

# Introduction to Monte Carlo Techniques



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# Introduction to Monte Carlo

- Lecture 1: The Monte Carlo method
  - ✦ theoretical foundations and limitations
  - ✦ parton-level event generation
- Lecture 2: Hadron-level event generation
  - ✦ parton showering
  - ✦ hadronization and underlying event
  - ✦ sample of results

# Why Monte Carlo?



- Something to do with gambling?
- Not a place but a method ...

# Monte Carlo Event Generation

# Monte Carlo Event Generation

- Aim is to produce simulated (particle-level) datasets like those from real collider events
  - ✦ i.e. lists of particle identities, momenta, ...
  - ✦ simulate quantum effects by (pseudo)random numbers
- Essential for:
  - ✦ Designing new experiments and data analyses
  - ✦ Correcting for detector and selection effects
  - ✦ Testing the SM and measuring its parameters
  - ✦ Estimating new signals and their backgrounds

# References

- A. Buckley et al., “General-purpose event generators for LHC physics”, Phys.Rept. 504 (2011) 145 (MCNET-11-01, arXiv: 1101.2599)
- M.H. Seymour & M. Marx, “Monte Carlo Event Generators”, MCNET-13-05, arXiv: 1304.6677
- A. Siódmok, “LHC event generation with general-purpose Monte Carlo tools”, Acta Phys. Polon. B44 (2013) 1587

# Monte Carlo Method

# Buffon's needle

G-L Leclerc, Comte de Buffon, 1707-1788



$$2 \times 10/5 = 4.000$$



# Buffon's needle

G-L Leclerc, Comte de Buffon, 1707-1788



$$2 \times 20 / 12 = 3.333$$

# Buffon's needle

G-L Leclerc, Comte de Buffon, 1707-1788



$$2 \times 30 / 16 = 3.750$$

# Buffon's needle

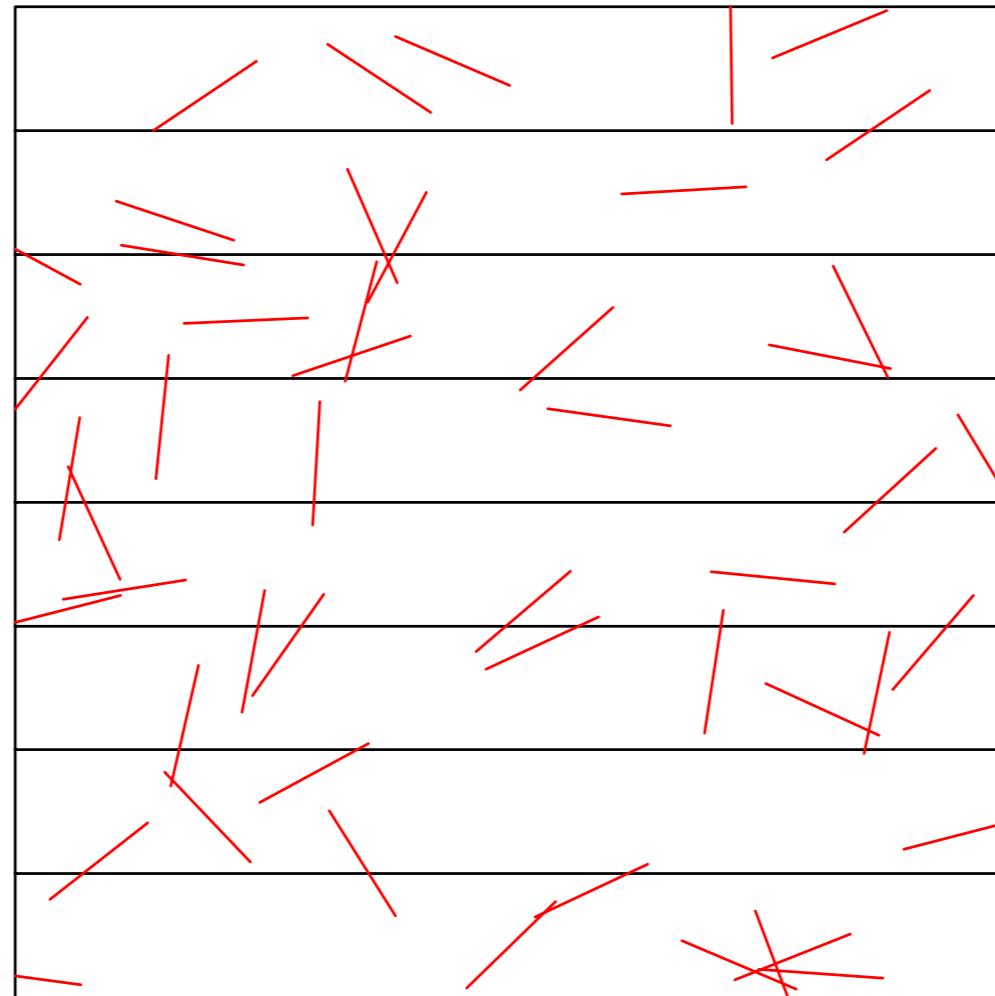
G-L Leclerc, Comte de Buffon, 1707-1788



$$2 \times 40 / 22 = 3.636$$

# Buffon's needle

G-L Leclerc, Comte de Buffon, 1707-1788



$$2 \times 50 / 28 = 3.571$$

# Buffon's needle

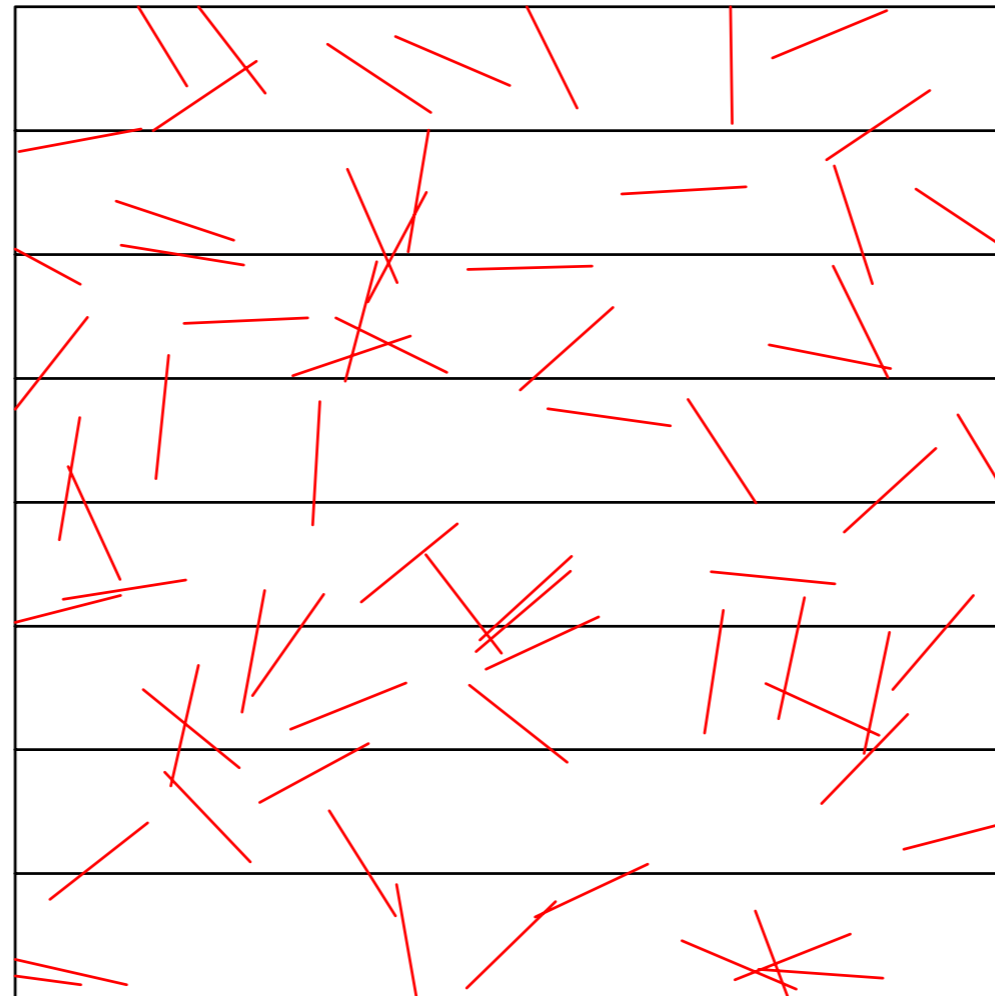
G-L Leclerc, Comte de Buffon, 1707-1788



$$2 \times 60 / 34 = 3.529$$

# Buffon's needle

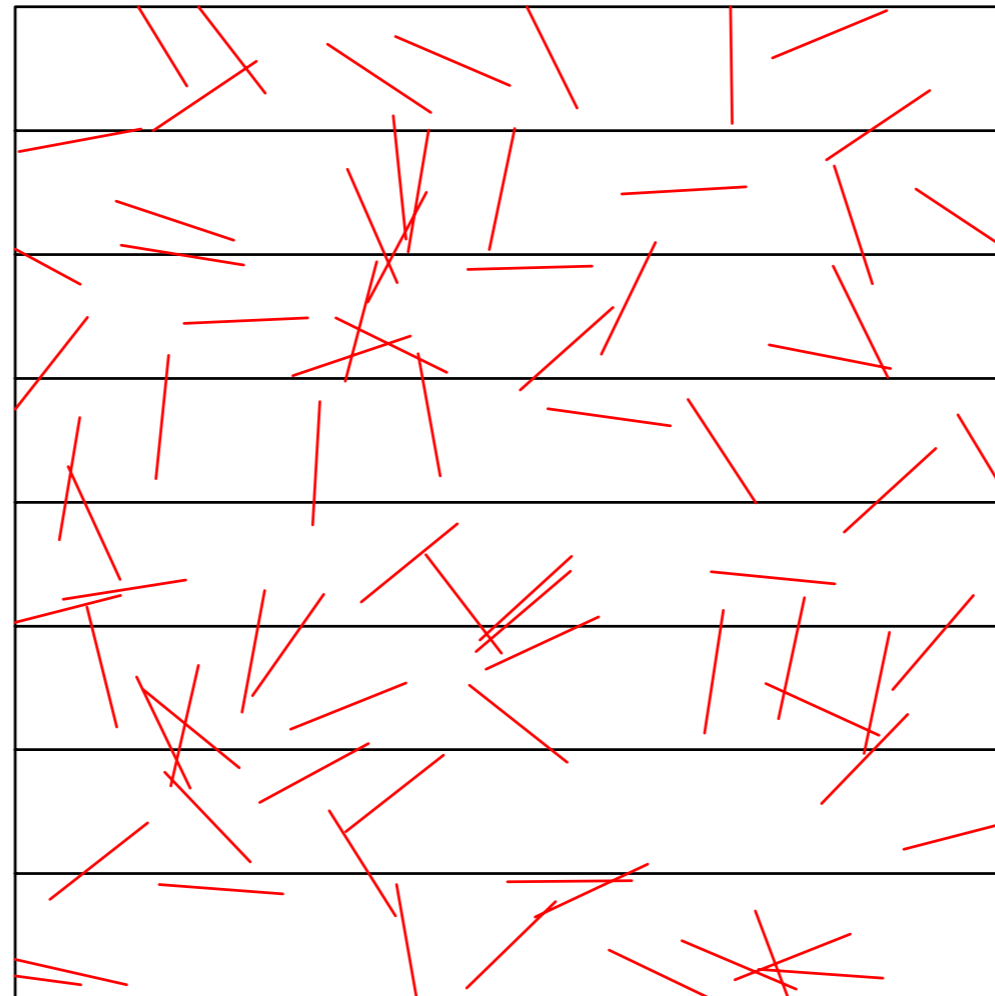
G-L Leclerc, Comte de Buffon, 1707-1788



$$2 \times 70 / 40 = 3.500$$

# Buffon's needle

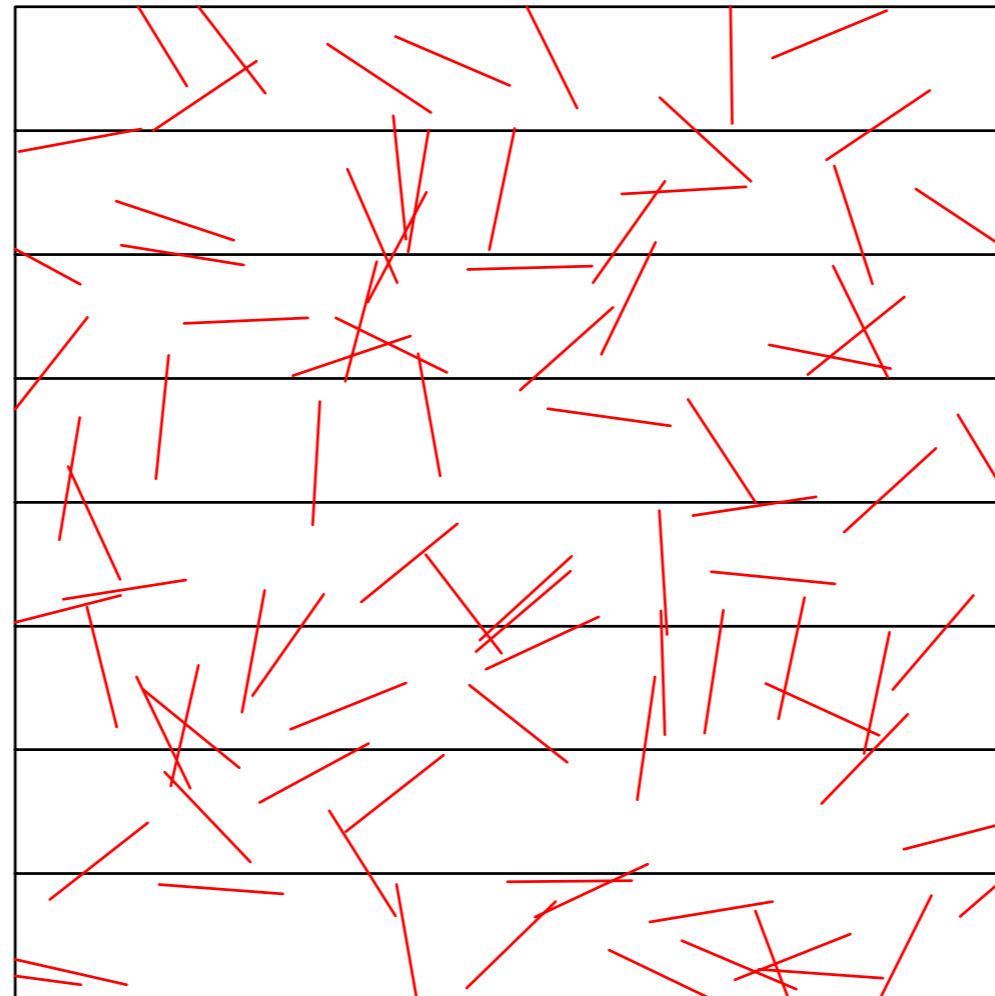
G-L Leclerc, Comte de Buffon, 1707-1788



$$2 \times 80 / 47 = 3.404$$

# Buffon's needle

G-L Leclerc, Comte de Buffon, 1707-1788



$$2 \times 90 / 55 = 3.273$$



# Buffon's needle

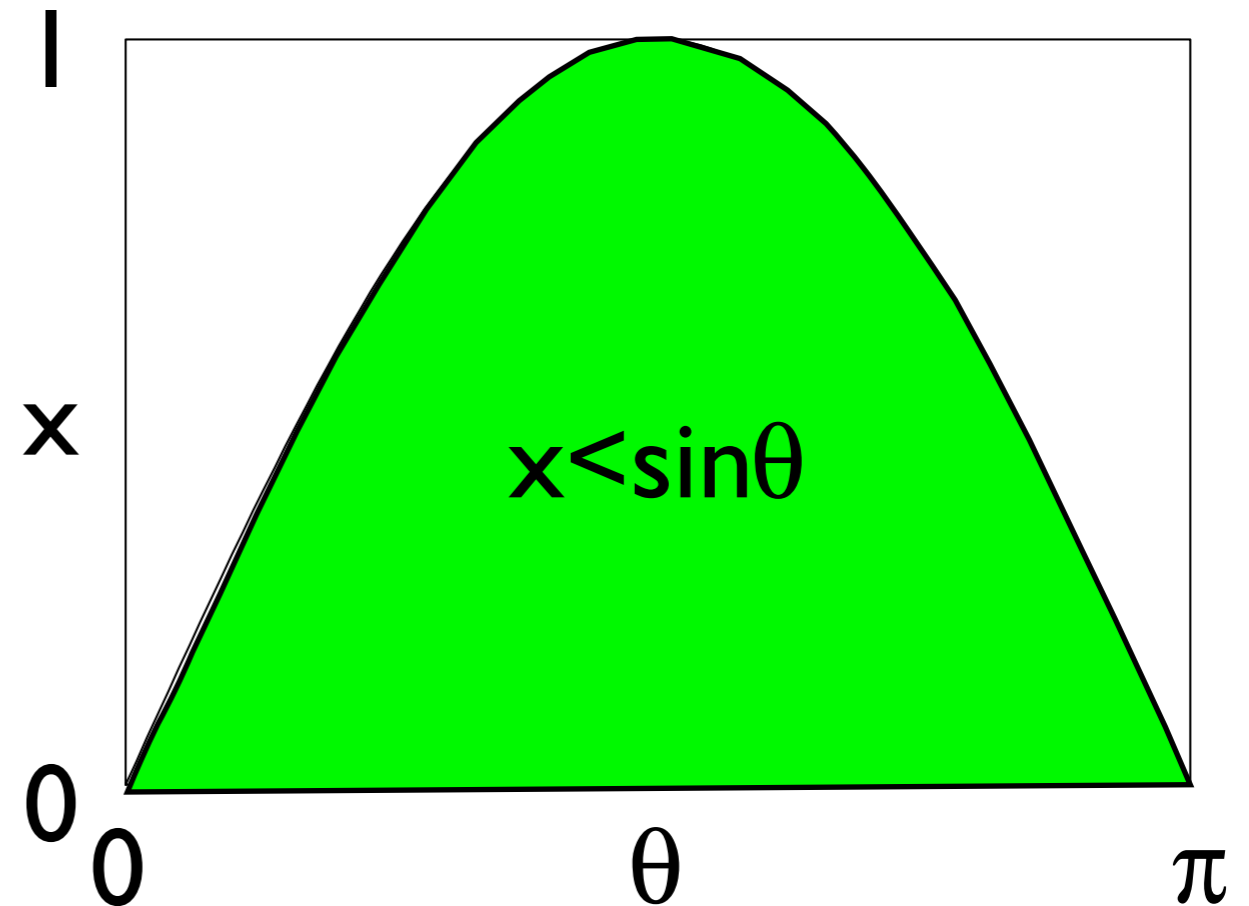
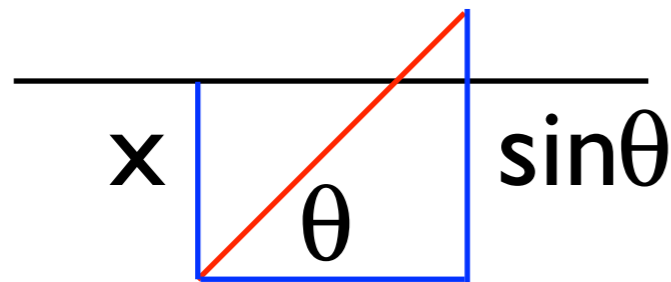
G-L Leclerc, Comte de Buffon, 1707-1788



$$2 \times 100 / 63 = 3.175$$

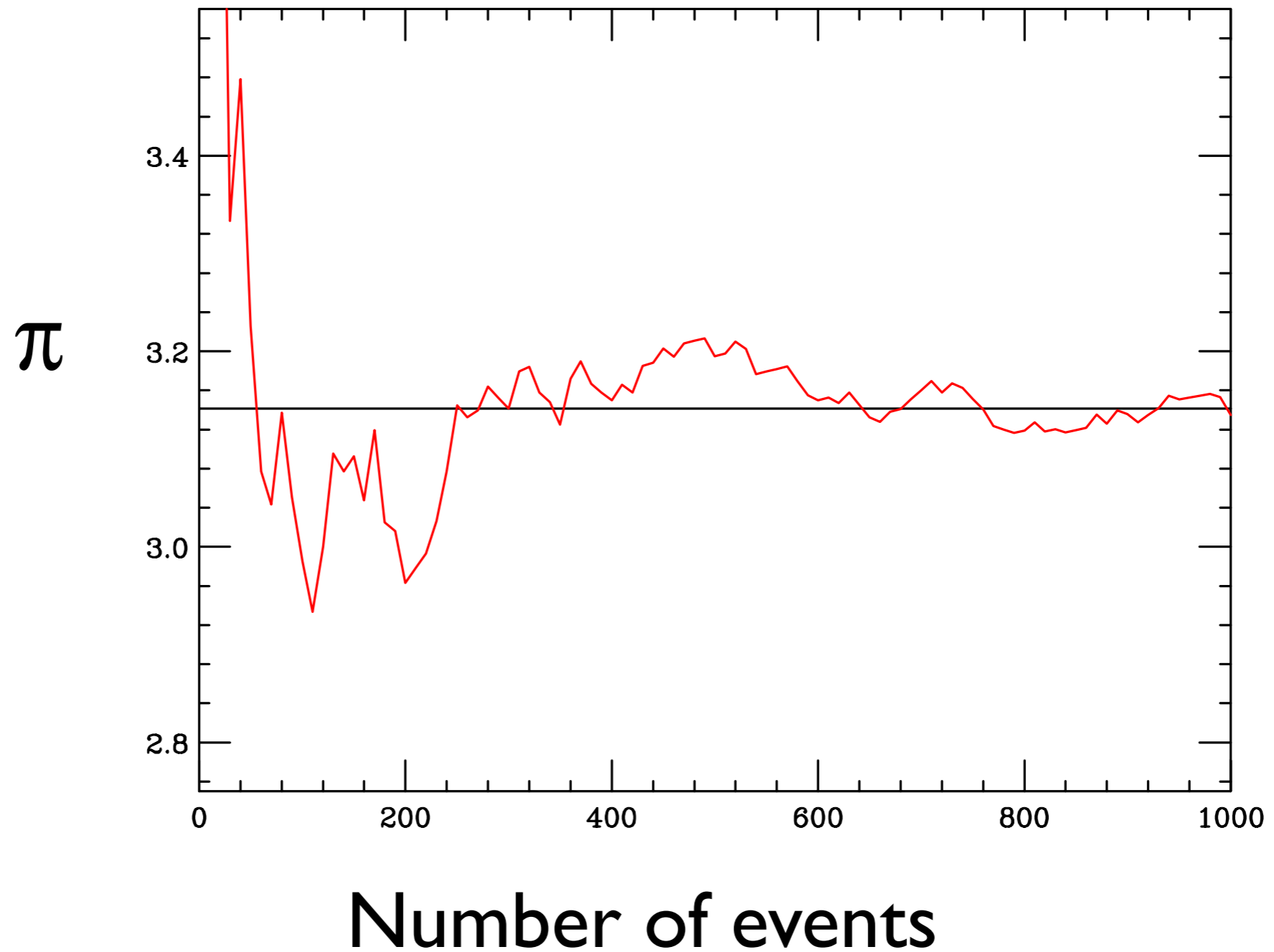
# Buffon's needle

**Events** (needle drops) are represented by random points in  $(\theta, x)$  **phase space**

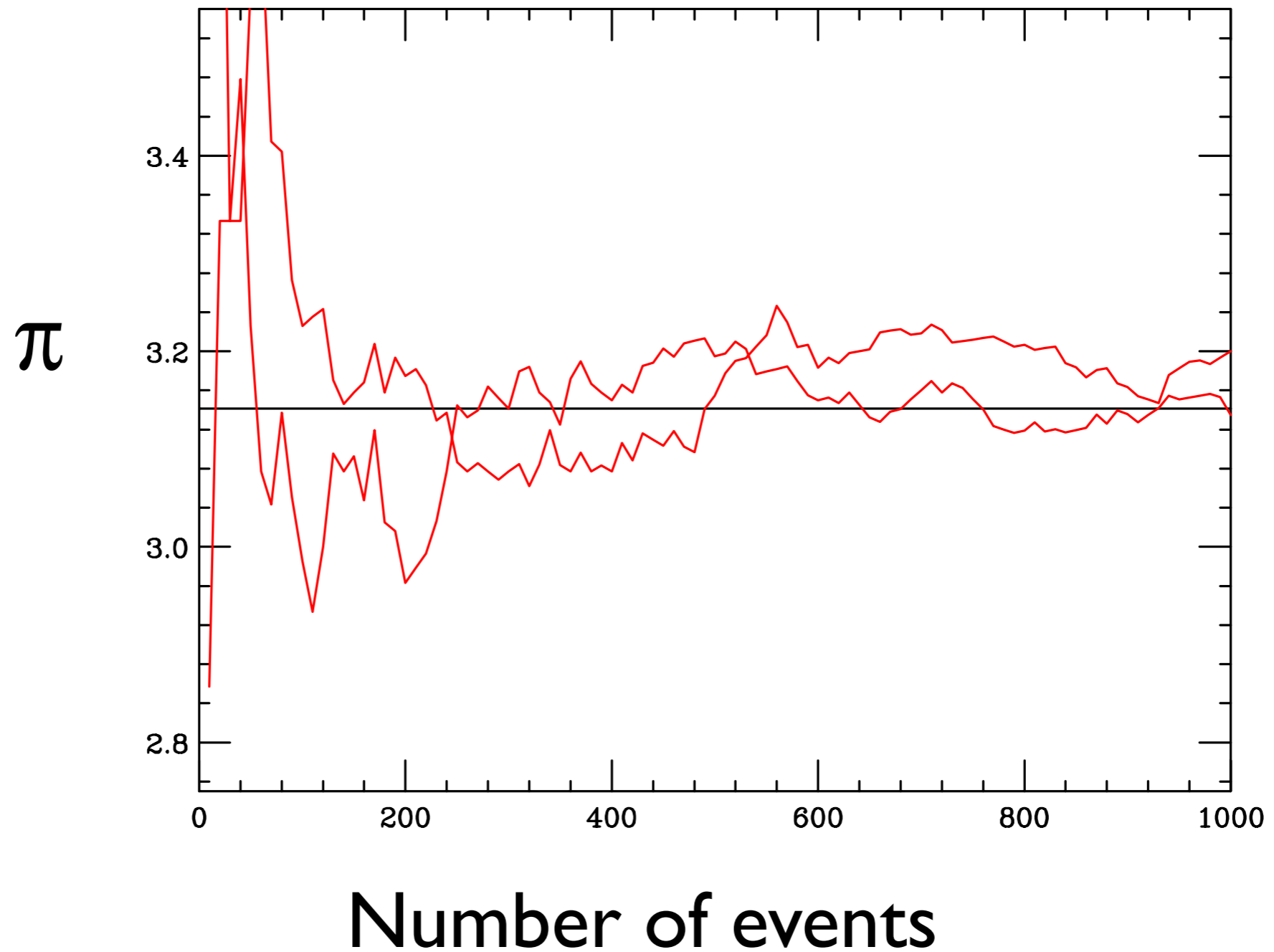


$$P(x < \sin\theta) = 2/\pi$$

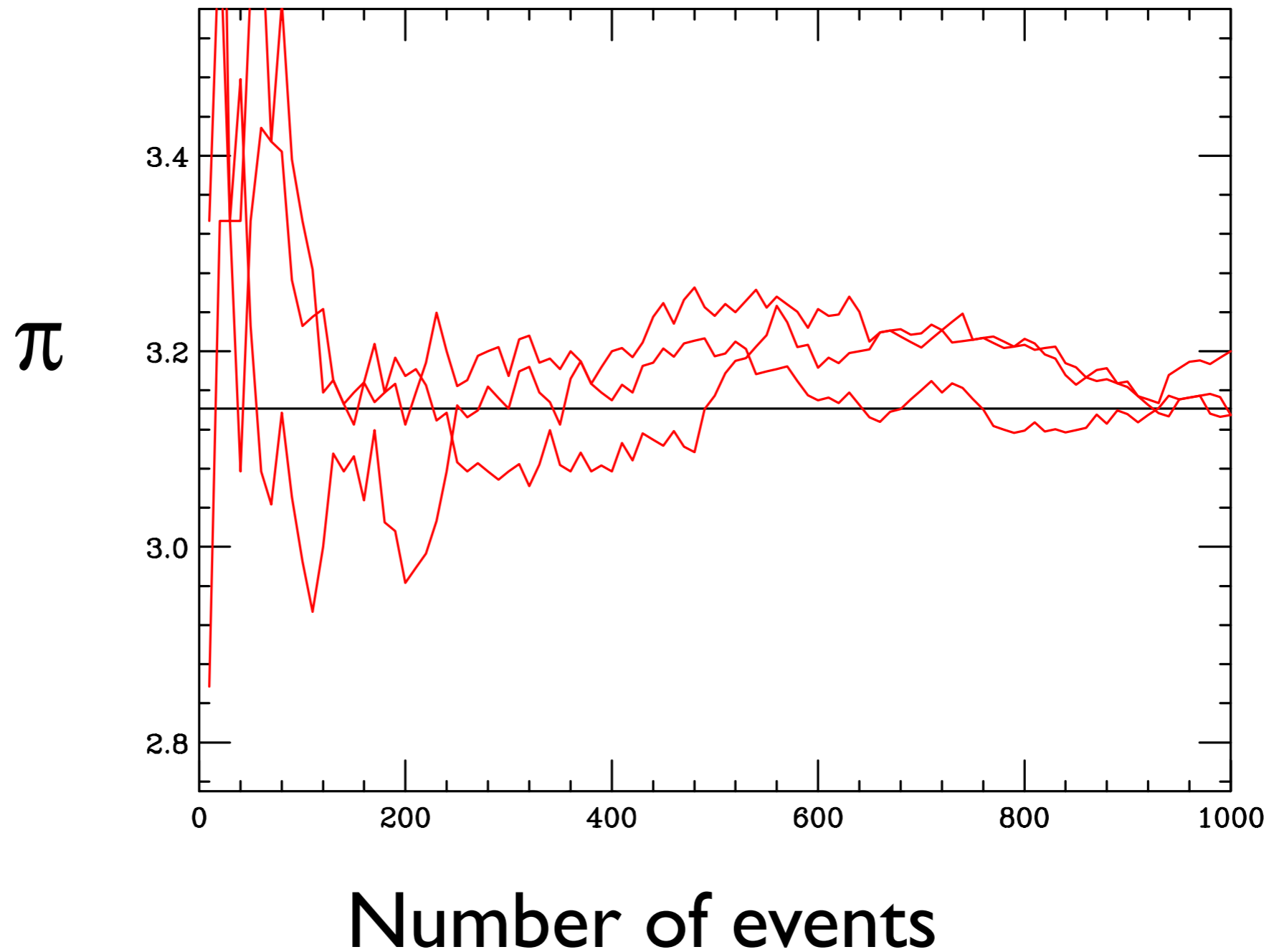
# Buffon's needle



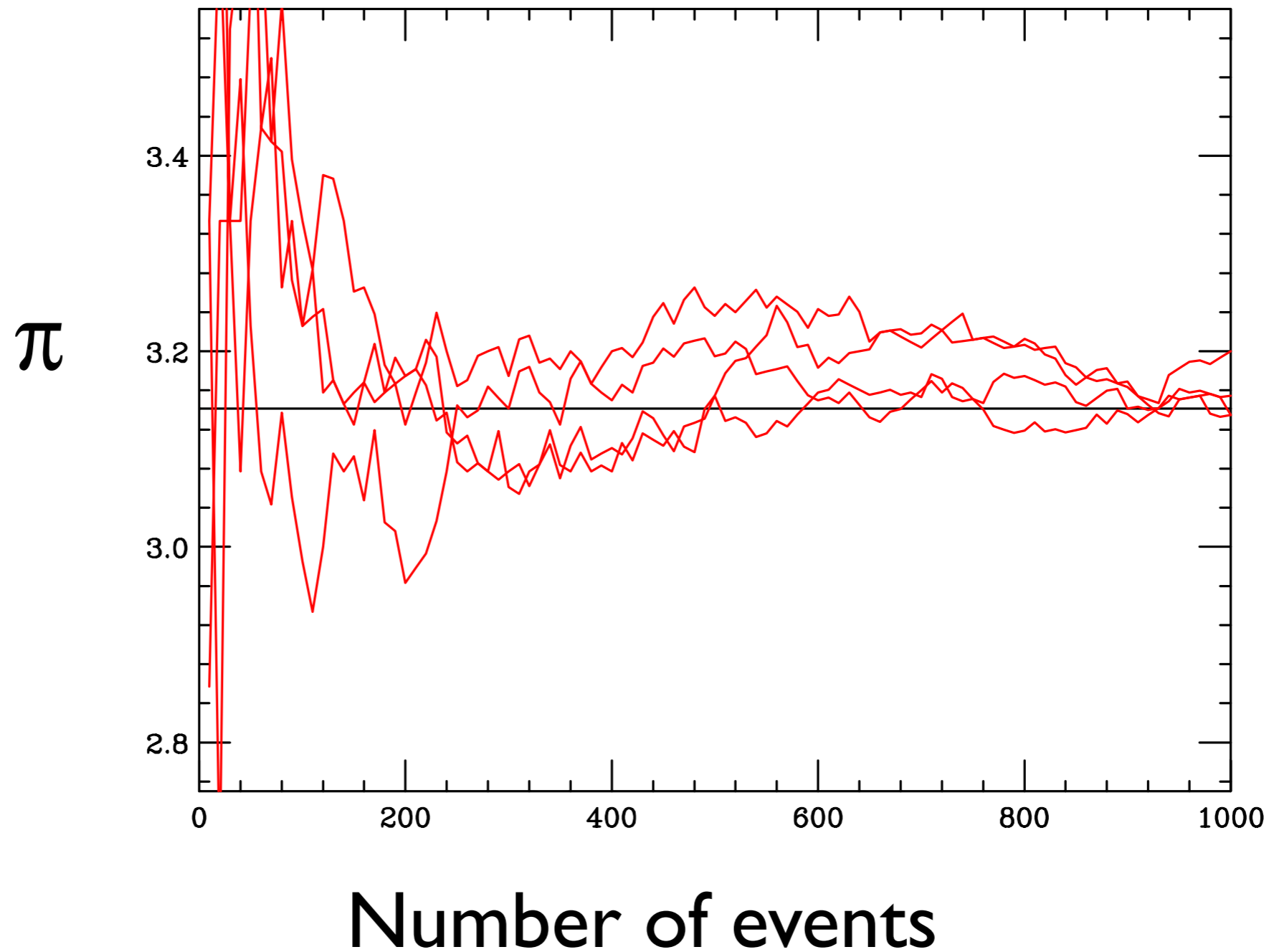
# Buffon's needle



# Buffon's needle



# Buffon's needle



# Some statistics

- **Expected value** of a discrete random variable  $x$  = probability-weighted sum over possible outcomes = expected mean of a large number of independent trials
  - ❖  $E[x] = x_1 p_1 + x_2 p_2 + x_3 p_3 + \dots$
  - ❖ Here  $x_1 = 1$  (needle on line,  $p_1 = 2/\pi$ ) or else  $x_2 = 0$  (needle off line). Hence  $E[x] = 2/\pi$
- **Variance** = Mean square deviation
  - ❖  $\text{Var}[x] = E[(x - E[x])^2] = E[x^2] - (E[x])^2$
  - ❖ Here  $\text{Var}[x] = p_1 - p_1^2 = 2/\pi(1 - 2/\pi)$
- **(RMS) Standard deviation**  $\sigma_x = \sqrt{\text{Var}[x]} = 0.481$  here

# Statistics (cont'd)

- Variances for uncorrelated random variables are additive

- ✦  $\text{Var}[x_1+x_2] = \text{Var}[x_1] + \text{Var}[x_2] + 2(\cancel{E[x_1x_2] - E[x_1]E[x_2]})$

- For  $N$  identical independent trials and  $S_N = x_1 + \dots + x_N$ ,

- ✦  $E[S_N] = N E[x], \text{Var}[S_N] = N \text{Var}[x], \sigma_{S_N} = \sqrt{N} \sigma_x$

- Here, for  $N$  needles,  $E[S_N] = 2N/\pi$ , so  $\sigma_\pi/\pi = \sigma_{S_N}/E[S_N] = \sqrt{N} \sigma_x / (2N/\pi)$ , i.e. standard deviation in estimate of  $\pi$  is

- ✦  $\sigma_\pi = \pi^2 \sigma_x / (2\sqrt{N}) = 2.37 / \sqrt{N}$

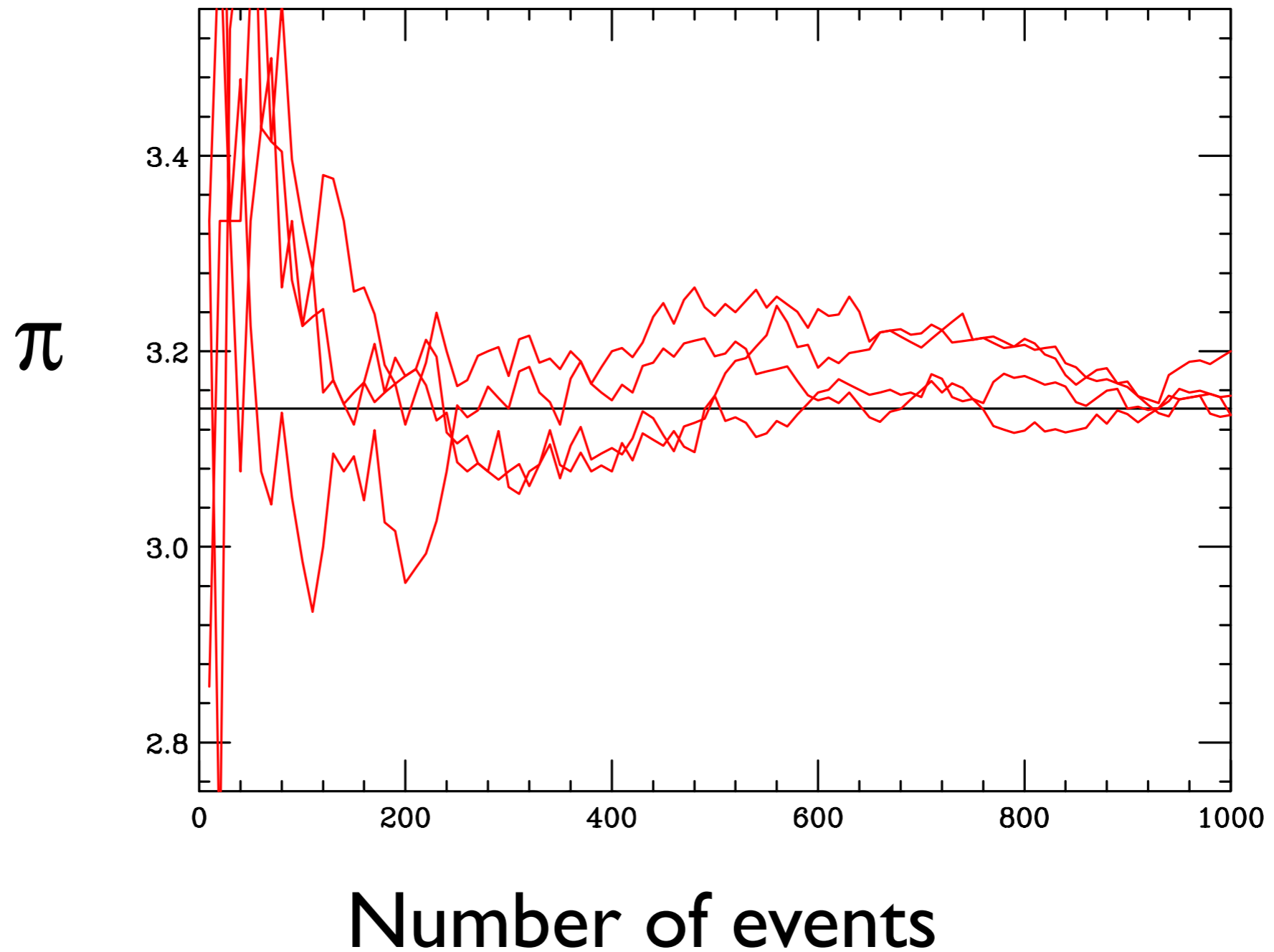
- $2N/S_N = \pi \pm \underbrace{2.37 / \sqrt{N}}_{1\sigma}$

Central limit theorem:

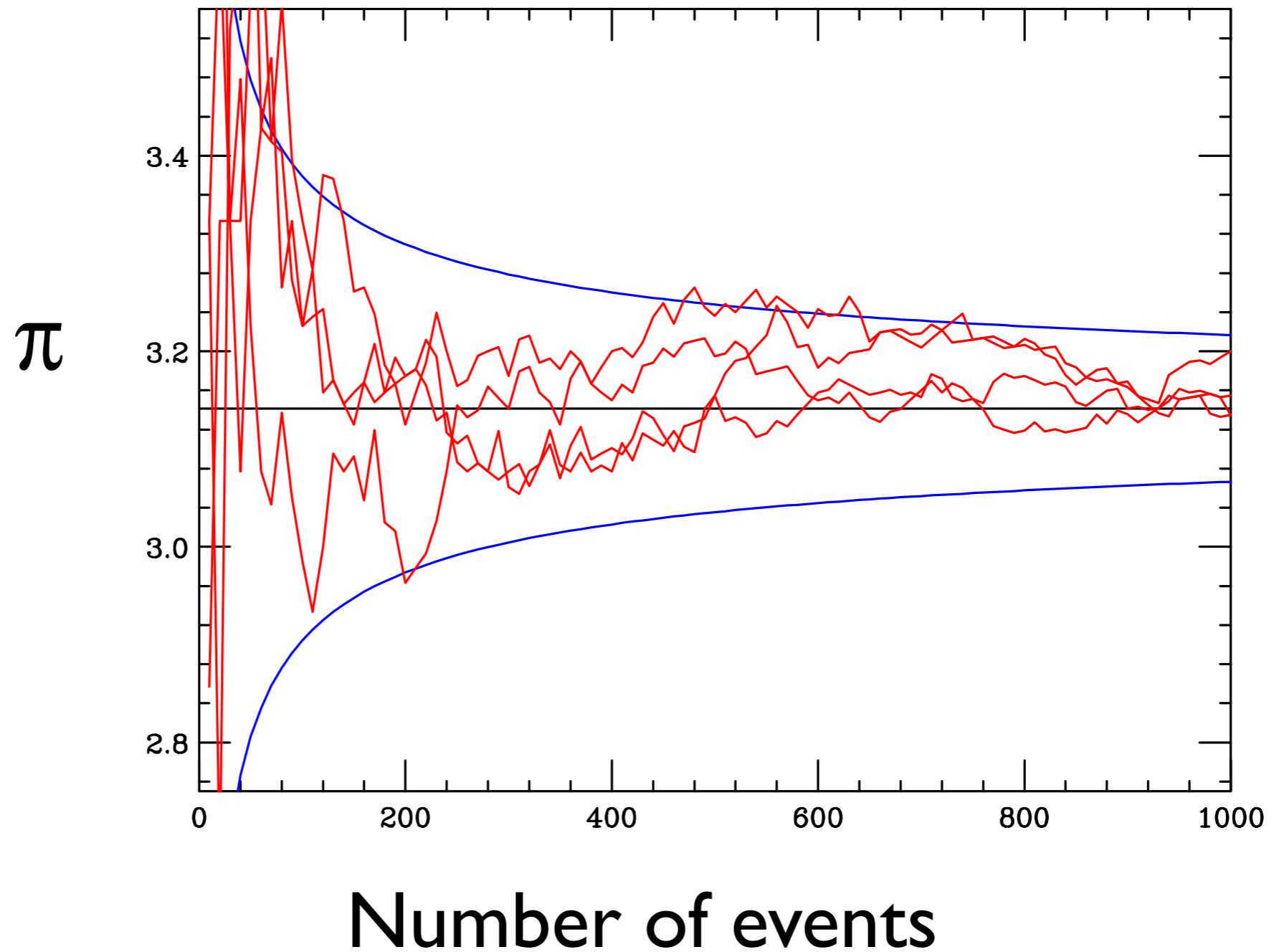
$$P(< 1\sigma) = 68\%$$



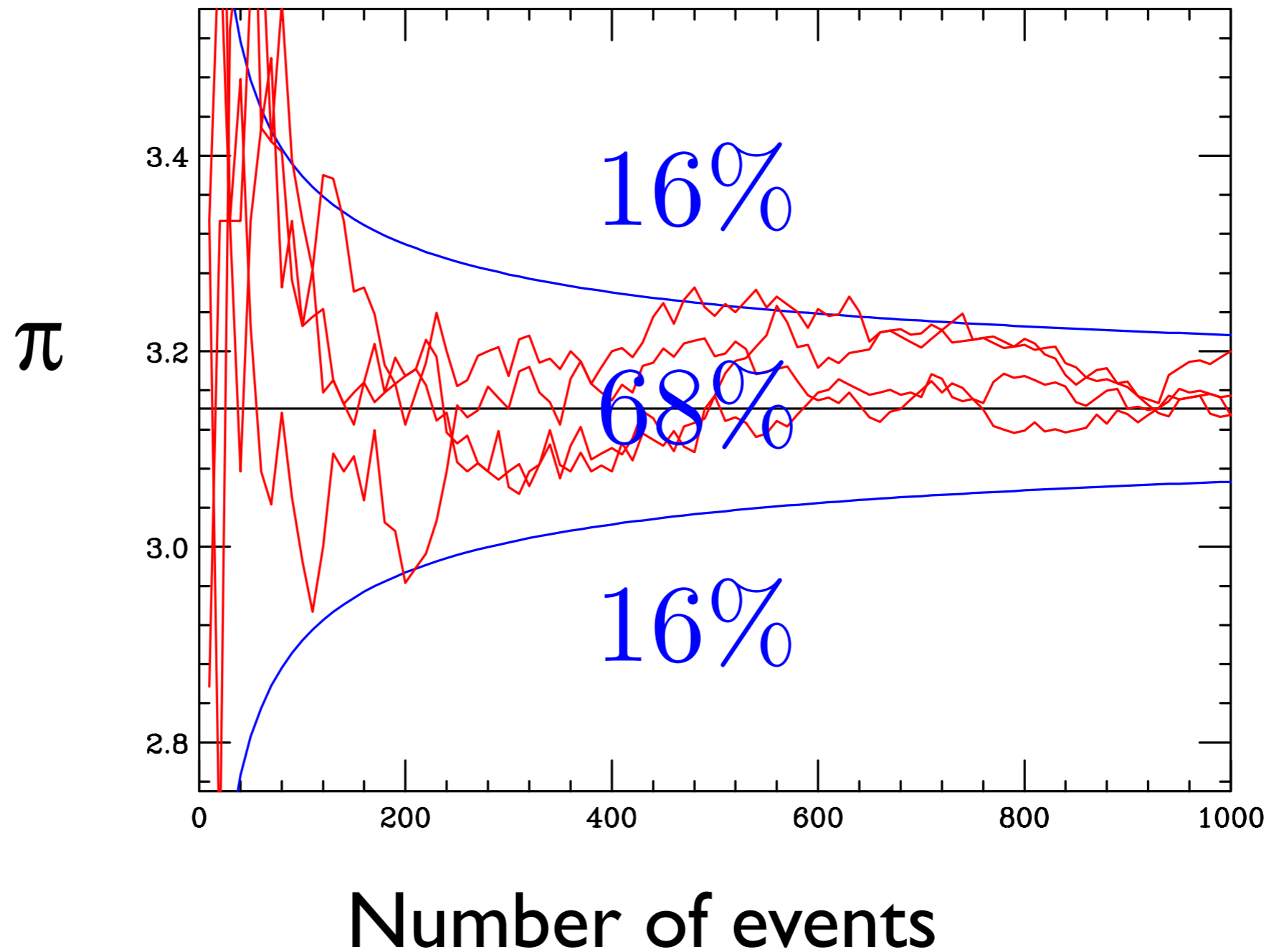
# Buffon's needle



# Buffon's needle



# Buffon's needle



# Monte Carlo Integration

- Basis of all Monte Carlo methods:

$$I = \int_a^b f(x) dx \approx \frac{1}{N} \sum_{i=1}^N \underbrace{(b-a)}_{\text{weight } w_i} f(x_i) \equiv I_N$$

where  $x_i$  are randomly (uniformly) distributed on  $[a,b]$ .

- Then  $I = \lim_{N \rightarrow \infty} I_N = E[w]$ ,  $\sigma_I = \sqrt{\text{Var}[w]/N}$

where  $\text{Var}[w] = E[(w - E[w])^2] = E[w^2] - (E[w])^2$

$$= (b-a) \int_a^b [f(x)]^2 dx - \left[ \int_a^b f(x) dx \right]^2 \equiv V$$

$$I = I_N \pm \sqrt{V/N}$$

Central limit theorem:  
 $P(< 1\sigma) = 68\%$

# Convergence

- Monte Carlo integrals governed by Central Limit

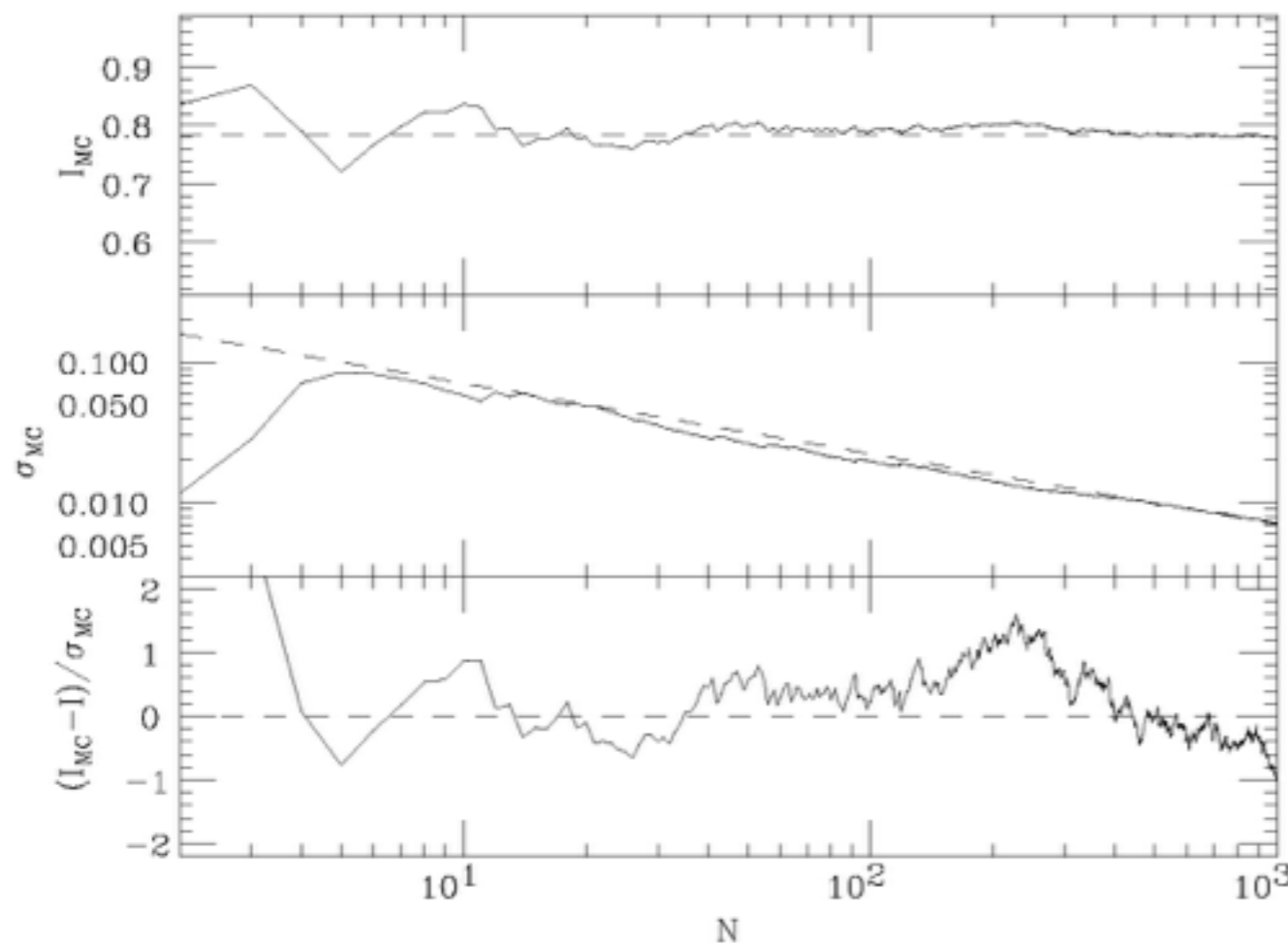
Theorem: error  $\propto 1/\sqrt{N}$

c.f. trapezium rule  $\propto 1/N^2$

Simpson's rule  $\propto 1/N^4$

only if derivatives exist and are finite, e.g.

$$\sqrt{1-x^2} \sim 1/N^{3/2}$$



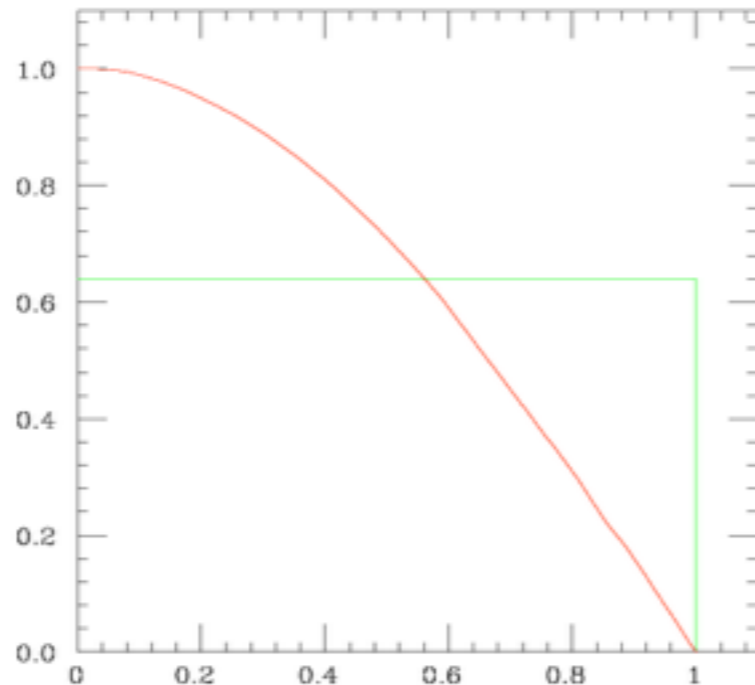
$$I = \int_0^1 \sqrt{1-x^2} dx = \frac{\pi}{4} = 0.785$$

$$\sqrt{V} = \sqrt{\frac{2}{3} - \frac{\pi^2}{16}} = 0.223$$

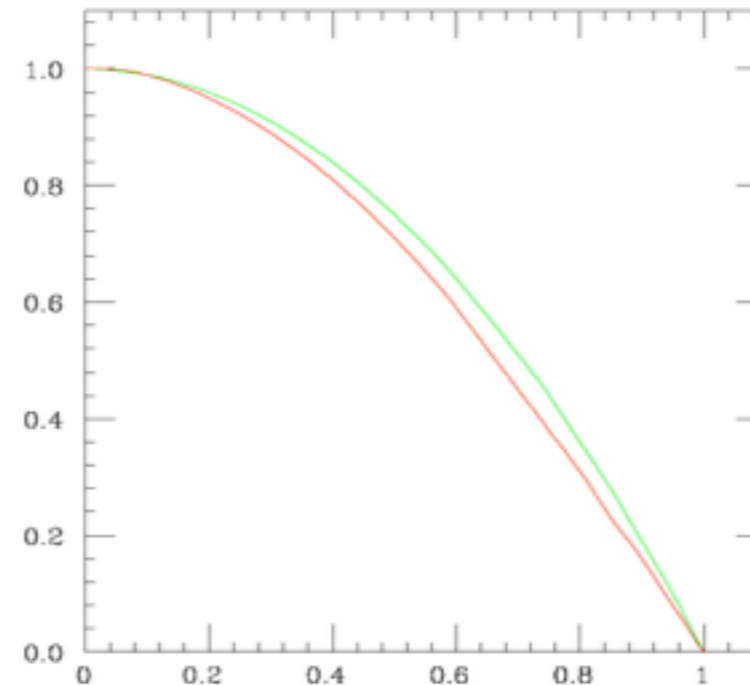
$$I = 0.785 \pm \frac{0.223}{\sqrt{N}}$$

# Importance Sampling

- Convergence is improved by putting more points in regions where integrand is largest
- Corresponds to a Jacobian transformation
- Variance is reduced (weights “flattened”)



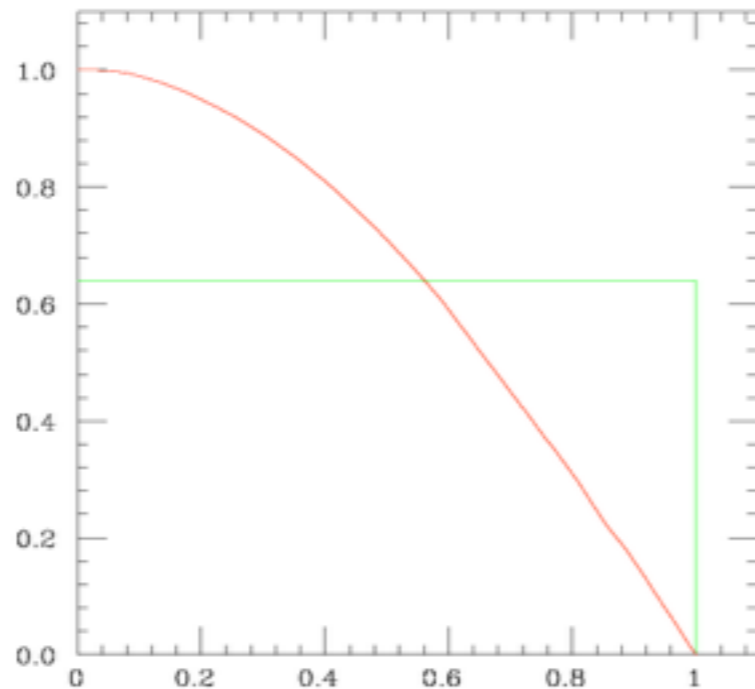
$$\begin{aligned} I &= \int_0^1 dx \cos \frac{\pi}{2} x \\ &= 0.637 \pm 0.308 / \sqrt{N} \end{aligned}$$



$$\begin{aligned} I &= \int_0^1 dx (1-x^2) \frac{\cos \frac{\pi}{2} x}{1-x^2} \\ &= \int d\rho \frac{\cos \frac{\pi}{2} x}{1-x^2} [x(\rho)] \\ &= 0.637 \pm 0.037 / \sqrt{N} \end{aligned}$$

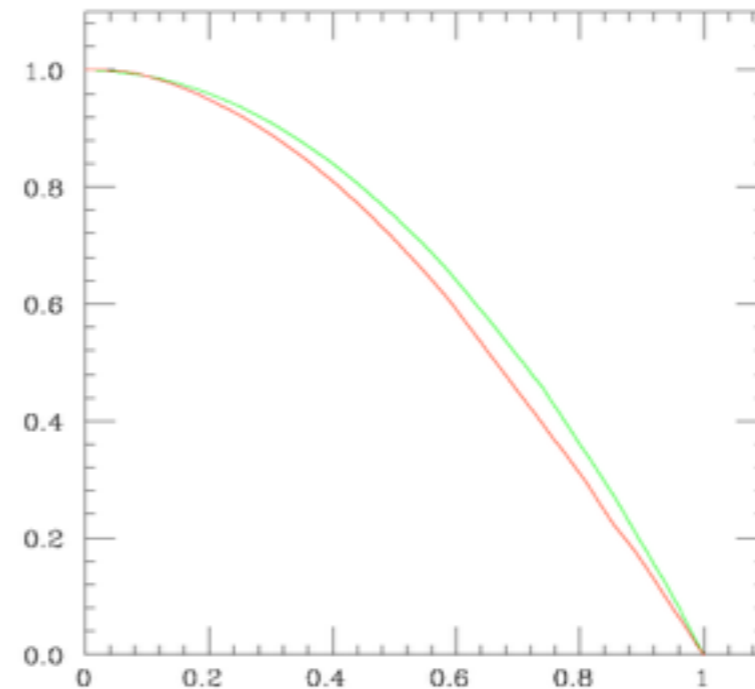
# Hit-and-Miss

- Accept points with probability =  $w_i/w_{\max}$  (provided all  $w_i \geq 0$ )
- Accepted points are distributed like real events (cf. Buffon's needle)
- MC efficiency  $\epsilon_{\text{MC}} = E[w]/w_{\max}$  improved by importance sampling



$$\epsilon_{\text{MC}} = 1/I = 2/\pi = 64\%$$

$$\sigma = \sqrt{\frac{\epsilon_{\text{MC}}(1 - \epsilon_{\text{MC}})}{N}} = \frac{0.48}{\sqrt{N}}$$



$$\epsilon_{\text{MC}} = \int_0^1 dx(1 - x^2)/I = 3/\pi = 95\%$$

$$\sigma = \sqrt{\frac{\epsilon_{\text{MC}}(1 - \epsilon_{\text{MC}})}{N}} = \frac{0.21}{\sqrt{N}}$$

# Multi-dimensional Integration

- Formalism extends trivially to many dimensions
- Particle physics: very many dimensions,  
e.g. phase space = 3 dimensions per particles,  
LHC event  $\sim 250$  hadrons.
- Monte Carlo error remains  $\propto 1/\sqrt{N}$
- Trapezium rule  $\propto 1/N^{2/d}$
- Simpson's rule  $\propto 1/N^{4/d}$



# Monte Carlo: Summary

## Disadvantages of Monte Carlo:

- Slow convergence in few dimensions.

## Advantages of Monte Carlo:

- Fast convergence in many dimensions.
- Arbitrarily complex integration regions (finite discontinuities not a problem).
- Few points needed to get first estimate (“feasibility limit”).
- Every additional point improves accuracy (“growth rate”).
- Easy error estimate.
- Hit-and-miss allows unweighted **event generation**, i.e. points distributed in phase space just like real events.

# Phase Space Generation

$$\sigma = \frac{1}{2s} \int |\mathcal{M}|^2 d\Pi_n(\sqrt{s})$$
$$\Gamma = \frac{1}{2M} \int |\mathcal{M}|^2 d\Pi_n(M)$$

- Phase space:

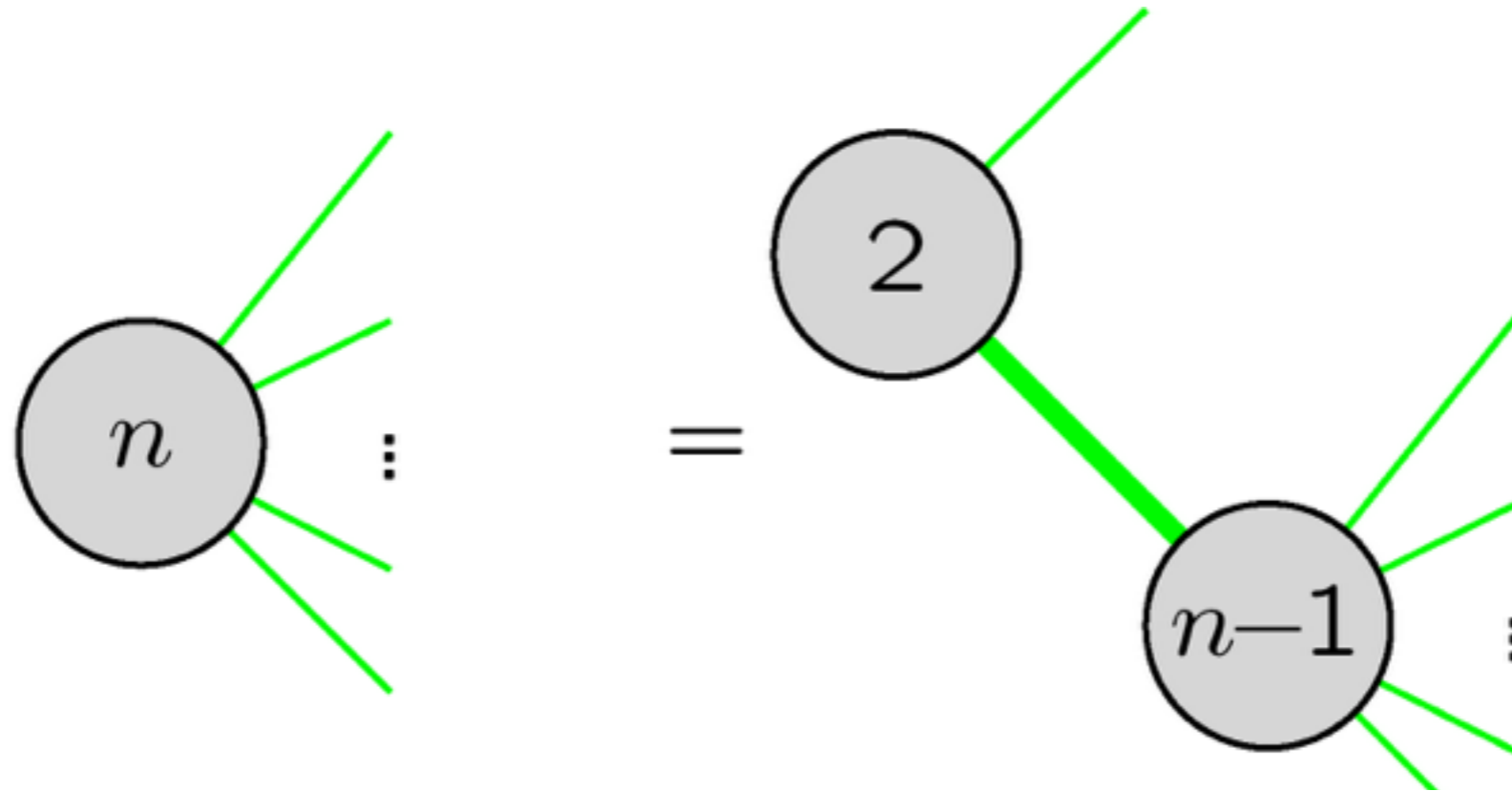
$$d\Pi_n(M) = \left[ \prod_{i=1}^n \frac{d^3 p_i}{(2\pi)^3 (2E_i)} \right] (2\pi)^4 \delta^{(4)} \left( p_0 - \sum_{i=1}^n p_i \right)$$

- Two-body easy:

$$d\Pi_2(M) = \frac{1}{8\pi} \frac{2p}{M} \frac{d\Omega}{4\pi}$$

# Phase Space Generation

- Other cases by recursive subdivision:

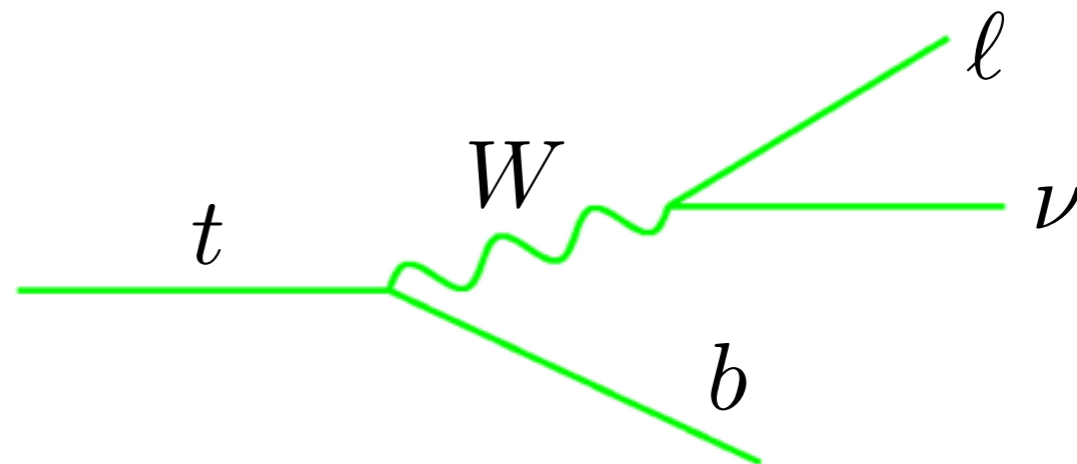


$$d\Pi_n(M) = \frac{1}{2\pi} \int_0^{(M-m)^2} dm_x^2 d\Pi_2(M) d\Pi_{n-1}(m_x)$$

- Or by 'democratic' algorithms: RAMBO, MAMBO  
Can be better, but matrix elements rarely flat.

# Particle Decays

- Simplest example  
e.g. top quark decay:



$$|\mathcal{M}|^2 = \frac{1}{2} \left( \frac{8\pi\alpha}{\sin^2 \theta_w} \right)^2 \frac{p_t \cdot p_\ell p_b \cdot p_\nu}{(m_W^2 - M_W^2)^2 + \Gamma_W^2 M_W^2}$$

$$\Gamma = \frac{1}{2M} \frac{1}{128\pi^3} \int |\mathcal{M}|^2 dm_W^2 \left( 1 - \frac{m_W^2}{M^2} \right) \frac{d\Omega}{4\pi} \frac{d\Omega_W}{4\pi}$$

Breit-Wigner peak of W very strong - but can be removed by importance sampling:

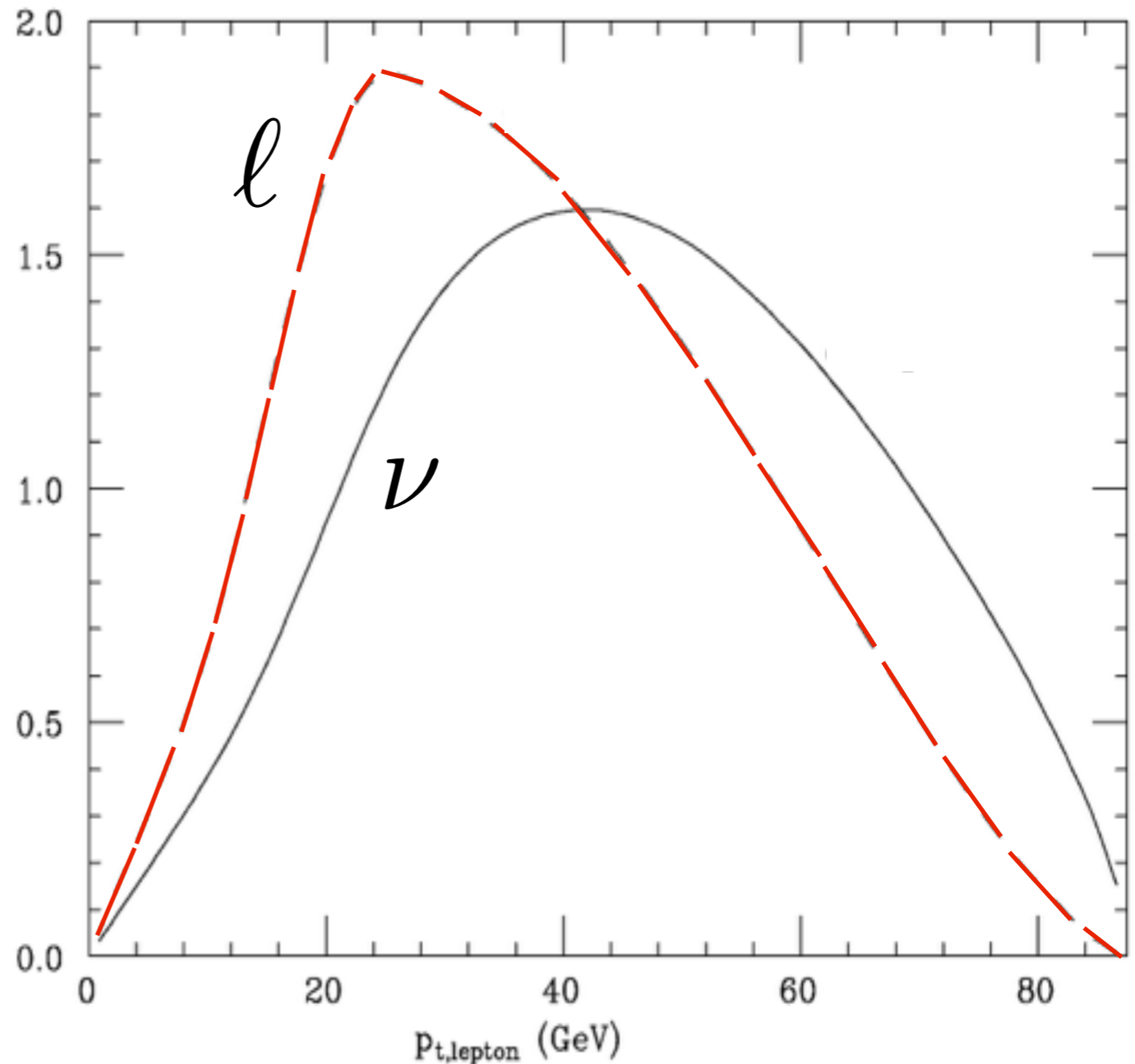
$$m_W^2 \rightarrow \arctan \left( \frac{m_W^2 - M_W^2}{\Gamma_W M_W} \right) \quad \text{(prove it!)}$$

# Associated Distributions

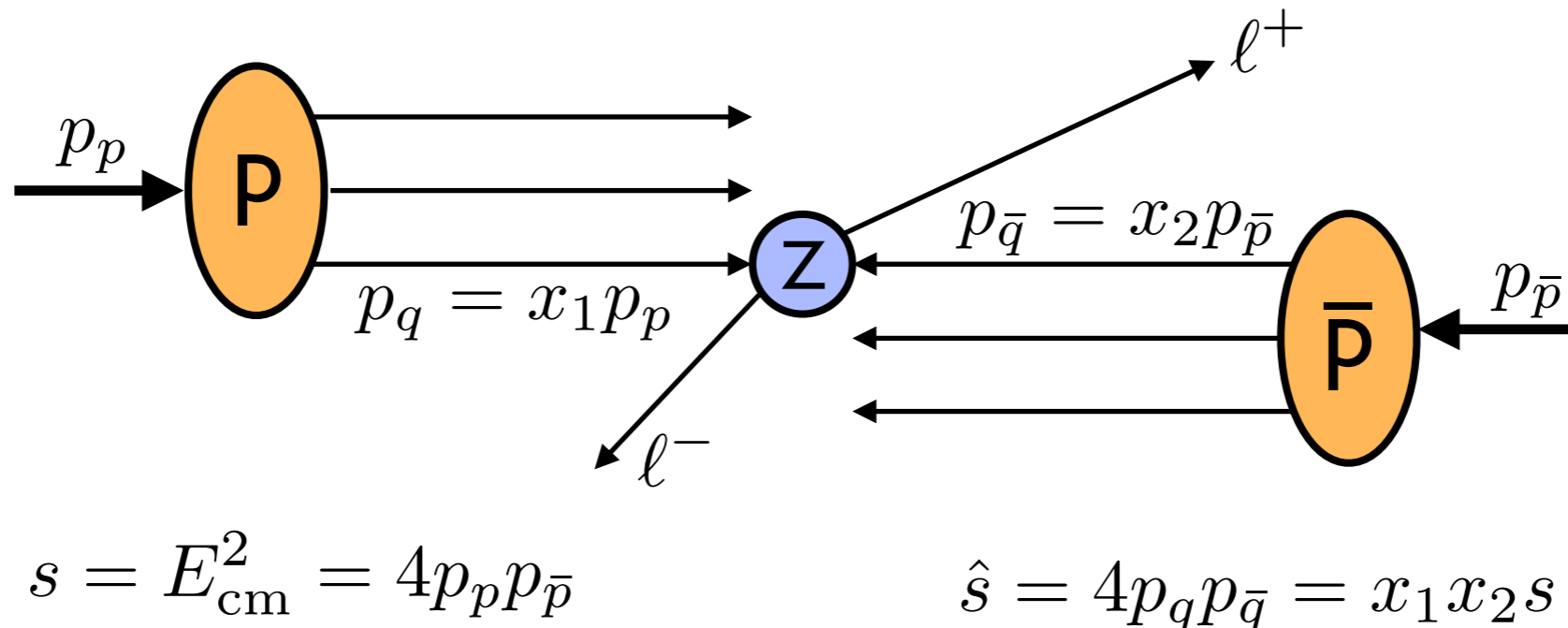
Big advantage of Monte Carlo integration:

- Simply histogram any associated quantities.
- Almost any other technique requires new integration for each observable.
- Can apply arbitrary cuts/smearing.

e.g. lepton momentum in top decays:

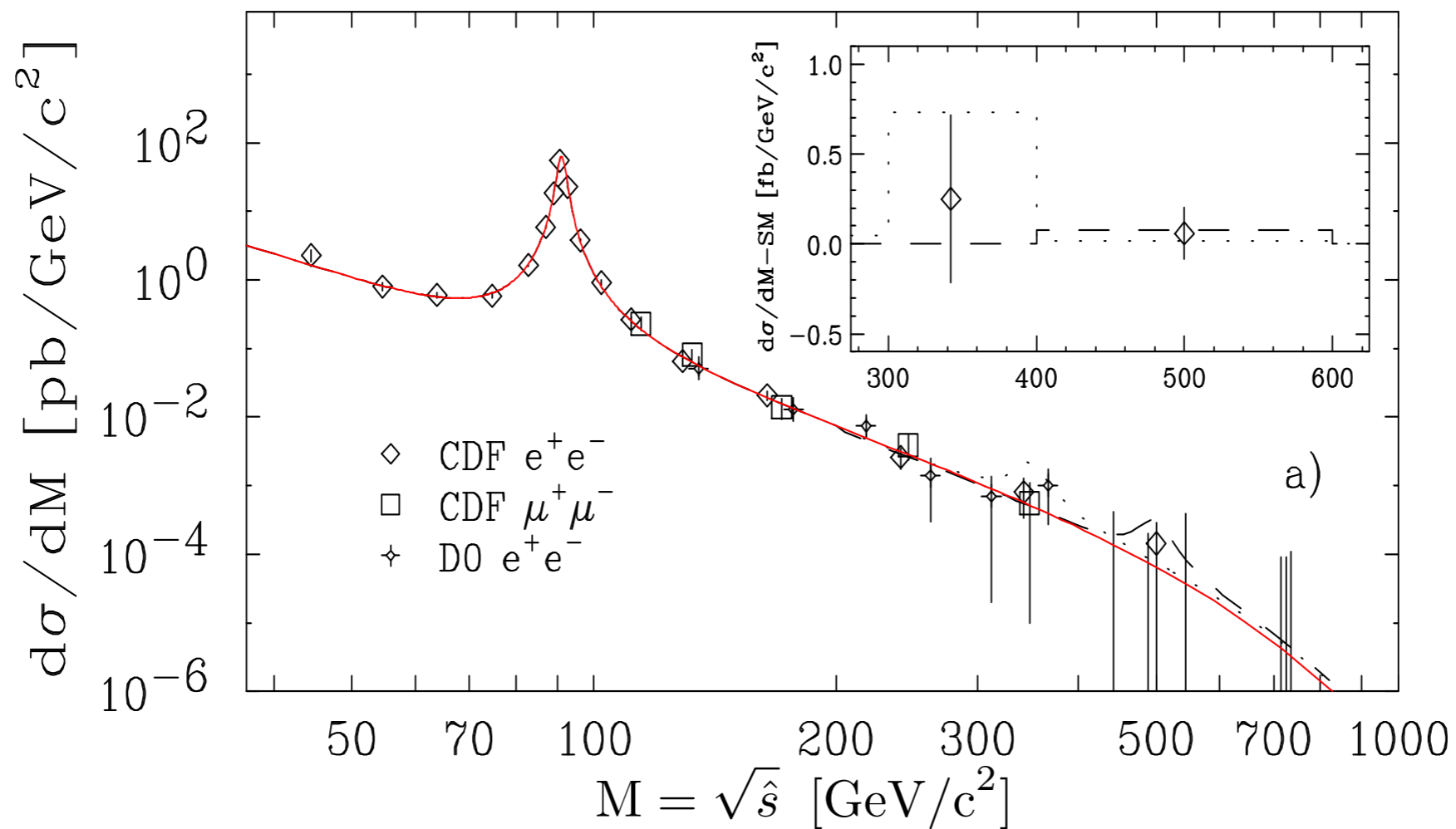


# Hadron-Hadron Cross Sections



- Consider e.g.  $p\bar{p} \rightarrow Z^0 \rightarrow \ell^+ \ell^-$
- Integrations over incoming parton momentum distributions:
 
$$\sigma(s) = \int_0^1 dx_1 f(x_1) \int_0^1 dx_2 f(x_2) \hat{\sigma}(x_1 x_2 s)$$
- Hard process cross section  $\hat{\sigma}(\hat{s})$  has strong peak, due to  $Z^0$  resonance: needs importance sampling (like  $W$  in top decay)

# $p\bar{p} \rightarrow \ell^+ \ell^-$ cross section



$$\hat{\sigma}_{q\bar{q} \rightarrow Z^0 \rightarrow \ell^+ \ell^-} = \frac{4\pi \hat{s}}{3M_Z^2} \frac{\Gamma_\ell \Gamma_q}{(\hat{s} - M_Z^2)^2 + \Gamma_Z^2 M_Z^2}$$

- “Background” is  $q\bar{q} \rightarrow \gamma^* \rightarrow \ell^+ \ell^-$

# Parton-Level Monte Carlo Calculations

Now we have everything we need to make parton-level cross section calculations and distributions

Can be largely automated...

- MADGRAPH
- GRACE
- COMPHEP
- AMEGIC++
- ALPGEN

But...

- Fixed parton/jet multiplicity
- No control of large higher-order corrections
- Parton level

→ **Need hadron level event generators**



# Summary of Lecture I

- Monte Carlo is a very convenient numerical integration method.
- Well-suited to particle physics: difficult integrands, many dimensions.
- Integrand non-negative  $\rightarrow$  hit-and-miss event generation.
- Hard process: use parton-level generator.
- Next: parton showers and hadron-level event generation