

# Random Number Toolbox



# Last time ....

- **Definition** of probability distributions, description of properties,  $\int = 1.0000$ , etc.
- **Moments** of distributions => mean, variance, skewness, kurtosis ...
  
- **Binomial distribution** for discrete probabilities of outcome of **N** trials with identical probability **p** of 'success' or 'failure'.
- Bayesian example of galaxy cluster sample, centrally-dominated or otherwise.
  
- **Poisson distribution** for many trials with rare possibility of successful outcome, probability of **n** events has mean value  **$\mu$** ,
- Example – photon arrival statistics, and how signal-to-noise ratio depends on integration time
  
- **Gaussian (Normal)** distribution, symmetrical, mean  **$\mu$** , variance  **$\sigma^2$** , the asymptotic result of previous two distributions for large **Np**,  **$\mu$** .
  
- **Central Limit Theorem => Miraculous!** Gaussian distributions everywhere....
- Examples – truncated exponential; two delta functions
  
- **Power-law distribution** – the distribution from hell, because it does not conform, and our (tacit / assumed) reliance on Central Limit Theorem is lost. Many pitfalls to navigate regarding indices.
- Example – the number magnitude counts from a deep image of the sky.

# Why generate random numbers?

On many occasions in hypothesis-testing and model-fitting we must have a set of numbers **distributed how we might guess the data to be.**

We may wish

- ☺ to check error propagation
- ☺ to test a test to see if it works as advertised;
- ☺ to test efficiency of tests;
- ☺ to find how many iterations we require to reach a given level of significance;
- ☺ to test our code.

**We gotta have these random numbers, of two kinds:**

- uniformly distributed,
- drawn randomly from a parent population of known frequency distribution.

# The pitfalls of random-number generators

Usual form: `x=random(idummy)`

No excuse for using bad random data.

EXAMPLE: RANDU, the infamous IBM random-number generator.

Cycle length - how long is it before the pseudo-random cycle is repeated?

Important to understand the characteristics of the generator.

Essential to follow the prescribed procedure.

Never forget that the routines generate pseudo-random numbers.

Numerical Recipes presents a number of methods, from single expressions to powerful routines.

# Random numbers from a given distribution

How do we draw a set of random numbers following a **given** frequency distribution?

Suppose we have a way of producing random numbers that are uniformly distributed, in say the variable  $\alpha$ ; and we have a functional form for our frequency distribution  $dn/dx = f(x)$ . We need a transformation  $x = x(\alpha)$  to distort the uniformity of  $\alpha$  to follow  $f(x)$ . But we know that

$$\frac{dn}{dx} = \frac{dn}{d\alpha} \frac{d\alpha}{dx}$$

and as  $dn/d\alpha$  is uniform, thus

$$\frac{dn}{dx} = \frac{d\alpha}{dx},$$

and

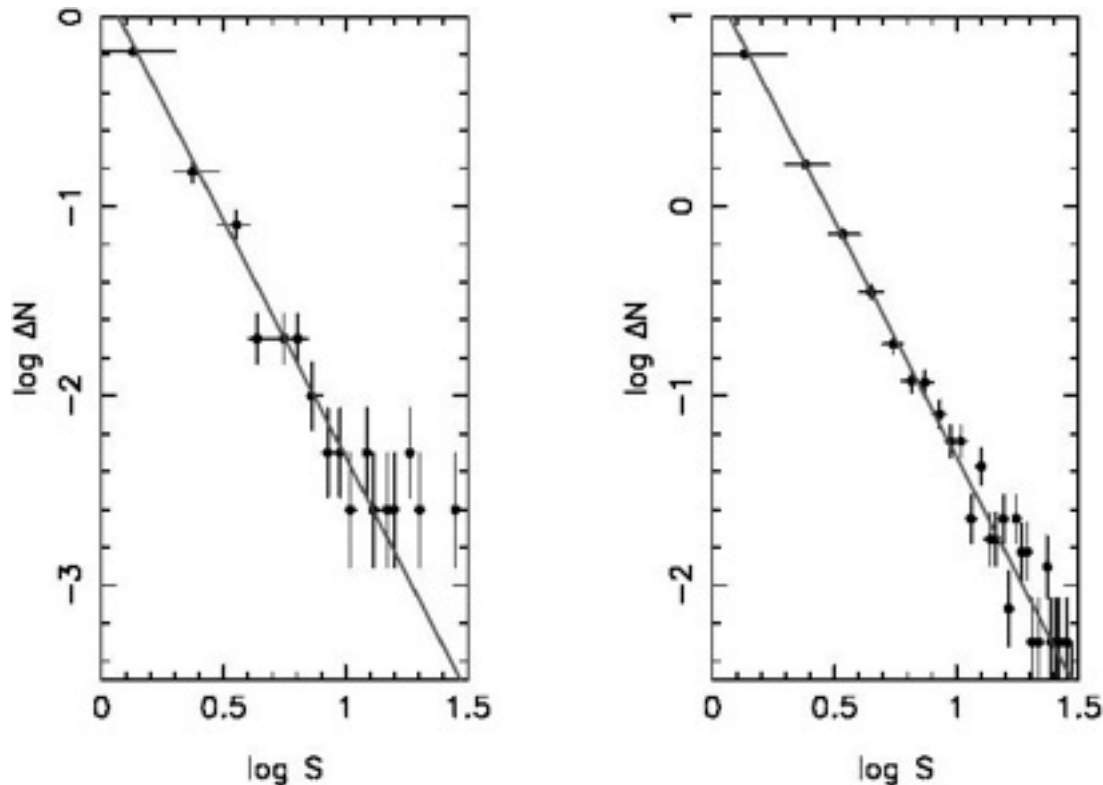
$$\alpha(x) = \int^x f(x)dx,$$

so that the required transformation is  $x = x(\alpha)$ .

**We therefore need  $x = f^{-1}(\alpha)$ , the inverse function of the integral of  $f(x)$ .**

# Randoms from a given distribution 2

EXAMPLE: A source-count distribution is given by  $f(x)dx = -1.5x^{-2.5}dx$ , a 'Euclidean' differential source count. Here  $d\alpha = -1.5x^{-2.5}dx$ ,  $\alpha = x^{-1.5}$ , and the transformation is  $x = f^{-1}(\alpha) = \alpha^{-1/1.5}$ .

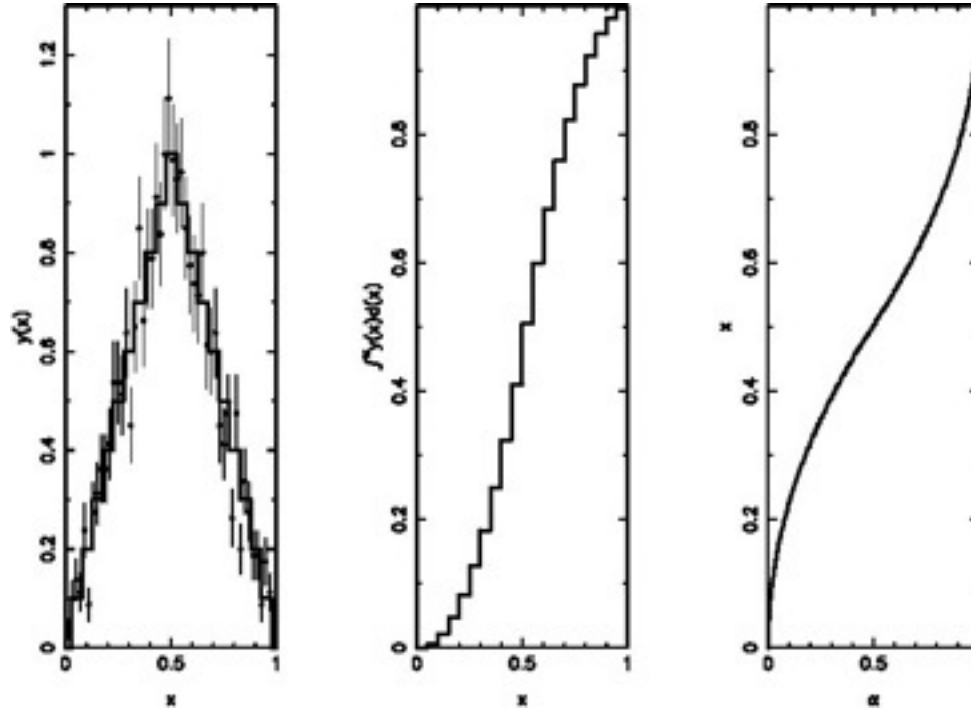


Differential source counts generated via Monte Carlo sampling with an initial uniform deviate, obeying the source-count law  $N(>S) = kS^{-1.5}$ . The straight line in each shows the anticipated count with slope -2.5. left:  $k = 1.0$ , 400 trials, right:  $k = 10.0$ , 4000 trials.

# Randoms from a given distribution 3

**The very same procedure works if we don't have a functional form for  $f(x)dx$ .** If this is a histogram, we need simply to calculate the integral version, and perform the reverse function operation as before.

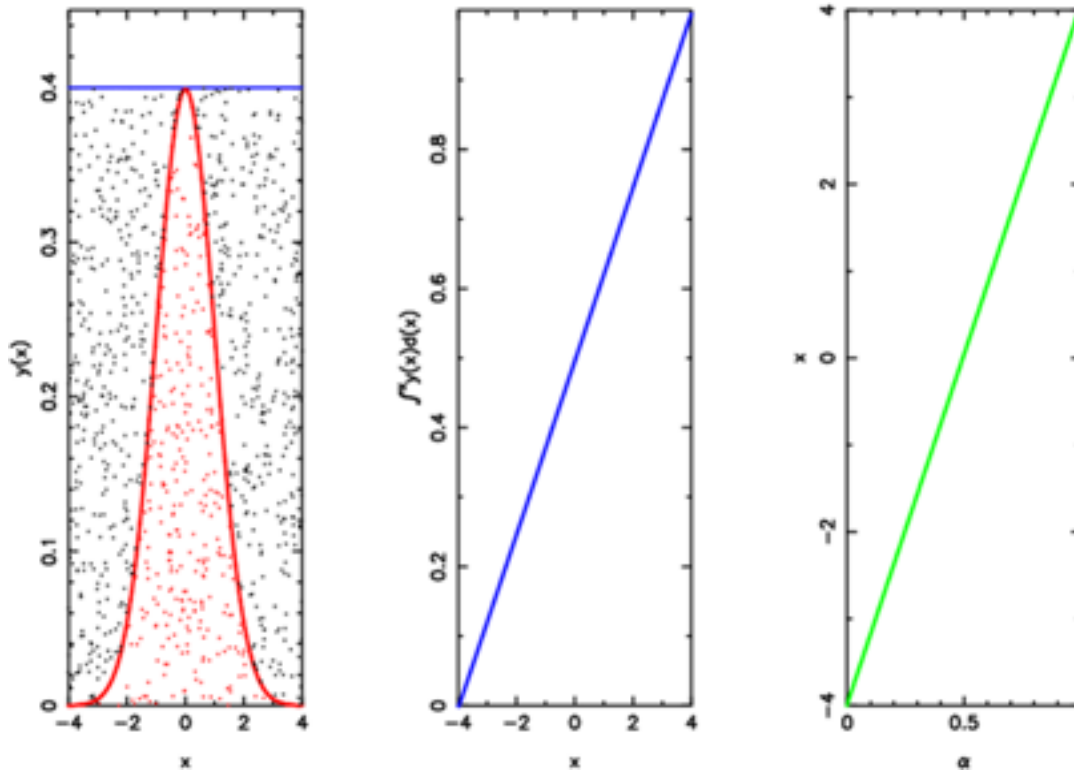
EXAMPLE:



An example of generating a Monte-Carlo distribution following a known histogram. Left: the step-ladder histogram, with points from 2000 trials, produced by a) integrating the function (middle) and b) transforming the axes to produce  $f^{-1}$  of the integrated distribution (right). The points with  $\sqrt{N}$  error bars in the left diagram are from drawing 2000 uniformly-distributed random numbers and transforming them according to the right diagram.

# Randoms from a distribution - rejection method

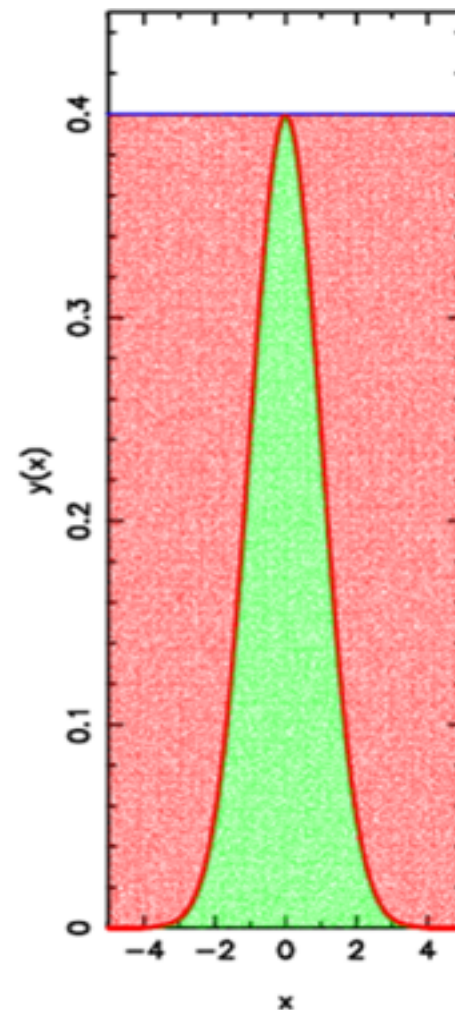
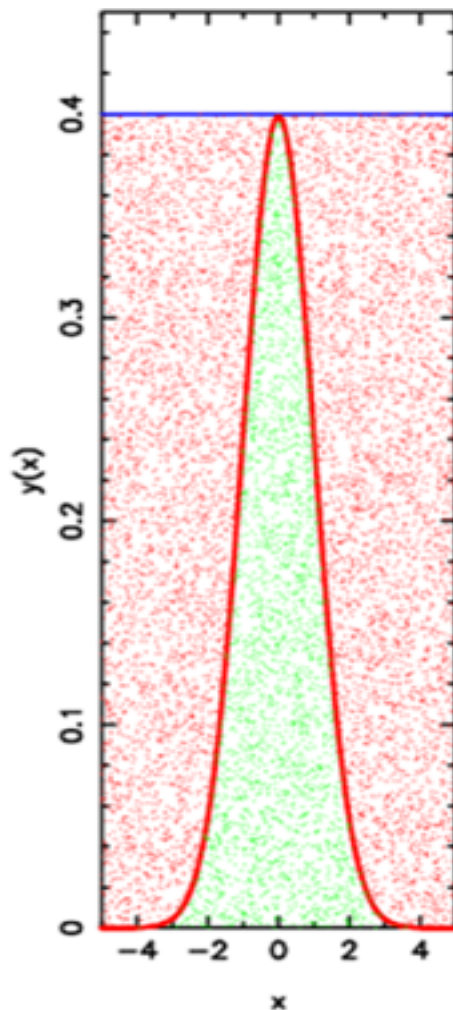
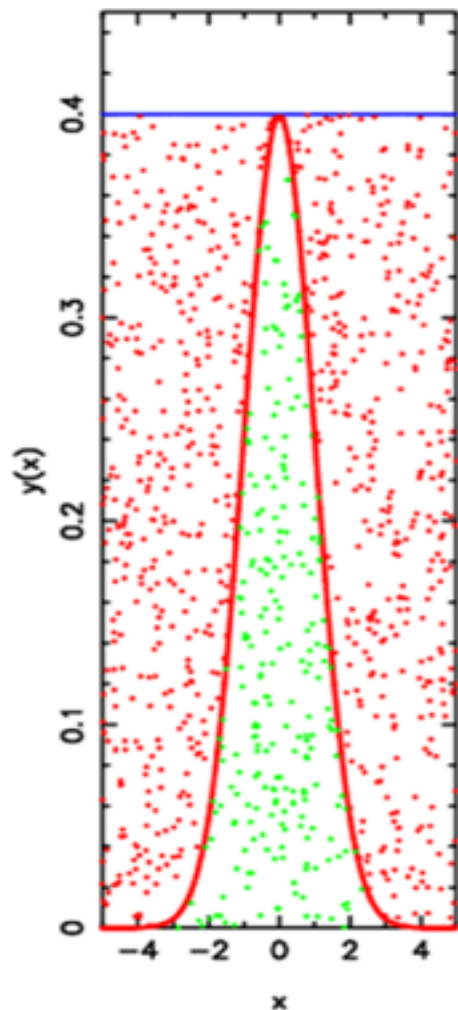
1. Plot the culprit distribution – non integrable, nasty
2. Find a nicely-behaved (integrable) one which looks a bit similar and lives higher.
3. Get the random values of  $x$  for this one, via the transform method.
4. Find a random distance up the  $y$ -axis for each of these  $x$  values
5. Reject the ones which lie outside the require distribution.



**Example 1:** Gaussian to  $\pm 5\sigma$  with elevated function (= uniform). Centre, right - transformation of the uniform function to give uniform  $x$  (and  $y$ ) coverage. 1000 trials; 241 points within Gaussian; hence area estimate =  $(241/1000) \times (0.4 \times 10.0) = 0.9640$ .

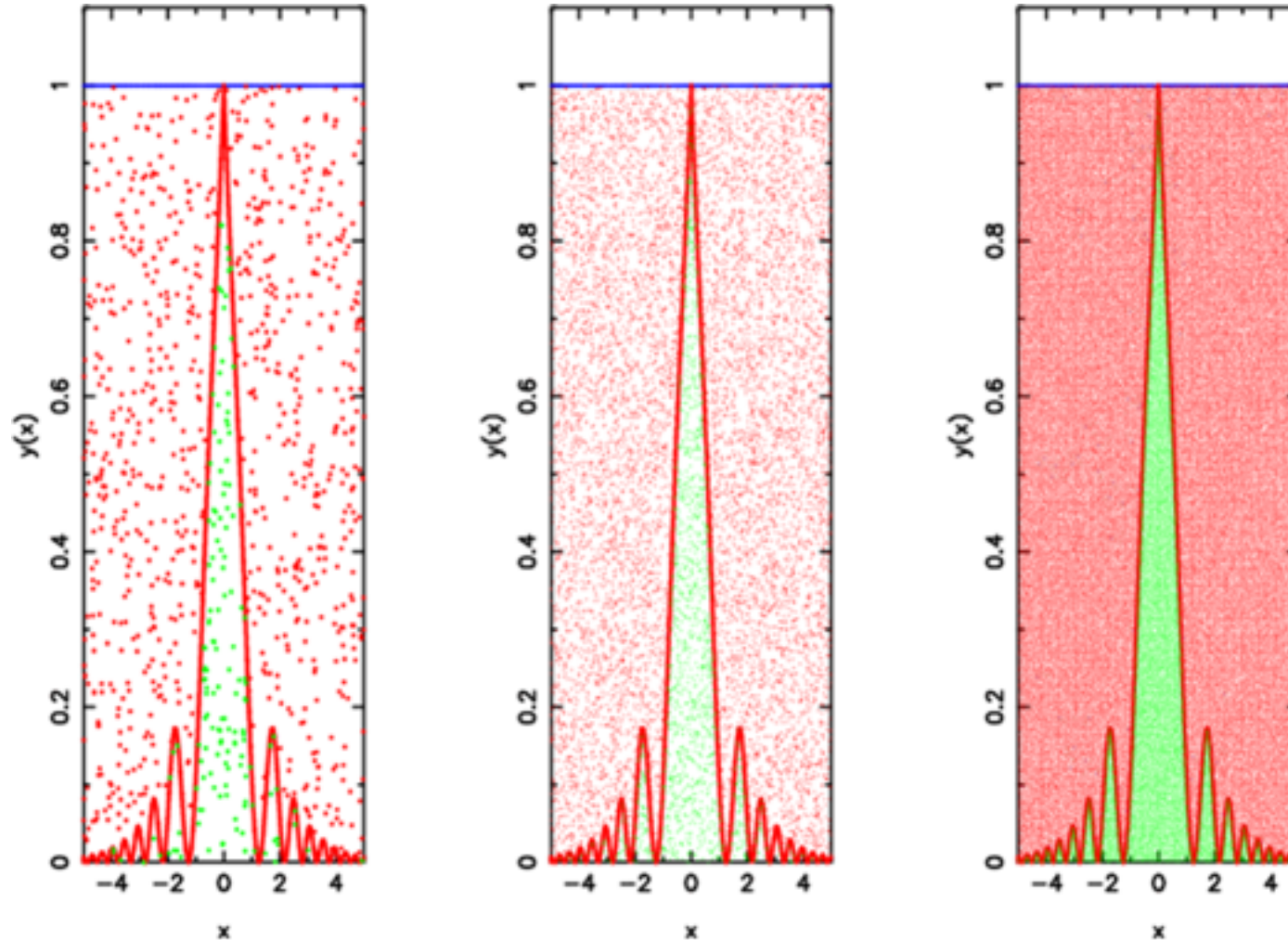


# Rejection method - Example 1 continued



Gaussians out to  $\pm 5$  sigma. Left 1000 points, 241 in zone, area =  $(241/1000) \times (10 \cdot 0.4) = 0.9640$ ; Centre 10000 points, 2540 in zone, area = 1.0160; Right  $10^6$  points, 250830 in zone, area = 1.0015

# Randoms via rejection - Example 2

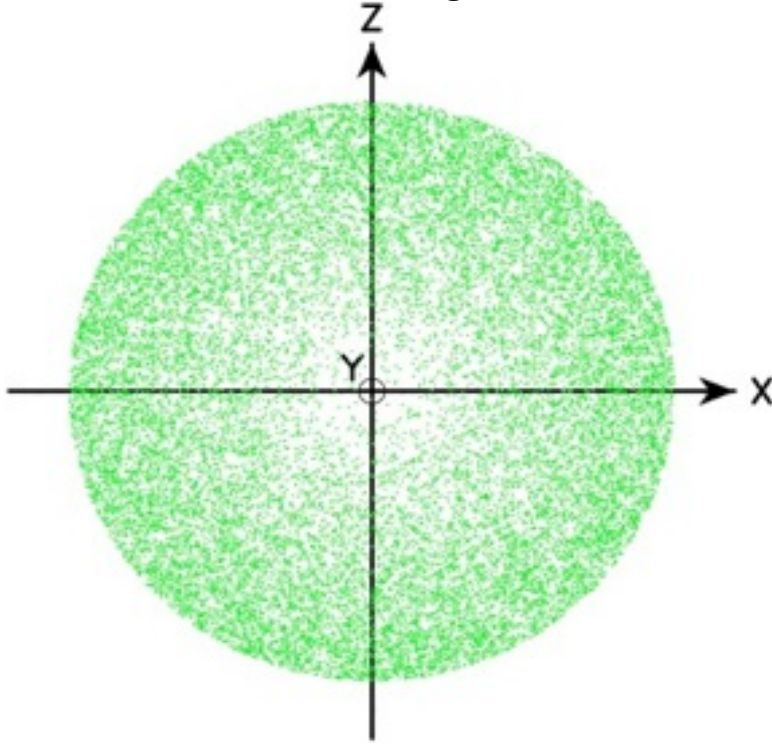


$f(x)=\exp^{-|x|}\cos(x^2)$ . Left, 1000 points, 152 in zone, area =  $(152/1000) \times (10 \cdot 1.0) = 1.5200$ ; Centre 10000 points, 1444 in zone, area = 1.4440; Right  $10^6$  points, 140229 in zone, area = 1.4023.

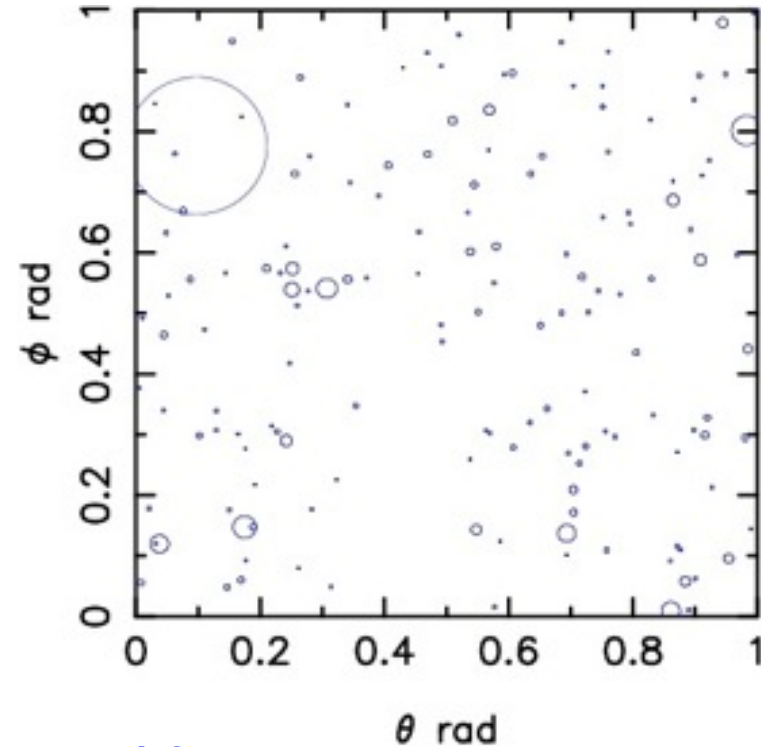
# Randoms from a distribution - Example 3

## Introducing the toy universe

Thin slice through centre



A view of the “sky”



Assume a flat Euclidean universe with  $r_{\max} = 1.0$ .

Populate this with  $10^6$  objects randomly but uniformly distributed, i.e.  $10^6$  values of  $(r_i, \theta_i, \phi_i)$

Assign each a luminosity  $L = 1.0$ , so that each produces a flux (at the centre) of  $1/r_i^2$

# Monte Carlo (random-number) Integration

**Numerical integration is a very important use of Monte Carlo.**

Highly technical! Outline here only.

Suppose we have a probability distribution  $\mathbf{f}(\mathbf{x})$  defined for  $\mathbf{a} < \mathbf{x} < \mathbf{b}$ . Draw  $\mathbf{N}$  random numbers  $\mathbf{X}$ , uniformly distributed between  $\mathbf{a}$  and  $\mathbf{b}$ , and calculate the function at these points.

Add these values of the function up, normalize - and this is our answer.

$$\int_a^b f(x) dx \simeq \frac{(b-a)}{N} \sum_i f(X_i).$$

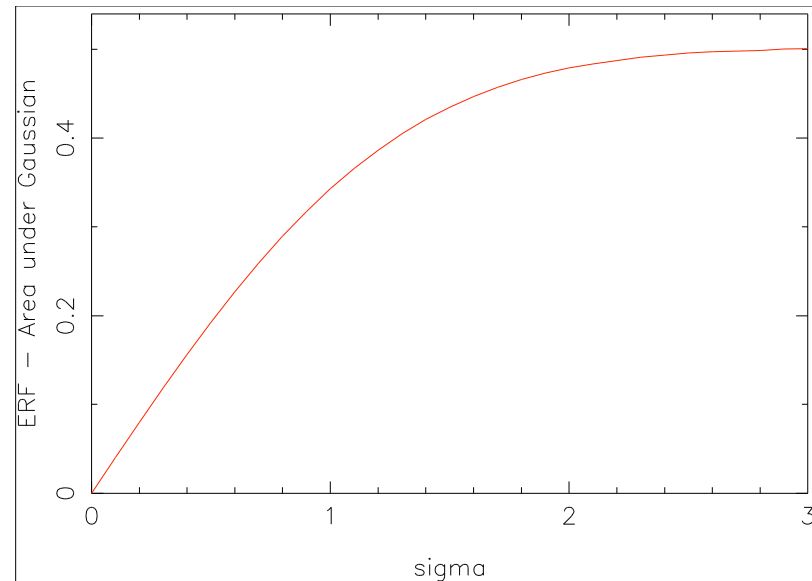
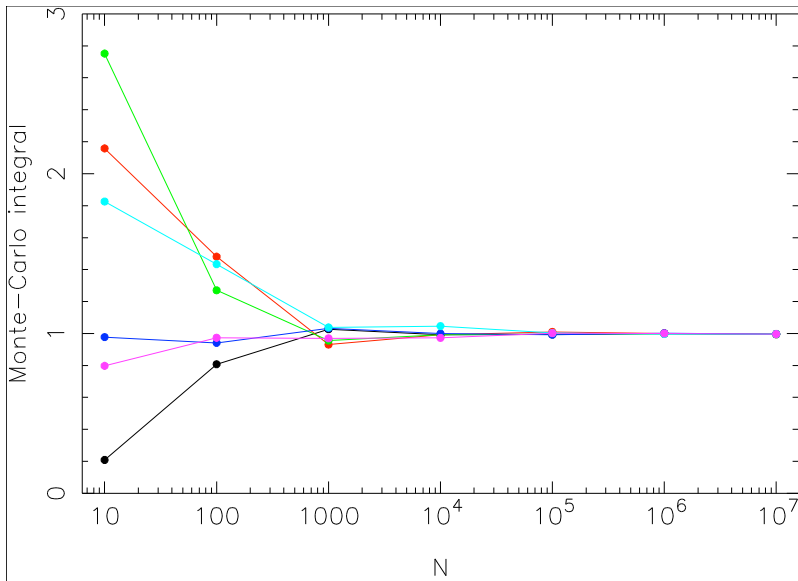
This is **Monte Carlo integration**.

If the  $\mathbf{X}_i$  are drawn from the distribution  $\mathbf{f}$  itself, then they will sample the regions where  $\mathbf{f}$  is large and the integration (for the same number of points) will be far more accurate. This technique is called importance sampling.

# MC Integration - Example (Gaussian)

Use a uniform random-number generator such as the function routine *ran1* of *Numerical Recipes*; make  $N$  calls to it, scaling the ( $0 \rightarrow 1$ ) random numbers to the range of  $\sigma$  required, say  $k\sigma$ . For each resulting value  $x_i$ , compute  $f(x_i) = \frac{1}{\sigma\sqrt{2\pi}} \exp[-\frac{x_i^2}{2\sigma^2}]$ . The integral from 0 to  $k\sigma$  is simply

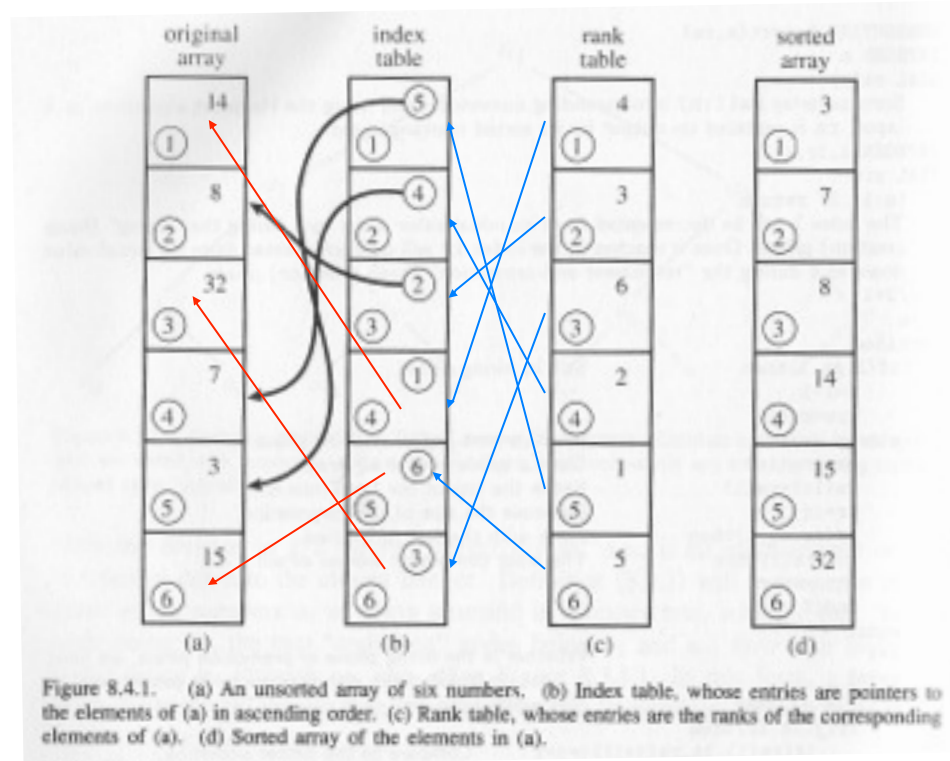
$$\frac{k}{N} \sum_{i=1}^N f_i(x).$$



Right - the result, using  $N=10^6$ . Left - using  $\pm 10\sigma$ , and varying  $N$ . The different curves are the results of different starting indices for the random-number generator. This **mindless** sum shows how stable MC integration is for well-behaved functions; we have uniformly sampled  $\pm 10\sigma$ , and the function is really a spike between  $\pm 2\sigma$ .

# Sorting, indexing, ranking

Note that in most cases, you want to sort non-destructively – unless it's a 1D 'table'. For non-destructive sorting, you'll need to think in terms of 4 arrays:



Borrowed from  
Numerical Recipes

For general sorting of a 1D array, of course you can do it directly; and it goes as  **$N!$**  in speed. Note how much efficiency you can gain by the sweat of others – there are many fast methods. **Mainly you need to look at *Numerical Recipes!***

# Sorting, indexing, ranking - Example

## The Francis and Wills (1999) sample of QSOs (quasars)

|          |       |      |       |      |      |       |      |      |      |      |       |       |       |
|----------|-------|------|-------|------|------|-------|------|------|------|------|-------|-------|-------|
| 0947+396 | 45.66 | 1.51 | 3.684 | 0.23 | 1.18 | 3.520 | 2.08 | 1.78 | 0.45 | 1.24 | 0.306 | 0.179 | 0.143 |
| 0953+414 | 45.83 | 1.57 | 3.496 | 0.25 | 1.26 | 3.432 | 2.19 | 1.78 | 0.40 | 1.24 | 0.164 | 0.189 | 0.093 |
| 1114+445 | 44.99 | 0.88 | 3.660 | 0.20 | 1.23 | 3.654 | 2.27 | 1.85 | 0.42 | 1.48 | 0.222 | 0.175 | 0.092 |
| 1115+407 | 45.41 | 1.89 | 3.236 | 0.54 | 0.78 | 3.403 | 1.90 | 1.51 | 0.33 | 1.14 | 0.385 | 0.228 | 0.134 |
| 1116+215 | 46.00 | 1.73 | 3.465 | 0.47 | 1.00 | 3.446 | 2.14 | 1.71 | 0.34 | 1.20 | 0.440 | 0.254 | 0.126 |
| 1202+281 | 44.77 | 1.22 | 3.703 | 0.29 | 1.56 | 3.434 | 2.72 | 2.41 | 0.69 | 1.87 | 0.164 | 0.154 | 0.098 |
| 1216+069 | 46.03 | 1.36 | 3.715 | 0.20 | 1.00 | 3.514 | 2.12 | 1.95 | 0.54 | 1.20 | 0.037 | 0.121 | 0.056 |
| 1226+023 | 46.74 | 0.94 | 3.547 | 0.57 | 0.70 | 3.477 | 1.64 | 1.44 | 0.45 | 1.00 | 0.280 | 0.174 | 0.018 |
| 1309+355 | 45.55 | 1.51 | 3.468 | 0.28 | 1.28 | 3.406 | 2.01 | 1.68 | 0.41 | 1.15 | 0.303 | 0.131 | 0.064 |
| 1322+659 | 45.42 | 1.69 | 3.446 | 0.59 | 0.90 | 3.351 | 2.19 | 1.85 | 0.41 | 1.30 | 0.291 | 0.135 | 0.097 |
| 1352+183 | 45.34 | 1.52 | 3.556 | 0.46 | 1.00 | 3.548 | 2.14 | 1.80 | 0.41 | 1.29 | 0.357 | 0.203 | 0.116 |
| 1402+261 | 45.74 | 1.93 | 3.281 | 1.23 | 0.30 | 3.229 | 1.91 | 1.59 | 0.39 | 1.09 | 0.568 | 0.227 | 0.161 |
| 1415+451 | 45.08 | 1.74 | 3.418 | 1.25 | 0.30 | 3.434 | 2.32 | 1.78 | 0.29 | 1.40 | 0.688 | 0.210 | 0.142 |
| 1427+480 | 45.54 | 1.41 | 3.405 | 0.36 | 1.76 | 3.300 | 2.03 | 1.82 | 0.49 | 1.21 | 0.265 | 0.126 | 0.117 |
| 1440+356 | 45.23 | 2.08 | 3.161 | 1.19 | 1.00 | 3.192 | 2.14 | 1.54 | 0.21 | 1.05 | 0.747 | 0.141 | 0.092 |
| 1444+407 | 45.92 | 1.91 | 3.394 | 1.45 | 0.30 | 3.479 | 1.99 | 1.34 | 0.21 | 1.06 | 0.809 | 0.335 | 0.164 |
| 1512+370 | 46.04 | 1.21 | 3.833 | 0.16 | 1.76 | 3.546 | 2.02 | 2.05 | 0.75 | 1.28 | 0.228 | 0.182 | 0.050 |
| 1626+554 | 45.48 | 1.94 | 3.652 | 0.32 | 0.95 | 3.631 | 2.14 | 1.80 | 0.39 | 1.36 | 0.197 | 0.217 | 0.118 |

# Sorting example, continued

*Sorting on column 3:*

*Index array:* 3 8 17 6 7 14 1 9 11 2 10 5 13 4 16 12 18 15

|          |       |      |       |      |      |       |      |      |      |      |       |       |       |
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| 1626+554 | 45.48 | 1.94 | 3.652 | 0.32 | 0.95 | 3.631 | 2.14 | 1.80 | 0.39 | 1.36 | 0.197 | 0.217 | 0.118 |
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