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MACHINE LEARNING

LAB MANUAL



Institut Supérieur des Études Technologiques de Bizerte

Available at <https://github.com/a-mhamdi/isetbz/>

HONOR CODE

THE UNIVERSITY OF NORTH CAROLINA AT CHAPEL HILL

Department of Physics and Astronomy

<http://physics.unc.edu/undergraduate-program/labs/general-info/>

“During this course, you will be working with one or more partners with whom you may discuss any points concerning laboratory work. However, you must write your lab report, in your own words.

Lab reports that contain identical language are not acceptable, so do not copy your lab partner’s writing.

If there is a problem with your data, include an explanation in your report. Recognition of a mistake and a well-reasoned explanation is more important than having high-quality data, and will be rewarded accordingly by your instructor. A lab report containing data that is inconsistent with the original data sheet will be considered a violation of the Honor Code.

Falsification of data or plagiarism of a report will result in prosecution of the offender(s) under the University Honor Code.

On your first lab report you must write out the entire honor pledge:

The work presented in this report is my own, and the data was obtained by my lab partner and me during the lab period.

On future reports, you may simply write “Laboratory Honor Pledge” and sign your name.”

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In order to activate the virtual environment and launch **Jupyter Notebook**, we recommend you to proceed as follow

- ① Press simultaneously the keys  &  on the keyboard. This will open the dialog box **Run**;
- ② Then enter **cmd** in the command line and confirm with  key on the keyboard;
- ③ Type the instruction **mlpy.bat** in the console prompt line;



- ④ Finally press the  key.
-

LEAVE THE SYSTEM CONSOLE ACTIVE.

1 | Getting Started with Python

Student's name

Score /20

Detailed Credits

Anticipation (4 points)
Management (2 points)
Testing (7 points)
Data Logging (3 points)
Interpretation (4 points)



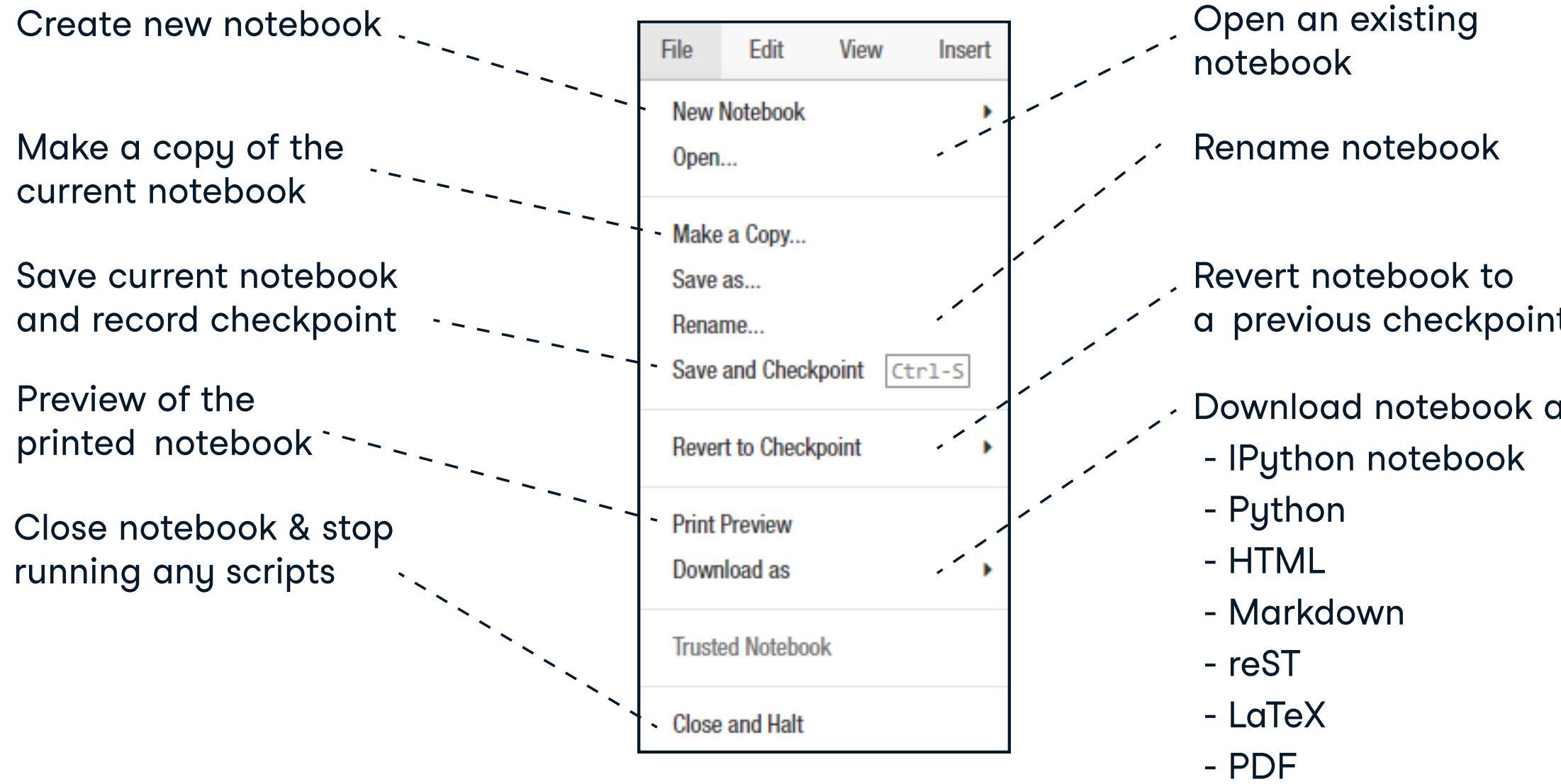
A full list of Cheat Sheets is accessible at <https://www.datacamp.com/community/data-science-cheatsheets>.

Python For Data Science

Jupyter Cheat Sheet

Learn Jupyter online at www.DataCamp.com

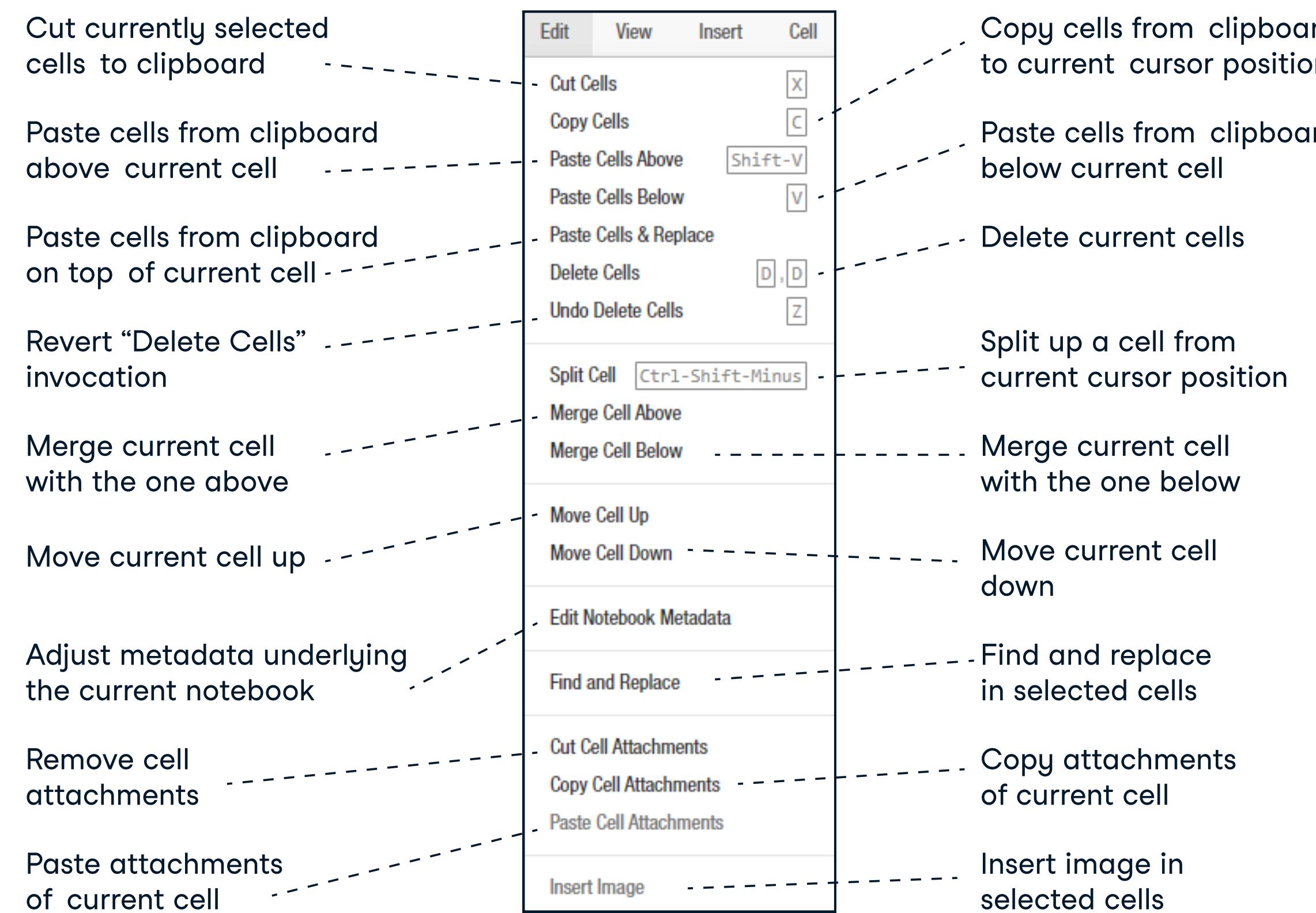
> Saving/Loading Notebooks



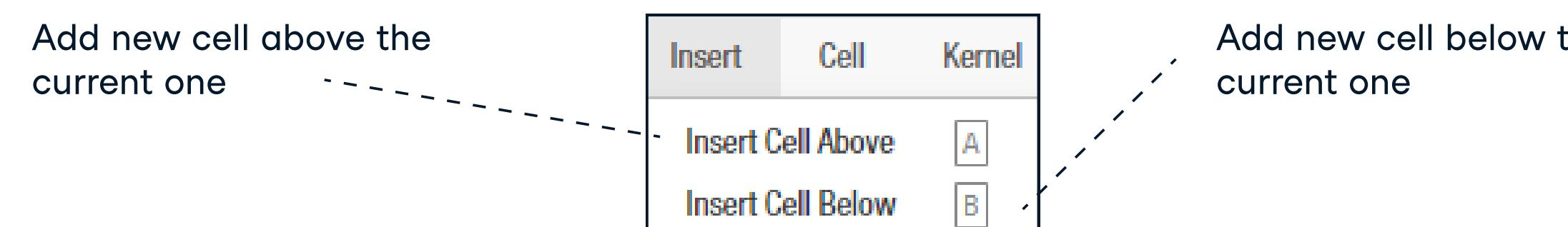
> Writing Code And Text

Code and text are encapsulated by 3 basic cell types: markdown cells, code cells, and raw NBConvert cells

Edit Cells



Insert Cells



> Working with Different Programming Languages

Kernels provide computation and communication with front-end interfaces like the notebooks. There are three main kernels:

IP[y]:



IPython

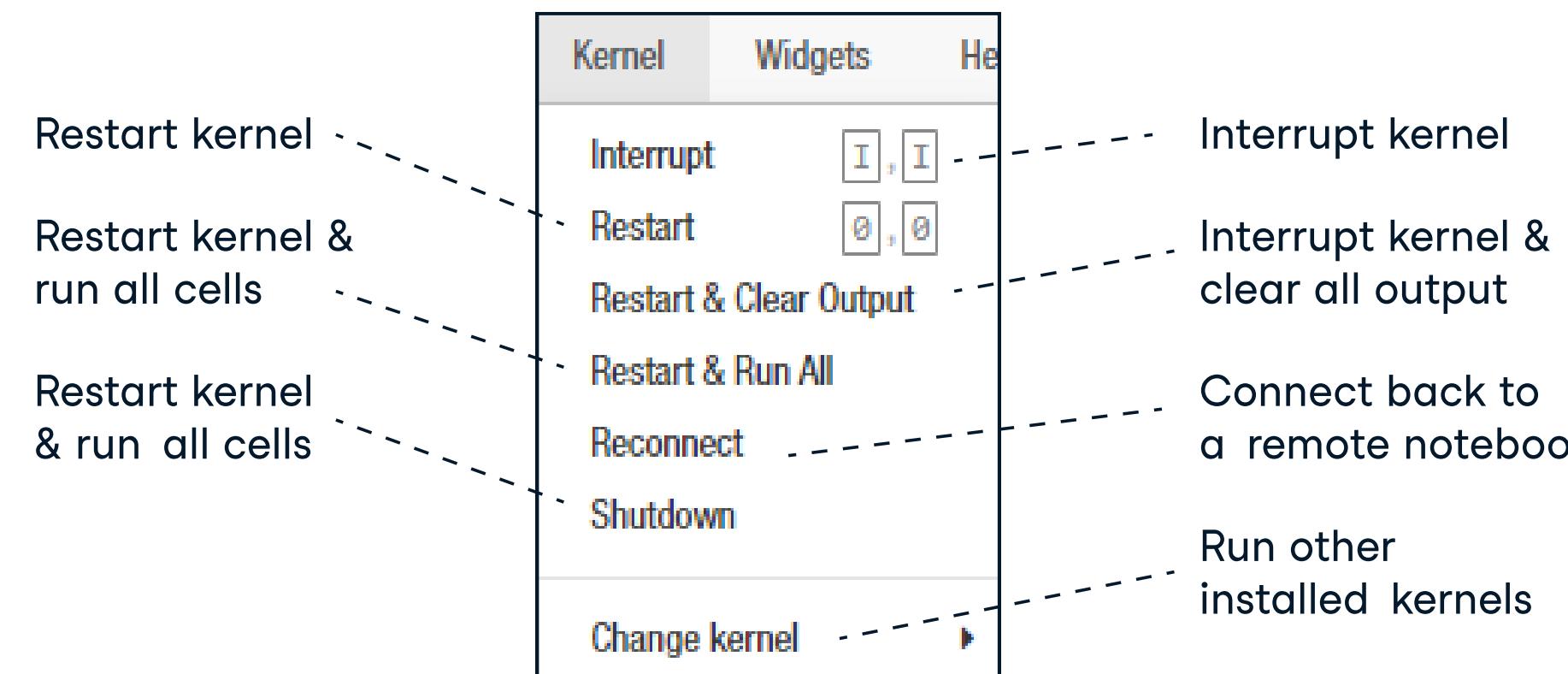


IRkernel

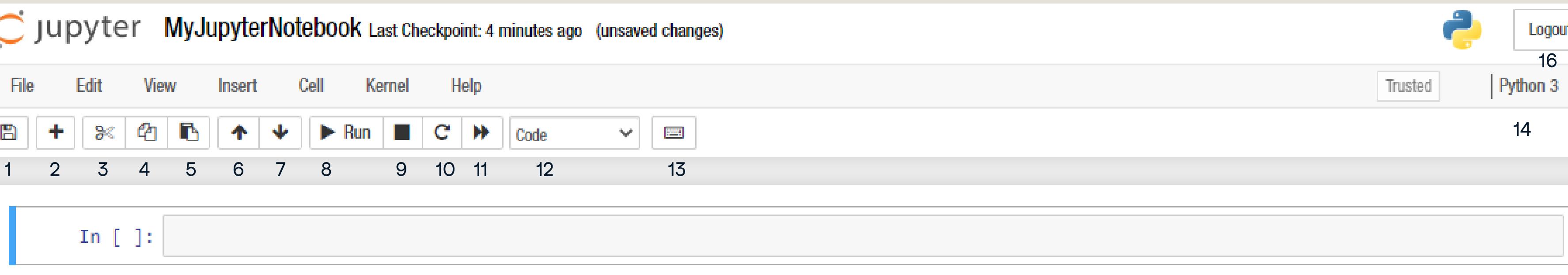


IJulia

Installing Jupyter Notebook will automatically install the IPython kernel.



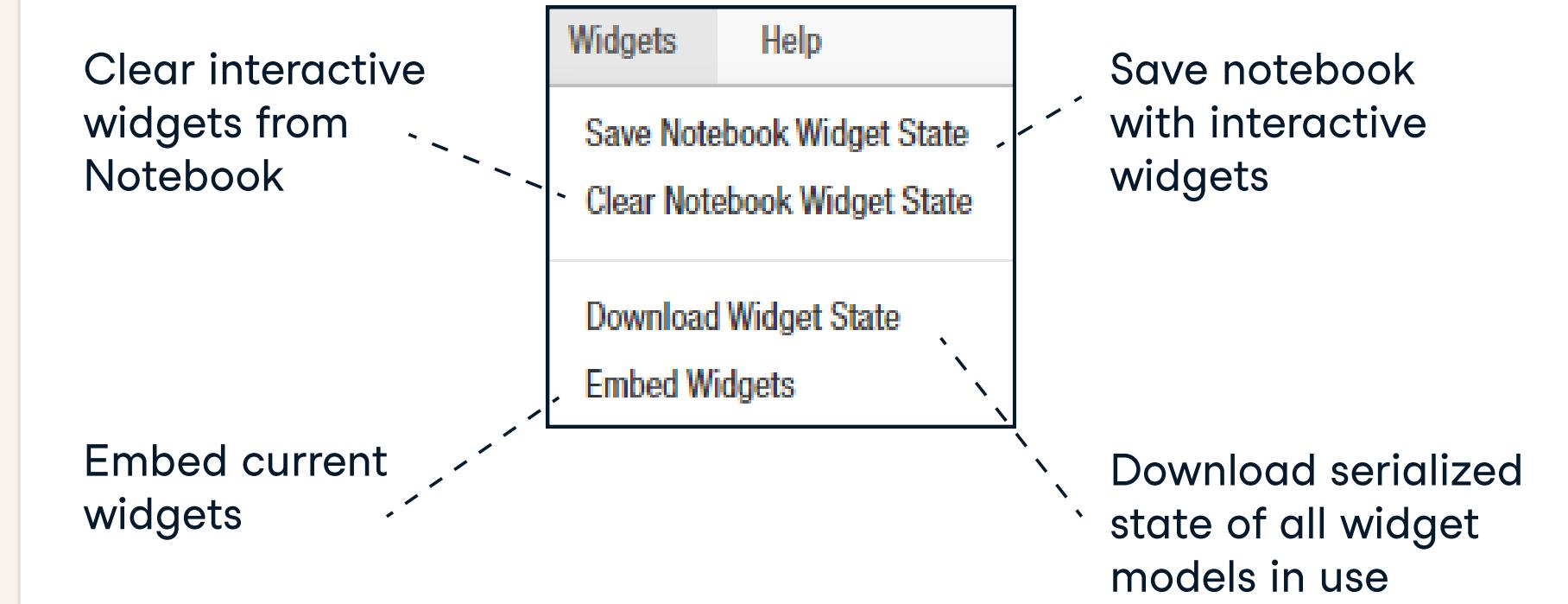
Command Mode:



> Widgets

Notebook widgets provide the ability to visualize and control changes in your data, often as a control like a slider, textbox, etc.

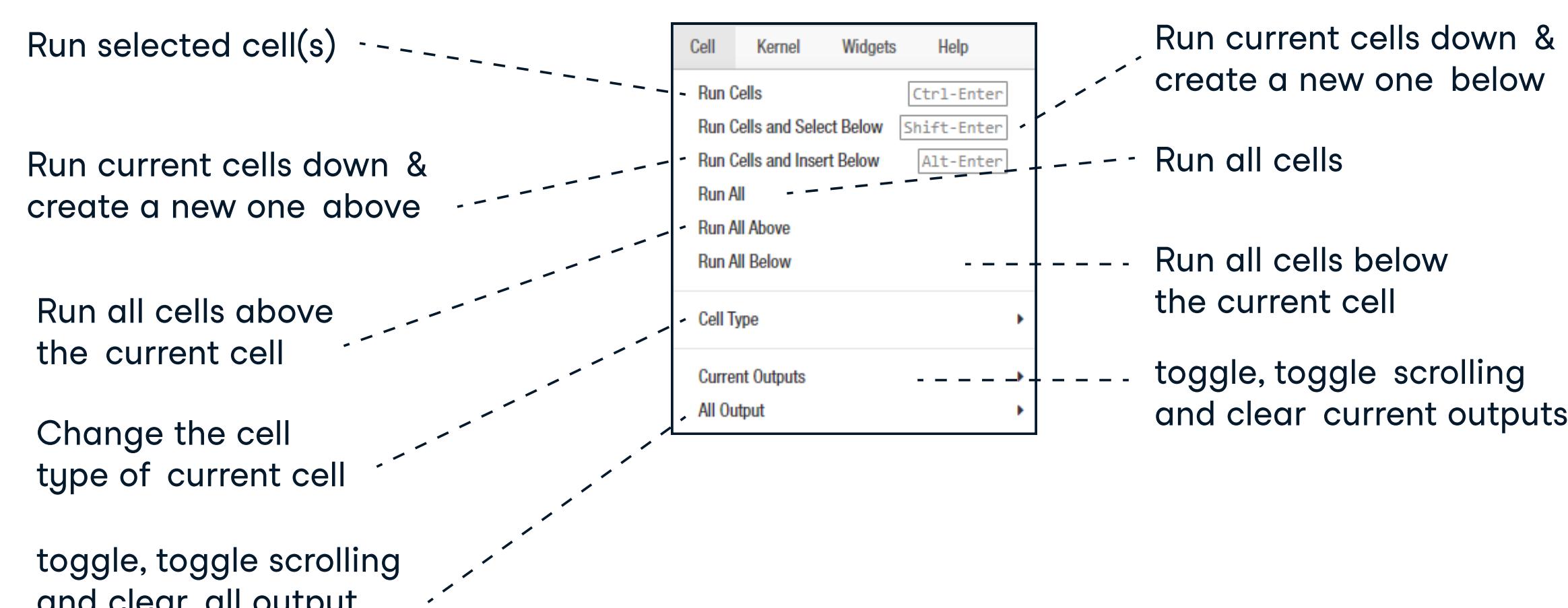
You can use them to build interactive GUIs for your notebooks or to synchronize stateful and stateless information between Python and JavaScript.



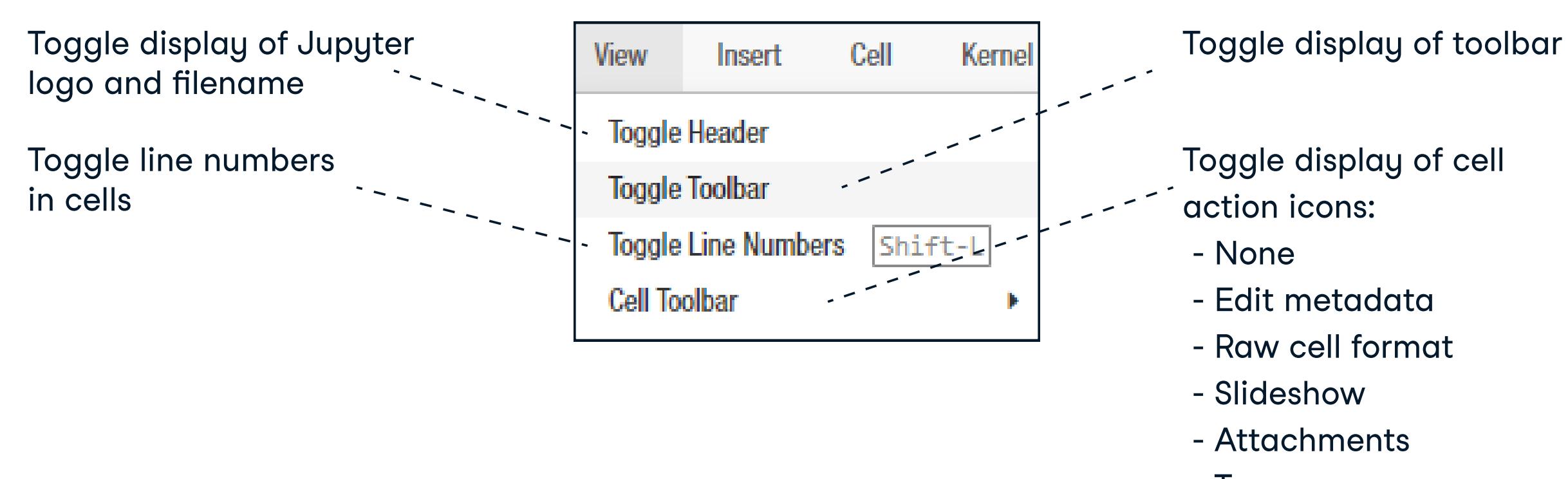
Edit Mode:

In []:

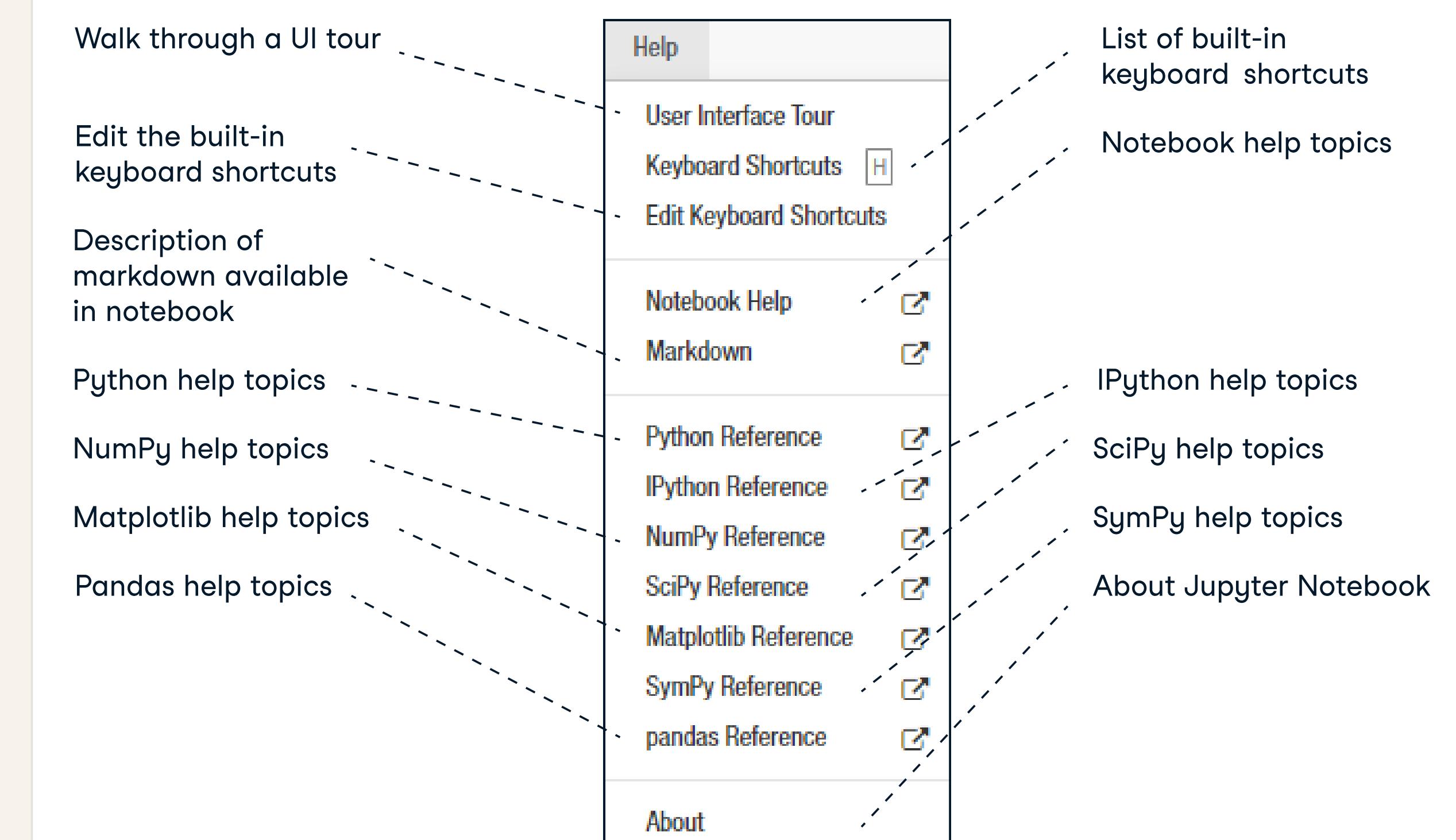
Executing Cells



View Cells



Asking For Help



Python For Data Science

python™ Basics Cheat Sheet

Learn Python Basics online at www.DataCamp.com

> Variables and Data Types

Variable Assignment

```
>>> x=5
>>> x
5
```

Calculations With Variables

```
>>> x+2 #Sum of two variables
7
>>> x-2 #Subtraction of two variables
3
>>> x*2 #Multiplication of two variables
10
>>> x**2 #Exponentiation of a variable
25
>>> x%2 #Remainder of a variable
1
>>> x/float(2) #Division of a variable
2.5
```

Types and Type Conversion

```
str()
'5', '3.45', 'True' #Variables to strings

int()
5, 3, 1 #Variables to integers

float()
5.0, 1.0 #Variables to floats

bool()
True, True, True #Variables to booleans
```

> Libraries

pandas	NumPy	matplotlib	learn
--------	-------	------------	-------

Import Libraries

```
>>> import numpy
>>> import numpy as np
```

Selective import

```
>>> from math import pi
```

> Strings

```
>>> my_string = 'thisStringIsAwesome'
>>> my_string
'thisStringIsAwesome'
```

String Operations

```
>>> my_string * 2
'thisStringIsAwesomethisStringIsAwesome'
>>> my_string + 'Innit'
'thisStringIsAwesomeInnit'
>>> 'm' in my_string
True
```

String Indexing

Index starts at 0

```
>>> my_string[3]
>>> my_string[4:9]
```

String Methods

```
>>> my_string.upper() #String to uppercase
>>> my_string.lower() #String to lowercase
>>> my_string.count('w') #Count String elements
>>> my_string.replace('e', 'i') #Replace String elements
>>> my_string.strip() #Strip whitespaces
```

> NumPy Arrays

Also see Lists

```
>>> my_list = [1, 2, 3, 4]
>>> my_array = np.array(my_list)
>>> my_2darray = np.array([[1,2,3],[4,5,6]])
```

Selecting Numpy Array Elements

Index starts at 0

```
Subset
>>> my_array[1] #Select item at index 1
2

Slice
>>> my_array[0:2] #Select items at index 0 and 1
array([1, 2])

Subset 2D Numpy arrays
>>> my_2darray[:,0] #my_2darray[rows, columns]
array([1, 4])
```

Numpy Array Operations

```
>>> my_array > 3
array([False, False, False, True], dtype=bool)
>>> my_array * 2
array([2, 4, 6, 8])
>>> my_array + np.array([5, 6, 7, 8])
array([6, 8, 10, 12])
```

Numpy Array Functions

```
>>> my_array.shape #Get the dimensions of the array
>>> np.append(other_array) #Append items to an array
>>> np.insert(my_array, 1, 5) #Insert items in an array
>>> np.delete(my_array,[1]) #Delete items in an array
>>> np.mean(my_array) #Mean of the array
>>> np.median(my_array) #Median of the array
>>> my_array.corrcoef() #Correlation coefficient
>>> np.std(my_array) #Standard deviation
```

> Lists

Also see NumPy Arrays

```
>>> a = 'is'
>>> b = 'nice'
>>> my_list = ['my', 'list', a, b]
>>> my_list2 = [[4,5,6,7], [3,4,5,6]]
```

Selecting List Elements

Index starts at 0

Subset

```
>>> my_list[1] #Select item at index 1
>>> my_list[-3] #Select 3rd last item
```

Slice

```
>>> my_list[1:3] #Select items at index 1 and 2
>>> my_list[1:] #Select items after index 0
>>> my_list[:3] #Select items before index 3
>>> my_list[:] #Copy my_list
```

Subset Lists of Lists

```
>>> my_list2[1][0] #my_list[list][itemOfList]
>>> my_list2[1][:2]
```

List Operations

```
>>> my_list + my_list
['my', 'list', 'is', 'nice', 'my', 'list', 'is', 'nice']
>>> my_list * 2
['my', 'list', 'is', 'nice', 'my', 'list', 'is', 'nice']
>>> my_list2 > 4
True
```

List Methods

```
>>> my_list.index(a) #Get the index of an item
>>> my_list.count(a) #Count an item
>>> my_list.append('!)') #Append an item at a time
>>> my_list.remove('!)') #Remove an item
>>> del(my_list[0:1]) #Remove an item
>>> my_list.reverse() #Reverse the list
>>> my_list.extend('!)') #Append an item
>>> my_list.pop(-1) #Remove an item
>>> my_list.insert(0,'!') #Insert an item
>>> my_list.sort() #Sort the list
```

> Python IDEs (Integrated Development Environment)

ANACONDA.

Leading open data science platform powered by Python

SPYDER

Free IDE that is included with Anaconda

jupyter

Create and share documents with live code

> Asking For Help

```
>>> help(str)
```

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Python For Data Science

NumPy Cheat Sheet

Learn NumPy online at www.DataCamp.com

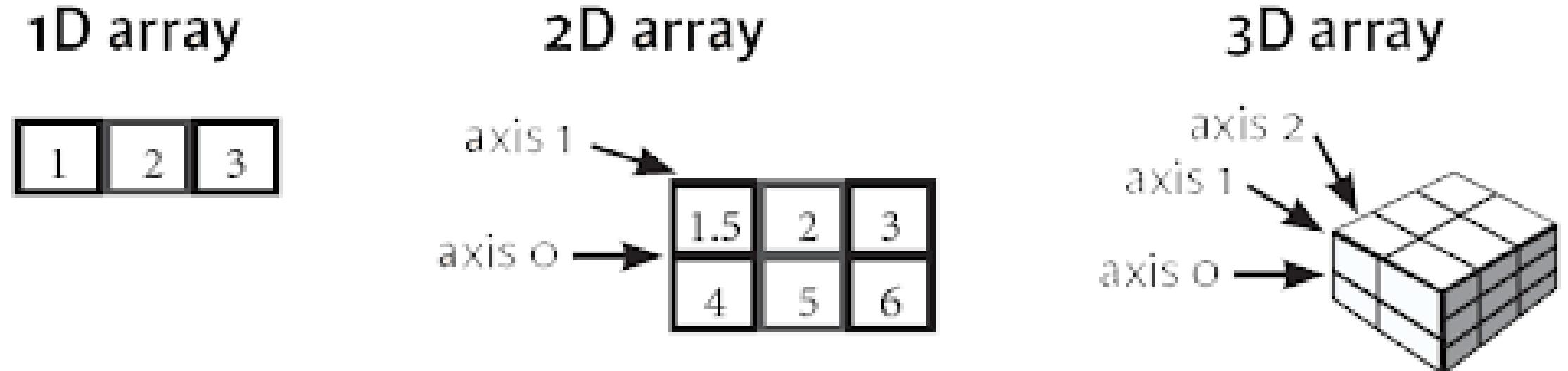
Numpy

The NumPy library is the core library for scientific computing in Python. It provides a high-performance multidimensional array object, and tools for working with these arrays.

Use the following import convention:

```
>>> import numpy as np
```

NumPy Arrays



Creating Arrays

```
>>> a = np.array([1,2,3])
>>> b = np.array([(1.5,2,3), (4,5,6)], dtype = float)
>>> c = np.array([(1.5,2,3), (4,5,6)],[(3,2,1), (4,5,6)]), dtype = float)
```

Initial Placeholders

```
>>> np.zeros((3,4)) #Create an array of zeros
>>> np.ones((2,3,4),dtype=np.int16) #Create an array of ones
>>> d = np.arange(10,25,5) #Create an array of evenly spaced values (step value)
>>> np.linspace(0,2,9) #Create an array of evenly spaced values (number of samples)
>>> e = np.full((2,2),7) #Create a constant array
>>> f = np.eye(2) #Create a 2x2 identity matrix
>>> np.random.random((2,2)) #Create an array with random values
>>> np.empty((3,2)) #Create an empty array
```

I/O

Saving & Loading On Disk

```
>>> np.save('my_array', a)
>>> np.savez('array.npz', a, b)
>>> np.load('my_array.npy')
```

Saving & Loading Text Files

```
>>> np.loadtxt("myfile.txt")
>>> np.genfromtxt("my_file.csv", delimiter=',')
>>> np.savetxt("myarray.txt", a, delimiter=" ")
```

Asking For Help

```
>>> np.info(np.ndarray.dtype)
```

Inspecting Your Array

```
>>> a.shape #Array dimensions
>>> len(a) #Length of array
>>> b.ndim #Number of array dimensions
>>> e.size #Number of array elements
>>> b.dtype #Data type of array elements
>>> b.dtype.name #Name of data type
>>> b.astype(int) #Convert an array to a different type
```

Data Types

```
>>> np.int64 #Signed 64-bit integer types
>>> np.float32 #Standard double-precision floating point
>>> np.complex #Complex numbers represented by 128 floats
>>> np.bool #Boolean type storing TRUE and FALSE values
>>> np.object #Python object type
>>> np.string_ #Fixed-length string type
>>> np_unicode_ #Fixed-length unicode type
```

Array Mathematics

Arithmetic Operations

```
>>> g = a - b #Subtraction
array([[-0.5, 0. , 0. ],
       [-3. , -3. , -3. ]])
>>> np.subtract(a,b) #Subtraction
>>> b + a #Addition
array([[ 2.5, 4. , 6. ],
       [ 5. , 7. , 9. ]])
>>> np.add(b,a) Addition
>>> a / b #Division
array([[ 0.66666667, 1. , 1. ],
       [ 0.25 , 0.4 , 0.5 ]])
>>> np.divide(a,b) #Division
>>> a * b #Multiplication
array([[ 1.5, 4. , 9. ],
       [ 4. , 10. , 18. ]])
>>> np.multiply(a,b) #Multiplication
>>> np.exp(b) #Exponentiation
>>> np.sqrt(b) #Square root
>>> np.sin(a) #Print sines of an array
>>> np.cos(b) #Element-wise cosine
>>> np.log(a) #Element-wise natural logarithm
>>> e.dot(f) #Dot product
array([[ 7., 7.],
       [ 7., 7.]])
```

Comparison

```
>>> a == b #Element-wise comparison
array([[False, True, True],
       [False, False, False]], dtype=bool)
>>> a < b #Element-wise comparison
array[[True, False, False], dtype=bool)
>>> np.array_equal(a, b) #Array-wise comparison
```

Aggregate Functions

```
>>> a.sum() #Array-wise sum
>>> a.min() #Array-wise minimum value
>>> b.max(axis=0) #Maximum value of an array row
>>> b.cumsum(axis=1) #Cumulative sum of the elements
>>> a.mean() #Mean
>>> b.median() #Median
>>> a.corrcoef() #Correlation coefficient
>>> np.std(b) #Standard deviation
```

Copying Arrays

```
>>> h = a.view() #Create a view of the array with the same data
>>> np.copy(a) #Create a copy of the array
>>> h = a.copy() #Create a deep copy of the array
```

Sorting Arrays

```
>>> a.sort() #Sort an array
>>> c.sort(axis=0) #Sort the elements of an array's axis
```

Subsetting, Slicing, Indexing

Subsetting

```
>>> a[2] #Select the element at the 2nd index
3
>>> b[1,2] #Select the element at row 1 column 2 (equivalent to b[1][2])
6.0
```

1	2	3
1.5	2	3
4	5	6

Slicing

```
>>> a[0:2] #Select items at index 0 and 1
array([1, 2])
>>> b[0:2,1] #Select items at rows 0 and 1 in column 1
array([ 2., 2.])
>>> b[:,1] #Select all items at row 0 (equivalent to b[0:, 1])
array([[1.5, 2., 3.]])
>>> c[1,...] #Same as [1,:,:]
array([[ 3., 2., 1.],
       [ 4., 5., 6.]]])
>>> a[ : :-1] #Reversed array a array([3, 2, 1])
```

1	2	3
1.5	2	3
4	5	6
1.5	2	3

Boolean Indexing

```
>>> a[a<2] #Select elements from a less than 2
array([1])
```

1	2	3
---	---	---

Fancy Indexing

```
>>> b[[1, 0, 1, 0],[0, 1, 2, 0]] #Select elements (1,0),(0,1),(1,2) and (0,0)
array([ 1., 2., 6., 1.5])
>>> b[[1, 0, 1, 0]][:, [0,1,2,0]] #Select a subset of the matrix's rows and columns
array([[ 4., 5., 6., 4.],
       [ 1.5, 2., 3., 1.5],
       [ 4., 5., 6., 4.],
       [ 1.5, 2., 3., 1.5]])
```

1	2	3
---	---	---

Array Manipulation

Transposing Array

```
>>> i = np.transpose(b) #Permute array dimensions
>>> i.T #Permute array dimensions
```

Changing Array Shape

```
>>> b.ravel() #Flatten the array
>>> g.reshape(3,-2) #Reshape, but don't change data
```

Adding/Removing Elements

```
>>> h.resize((2,6)) #Return a new array with shape (2,6)
>>> np.append(h,g) #Append items to an array
>>> np.insert(a, 1, 5) #Insert items in an array
>>> np.delete(a,[1]) #Delete items from an array
```

Combining Arrays

```
>>> np.concatenate((a,d),axis=0) #Concatenate arrays
array([[ 1, 2, 3, 4, 5, 6]])
>>> np.vstack((a,b)) #Stack arrays vertically (row-wise)
array([[ 1., 2., 3.],
       [ 4., 5., 6.],
       [ 1., 2., 3.],
       [ 4., 5., 6.],
       [ 1., 2., 3.],
       [ 4., 5., 6.]])
>>> np.r_[e,f] #Stack arrays vertically (row-wise)
>>> np.hstack((e,f)) #Stack arrays horizontally (column-wise)
array([[ 7., 7., 1., 0.],
       [ 7., 7., 0., 1.]])
>>> np.column_stack((a,d)) #Create stacked column-wise arrays
array([[ 1, 10],
       [ 2, 15],
       [ 3, 20]])
>>> np.c_[a,d] #Create stacked column-wise arrays
```

Splitting Arrays

```
>>> np.hsplit(a,3) #Split the array horizontally at the 3rd index
[array([1]),array([2]),array([3])]
>>> np.vsplit(c,2) #Split the array vertically at the 2nd index
[array([[ 1.5, 2., 1.],
       [ 4., 5., 6.]]),
 array([[ 3., 2., 3.],
       [ 4., 5., 6.]]])
```



Python For Data Science

Matplotlib Cheat Sheet

Learn Matplotlib online at www.DataCamp.com

Matplotlib

Matplotlib is a Python 2D plotting library which produces publication-quality figures in a variety of hardcopy formats and interactive environments across platforms.

Prepare The Data

1D Data

```
>>> import numpy as np
>>> x = np.linspace(0, 10, 100)
>>> y = np.cos(x)
>>> z = np.sin(x)
```

2D Data or Images

```
>>> data = 2 * np.random.random((10, 10))
>>> data2 = 3 * np.random.random((10, 10))
>>> Y, X = np.mgrid[-3:3:100j, -3:3:100j]
>>> U = -1 - X**2 + Y
>>> V = 1 + X - Y**2
>>> from matplotlib.cbook import get_sample_data
>>> img = np.load(get_sample_data('axes_grid/bivariate_normal.npy'))
```

Create Plot

```
>>> import matplotlib.pyplot as plt
```

Figure

```
>>> fig = plt.figure()
>>> fig2 = plt.figure(figsize=plt.figaspect(2.0))
```

Axes

All plotting is done with respect to an Axes. In most cases, a subplot will fit your needs. A subplot is an axes on a grid system.

```
>>> fig.add_axes()
>>> ax1 = fig.add_subplot(221) #row-col-num
>>> ax2 = fig.add_subplot(212)
>>> fig3, axes = plt.subplots(nrows=2, ncols=2)
>>> fig4, axes2 = plt.subplots(ncols=3)
```

Save Plot

```
>>> plt.savefig('foo.png') #Save figures
>>> plt.savefig('foo.png', transparent=True) #Save transparent figures
```

Show Plot

```
>>> plt.show()
```

Plotting Routines

1D Data

```
>>> fig, ax = plt.subplots()
>>> lines = ax.plot(x,y) #Draw points with lines or markers connecting them
>>> ax.scatter(x,y) #Draw unconnected points, scaled or colored
>>> axes[0,0].bar([1,2,3],[3,4,5]) #Plot vertical rectangles (constant width)
>>> axes[0,0].barh([0.5,1,2.5],[0,1,2]) #Plot horizontal rectangles (constant height)
>>> axes[1,1].axhline(0.45) #Draw a horizontal line across axes
>>> axes[0,1].axvline(0.65) #Draw a vertical line across axes
>>> ax.fill(x,y,color='blue') #Draw filled polygons
>>> ax.fill_between(x,y,color='yellow') #Fill between y-values and 0
```

2D Data

```
>>> fig, ax = plt.subplots()
>>> im = ax.imshow(img, #Colormapped or RGB arrays
                  cmap='gist_earth',
                  interpolation='nearest',
                  vmin=-2,
                  vmax=2)
>>> axes2[0].pcolor(data2) #Pseudocolor plot of 2D array
>>> axes2[0].pcolormesh(data) #Pseudocolor plot of 2D array
>>> CS = plt.contour(Y,X,U) #Plot contours
>>> axes2[2].contourf(data1) #Plot filled contours
>>> axes2[2]= ax.clabel(CS) #Label a contour plot
```

Vector Fields

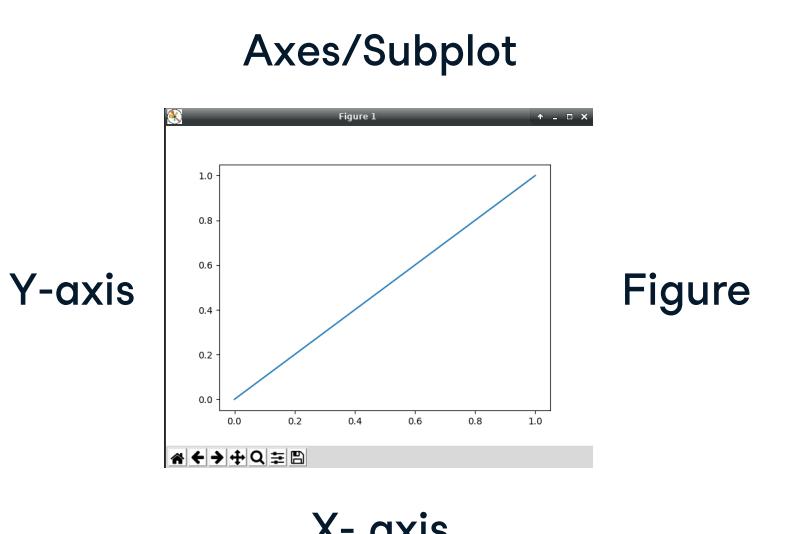
```
>>> axes[0,1].arrow(0,0,0.5,0.5) #Add an arrow to the axes
>>> axes[1,1].quiver(y,z) #Plot a 2D field of arrows
>>> axes[0,1].streamplot(X,Y,U,V) #Plot a 2D field of arrows
```

Data Distributions

```
>>> ax1.hist(y) #Plot a histogram
>>> ax3.boxplot(y) #Make a box and whisker plot
>>> ax3.violinplot(z) #Make a violin plot
```

Plot Anatomy & Workflow

Plot Anatomy



Workflow

The basic steps to creating plots with matplotlib are:

- 1 Prepare Data
 - 2 Create Plot
 - 3 Plot
 - 4 Customized Plot
 - 5 Save Plot
 - 6 Show Plot
- ```
>>> import matplotlib.pyplot as plt
>>> x = [1,2,3,4] #Step 1
>>> y = [10,20,25,30]
>>> fig = plt.figure() #Step 2
>>> ax = fig.add_subplot(111) #Step 3
>>> ax.plot(x, y, color='lightblue', linewidth=3) #Step 3, 4
>>> ax.scatter([2,4,6],
 [5,15,25],
 color='darkgreen',
 marker='^')
>>> ax.set_xlim(1, 6.5)
>>> plt.savefig('foo.png') #Step 5
>>> plt.show() #Step 6
```

## Close and Clear

```
>>> plt.cla() #Clear an axis
>>> plt.clf() #Clear the entire figure
>>> plt.close() #Close a window
```

## Plotting Cutomize Plot

### Colors, Color Bars & Color Maps

```
>>> plt.plot(x, x, x*x2, x, x*x3)
>>> ax.plot(x, y, alpha = 0.4)
>>> ax.plot(x, y, c='k')
>>> fig.colorbar(im, orientation='horizontal')
>>> im = ax.imshow(img,
 cmap='seismic')
```

### Markers

```
>>> fig, ax = plt.subplots()
>>> ax.scatter(x,y,marker=".")
>>> ax.plot(x,y,marker="o")
```

### Linestyles

```
>>> plt.plot(x,y,linewidth=4.0)
>>> plt.plot(x,y,ls='solid')
>>> plt.plot(x,y,ls='--')
>>> plt.plot(x,y,'--',x*x2,y**2,'-.')
>>> plt.setp(lines,color='r',linewidth=4.0)
```

### Text & Annotations

```
>>> ax.text(1,
 -2.1,
 'Example Graph',
 style='italic')
>>> ax.annotate("Sine",
 xy=(8, 0),
 xycoords='data',
 xytext=(10.5, 0),
 textcoords='data',
 arrowprops=dict(arrowstyle="→",
 connectionstyle="arc3"))

```

### MathText

```
>>> plt.title(r'$\sigma_{i=15}$', fontsize=20)
```

### Limits, Legends and Layouts

#### Limits & Autoscaling

```
>>> ax.margins(x=0.0,y=0.1) #Add padding to a plot
>>> ax.axis('equal') #Set the aspect ratio of the plot to 1
>>> ax.set(xlim=[0,10.5],ylim=[-1.5,1.5]) #Set limits for x-and y-axis
>>> ax.set_xlim(0,10.5) #Set limits for x-axis
```

#### Legends

```
>>> ax.set(title='An Example Axes', #Set a title and x-and y-axis labels
 ylabel='Y-Axis',
 xlabel='X-Axis')
>>> ax.legend(loc='best') #No overlapping plot elements
```

#### Ticks

```
>>> ax.xaxis.set(ticks=range(1,5), #Manually set x-ticks
 ticklabels=[3,100,-12,"foo"])
>>> ax.tick_params(axis='y', #Make y-ticks longer and go in and out
 direction='inout',
 length=10)
```

#### Subplot Spacing

```
>>> fig3.subplots_adjust(wspace=0.5, #Adjust the spacing between subplots
 hspace=0.3,
 left=0.125,
 right=0.9,
 top=0.9,
 bottom=0.1)
>>> fig.tight_layout() #Fit subplot(s) in to the figure area
```

#### Axis Spines

```
>>> ax1.spines['top'].set_visible(False) #Make the top axis line for a plot invisible
>>> ax1.spines['bottom'].set_position(('outward',10)) #Move the bottom axis line outward
```

# Python For Data Science

## Pandas Basics Cheat Sheet

Learn Pandas Basics online at [www.DataCamp.com](http://www.DataCamp.com)

### Pandas

The **Pandas** library is built on NumPy and provides easy-to-use **data structures** and **data analysis** tools for the Python programming language.

Use the following import convention:

```
>>> import pandas as pd
```

### Pandas Data Structures

#### Series

A **one-dimensional** labeled array capable of holding any data type

|         |   |    |
|---------|---|----|
| Index → | a | 3  |
|         | b | -5 |
|         | c | 7  |
|         | d | 4  |

#### Dataframe

A **two-dimensional** labeled data structure with columns of potentially different types

|           |         |         |                      |
|-----------|---------|---------|----------------------|
| Columns → | Country | Capital | Population           |
| Index →   | 0       | Belgium | Brussels 11190846    |
|           | 1       | India   | New Delhi 1303171035 |
|           | 2       | Brazil  | Brasilia 207847528   |

```
>>> s = pd.Series([3, -5, 7, 4], index=['a', 'b', 'c', 'd'])
>>> df = pd.DataFrame(data,
 columns=['Country', 'Capital', 'Population'])
```

### Dropping

```
>>> s.drop(['a', 'c']) #Drop values from rows (axis=0)
>>> df.drop('Country', axis=1) #Drop values from columns(axis=1)
```

### Asking For Help

```
>>> help(pd.Series.loc)
```

### Sort & Rank

```
>>> df.sort_index() #Sort by labels along an axis
>>> df.sort_values(by='Country') #Sort by the values along an axis
>>> df.rank() #Assign ranks to entries
```

### I/O

#### Read and Write to CSV

```
>>> pd.read_csv('file.csv', header=None, nrows=5)
>>> df.to_csv('myDataFrame.csv')
```

#### Read and Write to Excel

```
>>> pd.read_excel('file.xlsx')
>>> df.to_excel('dir/myDataFrame.xlsx', sheet_name='Sheet1')

Read multiple sheets from the same file
>>> xlsx = pd.ExcelFile('file.xlsx')
>>> df = pd.read_excel(xlsx, 'Sheet1')
```

#### Read and Write to SQL Query or Database Table

```
>>> from sqlalchemy import create_engine
>>> engine = create_engine('sqlite:///memory:')
>>> pd.read_sql("SELECT * FROM my_table;", engine)
>>> pd.read_sql_table('my_table', engine)
>>> pd.read_sql_query("SELECT * FROM my_table;", engine)

read_sql() is a convenience wrapper around read_sql_table() and read_sql_query()
>>> df.to_sql('myDF', engine)
```

### Retrieving Series/DataFrame Information

#### Basic Information

```
>>> df.shape #(rows,columns)
>>> df.index #Describe index
>>> df.columns #Describe DataFrame columns
>>> df.info() #Info on DataFrame
>>> df.count() #Number of non-NA values
```

#### Summary

```
>>> df.sum() #Sum of values
>>> df.cumsum() #Cumulative sum of values
>>> df.min()/df.max() #Minimum/maximum values
>>> df.idxmin()/df.idxmax() #Minimum/Maximum index value
>>> df.describe() #Summary statistics
>>> df.mean() #Mean of values
>>> df.median() #Median of values
```

### Applying Functions

```
>>> f = lambda x: x*2
>>> df.apply(f) #Apply function
>>> df.applymap(f) #Apply function element-wise
```

### Data Alignment

#### Internal Data Alignment

NA values are introduced in the indices that don't overlap:

```
>>> s3 = pd.Series([7, -2, 3], index=['a', 'c', 'd'])
>>> s + s3
a 10.0
b NaN
c 5.0
d 7.0
```

#### Arithmetic Operations with Fill Methods

You can also do the internal data alignment yourself with the help of the fill methods:

```
>>> s.add(s3, fill_value=0)
a 10.0
b -5.0
c 5.0
d 7.0
>>> s.sub(s3, fill_value=2)
>>> s.div(s3, fill_value=4)
>>> s.mul(s3, fill_value=3)
```

Learn Data Skills Online at  
[www.DataCamp.com](http://www.DataCamp.com)

# Python For Data Science

## Scikit-Learn Cheat Sheet

Learn Scikit-Learn online at [www.DataCamp.com](http://www.DataCamp.com)

### Scikit-learn

Scikit-learn is an open source Python library that implements a range of machine learning, preprocessing, cross-validation and visualization algorithms using a unified interface.



#### A Basic Example

```
>>> from sklearn import neighbors, datasets, preprocessing
>>> from sklearn.model_selection import train_test_split
>>> from sklearn.metrics import accuracy_score
>>> iris = datasets.load_iris()
>>> X, y = iris.data[:, :2], iris.target
>>> X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=33)
>>> scaler = preprocessing.StandardScaler().fit(X_train)
>>> X_train = scaler.transform(X_train)
>>> X_test = scaler.transform(X_test)
>>> knn = neighbors.KNeighborsClassifier(n_neighbors=5)
>>> knn.fit(X_train, y_train)
>>> y_pred = knn.predict(X_test)
>>> accuracy_score(y_test, y_pred)
```

### > Loading The Data

Also see NumPy & Pandas

Your data needs to be numeric and stored as NumPy arrays or SciPy sparse matrices. Other types that are convertible to numeric arrays, such as Pandas DataFrame, are also acceptable.

```
>>> import numpy as np
>>> X = np.random.random((10,5))
>>> y = np.array(['M', 'M', 'F', 'F', 'M', 'F', 'M', 'M', 'F', 'F'])
>>> X[X < 0.7] = 0
```

### > Training And Test Data

```
>>> from sklearn.model_selection import train_test_split
>>> X_train, X_test, y_train, y_test = train_test_split(X,
y,
random_state=0)
```

### > Model Fitting

**Supervised learning**

```
>>> lr.fit(X, y) #Fit the model to the data
>>> knn.fit(X_train, y_train)
>>> svc.fit(X_train, y_train)
```

**Unsupervised Learning**

```
>>> kmeans.fit(X_train) #Fit the model to the data
>>> pca_model = pca.fit_transform(X_train) #Fit to data, then transform it
```

### > Prediction

**Supervised Estimators**

```
>>> y_pred = svc.predict(np.random.random((2,5))) #Predict labels
>>> y_pred = lr.predict(X_test) #Predict labels
>>> y_pred = knn.predict_proba(X_test) #Estimate probability of a label
```

**Unsupervised Estimators**

```
>>> y_pred = kmeans.predict(X_test) #Predict labels in clustering algos
```

### > Preprocessing The Data

#### Standardization

```
>>> from sklearn.preprocessing import StandardScaler
>>> scaler = StandardScaler().fit(X_train)
>>> standardized_X = scaler.transform(X_train)
>>> standardized_X_test = scaler.transform(X_test)
```

#### Normalization

```
>>> from sklearn.preprocessing import Normalizer
>>> scaler = Normalizer().fit(X_train)
>>> normalized_X = scaler.transform(X_train)
>>> normalized_X_test = scaler.transform(X_test)
```

#### Binarization

```
>>> from sklearn.preprocessing import Binarizer
>>> binarizer = Binarizer(threshold=0.0).fit(X)
>>> binary_X = binarizer.transform(X)
```

#### Encoding Categorical Features

```
>>> from sklearn.preprocessing import LabelEncoder
>>> enc = LabelEncoder()
>>> y = enc.fit_transform(y)
```

#### Imputing Missing Values

```
>>> from sklearn.preprocessing import Imputer
>>> imp = Imputer(missing_values=0, strategy='mean', axis=0)
>>> imp.fit_transform(X_train)
```

#### Generating Polynomial Features

```
>>> from sklearn.preprocessing import PolynomialFeatures
>>> poly = PolynomialFeatures(5)
>>> poly.fit_transform(X)
```

### > Create Your Model

#### Supervised Learning Estimators

##### Linear Regression

```
>>> from sklearn.linear_model import LinearRegression
>>> lr = LinearRegression(normalize=True)
```

##### Support Vector Machines (SVM)

```
>>> from sklearn.svm import SVC
>>> svc = SVC(kernel='linear')
```

##### Naive Bayes

```
>>> from sklearn.naive_bayes import GaussianNB
>>> gnb = GaussianNB()
```

##### KNN

```
>>> from sklearn import neighbors
>>> knn = neighbors.KNeighborsClassifier(n_neighbors=5)
```

#### Unsupervised Learning Estimators

##### Principal Component Analysis (PCA)

```
>>> from sklearn.decomposition import PCA
>>> pca = PCA(n_components=0.95)
```

##### K Means

```
>>> from sklearn.cluster import KMeans
>>> kmeans = KMeans(n_clusters=3, random_state=0)
```

### > Evaluate Your Model's Performance

#### Classification Metrics

##### Accuracy Score

```
>>> knn.score(X_test, y_test) #Estimator score method
>>> from sklearn.metrics import accuracy_score #Metric scoring functions
>>> accuracy_score(y_test, y_pred)
```

##### Classification Report

```
>>> from sklearn.metrics import classification_report #Precision, recall, f1-score and support
>>> print(classification_report(y_test, y_pred))
```

##### Confusion Matrix

```
>>> from sklearn.metrics import confusion_matrix
>>> print(confusion_matrix(y_test, y_pred))
```

#### Regression Metrics

##### Mean Absolute Error

```
>>> from sklearn.metrics import mean_absolute_error
>>> y_true = [3, -0.5, 2]
>>> mean_absolute_error(y_true, y_pred)
```

##### Mean Squared Error

```
>>> from sklearn.metrics import mean_squared_error
>>> mean_squared_error(y_test, y_pred)
```

##### R<sup>2</sup> Score

```
>>> from sklearn.metrics import r2_score
>>> r2_score(y_true, y_pred)
```

#### Clustering Metrics

##### Adjusted Rand Index

```
>>> from sklearn.metrics import adjusted_rand_score
>>> adjusted_rand_score(y_true, y_pred)
```

##### Homogeneity

```
>>> from sklearn.metrics import homogeneity_score
>>> homogeneity_score(y_true, y_pred)
```

##### V-measure

```
>>> from sklearn.metrics import v_measure_score
>>> metrics.v_measure_score(y_true, y_pred)
```

#### Cross-Validation

```
>>> from sklearn.cross_validation import cross_val_score
>>> print(cross_val_score(knn, X_train, y_train, cv=4))
>>> print(cross_val_score(lr, X, y, cv=2))
```

### > Tune Your Model

#### Grid Search

```
>>> from sklearn.grid_search import GridSearchCV
>>> params = {"n_neighbors": np.arange(1,3),
"metric": ["euclidean", "cityblock"]}
>>> grid = GridSearchCV(estimator=knn,
param_grid=params)
>>> grid.fit(X_train, y_train)
>>> print(grid.best_score_)
>>> print(grid.best_estimator_.n_neighbors)
```

#### Randomized Parameter Optimization

```
>>> from sklearn.grid_search import RandomizedSearchCV
>>> params = {"n_neighbors": range(1,5), "weights": ["uniform", "distance"]}
>>> rsearch = RandomizedSearchCV(estimator=knn, param_distributions=params,
cv=4, n_iter=8, random_state=5)
>>> rsearch.fit(X_train, y_train)
>>> print(rsearch.best_score_)
```



# Python For Data Science

## Keras Cheat Sheet

Learn Keras online at [www.DataCamp.com](http://www.DataCamp.com)

## Keras

Keras is a powerful and easy-to-use deep learning library for Theano and TensorFlow that provides a high-level neural networks API to develop and evaluate deep learning models.

### A Basic Example

```
>>> import numpy as np
>>> from keras.models import Sequential
>>> from keras.layers import Dense
>>> data = np.random.random((1000,100))
>>> labels = np.random.randint(2,size=(1000,1))
>>> model = Sequential()
>>> model.add(Dense(32,
 activation='relu',
 input_dim=100))
>>> model.add(Dense(1, activation='sigmoid'))
>>> model.compile(optimizer='rmsprop',
 loss='binary_crossentropy',
 metrics=['accuracy'])
>>> model.fit(data,labels,epochs=10,batch_size=32)
>>> predictions = model.predict(data)
```

## Data

Your data needs to be stored as NumPy arrays or as a list of NumPy arrays. Ideally, you split the data in training and test sets, for which you can also resort to the `train_test_split` module of `sklearn.cross_validation`.

### Keras Data Sets

```
>>> from keras.datasets import boston_housing, mnist, cifar10, imdb
>>> (x_train,y_train),(x_test,y_test) = mnist.load_data()
>>> (x_train2,y_train2),(x_test2,y_test2) = boston_housing.load_data()
>>> (x_train3,y_train3),(x_test3,y_test3) = cifar10.load_data()
>>> (x_train4,y_train4),(x_test4,y_test4) = imdb.load_data(num_words=20000)
>>> num_classes = 10
```

### Other

```
>>> from urllib.request import urlopen
>>> data =
np.loadtxt(urlopen("http://archive.ics.uci.edu/ml/machine-learning-databases/pima-indians-diabetes/pima-indians-diabetes.data"), delimiter=",")
>>> X = data[:,0:8]
>>> y = data[:,8]
```

## Preprocessing

### Sequence Padding

```
>>> from keras.preprocessing import sequence
>>> x_train4 = sequence.pad_sequences(x_train4,maxlen=80)
>>> x_test4 = sequence.pad_sequences(x_test4,maxlen=80)
```

### One-Hot Encoding

```
>>> from keras.utils import to_categorical
>>> Y_train = to_categorical(y_train, num_classes)
>>> Y_test = to_categorical(y_test, num_classes)
>>> Y_train3 = to_categorical(y_train3, num_classes)
>>> Y_test3 = to_categorical(y_test3, num_classes)
```

## > Model Architecture

### Sequential Model

```
>>> from keras.models import Sequential
>>> model = Sequential()
>>> model2 = Sequential()
>>> model3 = Sequential()
```

### Multilayer Perceptron (MLP)

#### Binary Classification

```
>>> from keras.layers import Dense
>>> model.add(Dense(12,
 input_dim=8,
 kernel_initializer='uniform',
 activation='relu'))
>>> model.add(Dense(8,kernel_initializer='uniform',activation='relu'))
>>> model.add(Dense(1,kernel_initializer='uniform',activation='sigmoid'))
```

#### Multi-Class Classification

```
>>> from keras.layers import Dropout
>>> model.add(Dense(512,activation='relu',input_shape=(784,)))
>>> model.add(Dropout(0.2))
>>> model.add(Dense(512,activation='relu'))
>>> model.add(Dropout(0.2))
>>> model.add(Dense(10,activation='softmax'))
```

#### Regression

```
>>> model.add(Dense(64,activation='relu',input_dim=train_data.shape[1]))
>>> model.add(Dense(1))
```

### Convolutional Neural Network (CNN)

```
>>> from keras.layers import Activation,Conv2D,MaxPooling2D,Flatten
>>> model2.add(Conv2D(32,(3,3),padding='same',input_shape=x_train.shape[1:]))
>>> model2.add(Activation('relu'))
>>> model2.add(Conv2D(32,(3,3)))
>>> model2.add(Activation('relu'))
>>> model2.add(MaxPooling2D(pool_size=(2,2)))
>>> model2.add(Dropout(0.25))
>>> model2.add(Conv2D(64,(3,3), padding='same'))
>>> model2.add(Activation('relu'))
>>> model2.add(Conv2D(64,(3,3)))
>>> model2.add(Activation('relu'))
>>> model2.add(MaxPooling2D(pool_size=(2,2)))
>>> model2.add(Dropout(0.25))
>>> model2.add(Flatten())
>>> model2.add(Dense(512))
>>> model2.add(Activation('relu'))
>>> model2.add(Dropout(0.5))
>>> model2.add(Dense(num_classes))
>>> model2.add(Activation('softmax'))
```

### Recurrent Neural Network (RNN)

```
>>> from keras.layers import Embedding,LSTM
>>> model3.add(Embedding(20000,128))
>>> model3.add(LSTM(128,dropout=0.2,recurrent_dropout=0.2))
>>> model3.add(Dense(1,activation='sigmoid'))
```

## > Prediction

```
>>> model3.predict(x_test4, batch_size=32)
>>> model3.predict_classes(x_test4,batch_size=32)
```

Also see NumPy & Scikit-Learn

### Train and Test Sets

```
>>> from sklearn.model_selection import train_test_split
>>> X_train5,X_test5,y_train5,y_test5 = train_test_split(x, y,
 test_size=0.33,
 random_state=42)
```

### Standardization/Normalization

```
>>> from sklearn.preprocessing import StandardScaler
>>> scaler = StandardScaler().fit(x_train2)
>>> standardized_X = scaler.transform(x_train2)
>>> standardized_X_test = scaler.transform(x_test2)
```

## > Inspect Model

```
>>> model.output_shape #Model output shape
>>> model.summary() #Model summary representation
>>> model.get_config() #Model configuration
>>> model.get_weights() #list all weight tensors in the model
```

## > Compile Model

#### MLP: Binary Classification

```
>>> model.compile(optimizer='adam',
 loss='binary_crossentropy',
 metrics=['accuracy'])
```

#### MLP: Multi-Class Classification

```
>>> model.compile(optimizer='rmsprop',
 loss='categorical_crossentropy',
 metrics=['accuracy'])
```

#### MLP: Regression

```
>>> model.compile(optimizer='rmsprop',
 loss='mse',
 metrics=['mae'])
```

#### Recurrent Neural Network

```
>>> model3.compile(loss='binary_crossentropy',
 optimizer='adam',
 metrics=['accuracy'])
```

## > Model Training

```
>>> model3.fit(x_train4,
 y_train4,
 batch_size=32,
 epochs=15,
 verbose=1,
 validation_data=(x_test4,y_test4))
```

## > Evaluate Your Model's Performance

```
>>> score = model3.evaluate(x_test,
 y_test,
 batch_size=32)
```

## > Save/ Reload Models

```
>>> from keras.models import load_model
>>> model3.save('model_file.h5')
>>> my_model = load_model('my_model.h5')
```

## > Model Fine-tuning

### Optimization Parameters

```
>>> from keras.optimizers import RMSprop
>>> opt = RMSprop(lr=0.0001, decay=1e-6)
>>> model2.compile(loss='categorical_crossentropy',
 optimizer=opt,
 metrics=['accuracy'])
```

### Early Stopping

```
>>> from keras.callbacks import EarlyStopping
>>> early_stopping_monitor = EarlyStopping(patience=2)
>>> model3.fit(x_train4,
 y_train4,
 batch_size=32,
 epochs=15,
 validation_data=(x_test4,y_test4),
 callbacks=[early_stopping_monitor])
```

## 2 | Linear Regression

|                       |            |       |       |
|-----------------------|------------|-------|-------|
| <b>Student's name</b> | .....      | ..... | ..... |
|                       | .....      | ..... | ..... |
| <b>Score</b>          | <b>/20</b> | ..... | ..... |

### Detailed Credits

|                                  |       |       |       |
|----------------------------------|-------|-------|-------|
| <b>Anticipation (4 points)</b>   | ..... | ..... | ..... |
| <b>Management (2 points)</b>     | ..... | ..... | ..... |
| <b>Testing (7 points)</b>        | ..... | ..... | ..... |
| <b>Data Logging (3 points)</b>   | ..... | ..... | ..... |
| <b>Interpretation (4 points)</b> | ..... | ..... | ..... |



The notebook is available at <https://github.com/a-mhamdi/cosnip/> → Python → ml → linear-regression.ipynb

### Simple Linear Regression using artificial data

```
[1]: import numpy as np
import matplotlib.pyplot as plt

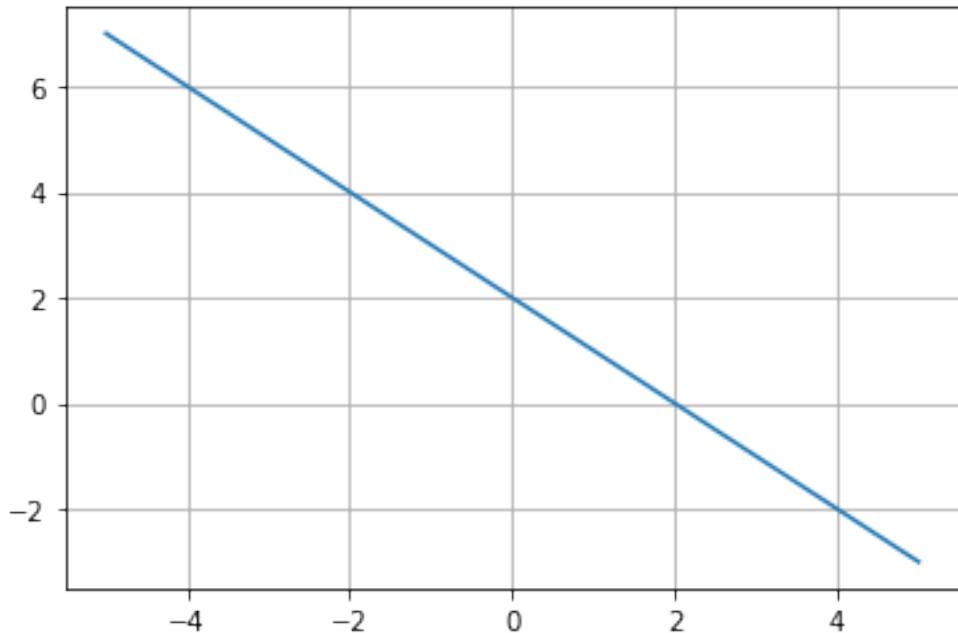
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
```

Consider the following equation:

$$y = -x + 2 \longrightarrow \begin{cases} a = -1 \\ b = 2 \end{cases}$$

```
[2]: x = np.linspace(-5,5,100)
y = -x + 2
```

```
[3]: plt.plot(x, y)
plt.grid()
```



A full description of the available methods can be retrieved from the official website of [scikit-learn](#).

| Syntax                                    | Description                                                |
|-------------------------------------------|------------------------------------------------------------|
| <code>fit(X, y[, sample_weight])</code>   | Fit linear model.                                          |
| <code>get_params([deep])</code>           | Get parameters for this estimator.                         |
| <code>predict(X)</code>                   | Predict using the linear model.                            |
| <code>score(X, y[, sample_weight])</code> | Return the coefficient of determination of the prediction. |
| <code>set_params(**params)</code>         | Set the parameters of this estimator.                      |

```
[4]: x = x.reshape(-1,1)
linear_reg = LinearRegression().fit(x, y)
```

```
[5]: linear_reg.score(x, y)
```

[5]: 1.0

Coefficient  $a$

```
[6]: linear_reg.coef_
```

```
[6]: array([-1.])
```

Intercept  $b$

```
[7]: linear_reg.intercept_
```

```
[7]: 2.0
```

Let's check for  $x = 5$ .

```
[8]: linear_reg.predict(np.array([5]).reshape(-1,1))
```

```
[8]: array([-3.])
```

### Simple Linear Regression using dataset

```
[9]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import os
```

Load the datasets.

```
[10]: dataset = pd.read_csv("./datasets/Weight_Height.csv")
```

Check the dataset.

```
[11]: dataset.head()
```

```
[11]: Gender Height Weight
0 Male 73.847017 241.893563
1 Male 68.781904 162.310473
2 Male 74.110105 212.740856
3 Male 71.730978 220.042470
4 Male 69.881796 206.349801
```

Check the dimensions of the loaded dataset.

```
[12]: dataset.shape
```

```
[12]: (10000, 3)
```

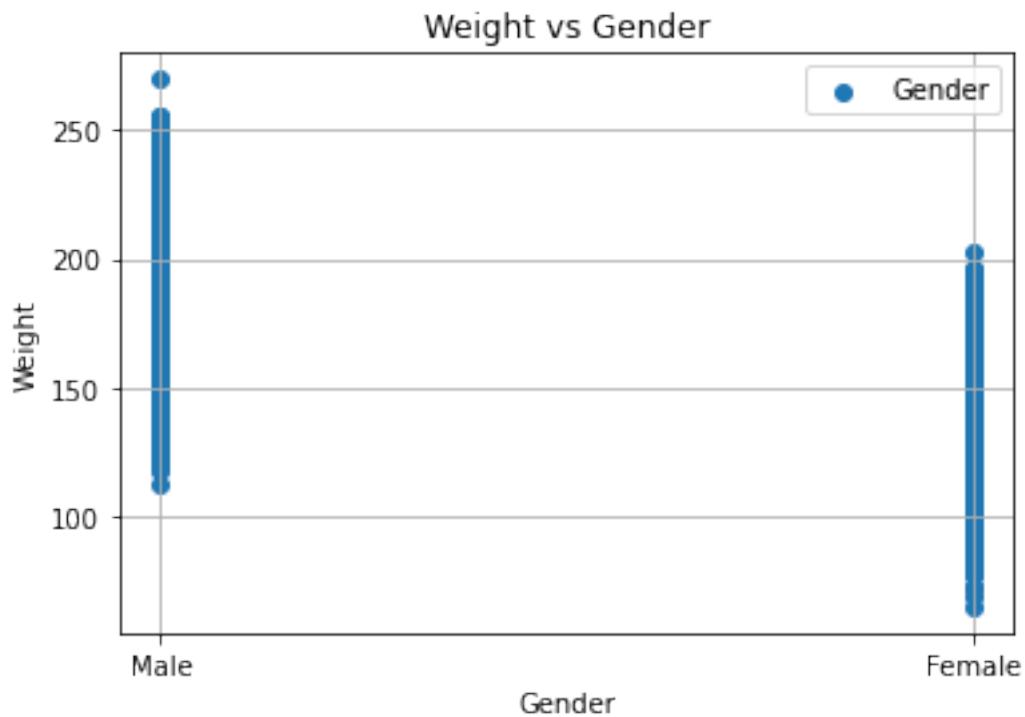
Check if there are null values in the dataset.

```
[13]: dataset.isnull().sum()
```

```
[13]: Gender 0
 Height 0
 Weight 0
 dtype: int64
```

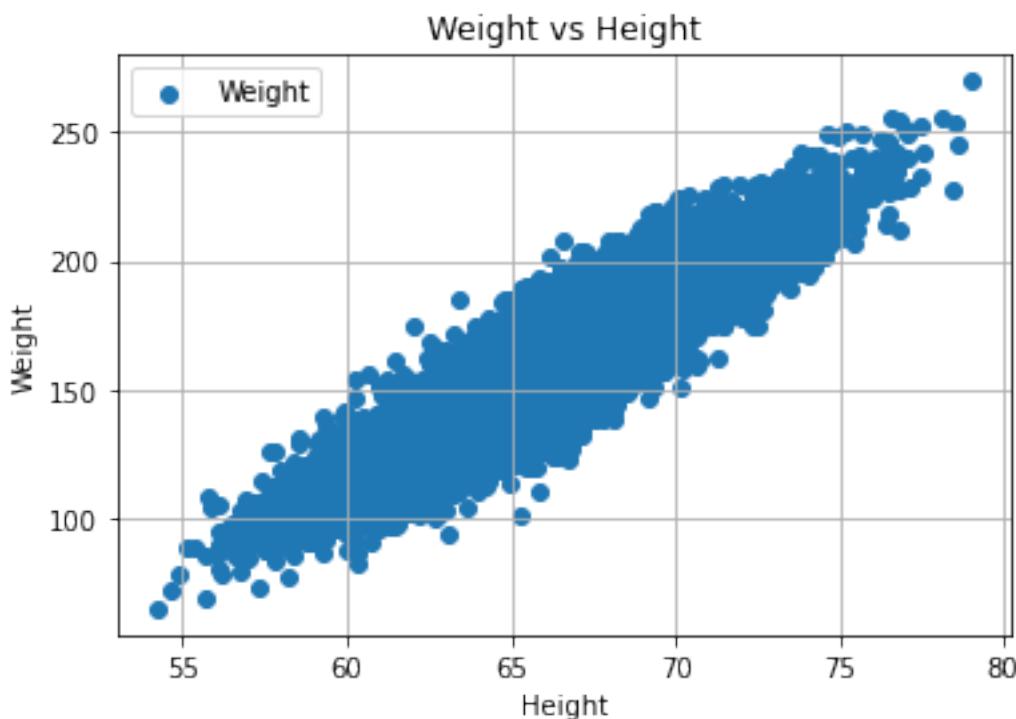
Plot  $Gender$  vs  $Weight$ .

```
[14]: x1 = dataset.iloc[:, 0].values
y1 = dataset.iloc[:, 2].values
plt.scatter(x1, y1, label='Gender')
plt.xlabel('Gender')
plt.ylabel('Weight')
plt.title('Weight vs Gender')
plt.grid()
plt.legend()
```



Plot *Height* vs *Weight*.

```
[15]: x2 = dataset.iloc[:, 1].values
y2 = dataset.iloc[:, 2].values
plt.scatter(x2,y2,label='Weight')
plt.xlabel('Height')
plt.ylabel('Weight')
plt.title('Weight vs Height')
plt.grid()
plt.legend()
```



```
[16]: X = dataset.iloc[:, 1].values
```

Target values y

```
[17]: y = dataset.iloc[:, 2].values
```

```
[18]: X_train, X_test, y_train, y_test = train_test_split(X.reshape(-1,1), y, test_size=0.2, random_state=123)
```

Create linear regression model.

```
[19]: w_h_regressor = LinearRegression()
w_h_regressor.fit(X_train, y_train)
```

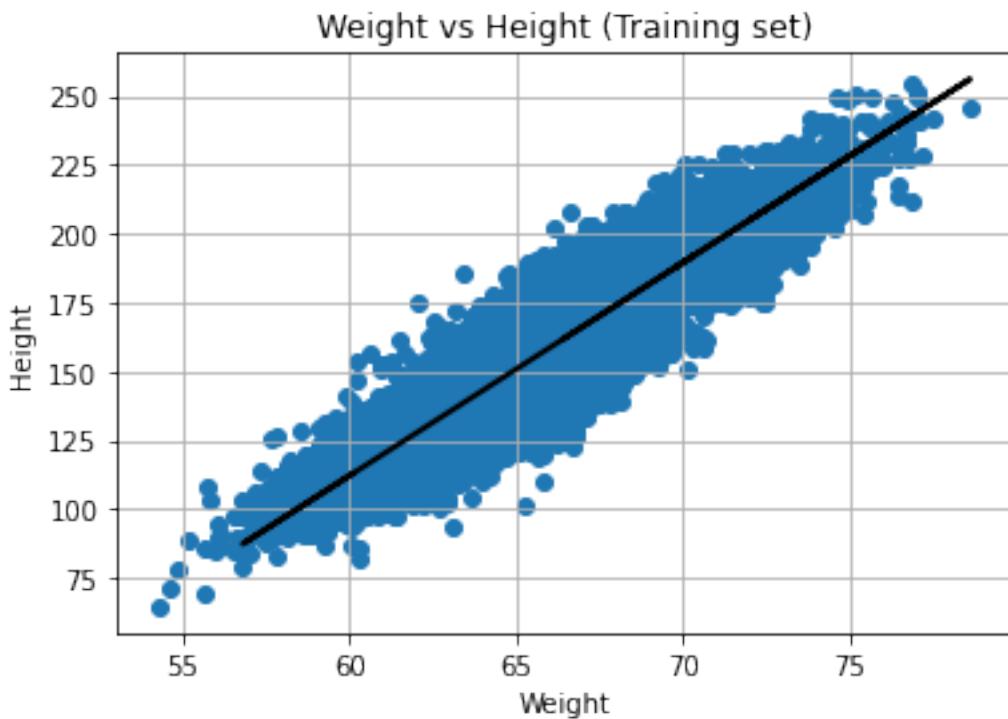
```
[19]: LinearRegression()
```

Predict the training set.

```
[20]: y_pred = w_h_regressor.predict(X_train)
```

Display the training set results

```
[21]: plt.scatter(X_train, y_train)
plt.plot(X_train, y_pred, color='black', linewidth=2)
plt.title('Weight vs Height (Training set)')
plt.xlabel('Weight')
plt.ylabel('Height')
plt.grid()
```

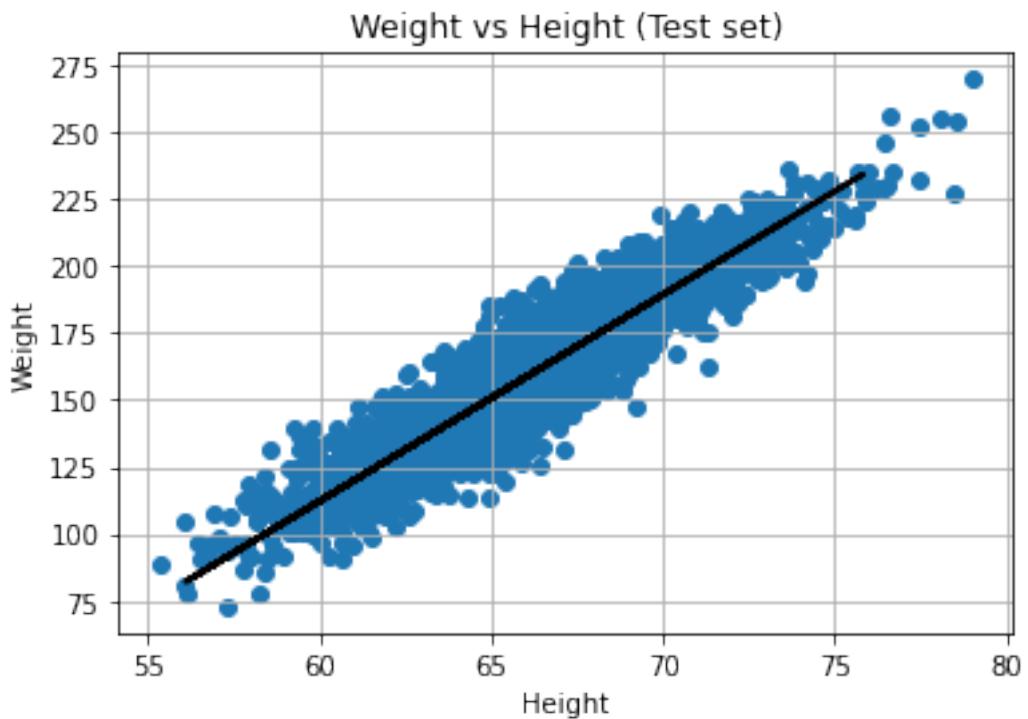


Predict the test set.

```
[22]: y_pred = w_h_regressor.predict(X_test)
```

Display the test set results.

```
[23]: plt.scatter(X_test, y_test)
plt.plot(X_test, y_pred, color='black', linewidth=2)
plt.title('Weight vs Height (Test set)')
plt.xlabel('Height')
plt.ylabel('Weight')
plt.grid()
```



Overall evaluation of the model

```
[24]: print('Coefficients: ', w_h_regressor.coef_)
```

Coefficients: [7.72896259]

The mean squared error

```
[25]: print('Mean squared error is {}'.format(np.mean((y_pred - y_test)** 2)))
```

Mean squared error is 143.22556010111649.

The more variance score approaches to 1, the more perfect is the prediction.

```
[26]: print('Variance score is {}'.format(w_h_regressor.score(X_test, y_test)))
```

Variance score is 0.8649031737206692.

# 3 | KNN for Classification

|                       |            |       |       |
|-----------------------|------------|-------|-------|
| <b>Student's name</b> | .....      | ..... | ..... |
|                       | .....      | ..... | ..... |
| <b>Score</b>          | <b>/20</b> | ..... | ..... |

## Detailed Credits

|                                  |       |       |       |
|----------------------------------|-------|-------|-------|
| <b>Anticipation (4 points)</b>   | ..... | ..... | ..... |
| <b>Management (2 points)</b>     | ..... | ..... | ..... |
| <b>Testing (7 points)</b>        | ..... | ..... | ..... |
| <b>Data Logging (3 points)</b>   | ..... | ..... | ..... |
| <b>Interpretation (4 points)</b> | ..... | ..... | ..... |



The notebook is available at <https://github.com/a-mhamdi/cosnip/> → Python → ml → clf-knn.ipynb

Load the necessary python modules

```
[1]: import numpy as np
 import pandas as pd
 import matplotlib.pyplot as plt
```

Load the datasets

```
[2]: df = pd.read_csv('./datasets/Diabetes.csv')
```

Print the first 5 rows of the dataframe.

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

|   | Pregnancies | Glucose | Diastolic | Triceps | Insulin | BMI  | DPF   | Age | \ |
|---|-------------|---------|-----------|---------|---------|------|-------|-----|---|
| 0 | 6           | 148     | 72        | 35      | 0       | 33.6 | 0.627 | 50  |   |
| 1 | 1           | 85      | 66        | 29      | 0       | 26.6 | 0.351 | 31  |   |
| 2 | 8           | 183     | 64        | 0       | 0       | 23.3 | 0.672 | 32  |   |
| 3 | 1           | 89      | 66        | 23      | 94      | 28.1 | 0.167 | 21  |   |
| 4 | 0           | 137     | 40        | 35      | 168     | 43.1 | 2.288 | 33  |   |

|   | Diabetes |
|---|----------|
| 0 | 1        |
| 1 | 0        |

```
2 1
3 0
4 1
```

Let's observe the shape of the dataframe.

```
[4]: df.shape
```

```
[4]: (768, 9)
```

Let's extract the features and target as numpy arrays.

```
[5]: X = df.drop('Diabetes', axis=1).values
y = df['Diabetes'].values
```

Split the data into two sets: train and test. We begin by importing the `train_test_split` from `sklearn` module.

```
[6]: from sklearn.model_selection import train_test_split
```

```
[7]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.
 ↪4, random_state=42, stratify=y)
```

It is time now to create a classifier using k-Nearest Neighbors algorithm. At first, the class `KNeighborsClassifier` has to be loaded.

```
[8]: from sklearn.neighbors import KNeighborsClassifier
```

```
[9]: # Setup arrays to store training and test accuracies
neighbors = np.arange(1,9)
train_accuracy = np.empty(len(neighbors))
test_accuracy = np.empty(len(neighbors))

for i,k in enumerate(neighbors):
 # Setup a knn classifier with k neighbors
 knn = KNeighborsClassifier(n_neighbors=k)

 # Fit the model
 knn.fit(X_train, y_train)

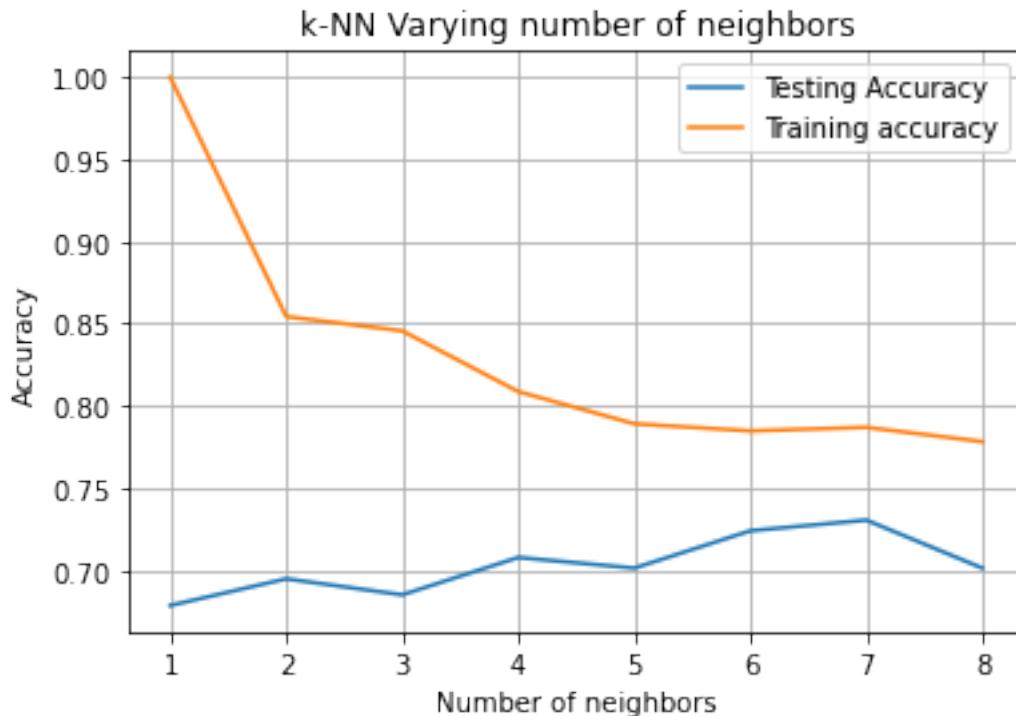
 # Compute accuracy on the training set
 train_accuracy[i] = knn.score(X_train, y_train)

 # Compute accuracy on the test set
 test_accuracy[i] = knn.score(X_test, y_test)
```

Generate some plots to see which number of neighbors is well suited for the classification task.

```
[10]: plt.title('k-NN Varying number of neighbors')
plt.plot(neighbors, test_accuracy, label='Testing Accuracy')
plt.plot(neighbors, train_accuracy, label='Training accuracy')
plt.legend()
```

```
plt.xlabel('Number of neighbors')
plt.ylabel('Accuracy')
plt.grid()
```



As shown above, 7 neighbors seem to be a suitable choice. So, let's setup a knn classifier with only  $k = 7$  neighbors.

```
[11]: knn = KNeighborsClassifier(n_neighbors=7)
```

Fit the model.

```
[12]: knn.fit(X_train,y_train)
```

```
[12]: KNeighborsClassifier(n_neighbors=7)
```

It is always a good manner to gather some score metrics.

```
[13]: knn.score(X_test,y_test)
```

```
[13]: 0.7305194805194806
```

```
Import confusion_matrix
```

```
[14]: from sklearn.metrics import confusion_matrix
```

Let's make some predictions using the classifier we built earlier.

```
[15]: y_pred = knn.predict(X_test)
```

```
[16]: confusion_matrix(y_test,y_pred)
```

```
[16]: array([[165, 36],
 [47, 60]])
```

A fancy way to display the confusion matrix, is to use the `crosstab` method.

```
[17]: pd.crosstab(y_test, y_pred, rownames=['True'], colnames=['Predicted'], margins=True)
```

```
[17]: Predicted 0 1 All
True
0 165 36 201
1 47 60 107
All 212 96 308
```

By importing `classification_report`, we can get some insights on how the model behaves.

```
[18]: from sklearn.metrics import classification_report
```

As a reminder, **F1-Score**, **Accuracy**, **Recall** and **Precision** are calculated as follow:

$$f1\text{-score} = \frac{2}{\frac{1}{\text{Recall}} + \frac{1}{\text{Precision}}}$$

$f1\text{-score}$  denotes the *Harmonic Mean of Recall & Precision*

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}}$$

It denotes the ratio of how much we got right over all cases. Recall, on the other hand, designates the ratio of how much positives do we got right over all actual positive cases.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

Precision, at last, is how much positives we got right over all positive predictions. It is given by:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

```
[19]: print(classification_report(y_test,y_pred))
```

|              | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0            | 0.78      | 0.82   | 0.80     | 201     |
| 1            | 0.62      | 0.56   | 0.59     | 107     |
| accuracy     |           |        | 0.73     | 308     |
| macro avg    | 0.70      | 0.69   | 0.70     | 308     |
| weighted avg | 0.73      | 0.73   | 0.73     | 308     |

## 4 | K-Means for Clustering

|                       |            |       |       |
|-----------------------|------------|-------|-------|
| <b>Student's name</b> | .....      | ..... | ..... |
|                       | .....      | ..... | ..... |
| <b>Score</b>          | <b>/20</b> | ..... | ..... |

### Detailed Credits

|                                  |       |       |       |
|----------------------------------|-------|-------|-------|
| <b>Anticipation (4 points)</b>   | ..... | ..... | ..... |
| <b>Management (2 points)</b>     | ..... | ..... | ..... |
| <b>Testing (7 points)</b>        | ..... | ..... | ..... |
| <b>Data Logging (3 points)</b>   | ..... | ..... | ..... |
| <b>Interpretation (4 points)</b> | ..... | ..... | ..... |



The notebook is available at <https://github.com/a-mhamdi/cosnip/> → Python → ml → clu-k-means.ipynb

```
[1]: import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

Let's begin by loading the *Mall\_Customers* datasets.

```
[2]: df = pd.read_csv('./datasets/Mall_Customers.csv')
```

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

```
[3]: CustomerID Genre Age Annual Income (k$) Spending Score (1-100)
0 1 Male 19 15 39
1 2 Male 21 15 81
2 3 Female 20 16 6
3 4 Female 23 16 77
4 5 Female 31 17 40
```

Renaming some columns is very handy for further data manipulation.

```
[4]: df.rename(columns={'Annual Income (k$)': 'Income', 'Spending Score (1-100)': 'Spending Score'}, inplace=True)
```

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

```
[5]: CustomerID Genre Age Income Spending Score
 0 1 Male 19 15 39
 1 2 Male 21 15 81
 2 3 Female 20 16 6
 3 4 Female 23 16 77
 4 5 Female 31 17 40
```

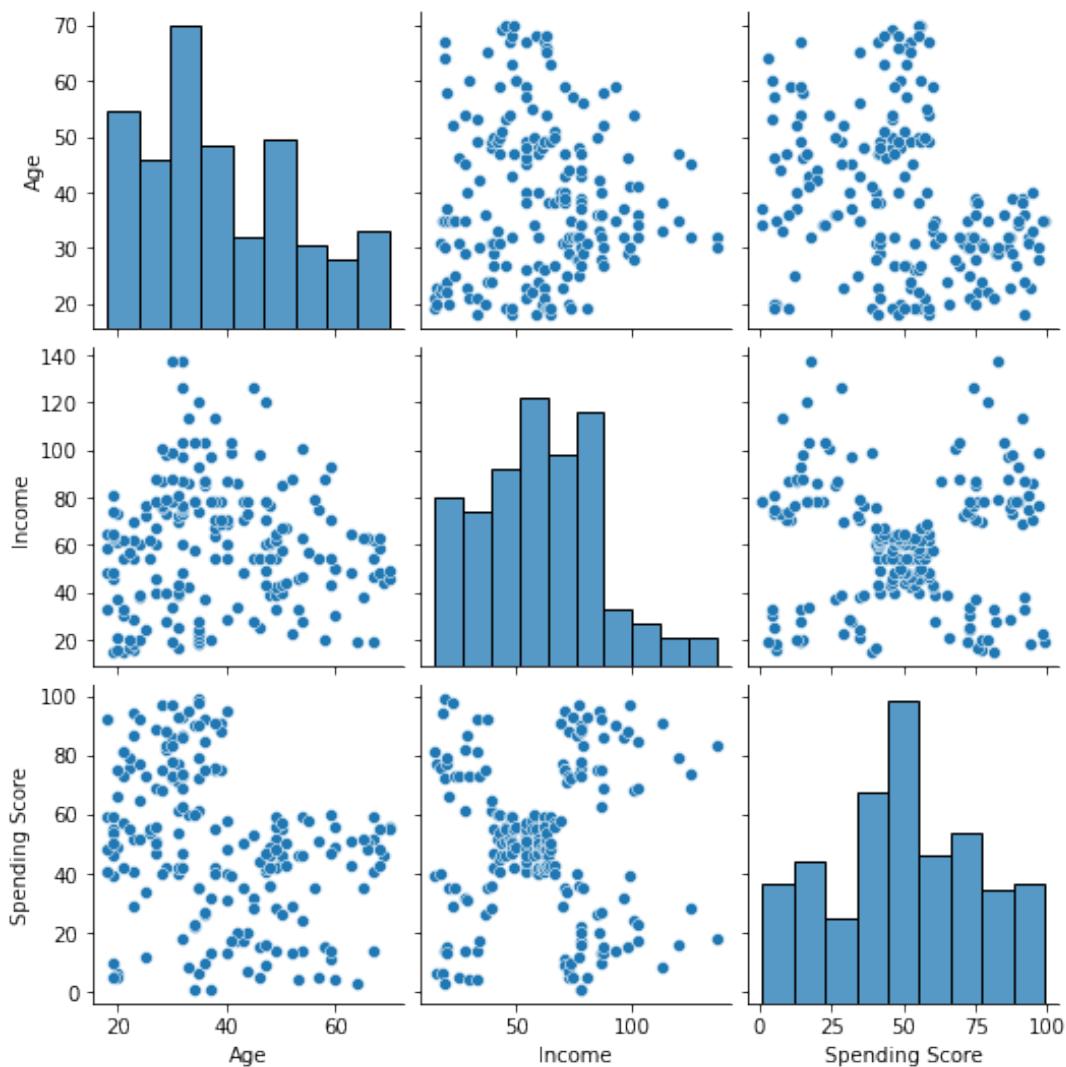
`df.describe()` allows to get useful insights from data.

```
[6]: df.describe()
```

```
[6]: CustomerID Age Income Spending Score
count 200.000000 200.000000 200.000000 200.000000
mean 100.500000 38.850000 60.560000 50.200000
std 57.879185 13.969007 26.264721 25.823522
min 1.000000 18.000000 15.000000 1.000000
25% 50.750000 28.750000 41.500000 34.750000
50% 100.500000 36.000000 61.500000 50.000000
75% 150.250000 49.000000 78.000000 73.000000
max 200.000000 70.000000 137.000000 99.000000
```

Check the correlation between *Age*, *Income* and *Spending Score*.

```
[7]: sns.pairplot(df[['Age', 'Income', 'Spending Score']])
```



```
[8]: from sklearn import cluster
```

We will perform **K-Means** Clustering with 5 clusters using only 2 Variables.

```
[9]: clu_k = cluster.KMeans(n_clusters=5 ,init="k-means++")
```

```
[10]: clu_k = clu_k.fit(df[['Spending Score','Income']])
```

Coordinates of the centers.

```
[11]: clu_k.cluster_centers_
```

```
[11]: array([[49.51851852, 55.2962963],
 [82.12820513, 86.53846154],
 [17.11428571, 88.2],
 [79.36363636, 25.72727273],
 [20.91304348, 26.30434783]])
```

```
[12]: df['Clusters'] = clu_k.labels_
```

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

```
[13]: CustomerID Genre Age Income Spending Score Clusters
0 1 Male 19 15 39 4
1 2 Male 21 15 81 3
2 3 Female 20 16 6 4
3 4 Female 23 16 77 3
4 5 Female 31 17 40 4
```

```
[14]: df['Clusters'].value_counts()
```

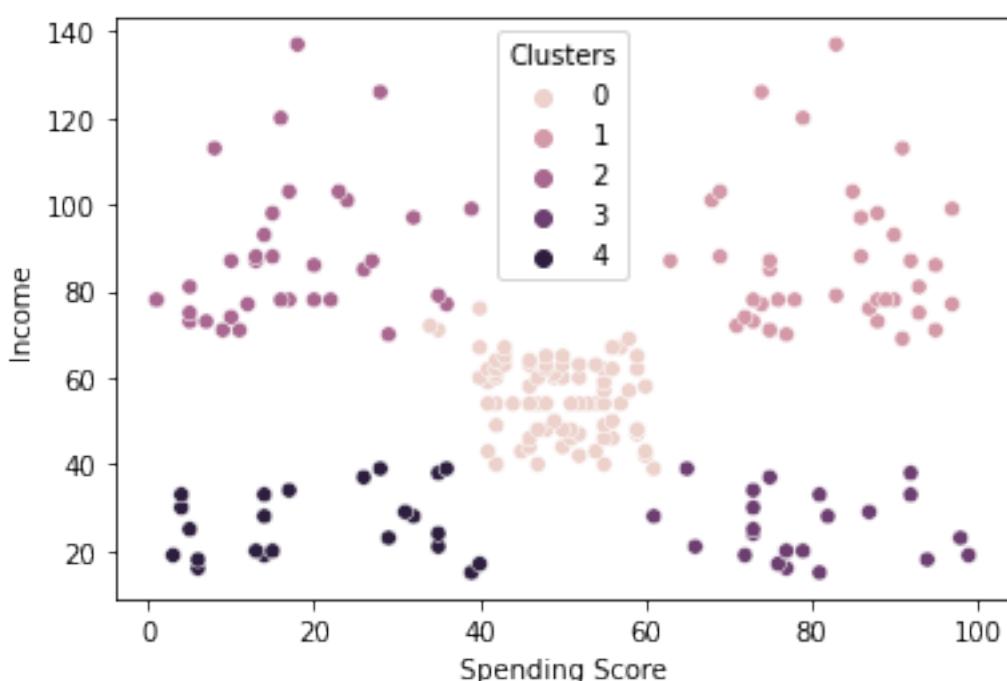
```
[14]: 0 81
1 39
2 35
4 23
3 22
Name: Clusters, dtype: int64
```

Let's save the new data frame to a new file.

```
[15]: df.to_csv('./datasets/Mall_Clusters.csv', index = False)
```

Plot the 5 clusters on a chart.

```
[16]: sns.scatterplot(x="Spending Score", y="Income", hue='Clusters', data=df)
```



# 5 | Binary Classifier using ANN

|                       |            |       |       |
|-----------------------|------------|-------|-------|
| <b>Student's name</b> | .....      | ..... | ..... |
|                       | .....      | ..... | ..... |
| <b>Score</b>          | <b>/20</b> | ..... | ..... |

**Detailed Credits**

|                                  |       |       |       |
|----------------------------------|-------|-------|-------|
| <b>Anticipation (4 points)</b>   | ..... | ..... | ..... |
| <b>Management (2 points)</b>     | ..... | ..... | ..... |
| <b>Testing (7 points)</b>        | ..... | ..... | ..... |
| <b>Data Logging (3 points)</b>   | ..... | ..... | ..... |
| <b>Interpretation (4 points)</b> | ..... | ..... | ..... |



The notebook is available at <https://github.com/a-mhamdi/cosnip/> → Python → ml → clf-ann.ipynb

```
[1]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

Import sklearn.

```
[2]: from sklearn.preprocessing import LabelEncoder, OneHotEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.compose import ColumnTransformer
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
```

Import keras.

```
[3]: from keras.models import Sequential
from keras.layers import Dense
```

Using TensorFlow backend.

Load the data using pandas.

```
[4]: df = pd.read_csv('./datasets/Churn_Modelling.csv')
```

```
[5]: df.head(3)
```

```
[5]: RowNumber CustomerId Surname CreditScore Geography Gender Age \
0 1 15634602 Hargrave 619 France Female 42
1 2 15647311 Hill 608 Spain Female 41
2 3 15619304 Onio 502 France Female 42

 Tenure Balance NumOfProducts HasCrCard IsActiveMember \
0 2 0.00 1 1 1
1 1 83807.86 1 0 1
2 8 159660.80 3 1 0

 EstimatedSalary Exited
0 101348.88 1
1 112542.58 0
2 113931.57 1
```

```
[6]: X = df.iloc[:, 3:13].values
y = df.iloc[:, 13].values

label_encoder_X_country = LabelEncoder()
label_encoder_X_gender = LabelEncoder()

X[:, 1] = label_encoder_X_country.fit_transform(X[:, 1])
X[:, 2] = label_encoder_X_gender.fit_transform(X[:, 2])

one_hot_encoder = ColumnTransformer([("Geography", OneHotEncoder(), [1])], remainder = 'passthrough')

X = one_hot_encoder.fit_transform(X)
X = np.array(X, dtype=float)
X = X[:, 1:]
```

Scale the features.

```
[7]: sc = StandardScaler()
X = sc.fit_transform(X)
```

Split the datasets into training & testing sets.

```
[8]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=0)
```

Define the artificial neural network architecture.

```
[9]: clf_ann = Sequential()
```

Input layer & first hidden layer

```
[10]: num_features = X_train.shape[1]
clf_ann.add(Dense(6, input_shape = (num_features,), activation = 'relu'))
```

Second hidden layer

```
[11]: clf_ann.add(Dense(6, activation = 'relu'))
```

Output layer

```
[12]: num_classes = 1
clf_ann.add(Dense(num_classes, activation = 'sigmoid'))
```

```
[13]: clf_ann.compile('Adam', loss = 'binary_crossentropy', metrics=['accuracy'])
```

An overall description of the neural network architecture.

```
[14]: clf_ann.summary()
```

Model: "sequential\_1"

| Layer (type)    | Output Shape | Param # |
|-----------------|--------------|---------|
| dense_1 (Dense) | (None, 6)    | 72      |
| dense_2 (Dense) | (None, 6)    | 42      |
| dense_3 (Dense) | (None, 1)    | 7       |

Total params: 121  
Trainable params: 121  
Non-trainable params: 0

Fit the classifier.

```
[15]: clf_ann.fit(x=X_train, y=y_train, batch_size=200, epochs=20, verbose=1)
```

```
Epoch 1/20
8000/8000 [=====] - 0s 21us/step - loss: 0.6352 -
accuracy: 0.6734
Epoch 2/20
8000/8000 [=====] - 0s 7us/step - loss: 0.5697 -
accuracy: 0.7575
Epoch 3/20
8000/8000 [=====] - 0s 7us/step - loss: 0.5312 -
accuracy: 0.7881
Epoch 4/20
8000/8000 [=====] - 0s 6us/step - loss: 0.5058 -
accuracy: 0.7961
Epoch 5/20
8000/8000 [=====] - 0s 8us/step - loss: 0.4867 -
accuracy: 0.8001
Epoch 6/20
8000/8000 [=====] - 0s 7us/step - loss: 0.4722 -
accuracy: 0.8020
Epoch 7/20
8000/8000 [=====] - 0s 6us/step - loss: 0.4607 -
accuracy: 0.8037
Epoch 8/20
8000/8000 [=====] - 0s 8us/step - loss: 0.4520 -
```

```
accuracy: 0.8065
Epoch 9/20
8000/8000 [=====] - 0s 9us/step - loss: 0.4454 -
accuracy: 0.8100
Epoch 10/20
8000/8000 [=====] - 0s 9us/step - loss: 0.4405 -
accuracy: 0.8135
Epoch 11/20
8000/8000 [=====] - 0s 7us/step - loss: 0.4366 -
accuracy: 0.8149
Epoch 12/20
8000/8000 [=====] - 0s 7us/step - loss: 0.4336 -
accuracy: 0.8160
Epoch 13/20
8000/8000 [=====] - 0s 7us/step - loss: 0.4310 -
accuracy: 0.8173
Epoch 14/20
8000/8000 [=====] - 0s 5us/step - loss: 0.4287 -
accuracy: 0.8171
Epoch 15/20
8000/8000 [=====] - 0s 5us/step - loss: 0.4270 -
accuracy: 0.8174
Epoch 16/20
8000/8000 [=====] - 0s 5us/step - loss: 0.4255 -
accuracy: 0.8179
Epoch 17/20
8000/8000 [=====] - 0s 5us/step - loss: 0.4240 -
accuracy: 0.8199
Epoch 18/20
8000/8000 [=====] - 0s 5us/step - loss: 0.4229 -
accuracy: 0.8199
Epoch 19/20
8000/8000 [=====] - 0s 5us/step - loss: 0.4215 -
accuracy: 0.8205
Epoch 20/20
8000/8000 [=====] - 0s 6us/step - loss: 0.4202 -
accuracy: 0.8219
```

[15]: <keras.callbacks.callbacks.History at 0x7f46f71cefa0>

Evaluate the model.

[16]: scores = clf\_ann.evaluate(x=X\_test, y=y\_test, batch\_size=100, verbose=1)

```
2000/2000 [=====] - 0s 10us/step
```

Let's predict an output.

[17]: y\_pred = clf\_ann.predict(X\_test)
y\_pred = (y\_pred > 0.5)

Define the confusion matrix.

```
[18]: cm = confusion_matrix(y_test, y_pred)
tp, fp, fn, tn = cm.ravel()
```

```
[19]: print('Accuracy is about {}%.' .format(100*(tp+tn)/sum((sum(cm)))))
```

Accuracy is about 83.2%.

```
[20]: print('\n
The loss value is: {}.\n\n\
The accuracy percentage is: {}%.' .format(scores[0], 100*scores[1]))
```

The loss value is: 0.4155806913971901.

The accuracy percentage is: 83.20000171661377%.

# 6 | Handwritten Digit Recognition

|                       |            |       |       |
|-----------------------|------------|-------|-------|
| <b>Student's name</b> | .....      | ..... | ..... |
|                       | .....      | ..... | ..... |
| <b>Score</b>          | <b>/20</b> | ..... | ..... |

**Detailed Credits**

|                                  |       |       |       |
|----------------------------------|-------|-------|-------|
| <b>Anticipation (4 points)</b>   | ..... | ..... | ..... |
| <b>Management (2 points)</b>     | ..... | ..... | ..... |
| <b>Testing (7 points)</b>        | ..... | ..... | ..... |
| <b>Data Logging (3 points)</b>   | ..... | ..... | ..... |
| <b>Interpretation (4 points)</b> | ..... | ..... | ..... |



The notebook is available at <https://github.com/a-mhamdi/cosnip/> → Python → ml → mnist-cnn.ipynb

Let's begin with importing all the required libraries.

```
[1]: import os

import numpy as np
from matplotlib import pyplot as plt

import tensorflow as tf

from keras.datasets import mnist
from keras.models import Sequential
from keras.layers import Dense, Dropout, Flatten
from keras.layers.convolutional import Conv2D, MaxPooling2D

from keras.utils import np_utils
from keras.models import model_from_json

from PIL import Image
```

Using TensorFlow backend.

```
[2]: import keras.backend.tensorflow_backend as tfback
from keras import backend as K
```

Check the current installed version of tensorflow and keras.

```
[3]: print("tf.__version__ is", tf.__version__)
print("tf.keras.__version__ is:", tf.keras.__version__)
```

```
tf.__version__ is 2.2.0
tf.keras.__version__ is: 2.3.0-tf
```

The following method allows to get a list of available **GPU** devices, formatted as strings.

```
[4]: def _get_available_gpus():
 #global _LOCAL_DEVICES
 if tfback._LOCAL_DEVICES is None:
 devices = tf.config.list_logical_devices()
 tfback._LOCAL_DEVICES = [x.name for x in devices]
 return [x for x in tfback._LOCAL_DEVICES if 'device:gpu' in x.lower()]
```

```
[5]: tfback._get_available_gpus = _get_available_gpus
```

```
[6]: # K.image_data_format() == 'channels_first'
K.set_image_dim_ordering('tf')
K.set_image_data_format('channels_last') # tf: TensorFlow, th: Theano
```

Fix random seed for reproducibility.

```
[7]: np.random.seed(0)
```

Load and normalize the data.

```
[8]: (X_train, y_train), (X_test, y_test) = mnist.load_data()
```

```
[9]: '''
img_idx = np.random.randint(0, high=X_test.shape[0])
plt.imshow(X_train[img_idx, :, :], cmap=plt.cm.gray_r,
 interpolation="nearest")
plt.show()
print("The output is {}".format(y_train[img_idx]))
'''
```

```
[9]: \nimg_idx = np.random.randint(0,
high=X_test.shape[0])\nplt.imshow(X_train[img_idx, :, :], cmap=plt.cm.gray_r,
interpolation="nearest")\nplt.show()\nprint("The output is\n{}.\n".format(y_train[img_idx]))\n'
```

```
[10]: num_samples_train = np.random.randint(0, high=X_train.shape[0], size=20000)
X_train = X_train[num_samples_train, :, :]
y_train = y_train[num_samples_train]
```

```
[11]: num_samples_test = np.random.randint(0, high=X_test.shape[0], size=4000)
X_test = X_test[num_samples_test, :, :]
y_test = y_test[num_samples_test]
```

Reshape the inputs.

```
[12]: X_train = X_train.reshape(X_train.shape[0], 28, 28, 1).astype('float32')
X_test = X_test.reshape(X_test.shape[0], 28, 28, 1).astype('float32')
```

Normalize the inputs from 0 → 255 to 0 → 1.

```
[13]: X_train = X_train/255
X_test = X_test/255
```

One hot encode the outputs.

```
[14]: y_train = np_utils.to_categorical(y_train)
y_test = np_utils.to_categorical(y_test)
```

Number of classes is 10.

```
[15]: num_classes = y_test.shape[1]
```

It is time now to define and build the model.

```
[16]: my_model = Sequential()
my_model.add(Conv2D(16, (5,5), input_shape=(28,28,1), activation='relu'))
my_model.add(MaxPooling2D(pool_size=(2,2)))
my_model.add(Conv2D(32, (3,3), activation='relu'))
my_model.add(MaxPooling2D(pool_size=(2,2)))
my_model.add(Dropout(0.2))
my_model.add(Flatten())
Fully Connected NN
my_model.add(Dense(128, activation='relu'))
my_model.add(Dense(50, activation='relu'))
my_model.add(Dense(num_classes, activation='softmax'))
```

```
[17]: my_model.summary()
```

Model: "sequential\_1"

| Layer (type)                   | Output Shape       | Param # |
|--------------------------------|--------------------|---------|
| conv2d_1 (Conv2D)              | (None, 24, 24, 16) | 416     |
| max_pooling2d_1 (MaxPooling2D) | (None, 12, 12, 16) | 0       |
| conv2d_2 (Conv2D)              | (None, 10, 10, 32) | 4640    |
| max_pooling2d_2 (MaxPooling2D) | (None, 5, 5, 32)   | 0       |
| dropout_1 (Dropout)            | (None, 5, 5, 32)   | 0       |
| flatten_1 (Flatten)            | (None, 800)        | 0       |
| dense_1 (Dense)                | (None, 128)        | 102528  |
| dense_2 (Dense)                | (None, 50)         | 6450    |

```

dense_3 (Dense) (None, 10) 510
=====
Total params: 114,544
Trainable params: 114,544
Non-trainable params: 0

 • List of losses
 • List of optimizers
 • List of metrics

```

[18]: `my_model.compile(loss='categorical_crossentropy', optimizer='adam',  
→metrics=['accuracy'])`

Fit the model.

[19]: `r = my_model.fit(x=X_train, y=y_train, validation_data=(X_test, y_test),  
→epochs=5, batch_size=100)  
  
print("Returned:", r)`

```

Train on 20000 samples, validate on 4000 samples
Epoch 1/5
20000/20000 [=====] - 4s 222us/step - loss: 0.5177 -
accuracy: 0.8479 - val_loss: 0.1281 - val_accuracy: 0.9657
Epoch 2/5
20000/20000 [=====] - 4s 186us/step - loss: 0.1278 -
accuracy: 0.9622 - val_loss: 0.0762 - val_accuracy: 0.9753
Epoch 3/5
20000/20000 [=====] - 4s 195us/step - loss: 0.0855 -
accuracy: 0.9735 - val_loss: 0.0746 - val_accuracy: 0.9735
Epoch 4/5
20000/20000 [=====] - 4s 193us/step - loss: 0.0656 -
accuracy: 0.9794 - val_loss: 0.0619 - val_accuracy: 0.9812
Epoch 5/5
20000/20000 [=====] - 4s 195us/step - loss: 0.0528 -
accuracy: 0.9837 - val_loss: 0.0526 - val_accuracy: 0.9810
Returned: <keras.callbacks.callbacks.History object at 0x7f89f0259d30>

```

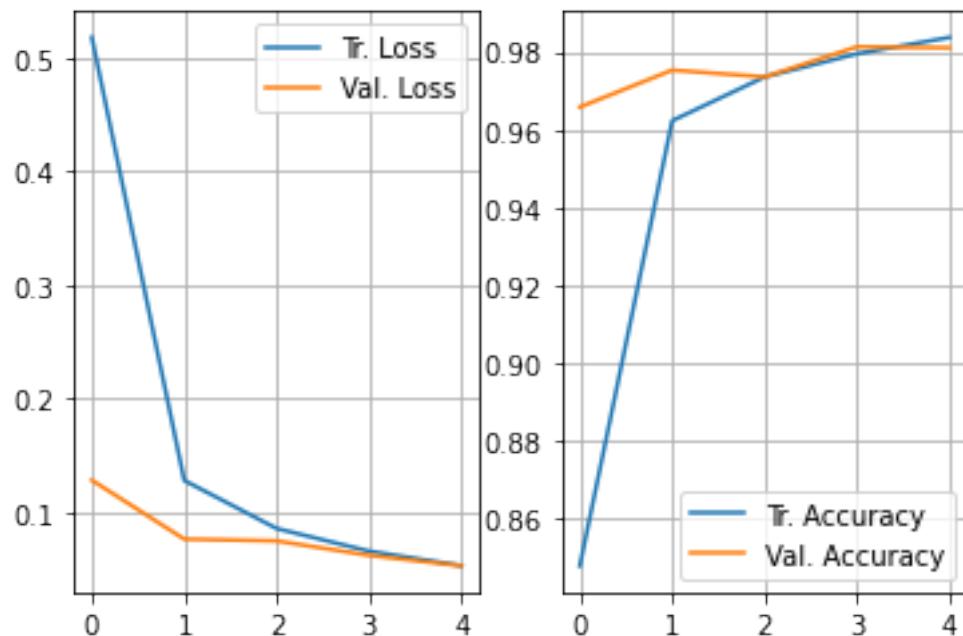
By printing the available keys, we should see: `dict_keys(['val_loss', 'val_accuracy', 'loss', 'accuracy'])`.

[20]: `print(r.history.keys())`

```
dict_keys(['val_loss', 'val_accuracy', 'loss', 'accuracy'])
```

[21]: `# Losses  
plt.subplot(1, 2, 1)  
plt.plot(r.history['loss'], label='Tr. Loss')  
plt.plot(r.history['val_loss'], label='Val. Loss')  
plt.grid()  
plt.legend()`

```
Accuracies
plt.subplot(1, 2, 2)
plt.plot(r.history['accuracy'], label='Tr. Accuracy')
plt.plot(r.history['val_accuracy'], label='Val. Accuracy')
plt.grid()
plt.legend()
```



Evaluate the model.

```
[22]: scores = my_model.evaluate(X_test, y_test, verbose=0)
print("CNN error: {}%".format(100*(1-scores[1])))
```

CNN error: 1.8999993801116943%

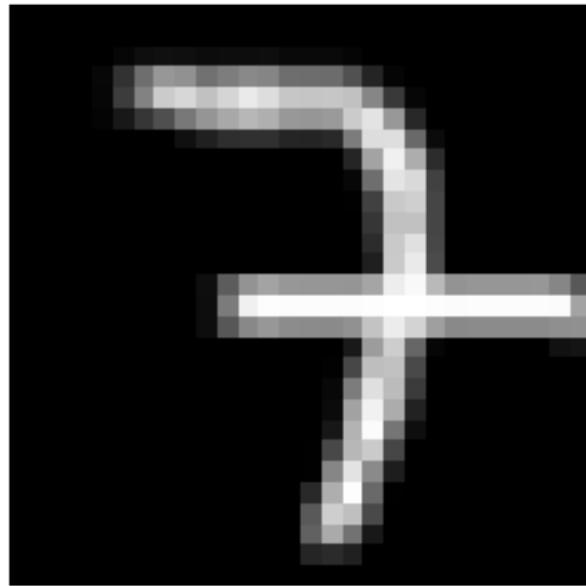
Test the model.

```
[23]: img = Image.open('to-test/7.png');
img = img.convert('L')
img = img.resize((28, 28))

array_img = (np.array(img))/255
in_data = array_img.reshape((1, 28, 28, 1)).astype('float32')

plt.imshow(array_img*255, cmap=plt.cm.gray_r, interpolation="nearest")
plt.axis('Off')
```

```
[23]: (-0.5, 27.5, 27.5, -0.5)
```



```
[24]: y_pred = my_model.predict(in_data)
_, idx = np.where(y_pred == np.max(y_pred))
print("Result is {}. Probability is {}%.".format(int(idx), 100*y_pred[0,int(idx)]))
```

Result is 7. Probability is 59.57772135734558%.



The overall scope of this manual is to introduce **Machine Learning**, through some numeric simulations, to the students at the department of **Electrical Engineering**.

The topics discussed in this manuscript are as follow:

- ① Getting started with Python
- ② Linear Regression
- ③ Classification
- ④ Clustering
- ⑤ CNN

Python; Jupyter; NumPy; Matplotlib; scikit-learn; machine learning; linear regression; classification; clustering; deep learning.