

CSCI 3022

intro to data science with probability & statistics

October 1, 2018

Expected Values

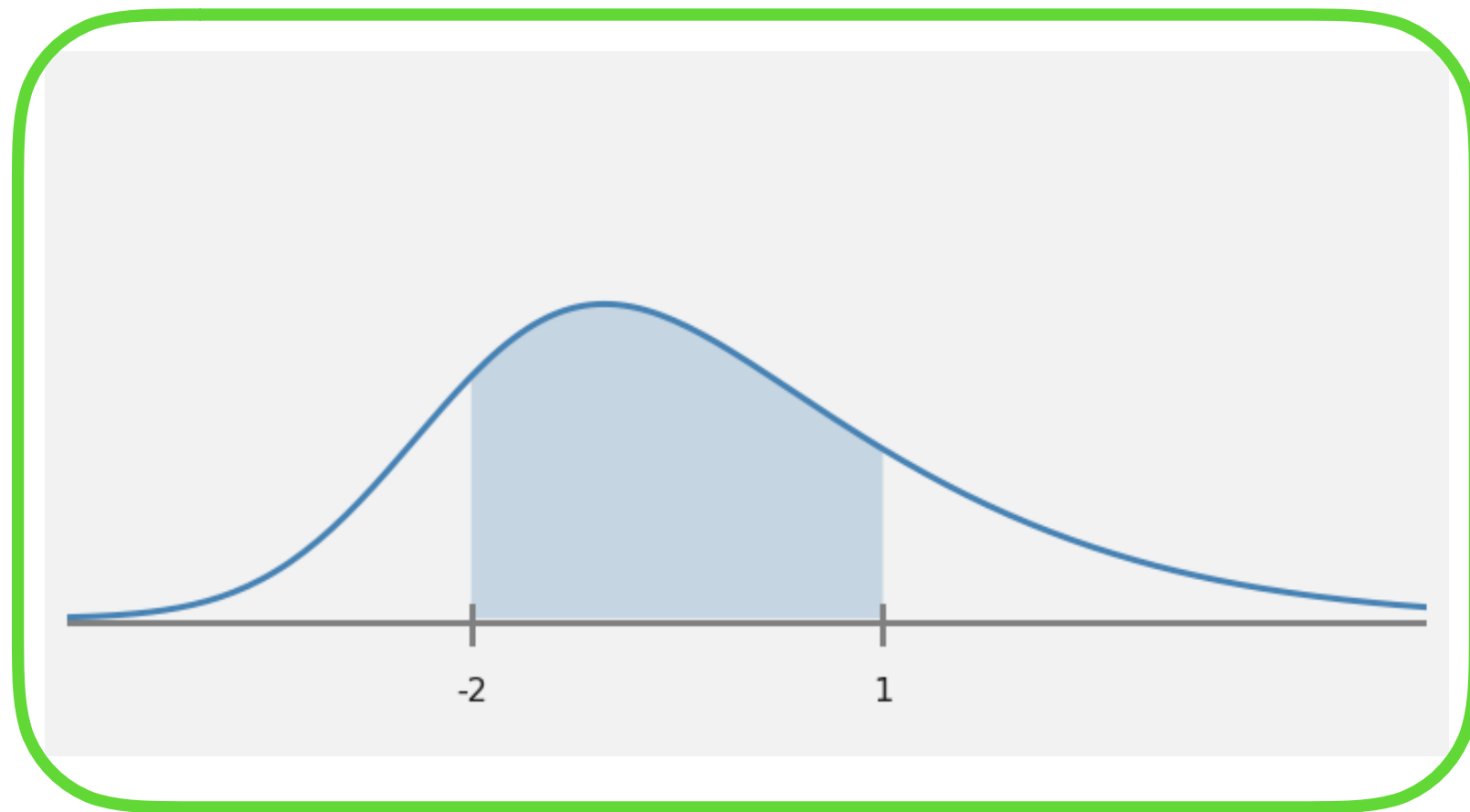
Stuff & Things

- **Homework 3** due next Friday. Suggested **milestones**:
 - Probs 1, 2, 3 done before the end of the week.
 - Probs 4, 5 done next week.
- **Midterm** next week. Weds, 6:30-8:00 PM. SEE PIAZZA for details..
- Midterm review *in class* next Monday.

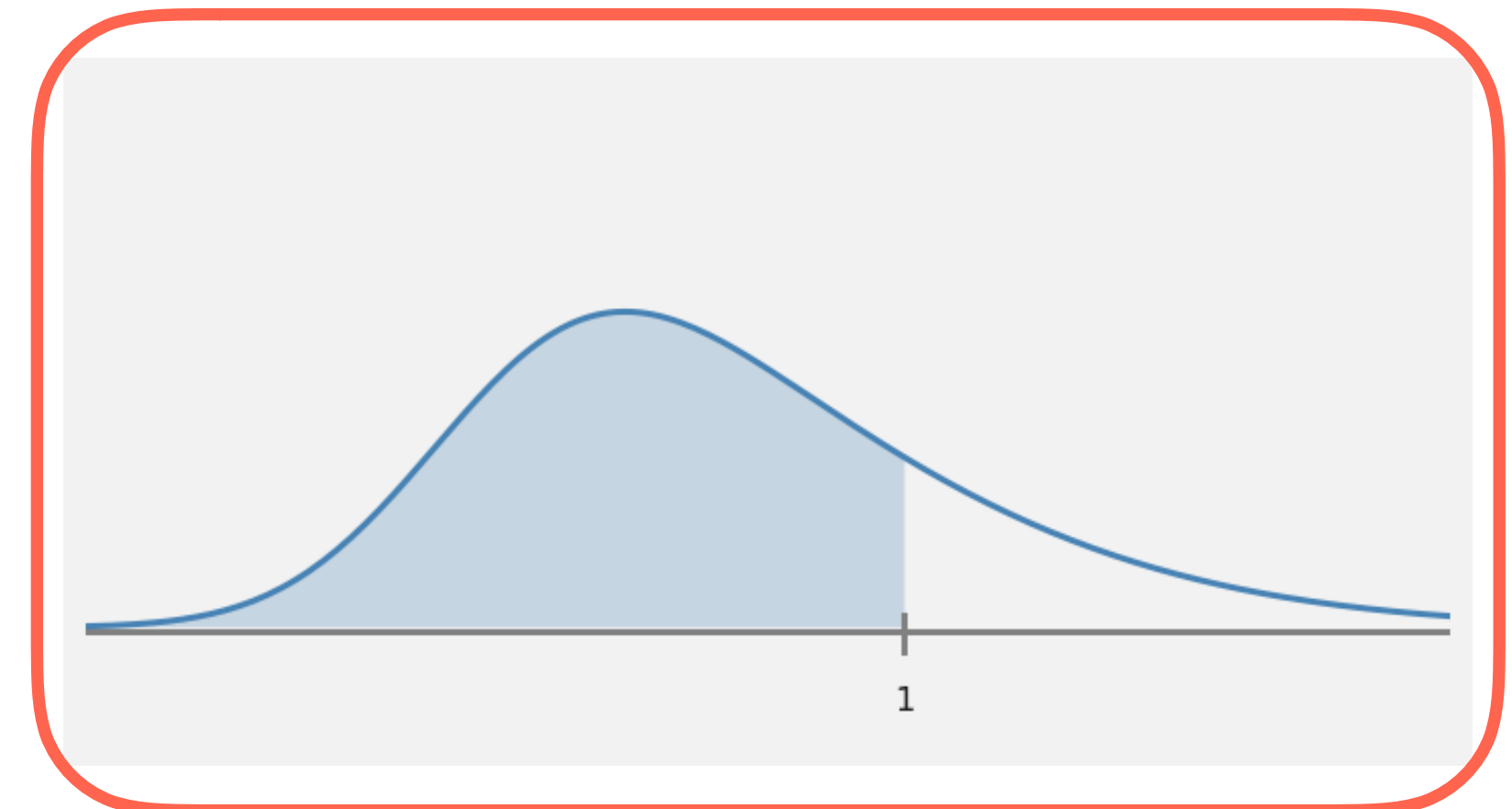
Last time on CSCI 3022:

- **Continuous random variables:**

$$P(a \leq X \leq b) = \int_a^b f(t) dt = F(b) - F(a)$$



- New distributions! Uniform, Exponential, Normal.



Homework Planning

- Suppose *hypothetically* that I write the homework questions as either: easy (takes 10 mins), medium (30 mins), or hard (60 mins).
- The probability that each question is easy, medium, or hard, is: 0.4, 0.35, 0.25, respectively.
- If a homework consists of 5 questions, what's the average time it takes to do the homework? *answer in minutes*

weighted
average

$$(0.4)10 + (0.35)30 + (0.25)60 = \mu$$

$P_r(\text{easy}) \times \text{Time if Easy} + P_r(\text{med}) \times \text{Time if Med} + P_r(\text{hard}) \times \text{Time if Hard}$

μ

$$\boxed{5\mu}$$

Expected Value

- Definition:** The *expectation* or *expected value* of a discrete random variable X that takes the values a_1, a_2, \dots and with PMF p is given by:

$$E[X] = \sum_i a_i P(X = a_i) = \sum_i a_i p(a_i)$$

means
Exp. Value of X

mins of problem is hard

$p_r(\text{hard})$

$$\frac{d}{dp} \left(-\frac{1}{p} \right) = +\frac{1}{p^2}$$

$$p(k) = p(1-p)^{k-1}$$

- Exercise:** What is the expected value of the geometric distribution?

$$\begin{aligned} E[X] &= \sum_i a_i \Pr(X=a_i) \\ &= \sum_{i=1}^{\infty} i p(1-p)^{i-1} \\ &= p \sum_{i=1}^{\infty} i (1-p)^{i-1} \\ &= p \sum_{n=0}^{\infty} (n+1) (1-p)^n \end{aligned}$$

$$\begin{aligned} &= p \left[\sum_{n=0}^{\infty} (1-p)^n + \sum_{n=0}^{\infty} n(1-p)^n \right] \\ &= p \left[\frac{1}{p} + \sum_{n=0}^{\infty} n(1-p)^n \right] \quad \text{geom series} \\ &= 1 + p(1-p) \sum_{n=0}^{\infty} n(1-p)^{n-1} \end{aligned}$$

$$= 1 + p(1-p) \frac{d}{dp} \left[-\sum_{n=0}^{\infty} (1-p)^n \right]$$

$$= 1 + p(1-p) \frac{d}{dp} \left(-\frac{1}{p} \right)$$

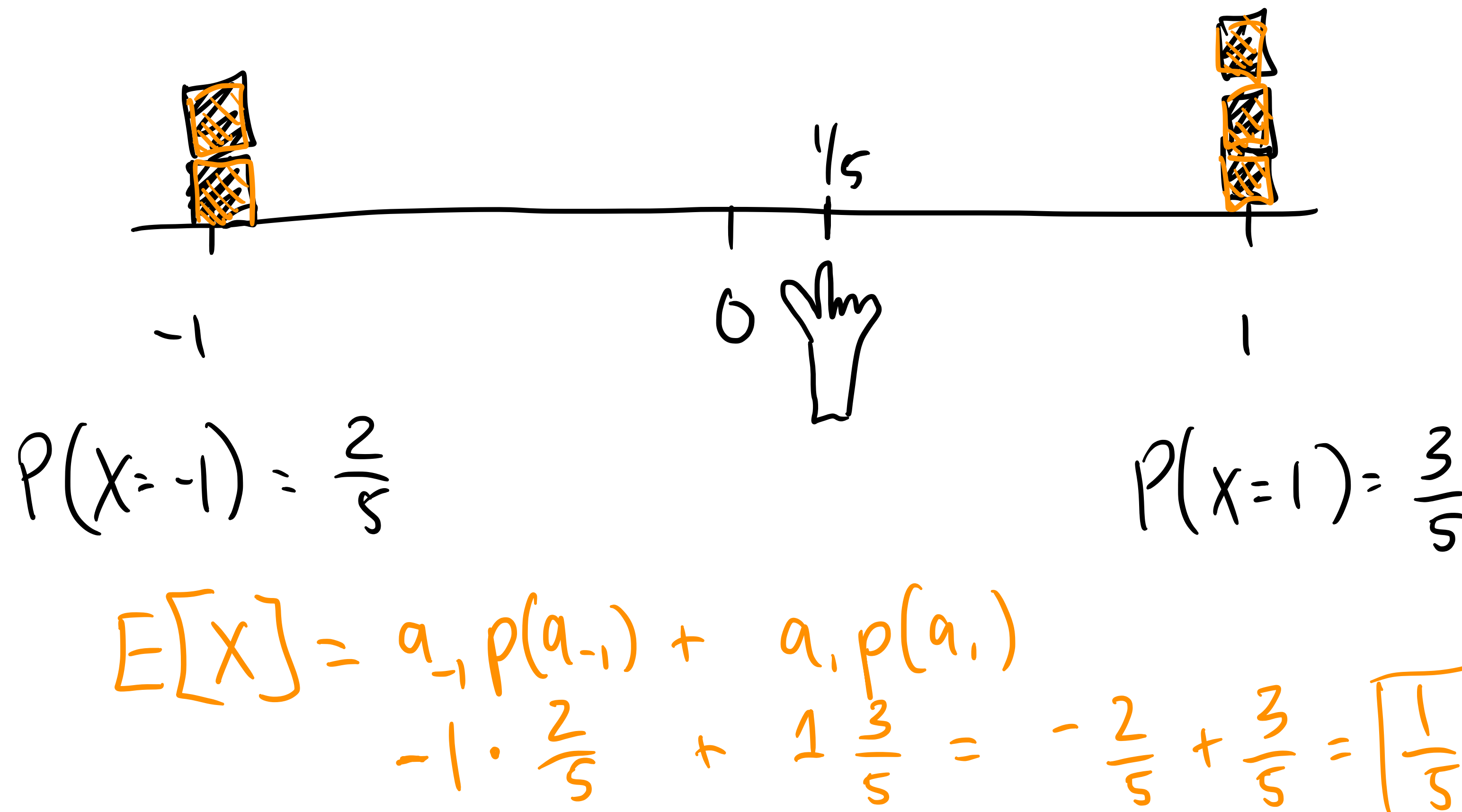
$$= 1 + \cancel{p(1-p)}$$

$$= 1 + \frac{1}{p} - \frac{p}{p} = \boxed{\frac{1}{p}}$$



Expected Value: center of gravity

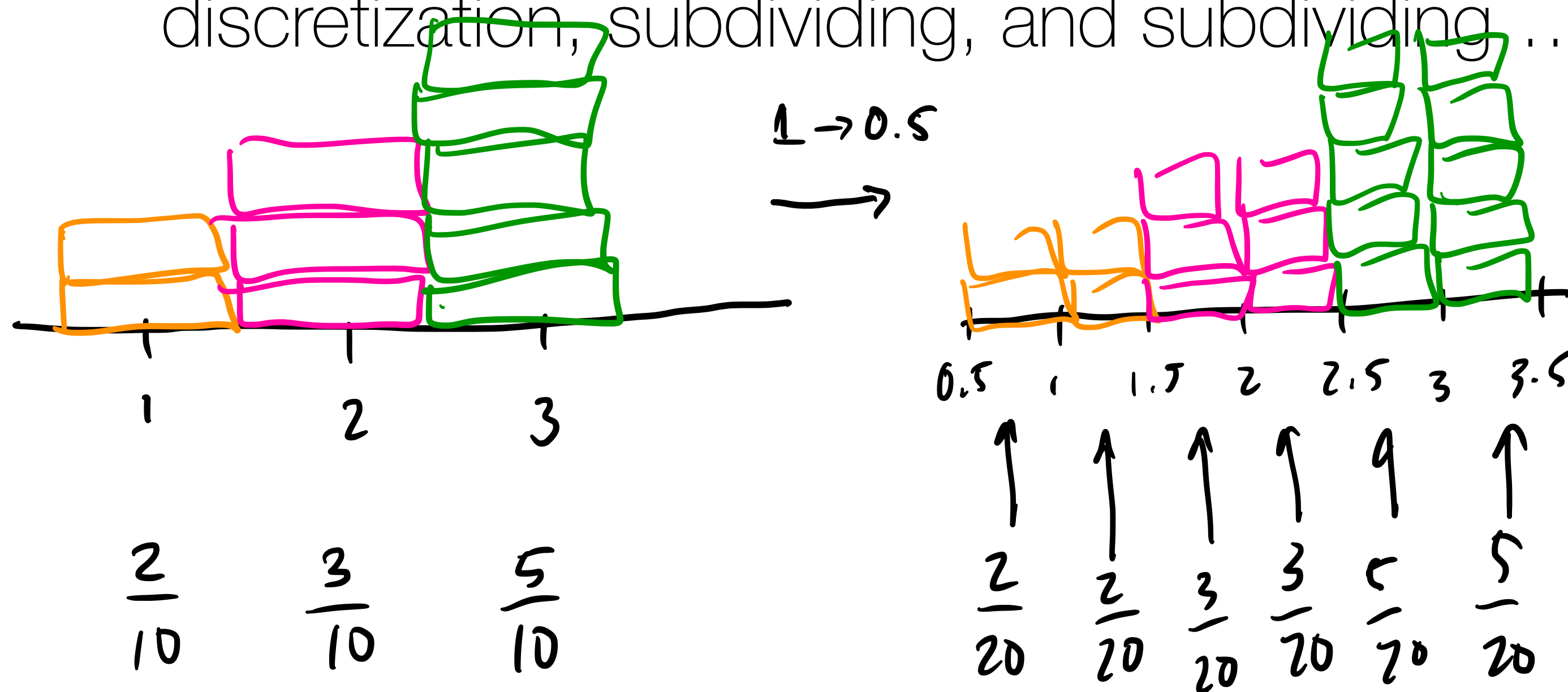
- **Note:** the expected value is the *center of gravity*.
- **Example:** suppose I stack 2 boxes at $x=-1$ and 3 boxes at position $x=1$. What is the expected value of this distribution of boxes?



What about continuous RVs?

before: $E[X] = \sum_i a_i p(a_i)$

- Back to box stacking. What if I have 2, 3, and 5 *physical* IRL boxes at positions 1, 2, and 3, respectively.
- The masses are not concentrated at a point. We can change our discretization, subdividing, and subdividing ...



take
it to
the limit

from PMF
to a PDF

$$E[X] = \int_{-\infty}^{\infty} x f(x) dx$$

\sum_i a_i $p(a_i)$

What about continuous RVs?

- Back to box stacking. What if I have 2, 3, and 5 *physical* IRL boxes at positions 1, 2, and 3, respectively.
- The masses are not concentrated at a point. We can change our discretization, subdividing, and subdividing...
- **Definition:** The *expectation* or *expected value* of a continuous random variable X with PDF f is the number:

$$E[X] = \int_{-\infty}^{\infty} x f(x) dx$$

Expected value: average, c. of. g

- The expected value $E[X]$ is also the average of a large number of draws of the random variable X .
- Even in the continuous case, $E[X]$ is the center of gravity.
- **Example:** What is the expectation of an exponential distribution?

$$X \sim \exp(\lambda)$$

$$f(x) = \lambda e^{-\lambda x} \quad x \geq 0$$

$$E[X] = \int_{-\infty}^{\infty} x f(x) dx$$

$$= \int_0^{\infty} x \lambda e^{-\lambda x} dx$$

integration by parts :-

$$= \frac{1}{\lambda}$$

recall geometric
 $E[X] = \frac{1}{p}$

Expected value of a normal

- Let $X \sim N(\mu, \sigma^2)$
- Then: $E[X] = \int_{-\infty}^{\infty} x \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} dx = \mu$

① change of variables.

$$z = x - \mu$$

$$x = z + \mu$$

$$\int_{-\infty}^{\infty} z \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{z}{\sigma}\right)^2} dz$$

$$\int_{-\infty}^{\infty} \mu \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{z}{\sigma}\right)^2} dz$$

0 because it's odd

+ μ

Change of variable trick

- Let X and Y be random variables and let $g : \mathcal{R} \rightarrow \mathcal{R}$ be a function.
- For X discrete and Y continuous, then:

$$E[g(X)] = \sum_i g(a_i) f(a_i)$$

↑
apply function
to values of
outcomes

↑
keep
probs. the
same

$$E[g(Y)] = \int_{-\infty}^{\infty} g(y) f(y) dy$$

same here

If $g(x) = x$

$$E[g(X)] = \sum_i a_i f(a_i) = E[X]$$

Change of variable trick

- Let X and Y be random variables and let $g : \mathcal{R} \rightarrow \mathcal{R}$ be a function.
- For X discrete and Y continuous, then:

$$E[g(X)] = \sum_i g(a_i) f(a_i)$$

$$E[g(X)] = \int_{-\infty}^{\infty} g(x) f(x) dx$$

- What happens if $g(x) = x$?
- What happens if $g(x) = rX + s$?

Handwritten derivation for $E[rX + s]$:

$$E[rX + s] = \sum_i (ra_i + s) f(a_i) = r \underbrace{\left(\sum_i a_i f(a_i) \right)}_{\text{distribute}} + s \left(\sum_i f(a_i) \right) = r E[X] + s$$

Annotations:

- const (orange) points to r in ra_i .
- const. (orange) points to s .
- $E[X]$ (blue) points to the sum $\sum_i a_i f(a_i)$.
- 1 (blue) points to the sum $\sum_i f(a_i)$.
- linearity of expectation.* (orange) written below the final result.

Linearity of Expectations

Fact: $E[rX + s] = rE[X] + s$

Proof: See prev. slide.

Summary

- **Definition:** The expectation or expected value of a discrete random variable X that takes the values a_1, a_2, \dots and with PMF p is given by:

$$E[X] = \sum_i a_i P(X = a_i) = \sum_i a_i p(a_i)$$

- **Definition:** The *expectation* or *expected value* of a continuous random variable X with PDF f is the number:

$$E[X] = \int_{-\infty}^{\infty} x f(x) dx$$

- **Change of Variables:** Let X be a RV and let $g : \mathcal{R} \rightarrow \mathcal{R}$ be a function

$$E[g(X)] = \sum_i g(a_i) f(a_i) \qquad E[g(X)] = \int_{-\infty}^{\infty} g(x) f(x) dx$$