Step 1

In [ ]:
```
import pandas as pd
from sklearn.model_selection import StratifiedShuffleSplit
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt
```

In [ ]:
```
data = pd.read_csv("car-data.csv")
data = data.drop("Car_Name", axis=1)
data.head()
```

Out[ ]:

	Year	Selling_Price	Present_Price	Kms_Driven	Fuel_Type	Seller_Type	Transmission	Owner
0	2014	3.35	5.59	27000	Petrol	Dealer	Manual	0
1	2013	4.75	9.54	43000	Diesel	Dealer	Manual	0
2	2017	7.25	9.85	6900	Petrol	Dealer	Manual	0
3	2011	2.85	4.15	5200	Petrol	Dealer	Manual	0
4	2014	4.60	6.87	42450	Diesel	Dealer	Manual	0

In [ ]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 301 entries, 0 to 300
Data columns (total 8 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Year           301 non-null    int64
 1   Selling_Price  301 non-null    float64
 2   Present_Price  301 non-null    float64
 3   Kms_Driven     301 non-null    int64
 4   Fuel_Type      301 non-null    object
 5   Seller_Type    301 non-null    object
 6   Transmission   301 non-null    object
 7   Owner          301 non-null    int64
dtypes: float64(2), int64(3), object(3)
memory usage: 18.9+ KB
```

In [ ]:
```
data.describe()
```

Out[ ]:

	Year	Selling_Price	Present_Price	Kms_Driven	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	8.644115	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 [ ]:

```
if data.isnull().values.any():
    print("There are missing values")
else:
    print("There are no missing values")
```

```
There are no missing values
```

Q1

a)

The numerical attributes are: Year, Selling_Price, Present_Price, Kms_Driven, Owner The categorical attributes are: Car_Name, Fuel_Type, Seller_Type, Transmission

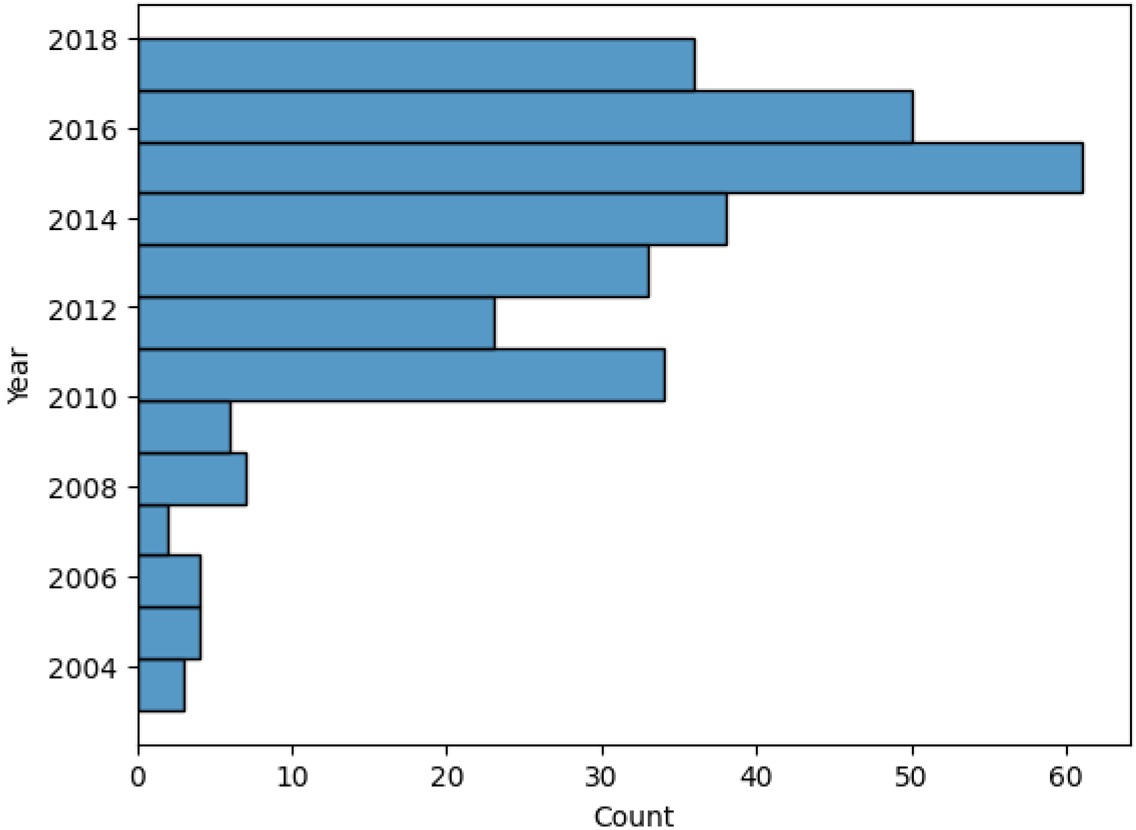
b)

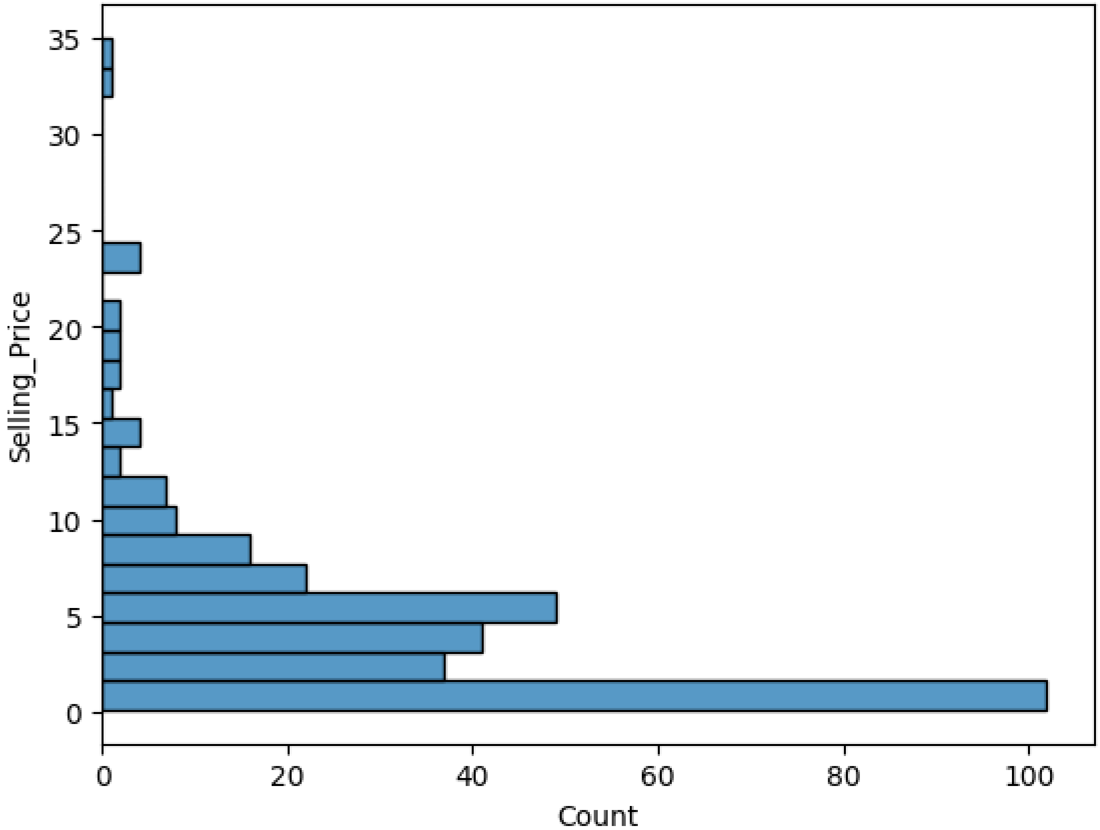
There are no missing data in the dataset.

Histograms:

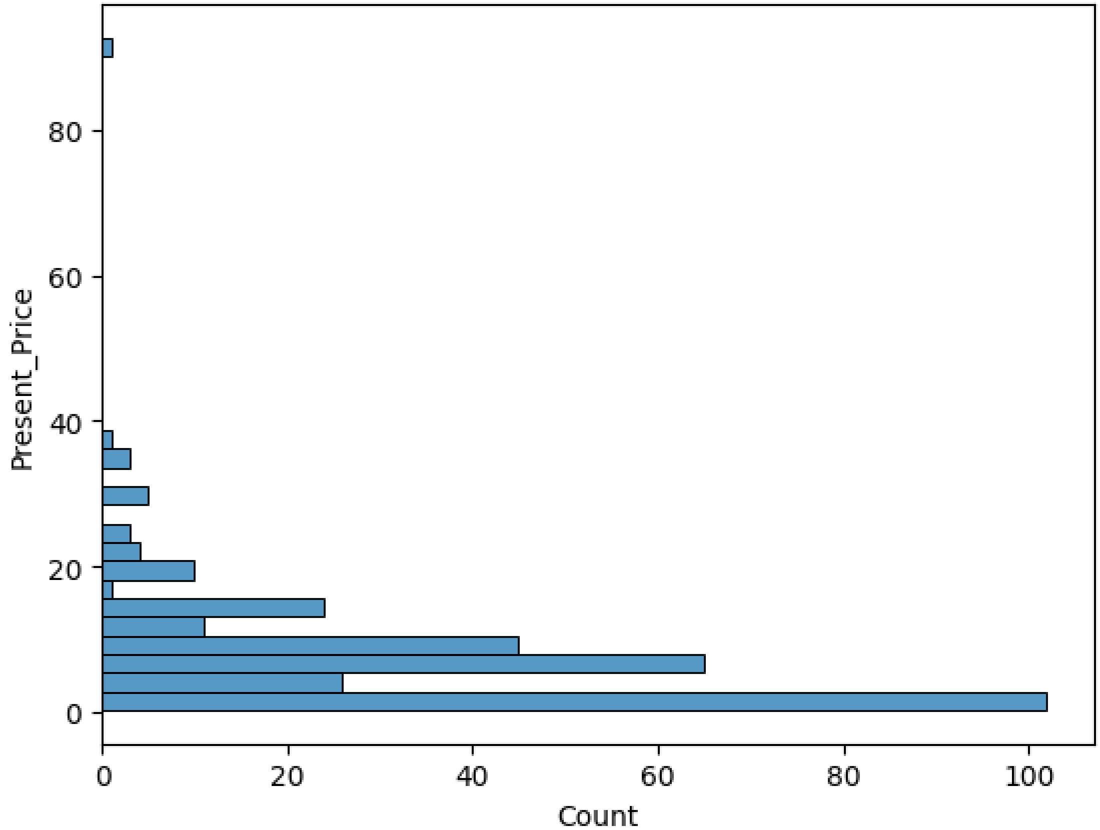
In [ ]:

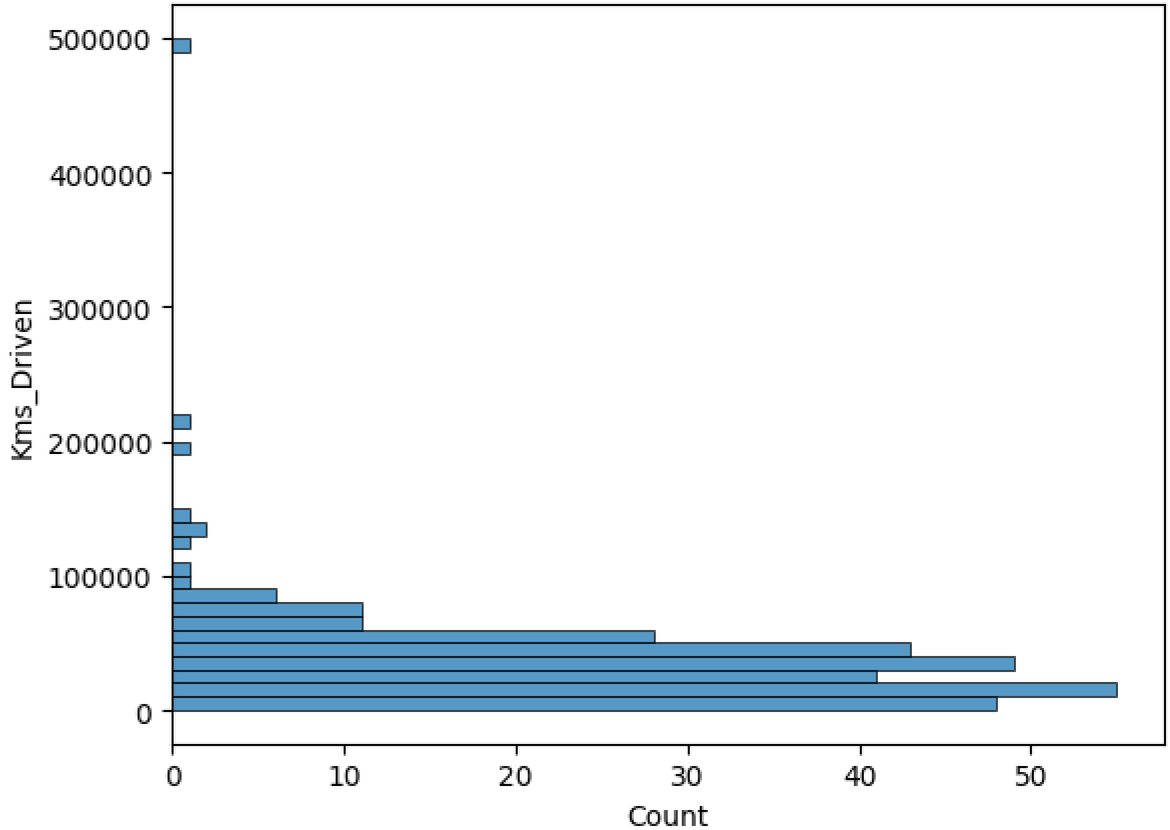
```
numerical_cols = data.select_dtypes(include=np.number).columns.tolist()

for numerical_col in numerical_cols:
    plt.figure()
    sns.histplot(data=data, y=numerical_col)
```


2018
2016
2014
2012
2010
2008
2006
2004
Year
0
10
20
30
40
50
60
Count

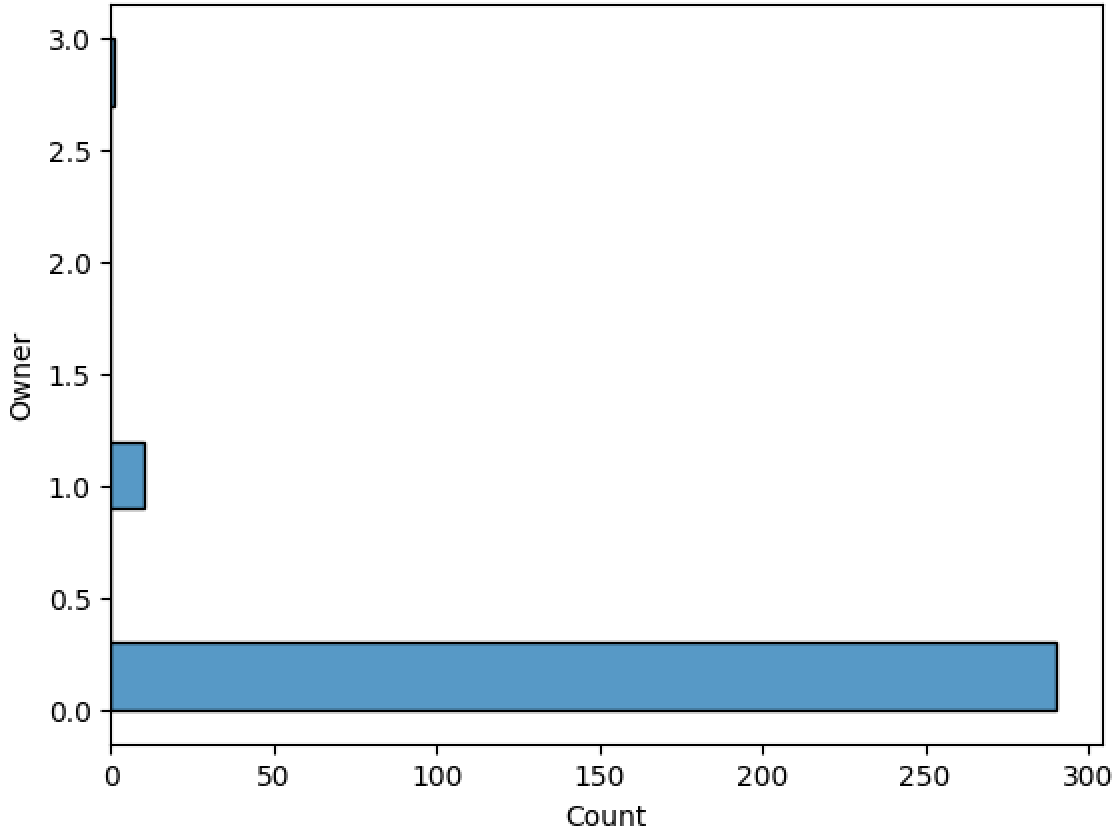


Selling_Price
Count
0
5
10
15
20
25
30
35
0
20
40
60
80
100


Present_Price
0
20
40
60
80
0
20
40
60
80
100
Count



500000
400000
300000
200000
100000
0
Kms_Driven
0
10
20
30
40
50
Count



Stratification and Test and Train Split

In [ ]:
```
def categorize_year(row):
    year_val = row["Year"]
    year = ""
    if 2003 <= year_val < 2006:
        year = "2003-2005"
    elif 2006 <= year_val < 2009:
        year = "2006-2008"
    elif 2009 <= year_val < 2012:
        year = "2009-2011"
    elif 2012 <= year_val < 2015:
        year = "2012-2014"
    else:
        year = "2015-2018"

    return year
```

```python
data["Year_Cat"] = data.apply(categorize_year, axis=1)

sss = StratifiedShuffleSplit(n_splits=1, test_size=0.2, random_state=42)

for train_index, test_index in sss.split(data, data["Year_Cat"]):
    strat_train_set = data.loc[train_index]
    strat_test_set = data.loc[test_index]

strat_train_set
```

Out[ ]:

	Year	Selling_Price	Present_Price	Kms_Driven	Fuel_Type	Seller_Type	Transmission	Owner	Year_Cat
206	2017	5.75	7.13	12479	Petrol	Dealer	Manual	0	2015-2018
140	2013	0.60	1.20	32000	Petrol	Individual	Manual	0	2012-2014
179	2010	0.31	1.05	213000	Petrol	Individual	Manual	0	2009-2011
24	2013	2.90	4.41	56879	Petrol	Dealer	Manual	0	2012-2014
49	2017	7.75	9.29	37000	Petrol	Dealer	Automatic	0	2015-2018
...	...	...	...	...	...	...	...	...	...
156	2017	0.48	0.52	15000	Petrol	Individual	Manual	0	2015-2018
278	2016	6.00	8.40	4000	Petrol	Dealer	Manual	0	2015-2018
158	2017	0.48	0.54	8600	Petrol	Individual	Manual	0	2015-2018
204	2015	2.75	4.43	28282	Petrol	Dealer	Manual	0	2015-2018
118	2015	1.10	1.47	26000	Petrol	Individual	Manual	0	2015-2018

240 rows × 9 columns

Step 2

Correlation Matrix of Training Data

In [ ]:

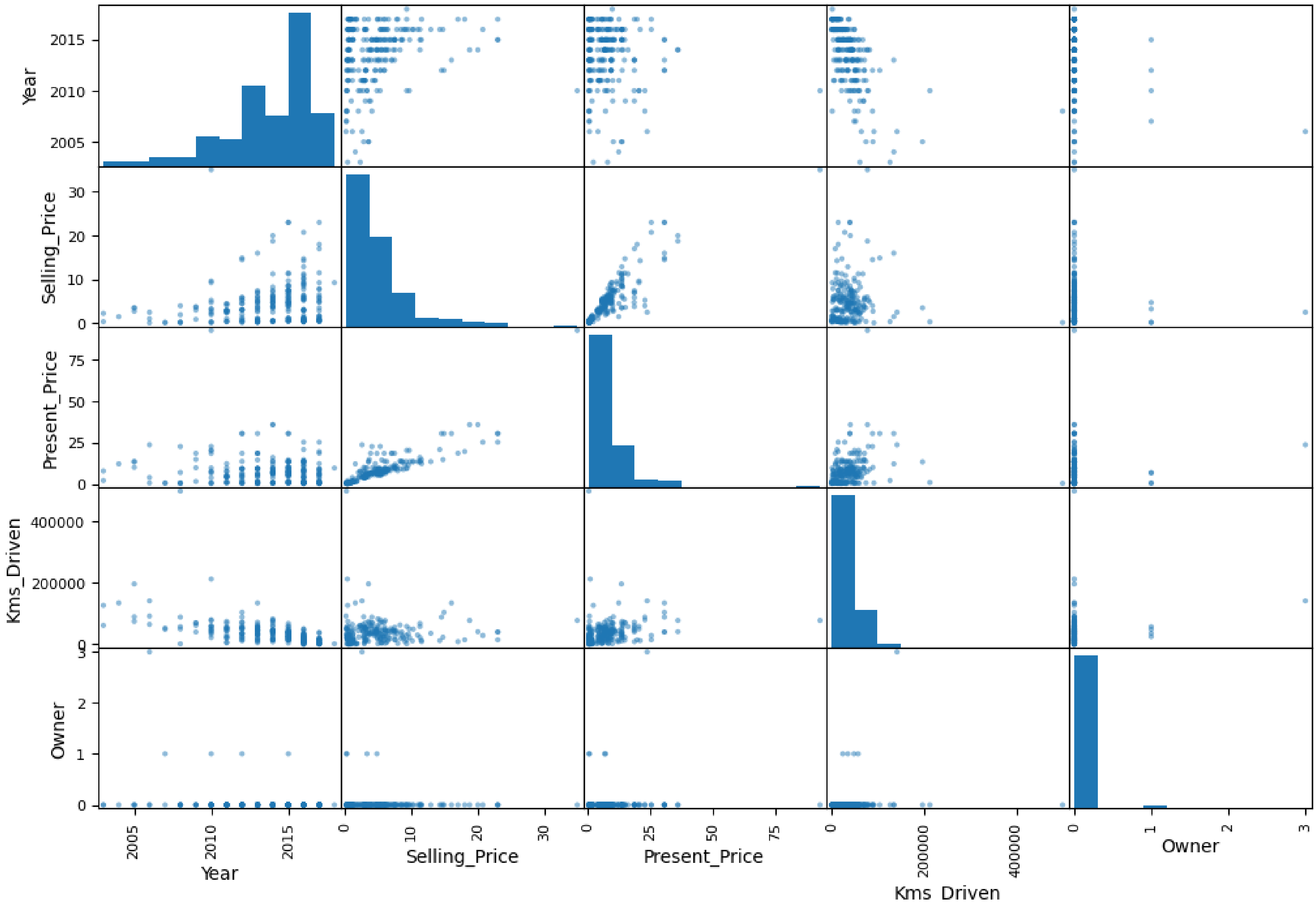
```python
corr_matrix = strat_train_set.corr(method="pearson", numeric_only=True)
corr_matrix["Selling_Price"]
```

Out[ ]:
```
Year             0.190091
Selling_Price    1.000000
Present_Price    0.874357
Kms_Driven       0.036837
Owner           -0.061959
Name: Selling_Price, dtype: float64
```

Scatter Plots of Numerical Attributes

In [ ]:
```python
from pandas.plotting import scatter_matrix

scatter_matrix(strat_train_set, figsize=(12, 8))
```

Out[ ]:
```
array([[<Axes: xlabel='Year', ylabel='Year'>,
        <Axes: xlabel='Selling_Price', ylabel='Year'>,
        <Axes: xlabel='Present_Price', ylabel='Year'>,
        <Axes: xlabel='Kms_Driven', ylabel='Year'>,
        <Axes: xlabel='Owner', ylabel='Year'>],
       [<Axes: xlabel='Year', ylabel='Selling_Price'>,
        <Axes: xlabel='Selling_Price', ylabel='Selling_Price'>,
        <Axes: xlabel='Present_Price', ylabel='Selling_Price'>,
        <Axes: xlabel='Kms_Driven', ylabel='Selling_Price'>,
        <Axes: xlabel='Owner', ylabel='Selling_Price'>],
       [<Axes: xlabel='Year', ylabel='Present_Price'>,
        <Axes: xlabel='Selling_Price', ylabel='Present_Price'>,
        <Axes: xlabel='Present_Price', ylabel='Present_Price'>,
        <Axes: xlabel='Kms_Driven', ylabel='Present_Price'>,
        <Axes: xlabel='Owner', ylabel='Present_Price'>],
       [<Axes: xlabel='Year', ylabel='Kms_Driven'>,
        <Axes: xlabel='Selling_Price', ylabel='Kms_Driven'>,
        <Axes: xlabel='Present_Price', ylabel='Kms_Driven'>,
        <Axes: xlabel='Kms_Driven', ylabel='Kms_Driven'>,
        <Axes: xlabel='Owner', ylabel='Kms_Driven'>],
       [<Axes: xlabel='Year', ylabel='Owner'>,
        <Axes: xlabel='Selling_Price', ylabel='Owner'>,
        <Axes: xlabel='Present_Price', ylabel='Owner'>,
        <Axes: xlabel='Kms_Driven', ylabel='Owner'>,
        <Axes: xlabel='Owner', ylabel='Owner'>]], dtype=object)
```



Creating Kilometers per Year ("Kms_Per_Year") Attribute

In [ ]:
```
strat_train_set["Kms_Per_Year"] = strat_train_set["Kms_Driven"] / \
    (strat_train_set["Year"].max()+1 - strat_train_set["Year"])
corr_matrix = strat_train_set.corr(method="pearson", numeric_only=True)
corr_matrix
```

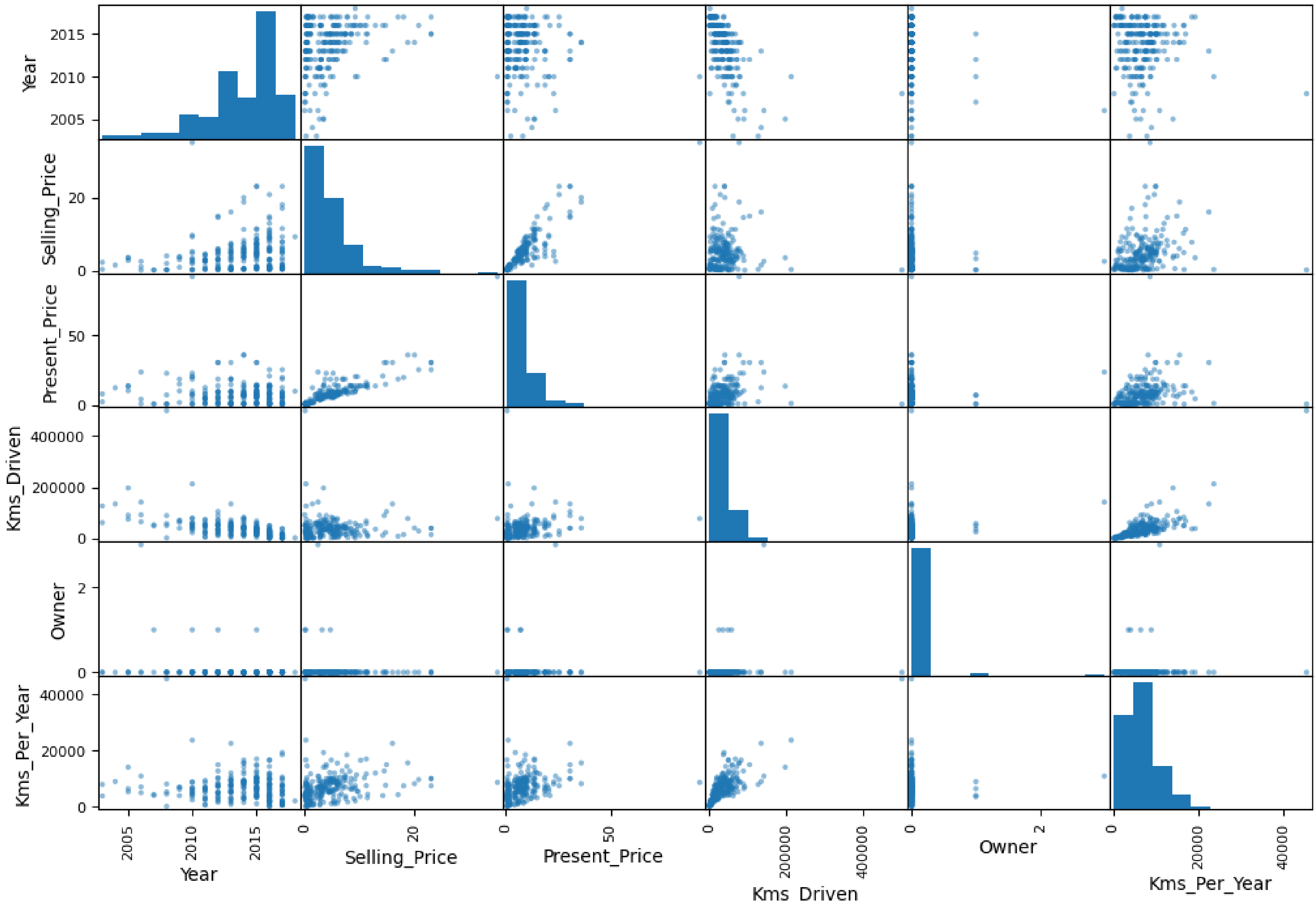
Out[ ]:

	Year	Selling_Price	Present_Price	Kms_Driven	Owner	Kms_Per_Year
Year	1.000000	0.190091	-0.109867	-0.540266	-0.205827	-0.084173
Selling_Price	0.190091	1.000000	0.874357	0.036837	-0.061959	0.259670
Present_Price	-0.109867	0.874357	1.000000	0.205722	0.063400	0.268039
Kms_Driven	-0.540266	0.036837	0.205722	1.000000	0.139661	0.781894
Owner	-0.205827	-0.061959	0.063400	0.139661	1.000000	0.028090
Kms_Per_Year	-0.084173	0.259670	0.268039	0.781894	0.028090	1.000000

In [ ]:

```
scatter_matrix(strat_train_set, figsize=(12, 8))
```

```
Out[ ]: array([[<Axes: xlabel='Year', ylabel='Year'>,
               <Axes: xlabel='Selling_Price', ylabel='Year'>,
               <Axes: xlabel='Present_Price', ylabel='Year'>,
               <Axes: xlabel='Kms_Driven', ylabel='Year'>,
               <Axes: xlabel='Owner', ylabel='Year'>,
               <Axes: xlabel='Kms_Per_Year', ylabel='Year'>],
              [<Axes: xlabel='Year', ylabel='Selling_Price'>,
               <Axes: xlabel='Selling_Price', ylabel='Selling_Price'>,
               <Axes: xlabel='Present_Price', ylabel='Selling_Price'>,
               <Axes: xlabel='Kms_Driven', ylabel='Selling_Price'>,
               <Axes: xlabel='Owner', ylabel='Selling_Price'>,
               <Axes: xlabel='Kms_Per_Year', ylabel='Selling_Price'>],
              [<Axes: xlabel='Year', ylabel='Present_Price'>,
               <Axes: xlabel='Selling_Price', ylabel='Present_Price'>,
               <Axes: xlabel='Present_Price', ylabel='Present_Price'>,
               <Axes: xlabel='Kms_Driven', ylabel='Present_Price'>,
               <Axes: xlabel='Owner', ylabel='Present_Price'>,
               <Axes: xlabel='Kms_Per_Year', ylabel='Present_Price'>],
              [<Axes: xlabel='Year', ylabel='Kms_Driven'>,
               <Axes: xlabel='Selling_Price', ylabel='Kms_Driven'>,
               <Axes: xlabel='Present_Price', ylabel='Kms_Driven'>,
               <Axes: xlabel='Kms_Driven', ylabel='Kms_Driven'>,
               <Axes: xlabel='Owner', ylabel='Kms_Driven'>,
               <Axes: xlabel='Kms_Per_Year', ylabel='Kms_Driven'>],
              [<Axes: xlabel='Year', ylabel='Owner'>,
               <Axes: xlabel='Selling_Price', ylabel='Owner'>,
               <Axes: xlabel='Present_Price', ylabel='Owner'>,
               <Axes: xlabel='Kms_Driven', ylabel='Owner'>,
               <Axes: xlabel='Owner', ylabel='Owner'>,
               <Axes: xlabel='Kms_Per_Year', ylabel='Owner'>],
              [<Axes: xlabel='Year', ylabel='Kms_Per_Year'>,
               <Axes: xlabel='Selling_Price', ylabel='Kms_Per_Year'>,
               <Axes: xlabel='Present_Price', ylabel='Kms_Per_Year'>,
               <Axes: xlabel='Kms_Driven', ylabel='Kms_Per_Year'>,
               <Axes: xlabel='Owner', ylabel='Kms_Per_Year'>,
               <Axes: xlabel='Kms_Per_Year', ylabel='Kms_Per_Year'>]],
             dtype=object)
```



In [ ]:
```python
car_labels = strat_train_set["Selling_Price"]

car_inputs = strat_train_set.drop("Selling_Price", axis=1)

car_inputs
```

Out[ ]:

	Year	Present_Price	Kms_Driven	Fuel_Type	Seller_Type	Transmission	Owner	Year_Cat	Kms_Per_Year
206	2017	7.13	12479	Petrol	Dealer	Manual	0	2015-2018	6239.500000
140	2013	1.20	32000	Petrol	Individual	Manual	0	2012-2014	5333.333333
179	2010	1.05	213000	Petrol	Individual	Manual	0	2009-2011	23666.666667
24	2013	4.41	56879	Petrol	Dealer	Manual	0	2012-2014	9479.833333
49	2017	9.29	37000	Petrol	Dealer	Automatic	0	2015-2018	18500.000000
...	...	...	...	...	...	...	...	...	...
156	2017	0.52	15000	Petrol	Individual	Manual	0	2015-2018	7500.000000
278	2016	8.40	4000	Petrol	Dealer	Manual	0	2015-2018	1333.333333
158	2017	0.54	8600	Petrol	Individual	Manual	0	2015-2018	4300.000000
204	2015	4.43	28282	Petrol	Dealer	Manual	0	2015-2018	7070.500000
118	2015	1.47	26000	Petrol	Individual	Manual	0	2015-2018	6500.000000

240 rows × 9 columns

One-Hot Encoding Demo

In [ ]:

```
from sklearn.preprocessing import OneHotEncoder

cat_encoder = OneHotEncoder()
categorical_cols = car_inputs.select_dtypes(include=object).columns.tolist()
car_inputs_cat = car_inputs[categorical_cols]
car_inputs_cat_1hot = cat_encoder.fit_transform(car_inputs_cat)
car_inputs_cat_1hot
```

Out[ ]:

```
<240x12 sparse matrix of type '<class 'numpy.float64'>'
	with 960 stored elements in Compressed Sparse Row format>
```

Step 3

Defining a transformer for adding the Kms_Per_Year attribute

In [ ]:

```
from sklearn.base import BaseEstimator, TransformerMixin
```

```python
class KmsPerYearAdder(BaseEstimator, TransformerMixin):
    def __init__(self, add_kms_per_year=True):
        self.add_kms_per_year = add_kms_per_year
        self.year_index = 0
        self.kms_driven_index = 2

    def fit(self, X: np.ndarray, y=None):
        return self

    def transform(self, X: np.ndarray):
        if self.add_kms_per_year:
            kms_per_year = X[:, self.kms_driven_index] / X[:, self.year_index]
            return np.c_[X, kms_per_year]

        return X
```

Numerical Pipeline

In [ ]:
```python
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline

num_pipeline = Pipeline([
    ("imputer", SimpleImputer(strategy="median")),
    ("attribute_adder", KmsPerYearAdder()),
    ("std_scaler", StandardScaler())
])
```

Column Transformer

In [ ]:
```python
from sklearn.compose import ColumnTransformer

numerical_car_cols = car_inputs.select_dtypes(include=np.number).columns.tolist()
categorical_cols   = car_inputs.select_dtypes(include=object   ).columns.tolist()

full_pipeline = ColumnTransformer([
    ("num", num_pipeline, numerical_car_cols),
    ("cat", OneHotEncoder(), categorical_cols)
])

cars_prepared = full_pipeline.fit_transform(car_inputs)
```

Step 4

In [ ]:
```
from sklearn.linear_model import LinearRegression

lin_reg = LinearRegression()
lin_reg.fit(cars_prepared, car_labels)
```

Out[ ]:
```
LinearRegression
LinearRegression()
```

Root Mean Squared Error

In [ ]:
```
from sklearn.metrics import mean_squared_error
car_predictions = lin_reg.predict(cars_prepared)
lin_mse = mean_squared_error(car_labels, car_predictions)
lin_rmse = np.sqrt(lin_mse)
lin_rmse
```

Out[ ]:
```
1.580422734366746
```

Decision Tree

In [ ]:
```
from sklearn.tree import DecisionTreeRegressor

tree_reg = DecisionTreeRegressor()
tree_reg.fit(cars_prepared, car_labels)
```

Out[ ]:
```
DecisionTreeRegressor
DecisionTreeRegressor()
```

In [ ]:
```
car_predictions = tree_reg.predict(cars_prepared)
tree_mse = mean_squared_error(car_labels, car_predictions)
tree_rmse = np.sqrt(tree_mse)
tree_rmse
```

Out[ ]:
```
0.0
```

Cross Validation, 10-Fold: Decision Tree

In [ ]:
```
from sklearn.model_selection import cross_val_score
scores = cross_val_score(tree_reg, cars_prepared, car_labels,
```

```python
                          scoring= "neg_mean_squared_error", cv=10)
tree_rmse_scores = np.sqrt(-scores)
```

In [ ]:
```python
def display_scores(scores):
    print(f"Scores: {scores}")
    print(f"Mean: {scores.mean()}")
    print(f"Standard Deviation: {scores.std()}")

display_scores(tree_rmse_scores)
```

```
Scores: [3.44794987 1.35254236 0.90720496 0.69294961 1.43773984 1.47689991
 1.06002555 0.9368987  1.00903213 1.07533522]
Mean: 1.3396578136640485
Standard Deviation: 0.7415087832400876
```

Cross Validation, 10-Fold: Linear Regression

In [ ]:
```python
lin_scores = cross_val_score(lin_reg, cars_prepared, car_labels,
                             scoring = "neg_mean_squared_error", cv=10)
lin_rmse_scores = np.sqrt(-lin_scores)
display_scores(lin_rmse_scores)
```

```
Scores: [2.6486431  1.66620457 1.9403383  1.88706817 2.72627307 2.08587967
 1.73762831 1.44726706 1.63627027 1.4196423 ]
Mean: 1.919521482886413
Standard Deviation: 0.43151098914610553
```

Cross Validation, 10-Fold: Random Forest Regression

In [ ]:
```python
from sklearn.ensemble import RandomForestRegressor

forest_reg = RandomForestRegressor()
forest_scores = cross_val_score(forest_reg, cars_prepared, car_labels,
                                scoring = "neg_mean_squared_error", cv=10)
forest_rmse_scores = np.sqrt(-forest_scores)
display_scores(forest_rmse_scores)
```

```
Scores: [4.01035876 1.17059493 0.66310998 0.77014134 1.22126345 1.12610142
 0.60244262 0.90107377 0.7646494  0.80264496]
Mean: 1.203238061953517
Standard Deviation: 0.9576884431490988
```

Random Forest Regression: Whole Training Set

In [ ]:
```python
forest_reg = RandomForestRegressor()
forest_reg.fit(cars_prepared, car_labels)
```

```python
car_predictions = forest_reg.predict(cars_prepared)

forest_mse = mean_squared_error(car_labels, car_predictions)
forest_rmse = np.sqrt(forest_mse)

forest_rmse
```

Out[ ]:
```
0.5857729652277119
```

Random Forest Regression: GridSearch for best hyper parameters

In [ ]:
```python
from sklearn.model_selection import GridSearchCV

param_grid = [
    {
        'n_estimators': [3,10,30],
        'max_features': [2,4,6,8],
    },
    {
        'bootstrap': [False],
        'n_estimators': [3,10],
        'max_features': [2,3,4]
    }
]

forest_reg = RandomForestRegressor()

grid_search = GridSearchCV(forest_reg, param_grid, cv=5,
                           scoring = "neg_mean_squared_error",
                           return_train_score=True)

grid_search.fit(cars_prepared, car_labels)

grid_search.best_params_
```

Out[ ]:
```
{'max_features': 8, 'n_estimators': 30}
```

In [ ]:
```python
grid_search.best_estimator_
```

Out[ ]:
```
RandomForestRegressor

RandomForestRegressor(max_features=8, n_estimators=30)
```

Important Features

```
In [ ]: grid_search.best_estimator_.feature_importances_
```

```
Out[ ]: array([5.61019038e-02, 4.94374545e-01, 3.17912433e-02, 8.79263910e-05,
               2.11483811e-02, 2.99055510e-02, 1.82391152e-04, 7.77959726e-02,
               4.40324003e-02, 1.04741623e-01, 5.27795632e-02, 2.32588506e-02,
               3.17307356e-02, 1.34941083e-03, 6.65039058e-05, 1.39919410e-02,
               2.21573545e-03, 1.44453223e-02])
```

```
In [ ]: final_model = grid_search.best_estimator_
        X_train = strat_train_set.drop("Selling_Price", axis=1).copy()
        Y_train = strat_train_set["Selling_Price"].copy()

        X_train_prepared = full_pipeline.transform(X_train)

        train_predictions = final_model.predict(X_train_prepared)
        train_mse = mean_squared_error(Y_train, train_predictions)
        train_rmse = np.sqrt(train_mse)
        train_rmse
```

```
Out[ ]: 0.770015917644516
```

Step 5

```
In [ ]: final_model = grid_search.best_estimator_

        strat_test_set["Kms_Per_Year"] = strat_test_set["Kms_Driven"] / \
            (strat_test_set["Year"].max() + 1 - strat_test_set["Year"])

        X_test = strat_test_set.drop("Selling_Price", axis=1).copy()


        Y_test = strat_test_set["Selling_Price"].copy()

        X_test_prepared = full_pipeline.transform(X_test)

        final_predictions = final_model.predict(X_test_prepared)
        final_mse = mean_squared_error(Y_test, final_predictions)
        final_rmse = np.sqrt(final_mse)
        final_rmse
```

```
Out[ ]: 1.8293852481521347
```

Confidence Interval

In [ ]:

```
from scipy import stats
confidence = 0.95
squared_errors = (final_predictions - Y_test.to_numpy()) ** 2

print(squared_errors)
stats.t.interval(confidence, len(squared_errors) - 1,
                loc = squared_errors.mean(),
                scale = stats.sem(squared_errors))
```

```
[4.44444444e-05 1.08900000e-03 1.11111111e-03 1.71610000e-02
 1.30802778e-01 9.83867778e-02 3.29476000e-01 7.20027778e-02
 1.36900000e-03 3.30027778e-02 2.26502500e+00 3.80250000e-02
 1.33712111e-01 1.69000000e-02 1.51052293e+02 1.19829511e+00
 8.77344444e-01 2.30400000e-03 5.94955111e-01 7.30080400e+00
 3.73777778e-04 5.98617778e-02 8.40277778e-01 2.01002778e-01
 1.07802778e-01 1.13067778e-02 9.71361111e-02 2.88011111e-03
 1.02346944e+00 2.87867778e-02 1.70844444e-03 8.10000000e-03
 1.60000000e-03 1.26187778e-02 1.22500000e-01 1.03361111e-02
 8.83600000e-03 6.78776178e+00 4.76694444e-02 7.93361111e-02
 2.05444444e-02 2.77377778e-01 8.41000000e-04 2.06401111e+00
 3.18027778e-02 1.09120111e-01 7.10087111e-01 1.06090000e-02
 8.10000000e-03 1.48433611e+00 1.71948444e-01 3.37579378e+00
 1.48225000e-01 7.74400000e-03 2.11661338e+01 6.00625000e-01
 6.55360000e-02 1.13777778e-02 8.21777778e-02 4.01111111e-03
 1.77802778e-01]
```

Out[ ]:

```
(-1.635979548262723, 8.329280320576018)
```

Coefficient of Determination (R^2)

In [ ]:

```
from sklearn.metrics import r2_score
r2_score(Y_test, final_predictions)
```

Out[ ]:

```
0.8988732980147371
```

In [ ]:

```
from joblib import dump

dump(final_model, 'car_model.joblib')
```

Out[ ]:

```
['car_model.joblib']
```