

PWC Python: NumPy & SciPy

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Arrays: Numpy

Lists aren't the ideal data type

Lists can do funny things that you don't expect, if you're not careful.

- Lists are just a collection of items, of any type.
- If you do mathematical operations on a list, you won't get what you expect.
- These are not the ideal data type for scientific computing.
- Arrays are a much better choice, but are not a native Python data type.

```
In [1]: a = [1, 2, 3, 4]
```

```
In [2]: a
```

```
Out[2]: [1, 2, 3, 4]
```

```
In [3]: b = [3, 5, 5, 6]
```

```
In [4]: b
```

```
Out[4]: [3, 5, 5, 6]
```

```
In [5]: 2 * a
```

```
Out[5]: [1, 2, 3, 4, 1, 2, 3, 4]
```

```
In [6]: a + b
```

```
Out[6]: [1, 2, 3, 4, 3, 5, 5, 6]
```



Useful arrays

Arrays are what we want to use

Almost everything that you want to do starts with NumPy.

- Contains arrays of various types and forms: zeros, ones, linspace, etc.
- linspace takes 2 or 3 arguments, the default number of entries is 50.

```
In [7]: from numpy import zeros,  
          ones, linspace
```

```
In [8]: zeros(5)  
Out[8]: array([ 0.,  0.,  0.,  0.,  0.])
```

```
In [9]: ones(5, dtype = int)  
Out[9]: array([ 1,  1,  1,  1,  1])
```

```
In [10]: zeros([2,2])
```

```
Out[10]:
```

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

```
In [11]: arange(5)
```

```
Out[11]: array([ 0,  1,  2,  3,  4])
```

```
In [12]: linspace(1,5)
```

```
Out[12]: array([ 1.,  1.08163265,  
                 1.16326531, 1.24489796,
```

```
.
```

```
.
```

```
4.67346939, 4.75510204,  
4.83673469, 4.91836735, 5. ])
```

```
In [13]: linspace(1, 5, 6)
```

```
Out[13]: array([1., 1.8, 2.6, 3.4,  
                4.2, 5.])
```

Accessing array elements

Elements of arrays are accessed using square brackets.

- Python is *row major* (like C++, Mathematica), NOT *column major* (like Fortran, MATLAB, R).
- This means the first index is the row, not the column.
- Indexing starts at zero.

```
In [14]: zeros([2, 3])
```

```
Out[14]:
```

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

```
In [15]: a = zeros([2,3])
```

```
In [16]: a[1,2] = 1
```

```
In [17]: a[0,1] = 2
```

```
In [18]: a
```

```
Out[18]:
```

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

```
In [19]: a[2,1] = 1
```

```
-----  
IndexError
```

```
<ipython-input-21-83f146d6c508> in
```

```
----> 1 a[2,1] = 1
```

```
IndexError: index (2) out of range
```

```
In [20]:
```



Copying arrays

Copying array variables

Use caution when copying array variables. There's a 'feature' here that is unexpected.

```
In [20]: a = 10; b = a; a = 20
```

```
In [21]: a, b
```

```
Out[21]: (20, 10)
```

```
In [22]: a = array([[1,2,3],  
                   [2,3,4]])
```

```
In [23]: b = a
```

```
In [24]: a[1,0] = -10
```

```
In [25]: a
```

```
Out[25]:
```

```
array([[1, 2, 3],  
       [-10, 3, 4]])
```

```
In [26]: b
```

```
Out[26]:
```

```
array([[1, 2, 3],  
       [-10, 3, 4]])
```

```
In [27]: b = a.copy()
```

```
In [28]: a[1,0] = 16
```

```
In [29]: a
```

```
Out[29]:
```

```
array([[1, 2, 3],  
       [16, 3, 4]])
```

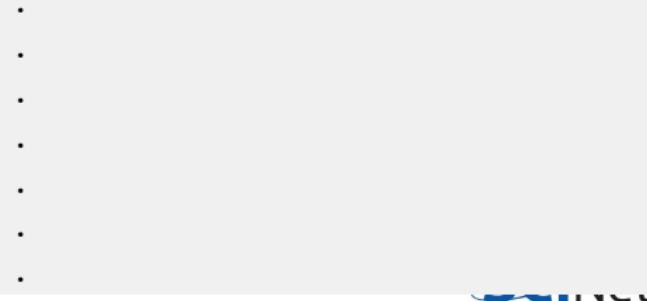
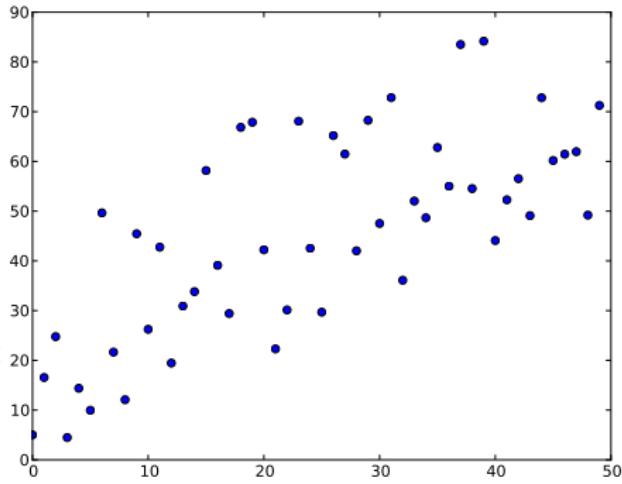
```
In [30]: b
```

```
Out[30]:
```

```
array([[1, 2, 3],  
       [-10, 3, 4]])
```

Polynomial fitting

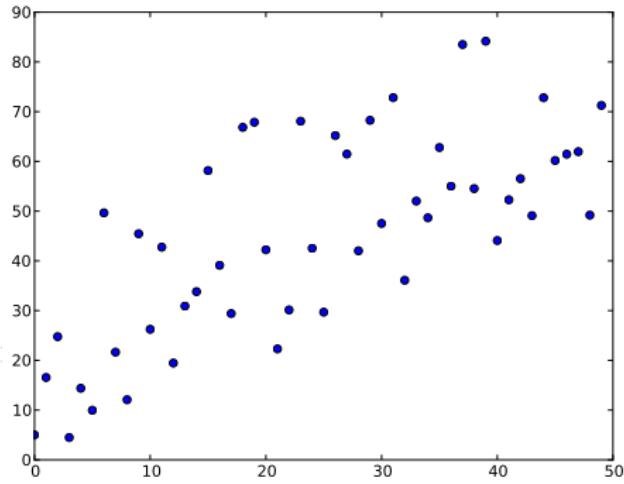
```
In [96]: from numpy import arange,  
          zeros, polyfit, polyval  
In [97]: import random  
In [98]: x = arange(50.)  
In [99]: y = zeros(50.)  
In [100]: for i in arange(50.):  
            y[i] = x[i] + 50.0 *  
In [101]: plot(x, y, 'o')  
In [102]:
```



Polynomial fitting

```
In [96]: from numpy import arange,  
          zeros, polyfit, polyval  
In [97]: import random  
In [98]: x = arange(50.)  
In [99]: y = zeros(50.)  
In [100]: for i in arange(50.):  
            y[i] = x[i] + 50.0 *  
In [101]: plot(x, y, 'o')  
In [102]: fit = polyfit(x, y, 1)  
In [103]: fit  
Out[103]: array([ 1.0073584,  
                  20.64695036])
```

```
In [104]:
```

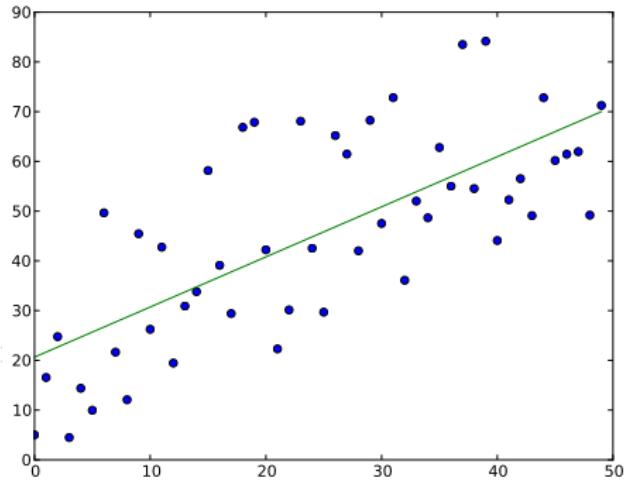


```
•  
•  
•  
•  
•  
•  
•
```

Polynomial fitting

```
In [96]: from numpy import arange,  
          zeros, polyfit, polyval  
In [97]: import random  
In [98]: x = arange(50.)  
In [99]: y = zeros(50.)  
In [100]: for i in arange(50.):  
            y[i] = x[i] + 50.0 *  
In [101]: plot(x, y, 'o')  
In [102]: fit = polyfit(x, y, 1)  
In [103]: fit  
Out[103]: array([ 1.0073584,  
                  20.64695036])
```

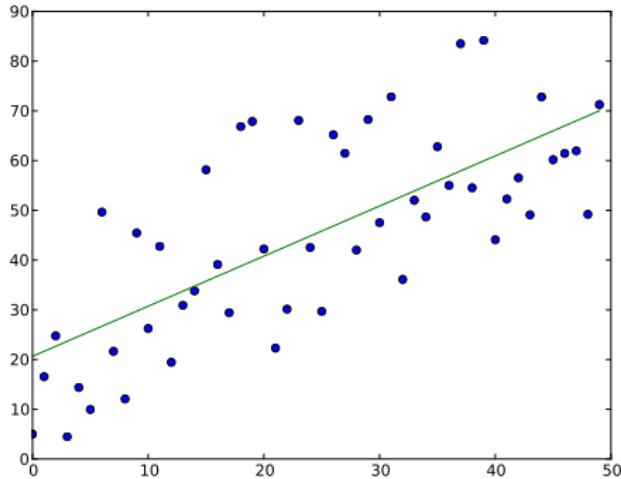
```
In [104]: plot(x,polyval(fit, x))
```



•
•
•
•
•
•

Polynomial fitting

```
In [96]: from numpy import arange,  
          zeros, polyfit, polyval  
In [97]: import random  
In [98]: x = arange(50.)  
In [99]: y = zeros(50.)  
In [100]: for i in arange(50.):  
            y[i] = x[i] + 50.0 *  
In [101]: plot(x, y, 'o')  
In [102]: fit = polyfit(x, y, 1)  
In [103]: fit  
Out[103]: array([ 1.0073584,  
                  20.64695036])  
  
In [104]: plot(x,polyval(fit, x))
```



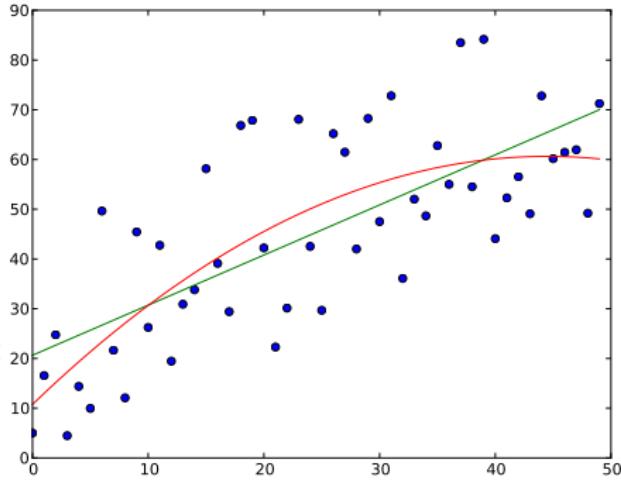
```
In [105]: fit = polyfit(x, y, 2)  
In [106]: fit  
Out[106]: array([-0.02520835,  
                  2.24256777,  
                 10.76527546])
```

```
In [107]:
```



Polynomial fitting

```
In [96]: from numpy import arange,  
          zeros, polyfit, polyval  
In [97]: import random  
In [98]: x = arange(50.)  
In [99]: y = zeros(50.)  
In [100]: for i in arange(50.):  
            y[i] = x[i] + 50.0 *  
                    random.random()  
In [101]: plot(x, y, 'o')  
In [102]: fit = polyfit(x, y, 1)  
In [103]: fit  
Out[103]: array([ 1.0073584,  
                  20.64695036])  
  
In [104]: plot(x,polyval(fit, x))
```



```
In [105]: fit = polyfit(x, y, 2)  
In [106]: fit  
Out[106]: array([-0.02520835,  
                  2.24256777,  
                  10.76527546])  
In [107]: plot(x, polyval(fit, x))
```



Matrix arithmetic

vector-vector & vector-scalar multiplication

1-D arrays are often called ‘vectors’.

- When vectors are multiplied you get element-by-element multiplication.
- When vectors are multiplied by a scalar (a 0-D array), you also get element-by-element multiplication.

```
In [31]: a = arange(4)
```

```
In [32]: a
```

```
Out[32]: array([0,1,2,3])
```

```
In [33]: b = arange(4.) + 3
```

```
In [34]: b
```

```
Out[34]: array([3.,4.,5.,6.])
```

```
In [35]: c = 2
```

```
In [36]: c
```

```
Out[36]: 2
```

```
In [37]: a * b
```

```
Out[37]: array([0.,4.,10.,18.])
```

```
In [38]: a * c
```

```
Out[38]: array([0,2,4,6])
```

```
In [39]: b * c
```

```
Out[39]: array([6.,8.,10.,12.])
```

Matrix-vector multiplication

A 2-D array is sometimes called a 'matrix'.

- Matrix-scalar multiplication gives element-by-element multiplication.
- Matrix-vector multiplication DOES NOT give the standard result!

```
In [40]: a = array([[1,2,3],  
                   [2,3,4]])
```

```
In [41]: a
```

```
Out[41]:  
array([[1, 2, 3],  
       [2, 3, 4]])
```

```
In [42]: b = arange(3) + 1
```

```
In [43]: b
```

```
Out[43]: array([1, 2, 3])
```

```
In [44]: a * b
```

```
Out[44]:
```

```
array([[ 1,  4,  9],  
       [ 2,  6, 12]])
```

$$\begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} * \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix} = \begin{bmatrix} a_{11} * b_1 + a_{12} * b_2 + a_{13} * b_3 \\ a_{21} * b_1 + a_{22} * b_2 + a_{23} * b_3 \\ a_{31} * b_1 + a_{32} * b_2 + a_{33} * b_3 \end{bmatrix}$$



Matrix-matrix multiplication

Not surprisingly, matrix-matrix multiplication doesn't work as expected either, instead doing the same thing as vector-vector multiplication.

```
In [45]: a = array([[1,2,3],  
                   [2,3,4]])
```

```
In [46]: b = array([[1,2,3],  
                   [2,3,4]])
```

```
In [47]: a
```

```
Out[47]:
```

```
array([[1, 2, 3],  
       [2, 3, 4]])
```

```
In [48]: a * b
```

```
Out[48]:
```

```
array([[ 1,  4,  9],  
       [ 4,  9, 16]])
```

$$\begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} * \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} =$$

$$\begin{bmatrix} a_{11} * b_{11} + a_{12} * b_{21} & a_{11} * b_{12} + a_{12} * b_{22} \\ a_{21} * b_{11} + a_{22} * b_{21} & a_{21} * b_{12} + a_{22} * b_{22} \end{bmatrix}$$



Scipy: matrix algebra, statistics, and more

How to do matrix algebra?

There are two solutions to these matrix multiplication problems.

- The specially built-in array fixes (using ‘array’ types).
- The matrix module (using ‘matrix’ types).

The latter option is a bit clunkier, so we recommend the ‘fixes’.

```
In [49]: from scipy import dot
```

```
In [50]: a = array([[1,2,3],  
                  [2,3,4]])
```

```
In [51]: b = array([[1,2,3],  
                  [2,3,4]])
```

```
In [52]: a
```

```
Out[52]:
```

```
array([[1, 2, 3],  
      [2, 3, 4]])
```

```
In [53]: a.transpose()
```

```
Out[53]:
```

```
array([[1, 2],  
      [2, 3],  
      [3, 4]])
```

```
In [54]: dot(a.transpose(), b)
```

```
Out[54]:
```

```
array([[ 5,  8, 11],  
      [ 8, 13, 18],  
      [11, 18, 25]])
```

```
In [55]: dot(b, a.transpose())
```

```
Out[55]:
```

```
array([[14, 20],  
      [20, 29]])
```

```
In [56]: c = arange(3) + 1
```

```
In [57]: dot(a,c)
```

```
Out[57]: array([14, 20])
```

linalg module

The linalg module

The linalg module contains useful functions for matrix algebra.

- Typical matrix functions: inv, det, norm...
- More advanced functions: eig, SVD, cholesky...
- Both NumPy and SciPy have a linalg module. Use SciPy, because it is always compiled with BLAS/LAPACK support.

```
In [58]: from scipy import dot, linalg  
In [59]: a = array([[1,2,3], [3,4,5], [1,1,2]])  
In [60]: linalg.det(a)  
Out[60]: -2.0
```

```
In [61]: dot(a, linalg.inv(a))  
Out[61]:  
array([[ 1.00000000e+00,  0.00000000e+00,  0.00000000e+00],  
       [ 2.77555756e-16,  1.00000000e+00,  0.00000000e+00],  
       [ 0.00000000e+00,  5.55111512e-17,  1.00000000e+00]])
```

Solving systems of equations

The linalg module comes with an important function: solve.
linalg.solve is used to solve the system of equations

$$Ax = b$$

$$\begin{bmatrix} 1 & 2 & 3 \\ 3 & 4 & 5 \\ 1 & 1 & 2 \end{bmatrix} * \begin{bmatrix} -0.5 \\ -0.5 \\ 1.5 \end{bmatrix} = \begin{bmatrix} 3 \\ 4 \\ 2 \end{bmatrix}$$

```
In [62]: a = array([[1,2,3],  
                  [3,4,5],  
                  [1,1,2]])
```

```
In [63]: a  
Out[63]:  
array([[ 1,  2,  3],  
      [ 3,  4,  5],  
      [ 1,  1,  2]])
```

```
In [64]: b = array([3, 4, 2])  
In [65]: b  
Out[65]: array([3, 4, 2])  
In [66]: x = linalg.solve(a, b)  
In [67]: x  
Out[67]: array([-0.5, -0.5, 1.5])
```

Statistics

Statistics

SciPy contains all of the statistical functions that you'll probably ever need.

- The `scipy.stats` module is based around the idea of a 'random variable' type.
- A whole variety of standard distributions are available:
 - ▶ Continuous distributions: Normal, Maxwell, Cauchy, Chi-squared, Gumbel Left-skewed, Gilbrat, Nakagami, ...
 - ▶ Discrete distributions: Poisson, Binomial, Geometric, Bernoulli, ...
- The 'random variables' have all of the statistical properties of the distributions built into them already: `cdf`, `pdf`, `mean`, `variance`, `moments`, ...

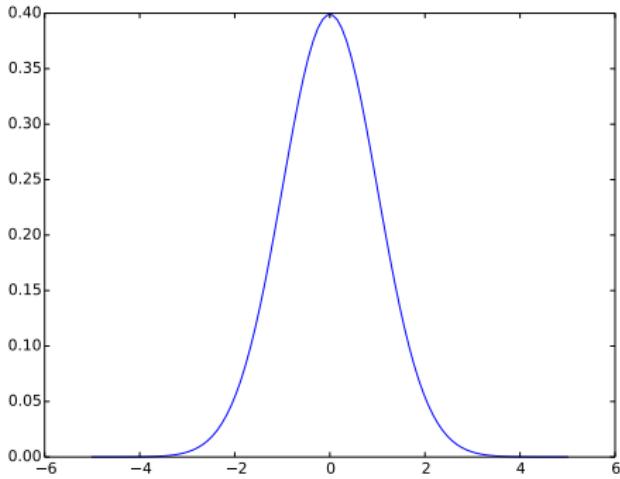
Normal distribution

All continuous distributions take loc and scale as keyword parameters to adjust the location and scale of the distribution. In general the distribution of a random variable X is obtained from $(X - \text{loc}) / \text{scale}$. The default values are loc = 0 and scale = 1.

```
In [68]: from scipy.stats import norm  
In [69]: x = linspace(-5, 5, 100)  
In [70]:
```

.

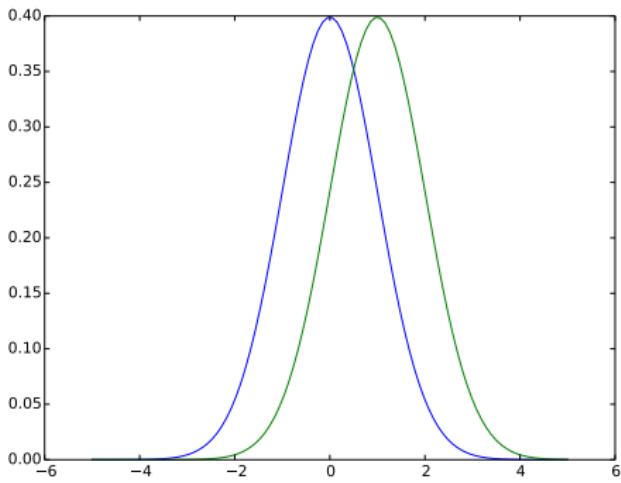
Normal distribution



All continuous distributions take `loc` and `scale` as keyword parameters to adjust the location and scale of the distribution. In general the distribution of a random variable X is obtained from $(X - \text{loc}) / \text{scale}$. The default values are `loc = 0` and `scale = 1`.

```
In [68]: from scipy.stats import norm  
In [69]: x = linspace(-5, 5, 100)  
In [70]: plot(x, norm.pdf(x))  
In [71]:  
.  
.
```

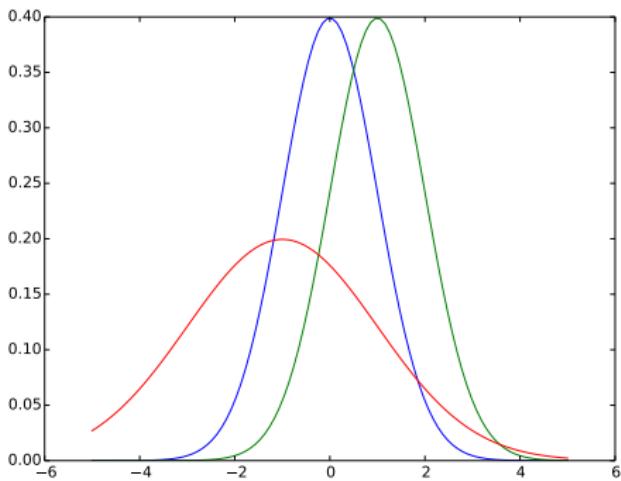
Normal distribution



All continuous distributions take `loc` and `scale` as keyword parameters to adjust the location and scale of the distribution. In general the distribution of a random variable X is obtained from $(X - \text{loc}) / \text{scale}$. The default values are `loc = 0` and `scale = 1`.

```
In [68]: from scipy.stats import norm  
In [69]: x = linspace(-5, 5, 100)  
In [70]: plot(x, norm.pdf(x))  
In [71]: plot(x, norm.pdf(x, loc = 1))  
In [72]:
```

Normal distribution

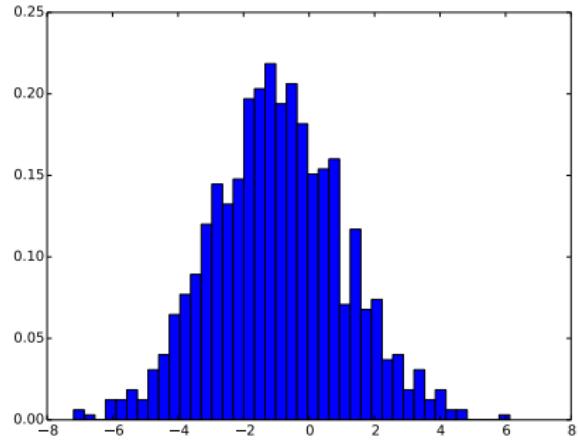


All continuous distributions take loc and scale as keyword parameters to adjust the location and scale of the distribution. In general the distribution of a random variable X is obtained from $(X - \text{loc}) / \text{scale}$. The default values are loc = 0 and scale = 1.

```
In [68]: from scipy.stats import norm  
In [69]: x = linspace(-5, 5, 100)  
In [70]: plot(x, norm.pdf(x))  
In [71]: plot(x, norm.pdf(x, loc = 1))  
In [72]: plot(x, norm.pdf(x, loc = -1, scale = 2))
```

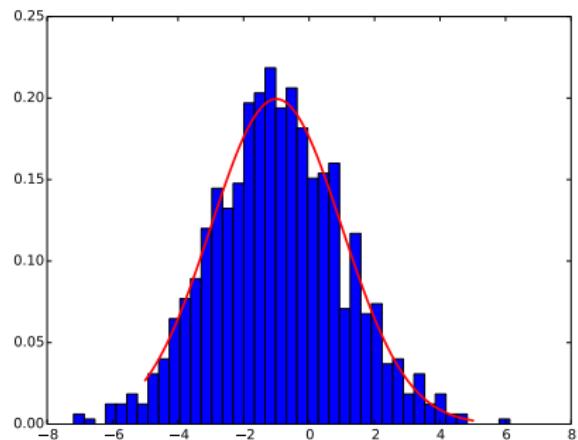
Normal Distribution - continued

```
In [73]: from pylab import hist  
In [74]: norm.mean(loc = -1, scale = 2)  
Out[74]: -1.0  
In [75]: norm.std(loc = -1, scale = 2)  
Out[75]: 2.0  
In [76]: norm.moment(3, loc = -1, scale = 2)  
Out[76]: -13.0  
In [77]: samples = norm.rvs(size = 1000, loc = -1, scale = 2)  
In [78]: h = hist(samples, bins = 41, normed = True)  
In [79]:
```



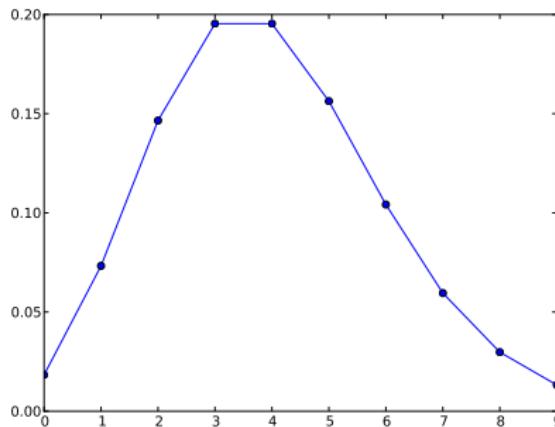
Normal Distribution - continued

```
In [73]: from pylab import hist  
In [74]: norm.mean(loc = -1, scale = 2)  
Out[74]: -1.0  
In [75]: norm.std(loc = -1, scale = 2)  
Out[75]: 2.0  
In [76]: norm.moment(3, loc = -1, scale = 2)  
Out[76]: -13.0  
In [77]: samples = norm.rvs(size = 1000, loc = -1, scale = 2)  
In [78]: h = hist(samples, bins = 41, normed = True)  
In [79]: plot(x,norm.pdf(x,loc = -1,scale = 2),'r',linewidth=2)
```



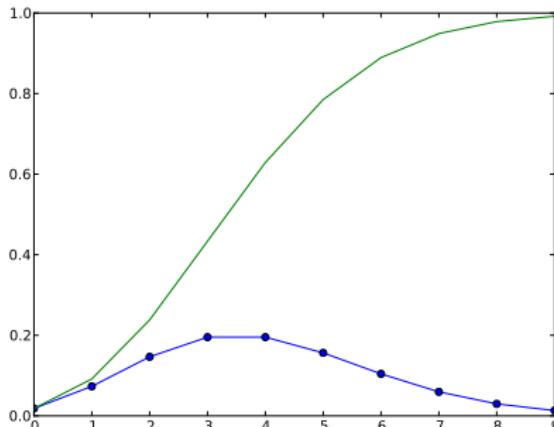
Poisson distribution

```
In [80]: from scipy.stats import poisson  
In [81]: x = arange(10)  
In [82]: poisson.mean(4)  
Out[82]: 4.0  
In [83]: poisson.var(4)  
Out[83]: 4.0  
In [84]: plot(x, poisson.pmf(x, 4), 'o-')  
In [85]:
```



Poisson distribution

```
In [80]: from scipy.stats import poisson  
In [81]: x = arange(10)  
In [82]: poisson.mean(4)  
Out[82]: 4.0  
In [83]: poisson.var(4)  
Out[83]: 4.0  
In [84]: plot(x, poisson.pmf(x, 4), 'o-')  
In [85]: plot(x, poisson.cdf(x, 4))
```



Note that discrete distributions have Probability Mass Functions (PMF) instead of Probability Distribution Functions (PDF).

What else is in SciPy?

SciPy is large

- Linear Algebra
- Statistics
- Special functions
- Numeric integration and ODEs
- Optimization
- Interpolation
- Fourier Transforrs
- File IO
- and more..



Summary

Summary

- When manipulating numbers in blocks, use the array type, not lists.
- Use the copy() function to copy array variables.
- Array types do element-by-element multiplication, addition, etc.
- If you want to do standard array arithmetic, use the built-in `scipy.linalg` functions: dot, inv, det, eig, etc.
- SciPy comes with fairly complete set of statistical distributions, tests, and functions. If you need it it's probably there.

NumPy: http://wiki.scipy.org/Tentative_Numpy_Tutorial

SciPy: <http://docs.scipy.org/doc/scipy/reference/tutorial>

