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01 - Reminders!

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HW 2 grades released

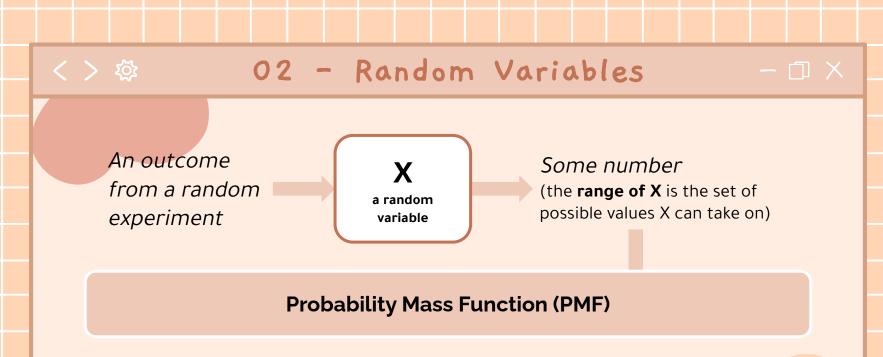
(regrade requests open ~24 hours after grades are released and close after a week)

HW 3

(written & coding part due yesterday)

Midterm on July 15 @ 3:30 - 5:20 in BAG131





P(X=k) probability that the random variable X will take on the value k what is the probability of an outcome that will result in X being k

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

Random Variables

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02

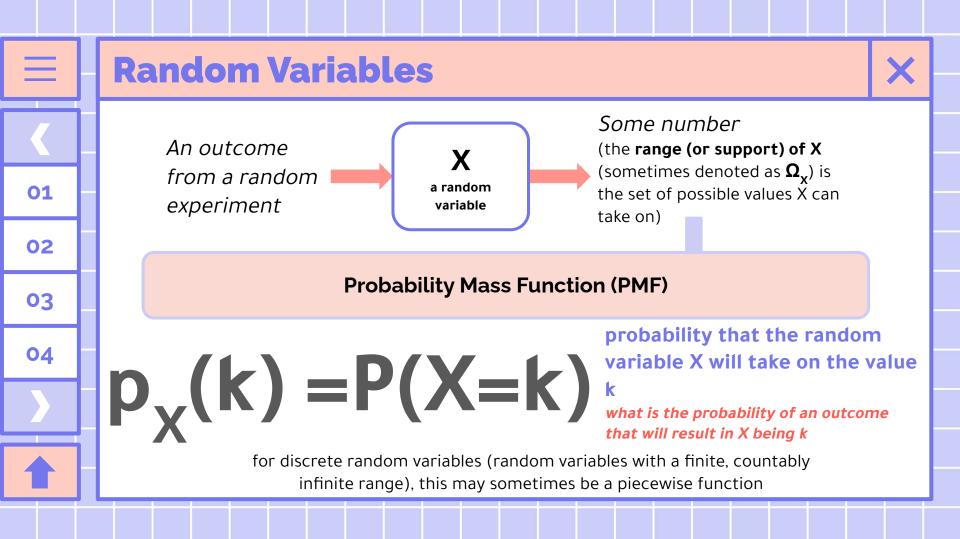
03

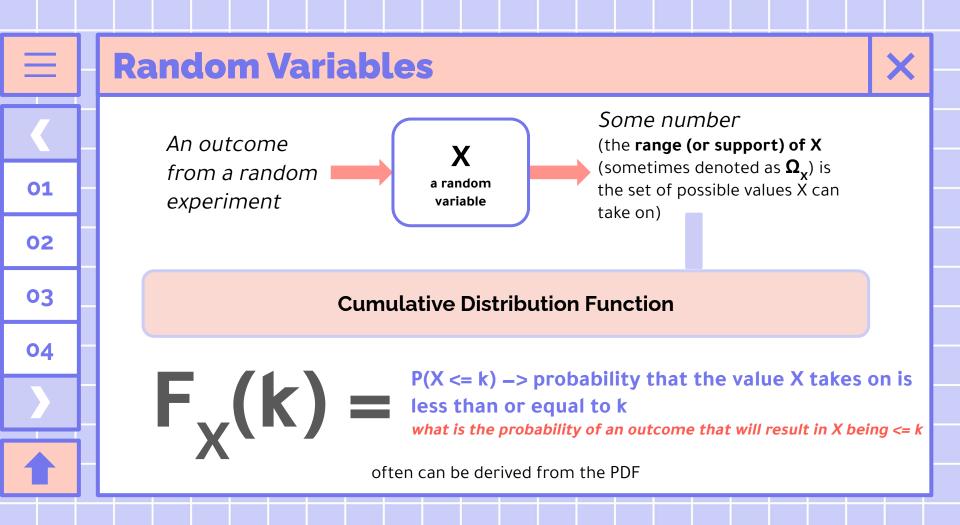
04

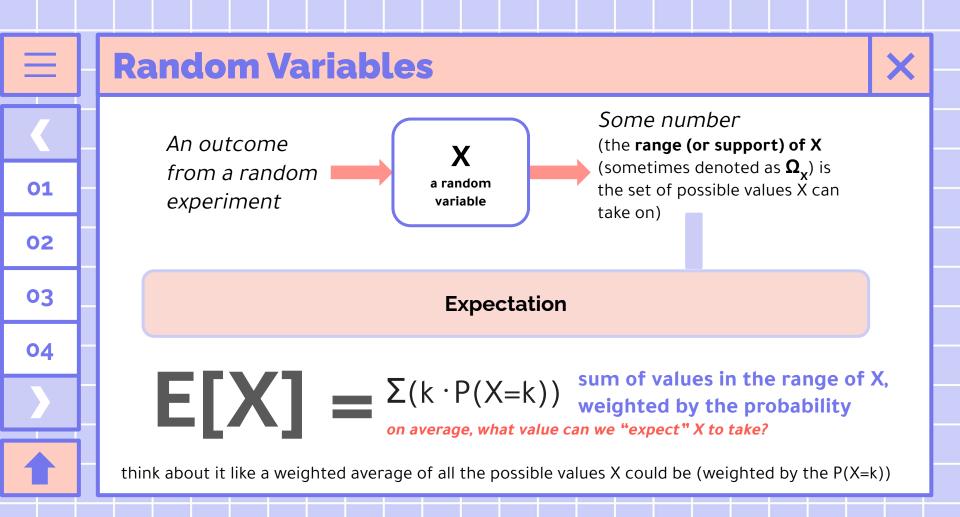
Random variable

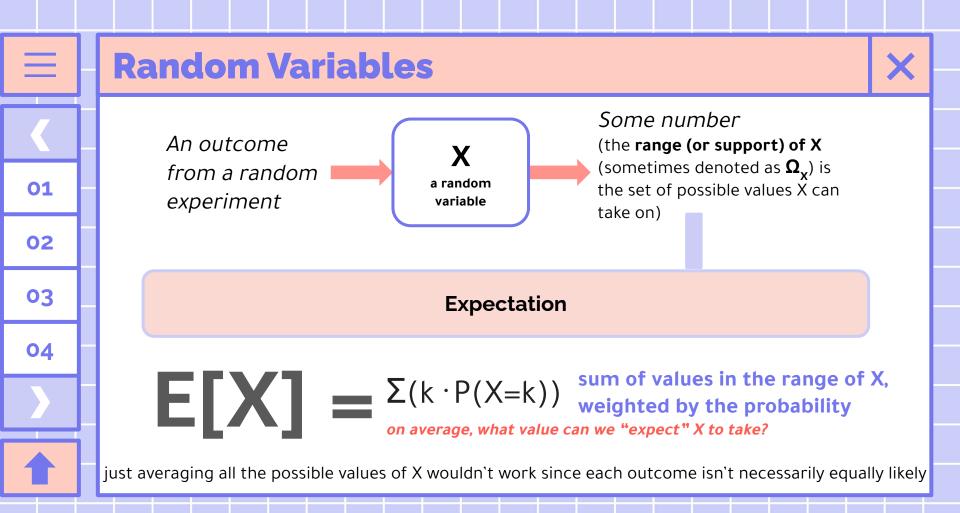
Captures a <u>quantitative property</u> (some numerical value that describes the outcome) of the outcome in a random experiment

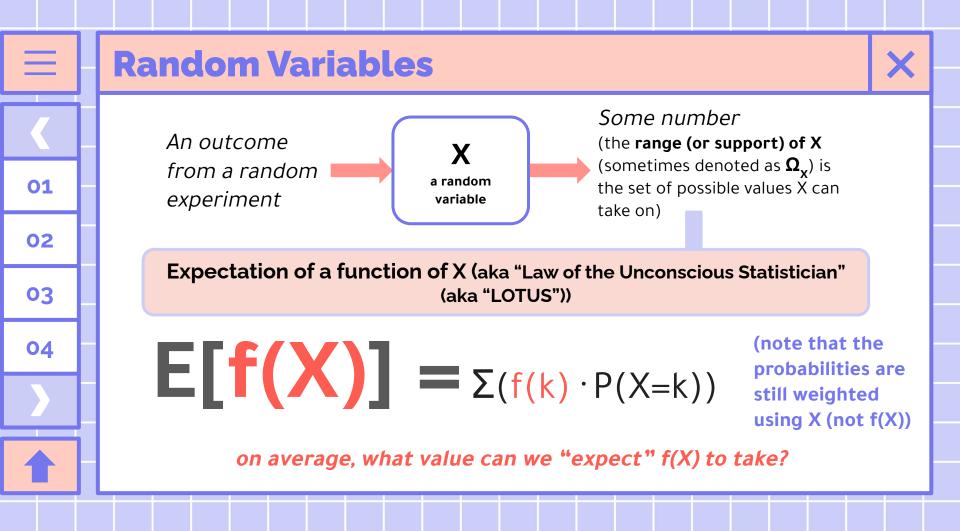
e.g., sum of the dices on an random experiment where we roll 2 dice

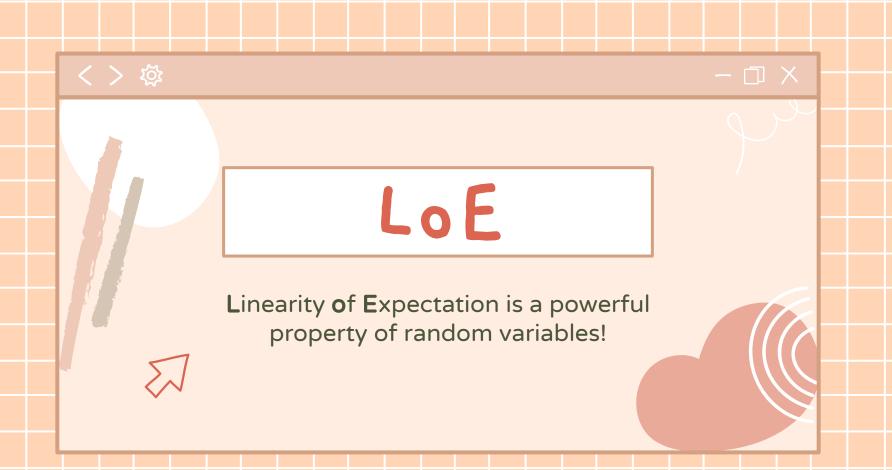












Random Variables

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

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

<> 🕸 02 - Linearity of Expectation - 🗆 ×

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this gives us a helpful tool to calculate expectations of complex RVs

<> 🕸 02 - Linearity of Expectation

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

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

this gives us a helpful **tool to calculate expectations of complex RVs**

DECOMPOSE into a sum of random variables X = X1 + X2 + ... + Xn

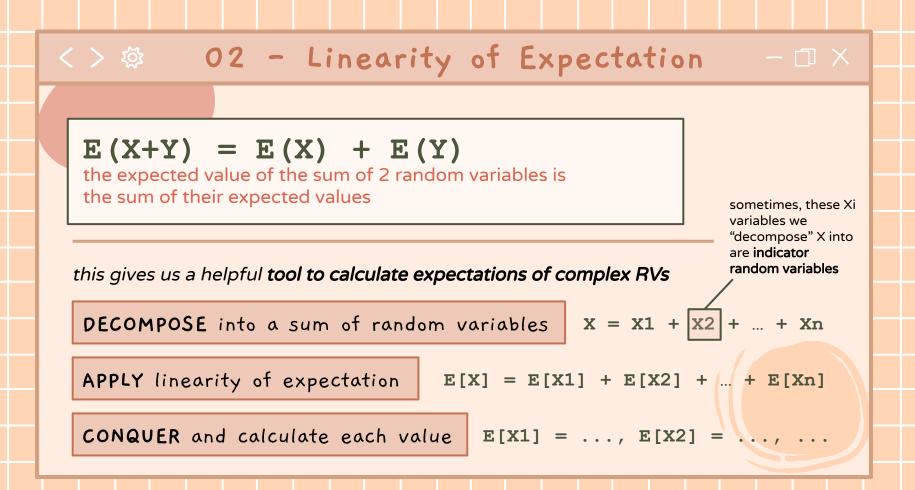
E(X+Y) = E(X) + E(Y)the expected value of the sum of 2 random variables is the sum of their expected values this gives us a helpful **tool to calculate expectations of complex RVs DECOMPOSE** into a sum of random variables X = X1 + X2 + ... + XnAPPLY linearity of expectation E[X] = E[X1] + E[X2] + ... + E[Xn]

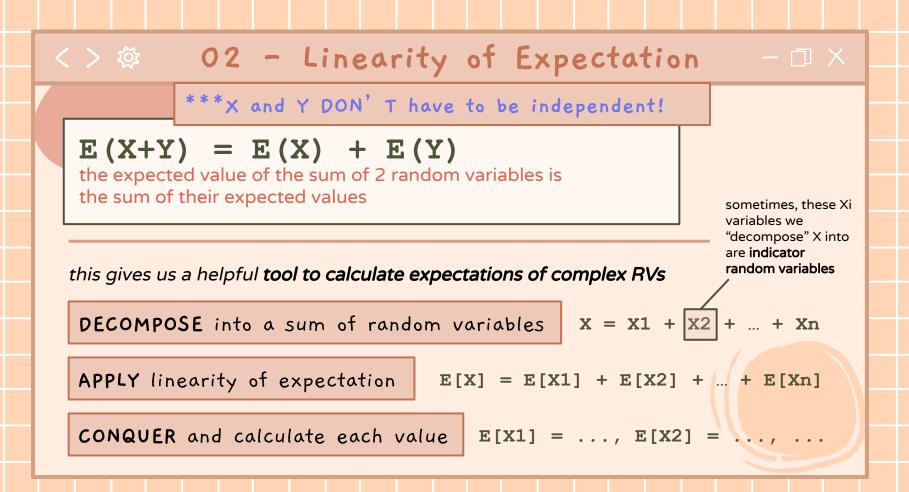
$$E(X+Y) = E(X) + E(Y)$$

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

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DECOMPOSE into a sum of random variablesX = X1 + X2 + ... + XnAPPLY linearity of expectationE[X] = E[X1] + E[X2] + ... + E[Xn]CONQUER and calculate each valueE[X1] = ..., E[X2] = ..., ...





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) this is why indicator RVs can be really useful when Note that E[X] = 1 * P(X=1) + 0 * P(X=0) = P(X=1)applying linearity of expectation!

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Additional slides for content that will be covered later in the week!

linearity of expectation is special! $E[X+Y] = E[X] + E[Y] \quad but \quad E[X^2] \neq (E[X])^2$ instead... $E[g(X)] = \Sigma(g(x) * P(X=x))$

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Variance

Variance is a another property of RVs (like expectation) that measures how much the values in the RV "vary"



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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

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Properties

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

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

03 - Variance

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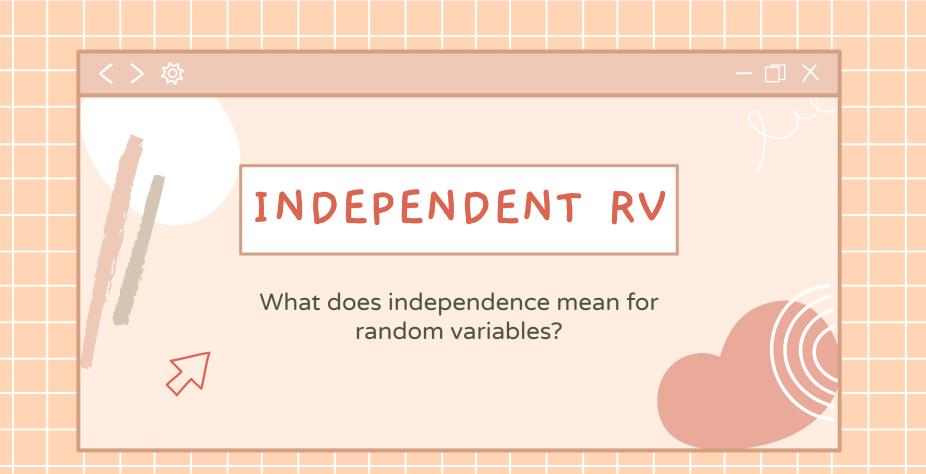
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 $Var(X) = E[X^2] - (E[X])^2$



Random variables X and Y are **independent** if, for all x, y in the ranges of X and Y:

Random Variable Independence

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

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

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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 -

 $\mathsf{E}(\mathsf{X} \cdot \mathsf{Y}) = \mathsf{E}[\mathsf{X}] \cdot \mathsf{E}[\mathsf{Y}]$

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

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

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

Additionally, there's **independent and identically distributed** (aka, "**i.i.d.** ") random variables

In addition to independence, i.i.d. random variables also **have the** same pmf.

For example, rolling a die twice, where X is the first roll number and Y is the second roll number

