data-wrangling

October 22, 2019

```
<a href="https://cocl.us/corsera_da0101en_notebook_top">
     <img src="https://s3-api.us-geo.objectstorage.softlayer.net/cf-courses-data/CognitiveClas
</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

[2]:
```
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

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

[3]:
```
filename = "https://s3-api.us-geo.objectstorage.softlayer.net/cf-courses-data/
↪CognitiveClass/DA0101EN/auto.csv"
```

Python list headers containing name of headers

[4]:
```
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”.

[5]:
```
df = pd.read_csv(filename, names = headers)
```

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

[6]:
```
# To see what the data set looks like, we'll use the head() method.
df.head()
```

[6]:
```
   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

[7]:
```python
import numpy as np

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

[7]:
```
   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.

[8]:
```python
missing_data = df.isnull()
missing_data.head(5)
```

[8]:
```
   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.

[9]:
```
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 li
    </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
    </ul>
</li>
```

Calculate the average of the column

```
[11]: 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

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

Calculate the mean value for ’bore’ column

```
[13]: 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

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

Question #1:

According to the example above, replace NaN in ”stroke” column by mean.

```
[16]: # Write your code below and press Shift+Enter to execute
      stroke_means=df["stroke"].astype('float').mean(axis=0)
      print("Average of stroke:", stroke_means)
      df["stroke"].replace(np.nan,stroke_means, inplace = True)
```

```
Average of stroke: 3.2554228855721394
```

Double-click here for the solution.

Calculate the mean value for the ’horsepower’ column:

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

```
Average horsepower: 104.25615763546799
```

Replace ”NaN” by mean value:

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

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

```
[20]: 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:

[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:

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

[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:

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

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

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

[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:

[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)
```

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

[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

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

[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

[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

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

[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.

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

[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]
```

[36]:
```python
# 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()
```

[36]:
```
   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 city-mpg  highway-mpg  \
0  3.47    2.68                9.0         111   5000.0       21           27
1  3.47    2.68                9.0         111   5000.0       21           27
2  2.68    3.47                9.0         154   5000.0       19           26
3  3.19    3.40               10.0         102   5500.0       24           30
4  3.19    3.40                8.0         115   5500.0       18           22

     price  city-L/100km  highway-L/100km
0  13495.0     11.190476         8.703704
1  16500.0     11.190476         8.703704
```

```
2  16500.0     12.368421         9.038462
3  13950.0      9.791667         7.833333
4  17450.0     13.055556        10.681818

[5 rows x 28 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".

[40]:
```python
# Write your code below and press Shift+Enter to execute
df["highway-L/100km"]=235/df["highway-mpg"]
df.rename(columns={'"highway-mpg"':'highway-L/100km'}, inplace=True)

#df.drop(['highway-mpg'],axis=1)
```

```
␣
↪---------------------------------------------------------------------------

    KeyError                                  Traceback (most recent call␣
↪last)

    ~/conda/envs/python/lib/python3.6/site-packages/pandas/core/indexes/base.
↪py in get_loc(self, key, method, tolerance)
      2896             try:
   -> 2897                 return self._engine.get_loc(key)
      2898             except KeyError:


    pandas/_libs/index.pyx in pandas._libs.index.IndexEngine.get_loc()


    pandas/_libs/index.pyx in pandas._libs.index.IndexEngine.get_loc()


    pandas/_libs/index.pyx in pandas._libs.index.IndexEngine.
↪_get_loc_duplicates()


    pandas/_libs/index.pyx in pandas._libs.index.IndexEngine.
↪_maybe_get_bool_indexer()


    KeyError: 'highway-mpg'
```

```
During handling of the above exception, another exception occurred:


    KeyError                                  Traceback (most recent call␣
↪last)

    <ipython-input-40-3feee4a5845a> in <module>
      1 # Write your code below and press Shift+Enter to execute
----> 2 df["highway-L/100km"]=235/df["highway-mpg"]
      3 df.rename(columns={'"highway-mpg"':'highway-L/100km'}, inplace=True)
      4
      5 #df.drop(['highway-mpg'],axis=1)


    ~/conda/envs/python/lib/python3.6/site-packages/pandas/core/frame.py in␣
↪__getitem__(self, key)
   2978             if self.columns.nlevels > 1:
   2979                 return self._getitem_multilevel(key)
-> 2980             indexer = self.columns.get_loc(key)
   2981             if is_integer(indexer):
   2982                 indexer = [indexer]


    ~/conda/envs/python/lib/python3.6/site-packages/pandas/core/indexes/base.
↪py in get_loc(self, key, method, tolerance)
   2897                 return self._engine.get_loc(key)
   2898             except KeyError:
-> 2899                 return self._engine.get_loc(self.
↪_maybe_cast_indexer(key))
   2900         indexer = self.get_indexer([key], method=method,␣
↪tolerance=tolerance)
   2901         if indexer.ndim > 1 or indexer.size > 1:


    pandas/_libs/index.pyx in pandas._libs.index.IndexEngine.get_loc()


    pandas/_libs/index.pyx in pandas._libs.index.IndexEngine.get_loc()


    pandas/_libs/index.pyx in pandas._libs.index.IndexEngine.
↪_get_loc_duplicates()


    pandas/_libs/index.pyx in pandas._libs.index.IndexEngine.
↪_maybe_get_bool_indexer()
```

```
KeyError: 'highway-mpg'
```

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)

[41]:
```
# 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".

[43]:
```
# Write your code below and press Shift+Enter to execute
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
```

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

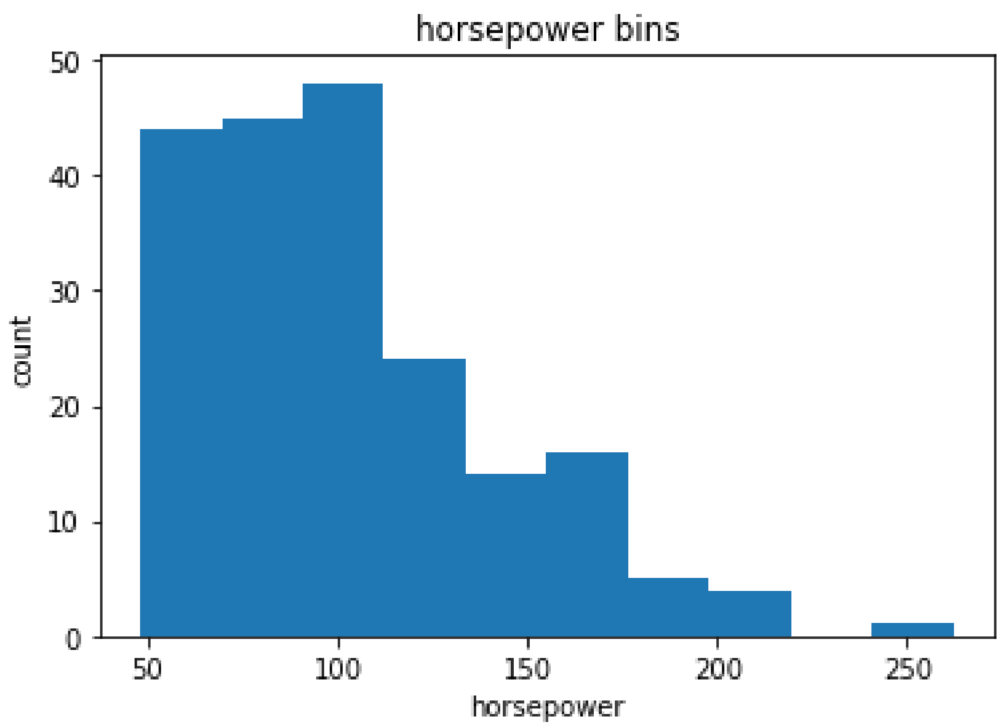
[45]:
```
df["horsepower"]=df["horsepower"].astype(int, copy=True)
```

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

[48]:
```
%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")
```

[48]:
```
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.

[49]:
```
bins = np.linspace(min(df["horsepower"]), max(df["horsepower"]), 4)
bins
```

[49]:
```
array([ 48.        , 119.33333333, 190.66666667, 262.        ])
```

We set group names:

[50]:
```
group_names = ['Low', 'Medium', 'High']
```

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

[52]:
```
df['horsepower-binned'] = pd.cut(df['horsepower'], bins, labels=group_names,␣
↪include_lowest=True )
df[['horsepower','horsepower-binned']].head(20)
```

[52]:

	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.

[53]:
```
df["horsepower-binned"].value_counts()
```

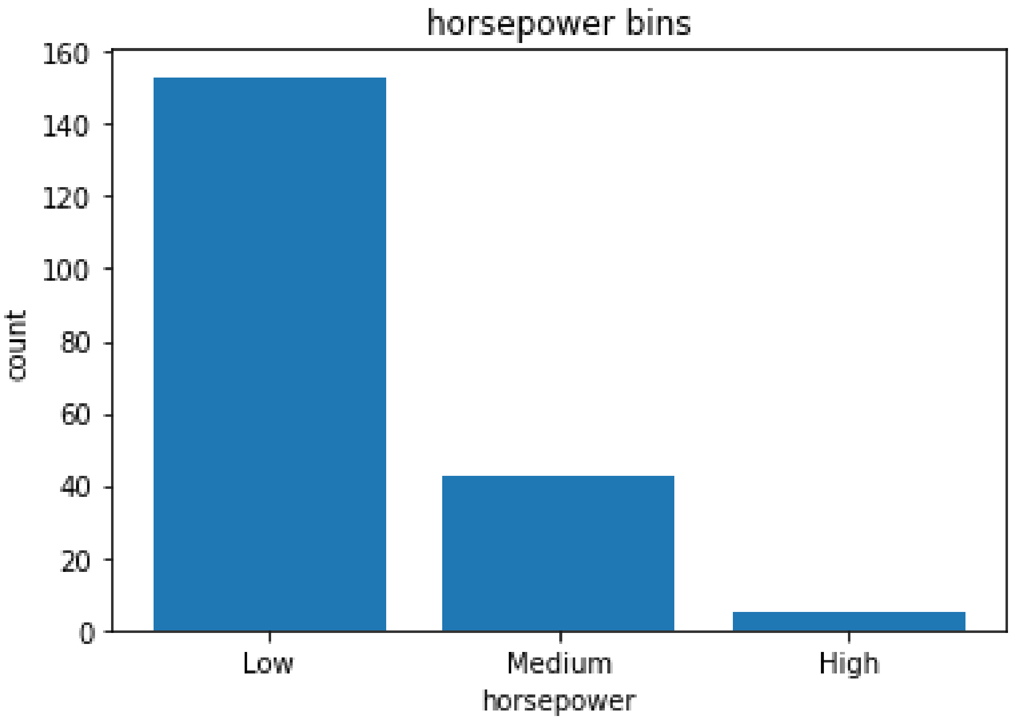
[53]:
```
Low       153
Medium     43
High        5
Name: horsepower-binned, dtype: int64
```

Lets plot the distribution of each bin.

[54]:
```
%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")
```

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



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

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.

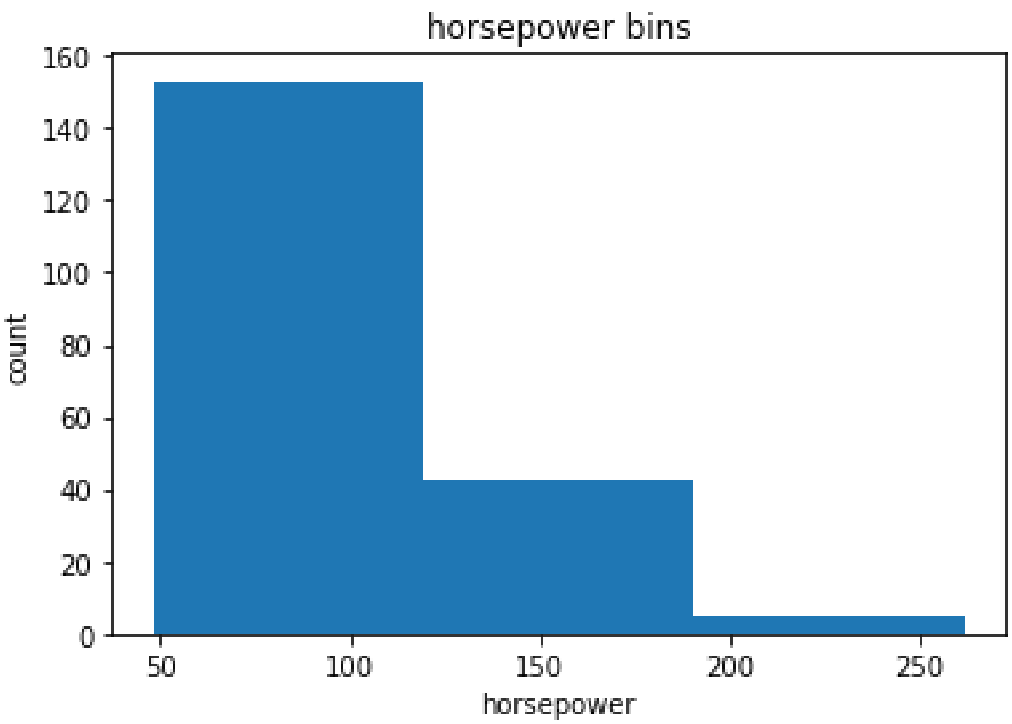
[55]:
```
%matplotlib inline
import matplotlib as plt
from matplotlib import pyplot
```

```
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")
```

[55]: 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. The

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 unde

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

[56]:
```python
df.columns
```

[56]:
```
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-L/100km', 'price', 'city-L/100km', 'highway-L/100km',
       'horsepower-binned'],
      dtype='object')
```

get indicator variables and assign it to data frame "dummy_variable_1"

[62]:
```python
dummy_variable_1 = pd.get_dummies(df["fuel-type"])
dummy_variable_1.head(87)
```

[62]:

	diesel	gas
0	0	1
1	0	1
2	0	1
3	0	1
4	0	1
..	…	…
82	0	1
83	0	1
84	0	1
85	0	1
86	0	1

```
[87 rows x 2 columns]
```

change column names for clarity

[75]:
```python
dummy_variable_1.rename(columns={'fuel-type-diesel':'gas', 'fuel-type-diesel':
 ↪'diesel'}, inplace=True)
dummy_variable_1.head(15)
```

[75]:

	diesel	gas
0	0	1
1	0	1
2	0	1
3	0	1
4	0	1
5	0	1
6	0	1
7	0	1

```
8           0     1
9           0     1
10          0     1
11          0     1
12          0     1
13          0     1
14          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.

[76]:
```python
# 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)
```

```
      ␣
↪---------------------------------------------------------------------------

       KeyError                                  Traceback (most recent call␣
↪last)

       <ipython-input-76-a92dbd6eade8> in <module>
         3
         4 # drop original column "fuel-type" from "df"
   ----> 5 df.drop("fuel-type", axis = 1, inplace=True)


       ~/conda/envs/python/lib/python3.6/site-packages/pandas/core/frame.py in␣
↪drop(self, labels, axis, index, columns, level, inplace, errors)
      4100                 level=level,
      4101                 inplace=inplace,
   -> 4102                 errors=errors,
      4103             )
      4104


       ~/conda/envs/python/lib/python3.6/site-packages/pandas/core/generic.py␣
↪in drop(self, labels, axis, index, columns, level, inplace, errors)
      3912             for axis, labels in axes.items():
      3913                 if labels is not None:
   -> 3914                     obj = obj._drop_axis(labels, axis, level=level,␣
↪errors=errors)
      3915
      3916             if inplace:
```

```
    ~/conda/envs/python/lib/python3.6/site-packages/pandas/core/generic.py␣
↪in _drop_axis(self, labels, axis, level, errors)
   3963                 labels_missing = (axis.get_indexer_for(labels) ==␣
↪-1).any()
   3964                 if errors == "raise" and labels_missing:
-> 3965                     raise KeyError("{} not found in axis".
↪format(labels))
   3966
   3967             slicer = [slice(None)] * self.ndim


    KeyError: "['fuel-type'] not found in axis"
```

[74]:
```
df.tail(15)
```

[74]:
```
     symboling  normalized-losses        make  aspiration num-of-doors  \
186          3                256  volkswagen           1          two
187          0                122  volkswagen           1         four
188          0                122  volkswagen           0         four
189          0                122  volkswagen           1         four
190         -2                103       volvo           1         four
191         -1                 74       volvo           1         four
192         -2                103       volvo           1         four
193         -1                 74       volvo           1         four
194         -2                103       volvo           0         four
195         -1                 74       volvo           0         four
196         -1                 95       volvo           1         four
197         -1                 95       volvo           0         four
198         -1                 95       volvo           1         four
199         -1                 95       volvo           0         four
200         -1                 95       volvo           0         four

    body-style drive-wheels engine-location  wheel-base    length  …  \
186  hatchback          fwd           front        94.5  0.796252  …
187      sedan          fwd           front       100.4  0.865930  …
188      sedan          fwd           front       100.4  0.865930  …
189      wagon          fwd           front       100.4  0.879865  …
190      sedan          rwd           front       104.3  0.907256  …
191      wagon          rwd           front       104.3  0.907256  …
192      sedan          rwd           front       104.3  0.907256  …
193      wagon          rwd           front       104.3  0.907256  …
194      sedan          rwd           front       104.3  0.907256  …
195      wagon          rwd           front       104.3  0.907256  …
196      sedan          rwd           front       109.1  0.907256  …
```

```
197      sedan          rwd          front       109.1  0.907256  …
198      sedan          rwd          front       109.1  0.907256  …
199      sedan          rwd          front       109.1  0.907256  …
200      sedan          rwd          front       109.1  0.907256  …

     horsepower  peak-rpm  city-mpg highway-L/100km    price  city-L/100km  \
186          90    5500.0        24               29   9980.0      9.791667
187         110    5500.0        19               24  13295.0     12.368421
188          68    4500.0        33               38  13845.0      7.121212
189          88    5500.0        25               31  12290.0      9.400000
190         114    5400.0        23               28  12940.0     10.217391
191         114    5400.0        23               28  13415.0     10.217391
192         114    5400.0        24               28  15985.0      9.791667
193         114    5400.0        24               28  16515.0      9.791667
194         162    5100.0        17               22  18420.0     13.823529
195         162    5100.0        17               22  18950.0     13.823529
196         114    5400.0        23               28  16845.0     10.217391
197         160    5300.0        19               25  19045.0     12.368421
198         134    5500.0        18               23  21485.0     13.055556
199         106    4800.0        26               27  22470.0      9.038462
200         114    5400.0        19               25  22625.0     12.368421

    highway-L/100km  horsepower-binned  diesel  gas
186        8.103448                Low       0    1
187        9.791667                Low       0    1
188        6.184211                Low       1    0
189        7.580645                Low       0    1
190        8.392857                Low       0    1
191        8.392857                Low       0    1
192        8.392857                Low       0    1
193        8.392857                Low       0    1
194       10.681818             Medium       0    1
195       10.681818             Medium       0    1
196        8.392857                Low       0    1
197        9.400000             Medium       0    1
198       10.217391             Medium       0    1
199        8.703704                Low       1    0
200        9.400000                Low       0    1

[15 rows x 30 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.

[73]:
```
# Write your code below and press Shift+Enter to execute
df_asp =pd.get_dummies(df['aspiration'])

df_asp.rename(columns = {'0':'std', '1':'turbo'})
```

[73]:
```
     0  1
0    0  1
1    0  1
2    0  1
3    0  1
4    0  1
..  .. ..
196  0  1
197  1  0
198  0  1
199  1  0
200  1  0

[201 rows x 2 columns]
```

Double-click here for the solution.

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
```

Double-click here for the solution.

save the new csv

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

Thank you for completing this notebook

<p><a href="https://cocl.us/corsera_da0101en_notebook_bottom"><img src="https://s3-api.us-geo.

About the Authors:

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