notebook

February 21, 2025

1 CarDekho Price Prediction

1.1 Data Cleaning

[2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

[3]:
```
df = pd.read_csv('./data/Cardekho.csv')
```

[4]:
```
# Get the first 10 rows
df.head(10)
```

[4]:

	Unnamed: 0	car_name	brand	model	vehicle_age	km_driven	seller_type	fuel_type	transmission_type	mileage	engine	max_power	seats
0	0	Maruti Alto	Maruti	Alto	9	120000	Individual	Petrol	Manual	19.70	796	46.30	5
1	1	Hyundai Grand	Hyundai	Grand	5	20000	Individual	Petrol	Manual	18.90	1197	82.00	5
2	2	Hyundai i20	Hyundai	i20	11	60000	Individual	Petrol	Manual	17.00	1197	80.00	5
3	3	Maruti Alto	Maruti	Alto	9	37000	Individual	Petrol	Manual	20.92	998	67.10	5
4	4	Ford Ecosport	Ford	Ecosport	6	30000	Dealer	Diesel	Manual	22.77	1498	98.59	5
5	5	Maruti Wagon R	Maruti	Wagon R	8	35000	Individual	Petrol	Manual	18.90	998	67.10	5
6	6	Hyundai i10	Hyundai	i10	8	40000	Dealer	Petrol	Manual	20.36	1197	78.90	5
7	7	Maruti Wagon R	Maruti	Wagon R	3	17512	Dealer	Petrol	Manual	20.51	998	67.04	5
8	8	Hyundai Venue	Hyundai	Venue	2	20000	Individual	Petrol	Automatic	18.15	998	118.35	5
9	12	Maruti Swift	Maruti	Swift	4	28321	Dealer	Petrol	Manual	16.60	1197	85.00	5

```
   selling_price
0         120000
1         550000
2         215000
3         226000
4         570000
5         350000
6         315000
7         410000
8        1050000
9         511000
```

[5]:
```
# Get the last 10 rows
df.tail(10)
```

[5]:
```
       Unnamed: 0         car_name     brand   model  vehicle_age  km_driven  \
15401       19531     Maruti Swift    Maruti   Swift            3      25000
15402       19533      Honda Amaze     Honda   Amaze            6      28000
15403       19534     Renault KWID   Renault    KWID            2       2700
15404       19535    Maruti Ertiga    Maruti  Ertiga            5      56829
15405       19536    Hyundai Grand   Hyundai   Grand            5       9229
15406       19537      Hyundai i10   Hyundai     i10            9      10723
15407       19540    Maruti Ertiga    Maruti  Ertiga            2      18000
15408       19541      Skoda Rapid     Skoda   Rapid            6      67000
15409       19542  Mahindra XUV500  Mahindra  XUV500            5    3800000
15410       19543       Honda City     Honda    City            2      13000

      seller_type fuel_type transmission_type  mileage  engine  max_power  \
15401  Individual    Petrol         Automatic    22.00    1197      81.80
15402      Dealer    Diesel            Manual    25.80    1498      98.60
15403      Dealer    Petrol            Manual    25.17     799      53.30
15404      Dealer    Diesel            Manual    20.77    1248      88.80
15405      Dealer    Petrol            Manual    18.90    1197      82.00
15406      Dealer    Petrol            Manual    19.81    1086      68.05
15407      Dealer    Petrol            Manual    17.50    1373      91.10
15408      Dealer    Diesel            Manual    21.14    1498     103.52
15409      Dealer    Diesel            Manual    16.00    2179     140.00
15410      Dealer    Petrol         Automatic    18.00    1497     117.60

       seats  selling_price
15401      5         590000
15402      5         525000
15403      5         395000
15404      7         895000
15405      5         545000
15406      5         250000
15407      7         925000
```

```
15408      5          425000
15409      7         1225000
15410      5         1200000
```

[6]:
```
# Get rows x columns
df.shape
```

[6]:
```
(15411, 14)
```

[7]:
```
# Get information about the data and it's types
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15411 entries, 0 to 15410
Data columns (total 14 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Unnamed: 0         15411 non-null  int64
 1   car_name           15411 non-null  object
 2   brand              15411 non-null  object
 3   model              15411 non-null  object
 4   vehicle_age        15411 non-null  int64
 5   km_driven          15411 non-null  int64
 6   seller_type        15411 non-null  object
 7   fuel_type          15411 non-null  object
 8   transmission_type  15411 non-null  object
 9   mileage            15411 non-null  float64
 10  engine             15411 non-null  int64
 11  max_power          15411 non-null  float64
 12  seats              15411 non-null  int64
 13  selling_price      15411 non-null  int64
dtypes: float64(2), int64(6), object(6)
memory usage: 1.6+ MB
```

By closely observing the dataset we find that there's a wanted column `Unnamed: 0`. It seems to be an index but we can delete it for keeping the data clean.

[8]:
```
df.drop(columns=['Unnamed: 0'], inplace=True)
df.head()
```

[8]:
```
         car_name    brand     model  vehicle_age  km_driven seller_type  \
0    Maruti Alto   Maruti      Alto            9     120000  Individual
1  Hyundai Grand  Hyundai     Grand            5      20000  Individual
2    Hyundai i20  Hyundai       i20           11      60000  Individual
3    Maruti Alto   Maruti      Alto            9      37000  Individual
4  Ford Ecosport     Ford  Ecosport            6      30000      Dealer

  fuel_type transmission_type  mileage  engine  max_power  seats  \
```

```
0    Petrol            Manual    19.70     796      46.30      5
1    Petrol            Manual    18.90    1197      82.00      5
2    Petrol            Manual    17.00    1197      80.00      5
3    Petrol            Manual    20.92     998      67.10      5
4    Diesel            Manual    22.77    1498      98.59      5

   selling_price
0         120000
1         550000
2         215000
3         226000
4         570000
```

[9]:
```
df.isnull().sum()
```

[9]:
```
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
```

[10]:
```
# Get statistical summary of the numeric data
df.describe()
```

[10]:
```
         vehicle_age     km_driven       mileage        engine     max_power  \
count  15411.000000  1.541100e+04  15411.000000  15411.000000  15411.000000
mean       6.036338  5.561648e+04     19.701151   1486.057751    100.588254
std        3.013291  5.161855e+04      4.171265    521.106696     42.972979
min        0.000000  1.000000e+02      4.000000    793.000000     38.400000
25%        4.000000  3.000000e+04     17.000000   1197.000000     74.000000
50%        6.000000  5.000000e+04     19.670000   1248.000000     88.500000
75%        8.000000  7.000000e+04     22.700000   1582.000000    117.300000
max       29.000000  3.800000e+06     33.540000   6592.000000    626.000000

              seats  selling_price
count  15411.000000   1.541100e+04
mean       5.325482   7.749711e+05
std        0.807628   8.941284e+05
```

```
min         0.000000   4.000000e+04
25%         5.000000   3.850000e+05
50%         5.000000   5.560000e+05
75%         5.000000   8.250000e+05
max         9.000000   3.950000e+07
```

As we can see here that in the **seats** column the min. is 0 which is practically immpossible so we need to take a closer look.

[11]:
```
zero_seats = df[df['seats'] == 0]
zero_seats
```

[11]:
```
           car_name   brand  model  vehicle_age  km_driven seller_type  \
3217     Honda City   Honda   City           18      40000  Individual
12619  Nissan Kicks  Nissan  Kicks            2      10000  Individual

      fuel_type transmission_type  mileage  engine  max_power  seats  \
3217     Petrol            Manual    13.00    1493     100.00      0
12619    Diesel            Manual    19.39    1461     108.49      0

       selling_price
3217          115000
12619        1154000
```

Upon inspecting we find `Honda City` and `Nissan Kicks` have 0 seats. Let's find the seat number in the dataset if there are any else replace values from online search.

[12]:
```
honda_df = df[df['car_name'] == 'Honda City']
honda_df
```

[12]:
```
         car_name  brand model  vehicle_age  km_driven seller_type fuel_type  \
23     Honda City  Honda  City            6      50000  Individual    Petrol
27     Honda City  Honda  City           14      77253      Dealer    Petrol
37     Honda City  Honda  City            6      31180      Dealer    Petrol
67     Honda City  Honda  City            8      70000  Individual    Petrol
79     Honda City  Honda  City            7      69000      Dealer    Diesel
…             …    …    …              …          …           …         …
15325  Honda City  Honda  City            7     220000      Dealer    Diesel
15330  Honda City  Honda  City            7     110000  Individual    Diesel
15369  Honda City  Honda  City            9      54311      Dealer    Petrol
15385  Honda City  Honda  City           10      28147      Dealer    Petrol
15410  Honda City  Honda  City            2      13000      Dealer    Petrol

      transmission_type  mileage  engine  max_power  seats  selling_price
23               Manual     17.4    1497      117.3      5         750000
27               Manual     17.7    1497       78.0      5         145000
37            Automatic     18.0    1497      117.3      5         700000
67               Manual     16.8    1497      116.3      5         545000
```

```
79              Manual     25.1    1498       98.6      5         550000
…                 …        …       …          …        …            …
15325           Manual     26.0    1498       98.6      5         550000
15330           Manual     26.0    1498       98.6      5         490000
15369           Manual     16.8    1497      116.3      5         465000
15385           Manual     17.0    1497      118.0      5         500000
15410        Automatic     18.0    1497      117.6      5        1200000

[757 rows x 13 columns]
```

[13]:
```
nissan_df = df[df['car_name'] == 'Nissan Kicks']
nissan_df
```

[13]:
```
          car_name   brand  model  vehicle_age  km_driven       seller_type  \
1259   Nissan Kicks  Nissan  Kicks            1      15000        Individual
2485   Nissan Kicks  Nissan  Kicks            1       7500        Individual
3111   Nissan Kicks  Nissan  Kicks            2       4000            Dealer
4937   Nissan Kicks  Nissan  Kicks            2      40000        Individual
9645   Nissan Kicks  Nissan  Kicks            2      11687  Trustmark Dealer
12619  Nissan Kicks  Nissan  Kicks            2      10000        Individual
13160  Nissan Kicks  Nissan  Kicks            2      10000        Individual
14275  Nissan Kicks  Nissan  Kicks            2       6200        Individual

      fuel_type transmission_type  mileage  engine  max_power  seats  \
1259     Petrol            Manual    14.23    1330     153.87      5
2485     Diesel            Manual    20.45    1461     108.50      5
3111     Petrol            Manual    14.23    1498     104.55      5
4937     Diesel            Manual    19.39    1461     108.00      5
9645     Petrol            Manual    14.23    1498     104.55      5
12619    Diesel            Manual    19.39    1461     108.49      0
13160    Petrol            Manual    14.23    1498     104.55      5
14275    Diesel            Manual    19.39    1461     108.00      5

       selling_price
1259         1000000
2485          850000
3111          890000
4937         1200000
9645          880000
12619        1154000
13160         950000
14275        1450000
```

We can conclude that both are 5 seater according to this dataset so let's replace values from 0 to 5

[14]:
```
df.replace({"car_name": "Honda City", "seats": 0}, {"seats": 5}, inplace=True)
df.replace({"car_name": "Nissan Kicks", "seats": 0}, {"seats": 5}, inplace=True)
```

Let's verify once again by apply `describe` method

[15]:
```
df.describe()
```

[15]:
```
        vehicle_age     km_driven       mileage        engine     max_power  \
count  15411.000000  1.541100e+04  15411.000000  15411.000000  15411.000000
mean       6.036338  5.561648e+04     19.701151   1486.057751    100.588254
std        3.013291  5.161855e+04      4.171265    521.106696     42.972979
min        0.000000  1.000000e+02      4.000000    793.000000     38.400000
25%        4.000000  3.000000e+04     17.000000   1197.000000     74.000000
50%        6.000000  5.000000e+04     19.670000   1248.000000     88.500000
75%        8.000000  7.000000e+04     22.700000   1582.000000    117.300000
max       29.000000  3.800000e+06     33.540000   6592.000000    626.000000

              seats  selling_price
count  15411.000000   1.541100e+04
mean       5.326131   7.749711e+05
std        0.805355   8.941284e+05
min        2.000000   4.000000e+04
25%        5.000000   3.850000e+05
50%        5.000000   5.560000e+05
75%        5.000000   8.250000e+05
max        9.000000   3.950000e+07
```

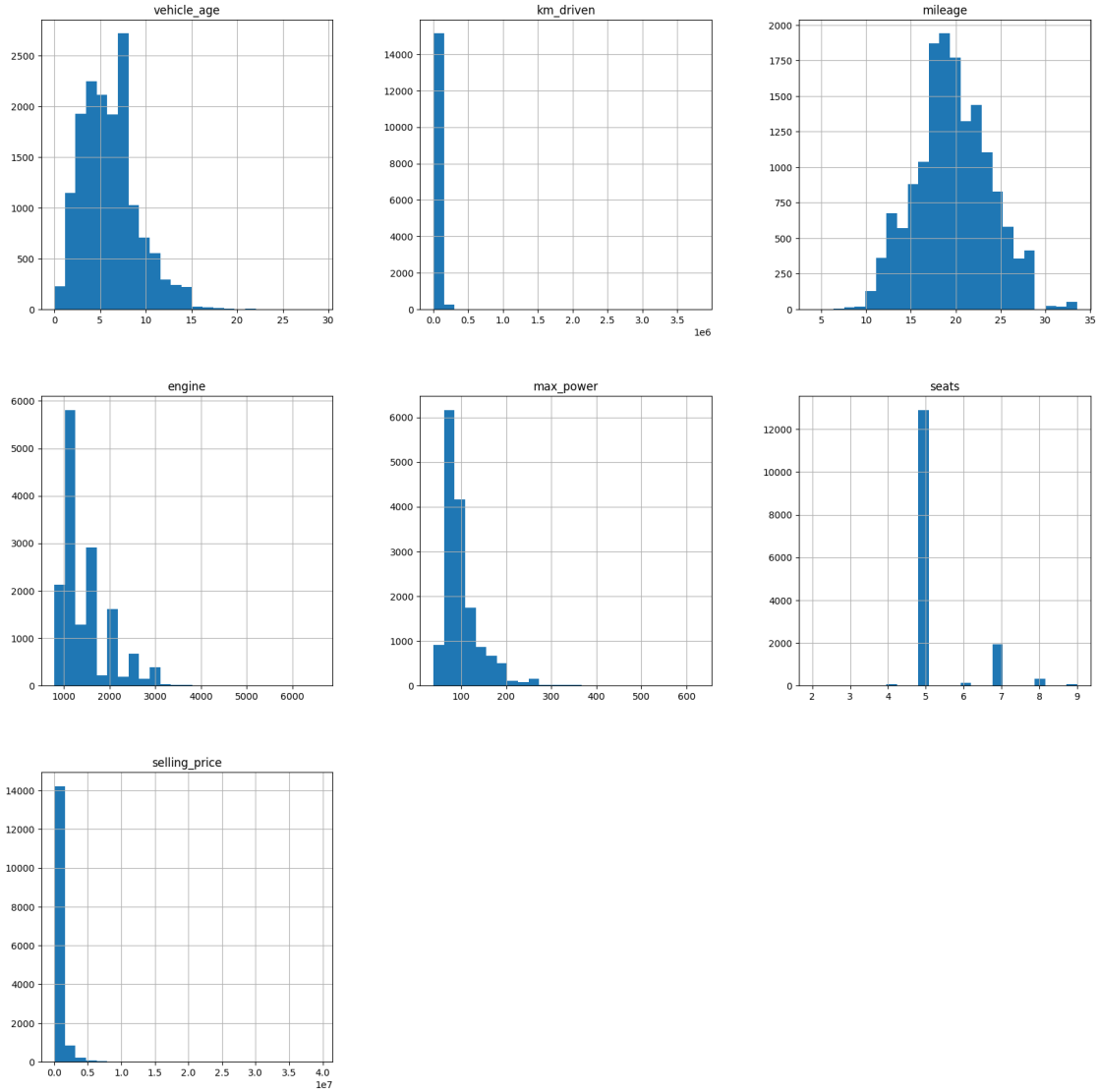
Now we can see that min for `seats` column is 2

1.2 Exploratory Data Analysis

1.2.1 Univariate Analysis

It involves the plotting the distribution of induvisual numerical figures to find any outliers or anamoly.

[16]:
```
df.hist(figsize=(20, 20), bins=25)
plt.show()
```



Here are the findings for each graphs of the numeric data:

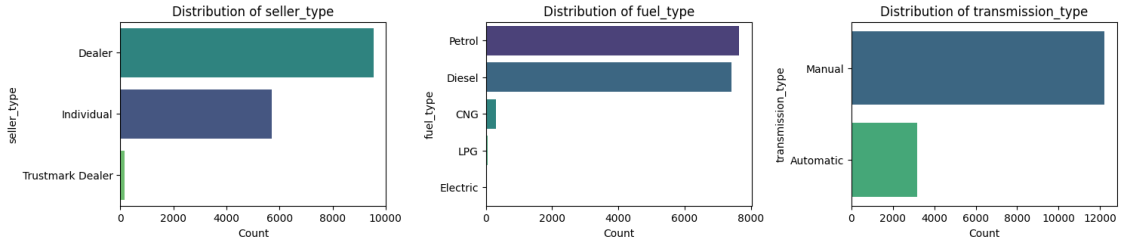
`Vehicle Age`: Most cars are between 1-7 years old, with a right-skewed distribution.
`Kilometers Driven`: Majority of cars have low mileage, but some outliers have very high usage.
`Mileage`: Mileage follows a roughly normal distribution, peaking around 18-22 km/l.
`Engine Capacity`: Most cars have engine sizes around 1000-2000 cc, with a few high-performance outliers.
`Max Power`: Skewed distribution, with most cars having power under 150 HP.
`Seats`: The majority of cars have 5 seats, with some having 4, 6, or 7 seats.
`Selling Price`: Selling price is highly right-skewed, indicating a few very high-priced cars.

[17]:
```
categorical_cols = ['seller_type', 'fuel_type', 'transmission_type']

plt.figure(figsize=(15, 15))
```

```
for i, col in enumerate(categorical_cols, 1):
    plt.subplot(5, 3, i)
    sns.countplot(y=df[col], order=df[col].value_counts().index,␣
 ↪palette="viridis", hue=df[col])
    plt.title(f'Distribution of {col}')
    plt.xlabel('Count')
    plt.ylabel(col)

plt.tight_layout()
plt.show()
```

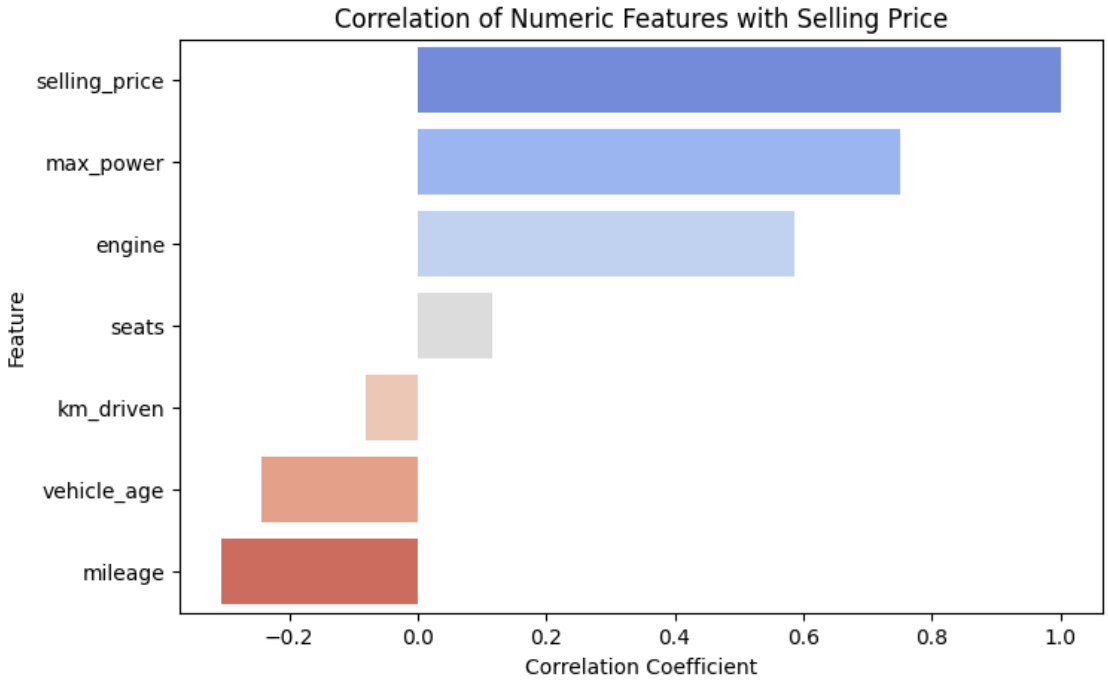


1.2.2 Bivariate analysis

Involves examining relationship between two variables. Here in this case between `selling_price` and other factors. This helps to find how different factors affect price of a vehicle.

[18]:
```
numeric_cols = df.select_dtypes(include=["int64", "float64"])
corr_with_selling_price = numeric_cols.corr()["selling_price"].sort_values(
    ascending=False
)

plt.figure(figsize=(8, 5))
sns.barplot(
    x=corr_with_selling_price.values,
    y=corr_with_selling_price.index,
    palette="coolwarm",
    hue=corr_with_selling_price.index,
)
plt.title("Correlation of Numeric Features with Selling Price")
plt.xlabel("Correlation Coefficient")
plt.ylabel("Feature")
plt.show()
```



Higher `max_power` and `engine capacity` positively impact the selling price, while `mileage` and `vehicle age` show a negative correlation, indicating that older and high-mileage cars tend to be cheaper.

Also, according to this dataset `seats` and `km_driven` have less impact on `selling_price`, it's better to drop them.

[19]:
```
df.drop(columns=['seats', 'km_driven'], inplace=True)
df.head()
```

[19]:

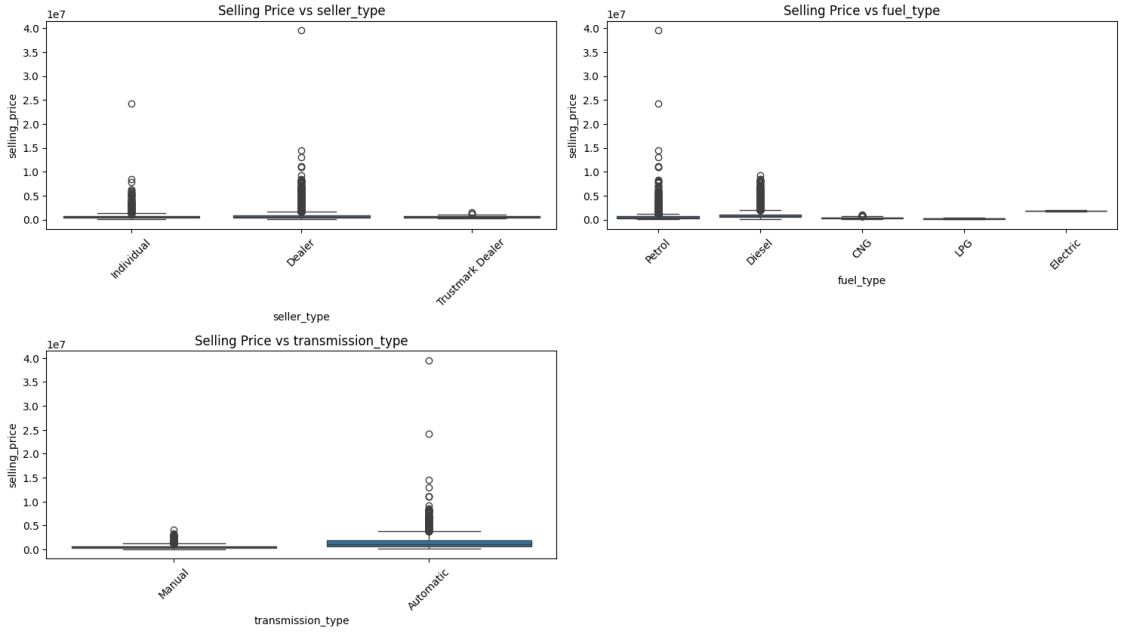
	car_name	brand	model	vehicle_age	seller_type	fuel_type	transmission_type	mileage	engine	max_power	selling_price
0	Maruti Alto	Maruti	Alto	9	Individual	Petrol	Manual	19.70	796	46.30	120000
1	Hyundai Grand	Hyundai	Grand	5	Individual	Petrol	Manual	18.90	1197	82.00	550000
2	Hyundai i20	Hyundai	i20	11	Individual	Petrol	Manual	17.00	1197	80.00	215000
3	Maruti Alto	Maruti	Alto	9	Individual	Petrol	Manual	20.92	998	67.10	226000
4	Ford Ecosport	Ford	Ecosport	6	Dealer	Diesel	Manual	22.77	1498	98.59	570000

[20]:
```
categorical_cols = ['seller_type', 'fuel_type', 'transmission_type']

plt.figure(figsize=(15, 12))

for i, col in enumerate(categorical_cols, 1):
    plt.subplot(3, 2, i)
    sns.boxplot(x=df[col], y=df['selling_price'])
    plt.xticks(rotation=45)
    plt.title(f"Selling Price vs {col}")

plt.tight_layout()
plt.show()
```



`Seller Type`: Dealers tend to have a wider range of selling prices, with some high-value outliers.
`Fuel Type`: Diesel and Petrol cars show the most variability, while CNG, LPG, and Electric vehicles have lower selling prices.
`Transmission Type`: Automatic cars generally have higher prices, whereas manual cars dominate the lower price range.

1.3 Data Preprocessing

After EDA we need to perform the following: 1. Remove irrelevant columns 2. Encode categorical data 3. Split the data for training and testing

[21]:
```
clean_df = df.copy()
clean_df.head()
```

[21]:
```
         car_name    brand     model  vehicle_age seller_type fuel_type  \
0    Maruti Alto   Maruti      Alto            9  Individual    Petrol
1  Hyundai Grand  Hyundai     Grand            5  Individual    Petrol
2    Hyundai i20  Hyundai       i20           11  Individual    Petrol
3    Maruti Alto   Maruti      Alto            9  Individual    Petrol
4  Ford Ecosport     Ford  Ecosport            6      Dealer    Diesel

  transmission_type  mileage  engine  max_power  selling_price
0            Manual    19.70     796      46.30         120000
1            Manual    18.90    1197      82.00         550000
2            Manual    17.00    1197      80.00         215000
3            Manual    20.92     998      67.10         226000
4            Manual    22.77    1498      98.59         570000
```

[22]:
```
clean_df.drop(columns=['car_name', 'brand', 'model'], inplace=True)
clean_df.to_csv('./data/cleaned_cardekho.csv', index=False, encoding='utf-8')
clean_df.head()
```

[22]:
```
   vehicle_age seller_type fuel_type transmission_type  mileage  engine  \
0            9  Individual    Petrol            Manual    19.70     796
1            5  Individual    Petrol            Manual    18.90    1197
2           11  Individual    Petrol            Manual    17.00    1197
3            9  Individual    Petrol            Manual    20.92     998
4            6      Dealer    Diesel            Manual    22.77    1498

   max_power  selling_price
0      46.30         120000
1      82.00         550000
2      80.00         215000
3      67.10         226000
4      98.59         570000
```

[23]:
```
clean_df = pd.get_dummies(clean_df, dtype=float)
clean_df.head()
```

[23]:
```
   vehicle_age  mileage  engine  max_power  selling_price  seller_type_Dealer  \
0            9    19.70     796      46.30         120000                 0.0
1            5    18.90    1197      82.00         550000                 0.0
2           11    17.00    1197      80.00         215000                 0.0
3            9    20.92     998      67.10         226000                 0.0
4            6    22.77    1498      98.59         570000                 1.0

   seller_type_Individual  seller_type_Trustmark Dealer  fuel_type_CNG  \
0                     1.0                           0.0            0.0
1                     1.0                           0.0            0.0
2                     1.0                           0.0            0.0
3                     1.0                           0.0            0.0
```

```
4                     0.0                           0.0            0.0

   fuel_type_Diesel  fuel_type_Electric  fuel_type_LPG  fuel_type_Petrol  \
0               0.0                 0.0            0.0               1.0
1               0.0                 0.0            0.0               1.0
2               0.0                 0.0            0.0               1.0
3               0.0                 0.0            0.0               1.0
4               1.0                 0.0            0.0               0.0

   transmission_type_Automatic  transmission_type_Manual
0                          0.0                       1.0
1                          0.0                       1.0
2                          0.0                       1.0
3                          0.0                       1.0
4                          0.0                       1.0
```

1.4 Building the regression model

Linear regression models the relationship between selling price and features by fitting a linear equation to minimize error. It predicts prices based on learned coefficients, assuming a linear relationship between variables.

[25]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
```

Split the dataset in ratio 80:20. 80% trains the model whereas 20% is used to test the predicted prices.

[27]:
```
X = clean_df.drop(columns=['selling_price'])
Y = clean_df['selling_price']

X.shape, Y.shape
```

[27]:
```
((15411, 14), (15411,))
```

[28]:
```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2,␣
 ↪random_state=42)

X_train.shape, X_test.shape, Y_train.shape, Y_test.shape
```

[28]:
```
((12328, 14), (3083, 14), (12328,), (3083,))
```

[29]:
```
regressor = LinearRegression()
regressor.fit(X_train, Y_train)

Y_pred = regressor.predict(X_test)
```

1.5 Evaluation Metrics

- **R-squared:** How much of the variance in the target variable is explained by the model.
- **Mean Absolute Error:** The average absolute difference between predicted and actual values.
- **Mean Squared Error:** The average squared difference between predicted and actual values.
- **Root Mean Squared Error:** The square root of the MSE, giving a more interpretable scale.

[30]:
```
r2 = r2_score(Y_test, Y_pred)
mae = mean_absolute_error(Y_test, Y_pred)
mse = mean_squared_error(Y_test, Y_pred)
rmse = mse ** 0.5

print(f'R² Score: {r2:.4f}')
print(f'MAE: {mae:.2f}')
print(f'MSE: {mse:.2f}')
print(f'RMSE: {rmse:.2f}')
```

```
R² Score: 0.6699
MAE: 278354.96
MSE: 248461571685.40
RMSE: 498459.20
```

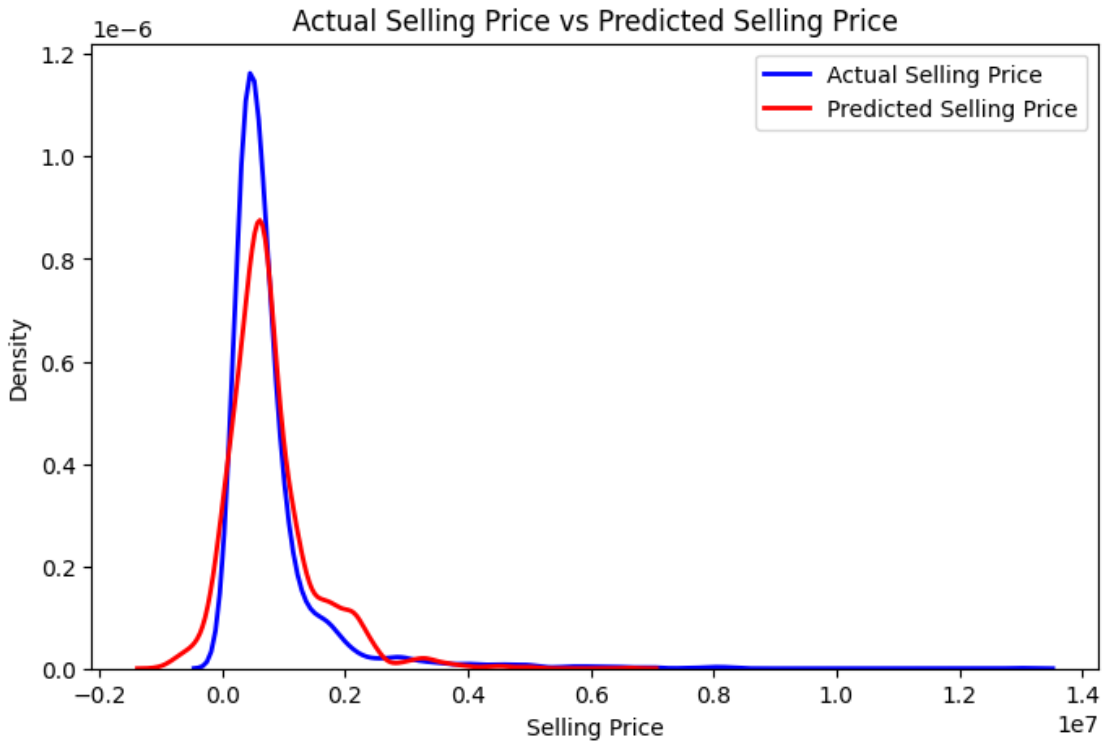
- **R² Score: 0.6699**
  The model explains approximately **67% of the variance** in selling prices, indicating a moderate fit. However, some factors influencing price are still unaccounted for.
- **Mean Absolute Error (MAE): 278,354.96**
  On average, the model's predictions deviate from actual prices by **2.78 lakhs**.
- **Mean Squared Error (MSE): 248,461,571,685.40**
  The high MSE suggests that large errors contribute significantly, indicating the presence of **outliers or high variance** in the data.
- **Root Mean Squared Error (RMSE): 498,459.20**
  The typical prediction error is around **4.98 lakhs**, which is relatively high and suggests potential room for model improvement.

1.6 Plotting the best fit line

[31]:
```
plt.figure(figsize=(8, 5))
sns.scatterplot(x=Y_test, y=Y_pred,alpha=0.5 ,palette='viridis', hue=Y_pred)
plt.plot([Y_test.min(), Y_test.max()], [Y_test.min(), Y_test.max()], '--r',␣
 ↪linewidth=2)
plt.xlabel("Actual Selling Price")
plt.ylabel("Predicted Selling Price")
plt.title("Actual Selling Price vs Predicted Selling Price")
plt.show()
```

Plotting the distribution plot for Predicted Prices and Actual Prices

[32]:
```
plt.figure(figsize=(8, 5))
sns.kdeplot(Y_test, label='Actual Selling Price', color='blue', linewidth=2)
sns.kdeplot(Y_pred, label='Predicted Selling Price', color='red', linewidth=2)
plt.xlabel("Selling Price")
plt.ylabel("Density")
plt.title("Actual Selling Price vs Predicted Selling Price")
plt.legend()
plt.show()
```



Actual vs. Predicted Selling Price Distribution

- The **blue curve** represents the actual selling price distribution, while the **red curve** shows the predicted values.
- The two distributions are closely aligned, indicating that the model's predictions generally follow the actual trend.
- Some deviations suggest **overestimation or underestimation** in certain price ranges, which could be improved with feature engineering or a more complex model.