

MATH 201 (SUMMER 2023, SESH A2)

LECTURE 7 : 05/24/23 (RECORDED ON 05/23) 0M

ANURAG SAHAY
OFF HRS: BY APPT (VIA ZOOM)

email: anuragsahay@rochester.edu

{ Zoom ID:
979-4693-0650

LECTURES:
9:00 AM - 11:15 AM (ET)
M, T, W, R

COURSE

WEB PAGE

<https://people.math.rochester.edu/grads/asahay/summer2023/math201/index.html>

ALL PHOTOS TAKEN
FROM TEXTBOOK

ANNOUNCEMENTS

- ① LECTURE 6, WEEK 2 H.W. IS UPLOADED. (PANOPTO/WEBSITE)
- ② OFFICE HOURS : THURS - AFTER CLASS. (11:15 - 12:15)
- ③ DEADLINES :
 - Ⓐ WW04 - FRI, MAY 26th
 - Ⓑ HW03 - SAT, MAY 27th
 - Ⓒ WW05 - TUES, MAY 30th } → TO BE UPLOADED
- ④ ERROR IN HW2 - SEE ANNOUNCEMENT ON BLACKBOARD
↳ ngpand@ur.rochester.edu

§ 3.3 EXPECTATION

RECALL: $X \rightarrow$ R.V.
(p.m.f., p.d.f., c.d.f.)

NOTATION : $E(X)$, $\bar{E}(X)$, $\mu \in \mathbb{R}$

ALSO CALLED : (MEAN / AVERAGE / 1st MOMENT)
EXPECTED VALUE

DISCRETE RVs

Definition 3.21. The expectation or mean of a discrete random variable X is defined by

$$E(X) = \sum_k k P(X = k) \tag{3.19}$$

where the sum ranges over all the possible values k of X . ♣

$X \in \{k_1, k_2, k_3, \dots\}$

p.m.f.

Example 3.22. Let Z denote the number from the roll of a fair die. Find $E(Z)$

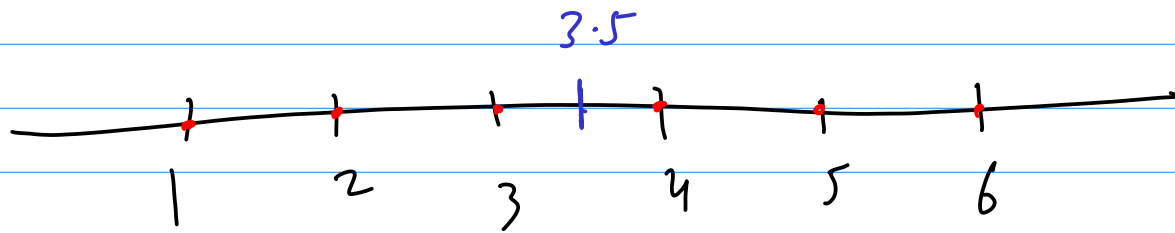
$$Z \in \{1, 2, 3, 4, 5, 6\}$$

$$P(Z = k) = \begin{cases} \frac{1}{6} & \text{IF } k \in \{1, \dots, 6\} \\ 0 & \text{o.w.} \end{cases}$$

$$E(Z) = \sum_k k \cdot P(Z = k)$$

$$= \underbrace{1 \cdot P(Z=1)}_{\frac{1}{6}} + \underbrace{2 \cdot P(Z=2)}_{\frac{1}{6}} + \dots + \underbrace{6 \cdot P(Z=6)}_{\frac{1}{6}}$$

$$= \frac{1}{6} (1 + 2 + \dots + 6) = \frac{21}{6} = \frac{7}{2} = 3.5$$



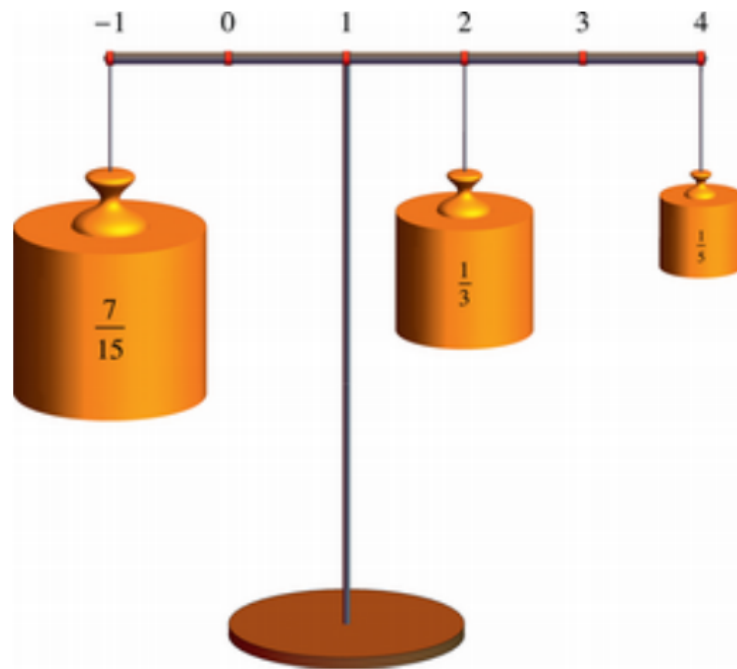


Figure 3.8. The expectation as the center of mass. If X takes the values $-1, 2, 4$ with probabilities $p_X(-1) = \frac{7}{15}$, $p_X(2) = \frac{1}{3}$, $p_X(4) = \frac{1}{5}$ then the expectation is $E[X] = -1 \cdot \frac{7}{15} + 2 \cdot \frac{1}{3} + 4 \cdot \frac{1}{5} = 1$. Hence the scale in the picture is perfectly balanced.

MEAN OF SOME PREVIOUSLY DEFINED DISTRIBUTIONS

$$\textcircled{1} \quad X \sim \text{Ben}(p) \quad X \in \{0, 1\}$$

$$P(X=1) = p, \quad P(X=0) = 1-p$$

$$E(X) = \sum_k k \cdot P(X=k) = 0 \cdot P(X=0) + 1 \cdot \underbrace{P(X=1)}_p = p$$

$$E(X) = p$$

SPECIAL CASE

: $A \subseteq \Omega$,

→ EVENT

I_A → INDICATOR RANDOM VARIABLE

$$I_A(\omega) = \begin{cases} 1 & \omega \in A \\ 0 & \omega \notin A \end{cases}$$

BERNOULLI

w/p =

$$P[I_A = 1] = P(\{\omega : \omega \in A\})$$

$$I_A \in \{0, 1\}$$

$$= P(A)$$

$$E(I_A) = p = \underline{P(A)}$$

$$\textcircled{2} \quad X \sim \text{Bin}(n, p)$$

$$X \in \{0, 1, \dots, n\}$$

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

$$E(X) = \sum_k k \cdot P(X = k) = \sum_{k=0}^n k \cdot \binom{n}{k} p^k (1-p)^{n-k}$$

$$= \sum_{k=1}^n k \cdot \frac{n!}{k! (n-k)!} p^k (1-p)^{n-k}$$

$k=0 \rightarrow$ NO CONTRIBUTION

$$\binom{n}{k} = \frac{n!}{k! (n-k)!}$$

$$= \sum_{k=1}^n \frac{n!}{(k-1)! (n-k)!} p^k (1-p)^{n-k}$$

$$= n p \sum_{k=1}^n \frac{(n-1)!}{(k-1)! (n-k)!} p^{k-1} (1-p)^{n-k}$$

$$= n p \sum_{k=1}^n \frac{(n-1)!}{(k-1)! (n-k)!} p^{k-1} (1-p)^{n-k}$$

$$\sum_{k=1}^n \frac{(n-1)!}{(k-1)!(n-k)!} p^{k-1} (1-p)^{n-k} \quad j = k-1$$

$$= \sum_{j=0}^{n-1} \frac{(n-1)!}{j!(n-1-j)!} p^j (1-p)^{n-1-j}$$

$$= [p + (1-p)]^{n-1} = 1$$

$$E(X) = np$$

0 0 0 0 0 ... 0
 p → n
 FORMALIZED.

③ Geom (p)

RECALL : $\frac{1}{1-t} = \sum_{k=0}^{\infty} t^k \quad (|t| < 1)$

$$\begin{aligned} \therefore \sum_{k=1}^{\infty} k \cdot t^{k-1} &= \sum_{k=1}^{\infty} \frac{d}{dt} [t^k] = \frac{d}{dt} \left(\sum_{k=1}^{\infty} t^k \right) \\ &= \frac{d}{dt} \left(\frac{1}{1-t} \right) = \frac{1}{(1-t)^2} \end{aligned}$$

$$\sum_{k=1}^{\infty} k \cdot t^{k-1} = (1-t)^{-2} \quad / \quad (t = q)$$

$$X \sim \text{Geom}(p)$$

$$X \in \{1, 2, 3, \dots\}$$

$$P(X=k) = p(1-p)^{k-1} = pq^{k-1}$$

$$[q := 1-p]$$

$$1-q = p$$

$$E(X) = \sum_{k=1}^{\infty} k \cdot P(X=k)$$

$$\begin{aligned} &= \sum_{k=1}^{\infty} k p q^{k-1} = p \sum_{k=1}^{\infty} k \cdot q^{k-1} \\ &= \frac{p}{(1-q)^2} \\ &= \frac{p}{p^2} = \frac{1}{p} \end{aligned}$$

RECALL

Geom(p)

0 0 0 0 0 ...
p p p p p

$$E(x) = \frac{1}{p}$$

CONT. R.V.

$P(X=k) = 0$, $E(X) = \sum_k k \cdot \underbrace{P(X=k)}_0$

↑ NOT COUNTABLE

CONTINUOUS
RV

Definition 3.26. The expectation or mean of a continuous random variable X with density function f is

$$E[X] = \int_{-\infty}^{\infty} x f(x) dx \tag{3.23}$$

An alternative symbol is $\mu = E[X]$.

$P(X \approx x) = P(X \in (x, x + \epsilon))$

COMPARE

$\sum_k k \cdot P(X=k)$

HEURISTIC : p.d.f \approx INFINITESIMAL p.m.f.

④

$X \sim \text{Unif}[a, b]$

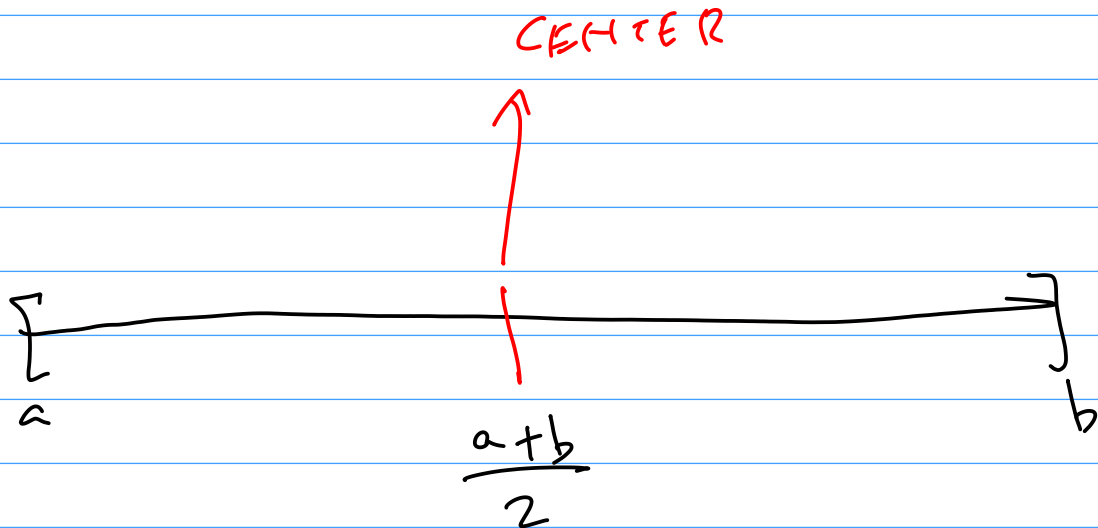
$$\text{p.d.f. } f(x) = \begin{cases} \frac{1}{b-a} & x \in [a, b] \\ 0 & x \notin [a, b] \end{cases}$$

$$E(x) = \int_{-\infty}^{\infty} x f(x) dx = \int_a^b x \left[\frac{1}{b-a} \right] dx$$

$$= \left(\frac{x^2}{2} \cdot \left[\frac{1}{b-a} \right] \right)_{x=a}^{x=b}$$

$$= \frac{(b^2 - a^2)}{2(b-a)} = \frac{b+a}{2}$$

$X \sim \text{Unif}[a, b]$



Q: DOES $E(X)$ ALWAYS EXIST?

A: NO!

IN FACT, ONE CAN HAVE

$$E(X) = \infty$$

$$E(X) = -\infty$$

OR $E(X) = \text{INDETERMINATE}$

(WILL BE COVERED IN
H.W.)

Example 3.32. In Example 1.30 a roll of a fair die determined the winnings (or loss) W of a player as follows:

$$W = \begin{cases} -1, & \text{if the roll is 1, 2, or 3} \\ 1, & \text{if the roll is 4} \\ 3, & \text{if the roll is 5 or 6.} \end{cases}$$

$P(X = -1) = \frac{1}{2}$
 $P(X = 1) = \frac{1}{6}$
 $P(X = 3) = \frac{1}{3}$

Let X denote the outcome of the die roll. The connection between X and W can be expressed as $W = g(X)$ where the function g is defined by $g(1) = g(2) = g(3) = -1$, $g(4) = 1$, and $g(5) = g(6) = 3$.

WHAT IS $E(W) = E(g(X))$?

$$\begin{aligned} E(W) &= \sum_{k \in \{-1, 1, 3\}} k \cdot P(X = k) = (-1) \cdot \frac{1}{2} + 1 \cdot \left(\frac{1}{6}\right) + 3 \cdot \left(\frac{1}{3}\right) \\ &= \frac{4}{6} = \frac{2}{3} \end{aligned}$$

$$W = g(X)$$

$$E(W) = E(g(X))$$

$$= \sum_{k=1}^6 g(k) \cdot P(X=k)$$

$$= g(1) \cdot \frac{1}{6} + g(2) \cdot \frac{1}{6} + \dots + g(6) \cdot \frac{1}{6}$$

$$= \frac{-1}{6} - \frac{1}{6} - \frac{1}{6} + \frac{1}{6} + \frac{3}{6} + \frac{3}{6}$$

$$= 4/6 = 2/3$$

Fact 3.33. Let g be a real-valued function defined on the range of a random variable X . If X is a discrete random variable then

$$E[g(X)] = \sum_k g(k)P(X = k) \quad (3.24)$$

while if X is a continuous random variable with density function f then

$$E[g(X)] = \int_{-\infty}^{\infty} g(x)f(x) dx. \quad (3.25)$$

Pf: DISCRETE CASE.

$$E(g(x)) = \sum_l l \cdot P(g(X) = l)$$

$$\{g(x) = l\} = X \in g^{-1}(l) \quad g^{-1}(l) = \{k : g(k) = l\}$$

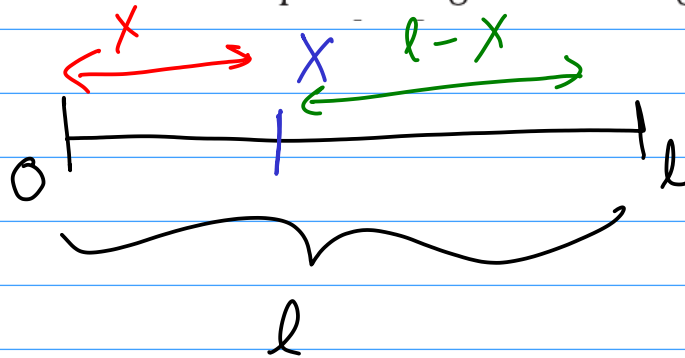
$$\begin{aligned} P(x \in g^{-1}(l)) &= \sum_{k \in g^{-1}(l)} P(x = k) \\ &= \sum_{k: g(k) = l} P(x = k) \end{aligned}$$

$$E(g(x)) = \sum_l \sum_{k: g(k) = l} g(k) P(x = k)$$

$$= \sum_k g(k) P(x = k)$$

目

Example 3.34. A stick of length l is broken at a uniformly chosen random location. What is the expected length of the longer piece?



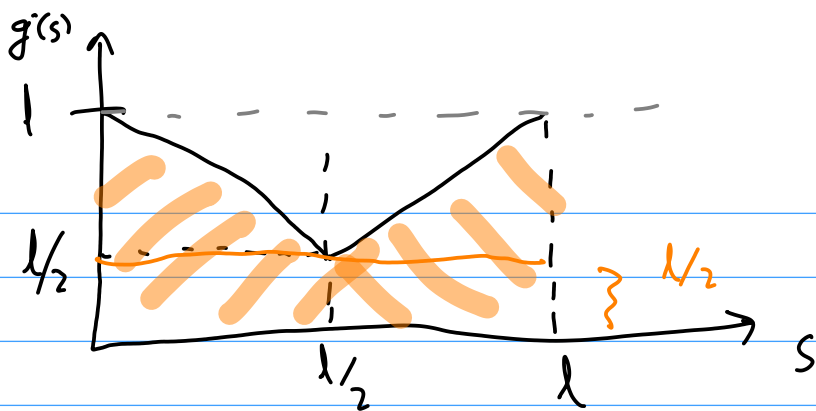
$$X \sim \text{Unif}[0, l]$$

$$Y = \text{LENGTH OF LONGER PIECE} = \max(X, l - X)$$

$E(Y) \rightarrow$ DIRECTLY IS HARD

$$Y = g(X)$$

$$g(s) = \max(s, l - s)$$



$$f(x) = \begin{cases} \frac{1}{l} & x \in [0, l] \\ 0 & \text{o.w.} \end{cases}$$

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

$$f = f_X$$

$$= \frac{1}{l} \int_0^l g(x) dx$$

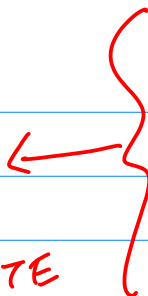
$$\left(= \int_0^{l/2} + \int_{l/2}^l \right)$$

$$= \frac{1}{l} \left[l/2 \cdot l + 2 \left[\frac{1}{2} \cdot \frac{l}{2} \cdot \frac{1}{2} \right] \right]$$

$$= \frac{1}{l} \left[\frac{l^2}{2} + \frac{l^2}{4} \right] = \frac{1}{l} \left[\frac{3l^2}{4} \right] = \frac{3l}{4}$$

□

c.d.f.



Example 3.20. Carter has an insurance policy on his car with a \$500 deductible. This means that if he gets into an accident he will personally pay for 100% of the repairs up to $\boxed{\$500}$ with the insurance company paying the rest. For example, if the repairs cost \$215, then Carter pays the whole amount. However, if the repairs cost \$832, then Carter pays \$500 and the remaining \$332 is covered by the insurance company.

NOT DISCRETE

NOT CONTINUOUS

Suppose that the cost of repairs for the next accident is uniformly distributed between \$100 and \$1500. Let X denote the amount Carter will have to pay. ~~Find the cumulative distribution function for X .~~

Example 3.38. (Revisiting Example 3.20) Recall from Example 3.20 the case of Carter and the \$500 deductible. Find the expected amount that Carter pays for his next accident.

$X =$ CARTER'S LIABILITY

$Y =$ ACTUAL COST OF ACCIDENT

$$X = \min(Y, 500)$$

$$= h(Y)$$

$$h(s) = \min(s, 500)$$

$$E(x) = E(h(Y))$$

$$= \int_{-\infty}^{\infty} h(x) f_Y(x) dx$$

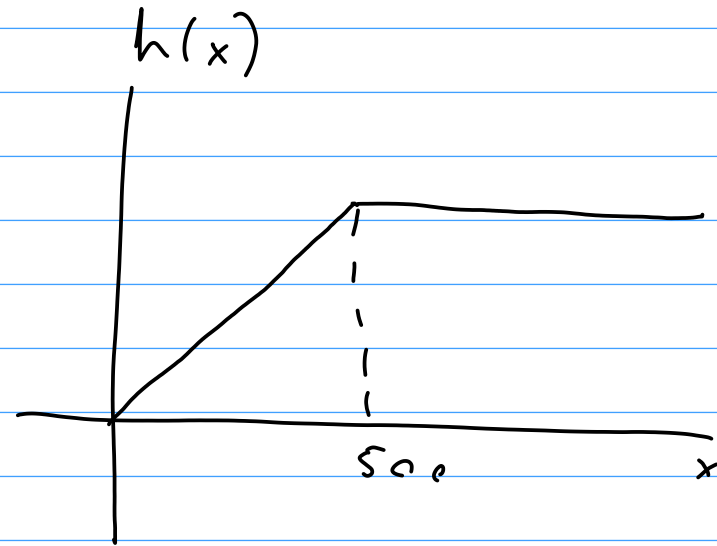
$$= \int_{100}^{1400} \frac{h(x)}{1400} dx$$

$$= \int_{100}^{500} \frac{x}{1400} dx + \int_{500}^{1400} \frac{500}{1400} dx$$

$$= 3100/7 \approx \$442.86$$

$f_Y \rightarrow$ p.d.f. of Y .

$$f_Y(x) = \begin{cases} \frac{1}{1400} & x \in [100, 1400] \\ 0 & \text{o.w.} \end{cases}$$



$$P(x=500) = 5/7 \rightarrow \text{BIG}$$

$$g(x) = x^n$$

$$X, X^n$$

$$E(X^n)$$



n th MOMENT

Fact 3.35. The n th moment of the random variable X is the expectation $E(X^n)$.

In the discrete case the n th moment is calculated by

$$E(X^n) = \sum_k k^n P(X = k). \quad (3.27)$$

If X has density function f its n th moment is given by

$$E(X^n) = \int_{-\infty}^{\infty} x^n f(x) dx. \quad (3.28)$$

The second moment, $E(X^2)$, is also called the *mean square*.

EXERCISE:

COMPUTE

① $E(X^n)$

② $E(Y^2)$

③ $E(Z^2)$

$X \sim \text{Unif}[a, b]$ } →

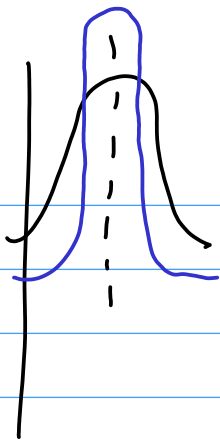
$Y \sim \text{Geom}(p)$

$Z \sim \text{Bin}(n, p)$ } → DO YOURSELF.

Example 3.36. Let $c > 0$ and let U be a uniform random variable on the interval $[0, c]$. Find the n th moment of U for all positive integers n .

$$U \sim \text{Unif}[a, b] \quad f(x) = \begin{cases} \frac{1}{c} & x \in [0, c] \\ 0 & \text{o.w.} \end{cases}$$

$$\begin{aligned} E(U^n) &= \int_{-\infty}^{\infty} x^n f(x) dx = \int_0^c x^n \cdot \frac{1}{c} dx \\ &= \frac{1}{c} \int_0^c x^n dx = \frac{1}{c} \cdot \frac{c^{n+1}}{n+1} = \frac{c^n}{n+1} \end{aligned}$$



§ 3.4 VARIANCE

Definition 3.44. Let X be a random variable with mean μ . The variance of X is defined by

$$\text{Var}(X) = E[(X - \mu)^2]. \quad (3.31)$$

An alternative symbol is $\sigma^2 = \text{Var}(X)$. ↖ $E(X)$

$$\sigma = \text{S.D.}(X) = \sqrt{\text{Var}(X)}$$

(STANDARD DEVIATION)

WHY NOT
 $E(|X - \mu|)$?

VARIANCE → MEAS. OF SPREAD

(WHEN $X \rightarrow$ DISC / CONT.)

Fact 3.45. Let X be a random variable with mean μ . Then

$$\text{Var}(X) = \sum_k (k - \mu)^2 P(X = k) \quad \text{if } X \text{ is discrete} \quad (3.32)$$

and

$$\text{Var}(X) = \int_{-\infty}^{\infty} (x - \mu)^2 f(x) dx \quad \text{if } X \text{ has density function } f. \quad (3.33)$$

Example 3.46. Consider two investment opportunities. One yields a profit of \$1 or a loss of \$1, each with probability $\frac{1}{2}$. The other one yields a profit of \$100 or a loss of \$100, also each with probability $\frac{1}{2}$. Let X denote the random outcome of the former and Y the latter. We have the probabilities

$$P(X = 1) = P(X = -1) = \frac{1}{2} \quad \text{and} \quad P(Y = 100) = P(Y = -100) = \frac{1}{2}.$$

$$E(X) = \sum_k k \cdot P(X=k) = 1 \cdot \left(\frac{1}{2}\right) + (-1) \cdot \frac{1}{2} = 0$$

$$E(Y) = \sum_k k \cdot P(Y=k) = (100) \cdot \frac{1}{2} + (-100) \cdot \frac{1}{2} = 0$$

$$\begin{aligned} \text{Var}(X) &= \sum_k (k - \mu)^2 P(X=k) = (1)^2 \cdot \left(\frac{1}{2}\right) + (-1)^2 \cdot \left(\frac{1}{2}\right) \\ &= 1 \end{aligned}$$

$$\text{Var}(Y) = \sum_k (k - \mu)^2 P(Y=k) = (100)^2 \cdot \frac{1}{2} + (-100)^2 \cdot \frac{1}{2} = 10000$$

Fact 3.48. (Alternative formula for the variance)

$$\text{Var}(X) = E(X^2) - (E[X])^2.$$

1st

MOMENT
SQUARED
(3.34)

2nd MOMENT

PI DISCRETE :

$$\text{Var}(X) = \sum_k (k - \mu)^2 P(X = k)$$

$$= \sum_k \left(\underline{k^2} - 2 \underline{k} \mu + \mu^2 \right) P(X = k)$$

$$= \sum_k k^2 P(X = k) - 2\mu \left(\sum_k k P(X = k) \right) + \mu^2 \sum_k P(X = k)$$

$$\text{Var}(X) = \sum_k k^2 P(X=k) - 2\mu \underbrace{\left(\sum_k k P(X=k) \right)}_{\mu} + \mu^2 \underbrace{\sum_k P(X=k)}_{1}$$

$$\sum_k P(X=k) = 1$$

$$\sum_k k \cdot P(X=k) = E(X) = \mu$$

$$\sum_k k^2 P(X=k) = E(X^2)$$

$$\text{Var}(X) = E(X^2) - 2\mu \cdot \mu + \mu^2$$

$$= E(X^2) - \mu^2$$

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



VARIANCE OF SOME RVs

$$f(x) = \begin{cases} \frac{1}{b-a} & x \in [a, b] \\ 0 & \text{o.w.} \end{cases}$$

(1) $X \sim \text{Unif}[a, b]$

$$E[X] = \frac{a+b}{2}$$

$$\text{Var}[X] = E[X^2] - (E[X])^2 = \frac{b^2 + ab + a^2}{3} - \left(\frac{a+b}{2}\right)^2$$

$$E[X^2] = \int_{-\infty}^{\infty} x^2 f(x) dx = \int_a^b \frac{x^2}{b-a} dx = \frac{x^3/3}{b-a} \Big|_a^b = \frac{b^2 + ab + a^2}{3}$$

$$\begin{aligned}\text{Var}[X] &= E[X^2] - (E[X])^2 = \frac{b^2 + ab + a^2}{3} - \left(\frac{a+b}{2}\right)^2 \\ &= \frac{b^2 + ab + a^2}{3} - \left[\frac{a^2 + 2ab + b^2}{4}\right] \\ &= \frac{a^2 + b^2 - 2ab}{12}\end{aligned}$$

$$\text{Var}[X] = \frac{(b-a)^2}{12}$$

② $\text{Ber}(p)$

$X \in \{0, 1\}$

$$P(X=1) = p$$

$$P(X=0) = 1-p$$

$$E(X) = p$$

$$E(X^2) = \sum_k k^2 P(X=k) = 0^2 \cdot (1-p) + 1^2 \cdot (p) \\ = p$$

$$\text{Var}(X) = E(X^2) - (E[X])^2 = p - p^2$$

$$\text{Var}(X) = p(1-p) = P(X=1)P(X=0)$$

$$X = I_A$$

$$\text{Var}[I_A] = P(A) \cdot P(A^c)$$

$$\uparrow$$
$$P(I_A = 1)$$

$$\uparrow$$
$$P(I_A = 0)$$

$$(3) \quad X \sim \text{Bin}(n, p)$$

$$E(X) = np$$

$$E(X^2) = n(n-1)p^2 + np$$

$$\text{Var}(X) = \underbrace{n(n-1)p^2 + np}_{E(X^2)} - \underbrace{n^2 p^2}_{E(X)^2}$$

$$= \cancel{n^2 p^2} - np^2 + np - \cancel{n^2 p^2}$$

$$\text{Var}(X) = np[1-p] = n \text{Var}[\text{Ber}(p)]$$

$$\textcircled{4} \quad X \sim \text{Geom}(p)$$

$$E(X) = \frac{1}{p}$$

$$q := 1 - p$$

$$E(X^2) = \frac{1+q}{p^2} = \frac{2-p}{p^2}$$

$$\text{Var}(X) = E(X^2) - E(X)^2 = \frac{2-p}{p^2} - \frac{1}{p^2}$$

$$= \frac{1-p}{p^2} = \frac{q}{p^2}$$

VARIANCE MEASURES SPREAD

Fact 3.54. For a random variable X , $\text{Var}(X) = 0$ if and only if $P(X = a) = 1$ for some real value a .

DF = DEGREE OF FREEDOM
DF = GENERATE

$$P(X = a) = 1$$

$$E(X) = a \cdot P(X = a) = a$$

$$E(X^2) = a^2 \cdot P(X = a) = a^2$$

DISCRETE

$$\text{Var}(X) = a^2 - (a)^2 = 0$$

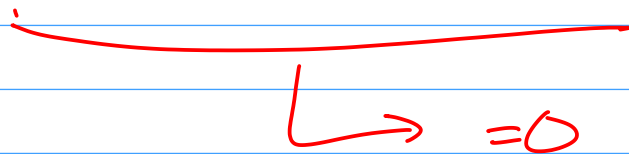
$$\text{Var}(X) = 0$$



$$\sum_k \underbrace{(k - \mu)^2}_{\geq 0} \underbrace{P(X = k)}_{\geq 0} = 0$$

≥ 0

≥ 0



$$(k - \mu)^2 P(X = k)$$

FOR EVERY k

$k = \mu$

$P(X = k) = 0$

$\Rightarrow P(X = k) = 0$

UNLESS $k = \mu$

$P(X = \mu) = 1$

AFFINE

WILL
BE GENERALIZED
BY LINEARITY
OF EXP.

Fact 3.52. Let X be a random variable and a and b real numbers. Then

$$E(aX + b) = aE(X) + b \quad (3.36)$$

and

$$\text{Var}(aX + b) = a^2 \text{Var}(X) \quad (3.37)$$

provided the mean and variance are well defined.

Pf
(for DISC.)

$x \mapsto ax + b$ (AFFINE)

$$\begin{aligned} E[aX + b] &= \sum_k (ak + b) \cdot P(X = k) = a \left(\sum_k k P(X = k) \right) + b \sum_k P(X = k) \\ &= a E(X) + b \end{aligned}$$

Handwritten annotations: A green arrow points from the term $\sum_k k P(X = k)$ to $E(X)$. A blue arrow points from the term $\sum_k P(X = k)$ to 1 .

$$\text{Var}(aX+b) = \mathbb{E}[(aX+b)^2] - \left(\mathbb{E}[aX+b]\right)^2$$

$a\mathbb{E}(X) + b$

$$\mathbb{E}[(aX+b)^2] = \sum_k (ak+b)^2 P(X=k)$$

$$= \sum_k [a^2 k^2 + 2abk + b^2] P(X=k)$$

$$= a^2 \sum_k k^2 P(X=k) + 2ab \sum_k k P(X=k) + b^2 \sum_k P(X=k)$$

$\mathbb{E}(X^2)$ $\mathbb{E}(X)$ 1

$$E((aX+b)^2) = a^2 E(X^2) + 2ab \underline{E(X)} + \underline{b^2}$$

$$\begin{aligned} [E(aX+b)]^2 &= (a E(X) + b)^2 \\ &= a^2 E(X)^2 + 2ab \underline{E(X)} + \underline{b^2} \end{aligned}$$

$$\begin{aligned} \text{Var}(aX+b) &= \boxed{} - \boxed{} \\ &= a^2 E(X^2) - a^2 E(X)^2 \\ &= a^2 [E(X^2) - E(X)^2] = a^2 \text{Var}(X) \end{aligned}$$

SEE YOU ON

THURSDAY