Used Car Price Prediction

Life Cycle of a Machine Learning Project

1: Understanding the Problem Statement
2: Data Collection
3: EDA (Exploratory Data Analysis)
4: Data Cleaning
5: Data Pre-Processing
6: Model Training
7: Choose Best Model

A) Problem Statement

1: The dataset comprises used cars sold on cardekho.com in India as well as important features of these cars.
2: If user can predict the price of the car based on input features.
3: Prediction results can be used to give new seller the price suggestion based on market condition.

B) Data Collection

1: The dataset is collected from scrapping from cardekho website.
2: The data consists of 13 columns and 15411 rows.

B.1) Importing data and required packages

Importing Pandas, Numpy, Matplotlib, Seaborn and Warnings Library

In [1]:
```
### importing libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplot inline

import warnings
warnings.filterwarnings('ignore')
```

```
C:\Users\Sachin Dev\AppData\Roaming\Python\Python38\site-packages\pandas\core\c
omputation\expressions.py:20: UserWarning: Pandas requires version '2.7.3' or n
ewer of 'numexpr' (version '2.7.1' currently installed).
  from pandas.core.computation.check import NUMEXPR_INSTALLED
UsageError: Line magic function `%matplot` not found.
```

Import csv Data as Pandas DataFrame

In [3]:
```
### read csv to import data
df = pd.read_csv('cardekho_dataset.csv')
```

Show Top 5 Rows

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

Out[4]:

	Unnamed: 0	car_name	brand	model	vehicle_age	km_driven	seller_type	fuel_type	transmi
0	0	Maruti Alto	Maruti	Alto	9	120000	Individual	Petrol	
1	1	Hyundai Grand	Hyundai	Grand	5	20000	Individual	Petrol	
2	2	Hyundai i20	Hyundai	i20	11	60000	Individual	Petrol	
3	3	Maruti Alto	Maruti	Alto	9	37000	Individual	Petrol	
4	4	Ford Ecosport	Ford	Ecosport	6	30000	Dealer	Diesel	

Delete Columns Unnamed:0 and again show Top 5 Rows

In [7]:
```
df.drop('Unnamed: 0',axis=1,inplace=True)
```

In [8]:
```
df.head()
```

Out[8]:

	car_name	brand	model	vehicle_age	km_driven	seller_type	fuel_type	transmission_type
0	Maruti Alto	Maruti	Alto	9	120000	Individual	Petrol	Manual
1	Hyundai Grand	Hyundai	Grand	5	20000	Individual	Petrol	Manual
2	Hyundai i20	Hyundai	i20	11	60000	Individual	Petrol	Manual
3	Maruti Alto	Maruti	Alto	9	37000	Individual	Petrol	Manual
4	Ford Ecosport	Ford	Ecosport	6	30000	Dealer	Diesel	Manual

Show Bottom 5 Rows

In [9]:
```
df.tail()
```

Out[9]:

	car_name	brand	model	vehicle_age	km_driven	seller_type	fuel_type	transmission_t
15406	Hyundai i10	Hyundai	i10	9	10723	Dealer	Petrol	Ma
15407	Maruti Ertiga	Maruti	Ertiga	2	18000	Dealer	Petrol	Ma
15408	Skoda Rapid	Skoda	Rapid	6	67000	Dealer	Diesel	Ma
15409	Mahindra XUV500	Mahindra	XUV500	5	3800000	Dealer	Diesel	Ma
15410	Honda City	Honda	City	2	13000	Dealer	Petrol	Autom

Shape of the Dataset

In [11]:
```
df.shape
```

Out[11]:
```
(15411, 13)
```

Our data has 15411 rows and 13 different features

Show features/columns of the Dataset

In [13]:
```
df.columns
```

Out[13]:
```
Index(['car_name', 'brand', 'model', 'vehicle_age', 'km_driven', 'seller_type',
       'fuel_type', 'transmission_type', 'mileage', 'engine', 'max_power',
       'seats', 'selling_price'],
      dtype='object')
```

Summary of Data

In [14]:
```python
### Display statistics of the DataFrame
df.describe()
```

Out[14]:

	vehicle_age	km_driven	mileage	engine	max_power	seats	sellin
count	15411.000000	1.541100e+04	15411.000000	15411.000000	15411.000000	15411.000000	1.5411
mean	6.036338	5.561648e+04	19.701151	1486.057751	100.588254	5.325482	7.7497
std	3.013291	5.161855e+04	4.171265	521.106696	42.972979	0.807628	8.9412
min	0.000000	1.000000e+02	4.000000	793.000000	38.400000	0.000000	4.0000
25%	4.000000	3.000000e+04	17.000000	1197.000000	74.000000	5.000000	3.8500
50%	6.000000	5.000000e+04	19.670000	1248.000000	88.500000	5.000000	5.5600
75%	8.000000	7.000000e+04	22.700000	1582.000000	117.300000	5.000000	8.2500
max	29.000000	3.800000e+06	33.540000	6592.000000	626.000000	9.000000	3.9500

Check Null Value Counts and DataTypes of the features

In [15]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15411 entries, 0 to 15410
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   car_name           15411 non-null  object 
 1   brand              15411 non-null  object 
 2   model              15411 non-null  object 
 3   vehicle_age        15411 non-null  int64  
 4   km_driven          15411 non-null  int64  
 5   seller_type        15411 non-null  object 
 6   fuel_type          15411 non-null  object 
 7   transmission_type  15411 non-null  object 
 8   mileage            15411 non-null  float64
 9   engine             15411 non-null  int64  
 10  max_power          15411 non-null  float64
 11  seats              15411 non-null  int64  
 12  selling_price      15411 non-null  int64  
dtypes: float64(2), int64(5), object(6)
memory usage: 1.5+ MB
```

Check duplicate values

In [16]:
```python
df.duplicated().sum()
```

Out[16]: 167

Check the number of unique values of each column

In [19]:
```
df.nunique()
```

Out[19]:
```
car_name             121
brand                 32
model                120
vehicle_age           24
km_driven           3688
seller_type            3
fuel_type              5
transmission_type      2
mileage              411
engine               110
max_power            342
seats                  8
selling_price       1086
dtype: int64
```

Section B Report

1: There are 15411 rows and 12 columns in the dataset.
2: There are no null values in the dataset.
3: Out of 12 features 6 are numeric features (vehicle_age,km_driven,mileage engine,max_power,seats,selling_price) and rest are categorical features
4: There are 167 duplicate values in total in the dataset.

In [ ]:
```

```

C) Exploring Data

Show Categories in columns

In [20]:
```
print("Categories in 'seller_type' variable: ",end = " ")
print(df['seller_type'].unique())
print("\n")

print("Categories in 'fuel_type' variable: ",end = " ")
print(df['fuel_type'].unique())
print("\n")

print("Categories in 'transmission_type' variable: ",end = " ")
print(df['transmission_type'].unique())
print("\n")

print("Categories in 'seats' variable: ",end = " ")
print(df['seats'].unique())
```

```
Categories in 'seller_type' variable:  ['Individual' 'Dealer' 'Trustmark Deale
r']


Categories in 'fuel_type' variable:  ['Petrol' 'Diesel' 'CNG' 'LPG' 'Electric']


Categories in 'transmission_type' variable:  ['Manual' 'Automatic']


Categories in 'seats' variable:  [5 8 7 6 4 2 9 0]
```

Check Cars with 0 Seats

In [21]:
```
df[df['seats'] == 0]
```

Out[21]:

	car_name	brand	model	vehicle_age	km_driven	seller_type	fuel_type	transmission_type
3217	Honda City	Honda	City	18	40000	Individual	Petrol	Manual
12619	Nissan Kicks	Nissan	Kicks	2	10000	Individual	Diesel	Manual

Define Numerical and Categorical Columns

In [22]:
```
numeric_features = [feature for feature in df.columns if df[feature].dtype !
categorical_features = [feature for feature in df.columns if df[feature].dty

### print columns
print(f"We have {len(categorical_features)} categorical_features: {numeric_f
print(f"We have {len(categorical_features)} categorical_features: {categoric
```

```
We have 6 categorical_features: ['vehicle_age', 'km_driven', 'mileage', 'engin
e', 'max_power', 'seats', 'selling_price']
We have 6 categorical_features: ['car_name', 'brand', 'model', 'seller_type',
'fuel_type', 'transmission_type']
```

Feature Information

1: car_name: Car's Full name, which includes brand and specific model name.

2: brand: Brand Name of the particular car.

3: model: Exact model name of the car of a particular brand.

4: seller_type: Which Type of seller is selling the used car

5: fuel_type: Fuel used in the used car, which was put up on sale.

6: transmission_type: Transmission used in the used car, which was put on sale.

7: vehicle_age: The count of years since car was bought.

8: mileage: It is the number of kilometer the car runs per litre.

9: engine: It is the engine capacity in cc(cubic centimeters)

10: max_power: Max power it produces in BHP.

11: seats: Total number of seats in car.

12: selling_price: The sale price which was put up on website.

In [24]:
```
### proportion of count data on categorical columns

for col in categorical_features:
    print(df[col].value_counts(normalize=True)*100)
    print("---------------------------------------------")
```

```
Hyundai i20          5.878918
Maruti Swift Dzire   5.775096
Maruti Swift         5.067809
Maruti Alto          5.048342
Honda City           4.912076
                       ...
Mercedes-AMG C       0.006489
Tata Altroz          0.006489
Ferrari GTC4Lusso    0.006489
Hyundai Aura         0.006489
Force Gurkha         0.006489
Name: car_name, Length: 121, dtype: float64
---------------------------------------------
Maruti           32.392447
Hyundai          19.349815
Honda             9.635974
Mahindra          6.560249
Toyota            5.145675
Ford              5.126209
Volkswagen        4.023100
Renault           3.478035
BMW               2.848615
Tata              2.790215
Mercedes-Benz     2.186750
Skoda             2.167283
Audi              1.245863
Datsun            1.103108
Jaguar            0.382843
Land Rover        0.330932
Jeep              0.266044
Kia               0.207644
Porsche           0.136266
Volvo             0.129777
MG                0.123289
Mini              0.110311
Nissan            0.071378
Lexus             0.064889
Isuzu             0.051911
Bentley           0.019467
Maserati          0.012978
ISUZU             0.012978
Ferrari           0.006489
Mercedes-AMG      0.006489
Rolls-Royce       0.006489
Force             0.006489
Name: brand, dtype: float64
---------------------------------------------
i20            5.878918
Swift Dzire    5.775096
Swift          5.067809
```

```
Alto           5.048342
City           4.912076
                 ...
Ghibli         0.006489
Altroz         0.006489
GTC4Lusso      0.006489
Aura           0.006489
Gurkha         0.006489
Name: model, Length: 120, dtype: float64
----------------------------------------------
Dealer              61.897346
Individual          36.980079
Trustmark Dealer     1.122575
Name: seller_type, dtype: float64
----------------------------------------------
Petrol      49.594446
Diesel      48.140938
CNG          1.953150
LPG          0.285510
Electric     0.025955
Name: fuel_type, dtype: float64
----------------------------------------------
Manual       79.326455
Automatic    20.673545
Name: transmission_type, dtype: float64
----------------------------------------------
```

D) Univariate Analysis

Taking one avriable at a time and analyzing it.
Eg:- PDF,CDF,boxplot etc.

Numerical Features

In [27]:

```
plt.figure(figsize=(15,15))
###The suptitle() method figure module of matplotlib library is used to Add
plt.suptitle("Univariate Analysis of Numerical Features",fontsize=20,fontwei

for i in range(len(numeric_features)):
    plt.subplot(5,3,i+1)
    sns.kdeplot(x=df[numeric_features[i]],shade=True,color='b')
    plt.xlabel(numeric_features[i])
    plt.tight_layout()
```

```
<ipython-input-27-8801f48397e8>:7: FutureWarning:

`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.

  sns.kdeplot(x=df[numeric_features[i]],shade=True,color='b')
<ipython-input-27-8801f48397e8>:7: FutureWarning:

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<ipython-input-27-8801f48397e8>:7: FutureWarning:

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<ipython-input-27-8801f48397e8>:7: FutureWarning:

`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.

  sns.kdeplot(x=df[numeric_features[i]],shade=True,color='b')
<ipython-input-27-8801f48397e8>:7: FutureWarning:

`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.

  sns.kdeplot(x=df[numeric_features[i]],shade=True,color='b')
<ipython-input-27-8801f48397e8>:7: FutureWarning:

`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.

  sns.kdeplot(x=df[numeric_features[i]],shade=True,color='b')
<ipython-input-27-8801f48397e8>:7: FutureWarning:

`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.

  sns.kdeplot(x=df[numeric_features[i]],shade=True,color='b')
```
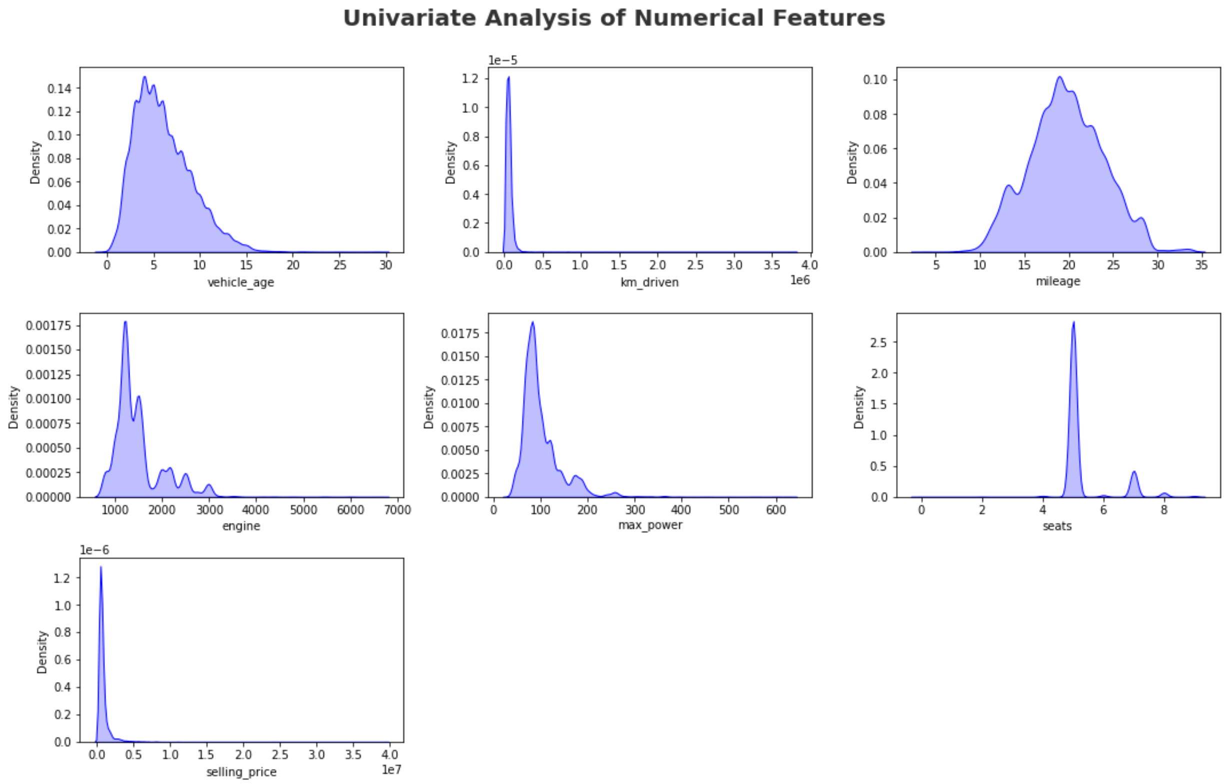



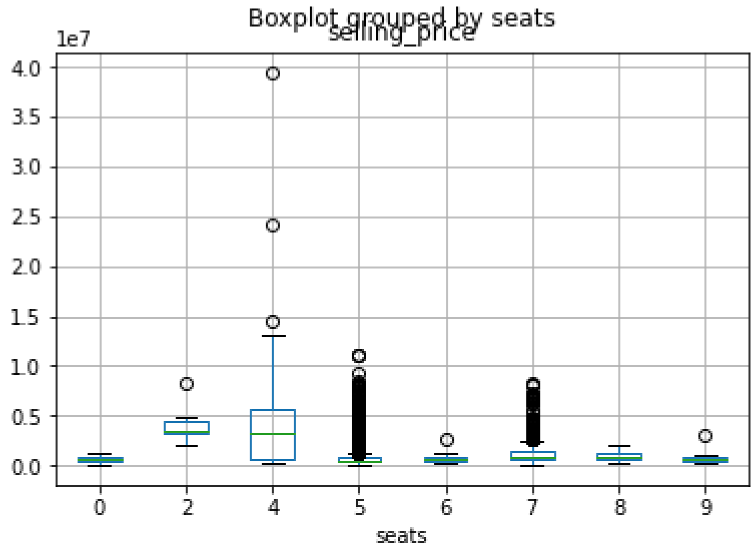
Report

1: Km_driven, max_power, selling_price, and engine are right skewed and postively skewed.

2: Outliers in km_driven, enginer, selling_price, and max power.

In [30]:
```
df.boxplot(by="seats",column=['selling_price'])
```

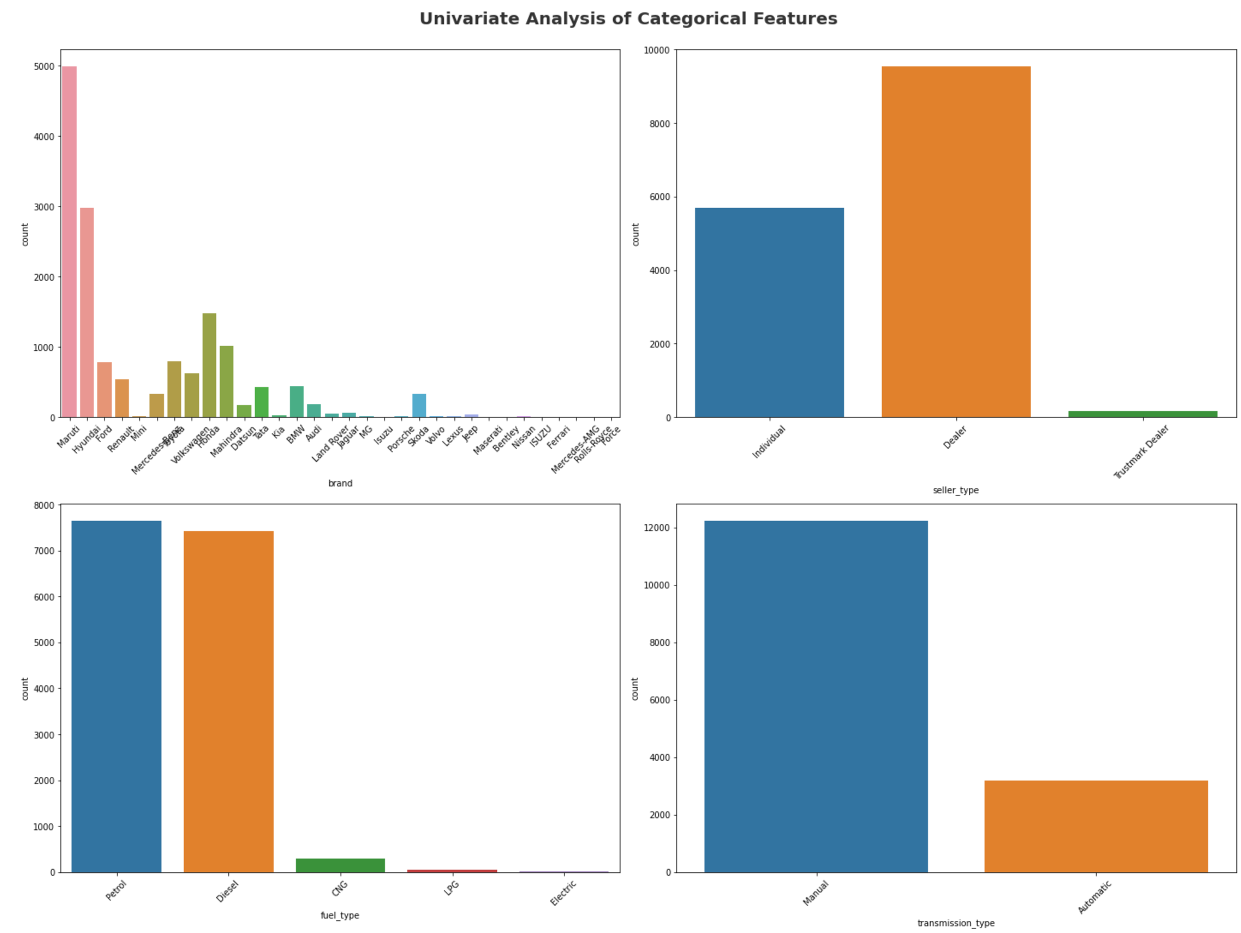
Out[30]: <AxesSubplot: title={'center': 'selling_price'}, xlabel='seats'>



Categorical Features

In [34]:

```
import warnings
warnings.filterwarnings('ignore')

##categorical features
plt.figure(figsize=(20,15))
plt.suptitle("Univariate Analysis of Categorical Features",fontsize=20,fontw
cat1 = ['brand','seller_type','fuel_type','transmission_type']

for i in range(len(cat1)):
    plt.subplot(2,2,i+1)
    sns.countplot(x=df[cat1[i]])
    plt.xlabel(cat1[i])
    plt.xticks(rotation=45)
    plt.tight_layout()
```



E) Multivariate Analysis

Multivariate Analysis is the analysis of more than one variable.

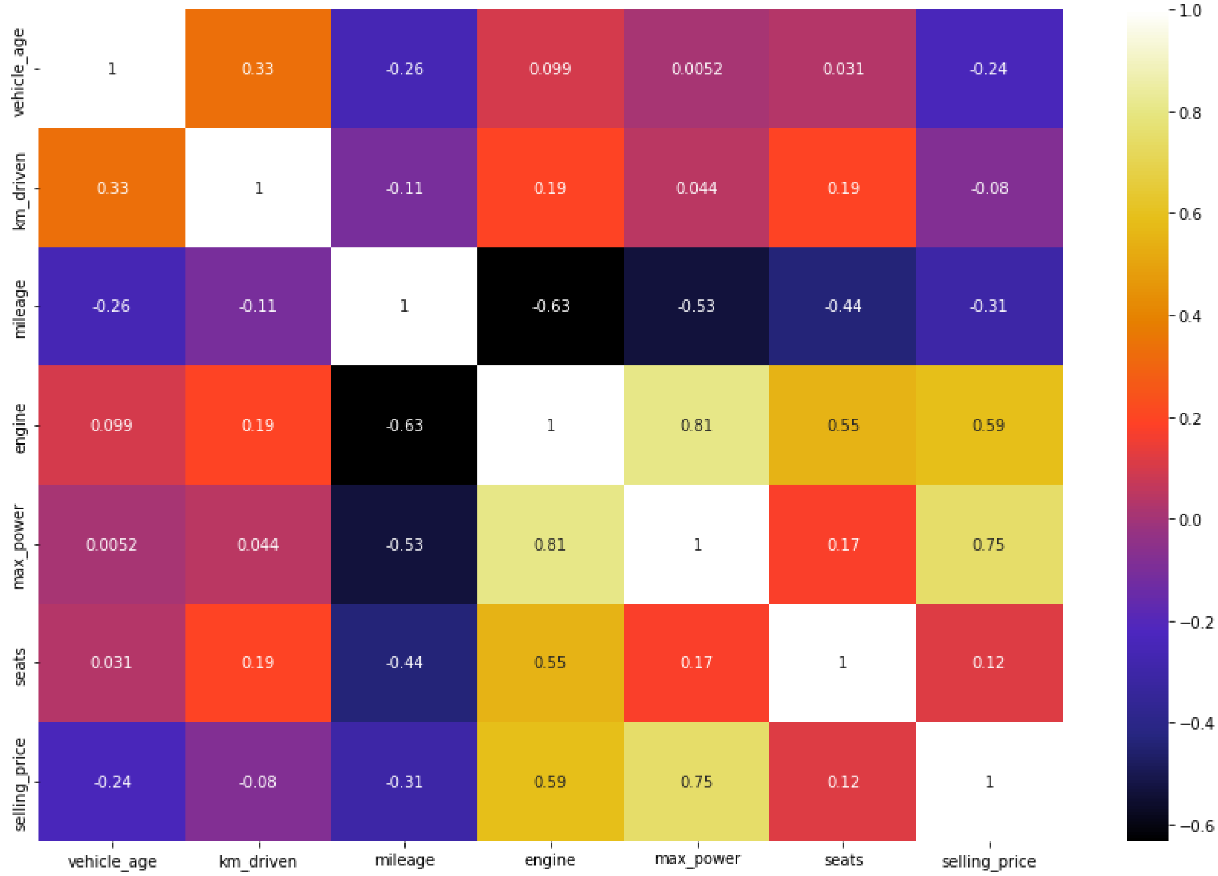
Check Multicollinearity of Numerical Features

In [37]:
```
df[numeric_features].corr()
```

Out[37]:

	vehicle_age	km_driven	mileage	engine	max_power	seats	selling_price
vehicle_age	1.000000	0.333891	-0.257394	0.098965	0.005208	0.030791	-0.241851
km_driven	0.333891	1.000000	-0.105239	0.192885	0.044421	0.192830	-0.080030
mileage	-0.257394	-0.105239	1.000000	-0.632987	-0.533128	-0.440280	-0.305549
engine	0.098965	0.192885	-0.632987	1.000000	0.807368	0.551236	0.585844
max_power	0.005208	0.044421	-0.533128	0.807368	1.000000	0.172257	0.750236
seats	0.030791	0.192830	-0.440280	0.551236	0.172257	1.000000	0.115033
selling_price	-0.241851	-0.080030	-0.305549	0.585844	0.750236	0.115033	1.000000

In [38]:
```
plt.figure(figsize = (15,10))
sns.heatmap(df.corr(),cmap='CMRmap',annot=True)
plt.show()
```



Report

1: Selling Price has Negative correlation with vehicle_age, km_driven, and mileage. i.e. If vehicle_age, km_driven, mileage increase then selling_price of the car decreases.
2: Selling_price has positive correlation with engine and max_power. It has a very weak postive correlation with seats.

Check Multicollinearity for Categorical Features

The test is applied when you have two categorical variables from a single population. It is used to determine whether there is a significant association between the two variables.

Here we test correlation of Categorical columns with Target column i.e Selling Price

In [43]:
```
### apply for 1 categorical feature

from scipy.stats import chi2_contingency
dataset_table = pd.crosstab(df['selling_price'],df['brand'])
dataset_table.head()
```

Out[43]:

brand	Audi	BMW	Bentley	Datsun	Ferrari	Force	Ford	Honda	Hyundai	ISUZU	...	Min
selling_price												
40000	0	0	0	0	0	0	0	0	0	0	...	0
45000	0	0	0	0	0	0	0	0	0	0	...	0
50000	0	0	0	0	0	0	0	1	0	0	...	0
55000	0	0	0	0	0	0	0	0	0	0	...	0
60000	0	0	0	0	0	0	0	0	1	0	...	0

5 rows × 32 columns

In [44]:
```
chi2_contingency(dataset_table)
```

Out[44]:
```
(125264.56097651123,
 0.0,
 33635,
 array([[0.01245863, 0.02848615, 0.00019467, ..., 0.05145675, 0.040231  ,
         0.00129777],
        [0.01245863, 0.02848615, 0.00019467, ..., 0.05145675, 0.040231  ,
         0.00129777],
        [0.0373759 , 0.08545844, 0.000584  , ..., 0.15437026, 0.12069301,
         0.00389332],
        ...,
        [0.01245863, 0.02848615, 0.00019467, ..., 0.05145675, 0.040231  ,
         0.00129777],
        [0.01245863, 0.02848615, 0.00019467, ..., 0.05145675, 0.040231  ,
         0.00129777],
        [0.01245863, 0.02848615, 0.00019467, ..., 0.05145675, 0.040231  ,
         0.00129777]]))
```

```
dof = observed.size - sum(observed.shape) + observed.ndim - 1
```

Parameters: **observed** : *array_like*

The contingency table. The table contains the observed frequencies (i.e. number of occurrences) in each category. In the two-dimensional case, the table is often described as an "R x C table".

correction : *bool, optional*

If True, *and* the degrees of freedom is 1, apply Yates' correction for continuity. The effect of the correction is to adjust each observed value by 0.5 towards the corresponding expected value.

lambda_ : *float or str, optional*

By default, the statistic computed in this test is Pearson's chi-squared statistic [2]. *lambda_* allows a statistic from the Cressie-Read power divergence family [3] to be used instead. See `scipy.stats.power_divergence` for details.

Returns: **chi2** : *float*

The test statistic.

p : *float*

The p-value of the test

dof : *int*

Degrees of freedom

expected : *ndarray, same shape as observed*

The expected frequencies, based on the marginal sums of the table.

In [47]:

```
p_value = chi2_contingency(pd.crosstab(df['selling_price'], df['brand']))[1]
p_value
```

Out[47]: 0.0

In [51]:

```
#### applying chi-square test for all categorical variables
from scipy.stats import chi2_contingency
chi2_test = []
for feature in categorical_features:
    ##if p_value<0.05
    if chi2_contingency(pd.crosstab(df['selling_price'],df[feature]))[1] < 0
        chi2_test.append("Reject Null Hypothesis")
    else:
        chi2_test.append("Fail to Reject Null Hypothesis")
result = pd.DataFrame(data=[categorical_features,chi2_test]).T
result.columns = ['Features','Hypothesis Result']
result
```

Out[51]:

	Features	Hypothesis Result
0	car_name	Reject Null Hypothesis
1	brand	Reject Null Hypothesis
2	model	Reject Null Hypothesis
3	seller_type	Reject Null Hypothesis
4	fuel_type	Reject Null Hypothesis
5	transmission_type	Reject Null Hypothesis

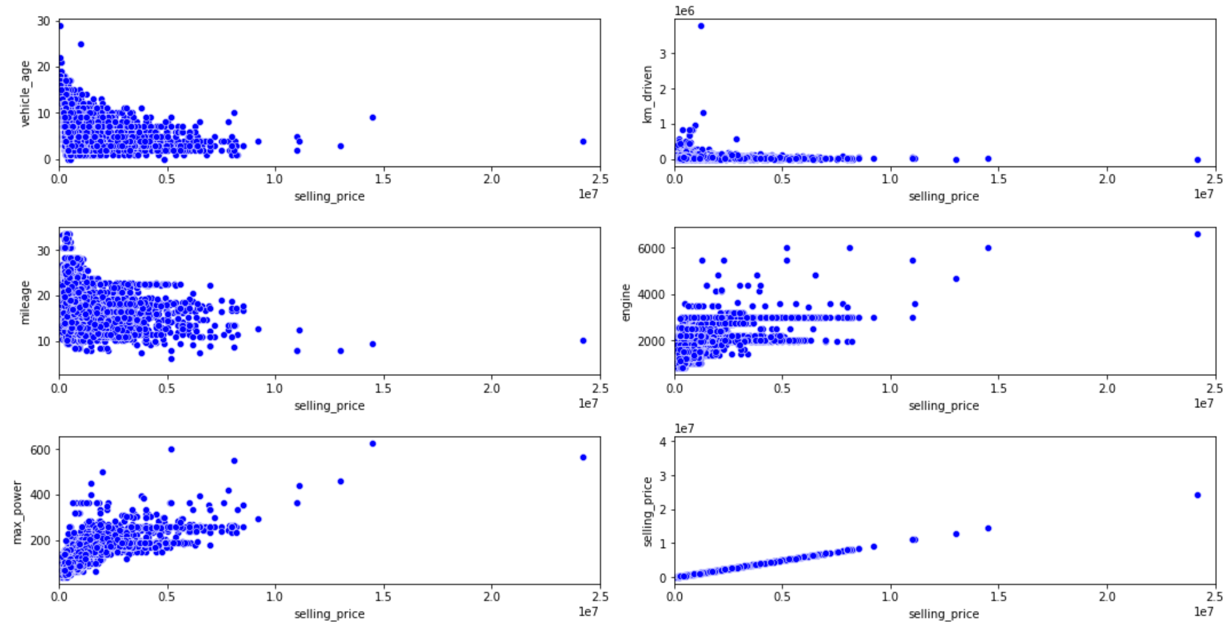
In [54]:

```
continuous_features = []
for feature in numeric_features:
    if len(df[feature].unique()) >= 10:
        continuous_features.append(feature)

continuous_features
```

Out[54]:

```
['vehicle_age', 'km_driven', 'mileage', 'engine', 'max_power', 'selling_price']
```

In [64]:
```
fig = plt.figure(figsize=(15, 20))

for i in range(0, len(continuous_features)):
    ax = plt.subplot(8, 2, i+1)

    sns.scatterplot(data= df ,x='selling_price', y=continuous_features[i], c
    plt.xlim(0,25000000) # Limit to 2.5 cr Rupees to view clean
    plt.tight_layout()
```



Report

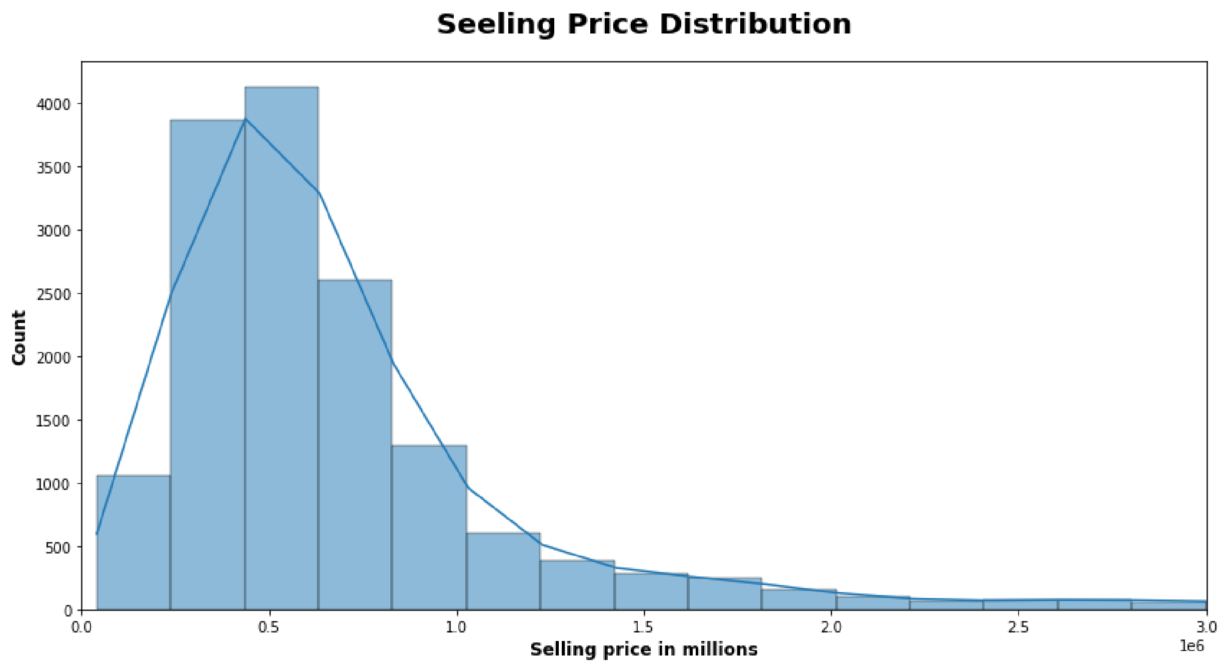
Lower Vehicle age has more selling price than Vehicle with more age.
Engine CC has positive effect on price.
Kms Driven has negative effect on selling price.

F) Visualization

F.1) Visualize the Target Feature

In [65]:

```
plt.subplots(figsize=(14,7))
sns.histplot(df.selling_price,bins=200,kde=True)
plt.title("Seeling Price Distribution", weight='bold', fontsize=20, pad=20)
plt.ylabel("Count",weight='bold',fontsize=12)
plt.xlabel("Selling price in millions", weight='bold', fontsize=12)
plt.xlim(0,3000000)
plt.show()
```



Target Variable is Skewed

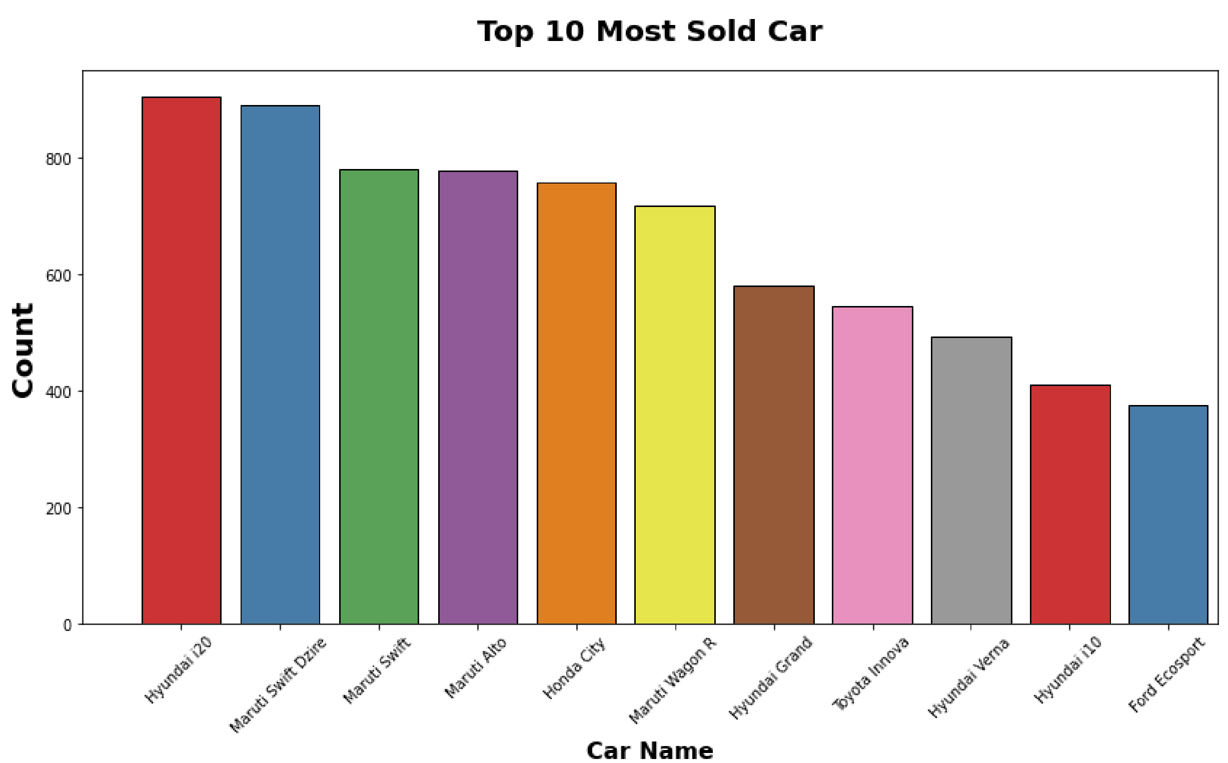
B.2) Most Selling Cars

In [67]:
```
### Top 10 most selling cars
df.car_name.value_counts()[0:10]
```

Out[67]:
```
Hyundai i20           906
Maruti Swift Dzire    890
Maruti Swift          781
Maruti Alto           778
Honda City            757
Maruti Wagon R        717
Hyundai Grand         580
Toyota Innova         545
Hyundai Verna         492
Hyundai i10           410
Name: car_name, dtype: int64
```

Most Selling used car is Hyundai i20

In [70]:
```
plt.subplots(figsize = (14,7))
sns.countplot(x="car_name",data=df,ec='black',palette="Set1",order=df['car_n
plt.title("Top 10 Most Sold Car", weight="bold",fontsize=20, pad=20)
plt.ylabel("Count", weight="bold", fontsize=20)
plt.xlabel("Car Name", weight="bold", fontsize=16)
plt.xticks(rotation= 45)
plt.xlim(-1,10.5)
plt.show()
```



Check mean price of Hyundai i20 which is most sold

In [71]:
```
i20 = df[df['car_name'] == 'Hyundai i20']['selling_price'].mean()
print(f'The mean price of Hyundai i20 is {i20:.2f} Rupees')
```

```
The mean price of Hyundai i20 is 543603.75 Rupees
```

Report:

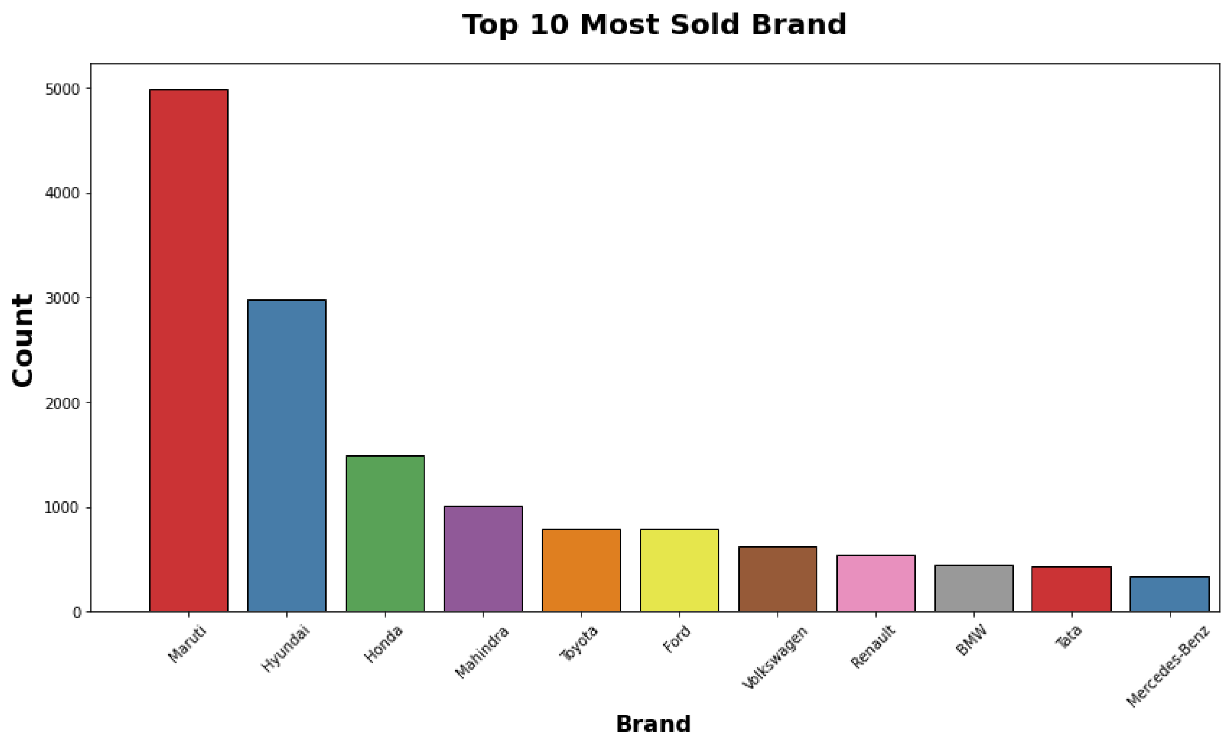
As per the Chart these are top 10 most selling cars in used car website.
Of the total cars sold Hyundai i20 shares 5.8% of total ads posted and followed by Maruti Swift Dzire.
Mean Price of Most Sold Car is 5.4 lakhs.
This Feature has impact on the Target Variable.

B.3) Most Selling Brands

In [72]:
```
df.brand.value_counts()[0:10]
```

Out[72]:
```
Maruti        4992
Hyundai       2982
Honda         1485
Mahindra      1011
Toyota         793
Ford           790
Volkswagen     620
Renault        536
BMW            439
Tata           430
Name: brand, dtype: int64
```

In [73]:
```
plt.subplots(figsize = (14,7))
sns.countplot(x="brand",data=df,ec='black',palette="Set1",order=df['brand'].
plt.title("Top 10 Most Sold Brand", weight="bold",fontsize=20, pad=20)
plt.ylabel("Count", weight="bold", fontsize=20)
plt.xlabel("Brand", weight="bold", fontsize=16)
plt.xticks(rotation= 45)
plt.xlim(-1,10.5)
plt.show()
```



Check the Mean price of Maruti brand which is most sold

In [74]:
```
maruti = df[df['brand'] == 'Maruti']['selling_price'].mean()
print(f"The mean price of Maruti is {maruti:.2f} Rs")
```

```
The mean price of Maruti is 487089.32 Rs
```

Report

1: AS per the chart, Maruti has the most share of Ads in Used Cars website and Maruti is the most sold brand.
2: Following Maruti we have Hyundai and Honda
3: Mean Price of Maruti Brand Cars is 4.87 Lakhs

B.4) Costliest Brand and Costliest Car

In [76]:

```
1 df.groupby('brand').selling_price.max()
```

Out[76]:

```
brand
Audi              6800000
BMW               8500000
Bentley          14500000
Datsun             650000
Ferrari          39500000
Force              700000
Ford              3200000
Honda             3200000
Hyundai           2600000
ISUZU             1900000
Isuzu             2300000
Jaguar            6300000
Jeep              5600000
Kia               3525000
Land Rover        9200000
Lexus             8000000
MG                2075000
Mahindra          2950000
Maruti            1225000
Maserati          6200000
Mercedes-AMG      5100000
Mercedes-Benz    13000000
Mini              3875000
Nissan            1450000
Porsche          11100000
Renault           1155000
Rolls-Royce      24200000
Skoda             3550000
Tata              1750000
Toyota            3650000
Volkswagen        1250000
Volvo             8195000
Name: selling_price, dtype: int64
```

In [77]:

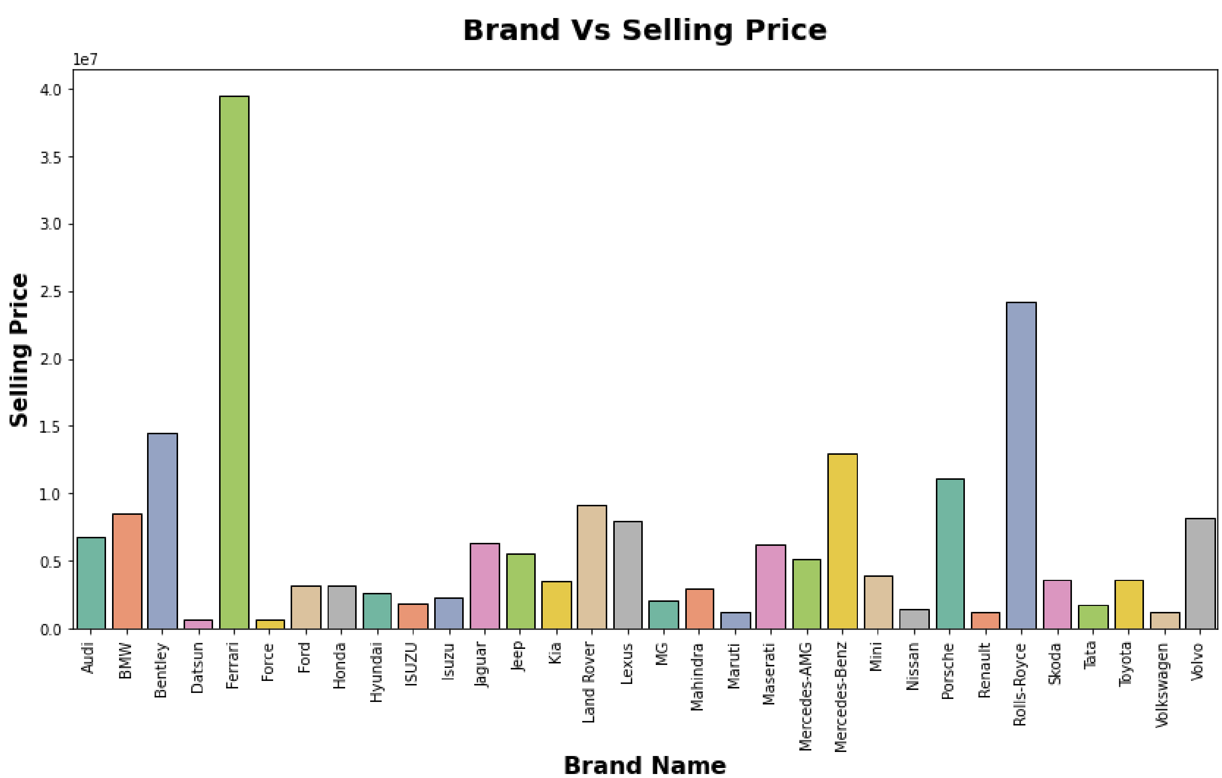
```
brand = df.groupby('brand').selling_price.max()
brand_df = brand.to_frame().sort_values('selling_price',ascending=False)[0:1
brand_df
```

Out[77]:

brand	selling_price
Ferrari	39500000
Rolls-Royce	24200000
Bentley	14500000
Mercedes-Benz	13000000
Porsche	11100000
Land Rover	9200000
BMW	8500000
Volvo	8195000
Lexus	8000000
Audi	6800000

In [79]:

```
plt.subplots(figsize = (14,7))
sns.barplot(x=brand.index,y=brand.values,ec='black',palette='Set2')
plt.title("Brand Vs Selling Price", weight="bold", fontsize=20, pad=20)
plt.ylabel("Selling Price", weight='bold', fontsize=15)
plt.xlabel("Brand Name", weight="bold", fontsize=16)
plt.xticks(rotation=90)
plt.show()
```



Report:

1: Costliest Brand sold is Ferrari at 3.95Cr.

2: Second most costliest car Brand is Rolls-Royce at 2.42Cr.

3: Brand name has very clear impact on selling price

B.5) Costliest Car

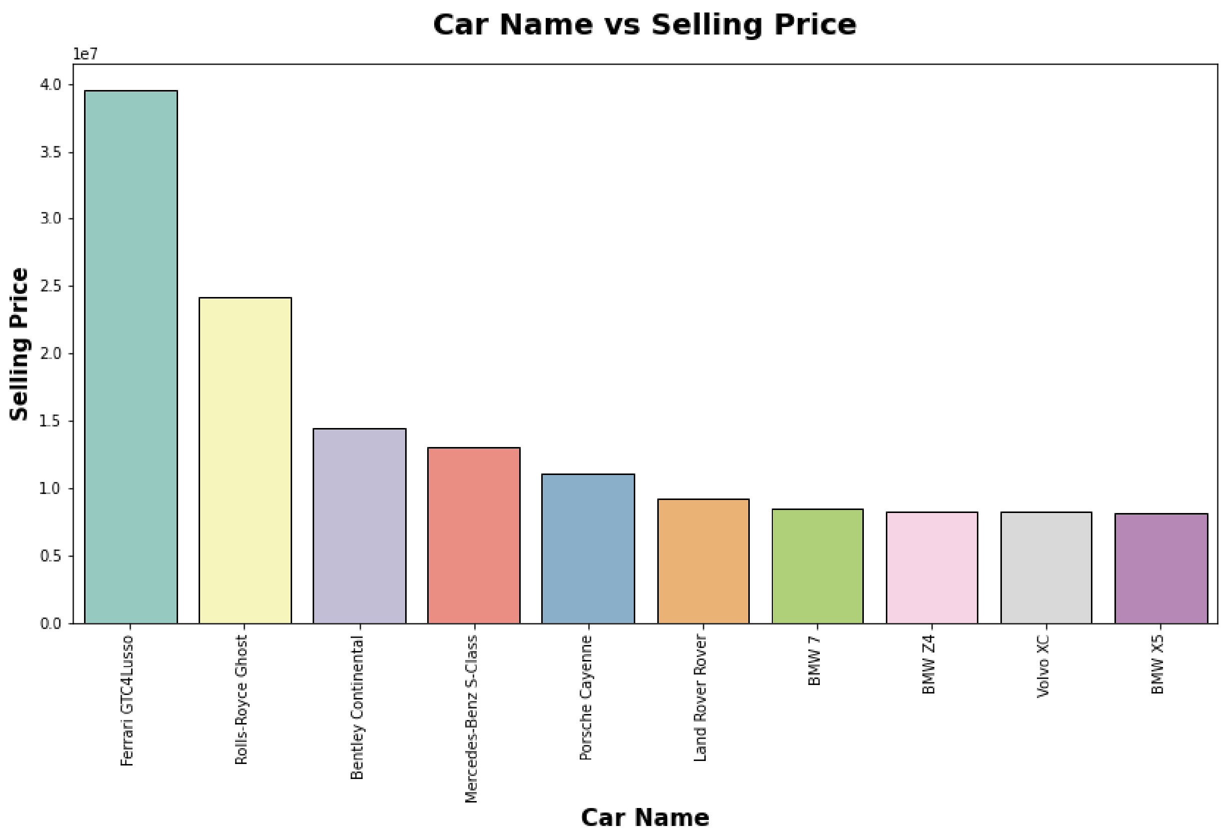
In [80]:

```
car = df.groupby('car_name').selling_price.max()
car = car.to_frame().sort_values('selling_price',ascending=False)[0:10]
car
```

Out[80]:

car_name	selling_price
Ferrari GTC4Lusso	39500000
Rolls-Royce Ghost	24200000
Bentley Continental	14500000
Mercedes-Benz S-Class	13000000
Porsche Cayenne	11100000
Land Rover Rover	9200000
BMW 7	8500000
BMW Z4	8250000
Volvo XC	8195000
BMW X5	8100000

In [83]:
```
plt.subplots(figsize=(14,7))
sns.barplot(x=car.index,y=car.selling_price,ec='black',palette='Set3')
plt.title("Car Name vs Selling Price", weight="bold",fontsize=20, pad=20)
plt.ylabel("Selling Price", weight="bold", fontsize=15)
plt.xlabel("Car Name", weight="bold", fontsize=16)
plt.xticks(rotation=90)
plt.show()
```



Report

1: Costliest Car sold is Ferrari GTC4 Lusso followed by Rolls Royce Ghost.
2: Ferrari selling price is 3.95 Crs.
3: Other than Ferrari other car has priced below 1.5cr.

Most Mileage Brand and Car Name

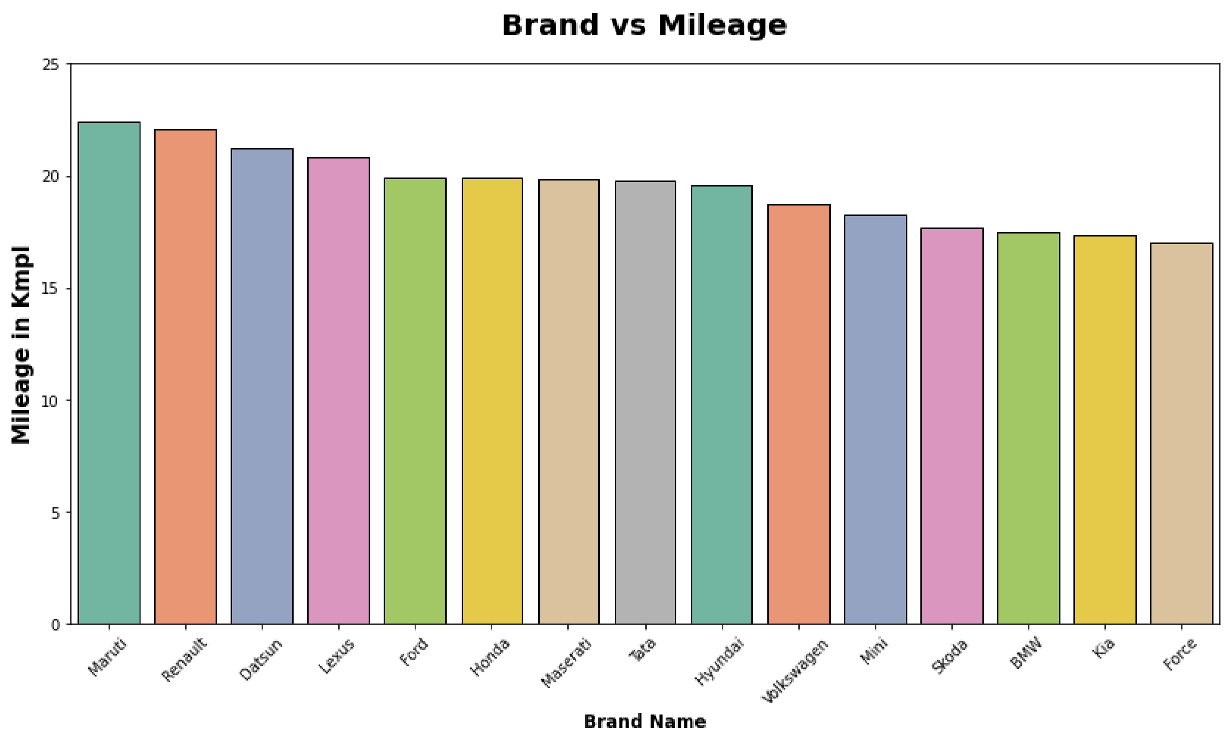
In [86]:
```
mileage = df.groupby('brand')['mileage'].mean().sort_values(ascending=False)
mileage.to_frame()
```

Out[86]:

brand	mileage
Maruti	22.430980
Renault	22.099142
Datsun	21.215647
Lexus	20.846000
Ford	19.922620
Honda	19.908795
Maserati	19.820000
Tata	19.755279
Hyundai	19.588776
Volkswagen	18.689774
Mini	18.287647
Skoda	17.667006
BMW	17.440182
Kia	17.323125
Force	17.000000

In [87]:

```
plt.subplots(figsize=(14,7))
sns.barplot(x=mileage.index, y=mileage.values, ec = "black", palette="Set2")
plt.title("Brand vs Mileage", weight="bold",fontsize=20, pad=20)
plt.ylabel("Mileage in Kmpl", weight="bold", fontsize=15)
plt.xlabel("Brand Name", weight="bold", fontsize=12)
plt.ylim(0,25)
plt.xticks(rotation=45)
plt.show()
```



Car with Highest Mileage

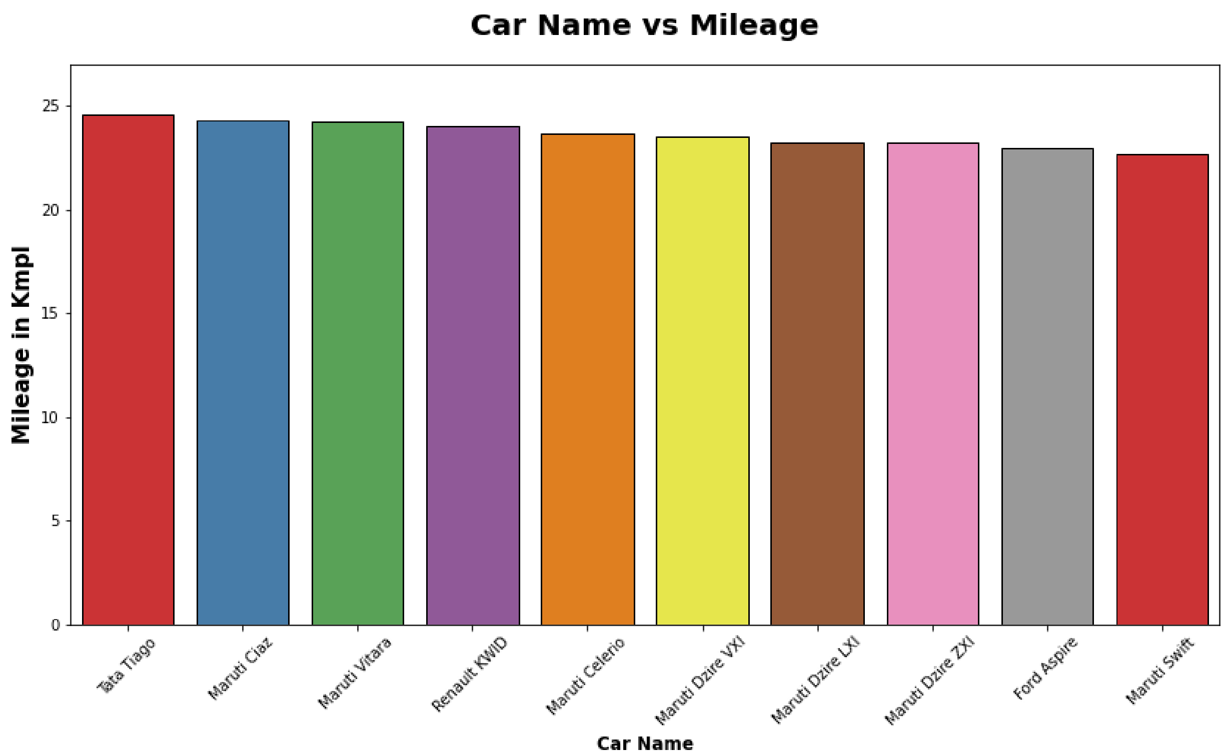
In [88]:
```
mileage_C= df.groupby('car_name')['mileage'].mean().sort_values(ascending=Fa
mileage_C.to_frame()
```

Out[88]:

car_name	mileage
Tata Tiago	24.625103
Maruti Ciaz	24.289046
Maruti Vitara	24.231932
Renault KWID	24.037810
Maruti Celerio	23.703502
Maruti Dzire VXI	23.512941
Maruti Dzire LXI	23.260000
Maruti Dzire ZXI	23.260000
Ford Aspire	22.993846
Maruti Swift	22.719910

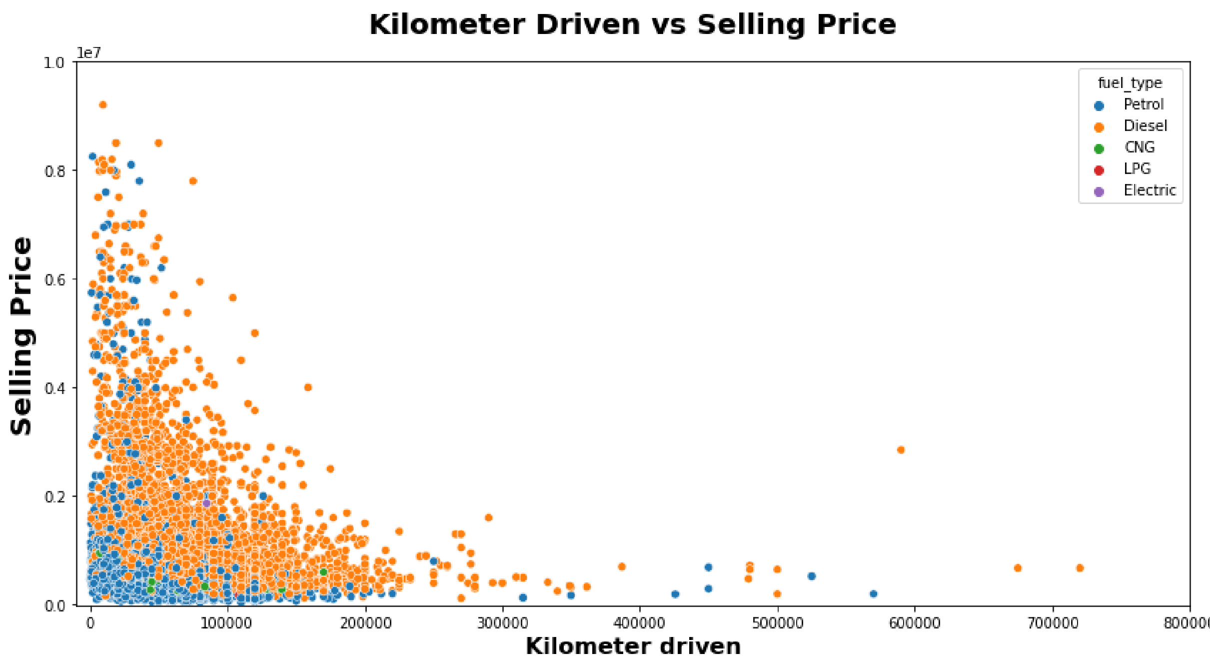
In [89]:

```
plt.subplots(figsize=(14,7))
sns.barplot(x=mileage_C.index, y=mileage_C.values, ec = "black", palette="Se
plt.title("Car Name vs Mileage", weight="bold",fontsize=20, pad=20)
plt.ylabel("Mileage in Kmpl", weight="bold", fontsize=15)
plt.xlabel("Car Name", weight="bold", fontsize=12)
plt.ylim(0,27)
plt.xticks(rotation=45)
plt.show()
```



Kilometer driven vs Selling Price

In [90]:
```
plt.subplots(figsize=(14,7))
sns.scatterplot(x="km_driven", y='selling_price', data=df,ec = "white",color
plt.title("Kilometer Driven vs Selling Price", weight="bold",fontsize=20, pa
plt.ylabel("Selling Price", weight="bold", fontsize=20)
plt.xlim(-10000,800000) #used limit for better visualization
plt.ylim(-10000,10000000)
plt.xlabel("Kilometer driven", weight="bold", fontsize=16)
plt.show()
```



Report

Many Cars were sold with kms between 0 to 20k Kilometers
Low Kms driven cars had more selling price compared to cars which had more kms driven.

Fuel Type Vs Selling Price

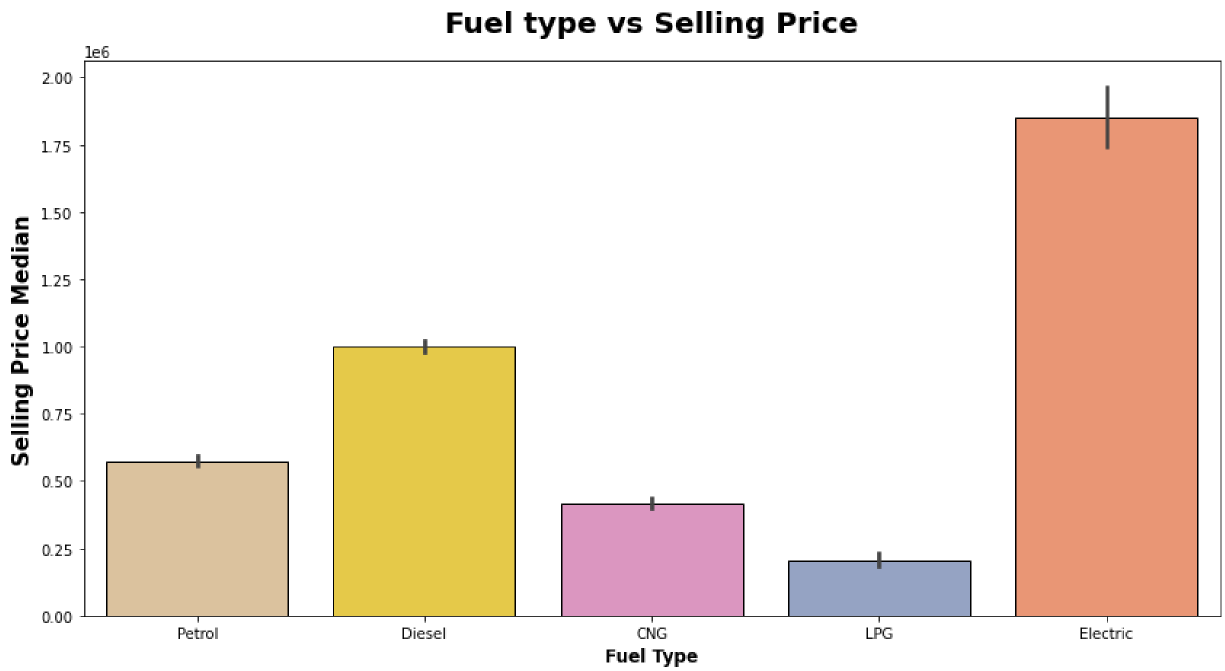
In [91]:
```
fuel = df.groupby('fuel_type')['selling_price'].median().sort_values(ascendi
fuel.to_frame()
```

Out[91]:

	selling_price
fuel_type	
Electric	1857500.0
Diesel	700000.0
Petrol	460000.0
CNG	370000.0
LPG	182500.0

In [92]:

```
plt.subplots(figsize=(14,7))
sns.barplot(x=df.fuel_type, y=df.selling_price, ec = "black", palette="Set2_
plt.title("Fuel type vs Selling Price", weight="bold",fontsize=20, pad=20)
plt.ylabel("Selling Price Median", weight="bold", fontsize=15)
plt.xlabel("Fuel Type", weight="bold", fontsize=12)
plt.show()
```



Report

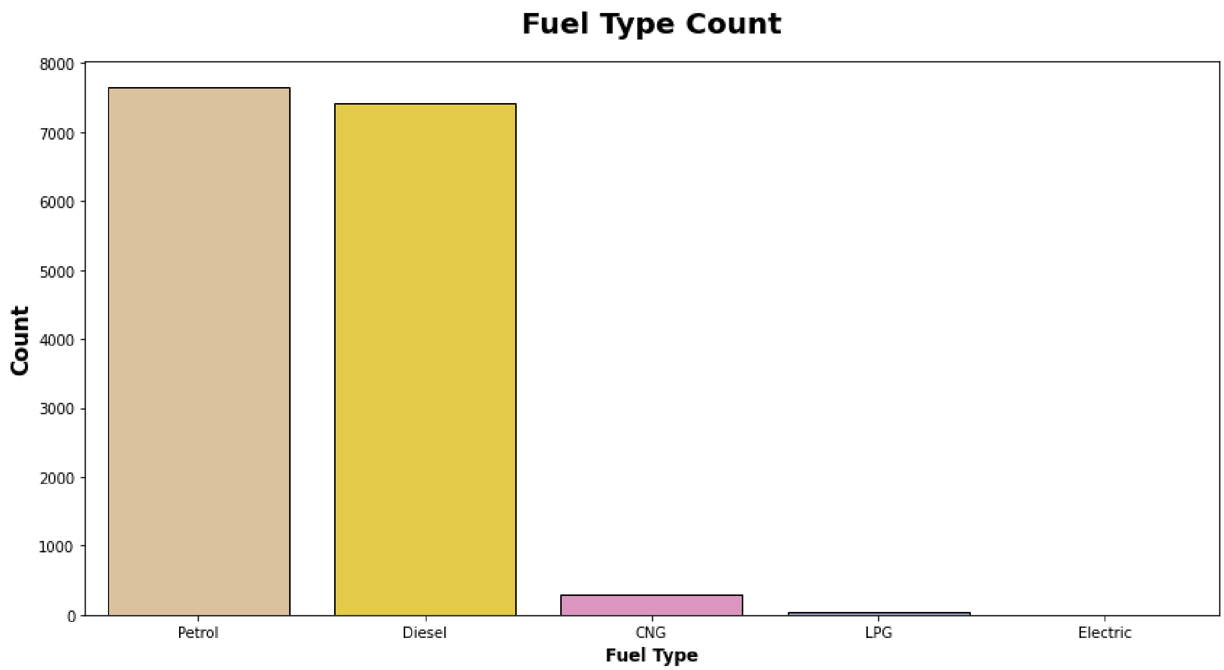
1: Electric cars have highers selling average price.

2: Followed by Diesel and Petrol.

3: Fuel Type is also important feature for the Target variable.

Most sold Fuel type

In [93]:
```
plt.subplots(figsize=(14,7))
sns.countplot(x=df.fuel_type, ec = "black", palette="Set2_r")
plt.title("Fuel Type Count", weight="bold",fontsize=20, pad=20)
plt.ylabel("Count", weight="bold", fontsize=15)
plt.xlabel("Fuel Type", weight="bold", fontsize=12)
plt.show()
```



Report

Petrol and Diesel dominate the used car market in the website.
The most sold fuel type Vechicle is Petrol.
Followed by diesel and CNG and least sold is Electric

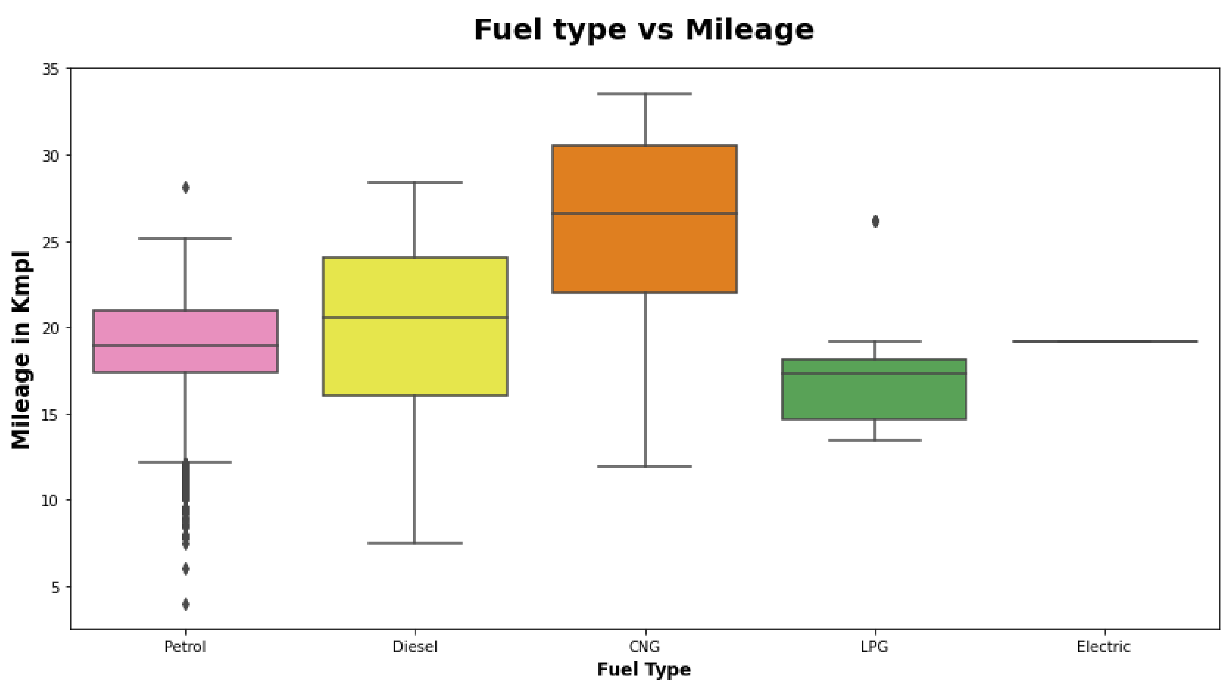
Fuel types available and mileage given

In [94]:
```
fuel_mileage = df.groupby('fuel_type')['mileage'].mean().sort_values(ascendi
fuel_mileage.to_frame()
```

Out[94]:

	mileage
fuel_type	
CNG	25.814651
Diesel	20.060030
Electric	19.160000
Petrol	19.123045
LPG	17.836364

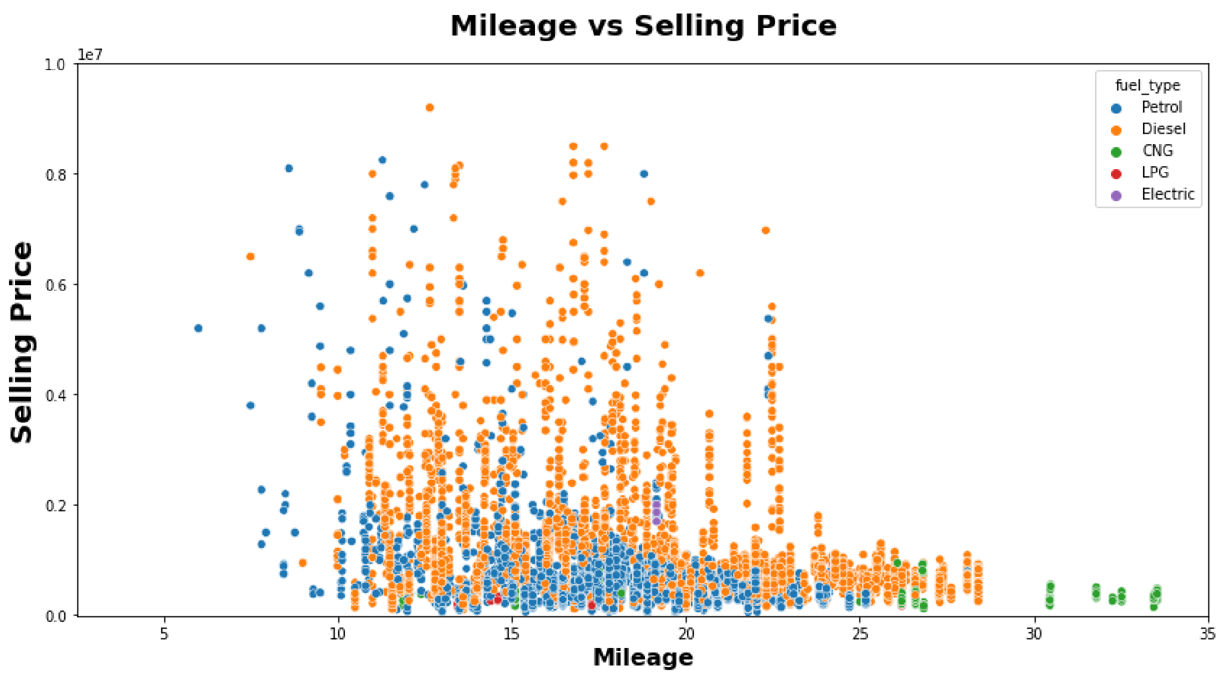
In [95]:
```
plt.subplots(figsize=(14,7))
sns.boxplot(x='fuel_type', y='mileage', data=df,palette="Set1_r")
plt.title("Fuel type vs Mileage", weight="bold",fontsize=20, pad=20)
plt.ylabel("Mileage in Kmpl", weight="bold", fontsize=15)
plt.xlabel("Fuel Type", weight="bold", fontsize=12)
plt.show()
```



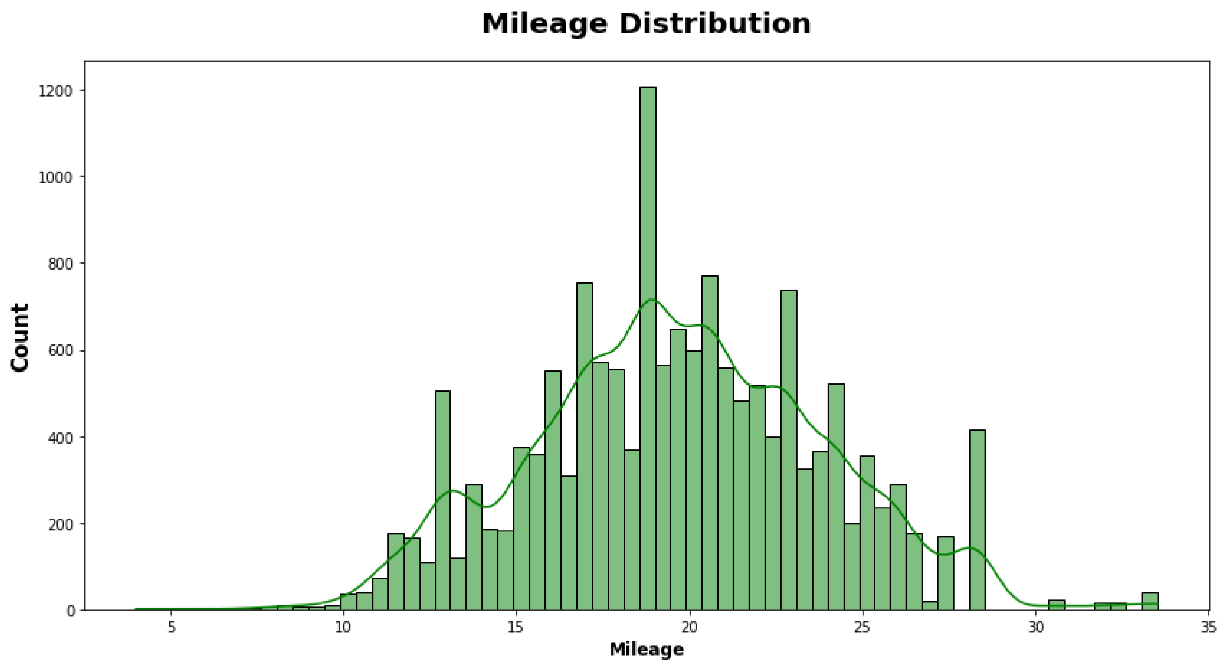
Mileage vs Selling Price

In [96]:

```
plt.subplots(figsize=(14,7))
sns.scatterplot(x="mileage", y='selling_price', data=df,ec = "white",color='
plt.title("Mileage vs Selling Price", weight="bold",fontsize=20, pad=20)
plt.ylabel("Selling Price", weight="bold", fontsize=20)
plt.ylim(-10000,10000000)
plt.xlabel("Mileage", weight="bold", fontsize=16)
plt.show()
```

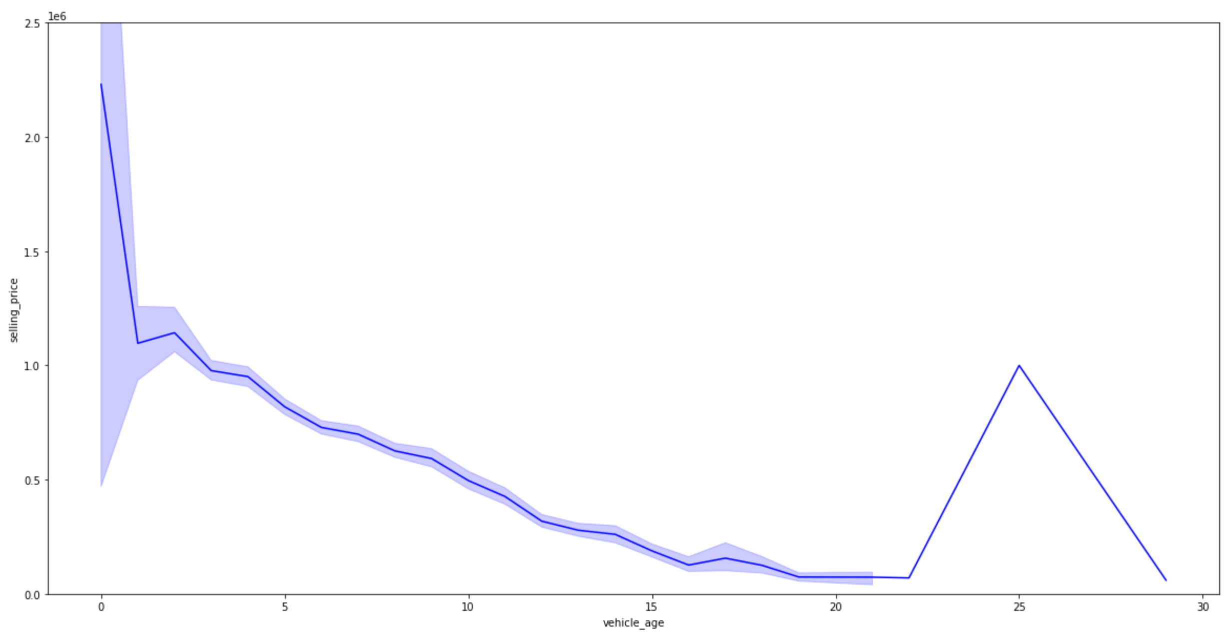


In [97]:
```
plt.subplots(figsize=(14,7))
sns.histplot(x=df.mileage, ec = "black", color='g', kde=True)
plt.title("Mileage Distribution", weight="bold",fontsize=20, pad=20)
plt.ylabel("Count", weight="bold", fontsize=15)
plt.xlabel("Mileage", weight="bold", fontsize=12)
plt.show()
```



Vehicle age vs Selling Price

In [98]:
```
plt.subplots(figsize=(20,10))
sns.lineplot(x='vehicle_age',y='selling_price',data=df,color='b')
plt.ylim(0,2500000)
plt.show()
```



Report

As the Vehicle age increases the price also get reduced.
Vehicle age has Negative impact on selling price

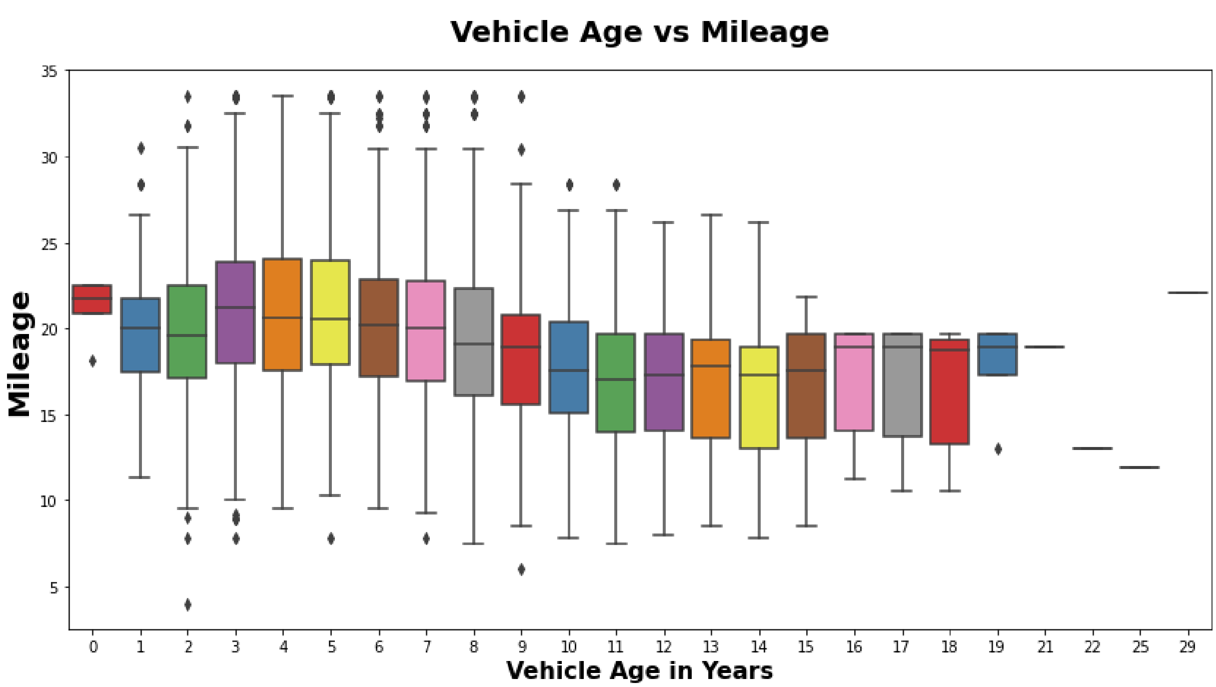
Vehicle age vs Mileage

In [99]:
```
vehicle_age = df.groupby('vehicle_age')['mileage'].median().sort_values(asce
vehicle_age.to_frame().head(5)
```

Out[99]:

vehicle_age	mileage
29	22.05
0	21.70
3	21.21
4	20.63
5	20.51

In [100]:
```
plt.subplots(figsize=(14,7))
sns.boxplot(x=df.vehicle_age, y= df.mileage, palette="Set1")
plt.title("Vehicle Age vs Mileage", weight="bold",fontsize=20, pad=20)
plt.ylabel("Mileage", weight="bold", fontsize=20)
plt.xlabel("Vehicle Age in Years", weight="bold", fontsize=16)
plt.show()
```



Report

As the Age of vehicle increases the median of mileage drops.
Newer Vehicles have more mileage median older vehicle.

In [101]:

```
oldest = df.groupby('car_name')['vehicle_age'].max().sort_values(ascending=F
oldest.to_frame()
```

Out[101]:

car_name	vehicle_age
Maruti Alto	29
BMW 3	25
Honda City	22
Maruti Wagon R	21
Mahindra Bolero	18
Mahindra Scorpio	18
Skoda Octavia	18
Honda CR-V	17
Mercedes-Benz E-Class	17
Honda Civic	15

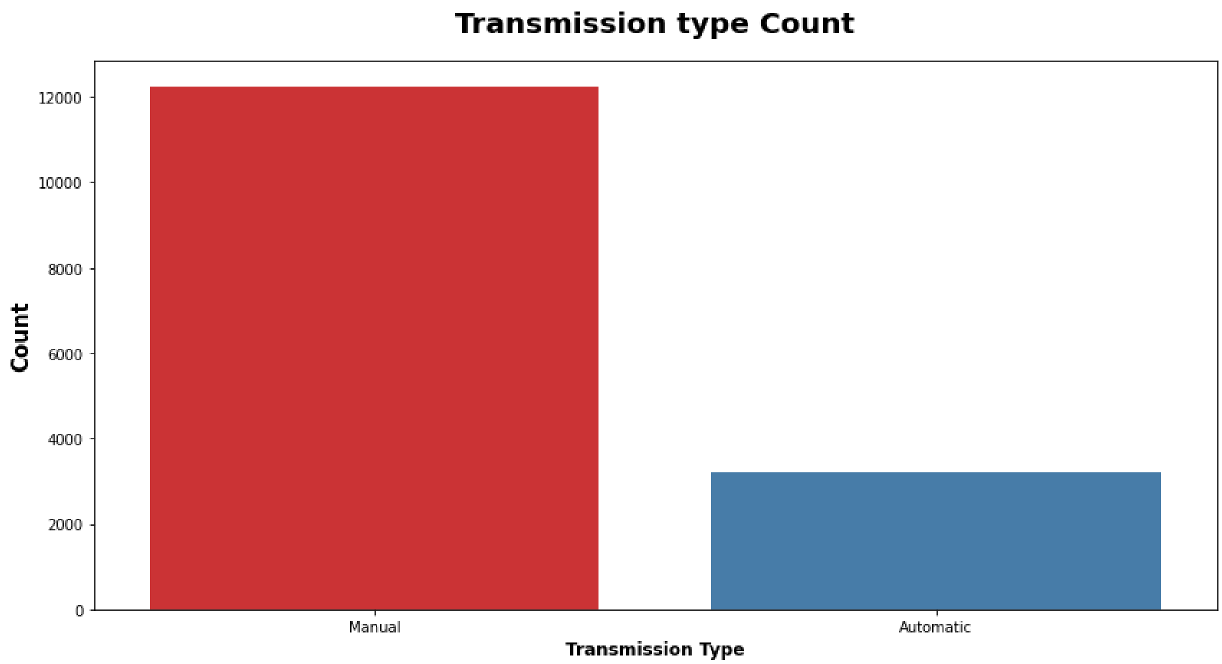
Report

Maruti Alto is the Oldest car available 29 years old in the used car website followed by BMW 3 for 25 years old.

Transmission Type

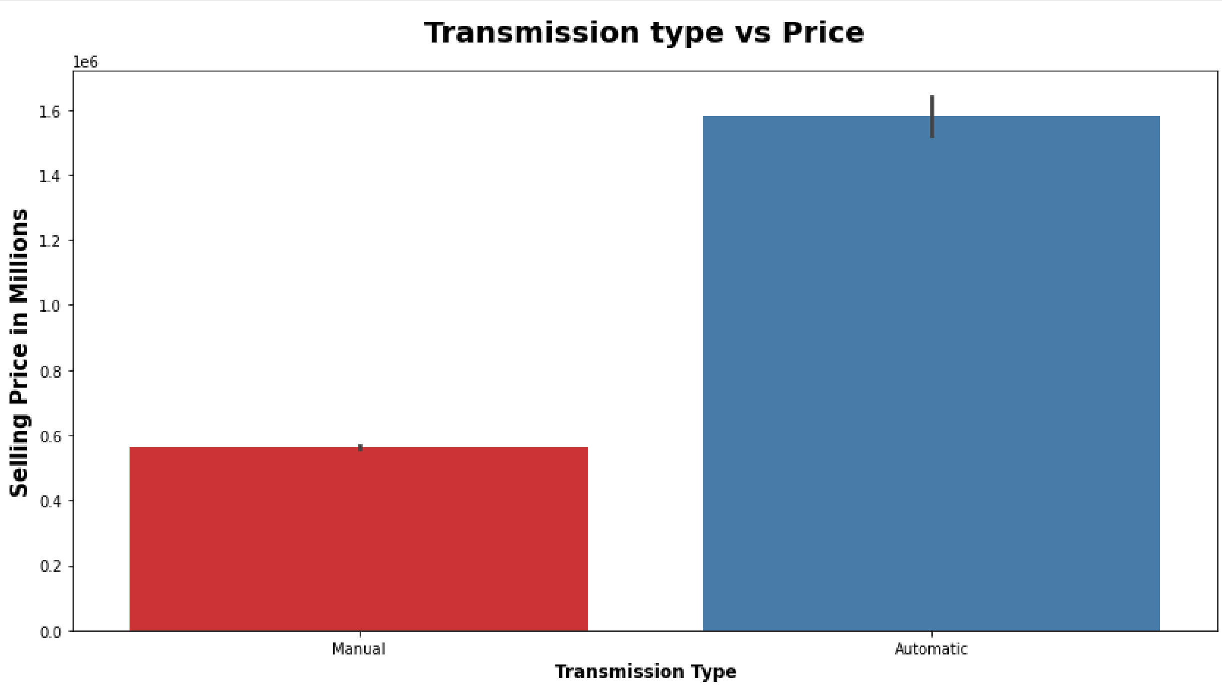
In [102]:

```
plt.subplots(figsize=(14,7))
sns.countplot(x='transmission_type', data=df,palette="Set1")
plt.title("Transmission type Count", weight="bold",fontsize=20, pad=20)
plt.ylabel("Count", weight="bold", fontsize=15)
plt.xlabel("Transmission Type", weight="bold", fontsize=12)
plt.show()
```



In [103]:

```
plt.subplots(figsize=(14,7))
sns.barplot(x='transmission_type', y='selling_price', data=df,palette="Set1"
plt.title("Transmission type vs Price", weight="bold",fontsize=20, pad=20)
plt.ylabel("Selling Price in Millions", weight="bold", fontsize=15)
plt.xlabel("Transmission Type", weight="bold", fontsize=12)
plt.show()
```



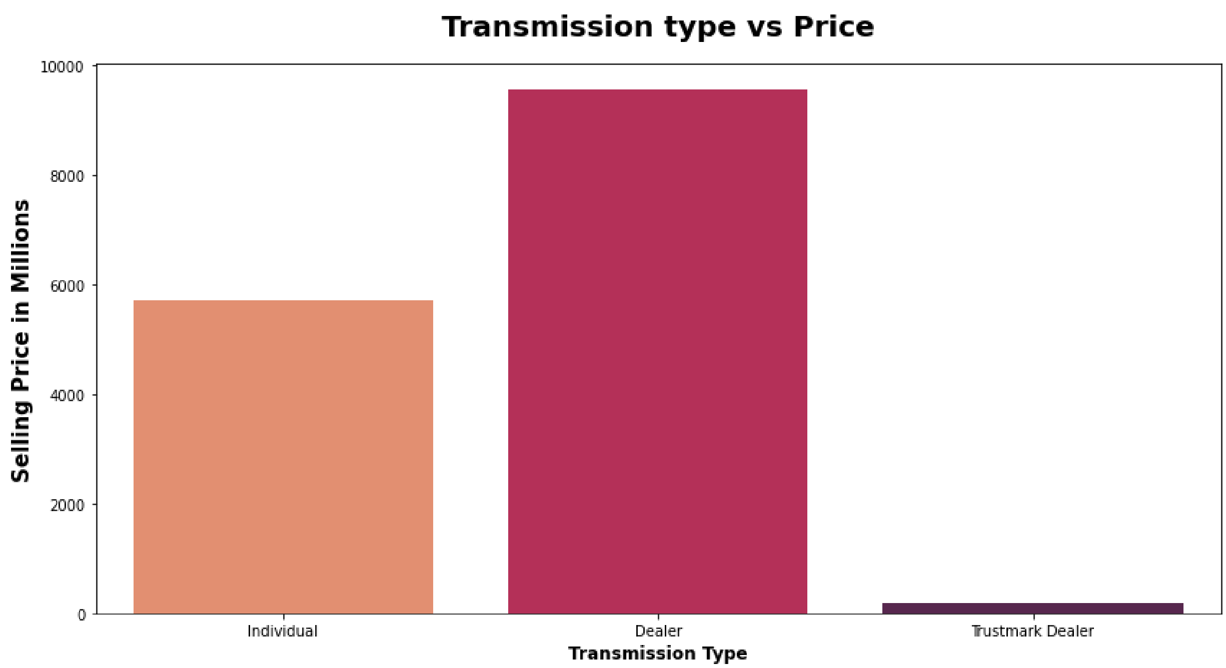
Report

Manual Transmission was found in most of the cars which was sold.
Automatic cars have more selling price than manual cars.

In [ ]:
```
1
```

Seller Type

In [104]:
```
plt.subplots(figsize=(14,7))
sns.countplot(x='seller_type', data=df,palette="rocket_r")
plt.title("Transmission type vs Price", weight="bold",fontsize=20, pad=20)
plt.ylabel("Selling Price in Millions", weight="bold", fontsize=15)
plt.xlabel("Transmission Type", weight="bold", fontsize=12)
plt.show()
```



In [105]:
```
dealer = df.groupby('seller_type')['selling_price'].median().sort_values(asc
dealer.to_frame()
```

Out[105]:

	selling_price
seller_type	
Dealer	591000.0
Trustmark Dealer	540000.0
Individual	507000.0

Report

Dealers have put more ads on used car website.
Dealers have put 9539 ads with median selling price of 5.91 Lakhs.
Followed by Individual with 5699 ads with median selling price of 5.4 Lakhs.

Dealers have more median selling price than Individual.

Final Report

The datatypes and Column names were right and there was 15411 rows and 13 columns
The selling_price column is the target to predict. i.e Regression Problem.
There are outliers in the km_driven, enginer, selling_price, and max power.
Dealers are the highest sellers of the used cars.
Skewness is found in few of the columns will check it after handling outliers.
Vehicle age has negative impact on the price.
Manual cars are mostly sold and automatic has higher selling average than manual cars.
Petrol is the most preffered choice of fuel in used car website, followed by diesel and LPG.
We just need less data cleaning for this dataset.

In [ ]:

```
1
```