USC University of Southern California

Data Analysis and Visualization using Pandas and Matplotlib

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Content

Introduction

Pandas

Matplotlib

Anaconda

Summary

Introduction

Pandas: open source data analysis and manipulation tool in Python

By the end of this lecture, you should be able to:

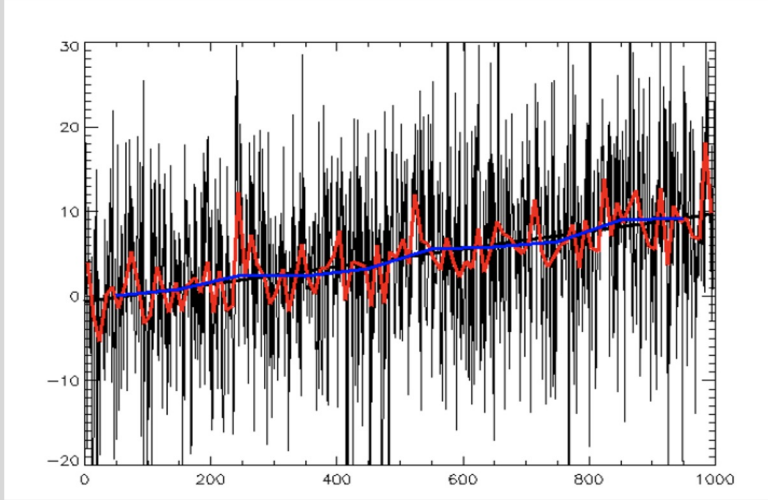
- Describe the value of Pandas to Data Science in Python
- Highlight the key data structures of Pandas

Documentation Page: https://pandas.pydata.org/docs/user_guide/index.html

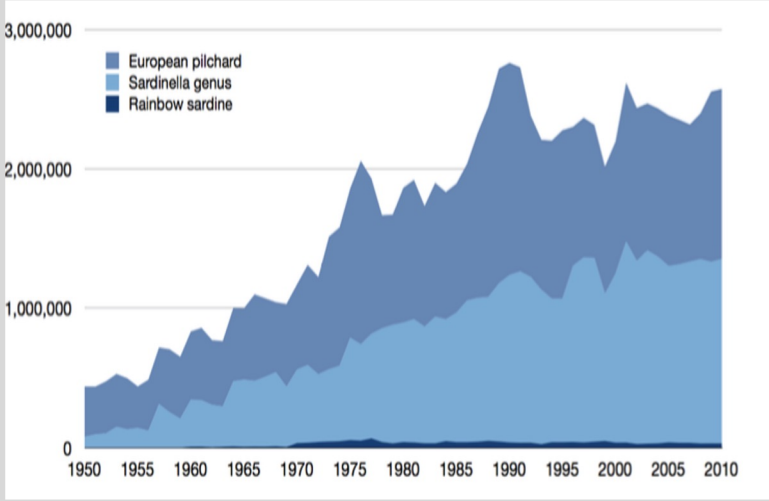
Benefits of Using Pandas

Key Benefits:

- Data variety support
- Data transformation & integration
- Data visualization



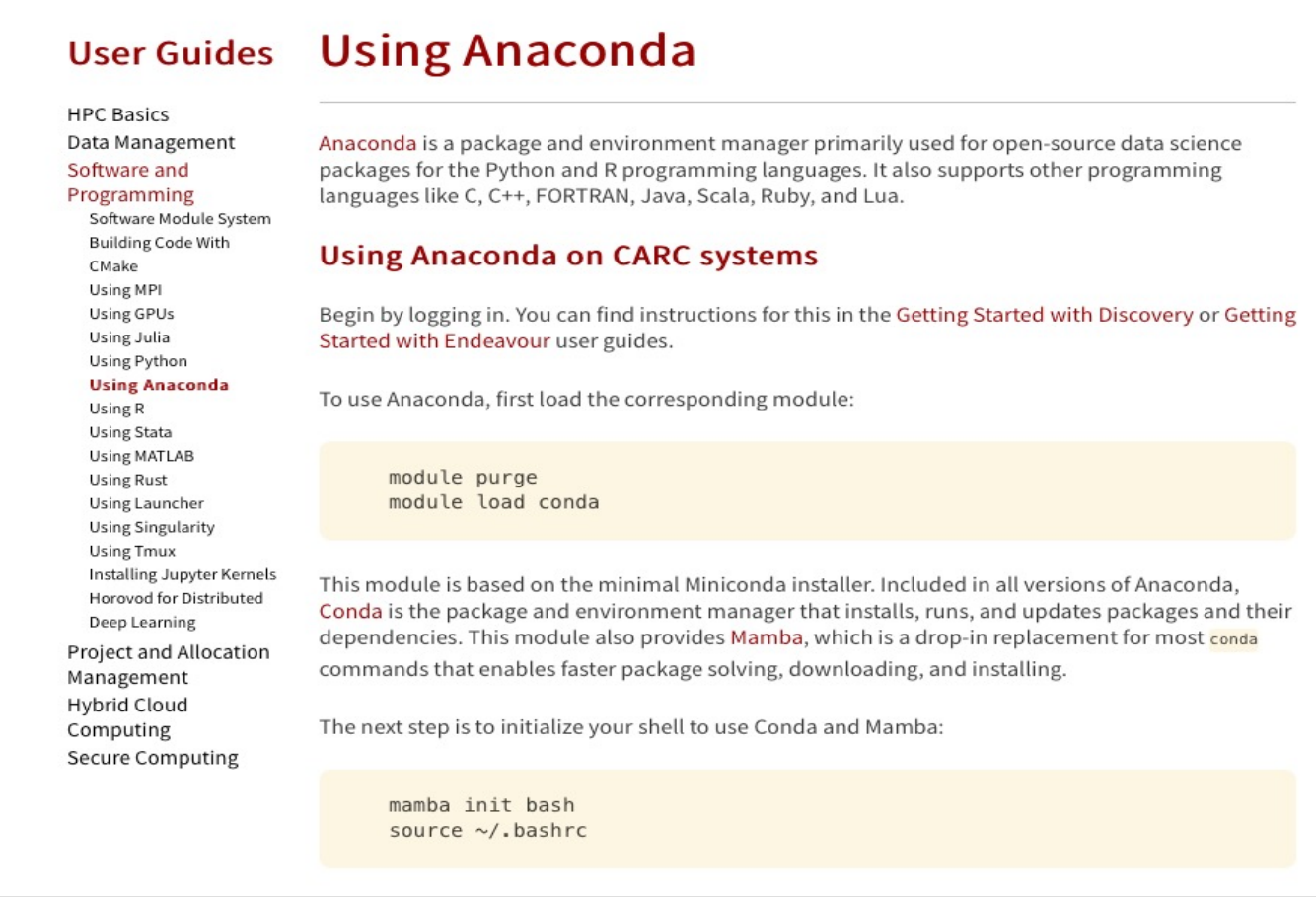
Time Series Data



Data Visualization

Using Anaconda on CARC

Anaconda: package and environment manager primarily used for open-source data science packages for the Python and R programming languages.



User Guides

- HPC Basics
- Data Management
- Software and Programming
  - Software Module System
  - Building Code With CMake
  - Using MPI
  - Using GPUs
  - Using Julia
  - Using Python
  - **Using Anaconda**
  - Using R
  - Using Stata
  - Using MATLAB
  - Using Rust
  - Using Launcher
  - Using Singularity
  - Using Tmux
  - Installing Jupyter Kernels
  - Horovod for Distributed Deep Learning
- Project and Allocation Management
- Hybrid Cloud Computing
- Secure Computing

Using Anaconda

Anaconda is a package and environment manager primarily used for open-source data science packages for the Python and R programming languages. It also supports other programming languages like C, C++, FORTRAN, Java, Scala, Ruby, and Lua.

Using Anaconda on CARC systems

Begin by logging in. You can find instructions for this in the Getting Started with Discovery or Getting Started with Endeavour user guides.

To use Anaconda, first load the corresponding module:

```
module purge
module load conda
```

This module is based on the minimal Miniconda installer. Included in all versions of Anaconda, Conda is the package and environment manager that installs, runs, and updates packages and their dependencies. This module also provides Mamba, which is a drop-in replacement for most `conda` commands that enables faster package solving, downloading, and installing.

The next step is to initialize your shell to use Conda and Mamba:

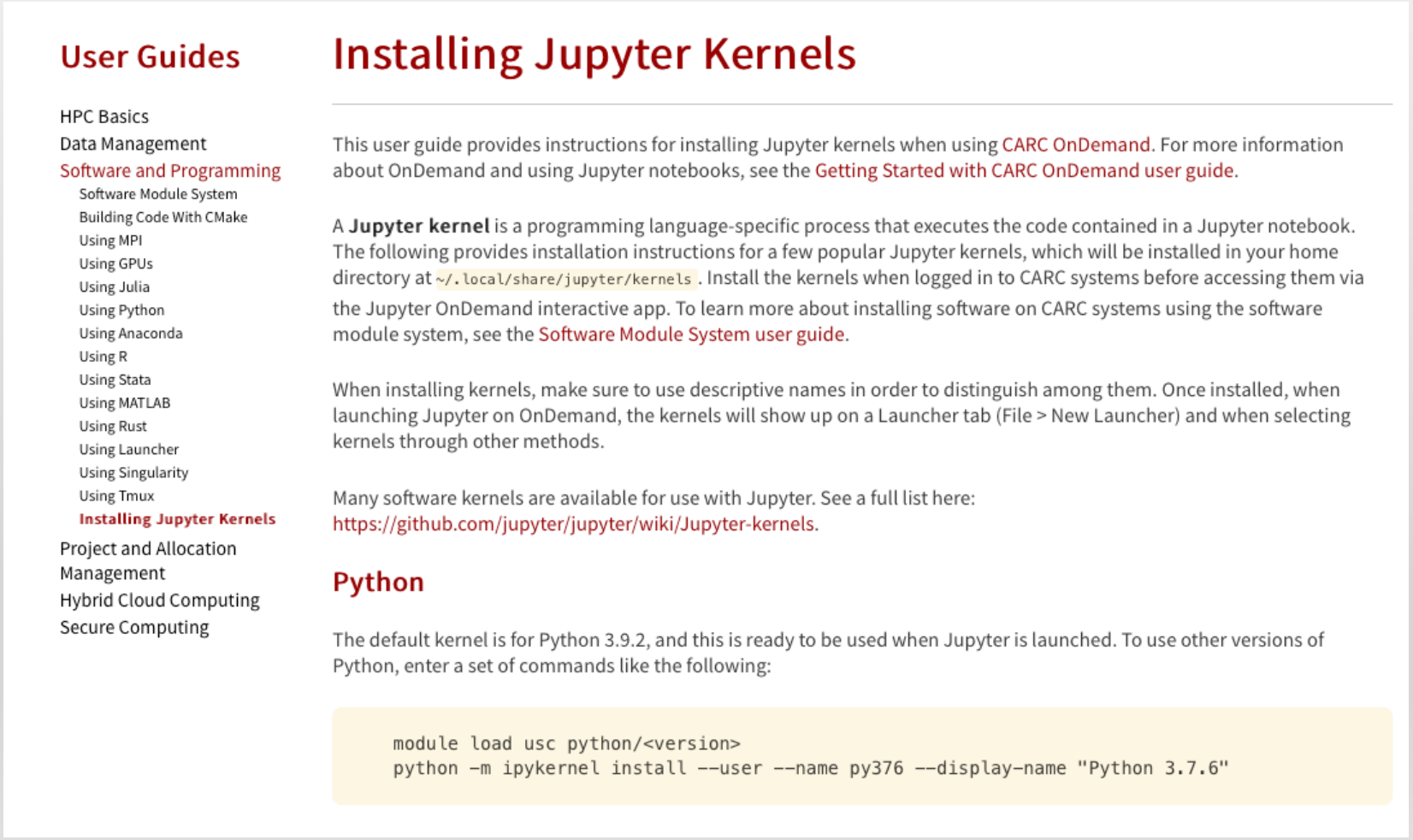
```
mamba init bash
source ~/.bashrc
```

https://www.carc.usc.edu/user-information/user-guides/software-and-programming/anaconda

```
mamba create -n 01-23
mamba activate 01-23
salloc
mamba install python
mamba install pandas
mamba install matplotlib
```

Creating Jupyter Kernel

A **Jupyter kernel** is a programming language-specific process that executes the code contained in a Jupyter notebook.



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Installing Jupyter Kernels

This user guide provides instructions for installing Jupyter kernels when using CARC OnDemand. For more information about OnDemand and using Jupyter notebooks, see the Getting Started with CARC OnDemand user guide.

A **Jupyter kernel** is a programming language-specific process that executes the code contained in a Jupyter notebook. The following provides installation instructions for a few popular Jupyter kernels, which will be installed in your home directory at `~/.local/share/jupyter/kernels`. Install the kernels when logged in to CARC systems before accessing them via the Jupyter OnDemand interactive app. To learn more about installing software on CARC systems using the software module system, see the Software Module System user guide.

When installing kernels, make sure to use descriptive names in order to distinguish among them. Once installed, when launching Jupyter on OnDemand, the kernels will show up on a Launcher tab (File > New Launcher) and when selecting kernels through other methods.

Many software kernels are available for use with Jupyter. See a full list here: https://github.com/jupyter/jupyter/wiki/Jupyter-kernels.

Python

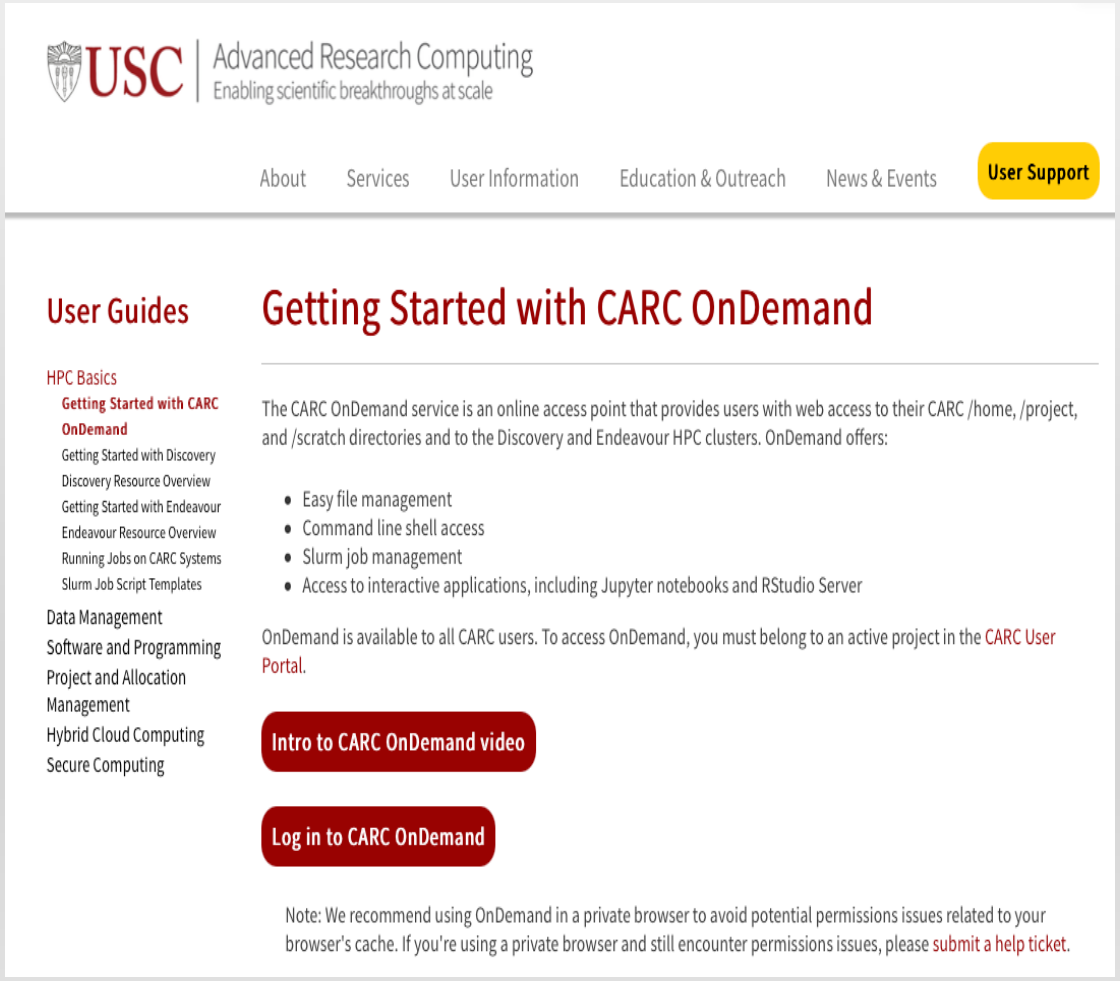
The default kernel is for Python 3.9.2, and this is ready to be used when Jupyter is launched. To use other versions of Python, enter a set of commands like the following:

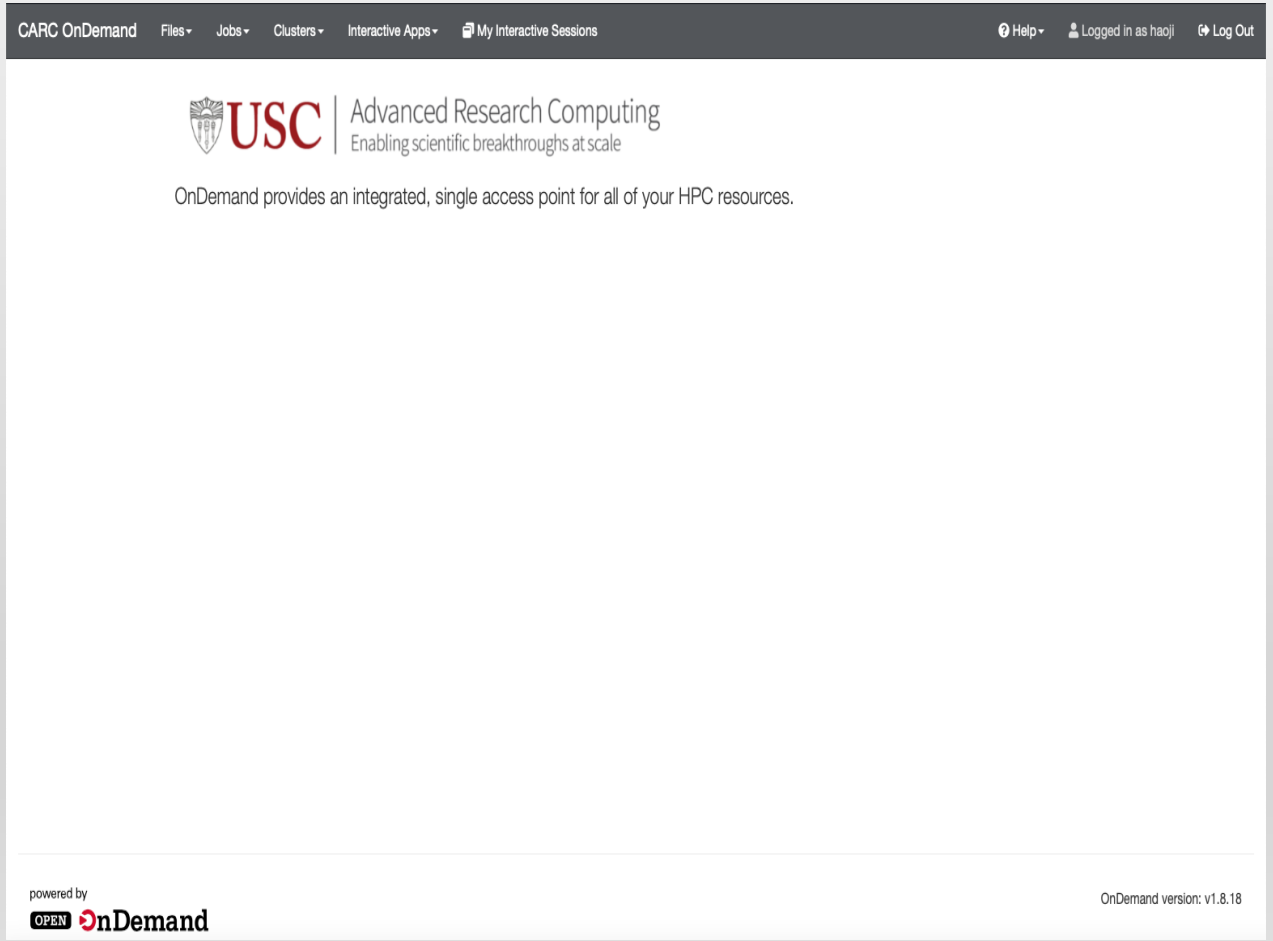
```
module load usc python/<version>
python -m ipykernel install --user --name py376 --display-name "Python 3.7.6"
```

https://www.carc.usc.edu/user-information/user-guides/software-and-programming/jupyter-kernels

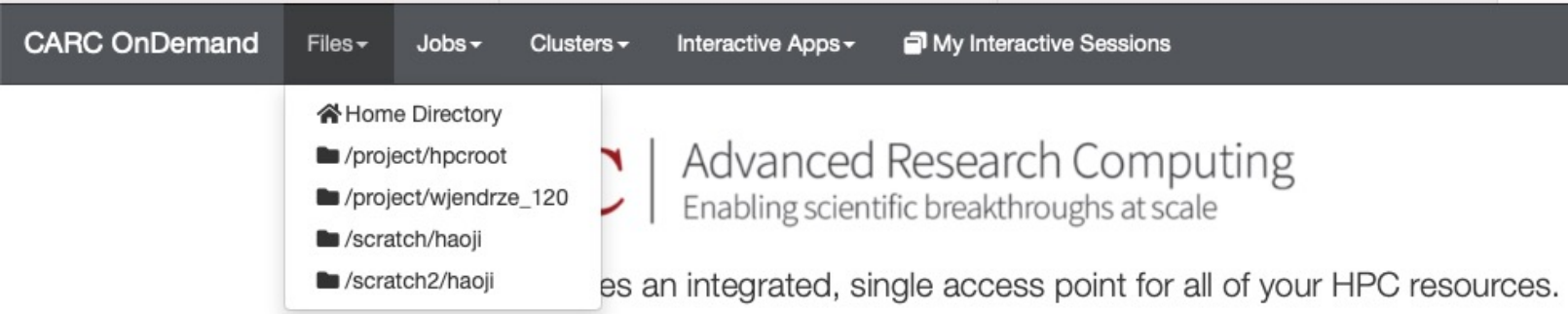
CARC Ondemand

Web Address: https://carc-ondemand.usc.edu

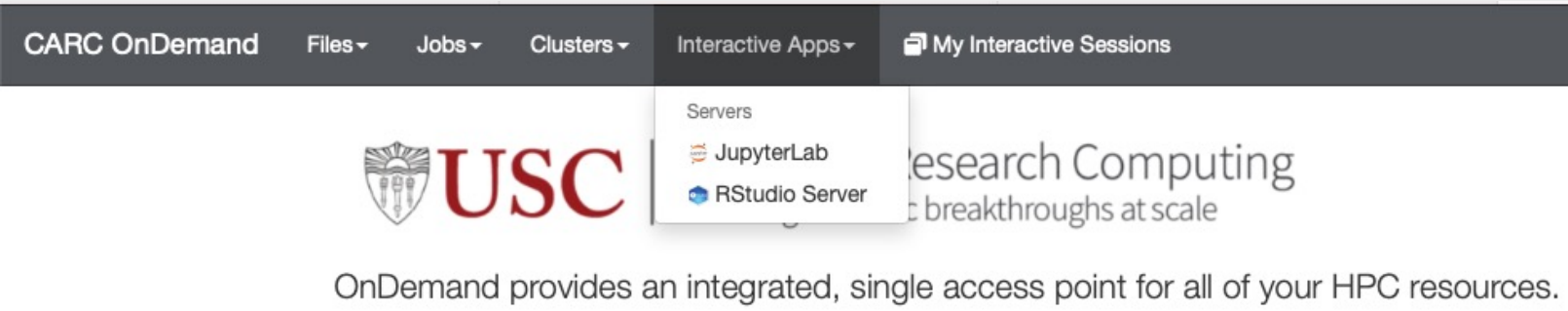




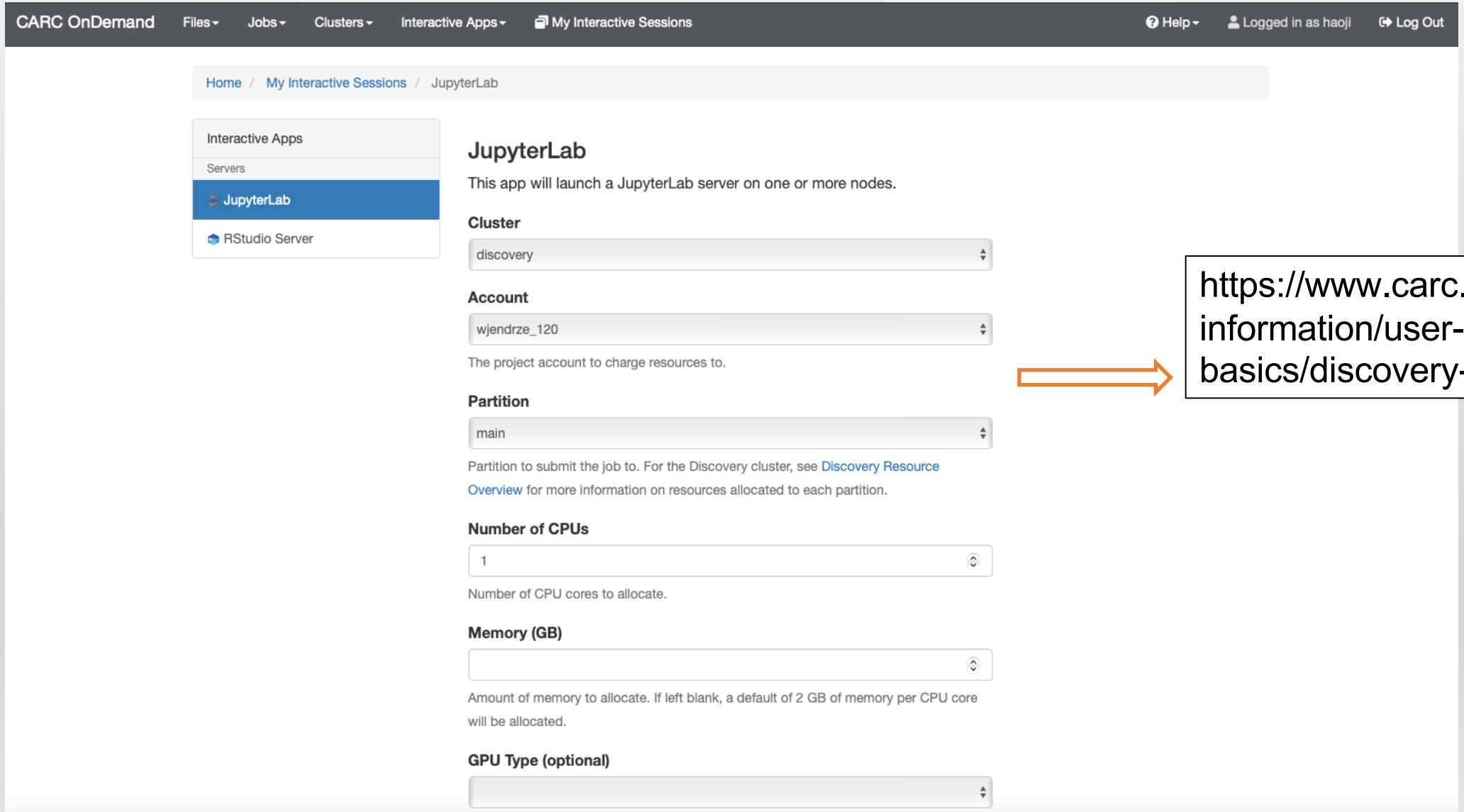
CARC Ondemand



CARC Ondemand



CARC Ondemand



https://www.carc.usc.edu/user-information/user-guides/hpc-basics/discovery-resources

Pandas Data Structure: Series

- 1-dimensional labelled array
- Supports many data types
- Axis labels -> index (get and set values by index label)

Pandas Data Structure: Series

```
[ ]: data = np.random.rand(5)
     pd.Series(data)
```

```
0    0.531397
1    0.010047
2    0.929603
3    0.627307
4    0.637857
dtype: float64
```

```
[ ]: pd.Series(data, index = ['Astronomy', 'Geology', 'Economics', 'English', 'History'])
```

```
Astronomy    0.531397
Geology      0.010047
Economics    0.929603
English      0.627307
History      0.637857
dtype: float64
```

Pandas Data Structure: DataFrame

```
[ ]: planets_data = np.array([[0.330, 4879, 3.7, 88.0],
                              [4.87, 12104, 8.9, 224.7],
                              [5.97, 12756, 9.8, 365.2 ],
                              [0.642, 6792, 3.7, 687.0],
                              [1898, 142984, 23.1, 4331],
                              [568, 120536, 9.0, 10747],
                              [86.8, 51118, 8.7, 30589],
                              [102, 49528, 11.0, 59800]])
     planets_data
```

```
array([[3.30000e-01, 4.87900e+03, 3.70000e+00, 8.80000e+01],
       [4.87000e+00, 1.21040e+04, 8.90000e+00, 2.24700e+02],
       [5.97000e+00, 1.27560e+04, 9.80000e+00, 3.65200e+02],
       [6.42000e-01, 6.79200e+03, 3.70000e+00, 6.87000e+02],
       [1.89800e+03, 1.42984e+05, 2.31000e+01, 4.33100e+03],
       [5.68000e+02, 1.20536e+05, 9.00000e+00, 1.07470e+04],
       [8.68000e+01, 5.11180e+04, 8.70000e+00, 3.05890e+04],
       [1.02000e+02, 4.95280e+04, 1.10000e+01, 5.98000e+04]])
```

Pandas Data Structure: DataFrame

```
[ ]: planets = pd.DataFrame(planets_data,
                            columns=['mass', 'diameter', 'gravity', 'period'],
                            index=['Mercury', 'Venus', 'Earth', 'Mars', 'Jupiter', 'Saturn','Uranus','Neptune'])
     planets
```

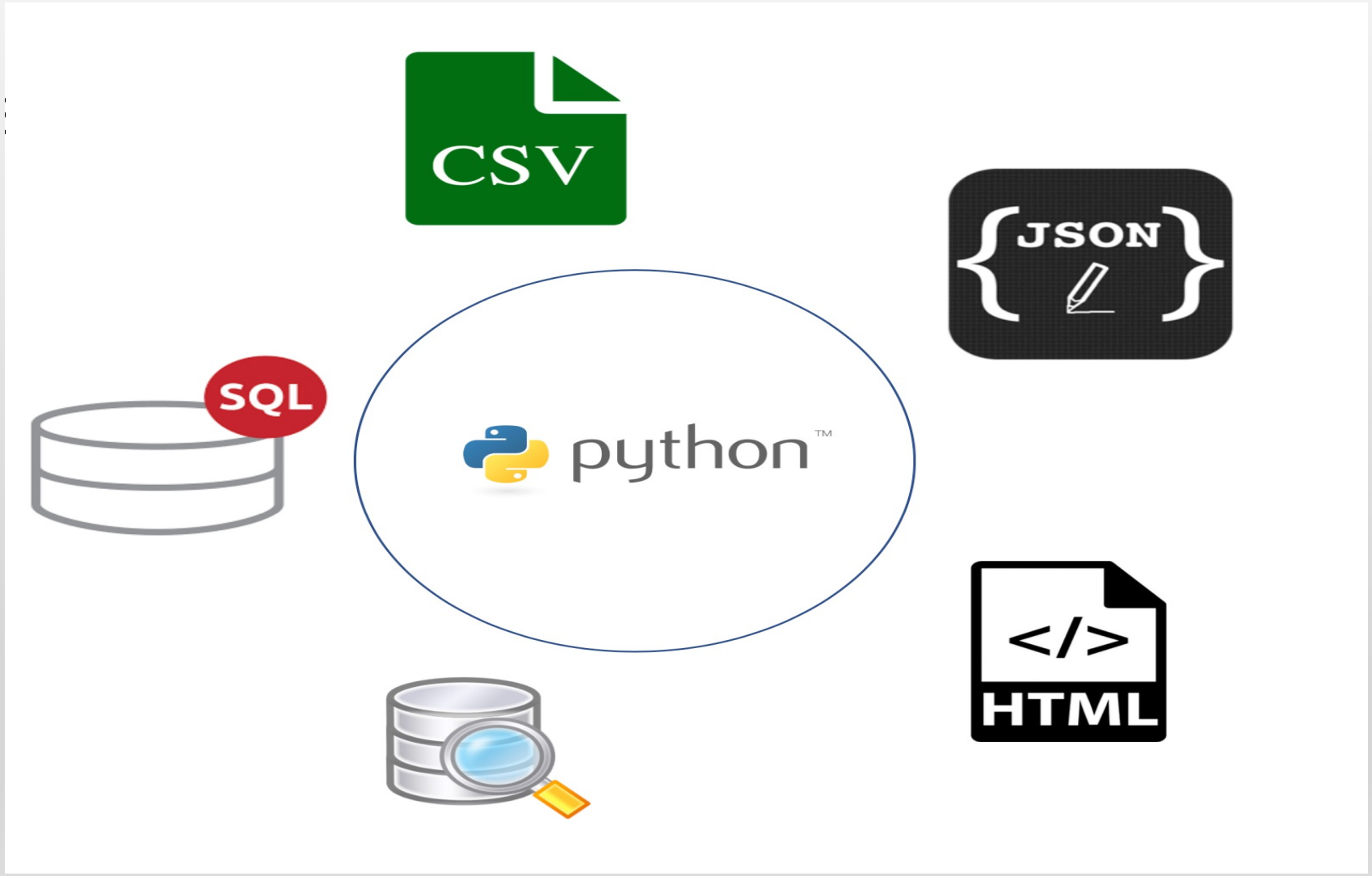
	mass	diameter	gravity	period
Mercury	0.330	4879.0	3.7	88.0
Venus	4.870	12104.0	8.9	224.7
Earth	5.970	12756.0	9.8	365.2
Mars	0.642	6792.0	3.7	687.0
Jupiter	1898.000	142984.0	23.1	4331.0
Saturn	568.000	120536.0	9.0	10747.0
Uranus	86.800	51118.0	8.7	30589.0
Neptune	102.000	49528.0	11.0	59800.0

Data Integration

By the end of this lecture, you should be able to:

- Describe the efficient and easy to use methods that pandas provides for importing data into memory
- Identify functions such as ‘read_csv” for reading a CSV file into a DataFrame
- Discuss about other data sources that pandas can directly import from

Pandas: Data Ingestion



Pandas: Data Ingestion

read_csv:

```
[ ]: solar_system = pd.read_csv('solar_system_abbr.csv', index_col=0)
     solar_system
```

Name	Type	Order from Sun	Diameter	Mass
Sun	Star	0	1392000.0	333000.00000
Mercury	Terrestrial planet	1	4878.0	0.05500
Venus	Terrestrial planet	2	12104.0	0.81500
Earth	Terrestrial planet	3	12756.0	1.00000
Mars	Terrestrial planet	4	6787.0	0.10700
Jupiter	Gas giant	6	142800.0	318.00000
Saturn	Gas giant	7	120000.0	95.00000
Uranus	Gas giant	8	51118.0	15.00000
Neptune	Gas giant	9	49528.0	17.00000
Ceres	Dwarf planet	5	974.6	0.00016
Pluto	Dwarf planet	10	2300.0	0.00200
Haumea	Dwarf planet	11	1300.0	0.00070
Makemake	Dwarf planet	12	1420.0	0.00067
Eris	Dwarf planet	13	2326.0	0.00280

Pandas: Descriptive Statistics

By the end of this section, you should be able to:

- Describe the capabilities of Pandas for performing statistical analysis on data
- Leverage frequently used functions such as describe()
- Explore other statistical functions in Pandas, which is constantly evolving

Pandas Data Structure: DataFrame

```
[ ]: solar_system.describe()
```

	Order from Sun	Diameter	Mass
count	14.0000	1.400000e+01	14.000000
mean	6.5000	1.285923e+05	23817.641666
std	4.1833	3.665235e+05	88988.845412
min	0.0000	9.746000e+02	0.000160
25%	3.2500	2.306500e+03	0.002200
50%	6.5000	9.445500e+03	0.461000
75%	9.7500	5.072050e+04	16.500000
max	13.0000	1.392000e+06	333000.000000

Pandas Data Structure: DataFrame

General functax for calling these function is data_frame.func()

Func = min()

Func= max()

Func = std()

Func = mode()

Func = median()

Func = any()

Func = all()

Pandas: Data Cleaning

By the end of this section, you should be able to:

- Explain why there is a need to clean data
- Describe data cleaning as an activity
- Leverage key methods pandas provides for data cleaning

Pandas: Data Cleaning

Real-world data is messy!

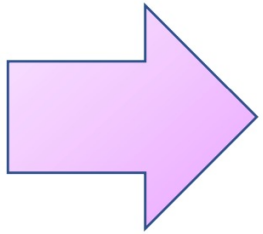
- Missing values
- Outliers in the data
- Invalid data (e.g. negative values for age)
- NaN value (np.nan)
- None value

Pandas: Data Cleaning

df.replace()

	0	1
0	-0.349596	-2.017159
1	9999.000000	9999.000000
2	9999.000000	9999.000000
3	0.113889	0.616122
4	0.014707	-1.731660
5	9999.000000	9999.000000
6	1.233087	0.720138
7	9999.000000	9999.000000
8	9999.000000	9999.000000
9	9999.000000	9999.000000

9999.0000



```
df=df.replace(9999.0, 0)
df
```

	0	1
0	-0.349596	-2.017159
1	0.000000	0.000000
2	0.000000	0.000000
3	0.113889	0.616122
4	0.014707	-1.731660
5	0.000000	0.000000
6	1.233087	0.720138
7	0.000000	0.000000
8	0.000000	0.000000
9	0.000000	0.000000

0.0000

Pandas: Data Cleaning

df.dropna()

```
df
```

	0	1	2
0	NaN	NaN	-0.335410
1	NaN	NaN	0.685743
2	0.077005	0.085073	0.565144
3	0.394961	-1.829587	0.494039
4	1.486227	-0.480726	-0.127278
5	NaN	NaN	-0.047668
6	NaN	NaN	-1.504804
7	-0.530518	-0.881817	-2.687352
8	0.825376	1.042468	-0.311527
9	0.097617	1.373572	-0.682435

```
df.dropna(axis=0)
```

	0	1	2
2	0.077005	0.085073	0.565144
3	0.394961	-1.829587	0.494039
4	1.486227	-0.480726	-0.127278
7	-0.530518	-0.881817	-2.687352
8	0.825376	1.042468	-0.311527
9	0.097617	1.373572	-0.682435

```
df.dropna(axis=1)
```

	2
0	-0.335410
1	0.685743
2	0.565144
3	0.494039
4	-0.127278
5	-0.047668
6	-1.504804
7	-2.687352
8	-0.311527
9	-0.682435

Pandas: Data Visualization

By the end of this section, you should be able to:

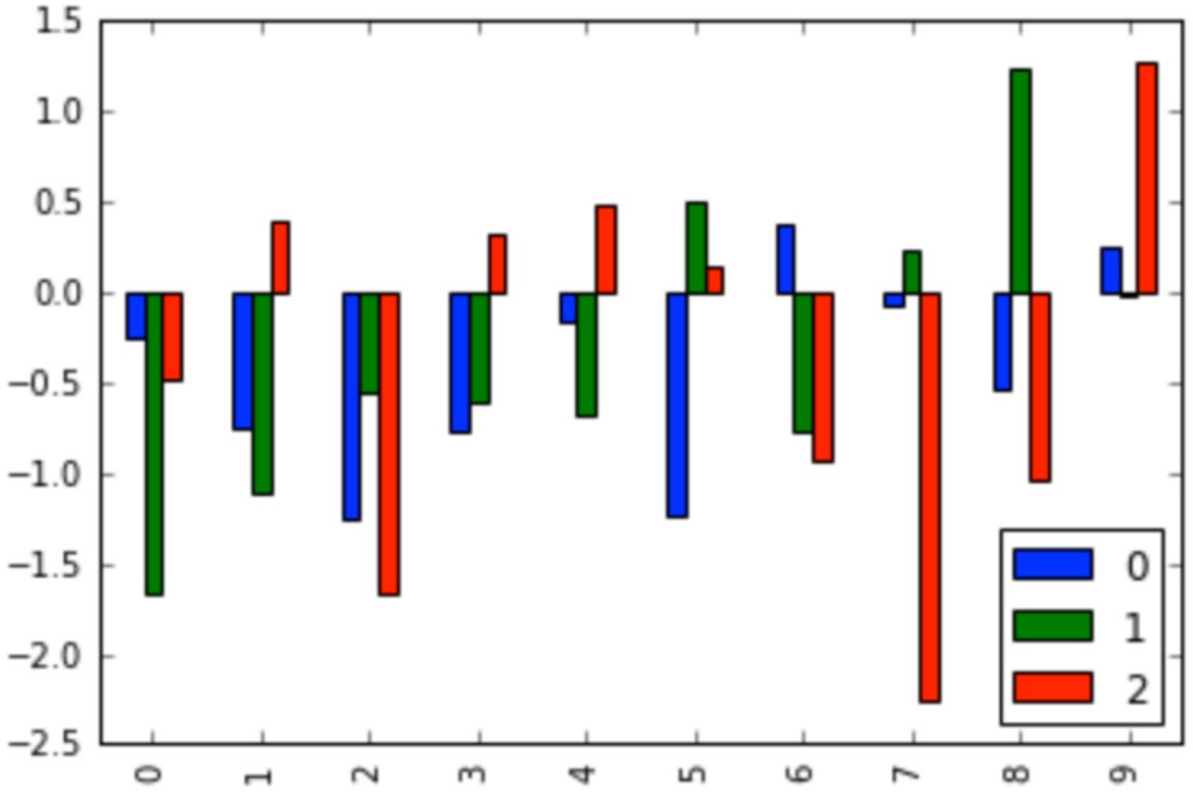
- Identify key plotting functions of Pandas
- Recognize the ease of utilization of Pandas methods for visualization

Pandas: Data Visualization

Comand: df.plot.bar()

```
df
```

	0	1	2
0	-0.260156	-1.666998	-0.492616
1	-0.762055	-1.114774	0.396817
2	-1.263953	-0.562550	-1.670459
3	-0.765183	-0.619429	0.316981
4	-0.165719	-0.678431	0.485722
5	-1.243191	0.494006	0.145171
6	0.373786	-0.769120	-0.929956
7	-0.081455	0.229613	-2.251816
8	-0.536697	1.228345	-1.040728
9	0.254220	-0.021794	1.268333

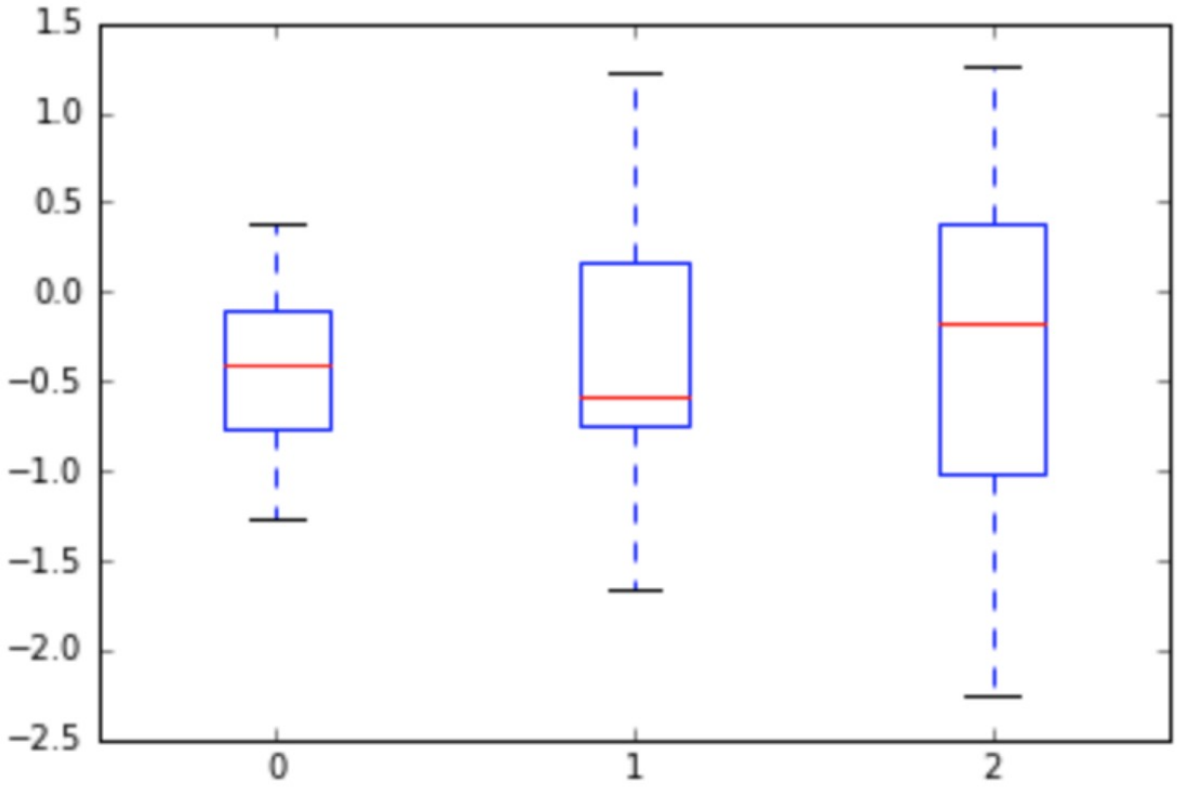


Pandas: Data Visualization

Comand: df.plot.box()

```
df
```

	0	1	2
0	-0.260156	-1.666998	-0.492616
1	-0.762055	-1.114774	0.396817
2	-1.263953	-0.562550	-1.670459
3	-0.765183	-0.619429	0.316981
4	-0.165719	-0.678431	0.485722
5	-1.243191	0.494006	0.145171
6	0.373786	-0.769120	-0.929956
7	-0.081455	0.229613	-2.251816
8	-0.536697	1.228345	-1.040728
9	0.254220	-0.021794	1.268333



Pandas: Data Visualization

Comand: df.plot()

```
df
```

	0	1	2
0	-0.260156	-1.666998	-0.492616
1	-0.762055	-1.114774	0.396817
2	-1.263953	-0.562550	-1.670459
3	-0.765183	-0.619429	0.316981
4	-0.165719	-0.678431	0.485722
5	-1.243191	0.494006	0.145171
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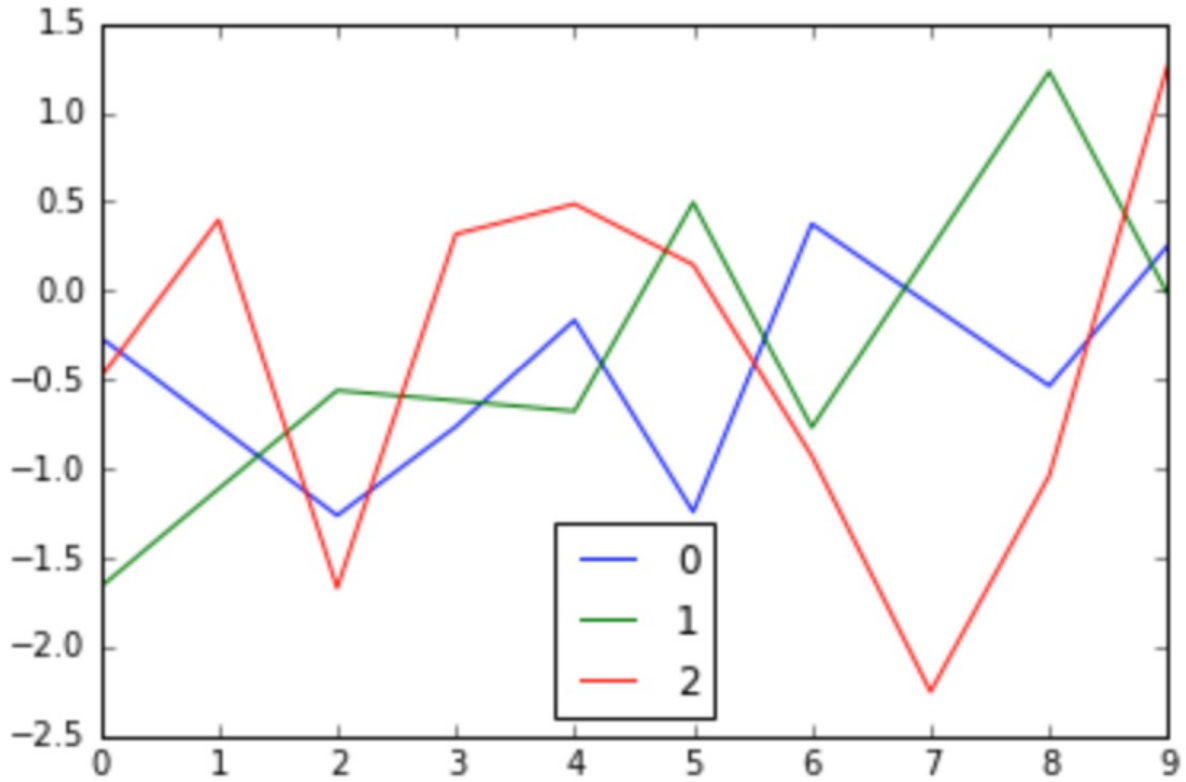


Pandas: Frequent data operations

By the end of this section, you should be able to:

- Handpick data (rows or columns) in a DataFrame using Pandas methods
- Add or Delete rows or columns in a DataFrame
- Perform aggregation operations / group by

Pandas: Frequent data operations

Slice out columns:

```
df
```

	sensor1	sensor2	sensor3
0	-0.260156	-1.666998	-0.492616
1	-0.762055	-1.114774	0.396817
2	-1.263953	-0.562550	-1.670459
3	-0.765183	-0.619429	0.316981
4	-0.165719	-0.678431	0.485722
5	-1.243191	0.494006	0.145171
6	0.373786	-0.769120	-0.929956
7	-0.081455	0.229613	-2.251816
8	-0.536697	1.228345	-1.040728
9	0.254220	-0.021794	1.268333

```
df['sensor1']
```

```
0   -0.260156
1   -0.762055
2   -1.263953
3   -0.765183
4   -0.165719
5   -1.243191
6    0.373786
7   -0.081455
8   -0.536697
9    0.254220
Name: sensor1, dtype: float64
```

Pandas: Frequent data operations

Filter out rows:

```
df
```

	sensor1	sensor2	sensor3
0	-0.260156	-1.666998	-0.492616
1	-0.762055	-1.114774	0.396817
2	-1.263953	-0.562550	-1.670459
3	-0.765183	-0.619429	0.316981
4	-0.165719	-0.678431	0.485722
5	-1.243191	0.494006	0.145171
6	0.373786	-0.769120	-0.929956
7	-0.081455	0.229613	-2.251816
8	-0.536697	1.228345	-1.040728
9	0.254220	-0.021794	1.268333

```
#Select rows where sensor2 is positive
df[df['sensor2'] > 0]
```

	sensor1	sensor2	sensor3
5	-1.243191	0.494006	0.145171
7	-0.081455	0.229613	-2.251816
8	-0.536697	1.228345	-1.040728

Pandas: Frequent data operations

Add a new row:

```
df
```

	sensor1	sensor2	sensor3
0	-0.260156	-1.666998	-0.492616
1	-0.762055	-1.114774	0.396817
2	-1.263953	-0.562550	-1.670459
3	-0.765183	-0.619429	0.316981
4	-0.165719	-0.678431	0.485722
5	-1.243191	0.494006	0.145171
6	0.373786	-0.769120	-0.929956
7	-0.081455	0.229613	-2.251816
8	-0.536697	1.228345	-1.040728
9	0.254220	-0.021794	1.268333

```
df.loc[10] = [11,22,33,44]
```

```
df
```

	sensor1	sensor2	sensor3	sensor4
0	-0.260156	-1.666998	-0.492616	0.242671
1	-0.762055	-1.114774	0.396817	0.157464
2	-1.263953	-0.562550	-1.670459	2.790434
3	-0.765183	-0.619429	0.316981	0.100477
4	-0.165719	-0.678431	0.485722	0.235925
5	-1.243191	0.494006	0.145171	0.021075
6	0.373786	-0.769120	-0.929956	0.864819
7	-0.081455	0.229613	-2.251816	5.070676
8	-0.536697	1.228345	-1.040728	1.083115
9	0.254220	-0.021794	1.268333	1.608669
10	11.000000	22.000000	33.000000	44.000000

Pandas: Frequent data operations

Delete a row:

```
df
```

	sensor1	sensor2	sensor3
0	-0.260156	-1.666998	-0.492616
1	-0.762055	-1.114774	0.396817
2	-1.263953	-0.562550	-1.670459
3	-0.765183	-0.619429	0.316981
4	-0.165719	-0.678431	0.485722
5	-1.243191	0.494006	0.145171
6	0.373786	-0.769120	-0.929956
7	-0.081455	0.229613	-2.251816
8	-0.536697	1.228345	-1.040728
9	0.254220	-0.021794	1.268333

```
df.drop(df.index[[5]])
```

	sensor1	sensor2	sensor3	sensor4
0	-0.260156	-1.666998	-0.492616	0.242671
1	-0.762055	-1.114774	0.396817	0.157464
2	-1.263953	-0.562550	-1.670459	2.790434
3	-0.765183	-0.619429	0.316981	0.100477
4	-0.165719	-0.678431	0.485722	0.235925
6	0.373786	-0.769120	-0.929956	0.864819
7	-0.081455	0.229613	-2.251816	5.070676
8	-0.536697	1.228345	-1.040728	1.083115
9	0.254220	-0.021794	1.268333	1.608669

Pandas: Frequent data operations

Delete a column:

```
df
```

	sensor1	sensor2	sensor3	sensor4
0	-0.260156	-1.666998	-0.492616	0.242671
1	-0.762055	-1.114774	0.396817	0.157464
2	-1.263953	-0.562550	-1.670459	2.790434
3	-0.765183	-0.619429	0.316981	0.100477
4	-0.165719	-0.678431	0.485722	0.235925
5	-1.243191	0.494006	0.145171	0.021075
6	0.373786	-0.769120	-0.929956	0.864819
7	-0.081455	0.229613	-2.251816	5.070676
8	-0.536697	1.228345	-1.040728	1.083115
9	0.254220	-0.021794	1.268333	1.608669

```
del df['sensor1']
```

```
df
```

	sensor2	sensor3	sensor4
0	-1.666998	-0.492616	0.242671
1	-1.114774	0.396817	0.157464
2	-0.562550	-1.670459	2.790434
3	-0.619429	0.316981	0.100477
4	-0.678431	0.485722	0.235925
5	0.494006	0.145171	0.021075
6	-0.769120	-0.929956	0.864819
7	0.229613	-2.251816	5.070676
8	1.228345	-1.040728	1.083115
9	-0.021794	1.268333	1.608669

Pandas: Merging DataFrames

By the end of this section, you should be able to:

- Explain that data is usually distributed across different locations and tables
- Combine data from distinct DataFrames to obtain the big picture
- Distinguish among different ways to combine datasets

Pandas: Merging DataFrames

Example Dataframes

```
left
```

	_key1	_key2	city	user_name
0	K0	z0	city_0	user_0
1	K1	z1	city_1	user_1
2	K2	z2	city_2	user_2
3	K3	z3	city_3	user_3

```
right
```

	_key1	_key2	hire_date	profession
0	K0	z0	h_0	p_0
1	K1	z1	h_1	p_1
2	K2	z2	h_2	p_2
3	K3	z3	h_3	p_3

Pandas: Merging DataFrames

Pandas.concat(): stack dataframes

```
pd.concat([left, left])
```

	_key1	_key2	city	user_name
0	K0	z0	city_0	user_0
1	K1	z1	city_1	user_1
2	K2	z2	city_2	user_2
3	K3	z3	city_3	user_3
0	K0	z0	city_0	user_0
1	K1	z1	city_1	user_1
2	K2	z2	city_2	user_2
3	K3	z3	city_3	user_3

Pandas: Merging DataFrames

Pandas.concat(): stack dataframes

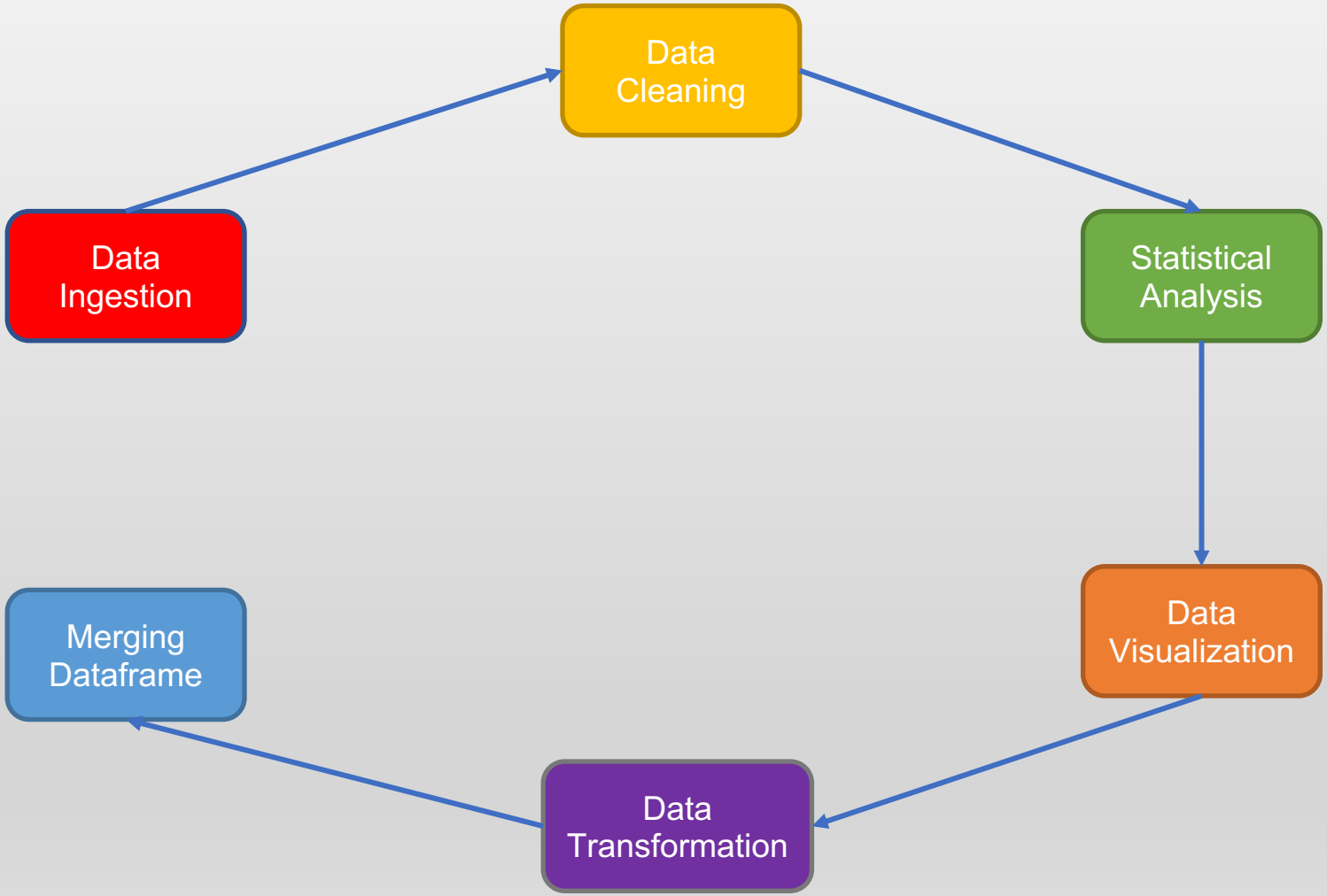
```
pd.concat([left, right])
```

	_key1	_key2	city	hire_date	profession	user_name
0	K0	z0	city_0	NaN	NaN	user_0
1	K1	z1	city_1	NaN	NaN	user_1
2	K2	z2	city_2	NaN	NaN	user_2
3	K3	z3	city_3	NaN	NaN	user_3
0	K0	z0	NaN	h_0	p_0	NaN
1	K1	z1	NaN	h_1	p_1	NaN
2	K2	z2	NaN	h_2	p_2	NaN
3	K3	z3	NaN	h_3	p_3	NaN

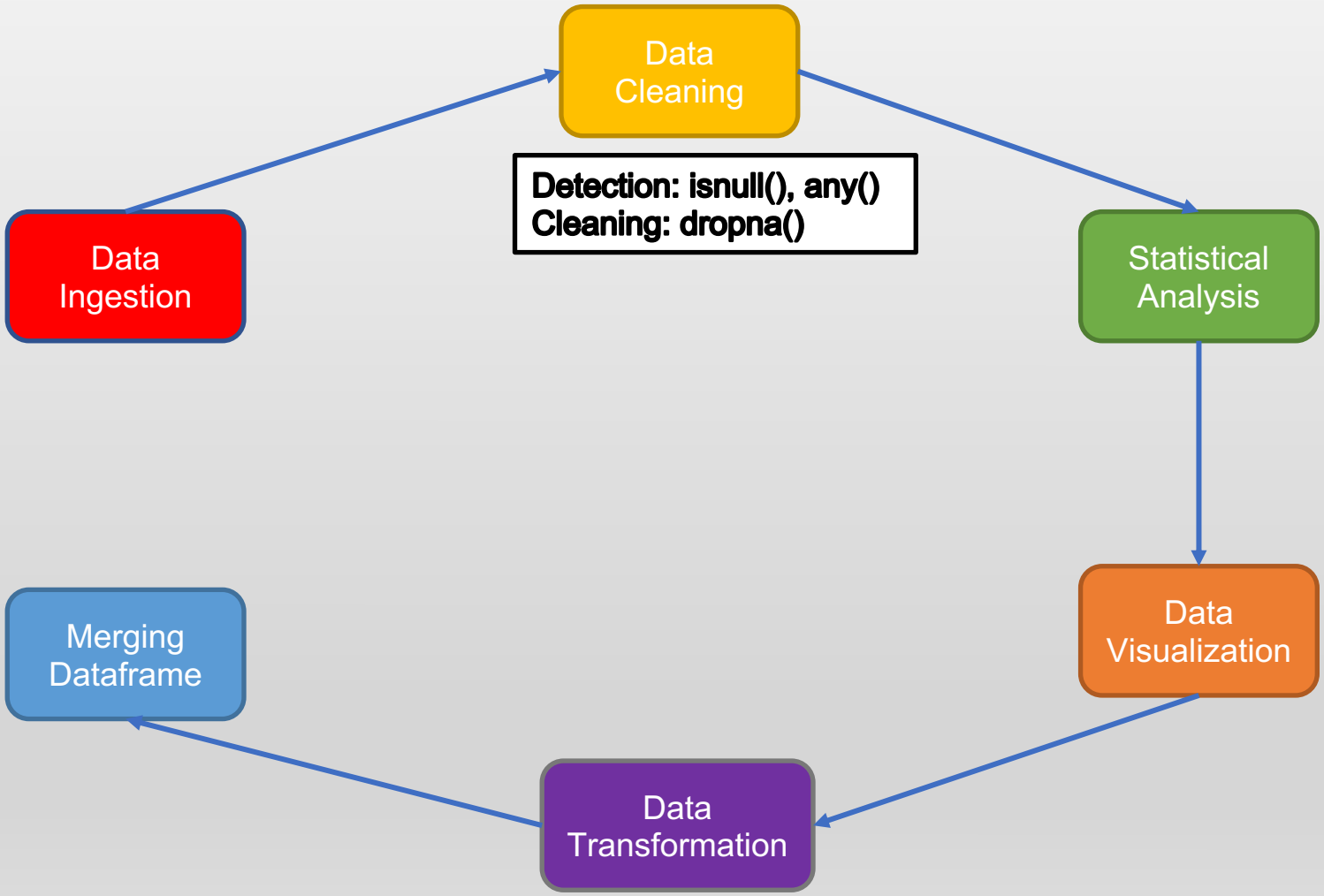
Pandas: Summary

read_csv()

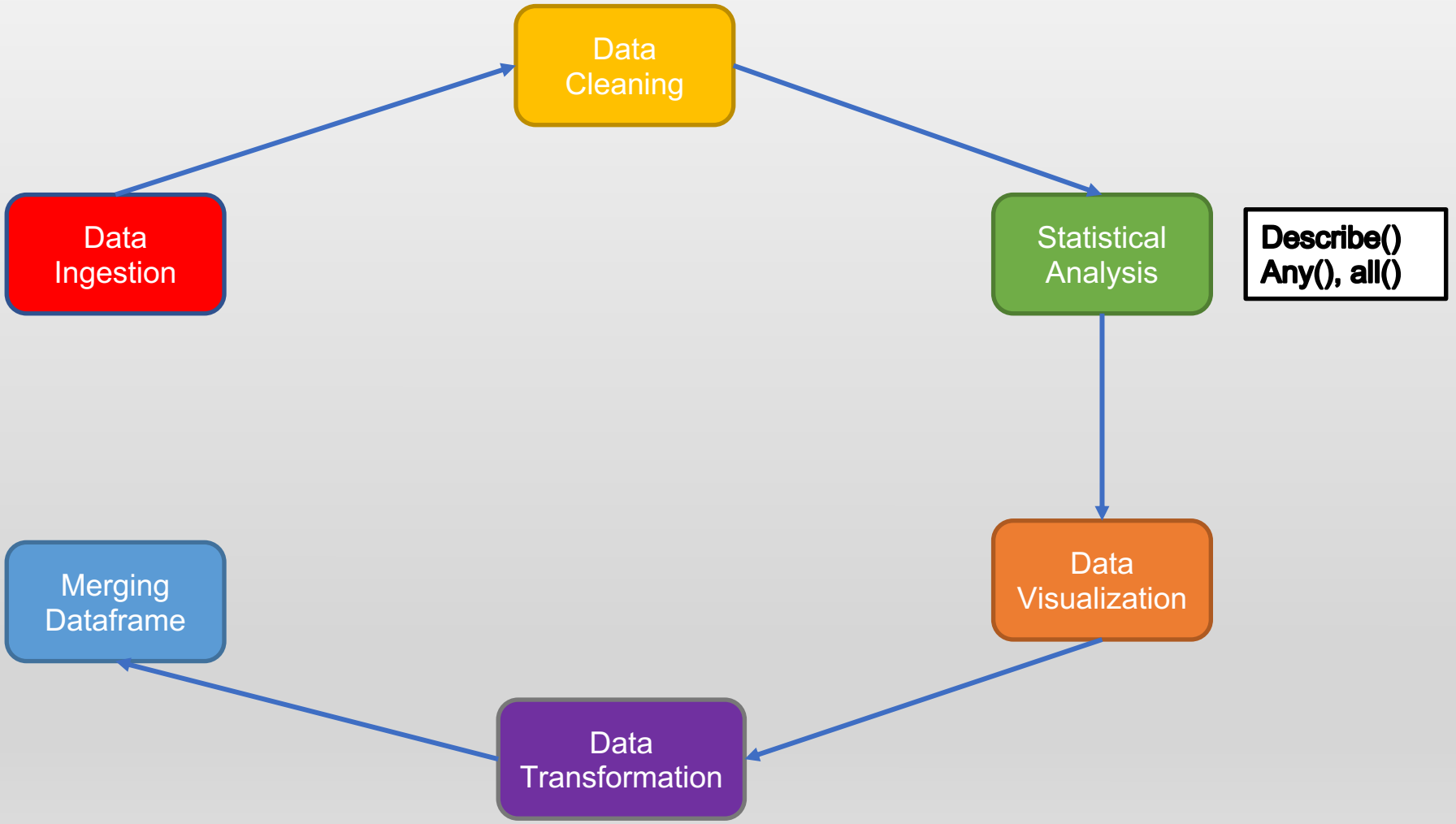
convert CSV file to Pandas Dataframe



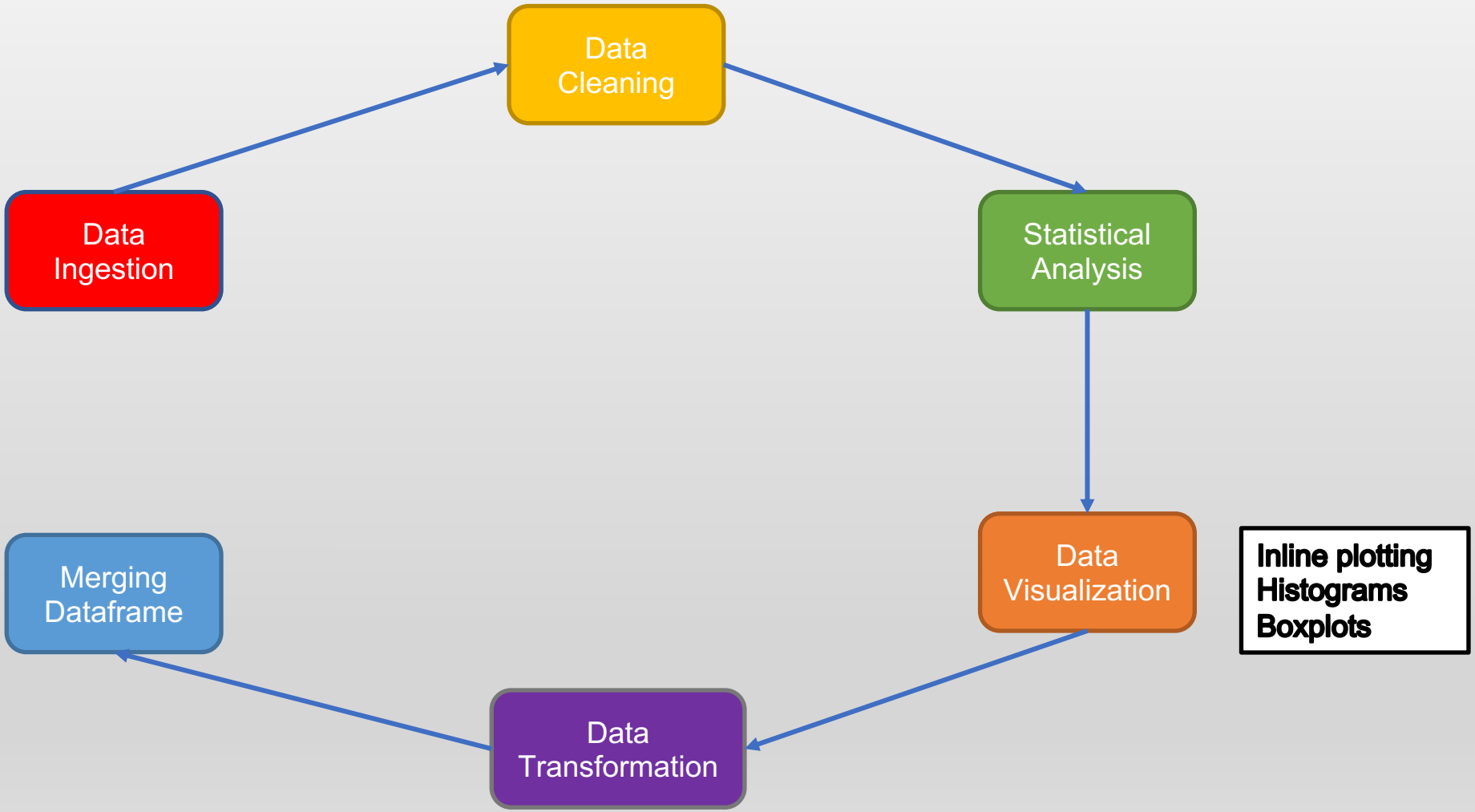
Pandas: Case Study



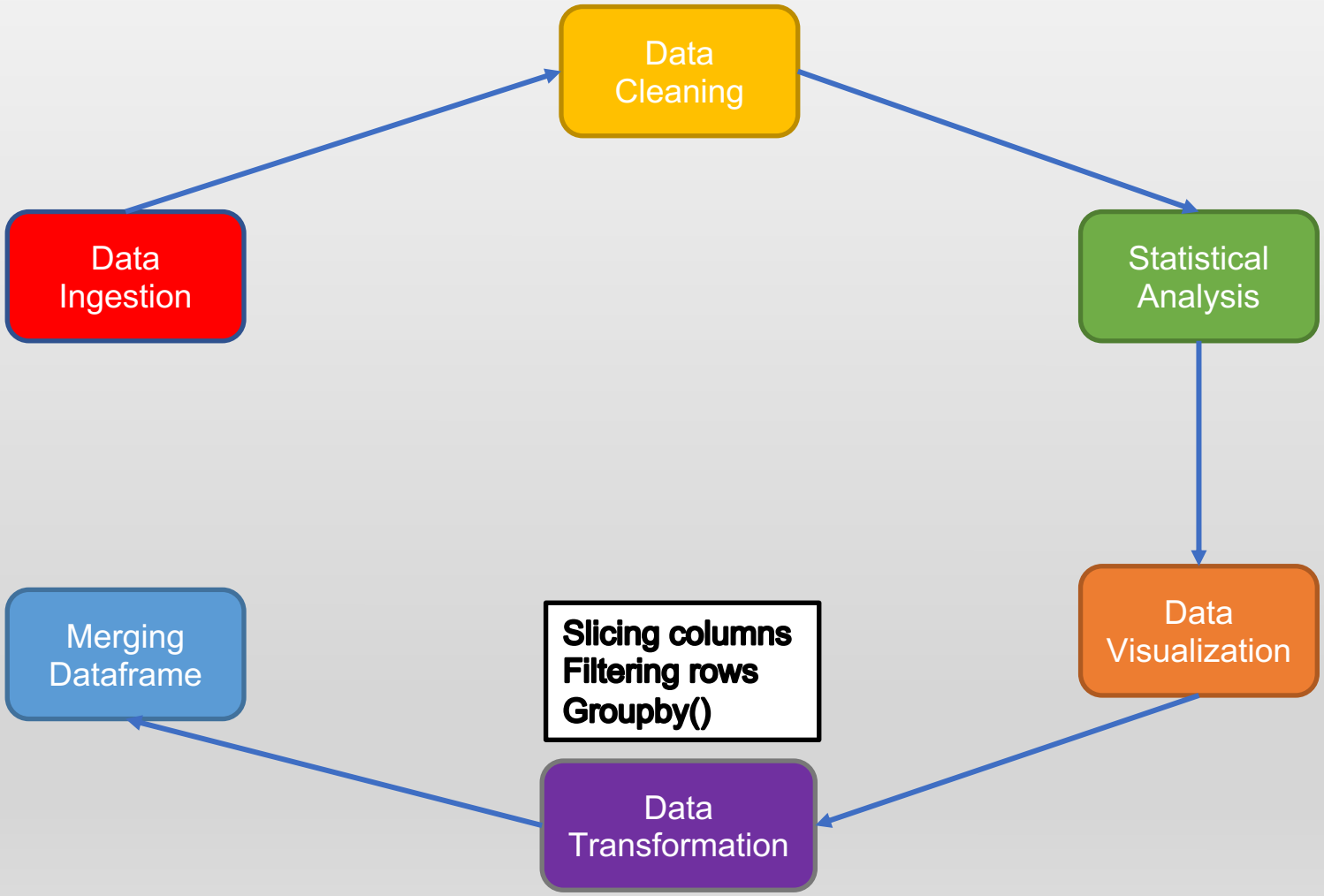
Pandas: Case Study



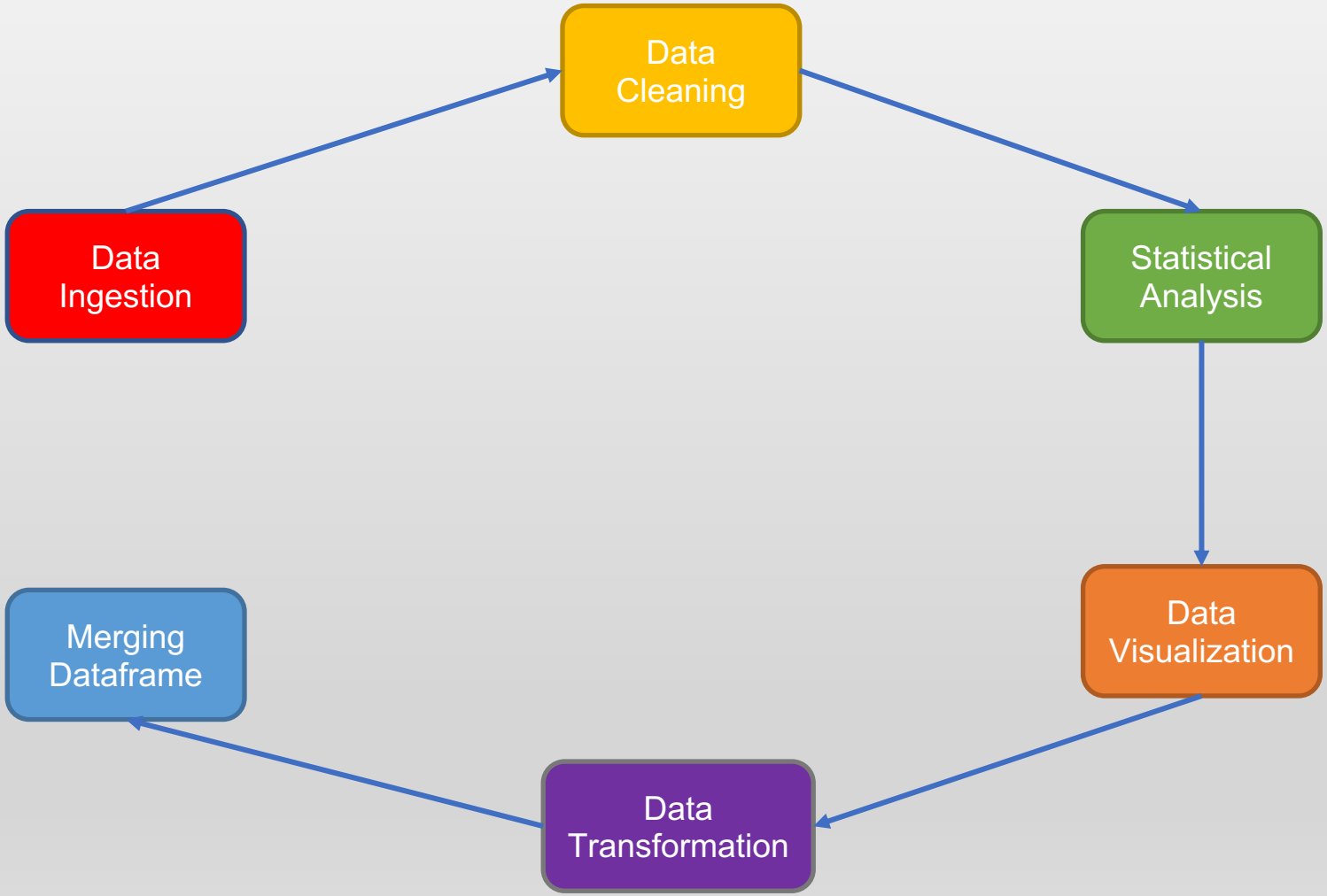
Pandas: Case Study



Pandas: Case Study



Pandas: Case Study



Matplotlib

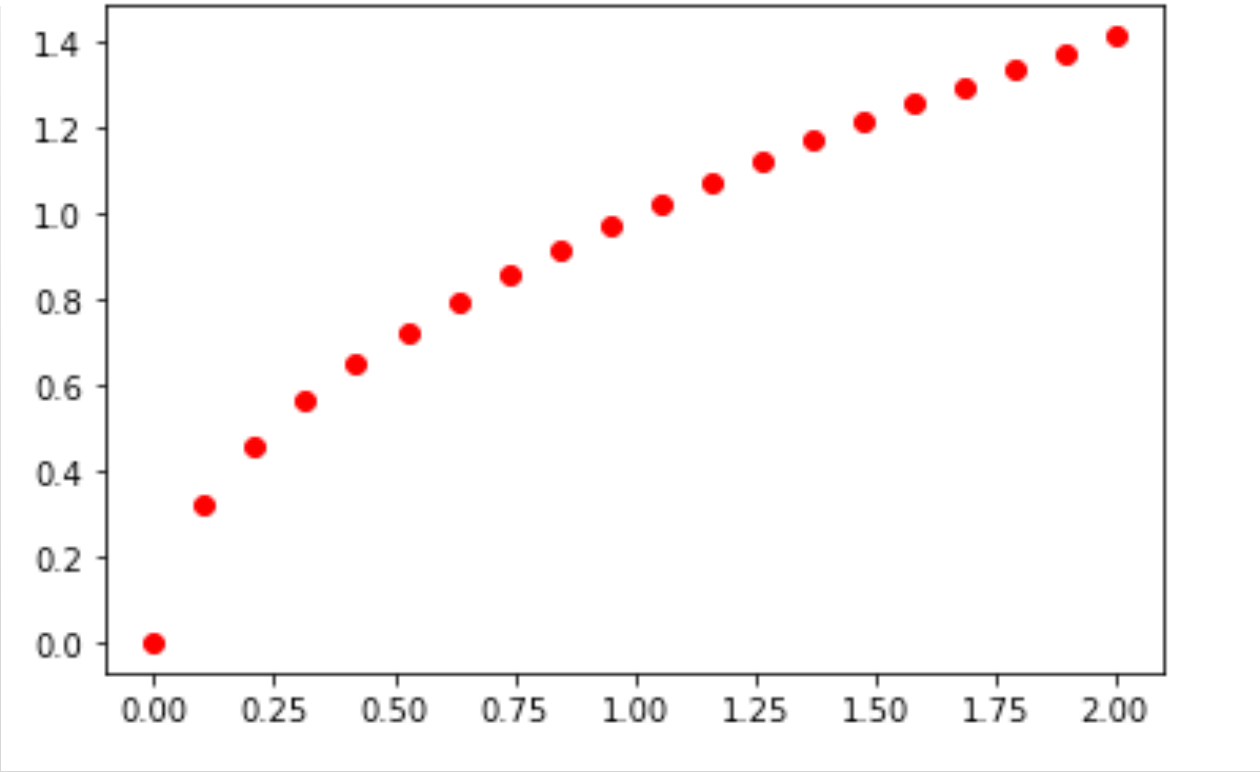
1. 2D plotting single line figure

```
[ ]: %matplotlib inline
     import numpy as np
     import matplotlib.pyplot as plt
     x = np.linspace(0.0, 2.0, 20)
     x
```

```
array([ 0.        ,  0.10526316,  0.21052632,  0.31578947,  0.42105263,
        0.52631579,  0.63157895,  0.73684211,  0.84210526,  0.94736842,
        1.05263158,  1.15789474,  1.26315789,  1.36842105,  1.47368421,
        1.57894737,  1.68421053,  1.78947368,  1.89473684,  2.        ])
```

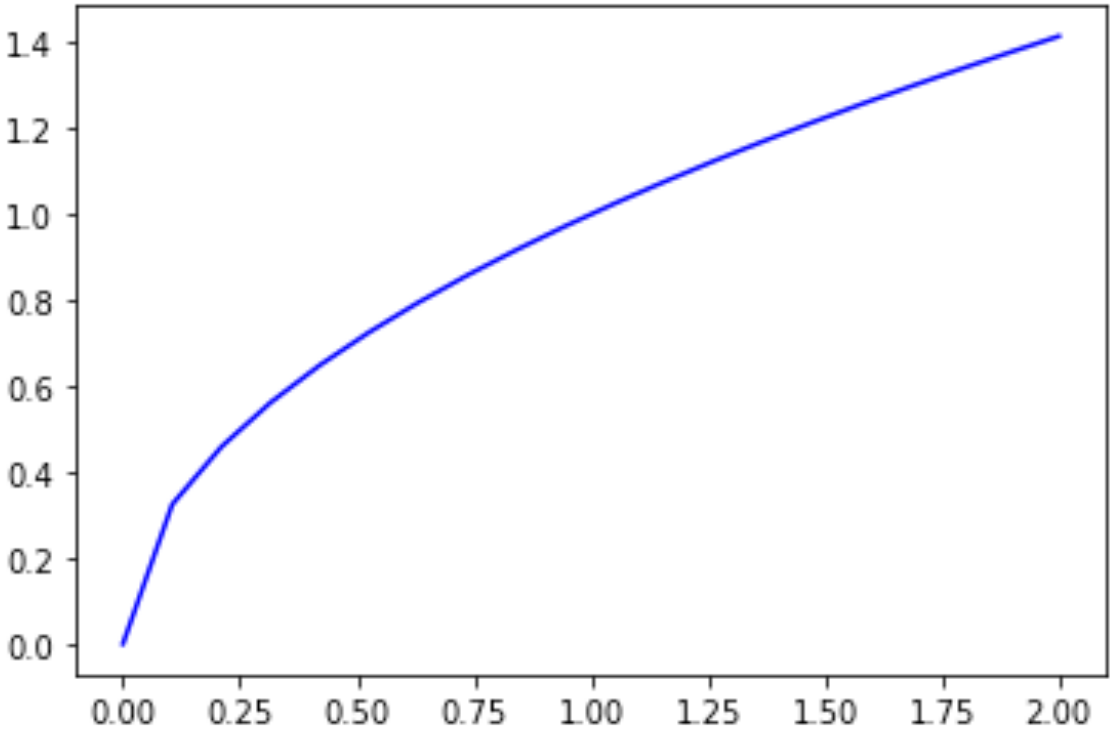
Matplotlib

```
[ ]: plt.plot(x, np.sqrt(x), 'ro')
     plt.show()
```



Matplotlib

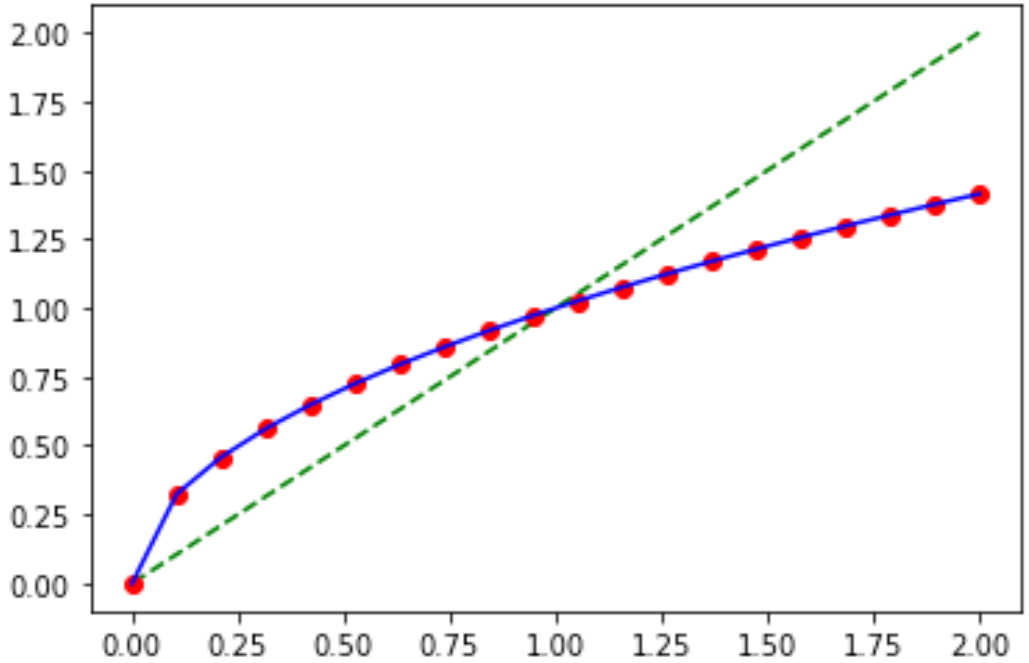
```
[ ]: plt.plot(x, np.sqrt(x), 'b-')
     plt.show()
```



Matplotlib

2. Multiple lines on the same figure

```
[ ]: plt.plot(x, x, 'g--', label='green') # green dashed line
     plt.plot(x, np.sqrt(x), 'ro', label='red') # red circles
     plt.plot(x, np.sqrt(x), 'b-', label='blue') # blue line
     plt.show()
```

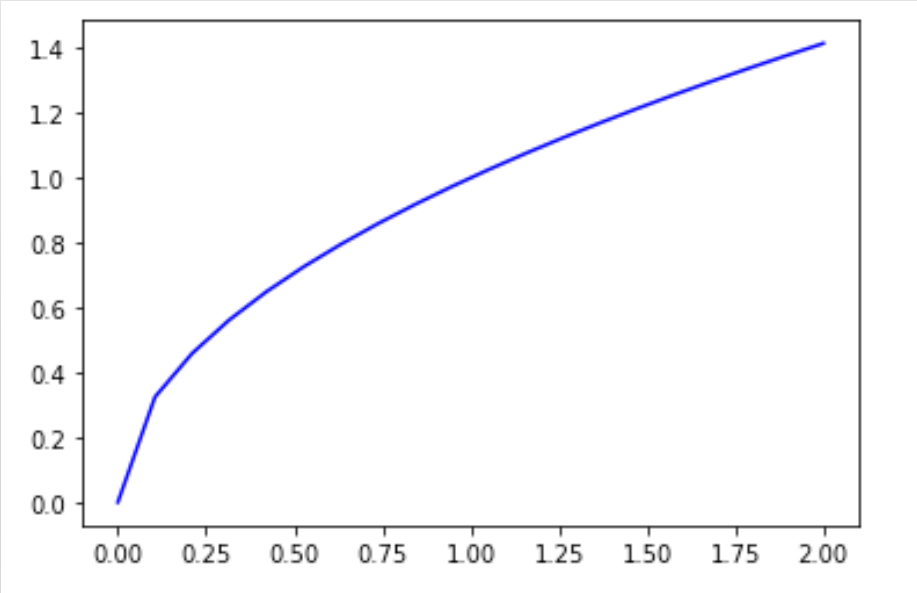


Matplotlib

3. Save a figure to a file

```
[ ]: plt.plot(x, np.sqrt(x), 'b-')

     plt.savefig('myfig.png') # can also save directly to pdf by just changing the file extension
```



Using Anaconda & Juypyter Kernel on CARC

Summary

Import

Transform

Visualize