

M362K: March 25th, 2024.

Section 3.2.

Expectation.

↳ expected value, mean (very rarely: average)

Inspiration: N tickets

N_1 w/ payoff x_1

N_2 w/ payoff x_2

⋮

N_m w/ payoff x_m

Money in → Lottery → Money out

$N \cdot P$

↑
price of
one ticket

$N_1 \cdot x_1 + N_2 \cdot x_2 + \dots + N_m \cdot x_m$

↑
if all is "fair"
("break-even price")

$$P = \frac{N_1}{N} x_1 + \frac{N_2}{N} x_2 + \dots + \frac{N_m}{N} x_m$$

for every $i=1..m$, p_i ... the probability of getting a ticket
w/ payoff x_i (if all tickets are
equally likely)

$$P = \sum_{i=1}^m p_i \cdot x_i$$

... a weighted average of
payoffs

Note: We already talked about the "mean" of the
binomial distribution Binomial(n, p).
We had

$$\mu = np$$

Def'n. The mean (expectation, expected value) of a probability distribution $P(x)$ over a finite set Ω of values x is

$$\mu = \sum_{\text{all } x} P(x) \cdot x$$

Def'n. Let X be a random variable on a finite Ω . The expectation (expected value, mean) of X is denoted by $\mathbb{E}[X]$ and it is defined as

$$\mathbb{E}[X] = \sum_{i=1}^m x_i p_X(x_i)$$

where $\{x_1, \dots, x_m\}$ is the support of X
and p_X is the pmf of X .

Addition Rules for Expectation.

Let X and Y be r.v.s on the same Ω , and let k be any constant (a real number).

Then,

$$\bullet \mathbb{E}[k \cdot X] = k \cdot \mathbb{E}[X]$$

homogeneity

$$\bullet \mathbb{E}[X + k] = \mathbb{E}[X] + k$$

translativity

$$\bullet \mathbb{E}[X + Y] = \mathbb{E}[X] + \mathbb{E}[Y]$$

additivity

$$\mathbb{E}[k \cdot X + Y] = k \cdot \mathbb{E}[X] + \mathbb{E}[Y] \quad \text{linearity}$$

More generally, for random variables $X_1, X_2, \dots, X_n$ on the same Ω and constants $k_1, k_2, \dots, k_n$, we have

$$\mathbb{E}[k_1 X_1 + k_2 X_2 + \dots + k_n X_n] = k_1 \mathbb{E}[X_1] + k_2 \mathbb{E}[X_2] + \dots + k_n \mathbb{E}[X_n].$$

Example. Indicator Random Variables.

A... an event in Ω ($A \subseteq \Omega$)

Define: $\mathbb{I}_A(\omega) = \begin{cases} 1 & \text{if } \omega \in A \\ 0 & \text{if } \omega \notin A \end{cases} = \begin{cases} 1 & \text{if } A \text{ happened} \\ 0 & \text{if } A \text{ did not happen} \end{cases}$

$\mathbb{E}[\mathbb{I}_A] = ?$

1° $\text{Support}(\mathbb{I}_A) = \{0, 1\}$

2° pmf = ? $p_{\mathbb{I}_A}(0) = \mathbb{P}[A^c]$, $p_{\mathbb{I}_A}(1) = \mathbb{P}[A]$

3° Use the def'n of $\mathbb{E}$:

$$\mathbb{E}[\mathbb{I}_A] = 0 \cdot \mathbb{P}[A^c] + 1 \cdot \mathbb{P}[A]$$

$$\mathbb{E}[\mathbb{I}_A] = \mathbb{P}[A]$$

Example.

$X \sim \text{Bernoulli}(p)$

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

$$\mathbb{E}[X] = p$$

Example.

$X \sim \text{Binomial}(n, p)$

$\mathbb{E}[X] = ?$

Method I. By def'n

$$\mathbb{E}[X] = \sum_{k=0}^n k \cdot p_X(k) = \sum_{k=0}^n k \cdot \binom{n}{k} p^k (1-p)^{n-k} = \dots$$

Method II. X... # of successes in i.i.d. Bernoulli trials

Introduce (n) indicator r.v.s (one for each trial)

$$j = 1 \dots n: \quad \mathbb{I}_j = \begin{cases} 1 & \text{if } j\text{th trial success} \\ 0 & \text{if } j\text{th trial is failure} \end{cases}$$

$$X = \mathbb{I}_1 + \mathbb{I}_2 + \dots + \mathbb{I}_n$$

$$\underline{\mathbb{E}[X]} = \mathbb{E}[I_1 + I_2 + \dots + I_n] \quad \text{linearity of } \mathbb{E}$$

$$= \underbrace{\mathbb{E}[I_1]}_p + \underbrace{\mathbb{E}[I_2]}_p + \dots + \underbrace{\mathbb{E}[I_n]}_p$$

$$= \underline{n \cdot p}$$

□

Whenever two r.v.s are identically dist'n, they have the same expectation.

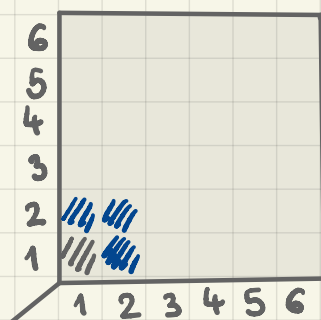
Example. We toss two dice independently.

Let X denote the maximum outcome on the two dice. What is the expectation of X ?

→: $\text{Support}(X) = \{1, 2, 3, 4, 5, 6\}$

Find the pmf $p_X(i)$ for $i = 1, 2, 3, 4, 5, 6$

fix i : $p_X(i) = \mathbb{P}[X=i]$



$$p_X(1) = \frac{1}{36}$$

$$p_X(2) = \frac{3}{36}$$

⋮

max equal to i

both dice are i

1

+

one is i ,
the other one
is smaller

$\frac{(i-1)}{+}$

$\frac{(i-1)}{+}$

$2i-1$

$$\mathbb{E}[X] = \sum_{i=1}^6 i \cdot p_X(i) = \sum_{i=1}^6 i \cdot \frac{2i-1}{36} = \dots = \frac{161}{36}$$

□