

Chapter 1: Python introduction

Werner Bauer



- 1 Python basics
- 2 NumPy and SciPy
- 3 Matplotlib
- 4 Simple algorithms
- 5 Python for data science with Pandas

- Python is an open source (freely available) programming language. There are many ways to install and use Python. One possible way is:
 - **Anaconda**: a Python distribution for scientific computing,
 - **Spyder**: a Python IDE, particularly suited for Matlab users.
- Using Anaconda, you can install Spyder as follows:

```
1 conda install spyder # execute this in a shell
```

- Install also already NumPy, SciPy, and Matplotlib:

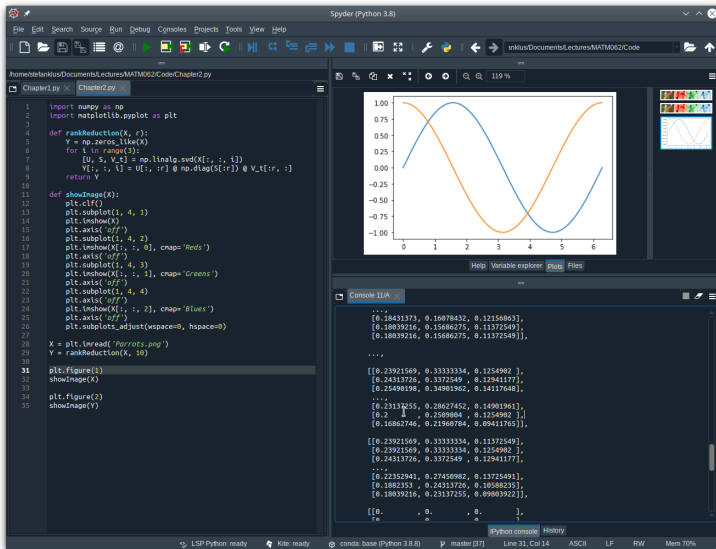
```
1 conda install numpy scipy matplotlib
```

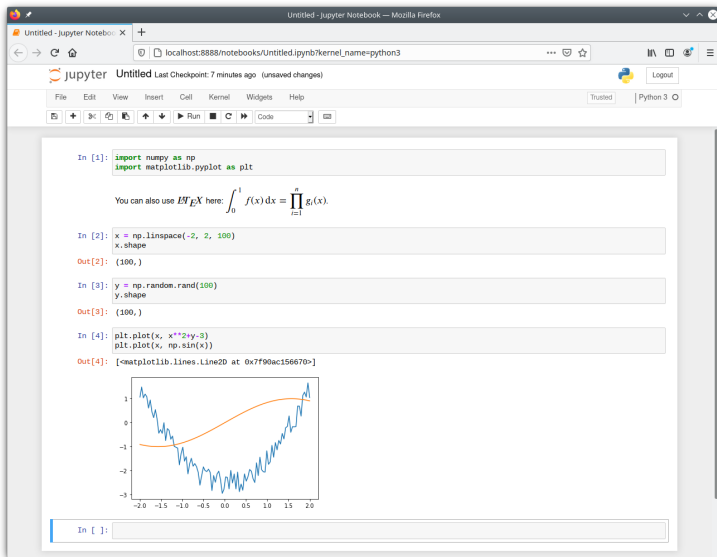
- If you want to use Jupyter notebooks:

```
1 conda install jupyter
```

- The obligatory “Hello, World!” program:

```
1 print("Hello, World!")
```





- Variable names must start with a letter or an underscore:

```
1 b = True      # boolean
2 n = 3         # integer
3 x = 1.41      # floating point number
4 z = 1 + 2j    # complex number
5 s = 'text'    # string
6 t = None      # empty value
```

- Print the variable:

```
1 print(b) # True
2 print(n) # 3
3 print(x) # 1.41
4 print(z) # (1+2j)
5 print(s) # text
6 print(t) # None
```

- Python automatically assigns a data type:

```
1 print(type(b)) # <class 'bool'>
2 print(type(n)) # <class 'int'>
3 print(type(x)) # <class 'float'>
4 print(type(z)) # <class 'complex'>
5 print(type(s)) # <class 'str'>
6 print(type(t)) # <class 'NoneType'>
```

Boolean variables

```
1 b = [False, True]
2
3 for i in b:
4     print("!{} = {}".format(i, not i))
5
6 # !False = True
7 # !True = False
8
9 for i in b:
10     for j in b:
11         print("{} & {} = {}".format(i, j, i and j))
12
13 # False & False = False
14 # False & True = False
15 # True & False = False
16 # True & True = True
17
18 for i in b:
19     for j in b:
20         print("{} | {} = {}".format(i, j, i or j))
21
22 # False | False = False
23 # False | True = True
24 # True | False = True
25 # True | True = True
```

A	$\neg A$
0	1
1	0

A	B	$A \wedge B$
0	0	0
0	1	0
1	0	0
1	1	1

A	B	$A \vee B$
0	0	0
0	1	1
1	0	1
1	1	1

- Note that Python uses 0-based indexing (unlike Matlab).
- Tuples are ordered and cannot be modified:

```
1 t = (2, 'a', 11.2, (3, 4), True)
2 print(t[2]) # 11.2
```

- Lists are ordered and can be modified:

```
1 l = [5, 4, 3]
2 l.append(2) # add 2 to the list
3 print(l) # [5, 4, 3, 2]
4 print(len(l)) # 4
5
6 l = l[::-1] # revert list
7 print(l) # [2, 3, 4, 5]
8
9 l.insert(1, 7) # insert 7 at the first index
10 print(l) # [2, 7, 3, 4, 5]
11
12 l.pop() # remove last item
13 print(l) # [2, 7, 3, 4]
```

- Access the last elements of a list using negative indices:

```
1 print(l[-1]) # 4
2 print(l[-2]) # 3
3 print(l[-3]) # 7
```


- Sets are unordered collections of variables:

```
1 s = {'a', 'b', 'c'}
2
3 print(s == {'b', 'a', 'c', 'a'}) # True
4
5 s.add('d') # add an element to the set
6 print(s)   # {'c', 'b', 'a', 'd'}
7
8 print('a' in s) # True
9 print('z' in s) # False
```


- Dictionaries are unordered collections of key-value pairs:

```
1 d = {'red': [1, 0, 0],
2      'green': [0, 1, 0],
3      'blue': [0, 0, 1]}
4
5 print(d['red']) # [1, 0, 0]
6 print(d.keys()) # dict_keys(['red', 'green', 'blue'])
7 print(d.values()) # dict_values([[1, 0, 0], [0, 1, 0], [0, 0, 1]])
8
9 print(d['yellow']) # KeyError: 'yellow'
```

- Use defaultdict if you want to provide a default value.

- Additional modules can be imported as follows:

```
1 import math
2 print(math.factorial(5)) # 120
3 dir(math) # prints a list of functions contained in math
```

- You can also write your own modules and import them.
- The imported modules need to be in the same directory or contained in the search path for module files.
- In Spyder, open the path manager  or use:

```
1 sys.path.insert(0, "/home/xyz/FolderName")
```

- Import only specific functions:

```
1 from math import factorial
2 factorial(5) # note that we can now write factorial instead of math.factorial
```

- It is also possible to give imported modules a new name:

```
1 import numpy as np           # these are common aliases
2 import scipy as sp           # which will often be used
3 import matplotlib.pyplot as plt # in what follows
```

For loops, while loops, and range

Python:

```
1 for i in range(10):  
2     print(i)  
3  
4 for i in range(10, 20):  
5     print(i)  
6  
7 for i in range(20, 30, 2):  
8     print(i)
```

Loop 1: 0,1,2,3,4,5,6,7,8,9

Loop 2: 10,11,12,13,14,15,16,17,18,19

Loop 3: 20,22,24,26,28

Python:

```
1 d = 256  
2 while d > 1:  
3     d = d//2  
4     print(d)
```

Output: 128,64,32,16,8,4,2,1

Matlab:

```
1 for i = 0:9  
2     fprintf('%d\n', i);  
3 end  
4 for i = 10:19  
5     fprintf('%d\n', i);  
6 end  
7 for i = 20:2:28  
8     fprintf('%d\n', i);  
9 end
```

Matlab:

```
1 d = 256;  
2 while d > 1  
3     d = d/2;  
4     fprintf('%d\n', d);  
5 end
```

Use / for floating point division and // for integer division.
That is, $5/2 = 2.5$ and $5//2 = 2$.

Break and continue

Python:

```
1 s = 0
2 for i in range(10):
3     s = s + i**2
4     if s > 50:
5         break
6 print(s) # 55
```

Matlab:

```
1 s = 0;
2 for i = 0:9
3     s = s + i^2;
4     if s > 50
5         break
6     end
7 end
8 disp(s); % 55
```

The break statement terminates the current loop.

Python:

```
1 for i in range(10):
2     if i % 2 == 0:
3         continue
4     print(i) # 1, 3, 5, 7, 9
```

Matlab:

```
1 for i = 0:9
2     if mod(i, 2) == 0
3         continue;
4     end
5     disp(i); % 1, 3, 5, 7, 9
6 end
```

The continue statement skips all the remaining statements and returns the control to the beginning of the loop.

Python:

```
1 def fibonacci():
2     x, y = 0, 1
3     while True:
4         x, y = y, x+y
5         yield y
6
7 g = fibonacci()
8
9 print(next(g)) # 1
10 # ...
11 print(next(g)) # 2
12 # ...
13 l = [next(g) for i in range(10)] # [3, 5, 8, 13, 21, 34, 55, 89, 144, 233]
```

- If a function contains at least one yield statement, it becomes a generator function.
- Yield pauses the function, saves its current state, and continues when the function is called again.
- There is no comparable Matlab feature.

Python:

```
1 for i in range(1, 5):  
2     if i % 2 == 0:  
3         print('even')  
4     else:  
5         print('odd')
```

Output: odd, even, odd, even

Python:

```
1 if expression:  
2     statements  
3 elif expression:  
4     statements  
5 else:  
6     statements
```

Matlab:

```
1 for i = 1:4  
2     if mod(i, 2) == 0  
3         fprintf('even\n')  
4     else  
5         fprintf('odd\n')  
6     end  
7 end
```

Matlab:

```
1 if expression  
2     statements  
3 elseif expression  
4     statements  
5 else  
6     statements  
7 end
```

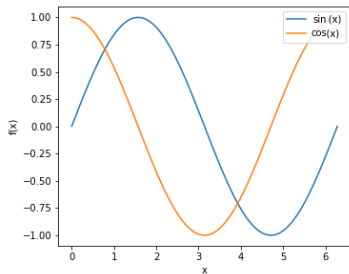
Indentation

Note that Python relies on the indentation to define a block of code. Other programming languages often use begin and end or { and } for this purpose.

Lambda functions and anonymous functions

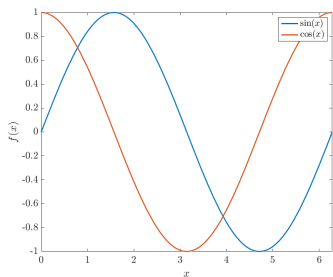
Python:

```
1 f = lambda x: math.sin(x)
2 g = lambda x: math.cos(x)
3 h = lambda x, y: x**2 + y**2
4 f(math.pi)
5 h(2, 3)
6 x = np.linspace(0, 2*math.pi, 100)
7 plt.plot(x, np.vectorize(f)(x))
8 plt.plot(x, np.vectorize(g)(x))
```



Matlab:

```
1 f = @(x) sin(x);
2 g = @(x) cos(x);
3 h = @(x, y) x^2 + y^2;
4 f(pi)
5 h(2, 3)
6 figure; hold on;
7 fplot(f, [0, 2*pi]);
8 fplot(g, [0, 2*pi]);
```



- Apply len to all items of the list:

```
1 tuple_lengths = list(map(len, [(1,), (1, 2), (1, 2, 3)])) # tuple_lengths = [1, 2, 3]
```

- Apply lambda function sequentially to pairs of values:

```
1 from functools import reduce
2 r = reduce((lambda x, y: x * y), [1, 2, 3, 4]) # r = 24
```

- This corresponds to:

```
1 r = 1
2 for i in [1, 2, 3, 4]:
3     r = r * i
```

- Filter values for which the lambda function returns True:

```
1 x = [7, -1, 3, 2, -3, -2]
2 y = [i for i in filter(lambda x: x>0, x)] # y = [7, 3, 2]
```

- You could also write:

```
1 y = [i for i in x if i > 0]
```


- Generate a list of all permutations of [1,2,3]:

```
1 x = [1, 2, 3]
2 y = list(itertools.permutations(x)) # the generator is converted to a list
3
4 print(y) # [(1, 2, 3), (1, 3, 2), (2, 1, 3), (2, 3, 1), (3, 1, 2), (3, 2, 1)]
```

- Generate a list of all combinations of [1,2,3,4]:

```
1 import itertools
2
3 x = [1, 2, 3, 4]
4 y = list(itertools.combinations(x, 3))
5
6 print(y) # [(1, 2, 3), (1, 2, 4), (1, 3, 4), (2, 3, 4)]
```

- Compute accumulated sums of [1,2,3,4,5]:

```
1 import itertools
2
3 x = [1, 2, 3, 4, 5]
4 y = list(itertools.accumulate(x))
5
6 print(y) # [1, 3, 6, 10, 15]
```

Function arguments

- Passing single argument:

```
1 def double(n):  
2     return 2*n  
3 double(2) # 4
```

- Passing multiple arguments to a function:

```
1 def func(*args): # args is a tuple that contains all parameters  
2     for i in args:  
3         print(i)  
4  
5 func(1, 'a', -2)  
6 # 1  
7 # a  
8 # -2  
9 l = [1, 'a', -2]  
10 func(*l) # * unpacks the list, same output as above  
11  
12 func(l) # [1, 'a', -2]
```

- Passing multiple named arguments to a function:

```
1 def func(**kwargs): # kwargs is a dictionary that contains keyword/value pairs  
2     for keyword, value in kwargs.items():  
3         print(f'{keyword} = {value}')  
4  
5 func(kw1=1, kw2='a', kw3=-2)  
6 # kw1 = 1  
7 # kw2 = a  
8 # kw3 = -2
```

- Can of course be combined.

```

1 class Fraction(object):
2     def __init__(self, a, b):
3         '''Initializer or constructor, called when you create a new object.'''
4         d = math.gcd(a, b) # greatest common divisor of a and b
5         self.a = a // d
6         self.b = b // d
7
8     def __repr__(self):
9         '''Prints fraction.'''
10        return "Fraction {}/{}".format(self.a, self.b)
11
12    def __add__(self, rhs):
13        '''Adds two fractions.'''
14        p = self.a * rhs.b + self.b * rhs.a
15        q = self.b * rhs.b
16        return Fraction(p, q)
17
18    def __eq__(self, rhs):
19        '''Checks if two fractions are equal.'''
20        return self.a * rhs.b == rhs.a * self.b
21
22 x1 = Fraction(1, 3) # x1 = 1/3
23 x2 = Fraction(1, 6) # x2 = 1/6
24 x3 = x1 + x2
25
26 print(x3) # Fraction 1/2
27 print(x3 == Fraction(2, 4)) # True
28
29 x4 = x1 - x2 # not implemented yet, define __sub__ function

```

Inheritance

```
1 class Person(object):
2     type = 'Person' # this is a class attribute, everything is by default public
3
4     def __init__(self, name, age):
5         self.name = name
6         self.age = age
7
8     def __str__(self):
9         return f'Name: {self.name}\nAge: {self.age}'
10
11     def increaseAge(self):
12         self.age += 1
13
14 class Student(Person): # inherits properties and functions from Person
15     type = 'Student'
16
17     def __init__(self, name, age, urn):
18         super().__init__(name, age)
19         self.urn = urn
20
21     def __str__(self):
22         return super().__str__() + f'\nURN: {self.urn}'
23
24 c1 = Person('Alice', 21)
25 c2 = Student('Bob', 22, 720283)
26 print(c1)      # Name: Alice, Age: 21
27 print(c1.type) # Person
28 print(c2)      # Name: Bob, Age: 22, URN: 720283
29 print(c2.type) # Student
30 c2.increaseAge() # calls the inherited function
31 print(c2.age)   # 23
```

Other useful features

- Different string formatting options:

```
1 x = 5
2 print("%d^2 = %d" % (x, x**2))      # 5^2 = 25 (old C-style formatting)
3 print("{}^2 = {}".format(x, x**2)) # 5^2 = 25 (newer)
4 print(f"{x}^2 = {x**2}")           # 5^2 = 25 (even newer)
```

- Don't add a newline to the string:

```
1 print("Don't end the line ", end="")
2 print("here!")
```

- Conversion of data types:

```
1 a = 123      # integer
2 b = '456'    # string
3
4 a = str(a)   # '123'
5 b = int(b)   # 456
```

- In-place operations:

```
1 a, b, c = 1, 2, 3
2 a += 2   # 3
3 b *= 3   # 6
4 c **= 4  # 81
```

- Conditional expressions:

```
1 def maxVal(a, b):  
2     return a if a > b else b  
3  
4 print(maxVal(2, 5)) # 5  
5 print(maxVal(7, 5)) # 7
```

- This is similar to the ternary operator in C++:

```
1 #include <iostream>  
2  
3 template<typename T>  
4 T maxVal(T a, T b)  
5 {  
6     return a > b ? a : b;  
7 }  
8  
9 int main()  
10 {  
11     std::cout << maxVal(2, 5) << "\n" << maxVal(7, 5) << std::endl;  
12 }
```

- List comprehension:

```
1 l1 = [1, 3, 2, 5, 4, 6]  
2 l2 = [i**2 for i in l1] # [1, 9, 4, 25, 16, 36]  
3 l3 = [2*i for i in l2 if i % 2 == 0] # [8, 32, 72]
```

- Use the keyword `pass` as a placeholder for future code:

```
1 def toBeImplemented():  
2     pass
```

- Enumerate items:

```
1 for index, item in enumerate(['th', 'st', 'nd', 'rd', 'th']):  
2     print('{}{}'.format(index, item)) # 0th, 1st, 2nd, 3rd, 4th
```

- Create dictionaries:

```
1 d = dict(x=11, y=22, z=33)  
2 print(d['y']) # 22
```

- Document your functions and classes with docstrings:

```
1 def sqr(x):  
2     '''This function returns x squared.'''  
3     return x**2 # note that in Matlab we would write x^2  
4  
5 print(sqr.__doc__) # This function returns x squared.
```

- Check whether objects are identical:

```
1 a = [1, 2, 3]
2 b = a.copy()
3 print(a == b) # True (compares the value of a and b)
4 print(a is b) # False (compares the identities of a and b)
5
6 s = 'text'
7 t = s
8 print(s == t) # True (compares the value of s and t)
9 print(s is t) # True (compares the identities of s and t)
```

- Note that Python uses reference counting:

```
1 from sys import getrefcount
2
3 s = 'some random text'
4 print(getrefcount(s)) # 3
5 t = s
6 print(getrefcount(s)) # 4
7 t = 'new text'
8 print(getrefcount(s)) # 3
```

- You can also compare the addresses:

```
1 s = 'some random text'
2 t = s
3 print(f"Address of s: {id(s)}") # 140512670168288
4 print(f"Address of t: {id(t)}") # 140512670168288
```


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Scalars, vectors, and matrices

Python:

```
1 n = 3
2 a = 1.5
3 x = np.array([1, 0, 2])
4 A = np.array([[1, 2, 3], [4, 5, 6], [7, 8, 9]])
5 B = np.zeros((n, n))
6 C = np.ones((n, n))
7 D = np.eye(n)
8 y = A @ x
9 M = A @ C
10 N = A.T
```

Matlab:

```
1 n = 3
2 a = 1.5
3 x = [1; 0; 2]
4 A = [1, 2, 3; 4, 5, 6; 7, 8, 9]
5 B = zeros(n)
6 C = ones(n)
7 D = eye(n)
8 y = A*x
9 M = A*C
10 N = A'
```

$$n = 3, a = 1.5, x = \begin{bmatrix} 1 \\ 0 \\ 2 \end{bmatrix}$$

$$A = \begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{bmatrix}, B = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}, C = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}, D = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$y = \begin{bmatrix} 7 \\ 16 \\ 25 \end{bmatrix}, M = \begin{bmatrix} 6 & 6 & 6 \\ 15 & 15 & 15 \\ 24 & 24 & 24 \end{bmatrix}, N = \begin{bmatrix} 1 & 4 & 7 \\ 2 & 5 & 8 \\ 3 & 6 & 9 \end{bmatrix}$$

Python:

```
1 n = 4
2 A = sp.linalg.hilbert(n) # Hilbert matrix of size 4
3 c = A[:, 1]             # second column
4 r = A[0, :]             # first row
5 s = A[:, 2, :]          # rows one and three, all columns
```

Matlab:

```
1 n = 4
2 A = hilb(n)
3 c = A(:, 2)
4 r = A(1, :)
5 s = A(1:2:end, :)
```

$n = 4$

$$A = \begin{bmatrix} 1 & \frac{1}{2} & \frac{1}{3} & \frac{1}{4} \\ \frac{1}{2} & \frac{1}{3} & \frac{1}{4} & \frac{1}{5} \\ \frac{1}{3} & \frac{1}{4} & \frac{1}{5} & \frac{1}{6} \\ \frac{1}{4} & \frac{1}{5} & \frac{1}{6} & \frac{1}{7} \end{bmatrix}, c = \begin{bmatrix} \frac{1}{2} \\ \frac{1}{3} \\ \frac{1}{4} \\ \frac{1}{5} \end{bmatrix}$$

$$r = \begin{bmatrix} 1 & \frac{1}{2} & \frac{1}{3} & \frac{1}{4} \end{bmatrix}$$

$$s = \begin{bmatrix} 1 & \frac{1}{2} & \frac{1}{3} & \frac{1}{4} \\ \frac{1}{3} & \frac{1}{4} & \frac{1}{5} & \frac{1}{6} \end{bmatrix}$$

Important differences

Python:

```
1 def f(x):
2     for i in range(len(x)):
3         x[i] = i+1
4
5 x = np.zeros(4) # [0, 0, 0, 0]
6 f(x)
7 print(x) # [1, 2, 3, 4]
```

Matlab:

```
1 x = zeros(4, 1);
2 f(x)
3 disp(x) % [0, 0, 0, 0]
4
5 function f(x)
6     for i = 1:length(x)
7         x(i) = i;
8     end
9 end
```

Python:

```
1 v = np.array(range(6)) # [0 1 2 3 4 5]
2 w = v[3:]              # [3 4 5]
3 w[0] = 99              # [99 4 5]
4 print(v)               # [0 1 2 99 4 5]
```

Matlab:

```
1 v = [0:5] % [0 1 2 3 4 5]
2 w = v(4:end) % [3 4 5]
3 w(1) = 99 % [99 4 5]
4 disp(v) % [0 1 2 3 4 5]
```

Matlab creates copies of vectors and matrices, Python does not. Use the `.copy()` function to create copies of NumPy arrays.

- Save variables into a Matlab-style MAT file:

```
1 import numpy as np
2 import scipy as sp
3 import scipy.io
4
5 n = 100
6 x = np.linspace(-1, 1, n)
7 y = x**2
8 A = np.eye(n)
9
10 sp.io.savemat('Results.mat', {'n':n, 'x':x, 'y':y, 'A':A})
```

- Load file in Matlab:

```
1 load Results
2 plot(x, y)
```

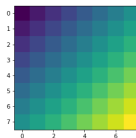
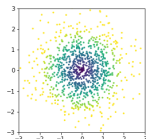
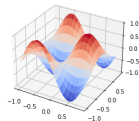
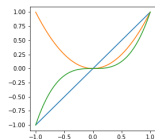
- Load variables from MAT file into main scope:

```
1 data = scipy.io.loadmat('Results.mat', squeeze_me=True)
2 for s in data.keys():
3     if s[:2] == '__' and s[-2:] == '__': continue
4     exec('%s = data["%s"]' % (s, s))
```

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Plotting

```
1 import numpy as np
2 import scipy as sp
3 import scipy.linalg
4 import matplotlib.pyplot as plt
5 from matplotlib import cm
6
7 fig = plt.figure(1); plt.clf()
8
9 plt.subplot(1, 4, 1)
10 x = np.linspace(-1, 1, 100)
11 plt.plot(x, x)
12 plt.plot(x, x**2)
13 plt.plot(x, x**3)
14
15 ax = fig.add_subplot(1, 4, 2, projection='3d')
16 x = np.arange(-1, 1, 0.1)
17 y = np.arange(-1, 1, 0.1)
18 X, Y = np.meshgrid(x, y)
19 Z = np.sin(np.pi*X) * np.cos(np.pi*Y)
20 ax.plot_surface(X, Y, Z, cmap=cm.coolwarm)
21
22 plt.subplot(1, 4, 3)
23 x = np.random.randn(2, 1000)
24 plt.scatter(x[0, :], x[1, :], s=4, \
25           c=np.sqrt(x[0, :]**2 + x[1, :]**2), vmin=0, vmax=2)
26 plt.xlim(-3, 3); plt.ylim(-3, 3);
27
28 plt.subplot(1, 4, 4)
29 plt.imshow(1/sp.linalg.hilbert(8))
```



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Scalar-vector multiplication and matrix-vector multiplication

Compute $y = \alpha x$.

Python:

```
1 import numpy as np
2 n = 5
3 alpha = 2
4 x = np.linspace(1,5,5) # [1., 2., 3., 4., 5.]
5
6 y = np.zeros(n)
7 for i in range(n):
8     y[i] = alpha*x[i]
```

Matlab:

```
1 n = 5;
2 alpha = 2;
3 x = [1:n]';
4
5 y = zeros(n, 1);
6 for i = 1:n
7     y(i) = alpha*x(i);
8 end
```

Compute $y = Ax$.

Python:

```
1 import numpy as np
2 A = np.random.rand(n, n)
3 x = np.random.rand(n)
4
5 y = np.zeros(n)
6 for i in range(n):
7     for j in range(n):
8         y[i] = y[i] + A[i, j]*x[j]
```

Matlab:

```
1 n = 5;
2 A = rand(n);
3 x = rand(n, 1);
4
5 y = zeros(n, 1);
6 for i = 1:n
7     for j = 1:n
8         y(i) = y(i) + A(i, j)*x(j);
9     end
10 end
```

Compute $C = AB$.

Python:

```
1 import numpy as np
2 n = 5
3 A = np.random.rand(n, n)
4 B = np.random.rand(n, n)
5
6 C = np.zeros((n, n))
7 for i in range(n):
8     for j in range(n):
9         for k in range(n):
10             C[i, j] = C[i, j] + A[i, k]*B[k, j]
```

Matlab:

```
1 n = 5;
2 A = rand(n);
3 B = rand(n);
4
5 C = zeros(n);
6 for i = 1:n
7     for j = 1:n
8         for k = 1:n
9             C(i, j) = C(i, j) + A(i, k)*B(k, j);
10        end
11    end
12 end
```

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- Importing Pandas (docu: <https://pandas.pydata.org/>)

```
1 import pandas as pd
2 # Creating series object 'data':
3 data = pd.Series([0.25, 0.5, 0.75, 1.0], index=['a', 'b', 'c', 'd'])
4 data
5 # Output:
6 a    0.25
7 b    0.50
8 c    0.75
9 d    1.00
10 dtype: float64 # NOTE: in the following we skip this line of output
```

- Accessing data (using dictionary-like expressions)

```
1 data['b'] # 0.5
2 'a' in data # True
3 data.keys() # Index(['a', 'b', 'c', 'd'], dtype='object')
4 list(data.items()) # [('a', 0.25), ('b', 0.5), ('c', 0.75), ('d', 1.0)]
```

- Modify series objects (similar to dict-syntax):

```
1 data['e'] = 1.25 # extend Series by assigning to a new index a value:
2 data # Output:
3 a    0.25
4 b    0.50
5 c    0.75
6 d    1.00
7 e    1.25
```

- slicing by explicit and implicit index

```
1 data['a':'c'] # explicit indexing
2 # Output:
3 a    0.25
4 b    0.50
5 data[0:2] # implicit indexing
6 # Output:
7 a    0.25
8 b    0.50
```

- Masking

```
1 data[(data > 0.3) & (data < 0.8)]
2 # Output:
3 b    0.50
4 c    0.75
```

- Fancy indexing (pass a list of indices):

```
1 data[['a', 'e']]
2 # Output:
3 a    0.25
4 e    1.25
```

Danger of confusion: if a series has explicit integer index an indexing operation such as `data[1]` will use the explicit indices, while a slicing operation like `data[1:3]` will use the implicit Python-style index

Alternative indexing:

```
1 data = pd.Series(['a', 'b', 'c'], index=[1, 3, 5])
```

- The loc attribute allows indexing and slicing that always references the explicit index:

```
1 data.loc[1]
2 # Output:
3 'a'
4
5 data.loc[1:3] # this includes key-value pair with external index 3
6 # Output:
7 1    a
8 3    b
```

- The iloc attribute allows indexing and slicing that always references the implicit Python-style index:

```
1 data.iloc[1]
2 # Output:
3 'b'
4
5 data.iloc[1:2] # using implicit indexing, last value for last index not included
6 # Output:
7 3    b
8
9 data.iloc[1:3]
10 # Output:
11 3    b
12 5    c
```

- DataFrame as a dictionary of related Series objects:

```
1 area = pd.Series({'California': 423967, 'Texas': 695662, 'New York': 141297,  
2                  'Florida': 170312, 'Illinois': 149995})  
3 pop = pd.Series({'California': 38332521, 'Texas': 26448193, 'New York': 19651127,  
4                  'Florida': 19552860, 'Illinois': 12882135})  
5 data = pd.DataFrame({'area':area, 'pop':pop})  
6  
7 print(data) # Output:  
8      area      pop  
9 California 423967 38332521  
10 Texas      695662 26448193  
11 New York   141297 19651127  
12 Florida    170312 19552860  
13 Illinois   149995 12882135  
14  
15 print(data['area']) # Output:  
16 California 423967  
17 Texas      695662  
18 New York   141297  
19 Florida    170312  
20 Illinois   149995
```

- Dictionary-style syntax similar to Series objects, e.g.:

```
1 data['density'] = data['pop'] / data['area']  
2  
3 print(data) # Output:  
4      area      pop      density  
5 California 423967 38332521 90.413926  
6 Texas      695662 26448193 38.018740  
7 New York   141297 19651127 139.076746  
8 Florida    170312 19552860 114.806121  
9 Illinois   149995 12882135 85.883763
```

- We can view DataFrame as enhanced two-dimensional array:

```

1 data.T # calculate transpose
2 # Output:
3      California      Texas      New York      Florida      Illinois
4 area  4.239670e+05  6.956620e+05  1.412970e+05  1.703120e+05  1.499950e+05
5 pop   3.833252e+07  2.644819e+07  1.965113e+07  1.955286e+07  1.288214e+07
6 density 9.041393e+01  3.801874e+01  1.390767e+02  1.148061e+02  8.588376e+01
7
8 data.values
9 # Output:
10 array([[4.23967000e+05, 3.83325210e+07, 9.04139261e+01],
11        [6.95662000e+05, 2.64481930e+07, 3.80187404e+01],
12        [1.41297000e+05, 1.96511270e+07, 1.39076746e+02],
13        [1.70312000e+05, 1.95528600e+07, 1.14806121e+02],
14        [1.49995000e+05, 1.28821350e+07, 8.58837628e+01]])

```

- DataFrame indexing follows style of dictionary:

```

1 data.values[0]
2 # output
3 array([4.23967000e+05, 3.83325210e+07, 9.04139261e+01])
4
5 data['area']
6 # Output:
7 California    423967
8 Texas         695662
9 New York      141297
10 Florida       170312
11 Illinois      149995
12
13 data['area']['California'] # Output:
14 423967

```


DataFrame (DF): Access and modify data in numpy like fashion:

- `iloc` (implicit indexing): index and column labels maintained

```
1 data.iloc[:3, :2] # Output:
2      area      pop
3 California 423967 38332521
4 Texas      695662 26448193
5 New York   141297 19651127
```

- `loc` (explicit indexing): index and column labels maintained

```
1 data.loc[:'Illinois', : 'pop'] # Output:
2      area      pop
3 California 423967 38332521
4 Texas      695662 26448193
5 New York   141297 19651127
6 Florida    170312 19552860
7 Illinois    149995 12882135
```

- Numpy masking, filtering, indexing works:

```
1 data.loc[data.density > 100, ['pop', 'density']] # Output:
2      pop      density
3 New York 19651127 139.076746
4 Florida  19552860 114.806121
5
6 data[0:1] # Output:
7      area      pop      density
8 California 423967 38332521 90.413926
9
10 data.iloc[0, 2] = 90 # modify value similar to numpy
11 data[0:1] # Output:
12      area      pop      density
13 California 423967 38332521 90.0
```

• Concatenating:

```
1 df1 = pd.DataFrame({'A': ['A0', 'A1', 'A2', 'A3'], 'B': ['B0', 'B1', 'B2', 'B3'],
2                     'C': ['C0', 'C1', 'C2', 'C3'], 'D': ['D0', 'D1', 'D2', 'D3']},
3                     index=[0, 1, 2, 3])
4
5 df2 = pd.DataFrame({'A': ['A4', 'A5', 'A6', 'A7'], 'B': ['B4', 'B5', 'B6', 'B7'],
6                     'C': ['C4', 'C5', 'C6', 'C7'], 'D': ['D4', 'D5', 'D6', 'D7']},
7                     index=[4, 5, 6, 7])
8
9 df3 = pd.DataFrame({'A': ['A8', 'A9', 'A10', 'A11'], 'B': ['B8', 'B9', 'B10', 'B11'],
10                    'C': ['C8', 'C9', 'C10', 'C11'], 'D': ['D8', 'D9', 'D10', 'D11']},
11                    index=[8, 9, 10, 11])
12
13
14 pd.concat([df1,df2,df3])
15
16 # Output:
17      A   B   C   D
18 0  A0  B0  C0  D0
19 1  A1  B1  C1  D1
20 2  A2  B2  C2  D2
21 3  A3  B3  C3  D3
22 4  A4  B4  C4  D4
23 5  A5  B5  C5  D5
24 6  A6  B6  C6  D6
25 7  A7  B7  C7  D7
26 8  A8  B8  C8  D8
27 9  A9  B9  C9  D9
28 10 A10 B10 C10 D10
29 11 A11 B11 C11 D11
```

• Concatenating:

```
pd.concat([df1,df2,df3],axis=1)
```

```
# Output:
```

	A	B	C	D	A	B	C	D	A	B	C	D
0	A0	B0	C0	D0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1	A1	B1	C1	D1	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2	A2	B2	C2	D2	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
3	A3	B3	C3	D3	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
4	NaN	NaN	NaN	NaN	A4	B4	C4	D4	NaN	NaN	NaN	NaN
5	NaN	NaN	NaN	NaN	A5	B5	C5	D5	NaN	NaN	NaN	NaN
6	NaN	NaN	NaN	NaN	A6	B6	C6	D6	NaN	NaN	NaN	NaN
7	NaN	NaN	NaN	NaN	A7	B7	C7	D7	NaN	NaN	NaN	NaN
8	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	A8	B8	C8	D8
9	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	A9	B9	C9	D9
10	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	A10	B10	C10	D10
11	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	A11	B11	C11	D11

- Merging DF: merge via a common Series (same column name by default)

```
1 left = pd.DataFrame({'key': ['K0', 'K1', 'K2', 'K3'],
2                       'A': ['A0', 'A1', 'A2', 'A3'],
3                       'B': ['B0', 'B1', 'B2', 'B3']})
4
5 right = pd.DataFrame({'key': ['K0', 'K1', 'K2', 'K3'],
6                       'C': ['C0', 'C1', 'C2', 'C3'],
7                       'D': ['D0', 'D1', 'D2', 'D3']})
8
9
10 pd.merge(left, right, how='inner', on='key')
11
12 # Output:
13    key  A  B  C  D
14 0  K0  A0 B0 C0 D0
15 1  K1  A1 B1 C1 D1
16 2  K2  A2 B2 C2 D2
17 3  K3  A3 B3 C3 D3
```

● Merging dataframes: inner, outer, left, right

```
1 left = pd.DataFrame({'key1': ['K0', 'K0', 'K1', 'K2'],
2                       'key2': ['K0', 'K1', 'K0', 'K1'],
3                       'A': ['A0', 'A1', 'A2', 'A3'],
4                       'B': ['B0', 'B1', 'B2', 'B3']})
5 right = pd.DataFrame({'key1': ['K0', 'K1', 'K1', 'K2'],
6                       'key2': ['K0', 'K0', 'K0', 'K0'],
7                       'C': ['C0', 'C1', 'C2', 'C3'],
8                       'D': ['D0', 'D1', 'D2', 'D3']})
9
10 print(pd.merge(left, right, how='inner', on=['key1', 'key2'])) #Output:
11   key1 key2  A  B  C  D
12 0  K0  K0  A0 B0 C0 D0
13 1  K1  K0  A2 B2 C1 D1
14 2  K1  K0  A2 B2 C2 D2
15
16 print(pd.merge(left, right, how='outer', on=['key1', 'key2'])) #Output:
17   key1 key2  A  B  C  D
18 0  K0  K0  A0 B0 C0 D0
19 1  K0  K1  A1 B1 NaN NaN
20 2  K1  K0  A2 B2 C1 D1
21 3  K1  K0  A2 B2 C2 D2
22 4  K2  K1  A3 B3 NaN NaN
23 5  K2  K0  NaN NaN C3 D3
24
25 print(pd.merge(left, right, how='left', on=['key1', 'key2'])) #Output:
26   key1 key2  A  B  C  D
27 0  K0  K0  A0 B0 C0 D0
28 1  K0  K1  A1 B1 NaN NaN
29 2  K1  K0  A2 B2 C1 D1
30 3  K1  K0  A2 B2 C2 D2
31 4  K2  K1  A3 B3 NaN NaN
32 # ..., how = 'right', .. works similarly
```

To group rows together and call aggregate functions:

```

1 data = {'Company': ['G00G', 'G00G', 'MSFT', 'MSFT', 'FB', 'FB'],
2         'Person': ['Sam', 'Charlie', 'Amy', 'Vanessa', 'Carl', 'Sarah'],
3         'Sales': [200, 120, 340, 124, 243, 350]}
4 df = pd.DataFrame(data)

```

Based on column name, `.groupby()` groups rows together, e.g. by 'Company'. This will create a `DataFrameGroupBy` object.

```

1 print(df.groupby('Company').describe()) # Output:
2      Sales
3      count  mean      std   min   25%   50%   75%   max
4 Company
5 FB        2.0  296.5   75.660426 243.0 269.75 296.5 323.25 350.0
6 G00G      2.0  160.0   56.568542 120.0 140.00 160.0 180.00 200.0
7 MSFT      2.0  232.0  152.735065 124.0 178.00 232.0 286.00 340.0
8
9 print(df.groupby('Company').count()) # Output:
10      Person  Sales
11 Company
12 FB         2     2
13 G00G        2     2
14 MSFT        2     2
15
16 print(df.groupby('Company').mean()) # Output
17      Sales
18 Company
19 FB     296.5
20 G00G    160.0
21 MSFT    232.0
22
23 print(df.groupby('Company').std()) # Output similar to .mean()

```

Detecting null values with `isnull()` and `notnull()`

- `isnull()` and `notnull()` return Boolean mask over data

```
1 import numpy as np
2 data = pd.Series([1, np.nan, 'hello', None])
3 data
4 # Output:
5 0      1
6 1     NaN
7 2   hello
8 3     None
9 data.isnull()
10 # Output:
11 0   False
12 1    True
13 2   False
14 3    True
15 data[data.notnull()] # similarly: data.dropna()
16 # Output:
17 0      1
18 2   hello
```

- `.dropna()` to drop null values

```
1 data = pd.Series([1, np.nan, 'hello', None])
2
3 data.dropna()
4 # Output:
5 0      1
6 2    hello
7
8 df = pd.DataFrame({'A': [1, 2, np.nan],
9                    'B': [5, np.nan, np.nan],
10                   'C': [1, 2, 3]})
11 df
12 # Output:
13      A      B      C
14 0  1.0  5.0   1
15 1  2.0  NaN   2
16 2  NaN  NaN   3
17
18 df.dropna(axis=0)
19 # Output:
20      A      B      C
21 0  1.0  5.0   1
22
23 df.dropna(axis=1)
24 # Output:
25      C
26 0    1
27 1    2
28 2    3
```


Filling null values with .fillna()

- Sometimes we want to fill rather than drop null values

```
1 df = pd.DataFrame({'A':[1,2,np.nan], 'B':[5,np.nan,np.nan], 'C':[1,2,3]})
2 print(df) # Output:
3      A    B  C
4 0  1.0  5.0  1
5 1  2.0  NaN  2
6 2  NaN  NaN  3
7
8 df.fillna(0) # fill NA with single values such as 0
9      A    B  C
10 0  1.0  5.0  1
11 1  2.0  0.0  2
12 2  0.0  0.0  3
13 df.fillna(method='ffill') # forward-fill (within columns); also backward-fill 'bfill' possible
14      A    B  C
15 0  1.0  5.0  1
16 1  2.0  5.0  2
17 2  2.0  5.0  3
18
19 df['A'].fillna(value=df['A'].mean()) # fill missing values per columns with e.g. mean:
20 0    1.0
21 1    2.0
22 2    1.5
23
24 print(df) # NOTE: df is not changed !!!
25      A    B  C
26 0  1.0  5.0  1
27 1  2.0  NaN  2
28 2  NaN  NaN  3
```

- NOTE: use **inplace=True** to overwrite values in df itself (default, as above: **inplace=False**)