


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

CSE 312 Spring 26
Lecture 22

Agenda

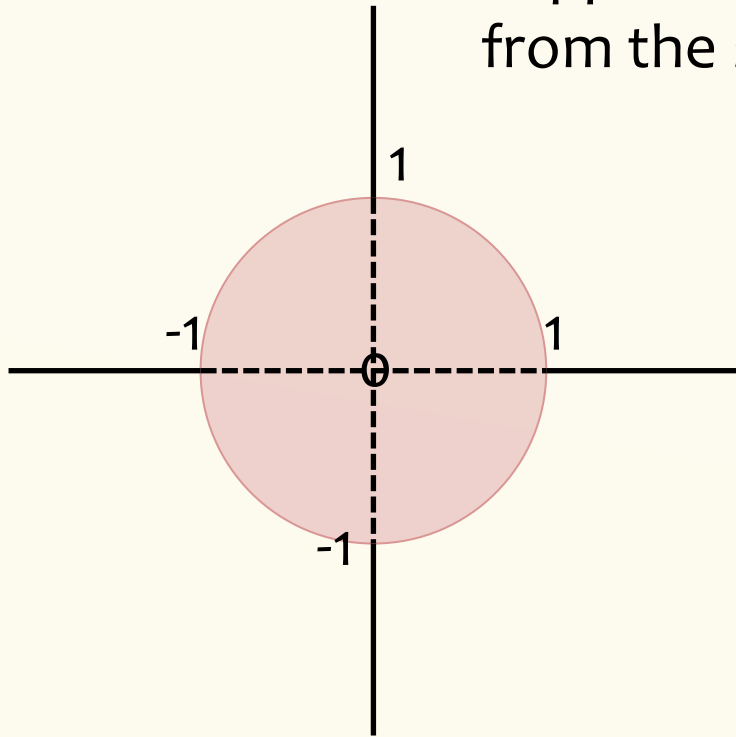
- Recap – joint continuous distns 
- Continuous law of total probability
- Law of total expectation

Reference Sheet

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

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 $x^2 + y^2 \leq 1$

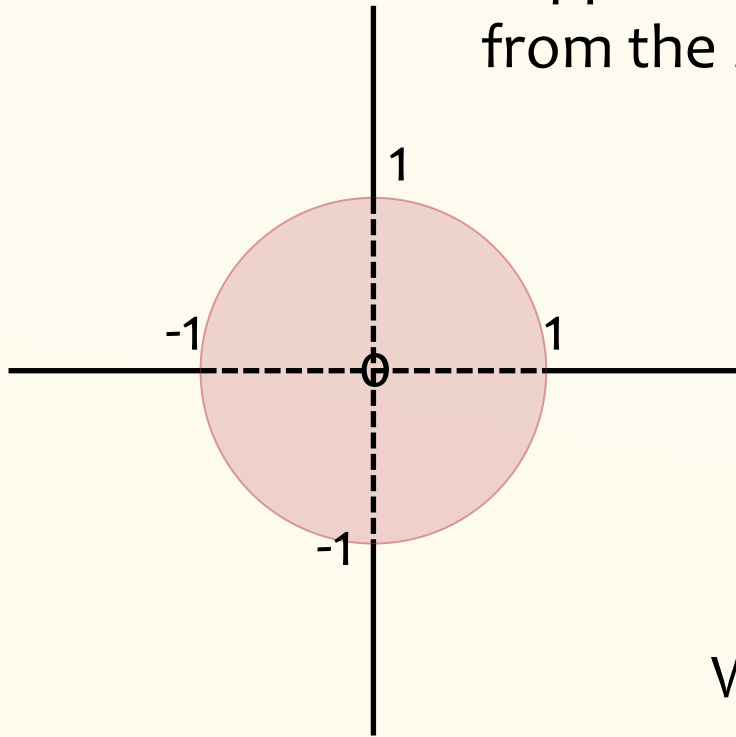


What is the joint density?

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

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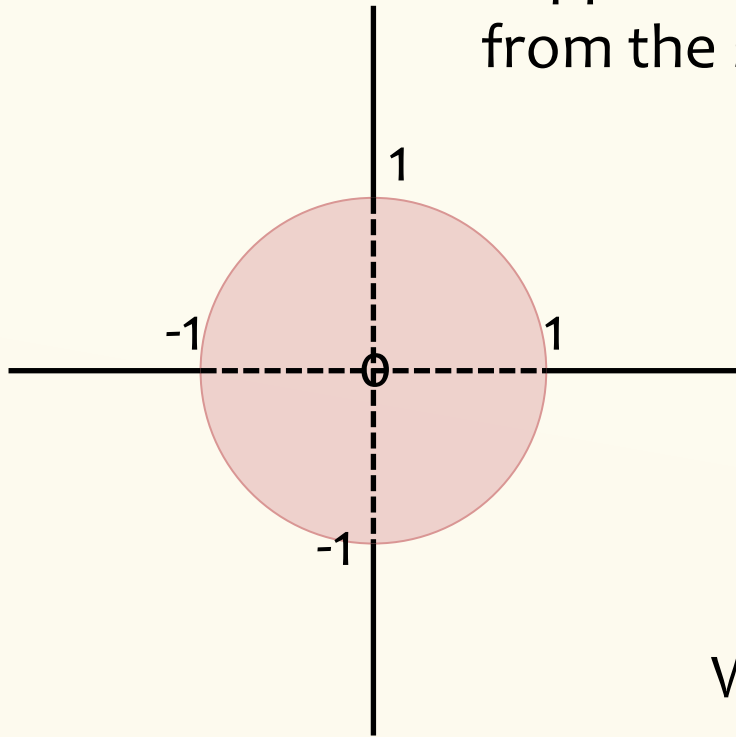
This is a disk of radius 1 which has area π

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

What is $f_X(x)$?

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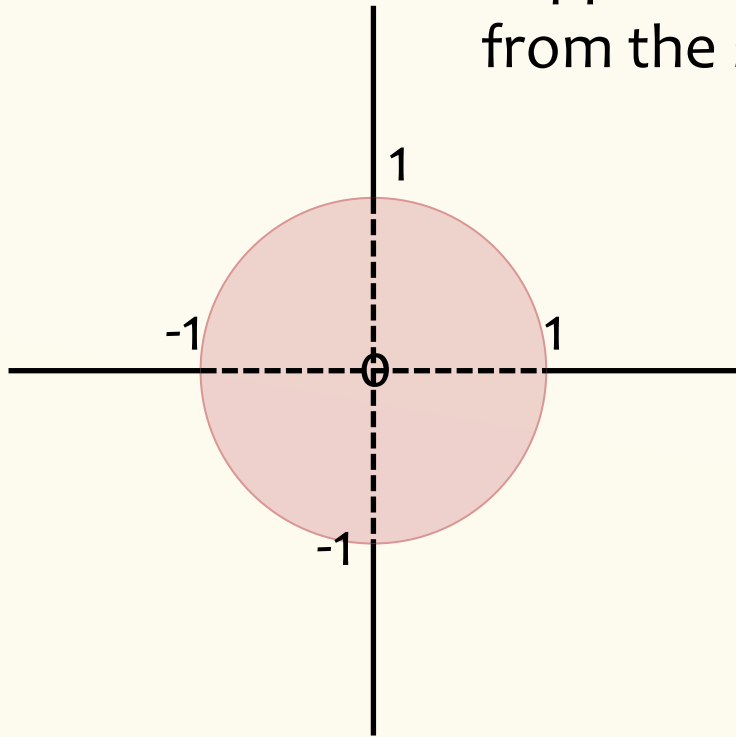
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What is $f_X(x)$?

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

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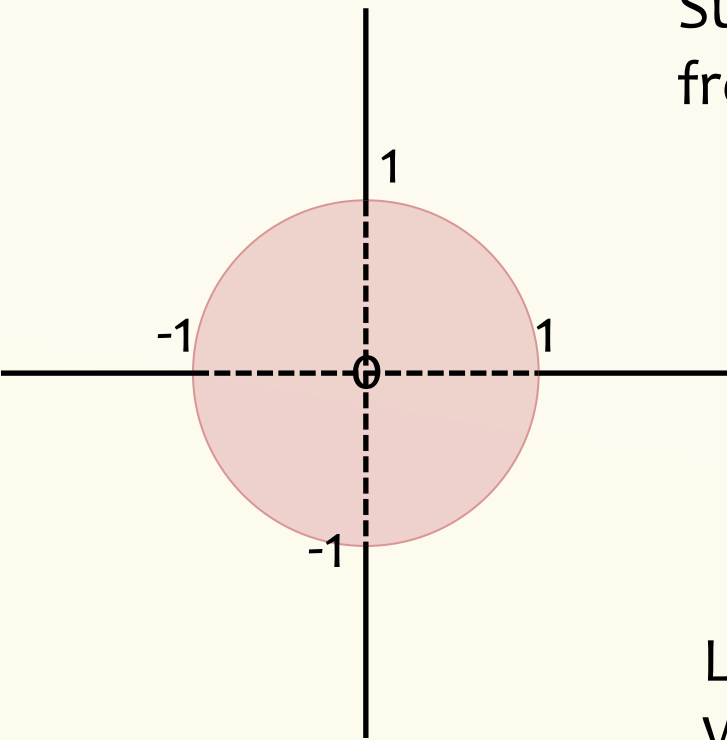
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$$\begin{aligned} f_X(x) &= \int_{-\sqrt{1-x^2}}^{\sqrt{1-x^2}} \frac{1}{\pi} dy & f_Y(y) &= \int_{-\sqrt{1-y^2}}^{\sqrt{1-y^2}} \frac{1}{\pi} dx \\ &= 2\sqrt{1-x^2}/\pi & &= 2\sqrt{1-y^2}/\pi \end{aligned}$$

Are X and Y independent?

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

Example – Uniform distribution on a unit disk



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

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 $E(D)$?

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 $f_X(x)$?

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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

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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 $P(\text{Next 10 flips are all heads})$?

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

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

$$\begin{aligned} &P[\text{Next 10 flips are all heads}] \\ &= \int_{-\infty}^{\infty} P(\text{Next 10 flips are all heads} | P = p) f_P(p) dp \end{aligned}$$

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 λ .

Jobs to be performed arrive according to a Poisson distribution with a rate of μ 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?

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.

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

$$\begin{aligned}\mathbb{E}[X] &= \sum_{x \in \Omega_X} x \cdot P(X = x) \\ &= \sum_{x \in \Omega_X} x \cdot \sum_{i=1}^n P(X = x | A_i) \cdot P(A_i) && \text{(by LTP)} \\ &= \sum_{i=1}^n P(A_i) \sum_{x \in \Omega_X} x \cdot P(X = x | A_i) && \text{(change order of sums)} \\ &= \sum_{i=1}^n P(A_i) \cdot \mathbb{E}[X | A_i] && \text{(def of cond. expect.)}\end{aligned}$$

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.

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

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

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

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

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

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

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

Example -- Elevator rides

The number X of people who enter an elevator on the ground floor is a Poisson random variable with mean 10. If there are N floors above the ground floor, and if each person is equally likely to get off at any one of the N floors, independently of where others get off, compute the expected number of stops the elevator will make before discharging all the passengers.

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$$\begin{aligned}\mathbb{E}[S] &= \sum_{i \geq 0} \mathbb{E}[S | N = i] \cdot P(N = i) \\ &= \sum_i \left(1 - \left(1 - \frac{1}{N} \right)^i \right) \cdot e^{-10} \cdot \frac{10^i}{i!}\end{aligned}$$

Reference Sheet (with continuous RVs)

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Conditional PMF/PDF	$p_{X Y}(x y) = \frac{p_{X,Y}(x, y)}{p_Y(y)}$	$f_{X Y}(x y) = \frac{f_{X,Y}(x, y)}{f_Y(y)}$
Conditional Expectation	$E[X Y = y] = \sum_x x p_{X Y}(x y)$	$E[X Y = y] = \int_{-\infty}^{\infty} x f_{X Y}(x y) dx$
Independence	$\forall x, y, p_{X,Y}(x, y) = p_X(x) p_Y(y)$	$\forall x, y, f_{X,Y}(x, y) = f_X(x) f_Y(y)$