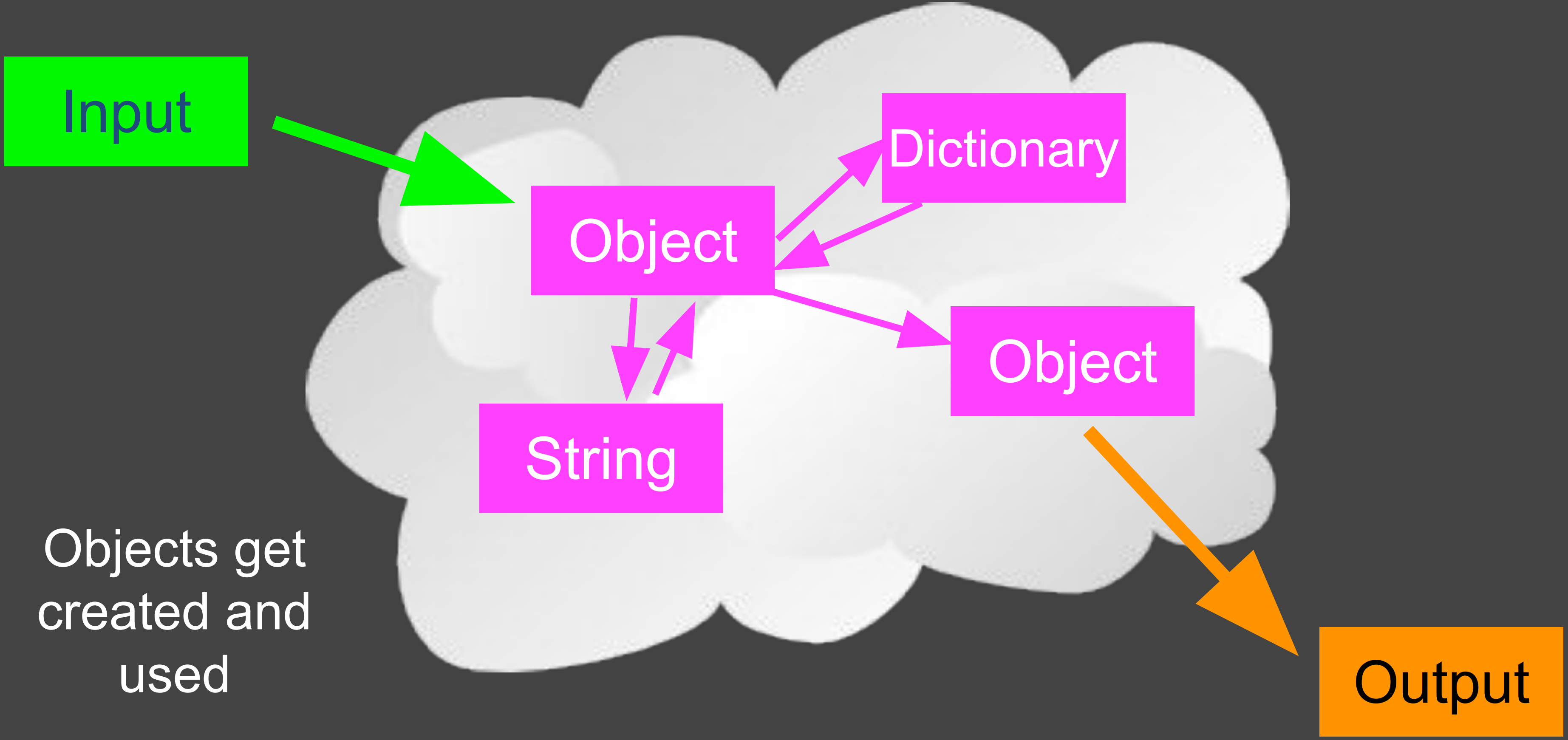
STATS 507
Data Analysis in Python

Week 5: OOP recap, **numpy**, scipy, and matplotlib

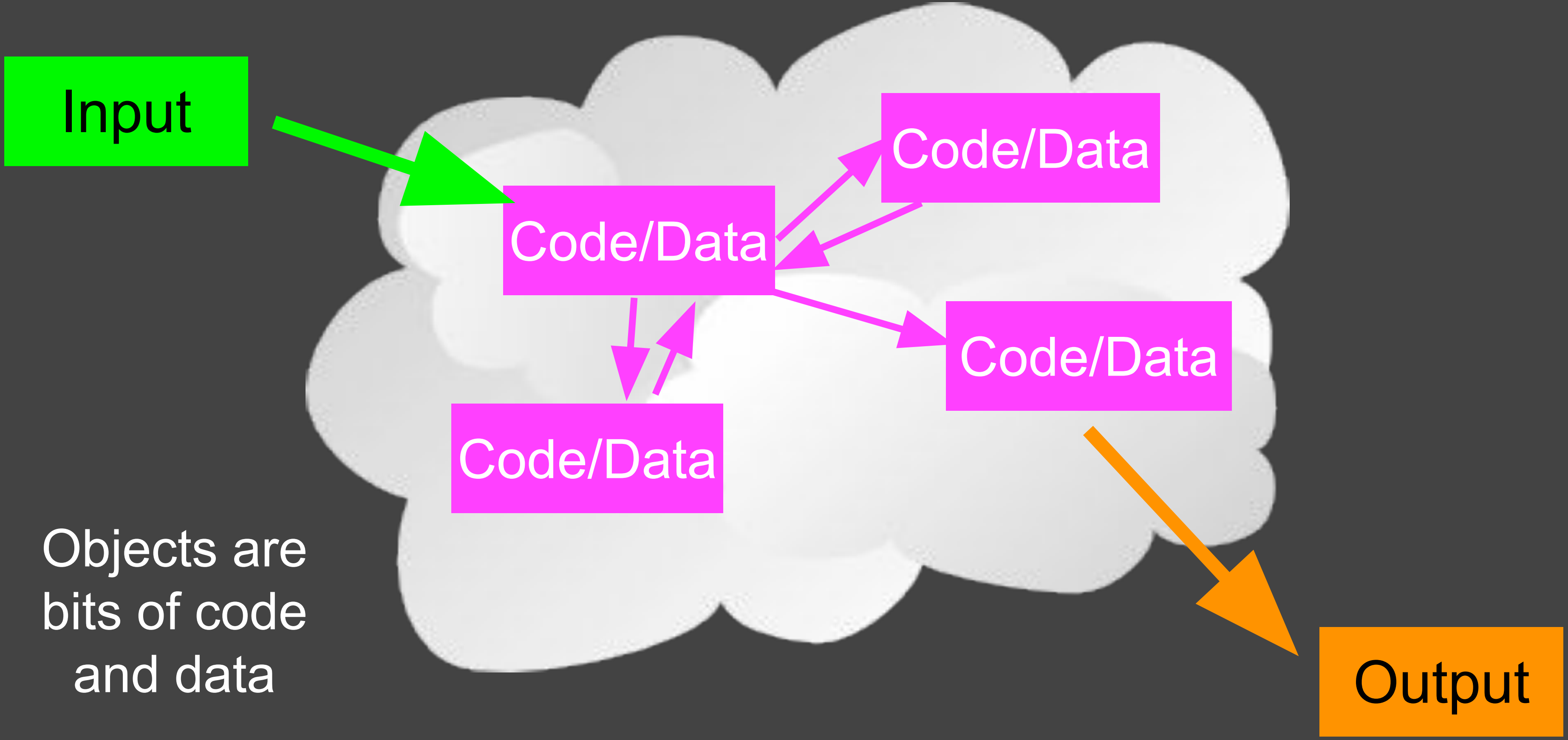
Adapted from slides by Keith Levin and Charles Severance

OOP at a high-level

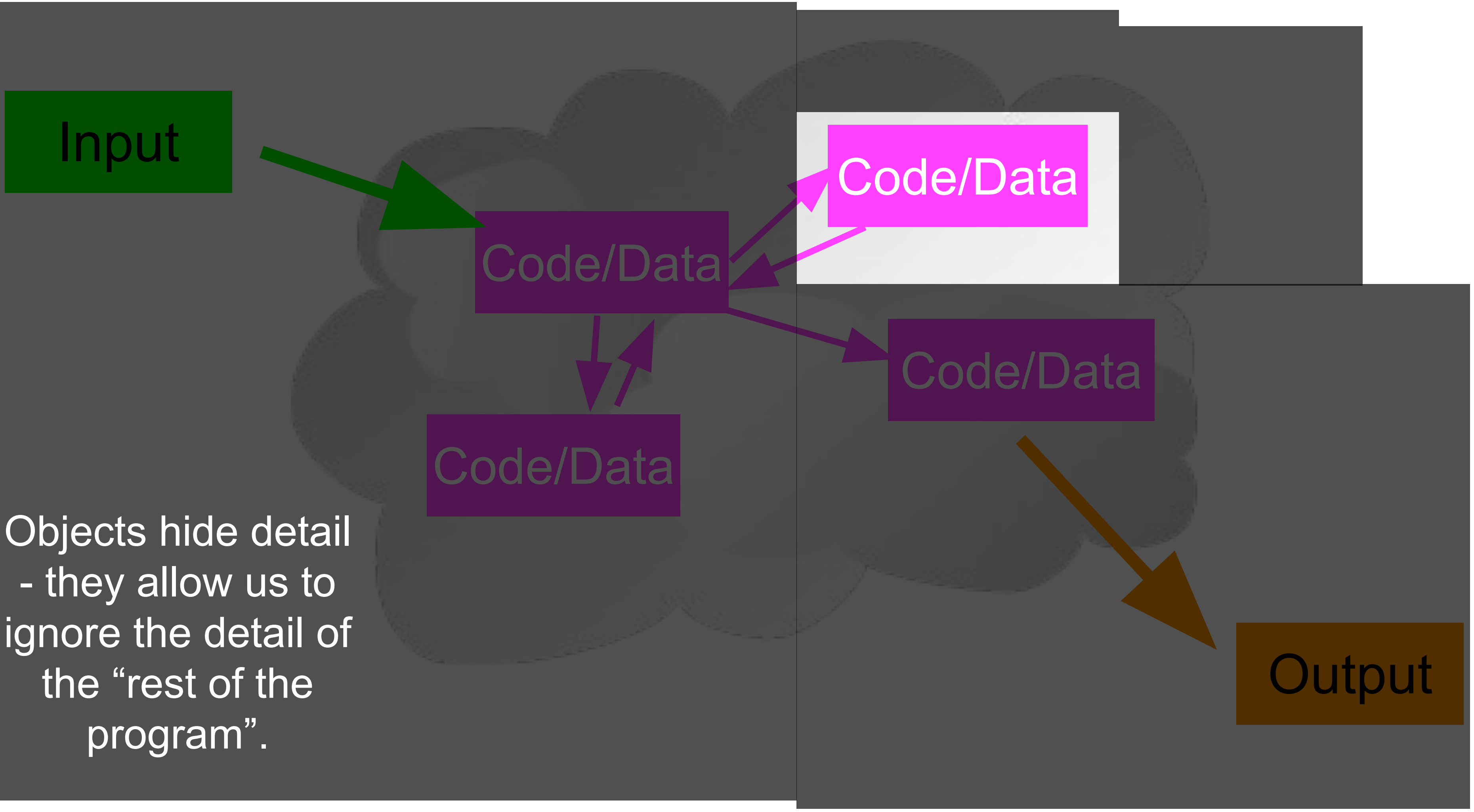
- A program is made up of many cooperating objects
- Instead of being the “whole program” - each object is a little “island” within the program and cooperatively working with other objects
- A program is made up of one or more objects working together - objects make use of each other’s capabilities



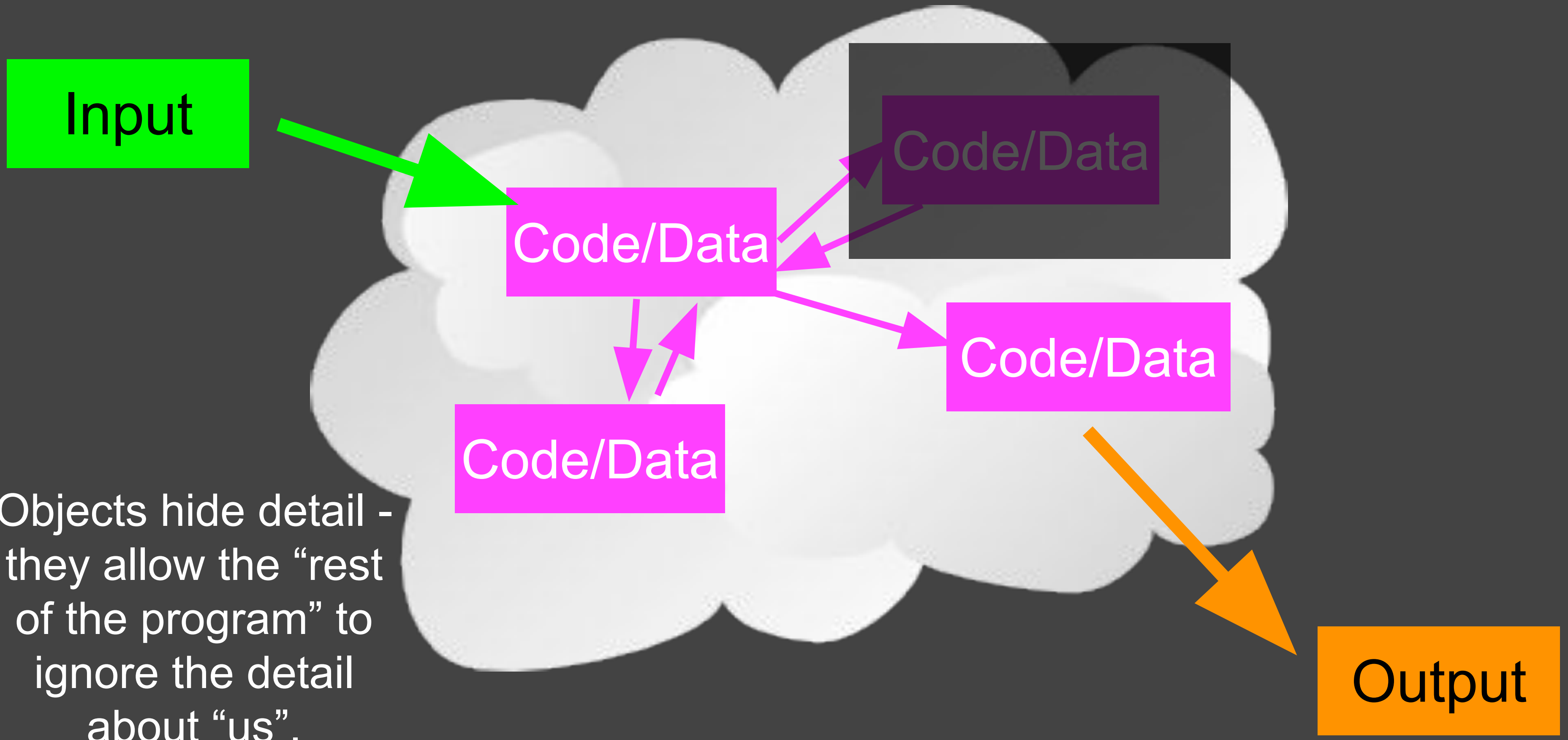
Objects get created and used



Objects are bits of code and data



Objects hide detail - they allow us to ignore the detail of the “rest of the program”.



Objects hide detail - they allow the “rest of the program” to ignore the detail about “us”.

Definitions

• Class - a template	e.g., Dog
• Object or Instance - A particular instance of a class	e.g., Lassie
• Method - A defined capability of a class	e.g., bark, sit
• Field or attribute- A bit of data in a class	e.g., fur color

A Sample Class

class is a reserved word

Each PartyAnimal object has a bit of code

Tell the an object to run the party() code within it

```
class PartyAnimal:
   x = 0

   def party(self) :
     self.x = self.x + 1
     print("So far",self.x)

an = PartyAnimal()

an.party()
an.party()
an.party()
```

This is the template for making PartyAnimal objects

Each PartyAnimal object has a bit of data

Construct a PartyAnimal object and store in an

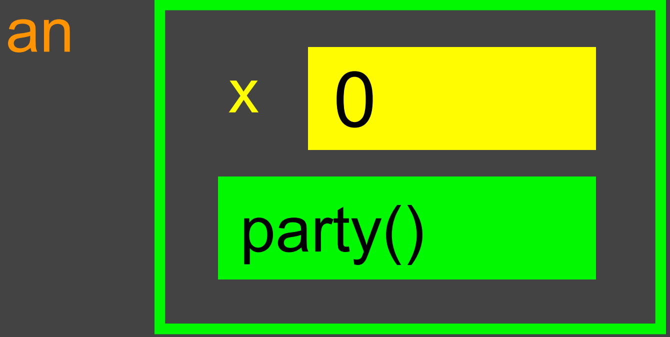
PartyAnimal.party(an)

```python
class PartyAnimal:
  x = 0

  def party(self) :
    self.x = self.x + 1
    print("So far",self.x)

an = PartyAnimal()

an.party()
an.party()
an.party()
```

```
$ python party1.py
```

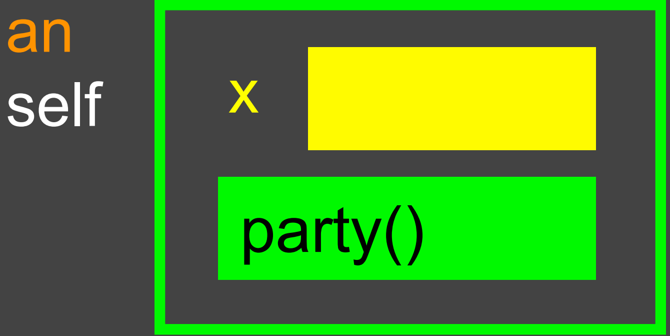
```
class PartyAnimal:
  x = 0

  def party(self) :
    self.x = self.x + 1
    print("So far",self.x)

an = PartyAnimal()

an.party()
an.party()
an.party()
```

```
$ python party1.py
```



```
class PartyAnimal:
  x = 0

  def party(self) :
    self.x = self.x + 1
    print("So far",self.x)

an = PartyAnimal()

an.party()
an.party()
an.party()
```

```
$ python party1.py
So far 1
So far 2
So far 3
```



PartyAnimal.party(an)

dir(): A Way to Find Object Capabilities

- The dir() command lists capabilities
- Ignore the ones with underscores - these are used by Python itself
- The rest are real operations that the object can perform
- It is like type() - it tells us something *about* a variable

```
>>> y = list()
>>> type(y)
<class 'list'>
>>> dir(x)
['__add__', '__class__',
'__contains__', '__delattr__',
'__delitem__', '__delslice__',
'__doc__', … '__setitem__',
'__setslice__', '__str__',
'append', 'clear', 'copy',
'count', 'extend', 'index',
'insert', 'pop', 'remove',
'reverse', 'sort']
>>>
```

```
class PartyAnimal:
   x = 0

   def party(self) :
     self.x = self.x + 1
     print("So far",self.x)

an = PartyAnimal()

print("Type", type(an))
print("Dir ", dir(an))
```

We can use dir() to find the "capabilities" of our newly created class.

```
$ python party3.py
Type <class '__main__.PartyAnimal'>
Dir  ['__class__', ... 'party', 'x']
```

Try dir() with a String

```
>>> x = 'Hello there'
>>> dir(x)
['__add__', '__class__', '__contains__', '__delattr__',
'__doc__', '__eq__', '__ge__', '__getattribute__',
'__getitem__', '__getnewargs__', '__getslice__', '__gt__',
'__hash__', '__init__', '__le__', '__len__', '__lt__',
'__repr__', '__rmod__', '__rmul__', '__setattr__', '__str__',
'capitalize', 'center', 'count', 'decode', 'encode', 'endswith',
'expandtabs', 'find', 'index', 'isalnum', 'isalpha', 'isdigit',
'islower', 'isspace', 'istitle', 'isupper', 'join', 'ljust',
'lower', 'lstrip', 'partition', 'replace', 'rfind', 'rindex',
'rjust', 'rpartition', 'rsplit', 'rstrip', 'split',
'splitlines', 'startswith', 'strip', 'swapcase', 'title',
'translate', 'upper', 'zfill']
```

Some Python Objects

```
>>> x = 'abc'
>>> type(x)
<class 'str'>
>>> type(2.5)
<class 'float'>
>>> type(2)
<class 'int'>
>>> y = list()
>>> type(y)
<class 'list'>
>>> z = dict()
>>> type(z)
<class 'dict'>
```

```
>>> dir(x)
[ … 'capitalize', 'casefold', 'center', 'count',
'encode', 'endswith', 'expandtabs', 'find',
'format', … 'lower', 'lstrip', 'maketrans',
'partition', 'replace', 'rfind', 'rindex', 'rjust',
'rpartition', 'rsplit', 'rstrip', 'split',
'splitlines', 'startswith', 'strip', 'swapcase',
'title', 'translate', 'upper', 'zfill']
>>> dir(y)
[… 'append', 'clear', 'copy', 'count', 'extend',
'index', 'insert', 'pop', 'remove', 'reverse',
'sort']
>>> dir(z)
[…, 'clear', 'copy', 'fromkeys', 'get', 'items',
'keys', 'pop', 'popitem', 'setdefault', 'update',
'values']
```

Object Lifecycle

- Objects are created, used, and discarded
- We have special blocks of code (methods) that get called
  - At the moment of creation (constructor)
  - At the moment of destruction (destructor)
- Constructors are used a lot
- Destructors are seldom used

Constructor

The primary purpose of the constructor is to set up some instance variables to have the proper initial values when the object is created

```
class PartyAnimal:
   x = 0

   def __init__(self):
     print('I am constructed')

   def party(self) :
     self.x = self.x + 1
     print('So far',self.x)

   def __del__(self):
     print('I am destructed', self.x)

an = PartyAnimal()
an.party()
an.party()
an = 42
print('an contains',an)
```

```
$ python party4.py
I am constructed
So far 1
So far 2
I am destructed 2
an contains 42
```

The constructor and destructor are optional. The constructor is typically used to set up variables. The destructor is seldom used.

Many Instances

- We can create lots of objects - the class is the template for the object
- We can store each distinct object in its own variable
- We call this having multiple instances of the same class
- Each instance has its own copy of the instance variables

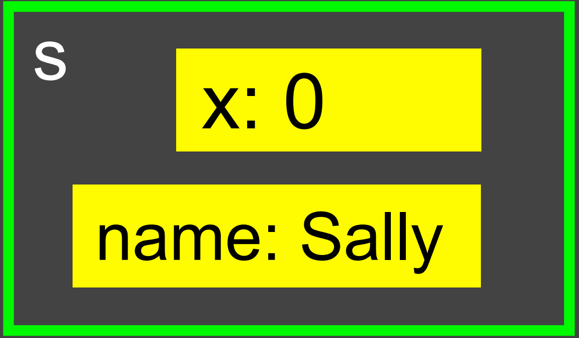
```
class PartyAnimal:
    x = 0
    name = ""
    def __init__(self, z):
      self.name = z
      print(self.name,"constructed")

    def party(self) :
      self.x = self.x + 1
      print(self.name,"party count",self.x)

s = PartyAnimal("Sally")
j = PartyAnimal("Jim")

s.party()
j.party()
s.party()
```

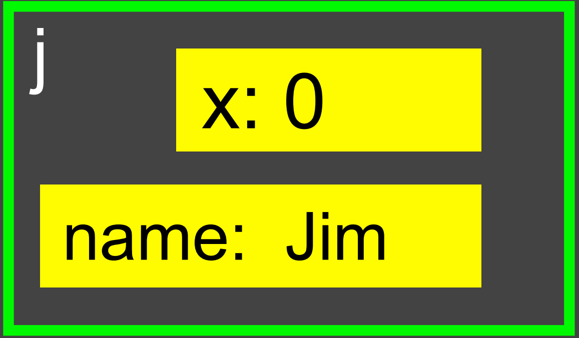
Constructors can have additional parameters. These can be used to set up instance variables for the particular instance of the class (i.e., for the particular object).

party5.py

```
class PartyAnimal:
    x = 0
    name = ""
    def __init__(self, z):
      self.name = z
      print(self.name,"constructed")

    def party(self) :
      self.x = self.x + 1
      print(self.name,"party count",self.x)

s = PartyAnimal("Sally")
j = PartyAnimal("Jim")

s.party()
j.party()
s.party()
```

We have two independent instances

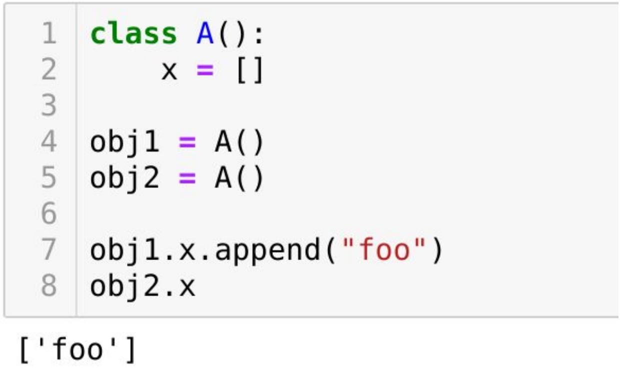




```python
class PartyAnimal:
   x = 0
   name = ""
   def __init__(self, z):
     self.name = z
     print(self.name,"constructed")

   def party(self) :
     self.x = self.x + 1
     print(self.name,"party count",self.x)

s = PartyAnimal("Sally")
j = PartyAnimal("Jim")

s.party()
j.party()
s.party()
```

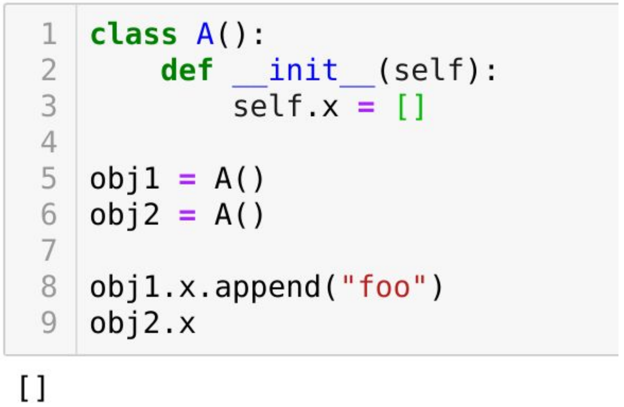
```
Sally constructed
Jim constructed
Sally party count 1
Jim party count 1
Sally party count 2
```

Instance variables vs class variables



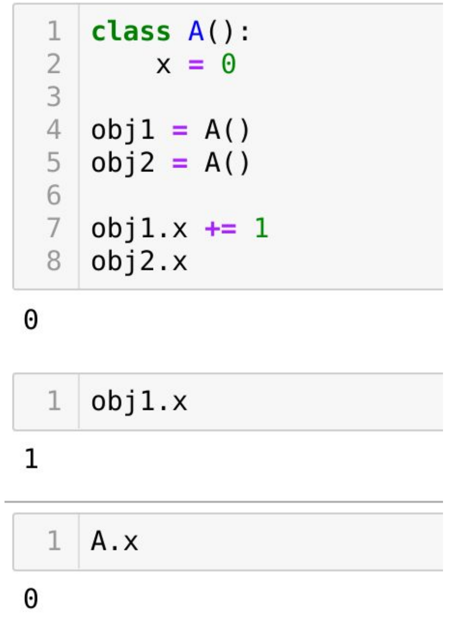
```python
class A():
    x = []

obj1 = A()
obj2 = A()

obj1.x.append("foo")
obj2.x
```

```
['foo']
```



```python
class A():
    def __init__(self):
        self.x = []

obj1 = A()
obj2 = A()

obj1.x.append("foo")
obj2.x
```

```
[]
```



```python
class A():
    x = 0

obj1 = A()
obj2 = A()

obj1.x += 1
obj2.x
```

```
0
```

```python
obj1.x
```

```
1
```

```python
A.x
```

```
0
```

Inheritance

- When we make a new class - we can reuse an existing class and inherit all the capabilities of an existing class and then add our own little bit to make our new class
- Another form of store and reuse
- Write once - reuse many times
- The new class (child) has all the capabilities of the old class (parent) - and then some more

Terminology: Inheritance

‘Subclasses’ are more specialized versions of a class, which inherit attributes and behaviors from their parent classes, and can introduce their own.

http://en.wikipedia.org/wiki/Object-oriented_programming

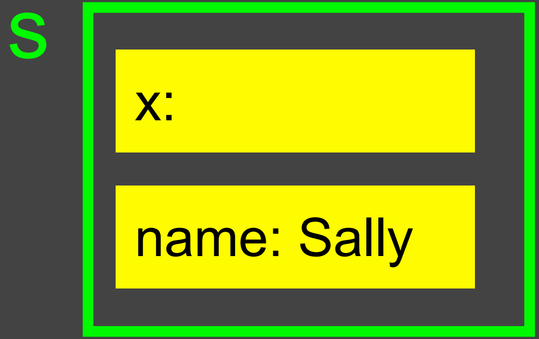
```
class PartyAnimal:
   x = 0
   name = ""
   def __init__(self, nam):
     self.name = nam
     print(self.name,"constructed")

   def party(self) :
     self.x = self.x + 1
     print(self.name,"party count",self.x)

class FootballFan(PartyAnimal):
   points = 0
   def touchdown(self):
      self.points = self.points + 7
      self.party()
      print(self.name,"points",self.points)
```

```
s = PartyAnimal("Sally")
s.party()

j = FootballFan("Jim")
j.party()
j.touchdown()
```

FootballFan is a class which extends PartyAnimal. It has all the capabilities of PartyAnimal and more.

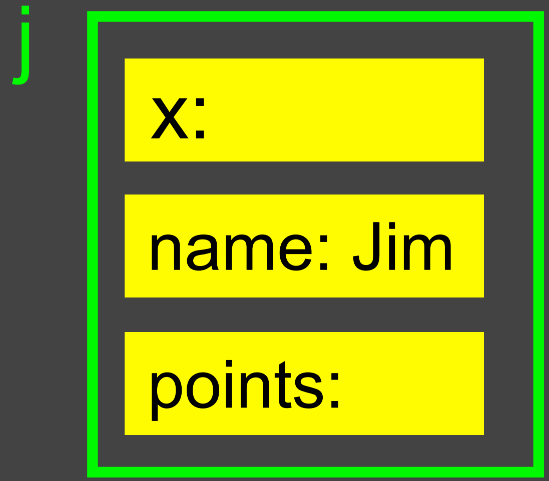
```
class PartyAnimal:
   x = 0
   name = ""
   def __init__(self, nam):
     self.name = nam
     print(self.name,"constructed")

   def party(self) :
     self.x = self.x + 1
     print(self.name,"party count",self.x)

class FootballFan(PartyAnimal):
   points = 0
   def touchdown(self):
      self.points = self.points + 7
      self.party()
      print(self.name,"points",self.points)
```

```
s = PartyAnimal("Sally")
s.party()

j = FootballFan("Jim")
j.party()
j.touchdown()
```



```
class PartyAnimal:
   x = 0
   name = ""
   def __init__(self, nam):
     self.name = nam
     print(self.name,"constructed")

   def party(self) :
     self.x = self.x + 1
     print(self.name,"party count",self.x)

class FootballFan(PartyAnimal):
   points = 0
   def touchdown(self):
      self.points = self.points + 7
      self.party()
      print(self.name,"points",self.points)
```

```
s = PartyAnimal("Sally")
s.party()

j = FootballFan("Jim")
j.party()
j.touchdown()
```



Definitions

- Class - a template
- Attribute – A variable within a class
- Method - A function within a class
- Object - A particular instance of a class
- Constructor – Code that runs when an object is created
- Inheritance - The ability to extend a class to make a new class.

NumPy

Numerical computing in Python: `numpy`

A free competitor to MATLAB.

Numpy quickstart guide: https://docs.scipy.org/doc/numpy-dev/user/quickstart.html

For MATLAB fans:
https://docs.scipy.org/doc/numpy-dev/user/numpy-for-matlab-users.html

Closely related package `scipy` is for optimization
    See https://docs.scipy.org/doc/

Installing packages

So far, we have only used built-in modules

    But there are many modules/packages that do not come preinstalled

Ways to install packages:

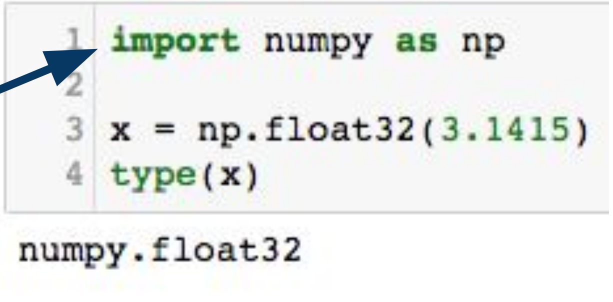
At the conda prompt or in terminal: `conda install numpy`

    https://conda.io/docs/user-guide/tasks/manage-pkgs.html

- Using pip (recommended): `pip install numpy`
    - https://pip.pypa.io/en/stable/
- Using UNIX/Linux package manager (not recommended)
- From source (not recommended)

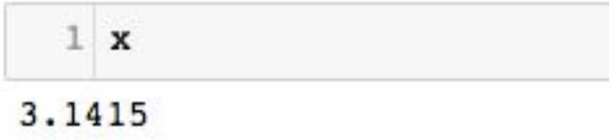
`numpy` data types

`import … as …` lets us import a package and give it a shorter name.



```
import numpy as np

x = np.float32(3.1415)
type(x)
```

```
numpy.float32
```



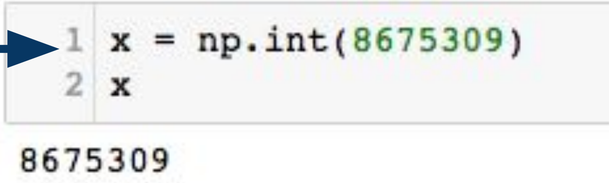
```
x
```

```
3.1415
```

Five basic numerical data types:

- boolean (`bool`)
- integer (`int`)
- unsigned integer (`uint`)
- floating point (`float`)
- complex (`complex`)

Note that this is not the same as a Python int.



```
x = np.int(8675309)
x
```

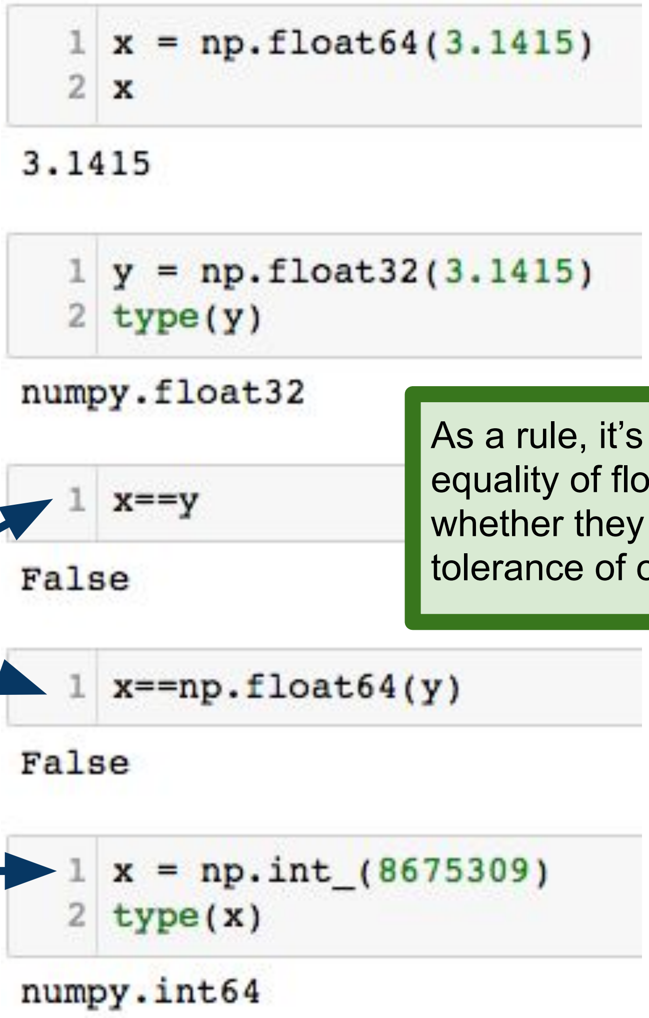
```
8675309
```

Many more complicated data types are available

e.g., each of the numerical types can vary in how many bits it uses

https://docs.scipy.org/doc/numpy/user/basics.types.html

numpy data types



```
x = np.float64(3.1415)
x
```

```
3.1415
```

```
y = np.float32(3.1415)
type(y)
```

```
numpy.float32
```

```
x==y
```

```
False
```

```
x==np.float64(y)
```

```
False
```

```
x = np.int_(8675309)
type(x)
```

```
numpy.int64
```

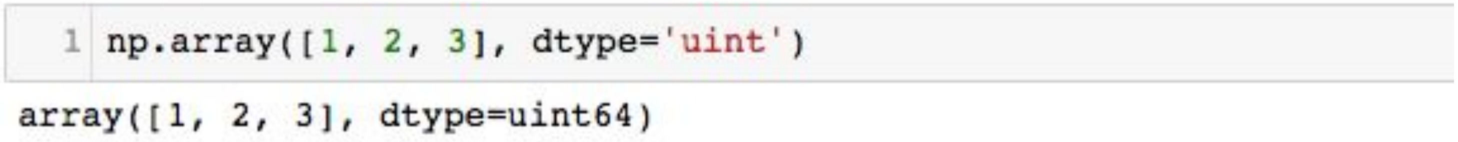
As a rule, it’s best never to check for equality of floats. Instead, check whether they are within some error tolerance of one another.

32-bit and 64-bit representations are distinct!

Data type followed by underscore uses the default number of bits. This default varies by system.

`numpy.array`: `numpy`’s version of Python array (i.e., list)

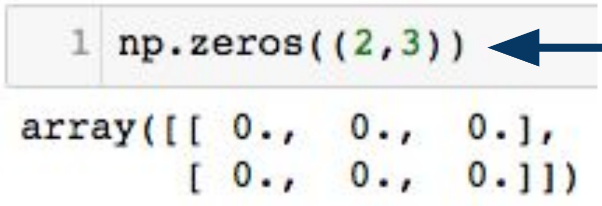
Can be created from a Python list…



```
np.array([1, 2, 3], dtype='uint')
```

```
array([1, 2, 3], dtype=uint64)
```

...by “shaping” an array…

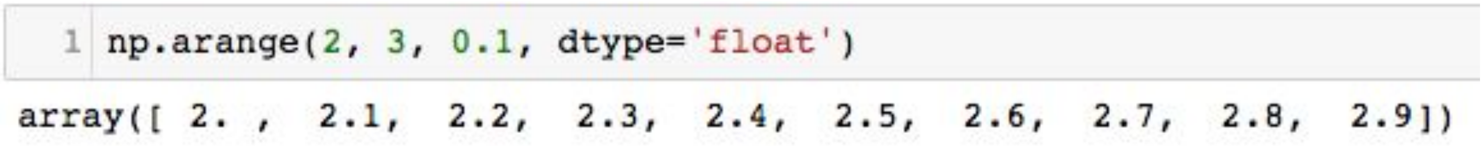


```
np.zeros((2,3))
```

```
array([[ 0.,  0.,  0.],
       [ 0.,  0.,  0.]])
```

`np.zeros` and `np.ones` generate arrays of 0s or 1s, respectively. Shape parameter (2,3) means to create a 2-D array with two rows and three columns.

...by “ranges”...



```
np.arange(2, 3, 0.1, dtype='float')
```

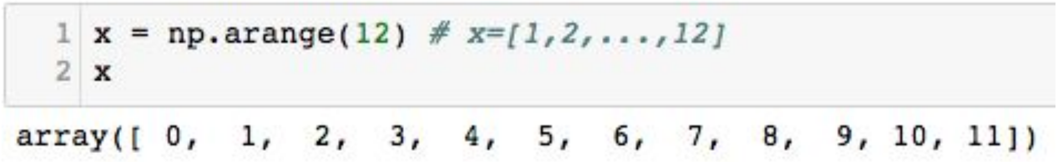
```
array([ 2. ,  2.1,  2.2,  2.3,  2.4,  2.5,  2.6,  2.7,  2.8,  2.9])
```

...or reading directly from a file

see https://docs.scipy.org/doc/numpy/user/basics.creation.html

`numpy` allows arrays of arbitrary dimension (tensors)

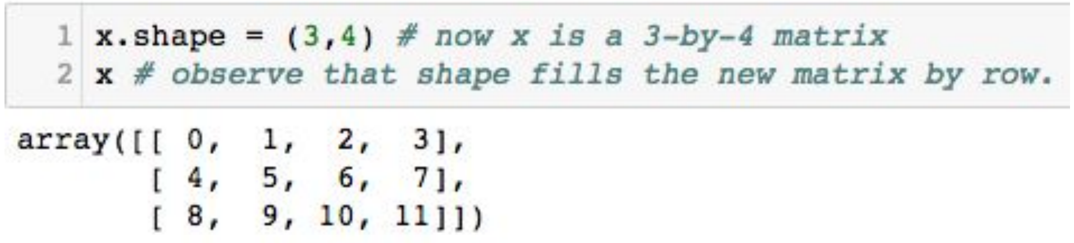
1-dimensional arrays:



```
x = np.arange(12) # x=[1,2,...,12]
x
```

```
array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11])
```

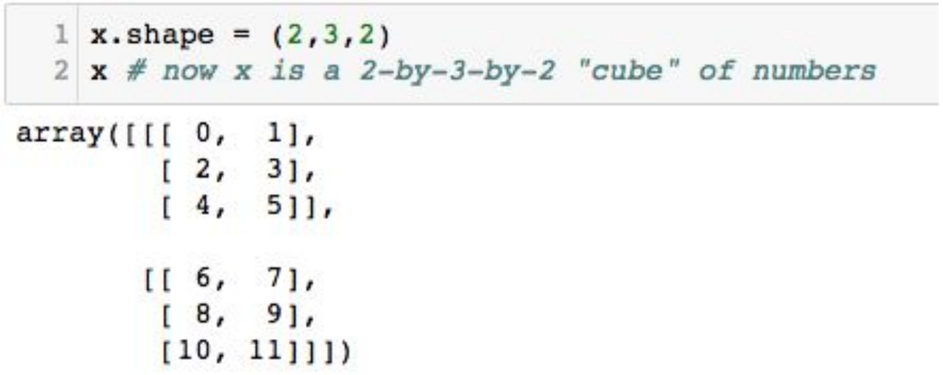
2-dimensional arrays (matrices):



```
x.shape = (3,4) # now x is a 3-by-4 matrix
x # observe that shape fills the new matrix by row.
```

```
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])
```

3-dimensional arrays (“3-tensor”):

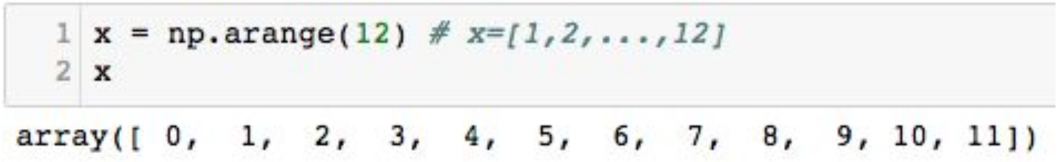


```
x.shape = (2,3,2)
x # now x is a 2-by-3-by-2 "cube" of numbers
```

```
array([[[ 0,  1],
        [ 2,  3],
        [ 4,  5]],

       [[ 6,  7],
        [ 8,  9],
        [10, 11]]])
```

numpy allows arrays of arbitrary dimension (tensors)

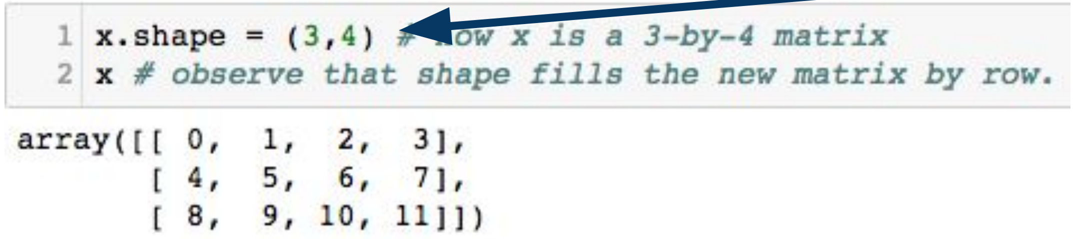
1-dimensional arrays:



```
x = np.arange(12) # x=[1,2,...,12]
x
```

```
array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11])
```

2-dimensional arrays (matrices):

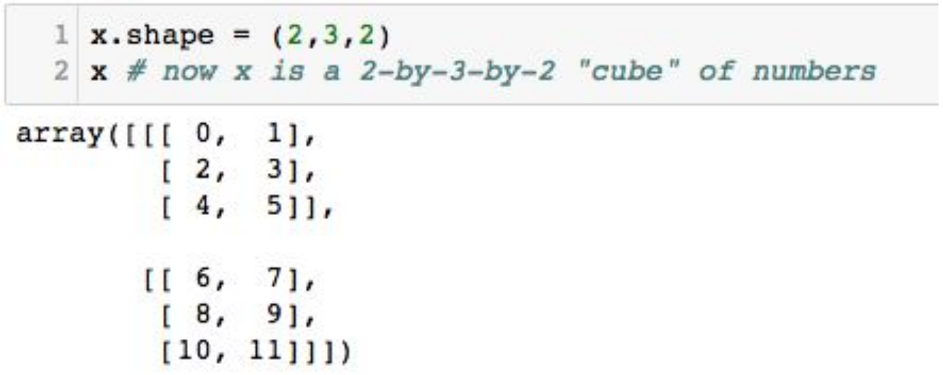


```
x.shape = (3,4) # now x is a 3-by-4 matrix
x # observe that shape fills the new matrix by row.
```

```
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])
```

Every numpy array has a `shape` attribute specifying its dimensions. For example, an array with shape (3,4) has two rows and three columns. An array with shape (2,3,2) is a 2-by-3-by-2 “box” of numbers.

3-dimensional arrays (“3-tensor”):



```
x.shape = (2,3,2)
x # now x is a 2-by-3-by-2 "cube" of numbers
```

```
array([[[ 0,  1],
        [ 2,  3],
        [ 4,  5]],

       [[ 6,  7],
        [ 8,  9],
        [10, 11]]])
```

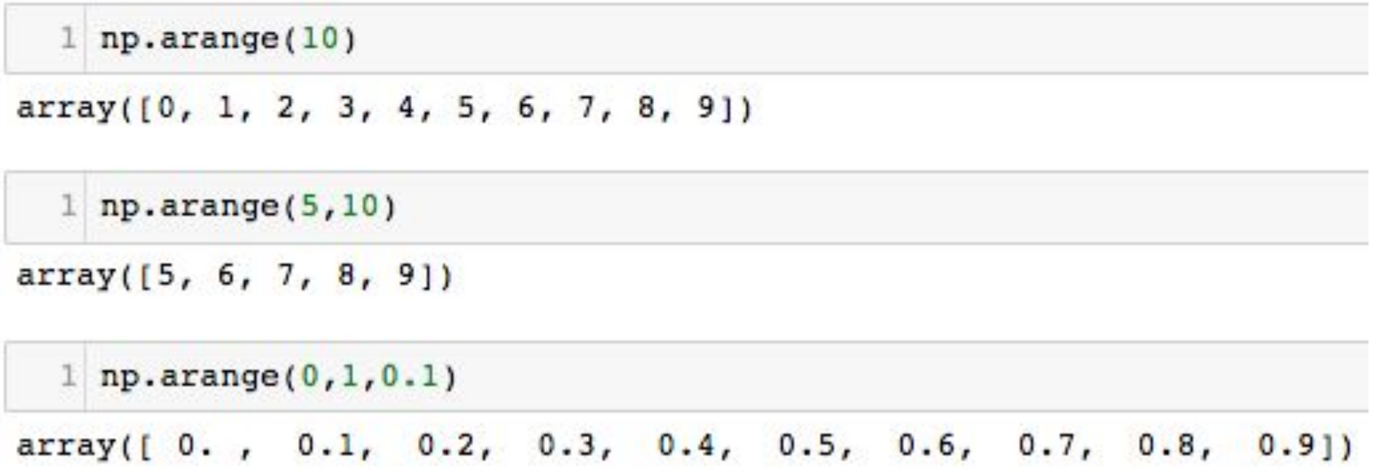
Think of the shape of an array as specifying how many indices we need to pick out an entry of the array. For example, to pick out a number from a 3-by-4 matrix, we must specify a row and a column.

More on `numpy.arange` creation

`np.arange(x)`: array version of Python's `range(x)`, like `[0,1,2,...,x-1]`

`np.arange(x,y)`: array version of `range(x,y)`, like `[x,x+1,...,y-1]`

`np.arange(x,y,z)`: array of elements `[x,y)` in `z`-size increments.



```
np.arange(10)
```

```
array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
```

```
np.arange(5,10)
```

```
array([5, 6, 7, 8, 9])
```

```
np.arange(0,1,0.1)
```

```
array([ 0. ,  0.1,  0.2,  0.3,  0.4,  0.5,  0.6,  0.7,  0.8,  0.9])
```

More on `numpy.arange` creation

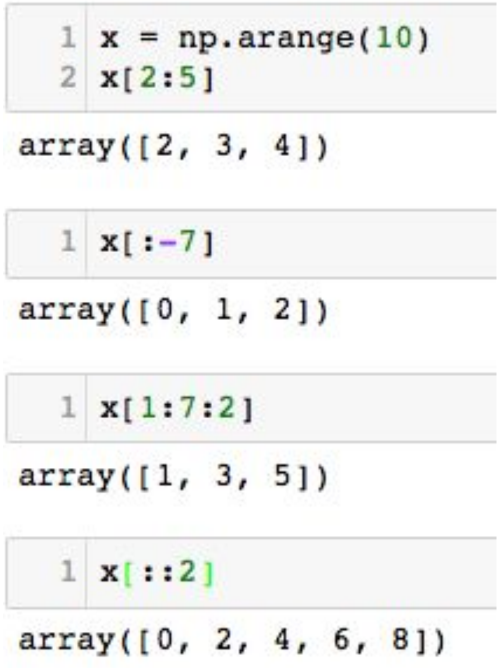
`np.arange(x)`: array version of Python’s `range(x)`, like `[0,1,2,...,x-1]`

`np.arange(x,y)`: array version of `range(x,y)`, like `[x,x+1,...,y-1]`

`np.arange(x,y,z)`: array of elements `[x,y)` in `z`-size increments.

Related useful functions, that give better/clearer control of start/endpoints and allow for multidimensional arrays:
https://docs.scipy.org/doc/numpy/reference/generated/numpy.linspace.html
https://docs.scipy.org/doc/numpy/reference/generated/numpy.ogrid.html
https://docs.scipy.org/doc/numpy/reference/generated/numpy.mgrid.html

`numpy` array indexing is highly expressive



```
x = np.arange(10)
x[2:5]
```

```
array([2, 3, 4])
```

```
x[:-7]
```

```
array([0, 1, 2])
```

```
x[1:7:2]
```

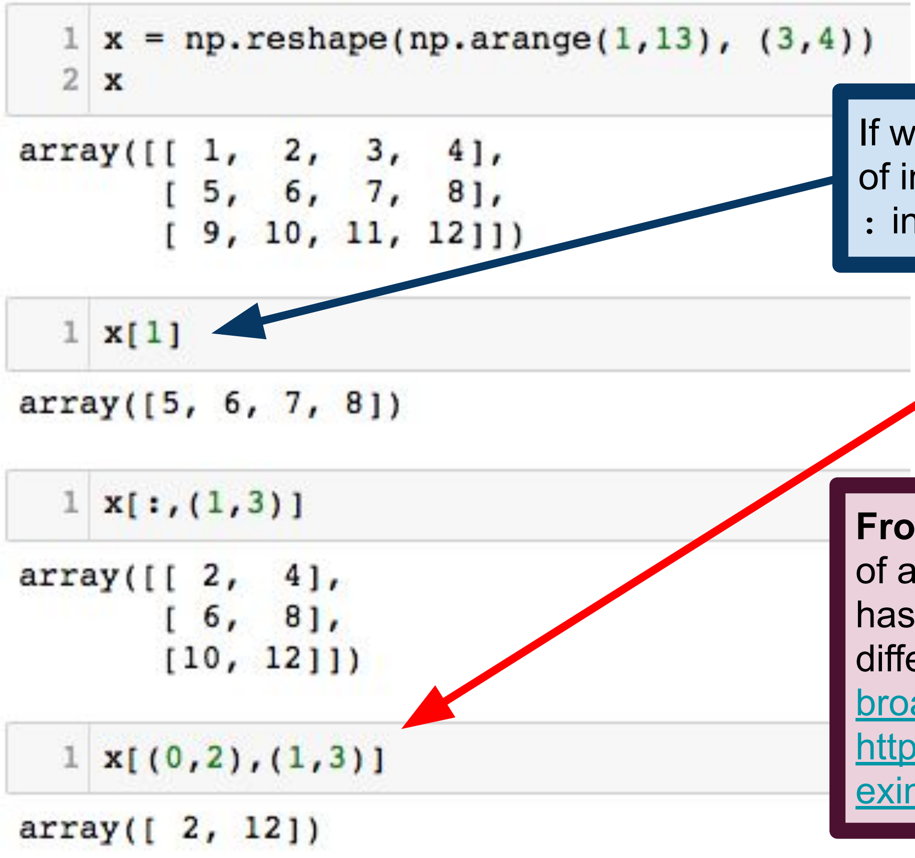
```
array([1, 3, 5])
```

```
x[::2]
```

```
array([0, 2, 4, 6, 8])
```

Slices, strides, indexing from the end, etc.
Just like with Python lists.

More array indexing



```
x = np.reshape(np.arange(1,13), (3,4))
x
```

```
array([[ 1,  2,  3,  4],
       [ 5,  6,  7,  8],
       [ 9, 10, 11, 12]])
```

```
x[1]
```

```
array([5, 6, 7, 8])
```

```
x[:,(1,3)]
```

```
array([[ 2,  4],
       [ 6,  8],
       [10, 12]])
```

```
x[(0,2),(1,3)]
```

```
array([ 2, 12])
```

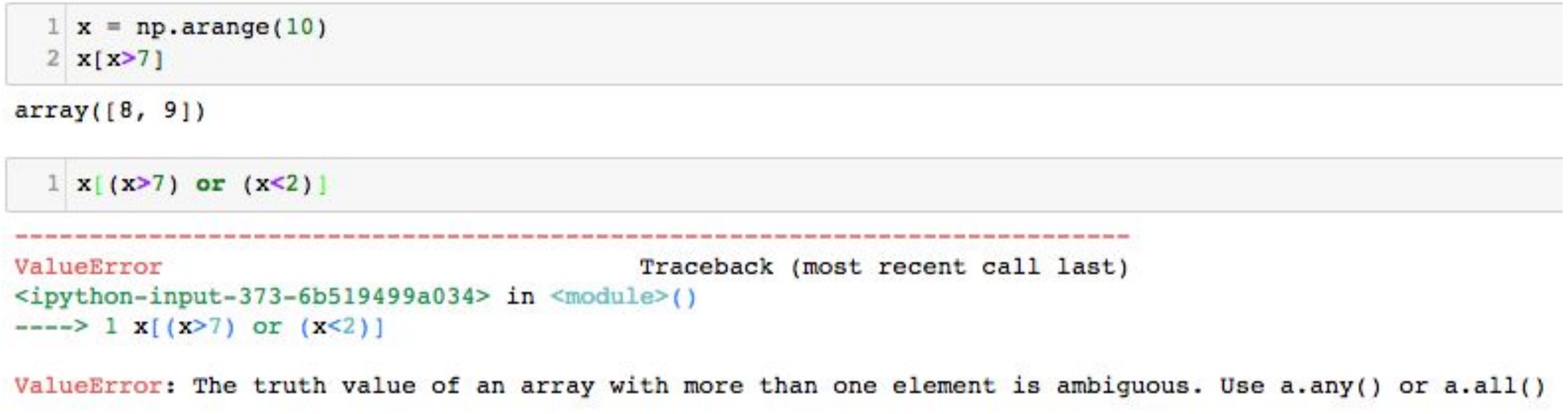
If we specify fewer than the number of indices, `numpy` assumes we mean `:` in the remaining indices.

Warning: if you're used to MATLAB or R, this behavior will seem weird to you.

From the documentation: When the index consists of as many integer arrays as the array being indexed has dimensions, the indexing is straight forward, but different from slicing. Advanced indexes always are broadcast and iterated as *one*.
https://docs.scipy.org/doc/numpy/reference/arrays.indexing.html#integer-array-indexing

More array indexing

Numpy allows MATLAB/R-like indexing by Booleans



```
x = np.arange(10)
x[x>7]
```

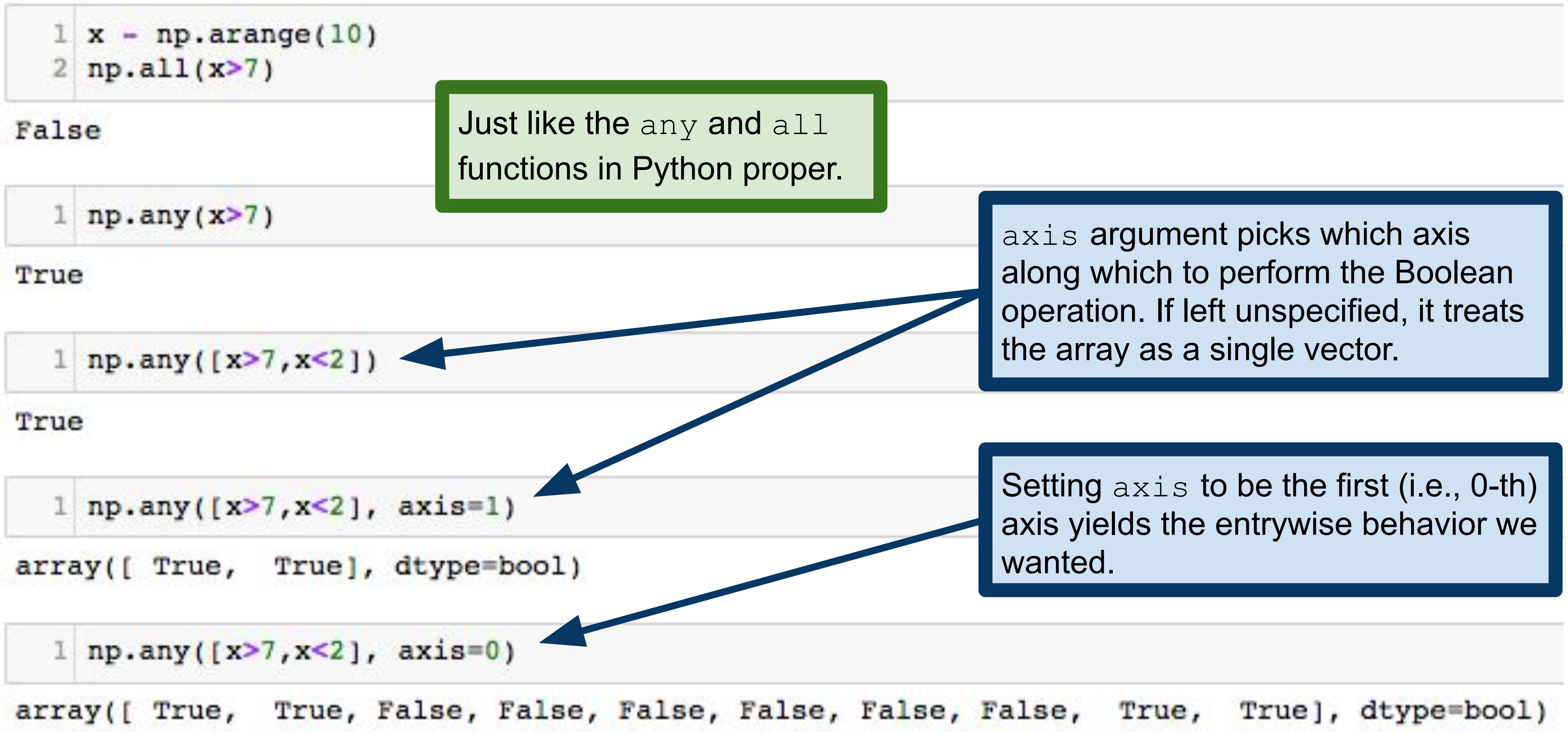
```
array([8, 9])
```

```
x[(x>7) or (x<2)]
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-373-6b519499a034> in <module>()
----> 1 x[(x>7) or (x<2)]

ValueError: The truth value of an array with more than one element is ambiguous. Use a.any() or a.all()
```

Believe it or not, this error is by design! The designers of `numpy` were concerned about ambiguities in Boolean vector operations. In essence, should `(x>7) or (x<2)` be a vector of Booleans or a single Boolean?

Boolean operations: `np.any()`, `np.all()`



```
x = np.arange(10)
np.all(x>7)
```

```
False
```

Just like the `any` and `all` functions in Python proper.

```
np.any(x>7)
```

```
True
```

```
np.any([x>7,x<2])
```

```
True
```

`axis` argument picks which axis along which to perform the Boolean operation. If left unspecified, it treats the array as a single vector.

```
np.any([x>7,x<2], axis=1)
```

```
array([ True,  True], dtype=bool)
```

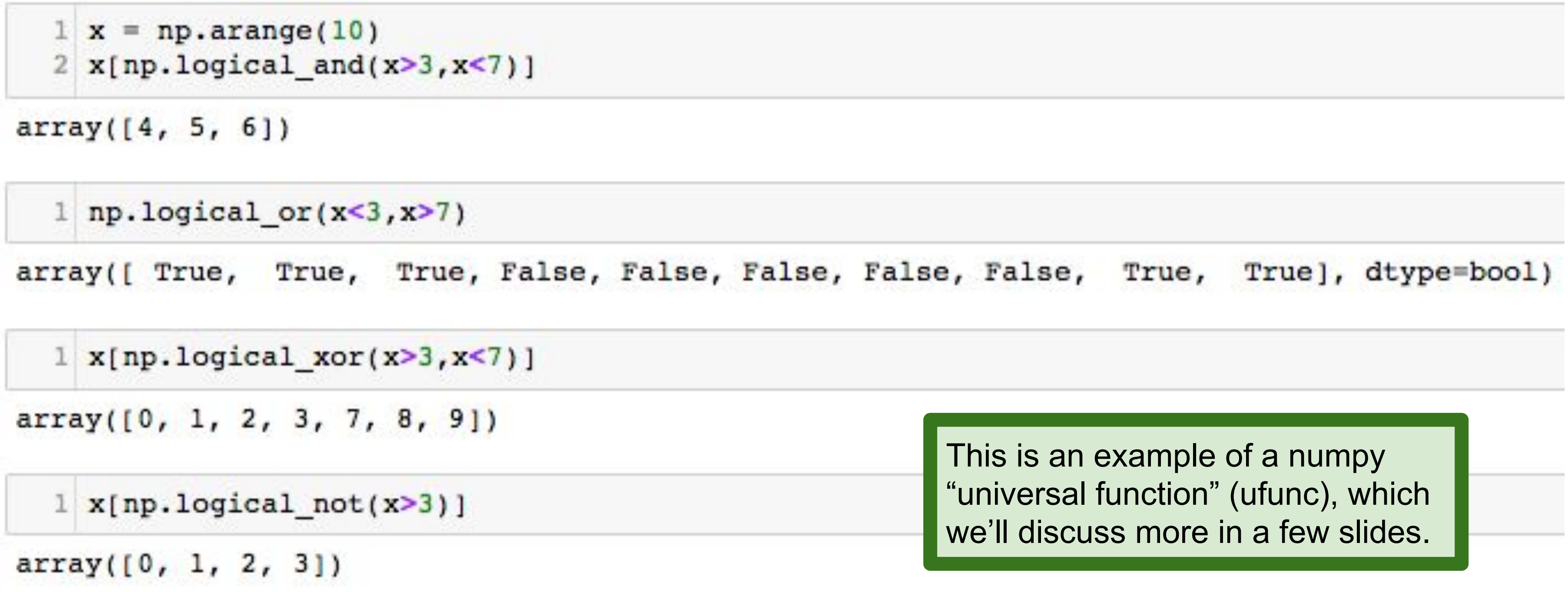
Setting `axis` to be the first (i.e., 0-th) axis yields the entrywise behavior we wanted.

```
np.any([x>7,x<2], axis=0)
```

```
array([ True,  True, False, False, False, False, False, False,  True,  True], dtype=bool)
```

Boolean operations: `np.logical_and()`

`numpy` also has built-in Boolean vector operations, which are simpler/clearer at the cost of the expressiveness of `np.any()`, `np.all()`.



```
x = np.arange(10)
x[np.logical_and(x>3,x<7)]
```

```
array([4, 5, 6])
```

```
np.logical_or(x<3,x>7)
```

```
array([ True,  True,  True, False, False, False, False, False,  True,  True], dtype=bool)
```

```
x[np.logical_xor(x>3,x<7)]
```

```
array([0, 1, 2, 3, 7, 8, 9])
```

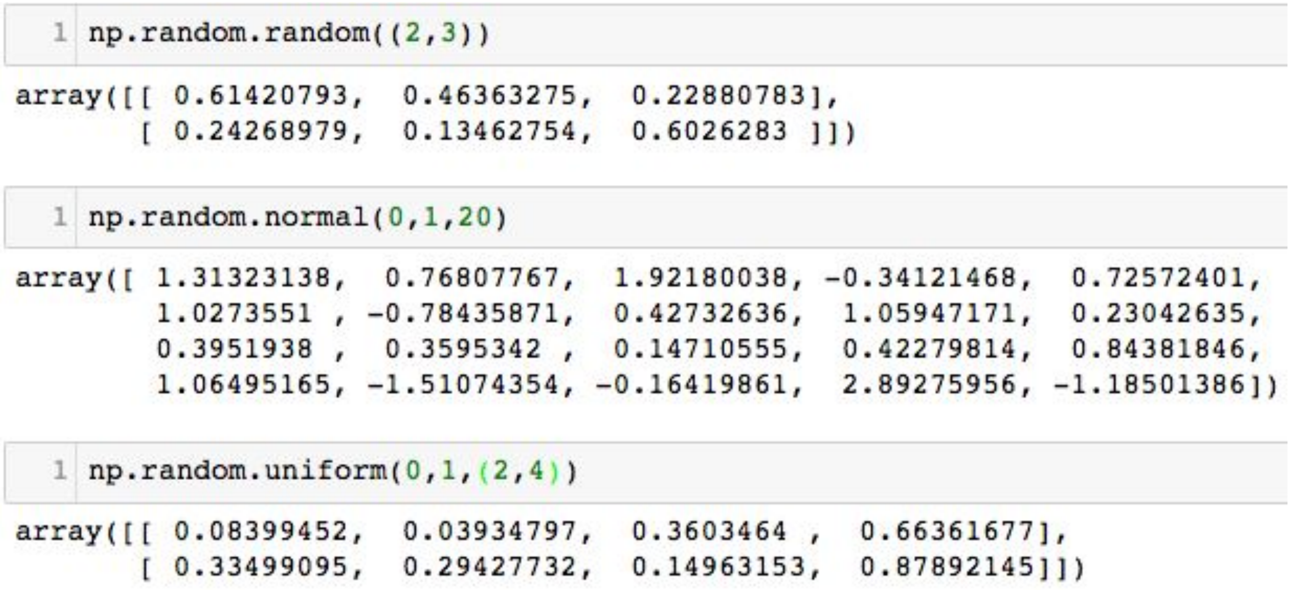
```
x[np.logical_not(x>3)]
```

```
array([0, 1, 2, 3])
```

This is an example of a numpy "universal function" (ufunc), which we'll discuss more in a few slides.

Random numbers in `numpy`

`np.random` contains methods for generating random numbers



```
np.random.random((2,3))
```

```
array([[ 0.61420793,  0.46363275,  0.22880783],
       [ 0.24268979,  0.13462754,  0.6026283 ]])
```

```
np.random.normal(0,1,20)
```

```
array([ 1.31323138,  0.76807767,  1.92180038, -0.34121468,  0.72572401,
        1.0273551 , -0.78435871,  0.42732636,  1.05947171,  0.23042635,
        0.3951938 ,  0.3595342 ,  0.14710555,  0.42279814,  0.84381846,
        1.06495165, -1.51074354, -0.16419861,  2.89275956, -1.18501386])
```

```
np.random.uniform(0,1,(2,4))
```

```
array([[ 0.08399452,  0.03934797,  0.3603464 ,  0.66361677],
       [ 0.33499095,  0.29427732,  0.14963153,  0.87892145]])
```

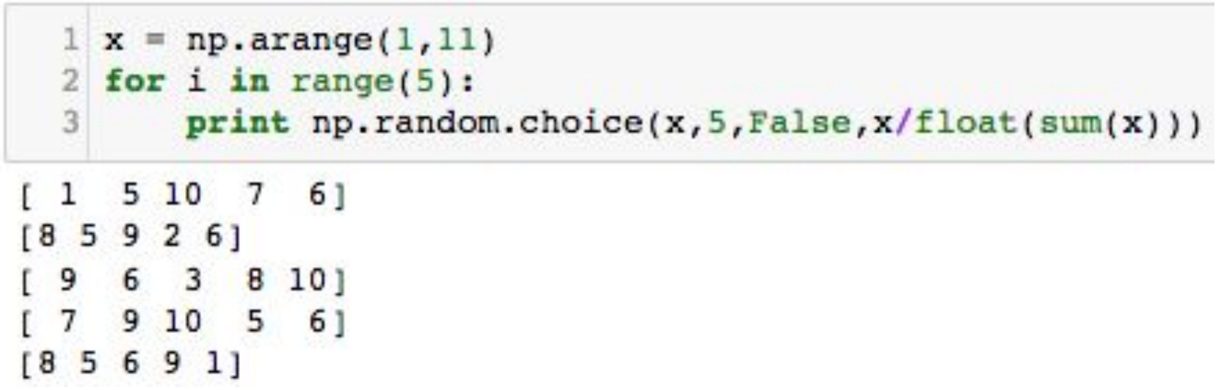
Lots more distributions:

https://docs.scipy.org/doc/numpy-1.14.0/reference/routines.random.html

`np.random.choice()`: random samples from data

`np.random.choice(x,[size,replace,p])`

Generates a sample of `size` elements from the array `x`, drawn with (`replace=True`) or without (`replace=False`) replacement, with element probabilities given by vector `p`.



```
x = np.arange(1,11)
for i in range(5):
    print np.random.choice(x,5,False,x/float(sum(x)))
```

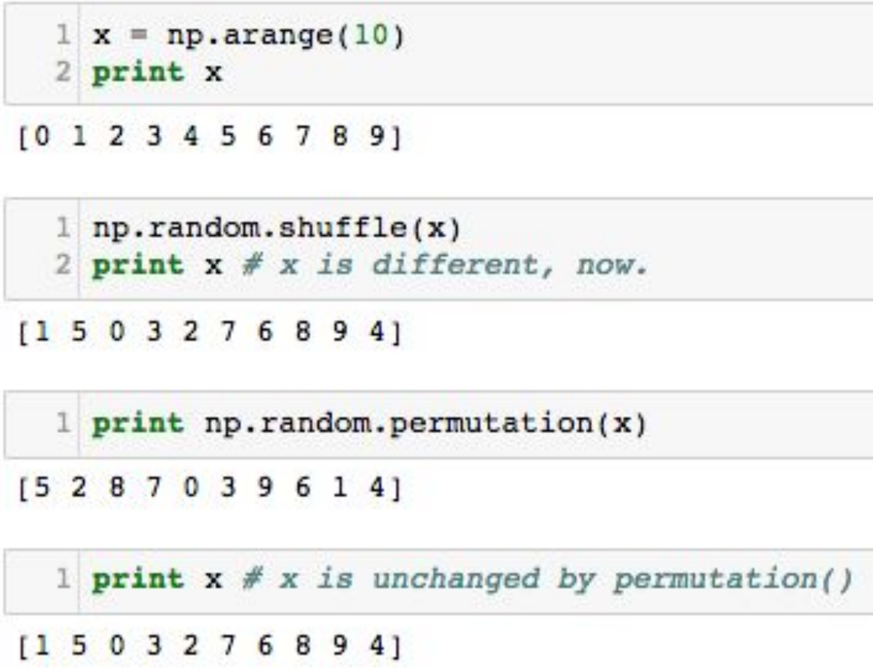
```
[ 1  5 10  7  6]
[8 5 9 2 6]
[ 9  6  3  8 10]
[ 7  9 10  5  6]
[8 5 6 9 1]
```

`shuffle()` **vs** `permutation()`

`np.random.shuffle(x)`
randomly permutes entries of `x` in place
so `x` itself is changed by this operation!

`np.random.permutation(x)`
returns a random permutation of `x`
and `x` remains unchanged.

Compare with the Python `list.sort()` and `sorted()` functions.



```
x = np.arange(10)
print x
```

```
[0 1 2 3 4 5 6 7 8 9]
```

```
np.random.shuffle(x)
print x # x is different, now.
```

```
[1 5 0 3 2 7 6 8 9 4]
```

```
print np.random.permutation(x)
```

```
[5 2 8 7 0 3 9 6 1 4]
```

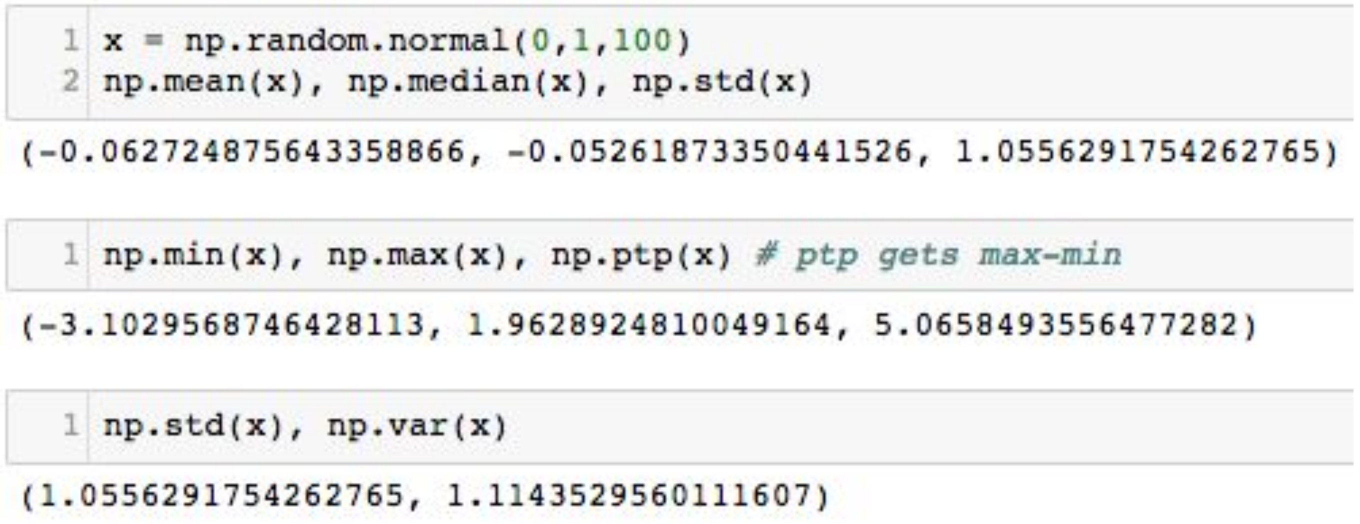
```
print x # x is unchanged by permutation()
```

```
[1 5 0 3 2 7 6 8 9 4]
```

Intermission

Statistics in `numpy`

`numpy` implements all the standard statistics functions you've come to expect



```
x = np.random.normal(0,1,100)
np.mean(x), np.median(x), np.std(x)
```

```
(-0.062724875643358866, -0.052618733504415 26, 1.0556291754262765)
```

```
np.min(x), np.max(x), np.ptp(x) # ptp gets max-min
```

```
(-3.1029568746428113, 1.9628924810049164, 5.0658493556477282)
```

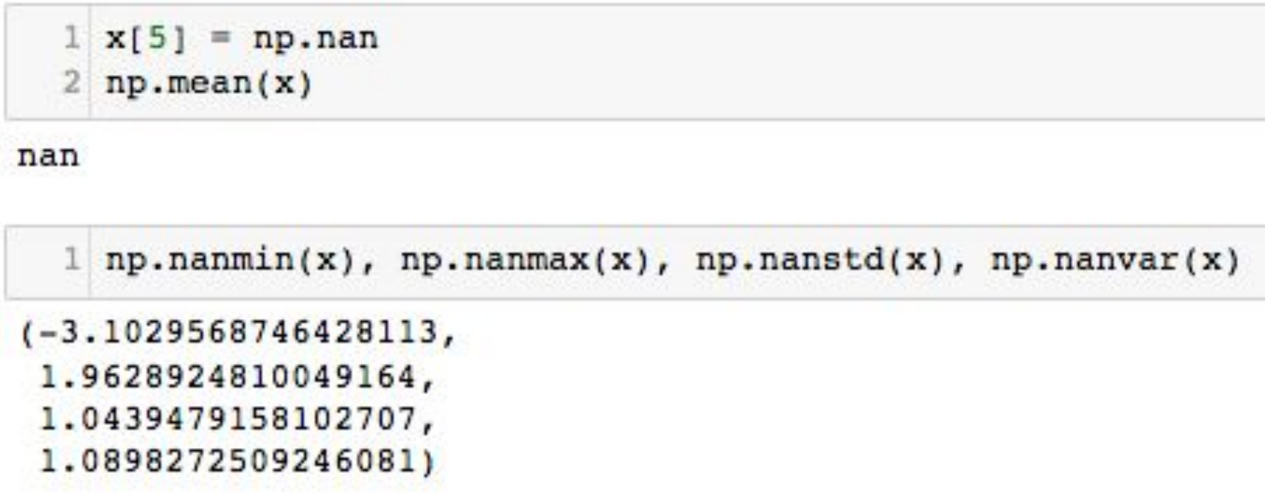
```
np.std(x), np.var(x)
```

```
(1.0556291754262765, 1.1143529560111607)
```

Statistics in `numpy` (cont'd)

NaN is short for "not a number". NaNs typically arise either because or improper mathematical operations (e.g., dividing by zero) or to represent missing data.

Numpy deals with NaNs more gracefully than MATLAB/R:



```
x[5] = np.nan
np.mean(x)
```

```
nan
```

```
np.nanmin(x), np.nanmax(x), np.nanstd(x), np.nanvar(x)
```

```
(-3.1029568746428113,
 1.9628924810049164,
 1.0439479158102707,
 1.0898272509246081)
```

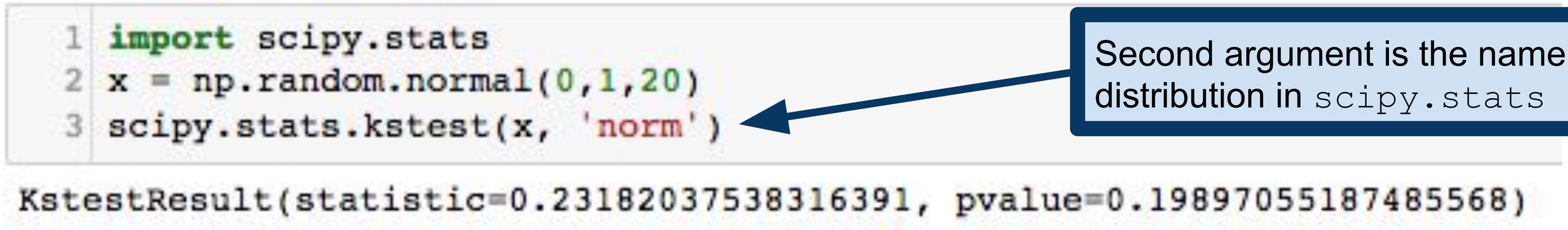
For more statistical functions, see:
https://docs.scipy.org/doc/numpy-1.8.1/reference/routines.statistics.html

Probability and statistics in `scipy`

`scipy` is a distinct Python package, part of the `numpy` ecosystem.

(Almost) all the distributions you could possibly ever want:
https://docs.scipy.org/doc/scipy/reference/stats.html#continuous-distributions
https://docs.scipy.org/doc/scipy/reference/stats.html#multivariate-distributions
https://docs.scipy.org/doc/scipy/reference/stats.html#discrete-distributions

More statistical functions (moments, kurtosis, statistical tests):
https://docs.scipy.org/doc/scipy/reference/stats.html#statistical-functions



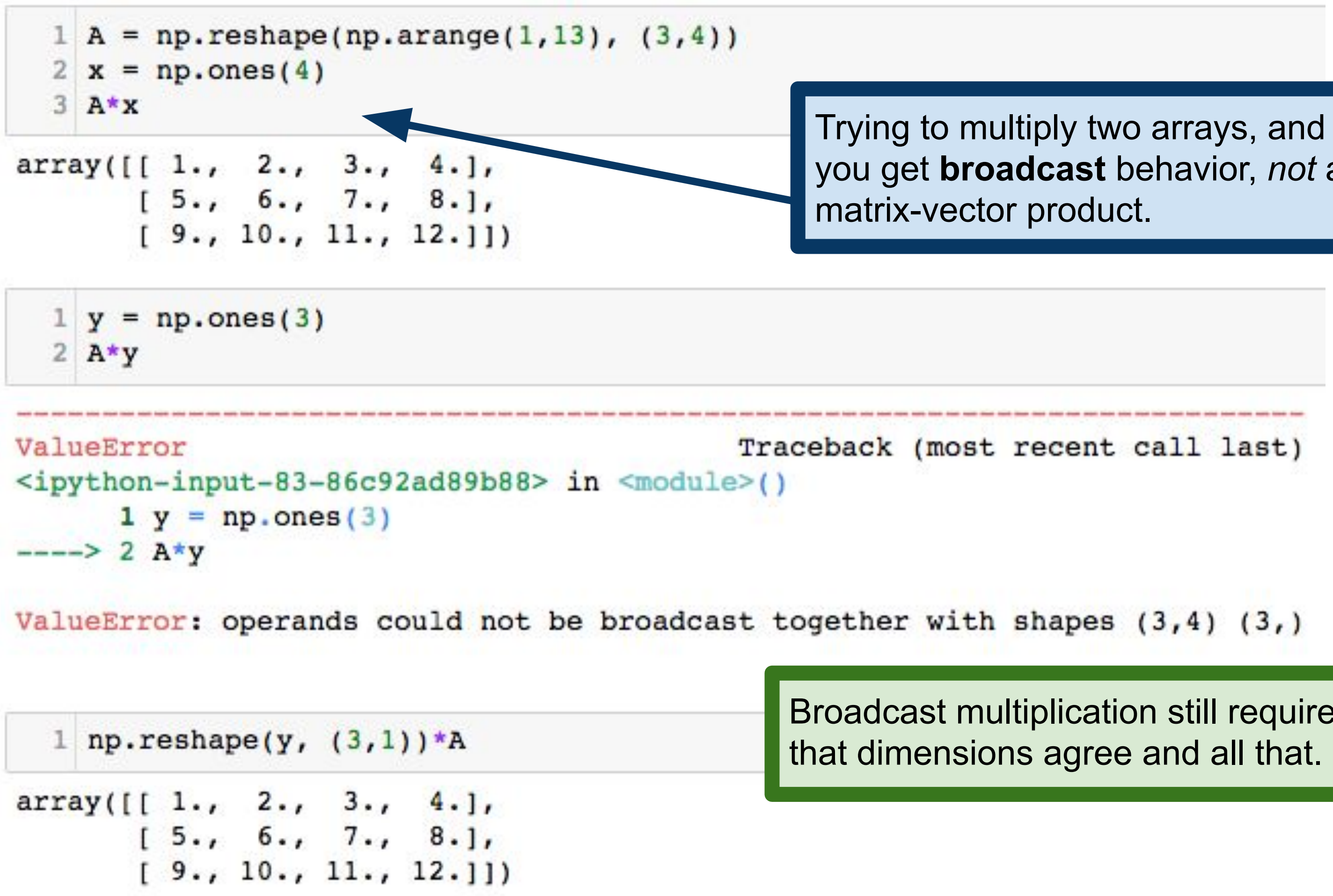
```python
import scipy.stats
x = np.random.normal(0,1,20)
scipy.stats.kstest(x, 'norm')
```

```
KstestResult(statistic=0.23182037538316391, pvalue=0.19897055187485568)
```

Second argument is the name of a distribution in `scipy.stats`

Kolmogorov-Smirnov test

Matrix-vector operations in `numpy`



```
A = np.reshape(np.arange(1,13), (3,4))
x = np.ones(4)
A*x
```

```
array([[  1.,   2.,   3.,   4.],
       [  5.,   6.,   7.,   8.],
       [  9.,  10.,  11.,  12.]])
```

Trying to multiply two arrays, and you get **broadcast** behavior, *not* a matrix-vector product.

```
y = np.ones(3)
A*y
```

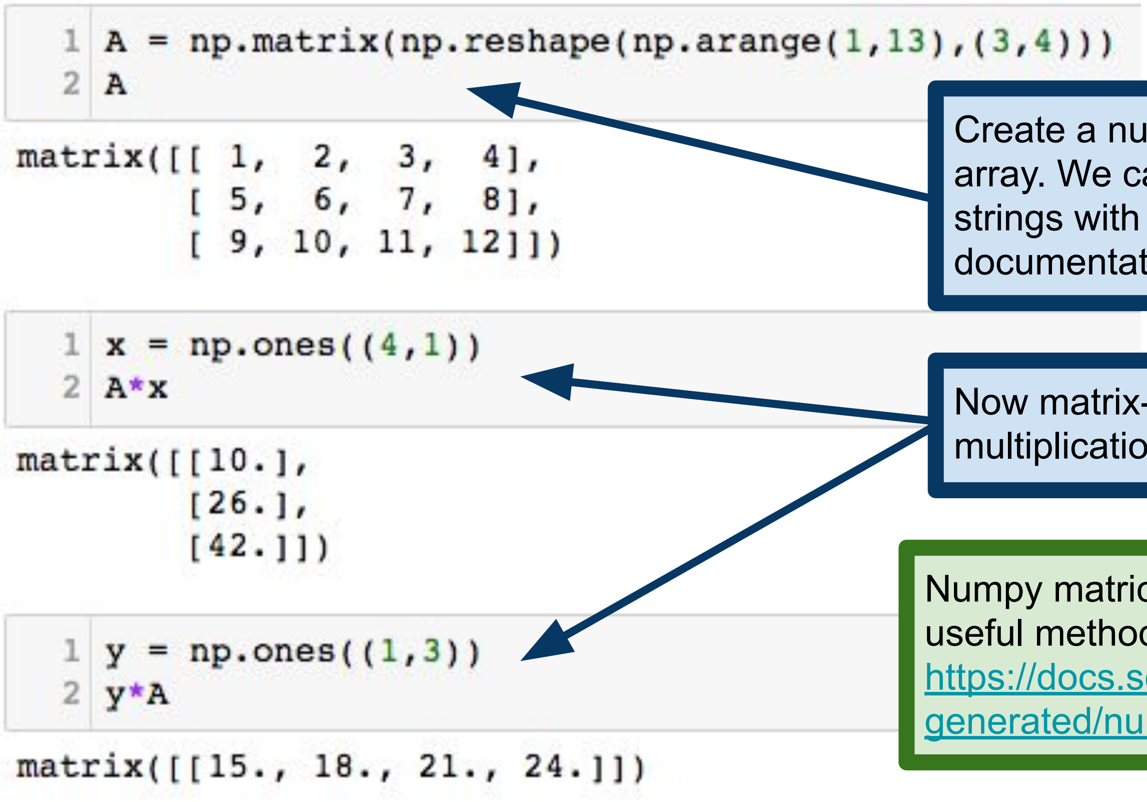
```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-83-86c92ad89b88> in <module>()
      1 y = np.ones(3)
----> 2 A*y

ValueError: operands could not be broadcast together with shapes (3,4) (3,)
```

```
np.reshape(y, (3,1))*A
```

```
array([[  1.,   2.,   3.,   4.],
       [  5.,   6.,   7.,   8.],
       [  9.,  10.,  11.,  12.]])
```

Broadcast multiplication still requires that dimensions agree and all that.

Matrix-vector operations in `numpy`



```
A = np.matrix(np.reshape(np.arange(1,13),(3,4)))
A
```

```
matrix([[ 1,  2,  3,  4],
        [ 5,  6,  7,  8],
        [ 9, 10, 11, 12]])
```

```
x = np.ones((4,1))
A*x
```

```
matrix([[10.],
        [26.],
        [42.]])
```

```
y = np.ones((1,3))
y*A
```

```
matrix([[15., 18., 21., 24.]])
```

Create a numpy matrix from a numpy array. We can also create matrices from strings with MATLAB-like syntax. See documentation.

Now matrix-vector and vector-matrix multiplication work as we want.

Numpy matrices support a whole bunch of useful methods. See documentation: https://docs.scipy.org/doc/numpy/reference/generated/numpy.matrix.html

`numpy/scipy` universal functions (ufuncs)

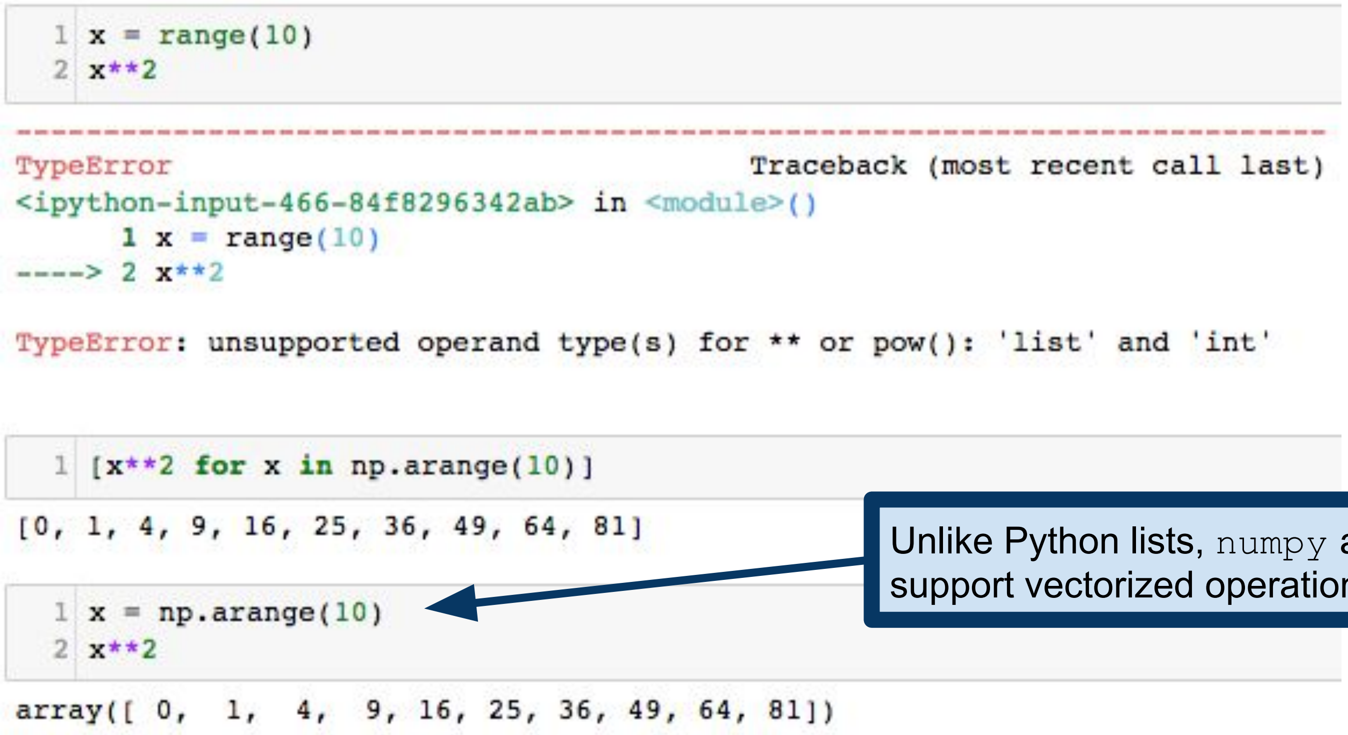
From the documentation:

> A universal function (or ufunc for short) is a function that operates on ndarrays in an element-by-element fashion, supporting array broadcasting, type casting, and several other standard features. That is, a ufunc is a “vectorized” wrapper for a function that takes a fixed number of scalar inputs and produces a fixed number of scalar outputs.
> https://docs.scipy.org/doc/numpy/reference/ufuncs.html

So ufuncs are vectorized operations, just like in R and MATLAB

ufuncs in action

List comprehensions are great, but they’re not well-suited to numerical computing



```
x = range(10)
x**2
```

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
<ipython-input-466-84f8296342ab> in <module>()
      1 x = range(10)
----> 2 x**2

TypeError: unsupported operand type(s) for ** or pow(): 'list' and 'int'
```

```
[x**2 for x in np.arange(10)]
```

```
[0, 1, 4, 9, 16, 25, 36, 49, 64, 81]
```

```
x = np.arange(10)
x**2
```

```
array([ 0,  1,  4,  9, 16, 25, 36, 49, 64, 81])
```

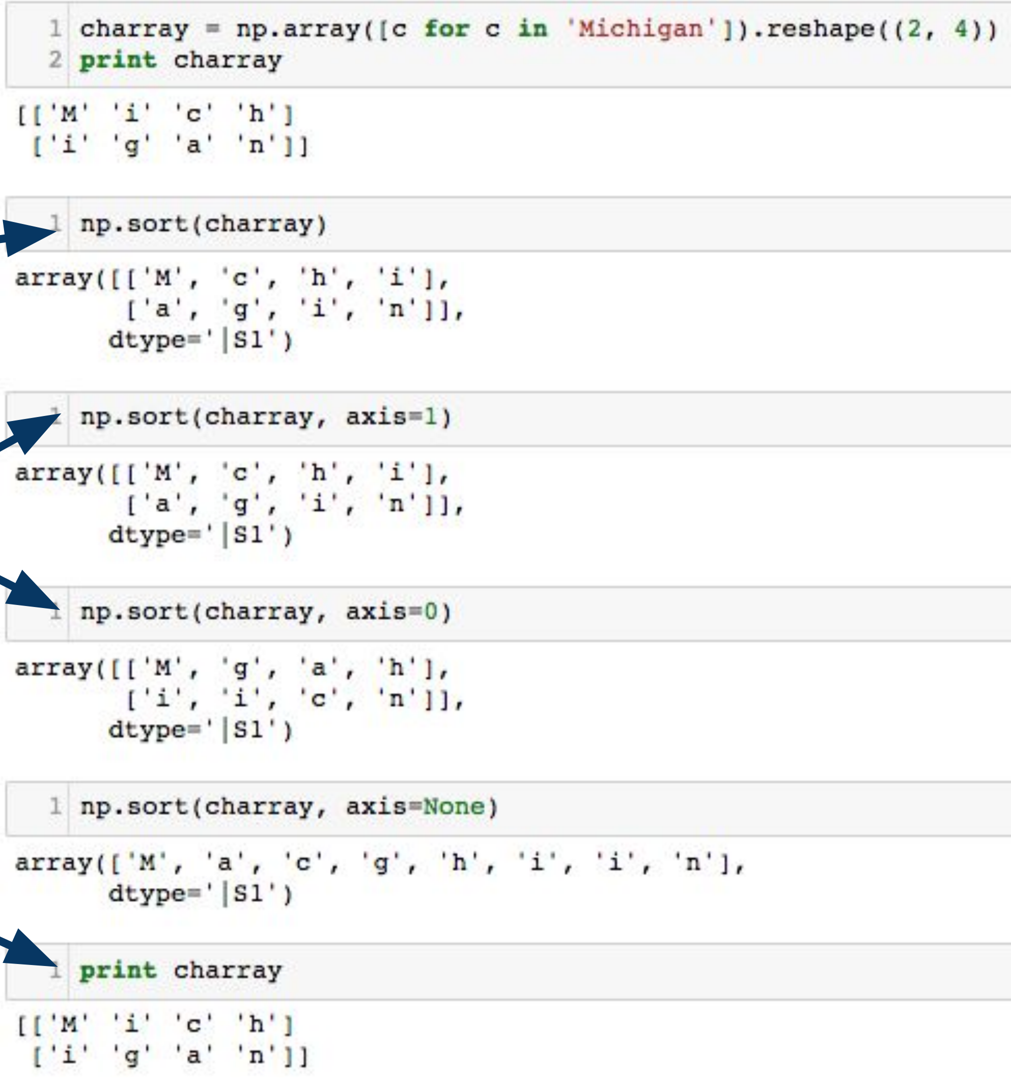
Unlike Python lists, `numpy` arrays support vectorized operations.

Sorting with `numpy/scipy`

ASCII rears its head-- capital letters are "earlier" than all lower-case by default.

Sorting is along the "last" axis by default. Note contrast with `np.any()`. To treat the array as a single vector, `axis` must be set to `None`.

Original array is unchanged by use of `np.sort()`, like Python's built-in `sorted()`



```
charray = np.array([c for c in 'Michigan']).reshape((2, 4))
print charray
```

```
[['M' 'i' 'c' 'h']
 ['i' 'g' 'a' 'n']]
```

```
np.sort(charray)
```

```
array([['M', 'c', 'h', 'i'],
       ['a', 'g', 'i', 'n']],
      dtype='|S1')
```

```
np.sort(charray, axis=1)
```

```
array([['M', 'c', 'h', 'i'],
       ['a', 'g', 'i', 'n']],
      dtype='|S1')
```

```
np.sort(charray, axis=0)
```

```
array([['M', 'g', 'a', 'h'],
       ['i', 'i', 'c', 'n']],
      dtype='|S1')
```

```
np.sort(charray, axis=None)
```

```
array(['M', 'a', 'c', 'g', 'h', 'i', 'i', 'n'],
      dtype='|S1')
```

```
print charray
```

```
[['M' 'i' 'c' 'h']
 ['i' 'g' 'a' 'n']]
```

A cautionary note

`numpy`/`scipy` have several similarly-named functions with different behaviors!

Example: `np.amax`, `np.ndarray.max`, `np.maximum`

The best way to avoid these confusions is to

1) Read the documentation carefully
2) Test your code!

Plotting with `matplotlib`

`matplotlib` is a plotting library for use in Python

Similar to R's `ggplot2` and MATLAB's plotting functions

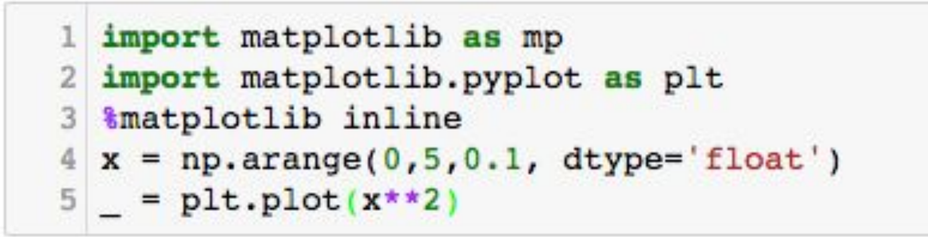
For MATLAB fans, `matplotlib.pyplot` implements MATLAB-like plotting:
http://matplotlib.org/users/pyplot_tutorial.html

Sample plots with code:
http://matplotlib.org/tutorials/introductory/sample_plots.html

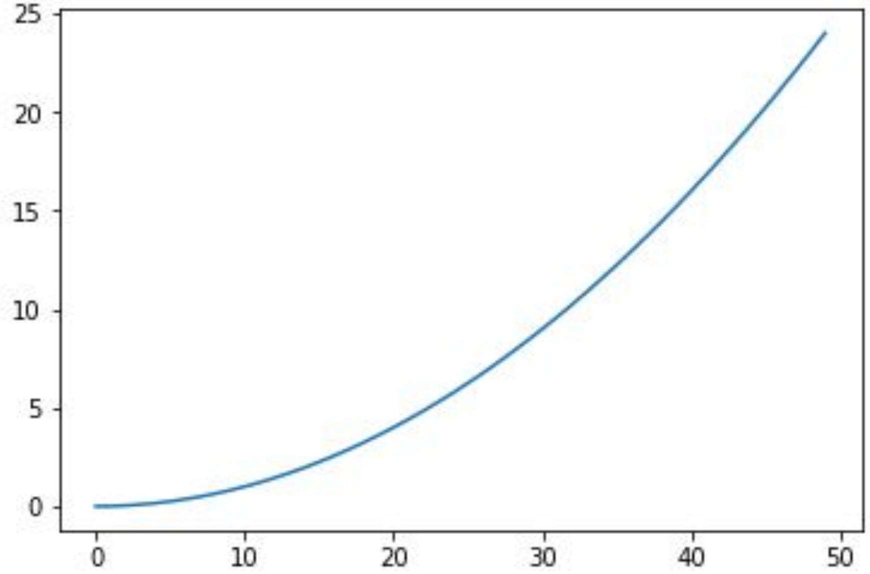
Basic plotting: `matplotlib.pyplot.plot`

`matplotlib.pyplot.plot(x,y)`
plots `y` as a function of `x`.

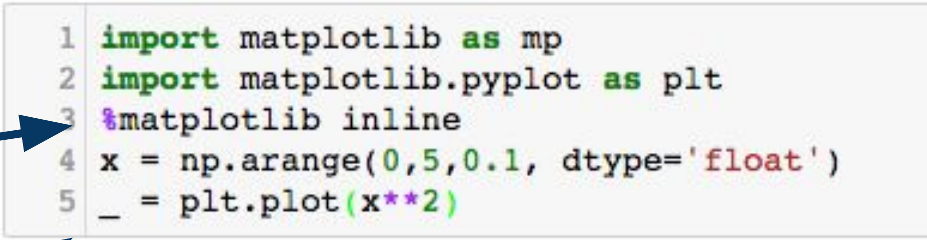
`matplotlib.pyplot(t)`
sets x-axis to `np.arange(len(t))`



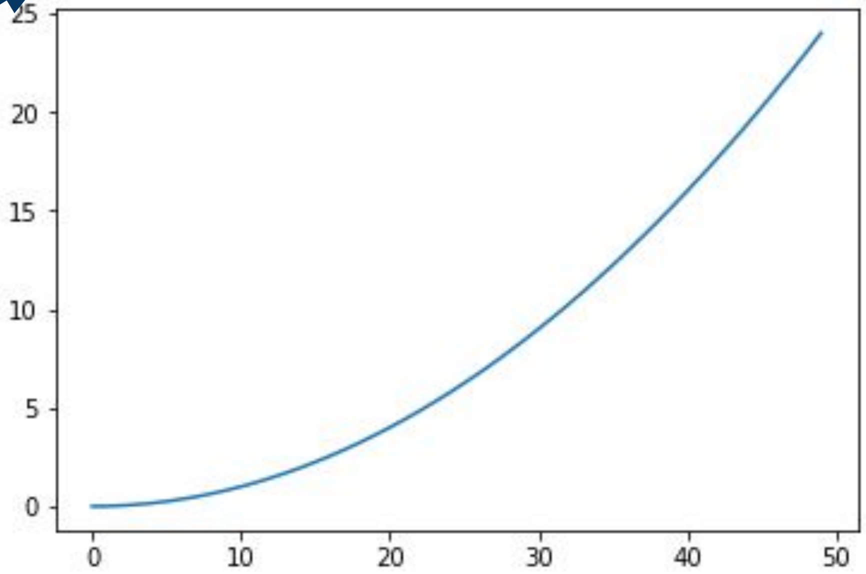
```
import matplotlib as mp
import matplotlib.pyplot as plt
%matplotlib inline
x = np.arange(0,5,0.1, dtype='float')
_ = plt.plot(x**2)
```



Basic plotting: `matplotlib.pyplot.plot`



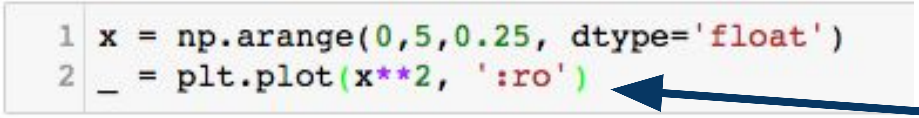
```
import matplotlib as mp
import matplotlib.pyplot as plt
%matplotlib inline
x = np.arange(0,5,0.1, dtype='float')
_ = plt.plot(x**2)
```



Jupyter “magic” command to make images appear in-line.

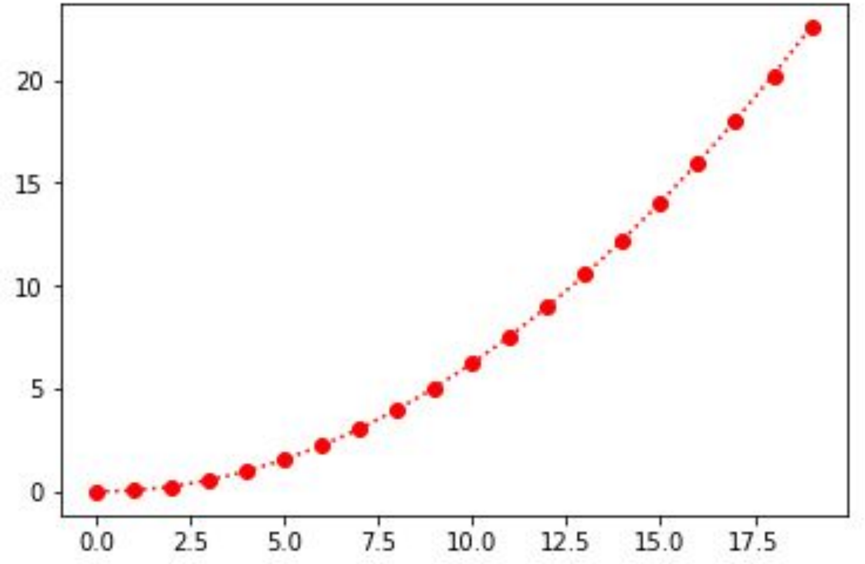
Reminder: Python `'_'` is a placeholder, similar to MATLAB `'~'`. Tells Python to treat this like variable assignment, but don’t store result anywhere.

Customizing plots

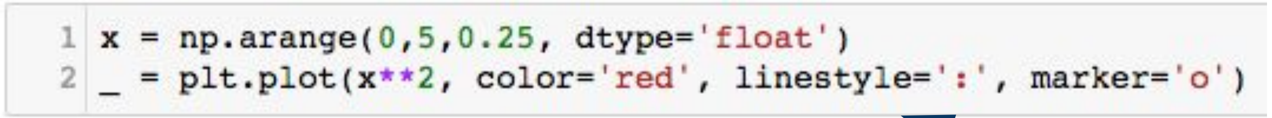


```
x = np.arange(0,5,0.25, dtype='float')
_ = plt.plot(x**2, ':ro')
```

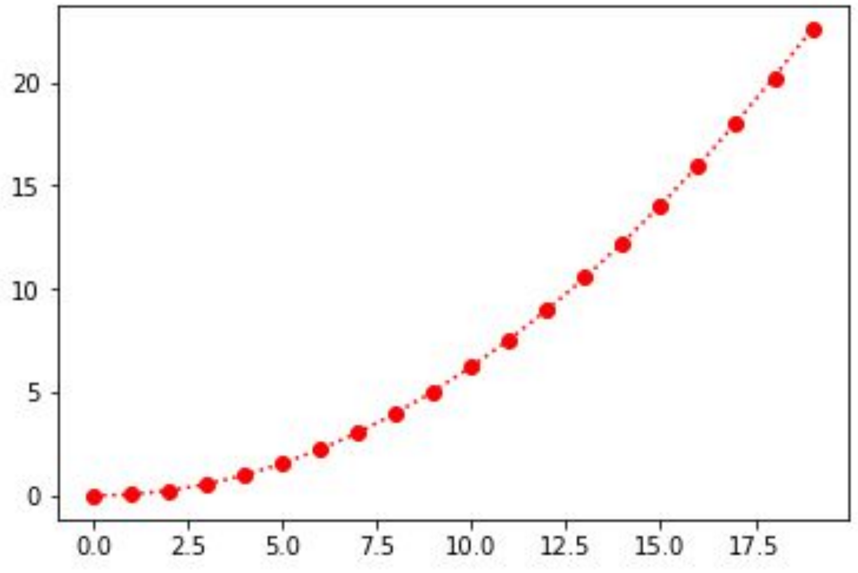
Second argument to `pyplot.plot` specifies line type, line color, and marker type.



Customizing plots



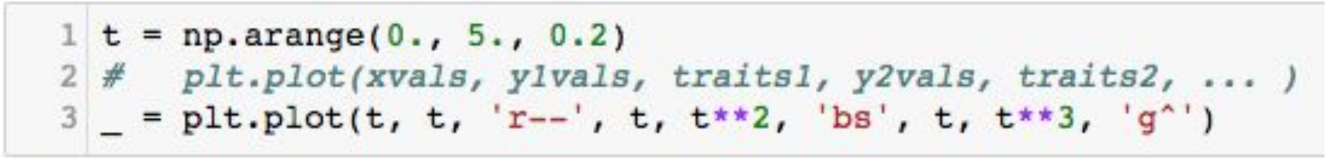
```
x = np.arange(0,5,0.25, dtype='float')
_ = plt.plot(x**2, color='red', linestyle=':', marker='o')
```



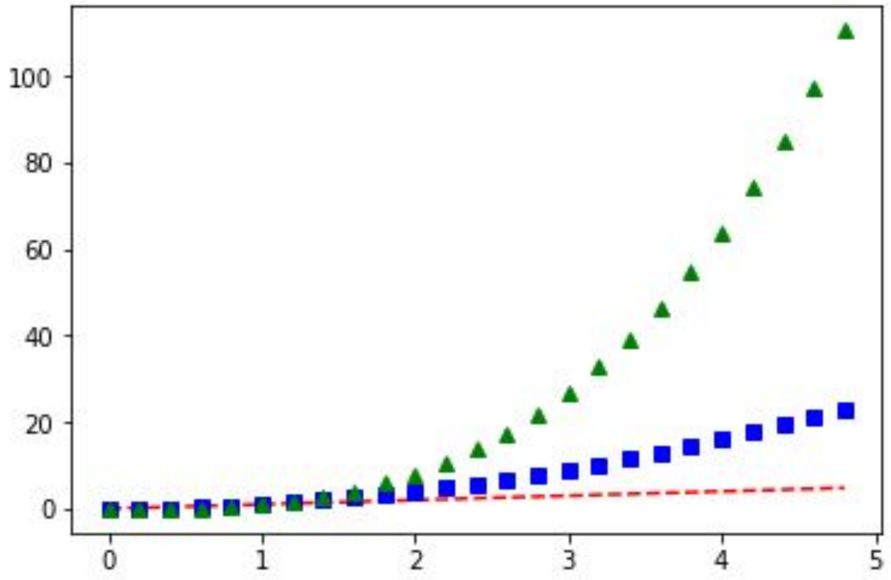
Long form of the command on the previous slide. Same plot!

A full list of the long-form arguments available to `pyplot.plot` are available in the table titled “Here are the available Line2D properties.”: http://matplotlib.org/users/pyplot_tutorial.html

Multiple lines in a single plot

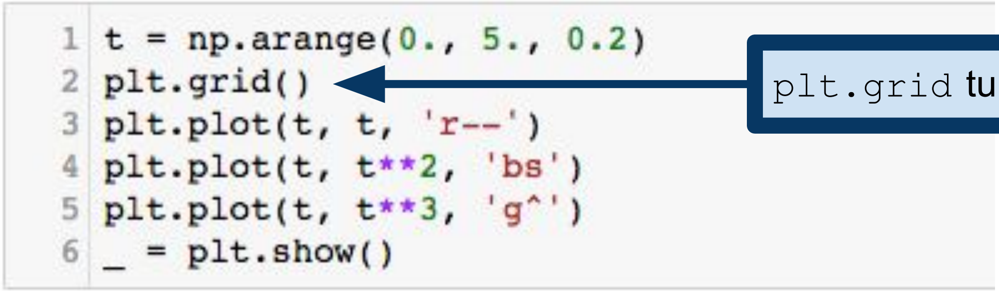


```
t = np.arange(0., 5., 0.2)
#   plt.plot(xvals, y1vals, traits1, y2vals, traits2, ... )
_ = plt.plot(t, t, 'r--', t, t**2, 'bs', t, t**3, 'g^')
```



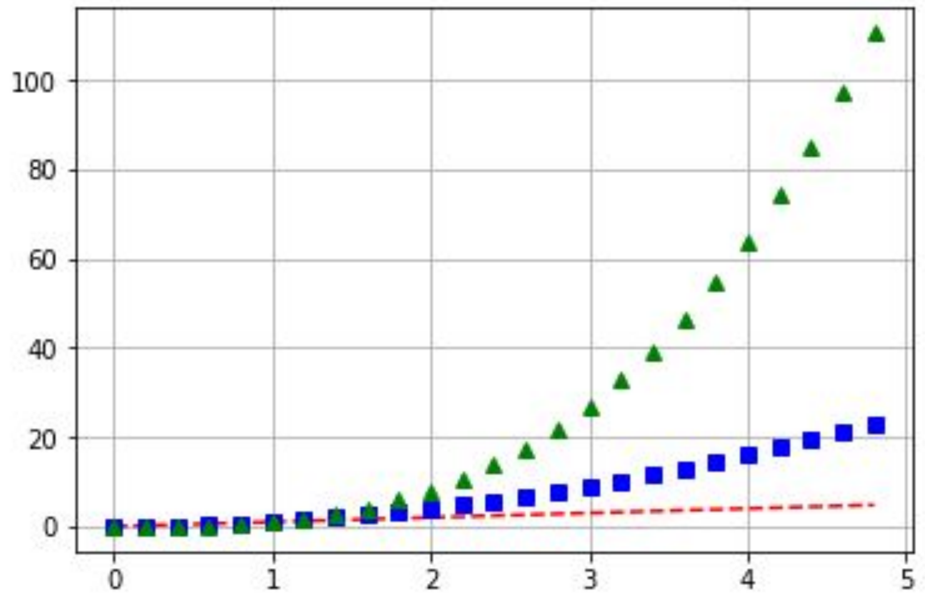
Note: more complicated specification of individual lines can be achieved by adding them to the plot one at a time.

Multiple lines in a single plot: long form



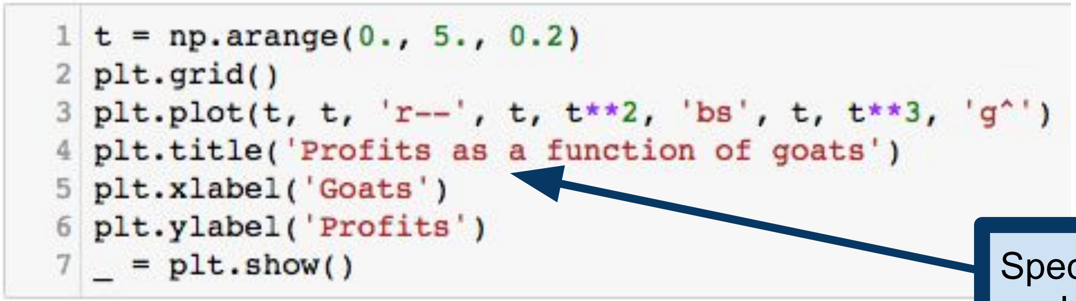
```
t = np.arange(0., 5., 0.2)
plt.grid()
plt.plot(t, t, 'r--')
plt.plot(t, t**2, 'bs')
plt.plot(t, t**3, 'g^')
_ = plt.show()
```

`plt.grid` turns grid lines on/off.



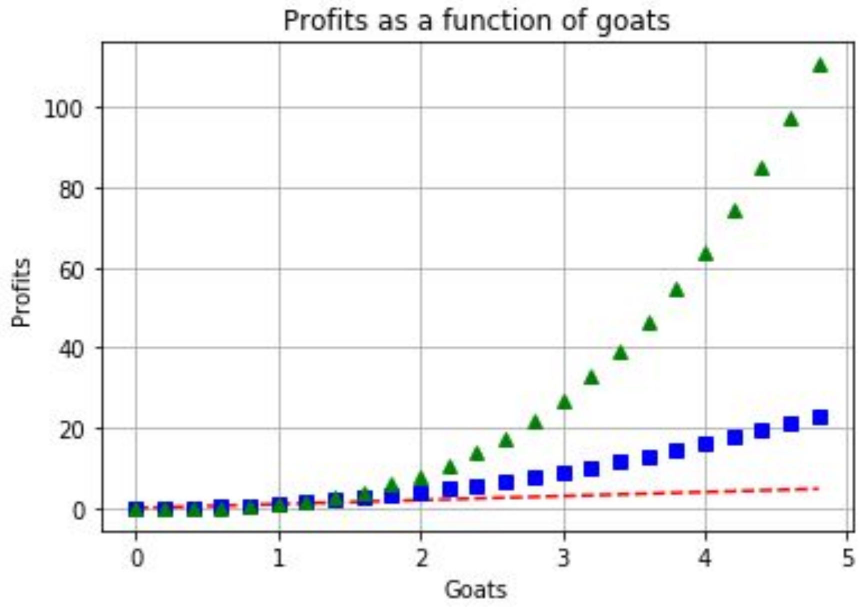
Note: same plot as previous slide, but specifying one line at a time so we could, if we wanted, use more complicated line attributes.

Titles and axis labels

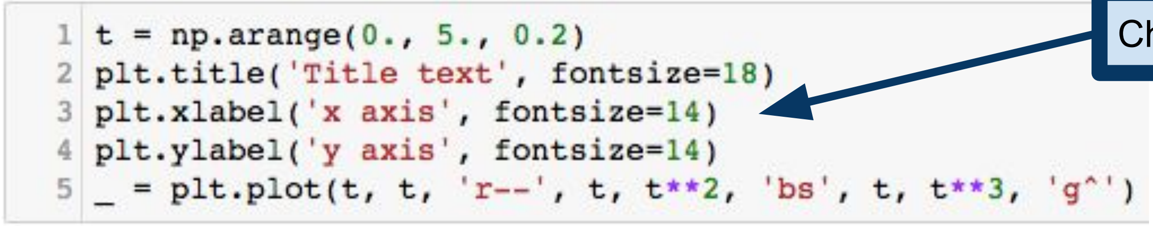


```
t = np.arange(0., 5., 0.2)
plt.grid()
plt.plot(t, t, 'r--', t, t**2, 'bs', t, t**3, 'g^')
plt.title('Profits as a function of goats')
plt.xlabel('Goats')
plt.ylabel('Profits')
_ = plt.show()
```

Specifying titles and axis labels couldn't be more straight-forward.

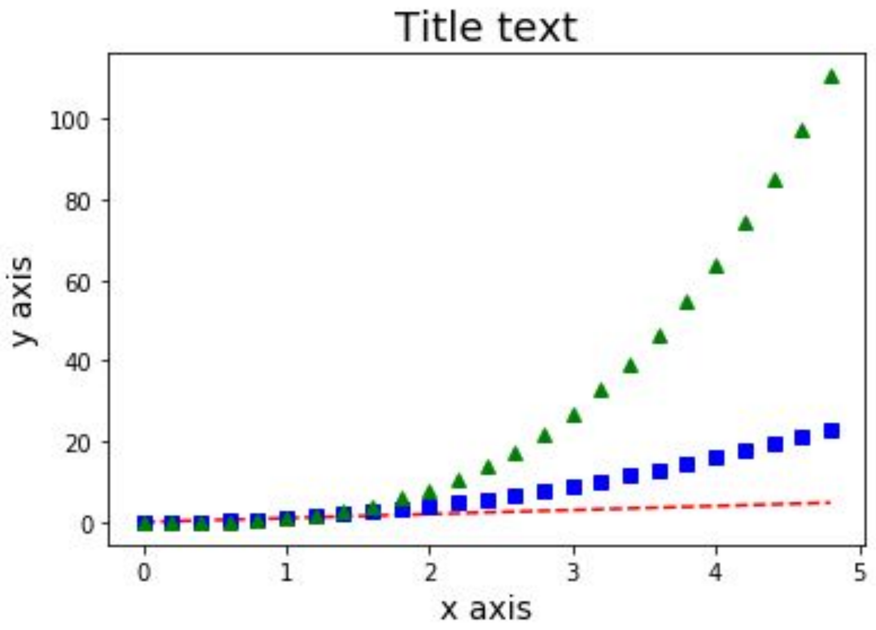


Titles and axis labels

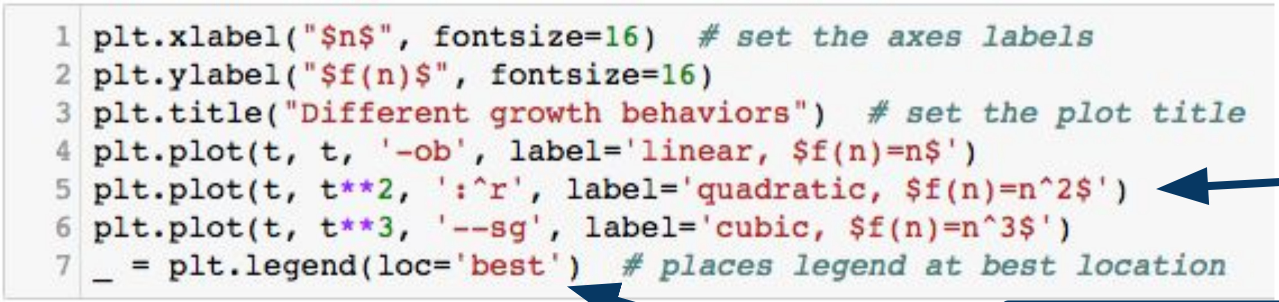


```
t = np.arange(0., 5., 0.2)
plt.title('Title text', fontsize=18)
plt.xlabel('x axis', fontsize=14)
plt.ylabel('y axis', fontsize=14)
_ = plt.plot(t, t, 'r--', t, t**2, 'bs', t, t**3, 'g^')
```

Change font sizes

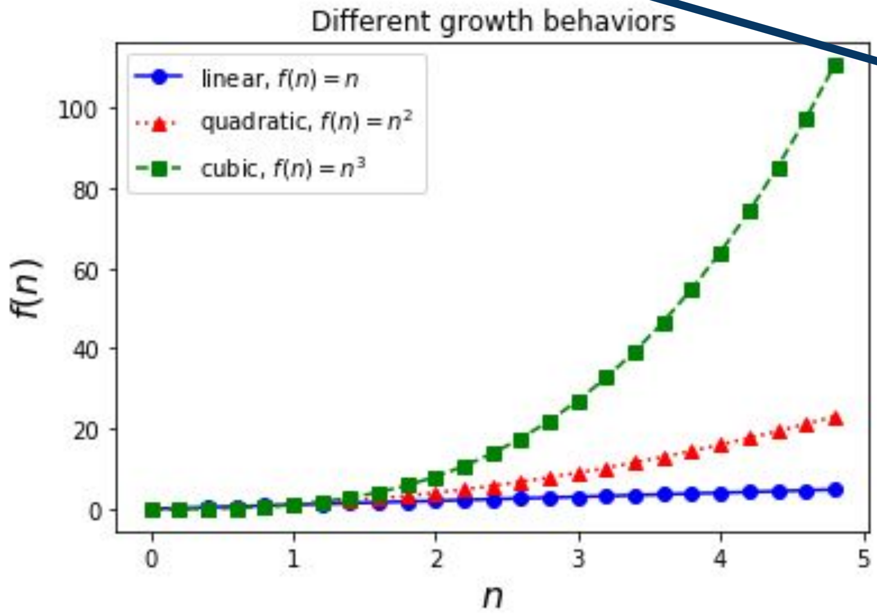


Legends



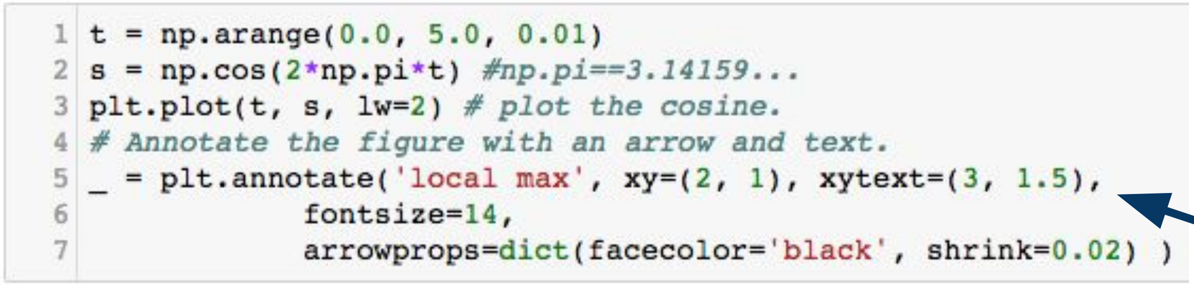
```
plt.xlabel("$n$", fontsize=16)  # set the axes labels
plt.ylabel("$f(n)$", fontsize=16)
plt.title("Different growth behaviors")  # set the plot title
plt.plot(t, t, '-ob', label='linear, $f(n)=n$')
plt.plot(t, t**2, ':^r', label='quadratic, $f(n)=n^2$')
plt.plot(t, t**3, '--sg', label='cubic, $f(n)=n^3$')
_ = plt.legend(loc='best')  # places legend at best location
```

Can use LaTeX in labels, titles, etc.

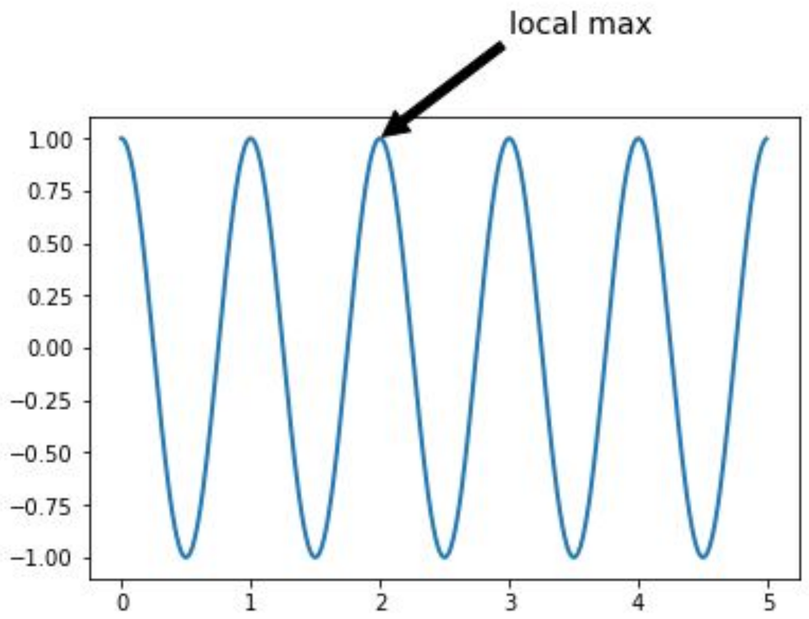


`pyplot.legend` generates legend based on label arguments passed to `pyplot.plot`. `loc='best'` tells `pyplot` to place the legend where it thinks is best.

Annotating figures



```
t = np.arange(0.0, 5.0, 0.01)
s = np.cos(2*np.pi*t) #np.pi==3.14159...
plt.plot(t, s, lw=2) # plot the cosine.
# Annotate the figure with an arrow and text.
_ = plt.annotate('local max', xy=(2, 1), xytext=(3, 1.5),
              fontsize=14,
              arrowprops=dict(facecolor='black', shrink=0.02) )
```

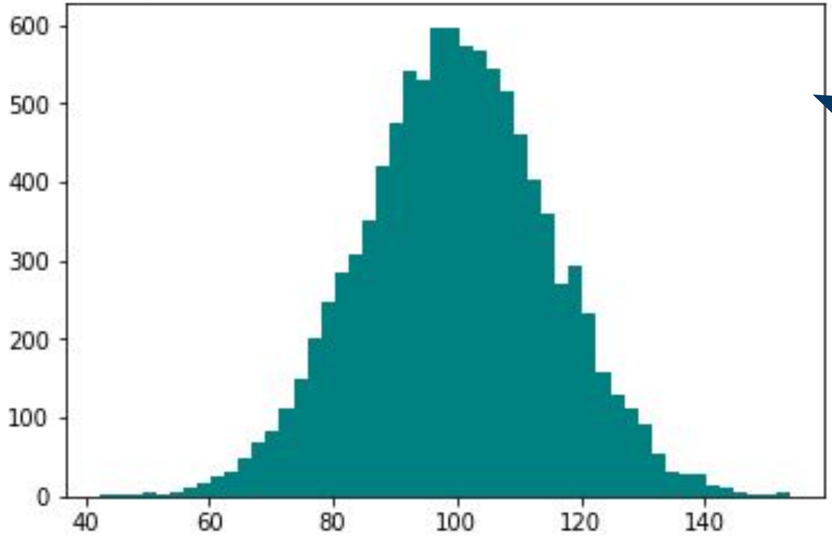


Specify text coordinates and coordinates of the arrowhead using the *coordinates of the plot itself*. This is pleasantly different from many other plotting packages, which require specifying coordinates in pixels or inches/cms.

Plotting histograms: `pyplot.hist()`

```python
mu, sigma = (100, 15)
x = np.random.normal(mu,sigma,10000)
# hist( data, nbins, ... )
(n, bins, patches) = plt.hist(x, 50, density=False, facecolor='teal')
n
```

```
array([  1.,   1.,   2.,   4.,   3.,   5.,  11.,  18.,  26.,  30.,  47.,
        68.,  82., 113., 150., 201., 246., 285., 309., 352., 420., 475.,
       541., 529., 597., 595., 572., 566., 543., 515., 462., 404., 360.,
       270., 294., 233., 159., 128., 111.,  92.,  54.,  32.,  28.,  28.,
        15.,  11.,   5.,   2.,   1.,   4.])
```

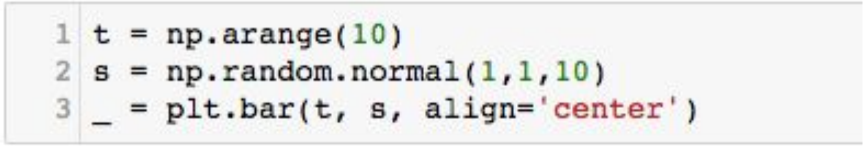


Bin counts. Note that if `density=True`, then these will be chosen so that the histogram “integrates” to 1.

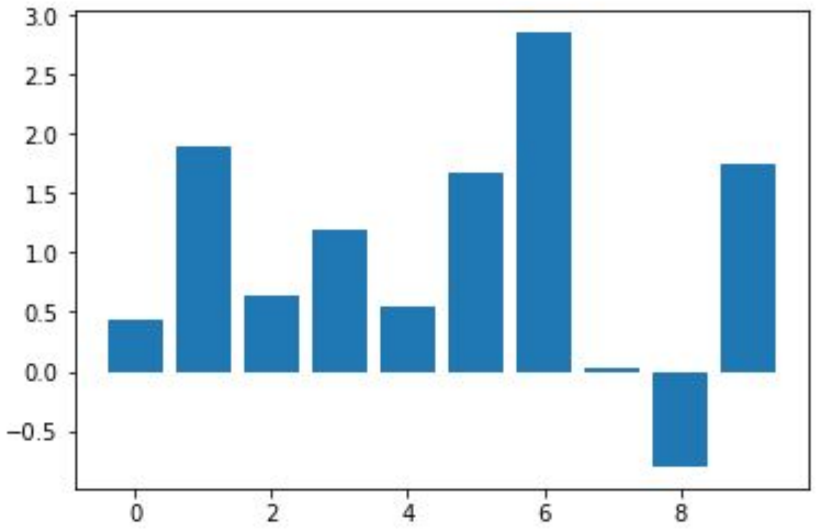
https://matplotlib.org/3.1.1/api/_as_gen/matplotlib.pyplot.hist.html

Bar plots

```
bar(x, height, *, align='center', **kwargs)
```



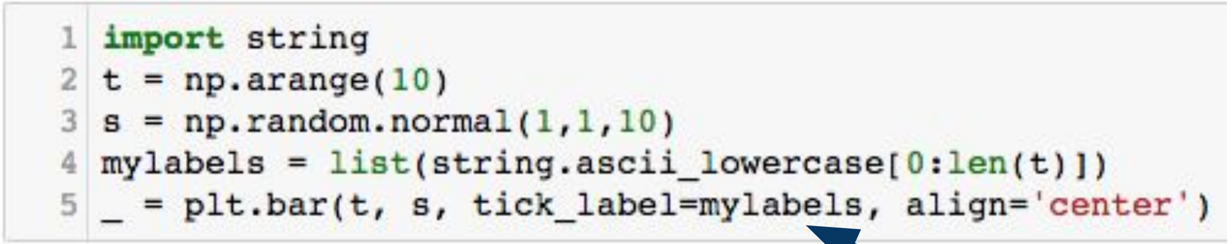
```
t = np.arange(10)
s = np.random.normal(1,1,10)
_ = plt.bar(t, s, align='center')
```



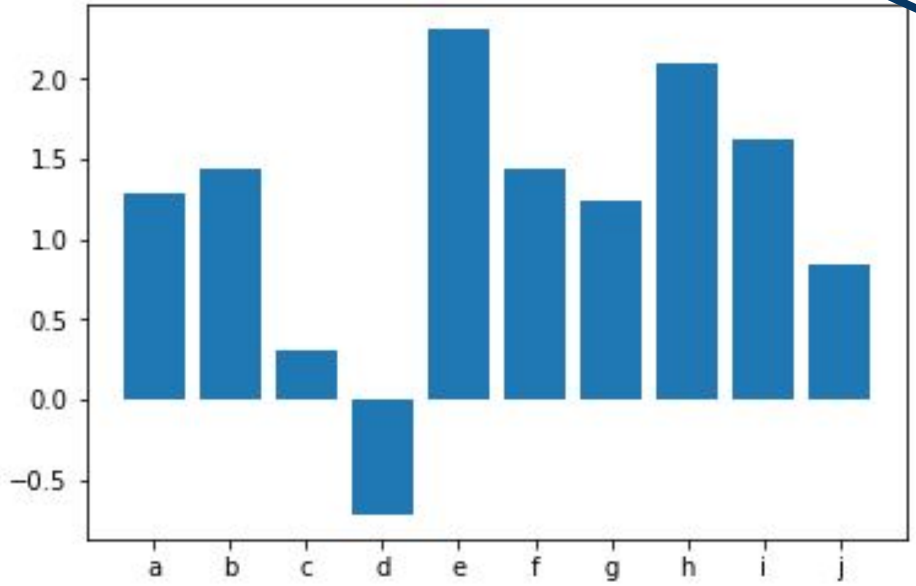
Full set of available arguments to `bar(...)` can be found at http://matplotlib.org/api/_as_gen/matplotlib.pyplot.bar.html#matplotlib.pyplot.bar

Horizontal analogue given by `barh` http://matplotlib.org/api/_as_gen/matplotlib.pyplot.barh.html#matplotlib.pyplot.barh

Tick labels

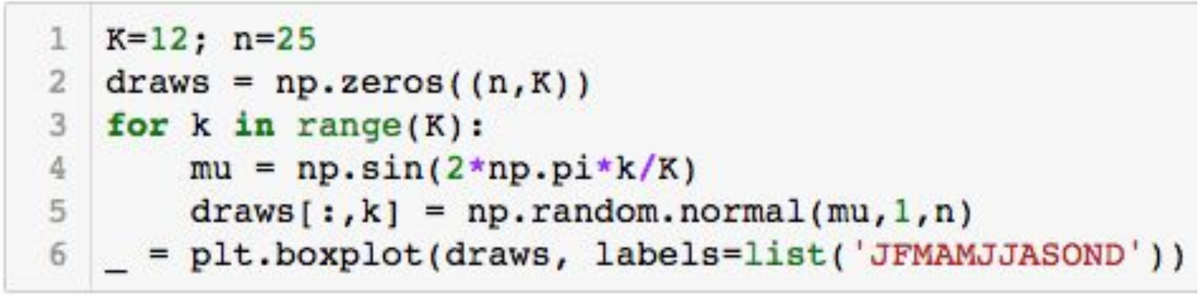


```
import string
t = np.arange(10)
s = np.random.normal(1,1,10)
mylabels = list(string.ascii_lowercase[0:len(t)])
_ = plt.bar(t, s, tick_label=mylabels, align='center')
```

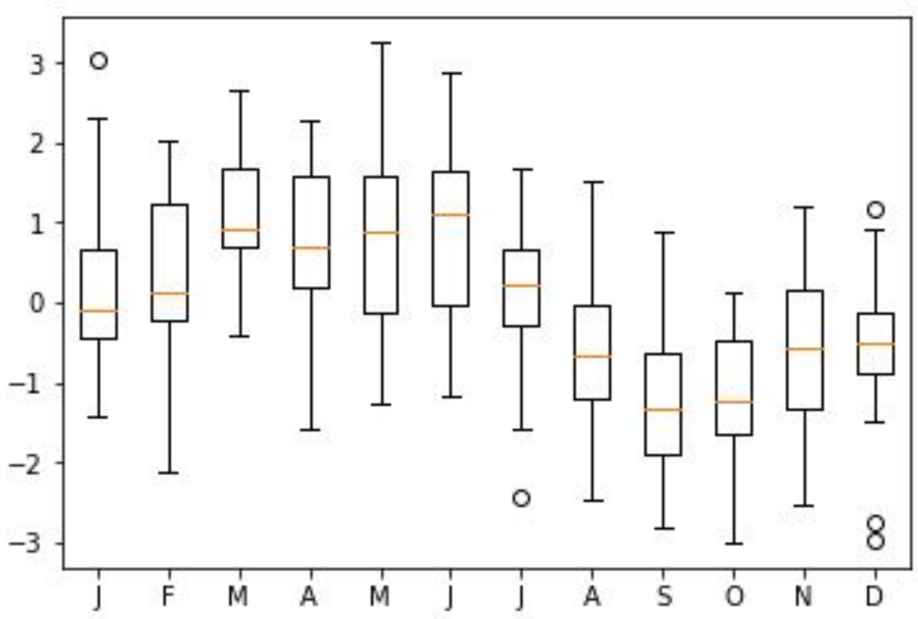


Can specify what the x-axis tick labels should be by using the `tick_label` argument to plot functions.

Box & whisker plots



```
K=12; n=25
draws = np.zeros((n,K))
for k in range(K):
    mu = np.sin(2*np.pi*k/K)
    draws[:,k] = np.random.normal(mu,1,n)
_ = plt.boxplot(draws, labels=list('JFMAMJJASOND'))
```



`plt.boxplot(x,...)` : `x` is the data. Many more optional arguments are available, most to do with how to compute medians, confidence intervals, whiskers, etc. See http://matplotlib.org/api/_as_gen/matplotlib.pyplot.boxplot.html#matplotlib.pyplot.boxplot

Pie Charts

Don’t use pie charts!

A table is nearly always better than a dumb pie chart; the only worse design than a pie chart is several of them, for then the viewer is asked to compare quantities located in spatial disarray both within and between charts [...] Given their low [information] density and failure to order numbers along a visual dimension, pie charts should never be used.

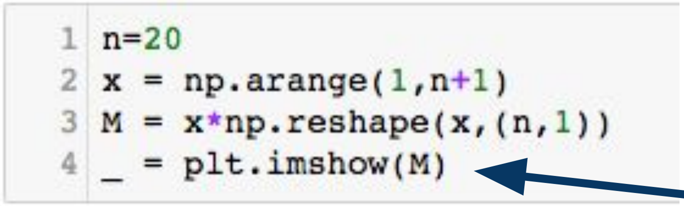
Edward Tufte
The Visual Display of Quantitative Information

But if you must…

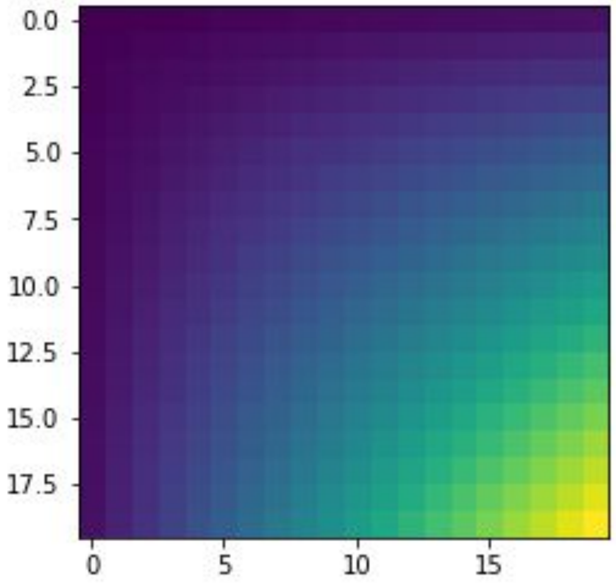
```
pyplot.pie(x, … )
```

http://matplotlib.org/api/_as_gen/matplotlib.pyplot.pie.html#matplotlib.pyplot.pie

Heatmaps and tiling

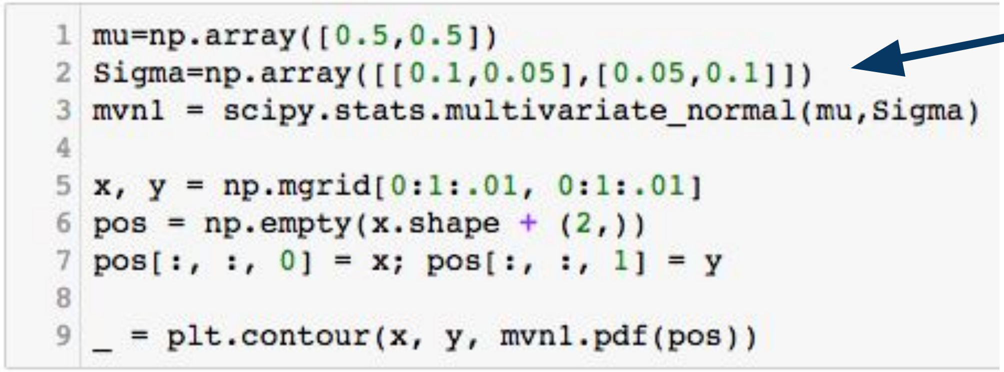


```
n=20
x = np.arange(1,n+1)
M = x*np.reshape(x,(n,1))
_ = plt.imshow(M)
```



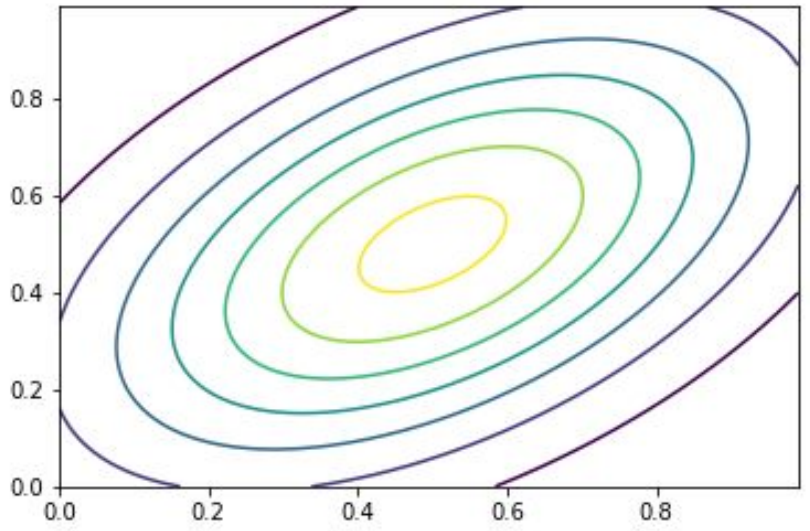
`imshow` is `matplotlib` analogue of MATLAB’s `imagesc`, R’s `image`. Lots of optional extra arguments for changing scale, color scheme, etc. See documentation: https://matplotlib.org/api/pyplot_api.html#matplotlib.pyplot.imshow

Drawing contours

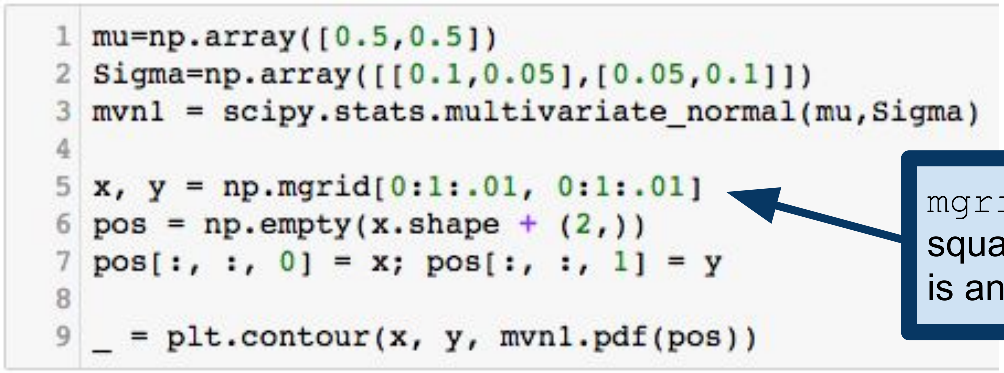


```
mu=np.array([0.5,0.5])
Sigma=np.array([[0.1,0.05],[0.05,0.1]])
mvn1 = scipy.stats.multivariate_normal(mu,Sigma)

x, y = np.mgrid[0:1:.01, 0:1:.01]
pos = np.empty(x.shape + (2,))
pos[:, :, 0] = x; pos[:, :, 1] = y

_ = plt.contour(x, y, mvn1.pdf(pos))
```

These three lines create an object, `mvn1`, representing a multivariate normal distribution.

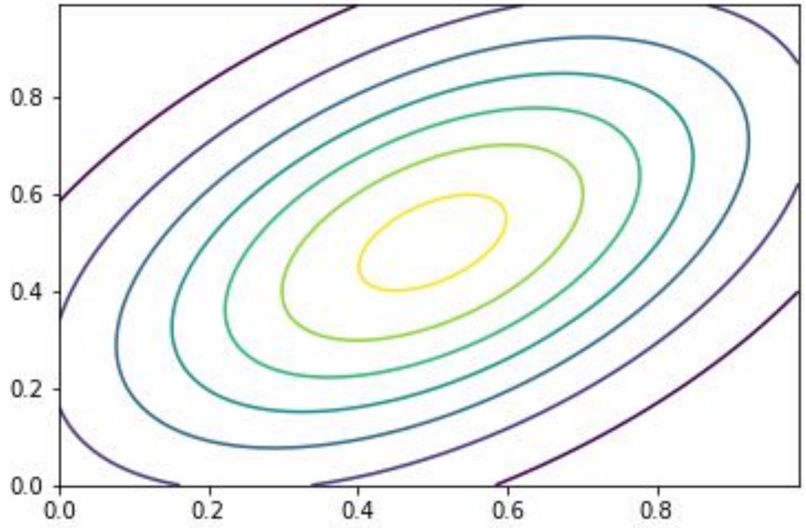


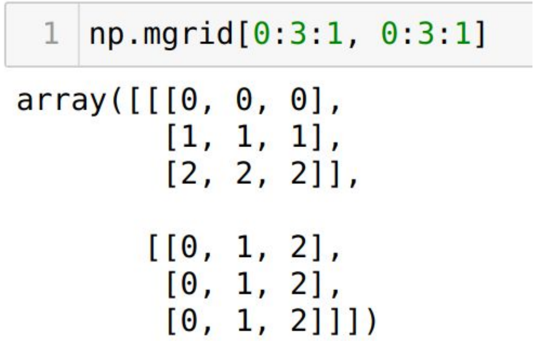
Drawing contours



```
mu=np.array([0.5,0.5])
Sigma=np.array([[0.1,0.05],[0.05,0.1]])
mvn1 = scipy.stats.multivariate_normal(mu,Sigma)

x, y = np.mgrid[0:1:.01, 0:1:.01]
pos = np.empty(x.shape + (2,))
pos[:, :, 0] = x; pos[:, :, 1] = y

_ = plt.contour(x, y, mvn1.pdf(pos))
```

`mgrid` is short for “mesh grid”. Note the syntax: square brackets instead of parentheses. `mgrid` is an object, not a function!

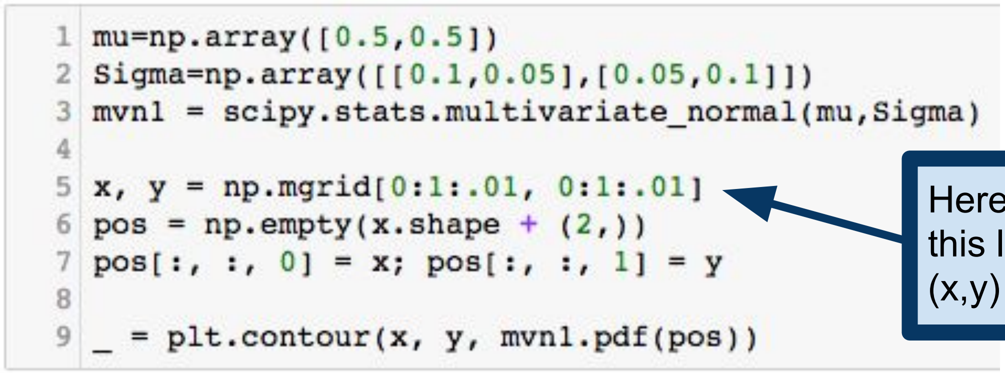




```
np.mgrid[0:3:1, 0:3:1]
```

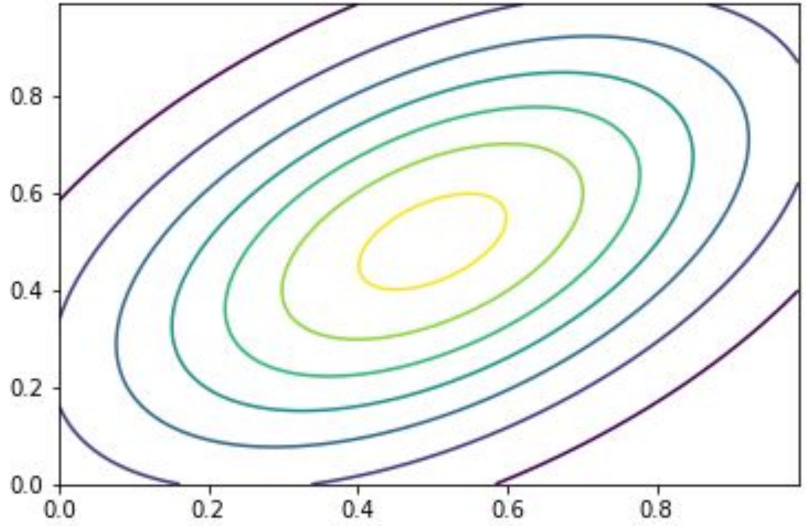
```
array([[[0, 0, 0],
        [1, 1, 1],
        [2, 2, 2]],

       [[0, 1, 2],
        [0, 1, 2],
        [0, 1, 2]]])
```

Drawing contours

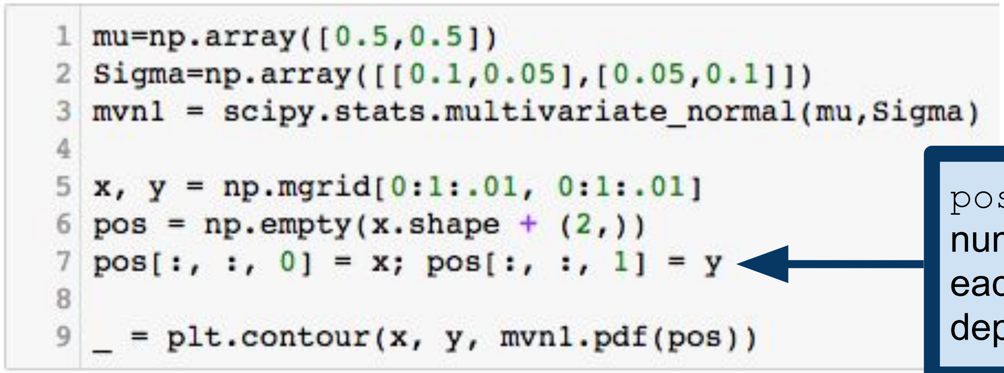


```
mu=np.array([0.5,0.5])
Sigma=np.array([[0.1,0.05],[0.05,0.1]])
mvn1 = scipy.stats.multivariate_normal(mu,Sigma)

x, y = np.mgrid[0:1:.01, 0:1:.01]
pos = np.empty(x.shape + (2,))
pos[:, :, 0] = x; pos[:, :, 1] = y

_ = plt.contour(x, y, mvn1.pdf(pos))
```

Here, `mgrid` generates a grid of (x,y) pairs, so this line actually generates a 100-by-100 grid of (x,y) coordinates, hence the tuple assignment.

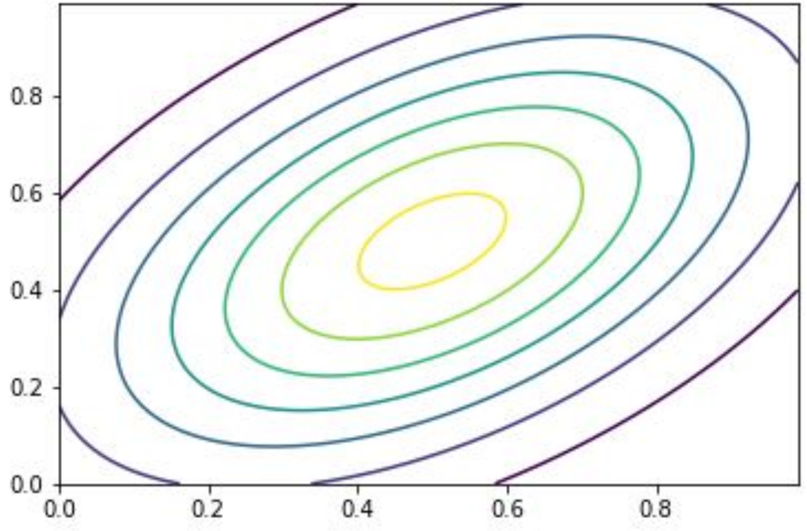


Drawing contours

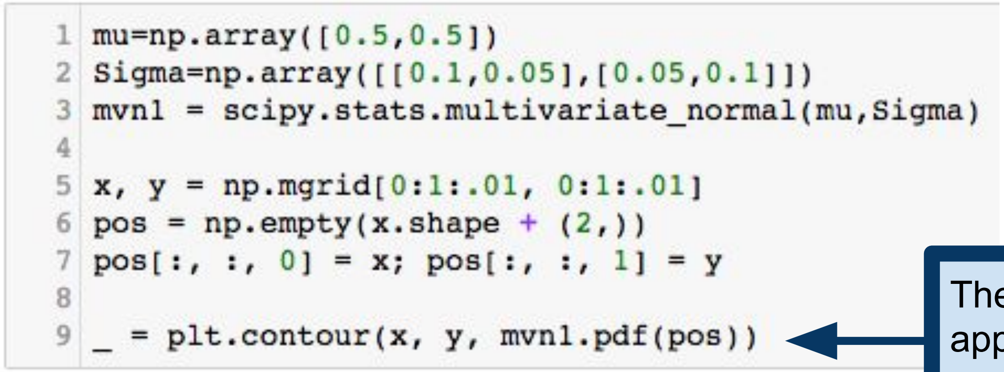


```
mu=np.array([0.5,0.5])
Sigma=np.array([[0.1,0.05],[0.05,0.1]])
mvn1 = scipy.stats.multivariate_normal(mu,Sigma)

x, y = np.mgrid[0:1:.01, 0:1:.01]
pos = np.empty(x.shape + (2,))
pos[:, :, 0] = x; pos[:, :, 1] = y

_ = plt.contour(x, y, mvn1.pdf(pos))
```

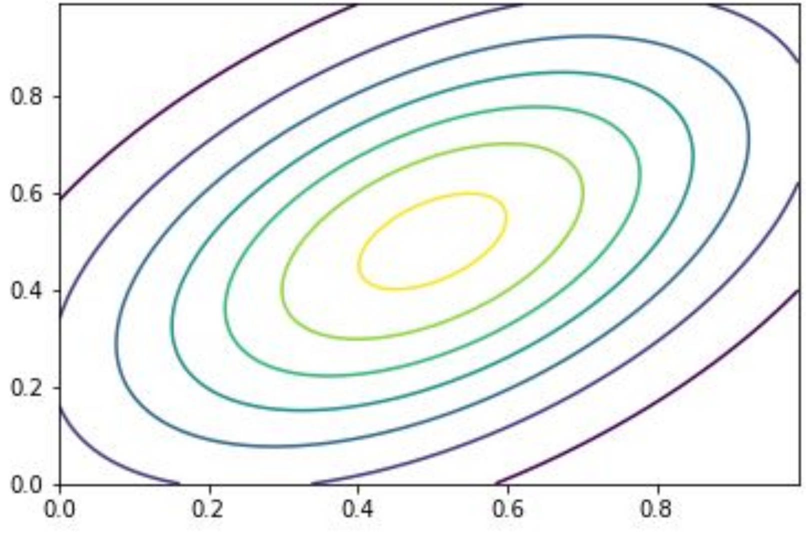
`pos` is a 3-dimensional array. Like a box of numbers. We're going to plot a surface, but at each (x,y) coordinate, the surface value depends on both x and y.



Drawing contours

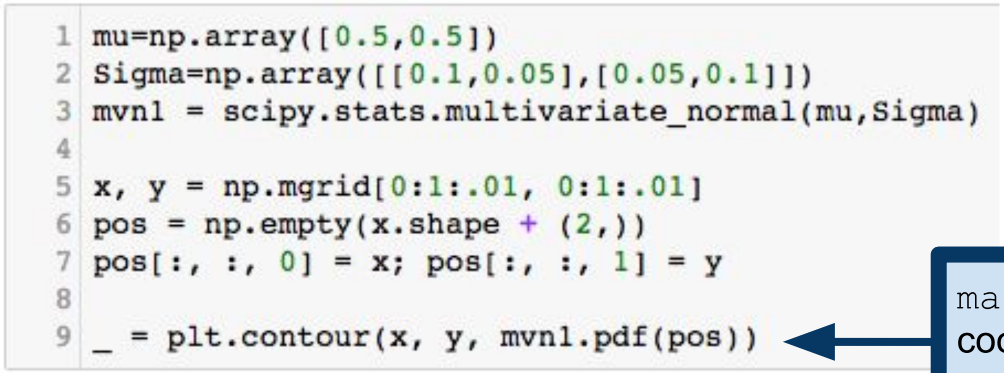


```
mu=np.array([0.5,0.5])
Sigma=np.array([[0.1,0.05],[0.05,0.1]])
mvn1 = scipy.stats.multivariate_normal(mu,Sigma)

x, y = np.mgrid[0:1:.01, 0:1:.01]
pos = np.empty(x.shape + (2,))
pos[:, :, 0] = x; pos[:, :, 1] = y

_ = plt.contour(x, y, mvn1.pdf(pos))
```

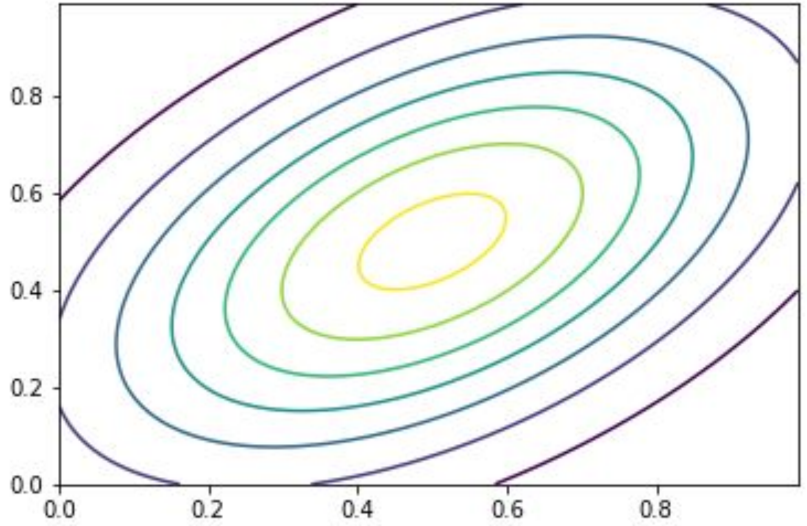


The reason for building `pos` the way we did is apparent if we read the documentation for `scipy.stats.(dist).pdf`.

Drawing contours



```
mu=np.array([0.5,0.5])
Sigma=np.array([[0.1,0.05],[0.05,0.1]])
mvn1 = scipy.stats.multivariate_normal(mu,Sigma)

x, y = np.mgrid[0:1:.01, 0:1:.01]
pos = np.empty(x.shape + (2,))
pos[:, :, 0] = x; pos[:, :, 1] = y

_ = plt.contour(x, y, mvn1.pdf(pos))
```



`matplotlib.contour` takes a set of x coordinates, a set of y coordinates, and an array of their corresponding values.

`matplotlib.contour` offers plenty of optional arguments for changing color schemes, spacing of contour lines, etc. https://matplotlib.org/api/contour_api.html

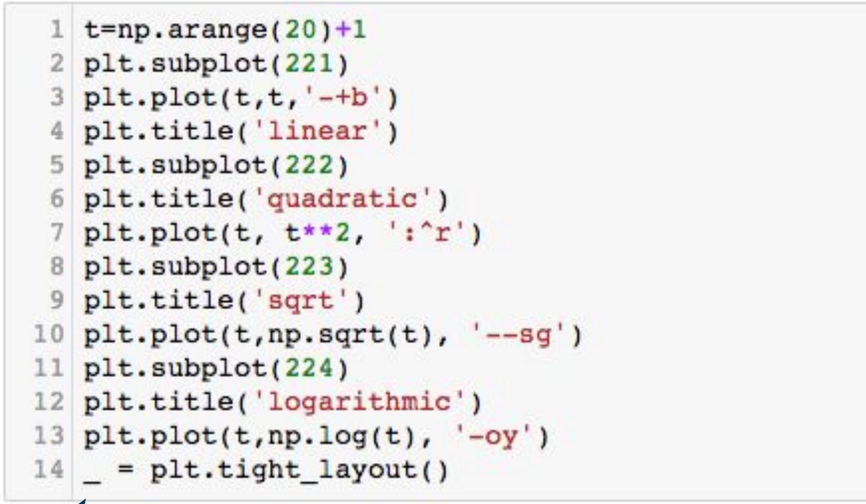
Subplots

`subplot(nrows, ncols, plot_number)`

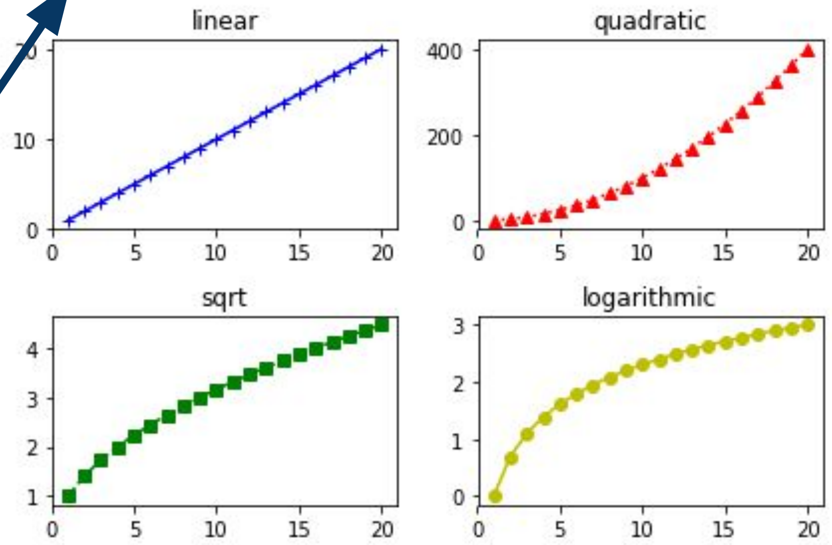
Shorthand: `subplot(XYZ)`

- Makes an `X`-by-`Y` plot
- Picks out the `Z`-th plot
- Counting in row-major order

`tight_layout()` automatically tries to clean things up so that subplots don't overlap. Without this command in this example, the labels "sqrt" and "logarithmic" overlap with the x-axis tick labels in the first row.



```
t=np.arange(20)+1
plt.subplot(221)
plt.plot(t,t,'-+b')
plt.title('linear')
plt.subplot(222)
plt.title('quadratic')
plt.plot(t, t**2, ':^r')
plt.subplot(223)
plt.title('sqrt')
plt.plot(t,np.sqrt(t), '--sg')
plt.subplot(224)
plt.title('logarithmic')
plt.plot(t,np.log(t), '-oy')
_ = plt.tight_layout()
```

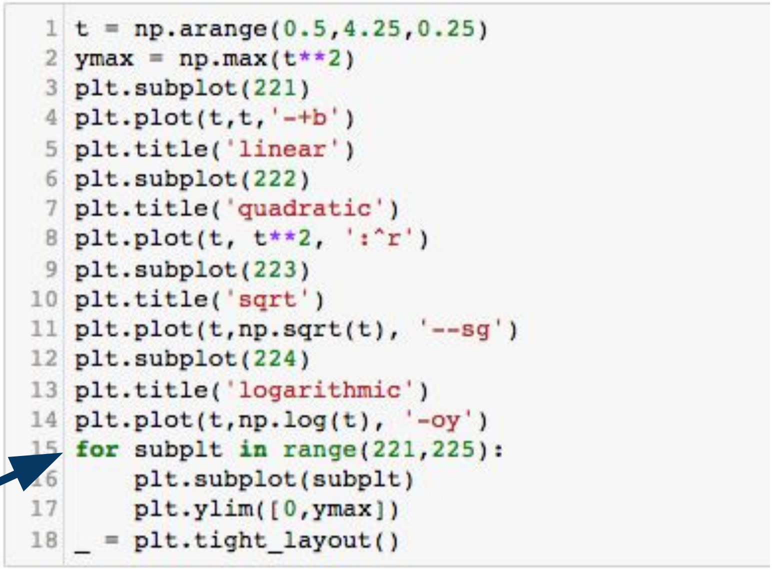


Specifying axis ranges

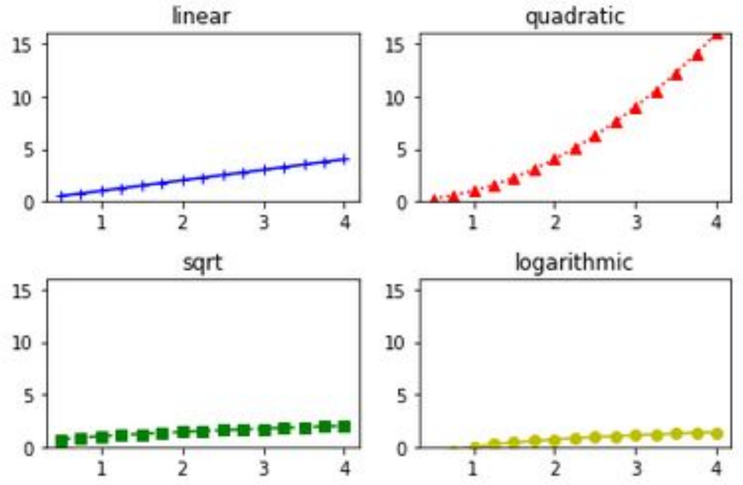
`plt.ylim([lower,upper])` sets y-axis limits

`plt.xlim([lower,upper])` for x-axis

For-loop goes through all of the subplots and sets their y-axis limits



```python
t = np.arange(0.5,4.25,0.25)
ymax = np.max(t**2)
plt.subplot(221)
plt.plot(t,t,'-+b')
plt.title('linear')
plt.subplot(222)
plt.title('quadratic')
plt.plot(t, t**2, ':^r')
plt.subplot(223)
plt.title('sqrt')
plt.plot(t,np.sqrt(t), '--sg')
plt.subplot(224)
plt.title('logarithmic')
plt.plot(t,np.log(t), '-oy')
for subplt in range(221,225):
    plt.subplot(subplt)
    plt.ylim([0,ymax])
_ = plt.tight_layout()
```



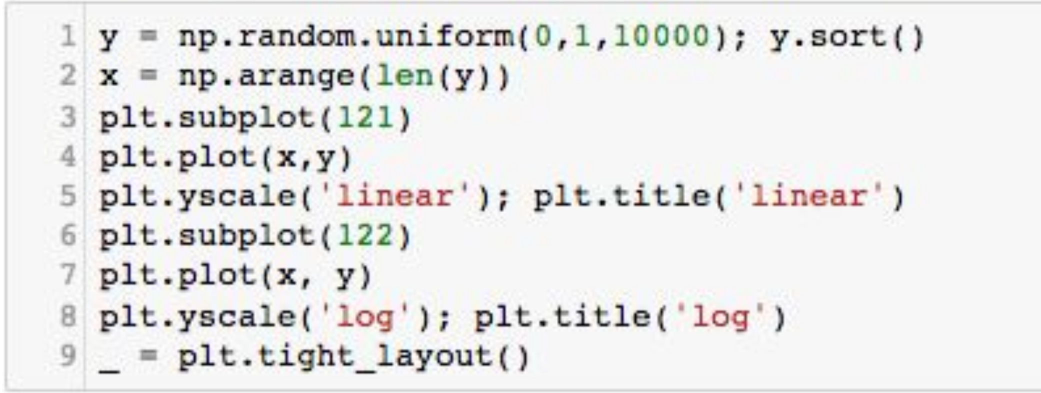
Nonlinear axes

Scale the axes with `plt.xscale` and `plt.yscale`

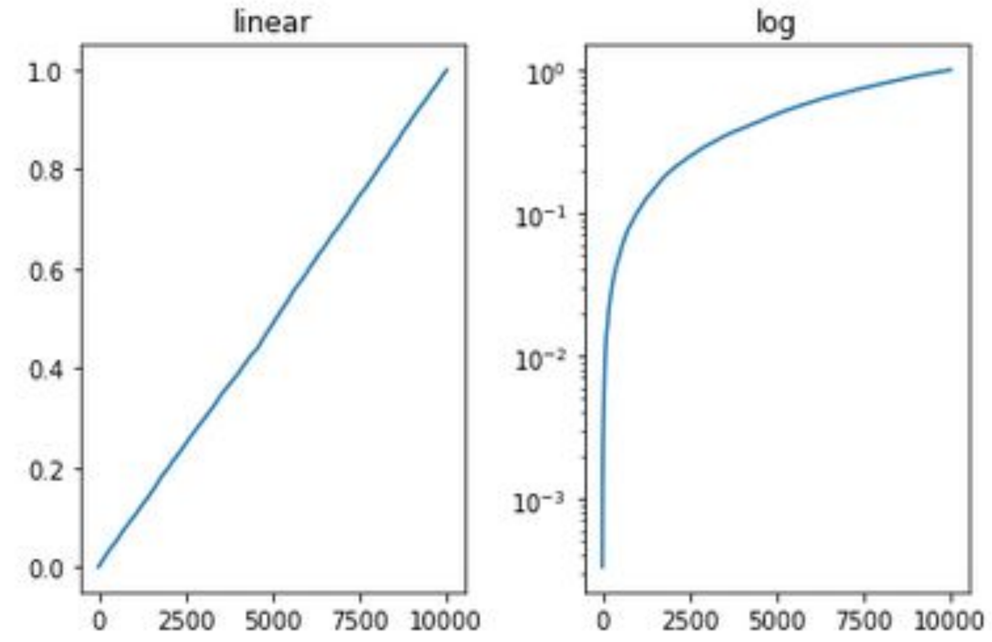
Built-in scales:

- Linear (`'linear'`)
- Log (`'log'`)
- Logit (`'logit'`)

Can also specify customized scales: https://matplotlib.org/devel/add_new_projection.html#adding-new-scales



```python
y = np.random.uniform(0,1,10000); y.sort()
x = np.arange(len(y))
plt.subplot(121)
plt.plot(x,y)
plt.yscale('linear'); plt.title('linear')
plt.subplot(122)
plt.plot(x, y)
plt.yscale('log'); plt.title('log')
_ = plt.tight_layout()
```



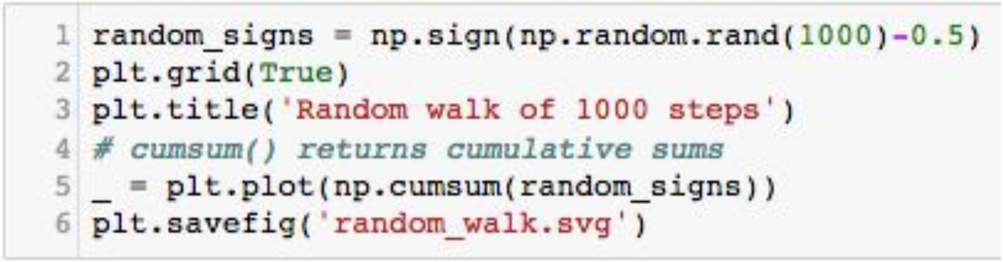
Saving images

`plt.savefig(filename)` will try to automatically figure out what file type you want based on the file extension.

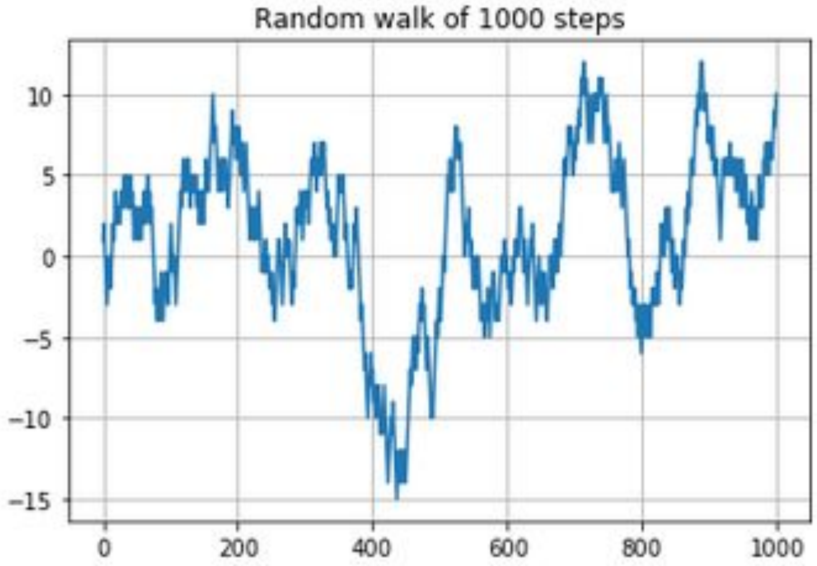
Can make it explicit using

```
plt.savefig('filename',
            format='fmt')
```

Options for specifying resolution, padding, etc: https://matplotlib.org/api/_as_gen/matplotlib.pyplot.savefig.html



```
random_signs = np.sign(np.random.rand(1000)-0.5)
plt.grid(True)
plt.title('Random walk of 1000 steps')
# cumsum() returns cumulative sums
_ = plt.plot(np.cumsum(random_signs))
plt.savefig('random_walk.svg')
```



Animations

`matplotlib.animate` package generates animations

I won’t require you to make any, but they’re fun to play around with (and they can be a great visualization tool)

The details are a bit tricky, so I recommend starting by looking at some of the example animations here: http://matplotlib.org/api/animation_api.html#examples

seaborn: statistical data visualization

“Seaborn is a library for making statistical graphics in Python. It is built on top of matplotlib and closely integrated with pandas data structures.”

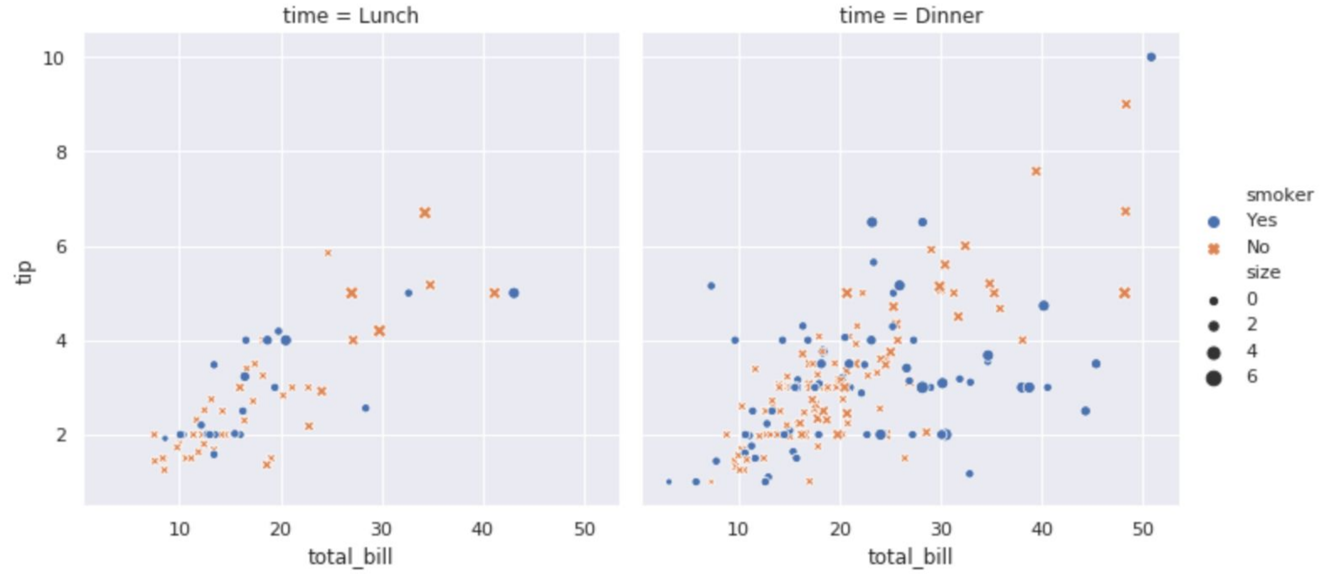
“A dataset-oriented API for examining relationships between multiple variables”

“Concise control over matplotlib figure styling with several built-in themes”

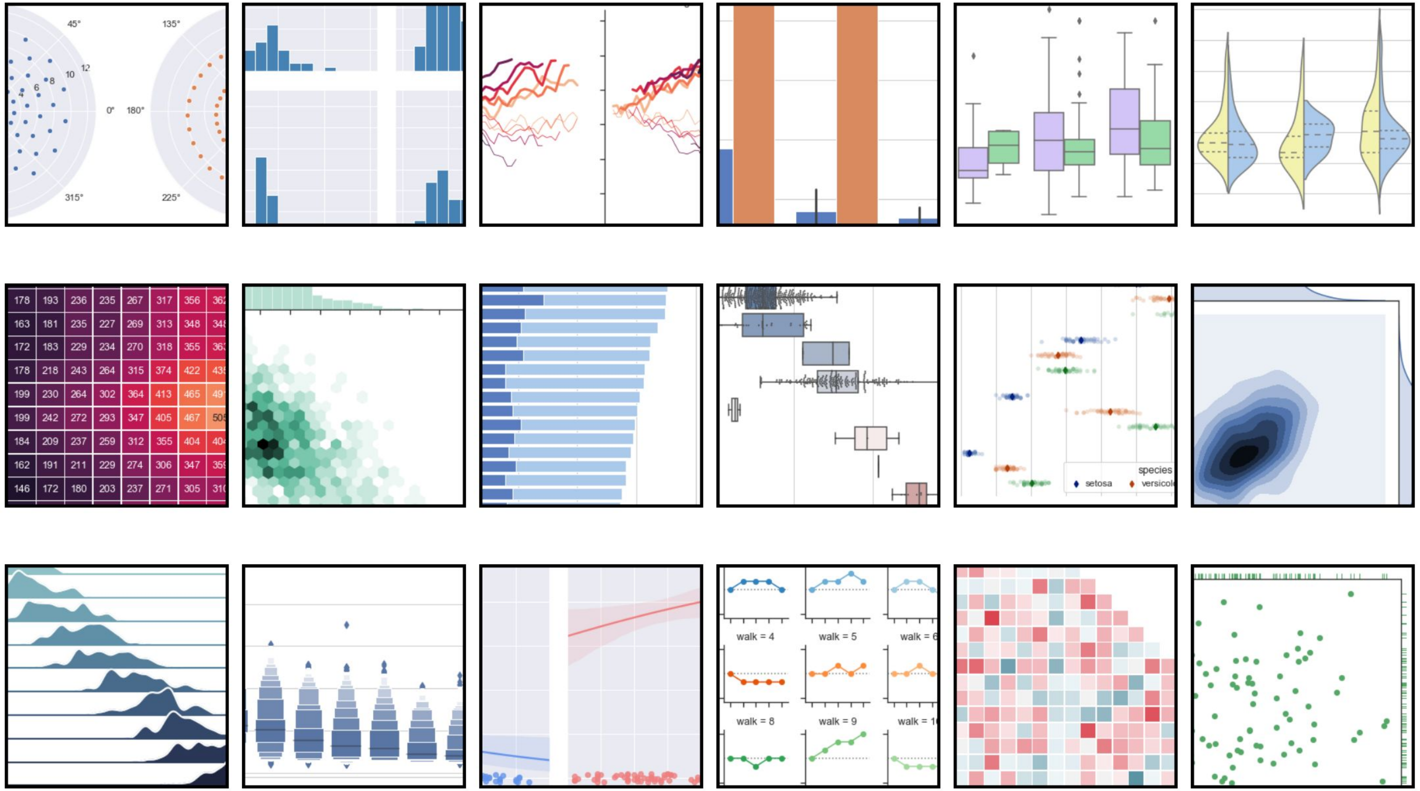
-- https://seaborn.pydata.org/introduction.html

Seaborn example

```python
import seaborn as sns
sns.set()
tips = sns.load_dataset("tips")
sns.relplot(x="total_bill", y="tip", col="time",
            hue="smoker", style="smoker", size="size",
            data=tips);
```

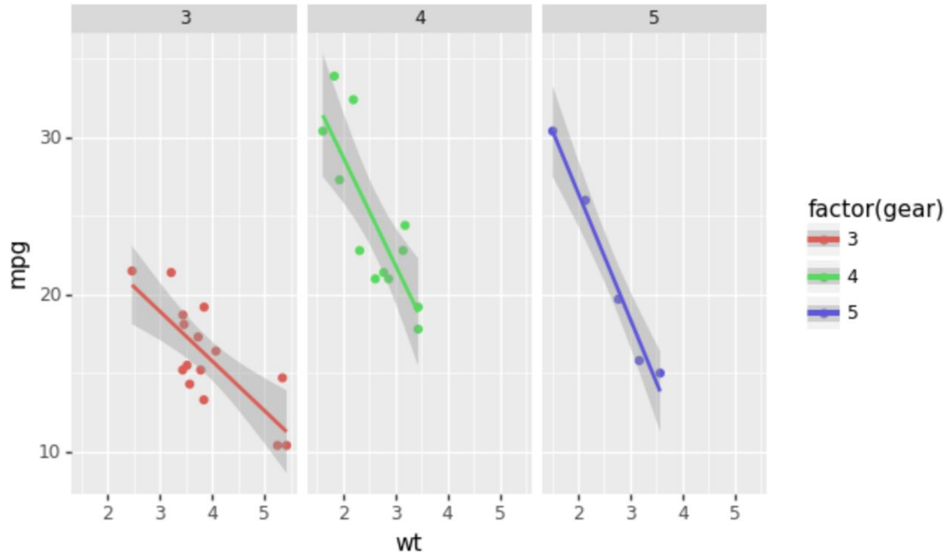


Seaborn gallery



Plotnine: 99% similar to ggplot2

```python
from plotnine import ggplot, geom_point, aes, stat_smooth, facet_wrap
from plotnine.data import mtcars

(ggplot(mtcars, aes('wt', 'mpg', color='factor(gear)'))
 + geom_point()
 + stat_smooth(method='lm')
 + facet_wrap('~gear'))
```


mpg
wt
factor(gear)