2_DA0101EN-2-Review-Data-Wrangling

October 25, 2021

1 Data Wrangling

Estimated time needed: **30** minutes

1.1 Objectives

After completing this lab you will be able to:

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

Table of Contents

What is the purpose of data wrangling?

Data wrangling is the process of converting data from the 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. We will be using this dataset throughout this course.

Import pandas

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

Reading the dataset from the URL and adding the related headers

First, we assign the URL of the dataset to "filename".

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

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

Then, we create a Python list headers containing name of 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"]
```

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

```
[ ]: df = pd.read_csv(filename, names = headers)
```

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

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

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

         body-style drive-wheels engine-location  wheel-base  …  engine-size  \
     0  convertible          rwd           front        88.6  …          130
     1  convertible          rwd           front        88.6  …          130
     2    hatchback          rwd           front        94.5  …          152
     3        sedan          fwd           front        99.8  …          109
     4        sedan          4wd           front        99.4  …          136

        fuel-system  bore  stroke compression-ratio horsepower  peak-rpm city-mpg  \
     0         mpfi  3.47    2.68               9.0        111      5000       21
     1         mpfi  3.47    2.68               9.0        111      5000       21
     2         mpfi  2.68    3.47               9.0        154      5000       19
```

```
3          mpfi  3.19    3.40               10.0         102       5500         24
4          mpfi  3.19    3.40                8.0         115       5500         18

  highway-mpg  price
0          27  13495
1          27  16500
2          26  16500
3          30  13950
4          22  17450

[5 rows x 26 columns]
```

As we can see, several question marks appeared in the dataframe; those are missing values which may hinder our 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

Identify and handle missing values

Identify missing values

Convert "?" to NaN

In the car dataset, 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. Here we use the function:

to replace A by B.

[ ]:
```python
import numpy as np

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

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

    body-style drive-wheels engine-location  wheel-base  …  engine-size  \
```

```
0  convertible          rwd          front        88.6  …           130
1  convertible          rwd          front        88.6  …           130
2    hatchback          rwd          front        94.5  …           152
3        sedan          fwd          front        99.8  …           109
4        sedan          4wd          front        99.4  …           136

  fuel-system  bore  stroke compression-ratio horsepower  peak-rpm city-mpg  \
0        mpfi  3.47    2.68               9.0        111      5000       21
1        mpfi  3.47    2.68               9.0        111      5000       21
2        mpfi  2.68    3.47               9.0        154      5000       19
3        mpfi  3.19    3.40              10.0        102      5500       24
4        mpfi  3.19    3.40               8.0        115      5500       18

  highway-mpg  price
0          27  13495
1          27  16500
2          26  16500
3          30  13950
4          22  17450

[5 rows x 26 columns]
```

Evaluating for Missing Data

The missing values are converted by default. We use the following functions to identify these missing values. There are 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.

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

[ ]:
```
   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               True  False      False       False         False
3      False              False  False      False       False         False
4      False              False  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, we 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 dataset. In the body of the for loop the method “.value_counts()” counts the number of “True” values.

[ ]:
```
missing_data.columns.values.tolist()
```

[ ]:
```
['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']
```

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

```
symboling
False    205
Name: symboling, dtype: int64

normalized-losses
False    164
True      41
Name: normalized-losses, dtype: int64

make
False    205
Name: make, dtype: int64

fuel-type
False    205
Name: fuel-type, dtype: int64

aspiration
False    205
Name: aspiration, dtype: int64

num-of-doors
False    203
True       2
Name: num-of-doors, dtype: int64

body-style
False    205
Name: body-style, dtype: int64

drive-wheels
False    205
Name: drive-wheels, dtype: int64

engine-location
False    205
Name: engine-location, dtype: int64
```

```
wheel-base
False    205
Name: wheel-base, dtype: int64

length
False    205
Name: length, dtype: int64

width
False    205
Name: width, dtype: int64

height
False    205
Name: height, dtype: int64

curb-weight
False    205
Name: curb-weight, dtype: int64

engine-type
False    205
Name: engine-type, dtype: int64

num-of-cylinders
False    205
Name: num-of-cylinders, dtype: int64

engine-size
False    205
Name: engine-size, dtype: int64

fuel-system
False    205
Name: fuel-system, dtype: int64

bore
False    201
True       4
Name: bore, dtype: int64

stroke
False    201
True       4
Name: stroke, dtype: int64

compression-ratio
```

```
False    205
Name: compression-ratio, dtype: int64

horsepower
False    203
True       2
Name: horsepower, dtype: int64

peak-rpm
False    203
True       2
Name: peak-rpm, dtype: int64

city-mpg
False    205
Name: city-mpg, dtype: int64

highway-mpg
False    205
Name: highway-mpg, dtype: int64

price
False    201
True       4
Name: price, 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

Deal with missing data

How to 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

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

Replace by mean:

"normalized-losses": 41 missing data, replace them with mean

"stroke": 4 missing data, replace them with mean

"bore": 4 missing data, replace them with mean

"horsepower": 2 missing data, replace them with mean

"peak-rpm": 2 missing data, replace them with mean

Replace by frequency:

"num-of-doors": 2 missing data, replace them with "four".

Reason: 84% sedans is four doors. Since four doors is most frequent, it is most likely to occur

Drop the whole row:

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

Reason: price is what we want to predict. Any data entry without price data cannot be used for prediction; therefore any row now without price data is not useful to us

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

[ ]:
```
df.isnull().sum()
```

[ ]:
```
symboling             0
normalized-losses    41
make                  0
fuel-type             0
aspiration            0
num-of-doors          2
body-style            0
drive-wheels          0
engine-location       0
wheel-base            0
length                0
width                 0
height                0
curb-weight           0
engine-type           0
num-of-cylinders      0
engine-size           0
fuel-system           0
bore                  4
stroke                4
```

```
compression-ratio     0
horsepower            2
peak-rpm              2
city-mpg              0
highway-mpg           0
price                 4
dtype: int64
```

[ ]:
```
type(df)
```

[ ]:
```
pandas.core.frame.DataFrame
```

[ ]:
```
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
```

[ ]:
```
df["normalized-losses"].nunique()
```

[ ]:
```
51
```

[ ]:
```
df["normalized-losses"].value_counts()
```

[ ]:
```
122.0    41
161      11
91        8
150       7
134       6
128       6
104       6
95        5
74        5
102       5
85        5
65        5
94        5
168       5
103       5
148       4
118       4
93        4
122       4
106       4
137       3
83        3
115       3
101       3
125       3
154       3
110       2
188       2
87        2
119       2
113       2
192       2
108       2
158       2
89        2
81        2
153       2
129       2
145       2
197       2
164       2
194       2
107       1
90        1
121       1
77        1
78        1
```

```
98         1
256        1
231        1
186        1
142        1
Name: normalized-losses, dtype: int64
```

[ ]:
```
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

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

Calculate the mean value for the "bore" column

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

```
Average of bore: 3.3297512437810957
```

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

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

Question #1:

Based on the example above, replace NaN in "stroke" column with the mean value.

[ ]:
```
df['stroke'].dtypes # its an object
```

[ ]:
```
dtype('O')
```

[ ]:
```
# Write your code below and press Shift+Enter to execute
#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: 3.2554228855721337
```

Click here for the solution

```
#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)
```

Calculate the mean value for the "horsepower" column

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

```
Average horsepower: 104.25615763546799
```

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

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

Calculate the mean value for "peak-rpm" column

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

```
Average peak rpm: 5125.369458128079
```

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

```
[ ]: 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:

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

```
[ ]: four    114
     two      89
     Name: num-of-doors, dtype: int64
```

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

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

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

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

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

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

```
[ ]: # 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)
```

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

[ ]:
```
   symboling normalized-losses         make fuel-type aspiration num-of-doors  \
0          3             122.0  alfa-romero       gas        std          two
1          3             122.0  alfa-romero       gas        std          two
2          1             122.0  alfa-romero       gas        std          two
3          2               164         audi       gas        std         four
4          2               164         audi       gas        std         four

    body-style drive-wheels engine-location  wheel-base  …  engine-size  \
0  convertible          rwd           front        88.6  …          130
1  convertible          rwd           front        88.6  …          130
2    hatchback          rwd           front        94.5  …          152
3        sedan          fwd           front        99.8  …          109
4        sedan          4wd           front        99.4  …          136

   fuel-system  bore  stroke compression-ratio horsepower  peak-rpm city-mpg  \
0         mpfi  3.47    2.68               9.0        111      5000       21
1         mpfi  3.47    2.68               9.0        111      5000       21
2         mpfi  2.68    3.47               9.0        154      5000       19
3         mpfi  3.19    3.40              10.0        102      5500       24
4         mpfi  3.19    3.40               8.0        115      5500       18

  highway-mpg  price
0          27  13495
1          27  16500
2          26  16500
3          30  13950
4          22  17450

[5 rows x 26 columns]
```

Good! Now, we have a dataset with no missing values.

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, we use:

.dtype() to check the data type

.astype() to change the data type

Let's list the data types for each column

[ ]:
```
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 we 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, 'bore' and 'stroke' variables are numerical values that describe the engines, so we should expect them to be of the type 'float' or 'int'; however, they are shown as type 'object'. We have to convert data types into a proper format for each column using the "astype()" method.

Convert data types to proper format

[ ]:
```
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

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

[ ]:
```
symboling               int64
normalized-losses       int32
make                   object
fuel-type              object
aspiration             object
num-of-doors           object
```

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

Wonderful!

Now we have finally obtained the cleaned dataset with no missing values with all data in its proper format.

Data Standardization

Data is usually collected from different agencies in different formats. (Data standardization is also a term for a particular type of data normalization where we 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 our dataset, the fuel consumption columns "city-mpg" and "highway-mpg" are represented by mpg (miles per gallon) unit. Assume we are developing an application in a country that accepts the fuel consumption with L/100km standard.

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

The formula for unit conversion is:

L/100km = 235 / mpg

We can do many mathematical operations directly in Pandas.

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

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

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

   engine-size  fuel-system  bore  stroke compression-ratio horsepower  \
0          130         mpfi  3.47    2.68               9.0        111
1          130         mpfi  3.47    2.68               9.0        111
2          152         mpfi  2.68    3.47               9.0        154
3          109         mpfi  3.19    3.40              10.0        102
4          136         mpfi  3.19    3.40               8.0        115

   peak-rpm city-mpg  highway-mpg    price
0    5000.0       21           27  13495.0
1    5000.0       21           27  16500.0
2    5000.0       19           26  16500.0
3    5500.0       24           30  13950.0
4    5500.0       18           22  17450.0

[5 rows x 26 columns]
```

[ ]:
```
# 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()
```

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

  num-of-doors   body-style drive-wheels engine-location  wheel-base  …  \
0          two  convertible          rwd           front        88.6  …
```

```
1          two  convertible          rwd          front        88.6  …
2          two    hatchback          rwd          front        94.5  …
3         four        sedan          fwd          front        99.8  …
4         four        sedan          4wd          front        99.4  …

  fuel-system  bore  stroke  compression-ratio horsepower peak-rpm  city-mpg  \
0        mpfi  3.47    2.68                9.0        111   5000.0        21
1        mpfi  3.47    2.68                9.0        111   5000.0        21
2        mpfi  2.68    3.47                9.0        154   5000.0        19
3        mpfi  3.19    3.40               10.0        102   5500.0        24
4        mpfi  3.19    3.40                8.0        115   5500.0        18

 highway-mpg    price  city-L/100km
0         27  13495.0     11.190476
1         27  16500.0     11.190476
2         26  16500.0     12.368421
3         30  13950.0      9.791667
4         22  17450.0     13.055556

[5 rows x 27 columns]
```

Question #2:

According to the example above, transform mpg to L/100km in the column of “highway-mpg” and change the name of column to “highway-L/100km”.

[ ]:
```
#df=df.drop('highway-L/100km', axis=1)
#df.head()
```

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

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

  fuel-system  bore  stroke  compression-ratio horsepower peak-rpm  city-mpg  \
0        mpfi  3.47    2.68                9.0        111   5000.0        21
1        mpfi  3.47    2.68                9.0        111   5000.0        21
2        mpfi  2.68    3.47                9.0        154   5000.0        19
3        mpfi  3.19    3.40               10.0        102   5500.0        24
```

```
4         mpfi  3.19    3.40                8.0        115    5500.0         18

  highway-mpg    price  city-L/100km
0           27  13495.0     11.190476
1           27  16500.0     11.190476
2           26  16500.0     12.368421
3           30  13950.0      9.791667
4           22  17450.0     13.055556

[5 rows x 27 columns]
```

[ ]:
```
# Write your code below and press Shift+Enter to execute

df['highway-mpg'] = 235/df["highway-mpg"]

# rename
df.rename(columns={'"highway-mpg"':'highway-L/100km'},inplace=True)
# check your transformed data
df.head()
```

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

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

   fuel-system  bore  stroke  compression-ratio horsepower peak-rpm  city-mpg  \
0         mpfi  3.47    2.68                9.0        111    5000.0         21
1         mpfi  3.47    2.68                9.0        111    5000.0         21
2         mpfi  2.68    3.47                9.0        154    5000.0         19
3         mpfi  3.19    3.40               10.0        102    5500.0         24
4         mpfi  3.19    3.40                8.0        115    5500.0         18

  highway-mpg    price  city-L/100km
0    8.703704  13495.0     11.190476
1    8.703704  16500.0     11.190476
2    9.038462  16500.0     12.368421
3    7.833333  13950.0      9.791667
4   10.681818  17450.0     13.055556
```

```
[5 rows x 27 columns]
```

Click here for the solution

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

# rename column name from "highway-mpg" to "highway-L/100km"
df.rename(columns={'"highway-mpg"':'highway-L/100km'}, inplace=True)

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

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, or scaling the variable so the variable values range from 0 to 1.

Example

To demonstrate normalization, let's say we want to scale the columns "length", "width" and "height".

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

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

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

Question #3:

According to the example above, normalize the column "height".

[ ]:
```
# Write your code below and press Shift+Enter to execute
df['height']=df['height']/df['height'].max()

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

[ ]:

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

Click here for the solution

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

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

Here we can see we've normalized "length", "width" and "height" in the range of [0,1].

Binning

Why binning?

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

Example:

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

We will use the pandas method 'cut' to segment the 'horsepower' column into 3 bins.

Example of Binning Data In Pandas

Convert data to correct format:

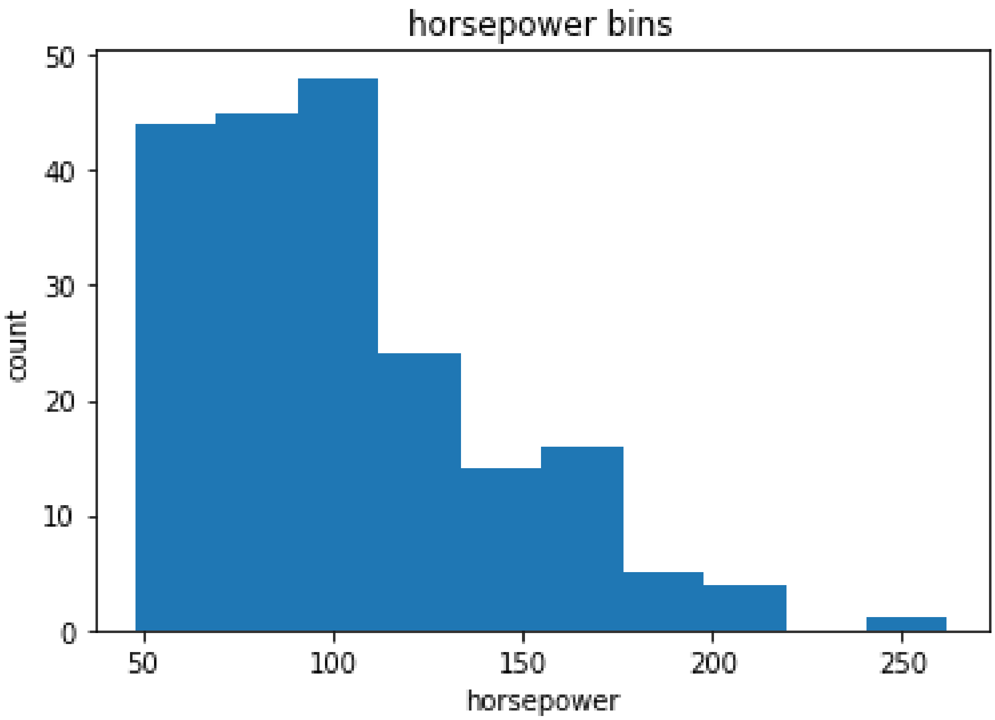
[ ]:
```
df["horsepower"]=df["horsepower"].astype(int, copy=True)
```

Let's plot the histogram of horsepower to see what the distribution of horsepower looks like.

[ ]:
```
%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")
```

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



We would like 3 bins of equal size bandwidth so we use numpy's linspace(start_value, end_value, numbers_generated function.

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

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

Since we are building 3 bins of equal length, there should be 4 dividers, so numbers_generated = 4.

We 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.

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

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

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

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

We set group names:

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

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

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

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

Let's see the number of vehicles in each bin:

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

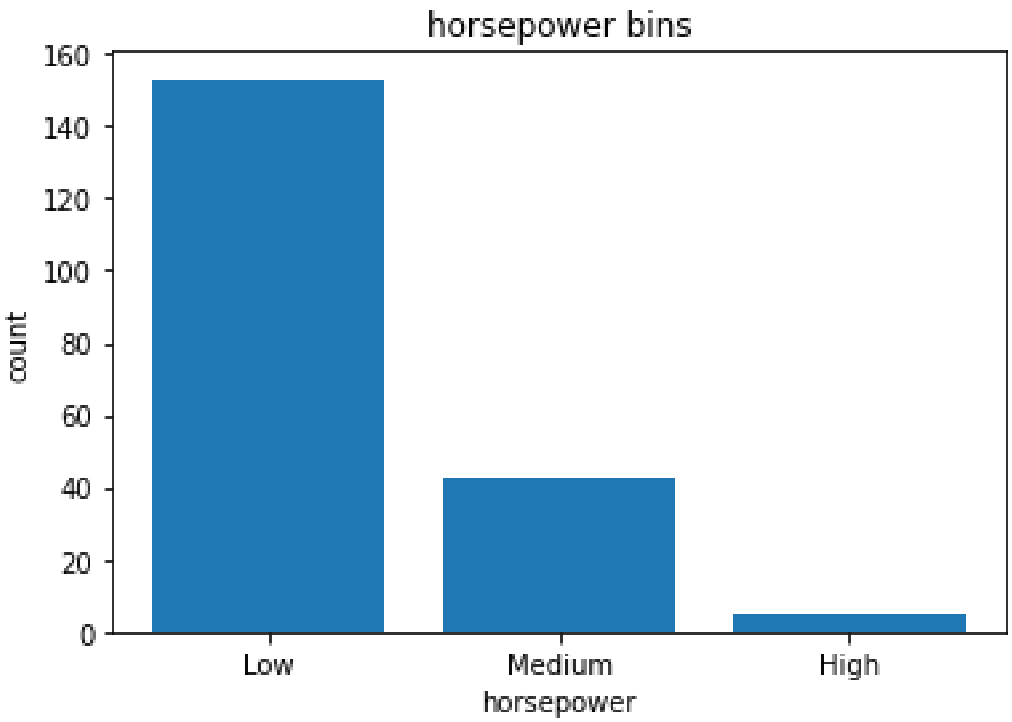
```
[ ]: Low       153
     Medium     43
     High        5
     Name: horsepower-binned, dtype: int64
```

Let's plot the distribution of each bin:

```
[ ]: %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")
```

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



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

We successfully narrowed down the intervals from 59 to 3!

Bins Visualization

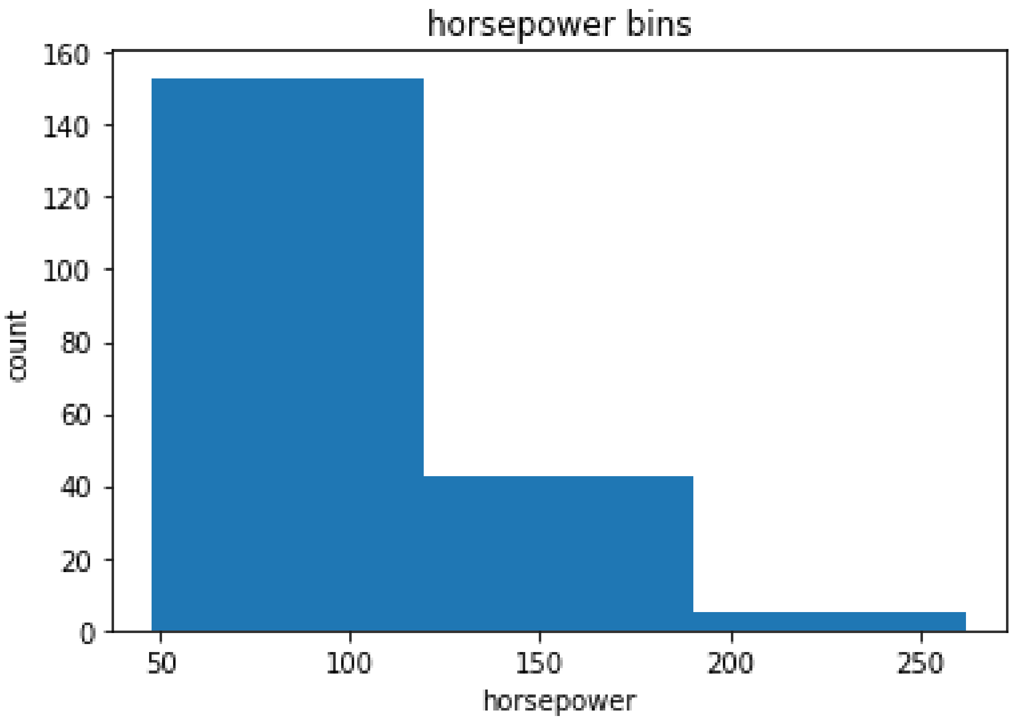
Normally, a histogram is used to visualize the distribution of bins we created above.

[ ]:
```
%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")
```

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



The plot above shows the binning result for the attribute "horsepower".

Indicator Variable (or Dummy 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 we use indicator variables?

We use indicator variables so we can use categorical variables for regression analysis in the later modules.

Example

We see 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, we convert "fuel-type" to indicator variables.

We will use pandas' method 'get_dummies' to assign numerical values to different categories of fuel type.

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

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

[ ]:
```
df["fuel-type"].value_counts()
```

[ ]:
```
gas       181
diesel     20
Name: fuel-type, dtype: int64
```

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

[ ]:
```
   diesel  gas
0       0    1
1       0    1
2       0    1
3       0    1
4       0    1
```

Change the column names for clarity:

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

[ ]:
```
   fuel-type-diesel  fuel-type-gas
0                 0              1
1                 0              1
2                 0              1
3                 0              1
4                 0              1
```

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

[ ]:
```
# 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)
```

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

[ ]:
```
   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    5000.0       21    8.703704  13495.0
1                9.0         111    5000.0       21    8.703704  16500.0
2                9.0         154    5000.0       19    9.038462  16500.0
3               10.0         102    5500.0       24    7.833333  13950.0
4                8.0         115    5500.0       18   10.681818  17450.0

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

[5 rows x 29 columns]
```

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

Question #4:

Similar to before, create an indicator variable for the column "aspiration"

[ ]:
```
# Write your code below and press Shift+Enter to execute
df["aspiration"].value_counts()
```

[ ]:
```
std      165
turbo     36
Name: aspiration, dtype: int64
```

[ ]:
```
dummy_variable_2 = pd.get_dummies(df["aspiration"])
dummy_variable_2.head()
```

[ ]:
```
   std  turbo
0    1      0
1    1      0
2    1      0
3    1      0
```

```
4    1       0
```

```
[ ]: # 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()
```

```
[ ]:    aspiration-std  aspiration-turbo
0                1                 0
1                1                 0
2                1                 0
3                1                 0
4                1                 0
```

Click here for the solution

```
# 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=

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

Question #5:

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

```
[ ]: # Write your code below and press Shift+Enter to execute
df=pd.concat([df,dummy_variable_2],axis=1)

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

Click here for the solution

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

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

Save the new csv:

```
[ ]: df.to_csv('clean_df.csv')
```

1.1.1 Thank you for completing this lab!

1.2 Author

Joseph Santarcangelo

1.2.1 Other Contributors

Mahdi Noorian PhD

Bahare Talayian

Eric Xiao

Steven Dong

Parizad

Hima Vasudevan

Fiorella Wenver

Yi Yao.

1.3 Change Log

Date (YYYY-MM-DD)	Version	Changed By	Change Description
2020-10-30	2.2	Lakshmi	Changed URL of csv
2020-09-09	2.1	Lakshmi	Updated Indicator Variables section
2020-08-27	2.0	Lavanya	Moved lab to course repo in GitLab

##