Car Price Prediction - Assignment Solution ¶

The solution is divided into the following sections:

- Data understanding and exploration
- Data cleaning
- Data preparation
- Model building and evaluation

1. Data Understanding and Exploration

Let's first have a look at the dataset and understand the size, attribute names etc.

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import linear_model
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
from sklearn.model_selection import GridSearchCV

import os

# hide warnings
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
# reading the dataset
cars = pd.read_csv("CarPrice_Assignment.csv")
```

In [3]:

```
# summary of the dataset: 205 rows, 26 columns, no null values
print(cars.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 205 entries, 0 to 204
Data columns (total 26 columns):
car_ID              205 non-null int64
symboling           205 non-null int64
CarName             205 non-null object
fueltype            205 non-null object
aspiration          205 non-null object
doornumber          205 non-null object
carbody             205 non-null object
drivewheel          205 non-null object
enginelocation      205 non-null object
wheelbase           205 non-null float64
carlength           205 non-null float64
carwidth            205 non-null float64
carheight           205 non-null float64
curbweight          205 non-null int64
enginetype          205 non-null object
cylindernumber      205 non-null object
enginesize          205 non-null int64
fuelsystem          205 non-null object
boreratio           205 non-null float64
stroke              205 non-null float64
compressionratio    205 non-null float64
horsepower          205 non-null int64
peakrpm             205 non-null int64
citympg             205 non-null int64
highwaympg          205 non-null int64
price               205 non-null float64
dtypes: float64(8), int64(8), object(10)
memory usage: 41.7+ KB
None
```

In [4]:
```
# head
cars.head()
```

Out[4]:

	car_ID	symboling	CarName	fueltype	aspiration	doornumber	carbody	drivewhe
0	1	3	alfa-romero giulia	gas	std	two	convertible	rwd
1	2	3	alfa-romero stelvio	gas	std	two	convertible	rwd
2	3	1	alfa-romero Quadrifoglio	gas	std	two	hatchback	rwd
3	4	2	audi 100 ls	gas	std	four	sedan	fwd
4	5	2	audi 100ls	gas	std	four	sedan	4wd

5 rows × 26 columns

Understanding the Data Dictionary

The data dictionary contains the meaning of various attributes; some non-obvious ones are:

In [5]:
```
# symboling: -2 (least risky) to +3 most risky
# Most cars are 0,1,2
cars['symboling'].astype('category').value_counts()
```

Out[5]:
```
 0    67
 1    54
 2    32
 3    27
-1    22
-2     3
Name: symboling, dtype: int64
```

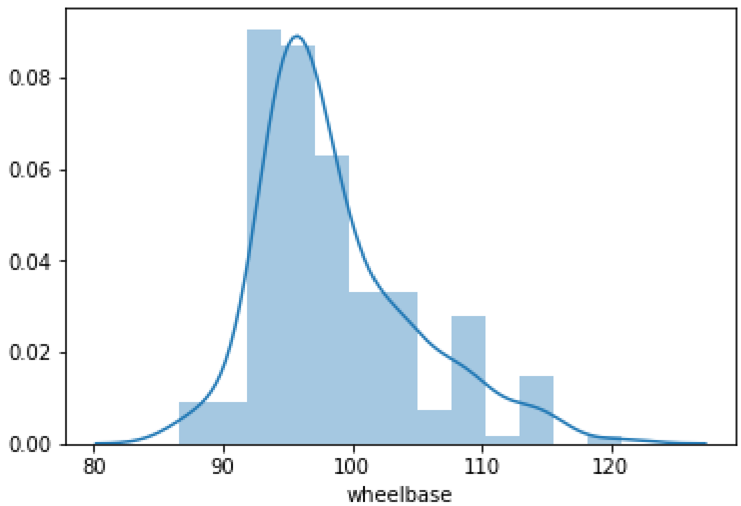
In [6]:
```
# aspiration: An (internal combustion) engine property showing
# whether the oxygen intake is through standard (atmospheric pressure)
# or through turbocharging (pressurised oxygen intake)

cars['aspiration'].astype('category').value_counts()
```

Out[6]:
```
std      168
turbo     37
Name: aspiration, dtype: int64
```

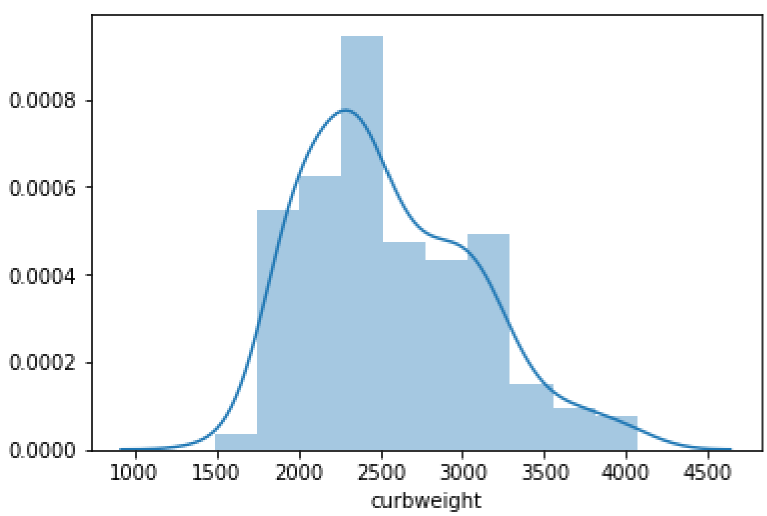
In [7]:
```
# drivewheel: frontwheel, rarewheel or four-wheel drive
cars['drivewheel'].astype('category').value_counts()
```

Out[7]:
```
fwd    120
rwd     76
4wd      9
Name: drivewheel, dtype: int64
```

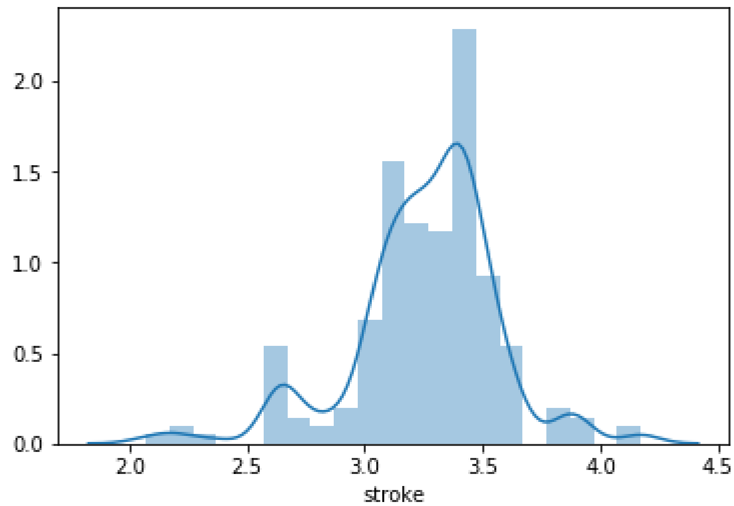
In [8]:
```
# wheelbase: distance between centre of front and rarewheels
sns.distplot(cars['wheelbase'])
plt.show()
```



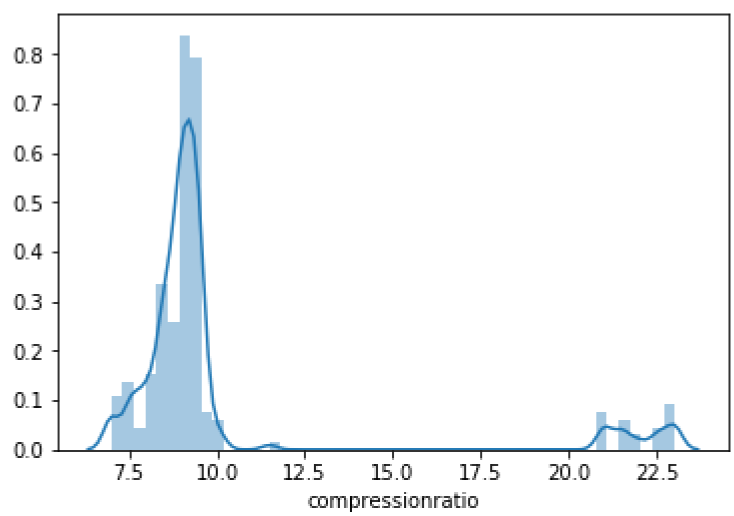
In [9]:
```
# curbweight: weight of car without occupants or baggage
sns.distplot(cars['curbweight'])
plt.show()
```



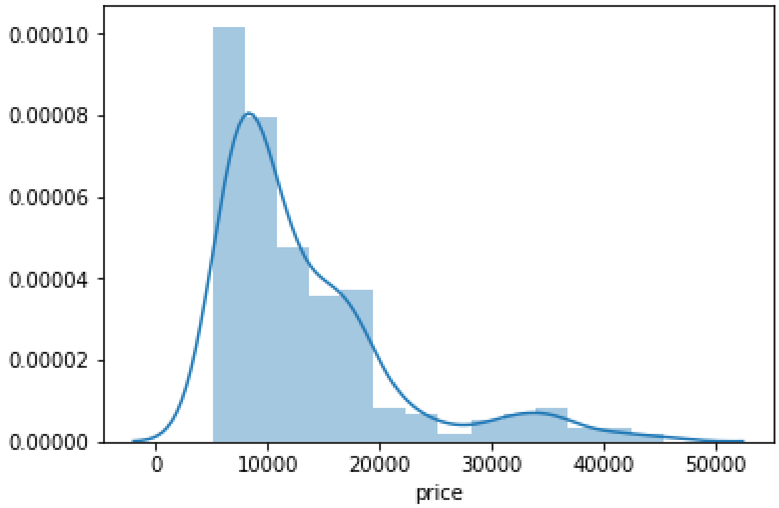
In [10]:
```
# stroke: volume of the engine (the distance traveled by the
# piston in each cycle)
sns.distplot(cars['stroke'])
plt.show()
```



In [11]:
```
# compression ration: ratio of volume of compression chamber
# at largest capacity to least capacity
sns.distplot(cars['compressionratio'])
plt.show()
```



In [12]:
```
# target variable: price of car
sns.distplot(cars['price'])
plt.show()
```



Data Exploration

To perform linear regression, the (numeric) target variable should be linearly related to *at least one another numeric variable*. Let's see whether that's true in this case.

We'll first subset the list of all (independent) numeric variables, and then make a **pairwise plot**.

In [20]:
```
# all numeric (float and int) variables in the dataset
cars_numeric = cars.select_dtypes(include=['float64', 'int64'])
cars_numeric.head()
```

Out[20]:

	car_ID	symboling	wheelbase	carlength	carwidth	carheight	curbweight	enginesize
0	1	3	88.6	168.8	64.1	48.8	2548	130
1	2	3	88.6	168.8	64.1	48.8	2548	130
2	3	1	94.5	171.2	65.5	52.4	2823	152
3	4	2	99.8	176.6	66.2	54.3	2337	109
4	5	2	99.4	176.6	66.4	54.3	2824	136

Here, although the variable `symboling` is numeric (int), we'd rather treat it as categorical since it has only 6 discrete values. Also, we do not want 'car_ID'.

In [21]:
```
# dropping symboling and car_ID
cars_numeric = cars_numeric.drop(['symboling'], axis=1)
cars_numeric.head()
```

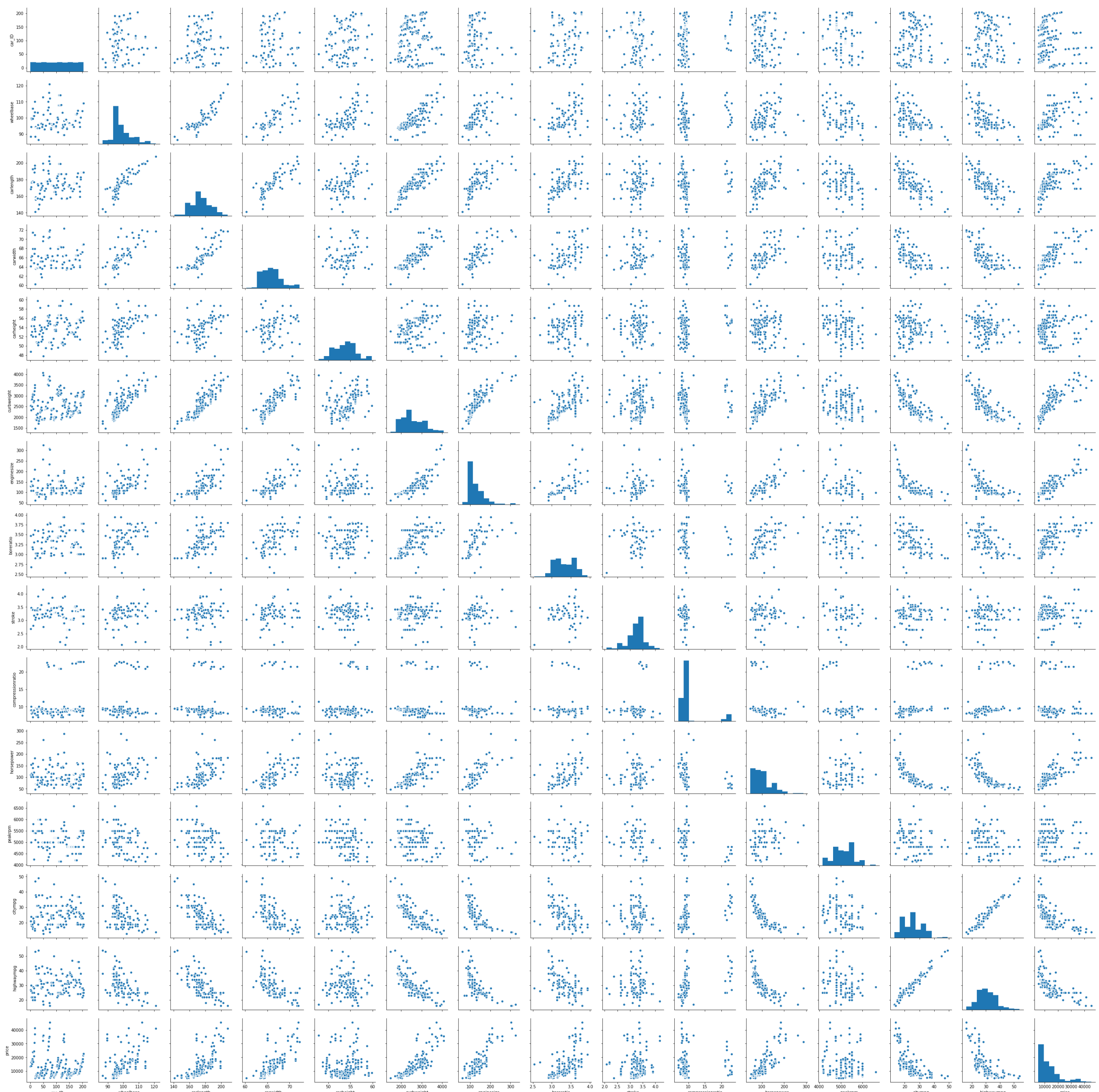
Out[21]:

	car_ID	wheelbase	carlength	carwidth	carheight	curbweight	enginesize	boreratio
0	1	88.6	168.8	64.1	48.8	2548	130	3.47
1	2	88.6	168.8	64.1	48.8	2548	130	3.47
2	3	94.5	171.2	65.5	52.4	2823	152	2.68
3	4	99.8	176.6	66.2	54.3	2337	109	3.19
4	5	99.4	176.6	66.4	54.3	2824	136	3.19

Let's now make a pairwise scatter plot and observe linear relationships.

In [22]:
```
# paiwise scatter plot

plt.figure(figsize=(20, 10))
sns.pairplot(cars_numeric)
plt.show()
```

```
<matplotlib.figure.Figure at 0x24e9998a278>
```



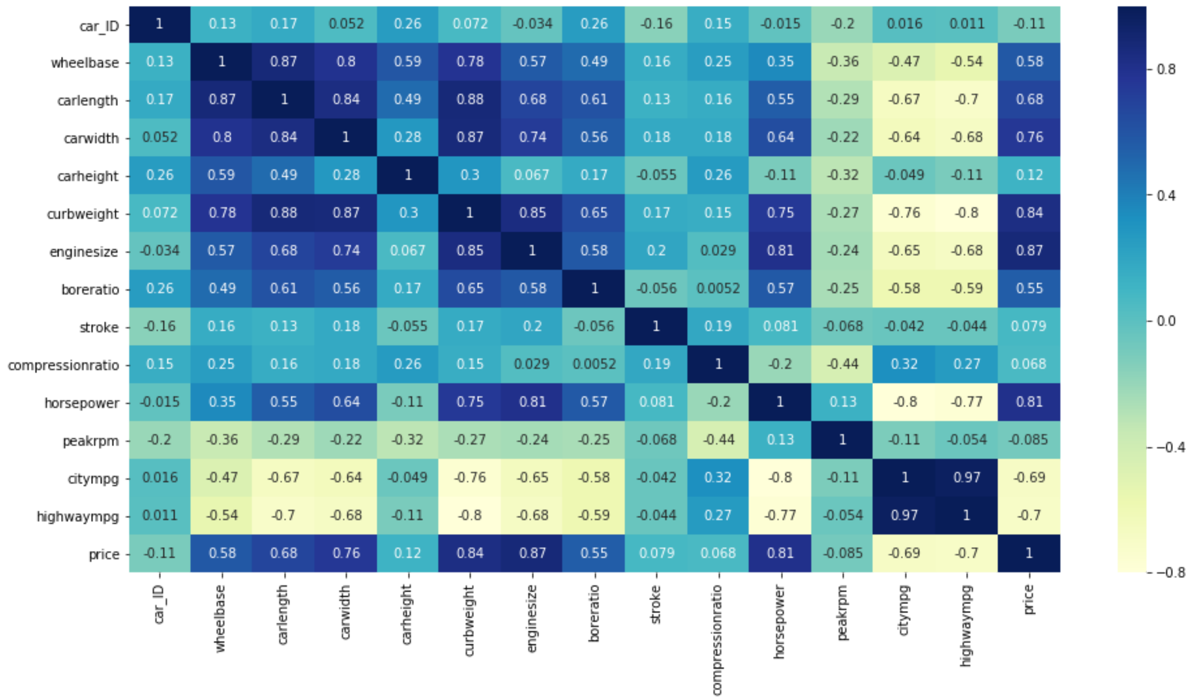
This is quite hard to read, and we can rather plot correlations between variables. Also, a heatmap is pretty useful to visualise multiple correlations in one plot.

In [23]:
```
# correlation matrix
cor = cars_numeric.corr()
cor
```

Out[23]:

	car_ID	wheelbase	carlength	carwidth	carheight	curbweight	en
car_ID	1.000000	0.129729	0.170636	0.052387	0.255960	0.071962	-0.
wheelbase	0.129729	1.000000	0.874587	0.795144	0.589435	0.776386	0.5
carlength	0.170636	0.874587	1.000000	0.841118	0.491029	0.877728	0.6
carwidth	0.052387	0.795144	0.841118	1.000000	0.279210	0.867032	0.7
carheight	0.255960	0.589435	0.491029	0.279210	1.000000	0.295572	0.0
curbweight	0.071962	0.776386	0.877728	0.867032	0.295572	1.000000	0.8
enginesize	-0.033930	0.569329	0.683360	0.735433	0.067149	0.850594	1.0
boreratio	0.260064	0.488750	0.606454	0.559150	0.171071	0.648480	0.5
stroke	-0.160824	0.160959	0.129533	0.182942	-0.055307	0.168790	0.2
compressionratio	0.150276	0.249786	0.158414	0.181129	0.261214	0.151362	0.0
horsepower	-0.015006	0.353294	0.552623	0.640732	-0.108802	0.750739	0.8
peakrpm	-0.203789	-0.360469	-0.287242	-0.220012	-0.320411	-0.266243	-0.
citympg	0.015940	-0.470414	-0.670909	-0.642704	-0.048640	-0.757414	-0.
highwaympg	0.011255	-0.544082	-0.704662	-0.677218	-0.107358	-0.797465	-0.
price	-0.109093	0.577816	0.682920	0.759325	0.119336	0.835305	0.8

In [24]:
```
# plotting correlations on a heatmap

# figure size
plt.figure(figsize=(16,8))

# heatmap
sns.heatmap(cor, cmap="YlGnBu", annot=True)
plt.show()
```



The heatmap shows some useful insights:

Correlation of price with independent variables:

- Price is highly (positively) correlated with wheelbase, carlength, carwidth, curbweight, enginesize, horsepower (notice how all of these variables represent the size/weight/engine power of the car)
- Price is negatively correlated to `citympg` and `highwaympg` (-0.70 approximately). This suggest that cars having high mileage may fall in the 'economy' cars category, and are priced lower (think Maruti Alto/Swift type of cars, which are designed to be affordable by the middle class, who value mileage more than horsepower/size of car etc.)

Correlation among independent variables:

- Many independent variables are highly correlated (look at the top-left part of matrix): wheelbase, carlength, curbweight, enginesize etc. are all measures of 'size/weight', and are positively correlated

Thus, while building the model, we'll have to pay attention to multicollinearity (especially linear models, such as linear and logistic regression, suffer more from multicollinearity).

2. Data Cleaning

Let's now conduct some data cleaning steps.

We've seen that there are no missing values in the dataset. We've also seen that variables are in the correct format, except `symboling`, which should rather be a categorical variable (so that dummy variable are created for the categories).

Note that it *can* be used in the model as a numeric variable also.

In [25]:
```
# variable formats
cars.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 205 entries, 0 to 204
Data columns (total 26 columns):
car_ID              205 non-null int64
symboling           205 non-null int64
CarName             205 non-null object
fueltype            205 non-null object
aspiration          205 non-null object
doornumber          205 non-null object
carbody             205 non-null object
drivewheel          205 non-null object
enginelocation      205 non-null object
wheelbase           205 non-null float64
carlength           205 non-null float64
carwidth            205 non-null float64
carheight           205 non-null float64
curbweight          205 non-null int64
enginetype          205 non-null object
cylindernumber      205 non-null object
enginesize          205 non-null int64
fuelsystem          205 non-null object
boreratio           205 non-null float64
stroke              205 non-null float64
compressionratio    205 non-null float64
horsepower          205 non-null int64
peakrpm             205 non-null int64
citympg             205 non-null int64
highwaympg          205 non-null int64
price               205 non-null float64
dtypes: float64(8), int64(8), object(10)
memory usage: 41.7+ KB
```

In [26]:
```
# converting symboling to categorical
cars['symboling'] = cars['symboling'].astype('object')
cars.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 205 entries, 0 to 204
Data columns (total 26 columns):
car_ID              205 non-null int64
symboling           205 non-null object
CarName             205 non-null object
fueltype            205 non-null object
aspiration          205 non-null object
doornumber          205 non-null object
carbody             205 non-null object
drivewheel          205 non-null object
enginelocation      205 non-null object
wheelbase           205 non-null float64
carlength           205 non-null float64
carwidth            205 non-null float64
carheight           205 non-null float64
curbweight          205 non-null int64
enginetype          205 non-null object
cylindernumber      205 non-null object
enginesize          205 non-null int64
fuelsystem          205 non-null object
boreratio           205 non-null float64
stroke              205 non-null float64
compressionratio    205 non-null float64
horsepower          205 non-null int64
peakrpm             205 non-null int64
citympg             205 non-null int64
highwaympg          205 non-null int64
price               205 non-null float64
dtypes: float64(8), int64(7), object(11)
memory usage: 41.7+ KB
```

Netx, we need to extract the company name from the column `CarName`.

In [27]:
```
# CarName: first few entries
cars['CarName'][:30]
```

Out[27]:
```
0            alfa-romero giulia
1           alfa-romero stelvio
2      alfa-romero Quadrifoglio
3                   audi 100 ls
4                    audi 100ls
5                      audi fox
6                    audi 100ls
7                     audi 5000
8                     audi 4000
9           audi 5000s (diesel)
10                     bmw 320i
11                     bmw 320i
12                       bmw x1
13                       bmw x3
14                       bmw z4
15                       bmw x4
16                       bmw x5
17                       bmw x3
18             chevrolet impala
19        chevrolet monte carlo
20          chevrolet vega 2300
21                dodge rampage
22          dodge challenger se
23                   dodge d200
24            dodge monaco (sw)
25           dodge colt hardtop
26              dodge colt (sw)
27         dodge coronet custom
28            dodge dart custom
29    dodge coronet custom (sw)
Name: CarName, dtype: object
```

Notice that the carname is what occurs before a space, e.g. alfa-romero, audi, chevrolet, dodge, bmx etc.

Thus, we need to simply extract the string before a space. There are multiple ways to do that.

In [28]:
```
# Extracting carname

# Method 1: str.split() by space
carnames = cars['CarName'].apply(lambda x: x.split(" ")[0])
carnames[:30]
```

Out[28]:
```
0     alfa-romero
1     alfa-romero
2     alfa-romero
3            audi
4            audi
5            audi
6            audi
7            audi
8            audi
9            audi
10            bmw
11            bmw
12            bmw
13            bmw
14            bmw
15            bmw
16            bmw
17            bmw
18      chevrolet
19      chevrolet
20      chevrolet
21          dodge
22          dodge
23          dodge
24          dodge
25          dodge
26          dodge
27          dodge
28          dodge
29          dodge
Name: CarName, dtype: object
```

In [29]:
```
# Method 2: Use regular expressions
import re

# regex: any alphanumeric sequence before a space, may contain a hyphen
p = re.compile(r'\w+-?\w+')
carnames = cars['CarName'].apply(lambda x: re.findall(p, x)[0])
print(carnames)
```

```
0      alfa-romero
1      alfa-romero
2      alfa-romero
3             audi
4             audi
5             audi
6             audi
7             audi
8             audi
9             audi
10             bmw
11             bmw
12             bmw
13             bmw
14             bmw
15             bmw
16             bmw
17             bmw
18       chevrolet
19       chevrolet
20       chevrolet
21           dodge
22           dodge
23           dodge
24           dodge
25           dodge
26           dodge
27           dodge
28           dodge
29           dodge
          ...
175         toyota
176         toyota
177         toyota
178         toyota
179         toyota
180         toyota
181        toyouta
182      vokswagen
183     volkswagen
184     volkswagen
185     volkswagen
186     volkswagen
187     volkswagen
188     volkswagen
189             vw
190             vw
191     volkswagen
192     volkswagen
193     volkswagen
194          volvo
195          volvo
196          volvo
197          volvo
198          volvo
199          volvo
200          volvo
```

```
201          volvo
202          volvo
203          volvo
204          volvo
Name: CarName, Length: 205, dtype: object
```

Let's create a new column to store the compnay name and check whether it looks okay.

In [30]:
```
# New column car_company
cars['car_company'] = cars['CarName'].apply(lambda x: re.findall(p, x)[0])
```

In [31]:
```
# look at all values
cars['car_company'].astype('category').value_counts()
```

Out[31]:
```
toyota         31
nissan         17
mazda          15
mitsubishi     13
honda          13
subaru         12
volvo          11
peugeot        11
volkswagen      9
dodge           9
buick           8
bmw             8
plymouth        7
audi            7
saab            6
porsche         4
isuzu           4
chevrolet       3
alfa-romero     3
jaguar          3
vw              2
maxda           2
renault         2
mercury         1
porcshce        1
toyouta         1
vokswagen       1
Nissan          1
Name: car_company, dtype: int64
```

Notice that **some car-company names are misspelled** - vw and vokswagen should be volkswagen, porcshce should be porsche, toyouta should be toyota, Nissan should be nissan, maxda should be mazda etc.

This is a data quality issue, let's solve it.

In [32]:
```
# replacing misspelled car_company names

# volkswagen
cars.loc[(cars['car_company'] == "vw") |
         (cars['car_company'] == "vokswagen")
         , 'car_company'] = 'volkswagen'

# porsche
cars.loc[cars['car_company'] == "porcshce", 'car_company'] = 'porsche'

# toyota
cars.loc[cars['car_company'] == "toyouta", 'car_company'] = 'toyota'

# nissan
cars.loc[cars['car_company'] == "Nissan", 'car_company'] = 'nissan'

# mazda
cars.loc[cars['car_company'] == "maxda", 'car_company'] = 'mazda'
```

In [33]:
```
cars['car_company'].astype('category').value_counts()
```

Out[33]:
```
toyota         32
nissan         18
mazda          17
honda          13
mitsubishi     13
subaru         12
volkswagen     12
volvo          11
peugeot        11
dodge           9
buick           8
bmw             8
plymouth        7
audi            7
saab            6
porsche         5
isuzu           4
alfa-romero     3
chevrolet       3
jaguar          3
renault         2
mercury         1
Name: car_company, dtype: int64
```

The `car_company` variable looks okay now. Let's now drop the car name variable.

In [34]:
```
# drop carname variable
cars = cars.drop('CarName', axis=1)
```

In [35]:
```
cars.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 205 entries, 0 to 204
Data columns (total 26 columns):
car_ID              205 non-null int64
symboling           205 non-null object
fueltype            205 non-null object
aspiration          205 non-null object
doornumber          205 non-null object
carbody             205 non-null object
drivewheel          205 non-null object
enginelocation      205 non-null object
wheelbase           205 non-null float64
carlength           205 non-null float64
carwidth            205 non-null float64
carheight           205 non-null float64
curbweight          205 non-null int64
enginetype          205 non-null object
cylindernumber      205 non-null object
enginesize          205 non-null int64
fuelsystem          205 non-null object
boreratio           205 non-null float64
stroke              205 non-null float64
compressionratio    205 non-null float64
horsepower          205 non-null int64
peakrpm             205 non-null int64
citympg             205 non-null int64
highwaympg          205 non-null int64
price               205 non-null float64
car_company         205 non-null object
dtypes: float64(8), int64(7), object(11)
memory usage: 41.7+ KB
```

In [36]:
```
# outliers
cars.describe()
```

Out[36]:

	car_ID	wheelbase	carlength	carwidth	carheight	curbweight	engine
count	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.00(
mean	103.000000	98.756585	174.049268	65.907805	53.724878	2555.565854	126.90
std	59.322565	6.021776	12.337289	2.145204	2.443522	520.680204	41.642
min	1.000000	86.600000	141.100000	60.300000	47.800000	1488.000000	61.000(
25%	52.000000	94.500000	166.300000	64.100000	52.000000	2145.000000	97.000(
50%	103.000000	97.000000	173.200000	65.500000	54.100000	2414.000000	120.00(
75%	154.000000	102.400000	183.100000	66.900000	55.500000	2935.000000	141.00(
max	205.000000	120.900000	208.100000	72.300000	59.800000	4066.000000	326.00(

In [37]:
```
cars.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 205 entries, 0 to 204
Data columns (total 26 columns):
car_ID              205 non-null int64
symboling           205 non-null object
fueltype            205 non-null object
aspiration          205 non-null object
doornumber          205 non-null object
carbody             205 non-null object
drivewheel          205 non-null object
enginelocation      205 non-null object
wheelbase           205 non-null float64
carlength           205 non-null float64
carwidth            205 non-null float64
carheight           205 non-null float64
curbweight          205 non-null int64
enginetype          205 non-null object
cylindernumber      205 non-null object
enginesize          205 non-null int64
fuelsystem          205 non-null object
boreratio           205 non-null float64
stroke              205 non-null float64
compressionratio    205 non-null float64
horsepower          205 non-null int64
peakrpm             205 non-null int64
citympg             205 non-null int64
highwaympg          205 non-null int64
price               205 non-null float64
car_company         205 non-null object
dtypes: float64(8), int64(7), object(11)
memory usage: 41.7+ KB
```

3. Data Preparation

Data Preparation

Let's now prepare the data and build the model.

In [45]:
```
# split into X and y
X = cars.loc[:, ['symboling', 'fueltype', 'aspiration', 'doornumber',
       'carbody', 'drivewheel', 'enginelocation', 'wheelbase', 'carlength',
       'carwidth', 'carheight', 'curbweight', 'enginetype', 'cylindernumber',
       'enginesize', 'fuelsystem', 'boreratio', 'stroke', 'compressionratio',
       'horsepower', 'peakrpm', 'citympg', 'highwaympg',
       'car_company']]

y = cars['price']
```

In [46]:
```
# creating dummy variables for categorical variables

# subset all categorical variables
cars_categorical = X.select_dtypes(include=['object'])
cars_categorical.head()
```

Out[46]:

	symboling	fueltype	aspiration	doornumber	carbody	drivewheel	enginelocation	e
0	3	gas	std	two	convertible	rwd	front	c
1	3	gas	std	two	convertible	rwd	front	c
2	1	gas	std	two	hatchback	rwd	front	c
3	2	gas	std	four	sedan	fwd	front	c
4	2	gas	std	four	sedan	4wd	front	c

In [47]:
```
# convert into dummies
cars_dummies = pd.get_dummies(cars_categorical, drop_first=True)
cars_dummies.head()
```

Out[47]:

	symboling_-1	symboling_0	symboling_1	symboling_2	symboling_3	fueltype_gas	a
0	0	0	0	0	1	1	0
1	0	0	0	0	1	1	0
2	0	0	1	0	0	1	0
3	0	0	0	1	0	1	0
4	0	0	0	1	0	1	0

5 rows × 55 columns

In [48]:
```
# drop categorical variables
X = X.drop(list(cars_categorical.columns), axis=1)
```

In [49]:
```
# concat dummy variables with X
X = pd.concat([X, cars_dummies], axis=1)
```

In [50]:
```
# scaling the features
from sklearn.preprocessing import scale

# storing column names in cols, since column names are (annoyingly) lost after
# scaling (the df is converted to a numpy array)
cols = X.columns
X = pd.DataFrame(scale(X))
X.columns = cols
X.columns
```

Out[50]:
```
Index(['wheelbase', 'carlength', 'carwidth', 'carheight', 'curbweight',
       'enginesize', 'boreratio', 'stroke', 'compressionratio', 'horsepower',
       'peakrpm', 'citympg', 'highwaympg', 'symboling_-1', 'symboling_0',
       'symboling_1', 'symboling_2', 'symboling_3', 'fueltype_gas',
       'aspiration_turbo', 'doornumber_two', 'carbody_hardtop',
       'carbody_hatchback', 'carbody_sedan', 'carbody_wagon', 'drivewheel_fw
d',
       'drivewheel_rwd', 'enginelocation_rear', 'enginetype_dohcv',
       'enginetype_l', 'enginetype_ohc', 'enginetype_ohcf', 'enginetype_ohc
v',
       'enginetype_rotor', 'cylindernumber_five', 'cylindernumber_four',
       'cylindernumber_six', 'cylindernumber_three', 'cylindernumber_twelve',
       'cylindernumber_two', 'fuelsystem_2bbl', 'fuelsystem_4bbl',
       'fuelsystem_idi', 'fuelsystem_mfi', 'fuelsystem_mpfi',
       'fuelsystem_spdi', 'fuelsystem_spfi', 'car_company_audi',
       'car_company_bmw', 'car_company_buick', 'car_company_chevrolet',
       'car_company_dodge', 'car_company_honda', 'car_company_isuzu',
       'car_company_jaguar', 'car_company_mazda', 'car_company_mercury',
       'car_company_mitsubishi', 'car_company_nissan', 'car_company_peugeot',
       'car_company_plymouth', 'car_company_porsche', 'car_company_renault',
       'car_company_saab', 'car_company_subaru', 'car_company_toyota',
       'car_company_volkswagen', 'car_company_volvo'],
      dtype='object')
```

In [51]:
```
# split into train and test
from sklearn.cross_validation import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                    train_size=0.7,
                                                    test_size = 0.3, random_st
ate=100)
```

3. Model Building and Evaluation

Ridge and Lasso Regression

Let's now try predicting car prices, a dataset used in simple linear regression, to perform ridge and lasso regression.

Ridge Regression

In [52]:
```
# list of alphas to tune
params = {'alpha': [0.0001, 0.001, 0.01, 0.05, 0.1,
 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 2.0, 3.0,
 4.0, 5.0, 6.0, 7.0, 8.0, 9.0, 10.0, 20, 50, 100, 500, 1000 ]}


ridge = Ridge()

# cross validation
folds = 5
model_cv = GridSearchCV(estimator = ridge,
                        param_grid = params,
                        scoring= 'neg_mean_absolute_error',
                        cv = folds,
                        return_train_score=True,
                        verbose = 1)
model_cv.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 28 candidates, totalling 140 fits

[Parallel(n_jobs=1)]: Done 140 out of 140 | elapsed:    0.4s finished
```

Out[52]:
```
GridSearchCV(cv=5, error_score='raise',
       estimator=Ridge(alpha=1.0, copy_X=True, fit_intercept=True, max_iter=N
one,
   normalize=False, random_state=None, solver='auto', tol=0.001),
       fit_params=None, iid=True, n_jobs=1,
       param_grid={'alpha': [0.0001, 0.001, 0.01, 0.05, 0.1, 0.2, 0.3, 0.4,
0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 2.0, 3.0, 4.0, 5.0, 6.0, 7.0, 8.0, 9.0, 10.0, 2
0, 50, 100, 500, 1000]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
       scoring='neg_mean_absolute_error', verbose=1)
```

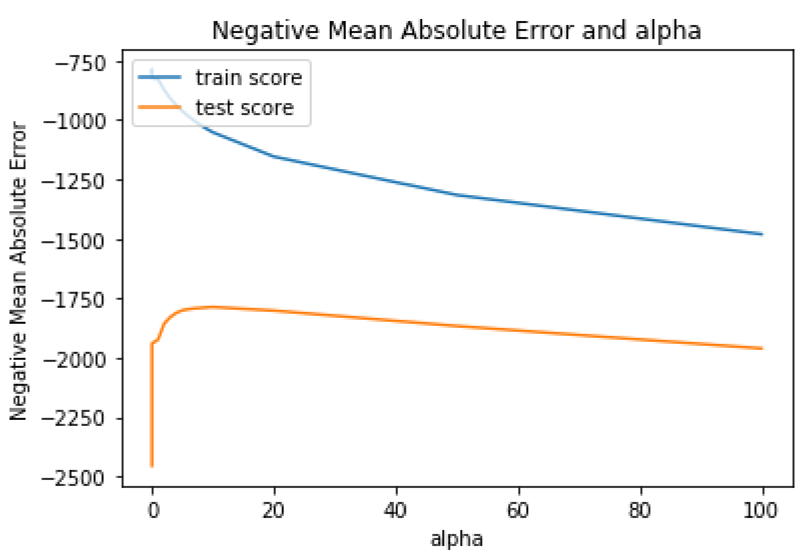
In [53]:
```
cv_results = pd.DataFrame(model_cv.cv_results_)
cv_results = cv_results[cv_results['param_alpha']<=200]
cv_results.head()
```

Out[53]:

	mean_fit_time	mean_score_time	mean_test_score	mean_train_score	param_alpha
0	0.002807	0.000503	-2455.668504	-793.046184	0.0001
1	0.002207	0.000501	-2449.633986	-792.778547	0.001
2	0.003008	0.000702	-2404.435462	-790.876517	0.01
3	0.002013	0.000494	-2276.161219	-788.409662	0.05
4	0.001905	0.000401	-2190.708689	-787.299687	0.1

5 rows × 21 columns

In [54]:
```
# plotting mean test and train scoes with alpha
cv_results['param_alpha'] = cv_results['param_alpha'].astype('int32')

# plotting
plt.plot(cv_results['param_alpha'], cv_results['mean_train_score'])
plt.plot(cv_results['param_alpha'], cv_results['mean_test_score'])
plt.xlabel('alpha')
plt.ylabel('Negative Mean Absolute Error')
plt.title("Negative Mean Absolute Error and alpha")
plt.legend(['train score', 'test score'], loc='upper left')
plt.show()
```



In [55]:
```
alpha = 15
ridge = Ridge(alpha=alpha)

ridge.fit(X_train, y_train)
ridge.coef_
```

Out[55]:
```
array([ 3.52557941e+02,  9.46530017e+01,  1.34511343e+03, -3.35849314e+02,
        1.16515775e+03,  1.33122540e+03, -1.18579444e+01, -2.84669666e+02,
        1.23313363e+01,  9.29481098e+02,  3.23313329e+02, -2.04711197e+01,
       -8.41293665e+01,  2.21783691e+02,  1.66376475e+02,  6.11555386e+01,
       -1.75468993e+01,  2.28698304e+02, -2.11820147e+02,  4.11053298e+02,
        1.01320701e+02,  2.63588369e+01, -5.29501748e+02, -2.71545584e+02,
       -2.23762142e+02, -2.44396310e+02,  2.61656901e+02,  9.20191503e+02,
       -1.93176012e+01, -2.18315631e+02,  3.13602886e+02,  2.38744211e+01,
        3.92105941e+00,  9.46640067e+01, -4.24237855e+02, -5.81409615e+02,
       -1.05817250e+02,  2.93070489e+02, -2.36048487e+02,  9.46640067e+01,
        5.15255069e+01, -1.79077288e+02,  2.11820147e+02, -1.44440927e-28,
       -3.95308641e+00, -1.36403005e+02, -1.44440927e-28,  3.35662090e+02,
        1.46679730e+03,  1.05750051e+03, -1.30931401e+02, -3.49739603e+02,
       -2.82007527e+02, -3.98771447e+01,  8.28333109e+02, -2.30841923e+02,
       -1.44440927e-28, -5.99411625e+02, -4.01098290e+02, -3.18047678e+02,
       -2.57350351e+02,  6.20255051e+02, -2.19413859e+02,  1.89789295e+02,
       -4.44216995e+02, -5.71822975e+02, -1.19897731e+02, -7.39919628e-01])
```

Lasso

In [56]:
```
lasso = Lasso()

# cross validation
model_cv = GridSearchCV(estimator = lasso,
                        param_grid = params,
                        scoring= 'neg_mean_absolute_error',
                        cv = folds,
                        return_train_score=True,
                        verbose = 1)

model_cv.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 28 candidates, totalling 140 fits

[Parallel(n_jobs=1)]: Done 140 out of 140 | elapsed:    1.9s finished
```

Out[56]:
```
GridSearchCV(cv=5, error_score='raise',
       estimator=Lasso(alpha=1.0, copy_X=True, fit_intercept=True, max_iter=1
000,
   normalize=False, positive=False, precompute=False, random_state=None,
   selection='cyclic', tol=0.0001, warm_start=False),
       fit_params=None, iid=True, n_jobs=1,
       param_grid={'alpha': [0.0001, 0.001, 0.01, 0.05, 0.1, 0.2, 0.3, 0.4,
0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 2.0, 3.0, 4.0, 5.0, 6.0, 7.0, 8.0, 9.0, 10.0, 2
0, 50, 100, 500, 1000]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
       scoring='neg_mean_absolute_error', verbose=1)
```

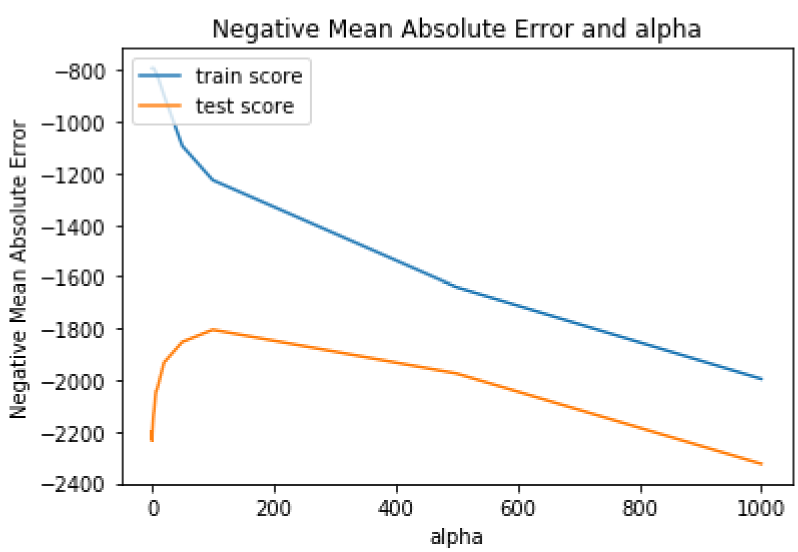
In [57]:
```
cv_results = pd.DataFrame(model_cv.cv_results_)
cv_results.head()
```

Out[57]:

	mean_fit_time	mean_score_time	mean_test_score	mean_train_score	param_alpha
0	0.020253	0.000703	-2200.571734	-792.317797	0.0001
1	0.015039	0.000402	-2200.636114	-792.315096	0.001
2	0.017645	0.000603	-2201.283963	-792.291655	0.01
3	0.014738	0.000502	-2204.263131	-792.251073	0.05
4	0.016644	0.000502	-2208.163365	-792.236231	0.1

5 rows × 21 columns

In [58]:
```
# plotting mean test and train scoes with alpha
cv_results['param_alpha'] = cv_results['param_alpha'].astype('float32')

# plotting
plt.plot(cv_results['param_alpha'], cv_results['mean_train_score'])
plt.plot(cv_results['param_alpha'], cv_results['mean_test_score'])
plt.xlabel('alpha')
plt.ylabel('Negative Mean Absolute Error')

plt.title("Negative Mean Absolute Error and alpha")
plt.legend(['train score', 'test score'], loc='upper left')
plt.show()
```



In [59]:
```
alpha =100

lasso = Lasso(alpha=alpha)

lasso.fit(X_train, y_train)
```

Out[59]:
```
Lasso(alpha=100, copy_X=True, fit_intercept=True, max_iter=1000,
   normalize=False, positive=False, precompute=False, random_state=None,
   selection='cyclic', tol=0.0001, warm_start=False)
```

In [60]:
```
lasso.coef_
```

Out[60]:
```
array([   0.        ,   -0.        , 1747.1052243 ,  -82.23183774,
       1780.64173078,  788.28807799,   -0.        ,   -0.        ,
          0.        , 1017.48820119,   84.89633333,    0.        ,
         -0.        ,    0.        ,   -0.        ,   -0.        ,
          0.        ,  246.519852  ,  -73.38572878,  120.56790634,
          0.        ,    0.        , -187.60748943,    0.        ,
        -96.25412649, -134.39227325,  294.27227486, 1218.02281069,
          0.        ,   -0.        ,    0.        ,   -0.        ,
         -0.        ,    0.        ,   -0.        , -202.47407284,
         -0.        ,  197.70712322,   -0.        ,    0.        ,
         -0.        ,   -0.        ,   58.81424436,   -0.        ,
          0.        ,   -0.        ,   -0.        ,  186.35685239,
       1805.30123983, 1210.72936345,    0.        ,   -0.        ,
         -0.        ,   78.54297249,  796.29612837,    0.        ,
         -0.        , -397.80411254,  -58.198149  , -377.78256238,
         -0.        ,  592.06274204, -163.73847377,   95.37139425,
       -198.09298955, -233.82794826,    0.        ,  206.40038676])
```