COGNITIVE CLASS

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Data Analysis with Python

Introduction

Welcome!

In this section, you will learn how to approach data acquisition in various ways, and obtain necessary insights from a dataset. By the end of this lab, you will successfully load the data into Jupyter Notebook, and gain some fundamental insights via Pandas Library.

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Estimated Time Needed: **10 min** </div>

Data Acquisition

There are various formats for a dataset, .csv, .json, .xlsx etc. The dataset can be stored in different places, on your local machine or sometimes online.
In this section, you will learn how to load a dataset into our Jupyter Notebook.
In our case, the Automobile Dataset is an online source, and it is in CSV (comma separated value) format. Let's use this dataset as an example to practice data reading.

- data source: https://archive.ics.uci.edu/ml/machine-learning-databases/autos/imports-85.data (https://archive.ics.uci.edu/ml/machine-learning-databases/autos/imports-85.data)
- data type: csv

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

In [10]:

Read Data

We use `pandas.read_csv()` function to read the csv file. In the bracket, we put the file path along with a quotation mark, so that pandas will read the file into a data frame from that address. The file path can be either an URL or your local file address.
Because the data does not include headers, we can add an argument `headers = None` inside the `read_csv()` method, so that pandas will not automatically set the first row as a header.
You can also assign the dataset to any variable you create.

This dataset was hosted on IBM Cloud object click HERE (https://cocl.us/DA101EN_object_storage) for free storage.

In [1]:

After reading the dataset, we can use the `dataframe.head(n)` method to check the top n rows of the dataframe; where n is an integer. Contrary to `dataframe.head(n)`, `dataframe.tail(n)` will show you the bottom n rows of the dataframe.

In [2]:

```
The first 5 rows of the dataframe
```

Out[2]:

	0	1	2	3	4	5	6	7	8	9	...	16	17	18	19	20
0	3	?	alfa-romero	gas	std	two	convertible	rwd	front	88.6	...	130	mpfi	3.47	2.68	9.0
1	3	?	alfa-romero	gas	std	two	convertible	rwd	front	88.6	...	130	mpfi	3.47	2.68	9.0
2	1	?	alfa-romero	gas	std	two	hatchback	rwd	front	94.5	...	152	mpfi	2.68	3.47	9.0
3	2	164	audi	gas	std	four	sedan	fwd	front	99.8	...	109	mpfi	3.19	3.40	10.0
4	2	164	audi	gas	std	four	sedan	4wd	front	99.4	...	136	mpfi	3.19	3.40	8.0

5 rows × 26 columns

Question #1:

check the bottom 10 rows of data frame "df".

In [3]:

Out[3]:

	0	1	2	3	4	5	6	7	8	9	...	16	17	18	19	2
195	-1	74	volvo	gas	std	four	wagon	rwd	front	104.3	...	141	mpfi	3.78	3.15	9.
196	-2	103	volvo	gas	std	four	sedan	rwd	front	104.3	...	141	mpfi	3.78	3.15	9.
197	-1	74	volvo	gas	std	four	wagon	rwd	front	104.3	...	141	mpfi	3.78	3.15	9.
198	-2	103	volvo	gas	turbo	four	sedan	rwd	front	104.3	...	130	mpfi	3.62	3.15	7.
199	-1	74	volvo	gas	turbo	four	wagon	rwd	front	104.3	...	130	mpfi	3.62	3.15	7.
200	-1	95	volvo	gas	std	four	sedan	rwd	front	109.1	...	141	mpfi	3.78	3.15	9.
201	-1	95	volvo	gas	turbo	four	sedan	rwd	front	109.1	...	141	mpfi	3.78	3.15	8.
202	-1	95	volvo	gas	std	four	sedan	rwd	front	109.1	...	173	mpfi	3.58	2.87	8.
203	-1	95	volvo	diesel	turbo	four	sedan	rwd	front	109.1	...	145	idi	3.01	3.40	23.
204	-1	95	volvo	gas	turbo	four	sedan	rwd	front	109.1	...	141	mpfi	3.78	3.15	9.

10 rows × 26 columns

Question #1 Answer:

Run the code below for the solution!

Double-click **here** for the solution.

Add Headers

Take a look at our dataset; pandas automatically set the header by an integer from 0.

To better describe our data we can introduce a header, this information is available at: https://archive.ics.uci.edu/ml/datasets/Automobile (https://archive.ics.uci.edu/ml/datasets/Automobile)

Thus, we have to add headers manually.

Firstly, we create a list "headers" that include all column names in order. Then, we use `dataframe.columns = headers` to replace the headers by the list we created.

In [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']
```

We replace headers and recheck our data frame

In [5]:

Out[5]:

	symboling	normalized-losses	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	whee ba
0	3	?	alfa-romero	gas	std	two	convertible	rwd	front	88
1	3	?	alfa-romero	gas	std	two	convertible	rwd	front	88
2	1	?	alfa-romero	gas	std	two	hatchback	rwd	front	94
3	2	164	audi	gas	std	four	sedan	fwd	front	99
4	2	164	audi	gas	std	four	sedan	4wd	front	99
5	2	?	audi	gas	std	two	sedan	fwd	front	99
6	1	158	audi	gas	std	four	sedan	fwd	front	105
7	1	?	audi	gas	std	four	wagon	fwd	front	105
8	1	158	audi	gas	turbo	four	sedan	fwd	front	105
9	0	?	audi	gas	turbo	two	hatchback	4wd	front	99

10 rows × 26 columns

we can drop missing values along the column "price" as follows

In [6]:

Out[6]:

	symboling	normalized-losses	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	w
0	3	?	alfa-romero	gas	std	two	convertible	rwd	front	
1	3	?	alfa-romero	gas	std	two	convertible	rwd	front	
2	1	?	alfa-romero	gas	std	two	hatchback	rwd	front	
3	2	164	audi	gas	std	four	sedan	fwd	front	
4	2	164	audi	gas	std	four	sedan	4wd	front	
...	...	...	...	...	...	...	...	...	...	
200	-1	95	volvo	gas	std	four	sedan	rwd	front	
201	-1	95	volvo	gas	turbo	four	sedan	rwd	front	
202	-1	95	volvo	gas	std	four	sedan	rwd	front	
203	-1	95	volvo	diesel	turbo	four	sedan	rwd	front	
204	-1	95	volvo	gas	turbo	four	sedan	rwd	front	

205 rows × 26 columns

Now, we have successfully read the raw dataset and add the correct headers into the data frame.

Question #2:

Find the name of the columns of the dataframe

In [18]:

Out[18]:

```
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
```

In [19]:

```
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-typ
e',
       'num-of-cylinders', 'engine-size', 'fuel-system', 'bore', 'stroke',
       'compression-ratio', 'horsepower', 'peak-rpm', 'city-mpg',
       'highway-mpg', 'price'],
      dtype='object')
```

Double-click **here** for the solution.

Save Dataset

Correspondingly, Pandas enables us to save the dataset to csv by using the `dataframe.to_csv()` method, you can add the file path and name along with quotation marks in the brackets.

For example, if you would save the dataframe **df** as **automobile.csv** to your local machine, you may use the syntax below:

In [29]:

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

Read/Save Other Data Formats

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

Basic Insight of Dataset

After reading data into Pandas dataframe, it is time for us to explore the dataset.
There are several ways to obtain essential insights of the data to help us better understand our dataset.

Data Types

Data has a variety of types.
The main types stored in Pandas dataframes are **object**, **float**, **int**, **bool** and **datetime64**. In order to better learn about each attribute, it is always good for us to know the data type of each column. In Pandas:

In [30]:

Out[30]:

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

returns a Series with the data type of each column.

In [31]:

```
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 a result, as shown above, it is clear to see that the data type of "symboling" and "curb-weight" are `int64`, "normalized-losses" is `object`, and "wheel-base" is `float64`, etc.

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

Describe

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

dataframe.describe()

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

In [32]:

Out[32]:

	symboling	wheel-base	length	width	height	curb-weight	engine-size
count	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000
mean	0.834146	98.756585	174.049268	65.907805	53.724878	2555.565854	126.907317
std	1.245307	6.021776	12.337289	2.145204	2.443522	520.680204	41.642693
min	-2.000000	86.600000	141.100000	60.300000	47.800000	1488.000000	61.000000
25%	0.000000	94.500000	166.300000	64.100000	52.000000	2145.000000	97.000000
50%	1.000000	97.000000	173.200000	65.500000	54.100000	2414.000000	120.000000
75%	2.000000	102.400000	183.100000	66.900000	55.500000	2935.000000	141.000000
max	3.000000	120.900000	208.100000	72.300000	59.800000	4066.000000	326.000000

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

You can add an argument `include = "all"` inside the bracket. Let's try it again.

In [33]:

Out[33]:

	symboling	normalized-losses	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	
count	205.000000	205	205	205	205	205	205	205	205	205.
unique	NaN	52	22	2	2	3	5	3	2	
top	NaN	?	toyota	gas	std	four	sedan	fwd	front	
freq	NaN	41	32	185	168	114	96	120	202	
mean	0.834146	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	98.
std	1.245307	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	6.
min	-2.000000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	86.
25%	0.000000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	94.
50%	1.000000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	97.
75%	2.000000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	102.
max	3.000000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	120.

11 rows × 26 columns

Now, it provides the statistical summary of all the columns, including object-typed attributes.
We can now see how many unique values, which is the top value and the frequency of top value in the object-typed columns.
Some values in the table above show as "NaN", this is because those numbers are not available regarding a particular column type.

Question #3:

You can select the columns of a data frame by indicating the name of each column, for example, you can select the three columns as follows:

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

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

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

Apply the method to ".describe()" to the columns 'length' and 'compression-ratio'.

In [34]:

Out[34]:

	length	compression-ratio
count	205.000000	205.000000
mean	174.049268	10.142537
std	12.337289	3.972040
min	141.100000	7.000000
25%	166.300000	8.600000
50%	173.200000	9.000000
75%	183.100000	9.400000
max	208.100000	23.000000

Double-click **here** for the solution.

Info

Another method you can use to check your dataset is:

dataframe.info

It provide a concise summary of your DataFrame.

In [35]:

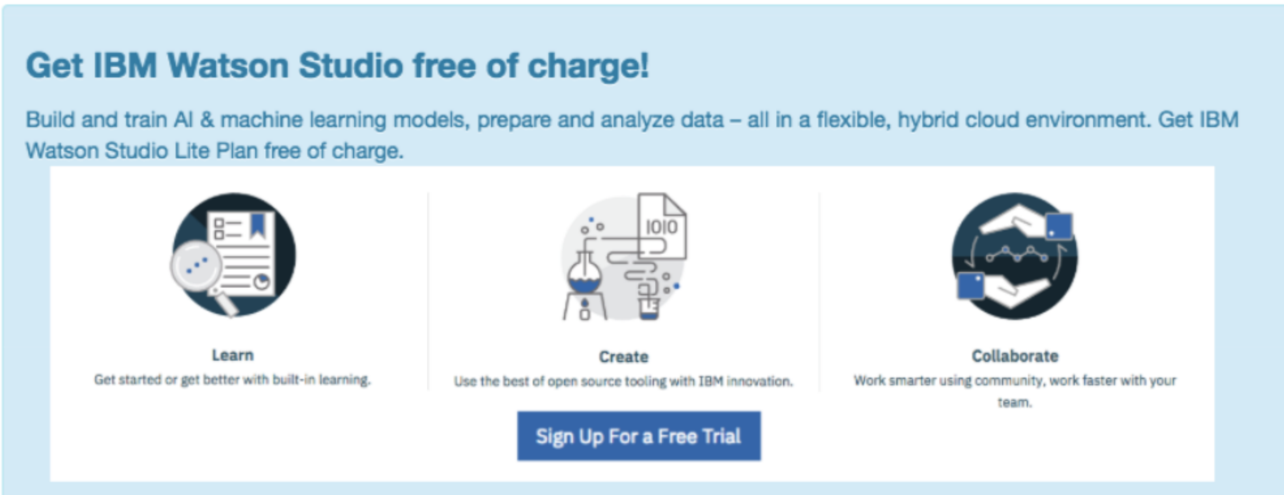
Out[35]:

```
<bound method DataFrame.info of      symboling normalized-losses         mak
e fuel-type aspiration  \
0            3                 ?  alfa-romero       gas        std
1            3                 ?  alfa-romero       gas        std
2            1                 ?  alfa-romero       gas        std
3            2               164         audi       gas        std
4            2               164         audi       gas        std
..         ...               ...          ...       ...        ...
200         -1                95        volvo       gas        std
201         -1                95        volvo       gas      turbo
202         -1                95        volvo       gas        std
203         -1                95        volvo    diesel      turbo
204         -1                95        volvo       gas      turbo

    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  ...
..           ...          ...          ...             ...         ...  ...
200         four        sedan          rwd           front       109.1  ...
201         four        sedan          rwd           front       109.1  ...
202         four        sedan          rwd           front       109.1  ...
203         four        sedan          rwd           front       109.1  ...
204         four        sedan          rwd           front       109.1  ...

     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
..           ...          ...   ...     ...               ...        ...
200          141         mpfi  3.78    3.15               9.5        114
201          141         mpfi  3.78    3.15               8.7        160
202          173         mpfi  3.58    2.87               8.8        134
203          145          idi  3.01    3.40              23.0        106
204          141         mpfi  3.78    3.15               9.5        114

     peak-rpm city-mpg highway-mpg  price
0        5000       21          27  13495
1        5000       21          27  16500
2        5000       19          26  16500
3        5500       24          30  13950
4        5500       18          22  17450
..        ...      ...         ...    ...
200      5400       23          28  16845
201      5300       19          25  19045
202      5500       18          23  21485
203      4800       26          27  22470
204      5400       19          25  22625

[205 rows x 26 columns]>
```

Here we are able to see the information of our dataframe, with the top 30 rows and the bottom 30 rows.

And, it also shows us the whole data frame has 205 rows and 26 columns in total.

Excellent! You have just completed the Introduction Notebook!



(https://cocl.us/corsera_da0101en_notebook_bottom)

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Joseph Santarcangelo (https://www.linkedin.com/in/joseph-s-50398b136/) is a Data Scientist at IBM, and holds a PhD in Electrical Engineering. His research focused on using Machine Learning, Signal Processing, and Computer Vision to determine how videos impact human cognition. Joseph has been working for IBM since he completed his PhD.

```
In [ ]:
```