


# Recap Continuous Joint Distributions, Law of Total Probability (continuous) Law of Total Expectation

CSE 312 Spring 26  
Lecture 22

# Agenda

- Recap – joint continuous distns 
- Continuous law of total probability
- Law of total expectation

$$f(x)dx \approx P(X \in [x, x+dx])$$

$$f_{X,Y}(x,y)dx dy \approx P(X \in [x, x+dx], Y \in [y, y+dy])$$

# Reference Sheet

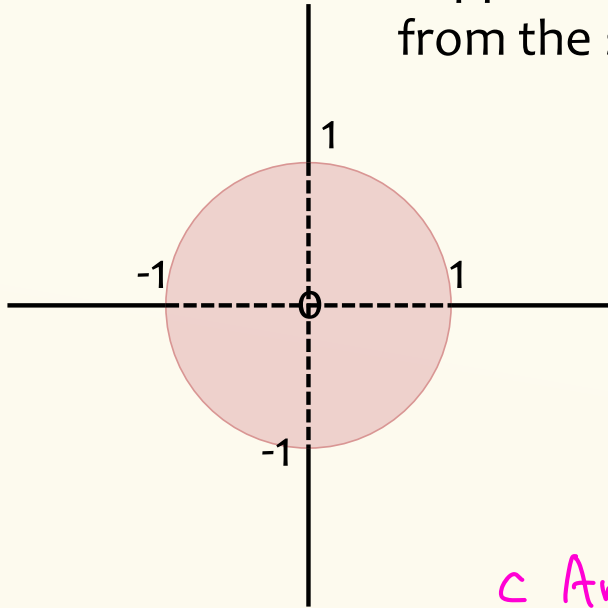
	Discrete	Continuous
<b>Joint PMF/PDF</b>	$p_{X,Y}(x, y) = P(X = x, Y = y)$	$f_{X,Y}(x, y) \neq P(X = x, Y = y)$
<b>Joint CDF</b>	$F_{X,Y}(x, y) = \sum_{t \leq x} \sum_{s \leq y} p_{X,Y}(t, s)$	$F_{X,Y}(x, y) = \int_{-\infty}^x \int_{-\infty}^y f_{X,Y}(t, s) ds dt$
<b>Normalization</b>	$\sum_x \sum_y p_{X,Y}(x, y) = 1$	$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{X,Y}(x, y) dx dy = 1$
<b>Marginal PMF/PDF</b>	$p_X(x) = \sum_y p_{X,Y}(x, y)$	$f_X(x) = \int_{-\infty}^{\infty} f_{X,Y}(x, y) dy$
<b>Expectation</b>	$E[g(X, Y)] = \sum_x \sum_y g(x, y) p_{X,Y}(x, y)$	$E[g(X, Y)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x, y) f_{X,Y}(x, y) dx dy$
<b>Independence</b>	$\forall x, y, p_{X,Y}(x, y) = p_X(x) p_Y(y)$	$\forall x, y, f_{X,Y}(x, y) = f_X(x) f_Y(y)$

$$\Omega_{X,Y} = \{(x,y) \mid f_{X,Y}(x,y) > 0\}$$

$$\Omega_{XY} = \Omega_X \times \Omega_Y$$

## Example – Uniform distribution on a unit disk

Suppose that a pair of random variables  $(X, Y)$  is chosen uniformly from the set of real points  $(x, y)$  such that  $x^2 + y^2 \leq 1$



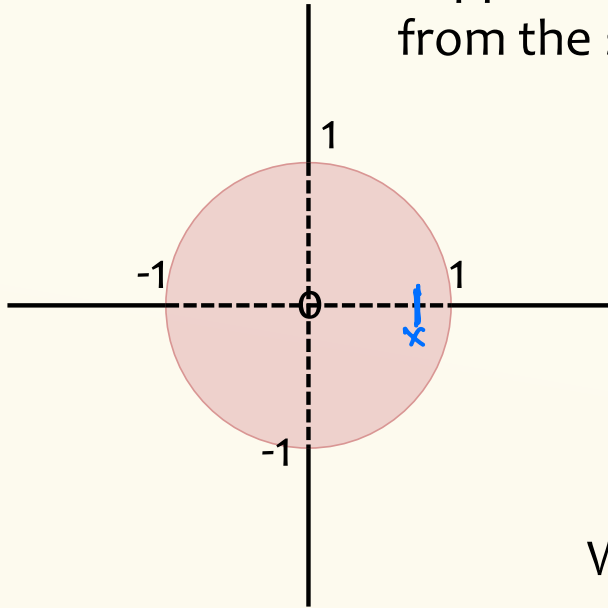
What is the joint density?

$$f_{X,Y}(x, y) = \begin{cases} c & \text{if } x^2 + y^2 \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

$$c \text{ Area of circle} = c\pi = 1$$

## Example – Uniform distribution on a unit disk

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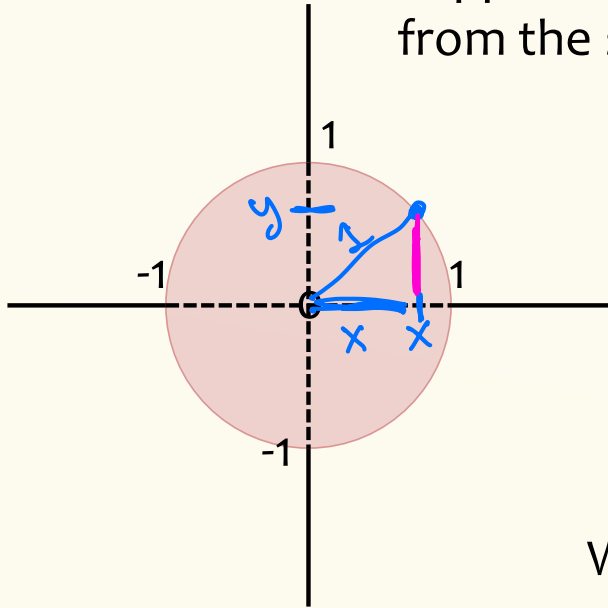
This is a disk of radius 1 which has area  $\pi$

$$f_{X,Y}(x, y) = \begin{cases} \frac{1}{\pi} & \text{if } x^2 + y^2 \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

What is  $f_X(x)$  ?

## Example – Uniform distribution on a unit disk

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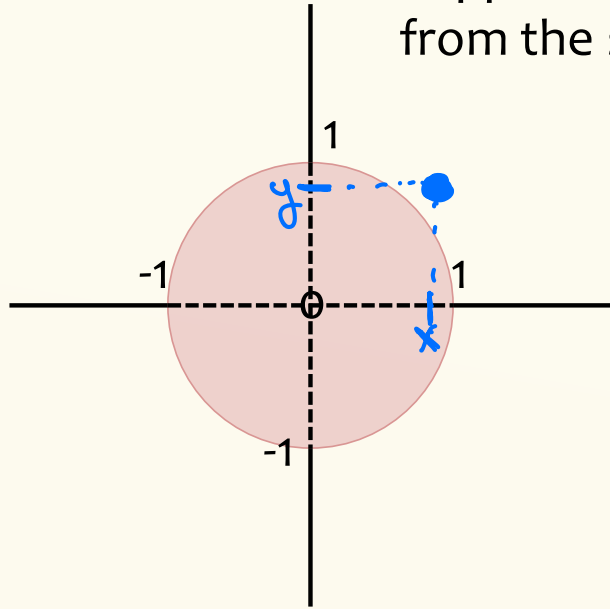
$$f_{X,Y}(x, y) = \begin{cases} \frac{1}{\pi} & \text{if } x^2 + y^2 \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

What is  $f_X(x)$  ?

$$\begin{aligned} f_X(x) &= \int_{-\sqrt{1-x^2}}^{\sqrt{1-x^2}} \frac{1}{\pi} dy \\ &= 2\sqrt{1-x^2}/\pi \end{aligned}$$

## Example – Uniform distribution on a unit disk

Suppose that a pair of random variables  $(X, Y)$  is chosen uniformly from the set of real points  $(x, y)$  such that  $x^2 + y^2 \leq 1$



This is a disk of radius 1 which has area  $\pi$

$$f_{X,Y}(x, y) = \begin{cases} \frac{1}{\pi} & \text{if } x^2 + y^2 \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

$$f_X(x) = \int_{-\sqrt{1-x^2}}^{\sqrt{1-x^2}} \frac{1}{\pi} dy \quad f_Y(y) = \int_{-\sqrt{1-y^2}}^{\sqrt{1-y^2}} \frac{1}{\pi} dx$$

$$= 2\sqrt{1-x^2}/\pi$$

$$= 2\sqrt{1-y^2}/\pi$$

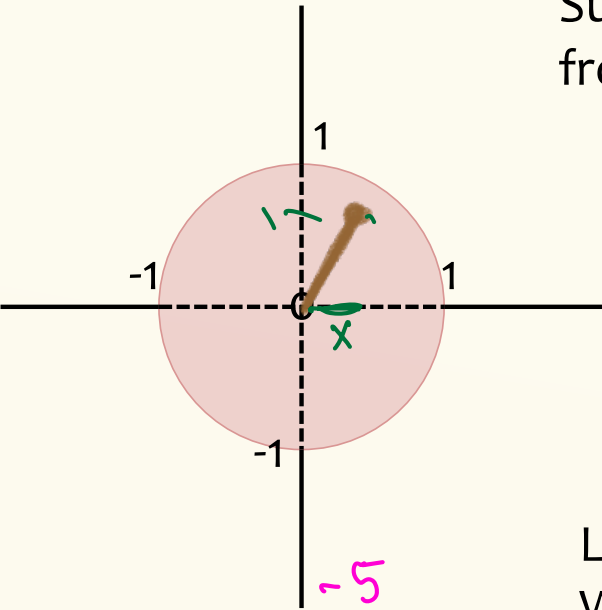
Are  $X$  and  $Y$  independent?

Is  $f_{X,Y}(x, y) = f_X(x) \cdot f_Y(y)$  for all  $x, y \in \mathbb{R}$ ?

$$x = 1 - \epsilon \quad y = 1 - \epsilon$$

# Example – Uniform distribution on a unit disk

Suppose that a pair of random variables  $(X, Y)$  is chosen uniformly from the set of real points  $(x, y)$  such that  $x^2 + y^2 \leq 1$



This is a disk of radius 1 which has area  $\pi$

$$f_{X,Y}(x, y) = \begin{cases} \frac{1}{\pi} & \text{if } x^2 + y^2 \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

Let  $D$  be the distance of the point  $(X, Y)$  from the origin. What is  $P(D \leq d)$ ? What is  $f_D(d)$ ? What is  $E(D)$ ?

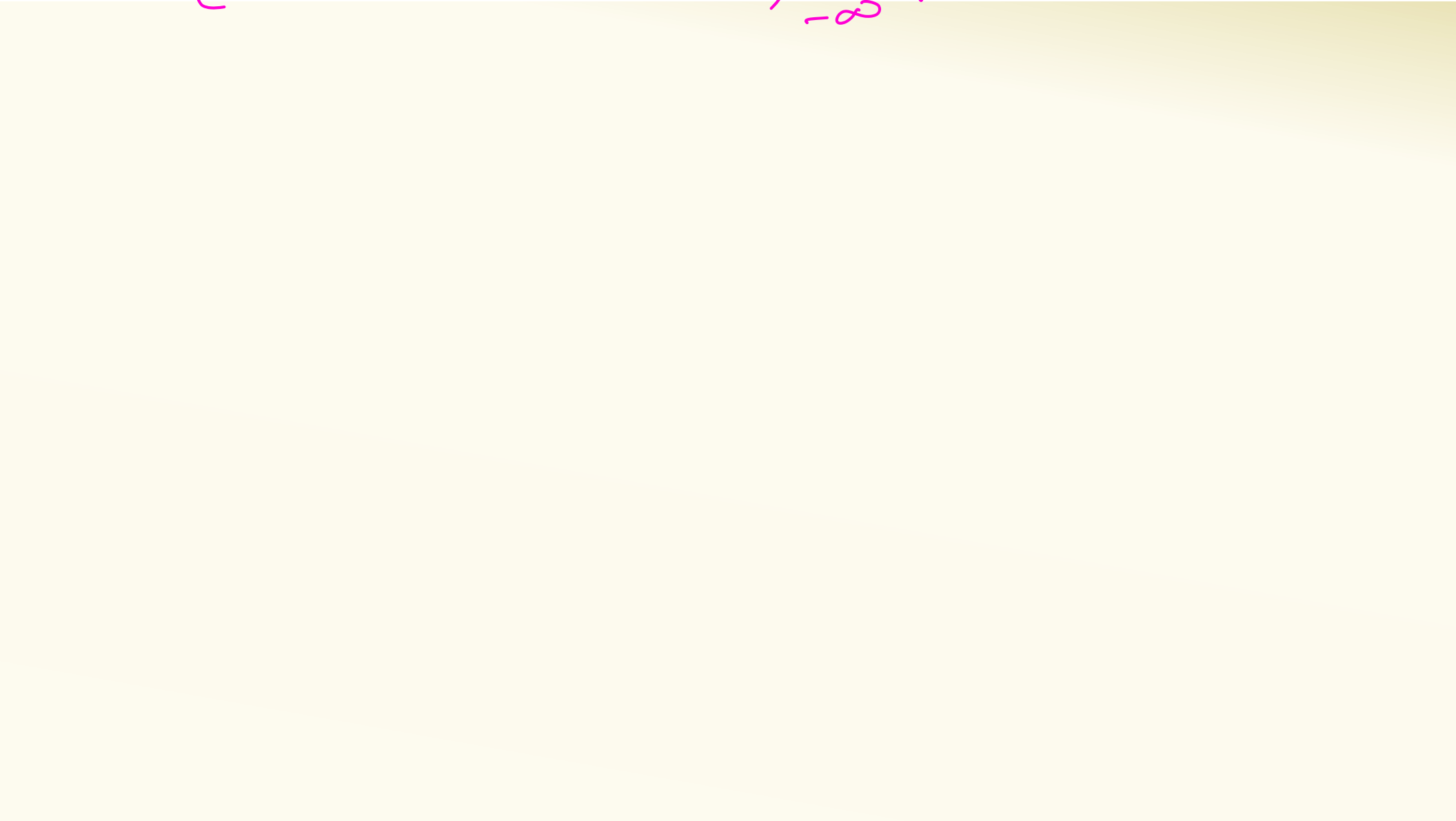
Handwritten notes and calculations:

$$P(D \leq d) = P(\sqrt{X^2 + Y^2} \leq d) = P(X^2 + Y^2 \leq d^2) = \iint_{x^2 + y^2 \leq d^2} f_{X,Y}(x, y) dx dy = \frac{\pi d^2}{\pi} = d^2$$

$f_D(d) = \begin{cases} 2d & \text{if } 0 \leq d \leq 1 \\ 0 & \text{o.w.} \end{cases}$

$E(D) = \int_0^1 x f_D(x) dx = \frac{2}{3}$

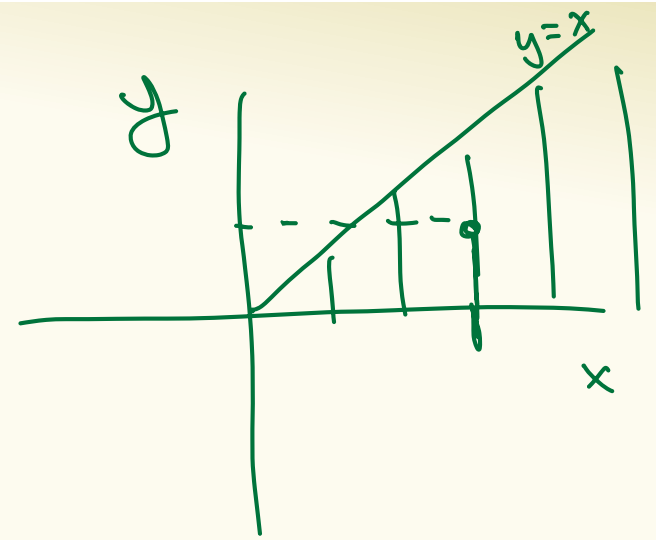
A pink arrow points from the boxed  $f_{X,Y}(x, y)$  in the integral to  $\frac{1}{\pi}$  written in pink.



## Example – More joint densities

The joint density of  $X$  and  $Y$  is

$$f_{X,Y}(x,y) = \begin{cases} 2e^{-x}e^{-2y} & 0 \leq x, y \leq \infty \\ 0 & \text{otherwise} \end{cases}$$



What is  $P(X > 1, Y < 1)$ ? What is  $P(X > Y)$ ? What is  $f_X(x)$ ?

$$\int_0^1 \int_0^{\infty} f_{X,Y}(x,y) dx dy$$

$$\int_0^{\infty} \int_0^x f_{X,Y}(x,y) dy dx$$

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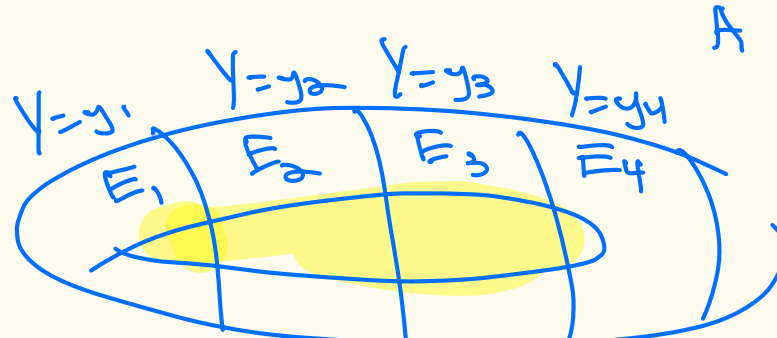
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$$f_{XYWZ}(x, y, w, z)$$

$$f_{XY}(x, y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{XYWZ}(x, y, w, z) dw dz$$

# Agenda

- Recap – joint continuous distns
- Continuous law of total probability ◀
- Law of total expectation



## Law of total probability

**Definition.** Let  $A$  be an event and  $Y$  a discrete random variable. Then

$$P[A] = \sum_{y \in \Omega_Y} P(A|Y = y)p_Y(y)$$

## Law of total probability

**Definition.** Let  $A$  be an event and  $Y$  a discrete random variable. Then

$$P[A] = \sum_{y \in \Omega_Y} P(A|Y = y)p_Y(y)$$

**Definition.** Let  $A$  be an event and  $Y$  a continuous random variable.  
Then

$$P[A] = \int_{-\infty}^{\infty} P(A|Y = y)f_Y(y)dy$$

## Example 1: use of law of total probability

We have a coin with unknown bias.

Specifically, the coin has probability  $P$  of heads where  $P \sim \text{Unif}(0,1)$ .

What is  $\mathbf{P}$ (Next 10 flips are all heads)?

$$f_P(p) = \begin{cases} 1 & x \in (0,1) \\ 0 & \text{o.w.} \end{cases}$$

**Definition.** Let  $A$  be an event and  $Y$  a continuous random variable. Then

$$P[A] = \int_{-\infty}^{\infty} P(A|Y=y) f_Y(y) dy$$

$$P(\text{next 10 flips are heads} | P=p) = p^{10}$$

$$P(\text{next 10 flips heads}) = \int_{-\infty}^{\infty} P(\text{next 10 H} | P=p) f_P(p) dp$$

## Example 1: use of law of total probability

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$P$ [Next 10 flips are all heads]

$$= \int_{-\infty}^{\infty} P(\text{Next 10 flips are all heads} | P = p) f_P(p) dp$$

$$= \int_0^1 p^{10} dp = \frac{1}{11}$$

## Example 2: use of law of total probability

A certain worker is able to complete jobs efficiently until they are too tired, which happens after a number of hours  $T$  which is exponential, with parameter  $\lambda$ .

$$T \sim \text{exp}(\lambda)$$

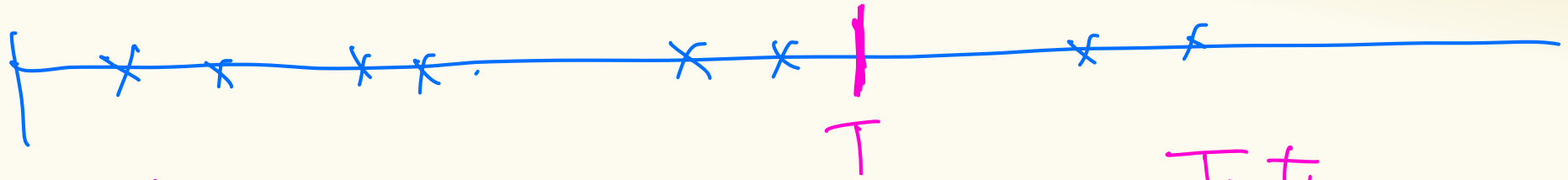
Jobs to be performed arrive according to a Poisson distribution with a rate of  $\mu$  jobs per hour. Any job that arrives before time  $T$  (i.e., before the worker is tired) is successfully completed.

What is the probability that the worker completes  $k$  jobs before they are too tired?

$$\# \text{ jobs in an hour} \sim \text{Poisson}(\mu)$$

$$\# \text{ jobs in 2 hours} \sim \text{Poisson}(2\mu)$$

# jobs in  $t$  hours  $\sim$  Poisson ( $\mu t$ )



$P$ (worker completes  $k$  jobs)

$T=t$

Poisson( $\mu t$ )

$$P(\text{complete } k \text{ jobs} | T=t) = e^{-\mu t} \frac{(\mu t)^k}{k!}$$

$$P(\text{complete } k \text{ jobs}) = \int_0^{\infty} P(\text{complete } k \text{ jobs} | T=t) f_T(t) dt$$

$$= \int_0^{\infty} e^{-\mu t} \frac{(\mu t)^k}{k!} \lambda e^{-\lambda t} dt = \left( \frac{\lambda}{\lambda + \mu} \right) \left( \frac{\mu}{\lambda + \mu} \right)^k \approx \text{Geom} \left( \frac{\lambda}{\lambda + \mu} \right)$$

**Definition.** Let  $A$  be an event and  $Y$  a continuous random variable. Then

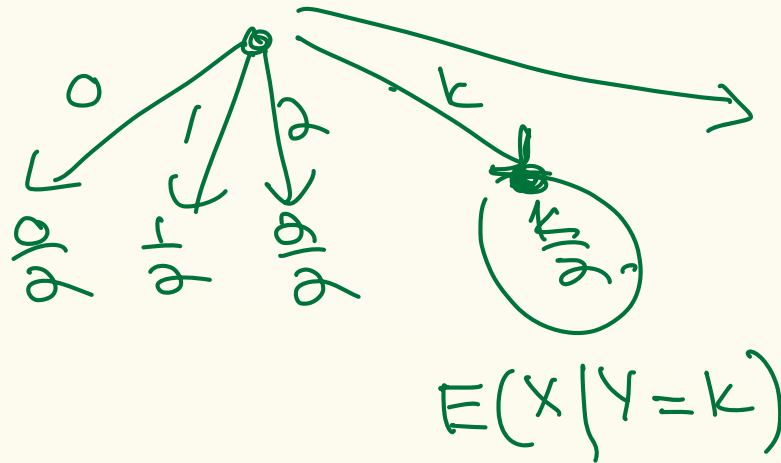
$$P[A] = \int_{-\infty}^{\infty} P(A|Y=y) f_Y(y) dy$$

# Agenda

- Recap – joint continuous distns
- Continuous law of total probability
- **Conditional expectation and Law of Total Expectation** ◀

# Conditional Expectation and Law of Total Expectation

Suppose someone gave us  $Y \sim \text{Poi}(5)$  fair coins and we wanted to compute the expected number of heads  $X$  from flipping those coins.  $E(X) = ?$



$$E(X) = \sum_{k=0}^{\infty} E(X|Y=k) P(Y=k)$$

# Conditional Expectation

**Definition.** Let  $X$  be a discrete random variable then the **conditional expectation** of  $X$  given event  $A$  is

$$\mathbb{E}[X | A] = \sum_{x \in \Omega_X} x \cdot P(X = x | A)$$

Notes:

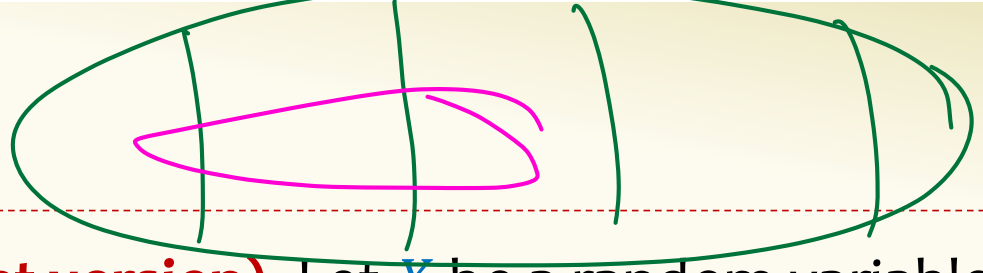
- Can be phrased as a “random variable version”

$$\mathbb{E}[X | Y = y]$$

- Linearity of expectation still applies here

$$\mathbb{E}[aX + bY + c | A] = a \mathbb{E}[X | A] + b \mathbb{E}[Y | A] + c$$

# Law of Total Expectation



**Law of Total Expectation (event version).** Let  $X$  be a random variable and let events  $A_1, \dots, A_n$  partition the sample space. Then,

$$\mathbb{E}[X] = \sum_{i=1}^n \mathbb{E}[X | A_i] \cdot P(A_i)$$

**Law of Total Expectation (random variable version).** Let  $X$  be a random variable and  $Y$  be a discrete random variable. Then,

$$\mathbb{E}[X] = \sum_{y \in \Omega_Y} \mathbb{E}[X | Y = y] \cdot P(Y = y)$$

# Proof of Law of Total Expectation

Follows from Law of Total Probability and manipulating sums

$$\mathbb{E}[X] = \sum_{x \in \Omega_X} x \cdot P(X = x)$$

$$= \sum_{x \in \Omega_X} x \cdot \sum_{i=1}^n P(X = x | A_i) \cdot P(A_i)$$

(by LTP)

$$= \sum_{i=1}^n P(A_i) \sum_{x \in \Omega_X} x \cdot P(X = x | A_i)$$

(change order of sums)

$$= \sum_{i=1}^n P(A_i) \cdot \mathbb{E}[X | A_i]$$

(def of cond. expect.)

## Example – Flipping a Random Number of Coins

Suppose someone gave us  $Y \sim \text{Poi}(5)$  fair coins and we wanted to compute the expected number of heads  $X$  from flipping those coins.

By the Law of Total Expectation

$$\begin{aligned}\mathbb{E}[X] &= \sum_{i=0}^{\infty} \mathbb{E}[X \mid Y = i] \cdot P(Y = i) = \sum_{i=0}^{\infty} \frac{i}{2} \cdot P(Y = i) \\ &= \frac{1}{2} \cdot \sum_{i=0}^{\infty} i \cdot P(Y = i) \\ &= \frac{1}{2} \cdot \mathbb{E}[Y] = \frac{1}{2} \cdot 5 = 2.5\end{aligned}$$

## Example – Computer Failures (a familiar example)

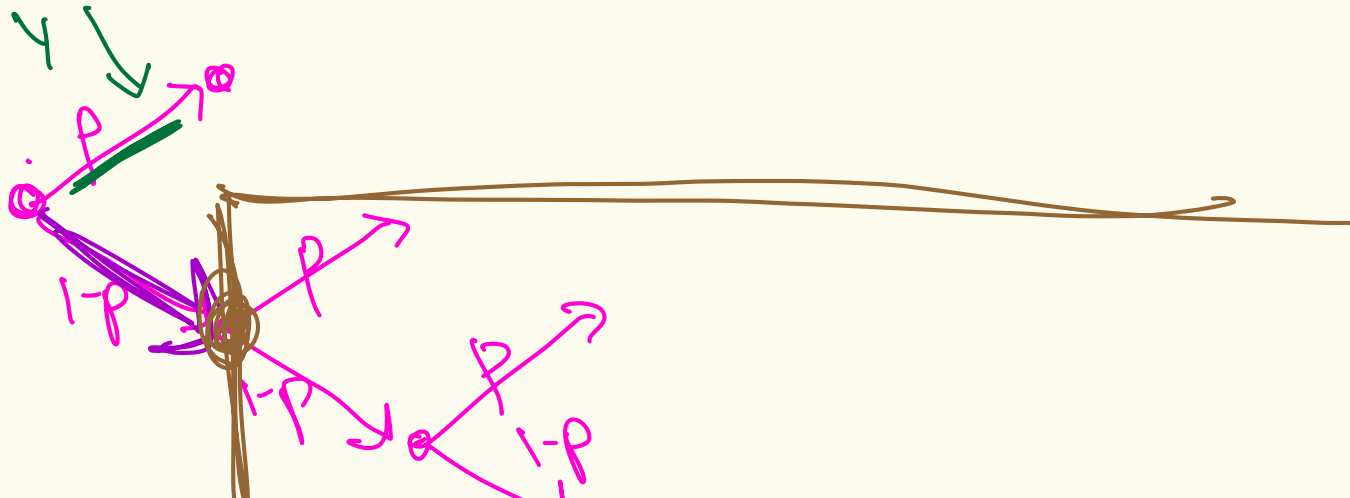
Suppose your computer operates in a sequence of steps, and that at each step  $i$  your computer will fail with probability  $p$  (independently of other steps).

Let  $X$  be the number of steps it takes your computer to fail.

$$X \sim \text{Geo}(p).$$

What is  $\mathbb{E}[X]$ ?

$$\mathbb{E}(X) = \sum_{k=1}^{\infty} k p (1-p)^{k-1} = \frac{1}{p}$$



Let  $Y$  be the indicator random variable for the event of failure in step 1

Then by LTE,  $\mathbb{E}[X] = \mathbb{E}[X | Y = 1] \cdot P(Y = 1) + \mathbb{E}[X | Y = 0] \cdot P(Y = 0)$

$$= 1 \cdot p + \mathbb{E}[X | Y = 0] \cdot (1 - p)$$

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

since if  $Y = 0$  experiment starting at step 2 looks like original experiment

Solving we get  $\mathbb{E}[X] = 1/p$