Out[2]: normalizeddrive- enginecity- hig bodyengine- enginefuelsymboling make width height horsepower location losses type style wheels type size mpg alfa-3 0 gas convertible rwd front 64.1 48.8 dohc 130 111 21 romero alfagas convertible 1 3 130 rwd front 64.1 48.8 dohc 111 21 romero alfa-2 152 1 gas hatchback rwd front 65.5 52.4 ohcv 154 19 romero 3 2 109 102 164 audi gas sedan fwd front 66.2 54.3 ohc 24 2 164 front 66.4 54.3 136 115 audi gas sedan 4wd ohc 18 In [3]: df.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 205 entries, 0 to 204 Data columns (total 15 columns): Column Non-Null Count Dtype # ----symboling 205 non-null int64 0 normalized-losses 205 non-null object 1 2 205 non-null object make 3 fuel-type 205 non-null object 205 non-null 4 body-style object drive-wheels 205 non-null object 5 205 non-null object 6 engine-location width 205 non-null 7 float64 height 205 non-null float64 8 205 non-null 9 engine-type object 205 non-null int64 10 engine-size 205 non-null object 11 horsepower 12 city-mpg 205 non-null int64 13 highway-mpg 205 non-null int64 14 price 205 non-null int64 dtypes: float64(2), int64(5), object(8) memory usage: 24.1+ KB In [4]: df['normalized-losses'].value_counts() Out[4]: ? 41 161 11 91 8 150 7 128 6 134 6 104 6 102 5 5 168 74 5 95 5 103 5 5 65 5 94 85 122 93 106 148 118 154 3 83 3 115 3 125 3 137 101 113 2 119 2 197 2 81 194 2 2 129 192 2 87 158 2 108 2 2 188 2 145 153 2 164 2 89 110 107 1 256 1 90 231 142 77 98 121 78 1 186 Name: normalized-losses, dtype: int64 In [5]: df['horsepower'].value_counts() Out[5]: 68 19 70 11 69 10 116 9 110 95 62 114 6 101 6 88 6 160 6 82 76 84 102 145 5 97 5 123 111 92 86 121 207 85 3 3 90 182 73 3 152 161 52 2 184 2 56 2 ? 94 2 162 2 112 2 2 156 2 100 176 2 155 2 48 1 140 1 262 1 115 1 175 1 135 1 78 1 154 1 142 1 58 1 60 1 120 1 64 1 106 1 288 1 200 1 134 1 143 1 55 1 72 1 Name: horsepower, dtype: int64 In [6]: df['normalized-losses'].replace("?", np.nan, inplace=True) df['horsepower'].replace("?", np.nan, inplace=True) df['normalized-losses']=df['normalized-losses'].astype('float') df['horsepower'] = df['horsepower'].astype('float') nmean = df['normalized-losses'].mean() hmean = df['horsepower'].mean() df['normalized-losses'].fillna(nmean,inplace=True) df['horsepower'].fillna(hmean,inplace=True) In [7]: df.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 205 entries, 0 to 204 Data columns (total 15 columns): Column Non-Null Count Dtype 0 symboling 205 non-null int64 normalized-losses 205 non-null float64 1 2 205 non-null object 3 fuel-type 205 non-null object 4 205 non-null object body-style drive-wheels 205 non-null object 205 non-null engine-location object 7 width 205 non-null float64 8 height 205 non-null float64 object 205 non-null 9 engine-type 10 engine-size 205 non-null int64 11 horsepower 205 non-null float64 12 205 non-null int64 city-mpg highway-mpg 205 non-null int64 13 int64 price 205 non-null dtypes: float64(4), int64(5), object(6) memory usage: 24.1+ KB In [8]: df.describe() Out[8]: normalizedhighwayenginewidth symboling height horsepower city-mpg price losses size mpg 205.000000 205.000000 205.000000 205.000000 205.000000 205.000000 205.000000 205.000000 205.000000 count 0.834146 53.724878 126.907317 104.256158 25.219512 30.751220 13227.478049 122.000000 65.907805 mean 1.245307 31.681008 2.145204 2.443522 41.642693 39.519211 6.542142 6.886443 7902.651615 std 60.300000 47.800000 61.000000 48.000000 13.000000 16.000000 5118.000000 min -2.000000 65.000000 25% 0.000000 101.000000 64.100000 52.000000 97.000000 70.000000 19.000000 25.000000 7788.000000 50% 1.000000 122.000000 54.100000 120.000000 95.000000 24.000000 30.000000 10345.000000 65.500000 **75**% 2.000000 137.000000 66.900000 55.500000 141.000000 116.000000 30.000000 34.000000 16500.000000 49.000000 54.000000 45400.000000 3.000000 256.000000 72.300000 59.800000 326.000000 288.000000 max In [9]: sns.pairplot(df) Out[9]: <seaborn.axisgrid.PairGrid at 0x29d950ca0d0> - 10 m In [10]: df_num = df.select_dtypes(['int64','float64']) df_cat = df.select_dtypes('object') In [11]: df_cat Out[11]: make fuel-type body-style drive-wheels engine-location engine-type 0 alfa-romero dohc gas convertible rwd front 1 alfa-romero gas convertible rwd front dohc 2 alfa-romero gas hatchback rwd front ohcv 3 audi sedan fwd front ohc gas audi sedan front gas 4wd ohc ••• 200 volvo gas sedan rwd front ohc 201 volvo sedan rwd front ohc gas 202 volvo sedan rwd front ohcv gas 203 volvo sedan front ohc diesel rwd 204 front ohc volvo gas sedan rwd 205 rows × 6 columns In [12]: df_num Out[12]: symboling normalized-losses width height engine-size horsepower city-mpg highway-mpg price 3 27 13495 0 122.0 64.1 48.8 130 111.0 21 3 122.0 111.0 27 16500 1 64.1 48.8 130 21 122.0 65.5 152 154.0 19 26 16500 52.4 3 2 102.0 30 13950 164.0 66.2 54.3 109 24 2 164.0 66.4 54.3 136 115.0 18 22 17450 ... 200 -1 95.0 68.9 55.5 141 114.0 23 28 16845 160.0 25 19045 201 -1 95.0 68.8 55.5 141 19 202 68.9 173 134.0 18 23 21485 -1 95.0 55.5 203 106.0 27 22470 -1 95.0 68.9 55.5 145 26 204 95.0 68.9 55.5 141 114.0 19 25 22625 205 rows × 9 columns In [13]: from sklearn.preprocessing import LabelEncoder for col in df_cat: le = LabelEncoder() df_cat[col] = le.fit_transform(df_cat[col]) In [14]: df_cat Out[14]: make fuel-type body-style drive-wheels engine-location engine-type 0 0 2 0 1 0 1 0 2 0 0 2 5 2 0 0 1 3 1 1 3 1 0 3 1 1 3 0 0 3 200 3 201 21 2 0 3 202 21 203 21 0 3 2 0 3 21 2 0 3 204 1 3 205 rows × 6 columns In [15]: df_new = pd.concat([df_cat, df_num], axis=1) In [16]: df_new.head() Out[16]: width height enginefuel- body- drive- engine- enginenormalizedcity- highwaysymboling horsepower make style wheels location mpg size type type losses mpg 122.0 64.1 48.8 130 111.0 21 27 1 0 1 0 2 0 0 3 122.0 64.1 48.8 130 111.0 21 27 154.0 2 122.0 0 0 65.5 52.4 152 19 26 3 1 0 3 109 24 30 3 1 1 2 164.0 66.2 54.3 102.0 3 1 1 0 0 3 164.0 66.4 54.3 136 115.0 18 22 In [17]: $x = df_{new.iloc}[:,:-1]$ $y = df_new.iloc[:,-1]$ In [18]: from sklearn.model_selection import train_test_split xtrain, xtest, ytrain, ytest =train_test_split(x,y, test_size=0.3, random_state=1) In [19]: from xgboost import XGBRegressor xgb = XGBRegressor() xgb.fit(xtrain, ytrain) ypred = xgb.predict(xtest) In [20]: from sklearn.metrics import mean_absolute_error as mae, mean_squared_error as mse, r2_score print(f"MAE-: {mae(ytest, ypred)}") print(f"MSE-: {mse(ytest, ypred)}") print(f"RMSE-: {np.sqrt(mse(ytest, ypred))}") print(f"R Squared-: {r2_score(ytest, ypred)}") MAE-: 2087.5291472404233 MSE-: 11211227.00085248 RMSE-: 3348.3170400743834 R Squared-: 0.8139518932966816 In [24]: from sklearn.model_selection import GridSearchCV xgb1 = XGBRegressor(random_state=1) params= { 'max_depth':range(3,10,2), 'min_child_weight':range(1,6,2), 'reg_alpha':[0, 0.001, 0.005, 0.01, 0.05], 'learning_rate': [0.01, 0.1], xgb_grid = GridSearchCV(xgb1, params, cv = 5, verbose=True) xgb_grid.fit(xtrain,ytrain) ypred=xgb_grid.predict(xtest) Fitting 5 folds for each of 120 candidates, totalling 600 fits [Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers. [Parallel(n_jobs=1)]: Done 600 out of 600 | elapsed: 1.1min finished In [25]: print(f"MAE-: {mae(ytest, ypred)}") print(f"MSE-: {mse(ytest, ypred)}") print(f"RMSE-: {np.sqrt(mse(ytest, ypred))}") print(f"R Squared-: {r2_score(ytest, ypred)}") MAE-: 1942.9898878528227 MSE-: 8040316.062336145 RMSE-: 2835.545108499624 R Squared-: 0.8665725365671237

In [1]: import numpy as np

df.head()

import pandas as pd
import seaborn as sns

import warnings

import matplotlib.pyplot as plt

warnings.filterwarnings("ignore")

In [2]: df = pd.read_csv("C:\\Users\\HP\\Downloads\\cars.csv")