

# CSCI 3022-002 Intro to Data Science

What is the **expected value** of the Bernoulli distribution with parameter  $p$ ?

## Announcements and Reminders

- ▶ Practicum posted <sup>probably Thursday</sup> soon! No HW next Monday!

## Last Time...: Expectation

**Definition:** *Expected Value:*

For a continuous random variable  $X$  with pdf  $f(x)$ , the *expected* value or *mean* value of  $X$  is denoted as  $E(X)$  and is calculated as:

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

For a discrete random variable with pmf  $f$ , this is

$$E[X] = \sum_{x \in \Omega} x \cdot P(X = x)$$

We interpret  $E[X]$  as the sample average value of a hypothetical “infinite” sample of the population. Our goal in data science is often to use sample statistics from our limited in size samples to make inferences about underlying population characteristics.

## Expected Value of a Function

Last time example R.V.  $X$ : <sup>(classes)</sup>

If a discrete r.v.  $X$  has a density  $P(X = x)$ , then the expected value of any function  $g(X)$  is computed as:

$$E[X] = 4.37$$

1. Continuous:

$$\int_{-\infty}^{\infty} g(x) f(x) dx$$

all outcomes

2. Discrete:

$$\sum_{x \in \Omega} g(x) \underbrace{f(x)}_{P(X=x)}$$

Note that  $E[g(X)]$  is computed in the same way that  $E(X)$  itself is, except that  $g(x)$  is substituted in place of  $x$ .

## Expected Value of a Function

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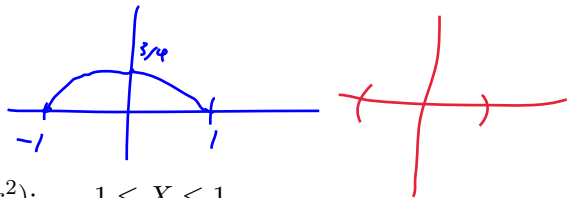
### 2. Discrete:

$$E[X] = \sum_x g(x) f(x)$$

Note that  $E[g(X)]$  is computed in the same way that  $E(X)$  itself is, except that  $g(x)$  is substituted in place of  $x$ .

# Expected Value of a Function

**Example:** A random variable  $X$  has pdf:



$$f(x) = \frac{3}{4}(1 - x^2); \quad -1 \leq X \leq 1$$

What is  $E(X^3)$ ?

$$E(X^3) = \int_{-1}^1 \underbrace{x^3}_{g(x)=x^3} \cdot \underbrace{\frac{3}{4}(1-x^2)}_{f(x)} dx = \int_{-1}^1 \frac{3}{4}x^3 - \frac{3}{4}x^5 dx$$

Symmetric odd integrand  $\Rightarrow 0$

Review: What is  $F(x)$ ?

$$\underbrace{F(x)}_{\text{left}} = \int_{-1}^x f(t) dt = \frac{3t}{4} - \frac{3t^3}{12} \Big|_{-1}^x = \frac{3x^4}{4 \cdot 4} - \frac{3x^6}{4 \cdot 6} \Big|_{-1}^1 = \left( \frac{3}{16} - \frac{3}{24} \right) - \left( \frac{3}{16} - \frac{3}{24} \right) = 0$$

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Review: What is  $F(x)$ ?

$$F(x) = \int_{-1}^x f(t) dt = \frac{3t}{4} - \frac{3t^3}{12} \Big|_{-1}^x$$

# Expected Value of a Linear Function

multiply by constants  
 $\downarrow$   $\downarrow$  add constants

If  $g(X)$  is a linear function of  $X$  (i.e.,  $g(X) = aX + b$ ) then  $E[g(X)]$  can be easily computed from  $E(X)$ .

## Theorem:

Let  $a, b \in \mathbb{R}$  and  $X$  be a random variable with density  $f$ . Then:

$$E[aX + b] = aE[X] + b$$

$$E[aX + b] = \int_{\text{all values}} (aX + b) f(x) dx = \int aX f(x) dx + \int b f(x) dx$$

$$= a \underbrace{\int X f(x) dx}_{\text{defn } E[X]} + b \underbrace{\int f(x) dx}_{\text{integrates to 1!}}$$

Proof:

Note: This works for continuous and discrete random variables.

$f$  is a pdf,  
 so overall outcomes



## Expected Value of a Linear Function

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### Theorem:

Let  $a, b \in \mathbb{R}$  and  $X$  be a random variable with density  $f$ . Then:

$$E[g(X)] = g(E[X])$$

$$E[aX + b] = aE[X] + b$$

Proof:

$E[aX + b] = \int (ax + b)f(x) dx = \underbrace{a}_{\text{and also } f \text{ is a pdf}} \int xf(x) dx + \underbrace{b}_{\text{pdf}} \int f(x) dx = aE[X] + b$ , since integration is also linear!

Note: This works for continuous and discrete random variables.

## Linear Expectation

### Example:

Consider a university having 15,000 students and let  $X$  equal the number of courses for which a randomly selected student is registered.

The pdf of  $X$  is given to you as follows:

$x$	1	2	3	4	5	6	7
$f(x) = P(X = x)$	.01,	.03	.13	.25	.39	.17	.02

Classes / student  
 $\swarrow$   
 $\leftarrow X$  takes that many

Earlier, we calculated that  $E(X)$  was 4.57. If students pay \$500 per course plus a \$100 per-semester registration fee, what is the average amount of money the university can expect a student to pay each a semester?

$E[\text{money}]$  where money:  $500 \cdot \text{classes} + 100$   
 $x$ : classes! money:  $g(x) = 500x + 100$

$$E[g(x)] = 500 \cdot E[X] + 100 = 500 \cdot 4.57 + 100$$

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Earlier, we calculated that  $E(X)$  was 4.57. If students pay \$500 per course plus a \$100 per-semester registration fee, what is the average amount of money the university can expect a student to pay each a semester?

$Money = 500 \cdot Courses + 100 = 500X + 100 = g(X)$ . Then,

$$E[g(X)] = g(E[X]) = 500 \cdot 4.57 + 100 = 2385.$$

## Opening sol:

The pmf of the Bernoulli is given by

$$f(x) = \begin{cases} p & x = 1 \\ 1 - p & x = 0 \end{cases}$$

*P(outcome)*      *outcome*  
↓

$$\begin{aligned} E[X] &= \sum x f(x) \\ &= \underbrace{0 \cdot P(X=0)}_0 + \underbrace{1 \cdot P(X=1)}_1 \\ &= 0(1-p) + 1 \cdot p \\ &= p. \end{aligned}$$

## Opening sol:

The pmf of the Bernoulli is given by

$$f(x) = \begin{cases} p & x = 1 \\ 1 - p & x = 0 \end{cases}$$

We now must sum over both outcomes while multiplying by the probability of those outcomes:

$$\begin{aligned} \sum_{x \in \{0,1\}} x f(x) &= \sum_{x \in \{0,1\}} x P(X = x) \\ &= 0 \cdot P(X = 0) + 1 \cdot P(X = 1) = 0 \cdot (1 - p) + 1 \cdot p = \boxed{p} \end{aligned}$$

... which makes perfect sense, since  $p$  is how often we “expect” a heads.

# Announcements and Reminders

- ▶ Practicum 1 tentatively posted tonight?
- ▶ Midterm 1 upcoming: takehome!

## EV Recap

1. **Expected Value:** The average value for  $X$  coming from a distribution (not a sample!).

Denoted  $E[X]$  or  $\mu$  or  $\mu_X$ .

Discrete:  $\sum_{x \in \Omega} x f(x)$ ; Continuous:  $\int_{x \in \Omega} x \cdot f(x) dx$

$\mu :=$  population average

how does  $\bar{X}$   
describe  $\mu_X$ ?

2. Expected value of a function  $g(X)$  of  $X$  is:

$$\sum_{x \in \Omega} g(x) f(x); \int_{x \in \Omega} g(x) \cdot f(x) dx$$

3.  $Y = g(X)$  is a *change of variables*.

4. Expectation is **linear**:  $E[aX + b] = aE[X] + b$  Proof: (2 slides ago.)

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3.  $Y = g(X)$  is a *change of variables*.

4. Expectation is **linear**:  $E[aX + b] = aE[X] + b$  Proof:

$E[aX + b] = \int (ax + b) f(x) dx = a \int x f(x) dx + b \int f(x) dx = aE[X] + b$ , since integration is also linear!



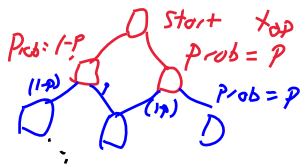
## Let's play Plinko!!

Let  $X$  be the random variable describing the result in each round of Plinko with  $n$  rows and probability  $p$  of moving to the right off of each peg. (Ignoring the edges for now.)

<https://www.youtube.com/watch?v=naUppHrHJpI>



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Neg binom

$$\begin{aligned}
 &P(\text{end in 2nd from left}) \\
 &= P(\text{moved R 1 time} \\
 &\quad \& \text{ moved L } n-1 \text{ times})
 \end{aligned}$$

$\begin{pmatrix} 0 \\ 0 \end{pmatrix} : \dots - - - - - \sum_n ?$

$P(\text{end in bin zero})$

$= P(\text{every single peg/juncture we go left})$

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Each row results in a move right with probability  $p$ , and a move left with probability  $1 - p$ . We have  $n$  rows... or *trials*

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Each row is a *Bernoulli*, and our ending bucket is the total number of right-hand moves over the entire experiment, or the sum of  $n$  Bernoullis!

independence ...  $\sum u_i, \text{ ok}$   $\cup$

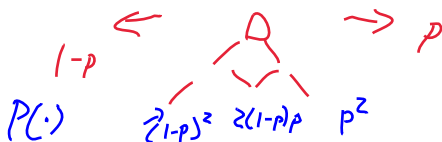
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For  $Y_i \stackrel{iid}{\sim} \text{Bern}(p)$ , we have  $X = \sum Y_i$ . So  $X$  is a **binomial** with parameters  $n$  and  $p$ .

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$$E[X] = \sum x f(x)$$

outcomes:  $\{0, 1, \dots, n\}$

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

intuition:  $np$

$$\sum x \binom{n}{x} p^x (1-p)^{n-x}$$

$$E_X[n=2]$$

$$0 \cdot P(X=0) + 1 \cdot P(X=1) + 2 \cdot P(X=2)$$

$$2(1-p)p + 2p^2$$

$$2p - 2p^2 + 2p^2 = 2p \checkmark$$

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We can use our knowledge about Bernoullis!  $X$  is a sum of Bernoulli r.v.s that each have mean or expected value of  $p$ .  $E[Y] = p$  if  $Y \sim \text{bern}(p)$ .

Let  $Y_1, Y_2, Y_3, \dots, Y_n$  be independent & identical Bernoulli R.V.s w/ probability (parameter)  $p$ .

GOAL:  $E[Y_1 + Y_2 + Y_3 + \dots + Y_n]$  but  $E[\cdot]$  is linear  
 $= E[Y_1] + E[Y_2] + E[Y_3] + \dots + E[Y_n]$ .

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$E[X] = E[Y_1 + Y_2 + Y_3 + \dots Y_n]$ , then use linearity:



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$E[X] = E[Y_1] + E[Y_2] + E[Y_3] + \dots + E[Y_n]$ . This works even though each  $Y_i$  is also a random variable!

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$E[X] = \underbrace{p + p + p + \dots + p}_{n \text{ times}} = np$ , since each  $Y$  is identical.

... which again makes perfect sense, since it's  $n$  tries that have a per-try expected value of  $p$ .

$$\sum_{k=0}^n x \binom{n}{k} p^k (1-p)^{n-k} = np.$$

## Plinko... is random?

Let  $X$  be the random variable describing the result in each round of Plinko with  $n$  rows and probability  $p$  of moving to the right off of each peg. (Ignoring the edges for now.) What is the *Variance* of  $X$ ?

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**Recall:** Sample Variance is  $\frac{\sum_{i=1}^n (X_i - \bar{X})^2}{n-1}$

Squared deviations  
add  $\frac{1}{n}$ , average.  
now: Expected

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Another way: sample variance is  $\underbrace{\frac{1}{n-1} \sum_{i=1}^n}_{\text{averaged out}} \underbrace{(X_i - \bar{X})^2}_{\text{squared deviations}}$

Population variance is this idea expressed as an expectation:

## Plinko... is random?

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Another way: sample variance is  $\underbrace{\frac{1}{n-1} \sum_{i=1}^n}_{\text{averaged out}} \underbrace{(X_i - \bar{X})^2}_{\text{squared deviations}}$

$\bar{X}$ : sample mean



$X_i - \bar{X}$



$X - E[X]$

Population variance is this idea expressed as an expectation:

$$Var[X] = E[\underbrace{(X - E[X])^2}_{\text{squared deviations}}] = E[(X - \mu_X)^2]$$

# Variance of a Random Variable

recall: Sample var:  $S^2$   
 " Std:  $S$

Greek  
 ↓ sigma!  
 $\sigma^2$

**Definition:** Variance:

For a discrete random variable  $X$  with pdf  $f(x)$ , the variance of  $X$  is denoted as  $\sigma^2$  and is calculated as:

$$\text{both: } \sigma^2 := E[\underbrace{(X - E[X])^2}_{g(x)}]$$

1. Continuous:

$$\int \underbrace{(X - \underbrace{E[X]}_{\mu_X})^2}_{\text{outcomes}} f(x) dx$$

2. Discrete:

$$\sum (X - \underbrace{E[X]}_{\mu_X})^2 f(x)$$

Note:

is  $E[X]$   
 random?

NO

The standard deviation (SD) of  $X$  is:

$$\sqrt{\sigma^2} = \sigma$$

## Variance of a Random Variable

**Definition:** *Variance:*

For a discrete random variable  $X$  with pdf  $f(x)$ , the *variance* of  $X$  is denoted as  $\underline{Var[X] = \sigma^2}$  and is calculated as:

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

1. Continuous:

$$Var[X] = \int_{x \in \Omega} (x - \mu_x)^2 \cdot f(x) dx$$

2. Discrete:

$$Var[X] = \sum_{x \in \Omega} (x - \mu_x)^2 f(x)$$

The standard deviation (SD) of  $X$  is:  $\sigma = \sqrt{\sigma^2}$



## Variance Calculated

We want more Plinko! Let's find the variance of a Bernoulli so we can build on it.

**Recall:** The pmf of the Bernoulli is given by

$$f(x) = \begin{cases} p & x = 1 \\ 1 - p & x = 0 \end{cases}$$

and we know that  $E[X] = p$ .

## Variance Calculated

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**Recall:** The pmf of the Bernoulli is given by

$$f(x) = \begin{cases} p & x = 1 \\ 1 - p & x = 0 \end{cases}$$

and we know that  $E[X] = p$ . We now must sum over both outcomes' deviations from the mean while multiplying by those probabilities

$$\begin{aligned} E[(X - E[X])^2] &= \sum_{x \in \{0,1\}} (x - p)^2 f(x) = \sum_{x \in \{0,1\}} (x - p)^2 P(X = x) \\ &= (0 - p)^2 \cdot P(X = 0) + (1 - p)^2 \cdot P(X = 1) = (0 - p)^2 \cdot (1 - p) + (1 - p)^2 \cdot p \\ &= (p)(1 - p)(p + 1 - p) = \boxed{p(1 - p)} \end{aligned}$$

## Let's play Plinko!!

Let  $X$  be the random variable describing the result in each round of Plinko with  $n$  rows and probability  $p$  of moving to the right off of each peg. (Ignoring the edges for now.) What is the *variance* of  $X$  follow?

Need to know: if two random variables are **independent**,

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

## Let's play Plinko!!

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Need to know: if two random variables are **independent**,

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

So for Plinko, where  $X = Y_1 + Y_2 + \cdots + Y_i$  but the  $Y_i$ 's are all independent,

$$Var[X] = Var\left[\underbrace{\sum Y_i}_{\text{indep}}\right] = \sum Var[Y] \underbrace{=}_{\text{ident}} n Var[Y_i] = \boxed{np(1-p)}$$

*Sanity Check!* Should variance be smaller if  $p \approx 1$  or  $p \approx 0$ ?

## Let's talk Variance

For a random variable  $X$  and constants  $a$  and  $b$ , if we define  $Y = aX + b$ ...  
 $E[Y] = aE[X] + b$  because Expectation  $E[\cdot]$  is **linear**. Is  $Var[\cdot]$ ?

1. What is  $Var[X + b]$ ?
2. What is  $Var[aX]$ ?

## Let's talk Variance

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1. What is  $Var[X + b]$ ?

Intuition: moving  $X$  doesn't change its spread!

2. What is  $Var[aX]$ ?

Intuition: multiplying  $X$  should change its spread!

## Non-linear Variance

For a random variable  $X$  and constants  $a$  and  $b$ , if we define  $Y = aX + b...$

What is  $Var[aX + b]$ ?

## Non-linear Variance

For a random variable  $X$  and constants  $a$  and  $b$ , if we define  $Y = aX + b...$

What is  $Var[aX + b]$ ?

$$\begin{aligned} Var[aX + b] &= \sum_{x \in \Omega} (aX + b - E[aX + b])^2 f(x) \\ &= \sum_{x \in \Omega} (aX + b - aE[X] - b)^2 f(x) \\ &= \sum_{x \in \Omega} (aX - aE[X])^2 f(x) \\ &= \sum_{x \in \Omega} a^2 (X - E[X])^2 f(x) \\ &= a^2 \sum_{x \in \Omega} (X - E[X])^2 f(x) \\ &= \boxed{a^2 Var[X]} \end{aligned}$$



# Daily Recap

Today we learned

1. Variance

Moving forward:

- nb day Friday!

Next time in lecture:

- Wrap-up and some more examples on populations.