HW 3

This assignment covers several aspects of Linear Regresstion. **DO NOT ERASE MARKDOWN CELLS AND INSTRUCTIONS IN YOUR HW submission**

- **Q** - QUESTION
- **A** - Where to input your answer

Instructions

Keep the following in mind for all notebooks you develop:

- Structure your notebook.
- Use headings with meaningful levels in Markdown cells, and explain the questions each piece of code is to answer or the reason it is there.
- Make sure your notebook can always be rerun from top to bottom (Kernel Tab -> Restart and Run All)
- Start working on this assignment as soon as possible. If you are a beginner in Python this might take a long time. One of the objectives of this assignment is to help you learn python and scikit-learn package.
- Follow README.md for homework submission instructions
- In this notebook we assume '../data/' location of all data files to be read and written

Related sklearn material and online tutorials

sklearn User Guide

sklearn data pre-processing

- train_test_split
- common_pittfalls
- train test split tutorial

sklearn multiple linear regression

- tutorial
- API documentation
- Linear Regression
- multiple linear regression tutorial

sklearn polynomial regression

- generate polynomial features
- polinomial regression tutorial

correlation

- correlation

Linear Regression

In jupyter notebook environment, commands starting with the symbol % are magic commands or magic functions. `%%timeit` is one of such function. It basically gives you the speed of execution of certain statement or blocks of codes.

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

Q1 Read the `car_data.csv` data (we assume ../data/ location of all data files to be read and written) from **data** folder using pandas. Replace the ??? in the code cell below to accomplish this taks.

A1 Replace ??? with code in the code cell below

In [ ]:
```
# Replace ??? with code in the code cell below

df = pd.read_csv('data/Car_data.csv')
```

In [ ]:
```
# View head of the data to confirm the correctness of your answer
df.head()
```

Out[ ]:

	car_ID	symboling	CarName	fueltype	aspiration	doornumber	carbody	drivewheel	enginel
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

Data cleaning and manipulation

Q2 Here, you will practice the usage of common data cleaning and manipulation functions in 3 steps.

1. Use isnull() to figure out the number of NaN values per column
2. Remove the column with majority NaN values (if any)
3. Check if there are still NaN values in the dataframe using `isna()` method

A2 Replace ??? with code in the code cell below

In [ ]:
```
# There is no missing data here on this dataset :
#df.?
#df.?
df.isnull().sum() # prints out each column individually with an integer. If the intege
# it will be noticed that there are no null values in this dataset
```

Out[ ]:
```
car_ID              0
symboling           0
CarName             0
fueltype            0
aspiration          0
doornumber          0
carbody             0
drivewheel          0
enginelocation      0
wheelbase           0
carlength           0
carwidth            0
carheight           0
curbweight          0
enginetype          0
cylindernumber      0
enginesize          0
fuelsystem          0
boreratio           0
stroke              0
compressionratio    0
horsepower          0
peakrpm             0
citympg             0
highwaympg          0
price               0
dtype: int64
```

In [ ]:
```
# lets get some statistical information :
# df.?
df.describe()
```

Out[ ]:

	car_ID	symboling	wheelbase	carlength	carwidth	carheight	curbweight	enginesiz
count	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.00000
mean	103.000000	0.834146	98.756585	174.049268	65.907805	53.724878	2555.565854	126.90731
std	59.322565	1.245307	6.021776	12.337289	2.145204	2.443522	520.680204	41.64269
min	1.000000	-2.000000	86.600000	141.100000	60.300000	47.800000	1488.000000	61.00000
25%	52.000000	0.000000	94.500000	166.300000	64.100000	52.000000	2145.000000	97.00000
50%	103.000000	1.000000	97.000000	173.200000	65.500000	54.100000	2414.000000	120.00000
75%	154.000000	2.000000	102.400000	183.100000	66.900000	55.500000	2935.000000	141.00000
max	205.000000	3.000000	120.900000	208.100000	72.300000	59.800000	4066.000000	326.00000

Q3: In this task, out of all categorical columns, we focus only on the `fueltype` column processing in 2 steps.

1. Use label encoder from sklearn and convert the `fueltype` categorical values to numerical values.
2. Create a new dataframe that contains only the numerical columns.

A3 Replace ??? with code in the code cell below.

In [ ]:

```
# Label Encoding for 2-class columns:
from sklearn.preprocessing import LabelEncoder
# le = ?
# df.?
le = LabelEncoder()
unique_labels = [*df['fueltype'].unique()]
le.fit(unique_labels)
df['fueltype'] = le.transform(df['fueltype']) # didn't necessarily create a new datafr
```

In [ ]:

```
# Create new dataframe with selected columns
#df=?
```

In [ ]:

```
df.head()
```

Out[ ]:

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

5 rows × 26 columns

Q4: Use seaborn histplot to plot a distribution graph for the engine sizes

A4 Replace ??? with code in the code cell below

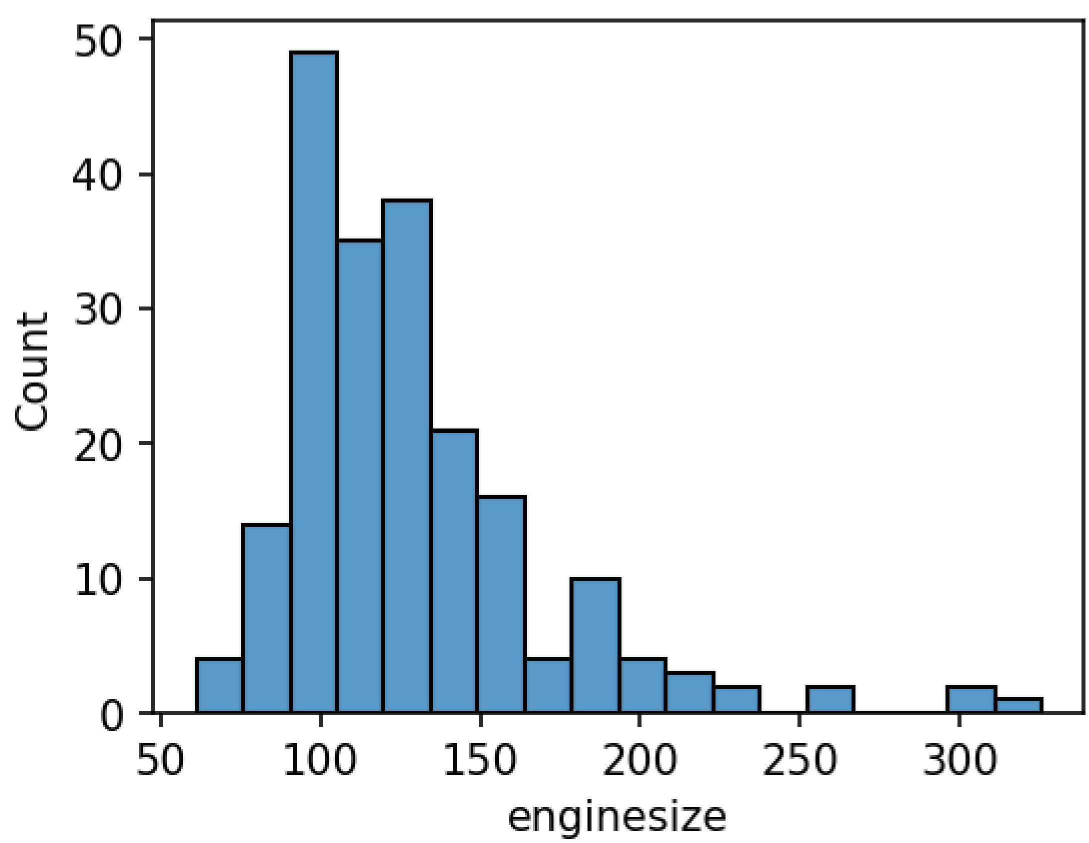
In [ ]:

```
plt.figure(figsize=(4,3),dpi=150)
sns.histplot(data=df['enginesize'])
```

```
c:\Users\Hunter\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```

Out[ ]:

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



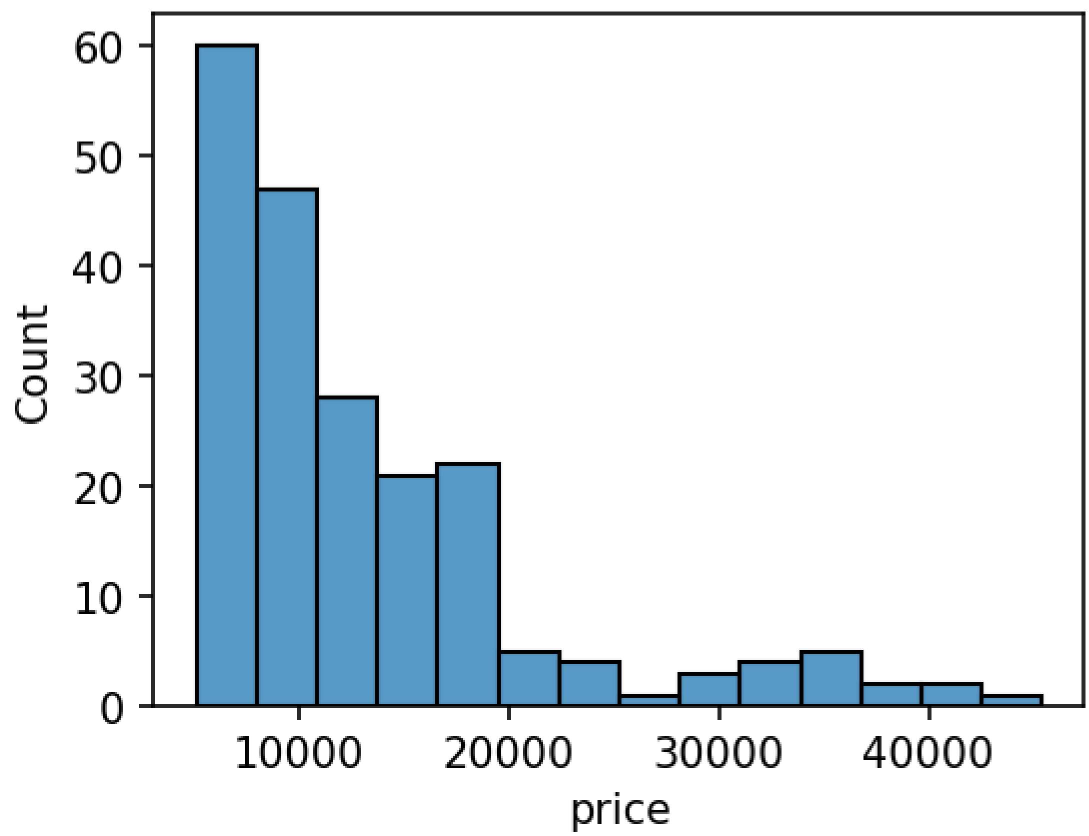
Q5: Use seaborn histplot to plot a distribution graph for the car prices

A5 Replace ??? with code in the code cell below

In [ ]:
```
plt.figure(figsize=(4,3),dpi=150)
sns.histplot(data=df['price'])
```

```
c:\Users\Hunter\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```

Out[ ]:
```
<Axes: xlabel='price', ylabel='Count'>
```

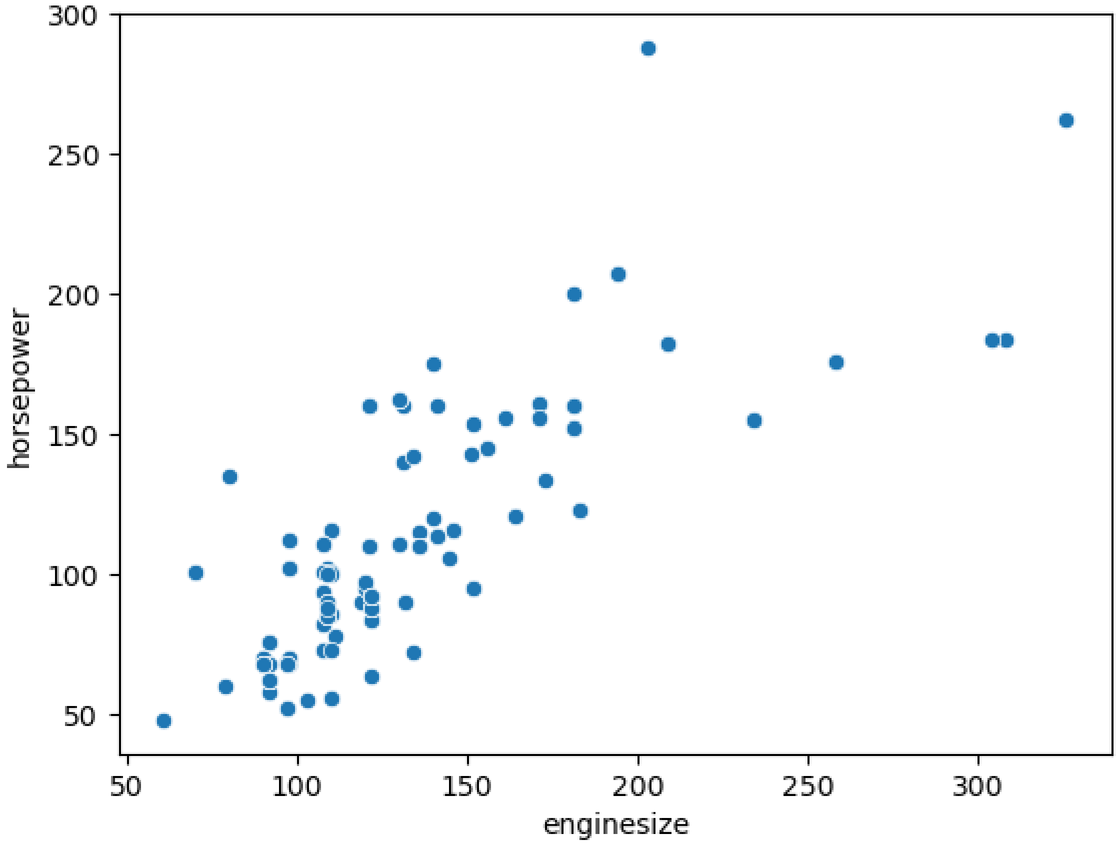


Q6: Use seaborn scatterplot to present the relation between enginesize and the horsepower of a car

A6 Replace ??? with code in the code cell below

In [ ]:
```
#sns.?
sns.scatterplot(x=df['enginesize'], y=df['horsepower'])
```

Out[ ]:
```
<Axes: xlabel='enginesize', ylabel='horsepower'>
```



Q7: There is a correlation between the car price and the horsepower of a car. If horsepower of a car increase, the price of the car also increases most of the time, and in this question you will use the seaborn scatterplot to present the relation between price and horsepower.

Next, use `hue` parameter of scatterplot function to illustrate datapoints that relate to specific fueltype category.

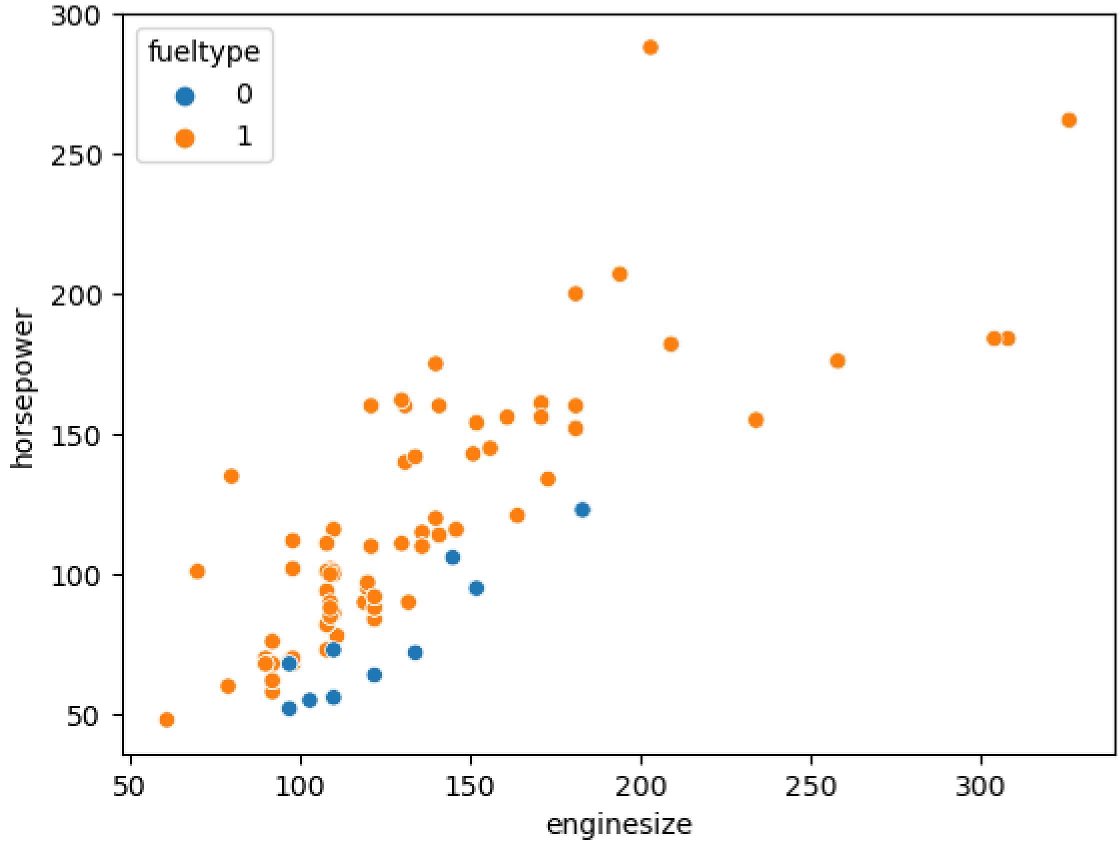
A7 Replace ??? with code in the code cell below

In [ ]:

```
#sns.?
sns.scatterplot(data=df, x=df['enginesize'], y=df['horsepower'], hue='fueltype')
```

Out[ ]:

```
<Axes: xlabel='enginesize', ylabel='horsepower'>
```



Q8: Use pairplot from sns to plot the data frame `df` and justify your feature selection.

A8: replace ??? with code in the code cell below.

In [ ]:
```
# 2. Use pairplot from sns to plot our data frame df
#sns.?
sns.pairplot(data=df)
```

```
c:\Users\Hunter\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
c:\Users\Hunter\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
c:\Users\Hunter\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
c:\Users\Hunter\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
c:\Users\Hunter\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
c:\Users\Hunter\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
c:\Users\Hunter\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
c:\Users\Hunter\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
c:\Users\Hunter\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
c:\Users\Hunter\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
c:\Users\Hunter\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
c:\Users\Hunter\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
c:\Users\Hunter\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.
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c:\Users\Hunter\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.
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c:\Users\Hunter\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```
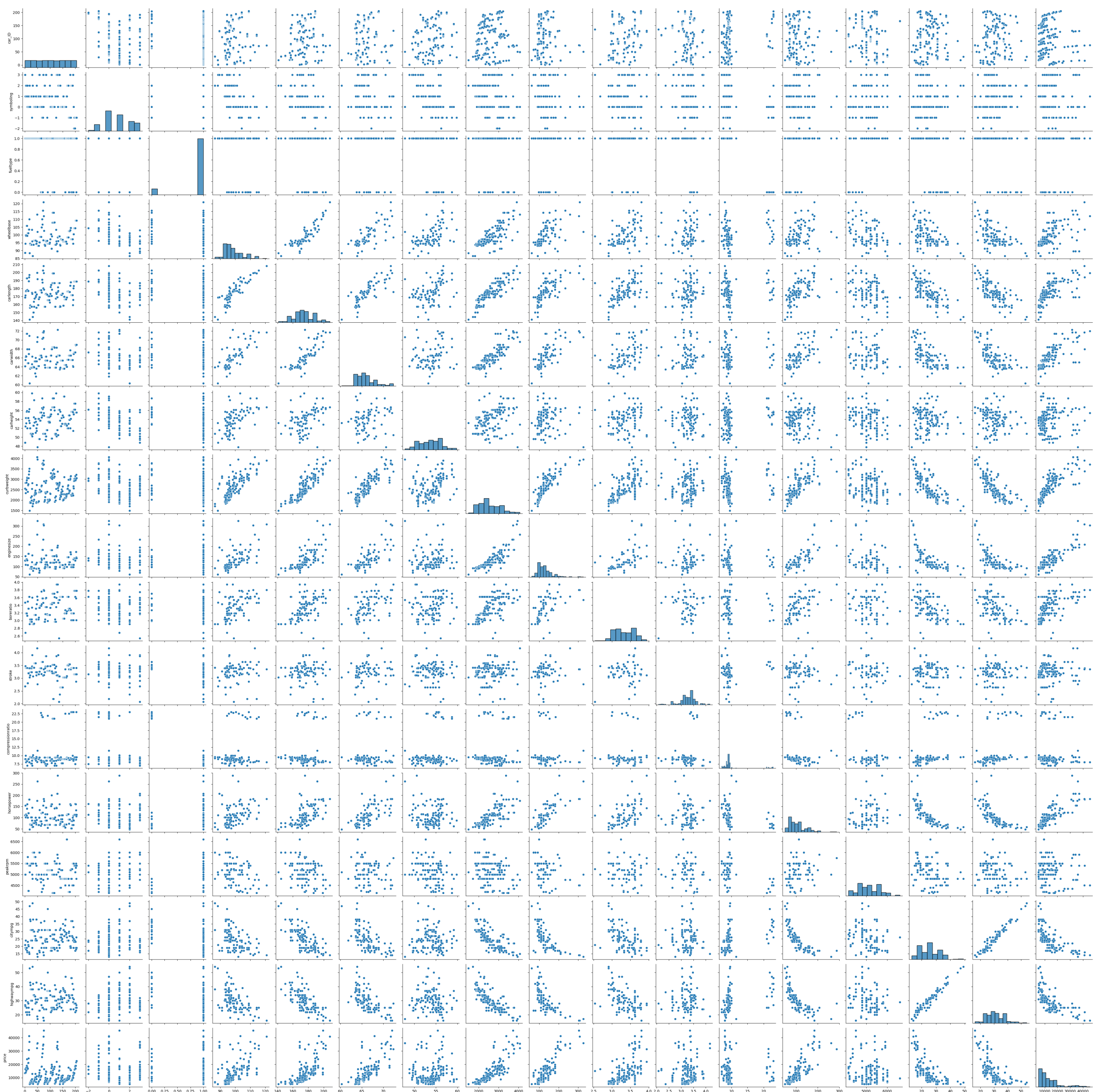

```
c:\Users\Hunter\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
c:\Users\Hunter\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
c:\Users\Hunter\anaconda3\Lib\site-packages\seaborn\axisgrid.py:118: UserWarning: The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```

Out[ ]:

```
<seaborn.axisgrid.PairGrid at 0x1c95727cf10>
```



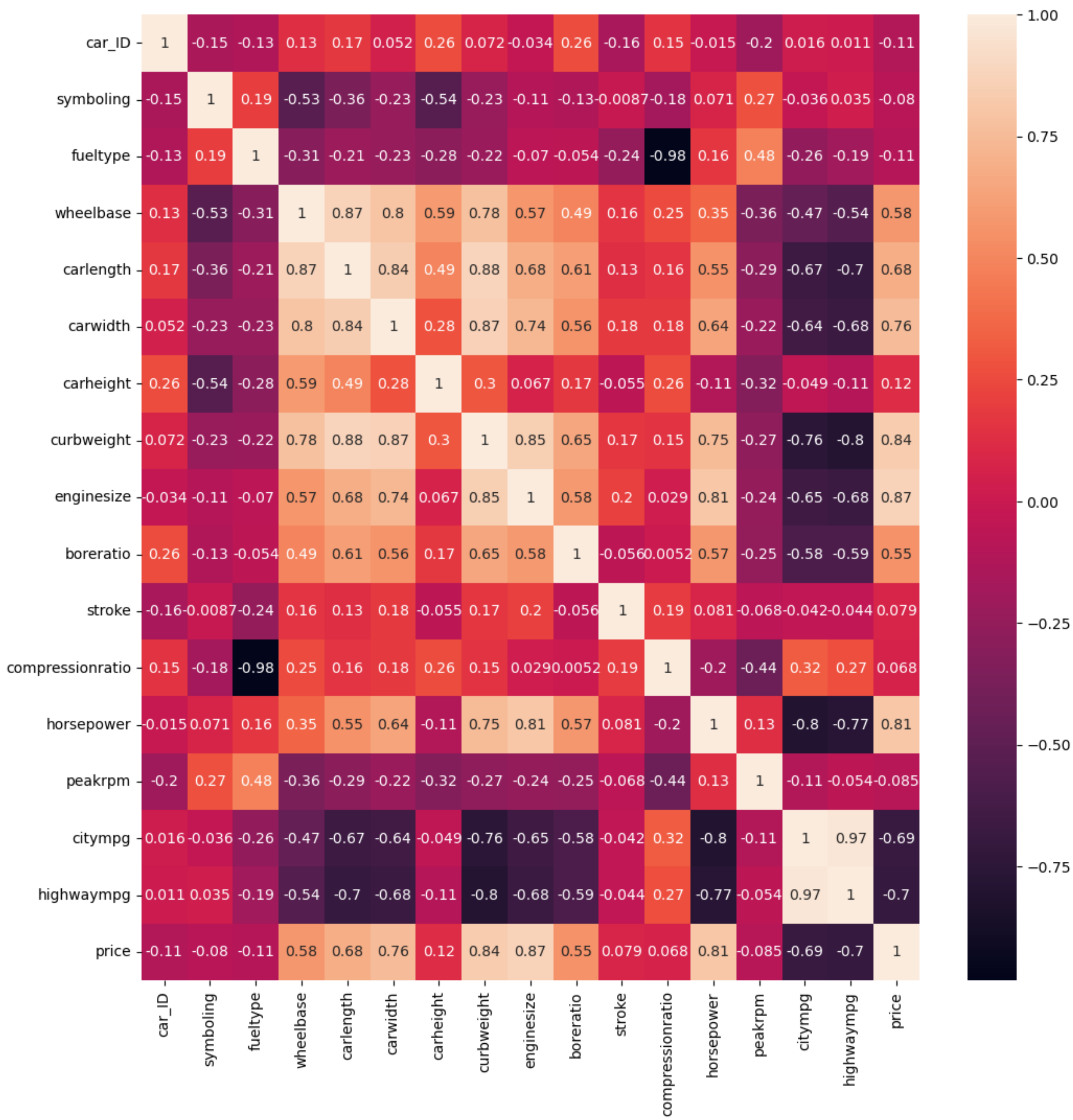
Q9 Data Visualization:

1. Use heatmap chart from seaborn library to findout the correlation between the columns in our dataset.
2. Update data frame 'df' to contain 5 columns from existing 'df' with the highest correlation to column "price". Also include price column in the updated data frame.

A9 Replace ??? with code in the code cell below

In [ ]:
```
#corr_matrix = df.corr()
#plt.figure(figsize=(12,12))
#sns.?

df.head() # CarName, aspiration, doornumber, carbody, drivewheel, enginelocation, fuel
corr_matrix = df.drop(columns=['CarName', 'aspiration', 'doornumber', 'carbody', 'driv
plt.figure(figsize=(12,12))
sns.heatmap(corr_matrix, annot=True)
```

Out[ ]: <Axes: >



In [ ]:
```
# Task 2: Update data frame 'df' to contain 5 columns from existing 'df' with the high
# is this 5 columns + the price column? enginesize = 87, curbweight = 84, horsepower =
#df=?
df = df[['price', 'enginesize', 'curbweight', 'horsepower', 'carwidth', 'highwaympg']]
df.head()
```

Out[ ]:

	price	enginesize	curbweight	horsepower	carwidth	highwaympg
0	13495.0	130	2548	111	64.1	27
1	16500.0	130	2548	111	64.1	27
2	16500.0	152	2823	154	65.5	26
3	13950.0	109	2337	102	66.2	30
4	17450.0	136	2824	115	66.4	22

Data Preparation

Q10 Pre-processing

1. Assign 'price' column value to y and rest of the columns to x

A10 Replace ??? with code in the code cell below

In [ ]:

```
#y =?
#X =?
#X
y = df['price']
X = df.drop(columns=['price'])
```

Q11 Use train_test_split to split the data set as train:test=(80%:20%) ratio.

A11 Replace ??? with code in the code cell below

In [ ]:

```
from sklearn.model_selection import train_test_split

# X_train, X_test, y_train, y_test =?
# View the shape of your data set
# X_train.shape, X_test.shape, y_train.shape, y_test.shape
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, random_state
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

Out[ ]:

```
((164, 5), (41, 5), (164,), (41,))
```

Regression Task

Multiple Linear Regression

Q12 Fit multiple linear regression model on training data using all predictors, see (i) Linear Regression Example; (ii) scikit-learn linear model

$$Y = \beta_0 + \beta_1 * x_1 + \beta_2 * x_2 + \ldots \beta_p * x_p$$

A12: Replace ??? with code in the code cell below

In [ ]:
```
from sklearn.linear_model import LinearRegression
#linear_model = ?
#linear_model.?
linear_model = LinearRegression()
linear_model.fit(X_train, y_train)
```

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

Q13: Model Scoring

1. Calculate the test MSE
2. Print the score from the model using test data

A13 Replace ??? with code in the code cell below

In [ ]:
```
### Treadway Test, this does not answer A13.
### The MSE seemed so large, that I decided to prove to myself that the MSE was correc
### I wrote my own MSE calculation within this cell, and it matches the MSE in the bel

# MSE = (1/n)sum(yi - yhat k )^2
# MSE = (1/n)sum(y actual - y predicted)^2
y_predict = linear_model.predict(X_test)
frame = pd.DataFrame({'y_test': y_test, 'y_predict': y_predict})
frame['difference'] = frame['y_test'] - frame['y_predict']
frame['square'] = frame['difference'] ** 2
#frame[:30]
frame.shape
mse_ = (1/frame.shape[0])*frame['square'].sum()
print(frame.head())
print(mse_)
# there's only 41 rows, but the differences between
```

```
        y_test      y_predict   difference        square
15   30760.000   25834.948104  4925.051896  2.425614e+07
9    17859.167   18803.324891  -944.157891  8.914341e+05
100   9549.000   11298.304551 -1749.304551  3.060066e+06
132  11850.000   13694.906024 -1844.906024  3.403678e+06
68   28248.000   23680.377070  4567.622930  2.086318e+07
14565923.040455319
```

In [ ]:
```
# Calculate the score on train and test sets
# Your code goes below
from sklearn.metrics import mean_squared_error
import matplotlib.pyplot as plt
#y_pred=?
#mse = ?   # Calculate the test MSE
#print("Test mean squared error (MSE): {:.2f}".format(mse))

y_pred = linear_model.predict(X_test)
mse = mean_squared_error(y_test, y_pred)
print("Test mean squared error (MSE): {:.2f}".format(mse))
print("Test Score: ", linear_model.score(X_test, y_test))
```

```
Test mean squared error (MSE): 14565923.04
Test Score:  0.8154904845465165
```

Polinomial Regression

Q14: Polynomial extension of the feature set captures the non-linear dependencies in the data

1. Create a polinomial feature transformer with degree **TWO** using sklearn library PolynomialFeatures
2. Transform the training dataset using the polinomial feature transformer

A14 Replace ??? with code in the code cell below

In [ ]:
```
from sklearn.preprocessing import PolynomialFeatures
#poly =?
#poly_features = ?
poly = PolynomialFeatures(2)
poly_features = poly.fit_transform(X_train)
```

Q15: Train the new model

1. Create a LinearRegression model using sklearn
2. Train the model using the transformed Train data(X_train)/ or Polinomial train data
3. Print the score for the Polinomial Regression for the Train data.

See (i) Linear Regression Example; (ii) Use the transformed X_train features inside the score() function for the correct model scores.

A15 Replace ??? with code in the code cell below

In [ ]:
```
#poly_reg_model = ?
#poly_reg_model.?

#poly_reg_model.?
poly_reg_model = LinearRegression()
poly_reg_model.fit(poly_features, y_train)
poly_reg_model.score(poly_features, y_train)
```

Out[ ]:
```
0.8887500925831316
```

In [ ]:
```
# May as well do the test set too
poly_features_test = poly.fit_transform(X_test)
poly_reg_model.score(poly_features_test, y_test)
```

Out[ ]:
```
0.7939905153296574
```