Automobile Data Analysis

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1 Importing Dataset

Estimated time needed: **15** minutes

1.1 Objectives

- Acquire data in various ways
- Obtain insights from data with Pandas library

Table of Contents

2 Data Acquisition

There are various formats for a data set: .csv, .json, .xlsx etc. The data set can be stored in different places, on your local machine or sometimes online.

In our case, the Automobile Data set is an online source, and it is in a CSV (comma separated value) format. Let's use this data set as an example to practice data reading.

Data source: https://archive.ics.uci.edu/ml/machine-learning-databases/autos/imports-85.data

Data type: csv

The Pandas Library is a useful tool that enables us to read various datasets into a data frame; our Jupyter notebook platforms have a built-in Pandas Library so that all we need to do is import Pandas without installing.

[1]:
```
import pandas as pd
import numpy as np
```

Read Data

We utilize the pandas.read_csv() function for reading CSV files.

[2]:
```
file_name="auto.csv"
```

Utilize the Pandas method `read_csv()` to load the data into a dataframe.

[3]:
```
df = pd.read_csv(file_name)
```

After reading the data set, we can use the data_frame.head(n) method to check the top n rows of the data frame, where n is an integer. Contrary to data_frame.head(n), data_frame.tail(n) will show you the bottom n rows of the data frame.

[4]:
```
# 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
```

[4]:
```
   3    ? alfa-romero  gas  std   two  convertible  rwd  front  88.6  …  \
0  3    ? alfa-romero  gas  std   two  convertible  rwd  front  88.6  …
1  1    ? alfa-romero  gas  std   two    hatchback  rwd  front  94.5  …
2  2  164        audi  gas  std  four        sedan  fwd  front  99.8  …
3  2  164        audi  gas  std  four        sedan  4wd  front  99.4  …
4  2    ?        audi  gas  std   two        sedan  fwd  front  99.8  …

   130  mpfi  3.47  2.68   9.0  111  5000  21  27  13495
0  130  mpfi  3.47  2.68   9.0  111  5000  21  27  16500
1  152  mpfi  2.68  3.47   9.0  154  5000  19  26  16500
2  109  mpfi  3.19  3.40  10.0  102  5500  24  30  13950
3  136  mpfi  3.19  3.40   8.0  115  5500  18  22  17450
4  136  mpfi  3.19  3.40   8.5  110  5500  19  25  15250

[5 rows x 26 columns]
```

[5]:
```
print("The last 10 rows of the dataframe\n")
df.tail(10)
```

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

[5]:
```
      3    ? alfa-romero     gas    std  two convertible  rwd  front   88.6  \
194  -1   74       volvo     gas    std four      wagon  rwd  front  104.3
195  -2  103       volvo     gas    std four      sedan  rwd  front  104.3
196  -1   74       volvo     gas    std four      wagon  rwd  front  104.3
197  -2  103       volvo     gas  turbo four      sedan  rwd  front  104.3
198  -1   74       volvo     gas  turbo four      wagon  rwd  front  104.3
199  -1   95       volvo     gas    std four      sedan  rwd  front  109.1
200  -1   95       volvo     gas  turbo four      sedan  rwd  front  109.1
201  -1   95       volvo     gas    std four      sedan  rwd  front  109.1
202  -1   95       volvo  diesel  turbo four      sedan  rwd  front  109.1
203  -1   95       volvo     gas  turbo four      sedan  rwd  front  109.1

      …  130  mpfi  3.47  2.68   9.0  111  5000  21  27  13495
194   …  141  mpfi  3.78  3.15   9.5  114  5400  23  28  13415
195   …  141  mpfi  3.78  3.15   9.5  114  5400  24  28  15985
```

```
196  …  141  mpfi  3.78  3.15   9.5  114  5400  24  28  16515
197  …  130  mpfi  3.62  3.15   7.5  162  5100  17  22  18420
198  …  130  mpfi  3.62  3.15   7.5  162  5100  17  22  18950
199  …  141  mpfi  3.78  3.15   9.5  114  5400  23  28  16845
200  …  141  mpfi  3.78  3.15   8.7  160  5300  19  25  19045
201  …  173  mpfi  3.58  2.87   8.8  134  5500  18  23  21485
202  …  145   idi  3.01  3.40  23.0  106  4800  26  27  22470
203  …  141  mpfi  3.78  3.15   9.5  114  5400  19  25  22625

[10 rows x 26 columns]
```

Add Headers

Take a look at the data set. Pandas automatically set the header with an integer starting from 0.

To better describe the data, you can introduce a header. This information is available at: https://archive.ics.uci.edu/ml/datasets/Automobile.

Thus, you have to add headers manually.

First, create a list "headers" that include all column names in order. Then, use dataframe.columns = headers to replace the headers with the list you created.

[6]:
```
# create headers list
headers = ["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"]
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', 'height', 'curb-weight', 'engine-type', 'num-of-cylinders', 'engine-
size', 'fuel-system', 'bore', 'stroke', 'compression-ratio', 'horsepower',
'peak-rpm', 'city-mpg', 'highway-mpg', 'price']
```

Replace headers and recheck our data frame:

[7]:
```
df.columns = headers
df.columns
```

[7]:
```
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')
```

You can also see the first 10 entries of the updated data frame and note that the headers are updated.

[8]:
```
df.head(10)
```

[8]:
```
   symboling normalized-losses         make fuel-type aspiration num-of-doors  \
0          3                 ?  alfa-romero       gas        std          two
1          1                 ?  alfa-romero       gas        std          two
2          2               164         audi       gas        std         four
3          2               164         audi       gas        std         four
4          2                 ?         audi       gas        std          two
5          1               158         audi       gas        std         four
6          1                 ?         audi       gas        std         four
7          1               158         audi       gas      turbo         four
8          0                 ?         audi       gas      turbo          two
9          2               192          bmw       gas        std          two

    body-style drive-wheels engine-location  wheel-base  …  engine-size  \
0  convertible          rwd           front        88.6  …          130
1    hatchback          rwd           front        94.5  …          152
2        sedan          fwd           front        99.8  …          109
3        sedan          4wd           front        99.4  …          136
4        sedan          fwd           front        99.8  …          136
5        sedan          fwd           front       105.8  …          136
6        wagon          fwd           front       105.8  …          136
7        sedan          fwd           front       105.8  …          131
8    hatchback          4wd           front        99.5  …          131
9        sedan          rwd           front       101.2  …          108

   fuel-system  bore  stroke compression-ratio horsepower  peak-rpm city-mpg  \
0         mpfi  3.47    2.68               9.0        111      5000       21
1         mpfi  2.68    3.47               9.0        154      5000       19
2         mpfi  3.19    3.40              10.0        102      5500       24
3         mpfi  3.19    3.40               8.0        115      5500       18
4         mpfi  3.19    3.40               8.5        110      5500       19
5         mpfi  3.19    3.40               8.5        110      5500       19
6         mpfi  3.19    3.40               8.5        110      5500       19
7         mpfi  3.13    3.40               8.3        140      5500       17
8         mpfi  3.13    3.40               7.0        160      5500       16
9         mpfi  3.50    2.80               8.8        101      5800       23

  highway-mpg  price
0          27  16500
1          26  16500
2          30  13950
```

```
3           22  17450
4           25  15250
5           25  17710
6           25  18920
7           20  23875
8           22      ?
9           29  16430

[10 rows x 26 columns]
```

Now, we need to replace the "?" symbol with NaN so the dropna() can remove the missing values:

[9]:
```
df1=df.replace('?',np.NaN)
```

You can drop missing values along the column "price" as follows:

[10]:
```
df=df1.dropna(subset=["price"], axis=0)
df.head(20)
```

[10]:
```
    symboling normalized-losses         make fuel-type aspiration  \
0           3               NaN  alfa-romero       gas        std
1           1               NaN  alfa-romero       gas        std
2           2               164         audi       gas        std
3           2               164         audi       gas        std
4           2               NaN         audi       gas        std
5           1               158         audi       gas        std
6           1               NaN         audi       gas        std
7           1               158         audi       gas      turbo
9           2               192          bmw       gas        std
10          0               192          bmw       gas        std
11          0               188          bmw       gas        std
12          0               188          bmw       gas        std
13          1               NaN          bmw       gas        std
14          0               NaN          bmw       gas        std
15          0               NaN          bmw       gas        std
16          0               NaN          bmw       gas        std
17          2               121    chevrolet       gas        std
18          1                98    chevrolet       gas        std
19          0                81    chevrolet       gas        std
20          1               118        dodge       gas        std

   num-of-doors   body-style drive-wheels engine-location  wheel-base  …  \
0           two  convertible          rwd           front        88.6  …
1           two    hatchback          rwd           front        94.5  …
2          four        sedan          fwd           front        99.8  …
3          four        sedan          4wd           front        99.4  …
4           two        sedan          fwd           front        99.8  …
5          four        sedan          fwd           front       105.8  …
```

```
6          four      wagon          fwd           front       105.8  …
7          four      sedan          fwd           front       105.8  …
9           two      sedan          rwd           front       101.2  …
10         four      sedan          rwd           front       101.2  …
11          two      sedan          rwd           front       101.2  …
12         four      sedan          rwd           front       101.2  …
13         four      sedan          rwd           front       103.5  …
14         four      sedan          rwd           front       103.5  …
15          two      sedan          rwd           front       103.5  …
16         four      sedan          rwd           front       110.0  …
17          two  hatchback          fwd           front        88.4  …
18          two  hatchback          fwd           front        94.5  …
19         four      sedan          fwd           front        94.5  …
20          two  hatchback          fwd           front        93.7  …

    engine-size  fuel-system  bore  stroke compression-ratio horsepower  \
0           130         mpfi  3.47    2.68              9.00        111
1           152         mpfi  2.68    3.47              9.00        154
2           109         mpfi  3.19    3.40             10.00        102
3           136         mpfi  3.19    3.40              8.00        115
4           136         mpfi  3.19    3.40              8.50        110
5           136         mpfi  3.19    3.40              8.50        110
6           136         mpfi  3.19    3.40              8.50        110
7           131         mpfi  3.13    3.40              8.30        140
9           108         mpfi  3.50    2.80              8.80        101
10          108         mpfi  3.50    2.80              8.80        101
11          164         mpfi  3.31    3.19              9.00        121
12          164         mpfi  3.31    3.19              9.00        121
13          164         mpfi  3.31    3.19              9.00        121
14          209         mpfi  3.62    3.39              8.00        182
15          209         mpfi  3.62    3.39              8.00        182
16          209         mpfi  3.62    3.39              8.00        182
17           61         2bbl  2.91    3.03              9.50         48
18           90         2bbl  3.03    3.11              9.60         70
19           90         2bbl  3.03    3.11              9.60         70
20           90         2bbl  2.97    3.23              9.41         68

    peak-rpm city-mpg highway-mpg  price
0       5000       21          27  16500
1       5000       19          26  16500
2       5500       24          30  13950
3       5500       18          22  17450
4       5500       19          25  15250
5       5500       19          25  17710
6       5500       19          25  18920
7       5500       17          20  23875
9       5800       23          29  16430
```

```
10       5800        23           29  16925
11       4250        21           28  20970
12       4250        21           28  21105
13       4250        20           25  24565
14       5400        16           22  30760
15       5400        16           22  41315
16       5400        15           20  36880
17       5100        47           53   5151
18       5400        38           43   6295
19       5400        38           43   6575
20       5500        37           41   5572

[20 rows x 26 columns]
```

Here, axis=0 means that the contents along the entire row will be dropped wherever the entity 'price' is found to be NaN

Now, you have successfully read the raw data set and added the correct headers into the data frame.

Find the name of the columns of the dataframe.

[11]:
```
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')
```

Save Dataset

Correspondingly, Pandas enables you to save the data set to CSV. By using the dataframe.to_csv() method, you can add the file path and name along with quotation marks in the brackets.

For example, if you save the data frame df as automobile.csv to your local machine, you may use the syntax below, where index = False means the row names will not be written.

[12]:
```
df.to_csv("usedCars.csv", index=False)
```

You can also read and save other file formats. You can use similar functions like **`pd.read_csv()`** and **`df.to_csv()`** for other data formats. The functions are listed in the following table:

Read/Save Other Data Formats

Data Formate	Read	Save
csv	`pd.read_csv()`	`df.to_csv()`
json	`pd.read_json()`	`df.to_json()`
excel	`pd.read_excel()`	`df.to_excel()`
hdf	`pd.read_hdf()`	`df.to_hdf()`

Data Formate	Read	Save
sql	`pd.read_sql()`	`df.to_sql()`
...	...	...

3 Basic Insights from the Data set

After reading data into Pandas dataframe, it is time for you to explore the data set.

There are several ways to obtain essential insights of the data to help you better understand it.

Data Types

Data has a variety of types.

The main types stored in Pandas data frames are object, float, int, bool and datetime64. In order to better learn about each attribute, you should always know the data type of each column. In Pandas:

[13]:
```
df.dtypes
```

[13]:
```
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
```

Returns a series with the data type of each column.

[14]:
```
# check the data type of data frame "df" by .dtypes
print(df.dtypes)
```

```
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
```

As shown above, you can clearly to see that the data type of "symboling" and "curb-weight" are int64, "normalized-losses" is object, and "wheel-base" is float64, etc.

These data types can be changed; you will learn how to accomplish this in a later module.

Describe

If we would like to get a statistical summary of each column such as count, column mean value, column standard deviation, etc., use the describe method:

[15]:
```
df.describe()
```

[15]:
```
        symboling  wheel-base      length       width      height  \
count  200.000000  200.000000  200.000000  200.000000  200.000000
mean     0.830000   98.848000  174.228000   65.898000   53.791500
std      1.248557    6.038261   12.347132    2.102904    2.428449
min     -2.000000   86.600000  141.100000   60.300000   47.800000
25%      0.000000   94.500000  166.675000   64.175000   52.000000
50%      1.000000   97.000000  173.200000   65.500000   54.100000
```

```
75%       2.000000  102.400000  183.500000   66.675000   55.525000
max       3.000000  120.900000  208.100000   72.000000   59.800000

       curb-weight  engine-size  compression-ratio    city-mpg  highway-mpg
count   200.000000   200.000000         200.000000  200.000000   200.000000
mean   2555.705000   126.860000          10.170100   25.200000    30.705000
std     518.594552    41.650501           4.014163    6.432487     6.827227
min    1488.000000    61.000000           7.000000   13.000000    16.000000
25%    2163.000000    97.750000           8.575000   19.000000    25.000000
50%    2414.000000   119.500000           9.000000   24.000000    30.000000
75%    2928.250000   142.000000           9.400000   30.000000    34.000000
max    4066.000000   326.000000          23.000000   49.000000    54.000000
```

This method will provide various summary statistics, excluding NaN (Not a Number) values.

This shows the statistical summary of all numeric-typed (int, float) columns. For example, the attribute "symboling" has 205 counts, the mean value of this column is 0.83, the standard deviation is 1.25, the minimum value is -2, 25th percentile is 0, 50th percentile is 1, 75th percentile is 2, and the maximum value is 3. However, what if you would also like to check all the columns including those that are of type object? You can add an argument include = "all" inside the bracket. Try it again.

[16]:
```python
# describe all the columns in "df"
df.describe(include = "all")
```

[16]:
```
         symboling normalized-losses    make fuel-type aspiration  \
count   200.000000               164     200       200        200
unique         NaN                51      22         2          2
top            NaN               161  toyota       gas        std
freq           NaN                11      32       180        164
mean      0.830000               NaN     NaN       NaN        NaN
std       1.248557               NaN     NaN       NaN        NaN
min      -2.000000               NaN     NaN       NaN        NaN
25%       0.000000               NaN     NaN       NaN        NaN
50%       1.000000               NaN     NaN       NaN        NaN
75%       2.000000               NaN     NaN       NaN        NaN
max       3.000000               NaN     NaN       NaN        NaN

       num-of-doors body-style drive-wheels engine-location  wheel-base  …  \
count           198        200          200             200  200.000000  …
unique            2          5            3               2         NaN  …
top            four      sedan          fwd           front         NaN  …
freq            113         94          118             197         NaN  …
mean            NaN        NaN          NaN             NaN   98.848000  …
std             NaN        NaN          NaN             NaN    6.038261  …
min             NaN        NaN          NaN             NaN   86.600000  …
25%             NaN        NaN          NaN             NaN   94.500000  …
```

```
50%              NaN        NaN          NaN               NaN   97.000000  …
75%              NaN        NaN          NaN               NaN  102.400000  …
max              NaN        NaN          NaN               NaN  120.900000  …

       engine-size  fuel-system  bore  stroke compression-ratio horsepower  \
count   200.000000          200   196     196        200.000000        198
unique         NaN            8    38      36               NaN         58
top            NaN         mpfi  3.62    3.40               NaN         68
freq           NaN           91    23      19               NaN         19
mean    126.860000          NaN   NaN     NaN         10.170100        NaN
std      41.650501          NaN   NaN     NaN          4.014163        NaN
min      61.000000          NaN   NaN     NaN          7.000000        NaN
25%      97.750000          NaN   NaN     NaN          8.575000        NaN
50%     119.500000          NaN   NaN     NaN          9.000000        NaN
75%     142.000000          NaN   NaN     NaN          9.400000        NaN
max     326.000000          NaN   NaN     NaN         23.000000        NaN

       peak-rpm    city-mpg highway-mpg  price
count       198  200.000000  200.000000    200
unique       22         NaN         NaN    185
top        5500         NaN         NaN  16500
freq         36         NaN         NaN      2
mean        NaN   25.200000   30.705000    NaN
std         NaN    6.432487    6.827227    NaN
min         NaN   13.000000   16.000000    NaN
25%         NaN   19.000000   25.000000    NaN
50%         NaN   24.000000   30.000000    NaN
75%         NaN   30.000000   34.000000    NaN
max         NaN   49.000000   54.000000    NaN

[11 rows x 26 columns]
```

Now it provides the statistical summary of all the columns, including object-typed attributes.

YOu can now see how many unique values there, which one is the top value, and the frequency of the top value in the object-typed columns.

Some values in the table above show “NaN”. Those numbers are not available regarding a particular column type.

You can select the columns of a dataframe by indicating the name of each column. For example, you can select the three columns as follows:

dataframe[[' column 1 ‘,column 2', ‘column 3']]

Where “column” is the name of the column, you can apply the method “.describe()” to get the statistics of those columns as follows:

dataframe[[' column 1 ‘,column 2', ‘column 3']].describe()

Apply the method to “.describe()” to the columns ‘length' and ‘compression-ratio'.

[17]:
```
df[['length', 'compression-ratio']].describe()
```

[17]:

	length	compression-ratio
count	200.000000	200.000000
mean	174.228000	10.170100
std	12.347132	4.014163
min	141.100000	7.000000
25%	166.675000	8.575000
50%	173.200000	9.000000
75%	183.500000	9.400000
max	208.100000	23.000000

Info

You can also use another method to check your data set:

dataframe.info() It provides a concise summary of your data frame.

This method prints information about a data frame including the index dtype and columns, non-null values and memory usage.

[18]:
```
# look at the info of "df"
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 200 entries, 0 to 203
Data columns (total 26 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   symboling          200 non-null    int64
 1   normalized-losses  164 non-null    object
 2   make               200 non-null    object
 3   fuel-type          200 non-null    object
 4   aspiration         200 non-null    object
 5   num-of-doors       198 non-null    object
 6   body-style         200 non-null    object
 7   drive-wheels       200 non-null    object
 8   engine-location    200 non-null    object
 9   wheel-base         200 non-null    float64
 10  length             200 non-null    float64
 11  width              200 non-null    float64
 12  height             200 non-null    float64
 13  curb-weight        200 non-null    int64
 14  engine-type        200 non-null    object
 15  num-of-cylinders   200 non-null    object
 16  engine-size        200 non-null    int64
 17  fuel-system        200 non-null    object
 18  bore               196 non-null    object
 19  stroke             196 non-null    object
 20  compression-ratio  200 non-null    float64
```

```
 21  horsepower         198 non-null    object
 22  peak-rpm           198 non-null    object
 23  city-mpg           200 non-null    int64
 24  highway-mpg        200 non-null    int64
 25  price              200 non-null    object
dtypes: float64(5), int64(5), object(16)
memory usage: 42.2+ KB
```

4 Data Wrangling

Estimated time needed: **30** minutes

4.1 Objectives

- Handle missing values
- Correct data formatting
- Standardize and normalize data

Table of Contents

Identify and handle missing values

Identify missing values

Deal with missing values

Correct data format

```
</li>
<li><a href="#Data-Standardization">Data standardization</a></li>
<li><a href="#Data-Normalization">Data normalization (centering/scaling)</a></li>
<li><a href="#Binning">Binning</a></li>
<li><a href="#Indicator-Variable">Indicator variable</a></li>
```

What is the purpose of data wrangling?

You use data wrangling to convert data from an initial format to a format that may be better for analysis.

What is the fuel consumption (L/100k) rate for the diesel car?

Import data

You can find the "Automobile Dataset" from the following link: https://archive.ics.uci.edu/ml/machine-learning-databases/autos/imports-85.data. You will be using this data set throughout this course.

Import pandas

[19]:
```
#install specific version of libraries used in lab
#! mamba install pandas==1.3.3
#! mamba install numpy=1.21.2
```

[20]:
```python
import pandas as pd
import matplotlib.pylab as plt
```

Reading the dataset from the URL and adding the related headers

This dataset was hosted on IBM Cloud object. Click HERE for free storage.

The functions below will download the dataset into your browser:

[21]:
```python
'''from pyodide.http import pyfetch

async def download(url, filename):
    response = await pyfetch(url)
    if response.status == 200:
        with open(filename, "wb") as f:
            f.write(await response.bytes())'''
```

[21]:
```
'from pyodide.http import pyfetch\n\nasync def download(url, filename):\n
response = await pyfetch(url)\n    if response.status == 200:\n        with
open(filename, "wb") as f:\n            f.write(await response.bytes())'
```

First, assign the URL of the data set to "filepath".

[22]:
```python
#file_path="https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/
↪IBMDeveloperSkillsNetwork-DA0101EN-SkillsNetwork/labs/Data%20files/auto.csv"
```

To obtain the dataset, utilize the download() function as defined above:

[23]:
```python
#await download(file_path, "usedcars.csv")
file_name="usedCars.csv"
```

Then, create a Python list headers containing name of headers.

[24]:
```python
'''headers = ["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"]'''
```

[24]:
```
'headers = ["symboling","normalized-losses","make","fuel-type","aspiration",
"num-of-doors","body-style",\n         "drive-wheels","engine-location","wheel-
base", "length","width","height","curb-weight","engine-type",\n         "num-of-
cylinders", "engine-size","fuel-system","bore","stroke","compression-
ratio","horsepower",\n         "peak-rpm","city-mpg","highway-mpg","price"]'
```

Use the Pandas method read_csv() to load the data from the web address. Set the parameter "names" equal to the Python list "headers".

[25]:
```python
df = pd.read_csv('usedCars.csv')
```

[26]:
```
#filepath = "https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/
↪IBMDeveloperSkillsNetwork-DA0101EN-SkillsNetwork/labs/Data%20files/auto.csv"
#df = pd.read_csv(filepath, header=headers)    # Utilize the same header list␣
↪defined above
```

Use the method head() to display the first five rows of the dataframe.

[27]:
```
# To see what the data set looks like, we'll use the head() method.
df.head()
```

[27]:
```
   symboling  normalized-losses         make fuel-type aspiration  \
0          3                NaN  alfa-romero       gas        std
1          1                NaN  alfa-romero       gas        std
2          2              164.0         audi       gas        std
3          2              164.0         audi       gas        std
4          2                NaN         audi       gas        std

  num-of-doors   body-style drive-wheels engine-location  wheel-base  …  \
0          two  convertible          rwd           front        88.6  …
1          two    hatchback          rwd           front        94.5  …
2         four        sedan          fwd           front        99.8  …
3         four        sedan          4wd           front        99.4  …
4          two        sedan          fwd           front        99.8  …

   engine-size  fuel-system  bore  stroke compression-ratio horsepower  \
0          130         mpfi  3.47    2.68               9.0      111.0
1          152         mpfi  2.68    3.47               9.0      154.0
2          109         mpfi  3.19    3.40              10.0      102.0
3          136         mpfi  3.19    3.40               8.0      115.0
4          136         mpfi  3.19    3.40               8.5      110.0

   peak-rpm city-mpg  highway-mpg  price
0    5000.0       21           27  16500
1    5000.0       19           26  16500
2    5500.0       24           30  13950
3    5500.0       18           22  17450
4    5500.0       19           25  15250

[5 rows x 26 columns]
```

As you can see, several question marks appeared in the data frame; those missing values may hinder further analysis.

So, how do we identify all those missing values and deal with them?

How to work with missing data?

Steps for working with missing data:

Identify missing data

Deal with missing data

Correct data format

5 Identify and handle missing values

5.0.1 Identify missing values

Convert "?" to NaN

In the car data set, missing data comes with the question mark "?". We replace "?" with NaN (Not a Number), Python's default missing value marker for reasons of computational speed and convenience. Use the function:

to replace A by B.

[28]:
```python
import numpy as np

# replace "?" to NaN
df.replace("?", np.nan, inplace = True)
df.head(5)
```

[28]:
```
   symboling  normalized-losses         make fuel-type aspiration  \
0          3                NaN  alfa-romero       gas        std
1          1                NaN  alfa-romero       gas        std
2          2              164.0         audi       gas        std
3          2              164.0         audi       gas        std
4          2                NaN         audi       gas        std

  num-of-doors   body-style drive-wheels engine-location  wheel-base  …  \
0          two  convertible          rwd           front        88.6  …
1          two    hatchback          rwd           front        94.5  …
2         four        sedan          fwd           front        99.8  …
3         four        sedan          4wd           front        99.4  …
4          two        sedan          fwd           front        99.8  …

   engine-size  fuel-system  bore  stroke compression-ratio horsepower  \
0          130         mpfi  3.47    2.68               9.0      111.0
1          152         mpfi  2.68    3.47               9.0      154.0
2          109         mpfi  3.19    3.40              10.0      102.0
3          136         mpfi  3.19    3.40               8.0      115.0
4          136         mpfi  3.19    3.40               8.5      110.0

   peak-rpm city-mpg  highway-mpg  price
0    5000.0       21           27  16500
1    5000.0       19           26  16500
2    5500.0       24           30  13950
3    5500.0       18           22  17450
4    5500.0       19           25  15250
```

```
[5 rows x 26 columns]
```

Evaluating for Missing Data

The missing values are converted by default. Use the following functions to identify these missing values. You can use two methods to detect missing data:

.isnull()

.notnull()

The output is a boolean value indicating whether the value that is passed into the argument is in fact missing data.

[29]:
```
missing_data = df.isnull()
missing_data.head(5)
```

[29]:
```
   symboling  normalized-losses   make  fuel-type  aspiration  num-of-doors  \
0      False               True  False      False       False         False
1      False               True  False      False       False         False
2      False              False  False      False       False         False
3      False              False  False      False       False         False
4      False               True  False      False       False         False

   body-style  drive-wheels  engine-location  wheel-base  …  engine-size  \
0       False         False            False       False  …        False
1       False         False            False       False  …        False
2       False         False            False       False  …        False
3       False         False            False       False  …        False
4       False         False            False       False  …        False

   fuel-system   bore  stroke  compression-ratio  horsepower  peak-rpm  \
0        False  False   False              False       False     False
1        False  False   False              False       False     False
2        False  False   False              False       False     False
3        False  False   False              False       False     False
4        False  False   False              False       False     False

   city-mpg  highway-mpg  price
0     False        False  False
1     False        False  False
2     False        False  False
3     False        False  False
4     False        False  False

[5 rows x 26 columns]
```

"True" means the value is a missing value while "False" means the value is not a missing value.

Count missing values in each column

Using a for loop in Python, you can quickly figure out the number of missing values in each column. As mentioned above, "True" represents a missing value and "False" means the value is present in the data set. In the body of the for loop the method ".value_counts()" counts the number of "True" values.

[30]:
```python
for column in missing_data.columns.values.tolist():
    print(column)
    print (missing_data[column].value_counts())
    print("")
```

```
symboling
symboling
False    200
Name: count, dtype: int64

normalized-losses
normalized-losses
False    164
True      36
Name: count, dtype: int64

make
make
False    200
Name: count, dtype: int64

fuel-type
fuel-type
False    200
Name: count, dtype: int64

aspiration
aspiration
False    200
Name: count, dtype: int64

num-of-doors
num-of-doors
False    198
True       2
Name: count, dtype: int64

body-style
body-style
False    200
Name: count, dtype: int64

drive-wheels
```

```
drive-wheels
False    200
Name: count, dtype: int64

engine-location
engine-location
False    200
Name: count, dtype: int64

wheel-base
wheel-base
False    200
Name: count, dtype: int64

length
length
False    200
Name: count, dtype: int64

width
width
False    200
Name: count, dtype: int64

height
height
False    200
Name: count, dtype: int64

curb-weight
curb-weight
False    200
Name: count, dtype: int64

engine-type
engine-type
False    200
Name: count, dtype: int64

num-of-cylinders
num-of-cylinders
False    200
Name: count, dtype: int64

engine-size
engine-size
False    200
Name: count, dtype: int64
```

```
fuel-system
fuel-system
False    200
Name: count, dtype: int64

bore
bore
False    196
True       4
Name: count, dtype: int64

stroke
stroke
False    196
True       4
Name: count, dtype: int64

compression-ratio
compression-ratio
False    200
Name: count, dtype: int64

horsepower
horsepower
False    198
True       2
Name: count, dtype: int64

peak-rpm
peak-rpm
False    198
True       2
Name: count, dtype: int64

city-mpg
city-mpg
False    200
Name: count, dtype: int64

highway-mpg
highway-mpg
False    200
Name: count, dtype: int64

price
price
False    200
```

```
Name: count, dtype: int64
```

Based on the summary above, each column has 205 rows of data and seven of the columns containing missing data:

"normalized-losses": 41 missing data

"num-of-doors": 2 missing data

"bore": 4 missing data

"stroke" : 4 missing data

"horsepower": 2 missing data

"peak-rpm": 2 missing data

"price": 4 missing data

5.0.2 Deal with missing data

How should you deal with missing data?

Drop data a. Drop the whole row b. Drop the whole column

Replace data a. Replace it by mean b. Replace it by frequency c. Replace it based on other functions

You should only drop whole columns if most entries in the column are empty. In the data set, none of the columns are empty enough to drop entirely. You have some freedom in choosing which method to replace data; however, some methods may seem more reasonable than others. Apply each method to 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 are four doors. Since four doors is most frequent, it is most likely to occur

`</li>`

Drop the whole row:

"price": 4 missing data, simply delete the whole row

Reason: You want to predict price. You cannot use any data entry without price data for prediction; therefore any row now without price data is not useful to you.

Calculate the mean value for the "normalized-losses" column

[31]:
```python
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
```

Replace "NaN" with mean value in "normalized-losses" column

[32]:
```python
df["normalized-losses"].replace(np.nan, avg_norm_loss, inplace=True)
```

Calculate the mean value for the "bore" column

[33]:
```python
avg_bore=df['bore'].astype('float').mean(axis=0)
print("Average of bore:", avg_bore)
```

```
Average of bore: 3.3300000000000005
```

Replace "NaN" with the mean value in the "bore" column

[34]:
```python
df["bore"].replace(np.nan, avg_bore, inplace=True)
```

Replace NaN in "stroke" column with the mean value.

[35]:
```python
#Calculate the mean vaule for "stroke" column
avg_stroke = df["stroke"].astype("float").mean(axis = 0)
print("Average of stroke:", avg_stroke)

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

```
Average of stroke: 3.2598469387755107
```

Calculate the mean value for the "horsepower" column

[36]:
```python
avg_horsepower = df['horsepower'].astype('float').mean(axis=0)
print("Average horsepower:", avg_horsepower)
```

```
Average horsepower: 103.35858585858585
```

Replace "NaN" with the mean value in the "horsepower" column

[37]:
```python
df['horsepower'].replace(np.nan, avg_horsepower, inplace=True)
```

Calculate the mean value for "peak-rpm" column

[38]:
```python
avg_peakrpm=df['peak-rpm'].astype('float').mean(axis=0)
print("Average peak rpm:", avg_peakrpm)
```

```
Average peak rpm: 5118.181818181818
```

Replace "NaN" with the mean value in the "peak-rpm" column

[39]:
```python
df['peak-rpm'].replace(np.nan, avg_peakrpm, inplace=True)
```

To see which values are present in a particular column, we can use the ".value_counts()" method:

[40]:
```python
df['num-of-doors'].value_counts()
```

[40]:
```
num-of-doors
four    113
two      85
Name: count, dtype: int64
```

You can see that four doors is the most common type. We can also use the ".idxmax()" method to calculate the most common type automatically:

[41]:
```python
df['num-of-doors'].value_counts().idxmax()
```

[41]:
```
'four'
```

The replacement procedure is very similar to what you have seen previously:

[42]:
```python
#replace the missing 'num-of-doors' values by the most frequent
df["num-of-doors"].replace(np.nan, "four", inplace=True)
```

Finally, drop all rows that do not have price data:

[43]:
```python
# simply drop whole row with NaN in "price" column
df.dropna(subset=["price"], axis=0, inplace=True)

# reset index, because we droped two rows
df.reset_index(drop=True, inplace=True)
```

[44]:
```python
df.head()
```

[44]:
```
   symboling  normalized-losses         make fuel-type aspiration  \
0          3              122.0  alfa-romero       gas        std
1          1              122.0  alfa-romero       gas        std
2          2              164.0         audi       gas        std
3          2              164.0         audi       gas        std
4          2              122.0         audi       gas        std

  num-of-doors   body-style drive-wheels engine-location  wheel-base  …  \
0          two  convertible          rwd           front        88.6  …
1          two    hatchback          rwd           front        94.5  …
2         four        sedan          fwd           front        99.8  …
3         four        sedan          4wd           front        99.4  …
4          two        sedan          fwd           front        99.8  …

   engine-size  fuel-system  bore  stroke compression-ratio horsepower  \
0          130         mpfi  3.47    2.68               9.0      111.0
1          152         mpfi  2.68    3.47               9.0      154.0
```

```
2           109         mpfi  3.19    3.40              10.0      102.0
3           136         mpfi  3.19    3.40               8.0      115.0
4           136         mpfi  3.19    3.40               8.5      110.0

   peak-rpm city-mpg  highway-mpg  price
0    5000.0       21           27  16500
1    5000.0       19           26  16500
2    5500.0       24           30  13950
3    5500.0       18           22  17450
4    5500.0       19           25  15250

[5 rows x 26 columns]
```

Now, you have a data set with no missing values.

5.0.3 Correct data format

We are almost there!

The last step in data cleaning is checking and making sure that all data is in the correct format (int, float, text or other).

In Pandas, you use:

.dtype() to check the data type

.astype() to change the data type

Let's list the data types for each column

[45]:
```
df.dtypes
```

[45]:
```
symboling              int64
normalized-losses    float64
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           float64
peak-rpm             float64
city-mpg               int64
highway-mpg            int64
price                  int64
dtype: object
```

As you can see above, some columns are not of the correct data type. Numerical variables should have type 'float' or 'int', and variables with strings such as categories should have type 'object'. For example, the numerical values 'bore' and 'stroke' describe the engines, so you should expect them to be of the type 'float' or 'int'; however, they are shown as type 'object'. You have to convert data types into a proper format for each column using the "astype()" method.

Convert data types to proper format

[46]:
```python
df[["bore", "stroke"]] = df[["bore", "stroke"]].astype("float")
df[["normalized-losses"]] = df[["normalized-losses"]].astype("int")
df[["price"]] = df[["price"]].astype("float")
df[["peak-rpm"]] = df[["peak-rpm"]].astype("float")
```

Let us list the columns after the conversion

[47]:
```python
df.dtypes
```

[47]:
```
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           float64
peak-rpm             float64
```

```
city-mpg               int64
highway-mpg            int64
price                float64
dtype: object
```

Now you finally obtained the cleansed data set with no missing values and with all data in its proper format.

5.1 Data Standardization

You usually collect data from different agencies in different formats. (Data standardization is also a term for a particular type of data normalization where you subtract the mean and divide by the standard deviation.)

What is standardization?

Standardization is the process of transforming data into a common format, allowing the researcher to make the meaningful comparison.

Example

Transform mpg to L/100km:

In your data set, the fuel consumption columns "city-mpg" and "highway-mpg" are represented by mpg (miles per gallon) unit. Assume you are developing an application in a country that accepts the fuel consumption with L/100km standard.

You will need to apply data transformation to transform mpg into L/100km.

Use this formula for unit conversion:

L/100km = 235 / mpg

You can do many mathematical operations directly using Pandas.

[48]:
```python
df.head()
```

[48]:
```
   symboling  normalized-losses         make fuel-type aspiration  \
0          3                122  alfa-romero       gas        std
1          1                122  alfa-romero       gas        std
2          2                164         audi       gas        std
3          2                164         audi       gas        std
4          2                122         audi       gas        std

  num-of-doors   body-style drive-wheels engine-location  wheel-base  …  \
0          two  convertible          rwd           front        88.6  …
1          two    hatchback          rwd           front        94.5  …
2         four        sedan          fwd           front        99.8  …
3         four        sedan          4wd           front        99.4  …
4          two        sedan          fwd           front        99.8  …

   engine-size  fuel-system  bore  stroke compression-ratio horsepower  \
```

```
0          130          mpfi  3.47    2.68                  9.0       111.0
1          152          mpfi  2.68    3.47                  9.0       154.0
2          109          mpfi  3.19    3.40                 10.0       102.0
3          136          mpfi  3.19    3.40                  8.0       115.0
4          136          mpfi  3.19    3.40                  8.5       110.0

   peak-rpm city-mpg  highway-mpg    price
0    5000.0       21           27  16500.0
1    5000.0       19           26  16500.0
2    5500.0       24           30  13950.0
3    5500.0       18           22  17450.0
4    5500.0       19           25  15250.0

[5 rows x 26 columns]
```

[49]:

```
# Convert mpg to L/100km by mathematical operation (235 divided by mpg)
df['city-L/100km'] = 235/df["city-mpg"]

# check your transformed data
df.head()
```

[49]:

```
   symboling  normalized-losses         make fuel-type aspiration  \
0          3                122  alfa-romero       gas        std
1          1                122  alfa-romero       gas        std
2          2                164         audi       gas        std
3          2                164         audi       gas        std
4          2                122         audi       gas        std

  num-of-doors   body-style drive-wheels engine-location  wheel-base  …  \
0          two  convertible          rwd           front        88.6  …
1          two    hatchback          rwd           front        94.5  …
2         four        sedan          fwd           front        99.8  …
3         four        sedan          4wd           front        99.4  …
4          two        sedan          fwd           front        99.8  …

   fuel-system  bore  stroke  compression-ratio horsepower peak-rpm  city-mpg  \
0         mpfi  3.47    2.68                9.0      111.0   5000.0        21
1         mpfi  2.68    3.47                9.0      154.0   5000.0        19
2         mpfi  3.19    3.40               10.0      102.0   5500.0        24
3         mpfi  3.19    3.40                8.0      115.0   5500.0        18
4         mpfi  3.19    3.40                8.5      110.0   5500.0        19

  highway-mpg    price  city-L/100km
0          27  16500.0     11.190476
1          26  16500.0     12.368421
2          30  13950.0      9.791667
3          22  17450.0     13.055556
```

```
4           25  15250.0     12.368421

[5 rows x 27 columns]
```

Transform mpg to L/100km in the column of "highway-mpg" and change the name of column to "highway-L/100km".

[50]:
```python
# transform mpg to L/100km by mathematical operation (235 divided by mpg)
df['highway-L/100km']=235/df["highway-mpg"]

# check your transformed data
df.head()
```

[50]:
```
   symboling  normalized-losses         make fuel-type aspiration  \
0          3                122  alfa-romero       gas        std
1          1                122  alfa-romero       gas        std
2          2                164         audi       gas        std
3          2                164         audi       gas        std
4          2                122         audi       gas        std

  num-of-doors   body-style drive-wheels engine-location  wheel-base  …  \
0          two  convertible          rwd           front        88.6  …
1          two    hatchback          rwd           front        94.5  …
2         four        sedan          fwd           front        99.8  …
3         four        sedan          4wd           front        99.4  …
4          two        sedan          fwd           front        99.8  …

   bore  stroke  compression-ratio  horsepower peak-rpm city-mpg  highway-mpg  \
0  3.47    2.68                9.0       111.0   5000.0       21           27
1  2.68    3.47                9.0       154.0   5000.0       19           26
2  3.19    3.40               10.0       102.0   5500.0       24           30
3  3.19    3.40                8.0       115.0   5500.0       18           22
4  3.19    3.40                8.5       110.0   5500.0       19           25

     price  city-L/100km  highway-L/100km
0  16500.0     11.190476         8.703704
1  16500.0     12.368421         9.038462
2  13950.0      9.791667         7.833333
3  17450.0     13.055556        10.681818
4  15250.0     12.368421         9.400000

[5 rows x 28 columns]
```

5.2 Data Normalization

Why normalization?

Normalization is the process of transforming values of several variables into a similar range. Typical normalizations include scaling the variable so the variable average is 0

scaling the variable so the variance is 1

scaling the variable so the variable values range from 0 to 1

Example

To demonstrate normalization, say you want to scale the columns "length", "width" and "height".

Target: normalize those variables so their value ranges from 0 to 1

Approach: replace the original value by (original value)/(maximum value)

[51]:
```
# replace (original value) by (original value)/(maximum value)
df['length'] = df['length']/df['length'].max()
df['width'] = df['width']/df['width'].max()
```

Normalize the column "height".

[52]:
```
df['height'] = df['height']/df['height'].max()

# show the scaled columns
df[["length","width","height"]].head()
```

[52]:

	length	width	height
0	0.811148	0.890278	0.816054
1	0.822681	0.909722	0.876254
2	0.848630	0.919444	0.908027
3	0.848630	0.922222	0.908027
4	0.851994	0.920833	0.887960

Here you've normalized "length", "width" and "height" to fall in the range of [0,1].

5.3 Binning

Why binning?

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

Example:

In your data set, "horsepower" is a real valued variable ranging from 48 to 288 and it has 59 unique values. What if you only care about the price difference between cars with high horsepower, medium horsepower, and little horsepower (3 types)? You can rearrange them into three 'bins' to simplify analysis.

Use the Pandas method 'cut' to segment the 'horsepower' column into 3 bins.

Example of Binning Data In Pandas

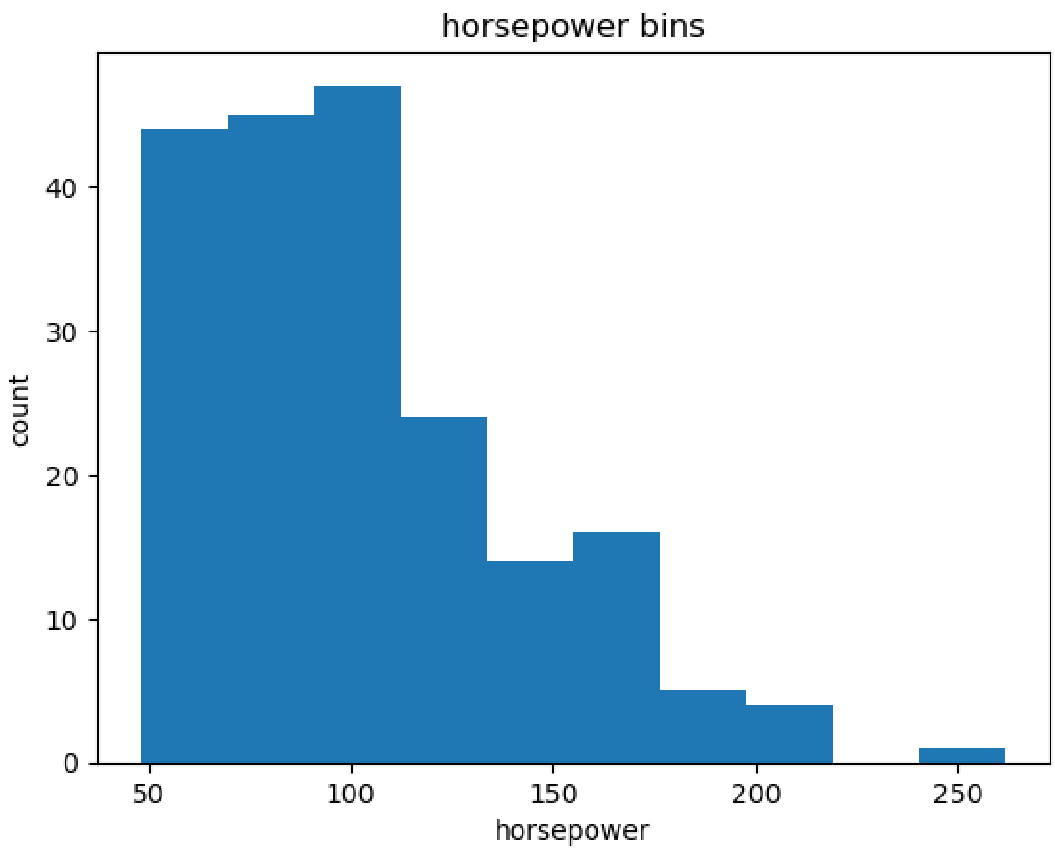
Convert data to correct format:

[53]:
```
df["horsepower"]=df["horsepower"].astype(int, copy=True)
```

Plot the histogram of horsepower to see the distribution of horsepower.

[54]:
```
%matplotlib inline
import matplotlib as plt
from matplotlib import pyplot
plt.pyplot.hist(df["horsepower"])

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

[54]:
```
Text(0.5, 1.0, 'horsepower bins')
```



Find 3 bins of equal size bandwidth by using Numpy's linspace(start_value, end_value, numbers_generated function.

Since you want to include the minimum value of horsepower, set start_value = min(df["horsepower"]).

Since you want to include the maximum value of horsepower, set end_value = max(df["horsepower"]).

Since you are building 3 bins of equal length, you need 4 dividers, so numbers_generated = 4.

Build a bin array with a minimum value to a maximum value by using the bandwidth calculated above. The values will determine when one bin ends and another begins.

[55]:
```
bins = np.linspace(min(df["horsepower"]), max(df["horsepower"]), 4)
bins
```

[55]:
```
array([ 48.        , 119.33333333, 190.66666667, 262.        ])
```

Set group names:

[56]:
```
group_names = ['Low', 'Medium', 'High']
```

Apply the function "cut" to determine what each value of `df['horsepower']` belongs to.

[57]:
```
df['horsepower-binned'] = pd.cut(df['horsepower'], bins, labels=group_names,␣
 ↪include_lowest=True )
df[['horsepower','horsepower-binned']].head(20)
```

[57]:

	horsepower	horsepower-binned
0	111	Low
1	154	Medium
2	102	Low
3	115	Low
4	110	Low
5	110	Low
6	110	Low
7	140	Medium
8	101	Low
9	101	Low
10	121	Medium
11	121	Medium
12	121	Medium
13	182	Medium
14	182	Medium
15	182	Medium
16	48	Low
17	70	Low
18	70	Low
19	68	Low

See the number of vehicles in each bin:

[58]:
```
df["horsepower-binned"].value_counts()
```

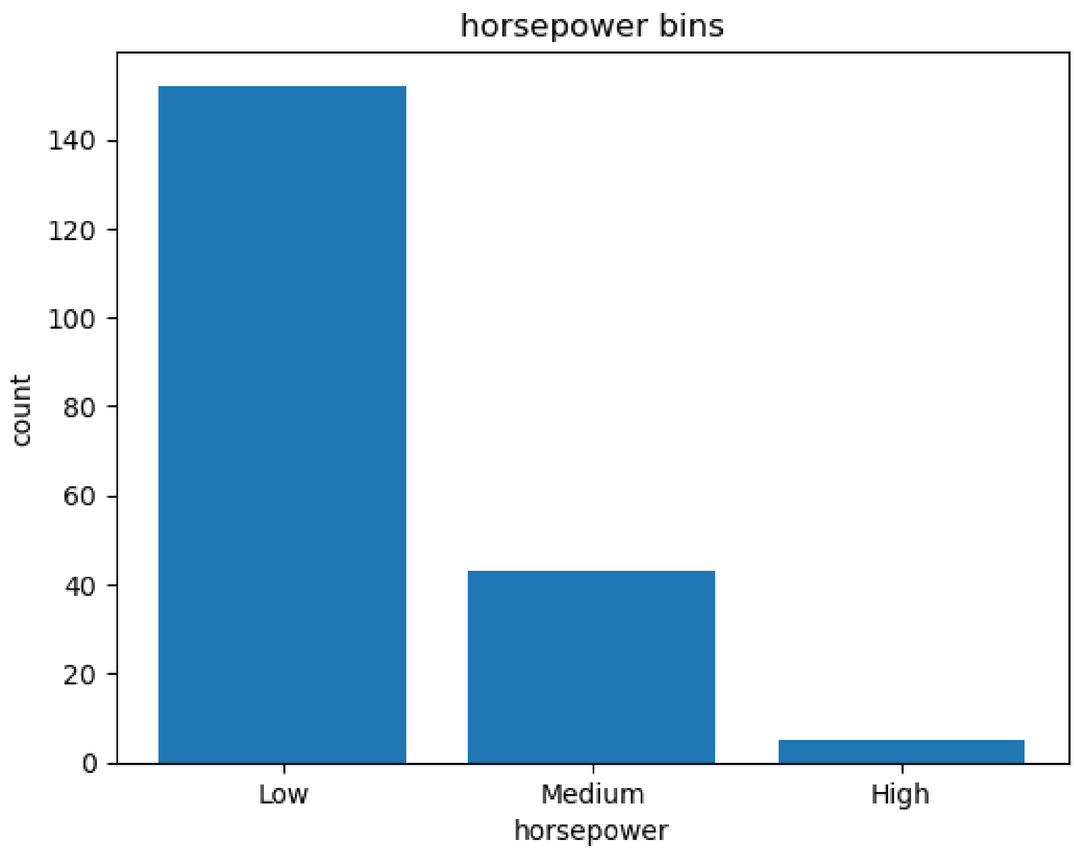
[58]:
```
horsepower-binned
Low       152
Medium     43
High        5
```

```
Name: count, dtype: int64
```

Plot the distribution of each bin:

[59]:
```
%matplotlib inline
import matplotlib as plt
from matplotlib import pyplot
pyplot.bar(group_names, df["horsepower-binned"].value_counts())

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

[59]:
```
Text(0.5, 1.0, 'horsepower bins')
```



Look at the data frame above carefully. You will find that the last column provides the bins for "horsepower" based on 3 categories ("Low", "Medium" and "High").

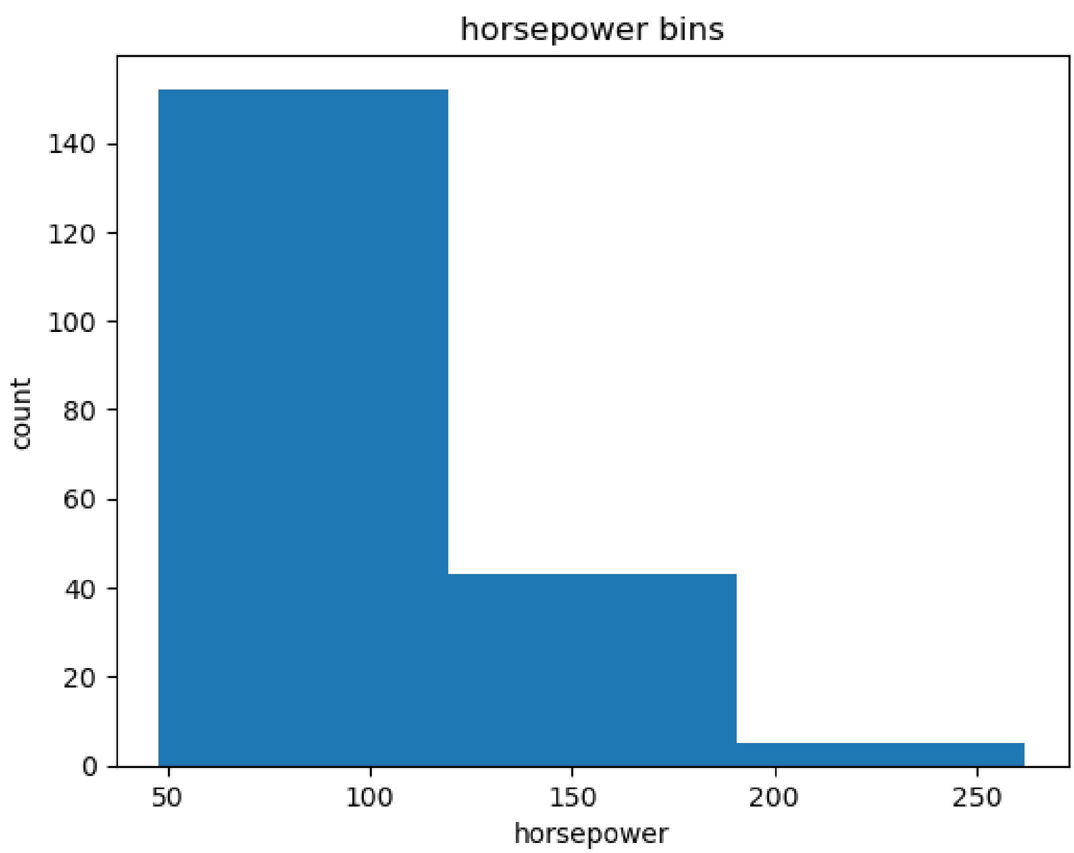
You successfully narrowed down the intervals from 59 to 3!

Bins Visualization

Normally, you use a histogram to visualize the distribution of bins we created above.

[60]:
```
%matplotlib inline
import matplotlib as plt
from matplotlib import pyplot


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

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

[60]:
```
Text(0.5, 1.0, 'horsepower bins')
```



The plot above shows the binning result for the attribute “horsepower”.

5.4 Indicator Variable

What is an indicator variable?

An indicator variable (or dummy variable) is a numerical variable used to label categories. They are called 'dummies' because the numbers themselves don't have inherent meaning.

Why use indicator variables?

You use indicator variables so you can use categorical variables for regression analysis in the later modules.

Example

The column "fuel-type" has two unique values: "gas" or "diesel". Regression doesn't understand words, only numbers. To use this attribute in regression analysis, you can convert "fuel-type" to indicator variables.

Use the Panda method 'get_dummies' to assign numerical values to different categories of fuel type.

[61]:
```
df.columns
```

[61]:
```
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', 'city-L/100km', 'highway-L/100km',
       'horsepower-binned'],
      dtype='object')
```

Get the indicator variables and assign it to data frame "dummy_variable_1":

[62]:
```
dummy_variable_1 = pd.get_dummies(df["fuel-type"])
dummy_variable_1.head()
```

[62]:
```
   diesel   gas
0   False  True
1   False  True
2   False  True
3   False  True
4   False  True
```

Change the column names for clarity:

[63]:
```
dummy_variable_1.rename(columns={'gas':'fuel-type-gas', 'diesel':
 ↪'fuel-type-diesel'}, inplace=True)
dummy_variable_1.head()
```

[63]:
```
   fuel-type-diesel  fuel-type-gas
0             False           True
```

```
1             False         True
2             False         True
3             False         True
4             False         True
```

In the data frame, column 'fuel-type' now has values for 'gas' and 'diesel' as 0s and 1s.

[64]:
```
# merge data frame "df" and "dummy_variable_1"
df = pd.concat([df, dummy_variable_1], axis=1)

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

[65]:
```
df.head()
```

[65]:
```
   symboling  normalized-losses         make aspiration num-of-doors  \
0          3                122  alfa-romero        std          two
1          1                122  alfa-romero        std          two
2          2                164         audi        std         four
3          2                164         audi        std         four
4          2                122         audi        std          two

    body-style drive-wheels engine-location  wheel-base    length  …  \
0  convertible          rwd           front        88.6  0.811148  …
1    hatchback          rwd           front        94.5  0.822681  …
2        sedan          fwd           front        99.8  0.848630  …
3        sedan          4wd           front        99.4  0.848630  …
4        sedan          fwd           front        99.8  0.851994  …

   horsepower  peak-rpm  city-mpg highway-mpg    price  city-L/100km  \
0         111    5000.0        21          27  16500.0     11.190476
1         154    5000.0        19          26  16500.0     12.368421
2         102    5500.0        24          30  13950.0      9.791667
3         115    5500.0        18          22  17450.0     13.055556
4         110    5500.0        19          25  15250.0     12.368421

  highway-L/100km  horsepower-binned  fuel-type-diesel  fuel-type-gas
0        8.703704                Low             False           True
1        9.038462             Medium             False           True
2        7.833333                Low             False           True
3       10.681818                Low             False           True
4        9.400000                Low             False           True

[5 rows x 30 columns]
```

The last two columns are now the indicator variable representation of the fuel-type variable. They're all 0s and 1s now.

Create an indicator variable for the column "aspiration"

[66]:
```python
# get indicator variables of aspiration and assign it to data frame␣
↪"dummy_variable_2"
dummy_variable_2 = pd.get_dummies(df['aspiration'])

# change column names for clarity
dummy_variable_2.rename(columns={'std':'aspiration-std', 'turbo':␣
↪'aspiration-turbo'}, inplace=True)

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

[66]:

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

Merge the new dataframe to the original dataframe, then drop the column 'aspiration'.

[67]:
```python
# merge the new dataframe to the original datafram
#df = pd.concat([df, dummy_variable_2], axis=1)
```

Save the new csv:

[68]:
```python
df.to_csv('usedCars.csv',index=None)
```

6 Exploratory Data Analysis

Estimated time needed: **30** minutes

6.1 Objectives

- Explore features or characteristics to predict price of car
- Analyze patterns and run descriptive statistical analysis
- Group data based on identified parameters and create pivot tables
- Identify the effect of independent attributes on price of cars

Table of Contents

What are the main characteristics that have the most impact on the car price?

6.2 Import Data from Module 2

Setup

Import libraries:

[69]:
```
#install specific version of libraries used in lab
#! mamba install pandas==1.3.3
#! mamba install numpy=1.21.2
#! mamba install scipy=1.7.1-y
#!  mamba install seaborn=0.9.0-y
```

[70]:
```
import pandas as pd
import numpy as np
import seaborn as sns
```

Download the updated dataset by running the cell below.

The functions below will download the dataset into your browser and store it in dataframe `df`:

This dataset was hosted on IBM Cloud object. Click HERE for free storage.

[71]:
```
'''from pyodide.http import pyfetch

async def download(url, filename):
    response = await pyfetch(url)
    if response.status == 200:
        with open(filename, "wb") as f:
            f.write(await response.bytes())'''
```

[71]:
```
'from pyodide.http import pyfetch\n\nasync def download(url, filename):\n
response = await pyfetch(url)\n    if response.status == 200:\n        with
open(filename, "wb") as f:\n            f.write(await response.bytes())'
```

[72]:
```
#file_path= "https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/
↪IBMDeveloperSkillsNetwork-DA0101EN-SkillsNetwork/labs/Data%20files/
↪automobileEDA.csv"
```

[73]:
```
file_name="usedCars.csv"
```

[74]:
```
df = pd.read_csv(file_name)
```

[75]:
```
#filepath='https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/
↪IBMDeveloperSkillsNetwork-DA0101EN-SkillsNetwork/labs/Data%20files/
↪automobileEDA.csv'
#df = pd.read_csv(filepath, header=None)
```

View the first 5 values of the updated dataframe using `dataframe.head()`

[76]:
```
df.head()
```

[76]:

```
   symboling  normalized-losses         make aspiration num-of-doors  \
0          3                122  alfa-romero        std          two   
1          1                122  alfa-romero        std          two   
2          2                164         audi        std         four   
3          2                164         audi        std         four   
4          2                122         audi        std          two   

    body-style drive-wheels engine-location  wheel-base    length  …  \
0  convertible          rwd           front        88.6  0.811148  …   
1    hatchback          rwd           front        94.5  0.822681  …   
2        sedan          fwd           front        99.8  0.848630  …   
3        sedan          4wd           front        99.4  0.848630  …   
4        sedan          fwd           front        99.8  0.851994  …   

   horsepower  peak-rpm  city-mpg highway-mpg    price  city-L/100km  \
0         111    5000.0        21          27  16500.0     11.190476   
1         154    5000.0        19          26  16500.0     12.368421   
2         102    5500.0        24          30  13950.0      9.791667   
3         115    5500.0        18          22  17450.0     13.055556   
4         110    5500.0        19          25  15250.0     12.368421   

  highway-L/100km  horsepower-binned  fuel-type-diesel  fuel-type-gas  
0        8.703704                Low             False           True  
1        9.038462             Medium             False           True  
2        7.833333                Low             False           True  
3       10.681818                Low             False           True  
4        9.400000                Low             False           True  

[5 rows x 30 columns]
```

6.3 Analyzing Individual Feature Patterns Using Visualization

Import visualization packages "Matplotlib" and "Seaborn". Don't forget about "%matplotlib inline" to plot in a Jupyter notebook.

[77]:

```python
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

How to choose the right visualization method?

When visualizing individual variables, it is important to first understand what type of variable you are dealing with. This will help us find the right visualization method for that variable.

[78]:

```python
# list the data types for each column
print(df.dtypes)
```

```
symboling              int64
normalized-losses      int64
```

```
make                  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             int64
peak-rpm             float64
city-mpg               int64
highway-mpg            int64
price                float64
city-L/100km         float64
highway-L/100km      float64
horsepower-binned     object
fuel-type-diesel        bool
fuel-type-gas           bool
dtype: object
```

[79]:
```
df['peak-rpm'].dtypes
```

[79]:
```
dtype('float64')
```

For example, we can calculate the correlation between variables of type "int64" or "float64" using the method "corr":

[80]:
```
numeric_df = df.select_dtypes(include=['float64', 'int64'])
numeric_df.corr()
```

[80]:
```
                   symboling  normalized-losses  wheel-base    length  \
symboling           1.000000           0.469772   -0.529145 -0.364511
normalized-losses   0.469772           1.000000   -0.057068  0.019433
wheel-base         -0.529145          -0.057068    1.000000  0.879005
length             -0.364511           0.019433    0.879005  1.000000
width              -0.237262           0.086961    0.814593  0.857271
height             -0.542261          -0.377664    0.583789  0.492955
curb-weight        -0.234743           0.099404    0.787584  0.881058
```

```
engine-size        -0.112069           0.112362    0.576779  0.685531
bore               -0.145667          -0.029867    0.501534  0.610817
stroke              0.008244           0.055759    0.144675  0.120888
compression-ratio  -0.181073          -0.114738    0.249689  0.159203
horsepower          0.074581           0.217323    0.375732  0.580477
peak-rpm            0.284011           0.239580   -0.364971 -0.286754
city-mpg           -0.030158          -0.225255   -0.480029 -0.667658
highway-mpg         0.041248          -0.182011   -0.552211 -0.700186
price              -0.083327           0.133999    0.589147  0.691044
city-L/100km        0.062423           0.238712    0.484047  0.659174
highway-L/100km    -0.033159           0.181247    0.584953  0.708466

                      width    height  curb-weight  engine-size      bore  \
symboling         -0.237262 -0.542261    -0.234743    -0.112069 -0.145667
normalized-losses  0.086961 -0.377664     0.099404     0.112362 -0.029867
wheel-base         0.814593  0.583789     0.787584     0.576779  0.501534
length             0.857271  0.492955     0.881058     0.685531  0.610817
width              1.000000  0.300995     0.867720     0.731100  0.548478
height             0.300995  1.000000     0.310660     0.076255  0.187794
curb-weight        0.867720  0.310660     1.000000     0.849090  0.644532
engine-size        0.731100  0.076255     0.849090     1.000000  0.572786
bore               0.548478  0.187794     0.644532     0.572786  1.000000
stroke             0.182855 -0.081273     0.168642     0.208004 -0.051087
compression-ratio  0.189008  0.259526     0.156444     0.029005  0.002021
horsepower         0.617032 -0.085725     0.758095     0.822656  0.566690
peak-rpm          -0.247388 -0.315756    -0.279411    -0.256702 -0.267010
city-mpg          -0.638155 -0.057087    -0.750390    -0.651002 -0.581365
highway-mpg       -0.684700 -0.111568    -0.795515    -0.679877 -0.590753
price              0.752795  0.137284     0.834420     0.872337  0.543431
city-L/100km       0.677111  0.008923     0.785868     0.745337  0.554069
highway-L/100km    0.739845  0.088903     0.837217     0.783593  0.558759

                     stroke  compression-ratio  horsepower  peak-rpm  \
symboling          0.008244          -0.181073    0.074581  0.284011
normalized-losses  0.055759          -0.114738    0.217323  0.239580
wheel-base         0.144675           0.249689    0.375732 -0.364971
length             0.120888           0.159203    0.580477 -0.286754
width              0.182855           0.189008    0.617032 -0.247388
height            -0.081273           0.259526   -0.085725 -0.315756
curb-weight        0.168642           0.156444    0.758095 -0.279411
engine-size        0.208004           0.029005    0.822656 -0.256702
bore              -0.051087           0.002021    0.566690 -0.267010
stroke             1.000000           0.186761    0.100351 -0.066173
compression-ratio  0.186761           1.000000   -0.214162 -0.436244
horsepower         0.100351          -0.214162    1.000000  0.108161
peak-rpm          -0.066173          -0.436244    0.108161  1.000000
city-mpg          -0.040677           0.330897   -0.822397 -0.116308
```

```
highway-mpg       -0.040282           0.267929   -0.804714 -0.059326
price              0.083296           0.071176    0.809779 -0.101519
city-L/100km       0.041470          -0.298898    0.889584  0.116510
highway-L/100km    0.051148          -0.222957    0.840687  0.018183

                   city-mpg  highway-mpg     price  city-L/100km  \
symboling         -0.030158     0.041248 -0.083327      0.062423
normalized-losses -0.225255    -0.182011  0.133999      0.238712
wheel-base        -0.480029    -0.552211  0.589147      0.484047
length            -0.667658    -0.700186  0.691044      0.659174
width             -0.638155    -0.684700  0.752795      0.677111
height            -0.057087    -0.111568  0.137284      0.008923
curb-weight       -0.750390    -0.795515  0.834420      0.785868
engine-size       -0.651002    -0.679877  0.872337      0.745337
bore              -0.581365    -0.590753  0.543431      0.554069
stroke            -0.040677    -0.040282  0.083296      0.041470
compression-ratio  0.330897     0.267929  0.071176     -0.298898
horsepower        -0.822397    -0.804714  0.809779      0.889584
peak-rpm          -0.116308    -0.059326 -0.101519      0.116510
city-mpg           1.000000     0.972024 -0.687186     -0.949692
highway-mpg        0.972024     1.000000 -0.705115     -0.929940
price             -0.687186    -0.705115  1.000000      0.790291
city-L/100km      -0.949692    -0.929940  0.790291      1.000000
highway-L/100km   -0.909113    -0.951133  0.801313      0.958312

                   highway-L/100km
symboling                -0.033159
normalized-losses         0.181247
wheel-base                0.584953
length                    0.708466
width                     0.739845
height                    0.088903
curb-weight               0.837217
engine-size               0.783593
bore                      0.558759
stroke                    0.051148
compression-ratio        -0.222957
horsepower                0.840687
peak-rpm                  0.018183
city-mpg                 -0.909113
highway-mpg              -0.951133
price                     0.801313
city-L/100km              0.958312
highway-L/100km           1.000000
```

The diagonal elements are always one; we will study correlation more precisely Pearson correlation in-depth at the end of the notebook.

[81]:
```python
# Write your code below and press Shift+Enter to execute
df[['bore', 'stroke', 'compression-ratio', 'horsepower']].corr()
```

[81]:

	bore	stroke	compression-ratio	horsepower
bore	1.000000	-0.051087	0.002021	0.566690
stroke	-0.051087	1.000000	0.186761	0.100351
compression-ratio	0.002021	0.186761	1.000000	-0.214162
horsepower	0.566690	0.100351	-0.214162	1.000000

Continuous Numerical Variables:

Continuous numerical variables are variables that may contain any value within some range. They can be of type "int64" or "float64". A great way to visualize these variables is by using scatterplots with fitted lines.

In order to start understanding the (linear) relationship between an individual variable and the price, we can use "regplot" which plots the scatterplot plus the fitted regression line for the data. This will be useful later on for visualizing the fit of the simple linear regression model as well.

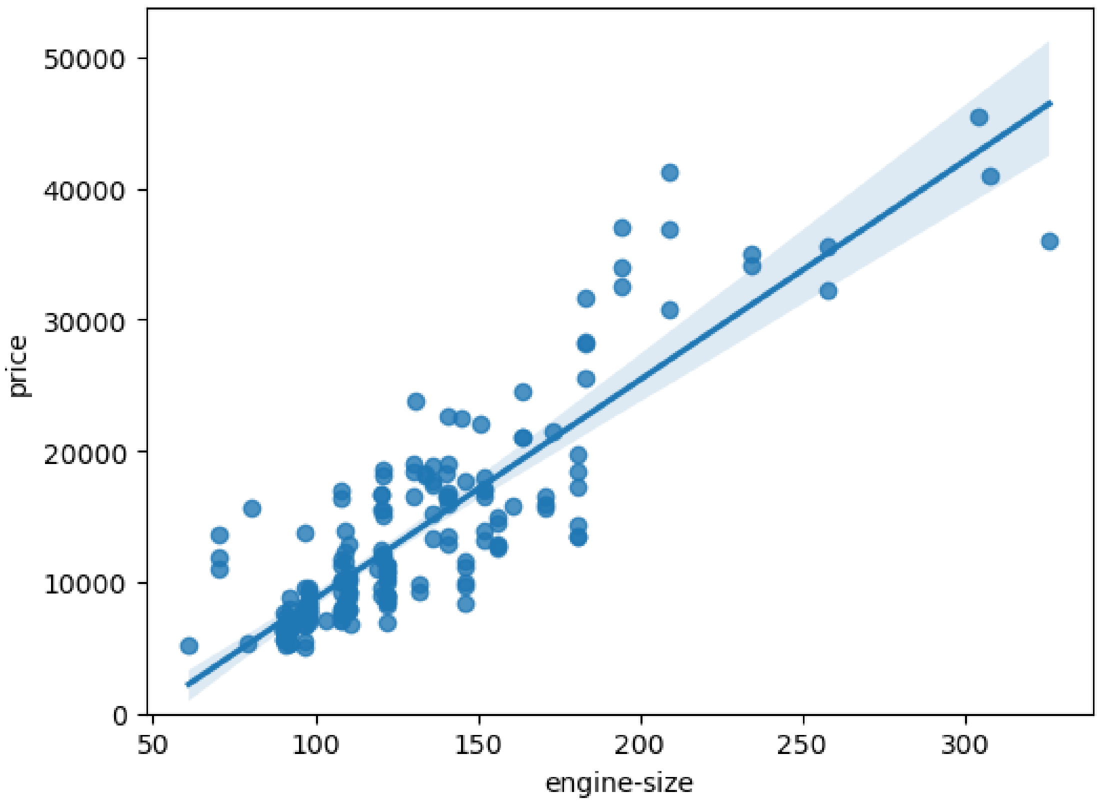
Let's see several examples of different linear relationships:

Positive Linear Relationship

Let's find the scatterplot of "engine-size" and "price".

[82]:
```python
# Engine size as potential predictor variable of price
sns.regplot(x="engine-size", y="price", data=df)
plt.ylim(0,)
```

[82]:
```
(0.0, 53738.88790772015)
```



As the engine-size goes up, the price goes up: this indicates a positive direct correlation between these two variables. Engine size seems like a pretty good predictor of price since the regression line is almost a perfect diagonal line.

We can examine the correlation between 'engine-size' and 'price' and see that it's approximately 0.87.

[83]:
```
df[["engine-size", "price"]].corr()
```

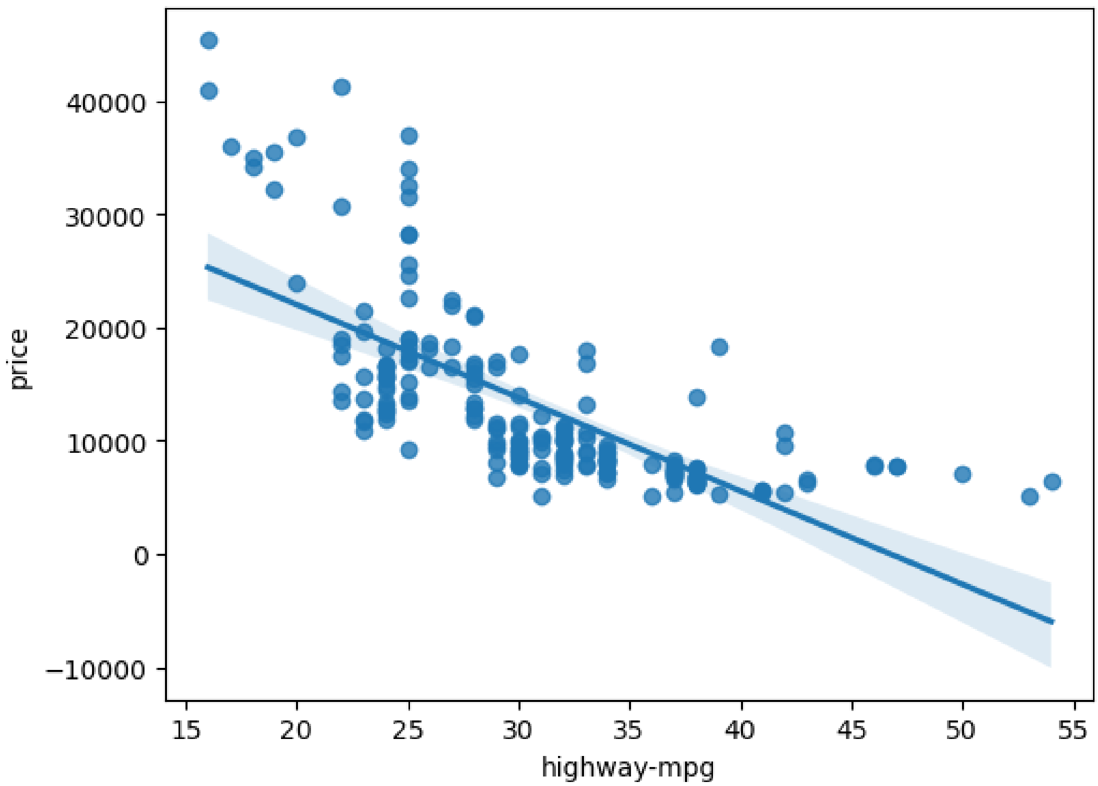
[83]:

	engine-size	price
engine-size	1.000000	0.872337
price	0.872337	1.000000

Highway mpg is a potential predictor variable of price. Let's find the scatterplot of "highway-mpg" and "price".

[84]:
```
sns.regplot(x="highway-mpg", y="price", data=df)
```

[84]: <Axes: xlabel='highway-mpg', ylabel='price'>



As highway-mpg goes up, the price goes down: this indicates an inverse/negative relationship between these two variables. Highway mpg could potentially be a predictor of price.

We can examine the correlation between 'highway-mpg' and 'price' and see it's approximately -0.704.

[85]:
```
df[['highway-mpg', 'price']].corr()
```

[85]:

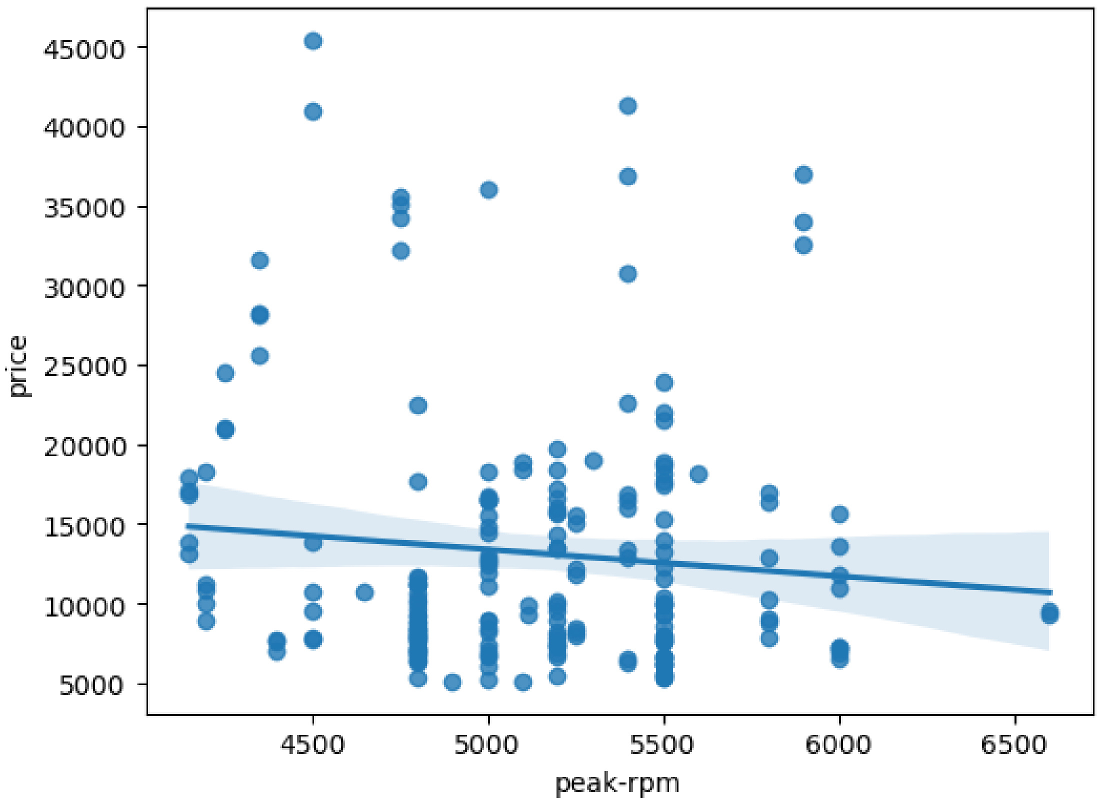
	highway-mpg	price
highway-mpg	1.000000	-0.705115
price	-0.705115	1.000000

Weak Linear Relationship

Let's see if "peak-rpm" is a predictor variable of "price".

[86]:
```
sns.regplot(x="peak-rpm", y="price", data=df)
```

[86]: <Axes: xlabel='peak-rpm', ylabel='price'>



Peak rpm does not seem like a good predictor of the price at all since the regression line is close to horizontal. Also, the data points are very scattered and far from the fitted line, showing lots of variability. Therefore, it's not a reliable variable.

We can examine the correlation between 'peak-rpm' and 'price' and see it's approximately -0.101616.

[87]:
```
df[['peak-rpm','price']].corr()
```

[87]:

	peak-rpm	price
peak-rpm	1.000000	-0.101519
price	-0.101519	1.000000

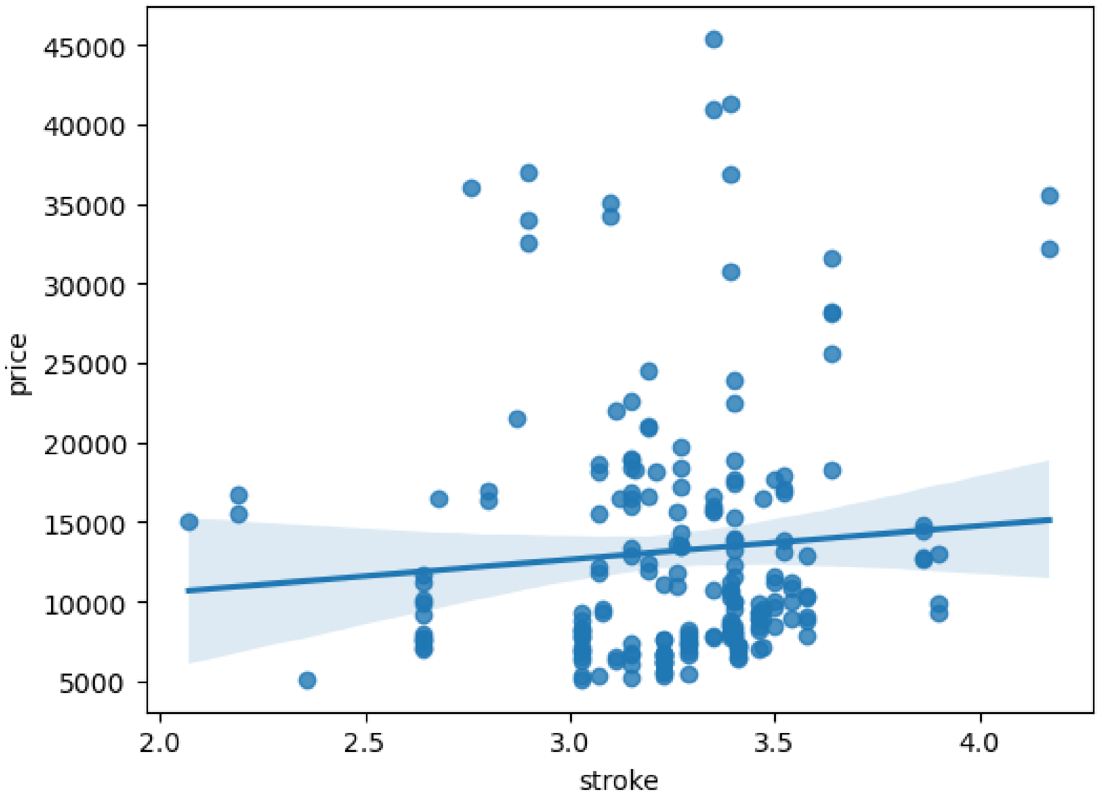
[88]:
```
# Write your code below and press Shift+Enter to execute
df[["stroke","price"]].corr()
```

[88]:

	stroke	price
stroke	1.000000	0.083296
price	0.083296	1.000000

[89]:
```
# Write your code below and press Shift+Enter to execute
sns.regplot(x="stroke", y="price", data=df)
```

[89]: <Axes: xlabel='stroke', ylabel='price'>



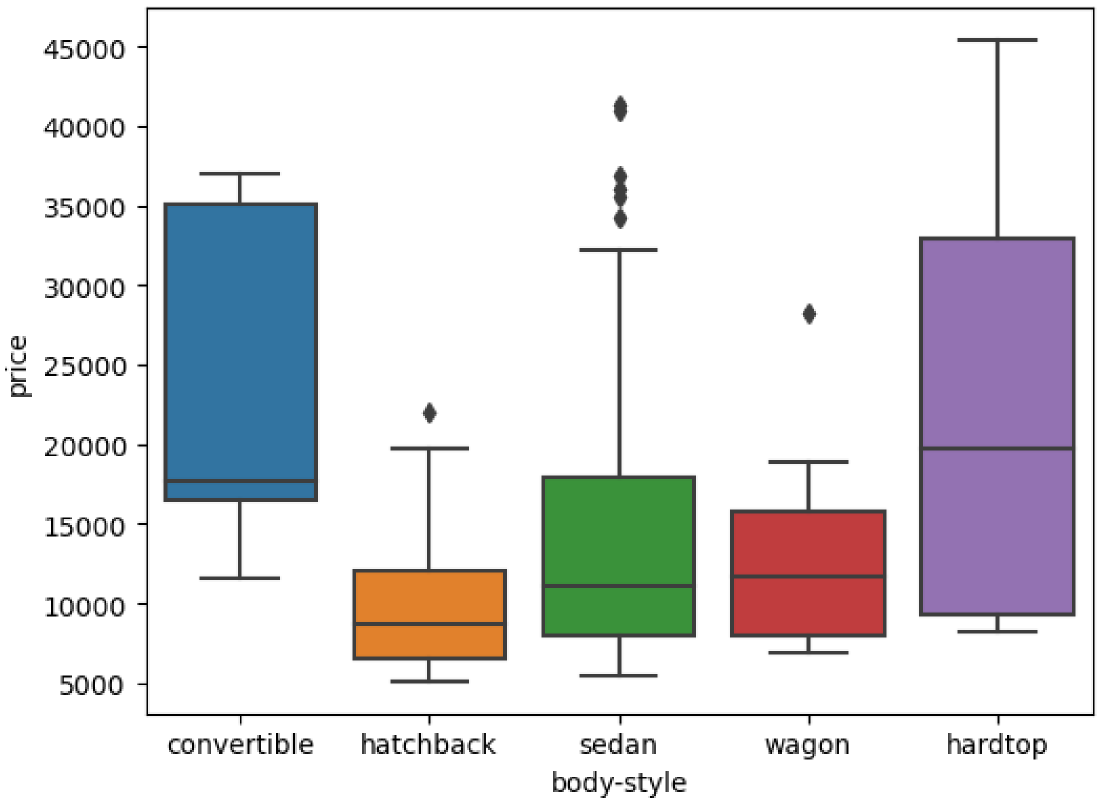
Categorical Variables

These are variables that describe a 'characteristic' of a data unit, and are selected from a small group of categories. The categorical variables can have the type "object" or "int64". A good way to visualize categorical variables is by using boxplots.

Let's look at the relationship between "body-style" and "price".

[90]:
```
sns.boxplot(x="body-style", y="price", data=df)
```

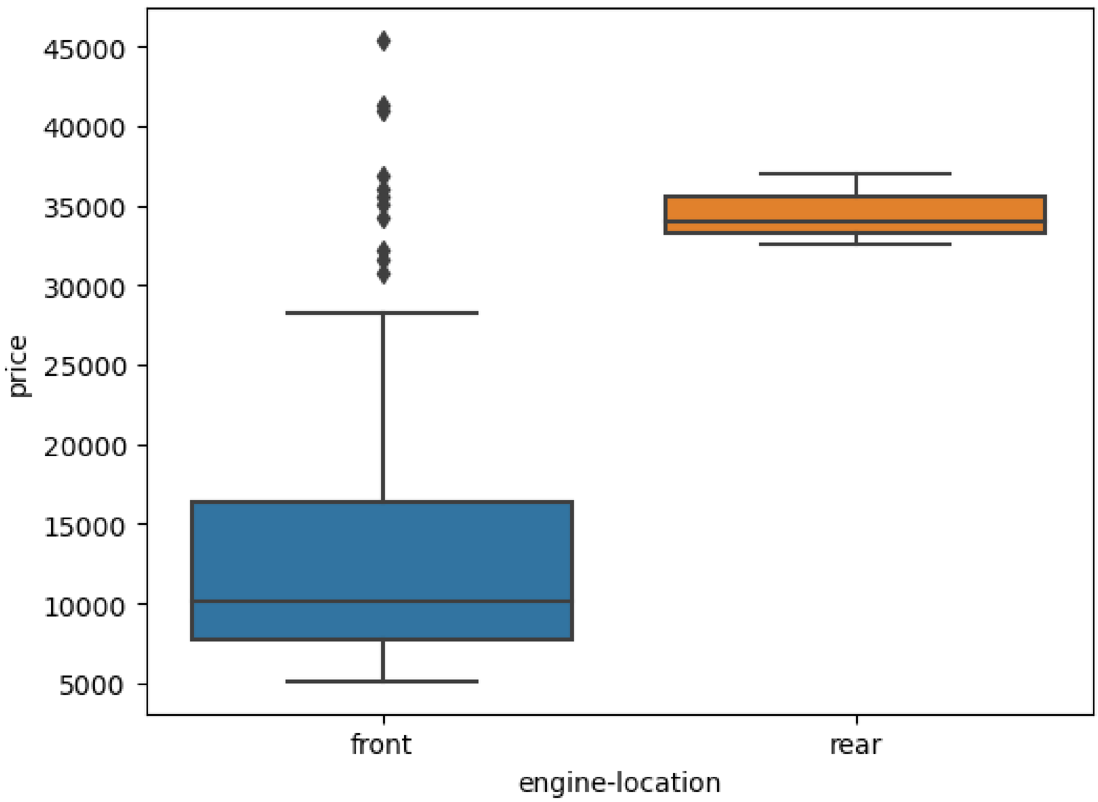
[90]: <Axes: xlabel='body-style', ylabel='price'>



We see that the distributions of price between the different body-style categories have a significant overlap, so body-style would not be a good predictor of price. Let's examine engine "engine-location" and "price":

[91]:
```
sns.boxplot(x="engine-location", y="price", data=df)
```

[91]:
```
<Axes: xlabel='engine-location', ylabel='price'>
```

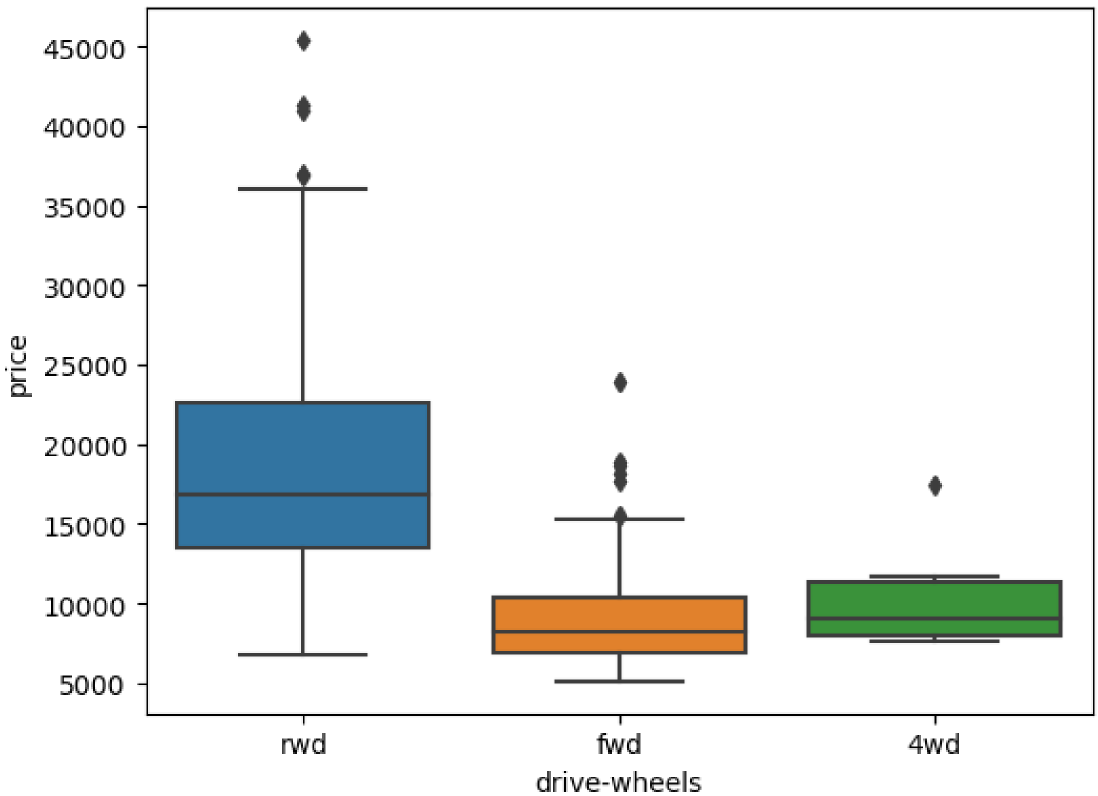


Here we see that the distribution of price between these two engine-location categories, front and rear, are distinct enough to take engine-location as a potential good predictor of price.

Let's examine "drive-wheels" and "price".

[92]:
```
# drive-wheels
sns.boxplot(x="drive-wheels", y="price", data=df)
```

[92]: <Axes: xlabel='drive-wheels', ylabel='price'>



Here we see that the distribution of price between the different drive-wheels categories differs. As such, drive-wheels could potentially be a predictor of price.

6.4 Descriptive Statistical Analysis

Let's first take a look at the variables by utilizing a description method.

The describe function automatically computes basic statistics for all continuous variables. Any NaN values are automatically skipped in these statistics.

This will show:

the count of that variable

the mean

the standard deviation (std)

the minimum value

the IQR (Interquartile Range: 25%, 50% and 75%)

the maximum value

We can apply the method "describe" as follows:

[93]:
```python
df.describe()
```

[93]:

	symboling	normalized-losses	wheel-base	length	width
count	200.000000	200.000000	200.000000	200.000000	200.000000
mean	0.830000	122.000000	98.848000	0.837232	0.915250
std	1.248557	32.076542	6.038261	0.059333	0.029207
min	-2.000000	65.000000	86.600000	0.678039	0.837500
25%	0.000000	100.250000	94.500000	0.800937	0.891319
50%	1.000000	122.000000	97.000000	0.832292	0.909722
75%	2.000000	138.250000	102.400000	0.881788	0.926042
max	3.000000	256.000000	120.900000	1.000000	1.000000

	height	curb-weight	engine-size	bore	stroke
count	200.000000	200.000000	200.000000	200.000000	200.000000
mean	0.899523	2555.705000	126.860000	3.330000	3.259847
std	0.040610	518.594552	41.650501	0.268562	0.314177
min	0.799331	1488.000000	61.000000	2.540000	2.070000
25%	0.869565	2163.000000	97.750000	3.150000	3.117500
50%	0.904682	2414.000000	119.500000	3.310000	3.290000
75%	0.928512	2928.250000	142.000000	3.582500	3.410000
max	1.000000	4066.000000	326.000000	3.940000	4.170000

	compression-ratio	horsepower	peak-rpm	city-mpg	highway-mpg
count	200.000000	200.000000	200.000000	200.000000	200.000000
mean	10.170100	103.355000	5118.181818	25.200000	30.705000
std	4.014163	37.455487	479.240110	6.432487	6.827227
min	7.000000	48.000000	4150.000000	13.000000	16.000000
25%	8.575000	70.000000	4800.000000	19.000000	25.000000
50%	9.000000	95.000000	5159.090909	24.000000	30.000000
75%	9.400000	116.000000	5500.000000	30.000000	34.000000
max	23.000000	262.000000	6600.000000	49.000000	54.000000

	price	city-L/100km	highway-L/100km
count	200.000000	200.000000	200.000000
mean	13205.690000	9.937914	8.041663
std	7966.982558	2.539415	1.844764
min	5118.000000	4.795918	4.351852
25%	7775.000000	7.833333	6.911765
50%	10270.000000	9.791667	7.833333
75%	16500.750000	12.368421	9.400000
max	45400.000000	18.076923	14.687500

The default setting of “describe” skips variables of type object. We can apply the method “describe” on the variables of type ‘object’ as follows:

[94]:
```python
df.describe(include=['object'])
```

[94]:
```
          make aspiration num-of-doors body-style drive-wheels  \
count      200        200          200        200          200
unique      22          2            2          5            3
top     toyota        std         four      sedan          fwd
freq        32        164          115         94          118

       engine-location engine-type num-of-cylinders fuel-system  \
count              200         200              200         200
unique               2           6                7           8
top              front         ohc             four        mpfi
freq               197         145              156          91

       horsepower-binned
count                200
unique                 3
top                  Low
freq                 152
```

Value Counts

Value counts is a good way of understanding how many units of each characteristic/variable we have. We can apply the "value_counts" method on the column "drive-wheels". Don't forget the method "value_counts" only works on pandas series, not pandas dataframes. As a result, we only include one bracket df['drive-wheels'], not two brackets df[['drive-wheels']].

[95]:
```
df['drive-wheels'].value_counts()
```

[95]:
```
drive-wheels
fwd    118
rwd     74
4wd      8
Name: count, dtype: int64
```

We can convert the series to a dataframe as follows:

[96]:
```
df['drive-wheels'].value_counts().to_frame()
```

[96]:
```
              count
drive-wheels
fwd             118
rwd              74
4wd               8
```

Let's repeat the above steps but save the results to the dataframe "drive_wheels_counts" and rename the column 'drive-wheels' to 'value_counts'.

[97]:
```
drive_wheels_counts = df['drive-wheels'].value_counts().to_frame()
drive_wheels_counts.rename(columns={'drive-wheels': 'value_counts'},␣
 ↪inplace=True)
```

```
drive_wheels_counts
```

[97]:

```
              count
drive-wheels
fwd             118
rwd              74
4wd               8
```

Now let's rename the index to 'drive-wheels':

[98]:

```
drive_wheels_counts.index.name = 'drive-wheels'
drive_wheels_counts
```

[98]:

```
              count
drive-wheels
fwd             118
rwd              74
4wd               8
```

We can repeat the above process for the variable 'engine-location'.

[99]:

```
# engine-location as variable
engine_loc_counts = df['engine-location'].value_counts().to_frame()
engine_loc_counts.rename(columns={'engine-location': 'value_counts'},␣
 ↪inplace=True)
engine_loc_counts.index.name = 'engine-location'
engine_loc_counts.head(10)
```

[99]:

```
                 count
engine-location
front              197
rear                 3
```

After examining the value counts of the engine location, we see that engine location would not be a good predictor variable for the price. This is because we only have three cars with a rear engine and 198 with an engine in the front, so this result is skewed. Thus, we are not able to draw any conclusions about the engine location.

6.5 Basics of Grouping

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

For example, let's group by the variable "drive-wheels". We see that there are 3 different categories of drive wheels.

[100]:

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

[100]:

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

If we want to know, on average, which type of drive wheel is most valuable, we can group "drive-wheels" and then average them.

We can select the columns 'drive-wheels', 'body-style' and 'price', then assign it to the variable "df_group_one".

[101]:
```
df_group_one = df[['drive-wheels','body-style','price']]
```

We can then calculate the average price for each of the different categories of data.

[102]:
```
# Assuming you want to analyze 'price' column based on 'drive-wheels'
df_group_one = df.groupby(['drive-wheels'], as_index=False)['price'].mean()
df_group_one
```

[102]:

	drive-wheels	price
0	4wd	10241.000000
1	fwd	9244.779661
2	rwd	19842.243243

From our data, it seems rear-wheel drive vehicles are, on average, the most expensive, while 4-wheel and front-wheel are approximately the same in price.

You can also group by multiple variables. For example, let's group by both 'drive-wheels' and 'body-style'. This groups the dataframe by the unique combination of 'drive-wheels' and 'body-style'. We can store the results in the variable 'grouped_test1'.

[103]:
```
# grouping results
df_gptest = df[['drive-wheels','body-style','price']]
grouped_test1 = df_gptest.groupby(['drive-wheels','body-style'],as_index=False).
↪mean()
grouped_test1
```

[103]:

	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	26563.250000
9	rwd	hardtop	24202.714286
10	rwd	hatchback	14337.777778
11	rwd	sedan	21711.833333
12	rwd	wagon	16994.222222

This grouped data is much easier to visualize when it is made into a pivot table. A pivot table is like an Excel spreadsheet, with one variable along the column and another along the row. We can convert the dataframe to a pivot table using the method "pivot" to create a pivot table from the groups.

In this case, we will leave the drive-wheels variable as the rows of the table, and pivot body-style to become the columns of the table:

[104]:
```
grouped_pivot = grouped_test1.pivot(index='drive-wheels',columns='body-style')
grouped_pivot
```

[104]:
```
                    price                                                \
body-style    convertible       hardtop     hatchback         sedan
drive-wheels
4wd                   NaN           NaN   7603.000000  12647.333333
fwd              11595.00   8249.000000   8396.387755   9811.800000
rwd              26563.25  24202.714286  14337.777778  21711.833333


body-style            wagon
drive-wheels
4wd             9095.750000
fwd             9997.333333
rwd            16994.222222
```

Often, we won't have data for some of the pivot cells. We can fill these missing cells with the value 0, but any other value could potentially be used as well. It should be mentioned that missing data is quite a complex subject and is an entire course on its own.

[105]:
```
grouped_pivot = grouped_pivot.fillna(0) #fill missing values with 0
grouped_pivot
```

[105]:
```
                    price                                                \
body-style    convertible       hardtop     hatchback         sedan
drive-wheels
4wd                  0.00      0.000000   7603.000000  12647.333333
fwd              11595.00   8249.000000   8396.387755   9811.800000
rwd              26563.25  24202.714286  14337.777778  21711.833333


body-style            wagon
drive-wheels
4wd             9095.750000
fwd             9997.333333
rwd            16994.222222
```

[106]:
```
df_gptest2 = df[['body-style','price']]
grouped_test_bodystyle = df_gptest2.groupby(['body-style'],as_index= False).
 ↪mean()
grouped_test_bodystyle
```

[106]:

```
     body-style         price
0   convertible  23569.600000
1       hardtop  22208.500000
2     hatchback   9957.441176
3         sedan  14459.755319
4         wagon  12371.960000
```

If you did not import “pyplot”, let’s do it again.

[107]:

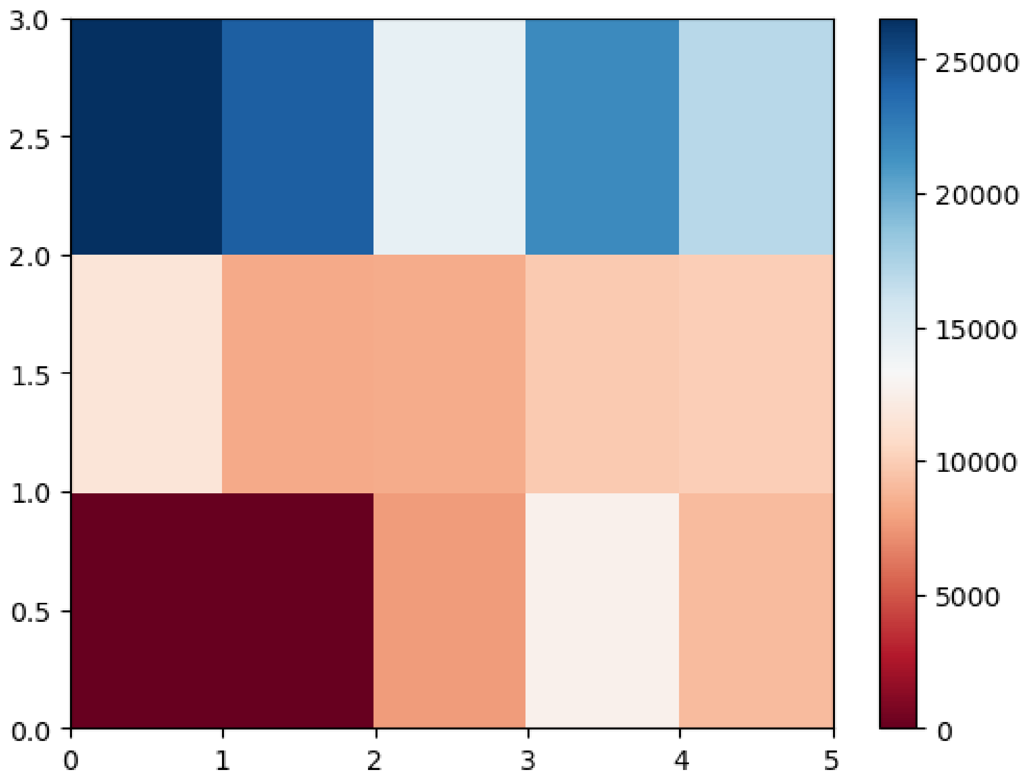
```
import matplotlib.pyplot as plt
%matplotlib inline
```

Variables: Drive Wheels and Body Style vs. Price

Let’s use a heat map to visualize the relationship between Body Style vs Price.

[108]:

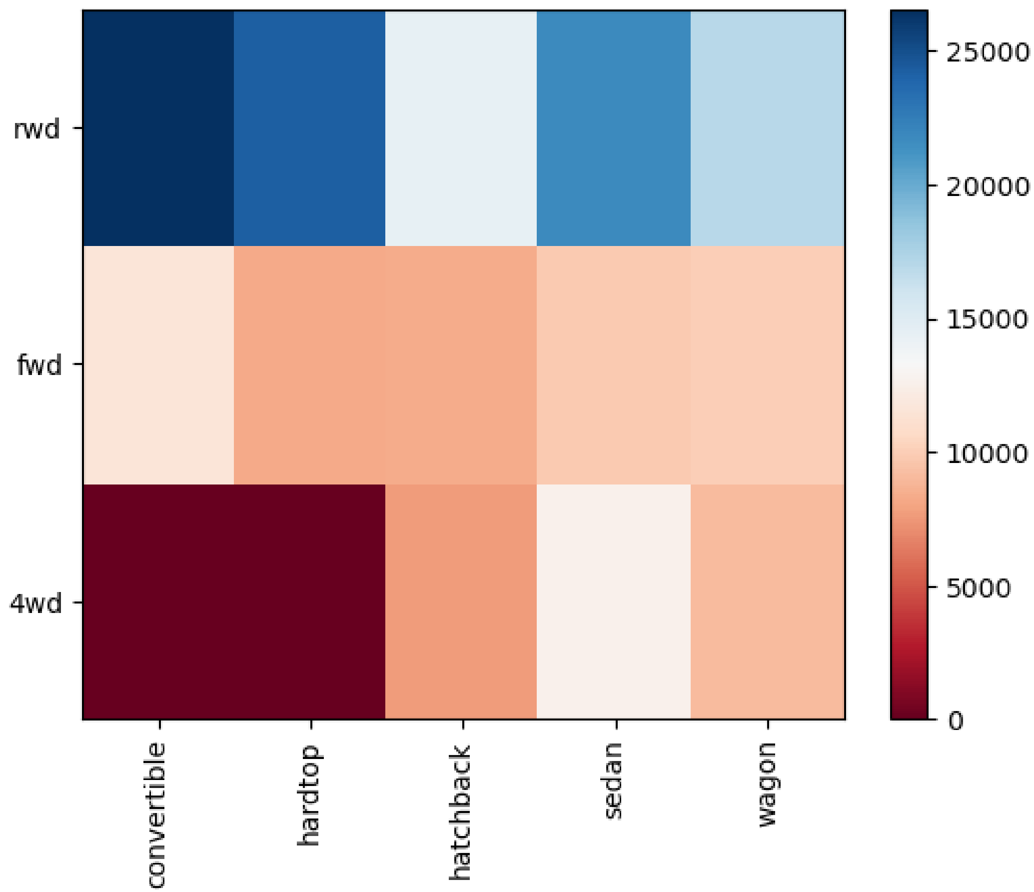
```
#use the grouped results
plt.pcolor(grouped_pivot, cmap='RdBu')
plt.colorbar()
plt.show()
```



The heatmap plots the target variable (price) proportional to colour with respect to the variables ‘drive-wheel’ and ‘body-style’ on the vertical and horizontal axis, respectively. This allows us to visualize how the price is related to ‘drive-wheel’ and ‘body-style’.

The default labels convey no useful information to us. Let's change that:

[109]:
```
fig, ax = plt.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
plt.xticks(rotation=90)

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



Visualization is very important in data science, and Python visualization packages provide great freedom. We will go more in-depth in a separate Python visualizations course.

The main question we want to answer in this module is, "What are the main characteristics which have the most impact on the car price?".

To get a better measure of the important characteristics, we look at the correlation of these variables with the car price. In other words: how is the car price dependent on this variable?

6.6 Correlation and Causation

Correlation: a measure of the extent of interdependence between variables.

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

It is important to know the difference between these two. Correlation does not imply causation. Determining correlation is much simpler the determining causation as causation may require independent experimentation.

Pearson Correlation

The Pearson Correlation measures the linear dependence between two variables X and Y.

The resulting coefficient is a value between -1 and 1 inclusive, where:

1: Perfect positive linear correlation.

0: No linear correlation, the two variables most likely do not affect each other.

-1: Perfect negative linear correlation.

Pearson Correlation is the default method of the function "corr". Like before, we can calculate the Pearson Correlation of the of the 'int64' or 'float64' variables.

[110]:
```
numeric_df = df.select_dtypes(include=['float64', 'int64'])
numeric_df.corr()
```

[110]:
```
                   symboling  normalized-losses  wheel-base    length  \
symboling           1.000000           0.469772   -0.529145 -0.364511
normalized-losses   0.469772           1.000000   -0.057068  0.019433
wheel-base         -0.529145          -0.057068    1.000000  0.879005
length             -0.364511           0.019433    0.879005  1.000000
width              -0.237262           0.086961    0.814593  0.857271
height             -0.542261          -0.377664    0.583789  0.492955
curb-weight        -0.234743           0.099404    0.787584  0.881058
engine-size        -0.112069           0.112362    0.576779  0.685531
bore               -0.145667          -0.029867    0.501534  0.610817
stroke              0.008244           0.055759    0.144675  0.120888
compression-ratio  -0.181073          -0.114738    0.249689  0.159203
horsepower          0.074581           0.217323    0.375732  0.580477
peak-rpm            0.284011           0.239580   -0.364971 -0.286754
city-mpg           -0.030158          -0.225255   -0.480029 -0.667658
highway-mpg         0.041248          -0.182011   -0.552211 -0.700186
price              -0.083327           0.133999    0.589147  0.691044
city-L/100km        0.062423           0.238712    0.484047  0.659174
highway-L/100km    -0.033159           0.181247    0.584953  0.708466

                      width    height  curb-weight  engine-size      bore  \
symboling         -0.237262 -0.542261    -0.234743    -0.112069 -0.145667
normalized-losses  0.086961 -0.377664     0.099404     0.112362 -0.029867
wheel-base         0.814593  0.583789     0.787584     0.576779  0.501534
length             0.857271  0.492955     0.881058     0.685531  0.610817
width              1.000000  0.300995     0.867720     0.731100  0.548478
height             0.300995  1.000000     0.310660     0.076255  0.187794
curb-weight        0.867720  0.310660     1.000000     0.849090  0.644532
engine-size        0.731100  0.076255     0.849090     1.000000  0.572786
bore               0.548478  0.187794     0.644532     0.572786  1.000000
stroke             0.182855 -0.081273     0.168642     0.208004 -0.051087
compression-ratio  0.189008  0.259526     0.156444     0.029005  0.002021
horsepower         0.617032 -0.085725     0.758095     0.822656  0.566690
peak-rpm          -0.247388 -0.315756    -0.279411    -0.256702 -0.267010
city-mpg          -0.638155 -0.057087    -0.750390    -0.651002 -0.581365
```

```
highway-mpg       -0.684700 -0.111568    -0.795515    -0.679877 -0.590753
price              0.752795  0.137284     0.834420     0.872337  0.543431
city-L/100km       0.677111  0.008923     0.785868     0.745337  0.554069
highway-L/100km    0.739845  0.088903     0.837217     0.783593  0.558759

                     stroke  compression-ratio  horsepower  peak-rpm  \
symboling          0.008244          -0.181073    0.074581  0.284011
normalized-losses  0.055759          -0.114738    0.217323  0.239580
wheel-base         0.144675           0.249689    0.375732 -0.364971
length             0.120888           0.159203    0.580477 -0.286754
width              0.182855           0.189008    0.617032 -0.247388
height            -0.081273           0.259526   -0.085725 -0.315756
curb-weight        0.168642           0.156444    0.758095 -0.279411
engine-size        0.208004           0.029005    0.822656 -0.256702
bore              -0.051087           0.002021    0.566690 -0.267010
stroke             1.000000           0.186761    0.100351 -0.066173
compression-ratio  0.186761           1.000000   -0.214162 -0.436244
horsepower         0.100351          -0.214162    1.000000  0.108161
peak-rpm          -0.066173          -0.436244    0.108161  1.000000
city-mpg          -0.040677           0.330897   -0.822397 -0.116308
highway-mpg       -0.040282           0.267929   -0.804714 -0.059326
price              0.083296           0.071176    0.809779 -0.101519
city-L/100km       0.041470          -0.298898    0.889584  0.116510
highway-L/100km    0.051148          -0.222957    0.840687  0.018183

                   city-mpg  highway-mpg     price  city-L/100km  \
symboling         -0.030158     0.041248 -0.083327      0.062423
normalized-losses -0.225255    -0.182011  0.133999      0.238712
wheel-base        -0.480029    -0.552211  0.589147      0.484047
length            -0.667658    -0.700186  0.691044      0.659174
width             -0.638155    -0.684700  0.752795      0.677111
height            -0.057087    -0.111568  0.137284      0.008923
curb-weight       -0.750390    -0.795515  0.834420      0.785868
engine-size       -0.651002    -0.679877  0.872337      0.745337
bore              -0.581365    -0.590753  0.543431      0.554069
stroke            -0.040677    -0.040282  0.083296      0.041470
compression-ratio  0.330897     0.267929  0.071176     -0.298898
horsepower        -0.822397    -0.804714  0.809779      0.889584
peak-rpm          -0.116308    -0.059326 -0.101519      0.116510
city-mpg           1.000000     0.972024 -0.687186     -0.949692
highway-mpg        0.972024     1.000000 -0.705115     -0.929940
price             -0.687186    -0.705115  1.000000      0.790291
city-L/100km      -0.949692    -0.929940  0.790291      1.000000
highway-L/100km   -0.909113    -0.951133  0.801313      0.958312

                   highway-L/100km
symboling                -0.033159
```

```
normalized-losses          0.181247
wheel-base                 0.584953
length                     0.708466
width                      0.739845
height                     0.088903
curb-weight                0.837217
engine-size                0.783593
bore                       0.558759
stroke                     0.051148
compression-ratio         -0.222957
horsepower                 0.840687
peak-rpm                   0.018183
city-mpg                  -0.909113
highway-mpg               -0.951133
price                      0.801313
city-L/100km               0.958312
highway-L/100km            1.000000
```

Sometimes we would like to know the significant of the correlation estimate.

P-value

What is this P-value? The P-value is the probability value that the correlation between these two variables is statistically significant. Normally, we choose a significance level of 0.05, which means that we are 95% confident that the correlation between the variables is significant.

By convention, when the

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.

We can obtain this information using "stats" module in the "scipy" library.

[111]:
```python
from scipy import stats
```

Wheel-Base vs. Price

Let's calculate the Pearson Correlation Coefficient and P-value of 'wheel-base' and 'price'.

[112]:
```python
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 =", p_value)
```

```
The Pearson Correlation Coefficient is 0.5891470005448705  with a P-value of P =
4.457019502050087e-20
```

Conclusion:

Since the p-value is < 0.001, the correlation between wheel-base and price is statistically significant, although the linear relationship isn't extremely strong (~0.585).

Horsepower vs. Price

Let's calculate the Pearson Correlation Coefficient and P-value of 'horsepower' and 'price'.

[113]:
```
pearson_coef, p_value = stats.pearsonr(df['horsepower'], df['price'])
print("The Pearson Correlation Coefficient is", pearson_coef, " with a P-value␣
↪of P = ", p_value)
```

```
The Pearson Correlation Coefficient is 0.8097789763551083  with a P-value of P =
9.887379251280244e-48
```

Conclusion:

Since the p-value is < 0.001, the correlation between horsepower and price is statistically significant, and the linear relationship is quite strong (~0.809, close to 1).

Length vs. Price

Let's calculate the Pearson Correlation Coefficient and P-value of 'length' and 'price'.

[114]:
```
pearson_coef, p_value = stats.pearsonr(df['length'], df['price'])
print("The Pearson Correlation Coefficient is", pearson_coef, " with a P-value␣
↪of P = ", p_value)
```

```
The Pearson Correlation Coefficient is 0.6910440897821907  with a P-value of P =
9.960963222347273e-30
```

Conclusion:

Since the p-value is < 0.001, the correlation between length and price is statistically significant, and the linear relationship is moderately strong (~0.691).

Width vs. Price

Let's calculate the Pearson Correlation Coefficient and P-value of 'width' and 'price':

[115]:
```
pearson_coef, p_value = stats.pearsonr(df['width'], df['price'])
print("The Pearson Correlation Coefficient is", pearson_coef, " with a P-value␣
↪of P =", p_value )
```

```
The Pearson Correlation Coefficient is 0.7527948631832613  with a P-value of P =
8.256714148307422e-38
```

Conclusion: Since the p-value is < 0.001, the correlation between width and price is statistically significant, and the linear relationship is quite strong (~0.751).

6.6.1 Curb-Weight vs. Price

Let's calculate the Pearson Correlation Coefficient and P-value of 'curb-weight' and 'price':

[116]:
```
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 = ", p_value)
```

```
The Pearson Correlation Coefficient is 0.8344204348498463  with a P-value of P =
3.9699775360213907e-53
```

Conclusion:

Since the p-value is < 0.001, the correlation between curb-weight and price is statistically significant, and the linear relationship is quite strong (~0.834).

Engine-Size vs. Price

Let's calculate the Pearson Correlation Coefficient and P-value of 'engine-size' and 'price':

[117]:
```
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 =", p_value)
```

```
The Pearson Correlation Coefficient is 0.8723367498521142  with a P-value of P =
1.8977171466561833e-63
```

Conclusion:

Since the p-value is < 0.001, the correlation between engine-size and price is statistically significant, and the linear relationship is very strong (~0.872).

Bore vs. Price

Let's calculate the Pearson Correlation Coefficient and P-value of 'bore' and 'price':

[118]:
```
pearson_coef, p_value = stats.pearsonr(df['bore'], df['price'])
print("The Pearson Correlation Coefficient is", pearson_coef, " with a P-value␣
  ↪of P =  ", p_value )
```

```
The Pearson Correlation Coefficient is 0.5434310033088079  with a P-value of P =
9.209749630850307e-17
```

Conclusion:

Since the p-value is < 0.001, the correlation between bore and price is statistically significant, but the linear relationship is only moderate (~0.521).

We can relate the process for each 'city-mpg' and 'highway-mpg':

City-mpg vs. Price

[119]:
```
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 = ", p_value)
```

```
The Pearson Correlation Coefficient is -0.6871861020862693  with a P-value of P
=  2.729256568478666e-29
```

Conclusion:

Since the p-value is < 0.001, the correlation between city-mpg and price is statistically significant, and the coefficient of about -0.687 shows that the relationship is negative and moderately strong.

Highway-mpg vs. Price

[120]:
```
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 = ", p_value )
```

```
The Pearson Correlation Coefficient is -0.7051147088046401  with a P-value of P
=  2.1973260531584746e-31
```

Conclusion: Since the p-value is < 0.001, the correlation between highway-mpg and price is statistically significant, and the coefficient of about -0.705 shows that the relationship is negative and moderately strong.

Conclusion: Important Variables

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.

7 Model Development

Estimated time needed: **30** minutes

7.1 Objectives

- Develop prediction models

Some questions we want to ask in this module

Do I know if the dealer is offering fair value for my trade-in?

Do I know if I put a fair value on my car?

In data analytics, we often use Model Development to help us predict future observations from the data we have.

A model will help us understand the exact relationship between different variables and how these variables are used to predict the result.

Setup

Import libraries:

[121]:
```
#install specific version of libraries used in lab
#! mamba install pandas==1.3.3-y
#! mamba install numpy=1.21.2-y
#! mamba install sklearn=0.20.1-y
```

[122]:
```
'''import piplite
await piplite.install('seaborn')'''
```

[122]:
```
"import piplite\nawait piplite.install('seaborn')"
```

[123]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

Load the data and store it in dataframe `df`:

This dataset was hosted on IBM Cloud object. Click HERE for free storage. Download it by running the cell below.

[124]:
```
'''from pyodide.http import pyfetch

async def download(url, filename):
    response = await pyfetch(url)
    if response.status == 200:
        with open(filename, "wb") as f:
            f.write(await response.bytes())'''
```

[124]:
```
'from pyodide.http import pyfetch\n\nasync def download(url, filename):\n
response = await pyfetch(url)\n    if response.status == 200:\n        with
open(filename, "wb") as f:\n            f.write(await response.bytes())'
```

[125]:
```python
file_path= "https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/
↪IBMDeveloperSkillsNetwork-DA0101EN-SkillsNetwork/labs/Data%20files/
↪automobileEDA.csv"

#await download(file_path, "usedcars.csv")
file_name="usedCars.csv"
```

[126]:
```python
df = pd.read_csv(file_name)
df.head()
```

[126]:
```
   symboling  normalized-losses         make aspiration num-of-doors  \
0          3                122  alfa-romero        std          two
1          1                122  alfa-romero        std          two
2          2                164         audi        std         four
3          2                164         audi        std         four
4          2                122         audi        std          two

    body-style drive-wheels engine-location  wheel-base    length  …  \
0  convertible          rwd           front        88.6  0.811148  …
1    hatchback          rwd           front        94.5  0.822681  …
2        sedan          fwd           front        99.8  0.848630  …
3        sedan          4wd           front        99.4  0.848630  …
4        sedan          fwd           front        99.8  0.851994  …

   horsepower  peak-rpm  city-mpg highway-mpg    price  city-L/100km  \
0         111    5000.0        21          27  16500.0     11.190476
1         154    5000.0        19          26  16500.0     12.368421
2         102    5500.0        24          30  13950.0      9.791667
3         115    5500.0        18          22  17450.0     13.055556
4         110    5500.0        19          25  15250.0     12.368421

  highway-L/100km  horsepower-binned  fuel-type-diesel  fuel-type-gas
0        8.703704                Low             False           True
1        9.038462             Medium             False           True
2        7.833333                Low             False           True
3       10.681818                Low             False           True
4        9.400000                Low             False           True

[5 rows x 30 columns]
```

[127]:
```python
#filepath = "https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/
↪IBMDeveloperSkillsNetwork-DA0101EN-SkillsNetwork/labs/Data%20files/
↪automobileEDA.csv"
#df = pd.read_csv(filepath, header=None)
```

1. Linear Regression and Multiple Linear Regression

Linear Regression

One example of a Data Model that we will be using is:

Simple Linear Regression

Simple Linear Regression is a method to help us understand the relationship between two variables:

The predictor/independent variable (X)

The response/dependent variable (that we want to predict)(Y)

The result of Linear Regression is a linear function that predicts the response (dependent) variable as a function of the predictor (independent) variable.

$$Y: Response\ Variable X: Predictor\ Variables$$

Linear Function

$$Yhat = a + bX$$

a refers to the intercept of the regression line, in other words: the value of Y when X is 0

b refers to the slope of the regression line, in other words: the value with which Y changes when X increases by 1 unit

Let's load the modules for linear regression:

[128]:
```
from sklearn.linear_model import LinearRegression
```

Create the linear regression object:

[129]:
```
lm = LinearRegression()
lm
```

[129]:
```
LinearRegression()
```

How could "highway-mpg" help us predict car price?

For this example, we want to look at how highway-mpg can help us predict car price. Using simple linear regression, we will create a linear function with "highway-mpg" as the predictor variable and the "price" as the response variable.

[130]:
```
X = df[['highway-mpg']]
Y = df['price']
```

Fit the linear model using highway-mpg:

[131]:
```
lm.fit(X,Y)
```

[131]:
```
LinearRegression()
```

We can output a prediction:

[132]:
```
Yhat=lm.predict(X)
Yhat[0:5]
```

[132]: array([16254.26934067, 17077.0977727 , 13785.78404458, 20368.41150083,
        17899.92620473])

What is the value of the intercept (a)?

[133]:
```
lm.intercept_
```

[133]: 38470.63700549668

What is the value of the slope (b)?

[134]:
```
lm.coef_
```

[134]: array([-822.82843203])

What is the final estimated linear model we get?

As we saw above, we should get a final linear model with the structure:

$$Yhat = a + bX$$

Plugging in the actual values we get:

Price = 38423.31 - 821.73 x highway-mpg

Create a linear regression object called "lm1".

[135]:
```
lm1=LinearRegression()
lm1
```

[135]: LinearRegression()

Train the model using "engine-size" as the independent variable and "price" as the dependent variable?

[136]:
```
# Write your code below and press Shift+Enter to execute
x=df[['engine-size']]
y=df['price']
lm1.fit(x,y)
yhat=lm1.predict(x)
yhat[0:5]
```

[136]: array([13729.63711709, 17400.60417954, 10225.53219385, 14730.80995231,
        14730.80995231])

Find the slope and intercept of the model.

Slope

[137]:
```
lm1.coef_
```

[137]: array([166.8621392])

Intercept

[138]:
```python
# Write your code below and press Shift+Enter to execute
lm1.intercept_
```

[138]: -7962.4409791630915

Equation of the predicted line, can use x and yhat or “engine-size” or “price”.

[139]:
```python
# using X and Y
Yhat=-7963.34 + 166.86*X

Price=-7963.34 + 166.86*df['engine-size']
```

Multiple Linear Regression

What if we want to predict car price using more than one variable?

If we want to use more variables in our model to predict car price, we can use Multiple Linear Regression. Multiple Linear Regression is very similar to Simple Linear Regression, but this method is used to explain the relationship between one continuous response (dependent) variable and two or more predictor (independent) variables. Most of the real-world regression models involve multiple predictors. We will illustrate the structure by using four predictor variables, but these results can generalize to any integer:

$$Y : Response\, Variable X_1 : Predictor\, Variable\, 1 X_2 : Predictor\, Variable\, 2 X_3 : Predictor\, Variable\, 3 X_4 : Predict$$

$$a : intercept b_1 : coefficients\, of\, Variable\, 1 b_2 : coefficients\, of\, Variable\, 2 b_3 : coefficients\, of\, Variable\, 3 b_4 : coef$$

The equation is given by:

$$Yhat = a + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4$$

From the previous section we know that other good predictors of price could be:

Horsepower

Curb-weight

Engine-size

Highway-mpg

Let’s develop a model using these variables as the predictor variables.

[140]:
```python
Z = df[['horsepower', 'curb-weight', 'engine-size', 'highway-mpg']]
```

Fit the linear model using the four above-mentioned variables.

[141]:
```python
lm.fit(Z, df['price'])
```

[141]:
```
LinearRegression()
```

What is the value of the intercept(a)?

[142]:
```python
lm.intercept_
```

[142]:
```
-15814.43913901131
```

What are the values of the coefficients (b1, b2, b3, b4)?

[143]:
```python
lm.coef_
```

[143]:
```
array([53.64350321,  4.70621169, 81.46397065, 36.26760488])
```

What is the final estimated linear model that we get?

As we saw above, we should get a final linear function with the structure:

$$Yhat = a + b_1 X_1 + b_2 X_2 + b_3 X_3 + b_4 X_4$$

What is the linear function we get in this example?

Price = -15678.742628061467 + 52.65851272 x horsepower + 4.69878948 x curb-weight + 81.95906216 x engine-size + 33.58258185 x highway-mpg

Create and train a Multiple Linear Regression model "lm2" where the response variable is "price", and the predictor variable is "normalized-losses" and "highway-mpg".

[144]:
```python
lm2=LinearRegression()
Z1 = df[['normalized-losses', 'highway-mpg']]
lm2.fit(Z1,y)
```

[144]:
```
LinearRegression()
```

Find the coefficient of the model.

[145]:
```python
# Write your code below and press Shift+Enter to execute
lm2.coef_
```

[145]:
```
array([   1.45409594, -821.58496582])
```

2. Model Evaluation Using Visualization

Now that we've developed some models, how do we evaluate our models and choose the best one? One way to do this is by using a visualization.

Import the visualization package, seaborn:

[146]:
```python
# import the visualization package: seaborn
import seaborn as sns
%matplotlib inline
```

Regression Plot

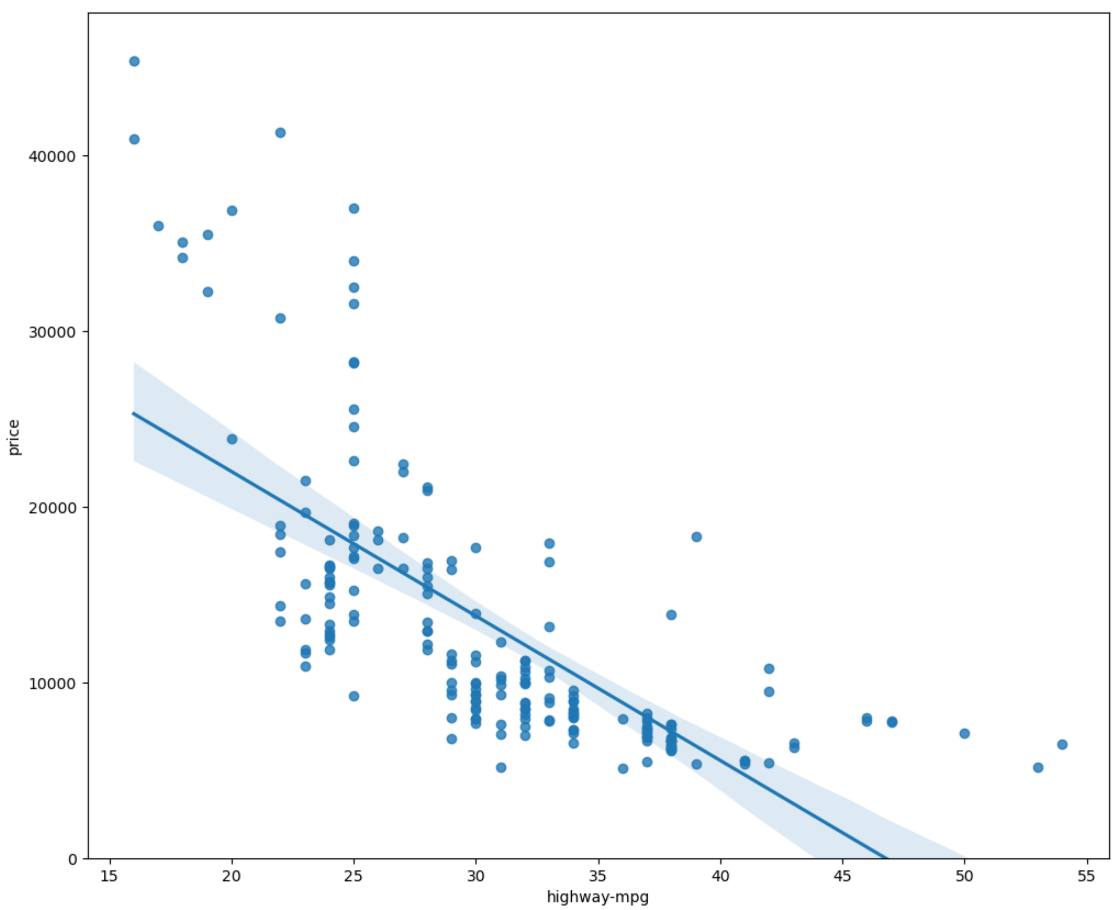
When it comes to simple linear regression, an excellent way to visualize the fit of our model is by using regression plots.

This plot will show a combination of a scattered data points (a scatterplot), as well as the fitted linear regression line going through the data. This will give us a reasonable estimate of the relationship between the two variables, the strength of the correlation, as well as the direction (positive or negative correlation).

Let's visualize **highway-mpg** as potential predictor variable of price:

[147]:
```python
width = 12
height = 10
plt.figure(figsize=(width, height))
sns.regplot(x="highway-mpg", y="price", data=df)
plt.ylim(0,)
```

[147]: (0.0, 48180.10936597729)



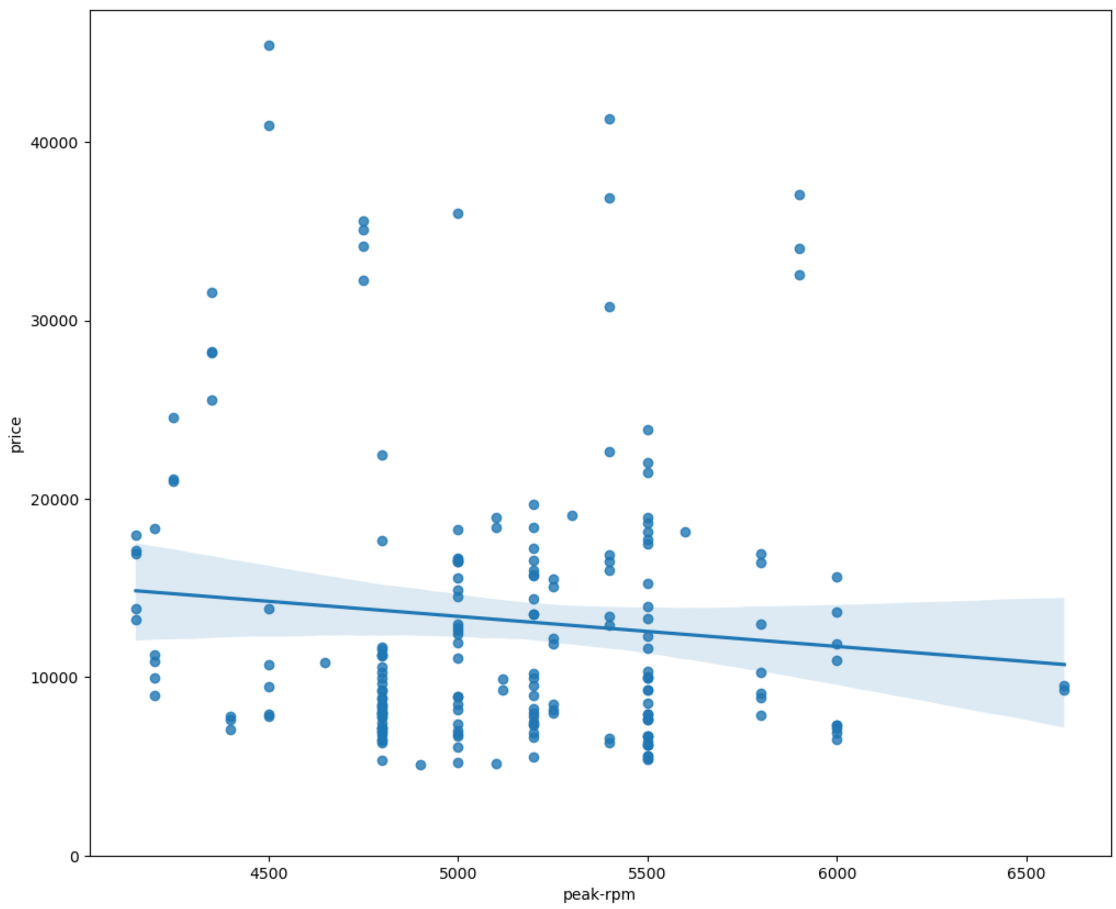
We can see from this plot that price is negatively correlated to highway-mpg since the regression slope is negative.

One thing to keep in mind when looking at a regression plot is to pay attention to how scattered the data points are around the regression line. This will give you a good indication of the variance of the data and whether a linear model would be the best fit or not. If the data is too far off from the line, this linear model might not be the best model for this data.

Let's compare this plot to the regression plot of "peak-rpm".

[148]:
```
plt.figure(figsize=(width, height))
sns.regplot(x="peak-rpm", y="price", data=df)
plt.ylim(0,)
```

[148]: (0.0, 47414.1)



Comparing the regression plot of "peak-rpm" and "highway-mpg", we see that the points for "highway-mpg" are much closer to the generated line and, on average, decrease. The points for “peak-rpm” have more spread around the predicted line and it is much harder to determine if the points are decreasing or increasing as the “peak-rpm” increases.

Given the regression plots above, is “peak-rpm” or “highway-mpg” more strongly correlated with “price”?Can use the method “.corr()” to verify your answer.

[149]:
```
# Write your code below and press Shift+Enter to execute
df[["peak-rpm","highway-mpg","price"]].corr()
```

[149]:

	peak-rpm	highway-mpg	price
peak-rpm	1.000000	-0.059326	-0.101519
highway-mpg	-0.059326	1.000000	-0.705115
price	-0.101519	-0.705115	1.000000

Residual Plot

A good way to visualize the variance of the data is to use a residual plot.

What is a residual?

The difference between the observed value (y) and the predicted value (Yhat) is called the residual (e). When we look at a regression plot, the residual is the distance from the data point to the fitted regression line.

So what is a residual plot?

A residual plot is a graph that shows the residuals on the vertical y-axis and the independent variable on the horizontal x-axis.

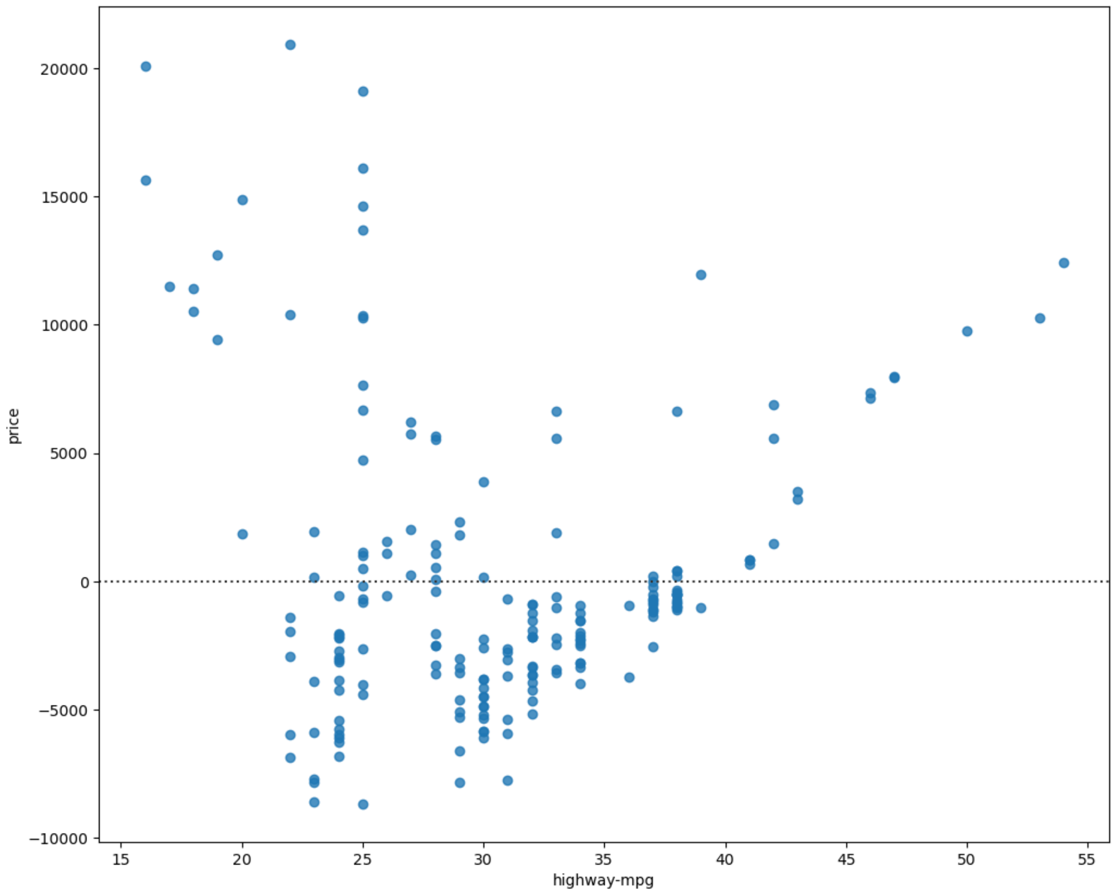
What do we pay attention to when looking at a residual plot?

We look at the spread of the residuals:

- If the points in a residual plot are randomly spread out around the x-axis, then a linear model is appropriate for the data.

Why is that? Randomly spread out residuals means that the variance is constant, and thus the linear model is a good fit for this data.

[150]:
```
width = 12
height = 10
plt.figure(figsize=(width, height))
sns.residplot(x=df['highway-mpg'], y=df['price'])
plt.show()
```



What is this plot telling us?

We can see from this residual plot that the residuals are not randomly spread around the x-axis, leading us to believe that maybe a non-linear model is more appropriate for this data.

Multiple Linear Regression

How do we visualize a model for Multiple Linear Regression? This gets a bit more complicated because you can't visualize it with regression or residual plot.

One way to look at the fit of the model is by looking at the distribution plot. We can look at the distribution of the fitted values that result from the model and compare it to the distribution of the actual values.

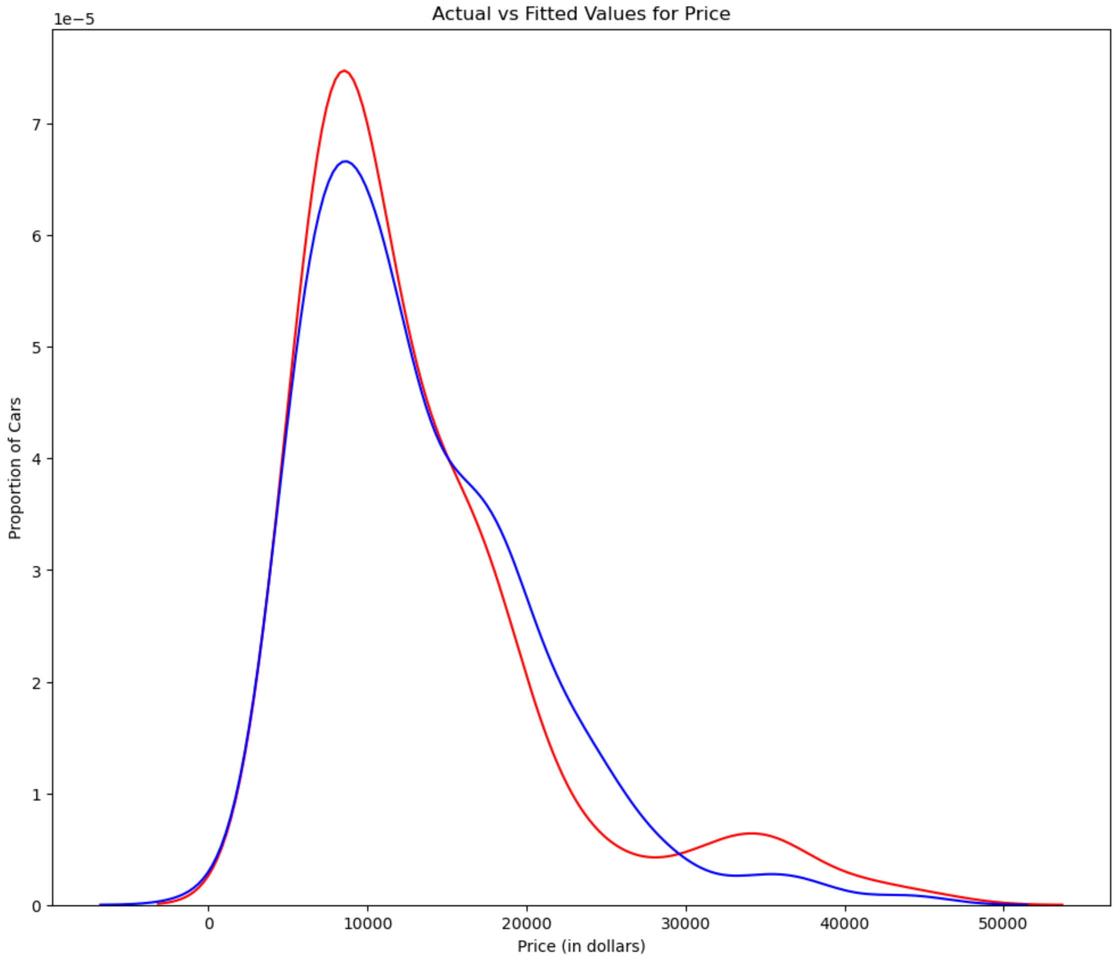
First, let's make a prediction:

[151]:
```
Y_hat = lm.predict(Z)
```

[152]:
```
plt.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)


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

plt.show()
plt.close()
```

```
C:\Users\DHESIKA\AppData\Local\Temp\ipykernel_12304\4196657742.py:4:
UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `kdeplot` (an axes-level function for kernel density
plots).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  ax1 = sns.distplot(df['price'], hist=False, color="r", label="Actual Value")
C:\Users\DHESIKA\AppData\Local\Temp\ipykernel_12304\4196657742.py:5:
UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `kdeplot` (an axes-level function for kernel density
plots).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(Y_hat, hist=False, color="b", label="Fitted Values" , ax=ax1)
```



We can see that the fitted values are reasonably close to the actual values since the two distributions overlap a bit. However, there is definitely some room for improvement.

3. Polynomial Regression and Pipelines

Polynomial regression is a particular case of the general linear regression model or multiple linear regression models.

We get non-linear relationships by squaring or setting higher-order terms of the predictor variables.

There are different orders of polynomial regression:

Quadratic - 2nd Order

$$Yhat = a + b_1X + b_2X^2$$

Cubic - 3rd Order

$$Yhat = a + b_1X + b_2X^2 + b_3X^3$$

Higher-Order:

$$Y = a + b_1 X + b_2 X^2 + b_3 X^3 \ldots$$

We saw earlier that a linear model did not provide the best fit while using "highway-mpg" as the predictor variable. Let's see if we can try fitting a polynomial model to the data instead.

We will use the following function to plot the data:

[153]:
```python
def PlotPolly(model, independent_variable, dependent_variabble, Name):
    x_new = np.linspace(15, 55, 100)
    y_new = model(x_new)

    plt.plot(independent_variable, dependent_variabble, '.', x_new, y_new, '-')
    plt.title('Polynomial Fit with Matplotlib for Price ~ Length')
    ax = plt.gca()
    ax.set_facecolor((0.898, 0.898, 0.898))
    fig = plt.gcf()
    plt.xlabel(Name)
    plt.ylabel('Price of Cars')

    plt.show()
    plt.close()
```

Let's get the variables:

[154]:
```python
x = df['highway-mpg']
y = df['price']
```

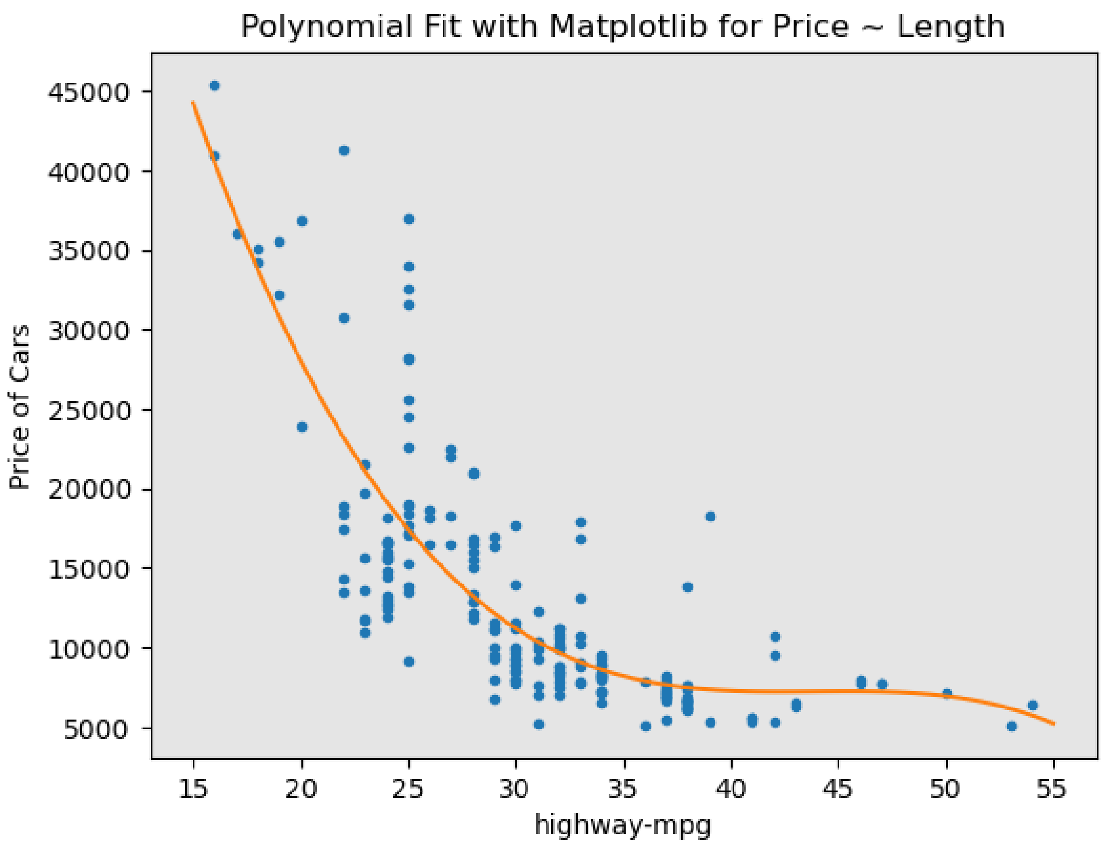
Let's fit the polynomial using the function polyfit, then use the function poly1d to display the polynomial function.

[155]:
```python
# Here we use a polynomial of the 3rd order (cubic)
f = np.polyfit(x, y, 3)
p = np.poly1d(f)
print(p)
```

```
        3         2
-1.552 x + 204.2 x - 8948 x + 1.378e+05
```

Let's plot the function:

[156]:
```python
PlotPolly(p, x, y, 'highway-mpg')
```



[157]:
```
np.polyfit(x, y, 3)
```

[157]:
```
array([-1.55173297e+00,  2.04232144e+02, -8.94817574e+03,  1.37751367e+05])
```

We can already see from plotting that this polynomial model performs better than the linear model. This is because the generated polynomial function "hits" more of the data points.

Create 11 order polynomial model with the variables x and y from above.

[158]:
```
# Write your code below and press Shift+Enter to execute
x = df['highway-mpg']
y = df['price']
f = np.polyfit(x, y, 11)
p = np.poly1d(f)
print(p)
```

```
            11             10             9           8         7
-1.273e-08 x  + 4.839e-06 x  - 0.0008229 x + 0.08259 x - 5.432 x
          6        5             4             3             2
 + 245.6 x - 7786 x + 1.729e+05 x - 2.634e+06 x + 2.62e+07 x - 1.532e+08 x +
3.987e+08
```

The analytical expression for Multivariate Polynomial function gets complicated. For example, the expression for a second-order (degree=2) polynomial with two variables is given by:

$$Yhat = a + b_1X_1 + b_2X_2 + b_3X_1X_2 + b_4X_1^2 + b_5X_2^2$$

We can perform a polynomial transform on multiple features. First, we import the module:

[159]:
```
from sklearn.preprocessing import PolynomialFeatures
```

We create a PolynomialFeatures object of degree 2:

[160]:
```
pr=PolynomialFeatures(degree=2)
pr
```

[160]:
```
PolynomialFeatures()
```

[161]:
```
Z_pr=pr.fit_transform(Z)
```

In the original data, there are 200 samples and 4 features.

[162]:
```
Z.shape
```

[162]:
```
(200, 4)
```

After the transformation, there are 200 samples and 15 features.

[163]:
```
Z_pr.shape
```

[163]:
```
(200, 15)
```

Pipeline

Data Pipelines simplify the steps of processing the data. We use the module Pipeline to create a pipeline. We also use StandardScaler as a step in our pipeline.

[164]:
```
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
```

We create the pipeline by creating a list of tuples including the name of the model or estimator and its corresponding constructor.

[165]:
```
Input=[('scale',StandardScaler()), ('polynomial',␣
↪PolynomialFeatures(include_bias=False)), ('model',LinearRegression())]
```

We input the list as an argument to the pipeline constructor:

[166]:
```
pipe=Pipeline(Input)
pipe
```

[166]:
```
Pipeline(steps=[('scale', StandardScaler()),
                ('polynomial', PolynomialFeatures(include_bias=False)),
```

```
                ('model', LinearRegression())])
```

First, we convert the data type Z to type float to avoid conversion warnings that may appear as a result of StandardScaler taking float inputs.

Then, we can normalize the data, perform a transform and fit the model simultaneously.

[167]:
```python
Z = Z.astype(float)
pipe.fit(Z,y)
```

[167]:
```
Pipeline(steps=[('scale', StandardScaler()),
                ('polynomial', PolynomialFeatures(include_bias=False)),
                ('model', LinearRegression())])
```

Similarly, we can normalize the data, perform a transform and produce a prediction simultaneously.

[168]:
```python
ypipe=pipe.predict(Z)
ypipe[0:4]
```

[168]:
```
array([13095.64294486, 18226.1683919 , 10389.2689322 , 16122.24836083])
```

Create a pipeline that standardizes the data, then produce a prediction using a linear regression model using the features Z and target y.

[169]:
```python
# Write your code below and press Shift+Enter to execute
Input=[("scale",StandardScaler()),("model",LinearRegression())]
pipe=Pipeline(Input)
Z = Z.astype(float)
pipe.fit(Z,y)
ypipe=pipe.predict(Z)
ypipe[0:4]
```

[169]:
```
array([13700.95861278, 19057.77721438, 10623.21584883, 15521.89285072])
```

4. Measures for In-Sample Evaluation

When evaluating our models, not only do we want to visualize the results, but we also want a quantitative measure to determine how accurate the model is.

Two very important measures that are often used in Statistics to determine the accuracy of a model are:

R^2 / R-squared

Mean Squared Error (MSE)

R-squared

R squared, also known as the coefficient of determination, is a measure to indicate how close the data is to the fitted regression line.

The value of the R-squared is the percentage of variation of the response variable (y) that is explained by a linear model.

Mean Squared Error (MSE)

The Mean Squared Error measures the average of the squares of errors. That is, the difference between actual value (y) and the estimated value (ŷ).

Model 1: Simple Linear Regression

Let's calculate the R^2:

[170]:
```
#highway_mpg_fit
lm.fit(X, Y)
# Find the R^2
print('The R-square is: ', lm.score(X, Y))
```

```
The R-square is:  0.49718675257265277
```

We can say that ~49% of the variation of the price is explained by this simple linear model "horsepower_fit".

Let's calculate the MSE:

We can predict the output i.e., "yhat" using the predict method, where X is the input variable:

[171]:
```
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:  [16254.26934067 17077.0977727
13785.78404458 20368.41150083]
```

Let's import the function mean_squared_error from the module metrics:

[172]:
```
from sklearn.metrics import mean_squared_error
```

We can compare the predicted results with the actual results:

[173]:
```
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:  31755395.41081295
```

Model 2: Multiple Linear Regression

Let's calculate the R^2:

[174]:
```
# 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:  0.8094411114508352
```

We can say that ~80 % of the variation of price is explained by this multiple linear regression "multi_fit".

Let's calculate the MSE.

We produce a prediction:

[175]:
```
Y_predict_multifit = lm.predict(Z)
```

We compare the predicted results with the actual results:

[176]:
```
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:
12034831.790700043
```

Model 3: Polynomial Fit

Let's calculate the R^2.

Let's import the function r2_score from the module metrics as we are using a different function.

[177]:
```
from sklearn.metrics import r2_score
```

We apply the function to get the value of R^2:

[178]:
```
r_squared = r2_score(y, p(x))
print('The R-square value is: ', r_squared)
```

```
The R-square value is:  0.7032923281262173
```

We can say that ~70 % of the variation of price is explained by this polynomial fit.

MSE

We can also calculate the MSE:

[179]:
```
mean_squared_error(df['price'], p(x))
```

[179]:
```
18738705.652609386
```

5. Prediction and Decision Making
   Prediction

In the previous section, we trained the model using the method fit. Now we will use the method predict to produce a prediction. Lets import pyplot for plotting; we will also be using some functions from numpy.

[180]:
```
import matplotlib.pyplot as plt
import numpy as np

%matplotlib inline
```

Create a new input:

[181]:
```
new_input=np.arange(1, 100, 1).reshape(-1, 1)
```

Fit the model:

[182]:
```
lm.fit(X, Y)
lm
```

[182]:
```
LinearRegression()
```

Produce a prediction:

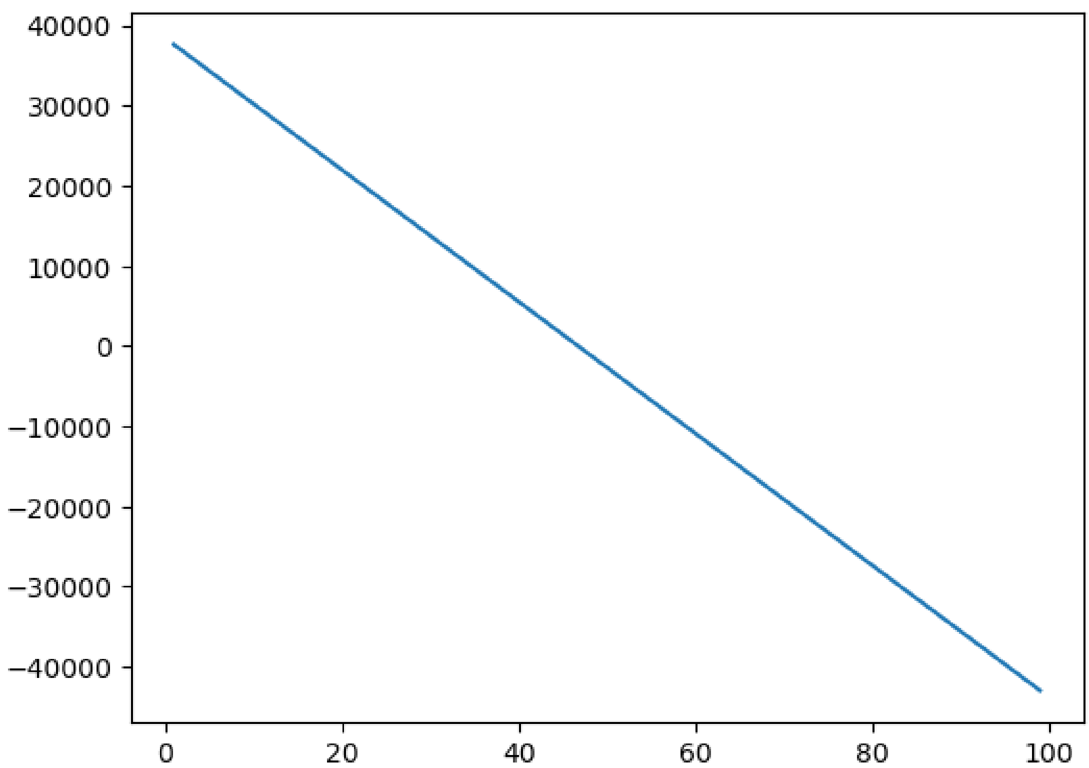
[183]:
```
yhat=lm.predict(new_input)
yhat[0:5]
```

```
D:\Users\DHESIKA\anaconda3\Lib\site-packages\sklearn\base.py:464: UserWarning: X
does not have valid feature names, but LinearRegression was fitted with feature
names
  warnings.warn(
```

[183]:
```
array([37647.80857347, 36824.98014144, 36002.15170941, 35179.32327737,
       34356.49484534])
```

We can plot the data:

[184]:
```
plt.plot(new_input, yhat)
plt.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: 0.497

MSE:3.17 x10^7

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

R-squared: 0.809

MSE: 1.2 x10^7

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

R-squared: 0.703

MSE: 1.87 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 3.17x10^7 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 (~0.49) is very small compared to the R-squared for the MLR (~0.80).

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 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.

8 Model Evaluation and Refinement

Estimated time needed: **30** minutes

8.1 Objectives

After completing this lab you will be able to:

- Evaluate and refine prediction models

Table of Contents

Model Evaluation

Over-fitting, Under-fitting and Model Selection

Ridge Regression

Grid Search

If you are running the lab in your browser in Skills Network lab, so need to install the libraries using piplite.

[185]:
```
#you are running the lab in your  browser, so we will install the libraries␣
↪using ``piplite``
'''import piplite
await piplite.install(['pandas'])
await piplite.install(['matplotlib'])
await piplite.install(['scipy'])
await piplite.install(['scikit-learn'])
await piplite.install(['seaborn'])'''
```

[185]:
```
"import piplite\nawait piplite.install(['pandas'])\nawait
piplite.install(['matplotlib'])\nawait piplite.install(['scipy'])\nawait
piplite.install(['scikit-learn'])\nawait piplite.install(['seaborn'])"
```

If you run the lab locally using Anaconda, you can load the correct library and versions by uncommenting the following:

[186]:
```
#If you run the lab locally using Anaconda, you can load the correct library␣
↪and versions by uncommenting the following:
#install specific version of libraries used in lab
#! mamba install pandas==1.3.3-y
#! mamba install numpy=1.21.2-y
#! mamba install sklearn=0.20.1-y
```

Import libraries:

[187]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
```

This function will download the dataset into your browser

[188]:
```
#This function will download the dataset into your browser

'''from pyodide.http import pyfetch

async def download(url, filename):
    response = await pyfetch(url)
    if response.status == 200:
        with open(filename, "wb") as f:
            f.write(await response.bytes())'''
```

[188]:
```
'from pyodide.http import pyfetch\n\nasync def download(url, filename):\n
response = await pyfetch(url)\n    if response.status == 200:\n        with
open(filename, "wb") as f:\n            f.write(await response.bytes())'
```

This dataset was hosted on IBM Cloud object. Click HERE for free storage.

you will need to download the dataset; using the 'download()' function.

[189]:
```
#you will need to download the dataset;
#await download('https://cf-courses-data.s3.us.cloud-object-storage.appdomain.
↪cloud/IBMDeveloperSkillsNetwork-DA0101EN-SkillsNetwork/labs/Data%20files/
↪module_5_auto.csv','module_5_auto.csv')
```

Load the data and store it in dataframe df:

[190]:
```
df = pd.read_csv("usedcarsfinal.csv", header=0)
```

[191]:
```
df.head()
```

[191]:
```
   symboling  normalized-losses         make aspiration num-of-doors  \
0          3                122  alfa-romero        std          two
1          3                122  alfa-romero        std          two
2          1                122  alfa-romero        std          two
```

```
3          2                164          audi         std          four
4          2                164          audi         std          four

    body-style drive-wheels engine-location  wheel-base    length  …  \
0  convertible          rwd           front        88.6  0.811148  …
1  convertible          rwd           front        88.6  0.811148  …
2    hatchback          rwd           front        94.5  0.822681  …
3        sedan          fwd           front        99.8  0.848630  …
4        sedan          4wd           front        99.4  0.848630  …

   compression-ratio  horsepower  peak-rpm city-mpg highway-mpg    price  \
0                9.0       111.0    5000.0       21          27  13495.0
1                9.0       111.0    5000.0       21          27  16500.0
2                9.0       154.0    5000.0       19          26  16500.0
3               10.0       102.0    5500.0       24          30  13950.0
4                8.0       115.0    5500.0       18          22  17450.0

  city-L/100km  horsepower-binned  diesel  gas
0    11.190476             Medium       0    1
1    11.190476             Medium       0    1
2    12.368421             Medium       0    1
3     9.791667             Medium       0    1
4    13.055556             Medium       0    1

[5 rows x 29 columns]
```

First, let's only use numeric data:

[192]:
```
df=df._get_numeric_data()
df.head()
```

[192]:
```
   symboling  normalized-losses  wheel-base    length     width  height  \
0          3                122        88.6  0.811148  0.890278    48.8
1          3                122        88.6  0.811148  0.890278    48.8
2          1                122        94.5  0.822681  0.909722    52.4
3          2                164        99.8  0.848630  0.919444    54.3
4          2                164        99.4  0.848630  0.922222    54.3

   curb-weight  engine-size  bore  stroke  compression-ratio  horsepower  \
0         2548          130  3.47    2.68                9.0       111.0
1         2548          130  3.47    2.68                9.0       111.0
2         2823          152  2.68    3.47                9.0       154.0
3         2337          109  3.19    3.40               10.0       102.0
4         2824          136  3.19    3.40                8.0       115.0

   peak-rpm  city-mpg  highway-mpg    price  city-L/100km  diesel  gas
0    5000.0        21           27  13495.0     11.190476       0    1
1    5000.0        21           27  16500.0     11.190476       0    1
```

```
2   5000.0          19              26  16500.0     12.368421       0    1
3   5500.0          24              30  13950.0      9.791667       0    1
4   5500.0          18              22  17450.0     13.055556       0    1
```

[193]:
```
df.columns
```

[193]:
```
Index(['symboling', 'normalized-losses', 'wheel-base', 'length', 'width',
       'height', 'curb-weight', 'engine-size', 'bore', 'stroke',
       'compression-ratio', 'horsepower', 'peak-rpm', 'city-mpg',
       'highway-mpg', 'price', 'city-L/100km', 'diesel', 'gas'],
      dtype='object')
```

Libraries for plotting:

[194]:
```
#df.drop("highway-L/100km",axis=1,inplace=True)
```

[195]:
```
from ipywidgets import interact, interactive, fixed, interact_manual
```

Functions for Plotting

[196]:
```
def DistributionPlot(RedFunction, BlueFunction, RedName, BlueName, Title):
    width = 12
    height = 10
    plt.figure(figsize=(width, height))

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

    plt.title(Title)
    plt.xlabel('Price (in dollars)')
    plt.ylabel('Proportion of Cars')
    plt.show()
    plt.close()
```

[197]:
```
def PollyPlot(xtrain, xtest, y_train, y_test, lr,poly_transform):
    width = 12
    height = 10
    plt.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)


plt.plot(xtrain, y_train, 'ro', label='Training Data')
plt.plot(xtest, y_test, 'go', label='Test Data')
plt.plot(x, lr.predict(poly_transform.fit_transform(x.reshape(-1, 1))),␣
↪label='Predicted Function')
plt.ylim([-10000, 60000])
plt.ylabel('Price')
plt.legend()
```

Part 1: Training and Testing

An important step in testing your model is to split your data into training and testing data. We will place the target data price in a separate dataframe y_data:

[198]:
```
y_data = df['price']
```

Drop price data in dataframe **x_data**:

[199]:
```
x_data=df.drop('price',axis=1)
```

Now, we randomly split our data into training and testing data using the function train_test_split.

[200]:
```
from sklearn.model_selection import train_test_split


x_train, x_test, y_train, y_test = train_test_split(x_data, y_data, test_size=0.
↪10, random_state=1)


print("number of test samples :", x_test.shape[0])
print("number of training samples:",x_train.shape[0])
```

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

The test_size parameter sets the proportion of data that is split into the testing set. In the above, the testing set is 10% of the total dataset.

Use the function "train_test_split" to split up the dataset such that 40% of the data samples will be utilized for testing. Set the parameter "random_state" equal to zero. The output of the function should be the following: "x_train1" , "x_test1", "y_train1" and "y_test1".

[201]:
```
x_train1, x_test1, y_train1, y_test1 = train_test_split(x_data, y_data,␣
↪test_size=0.4, random_state=0)
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
```

Let's import LinearRegression from the module linear_model.

[202]:
```
from sklearn.linear_model import LinearRegression
```

We create a Linear Regression object:

[203]:
```
lre=LinearRegression()
```

We fit the model using the feature "horsepower":

[204]:
```
lre.fit(x_train[['horsepower']], y_train)
```

[204]:
```
LinearRegression()
```

Let's calculate the R^2 on the test data:

[205]:
```
lre.score(x_test[['horsepower']], y_test)
```

[205]:
```
0.36358755750788263
```

We can see the R^2 is smaller using the test data compared to the training data.

[206]:
```
lre.score(x_train[['horsepower']], y_train)
```

[206]:
```
0.6619724197515104
```

Find the R^2 on the test data using 40% of the dataset for testing.

[207]:
```
x_train1, x_test1, y_train1, y_test1 = train_test_split(x_data, y_data,␣
↪test_size=0.4, random_state=0)
lre.fit(x_train1[['horsepower']],y_train1)
lre.score(x_test1[['horsepower']],y_test1)
```

[207]:
```
0.7139364665406973
```

Sometimes you do not have sufficient testing data; as a result, you may want to perform cross-validation. Let's go over several methods that you can use for cross-validation.

Cross-Validation Score

Let's import cross_val_score from the module model_selection.

[208]:
```
from sklearn.model_selection import cross_val_score
```

We input the object, the feature ("horsepower"), and the target data (y_data). The parameter 'cv' determines the number of folds. In this case, it is 4.

[209]:
```
Rcross = cross_val_score(lre, x_data[['horsepower']], y_data, cv=4)
```

The default scoring is R^2. Each element in the array has the average R^2 value for the fold:

[210]:
```
Rcross
```

[210]:
```
array([0.7746232 , 0.51716687, 0.74785353, 0.04839605])
```

We can calculate the average and standard deviation of our estimate:

[211]:
```
print("The mean of the folds are", Rcross.mean(), "and the standard deviation␣
↪is" , Rcross.std())
```

```
The mean of the folds are 0.522009915042119 and the standard deviation is
0.29118394447560286
```

We can use negative squared error as a score by setting the parameter 'scoring' metric to 'neg_mean_squared_error'.

[212]:
```
-1 * cross_val_score(lre,x_data[['horsepower']],␣
↪y_data,cv=4,scoring='neg_mean_squared_error')
```

[212]:
```
array([20254142.84026704, 43745493.26505169, 12539630.34014931,
       17561927.7224759 ])
```

Calculate the average R^2 using two folds, then find the average R^2 for the second fold utilizing the "horsepower" feature:

[213]:
```
Rc=cross_val_score(lre,x_data[['horsepower']], y_data,cv=2)
Rc.mean()
```

[213]:
```
0.5166761697127429
```

You can also use the function 'cross_val_predict' to predict the output. The function splits up the data into the specified number of folds, with one fold for testing and the other folds are used for training. First, import the function:

[214]:
```
from sklearn.model_selection import cross_val_predict
```

We input the object, the feature "horsepower", and the target data y_data. The parameter 'cv' determines the number of folds. In this case, it is 4. We can produce an output:

[215]:
```
yhat = cross_val_predict(lre,x_data[['horsepower']], y_data,cv=4)
yhat[0:5]
```

[215]:
```
array([14141.63807508, 14141.63807508, 20814.29423473, 12745.03562306,
       14762.35027598])
```

Part 2: Overfitting, Underfitting and Model Selection

It turns out that the test data, sometimes referred to as the "out of sample data", is a much better measure of how well your model performs in the real world. One reason for this is overfitting.

Let's go over some examples. It turns out these differences are more apparent in Multiple Linear Regression and Polynomial Regression so we will explore overfitting in that context.

Let's create Multiple Linear Regression objects and train the model using 'horsepower', 'curb-weight', 'engine-size' and 'highway-mpg' as features.

[216]:
```
lr = LinearRegression()
lr.fit(x_train[['horsepower', 'curb-weight', 'engine-size', 'highway-mpg']],␣
 ↪y_train)
```

[216]:
```
LinearRegression()
```

Prediction using training data:

[217]:
```
yhat_train = lr.predict(x_train[['horsepower', 'curb-weight', 'engine-size',␣
 ↪'highway-mpg']])
yhat_train[0:5]
```

[217]:
```
array([ 7426.6731551 , 28323.75090803, 14213.38819709,  4052.34146983,
        34500.19124244])
```

Prediction using test data:

[218]:
```
yhat_test = lr.predict(x_test[['horsepower', 'curb-weight', 'engine-size',␣
 ↪'highway-mpg']])
yhat_test[0:5]
```

[218]:
```
array([11349.35089149,  5884.11059106, 11208.6928275 ,  6641.07786278,
        15565.79920282])
```

Let's perform some model evaluation using our training and testing data separately. First, we import the seaborn and matplotlib library for plotting.

[219]:
```
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
```

Let's examine the distribution of the predicted values of the training data.

[220]:
```
Title = 'Distribution  Plot of  Predicted Value Using Training Data vs Training␣
 ↪Data Distribution'
DistributionPlot(y_train, yhat_train, "Actual Values (Train)", "Predicted␣
 ↪Values (Train)", Title)
```

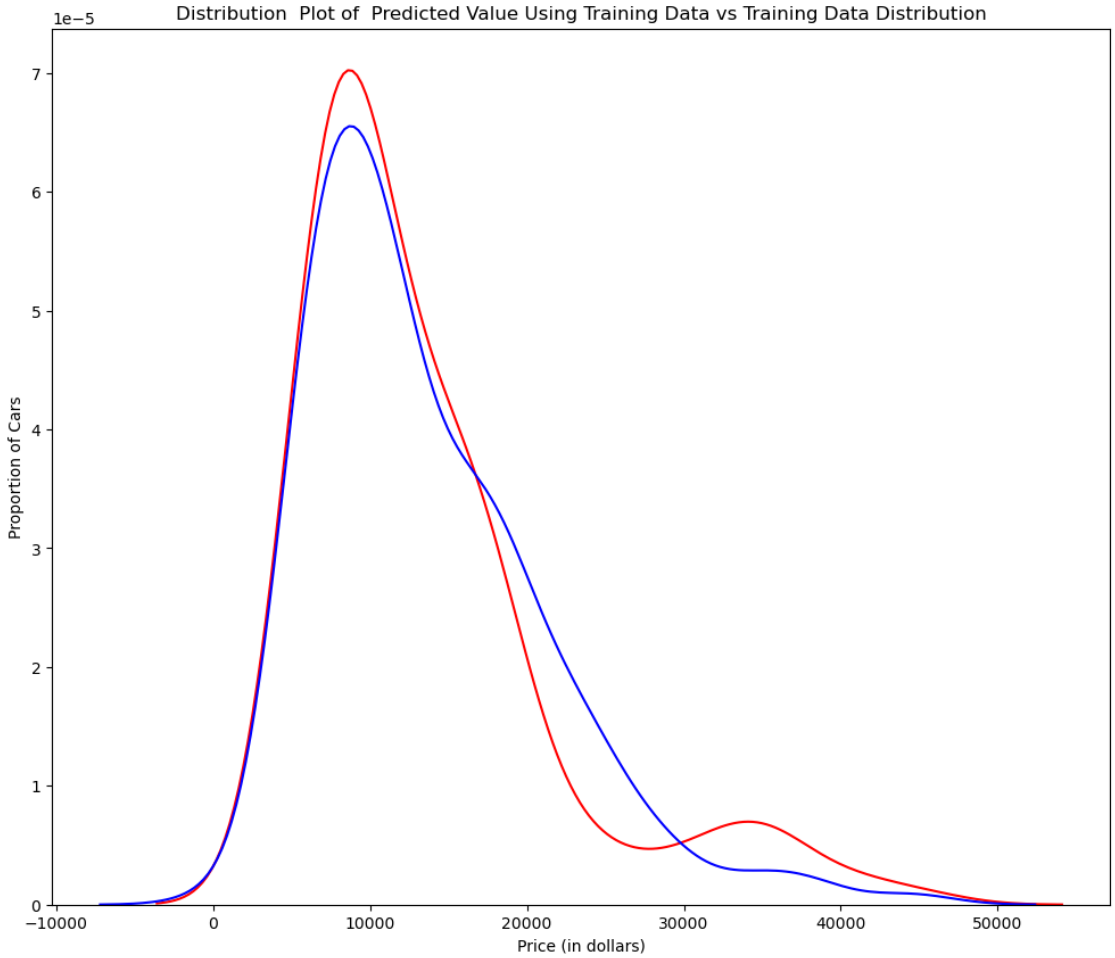
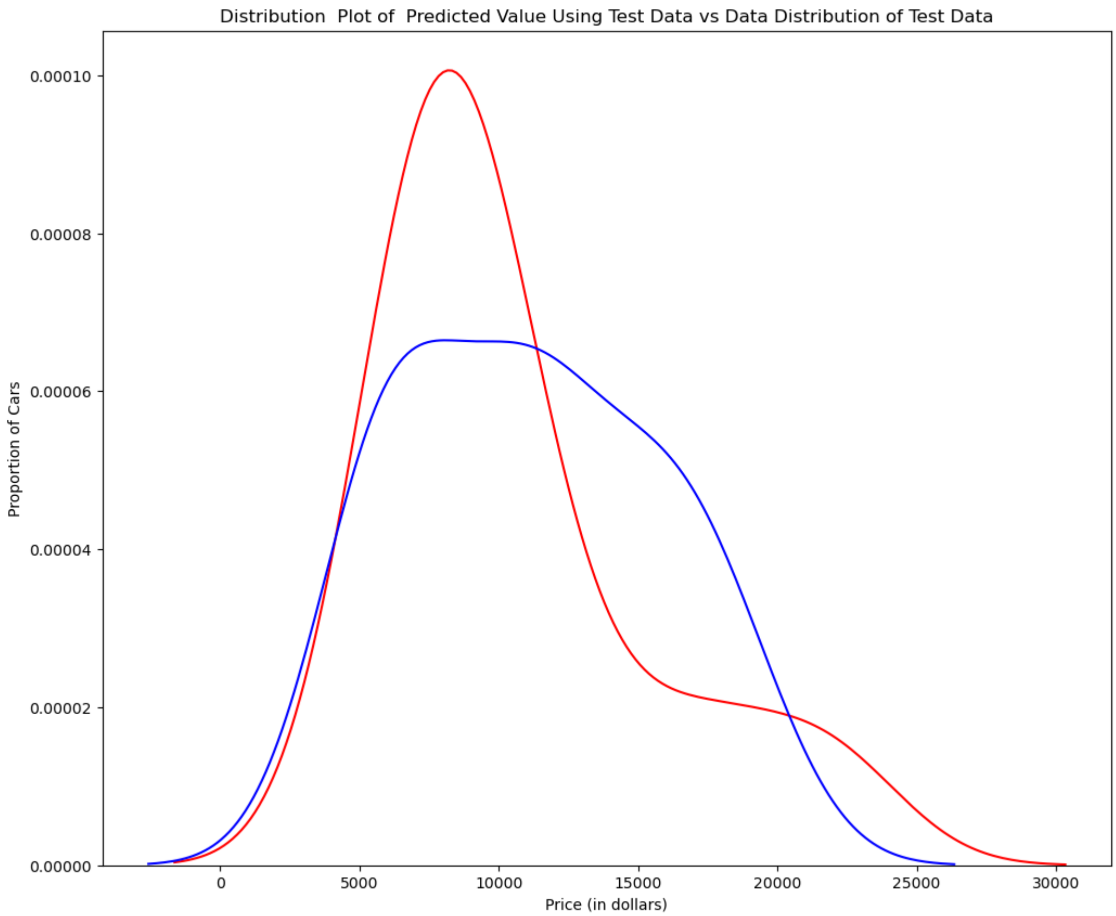


Figure 1: Plot of predicted values using the training data compared to the actual values of the training data.

So far, the model seems to be doing well in learning from the training dataset. But what happens when the model encounters new data from the testing dataset? When the model generates new values from the test data, we see the distribution of the predicted values is much different from the actual target values.

[221]:
```
Title='Distribution  Plot of  Predicted Value Using Test Data vs Data␣
 ↪Distribution of Test Data'
DistributionPlot(y_test,yhat_test,"Actual Values (Test)","Predicted Values␣
 ↪(Test)",Title)
```



Comparing Figure 1 and Figure 2, it is evident that the distribution of the test data in Figure 1 is much better at fitting the data. This difference in Figure 2 is apparent in the range of 5000 to 15,000. This is where the shape of the distribution is extremely different. Let's see if polynomial regression also exhibits a drop in the prediction accuracy when analysing the test dataset.

Figure 2: Plot of predicted value using the test data compared to the actual values of the test data.

[222]:
```
from sklearn.preprocessing import PolynomialFeatures
```

Overfitting

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, not the underlying process that generated the relationship. Let's create a degree 5 polynomial model.

Let's use 55 percent of the data for training and the rest for testing:

[223]:
```
x_train, x_test, y_train, y_test = train_test_split(x_data, y_data, test_size=0.
↪45, random_state=0)
```

We will perform a degree 5 polynomial transformation on the feature 'horsepower'.

[224]:
```
pr = PolynomialFeatures(degree=5)
x_train_pr = pr.fit_transform(x_train[['horsepower']])
x_test_pr = pr.fit_transform(x_test[['horsepower']])
pr
```

[224]:
```
PolynomialFeatures(degree=5)
```

Now, let's create a Linear Regression model "poly" and train it.

[225]:
```
poly = LinearRegression()
poly.fit(x_train_pr, y_train)
```

[225]:
```
LinearRegression()
```

We can see the output of our model using the method "predict." We assign the values to "yhat".

[226]:
```
yhat = poly.predict(x_test_pr)
yhat[0:5]
```

[226]:
```
array([ 6728.58615619,  7307.91973653, 12213.73734432, 18893.37966315,
       19996.10669225])
```

Let's take the first five predicted values and compare it to the actual targets.

[227]:
```
print("Predicted values:", yhat[0:4])
print("True values:", y_test[0:4].values)
```

```
Predicted values: [ 6728.58615619  7307.91973653 12213.73734432 18893.37966315]
True values: [ 6295. 10698. 13860. 13499.]
```

We will use the function "PollyPlot" that we defined at the beginning of the lab to display the training data, testing data, and the predicted function.

[228]:
```
PollyPlot(x_train['horsepower'], x_test['horsepower'], y_train, y_test, poly,pr)
```

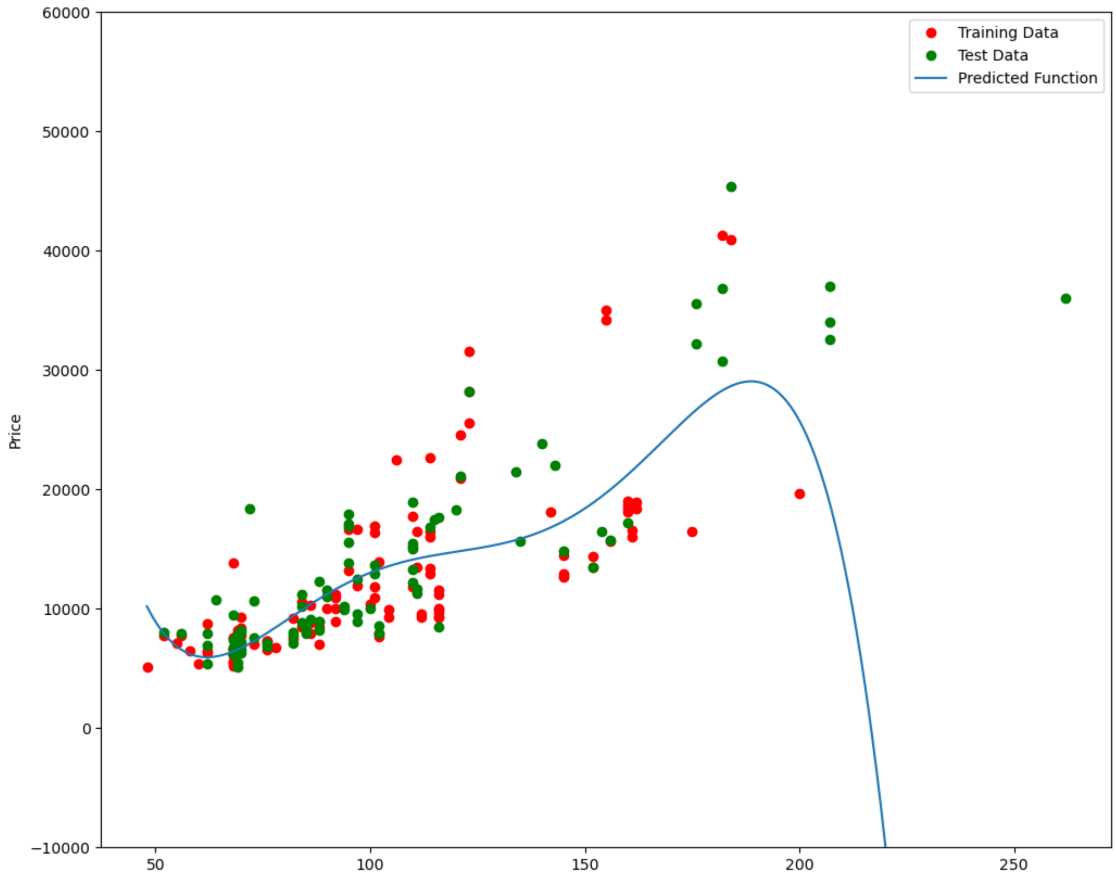


Figure 3: A polynomial regression model where red dots represent training data, green dots represent test data, and the blue line represents the model prediction.

We see that the estimated function appears to track the data but around 200 horsepower, the function begins to diverge from the data points.

R^2 of the training data:

[229]:
```
poly.score(x_train_pr, y_train)
```

[229]: 0.5567716897727109

R^2 of the test data:

[230]:
```
poly.score(x_test_pr, y_test)
```

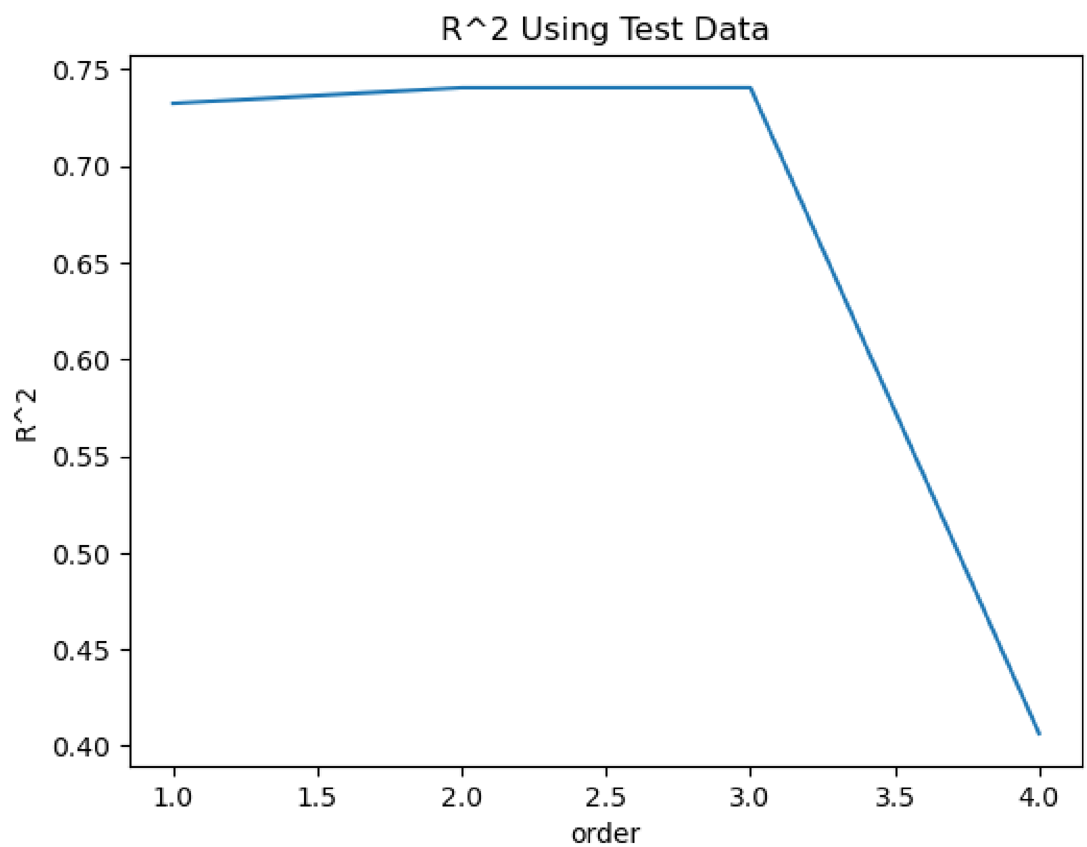
[230]: -29.870994900857237

We see the R^2 for the training data is 0.750 while the R^2 on the test data was -405.29. The lower the R^2, the worse the model. A negative R^2 is a sign of overfitting.

Let's see how the R^2 changes on the test data for different order polynomials and then plot the results:

[231]:
```
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))

plt.plot(order, Rsqu_test)
plt.xlabel('order')
plt.ylabel('R^2')
plt.title('R^2 Using Test Data')
```

[231]:
```
Text(0.5, 1.0, 'R^2 Using Test Data')
```



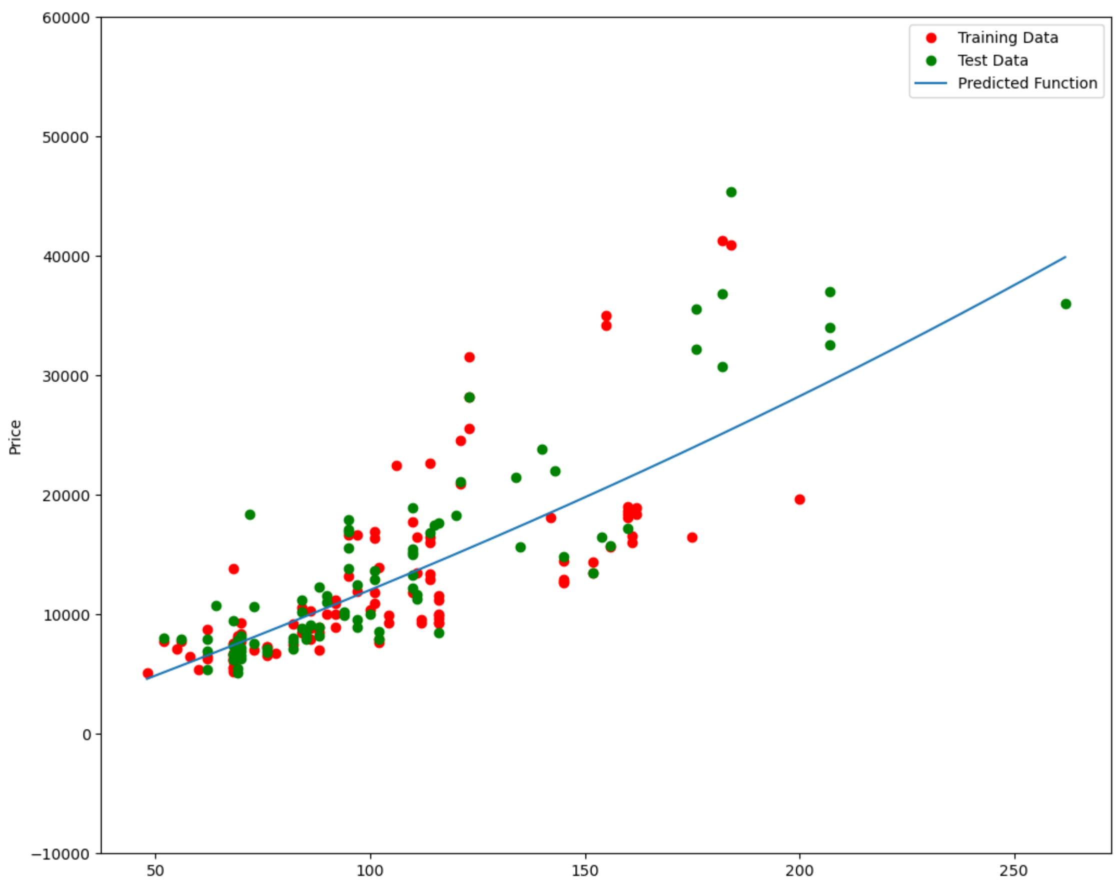
We see the R^2 gradually increases until an order three polynomial is used. Then, the R^2 dramatically decreases at an order four polynomial.

The following function will be used in the next section. Please run the cell below.

[232]:
```
def f(order, test_data):
    x_train, x_test, y_train, y_test = train_test_split(x_data, y_data,␣
 ↪test_size=test_data, random_state=0)
    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)
```

The following interface allows you to experiment with different polynomial orders and different amounts of data.

[233]:
```
interact(f, order=(0, 6, 1), test_data=(0.05, 0.95, 0.05))
```



```
interactive(children=(IntSlider(value=3, description='order', max=6),␣
↪FloatSlider(value=0.45, description='tes…
```

[233]:
```
<function __main__.f(order, test_data)>
```

We can perform polynomial transformations with more than one feature. Create a "PolynomialFeatures" object "pr1" of degree two.

[234]:
```
pr1=PolynomialFeatures(degree=2)
```

Transform the training and testing samples for the features 'horsepower', 'curb-weight', 'engine-size' and 'highway-mpg'. Hint: use the method "fit_transform".

[235]:
```
x_train_pr1=pr1.fit_transform(x_train[['horsepower', 'curb-weight',␣
↪'engine-size', 'highway-mpg']])

x_test_pr1=pr1.fit_transform(x_test[['horsepower', 'curb-weight',␣
↪'engine-size', 'highway-mpg']])
```

How many dimensions does the new feature have?

[236]:
```
x_train_pr1.shape #there are now 15 features
```

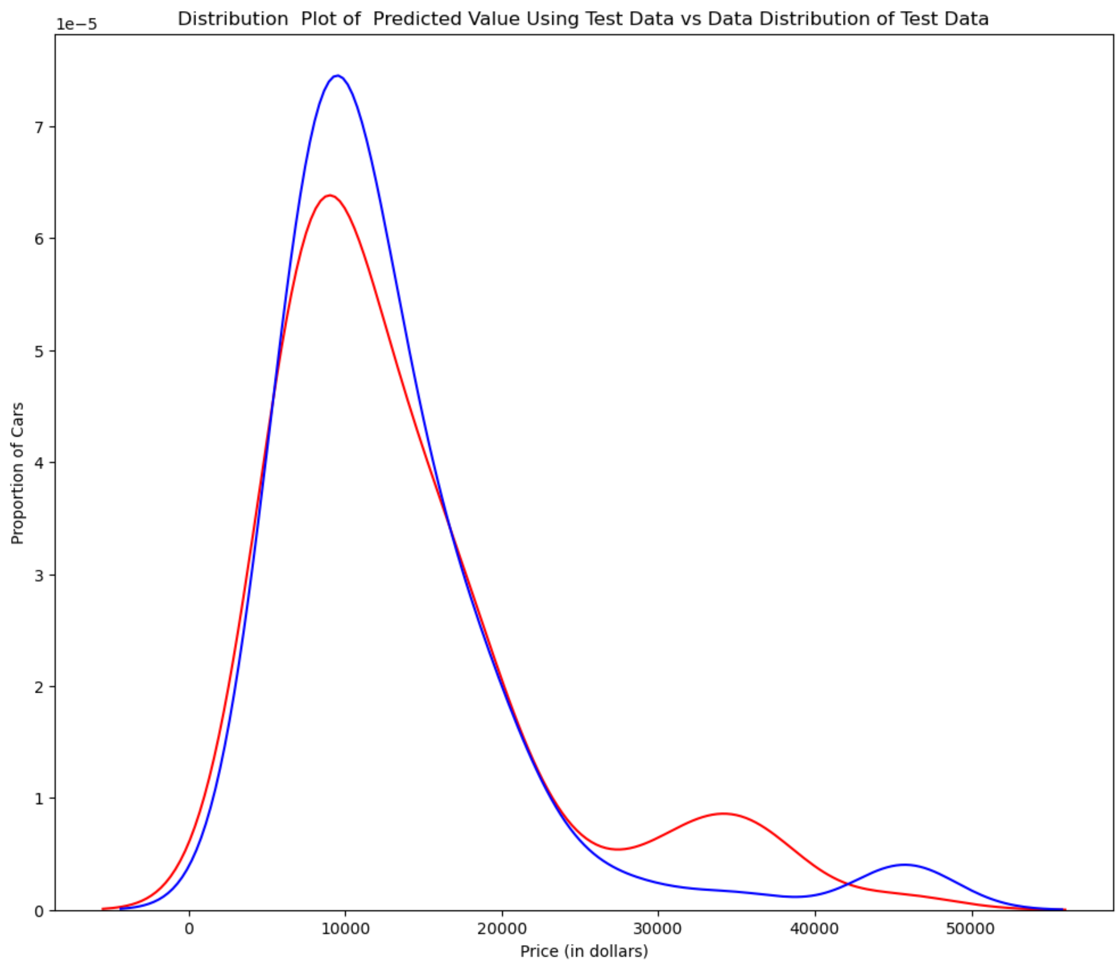
[236]:
```
(110, 15)
```

Create a linear regression model "poly1". Train the object using the method "fit" using the polynomial features.

[237]:
```
poly1=LinearRegression().fit(x_train_pr1,y_train)
```

Use the method "predict" to predict an output on the polynomial features, then use the function "DistributionPlot" to display the distribution of the predicted test output vs. the actual test data.

[238]:
```
yhat_test1=poly1.predict(x_test_pr1)

Title='Distribution  Plot of  Predicted Value Using Test Data vs Data␣
↪Distribution of Test Data'

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



Using the distribution plot above, describe (in words) the two regions where the predicted prices are less accurate than the actual prices.

[239]:
```
#The predicted value is higher than actual value for cars where the price␣
↪$10,000 range, conversely the predicted price is lower than the price cost␣
↪in the $30,000 to $40,000 range. As such the model is not as accurate in␣
↪these ranges.
```

Part 3: Ridge Regression

In this section, we will review Ridge Regression and see how the parameter alpha changes the model. Just a note, here our test data will be used as validation data.

Let's perform a degree two polynomial transformation on our data.

[240]:
```
pr=PolynomialFeatures(degree=2)
x_train_pr=pr.fit_transform(x_train[['horsepower', 'curb-weight',␣
↪'engine-size', 'highway-mpg','normalized-losses','symboling']])
```

```
x_test_pr=pr.fit_transform(x_test[['horsepower', 'curb-weight', 'engine-size',␣
↪'highway-mpg','normalized-losses','symboling']])
```

Let's import Ridge from the module linear models.

[241]:
```
from sklearn.linear_model import Ridge
```

Let's create a Ridge regression object, setting the regularization parameter (alpha) to 0.1

[242]:
```
RigeModel=Ridge(alpha=1)
```

Like regular regression, you can fit the model using the method fit.

[243]:
```
RigeModel.fit(x_train_pr, y_train)
```

[243]:
```
Ridge(alpha=1)
```

Similarly, you can obtain a prediction:

[244]:
```
yhat = RigeModel.predict(x_test_pr)
```

Let's compare the first five predicted samples to our test set:

[245]:
```
print('predicted:', yhat[0:4])
print('test set :', y_test[0:4].values)
```

```
predicted: [ 6570.82441941  9636.24891471 20949.92322737 19403.60313255]
test set : [ 6295. 10698. 13860. 13499.]
```

We select the value of alpha that minimizes the test error. To do so, we can use a for loop. We have also created a progress bar to see how many iterations we have completed so far.

[246]:
```
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_train_pr, y_train)
    pbar.set_postfix({"Test Score": test_score, "Train Score": train_score})

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

```
100%|                         | 1000/1000 [00:09<00:00,
100.30it/s, Test Score=0.564, Train Score=0.859]
```

We can plot out the value of R^2 for different alphas:

[247]:
```python
width = 12
height = 10
plt.figure(figsize=(width, height))

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

[247]:
```
<matplotlib.legend.Legend at 0x1acd5f49e90>
```

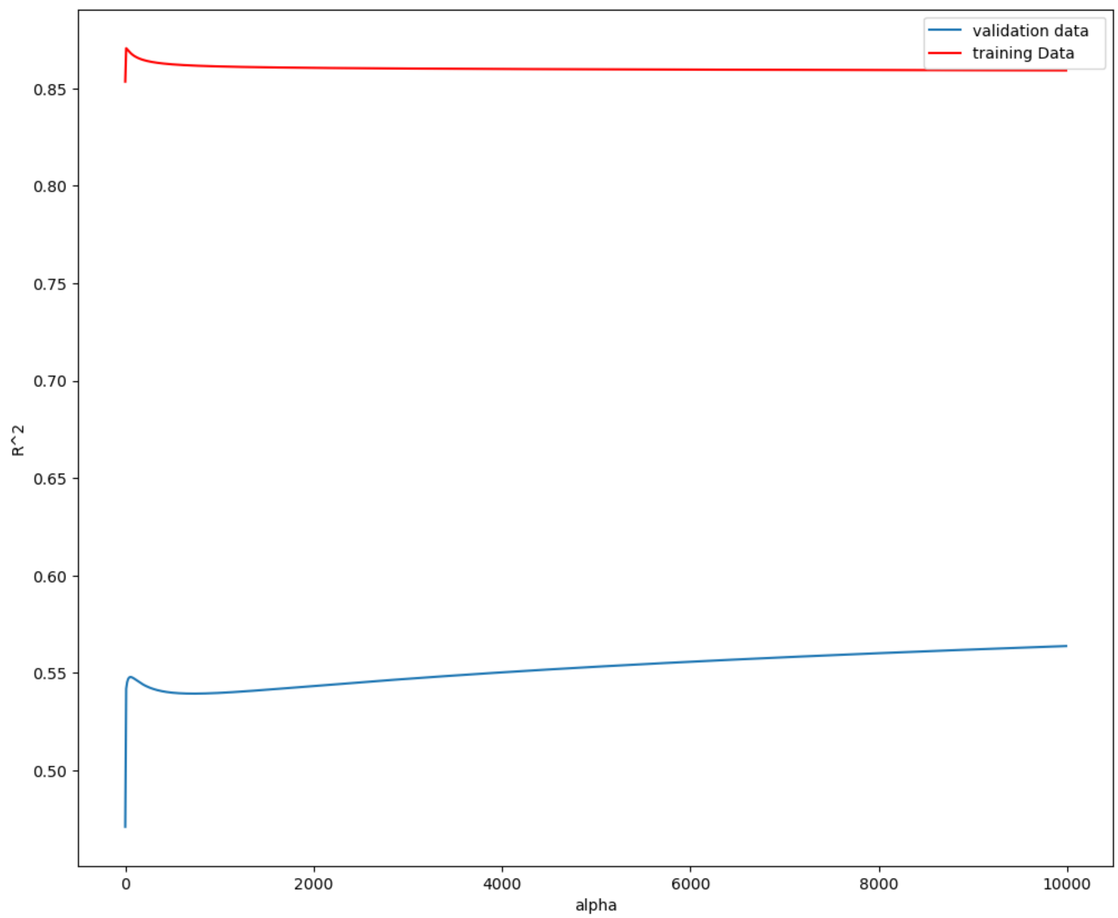


Figure 4: The blue line represents the R^2 of the validation data, and the red line represents the R^2 of the training data. The x-axis represents the different values of Alpha.

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.

Perform Ridge regression. Calculate the R^2 using the polynomial features, use the training data to train the model and use the test data to test the model. The parameter alpha should be set to 10.

[248]:
```
RigeModel = Ridge(alpha=10)
RigeModel.fit(x_train_pr, y_train)
RigeModel.score(x_test_pr, y_test)
```

[248]:
```
0.5418576440206405
```

Part 4: Grid Search

The term alpha is a hyperparameter. Sklearn has the class GridSearchCV to make the process of finding the best hyperparameter simpler.

Let's import GridSearchCV from the module model_selection.

[249]:
```
from sklearn.model_selection import GridSearchCV
```

We create a dictionary of parameter values:

[250]:
```
parameters1= [{'alpha': [0.001,0.1,1, 10, 100, 1000, 10000, 100000, 100000]}]
parameters1
```

[250]:
```
[{'alpha': [0.001, 0.1, 1, 10, 100, 1000, 10000, 100000, 100000]}]
```

Create a Ridge regression object:

[251]:
```
RR=Ridge()
RR
```

[251]:
```
Ridge()
```

Create a ridge grid search object:

[252]:
```
Grid1 = GridSearchCV(RR, parameters1,cv=4)
```

Fit the model:

[253]:
```
Grid1.fit(x_data[['horsepower', 'curb-weight', 'engine-size', 'highway-mpg']],␣
↪y_data)
```

[253]:
```
GridSearchCV(cv=4, estimator=Ridge(),
             param_grid=[{'alpha': [0.001, 0.1, 1, 10, 100, 1000, 10000, 100000,
                                    100000]}])
```

The object finds the best parameter values on the validation data. We can obtain the estimator with the best parameters and assign it to the variable BestRR as follows:

[254]:
```
BestRR=Grid1.best_estimator_
BestRR
```

[254]: Ridge(alpha=10000)

We now test our model on the test data:

[255]:
```
BestRR.score(x_test[['horsepower', 'curb-weight', 'engine-size',␣
↪'highway-mpg']], y_test)
```

[255]: 0.841164983103615

Perform a grid search for the alpha parameter and the normalization parameter, then find the best values of the parameters:

[256]:
```
parameters2 = [{'alpha': [0.001, 0.1, 1, 10, 100, 1000, 10000, 100000, 100000]}]

Grid2 = GridSearchCV(Ridge(), parameters2, cv=4)
Grid2.fit(x_data[['horsepower', 'curb-weight', 'engine-size', 'highway-mpg']],␣
↪y_data)
best_alpha = Grid2.best_params_['alpha']
best_ridge_model = Ridge(alpha=best_alpha)
best_ridge_model.fit(x_data[['horsepower', 'curb-weight', 'engine-size',␣
↪'highway-mpg']], y_data)
```

[256]: Ridge(alpha=10000)

##