

# Unbiased Variance Estimation

(The mystery of the missing man)

Evaluate bias

Understand behavior

Unbiased estimator

Resolve mystery

Dispel half-truth



# Mystery of the Missing Man

Sample mean

$$\bar{X} \stackrel{\text{def}}{=} \frac{1}{n} \sum_{i=1}^n X_i$$

$$E(\bar{X}) = \mu$$

Unbiased

“Raw” sample variance

$$\text{“}S^2\text{”} \stackrel{\text{def}}{=} \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^2$$

Experiments

$$E(\text{“}S^2\text{”}) \approx \frac{n-1}{n} \cdot \sigma^2$$

Biased

Mystery

Height of 10 people

Mean

Add

Normalize by

Variance

10

9

Show

$$E(\text{“}S^2\text{”}) = \frac{n-1}{n} \cdot \sigma^2$$

Why

How to fix

# Partial Explanation

“ $S^2$ ”  $\stackrel{\text{def}}{=} \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^2$  Show  $E(\text{“}S^2\text{”}) = \frac{n-1}{n} \cdot \sigma^2$  “ $S^2$ ” under-estimates  $\sigma^2$

Given n points  $x_1, \dots, x_n$   $\sum_{i=1}^n (x_i - a)^2$  minimized for  $a = \frac{x_1 + \dots + x_n}{n}$

1, -1  $(1 - a)^2 + (-1 - a)^2 = 2 + 2a^2$  minimized for  $a=0$  average

$\sigma^2 \stackrel{\text{def}}{=} E(X - \mu)^2$   $\mu \approx$  average of observations, not exactly

“ $S^2$ ”  $\stackrel{\text{def}}{=} \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^2$   $\bar{X}$  is exact average Lower sum

Explains “ $S^2$ ” under-estimates  $\sigma^2$

Does not Explain  $\frac{n-1}{n}$  Nor capture whole reason

complex

$$E(\text{"S}^2\text{"}) = E \left( \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^2 \right)$$

LE

$$= \frac{1}{n} E \left( \sum_{i=1}^n (X_i - \bar{X})^2 \right)$$

LE

$$= \frac{1}{n} \sum_{i=1}^n E(X_i - \bar{X})^2$$


$$= \frac{1}{n} \sum_{i=1}^n E(X_1 - \bar{X})^2$$

$$= E(X_1 - \bar{X})^2$$

Intuitive

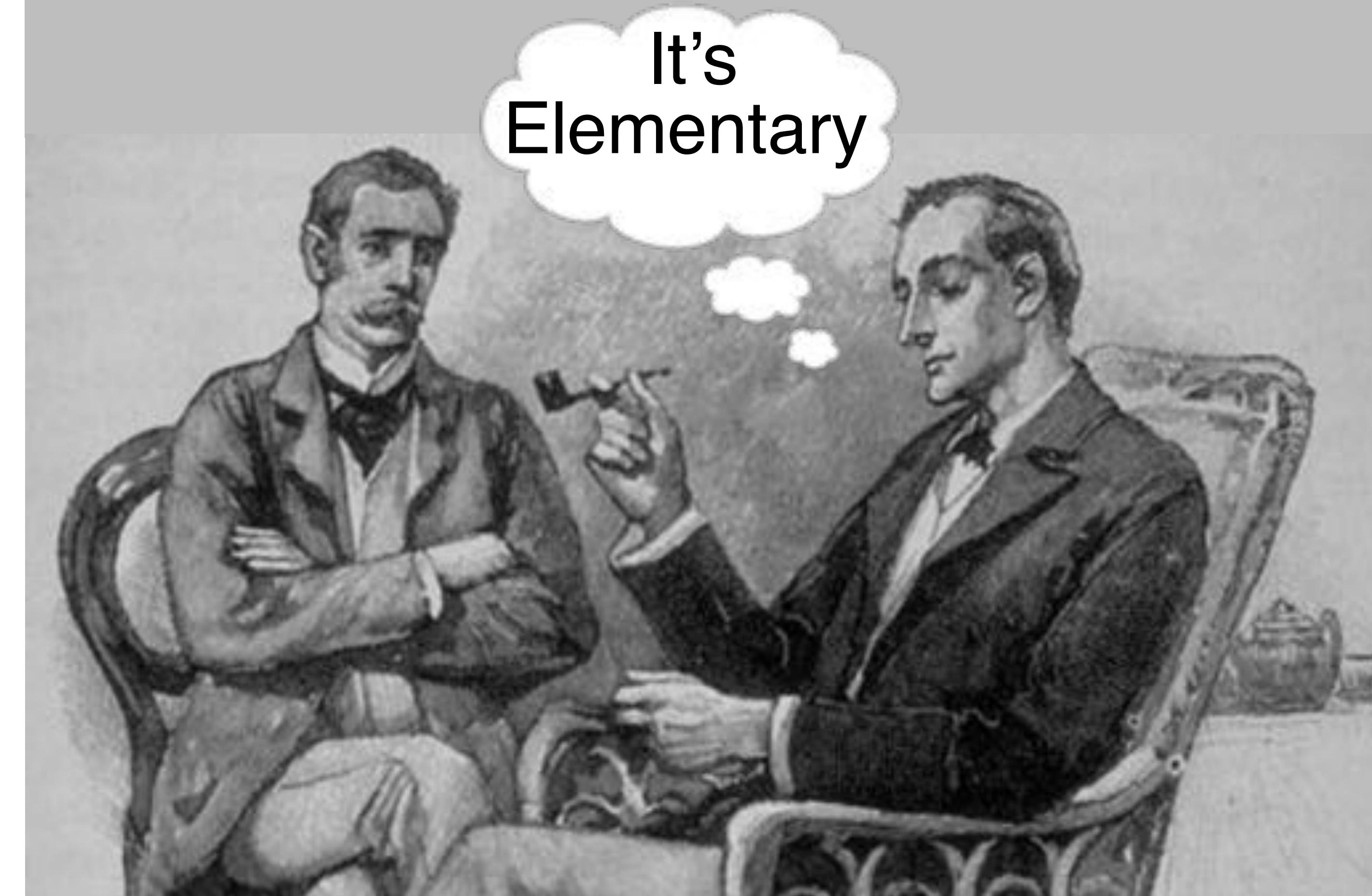
Simple

Elementary

Easier

understand

explain



# Recall: Bernoulli



**zZz**

B<sub>p</sub>

$$P(1) = p$$

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

$$\sigma^2 = pq$$

n=2

$$x_1, x_2$$

$$\bar{x} = \frac{x_1+x_2}{2}$$

$$\text{"S}^2\text{"}(x_1, x_2) = \frac{1}{2}((x_1 - \bar{x})^2 + (x_2 - \bar{x})^2)$$

X <sub>1</sub> , X <sub>2</sub>	P(X <sub>1</sub> , X <sub>2</sub> )	$\bar{x}$	"S <sup>2</sup> "
0,0	q <sup>2</sup>	0	$\frac{1}{2} ((0 - 0)^2 + (0 - 0)^2) = 0$
0,1	qp	$\frac{1}{2}$	$\frac{1}{2} \left( (0 - \frac{1}{2})^2 + (1 - \frac{1}{2})^2 \right) = \frac{1}{2} \cdot (\frac{1}{4} + \frac{1}{4}) = \frac{1}{4}$
1,0	pq	$\frac{1}{2}$	$\frac{1}{4}$
1,1	p <sup>2</sup>	1	0

Could get unwieldy!

$$E(\text{"S}^2\text"}) = \sum_{x_1, x_2} p(x_1, x_2) \cdot \text{"S}^2\text"(x_1, x_2)$$

$$= q^2 \cdot 0 + qp \cdot \frac{1}{4} + pq \cdot \frac{1}{4} + p^2 \cdot 0 = \frac{pq}{2} = \frac{\sigma^2}{2} !$$

# Bernoulli



B<sub>P</sub>

$$P(1) = p$$

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

$$\sigma^2 = E(X-\mu)^2 = p(1-p) = pq$$

Simplified calculation

n=2

X<sub>1</sub>, X<sub>2</sub>

$$E(\text{"S}^2\text{"}) = E(X_1 - \bar{X})^2$$

$$= \sum_{x_1, x_2} p(x_1, x_2) \cdot (x_1 - \bar{x})^2$$

$$= 2 \cdot pq \cdot \frac{1}{4} = \frac{1}{2}pq = \frac{1}{2}\sigma^2 \quad \checkmark$$

x <sub>1</sub> , x <sub>2</sub>	p(x <sub>1</sub> , x <sub>2</sub> )	$\bar{x}$	(x <sub>1</sub> - $\bar{x}$ ) <sup>2</sup>
0,0	q <sup>2</sup>	0	0
0,1	qp	$\frac{1}{2}$	$\frac{1}{4}$
1,0	pq	$\frac{1}{2}$	$\frac{1}{4}$
1,1	p <sup>2</sup>	1	0

Simpler

Easier to analyze

# Simplified Formulation

Want to show

$$E(\text{"S}^2\text{"}) = \frac{n-1}{n} \cdot \sigma^2$$

Asymmetric, unclear

$$\dots \rightarrow \stackrel{\text{def}}{=} E(X_1 - \mu)^2 \quad X_1 \sim p$$

$$\dots \rightarrow \stackrel{\text{def}}{=} E\left(\frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^2\right) = E(X_1 - \bar{X})^2$$

Show

$$E(X_1 - \bar{X})^2 = \frac{n-1}{n} \cdot E(X_1 - \mu)^2$$

Symmetric, shows difference

Simplistic Argument

$\bar{X}$  includes  $X_1$ , hence closer than  $\mu$

First n=2

General n

Doesn't explain  $\frac{n-1}{n}$

Not whole story

**n=2**

$$E(X_1 - \bar{X})^2 = \frac{1}{2} \cdot E(X_1 - \mu)^2 = \frac{\sigma^2}{2}$$

De-couple  $X_1$  from  $\bar{X}$

$$X_1 - \bar{X} = X_1 - \frac{X_1 + X_2}{2} = \frac{X_1 - X_2}{2}$$

$$E(X_1 - \bar{X})^2 = E\left(\frac{X_1 - X_2}{2}\right)^2 = \frac{1}{4} \cdot E(X_1 - X_2)^2$$

$X_2 \perp\!\!\!\perp X_1$  If difference was just from correlation between  $X_1$  and  $\bar{X}$

we would get  $\frac{1}{4} \cdot E(X_1 - \mu)^2 = \frac{\sigma^2}{4}$ . Even smaller!

Not whole story. Randomness of  $X_2$  reverses half of decrease. Show  $E(X_1 - X_2)^2 = 2 \cdot E(X_1 - \mu)^2$

gain  $\frac{1}{4}$  from proximity

lose 2 for randomness

$$E(X_1 - \bar{X})^2 = \frac{1}{4} \cdot E(X_1 - X_2)^2 = \frac{1}{4} \cdot 2 \cdot E(X_1 - \mu)^2 = \frac{\sigma^2}{2}$$

$$E(X_1 - X_2)^2 = 2 \cdot E(X_1 - \mu)^2$$

$$E(X_1 - X_2) = \mu - \mu = 0$$

$$E(X_1 - \mu) = \mu - \mu = 0$$

Both 0-mean

For 0-mean random variable Z

$$E(Z^2) = V(Z)$$

$$E(X_1 - X_2)^2 = 2 \cdot E(X_1 - \mu)^2 \iff V(X_1 - X_2) = 2 \cdot V(X_1)$$

$$V(X_1 - X_2) \stackrel{\text{def}}{=} V(X_1) + V(X_2) = 2 \cdot V(X_1)$$



DONE

# Summary for n=2

$$E(\text{“}S^2\text{”}) \stackrel{\text{def}}{=} E \left( \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^2 \right) \quad \left. \begin{array}{l} \\ \\ = E(X_1 - \bar{X})^2 \\ = E\left(\frac{X_1 - X_2}{2}\right)^2 \end{array} \right\} \text{any } n$$

LE

$$= \frac{1}{4} \cdot E(X_1 - X_2)^2$$

¼ from  $\bar{X}$  being closer than  $\mu$  to  $X_1$

0-mean

$$= \frac{1}{4} \cdot V(X_1 - X_2)$$

⊥

$$\stackrel{\perp}{=} \frac{1}{4} \cdot (V(X_1) + V(X_2))$$

iid

$$= \frac{1}{4} \cdot 2 \cdot V(X_1)$$

2 from  $\bar{X}$  being random

$$= \frac{1}{4} \cdot 2 \cdot \sigma^2 = \frac{\sigma^2}{2}$$

1/2 together

# General n

$$\begin{aligned}
 E(\text{"S}^2\text{"}) &= E\left(\frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^2\right) \\
 &\stackrel{\text{color}}{=} E(X_1 - \bar{X})^2 \\
 &= E\left(\frac{n-1}{n}\left(X_1 - \frac{X_2 + \dots + X_n}{n-1}\right)\right)^2
 \end{aligned}$$

$$\begin{aligned}
 X_1 - \bar{X} &= X_1 - \frac{X_1 + \dots + X_n}{n} \\
 &= \frac{(n-1)X_1 - X_2 - \dots - X_n}{n} \\
 &= \frac{n-1}{n} \left(X_1 - \frac{X_2 + \dots + X_n}{n-1}\right)
 \end{aligned}$$

**LOE**

$$\stackrel{\text{LOE}}{=} \left(\frac{n-1}{n}\right)^2 \cdot E\left(X_1 - \frac{X_2 + \dots + X_n}{n-1}\right)^2 \quad \left(\frac{n-1}{n}\right)^2 \text{ as } \bar{X} \text{ closer than } \mu \text{ to } X_1$$

0-mean

$$= \left(\frac{n-1}{n}\right)^2 \cdot V\left(X_1 - \frac{X_2 + \dots + X_n}{n-1}\right)$$

$\perp\!\!\!\perp$

$$= \left(\frac{n-1}{n}\right)^2 \cdot [V(X_1) + V\left(\frac{X_2 + \dots + X_n}{n-1}\right)]$$

iid, var. scaling

$$\stackrel{\text{iid, var. scaling}}{=} \left(\frac{n-1}{n}\right)^2 \cdot [\sigma^2 + \frac{\sigma^2}{n-1}]$$

$$= \left(\frac{n-1}{n}\right)^2 \cdot \frac{n}{n-1} \cdot \sigma^2$$

$$\stackrel{\text{iid, var. scaling}}{=} \frac{n-1}{n} \cdot \sigma^2$$

$\frac{n}{n-1}$  from  $\bar{X}$  being random

$\frac{n-1}{n}$  together

# Unbiased Variance Estimate

“Raw” sample variance

$$\text{“}S^2\text{”} = \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^2$$

$$E(\text{“}S^2\text{”}) = \frac{n-1}{n} \cdot \sigma^2$$

Bessel's Correction

$$S^2 = \frac{n}{n-1} \cdot \text{“}S^2\text{”} = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2$$

$$E(S^2) = \sigma^2$$

Unbiased estimator of variance

$S^2$  typically called sample variance

theoretically interesting

Large sample

Small difference

# ExSample



n = 5

2, 1, 4, 2, 6

Saw

$$\bar{X} = \frac{1}{n} \sum_{i=1}^n X_i = \frac{2+1+4+2+6}{5} = 3$$

“S<sup>2</sup>” = 3.2

$$\times \frac{5}{4}$$

$$\times \frac{n}{n-1}$$

$$S^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2 = \frac{1+4+1+1+9}{4} = \frac{16}{4} = 4$$

Unbiased estimate of  $\sigma^2$

One-pass calculation

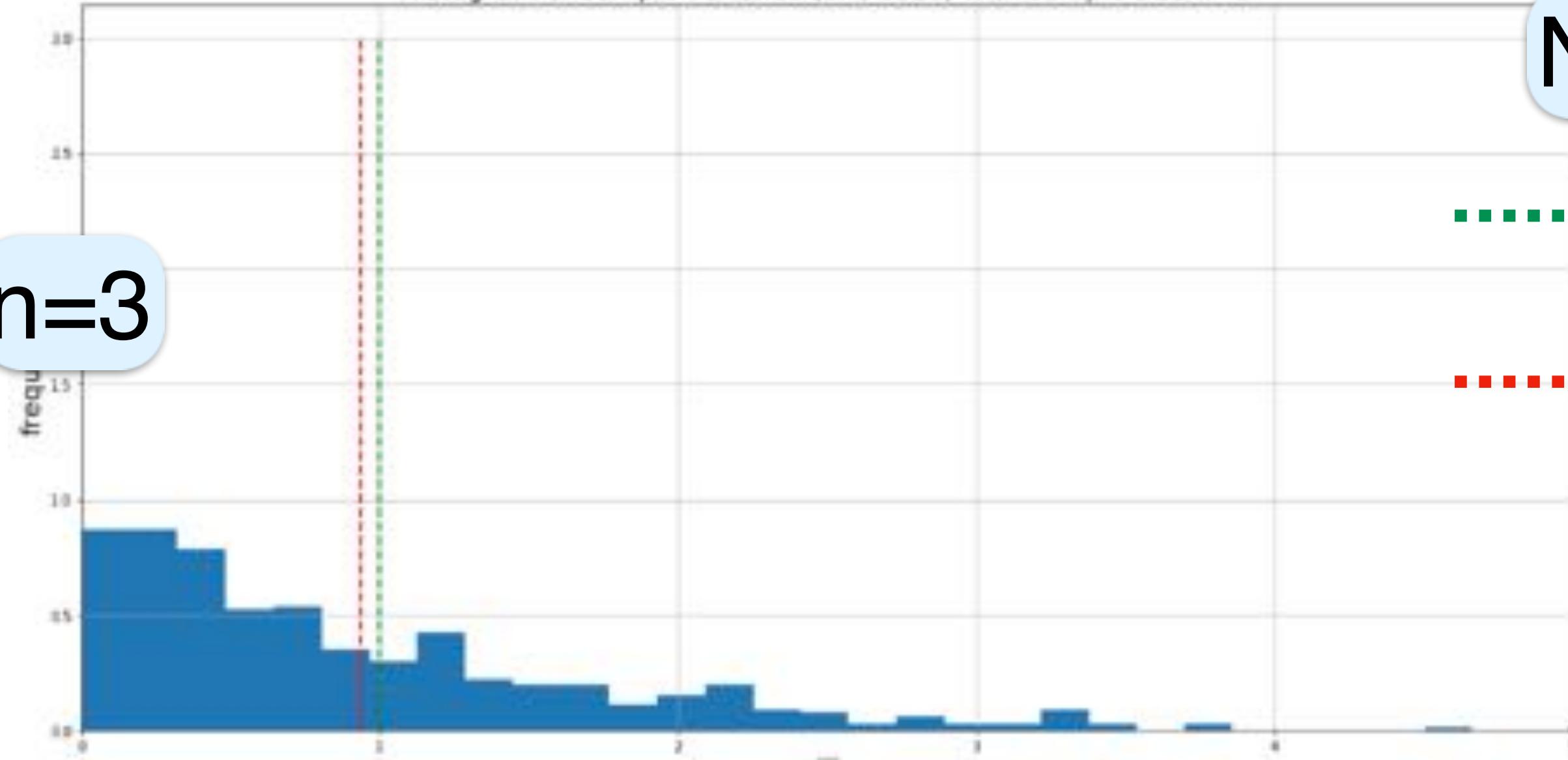
$$\text{“S}^2\text{”} = \frac{1}{n} \sum_{i=1}^n X_i^2 - \bar{X}^2 \rightarrow S^2 = \frac{1}{n-1} \left( \sum_{i=1}^n X_i^2 - n \bar{X}^2 \right)$$

# Final Simulations

r=500

r=3000

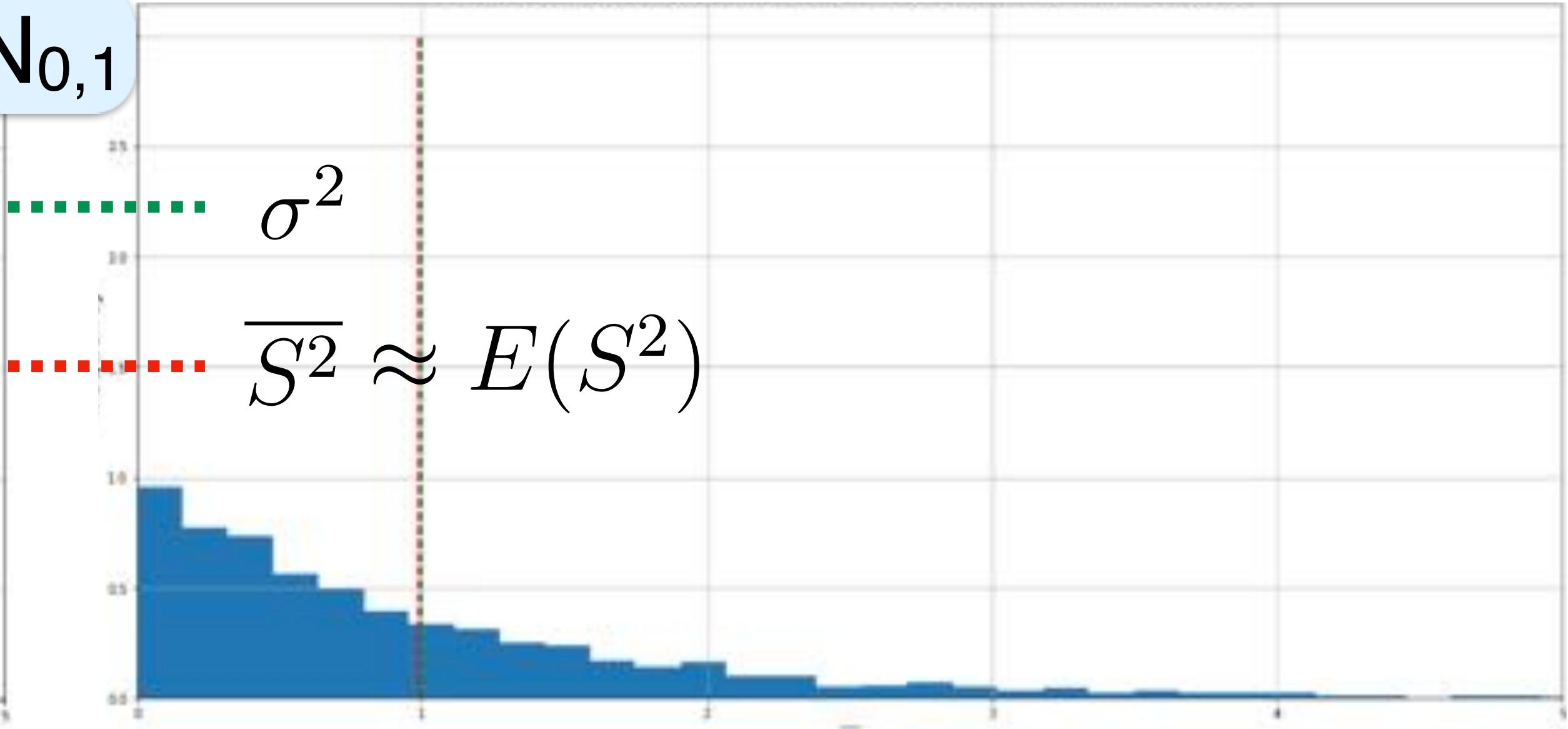
n=3



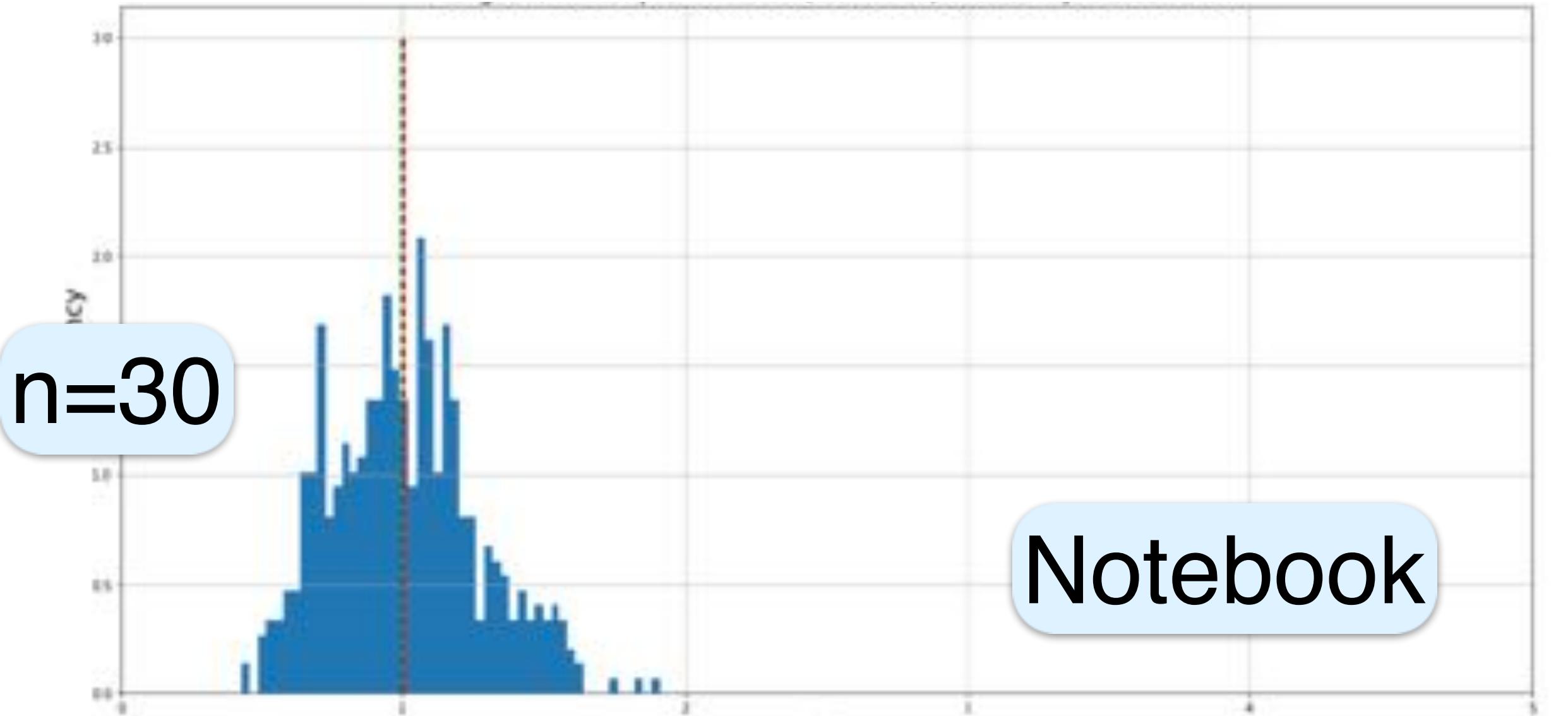
$N_{0,1}$

$\sigma^2$

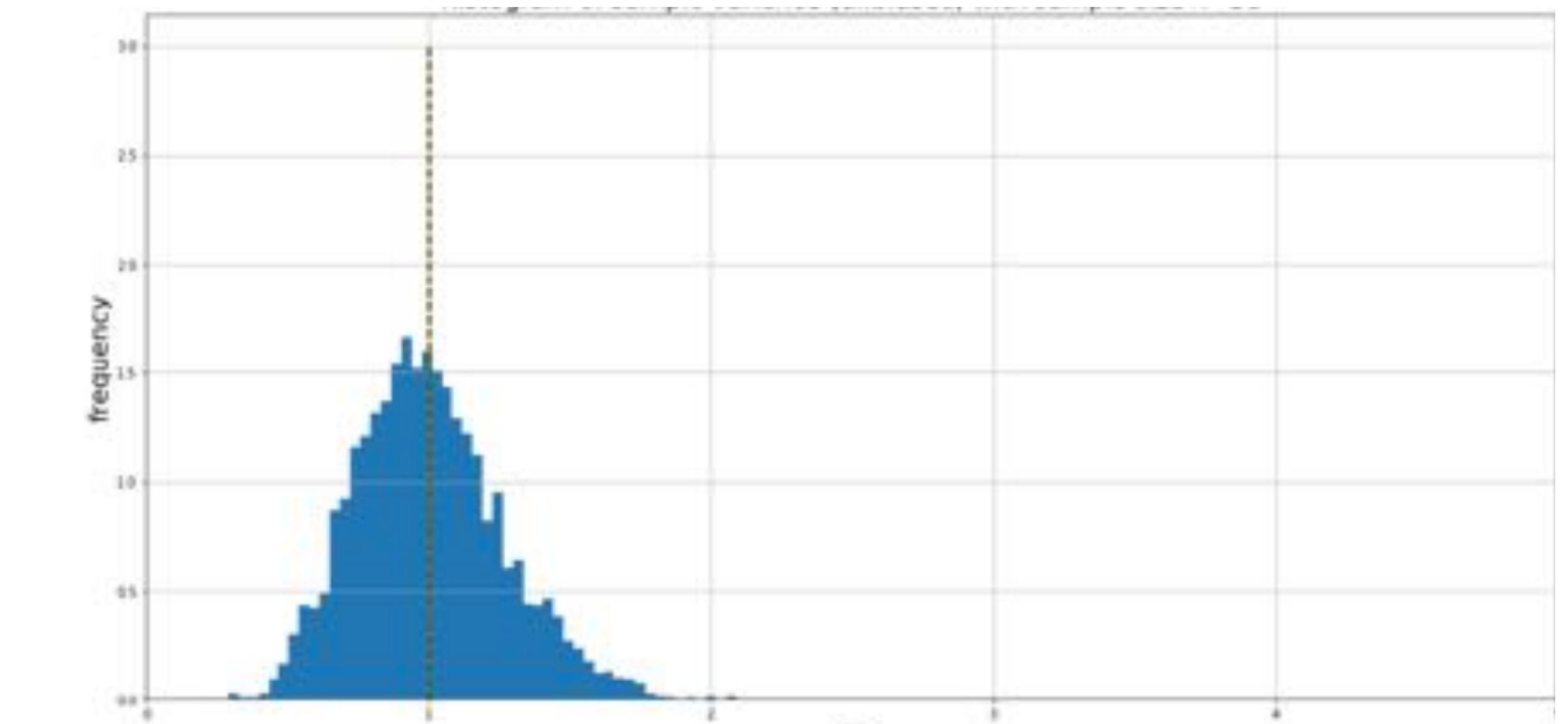
$\overline{S^2} \approx E(S^2)$



n=30



Notebook



# Unbiased Variance Estimation

(The mystery of the missing man)

Evaluate bias

Understand behavior

Unbiased estimator

Bessel Correction

$$\frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2$$

Resolve mystery

Dispel half-truth

Estimating  $\sigma$



# Estimating the Standard Deviation

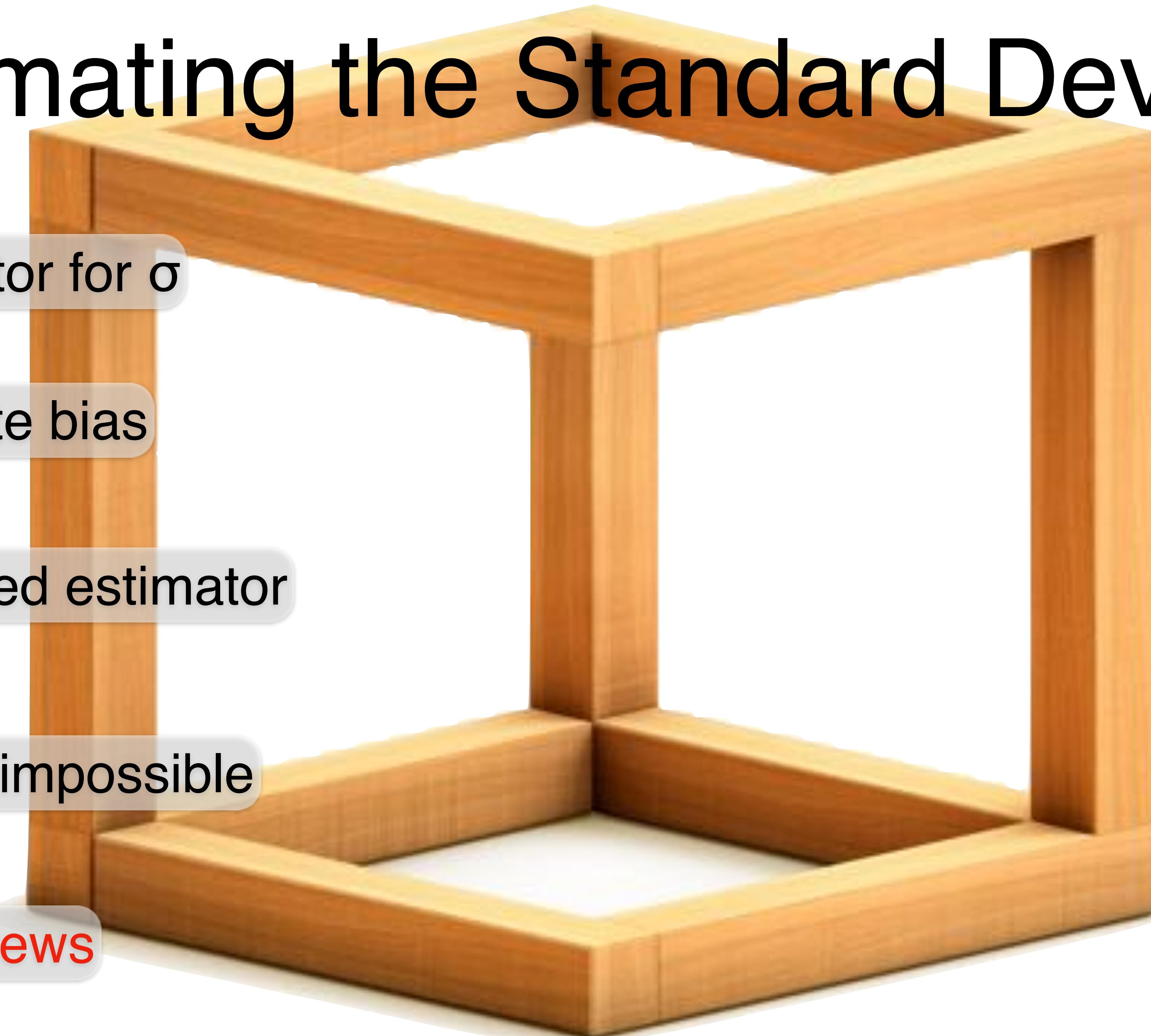
Estimator for  $\sigma$

Evaluate bias

Unbiased estimator

Easy x impossible

Good news



$$\sigma^2 \rightarrow \sigma$$

Variance estimator

$$S^2 \stackrel{\text{def}}{=} \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2$$

Showed

$$E(S^2) = \sigma^2$$

$S^2$  is an unbiased estimator for  $\sigma^2$

Estimating  $\sigma$

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

$$S \stackrel{\text{def}}{=} +\sqrt{S^2} = +\sqrt{\frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2}$$

Standard Standard-Deviation estimator

Example

Evaluation

Possible alternatives

# ExSample

n = 5

2, 1, 4, 2, 6

Saw

$$\bar{X} = \frac{1}{n} \sum_{i=1}^n X_i = \frac{2+1+4+2+6}{5} = 3$$

$$S^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2 = \frac{1+4+1+1+9}{4} = \frac{16}{4} = 4$$

Estimate for  $\sigma^2$

Estimate for  $\sigma$

$$S = \sqrt{S^2} = \sqrt{4} = 2$$

# Unbiased?

Is  $S$  an unbiased estimator for  $\sigma$ ?

$S^2$  is an unbiased variance estimator

$$(ES)^2 \leq E(S^2) = \sigma^2$$

$$E(S^2) = (ES)^2 + V(S) \geq (ES)^2$$

= iff  $V(S)=0$  iff  $S$  is a constant

$ES \leq \sigma$  < whenever  $X$  is not a constant

On average  $S$  underestimates  $\sigma$

Concrete example

# S Strictly Underestimates $\sigma$

B<sub>p</sub>

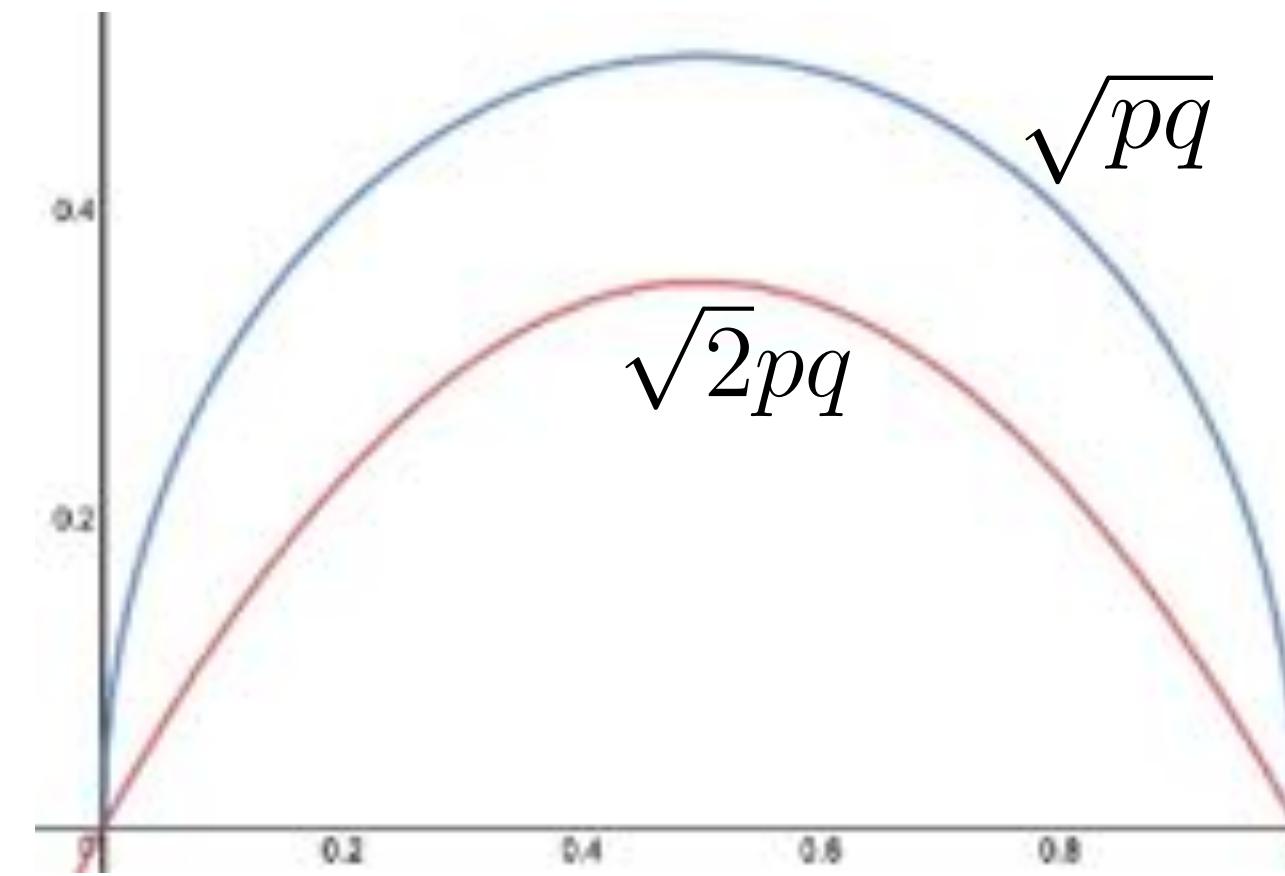
$$\sigma = \sqrt{p(1-p)} = \sqrt{pq}$$

n=2

Show  $E(S) < \sqrt{pq}$

$X_1, X_2$	$P(X_1, X_2)$	$\bar{x}$	$s^2$	$s$
0,0	$q^2$	0	0	0
0,1	$qp$	$\frac{1}{2}$	$\frac{1}{2}$	$\frac{1}{\sqrt{2}}$
1,0	$pq$	$\frac{1}{2}$	$\frac{1}{2}$	$\frac{1}{\sqrt{2}}$
1,1	$p^2$	1	0	0

$$S^2 = \frac{1}{1} \left( (0 - \frac{1}{2})^2 + (1 - \frac{1}{2})^2 \right) = \frac{1}{2}$$



$$E(S) = q^2 \cdot 0 + qp \cdot \frac{1}{\sqrt{2}} + pq \cdot \frac{1}{\sqrt{2}} + p^2 \cdot 0 = \sqrt{2} \cdot pq < \sqrt{pq}$$

# Unbiased Estimator for $\sigma$ ?

Is there an unbiased estimator for  $\sigma$ ?

If  $p$  is known, so is  $\sigma$ , so nothing to estimate

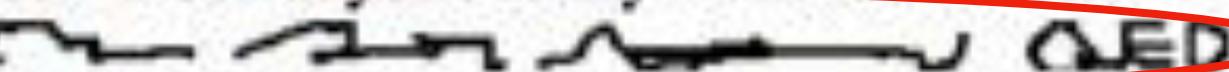
Estimator must work for all distributions

For all  $p$        $E(\bar{X}) = \mu$        $E(S^2) = \sigma^2$

Is there estimator  $\hat{\sigma}$  s.t. for all distributions     $E(\hat{\sigma}(X^n)) = \sigma$

NO    There is no general unbiased estimator for  $\sigma$  !

How do you prove the impossible?

- **Proof by obviousness:** "The proof is so clear that it need not be mentioned."
- **Proof by general agreement:** "All in favor?..."
- **Proof by imagination:** "Well, we'll pretend it's true..."
- **Proof by convenience:** "It would be very nice if it were true, so..."
- **Proof by necessity:** "It had better be true, or the entire structure of mathematics would crumble to the ground."
- **Proof by plausibility:** "It sounds good, so it must be true."
- **Proof by intimidation:** "Don't be stupid; of course it's true!"
- **Proof by lack of sufficient time:** "Because of the time constraint, I'll leave the proof to you."
- **Proof by postponement:** "The proof for this is long and arduous, so it is given to you in the appendix."
- **Proof by accident:** "Hey, what have we here?!"
- **Proof by insignificance:** "Who really cares anyway?"
- **Proof by mumbo-jumbo:**  $\forall \alpha \in \Phi, \exists \beta \ni \alpha * \beta = \epsilon, \dots$
- **Proof by profanity:** (example omitted)
- **Proof by definition:** "We define it to be true."
- **Proof by tautology:** "It's true because it's true."
- **Proof by plagiarism:** "As we see on page 289,..."
- **Proof by lost reference:** "I know I saw it somewhere...."
- **Proof by calculus:** "This proof requires calculus, so we'll skip it."
- **Proof by terror:** When intimidation fails...
- **Proof by lack of interest:** "Does anyone really want to see this?"
- **Proof by illegibility:** 
- **Proof by logic:** "If it is on the problem sheet, it must be true!"
- **Proof by majority rule:** Only to be used if general agreement is impossible.
- **Proof by clever variable choice:** "Let A be the number such that this proof works..."
- **Proof by tessellation:** "This proof is the same as the last."
- **Proof by divine word:** "...And the Lord said, 'Let it be true,' and it was true."
- **Proof by stubbornness:** "I don't care what you say- it is true."
- **Proof by simplification:** "This proof reduced to the statement  $1 + 1 = 2$ ."
- **Proof by hasty generalization:** "Well, it works for 17, so it works for all reals."
- **Proof by deception:** "Now everyone turn their backs..."
- **Proof by supplication:** "Oh please, let it be true."
- **Proof by poor analogy:** "Well, it's just like..."
- **Proof by avoidance:** Limit of proof by postponement as it approaches infinity
- **Proof by design:** If it's not true in today's math, invent a new system in which it is.
- **Proof by authority:** "Well, Don Knuth says it's true, so it must be!"
- **Proof by intuition:** "I have this gut feeling."

# Proof Techniques

Handwaving

As you can see...

Induction

True for 1, 2, 3, so must be true

Example

True for this trivial example  
so must be true

# No Unbiased $\sigma$ Estimator

Even for  $B_p$

p unknown

No unbiased estimator

No unbiased estimators for general distributions

Show for  $n=2$  samples

Similar for any n

How do you prove the impossible?

$\hat{\sigma}$  Any estimator for  $\sigma$  for  $B_p$  distributions

$\hat{\sigma}(x_1, x_2)$  Estimate of  $\sigma$  when observing  $x_1, x_2$

Predetermined constants

$$\begin{aligned} E(\hat{\sigma}(X_1, X_2)) &= \sum_{x_1, x_2} p(x_1, x_2) \hat{\sigma}(x_1, x_2) \\ &= P(0, 0)\hat{\sigma}(0, 0) + P(0, 1)\hat{\sigma}(0, 1) + P(1, 0)\hat{\sigma}(1, 0) + P(1, 1)\hat{\sigma}(1, 1) \\ &= (1 - p)^2\hat{\sigma}(0, 0) + (1 - p)p\hat{\sigma}(0, 1) + p(1 - p)\hat{\sigma}(1, 0) + p^2\hat{\sigma}(1, 1) \end{aligned}$$

Polynomial in  $p$  degree-2 polynomial

$\sigma = \sqrt{p(1 - p)}$  Not a polynomial in  $p$

The two functions differ For some  $p$   $E(\hat{\sigma}(X_1, X_2)) \neq \sigma$

# Impossibility

How did we prove the impossible?

Easily!

Estimators for  $B_p$

Showed that for any estimator  $\hat{\sigma}$

$$E(\hat{\sigma}(X_1, X_2))$$

polynomial in p

$$\sigma = \sqrt{p(1 - p)}$$

not polynomial in p

Except: How do you prove?

For some p

$$E(\hat{\sigma}(X_1, X_2)) \neq \sigma$$

"Don't be stupid; of course it's true!"

Therefore

$\hat{\sigma}$  not unbiased

Despite joke

Complete proof

Give up?

# Good News

Bias not so bad



Provides more freedom

Best estimator (MSE) often biased

As the number of samples n increases

$S \rightarrow \sigma$

Consistent

# Estimating the Standard Deviation

Estimator for  $\sigma$

$$S \stackrel{\text{def}}{=} +\sqrt{S^2} = +\sqrt{\frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2}$$

Evaluate bias

$$ES \leq \sigma < \text{for non-constant distributions}$$

Unbiased estimator

Easy x impossible

Simple proof: no unbiased estimator

Good news

Some bias okay as long as MSE small