# CarDekho Price Prediction

```
# Import the 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, RandomizedSearchCV
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error
```

```
# Import the dataset
df = pd.read_csv('Cardekho-raw-dataset.csv')
df.head()
```

| | car_name | brand | model | vehicle_age | km_driven | seller_type | fuel_type | transmission_type | mileage | engine | max_power | seats | selling_price |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | Maruti Alto | Maruti | Alto | 9 | 120000 | Individual | Petrol | Manual | 19.70 | 796 | 46.30 | 5 | 120000 |
| **1** | Hyundai Grand | Hyundai | Grand | 5 | 20000 | Individual | Petrol | Manual | 18.90 | 1197 | 82.00 | 5 | 550000 |
| **2** | Hyundai i20 | Hyundai | i20 | 11 | 60000 | Individual | Petrol | Manual | 17.00 | 1197 | 80.00 | 5 | 215000 |
| **3** | Maruti Alto | Maruti | Alto | 9 | 37000 | Individual | Petrol | Manual | 20.92 | 998 | 67.10 | 5 | 226000 |
| **4** | Ford Ecosport | Ford | Ecosport | 6 | 30000 | Dealer | Diesel | Manual | 22.77 | 1498 | 98.59 | 5 | 570000 |

```
# Check the concise summary of the dataset
df.info()
```

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

```
# Check the shape of the dataset
df.shape
```

```
(15411, 13)
```

```python
# Check statistics of numerical columns
df.describe()
```

| | vehicle_age | km_driven | mileage | engine | max_power | seats | selling_price |
|---|---|---|---|---|---|---|---|
| **count** | 15411.000000 | 1.541100e+04 | 15411.000000 | 15411.000000 | 15411.000000 | 15411.000000 | 1.541100e+04 |
| **mean** | 6.036338 | 5.561648e+04 | 19.701151 | 1486.057751 | 100.588254 | 5.325482 | 7.749711e+05 |
| **std** | 3.013291 | 5.161855e+04 | 4.171265 | 521.106696 | 42.972979 | 0.807628 | 8.941284e+05 |
| **min** | 0.000000 | 1.000000e+02 | 4.000000 | 793.000000 | 38.400000 | 0.000000 | 4.000000e+04 |
| **25%** | 4.000000 | 3.000000e+04 | 17.000000 | 1197.000000 | 74.000000 | 5.000000 | 3.850000e+05 |
| **50%** | 6.000000 | 5.000000e+04 | 19.670000 | 1248.000000 | 88.500000 | 5.000000 | 5.560000e+05 |
| **75%** | 8.000000 | 7.000000e+04 | 22.700000 | 1582.000000 | 117.300000 | 5.000000 | 8.250000e+05 |
| **max** | 29.000000 | 3.800000e+06 | 33.540000 | 6592.000000 | 626.000000 | 9.000000 | 3.950000e+07 |

```python
# Check unique values of the 'brand' column
df['brand'].unique()
```

```
array(['Maruti', 'Hyundai', 'Ford', 'Renault', 'Mini', 'Mercedes-Benz',
       'Toyota', 'Volkswagen', 'Honda', 'Mahindra', 'Datsun', 'Tata',
       'Kia', 'BMW', 'Audi', 'Land Rover', 'Jaguar', 'MG', 'Isuzu',
       'Porsche', 'Skoda', 'Volvo', 'Lexus', 'Jeep', 'Maserati',
       'Bentley', 'Nissan', 'ISUZU', 'Ferrari', 'Mercedes-AMG',
       'Rolls-Royce', 'Force'], dtype=object)
```

```python
# Check value counts of the 'brand' column
df['brand'].value_counts()
```

```
brand
Maruti           4992
Hyundai          2982
Honda            1485
Mahindra         1011
Toyota            793
Ford              790
Volkswagen        620
Renault           536
BMW               439
Tata              430
Mercedes-Benz     337
Skoda             334
Audi              192
Datsun            170
Jaguar             59
Land Rover         51
Jeep               41
Kia                32
Porsche            21
Volvo              20
MG                 19
Mini               17
Nissan             11
Lexus              10
Isuzu               8
Bentley             3
Maserati            2
ISUZU               2
Ferrari             1
Mercedes-AMG        1
Rolls-Royce         1
Force               1
Name: count, dtype: int64
```

```
# Check value counts of the 'car_name' column
df['car_name'].value_counts()
```

```
car_name
Hyundai i20               906
Maruti Swift Dzire        890
Maruti Swift              781
Maruti Alto               778
Honda City                757
                         ...
Mercedes-AMG C              1
Rolls-Royce Ghost           1
Maserati Quattroporte       1
Isuzu MUX                   1
Force Gurkha                1
Name: count, Length: 121, dtype: int64
```

```
# Normalize the fuel_type based on it's value_counts
df['fuel_type'].value_counts(normalize=True)*100
```

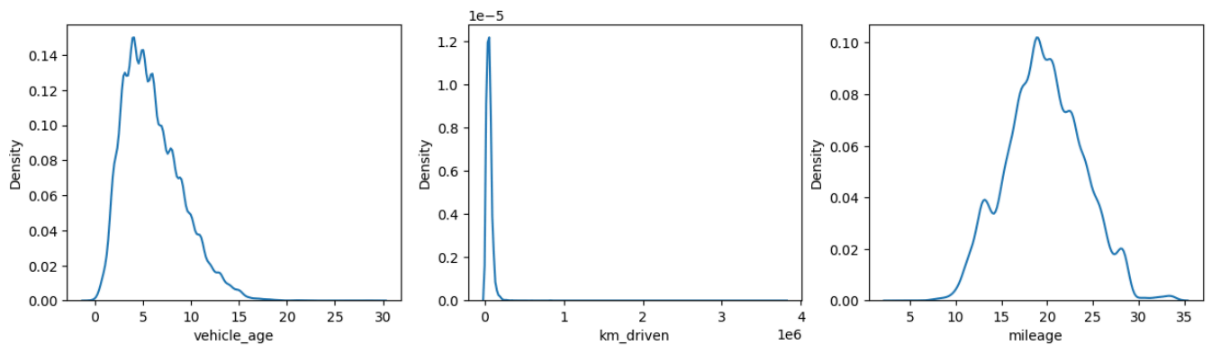
```
fuel_type
Petrol      49.594446
Diesel      48.140938
CNG          1.953150
LPG          0.285510
Electric     0.025955
Name: proportion, dtype: float64
```

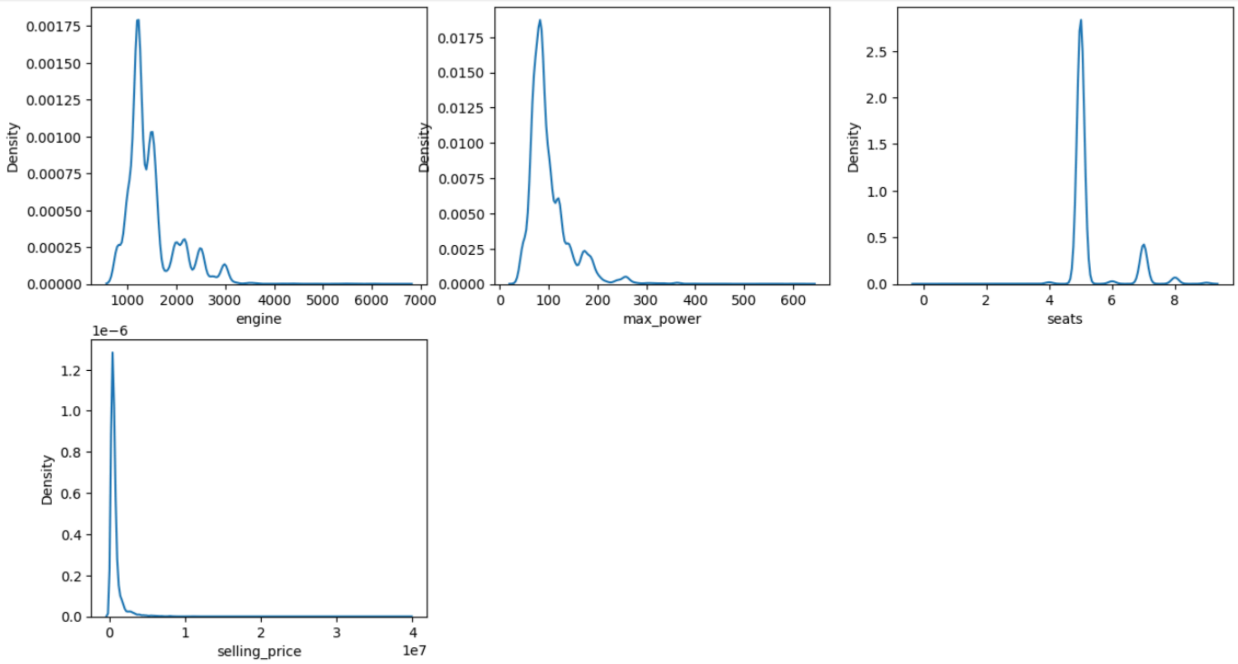
```
# Check the mean of the mileage column
round(float(df['mileage'].mean()),2)
```

```
19.7
```

```
# Plot the density graphs of each of the numerical columns
num_columns = ['vehicle_age', 'km_driven', 'mileage', 'engine', 'max_power', 'seats','selling_price']
plt.figure(figsize=(15, 30))
for i in range(len(num_columns)):
    plt.subplot(7, 3, i+1)
    sns.kdeplot(data = df[num_columns[i]])

plt.show()
```






**Overall Insights**

1️⃣ Right-Skewed Variables:

Variables like km_driven, selling_price, and max_power exhibit strong right skewness, meaning most values are clustered at the lower end, with a few high-value outliers.

To improve model performance, applying log or square root transformations may help normalize these distributions.

2️⃣ Concentrated Distributions:

Features like seats and vehicle_age are highly concentrated around common values (e.g., 5 seats, vehicle age between 0-10 years).

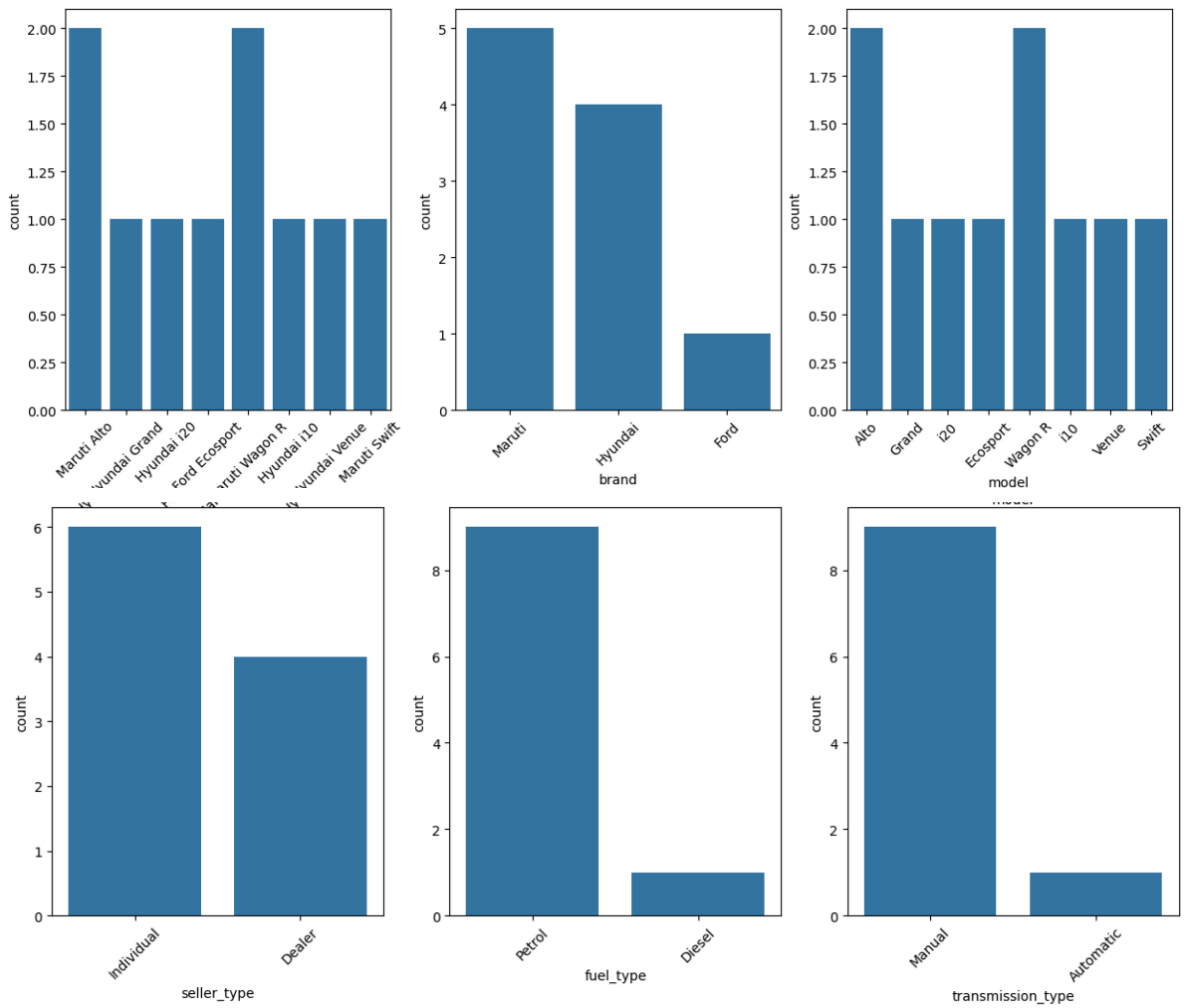
This suggests a preference for newer vehicles and standard mid-sized cars, aligning with general market trends.

3️⃣ Diverse Vehicle Segments:

The multimodal distribution of engine size and the wide range of max_power indicate the dataset includes multiple vehicle categories (e.g., compact cars, SUVs, performance vehicles).

```python
# Plot the countplots of each of the categorical columns
cat_columns = ['car_name', 'brand', 'model', 'seller_type', 'fuel_type', 'transmission_type']
plt.figure(figsize=(15, 12))
for i in range(len(cat_columns)):
    plt.subplot(2, 3, i+1)
    plt.xticks(rotation = 45)
    sns.countplot(x = df[cat_columns[i]].head(10))

plt.show()
```



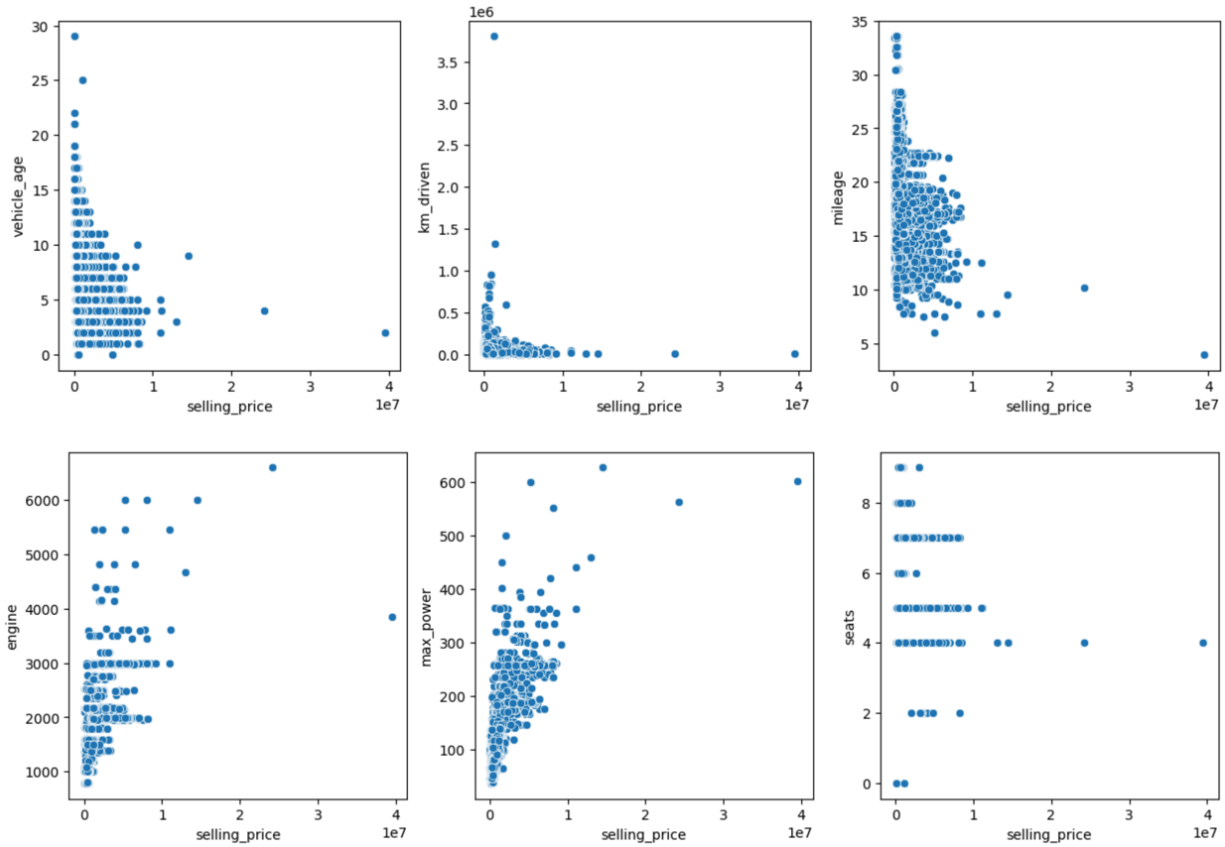

**Insights**

- The dataset skews toward manual transmission and petrol-fueled cars sold by individuals.
- Maruti is the dominant brand, with the Maruti Alto and Hyundai Grand leading among models.
- Diesel cars and automatic transmissions are underrepresented, potentially indicating limited availability or demand in the dataset.

```python
# Plot the relationship of each variable with the selling price (Target variable)
numerical_columns = ['vehicle_age', 'km_driven', 'mileage', 'engine', 'max_power', 'seats']

plt.figure(figsize=(15, 10))
for i in range(len(numerical_columns)):
    plt.subplot(2, 3, i+1)
    sns.scatterplot(data = df, x = 'selling_price', y = numerical_columns[i])

plt.show()
```



**Interpretation of Scatterplots**

1️⃣ Vehicle Age vs. Selling Price

Observation: Older vehicles generally have lower selling prices, showing an inverse relationship between age and price.

Outliers: Some older vehicles are priced unusually high, possibly due to factors like brand value, limited edition models, or modifications.

2️⃣ Kilometers Driven vs. Selling Price

Observation: Cars with lower mileage tend to be priced higher, while those with higher mileage are concentrated at lower prices.

Clusters: A distinct cluster of low-priced, low-mileage vehicles suggests a segment of budget-friendly, lightly used cars.

3️⃣ Mileage vs. Selling Price

Observation: No strong correlation is observed, though cars with lower mileage tend to be priced around the average selling price.

Possible Explanation: Other factors (e.g., brand, condition, model year) might have a stronger influence on price than mileage alone.

4️⃣ Engine Size vs. Selling Price

Observation: A positive correlation is evident—vehicles with larger engine capacities tend to have higher prices.

Implication: Buyers likely associate larger engines with better performance, influencing pricing trends.

5️⃣ Max Power vs. Selling Price

Observation: A clear positive trend—higher power output is generally associated with higher prices.

Outliers: Some extreme cases exist where vehicles with very high power levels have significantly higher prices, possibly due to performance or luxury branding.

6️⃣ Seats vs. Selling Price

Observation: No clear relationship between seating capacity and selling price.

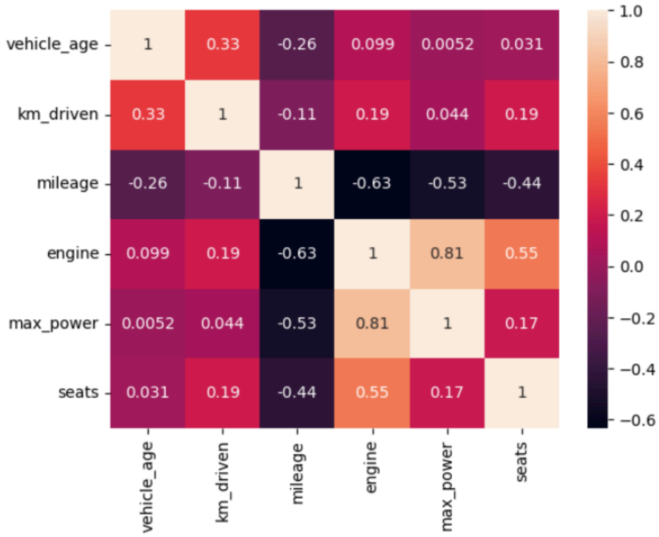
Market Trend: Most cars have 4 or 5 seats, and pricing appears to be influenced more by other factors like brand, model, and features rather than the number of seats.

```python
# Multi-variate analysis - to check the correlation between all the combination of numerical features
num_columns = ['vehicle_age', 'km_driven', 'mileage', 'engine', 'max_power', 'seats','selling_price']
df[num_columns].corr()
```

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

```python
# Plot the heatmap of the correlation between each of the numerical features
sns.heatmap(data = df[numerical_columns].corr(), annot=True)
```

<Axes: >




**Insights**

**The Strongest Relationships:**

- Engine vs. Max Power (0.81): Strongly linked, as expected for vehicle specifications.
- Engine vs. Mileage (-0.63): Indicates a trade-off between performance (engine size) and efficiency (mileage).

**The Weakest Relationships:**

- Vehicle Age vs. Max Power (0.0052): No notable effect of age on power.
- Km Driven vs. Max Power (0.044): Distance traveled doesn't significantly impact the power of the vehicle.

```python
# Create a copy of the dataframe to model the data
model_data = df.copy()
model_data.head()
```

| | car_name | brand | model | vehicle_age | km_driven | seller_type | fuel_type | transmission_type | mileage | engine | max_power | seats | selling_price |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | Maruti Alto | Maruti | Alto | 9 | 120000 | Individual | Petrol | Manual | 19.70 | 796 | 46.30 | 5 | 120000 |
| **1** | Hyundai Grand | Hyundai | Grand | 5 | 20000 | Individual | Petrol | Manual | 18.90 | 1197 | 82.00 | 5 | 550000 |
| **2** | Hyundai i20 | Hyundai | i20 | 11 | 60000 | Individual | Petrol | Manual | 17.00 | 1197 | 80.00 | 5 | 215000 |
| **3** | Maruti Alto | Maruti | Alto | 9 | 37000 | Individual | Petrol | Manual | 20.92 | 998 | 67.10 | 5 | 226000 |
| **4** | Ford Ecosport | Ford | Ecosport | 6 | 30000 | Dealer | Diesel | Manual | 22.77 | 1498 | 98.59 | 5 | 570000 |

```python
# Drop the noise in the data (unwanted columns)
model_data.drop(labels=['car_name', 'brand', 'model', 'seller_type'], axis=1, inplace=True)
```

```python
model_data.head()
```

| | vehicle_age | km_driven | fuel_type | transmission_type | mileage | engine | max_power | seats | selling_price |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 9 | 120000 | Petrol | Manual | 19.70 | 796 | 46.30 | 5 | 120000 |
| **1** | 5 | 20000 | Petrol | Manual | 18.90 | 1197 | 82.00 | 5 | 550000 |
| **2** | 11 | 60000 | Petrol | Manual | 17.00 | 1197 | 80.00 | 5 | 215000 |
| **3** | 9 | 37000 | Petrol | Manual | 20.92 | 998 | 67.10 | 5 | 226000 |
| **4** | 6 | 30000 | Diesel | Manual | 22.77 | 1498 | 98.59 | 5 | 570000 |

```python
# Convert the categorical variables into a set of binary(0,1)
model_data = pd.get_dummies(model_data, dtype = int)
model_data.head()
```

| | vehicle_age | km_driven | mileage | engine | max_power | seats | selling_price | fuel_type_CNG | fuel_type_Diesel | fuel_type_Electric | fuel_type_LPG | fuel_type_Petrol | transm |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 9 | 120000 | 19.70 | 796 | 46.30 | 5 | 120000 | 0 | 0 | 0 | 0 | 1 | |
| **1** | 5 | 20000 | 18.90 | 1197 | 82.00 | 5 | 550000 | 0 | 0 | 0 | 0 | 1 | |
| **2** | 11 | 60000 | 17.00 | 1197 | 80.00 | 5 | 215000 | 0 | 0 | 0 | 0 | 1 | |
| **3** | 9 | 37000 | 20.92 | 998 | 67.10 | 5 | 226000 | 0 | 0 | 0 | 0 | 1 | |
| **4** | 6 | 30000 | 22.77 | 1498 | 98.59 | 5 | 570000 | 0 | 1 | 0 | 0 | 0 | |

```python
# Drop the column of selling_price from the independent variable
X = model_data.drop('selling_price', axis=1)
X.head()
```

| | vehicle_age | km_driven | mileage | engine | max_power | seats | fuel_type_CNG | fuel_type_Diesel | fuel_type_Electric | fuel_type_LPG | fuel_type_Petrol | transmission_type_Au |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 9 | 120000 | 19.70 | 796 | 46.30 | 5 | 0 | 0 | 0 | 0 | 1 | |
| **1** | 5 | 20000 | 18.90 | 1197 | 82.00 | 5 | 0 | 0 | 0 | 0 | 1 | |
| **2** | 11 | 60000 | 17.00 | 1197 | 80.00 | 5 | 0 | 0 | 0 | 0 | 1 | |
| **3** | 9 | 37000 | 20.92 | 998 | 67.10 | 5 | 0 | 0 | 0 | 0 | 1 | |
| **4** | 6 | 30000 | 22.77 | 1498 | 98.59 | 5 | 0 | 1 | 0 | 0 | 0 | |

```python
# For getting the target variable we will just have selling_price
Y = model_data['selling_price']
Y.head()
```

```
0    120000
1    550000
2    215000
3    226000
4    570000
Name: selling_price, dtype: int64
```

```python
# Divide data into Train & Test data
train_X, test_X, train_Y, test_Y = train_test_split(X,Y, test_size=0.2)
train_X
# 80% data goes to Train & 20% goes to Test
```

| | vehicle_age | km_driven | mileage | engine | max_power | seats | fuel_type_CNG | fuel_type_Diesel | fuel_type_Electric | fuel_type_LPG | fuel_type_Petrol | transmission_typ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **4040** | 9 | 75000 | 15.96 | 2523 | 62.10 | 7 | 0 | 1 | 0 | 0 | 0 | |
| **649** | 7 | 40000 | 19.10 | 1197 | 85.80 | 5 | 0 | 0 | 0 | 0 | 1 | |
| **2316** | 4 | 73630 | 15.10 | 1196 | 73.00 | 5 | 1 | 0 | 0 | 0 | 0 | |
| **2699** | 5 | 15000 | 19.44 | 1198 | 67.00 | 7 | 0 | 0 | 0 | 0 | 1 | |
| **6662** | 11 | 65000 | 17.00 | 1497 | 118.00 | 5 | 0 | 0 | 0 | 0 | 1 | |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| **3847** | 5 | 115000 | 28.09 | 1248 | 88.50 | 5 | 0 | 1 | 0 | 0 | 0 | |
| **11069** | 7 | 54159 | 18.50 | 1197 | 82.85 | 5 | 0 | 0 | 0 | 0 | 1 | |
| **13658** | 7 | 65694 | 17.01 | 1591 | 121.30 | 5 | 0 | 0 | 0 | 0 | 1 | |
| **10149** | 3 | 53546 | 18.90 | 1197 | 81.86 | 5 | 0 | 0 | 0 | 0 | 1 | |
| **6645** | 3 | 120000 | 19.95 | 1197 | 81.80 | 5 | 0 | 0 | 0 | 0 | 1 | |

12328 rows × 13 columns

```python
# Applying LinearRegression for training the model
Regressor = LinearRegression().fit(train_X,train_Y)
Regressor
```

```
LinearRegression
LinearRegression()
```

```python
# Getting the predictions
Prediction = Regressor.predict(test_X)
print(Prediction)
print(test_Y)
```

```
[ 690429.02141406 2104401.12138994 2133355.31455244 ... 1086941.02167037
  573854.55268878  -13602.35349857]
9893      585000
13421    2975000
1344     2700000
2135      529000
0         120000
           ...
10430    3200000
12708     359000
4274      285000
7724      685000
14719     350000
Name: selling_price, Length: 3083, dtype: int64
```

```python
test_X['predicted_sales_price'] = Prediction

test_X['actual_price'] = test_Y

# Calculate the difference between the predicted sales price and the actual price
test_X['difference'] = test_X['predicted_sales_price'] - test_X['actual_price']

# Display the predicted sales price, actual price and the difference
test_X[['predicted_sales_price', 'actual_price', 'difference']]
```

| | predicted_sales_price | actual_price | difference |
|---|---|---|---|
| **9893** | 6.904290e+05 | 585000 | 105429.021414 |
| **13421** | 2.104401e+06 | 2975000 | -870598.878610 |
| **1344** | 2.133355e+06 | 2700000 | -566644.685448 |
| **2135** | 6.548082e+05 | 529000 | 125808.198033 |
| **0** | -4.238569e+05 | 120000 | -543856.872975 |
| **...** | ... | ... | ... |
| **10430** | 2.244592e+06 | 3200000 | -955407.885372 |
| **12708** | 2.589464e+05 | 359000 | -100053.636712 |
| **4274** | 1.086941e+06 | 285000 | 801941.021670 |
| **7724** | 5.738546e+05 | 685000 | -111145.447311 |
| **14719** | -1.360235e+04 | 350000 | -363602.353499 |

3083 rows × 3 columns

```python
# Calculate the root mean squared error for the prediction
mse = []
mse.append(mean_squared_error(y_true = test_Y, y_pred = Prediction))

rmse = []
rmse.append(np.sqrt(mse[0]))

print(f"The Root Mean Squared Error is : {rmse[0].round(2)}")
```

```
The Root Mean Squared Error is : 456212.83
```