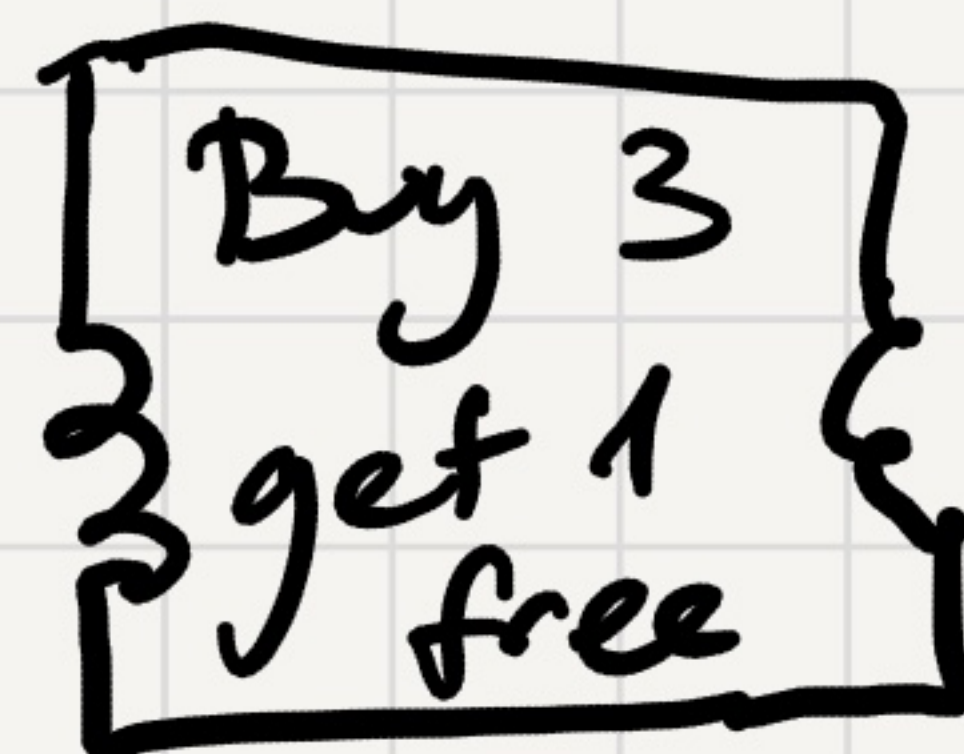
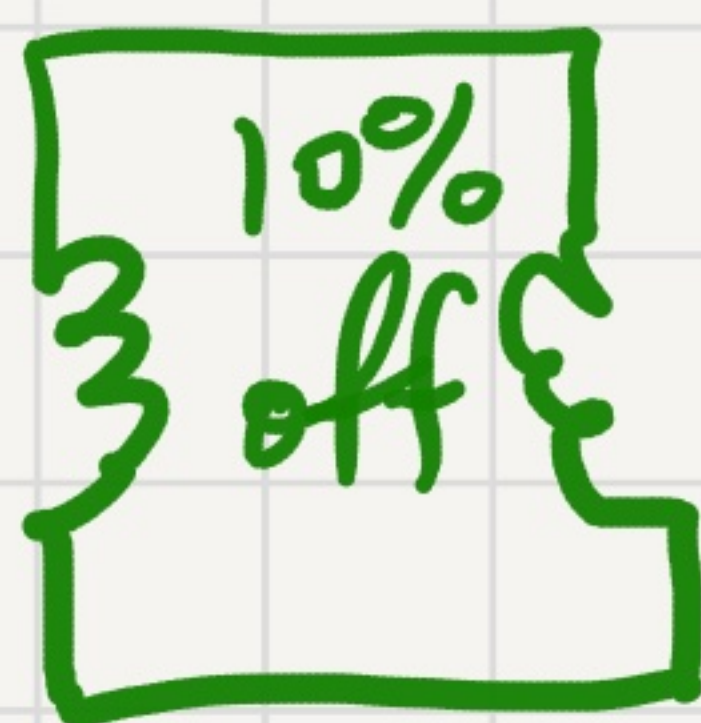


## Coupon Collector

Suppose there's a coupon inside every cereal box.



Suppose there are  $n$  types of coupons  
and each box has a random type.

How many boxes do you need to purchase  
until you get all coupons?

## Coupon Collector

Experiment: Get random coupons from  $\{1, \dots, n\}$  until you have all types of coupons.

$X$  - # of boxes until you get all  $n$  types.

Example:  $n=3$

2 2 2 1 1 2 1 3

Idea: Write  $X$  as the sum  $X_1 + X_2 + X_3$

# Coupon Collector

Experiment: Get random coupons from  $\{1, \dots, n\}$  until you have all types of coupons.

$X$  - # of boxes until you get all  $n$  types.

Example:  $n=3$

2	2	2	1	1	2	1	3
$X_1$	$X_2$			$X_3$			

Idea: Write  $X$  as the sum  $X_1 + X_2 + X_3$

$X_1$  - # boxes until we get first type

$X_2$  - # boxes until we get second type after we got first type.

$X_3$  - # boxes until we get third type after we got second type

# Coupon Collector

Experiment: Get random coupons from  $\{1, \dots, n\}$  until you have all types of coupons.

$X$  - # of boxes until you get all  $n$  types.

Example:  $n=3$

$E[X] = ?$

2 | 2 2 1 | 1 2 1 3 |  
 $X_1$       $X_2$               $X_3$

Idea: Write  $X$  as the sum  $X_1 + X_2 + X_3$

1 =  $X_1$  - # boxes until we get first type

$\text{Geo}(\frac{2}{3}) \leftarrow X_2$  - # boxes until we get second type after we got first type.

$\text{Geo}(\frac{1}{3}) \leftarrow X_3$  - # boxes until we get third type after we got second type

# Coupon Collector

Experiment: Get random coupons from  $\{1, \dots, n\}$  until you have all types of coupons.

$X$  - # of boxes until you get all  $n$  types.

Example:  $n=3$

2 | 2 2 1 | 1 2 1 3 |  
 $X_1$       $X_2$               $X_3$

$$\begin{aligned} E[X] &= E[X_1] + E[X_2] + E[X_3] \\ &= 1 + \frac{3}{2} + 3 = 5.5 \end{aligned}$$

Idea: Write  $X$  as the sum  $X_1 + X_2 + X_3$

1 =  $X_1$  - # boxes until we get first type

$\text{Geo}(\frac{2}{3}) \leftarrow X_2$  - # boxes until we get second type after we got first type.

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## General Case:

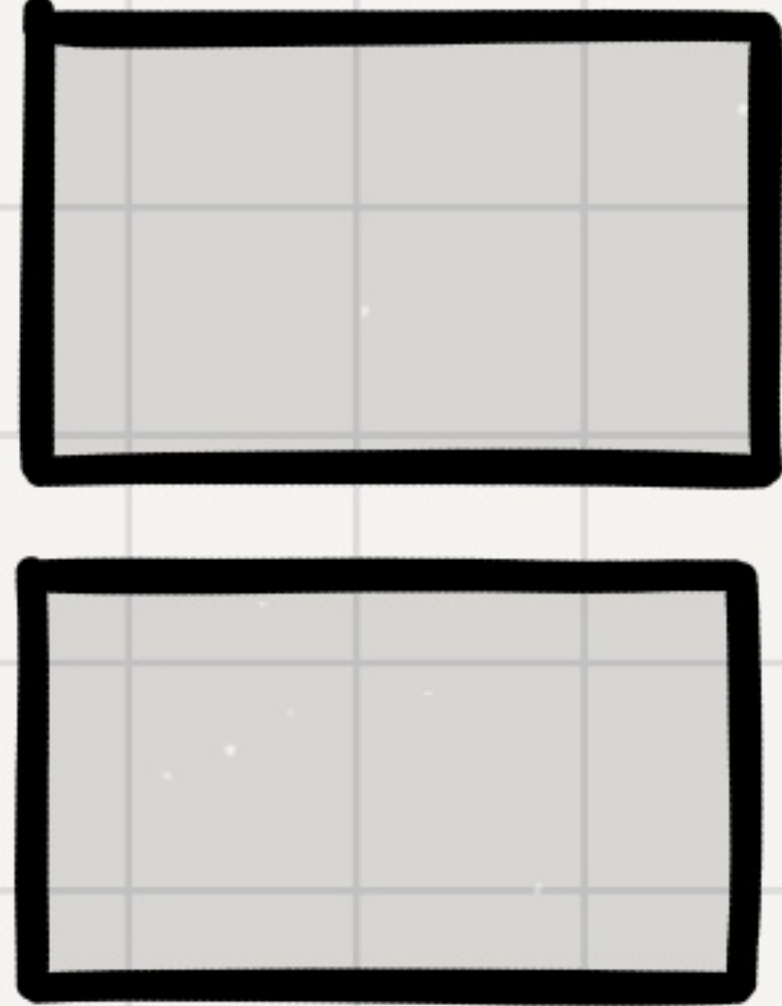
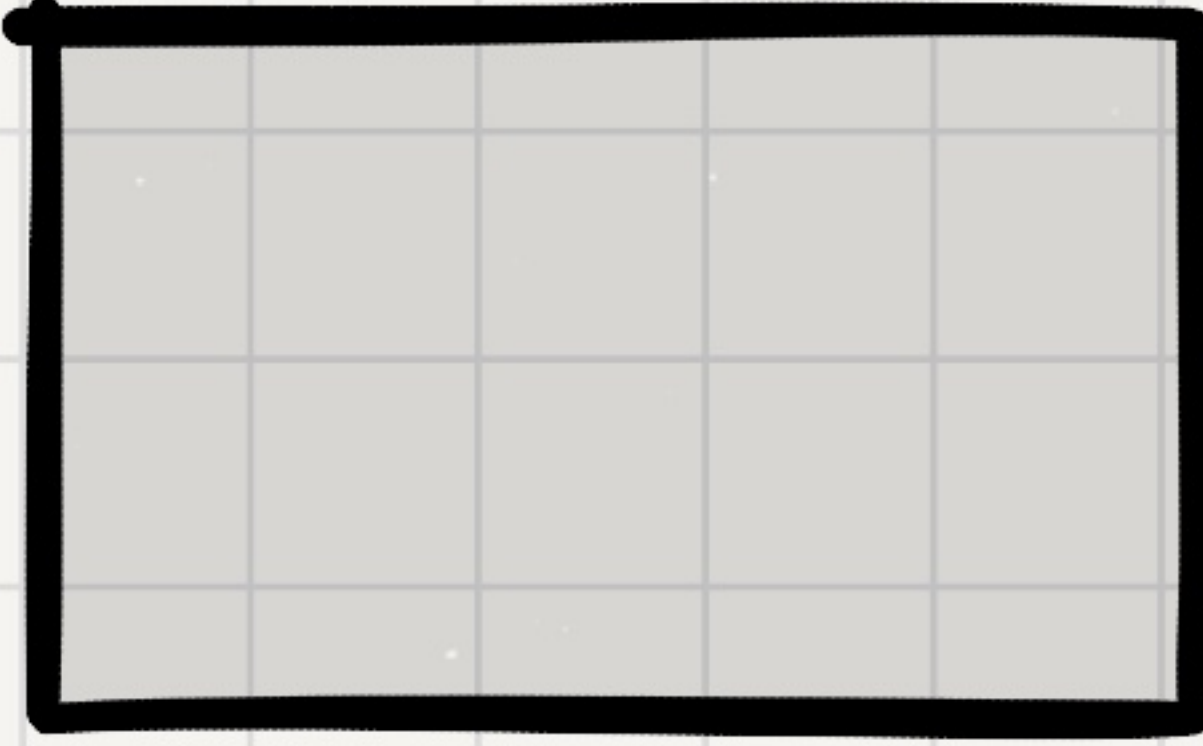


Write  $X = X_1 + X_2 + \dots + X_n$

$X_i$  - #boxes until we get  $i$  unique types after we got  $(i-1)$  unique types.

## General Case:

Write  $X = X_1 + X_2 + \dots + X_n$

$X_i$  - #boxes until we get  $i$  unique types after we got  $(i-1)$  unique types.

- $X_1 = 1$
- $X_2 = \begin{cases} 1, & \text{w.p.} \\ 2, & \text{w.p.} \\ \vdots \end{cases}$    $X_2 \sim$  
- $X_3 \sim$  
- $\vdots$
- $X_i \sim$  

## General Case:

Write  $X = X_1 + X_2 + \dots + X_n$

$X_i$  - #boxes until we get  $i$  unique types after we got  $(i-1)$  unique types.

- $X_1 = 1$
- $X_2 = \begin{cases} 1 & \text{w.p. } \frac{n-1}{n} \\ 2 & \text{w.p. } \frac{1}{n} \cdot \frac{n-1}{n} \\ \vdots & \end{cases} \quad X_2 \sim \text{Geo}\left(\frac{n-1}{n}\right)$
- $X_3 \sim \text{Geo}\left(\frac{n-2}{n}\right)$
- $X_i \sim \text{Geo}\left(\frac{n-(i-1)}{n}\right)$

$$E[X] = E[X_1] + \dots + E[X_n] =$$



## Balls in Bins

Suppose you throw balls in  $n$  bins

How many balls do you need to throw until  
all bins are non-empty?

## Functions of Random Variables

Suppose  $X$  is a r.v. and  $g: \mathbb{R} \rightarrow \mathbb{R}$

Then  $Y = g(X)$  is also a r.v.

$$Y(\omega) = g(X(\omega)). \quad \underline{Q}: \text{Calculate } [E[Y]]$$

---

# Functions of Random Variables

Suppose  $X$  is a r.v. and  $g: \mathbb{R} \rightarrow \mathbb{R}$

Then  $Y = g(X)$  is also a r.v.

$$Y(\omega) = g(X(\omega)). \quad \text{Q: Calculate } E[Y]$$

Method 1: Compute the dist of  $Y$  from the dist of  $X$

Method 2:  $E[Y] = \sum_{\omega \in \Omega} g(X(\omega)) \cdot \text{Pr}[\omega]$

"LOTUS"

$$= \sum_x \sum_{\omega: X(\omega)=x} g(x) \cdot \text{Pr}[\omega]$$

$$= \sum_x g(x) \cdot \sum_{\omega: X(\omega)=x} \text{Pr}[\omega] = \sum_x g(x) \cdot \text{Pr}[X=x]$$

## Variance

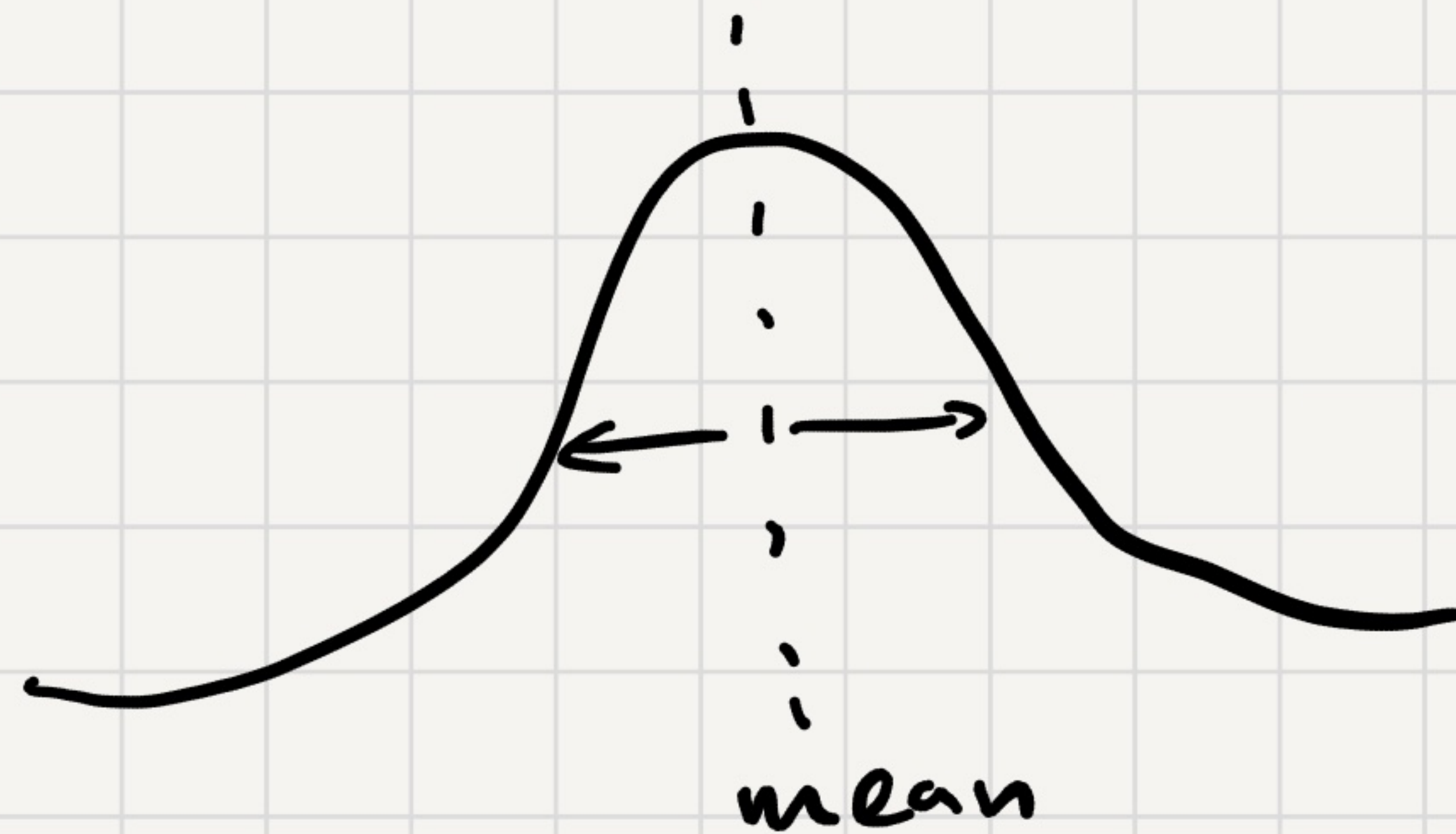
Suppose we have some r.v.  $X$

$E[X]$  - the average value  $X$  would get if we run the experiment many times.

But if we run the experiment only once, we still would like a guarantee on how close  $X$  is to its mean.

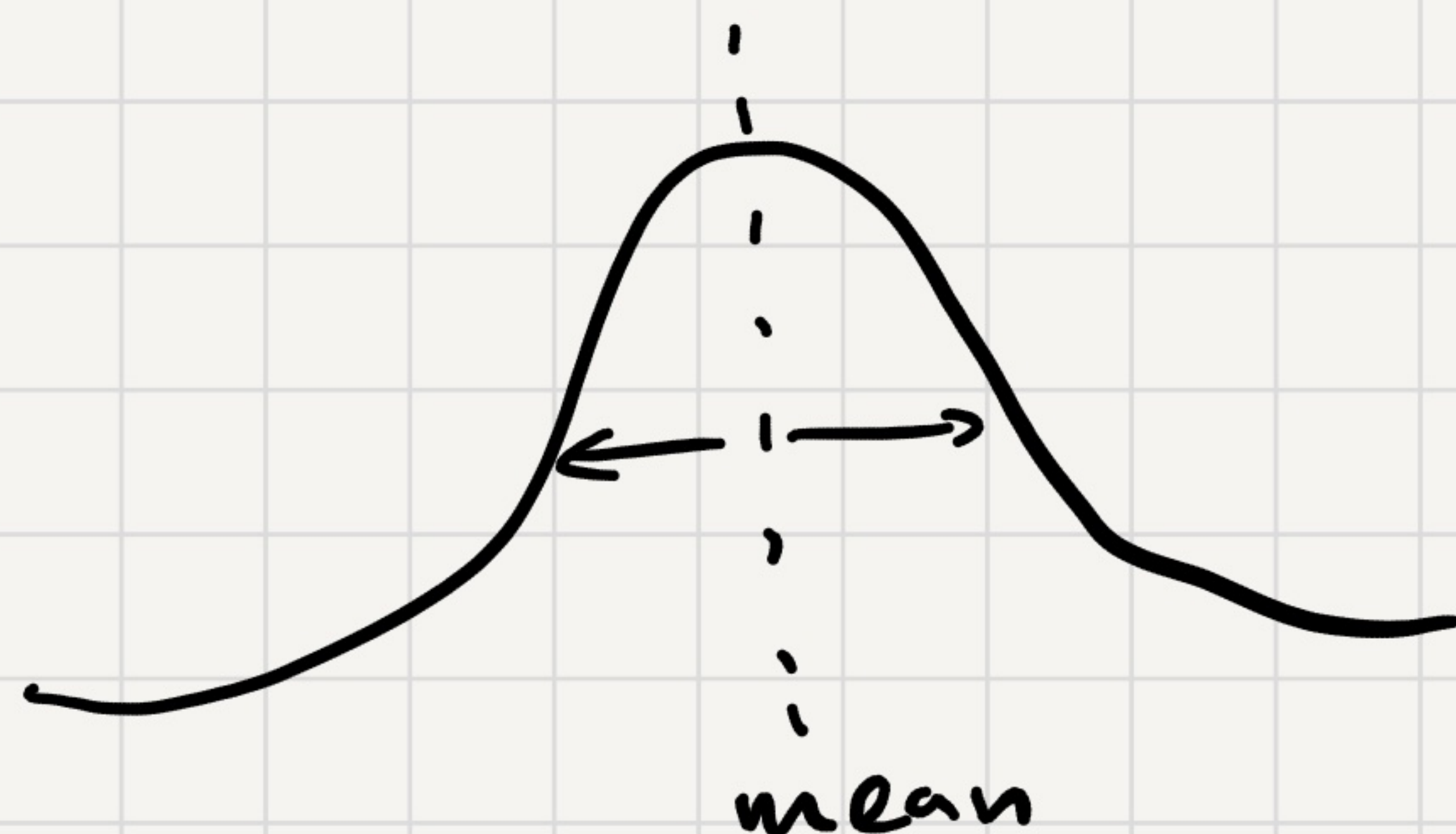
# Variance

The variance measures the deviation of  $X$  from its mean.



## Variance

The variance measures the <sup>expected</sup> deviation <sup>squared</sup> of  $X$  from its mean.



Def'n: The variance of a r.v.  $X$  is defined as

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

Measures the expected deviation squared.

$$\sigma(X) = \text{stdev}(X) = \sqrt{\text{Var}(X)}$$

# Variance

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Fact:

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

# Variance

Def'n: The variance of a r.v.  $X$  is defined as

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

Fact:

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

Proof:

Let  $\mu = E[X]$ .

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

$$= E[X^2 - 2\mu X + \mu^2]$$

$$= E[X^2] - 2\mu \underbrace{E[X]}_{\mu} + \mu^2$$

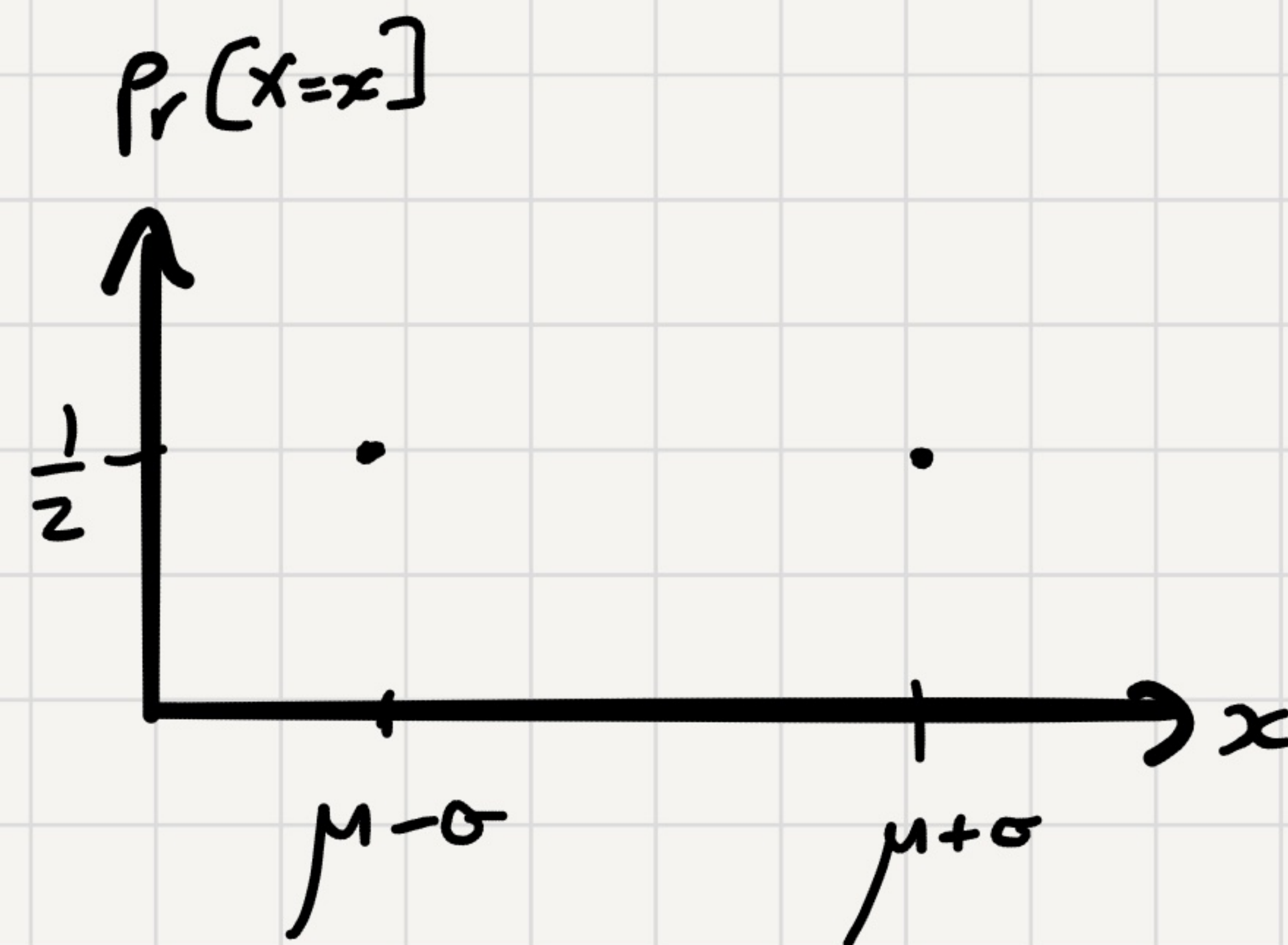
$$= E[X^2] - \mu^2 = E[X^2] - E[X]^2.$$



## Simple Example

$$X = \begin{cases} \mu + \sigma & \text{w.p. } \frac{1}{2} \\ \mu - \sigma & \text{w.p. } \frac{1}{2} \end{cases}$$

$$E X = ?$$

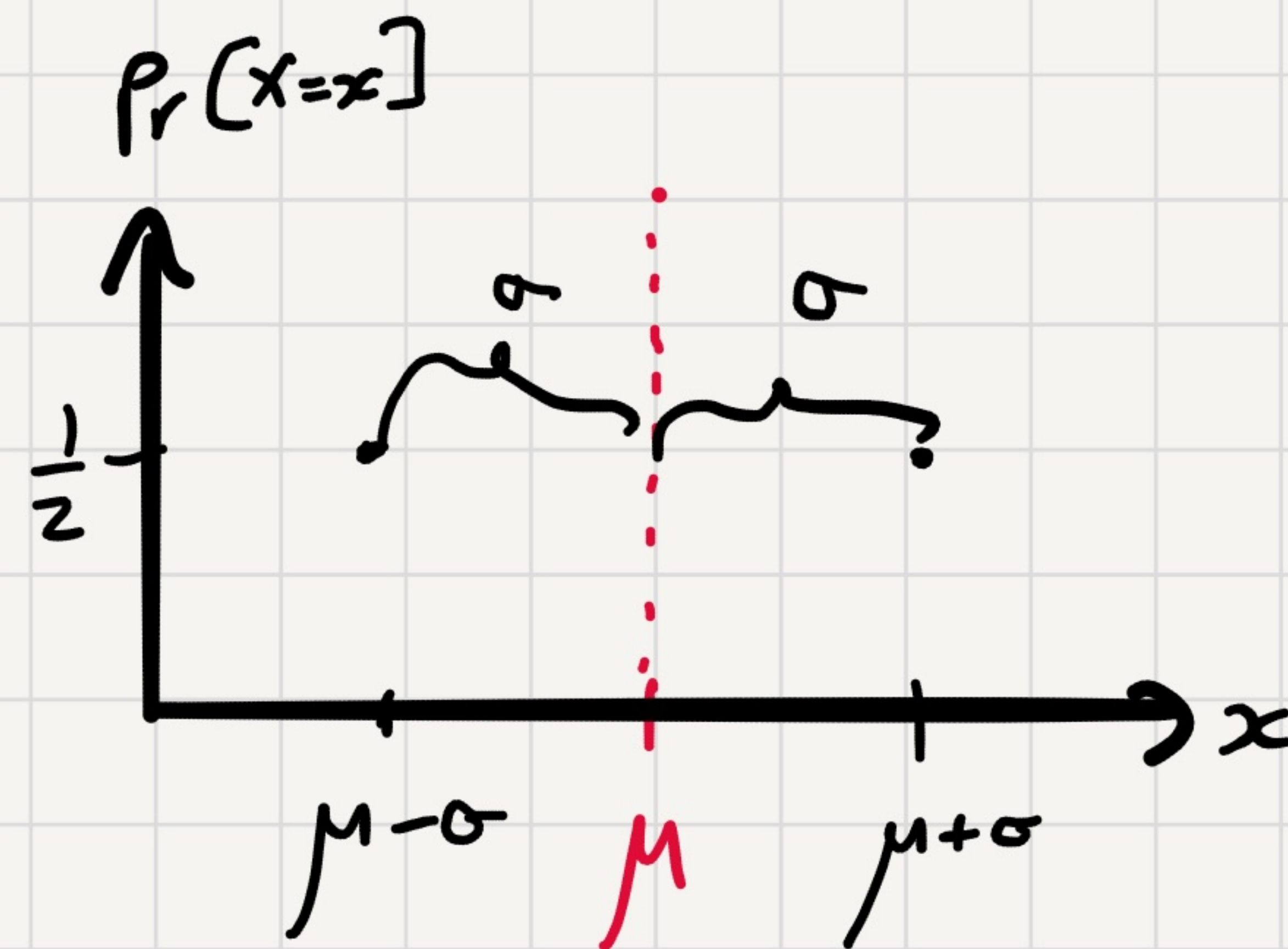


$$\text{Var}(X) = E[(X - E X)^2] = ?$$

## Simple Example

$$X = \begin{cases} \mu + \sigma & \text{w.p. } \frac{1}{2} \\ \mu - \sigma & \text{w.p. } \frac{1}{2} \end{cases}$$

$$E X = \frac{(\mu + \sigma) + (\mu - \sigma)}{2} = \mu$$



$$\begin{aligned} \text{Var}(X) &= E[(X - EX)^2] = \frac{1}{2} \cdot (\mu + \sigma - \mu)^2 + \frac{1}{2} \cdot (\mu - \sigma - \mu)^2 \\ &= \frac{1}{2} \sigma^2 + \frac{1}{2} \sigma^2 = \sigma^2 \end{aligned}$$

Facts:

For any  $c \in \mathbb{R}$ , r.v.  $X$

1.  $\text{Var}(c \cdot X) = c^2 \cdot \text{Var}(X)$ .

Scales by  $c^2$

2.  $\text{Var}(c + X) = \text{Var}(X)$ .

shifts center

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2.  $\text{Var}(c + X) = \text{Var}(X)$ . shifts center

Proof:

1. 
$$\begin{aligned} \text{Var}(c \cdot X) &= \mathbb{E}[(cX)^2] - \mathbb{E}[cX]^2 \\ &= c^2 \cdot \mathbb{E}[X^2] - c^2 \cdot \mathbb{E}[X]^2 = c^2 \cdot \text{Var}(X). \end{aligned}$$

2. 
$$\begin{aligned} \text{Var}(c+X) &= \mathbb{E}[(c+X - \mathbb{E}(c+X))^2] \\ &= \mathbb{E}[(c+X - c - \mathbb{E}X)^2] \\ &= \mathbb{E}[(X - \mathbb{E}X)^2] = \text{Var}(X). \end{aligned}$$

Facts: For any  $c \in \mathbb{R}$ , r.v.  $X$

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shifts center

If  $X$  and  $Y$  are r.v.s.

what's  $\text{Var}(X + Y) = ?$

Recap

## Independent Random Variables

Def'n: We say that two r.v.s  $X$  and  $Y$  are independent if

$$\Pr[X=a, Y=b] = \Pr[X=a] \cdot \Pr[Y=b]$$

for all  $a \in \text{range}(X)$   
 $b \in \text{range}(Y)$ .

Fact: If  $X$  &  $Y$  are indep.

$$\Pr[X=a | Y=b] = \Pr[X=a]$$

Theorem: If  $X$  and  $Y$  are independent r.v.s

then 
$$E[XY] = E[X] \cdot E[Y]$$

---

Theorem: If  $X$  and  $Y$  are independent r.v.s

then 
$$E[X \cdot Y] = E[X] \cdot E[Y]$$

---

Proof:

$$\begin{aligned} E[X \cdot Y] &= \sum_{a,b} a \cdot b \cdot \Pr[X=a, Y=b] \\ &= \sum_{a,b} a \cdot b \cdot \Pr[X=a] \cdot \Pr[Y=b] \\ &= \left( \sum_a a \cdot \Pr[X=a] \right) \cdot \left( \sum_b b \cdot \Pr[Y=b] \right) \\ &= E[X] \cdot E[Y]. \end{aligned}$$



Theorem: If  $X$  and  $Y$  are independent r.v.s, then

$$\text{Var}(X+Y) = \text{Var}(X) + \text{Var}(Y).$$

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Proof:  $E[(X+Y)^2] = E[X^2] + 2E[XY] + E[Y^2]$

$$\begin{aligned} (E[X+Y])^2 &= (EX + EY)^2 \\ &= (EX)^2 + 2(EX)(EY) + (EY)^2 \end{aligned}$$

Theorem: If  $X$  and  $Y$  are independent r.v.s, then

$$\text{Var}(X+Y) = \text{Var}(X) + \text{Var}(Y).$$

Proof:

$$\begin{cases} \mathbb{E}[(X+Y)^2] = \mathbb{E}[X^2] + 2\mathbb{E}[XY] + \mathbb{E}[Y^2] \\ (\mathbb{E}[X+Y])^2 = (\mathbb{E}X + \mathbb{E}Y)^2 \\ = (\mathbb{E}X)^2 + 2(\mathbb{E}X)(\mathbb{E}Y) + (\mathbb{E}Y)^2 \end{cases}$$

---

$$\begin{aligned} \text{Var}(X+Y) &= \mathbb{E}[X^2] - (\mathbb{E}X)^2 + 2\mathbb{E}[XY] - 2(\mathbb{E}X)(\mathbb{E}Y) \\ &\quad + \mathbb{E}[Y^2] - (\mathbb{E}Y)^2 \end{aligned}$$

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$$\begin{aligned} \text{Var}(X+Y) &= \mathbb{E}[X^2] - (\mathbb{E}X)^2 + 2\mathbb{E}[XY] - 2(\mathbb{E}X)(\mathbb{E}Y) \\ &\quad + \mathbb{E}[Y^2] - (\mathbb{E}Y)^2 \\ &= \text{Var}(X) + 0 + \text{Var}(Y) \end{aligned}$$

↑  
since  $X, Y$  are indep.

Theorem: If  $X_1, X_2, \dots, X_n$  are pairwise independent r.v.s then

$$\text{Var}(X_1 + \dots + X_n) = \text{Var}(X_1) + \dots + \text{Var}(X_n)$$

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Proof: (Similar)

$$E[(X_1 + \dots + X_n)^2] = \sum_{i=1}^n E[X_i^2] + \sum_{i \neq j} E[X_i X_j]$$

$$E[X_1 + \dots + X_n]^2 = \sum_{i=1}^n E[X_i]^2 + \sum_{i \neq j} E[X_i] E[X_j]$$

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$$- E[X_1 + \dots + X_n]^2 = \sum_{i=1}^n E[X_i]^2 + \sum_{i \neq j} E[X_i] E[X_j]$$

---

$$\begin{aligned} \text{Var}(X_1 + \dots + X_n) &= \sum_{i=1}^n E[X_i^2] - E[X_i]^2 + \sum_{i \neq j} E[X_i X_j] - (E[X_i] E[X_j]) \\ &= \sum_{i=1}^n \text{Var}(X_i) + 0 \end{aligned}$$



Facts: For any  $c \in \mathbb{R}$ , r.v.  $X$

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Scales by  $c^2$

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Q: If  $X$  and  $Y$  are r.v.s.  
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Example 1:  $X, Y$  ind.

Example 2:  $X, Y$  r.v.s  $Y = X$

Example 3:  $X, Y$  r.v.s  $Y = -X$

## Variance of a Binomial Distribution

$X \sim \text{Bin}(n, p)$  models # of heads  
in  $n$  coin tosses w. heads prob.  $p$ .

$$\Pr[X=i] = \binom{n}{i} \cdot p^i \cdot (1-p)^{n-i}$$

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

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$$X = X_1 + \dots + X_n \quad X_i = \text{indicator that } i\text{th flip is heads.}$$

$$\mathbb{E}X = \mathbb{E}X_1 + \dots + \mathbb{E}X_n = n \cdot p.$$

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

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$$E[X] = E[X_1 + \dots + X_n] = n \cdot p.$$

$$\text{Var}(X) = \text{Var}(X_1 + \dots + X_n) \stackrel{\uparrow}{=} \text{Var}(X_1) + \dots + \text{Var}(X_n)$$

$$\text{Var}(X_1) = ?$$

$X_1, \dots, X_n$   
are pairwise indep.

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$$\text{Var}(X) = \text{Var}(X_1 + \dots + X_n) = \text{Var}(X_1) + \dots + \text{Var}(X_n)$$

$$\text{Var}(X_i) = E[X_i^2] - E[X_i]^2 = p - p^2 = p \cdot (1-p)$$

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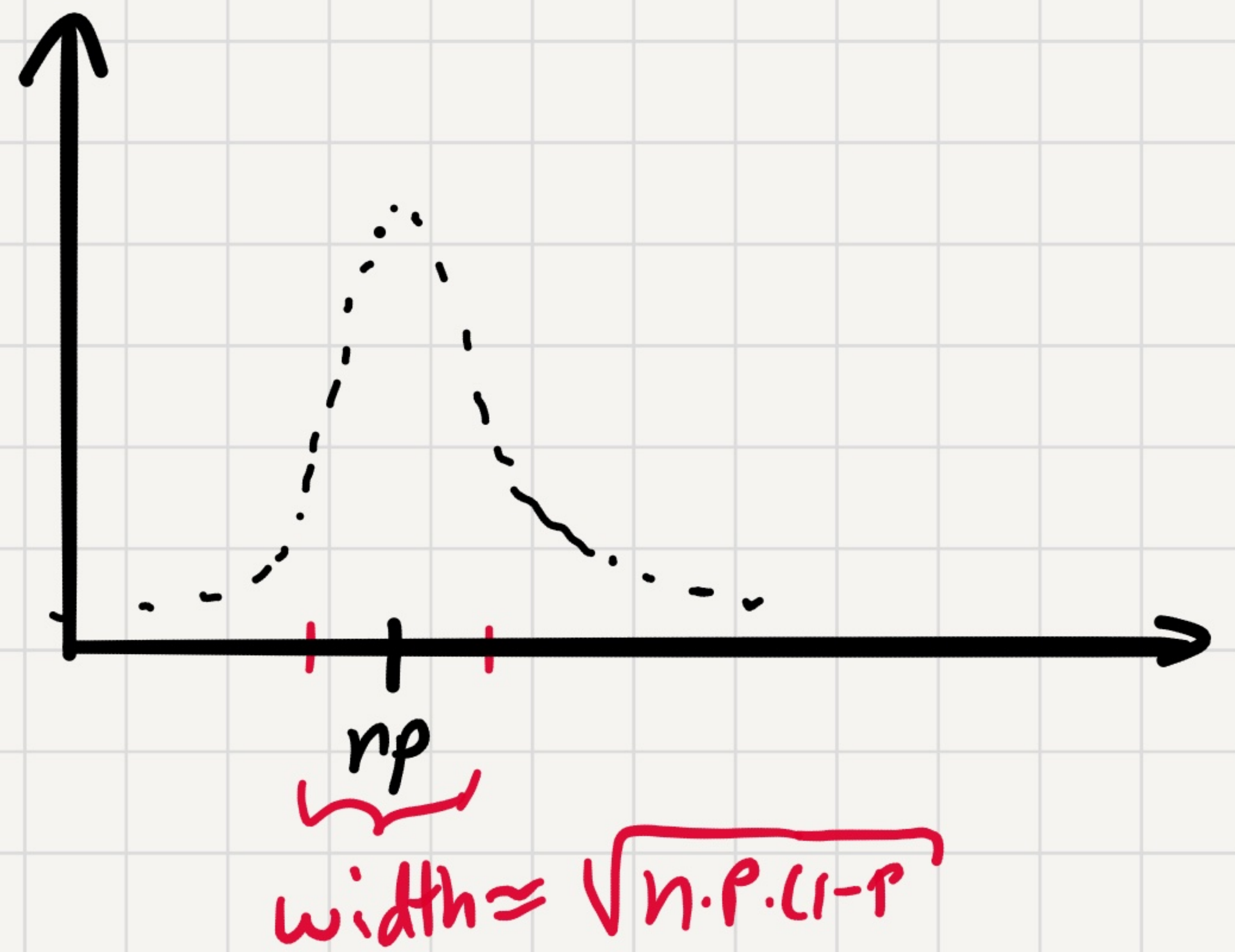
$$\mathbb{E}X = np$$

Scales  
linearly  
with  $n$

$$\text{Var}(X) = n \cdot p \cdot (1-p) \leq \frac{n}{4}$$

$$\text{stdev}(X) = \sqrt{n \cdot p \cdot (1-p)} \leq \frac{\sqrt{n}}{2}$$

Scales  
like  $\sqrt{n}$



## Number of Fixed Points - Variance

Handout assignment at random to  $n$  students

$X$  = number of students who got their own assignment.

$$\Omega = \{ \pi : \pi \text{ is a permutation of } \{1, \dots, n\} \}$$



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$X = X_1 + X_2 + \dots + X_n$        $X_i = \text{indicator that } \pi(i) = i$

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

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

$$\begin{aligned} \mathbb{E}[X^2] &= \mathbb{E}[(X_1 + \dots + X_n)^2] = \mathbb{E}\left[\sum_{i=1}^n X_i^2 + \sum_{i \neq j} X_i X_j\right] \\ &= \sum_{i=1}^n \mathbb{E}[X_i^2] + \sum_{i \neq j} \mathbb{E}[X_i X_j] \end{aligned}$$

# Number of Fixed Points - Variance

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

$$\begin{aligned} E[X^2] &= E[(X_1 + \dots + X_n)^2] = E\left[\sum_{i=1}^n X_i^2 + \sum_{i \neq j} X_i X_j\right] \\ &= \sum_{i=1}^n E[X_i^2] + \sum_{i \neq j} E[X_i X_j] \end{aligned}$$

$$E[X_i X_j] = \Pr[\pi(i) = i, \pi(j) = j] = \frac{1}{n} \cdot \frac{1}{n-1}$$

are  $X_i, X_j$  indep?

$$E[X^2] = \sum_{i=1}^n E[X_i^2] + \sum_{i \neq j} \frac{1}{n} \cdot \frac{1}{n-1} = n \cdot \frac{1}{n} + n \cdot (n-1) \frac{1}{n} \frac{1}{n-1} = 2.$$

Poll: What's true

1.  $X_i$  &  $X_j$  are ind.

$$2. \mathbb{E}[X_i X_j] = \Pr[X_i X_j = 1]$$

$$3. \mathbb{E}[X_i X_j] = \Pr[X_i = 1 \cap X_j = 1]$$

$$4. X_i^2 = X_i$$

## Covariance

If  $X$  and  $Y$  are r.v.s their co-variance is

$$\text{Cov}(X, Y) = E[(X - EX)(Y - EY)]$$

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Fact:  $\text{Cov}(X, Y) = E[XY] - (EX)(EY)$

Proof: let  $\mu_x = EX$      $\mu_y = EY$

$$\begin{aligned}\text{Cov}(X, Y) &= E[(X - \mu_x)(Y - \mu_y)] \\ &= E[XY] - \mu_x E[Y] - \mu_y E[X] + \mu_x \mu_y \\ &= E[XY] - \mu_x \mu_y = E[XY] - (EX)(EY).\end{aligned}$$

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If  $X$  and  $Y$  are r.v.s their co-variance is

$$\text{Cov}(X, Y) = E[(X - EX)(Y - EY)]$$

Fact:  $\text{Cov}(X, Y) = E[XY] - (EX) \cdot (EY)$

Corollary: If  $X$  and  $Y$  are independent then

$$\text{Cov}(X, Y) = 0.$$



Recap

Theorem: If  $X$  and  $Y$  are independent r.v.s, then

$$\text{Var}(X+Y) = \text{Var}(X) + \text{Var}(Y).$$

Proof:

$$\begin{cases} E[(X+Y)^2] = E[X^2] + 2E[XY] + E[Y^2] \\ (E[X+Y])^2 = (EX + EY)^2 \end{cases}$$

$$= (EX)^2 + 2(EX)(EY) + (EY)^2$$

$$\begin{aligned} \text{Var}(X+Y) &= E[X^2] - (EX)^2 + 2E[XY] - 2(EX)(EY) \\ &\quad + E[Y^2] - (EY)^2 \\ &= \text{Var}(X) + 0 + \text{Var}(Y) \end{aligned}$$

The only point where we used that  $X$  &  $Y$  are indep.

Theorem: If  $X$  and  $Y$  are r.v.s

$$\text{Var}(X+Y) = \text{Var}(X) + \text{Var}(Y) + 2\text{Cov}(X, Y)$$

Proof: 
$$\left\{ \begin{aligned} E[(X+Y)^2] &= E[X^2] + 2E[XY] + E[Y^2] \\ (E[X+Y])^2 &= (EX + EY)^2 \\ &= (EX)^2 + 2(EX) \cdot (EY) + (EY)^2 \end{aligned} \right.$$

$$\begin{aligned} \text{Var}(X+Y) &= E[X^2] - (EX)^2 + 2E[XY] - 2(EX)(EY) \\ &\quad + E[Y^2] - (EY)^2 \\ &= \text{Var}(X) + 2 \cdot \text{Cov}(X, Y) + \text{Var}(Y) \end{aligned}$$