

■ Random Variables



An outcome from a random experiment

a random variable

Some number

(the support of X is the set of possible values X can take on)

Probability Mass Function (PMF)

P(X=k) probability the value k what is the pro

probability that the random variable X will take on the value k

what is the probability of an outcome that will result in \boldsymbol{X} being \boldsymbol{k}

for discrete random variables (random variables with afinite, countably infinite range), this may sometimes be a piecewise function

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Random Variables



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Cumulative Distribution Function

P(X <= k) -> probability that the value X takes on is less than or equal to k

what is the probability of an outcome that will result in X being <= k

often can be derived from the PDF

Random Variables



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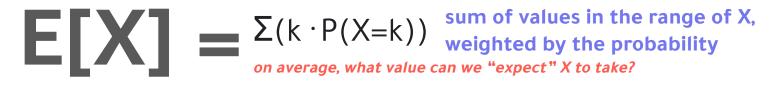
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An outcome from a random experiment Some number (the support of X is the set of possible values X can take on)

Expectation



think about it like a weighted average of all the possible values X could be (weighted by the P(X=k)

Random Variables



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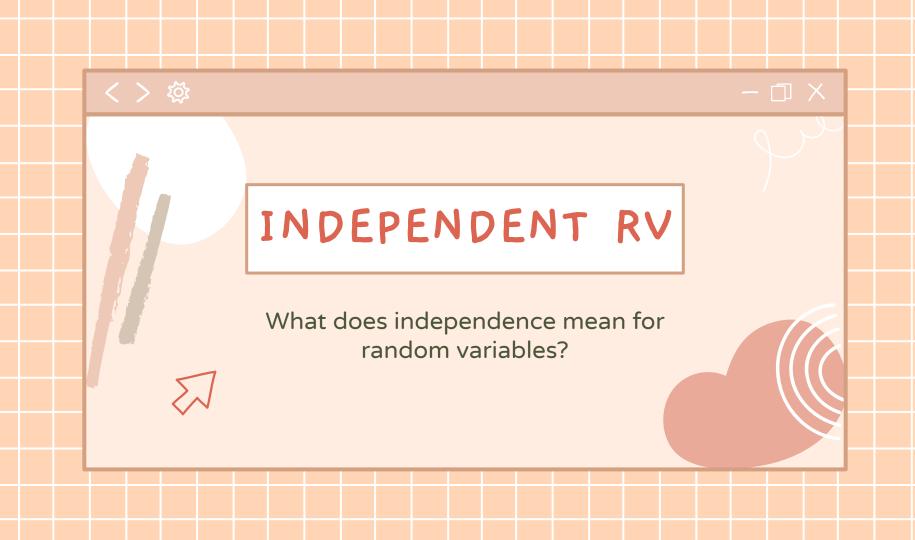




Expectation

$$= \sum (k \cdot P(X=k)) \text{ sum of values in the range of } X,$$
 weighted by the probability on average, what value can we "expect" X to take?

just averaging all the possible values of X wouldn't work since each outcome isn't necessarily equally likely







Random variables X and Y are independent if -

$$P(X=x, Y=y) = P(X=x) \cdot P(Y=y)$$

Knowing the value of X doesn't help "guess" what Y is

< > Random Variable Independence

Random variables X and Y are independent if –

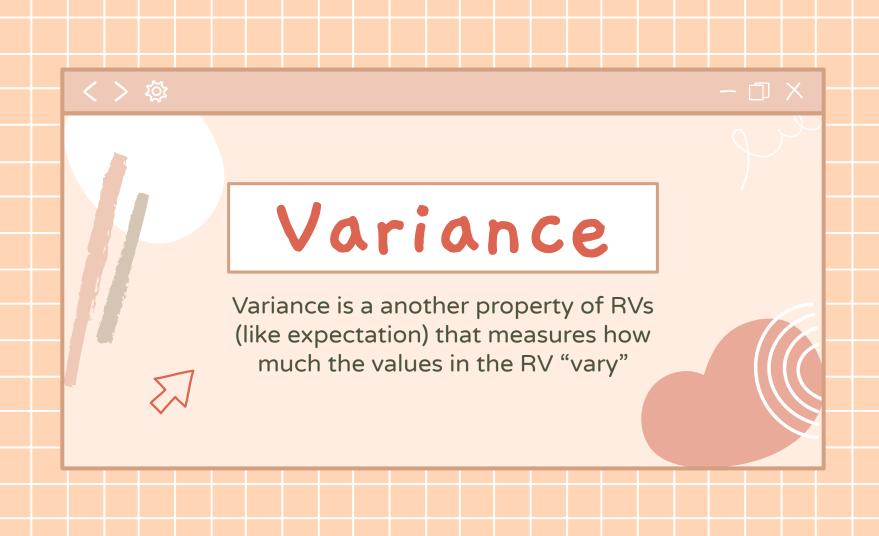
$$P(X=x, Y=y) = P(X=x) \cdot P(Y=y)$$

Knowing the value of X doesn't help "guess" what Y is

it's a useful property! if X and Y are independent random variables then —

$$E(X \cdot Y) = E[X] \cdot E[Y]$$

$$Var(X + Y) = Var[X] + Var[Y]$$
 Linearity of variance holds



03 - Variance



Random Variables

allow us to represent a quantitative property of a random experiment

VARIANCE - how "different" are values from the expectectation "on average"

every random variable has some variance

$$Var(X) = E[(X-E(X))^2] = \Sigma_x(P(X=x)*(x-E(X))^2)$$

expected value of the squared distance between each RV outcome and the expected value of RV

add up all the squared distances weighted by their probabilities

variance = (standard deviation)²



03 - Variance

- □ X

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Properties

$$Var(a \cdot X + b) = a^2 \cdot Var(X)$$

 $Var(X) = E[X^2] - (E[X])^2$







Random Variables

allow us to represent a quantitative property of a random experiment

EXPECTATION - weighted average of possible outcomes

you could use "brute force" and use the formula for expectation ($\mathbb{E}[X] = \sum (x * \mathbb{P}(x))$) sometimes, just applying the formula can be messy, so LoE comes in handy

LINEARITY OF EXPECTATION (LoE) is one important property

$$E(X+Y) = E(X) + E(Y)$$

the expected value of the sum of 2 random variables is the sum of their expected values

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APPLY linearity of expectation

$$E[X] = E[X1] + E[X2] + ... + E[Xn]$$

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CONQUER and calculate each value E[X1] = ..., E[X2] = ..., ...

$$\ldots, \ \mathbf{E}[\mathbf{X2}] = \ldots, \ldots$$

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sometimes, these Xi variables we "decompose" X into are indicator random variables

Indicator Random Variables

we can define a indicator random variable X for an event A

$$X = \begin{cases} 1 & \text{if event A happens} \\ 0 & \text{if event A doesn't happen} \end{cases}$$

^ X tells us whether event A will happen \rightarrow so, P(X = 1) = P(A)

Note that
$$E[X] = 1 * P(X=1) + 0 * P(X=0) = P(X=1)$$

this is why indicator RVs can be really useful when applying linearity of expectation!

linearity of expectation is special!

$$E[X+Y] = E[X] + E[Y]$$
 but $E[X^2] \neq (E[X])^2$ instead...

$$E[g(X)] = \Sigma(g(x) * P(X=x))$$

