

## Lecture 4.1: Discrete Expectation + Variance

2013/09/23

## Previously... Discrete Random Variables

### Definition

*If the set of all possible values of a random variable  $X$  is a countable set,  $x_1, x_2, \dots$ , then  $X$  is called a **discrete random variable**. The function*

$$f(x) = \mathbb{P}(X = x) \text{ for } x = x_1, x_2, \dots$$

*that assigns the probability to each possible value  $x$  will be called the **probability mass function** (PMF). Note: called a discrete probability density function in text, while some other texts use  $p(x)$*

## Previously... Properties

### Theorem

*A function  $f(x)$  is a discrete pdf IFF it satisfies both of the following properties for at most a countably infinite set of real  $x_1, x_2, \dots$*

- 1.  $f(x_i) \geq 0$  for all  $x_i$ : non-negative prob*
- 2.  $\sum_{x_i} f(x_i) = 1$ : sums to one*

## Previously... Bernoulli Random Variable

Suppose we have a trial/experiment whose outcome can be classified as “success” or “failure.” Let  $X = 1$  if the outcome is a success and  $X = 0$  if the outcome is a failure, then

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

where  $0 \leq p \leq 1$  is the probability of a success.

## Previously... Binomial Random Variable

Say we have  $n$  independent trials of a Bernoulli random variable each with probability of success  $p$ . Then the probability that we have  $x$  successes (I used  $k$  last class) is

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

We say that  $X$  is a  $\text{Binomial}(n, p)$  distribution.

**Example:**  $n = 10$  die rolls and define getting a 1 as a success i.e.  $p = \frac{1}{6}$ . Let  $X$  be the (random) number of 1's. Then  $X \sim \text{Binomial}(10, \frac{1}{6})$

## Previously... Geometric Random Variable

Once again say we have success/failure Bernoulli trials with probability  $p$  of success. What is the probability that it takes  $x$  independent trials until we get a success?

$$f(x) = \mathbb{P}(X = x) = (1 - p)^{x-1}p$$

We say  $X \sim \text{Geometric}(p)$  distribution.

# Goals for Today

- ▶ Think intuitively build up the notion of expected value and variance
- ▶ Define them mathematically
- ▶ Derive the expected value of a Binomial( $n, p$ ) RV
- ▶ Go over some properties of expectation and variance

# Intuitively Thinking: Expected Value

Easy example: Coin flips. Say we flip a fair coin  $n = 10$  times with probability  $p = \frac{1}{2}$  of heads.

How many heads do you **expect** to get?

$$n \times p = 10 \times \frac{1}{2} = 5$$



## Intuitively Thinking: Expected Value

Slightly more complicated example: Say you have a discrete random variable  $X$  with PMF:

$x$	2	3	4	10	11
$f(x) = \mathbb{P}(X = x)$	$\frac{15}{100}$	$\frac{25}{100}$	$\frac{10}{100}$	$\frac{30}{100}$	$\frac{20}{100}$

E.g. We observe  $X = 3$  with prob .25

Is the value we expect to observe:

$$\frac{2 + 3 + 4 + 10 + 11}{5} = 6 ?$$

## Intuitively Thinking: Expected Value

No, each of the  $x$ 's have different **probability** of occurring.

For each  $x$ , we assign weight  $f(x) = \mathbb{P}(X = x)$ .

i.e. for all  $x$ , we have  $x \cdot f(x)$ :

$$2 \times \frac{15}{100} + 3 \times \frac{25}{100} + 4 \times \frac{10}{100} + 10 \times \frac{30}{100} + 11 \times \frac{20}{100}$$

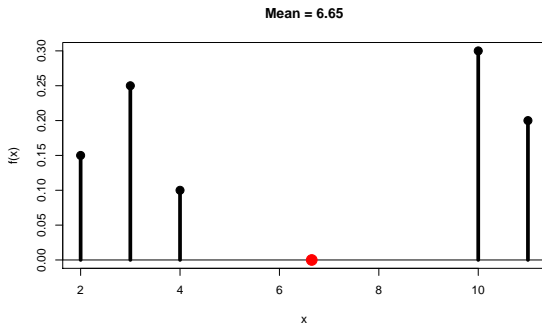
and not 
$$2 \times \frac{1}{5} + 3 \times \frac{1}{5} + 4 \times \frac{1}{5} + 10 \times \frac{1}{5} + 11 \times \frac{1}{5}$$

# Expected Value

The **expected value** is a **weighted average** of all possible values  $x$ .  
This can be thought of as a measure of **center**.

# Expected Value

You can also think of the mean as the **center of mass or balance point** (marked with red point):



## Expected Value of a Binomial( $n, p$ )

If  $X \sim \text{Binomial}(n, p)$  i.e.  $X$  is distributed Binomial with  $n$  trials and probability of success  $p$ , then

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

We also know that for PMF's:

$$\sum_x f(x) = 1$$

so in our case

$$\sum_{x=0}^n f(x) = 1$$

## Expected Value of a Binomial( $n, p$ )

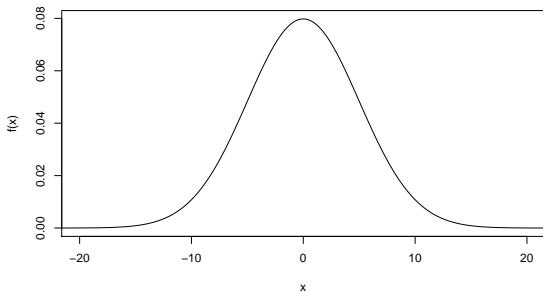
## Expected Value of a Binomial( $n, p$ )

# Linearity of Expectations



## Intuitively Thinking: Measures of Spread

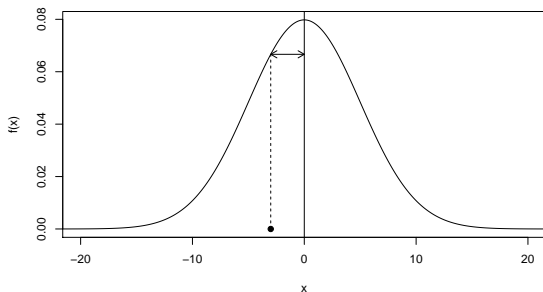
Consider the following (continuous) distribution with  $\mu = 0$ . Let's build a measure of **expected “spread”**.



Let's define “spread” as the **absolute deviation from  $\mu$** :  $|x - \mu|$ .  
i.e. +’ve & -’ve deviations of the same magnitude are treated the same.

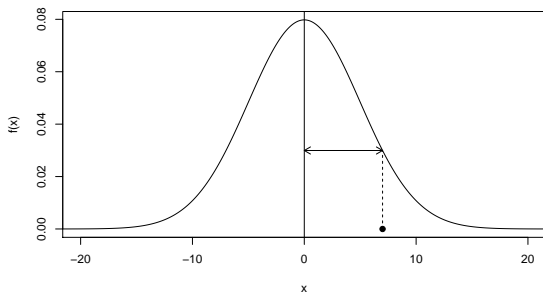
## Intuitively Thinking: Measures of Spread

When  $x = -3.0$ , the abs. deviation from  $\mu$  is  $|-3.0 - \mu| = 3.0$ .  
Note  $f(x) = P(X = x) = 0.066$ .



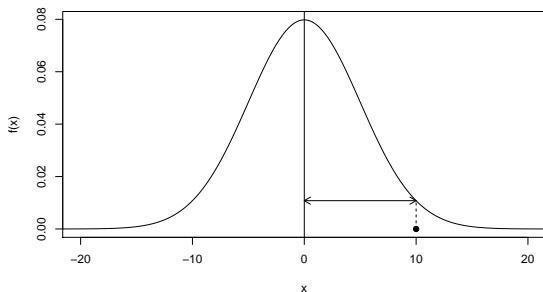
# Intuitively Thinking: Measures of Spread

When  $x = 7.0$ , the abs. deviation from  $\mu$  is  $|7.0 - \mu| = 7.0$ .  
Note  $f(x) = P(X = x) = 0.030$ .



# Intuitively Thinking: Measures of Spread

When  $x = 10.0$ , the abs. deviation from  $\mu$  is  $|10.0 - \mu| = 10.0$ .  
Note  $f(x) = P(X = x) = 0.011$ .



## Intuitively Thinking: Measures of Spread

$x$	Abs Deviation $ x - \mu $	Weight $f(x) = P(X = x)$
-3.0	$ -3.0 - 0  = 3.0$	0.066
7.0	$ 7.0 - 0  = 7.0$	0.030
10.0	$ 10.0 - 0  = 10.0$	0.011

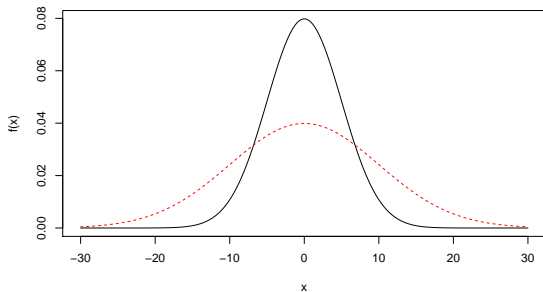
So say we do this for **all**  $x$  and take a **weighted average** of the  $|x - \mu|$  where the weights are  $f(x)$ .

Voilà: Our notion of **expected spread**.

# Variance

# Variance

Both the following curves have the same mean, but the dashed red curve has bigger variance than the the black one.



# Standard Deviation



## Alternate Expression of Variance

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## Next Time

- ▶ More on discrete random variables