

## Lecture 4: Random Variable, Part II

Yi, Yung (이웅)

EE210: Probability and Introductory Random Processes  
KAIST EE

August 31, 2021

- (1) Continuous Random Variable and PDF (Probability Density Function)
- (2) CDF (Cumulative Distribution Function)
- (3) Exponential RVs
- (4) Gaussian (Normal) RVs
- (5) Continuous RVs: Joint, Conditioning, and Independence
- (6) Bayes' rule for RVs

- (1) Continuous Random Variable and PDF (Probability Density Function)
- (2) CDF (Cumulative Distribution Function)
- (3) Exponential RVs
- (4) Gaussian (Normal) RVs
- (5) Continuous RVs: Joint, Conditioning, and Independence
- (6) Bayes' rule for RVs



- Many cases when random variables have “continuous values”, e.g., velocity of a car



- Many cases when random variables have “continuous values”, e.g., velocity of a car

A rv  $X$  is **continuous** if  $\exists$  a function  $f_X$ , called **probability density function (PDF)**, s.t.

$$\mathbb{P}(X \in B) = \int_B f_X(x) dx, \quad \text{every subset } B \in \mathbb{R}$$

- Many cases when random variables have “continuous values”, e.g., velocity of a car

A rv  $X$  is **continuous** if  $\exists$  a function  $f_X$ , called **probability density function (PDF)**, s.t.

$$\mathbb{P}(X \in B) = \int_B f_X(x) dx, \quad \text{every subset } B \in \mathbb{R}$$

- All of the concepts and methods (expectation, PMFs, and conditioning) for discrete rvs have continuous counterparts

- Many cases when random variables have “continuous values”, e.g., velocity of a car

A rv  $X$  is **continuous** if  $\exists$  a function  $f_X$ , called **probability density function (PDF)**, s.t.

$$\mathbb{P}(X \in B) = \int_B f_X(x) dx, \quad \text{every subset } B \in \mathbb{R}$$

- All of the concepts and methods (expectation, PMFs, and conditioning) for discrete rvs have continuous counterparts



- $\mathbb{P}(a \leq X \leq b) = \sum_{x:a \leq x \leq b} p_X(x)$
- $p_X(x) \geq 0, \sum_x p_X(x) = 1$

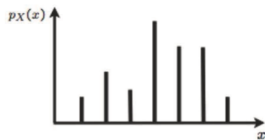


- Many cases when random variables have “continuous values”, e.g., velocity of a car

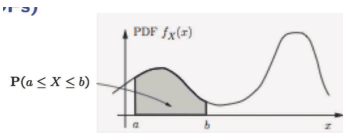
A rv  $X$  is **continuous** if  $\exists$  a function  $f_X$ , called **probability density function (PDF)**, s.t.

$$\mathbb{P}(X \in B) = \int_B f_X(x) dx, \quad \text{every subset } B \in \mathbb{R}$$

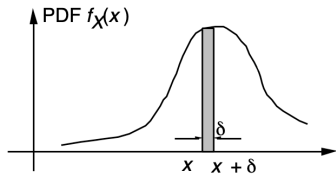
- All of the concepts and methods (expectation, PMFs, and conditioning) for discrete rvs have continuous counterparts



- $\mathbb{P}(a \leq X \leq b) = \sum_{x:a \leq x \leq b} p_X(x)$
- $p_X(x) \geq 0, \sum_x p_X(x) = 1$

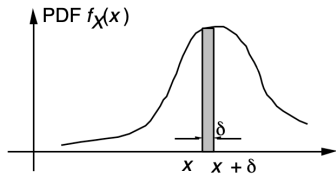


- $\mathbb{P}(a \leq X \leq b) = \int_a^b f_X(x) dx$
- $f_X(x) \geq 0, \int_{-\infty}^{\infty} f_X(x) dx = 1$



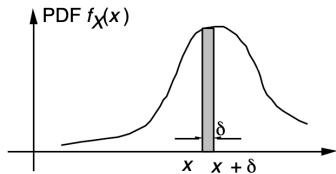
- $\mathbb{P}(a \leq X \leq a + \delta) \approx$

Examples



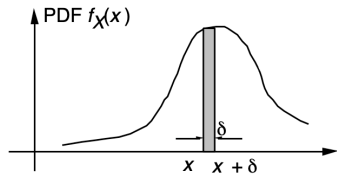
- $\mathbb{P}(a \leq X \leq a + \delta) \approx f_X(a) \cdot \delta$

## Examples



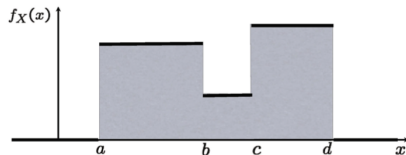
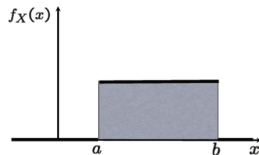
- $\mathbb{P}(a \leq X \leq a + \delta) \approx f_X(a) \cdot \delta$
- $\mathbb{P}(X = a) = 0$

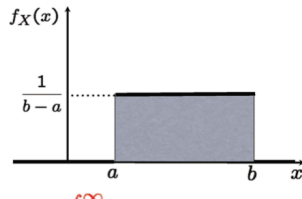
## Examples



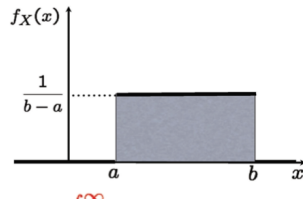
- $\mathbb{P}(a \leq X \leq a + \delta) \approx f_X(a) \cdot \delta$
- $\mathbb{P}(X = a) = 0$

## Examples

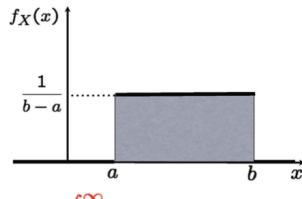




- $\mathbb{E}[X] = \int_{-\infty}^{\infty} x f_X(x) dx =$
- $\mathbb{E}[X^2] = \int_{-\infty}^{\infty} x^2 f_X(x) dx =$
- $\text{var}[X] =$

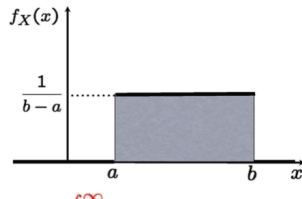


- $\mathbb{E}[X] = \int_{-\infty}^{\infty} x f_X(x) dx = \int_a^b \frac{x}{b-a} dx = \frac{1}{b-a} \frac{b^2 - a^2}{2} = \frac{b+a}{2}$
- $\mathbb{E}[X^2] = \int_{-\infty}^{\infty} x^2 f_X(x) dx =$
- $\text{var}[X] =$



- $\mathbb{E}[X] = \int_{-\infty}^{\infty} x f_X(x) dx = \int_a^b \frac{x}{b-a} dx = \frac{1}{b-a} \frac{b^2 - a^2}{2} = \frac{b+a}{2}$
- $\mathbb{E}[X^2] = \int_{-\infty}^{\infty} x^2 f_X(x) dx = \int_a^b \frac{x^2}{b-a} dx = \frac{1}{b-a} \frac{b^3 - a^3}{3} = \frac{a^2 + ab + b^2}{3}$
- $\text{var}[X] =$





- $\mathbb{E}[X] = \int_{-\infty}^{\infty} x f_X(x) dx = \int_a^b \frac{x}{b-a} dx = \frac{1}{b-a} \frac{b^2 - a^2}{2} = \frac{b+a}{2}$
- $\mathbb{E}[X^2] = \int_{-\infty}^{\infty} x^2 f_X(x) dx = \int_a^b \frac{x^2}{b-a} dx = \frac{1}{b-a} \frac{b^3 - a^3}{3} = \frac{a^2 + ab + b^2}{3}$
- $\text{var}[X] = \frac{a^2 + ab + b^2}{3} - \frac{a^2 + 2ab + b^2}{4}$

- (1) Continuous Random Variable and PDF (Probability Density Function)
- (2) CDF (Cumulative Distribution Function)
- (3) Exponential RVs
- (4) Gaussian (Normal) RVs
- (5) Continuous RVs: Joint, Conditioning, and Independence
- (6) Bayes' rule for RVs

- Discrete: PMF, Continuous: PDF

- Discrete: PMF, Continuous: PDF
- Can we describe all rvs with a single mathematical concept?

- Discrete: PMF, Continuous: PDF
- Can we describe all rvs with a single mathematical concept?

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

$$\begin{cases} \sum_{k \leq x} p_X(k), & \text{discrete} \\ \int_{-\infty}^x f_X(t) dt, & \text{continuous} \end{cases}$$

- Discrete: PMF, Continuous: PDF
- Can we describe all rvs with a single mathematical concept?

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

$$\begin{cases} \sum_{k \leq x} p_X(k), & \text{discrete} \\ \int_{-\infty}^x f_X(t) dt, & \text{continuous} \end{cases}$$

- always well defined, because we can always compute the probability for the event  $\{X \leq x\}$

- Discrete: PMF, Continuous: PDF
- Can we describe all rvs with a single mathematical concept?

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

$$\begin{cases} \sum_{k \leq x} p_X(k), & \text{discrete} \\ \int_{-\infty}^x f_X(t) dt, & \text{continuous} \end{cases}$$

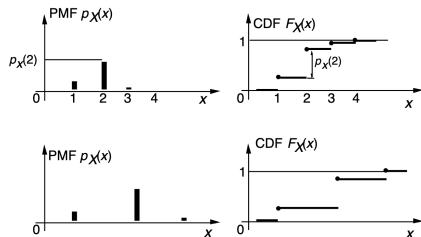
- always well defined, because we can always compute the probability for the event  $\{X \leq x\}$
- CCDF (Complementary CDF):  $\mathbb{P}(X > x)$

- Discrete: PMF, Continuous: PDF
- Can we describe all rvs with a single mathematical concept?

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

$$\begin{cases} \sum_{k \leq x} p_X(k), & \text{discrete} \\ \int_{-\infty}^x f_X(t) dt, & \text{continuous} \end{cases}$$

- always well defined, because we can always compute the probability for the event  $\{X \leq x\}$
- CCDF (Complementary CDF):  $\mathbb{P}(X > x)$



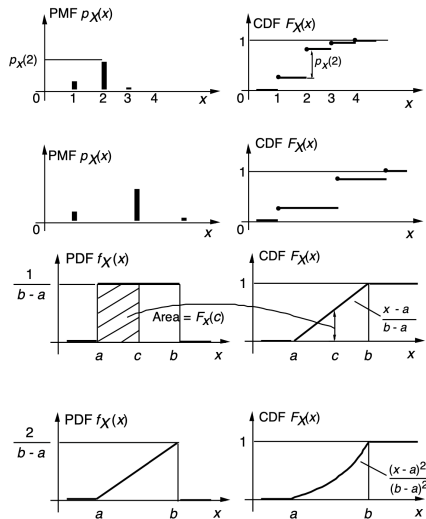


- Discrete: PMF, Continuous: PDF
- Can we describe all rvs with a single mathematical concept?

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

$$\begin{cases} \sum_{k \leq x} p_X(k), & \text{discrete} \\ \int_{-\infty}^x f_X(t) dt, & \text{continuous} \end{cases}$$

- always well defined, because we can always compute the probability for the event  $\{X \leq x\}$
- CCDF (Complementary CDF):  $\mathbb{P}(X > x)$





- Non-decreasing

- Non-decreasing
- $F_X(x)$  tends to 1, as  $x \rightarrow \infty$  and  $F_X(x)$  tends to 0, as  $x \rightarrow -\infty$

- Non-decreasing
- $F_X(x)$  tends to 1, as  $x \rightarrow \infty$  and  $F_X(x)$  tends to 0, as  $x \rightarrow -\infty$
- If  $X$  is discrete,
  - $F_X(x)$  is a piecewise constant function of  $x$ .
  - $p_X(k) = F_X(k) - F_X(k - 1)$

- Non-decreasing
- $F_X(x)$  tends to 1, as  $x \rightarrow \infty$  and  $F_X(x)$  tends to 0, as  $x \rightarrow -\infty$
- If  $X$  is discrete,
  - $F_X(x)$  is a piecewise constant function of  $x$ .
  - $p_X(k) = F_X(k) - F_X(k - 1)$
- If  $X$  is continuous
  - $F_X(x)$  is a continuous function of  $x$ .
  - $F_X(x) = \int_{-\infty}^x f_X(t)dt$  and  $f_X(x) = \frac{dF_X}{dx}(x)$

- Take a test three times, and your final score will be the maximum of test scores
- $X = \max\{X_1, X_2, X_3\}$ , and  $X_i \in \{1, 2, \dots, 10\}$  uniformly at random
- **Question.**  $p_X(x)$ ?
- Approach 1:  $\mathbb{P}(\max\{X_1, X_2, X_3\} = x)$ ?
- Approach 2

$$\begin{aligned} F_X(x) &= \mathbb{P}(\max\{X_1, X_2, X_3\} \leq x) = \mathbb{P}(X_1 \leq x, X_2 \leq x, X_3 \leq x) \\ &= \mathbb{P}(X_1 \leq x) \cdot \mathbb{P}(X_2 \leq x) \cdot \mathbb{P}(X_3 \leq x) = \left(\frac{x}{10}\right)^3 \end{aligned}$$

Thus,

$$p_X(x) = \left(\frac{x}{10}\right)^3 - \left(\frac{x-1}{10}\right)^3, \quad x = 1, 2, \dots, 10$$

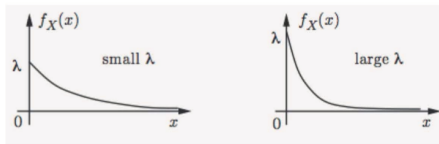
- (1) Continuous Random Variable and PDF (Probability Density Function)
- (2) CDF (Cumulative Distribution Function)
- (3) Exponential RVs
- (4) Gaussian (Normal) RVs
- (5) Continuous RVs: Joint, Conditioning, and Independence
- (6) Bayes' rule for RVs





- A rv  $X$  is called **exponential with  $\lambda$** , if

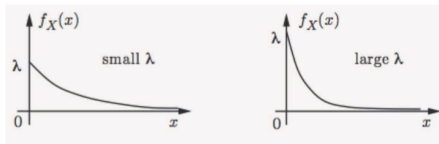
$$f_X(x) = \begin{cases} \lambda e^{-\lambda x}, & x \geq 0 \\ 0, & x < 0 \end{cases}$$



- A rv  $X$  is called **exponential with  $\lambda$** , if

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

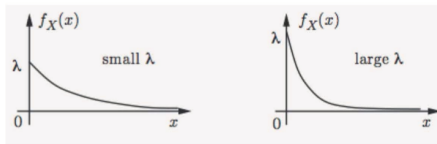
- CDF  $F_X(x) = \int_0^x \lambda e^{-\lambda s} ds = 1 - e^{-\lambda x}$



- A rv  $X$  is called **exponential with  $\lambda$** , if

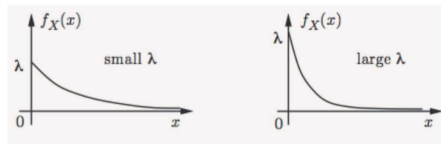
$$f_X(x) = \begin{cases} \lambda e^{-\lambda x}, & x \geq 0 \\ 0, & x < 0 \end{cases}$$

- CDF  $F_X(x) = \int_0^x \lambda e^{-\lambda s} ds = 1 - e^{-\lambda x}$
- CCDF  $\mathbb{P}(X > x) = e^{-\lambda x}$



- A rv  $X$  is called **exponential with  $\lambda$** , if

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



- CDF  $F_X(x) = \int_0^x \lambda e^{-\lambda s} ds = 1 - e^{-\lambda x}$
- CCDF  $\mathbb{P}(X > x) = e^{-\lambda x}$
- (Check)  $\mathbb{E}[X] = 1/\lambda$ ,  $\mathbb{E}[X^2] = 2/\lambda^2$ ,  $\text{var}[X] = 1/\lambda^2$

- $\mathbb{E}(X) = 1/\lambda$ . Use **integration by parts**:  $\int u dv = uv - \int v du$

$$\int_0^{\infty} x \lambda e^{-\lambda x} dx = (-x e^{-\lambda x}) \Big|_0^{\infty} + \int_0^{\infty} e^{-\lambda x} dx = 0 - \frac{e^{-\lambda x}}{\lambda} \Big|_0^{\infty} = \frac{1}{\lambda}$$

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

$$\int_0^{\infty} x^2 \lambda e^{-\lambda x} dx = (-x^2 e^{-\lambda x}) \Big|_0^{\infty} + \int_0^{\infty} 2x e^{-\lambda x} dx = 0 + \frac{2}{\lambda} \mathbb{E}(X) = \frac{2}{\lambda^2}$$

- $\text{var}(X) = \mathbb{E}(X^2) - (\mathbb{E}(X))^2 = \frac{1}{\lambda^2}$

- $\mathbb{P}(X > x) = e^{-\lambda x}$

- $\mathbb{P}(X > x) = e^{-\lambda x}$
- Appropriate for modeling a waiting time until an incident of interest takes place
  - $\mathbb{P}(X > x)$ : exponentially decays
  - message arriving at a computer, some equipment breaking down, a light bulb burning out, etc



- $\mathbb{P}(X > x) = e^{-\lambda x}$
- Appropriate for modeling a waiting time until an incident of interest takes place
  - $\mathbb{P}(X > x)$ : exponentially decays
  - message arriving at a computer, some equipment breaking down, a light bulb burning out, etc
- (Q) What is the discrete rv which models a waiting time? Geometric

- $\mathbb{P}(X > x) = e^{-\lambda x}$
- Appropriate for modeling a waiting time until an incident of interest takes place
  - $\mathbb{P}(X > x)$ : exponentially decays
  - message arriving at a computer, some equipment breaking down, a light bulb burning out, etc
- (Q) What is the discrete rv which models a waiting time? Geometric
- What is the relationship between exponential rv and geometric rv? We will see this relationship soon, but let's look at an example first.

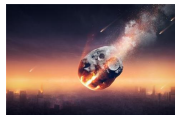
- A very small meteorite first lands anywhere in Korea



- A very small meteorite first lands anywhere in Korea
- Time of landing is modeled as an exponential rv with mean 10 days



- A very small meteorite first lands anywhere in Korea
- Time of landing is modeled as an exponential rv with mean 10 days
- The current time is midnight. What is the probability that a meteorite first lands some time between 6 a.m. and 6 p.m. of the first day?



VIDEO PAUSE

- A very small meteorite first lands anywhere in Korea
- Time of landing is modeled as an exponential rv with mean 10 days
- The current time is midnight. What is the probability that a meteorite first lands some time between 6 a.m. and 6 p.m. of the first day?
- (Solution)
  - $\mathbb{E}(X) = 1/\lambda = 10$ . Thus,  $\lambda = \frac{1}{10}$ .



VIDEO PAUSE



- A very small meteorite first lands anywhere in Korea
- Time of landing is modeled as an exponential rv with mean 10 days
- The current time is midnight. What is the probability that a meteorite first lands some time between 6 a.m. and 6 p.m. of the first day?

VIDEO PAUSE

- (Solution)
  - $\mathbb{E}(X) = 1/\lambda = 10$ . Thus,  $\lambda = \frac{1}{10}$ .
  - 6 a.m. from midnight =  $1/4$  day, 6 p.m. from midnight =  $3/4$  day

$$\mathbb{P}(1/4 \leq X \leq 3/4) = \mathbb{P}(X \geq 1/4) - \mathbb{P}(X \geq 3/4) = e^{-1/40} - e^{-3/40} = 0.0476$$

- Models a system evolution over time: Continuous time vs. Discrete time.



- Models a system evolution over time: Continuous time vs. Discrete time.
  - **Example.** Customer arrivals at my shop
  - **Modeling 1:** Every 30 minute I record the number of customers for each 30-min window
  - **Modeling 2:** I record the exact time of each customer's arrival

- Models a system evolution over time: Continuous time vs. Discrete time.
  - **Example.** Customer arrivals at my shop
  - **Modeling 1:** Every 30 minute I record the number of customers for each 30-min window
  - **Modeling 2:** I record the exact time of each customer's arrival
  - In modeling 1, every 10 minute? every 1 minute? every 1 sec? every 0.0000001 sec?

- Models a system evolution over time: Continuous time vs. Discrete time.
  - **Example.** Customer arrivals at my shop
  - **Modeling 1:** Every 30 minute I record the number of customers for each 30-min window
  - **Modeling 2:** I record the exact time of each customer's arrival
  - In modeling 1, every 10 minute? every 1 minute? every 1 sec? every 0.0000001 sec?
- In many cases, continuous case is some type of **limit** of its corresponding discrete case.

- Models a system evolution over time: Continuous time vs. Discrete time.
  - **Example.** Customer arrivals at my shop
  - **Modeling 1:** Every 30 minute I record the number of customers for each 30-min window
  - **Modeling 2:** I record the exact time of each customer's arrival
  - In modeling 1, every 10 minute? every 1 minute? every 1 sec? every 0.0000001 sec?
- In many cases, continuous case is some type of **limit** of its corresponding discrete case.
- Can we mathematically describe how geometric and exponential rvs meet each other in the limit?

- 'slot' is one unit time, e.g., 1 hour, 30 mins, 1 min, 10 sec, etc.

- 'slot' is one unit time, e.g., 1 hour, 30 mins, 1 min, 10 sec, etc.
- Continuous system = Discrete system with
  - infinitely many slots whose duration is infinitely small.
  - success probability  $p$  over one slot decreases to 0 in the limit

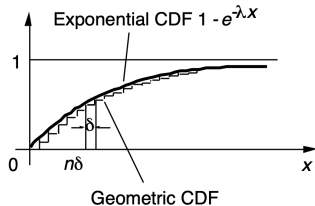
- 'slot' is one unit time, e.g., 1 hour, 30 mins, 1 min, 10 sec, etc.
- Continuous system = Discrete system with
  - infinitely many slots whose duration is infinitely small.
  - success probability  $p$  over one slot decreases to 0 in the limit
- Given  $X^{exp} \sim \exp(\lambda)$ , let us construct a geometric RV  $X_{\delta}^{geo}$

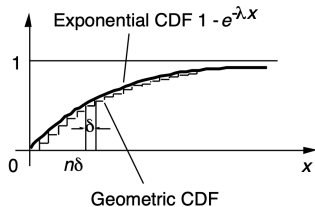
- 'slot' is one unit time, e.g., 1 hour, 30 mins, 1 min, 10 sec, etc.
- Continuous system = Discrete system with
  - infinitely many slots whose duration is infinitely small.
  - success probability  $p$  over one slot decreases to 0 in the limit
- Given  $X^{exp} \sim \exp(\lambda)$ , let us construct a geometric RV  $X_{\delta}^{geo}$ 
  - Set the length of a slot to be  $\delta$ , which is a parameter.



- 'slot' is one unit time, e.g., 1 hour, 30 mins, 1 min, 10 sec, etc.
- Continuous system = Discrete system with
  - infinitely many slots whose duration is infinitely small.
  - success probability  $p$  over one slot decreases to 0 in the limit
- Given  $X^{exp} \sim \exp(\lambda)$ , let us construct a geometric RV  $X_{\delta}^{geo}$ 
  - Set the length of a slot to be  $\delta$ , which is a parameter.
  - Set the success probability  $p_{\delta}$  over a slot to be  $p_{\delta} = 1 - e^{-\lambda\delta}$  (this looks magical, whose secret will be uncovered soon)

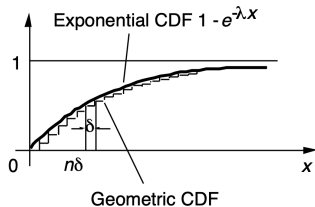
- 'slot' is one unit time, e.g., 1 hour, 30 mins, 1 min, 10 sec, etc.
- Continuous system = Discrete system with
  - infinitely many slots whose duration is infinitely small.
  - success probability  $p$  over one slot decreases to 0 in the limit
- Given  $X^{exp} \sim \exp(\lambda)$ , let us construct a geometric RV  $X_{\delta}^{geo}$ 
  - Set the length of a slot to be  $\delta$ , which is a parameter.
  - Set the success probability  $p_{\delta}$  over a slot to be  $p_{\delta} = 1 - e^{-\lambda\delta}$  (this looks magical, whose secret will be uncovered soon)
  - $\mathbb{P}(X_{\delta}^{geo} \leq n) = 1 - (1 - p_{\delta})^n = 1 - e^{-\lambda\delta n}$





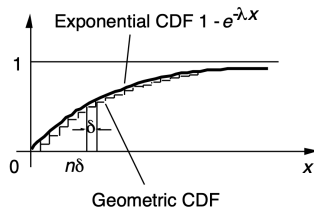
- Note that  $\mathbb{P}(X^{exp} \leq x) = 1 - e^{-\lambda x}$ . Then, when  $x = n\delta$ ,  $n = 1, 2, \dots$

$$\mathbb{P}(X^{exp} \leq x) = 1 - e^{-\lambda \delta n} =$$



- Note that  $\mathbb{P}(X^{exp} \leq x) = 1 - e^{-\lambda x}$ . Then, when  $x = n\delta$ ,  $n = 1, 2, \dots$

$$\mathbb{P}(X^{exp} \leq x) = 1 - e^{-\lambda \delta n} = \mathbb{P}(X_{\delta}^{geo} \leq n)$$



- Note that  $\mathbb{P}(X^{exp} \leq x) = 1 - e^{-\lambda x}$ . Then, when  $x = n\delta$ ,  $n = 1, 2, \dots$

$$\mathbb{P}(X^{exp} \leq x) = 1 - e^{-\lambda \delta n} = \mathbb{P}(X_{\delta}^{geo} \leq n)$$

- If we choose sufficiently small  $\delta$ , the slot length  $\downarrow$  and  $p_{\delta} \downarrow$

$$\mathbb{P}(X_{\delta}^{geo} \leq n) \xrightarrow{\delta \rightarrow 0} \mathbb{P}(X^{exp} \leq x), \quad x = n\delta$$

- (1) Continuous Random Variable and PDF (Probability Density Function)
- (2) CDF (Cumulative Distribution Function)
- (3) Exponential RVs
- (4) Gaussian (Normal) RVs
- (5) Continuous RVs: Joint, Conditioning, and Independence
- (6) Bayes' rule for RVs

- **Standard** Normal  $\mathcal{N}(0, 1)$

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

- $\mathbb{E}[X] = 0$
- $\text{var}[X] = 1$



- **Standard** Normal  $\mathcal{N}(0, 1)$

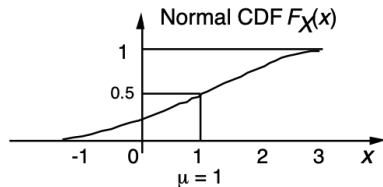
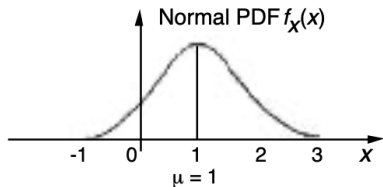
$$f_X(x) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2}$$

- $\mathbb{E}[X] = 0$
- $\text{var}[X] = 1$

- General Normal  $\mathcal{N}(\mu, \sigma^2)$

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

- $\mathbb{E}[X] = \mu$
- $\text{var}[X] = \sigma^2$



- PDF's normalization property:  $\frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-(x-\mu)^2/2\sigma^2} dx = 1$

- PDF's normalization property:  $\frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-(x-\mu)^2/2\sigma^2} dx = 1$ 
  - A little bit boring :-). See Problem 14 at pp 189.

- PDF's normalization property:  $\frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-(x-\mu)^2/2\sigma^2} dx = 1$ 
  - A little bit boring :-). See Problem 14 at pp 189.
- Expectation
  - $f_X(x)$  is symmetric in terms of  $x = \mu$ . Thus, we should have  $\mathbb{E}(X) = \mu$ .

- PDF's normalization property:  $\frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-(x-\mu)^2/2\sigma^2} dx = 1$ 
  - A little bit boring :-). See Problem 14 at pp 189.
- Expectation
  - $f_X(x)$  is symmetric in terms of  $x = \mu$ . Thus, we should have  $\mathbb{E}(X) = \mu$ .
- Variance

$$\begin{aligned} \text{var}(X) &= \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} (x - \mu)^2 e^{-(x-\mu)^2/2\sigma^2} dx \stackrel{y=\frac{x-\mu}{\sigma}}{=} \frac{\sigma^2}{\sqrt{2\pi}} \int_{-\infty}^{\infty} y^2 e^{-y^2/2} dy \\ &= \frac{\sigma^2}{\sqrt{2\pi}} (-ye^{-y^2/2}) \Big|_{-\infty}^{\infty} + \frac{\sigma^2}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-y^2/2} dy = \frac{\sigma^2}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-y^2/2} dy = \sigma^2 \end{aligned}$$

$$\int u dv = uv - \int v du: u = y \text{ and } dv = ye^{-y^2/2} \rightarrow du = dy \text{ and } v = -e^{-y^2/2}$$



- Linear transformation preserves normality (we will verify this in Lecture 5)

If  $X \sim \mathcal{N}(\mu, \sigma^2)$ , then for  $a \neq 0$  and  $b$ ,  $Y = aX + b \sim \mathcal{N}(a\mu + b, a^2\sigma^2)$ .

- Linear transformation preserves normality (we will verify this in Lecture 5)

If  $X \sim \mathcal{N}(\mu, \sigma^2)$ , then for  $a \neq 0$  and  $b$ ,  $Y = aX + b \sim \mathcal{N}(a\mu + b, a^2\sigma^2)$ .

- Thus, every normal rv can be :

If  $X \sim \mathcal{N}(\mu, \sigma^2)$ , then   $\sim \mathcal{N}(0, 1)$



- Linear transformation preserves normality (we will verify this in Lecture 5)

If  $X \sim \mathcal{N}(\mu, \sigma^2)$ , then for  $a \neq 0$  and  $b$ ,  $Y = aX + b \sim \mathcal{N}(a\mu + b, a^2\sigma^2)$ .

- Thus, every normal rv can be **standardized**:

If  $X \sim \mathcal{N}(\mu, \sigma^2)$ , then  $Y = \frac{X - \mu}{\sigma} \sim \mathcal{N}(0, 1)$

- Linear transformation preserves normality (we will verify this in Lecture 5)

If  $X \sim \mathcal{N}(\mu, \sigma^2)$ , then for  $a \neq 0$  and  $b$ ,  $Y = aX + b \sim \mathcal{N}(a\mu + b, a^2\sigma^2)$ .

- Thus, every normal rv can be **standardized**:

If  $X \sim \mathcal{N}(\mu, \sigma^2)$ , then  $Y = \frac{X - \mu}{\sigma} \sim \mathcal{N}(0, 1)$

- Thus, we can make the **table** which records the following CDF values:

$$\Phi(y) = \mathbb{P}(Y \leq y) = \mathbb{P}(Y < y) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^y e^{-t^2/2} dt$$

- Annual snowfall  $X$  is modeled as  $\mathcal{N}(60, 20^2)$ . What is the probability that this year's snowfall is at least 80 inches?

	.00	.01	.02	.03	.04	.05	.06	.07	.08	.09
0.0	.5000	.5040	.5080	.5120	.5160	.5199	.5239	.5279	.5319	.5359
0.1	.5398	.5438	.5478	.5517	.5557	.5596	.5636	.5675	.5714	.5753
0.2	.5793	.5832	.5871	.5910	.5948	.5987	.6026	.6064	.6103	.6141
0.3	.6179	.6217	.6255	.6293	.6331	.6368	.6406	.6443	.6480	.6517
0.4	.6554	.6591	.6628	.6664	.6700	.6736	.6772	.6808	.6844	.6879
0.5	.6915	.6950	.6985	.7019	.7054	.7088	.7123	.7157	.7190	.7224
0.6	.7257	.7291	.7324	.7357	.7389	.7422	.7454	.7486	.7517	.7549
0.7	.7580	.7611	.7642	.7673	.7704	.7734	.7764	.7794	.7823	.7852
0.8	.7881	.7910	.7939	.7967	.7995	.8023	.8051	.8078	.8106	.8133
0.9	.8159	.8186	.8212	.8238	.8264	.8289	.8315	.8340	.8365	.8389
1.0	.8413	.8438	.8461	.8485	.8508	.8531	.8554	.8577	.8599	.8621
1.1	.8643	.8665	.8686	.8708	.8729	.8749	.8770	.8790	.8810	.8830
1.2	.8849	.8869	.8888	.8907	.8925	.8944	.8962	.8980	.8997	.9015
1.3	.9032	.9049	.9066	.9082	.9099	.9115	.9131	.9147	.9162	.9177
1.4	.9192	.9207	.9222	.9236	.9251	.9265	.9279	.9292	.9306	.9319
1.5	.9332	.9345	.9357	.9370	.9382	.9394	.9406	.9418	.9429	.9441
1.6	.9452	.9463	.9474	.9484	.9495	.9505	.9515	.9525	.9535	.9545
1.7	.9554	.9564	.9573	.9582	.9591	.9599	.9608	.9616	.9625	.9633
1.8	.9641	.9649	.9656	.9664	.9671	.9678	.9686	.9693	.9699	.9706
1.9	.9713	.9719	.9726	.9732	.9738	.9744	.9750	.9756	.9761	.9767
2.0	.9772	.9778	.9783	.9788	.9793	.9798	.9803	.9808	.9812	.9817
2.1	.9821	.9826	.9830	.9834	.9838	.9842	.9846	.9850	.9854	.9857
2.2	.9861	.9864	.9868	.9871	.9875	.9878	.9881	.9884	.9887	.9890
2.3	.9893	.9896	.9898	.9901	.9904	.9906	.9909	.9911	.9913	.9916
2.4	.9918	.9920	.9922	.9925	.9927	.9929	.9931	.9932	.9934	.9936
2.5	.9938	.9940	.9941	.9943	.9945	.9946	.9948	.9949	.9951	.9952
2.6	.9953	.9955	.9956	.9957	.9959	.9960	.9961	.9962	.9963	.9964
2.7	.9965	.9966	.9967	.9968	.9969	.9970	.9971	.9972	.9973	.9974
2.8	.9974	.9975	.9976	.9977	.9977	.9978	.9979	.9979	.9980	.9981
2.9	.9981	.9982	.9982	.9983	.9984	.9984	.9985	.9985	.9986	.9986

- Annual snowfall  $X$  is modeled as  $\mathcal{N}(60, 20^2)$ . What is the probability that this year's snowfall is at least 80 inches?
- $Y = \frac{X-60}{20}$ .

	.00	.01	.02	.03	.04	.05	.06	.07	.08	.09
0.0	.5000	.5040	.5080	.5120	.5160	.5199	.5239	.5279	.5319	.5359
0.1	.5398	.5438	.5478	.5517	.5557	.5596	.5636	.5675	.5714	.5753
0.2	.5793	.5832	.5871	.5910	.5948	.5987	.6026	.6064	.6103	.6141
0.3	.6179	.6217	.6255	.6293	.6331	.6368	.6406	.6443	.6480	.6517
0.4	.6554	.6591	.6628	.6664	.6700	.6736	.6772	.6808	.6844	.6879
0.5	.6915	.6950	.6985	.7019	.7054	.7088	.7123	.7157	.7190	.7224
0.6	.7257	.7291	.7324	.7357	.7389	.7422	.7454	.7486	.7517	.7549
0.7	.7580	.7611	.7642	.7673	.7704	.7734	.7764	.7794	.7823	.7852
0.8	.7881	.7910	.7939	.7967	.7995	.8023	.8051	.8078	.8106	.8133
0.9	.8159	.8186	.8212	.8238	.8264	.8289	.8315	.8340	.8365	.8389
1.0	.8413	.8438	.8461	.8485	.8508	.8531	.8554	.8577	.8599	.8621
1.1	.8643	.8665	.8686	.8708	.8729	.8749	.8770	.8790	.8810	.8830
1.2	.8849	.8869	.8888	.8907	.8925	.8944	.8962	.8980	.8997	.9015
1.3	.9032	.9049	.9066	.9082	.9099	.9115	.9131	.9147	.9162	.9177
1.4	.9192	.9207	.9222	.9236	.9251	.9265	.9279	.9292	.9306	.9319
1.5	.9332	.9345	.9357	.9370	.9382	.9394	.9406	.9418	.9429	.9441
1.6	.9452	.9463	.9474	.9484	.9495	.9505	.9515	.9525	.9535	.9545
1.7	.9554	.9564	.9573	.9582	.9591	.9599	.9608	.9616	.9625	.9633
1.8	.9641	.9649	.9656	.9664	.9671	.9678	.9686	.9693	.9699	.9706
1.9	.9713	.9719	.9726	.9732	.9738	.9744	.9750	.9756	.9761	.9767
2.0	.9772	.9778	.9783	.9788	.9793	.9798	.9803	.9808	.9812	.9817
2.1	.9821	.9826	.9830	.9834	.9838	.9842	.9846	.9850	.9854	.9857
2.2	.9861	.9864	.9868	.9871	.9875	.9878	.9881	.9884	.9887	.9890
2.3	.9893	.9896	.9898	.9901	.9904	.9906	.9909	.9911	.9913	.9916
2.4	.9918	.9920	.9922	.9925	.9927	.9929	.9931	.9932	.9934	.9936
2.5	.9938	.9940	.9941	.9943	.9945	.9946	.9948	.9949	.9951	.9952
2.6	.9953	.9955	.9956	.9957	.9959	.9960	.9961	.9962	.9963	.9964
2.7	.9965	.9966	.9967	.9968	.9969	.9970	.9971	.9972	.9973	.9974
2.8	.9974	.9975	.9976	.9977	.9977	.9978	.9979	.9979	.9980	.9981
2.9	.9981	.9982	.9982	.9983	.9984	.9984	.9985	.9985	.9986	.9986

- Annual snowfall  $X$  is modeled as  $\mathcal{N}(60, 20^2)$ . What is the probability that this year's snowfall is at least 80 inches?
- $Y = \frac{X-60}{20}$ .

$$\begin{aligned}\mathbb{P}(X \geq 80) &= \mathbb{P}(Y \geq \frac{80 - 60}{20}) \\ &= \mathbb{P}(Y \geq 1) = 1 - \Phi(1) \\ &= 1 - 0.8413 = 0.1587\end{aligned}$$

	.00	.01	.02	.03	.04	.05	.06	.07	.08	.09
0.0	.5000	.5040	.5080	.5120	.5160	.5199	.5239	.5279	.5319	.5359
0.1	.5398	.5438	.5478	.5517	.5557	.5596	.5636	.5675	.5714	.5753
0.2	.5793	.5832	.5871	.5910	.5948	.5987	.6026	.6064	.6103	.6141
0.3	.6179	.6217	.6255	.6293	.6331	.6368	.6406	.6443	.6480	.6517
0.4	.6554	.6591	.6628	.6664	.6700	.6736	.6772	.6808	.6844	.6879
0.5	.6915	.6950	.6985	.7019	.7054	.7088	.7123	.7157	.7190	.7224
0.6	.7257	.7291	.7324	.7357	.7389	.7422	.7454	.7486	.7517	.7549
0.7	.7580	.7611	.7642	.7673	.7704	.7734	.7764	.7794	.7823	.7852
0.8	.7881	.7910	.7939	.7967	.7995	.8023	.8051	.8078	.8106	.8133
0.9	.8159	.8186	.8212	.8238	.8264	.8289	.8315	.8340	.8365	.8389
1.0	.8413	.8438	.8461	.8485	.8508	.8531	.8554	.8577	.8599	.8621
1.1	.8643	.8665	.8686	.8708	.8729	.8749	.8770	.8790	.8810	.8830
1.2	.8849	.8869	.8888	.8907	.8925	.8944	.8962	.8980	.8997	.9015
1.3	.9032	.9049	.9066	.9082	.9099	.9115	.9131	.9147	.9162	.9177
1.4	.9192	.9207	.9222	.9236	.9251	.9265	.9279	.9292	.9306	.9319
1.5	.9332	.9345	.9357	.9370	.9382	.9394	.9406	.9418	.9429	.9441
1.6	.9452	.9463	.9474	.9484	.9495	.9505	.9515	.9525	.9535	.9545
1.7	.9554	.9564	.9573	.9582	.9591	.9599	.9608	.9616	.9625	.9633
1.8	.9641	.9649	.9656	.9664	.9671	.9678	.9686	.9693	.9699	.9706
1.9	.9713	.9719	.9726	.9732	.9738	.9744	.9750	.9756	.9761	.9767
2.0	.9772	.9778	.9783	.9788	.9793	.9798	.9803	.9808	.9812	.9817
2.1	.9821	.9826	.9830	.9834	.9838	.9842	.9846	.9850	.9854	.9857
2.2	.9861	.9864	.9868	.9871	.9875	.9878	.9881	.9884	.9887	.9890
2.3	.9893	.9896	.9898	.9901	.9904	.9906	.9909	.9911	.9913	.9916
2.4	.9918	.9920	.9922	.9925	.9927	.9929	.9931	.9932	.9934	.9936
2.5	.9938	.9940	.9941	.9943	.9945	.9946	.9948	.9949	.9951	.9952
2.6	.9953	.9955	.9956	.9957	.9959	.9960	.9961	.9962	.9963	.9964
2.7	.9965	.9966	.9967	.9968	.9969	.9970	.9971	.9972	.9973	.9974
2.8	.9974	.9975	.9976	.9977	.9977	.9978	.9979	.9979	.9980	.9981
2.9	.9981	.9982	.9982	.9983	.9984	.9984	.9985	.9985	.9986	.9986

- Central limit theorem
  - One of the most remarkable findings in the probability theory
  - Sum of **any** random variables  $\approx$  Normal random variable
- Modeling aggregate noise with many small, independent noise terms
- Convenient analytical properties, allowing closed forms in many cases
- Highly popular in communication and machine learning areas

---

<sup>0</sup>Central limit theorem: 중심극한정리

- (1) Continuous Random Variable and PDF (Probability Density Function)
- (2) CDF (Cumulative Distribution Function)
- (3) Exponential RVs
- (4) Gaussian (Normal) RVs
- (5) Continuous RVs: Joint, Conditioning, and Independence
- (6) Bayes' rule for RVs

Two continuous rvs are  if a non-negative function  $f_{X,Y}(x,y)$  (called joint PDF) satisfies: for **every subset**  $B$  of the two dimensional plane,

$$\mathbb{P}((X, Y) \in B) = \iint_{(x,y) \in B} f_{X,Y}(x,y) dx dy,$$



Two continuous rvs are **jointly continuous** if a non-negative function  $f_{X,Y}(x,y)$  (called joint PDF) satisfies: for **every subset**  $B$  of the two dimensional plane,

$$\mathbb{P}((X, Y) \in B) = \iint_{(x,y) \in B} f_{X,Y}(x,y) dx dy,$$

Two continuous rvs are **jointly continuous** if a non-negative function  $f_{X,Y}(x,y)$  (called joint PDF) satisfies: for **every subset**  $B$  of the two dimensional plane,

$$\mathbb{P}((X, Y) \in B) = \iint_{(x,y) \in B} f_{X,Y}(x,y) dx dy,$$

1. The joint PDF is used to calculate probabilities

$$\mathbb{P}[(X, Y) \in B] = \iint_{(x,y) \in B} f_{X,Y}(x,y) dx dy$$

Our particular interest:  $B = \{(x,y) \mid a \leq x \leq b, c \leq y \leq d\}$

2. The **marginal** PDFs of  $X$  and  $Y$  are from the joint PDF as:

$$f_X(x) = \int_{-\infty}^{\infty} f_{X,Y}(x,y)dy, \quad f_Y(y) = \int_{-\infty}^{\infty} f_{X,Y}(x,y)dx$$

2. The **marginal** PDFs of  $X$  and  $Y$  are from the joint PDF as:

$$f_X(x) = \int_{-\infty}^{\infty} f_{X,Y}(x,y)dy, \quad f_Y(y) = \int_{-\infty}^{\infty} f_{X,Y}(x,y)dx$$

3. The **joint CDF** is defined by  $F_{X,Y}(x,y) = \mathbb{P}(X \leq x, Y \leq y)$ , and determines the joint PDF as:

$$f_{X,Y}(x,y) = \frac{\partial^2 F_{x,y}}{\partial x \partial y}(x,y)$$

2. The **marginal** PDFs of  $X$  and  $Y$  are from the joint PDF as:

$$f_X(x) = \int_{-\infty}^{\infty} f_{X,Y}(x,y)dy, \quad f_Y(y) = \int_{-\infty}^{\infty} f_{X,Y}(x,y)dx$$

3. The **joint CDF** is defined by  $F_{X,Y}(x,y) = \mathbb{P}(X \leq x, Y \leq y)$ , and determines the joint PDF as:

$$f_{X,Y}(x,y) = \frac{\partial^2 F_{x,y}}{\partial x \partial y}(x,y)$$

4. A function  $g(X, Y)$  of  $X$  and  $Y$  defines a new random variable, and

$$\mathbb{E}[g(X, Y)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x,y) f_{X,Y}(x,y) dx dy$$

\* Conditional PDF, given an event  $A$

\* Conditional PDF, given  $\{X \in C\}$

**Notation:**  $A$  is an event, but  $B$  and  $C$  is a subset that includes the possible values which can be taken by the rv  $X$ . Sorry for the confusion, if any.

\* Conditional PDF, given an event  $A$

- $f_X(x) \cdot \delta \approx \mathbb{P}(x \leq X \leq x + \delta)$   
 $f_{X|A}(x) \cdot \delta \approx \mathbb{P}(x \leq X \leq x + \delta | A)$

\* Conditional PDF, given  $\{X \in C\}$

**Notation:**  $A$  is an event, but  $B$  and  $C$  is a subset that includes the possible values which can be taken by the rv  $X$ . Sorry for the confusion, if any.

\* Conditional PDF, given an event  $A$

- $f_X(x) \cdot \delta \approx \mathbb{P}(x \leq X \leq x + \delta)$   
 $f_{X|A}(x) \cdot \delta \approx \mathbb{P}(x \leq X \leq x + \delta | A)$
- $\mathbb{P}(X \in B) = \int_B f_X(x) dx$   
 $\mathbb{P}(X \in B | A) = \int_B f_{X|A}(x) dx$

\* Conditional PDF, given  $\{X \in C\}$

**Notation:**  $A$  is an event, but  $B$  and  $C$  is a subset that includes the possible values which can be taken by the rv  $X$ . Sorry for the confusion, if any.



\* Conditional PDF, given an event  $A$

- $f_X(x) \cdot \delta \approx \mathbb{P}(x \leq X \leq x + \delta)$   
 $f_{X|A}(x) \cdot \delta \approx \mathbb{P}(x \leq X \leq x + \delta | A)$
- $\mathbb{P}(X \in B) = \int_B f_X(x) dx$   
 $\mathbb{P}(X \in B | A) = \int_B f_{X|A}(x) dx$
- $\int f_{X|A}(x) dx = 1$

\* Conditional PDF, given  $\{X \in C\}$

**Notation:**  $A$  is an event, but  $B$  and  $C$  is a subset that includes the possible values which can be taken by the rv  $X$ . Sorry for the confusion, if any.

\* Conditional PDF, given an event  $A$ 

- $f_X(x) \cdot \delta \approx \mathbb{P}(x \leq X \leq x + \delta)$   
 $f_{X|A}(x) \cdot \delta \approx \mathbb{P}(x \leq X \leq x + \delta | A)$
- $\mathbb{P}(X \in B) = \int_B f_X(x) dx$   
 $\mathbb{P}(X \in B | A) = \int_B f_{X|A}(x) dx$
- $\int f_{X|A}(x) dx = 1$

\* Conditional PDF, given  $\{X \in C\}$ 

$$f_{X|\{X \in C\}}(x) \cdot \delta \approx \mathbb{P}(x \leq X \leq x + \delta | X \in C)$$

$$f_{X|\{X \in C\}}(x) = \begin{cases} 0, & \text{if } x \notin C \\ \frac{f_X(x)}{\mathbb{P}(X \in C)}, & \text{if } x \in C \end{cases}$$

**Notation:**  $A$  is an event, but  $B$  and  $C$  is a subset that includes the possible values which can be taken by the rv  $X$ . Sorry for the confusion, if any.

## \* Conditional PDF, given an event $A$

- $f_X(x) \cdot \delta \approx \mathbb{P}(x \leq X \leq x + \delta)$   
 $f_{X|A}(x) \cdot \delta \approx \mathbb{P}(x \leq X \leq x + \delta | A)$
- $\mathbb{P}(X \in B) = \int_B f_X(x) dx$   
 $\mathbb{P}(X \in B | A) = \int_B f_{X|A}(x) dx$
- $\int f_{X|A}(x) dx = 1$

## \* Conditional PDF, given $\{X \in C\}$

$$f_{X|\{X \in C\}}(x) \cdot \delta \approx \mathbb{P}(x \leq X \leq x + \delta | X \in C)$$

$$f_{X|\{X \in C\}}(x) = \begin{cases} 0, & \text{if } x \notin C \\ \frac{f_X(x)}{\mathbb{P}(X \in C)}, & \text{if } x \in C \end{cases}$$

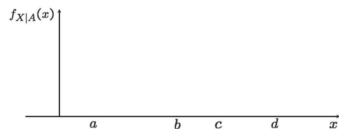
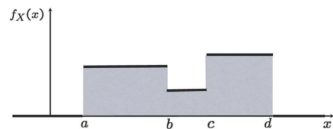
(Q) In the discrete, we consider the event  $\{X = x\}$ , not  $\{X \in B\}$ . Why?

**Notation:**  $A$  is an event, but  $B$  and  $C$  is a subset that includes the possible values which can be taken by the rv  $X$ . Sorry for the confusion, if any.

- $\mathbb{E}[X] = \int x f_X(x) dx$   
 $\mathbb{E}[X|A] = \int x f_{X|A}(x) dx$

- $\mathbb{E}[X] = \int x f_X(x) dx$   
 $\mathbb{E}[X|A] = \int x f_{X|A}(x) dx$
- $\mathbb{E}[g(X)] = \int g(x) f_X(x) dx$   
 $\mathbb{E}[g(X)|A] = \int g(x) f_{X|A}(x) dx$

$$A = \left\{ \frac{a+b}{2} \leq X \leq b \right\}$$

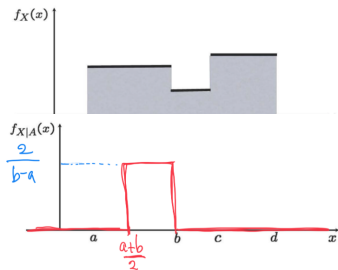


- $\mathbb{E}[X] = \int x f_X(x) dx$   
 $\mathbb{E}[X|A] = \int x f_{X|A}(x) dx$
- $\mathbb{E}[g(X)] = \int g(x) f_X(x) dx$   
 $\mathbb{E}[g(X)|A] = \int g(x) f_{X|A}(x) dx$

$$\mathbb{E}[X|A] =$$

$$\mathbb{E}[X^2|A] =$$

$$A = \left\{ \frac{a+b}{2} \leq X \leq b \right\}$$



- $\mathbb{E}[X] = \int x f_X(x) dx$

$$\mathbb{E}[X|A] = \int x f_{X|A}(x) dx$$

- $\mathbb{E}[g(X)] = \int g(x) f_X(x) dx$

$$\mathbb{E}[g(X)|A] = \int g(x) f_{X|A}(x) dx$$

$$\mathbb{E}[X|A] = \int_{(a+b)/2}^b x \frac{2}{b-a} dx = \frac{a}{4} + \frac{3b}{4}$$

$$\mathbb{E}[X^2|A] = \int_{(a+b)/2}^b x^2 \frac{2}{b-a} dx =$$

- **Remember:** Exponential rv is a continuous counterpart of geometric rv.



- **Remember:** Exponential rv is a continuous counterpart of geometric rv.
- Thus, expected to be memoryless. Remember the definition?

- **Remember:** Exponential rv is a continuous counterpart of geometric rv.
- Thus, expected to be memoryless. Remember the definition?

**Definition.** A random variable  $X$  is called memoryless if, for any  $n, m \geq 0$ ,

- **Remember:** Exponential rv is a continuous counterpart of geometric rv.
- Thus, expected to be memoryless. Remember the definition?

**Definition.** A random variable  $X$  is called memoryless if, for any  $n, m \geq 0$ ,

$$\mathbb{P}(X > n + m | X > m) = \mathbb{P}(X > n)$$

- **Proof.** Note that the exponential rv's CCDF  $\mathbb{P}(X > x) = e^{-\lambda x}$ .

- **Remember:** Exponential rv is a continuous counterpart of geometric rv.
- Thus, expected to be memoryless. Remember the definition?

**Definition.** A random variable  $X$  is called memoryless if, for any  $n, m \geq 0$ ,

$$\mathbb{P}(X > n + m | X > m) = \mathbb{P}(X > n)$$

- **Proof.** Note that the exponential rv's CCDF  $\mathbb{P}(X > x) = e^{-\lambda x}$ . Then,

$$\mathbb{P}(X > n + m | X > m) = \frac{\mathbb{P}(X > n + m)}{\mathbb{P}(X > m)} = \frac{e^{-\lambda(n+m)}}{e^{-\lambda m}} = e^{-\lambda n} = \mathbb{P}(X > n)$$

Partition of  $\Omega$  into  $A_1, A_2, A_3, \dots$

\* Discrete case

\* Continuous case

Partition of  $\Omega$  into  $A_1, A_2, A_3, \dots$

\* Discrete case

## Total Probability Theorem

$$\begin{aligned} p_X(x) &= \sum_i \mathbb{P}(A_i) \mathbb{P}(X = x | A_i) \\ &= \sum_i \mathbb{P}(A_i) p_{X|A_i}(x) \end{aligned}$$

## Total Expectation Theorem

$$\mathbb{E}[X] = \sum_i \mathbb{P}(A_i) \mathbb{E}[X | A_i]$$

\* Continuous case

Partition of  $\Omega$  into  $A_1, A_2, A_3, \dots$

\* Discrete case

## Total Probability Theorem

$$\begin{aligned} p_X(x) &= \sum_i \mathbb{P}(A_i) \mathbb{P}(X = x | A_i) \\ &= \sum_i \mathbb{P}(A_i) p_{X|A_i}(x) \end{aligned}$$

## Total Expectation Theorem

$$\mathbb{E}[X] = \sum_i \mathbb{P}(A_i) \mathbb{E}[X | A_i]$$

\* Continuous case

## Total Probability Theorem

$$f_X(x) = \sum_i \mathbb{P}(A_i) f_{X|A_i}(x)$$

Partition of  $\Omega$  into  $A_1, A_2, A_3, \dots$

\* Discrete case

## Total Probability Theorem

$$\begin{aligned} p_X(x) &= \sum_i \mathbb{P}(A_i) \mathbb{P}(X = x | A_i) \\ &= \sum_i \mathbb{P}(A_i) p_{X|A_i}(x) \end{aligned}$$

## Total Expectation Theorem

$$\mathbb{E}[X] = \sum_i \mathbb{P}(A_i) \mathbb{E}[X | A_i]$$

\* Continuous case

## Total Probability Theorem

$$f_X(x) = \sum_i \mathbb{P}(A_i) f_{X|A_i}(x)$$

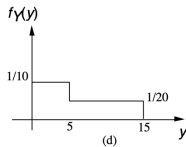
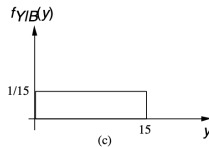
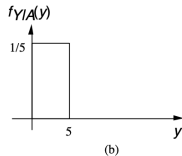
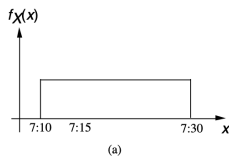
## Total Expectation Theorem

$$\mathbb{E}[X] = \sum_i \mathbb{P}(A_i) \mathbb{E}[X | A_i]$$



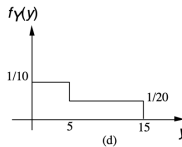
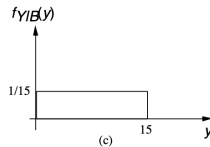
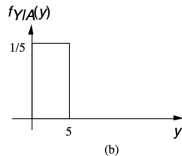
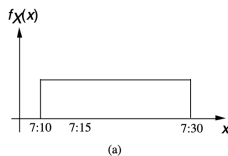
## Example: Train Arrival

- The train's arrival every quarter hour (0, 15min, 30min, 45min).
- Your arrival  $\sim \mathcal{U}(7:10, 7:30)$  am.



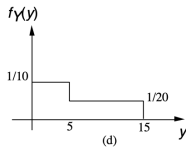
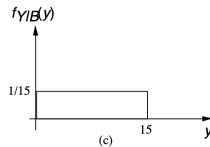
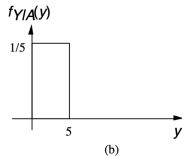
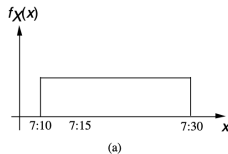
## Example: Train Arrival

- The train's arrival every quarter hour (0, 15min, 30min, 45min).
- Your arrival  $\sim \mathcal{U}(7:10, 7:30)$  am.
- What is the PDF of waiting time for the first train?



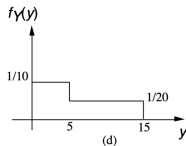
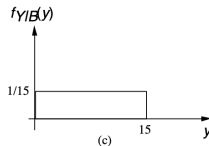
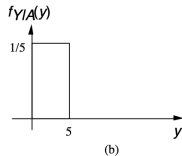
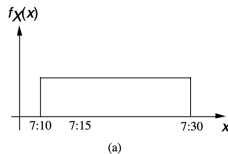
## Example: Train Arrival

- The train's arrival every quarter hour (0, 15min, 30min, 45min).
- Your arrival  $\sim \mathcal{U}(7:10, 7:30)$  am.
- What is the PDF of waiting time for the first train?
- $X$  : your arrival time,  $Y$  : waiting time.



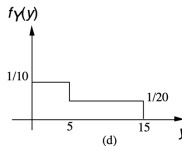
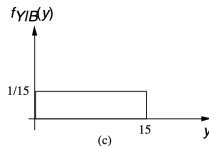
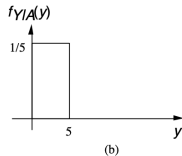
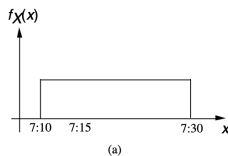
## Example: Train Arrival

- The train's arrival every quarter hour (0, 15min, 30min, 45min).
- Your arrival  $\sim \mathcal{U}(7:10, 7:30)$  am.
- What is the PDF of waiting time for the first train?
- $X$  : your arrival time,  $Y$  : waiting time.
- The value of  $X$  makes a different waiting time. So, consider two events:  
 $A = \{7:10 \leq X \leq 7:15\}$   
 $B = \{7:15 \leq X \leq 7:30\}$



## Example: Train Arrival

- The train's arrival every quarter hour (0, 15min, 30min, 45min).
- Your arrival  $\sim \mathcal{U}(7:10, 7:30)$  am.
- What is the PDF of waiting time for the first train?
- $X$  : your arrival time,  $Y$  : waiting time.
- The value of  $X$  makes a different waiting time. So, consider two events:  
 $A = \{7:10 \leq X \leq 7:15\}$   
 $B = \{7:15 \leq X \leq 7:30\}$



VIDEO PAUSE

$$f_Y(y) = \mathbb{P}(A)f_{Y|A}(y) + \mathbb{P}(B)f_{Y|B}(y)$$

$$\text{for } 0 \leq y \leq 5$$

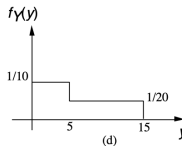
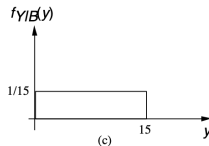
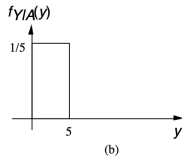
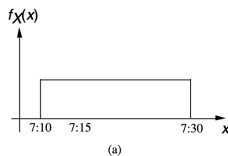
$$\text{for } 5 < y \leq 15$$

## Example: Train Arrival

- The train's arrival every quarter hour (0, 15min, 30min, 45min).
- Your arrival  $\sim \mathcal{U}(7:10, 7:30)$  am.
- What is the PDF of waiting time for the first train?
- $X$  : your arrival time,  $Y$  : waiting time.
- The value of  $X$  makes a different waiting time. So, consider two events:

$$A = \{7:10 \leq X \leq 7:15\}$$

$$B = \{7:15 \leq X \leq 7:30\}$$



$$f_Y(y) = \mathbb{P}(A)f_{Y|A}(y) + \mathbb{P}(B)f_{Y|B}(y)$$

$$f_Y(y) = \frac{1}{4} \frac{1}{5} + \frac{3}{4} \frac{1}{15} = \frac{1}{10}, \quad \text{for } 0 \leq y \leq 5$$

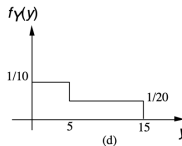
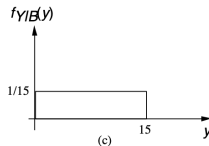
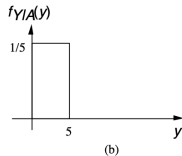
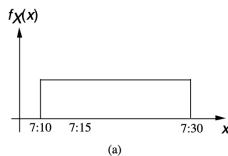
$$\text{for } 5 < y \leq 15$$

## Example: Train Arrival

- The train's arrival every quarter hour (0, 15min, 30min, 45min).
- Your arrival  $\sim \mathcal{U}(7:10, 7:30)$  am.
- What is the PDF of waiting time for the first train?
- $X$  : your arrival time,  $Y$  : waiting time.
- The value of  $X$  makes a different waiting time. So, consider two events:

$$A = \{7:10 \leq X \leq 7:15\}$$

$$B = \{7:15 \leq X \leq 7:30\}$$



$$f_Y(y) = \mathbb{P}(A)f_{Y|A}(y) + \mathbb{P}(B)f_{Y|B}(y)$$

$$f_Y(y) = \frac{1}{4} \frac{1}{5} + \frac{3}{4} \frac{1}{15} = \frac{1}{10}, \quad \text{for } 0 \leq y \leq 5$$

$$f_Y(y) = \frac{1}{4} 0 + \frac{3}{4} \frac{1}{15} = \frac{1}{20}, \quad \text{for } 5 < y \leq 15$$

- $p_{X|Y}(x|y) = \frac{p_{X,Y}(x,y)}{p_Y(y)}$



- $p_{X|Y}(x|y) = \frac{p_{X,Y}(x,y)}{p_Y(y)}$
- Similarly, for  $f_Y(y) > 0$ ,

$$f_{X|Y}(x|y) = \frac{f_{X,Y}(x,y)}{f_Y(y)}$$

- $p_{X|Y}(x|y) = \frac{p_{X,Y}(x,y)}{p_Y(y)}$
- Similarly, for  $f_Y(y) > 0$ ,

$$f_{X|Y}(x|y) = \frac{f_{X,Y}(x,y)}{f_Y(y)}$$

- Remember: For a fixed event  $A$ ,  $\mathbb{P}(\cdot|A)$  is a legitimate probability law.

- $p_{X|Y}(x|y) = \frac{p_{X,Y}(x,y)}{p_Y(y)}$
- Similarly, for  $f_Y(y) > 0$ ,

$$f_{X|Y}(x|y) = \frac{f_{X,Y}(x,y)}{f_Y(y)}$$

- Remember: For a fixed event  $A$ ,  $\mathbb{P}(\cdot|A)$  is a legitimate probability law.
- Similarly, For a fixed  $y$ ,  $f_{X|Y}(x|y)$  is a legitimate PDF, since

$$\int_{-\infty}^{\infty} f_{X|Y}(x|y) dx = \frac{\int_{-\infty}^{\infty} f_{X,Y}(x,y) dx}{f_Y(y)} = 1$$

- $p_{X|Y}(x|y) = \frac{p_{X,Y}(x,y)}{p_Y(y)}$

- Similarly, for  $f_Y(y) > 0$ ,

$$f_{X|Y}(x|y) = \frac{f_{X,Y}(x,y)}{f_Y(y)}$$

- Remember: For a fixed event  $A$ ,  $\mathbb{P}(\cdot|A)$  is a legitimate probability law.
- Similarly, For a fixed  $y$ ,  $f_{X|Y}(x|y)$  is a legitimate PDF, since

$$\int_{-\infty}^{\infty} f_{X|Y}(x|y) dx = \frac{\int_{-\infty}^{\infty} f_{X,Y}(x,y) dx}{f_Y(y)} = 1$$

- Multiplication rule.

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

- $p_{X|Y}(x|y) = \frac{p_{X,Y}(x,y)}{p_Y(y)}$
- Similarly, for  $f_Y(y) > 0$ ,

$$f_{X|Y}(x|y) = \frac{f_{X,Y}(x,y)}{f_Y(y)}$$

- Remember: For a fixed event  $A$ ,  $\mathbb{P}(\cdot|A)$  is a legitimate probability law.
- Similarly, For a fixed  $y$ ,  $f_{X|Y}(x|y)$  is a legitimate PDF, since

$$\int_{-\infty}^{\infty} f_{X|Y}(x|y) dx = \frac{\int_{-\infty}^{\infty} f_{X,Y}(x,y) dx}{f_Y(y)} = 1$$

- **Multiplication rule.**

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

- **Total prob./exp. theorem.**

$$f_X(x) = \int_{-\infty}^{\infty} f_Y(y) f_{X|Y}(x|y) dy$$

$$\mathbb{E}[X|Y=y] = \int_{-\infty}^{\infty} x f_{X|Y}(x|y) dx$$

$$\mathbb{E}[X] = \int_{-\infty}^{\infty} f_Y(y) \mathbb{E}[X|Y=y] dy$$

- $p_{X|Y}(x|y) = \frac{p_{X,Y}(x,y)}{p_Y(y)}$
- Similarly, for  $f_Y(y) > 0$ ,

$$f_{X|Y}(x|y) = \frac{f_{X,Y}(x,y)}{f_Y(y)}$$

- Remember: For a fixed event  $A$ ,  $\mathbb{P}(\cdot|A)$  is a legitimate probability law.
- Similarly, For a fixed  $y$ ,  $f_{X|Y}(x|y)$  is a legitimate PDF, since

$$\int_{-\infty}^{\infty} f_{X|Y}(x|y) dx = \frac{\int_{-\infty}^{\infty} f_{X,Y}(x,y) dx}{f_Y(y)} = 1$$

- **Multiplication rule.**

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

- **Total prob./exp. theorem.**

$$f_X(x) = \int_{-\infty}^{\infty} f_Y(y) f_{X|Y}(x|y) dy$$

$$\mathbb{E}[X|Y=y] = \int_{-\infty}^{\infty} x f_{X|Y}(x|y) dx$$

$$\mathbb{E}[X] = \int_{-\infty}^{\infty} f_Y(y) \mathbb{E}[X|Y=y] dy$$

- **Independence**

$$f_{X,Y}(x,y) = f_X(x) f_Y(y), \quad \text{for all } x \text{ and } y$$

(Prob 21 at pp. 191)

- Break a stick of length  $l$  twice
  - first break at  $Y \sim \mathcal{U}[0, l]$
  - second break at  $X \sim \mathcal{U}[0, Y]$

---

<sup>0</sup> $\mathcal{U}[a, b]$ : continuous uniform random variable over the interval  $[a, b]$

(Prob 21 at pp. 191)

- Break a stick of length  $l$  twice
  - first break at  $Y \sim \mathcal{U}[0, l]$
  - second break at  $X \sim \mathcal{U}[0, Y]$

(a) joint PDF  $f_{X,Y}(x, y)$ ?

$$f_Y(y) = \frac{1}{l}, \quad 0 \leq y \leq l$$

$$f_{X|Y}(x|y) = \frac{1}{y}, \quad 0 \leq x \leq y$$

Using  $f_{X,Y}(x, y) = f_Y(y)f_{X|Y}(x|y)$ ,

$$f_{X,Y}(x, y) = \begin{cases} \frac{1}{l} \cdot \frac{1}{y}, & 0 \leq x \leq y \leq l, \\ 0, & \text{otherwise} \end{cases}$$

---

${}^0\mathcal{U}[a, b]$ : continuous uniform random variable over the interval  $[a, b]$



(Prob 21 at pp. 191)

- Break a stick of length  $l$  twice
  - first break at  $Y \sim \mathcal{U}[0, l]$
  - second break at  $X \sim \mathcal{U}[0, Y]$

(a) joint PDF  $f_{X,Y}(x, y)$ ?

$$f_Y(y) = \frac{1}{l}, \quad 0 \leq y \leq l$$

$$f_{X|Y}(x|y) = \frac{1}{y}, \quad 0 \leq x \leq y$$

Using  $f_{X,Y}(x, y) = f_Y(y)f_{X|Y}(x|y)$ ,

$$f_{X,Y}(x, y) = \begin{cases} \frac{1}{l} \cdot \frac{1}{y}, & 0 \leq x \leq y \leq l, \\ 0, & \text{otherwise} \end{cases}$$

(b) marginal PDF  $f_X(x)$ ?

$$\begin{aligned} f_X(x) &= \int f_{X,Y}(x, y) dy = \int_x^l \frac{1}{ly} dy \\ &= \frac{1}{l} \ln(l/x), \quad 0 \leq x \leq l \end{aligned}$$

---

$^0\mathcal{U}[a, b]$ : continuous uniform random variable over the interval  $[a, b]$

(c) Evaluate  $\mathbb{E}(X)$ , using  $f_X(x)$

(d) Evaluate  $\mathbb{E}(X)$ , using  $X = Y \cdot (X/Y)$

If  $Y \perp\!\!\!\perp X/Y$ , it becomes easy, but true?

(e) Evaluate  $\mathbb{E}(X)$ , using TET

(c) Evaluate  $\mathbb{E}(X)$ , using  $f_X(x)$

$$\begin{aligned}\mathbb{E}(X) &= \int_0^l x f_X(x) dx = \int_0^l \frac{x}{l} \ln(l/x) dx \\ &= \frac{l}{4}\end{aligned}$$

(d) Evaluate  $\mathbb{E}(X)$ , using  $X = Y \cdot (X/Y)$

If  $Y \perp\!\!\!\perp X/Y$ , it becomes easy, but true?

(e) Evaluate  $\mathbb{E}(X)$ , using TET

(c) Evaluate  $\mathbb{E}(X)$ , using  $f_X(x)$

$$\begin{aligned}\mathbb{E}(X) &= \int_0^l x f_X(x) dx = \int_0^l \frac{x}{l} \ln(l/x) dx \\ &= \frac{l}{4}\end{aligned}$$

(d) Evaluate  $\mathbb{E}(X)$ , using  $X = Y \cdot (X/Y)$

If  $Y \perp\!\!\!\perp X/Y$ , it becomes easy, but true?  
Yes, because whatever  $Y$  is, the fraction  $X/Y$  does not depend on it.

$$\mathbb{E}(X) = \mathbb{E}(Y)\mathbb{E}(X/Y) = \frac{l}{2} \cdot \frac{1}{2} = \frac{l}{4}$$

(e) Evaluate  $\mathbb{E}(X)$ , using TET

(c) Evaluate  $\mathbb{E}(X)$ , using  $f_X(x)$

$$\begin{aligned}\mathbb{E}(X) &= \int_0^l x f_X(x) dx = \int_0^l \frac{x}{l} \ln(l/x) dx \\ &= \frac{l}{4}\end{aligned}$$

(d) Evaluate  $\mathbb{E}(X)$ , using  $X = Y \cdot (X/Y)$

If  $Y \perp\!\!\!\perp X/Y$ , it becomes easy, but true?  
Yes, because whatever  $Y$  is, the fraction  $X/Y$  does not depend on it.

$$\mathbb{E}(X) = \mathbb{E}(Y)\mathbb{E}(X/Y) = \frac{l}{2} \cdot \frac{1}{2} = \frac{l}{4}$$

(e) Evaluate  $\mathbb{E}(X)$ , using TET

$$\begin{aligned}0\mathbb{E}[X] &= \int_{-\infty}^{\infty} f_Y(y) \mathbb{E}[X|Y=y] dy \\ &= \int_0^l \frac{1}{l} \mathbb{E}[X|Y=y] dy = \int_0^l \frac{1}{l} \frac{y}{2} dy = \frac{l}{4}\end{aligned}$$

(c) Evaluate  $\mathbb{E}(X)$ , using  $f_X(x)$

$$\begin{aligned}\mathbb{E}(X) &= \int_0^l x f_X(x) dx = \int_0^l \frac{x}{l} \ln(l/x) dx \\ &= \frac{l}{4}\end{aligned}$$

(d) Evaluate  $\mathbb{E}(X)$ , using  $X = Y \cdot (X/Y)$

If  $Y \perp\!\!\!\perp X/Y$ , it becomes easy, but true?  
Yes, because whatever  $Y$  is, the fraction  $X/Y$  does not depend on it.

$$\mathbb{E}(X) = \mathbb{E}(Y)\mathbb{E}(X/Y) = \frac{l}{2} \cdot \frac{1}{2} = \frac{l}{4}$$

(e) Evaluate  $\mathbb{E}(X)$ , using TET

$$\begin{aligned}0\mathbb{E}[X] &= \int_{-\infty}^{\infty} f_Y(y) \mathbb{E}[X|Y=y] dy \\ &= \int_0^l \frac{1}{l} \mathbb{E}[X|Y=y] dy = \int_0^l \frac{1}{l} \frac{y}{2} dy = \frac{l}{4}\end{aligned}$$

- **Message.** There are many ways to reach our goal. Of crucial importance is how to find the best way!

- (1) Continuous Random Variable and PDF (Probability Density Function)
- (2) CDF (Cumulative Distribution Function)
- (3) Exponential RVs
- (4) Gaussian (Normal) RVs
- (5) Continuous RVs: Joint, Conditioning, and Independence
- (6) Bayes' rule for RVs

- $X$ : state/cause/original value  $\rightarrow Y$ : result/resulting action/noisy measurement
- Given:  $\mathbb{P}(X)$  and  $\mathbb{P}(Y|X)$  (cause  $\rightarrow$  result)
- Inference:  $\mathbb{P}(X|Y)$ ?



- $X$ : state/cause/original value  $\rightarrow Y$ : result/resulting action/noisy measurement
- Given:  $\mathbb{P}(X)$  and  $\mathbb{P}(Y|X)$  (cause  $\rightarrow$  result)
- Inference:  $\mathbb{P}(X|Y)$ ?

$$p_{X,Y}(x,y) = p_X(x)p_{Y|X}(y|x)$$

$$= p_Y(y)p_{X|Y}(x|y)$$

$$p_{X|Y}(x|y) = \frac{p_X(x)p_{Y|X}(y|x)}{p_Y(y)}$$

$$p_Y(y) = \sum_{x'} p_X(x')p_{Y|X}(y|x')$$

$$f_{X,Y}(x,y) = f_X(x)f_{Y|X}(y|x)$$

$$= f_Y(y)f_{X|Y}(x|y)$$

$$f_{X|Y}(x|y) = \frac{f_X(x)f_{Y|X}(y|x)}{f_Y(y)}$$

$$f_Y(y) = \int f_X(x')f_{Y|X}(y|x')dx'$$

- A light bulb  $Y \sim \exp(\lambda)$ . However, there are some quality control problems. So, the parameter  $\lambda$  of  $Y$  is actually a random variable, denoted by  $\Lambda$ , which is  $\Lambda \sim \mathcal{U}[1, 3/2]$ . We test a light bulb and record its lifetime.

- A light bulb  $Y \sim \exp(\lambda)$ . However, there are some quality control problems. So, the parameter  $\lambda$  of  $Y$  is actually a random variable, denoted by  $\Lambda$ , which is  $\Lambda \sim \mathcal{U}[1, 3/2]$ . We test a light bulb and record its lifetime.
- **Question.** What can we say about the underlying parameter  $\lambda$ ? In other words, what is  $f_{\Lambda|Y}(\lambda|y)$ ?

- A light bulb  $Y \sim \exp(\lambda)$ . However, there are some quality control problems. So, the parameter  $\lambda$  of  $Y$  is actually a random variable, denoted by  $\Lambda$ , which is  $\Lambda \sim \mathcal{U}[1, 3/2]$ . We test a light bulb and record its lifetime.
- **Question.** What can we say about the underlying parameter  $\lambda$ ? In other words, what is  $f_{\Lambda|Y}(\lambda|y)$ ?
- $f_{\Lambda}(\lambda) = 2$  for  $1 \leq \lambda \leq 3/2$  and  $f_{Y|\Lambda}(y|\lambda) = \text{pdf of } \exp(\lambda)$ . Then, the inference about the parameter given the lifetime of a light bulb is:

- A light bulb  $Y \sim \exp(\lambda)$ . However, there are some quality control problems. So, the parameter  $\lambda$  of  $Y$  is actually a random variable, denoted by  $\Lambda$ , which is  $\Lambda \sim \mathcal{U}[1, 3/2]$ . We test a light bulb and record its lifetime.
- **Question.** What can we say about the underlying parameter  $\lambda$ ? In other words, what is  $f_{\Lambda|Y}(\lambda|y)$ ?
- $f_{\Lambda}(\lambda) = 2$  for  $1 \leq \lambda \leq 3/2$  and  $f_{Y|\Lambda}(y|\lambda) = \text{pdf of } \exp(\lambda)$ . Then, the inference about the parameter given the lifetime of a light bulb is:

$$f_{\Lambda|Y}(\lambda|y) = \frac{f_{\Lambda}(\lambda)f_{Y|\Lambda}(y|\lambda)}{\int_{-\infty}^{\infty} f_{\Lambda}(t)f_{Y|\Lambda}(y|t)dt}$$

- $X$ : **parameter**  $\rightarrow Y$ : result of **my model**
- Given:  $\mathbb{P}(X)$  and  $\mathbb{P}(Y|X)$  (parameter  $\rightarrow$  model)
- Inference:  $\mathbb{P}(X|Y)$ ? Probabilistic feature of the parameter given the result of the model?

Example.

- $X$ : **parameter**  $\rightarrow Y$ : result of **my model**
- Given:  $\mathbb{P}(X)$  and  $\mathbb{P}(Y|X)$  (parameter  $\rightarrow$  model)
- Inference:  $\mathbb{P}(X|Y)$ ? Probabilistic feature of the parameter given the result of the model?

## Example.

1. Light bulb's lifetime  $Y \sim \exp(\lambda)$ . Given the lifetime  $y$ , the modified belief about  $\lambda$ ?

- $X$ : **parameter**  $\rightarrow Y$ : result of **my model**
- Given:  $\mathbb{P}(X)$  and  $\mathbb{P}(Y|X)$  (parameter  $\rightarrow$  model)
- Inference:  $\mathbb{P}(X|Y)$ ? Probabilistic feature of the parameter given the result of the model?

## Example.

1. Light bulb's lifetime  $Y \sim \exp(\lambda)$ . Given the lifetime  **$y$** , the modified belief about  **$\lambda$** ?
2. Romeo and Juliet start dating, but Romeo will be late by a random variable  $Y \sim \mathcal{U}[0, \theta]$ . Given the time of being late  **$y$** , the modified belief about  **$\theta$** ?



$K$ : discrete,  $Y$ : continuous

$K$ : discrete,  $Y$ : continuous

- Inference of  $K$  given  $Y$

- Inference of  $Y$  given  $K$

$K$ : discrete,  $Y$ : continuous

- Inference of  $K$  given  $Y$

$$p_{K|Y}(k|y) = \frac{p_K(k)f_{Y|K}(y|k)}{f_Y(y)}$$

$$f_Y(y) = \sum_{k'} p_K(k')f_{Y|K}(y|k')$$

- Inference of  $Y$  given  $K$

$K$ : discrete,  $Y$ : continuous

- Inference of  $K$  given  $Y$

$$p_{K|Y}(k|y) = \frac{p_K(k)f_{Y|K}(y|k)}{f_Y(y)}$$

$$f_Y(y) = \sum_{k'} p_K(k')f_{Y|K}(y|k')$$

- $f_{Y|K}(y|k) = f_{Y|A}(y)$ , where  $A = \{K = k\}$

- Inference of  $Y$  given  $K$

$K$ : discrete,  $Y$ : continuous

- Inference of  $K$  given  $Y$

$$p_{K|Y}(k|y) = \frac{p_K(k)f_{Y|K}(y|k)}{f_Y(y)}$$

$$f_Y(y) = \sum_{k'} p_K(k')f_{Y|K}(y|k')$$

- $f_{Y|K}(y|k) = f_{Y|A}(y)$ , where  $A = \{K = k\}$

- Inference of  $Y$  given  $K$

$$f_{Y|K}(y|k) = \frac{f_Y(y)p_{K|Y}(k|y)}{p_K(k)}$$

$$p_K(k) = \int f_Y(y')p_{K|Y}(k|y')dy'$$

$K$ : discrete,  $Y$ : continuous

- Inference of  $K$  given  $Y$

$$p_{K|Y}(k|y) = \frac{p_K(k)f_{Y|K}(y|k)}{f_Y(y)}$$

$$f_Y(y) = \sum_{k'} p_K(k')f_{Y|K}(y|k')$$

- $f_{Y|K}(y|k) = f_{Y|A}(y)$ , where  $A = \{K = k\}$

- Inference of  $Y$  given  $K$

$$f_{Y|K}(y|k) = \frac{f_Y(y)p_{K|Y}(k|y)}{p_K(k)}$$

$$p_K(k) = \int f_Y(y')p_{K|Y}(k|y')dy'$$

- Wait!  $p_{K|Y}(k|y)$ ? Well-defined?

$$p_{K|Y}(k|y) = \frac{\mathbb{P}(K = k, Y = y)}{\mathbb{P}(Y = y)} = \frac{0}{0}$$

- For small  $\delta$  (in other words, taking the limit as  $\delta \rightarrow 0$ ).

Let  $A = \{K = k\}$ .

$$\begin{aligned} p_{K|Y}(k|y) &\approx \mathbb{P}(A|y \leq Y \leq y + \delta) \\ &= \frac{\mathbb{P}(A)\mathbb{P}(y \leq Y \leq y + \delta|A)}{\mathbb{P}(y \leq Y \leq y + \delta)} \\ &\approx \frac{\mathbb{P}(A)f_{Y|A}(y)\delta}{f_Y(y)\delta} \\ &= \frac{\mathbb{P}(A)f_{Y|A}(y)}{f_Y(y)} \end{aligned}$$

Inference of discrete  $K$  given continuous  $Y$ :

$$p_{K|Y}(k|y) = \frac{p_K(k)f_{Y|K}(y|k)}{f_Y(y)}, \quad f_Y(y) = \sum_{k'} p_K(k')f_{Y|K}(y|k')$$



Inference of discrete  $K$  given continuous  $Y$ :

$$p_{K|Y}(k|y) = \frac{p_K(k)f_{Y|K}(y|k)}{f_Y(y)}, \quad f_Y(y) = \sum_{k'} p_K(k')f_{Y|K}(y|k')$$

- $K$ : -1, +1, original signal, equally likely.  $p_K(1) = 1/2, p_K(-1) = 1/2$ .

Inference of discrete  $K$  given continuous  $Y$ :

$$p_{K|Y}(k|y) = \frac{p_K(k)f_{Y|K}(y|k)}{f_Y(y)}, \quad f_Y(y) = \sum_{k'} p_K(k')f_{Y|K}(y|k')$$

- $K$ : -1, +1, original signal, equally likely.  $p_K(1) = 1/2, p_K(-1) = 1/2$ .
- $Y$ : measured signal with Gaussian noise,  $Y = K + W, W \sim \mathcal{N}(0, 1)$

Inference of discrete  $K$  given continuous  $Y$ :

$$p_{K|Y}(k|y) = \frac{p_K(k)f_{Y|K}(y|k)}{f_Y(y)}, \quad f_Y(y) = \sum_{k'} p_K(k')f_{Y|K}(y|k')$$

- $K$ : -1, +1, original signal, equally likely.  $p_K(1) = 1/2, p_K(-1) = 1/2$ .
- $Y$ : measured signal with Gaussian noise,  $Y = K + W, W \sim \mathcal{N}(0, 1)$
- Your received signal = 0.7. What's your guess about the original signal?

Inference of discrete  $K$  given continuous  $Y$ :

$$p_{K|Y}(k|y) = \frac{p_K(k)f_{Y|K}(y|k)}{f_Y(y)}, \quad f_Y(y) = \sum_{k'} p_K(k')f_{Y|K}(y|k')$$

- $K$ : -1, +1, original signal, equally likely.  $p_K(1) = 1/2, p_K(-1) = 1/2$ .
- $Y$ : measured signal with Gaussian noise,  $Y = K + W, W \sim \mathcal{N}(0, 1)$
- Your received signal = 0.7. What's your guess about the original signal?
- Your received signal = -0.2. What's your guess about the original signal?

Inference of discrete  $K$  given continuous  $Y$ :

$$p_{K|Y}(k|y) = \frac{p_K(k)f_{Y|K}(y|k)}{f_Y(y)}, \quad f_Y(y) = \sum_{k'} p_K(k')f_{Y|K}(y|k')$$

- $K$ : -1, +1, original signal, equally likely.  $p_K(1) = 1/2, p_K(-1) = 1/2$ .
- $Y$ : measured signal with Gaussian noise,  $Y = K + W, W \sim \mathcal{N}(0, 1)$
- Your received signal = 0.7. What's your guess about the original signal? **+1**
- Your received signal = -0.2. What's your guess about the original signal? **-1**
- Your intuition: If positive received signal, +1. If negative received signal, -1. How can we mathematically verify this?

- $Y|\{K = 1\} \sim \mathcal{N}(1, 1)$  and  $Y|\{K = -1\} \sim \mathcal{N}(-1, 1)$ .  
(Remind: linear transformation preserves normality.)

- $Y|\{K = 1\} \sim \mathcal{N}(1, 1)$  and  $Y|\{K = -1\} \sim \mathcal{N}(-1, 1)$ .  
(Remind: linear transformation preserves normality.)

$$f_{Y|K}(y|k) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(y-k)^2}, \quad k = 1, -1$$

- $Y|\{K = 1\} \sim \mathcal{N}(1, 1)$  and  $Y|\{K = -1\} \sim \mathcal{N}(-1, 1)$ .  
(Remind: linear transformation preserves normality.)

$$f_{Y|K}(y|k) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(y-k)^2}, \quad k = 1, -1$$

$$f_Y(y) = \frac{1}{2} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(y+1)^2} + \frac{1}{2} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(y-1)^2} \quad (\text{from TPT})$$



- $Y|\{K = 1\} \sim \mathcal{N}(1, 1)$  and  $Y|\{K = -1\} \sim \mathcal{N}(-1, 1)$ .  
(Remind: linear transformation preserves normality.)

$$f_{Y|K}(y|k) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(y-k)^2}, \quad k = 1, -1$$

$$f_Y(y) = \frac{1}{2} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(y+1)^2} + \frac{1}{2} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(y-1)^2} \quad (\text{from TPT})$$

- Probability that  $K = 1$ , given  $Y = y$ ? After some algebra,

$$p_{K|Y}(1|y) = \frac{1}{1 + e^{-2y}}$$

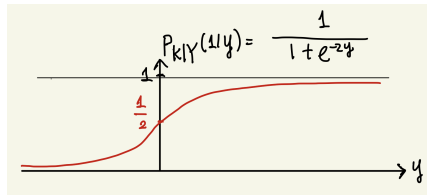
- $Y|\{K = 1\} \sim \mathcal{N}(1, 1)$  and  $Y|\{K = -1\} \sim \mathcal{N}(-1, 1)$ .  
(Remind: linear transformation preserves normality.)

$$f_{Y|K}(y|k) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(y-k)^2}, \quad k = 1, -1$$

$$f_Y(y) = \frac{1}{2} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(y+1)^2} + \frac{1}{2} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(y-1)^2} \quad (\text{from TPT})$$

- Probability that  $K = 1$ , given  $Y = y$ ? After some algebra,

$$p_{K|Y}(1|y) = \frac{1}{1 + e^{-2y}}$$



- $Y|\{K = 1\} \sim \mathcal{N}(1, 1)$  and  $Y|\{K = -1\} \sim \mathcal{N}(-1, 1)$ .  
(Remind: linear transformation preserves normality.)

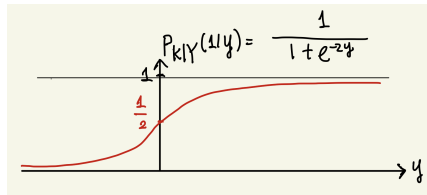
$$f_{Y|K}(y|k) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(y-k)^2}, \quad k = 1, -1$$

$$f_Y(y) = \frac{1}{2} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(y+1)^2} + \frac{1}{2} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(y-1)^2} \quad (\text{from TPT})$$

- Probability that  $K = 1$ , given  $Y = y$ ? After some algebra,

$$p_{K|Y}(1|y) = \frac{1}{1 + e^{-2y}}$$

- If  $y > 0$ , the inference probability for  $K = 1$  exceeds  $\frac{1}{2}$ . So, original signal = 1.



- $Y|\{K = 1\} \sim \mathcal{N}(1, 1)$  and  $Y|\{K = -1\} \sim \mathcal{N}(-1, 1)$ .  
(Remind: linear transformation preserves normality.)

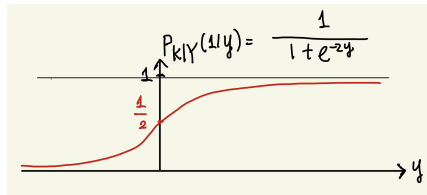
$$f_{Y|K}(y|k) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(y-k)^2}, \quad k = 1, -1$$

$$f_Y(y) = \frac{1}{2} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(y+1)^2} + \frac{1}{2} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(y-1)^2} \quad (\text{from TPT})$$

- Probability that  $K = 1$ , given  $Y = y$ ? After some algebra,

$$p_{K|Y}(1|y) = \frac{1}{1 + e^{-2y}}$$

- If  $y > 0$ , the inference probability for  $K = 1$  exceeds  $\frac{1}{2}$ . So, original signal = 1.
- Similarly, compute  $p_{K|Y}(-1|y)$  and then do the inference



Questions?

- 1) What do we mean by “continuous” in continuous random variables?
- 2) Explain PDF and CDF. Why do we need CDF?
- 3) What are joint/marginal/conditional PDFs?
- 4) Explain the relationship between Geometric rvs and Exponential rvs.
- 5) Explain how normality is preserved under linear transformation for Normal (Gaussian) rvs.
- 6) Explain how we can use Bayes' rule for parameter learning.
- 7) Explain the version of Bayes' rule for continuous and mixed random variables.