

Probability and Random Processes

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18 November 2022

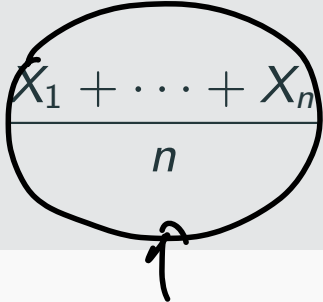
Jacobs University

The weak law of large numbers

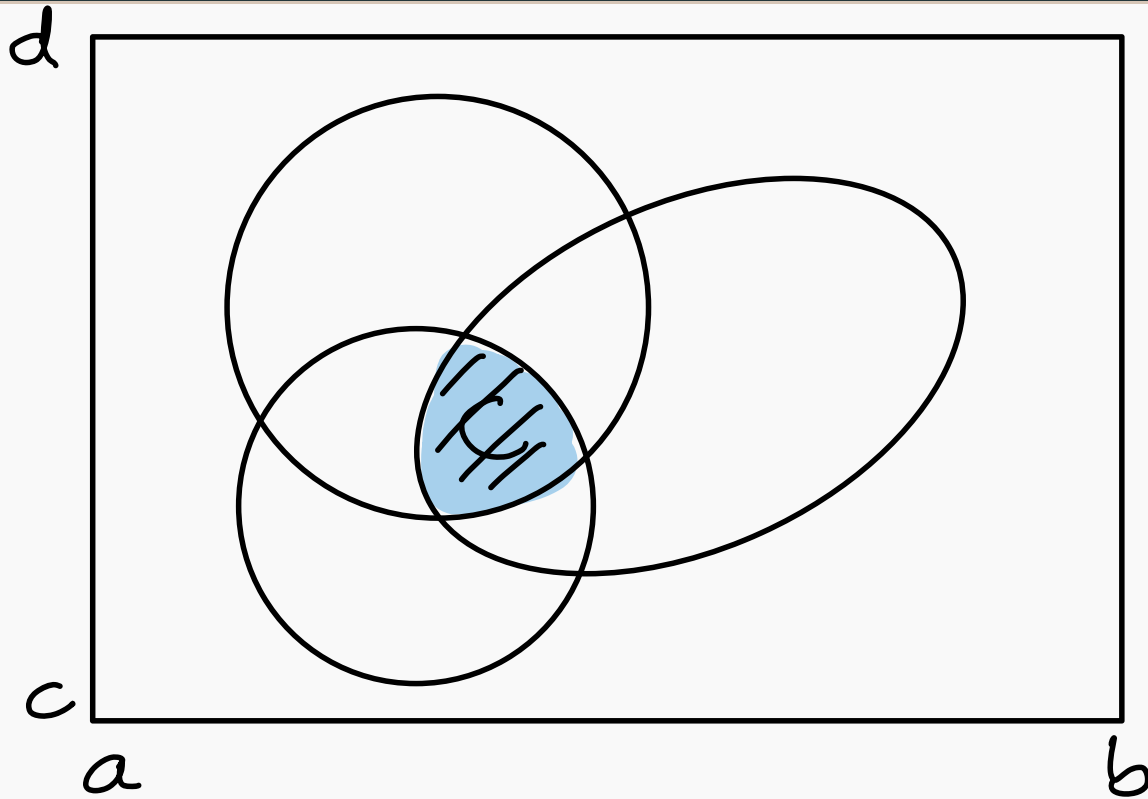
The Weak Law of Large Numbers

Consider a sequence X_n of **identically distributed independent** random variables. Suppose that they have **finite expectation μ** and **finite variance**. Then, for every $\epsilon > 0$, we have

$$\lim_{n \rightarrow \infty} \mathbb{P} \left[\left| \frac{X_1 + \dots + X_n}{n} - \mu \right| > \epsilon \right] = 0.$$


empirical average

Application: Monte Carlo algorithm (toy version)



Area of box

$$= (d - c)(b - a)$$

$x \in [a, b]$ random
uniform

$y \in [c, d]$ random
uniform.

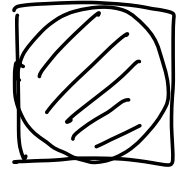
$$\mathbb{P}[(x, y) \text{ is in } C] = \frac{\text{area of } C}{(d - c)(b - a)}$$

$$\text{area of } C = (d - c)(b - a) \underbrace{\mathbb{P}[(x, y) \text{ is in } C]}_P.$$

Suppose $(X_1, Y_1), (X_2, Y_2), \dots$ are independently
chosen from the box according to the uniform distribution

Z_1, Z_2, \dots all Bernoulli

$$Z_i = \begin{cases} 1 & (X_n, Y_n) \text{ is in } C \\ 0 & (X_n, Y_n) \text{ is not in } C. \end{cases}$$



$$P[Z_i = 1] = P[(X_n, Y_n) \text{ is in } C] = p$$

Z_i is a Bernoulli RV with parameter p .

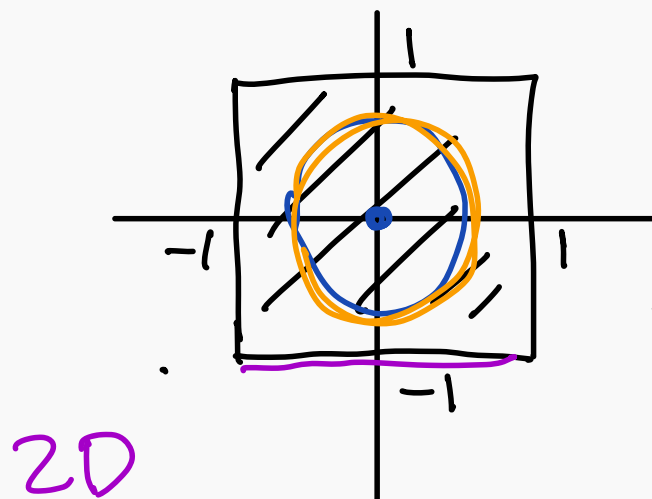
$$\mu = E[Z_i] = p$$

LLN

$$P \left[\left| \frac{Z_1 + Z_2 + \dots + Z_n}{n} - p \right| > \epsilon \right] \rightarrow 0$$

when
 $n \rightarrow \infty$

Concentration of measure phenomenon



2D

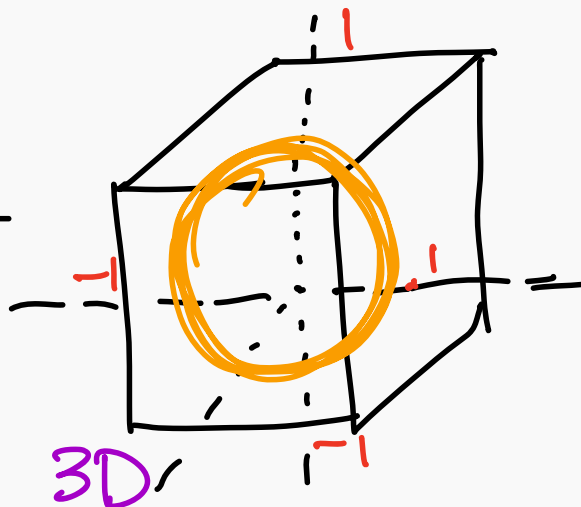
$$(x_1, x_2)$$

$$-1 \leq x_1 \leq 1$$

$$-1 \leq x_2 \leq 1$$

$$\text{2-dim volume area} = 2^2$$

$$0 \leq \text{distance} \leq \sqrt{2}$$



3D

$$-1 \leq x_1 \leq 1$$

$$-1 \leq x_2 \leq 1$$

$$-1 \leq x_3 \leq 1$$

$$\text{volume} = 2^3$$

$$0 \leq \text{distance} \leq \sqrt{3}$$

n-dim hypercube/cube

nD

$$-1 \leq x_1 \leq 1$$

$$-1 \leq x_2 \leq 1$$

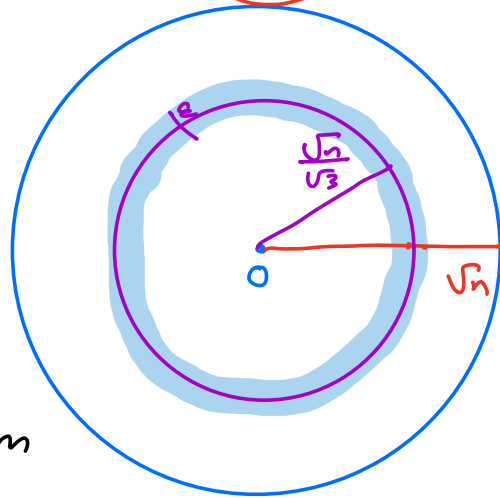
$$-1 \leq x_n \leq 1$$

$$\text{volume} = 2^n$$

$$0 \leq \text{distance} \leq \sqrt{n}$$

- Most of the volume of the n dim cube is near the sphere of radius $\sqrt{\frac{n}{3}}$ centred at the origin.

$$\frac{\sqrt{n}}{\sqrt{3}}$$



$$X = (X_1, X_2, \dots, X_n) \text{ } n\text{-dim cube}$$

X_1, X_2, \dots, X_n are picked from $[-1, 1]$ independently.

distance from the point X to the origin's

$$D = \sqrt{X_1^2 + X_2^2 + \dots + X_n^2} \text{ random variable}$$

Consider the random variable

$$Y_1 = X_1^2, \quad Y_2 = X_2^2, \quad \dots \quad Y_n = X_n^2.$$

X_i^2 comes from $[0, 1]$.

$$E[X_i^2] = \int_{-1}^1 x^2 \cdot f(x) dx = \int_{-1}^1 \frac{1}{2} x^2 dx$$

$$= \frac{1}{2} \cdot \frac{x^3}{3} \Big|_{-1}^1 = \frac{1}{3}$$

$$\boxed{E[h(X)] = \int_{-\infty}^{+\infty} h(x) f(x) dx} \quad h(x) = x^2$$

LLN $n \rightarrow \infty$

$$P\left[\left|\frac{X_1^2 + X_2^2 + \dots + X_n^2}{n} - \frac{1}{3}\right| > \epsilon\right] \rightarrow 0$$

n large, with a prob. close to 1

$$\frac{1}{3} - \epsilon < \frac{X_1^2 + \dots + X_n^2}{n} < \frac{1}{3} + \epsilon$$

$$\sqrt{n\left(\frac{1}{3} - \epsilon\right)} < \underbrace{\sqrt{X_1^2 + \dots + X_n^2}}_D < \sqrt{n\left(\frac{1}{3} + \epsilon\right)}$$

Concentration of measure phenomenon II

A point is randomly chosen from

$$Q_n = \{x = (x_1, \dots, x_n) : -1 \leq x_i \leq 1.\}$$

Set

$$A_n = \left\{ x \mid (1 - \epsilon) \sqrt{\frac{n}{3}} < \|x\| < (1 + \epsilon) \sqrt{\frac{n}{3}} \right\}.$$

Then for any given $\epsilon > 0$ we have $\mathbb{P}[A_n] \rightarrow 1$ as $n \rightarrow \infty$.

The idea of the central limit theorem

The Central limit theorem

The Central limit theorem

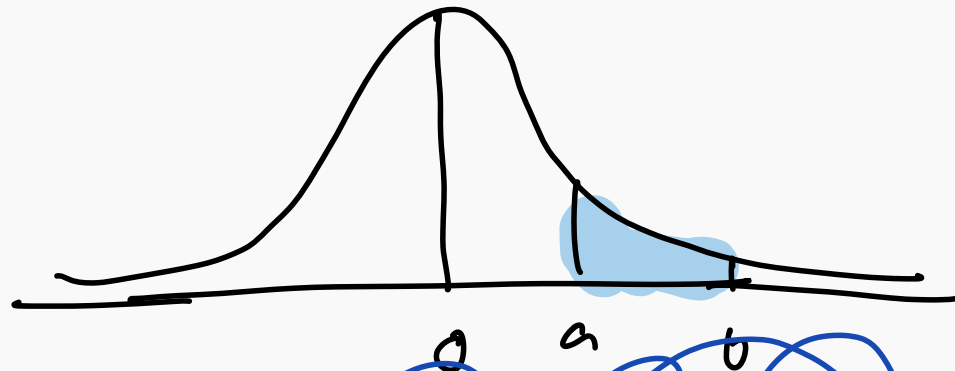
Let X_1, X_2, \dots be i.i.d. with $\mathbb{E}[X_i] = \mu$ and $\text{Var}[X_i] = \sigma^2$. Then the distribution of

$$Z_n = \frac{\overbrace{X_1 + \dots + X_n}^{\text{sum}} - \underbrace{n\mu}_{\text{centered sum}}}{\sqrt{n}\sigma}$$

converges to the distribution of a standard normal distribution. In other words:

$$\lim_{n \rightarrow \infty} \mathbb{P}(\underbrace{a \leq Z_n \leq b}_{\text{underbrace{}}}) = \frac{1}{\sqrt{2\pi}} \int_a^b e^{-y^2/2} dy. \quad (1)$$

$$\mu = 1$$



$$\mathbb{P}(a \leq \underbrace{X_1 + \dots + X_n}_{\text{sum}} \leq b) = \mathbb{P}(a \leq \underbrace{X_1 + \dots + X_n}_{\text{sum}} \leq b)$$

$\text{Var}(X_1 + \dots + X_n) = n \text{Var} X_i = n\sigma^2$

Application

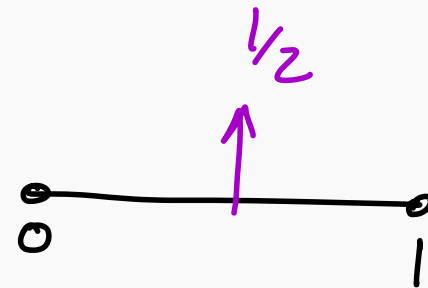
24 numbers are randomly and independently chosen from the interval $[0, 1]$ according to the uniform distribution. Find the approximate value of the probability that the sum of the numbers is at least 8.

$$S_{24} = X_1 + X_2 + \dots + X_{24} \quad X_i \text{ has uniform distribn in } [0, 1]$$

$$E[X_i] = \frac{1}{2} = \mu$$

$$\text{Var}[X_i] = E[X^2] - E[X]^2$$

$$E[X^2] = \int_0^1 x^2 dx = \frac{1}{3}$$



$$\text{Var}[X_i] = \frac{1}{3} - \left(\frac{1}{2}\right)^2 = \frac{1}{3} - \frac{1}{4} = \frac{1}{12} = \sigma^2 \Rightarrow \sigma = \sqrt{\frac{1}{12}} = \frac{1}{2\sqrt{3}}$$

$$S_{24} = \frac{X_1 + \dots + X_{24}}{24} \approx \frac{1}{2}$$

$$n = 24$$

$$\mu = \frac{1}{2}$$

$$\frac{X_1 + \dots + X_{24} - 12}{\sqrt{24} \cdot \sqrt{\frac{1}{12}}} \sim \begin{matrix} \text{stand} \\ \text{normal} \\ \text{distn} \end{matrix}$$

$$P\left(a < \frac{X_1 + \dots + X_{24} - 12}{\sqrt{2}} < b\right) \approx P(a < N < b)$$

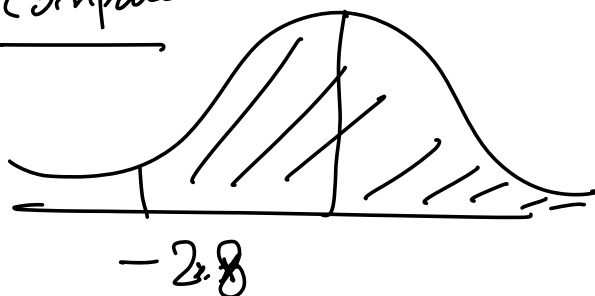
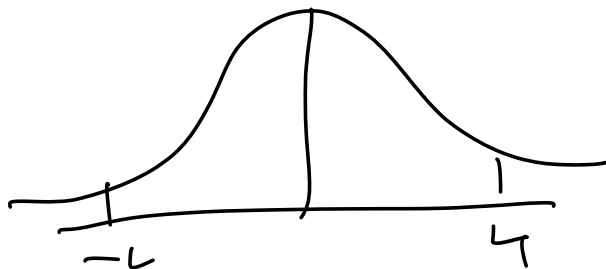
$\frac{S_n - n\mu}{\sqrt{n}\sigma}$

\downarrow
stand normal

$$P(S \geq 8) = P\left(\frac{S - 12}{\sqrt{2}} > \frac{8 - 12}{\sqrt{2}}\right)$$

$$= P\left(\frac{S - 12}{\sqrt{2}} > \frac{-4}{\sqrt{2}}\right) \approx P\left(N > \frac{-4}{\sqrt{2}}\right)$$

$$\approx P(N > -2.8) \rightarrow \text{compute}$$



Moment generating functions of a random variable

Definition

Consider the following expected value:

$$M_X(t) = \mathbb{E} \left[e^{tX} \right].$$

It is called the **moment generating function** for X .

X any variable.

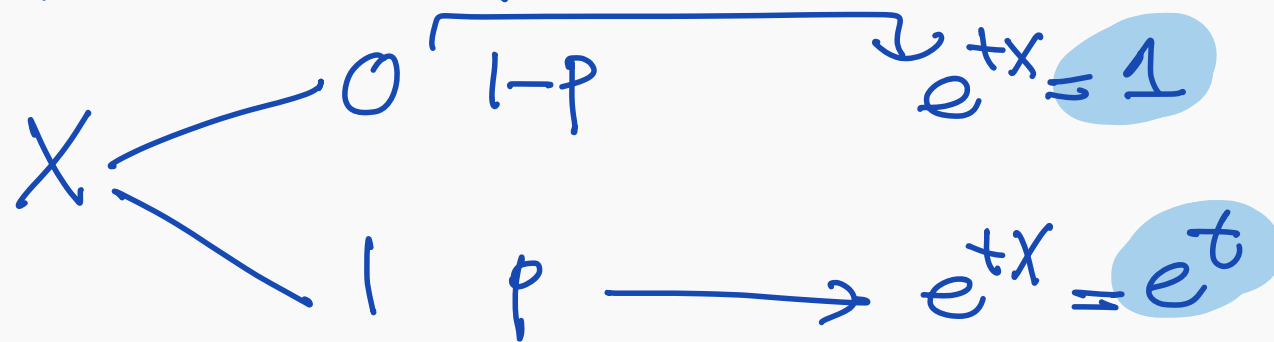
Example

Find the moment generating function for a Bernoulli random variable with parameter p .

$$M_X(t) = E[e^{tx}] = p \cdot e^t + (1-p) \cdot 1$$

$$M_X(t) = pe^t + 1 - p$$

X Bernoulli with parameter p



Example

Find the moment generating function for a Poisson random variable with parameter λ .

Poisson: $k = 0, 1, 2, \dots$

$$P(X=k) = \frac{e^{-\lambda} \cdot \lambda^k}{k!} \quad X=k \Rightarrow e^{tX} = \underbrace{e^{tk}}$$

$$E[e^{tX}] = \sum_{k=0}^{\infty} \frac{e^{-\lambda} \lambda^k}{k!} e^{tk} = e^{-\lambda} \sum_{k=0}^{\infty} \frac{(\lambda e^t)^k}{k!}$$

$$e^x = \sum_{k=0}^{\infty} \frac{x^k}{k!}$$

$$= e^{-\lambda} \cdot e^{\lambda e^t} \rightarrow x$$

$$M_X(t) = e^{\lambda(e^t - 1)}$$