

# Expected Value, Variance

Hayk Aprikyan, Hayk Tarkhanyan

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Would you play this game? What if instead of \$36, you won \$150 if it fell on 8?

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Since the chance of winning is only  $\frac{1}{38}$ , if you play it a couple of thousands times (say 38000), then you can expect to win about  $\approx 1000$  times and lose  $\approx 37000$  times. Your net revenue would then be:

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Should we say the average winning is  $\frac{1000000 + (-300)}{2} = 499.850$  dram? No!  
The chances of winning are 3999 times less than the chances of losing:

$$\mathbb{P}[X = 1.000.000] = \frac{1}{4000} < \frac{3999}{4000} = \mathbb{P}[X = -300]$$

and we should take this into account.

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The actual average value of a random variable  $X$  is called the *expected value* or the *expectation* of  $X$  and is denoted by  $\mathbb{E}[X]$ .

## Definition

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In words, the expected value is the **weighted average** of all its possible values – where each of the values is weighted by its probability.

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In the lottery example, the expected winning amount is:

$$\mathbb{E}[X] = 1000000 \cdot \frac{1}{4000} + (-300) \cdot \frac{3999}{4000} = -50.25$$

i.e. on average, you would be losing 50.25 dram per ticket.

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$$\mathbb{E}[X] = \frac{1}{6} \cdot 1 + \frac{1}{6} \cdot 2 + \frac{1}{6} \cdot 3 + \frac{1}{6} \cdot 4 + \frac{1}{6} \cdot 5 + \frac{1}{6} \cdot 6 = 3.5$$

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It is important to note that the expected value **does not have to be** one of the possible values of the random variable! In the above example,  $X$  can only take integer values from 1 to 6, yet its expected value is 3.5.

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so the expected average point where the fly lands is the midpoint of the interval, i.e. 0.5.

Could be also ask about the square of the distance from 0, i.e. what is  $\mathbb{E}[X^2]$ ?

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## Theorem

If  $X$  is a discrete random variable, then

$$\mathbb{E}[g(X)] = \sum_x g(x) \cdot \mathbb{P}[X = x]$$

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## Question

If  $\mathbb{E}[X] = 5$ , what do you think is  $\mathbb{E}[2X + 3]$ ?

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## Theorem

If  $X$  and  $Y$  are independent random variables, then

$$\mathbb{E}[XY] = \mathbb{E}[X] \cdot \mathbb{E}[Y]$$

The converse is not always true.

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If  $X$  denotes the winnings of the first game, and  $Y$  of the second game, we can say that  $Y$  has a **higher variance** than  $X$ :

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The standard deviation shows how much, *on average*, do the values of the random variable deviate from their average  $\mathbb{E}[X]$ .

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and the standard deviation is:

$$\sigma_X = \sqrt{\text{Var}[X]} \approx \sqrt{2.92} \approx 1.71$$

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$$\text{Var}[X + Y] = \text{Var}[X] + \text{Var}[Y]$$

# Variance

## Properties

- ①  $\text{Var}[X] \geq 0$ ,
- ② If  $X$  is constant,  $\text{Var}[X] = 0$ ,
- ③  $\text{Var}[aX] = a^2 \cdot \text{Var}[X]$  for any  $a \in \mathbb{R}$ ,
- ④  $\text{Var}[X + Y] \neq \text{Var}[X] + \text{Var}[Y]$ , instead:

$$\text{Var}[X + Y] = \text{Var}[X] + \text{Var}[Y] + 2(\mathbb{E}[XY] - \mathbb{E}[X]\mathbb{E}[Y])$$

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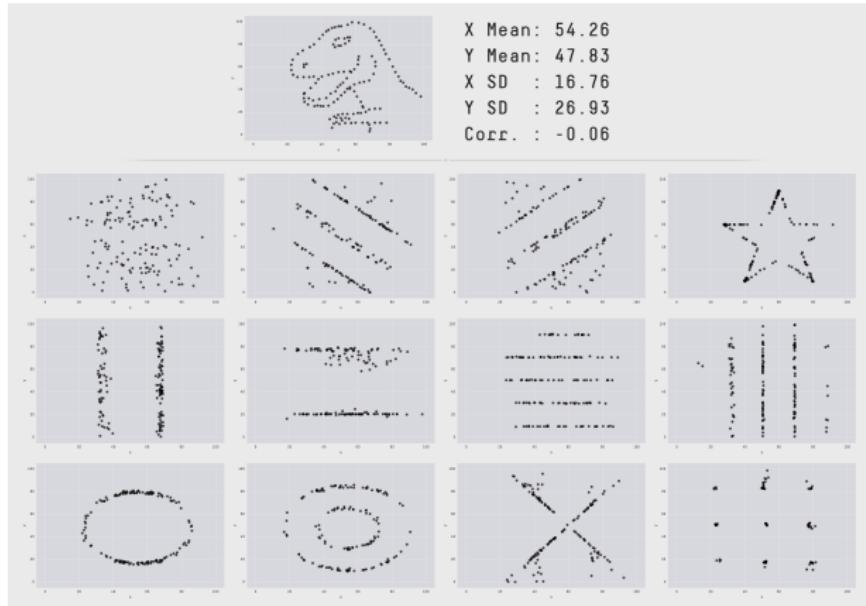
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Why do you think the 4th point makes sense?

# Variance

## Warning

Expected value and variance are very useful to describe random variables,  
**but they are not everything!** They do not replace CDF/PDF/PMF!



# Markov's Inequality (optional)

## Example

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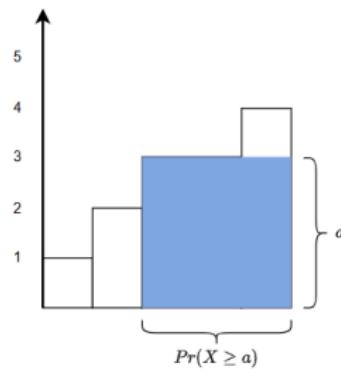
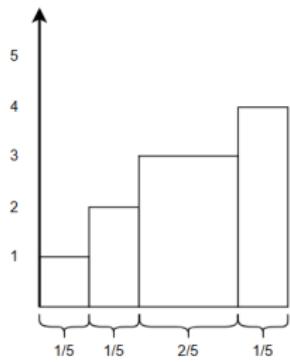
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so your friend is lying!

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We can also prove Markov visually. Let  $X$  be a random variable taking values  $\{1, 2, 3, 4\}$  with probabilities:

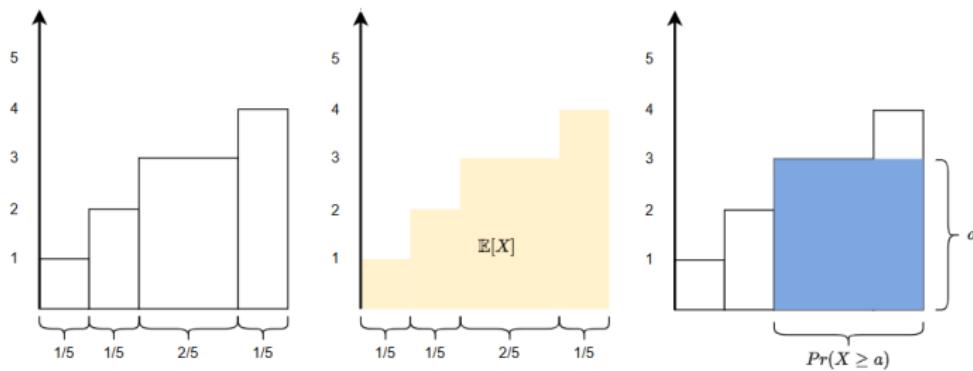
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## Question

Can you use Markov to prove *Chebyshev's inequality*?

$$\mathbb{P}[|X - \mathbb{E}[X]| \geq a] \leq \frac{\text{Var}[X]}{a^2}$$

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Why is this true? Because we are plugging in  $X$  into the function  $g(x) = x^2$ , which is a **convex** function.

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Same thing holds for random variables:

### Jensen's Inequality

If  $X$  is a random variable and  $g(x)$  is any convex function, then

$$\mathbb{E}[g(X)] \geq g(\mathbb{E}[X])$$

## Cauchy-Schwarz Inequality (optional)

In **linear algebra**, we had this Cauchy-Schwarz inequality for vectors  $\mathbf{a}, \mathbf{b} \in \mathbb{R}^n$ :

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In particular, if  $\mathbb{E}[X] = 0$  and  $\mathbb{E}[Y] = 0$ , this becomes:

$$|\mathbb{E}[XY]| \leq \sqrt{\text{Var}[X]} \cdot \sqrt{\text{Var}[Y]}$$

## Sample Mean and Sample Variance (optional)

### Question

Let  $X$  denote the height of a randomly chosen person from Artik. How would you estimate  $\mathbb{E}[X]$  and  $\text{Var}[X]$ ?

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## Definition

The average of the samples is called the *sample mean*:

$$\bar{x} = \frac{X_1 + X_2 + \cdots + X_n}{n}$$

and the quantity below is called the *sample variance*:

$$s^2 = \frac{(X_1 - \bar{x})^2 + (X_2 - \bar{x})^2 + \cdots + (X_n - \bar{x})^2}{n - 1}$$