Used Car Price Prediction

Life cycle of Machine learning Project

- Understanding the Problem Statement
- Data Collection
- Exploratory data analysis
- Data Cleaning
- Data Pre-Processing
- Model Training
- Choose best model

1) Problem statement.

- This dataset comprises used cars sold on cardehko.com in India as well as important features of these cars.
- If user can predict the price of the car based on input features.
- Prediction results can be used to give new seller the price suggestion based on market condition.

2) Data Collection.

- The Dataset is collected from scrapping from cardheko webiste
- The data consists of 13 column and 15411 rows.

2.1 Import Data and Required Packages

Importing Pandas, Numpy, Matplotlib, Seaborn and Warings Library.

In [3]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
import warnings
from six.moves import urllib

warnings.filterwarnings("ignore")

%matplotlib inline
```

Download and Import the CSV Data as Pandas DataFrame

In [4]:
```
download_dir = "./data/"

download_url = "https://raw.githubusercontent.com/aravind9722/datasets-for-M

os.makedirs(download_dir,exist_ok=True)

filename = os.path.basename(download_url)

download_file_path = os.path.join(download_dir, filename)

urllib.request.urlretrieve(download_url, download_file_path)

df = pd.read_csv(download_file_path, index_col=[0])
```

Show Top 5 Records

In [5]:
```
df.head()
```

Out[5]:

	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

Shape of the dataset

In [6]:
```
df.shape
```

Out[6]: (15411, 13)

Summary of the dataset

In [7]:

```
# Display summary statistics for a dataframe
df.describe()
```

Out[7]:

	vehicle_age	km_driven	mileage	engine	max_power	seats	selling
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 Datatypes in the dataset

In [8]:

```
# Check Null and Dtypes
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 15411 entries, 0 to 19543
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: 1.6+ MB
```

3. EXPLORING DATA

In [9]:

```
# define numerical & categorical columns
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('We have {} numerical features : {}'.format(len(numeric_features), num
print('\nWe have {} categorical features : {}'.format(len(categorical_featur
```

```
We have 7 numerical 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

- **car_name:** Car's Full name, which includes brand and specific model name.
- **brand:** Brand Name of the particular car.
- **model:** Exact model name of the car of a particular brand.
- **seller_type:** Which Type of seller is selling the used car
- **fuel_type:** Fuel used in the used car, which was put up on sale.
- **transmission_type:** Transmission used in the used car, which was put on sale.
- **vehicle_age:** The count of years since car was bought.
- **mileage:** It is the number of kilometer the car runs per litre.
- **engine:** It is the engine capacity in cc(cubic centimeters)
- **max_power:** Max power it produces in BHP.
- **seats:** Total number of seats in car.
- **selling_price:** The sale price which was put up on website.

In [10]:
```
# 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
---------------------------
```

Univariate Analysis

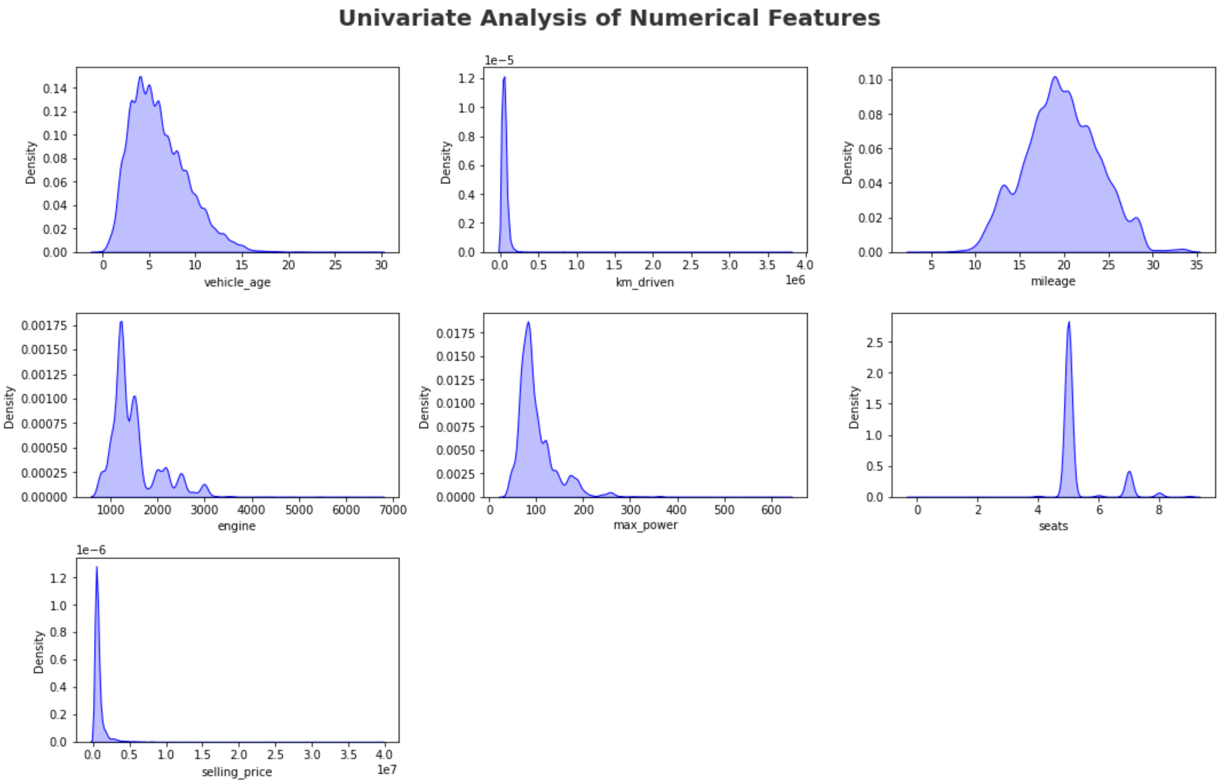
- The term univariate analysis refers to the analysis of one variable prefix “uni” means “one.” The purpose of univariate analysis is to understand the distribution of values for a single variable.

Numerical Features

In [12]:

```
plt.figure(figsize=(15, 15))
plt.suptitle('Univariate Analysis of Numerical Features', fontsize=20, fontw

for i in range(0, 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()
```

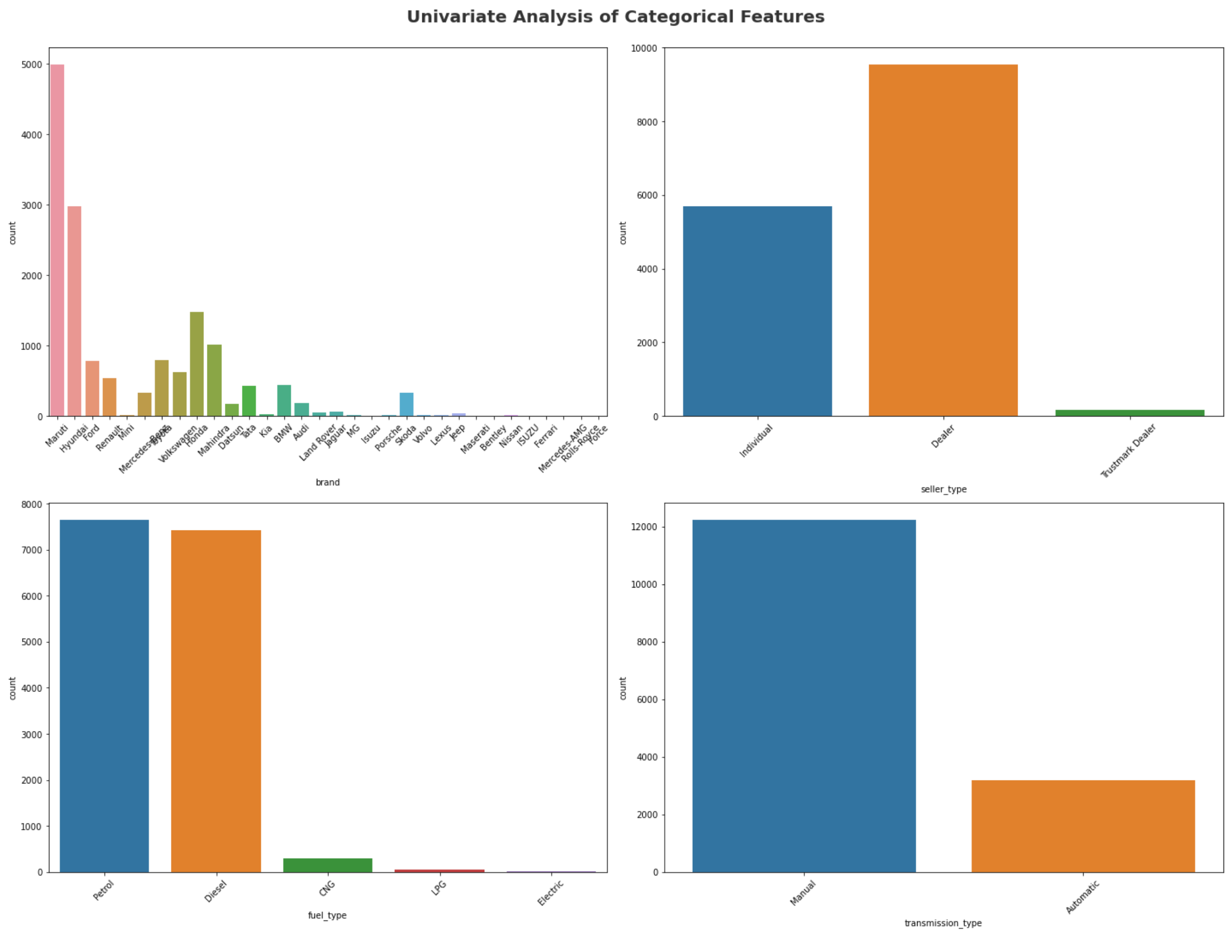


Report

- Km_driven, max_power, selling_price, and engine are right skewed and postively skewed.
- Outliers in km_driven, enginer, selling_price, and max power.

Categorical Features

In [13]:
```python
# categorical columns
plt.figure(figsize=(20, 15))
plt.suptitle('Univariate Analysis of Categorical Features', fontsize=20, fon
cat1 = [ 'brand', 'seller_type', 'fuel_type', 'transmission_type']
for i in range(0, 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()
```



Multivariate Analysis

- Multivariate analysis is the analysis of more than one variable.

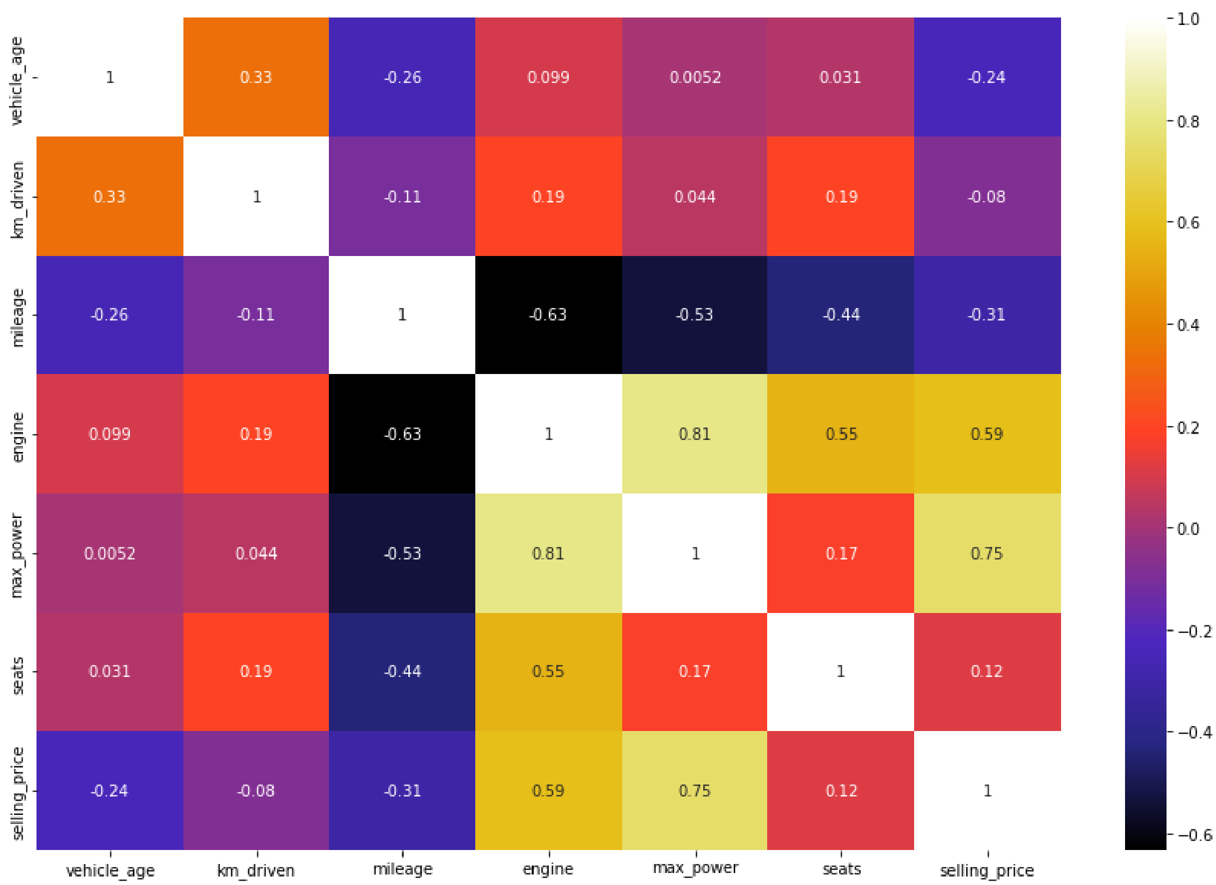
Check Multicollinearity in Numerical features

In [14]:
```
df[(list(df.columns)[1:])].corr()
```

Out[14]:

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



Report

- Our target column ProdTaken has a weak negative correlation on Age and MontlyIncome.
- The NumberOfFollowups and Passport columns also have a weak positive correlation with ProdTaken.

- The NumberOfPersonVisiting and NumberOfChildrenVisiting columns have a strong enough positive correlation.

Check Multicollinearity for Categorical features

- **A chi-squared test (also chi-square or χ2 test) is a statistical hypothesis test that is valid to perform when the test statistic is chi-squared distributed under the null hypothesis, specifically Pearson's chi-squared test**
- **A chi-square statistic is one way to show a relationship between two categorical variables.**
- **Here we test correlation of Categorical columns with Target column i.e Selling Price**

In [16]:

```
from scipy.stats import chi2_contingency
chi2_test = []
for feature in categorical_features:
    if chi2_contingency(pd.crosstab(df['selling_price'], df[feature]))[1] <
        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 = ['Column', 'Hypothesis Result']
result
```

Out[16]:

	Column	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

Checking Null Values

In [17]:
```
df.isnull().sum()
```

Out[17]:
```
car_name             0
brand                0
model                0
vehicle_age          0
km_driven            0
seller_type          0
fuel_type            0
transmission_type    0
mileage              0
engine               0
max_power            0
seats                0
selling_price        0
dtype: int64
```

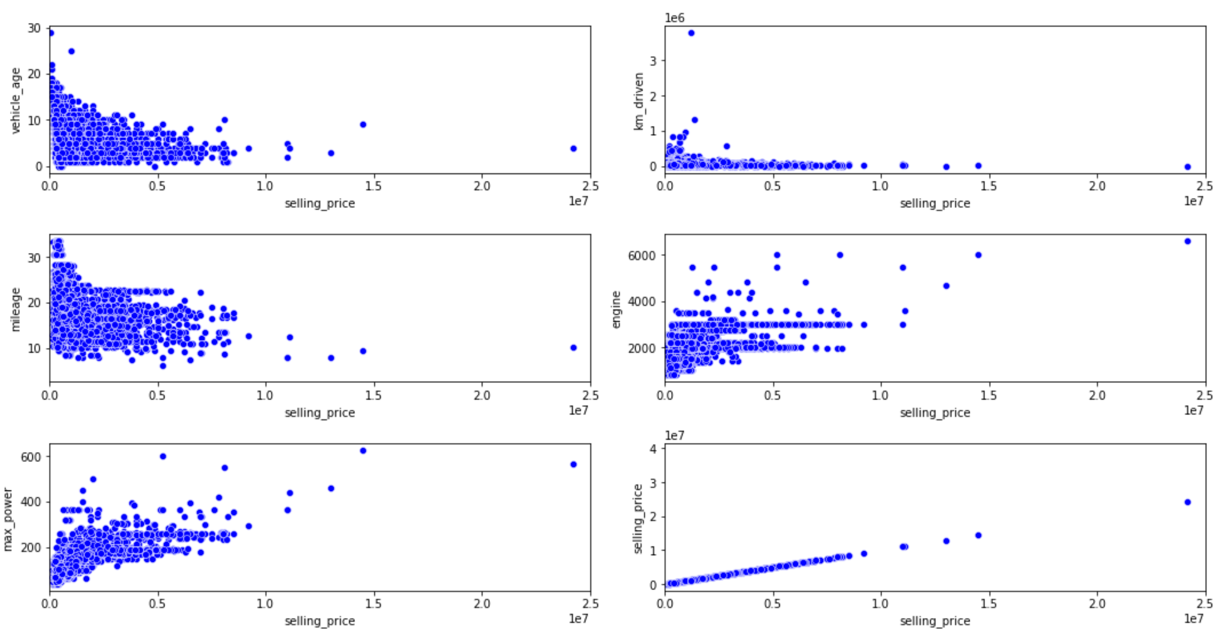
In [18]:
```
continues_features=[feature for feature in numeric_features if len(df[featur
print('Num of continues features :',continues_features)
```

```
Num of continues features : ['vehicle_age', 'km_driven', 'mileage', 'engine',
'max_power', 'selling_price']
```

In [19]:
```
fig = plt.figure(figsize=(15, 20))

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

    sns.scatterplot(data= df ,x='selling_price', y=continues_features[i], co
    plt.xlim(0,25000000) # Limit to 25 Lakhs Rupees to view clean
    plt.tight_layout()
```



Initial Analysis Report

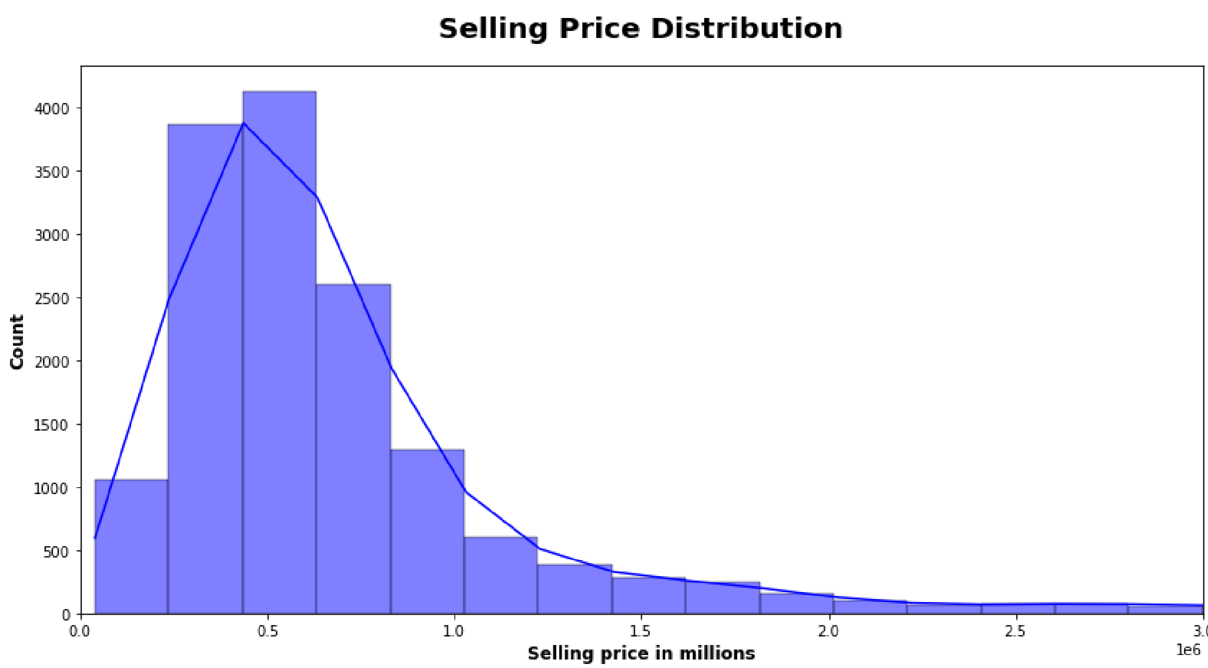
Report

- **Lower Vehicle age has more selling price than Vehicle with more age.**
- **Engine CC has positive effect on price,Vehicle with 2000 cc and below are mostly priced below 5lakh.**
- **Kms Driven has negative effect on selling price.**

4. Visualization

4.1 Visualize the Target Feature

In [20]:
```
plt.subplots(figsize=(14,7))
sns.histplot(df.selling_price, bins=200, kde=True, color = 'b')
plt.title("Selling 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()
```



- From the chart it is clear that the Target Variable Skewed

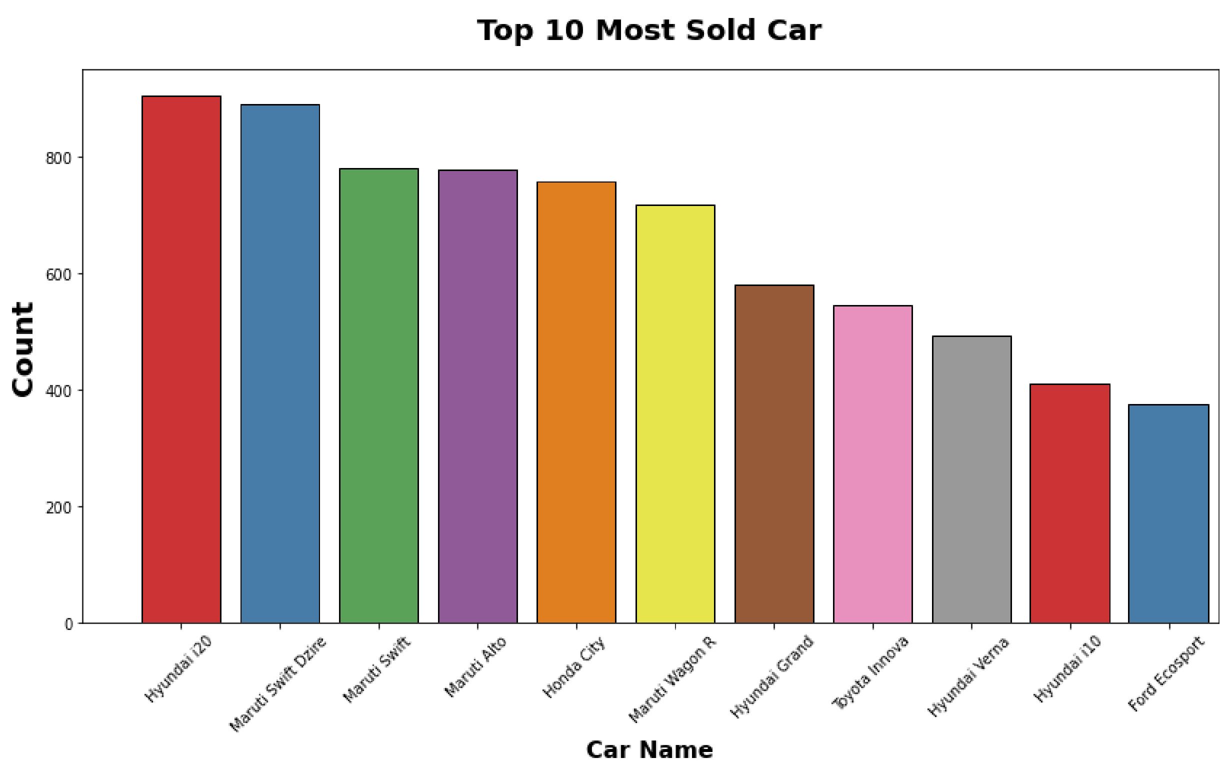
4.2 Most Selling car in Used car website?

In [21]:
```
df.car_name.value_counts()[0:10]
```

Out[21]:
```
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 [22]:
```
plt.subplots(figsize=(14,7))
sns.countplot(x="car_name", data=df,ec = "black",palette="Set1",order = df['
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 [23]:
```
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:

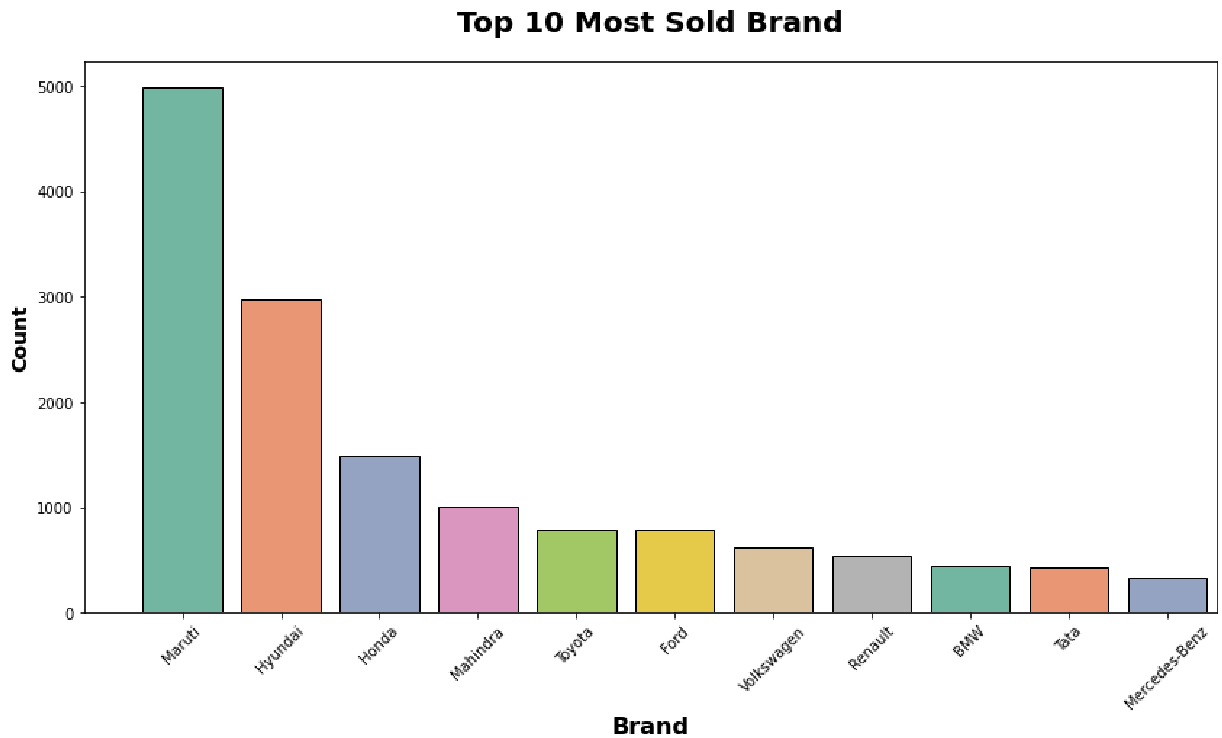
- As per the Chart these are top 10 most selling cars in used car website.
- Of the total cars sold Hyundai i20 shares 5.8% of total ads posted and followed by Maruti Swift Dzire.
- Mean Price of Most Sold Car is 5.4 lakhs.
- This Feature has impact on the Target Variable.

Most selling brand

In [24]:
```
df.brand.value_counts()[0:10]
```

Out[24]:
```
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 [25]:
```
plt.subplots(figsize=(14,7))
sns.countplot(x="brand", data=df,ec = "black",palette="Set2",order = df['bra
plt.title("Top 10 Most Sold Brand", weight="bold",fontsize=20, pad=20)
plt.ylabel("Count", weight="bold", fontsize=14)
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 [26]:
```
maruti = df[df['brand'] == 'Maruti']['selling_price'].mean()
print(f'The mean price of Maruti is {maruti:.2f} Rupees')
```

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

Report:

- As per the Chart Maruti has the most share of Ads in Used car website and Maruti is the most sold brand.
- Following Maruti we have Hyundai and Honda.
- Mean Price of Maruti Brand is 4.8 lakhs.

Costliest Brand and Costliest Car

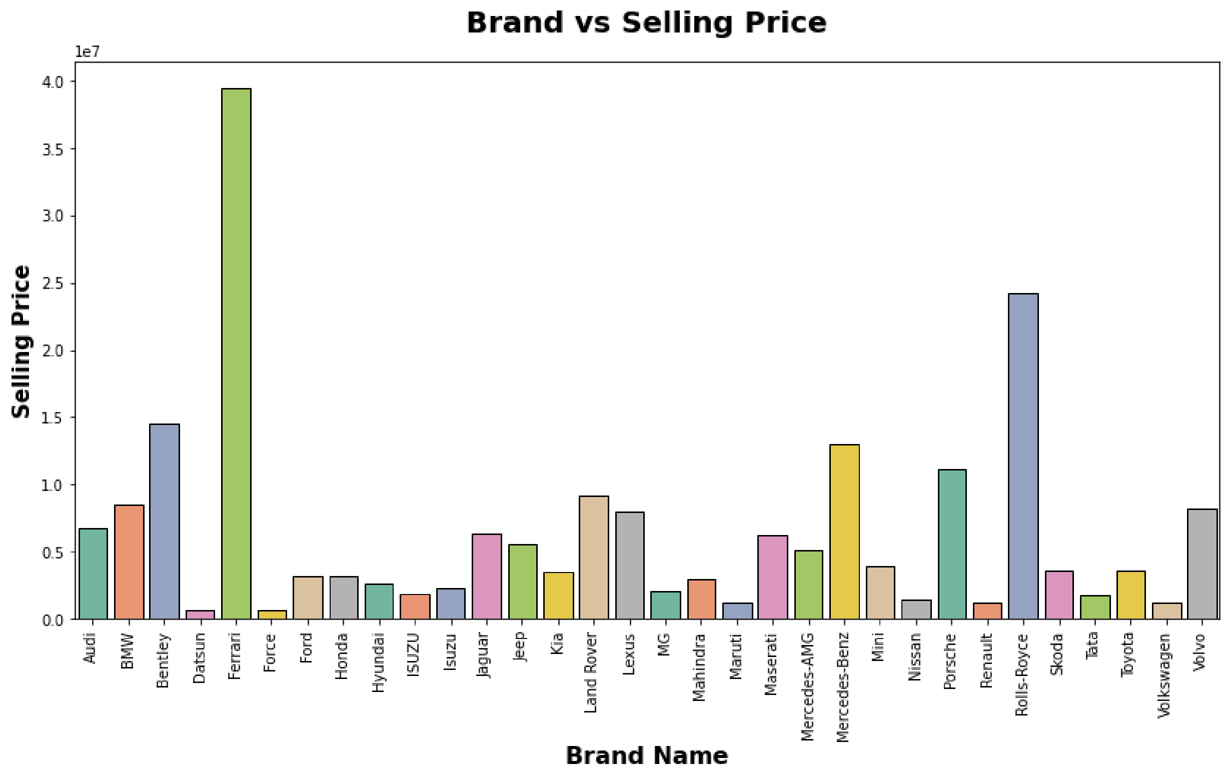
In [27]:

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

Out[27]:

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 [28]:
```
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:

- Costliest Brand sold is Ferrari at 3.95 Crores.
- Second most costliest car Brand is Rolls-Royce as 2.42 Crores.
- Brand name has very clear impact on selling price.

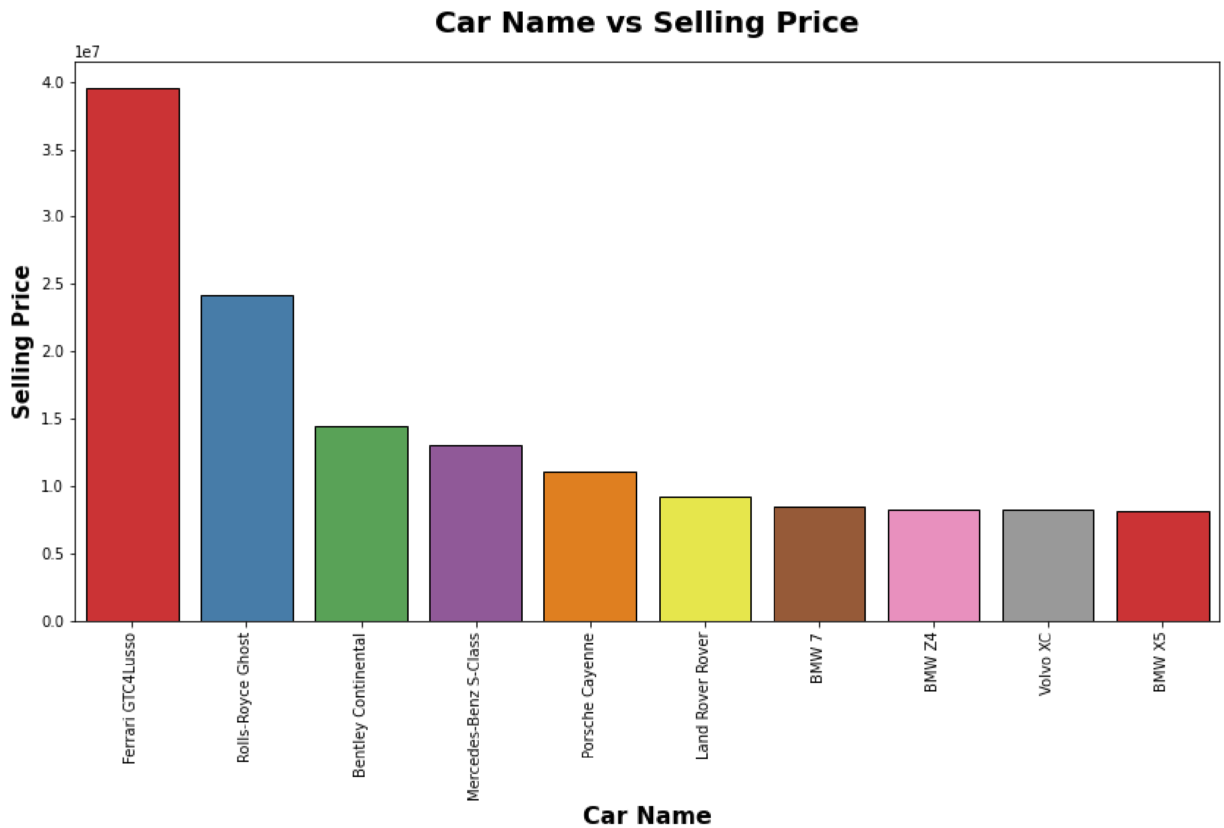
Costliest Car

In [29]:
```
car= df.groupby('car_name').selling_price.max()
car =car.to_frame().sort_values('selling_price',ascending=False)[0:10]
car
```

Out[29]:

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 [30]:
```
plt.subplots(figsize=(14,7))
sns.barplot(x=car.index, y=car.selling_price,ec = "black",palette="Set1")
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

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

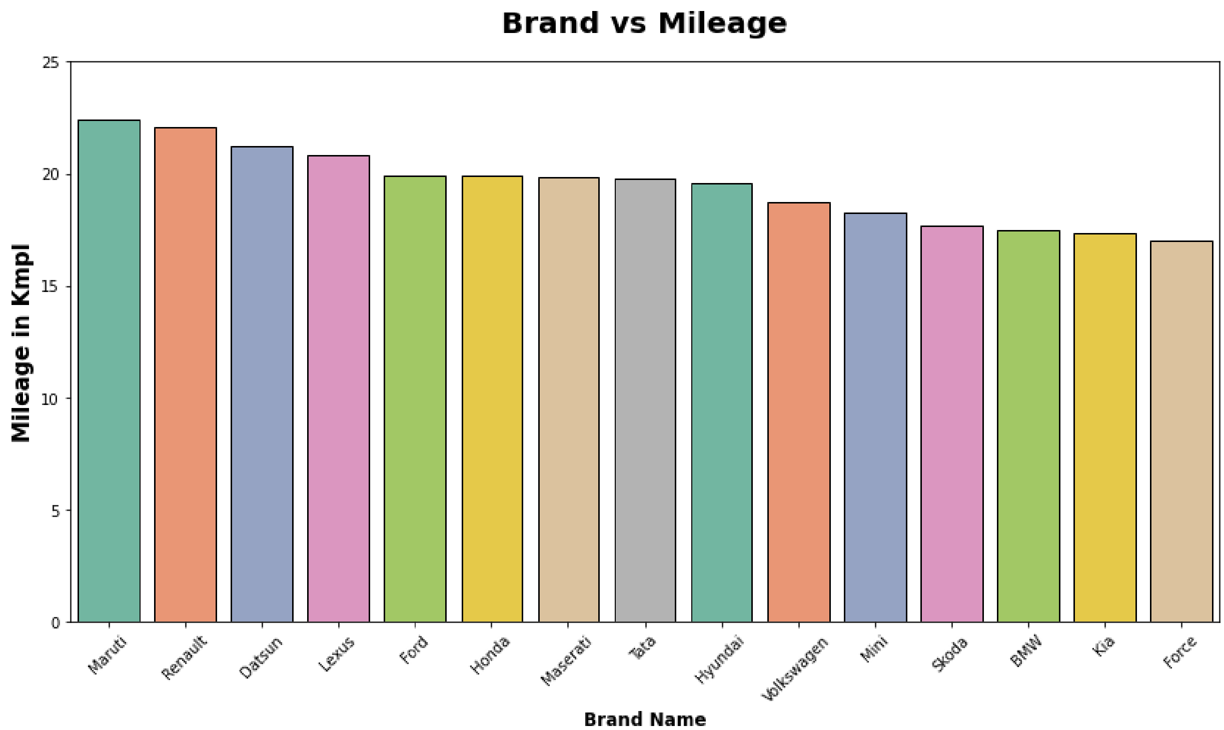
Most Mileage Brand and Car Name

In [31]:
```
mileage= df.groupby('brand')['mileage'].mean().sort_values(ascending=False).
mileage.to_frame()
```

Out[31]:

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 [32]:
```
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()
```



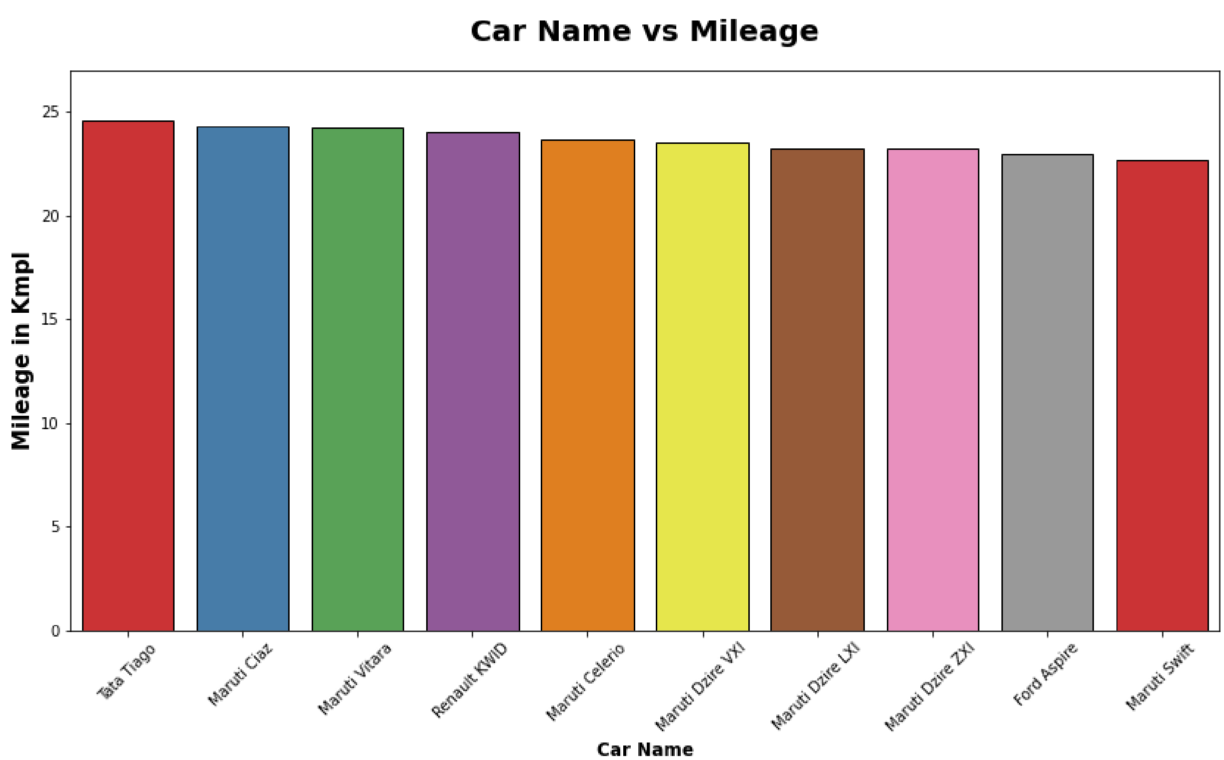
Car with Highest Mileage

In [33]:
```
mileage_C= df.groupby('car_name')['mileage'].mean().sort_values(ascending=Fa
mileage_C.to_frame()
```

Out[33]:

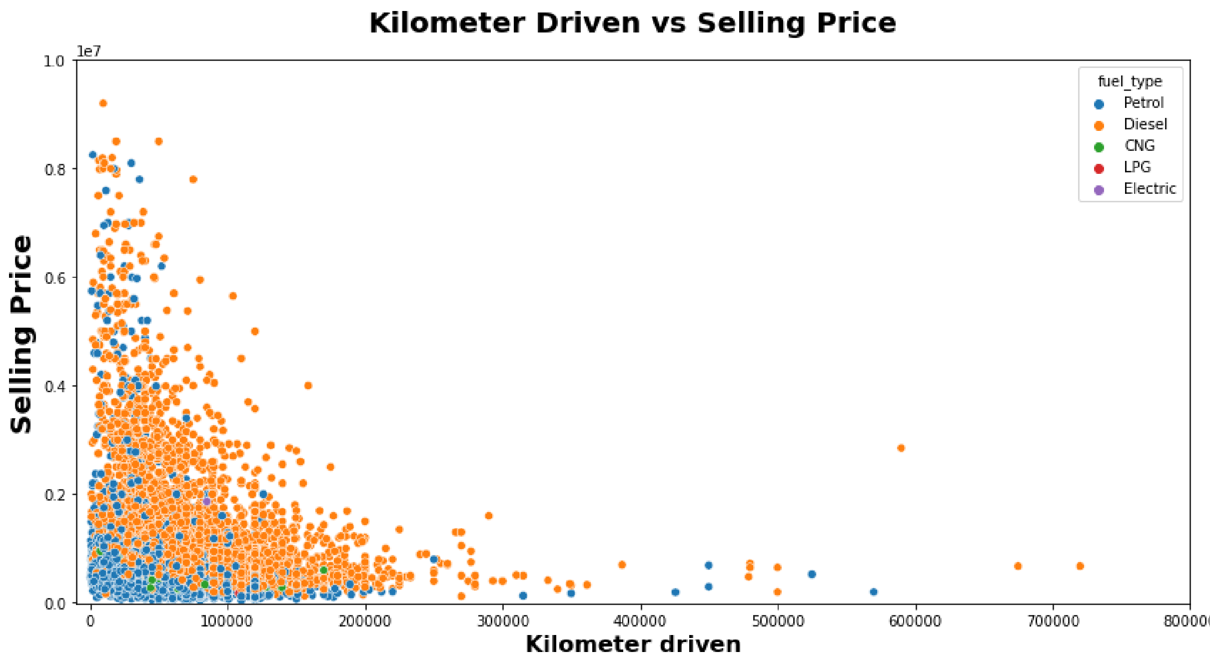
car_name	mileage
Tata Tiago	24.625103
Maruti Ciaz	24.289046
Maruti Vitara	24.231932
Renault KWID	24.037810
Maruti Celerio	23.703502
Maruti Dzire VXI	23.512941
Maruti Dzire LXI	23.260000
Maruti Dzire ZXI	23.260000
Ford Aspire	22.993846
Maruti Swift	22.719910

In [34]:
```
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 [35]:
```
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.

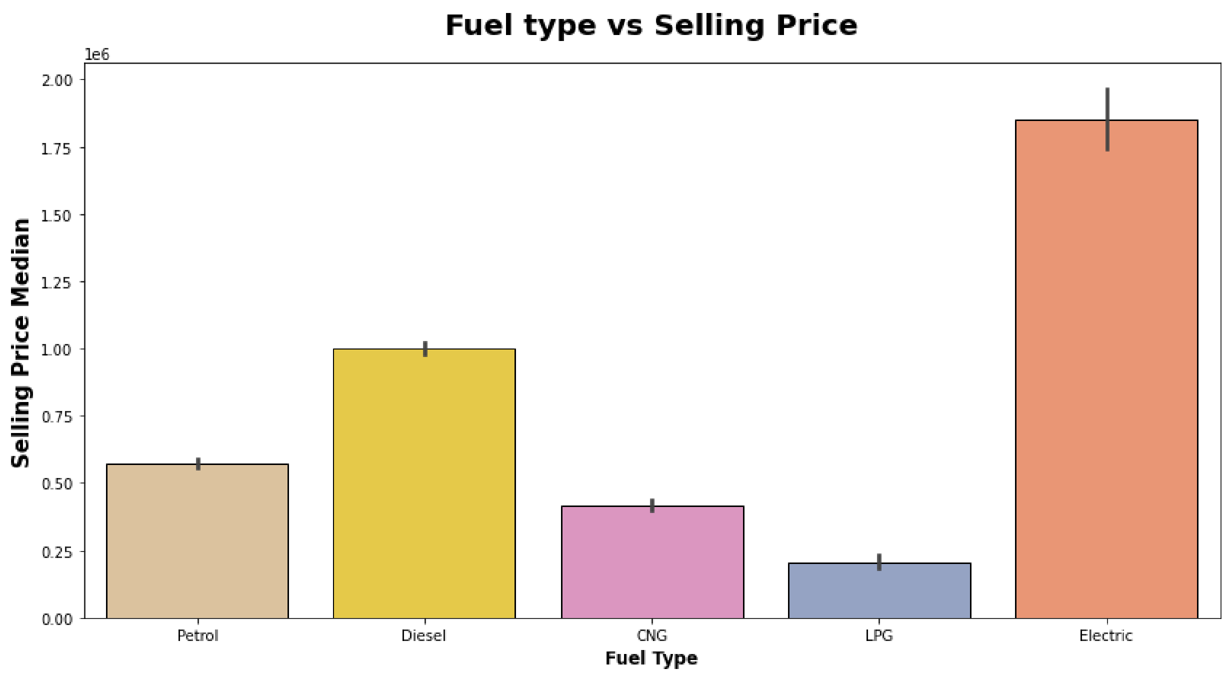
Fuel Type Selling Price

In [36]:
```
fuel = df.groupby('fuel_type')['selling_price'].median().sort_values(ascendi
fuel.to_frame()
```

Out[36]:

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

In [37]:
```
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()
```

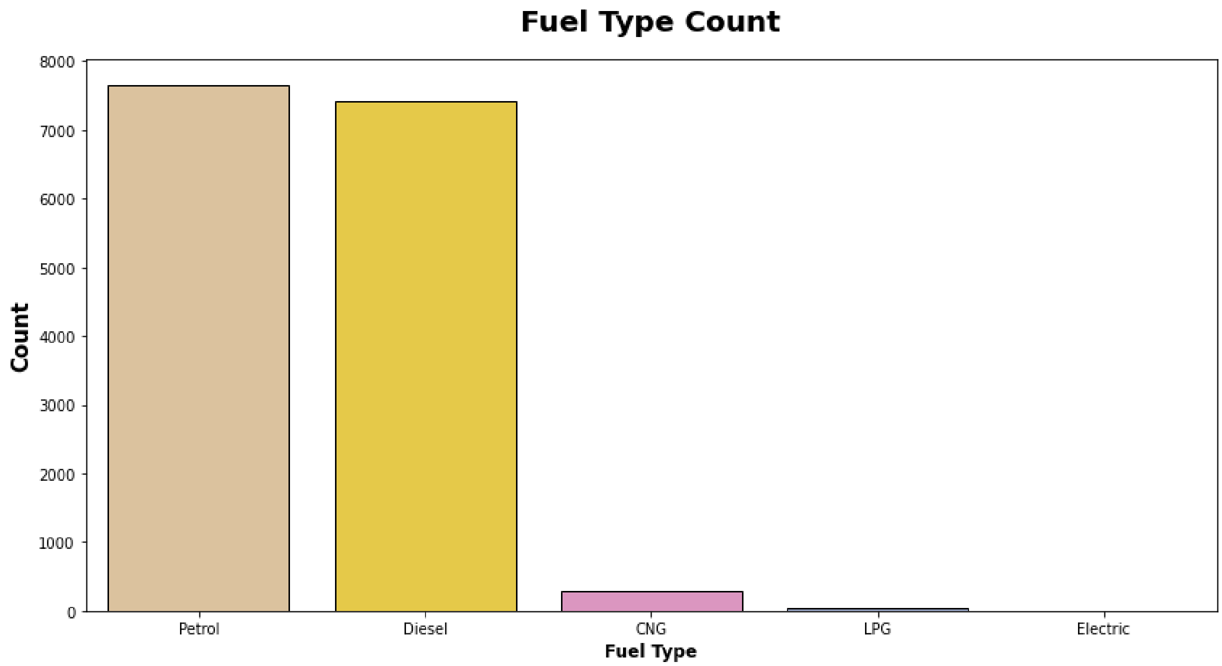


Report

- Electric cars have highers selling average price.
- Followed by Diesel and Petrol.
- Fuel Type is also important feature for the Target variable.

Most sold Fuel type

In [38]:
```
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

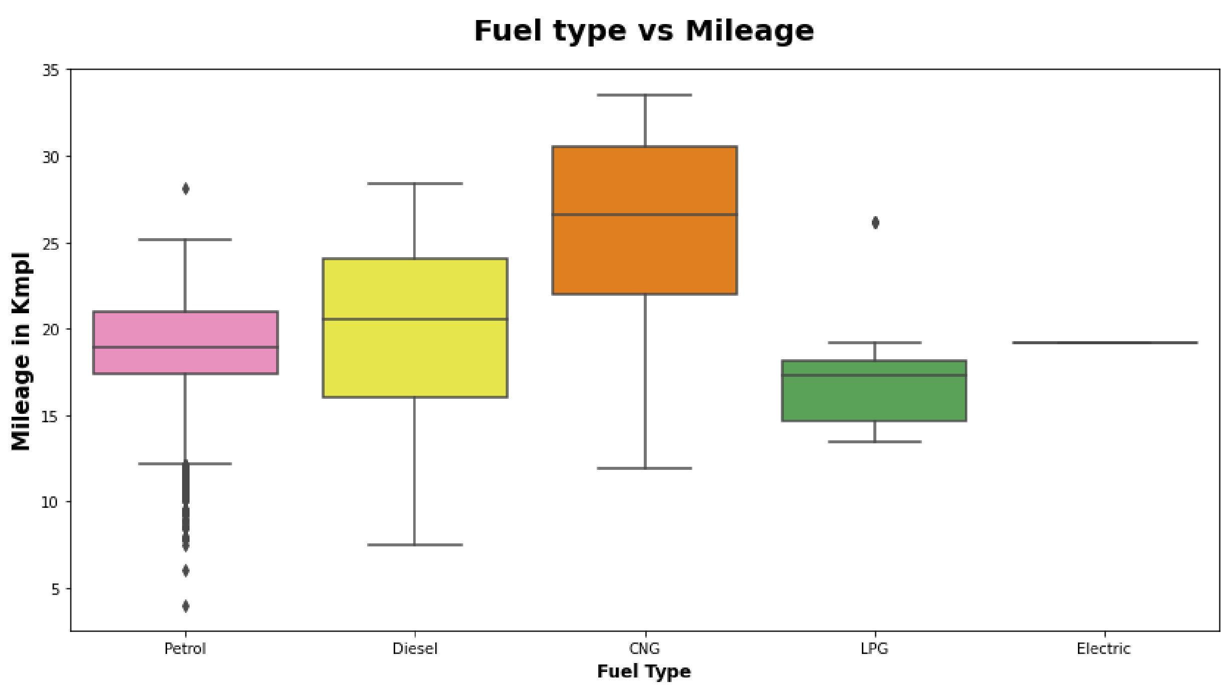
Fuel types available and mileage given

In [39]:
```
fuel_mileage = df.groupby('fuel_type')['mileage'].mean().sort_values(ascendi
fuel_mileage.to_frame()
```

Out[39]:

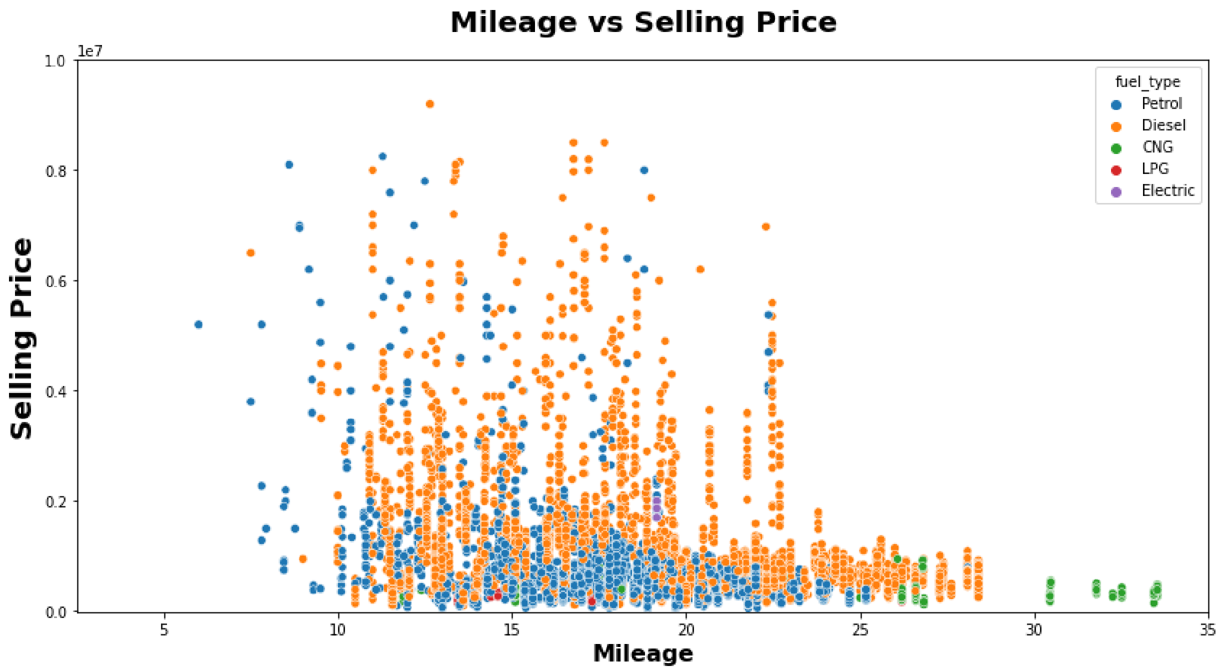
fuel_type	mileage
CNG	25.814651
Diesel	20.060030
Electric	19.160000
Petrol	19.123045
LPG	17.836364

In [40]:
```
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()
```



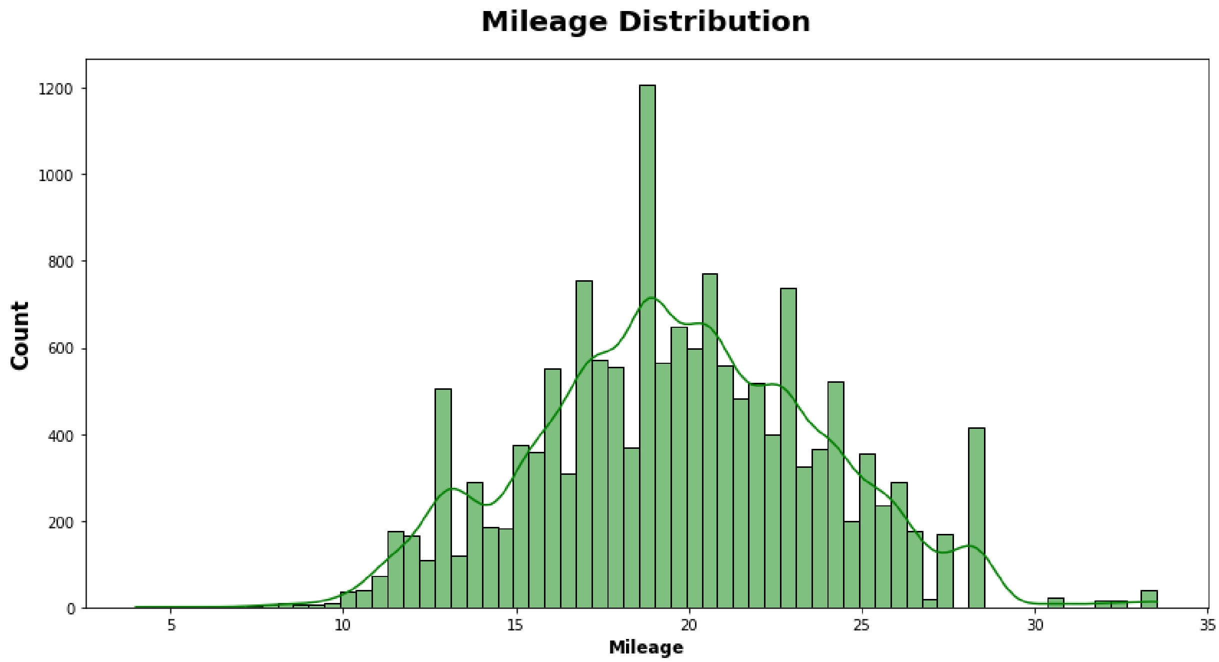
Mileage vs Selling Price

In [41]:
```
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 [42]:

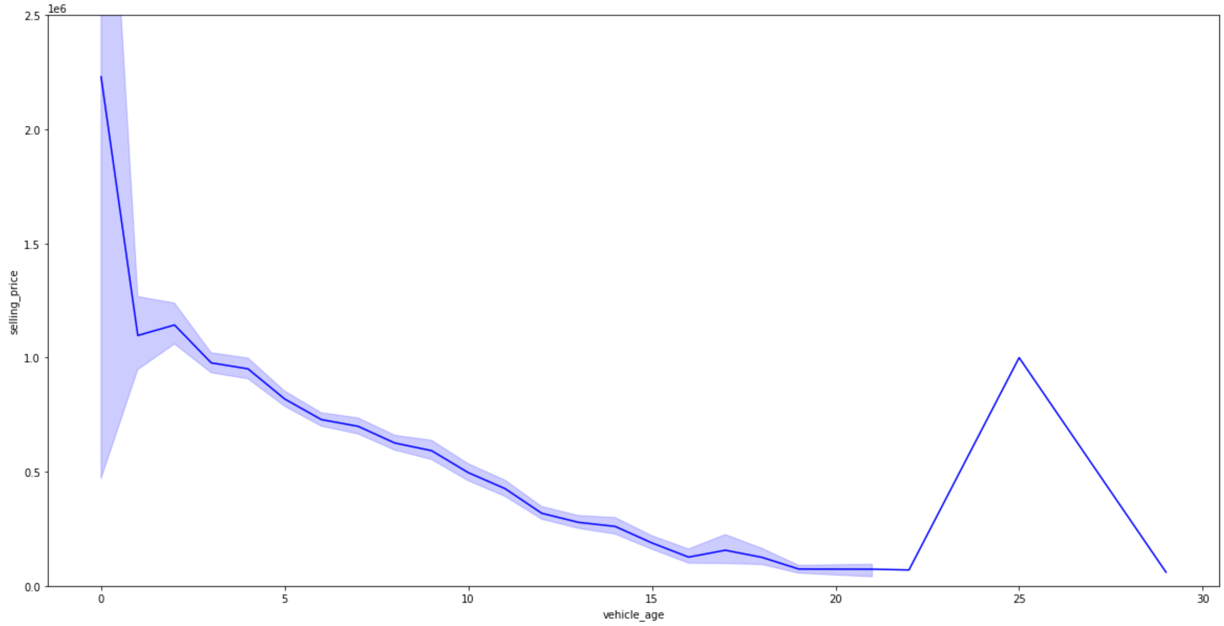
```
plt.subplots(figsize=(14,7))
sns.histplot(x=df.mileage, ec = "black", color='g', kde=True)
plt.title("Mileage Distribution", weight="bold",fontsize=20, pad=20)
plt.ylabel("Count", weight="bold", fontsize=15)
plt.xlabel("Mileage", weight="bold", fontsize=12)
plt.show()
```



Vehicle age vs Selling Price

In [43]:

```
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

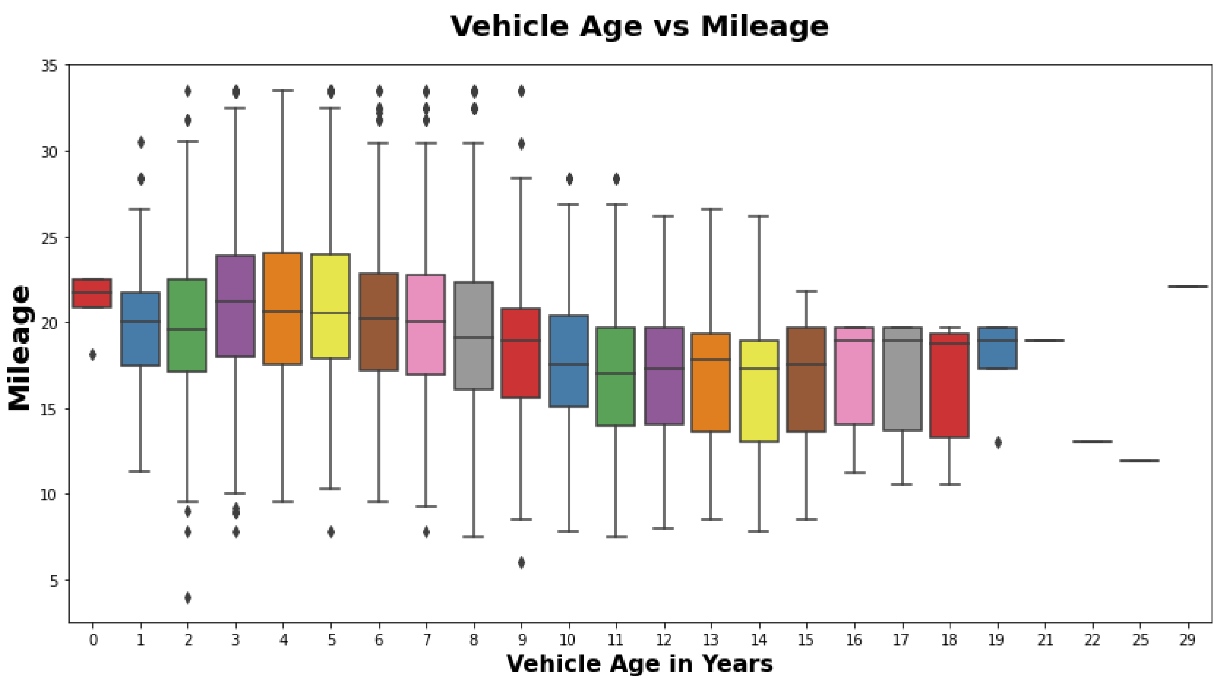
In [44]:

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

Out[44]:

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

In [45]:
```
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 [46]:
```
oldest = df.groupby('car_name')['vehicle_age'].max().sort_values(ascending=F
oldest.to_frame()
```

Out[46]:

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

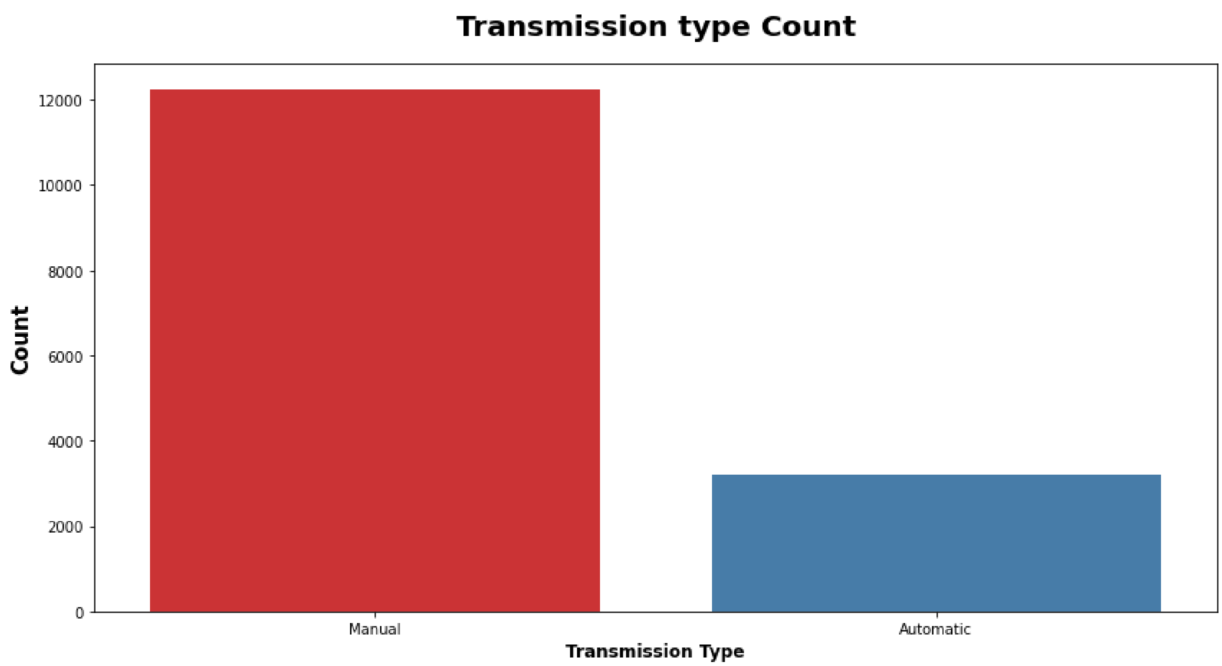
Report

- 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

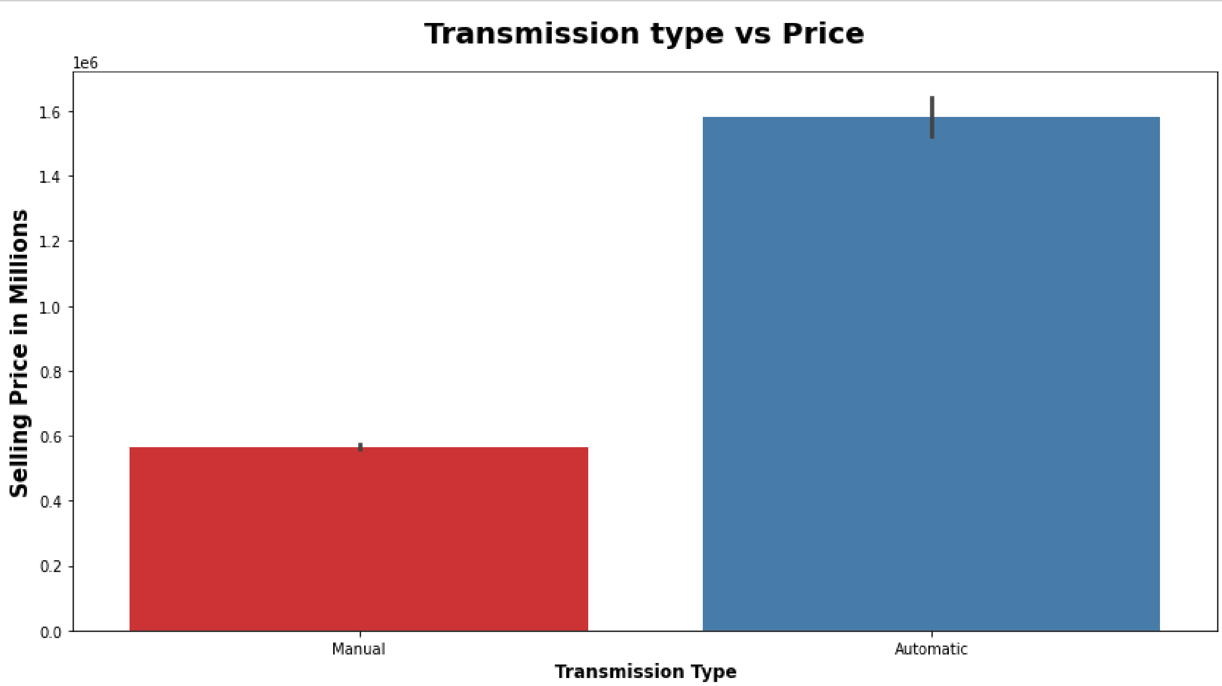
In [47]:

```
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 [48]:

```
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()
```



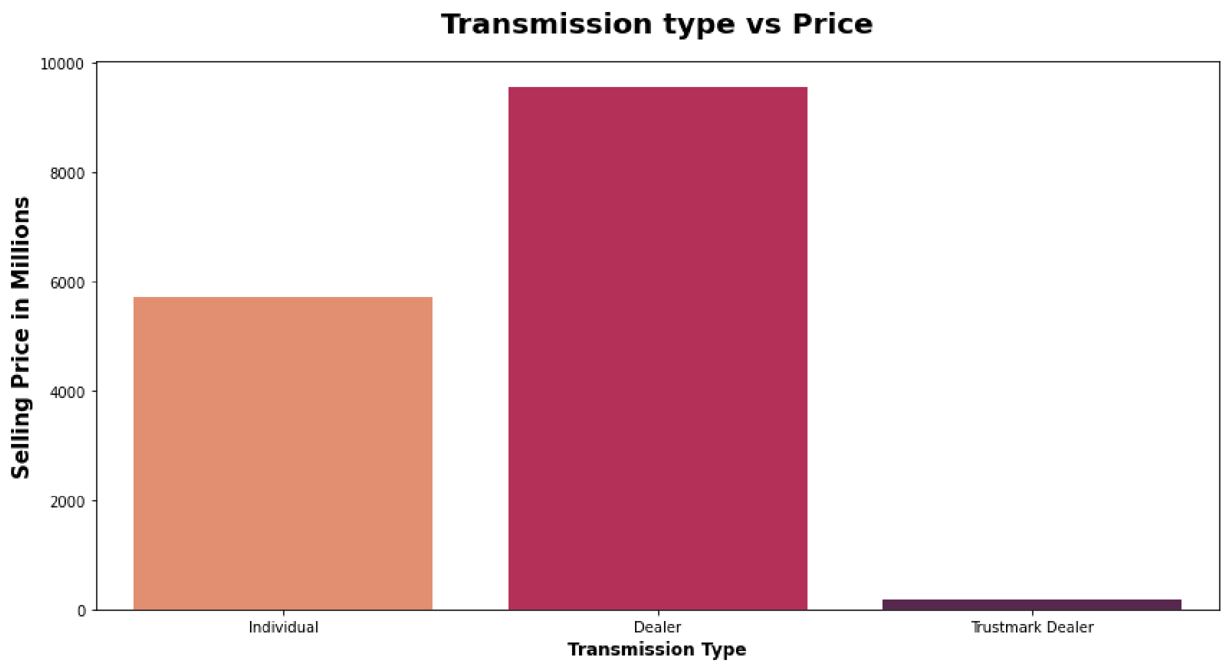
Report

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

Seller Type

In [49]:

```
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 [50]:

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

Out[50]:

seller_type	selling_price
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.