

Statistical Data Analysis 1

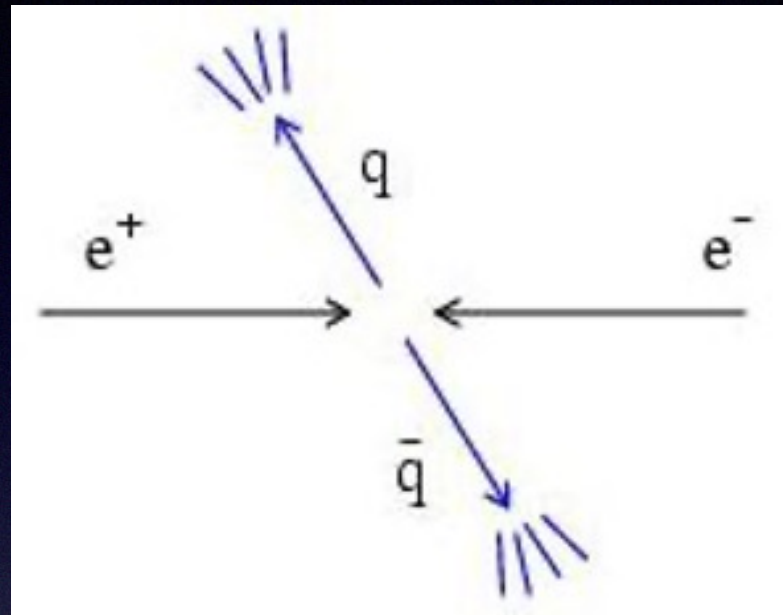
Tae Jeong Kim
(Hanyang University)

For 32nd Vietnam School of Physics:
Particle Physics and Dark Matter
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Disclaimer

- Materials for this slide are mainly from the book of “Statistical Data Analysis” by Glen Cowan

Data Analysis in Particle Physics



Observe events of a certain type

- Estimate parameters
- Quantify the uncertainty of the parameter estimates (most important)
 - we will have completely different conclusion depending on the uncertainty
- Test hypothesis (Dark matter, SuperSymmetry, Any new physics...)

Dealing with uncertainty

- Statistical uncertainty
 - Random measurement errors
 - We can not repeat the experiment infinitely
- Systematic uncertainty
 - Theory is not deterministic (Quantum Mechanics)
 - We don't have a perfect experiment (limited cost)

We can quantify the uncertainty using probability

What is probability?

- Relative frequency

$$P(A) = \lim_{n \rightarrow \infty} \frac{\text{times outcome is } A}{n}$$

- Subjective probability

$$P(A) = \text{degree of belief that } A \text{ is true}$$

- Mostly the frequency interpretation is useful
- Subjective probability can provide more natural treatment of non-repeatable phenomena
 - Probability that Big Bang happened
 - Probability that Dark Matter candidate exists₅

Bayes' theorem

- From the definition of conditional probability, we have

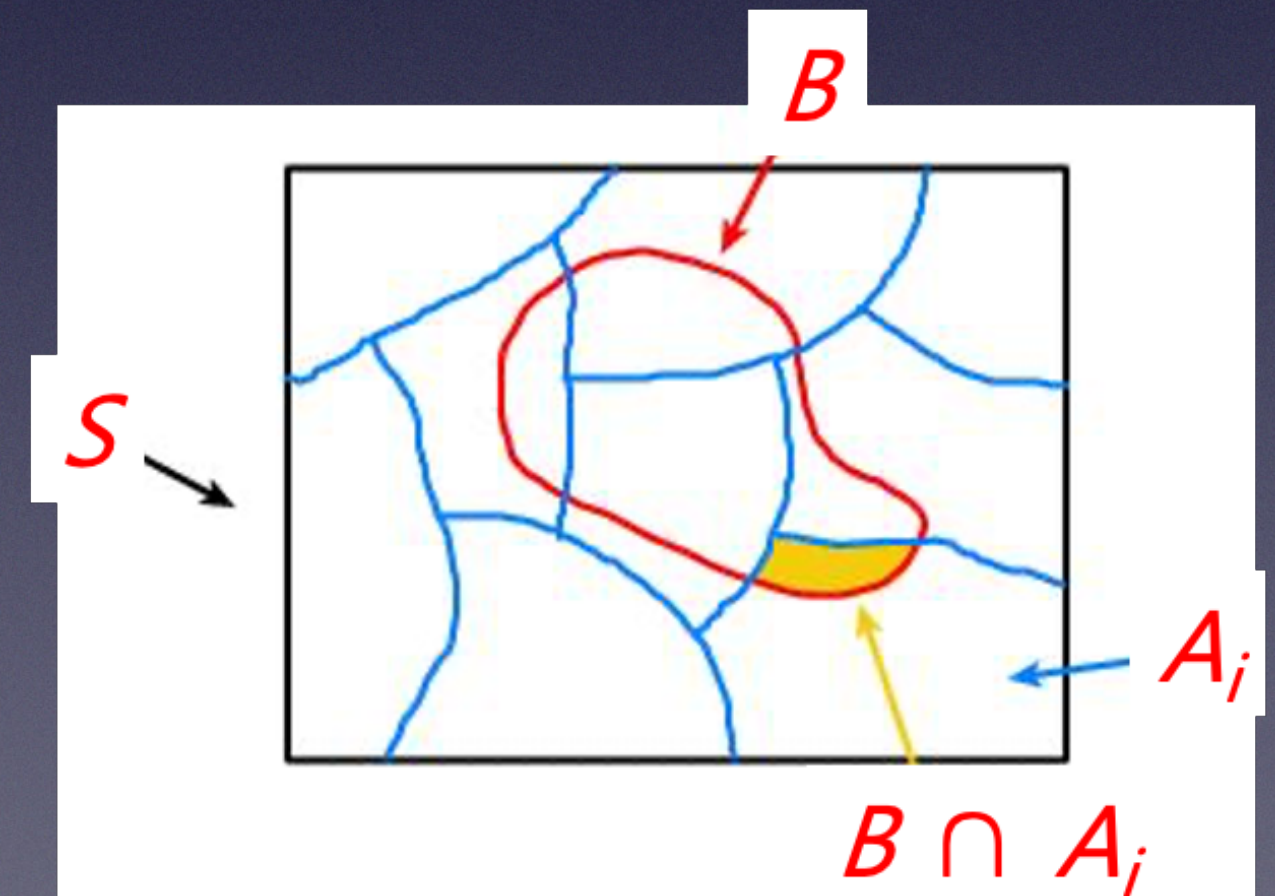
$$P(A | B) = \frac{P(A \cap B)}{P(B)} \text{ and } P(B | A) = \frac{P(B \cap A)}{P(A)}$$

- But $P(A \cap B) = P(B \cap A)$, so

$$P(A | B) = \frac{P(B | A)P(A)}{P(B)}$$

Using the law of total probability $\rightarrow$

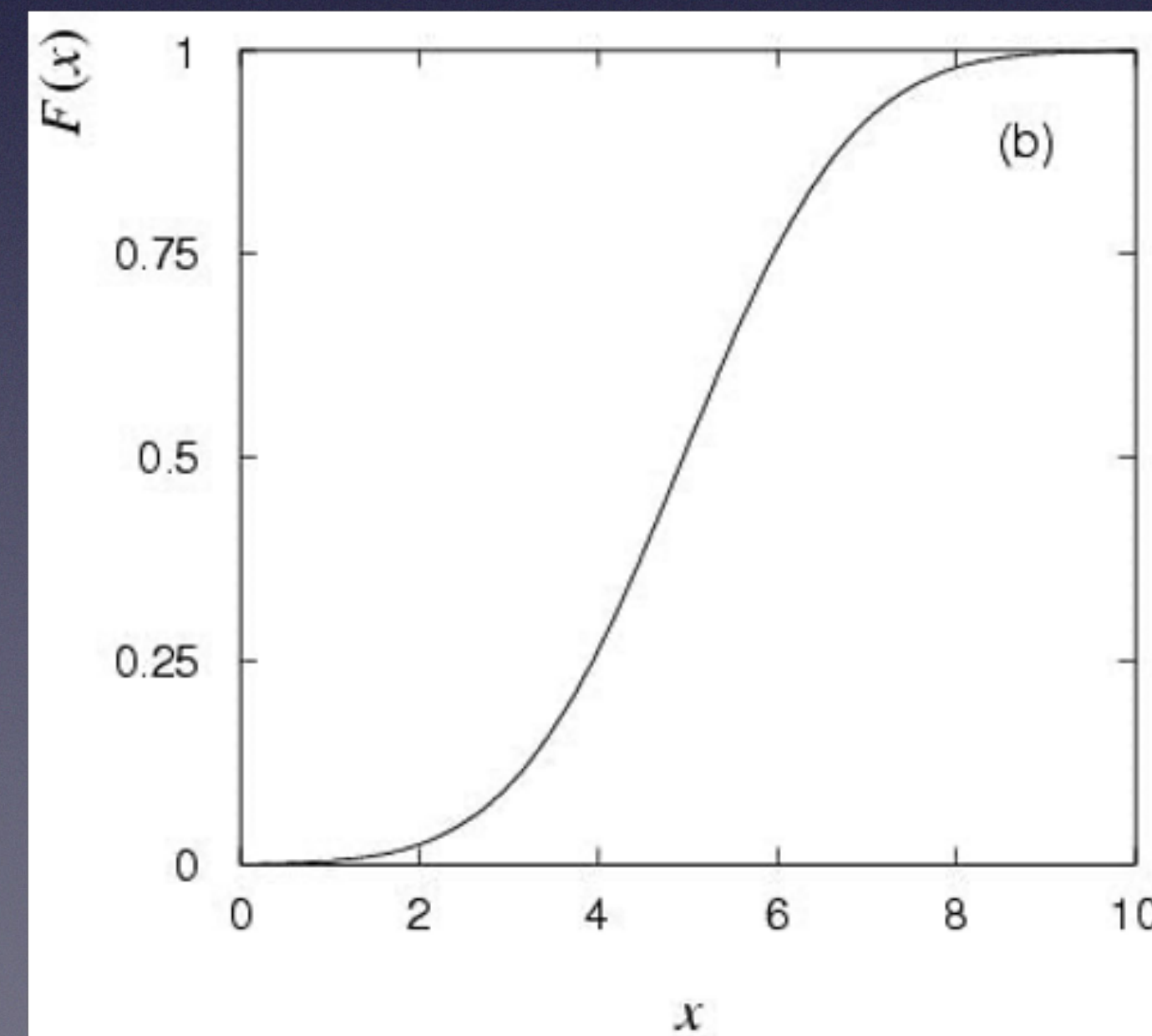
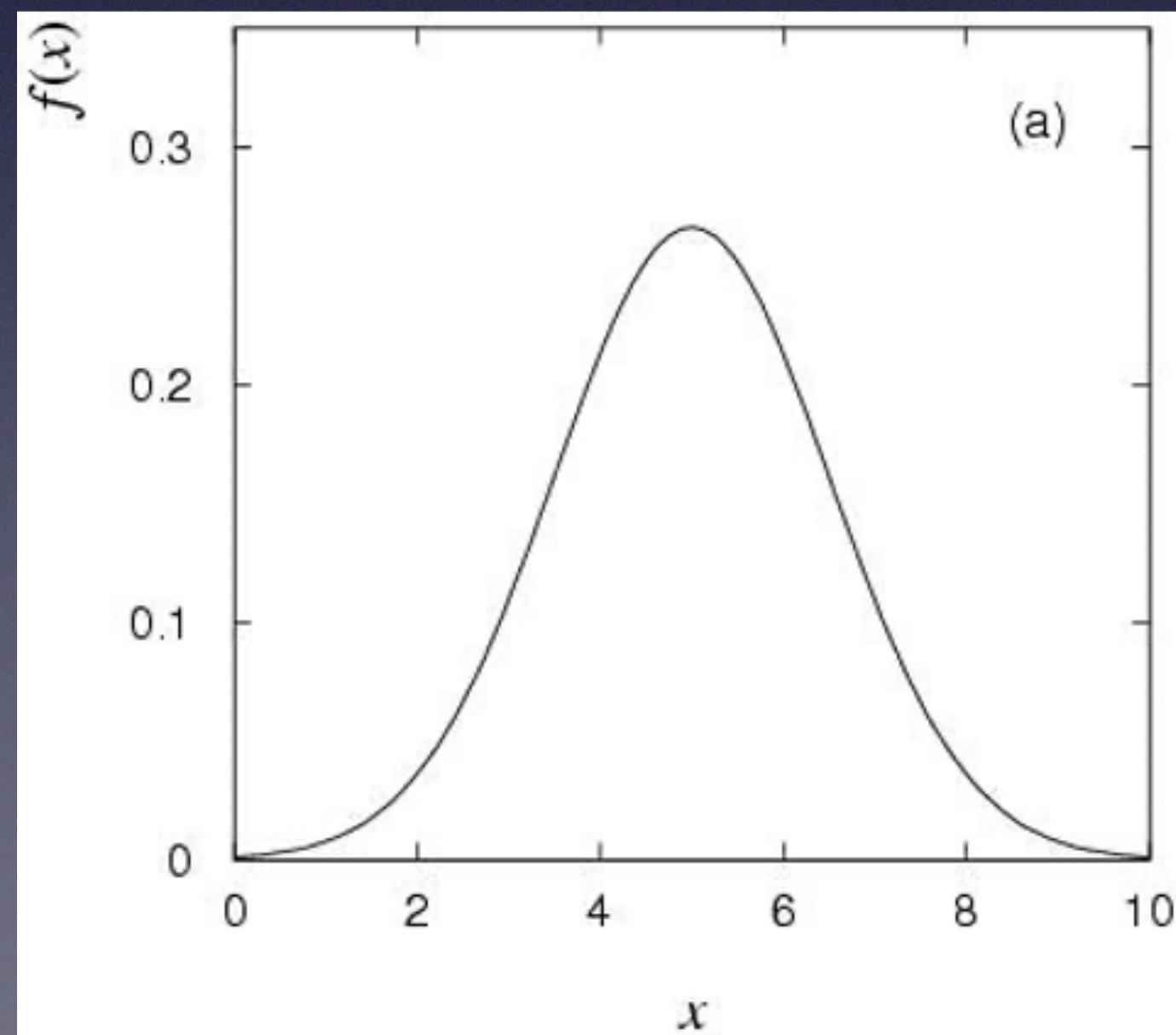
$$P(A | B) = \frac{P(B | A)P(A)}{\sum_i P(B | A_i)P(A_i)}$$



Cumulative distribution function

- Probability to have outcome less than or equal to x is

$$\int_{-\infty}^x f(x') dx' \equiv F(x)$$



Bayesian Statistics

- In Bayesian statistics, use subjective probability for hypotheses:

Probability of the data assuming hypothesis H (likelihood)

Prior probability before seeing the data

$$P(H | obs) = \frac{P(obs | H)P(H)}{\int P(obs | H)P(H)dH}$$

Posterior probability after seeing the data

Sum over all possible hypotheses

- No unique prescription for priors (subjective) $\rightarrow$ probability given data will change depending on the priors

Example of Bayes' theorem

- Suppose the probability to have a disease D is

$$\begin{array}{lcl} P(D) & = & 0.001 \\ P(\text{no } D) & = & 0.999 \end{array}$$

(Prior probabilities)

- Consider a test for disease: result + or -

$$\begin{array}{lcl} P(+|D) & = & 0.98 \\ P(-|D) & = & 0.02 \end{array}$$

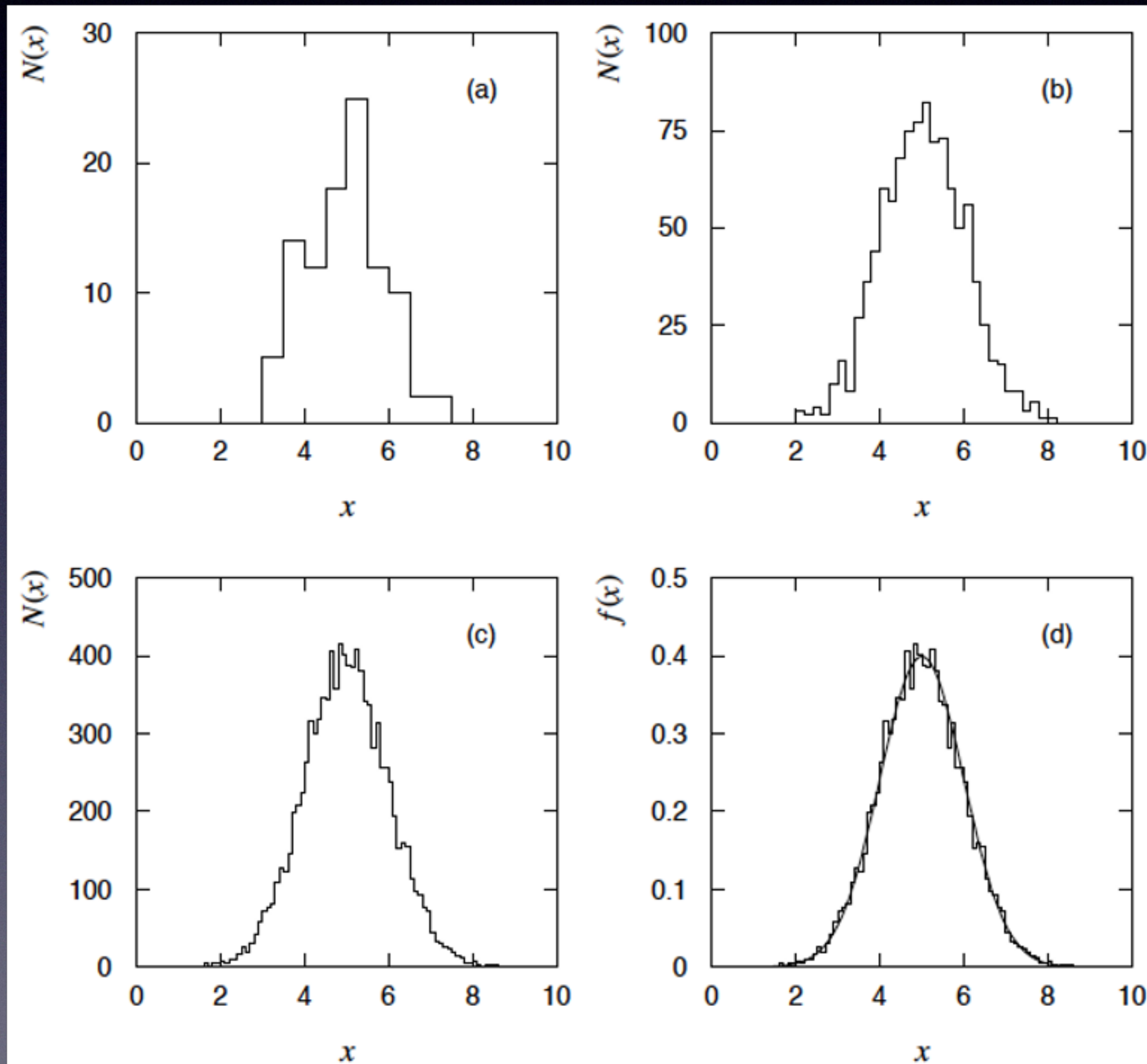
$$\begin{array}{lcl} P(+|\text{no } D) & = & 0.03 \\ P(-|\text{no } D) & = & 0.97 \end{array}$$

- Suppose your result is +. How worried should you be?

$$\begin{aligned} p(D|+) &= \frac{P(+|D)P(D)}{P(+|D)P(D) + P(+|\text{no } D)P(\text{no } D)} \\ &= \frac{0.98 \times 0.001}{0.98 \times 0.001 + 0.03 \times 0.999} \\ &= 0.032 \end{aligned}$$

- You are probably OK!
 - My degree of belief that I have the disease is 3.2%
 - Doctor's viewpoint: 3.2% of people like this have the disease

Histograms and PDF



- From Histogram

$$f(x) = \frac{N(x)}{n\Delta x}, \Delta x \rightarrow 0$$

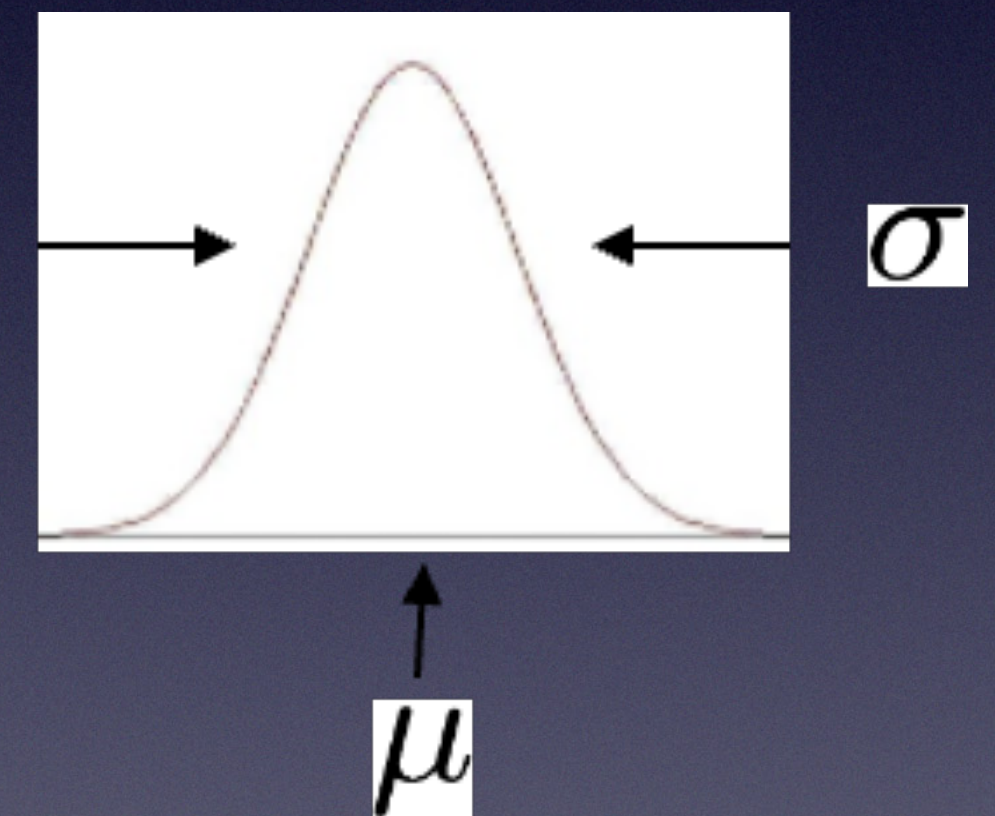
- To PDF (Probability Distribution Function)

Expectation values

- Consider a continuous random variable x with PDF $f(x)$
- Define expectation values as

$$E[x] = \int x f(x) dx = \mu$$

- Variance $V[x] = E[x^2] - \mu^2 = E[(x - \mu)^2] = \sigma^2$
- Standard deviation $\sigma \sim$ width of PDF



Covariance and correlation

- Covariance with x and y

$$\text{COV}[x, y] = E(xy) - \mu_x \mu_y = E[(x - \mu_x)(y - \mu_y)]$$

- Correlation coefficient defined as

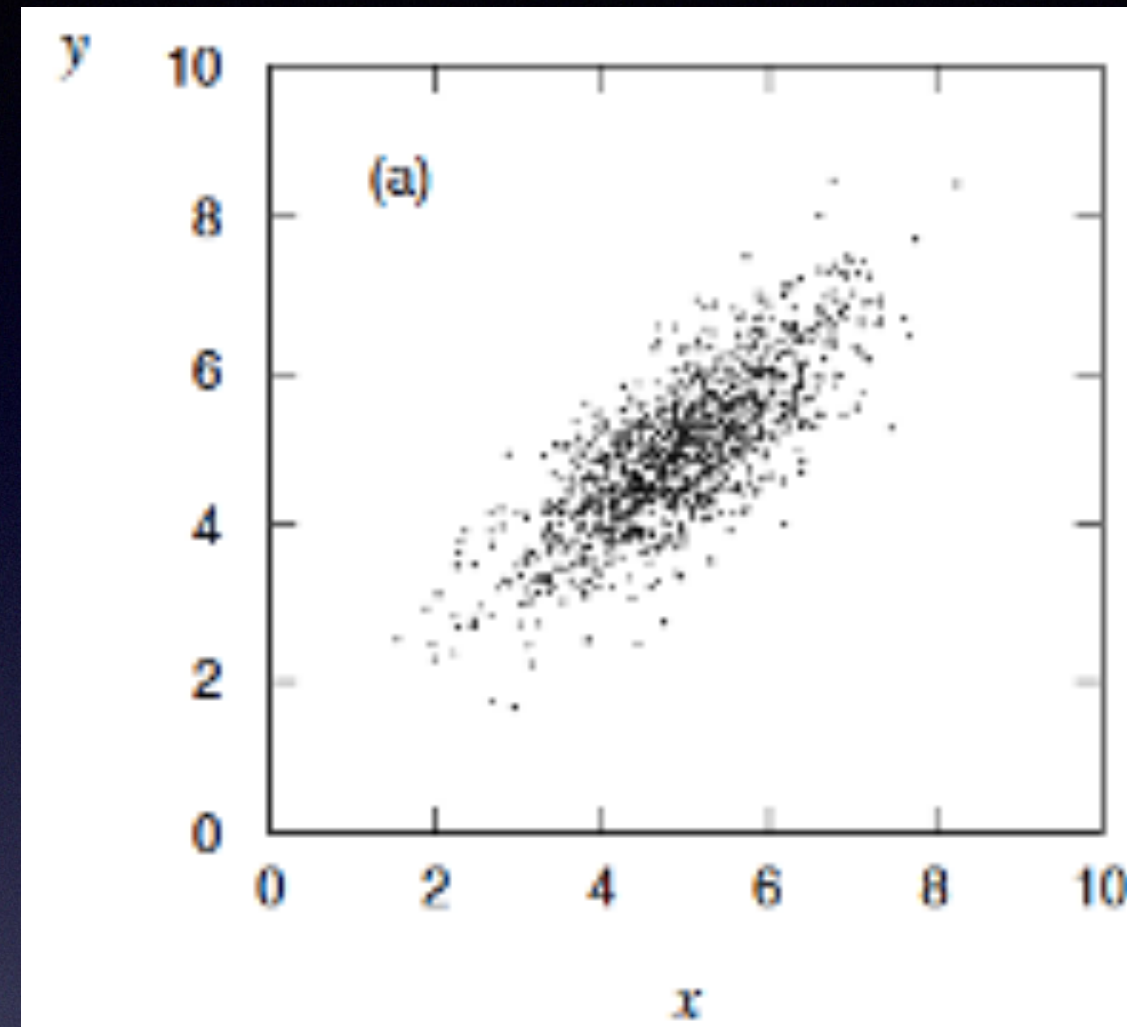
$$\rho_{xy} = \frac{\text{COV}[x, y]}{\sigma_x \sigma_y}$$

- If x and y are independent

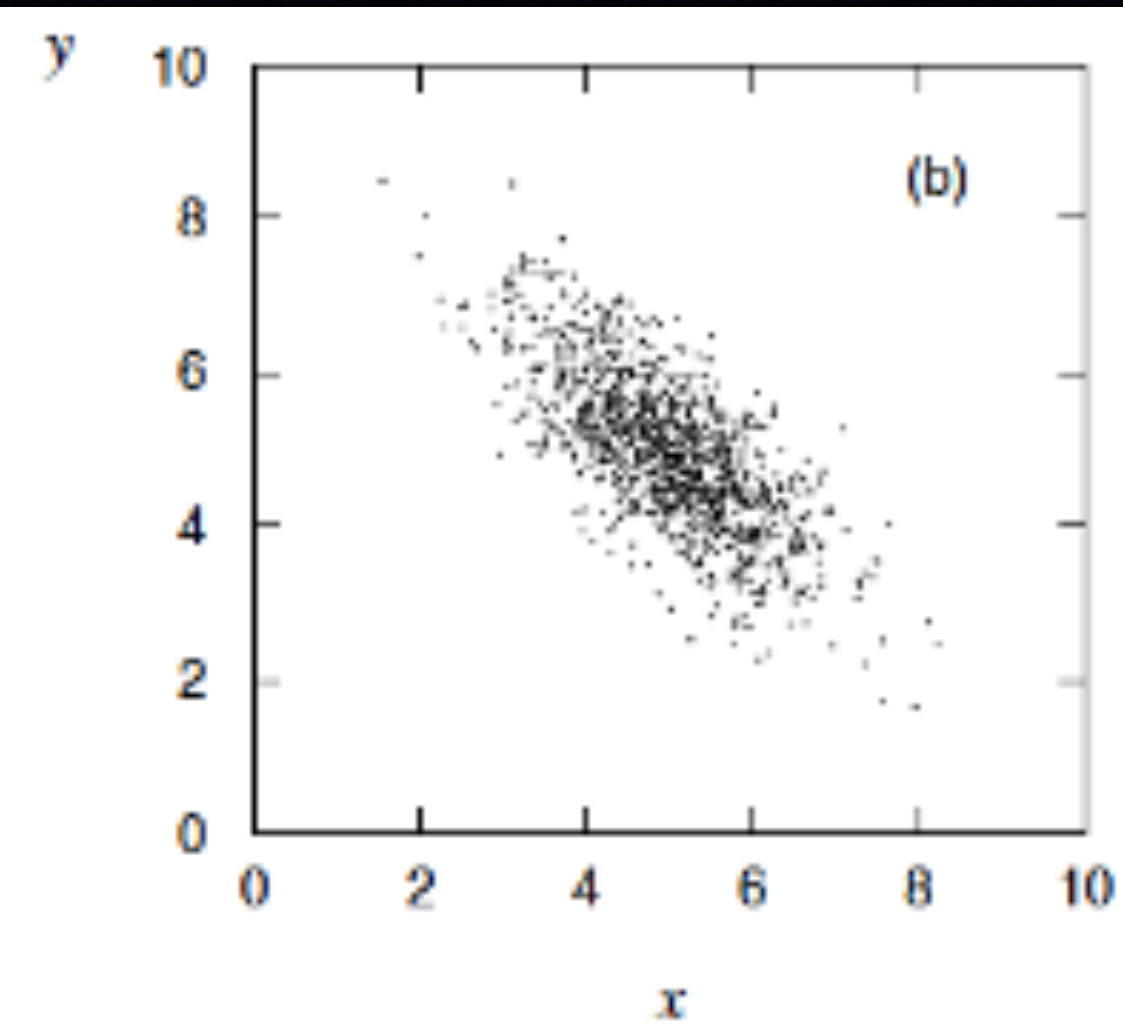
$$\text{COV}[x, y] = 0$$

Correlation

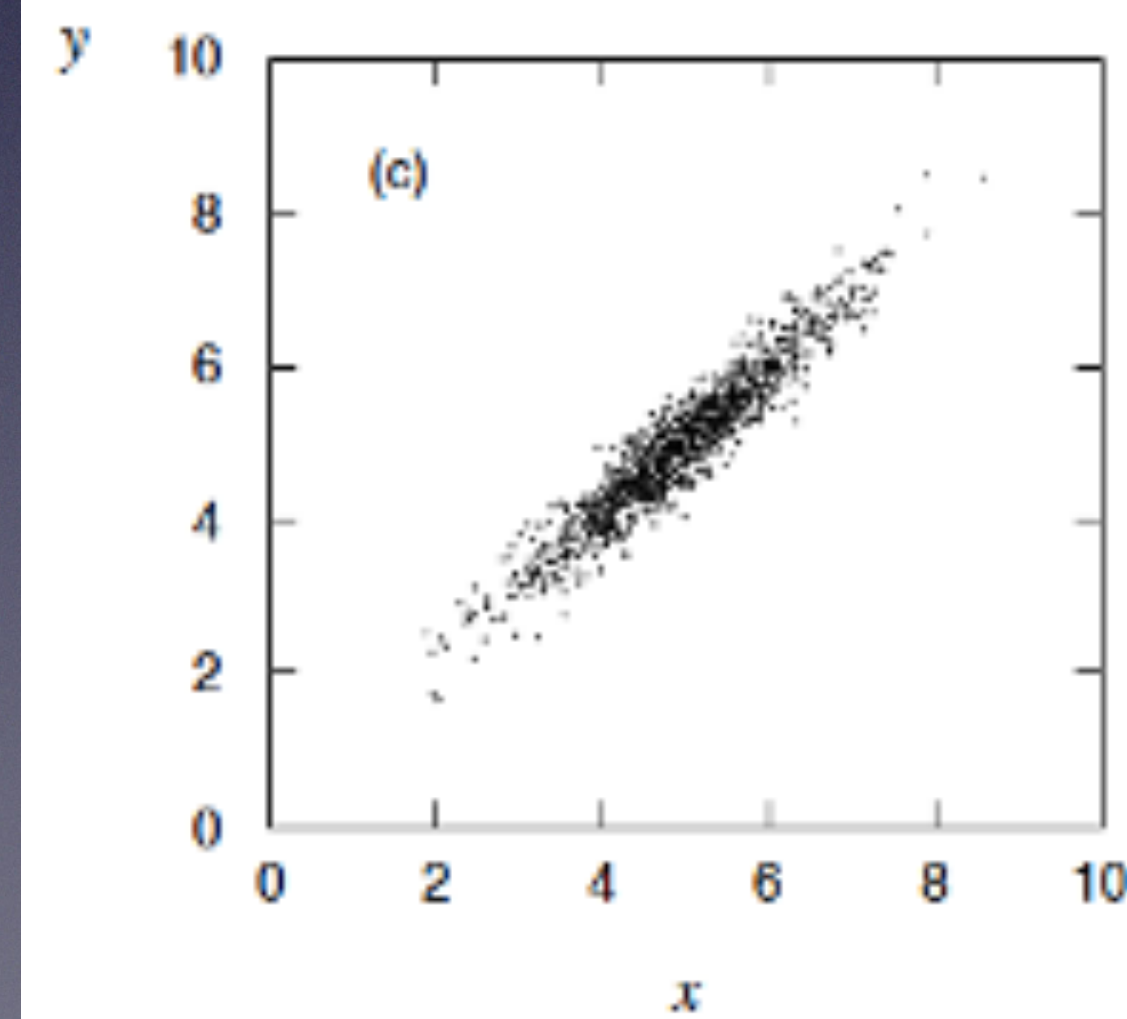
$$\rho = 0.75$$



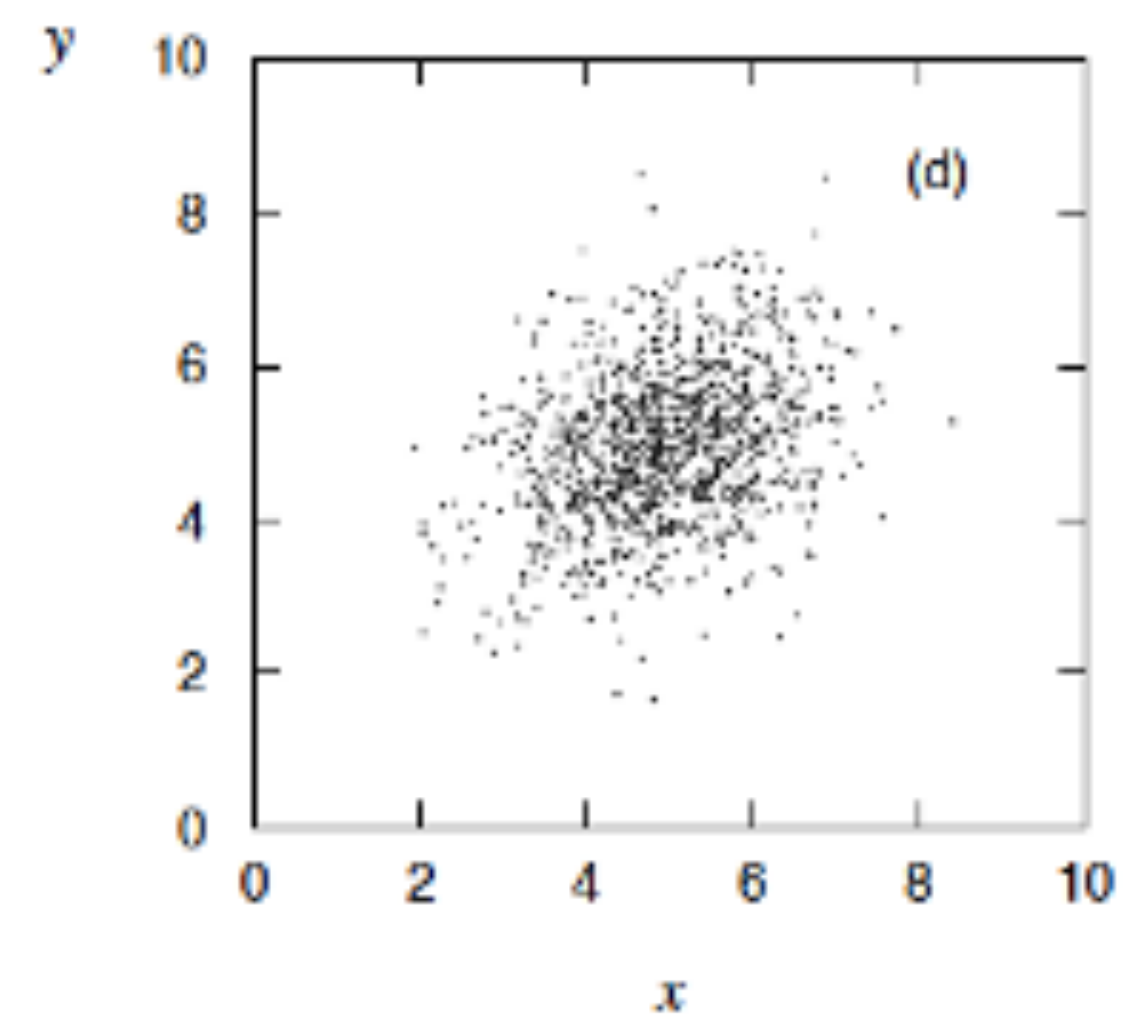
$$\rho = -0.75$$



$$\rho = 0.95$$



$$\rho = 0.25$$



Combination of measurements

- Consider two measurements $a = m_1 \pm \sigma_1$
 $b = m_2 \pm \sigma_2$

- Minimize χ^2 to determine the best m $\chi^2 = \frac{(m - m_1)^2}{\sigma_1^2} + \frac{(m - m_2)^2}{\sigma_2^2}$

$$\frac{\partial \chi^2}{\partial m} = 0$$

Weight average

$$m = \hat{m} = \frac{\frac{m_1}{\sigma_1^2} + \frac{m_2}{\sigma_2^2}}{\frac{1}{\sigma_1^2} + \frac{1}{\sigma_2^2}} = \frac{\omega_1 m_1 + \omega_2 m_2}{\omega_1 + \omega_2}$$

The uncertainty on $\hat{m}$ is

$$\hat{m} = \frac{1}{\frac{1}{\sigma_1^2} + \frac{1}{\sigma_2^2}}$$

Combination with correlation

$$\chi^2 = (m - m_1 \quad m - m_2) \begin{pmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{pmatrix} \begin{pmatrix} m - m_1 \\ m - m_2 \end{pmatrix}$$

Solution of the minimization of χ^2

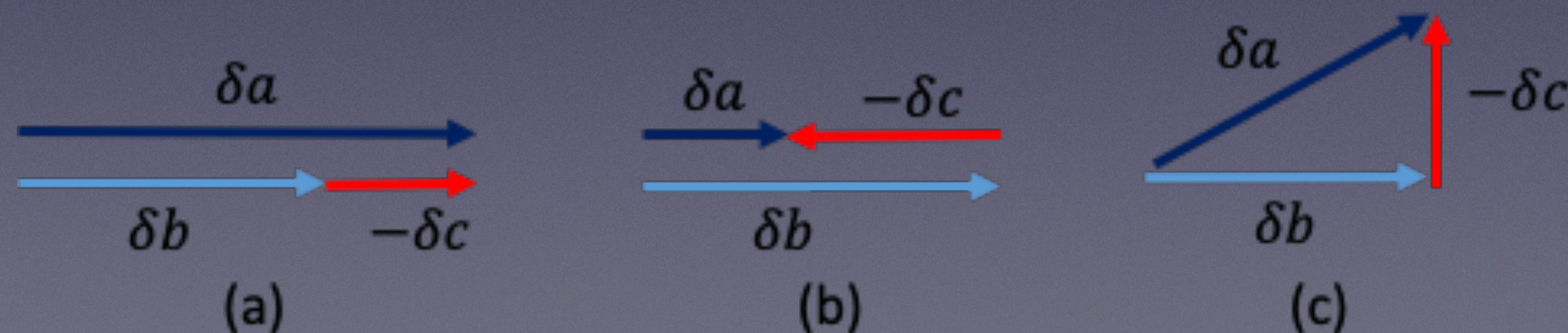
$$\hat{m} = \frac{m_1(\sigma_2^2 - \rho\sigma_1\sigma_2) + m_2(\sigma_1^2 - \rho\sigma_1\sigma_2)}{\sigma_1^2 - 2\rho\sigma_1\sigma_2 + \sigma_2^2}$$

The uncertainty becomes $\sigma_m^2 = \frac{\sigma_1^2\sigma_2^2(1 - \rho)^2}{\sigma_1^2 - 2\rho\sigma_1\sigma_2 + \sigma_2^2}$

Error propagation - linear

- example: $a = b - c$
- What is the uncertainty on a ?
- $\sigma_a^2 = \sigma_b^2 + \sigma_c^2 - 2\text{COV}[b, c] \rightarrow$

If the variables are uncorrelated:
add errors quadratically for the sum



Error propagation - nonlinear

- example: $a = b/c$
- What is the uncertainty on a ?

- $$\frac{\sigma_a^2}{a^2} = \frac{\sigma_b^2}{b^2} + \frac{\sigma_c^2}{c^2} - 2 \frac{\text{COV}[b, c]}{bc} \rightarrow$$

If the variables are uncorrelated:
add relative errors quadratically
for the ratio

Distributions

Distribution/PDF	Example use in HEP
Binomial	Branching ratio
Multinomial	Histogram with fixed N
Poisson	Number of events found
Uniform	Monte Carlo method
Exponential	Decay time
Gaussian	Measurement error
Chi-square	Goodness-of-fit
Briet-Wigner	Mass of resonance
Landau	Ionization energy loss

Binomial distribution

- Consider N independent experiment (like tossing a coin)
 - When the outcome is “success” or “failure”
 - Probability of success is p
- Probability of having n times success: $p^n(1 - p)^{N-n}$ (order is not important)

there are $\frac{N!}{n!(N - n)!}$ permutations to n success in

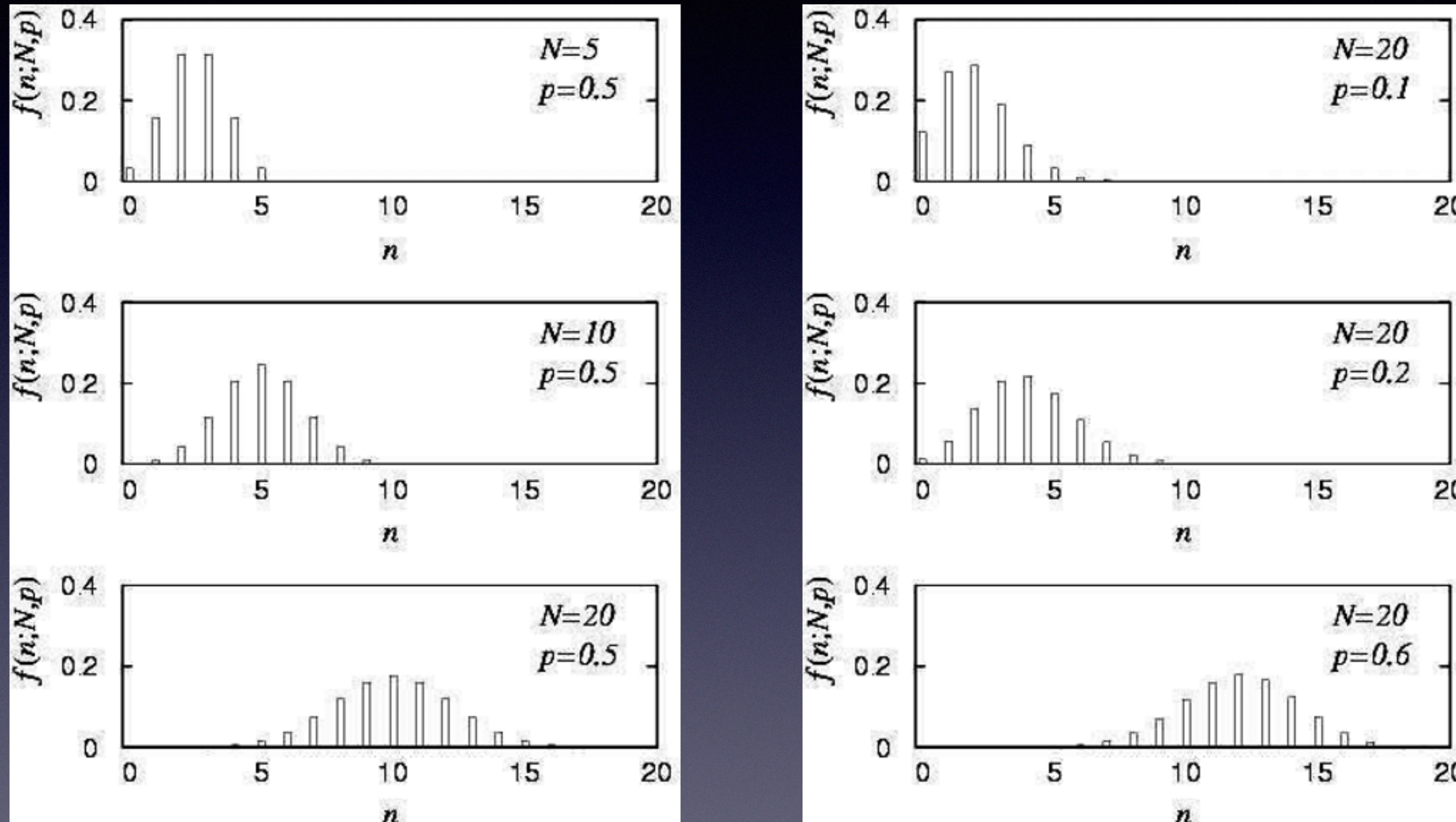
Binomial distribution

- The binomial distribution is

$$f(n; N, p) = \frac{N!}{n!(N-n)!} p^n (1-p)^{N-n}$$

- For the expectation value and variance
 - $E[n] = Np$
 - $V[n] = E(n^2) - (E[n])^2 = Np(1-p)$

Binomial distribution



- Example: observe N decays of W boson, what is the number of $W \rightarrow \mu\nu$? this follows the binomial where p is branching ratio

Multinomial distribution

- Like binomial but now m outcomes instead of two, probabilities are

$$\vec{p} = (p_1, \dots, p_m) \quad \sum_{i=1}^m p_i = 1$$

- For N trials, we want the probability to obtain: n_1 of outcome 1
 n_2 of outcome 2
 $\vdots$
 n_m of outcome m

- This is the multinomial distribution for $\vec{n} = (n_1, \dots, n_m)$

$$f(\vec{n}; N, \vec{p}) = \frac{N!}{n_1! n_2! \dots n_m!} p_1^{n_1} p_2^{n_2} \dots p_m^{n_m}$$

Multinomial distribution

- For all n_i individually binomial with parameters N, p_i

$$E[n_i] = Np_i, \quad V[n_i] = Np_i(1 - p_i)$$

$$\text{Covariance } V_{ij} = Np_i(\delta_{ij} - p_j), \quad V_{ij} = -Np_i p_j \text{ for } i \neq j$$

→ negatively correlated

- Example: $\vec{n} = (n_1, \dots, n_m)$ represents a histogram with m bins, N total entries, all entries independent

→ One bin goes up, the other bin goes down

Poisson distribution

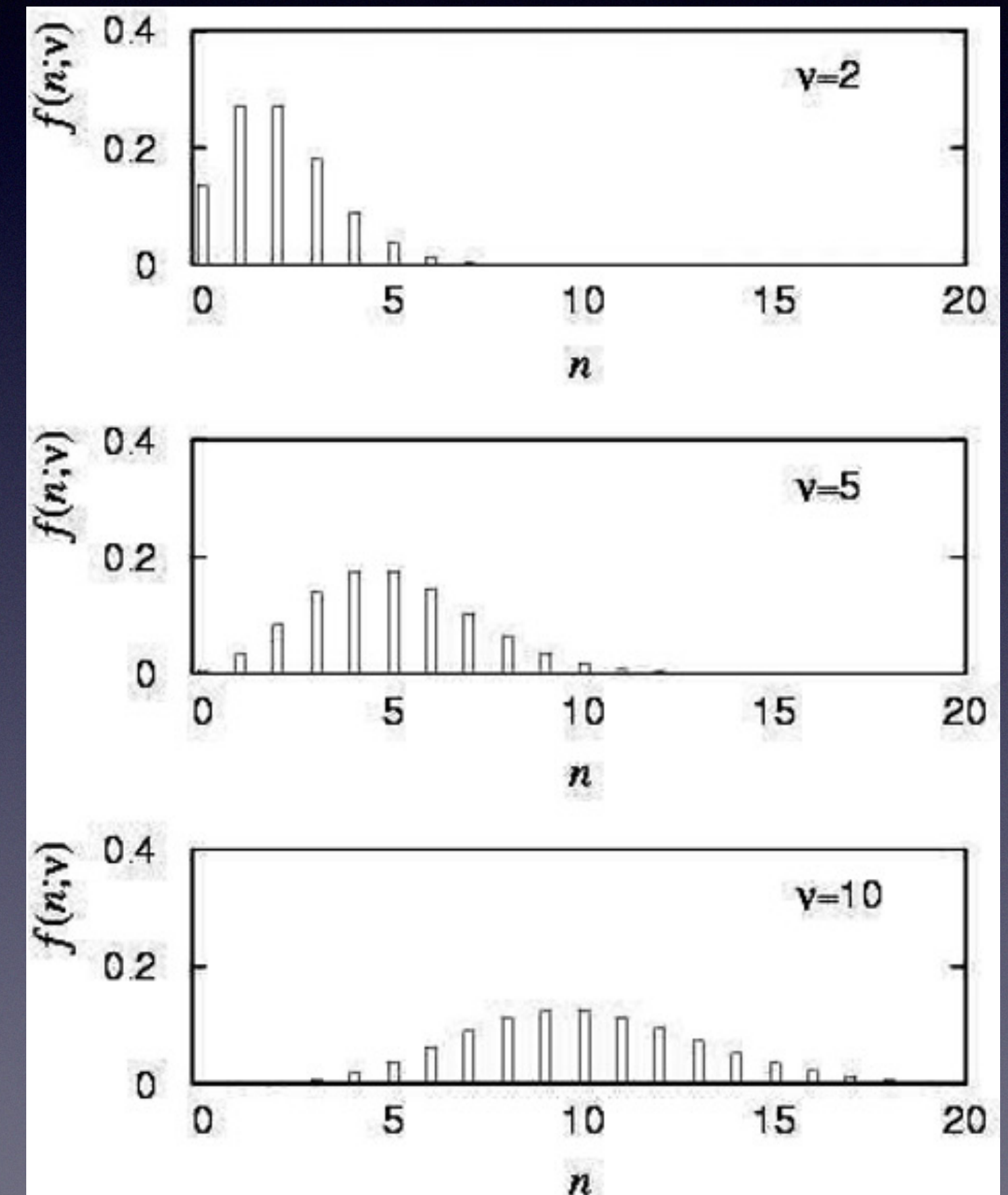
- probability is small ($p \rightarrow 0$) and the number of experiments is large ($N \rightarrow \infty$), n follows the Poisson distribution:

$$f(n; \nu) = \frac{\nu^n}{n!} e^{-\nu} \quad (n \geq 0)$$

$$E[n] = \nu, \quad V[n] = \nu$$

- Example: number of expected events with the cross section σ with integrated luminosity $\mathcal{L}$

$$\nu = \sigma \int \mathcal{L} dt$$



Uniform distribution

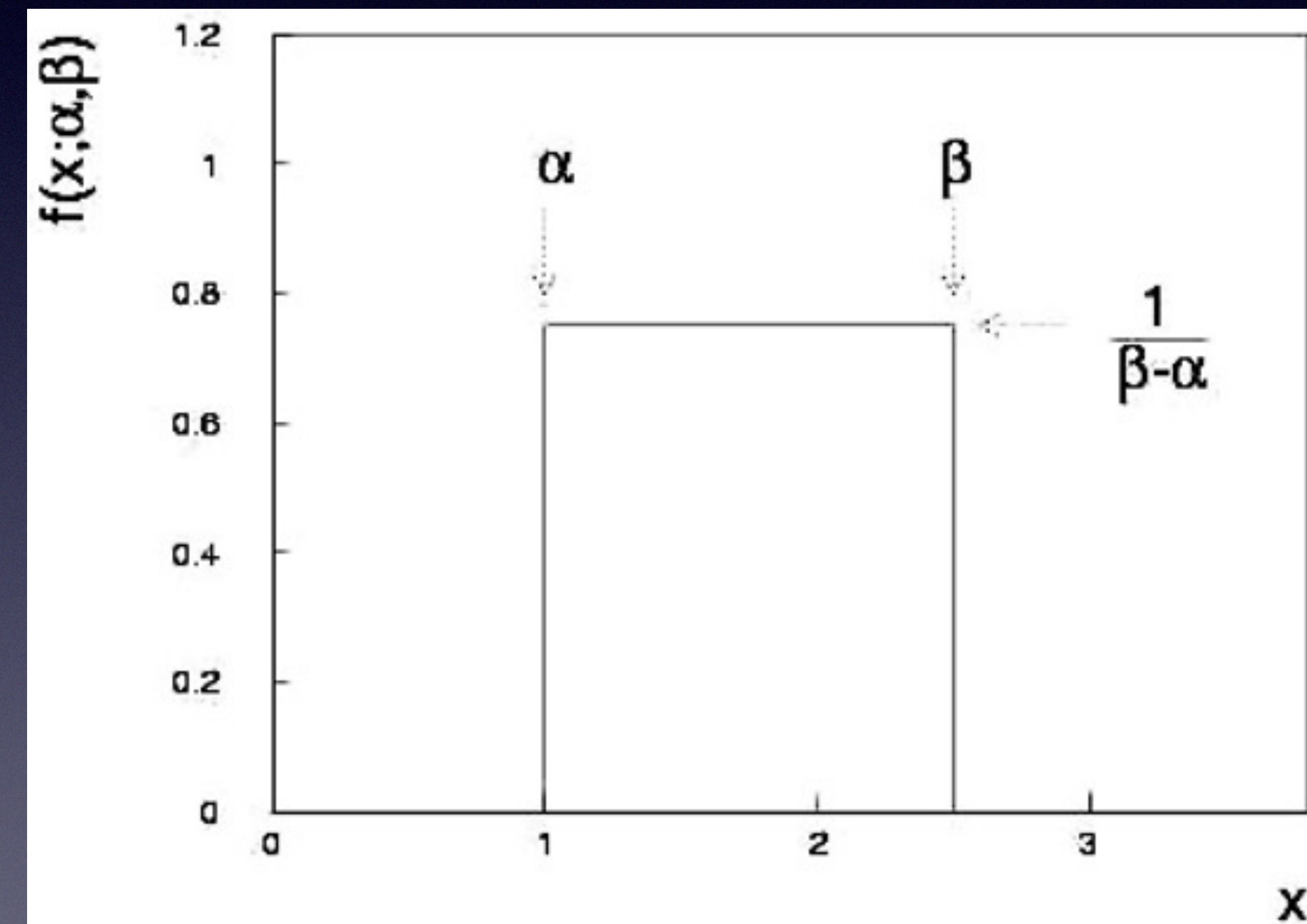
- Consider a continuous random variable x with $-\infty < x < \infty$

$$f(x; \alpha, \beta) = \frac{1}{\beta - \alpha} (\alpha < x < \beta)$$

$$E[x] = \frac{1}{2}(\alpha + \beta), \quad V[x] = \frac{1}{12}(\beta - \alpha)^2$$

- Example: measure the spatial resolution of the detector using a scintillator as a trigger with cosmic muons

$$\sigma_t = \sqrt{\sigma_d^2 + \frac{w}{\sqrt{12}}} \quad (w \text{ is the width of the scintillator})$$



Exponential distribution

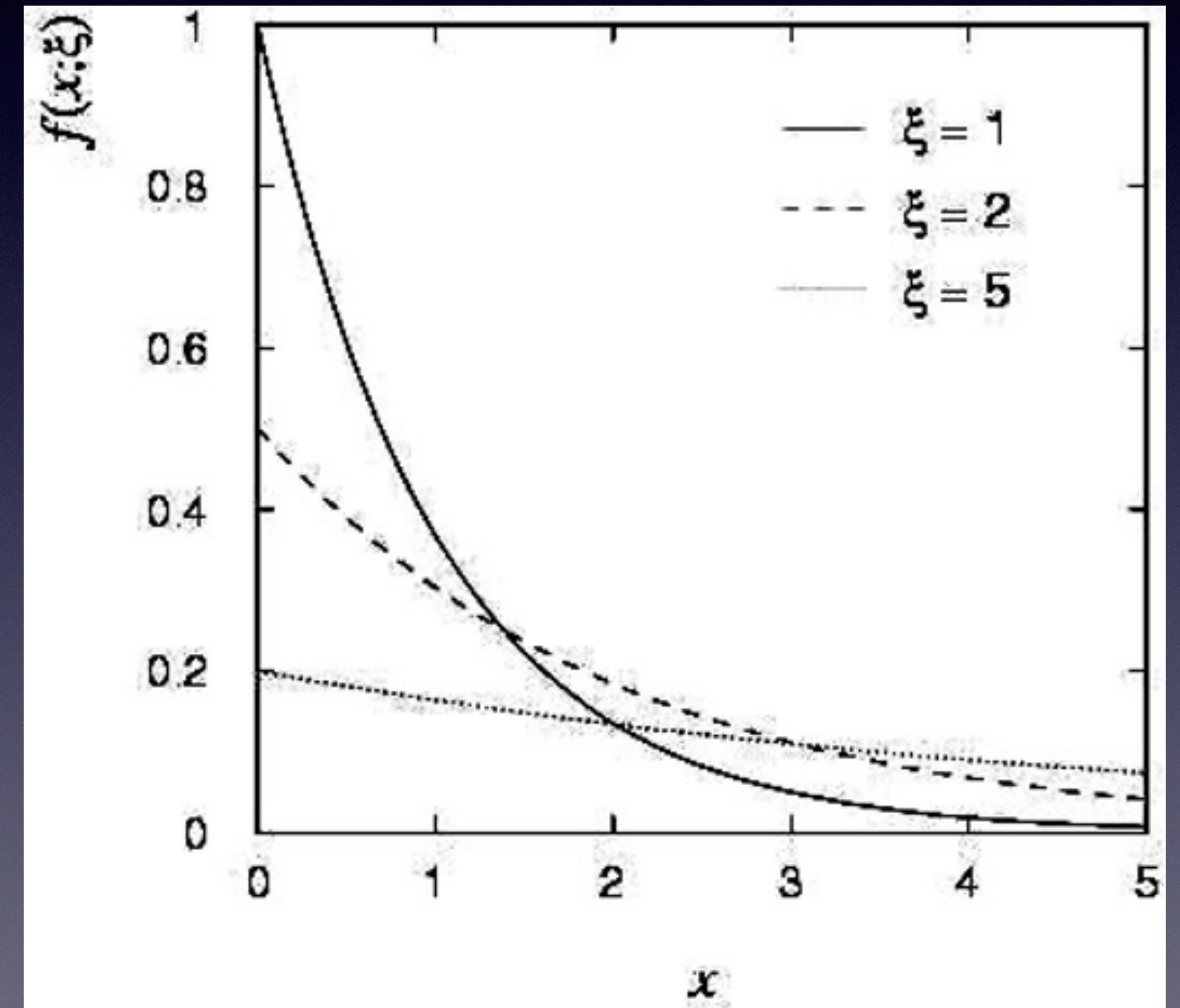
- Exponential PDF

$$f(x; \xi) = \frac{1}{\xi} e^{-x/\xi} \quad (x \geq 0)$$

$$E[x] = \xi, \quad V[x] = \xi^2$$

- Example: decay time t of an unstable particle

$$f(t; \tau) = \frac{1}{\tau} e^{-t/\tau} \quad (\tau = \text{mean lifetime})$$



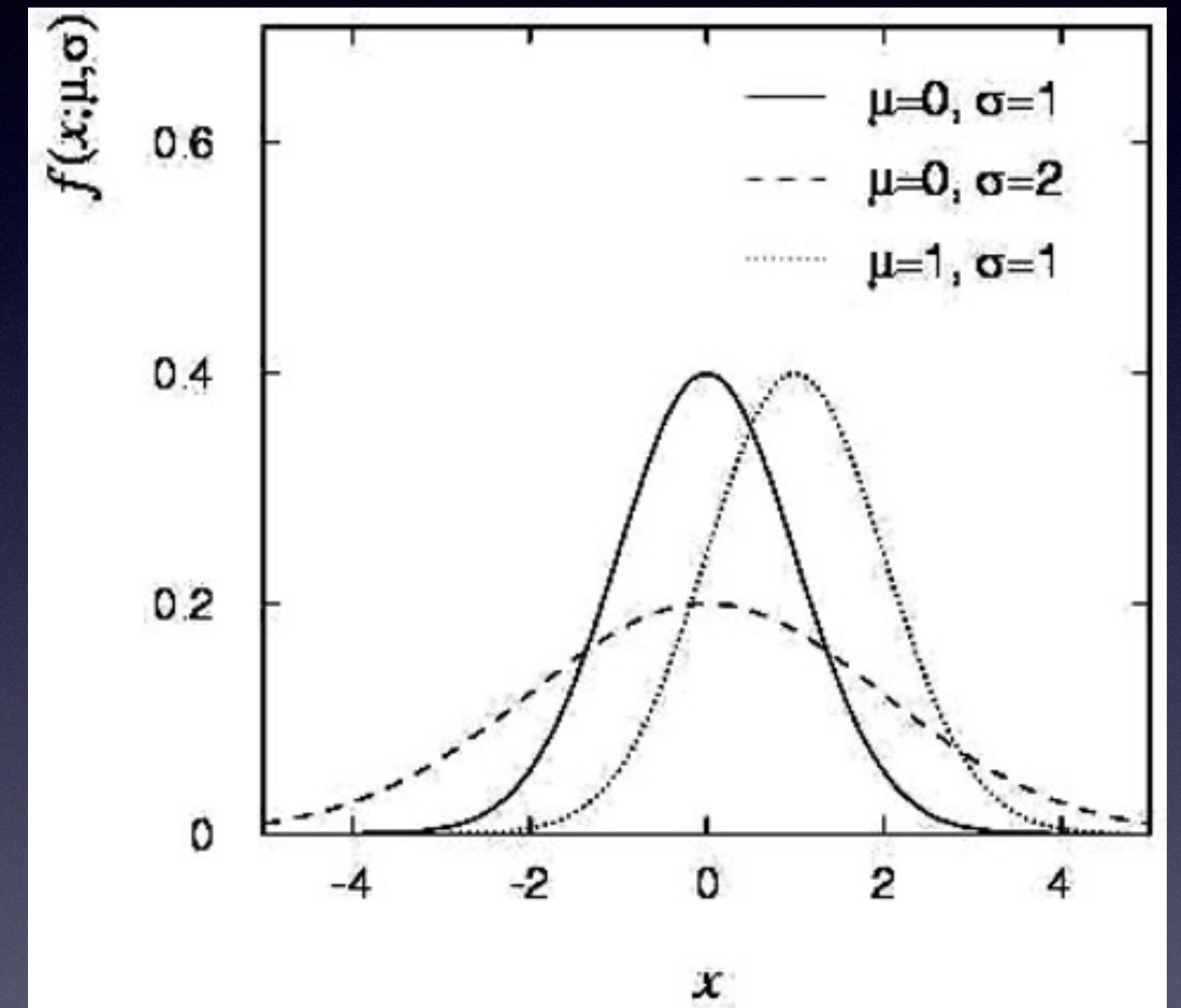
Gaussian distribution

- Gaussian PDF

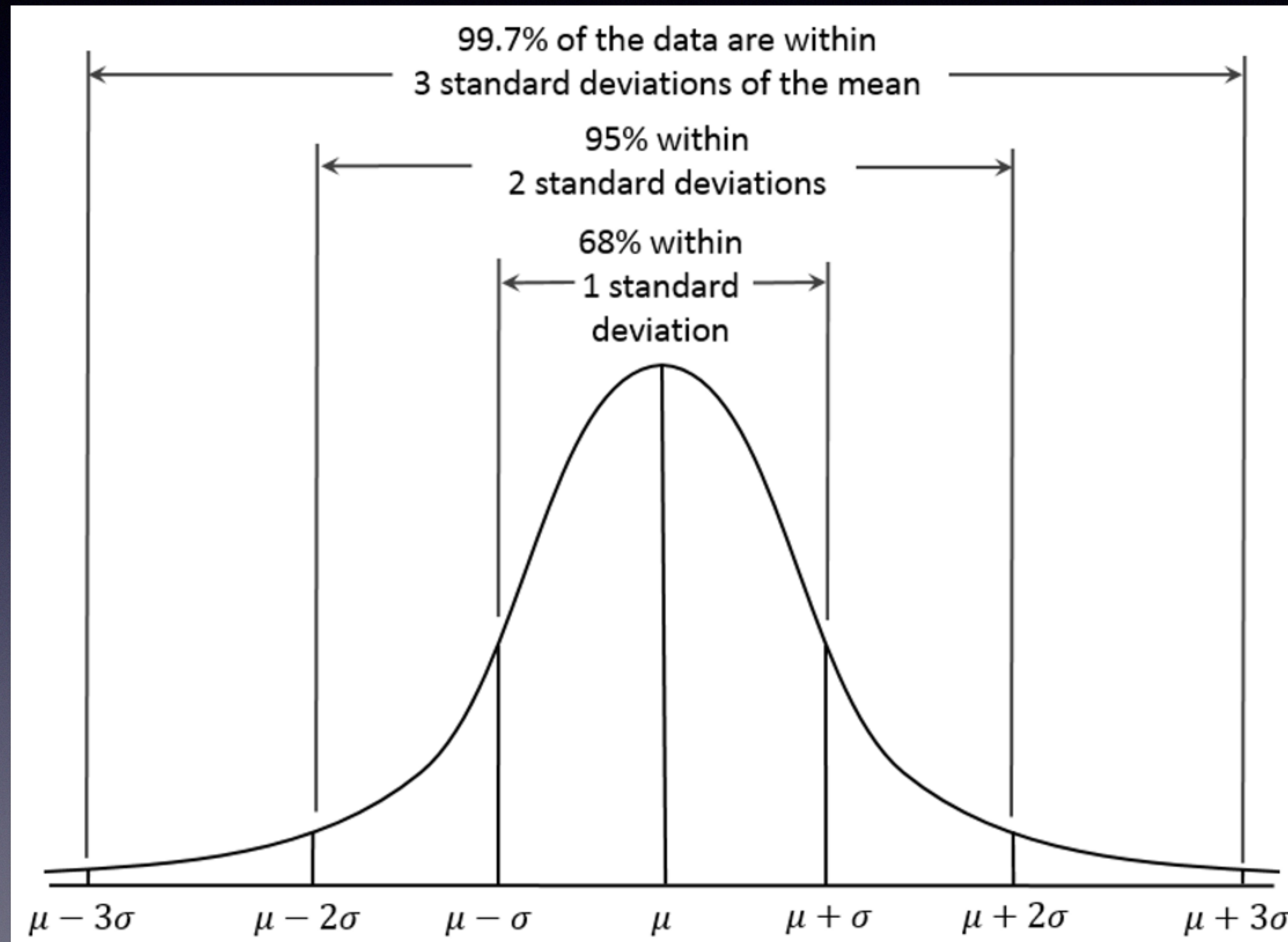
$$f(x; \mu, \sigma) = \frac{1}{\sqrt{2\pi}\sigma} e^{-(x-\mu)^2/2\sigma^2}$$

$$E[x] = \mu, \quad V[x] = \sigma^2$$

- If y is Gaussian with m , then $x = (y - m)/\sigma$ follows the standard Gaussian with $m = 0, \sigma = 1$



Gaussian distribution



$4 \sigma \sim 99.994\%$
 $5 \sigma \sim 99.99994\%$

Gaussian PDF and the Central Limit Theorem

- For arbitrary PDFs with n independent random variable x_i with finite variance σ_i^2 , consider the sum

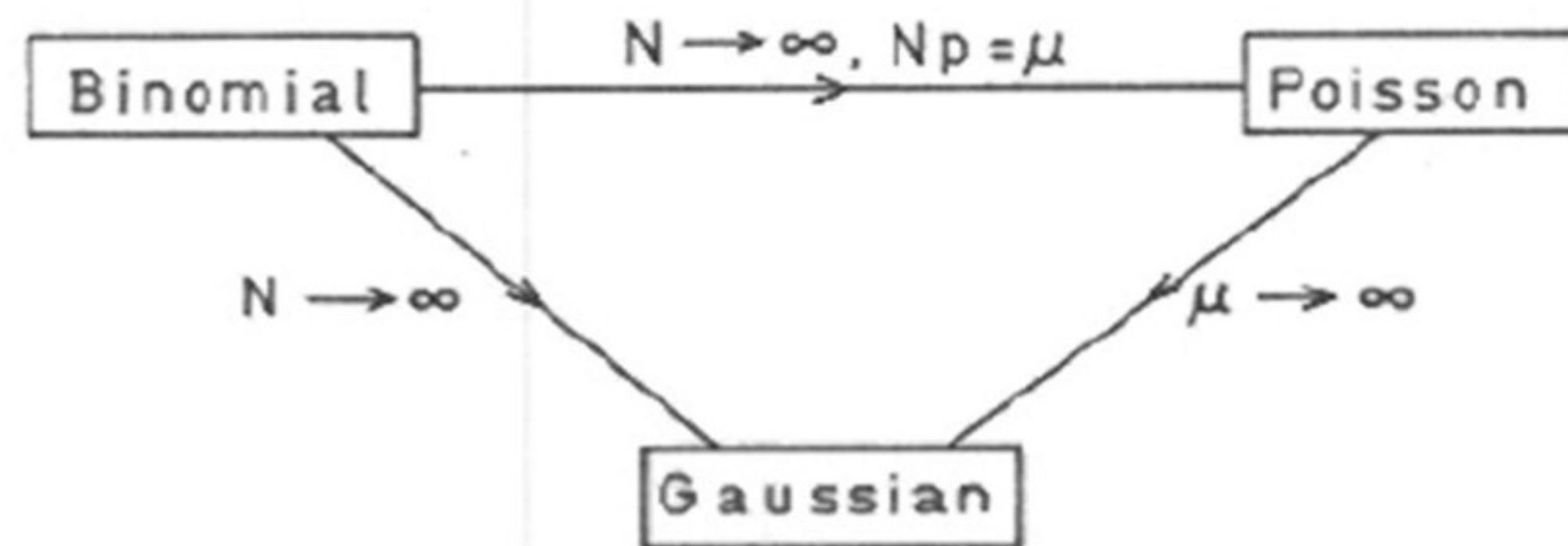
$$y = \sum_{i=1}^n x_i$$

- In the limit $n \rightarrow \infty$, y is a Gaussian random variable with

$$E[y] = \sum_{i=1}^n \mu_i \quad V[n] = \sum_{i=1}^n \sigma_i^2$$

- Measurement errors are often the sum of many contributions, so frequently measured values can be treated as Gaussian random variable x

Relationships among Binomial, Poisson and Gaussian distributions



Chi-square (χ^2) distribution

- The Chi-square PDF for the continuous variable z is defined by

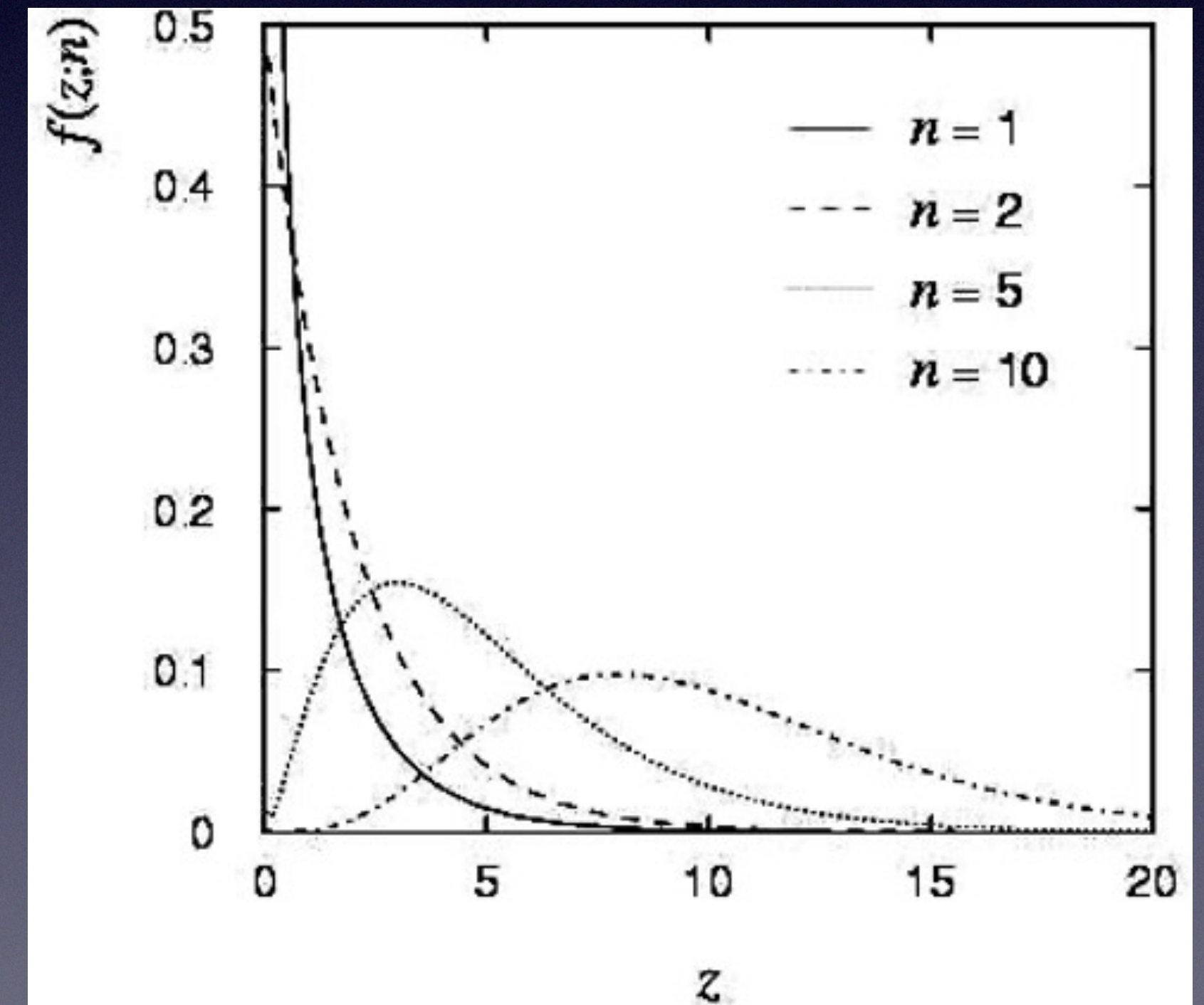
$$f(z; n) = \frac{1}{2^{n/2}\Gamma(n/2)} z^{(n/2)-1} e^{-z/2}$$

$$E[z] = n, \quad V[z] = 2n$$

- For independent Gaussian x_i ,

$$\chi^2_{min} = z = \sum_{i=1}^n \frac{(x_i - \mu_i)^2}{\sigma_i^2}$$

follows χ^2 PDF with n degree of freedom
expected to have $\chi^2/\text{dof} \sim 1$



Breit-Wigner distribution

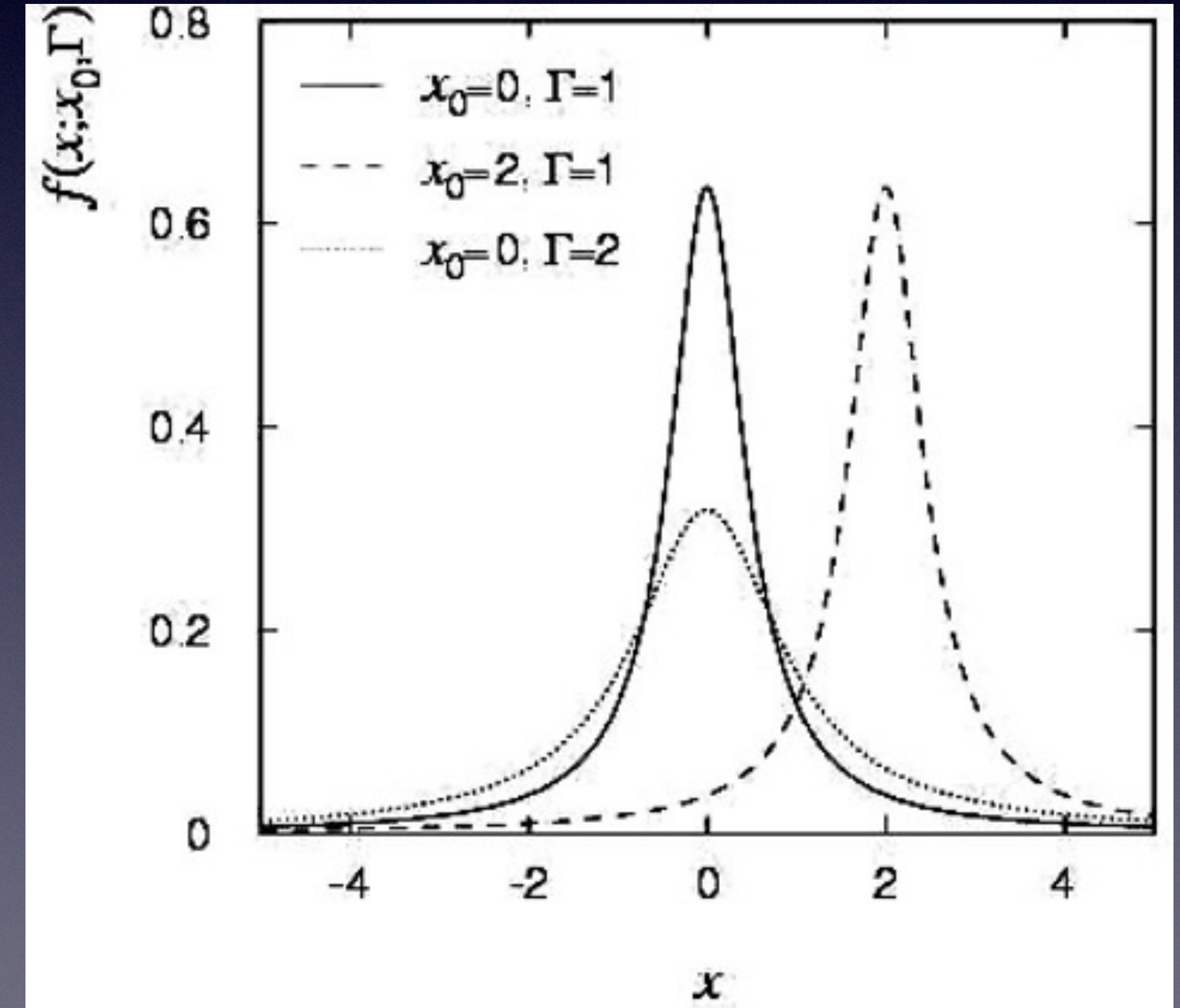
- The Breit-Wigner PDF for the continuous variable x is defined by

$$f(x; \Gamma, x_0) = \frac{1}{\pi} \frac{\Gamma/2}{\Gamma^2/4 + (x - x_0)^2}$$

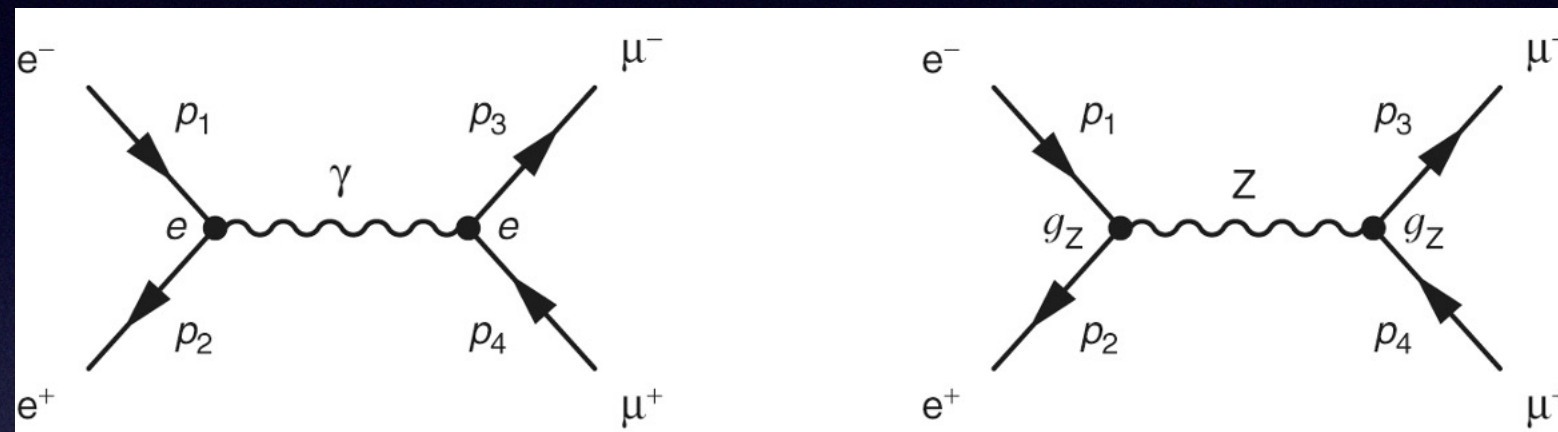
x_0 = mode (most probable value)

Γ = full width at half maximum

- Example: mass of resonance particle, e.g. Z boson, Higgs boson,...
- Γ = decay rate (inverse of mean lifetime)

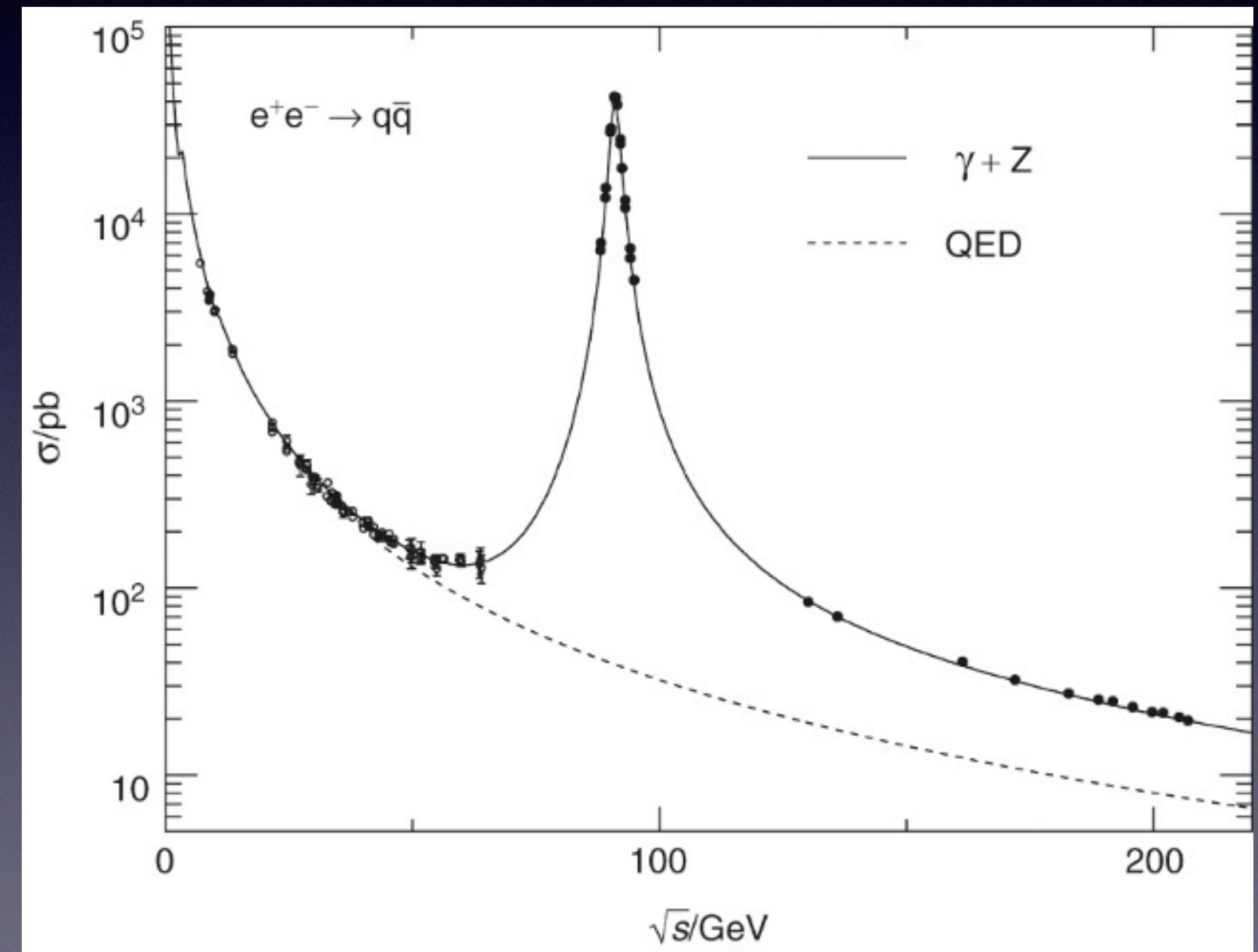


The Briet-Wigner resonance



- Cross-section for $e^+e^- \rightarrow \mu^+\mu^-(q\bar{q})$ is proportional to

$$\sigma \propto |M|^2 \propto \frac{1}{m_Z^2 \Gamma_Z^2 + (s - m_Z^2)^2}$$



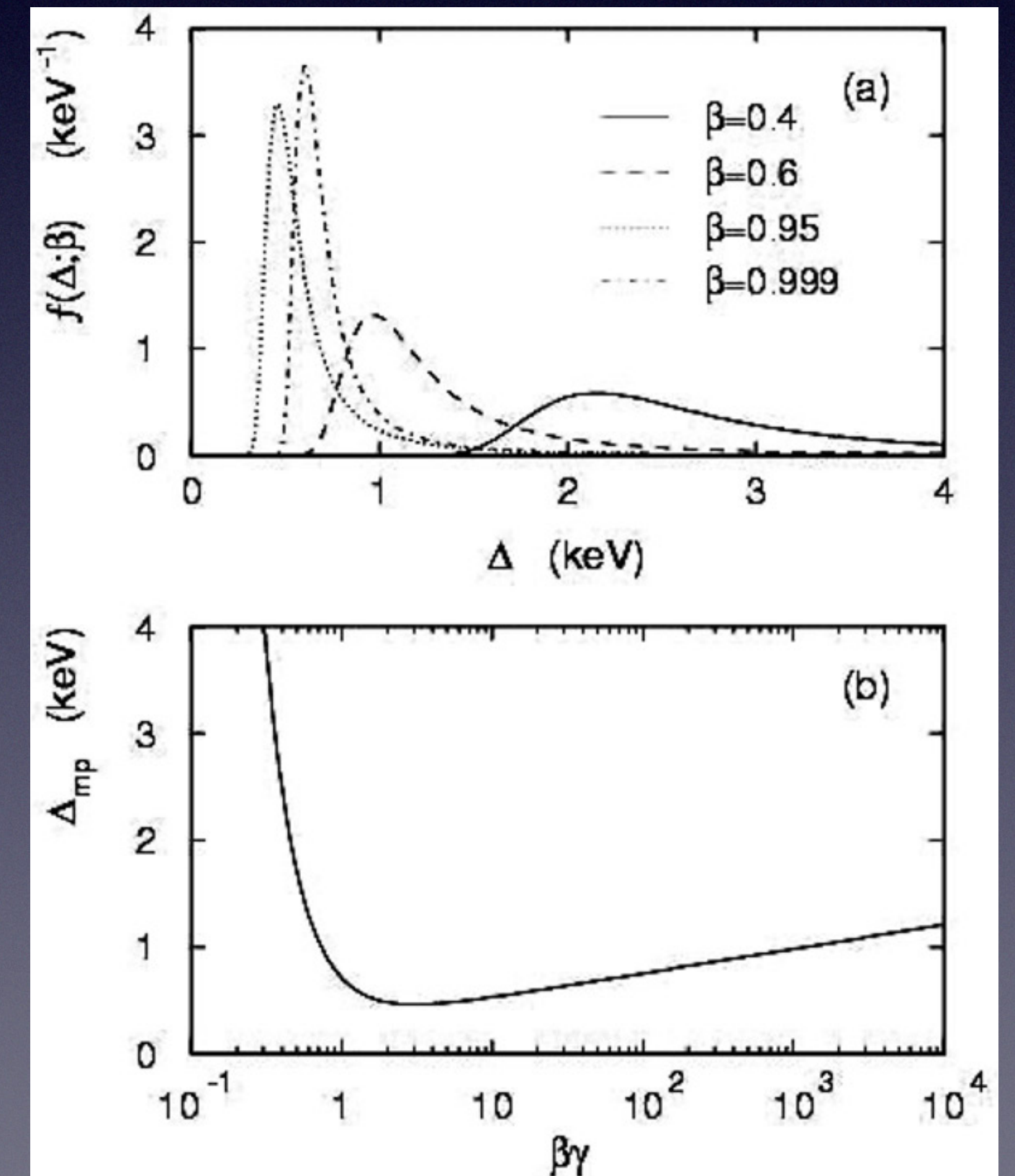
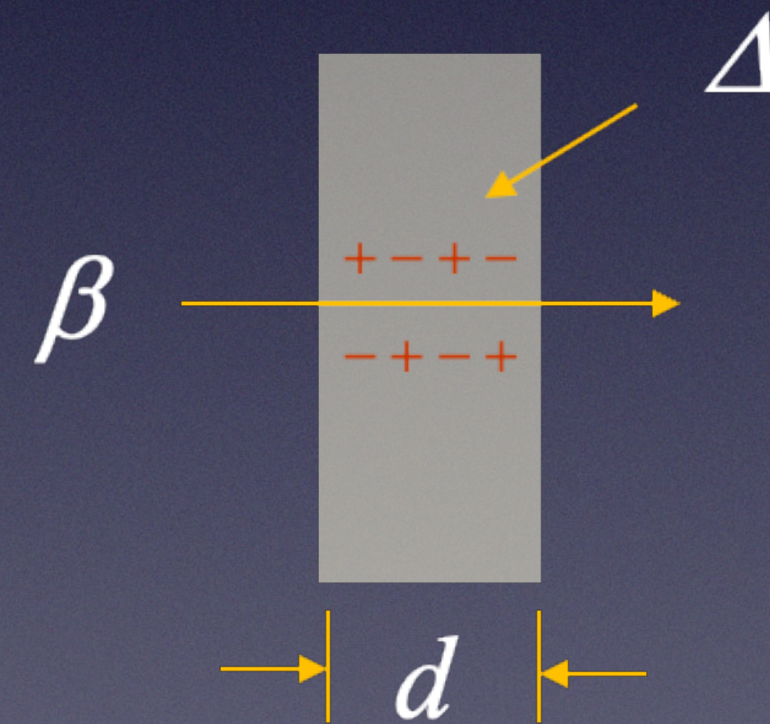
Landau distribution

- For a charged particle with $\beta = v/c$ traversing a layer of matter of thickness d , the energy loss Δ follows the Landau PDF

$$f(\Delta; \beta) = \frac{1}{\xi} \phi(\lambda)$$

$$\phi(\lambda) = \frac{1}{\pi} \int_0^\infty e^{-t \ln t - \lambda t} \sin(\pi t) dt$$

$$\lambda = \frac{1}{\xi} [\Delta - \Delta_0]$$



The Monte Carlo method

- A numerical technique for calculating probabilities and related quantities using sequences of random numbers
- Usual steps
 1. Generate random numbers $r_1, r_2, \dots, r_m$ uniform between 0 and 1
 2. Use these random numbers to produce another sequence $x_1, x_2, \dots, x_m$ that follows some PDF $f(x)$
 3. Use these x values to estimate some property of $f(x)$
 - A. Integration between $a < x < b$: $\int_a^b f(x)dx$
 - B. We can also use MC for testing statistical procedures

Random number generator

- Goal is to generate uniformly distributed values in $[0,1]$
- We can achieve this goal manually by tossing coin
 - e.g. 32 bit number: toss 32 times to get one number (too tiring)
 - This would be truly random number
- How do we implement this in computer algorithm to generate $r_1, r_2, \dots, r_n$

multiplicative
linear
congruential
generator
(MLCG)



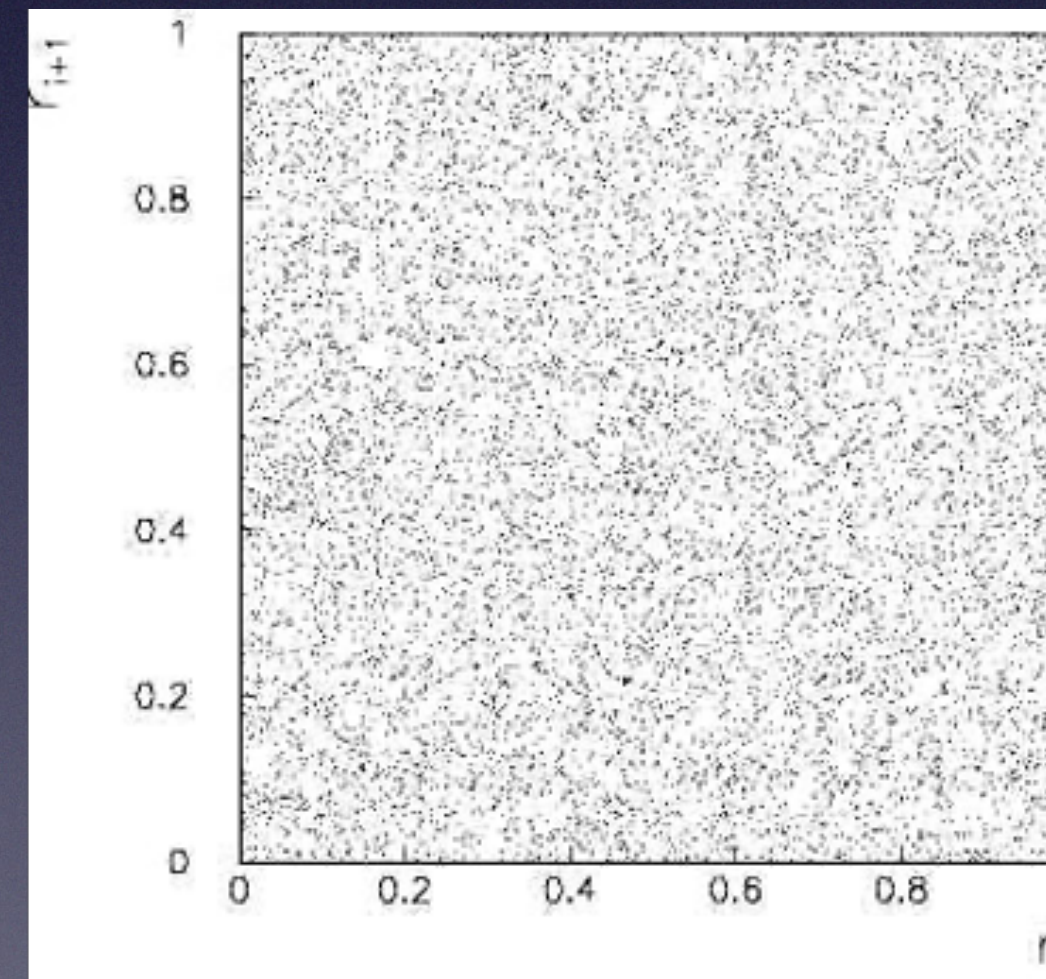
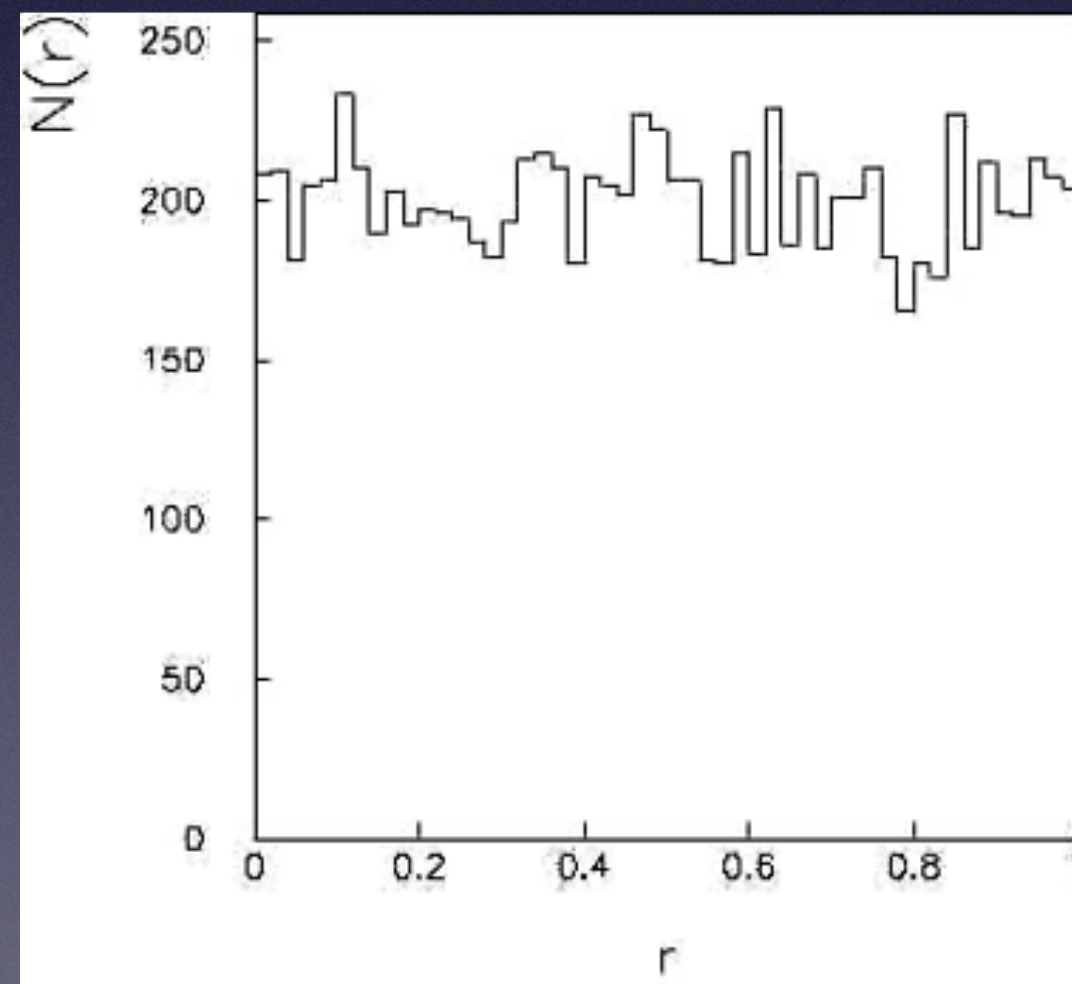
$$a=3, m=7, n_0=1$$

$$\begin{aligned}n_1 &= (3 \cdot 1) \bmod 7 = 3 \\n_2 &= (3 \cdot 3) \bmod 7 = 2 \\n_3 &= (3 \cdot 2) \bmod 7 = 6 \\n_4 &= (3 \cdot 6) \bmod 7 = 4 \\n_5 &= (3 \cdot 4) \bmod 7 = 5 \\n_6 &= (3 \cdot 5) \bmod 7 = 1\end{aligned}$$

- The sequence is periodic!
- Choose a, m to obtain long period
- Still only use a subset of a single period of the sequence

Random number generator

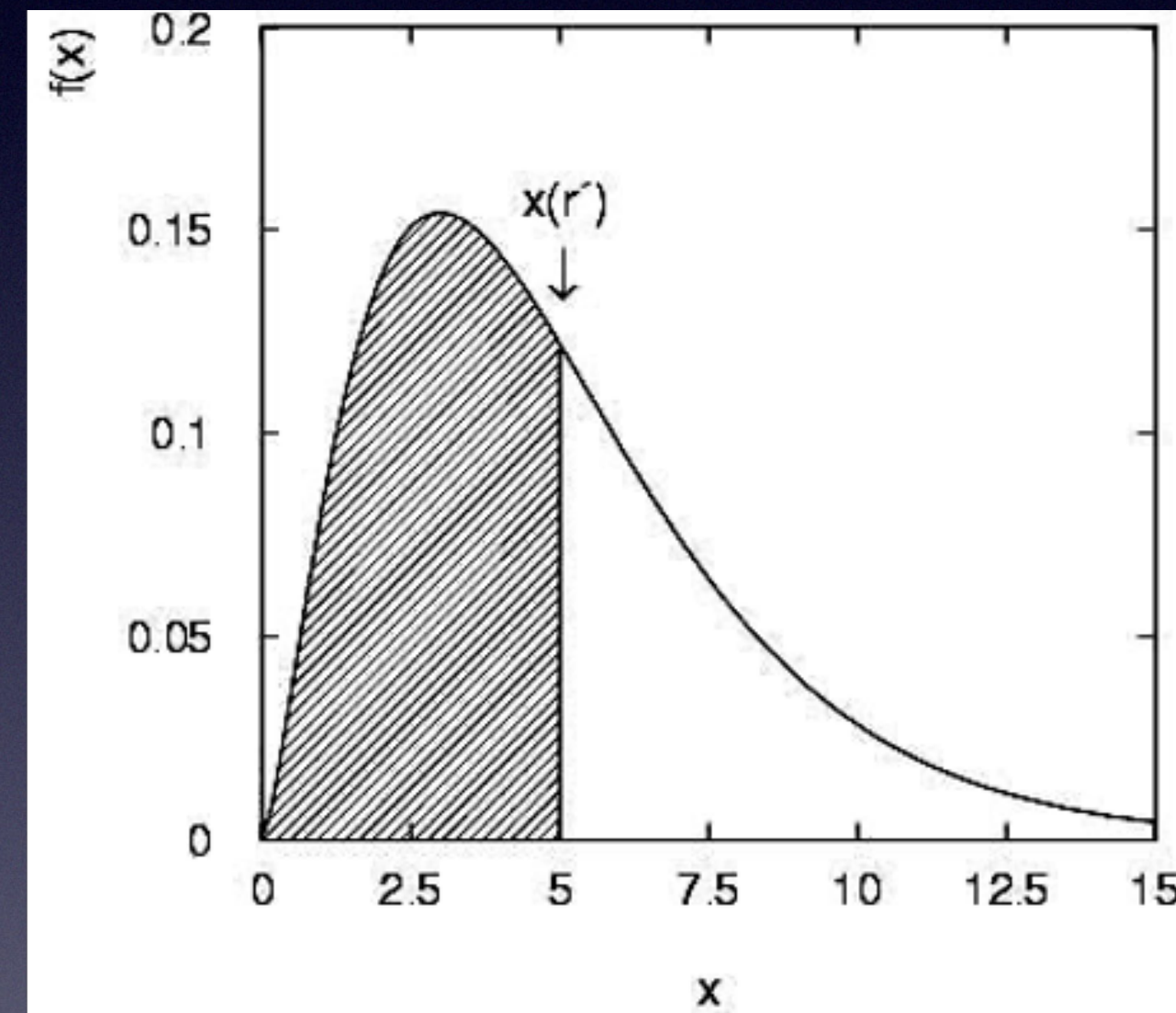
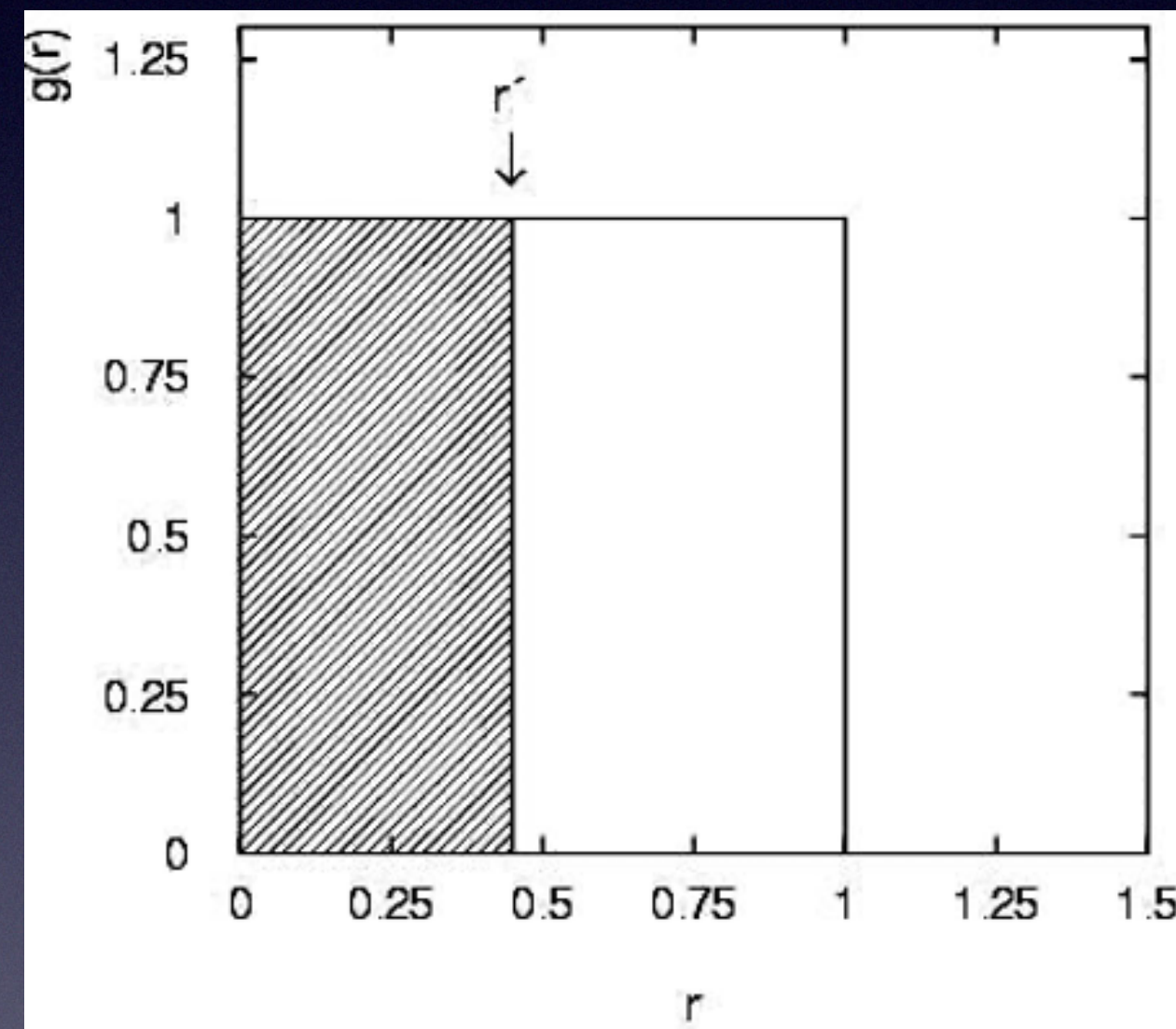
- Can we say the variable $r_i = n_i/m$ are random in $[0,1]$?
- uniform distribution in $[0,1]$ and all values are independent as long as subset is used
- $a=40692$, $m=2147483399$ (maximum period: $m - 1$)



- Far better algorithm is available with TRandom3 in ROOT, period $2^{19937} - 1$

Transformation method

- Given $r_1, r_2, \dots, r_n$ uniform in $[0, 1]$, find $x_1, x_2, \dots, x_n$ that follow $f(x)$ by finding a suitable transformation $x(r)$



- Use the fact that the probability should be the same $P(r \leq r') = P(x \leq x(r'))$

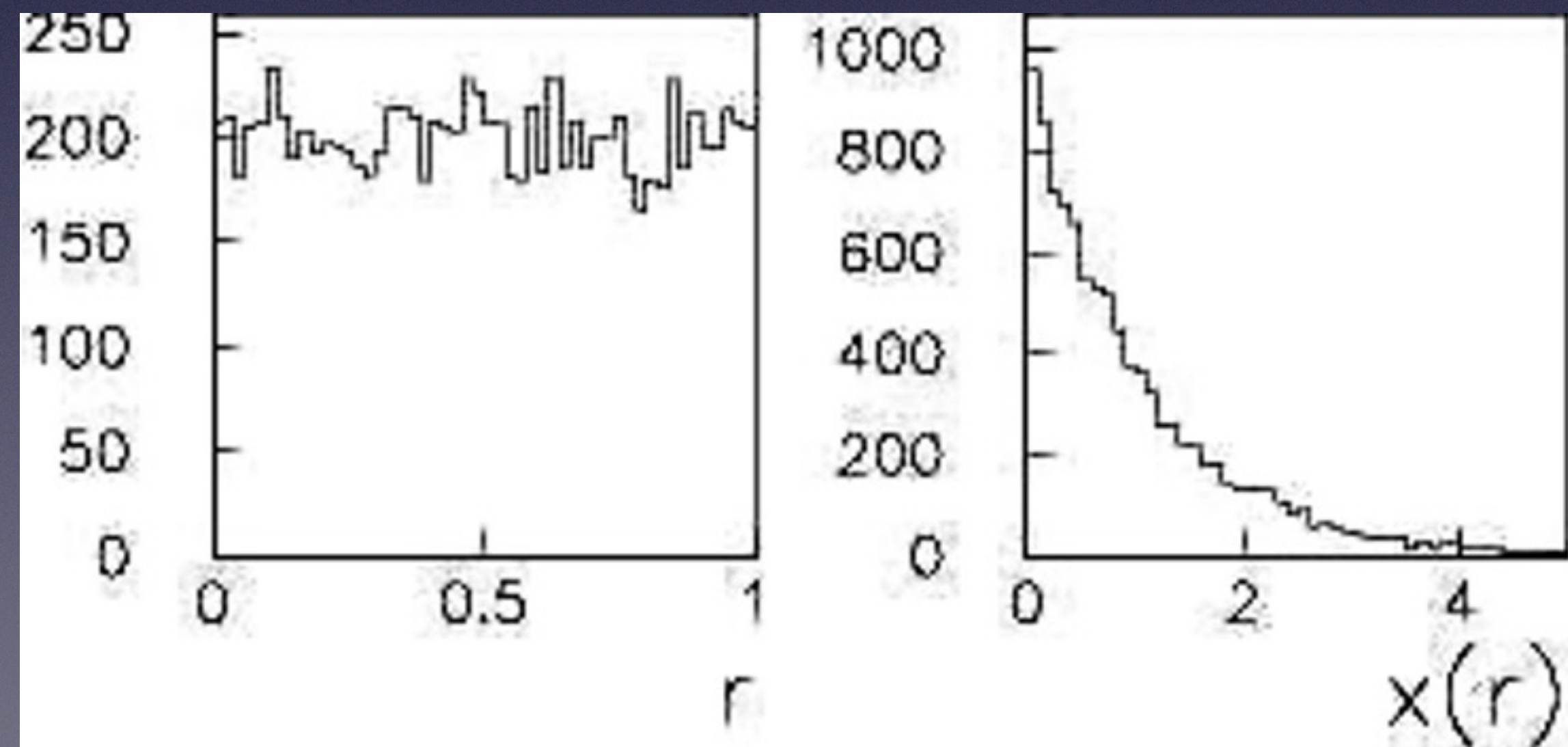
$$r' = \int_{-\infty}^{x(r')} f(x') dx' = F(x)$$

transformation method

- Exponential PDF: $f(x; \xi) = \frac{1}{\xi} e^{-x/\xi} \quad (x \geq 0)$

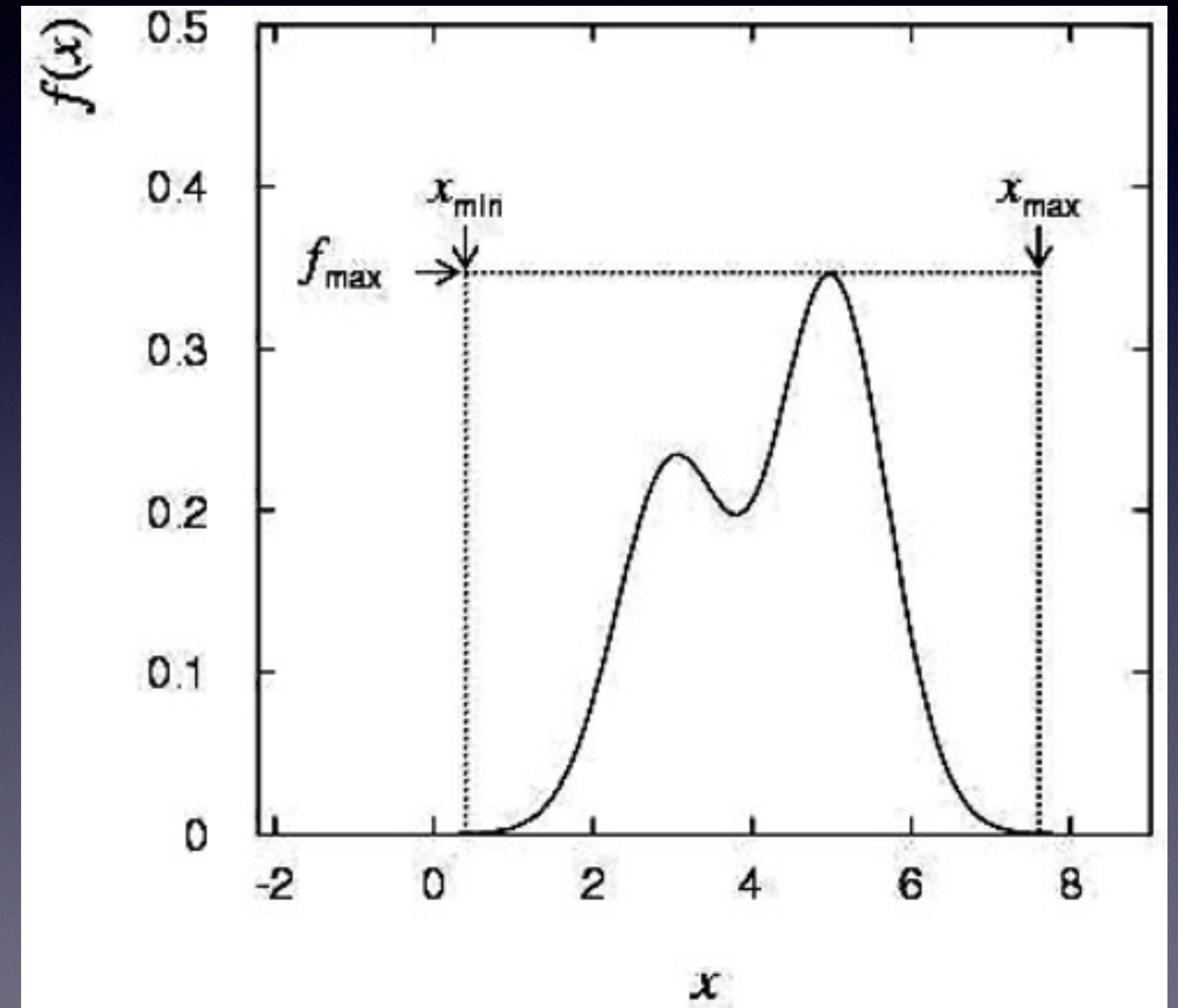
from the previous slide, the condition of $\int_0^x \frac{1}{\xi} e^{-x'/\xi} dx' = r$

→ $x = -\xi \ln r$



The acceptance-rejection method

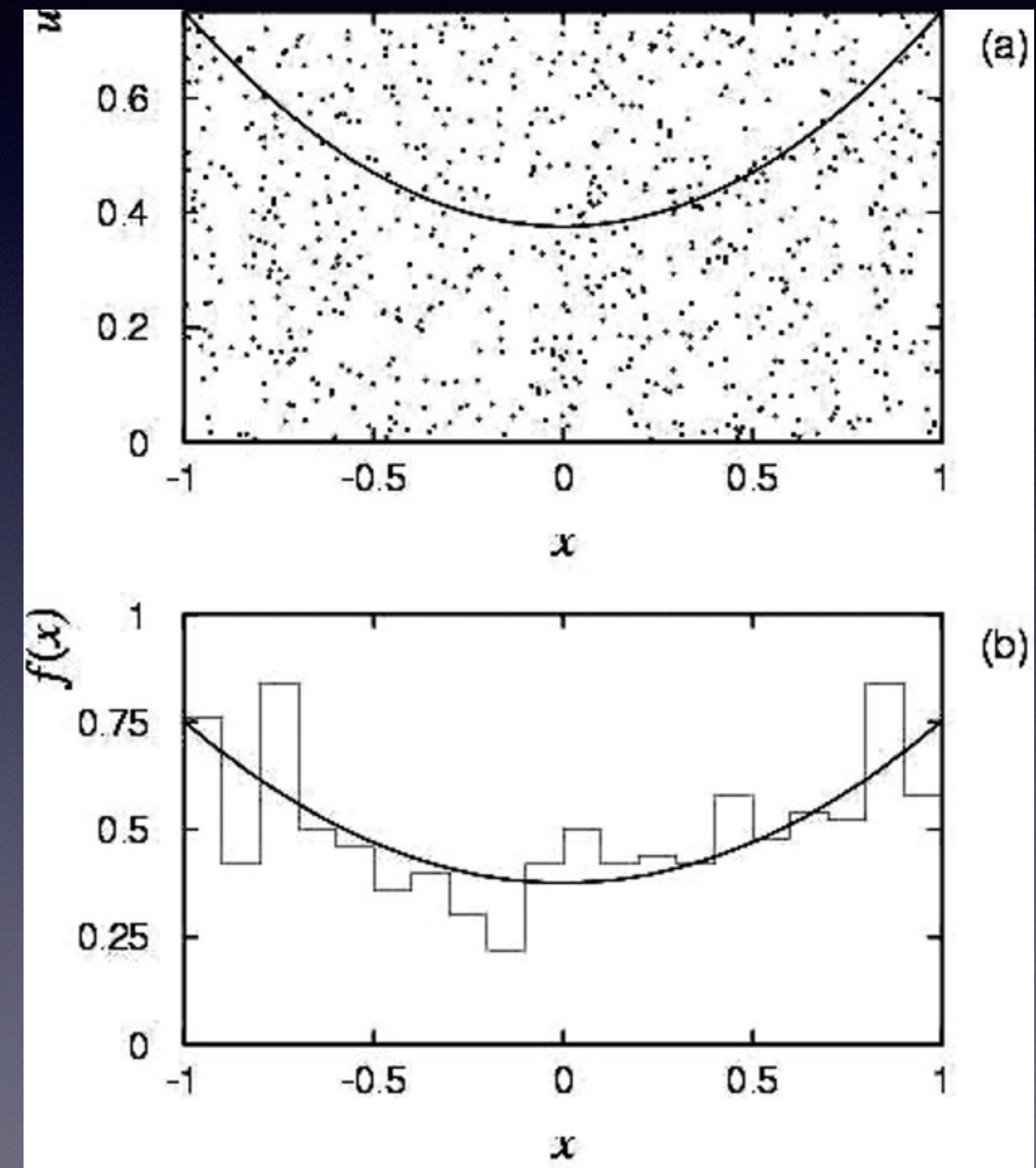
1. Generate a random number x , uniform in $[x_{min}, x_{max}]$, i.e.
 $x = x_{min} + r_1(x_{max} - x_{min})$ where r_1 is random number in $[0,1]$
2. Generate 2nd independent random number y uniformly distributed between 0 and f_{max} i.e. $y = r_2 f_{max}$
3. If $y > f(x)$, then accept x , If not, reject x and repeat



Example with acceptance-rejection method

$$f(x) = \frac{3}{8}(1 + x^2)$$
$$(-1 \leq x \leq 1)$$

- If dot below curve, use x value in histogram



Monte Carlo event generators

- Simple example: $e^+e^- \rightarrow \mu^+\mu^-$
- Generate $\cos \theta$ and ϕ

$$f(\cos \theta; A_{\text{FB}}) \propto (1 + \frac{8}{3}A_{\text{FB}} \cos \theta + \cos^2 \theta)$$

$$g(\phi) = \frac{1}{2\pi} (0 \leq \phi \leq 2\pi)$$

- Less simple: event generators for a variety of reactions: ($pp \rightarrow$ hadrons, DY, SUSY)
 - PYTHIA, HERWIG, ...
- Output = events; for each event, we get a list of generated particles and their momentum vectors, type, etc

Monte Carlo detector simulation

- Take the particle list and momenta from generator as input
- Simulates detector response:
 - multiple Coulomb scattering (generate scattering angle)
 - particle decays (generate lifetime)
 - ionization energy loss (generate Δ)
 - electromagnetic and hadronic showers
 - production of signal, electronics response,...
- Output = simulated raw data
 - input to reconstruction algorithm: tracking finding, fitting, etc
- We usually compare distributions at detector level given a certain hypothesis with the real data
- Also can estimate acceptance = #events found/#events generated
- Programming package: **GEANT4**