Data Analysis with Python

Importing the datasets

1. Acquire the data
2. Obtain basic insights from the data

Link to the Automobile Data Set.

In [342…

```
#! pip install ipywidgets
```

In [402…

```
# ! pip install tqdm
```

In [412…

```
# import the required libraries
import pandas as pd
import numpy as np
import matplotlib.pylab as pylab
import matplotlib.pyplot as pyplot
import seaborn as sns
from scipy import stats
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import PolynomialFeatures
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score
from ipywidgets import interact, interactive, fixed, interact_manual
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import cross_val_predict
from sklearn.linear_model import Ridge
from sklearn.model_selection import GridSearchCV
from tqdm import tqdm
%matplotlib inline
```

In [26]:

```
pd.options.mode.chained_assignment = None  # default='warn'
```

In [173…

```
# Read the online file by the URL provides above, and assign it to variable "df"
other_path = "https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBMDev
df = pd.read_csv(other_path, header=None)
```

In [174…

```
# show the first 5 rows using dataframe.head() method
print("The first 5 rows of the dataframe:")
df.head(5)
```

The first 5 rows of the dataframe:

Out[174…

0	1	2	3	4	5	6	7	8	9	...	16	17	18	19	20	21

	0	1	2	3	4	5	6	7	8	9	...	16	17	18	19	20	21	
0	3	?	alfa-romero	gas	std	two	convertible	rwd	front	88.6	...	130	mpfi	3.47	2.68	9.0	111	5
1	3	?	alfa-romero	gas	std	two	convertible	rwd	front	88.6	...	130	mpfi	3.47	2.68	9.0	111	5
2	1	?	alfa-romero	gas	std	two	hatchback	rwd	front	94.5	...	152	mpfi	2.68	3.47	9.0	154	5
3	2	164	audi	gas	std	four	sedan	fwd	front	99.8	...	109	mpfi	3.19	3.40	10.0	102	5
4	2	164	audi	gas	std	four	sedan	4wd	front	99.4	...	136	mpfi	3.19	3.40	8.0	115	5

5 rows × 26 columns

In [175…

```
# show the last 10 rows of the dataframe
print("The last 10 rows of the dataframe: \n")
df.tail(10)
```

```
The last 10 rows of the dataframe:
```

Out[175…

	0	1	2	3	4	5	6	7	8	9	...	16	17	18	19	20	21
195	-1	74	volvo	gas	std	four	wagon	rwd	front	104.3	...	141	mpfi	3.78	3.15	9.5	114
196	-2	103	volvo	gas	std	four	sedan	rwd	front	104.3	...	141	mpfi	3.78	3.15	9.5	114
197	-1	74	volvo	gas	std	four	wagon	rwd	front	104.3	...	141	mpfi	3.78	3.15	9.5	114
198	-2	103	volvo	gas	turbo	four	sedan	rwd	front	104.3	...	130	mpfi	3.62	3.15	7.5	162
199	-1	74	volvo	gas	turbo	four	wagon	rwd	front	104.3	...	130	mpfi	3.62	3.15	7.5	162
200	-1	95	volvo	gas	std	four	sedan	rwd	front	109.1	...	141	mpfi	3.78	3.15	9.5	114
201	-1	95	volvo	gas	turbo	four	sedan	rwd	front	109.1	...	141	mpfi	3.78	3.15	8.7	160
202	-1	95	volvo	gas	std	four	sedan	rwd	front	109.1	...	173	mpfi	3.58	2.87	8.8	134
203	-1	95	volvo	diesel	turbo	four	sedan	rwd	front	109.1	...	145	idi	3.01	3.40	23.0	106
204	-1	95	volvo	gas	turbo	four	sedan	rwd	front	109.1	...	141	mpfi	3.78	3.15	9.5	114

10 rows × 26 columns

Cleaning the Dataset

Add Headers

In [176…

```
# create headers list
headers = ["symboling","normalized-losses","make","fuel-type","aspiration", "num-of-doo
         "drive-wheels","engine-location","wheel-base", "length","width","height","curb
         "num-of-cylinders", "engine-size","fuel-system","bore","stroke","compression-r
```

```
         "peak-rpm","city-mpg","highway-mpg","price"]
print("headers\n", headers)
```

```
headers
 ['symboling', 'normalized-losses', 'make', 'fuel-type', 'aspiration', 'num-of-doors',
'body-style', 'drive-wheels', 'engine-location', 'wheel-base', 'length', 'width', 'heigh
t', 'curb-weight', 'engine-type', 'num-of-cylinders', 'engine-size', 'fuel-system', 'bor
e', 'stroke', 'compression-ratio', 'horsepower', 'peak-rpm', 'city-mpg', 'highway-mpg',
'price']
```

In [177…

```
# replace the headers and recheck the dataframe
df.columns = headers
df.head(10)
```

Out[177…

	symboling	normalized-losses	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base	...
0	3	?	alfa-romero	gas	std	two	convertible	rwd	front	88.6	...
1	3	?	alfa-romero	gas	std	two	convertible	rwd	front	88.6	...
2	1	?	alfa-romero	gas	std	two	hatchback	rwd	front	94.5	...
3	2	164	audi	gas	std	four	sedan	fwd	front	99.8	...
4	2	164	audi	gas	std	four	sedan	4wd	front	99.4	...
5	2	?	audi	gas	std	two	sedan	fwd	front	99.8	...
6	1	158	audi	gas	std	four	sedan	fwd	front	105.8	...
7	1	?	audi	gas	std	four	wagon	fwd	front	105.8	...
8	1	158	audi	gas	turbo	four	sedan	fwd	front	105.8	...
9	0	?	audi	gas	turbo	two	hatchback	4wd	front	99.5	...

10 rows × 26 columns

Handle missing values

In [178…

```
# replace the ? symbol with NaN so the dropna() can remove the missing values
df1=df.replace('?',np.NaN)
```

In [179…

```
# drop the missing values along the price column and view the data
df=df1.dropna(subset=["price"], axis=0)
df.head(20)
```

Out[179…

	symboling	normalized-losses	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base	.

	symboling	normalized-losses	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base	.
0	3	NaN	alfa-romero	gas	std	two	convertible	rwd	front	88.6	.
1	3	NaN	alfa-romero	gas	std	two	convertible	rwd	front	88.6	.
2	1	NaN	alfa-romero	gas	std	two	hatchback	rwd	front	94.5	.
3	2	164	audi	gas	std	four	sedan	fwd	front	99.8	.
4	2	164	audi	gas	std	four	sedan	4wd	front	99.4	.
5	2	NaN	audi	gas	std	two	sedan	fwd	front	99.8	.
6	1	158	audi	gas	std	four	sedan	fwd	front	105.8	.
7	1	NaN	audi	gas	std	four	wagon	fwd	front	105.8	.
8	1	158	audi	gas	turbo	four	sedan	fwd	front	105.8	.
10	2	192	bmw	gas	std	two	sedan	rwd	front	101.2	.
11	0	192	bmw	gas	std	four	sedan	rwd	front	101.2	.
12	0	188	bmw	gas	std	two	sedan	rwd	front	101.2	.
13	0	188	bmw	gas	std	four	sedan	rwd	front	101.2	.
14	1	NaN	bmw	gas	std	four	sedan	rwd	front	103.5	.
15	0	NaN	bmw	gas	std	four	sedan	rwd	front	103.5	.
16	0	NaN	bmw	gas	std	two	sedan	rwd	front	103.5	.
17	0	NaN	bmw	gas	std	four	sedan	rwd	front	110.0	.
18	2	121	chevrolet	gas	std	two	hatchback	fwd	front	88.4	.
19	1	98	chevrolet	gas	std	two	hatchback	fwd	front	94.5	.
20	0	81	chevrolet	gas	std	four	sedan	fwd	front	94.5	.

20 rows × 26 columns

In [180…

```
# check the column names
print(df.columns)
```

```
Index(['symboling', 'normalized-losses', 'make', 'fuel-type', 'aspiration',
       'num-of-doors', 'body-style', 'drive-wheels', 'engine-location',
       'wheel-base', 'length', 'width', 'height', 'curb-weight', 'engine-type',
       'num-of-cylinders', 'engine-size', 'fuel-system', 'bore', 'stroke',
       'compression-ratio', 'horsepower', 'peak-rpm', 'city-mpg',
       'highway-mpg', 'price'],
      dtype='object')
```

In [181…

```
# save the dataset as a csv. Use index = false so the row names won't be written
df.to_csv("automobile.csv", index=False)
```

Basic Insights of the Data

In [182…

```
# check the types of the data
df.dtypes
```

Out[182…

```
symboling              int64
normalized-losses     object
make                  object
fuel-type             object
aspiration            object
num-of-doors          object
body-style            object
drive-wheels          object
engine-location       object
wheel-base           float64
length               float64
width                float64
height               float64
curb-weight            int64
engine-type           object
num-of-cylinders      object
engine-size            int64
fuel-system           object
bore                  object
stroke                object
compression-ratio    float64
horsepower            object
peak-rpm              object
city-mpg               int64
highway-mpg            int64
price                 object
dtype: object
```

In [183…

```
# get summary statistics
df.describe()
```

Out[183…

	symboling	wheel-base	length	width	height	curb-weight	engine-size	compressio rat
count	201.000000	201.000000	201.000000	201.000000	201.000000	201.000000	201.000000	201.0000
mean	0.840796	98.797015	174.200995	65.889055	53.766667	2555.666667	126.875622	10.1642
std	1.254802	6.066366	12.322175	2.101471	2.447822	517.296727	41.546834	4.0049
min	-2.000000	86.600000	141.100000	60.300000	47.800000	1488.000000	61.000000	7.0000
25%	0.000000	94.500000	166.800000	64.100000	52.000000	2169.000000	98.000000	8.6000
50%	1.000000	97.000000	173.200000	65.500000	54.100000	2414.000000	120.000000	9.0000
75%	2.000000	102.400000	183.500000	66.600000	55.500000	2926.000000	141.000000	9.4000
max	3.000000	120.900000	208.100000	72.000000	59.800000	4066.000000	326.000000	23.0000

In [184…

```
# get summary statistics including non-numerical values
df.describe(include = 'all')
```

Out[184…

	symboling	normalized-losses	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base
count	201.000000	164	201	201	201	199	201	201	201	201.000000
unique	NaN	51	22	2	2	2	5	3	2	NaN
top	NaN	161	toyota	gas	std	four	sedan	fwd	front	NaN
freq	NaN	11	32	181	165	113	94	118	198	NaN
mean	0.840796	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	98.797015
std	1.254802	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	6.066366
min	-2.000000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	86.600000
25%	0.000000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	94.500000
50%	1.000000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	97.000000
75%	2.000000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	102.400000
max	3.000000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	120.900000

11 rows × 26 columns

In [185…

```
# use .describe() on columns length and compression-ratio
df[['length', 'compression-ratio']].describe()
```

Out[185…

	length	compression-ratio
count	201.000000	201.000000
mean	174.200995	10.164279
std	12.322175	4.004965
min	141.100000	7.000000
25%	166.800000	8.600000
50%	173.200000	9.000000
75%	183.500000	9.400000
max	208.100000	23.000000

In [186…

```
# get a concise summary of the dataframe
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 201 entries, 0 to 204
Data columns (total 26 columns):
 #   Column             Non-Null Count  Dtype 
---  ------             --------------  ----- 
 0   symboling          201 non-null    int64 
 1   normalized-losses  164 non-null    object
 2   make               201 non-null    object
```

```
 3   fuel-type          201 non-null    object
 4   aspiration         201 non-null    object
 5   num-of-doors       199 non-null    object
 6   body-style         201 non-null    object
 7   drive-wheels       201 non-null    object
 8   engine-location    201 non-null    object
 9   wheel-base         201 non-null    float64
 10  length             201 non-null    float64
 11  width              201 non-null    float64
 12  height             201 non-null    float64
 13  curb-weight        201 non-null    int64
 14  engine-type        201 non-null    object
 15  num-of-cylinders   201 non-null    object
 16  engine-size        201 non-null    int64
 17  fuel-system        201 non-null    object
 18  bore               197 non-null    object
 19  stroke             197 non-null    object
 20  compression-ratio  201 non-null    float64
 21  horsepower         199 non-null    object
 22  peak-rpm           199 non-null    object
 23  city-mpg           201 non-null    int64
 24  highway-mpg        201 non-null    int64
 25  price              201 non-null    object
dtypes: float64(5), int64(5), object(16)
memory usage: 42.4+ KB
```

Data Wrangling

1. Handle more missing values
2. Correct the data format
3. Standardize and normalize the data

Handle Missing Values

In [187…

```
# convert ? to NaN.
df.replace("?", np.nan, inplace = True)
df.head(10)
```

Out[187…

	symboling	normalized-losses	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base	...
0	3	NaN	alfa-romero	gas	std	two	convertible	rwd	front	88.6	...
1	3	NaN	alfa-romero	gas	std	two	convertible	rwd	front	88.6	...
2	1	NaN	alfa-romero	gas	std	two	hatchback	rwd	front	94.5	...
3	2	164	audi	gas	std	four	sedan	fwd	front	99.8	...
4	2	164	audi	gas	std	four	sedan	4wd	front	99.4	...
5	2	NaN	audi	gas	std	two	sedan	fwd	front	99.8	...
6	1	158	audi	gas	std	four	sedan	fwd	front	105.8	...
7	1	NaN	audi	gas	std	four	wagon	fwd	front	105.8	...

	symboling	normalized-losses	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base	...
8	1	158	audi	gas	turbo	four	sedan	fwd	front	105.8	...
10	2	192	bmw	gas	std	two	sedan	rwd	front	101.2	...

10 rows × 26 columns

In [188…

```
# evaluate for missing data
missing_data = df.isnull()
missing_data.head(5)
# true means the value is missing
```

Out[188…

	symboling	normalized-losses	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base	...	engin si
0	False	True	False	False	False	False	False	False	False	False	...	Fal
1	False	True	False	False	False	False	False	False	False	False	...	Fal
2	False	True	False	False	False	False	False	False	False	False	...	Fal
3	False	False	False	False	False	False	False	False	False	False	...	Fal
4	False	False	False	False	False	False	False	False	False	False	...	Fal

5 rows × 26 columns

In [189…

```
# count the number of missing values in each column
for column in missing_data.columns.values.tolist():
    print(column)
    print (missing_data[column].value_counts())
    print("")
```

```
symboling
False    201
Name: symboling, dtype: int64

normalized-losses
False    164
True      37
Name: normalized-losses, dtype: int64

make
False    201
Name: make, dtype: int64

fuel-type
False    201
Name: fuel-type, dtype: int64

aspiration
False    201
Name: aspiration, dtype: int64
```

```
num-of-doors
False    199
True       2
Name: num-of-doors, dtype: int64

body-style
False    201
Name: body-style, dtype: int64

drive-wheels
False    201
Name: drive-wheels, dtype: int64

engine-location
False    201
Name: engine-location, dtype: int64

wheel-base
False    201
Name: wheel-base, dtype: int64

length
False    201
Name: length, dtype: int64

width
False    201
Name: width, dtype: int64

height
False    201
Name: height, dtype: int64

curb-weight
False    201
Name: curb-weight, dtype: int64

engine-type
False    201
Name: engine-type, dtype: int64

num-of-cylinders
False    201
Name: num-of-cylinders, dtype: int64

engine-size
False    201
Name: engine-size, dtype: int64

fuel-system
False    201
Name: fuel-system, dtype: int64

bore
False    197
True       4
Name: bore, dtype: int64

stroke
False    197
True       4
Name: stroke, dtype: int64

compression-ratio
```

```
False    201
Name: compression-ratio, dtype: int64

horsepower
False    199
True       2
Name: horsepower, dtype: int64

peak-rpm
False    199
True       2
Name: peak-rpm, dtype: int64

city-mpg
False    201
Name: city-mpg, dtype: int64

highway-mpg
False    201
Name: highway-mpg, dtype: int64

price
False    201
Name: price, dtype: int64
```

How to deal with missing data?

1. Drop data
   a. Drop the whole row
   b. Drop the whole column
2. Replace data
   a. Replace it by mean
   b. Replace it by frequency
   c. Replace it based on other functions

Whole columns should be dropped only if most entries in the column are empty. In our dataset, none of the columns are empty enough to drop entirely. We have some freedom in choosing which method to replace data; however, some methods may seem more reasonable than others. We will apply each method to many different columns:

Replace by mean:

- "normalized-losses": 41 missing data, replace them with mean
- "stroke": 4 missing data, replace them with mean
- "bore": 4 missing data, replace them with mean
- "horsepower": 2 missing data, replace them with mean
- "peak-rpm": 2 missing data, replace them with mean

Replace by frequency:

- "num-of-doors": 2 missing data, replace them with "four".
  - Reason: 84% sedans is four doors. Since four doors is most frequent, it is most likely to occur

Drop the whole row:

- "price": 4 missing data, simply delete the whole row
  - Reason: price is what we want to predict. Any data entry without price data cannot be used for prediction; therefore any row now without price data is not useful to us

In [190…

```
# calculate the mean value of normalized-losses
avg_norm_loss = df["normalized-losses"].astype("float").mean(axis=0)
print("Average of normalized-losses:", avg_norm_loss)
```

```
Average of normalized-losses: 122.0
```

In [191…

```
# replace NaN with mean value in normalized-losses
df["normalized-losses"].replace(np.nan, avg_norm_loss, inplace=True)
```

In [192…

```
# calculate mean value of bore
avg_bore=df['bore'].astype('float').mean(axis=0)
print("Average of bore:", avg_bore)
```

```
Average of bore: 3.330710659898477
```

In [193…

```
# replace NaN with mean value of bore
df["bore"].replace(np.nan, avg_bore, inplace=True)
```

In [194…

```
# calculate mean value for stroke
avg_stroke = df["stroke"].astype("float").mean(axis = 0)
print("Average of stroke:", avg_stroke)
```

```
Average of stroke: 3.256903553299492
```

In [195…

```
# replace NaN with mean value for stroke
df["stroke"].replace(np.nan, avg_stroke, inplace = True)
```

In [196…

```
# calculate mean value for horsepower
avg_horsepower = df['horsepower'].astype('float').mean(axis=0)
print("Average horsepower:", avg_horsepower)
```

```
Average horsepower: 103.39698492462311
```

In [197…

```
# replace NaN with mean value for horsepower
df['horsepower'].replace(np.nan, avg_horsepower, inplace=True)
```

In [198…

```
# calculate the mean value for peak-rpm
avg_peakrpm=df['peak-rpm'].astype('float').mean(axis=0)
print("Average peak rpm:", avg_peakrpm)
```

```
Average peak rpm: 5117.587939698493
```

In [199…

```
# replace NaN with mean value of peak-rpm
df['peak-rpm'].replace(np.nan, avg_peakrpm, inplace=True)
```

In [200…
```
# check which values are present in a num-of-doors column
df['num-of-doors'].value_counts()
```

Out[200…
```
four    113
two      86
Name: num-of-doors, dtype: int64
```

In [201…
```
# alternatively use .idxmax() to get the most common value
df['num-of-doors'].value_counts().idxmax()
```

Out[201…
```
'four'
```

In [202…
```
# replace the missing num of doors value with the most frequent value
df["num-of-doors"].replace(np.nan, "four", inplace=True)
```

In [203…
```
# drop all rows that do not have price data
df.dropna(subset=["price"], axis=0, inplace=True)
```

In [204…
```
# reset the index due to the dropped rows
df.reset_index(drop=True, inplace=True)
```

In [205…
```
# view the cleaned dataset
df.head()
```

Out[205…

	symboling	normalized-losses	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base	...
0	3	122.0	alfa-romero	gas	std	two	convertible	rwd	front	88.6	...
1	3	122.0	alfa-romero	gas	std	two	convertible	rwd	front	88.6	...
2	1	122.0	alfa-romero	gas	std	two	hatchback	rwd	front	94.5	...
3	2	164	audi	gas	std	four	sedan	fwd	front	99.8	...
4	2	164	audi	gas	std	four	sedan	4wd	front	99.4	...

5 rows × 26 columns

Correct Data Format

In [206…
```
# double check the data types for each column
df.dtypes
# we want numerical objects to be float or int
# variables with strings should be type object
```

Out[206…
```
symboling                int64
```

```
normalized-losses     object
make                  object
fuel-type             object
aspiration            object
num-of-doors          object
body-style            object
drive-wheels          object
engine-location       object
wheel-base           float64
length               float64
width                float64
height               float64
curb-weight            int64
engine-type           object
num-of-cylinders      object
engine-size            int64
fuel-system           object
bore                  object
stroke                object
compression-ratio    float64
horsepower            object
peak-rpm              object
city-mpg               int64
highway-mpg            int64
price                 object
dtype: object
```

In [207…

```
# convert bore and stroke to float
df[["bore", "stroke"]] = df[["bore", "stroke"]].astype("float")
```

In [208…

```
# convert normalized-losses to int
df[["normalized-losses"]] = df[["normalized-losses"]].astype("int")
```

In [209…

```
# convert price to float
df[["price"]] = df[["price"]].astype("float")
```

In [210…

```
# convert peak-rpm to float
df[["peak-rpm"]] = df[["peak-rpm"]].astype("float")
```

In [211…

```
# double check types
df.dtypes
```

Out[211…

```
symboling              int64
normalized-losses      int32
make                  object
fuel-type             object
aspiration            object
num-of-doors          object
body-style            object
drive-wheels          object
engine-location       object
wheel-base           float64
length               float64
width                float64
height               float64
curb-weight            int64
engine-type           object
```

```
num-of-cylinders      object
engine-size            int64
fuel-system           object
bore                 float64
stroke               float64
compression-ratio    float64
horsepower            object
peak-rpm             float64
city-mpg               int64
highway-mpg            int64
price                float64
dtype: object
```

Data Standardization

Standardization is the process of transforming the data into a common format, which allows for meaningful comparisons.

In [212…

```
# scale the columns length, width, and height to normalize these variables between 0 an
# replace (original value) by (original value)/(maximum value)
df['length'] = df['length']/df['length'].max()
df['width'] = df['width']/df['width'].max()
df['height'] = df['height']/df['height'].max()
```

In [213…

```
# view data
df[["length","width","height"]].head()
```

Out[213…

	length	width	height
0	0.811148	0.890278	0.816054
1	0.811148	0.890278	0.816054
2	0.822681	0.909722	0.876254
3	0.848630	0.919444	0.908027
4	0.848630	0.922222	0.908027

Binning

Binning is the process of transforming continuous numerical variables into discrete categorical bins for grouped analysis.

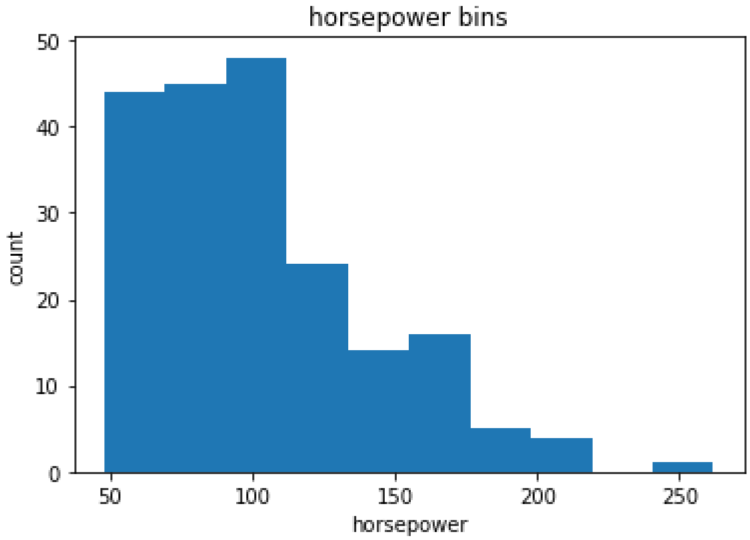
In [214…

```
# bin the horsepower data
# first convert to the correct datatype
df["horsepower"]=df["horsepower"].astype(int, copy=True)
```

In [215…

```
# plot the histogram of horsepower to see the distribution
pyplot.hist(df["horsepower"])

# set the labels and plot title
pyplot.xlabel("horsepower")
pyplot.ylabel("count")
pyplot.title("horsepower bins")
```

Out[215…
```
Text(0.5, 1.0, 'horsepower bins')
```



In [216…
```python
# we want 3 bins of equal size, so use numpy's Linspace() function
bins = np.linspace(min(df["horsepower"]), max(df["horsepower"]), 4)
bins
```

Out[216…
```
array([ 48.        , 119.33333333, 190.66666667, 262.        ])
```

In [217…
```python
# set group names
group_names = ['Low', 'Medium', 'High']
```

In [218…
```python
# apply cut function to determine to which bin each value of horsepower belongs
df['horsepower-binned'] = pd.cut(df['horsepower'], bins, labels=group_names, include_lo
df[['horsepower','horsepower-binned']].head(20)
```

Out[218…

	horsepower	horsepower-binned
0	111	Low
1	111	Low
2	154	Medium
3	102	Low
4	115	Low
5	110	Low
6	110	Low
7	110	Low
8	140	Medium
9	101	Low
10	101	Low
11	121	Medium

	horsepower	horsepower-binned
12	121	Medium
13	121	Medium
14	182	Medium
15	182	Medium
16	182	Medium
17	48	Low
18	70	Low
19	70	Low

In [219…

```
# observe the number of vehicles in each bin
df["horsepower-binned"].value_counts()
```

Out[219…

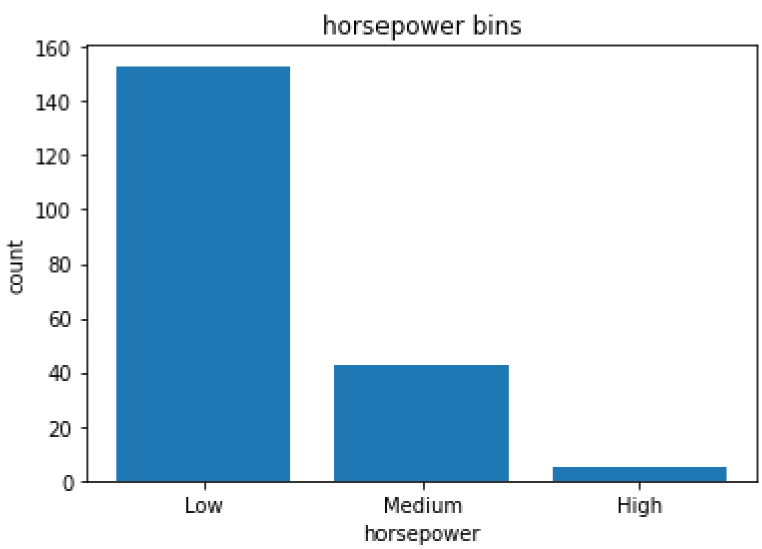
```
Low       153
Medium     43
High        5
Name: horsepower-binned, dtype: int64
```

In [220…

```
# plot the distribution of each bin
pyplot.bar(group_names, df["horsepower-binned"].value_counts())

# set x/y labels and plot title
pyplot.xlabel("horsepower")
pyplot.ylabel("count")
pyplot.title("horsepower bins")
# this successfully narrowed down intervals from 57 to 3
```

Out[220…

```
Text(0.5, 1.0, 'horsepower bins')
```



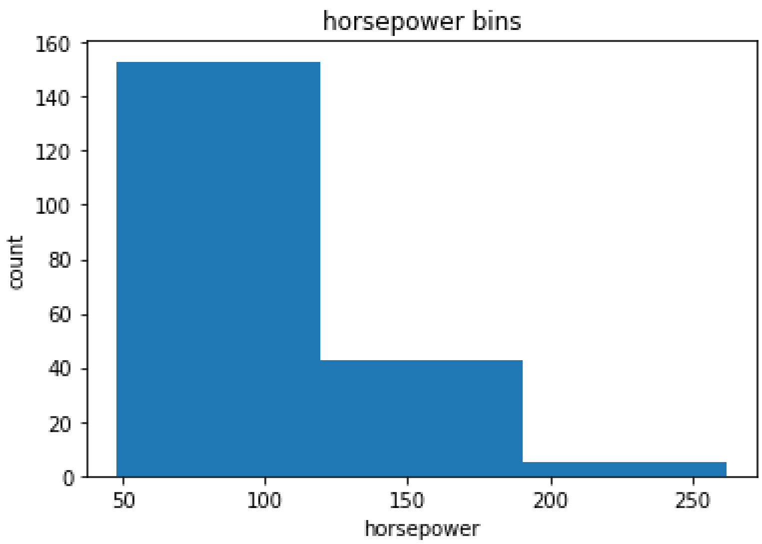
In [221…

```
# use a histogram to plot horsepower with 3 bins

# draw historgram of attribute "horsepower" with bins = 3
pyplot.hist(df["horsepower"], bins = 3)
```

```python
# set x/y labels and plot title
pyplot.xlabel("horsepower")
pyplot.ylabel("count")
pyplot.title("horsepower bins")
```

Out[221…

```
Text(0.5, 1.0, 'horsepower bins')
```



Indicator / Dummy Variables

A dummy variable is a numerical variable used to label categories. They allow us to use categorical variables for regression analysis.

In [222…

```python
# create dummy variables for fuel-type
dummy_variable_1 = pd.get_dummies(df["fuel-type"])
dummy_variable_1.head()
```

Out[222…

	diesel	gas
0	0	1
1	0	1
2	0	1
3	0	1
4	0	1

In [223…

```python
# change column names for clarity
dummy_variable_1.rename(columns={'gas':'fuel-type-gas', 'diesel':'fuel-type-diesel'}, i
dummy_variable_1.head()
```

Out[223…

	fuel-type-diesel	fuel-type-gas
0	0	1
1	0	1

	fuel-type-diesel	fuel-type-gas
2	0	1
3	0	1
4	0	1

In [224…

```
# merge data frame "df" and "dummy_variable_1"
df = pd.concat([df, dummy_variable_1], axis=1)
```

In [225…

```
# drop original column "fuel-type" from "df"
df.drop("fuel-type", axis = 1, inplace=True)
```

In [226…

```
# view data
df.head()
```

Out[226…

	symboling	normalized-losses	make	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base	length
0	3	122	alfa-romero	std	two	convertible	rwd	front	88.6	0.811148
1	3	122	alfa-romero	std	two	convertible	rwd	front	88.6	0.811148
2	1	122	alfa-romero	std	two	hatchback	rwd	front	94.5	0.822681
3	2	164	audi	std	four	sedan	fwd	front	99.8	0.848630
4	2	164	audi	std	four	sedan	4wd	front	99.4	0.848630

5 rows × 28 columns

In [227…

```
# create a dummy variable for aspiration
dummy_variable_2 = pd.get_dummies(df['aspiration'])
```

In [228…

```
# change column names for clarity
dummy_variable_2.rename(columns={'std':'aspiration-std', 'turbo': 'aspiration-turbo'},
```

In [229…

```
# show first 5 instances of data frame "dummy_variable_1"
dummy_variable_2.head()
```

Out[229…

	aspiration-std	aspiration-turbo
0	1	0
1	1	0

	aspiration-std	aspiration-turbo
2	1	0
3	1	0
4	1	0

In [230…

```
# merge the new dataframe to the original datafram
df = pd.concat([df, dummy_variable_2], axis=1)
```

In [231…

```
# drop original column "aspiration" from "df"
df.drop('aspiration', axis = 1, inplace=True)
```

In [232…

```
df.head()
```

Out[232…

	symboling	normalized-losses	make	num-of-doors	body-style	drive-wheels	engine-location	wheel-base	length	width	...
0	3	122	alfa-romero	two	convertible	rwd	front	88.6	0.811148	0.890278	..
1	3	122	alfa-romero	two	convertible	rwd	front	88.6	0.811148	0.890278	..
2	1	122	alfa-romero	two	hatchback	rwd	front	94.5	0.822681	0.909722	..
3	2	164	audi	four	sedan	fwd	front	99.8	0.848630	0.919444	..
4	2	164	audi	four	sedan	4wd	front	99.4	0.848630	0.922222	..

5 rows × 29 columns

In [233…

```
# save this dataset to csv
df.to_csv('clean_df.csv')
```

Exploratory Data Analysis

1. Analyze individual feature patterns with visualization
2. Use descriptive statistical analysis
3. Use grouping
4. Utilize correlation
5. ANOVA

Analyze Individual Feature Patterns

In [234…

```
# use .corr() to calculate the correlation of the dataset
df.corr()
```

Out[234…

	symboling	normalized-losses	wheel-base	length	width	height	curb-weight	engine-size
symboling	1.000000	0.466264	-0.535987	-0.365404	-0.242423	-0.550160	-0.233118	-0.110581
normalized-losses	0.466264	1.000000	-0.056661	0.019424	0.086802	-0.373737	0.099404	0.112360
wheel-base	-0.535987	-0.056661	1.000000	0.876024	0.814507	0.590742	0.782097	0.572027
length	-0.365404	0.019424	0.876024	1.000000	0.857170	0.492063	0.880665	0.685025
width	-0.242423	0.086802	0.814507	0.857170	1.000000	0.306002	0.866201	0.729436
height	-0.550160	-0.373737	0.590742	0.492063	0.306002	1.000000	0.307581	0.074694
curb-weight	-0.233118	0.099404	0.782097	0.880665	0.866201	0.307581	1.000000	0.849072
engine-size	-0.110581	0.112360	0.572027	0.685025	0.729436	0.074694	0.849072	1.000000
bore	-0.139896	-0.029800	0.493203	0.608941	0.544879	0.180327	0.644041	0.572516
stroke	-0.007992	0.055127	0.157964	0.123913	0.188814	-0.060822	0.167412	0.205806
compression-ratio	-0.182196	-0.114713	0.250313	0.159733	0.189867	0.259737	0.156433	0.028889
horsepower	0.075776	0.217300	0.371297	0.579688	0.614972	-0.086901	0.758001	0.822636
peak-rpm	0.279719	0.239544	-0.360233	-0.286035	-0.245852	-0.309913	-0.279350	-0.256753
city-mpg	-0.035527	-0.225016	-0.470606	-0.665192	-0.633531	-0.049800	-0.749543	-0.650546
highway-mpg	0.036233	-0.181877	-0.543304	-0.698142	-0.680635	-0.104812	-0.794889	-0.679571
price	-0.082391	0.133999	0.584642	0.690628	0.751265	0.135486	0.834415	0.872335
fuel-type-diesel	-0.196735	-0.101546	0.307237	0.211187	0.244356	0.281578	0.221046	0.070779
fuel-type-gas	0.196735	0.101546	-0.307237	-0.211187	-0.244356	-0.281578	-0.221046	-0.070779
aspiration-std	0.054615	0.006911	-0.256889	-0.230085	-0.305732	-0.090336	-0.321955	-0.110040
aspiration-turbo	-0.054615	-0.006911	0.256889	0.230085	0.305732	0.090336	0.321955	0.110040

In [235…

```python
# get the correlation between bore, stroke, compression-ratio, and horsepower
df[['bore', 'stroke', 'compression-ratio', 'horsepower']].corr()
```

Out[235…

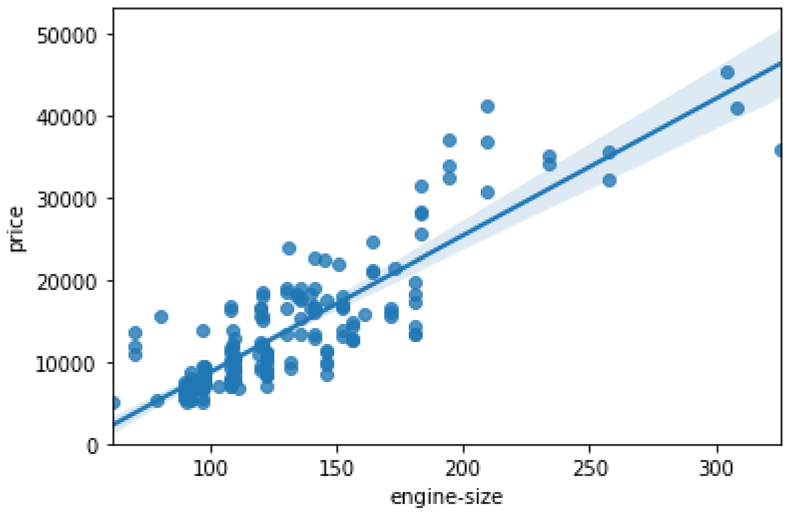
	bore	stroke	compression-ratio	horsepower
bore	1.000000	-0.055390	0.001250	0.566786
stroke	-0.055390	1.000000	0.187854	0.097598
compression-ratio	0.001250	0.187854	1.000000	-0.214392
horsepower	0.566786	0.097598	-0.214392	1.000000

In [236…

```
# analyze engine size and price using a scatterplot
# Engine size as potential predictor variable of price
sns.regplot(x="engine-size", y="price", data=df)
pyplot.ylim(0,)
```

Out[236…

```
(0.0, 53155.51660301515)
```



In [237…

```
# examine engine size and price correlation
df[["engine-size", "price"]].corr()
# may be a good indicator of price
```

Out[237…

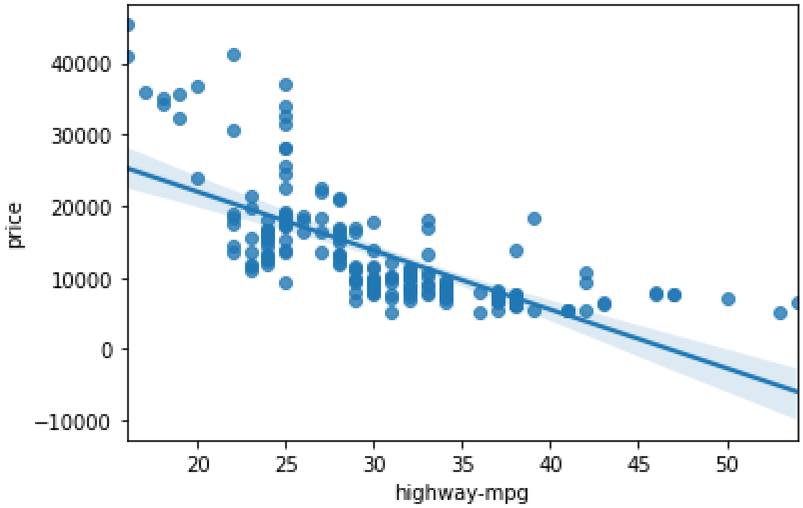
	engine-size	price
engine-size	1.000000	0.872335
price	0.872335	1.000000

In [238…

```
# create scatterplot of highway-mpg and price
sns.regplot(x="highway-mpg", y="price", data=df)
# could be a good indicator of price
```

Out[238…

```
<AxesSubplot:xlabel='highway-mpg', ylabel='price'>
```



In [239…

```
# examine correlation between highway-mpg and price
df[['highway-mpg', 'price']].corr()
```

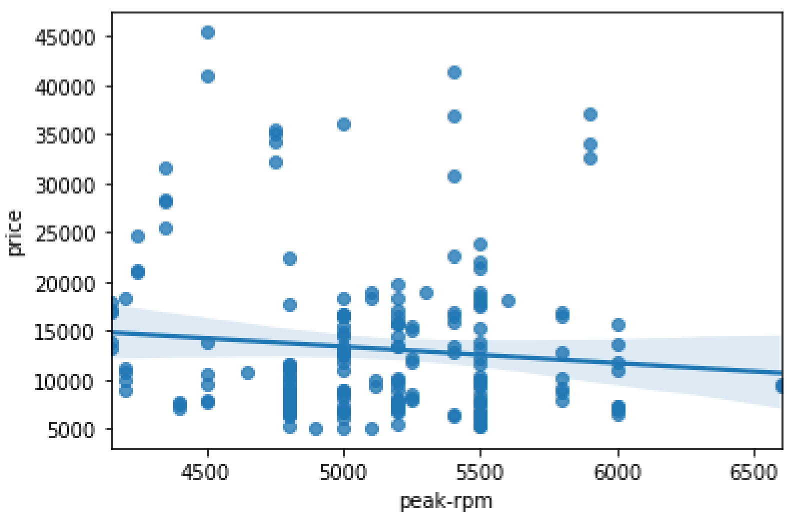
Out[239…

	highway-mpg	price
highway-mpg	1.000000	-0.704692
price	-0.704692	1.000000

In [240…

```
# create scatterplot for peak-rpm and price
sns.regplot(x="peak-rpm", y="price", data=df)
# does not seem like a good indicator of price
```

Out[240… <AxesSubplot:xlabel='peak-rpm', ylabel='price'>



In [241…

```
# examine correlation of peak-rpm and price
df[['peak-rpm','price']].corr()
# weak linear relationship
```

Out[241…

	peak-rpm	price
peak-rpm	1.000000	-0.101542

	peak-rpm	price
price	-0.101542	1.000000

In [242...

```
# find correlation of stroke and price
df[["stroke","price"]].corr()
```

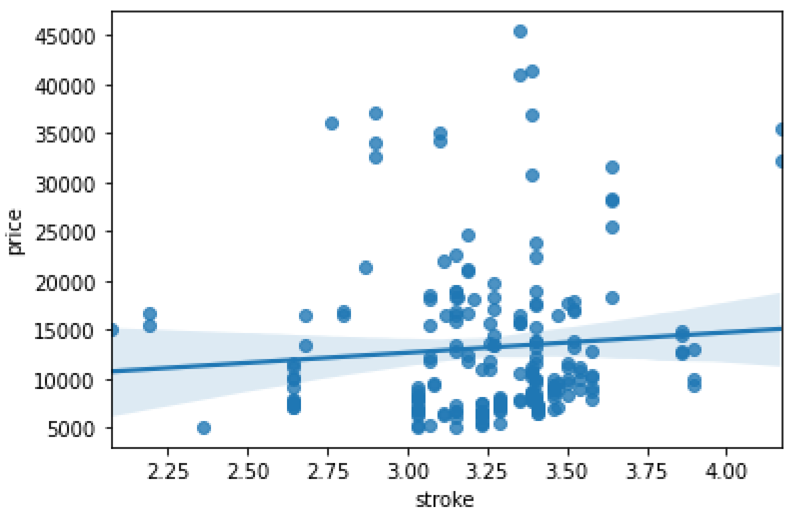
Out[242...

	stroke	price
stroke	1.000000	0.082267
price	0.082267	1.000000

In [243...

```
# There is a weak correlation between the variable 'stroke' and 'price.' as such regres
sns.regplot(x="stroke", y="price", data=df)
```

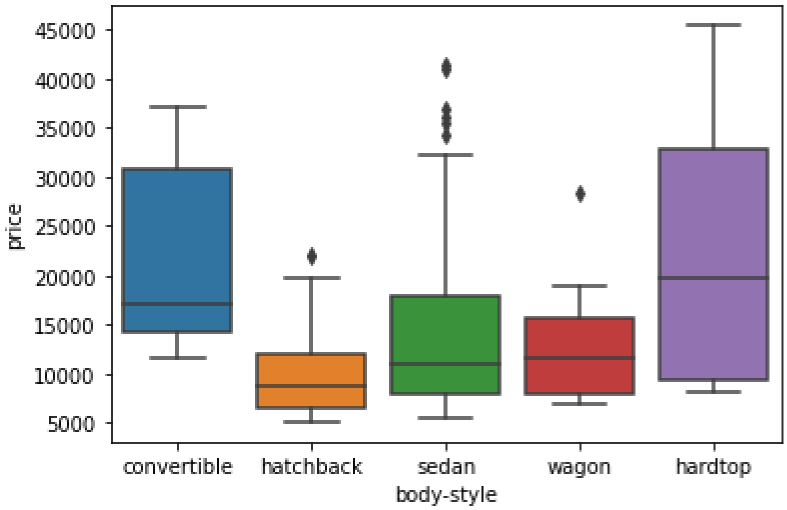
Out[243... <AxesSubplot:xlabel='stroke', ylabel='price'>



In [244...

```
# use boxplots to better understand categorical variables
# analyze body-style and price relationship
sns.boxplot(x="body-style", y="price", data=df)
# there is significant overlap, so body style is not a good indicator of price
```

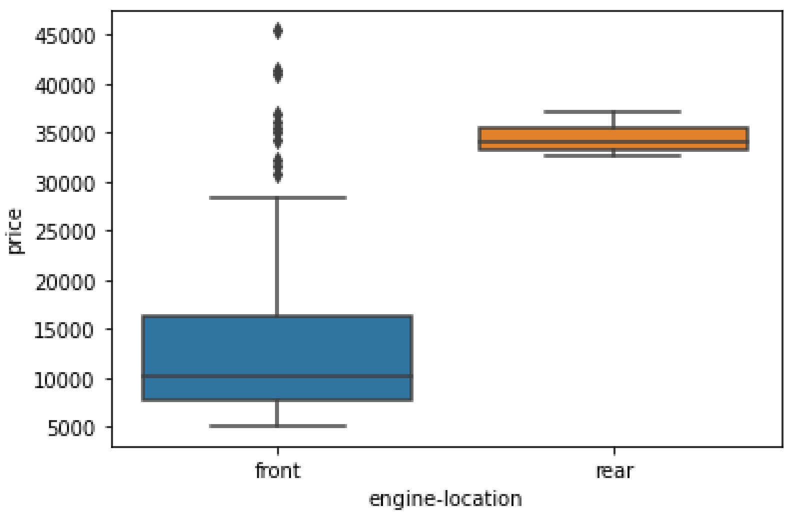
Out[244... <AxesSubplot:xlabel='body-style', ylabel='price'>



In [245…

```
# plot engine-location and price
sns.boxplot(x="engine-location", y="price", data=df)
# engine could potentially be a good indicator of price
```

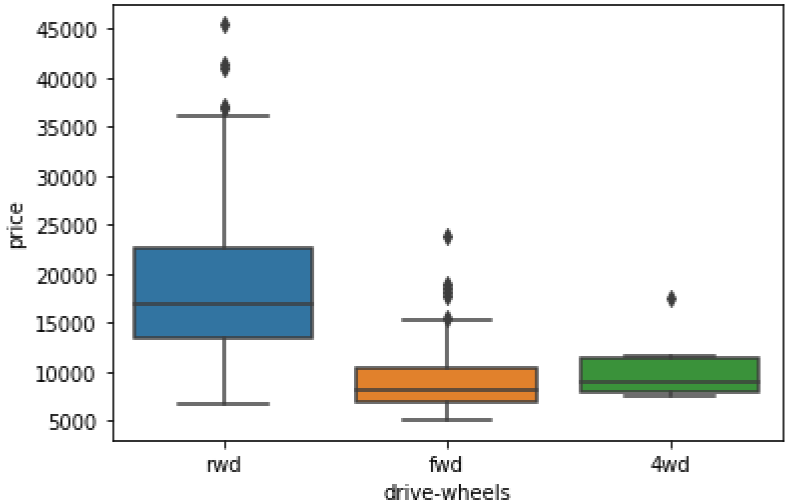
Out[245… <AxesSubplot:xlabel='engine-location', ylabel='price'>



In [246…

```
# plot drive-wheels and price
sns.boxplot(x="drive-wheels", y="price", data=df)
# potentially a good indicator of price
```

Out[246… <AxesSubplot:xlabel='drive-wheels', ylabel='price'>



Descriptive Statistical Analysis

In [247…

```
# get basic statistics
df.describe()
```

Out[247…

	symboling	normalized-losses	wheel-base	length	width	height	curb-weight	engine-size
count	201.000000	201.00000	201.000000	201.000000	201.000000	201.000000	201.000000	201.00000
mean	0.840796	122.00000	98.797015	0.837102	0.915126	0.899108	2555.666667	126.87562
std	1.254802	31.99625	6.066366	0.059213	0.029187	0.040933	517.296727	41.54683
min	-2.000000	65.00000	86.600000	0.678039	0.837500	0.799331	1488.000000	61.00000
25%	0.000000	101.00000	94.500000	0.801538	0.890278	0.869565	2169.000000	98.00000
50%	1.000000	122.00000	97.000000	0.832292	0.909722	0.904682	2414.000000	120.00000
75%	2.000000	137.00000	102.400000	0.881788	0.925000	0.928094	2926.000000	141.00000
max	3.000000	256.00000	120.900000	1.000000	1.000000	1.000000	4066.000000	326.00000

In [248…

```
# include objects in descriptive statistics
df.describe(include = ['object'])
```

Out[248…

	make	num-of-doors	body-style	drive-wheels	engine-location	engine-type	num-of-cylinders	fuel-system
count	201	201	201	201	201	201	201	201
unique	22	2	5	3	2	6	7	8
top	toyota	four	sedan	fwd	front	ohc	four	mpfi
freq	32	115	94	118	198	145	157	92

In [249…

```
# use value_counts() to get an understanding of how many units of drive-wheels we have
# note value_counts() only works on pandas series, not dataframes, so only use one brac
```

```
df['drive-wheels'].value_counts()
```

Out[249…

```
fwd    118
rwd     75
4wd      8
Name: drive-wheels, dtype: int64
```

In [250…

```
# convert it into a dataframe
drive_wheels_counts = df['drive-wheels'].value_counts().to_frame()
```

In [251…

```
# rename columns
drive_wheels_counts.rename(columns={'drive-wheels': 'value_counts'}, inplace=True)
drive_wheels_counts
```

Out[251…

	value_counts
fwd	118
rwd	75
4wd	8

In [252…

```
# get engine-location count data
engine_loc_counts = df['engine-location'].value_counts().to_frame()
```

In [253…

```
# rename columns
engine_loc_counts.rename(columns={'engine-location': 'value_counts'}, inplace=True)
```

In [254…

```
# update index name
engine_loc_counts.index.name = 'engine-location'
engine_loc_counts.head(10)
```

Out[254…

	value_counts
engine-location	
front	198
rear	3

Grouping Basics

The groupby method groups data by different categories, based off one or several variables, and analysis is then performed on individual groups.

In [255…

```
# group drive-wheels
df['drive-wheels'].unique()
```

Out[255…

```
array(['rwd', 'fwd', '4wd'], dtype=object)
```

In [256…

```
# group drive-wheels, body-style, and price
df_group_one = df[['drive-wheels','body-style','price']]
```

In [257…

```
# calculate the average price for each category of data
df_group_one = df_group_one.groupby(['drive-wheels'],as_index=False).mean()
df_group_one
```

Out[257…

	drive-wheels	price
0	4wd	10241.000000
1	fwd	9244.779661
2	rwd	19757.613333

In [258…

```
# group by multiple variables drive-wheels, body-style, price
df_gptest = df[['drive-wheels','body-style','price']]
grouped_test1 = df_gptest.groupby(['drive-wheels','body-style'],as_index=False).mean()
grouped_test1
# this data is much easier to visualize with a pivot table
```

Out[258…

	drive-wheels	body-style	price
0	4wd	hatchback	7603.000000
1	4wd	sedan	12647.333333
2	4wd	wagon	9095.750000
3	fwd	convertible	11595.000000
4	fwd	hardtop	8249.000000
5	fwd	hatchback	8396.387755
6	fwd	sedan	9811.800000
7	fwd	wagon	9997.333333
8	rwd	convertible	23949.600000
9	rwd	hardtop	24202.714286
10	rwd	hatchback	14337.777778
11	rwd	sedan	21711.833333
12	rwd	wagon	16994.222222

In [259…

```
# set up data for pivot table with drive wheels in rows, body-style to columns
grouped_pivot = grouped_test1.pivot(index='drive-wheels',columns='body-style')
grouped_pivot
```

Out[259…

					price
body-style	**convertible**	**hardtop**	**hatchback**	**sedan**	**wagon**
drive-wheels					

	price				
body-style	convertible	hardtop	hatchback	sedan	wagon
drive-wheels					
4wd	NaN	NaN	7603.000000	12647.333333	9095.750000
fwd	11595.0	8249.000000	8396.387755	9811.800000	9997.333333
rwd	23949.6	24202.714286	14337.777778	21711.833333	16994.222222

In [260…

```
# if there is some missing data, fill in
grouped_pivot = grouped_pivot.fillna(0) #fill missing values with 0
grouped_pivot
```

Out[260…

	price				
body-style	convertible	hardtop	hatchback	sedan	wagon
drive-wheels					
4wd	0.0	0.000000	7603.000000	12647.333333	9095.750000
fwd	11595.0	8249.000000	8396.387755	9811.800000	9997.333333
rwd	23949.6	24202.714286	14337.777778	21711.833333	16994.222222

In [261…

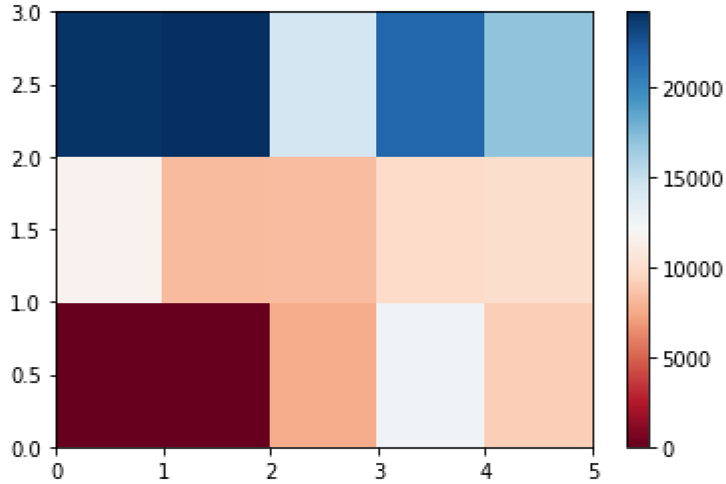
```
# use the groupby function to get the average price for each car based on body style
df_gptest2 = df[['body-style','price']]
grouped_test_bodystyle = df_gptest2.groupby(['body-style'],as_index= False).mean()
grouped_test_bodystyle
```

Out[261…

	body-style	price
0	convertible	21890.500000
1	hardtop	22208.500000
2	hatchback	9957.441176
3	sedan	14459.755319
4	wagon	12371.960000

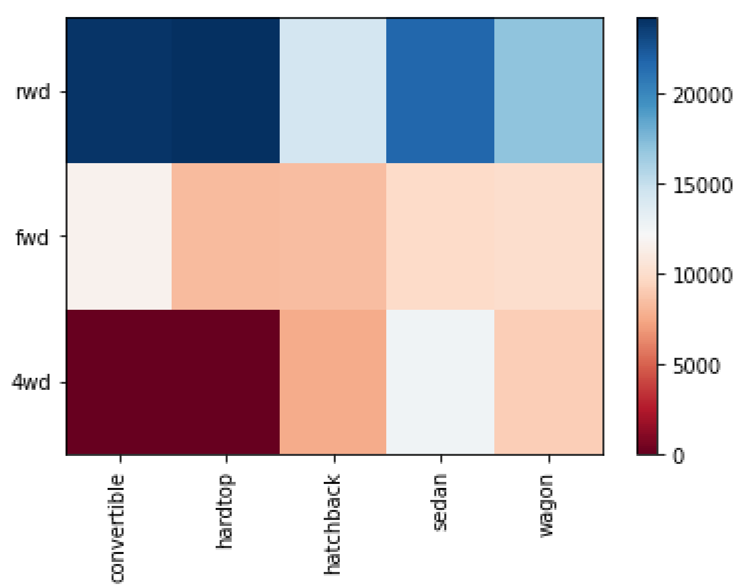
In [262…

```
# use a heat map to visualize body style vs price
pyplot.pcolor(grouped_pivot, cmap='RdBu')
pyplot.colorbar()
pyplot.show()
```



In [263…

```
# update plot with detailed information
fig, ax = pyplot.subplots()
im = ax.pcolor(grouped_pivot, cmap='RdBu')

#label names
row_labels = grouped_pivot.columns.levels[1]
col_labels = grouped_pivot.index

#move ticks and labels to the center
ax.set_xticks(np.arange(grouped_pivot.shape[1]) + 0.5, minor=False)
ax.set_yticks(np.arange(grouped_pivot.shape[0]) + 0.5, minor=False)

#insert labels
ax.set_xticklabels(row_labels, minor=False)
ax.set_yticklabels(col_labels, minor=False)

#rotate label if too long
pyplot.xticks(rotation=90)

fig.colorbar(im)
pyplot.show()
```



Correlation and Causation

Correlation: a measure of the extent of interdependence between variables

Causation: the relationship between cause and effect between two variables.

Correlation does not imply causation. Determining correlation is much simpler than determining causation as causation may require independent experimentation.

Pearson Correlation:

- Measures the linear dependence between two variables X and Y.
- The resulting coefficient is a value between -1 and 1 where:
  - 1: perfect positive linear correlation
  - 0: no linear correlation
  - -1: perfect negative linear correlation
- Pearson correlation is the default method of function .corr()

P-value:

- The probability that the correlation between two variables is statistically significant.
- Normally we choose a significance level of .05, which means we are 95% confident that the correlation is significant.
- By convention:
  - p-value is $<$ 0.001: we say there is strong evidence that the correlation is significant.
  - the p-value is $<$ 0.05: there is moderate evidence that the correlation is significant.
  - the p-value is $<$ 0.1: there is weak evidence that the correlation is significant.
  - the p-value is $>$ 0.1: there is no evidence that the correlation is significant.
- Obtain this information using the stats module of the SciPy library.

In [264…

```
# calculate the pearson correlation coefficient and p value of wheel base and price
pearson_coef, p_value = stats.pearsonr(df['wheel-base'], df['price'])
print("The Pearson Correlation Coefficient is", pearson_coef, " with a P-value of P =",
# since the p-value is <.001, the correlation is statistically significant
# though the linear relationship isn't super strong
```

```
The Pearson Correlation Coefficient is 0.584641822265508  with a P-value of P = 8.076488
270733218e-20
```

In [265…

```
# pearson correlation of horsepower vs price
pearson_coef, p_value = stats.pearsonr(df['horsepower'], df['price'])
print("The Pearson Correlation Coefficient is", pearson_coef, " with a P-value of P = "
# statistically significant and moderately strong relationship
```

```
The Pearson Correlation Coefficient is 0.8097290352560285  with a P-value of P =  5.9240
01027593172e-48
```

In [266…

```
# pearson correlation of width vs price
pearson_coef, p_value = stats.pearsonr(df['width'], df['price'])
print("The Pearson Correlation Coefficient is", pearson_coef, " with a P-value of P =",
# statistically significant and strong linear relationship
```

```
The Pearson Correlation Coefficient is 0.7512653440522672  with a P-value of P = 9.20033
551048217e-38
```

In [267…

```
# curb weight vs price
pearson_coef, p_value = stats.pearsonr(df['curb-weight'], df['price'])
print( "The Pearson Correlation Coefficient is", pearson_coef, " with a P-value of P =
# statistically significant and quite strong relationship
```

```
The Pearson Correlation Coefficient is 0.8344145257702843  with a P-value of P =  2.1895
77238894065e-53
```

In [268…

```
# engine-size vs price
pearson_coef, p_value = stats.pearsonr(df['engine-size'], df['price'])
print("The Pearson Correlation Coefficient is", pearson_coef, " with a P-value of P =",
# statistically significant and very strong relationship
```

```
The Pearson Correlation Coefficient is 0.8723351674455182  with a P-value of P = 9.26549
1622200232e-64
```

In [127…

```
# bore vs price
pearson_coef, p_value = stats.pearsonr(df['bore'], df['price'])
print("The Pearson Correlation Coefficient is", pearson_coef, " with a P-value of P =
# statistically significant and moderate linear relationship
```

```
The Pearson Correlation Coefficient is 0.5431537659807734  with a P-value of P =   8.051
208825441016e-17
```

In [269…

```
# city-mpg vs price
pearson_coef, p_value = stats.pearsonr(df['city-mpg'], df['price'])
print("The Pearson Correlation Coefficient is", pearson_coef, " with a P-value of P = "
# statistically significant and negative moderately strong relationship
```

```
The Pearson Correlation Coefficient is -0.6865710067844678  with a P-value of P =  2.321
132065567641e-29
```

In [270…

```
# highway mpg vs price
pearson_coef, p_value = stats.pearsonr(df['highway-mpg'], df['price'])
print( "The Pearson Correlation Coefficient is", pearson_coef, " with a P-value of P =
# statistically significant and negative moderately strong relationship
```

```
The Pearson Correlation Coefficient is -0.704692265058953  with a P-value of P =  1.7495
471144476358e-31
```

ANOVA

ANOVA:

- Analysis of Variance (ANOVA) is a statistical method used to test whether there are significant differences between the means of two or more groups.
- Returns two parameters:
  - F-Test score: ANOVA assumes the means of all groups are the same, calculates how much teh actual means deviate from teh assumption and reports it as the Ftest score. A larger score indicates a larger difference between the means.
  - P-value: tells how statistically significant the calculated score value is.
- If the price variable is strongly correlated with the variable we're analyzing, we expect ANOVA to return a sizeable F-test score and a small p-value.

In [271…

```
# group drive-wheels data to see if it impacts price
grouped_test2=df_gptest[['drive-wheels', 'price']].groupby(['drive-wheels'])
grouped_test2.head(2)
```

Out[271…

	drive-wheels	price
0	rwd	13495.0
1	rwd	16500.0
3	fwd	13950.0
4	4wd	17450.0
5	fwd	15250.0
136	4wd	7603.0

In [272…

```
df_gptest
```

Out[272…

	drive-wheels	body-style	price
0	rwd	convertible	13495.0
1	rwd	convertible	16500.0
2	rwd	hatchback	16500.0
3	fwd	sedan	13950.0
4	4wd	sedan	17450.0
...	...	...	...
196	rwd	sedan	16845.0
197	rwd	sedan	19045.0
198	rwd	sedan	21485.0
199	rwd	sedan	22470.0
200	rwd	sedan	22625.0

201 rows × 3 columns

In [273…

```
# use f_oneway in stats module to get f-test score and p-value
# ANOVA
f_val, p_val = stats.f_oneway(grouped_test2.get_group('fwd')['price'], grouped_test2.ge

print( "ANOVA results: F=", f_val, ", P =", p_val)
# large f-score, small p-value indicates almost certain significance.
# does this mean all 3 tested groups are this highly correlated?
# examine them separately
```

```
ANOVA results: F= 67.95406500780399 , P = 3.3945443577151245e-23
```

In [274…

```
# FWD and RWD
f_val, p_val = stats.f_oneway(grouped_test2.get_group('fwd')['price'], grouped_test2.ge
```

```
print( "ANOVA results: F=", f_val, ", P =", p_val )
```

```
ANOVA results: F= 130.5533160959111 , P = 2.2355306355677845e-23
```

In [275…

```
# 4WD and RWD
f_val, p_val = stats.f_oneway(grouped_test2.get_group('4wd')['price'], grouped_test2.ge

print( "ANOVA results: F=", f_val, ", P =", p_val)
```

```
ANOVA results: F= 8.580681368924756 , P = 0.004411492211225333
```

In [276…

```
# 4WD and FWD
f_val, p_val = stats.f_oneway(grouped_test2.get_group('4wd')['price'], grouped_test2.ge

print("ANOVA results: F=", f_val, ", P =", p_val)
```

```
ANOVA results: F= 0.665465750252303 , P = 0.41620116697845666
```

We now have a better idea of what our data looks like and which variables are important to take into account when predicting the car price. We have narrowed it down to the following variables:

Continuous numerical variables:

- Length
- Width
- Curb-weight
- Engine-size
- Horsepower
- City-mpg
- Highway-mpg
- Wheel-base
- Bore

Categorical variables:

- Drive-wheels

As we now move into building machine learning models to automate our analysis, feeding the model with variables that meaningfully affect our target variable will improve our model's prediction performance.

Model Development

1. Linear Regression and Multiple Linear Regression
2. Model Evaluation with Visualization
3. Polynomial Regression and Pipelines
4. Measures for In-Sample Evaluation
5. Prediction and Decision Making

Linear Regression

SLR:

- Simple linear regression is a method to help us understand the relationship between two variables:
  - predictor / independent variable (X)
  - response / dependent / target variable that we want to predict (Y)
- SLR's result is a linear function that predicts the response variable as a function of the predictor variable.

In [277…

```
# create linear regression object
lm = LinearRegression()
lm
```

Out[277…

```
LinearRegression()
```

In [278…

```
# observe if highway-mpg could be a predictor of price
# set x and y
X = df[['highway-mpg']]
Y = df['price']
```

In [279…

```
# fit the linear model
lm.fit(X,Y)
```

Out[279…

```
LinearRegression()
```

In [280…

```
# output a prediction
Yhat=lm.predict(X)
Yhat[0:5]
```

Out[280…

```
array([16236.50464347, 16236.50464347, 17058.23802179, 13771.3045085 ,
       20345.17153508])
```

In [281…

```
# get the value of the intercept
lm.intercept_
```

Out[281…

```
38423.3058581574
```

In [282…

```
# get value of slope
lm.coef_
```

Out[282…

```
array([-821.73337832])
```

In [283…

```
# create linear regression object to be used for engine-size
lm1 = LinearRegression()
```

In [284…

```
# fit the object
lm1.fit(df[['engine-size']], df[['price']])
```

Out[284… LinearRegression()

In [285…
```
# get the slope
lm1.coef_
```

Out[285… array([[166.86001569]])

In [286…
```
# get the intercept
lm1.intercept_
```

Out[286… array([-7963.33890628])

In [287…
```
# get the equation of the predicted line
Yhat=-7963.34 + 166.86*X
Yhat
```

Out[287…

	highway-mpg
0	-3458.12
1	-3458.12
2	-3624.98
3	-2957.54
4	-4292.42
...	...
196	-3291.26
197	-3791.84
198	-4125.56
199	-3458.12
200	-3791.84

201 rows × 1 columns

Multiple Linear Regression

MLR:

- If we want to use more variables in the model to predict car price, use MLR.
- It's very similar to SLR, but can be used to explain the relationship between one continuous dependent varaible and two+ independent variables.

From previous sections, we know other potential good predictors of price include:

- horsepower
- curb-weight
- engine-size

- highway-mpg

In [288…

```
# develop a model using the above variables as the predictors
# get a sub dataframe
Z = df[['horsepower', 'curb-weight', 'engine-size', 'highway-mpg']]
```

In [289…

```
# fit the linear model
lm.fit(Z, df['price'])
```

Out[289…

```
LinearRegression()
```

In [290…

```
# get value of intercept
lm.intercept_
```

Out[290…

```
-15831.93096029949
```

In [291…

```
# what are the values of the coefficients?
lm.coef_
```

Out[291…

```
array([53.66247317,  4.70938694, 81.44600167, 36.55016267])
```

In [292…

```
# train an MLR model with predictors normalized-losses and highway-mpg
lm2 = LinearRegression()
lm2.fit(df[['normalized-losses' , 'highway-mpg']],df['price'])
```

Out[292…

```
LinearRegression()
```

In [293…

```
# get coefficients
lm2.coef_
```

Out[293…

```
array([   1.49789586, -820.45434016])
```

Model Evaluation using Visualization

One way to evaluate the models and choose which one is the best option is to use visualization tools such as:

- Regression plots
- Residual plots
- Distribution plots

Regression Plots:

- an excellent way to visualize SLR
- shows a combination of scatterplot and a fitted linear regression line
- gives a reasonable estimate of the relationship, strength of the correlation, and direction.

Residual Plots:

- The residual is the difference between the observed value Y and the predicted value Yhat.
- when looking at a regression plot, the residual is the distance between a data point to the fitted line.
- a residual plot shows the residuals on the y-axis and the independent on the x-axis.
- If the points on the residual are randomly spread out around the x-axis, a linear model is appropriate for the data.

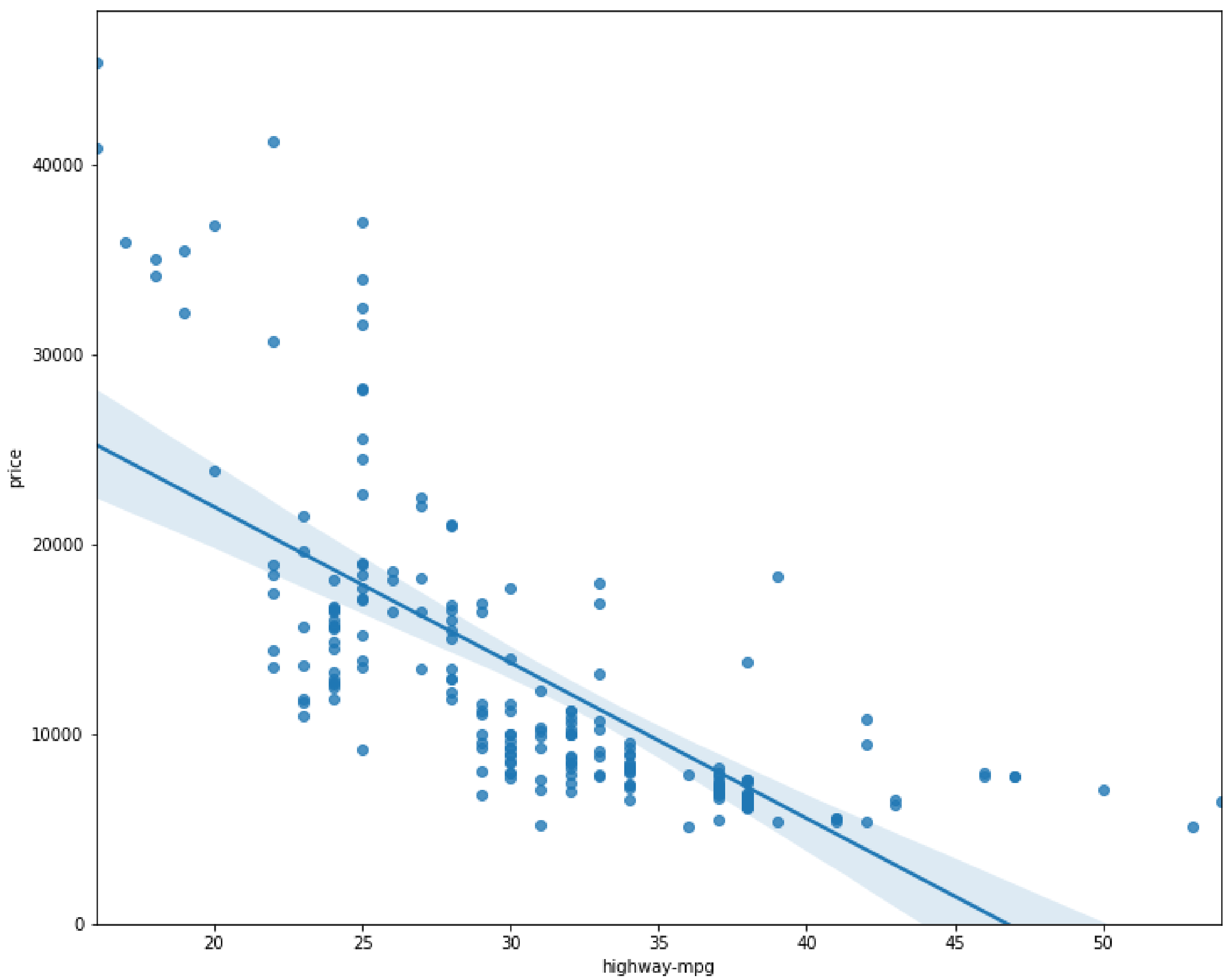
Distribution Plots:

- Useful for visualizing MLR
- Observe the fit of the model by looking at the distribution plot.
- Compare the distribution of the fitted values that result from the model and compare it to the distribution of the actual values.

In [294…

```
# visualize highway mpg as a potential predictor of price
width = 12
height = 10
pyplot.figure(figsize=(width, height))
sns.regplot(x="highway-mpg", y="price", data=df)
pyplot.ylim(0,)
```

Out[294… (0.0, 48173.16523919806)

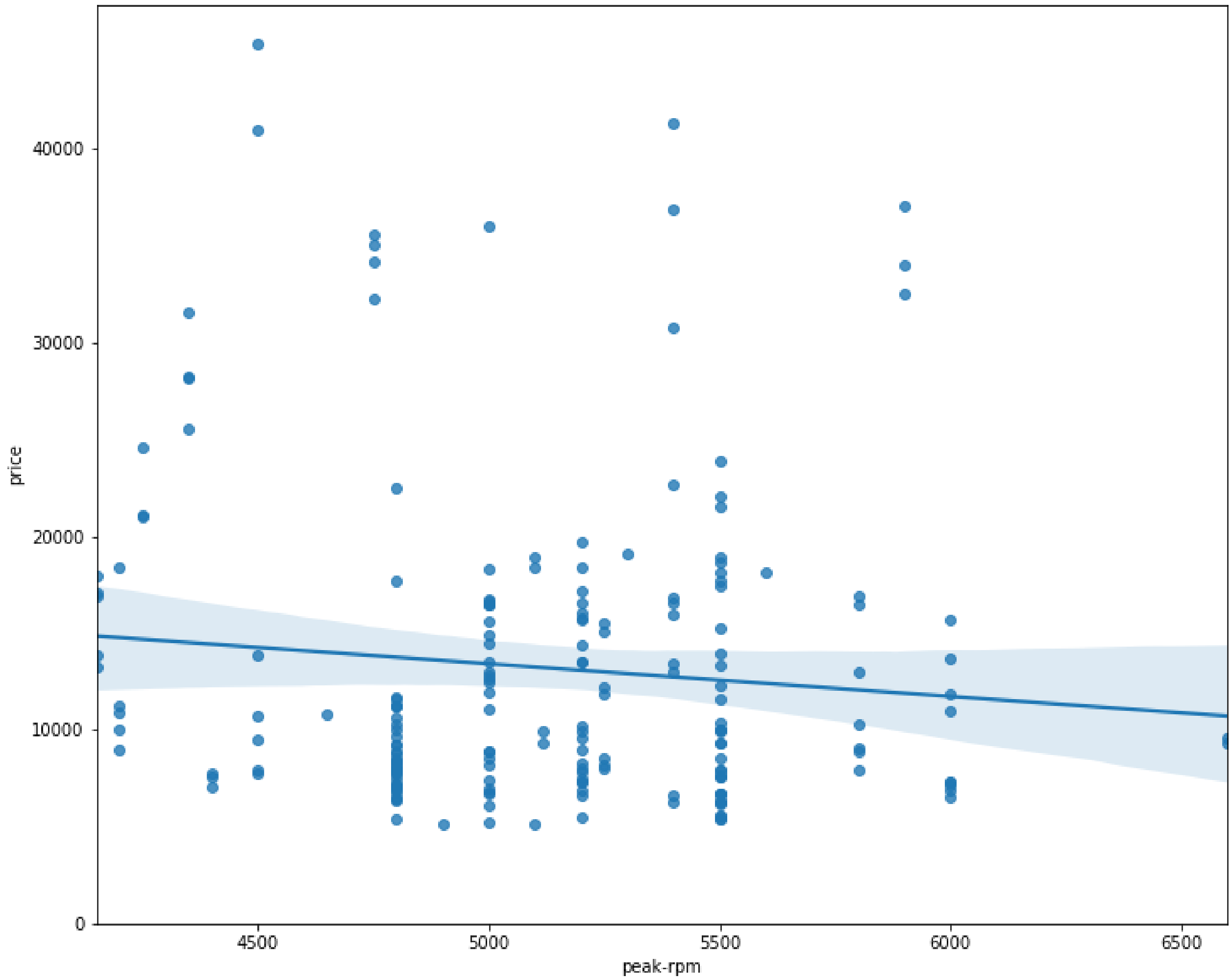


In [295…

```
# plot peak-rpm
pyplot.figure(figsize=(width, height))
sns.regplot(x="peak-rpm", y="price", data=df)
pyplot.ylim(0,)
#
```

Out[295…

```
(0.0, 47414.1)
```



In [296…

```
# between highway-mpg and peak-rpm, which is more strongly correlated with price?
df[["peak-rpm","highway-mpg","price"]].corr()
# highway-mpg
```

Out[296…

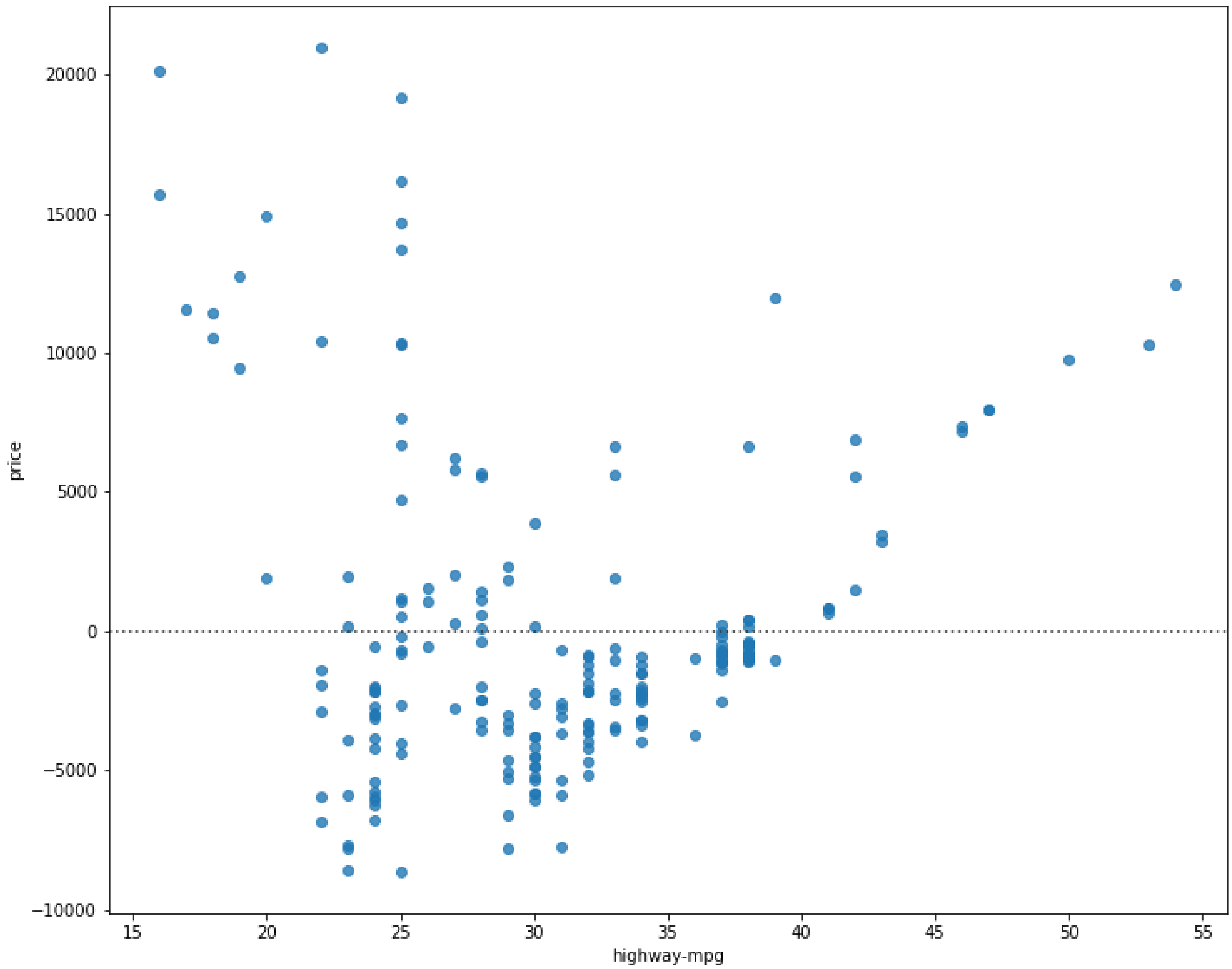
	peak-rpm	highway-mpg	price
peak-rpm	1.000000	-0.058605	-0.101542
highway-mpg	-0.058605	1.000000	-0.704692
price	-0.101542	-0.704692	1.000000

In [297…

```
# create a residual plot for highway-mpg
width = 12
height = 10
pyplot.figure(figsize=(width, height))
sns.residplot(df['highway-mpg'], df['price'])
```

```
pyplot.show()
# the residuals aren't randomly spread around the axis, so perhaps a non-linear model i
```

```
C:\Users\orgil\AppData\Roaming\Python\Python39\site-packages\seaborn\_decorators.py:36:
FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, th
e only valid positional argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```



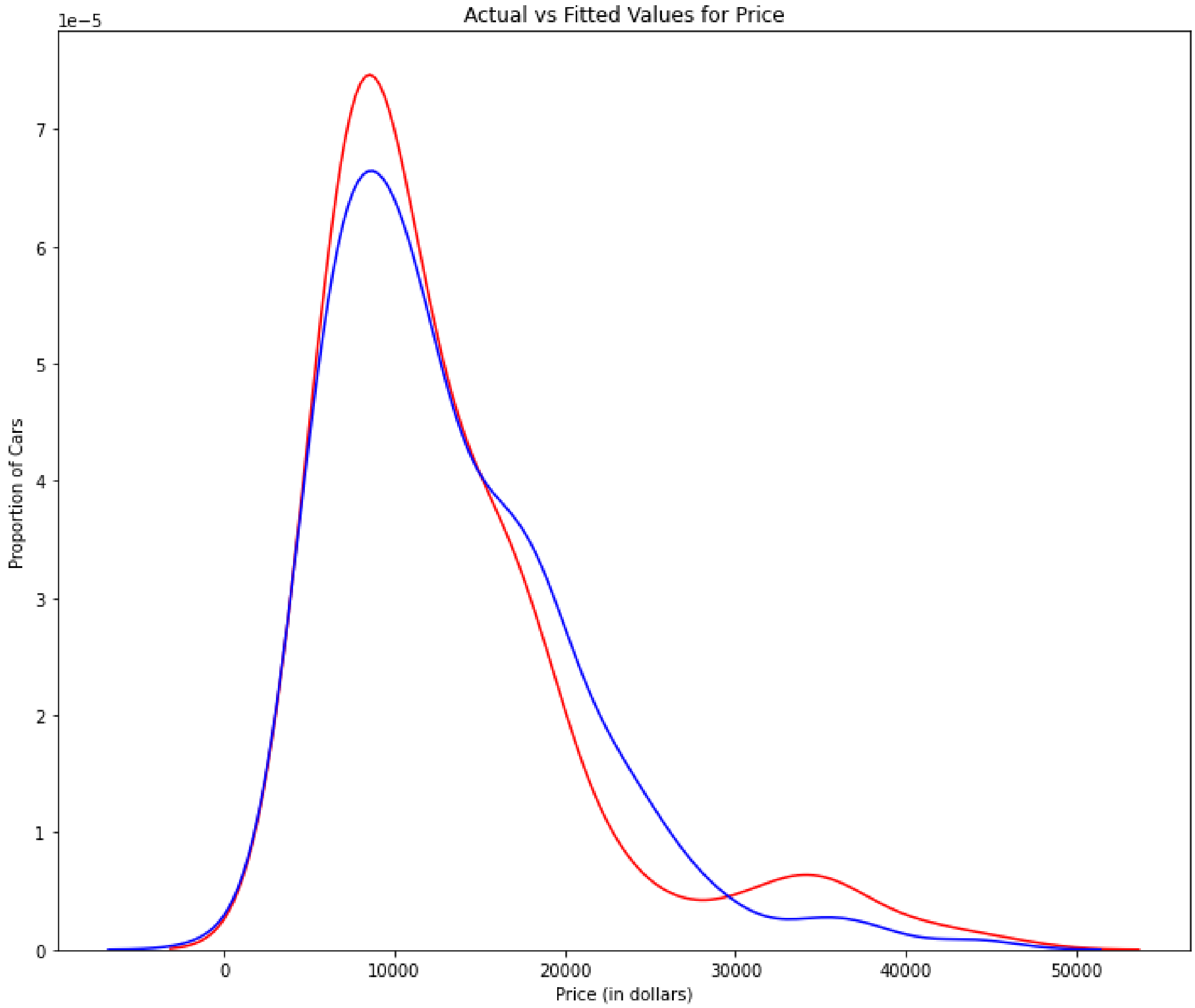
In [298…

```
# make a prediction for MLR
Y_hat = lm.predict(Z)
```

In [299…

```
# plot the distribution
pyplot.figure(figsize=(width, height))


ax1 = sns.distplot(df['price'], hist=False, color="r", label="Actual Value")
sns.distplot(Y_hat, hist=False, color="b", label="Fitted Values" , ax=ax1)


pyplot.title('Actual vs Fitted Values for Price')
pyplot.xlabel('Price (in dollars)')
pyplot.ylabel('Proportion of Cars')

pyplot.show()
pyplot.close()
# the fitted values are reasonably close tot eh actual values, but there is room for im
```

```
C:\Users\orgil\AppData\Roaming\Python\Python39\site-packages\seaborn\distributions.py:25
57: FutureWarning: `distplot` is a deprecated function and will be removed in a future v
ersion. Please adapt your code to use either `displot` (a figure-level function with sim
ilar flexibility) or `kdeplot` (an axes-level function for kernel density plots).
  warnings.warn(msg, FutureWarning)
C:\Users\orgil\AppData\Roaming\Python\Python39\site-packages\seaborn\distributions.py:25
57: FutureWarning: `distplot` is a deprecated function and will be removed in a future v
ersion. Please adapt your code to use either `displot` (a figure-level function with sim
ilar flexibility) or `kdeplot` (an axes-level function for kernel density plots).
  warnings.warn(msg, FutureWarning)
```



Polynomial Regression

Polynomial Regression

- A particular case of the SLR or MLR models.
- We get non-linear relationships by using higher-order terms of the predictor variables.

In [300…

```
# use a non-linear model for highway-mpg
# define plotpolly function to plot the data
def PlotPolly(model, independent_variable, dependent_variabble, Name):
    x_new = np.linspace(15, 55, 100)
    y_new = model(x_new)

    pyplot.plot(independent_variable, dependent_variabble, '.', x_new, y_new, '-')
```

```
    pyplot.title('Polynomial Fit with Matplotlib for Price ~ Length')
    ax = pyplot.gca()
    ax.set_facecolor((0.898, 0.898, 0.898))
    fig = pyplot.gcf()
    pyplot.xlabel(Name)
    pyplot.ylabel('Price of Cars')

    pyplot.show()
    pyplot.close()
```

In [301…

```
# get the variables
x = df['highway-mpg']
y = df['price']
```

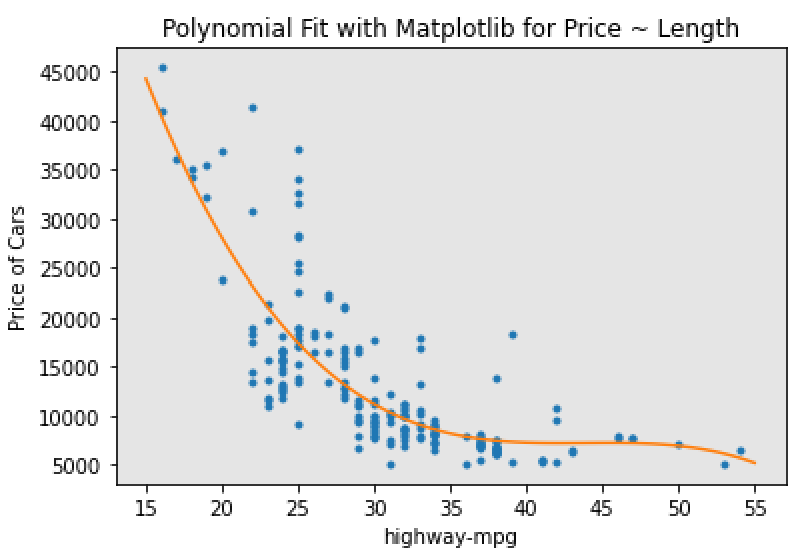
In [302…

```
# fit the polynomial
# Here we use a polynomial of the 3rd order (cubic)
f = np.polyfit(x, y, 3)
p = np.poly1d(f)
print(p)
```

```
        3         2
-1.557 x + 204.8 x - 8965 x + 1.379e+05
```

In [303…

```
# plot the function
PlotPolly(p, x, y, 'highway-mpg')
```



In [304…

```
df.head()
```

Out[304…

	symboling	normalized-losses	make	num-of-doors	body-style	drive-wheels	engine-location	wheel-base	length	width	…
0	3	122	alfa-romero	two	convertible	rwd	front	88.6	0.811148	0.890278	…
1	3	122	alfa-romero	two	convertible	rwd	front	88.6	0.811148	0.890278	…

	symboling	normalized-losses	make	num-of-doors	body-style	drive-wheels	engine-location	wheel-base	length	width	...
2	1	122	alfa-romero	two	hatchback	rwd	front	94.5	0.822681	0.909722	..
3	2	164	audi	four	sedan	fwd	front	99.8	0.848630	0.919444	..
4	2	164	audi	four	sedan	4wd	front	99.4	0.848630	0.922222	..

5 rows × 29 columns

In [305…

```
# plotting indicates that this polynomial model fits better than the linear model
# because the generated polynomial function 'hits' more of the data points.
np.polyfit(x, y, 3)
```

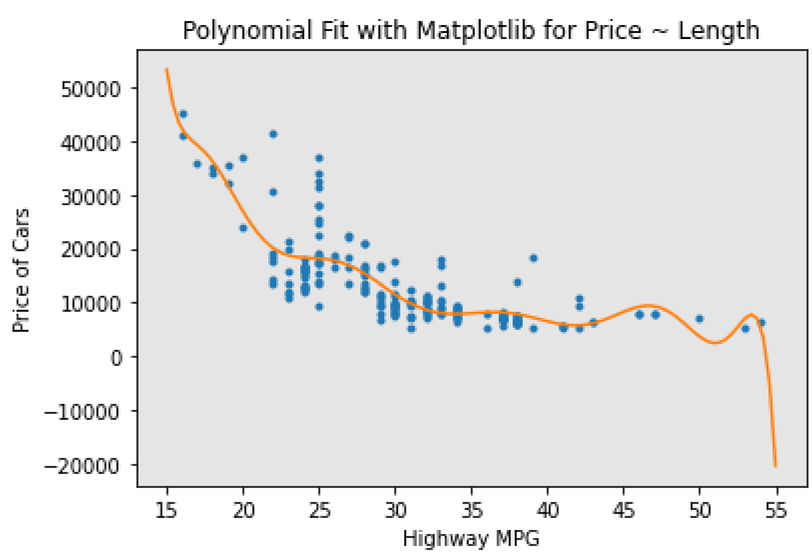
Out[305…

```
array([-1.55663829e+00,  2.04754306e+02, -8.96543312e+03,  1.37923594e+05])
```

In [306…

```
# try an 11th order polynomial model
# Here we use a polynomial of the 11rd order (cubic)
f1 = np.polyfit(x, y, 11)
p1 = np.poly1d(f1)
print(p1)
PlotPolly(p1,x,y, 'Highway MPG')
```

```
            11             10            9           8         7
-1.243e-08 x  + 4.722e-06 x  - 0.0008028 x + 0.08056 x - 5.297 x
         6         5             4             3             2
 + 239.5 x - 7588 x + 1.684e+05 x - 2.565e+06 x + 2.551e+07 x - 1.491e+08 x + 3.879e+08
```



In [309…

```
# create a polynomial feature object
pr=PolynomialFeatures(degree=2)
```

In [310…

```
# fit the object
Z_pr=pr.fit_transform(Z)
```

In [311…

```
# original data shape
Z.shape
```

Out[311… (201, 4)

In [312…

```
# transformed shape
Z_pr.shape
```

Out[312… (201, 15)

Pipelines

Pipelines simplify the steps of processing the data.

In [314…

```
# create a list of tuples with the name of the model/estimator and its constructor
Input=[('scale',StandardScaler()), ('polynomial', PolynomialFeatures(include_bias=False
```

In [315…

```
# input the list as an argument to the pipeline constructor
pipe=Pipeline(Input)
pipe
```

Out[315…

```
Pipeline(steps=[('scale', StandardScaler()),
                ('polynomial', PolynomialFeatures(include_bias=False)),
                ('model', LinearRegression())])
```

In [316…

```
# convert the data type of z to float to avoid conversion warnings
Z = Z.astype(float)
```

In [317…

```
# use the pipeline to normalize the data, perform the transformation, and fit the model
pipe.fit(Z,y)
```

Out[317…

```
Pipeline(steps=[('scale', StandardScaler()),
                ('polynomial', PolynomialFeatures(include_bias=False)),
                ('model', LinearRegression())])
```

In [318…

```
# use the pipeline to normalize the data, perform a transformation, and produce a predi
ypipe=pipe.predict(Z)
ypipe[0:4]
```

Out[318…

```
array([13103.67557905, 13103.67557905, 18229.84126783, 10394.17656982])
```

In [319…

```
# create a pipeline that standardizes the data, produces a prediction using a linear re
Input=[('scale',StandardScaler()),('model',LinearRegression())]
pipe=Pipeline(Input)

# fit the pipeline
pipe.fit(Z,y)

# get a prediction
ypipe=pipe.predict(Z)
ypipe[0:10]
```

Out[319…
```
array([13698.95609311, 13698.95609311, 19056.78572196, 10621.59764327,
       15519.32197778, 13867.78444008, 15454.84783873, 15972.88040209,
       17614.41285158, 10723.08344825])
```

Measures for In-Sample evaluation

When evaluating models, not only do we want visualizations of the results but we also need a quantitative measure to determine the accuracy of the model.

Two important measures often used are:

- R-squared
- Mean Squared Error (MSE)

R-Squared:

- coefficient of determination
- a measure to indicate how close the data is to the fitted regression line
- the value of R-Squared if the percentage of variation of the response variable (y) that is explained by the linear model
- when comparing models, the model with the higher Rsquare value is a better fit for the data.

MSE:

- measures the average of the square of errors, i.e. the difference between actual value Y and estimated value Yhat
- when comparing models, the model with the smallest MSE is a better fit for the data.

In [320…
```
# calculate Rsquare of SLR model
#highway_mpg_fit
lm.fit(X, Y)
# Find the R^2
print('The R-square is: ', lm.score(X, Y))
```

```
The R-square is:  0.4965911884339176
```

In [321…
```
# calculate MSE
Yhat=lm.predict(X)
print('The output of the first four predicted value is: ', Yhat[0:4])
```

```
The output of the first four predicted value is:  [16236.50464347 16236.50464347 17058.2
3802179 13771.3045085 ]
```

In [323…
```
# compare predicted results with actual results
mse = mean_squared_error(df['price'], Yhat)
print('The mean square error of price and predicted value is: ', mse)
```

```
The mean square error of price and predicted value is:  31635042.944639888
```

In [324…
```
# calculate Rsquare of MLR model
# fit the model
lm.fit(Z, df['price'])
```

```
# Find the R^2
print('The R-square is: ', lm.score(Z, df['price']))
```

```
The R-square is:  0.80943904228153
```

In [325…

```
# get a prediction
Y_predict_multifit = lm.predict(Z)
```

In [326…

```
# compare predicted results with actual results
print('The mean square error of price and predicted value using multifit is: ', \
      mean_squared_error(df['price'], Y_predict_multifit))
```

```
The mean square error of price and predicted value using multifit is:  11975165.99330355
```

In [328…

```
# get Rsquare of Polynomial model
r_squared = r2_score(y, p(x))
print('The R-square value is: ', r_squared)
```

```
The R-square value is:  0.674194666390652
```

In [329…

```
# get MSE of polynomial model
mean_squared_error(df['price'], p(x))
```

Out[329…

```
20474146.426361218
```

Prediction and Decision Making

Use the method predict to produce a prediction.

In [330…

```
# create new input
new_input=np.arange(1, 100, 1).reshape(-1, 1)
```

In [331…

```
# fit the model
lm.fit(X, Y)
```

Out[331…

```
LinearRegression()
```

In [332…

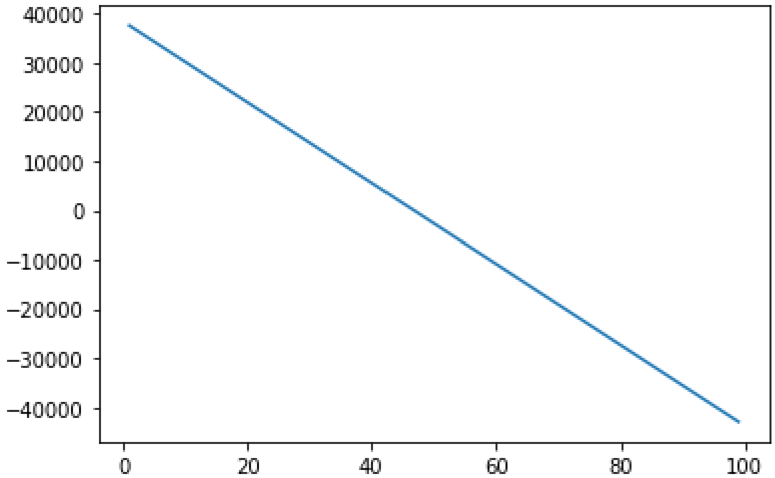
```
# produce prediction
yhat=lm.predict(new_input)
yhat[0:5]
```

Out[332…

```
array([37601.57247984, 36779.83910151, 35958.10572319, 35136.37234487,
       34314.63896655])
```

In [333…

```
# plot the data
pyplot.plot(new_input, yhat)
pyplot.show()
```



Decision Making: Determining a Good Model Fit

Now that we have visualized the different models, and generated the R-squared and MSE values for the fits, how do we determine a good model fit?

- *What is a good R-squared value?*

When comparing models, **the model with the higher R-squared value is a better fit** for the data.

- *What is a good MSE?*

When comparing models, **the model with the smallest MSE value is a better fit** for the data.

Let's take a look at the values for the different models.

Simple Linear Regression: Using Highway-mpg as a Predictor Variable of Price.

- R-squared: 0.49659118843391759
- MSE: 3.16 x10^7

Multiple Linear Regression: Using Horsepower, Curb-weight, Engine-size, and Highway-mpg as Predictor Variables of Price.

- R-squared: 0.80896354913783497
- MSE: 1.2 x10^7

Polynomial Fit: Using Highway-mpg as a Predictor Variable of Price.

- R-squared: 0.6741946663906514
- MSE: 2.05 x 10^7

Simple Linear Regression Model (SLR) vs Multiple Linear Regression Model (MLR)

Usually, the more variables you have, the better your model is at predicting, but this is not always true. Sometimes you may not have enough data, you may run into numerical problems, or many of the variables may not be useful and even act as noise. As a result, you should always check the MSE and R^2.

In order to compare the results of the MLR vs SLR models, we look at a combination of both the R-squared and MSE to make the best conclusion about the fit of the model.

- **MSE**: The MSE of SLR is 3.16x10^7 while MLR has an MSE of 1.2 x10^7. The MSE of MLR is much smaller.
- **R-squared**: In this case, we can also see that there is a big difference between the R-squared of the SLR and the R-squared of the MLR. The R-squared for the SLR (~0.497) is very small compared to the R-squared for the MLR (~0.809).

This R-squared in combination with the MSE show that MLR seems like the better model fit in this case compared to SLR.

Simple Linear Model (SLR) vs. Polynomial Fit

- **MSE**: We can see that Polynomial Fit brought down the MSE, since this MSE is smaller than the one from the SLR.
- **R-squared**: The R-squared for the Polynomial Fit is larger than the R-squared for the SLR, so the Polynomial Fit also brought up the R-squared quite a bit.

Since the Polynomial Fit resulted in a lower MSE and a higher R-squared, we can conclude that this was a better fit model than the simple linear regression for predicting "price" with "highway-mpg" as a predictor variable.

Multiple Linear Regression (MLR) vs. Polynomial Fit

- **MSE**: The MSE for the MLR is smaller than the MSE for the Polynomial Fit.
- **R-squared**: The R-squared for the MLR is also much larger than for the Polynomial Fit.

Conclusion

Comparing these three models, we conclude that **the MLR model is the best model** to be able to predict price from our dataset. This result makes sense since we have 27 variables in total and we know that more than one of those variables are potential predictors of the final car price.

Model Evaluation

1. Model Evaluation
2. Overfitting, Underfitting, and Model Selection
3. Ridge Regression
4. Grid Search

In [338…

```
# Import clean data
path = 'https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBMDeveloper
df = pd.read_csv(path)
```

In [339…

```
# save the data
df.to_csv('module_5_auto.csv')
```

In [340…

```
# get numeric data only
df=df._get_numeric_data()
df.head()
```

Out[340...

	Unnamed: 0	Unnamed: 0.1	symboling	normalized-losses	wheel-base	length	width	height	curb-weight	engine-size
0	0	0	3	122	88.6	0.811148	0.890278	48.8	2548	130
1	1	1	3	122	88.6	0.811148	0.890278	48.8	2548	130
2	2	2	1	122	94.5	0.822681	0.909722	52.4	2823	152
3	3	3	2	164	99.8	0.848630	0.919444	54.3	2337	109
4	4	4	2	164	99.4	0.848630	0.922222	54.3	2824	136

5 rows × 21 columns

In [344...

```
# functions for plotting
def DistributionPlot(RedFunction, BlueFunction, RedName, BlueName, Title):
    width = 12
    height = 10
    pyplot.figure(figsize=(width, height))

    ax1 = sns.distplot(RedFunction, hist=False, color="r", label=RedName)
    ax2 = sns.distplot(BlueFunction, hist=False, color="b", label=BlueName, ax=ax1)

    pyplot.title(Title)
    pyplot.xlabel('Price (in dollars)')
    pyplot.ylabel('Proportion of Cars')

    pyplot.show()
    pyplot.close()
```

In [345...

```
def PollyPlot(xtrain, xtest, y_train, y_test, lr,poly_transform):
    width = 12
    height = 10
    pyplot.figure(figsize=(width, height))


    #training data
    #testing data
    # lr:  linear regression object
    #poly_transform:  polynomial transformation object

    xmax=max([xtrain.values.max(), xtest.values.max()])

    xmin=min([xtrain.values.min(), xtest.values.min()])

    x=np.arange(xmin, xmax, 0.1)


    pyplot.plot(xtrain, y_train, 'ro', label='Training Data')
    pyplot.plot(xtest, y_test, 'go', label='Test Data')
    pyplot.plot(x, lr.predict(poly_transform.fit_transform(x.reshape(-1, 1))), label='P
    pyplot.ylim([-10000, 60000])
```

```
    pyplot.ylabel('Price')
    pyplot.legend()
```

Training and Testing

It's important to split your data into training and testing data.

In [346…

```
# target data
y_data = df['price']
```

In [347…

```
# drop price data in dataframe
x_data=df.drop('price',axis=1)
```

In [350…

```
# randomly split the data into training and testing data
x_train, x_test, y_train, y_test = train_test_split(x_data, y_data, test_size=0.10, ran


print("number of test samples :", x_test.shape[0])
print("number of training samples:",x_train.shape[0])
# 10% of the dataset is for testing.
```

```
number of test samples : 21
number of training samples: 180
```

In [351…

```
# use train_test_split to split upt he dataset so that 40% is used for testing and rand
x_train1, x_test1, y_train1, y_test1 = train_test_split(x_data, y_data, test_size=0.4,
print("number of test samples :", x_test1.shape[0])
print("number of training samples:",x_train1.shape[0])
```

```
number of test samples : 81
number of training samples: 120
```

In [352…

```
# create linear regression object
lre=LinearRegression()
```

In [353…

```
# fit the model using feature horsepower
lre.fit(x_train[['horsepower']], y_train)
```

Out[353…

```
LinearRegression()
```

In [354…

```
# calculate rsquared on test data
lre.score(x_test[['horsepower']], y_test)
```

Out[354…

```
0.36358755750788263
```

In [355…

```
# calculate Rsquared on training data
lre.score(x_train[['horsepower']], y_train)

# the Rsquared is much smaller on the test data
```

Out[355… 0.6619724197515104

In [356…

```
# find the rsquare for the test data that uses 40% of the data for testing
x_train1, x_test1, y_train1, y_test1 = train_test_split(x_data, y_data, test_size=0.4,
lre.fit(x_train1[['horsepower']],y_train1)
lre.score(x_test1[['horsepower']],y_test1)
```

Out[356… 0.7139364665406973

Cross Validation Score

In [358…

```
# input the object, the feature, and the target data
Rcross = cross_val_score(lre, x_data[['horsepower']], y_data, cv=4)
```

In [360…

```
# the default score is rsquared.
# each element in the array has the average Rsquare value for the fold
Rcross
```

Out[360… array([0.7746232 , 0.51716687, 0.74785353, 0.04839605])

In [361…

```
# calculate the average and standard deviation of the estimate
print("The mean of the folds are", Rcross.mean(), "and the standard deviation is" , Rcr
```

```
The mean of the folds are 0.522009915042119 and the standard deviation is 0.291183944475
6029
```

In [362…

```
# use negative squared error as a score
-1 * cross_val_score(lre,x_data[['horsepower']], y_data,cv=4,scoring='neg_mean_squared_
```

Out[362…

```
array([20254142.84026702, 43745493.2650517 , 12539630.34014931,
       17561927.7224759 ])
```

In [363…

```
# calculate rsquared using two folds and get the average
Rc=cross_val_score(lre,x_data[['horsepower']], y_data,cv=2)
Rc.mean()
```

Out[363… 0.5166761697127429

In [366…

```
# use cross_val_predict to predict the output
yhat = cross_val_predict(lre,x_data[['horsepower']], y_data,cv=4)
yhat[0:5]
```

Out[366…

```
array([14141.63807508, 14141.63807508, 20814.29423473, 12745.03562306,
       14762.35027598])
```

Overfitting, Underfitting, and Model Selection

The test data (aka "out of sample data") is a much better measure of how well a model performs in the real world. One reason for this is overfitting.

Many of these differences are more apparent in MLR and Polynomial Regression.

In [367…

```
# create MLR objects and train them
lr = LinearRegression()
lr.fit(x_train[['horsepower', 'curb-weight', 'engine-size', 'highway-mpg']], y_train)
```

Out[367…

```
LinearRegression()
```

In [368…

```
# get prediction using training data
yhat_train = lr.predict(x_train[['horsepower', 'curb-weight', 'engine-size', 'highway-m
yhat_train[0:5]
```

Out[368…

```
array([ 7426.6731551 , 28323.75090803, 14213.38819709,  4052.34146983,
       34500.19124244])
```

In [369…

```
# get prediction using test data
yhat_test = lr.predict(x_test[['horsepower', 'curb-weight', 'engine-size', 'highway-mpg
yhat_test[0:5]
```

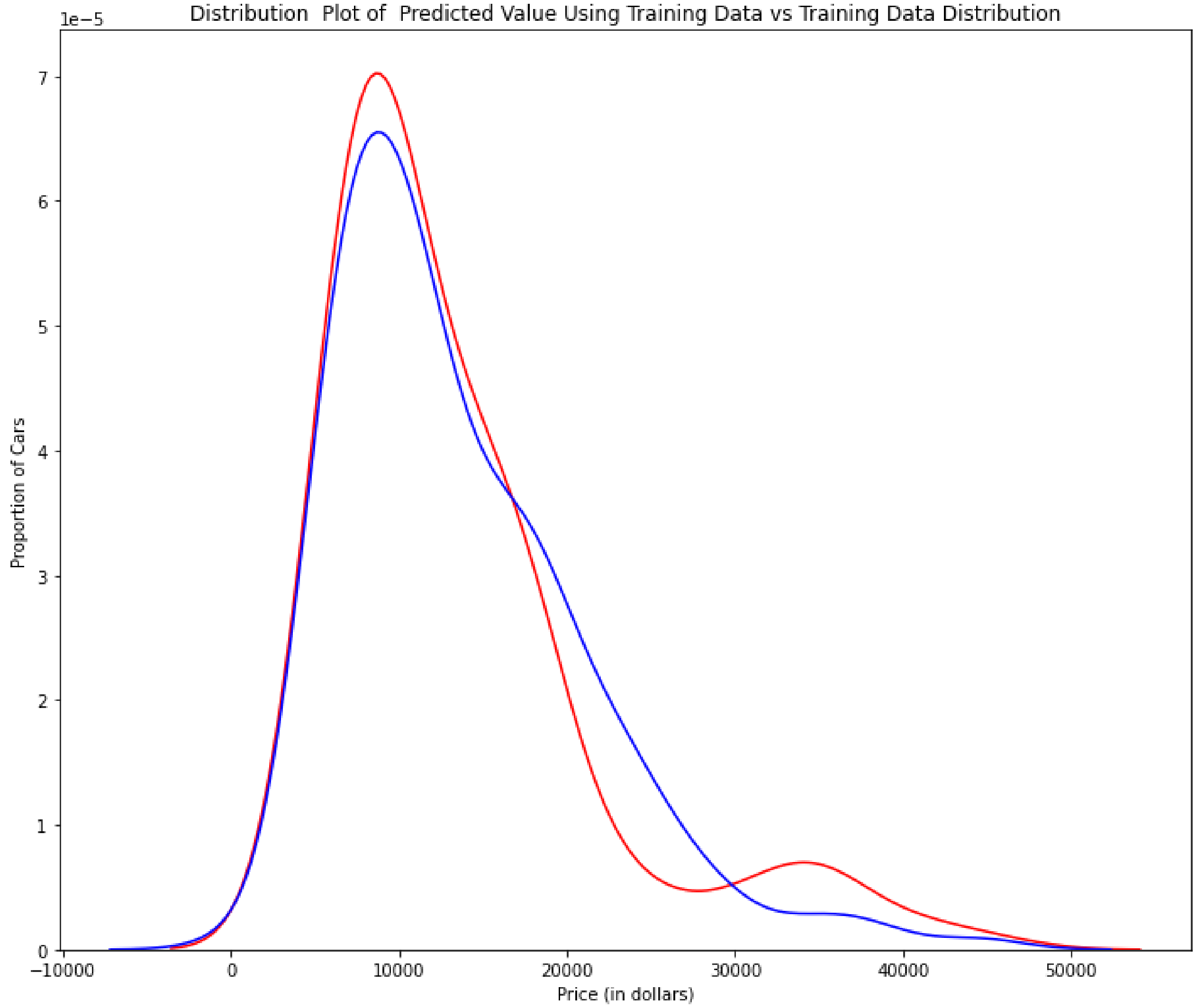
Out[369…

```
array([11349.35089149,  5884.11059106, 11208.6928275 ,  6641.07786278,
       15565.79920282])
```

In [372…

```
# perform some model evaluation with plotting
Title = 'Distribution  Plot of  Predicted Value Using Training Data vs Training Data Di
DistributionPlot(y_train, yhat_train, "Actual Values (Train)", "Predicted Values (Train

# plot of predicted values using training data compared to actual values of training da
```

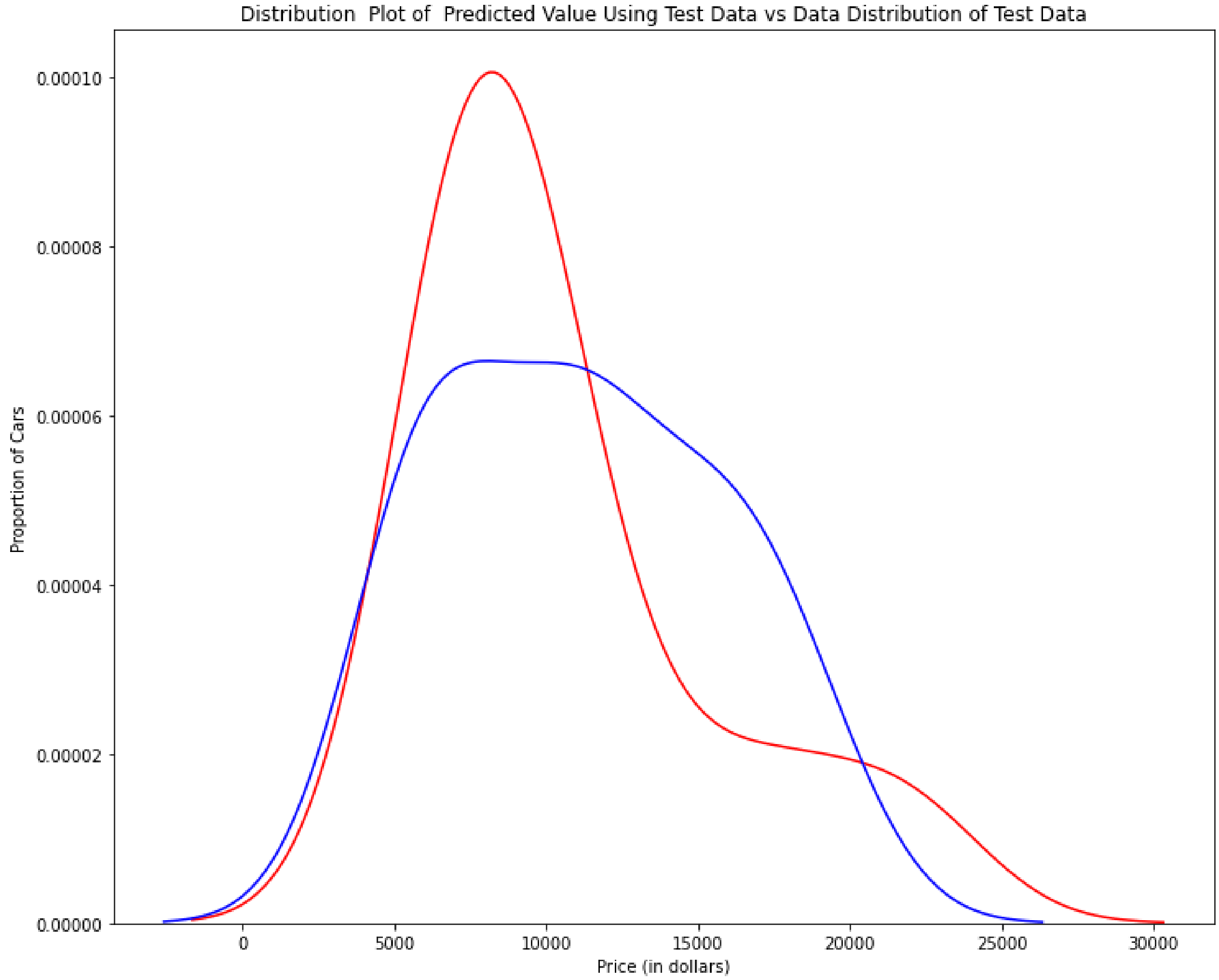
```
C:\Users\orgil\AppData\Roaming\Python\Python39\site-packages\seaborn\distributions.py:25
57: FutureWarning: `distplot` is a deprecated function and will be removed in a future v
ersion. Please adapt your code to use either `displot` (a figure-level function with sim
ilar flexibility) or `kdeplot` (an axes-level function for kernel density plots).
  warnings.warn(msg, FutureWarning)
C:\Users\orgil\AppData\Roaming\Python\Python39\site-packages\seaborn\distributions.py:25
57: FutureWarning: `distplot` is a deprecated function and will be removed in a future v
ersion. Please adapt your code to use either `displot` (a figure-level function with sim
ilar flexibility) or `kdeplot` (an axes-level function for kernel density plots).
  warnings.warn(msg, FutureWarning)
```



In [373…

```
# plot of predicted value using test data vs actual values of test data
Title='Distribution  Plot of  Predicted Value Using Test Data vs Data Distribution of T
DistributionPlot(y_test,yhat_test,"Actual Values (Test)","Predicted Values (Test)",Titl
```

```
C:\Users\orgil\AppData\Roaming\Python\Python39\site-packages\seaborn\distributions.py:25
57: FutureWarning: `distplot` is a deprecated function and will be removed in a future v
ersion. Please adapt your code to use either `displot` (a figure-level function with sim
ilar flexibility) or `kdeplot` (an axes-level function for kernel density plots).
  warnings.warn(msg, FutureWarning)
C:\Users\orgil\AppData\Roaming\Python\Python39\site-packages\seaborn\distributions.py:25
57: FutureWarning: `distplot` is a deprecated function and will be removed in a future v
ersion. Please adapt your code to use either `displot` (a figure-level function with sim
ilar flexibility) or `kdeplot` (an axes-level function for kernel density plots).
  warnings.warn(msg, FutureWarning)
```



Comparing these two graphs, it is evident that the test data of the first plot is much better at fitting the data.

The largest difference in the second plot is in teh range of 5000-15000, where the shape is very different.

Let's see if a polynomial regression also exhibits a drop in prediction accuracy when analyzing the test data set.

Overfitting occurs when the model fits the noise, but not the underlying process. Therefore, when testing your model using the test set, your model does not perform as well since it is modelling noise.

In [374…

```
# use a 55% of data for training
x_train, x_test, y_train, y_test = train_test_split(x_data, y_data, test_size=0.45, ran
```

In [375…

```
# perform degre 5 polynomial transformation
pr = PolynomialFeatures(degree=5)
x_train_pr = pr.fit_transform(x_train[['horsepower']])
x_test_pr = pr.fit_transform(x_test[['horsepower']])
pr
```

Out[375… PolynomialFeatures(degree=5)

In [376…

```
# create linear regression model
poly = LinearRegression()
poly.fit(x_train_pr, y_train)
```

Out[376… LinearRegression()

In [377…

```
# see the output of the model with predict
yhat = poly.predict(x_test_pr)
yhat[0:5]
```

Out[377…

```
array([ 6728.65566037,  7307.9878638 , 12213.7877412 , 18893.24796457,
       19995.95185894])
```

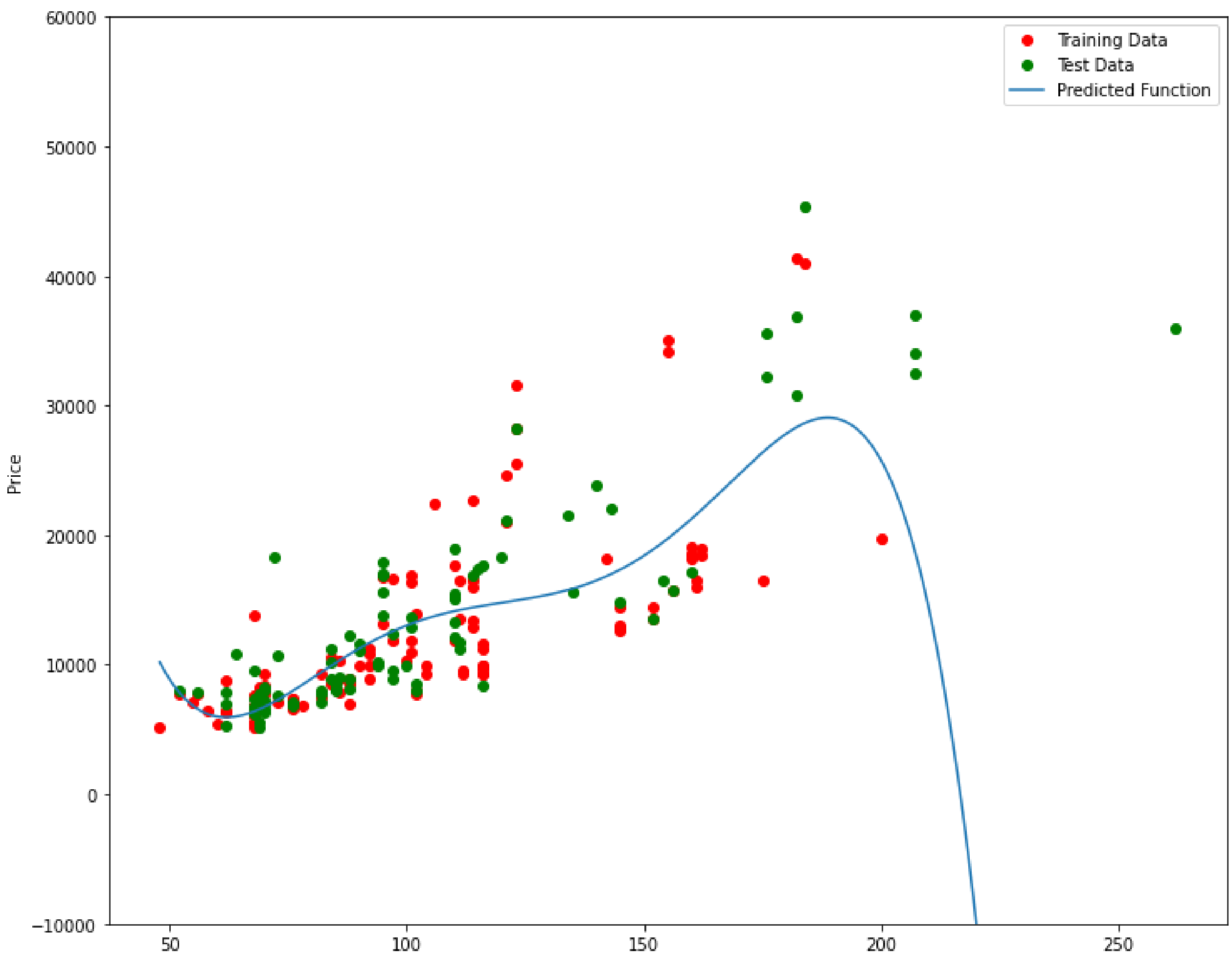
In [378…

```
# compare predicted values to actual values
print("Predicted values:", yhat[0:4])
print("True values:", y_test[0:4].values)
```

```
Predicted values: [ 6728.65566037  7307.9878638  12213.7877412  18893.24796457]
True values: [ 6295. 10698. 13860. 13499.]
```

In [380…

```
# use pollyplot to display the training data, testing data, and predicted function
PollyPlot(x_train[['horsepower']], x_test[['horsepower']], y_train, y_test, poly,pr)

# the estimated function appears to track the data, but diverges around 200 horsepower
```



In [381…

```
# get Rsquare of training data
poly.score(x_train_pr, y_train)
```

Out[381… 0.5567716902121724

In [382…

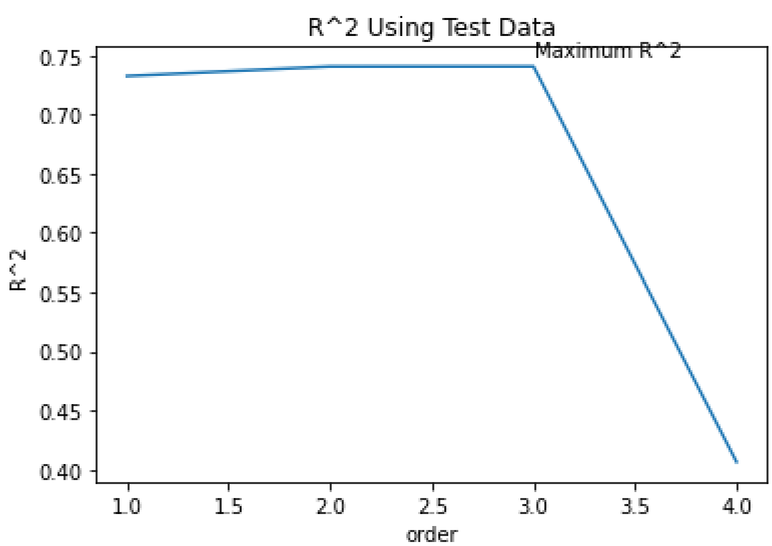
```
# get rsquare of test data
poly.score(x_test_pr, y_test)
```

Out[382… -29.871340540625788

In [383…

```
# observe how rsquare changes for the test data for different order polynomials, then p
Rsqu_test = []

order = [1, 2, 3, 4]
for n in order:
    pr = PolynomialFeatures(degree=n)

    x_train_pr = pr.fit_transform(x_train[['horsepower']])

    x_test_pr = pr.fit_transform(x_test[['horsepower']])

    lr.fit(x_train_pr, y_train)

    Rsqu_test.append(lr.score(x_test_pr, y_test))

pyplot.plot(order, Rsqu_test)
pyplot.xlabel('order')
pyplot.ylabel('R^2')
pyplot.title('R^2 Using Test Data')
pyplot.text(3, 0.75, 'Maximum R^2 ')
# rsquare gradually increases until an order 3 polynomial is used.
```

Out[383… Text(3, 0.75, 'Maximum R^2 ')



In [384…

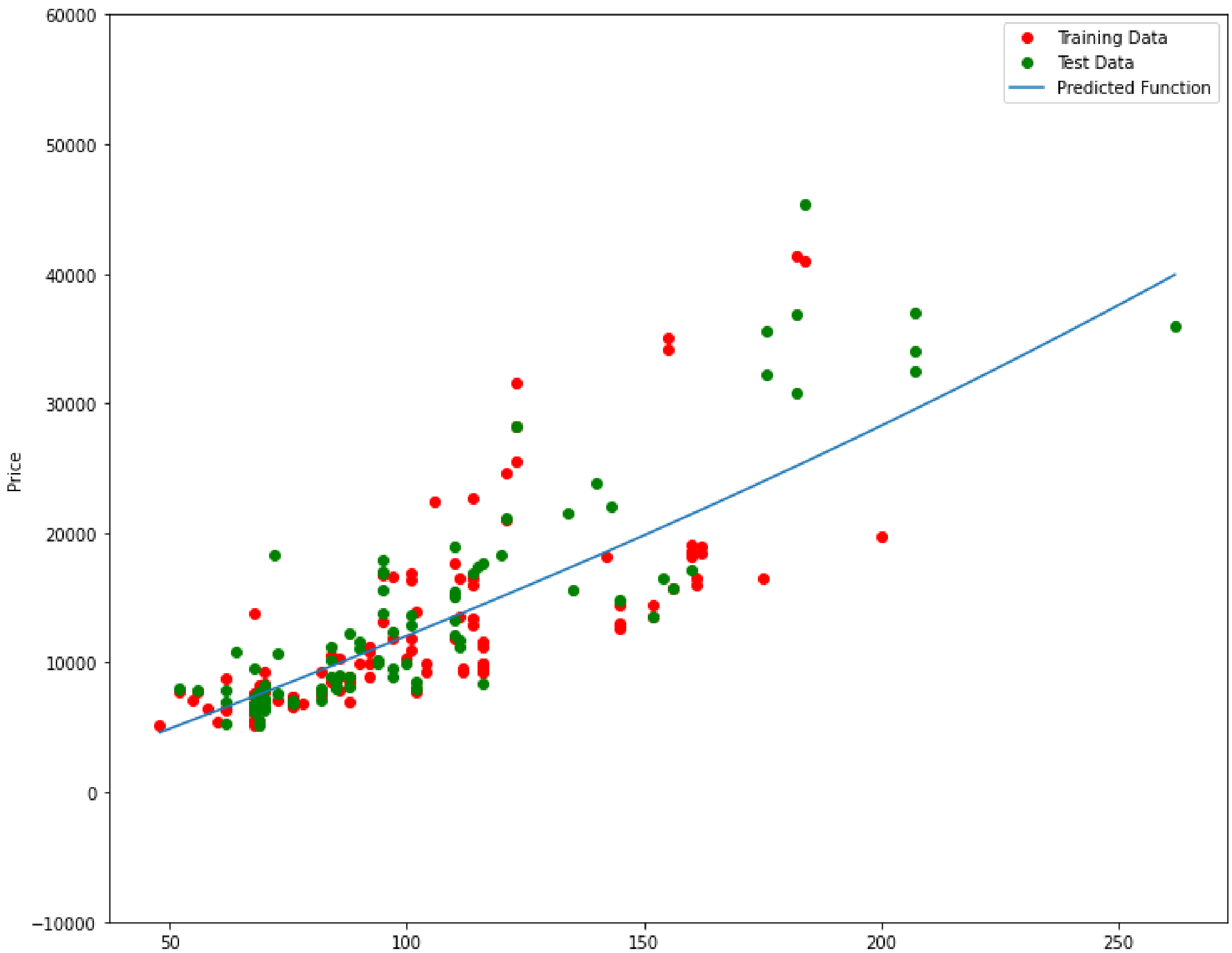
```
# function used in next section
def f(order, test_data):
    x_train, x_test, y_train, y_test = train_test_split(x_data, y_data, test_size=test_
    pr = PolynomialFeatures(degree=order)
```

```
    x_train_pr = pr.fit_transform(x_train[['horsepower']])
    x_test_pr = pr.fit_transform(x_test[['horsepower']])
    poly = LinearRegression()
    poly.fit(x_train_pr,y_train)
    PollyPlot(x_train[['horsepower']], x_test[['horsepower']], y_train,y_test, poly, pr
```

In [387…

```
# interface used to interact with the polynomial orders
interact(f, order=(0, 6, 1), test_data=(0.05, 0.95, 0.05))
```

Out[387… <function __main__.f(order, test_data)>



In [388…

```
# create polynomial features object of degree 2
pr1=PolynomialFeatures(degree=2)
```

In [389…

```
# transform the training and testing samples for horsepower, curbweight, engine size, a
x_train_pr1=pr1.fit_transform(x_train[['horsepower', 'curb-weight', 'engine-size', 'hig

x_test_pr1=pr1.fit_transform(x_test[['horsepower', 'curb-weight', 'engine-size', 'highw
```

In [390…

```
# find dimensions of new feature
x_train_pr1.shape #there are now 15 features
```

Out[390… (110, 15)

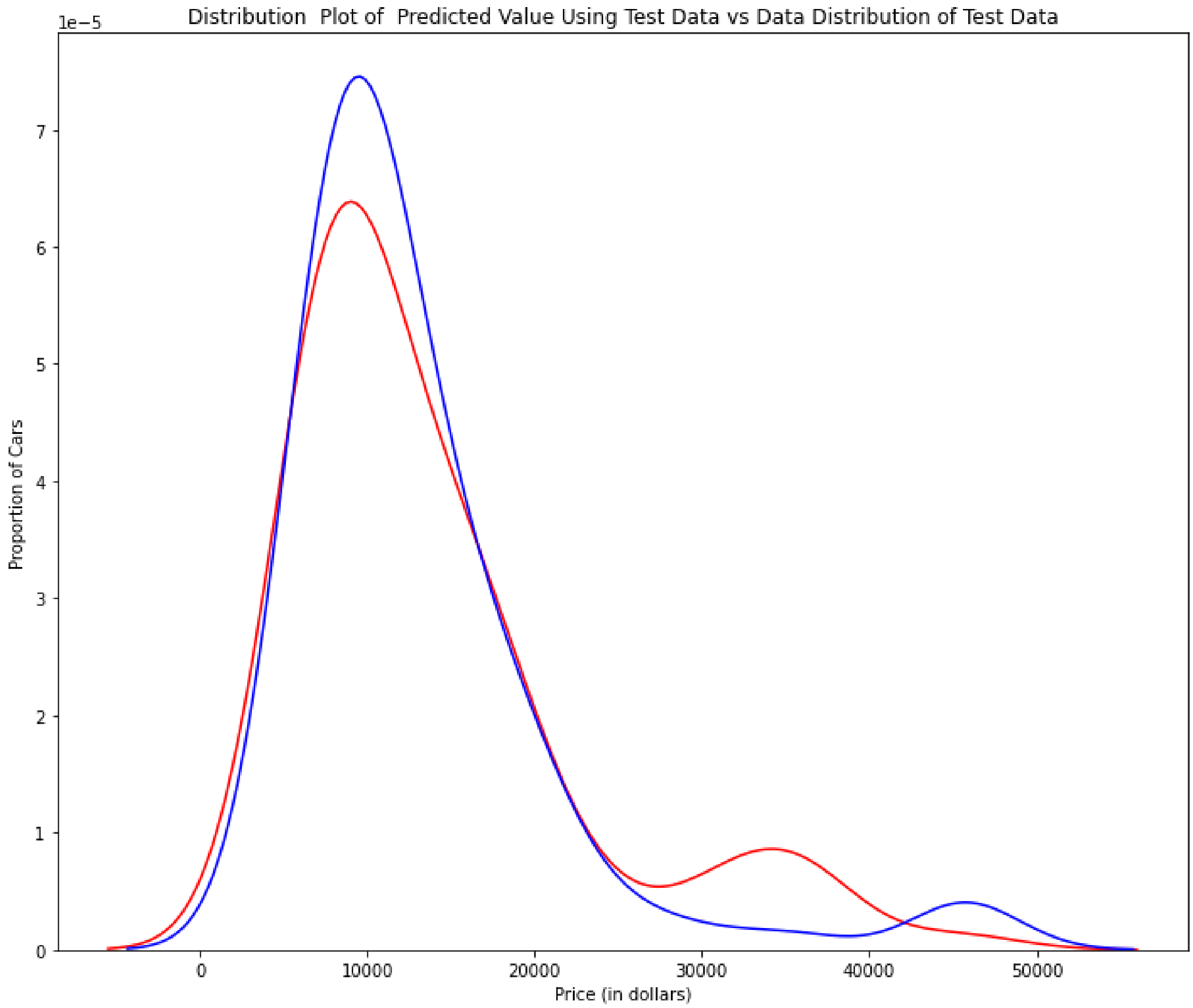
In [391…

```
# create linear regression model
poly1=LinearRegression().fit(x_train_pr1,y_train)
```

In [392…

```
# use predict to get an output on polynomial features
yhat_test1=poly1.predict(x_test_pr1)

# plot the distribution
Title='Distribution  Plot of  Predicted Value Using Test Data vs Data Distribution of T

DistributionPlot(y_test, yhat_test1, "Actual Values (Test)", "Predicted Values (Test)",
```

```
C:\Users\orgil\AppData\Roaming\Python\Python39\site-packages\seaborn\distributions.py:25
57: FutureWarning: `distplot` is a deprecated function and will be removed in a future v
ersion. Please adapt your code to use either `displot` (a figure-level function with sim
ilar flexibility) or `kdeplot` (an axes-level function for kernel density plots).
  warnings.warn(msg, FutureWarning)
C:\Users\orgil\AppData\Roaming\Python\Python39\site-packages\seaborn\distributions.py:25
57: FutureWarning: `distplot` is a deprecated function and will be removed in a future v
ersion. Please adapt your code to use either `displot` (a figure-level function with sim
ilar flexibility) or `kdeplot` (an axes-level function for kernel density plots).
  warnings.warn(msg, FutureWarning)
```



the predicted value is higher than the actual value for cars where the price is in the 10,000 range.

Conversely, the predicted price is lower than the actual price in the 30-40k range.

The model is not as accurate at these ranges.

Ridge Regression

In [393…

```
# perform a degree 2 polynomial transformation
pr=PolynomialFeatures(degree=2)
x_train_pr=pr.fit_transform(x_train[['horsepower', 'curb-weight', 'engine-size', 'highw
x_test_pr=pr.fit_transform(x_test[['horsepower', 'curb-weight', 'engine-size', 'highway
```

In [405…

```
# create ridge object
RigeModel=Ridge(alpha=1)
```

In [406…

```
# fit the model
RigeModel.fit(x_train_pr, y_train)
```

Out[406… Ridge(alpha=1)

In [407…

```
# obtain prediction
yhat = RigeModel.predict(x_test_pr)
```

In [408…

```
# compare predicted samples to test set
print('predicted:', yhat[0:4])
print('test set :', y_test[0:4].values)
```

```
predicted: [ 6570.82441941  9636.2489147  20949.92322737 19403.60313256]
test set : [ 6295. 10698. 13860. 13499.]
```

In [409…

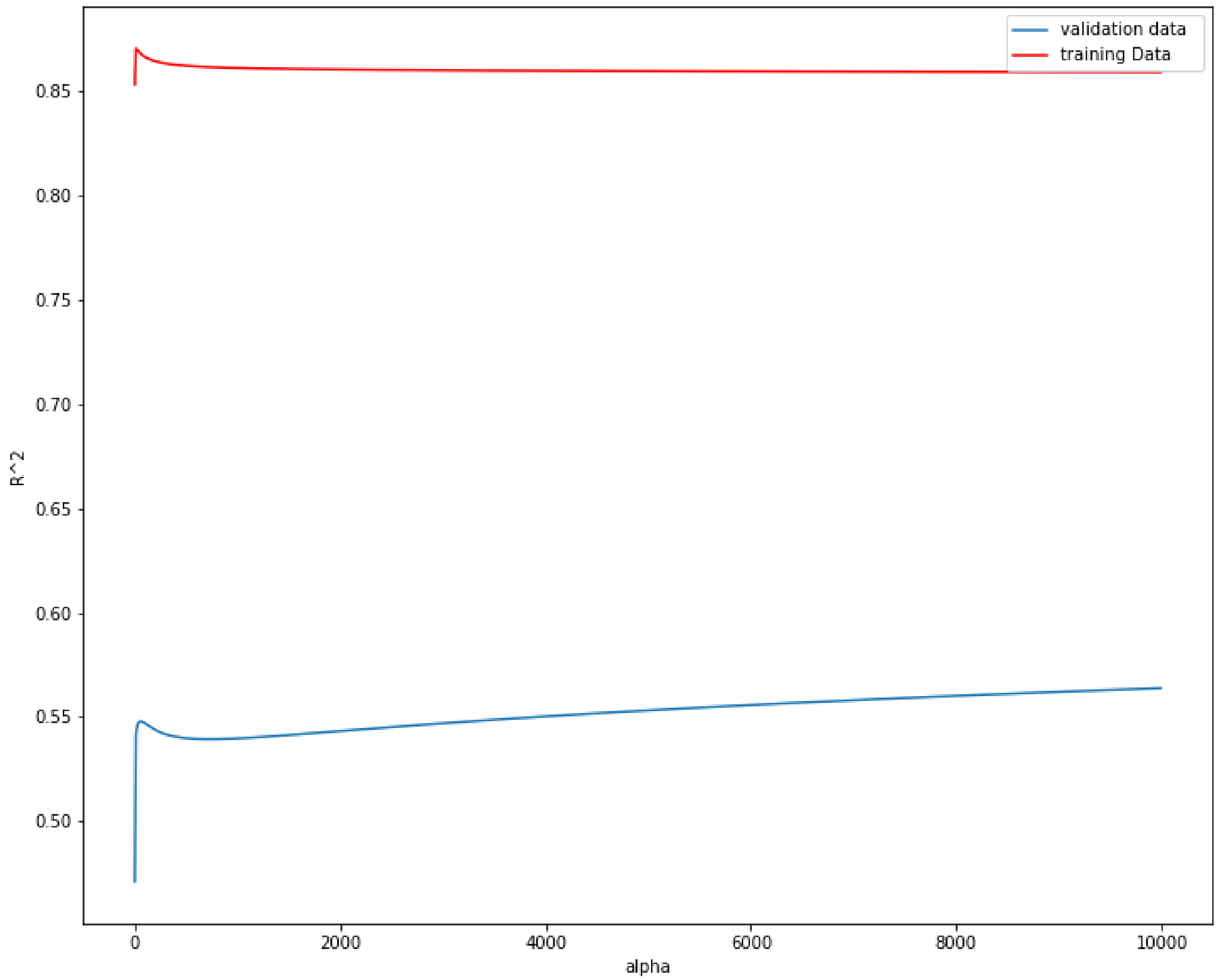
```
# select the value of alpha that minimizes test error.

from tqdm import tqdm

Rsqu_test = []
Rsqu_train = []
dummy1 = []
Alpha = 10 * np.array(range(0,1000))
pbar = tqdm(Alpha)

for alpha in pbar:
    RigeModel = Ridge(alpha=alpha)
    RigeModel.fit(x_train_pr, y_train)
    test_score, train_score = RigeModel.score(x_test_pr, y_test), RigeModel.score(x_tra

    pbar.set_postfix({"Test Score": test_score, "Train Score": train_score})

    Rsqu_test.append(test_score)
    Rsqu_train.append(train_score)
```

```
100%|████████████████████████████████████████| 1000/1000 [00:02<00:00, 482.28it/s, Test
Score=0.564, Train Score=0.859]
```

In [410…

```
# plot the value of Rsquare for different alphas
width = 12
height = 10
pyplot.figure(figsize=(width, height))

pyplot.plot(Alpha,Rsqu_test, label='validation data  ')
pyplot.plot(Alpha,Rsqu_train, 'r', label='training Data ')
pyplot.xlabel('alpha')
pyplot.ylabel('R^2')
pyplot.legend()
```

Out[410… <matplotlib.legend.Legend at 0x245f7cf5190>



The blue line represents the R^2 of the validation data, and the red line represents the R^2 of the training data. The x-axis represents the different values of Alpha.

Here the model is built and tested on the same data, so the training and test data are the same.

The red line in Figure 4 represents the R^2 of the training data. As alpha increases the R^2 decreases. Therefore, as alpha increases, the model performs worse on the training data

The blue line represents the R^2 on the validation data. As the value for alpha increases, the R^2 increases and converges at a point.

In [411…

```
# calculate rsquare using polynomial features
```

```
RigeModel = Ridge(alpha=10)
RigeModel.fit(x_train_pr, y_train)
RigeModel.score(x_test_pr, y_test)
```

Out[411… 0.5418576440206702

Grid Search

In [413…
```
# create dictionary of parameter values
parameters1= [{'alpha': [0.001,0.1,1, 10, 100, 1000, 10000, 100000, 100000]}]
parameters1
```

Out[413… [{'alpha': [0.001, 0.1, 1, 10, 100, 1000, 10000, 100000, 100000]}]

In [414…
```
# create ridge regression object
RR=Ridge()
RR
```

Out[414… Ridge()

In [417…
```
# create ridge gridsearch object
Grid1 = GridSearchCV(RR, parameters1,cv=4)
```

In [418…
```
# fit the model
Grid1.fit(x_data[['horsepower', 'curb-weight', 'engine-size', 'highway-mpg']], y_data)
```

Out[418…
```
GridSearchCV(cv=4, estimator=Ridge(),
             param_grid=[{'alpha': [0.001, 0.1, 1, 10, 100, 1000, 10000, 100000,
                                    100000]}])
```

In [419…
```
# find the best parameter values on the validation data
# obtain the estimator with best parameters
BestRR=Grid1.best_estimator_
BestRR
```

Out[419… Ridge(alpha=10000)

In [420…
```
# test model on the test data
BestRR.score(x_test[['horsepower', 'curb-weight', 'engine-size', 'highway-mpg']], y_tes
```

Out[420… 0.8411649831036152

In [421…
```
# perform a grid search for the alpha parameter and normalization parameter and find th
parameters2= [{'alpha': [0.001,0.1,1, 10, 100, 1000,10000,100000,100000],'normalize':[T
Grid2 = GridSearchCV(Ridge(), parameters2,cv=4)
Grid2.fit(x_data[['horsepower', 'curb-weight', 'engine-size', 'highway-mpg']],y_data)
Grid2.best_estimator_
```

Out[421… Ridge(alpha=0.1, normalize=True)