

# Stochastic Processes

## Lecture 2

CYS 2020/2021

### Probability Review (second part)

- Major discrete distributions

Bernoulli - Binomial - Geometric - Poisson

- Major continuous distributions

Normal = Exponential = Uniform = Gamma

- Conditional distributions:

discrete case, continuous case

random sums and their moments

$A, B \subseteq \Sigma$

$$\boxed{P[B] > 0}$$

$$P[A|B] := \frac{P[A \cap B]}{P[B]}$$

↑

$A$  and  $B$  are independent

$\Leftrightarrow$

$$P[A|B] = P[A]$$

←

$\Leftrightarrow$

$$\frac{P[A \cap B]}{P[B]} = P[A]$$

$\Leftrightarrow$

$$P[A \cap B] = P[A] \cdot P[B]$$

$A, B, C$  they are indep. iff.

$$P[A \cap B] = P[A] \cdot P[B]$$

$$P[B \cap C] = P[B] \cdot P[C]$$

$$P[A \cap C] = P[A] \cdot P[C]$$

$$\rightarrow P[A \cap B \cap C] = P[A] \cdot P[B] \cdot P[C]$$

# Random Vectors

$$X = (X_1, \dots, X_n) : \Omega \rightarrow \mathbb{R}^n$$

$n = 2$

$$(X_1, X_2)$$

Joint distribution function

$$F_{X_1, X_2}(x_1, x_2) = P\left[\underbrace{X_1 \leq x_1}_{\text{A}_1}, \underbrace{X_2 \leq x_2}_{\text{A}_2}\right]$$

- discrete random vectors

$$p(x_1, x_2) := P[X_1 = x_1, X_2 = x_2]$$

Joint prob. mass function

there exist  $\geq$  finite or countable set of values  
 $(x_1, x_2) \in \mathbb{R}^2$  s.t.

- $p(x_1, x_2) > 0$

- $\sum_{x_1, x_2 \in \mathbb{R}^2} p(x_1, x_2) = 1$

continuous random vectors ( $n=2$ )

$$X = (X_1, X_2)$$

$$F_{X_1, X_2}(x_1, x_2) = \int_{-\infty}^{x_1} \int_{-\infty}^{x_2} f(s, t) ds dt$$

$f_{X_1, X_2}$  - joint distribution density

$$f_{X_1, X_2} \geq 0, \quad \iint_{\mathbb{R}^2} f_{X_1, X_2}(s, t) ds dt = 1$$

In both cases, from the joint distribution we can derive the marginal distributions of the single components of  $X = (X_1, X_2, \dots, X_n)$

$$X = (X_1, X_2)$$

$$\underbrace{F_{X_1}(x_1)}_{=} = \lim_{x_2 \uparrow +\infty} F_{X_1, X_2}(x_1, x_2)$$

$$\underbrace{F_{X_2}(x_2)}_{=} = \lim_{x_1 \uparrow +\infty} F_{X_1, X_2}(x_1, x_2)$$

Joint mass function

$$P_{X_1}(x_1) = \sum_{x_2 \in \mathbb{R}} P_{X_1, X_2}(x_1, x_2)$$

Joint density function (continuous r.v.)

$$f_{X_2}(x_2) = \int_{-\infty}^{+\infty} f_{X_1, X_2}(x_1, x_2) dx_1$$

↑ marginal density



$X$  and  $Y$  are INDEPENDENT?

$$P[A \cap B] = P[A] \cdot P[B]$$

$$\begin{aligned} F_{X,Y}(x,y) &= P[\underbrace{X \leq x}, \underbrace{Y \leq y}] \\ &= P[X \leq x] \cdot P[Y \leq y] \end{aligned}$$

$$F_{X,Y}(x,y) = F_X(x) \cdot F_Y(y) \quad \forall x, y \in \mathbb{R}$$

discrete case this is equivalent to say

$$P_{X,Y}(x,y) = P_X(x) \cdot P_Y(y)$$

Just like in the continuous case the indep. will be equivalent  
too

$$f_{X,Y}(x,y) = f_X(x) \cdot f_Y(y)$$



Moments:

discrete r.v. the n-th moment

$$\mathbb{E}[X^n] := \sum_i x_i^n \cdot P[X=x_i]$$

expectation

cont. case

$$\mathbb{E}[X^n] := \int_{-\infty}^{+\infty} x^n f(x) dx$$

the infinite sum (the integral) converges absolutely.

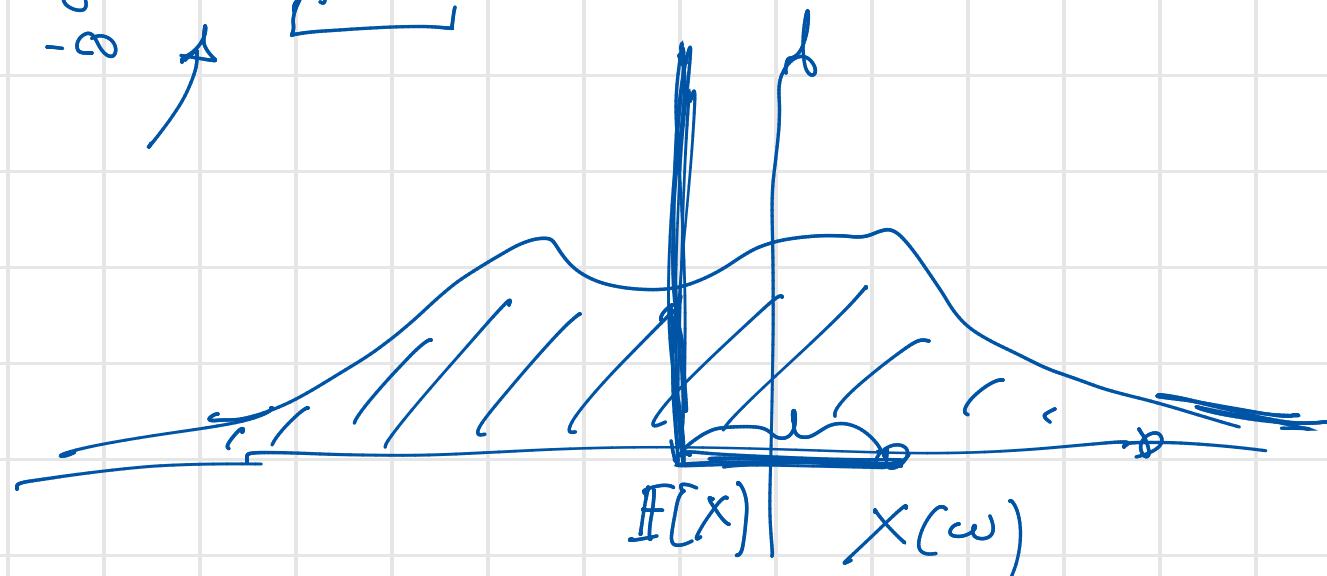
$$\sum_i |x_i|^n P[X=x_i] < +\infty, \quad \int_{-\infty}^{+\infty} |x|^n f(x) dx < +\infty$$

$\mu = 1$

## The expectation (meze)

$$E[X] = \sum_i x_i p(x_i)$$

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



Variance

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

2nd - central moment

## discrete - case

- Bernoulli r.v.
- Binomial r.v.
- Geometric r.v.
- Poisson r.v.

Bernoulli

$$p \in [0, 1]$$

$$X : \Omega \rightarrow \mathbb{R}$$

$$\{0, 1\}$$

$$P[X=0] = 1-p = p(0)$$

$$P[X=1] = p = p(1)$$

$X = 1 \iff$  we win

$X = 0 \iff$  we lose

$$\begin{aligned} E[X] &= \sum_i x_i P[X=x_i] = 0 \cdot p(0) + 1 \cdot p(1) \\ &= p \end{aligned}$$

$$\text{Var}[X] = \mathbb{E}[(X - \mathbb{E}[X])^2]$$

always true

$$= \mathbb{E}[X^2] - (\mathbb{E}[X])^2$$

$$\mathbb{E}[g(X)] = \sum_i g(x_i) \cdot P[X=x_i]$$

$\int_{-\infty}^{+\infty} g(x) \cdot f_x(x) dx$

Bernoulli:

$$\mathbb{E}[X^2] = 0^2 \cdot p(0) + 1^2 \cdot p(1)$$

$$= p$$

$$\text{Var}[X] = p - (p)^2 = p - p^2 = p(1-p)$$

- Binomial r.v.

Bernoulli :  $A \in \mathcal{S}$   
 $P[A] = p$

$\times$  Bernoulli r.v.

$X = \mathbb{1}_A$  indicator function

$\mathbb{1}_A : \mathcal{S} \rightarrow \mathbb{R}$

$$\mathbb{1}_A(\omega) = \begin{cases} 1 & \omega \in A \\ 0 & \omega \notin A \end{cases}$$

(Prove)

$$E[\mathbb{1}_A] = P[A] = p$$

[

$A_1, A_2, \dots, A_n \in \mathcal{S}$ , independent and

s.t.  $P[A_i] = p \quad \forall i = 1, \dots, n$ .

$Y$  = Binomial random variable of parameters  
 $p$  and  $n$

$Y$  counts the total number of events

few up  $A_1, \dots, A_n$  that occur.

$$\{0, 1, 2, \dots, n\} \ni Y$$

$$P[Y = k] = \binom{n}{k} p^k (1-p)^{n-k}$$

$$k \in \{0, 1, \dots, n\}$$

$\underbrace{A_1, A_2, \dots, A_n}$

exactly  $k$  occurs.

Binomial coeff.

$$\binom{n}{k} = \frac{n!}{k!(n-k)!}$$

$$n! = n(n-1)(n-2) \dots 2 \cdot 1$$

## Continuous r.v.

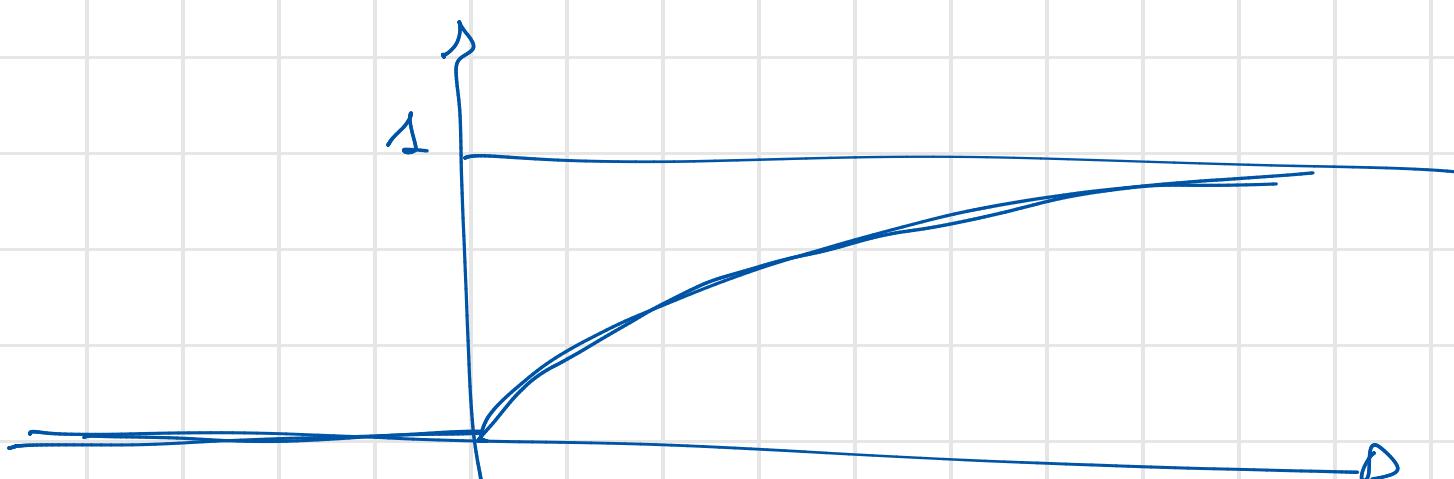
- Normal

- Exponential

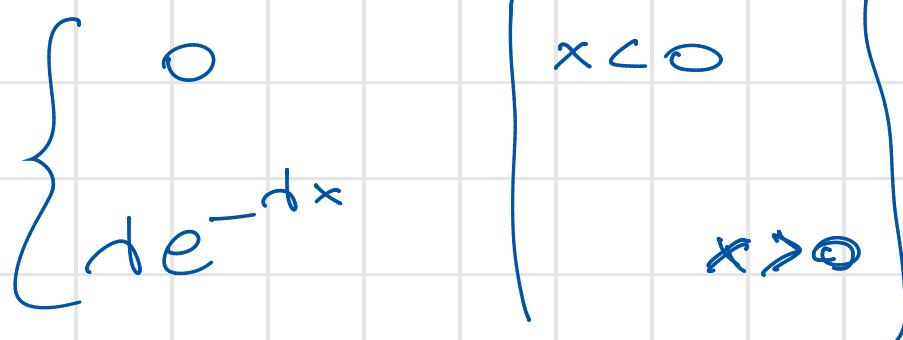
$$\lambda \in (0, +\infty)$$

$X$  is an exponential r.v. with parameter  $\lambda$

$$F_X(x) = \begin{cases} 0 & x < 0 \\ 1 - e^{-\lambda x} & x \geq 0 \end{cases}$$



$$f_X(x) = \frac{d}{dx} F_X(x) = \begin{cases} 0 & x < 0 \\ \lambda e^{-\lambda x} & x \geq 0 \end{cases}$$



$$F_X = \int f$$

$$f = \frac{d}{dx} F$$

$$E[X] = \frac{1}{\lambda}, \quad \text{Var}[X] = \frac{1}{\lambda^2}$$

Memory less property

$$s, t > 0$$

$$P[X > s+t | X > t] = P[X > s]$$

$$\frac{P[X > s+t, X > t]}{P[X > t]}$$

$$= \frac{P[X > s+t]}{P[X > t]} = \frac{e^{-\lambda(s+t)}}{e^{-\lambda t}}$$

$$(X > s+t) \subseteq (X > t)$$

$$= e^{-\lambda s - \lambda t + \lambda t} \\ = e^{-\lambda s} = P[X > s]$$

$$X > 0$$

$$F(x) = 1 - e^{-\lambda x} = P[X \leq x]$$

$$P[X > x] = 1 - P[X \leq x] = e^{-\lambda x}$$

The exponential distribution is the only random variable that satisfies the memoryless property !!

$$\boxed{P[X > s+t] = P[X > s] \cdot P[X > t]}$$

Euler equation

$$g(s+t) = g(s) \cdot g(t) \quad s, t \geq 0$$

$$g(s) = e^{-\lambda s}$$

- Conditional probability and  
Conditional expectation.

$$P[A|B] = \frac{P[A \cap B]}{P[B]}$$

$(X, Y)$  joint discrete r. vector

$$P_{X,Y}(x,y) = P[X=x, Y=y]$$

Joint mass function

$$P_{X|Y}(x|y) = \frac{P[X=x, Y=y]}{P[Y=y]} = \frac{P_{X,Y}(x,y)}{P_Y(y)}$$

Conditional probability mass function

if  $P_Y(y) \neq 0$

fixed  $y$  s.t.  $P_Y(y) > 0$

$x \mapsto P_{X|Y}(x|y)$  is  $\geq$  prob. mass function

$$\mathbb{E}[g(x) \mid Y=y] := \sum_{\substack{x \\ (\times)}} g(x) P_{X|Y}(x|y)$$

$$\mathbb{E}[g(x)] = \sum_y \mathbb{E}[g(x) \mid Y=y] \cdot P_Y(y)$$

$\parallel$

$$\boxed{\mathbb{E}[\mathbb{E}[g(x) \mid Y]]}$$

$$h(y) = \mathbb{E}[g(x) \mid Y=y]$$

$$\mathbb{E}[g(x) \mid Y] := h(Y)$$

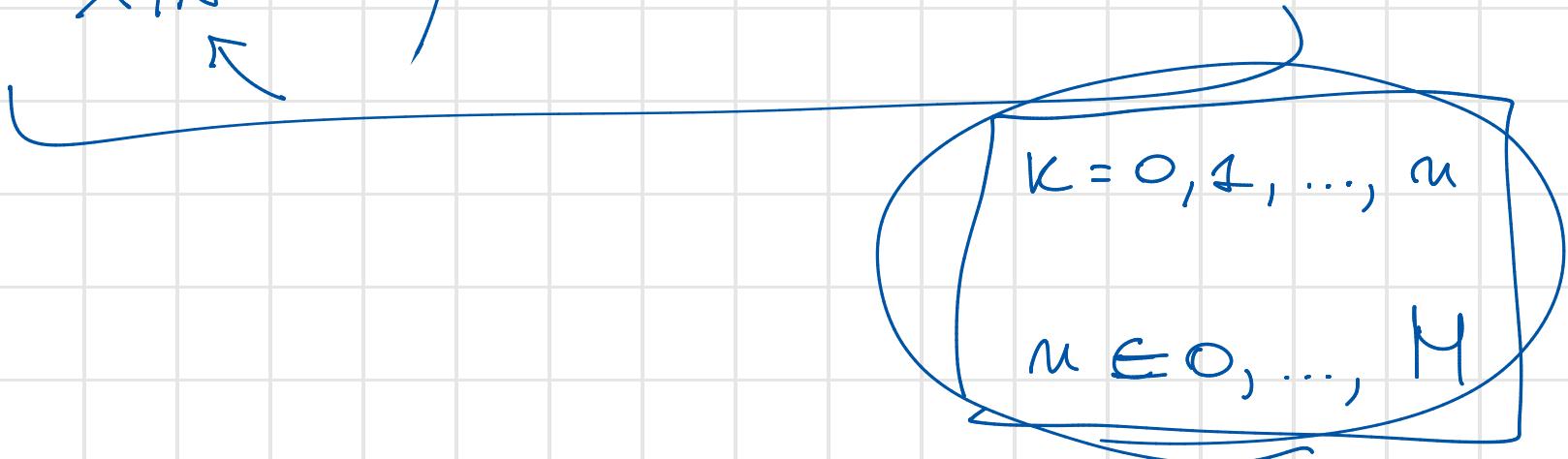
Example

$X$  binomial r.v. with  
parameter  $p$  and  $N$

$$X \sim \text{Bin}(p, N)$$

$$N \sim \text{Bin}(q, M)$$

$$\rightarrow P_{X|N}(k|\mu) = \binom{\mu}{k} p^k (1-p)^{\mu-k}$$



$$\rightarrow P_N(\mu) = \binom{M}{\mu} q^\mu (1-q)^{M-\mu}$$

$$P[X=k] = \sum_m P[X=k, N=\mu] = \sum_{\mu \in \mathbb{N}} P_{X|N}(x|\mu) P_N(\mu)$$

marginal distribution

$$P_{X,N}(x|\mu) = \frac{P_{X|N}(x|\mu)}{P_N(\mu)}$$

$$P_{X,N}(x|\mu) = P_{X|N}(x|\mu) \cdot P_N(\mu)$$

$$= \sum_{n=0}^M P_{X|N}(x|n) \cdot P_N(n)$$

$$= \sum_{n=0}^M \binom{M}{n} p^n (1-p)^{M-n} \cdot \binom{M}{n} q^n (1-q)^{M-n}$$

$$= \dots = \binom{M}{k} (pq)^k (1-pq)^{M-k} \quad k=0, \dots, M$$

$$X \sim \text{Bin}(pq, M)$$

$$P[X_1=x_1, X_2=x_2] = P[X_2=x_2 | X_1=x_1] \cdot P[X_1=x_1]$$

↑

↑

1 → 2 → 3 → 4

