data-wrangling

January 26, 2019

```
<a href="http://cocl.us/DA0101EN_NotbookLink_Top">
     <img src="https://s3-api.us-geo.objectstorage.softlayer.net/cf-courses-data/CognitiveClass/
</a>
```

Data Analysis with Python
Data Wrangling
Welcome!
By the end of this notebook, you will have learned the basics of Data Wrangling!
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```

Estimated Time Needed: 30 min
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 Data Set" from the following link: https://archive.ics.uci.edu/ml/machine-learning-databases/autos/imports-85.data. We will be using this data set throughout this course.
Import pandas

```
In [1]: import pandas as pd
        import matplotlib.pylab as plt
```

Reading the data set from the URL and adding the related headers.
URL of the dataset

```
In [2]: filename = "https://s3-api.us-geo.objectstorage.softlayer.net/cf-courses-data/CognitiveC
```

Python list headers containing name of headers

```
In [3]: headers = ["symboling","normalized-losses","make","fuel-type","aspiration", "num-of-door
                   "drive-wheels","engine-location","wheel-base", "length","width","height","curb-
                   "num-of-cylinders", "engine-size","fuel-system","bore","stroke","compression-ra
                   "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".

```
In [4]: df = pd.read_csv(filename, names = headers)
```

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

```
In [5]: # To see what the data set looks like, we'll use the head() method.
        df.head()
```

Out[5]:

	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:

```
<li>dentify missing data</li>
<li>deal with missing data</li>
<li>correct data format</li>
```

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), which is Python's default missing value marker, for reasons of computational speed and convenience. Here we use the function:

to replace A by B

```
In [6]: import numpy as np

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

Out[6]:

	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]
```

dentify_missing_values

Evaluating for Missing Data

The missing values are converted to Python's default. We use Python's built-in functions to identify these missing values. There are two methods to detect missing data:

```
<li><b>.isnull()</b></li>
<li><b>.notnull()</b></li>
```

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

```
In [7]: missing_data = df.isnull()
        missing_data.head(5)
```

```
Out[7]:    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" stands for missing value, while "False" stands for not 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, "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.

```
In [8]: 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, seven columns containing missing data:

```
<li>"normalized-losses": 41 missing data</li>
<li>"num-of-doors": 2 missing data</li>
<li>"bore": 4 missing data</li>
<li>"stroke" : 4 missing data</li>
<li>"horsepower": 2 missing data</li>
<li>"peak-rpm": 2 missing data</li>
<li>"price": 4 missing data</li>
```

Deal with missing data
How to deal with missing data?

```
<li>drop data<br>
    a. drop the whole row<br>
    b. drop the whole column
</li>
<li>replace data<br>
    a. replace it by mean<br>
```

```
    b. replace it by frequency<br>
    c. replace it based on other functions
</li>
```

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:

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

Replace by frequency:

```
<li>"num-of-doors": 2 missing data, replace them with "four".
    <ul>
        <li>Reason: 84% sedans is four doors. Since four doors is most frequent, it is most like
    </ul>
</li>
```

Drop the whole row:

```
<li>"price": 4 missing data, simply delete the whole row
    <ul>
        <li>Reason: price is what we want to predict. Any data entry without price data cannot b
    </ul>
</li>
```

Calculate the average of the column

```
In [9]: 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" by mean value in "normalized-losses" column

```
In [10]: df["normalized-losses"].replace(np.nan, avg_norm_loss, inplace=True)
```

Calculate the mean value for 'bore' column

```
In [11]: avg_bore=df['bore'].astype('float').mean(axis=0)
         print("Average of bore:", avg_bore)
```

```
Average of bore: 3.3297512437810943
```

Replace NaN by mean value

```
In [12]: df["bore"].replace(np.nan, avg_bore, inplace=True)
```

Question #1:
According to the example above, replace NaN in "stroke" column by mean.

```
In [16]: # 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: 3.2554228855721394
```

Double-click here for the solution.
Calculate the mean value for the 'horsepower' column:

```
In [17]: avg_horsepower = df['horsepower'].astype('float').mean(axis=0)
         print("Average horsepower:", avg_horsepower)
```

```
Average horsepower: 104.25615763546799
```

Replace "NaN" by mean value:

```
In [18]: df['horsepower'].replace(np.nan, avg_horsepower, inplace=True)
```

Calculate the mean value for 'peak-rpm' column:

```
In [19]: avg_peakrpm=df['peak-rpm'].astype('float').mean(axis=0)
         print("Average peak rpm:", avg_peakrpm)
```

```
Average peak rpm: 5125.369458128079
```

Replace NaN by mean value:

```
In [21]: 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:

```
In [22]: df['num-of-doors'].value_counts()
```

```
Out[22]: 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 for us the most common type automatically:

```
In [23]: df['num-of-doors'].value_counts().idxmax()
```

```
Out[23]: 'four'
```

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

```
In [24]: #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:

```
In [25]: # 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)
```

```
In [26]: df.head()
```

```
Out[26]:    symboling normalized-losses         make fuel-type aspiration num-of-doors  \
         0          3                122  alfa-romero       gas        std          two
         1          3                122  alfa-romero       gas        std          two
         2          1                122  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 obtain the 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

Lets list the data types for each column

```
In [27]: df.dtypes
```

```
Out[27]: 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

```
In [28]: 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

```
In [29]: df.dtypes
```

```
Out[29]: symboling             int64
         normalized-losses     int64
         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 finally obtain the cleaned dataset with no missing values and all data in its proper format.

Data Standardization

Data is usually collected from different agencies with 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 which allows 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 accept 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.

```
In [30]: df.head()
```

Out[30]:

	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]

```
In [31]: # 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()
```

Out[31]:

	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  \
0      ...              mpfi  3.47    2.68                9.0        111
1      ...              mpfi  3.47    2.68                9.0        111
2      ...              mpfi  2.68    3.47                9.0        154
3      ...              mpfi  3.19    3.40               10.0        102
4      ...              mpfi  3.19    3.40                8.0        115

  peak-rpm  city-mpg highway-mpg    price  city-L/100km
0   5000.0        21          27  13495.0     11.190476
1   5000.0        21          27  16500.0     11.190476
2   5000.0        19          26  16500.0     12.368421
3   5500.0        24          30  13950.0      9.791667
4   5500.0        18          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".

```
In [32]: # Write your code below and press Shift+Enter to execute
         # Convert 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()
```

```
Out[32]:    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

        ...         bore  stroke  compression-ratio  horsepower peak-rpm  \
0       ...         3.47    2.68                9.0         111   5000.0
1       ...         3.47    2.68                9.0         111   5000.0
2       ...         2.68    3.47                9.0         154   5000.0
3       ...         3.19    3.40               10.0         102   5500.0
4       ...         3.19    3.40                8.0         115   5500.0

  city-mpg  highway-mpg    price  city-L/100km  highway-L/100km
0       21           27  13495.0     11.190476         8.703704
1       21           27  16500.0     11.190476         8.703704
2       19           26  16500.0     12.368421         9.038462
3       24           30  13950.0      9.791667         7.833333
4       18           22  17450.0     13.055556        10.681818

[5 rows x 28 columns]
```

Double-click here for the solution.

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 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)

```
In [33]: # replace (original value) by (original value)/(maximum value)
         df['length'] = df['length']/df['length'].max()
         df['width'] = df['width']/df['width'].max()
```

Questiont #3:

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

```
In [34]: # Write your code below and press Shift+Enter to execute
         # replace (original value) by (original value)/(maximum value)
         df['height'] = df['height']/df['height'].max()
```

Double-click here for the solution.

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 'b
```

Example:

In our dataset, "horsepower" is a real valued variable ranging from 48 to 288, it has 57 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

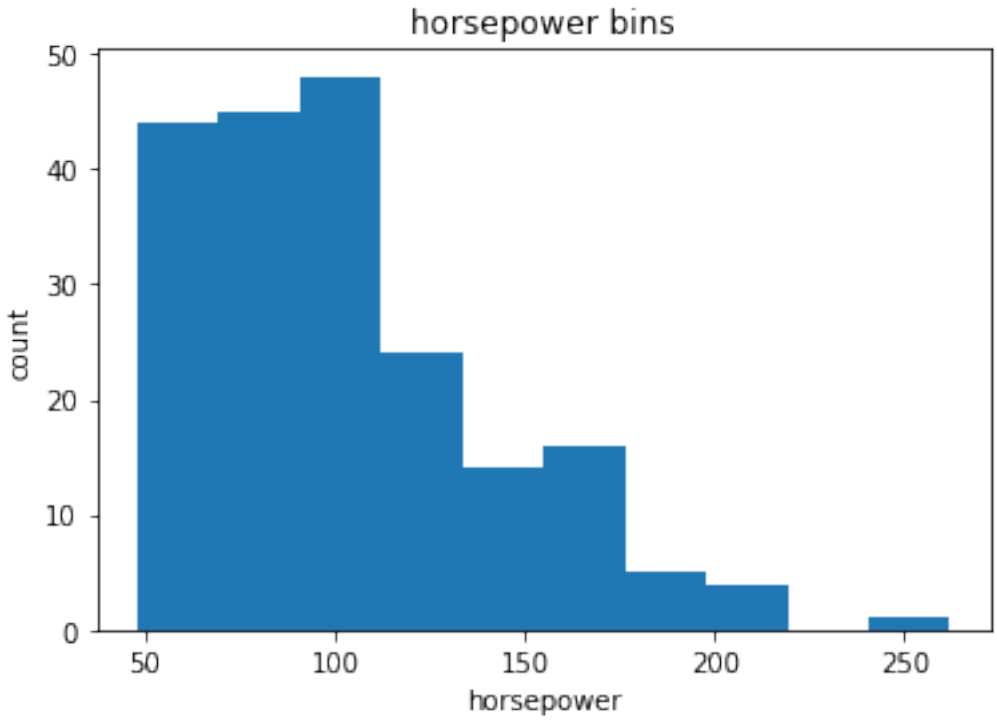
```
In [35]: df["horsepower"]=df["horsepower"].astype(int, copy=True)
```

Lets plot the histogram of horspower, to see what the distribution of horsepower looks like.

```
In [36]: %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")
```

```
Out[36]: 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, with bandwidth calculated above. The bins will be values used to determine when one bin ends and another begins.

```
In [40]: bins = np.linspace(min(df["horsepower"]), max(df["horsepower"]), 4)
         bins
```

```
Out[40]: array([ 48.        , 119.33333333, 190.66666667, 262.        ])
```

We set group names:

```
In [41]: group_names = ['Low', 'Medium', 'High']
```

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

```
In [42]: df['horsepower-binned'] = pd.cut(df['horsepower'], bins, labels=group_names, include_lo
         df[['horsepower','horsepower-binned']].head(20)
```

```
Out[42]:     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
```

Lets see the number of vehicles in each bin.

```
In [43]: df["horsepower-binned"].value_counts()
```

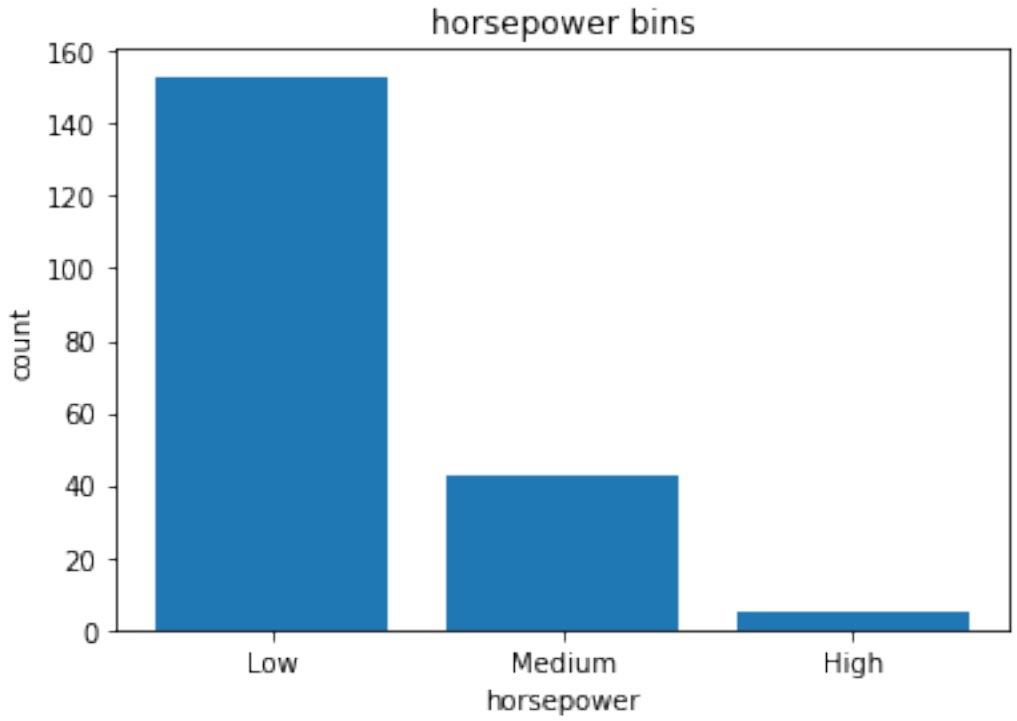
```
Out[43]: Low       153
         Medium     43
         High        5
         Name: horsepower-binned, dtype: int64
```

Lets plot the distribution of each bin.

```
In [44]: %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")
```

```
Out[44]: Text(0.5, 1.0, 'horsepower bins')
```




```
Check the dataframe above carefully, you will find the last column provides the bins for "horsep

We successfully narrow the intervals from 57 to 3!
```

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

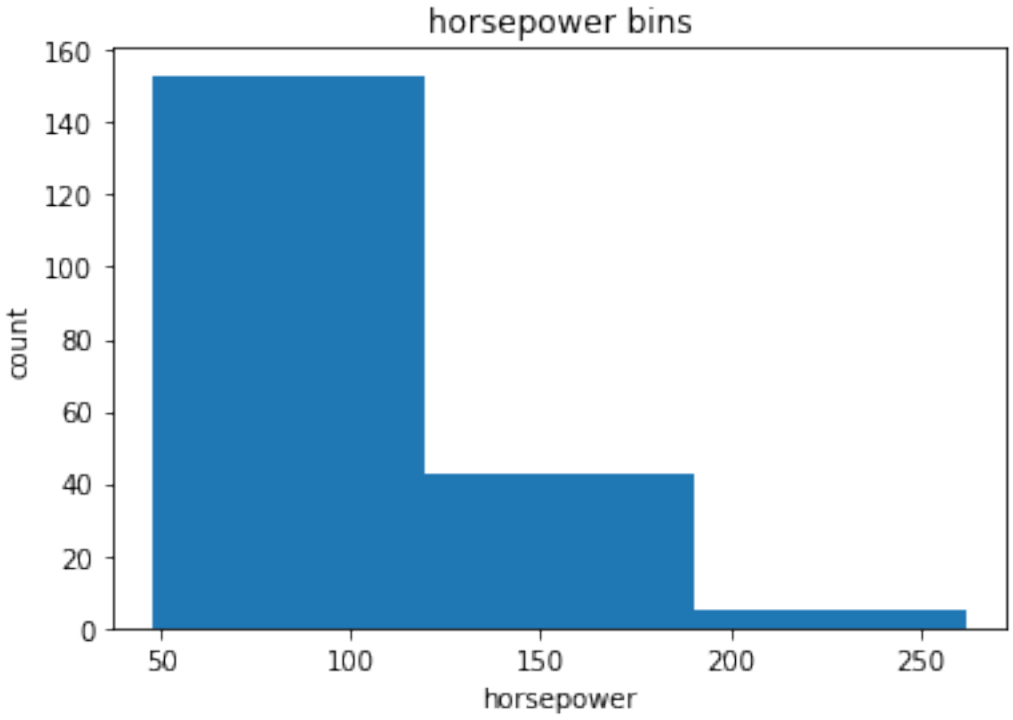
```
In [45]: %matplotlib inline
         import matplotlib as plt
         from matplotlib import pyplot

         a = (0,1,2)

         # 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")

Out[45]: Text(0.5, 1.0, 'horsepower bins')
```



The plot above shows the binning result for 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
```

Why 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 under

We will use the panda's method 'get_dummies' to assign numerical values to different categories
```

```
In [46]: df.columns
```

```
Out[46]: 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 indicator variables and assign it to data frame "dummy_variable_1"

```
In [52]: dummy_variable_1 = pd.get_dummies(df["fuel-type"])
         dummy_variable_1.head()
```

```
Out[52]:    diesel  gas
         0       0    1
         1       0    1
         2       0    1
         3       0    1
         4       0    1
```

change column names for clarity

```
In [53]: dummy_variable_1.rename(columns={'gas':'fuel-type-gas', 'diesel':'fuel-type-diesel'}, i
         dummy_variable_1.head()
```

```
Out[53]:    fuel-type-diesel  fuel-type-gas
         0                 0              1
         1                 0              1
         2                 0              1
         3                 0              1
         4                 0              1
```

We now have the value 0 to represent "gas" and 1 to represent "diesel" in the column "fuel-type". We will now insert this column back into our original dataset.

```
In [61]: # 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)
```

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

```
Out[65]:    symboling  normalized-losses         make num-of-doors   body-style  \
          0          3                122  alfa-romero          two  convertible
          1          3                122  alfa-romero          two  convertible
          2          1                122  alfa-romero          two    hatchback
          3          2                164         audi         four        sedan
          4          2                164         audi         four        sedan

            drive-wheels engine-location  wheel-base    length     width  ...    \
          0          rwd           front        88.6  0.811148  0.890278  ...
          1          rwd           front        88.6  0.811148  0.890278  ...
          2          rwd           front        94.5  0.822681  0.909722  ...
          3          fwd           front        99.8  0.848630  0.919444  ...
          4          4wd           front        99.4  0.848630  0.922222  ...

             city-mpg  highway-mpg    price city-L/100km  highway-L/100km  \
          0        21           27  13495.0    11.190476         8.703704
          1        21           27  16500.0    11.190476         8.703704
          2        19           26  16500.0    12.368421         9.038462
          3        24           30  13950.0     9.791667         7.833333
          4        18           22  17450.0    13.055556        10.681818

            horsepower-binned  fuel-type-diesel  fuel-type-gas  std  turbo
          0               Low                 0              1    1      0
          1               Low                 0              1    1      0
          2            Medium                 0              1    1      0
          3               Low                 0              1    1      0
          4               Low                 0              1    1      0

          [5 rows x 31 columns]
```

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

Question #4:

As above, create indicator variable to the column of "aspiration": "std" to 0, while "turbo" to 1.

```
In [67]: # Write your code below and press Shift+Enter to execute
         #dummy_variable_2 = pd.get_dummies(df["aspiration"])
         #dummy_variable_2.head()
         #change column names for clarity
         # dummy_variable_2.rename(columns={'std':'aspiration-std', 'turbo': 'aspiration-turbo'}

         # show first 5 instances of data frame "dummy_variable_1"
         # dummy_variable_2.head()
         # change column names for clarity
         df.rename(columns={'std':'aspiration-std', 'turbo': 'aspiration-turbo'}, inplace=True)
```

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

Out[67]:

	symboling	normalized-losses	make	num-of-doors	body-style	drive-wheels	engine-location	wheel-base	length	width	...	city-mpg	highway-mpg	price	city-L/100km	highway-L/100km	horsepower-binned	fuel-type-diesel	fuel-type-gas	aspiration-std	aspiration-turbo
0	3	122	alfa-romero	two	convertible	rwd	front	88.6	0.811148	0.890278	...	21	27	13495.0	11.190476	8.703704	Low	0	1	1	0
1	3	122	alfa-romero	two	convertible	rwd	front	88.6	0.811148	0.890278	...	21	27	16500.0	11.190476	8.703704	Low	0	1	1	0
2	1	122	alfa-romero	two	hatchback	rwd	front	94.5	0.822681	0.909722	...	19	26	16500.0	12.368421	9.038462	Medium	0	1	1	0
3	2	164	audi	four	sedan	fwd	front	99.8	0.848630	0.919444	...	24	30	13950.0	9.791667	7.833333	Low	0	1	1	0
4	2	164	audi	four	sedan	4wd	front	99.4	0.848630	0.922222	...	18	22	17450.0	13.055556	10.681818	Low	0	1	1	0

[5 rows x 31 columns]

Double-click here for the solution.

Question #5:

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

```
In [64]: # Write your code below and press Shift+Enter to execute
         # 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("aspiration", axis = 1, inplace=True)
```

Double-click here for the solution.
save the new csv

```
In [68]: df.to_csv('clean_df.csv')
```

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```

About the Authors:

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