CSE 312 Foundations of Computing II

Lecture 12: Multiple Random Variables, Linearity of Expectation.



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Midterm Information

- Next Friday
 - Closed book, but we will provide important / needed formulas along with the midterm.
 - Covers materials until this Wednesday (HWs 1-4, Sections 0-4).
- Practice midterms online soon
 - They aren't mine, but they will follow a similar spirit.
- Sections will be for midterm review.
- Use edstem for questions.
- Links to extra reading materials / past offerings of CSE312.

Multiple Random Variables

We can define <u>several</u> random variables in the same probability space.

Example: Two dice rolls

- X = 1st outcome
- Y = 2nd outcome
- Z =sum of both outcomes

(joint) probability that X = x and Y = y

Probability that X = x **conditioned on** Y = y



Multiple Random Variables

Example: Two dice rolls

- X = 1st outcome
- Y = 2nd outcome
- Z =sum of both outcomes

e.g.
$$\mathbb{P}(X = 3, Z = 6) = \mathbb{P}(\{(3,3)\}) = \frac{1}{36}, \mathbb{P}(X = 3 \mid Z = 6) = \frac{1/36}{5/36} = \frac{1}{5}$$

Also note: $Z(\omega) = X(\omega) + Y(\omega)$ for all $\omega \in \Omega$

Therefore: We can write X + Y instead of Z

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$$\mathbb{P}(X = x, Y = y) = \mathbb{P}(\{X = x\} \cap \{Y = y\})$$

- $\mathbb{P}(X = x \mid Y = y) = \mathbb{P}(\{X = x\} \mid \{Y = y\})$

Chain Rule

The chain rule also naturally extends to random variables. E.g.,

$$\mathbb{P}(X = x, Y = y) = \mathbb{P}(X = x) \cdot \mathbb{P}(Y = y | X = x)$$

Another Example

Example: Two dice rolls

- $X_1 = #$ of times 1 appears
- $X_2 = #$ of times 2 appears



<u>Joint</u> PMF for X_1 and X_2 $\mathbb{P}(X_1 = a, X_2 = b)$ for all $a, b \in \{0, 1, 2\}$

Marginal Distribution

The joint PMF of two (or more) RVs gives the PMFs of the individual random variables (aka, the "marginal distribution"). E.g,

$$\mathbb{P}(X = x) = \sum_{y} \mathbb{P}(X = x, Y = y)$$
 (Law of total Probability)



$$\mathbb{P}(X_2 = 0) = \frac{4}{9} + \frac{2}{9} + \frac{1}{36} = \frac{25}{36}$$
$$\mathbb{P}(X_2 = 1) = \frac{2}{9} + \frac{1}{18} = \frac{10}{36}$$
$$\mathbb{P}(X_2 = 2) = \frac{1}{36}$$

Example – Coin Tosses

We flip n coins, each one heads with probability p

- $X_i = \begin{cases} 1, \ i-\text{th outcome is heads} \\ 0, \ i-\text{th outcome is tails.} \end{cases}$
- Z = number of heads

 $\mathbb{P}(X_i = 1) = p$ $\mathbb{P}(X_i = 0) = 1 - p$

"Bernoulli distributed"

Binomial:
$$\mathbb{P}(Z = k) = \binom{n}{k} p^k (1 - p)^{n-k}$$

Fact.
$$Z = \sum_{i=1}^{n} X_i$$

Expectation – Refresher

Definition. The **expectation** of a (discrete) RV *X* is

$$\mathbb{E}(X) = \sum_{x} x \cdot p_X(x) = \sum_{x} x \cdot \mathbb{P}(X = x)$$

Often: $X = X_1 + \dots + X_n$, and the **RVs** X_1, \dots, X_n are easier to understand.

Linearity of Expectation

Theorem. For any two random variables *X* and *Y*,

 $\mathbb{E}(X+Y) = \mathbb{E}(X) + \mathbb{E}(Y).$

Or, more generally: For any random variables $X_1, ..., X_n$, $\mathbb{E}(X_1 + \cdots + X_n) = \mathbb{E}(X_1) + \cdots + \mathbb{E}(X_n).$

Because: $\mathbb{E}(X_1 + \dots + X_n) = \mathbb{E}((X_1 + \dots + X_{n-1}) + X_n)$ = $\mathbb{E}(X_1 + \dots + X_{n-1}) + \mathbb{E}(X_n) = \dots$

Linearity of Expectation – Proof

Theorem. For any two random variables X and Y, $\mathbb{E}[X + Y] = \mathbb{E}[X] + \mathbb{E}[Y].$

 $\mathbb{E}(X+Y) = \sum_{z} z \cdot \mathbb{P}(X+Y=z)$ $= \sum_{Z_1,Z_2} (z_1 + z_2) \cdot \mathbb{P}(X = z_1, Y = z_2)$ $= \sum_{Z_1, Z_2} z_1 \cdot \mathbb{P}(X = z_1, Y = z_2) + \sum_{Z_1, Z_2} z_2 \cdot \mathbb{P}(X = z_1, Y = z_2)$ $= \sum_{z_1} z_1 \cdot \sum_{z_2} \mathbb{P}(X = z_1, Y = z_2) + \sum_{z_2} z_2 \cdot \sum_{z_1} \mathbb{P}(X = z_1, Y = z_2)$ $= \sum_{z_1} z_1 \cdot \mathbb{P}(X = z_1) + \sum_{z_2} z_2 \cdot \mathbb{P}(Y = z_2)$ $= \mathbb{E}(X) + \mathbb{E}(Y)$

Linearity of Expectation – Even stronger

Theorem. For any random variables $X_1, ..., X_n$, and real numbers $a_1, ..., a_n \in \mathbb{R}$, $\mathbb{E}(a_1X_1 + \cdots + a_nX_n) = a_1\mathbb{E}(X_1) + \cdots + a_n\mathbb{E}(X_n).$

Very important: In general, we do <u>not</u> have $\mathbb{E}(X \cdot Y) = \mathbb{E}(X) \cdot \mathbb{E}(Y)$

Example – Coin Tosses

We flip n coins, each one heads with probability p

- $X_i = \begin{cases} 1, \ i-\text{th outcome is heads} \\ 0, \ i-\text{th outcome is tails.} \end{cases}$
- Z = number of heads

Binomial: $\mathbb{P}(Z = k) = \binom{n}{k} p^k (1-p)^{n-k}$

Fact. $Z = X_1 + \dots + X_n$

 $\rightarrow \mathbb{E}(Z) = \mathbb{E}(X_1 + \dots + X_n) = \mathbb{E}(X_1) + \dots + \mathbb{E}(X_n) = n \cdot p$

$$\mathbb{E}(X_i) = p \cdot 1 + (1-p) \cdot 0 = p$$

 $\mathbb{P}(X_i = 1) = p$ $\mathbb{P}(X_i = 0) = 1 - p$

(Non-trivial) Example – Coupon Collector Problem

Say each round we get a random coupon $X_i \in \{1, ..., n\}$, how many rounds (in expectation) until we have one of each coupon?

Formally: Outcomes in Ω are sequences of integers in $\{1, \dots, n\}$ where each integer appears at least once (+ cannot be shortened).

Example,
$$n = 3$$
:
 $\Omega = \{(1,2,3), (1,1,2,3), (1,2,2,3), (1,2,3), (1,1,1,3,3,3,3,3,3,2), \dots\}$
 $\mathbb{P}((1,2,3)) = \frac{1}{3} \cdot \frac{1}{3} \cdot \frac{1}{3} \cdots \mathbb{P}((1,1,2,2,2,3)) = \left(\frac{1}{3}\right)^6 \cdots$

Say each round we get a random coupon $X_i \in \{1, ..., n\}$, how many rounds (in expectation) until we have one of each coupon?

 $T_i = #$ of rounds until we have accumulated *i* distinct coupons [Aka: length of the sampled ω]

Wanted: $\mathbb{E}(T_n)$

 $Z_i = T_i - T_{i-1}$

of rounds needed to go from i - 1 to i coupons

 $T_i = #$ of rounds until we have accumulated *i* distinct coupons $Z_i = T_i - T_{i-1}$

 $T_n = T_1 + (T_2 - T_1) + (T_3 - T_2) + \dots + (T_n - T_{n-1}) = T_1 + Z_2 + \dots + Z_n$ $\mathbb{E}(T_n) = \mathbb{E}(T_1) + \mathbb{E}(Z_2) + \mathbb{E}(Z_3) + \dots + \mathbb{E}(Z_n)$ $= 1 + \mathbb{E}(Z_2) + \mathbb{E}(Z_3) + \dots + \mathbb{E}(Z_n)$

 $T_i = \#$ of rounds until we have accumulated *i* distinct coupons $Z_i = T_i - T_{i-1}$

If we have accumulated i - 1 coupons, the number of attempts needed to get the *i*-th coupon is **geometric** with parameter $p = 1 - \frac{i-1}{n}$.

$$\mathbb{P}_{Z_i}(1) = p \quad \mathbb{P}_{Z_i}(2) = (1-p)p \quad \cdots \quad \mathbb{P}_{Z_i}(i) = (1-p)^{i-1}p$$

$$\mathbb{E}[Z_i] = \frac{1}{p} = \frac{n}{n-i+1}$$

 $T_i = \#$ of rounds until we have accumulated *i* distinct coupons

$$Z_{i} = T_{i} - T_{i-1} \qquad \mathbb{E}(Z_{i}) = \frac{1}{p} = \frac{n}{n-i+1}$$

$$\mathbb{E}(T_{n}) = 1 + \mathbb{E}(Z_{2}) + \mathbb{E}(Z_{3}) + \dots + \mathbb{E}(Z_{n})$$

$$= 1 + \frac{n}{n-1} + \frac{n}{n-2} + \dots + \frac{n}{1}$$

$$= n \cdot \left(\frac{1}{n} + \frac{1}{n-1} + \dots + \frac{1}{2} + 1\right) = n \cdot H_{n} \approx n \cdot \ln(n)$$

$$n \cdot \ln(n) \leq H_{n} \leq \ln(n) + 1$$

Distributions – Recap

We have encountered some important distributions, let us summarize them

| Name | Params | Range | PMF |
|-----------|--------------|-----------------------------|--|
| Bernoulli | p | {0,1} | p(1) = p, p(0) = 1 - p |
| Geometric | p | $\{1,2,3,\} = \mathbb{N}^+$ | $\mathbb{p}(i) = (1-p)^{i-1}p$ |
| Binomial | n , p | {0,1,, <i>n</i> } | $\mathbb{p}(k) = \binom{n}{k} p^k (1-p)^{n-k}$ |

