

Probability and Random Processes

Keivan Mallahi-Karai

16 November 2022

Jacobs University

Agenda

1.

1. Problem Set **5** is due tonight 23:59.
2. Problem Set **6** will be posted today and is due on 25.11.22.
3. Practice exam II in one week.

Tail behavior of random variables

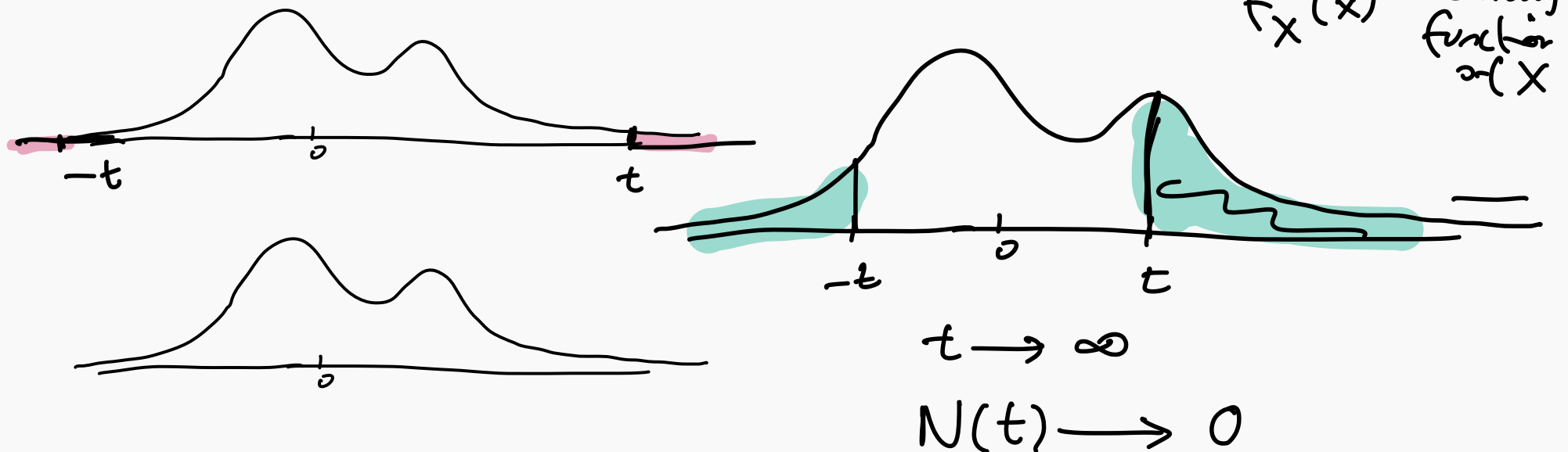
$$X \geq t \text{ or } X \leq -t$$

Let X be a random variable. Define

$$N(t) = \mathbb{P}[|X| \geq t]$$

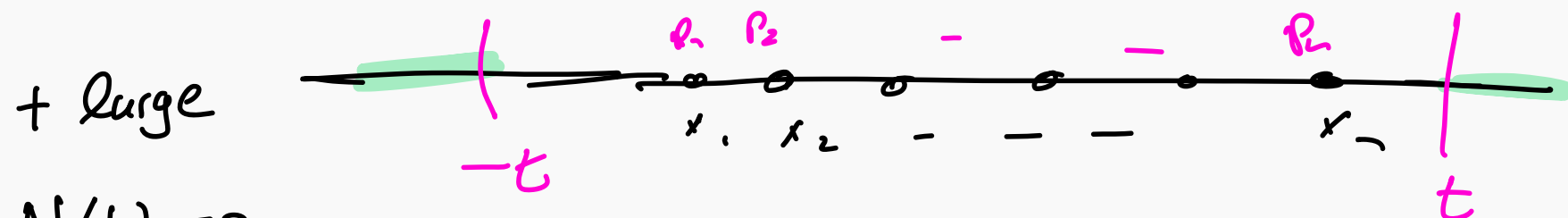
$$t \geq 0$$

This function describes the probability of X taking large values.



Examples

Example 1: X takes only finitely many values. Determine $N(t)$.



for t sufficiently large.

values of X are bounded

X uniform distribution on $[0,1]$



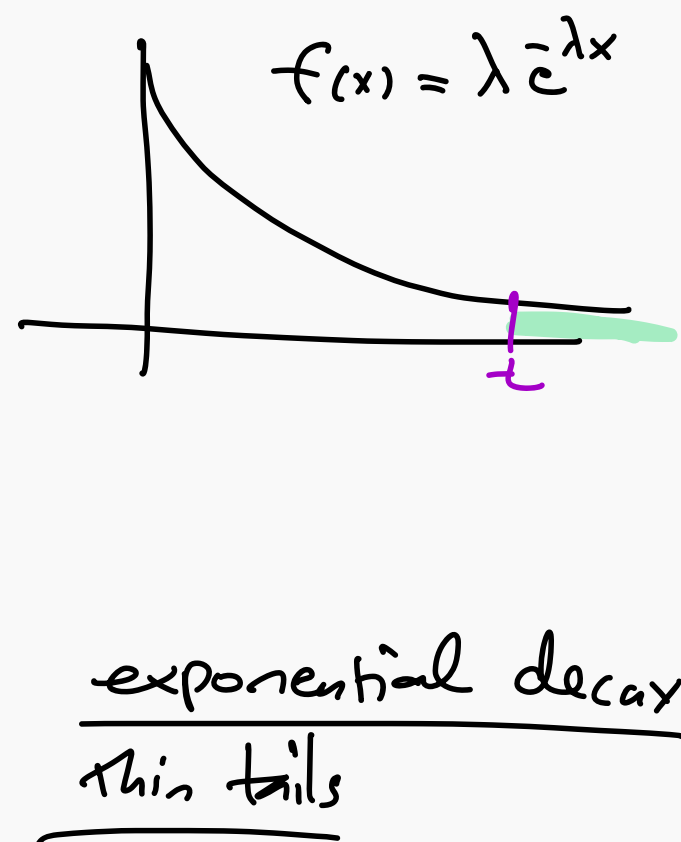
$N(t) = 0$ if $\underline{t > 1}$

Examples 2

Let X be an exponential random variable with parameter λ . Compute $N(t)$.

$$\begin{aligned} N(t) &= \mathbb{P}(|X| \geq t) \\ &= \mathbb{P}(X \geq t) \\ &= \int_t^{\infty} \lambda e^{-\lambda x} dx \end{aligned}$$

$$= -e^{-\lambda x} \Big|_t^{\infty} = e^{-\lambda t}$$

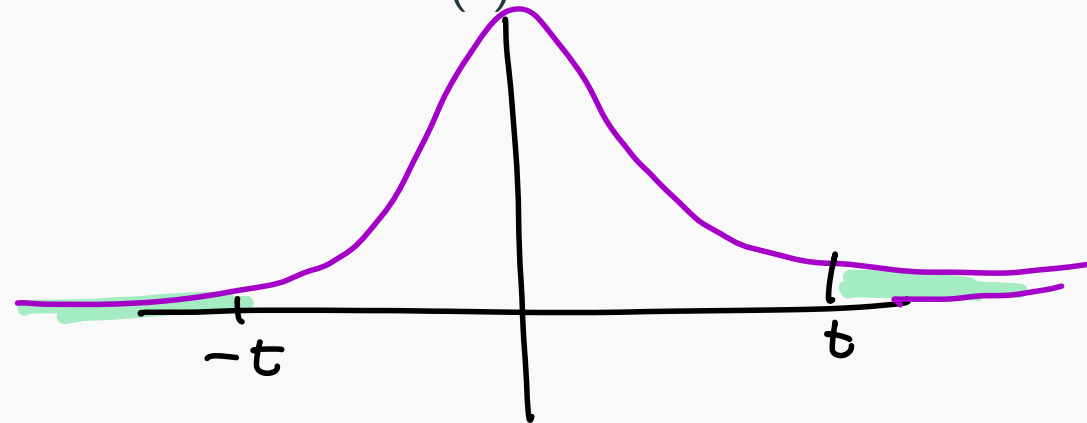


Normal (Gaussian) random variables

$$\mu=0, \sigma=1$$

Let X be a standard Normal random variable. Estimate $N(t)$

$$f_X(x) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2}$$



$$N(t) = \mathbb{P}(|X| \geq t)$$

$$\stackrel{\text{Symmetry}}{=} 2 \mathbb{P}(X \geq t) = 2 \int_t^{\infty} \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx$$

$$= \frac{2}{\sqrt{2\pi}} \int_t^{\infty} e^{-x^2/2} dx \leq \frac{2}{\sqrt{2\pi}} \int_t^{\infty} \frac{x}{t} e^{-x^2/2} dx$$

$$= \frac{2}{\sqrt{2\pi} t} \int_t^{\infty} x e^{-x^2/2} dx$$

Substition $\frac{x^2}{2} = u$ $du = \frac{2x}{2} dx = x dx$

$$= \frac{2}{\sqrt{2\pi} t} \int_{\frac{t^2}{2}}^{\infty} e^{-u} du$$

$$\begin{aligned} x=t &\rightarrow u = \frac{t^2}{2} \\ x=\infty &\rightarrow u=\infty \end{aligned}$$

$$= \frac{2}{\sqrt{2\pi} t} -e^{-u} \Big|_{\frac{t^2}{2}}^{\infty} = \frac{2}{\sqrt{2\pi} t} e^{-\frac{t^2}{2}}$$

$t \rightarrow \infty$

$$\lambda t < \frac{t^2}{2}$$

Compare

$$e^{-\lambda t} \text{ exponential decay}$$

Markov's inequality

Theorem

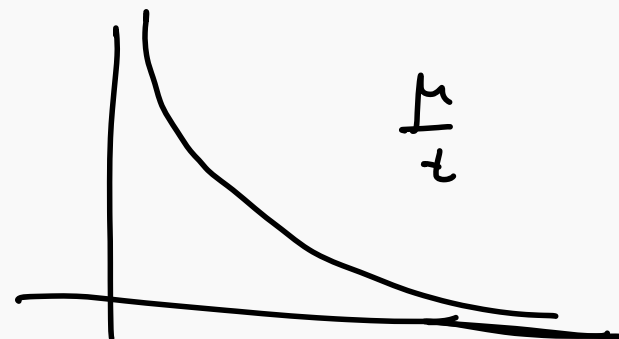
Suppose that a positive random variable X has a finite expectation μ . Then

$$N(t) = \mathbb{P}[X \geq t] \leq \frac{\mu}{t}.$$

for $t > 0$.

why?

Compare random variable X
with another random variable Y

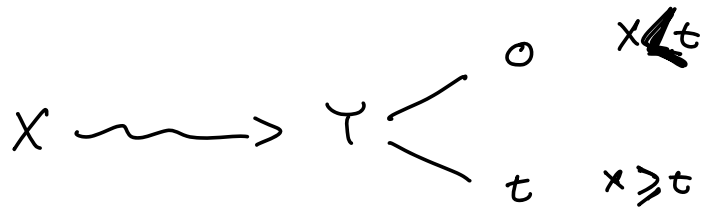


$$Y = \begin{cases} 0 & X \leq t \\ t & X \geq t \end{cases}$$

relation between X, Y

notice $Y \leq X$ true when $X \leq t$
 $Y = t, X \geq t$ when $X \geq t$

Summary



and

observation: $Y \leq X$

$$\Rightarrow E[Y] \leq \underbrace{E[X]}_{\mu}$$

$$\begin{aligned} E[Y] &= 0 \cdot P(X < t) + t \cdot P(X \geq t) \\ &= t P(X \geq t) \end{aligned}$$

$$t P(X \geq t) \leq \mu \Rightarrow \boxed{P(X \geq t) \leq \frac{\mu}{t}}$$

$\mu=1$

$$\boxed{P(X \geq 10) \leq \frac{1}{10}}$$

Example

A coin is weighted so that its probability of landing on heads is $1/6$. Suppose the coin is flipped 24 times. Find a bound for the probability it lands on heads at least 20 times.

$$P(\# \text{ head} \geq 20) = \binom{24}{20} \left(\frac{1}{6}\right)^{20} \left(\frac{5}{6}\right)^4 + \binom{24}{21} \left(\frac{1}{6}\right)^{21} \left(\frac{5}{6}\right)^3 + \dots + \binom{24}{24} \left(\frac{1}{6}\right)^{24}.$$

$$P(\# \text{ head} \geq 20) \leq \frac{\mathbb{E}[X]}{\underset{\substack{\uparrow t \\ 20}}{t}} = \frac{4}{20} = \frac{1}{5} = 0.2$$

$$\mathbb{E}[X] = 24 \cdot \frac{1}{6} = 4$$

$$P(\text{heads} \leq 20) = P(\text{tails} \geq 4) \leq \frac{20}{4} = 5$$

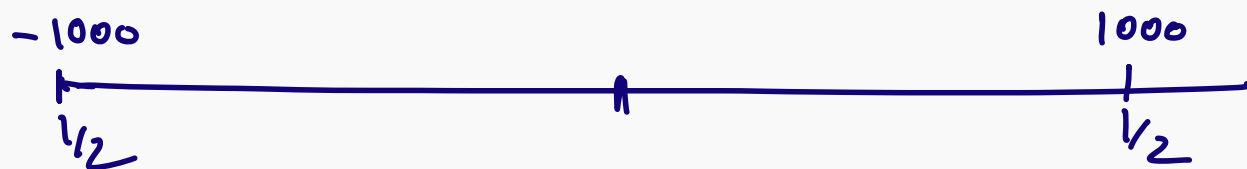
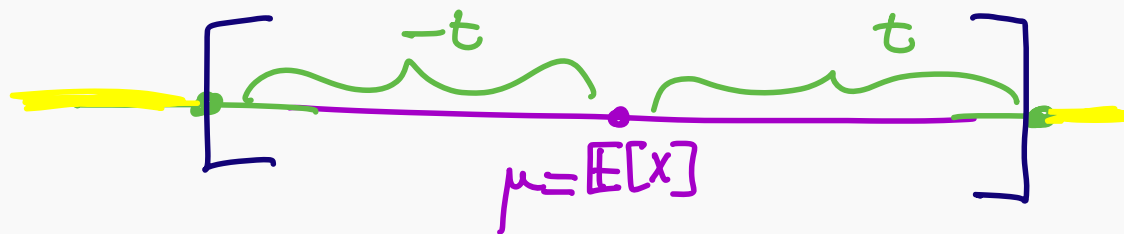
Proof of Markov's inequality

Chebyshev's inequality

Theorem

Suppose that X has finite expectation and finite variance. Then

$$\mathbb{P}[|X - \mathbb{E}(X)| > t] \leq \frac{\text{Var}[X]}{t^2}.$$



$$\mathbb{E}[X] = \frac{1}{2} \cdot 1000 + \frac{1}{2} \cdot (-1000)$$

$$\text{standard deviation } \sigma = \sqrt{\text{Varian}(x)} \Rightarrow \text{Var}[X] = \sigma^2 \approx 0.$$

$$P[|X - E[X]| \geq t] \leq \frac{\text{Var}[X]}{t^2} = \frac{\sigma^2}{t^2}$$

$$t = 10\sigma \quad \downarrow$$

$$P[|X - E[X]| \geq 10\sigma] \leq \frac{\sigma^2}{(10\sigma)^2} = \frac{1}{100}.$$

Proof of Chebyshev's inequality

Sum of Independent Random Variables

Definition

A sequence of random variables X_1, X_2, \dots is called *independent and identically distributed* (in short, *i.i.d.*) if X_i are independent and have a common distribution function.

Suppose X_1, X_2, \dots be an i.i.d sequence of random variables. Then define

$$S_n = X_1 + \dots + X_n$$

and consider

$$\frac{S_n}{n} = \frac{X_1 + \dots + X_n}{n}$$

expect $\frac{S_n}{n}$ must be around $\frac{1}{2}$.

X_n Bernoulli $p = \frac{1}{2}$

$$X_n = \begin{cases} 0 & \frac{1}{2} \\ 1 & \frac{1}{2} \end{cases}$$

$$X_1 + \dots + X_n$$

The weak law of large numbers

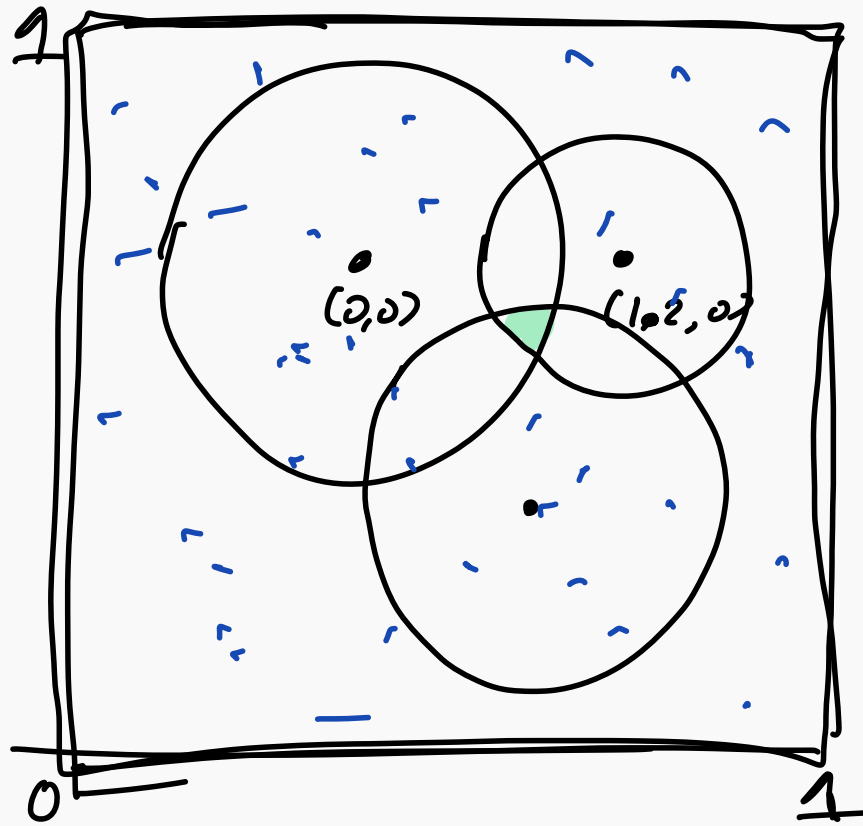
The Weak Law of Large Numbers

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

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

Application: Monte Carlo algorithm (toy version)

Region in \mathbb{R}^3 defined by some algebraic inequalities



$$x^2 + y^2 \leq 1$$

$$X_n = \begin{cases} 1 & \text{if the sample is in the region } R \\ 0 & \text{otherwise} \end{cases}$$

$$\frac{X_1 + \dots + X_n}{n} = \frac{\# \text{ points in } R}{n}$$

n very large

$$E[X_n] = \underline{\text{area of region}}$$

Concentration of measure phenomenon

