CSE 312 Foundations of Computing II

Lecture 18: Joint Distributions

Midterm

- Grading is not finished in time for today
 - After grading I will review for fairness before releasing grades
 - With the Friday holiday, grades won't be ready until Monday
 - Solutions will be posted on Canvas pages for Monday

 Please focus on the course content and problem sets while you are waiting...

Agenda

- Joint Distributions
 - Cartesian Products
 - Joint PMFs and Joint Range
 - Marginal Distribution
- Conditional Expectation and Law of Total Expectation

Why joint distributions?

- Given all of its user's ratings for different movies, and any preferences you have expressed, Netflix wants to recommend a new movie for you.
- Given a large amount of medical data correlating symptoms and personal history with diseases, predict what is ailing a person with a particular medical history and set of symptoms.
- Given current traffic, pedestrian locations, weather, lights, etc. decide whether a self-driving car should slow down or come to a stop

Review Cartesian Product

Definition. Let *A* and *B* be sets. The **Cartesian product** of *A* and *B* is denoted

 $A \times B = \{(a, b) : a \in A, b \in B\}$

Example.

 $\{1,2,3\} \times \{4,5\} = \{(1,4), (1,5), (2,4), (2,5), (3,4), (3,5)\}$

If A and B are finite sets, then $|A \times B| = |A| \cdot |B|$.

The sets don't need to be finite! You can have $\mathbb{R} \times \mathbb{R}$ (often denoted \mathbb{R}^2)

Joint PMFs and Joint Range

Definition. Let *X* and *Y* be discrete random variables. The **Joint PMF** of *X* and *Y* is

$$p_{X,Y}(a,b) = P(X = a, Y = b)$$

Definition. The **joint range** of $p_{X,Y}$ is $\Omega_{X,Y} = \{(c,d) : p_{X,Y}(c,d) > 0\} \subseteq \Omega_X \times \Omega_Y$

Note that

$$\sum_{(s,t)\in\Omega_{X,Y}}p_{X,Y}(s,t)=1$$

Example – Weird 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.

 $\Omega_X = \{1, 2, 3, 4\} \text{ and } \Omega_Y = \{1, 2, 3, 4\}$

In this problem, the joint PMF is if

 $p_{X,Y}(x,y) = \begin{cases} 1/16 & \text{if } x, y \in \Omega_{X,Y} \\ 0 & \text{otherwise} \end{cases}$

and the joint range is (since all combinations have non-zero probability) $\Omega_{X,Y} = \Omega_X \times \Omega_Y$

X\Y	1	2	3	4
1	1/16	1/16	1/16	1/16
2	1/16	1/16	1/16	1/16
3	1/16	1/16	1/16	1/16
4	1/16	1/16	1/16	1/16



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 $W = \max(X, Y)$ $\Omega_U = \{1, 2, 3, 4\}$ and $\Omega_W = \{1, 2, 3, 4\}$

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

Poll: pollev.com/paulbeame028 What is $p_{U,W}(1,3) = P(U = 1, W = 3)$? a. 1/16 b. 2/16 c. 1/2 d. Not sure



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 $W = \max(X, Y)$ $\Omega_{U} = \{1, 2, 3, 4\}$ and $\Omega_{W} = \{1, 2, 3, 4\}$

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

The joint PMF $p_{U,W}(u, w) = P(U = u, W = w)$ is

 $p_{U,W}(u,w) = \begin{cases} 2/16 & \text{if } (u,w) \in \Omega_U \times \Omega_W \text{ where } w > u \\ 1/16 & \text{if } (u,w) \in \Omega_U \times \Omega_W \text{ where } w = u \\ 0 & \text{otherwise} \end{cases}$

U\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



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 $W = \max(X, Y)$

Suppose we didn't know how to compute P(U = u) directly. Can we figure it out if we know $p_{U,W}(u, w)$?

Just apply LTP over the possible values of W:

 $p_U(1) = 7/16$ $p_U(2) = 5/16$ $p_U(3) = 3/16$ $p_U(4) = 1/16$

U\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



Marginal PMF

Definition. Let *X* and *Y* be discrete random variables and $p_{X,Y}(a, b)$ their joint PMF. The marginal PMF of *X*

$$p_X(a) = \sum_{b \in \Omega_Y} p_{X,Y}(a,b)$$

Similarly, $p_Y(b) = \sum_{a \in \Omega_X} p_{X,Y}(a, b)$

Continuous distributions on $\mathbb{R} \times \mathbb{R}$

Definition. The joint probability density function (PDF) of continuous random variables *X* and *Y* is a function $f_{X,Y}$ defined on $\mathbb{R} \times \mathbb{R}$ such that

- $f_{X,Y}(x,y) \ge 0$ for all $x, y \in \mathbb{R}$
- $\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{X,Y}(x,y) dx dy = 1$

for $A \subseteq \mathbb{R} \times \mathbb{R}$ the probability that $(X, Y) \in A$ is $\iint_A f_{X,Y}(x, y) dxdy$

The (marginal) PDFs f_X and f_Y are given by

- $-f_X(x) = \int_{-\infty}^{\infty} f_{X,Y}(x,y) \, \mathrm{d}y$
- $-f_Y(y) = \int_{-\infty}^{\infty} f_{X,Y}(x,y) \, \mathrm{d}x$



Independence and joint distributions

Definition. Discrete random variables *X* and *Y* are **independent** iff

• $p_{X,Y}(x,y) = p_X(x) \cdot p_Y(y)$ for all $x \in \Omega_X$, $y \in \Omega_Y$

Definition. Continuous random variables *X* and *Y* are **independent** iff • $f_{X,Y}(x, y) = f_X(x) \cdot f_Y(y)$ for all $x, y \in \mathbb{R}$

Example – Uniform distribution on a unit disk



Joint Expectation

Definition. Let *X* and *Y* be discrete random variables and $p_{X,Y}(a, b)$ their joint PMF. The **expectation** of some function g(x, y) with inputs *X* and *Y*

$$\mathbb{E}[g(X,Y)] = \sum_{a \in \Omega_X} \sum_{b \in \Omega_Y} g(a,b) \cdot p_{X,Y}(a,b)$$

Brain Break



Agenda

- Joint Distributions
 - Cartesian Products
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 - Marginal Distribution
- Conditional Expectation and Law of Total Expectation

Conditional Expectation

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

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

Notes:

• Can be phrased as a "random variable version"

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

• Linearity of expectation still applies here $\mathbb{E}[aX + bY + c \mid A] = a \mathbb{E}[X \mid A] + b \mathbb{E}[Y \mid A] + c$

Law of Total Expectation

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

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

Law of Total Expectation (random variable version). Let *X* be a random variable and *Y* be a discrete random variable. Then, $\mathbb{E}[X] = \sum_{y \in \Omega_Y} \mathbb{E}[X \mid Y = y] \cdot P(Y = y)$

Proof of Law of Total Expectation

Follows from Law of Total Probability and manipulating sums

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

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

$$= \sum_{i=1}^n P(A_i) \sum_{x \in \Omega_X} x \cdot P(X = x | A_i)$$
(by LTP)
(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 $Y \sim Poi(5)$ fair coins and we wanted to compute the expected number of heads X from flipping those coins.

By the Law of Total Expectation

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

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

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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
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Covariance: How correlated are *X* and *Y*?

Recall that if X and Y are independent, $\mathbb{E}[XY] = \mathbb{E}[X] \cdot \mathbb{E}[Y]$

Definition: The **covariance** of random variables *X* and *Y*, $Cov(X, Y) = \mathbb{E}[XY] - \mathbb{E}[X] \cdot \mathbb{E}[Y]$

Unlike variance, covariance can be positive or negative. It has has value 0 if the random variables are independent.

 $\operatorname{Cov}(X,Y) = \mathbb{E}[XY] - \mathbb{E}[X] \cdot \mathbb{E}[Y]$

Two Covariance examples:

Suppose *X* ~ Bernoulli(*p*)

If random variable Y = X then $Cov(X, Y) = \mathbb{E}[X^2] - \mathbb{E}[X]^2 = Var(X) = p(1 - p)$

If random variable
$$Z = -X$$
 then
 $Cov(X, Z) = \mathbb{E}[XZ] - \mathbb{E}[X] \cdot \mathbb{E}[Z]$
 $= \mathbb{E}[-X^2] - \mathbb{E}[X] \cdot \mathbb{E}[-X]$
 $= -\mathbb{E}[X^2] + \mathbb{E}[X]^2 = -Var(X) = -p(1-p)$

Reference Sheet (with continuous RVs)

	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	$F_{X,Y}(x,y) = \sum_{t \le x} \sum_{s \le y} p_{X,Y}(t,s)$	$F_{X,Y}(x,y) = \int_{-\infty}^{x} \int_{-\infty}^{y} f_{X,Y}(t,s) ds dt$
Normalization	$\sum_{x}\sum_{y}p_{X,Y}(x,y)=1$	$\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}f_{X,Y}(x,y)dxdy=1$
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	$E[g(X,Y)] = \sum_{x} \sum_{y} g(x,y) p_{X,Y}(x,y)$	$E[g(X,Y)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x,y) f_{X,Y}(x,y) dx dy$
Conditional PMF/PDF	$p_{X Y}(x y) = \frac{p_{X,Y}(x,y)}{p_Y(y)}$	$f_{X \mid Y}(x \mid y) = \frac{f_{X,Y}(x, y)}{f_Y(y)}$
Conditional Expectation	$E[X \mid Y = y] = \sum_{x} x p_{X \mid Y}(x \mid y)$	$E[X \mid Y = y] = \int_{-\infty}^{\infty} x f_{X \mid Y}(x \mid y) dx$
Independence	$\forall x, y, p_{X,Y}(x, y) = p_X(x)p_Y(y)$	$\forall x, y, f_{X,Y}(x, y) = f_X(x)f_Y(y)$