Car Price Prediction

This Jupyter Notebook was created by [Dajah Vincent (https://www.linkedin.com/in/dajahvincent/)](https://www.linkedin.com/in/dajahvincent/)

- Adding Data Manipulation and Visualization Libraries

In [1]:
```
#Importing data manipulation and visualization libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

- Reading the csv data

In [2]:
```
#Reading the CSV file containing the datasets
car_price = pd.read_csv("car data.csv")
```

In [3]:
```
#Viewing the first 10 rows from the dataset
car_price.head(10)
```

Out[3]:

	Car_Name	Year	Selling_Price	Present_Price	Driven_kms	Fuel_Type	Selling_type	Transmission	Owner
0	ritz	2014	3.35	5.59	27000	Petrol	Dealer	Manual	0
1	sx4	2013	4.75	9.54	43000	Diesel	Dealer	Manual	0
2	ciaz	2017	7.25	9.85	6900	Petrol	Dealer	Manual	0
3	wagon r	2011	2.85	4.15	5200	Petrol	Dealer	Manual	0
4	swift	2014	4.60	6.87	42450	Diesel	Dealer	Manual	0
5	vitara brezza	2018	9.25	9.83	2071	Diesel	Dealer	Manual	0
6	ciaz	2015	6.75	8.12	18796	Petrol	Dealer	Manual	0
7	s cross	2015	6.50	8.61	33429	Diesel	Dealer	Manual	0
8	ciaz	2016	8.75	8.89	20273	Diesel	Dealer	Manual	0
9	ciaz	2015	7.45	8.92	42367	Diesel	Dealer	Manual	0

In [4]:
```
#Viewing the last 10 rows from the dataset
car_price.tail(10)
```

Out[4]:

	Car_Name	Year	Selling_Price	Present_Price	Driven_kms	Fuel_Type	Selling_type	Transmission	Owner
291	brio	2015	5.40	6.10	31427	Petrol	Dealer	Manual	0
292	jazz	2016	6.40	8.40	12000	Petrol	Dealer	Manual	0
293	city	2010	3.25	9.90	38000	Petrol	Dealer	Manual	0
294	amaze	2014	3.75	6.80	33019	Petrol	Dealer	Manual	0
295	city	2015	8.55	13.09	60076	Diesel	Dealer	Manual	0
296	city	2016	9.50	11.60	33988	Diesel	Dealer	Manual	0
297	brio	2015	4.00	5.90	60000	Petrol	Dealer	Manual	0
298	city	2009	3.35	11.00	87934	Petrol	Dealer	Manual	0
299	city	2017	11.50	12.50	9000	Diesel	Dealer	Manual	0
300	brio	2016	5.30	5.90	5464	Petrol	Dealer	Manual	0

Exploratory Data Analysis - EDA

In [5]:
```
#Viewing quick overview of the datasets containing numerical values
car_price.describe()
```

Out[5]:

	Year	Selling_Price	Present_Price	Driven_kms	Owner
count	301.000000	301.000000	301.000000	301.000000	301.000000
mean	2013.627907	4.661296	7.628472	36947.205980	0.043189
std	2.891554	5.082812	8.642584	38886.883882	0.247915
min	2003.000000	0.100000	0.320000	500.000000	0.000000
25%	2012.000000	0.900000	1.200000	15000.000000	0.000000
50%	2014.000000	3.600000	6.400000	32000.000000	0.000000
75%	2016.000000	6.000000	9.900000	48767.000000	0.000000
max	2018.000000	35.000000	92.600000	500000.000000	3.000000

In [6]:
```
#Viewing informations about the dataframe
car_price.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 301 entries, 0 to 300
Data columns (total 9 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Car_Name       301 non-null    object 
 1   Year           301 non-null    int64  
 2   Selling_Price  301 non-null    float64
 3   Present_Price  301 non-null    float64
 4   Driven_kms     301 non-null    int64  
 5   Fuel_Type      301 non-null    object 
 6   Selling_type   301 non-null    object 
 7   Transmission   301 non-null    object 
 8   Owner          301 non-null    int64  
dtypes: float64(2), int64(3), object(4)
memory usage: 21.3+ KB
```

In [7]:
```
#Checking the sum of columns that have null or empty values
car_price.isnull().sum()
```

Out[7]:
```
Car_Name         0
Year             0
Selling_Price    0
Present_Price    0
Driven_kms       0
Fuel_Type        0
Selling_type     0
Transmission     0
Owner            0
dtype: int64
```

In [8]:
```
#Checking the dataframe for rows with duplicated values
car_price.duplicated().sum()
```

Out[8]:
```
2
```

In [9]:
```
#Dropping rows with duplicated values from the dataframe
car_price.drop_duplicates(inplace=True)
```

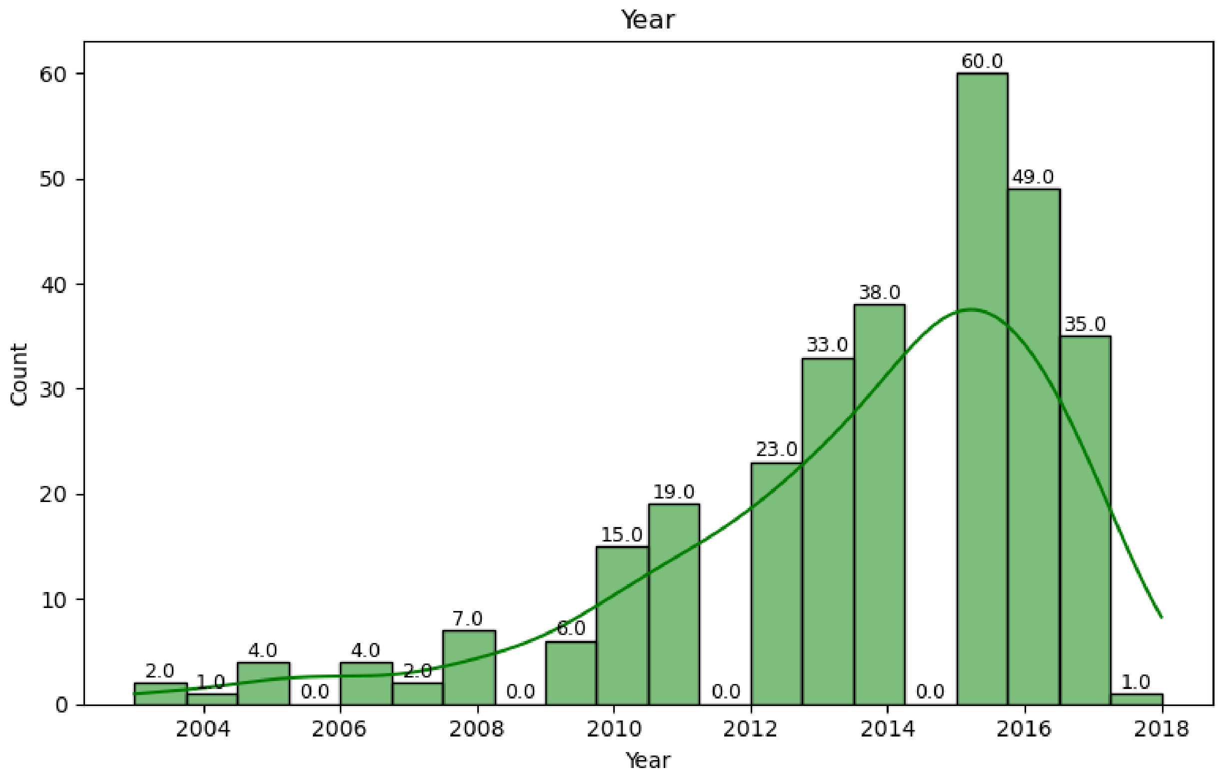
In [10]:
```
#Rechecking the dataframe for rows with duplicated values
car_price.duplicated().sum()
```

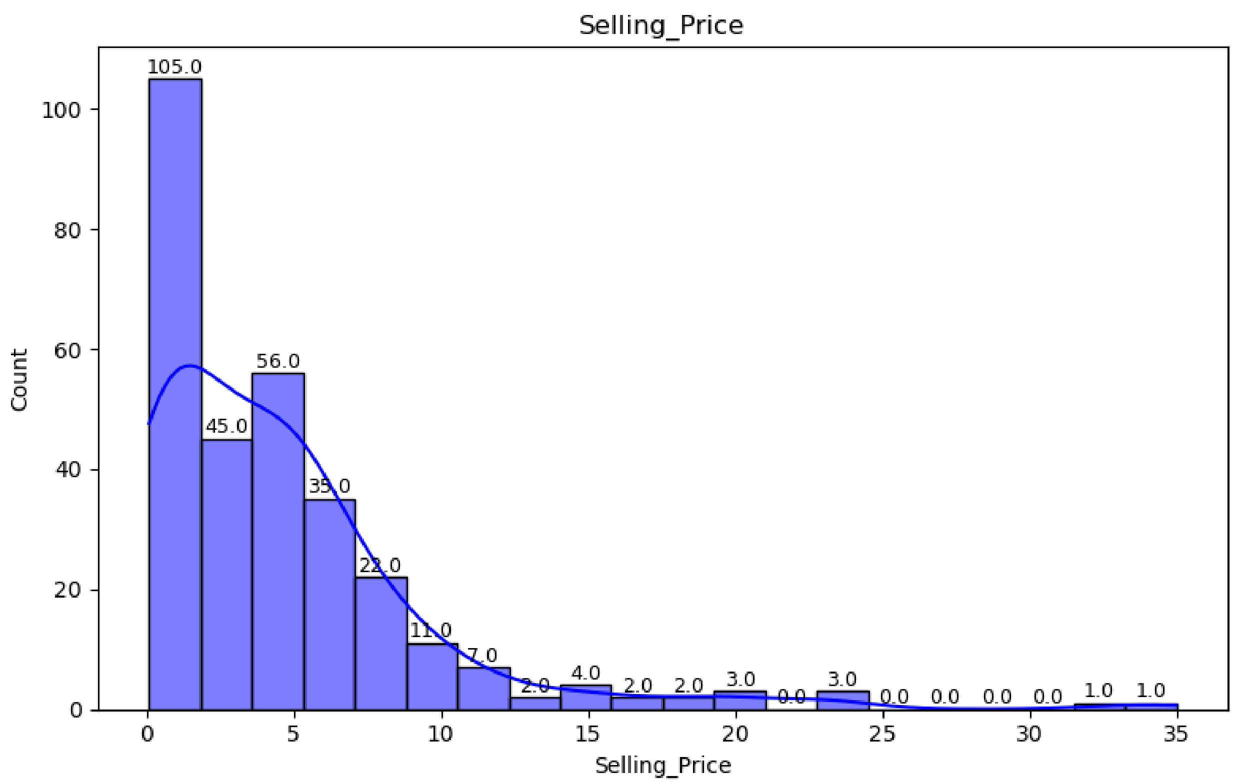
Out[10]:
```
0
```

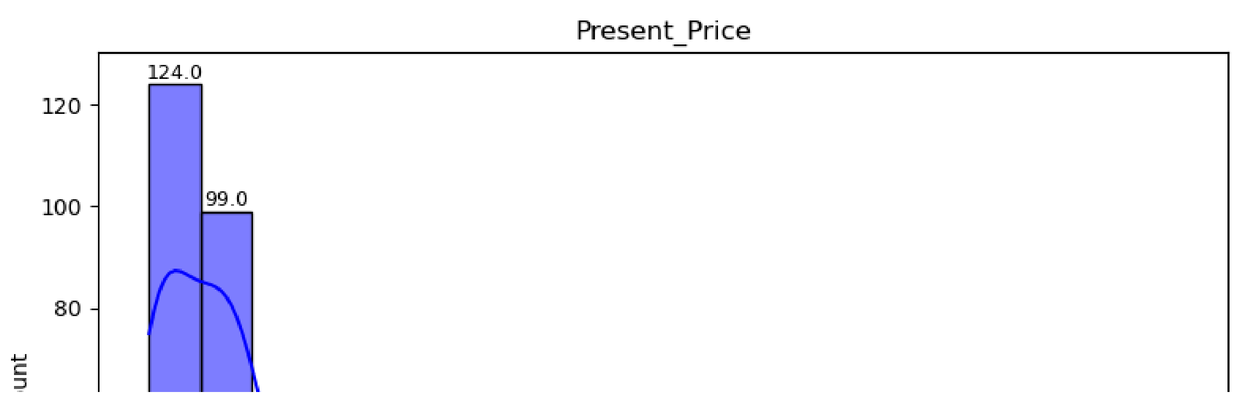
- Adding Visualization

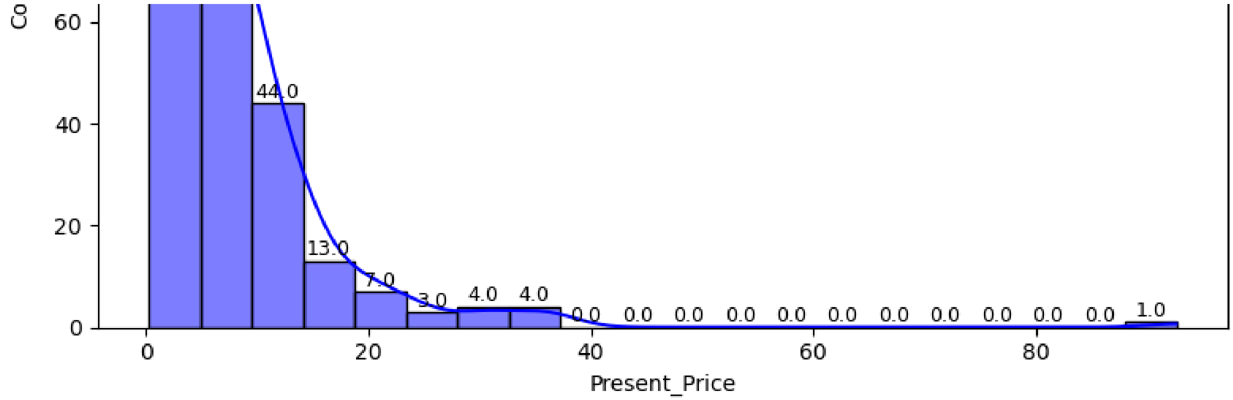
In [11]:

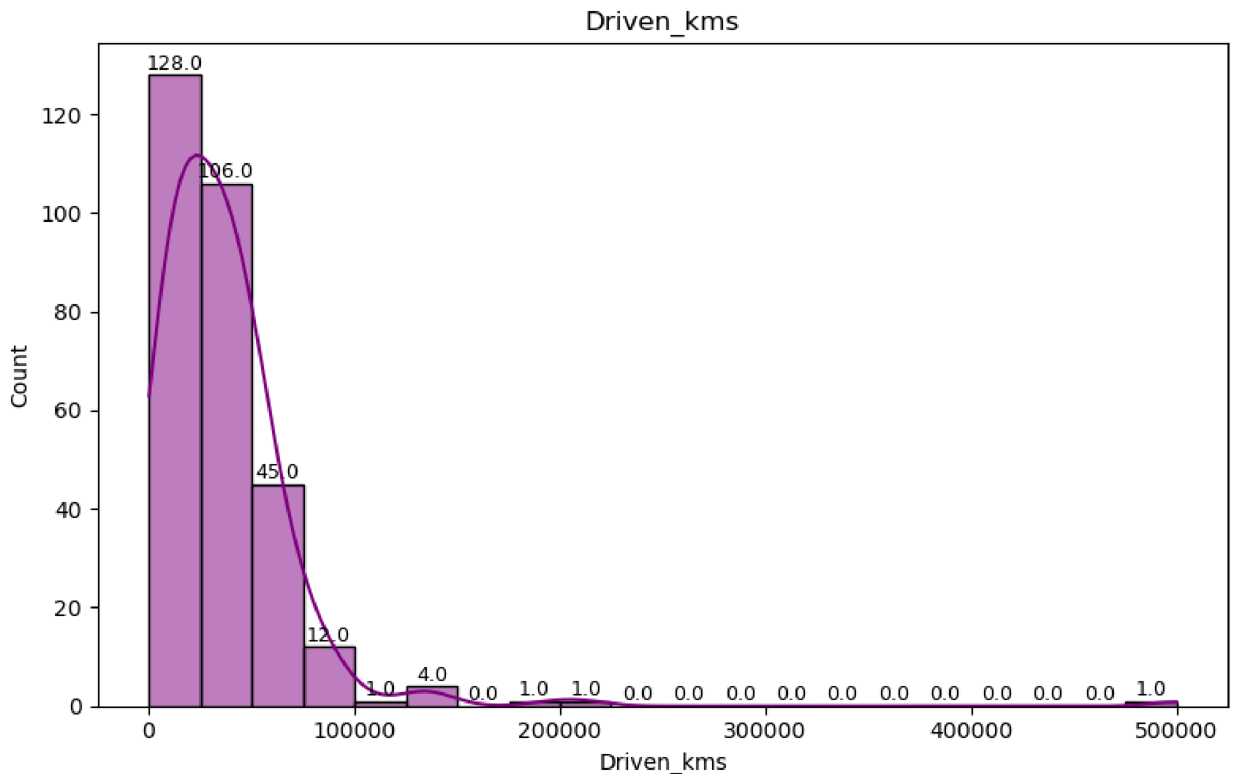
```python
import seaborn as sns
import matplotlib.pyplot as plt

def plot_histograms(data, features, colors):
    # Create a figure with appropriate size
    plt.figure(figsize=(8, len(features) * 5))

    # Loop over each feature to create a subplot with a unique color
    for index, feature in enumerate(features):
        plt.subplot(len(features), 1, index + 1)
        ax = sns.histplot(data[feature], bins=20, kde=True, color=colors[index])
        plt.title(feature)

        # Add labels to each bar
        for p in ax.patches:
            ax.annotate(f"{p.get_height():.1f}",
                        (p.get_x() + p.get_width() / 2., p.get_height()),
                        ha='center', va='center',
                        fontsize=9, color='black',
                        xytext=(0, 5),
                        textcoords='offset points')

    # Adjust layout to prevent overlap
    plt.tight_layout()

    # Show the plot
    plt.show()

# Example usage:
# Assuming 'car_price' is a pandas DataFrame containing the data
plot_histograms(car_price, ['Year', 'Selling_Price', 'Present_Price', 'Driven_kms', 'Owne
```

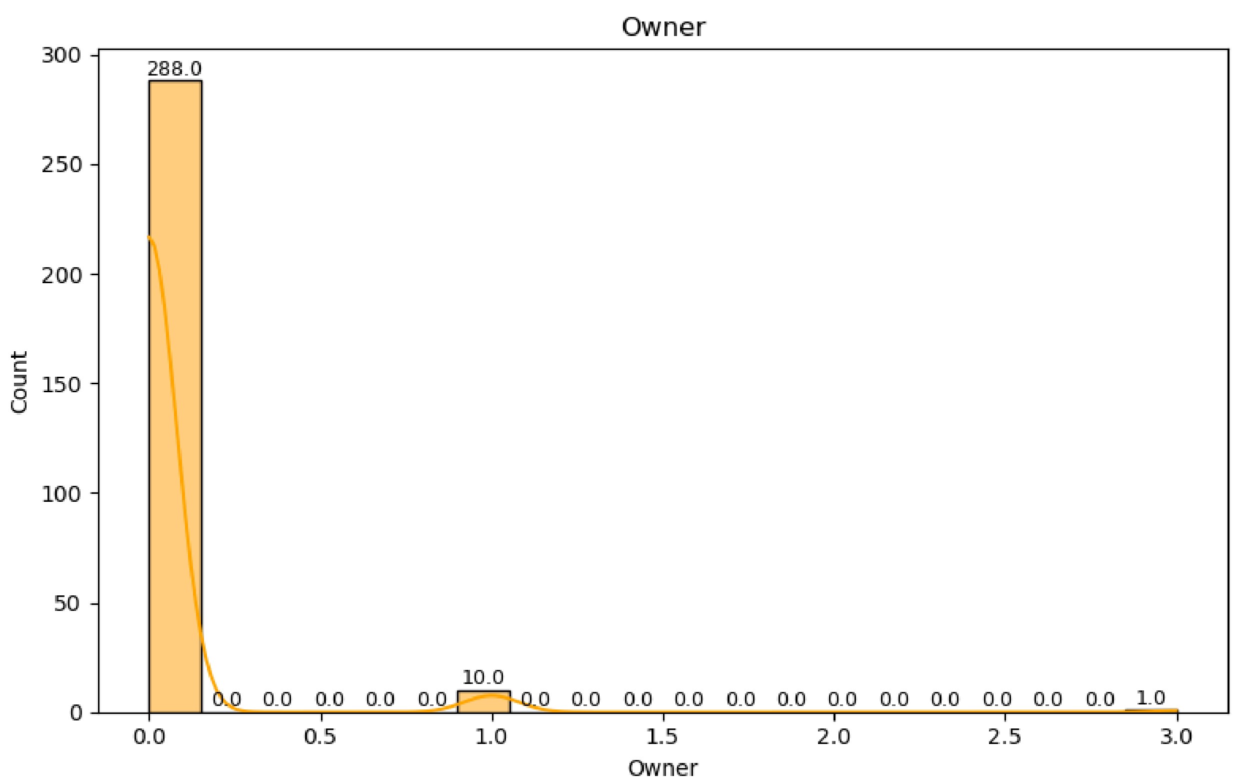

Year
60.0
49.0
38.0
35.0
33.0
23.0
19.0
15.0
7.0
6.0
4.0
4.0
2.0
2.0
1.0
1.0
0.0
0.0
0.0
0.0
Count
0
10
20
30
40
50
60
2004
2006
2008
2010
2012
2014
2016
2018
Year


Selling_Price
105.0
45.0
56.0
35.0
22.0
11.0
7.0
2.0
4.0
2.0
2.0
3.0
0.0
3.0
0.0
0.0
0.0
0.0
1.0
1.0
Count
0
20
40
60
80
100
0
5
10
15
20
25
30
35
Selling_Price


Present_Price
124.0
99.0
80
100
120


Co
44.0
13.0
7.0
3.0
4.0
4.0
0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0
1.0
0 20 40 60 80
0 20 40 60
Present_Price


Driven_kms
128.0
106.0
45.0
12.0
1.0
4.0
0.0
1.0
1.0
0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0
1.0
Count
0 20 40 60 80 100 120
0 100000 200000 300000 400000 500000
Driven_kms

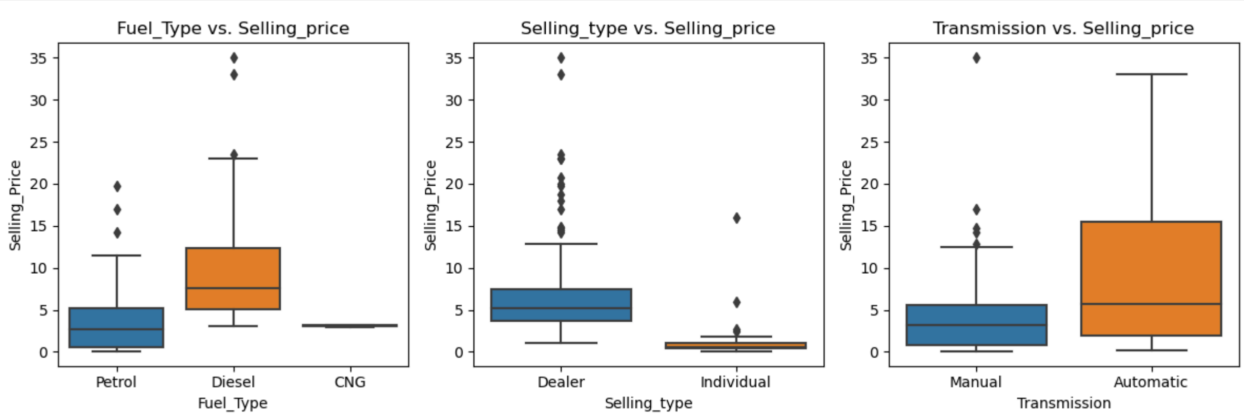

Owner
288.0
0.0 0.0 0.0 0.0 0.0
10.0
0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0
1.0
Count
0 50 100 150 200 250 300
0.0 0.5 1.0 1.5 2.0 2.5 3.0
Owner

- Feature Engineering

In [12]:
```
category_cols = ['Fuel_Type', 'Selling_type', 'Transmission']
unique_categories = {col: car_price[col].unique() for col in category_cols}

# Print the unique categories for each column
for col, categories in unique_categories.items():
    print(f"Category in {col} is: {categories}")
```

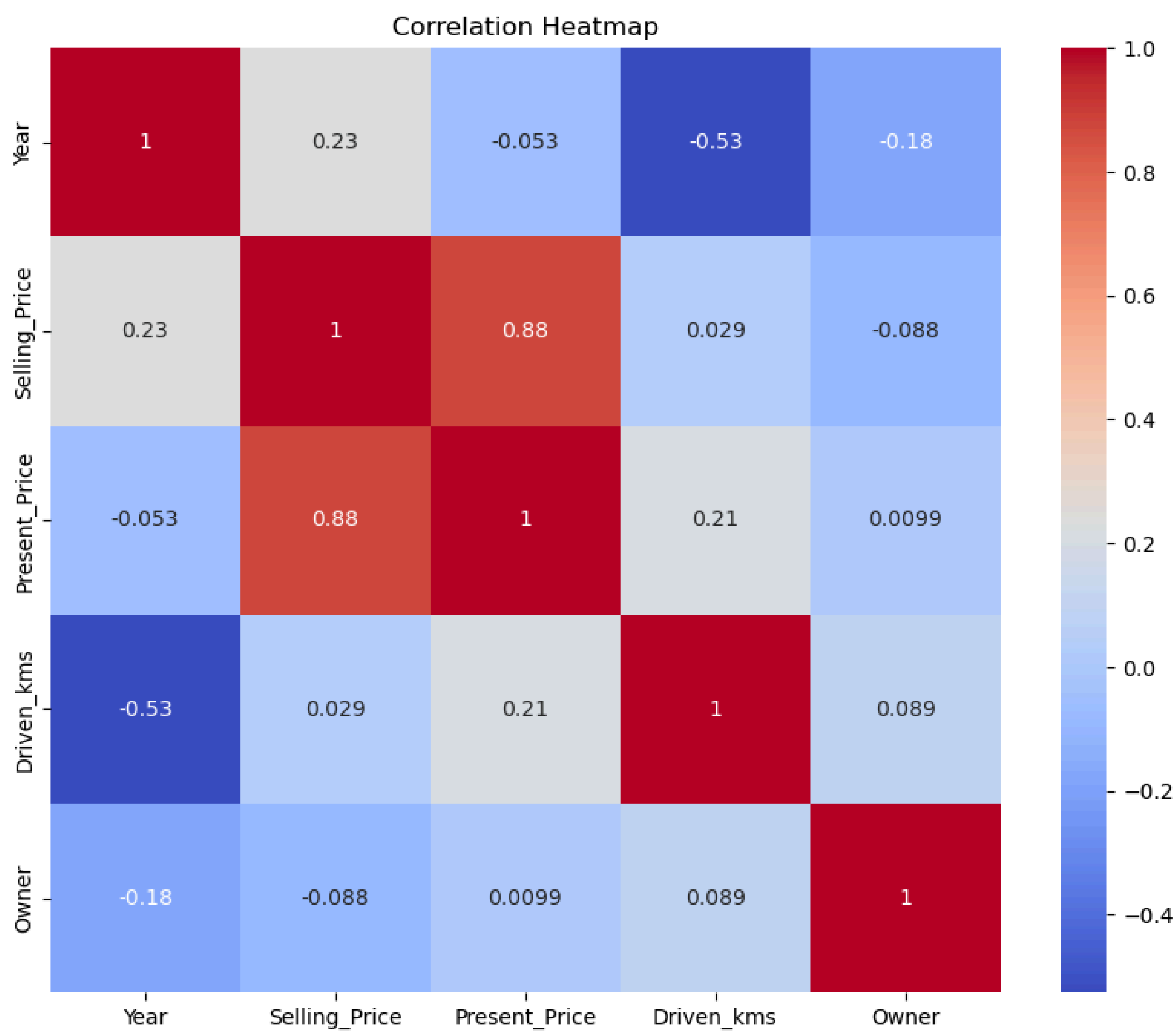
```
Category in Fuel_Type is: ['Petrol' 'Diesel' 'CNG']
Category in Selling_type is: ['Dealer' 'Individual']
Category in Transmission is: ['Manual' 'Automatic']
```

In [13]:
```
def plot_categorical_features_vs_price(dataframe, category_columns, price_column):
    # Check if all category columns and price column exist in the dataframe
    missing_columns = [col for col in category_columns + [price_column] if col not in data
    if missing_columns:
        print(f"Warning: The following columns are missing from the dataframe: {missing_co
        return

    # Create subplots
    num_plots = len(category_columns)
    num_rows = (num_plots + 2) // 3  # Calculate the number of rows needed
    plt.figure(figsize=(12, num_rows * 4))

    # Loop through each categorical column and plot
    for i, feature in enumerate(category_columns):
        plt.subplot(num_rows, 3, i + 1)
        sns.boxplot(data=dataframe, x=feature, y=price_column)
        plt.title(f'{feature} vs. {price_column.capitalize()}')

    plt.tight_layout()
    plt.show()

# Example usage:
plot_categorical_features_vs_price(car_price, category_cols, 'Selling_Price')
```



In [14]:

```
def plot_correlation_heatmap(dataframe, numerical_features):
    # Check if all numerical features exist in the dataframe
    missing_columns = [col for col in numerical_features if col not in dataframe.columns]
    if missing_columns:
        print(f"Warning: The following columns are missing from the dataframe: {missing_c
        return

    # Calculate the correlation matrix
    correlation_matrix = dataframe[numerical_features].corr()

    # Plot the heatmap
    plt.figure(figsize=(10, 8))
    sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
    plt.title('Correlation Heatmap')
    plt.show()

# Example usage:
# Assuming 'df' is a pandas DataFrame with the specified numerical features
numerical_features = ["Year", "Selling_Price", "Present_Price", "Driven_kms", "Owner"]
plot_correlation_heatmap(car_price, numerical_features)
```



Features Engineering

In [16]:

```python
def encode_categorical_variables(dataframe, categorical_columns):

    label_encoder = LabelEncoder()
    for column in categorical_columns:
        dataframe[column] = label_encoder.fit_transform(dataframe[column])

    return dataframe

# Example usage:
# Assuming 'df' is a pandas DataFrame with categorical columns
categorical_columns = ['Fuel_Type', 'Selling_type', 'Transmission']
encoded_df = encode_categorical_variables(car_price, categorical_columns)

numerical_columns = ['Year', 'Present_Price', 'Driven_kms', 'Owner']
# Feature scaling
scaler = StandardScaler()
car_price[numerical_columns] = scaler.fit_transform(car_price[numerical_columns])
car_price
```

Out[16]:

	Car_Name	Year	Selling_Price	Present_Price	Driven_kms	Fuel_Type	Selling_type	Transmission	
0	ritz	0.132992	3.35	-0.228138	-0.254603	2	0	1	-0
1	sx4	-0.212787	4.75	0.233742	0.156181	1	0	1	-0
2	ciaz	1.170329	7.25	0.269991	-0.770651	2	0	1	-0
3	wagon r	-0.904345	2.85	-0.396520	-0.814297	2	0	1	-0
4	swift	0.132992	4.60	-0.078466	0.142061	1	0	1	-0
...	...	...	...	...	...	...	...	...	
296	city	0.824550	9.50	0.474622	-0.075193	1	0	1	-0
297	brio	0.478771	4.00	-0.191889	0.592640	2	0	1	-0
298	city	-1.595904	3.35	0.404463	1.309818	2	0	1	-0
299	city	1.170329	11.50	0.579860	-0.716735	1	0	1	-0
300	brio	0.824550	5.30	-0.191889	-0.807519	2	0	1	-0

299 rows × 9 columns

In [17]:
```
def scale_numerical_features(dataframe, numerical_columns):

    scaler = StandardScaler()
    dataframe[numerical_columns] = scaler.fit_transform(dataframe[numerical_columns])
    return dataframe

# Example usage:
numerical_columns = ['Year', 'Present_Price', 'Driven_kms', 'Owner']
scaled_df = scale_numerical_features(car_price, numerical_columns)
scaled_df
```

Out[17]:

	Car_Name	Year	Selling_Price	Present_Price	Driven_kms	Fuel_Type	Selling_type	Transmission	
0	ritz	0.132992	3.35	-0.228138	-0.254603	2	0	1	-0
1	sx4	-0.212787	4.75	0.233742	0.156181	1	0	1	-0
2	ciaz	1.170329	7.25	0.269991	-0.770651	2	0	1	-0
3	wagon r	-0.904345	2.85	-0.396520	-0.814297	2	0	1	-0
4	swift	0.132992	4.60	-0.078466	0.142061	1	0	1	-0
...	...	...	...	...	...	...	...	...	
296	city	0.824550	9.50	0.474622	-0.075193	1	0	1	-0
297	brio	0.478771	4.00	-0.191889	0.592640	2	0	1	-0
298	city	-1.595904	3.35	0.404463	1.309818	2	0	1	-0
299	city	1.170329	11.50	0.579860	-0.716735	1	0	1	-0
300	brio	0.824550	5.30	-0.191889	-0.807519	2	0	1	-0

299 rows × 9 columns

Machine Learning Model Training & Evaluation

In [39]:
```
#importing machine learning models and evaluation metrics

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
from tabulate import tabulate
```

In [38]:
```python
#Split the data into features (X) and target (y)
X = car_price.drop(['Selling_Price', 'Car_Name'], axis = 1)
y = car_price['Selling_Price']

#To split the datasets between training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.4, random_state=42)

#Initializing Linear Regression model
model = LinearRegression()

#Fitting the model to the training data
model.fit(X_train, y_train)

#Making predictions on the testing dataset
y_predict = model.predict(X_test)

#Evaluating the model performance
mse = mean_squared_error(y_test, y_predict)
mae = mean_absolute_error(y_test, y_predict)
r2_square = r2_score(y_test, y_predict)

#Creating a table using the tabulate library to efficiently display the models evaluation
results_table = [
    ["R-squared", r2_square],
    ["Mean Squared Error", mse],
    ["Mean Absolute Error", mae]
]

# Print the results in a tabulated format
print(tabulate(results_table, headers=["Metric", "Value"], tablefmt="grid"))
```

```
+---------------------+----------+
| Metric              |    Value |
+=====================+==========+
| R-squared           | 0.778644 |
+---------------------+----------+
| Mean Squared Error  | 4.37759  |
+---------------------+----------+
| Mean Absolute Error | 1.29518  |
+---------------------+----------+
```

Making Predictions of Car Prices Against Actual Car Price

In [55]:
```
pred_df = pd.DataFrame({'Actual Price Value':y_test,'Predicted Price Value':y_predict,'Va
pred_df
```

Out[55]:

	Actual Price Value	Predicted Price Value	Variance
283	8.99	7.552126	1.437874
267	8.35	7.494551	0.855449
166	0.45	1.286506	-0.836506
9	7.45	6.788805	0.661195
78	5.25	11.716672	-6.466672
...	...	...	...
126	0.90	1.808141	-0.908141
141	0.60	1.273614	-0.673614
154	0.50	0.687647	-0.187647
206	5.75	5.840494	-0.090494
56	4.50	5.023498	-0.523498

120 rows × 3 columns

In [62]:

```python
#Importing the random and tabulate libraries to pick datapoints and show predictions resul
import random
from tabulate import tabulate

#Create a DataFrame with the relevant columns
pred_df = pd.DataFrame({
    'Actual Price Value': y_test,
    'Predicted Price Value': y_predict,
    'Variance': y_test - y_predict
})

#Randomly sampling data points for the predictions (10 data points)
random_indices = random.sample(range(len(pred_df)), 10)
sampled_pred_df = pred_df.iloc[random_indices]

#Create a table to display the sampled results
results_table = [
    ["Index", "Actual Price", "Predicted Price", "Variance"]
]
for idx, row in sampled_pred_df.iterrows():
    results_table.append([idx, f"{row['Actual Price Value']:.3f}", f"{row['Predicted Price

print(tabulate(results_table, headers="firstrow", tablefmt="grid"))
```

```
+---------+----------------+-------------------+------------+
|   Index |   Actual Price |   Predicted Price |   Variance |
+=========+================+===================+============+
|     225 |           2.7  |             2.578 |       0.12 |
+---------+----------------+-------------------+------------+
|      34 |           5.5  |             6.048 |      -0.55 |
+---------+----------------+-------------------+------------+
|     174 |           0.38 |             0.77  |      -0.39 |
+---------+----------------+-------------------+------------+
|      61 |           4.5  |             5.211 |      -0.71 |
+---------+----------------+-------------------+------------+
|      87 |           5.9  |             6.701 |      -0.8  |
+---------+----------------+-------------------+------------+
|     230 |           6.15 |             6.283 |      -0.13 |
+---------+----------------+-------------------+------------+
|     241 |           4.75 |             5.707 |      -0.96 |
+---------+----------------+-------------------+------------+
|     221 |           4.5  |             6.071 |      -1.57 |
+---------+----------------+-------------------+------------+
|     156 |           0.48 |             1.532 |      -1.05 |
+---------+----------------+-------------------+------------+
|      64 |          33    |            21.54  |      11.46 |
+---------+----------------+-------------------+------------+
```