

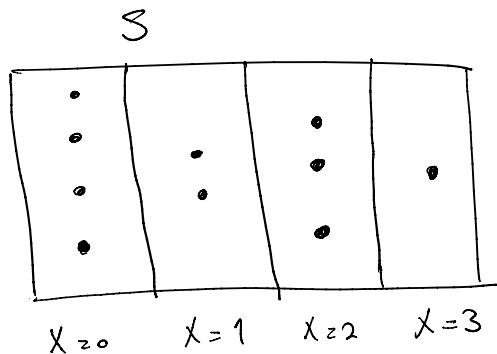
Proof of linearity of expectation Value. (Discrete Case)

Story Prof: Imagine Pebble world.

$$E(X) = \sum_x x \cdot P(X=x) = \sum_s x(s) P(\{s\})$$

grouped way
ungrouped way

of averaging
of averaging



Instead of summing over R.V's, we sum over the events, times the R.v assigned to event.

(So the Probability of each event becomes $\frac{1}{\text{size}(s)}$ in the discrete case)

Formally,

X, Y are Functions

$$E(X+Y) = \sum_s (\overbrace{X+Y}^{\text{functions}})(s) P(\{s\}) = \sum_s (X(s)+Y(s)) P(\{s\})$$

$$= \sum_s X(s) P(\{s\}) + \sum_s Y(s) P(\{s\}) = E(X) + E(Y)$$

$$E(cX) = c \cdot E(X)$$

$E(X)$ is Proven similarly if we think of it as $E(X + \underbrace{\dots + X}_{c \text{ times}})$

Negative Binomial Distribution:

Negative Binomial Distribution.

Consider $X \sim NB(r, p)$

Story: Considering $Bern(p)$ trials, find # Failures before r -th success.

P.M.F.: we know that the last trial was a ^{Fixed} success, which happened with Probability $\frac{1}{2}$.

$$P(X=n) = \binom{n+r-1}{n} p^r (1-p)^n$$

n-r-1 trials before the r -th success, all possible configurations of

Success and Failure equally likely. (r Success, $n-r$ Fail)

Expected Value of $X \sim NB(r, p)$

$$\mathbb{E}(X) = \mathbb{E}(X_1 + \dots + X_r) = \mathbb{E}(X_1) + \dots + \mathbb{E}(X_r) = r \frac{q}{p}$$

where X_j is # failures between $(j-1)$ st and j -th success;

$$X_j \sim Geom(p).$$

Intuition: Between every two successes, the \mathbb{E} of # failures is exactly the same as # failures before 1st success. P.Z.

Side note: First Success Distribution $X \sim FS(p)$

It's the same as the geometric distribution, but we want to count the success itself as well. (Time until 1st success, Counting the success.)

Let $Y = X - 1$, then $Y \sim Geom(p)$

$$\text{Expectation Value} \Rightarrow E(X) = E(Y) + 1 = \frac{q}{p} + \frac{1}{p} = \frac{1}{p}$$

Example: Putnam exam question:

Say we have a random permutation of $1, 2, \dots, n$ where $n \geq 2$.

Find the Expected Value # of local maxima.

3 2 1 4 7 5 6

These are the local maxima.

Answer: Let I_j be indicator R.v of Position j having a local maxima. $1 \leq j \leq n$

$$E(I_1 + \dots + I_n) = E(I_1) + \dots + E(I_n) = \frac{n-2}{3} + \frac{2}{2} = \frac{n+1}{3}$$

Intuition: For the borderline positions I_1 and I_n , they have only one neighbor,

For two random numbers (x, y) $x < y$ $\Pr[x < y] = \frac{1}{2}$

For two random numbers (a, b) , there's a 50% chance of $a > b \rightarrow 2 \times \frac{1}{2}$

For the middle cases, it has two neighbors and just like before, for three numbers

(a, b, c) , there's a $\frac{1}{3}$ chance of b being the max.

St. Petersburg's Paradox

Playing a game, you'll get $\$2^X$ where X is the #Flips of Fair Coin toss until

the first Heads, including the Success.

Formally, $Y = 2^X$, Find $IE(Y)$.

$$IE(Y) = \sum_{K=1}^{\infty} 2^K \cdot \frac{1}{2^K} = \sum_{K=1}^{\infty} 1 = \infty.$$

So, if there's no limit on how much money you can make, $\Rightarrow IE(X) = \infty$.

But imagine there is a hard cap on the amount of money to win, then:

Assume max is $\$2^{40} \rightarrow \sum_{K=1}^{40} 1 = \40

Note: Don't make this mistake:

$$\mathbb{E}(X) = \mathbb{E}(2^X) \neq 2^{\mathbb{E}(X)}.$$

Linearity of expectation doesn't give this. And this what tricks so many people