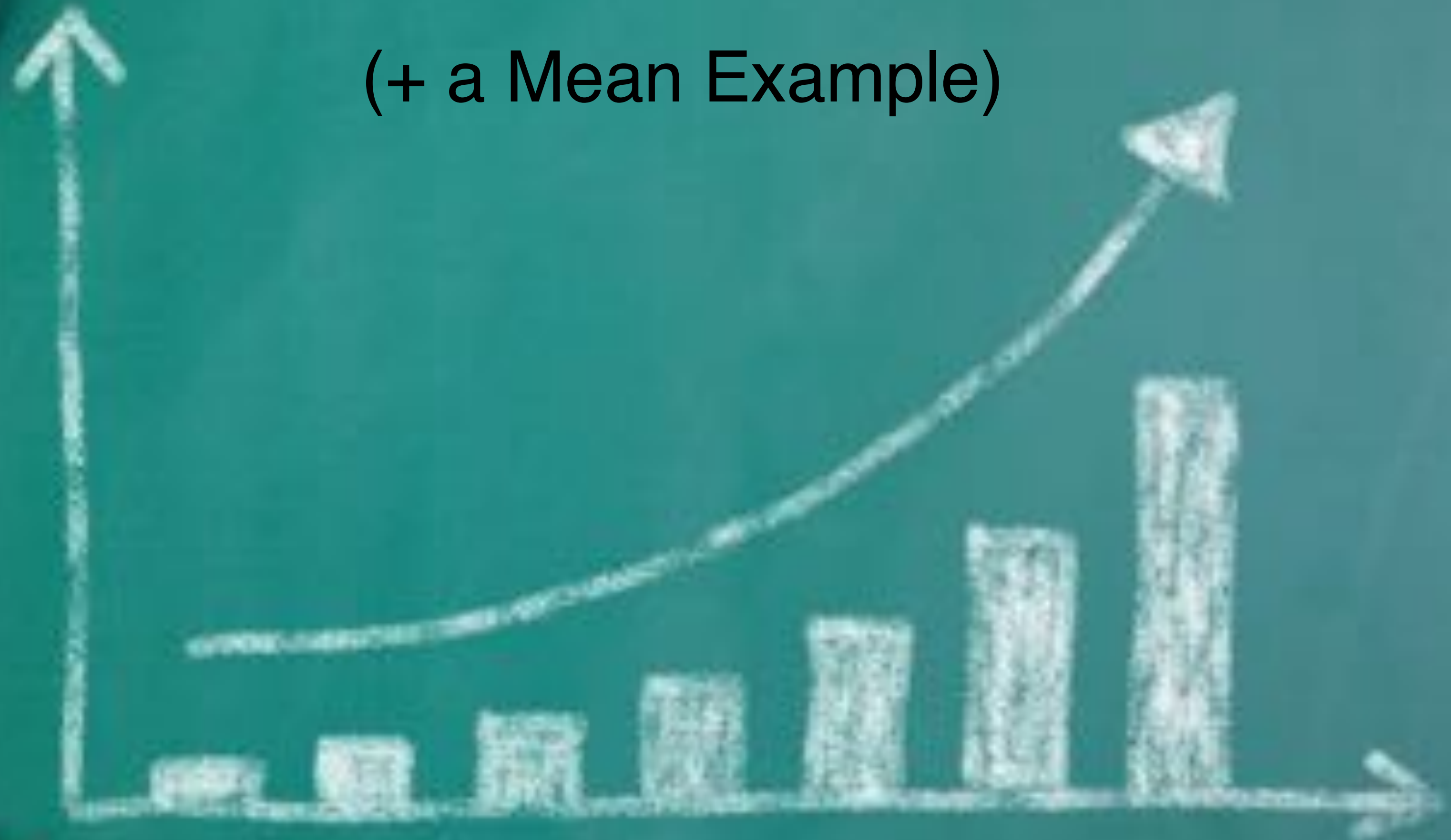


Parameter Estimation

(+ a Mean Example)



Estimators

p Unknown distribution or population

θ Parameter of p wish to estimate Mean example μ σ , max, mode

Sample $X^n \stackrel{\text{def}}{=} X_1, X_2, \dots, X_n \sim p \perp\!\!\!\perp X^3 = 5, -2, 6$

\wedge for estimate

Estimator for θ function $\hat{\theta} : \mathbb{R}^n \rightarrow \mathbb{R}$ Maps X^n to \mathbb{R}

Upon observing X^n , estimate θ as $\hat{\theta}(X^n) \stackrel{\text{def}}{=} \hat{\Theta}$

μ $\hat{\theta}(X^n) :$ $\frac{X_1 + \dots + X_n}{n}$ $\frac{\min\{X_i\} + \max\{X_i\}}{2}$ $X_1 \cdot X_2$

5, -2, 6 $\hat{\Theta} :$ 3 2 -10

Observations

Distribution parameter θ

Constant

Mean 3.2

Estimate $\hat{\Theta} \stackrel{\text{def}}{=} \hat{\theta}(X^n)$

Random variable

Ideally close to θ

Once sample X^n drawn

Determines $\hat{\Theta}$

Single value

3.5

Point estimate

vs. interval

[3,4]

Any function is an estimator

Come up with an estimator?

How to

Evaluate its performance?



SAMPLE

Apply sample to any parameter 



Sample X

Property

X

sample X

min

$$X_{\min} \quad \min_x \{x : p(x) > 0\}$$

sample min

$$\min_i \{X_i\}$$

max

$$X_{\max} \quad \max_x \{x : p(x) > 0\}$$

sample max

$$\max_i \{X_i\}$$

mean

$$\mu \quad \sum_x x \cdot p(x)$$

sample mean

$$\frac{1}{n} \sum_{i=1}^n X_i$$

Simple

If sample is whole population, exact

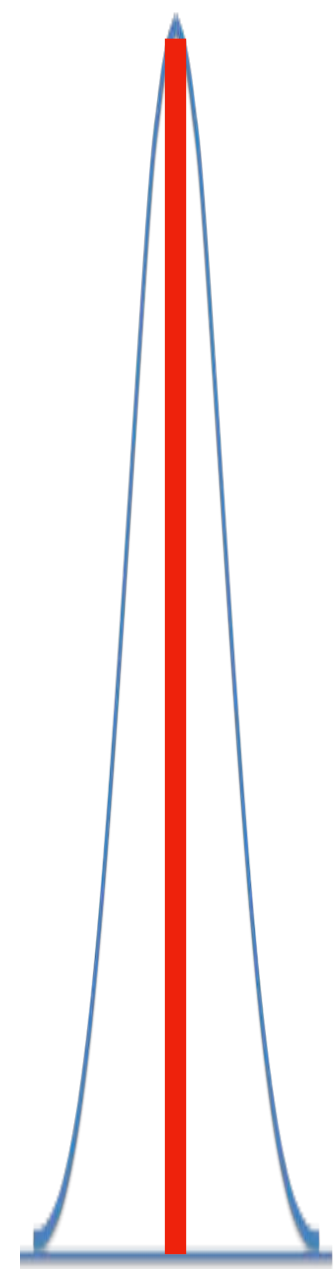
Sometimes works well

Even for small samples

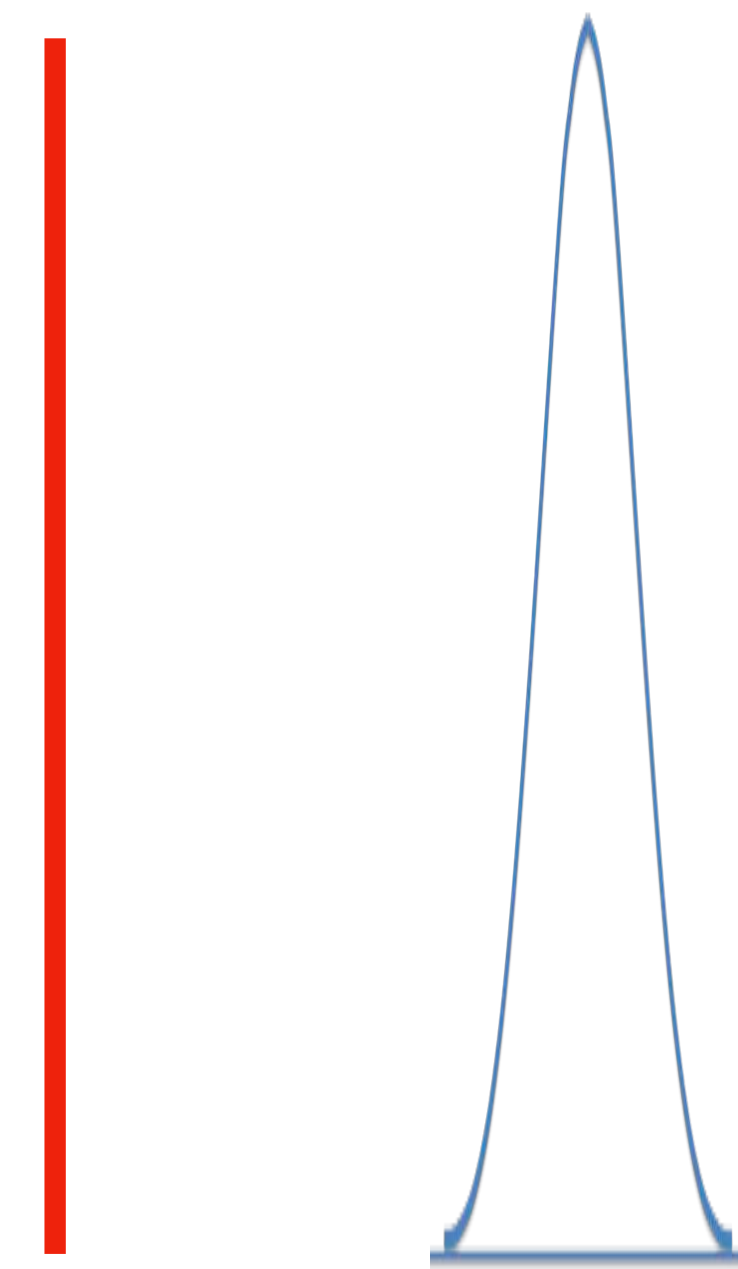
Estimator Evaluation

Parameter may have several estimators

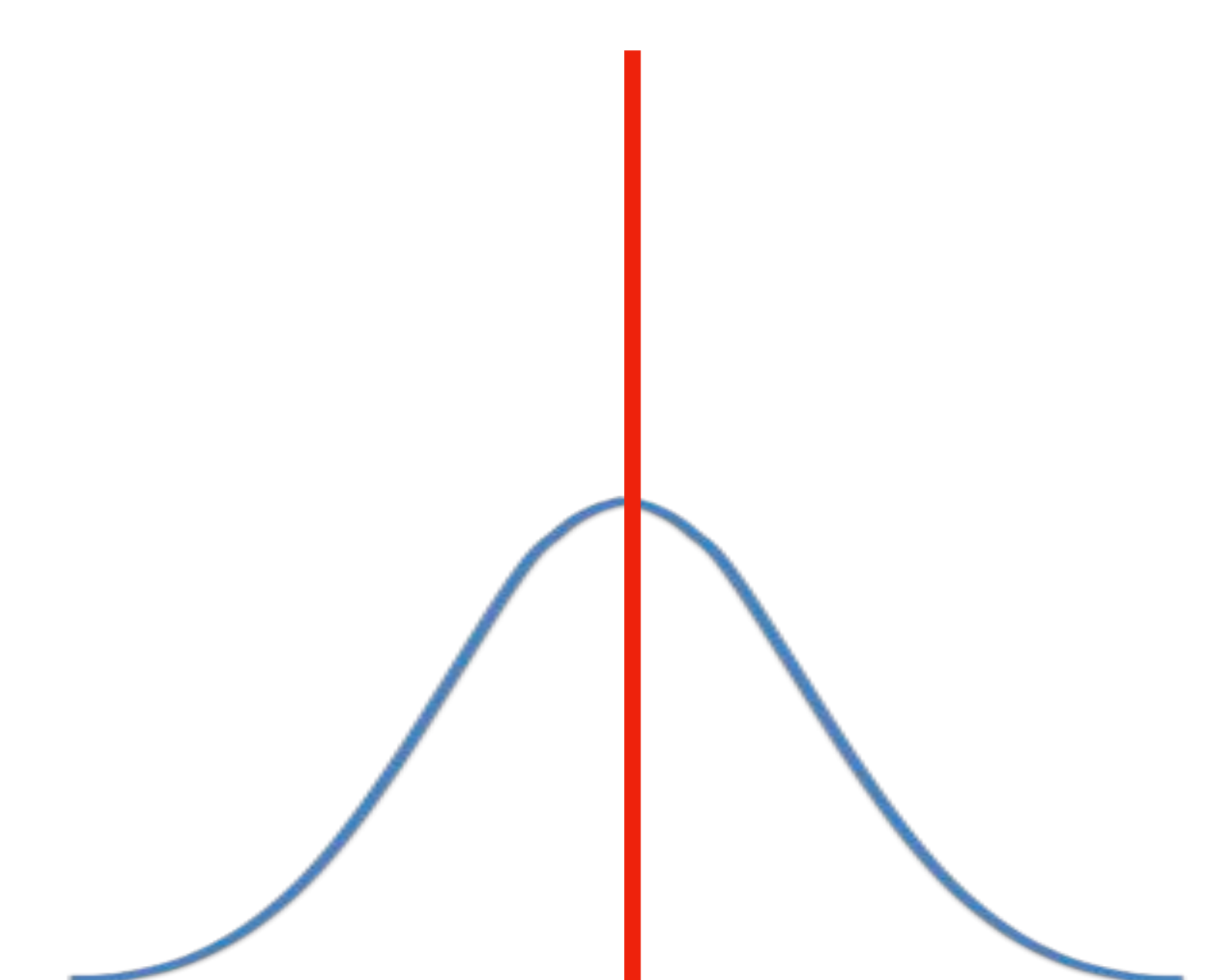
Evaluate quality of estimator for a parameter



Good



Bias



Variance

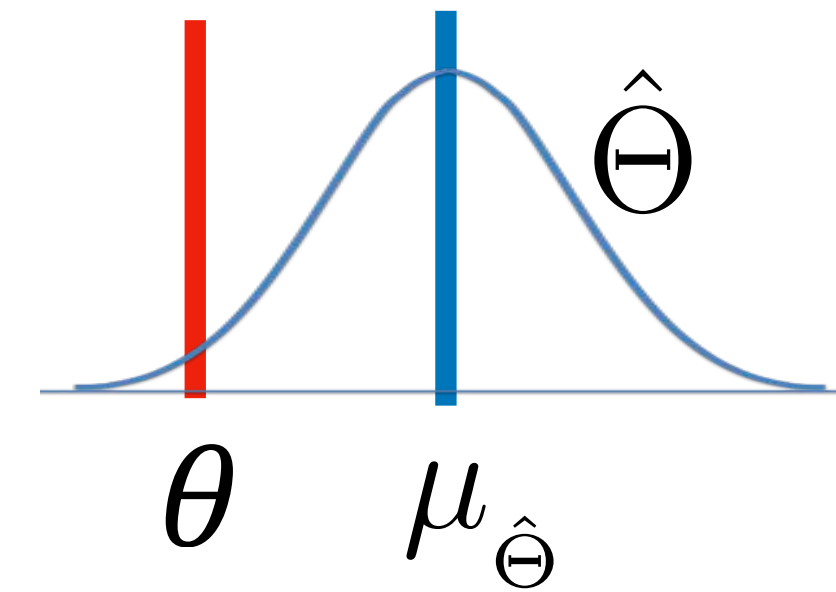
Bias

$\hat{\Theta}$ estimator for θ

Bias of $\hat{\Theta}$ is its expected overestimate of θ

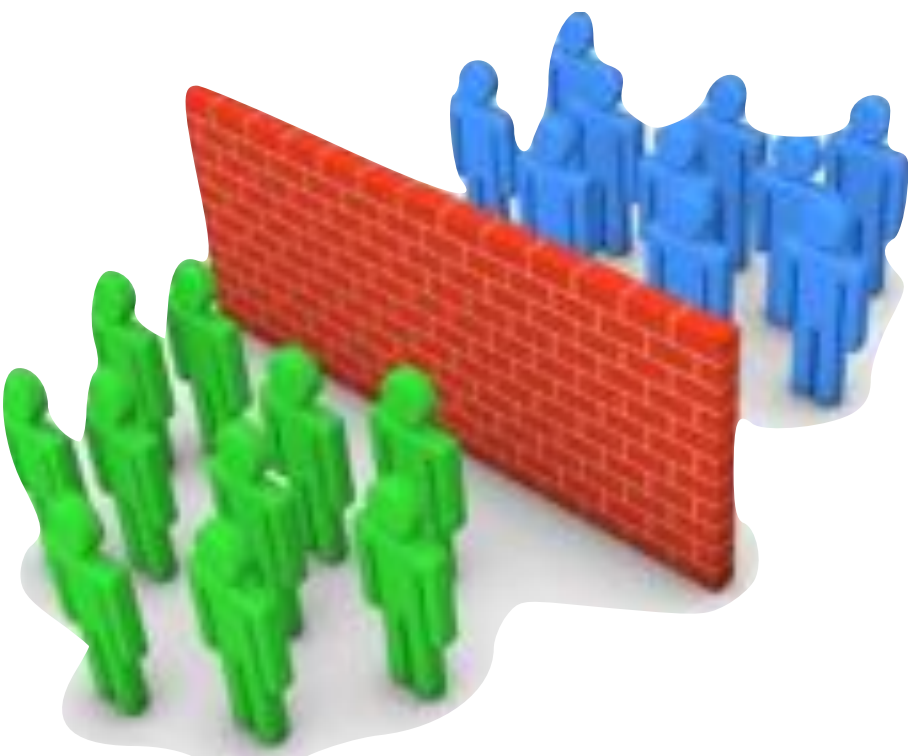
$$\text{Bias}_{\theta}(\hat{\Theta}) \stackrel{\text{def}}{=} E(\hat{\Theta} - \theta) = \mu_{\hat{\Theta}} - \theta$$

$$\rightarrow \text{Bias}(\hat{\Theta})$$



Estimator with 0 bias is **unbiased**

$$\mu_{\hat{\Theta}} = \theta$$



Bias = Inequality

Variance

$$V(\hat{\Theta}) = E(\hat{\Theta} - \mu_{\hat{\Theta}})^2$$

Unrelated to θ

Ideally 0 bias variance

Typically tradeoff

Mean Example

Unknown distribution or population p

Estimate mean μ

n samples

$$X_1, \dots, X_n \sim p \perp$$

Sample mean

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

Evaluate

Bias

Variance



Weak Law of Large Numbers

Sample Mean - Bias

Sample mean

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

Expectation

$$\begin{aligned} E(\overline{X}) &= E\left(\frac{1}{n} \sum_{i=1}^n X_i\right) \\ &= \frac{1}{n} \sum_{i=1}^n E(X_i) = \mu \end{aligned}$$

Bias

$$\text{Bias}(\overline{X}) = E(\overline{X}) - \mu = \mu - \mu = 0$$

Sample mean is unbiased estimator for distribution mean

Sample Mean - Variance

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

$$= \frac{1}{n^2} V\left(\sum_{i=1}^n X_i\right)$$

$$\stackrel{\textcircled{II}}{=} \frac{1}{n^2} \sum_{i=1}^n V(X_i)$$

$$= \frac{1}{n^2} \sum_{i=1}^n \sigma^2$$

$$= \frac{\sigma^2}{n}$$

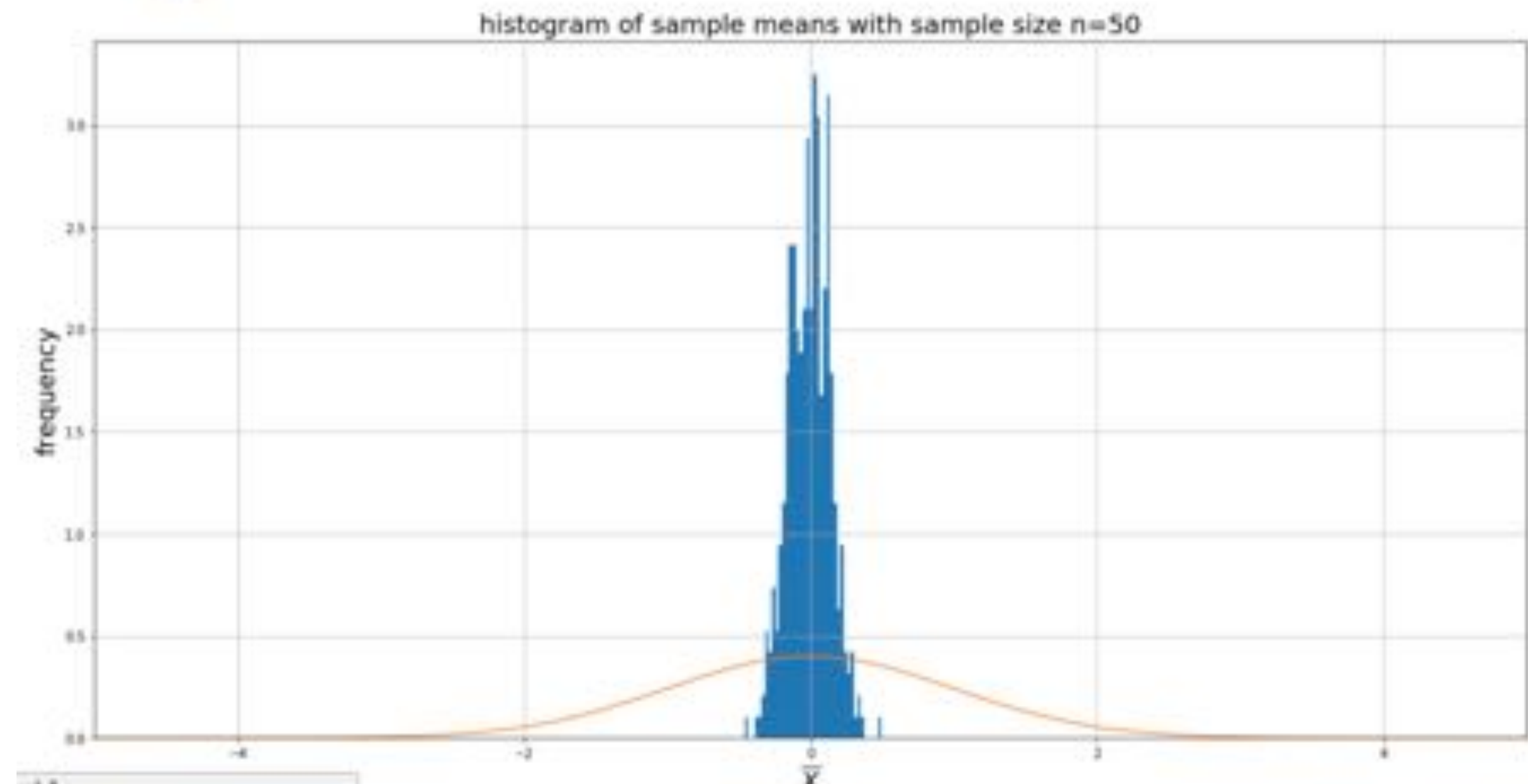
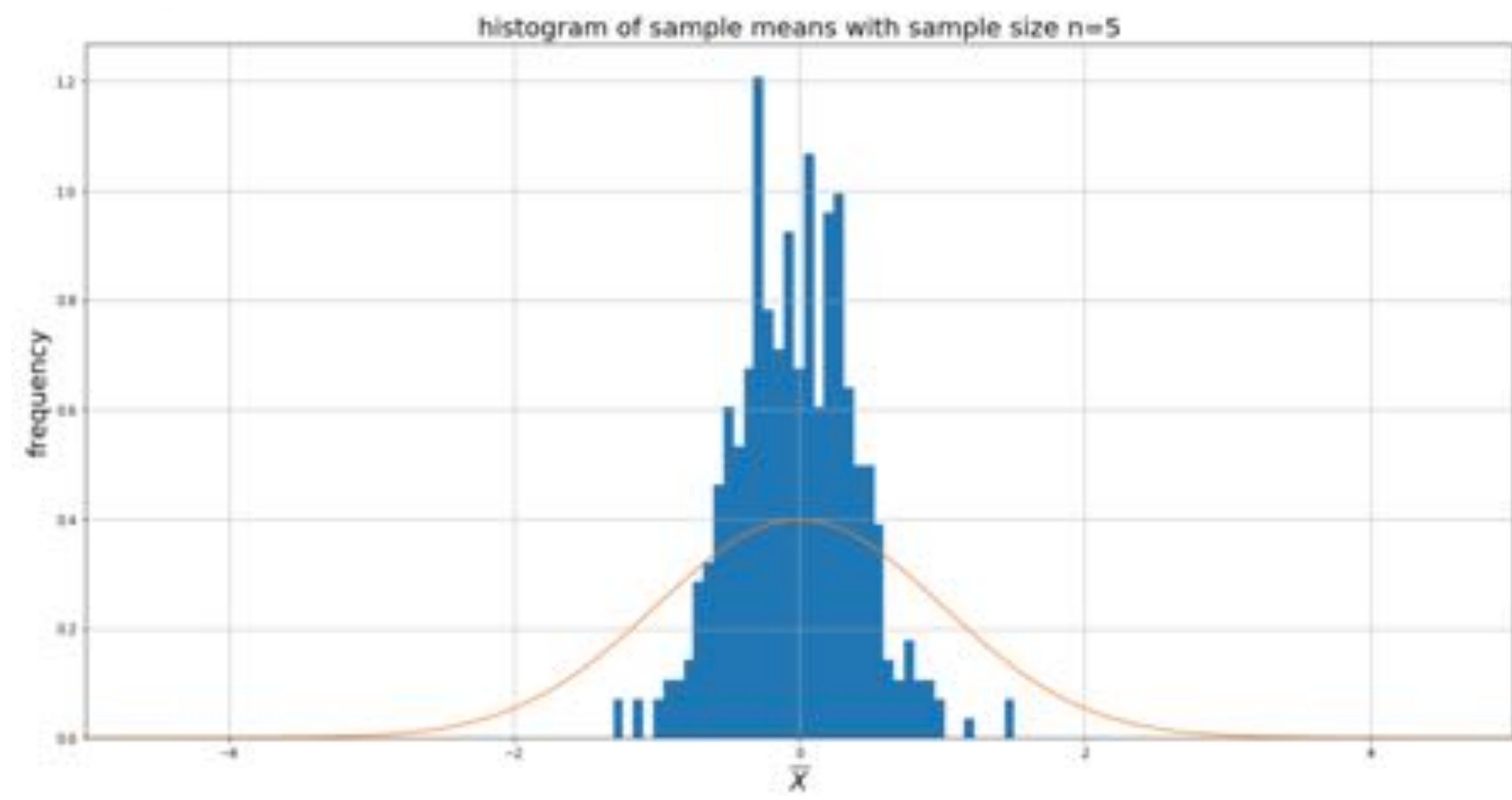
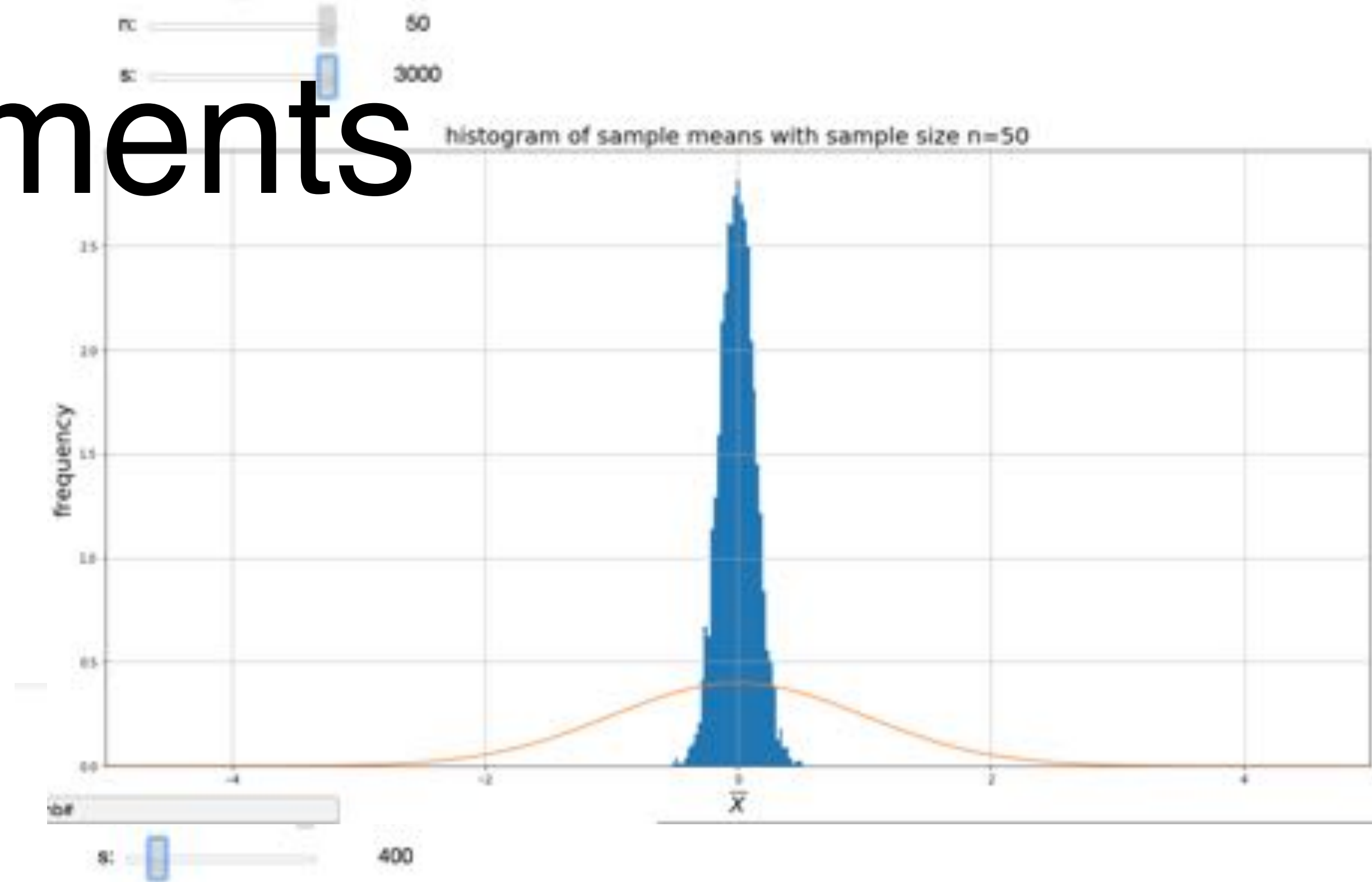
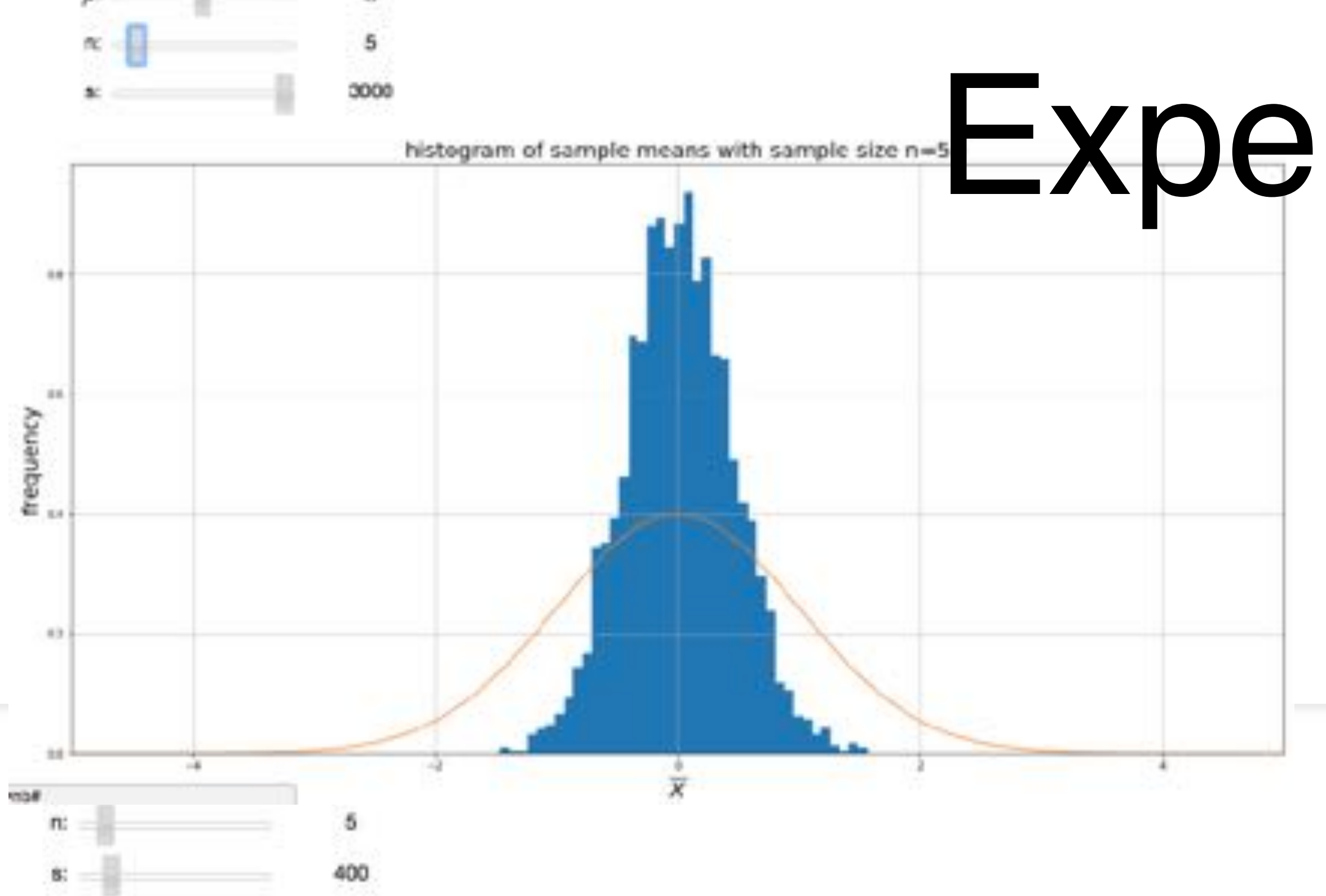
$$\sigma_{\bar{X}} = \frac{\sigma}{\sqrt{n}}$$

Will return

Increases with σ

Decreases with n

Experiments



Mean Squared Error

Single measure for performance of estimator $\hat{\Theta}$ for θ

MSE of $\hat{\Theta}$ is its expected squared distance from θ

$$\text{MSE}_{\theta}(\hat{\Theta}) \stackrel{\text{def}}{=} E(\hat{\Theta} - \theta)^2 \rightarrow \text{MSE}(\hat{\Theta})$$

Common in science and engineering

Communication

Transportation

Production

Need to re-evaluate?

Relate to bias and variance

Bias-Variance Bromance

$$\text{MSE} = \text{Bias}^2 + \text{Variance}$$

$$E(X^2) = E^2(X) + V(X)$$

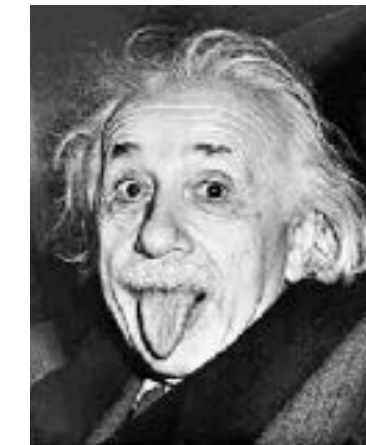
$$\text{MSE}(\Theta) = E(\Theta - \theta)^2$$

$$= E^2(\Theta - \theta) + V(\Theta - \theta)$$

$$E(\Theta - \theta) \stackrel{\text{def}}{=} \text{Bias}(\Theta)$$

$$V(\Theta - \theta) = V(\Theta)$$

$$= \text{Bias}^2(\Theta) + V(\Theta)$$



$$\text{Energy} = \mu^2 + \sigma^2$$

MSE of Sample Mean

$$\text{MSE}_{\mu}(\bar{X}) = \text{Bias}_{\mu}^2(\bar{X}) + V(\bar{X}) = \frac{\sigma^2}{n}$$

Increases with σ

Decreases with n

Same estimator works for all distributions

Accuracy (MSE) independent of population size

Parameter Estimation

(+ a Mean Example)

