Indian Used Car Price Prediction

The aim of this project to predict the price of the used cars in indian metro cities by analyzing the car's features such as company, model, variant, fuel type, quality score and many more.

About the Dataset

The "Indian IT Cities Used Car Dataset 2023" is a comprehensive collection of data that offers valuable insights into the used car market across major metro cities in India. This dataset provides a wealth of information on a wide range of used car listings, encompassing details such as car models, variants, pricing, fuel types, dealer locations, warranty information, colors, kilometers driven, body styles, transmission types, ownership history, manufacture dates, model years, dealer names, CNG kit availability, and quality scores.

Data Dictionary

Column Name	Description
ID	Unique ID for each listing
Company	Name of the car manufacturer
Model	Name of the car model
Variant	Name of the car variant
Fuel Type	Fuel type of the car
Color	Color of the car
Killometer	Number of kilometers driven by the car
Body Style	Body style of the car
Transmission Type	Transmission type of the car
Manufacture Date	Manufacture date of the car
Model Year	Model year of the car
CngKit	Whether the car has a CNG kit or not
Price	Price of the car
Owner Type	Number of previous owners of the car
Dealer State	State in which the car is being sold
Dealer Name	Name of the dealer selling the car
City	City in which the car is being sold
Warranty	Warranty offered by the dealer

Column Name	Description
Quality Score	Quality score of the car

In [ ]:
```
#Importing the required libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [ ]:
```
#Loading the dataset
df = pd.read_csv('usedCars.csv')
df.head()
```

Out[ ]:

	Id	Company	Model	Variant	FuelType	Colour	Kilometer	BodySt
0	555675	MARUTI SUZUKI	CELERIO(2017-2019)	1.0 ZXI AMT O	PETROL	Silver	33197	HATCHB/
1	556383	MARUTI SUZUKI	ALTO	LXI	PETROL	Red	10322	HATCHB/
2	556422	HYUNDAI	GRAND I10	1.2 KAPPA ASTA	PETROL	Grey	37889	HATCHB/
3	556771	TATA	NEXON	XT PLUS	PETROL	A Blue	13106	HATCHB/
4	559619	FORD	FIGO	EXI DURATORQ 1.4	DIESEL	Silver	104614	HATCHB/

Data Preprocessing Part 1

In [ ]:
```
#Shape of the dataset
df.shape
```

Out[ ]: (1064, 19)

In [ ]:
```
#colums in the dataset
df.columns
```

Out[ ]:
```
Index(['Id', 'Company', 'Model', 'Variant', 'FuelType', 'Colour', 'Kilometer',
       'BodyStyle', 'TransmissionType', 'ManufactureDate', 'ModelYear',
       'CngKit', 'Price', 'Owner', 'DealerState', 'DealerName', 'City',
       'Warranty', 'QualityScore'],
      dtype='object')
```

In [ ]:
```
#dropping column ID, as it is a identifier and not required for analysis
df.drop('Id',axis=1,inplace=True)
```

In [ ]:
```
#Column Data Types
df.dtypes
```

```
Out[ ]: Company              object
        Model                object
        Variant              object
        FuelType             object
        Colour               object
        Kilometer             int64
        BodyStyle            object
        TransmissionType     object
        ManufactureDate      object
        ModelYear             int64
        CngKit               object
        Price                object
        Owner                object
        DealerState          object
        DealerName           object
        City                 object
        Warranty              int64
        QualityScore        float64
        dtype: object
```

Type casting Price column to float

```
In [ ]: def convert_amount(amount_str):
            if "Lakhs" in amount_str:
                return float(amount_str.replace(' Lakhs', '').replace(',', '')) * 100000
            else:
                return float(amount_str.replace(',', ''))

        df['Price'] = df['Price'].apply(convert_amount)
```

```
In [ ]: #Checking for null values percentage wise
        df.isnull().sum()/df.shape[0]*100
```

```
Out[ ]: Company              0.000000
        Model                0.000000
        Variant              0.000000
        FuelType             0.093985
        Colour               0.000000
        Kilometer            0.000000
        BodyStyle            0.000000
        TransmissionType    67.105263
        ManufactureDate      0.000000
        ModelYear            0.000000
        CngKit              97.932331
        Price                0.000000
        Owner                0.000000
        DealerState          0.000000
        DealerName           0.000000
        City                 0.000000
        Warranty             0.000000
        QualityScore         0.000000
        dtype: float64
```

Here in the dataset, three columns have missing values - FuelType, TransmissionType and CngKit. I will be removing the CngKit column becuase in majority of the cars don't run on CNG and the CNG cars can be easily identified from the FuelType column. So we will replace the null values with 'No' in CngKit column. In case of the TransmissionType, 67%

data is missing, so we can't include this column in our analysis. In case of the FuelType, we will drop the rows with null values.

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

In [ ]:
```
#Dropping TransmissionType column
df.drop('TransmissionType',axis=1,inplace=True)
```

In [ ]:
```
#Removing null values from FuelType column
df['FuelType'].dropna(inplace=True)
```

Dropping ManufacturerDate column as it the age of the car and we already have the ModelYear column

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

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

Changing the model year column to car age column

In [ ]:
```
df['ModelYear'] = 2023 - df['ModelYear']
df.rename(columns={'ModelYear':'Age'},inplace=True)
```

In [ ]:
```
for i in df.columns:
    print(i,df[i].nunique())
```

```
Company 23
Model 218
FuelType 5
Colour 76
Kilometer 1006
BodyStyle 10
Age 17
Price 362
Owner 4
DealerState 10
DealerName 57
City 11
Warranty 2
QualityScore 43
```

Descriptive Statistics

In [ ]:
```
df.describe()
```

Out[ ]:

	Kilometer	Age	Price	Warranty	QualityScore
count	1064.000000	1064.000000	1.064000e+03	1064.000000	1064.000000
mean	52807.187970	6.135338	8.350536e+05	0.738722	7.770207
std	33840.296979	2.996786	5.726538e+05	0.439538	0.719717
min	101.000000	0.000000	9.500000e+04	0.000000	0.000000
25%	32113.500000	4.000000	4.850000e+05	0.000000	7.500000
50%	49432.000000	6.000000	6.750000e+05	1.000000	7.800000
75%	68828.500000	8.000000	9.850000e+05	1.000000	8.100000
max	640000.000000	20.000000	8.500000e+06	1.000000	9.400000

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

Out[ ]:

	Company	Model	FuelType	Colour	Kilometer	BodyStyle	Age	Price
0	MARUTI SUZUKI	CELERIO(2017-2019)	PETROL	Silver	33197	HATCHBACK	5	575000.0
1	MARUTI SUZUKI	ALTO	PETROL	Red	10322	HATCHBACK	2	435000.0
2	HYUNDAI	GRAND I10	PETROL	Grey	37889	HATCHBACK	8	470000.0
3	TATA	NEXON	PETROL	A Blue	13106	HATCHBACK	3	990000.0
4	FORD	FIGO	DIESEL	Silver	104614	HATCHBACK	13	270000.0

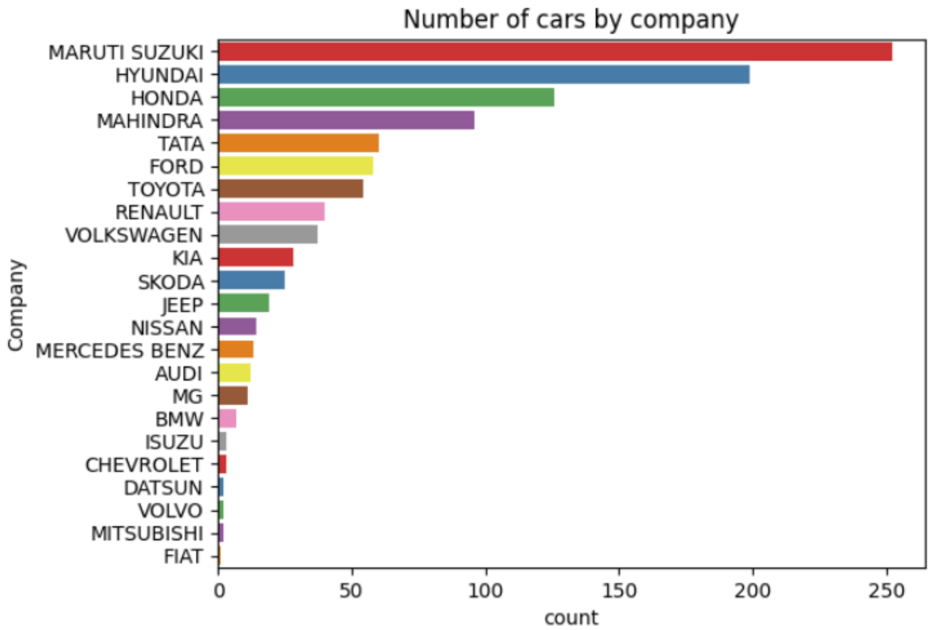
Exploratory Data Analysis

In the exploratory data analysis, I will be looking at the distribution of data across all the columns, in order to understand the data in a better way. After that I will be looking at the relationship between the target variable and the independent variables.

Car Company

In [ ]:
```
#Number of cars by company
sns.countplot(df['Company'],order=df['Company'].value_counts().index, palette =
```

Out[ ]:
```
Text(0.5, 1.0, 'Number of cars by company')
```

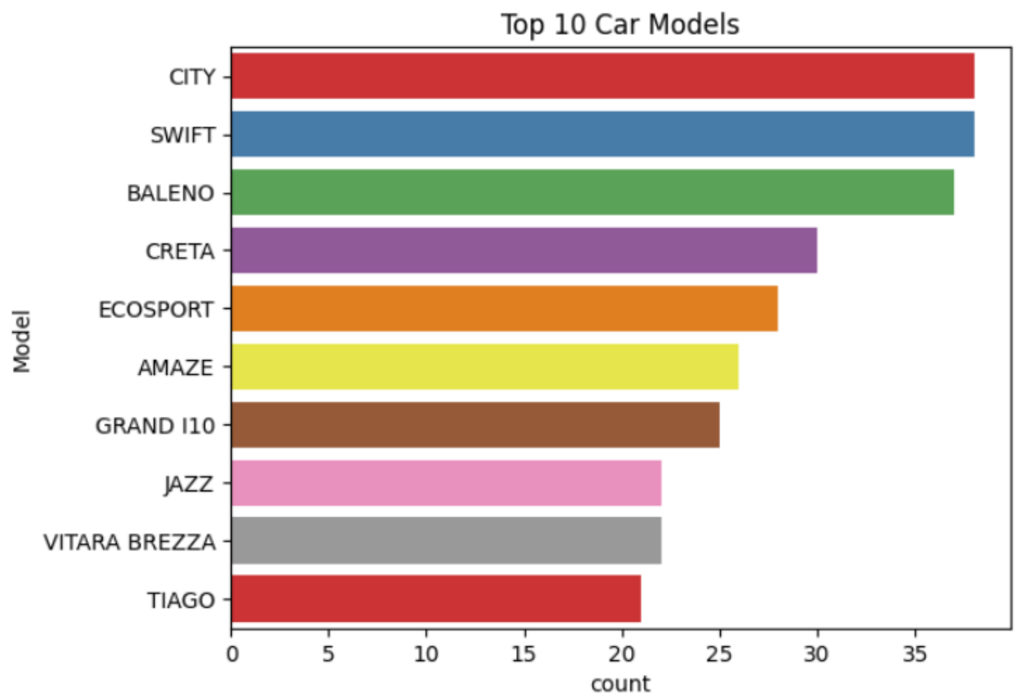


From this graph, we get know about the distribution of cars in the dataset from different companies.There are total 23 companies in the dataset, out which Maruti Suzuki, Hyundai, Honda, Mahindra and Tata are the top five companies who used cars are for sale. Therefore, we can assume that these company's car are more durable and have a good resale value.

Top 10 Car Models

In [ ]:
```
#Top 10 cars models by number
sns.countplot(df['Model'],order=df['Model'].value_counts().iloc[:10].index, pale
```

Out[ ]:
```
Text(0.5, 1.0, 'Top 10 Car Models')
```

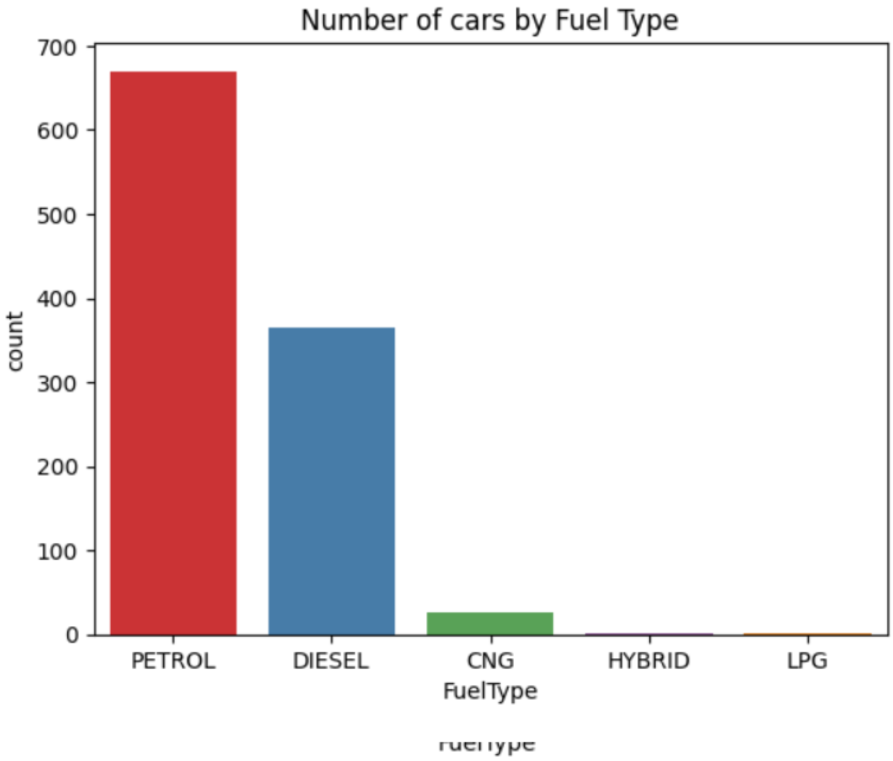


Honda City and Swift are the top two car models in the dataset, followed by Baleno, Creata and EcoSport. Therefore, we can assume that these car models are more durable and have a good resale value. Moreover, this graph also shows that Honda City and Swift are more in demand in the used car market.

Car Fuel Type

In [ ]:
```
#Cars count by fuel type
sns.countplot(x = 'FuelType', data = df, palette = 'Set1').set_title('Number of
```

Out[ ]:
```
Text(0.5, 1.0, 'Number of cars by Fuel Type')
```



Majority of cars for resale have a petrol engine which is more than 650 cars, followed by 350 cars with diesel engine. Very few of the cars have CNG engine and negligible number of cars are hybrid or on LPG. Thereofore, we can assume that petrol and diesel cars are more in demand in the used car market.

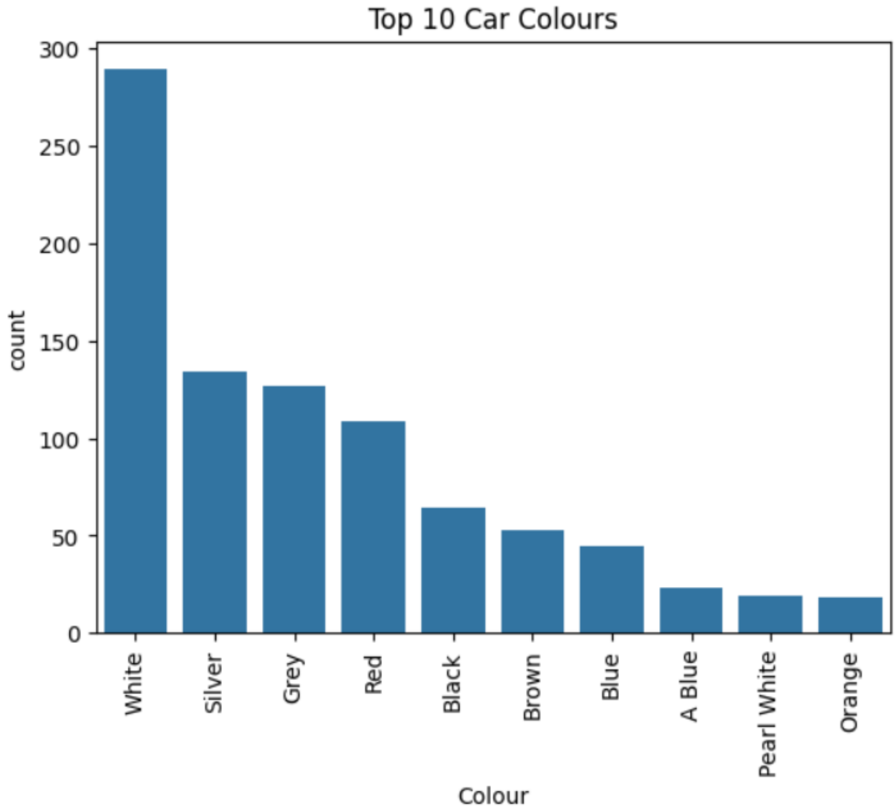
Top 10 Colors for Cars

In [ ]:

```
#Top 10 colors of cars
sns.countplot(x = 'Colour', data = df, order = df['Colour'].value_counts().iloc[
plt.xticks(rotation = 90)
```

Out[ ]:

```
([0, 1, 2, 3, 4, 5, 6, 7, 8, 9],
 [Text(0, 0, 'White'),
  Text(1, 0, 'Silver'),
  Text(2, 0, 'Grey'),
  Text(3, 0, 'Red'),
  Text(4, 0, 'Black'),
  Text(5, 0, 'Brown'),
  Text(6, 0, 'Blue'),
  Text(7, 0, 'A Blue'),
  Text(8, 0, 'Pearl White'),
  Text(9, 0, 'Orange')])
```



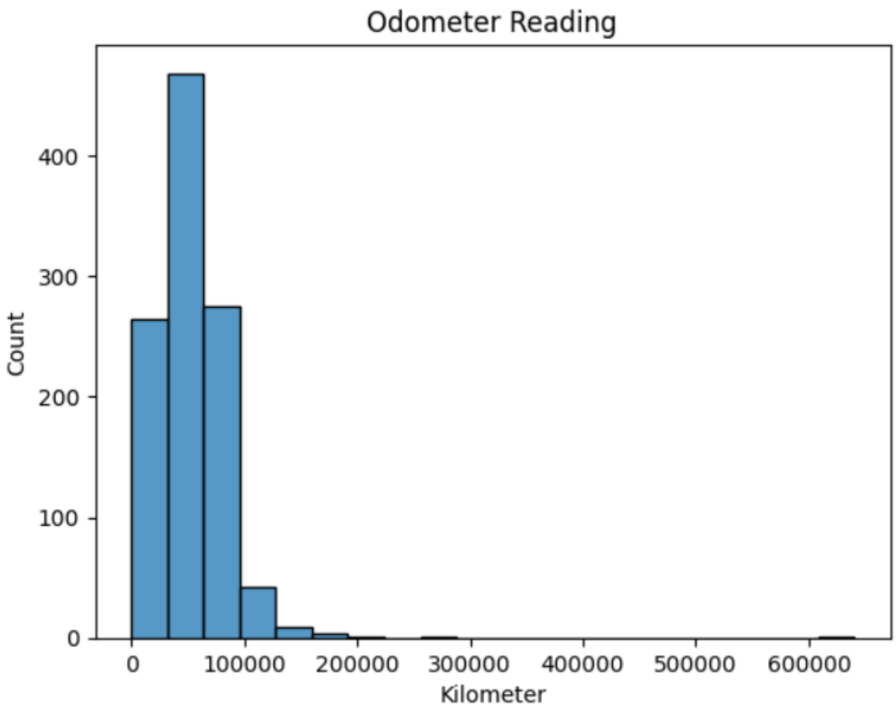
Colour

Although color of car has no impact on the cars performance, but still it plays a major role in the car demand. From the graph, we can see that white color is the most preferred color for the used cars, followed by silver, grey, red and black. Therefore, we can assume that white, silver, grey, red and black color cars are more in demand in the used car market will have a good resale value.

Odometre Reading

In [ ]:
```
#Odometer reading distribution
sns.histplot(x = 'Kilometer', data = df, bins = 20).set_title('Odometer Reading'
```

Out[ ]:
```
Text(0.5, 1.0, 'Odometer Reading')
```



This graph shows the distribution of the odometer readings of the cars in the dataset. From the graph, we can see that most of the cars have odometer reading less than 100000 km. To be more particular majority of cars are driven for 30000 km to 50000 km. Thefore, we can assume that cars with odometer reading less than 100000 km are more in demand in the used car market will have a good resale value.

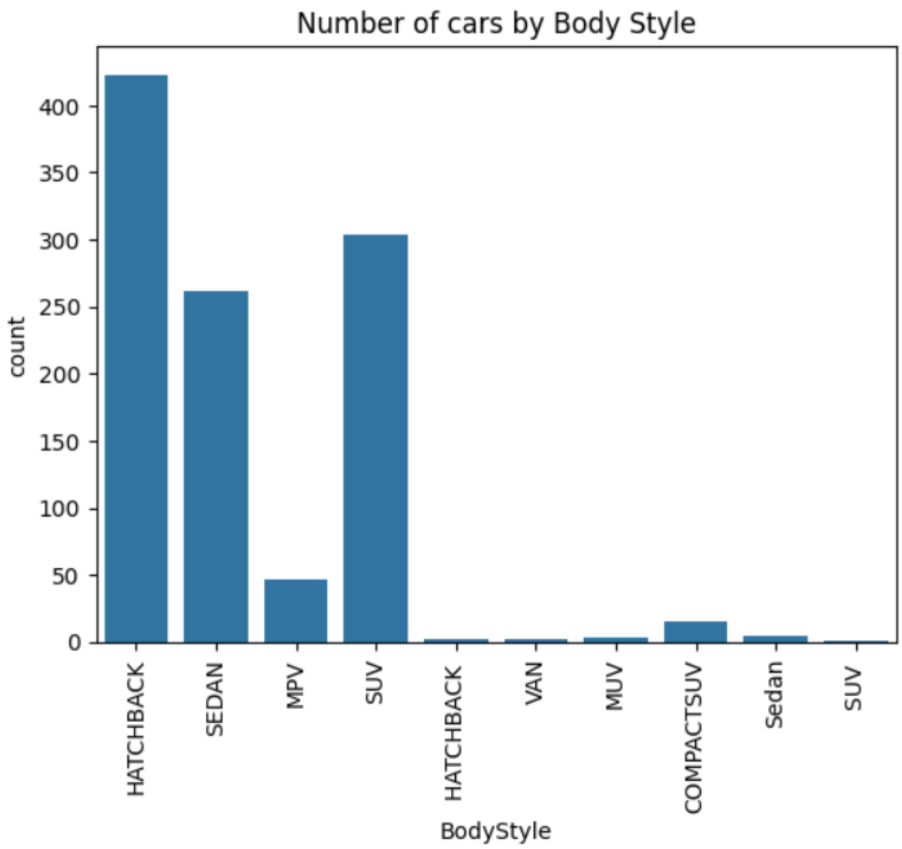
Body Style

In [ ]:

```
#Body style count
sns.countplot(x = 'BodyStyle', data = df).set_title('Number of cars by Body Styl
plt.xticks(rotation = 90)
```

Out[ ]:

```
([0, 1, 2, 3, 4, 5, 6, 7, 8, 9],
 [Text(0, 0, 'HATCHBACK'),
  Text(1, 0, 'SEDAN'),
  Text(2, 0, 'MPV'),
  Text(3, 0, 'SUV'),
  Text(4, 0, 'HATCHBACK '),
  Text(5, 0, 'VAN'),
  Text(6, 0, 'MUV'),
  Text(7, 0, 'COMPACTSUV'),
  Text(8, 0, 'Sedan'),
  Text(9, 0, 'SUV ')])
```

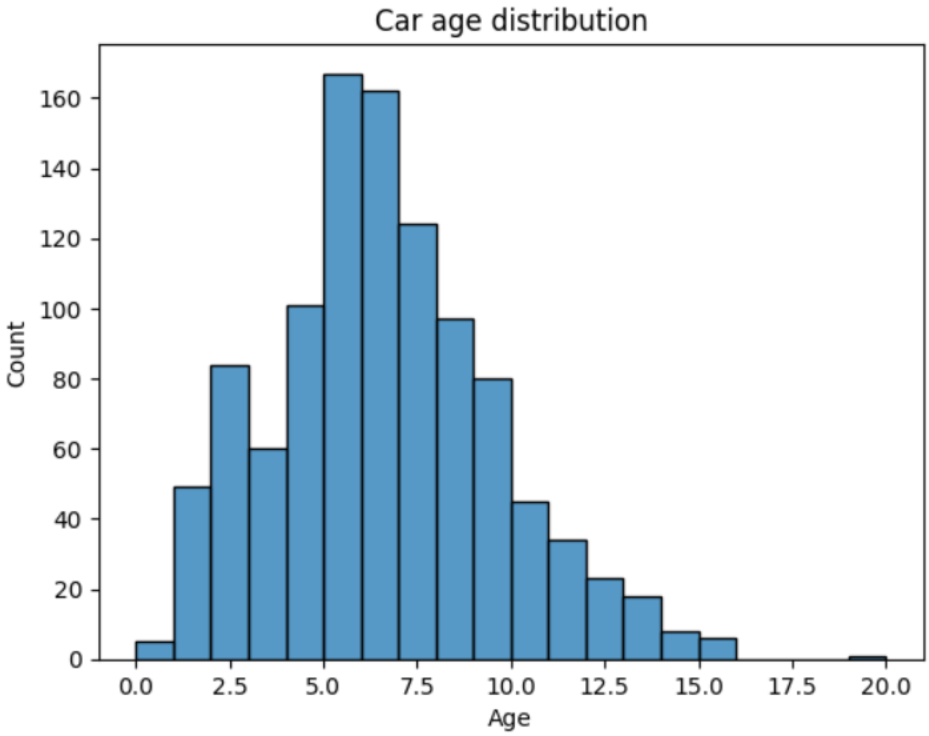


According to this graph, most of the cars have HatchBack, SUV and Sedan body style, which tells us about the market demand of these body styles. Therefore, we can assume that cars with HatchBack, SUV and Sedan body style are more in demand in the used car market will have a good resale value.

Car Age Distribution

In [ ]:
```
#Car age distribution
sns.histplot(x = 'Age', data = df, bins = 20).set_title('Car age distribution')
```

Out[ ]:
```
Text(0.5, 1.0, 'Car age distribution')
```



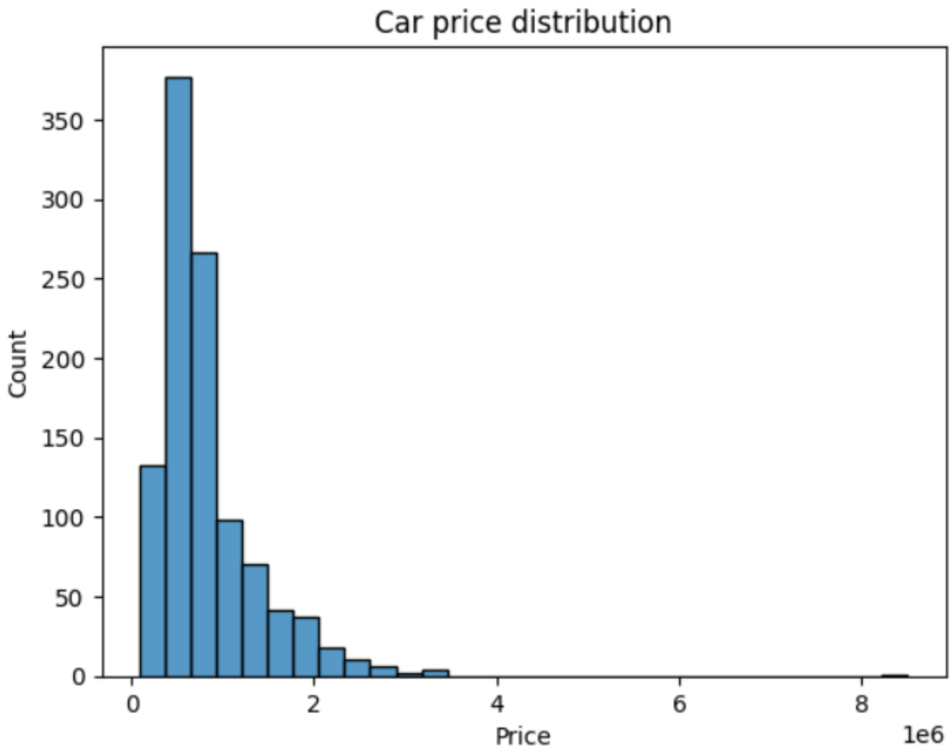
Age of the car plays an important role in deciding its resale value. Here, in the dataset cars that age between 5 to 7 years are more in number. Moreover majority of the cars age more than 5 years, which affect their resale value. However, there are still significant number of cars with age less than 5 years, thereofore, I assume they would have higher resale value.

In addition to that, we can see than one car has age near 20 years which could be an outlier.

Price Distribution

In [ ]:
```
#Price distribution
sns.histplot(x = 'Price', data =df, bins = 30).set_title('Car price distribution
```

Out[ ]:
```
Text(0.5, 1.0, 'Car price distribution')
```



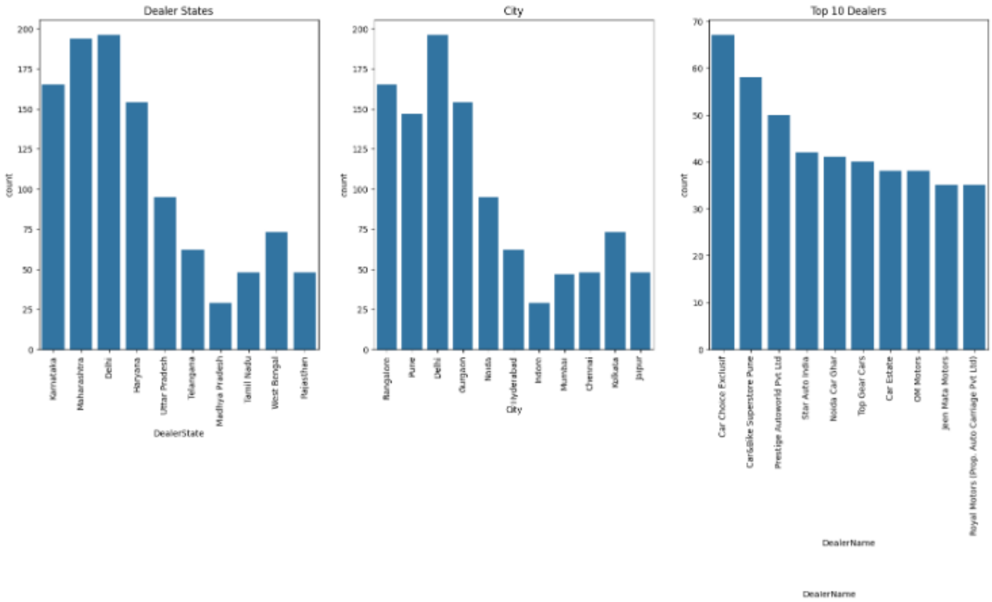
This graph help us to know about the distribution of the car prices in the dataset. In the dataset, most of the cars have price is between 3 to 9 lakhs, with maximum cars between 3 to 6 lakhs. Therefore, we can assume that cars with price between 3 to 9 lakhs are more in demand in the used car market. Moreover there are some cars with resale price more than 20 lakhs, which could be possible for luxury cars or it could be an outlier.

Location based Distribution

In [ ]:

```
fig, ax = plt.subplots(1,3,figsize=(20,7))

#Dealer State
sns.countplot(x = 'DealerState', data = df, ax = ax[0]).set_title('Dealer States
ax[0].set_xticklabels(ax[0].get_xticklabels(), rotation = 90)

#City
sns.countplot(x = 'City', data = df, ax = ax[1]).set_title('City')
ax[1].set_xticklabels(ax[1].get_xticklabels(), rotation = 90)

#top 10 dealers
sns.countplot(x = 'DealerName', data = df, order = df['DealerName'].value_counts
ax[2].set_xticklabels(ax[2].get_xticklabels(), rotation = 90)
```

```
Out[ ]: [Text(0, 0, 'Car Choice Exclusif'),
 Text(1, 0, 'Car&Bike Superstore Pune'),
 Text(2, 0, 'Prestige Autoworld Pvt Ltd'),
 Text(3, 0, 'Star Auto India'),
 Text(4, 0, 'Noida Car Ghar'),
 Text(5, 0, 'Top Gear Cars'),
 Text(6, 0, 'Car Estate'),
 Text(7, 0, 'OM Motors'),
 Text(8, 0, 'Jeen Mata Motors'),
 Text(9, 0, 'Royal Motors (Prop. Auto Carriage Pvt Ltd)')]
```

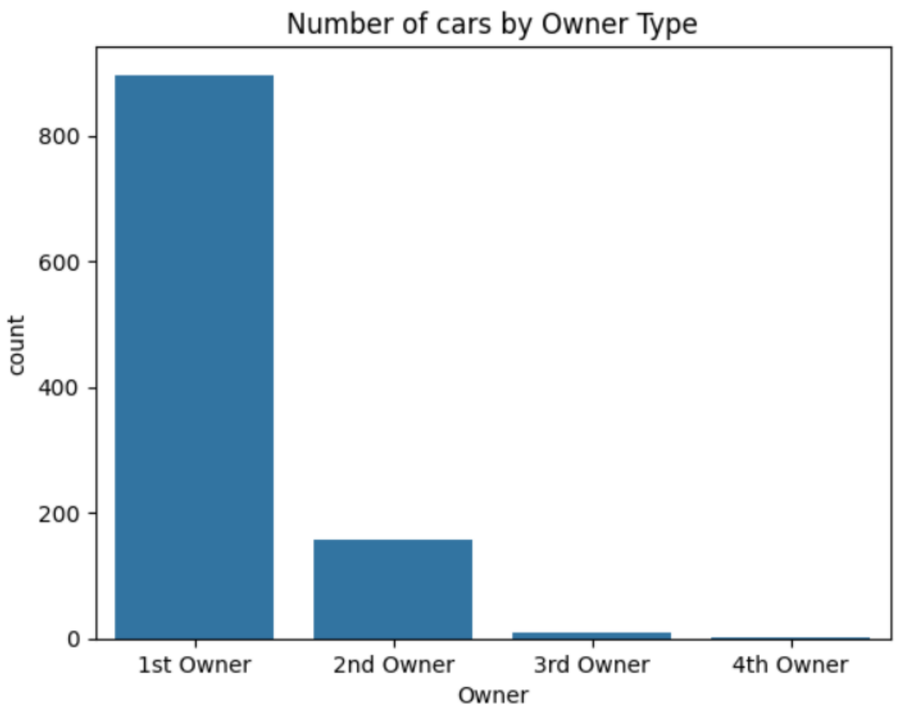


These graphs shows the distribution of cars based on their dealer state, city and Dealer Name. In the dealer state graph, we see that Delhi and Maharashtra have the highest number of used cars for sale followed by Karnataka and Haryana. In the dealer city graph, we see that Delhi has the highest number of cars which is obvious from the the previous graph, however in contrast to the previous graph, Banglore has more used cars for sale than Pune, infact Pune has lower car count than Gurgaon. In the dealer name graph, we see that Car Choice Exclusif, Car&Bike Superstore Pune and Prestige Autoworld Pvt Ltd are moung the top 3 dealers with highest number of used cars for sale.

Car Owner Type

```
In [ ]: sns.countplot(x = 'Owner', data = df).set_title('Number of cars by Owner Type')
```

```
Out[ ]: Text(0.5, 1.0, 'Number of cars by Owner Type')
```

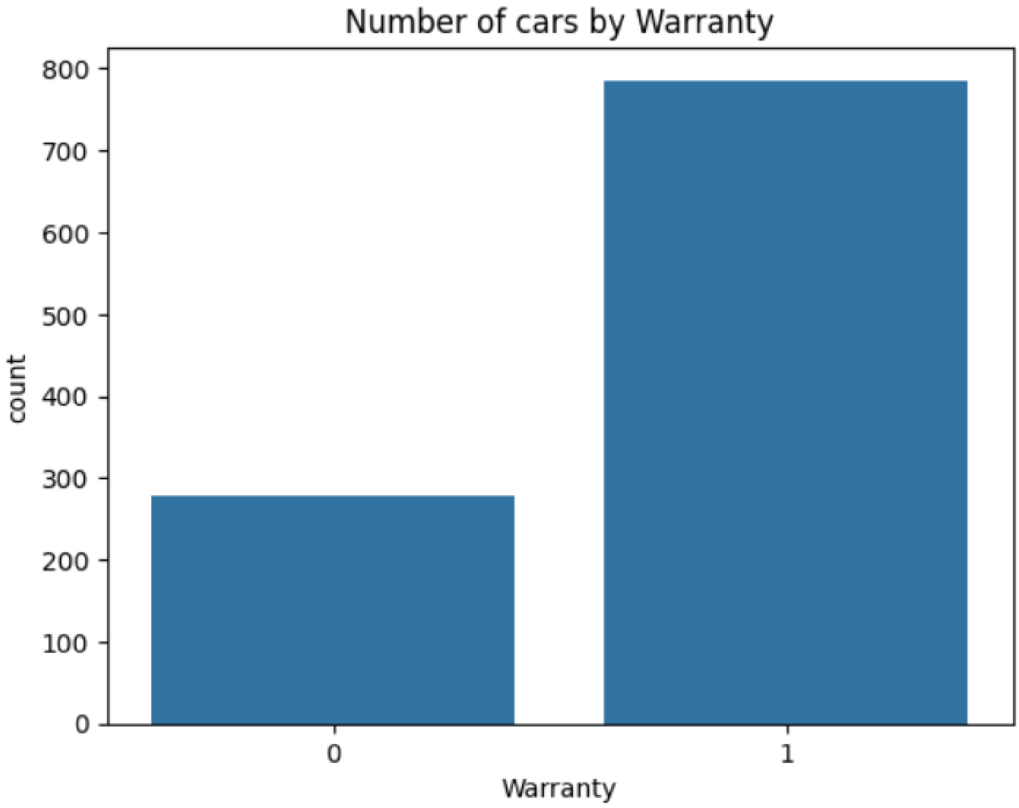


The car owner type has a huge impact on its resale value. Majority of the cars that are been sold are 1at Owner cars followed by 2nd Owner cars which are significantly less in number as compared to 1st Owner. Moreover, the 3rd and 4th owner cars are very less in number. Therefore, we can assume that 1st Owner cars are more preferred in the used car market and have a good resale value.

Warranty

In [ ]:
```
sns.countplot(x = 'Warranty', data = df).set_title('Number of cars by Warranty')
```

Out[ ]:
```
Text(0.5, 1.0, 'Number of cars by Warranty')
```

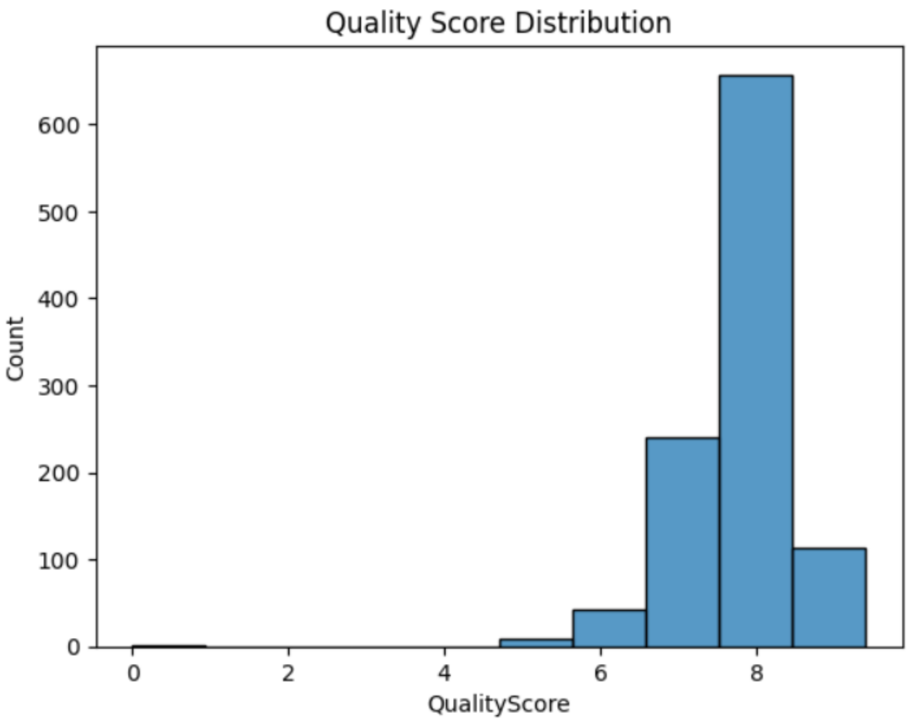


This graphs shows the number of used cars for sale that come with a warranty from the dealership company. The warranty plays a major role and customers prefer to purchase a car with warranty, it has been shown in the dataset as well, where we can see than the number cars with warranty is almost twice the number of cars without warranty.

Quality Score Distribution

In [ ]:
```
sns.histplot(x = 'QualityScore', data = df, bins = 10).set_title('Quality Score
```

Out[ ]:
```
Text(0.5, 1.0, 'Quality Score Distribution')
```



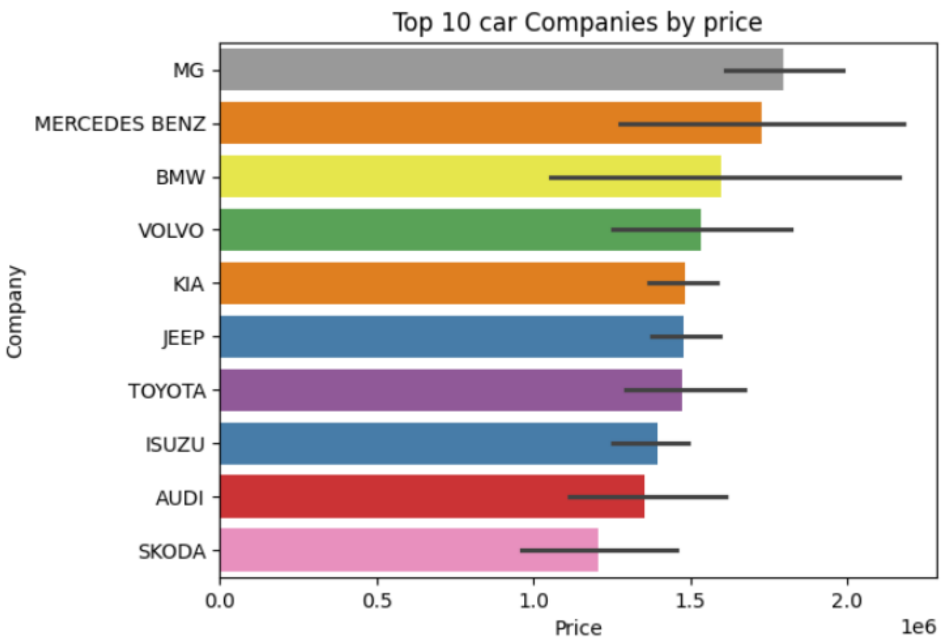
Quality score is an important feature which has a huge impact on the car sales and its preference by the customers. Cars with higher quality scores tend to have a much higher resale value and are more preferred by the customers. In the dataset, most of the cars have a decent quality score between 7-8, which highlights that the cars are thoroughly checked before being sold in the used car market. However, there are some cars with quality score less than 5, which could be due to the fact that they are not in good condition or they are very old.

Till now, I have visualized the distribution of the data and got a better understanding of the data. Now, I will be looking at the relationship between the Car Price aans the independent variables.

Top 10 Car Companies by Price

In [ ]:
```
#Top 10 car companies by price
sns.barplot(y = 'Company', x = 'Price', data = df, order = df.groupby('Company')
```

Out[ ]:
```
Text(0.5, 1.0, 'Top 10 car Companies by price')
```



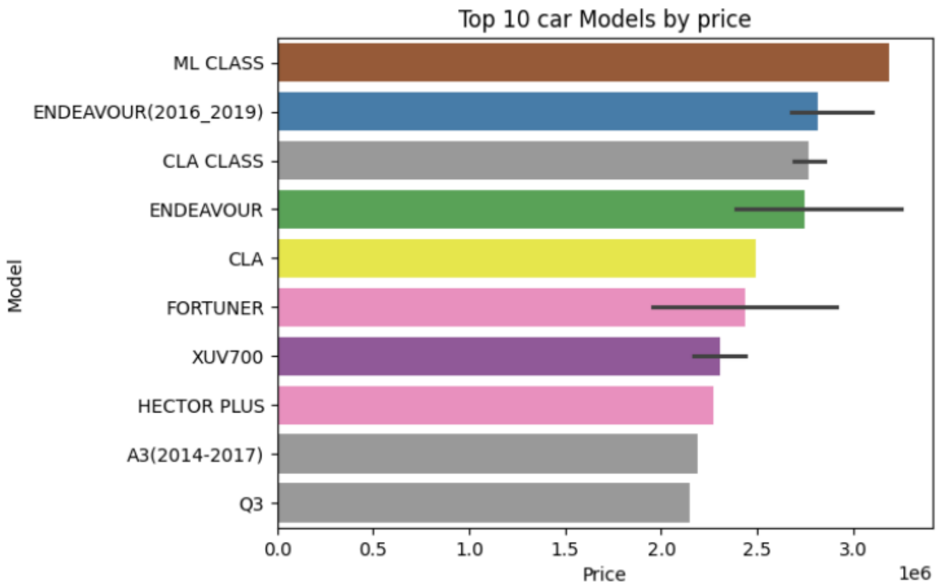
This graphs highlights the top 10 car companies in the dataset with the highest resale value. The MG, Mercedes Benz and BMW are the top 3 car companies with the highest resale value, since these are luxury car companies. The list also includes Volvo. followed by KIA, Jeep and Toyota. Surprisingly Audi has much lower resale price has compared to the other luxury car companies which might be due to other features.

Moreover, my prevous hypothesis, about the car companies -Maruti Suzuki, Hyundai, Honda, Mahindra and Tata, was wrong as they are not in the top 10 list. This means that these companies cars are in greater number due to their demand because of low price

Top 10 Car Models by Price

In [ ]:
```
#Top 10 car models by price
sns.barplot(y = 'Model', x = 'Price', data = df, order = df.groupby('Model')['Pr
```

Out[ ]:
```
Text(0.5, 1.0, 'Top 10 car Models by price')
```



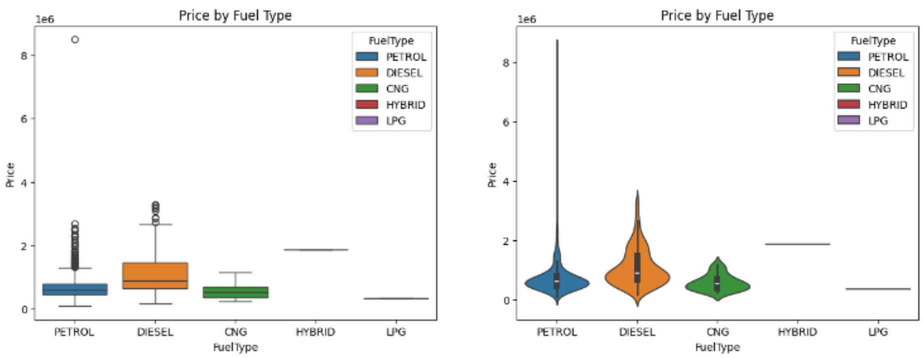
This graph shows the relation between the car model and it resale value and we can see that it shows similarity woth the previous graph. The car models - ML Class, Endeavour(2016_2019), CLA class are the top three models with highest resale value, followed by CLA, Fortuner and XUV700. Like the previous graph, the audi model A3 is at the 9th position with a much lower resale value as compared to the other models.

In the car model also my hypothesis was wrong as I assummed that Honda City and Swift are the top two car models in the dataset, followed by Baleno, Creata and EcoSport. Therefore, we came to know that these car in higher number due to their high demnad because of low price.

Car Fuel Type and Price

In [ ]:
```
fig, ax = plt.subplots(1,2,figsize=(15,5))
sns.boxplot(x = 'FuelType', y = 'Price', data = df, ax = ax[0], hue = 'FuelType'
sns.violinplot(x = 'FuelType', y = 'Price', data = df, ax = ax[1], hue = 'FuelTy
```

Out[ ]:
```
Text(0.5, 1.0, 'Price by Fuel Type')
```

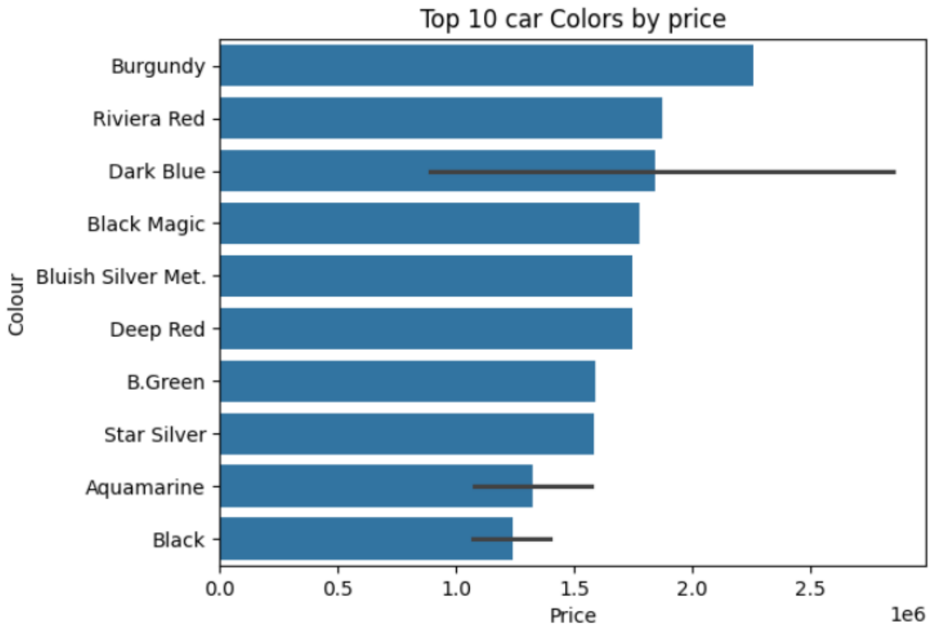


The above plots visualizes the relationship between the car fuel type and its resale value. In the boxplot we can see than cars with diesel fuel type have higher resale value than petrol and CNG and LPG. In the violin plot, we can see that the distribution of the price for diesel cars is more concentrated between 10 to 20 lakh as compared to Petrol. From this it is cleared that, customers prefer petrol and diesel car than other fuel type and the diesel cars are more in demand in the used car market.

Top 10 Car Colors by Price

In [ ]:
```
#Top 10 car colors by price
sns.barplot(y = 'Colour', x = 'Price', data = df, order = df.groupby('Colour')['
```

Out[ ]:
```
Text(0.5, 1.0, 'Top 10 car Colors by price')
```



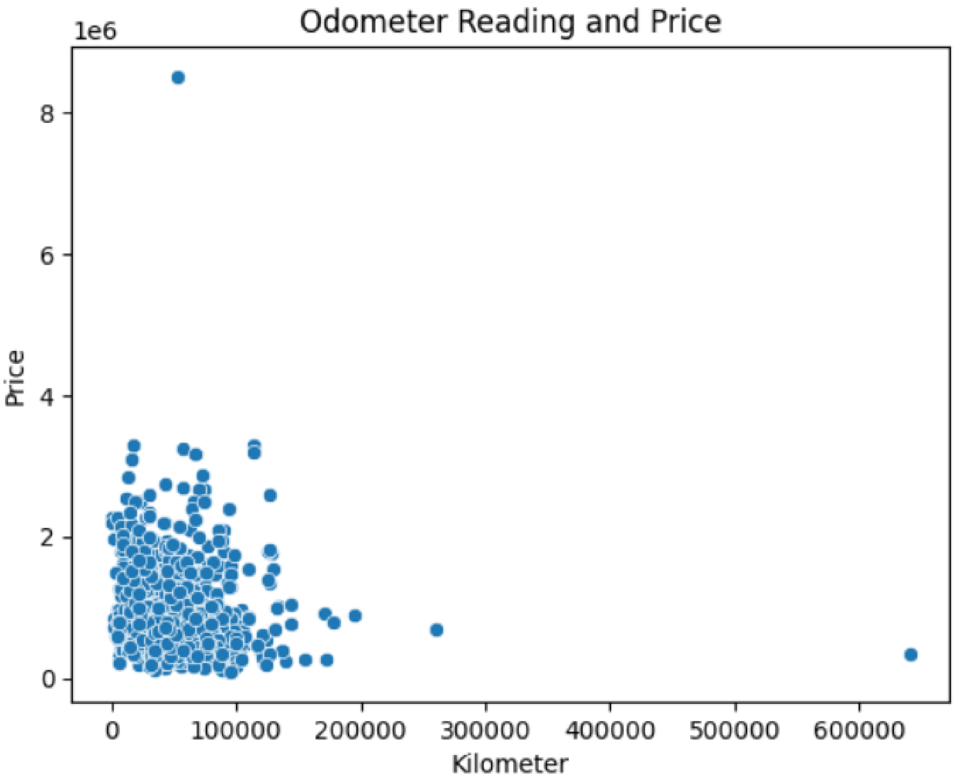
The cars with colors like Burgundy, Riviera Red and Dark Blue have higher resale value as compared to other colors. This shows that color of the car does matter and plays a major role in the resale value of the car.

Moreover, we also came to know that exotic colors have more price but they are not in demand in the used car market.

Odometer Reading and Price

In [ ]:
```
sns.scatterplot(x = 'Kilometer', y = 'Price', data = df).set_title('Odometer Rea
```

Out[ ]:
```
Text(0.5, 1.0, 'Odometer Reading and Price')
```

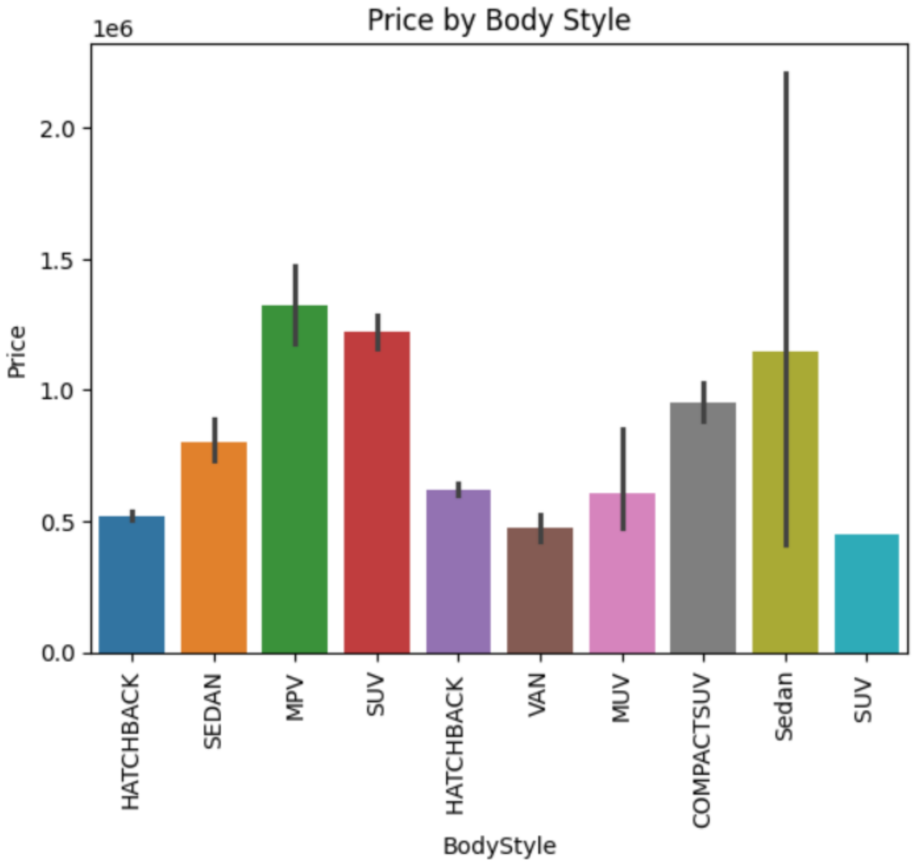


In the scatter plot we can see than the data is concentrated near the origin, which means that most of the cars have odometer reading less than 100000 km. In addition to that the cars with less odometer reading shows higher resale value and as the odometer reading increases the resale value decreases. Therefore, my hypothesis was correct that cars with odometer reading less than 100000 km are more in demand in the used car market will have a good resale value.

Body Style and Price

In [ ]:
```
sns.barplot(x = 'BodyStyle', y = 'Price', data = df, hue = 'BodyStyle').set_titl
plt.xticks(rotation = 90)
```

Out[ ]:
```
([0, 1, 2, 3, 4, 5, 6, 7, 8, 9],
 [Text(0, 0, 'HATCHBACK'),
  Text(1, 0, 'SEDAN'),
  Text(2, 0, 'MPV'),
  Text(3, 0, 'SUV'),
  Text(4, 0, 'HATCHBACK '),
  Text(5, 0, 'VAN'),
  Text(6, 0, 'MUV'),
  Text(7, 0, 'COMPACTSUV'),
  Text(8, 0, 'Sedan'),
  Text(9, 0, 'SUV ')])
```

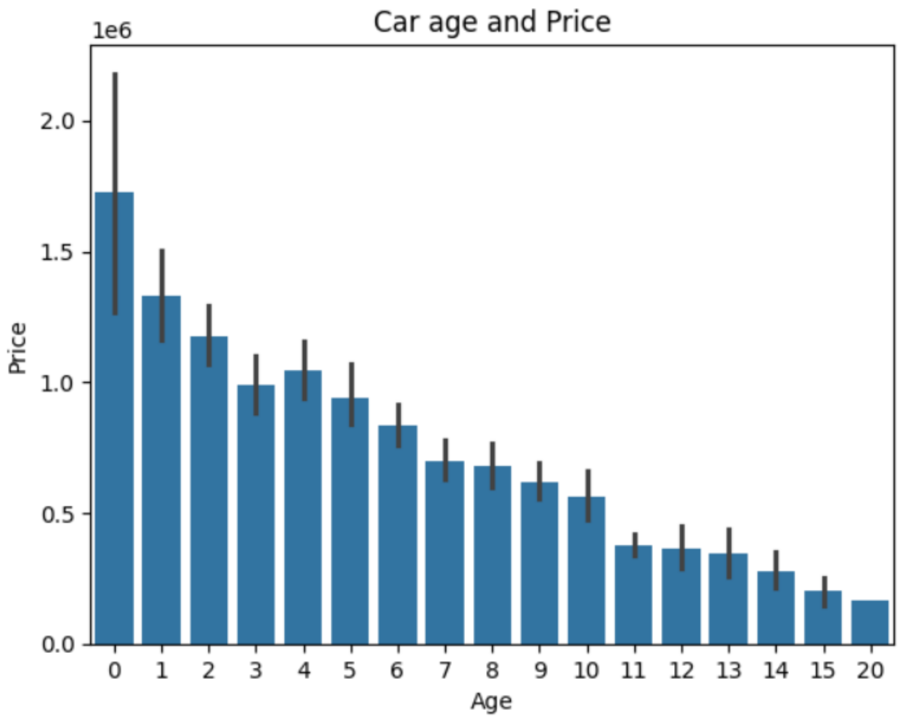


MPV, SUV and Sedan are the top 3 car body styles with the highest resale value. Therefore, we can assume that these body styles are more preferred in the used car market and have a good resale value. This also shows that my assumption was correct however, the Hatchback body style cars despite being in majority have lower resale value.

Car Age and Price

In [ ]:
```
sns.barplot(x = 'Age', y = 'Price', data = df).set_title('Car age and Price')
```

Out[ ]:
```
Text(0.5, 1.0, 'Car age and Price')
```

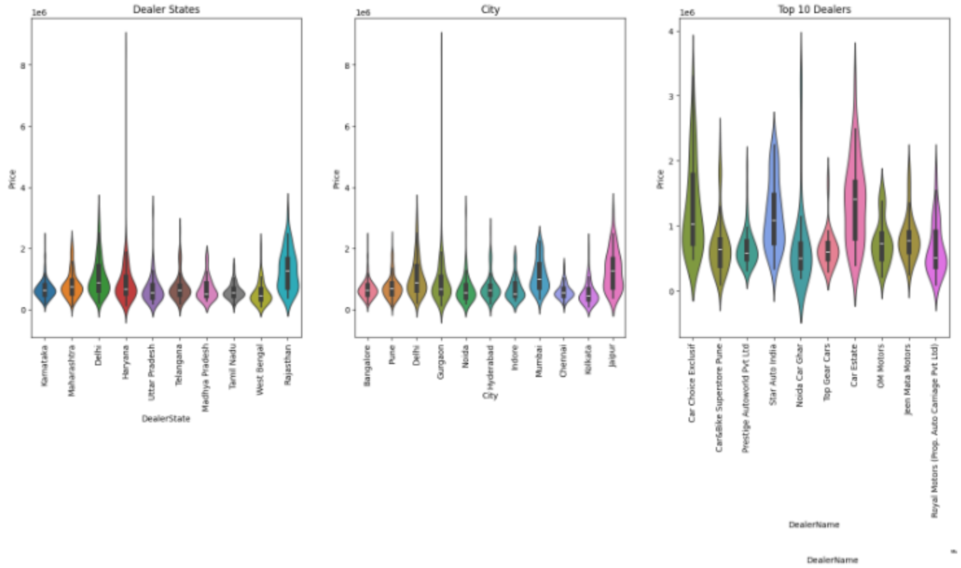


As we discussed earlier, age is a key determinant for a car's resale value and this graph clearly visulaizes the relation of the age with car price. The cars with age less than a year has then highest price and as the age increases the prices decreases gradually. Therefore, my hypothesis was correct that cars with age less than 5 years have higher resale value.

Location based Price Distribution

In [ ]:
```
fig, ax = plt.subplots(1,3,figsize=(20,7))

#Dealer State
sns.violinplot(x = 'DealerState', y = 'Price', data = df, ax = ax[0], hue = 'Dea
ax[0].set_xticklabels(ax[0].get_xticklabels(), rotation = 90)

#City
sns.violinplot(x = 'City',y = 'Price', data = df, ax = ax[1], hue = 'City').set_
ax[1].set_xticklabels(ax[1].get_xticklabels(), rotation = 90)

#top 10 dealers
sns.violinplot(x = 'DealerName',y = 'Price', data = df, order = df['DealerName']
ax[2].set_xticklabels(ax[2].get_xticklabels(), rotation = 90)
```

```
Out[ ]: [Text(0, 0, 'Car Choice Exclusif'),
         Text(1, 0, 'Car&Bike Superstore Pune'),
         Text(2, 0, 'Prestige Autoworld Pvt Ltd'),
         Text(3, 0, 'Star Auto India'),
         Text(4, 0, 'Noida Car Ghar'),
         Text(5, 0, 'Top Gear Cars'),
         Text(6, 0, 'Car Estate'),
         Text(7, 0, 'OM Motors'),
         Text(8, 0, 'Jeen Mata Motors'),
         Text(9, 0, 'Royal Motors (Prop. Auto Carriage Pvt Ltd)')]
```

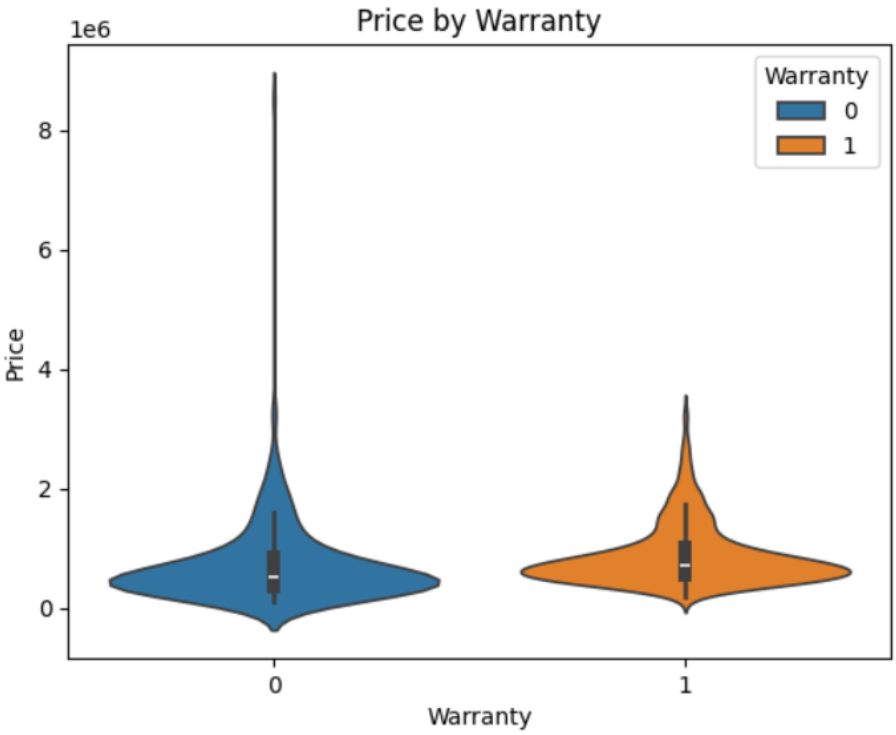


In the above graph we can see the price distribution based on the state, city and the dealer name. In the state graph, we can see that the cars in Rajastan have the highest price followed by Delhi. Moreover, there are some outliers in the graph which os visible from the violinplot where there is strong peak incase of Haryana. In the city graph, we can see that the cars in Jaipur have the highest price followed by Mumbai and Delhi. Moreover, there are some outliers in the graph which os visible from the violinplot where there is strong peak incase of Gurgaon. In the dealer name graph, we can see the top 10 dealers along with their price distribution. Here, Car Estate has the highest price followed by Star Auto India and Car Choice. Moreover, there are some outliers in the graph which os visible from the violinplot where there is strong peak incase of Noida Car Ghar.

Car Owner Type and Price

```
In [ ]: sns.violinplot(x = 'Owner', y = 'Price', data = df, hue = 'Owner').set_title('Pr
```

```
Out[ ]: Text(0.5, 1.0, 'Price by Owner Type')
```



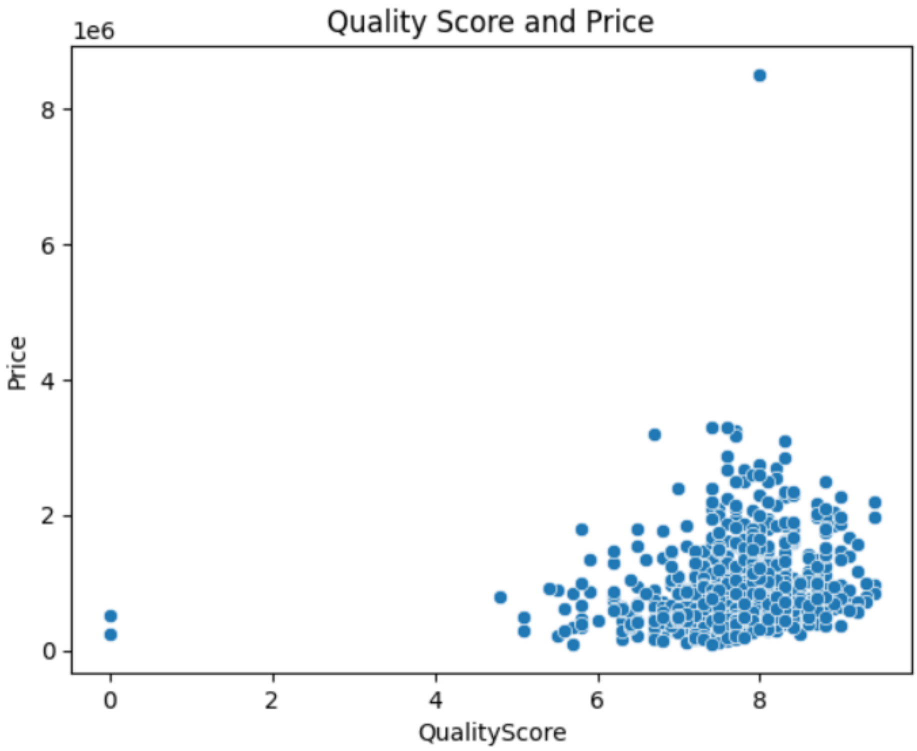
Here, we can see some change in the violinplot of the cars with and without warranty. The cars with warranty tends to have slightly higher price than the cars without warranty. Therefore, we can assume that cars with warranty are more preferred in the used car market and have a good resale value.

Here, we can see some change in the violinplot of the cars with and without warranty. The cars with warranty tends to have slightly higher price than the cars without warranty. Therefore, we can assume that cars with warranty are more preferred in the used car market and have a good resale value.

Quality Score and Price

In [ ]:
```
sns.scatterplot(x = 'QualityScore', y = 'Price', data = df).set_title('Quality S
```

Out[ ]:
```
Text(0.5, 1.0, 'Quality Score and Price')
```



We can see a very high concentration near the quality score 7 and above having much higher price than the cars with quality score less than 7. Therefore, we can assume that cars with quality score 7 and above are more preferred in the used car market and have a good resale value.

Data Preprocessing Part 2

Dropping column car model beacause, it has too many unique values and it will increase the dimensionality of the dataset.

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

Label Encoding

In [ ]:
```
#columns for label encoding
cols = df.select_dtypes(include=['object']).columns

from sklearn.preprocessing import LabelEncoder
#Label encoding object
le = LabelEncoder()

#label encoding for object type columns
for i in cols:
    le.fit(df[i])
    df[i] = le.transform(df[i])
    print(i, df[i].unique())
```

```
Company [12  7 19  5 13 21 11  6 17 16  9  4 20 10  1  3 18 14  0  8 22 15  2]
FuelType [4 1 0 2 5 3]
Colour [61 56 34  0  9 11 66 47 49 38 14 71 72 30 74 52 39 28 60  7 54 62 40 13
 20 70 63 12 24 23 35 26 29 15 31  1 68  4  8 73 22 44 57 65 42 50 32 64
 19 43 46 33 16 27 53 25 10 69 51 17  6 48 59 58  5  3 18 45 67 36 21 55
  2 37 75 41]
BodyStyle [1 5 3 6 2 9 4 0 8 7]
Owner [0 1 2 3]
DealerState [2 4 0 1 8 7 3 6 9 5]
DealerName [52 38  4  1 56 29  0 34 47 51 11 21  9 10 43 33  7 16  5 12 42 17 27
50
 45  6 20 36 23 41 32 31 18  2 48 15 54 40 55 13 49 25 35 46 24 14 44 19
 39 28 26  3 53 30  8 22 37]
City [ 0 10  2  3  9  4  5  8  1  7  6]
```

Outlier Removal

In [ ]:

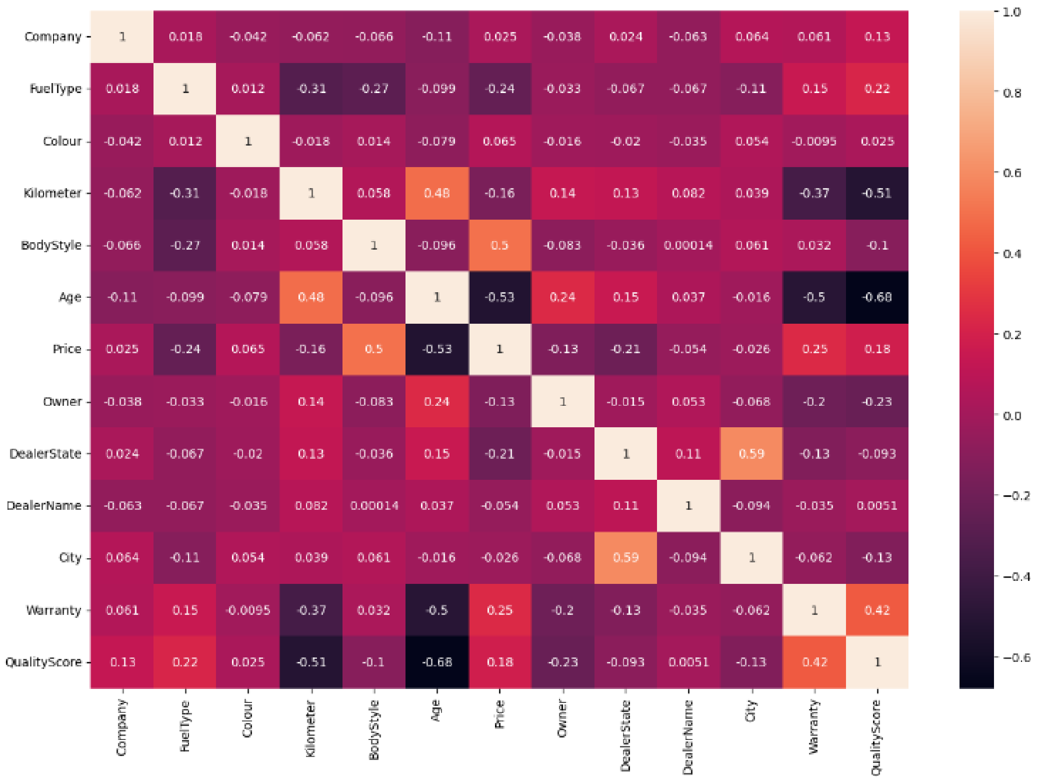
```
#Using IQRS to remove outliers

#columns for outlier removal
cols = df.select_dtypes(include=['int64','float64']).columns
Q1 = df[cols].quantile(0.25)
Q3 = df[cols].quantile(0.75)

IQR = Q3 - Q1

#Removing outliers
df = df[~((df[cols] < (Q1 - 1.5 * IQR)) |(df[cols] > (Q3 + 1.5 * IQR))).any(axis
```

Correlation Matrix Heatmap

In [ ]:

```
plt.figure(figsize=(15,10))
sns.heatmap(df.corr(), annot=True)
```

Out[ ]: <Axes: >



Train Test Split

In [ ]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(df.drop('Price',axis=1), df[
```

Model Building

I will be using the following regression models:

- Decision Tree Regressor
- Random Forest Regressor
- Ridge Regressor

Decision Tree Regressor

In [ ]:
```
from sklearn.tree import DecisionTreeRegressor
#Decision Tree Regressor Object
dtr = DecisionTreeRegressor()
```

Hyperparameter Tuning

In [ ]:
```
from sklearn.model_selection import GridSearchCV

#parameters for grid search
para = {
    'max_depth' : [2,4,6,8],
    'min_samples_leaf' : [2,4,6,8],
```

```
    'min_samples_split' : [2,4,6,8],
    'random_state' : [0,42]
}

#Grid Search Object
grid = GridSearchCV(estimator=dtr, param_grid=para, cv=5, n_jobs=-1, verbose=2)

#Fitting the model
grid.fit(X_train, y_train)

#Best parameters
print(grid.best_params_)
```

```
Fitting 5 folds for each of 128 candidates, totalling 640 fits
{'max_depth': 6, 'min_samples_leaf': 2, 'min_samples_split': 2, 'random_state': 4
2}
```

In [ ]:

```
#decision tree regressor with best parameters
dtr = DecisionTreeRegressor(max_depth=6, min_samples_leaf=2, min_samples_split=2

#Fitting the model
dtr.fit(X_train, y_train)

#Training score
print(dtr.score(X_train, y_train))
```

```
0.7445153281346839
```

In [ ]:

```
#Prediction
dtr_pred = dtr.predict(X_test)
```

Random Forest Regressor

In [ ]:

```
from sklearn.ensemble import RandomForestRegressor
#Random Forest Regressor Object
rfr = RandomForestRegressor()
```

Hyperparameter Tuning

In [ ]:

```
from sklearn.model_selection import GridSearchCV

#parameters for grid search
para = {
    'max_depth' : [2,4,6,8],
    'min_samples_leaf' : [2,4,6,8],
    'min_samples_split' : [2,4,6,8],
    'random_state' : [0,42]
}

#Grid Search Object
grid = GridSearchCV(estimator=rfr, param_grid=para, cv=5, n_jobs=-1, verbose=2)

#Fitting the model
grid.fit(X_train, y_train)

#Best parameters
print(grid.best_params_)
```

```
Fitting 5 folds for each of 128 candidates, totalling 640 fits
{'max_depth': 8, 'min_samples_leaf': 2, 'min_samples_split': 2, 'random_state':
0}
```

In [ ]:
```python
#Random Forest Regressor with best parameters
rfr = RandomForestRegressor(max_depth=8, min_samples_leaf=2, min_samples_split=2

#Fitting the model
rfr.fit(X_train, y_train)

#Training score
print(rfr.score(X_train, y_train))
```

```
0.8781873430425237
```

In [ ]:
```python
#Prediction
rfr_pred = rfr.predict(X_test)
```

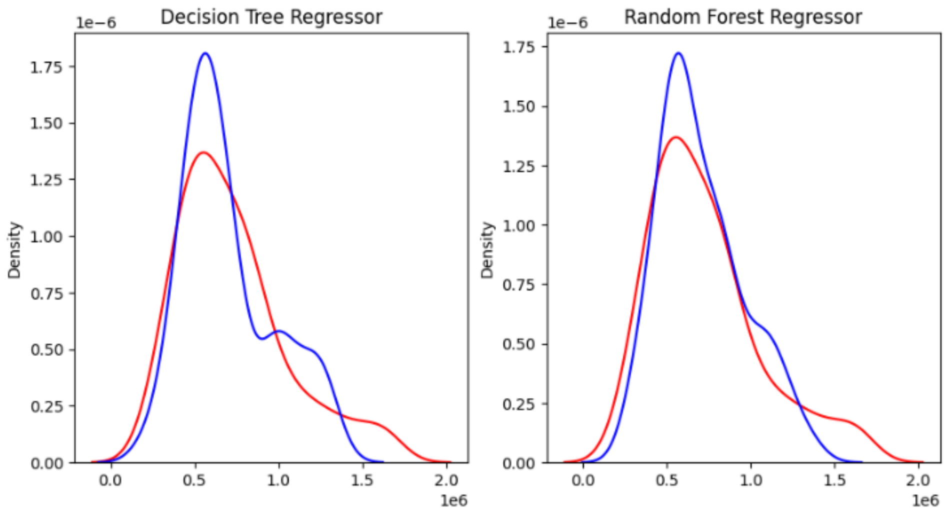
Model Evaluation

Model Evaluation

Distribution Plot

In [ ]:
```python
fig,ax = plt.subplots(1,2,figsize=(10,5))

#decision tree regressor
sns.distplot(x = y_test, ax = ax[0], color = 'r', hist = False, label = 'Actual'
sns.distplot(x = dtr_pred, ax = ax[0], color = 'b', hist = False, label = 'Predi

#random forest regressor
sns.distplot(x = y_test, ax = ax[1], color = 'r', hist = False, label = 'Actual'
sns.distplot(x = rfr_pred, ax = ax[1], color = 'b', hist = False, label = 'Predi
```

Out[ ]:
```
<Axes: title={'center': 'Random Forest Regressor'}, ylabel='Density'>
```



Model Metrics

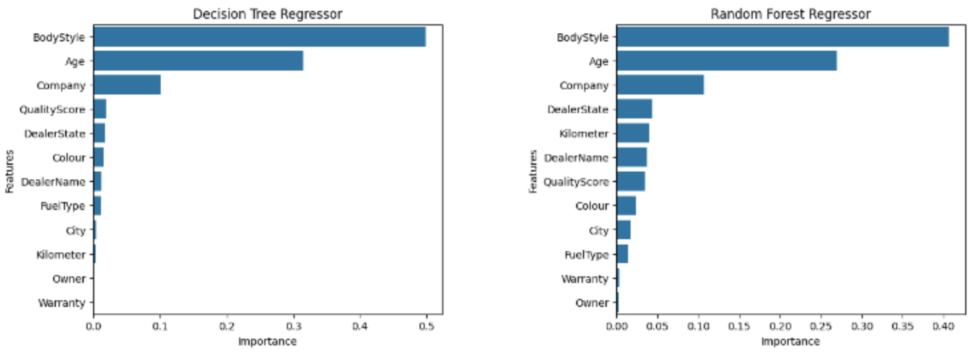
```
In [ ]: from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score

        #Decision Tree Regressor
        print('Decision Tree Regressor')
        print('Mean Squared Error : ', mean_squared_error(y_test, dtr_pred))
        print('Mean Absolute Error : ', mean_absolute_error(y_test, dtr_pred))
        print('R2 Score : ', r2_score(y_test, dtr_pred))

        #Random Forest Regressor
        print('Random Forest Regressor')
        print('Mean Squared Error : ', mean_squared_error(y_test, rfr_pred))
        print('Mean Absolute Error : ', mean_absolute_error(y_test, rfr_pred))
        print('R2 Score : ', r2_score(y_test, rfr_pred))
```

```
Decision Tree Regressor
Mean Squared Error :  46746127636.183586
Mean Absolute Error :  161645.14749542723
R2 Score :  0.5660724036960223
Random Forest Regressor
Mean Squared Error :  31811887039.002945
Mean Absolute Error :  134717.2267038187
R2 Score :  0.704701621829243
```

Feature Importance

```
In [ ]: fig, ax = plt.subplots(1,2,figsize=(15, 5))
        fig.subplots_adjust(wspace=0.5)

        #Decision Tree Regressor
        feature_df = pd.DataFrame({'Features':X_train.columns, 'Importance':dtr.feature_
        feature_df.sort_values(by='Importance', ascending=False, inplace=True)
        sns.barplot(x = 'Importance', y = 'Features', data = feature_df, ax = ax[0]).set

        #Random Forest Regressor
        feature_df = pd.DataFrame({'Features':X_train.columns, 'Importance':rfr.feature_
        feature_df.sort_values(by='Importance', ascending=False, inplace=True)
        sns.barplot(x = 'Importance', y = 'Features', data = feature_df, ax = ax[1]).set
```

```
Out[ ]: Text(0.5, 1.0, 'Random Forest Regressor')
```



Conclusion

From the exploratory data analysis, I have revealed two major facts about the used car market: which are demand and price. The demand of low price used car is pretty high as compared to the to expensive ones, which highlights the customers attraction towards budget cars. But upon studying the graph I also came to know about some interesting facts about the used car market. Beginning with the car companies, companies like- MG, Mercedes Benz, BMW, Volvo and KIA have the highest price but Maruti Suzuki, Hyundai, Honda, Mahindra and Tata car are in higher demand. This highlights that customer prefer to buy new luxury cars instead of used ones.

Majority of the cars run either on petrol or diesel, with diesel cars having slightly higher price. I also came to know that car is major player in the market. Cars like white, grey, silver and black are in higher demand but exotic colors like burgundy, riviera red, dark blue, black magic have higher price. Coming to the car's odometer reading, most of the cars have reading less than 10,000 km, and cars with lower odometer reading have the higher price.

Cars with bodystyle like HatchBack, SUV and Sedan are most preferred by the customers whereas the bodystyle like MPV, SUV and Sedan are the top most expensive ones. Age of the car also play a major role in its resale value. As the car age increases, it resale value decreases. Therefore, cars than age less than 5 years have higher price and prefferred more. Car price also changes by location. Delhi, Maharashtra and Rajasthan are the top three states with the highest price and Car Estate, Star Auto India and Car Choice are the top three dealers with the highest price.

> Cars with bodystyle like HatchBack, SUV and Sedan are most preferred by the customers whereas the bodystyle like MPV, SUV and Sedan are the top most expensive ones. Age of the car also play a major role in its resale value. As the car age increases, it resale value decreases. Therefore, cars than age less than 5 years have higher price and prefferred more. Car price also changes by location. Delhi, Maharashtra and Rajasthan are the top three states with the highest price and Car Estate, Star Auto India and Car Choice are the top three dealers with the highest price.

> Customers usually prefer the car with 1st owner type resulting in hugher demand as well as higher price. Cars that comes with a warranty provudes an assurance to the customer, resulting in a little bit higher price. The last feature i.e. Quality score also dictates the car price, where cars with higher quality score have higher price.
>
> Coming to the machine learning models, I have used Descision tree regressor and random forest regressor to predict the car price. The random forest regressor model performed better than the decision tree regressor model. Moreover, from the feature importance graph, we can see that the car age, bodystyle and comapny are the key features that affect the car price.