data-wrangling

June 9, 2020

    <img src="https://s3-api.us-geo.objectstorage.softlayer.net/cf-courses-data/CognitiveClas

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

[45]:
```
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

[46]:
```
filename = "https://s3-api.us-geo.objectstorage.softlayer.net/cf-courses-data/
↪CognitiveClass/DA0101EN/auto.csv"
```

Python list headers containing name of headers

[47]:
```
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".

[48]:
```
df = pd.read_csv(filename, names = headers)
```

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

[49]:
```
# To see what the data set looks like, we'll use the head() method.
df.head()
```

[49]:
```
   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:

dentify 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), 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

[50]:
```python
import numpy as np

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

[50]:
```
   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:

.isnull()

.notnull()

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

[51]:
```
missing_data = df.isnull()
missing_data.head(5)
```

[51]:
```
   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.

[52]:
```
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:

“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 average of the column

[53]:
```
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

[54]:
```
df["normalized-losses"].replace(np.nan, avg_norm_loss, inplace=True)
```

Calculate the mean value for ‘bore’ column

[55]:
```
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

[56]:
```
df["bore"].replace(np.nan, avg_bore, inplace=True)
```

Question #1:

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

[57]:
```
# Write your code below and press Shift+Enter to execute
avg_stroke = df['stroke'].astype('float').mean(axis=0)
df['stroke'].replace(np.nan,avg_stroke,inplace=True)
```

Double-click here for the solution.

Calculate the mean value for the ‘horsepower’ column:

[58]:
```
avg_horsepower = df['horsepower'].astype('float').mean(axis=0)
print("Average horsepower:", avg_horsepower)
```

Average horsepower: 104.25615763546799

Replace “NaN” by mean value:

[59]:
```
df['horsepower'].replace(np.nan, avg_horsepower, inplace=True)
```

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

[60]:
```
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:

[61]:
```
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:

[62]:
```
df['num-of-doors'].value_counts()
```

[62]:
```
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:

[63]:
```python
df['num-of-doors'].value_counts().idxmax()
```

[63]:
```
'four'
```

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

[64]:
```python
#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:

[65]:
```python
# simply drop whole row with NaN in "price" column
df.dropna(subset=["price"], axis=0, inplace=True)

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

[66]:
```python
df.head()
```

[66]:
```
   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

[67]:
```
df.dtypes
```

[67]:
```
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

[68]:
```
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

[69]:
```
df.dtypes
```

[69]:
```
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.

[70]:
```
df.head()
```

[70]:
```
   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]
```

[71]:

```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()
```

[71]:

```
   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".

[72]:
```
# Write your code below and press Shift+Enter to execute
df.rename(columns={'highway-mpg':'high-L'},inplace=True)
df.head()
```

[72]:
```
   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

  high-L    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]
```

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)

[73]:
```
# 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".

[74]:
```
# Write your code below and press Shift+Enter to execute
```

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 'bins', for grouped analysis.

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

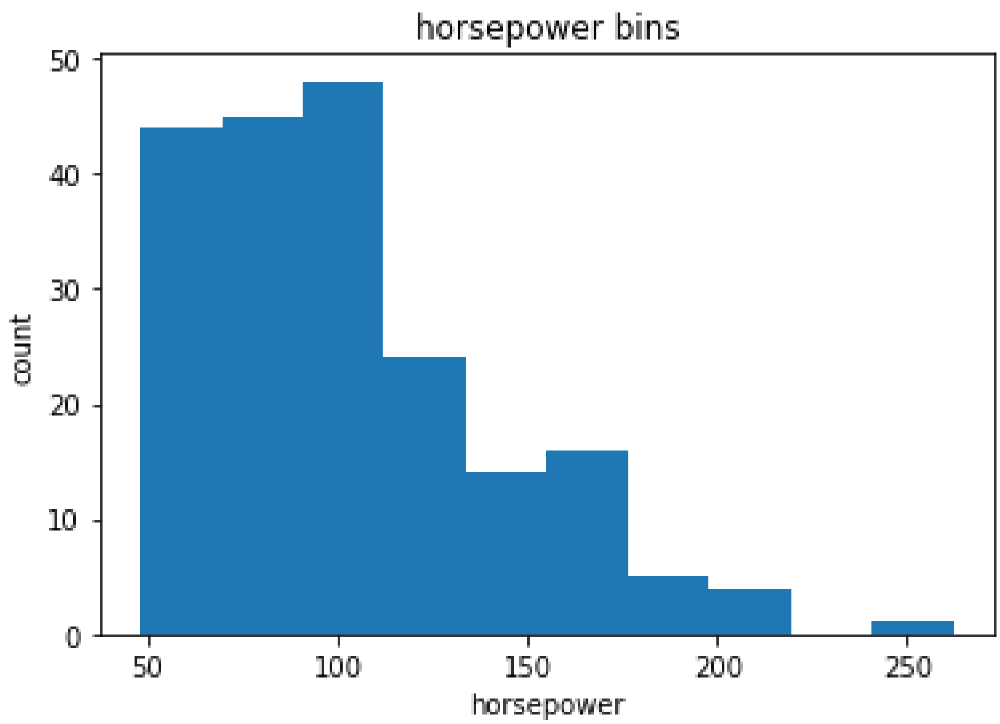
[75]:
```
df["horsepower"]=df["horsepower"].astype(int, copy=True)
```

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

[76]:
```
%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")
```

[76]: 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.

[77]:
```
bins = np.linspace(min(df["horsepower"]), max(df["horsepower"]), 4)
bins
```

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

We set group names:

[78]:
```
group_names = ['Low', 'Medium', 'High']
```

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

[79]:
```
df['horsepower-binned'] = pd.cut(df['horsepower'], bins, labels=group_names,␣
↪include_lowest=True )
df[['horsepower','horsepower-binned']].head(20)
```

[79]:
```
    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.

[80]:
```
df["horsepower-binned"].value_counts()
```

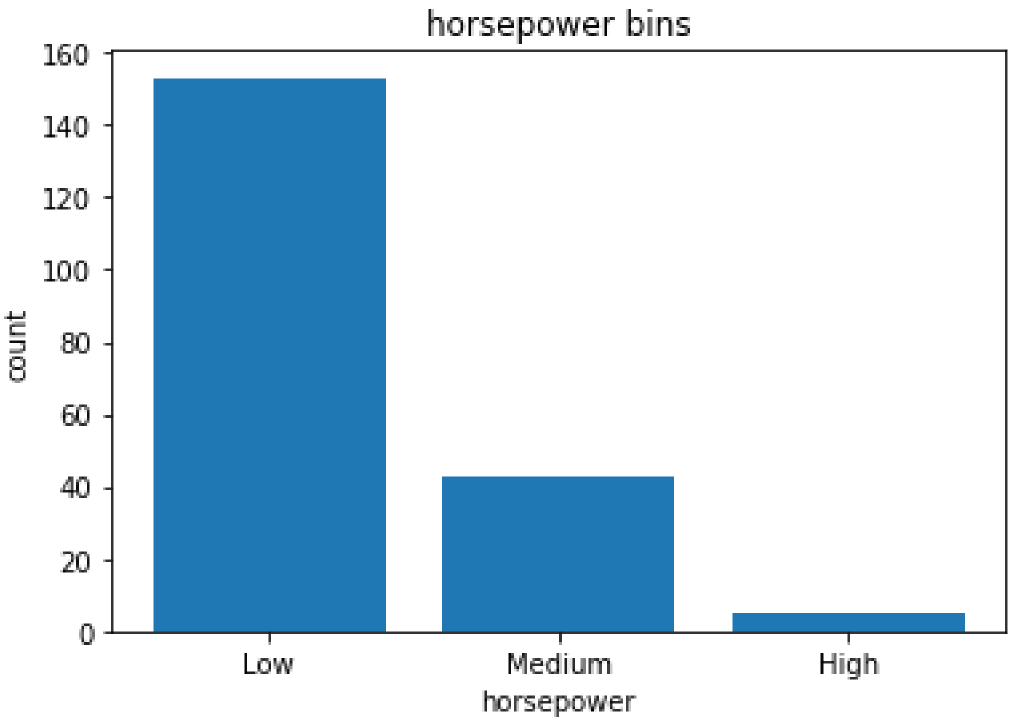
[80]:
```
Low       153
Medium     43
High        5
Name: horsepower-binned, dtype: int64
```

Lets plot the distribution of each bin.

[81]:
```
%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")
```

[81]:
```
Text(0.5, 1.0, 'horsepower bins')
```



Check the dataframe above carefully, you will find the last column provides the bins for "horsepower" with 3 categories ("Low","Medium" and "High").

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.

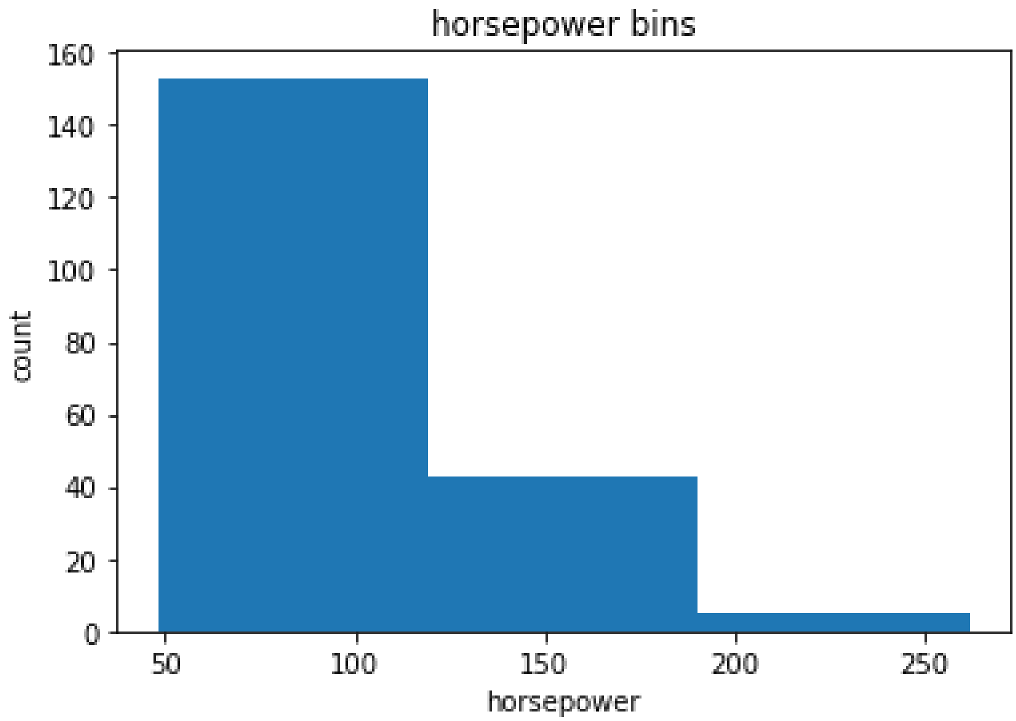
[82]:
```
%matplotlib inline
import matplotlib as plt
from matplotlib import pyplot

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")
```

[82]:
```
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 are called ‘dummies’ because the numbers themselves don’t have inherent meaning.

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 understand words, only numbers. To use this attribute in regression analysis, we convert “fuel-type” into indicator variables.

We will use the panda’s method ‘get_dummies’ to assign numerical values to different categories of fuel type.

[83]:
```
df.columns
```

[83]:
```
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', 'high-L',
       'price', 'city-L/100km', 'horsepower-binned'],
      dtype='object')
```

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

[84]:
```
dummy_variable_1 = pd.get_dummies(df["fuel-type"])
dummy_variable_1.head()
```

[84]:
```
   diesel  gas
0       0    1
1       0    1
2       0    1
3       0    1
4       0    1
```

change column names for clarity

[85]:
```
dummy_variable_1.rename(columns={'fuel-type-diesel':'gas', 'fuel-type-diesel':
 ↪'diesel'}, inplace=True)
dummy_variable_1.head()
```

[85]:
```
   diesel  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.

[86]:
```
# 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)
```

[87]:
```
df.head()
```

[87]:
```
   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 high-L    price  \
0                9.0         111    5000.0       21      27  13495.0
1                9.0         111    5000.0       21      27  16500.0
2                9.0         154    5000.0       19      26  16500.0
3               10.0         102    5500.0       24      30  13950.0
4                8.0         115    5500.0       18      22  17450.0

  city-L/100km  horsepower-binned  diesel  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. 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.

[88]:
```
# Write your code below and press Shift+Enter to execute
```

Double-click here for the solution.

Question #5:

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

[89]:
```
# Write your code below and press Shift+Enter to execute
```

Double-click here for the solution.

save the new csv

[90]:
```
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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