Linear Regression

Regression models make the use of features to understand the relationship among the continuous features and the output variable. That is, they use the pattern that is learned to determine the value of the new data points.

- **Objective:** Predicts a continuous numerical value based on input features.
- **Output:** Continuous values (real numbers).
- **Example Problem:** Predicting house prices based on size, location, and other features

Case Senario: CAR DEKHO

About Car Dekho

CarDekho, founded in 2008 by Amit Jain and Anurag Jain, is India's leading automotive platform for buying and selling new and used cars. It offers car reviews, comparisons, prices, expert advice, and innovative tools like 360-degree views. CarDekho also partners with dealers, financial institutions, and insurance providers to enhance the car ownership experience. It has expanded operations to Southeast Asia and the UAE and is valued at over $1 billion.

Problem Statement:

The used car market in India is a dynamic and ever-changing landscape. Prices can fluctuate wildly based on a variety of factors including the make and model of the car, its mileage, its condition and the current market conditions. As a result, it can be difficult for sellers to accurately price their cars

Approach:

We propose to develop a machine learning model that can predict the price of a used car based on its features. The model will be trained on a dataset of used cars that have been sold on Cardekho.com in India. The model will then be able to be used to predict the price of any used car, given its features.

Objective

To predict Car Price using Machine Learning Model.

Benefits:

The benefits of this solution include:

- Sellers will be able to more accurately price their cars which will help them to sell their cars faster and for a higher price.
- Buyers will be able to find cars that are priced more competitively.
- The overall used car market in India will become more efficient

```
# Importing necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
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

#Load the dataset
data = "Cardekho.csv"
df =pd.read_csv(data)

# Check the first few rows of the dataset
df.head()

   Unnamed: 0       car_name    brand     model  vehicle_age
km_driven  \
0           0    Maruti Alto   Maruti      Alto            9
120000
1           1  Hyundai Grand  Hyundai     Grand            5
20000
2           2    Hyundai i20  Hyundai       i20           11
60000
3           3    Maruti Alto   Maruti      Alto            9
37000
4           4  Ford Ecosport     Ford  Ecosport            6
30000

  seller_type fuel_type transmission_type  mileage  engine  max_power
seats  \
0  Individual    Petrol            Manual    19.70     796      46.30
5
1  Individual    Petrol            Manual    18.90    1197      82.00
5
2  Individual    Petrol            Manual    17.00    1197      80.00
5
3  Individual    Petrol            Manual    20.92     998      67.10
5
4      Dealer    Diesel            Manual    22.77    1498      98.59
5

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

```
# Get a concise summary of the dataset
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
```

```
# Check the shape of the data (rows and columns)
df.shape
```

```
(15411, 14)
```

```
# Data cleaning: Drop unwanted columns
df.drop(columns=['Unnamed: 0'], inplace=True)

#Checking null values
df.isnull().sum()
```

```
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
```

```
# Checking Duplicate values
df.duplicated().sum()
```

```
np.int64(167)
```

```
# Statistical summary of numerical columns
df.describe()
```

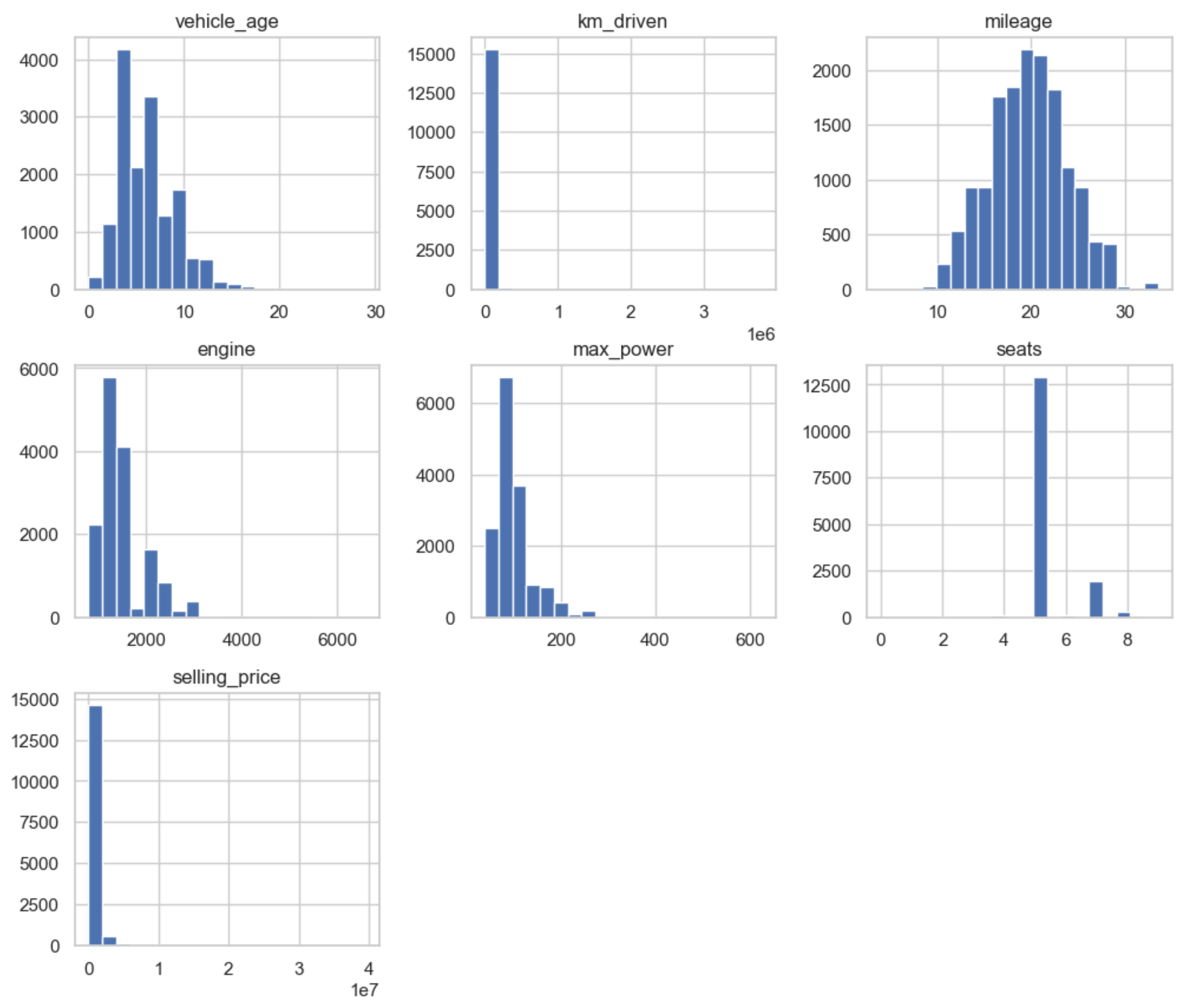
```
        vehicle_age     km_driven        mileage        engine
max_power  \
count  15411.000000  1.541100e+04   15411.000000  15411.000000
15411.000000
mean       6.036338  5.561648e+04      19.701151   1486.057751
100.588254
std        3.013291  5.161855e+04       4.171265    521.106696
42.972979
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
```

Exploratory Data Analysis (EDA)

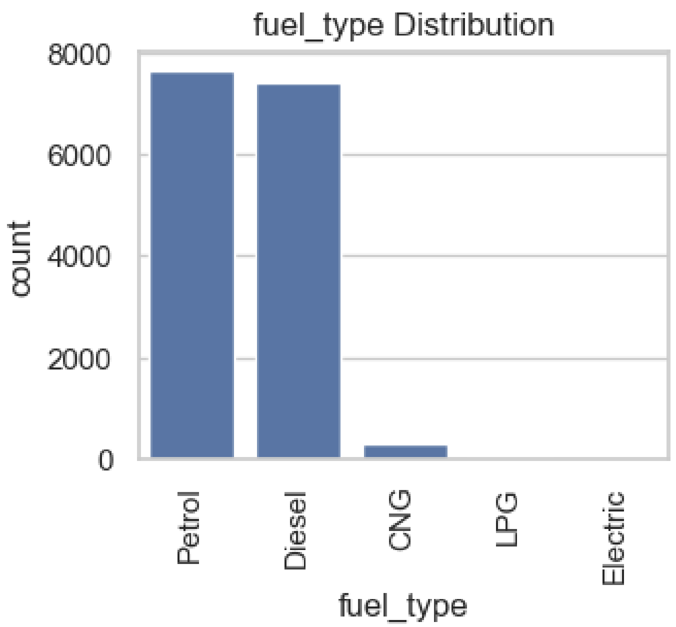
Univariate Analysis (Examining individual variables)

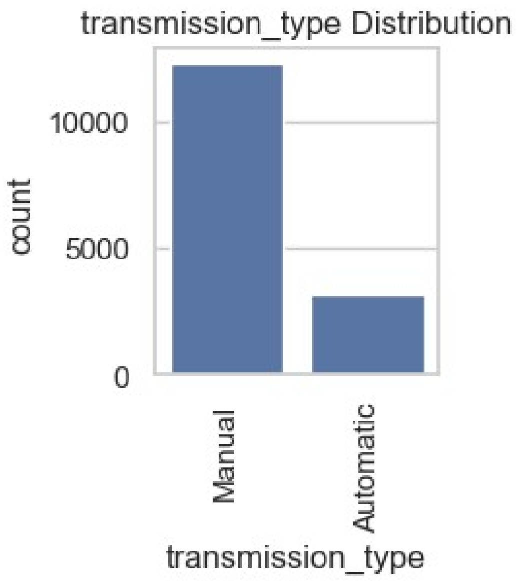
Univariate analysis involves looking at the distribution of individual features. This helps in understanding if any outliers are present and the overall distribution of the data.

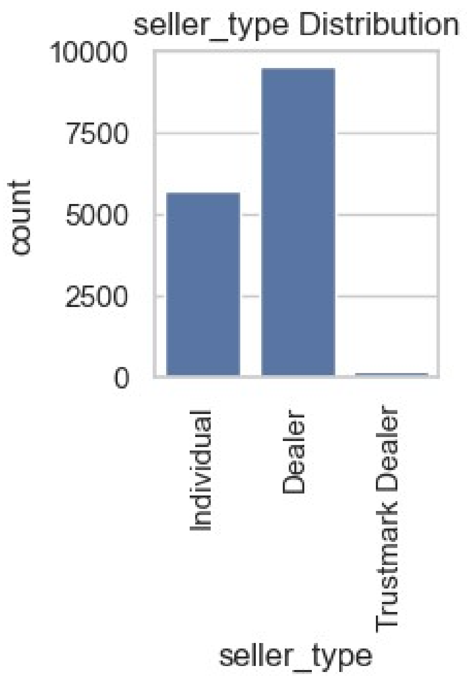
```
# Plot histograms for numerical features
df.hist(figsize=(12, 10), bins=20)
plt.show()
```



```
df.columns

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

# Categorical features
categorical_features = ["fuel_type", "transmission_type",
"seller_type"]
plt.figure(figsize=(12, 6))

# Loop through each categorical feature and plot the count plot
for i, feature in enumerate(categorical_features):
    plt.subplot(2, 3, i+1)
    sns.countplot(x=feature, data=df)
    plt.title(f'{feature} Distribution')
    plt.xticks(rotation = 90)
    plt.show()
```



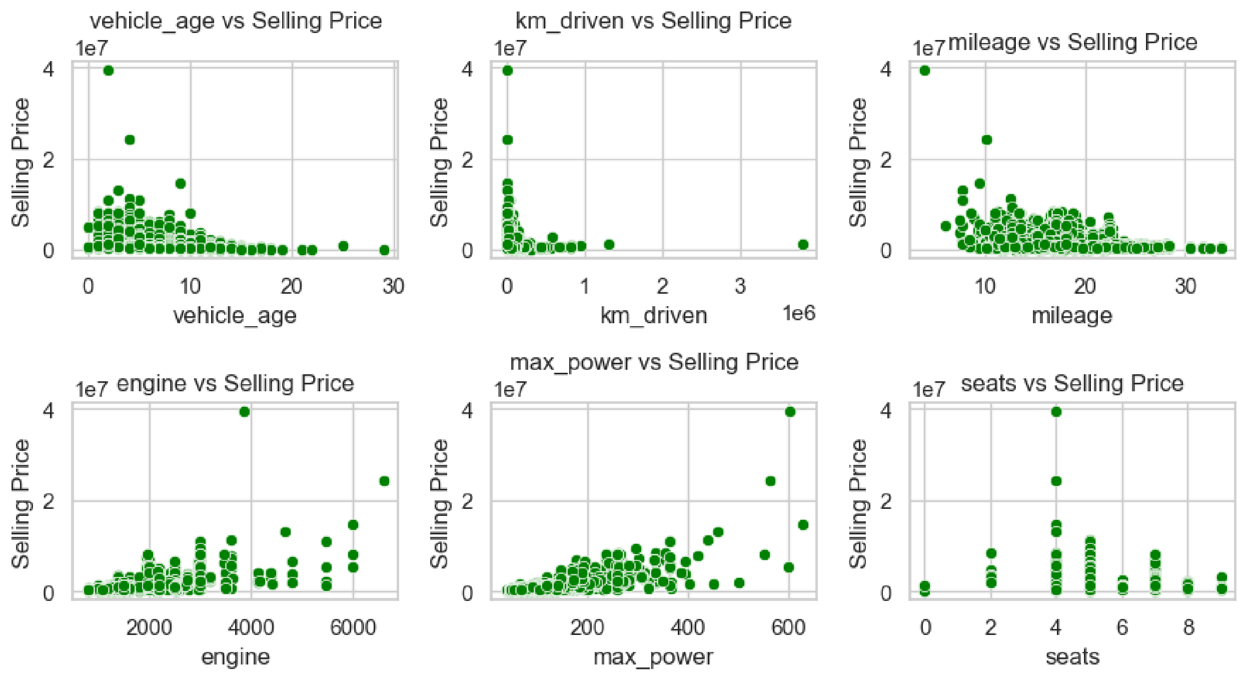




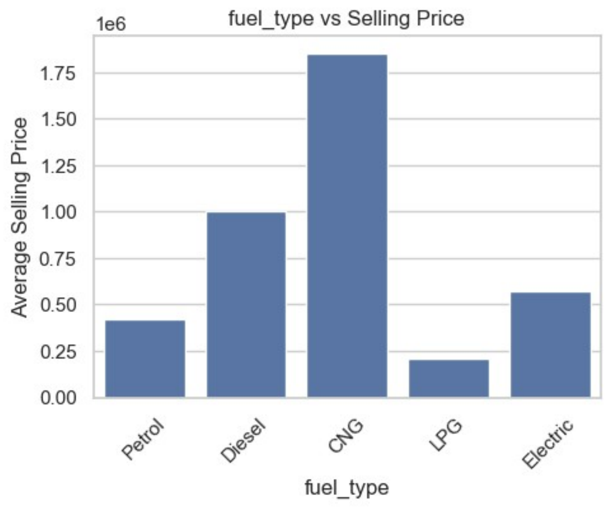
Bivariate Analysis (Examining the relationship between two variables)

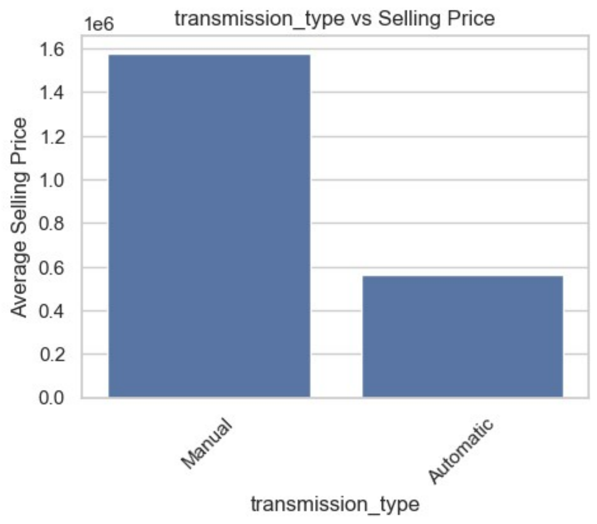
We examine the relationship between the target variable (selling_price) and other features. This step typically helps in understanding which features have strong correlations with the target variable.

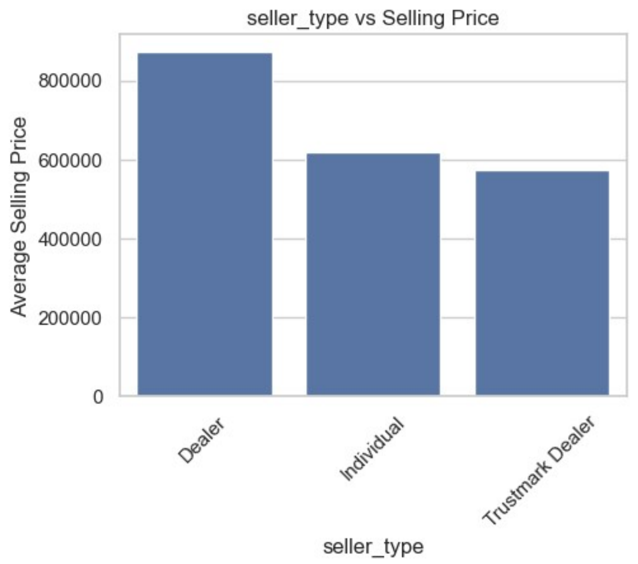
```
# Numerical features
numerical_features = ['vehicle_age', 'km_driven', 'mileage', 'engine', 
'max_power', 'seats']

# Create subplots for scatter plots
plt.figure(figsize=(9,5))

# Scatter plot for each numerical feature vs selling price
for i, feature in enumerate(numerical_features):
    plt.subplot(2, 3, i+1)
    sns.scatterplot(x=df[feature], y=df['selling_price'], 
color='green')
    plt.title(f'{feature} vs Selling Price')
    plt.xlabel(feature)
    plt.ylabel('Selling Price')

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



```python
# Categorical features to analyze
categorical_features = ['fuel_type', 'transmission_type',
'seller_type']

# Set figure size for the plots
plt.figure(figsize=(10,12))

# Create subplots for bar plots of categorical features vs selling
price
for i, feature in enumerate(categorical_features):
    plt.subplot(3,2, i +1)
    sns.barplot(x=df[feature].value_counts().index,
                y=df.groupby(feature)['selling_price'].mean().values)
    plt.title(f'{feature} vs Selling Price')
    plt.xlabel(feature)
    plt.ylabel('Average Selling Price')
    plt.xticks(rotation=45)

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







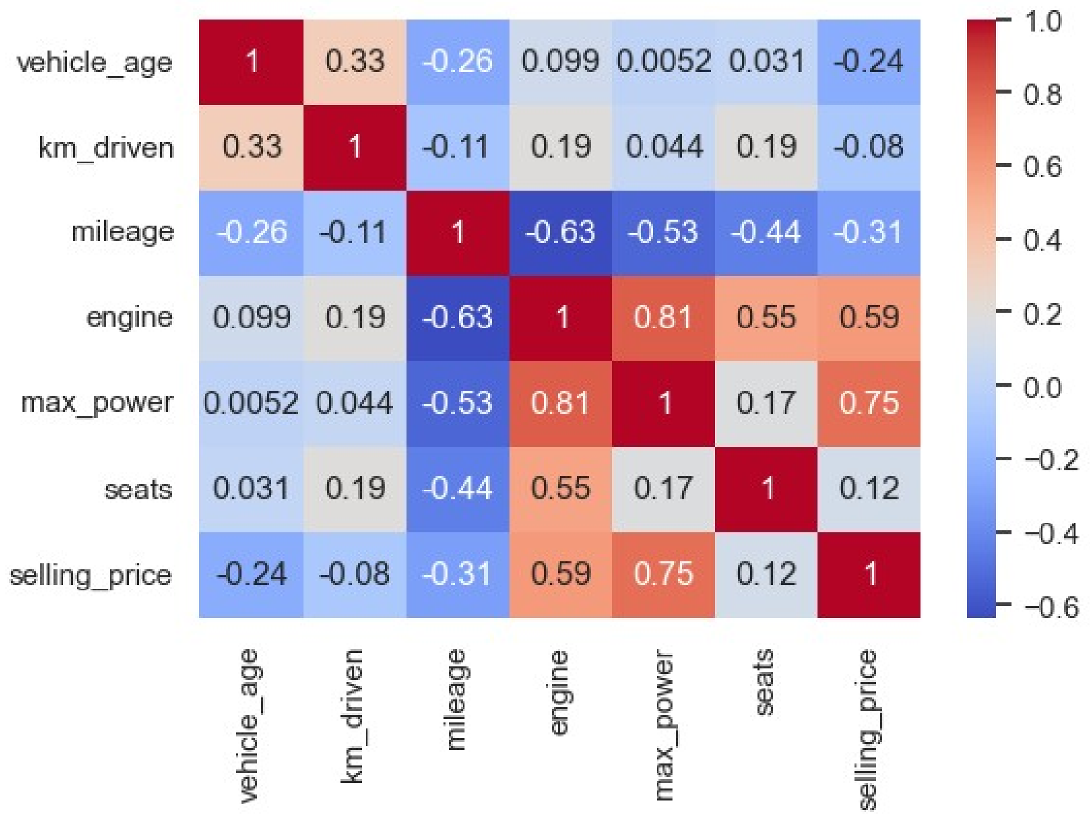
Multivariate Analysis (Correlation between multiple variables)

```
# List of numerical features you want to calculate correlation for
numerical_features = ['vehicle_age', 'km_driven', 'mileage', 'engine',
'max_power', 'seats', 'selling_price']

# Calculate the correlation matrix for selected numerical features
correlation_matrix = df[numerical_features].corr()

# Display the correlation matrix
print(correlation_matrix)
```

```
               vehicle_age  km_driven   mileage    engine
max_power  \
vehicle_age       1.000000   0.333891 -0.257394  0.098965   0.005208
```

```
km_driven          0.333891   1.000000 -0.105239  0.192885   0.044421

mileage           -0.257394  -0.105239  1.000000 -0.632987  -0.533128

engine             0.098965   0.192885 -0.632987  1.000000   0.807368

max_power          0.005208   0.044421 -0.533128  0.807368   1.000000

seats              0.030791   0.192830 -0.440280  0.551236   0.172257

selling_price     -0.241851  -0.080030 -0.305549  0.585844   0.750236


                  seats  selling_price
vehicle_age    0.030791      -0.241851
km_driven      0.192830      -0.080030
mileage       -0.440280      -0.305549
engine         0.551236       0.585844
max_power      0.172257       0.750236
seats          1.000000       0.115033
selling_price  0.115033       1.000000
```

```python
#Plot the heatmap for checking the correlation
plt.figure(figsize=(6,4))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.show()
```



Summary of Correlation Insights:

1. **Vehicle Age vs. Selling Price**:
   - **Negative correlation (-0.24)**: Older cars usually have lower prices.
2. **Kilometers Driven vs. Selling Price**:
   - **Weak negative correlation (-0.08)**: Minor effect on selling price.
3. **Mileage vs. Selling Price**:
   - **Moderate negative correlation (-0.31)**: Low-mileage cars tend to have higher prices.
4. **Engine Capacity vs. Selling Price**:
   - **Moderate positive correlation (0.59)**: Larger engines often lead to higher prices.
5. **Max Power vs. Selling Price**:
   - **Strong positive correlation (0.75)**: Higher max power correlates with higher prices.
6. **Seats vs. Selling Price**:
   - **Weak positive correlation (0.12)**: Minor effect on price.

Other Key Insights:

- **Mileage & Engine Capacity**: Strong negative correlation (-0.63).
- **Mileage & Max Power**: Moderate negative correlation (-0.53).

Conclusion:

- **Max Power** is the strongest predictor of **selling price**.

- **Vehicle age**, **mileage**, and **km driven** have expected negative correlations with selling price.

Data Preprocessing

After the EDA, we need to:

- Drop irrelevant columns that won't help in predicting the target variable.
- Encode categorical variables (e.g., fuel_type, transmission_type) into numerical representations.
- Split the data into training and testing sets.

```
model_data = df.copy()
model_data.head()

         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

# Drop irrelevant columns
model_data.drop(labels =
['car_name','brand','model','seller_type'],axis = 1, inplace = True)

model_data = pd.get_dummies(model_data,dtype = float)
model_data

       vehicle_age  km_driven  mileage  engine  max_power  seats  \
0                9     120000    19.70     796      46.30      5
```

```
1                5      20000    18.90    1197      82.00      5
2               11      60000    17.00    1197      80.00      5
3                9      37000    20.92     998      67.10      5
4                6      30000    22.77    1498      98.59      5
...            ...        ...      ...     ...        ...    ...
15406            9      10723    19.81    1086      68.05      5
15407            2      18000    17.50    1373      91.10      7
15408            6      67000    21.14    1498     103.52      5
15409            5    3800000    16.00    2179     140.00      7
15410            2      13000    18.00    1497     117.60      5

       selling_price  fuel_type_CNG  fuel_type_Diesel
fuel_type_Electric  \
0             120000            0.0               0.0
0.0
1             550000            0.0               0.0
0.0
2             215000            0.0               0.0
0.0
3             226000            0.0               0.0
0.0
4             570000            0.0               1.0
0.0
...              ...            ...               ...
...
15406         250000            0.0               0.0
0.0
15407         925000            0.0               0.0
0.0
15408         425000            0.0               1.0
0.0
15409        1225000            0.0               1.0
0.0
15410        1200000            0.0               0.0
0.0

       fuel_type_LPG  fuel_type_Petrol  transmission_type_Automatic  \
0                0.0               1.0                          0.0
1                0.0               1.0                          0.0
2                0.0               1.0                          0.0
3                0.0               1.0                          0.0
4                0.0               0.0                          0.0
...              ...               ...                          ...
15406            0.0               1.0                          0.0
15407            0.0               1.0                          0.0
15408            0.0               0.0                          0.0
15409            0.0               0.0                          0.0
15410            0.0               1.0                          1.0

       transmission_type_Manual
```

```
0                            1.0
1                            1.0
2                            1.0
3                            1.0
4                            1.0
...                          ...
15406                        1.0
15407                        1.0
15408                        1.0
15409                        1.0
15410                        0.0

[15411 rows x 14 columns]
```

Understanding Features (X) and Target (y)

In any supervised learning task, the dataset consists of two main components:

- **Features (X):** These are the input variables that are used to predict the target. In the case of predicting house prices, features are the characteristics of the house such as:
  - Number of bedrooms
  - Square footage of the living area
  - Lot size
  - Age of the house
  - Location (like postal code, latitude, longitude, etc.)
- **Target (y): This is the output or the variable you want to predict. In your case, the target is the Price of the house.**

Why Split the Dataset?

- In supervised learning, we use the features (X) to make predictions about the target (y). The features contain the information that will help the machine learning model learn the relationship with the target.

- We separate these two components so that the model can learn the mapping from X (inputs) to y (output). Here's why we do it:

  - **X (Features):** These are the predictors (independent variables), which will help the model learn patterns or relationships that influence the target variable (Price). These features will be fed into the model to predict the price.

  - **y (Target):** This is the variable we want to predict. The machine learning model will try to map the inputs (X) to the correct output (y), in this case, the house price.

```python
# Define features (X) and target (Y)
X = model_data.drop('selling_price', axis=1)  # Independent variables
Y = model_data['selling_price']  # Target variable
```

Splitting the Data into Training and Test Sets

- It’s important to separate the data into training and testing sets to evaluate the performance of the model.

```
# Split data into training (80%) and testing (20%) sets
train_X, test_X, train_Y, test_Y = train_test_split(X, Y, 
test_size=0.2)

print(f"Training set size: {train_X.shape}, Testing set size: 
{test_X.shape}")
X = model_data.drop('selling_price', axis = 1)

Training set size: (12328, 13), Testing set size: (3083, 13)
```

Train the Regression Model

```
# Initialize the Linear Regression model
regressor = LinearRegression()

# Train the model on the training data
regressor.fit(train_X, train_Y)

# Predict on the test data
predictions = regressor.predict(test_X)

# Show the first few predicted values
print(predictions[:5])

[ 319789.06230089 2582140.59940556  625455.66304741  297957.19031012
  231022.12261288]

print(test_Y)

5243      600000
12256    5000000
10172     335000
12725     665000
11388     275000
          ...   
5712     1064000
15239     425000
1864     1185000
7700      295000
7409      440000
Name: selling_price, Length: 3083, dtype: int64

test_X['predicted_sales_price'] = predictions

test_X['Actual_price'] = test_Y
```

```
test_X['difference'] = test_X['predicted_sales_price'] -
test_X['Actual_price']

test_X

       vehicle_age  km_driven  mileage  engine  max_power  seats  \
5243             9     110000    20.77    1248      88.80      7
12256            2       9000    22.48    1995     187.74      5
10172            8      56000    16.09    1598     103.20      5
12725            5      60240    15.96    2523      62.10      7
11388           10      53000    16.10    1298      88.20      5
...            ...        ...      ...     ...        ...    ...
5712             2      20000    25.47    1248      88.50      7
15239            8      45529    19.10    1197      85.80      5
1864             8      71000    19.27    2143     170.00      5
7700             7      41423    21.79     998      67.05      5
7409             7      63407    20.00    1399      68.05      5

       fuel_type_CNG  fuel_type_Diesel  fuel_type_Electric
fuel_type_LPG  \
5243             0.0               1.0                 0.0
0.0
12256            0.0               1.0                 0.0
0.0
10172            0.0               0.0                 0.0
0.0
12725            0.0               1.0                 0.0
0.0
11388            0.0               0.0                 0.0
0.0
...              ...               ...                 ...
...
5712             0.0               1.0                 0.0
0.0
15239            0.0               0.0                 0.0
0.0
1864             0.0               1.0                 0.0
0.0
7700             0.0               0.0                 0.0
0.0
7409             0.0               1.0                 0.0
0.0

       fuel_type_Petrol  transmission_type_Automatic  \
5243                0.0                          0.0
12256               0.0                          1.0
10172               1.0                          0.0
12725               0.0                          0.0
11388               1.0                          0.0
...                 ...                          ...
```

```
5712                0.0                        0.0
15239               1.0                        0.0
1864                0.0                        1.0
7700                1.0                        0.0
7409                0.0                        0.0

       transmission_type_Manual  predicted_sales_price
Actual_price  \
5243                        1.0           3.197891e+05       600000

12256                       0.0           2.582141e+06      5000000

10172                       1.0           6.254557e+05       335000

12725                       1.0           2.979572e+05       665000

11388                       1.0           2.310221e+05       275000

...                         ...                    ...          ...

5712                        1.0           9.161350e+05      1064000

15239                       1.0           3.673003e+05       425000

1864                        0.0           1.842414e+06      1185000

7700                        1.0           1.699719e+05       295000

7409                        1.0           1.729950e+05       440000


         difference
5243  -2.802109e+05
12256 -2.417859e+06
10172  2.904557e+05
12725 -3.670428e+05
11388 -4.397788e+04
...             ...
5712  -1.478650e+05
15239 -5.769969e+04
1864   6.574140e+05
7700  -1.250281e+05
7409  -2.670050e+05

[3083 rows x 16 columns]
```

Model Evaluation

1. Mean Squared Error (MSE)

What is MSE?

MSE measures the average squared differences between the predicted and actual values. It quantifies how far off your model's predictions are, penalizing larger errors more heavily due to squaring.

Why Use MSE?

- **Penalizes Larger Errors**: Squaring the error ensures that large deviations get penalized more.
- **Simple and Effective**: It provides a clear metric for model evaluation, with lower values indicating better performance.

Formula:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2$$

Where:

- (y_i): True value
- (\hat{y}_i): Predicted value
- (n): Number of observations

Interpretation:

- **Low MSE**: Indicates predictions are close to actual values.
- **High MSE**: Indicates poor prediction accuracy.
- **Unit**: The unit of MSE is the square of the target variable's unit, making it less interpretable than RMSE.

2. Root Mean Squared Error (RMSE)

What is RMSE?

RMSE is the square root of MSE. It expresses the error in the same units as the target variable, making it more interpretable than MSE.

Why Use RMSE?

- **Intuitive**: Errors are presented in the same units as the target variable.
- **Magnitude of Error**: Gives a clear idea of the typical prediction error.

Formula:

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}$$

Interpretation:

- **Lower RMSE**: Better prediction accuracy.
- **Higher RMSE**: Indicates larger errors.
- **Unit**: Same as the target variable.

Why RMSE over MSE?

- While MSE tells you the average squared error, RMSE provides an error measure that's easier to interpret in the context of the problem (e.g., INR for car prices).

3. R-squared (R^2)

What is R-squared?

R-squared measures the proportion of variance in the target variable that's explained by the features in the model. It's a relative metric and ranges from 0 to 1 (or negative if the model is worse than a baseline).

Why Use R-squared?

- **Explains Variance**: Shows how well the independent variables explain the variability of the dependent variable.
- **Model Fit**: A higher R^2 indicates a better fit.

Formula:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} \left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{n} \left(y_i - \acute{y}\right)^2}$$

Where:

- (y_i): True value
- (\hat{y}_i): Predicted value
- (\bar{y}): Mean of the actual values

Interpretation:

- **R^2 = 1**: Perfect fit; all variance is explained by the model.
- **R^2 = 0**: The model explains none of the variance (equivalent to predicting the mean).
- **R^2 < 0**: The model performs worse than the mean predictor.

Why Use All Three Metrics?

- **MSE**: Focuses on the absolute size of the error.
- **RMSE**: Scales this error to the same unit as the target variable for easier interpretation.
- **R-squared**: Provides insight into how well the model fits the data and explains variance.

```
# Calculate Mean Squared Error (MSE) and Root Mean Squared Error
(RMSE)
```

```
mse = mean_squared_error(test_Y, predictions)
rmse = np.sqrt(mse)
r2 = r2_score(test_Y,predictions)

print(f"Mean Squared Error (MSE): {mse}")
print(f"Root Mean Squared Error (RMSE): {rmse}")
print(f"R-squared: {r2}")

Mean Squared Error (MSE): 204566383684.87823
Root Mean Squared Error (RMSE): 452290.15430902125
R-squared: 0.6731027242911729
```

1. Mean Squared Error (MSE): 204,566,383,684.88

- **MSE** is a measure of how far your predictions are from the true values. In this case, the **MSE is 204,566,383,684.88**, which is quite large.
- **Interpretation**: The MSE value is hard to interpret directly, as it's in squared units (in this case, squared INR or the unit of the target variable). The larger the MSE, the worse the model is at making predictions.
- **Why it matters**: This gives an overall measure of how off the model's predictions are, but because it's squared, it overemphasizes larger errors.

2. Root Mean Squared Error (RMSE): 452,290.15

- **RMSE** is simply the square root of MSE, so it gives you a clearer idea of the magnitude of the prediction error.
- **Interpretation**: An RMSE of ₹452,290.15 means that, on average, the model’s predictions are off by ₹452,290.15 for each prediction. This is a more interpretable value because it’s in the same units as the target variable (car prices).
- **Why it matters**: Lower RMSE means the model's predictions are closer to the actual values, so the goal is to minimize this number as much as possible.

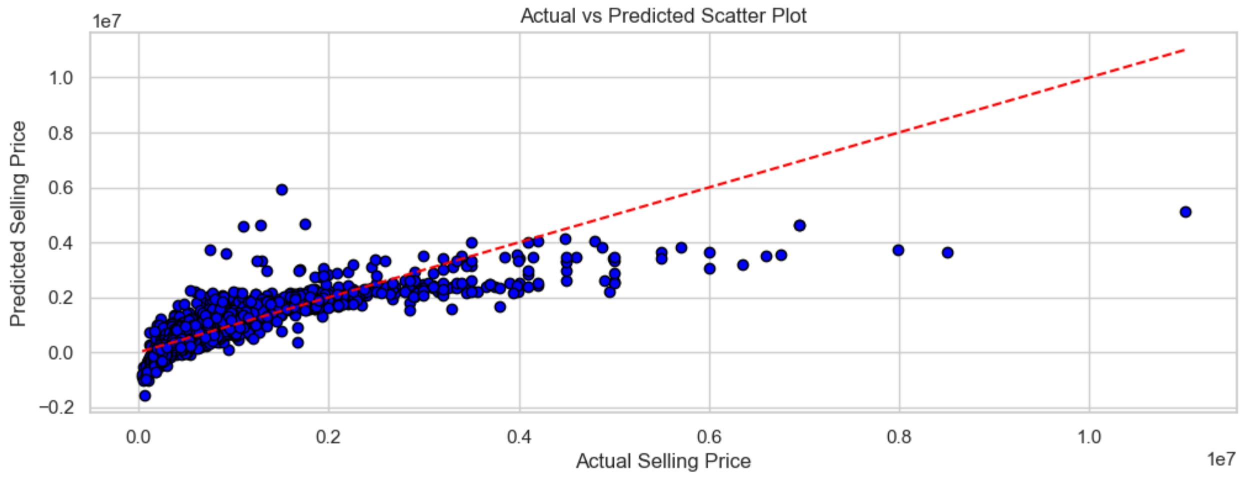
3. R-squared (R^2): 0.6731 (or 67.31%)

- **R-squared** is a measure of how well the model explains the variability in the target variable. It shows the proportion of the variance in the target variable (selling price) that is explained by the model.
- **Interpretation**: An **R^2 of 0.6731** means that **67.31%** of the variance in car prices is explained by the model. This is a fairly decent result, indicating that the model explains a substantial amount of the variability, but there is still 32.69% of the variance that remains unexplained.
- **Why it matters**: A higher R^2 is generally better, but a "good" R^2 depends on the context. In some domains, an R^2 of 0.67 can be acceptable, especially when predicting something as variable as car prices.

Visualizing the Predictions

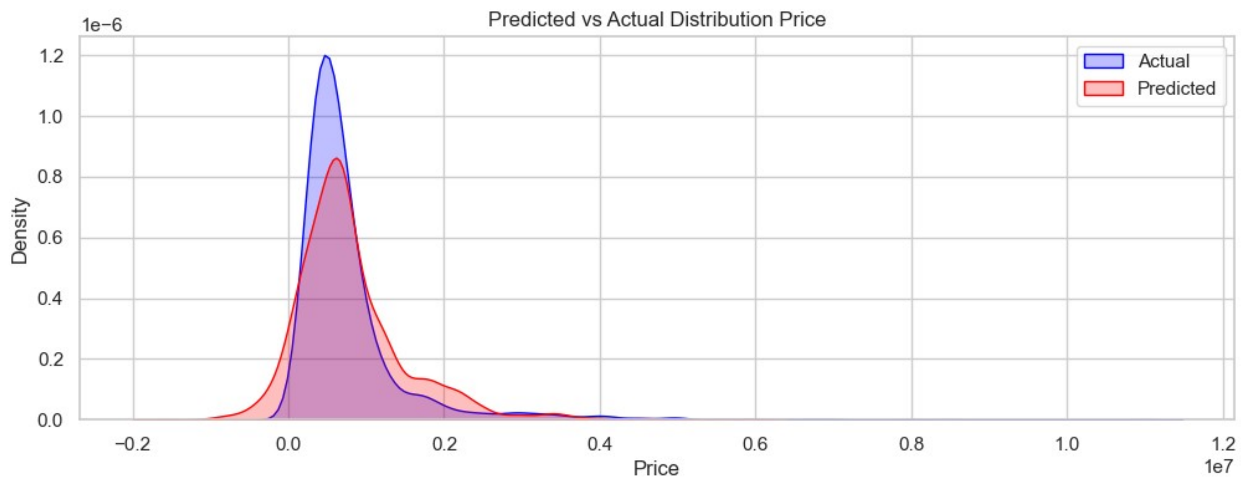
```
# Actual vs Predicted Scatter Plot
plt.figure(figsize=(12,4))
plt.scatter(test_Y, predictions, color='blue',edgecolor='black')
```

```python
plt.plot([test_Y.min(), test_Y.max()], [test_Y.min(), test_Y.max()],
color='red', linestyle='--')  # Ideal line
plt.title('Actual vs Predicted Scatter Plot')
plt.xlabel('Actual Selling Price')
plt.ylabel('Predicted Selling Price')
plt.show()
```



The red dashed line represents the ideal line (where predicted values exactly match actual values). The scatter points show how close your predictions are to the actual prices. The closer the points are to the red line, the better the model.

```python
# Plotting Actual vs Predicted Distribution Price
plt.figure(figsize=(12,4))
sns.kdeplot(test_Y, color='blue', label='Actual', fill=True)
sns.kdeplot(predictions, color='red', label='Predicted', fill=True)
plt.title('Predicted vs Actual Distribution Price')
plt.xlabel('Price')
plt.ylabel('Density')
plt.legend()
plt.show()
```



In a good model, the predicted price distribution should closely match the actual price distribution. Any significant difference suggests the model isn't capturing the distribution of prices well.