Car Price Prediction

Importing Libraries

```
# Import necessary libraries
import numpy as np
import pandas as pd
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.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
import xgboost as xgb
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.preprocessing import OneHotEncoder, LabelEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.neural_network import MLPRegressor
```

Load the Dataset

```
# Load the dataset
df = pd.read_csv('/content/car data.csv')

df.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

df.columns
```

```
Index(['Car_Name', 'Year', 'Selling_Price', 'Present_Price',
'Driven_kms',
       'Fuel_Type', 'Selling_type', 'Transmission', 'Owner'],
      dtype='object')
```

Checking for NULL values

```
df.isnull().sum()
```

```
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
```

```
df.describe()
```

```
              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
```

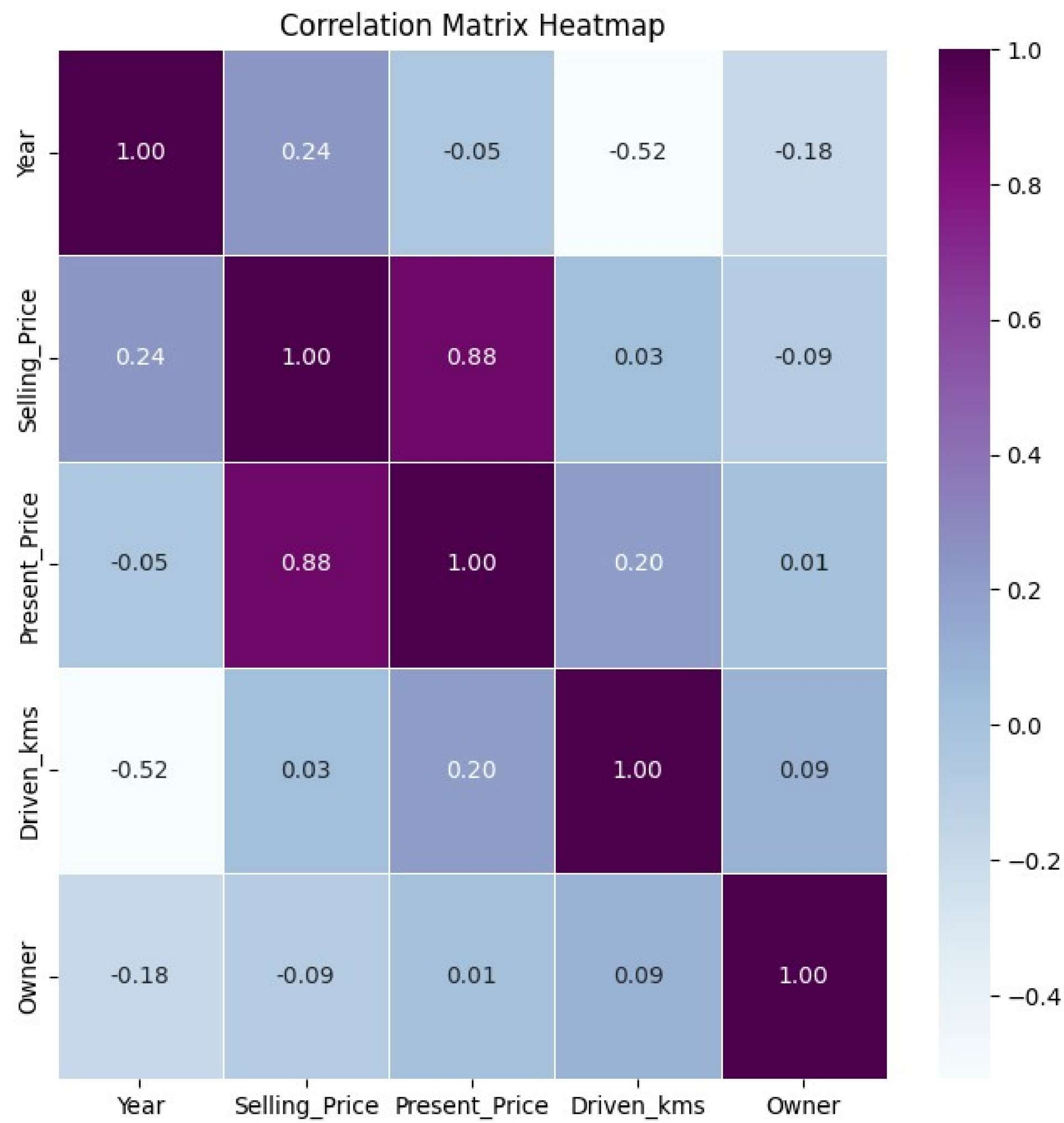
```
df.shape
```

```
(301, 9)
```

```
df.sample(4)
```

```
         Car_Name  Year  Selling_Price  Present_Price  Driven_kms
Fuel_Type  \
131  Yamaha FZ 16  2015           0.75           0.82       18000
Petrol
```

```
230         verna  2013           6.15           9.40       45000
Diesel
40         baleno  2016           5.85           7.87       24524
Petrol
222           i20  2014           6.00           7.60       77632
Diesel

    Selling_type Transmission  Owner
131   Individual       Manual      0
230       Dealer       Manual      0
40        Dealer    Automatic      0
222       Dealer       Manual      0

# Calculate the correlation matrix
numeric_columns =  df[['Year', 'Selling_Price', 'Present_Price',
'Driven_kms','Owner']]
correlation_matrix = numeric_columns.corr()

# Create a heatmap of the correlation matrix
plt.figure(figsize=(8, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='BuPu', fmt=".2f",
linewidths=0.5)
plt.title('Correlation Matrix Heatmap')
plt.show()
```

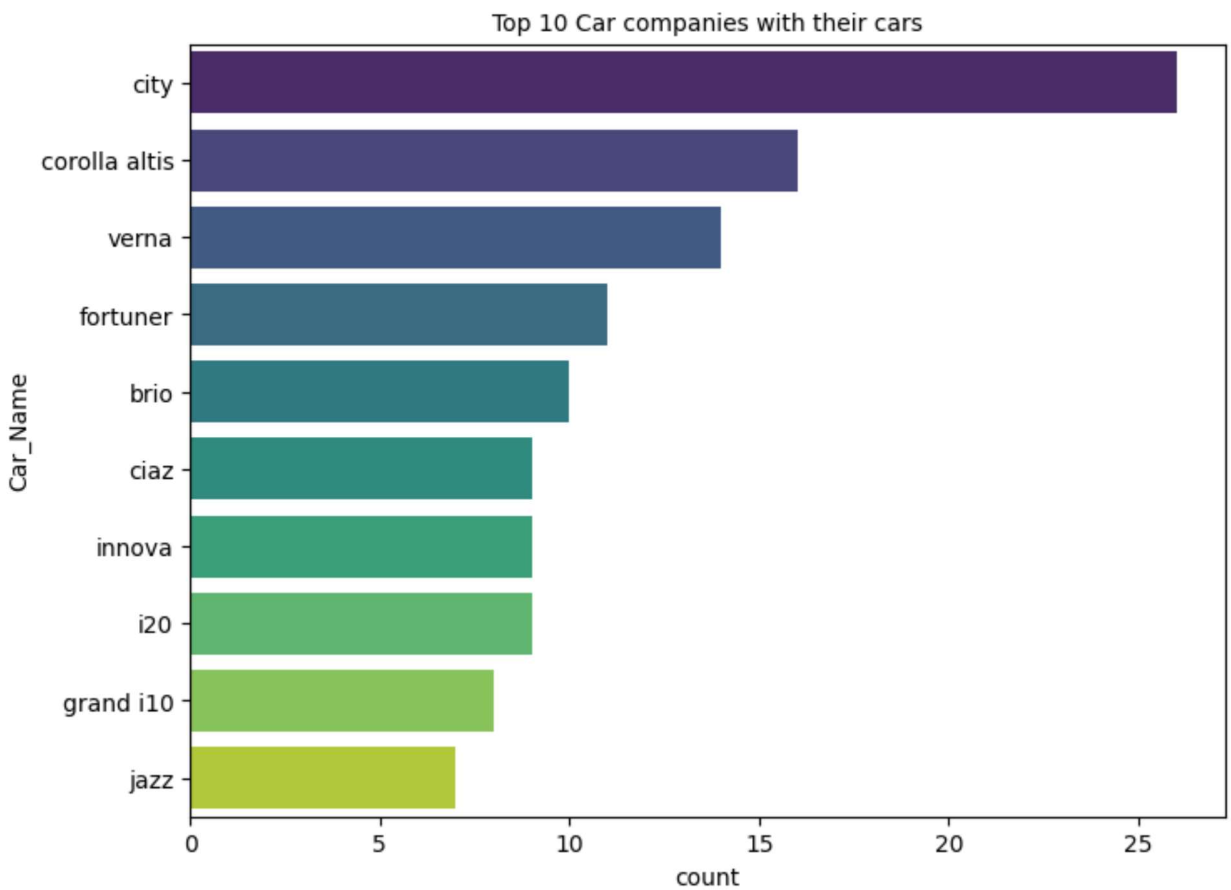



```
#top_car
top_car = df['Car_Name'].value_counts().nlargest(10)
```

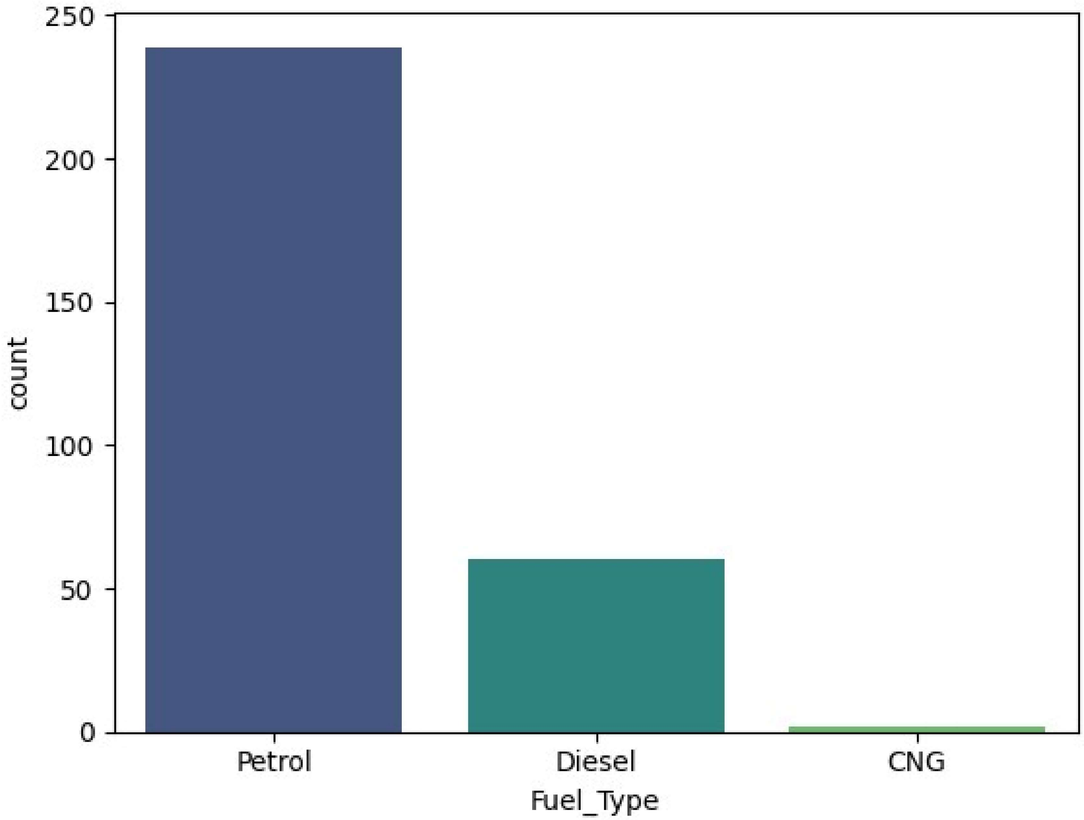
Top 10 Companies with highest number of used cars for sale

```
plt.figure(figsize = (8, 6))
sns.countplot(y = df.Car_Name, order=top_car.index, palette='viridis')
plt.title("Top 10 Car companies with their cars", fontsize = 10)
plt.show()
```

```
<ipython-input-174-0c8082dd914f>:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `y` variable to `hue` and set
`legend=False` for the same effect.

  sns.countplot(y = df.Car_Name, order=top_car.index,
palette='viridis')
```




```
df['Fuel_Type'].value_counts()

Petrol    239
Diesel     60
CNG         2
Name: Fuel_Type, dtype: int64

sns.countplot(x=df['Fuel_Type'],hue=df['Fuel_Type'],
palette='viridis')

<Axes: xlabel='Fuel_Type', ylabel='count'>
```

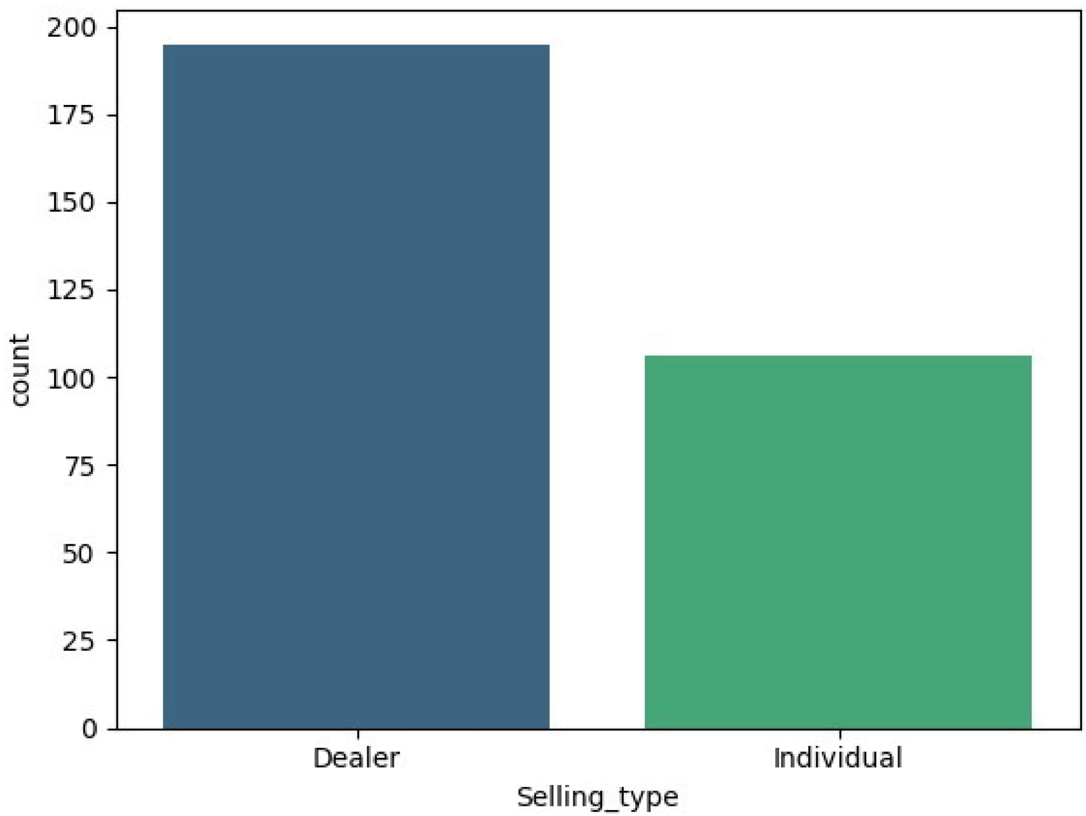



```
df['Selling_type'].value_counts()
```

```
Dealer        195
Individual    106
Name: Selling_type, dtype: int64
```

```
sns.countplot(x=df['Selling_type'],hue=df['Selling_type'],
palette='viridis')
```

```
<Axes: xlabel='Selling_type', ylabel='count'>
```




```
df['Transmission'].value_counts()
```

```
Manual       261
Automatic     40
Name: Transmission, dtype: int64
```

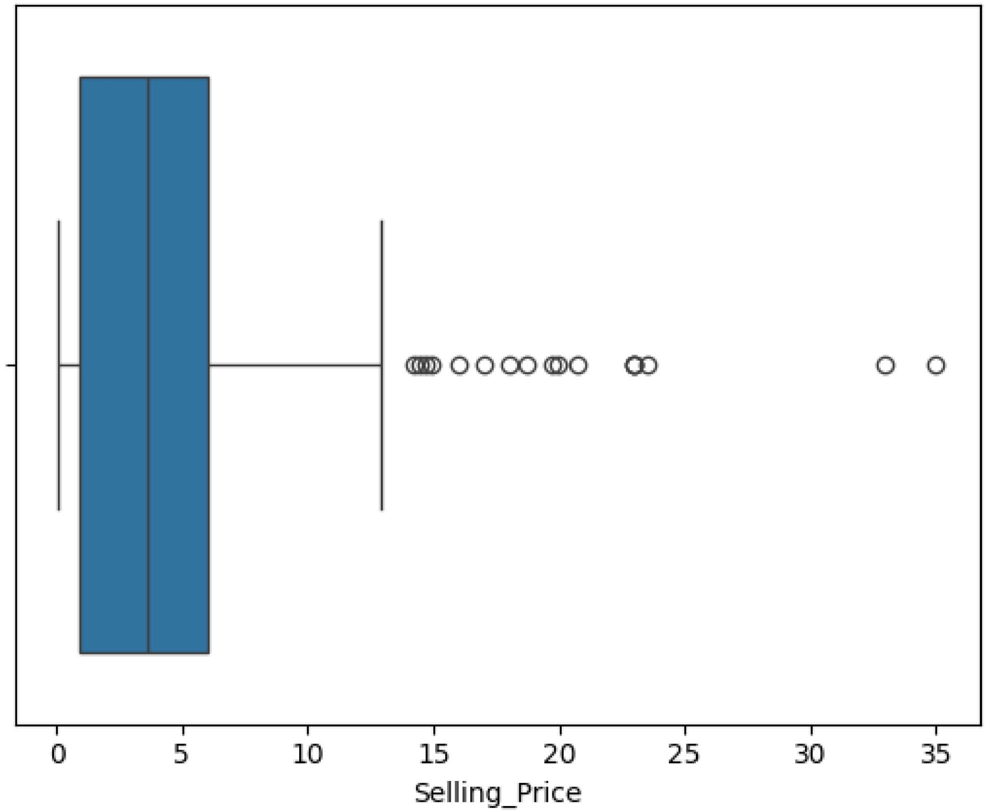
We can see that most of the cars are 'Manual'

```
df['Owner'].value_counts()
```

```
0    290
1     10
3      1
Name: Owner, dtype: int64
```

```
sns.boxplot(x=df['Selling_Price'])
```

```
<Axes: xlabel='Selling_Price'>
```



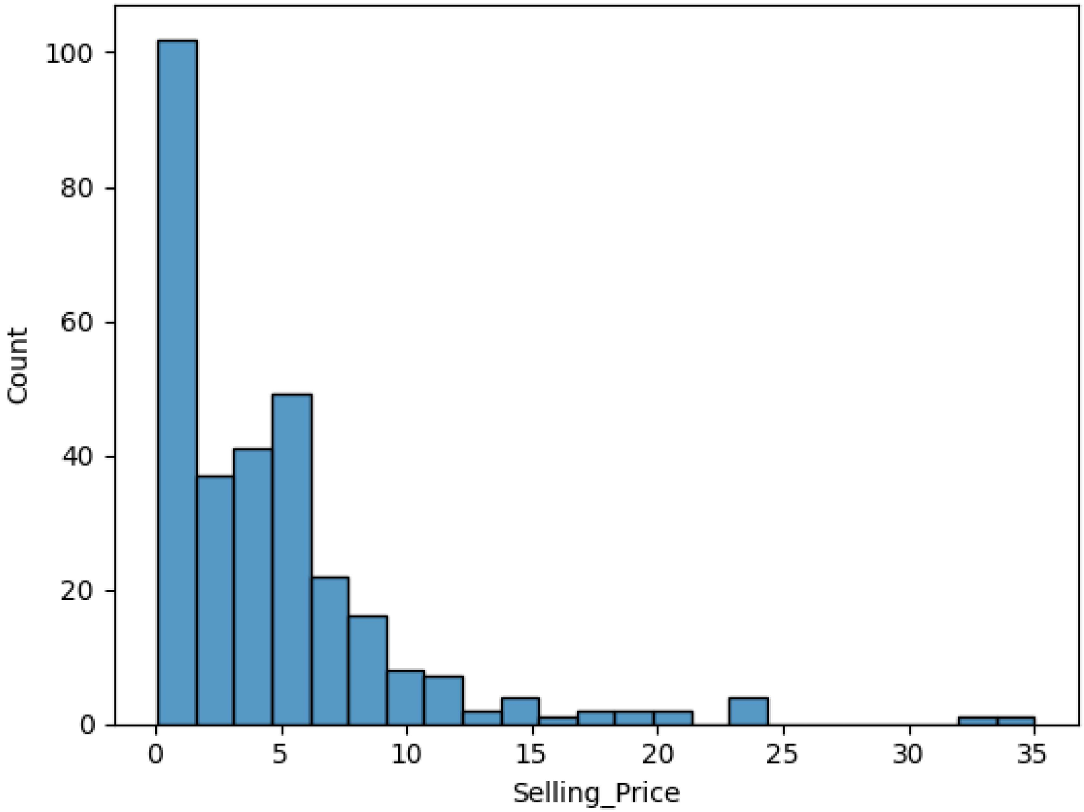

```
percentile_75 = np.percentile(df['Selling_Price'],75)
sum(df['Selling_Price']>percentile_75)
```

```
74
```

There are 74 cars out of 301 having Selling_Price > 75th_Percentile

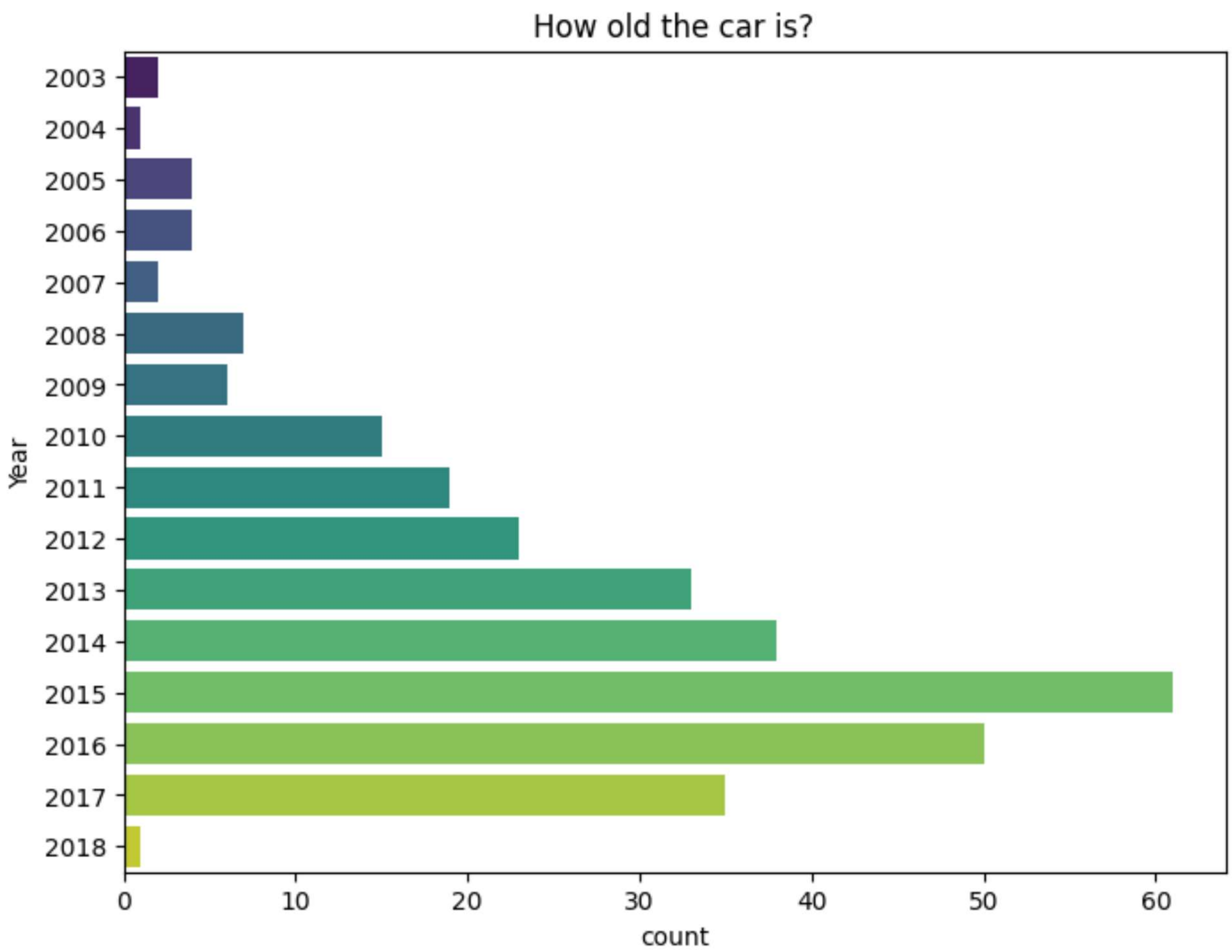
```
sns.histplot(df['Selling_Price'])
```

```
<Axes: xlabel='Selling_Price', ylabel='Count'>
```




```
plt.figure(figsize = (8,6))
sns.countplot(y=df['Year'],palette = 'viridis')
plt.title('How old the car is?')
plt.show()
```

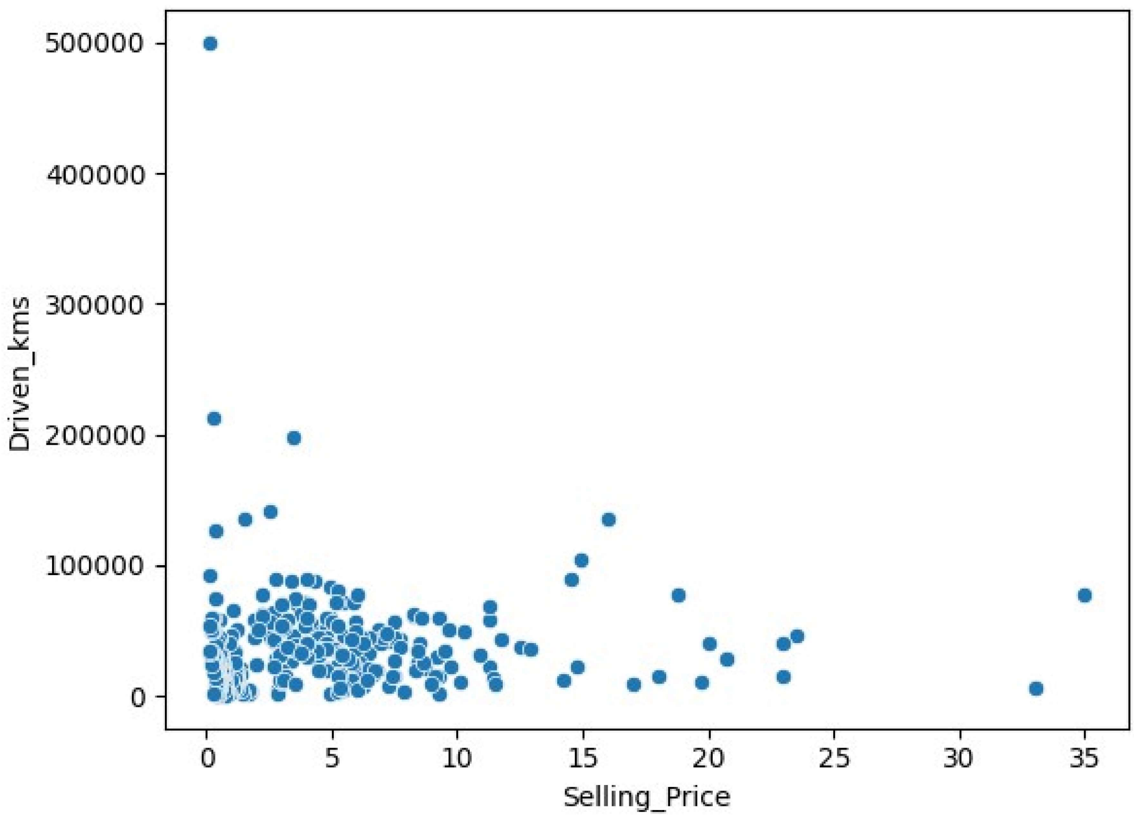
```
<ipython-input-182-90ef0c4da9b3>:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `y` variable to `hue` and set
`legend=False` for the same effect.

  sns.countplot(y=df['Year'],palette = 'viridis')
```



Most of the car models are of 2015

```
sns.scatterplot(x=df['Selling_Price'],y=df['Driven_kms'])
```

```
<Axes: xlabel='Selling_Price', ylabel='Driven_kms'>
```



Non_numeric Columns

```
# Extracting non-numerical columns
df.select_dtypes(include=['object']).columns

Index(['Car_Name', 'Fuel_Type', 'Selling_type', 'Transmission'],
dtype='object')
```

Label Encoding

```
# Create a LabelEncoder object
label_encoder = LabelEncoder()

# Convert the categorical columns to numerical using LabelEncoder
df['Car_Name'] = label_encoder.fit_transform(df['Car_Name'])
df['Fuel_Type'] = label_encoder.fit_transform(df['Fuel_Type'])
df['Selling_type'] = label_encoder.fit_transform(df['Selling_type'])
df['Transmission'] = label_encoder.fit_transform(df['Transmission'])

df.head()

   Car_Name  Year  Selling_Price  Present_Price  Driven_kms  Fuel_Type
\
0        90  2014           3.35           5.59       27000          2
```

```
1         93  2013           4.75          9.54       43000         1

2         68  2017           7.25          9.85        6900         2

3         96  2011           2.85          4.15        5200         2

4         92  2014           4.60          6.87       42450         1


   Selling_type  Transmission  Owner
0             0             1      0
1             0             1      0
2             0             1      0
3             0             1      0
4             0             1      0
```

Splitting into training and Testing data

```
# Select features (X) and target variable (y)
X = df.drop('Selling_Price', axis=1)
y = df['Selling_Price']

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=35)
```

Scaling the data_points to a common range

```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

Model Building

- Linear Regression
- Decision Tree Regressor
- Random Forest Regressor
- XGBoost Regressor
- MLP Regressor

```

# Linear Regression
linear_reg = LinearRegression()
linear_reg.fit(X_train_scaled, y_train)
linear_reg_predictions = linear_reg.predict(X_test_scaled)

# Decision Tree Regressor
```

```
decision_tree_reg = DecisionTreeRegressor(random_state=42)
decision_tree_reg.fit(X_train_scaled, y_train)
decision_tree_predictions = decision_tree_reg.predict(X_test_scaled)

# Random Forest Regressor
random_forest_reg = RandomForestRegressor(n_estimators=100,
random_state=42)
random_forest_reg.fit(X_train_scaled, y_train)
random_forest_predictions = random_forest_reg.predict(X_test_scaled)

# XGBoost Regressor
xgboost_reg = xgb.XGBRegressor(objective ='reg:squarederror',
colsample_bytree = 0.3, learning_rate = 0.1,
                               max_depth = 5, alpha = 10, n_estimators
= 100, random_state=42)
xgboost_reg.fit(X_train_scaled, y_train)
xgboost_predictions = xgboost_reg.predict(X_test_scaled)

# MLP Regressor
mlp_reg = MLPRegressor(hidden_layer_sizes=(100,), max_iter=1000,
random_state=42)
mlp_reg.fit(X_train_scaled, y_train)
mlp_predictions = mlp_reg.predict(X_test_scaled)
```

Model Evaluation

- Mean_Squared_Error
- R_Squared_Error

```
# Evaluate the models
models = {'Linear Regression': linear_reg, 'Decision Tree Regressor':
decision_tree_reg,
          'Random Forest Regressor': random_forest_reg, 'XGBoost
Regressor': xgboost_reg,
          'MLP Regressor': mlp_reg}

for name, model in models.items():
    predictions = model.predict(X_test_scaled)
    mse = mean_squared_error(y_test, predictions)
    r2 = r2_score(y_test, predictions)
    print(f'{name} - Mean Squared Error: {mse}, R-squared: {r2}')
```

```
Linear Regression - Mean Squared Error: 6.507819977947056, R-squared:
0.7688828477496812
Decision Tree Regressor - Mean Squared Error: 2.2728442622950817, R-
squared: 0.9192827559474342
Random Forest Regressor - Mean Squared Error: 3.4803063719672105, R-
```

```
squared: 0.8764012372233072
XGBoost Regressor - Mean Squared Error: 7.163230503468686, R-squared:
0.7456067561050521
MLP Regressor - Mean Squared Error: 1.486528994040077, R-squared:
0.9472077671164387
```

The best Model is MLP Regressor having least mse (1.49) and highest r2_score (0.95)

```
# Model names
models = ['Linear Regression', 'Decision Tree', 'Random Forest',
'XGBoost', 'MLP']

# Corresponding MSE and R² scores
mse_scores = [6.51, 2.27, 3.48, 7.16, 1.49]
r2_scores = [0.77, 0.92, 0.88, 0.75, 0.95]

# Create a DataFrame for easy plotting
performance_df = pd.DataFrame({'Model': models, 'MSE': mse_scores, 'R-
squared': r2_scores})

# Plotting
plt.figure(figsize=(12, 6))

# Bar plot for MSE
plt.subplot(1, 2, 1)
sns.barplot(x='MSE', y='Model', data=performance_df,
palette='viridis')
plt.title('Mean Squared Error (MSE)')
plt.xlabel('MSE')

# Bar plot for R-squared
plt.subplot(1, 2, 2)
sns.barplot(x='R-squared', y='Model', data=performance_df,
palette='viridis')
plt.title('R-squared Score')
plt.xlabel('R-squared')

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

```
<ipython-input-196-3f4029ee130f>:16: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `y` variable to `hue` and set
`legend=False` for the same effect.

  sns.barplot(x='MSE', y='Model', data=performance_df,
palette='viridis')
<ipython-input-196-3f4029ee130f>:22: FutureWarning:
```

```
Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `y` variable to `hue` and set
`legend=False` for the same effect.

  sns.barplot(x='R-squared', y='Model', data=performance_df,
palette='viridis')
```