Car Price Prediction

Main objective:

Goal is to predict the price of the car using regression models given multible featureslisted below

Description of the data set:

Here we use data that studies informations about cars including the following parameters:

1. (Make)>> the manifacture company of the car
2. (Model)>> the model of the car
3. (Year)>> year of manifacture
4. (Engine Fuel Type)
5. (Engine HP) >> Horse Power
6. (Engine Cylinders)>> number of cylinders
7. (Transmission Type)>> Automatic/Manual
8. (Driven_Wheels)>>Front/all
   A. (Number of Doors)
   B. (Market Category)>>crossover/Luxury
   C. (Vehicle Size)
   D. (Vehicle Style)
   E. (highway MPG)
   F. (city mpg)
   G. (Popularity)
   H. (MSRP)>> Manufacturer's Suggested [Retail Price]>> Our Target

Plan for data exploration:

1. cleaning data
   - removing unimportant data
   - dealing with missing (NaN) values if found.
2. feature engineering
   - visualizing the data and see the data distribution
   - deal with skewed distribution if found
3. Variable Selection
   - encoding for categorical variables
   - feature scalling for continuous variables
4. Spliting the Data & implementing Cross Validation
   - Train-Test split
   -
5. linear regression model
   - Linear regression
   - regulation using Ridge and Lasso

In [ ]:

```
# importing
```

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
from sklearn.preprocessing import StandardScaler, PolynomialFeatures
from sklearn.model_selection import KFold, cross_val_predict, GridSearchCV, train_te
from sklearn.metrics import r2_score, mean_squared_error, mean_absolute_error
from sklearn.pipeline import Pipeline

%matplotlib inline
```

1. cleaning data

In [ ]:

```
df = pd.read_csv("data/data.csv")
df.head(3).T
```

Out[ ]:

	0	1	2
Make	BMW	BMW	BMW
Model	1 Series M	1 Series	1 Series
Year	2011	2011	2011
Engine Fuel Type	premium unleaded (required)	premium unleaded (required)	premium unleaded (required)
Engine HP	335.0	300.0	300.0
Engine Cylinders	6.0	6.0	6.0
Transmission Type	MANUAL	MANUAL	MANUAL
Driven_Wheels	rear wheel drive	rear wheel drive	rear wheel drive
Number of Doors	2.0	2.0	2.0
Market Category	Factory Tuner,Luxury,High-Performance	Luxury,Performance	Luxury,High-Performance
Vehicle Size	Compact	Compact	Compact
Vehicle Style	Coupe	Convertible	Coupe
highway MPG	26	28	28
city mpg	19	19	20
Popularity	3916	3916	3916
MSRP	46135	40650	36350

In [ ]:

```
df.shape
```

Out[ ]:

```
(11914, 16)
```

In [ ]:

```
df.describe()
```

Out[ ]:

	Year	Engine HP	Engine Cylinders	Number of Doors	highway MPG	city mpg	Populi
count	11914.000000	11845.00000	11884.000000	11908.000000	11914.000000	11914.000000	11914.00(
mean	2010.384338	249.38607	5.628829	3.436093	26.637485	19.733255	1554.91
std	7.579740	109.19187	1.780559	0.881315	8.863001	8.987798	1441.85!
min	1990.000000	55.00000	0.000000	2.000000	12.000000	7.000000	2.00(
25%	2007.000000	170.00000	4.000000	2.000000	22.000000	16.000000	549.00(
50%	2015.000000	227.00000	6.000000	4.000000	26.000000	18.000000	1385.00(
75%	2016.000000	300.00000	6.000000	4.000000	30.000000	22.000000	2009.00(
max	2017.000000	1001.00000	16.000000	4.000000	354.000000	137.000000	5657.00(

In [ ]:

```
df.dtypes.to_frame().rename(columns={0:'Data Type'})
```

Out[ ]:

	Data Type
Make	object
Model	object
Year	int64
Engine Fuel Type	object
Engine HP	float64
Engine Cylinders	float64
Transmission Type	object
Driven_Wheels	object
Number of Doors	float64
Market Category	object
Vehicle Size	object
Vehicle Style	object
highway MPG	int64
city mpg	int64
Popularity	int64
MSRP	int64

In [ ]:

```
df.columns = df.columns.str.lower().str.replace(' ', '_')
string_columns = df.dtypes[df.dtypes == 'object'].index
for col in string_columns:
 df[col] = df[col].str.lower().str.replace(' ', '_')
```

In [ ]:

```
df.head(3).T
```

Out[ ]:

	0	1

	0	1	
make	bmw	bmw	bn
model	1_series_m	1_series	1_seri
year	2011	2011	20
engine_fuel_type	premium_unleaded_(required)	premium_unleaded_(required)	premium_unleaded_(require
engine_hp	335.0	300.0	30(
engine_cylinders	6.0	6.0	(
transmission_type	manual	manual	manu
driven_wheels	rear_wheel_drive	rear_wheel_drive	rear_wheel_dri
number_of_doors	2.0	2.0	ż
market_category	factory_tuner,luxury,high-performance	luxury,performance	luxury,high-performan
vehicle_size	compact	compact	compa
vehicle_style	coupe	convertible	cou
highway_mpg	26	28	
city_mpg	19	19	
popularity	3916	3916	39
msrp	46135	40650	363

In [ ]:

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

Out[ ]:

```
make                   0
model                  0
year                   0
engine_fuel_type       3
engine_hp             69
engine_cylinders      30
transmission_type      0
driven_wheels          0
number_of_doors        6
market_category     3742
vehicle_size           0
vehicle_style          0
highway_mpg            0
city_mpg               0
popularity             0
msrp                   0
dtype: int64
```

In [ ]:

```
df = df.fillna(0)
```

In [ ]:

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

Out[ ]:

```
make                0
model               0
year                0
engine_fuel_type    0
```

```
engine_hp            0
engine_cylinders     0
transmission_type    0
driven_wheels        0
number_of_doors      0
market_category      0
vehicle_size         0
vehicle_style        0
highway_mpg          0
city_mpg             0
popularity           0
msrp                 0
dtype: int64
```

In [ ]:

```
(df['model'].value_counts() == 1).sum()
```

Out[ ]:

```
40
```

Log transforming skewed variables

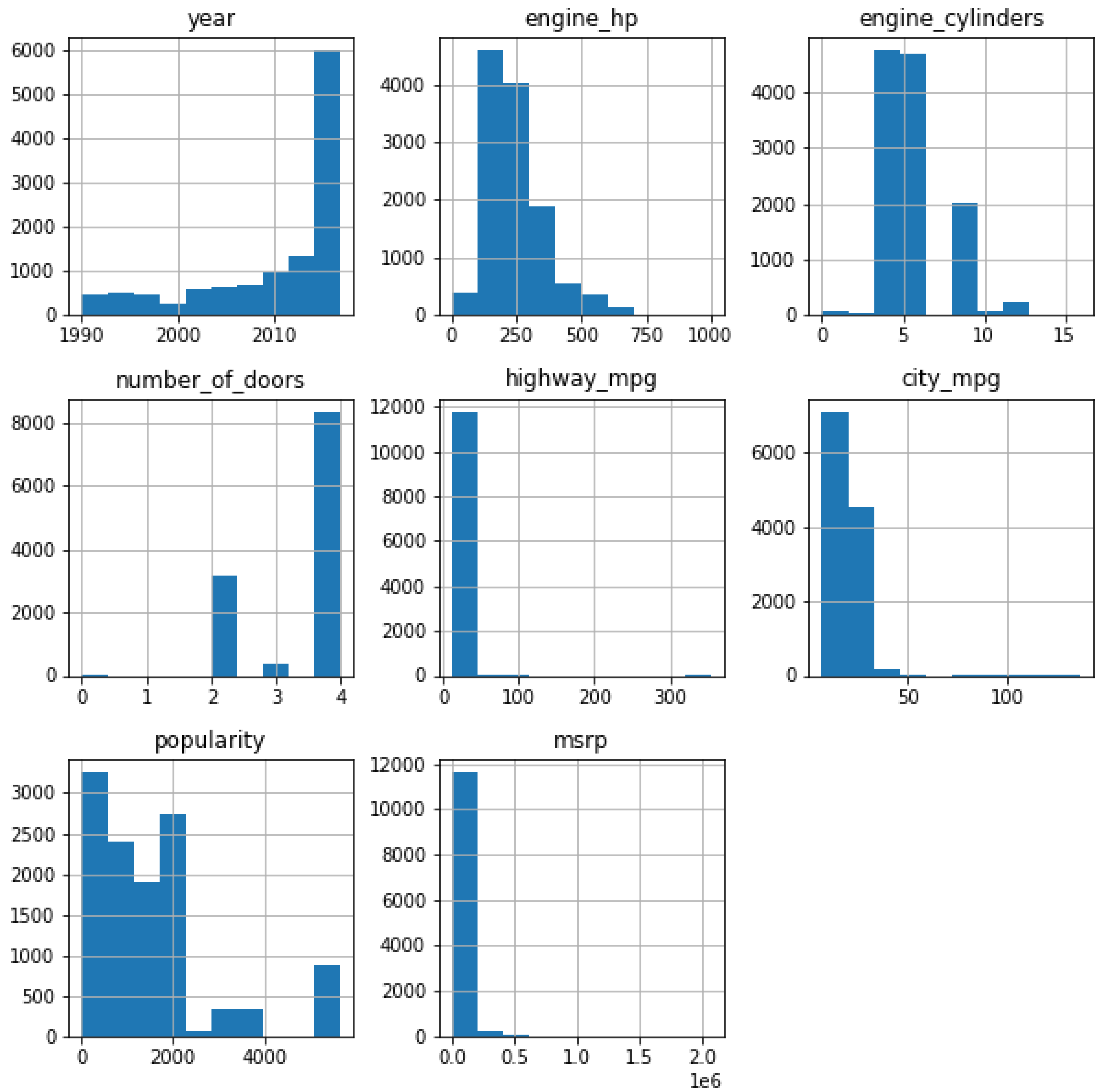
In [ ]:

```
# Create a list of float colums to check for skewing
mask = df.dtypes != object
num_cols = df.columns[mask]

skew_limit = 0.75 # define a limit above which we will log transform
skew_vals = df[num_cols].skew()
```

In [ ]:

```
viz = df[num_cols]
viz.hist(figsize=(10,10))
plt.show()
```



In [ ]:

```
# Showing the skewed columns
skew_cols = (skew_vals
             .sort_values(ascending=False)
             .to_frame()
             .rename(columns={0:'Skew'})
             .query('abs(Skew) > {}'.format(skew_limit)))

skew_cols
```

Out[ ]:

	Skew
msrp	11.771987
highway_mpg	7.573931
city_mpg	7.106681
popularity	1.653443
engine_hp	1.211076
engine_cylinders	0.877085
number_of_doors	-0.981560
year	-1.221981

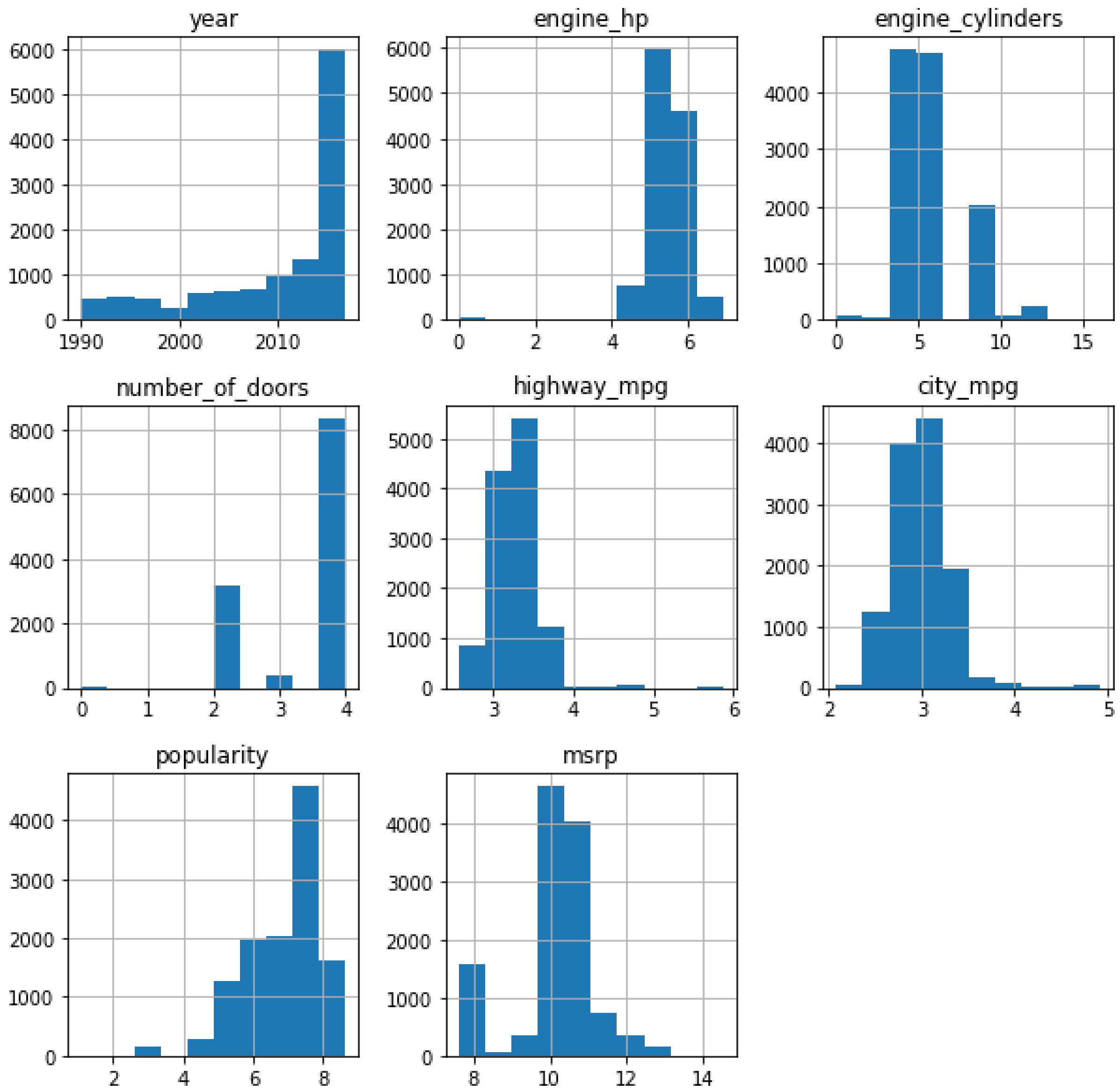
In [ ]:
```
skew_cols.Skew[skew_cols.Skew>1]
```

Out[ ]:
```
msrp           11.771987
highway_mpg     7.573931
city_mpg        7.106681
popularity      1.653443
engine_hp       1.211076
Name: Skew, dtype: float64
```

In [ ]:
```
# Perform the skew transformation:
for col in skew_cols.Skew[skew_cols.Skew>1].index.values:

    df[col] = df[col].apply(np.log1p)
```

In [ ]:
```
viz = df[num_cols]
viz.hist(figsize=(10,10))
plt.show()
```



In [ ]:
```
skew_vals = df[num_cols].skew()
skew_cols = (skew_vals
             .sort_values(ascending=False)
             .to_frame()
             .rename(columns={0:'Skew'})
```

```
            .query('abs(Skew) > {}'.format(skew_limit))

skew_cols
```

Out[ ]:

	Skew
city_mpg	1.530185
engine_cylinders	0.877085
highway_mpg	0.796524
popularity	-0.781916
msrp	-0.917868
number_of_doors	-0.981560
year	-1.221981
engine_hp	-4.479222

One Hot Encoding

In [ ]:

```
# Select the object (string) columns
mask = df.dtypes == object
categorical_cols = df.columns[mask]
```

In [ ]:

```
# Determine number of unique values in each categorical column
num_ohc_cols = df[categorical_cols].apply(lambda x: x.nunique()).sort_values(ascendi
num_ohc_cols
```

Out[ ]:

```
model                914
market_category       72
make                  48
vehicle_style         16
engine_fuel_type      11
transmission_type      5
driven_wheels          4
vehicle_size           3
dtype: int64
```

In [ ]:

```
#we will remove 'model' column
num_ohc_cols= num_ohc_cols.drop('model')
df = df.drop(columns='model')
```

In [ ]:

```
# No need to encode if there is only one value
small_num_ohc_cols = num_ohc_cols.loc[num_ohc_cols>1]

# Number of one-hot columns is one less than the number of categories
small_num_ohc_cols -= 1
small_num_ohc_cols.sum()
```

Out[ ]:

```
152
```

This is 152 columns, assuming the original ones are dropped.

In [ ]:

```
from sklearn.preprocessing import OneHotEncoder, LabelEncoder
# The encoders
```

```
le = LabelEncoder()
ohc = OneHotEncoder()

# Copy of the data
data_ohc = df.copy()

for col in num_ohc_cols.index:

    # Integer encode the string categories
    # dat = le.fit_transform(data_ohc[col]).astype(str)

    # Remove the original column from the dataframe
    data_ohc = data_ohc.drop(col, axis=1)

    # One hot encode the data--this returns a sparse array
    new_dat = ohc.fit_transform(dat.reshape(-1,1))

    # Create unique column names
    n_cols = new_dat.shape[1]
    col_names = ['_'.join([col, str(x)]) for x in range(n_cols)]

    # Create the new dataframe
    new_df = pd.DataFrame(new_dat.toarray(),
                          index=data_ohc.index,
                          columns=col_names)

    # Append the new data to the dataframe
    data_ohc = pd.concat([data_ohc, new_df], axis=1)
```

In [ ]:

```
# Column difference is as calculated below
data_ohc.shape[1] - df.shape[1]
```

Out[ ]: 189

In [ ]:

```
df_final = data_ohc.copy()
df_final.head()
```

Out[ ]:

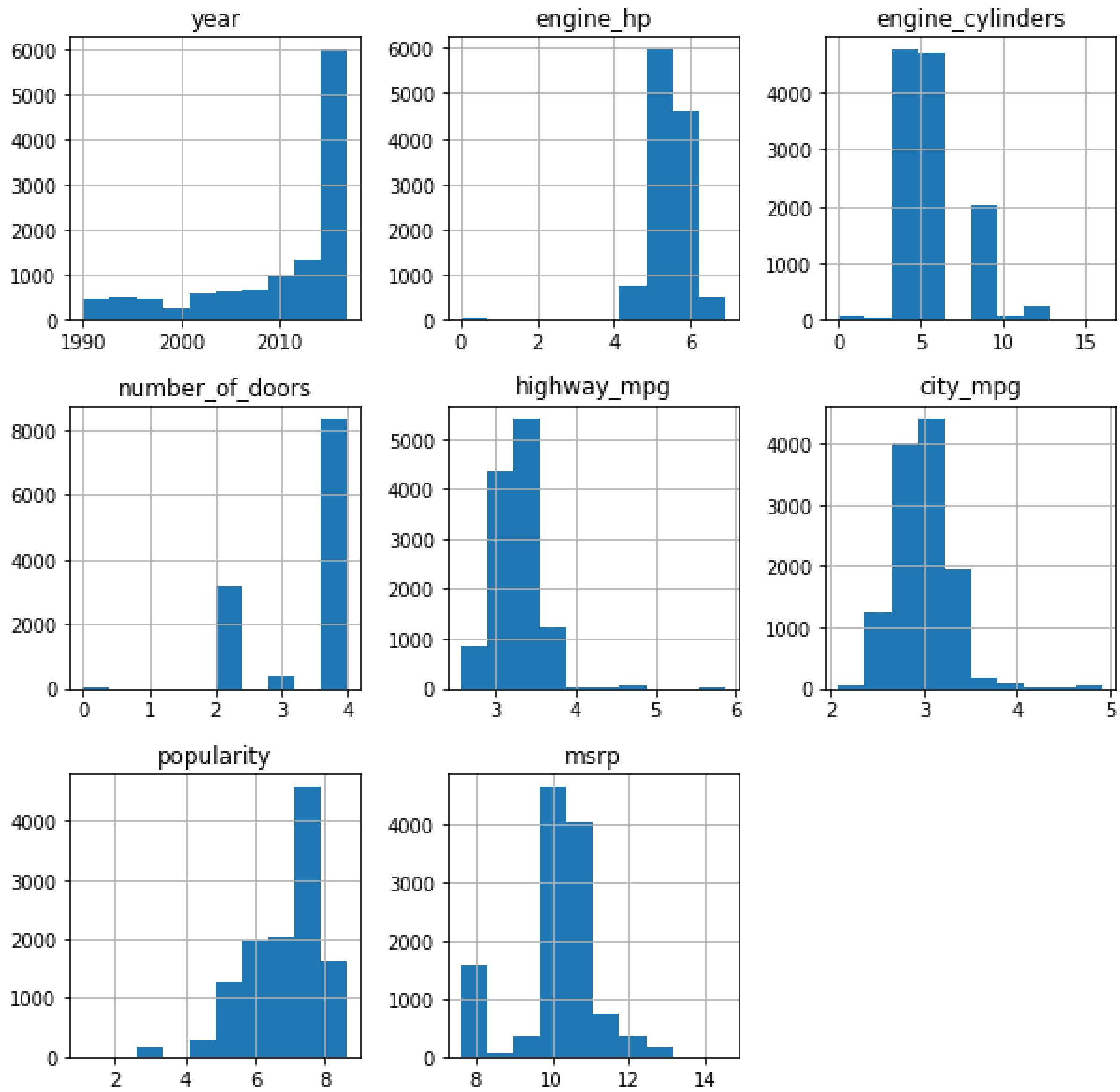
	year	engine_hp	engine_cylinders	number_of_doors	highway_mpg	city_mpg	popularity	m
0	2011	5.817111	6.0	2.0	3.295837	2.995732	8.273081	10.739
1	2011	5.707110	6.0	2.0	3.367296	2.995732	8.273081	10.612
2	2011	5.707110	6.0	2.0	3.367296	3.044522	8.273081	10.500
3	2011	5.442418	6.0	2.0	3.367296	2.944439	8.273081	10.290
4	2011	5.442418	6.0	2.0	3.367296	2.944439	8.273081	10.448

5 rows × 204 columns

Data Vizualization

In [ ]:

```
viz = df_final[num_cols]
viz.hist(figsize=(10,10))
plt.show()
```

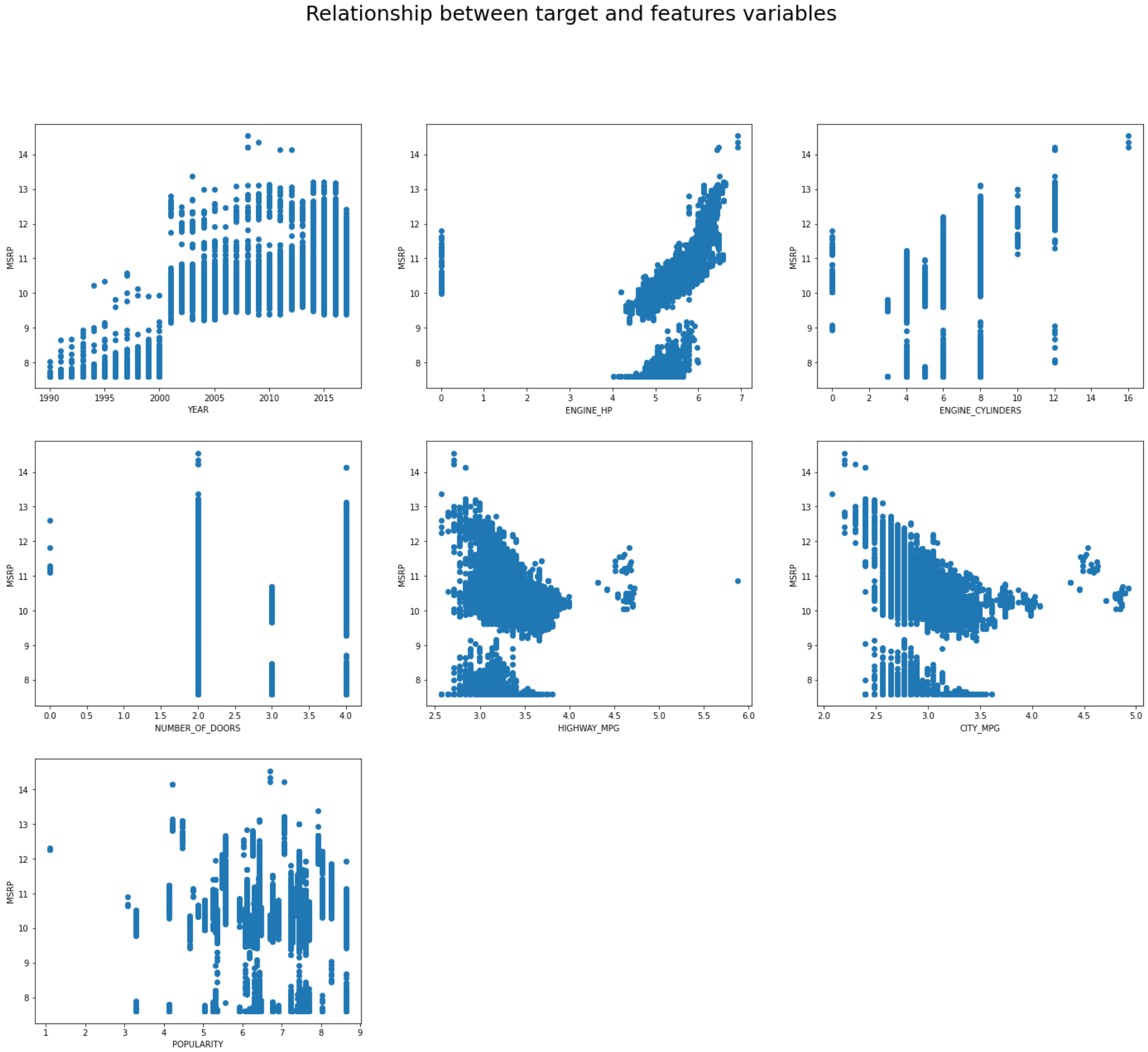


Now, let's plot each of these features against the msrp, to see how linear their relationship is:

In [ ]:

```
plt.figure(figsize=(24,20))
plt.suptitle('Relationship between target and features variables', size=25)

for var , i in zip(num_cols,np.arange(1,len(num_cols))):
    # if var == 'msrp':
    #     continue
    plt.subplot(3,3,i)
    plt.scatter(df_final[var], df_final.msrp)
    plt.xlabel(f"{var.upper()}")
    plt.ylabel("MSRP")
```



In [ ]:

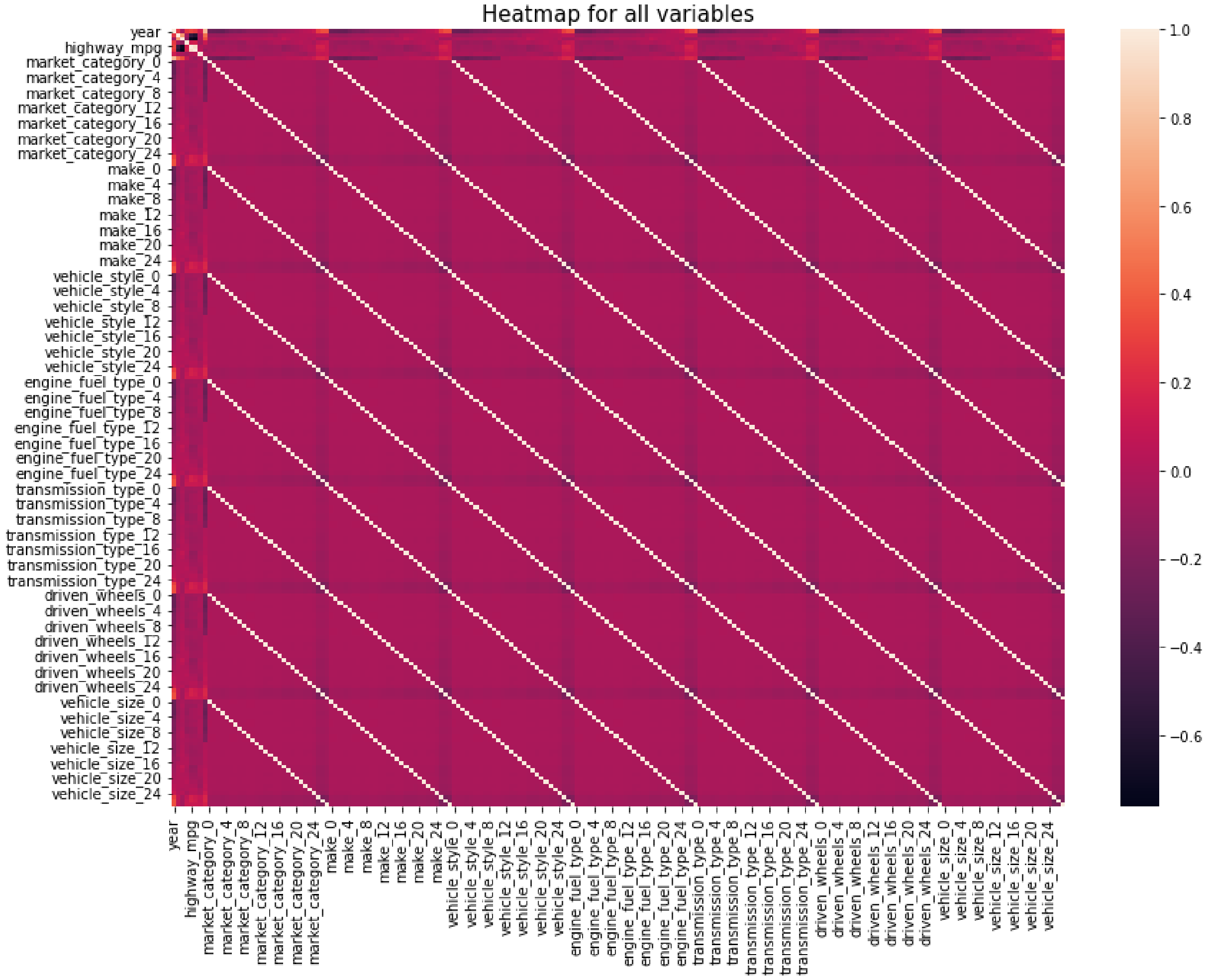
```
corr = df_final.corr()
```

In [ ]:

```
plt.figure(figsize=(14,10))
sns.heatmap(corr)
plt.title('Heatmap for all variables', size=15)
```

Out[ ]:

```
Text(0.5, 1.0, 'Heatmap for all variables')
```



Pre-processing

In [ ]:

```
y_col = 'msrp'
feature_cols = [x for x in df_final.columns if x != y_col]
X = df_final[feature_cols]
y = df_final[y_col]
```

In [ ]:

```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                     test_size=0.3, random_state=42)
```

In [ ]:

```
def rmse(ytrue, ypredicted):
    return np.sqrt(mean_squared_error(ytrue, ypredicted))
```

Linear Regression Model with k-fold

In [ ]:

```
# Cross validation
kf = KFold(shuffle=True, random_state=72018, n_splits=3)
for train_index, test_index in kf.split(X):
    print("Train index:", train_index[:10], len(train_index))
    print("Test index:",test_index[:10], len(test_index))
    print('')
```

```
Train index: [ 0  2  4  5  8  9 10 11 12 13] 7942
Test index: [ 1  3  6  7 16 18 22 24 27 29] 3972
```

```
Train index: [ 0  1  2  3  4  6  7  8 10 12] 7943
Test index: [ 5  9 11 13 14 15 17 21 25 26] 3971

Train index: [ 1  3  5  6  7  9 11 13 14 15] 7943
Test index: [ 0  2  4  8 10 12 19 20 23 28] 3971
```

In [ ]:

```
scores = []
lr = LinearRegression()

for train_index, test_index in kf.split(X):
    X_train, X_test, y_train, y_test = (X.iloc[train_index, :],
                                        X.iloc[test_index, :],
                                        y[train_index],
                                        y[test_index])

    lr.fit(X_train, y_train)

    y_pred = lr.predict(X_test)

    score = r2_score(y_test.values, y_pred)

    scores.append(score)

scores
```

Out[ ]:

```
[0.8817123226487079, 0.8883290998836573, 0.8822073564797046]
```

Pipeline and cross_val_predict

In [ ]:

```
s = StandardScaler()
lr = LinearRegression()

estimator = Pipeline([("scaler", s),
                      ("regression", lr)])
```

cross_val_predict is a function that does K-fold cross validation for us, appropriately fitting and transforming at every step of the way.

In [ ]:

```
predictions = cross_val_predict(estimator, X, y, cv=kf)
r2_score(y, predictions)
```

Out[ ]:

```
0.8839687957509155
```

In [ ]:

```
np.mean(scores) # almost identical!
```

Out[ ]:

```
0.8838505715198491
```

Linear Regression with train_test_split

In [ ]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,
                                                    random_state=72018)

s = StandardScaler()
lr_s = LinearRegression()
X_train_s = s.fit_transform(X_train)
lr_s.fit(X_train_s, y_train)
```

```
X_test_s = s.transform(X_test)
y_pred_s = lr_s.predict(X_test_s)
linear_r2 = r2_score(y_pred_s, y_test)
linear_r2
```

Out[ ]: 0.8715094693047795

In [ ]:

```
linear_reg_rmse = rmse(y_test, y_pred_s)
print(linear_reg_rmse)

linear_mae = mean_absolute_error(y_test, y_pred_s)
print(linear_mae)

linear_mse = mean_squared_error(y_test, y_pred_s)
print(linear_mse)
```

```
0.37758727630251987
0.27565789951777925
0.1425721512255555
```

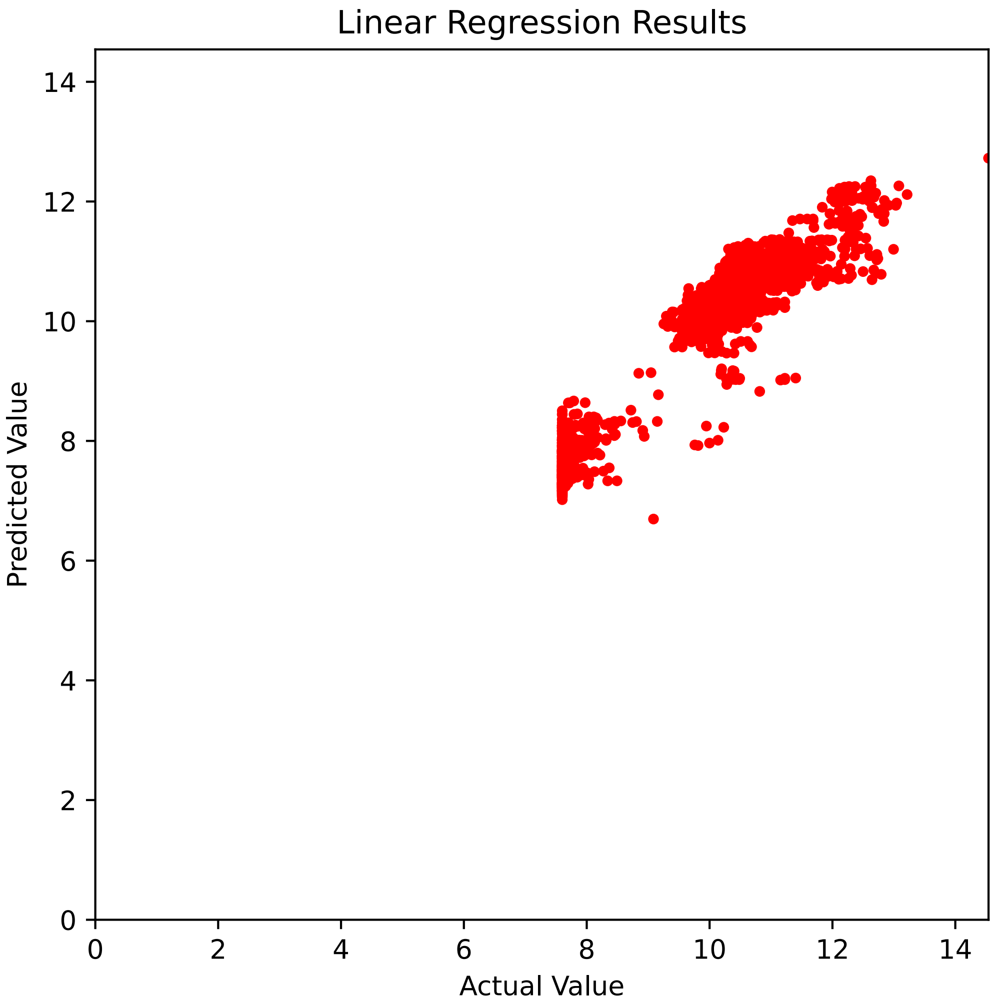
In [ ]:

```
f = plt.figure(figsize=(6,6))
ax = plt.axes()

ax.plot(y_test, y_pred_s, color='red',
         marker='o', ls='', ms=3.0)

lim = (0, y_test.max())

ax.set(xlabel='Actual Value',
       ylabel='Predicted Value',
       xlim=lim,
       ylim=lim,
       title='Linear Regression Results')
plt.show()
```



In [ ]:

```
# pair the feature names with the coefficients
pd.DataFrame(list(zip(X.columns, lr_s.coef_))).rename(columns={0: 'feature',1:'coeff
```

Out[ ]:

	feature	coefficient
0	year	-7.921316e+11
1	engine_hp	6.573486e-02
2	engine_cylinders	3.902702e-01
3	number_of_doors	-8.726883e-02
4	highway_mpg	2.245712e-02
...	...	...
198	vehicle_size_23	-6.061041e+11
199	vehicle_size_24	8.457536e+11
200	vehicle_size_25	-8.397046e+11
201	vehicle_size_26	-8.373025e+11
202	vehicle_size_27	-7.657143e+11

203 rows × 2 columns

Hyperparameter tuning

In [ ]:

```
# Lassso Regression
alphas = np.geomspace(0.001, 1.0, 20)
scores = []
coefs = []
for alpha in alphas:
    las = Lasso(alpha=alpha, max_iter=100000)

    estimator = Pipeline([
        ("scaler", s),
        ("lasso_regression", las)])

    predictions = cross_val_predict(estimator, X, y, cv = kf)

    score = r2_score(y, predictions)

    scores.append(score)
```

In [ ]:

```
pd.DataFrame(list(zip(alphas,scores))).rename(columns={0: 'alpha',1:'score'})
```

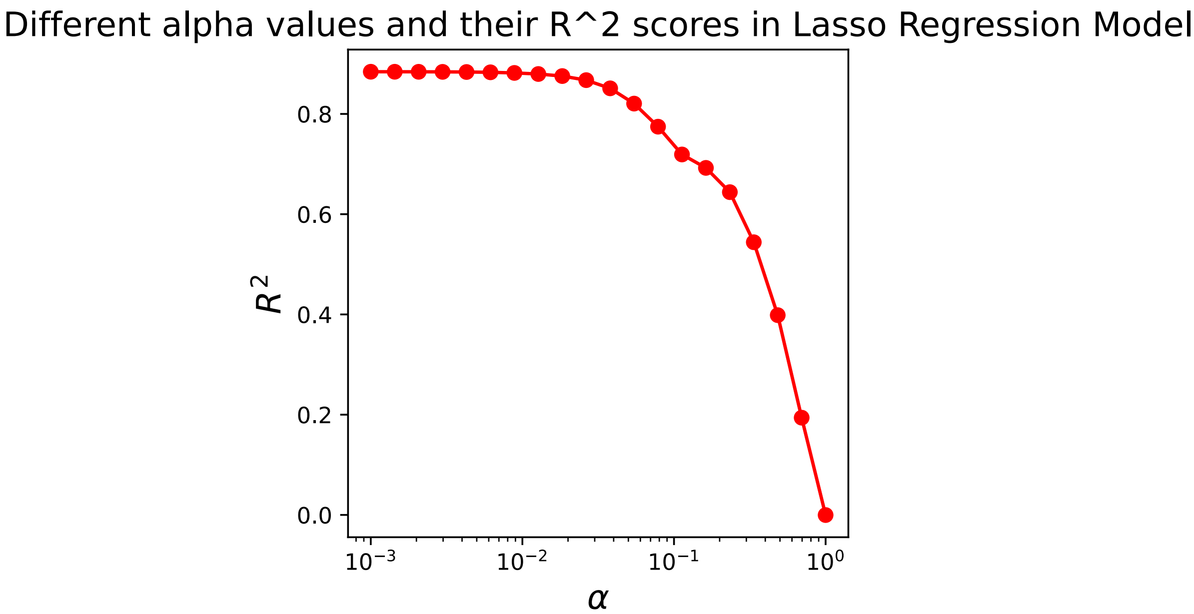
Out[ ]:

	alpha	score
0	0.001000	0.884177
1	0.001438	0.884142
2	0.002069	0.884070
3	0.002976	0.883935
4	0.004281	0.883654
5	0.006158	0.883061
6	0.008859	0.881824
7	0.012743	0.879667
8	0.018330	0.875554
9	0.026367	0.867410
10	0.037927	0.851074
11	0.054556	0.820614
12	0.078476	0.774570
13	0.112884	0.719125
14	0.162378	0.692354
15	0.233572	0.643950
16	0.335982	0.544029
17	0.483293	0.398536
18	0.695193	0.193979
19	1.000000	-0.000270

In [ ]:

```
plt.figure(figsize=(4,4))
plt.semilogx(alphas, scores, '-o', color='red')
plt.xlabel('$\\alpha$', size=15)
plt.ylabel('$R^2$', size=15)
```

```
plt.title('Different alpha values and their R^2 scores in Lasso Regression Model', s
plt.show()
```



Add Polynomial Features to Pipeline and use Grid Search CV

In [ ]:

```
estimator = Pipeline([("scaler", StandardScaler()),
        ("polynomial_features", PolynomialFeatures()),
        ("lasso_regression", Lasso())])

params = {
    'polynomial_features__degree': [1, 2, 3],
    'lasso_regression__alpha': np.geomspace(0.06, 6.0, 20)
}

grid = GridSearchCV(estimator, params, cv=kf)
```

In [ ]:

```
grid.fit(X, y)
```

```
C:\Users\ZolTA\AppData\Local\Programs\Python\Python39\lib\site-packages\sklearn\mode
l_selection\_validation.py:372: FitFailedWarning:
60 fits failed out of a total of 180.
The score on these train-test partitions for these parameters will be set to nan.
If these failures are not expected, you can try to debug them by setting error_score
='raise'.

Below are more details about the failures:
--------------------------------------------------------------------------------
20 fits failed with the following error:
Traceback (most recent call last):
  File "C:\Users\ZolTA\AppData\Local\Programs\Python\Python39\lib\site-packages\skle
arn\model_selection\_validation.py", line 681, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "C:\Users\ZolTA\AppData\Local\Programs\Python\Python39\lib\site-packages\skle
arn\pipeline.py", line 390, in fit
    Xt = self._fit(X, y, **fit_params_steps)
  File "C:\Users\ZolTA\AppData\Local\Programs\Python\Python39\lib\site-packages\skle
arn\pipeline.py", line 348, in _fit
    X, fitted_transformer = fit_transform_one_cached(
  File "C:\Users\ZolTA\AppData\Local\Programs\Python\Python39\lib\site-packages\jobl
ib\memory.py", line 349, in __call__
    return self.func(*args, **kwargs)
```

```
  File "C:\Users\ZolTA\AppData\Local\Programs\Python\Python39\lib\site-packages\skle
arn\pipeline.py", line 893, in _fit_transform_one
    res = transformer.fit_transform(X, y, **fit_params)
  File "C:\Users\ZolTA\AppData\Local\Programs\Python\Python39\lib\site-packages\skle
arn\base.py", line 850, in fit_transform
    return self.fit(X, y, **fit_params).transform(X)
  File "C:\Users\ZolTA\AppData\Local\Programs\Python\Python39\lib\site-packages\skle
arn\preprocessing\_polynomial.py", line 421, in transform
    XP = np.empty(
numpy.core._exceptions._ArrayMemoryError: Unable to allocate 85.0 GiB for an array w
ith shape (7942, 1435820) and data type float64

--------------------------------------------------------------------------------
40 fits failed with the following error:
Traceback (most recent call last):
  File "C:\Users\ZolTA\AppData\Local\Programs\Python\Python39\lib\site-packages\skle
arn\model_selection\_validation.py", line 681, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "C:\Users\ZolTA\AppData\Local\Programs\Python\Python39\lib\site-packages\skle
arn\pipeline.py", line 390, in fit
    Xt = self._fit(X, y, **fit_params_steps)
  File "C:\Users\ZolTA\AppData\Local\Programs\Python\Python39\lib\site-packages\skle
arn\pipeline.py", line 348, in _fit
    X, fitted_transformer = fit_transform_one_cached(
  File "C:\Users\ZolTA\AppData\Local\Programs\Python\Python39\lib\site-packages\jobl
ib\memory.py", line 349, in __call__
    return self.func(*args, **kwargs)
  File "C:\Users\ZolTA\AppData\Local\Programs\Python\Python39\lib\site-packages\skle
arn\pipeline.py", line 893, in _fit_transform_one
    res = transformer.fit_transform(X, y, **fit_params)
  File "C:\Users\ZolTA\AppData\Local\Programs\Python\Python39\lib\site-packages\skle
arn\base.py", line 850, in fit_transform
    return self.fit(X, y, **fit_params).transform(X)
  File "C:\Users\ZolTA\AppData\Local\Programs\Python\Python39\lib\site-packages\skle
arn\preprocessing\_polynomial.py", line 421, in transform
    XP = np.empty(
numpy.core._exceptions._ArrayMemoryError: Unable to allocate 85.0 GiB for an array w
ith shape (7943, 1435820) and data type float64

  warnings.warn(some_fits_failed_message, FitFailedWarning)
C:\Users\ZolTA\AppData\Local\Programs\Python\Python39\lib\site-packages\sklearn\mode
l_selection\_search.py:969: UserWarning: One or more of the test scores are non-fini
te: [ 8.10337408e-01  9.28894648e-01             nan  7.78480861e-01
  9.24264552e-01             nan  7.42236701e-01  9.16787374e-01
             nan  7.11300776e-01  9.04723699e-01             nan
  6.94585061e-01  8.85105693e-01             nan  6.67791201e-01
  8.53355565e-01             nan  6.24266711e-01  8.13969410e-01
             nan  5.53749143e-01  7.79168551e-01             nan
  4.47274669e-01  7.57645920e-01             nan  3.58436258e-01
  7.22688051e-01             nan  2.14168296e-01  6.77931737e-01
             nan -4.76904814e-04  6.39046034e-01             nan
 -4.76904814e-04  5.75916200e-01             nan -4.76904814e-04
  4.73422565e-01             nan -4.76904814e-04  3.07015052e-01
             nan -4.76904814e-04  5.45804557e-02             nan
 -4.76904814e-04 -4.76904814e-04             nan -4.76904814e-04
 -4.76904814e-04             nan -4.76904814e-04 -4.76904814e-04
             nan -4.76904814e-04 -4.76904814e-04             nan]
  warnings.warn(
```

Out[ ]:

```
GridSearchCV(cv=KFold(n_splits=3, random_state=72018, shuffle=True),
             estimator=Pipeline(steps=[('scaler', StandardScaler()),
                                       ('polynomial_features',
                                        PolynomialFeatures()),
                                       ('lasso_regression', Lasso())]),
             param_grid={'lasso_regression__alpha': array([0.06      , 0.0764565 ,
0.0974266 , 0.12414828, 0.15819905,
```

```
       0.2015891 , 0.25687994, 0.32733569, 0.41711568, 0.53152007,
       0.67730274, 0.86306993, 1.09978843, 1.40143288, 1.78581086,
       2.27561411, 2.89975814, 3.69508927, 4.70855982, 6.        ]),
                           'polynomial_features__degree': [1, 2, 3]})
```

In [ ]:

```
grid.best_score_, grid.best_params_
```

Out[ ]:

```
(0.9288946480400521,
 {'lasso_regression__alpha': 0.06, 'polynomial_features__degree': 2})
```

In [ ]:

```
y_predict = grid.predict(X)
lasso_r2 = r2_score(y, y_predict)
print(f'lasso_r2 = {lasso_r2}')
lasso_rmse = rmse(y, y_predict)
print(f'lasso_rmse = {lasso_rmse}')
lasso_mae = mean_absolute_error(y, y_predict)
print(f'lasso_mae = {lasso_mae}')
lasso_mse = mean_squared_error(y, y_predict)
print(f'lasso_mse = {lasso_mse}')
```

```
lasso_r2 = 0.9292161456086717
lasso_rmse = 0.2941625820362163
lasso_mae = 0.21386585879610043
lasso_mse = 0.0865316246702137
```

In [ ]:

```
# Ridge Regression
pf = PolynomialFeatures(degree=2)
alphas = np.geomspace(0.06, 6.0, 20)
scores=[]
for alpha in alphas:
    ridge = Ridge(alpha=alpha, max_iter=100000)

    estimator = Pipeline([
        ("scaler", s),
        ("polynomial_features", pf),
        ("ridge_regression", ridge)])

    predictions = cross_val_predict(estimator, X, y, cv = kf)
    score = r2_score(y, predictions)
    scores.append(score)
```

In [ ]:

```
pd.DataFrame(list(zip(alphas,scores))).rename(columns={0: 'alpha',1:'score'})
```

Out[ ]:

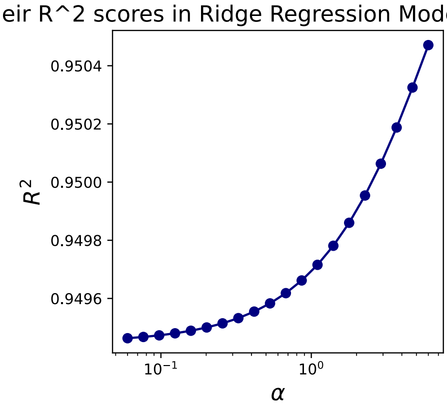
	alpha	score
0	0.060000	0.949463
1	0.076456	0.949468
2	0.097427	0.949473
3	0.124148	0.949480
4	0.158199	0.949489
5	0.201589	0.949500
6	0.256880	0.949514
7	0.327336	0.949532
8	0.417116	0.949555

	alpha	score
9	0.531520	0.949583
10	0.677303	0.949618
11	0.863070	0.949662
12	1.099788	0.949716
13	1.401433	0.949781
14	1.785811	0.949860
15	2.275614	0.949954
16	2.899758	0.950063
17	3.695089	0.950188
18	4.708560	0.950325
19	6.000000	0.950471

In [ ]:

```
plt.figure(figsize=(4,4))
plt.semilogx(alphas, scores, '-o', color='navy')
plt.xlabel('$\\alpha$', size=15)
plt.ylabel('$R^2$', size=15)
plt.title('Different alpha values and their R^2 scores in Ridge Regression Model wit
          size=15)
plt.show()
```

Different alpha values and their R^2 scores in Ridge Regression Model with 2rd degree Polynomial Features



In [ ]:

```
estimator = Pipeline([("scaler", StandardScaler()),
        ("polynomial_features", PolynomialFeatures()),
        ("ridge_regression", Ridge())])

params = {
    'polynomial_features__degree': [1, 2, 3],
    'ridge_regression__alpha': np.geomspace(0.06, 6.0, 20)
}

grid = GridSearchCV(estimator, params, cv=kf)
```

In [ ]:

```
grid.fit(X, y)
```

```
C:\Users\ZolTA\AppData\Local\Programs\Python\Python39\lib\site-packages\sklearn\mode
l_selection\_validation.py:372: FitFailedWarning:
60 fits failed out of a total of 180.
The score on these train-test partitions for these parameters will be set to nan.
```

```
If these failures are not expected, you can try to debug them by setting error_score
='raise'.

Below are more details about the failures:
--------------------------------------------------------------------------------
20 fits failed with the following error:
Traceback (most recent call last):
  File "C:\Users\ZolTA\AppData\Local\Programs\Python\Python39\lib\site-packages\skle
arn\model_selection\_validation.py", line 681, in _fit_and_score
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numpy.core._exceptions._ArrayMemoryError: Unable to allocate 85.0 GiB for an array w
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  File "C:\Users\ZolTA\AppData\Local\Programs\Python\Python39\lib\site-packages\jobl
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    return self.func(*args, **kwargs)
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  warnings.warn(some_fits_failed_message, FitFailedWarning)
C:\Users\ZolTA\AppData\Local\Programs\Python\Python39\lib\site-packages\sklearn\mode
l_selection\_search.py:969: UserWarning: One or more of the test scores are non-fini
te: [0.88409202 0.88409203 0.88409203 0.88409204 0.88409205 0.88409206
 0.88409208 0.8840921  0.88409213 0.88409216 0.8840922  0.88409226
 0.88409233 0.88409241 0.88409252 0.88409266 0.88409282 0.88409303
 0.88409329 0.8840936  0.94944473 0.9494489  0.94945419 0.9494609
```

```
 0.94946942 0.94948019 0.94949382 0.949511   0.94953261 0.94955968
 0.94959346 0.94963534 0.94968691 0.9497498  0.94982561 0.94991565
 0.95002058 0.95013998 0.95027179 0.95041174        nan        nan
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan]
  warnings.warn(
```

Out[ ]:

```
GridSearchCV(cv=KFold(n_splits=3, random_state=72018, shuffle=True),
             estimator=Pipeline(steps=[('scaler', StandardScaler()),
                                       ('polynomial_features',
                                        PolynomialFeatures()),
                                       ('ridge_regression', Ridge())]),
             param_grid={'polynomial_features__degree': [1, 2, 3],
                         'ridge_regression__alpha': array([0.06      , 0.0764565 ,
0.0974266 , 0.12414828, 0.15819905,
       0.2015891 , 0.25687994, 0.32733569, 0.41711568, 0.53152007,
       0.67730274, 0.86306993, 1.09978843, 1.40143288, 1.78581086,
       2.27561411, 2.89975814, 3.69508927, 4.70855982, 6.        ])})
```

In [ ]:

```
grid.best_score_, grid.best_params_
```

Out[ ]:

```
(0.9504117448554849,
 {'polynomial_features__degree': 2, 'ridge_regression__alpha': 6.0})
```

In [ ]:

```
y_predict = grid.predict(X)
ridge_r2 = r2_score(y, y_predict)
print(f'ridge_r2 = {ridge_r2}')
ridge_rmse = rmse(y, y_predict)
print(f'ridge_rmse = {ridge_rmse}')
ridge_mae = mean_absolute_error(y, y_predict)
print(f'ridge_mae = {ridge_mae}')
ridge_mse = mean_squared_error(y, y_predict)
print(f'ridge_mse = {ridge_mse}')
```

```
ridge_r2 = 0.9538489904485896
ridge_rmse = 0.23752587573431147
ridge_mae = 0.17218486441769787
ridge_mse = 0.05641854164335157
```

Model Evaluation Metrics for Regression

Mean Absolute Error (MAE) represents the average of the absolute difference between the actual and predicted values in the dataset. It measures the average of the residuals in the dataset.

Mean Squared Error (MSE) represents the average of the squared difference between the original and predicted values in the data set. It measures the variance of the residuals.

Root Mean Squared Error (RMSE) is the square root of Mean Squared error. It measures the standard deviation of residuals.

R-squared (R2) which is the proportion of variation in the outcome that is explained by the predictor variables. In multiple regression models, R2 corresponds to the squared correlation between the observed outcome values and the predicted values by the model. The Higher the R-squared, the better the model. The coefficient of determination or R-squared represents the proportion of the variance in the dependent variable which is explained by the linear regression model. It is a scale-free score i.e. irrespective of the values being small or large, the value of R square will be less than one.

Now, let's compare how different metrics looks like in different model: Linear Regression, Lasso and Ridge Regression

In [ ]:

```
rmse_vals = [linear_reg_rmse, ridge_rmse, lasso_rmse]
r2_vals = [linear_r2, ridge_r2, lasso_r2]
mae_vals = [linear_mae, ridge_mae, lasso_mae]
mse_vals = [linear_mse, ridge_mse, lasso_mse]

labels = ['Linear', 'Ridge', 'Lasso']

metrics = {'MAE': mae_vals, 'MSE': mse_vals, 'RMSE': rmse_vals, 'R^2': r2_vals}
metrics_df = pd.DataFrame(metrics, index=labels)

metrics_df
```

Out[ ]:

	MAE	MSE	RMSE	R^2
Linear	0.275658	0.142572	0.377587	0.871509
Ridge	0.172185	0.056419	0.237526	0.953849
Lasso	0.213866	0.086532	0.294163	0.929216

Conclusion

This analysis shows that feature engineering can have a large effect on the model performance, and if the data are sufficiently large, cross-validation should be preferred over train-test-split to construct model evaluation. In my case, even though the predictors have high multicollinearity, their coefficients were not shrunk by the Lasso model, and it is shown that regularization does not always make big improvement on a given model. In the end, the Lasso regression has the highest R^2 when predicting on the test set, and categories of car model appear to be the most important features to predict a car price. Also, Lasso did shrink some of the features that are not so important in terms of prediction.