

# Session 13

# Recall...

13.1

## Ex. 1 Gaussian RV

A RV  $X$  is Gaussian if it has a pdf of the form

$$f_X(x) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left\{-\frac{(x-\mu)^2}{2\sigma^2}\right\}, \forall x \in \mathbb{R}$$

where  $\mu \in \mathbb{R}$  and  $\sigma > 0$ .

n.b.  $F_X(x) = \int_{-\infty}^x f_X(\alpha) d\alpha = \Phi\left(\frac{x-\mu}{\sigma}\right)$   $\left( G\left(\frac{x-\mu}{\sigma}\right) \right)$   
in Popoulis

where  $\Phi(r) = \int_{-\infty}^r \frac{1}{\sqrt{2\pi}} e^{-z^2/2} dz$

$\mathcal{N}[\mu, \sigma^2]$

Recall...

Ex. 2 Uniformly Distributed RV

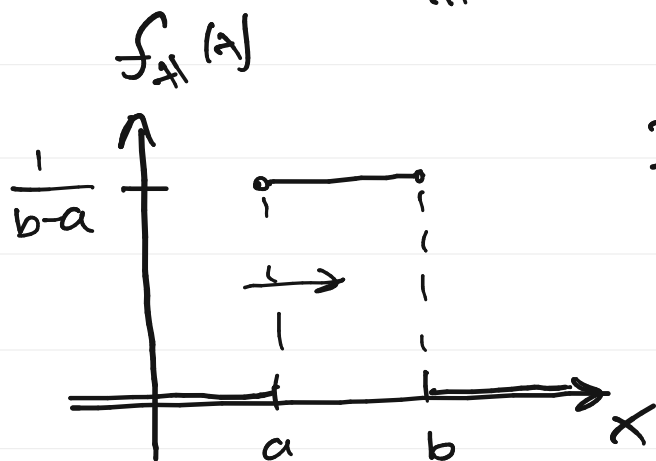
13.2

A RV has a uniform distribution,

$$X \sim U[a, b], \quad a < b$$

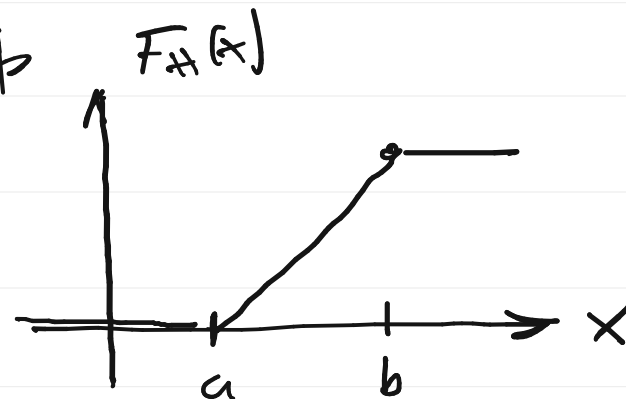
if

$$f_{\#}(x) = \frac{1}{b-a} \cdot \mathbb{1}_{[a, b]}(x)$$



Integrate

$\Rightarrow$



### Ex. 3 Binomially Distributed RV

13.3

A binomially distributed RV is a discrete RV taking on values in the set  $\{0, 1, 2, \dots, n\} \subset \mathbb{R}$

with pmf

$$P_{\#}(k) = \binom{n}{k} p^k (1-p)^{n-k}, \quad k=0, 1, 2, \dots, n$$

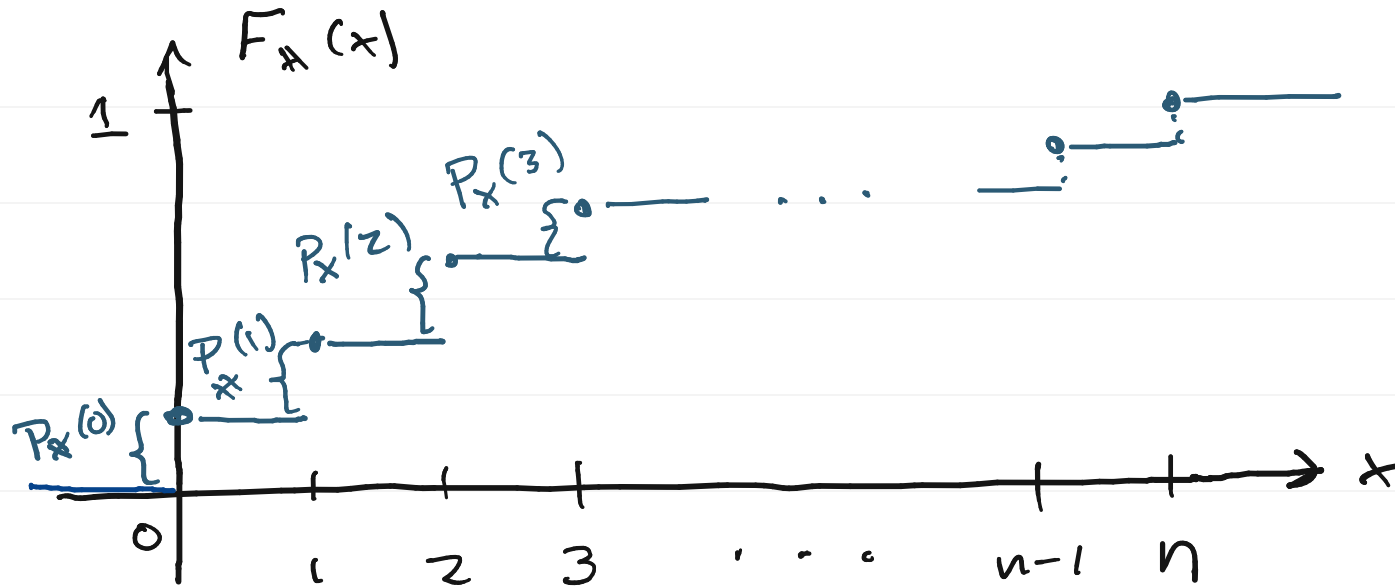
$p \in [0, 1]$

The cdf of this RV is

$$F_{\#}(x) = P(\{X \leq x\}) = \sum_{k=0}^{m(x)} \binom{n}{k} p^k (1-p)^{n-k}$$

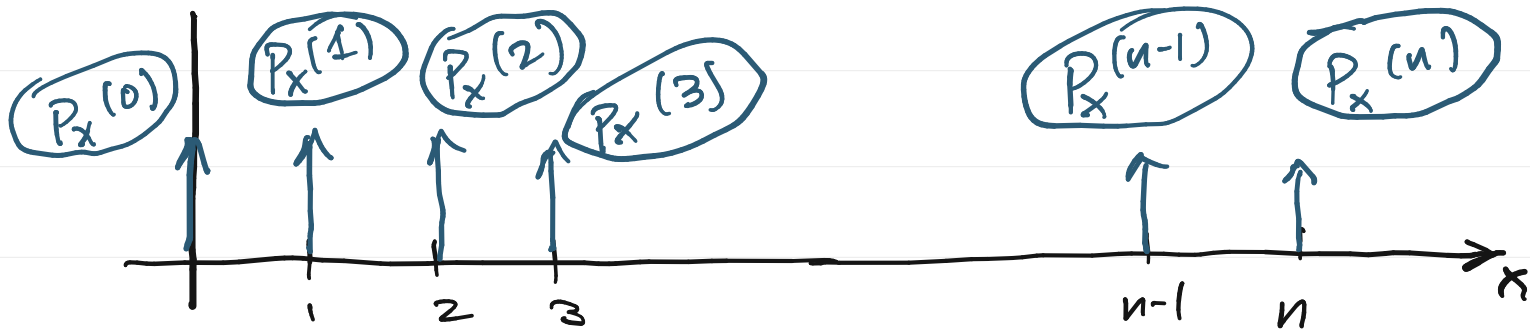
where  $m(x)$  is an integer such that

$$m(x) \leq x < m(x) + 1.$$



$$f_X(x) = \frac{dF_X(x)}{dx} = \sum_{k=0}^n P_X(k) \delta(x-k)$$

$$= \sum_{k=0}^n \binom{n}{k} p^k (1-p)^{n-k} \delta(x-k)$$



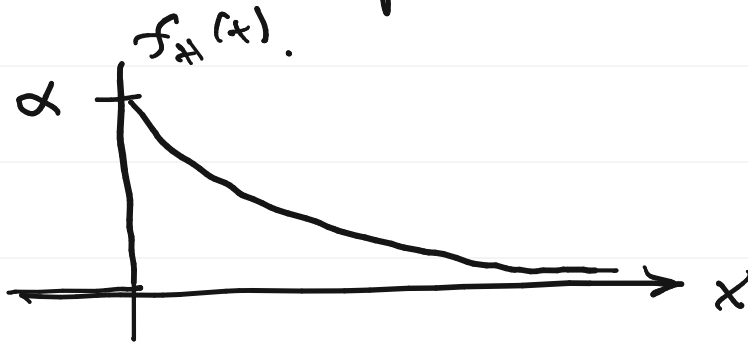
## Ex. 4 Exponentially Distributed RV

13.5

A RV  $X$  with a pdf of the form

$$f_{\#}(x) = \alpha e^{-\alpha x} \cdot \mathbb{1}_{[0, \infty)}(x) = \begin{cases} \alpha e^{-\alpha x}, & x \geq 0 \\ 0, & x < 0 \end{cases}$$

where  $\alpha > 0$  is called the parameter of the exponential RV.



See examples of other types  
of RVs in Papoulis

13.6

You should know the following pdfs  
and pmfs:

pmfs

Binomial  
Poisson  
Geometric

pdfs

Gaussian  
Exponential  
Uniform

## Conditional Distributions

13.7

Given  $(\mathcal{S}, \mathcal{F}, P)$  with a RV  $X$  defined on it, and given  $A, M \in \mathcal{F}$ , we know that

$$P(A|M) = \frac{P(A \cap M)}{P(M)}, \quad P(M) > 0.$$

Take  $A = \{X \leq x\} = \{\omega \in \mathcal{S} : X(\omega) \leq x\}$

Then  $P(A|M) = P(\{X \leq x\} | M)$

This is a conditional cdf of  $X$  conditioned on the event  $M \in \mathcal{F}$ .



Defn: The conditional cdf of the  
RV  $X$  conditioned on  $M \in \mathcal{F}$  is

13.8

$$F_{\#}(x|M) = P(\{X \leq x\} | M) \\ = \frac{P(\{X \leq x\} \cap M)}{P(M)}, \quad x \in \mathbb{R}$$

The defn. of  $F_{\#}(x|M)$  is just like the defn. of  $F_{\#}(x)$ , except we use the conditional prob. measure  $P(\cdot|M)$  instead of  $P(\cdot)$ .

$P(\cdot | M) \implies F_{\#}(x | M)$   
is a valid prob. measure      is a valid cdf

$\therefore F_{\#}(x | M)$  has all the properties of a valid cdf.

e.g.  $P(\{a < X \leq b\} | M) = F_{\#}(b | M) - F_{\#}(a | M)$

Defn: The conditional probability density function (conditional pdf) of  $X$  conditioned on  $M \in \mathcal{F}$  is

$$f_{X|M}(x|M) \triangleq \frac{dF_{X|M}(x|M)}{dx}.$$

n.b.  $F_{X|M}(x|M)$  is a valid cdf  $\xRightarrow{\frac{d}{dx}}$   $f_{X|M}(x|M)$  is a valid pdf

e.g.  $P(\{a < X \leq b\} | M) = \int_a^b f_{X|M}(x|M) dx$

In general, we must know the underlying structure of  $(\Omega, \mathcal{F}, P)$  and the mapping  $X$  to determine  $F_X(X|M)$  or  $f_X(X|M)$ .

But sometimes we can describe the event  $M \in \mathcal{F}$  in terms of the RV  $X$ .

e.g. 1.  $M = \{X \leq a\}$ ,  $a \in \mathbb{R}$ .

2.  $M = \{b < X \leq a\}$ ,  $a, b \in \mathbb{R}$   
 $b <$

1. Let  $M = \{X \leq a\}$ ,  $a \in \mathbb{R}$

13.12

$$\begin{aligned} F_{\#}(x|M) &= P(\{X \leq x\} | \{X \leq a\}) \\ &= \frac{P(\{X \leq x\} \cap \{X \leq a\})}{P(\{X \leq a\})} \end{aligned}$$

TWO CASES:  $x > a$  and  $x \leq a$ .

1. Let  $M = \{X \leq a\}$

(a)  $x > a$


$$\underline{\{X \leq x\}} \cap \underline{\{X \leq a\}} = \underline{\{X \leq a\}}$$



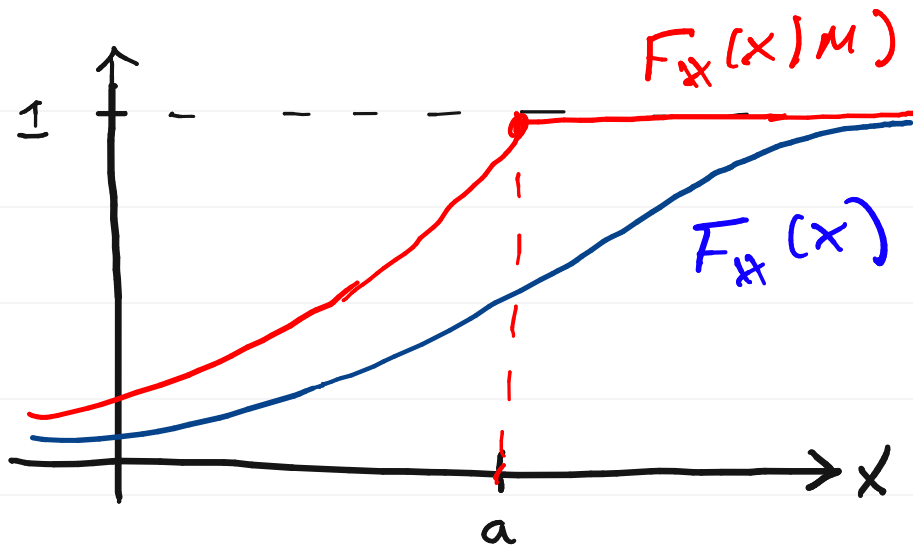
$$F_X(x|M) = \frac{P(\{X \leq a\})}{P(\{X \leq a\})} = \frac{F_X(a)}{F_X(a)} = 1$$

(b): IF  $x \leq a$ :

$$\underline{\{X \leq x\}} \cap \underline{\{X \leq a\}} = \underline{\{X \leq x\}}$$

$$F_{X|M}(x) = \frac{P(\{X \leq x\})}{P(\{X \leq a\})} = \frac{F_X(x)}{F_X(a)}$$


$$\therefore F_{X|M}(x) = \begin{cases} \frac{F_X(x)}{F_X(a)}, & x \leq a \\ 1, & x > a \end{cases}$$



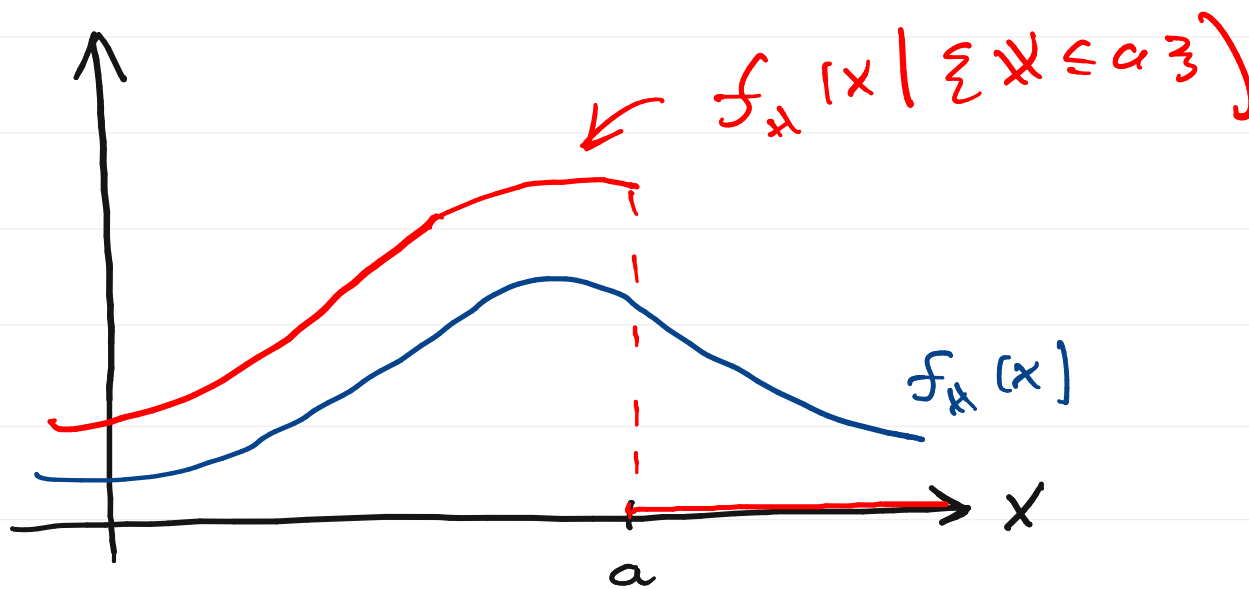
Conditional pdf:

$$f_X(x|M) = \frac{\int F_X(x | \{x \leq a\})}{dx}$$

$$= \begin{cases} \frac{f_X(x)}{F_X(a)}, & x \leq a \\ 0, & x > a \end{cases}$$



13.16



2.  $M = \{b < X \leq a\}$ ,  $b < a$ .

13.17

$$\begin{aligned} F_X(x|M) &= P(\{X \leq x\} | \{b < X \leq a\}) \\ &= \frac{P(\{X \leq x\} \cap \{b < X \leq a\})}{P(\{b < X \leq a\})} \end{aligned}$$

Three distinct regions:

(a)  $x > a$

(b)  $b < x \leq a$

(c)  $x \leq b$



Analyzing these 3 cases, we get  
(exercise)

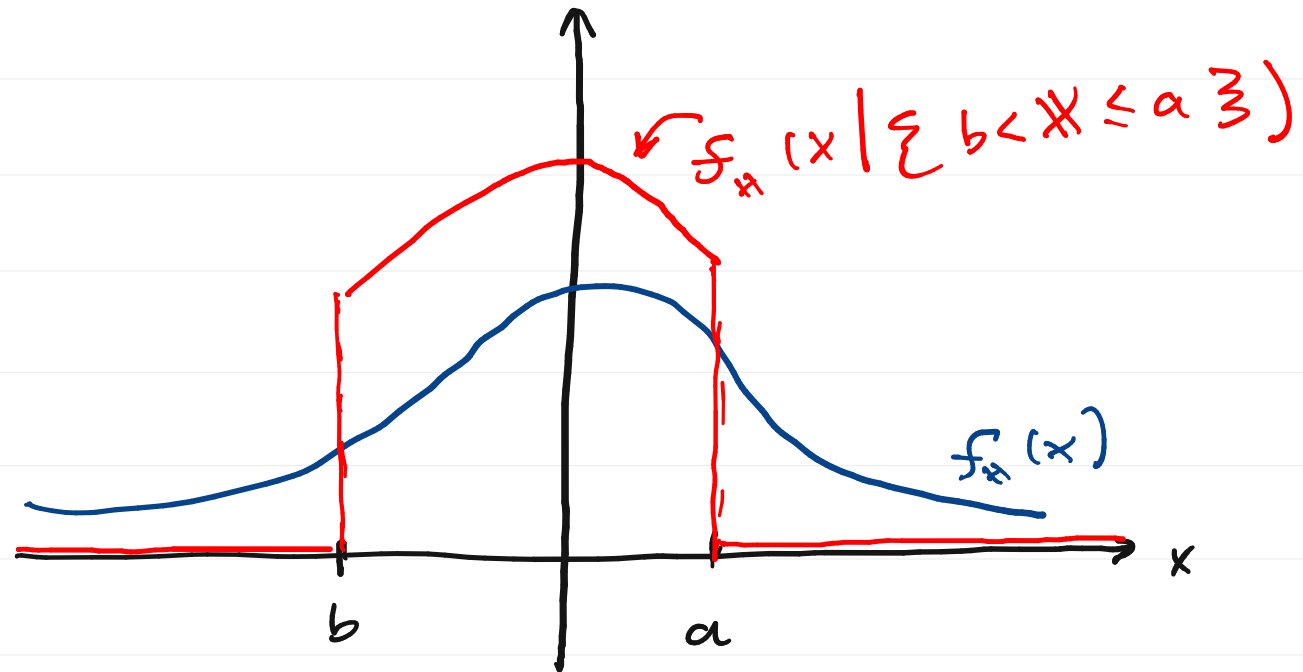
$$F_X(x|M) = \begin{cases} 1, & x > a \\ 0, & x \leq b \\ \frac{F_X(x) - F_X(b)}{F_X(a) - F_X(b)}, & b < x \leq a \end{cases}$$

The corresponding conditional pdf is

$$f_X(x | \{b < X \leq a\}) = \frac{dF_X(x | \{b < X \leq a\})}{dx}$$

$$= \begin{cases} 0, & x > a \\ 0, & x \leq b \\ \frac{f_X(x)}{F_X(a) - F_X(b)}, & b < x \leq a \end{cases}$$

A picture of these pdfs appears  
as follows:



## The Total Prob. Law and Bayes Theorem

13.20

Given a RV  $X$  on  $(\mathcal{S}, \mathcal{F}, P)$ , let  $\{A_1, \dots, A_n\}$  be a partition of  $\mathcal{S}$ , with  $A_k \in \mathcal{F}$ ,  $k=1, \dots, n$ .

Then

$$P(\{X \leq x\}) = P(\{X \leq x\} | A_1) P(A_1) + P(\{X \leq x\} | A_2) P(A_2) \\ + \dots + P(\{X \leq x\} | A_n) P(A_n) \quad \dots (1)$$

But note that

$$P(\{X \leq x\}) = F_X(x)$$

$$P(\{X \leq x\} | A_k) = F_X(x | A_k)$$

$$\therefore F_{\#}(x) = F_{\#}(x|A_1)P(A_1) + F_{\#}(x|A_2)P(A_2) + \dots + F_{\#}(x|A_n)P(A_n) \quad \text{--- (1A)}$$

note  $f_{\#}(x) = \frac{dF_{\#}(x)}{dx}$

and  $f_{\#}(x|A_k) = \frac{dF_{\#}(x|A_k)}{dx}$

$$\Rightarrow f_{\#}(x) = f_{\#}(x|A_1)P(A_1) + f_{\#}(x|A_2)P(A_2) + \dots + f_{\#}(x|A_n)P(A_n) \quad \text{--- (1B)}$$

2. Recall Bayes Formula:

13.22

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

Let  $B = \{X \leq x\}$ . Then

$$\begin{aligned} P(A | \{X \leq x\}) &= \frac{P(\{X \leq x\} | A) P(A)}{P(\{X \leq x\})} \\ &= \frac{F_{\#}(x|A) P(A)}{F_{\#}(x)} \end{aligned}$$

$$\therefore P(A | \{X \leq x\}) = \frac{F_{\#}(x|A) P(A)}{F_{\#}(x)}$$