

**CSE 312**

# **Foundations of Computing II**

**19: More Joint Distributions; Law of Total Expectation**

# Agenda

- Bit more on joint distributions
- Law of Total Expectation and LTP (continuous)



## 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>	$F_X(x) = \sum_{t \leq x} p_X(t)$	$F_X(x) = \int_{-\infty}^x f_X(t) dt$
<b>Normalization</b>	$\sum_x p_X(x) = 1$	$\int_{-\infty}^{\infty} f_X(x) dx = 1$
<b>Expectation</b>	$\mathbb{E}[g(X)] = \sum_x g(x) p_X(x)$	$\mathbb{E}[g(X)] = \int_{-\infty}^{\infty} g(x) f_X(x) dx$

## Jointly distributed random variables

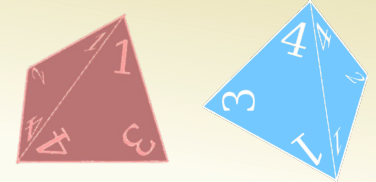
$X$	$Y$
Grade on exam	Amount of sleep the night before
Performance of Microsoft stock	Performance of Amazon stock
Grade of person A on exam in 312	Grade of person B on exam in 332
Number of job interviews to get a job	State of the economy

$X_1$  blood pressure

$X_2$  temperature

$X_3$  blood glucose

$X_4$  kidney function

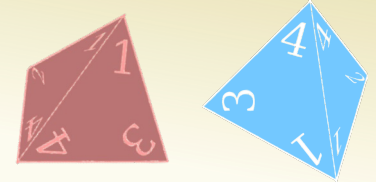


$X$  is the number of of job interviews you need to do to get a job.

$Y$  is the state of the economy. (Bad = 1, Below Avg = 2, Above Avg = 3, Excellent = 4)

- Valid joint probability mass function?

$x/y$	Bad	Below Avg	Above Avg	Excellent
1	0.01	0.05	0.08	0.12
2	0.03	0.05	0.06	0.12
3	0.03	0.12	0.04	0.05
4	0.08	0.12	0.03	0.01

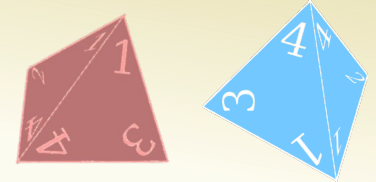


$X$  is the number of of job interviews you need to do to get a job.

$Y$  is the state of the economy. (Bad = 1, Below Avg = 2, Above Avg = 3, Excellent = 4)

- Probability a student gets a job in one interview and economy is excellent?

$x/y$	Bad	Below Avg	Above Avg	Excellent
1	0.01	0.05	0.08	0.12
2	0.03	0.05	0.06	0.12
3	0.03	0.12	0.04	0.05
4	0.08	0.12	0.03	0.01

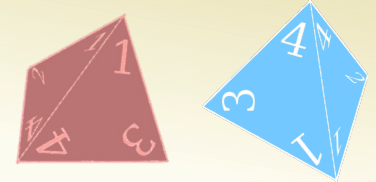


$X$  is the number of of job interviews you need to do to get a job.

$Y$  is the state of the economy. (Bad = 1, Below Avg = 2, Above Avg =3, Excellent = 4

- Probability a student gets a job in at most 3 interviews and economy below avg?

$x/y$	Bad	Below Avg	Above Avg	Excellent
1	0.01	0.05	0.08	0.12
2	0.03	0.05	0.06	0.12
3	0.03	0.12	0.04	0.05
4	0.08	0.12	0.03	0.01



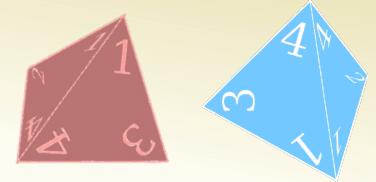
$X$  is the number of of job interviews you need to do to get a job.

$Y$  is the state of the economy. (Bad = 1, Below Avg = 2, Above Avg =3, Excellent = 4

- A student takes exactly 3 interviews to get a job?

$x/Y$	Bad	Below Avg	Above Avg	Excellent
1	0.01	0.05	0.08	0.12
2	0.03	0.05	0.06	0.12
3	0.03	0.12	0.04	0.05
4	0.08	0.12	0.03	0.01



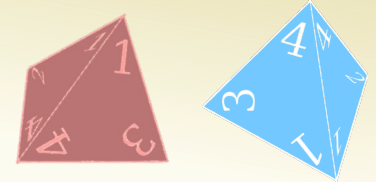


$X$  is the number of of job interviews you need to do to get a job.

$Y$  is the state of the economy. (Bad = 1, Below Avg = 2, Above Avg = 3, Excellent = 4)

- A student gets a job in one interview given that the economy is below average?

$x/y$	Bad	Below Avg	Above Avg	Excellent
1	0.01	0.05	0.08	0.12
2	0.03	0.05	0.06	0.12
3	0.03	0.12	0.04	0.05
4	0.08	0.12	0.03	0.01



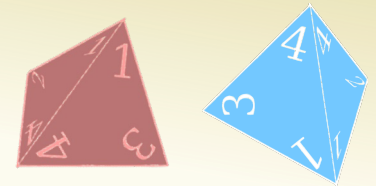
$X$  is the number of of job interviews you need to do to get a job.

$Y$  is the state of the economy. (Bad = 1, Below Avg = 2, Above Avg = 3, Excellent = 4)

- Are these random variables independent?

$x/y$	Bad	Below Avg	Above Avg	Excellent
1	0.01	0.05	0.08	0.12
2	0.03	0.05	0.06	0.12
3	0.03	0.12	0.04	0.05
4	0.08	0.12	0.03	0.01

## Example – Weirder Dice



Suppose I roll two fair 4-sided die independently. Let  $X$  be the value of the first die, and  $Y$  be the value of the second die. Let  $U = \min(X, Y)$  and  $W = \max(X, Y)$

$$\Omega_U = \{1, 2, 3, 4\} \text{ and } \Omega_W = \{1, 2, 3, 4\}$$

$$\Omega_{U,W} = \{(u, w) \in \Omega_U \times \Omega_W : u \leq w\} \neq \Omega_U \times \Omega_W$$

Are  $U$  and  $W$  independent?

$u \setminus w$	1	2	3	4
1	1/16	2/16	2/16	2/16
2	0	1/16	2/16	2/16
3	0	0	1/16	2/16
4	0	0	0	1/16

## A quick check for independence

The check:  $\Omega_X \times \Omega_Y$  must equal  $\Omega_{X,Y}$  for independence.

Suppose that there is some  $(a, b) \in \Omega_X \times \Omega_Y$ , but not in  $\Omega_{X,Y}$ .

Then:  $p_{X,Y}(a, b) = 0$

But:  $p_X(a) > 0$  and  $p_Y(b) > 0$

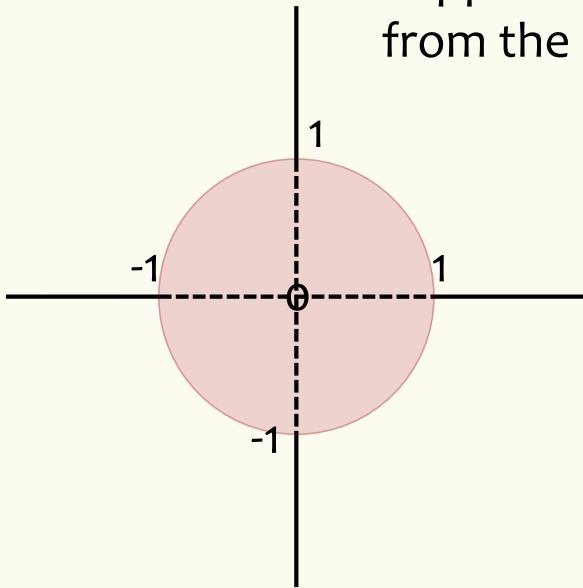
But beware, the converse is not true:  $\Omega_X \times \Omega_Y = \Omega_{X,Y}$  does not imply independence!

## Joint distributions

	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>	$\forall x, y, p_{X,Y}(x, y) = p_X(x) p_Y(y)$	$\forall x, y, f_{X,Y}(x, y) = f_X(x) f_Y(y)$

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

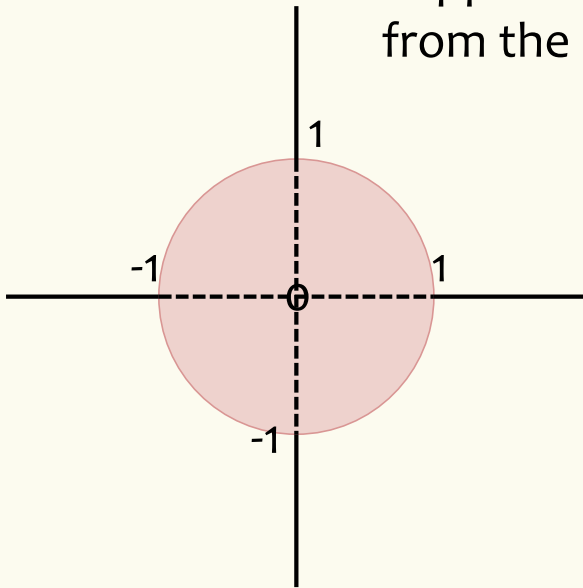


What is the joint density?

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

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



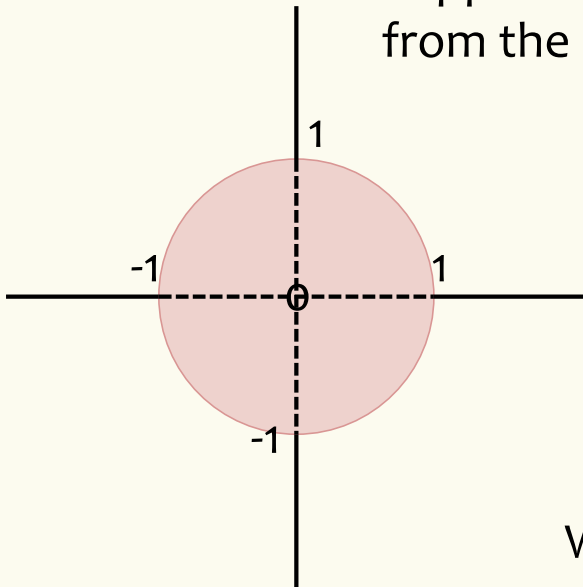
This is a disk of radius 1 which has area  $\pi$

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

Are  $X$  and  $Y$  independent?

## 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  $\pi$

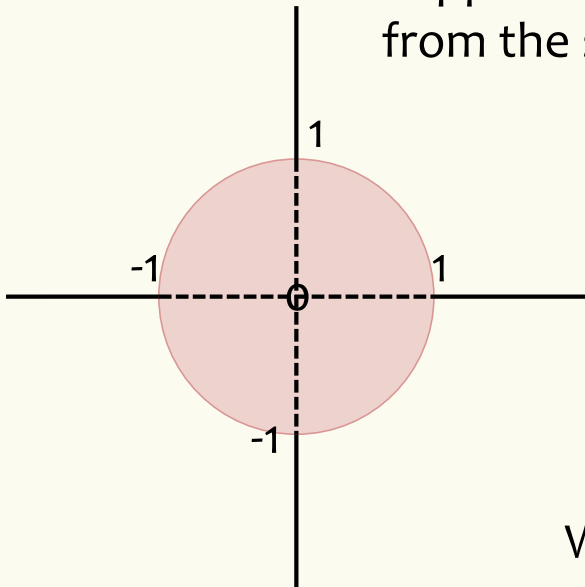
$$f_{X,Y}(x, y) = \begin{cases} \frac{1}{\pi} & \text{if } x^2 + y^2 \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

What is  $f_X(x)$ ?



## 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  $\pi$

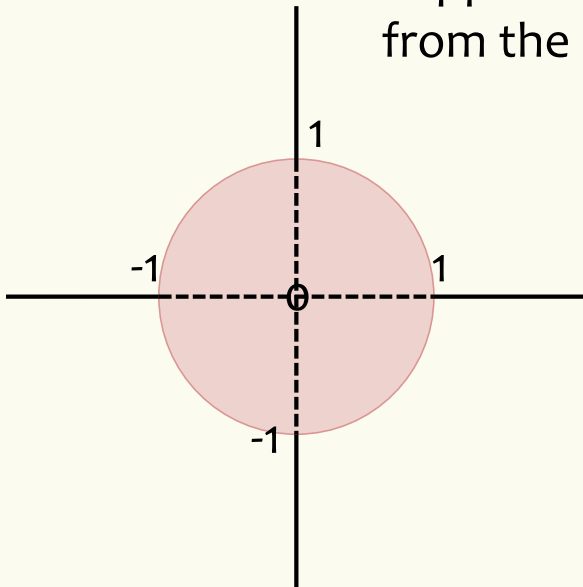
$$f_{X,Y}(x, y) = \begin{cases} \frac{1}{\pi} & \text{if } x^2 + y^2 \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

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  $\pi$

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

Are  $X$  and  $Y$  independent?

## Agenda

- Bit more on joint distributions
- Law of Total Expectation and LTP (continuous) 

## 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.** If  $X$  is a discrete random variable then the **conditional expectation** of  $X$  given event  $A$  is

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

Note:

- 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

$$\mathbb{E}[X] = \sum_{i=0}^{\infty} \mathbb{E}[X \mid Y = i] \cdot P(Y = i) =$$



## 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

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

## Example -- 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.



## 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 use of law of total probability

Suppose that the time until server 1 crashes is  $X \sim \text{Exp}(\lambda)$  and the time until server 2 crashes is independent, with  $Y \sim \text{Exp}(\mu)$ .

What is the probability that server 1 crashes before server 2?

## Example use of law of total probability

$X \sim \text{Exp}(\lambda), Y \sim \text{Exp}(\mu)$ .

What is the probability that  $Y > X$ ?

$$P(Y > X) = \int_0^{\infty} \Pr(Y > X | X = x) f_X(x) dx$$

$$= \int_0^{\infty} \Pr(Y > x | X = x) \lambda e^{-\lambda x} dx$$

$$= \int_0^{\infty} \Pr(Y > x) \lambda e^{-\lambda x} dx$$

$$= \int_0^{\infty} e^{-\mu x} \lambda e^{-\lambda x} dx$$

$$= \frac{\lambda}{\lambda + \mu} \int_0^{\infty} (\lambda + \mu) \cdot e^{-\mu x} e^{-\lambda x} dx$$

$$= \frac{\lambda}{\lambda + \mu}$$

## Alternative approach

$X \sim \text{Exp}(\lambda), Y \sim \text{Exp}(\mu)$ .

What is the probability that  $Y > X$ ?

$$\begin{aligned} P(Y > X) &= \int_{x=0}^{\infty} \int_{y=x}^{\infty} f_{X,Y}(x, y) dy dx \\ &= \int_{x=0}^{\infty} \int_{y=x}^{\infty} f_X(x) \cdot f_Y(y) dy dx \end{aligned}$$

## Reference Sheet (with continuous RVs)

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