
1	Skoda	Rapid	1.5 TDI AMBITION	3.70	110000 - 120000 Km	Diesel	Individual	Mai
2	Honda	City	2017-2020 EXI	1.58	130000 - 140000 Km	Petrol	Individual	Mai

Fuel

- Fuel has 4 unique categores petrol,diesel,cng,lpg.
- CNG and LPG are alternate fuels and intended to offer simialr benifits hence combiing them as CleanFuel.
- Both of them are in the same selling price range.

```
carsData.loc[(carsData['fuel'] == 'Petrol + LPG') | (carsData['fuel']== 'Petrol + CNG'),'f
```

Seats Category

- Its a numerical feature but should be considered as categorical since it has no order.
- creating seats categories as <=5, 6 to 8 , 9<

```
# assigning values for seats 5 and less than 5
carsData.loc[carsData['seats'] <=5,'seats_cat'] = '5andBelow'

# Using '==' coz post above operation datatype would be string
# assigning values for seats 6 to 8
carsData.loc[(carsData['seats'] >= 6) & (carsData['seats'] <= 8),'seats_cat'] = 'btwn6and8

# assigning values for seats 9 and greater than 9
carsData.loc[carsData['seats'] >= 9,'seats_cat'] = '9andAbobe'
```

```
carsData.head()
```

	make	model	variant	selling_price	km_driven	fuel	seller_type	transmiss
0	Maruti	Swift Dzire	VDI	4.50	140000 - 150000 Km	Diesel	Individual	Mai
1	Skoda	Rapid	1.5 TDI AMBITION	3.70	110000 - 120000 Km	Diesel	Individual	Mai
2	Honda	City	2017-2020 EXI	1.58	130000 - 140000 Km	Petrol	Individual	Mai
			DIESEL					

```
print('Total duplicate rows:',carsData.duplicated().sum())
```

```
Total duplicate rows: 1742
```

```
# Check for duplicate records and drop them.
print('Total duplicate rows:',carsData.duplicated().sum())
carsData.drop_duplicates(inplace=True)
print("Shape of the data post removing duplicates: ",carsData.shape)
```

```
Total duplicate rows: 1742
Shape of the data post removing duplicates:  (11380, 16)
```

Exploratory data analysis (EDA)

Basic Statistics

```
# numerical overview of features
carsData.describe()
```

Observation

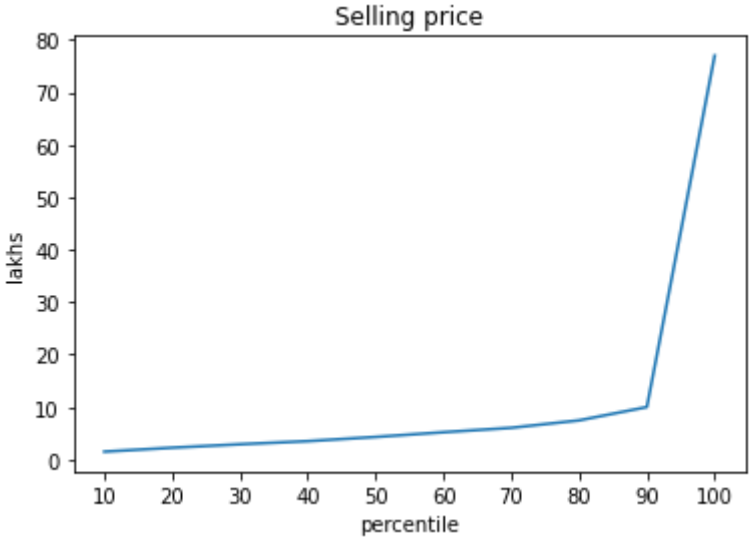
- Selling price (Target variable) : 75% of the cars selling price is less than 7 lakhs but max selling price is 77 Lakhs -> huge outlier problem.
- Similar outlier problem noticed in other features but not as hughe as selling price.

min	0.200000	4.087500	0.400000	17.750000	4.000000	1.000

Selling_price

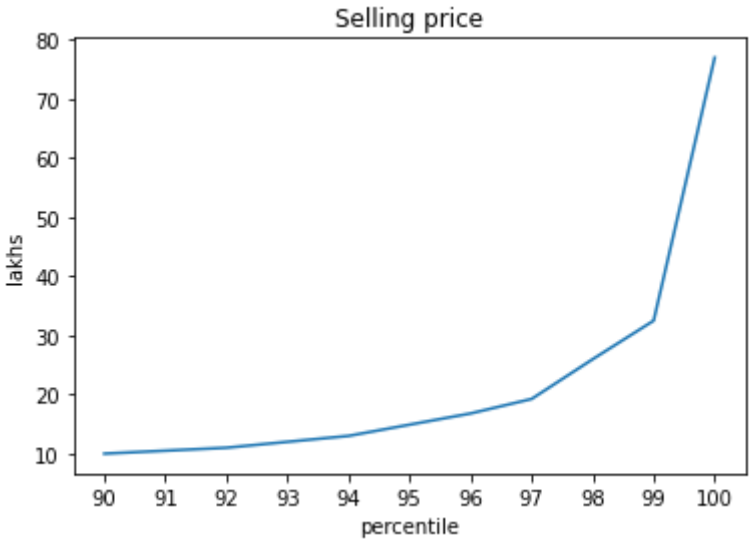
50%	4.300000	18.900000	1.250000	82.000000	5.000000	8.000

```
# Understanding selling price with percentile( 10 to 100)
percentile_10_100 = [round(np.percentile(carsData.selling_price,i),2) for i in range(10,11
plt.plot(range(10,110,10), percentile_10_100)
plt.title("Selling price")
plt.xlabel('percentile')
plt.ylabel('lakhs')
plt.xticks(range(10,110,10))
plt.show()
```



- understanding the sudden spike in value between 90 to 100 percentile

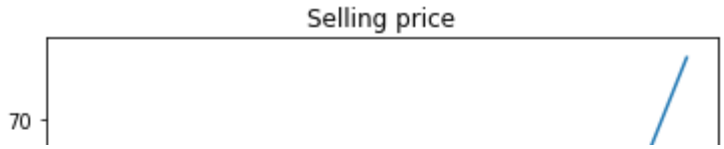
```
# percentile between ( 90 to 100)
percentile_90_100 = [round(np.percentile(carsData.selling_price,i),2) for i in range(90,10
plt.plot(range(90,101), percentile_90_100)
plt.title("Selling price")
plt.xlabel('percentile')
plt.ylabel('lakhs')
plt.xticks(range(90,101))
plt.show()

# Selling price at 97, 98, 99 percentile
for i in range(97,100):
  print('Selling price at {} percentile: {} Lakhs'.format(i,round(np.percentile(carsData.s
```




```
Selling price at 97 percentile: 19.25 Lakhs
Selling price at 98 percentile: 25.97 Lakhs
```

- between 99 to 100 percentile there is spike from 35lakhs to 80 lakhs

```
# percentile between ( 90 to 100)
percentile_99_100 = [round(np.percentile(carsData.selling_price,i),2) for i in np.linspace
plt.plot(np.linspace(99,100,11), percentile_99_100)
plt.title("Selling price")
plt.xlabel('percentile')
plt.ylabel('lakhs')
plt.xticks(np.linspace(99,100,11))
plt.show()

# Selling price between 99 to 100 percentile
for i in np.linspace(99,100,11):
  print('Selling price at {} percentile: {} Lakhs'.format(i,round(np.percentile(carsData.s
```



- There is no spike between 99 to 100 percentile.

```
# Drop cars more then 99 percentile
highSellingCars = carsData.loc[carsData['selling_price'] > np.percentile(carsData.selling_
print("Cars selling price greater than 30 lakhs:\n",pd.DataFrame(highSellingCars))
print("\nTotal sum of cars:",highSellingCars.sum())
```

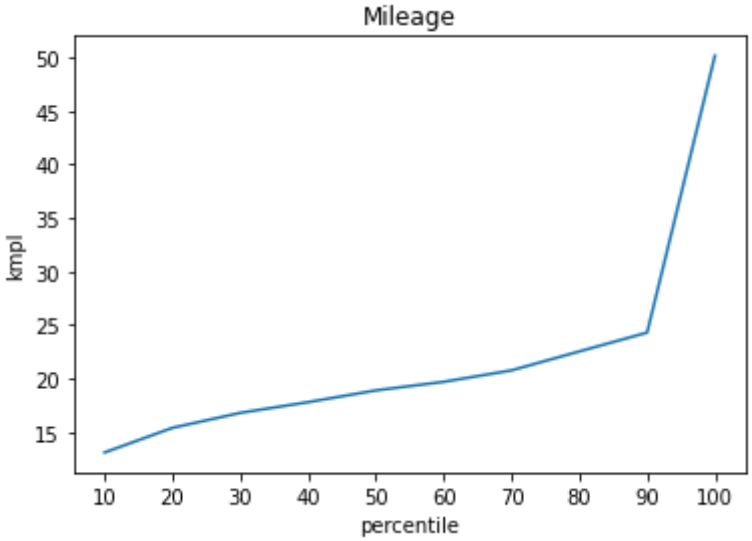
```
Cars selling price greater than 30 lakhs:
                                    0
make          model
BMW           5-Series             19
Land Rover    Discovery            10
BMW           X1                    8
Toyota        Fortuner              8
BMW           X3                    7
Land Rover    Range Rover Evoque    6
BMW           X4                    5
              3-Series              4
              6-Series              4
Ford          Endeavour             4
Jaguar        XF                    4
Audi          A6                    4
              A4                    3
Volvo         XC40                  3
Mercedes-Benz GL-Class              3
Lexus         ES                    3
Land Rover    Discovery Sport       3
Mercedes-Benz S-Class               2
Audi          Q5                    2
Jeep          Wrangler              1
Mercedes-Benz C-Class               1
              E-Class               1
Jaguar        XE                    1
Mercedes-Benz GLS                   1
              M-Class               1
Skoda         Kodiaq                1
              Octavia               1
              Superb                1
BMW           X5                    1
Volvo         XC60                  1

Total sum of cars: 113
```

- Cannot cap car price because model will get trained on wrong price.
- drop high value cars with less counts for better model performance.

```
high_val_index = carsData.loc[carsData['selling_price'] > np.percentile(carsData.selling_p
carsData.drop(index=high_val_index, axis=0, inplace=True)
```

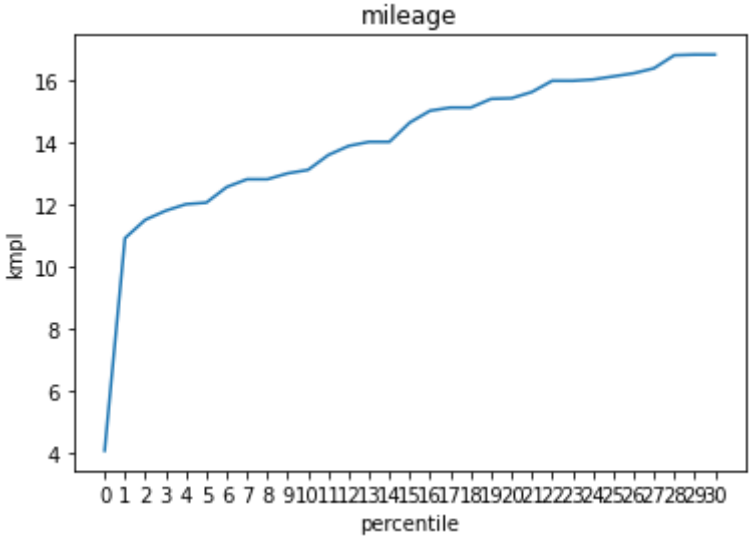
Mileage

```
# Understanding Mileage percentile( 10 to 100)
percentile_10_100 = [round(np.percentile(carsData.mileage,i),2) for i in range(10,110,10)]
plt.plot(range(10,110,10), percentile_10_100)
plt.title("Mileage")
plt.xlabel('percentile')
plt.ylabel('kmpl')
plt.xticks(range(10,110,10))
plt.show()
```



- understanding the dip before 30 percentile.

```
# percentile between ( 0 to 30)
percentile_0_30 = [round(np.percentile(carsData.mileage,i),2) for i in range(0,31)]
plt.plot(range(0,31), percentile_0_30)
plt.title("mileage")
plt.xlabel('percentile')
plt.ylabel('kmpl')
plt.xticks(range(0,31))
plt.show()

# Mileage at 97, 98, 99 percentile
for i in range(0,31):
  print('Mileage at {} percentile: {} kmpl'.format(i,round(np.percentile(carsData.mileage,
```

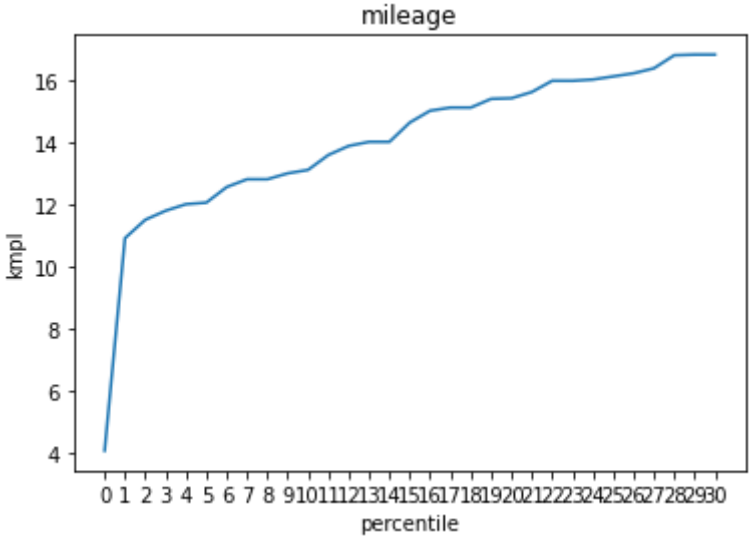



```
Mileage at 0 percentile: 4.09 kmpl
Mileage at 1 percentile: 10.91 kmpl
Mileage at 2 percentile: 11.5 kmpl
Mileage at 3 percentile: 11.79 kmpl
Mileage at 4 percentile: 12.0 kmpl
Mileage at 5 percentile: 12.05 kmpl
Mileage at 6 percentile: 12.55 kmpl
Mileage at 7 percentile: 12.8 kmpl
Mileage at 8 percentile: 12.8 kmpl
Mileage at 9 percentile: 12.99 kmpl
Mileage at 10 percentile: 13.1 kmpl
Mileage at 11 percentile: 13.58 kmpl
Mileage at 12 percentile: 13.87 kmpl
Mileage at 13 percentile: 14.0 kmpl
Mileage at 14 percentile: 14.0 kmpl
Mileage at 15 percentile: 14.62 kmpl
Mileage at 16 percentile: 15.0 kmpl
Mileage at 17 percentile: 15.1 kmpl
Mileage at 18 percentile: 15.1 kmpl
Mileage at 19 percentile: 15.38 kmpl
Mileage at 20 percentile: 15.4 kmpl
Mileage at 21 percentile: 15.6 kmpl
Mileage at 22 percentile: 15.96 kmpl
Mileage at 23 percentile: 15.96 kmpl
Mileage at 24 percentile: 16.0 kmpl
```

- between 0 to 1 percentile

```
Mileage at 27 percentile: 16.36 kmpl
```

```
# percentile between ( 0 to 1)
percentile_0_30 = [round(np.percentile(carsData.mileage,i),2) for i in range(0,31)]
plt.plot(range(0,31), percentile_0_30)
plt.title("mileage")
plt.xlabel('percentile')
plt.ylabel('kmpl')
plt.xticks(range(0,31))
plt.show()

# Mileage at 97, 98, 99 percentile
for i in range(0,31):
  print('Mileage at {} percentile: {} kmpl'.format(i,round(np.percentile(carsData.mileage,
```

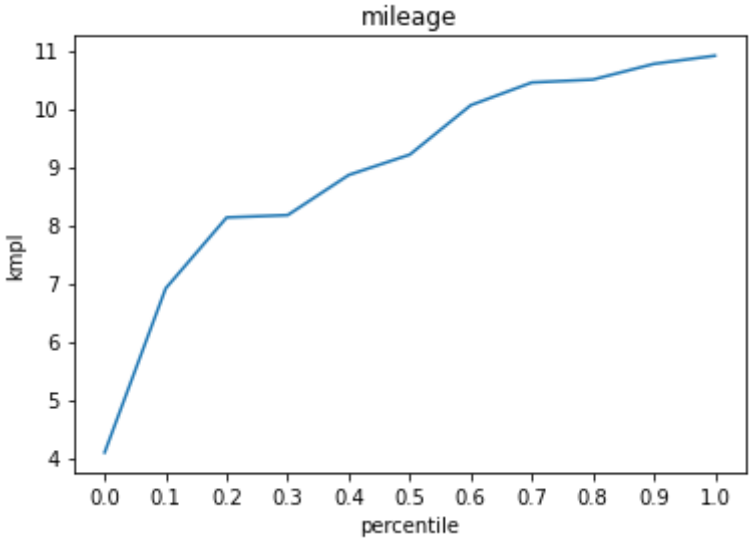



```
Mileage at 0 percentile: 4.09 kmpl
Mileage at 1 percentile: 10.91 kmpl
Mileage at 2 percentile: 11.5 kmpl
Mileage at 3 percentile: 11.79 kmpl
Mileage at 4 percentile: 12.0 kmpl
Mileage at 5 percentile: 12.05 kmpl
Mileage at 6 percentile: 12.55 kmpl
Mileage at 7 percentile: 12.8 kmpl
Mileage at 8 percentile: 12.8 kmpl
Mileage at 9 percentile: 12.99 kmpl
Mileage at 10 percentile: 13.1 kmpl
Mileage at 11 percentile: 13.58 kmpl
Mileage at 12 percentile: 13.87 kmpl
Mileage at 13 percentile: 14.0 kmpl
Mileage at 14 percentile: 14.0 kmpl
Mileage at 15 percentile: 14.62 kmpl
Mileage at 16 percentile: 15.0 kmpl
Mileage at 17 percentile: 15.1 kmpl
Mileage at 18 percentile: 15.1 kmpl
Mileage at 19 percentile: 15.38 kmpl
Mileage at 20 percentile: 15.4 kmpl
Mileage at 21 percentile: 15.6 kmpl
Mileage at 22 percentile: 15.96 kmpl
Mileage at 23 percentile: 15.96 kmpl
Mileage at 24 percentile: 16.0 kmpl
Mileage at 25 percentile: 16.1 kmpl
Mileage at 26 percentile: 16.2 kmpl
Mileage at 27 percentile: 16.36 kmpl
Mileage at 28 percentile: 16.78 kmpl
Mileage at 29 percentile: 16.8 kmpl
Mileage at 30 percentile: 16.8 kmpl
```

- understanding the sudden spike in value between 90 to 100 percentile

```
# percentile between ( 0 to 1)
percentile_0_1 = [round(np.percentile(carsData.mileage,i),2) for i in np.linspace(0,1,11)]
plt.plot(np.linspace(0,1,11), percentile_0_1)
plt.title("mileage")
plt.xlabel('percentile')
plt.ylabel('kmpl')
```

```
plt.xticks(np.linspace(0,1,11))
plt.show()

# Mileage
for i in np.linspace(0,1,11):
  print('Mileage at {} percentile: {} kmpl'.format(round(i,2),round(np.percentile(carsData
```




```
Mileage at 0.0 percentile: 4.09 kmpl
Mileage at 0.1 percentile: 6.91 kmpl
Mileage at 0.2 percentile: 8.13 kmpl
Mileage at 0.3 percentile: 8.17 kmpl
Mileage at 0.4 percentile: 8.86 kmpl
Mileage at 0.5 percentile: 9.21 kmpl
Mileage at 0.6 percentile: 10.06 kmpl
Mileage at 0.7 percentile: 10.45 kmpl
Mileage at 0.8 percentile: 10.5 kmpl
Mileage at 0.9 percentile: 10.77 kmpl
Mileage at 1.0 percentile: 10.91 kmpl
```

```
# cars less than 1 percentile
lowMileageCars = carsData.loc[carsData['mileage'] < np.percentile(carsData.mileage,0.1),['
print("Cars mileage less than 1 percentile:\n",pd.DataFrame(lowMileageCars))
print("\nTotal sum of cars:",lowMileageCars.sum())
```

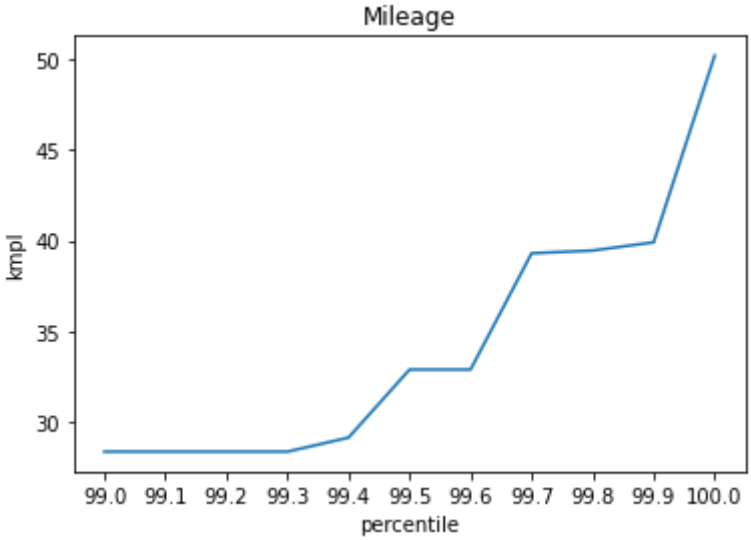
```
Cars mileage less than 1 percentile:
                                          0
make          model    fuel
Maruti        Alto     Petrol + AltFuel  2
Audi          A6       Diesel            1
Ford          Ikon     Diesel            1
Honda         Civic    Petrol            1
Hyundai       Sonata   Diesel            1
MG            Hector   Diesel            1
Mercedes-Benz B-Class  Petrol            1
Mitsubishi    Pajero   Diesel            1
Skoda         Octavia  Petrol            1
              Superb   Petrol            1
Toyota        Fortuner Diesel            1

Total sum of cars: 12
```

- incorrect data noted hence drop

```
low_kmpl_index = carsData.loc[carsData['mileage'] < np.percentile(carsData.mileage,0.1)].i
carsData.drop(index=low_kmpl_index, axis=0, inplace = True)
```

- Analyzing variance above 90 percentile

```
# percentile between ( 90 to 100)
percentile_99_100 = [round(np.percentile(carsData.mileage,i),2) for i in np.linspace(99,10
plt.plot(np.linspace(99,100,11), percentile_99_100)
plt.title("Mileage")
plt.xlabel('percentile')
plt.ylabel('kmpl')
plt.xticks(np.linspace(99,100,11))
plt.show()

# Mileage between 99 to 100 percentile
for i in np.linspace(99,100,11):
  print('Mileage at {} percentile: {} kmpl'.format(i,round(np.percentile(carsData.mileage,
```




```
Mileage at 99.0 percentile: 28.4 kmpl
Mileage at 99.1 percentile: 28.4 kmpl
Mileage at 99.2 percentile: 28.4 kmpl
Mileage at 99.3 percentile: 28.4 kmpl
Mileage at 99.4 percentile: 29.17 kmpl
Mileage at 99.5 percentile: 32.91 kmpl
Mileage at 99.6 percentile: 32.91 kmpl
Mileage at 99.7 percentile: 39.3 kmpl
Mileage at 99.8 percentile: 39.45 kmpl
Mileage at 99.9 percentile: 39.9 kmpl
Mileage at 100.0 percentile: 50.16 kmpl
```

- There is high spike between 99 to 100 percentile.

```
# cars more then 99.4 percentile
highMileageCars = carsData.loc[carsData['mileage'] > np.percentile(carsData.mileage,99.4),
```

```
print("Cars mileage greater than 99 percentile:\n",pd.DataFrame(highMileageCars))
print("\nTotal sum of cars:",highMileageCars.sum())
```

```
Cars mileage greater than 99 percentile:
                                    0
make    model  fuel
Maruti  Eeco   Petrol + AltFuel  26
        Wagon  Petrol + AltFuel  25
        Alto   Petrol + AltFuel   8
        Zen    Petrol + AltFuel   3
Hyundai EON    Petrol + AltFuel   1
        Grand  Petrol + AltFuel   1
Maruti  Ertiga Petrol + AltFuel   1
        SX4    Petrol + AltFuel   1
        Swift  Petrol + AltFuel   1
Tata    Indica Petrol + AltFuel   1

Total sum of cars: 68
```

- capping max mileage to 99.4 percentile value.

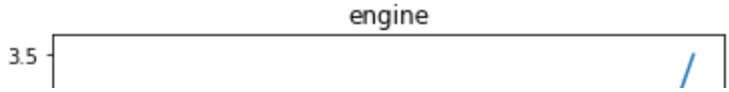
```
high_kmpl_index = carsData.loc[carsData['mileage'] > np.percentile(carsData.mileage,94)].i
carsData.loc[high_kmpl_index,'mileage'] = round(np.percentile(carsData.mileage,94),2)
```

```

```

```

```

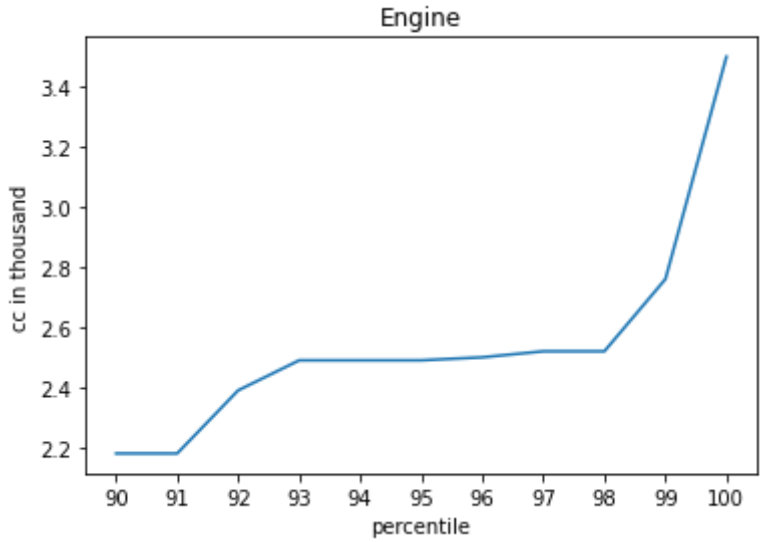
Engine

```
# Understanding Engine with percentile( 10 to 100)
percentile_10_100 = [round(np.percentile(carsData.engine,i),2) for i in range(10,110,10)]
plt.plot(range(10,110,10), percentile_10_100)
plt.title("engine")
plt.xlabel('percentile')
plt.ylabel('cc in thousands')
plt.xticks(range(10,110,10))
plt.show()
```



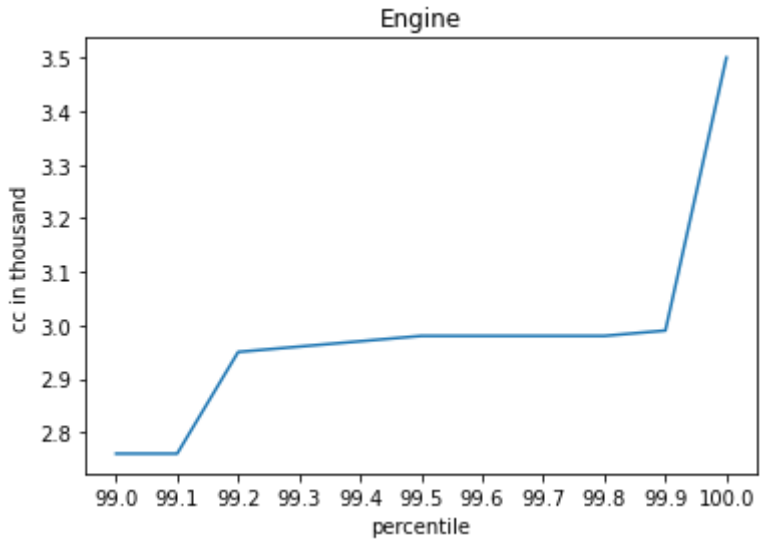
- understanding the sudden spike in value between 90 to 100 percentile

```
# percentile between ( 90 to 100)
percentile_90_100 = [round(np.percentile(carsData.engine,i),2) for i in range(90,101)]
plt.plot(range(90,101), percentile_90_100)
plt.title("Engine")
plt.xlabel('percentile')
plt.ylabel('cc in thousand')
plt.xticks(range(90,101))
plt.show()

# engine at 97, 98, 99 percentile
for i in range(97,100):
  print('engine at {} percentile: {} cc'.format(i,round(np.percentile(carsData.engine,i),2
```




```
engine at 97 percentile: 2.52 cc
engine at 98 percentile: 2.52 cc
engine at 99 percentile: 2.76 cc
```

```
# percentile between ( 90 to 100)
percentile_99_100 = [round(np.percentile(carsData.engine,i),2) for i in np.linspace(99,100
plt.plot(np.linspace(99,100,11), percentile_99_100)
plt.title("Engine")
plt.xlabel('percentile')
plt.ylabel('cc in thousand')
plt.xticks(np.linspace(99,100,11))
plt.show()

# Selling price between 99 to 100 percentile
for i in np.linspace(99,100,11):
  print('Engine at {} percentile: {} cc'.format(i,round(np.percentile(carsData.engine,i),2
```




```
Engine at 99.0 percentile: 2.76 cc
Engine at 99.1 percentile: 2.76 cc
Engine at 99.2 percentile: 2.95 cc
Engine at 99.3 percentile: 2.96 cc
Engine at 99.4 percentile: 2.97 cc
Engine at 99.5 percentile: 2.98 cc
Engine at 99.6 percentile: 2.98 cc
Engine at 99.7 percentile: 2.98 cc
Engine at 99.8 percentile: 2.98 cc
```

- There is spike between 99.9 to 100 percentile.

```
# Drop cars more then 99.9 percentile
highEngineCars = carsData.loc[carsData['engine'] > np.percentile(carsData.engine,99.9),['m
print("Cars engine greater than 99 percentile:\n",pd.DataFrame(highEngineCars))
print("\nTotal sum of cars:",highEngineCars.sum())
```

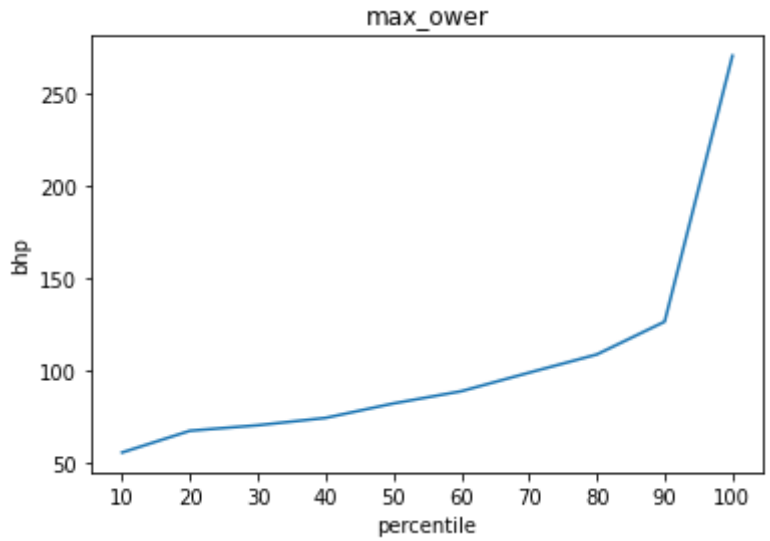
```
Cars engine greater than 99 percentile:
                          0
make          model
Ford          Endeavour  4
Honda         Accord     2
Mercedes-Benz E-Class    1

Total sum of cars: 7
```

- Cannot cap car price because model will get trained on wrong data.
- drop high value cars with less counts for better model performance.

```
high_engine_index = carsData.loc[carsData['engine'] > np.percentile(carsData.engine,99.9)]
carsData.drop(index=high_engine_index, axis=0, inplace=True)
```

Max Power

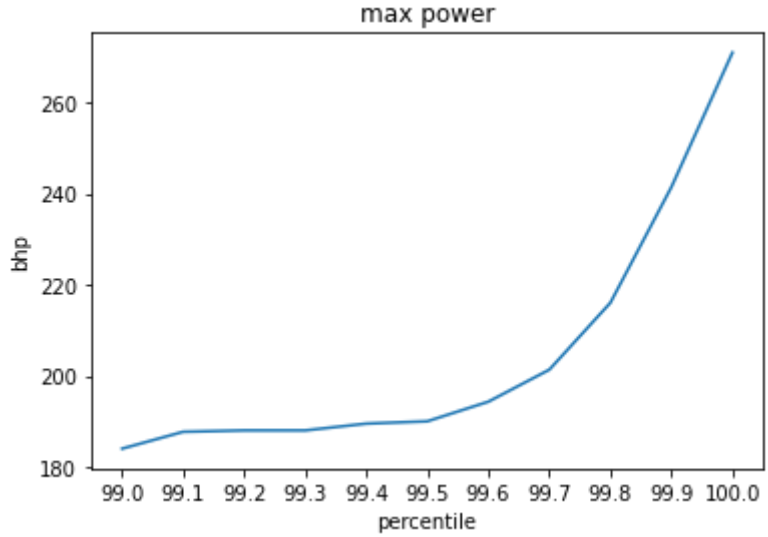
```
# Understanding max_power with percentile( 10 to 100)
percentile_10_100 = [round(np.percentile(carsData.max_power,i),2) for i in range(10,110,10
plt.plot(range(10,110,10), percentile_10_100)
plt.title("max_ower")
plt.xlabel('percentile')
plt.ylabel('bhp')
plt.xticks(range(10,110,10))
plt.show()
```



- understanding the sudden spike in value between 90 to 100 percentile

```
# percentile between ( 90 to 100)
percentile_90_100 = [round(np.percentile(carsData.max_power,i),2) for i in range(90,101)]
plt.plot(range(90,101), percentile_90_100)
plt.title("max power")
plt.xlabel('percentile')
plt.ylabel('bhp')
plt.xticks(range(90,101))
plt.show()

# power at 97, 98, 99 percentile
for i in range(97,100):
  print('Max power at {} percentile: {} bhp'.format(i,round(np.percentile(carsData.max_pow
```


```
# percentile between ( 90 to 100)
percentile_99_100 = [round(np.percentile(carsData.max_power,i),2) for i in np.linspace(99,
plt.plot(np.linspace(99,100,11), percentile_99_100)
plt.title("max power")
plt.xlabel('percentile')
plt.ylabel('bhp')
plt.xticks(np.linspace(99,100,11))
plt.show()

# power between 99 to 100 percentile
for i in np.linspace(99,100,11):
  print('power at {} percentile: {} cc'.format(i,round(np.percentile(carsData.max_power,i)
```




```
power at 99.0 percentile: 184.0 cc
power at 99.1 percentile: 187.7 cc
power at 99.2 percentile: 188.0 cc
power at 99.3 percentile: 188.0 cc
power at 99.4 percentile: 189.49 cc
power at 99.5 percentile: 190.0 cc
power at 99.6 percentile: 194.3 cc
power at 99.7 percentile: 201.33 cc
power at 99.8 percentile: 216.01 cc
power at 99.9 percentile: 241.4 cc
power at 100.0 percentile: 270.9 cc
```

- There is spike between 99.8 to 100 percentile.

```
# Drop cars more then 99.9 percentile
highPowerCars = carsData.loc[carsData['max_power'] > np.percentile(carsData.max_power,99.8
print("Cars power greater than 99 percentile:\n",pd.DataFrame(highPowerCars))
print("\nTotal sum of cars:",highPowerCars.sum())
```

```
Cars power greater than 99 percentile:
                          0
make          model
BMW           5-Series  7
Audi          Q7        6
BMW           7-Series  3
Audi          Q5        2
Jaguar        XF        2
BMW           X5        1
Mercedes-Benz GL-Class  1
              M-Class   1

Total sum of cars: 23
```

- Cannot cap car price because model will get trained on wrong data.
- drop high power cars with less counts for better model performance.

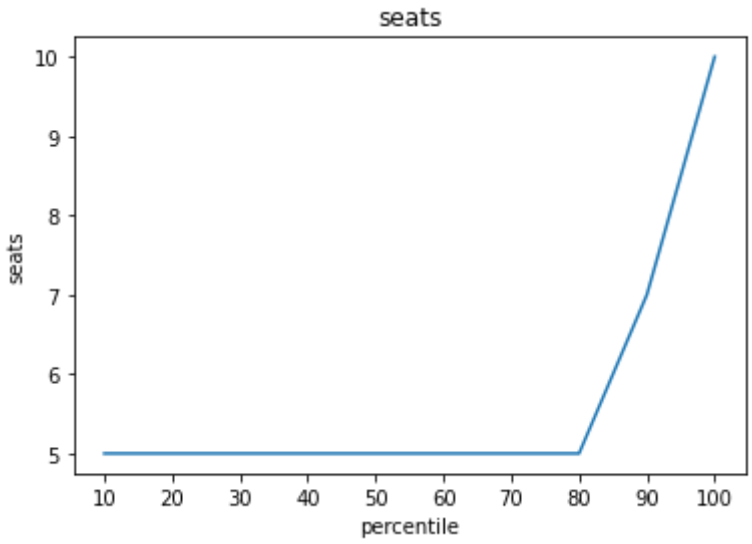
```
high_power_index = carsData.loc[carsData['max_power'] > np.percentile(carsData.max_power,9
carsData.drop(index=high_power_index, axis=0, inplace=True)
```

```

```

```

```

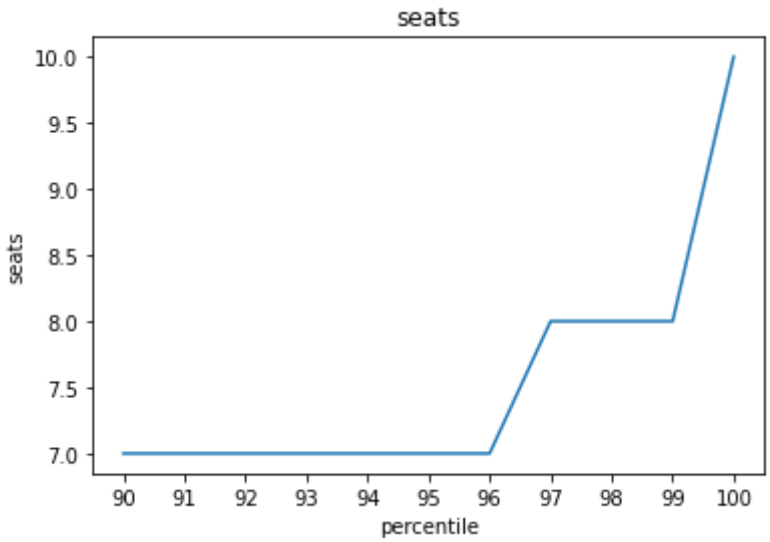
Seats

```
# Understanding seats with percentile( 10 to 100)
percentile_10_100 = [round(np.percentile(carsData.seats,i),2) for i in range(10,110,10)]
plt.plot(range(10,110,10), percentile_10_100)
plt.title("seats")
plt.xlabel('percentile')
plt.ylabel('seats')
plt.xticks(range(10,110,10))
plt.show()
```



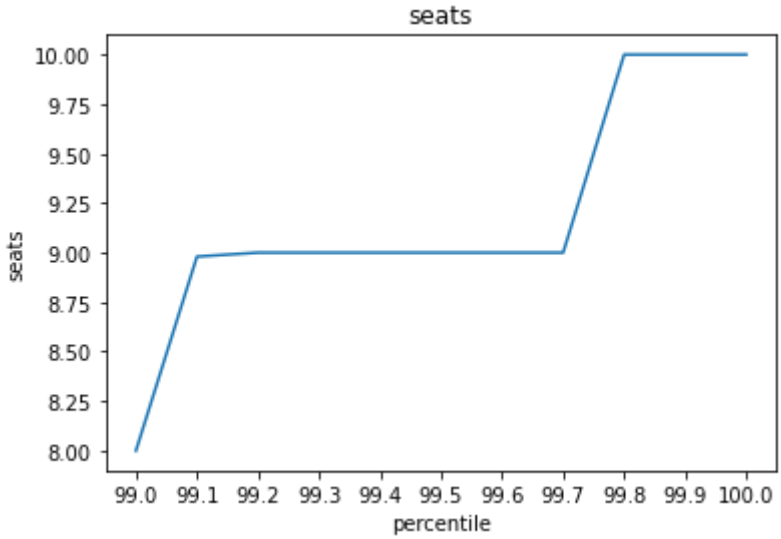
- understanding the sudden spike in value between 80 to 100 percentile

```
# percentile between ( 90 to 100)
percentile_90_100 = [round(np.percentile(carsData.seats,i),2) for i in range(90,101)]
plt.plot(range(90,101), percentile_90_100)
plt.title("seats")
plt.xlabel('percentile')
plt.ylabel('seats')
plt.xticks(range(90,101))
plt.show()

# seats at 97, 98, 99 percentile
for i in range(97,100):
  print('Seats at {} percentile: {} seats'.format(i,round(np.percentile(carsData.seats,i),
```




```
Seats at 97 percentile: 8.0 seats
Seats at 98 percentile: 8.0 seats
Seats at 99 percentile: 8.0 seats
```

```
# percentile between ( 90 to 100)
percentile_99_100 = [round(np.percentile(carsData.seats,i),2) for i in np.linspace(99,100,
plt.plot(np.linspace(99,100,11), percentile_99_100)
plt.title("seats")
plt.xlabel('percentile')
plt.ylabel('seats')
plt.xticks(np.linspace(99,100,11))
plt.show()

# power between 99 to 100 percentile
for i in np.linspace(99,100,11):
  print('Seats at {} percentile: {} seats'.format(i,round(np.percentile(carsData.seats,i),
```




```
Seats at 99.0 percentile: 8.0 seats
Seats at 99.1 percentile: 8.98 seats
Seats at 99.2 percentile: 9.0 seats
Seats at 99.3 percentile: 9.0 seats
Seats at 99.4 percentile: 9.0 seats
```

- There is spike between 99. to 100 percentile.

```
Seats at 99.8 percentile: 10.0 seats
```

```
# cars more then 99 percentile
highSeatsCars = carsData.loc[carsData['seats'] >8,['make','model']].value_counts()
print("Cars age greater than 99 percentile:\n",pd.DataFrame(highSeatsCars))
print("\nTotal sum of cars:",highSeatsCars.sum())
```

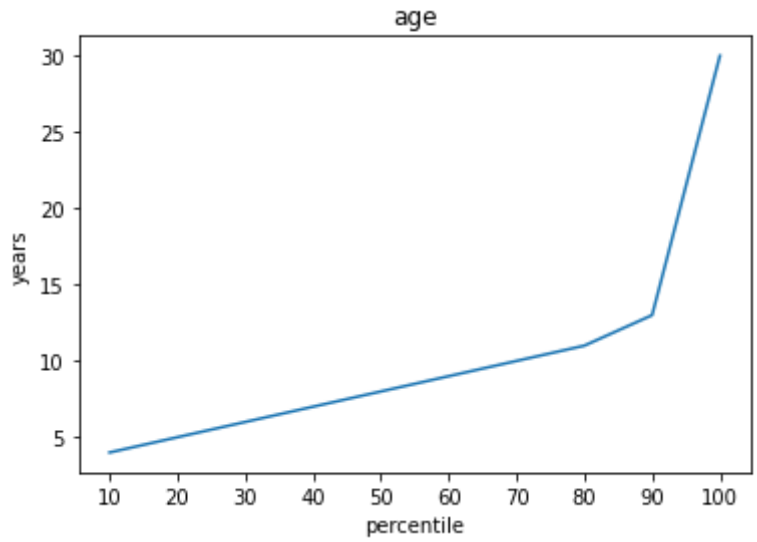
```
Cars age greater than 99 percentile:
                     0
make      model
Mahindra  Bolero   35
Chevrolet Tavera   33
Mahindra  Scorpio  22
Tata      Sumo      8
Mahindra  TUV       2
          Xylo      1
Toyota    Qualis    1

Total sum of cars: 102
```

- There are 102 cars hence not dropping.

Age

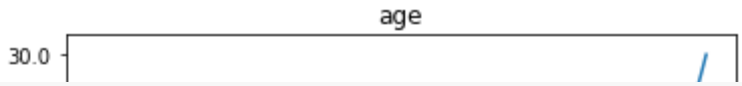
```
# Understanding seats with percentile( 10 to 100)
percentile_10_100 = [round(np.percentile(carsData.age,i),2) for i in range(10,110,10)]
```

```
plt.plot(range(10,110,10), percentile_10_100)
plt.title("age")
plt.xlabel('percentile')
plt.ylabel('years')
plt.xticks(range(10,110,10))
plt.show()
```

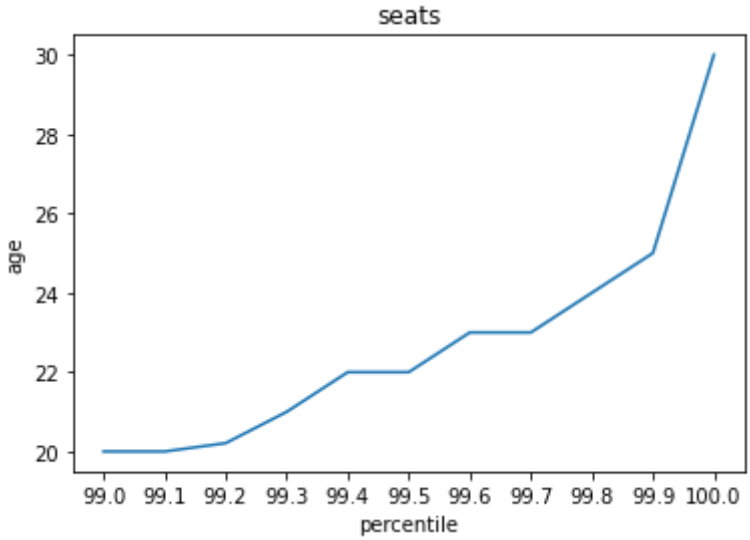


- understanding the sudden spike in value between 80 to 100 percentile

```
# percentile between ( 90 to 100)
percentile_90_100 = [round(np.percentile(carsData.age,i),2) for i in range(90,101)]
plt.plot(range(90,101), percentile_90_100)
plt.title("age")
plt.xlabel('percentile')
plt.ylabel('years')
plt.xticks(range(90,101))
plt.show()

# seats at 97, 98, 99 percentile
for i in range(97,100):
  print('age at {} percentile: {} years'.format(i,round(np.percentile(carsData.age,i),2)))
```




```
# percentile between ( 90 to 100)
percentile_99_100 = [round(np.percentile(carsData.age,i),2) for i in np.linspace(99,100,11
plt.plot(np.linspace(99,100,11), percentile_99_100)
plt.title("seats")
plt.xlabel('percentile')
plt.ylabel('age')
plt.xticks(np.linspace(99,100,11))
plt.show()

# power between 99 to 100 percentile
for i in np.linspace(99,100,11):
  print('age at {} percentile: {} years'.format(i,round(np.percentile(carsData.age,i),2)))
```




```
age at 99.0 percentile: 20.0 years
age at 99.1 percentile: 20.0 years
age at 99.2 percentile: 20.21 years
age at 99.3 percentile: 21.0 years
age at 99.4 percentile: 22.0 years
age at 99.5 percentile: 22.0 years
age at 99.6 percentile: 23.0 years
age at 99.7 percentile: 23.0 years
age at 99.8 percentile: 24.0 years
age at 99.9 percentile: 25.0 years
age at 100.0 percentile: 30.0 years
```

- There is spike between 99. to 100 percentile.

```
# cars more then 99.9 percentile
highAgeCars = carsData.loc[carsData['age'] > np.percentile(carsData.age,99.9),['make','mod
print("Cars age greater than 99.9 percentile:\n",pd.DataFrame(highAgeCars))
print("\nTotal sum of cars:",highAgeCars.sum())
```

```
Cars age greater than 99.9 percentile:
                0
make   model
Maruti 800    5
```

```
        Gypsy  1

Total sum of cars: 6
```

- Cannot cap car age because model will get trained on wrong data.
- drop high age cars with less counts for better model performance.

```
high_age_index = carsData.loc[carsData['age'] > np.percentile(carsData.age,99.9)].index
carsData.drop(index=high_age_index, axis=0, inplace=True)
```

```
# Categorical Features Overview
carsData.describe(include='object')
```

	make	model	variant	km_driven	fuel	seller_type	transmission	owner	be
count	11219	11219	11219	11219	11219	11219	11219	11219	
unique	24	171	2559	42	3	5	2	6	
top	Maruti	Alto	VDI	60000 - 70000 Km	Diesel	Individual	Manual	1st owner	

Observation Out of total 11k cars:

- 9k cars have 5 seats or below.
- 10k cars are manual driven or individual seller.
- Varient feature has 2.6k unique categories.
- 9k cars are from best resale brands i.e the depreciation rate is low.
- 6k cars are with diesel fuel.

Data Visualization

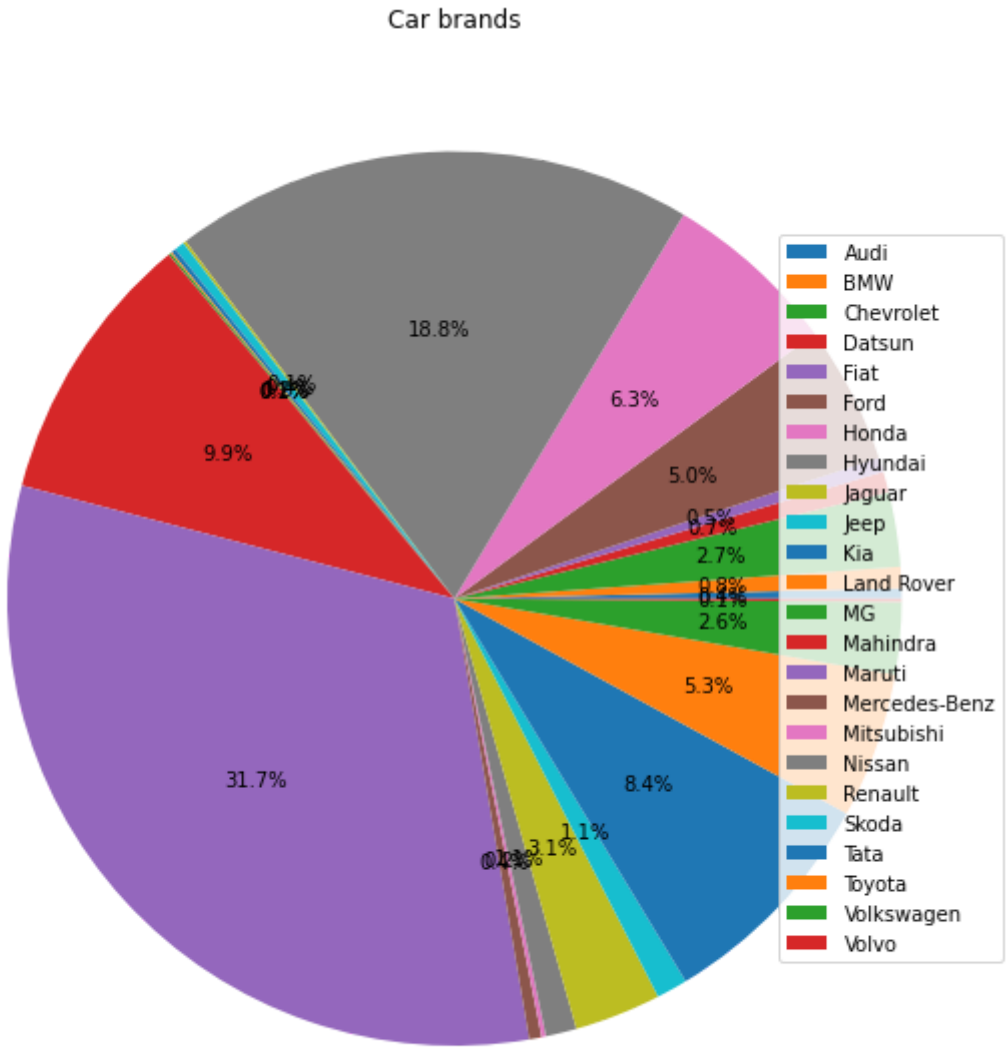
- Visualizing unique features and its observation

Univariant analysis

Make(brand name)

```
# Pie chart to observe the total percentage share of each brand in the dataset
carsMakeCounts = np.unique(carsData['make'], return_counts=True)
```

```
plt.figure(figsize=(10,20))
plt.pie(carsMakeCounts[1],autopct='%1.1f%%')
plt.title("Car brands")
plt.legend(carsMakeCounts[0], loc = 7)
plt.show()
```

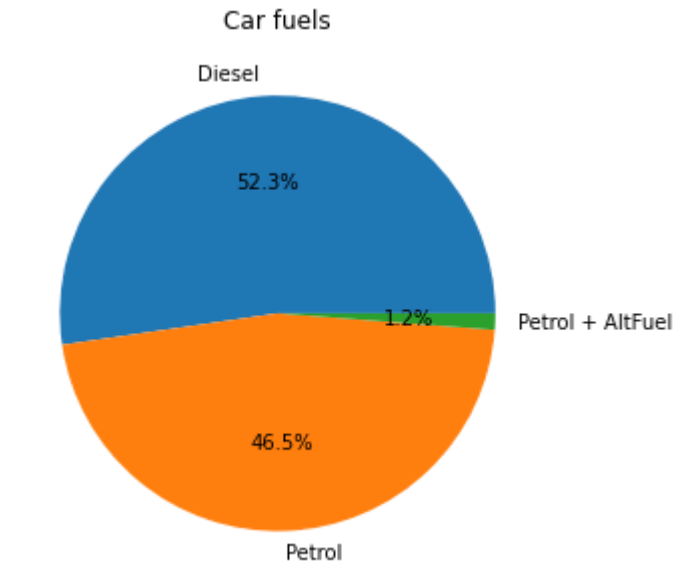


Observation

- About 75 % of cars brands are Maruti, Hyundai, Mahindra, Tata, Honda, Toyota, Ford.
- Out of which 30% share is with Maruti
- Rate of depreciation affects differently for different country car brands.

Fuel

```
carsFuelCounts = np.unique(carsData['fuel'], return_counts=True)
plt.figure(figsize=(5,5))
plt.pie(carsFuelCounts[1], labels = carsFuelCounts[0], autopct='%1.1f%%')
plt.title("Car fuels")
plt.show()
```

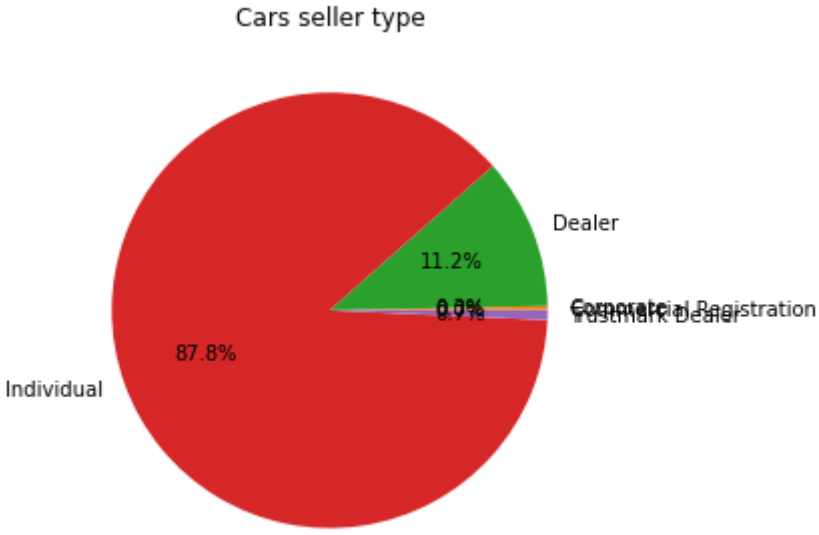


Observation

- Diesel and Petrol make almost 97% of the used cars in the data.

Seller type

```
carsSellerCounts = np.unique(carsData['seller_type'], return_counts=True)
plt.figure(figsize=(5,5))
plt.pie(carsSellerCounts[1], labels = carsSellerCounts[0], autopct='%1.1f%%')
plt.title("Cars seller type")
plt.show()
```

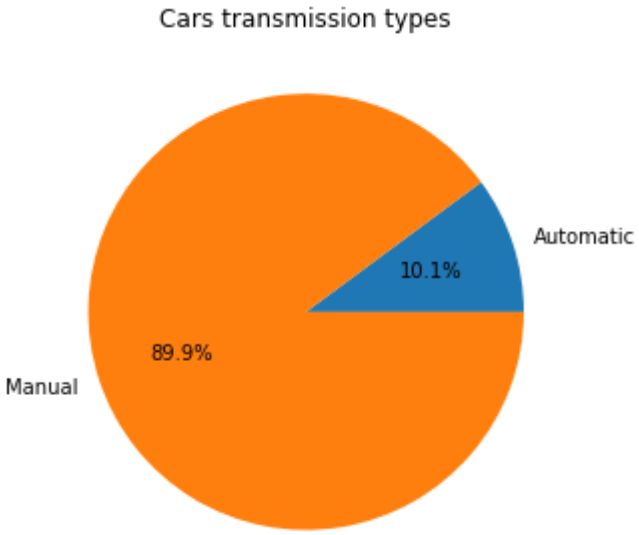


Observation

- Most of the cars are sold by Individual.
- Cars sold by dealer will have dealer commission included.

Transmission

```
carsTransmissionCounts = np.unique(carsData['transmission'], return_counts=True)
plt.figure(figsize=(5,5))
plt.pie(carsTransmissionCounts[1], labels = carsTransmissionCounts[0], autopct='%1.1f%%')
plt.title("Cars transmission types")
plt.show()
```

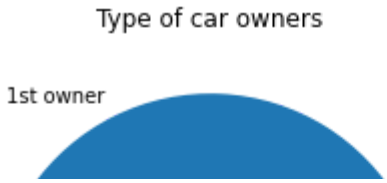


Observation

- Majority of the cars have manual transmission.
- Manual transmission are known to be relaible than automatic and can affect selling price.
- The cost of owining a automatic in the first place is higher than manual.

Owner

```
carsownerCounts = np.unique(carsData['owner'], return_counts=True)
plt.figure(figsize=(5,5))
plt.pie(carsownerCounts[1], labels = carsownerCounts[0], autopct='%1.1f%%')
plt.title("Type of car owners")
plt.show()
```

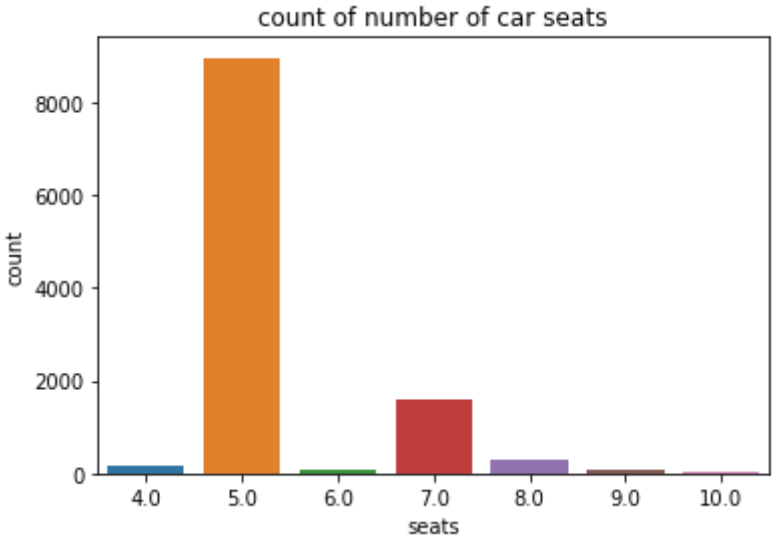


Observation

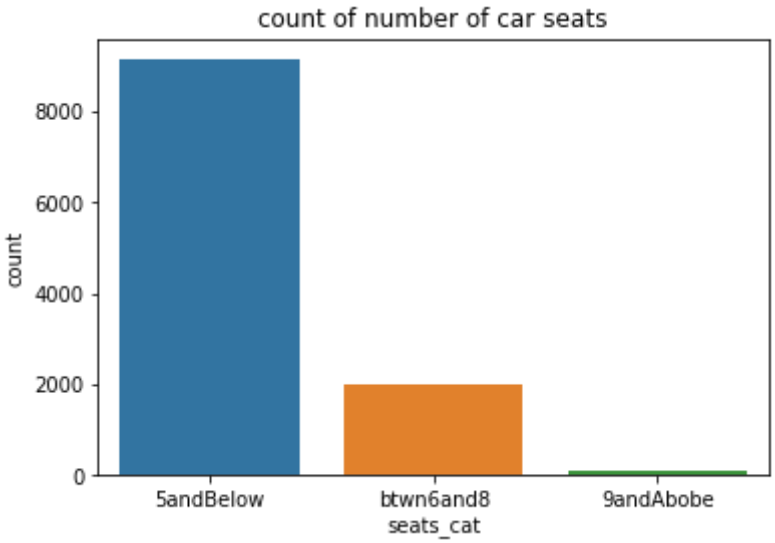
- Majority of the cars are sold by first owner and then followed by second owner.
- Major depreciation will be observed first and second owner's car.

Seats

```
sns.countplot(x=carsData['seats'])
plt.title("count of number of car seats")
plt.show()
```




```
sns.countplot(x=carsData['seats_cat'])
plt.title("count of number of car seats")
plt.show()
```

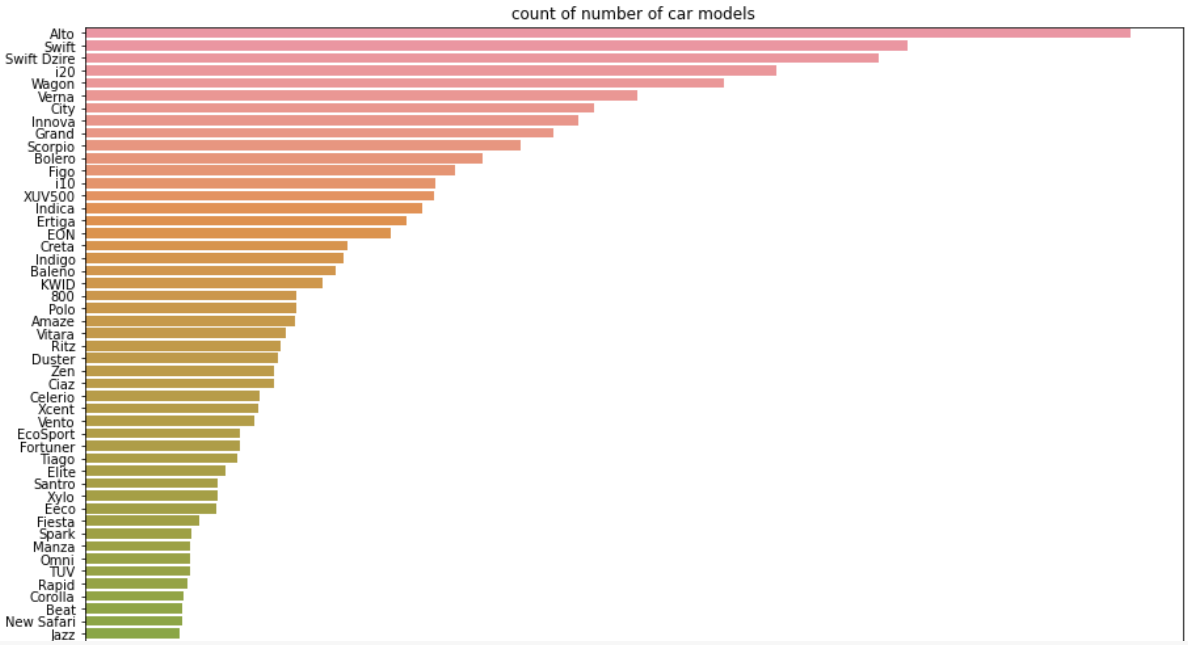


Observation

- Majority of the cars in the data are 5 seater followed by 7 seater.
- very few 10 and 14 seater cars.
- need to check bivarriant analysis with respect to selling price to check how does number of seats affect.
- cars with 2 seats are noted need to analyze ans handel if incorrect data.

Model

```
plt.figure(figsize=(15,30))
sns.countplot(y='model', data = carsData, order = carsData['model'].value_counts().index)
plt.title("count of number of car models")
plt.xticks(rotation = 45)
plt.show()
```



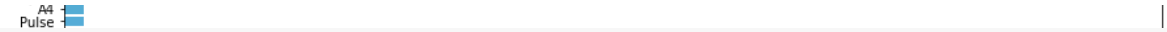

```
modelCount = carsData.model.value_counts()
modelCount[modelCount<3].index.unique()
```

```
Index(['Xenon', 'C-Class', 'Q5', 'XC60', 'Kodiaq', 'Qualis', 'M-Class',
       'A-Class', 'Discovery'],
      dtype='object')
```

Observation

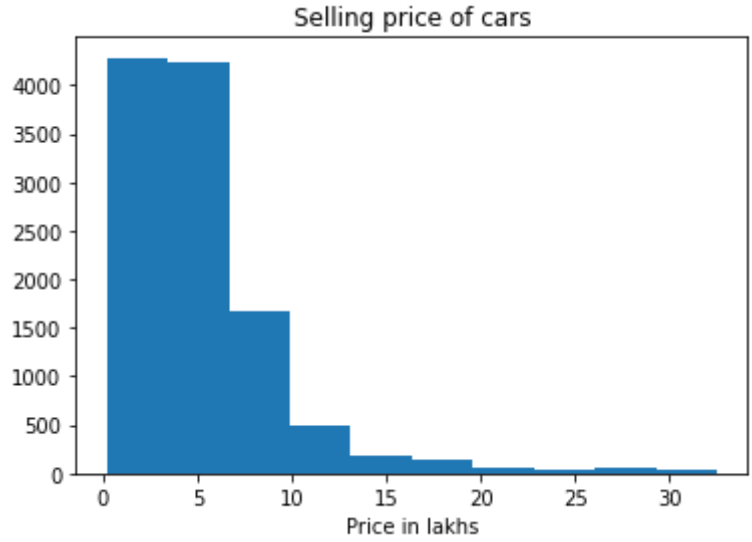
- Too many model categories to one hot encode, should find alternate way for encoding or drop the feaure.
- Use catboost model.
- count of models are very less for majority of the models.
- Club these cars counts as Indian, German etc in feature engineering.

Selling Price




```
plt.boxplot(x=carsData['selling_price'].values, labels=['Selling price'])
plt.title("Selling price of cars")
plt.ylabel("Price in lakhs")
plt.show()
```


```
plt.hist(x=carsData['selling_price'].values)
plt.title("Selling price of cars")
plt.xlabel("Price in lakhs")
plt.show()
```

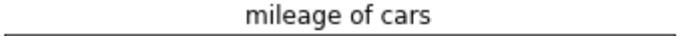


Observation

- Selling price is a dependent fearure.
- Most of the car value lies below 15 lakhs.
- Potential outliers observed, positive skewed distribution
- All outliers are valid values i.e no human error but needs to be treated.

Mileage

```
plt.boxplot(x=carsData['mileage'].values,labels=['mileage'])
plt.title("mileage of cars")
plt.ylabel("kmpl")
plt.show()
```

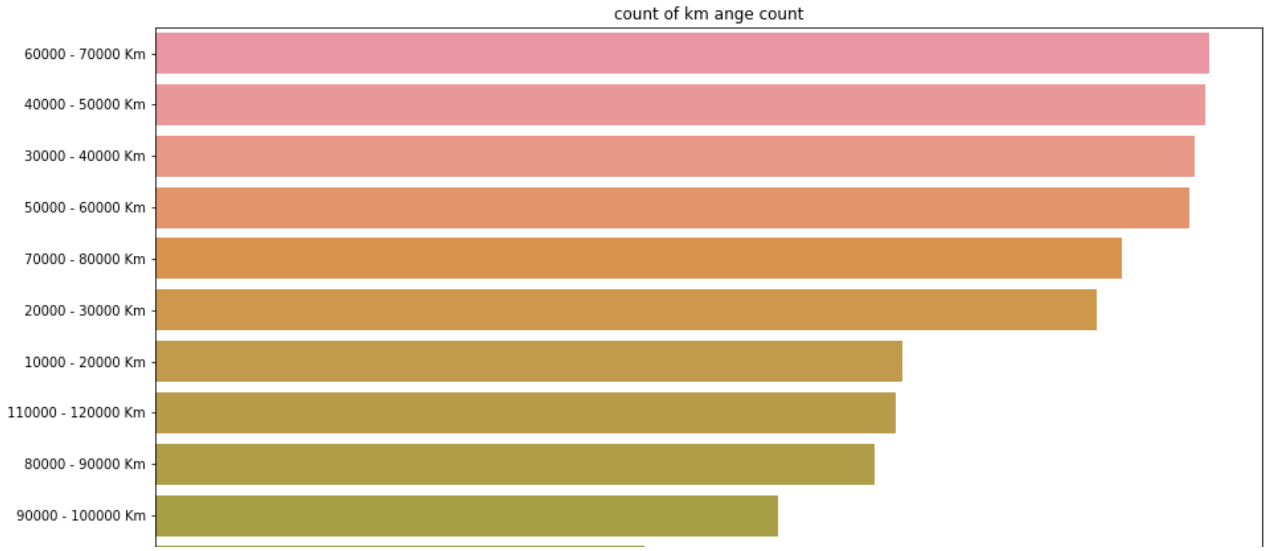


Observation

- 95% of the cars have milege between 10 kmpl and 25 kmpl.
- Median milage is around 20 kmpl.

km driven

```
plt.figure(figsize=(15,30))
sns.countplot(y='km_driven', data = carsData, order = carsData['km_driven'].value_counts()
plt.title("count of km ange count")
plt.xticks(rotation = 45)
plt.show()
```



Observation

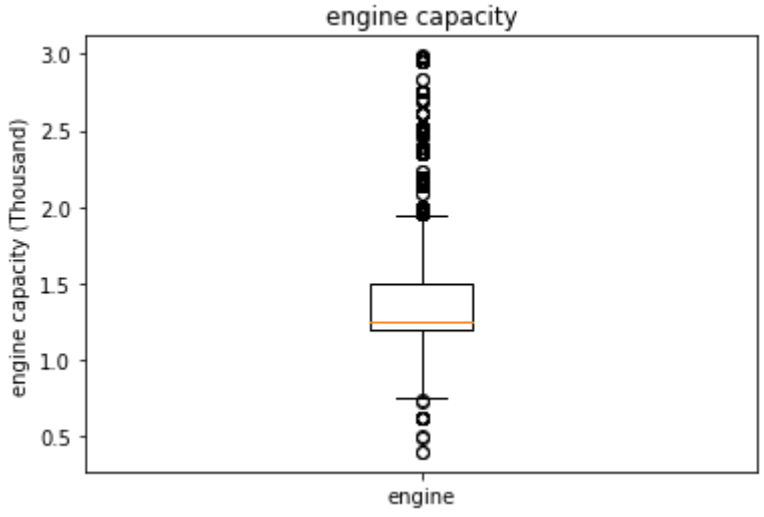
- Positive skewed data having large outliers.
- 95% of cars have run below 2.5 lakh km.
- cars greater than 3 lakh is possible.

150000 - 160000 Km

Engine capacity

190000 - 200000 Km

```
plt.boxplot(x=carsData['engine'].values,labels=['engine'])
plt.title("engine capacity")
plt.ylabel("engine capacity (Thousand)")
plt.show()
```

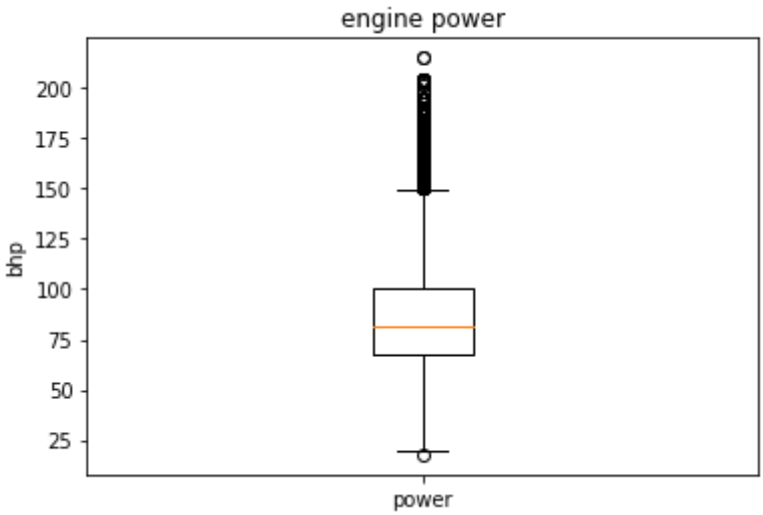


Observation

- 95% of the cars have engine size less than 2000 CC.
- 50% of the cars have engine size between 1000 to 2000 CC.
- Potential outliers observed.
- larger engine size are ususlly with sports car and hence can affect selling price.

Engine power

```
plt.boxplot(x=carsData['max_power'].values,labels=['power'])
plt.title("engine power")
plt.ylabel("bhp")
plt.show()
```




```
# Analyzing outlier
carsData[carsData['max_power']>200]
```

	make	model	variant	selling_price	km_driven	fuel	seller_type
141	Mercedes-Benz	E-Class	E250 EDITION E	27.00	30000 - 40000 Km	Diesel	Dealer
681	Mercedes-Benz	E-Class	E250 CDI AVANTGARDE	30.00	30000 - 40000 Km	Diesel	Individual
1060	Mercedes-Benz	E-Class	E250 CDI AVANTGARDE	29.00	30000 - 40000 Km	Diesel	Dealer
3461	Mercedes-Benz	E-Class	E 250 ELEGANCE	11.90	70000 - 80000 Km	Petrol	Individual
					90000 -		

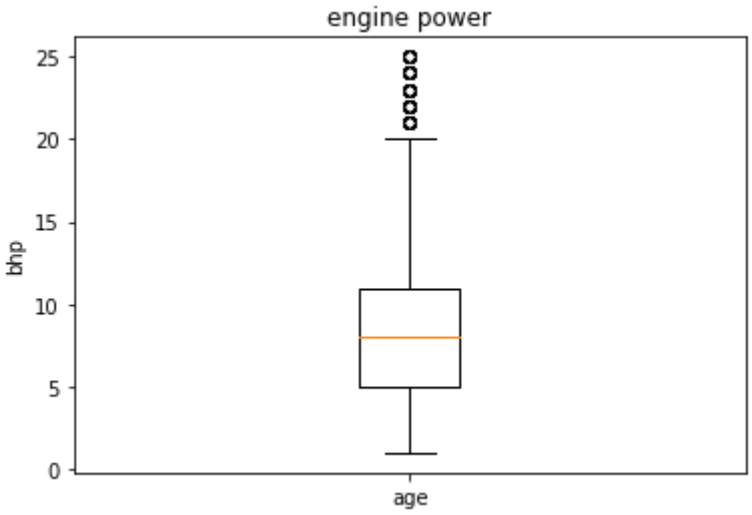
Observation

- 95% of the cars have less than 150 bhp.
- potential outliers observed.
- As BHP increases car goes into sports car category and selling price depreciates at a higher rate compared to lower bhp cars.

		New			80000		

Age


```
plt.boxplot(x=carsData['age'].values,labels=['age'])
plt.title("engine power")
plt.ylabel("bhp")
plt.show()
```

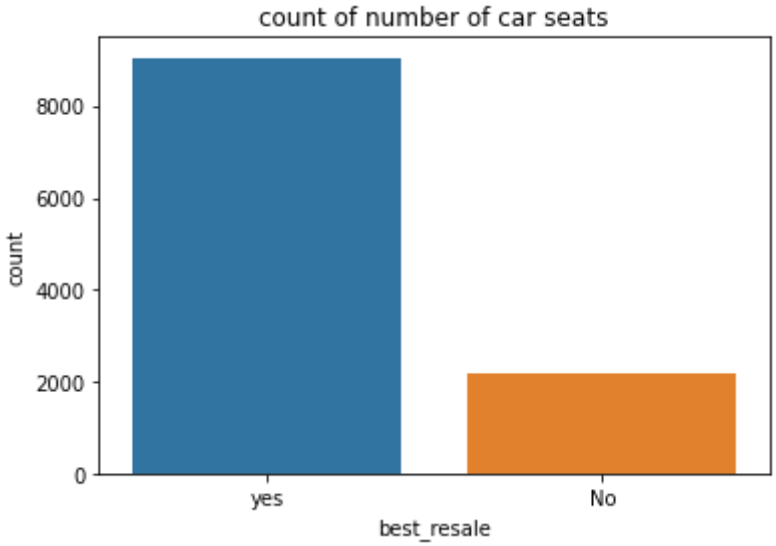


Observation

- Potential outliers observed.
- 95% of the cars are below 20 years of age.
- Age inverse proportional to selling price.

Best Resale

```
sns.countplot(x=carsData['best_resale'])
plt.title("count of number of car seats")
plt.show()
```



Observation

- There are more than 50% of cars with best resale compared to lease resale cars.

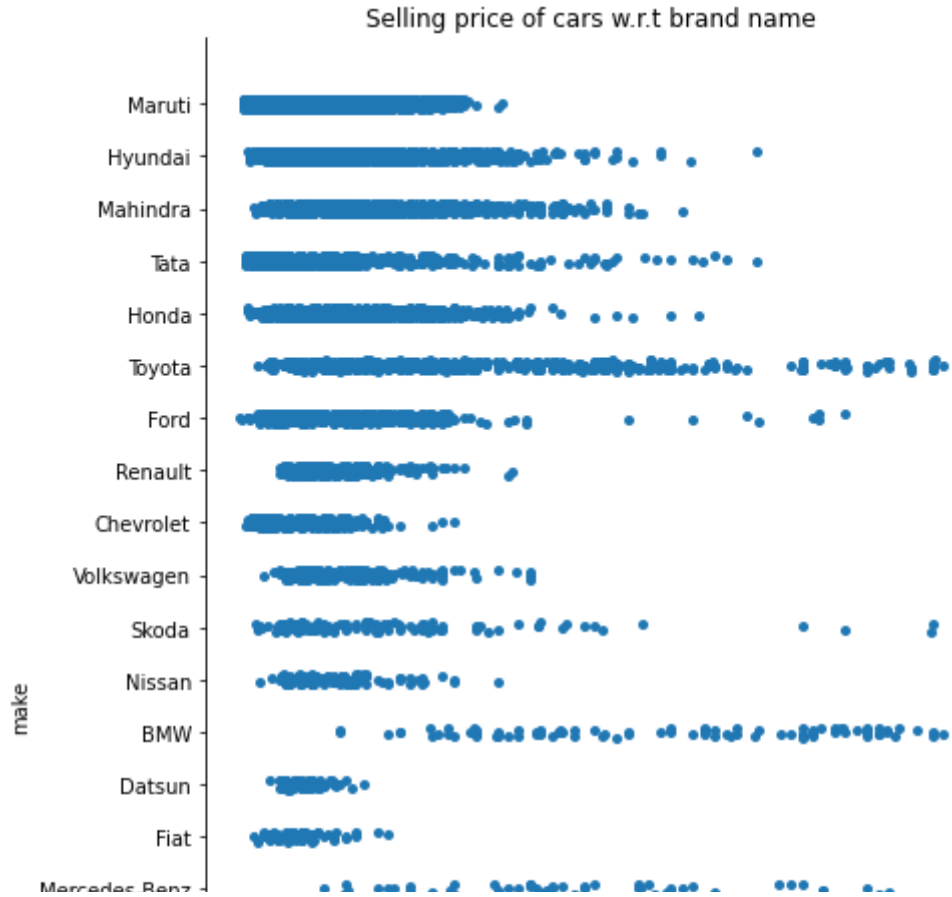
Bivariant Analysis

analyzing all the univariant with respect to selling price(dependent feature)

Make vs Selling price

```
sns.catplot(data=carsData, y="make", x="selling_price",height=10, aspect=0.7,
            order = carsData['make'].value_counts().index)
plt.title("Selling price of cars w.r.t brand name")
plt.plot()
```

[ ]



Observation

- Majority of the cars brands having large used car market share have selling price less than 20 lakhs.
- This feature shows wht is the starting and ending selling price for each brand

Fuel vs Selling price

```
sns.catplot(data=carsData, x="fuel", y="selling_price",height=8, aspect=1)
plt.title("Selling price vs fuel")
plt.plot()
```

[ ]

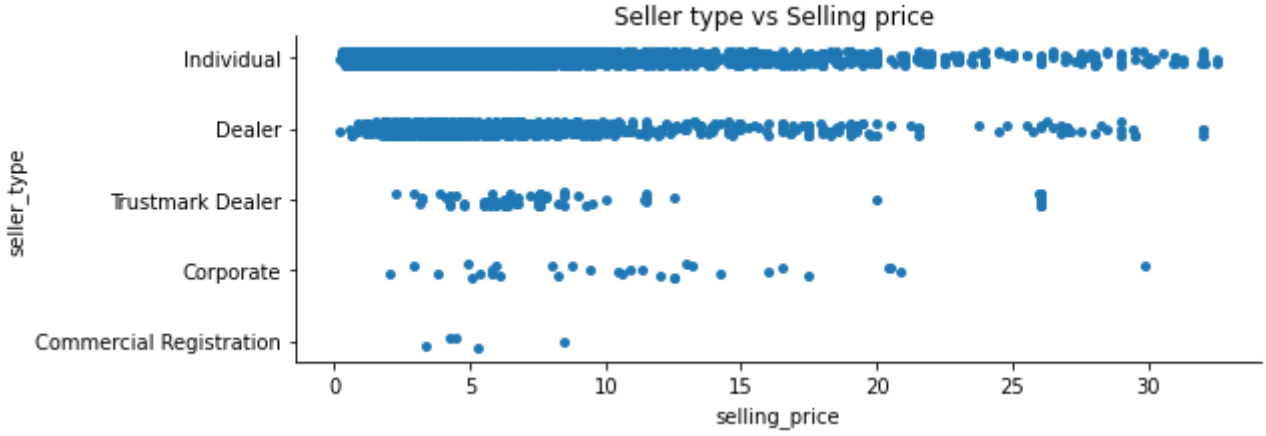
Observation

- LPG and CNG fule type with aroud 1% of cars in the data set have selling price around 10 lakhs.
- Outliers with few highest selling price more than 50 lakh observed in petrol and diesel.

Seller type vs Selling price

```
sns.catplot(data=carsData, y="seller_type", x="selling_price",height=3, aspect=3)
plt.title("Seller type vs Selling price ")
plt.plot()
```

[ ]



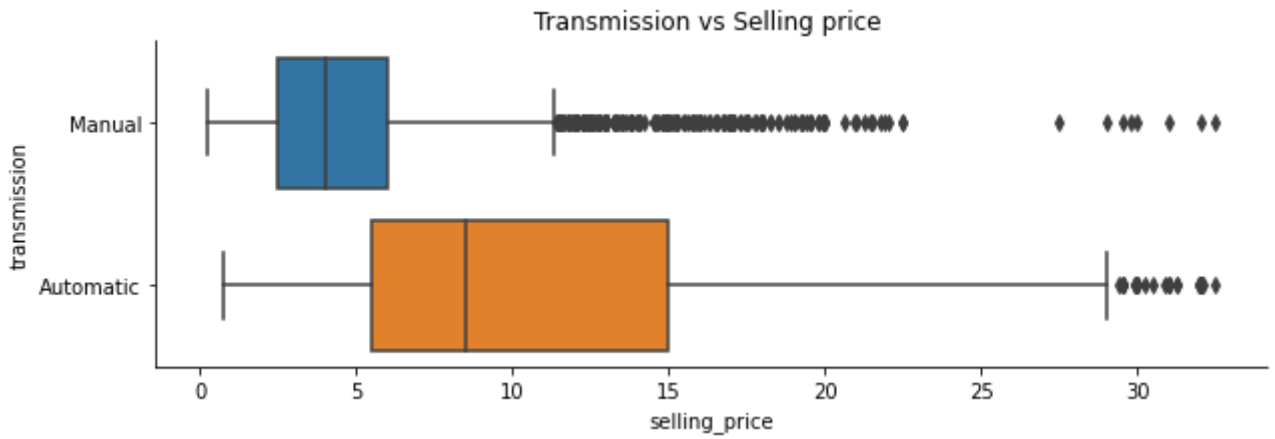
Observation

- Individual and Dealer seller type has cars in all price range.
- Trustmark Dealer and Commercial Registration has cars selling less than 30 lakhs.

Transmission vs Selling price

```
sns.catplot(data=carsData, y="transmission", x="selling_price",height=3, aspect=3, kind="b
plt.title("Transmission vs Selling price ")
plt.plot()
```

```
[]
```




```
carsData[(carsData['selling_price']>25) & (carsData['transmission']=='Manual')]['model']
```

```
350         Fortuner
1821        Fortuner
1990     New C-Class
2881        Fortuner
8736        Fortuner
9131          Innova
9602          Innova
10149       Fortuner
Name: model, dtype: object
```

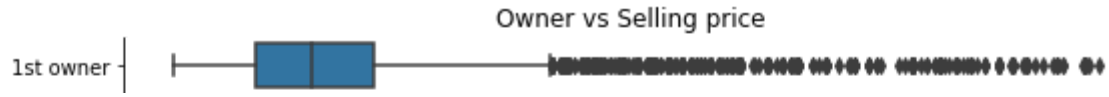
Observation

- Median selling price of autimatic is at 10 lakh
- 95% of manual transmission is below 10 lakh.
- No data error with outlier.

Owner vs Selling price

```
sns.catplot(data=carsData, y="owner", x="selling_price",height=3, aspect=3, kind="box")
plt.title("Owner vs Selling price ")
plt.plot()
```

[ ]



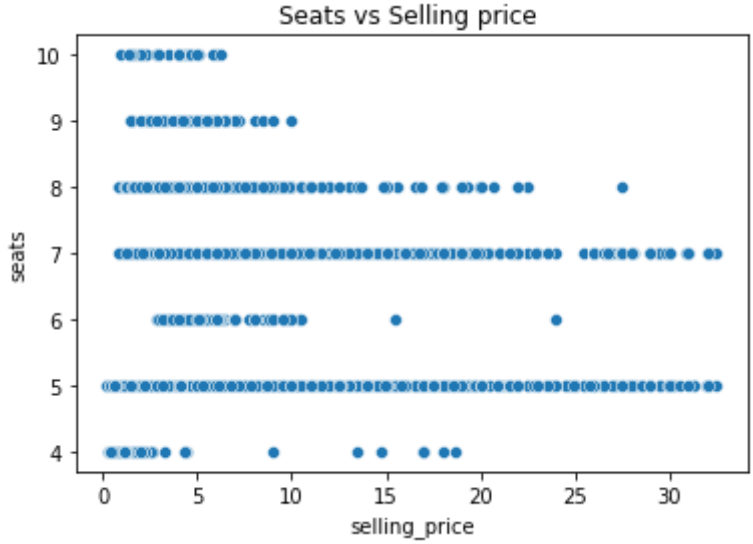
Observation

- Majority of the outliers are noted for first and second owner.

Seats vs Selling price

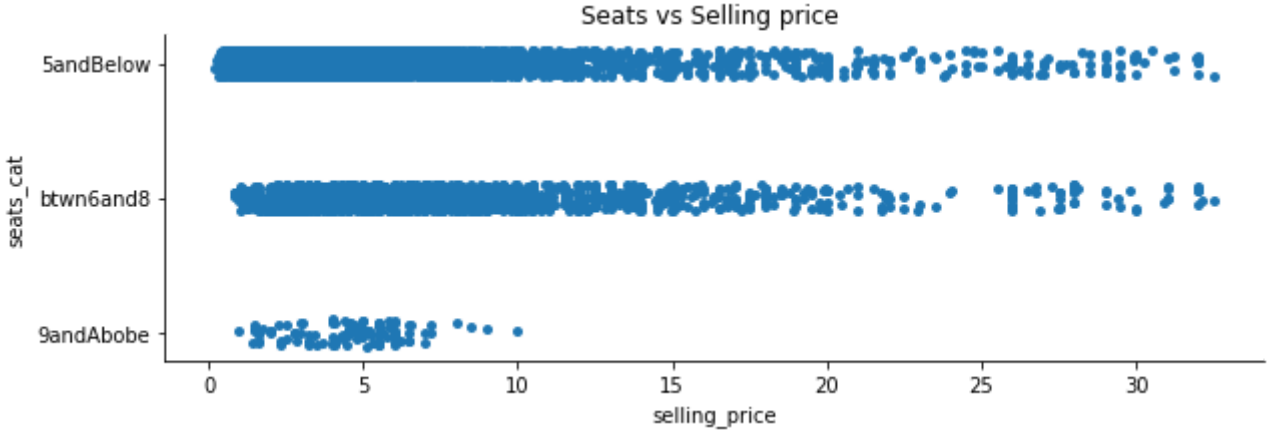
```
sns.scatterplot(data=carsData, y="seats", x="selling_price")
plt.title("Seats vs Selling price ")
plt.plot()
```

[ ]




```
sns.catplot(data=carsData, y="seats_cat", x="selling_price",height=3, aspect=3)
plt.title("Seats vs Selling price ")
plt.plot()
```

[ ]



Observation

- 5 and 7 seater cars are present in all selling price.

Model vs Selling price

```
sns.catplot(data=carsData, y="model", x="selling_price",height=25, aspect=0.5,
            order = carsData['model'].value_counts().index)
plt.title("Selling price vs Model")
plt.plot()
```

[]

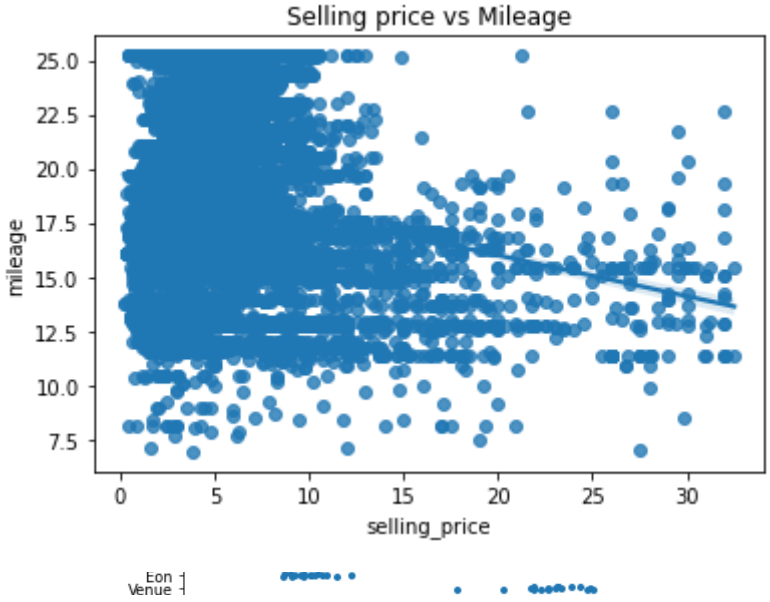
Observation

- Majority of the cars models are less than 20 lakhs.

Milege vs Selling price


```
sns.regplot(data=carsData, y="mileage", x="selling_price")
plt.title("Selling price vs Mileage")
plt.plot()
```

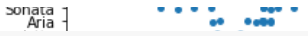
[]



Observation

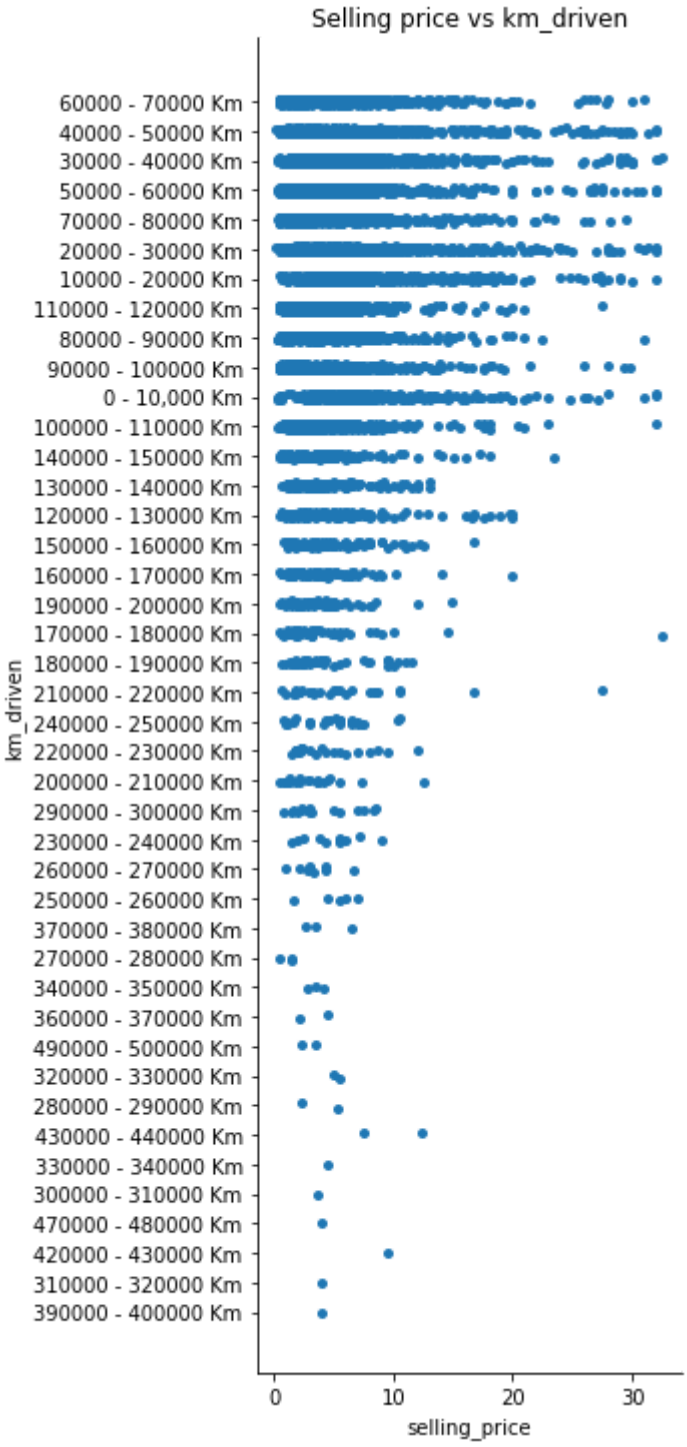
- Higher mileage for cars below 15 lakhs.
- low mileage with high selling price.

KM driven vs Selling price




```
sns.catplot(data=carsData, y="km_driven", x="selling_price",height=10, aspect=0.5,
            order = carsData['km_driven'].value_counts().index)
plt.title("Selling price vs km_driven")
plt.plot()
```

[]



Observation

- Cars with greater than 2 lakh km sell less than 20 lakhs..

Engine capacity vs Selling price

```
sns.regplot(data=carsData, y="engine", x="selling_price")
plt.title("Selling price vs Engine")
plt.ylabel('engine capacity(cc)')
plt.plot()
```

[ ]

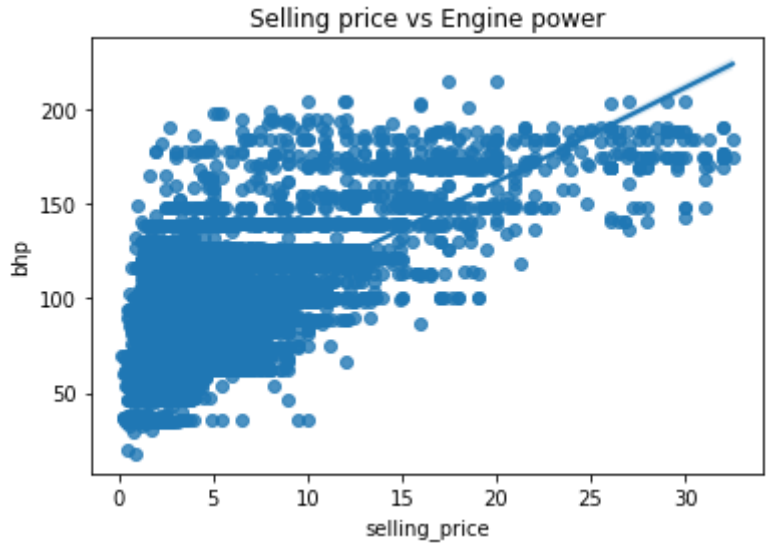
Observation

- cars with higher engine capacity tend to have high selling price.

Engine power vs Selling price

```
sns.regplot(data=carsData, y="max_power", x="selling_price")
plt.title("Selling price vs Engine power")
plt.ylabel("bhp")
plt.plot()
```

[ ]



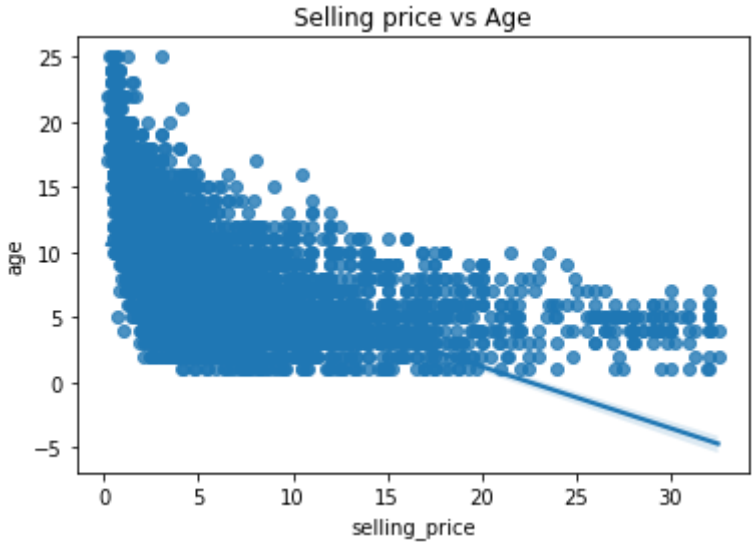
Observation

- Similar observation noted in Engine capacity.
- Usually higher capacity engine tend to have high power.

Age vs Selling price

```
sns.regplot(data=carsData, y="age", x="selling_price")
plt.title("Selling price vs Age")
plt.plot()
```

```
[]
```



Observation

- Cars tend to have higher selling price with lower age.
- as age increases selling price decreases.

Best resale vs selling price

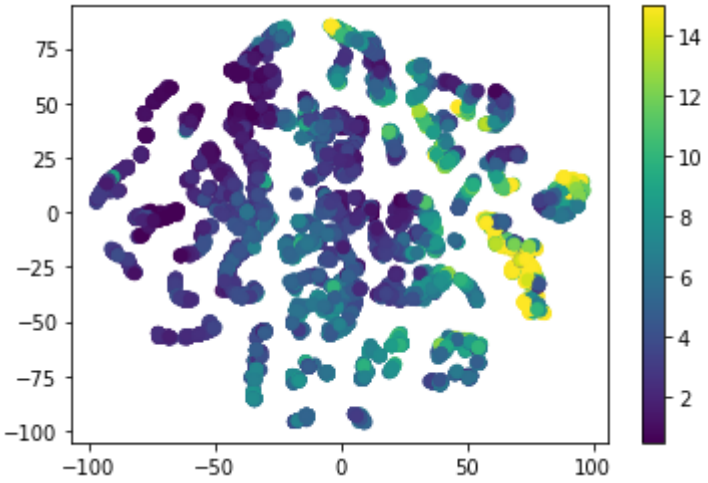
```
sns.catplot(data=carsData, y="best_resale", x="selling_price",height=3, aspect=3)
plt.title("Best Resale vs Selling price ")
plt.plot()
```

```
[]
```

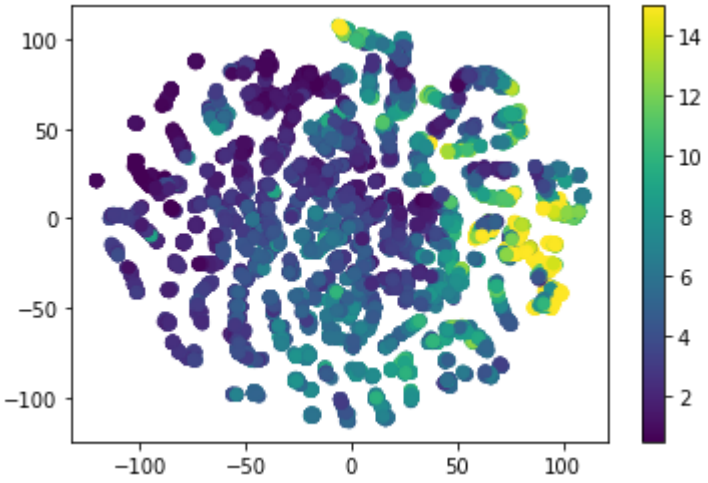
Multivariant analysis

```
# From basic statistical analysis 75% of the selling price is around 6.5 lakhs but max val
# Hence color limit(clim)= 15
```

```
xtsne=TSNE(perplexity=50)
results=xtsne.fit_transform(carsData[['mileage', 'engine', 'max_power', 'seats', 'age']])
vis_x = results[:, 0]
vis_y = results[:, 1]
plt.scatter(vis_x, vis_y, c=carsData['selling_price'])
plt.colorbar()
plt.clim(0.5, 15)
plt.show()
```




```
xtsne=TSNE(perplexity=30)
results=xtsne.fit_transform(carsData[['mileage', 'engine', 'max_power', 'seats', 'age']])
vis_x = results[:, 0]
vis_y = results[:, 1]
plt.scatter(vis_x, vis_y, c=carsData['selling_price'])
plt.colorbar()
plt.clim(0.5, 15)
plt.show()
```



Observation

- Color bar indicates in lakhs.
- Cars price more then 14 laks have a seperate cluster.
- Darker clusters are of car price less than 4 lakhs.

Feature selection

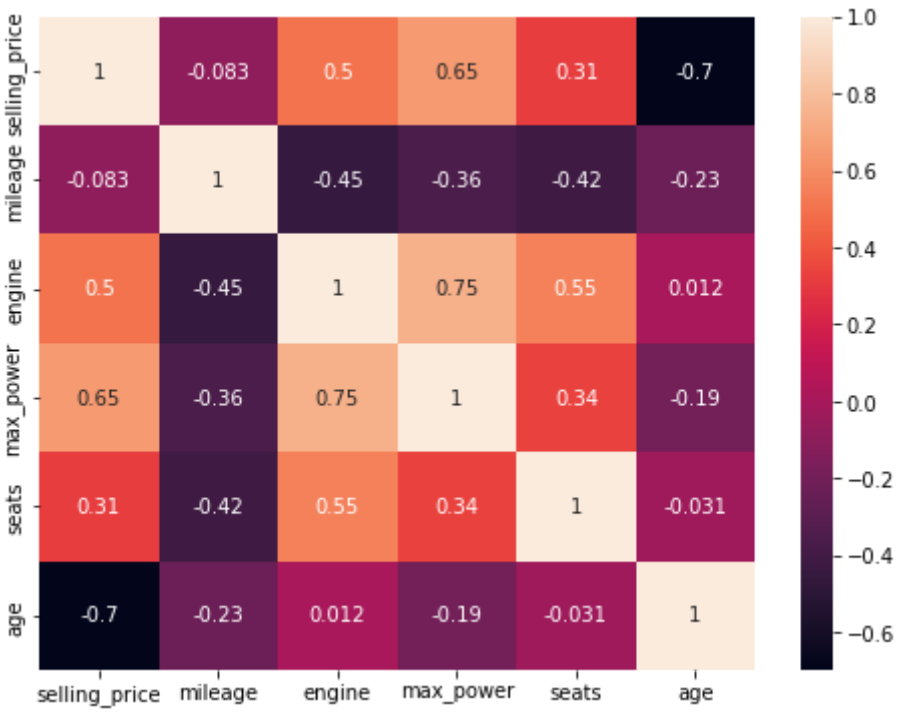
- Corelation coefficient - numerical
- chi square test for categorical
- Decision feature selection.

Correlation Test(numeric vs numerical features)

Using Spearman corelation because:

- we have pairs of continuous variables and the relationships between them don't follow a straight line but they follow a monotonic relationship.
- Outliers are observed in most of the features.

```
plt.figure(figsize=(8,6))
sns.heatmap(carsData.corr(method='spearman'), annot=True)
plt.show()
```



Numerical Feature Selection

- Used spearman rank corelation since there is no linear relationship between independent and dependent features.
- 1) Age is negatively corelated to selling price (target).
- 2) max power and Engine are positive.

NOTE

- 1) Max power and engine are multi colinear, drop engine if using linear regression.

CatBoost model for categorical feature selection

```
#List of categorical columns
categoricalColumns = carsData.select_dtypes(include=["object"]).columns.tolist()
carsCatData = carsData[categoricalColumns]
print("Names of categorical columns : ", categoricalColumns)
carsCatData.head()
```

```
Names of categorical columns :  ['make', 'model', 'variant', 'km_driven', 'fuel', 's
```

	make	model	variant	km_driven	fuel	seller_type	transmission	owner	bes
0	Maruti	Swift Dzire	VDI	140000 - 150000 Km	Diesel	Individual	Manual	1st owner	
1	Skoda	Rapid	1.5 TDI AMBITION	110000 - 120000 Km	Diesel	Individual	Manual	2nd owner	
2	Honda	City	2017-2020 EXI	130000 - 140000	Petrol	Individual	Manual	3rd	

```
#creating independent variables as X and target/dependent variable as y
y= carsData['selling_price']
X= carsCatData

#Let’s split X and y using Train test split
# Stratify y so that ML model gets trained on testing car models.
X_train,X_test,y_train,y_test = train_test_split(X,y,train_size=0.8,random_state= 42, stra

#get shape of train and test data
print("train data size:",X_train.shape)
print("test data size:",X_test.shape)
```

```
train data size: (8975, 10)
test data size: (2244, 10)
```

```
# Define list of categorical features, If no categorical features are defined, CatBoost wi

#Get location of categorical columns
cat_features_indx = [X.columns.get_loc(col) for col in carsCatData]
print("Location of categorical columns : ",cat_features_indx)
```

```
Location of categorical columns :  [0, 1, 2, 3, 4, 5, 6, 7, 8, 9]
```

```
# importing Pool
from catboost import Pool
#Creating pool object for train dataset. we give information of categorical fetures to par
train_data = Pool(data=X_train,
                  label=y_train,
                  cat_features=cat_features_indx
```

```
                 )

#Creating pool object for test dataset
test_data = Pool(data=X_test,
                  label=y_test,
                  cat_features=cat_features_indx
                 )
```

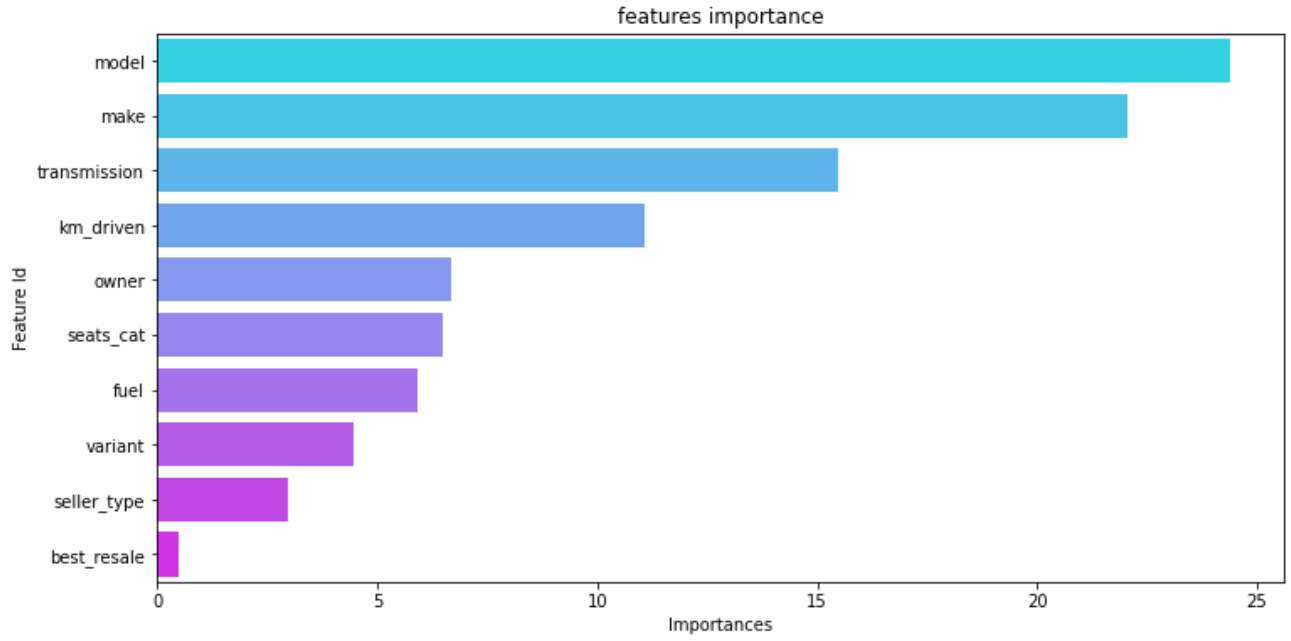
```
#build model
cars_cat_model = CatBoostRegressor(loss_function='RMSE')
# Fit model
cars_cat_model.fit( train_data,
               eval_set=(test_data))
```

```
Learning rate set to 0.071866
0:      learn: 4.0825332        test: 4.1558637 best: 4.1558637 (0)     total: 87.
1:      learn: 3.9120177        test: 3.9864508 best: 3.9864508 (1)     total: 122
2:      learn: 3.7611470        test: 3.8414791 best: 3.8414791 (2)     total: 162
3:      learn: 3.6204444        test: 3.7030881 best: 3.7030881 (3)     total: 189
4:      learn: 3.4908294        test: 3.5728106 best: 3.5728106 (4)     total: 214
5:      learn: 3.3656419        test: 3.4402338 best: 3.4402338 (5)     total: 273
6:      learn: 3.2598334        test: 3.3352368 best: 3.3352368 (6)     total: 304
7:      learn: 3.1679772        test: 3.2448308 best: 3.2448308 (7)     total: 321
8:      learn: 3.0761825        test: 3.1540656 best: 3.1540656 (8)     total: 339
9:      learn: 2.9929412        test: 3.0668317 best: 3.0668317 (9)     total: 376
10:     learn: 2.9156234        test: 2.9882163 best: 2.9882163 (10)    total: 423
11:     learn: 2.8449461        test: 2.9165840 best: 2.9165840 (11)    total: 456
12:     learn: 2.7785181        test: 2.8455647 best: 2.8455647 (12)    total: 481
13:     learn: 2.7206299        test: 2.7912334 best: 2.7912334 (13)    total: 518
14:     learn: 2.6727260        test: 2.7452800 best: 2.7452800 (14)    total: 548
15:     learn: 2.6271417        test: 2.6978765 best: 2.6978765 (15)    total: 579
16:     learn: 2.5822910        test: 2.6491121 best: 2.6491121 (16)    total: 598
17:     learn: 2.5441416        test: 2.6110394 best: 2.6110394 (17)    total: 626
18:     learn: 2.5100561        test: 2.5767824 best: 2.5767824 (18)    total: 656
19:     learn: 2.4713934        test: 2.5398347 best: 2.5398347 (19)    total: 682
20:     learn: 2.4408605        test: 2.5079732 best: 2.5079732 (20)    total: 721
21:     learn: 2.4140422        test: 2.4814954 best: 2.4814954 (21)    total: 739
22:     learn: 2.3872973        test: 2.4520602 best: 2.4520602 (22)    total: 753
23:     learn: 2.3616004        test: 2.4221835 best: 2.4221835 (23)    total: 794
24:     learn: 2.3412705        test: 2.4007086 best: 2.4007086 (24)    total: 827
25:     learn: 2.3234668        test: 2.3830174 best: 2.3830174 (25)    total: 864
26:     learn: 2.3065518        test: 2.3648248 best: 2.3648248 (26)    total: 922
27:     learn: 2.2844317        test: 2.3426735 best: 2.3426735 (27)    total: 958
28:     learn: 2.2667402        test: 2.3248852 best: 2.3248852 (28)    total: 989
29:     learn: 2.2501441        test: 2.3071525 best: 2.3071525 (29)    total: 1.0
30:     learn: 2.2323254        test: 2.2892967 best: 2.2892967 (30)    total: 1.0
31:     learn: 2.2165967        test: 2.2707923 best: 2.2707923 (31)    total: 1.1
32:     learn: 2.2048009        test: 2.2605418 best: 2.2605418 (32)    total: 1.1
33:     learn: 2.1934587        test: 2.2500757 best: 2.2500757 (33)    total: 1.1
34:     learn: 2.1788948        test: 2.2336973 best: 2.2336973 (34)    total: 1.1
35:     learn: 2.1672287        test: 2.2230948 best: 2.2230948 (35)    total: 1.2
36:     learn: 2.1580385        test: 2.2165286 best: 2.2165286 (36)    total: 1.2
37:     learn: 2.1510317        test: 2.2115390 best: 2.2115390 (37)    total: 1.3
38:     learn: 2.1416387        test: 2.2006738 best: 2.2006738 (38)    total: 1.3
39:     learn: 2.1330672        test: 2.1914030 best: 2.1914030 (39)    total: 1.3
40:     learn: 2.1264784        test: 2.1856450 best: 2.1856450 (40)    total: 1.3
41:     learn: 2.1195073        test: 2.1792374 best: 2.1792374 (41)    total: 1.4
42:     learn: 2.1120062        test: 2.1719754 best: 2.1719754 (42)    total: 1.4
```

```
43:     learn: 2.1068657        test: 2.1663461 best: 2.1663461 (43)    total: 1.4
44:     learn: 2.0996245        test: 2.1600150 best: 2.1600150 (44)    total: 1.5
45:     learn: 2.0943913        test: 2.1554000 best: 2.1554000 (45)    total: 1.5
46:     learn: 2.0878501        test: 2.1502637 best: 2.1502637 (46)    total: 1.5
47:     learn: 2.0837083        test: 2.1463434 best: 2.1463434 (47)    total: 1.6
48:     learn: 2.0791265        test: 2.1433023 best: 2.1433023 (48)    total: 1.6
49:     learn: 2.0744536        test: 2.1382450 best: 2.1382450 (49)    total: 1.6
50:     learn: 2.0700657        test: 2.1347269 best: 2.1347269 (50)    total: 1.6
51:     learn: 2.0661785        test: 2.1324032 best: 2.1324032 (51)    total: 1.7
52:     learn: 2.0625442        test: 2.1284134 best: 2.1284134 (52)    total: 1.7
53:     learn: 2.0586150        test: 2.1249766 best: 2.1249766 (53)    total: 1.8
54:     learn: 2.0553706        test: 2.1246896 best: 2.1246896 (54)    total: 1.8
```

```
# Create a dataframe of feature importance
df_feature_importance = pd.DataFrame(cars_cat_model.get_feature_importance(prettified=True
#plotting feature importance
plt.figure(figsize=(12, 6));
feature_plot= sns.barplot(x="Importances", y="Feature Id", data=df_feature_importance,pale
plt.title('features importance')
```

```
Text(0.5, 1.0, 'features importance')
```



Observation

- Make, model, transission, km_driven, Owner, Seats_cat and fuel have high feature importance compared to the rest.

```
# Cleaned cars data export as CSV
#carsData.to_csv("/content/cleaned_carsData.csv",index=False)

eval = pd.read_csv("/content/cleaned_carsData.csv")
eval.head(3)
```

	make	model	variant	selling_price	km_driven	fuel	seller_type	transmissi
0	Maruti	Swift Dzire	VDI	4.50	140000 - 150000 Km	Diesel	Individual	Manu
1	Skoda	Rapid	1.5 TDI AMBITION	3.70	110000 - 120000 Km	Diesel	Individual	Manu
2	Honda	City	2017-2020 EXI	1.58	130000 - 140000 Km	Petrol	Individual	Manu

```
# Feature selection considering both numerical and catagorical.
finalFeatureLst = ['make', 'model','transmission','km_driven','fuel','owner','age', 'max_p
```

```
# Finale dataframe for encoding
final_carsData = carsData[finalFeatureLst].copy()
final_carsData.head()
```

	make	model	transmission	km_driven	fuel	owner	age	max_power	engine	sel
0	Maruti	Swift Dzire	Manual	140000 - 150000 Km	Diesel	1st owner	8.0	74.00	1.25	
1	Skoda	Rapid	Manual	110000 - 120000 Km	Diesel	2nd owner	8.0	103.52	1.50	
				130000 -						

```
# Performing get dummies before split since selected categorial features will not have new

final_carsData = final_carsData.join(pd.get_dummies(final_carsData[['transmission','fuel',
#final_carsData.drop(['transmission','fuel','owner'],axis=1, inplace=True)

# Has both one hot encoded and parent features
final_carsData.head(3)
```

	make	model	transmission	km_driven	fuel	owner	age	max_power	engine	sell
0	Maruti	Swift Dzire	Manual	140000 - 150000 Km	Diesel	1st owner	8.0	74.00	1.25	

Train Test & CV Split

```
# No CV split seperately because data size is small.
# We will use sklearn cross validation and k forld cross validation to validate the model

# Choosing independent(X) and dependent feature(y)
X = final_carsData.drop("selling_price", axis = 1)
y = final_carsData['selling_price']

# Stratify split ['make'] since we require all the brands to be present in train and test.
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.2, random_state = 35, str
#X_train,X_cv,y_train,y_cv = train_test_split(X_train,y_train,test_size=0.2, random_state

#get shape of train and test data
print("train data size:",X_train.shape)
print("test data size:",X_test.shape)

print("train data size:",y_train.shape)
print("test data size:",y_test.shape)
```

```
train data size: (8975, 17)
test data size: (2244, 17)
train data size: (8975,)
test data size: (2244,)
```

Feature Encoding

```
# List of categorical features
final_carsData.select_dtypes(include=['object']).columns
```

```
Index(['make', 'model', 'transmission', 'km_driven', 'fuel', 'owner'],
dtype='object')
```

```
# Creating multiple train test split


# 1) for ML models that do not need encoding and scaling
X_tr_wo_enc = X_train[['make','model', 'transmission', 'km_driven', 'fuel', 'owner', 'age'
X_te_wo_enc = X_test[['make','model', 'transmission', 'km_driven', 'fuel', 'owner', 'age',
```

```
# Create new train test data for encoded data for features need to be encoded and already
X_train_enc = X_train[['make', 'model', 'km_driven','age',
       'max_power', 'engine', 'transmission_Manual', 'fuel_Petrol',
       'fuel_Petrol + AltFuel', 'owner_2nd owner', 'owner_3rd owner',
       'owner_4th & above owner', 'owner_Test Drive Car',
       'owner_UnRegistered Car']].copy()
X_test_enc = X_test[['make', 'model', 'km_driven','age',
       'max_power', 'engine', 'transmission_Manual', 'fuel_Petrol',
       'fuel_Petrol + AltFuel', 'owner_2nd owner', 'owner_3rd owner',
       'owner_4th & above owner', 'owner_Test Drive Car',
       'owner_UnRegistered Car']].copy()
```

```
# Source: https://medium.com/analytics-vidhya/categorical-variable-encoding-techniques-17e

# 1) Make, Model and km_driven has too many categories and we will encode based on frequer

freq_enc_feat = ['make', 'model', 'km_driven']

for col in freq_enc_feat:

  # Creating dictonary of value and count on train data [fit]
  count_map = X_train_enc[col].value_counts().to_dict()

  # Map the column with dictonary values on train and test data - no data leakage,[transfo
  X_train_enc[col] = X_train_enc[col].map(count_map)
  X_test_enc[col] = X_test_enc[col].map(count_map)

  # Possible null values in test data while mapping and will replace them with least occur
  if X_test_enc[col].isnull().any():
    X_test_enc[col].fillna(X_test_enc[col].min(),inplace=True)
```

```
# Splitting numerical and categorica features for ease of trasnsformation
num_feat = ['make','model','km_driven','age','max_power','engine']
cat_feat = ['transmission_Manual', 'fuel_Petrol', 'fuel_Petrol + AltFuel',
       'owner_2nd owner', 'owner_3rd owner', 'owner_4th & above owner',
       'owner_Test Drive Car', 'owner_UnRegistered Car']

X_train_enc_num = X_train_enc[num_feat].copy()
X_test_enc_num = X_test_enc[num_feat].copy()

X_train_enc_cat = X_train_enc[cat_feat].copy()
X_test_enc_cat = X_test_enc[cat_feat].copy()
```

```
# Drop multi colinear feature
# Engine and max power are colinear, since max_power is highly corelated with Y we will dr

X_train_enc_num.drop('engine',axis=1,inplace=True)
X_test_enc_num.drop('engine',axis=1,inplace=True)
```

```
# Normalizing numerical data
```

```
norm = MinMaxScaler()
X_tr_norm = norm.fit_transform(X_train_enc_num)
X_te_norm = norm.transform(X_test_enc_num)
```

```
# Combining whole data using H stack

final_train = np.hstack((X_tr_norm,X_train_enc_cat))
final_test = np.hstack((X_te_norm,X_test_enc_cat))
```

Predective modelling

CatBoost Regressor

```
# Since no need for encoding using features prior to encoding

# Define list of categorical features, If no categorical features are defined, CatBoost wi

#List of categorical columns
categoricalColumns = X_tr_wo_enc.select_dtypes(include=["object"]).columns.tolist()
print("Names of categorical columns : ", categoricalColumns)
#Get location of categorical columns
cat_features = [X_tr_wo_enc.columns.get_loc(col) for col in categoricalColumns]
print("Location of categorical columns : ",cat_features)
```

```
Names of categorical columns :  ['make', 'model', 'transmission', 'km_driven', 'fuel
Location of categorical columns :  [0, 1, 2, 3, 4, 5]
```

```
# catboost regressor with inbuilt random_search method

train_data = Pool(data = X_tr_wo_enc, label = y_train, cat_features = cat_features )
train_labels = y_train

cat_model = CatBoostRegressor(loss_function='RMSE')


grid = {'learning_rate': [0.03,0.05,0.07,0.1],
        'depth': [1,2,3,4],
        'iterations' : [100,500,1000,2000,3000]}

randomized_search_result = cat_model.randomized_search(grid,train_data)
```

```
Streaming output truncated to the last 5000 lines.
1009:   learn: 0.9878632        test: 1.1220845 best: 1.1220029 (1007)  total: 14.
1010:   learn: 0.9875993        test: 1.1219871 best: 1.1219871 (1010)  total: 14.
1011:   learn: 0.9874008        test: 1.1220212 best: 1.1219871 (1010)  total: 14.
1012:   learn: 0.9873076        test: 1.1220181 best: 1.1219871 (1010)  total: 14.
1013:   learn: 0.9869989        test: 1.1217136 best: 1.1217136 (1013)  total: 14.
```

```
1014:   learn: 0.9869638        test: 1.1217103 best: 1.1217103 (1014)  total: 14.
1015:   learn: 0.9868692        test: 1.1215406 best: 1.1215406 (1015)  total: 14.
1016:   learn: 0.9868504        test: 1.1215343 best: 1.1215343 (1016)  total: 14.
1017:   learn: 0.9867198        test: 1.1215159 best: 1.1215159 (1017)  total: 14.
1018:   learn: 0.9865322        test: 1.1214965 best: 1.1214965 (1018)  total: 14.
1019:   learn: 0.9862818        test: 1.1211610 best: 1.1211610 (1019)  total: 14.
1020:   learn: 0.9861289        test: 1.1208109 best: 1.1208109 (1020)  total: 14.
1021:   learn: 0.9860696        test: 1.1207816 best: 1.1207816 (1021)  total: 14.
1022:   learn: 0.9859806        test: 1.1207572 best: 1.1207572 (1022)  total: 14.
1023:   learn: 0.9856999        test: 1.1209070 best: 1.1207572 (1022)  total: 14.
1024:   learn: 0.9856651        test: 1.1209940 best: 1.1207572 (1022)  total: 14.
1025:   learn: 0.9855425        test: 1.1208738 best: 1.1207572 (1022)  total: 14.
1026:   learn: 0.9853734        test: 1.1208802 best: 1.1207572 (1022)  total: 14.
1027:   learn: 0.9853517        test: 1.1208532 best: 1.1207572 (1022)  total: 14.
1028:   learn: 0.9850600        test: 1.1206655 best: 1.1206655 (1028)  total: 14.
1029:   learn: 0.9849789        test: 1.1207952 best: 1.1206655 (1028)  total: 14.
1030:   learn: 0.9848915        test: 1.1208805 best: 1.1206655 (1028)  total: 14.
1031:   learn: 0.9848297        test: 1.1209144 best: 1.1206655 (1028)  total: 14.
1032:   learn: 0.9847992        test: 1.1208890 best: 1.1206655 (1028)  total: 14.
1033:   learn: 0.9845690        test: 1.1210286 best: 1.1206655 (1028)  total: 14.
1034:   learn: 0.9845223        test: 1.1210300 best: 1.1206655 (1028)  total: 14.
1035:   learn: 0.9845083        test: 1.1210181 best: 1.1206655 (1028)  total: 14.
1036:   learn: 0.9844282        test: 1.1211727 best: 1.1206655 (1028)  total: 14.
1037:   learn: 0.9842408        test: 1.1213211 best: 1.1206655 (1028)  total: 14.
1038:   learn: 0.9840245        test: 1.1211700 best: 1.1206655 (1028)  total: 14.
1039:   learn: 0.9839486        test: 1.1212890 best: 1.1206655 (1028)  total: 14.
1040:   learn: 0.9837844        test: 1.1213246 best: 1.1206655 (1028)  total: 14.
1041:   learn: 0.9837002        test: 1.1213262 best: 1.1206655 (1028)  total: 14.
1042:   learn: 0.9836417        test: 1.1212831 best: 1.1206655 (1028)  total: 14.
1043:   learn: 0.9834364        test: 1.1211114 best: 1.1206655 (1028)  total: 14.
1044:   learn: 0.9833096        test: 1.1213505 best: 1.1206655 (1028)  total: 14.
1045:   learn: 0.9831783        test: 1.1213234 best: 1.1206655 (1028)  total: 14.
1046:   learn: 0.9831206        test: 1.1213229 best: 1.1206655 (1028)  total: 14.
1047:   learn: 0.9830055        test: 1.1213323 best: 1.1206655 (1028)  total: 14.
1048:   learn: 0.9829613        test: 1.1213324 best: 1.1206655 (1028)  total: 14.
1049:   learn: 0.9829331        test: 1.1214719 best: 1.1206655 (1028)  total: 14.
1050:   learn: 0.9828660        test: 1.1215462 best: 1.1206655 (1028)  total: 14.
1051:   learn: 0.9828166        test: 1.1217132 best: 1.1206655 (1028)  total: 14.
1052:   learn: 0.9827466        test: 1.1217217 best: 1.1206655 (1028)  total: 14.
1053:   learn: 0.9827412        test: 1.1216940 best: 1.1206655 (1028)  total: 14.
1054:   learn: 0.9826709        test: 1.1217280 best: 1.1206655 (1028)  total: 14.
1055:   learn: 0.9826074        test: 1.1217345 best: 1.1206655 (1028)  total: 14.
1056:   learn: 0.9825684        test: 1.1217302 best: 1.1206655 (1028)  total: 14.
1057:   learn: 0.9822766        test: 1.1217779 best: 1.1206655 (1028)  total: 14.
1058:   learn: 0.9820993        test: 1.1217520 best: 1.1206655 (1028)  total: 14.
1059:   learn: 0.9819276        test: 1.1217040 best: 1.1206655 (1028)  total: 14.
1060:   learn: 0.9817805        test: 1.1217566 best: 1.1206655 (1028)  total: 14.
1061:   learn: 0.9817617        test: 1.1217543 best: 1.1206655 (1028)  total: 14.
1062:   learn: 0.9817005        test: 1.1217646 best: 1.1206655 (1028)  total: 14.
1063:   learn: 0.9816492        test: 1.1217549 best: 1.1206655 (1028)  total: 14
```

```
#randomized_search_result

def randomized_result(model,xtrain,xtest,ytest):
    """
    Returns predicted value w.r.t regression metrics and visualization
    """
```

```
   # Predict
    y_predict= model.predict(xtest)
    # median_absolute_error
    median_abs_err_test = median_absolute_error(ytest,y_predict)
    # MAE
    Mae_test = mean_absolute_error(ytest,y_predict)
    #RMSE
    Rmse_test = math.sqrt(mean_squared_error(ytest,y_predict))
    #R2 Score
    r2_test = r2_score(ytest,y_predict)
    # Adjusted R2 Score
    n= xtrain.shape[0] # total no of datapoints
    p= xtrain.shape[1] # total no of independent features
    adj_r2_test = 1-(((1-r2_test)*(n-1))/(n-p-1))
    #print results
    print("Evaluation on test data")
    print("MAD: {:.2f}".format(median_abs_err_test))
    print("MAE: {:.2f}".format(Mae_test))
    print("RMSE: {:.2f}".format(Rmse_test))
    print("R2: {:.2f}".format(r2_test))
    print("Adjusted R2: {:.2f}\n".format(adj_r2_test))

    print("Visualizing the Predicted\n")
    plt.scatter(y_test,y_predict)
    plt.title('Selling price Actual vs Predicted')
    sns.displot(y_test-y_predict)
    plt.xlabel("Selling price error")
    plt.show()

# #randomized_search_result
randomized_result(cat_model,X_tr_wo_enc,X_te_wo_enc,y_test)
```

```
Evaluation on test data
MAD: 0.45
MAE: 0.73
RMSE: 1.20
R2: 0.92
Adjusted R2: 0.92

Visualizing the Predicted
```

Observation

- **From metrics**
- Error of Rupees 45 to 73 thousand differece in selling price.
- Model is able to explain 92% of variance in selling price.
- **From visualition**
- Car Values predicted greater than 15 lakhs are spread out.
- Most of the errors are close to zero but a few have large variance.

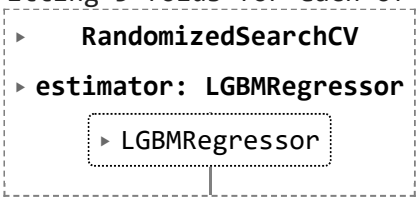
Light GBM Regression

```
# make dtype as 'category' for categorical features

# To get all the column name with object type
list_obj_cols = X_tr_wo_enc.columns[X_tr_wo_enc.dtypes == "object"].tolist()

# Train
for obj_col in list_obj_cols:
    X_tr_wo_enc[obj_col] = X_tr_wo_enc[obj_col].astype("category")

#Test
for obj_col in list_obj_cols:
    X_te_wo_enc[obj_col] = X_te_wo_enc[obj_col].astype("category")
```

```
#build model
lgbmr = lgb.LGBMRegressor(loss_function='RMSE')

# Parameters to be used for RandomizedSearchCV-
rs_params = {
      'n_estimators' : [100,300,500,900,1200,1700,3000],
```

```
        'learning_rate ': [0.1,0.3,0.5,0.7, 1],
        'num_leaves': [10,30,50,70,100]

}

lgb_rs = RandomizedSearchCV(estimator=lgbmr,param_distributions=rs_params,n_jobs=-1,cv=5,

# Fit model
lgb_rs.fit(X_tr_wo_enc,y_train)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
```




```
#randomized_search_result
randomized_result(lgb_rs,X_tr_wo_enc,X_te_wo_enc,y_test)
```

```
Evaluation on test data
MAD: 0.43
MAE: 0.71
RMSE: 1.18
R2: 0.93
Adjusted R2: 0.93

Visualizing the Predicted
```

Observation

- **From metrics**
- Error of Rupees 43 to 71 thousand differece in selling price.
- Model is able to explain 93% of variance in selling price.
- **From visualition**
- Car Values predicted greater than 15 lakhs are spread out.
- Most of the errors are close to zero but a few have large variance.

Random Forest Regression

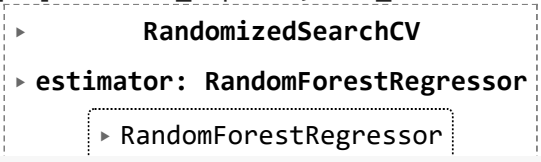
```
# Creating a base model to run random search
rf_reg = RandomForestRegressor()

# Number of trees in random forest
n_estim = [int(x) for x in np.linspace(start=100, stop=1200, num=12)]
max_feat = [7,'sqrt','log2']
max_dept = [1,3,5]
min_sample_split = [2,5,10,15,100]
min_sample_leaf = [1,2,5,10]
```

```
# creating random grid

random_grid = {'n_estimators':n_estim,
               'max_features':max_feat,
               'max_depth':max_dept,
               'min_samples_split':min_sample_split,
               'min_samples_leaf':min_sample_leaf}
print(random_grid)
```

```
{'n_estimators': [100, 200, 300, 400, 500, 600, 700, 800, 900, 1000, 1100, 1200], 'm
```

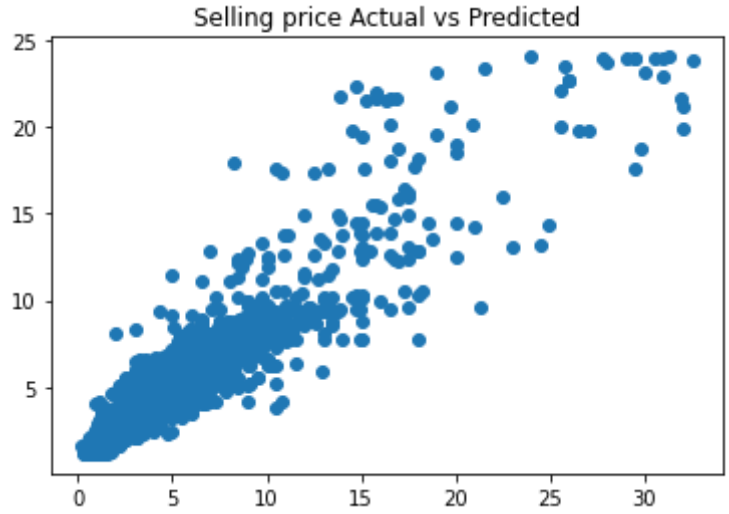
```
rs_rf_reg = RandomizedSearchCV(estimator=rf_reg,param_distributions=random_grid,
                               scoring='neg_mean_squared_error', n_iter=10,
                               cv=5, verbose=2, n_jobs=1, random_state = 35)

rs_rf_reg.fit(final_train,y_train)
```

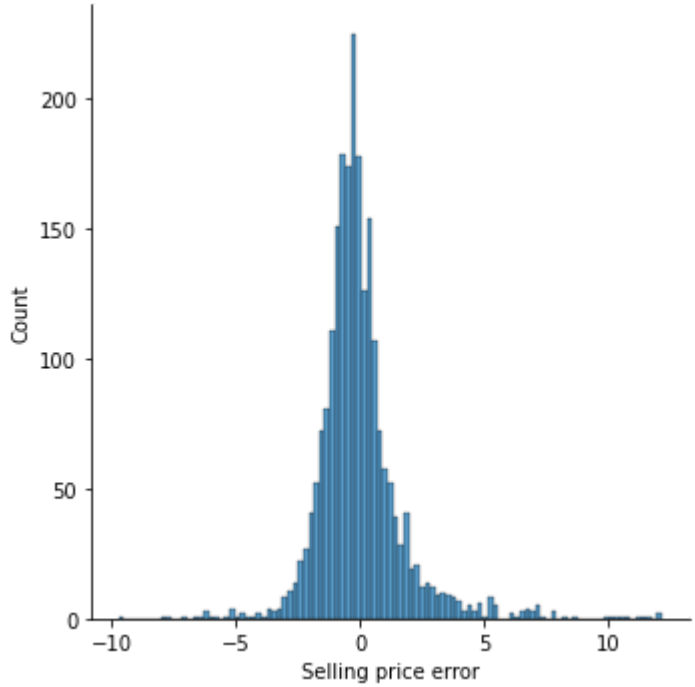
```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=1, min_samples_split=100,
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=1, min_samples_split=100,
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=1, min_samples_split=100,
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=1, min_samples_split=100,
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=1, min_samples_split=100,
[CV] END max_depth=3, max_features=log2, min_samples_leaf=2, min_samples_split=10, n
[CV] END max_depth=3, max_features=log2, min_samples_leaf=2, min_samples_split=10, n
[CV] END max_depth=3, max_features=log2, min_samples_leaf=2, min_samples_split=10, n
[CV] END max_depth=3, max_features=log2, min_samples_leaf=2, min_samples_split=10, n
[CV] END max_depth=3, max_features=log2, min_samples_leaf=2, min_samples_split=10, n
[CV] END max_depth=3, max_features=7, min_samples_leaf=10, min_samples_split=100, n_
[CV] END max_depth=3, max_features=7, min_samples_leaf=10, min_samples_split=100, n_
[CV] END max_depth=3, max_features=7, min_samples_leaf=10, min_samples_split=100, n_
[CV] END max_depth=3, max_features=7, min_samples_leaf=10, min_samples_split=100, n_
[CV] END max_depth=3, max_features=7, min_samples_leaf=10, min_samples_split=100, n_
[CV] END max_depth=5, max_features=7, min_samples_leaf=10, min_samples_split=100, n_
[CV] END max_depth=5, max_features=7, min_samples_leaf=10, min_samples_split=100, n_
[CV] END max_depth=5, max_features=7, min_samples_leaf=10, min_samples_split=100, n_
[CV] END max_depth=5, max_features=7, min_samples_leaf=10, min_samples_split=100, n_
[CV] END max_depth=5, max_features=7, min_samples_leaf=10, min_samples_split=100, n_
[CV] END max_depth=1, max_features=7, min_samples_leaf=10, min_samples_split=2, n_es
[CV] END max_depth=1, max_features=7, min_samples_leaf=10, min_samples_split=2, n_es
[CV] END max_depth=1, max_features=7, min_samples_leaf=10, min_samples_split=2, n_es
[CV] END max_depth=1, max_features=7, min_samples_leaf=10, min_samples_split=2, n_es
[CV] END max_depth=1, max_features=7, min_samples_leaf=10, min_samples_split=2, n_es
[CV] END max_depth=1, max_features=7, min_samples_leaf=10, min_samples_split=5, n_es
[CV] END max_depth=1, max_features=7, min_samples_leaf=10, min_samples_split=5, n_es
[CV] END max_depth=1, max_features=7, min_samples_leaf=10, min_samples_split=5, n_es
[CV] END max_depth=1, max_features=7, min_samples_leaf=10, min_samples_split=5, n_es
[CV] END max_depth=1, max_features=7, min_samples_leaf=10, min_samples_split=5, n_es
[CV] END max_depth=1, max_features=log2, min_samples_leaf=2, min_samples_split=10, n
[CV] END max_depth=1, max_features=log2, min_samples_leaf=2, min_samples_split=10, n
[CV] END max_depth=1, max_features=log2, min_samples_leaf=2, min_samples_split=10, n
[CV] END max_depth=1, max_features=log2, min_samples_leaf=2, min_samples_split=10, n
[CV] END max_depth=1, max_features=log2, min_samples_leaf=2, min_samples_split=10, n
[CV] END max_depth=3, max_features=log2, min_samples_leaf=1, min_samples_split=2, n_
[CV] END max_depth=3, max_features=log2, min_samples_leaf=1, min_samples_split=2, n_
[CV] END max_depth=3, max_features=log2, min_samples_leaf=1, min_samples_split=2, n_
[CV] END max_depth=3, max_features=log2, min_samples_leaf=1, min_samples_split=2, n_
[CV] END max_depth=3, max_features=log2, min_samples_leaf=1, min_samples_split=2, n_
[CV] END max_depth=1, max_features=7, min_samples_leaf=5, min_samples_split=100, n_e
[CV] END max_depth=1, max_features=7, min_samples_leaf=5, min_samples_split=100, n_e
[CV] END max_depth=1, max_features=7, min_samples_leaf=5, min_samples_split=100, n_e
[CV] END max_depth=1, max_features=7, min_samples_leaf=5, min_samples_split=100, n_e
[CV] END max_depth=1, max_features=7, min_samples_leaf=5, min_samples_split=100, n_e
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=10, min_samples_split=100,
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=10, min_samples_split=100,
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=10, min_samples_split=100,
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=10, min_samples_split=100,
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=10, min_samples_split=100,
```




```
#randomized_search_result
randomized_result(rs_rf_reg,final_train,final_test,y_test)
```

```
Evaluation on test data
MAD: 0.74
MAE: 1.14
RMSE: 1.79
R2: 0.83
Adjusted R2: 0.83

Visualizing the Predicted
```





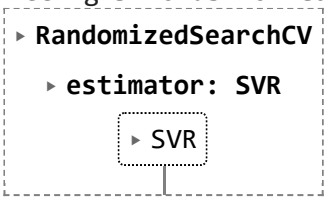
Observation

- **From metrics**
- Error of Rupees 74 to 114 thousand differece in selling price.
- Model is able to explain 83% of variance in selling price.
- **From visualition**
- Car Values predicted greater than 15 lakhs are spread out.
- Most of the errors are close to zero but a few have large variance.

Support Vector Regressor

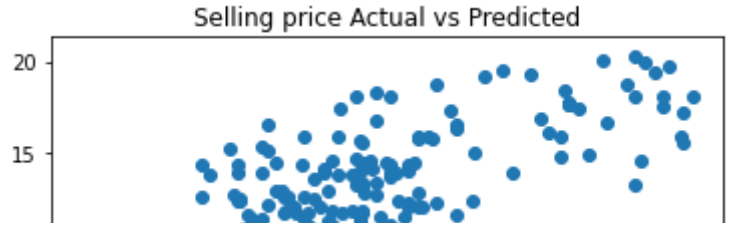
```
svr = SVR(kernel = 'rbf')
param = {
    'kernel': ('linear', 'rbf','poly'),
     'C': [0.01,0.1,0.5,1,3,7],
     'gamma': [1e-7, 1e-4, 'scale'],
     'epsilon': [0.1,0.3,0.5,0.7,0.9]
}

rs_svr = RandomizedSearchCV(estimator=svr,param_distributions=param, n_jobs=-1, cv=5, rand
                            scoring='neg_mean_squared_error', n_iter=10,verbose=2)
rs_svr.fit(final_train, y_train)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
```




```
#randomized_search_result
randomized_result(rs_svr,final_train,final_test,y_test)
```

```
Evaluation on test data
MAD: 0.70
MAE: 1.17
RMSE: 2.02
R2: 0.78
Adjusted R2: 0.78

Visualizing the Predicted
```



Observation

- **From metrics**
- Error of Rupees 70 to 117 thousand differece in selling price.
- Cat boost is able to explain 78% of variance in selling price.
- **From visualition**
- Car Values predicted greater than 15 lakhs are spread out.
- Most of the errors are close to zero but a few have large variance.

Decision Tree Regression

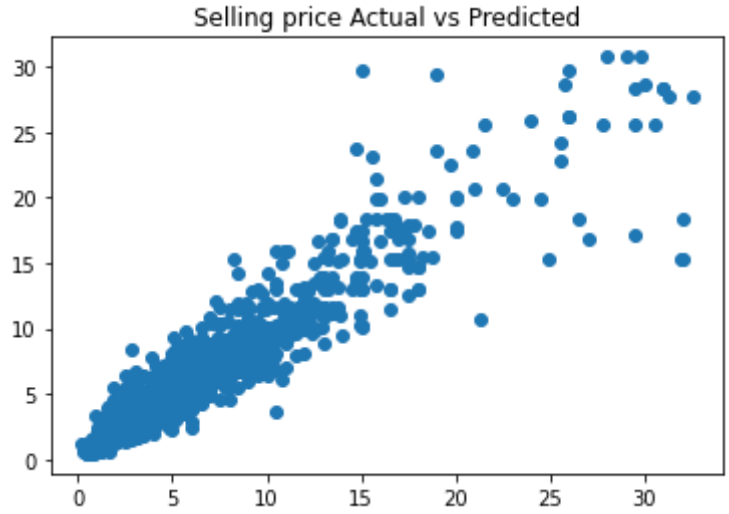
```
dtr = DecisionTreeRegressor()
dt_param = {
    'max_depth':[10,50,100,300,500,1000],
    'min_samples_split':[2,5,7,9],
    'min_samples_leaf':[1,3,5]}

rs_dtr = RandomizedSearchCV(estimator=dtr, param_distributions=dt_param, n_jobs=-1, cv=10,
                            scoring='neg_mean_squared_error', n_iter=10,verbose=2)

rs_dtr.fit(final_train,y_train)
```

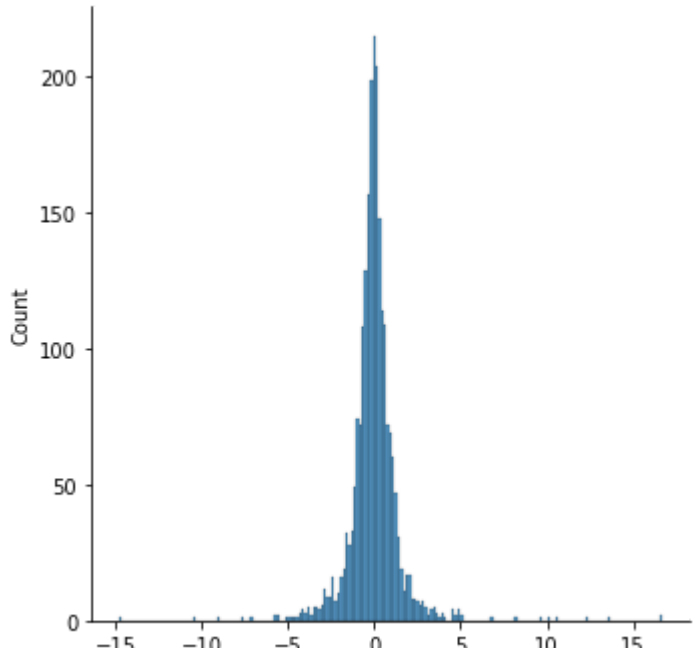
```
Fitting 10 folds for each of 10 candidates, totalling 100 fits
```

RandomizedSearchCV
estimator: DecisionTreeRegressor
DecisionTreeRegressor

```
#randomized_search_result
randomized_result(rs_dtr,final_train,final_test,y_test)
```

```
Evaluation on test data
MAD: 0.52
MAE: 0.86
RMSE: 1.48
R2: 0.88
Adjusted R2: 0.88

Visualizing the Predicted
```





Observation

- **From metrics**
- Error of Rupees 52 to 86 thousand differece in selling price.
- Model is able to explain 88% of variance in selling price.
- **From visualition**
- Car Values predicted greater than 15 lakhs are spread out.
- Most of the errors are close to zero but a few have large variance.

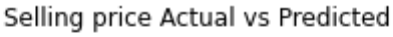
KNN Regressor

```
knr = KNeighborsRegressor()
knr_param = {
    'leaf_size':[10,20,30,50,70],
    'n_neighbors':[2,5,7,9]
}

rs_knr = RandomizedSearchCV(estimator=knr, param_distributions=knr_param, n_jobs=-1, cv=10
                            scoring='neg_mean_squared_error', n_iter=10,verbose=2)

rs_knr.fit(final_train,y_train)
```

```
Fitting 10 folds for each of 10 candidates, totalling 100 fits
```


```
#randomized_search_result
randomized_result(rs_knr,final_train,final_test,y_test)
```

```
Evaluation on test data
MAD: 0.59
MAE: 1.03
RMSE: 1.78
R2: 0.83
Adjusted R2: 0.83

Visualizing the Predicted
```



Observation

- **From metrics**
- Error of Rupees 59 to 103 thousand differece in selling price.
- Cat boost is able to explain 83% of variance in selling price.
- **From visualition**
- Car Values predicted greater than 15 lakhs are spread out.
- Most of the errors are close to zero but a few have large variance.

Neural Network Regression

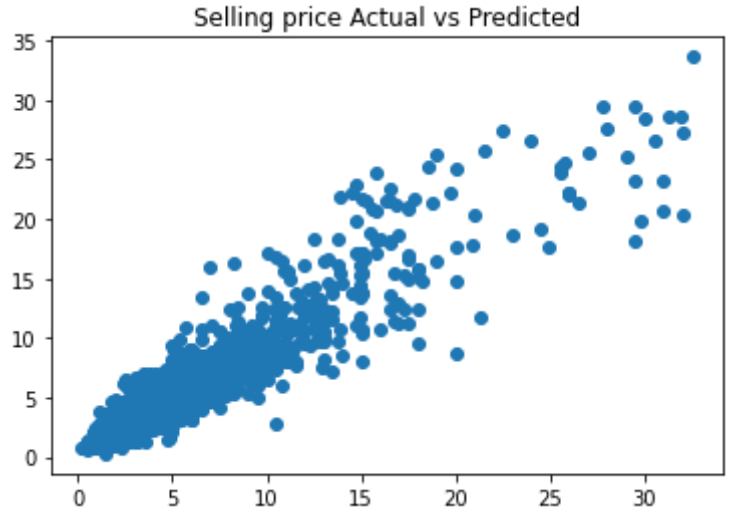
Sklearn MLP Regressor

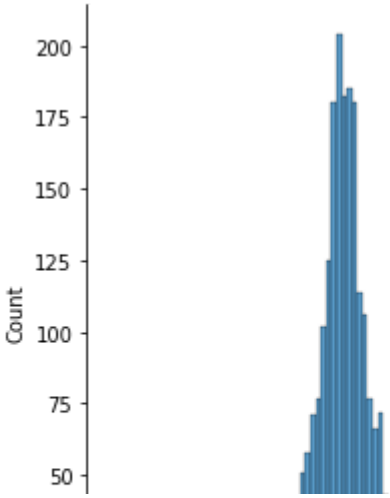

```
mlpr = MLPRegressor(random_state=35,early_stopping=True, verbose=True)

param = {
    'activation':['relu'],
    'alpha': [0.0001,0.001, 0.005, 0.01, 0.05, 0.09, 0.1],
    'hidden_layer_sizes' : [(10,10),(20,30),(40,50),(10,100)],
    'learning_rate' : ['adaptive','constant'],
    'learning_rate_init' : [0.0001,0.001,0.005,0.01],
    'max_iter' : [500,1000,3000]

}

rs_mlpr = RandomizedSearchCV(estimator=mlpr,param_distributions=param, random_state=35, n_

# Train the model

rs_mlpr.fit(final_train, y_train)
```

```
Iteration 1, loss = 14.21090966
Validation score: -0.039472
Iteration 2, loss = 6.86514338
Validation score: 0.555500
Iteration 3, loss = 3.24500218
Validation score: 0.721084
Iteration 4, loss = 2.21403564
Validation score: 0.795228
Iteration 5, loss = 1.80573249
Validation score: 0.817797
Iteration 6, loss = 1.62785445
Validation score: 0.831759
Iteration 7, loss = 1.53078858
Validation score: 0.838541
Iteration 8, loss = 1.44977822
Validation score: 0.843108
Iteration 9, loss = 1.40252413
Validation score: 0.849033
Iteration 10, loss = 1.38492898
Validation score: 0.841560
Iteration 11, loss = 1.35143393
Validation score: 0.851102
Iteration 12, loss = 1.31950251
Validation score: 0.849266
Iteration 13, loss = 1.30280505
Validation score: 0.854793
Iteration 14, loss = 1.28370731
Validation score: 0.850163
Iteration 15, loss = 1.27500249
Validation score: 0.859387
Iteration 16, loss = 1.26242340
Validation score: 0.848315
Iteration 17, loss = 1.26201300
Validation score: 0.853877
Iteration 18, loss = 1.25581723
Validation score: 0.857668
Iteration 19, loss = 1.23442502
Validation score: 0.855311
Iteration 20, loss = 1.24077521
Validation score: 0.856524
Iteration 21, loss = 1.22939116
Validation score: 0.861235
Iteration 22, loss = 1.22390103
Validation score: 0.861628
Iteration 23, loss = 1.21587228
Validation score: 0.859319
Iteration 24, loss = 1.22014071
Validation score: 0.847926
Iteration 25, loss = 1.24441879
```

```
#randomized_search_result
randomized_result(rs_mlpr,final_train,final_test,y_test)
```

```
Evaluation on test data
MAD: 0.66
MAE: 1.02
RMSE: 1.59
R2: 0.87
Adjusted R2: 0.87

Visualizing the Predicted
```





Observation

- **From metrics**
- Error of Rupees 66 to 102 thousand differece in selling price.
- Model is able to explain 87% of variance in selling price.
- **From visualition**
- Car Values predicted greater than 15 lakhs are spread out.
- Most of the errors are close to zero but a few have large variance.

Tensorflow Regression

```
# Creating model using the Sequential in tensorflow

reg_nn = Sequential()
```

```
# Input layer
reg_nn.add(Dense(8,input_shape=(13,)))

# Adding first Dense layer and dropout
reg_nn.add(Dense(160, kernel_initializer='normal', activation='relu'))
reg_nn.add(Dropout(0.2))

# Add second layer
reg_nn.add(Dense(480, kernel_initializer='normal', activation='relu'))
reg_nn.add(Dropout(0.2))

# Add third layer
reg_nn.add(Dense(260, kernel_initializer='normal', activation='relu'))
#reg_model.add(Dropout(0.2))

# Output node, liner activatino for regression
reg_nn.add(Dense(1, kernel_initializer='normal', activation='linear'))

# summery
reg_nn.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 8)                 112

 dense_1 (Dense)             (None, 160)               1440

 dropout (Dropout)           (None, 160)               0

 dense_2 (Dense)             (None, 480)               77280

 dropout_1 (Dropout)         (None, 480)               0

 dense_3 (Dense)             (None, 260)               125060

 dense_4 (Dense)             (None, 1)                 261

=================================================================
Total params: 204,153
Trainable params: 204,153
Non-trainable params: 0
_________________________________________________________________
```

```
reg_nn.compile(optimizer=Adam(learning_rate=1e-3),
               loss=MeanSquaredError(),
               metrics= RootMeanSquaredError())
```

```
reg_nn.fit(final_train,y_train.values,
           epochs=30, batch_size=64,validation_split=0.2)
```

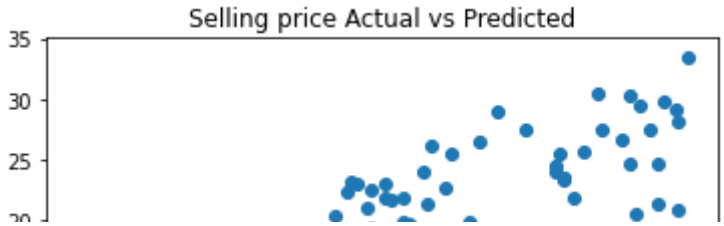
```
Epoch 1/30
113/113 [==============================] - 3s 12ms/step - loss: 13.9332 - root_mea
Epoch 2/30
```

```
113/113 [==============================] - 1s 10ms/step - loss: 4.6385 - root_mean
Epoch 3/30
113/113 [==============================] - 1s 10ms/step - loss: 3.7387 - root_mean
Epoch 4/30
113/113 [==============================] - 1s 10ms/step - loss: 3.2636 - root_mean
Epoch 5/30
113/113 [==============================] - 2s 22ms/step - loss: 3.1192 - root_mean
Epoch 6/30
113/113 [==============================] - 3s 30ms/step - loss: 3.0215 - root_mean
Epoch 7/30
113/113 [==============================] - 3s 23ms/step - loss: 2.9132 - root_mean
Epoch 8/30
113/113 [==============================] - 2s 20ms/step - loss: 2.9243 - root_mean
Epoch 9/30
113/113 [==============================] - 2s 17ms/step - loss: 2.8451 - root_mean
Epoch 10/30
113/113 [==============================] - 2s 19ms/step - loss: 2.7317 - root_mean
Epoch 11/30
113/113 [==============================] - 2s 14ms/step - loss: 2.7176 - root_mean
Epoch 12/30
113/113 [==============================] - 2s 15ms/step - loss: 2.6855 - root_mean
Epoch 13/30
113/113 [==============================] - 2s 17ms/step - loss: 2.7161 - root_mean
Epoch 14/30
113/113 [==============================] - 2s 17ms/step - loss: 2.5961 - root_mean
Epoch 15/30
113/113 [==============================] - 2s 18ms/step - loss: 2.6768 - root_mean
Epoch 16/30
113/113 [==============================] - 2s 16ms/step - loss: 2.6634 - root_mean
Epoch 17/30
113/113 [==============================] - 2s 19ms/step - loss: 2.6843 - root_mean
Epoch 18/30
113/113 [==============================] - 2s 16ms/step - loss: 2.6386 - root_mean
Epoch 19/30
113/113 [==============================] - 2s 16ms/step - loss: 2.5443 - root_mean
Epoch 20/30
113/113 [==============================] - 3s 23ms/step - loss: 2.5662 - root_mean
Epoch 21/30
113/113 [==============================] - 3s 23ms/step - loss: 2.4985 - root_mean
Epoch 22/30
113/113 [==============================] - 2s 17ms/step - loss: 2.5641 - root_mean
Epoch 23/30
113/113 [==============================] - 1s 12ms/step - loss: 2.5142 - root_mean
Epoch 24/30
113/113 [==============================] - 2s 19ms/step - loss: 2.4338 - root_mean
Epoch 25/30
113/113 [==============================] - 2s 22ms/step - loss: 2.4115 - root_mean
Epoch 26/30
113/113 [==============================] - 2s 15ms/step - loss: 2.4197 - root_mean
Epoch 27/30
113/113 [==============================] - 1s 10ms/step - loss: 2.4891 - root_mean
Epoch 28/30
113/113 [==============================] - 2s 17ms/step - loss: 2.3900 - root_mean
```

```
# randomized_search_result

# Predict
y_predict= reg_nn.predict(final_test)
```

```
# median_absolute_error
median_abs_err_test = median_absolute_error(y_test,y_predict)
# MAE
Mae_test = mean_absolute_error(y_test,y_predict)
#RMSE
Rmse_test = math.sqrt(mean_squared_error(y_test,y_predict))
#R2 Score
r2_test = r2_score(y_test,y_predict)
# Adjusted R2 Score
n= final_train.shape[0] # total no of datapoints
p= final_train.shape[1] # total no of independent features
adj_r2_test = 1-(((1-r2_test)*(n-1))/(n-p-1))
#print results
print("Evaluation on test data")
print("MAD: {:.2f}".format(median_abs_err_test))
print("MAE: {:.2f}".format(Mae_test))
print("RMSE: {:.2f}".format(Rmse_test))
print("R2: {:.2f}".format(r2_test))
print("Adjusted R2: {:.2f}\n".format(adj_r2_test))

print("Visualizing the Predicted\n")
plt.scatter(y_test,y_predict)
plt.title('Selling price Actual vs Predicted')
sns.displot(y_test.values.reshape(-1,1)-y_predict)
plt.xlabel("Selling price error")
plt.show()
```

```
71/71 [==============================] - 0s 4ms/step
Evaluation on test data
MAD: 0.68
MAE: 1.02
RMSE: 1.56
R2: 0.87
Adjusted R2: 0.87

Visualizing the Predicted
```



Observation

- **From metrics**
- Error of Rupees 68 to 102 thousand differece in selling price.
- Model is able to explain 87% of variance in selling price.
- **From visualition**
- Car Values predicted greater than 15 lakhs are spread out.
- Most of the errors are close to zero but a few have large variance.

Summary

```
# Specify the Column Names while initializing the Table

evaluation_table = PrettyTable(["Regression Model", "MAD", "MAE", "R2","adj R2"])

# adding rows
evaluation_table.add_row(["Cat Boost",0.45,0.73,0.92,0.92])
evaluation_table.add_row(["Light GBM",0.43,0.71,0.93,0.93])
evaluation_table.add_row(["Random Forest",0.74,1.14,0.83,0.83])
evaluation_table.add_row(["Support Vector",0.70,1.17,0.78,0.78])
evaluation_table.add_row(["Decision Tree",0.52,0.86,0.88,0.88])
evaluation_table.add_row(["KNN",0.59,1.03,0.83,0.83])
evaluation_table.add_row(["ANN sklearn",0.66,1.02,0.87,0.87])
evaluation_table.add_row(["ANN TF",0.68,1.02,0.87,0.87])

#Print
print(evaluation_table)
```

```
+------------------+------+------+------+--------+
| Regression Model | MAD  | MAE  |  R2  | adj R2 |
```