

CSE 312

# Foundations of Computing II

## Lecture 12: Continuous Random Variables




**Aleks Jovicic**

Slide Credit: Based on Stefano Tessaro's slides for 312 19au incorporating ideas from Anna Karlin, Alex Tsun, Rachel Lin, Hunter Schafer & myself 😊

# Agenda

$$X \sim \text{Bin}(\hat{10}, \hat{0.7})$$

- Poisson RV 
- Continuous Random Variables
- Probability Density Function
- Cumulative Distribution Function
- Expectation and Variance

# Poisson Distribution

- Suppose “events” happen, independently, at an *average* rate of  $\lambda$  per unit time.
- Let  $X$  be the *actual* number of events happening in a given time unit. Then  $X$  is a Poisson r.v. with parameter  $\lambda$  (denoted  $X \sim \text{Poi}(\lambda)$ ) and has distribution (PMF):

$$\mathbb{P}(X = i) = e^{-\lambda} \cdot \frac{\lambda^i}{i!}$$

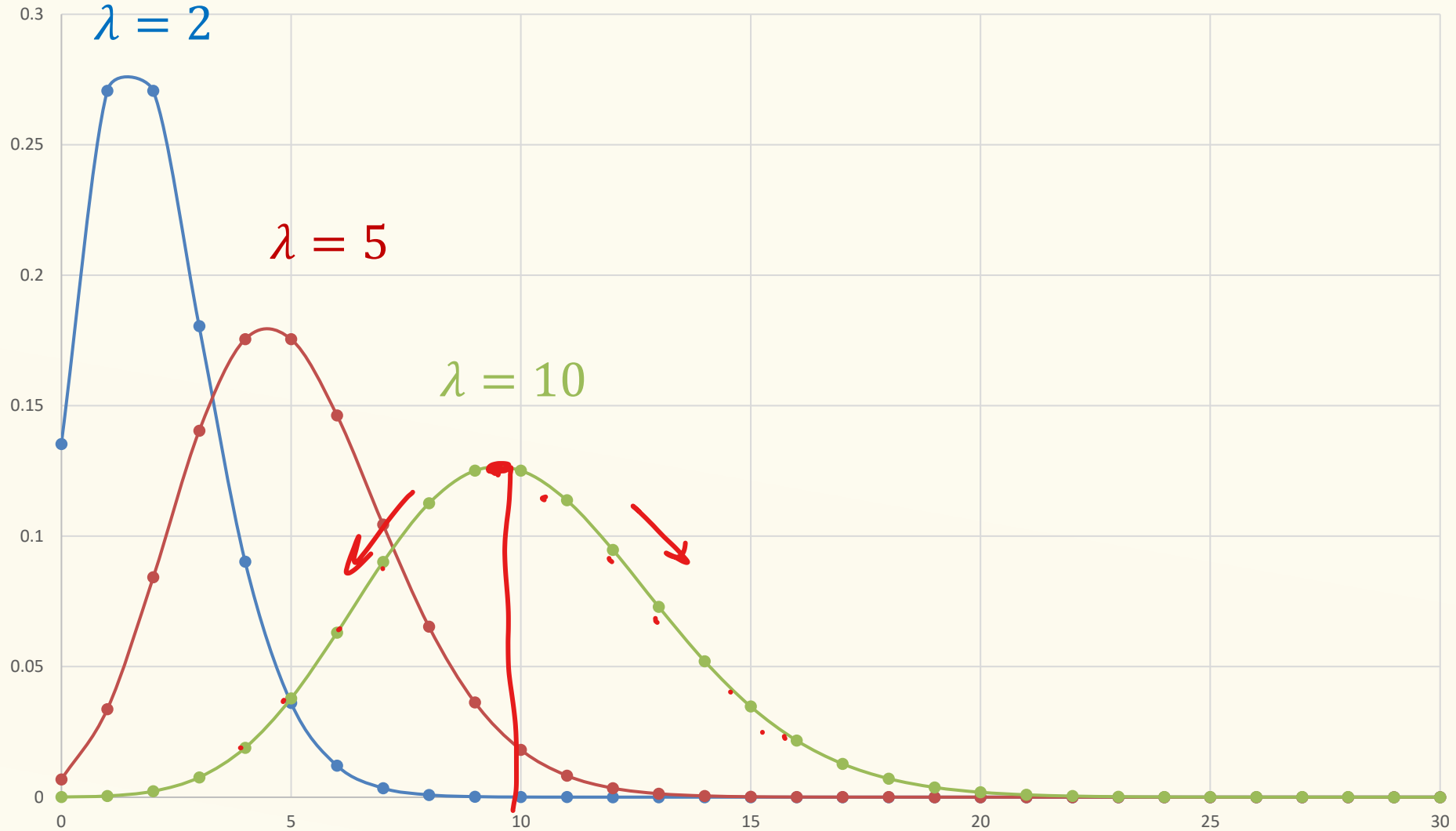
Several examples of “Poisson processes”:

- # of cars passing through a certain town in 1 hour
  - # of requests to web servers in a minute
  - # of photons hitting a light detector in a given interval
  - # of patients arriving to ER within an hour
- Assume fixed average rate

# Probability Mass Function

$[0, \infty)$

$$\mathbb{P}(X = i) = e^{-\lambda} \cdot \frac{\lambda^i}{i!}$$



# Validity of Distribution

$$\mathbb{P}(X = i) = e^{-\lambda} \cdot \frac{\lambda^i}{i!}$$

We first want to verify that Poisson probabilities sum up to 1.

$$\sum_{i=0}^{\infty} \mathbb{P}(X = i) =$$

$$\text{Fact. } \sum_{i=0}^{\infty} \frac{x^i}{i!} = e^x$$

# Validity of Distribution

$$\mathbb{P}(X = i) = e^{-\lambda} \cdot \frac{\lambda^i}{i!}$$

We first want to verify that Poisson probabilities sum up to 1.

$$\sum_{i=0}^{\infty} \mathbb{P}(X = i) = e^{-\lambda} \sum_{i=0}^{\infty} \frac{\lambda^i}{i!} = e^{-\lambda} e^{\lambda} = 1$$

**Fact.**  $\sum_{i=0}^{\infty} \frac{x^i}{i!} = e^x$

## Expectation

$$\mathbb{P}(X = i) = e^{-\lambda} \cdot \frac{\lambda^i}{i!}$$

**Theorem.** If  $X$  is a Poisson RV with parameter  $\lambda$ , then

$$\mathbb{E}(X) = \lambda$$

**Proof.**  $\mathbb{E}(X) = \sum_{i=0}^{\infty} i \cdot \mathbb{P}(X = i)$

# Expectation

$\text{Poi}(\lambda)$

$$\mathbb{P}(X = i) = e^{-\lambda} \cdot \frac{\lambda^i}{i!}$$

**Theorem.** If  $X$  is a Poisson RV with parameter  $\lambda$ , then

$$\mathbb{E}(X) = \lambda$$

**Proof.**

$$\begin{aligned}\mathbb{E}(X) &= \sum_{i=0}^{\infty} e^{-\lambda} \cdot \frac{\lambda^i}{i!} \cdot i = \sum_{i=1}^{\infty} e^{-\lambda} \cdot \frac{\lambda^i}{(i-1)!} \\ &= \lambda \sum_{i=1}^{\infty} e^{-\lambda} \cdot \frac{\lambda^{i-1}}{(i-1)!} \\ &= \lambda \sum_{i=0}^{\infty} e^{-\lambda} \cdot \frac{\lambda^i}{i!} = \lambda \cdot 1 = \lambda\end{aligned}$$

= 1 (see prior slides!)



## Variance

$$\mathbb{P}(X = i) = e^{-\lambda} \cdot \frac{\lambda^i}{i!}$$

**Theorem.** If  $X$  is a Poisson RV with parameter  $\lambda$ , then  $\text{Var}(X) = \lambda$

**Proof.** 
$$\mathbb{E}(X^2) = \sum_{i=0}^{\infty} e^{-\lambda} \cdot \frac{\lambda^i}{i!} \cdot i^2 = \lambda^2 + \lambda$$



$$\text{Var}(X) = \mathbb{E}(X^2) - \mathbb{E}(X)^2 = \lambda^2 + \lambda - \lambda^2 = \lambda$$

# Variance

$$\mathbb{P}(X = i) = e^{-\lambda} \cdot \frac{\lambda^i}{i!}$$

**Theorem.** If  $X$  is a Poisson RV with parameter  $\lambda$ , then  $\text{Var}(X) = \lambda$

**Proof.**

$$\begin{aligned}\mathbb{E}(X^2) &= \sum_{i=0}^{\infty} e^{-\lambda} \cdot \frac{\lambda^i}{i!} \cdot i^2 = \sum_{i=1}^{\infty} e^{-\lambda} \cdot \frac{\lambda^i}{(i-1)!} i \\ &= \lambda \sum_{i=1}^{\infty} e^{-\lambda} \cdot \frac{\lambda^{i-1}}{(i-1)!} \cdot i = \lambda \sum_{j=0}^{\infty} e^{-\lambda} \cdot \frac{\lambda^j}{j!} \cdot (j+1) \\ &= \lambda \left[ \underbrace{\sum_{j=0}^{\infty} e^{-\lambda} \cdot \frac{\lambda^j}{j!} \cdot j}_{= \mathbb{E}(X) = \lambda} + \underbrace{\sum_{j=0}^{\infty} e^{-\lambda} \cdot \frac{\lambda^j}{j!}}_{= 1} \right] = \lambda^2 + \lambda\end{aligned}$$

Similar to the previous proof  
Verify offline.



$$\text{Var}(X) = \mathbb{E}(X^2) - \mathbb{E}(X)^2 = \lambda^2 + \lambda - \lambda^2 = \lambda$$

# Poisson Random Variables

**Definition.** A **Poisson random variable**  $X$  with parameter  $\lambda \geq 0$  is such that for all  $i = 0, 1, 2, 3 \dots$ ,

$$\mathbb{P}(X = i) = e^{-\lambda} \cdot \frac{\lambda^i}{i!}$$

**Notation:**  $X \sim \text{Poi}(\lambda)$

**PMF:**  $\Pr(X = i) = e^{-\lambda} \cdot \frac{\lambda^i}{i!}$

**Expectation:**  $E[X] = \lambda$

**Variance:**  $\text{Var}(X) = \lambda$

# Sum of Independent Poisson RVs

**Theorem.** Let  $X \sim Poi(\lambda_1)$  and  $Y \sim Poi(\lambda_2)$  such that  $\lambda = \lambda_1 + \lambda_2$ .

Let  $Z = (X + Y)$ . For all  $k = 0, 1, 2, 3, \dots$ ,

$$\mathbb{P}(Z = k) = e^{-\lambda} \cdot \frac{\lambda^k}{k!}$$

More generally, let  $X_1 \sim Poi(\lambda_1), \dots, X_n \sim Poi(\lambda_n)$  such that  $\lambda = \sum_i \lambda_i$ .


Let  $Z = \sum_i X_i$

$$\mathbb{P}(Z = k) = e^{-\lambda} \cdot \frac{\lambda^k}{k!}$$

## Poisson Example

There are two ERs in a small town that act independently. The first has an average of 4 patients admitted per hour, and the second has an average of 3. What is the likelihood that in the next hour, 10 patients are admitted across both ERs?

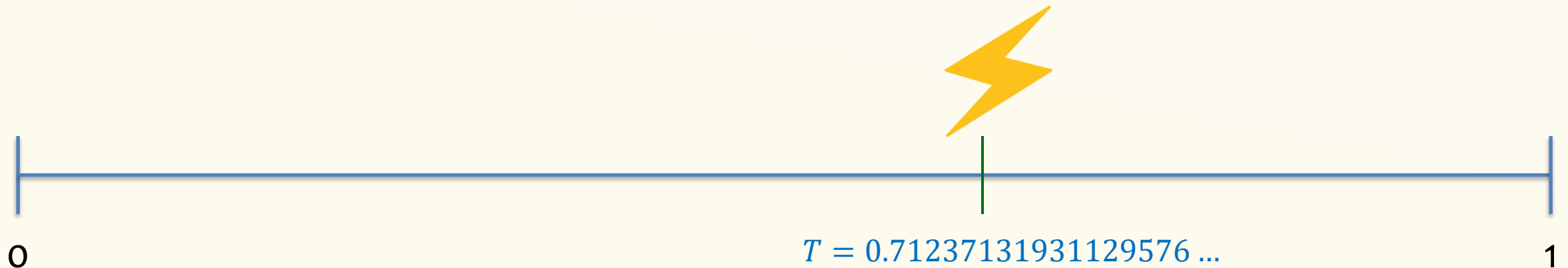
# Agenda

- Poisson RV
- Continuous Random Variables 
- Probability Density Function
- Cumulative Distribution Function
- Expectation and Variance

## Example – Lightning Strike

Lightning strikes a pole within a one-minute time frame

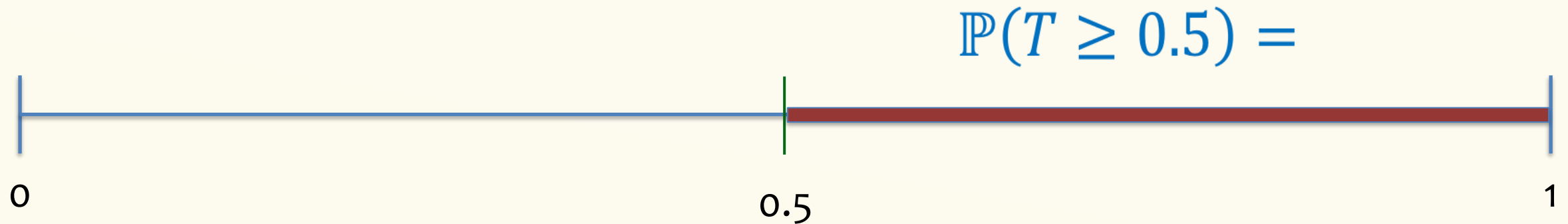
- $T$  = time of lightning strike
- Every time within  $[0,1]$  is equally likely
  - Time measured with infinitesimal precision.



The outcome space is not discrete

Lightning strikes a pole within a one-minute time frame

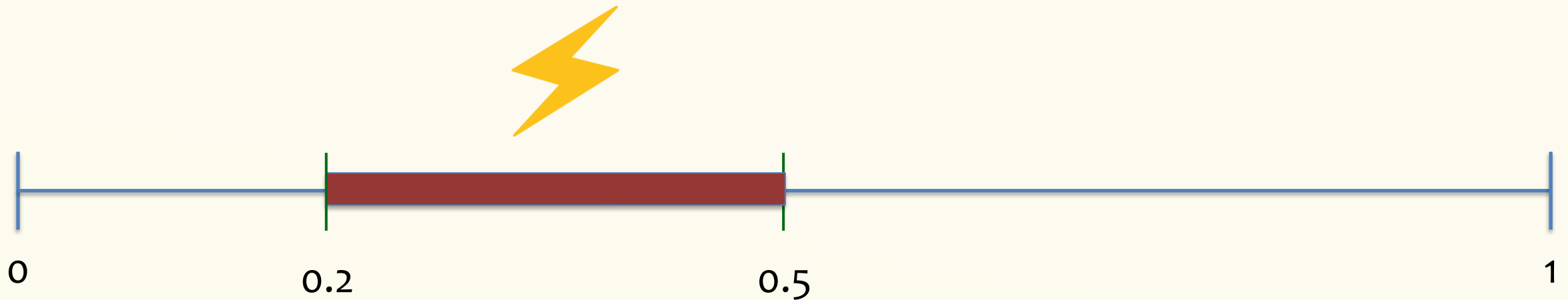
- $T$  = time of lightning strike
- Every point in time within  $[0,1]$  is equally likely





Lightning strikes a pole within a one-minute time frame

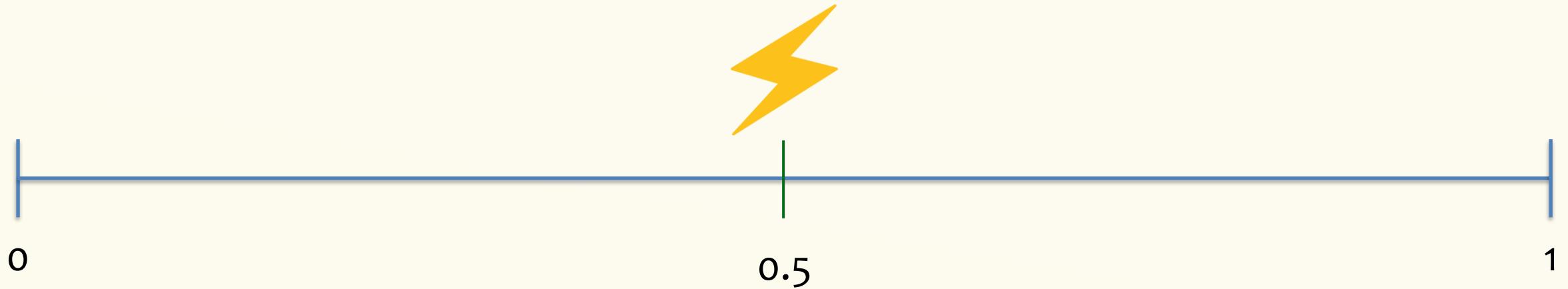
- $T$  = time of lightning strike
- Every point in time within  $[0,1]$  is equally likely



$$\mathbb{P}(0.2 \leq T \leq 0.5) =$$

Lightning strikes a pole within a one-minute time frame

- $T$  = time of lightning strike
- Every point in time within  $[0,1]$  is equally likely




$$\mathbb{P}(T = 0.5) =$$

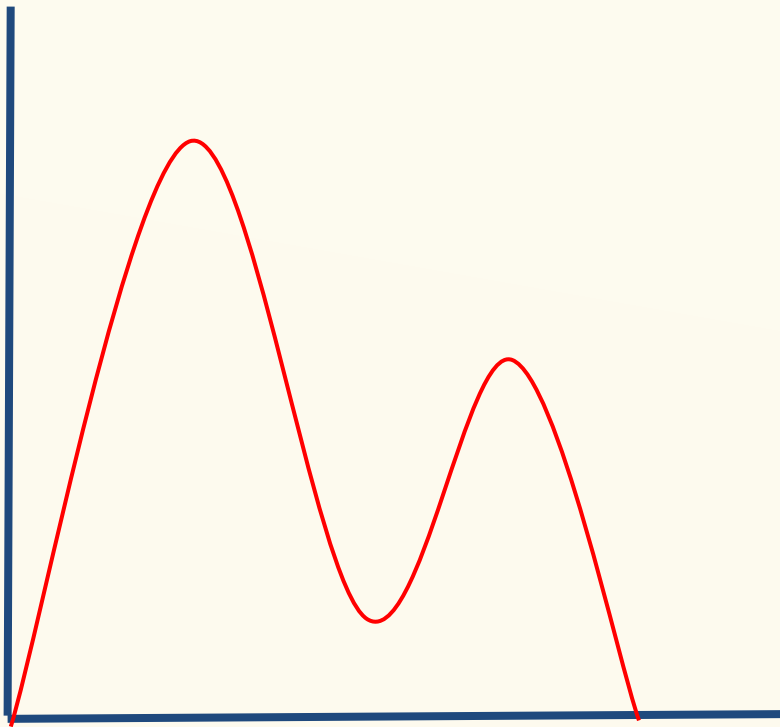
## Bottom line

- This gives rise to a different type of random variable
- $\mathbb{P}(T = x) = 0$  for all  $x \in [0,1]$
- Yet, somehow we want
  - $\mathbb{P}(T \in [0,1]) = 1$
  - $\mathbb{P}(T \in [a, b]) = b - a$
  - ...
- How do we model the behavior of  $T$ ?

# Agenda

- Poisson RV
- Continuous Random Variables
- **Probability Density Function** 
- Cumulative Distribution Function
- Expectation and Variance

**Definition.** A **continuous random variable**  $X$  is defined by a **probability density function (PDF)**  $f_X: \mathbb{R} \rightarrow \mathbb{R}$ , such that

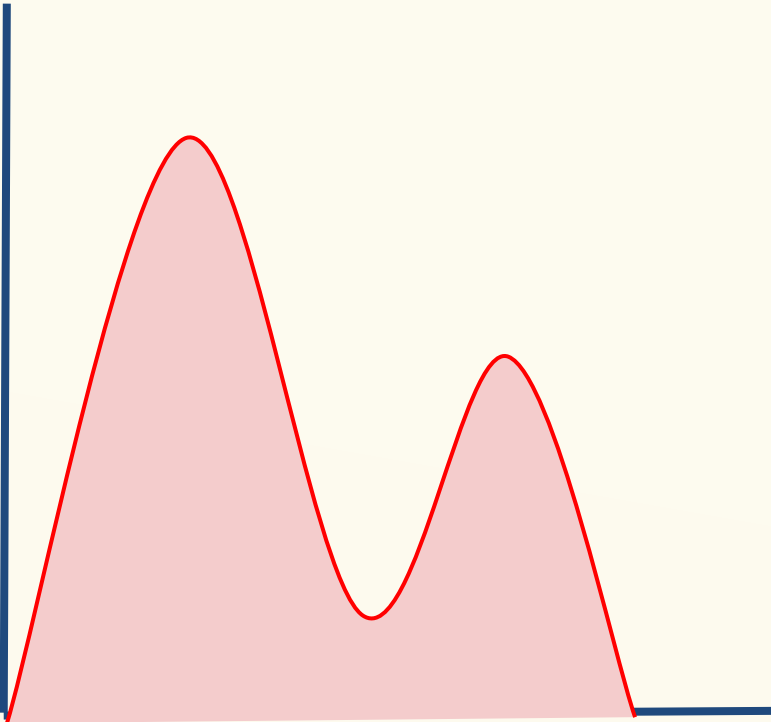


**Non-negativity:**  $f_X(x) \geq 0$  for all  $x \in \mathbb{R}$

# Probability Density Function - Intuition

**Non-negativity:**  $f_X(x) \geq 0$  for all  $x \in \mathbb{R}$

**Normalization:**  $\int_{-\infty}^{+\infty} f_X(x) dx = 1$

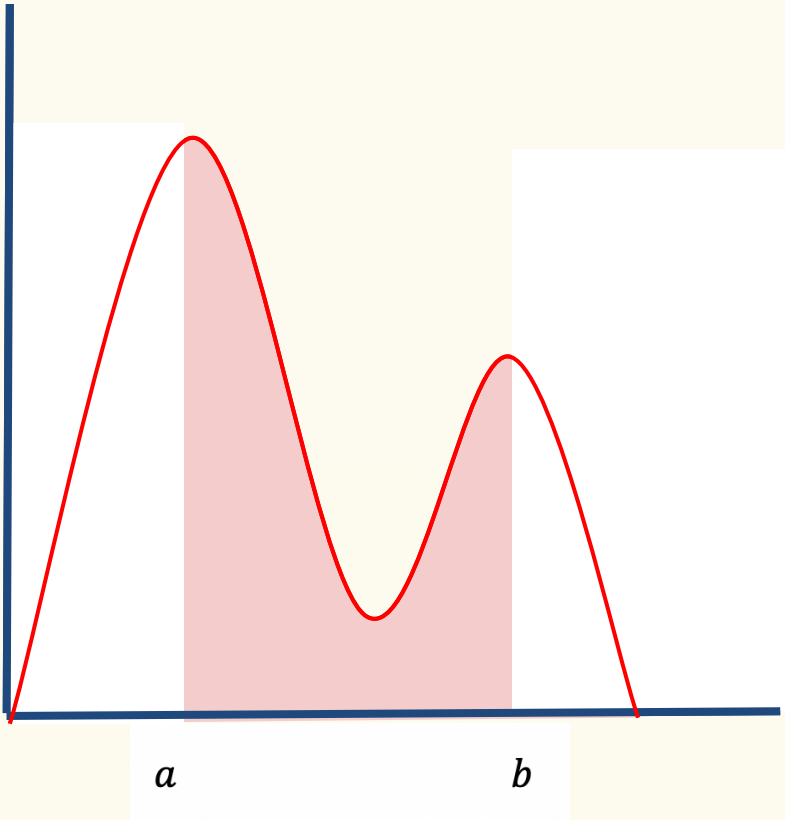


# Probability Density Function - Intuition

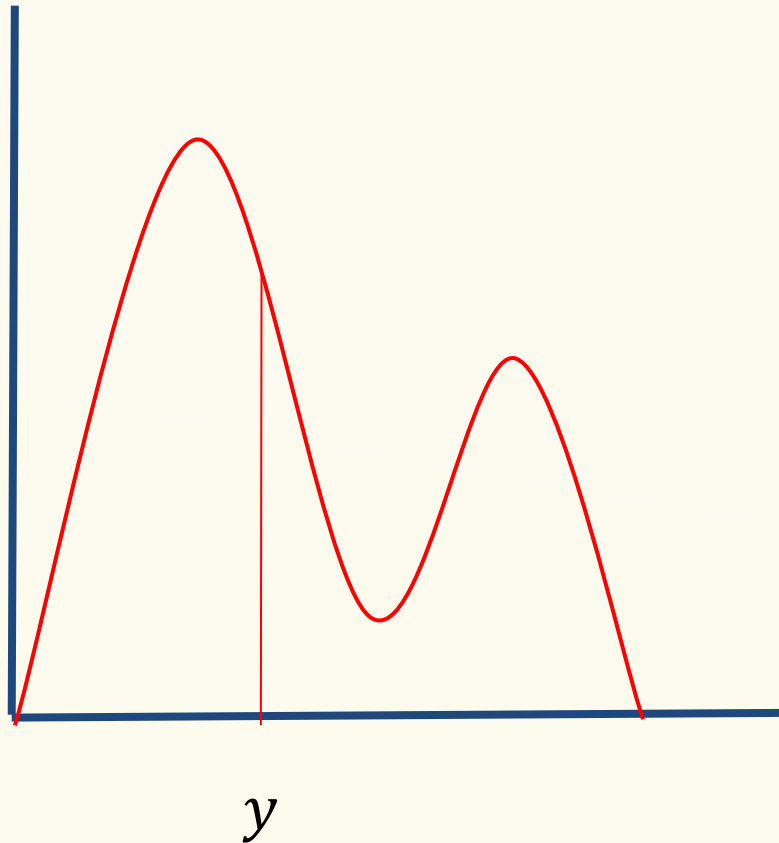
**Non-negativity:**  $f_X(x) \geq 0$  for all  $x \in \mathbb{R}$

**Normalization:**  $\int_{-\infty}^{+\infty} f_X(x) dx = 1$

$$P(a \leq X \leq b) = \int_a^b f_X(x) dx$$



# Probability Density Function - Intuition



**Non-negativity:**  $f_X(x) \geq 0$  for all  $x \in \mathbb{R}$

**Normalization:**  $\int_{-\infty}^{+\infty} f_X(x) dx = 1$

$$P(a \leq X \leq b) = \int_a^b f_X(x) dx$$

$$P(X = y) = P(y \leq X \leq y) = \int_y^y f_X(x) dx = 0$$

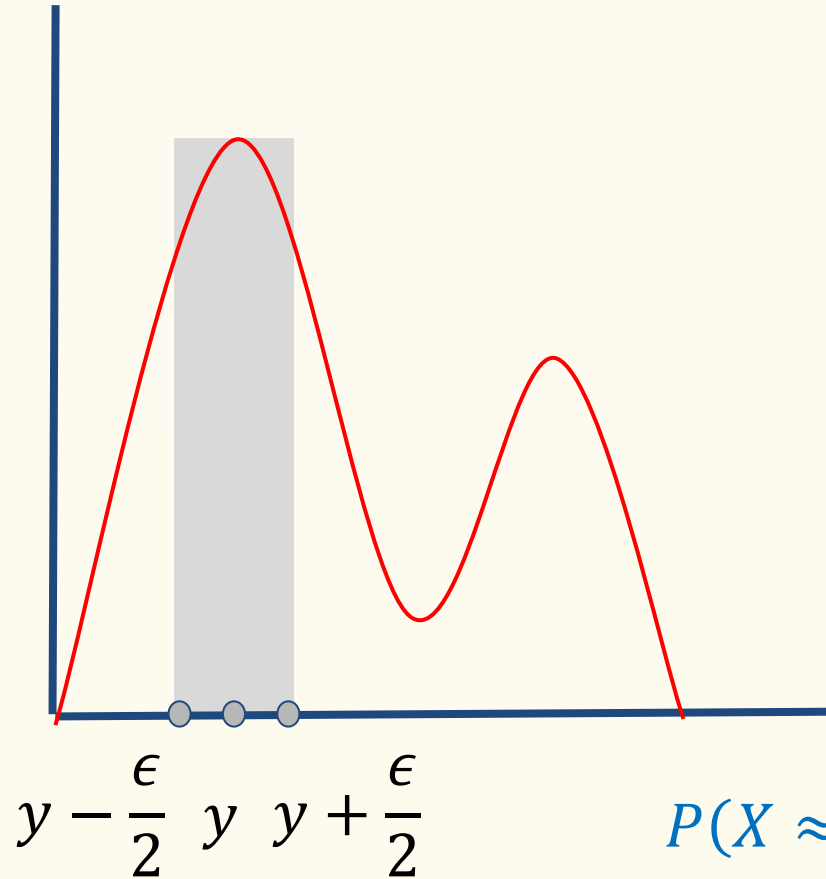


**Density  $\neq$  Probability**

$$f_X(y) \neq 0 \quad \mathbb{P}(X = y) = 0$$



# Probability Density Function - Intuition



**Non-negativity:**  $f_X(x) \geq 0$  for all  $x \in \mathbb{R}$

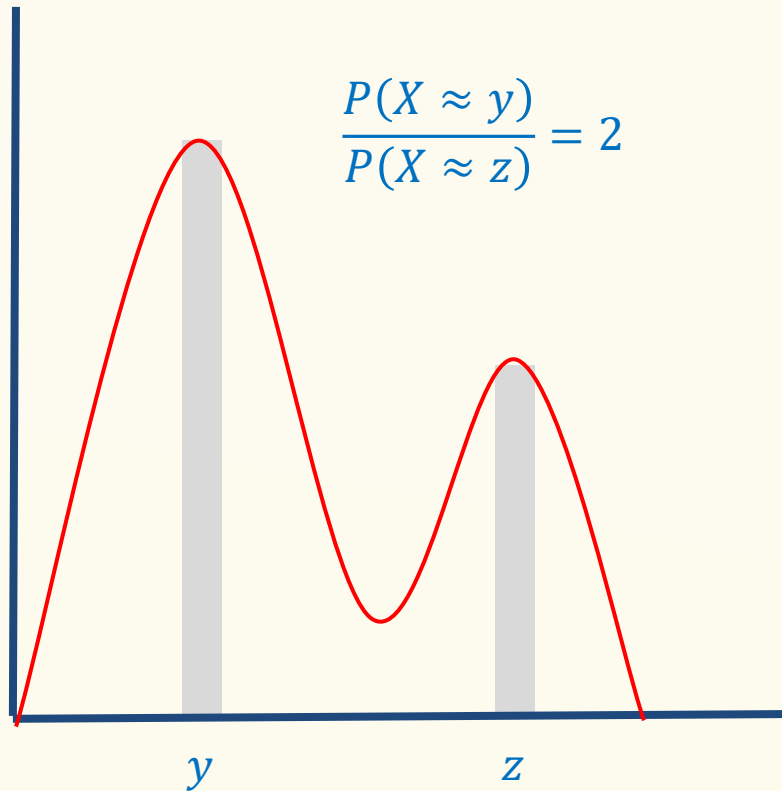
**Normalization:**  $\int_{-\infty}^{+\infty} f_X(x) dx = 1$

$$P(a \leq X \leq b) = \int_a^b f_X(x) dx$$

$$P(X = y) = P(y \leq X \leq y) = \int_y^y f_X(x) dx = 0$$

$$P(X \approx y) \approx P\left(y - \frac{\epsilon}{2} \leq X \leq y + \frac{\epsilon}{2}\right) = \int_{y - \frac{\epsilon}{2}}^{y + \frac{\epsilon}{2}} f_X(x) dx \approx \epsilon f_X(y)$$

# Probability Density Function - Intuition



**Non-negativity:**  $f_X(x) \geq 0$  for all  $x \in \mathbb{R}$

**Normalization:**  $\int_{-\infty}^{+\infty} f_X(x) dx = 1$

$$P(a \leq X \leq b) = \int_a^b f_X(x) dx$$

$$P(X = y) = P(y \leq X \leq y) = \int_y^y f_X(x) dx = 0$$

$$P(X \approx y) \approx P\left(y - \frac{\epsilon}{2} \leq X \leq y + \frac{\epsilon}{2}\right) = \int_{y - \frac{\epsilon}{2}}^{y + \frac{\epsilon}{2}} f_X(x) dx \approx \epsilon f_X(y)$$

$$\frac{P(X \approx y)}{P(X \approx z)} \approx \frac{\epsilon f_X(y)}{\epsilon f_X(z)} = \frac{f_X(y)}{f_X(z)}$$

**Definition.** A **continuous random variable**  $X$  is defined by a **probability density function** (PDF)  $f_X: \mathbb{R} \rightarrow \mathbb{R}$ , such that

**Non-negativity:**  $f_X(x) \geq 0$  for all  $x \in \mathbb{R}$

**Normalization:**  $\int_{-\infty}^{+\infty} f_X(x) dx = 1$

$$P(a \leq X \leq b) = \int_a^b f_X(x) dx$$

$$P(X = y) = P(y \leq X \leq y) = \int_y^y f_X(x) dx = 0$$

$$P(X \approx y) \approx P\left(y - \frac{\epsilon}{2} \leq X \leq y + \frac{\epsilon}{2}\right) = \int_{y - \frac{\epsilon}{2}}^{y + \frac{\epsilon}{2}} f_X(x) dx \approx \epsilon f_X(y)$$

$$\frac{P(X \approx y)}{P(X \approx z)} \approx \frac{\epsilon f_X(y)}{\epsilon f_X(z)} = \frac{f_X(y)}{f_X(z)}$$

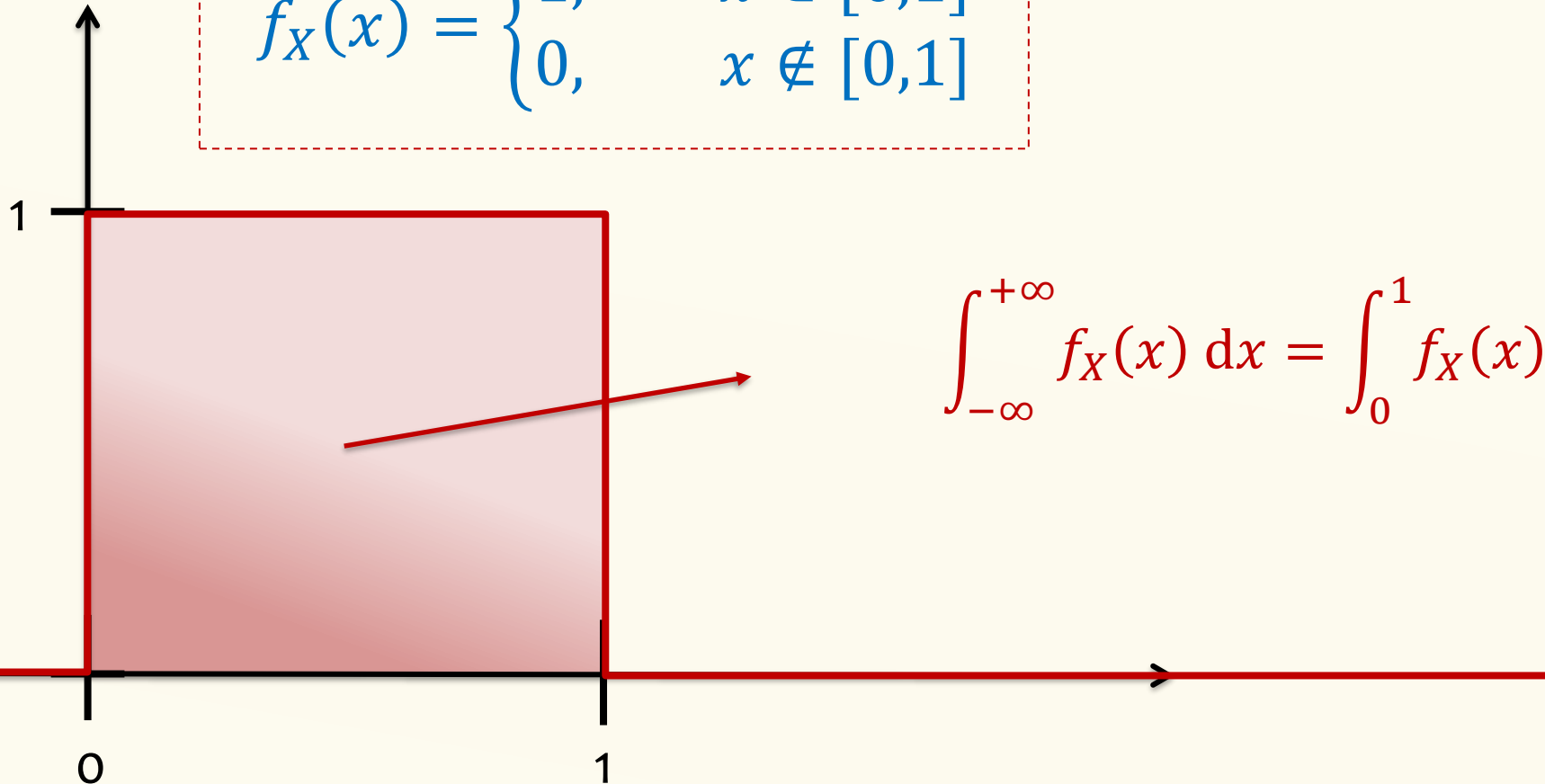
# PDF of Uniform RV

$$X \sim \text{Unif}(0,1)$$

**Non-negativity:**  $f_X(x) \geq 0$  for all  $x \in \mathbb{R}$

**Normalization:**  $\int_{-\infty}^{+\infty} f_X(x) dx = 1$

$$f_X(x) = \begin{cases} 1, & x \in [0,1] \\ 0, & x \notin [0,1] \end{cases}$$



$$\int_{-\infty}^{+\infty} f_X(x) dx = \int_0^1 f_X(x) dx = 1 \cdot 1 = 1$$

# Probability of Event

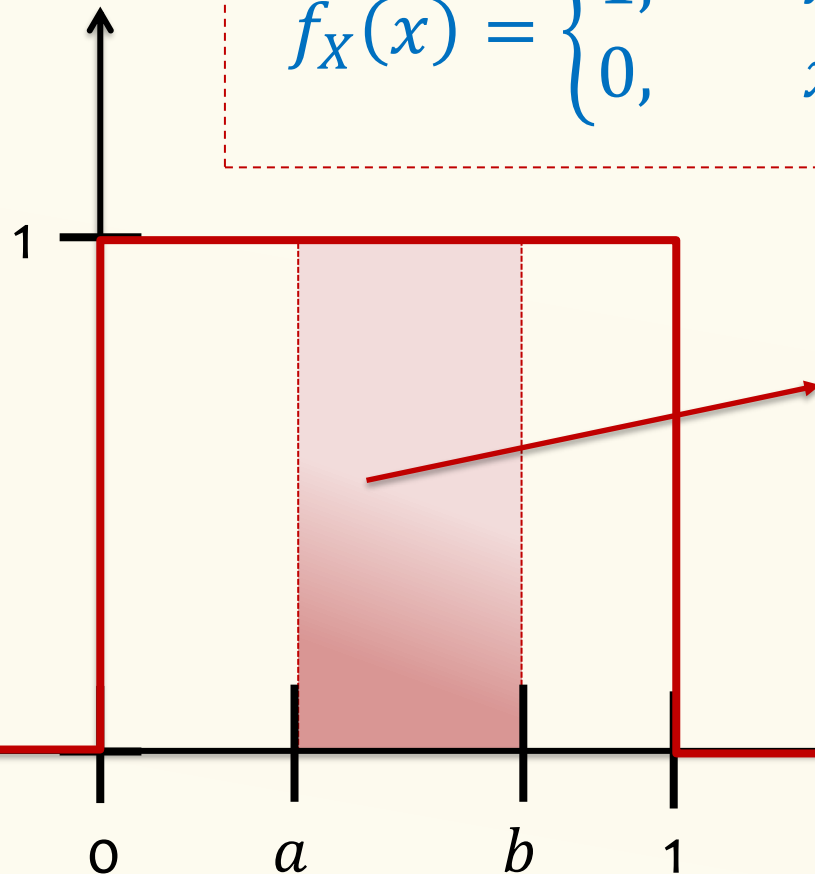
$X \sim \text{Unif}(0,1)$

**Non-negativity:**  $f_X(x) \geq 0$  for all  $x \in \mathbb{R}$

$$f_X(x) = \begin{cases} 1, & x \in [0,1] \\ 0, & x \notin [0,1] \end{cases}$$

**Normalization:**  $\int_{-\infty}^{+\infty} f_X(x) dx = 1$

$$P(a \leq X \leq b) = \int_a^b f_X(x) dx$$



1. If  $0 \leq a$  and  $b \leq 1$

$$\mathbb{P}(a \leq X \leq b) = b - a$$

2. If  $a < 0$  and  $0 \leq b \leq 1$

$$\mathbb{P}(a \leq X \leq b) = b$$

3. If  $a \geq 0$  and  $b > 1$

$$\mathbb{P}(a \leq X \leq b) = b - a$$

4. If  $a < 0$  and  $b > 1$

$$\mathbb{P}(a \leq X \leq b) = 1$$

- A. All of them are correct
- B. Only 1, 2, 4 are right
- C. Only 1 is right
- D. Only 1 and 2 are right**



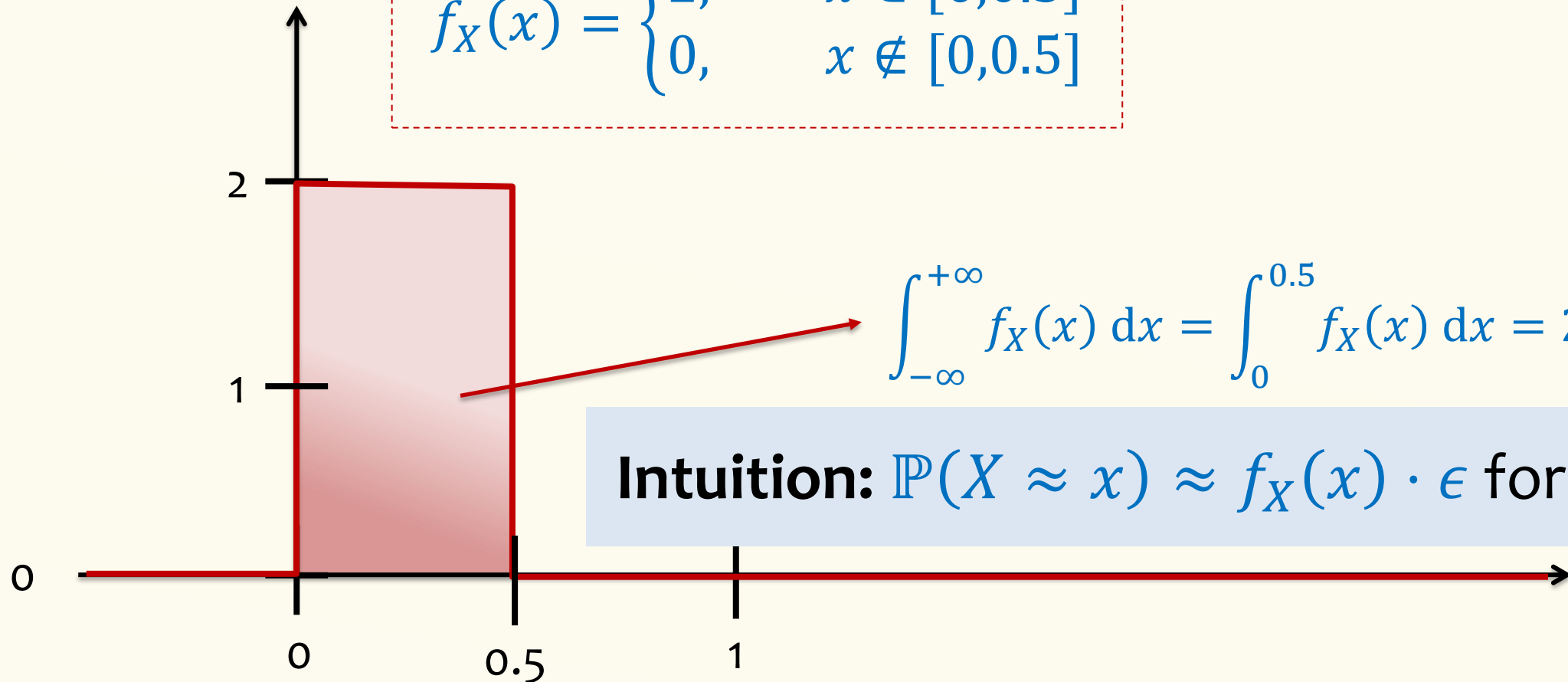
Density  $\neq$  Probability

$f_X(x) \gg 1$  is possible!

# PDF of Uniform RV

$X \sim \text{Unif}(0,0.5)$

$$f_X(x) = \begin{cases} 2, & x \in [0,0.5] \\ 0, & x \notin [0,0.5] \end{cases}$$

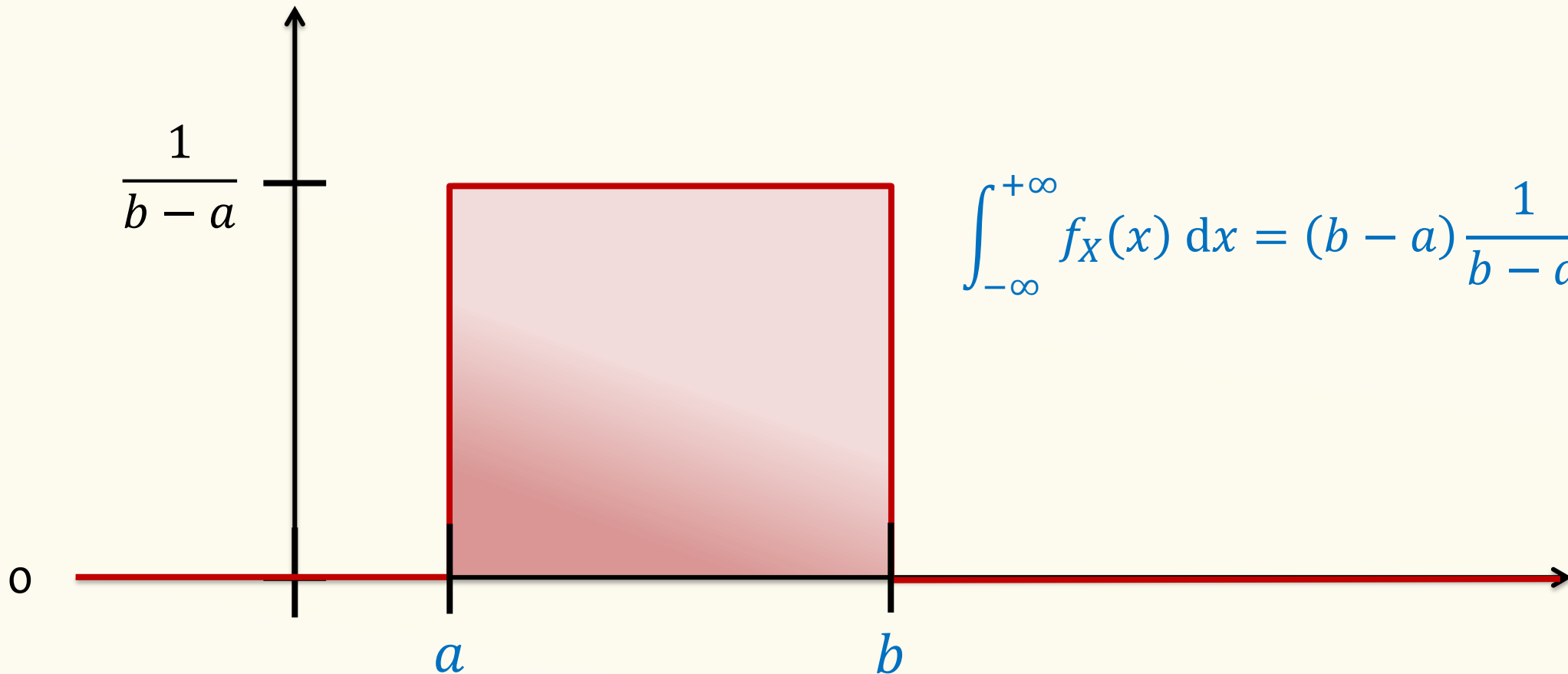


**Intuition:**  $\mathbb{P}(X \approx x) \approx f_X(x) \cdot \epsilon$  for small  $\epsilon$

# Uniform Distribution


$X \sim \text{Unif}(a, b)$

$$f_X(x) = \begin{cases} \frac{1}{b-a} & x \in [a, b] \\ 0 & \text{else} \end{cases}$$



$$\int_{-\infty}^{+\infty} f_X(x) dx = (b-a) \frac{1}{b-a} = 1$$

# Agenda

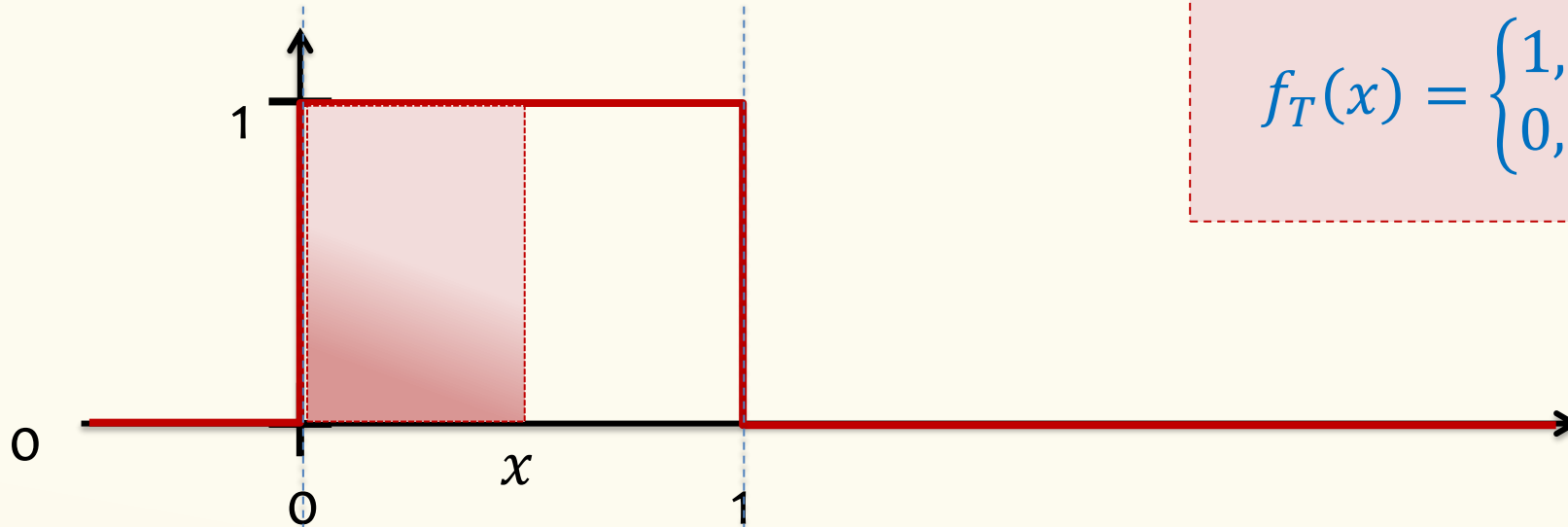
- Poisson RV
- Continuous Random Variables
- Probability Density Function
- **Cumulative Distribution Function** 
- Expectation and Variance



**Example.**  $T \sim \text{Unif}(0,1)$

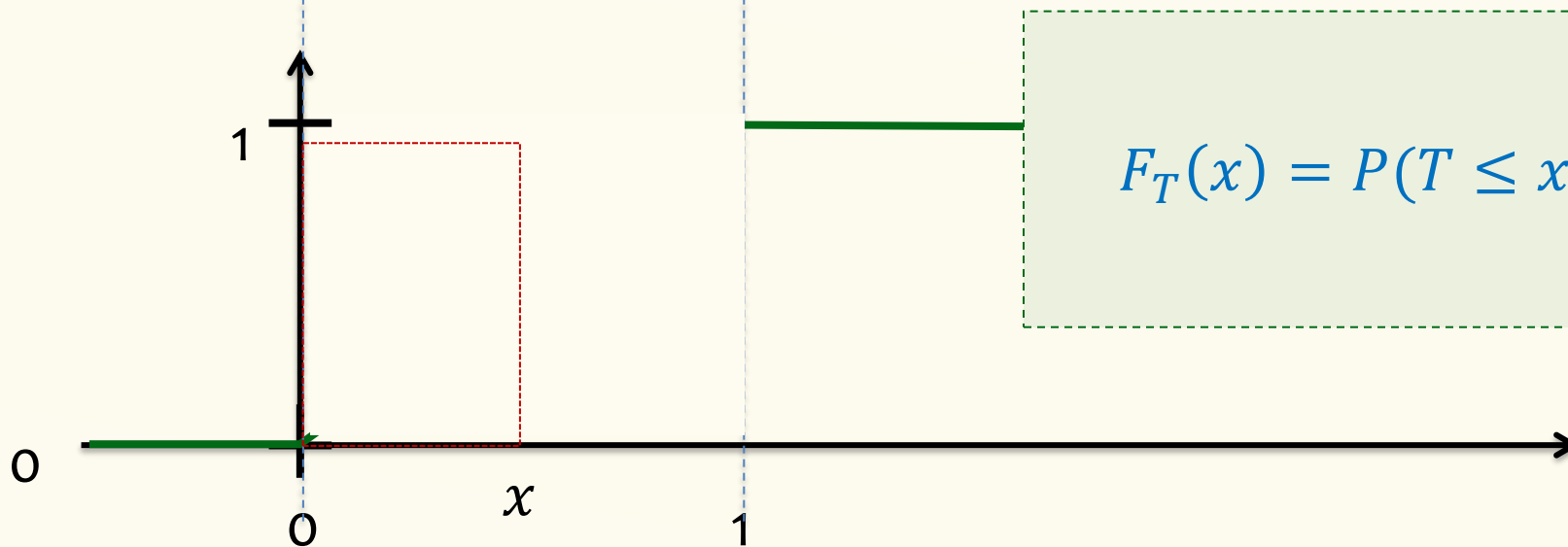
### Probability Density Function

$$f_T(x) = \begin{cases} 1, & x \in [0,1] \\ 0, & x \notin [0,1] \end{cases}$$



### Cumulative Distribution Function

$$F_T(x) = P(T \leq x) = \begin{cases} 0 & x \leq 0 \\ ? & 0 \leq x \leq 1 \\ 1 & 1 \leq x \end{cases}$$



# Cumulative Distribution Function

**Definition.** The **cumulative distribution function (cdf)** of  $X$  is

$$F_X(a) = \mathbb{P}(X \leq a) = \int_{-\infty}^a f_X(x) dx$$

By the fundamental theorem of Calculus  $f_X(x) = \frac{d}{dx} F(x)$

# Cumulative Distribution Function

**Definition.** The **cumulative distribution function (cdf)** of  $X$  is

$$F_X(a) = \mathbb{P}(X \leq a) = \int_{-\infty}^a f_X(x) dx$$

By the fundamental theorem of Calculus  $f_X(x) = \frac{d}{dx} F(x)$

Therefore:  $\mathbb{P}(X \in [a, b]) = F(b) - F(a)$

$F_X$  is monotone increasing, since  $f_X(x) \geq 0$ . That is  $F_X(c) \leq F_X(d)$  for  $c \leq d$

$\lim_{a \rightarrow -\infty} F_X(a) = P(X \leq -\infty) = 0$      $\lim_{a \rightarrow +\infty} F_X(a) = P(X \leq +\infty) = 1$

# From Discrete to Continuous

	<b>Discrete</b>	<b>Continuous</b>
<b>PMF/PDF</b>	$p_X(x) = P(X = x)$	$f_X(x) \neq P(X = x) = 0$
<b>CDF</b>	$F_X(x) = \sum_{t < x} p_X(t)$	$F_X(x) = \int_{-\infty}^x f_X(t) dt$
<b>Normalization</b>	$\sum_x p_X(x) = 1$	$\int_{-\infty}^{\infty} f_X(x) dx = 1$
<b>Expectation</b>	$\mathbb{E}[g(X)] = \sum_x g(x)p_X(x)$	$\mathbb{E}[g(X)] = \int_{-\infty}^{\infty} g(x)f_X(x) dx$

# Agenda

- Poisson RV
- Continuous Random Variables
- Probability Density Function
- Cumulative Distribution Function
- Expectation and Variance



# Expectation of a Continuous RV

**Definition.** The **expected value** of a continuous RV  $X$  is defined as

$$\mathbb{E}(X) = \int_{-\infty}^{+\infty} f_X(x) \cdot x \, dx$$

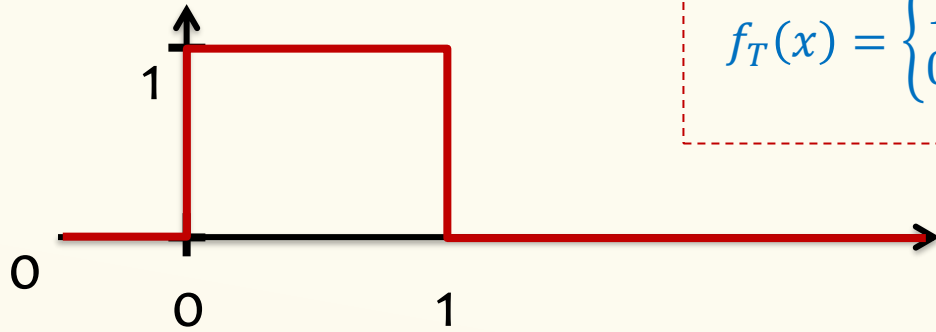
**Fact.**  $\mathbb{E}(aX + bY + c) = a\mathbb{E}(X) + b\mathbb{E}(Y) + c$

**Definition.** The **variance** of a continuous RV  $X$  is defined as

$$\text{Var}(X) = \int_{-\infty}^{+\infty} f_X(x) \cdot (x - \mathbb{E}(X))^2 \, dx = \mathbb{E}(X^2) - \mathbb{E}(X)^2$$

# Expectation of a Continuous RV

**Example.**  $T \sim \text{Unif}(0,1)$



$$f_T(x) = \begin{cases} 1, & x \in [0,1] \\ 0, & x \notin [0,1] \end{cases}$$

**Definition.**

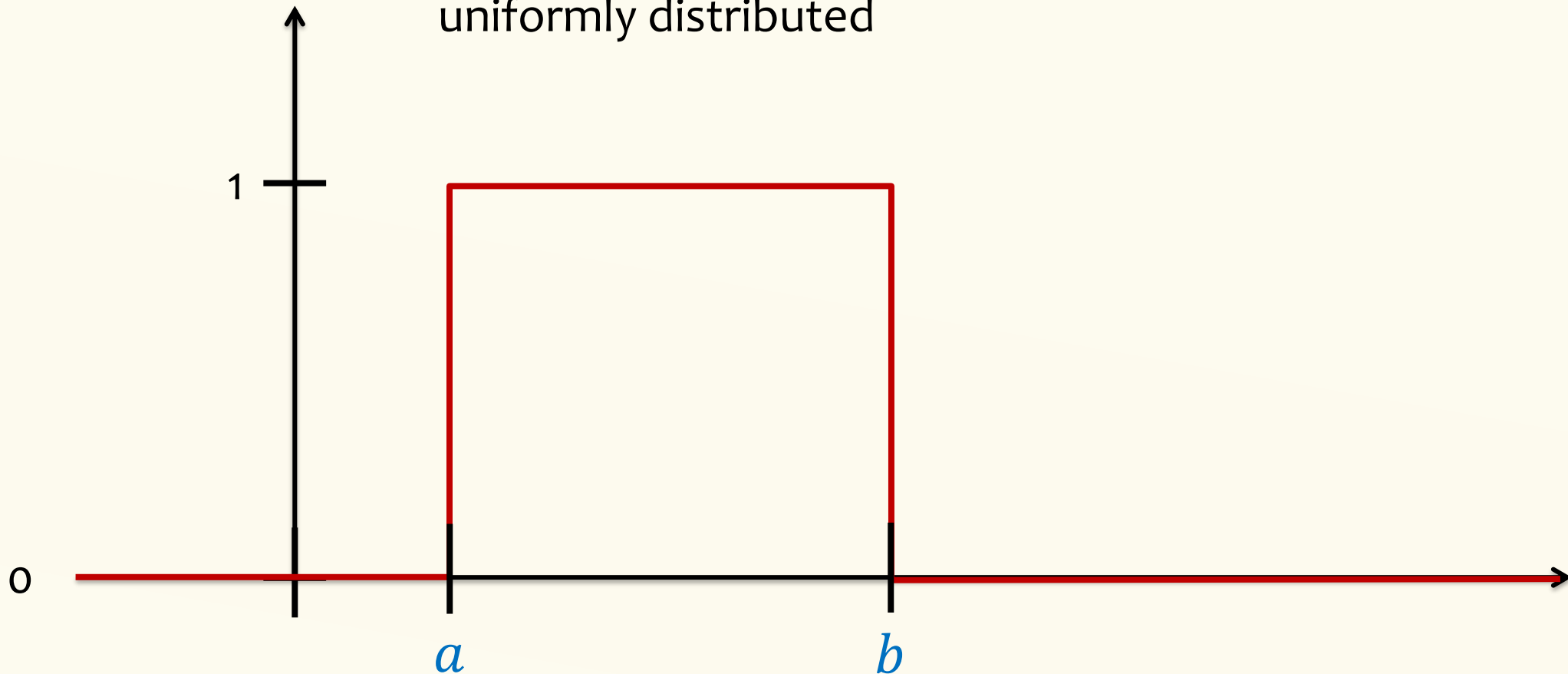
$$\mathbb{E}(X) = \int_{-\infty}^{+\infty} f_X(x) \cdot x \, dx$$

# Uniform Distribution

$$X \sim \text{Unif}(a, b)$$

We also say that  $X$  follows the uniform distribution / is uniformly distributed

$$f_X(x) = \begin{cases} \frac{1}{b-a} & x \in [a, b] \\ 0 & \text{else} \end{cases}$$





## Uniform Density – Expectation

$$X \sim \text{Unif}(a, b)$$

$$\mathbb{E}(X) = \int_{-\infty}^{+\infty} f_X(x) \cdot x \, dx$$

$$f_X(x) = \begin{cases} \frac{1}{b-a} & x \in [a, b] \\ 0 & \text{else} \end{cases}$$

# Uniform Density – Expectation

$$X \sim \text{Unif}(a, b)$$

$$f_X(x) = \begin{cases} \frac{1}{b-a} & x \in [a, b] \\ 0 & \text{else} \end{cases}$$

$$\mathbb{E}(X) = \int_{-\infty}^{+\infty} f_X(x) \cdot x \, dx$$

$$\begin{aligned} &= \frac{1}{b-a} \int_a^b x \, dx = \frac{1}{b-a} \left( \frac{x^2}{2} \right) \Big|_a^b = \frac{1}{b-a} \left( \frac{b^2 - a^2}{2} \right) \\ &= \frac{(b-a)(a+b)}{2(b-a)} = \frac{a+b}{2} \end{aligned}$$

## Uniform Density – Variance

$$X \sim \text{Unif}(a, b)$$

$$\mathbb{E}(X^2) = \int_{-\infty}^{+\infty} f_X(x) \cdot x^2 \, dx$$

$$f_X(x) = \begin{cases} \frac{1}{b-a} & x \in [a, b] \\ 0 & \text{else} \end{cases}$$

## Uniform Density – Variance

$$X \sim \text{Unif}(a, b)$$

$$f_X(x) = \begin{cases} \frac{1}{b-a} & x \in [a, b] \\ 0 & \text{else} \end{cases}$$

$$\mathbb{E}(X^2) = \int_{-\infty}^{+\infty} f_X(x) \cdot x^2 \, dx$$

$$= \frac{1}{b-a} \int_a^b x^2 \, dx = \frac{1}{b-a} \left( \frac{x^3}{3} \right) \Big|_a^b = \frac{b^3 - a^3}{3(b-a)}$$

$$= \frac{(b-a)(b^2 + ab + a^2)}{3(b-a)} = \frac{b^2 + ab + a^2}{3}$$

## Uniform Density – Variance

$$\mathbb{E}(X^2) = \frac{b^2 + ab + a^2}{3} \quad \mathbb{E}(X) = \frac{a + b}{2}$$

$$X \sim \text{Unif}(a, b)$$

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

$$= \frac{b^2 + ab + a^2}{3} - \frac{a^2 + 2ab + b^2}{4}$$

$$= \frac{4b^2 + 4ab + 4a^2}{12} - \frac{3a^2 + 6ab + 3b^2}{12}$$

$$= \frac{b^2 - 2ab + a^2}{12} = \frac{(b - a)^2}{12}$$