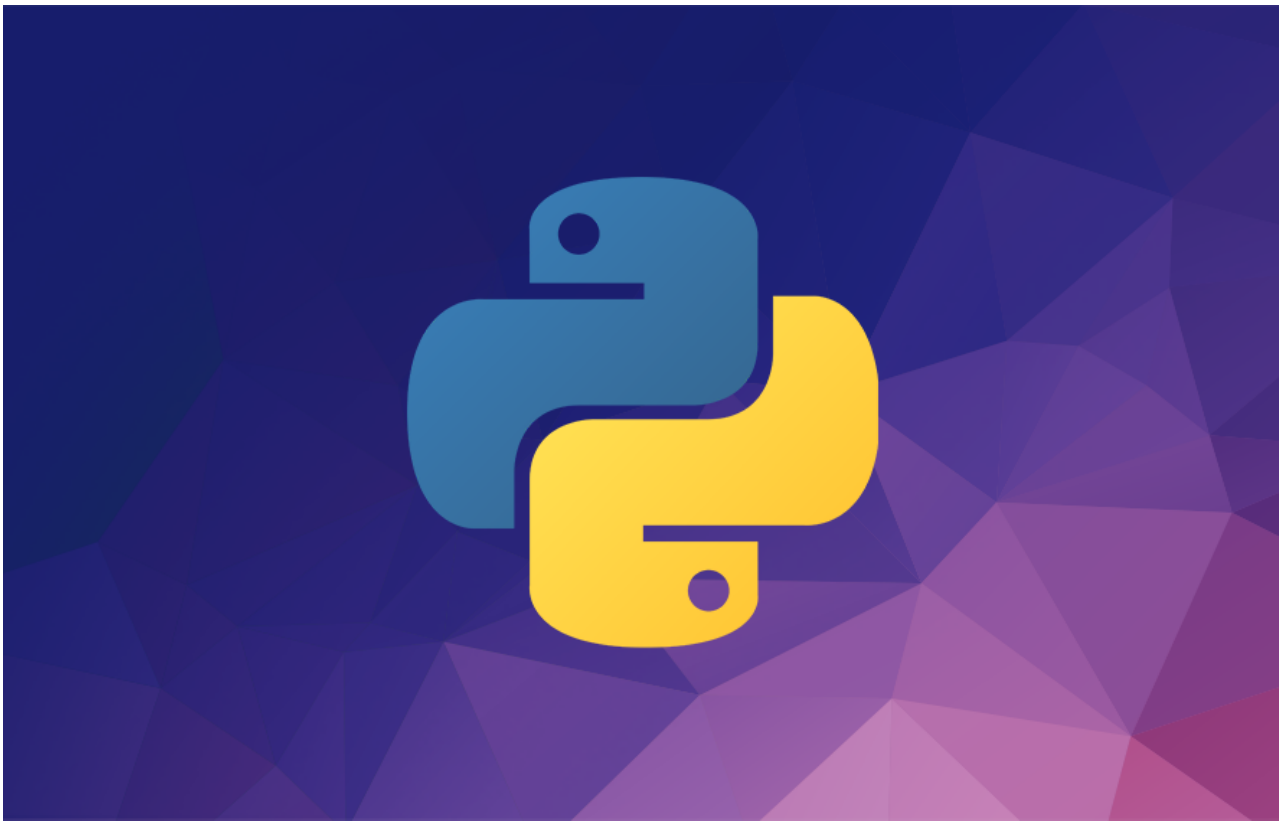
Python Cheat Sheet

Mosh Hamedani



Code with Mosh (codewithmosh.com)

1st Edition

About this Cheat Sheet

This cheat sheet includes the materials I've covered in my Python tutorial for Beginners on YouTube. Both the YouTube tutorial and this cheat cover the core language constructs but they are not complete by any means.

If you want to learn everything Python has to offer and become a Python expert, check out my Complete Python Programming Course:

http://bit.ly/complete-python-course

About the Author

Hi! My name is Mosh Hamedani. I'm a software engineer with two decades of experience and I've taught over three million how to code or how to become a professional software engineer. It's my mission to make software engineering simple and accessible to everyone.

https://codewithmosh.com

https://youtube.com/user/programmingwithmosh

https://twitter.com/moshhamedani

https://facebook.com/programmingwithmosh/

Variables

We use variables to temporarily store data in computer's memory.

```
price = 10

rating = 4.9

course_name = 'Python for Beginners'

is_published = True
```

In the above example,

- **price** is an *integer* (a whole number without a decimal point)
- **rating** is a *float* (a number with a decimal point)
- **course_name** is a *string* (a sequence of characters)
- **is_published** is a *boolean*. Boolean values can be True or False.

Comments

We use comments to add notes to our code. Good comments explain the hows and whys, not what the code does. That should be reflected in the code itself. Use comments to add reminders to yourself or other developers, or also explain your assumptions and the reasons you've written code in a certain way.

```
# This is a comment and it won't get executed.
# Our comments can be multiple lines.
```

Receiving Input

We can receive input from the user by calling the **input()** function.

```
birth_year = int(input('Birth year: '))
```

The **input()** function always returns data as a string. So, we're converting the result into an integer by calling the built-in **int()** function.

Strings

We can define strings using single (‘ ‘) or double (“ “) quotes.

To define a multi-line string, we surround our string with tripe quotes (“””).

We can get individual characters in a string using square brackets [].

```
course = ‘Python for Beginners’
course[0]   # returns the first character
course[1]   # returns the second character
course[-1]  # returns the first character from the end
course[-2]  # returns the second character from the end
```

We can slice a string using a similar notation:

```
course[1:5]
```

The above expression returns all the characters starting from the index position of 1 to 5 (but excluding 5). The result will be **ytho**

If we leave out the start index, 0 will be assumed.

If we leave out the end index, the length of the string will be assumed.

We can use formatted strings to dynamically insert values into our strings:

```
name = ‘Mosh’

message = f’Hi, my name is {name}’


message.upper()   # to convert to uppercase

message.lower()   # to convert to lowercase

message.title()   # to capitalize the first letter of every word

message.find(‘p’) # returns the index of the first occurrence of p
                   (or -1 if not found)

message.replace(‘p’, ‘q’)
```

To check if a string contains a character (or a sequence of characters), we use the **in** operator:

```
contains = 'Python' in course
```

Arithmetic Operations

```
+

-

*

/     # returns a float

//    # returns an int

%     # returns the remainder of division

**    # exponentiation - x ** y = x to the power of y
```

Augmented assignment operator:

```
x = x + 10

x += 10
```

Operator precedence:

1. parenthesis
2. exponentiation
3. multiplication / division
4. addition / subtraction

If Statements

```
if is_hot:
    print("hot day")
elif is_cold:
    print("cold day")
else:
    print("beautiful day")
```

Logical operators:

```
if has_high_income and has_good_credit:
    ...
if has_high_income or has_good_credit:
    ...
is_day = True
is_night = not is_day
```

Comparison operators

```
a > b
a >= b (greater than or equal to)
a < b
a <= b
a == b (equals)
a != b (not equals)
```

While loops

```
i = 1
while i < 5:
    print(i)
    i += 1
```

For loops

```
for i in range(1, 5):
    print(i)
```

- **range(5):** generates 0, 1, 2, 3, 4
- **range(1, 5):** generates 1, 2, 3, 4
- **range(1, 5, 2):** generates 1, 3

Lists

```
numbers = [1, 2, 3, 4, 5]
numbers[0]            # returns the first item
numbers[1]            # returns the second item
numbers[-1]           # returns the first item from the end
numbers[-2]           # returns the second item from the end


numbers.append(6)     # adds 6 to the end
numbers.insert(0, 6) # adds 6 at index position of 0
numbers.remove(6)     # removes 6
numbers.pop()         # removes the last item
numbers.clear()       # removes all the items
numbers.index(8)      # returns the index of first occurrence of 8
numbers.sort()        # sorts the list
numbers.reverse()     # reverses the list
numbers.copy()        # returns a copy of the list
```

Tuples

They are like read-only lists. We use them to store a list of items. But once we define a tuple, we cannot add or remove items or change the existing items.

```
coordinates = (1, 2, 3)
```

We can unpack a list or a tuple into separate variables:

```
x, y, z = coordinates
```

Dictionaries

We use dictionaries to store key/value pairs.

```
customer = {
    "name": "John Smith",
    "age": 30,
    "is_verified": True
}
```

We can use strings or numbers to define keys. They should be unique. We can use any types for the values.

```
customer["name"]                # returns "John Smith"
customer["type"]                # throws an error
customer.get("type", "silver") # returns "silver"
customer["name"] = "new name"
```

Functions

We use functions to break up our code into small chunks. These chunks are easier to read, understand and maintain. If there are bugs, it's easier to find bugs in a small chunk than the entire program. We can also re-use these chunks.

```
def greet_user(name):
    print(f"Hi {name}")


greet_user("John")
```

Parameters are placeholders for the data we can pass to functions. **Arguments** are the actual values we pass.

We have two types of arguments:

- Positional arguments: their position (order) matters
- Keyword arguments: position doesn't matter - we prefix them with the parameter name.

```
# Two positional arguments
greet_user("John", "Smith")

# Keyword arguments
calculate_total(order=50, shipping=5, tax=0.1)
```

Our functions can return values. If we don't use the return statement, by default **None** is returned. None is an object that represents the absence of a value.

```
def square(number):
    return number * number

result = square(2)
print(result)  # prints 4
```

Exceptions

Exceptions are errors that crash our programs. They often happen because of bad input or programming errors. It's our job to anticipate and handle these exceptions to prevent our programs from cashing.

```
try:
    age = int(input('Age: '))
    income = 20000
    risk = income / age
    print(age)
except ValueError:
    print('Not a valid number')
except ZeroDivisionError:
    print('Age cannot be 0')
```

Classes

We use classes to define new types.

```
class Point:
    def __init__(self, x, y):
        self.x = x
        self.y = y
    def move(self):
        print("move")
```

When a function is part of a class, we refer to it as a **method**.

Classes define templates or blueprints for creating objects. An object is an instance of a class. Every time we create a new instance, that instance follows the structure we define using the class.

```
point1 = Point(10, 5)
point2 = Point(2, 4)
```

__init__ is a special method called constructor. It gets called at the time of creating new objects. We use it to initialize our objects.

Inheritance

Inheritance is a technique to remove code duplication. We can create a *base class* to define the common methods and then have other classes inherit these methods.

```
class Mammal:
  def walk(self):
     print("walk")

class Dog(Mammal):
  def bark(self):
     print("bark")


dog = Dog()
dog.walk()   # inherited from Mammal
dog.bark()   # defined in Dog
```

Modules

A module is a file with some Python code. We use modules to break up our program into multiple files. This way, our code will be better organized. We won't have one gigantic file with a million lines of code in it!

There are 2 ways to import modules: we can import the entire module, or specific objects in a module.

```
# importing the entire converters module
import converters
converters.kg_to_lbs(5)

# importing one function in the converters module
from converters import kg_to_lbs
kg_to_lbs(5)
```

Packages

A package is a directory with **__init__.py** in it. It can contain one or more modules.

```
# importing the entire sales module
from ecommerce import sales
sales.calc_shipping()

# importing one function in the sales module
from ecommerce.sales import calc_shipping
calc_shipping()
```

Python Standard Library

Python comes with a huge library of modules for performing common tasks such as sending emails, working with date/time, generating random values, etc.

Random Module

```
import random

random.random()       # returns a float between 0 to 1
random.randint(1, 6)  # returns an int between 1 to 6

members = ['John', 'Bob', 'Mary']
leader = random.choice(members) # randomly picks an item
```

Pypi

Python Package Index (pypi.org) is a directory of Python packages published by Python developers around the world. We use **pip** to install or uninstall these packages.

```
pip install openpyxl
```

```
pip uninstall openpyxl
```

Want to Become a Python Expert?

If you're serious about learning Python and getting a job as a Python developer, I highly encourage you to enroll in my Complete Python Course. Don't waste your time following disconnected, outdated tutorials. My Complete Python Course has everything you need in one place:

- 12 hours of HD video
- Unlimited access - watch it as many times as you want
- Self-paced learning - take your time if you prefer
- Watch it online or download and watch offline
- Certificate of completion - add it to your resume to stand out
- 30-day money-back guarantee - no questions asked

The price for this course is $149 but the first 200 people who have downloaded this cheat sheet can get it for $14.99 using the coupon code **CHEATSHEET**:

http://bit.ly/complete-python-course

datacamp

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
>>> ax3 = 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[1,0].barh([0.5,1,2.5],[0,1,2]) #Plot horiontal 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

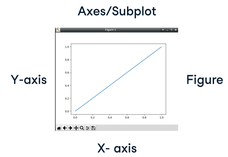
```
>>> axes[0,1].arrow(0,0,0.5,0.5) #Add an arrow to the axes
>>> axes[1,1].quiver(y,z) #Plot a 2D field of arrows
>>> axes[0,1].streamplot(X,Y,U,V) #Plot a 2D field of arrows
```

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, x**2, x, x**3)
>>> 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**2,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
```

datacamp

Python For Data Science
NumPy Cheat Sheet

Learn NumPy online at www.DataCamp.com

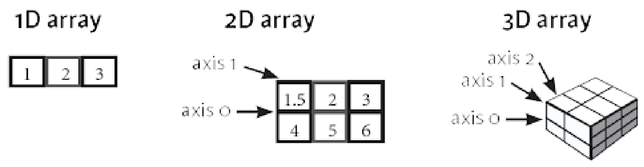
Numpy

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 < 2 #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
```

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., 5.])
>>> 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])
```

Boolean Indexing

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

Fancy Indexing

```
>>> b[[1, 0, 1, 0],[0, 1, 2, 0]] #Select elements (1,0),(0,1),(1,2) and (0,0)
 array([ 4. , 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]])
```

> 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, 10, 15, 20])
>>> np.vstack((a,b)) #Stack arrays vertically (row-wise)
 array([[ 1. , 2. , 3. ],
        [ 1.5, 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.]]])]
```

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Python For Data Science

Pandas Basics Cheat Sheet

Learn Pandas Basics online at 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

```
>>> s = pd.Series([3, -5, 7, 4], index=['a', 'b', 'c', 'd'])
```

Dataframe

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

Columns →

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

```
>>> data = {'Country': ['Belgium', 'India', 'Brazil'],
            'Capital': ['Brussels', 'New Delhi', 'Brasília'],
            'Population': [11190846, 1303171035, 207847528]}
>>> 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.xls')
>>> 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)
```

> Selection

Also see NumPy Arrays

Getting

```
>>> s['b'] #Get one element
 -5
>>> df[1:] #Get subset of a DataFrame
   Country Capital Population
 1 India New Delhi 1303171035
 2 Brazil Brasília 207847528
```

Selecting, Boolean Indexing & Setting

By Position

```
>>> df.iloc[[0],[0]] #Select single value by row & column
 'Belgium'
>>> df.iat([0],[0])
 'Belgium'
```

By Label

```
>>> df.loc[[0], ['Country']] #Select single value by row & column labels
 'Belgium'
>>> df.at([0], ['Country'])
 'Belgium'
```

By Label/Position

```
>>> df.ix[2] #Select single row of subset of rows
 Country Brazil
 Capital Brasília
 Population 207847528
>>> df.ix[:,'Capital'] #Select a single column of subset of columns
 0 Brussels
 1 New Delhi
 2 Brasília
>>> df.ix[1,'Capital'] #Select rows and columns
 'New Delhi'
```

Boolean Indexing

```
>>> s[~(s > 1)] #Series s where value is not >1
>>> s[(s < -1) | (s > 2)] #s where value is <-1 or >2
>>> df[df['Population']>1200000000] #Use filter to adjust DataFrame
```

Setting

```
>>> s['a'] = 6 #Set index a of Series s to 6
```

> 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() #Cummulative 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_values=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)
```

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Python For Data Science
Scikit-Learn Cheat Sheet

Learn Scikit-Learn online at 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','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

```
>>> k_means.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 = k_means.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
>>> k_means = 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^2 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_)
```

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Python For Data Science

SciPy Cheat Sheet

Learn SciPy online at www.DataCamp.com

SciPy

The **SciPy** library is one of the core packages for scientific computing that provides mathematical algorithms and convenience functions built on the NumPy extension of Python.

> Interacting With NumPy

Also see NumPy

```
>>> import numpy as np
>>> a = np.array([1,2,3])
>>> b = np.array([(1+5j,2j,3j), (4j,5j,6j)])
>>> c = np.array([[(1.5,2,3), (4,5,6)], [(3,2,1), (4,5,6)]])
```

Index Tricks

```
>>> np.mgrid[0:5,0:5] #Create a dense meshgrid
>>> np.ogrid[0:2,0:2] #Create an open meshgrid
>>> np.r_[[3,[0]*5,-1:1:10j] #Stack arrays vertically (row-wise)
>>> np.c_[b,c] #Create stacked column-wise arrays
```

Shape Manipulation

```
>>> np.transpose(b) #Permute array dimensions
>>> b.flatten() #Flatten the array
>>> np.hstack((b,c)) #Stack arrays horizontally (column-wise)
>>> np.vstack((a,b)) #Stack arrays vertically (row-wise)
>>> np.hsplit(c,2) #Split the array horizontally at the 2nd index
>>> np.vpslit(d,2) #Split the array vertically at the 2nd index
```

Polynomials

```
>>> from numpy import poly1d
>>> p = poly1d([3,4,5]) #Create a polynomial object
```

Vectorizing Functions

```
>>> def myfunc(a): if a < 0:
        return a*2
        else:
        return a/2
>>> np.vectorize(myfunc) #Vectorize functions
```

Type Handling

```
>>> np.real(c) #Return the real part of the array elements
>>> np.imag(c) #Return the imaginary part of the array elements
>>> np.real_if_close(c,tol=1000) #Return a real array if complex parts close to 0
>>> np.cast['f'](np.pi) #Cast object to a data type
```

Other Useful Functions

```
>>> np.angle(b,deg=True) #Return the angle of the complex argument
>>> g = np.linspace(0,np.pi,num=5) #Create an array of evenly spaced values(number of samples)
>>> g [3:] += np.pi
>>> np.unwrap(g) #Unwrap
>>> np.logspace(0,10,3) #Create an array of evenly spaced values (log scale)
>>> np.select([c<4],[c*2]) #Return values from a list of arrays depending on conditions
>>> misc.factorial(a) #Factorial
>>> misc.comb(10,3,exact=True) #Combine N things taken at k time
>>> misc.central_diff_weights(3) #Weights for Np-point central derivative
>>> misc.derivative(myfunc,1.0) #Find the n-th derivative of a function at a point
```

> Linear Algebra

Also see NumPy

You'll use the `linalg` and `sparse` modules.
Note that `scipy.linalg` contains and expands on `numpy.linalg`.

```
>>> from scipy import linalg, sparse
```

Creating Matrices

```
>>> A = np.matrix(np.random.random((2,2)))
>>> B = np.asmatrix(b)
>>> C = np.mat(np.random.random((10,5)))
>>> D = np.mat([[3,4], [5,6]])
```

Basic Matrix Routines

Inverse

```
>>> A.I #Inverse
>>> linalg.inv(A) #Inverse
>>> A.T #Tranpose matrix
>>> A.H #Conjugate transposition
>>> np.trace(A) #Trace
```

Norm

```
>>> linalg.norm(A) #Frobenius norm
>>> linalg.norm(A,1) #L1 norm (max column sum)
>>> linalg.norm(A,np.inf) #L inf norm (max row sum)
```

Rank

```
>>> np.linalg.matrix_rank(C) #Matrix rank
```

Determinant

```
>>> linalg.det(A) #Determinant
```

Solving linear problems

```
>>> linalg.solve(A,b) #Solver for dense matrices
>>> E = np.mat(a).T #Solver for dense matrices
>>> linalg.lstsq(D,E) #Least-squares solution to linear matrix equation
```

Generalized inverse

```
>>> linalg.pinv(C) #Compute the pseudo-inverse of a matrix (least-squares solver)
>>> linalg.pinv2(C) #Compute the pseudo-inverse of a matrix  (SVD)
```

Creating Sparse Matrices

```
>>> F = np.eye(3, k=1) #Create a 2X2 identity matrix
>>> G = np.mat(np.identity(2)) #Create a 2x2 identity matrix
>>> C[C > 0.5] = 0
>>> H = sparse.csr_matrix(C) #Compressed Sparse Row matrix
>>> I = sparse.csc_matrix(D) #Compressed Sparse Column matrix
>>> J = sparse.dok_matrix(A) #Dictionary Of Keys matrix
>>> E.todense() #Sparse matrix to full matrix
>>> sparse.isspmatrix_csc(A) #Identify sparse matrix
```

Sparse Matrix Routines

Inverse

```
>>> sparse.linalg.inv(I) #Inverse
```

Norm

```
>>> sparse.linalg.norm(I) #Norm
```

Solving linear problems

```
>>> sparse.linalg.spsolve(H,I) #Solver for sparse matrices
```

Sparse Matrix Functions

```
>>> sparse.linalg.expm(I) #Sparse matrix exponential
```

Sparse Matrix Decompositions

```
>>> la, v = sparse.linalg.eigs(F,1) #Eigenvalues and eigenvectors
>>> sparse.linalg.svds(H, 2) #SVD
```

> Asking For Help

```
>>> help(scipy.linalg.diagsvd)
>>> np.info(np.matrix)
```

Matrix Functions

Addition

```
>>> np.add(A,D) #Addition
```

Subtraction

```
>>> np.subtract(A,D) #Subtraction
```

Division

```
>>> np.divide(A,D) #Division
```

Multiplication

```
>>> np.multiply(D,A) #Multiplication
>>> np.dot(A,D) #Dot product
>>> np.vdot(A,D) #Vector dot product
>>> np.inner(A,D) #Inner product
>>> np.outer(A,D) #Outer product
>>> np.tensordot(A,D) #Tensor dot product
>>> np.kron(A,D) #Kronecker product
```

Exponential Functions

```
>>> linalg.expm(A) #Matrix exponential
>>> linalg.expm2(A) #Matrix exponential (Taylor Series)
>>> linalg.expm3(D) #Matrix exponential (eigenvalue decomposition)
```

Logarithm Function

```
>>> linalg.logm(A) #Matrix logarithm
```

Trigonometric Functions

```
>>> linalg.sinm(D) Matrix sine
>>> linalg.cosm(D) Matrix cosine
>>> linalg.tanm(A) Matrix tangent
```

Hyperbolic Trigonometric Functions

```
>>> linalg.sinhm(D) #Hypberbolic matrix sine
>>> linalg.coshm(D) #Hyperbolic matrix cosine
>>> linalg.tanhm(A) #Hyperbolic matrix tangent
```

Matrix Sign Function

```
>>> np.sigm(A) #Matrix sign function
```

Matrix Square Root

```
>>> linalg.sqrtm(A) #Matrix square root
```

Arbitrary Functions

```
>>> linalg.funm(A, lambda x: x*x) #Evaluate matrix function
```

Decompositions

Eigenvalues and Eigenvectors

```
>>> la, v = linalg.eig(A) #Solve ordinary or generalized eigenvalue problem for square matrix
>>> l1, l2 = la #Unpack eigenvalues
>>> v[:,0] #First eigenvector
>>> v[:,1] #Second eigenvector
>>> linalg.eigvals(A) #Unpack eigenvalues
```

Singular Value Decomposition

```
>>> U,s,Vh = linalg.svd(B) #Singular Value Decomposition (SVD)
>>> M,N = B.shape
>>> Sig = linalg.diagsvd(s,M,N) #Construct sigma matrix in SVD
```

LU Decomposition

```
>>> P,L,U = linalg.lu(C) #LU Decomposition
```