STAT 135
4. An introduction to inference

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Probability prerequisites (e.g. STAT 134)

Be familiar with common distributions:

$N(\mu, \sigma)$, $Binom(p)$, $Unif(min, max)$, $\Gamma(\alpha, \beta)$ (gamma), etc

And know how to work with their densities and compete their expectations and variances.

E.g. if $X \sim N(\mu, \sigma)$, then

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

And $E(X) = \mu$, $Var(X) = \sigma^2$

Probability prerequisites (e.g. STAT 134)

Other topics you should be familiar with are:

Limiting results such as the **central limit theorem** (CLT), e.g., $\frac{\overline{X} - \mu}{\sigma/\sqrt{n}} \to N(0,1)$

Conditional probabilities, e.g. $P(X = x \mid Y)$

Independence of random variables, e.g. X and Y and independent if:
$F_{X,Y}(x, y) = F_X(x)F_Y(y)$

Probabilistic properties of random variable distributions, e.g., if X has a symmetric dist then $P(|X - a| > b) = P(X - a < -b) + P(X - a > b)$

Calculus prerequisites

Know how to find the value of x that minimizes (or maximizes) a function f(x)

i.e., know how to compete derivatives. E.g.: if

$$f(x) = e^{(x-5)^2}$$

Then to find the value of x that minimizes or maximizes this function, differentiate with respect to x

$$\frac{df(x)}{dx} = 2(x-5)e^{(x-5)^2}$$

Setting to zero and solving for x gives $x = 5$

Linear algebra prerequesits

Know how to:

- Invert a matrix
- Multiply matrices together
- (Compute the expected value and variance of a random matrix)

Parameters and estimates

Parameters and populations

A **population** is the complete set of individuals or entities that we are interested in. We usually only have data on a subset of them.

A **parameter** is any quantifiable feature of a **population**.

Bushfire example

What is the **population**? All animals that were living in the burnt area

What is the **parameter** of interest? The proportion of the animals that were killed by the fires

Photo credit: NYTimes

What is the <u>population</u> and <u>parameter</u> of interest for the following questions:

An insurance company hoping to update its rates has conducted a review of its members' data to determine what the average annual claim amounts are for Male customers aged 18-25.

What is the population? *All male customers aged 18-25*

What is the parameter of interest? The average annual claim amounts

What is the <u>population</u> and <u>parameter</u> of interest for the following questions:

Kaiser is using data collected from their patients to provide an estimate of the proportion of American women who will develop breast cancer over their lifetimes.

What is the population? *All American women*

What is the parameter of interest? *The proportion who will develop breast cancer in their lifetimes*

Common parameters of interest in statistics

In statistics, the most *common* population parameters we are interested in are:

- **Mean**
- **Proportions** (Note: Proportions are essentially averages of binary data)

And since we will often assume a distribution, explicit examples of parameters we're interested in include:

- μ and σ from a $N(\mu, \sigma)$ distribution
- p from a $Binomial(n, p)$ distribution
- Etc

Inference

Inference involves using **data** to compute an **estimate** of a **population parameter** of interest

The “population” should always be defined in the context of where the results will be applied

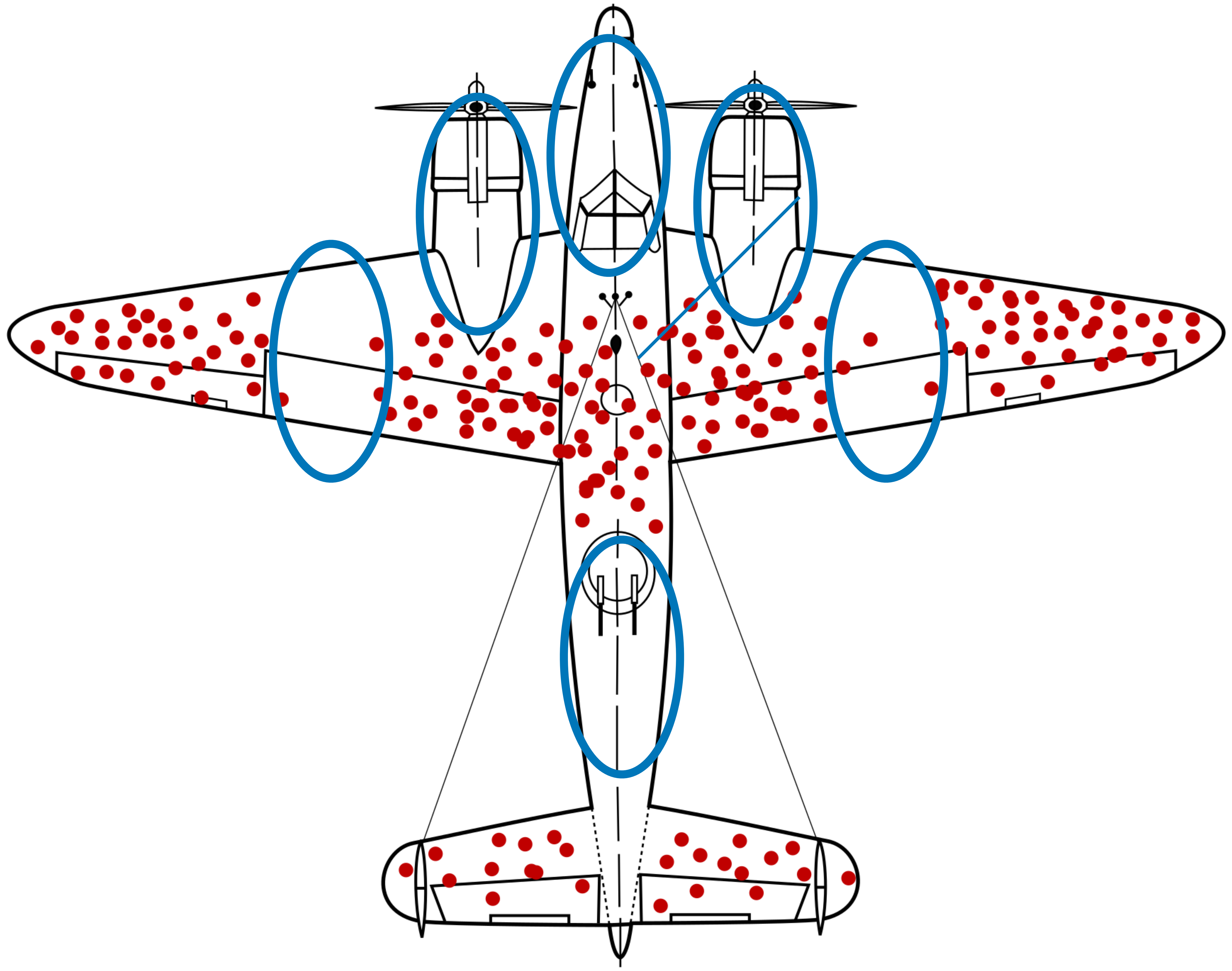
Accurate inference is only possible when the data is representative of the population (i.e., the data is **unbiased**)

Bias in data

Bias in data

Each dot corresponds to a place that a returning plane has been hit

Where should you reinforce the plane’s armor?



If the bullets hit here, the plane goes down and does not return

The data is a **biased** representation of where the planes are getting hit

This is known as “survivorship bias”

Is this a random sample from the “population” of all places that the planes get hit?

Bias in data

Data is biased if it does not reflect the population it was designed to represent

Biased data leads to biased results

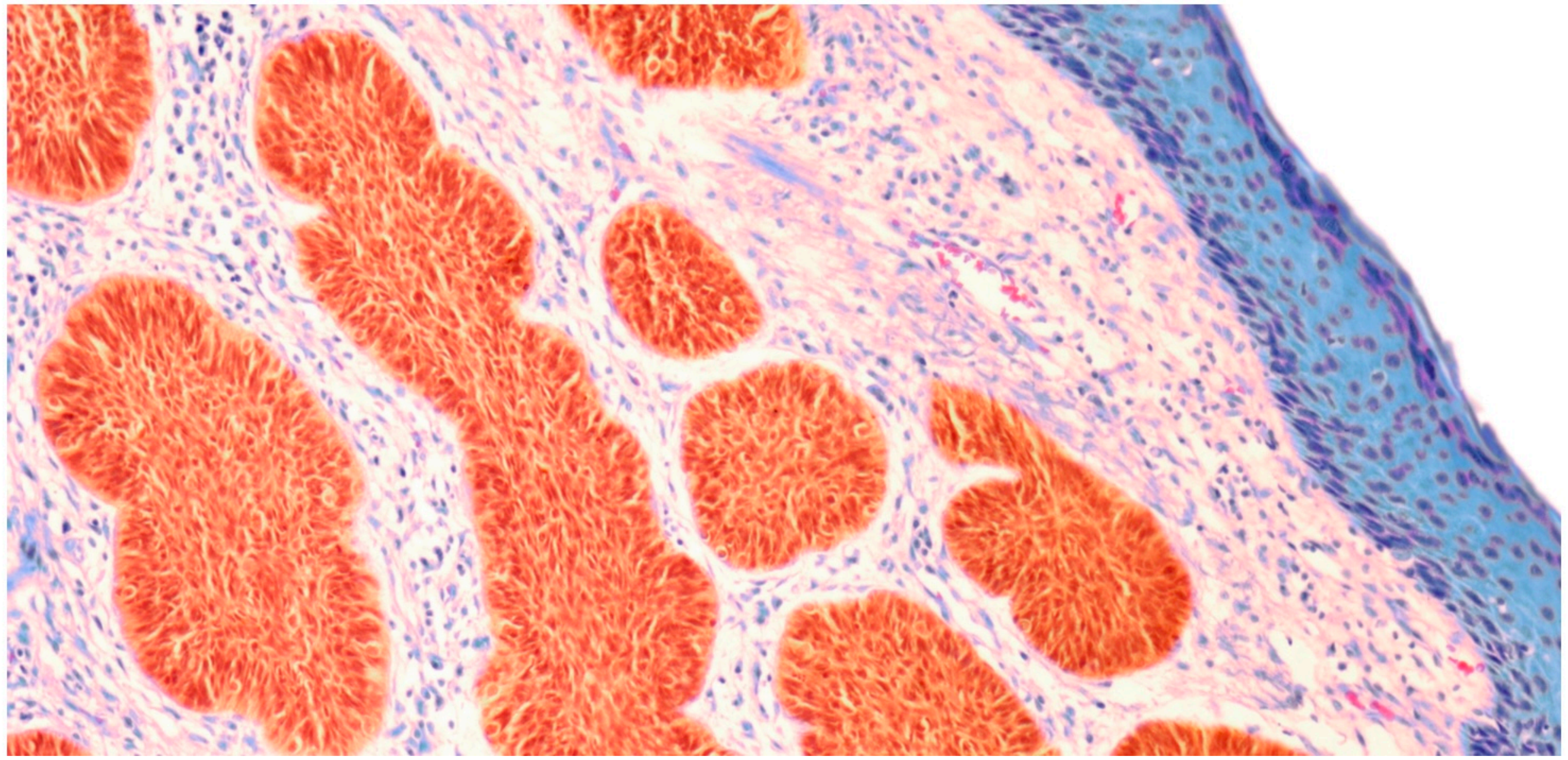
Example: If AI-driven skin cancer detection is built only using patients with light skin tones but is used to detect skin cancer in racially diverse patients, the algorithm might be biased

Popular Latest *The Atlantic* Sign In

AI-Driven Dermatology Could Leave Dark-Skinned Patients Behind

Machine learning has the potential to save thousands of people from skin cancer each year—while putting others at greater risk.

By Angela Lashbrook



https://www.theatlantic.com/health/archive/2018/08/machine-learning-dermatology-skin-color/567619/

Bias in data

Does this example involve biased data?

Population: All American adults
Parameter: Proportion who are worried about climate change
Data: A street-corner survey asking people whether they are worried about climate change

BIASED!

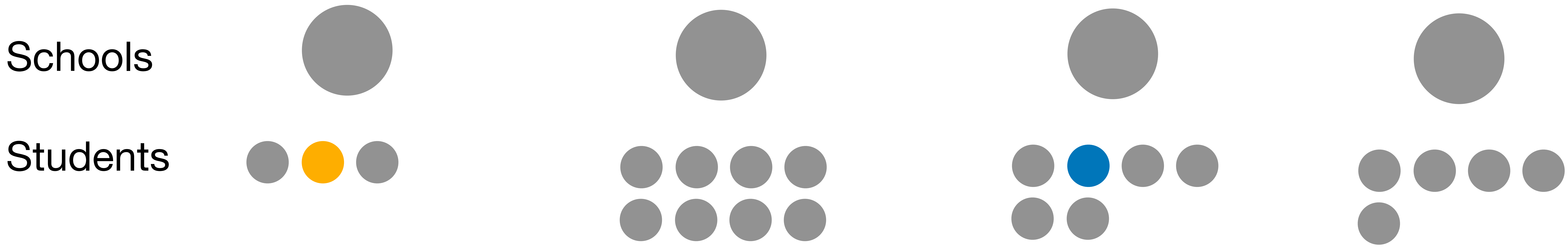
Bias in data

Does this example involve biased data?

Population: Children in the Alameda school district
Parameter: The average commute time from home to school
Data: All children from 10 *randomly selected schools* in Alameda county

UNBIASED!

Bias in data



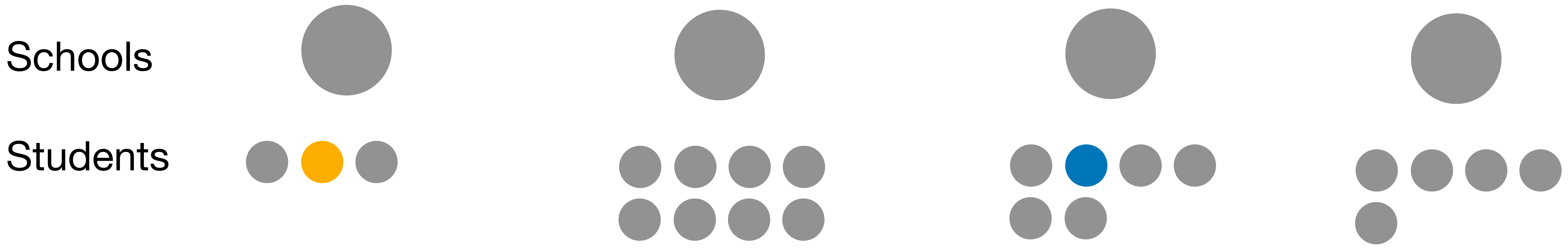
If we **randomly select 2 of the 4 schools** and include ***all* students** from the selected school in our sample

P(orange student selected) = P(orange student's school selected) = $\frac{1}{2} = 0.5$

P(blue student selected) = P(blue student's school selected) = $\frac{1}{2} = 0.5$

The sample of ***all* children** from 2 *randomly selected schools* is an **unbiased** sample of all of the children in these 4 schools

Bias in data



What if we randomly select 2 of the 4 schools **and then select two students at random from each of the selected schools**?

P(orange student selected) = P(orange student's school selected & orange student is selected) $= \frac{1}{2} \times \frac{2}{3} = 0.333$

P(blue student selected) = P(Blue student's school selected & blue student is selected) $= \frac{1}{2} \times \frac{2}{6} = 0.167$

The sample of ***two randomly selected children*** children from each of 2 *randomly selected schools* is a **biased** sample of all the children in these 4 schools, unless all of the schools have the same number of students

Bias in data

Does this example involve biased data?

Population: Everyone enrolled in STAT 135 this semester
Parameter: The proportion of you who prefer zoom class versus in person
Data: Everyone who fills out the following survey

Random sampling

Random samples: a special case of unbiased data

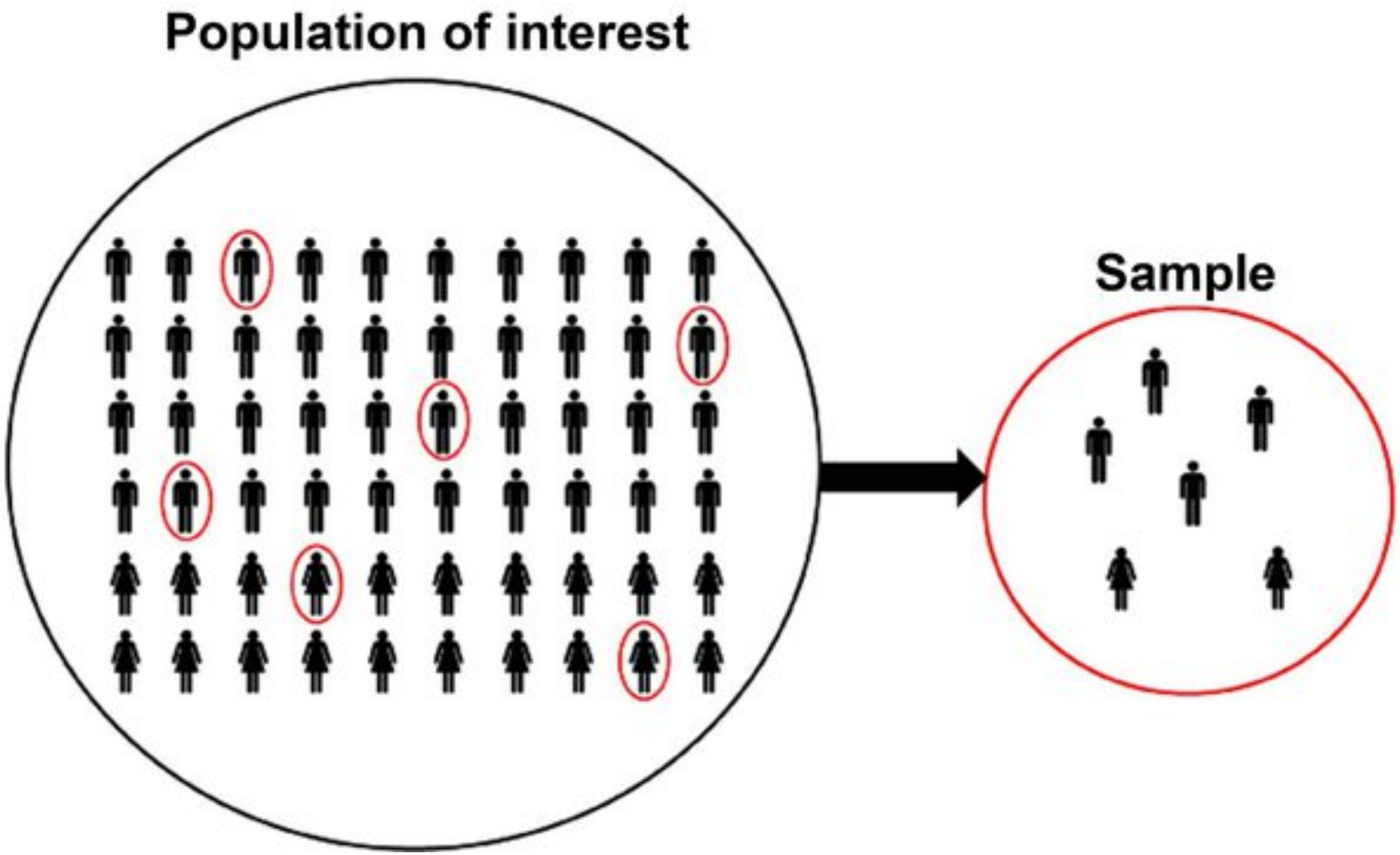


Image stolen from this quora post, which was probably stolen from somewhere else

When a dataset consists of **randomly sampled** observations from the population of interest, it is considered *representative* of that population and is thus **unbiased**.

Under random sampling, everyone in the population has an *equal* chance of being included

Another bias example

Does this example involve biased data?

Population: All Berkeley students enrolled this semester
Parameter: The proportion of Berkeley students who are excited about the upcoming semester
Data: A survey asking a *random sample* of 50 people in this class their excitement level about the upcoming semester

BIASED!

Random variables

Random variables

We use **random variables** to represent all possible values that an unknown quantity could take when we observe it

Population:

X denotes a randomly selected observation from the population

The randomness in X comes from the random sampling process

Observed sample:

6 1 4 9 2 0 1 3

x denotes an observed data point in our sample

Random variables

There are many different possible samples that we *could* have taken.

Population:

? ? ? ? ? ? ? ? ? ? ? ?
? ? ? ? ? ? ? ? ? ? ? ?
? ? ? ? ? ? ? ? ? ? ? ?

$\mu = 3.9$

Observed sample:

7 2 3 8 3 5 4 2

Sample mean: $\bar{x} = 4.6$

Observed sample:

6 1 4 9 2 0 1 3

Sample mean: $\bar{x} = 3.3$

Observed sample:

3 4 4 8 1 7 4 5

Sample mean: $\bar{x} = 4.4$

Random variables

But we usually only ever observe one:

Population:

? ? ? ? ? ? ? ? ? ? ? ?
? ? ? ? ? ? ? ? ? ? ? ?
? ? ? ? ? ? ? ? ? ? ? ?

$\mu = 3.9$

↓

Observed sample:

6 1 4 9 2 0 1 3

Sample mean: $\bar{x} = 3.3$

Where does the randomness come from?

Every random variable has a real-world source of “uncertainty”/ “randomness” that it is supposed to reflect. This could be:

1. The random sampling of the dataset (this is the source of randomness that we will consider in this course)
2. Measurement error
3. …

Whenever you’re working with a random variable, pause to consider where the randomness or “source of uncertainty” came from.

In statistical inference, this randomness is almost always the random sampling.

Random variables

Is the following quantity a random variable?

Population:

? ? ? ? ? ? ? ? ? ? ? ?
? ? ? ? ? ? ? ? ? ? ? ?
? ? ? ? ? ? ? ? ? ? ? ?

Observed sample:

6 1 4 9 2 0 1 3

Sample mean: $\bar{x} = 3.3$

$\boxed{\mu = ?}$

No, the population mean is a **fixed** property of the population

(…Unless we're Bayesians)

Random variables

Is the following quantity a random variable?

No, the underlying population value is not a random variable.

The randomness in the random variable comes from the random sampling

Population:

? ? ? ? ? ? ? ? ? ? ? ?
? ? ? ? ? ? ? ? ? ? ? ?
$\boxed{?}$? ? ? ? ? ? ? ? ? ? ?

$\mu = ?$

Observed sample:

6 1 4 9 2 0 1 3

Sample mean: $\bar{x} = 3.3$

Random variables

Is the following quantity a random variable?

Population:

? ? ? ? ? ? ? ? ? ? ? ?
? ? ? ? ? ? ? ? ? ? ? ?
? ? ? ? ? ? ? ? ? ? ? ?

$\mu = ?$

Observed sample:

$\boxed{6}$ 1 4 9 2 0 1 3

Sample mean: $\bar{x} = 3.3$

X

No, an observed data point in our sample is a fixed number

But… the **hypothetical version** of this sampled data point (i.e. before we look at it) ***is* a random variable**

Random variables

Is the following quantity a random variable?

Population:

? ? ? ? ? ? ? ? ? ? ? ?
? ? ? ? ? ? ? ? ? ? ? ?
? ? ? ? ? ? ? ? ? ? ? ?

$\mu = ?$

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

Observed sample:

6 1 4 9 2 0 1 3

Sample mean: $\boxed{\bar{x}} = 3.3$

No, the sample mean of our observed sample is a **fixed** number

But… the **sample mean *based on the random variables* is a random variable**

Independent and identically distributed data

Independent and Identically Distributed (IID) is essentially equivalent to random sampling

IID means that every unit in the population is essentially equivalent and that drawing one into the sample says nothing about how likely the others are to be drawn into the sample

Population:

? ? ? ? ? ? ? ? ? ? ? ?
? ? ? ? ? ? ? ? ? ? ? ?
? ? ? ? ? ? ? ? ? ? ? ?

$\mu = ?$

$$X$$

The expected value of IID random variables is equal to the population mean:

$$E(X) = \mu$$

Estimating parameters

The sample mean as an estimate of the population mean

Population:

? ? ? ? ? ? ? ? ? ? ? ?
? ? ? ? ? ? ? ? ? ? ? ?
? ? ? ? ? ? ? ? ? ? ? ?

$\mu = ?$

Observed sample:

6 1 4 9 2 0 1 3

Sample mean: $\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$ = 3.3

The sample mean is a common estimate of the population mean

But how **good** is the sample mean as an estimate of the population mean?

Evaluating parameter estimates

Two common metrics of parameter estimate performance:

Bias

How close is the sample mean to the population mean?

Variance

How much would the sample mean differ if we had collected a slightly different sample?

Theoretical evaluations of parameter estimates:

1. **Bias**

Parameter bias

A parameter estimate is biased if it is inherently not capturing the unknown population parameter that it is supposed to represent

The **bias** of an estimate, $\hat{\theta}$, of population parameter, θ, is:

$$Bias(\hat{\theta}) = E(\hat{\theta}) - \theta$$

A parameter estimate is **unbiased** if the bias is equal to 0.

Notation:

- θ is the population parameter
- $\hat{\theta}$ is an estimate of the population parameter from the data

The sample mean is an unbiased estimate of the population mean

Theorem: when the observations in a sample *are IID from a population with mean* μ, the sample mean, $\hat{\mu} = \frac{1}{n}\sum_{i=1}^{n} X_i$, is an unbiased estimate of μ.

Proof:

$$E(\hat{\mu}) = E\left(\frac{1}{n}\sum_{i=1}^{n} X_i\right) = \frac{1}{n}\sum_{i=1}^{n} E(X_i)$$

$$= \frac{1}{n} n\mu$$

$$= \mu$$

Parameter bias

True or False: a parameter estimate from a sample is biased if it is *not* equal to the underlying population quantity it is supposed to represent?

False. Even if the parameter estimate is unbiased, there is no guarantee that the parameter computed from a specific sample of data points will be **exactly** equal to the underlying population parameter

? ? ? ? ? ? ? ? ? ? ? ?
? ? ? ? ? ? ? ? ? ? ? ?
? ? ? ? ? ? ? ? ? ? ? ?

$\mu = 3.9$

Random sample

9 6 2 9 3 5 1 2

$\bar{x} = 4.6$

Unbiasedness is referring to the Expected value of the estimate, not the sample estimate itself

The sample standard deviation is a *biased* for the population standard deviation

Theorem: when the observations in a sample are IID from a distribution with mean μ and standard deviation, σ:
The sample standard deviation, $\hat{\sigma} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_i - \bar{X})^2}$, is a *biased* estimate of σ.

Proof: Homework 1

You will show that the "sample-size adjusted" sample variance estimate is unbiased for the population variance

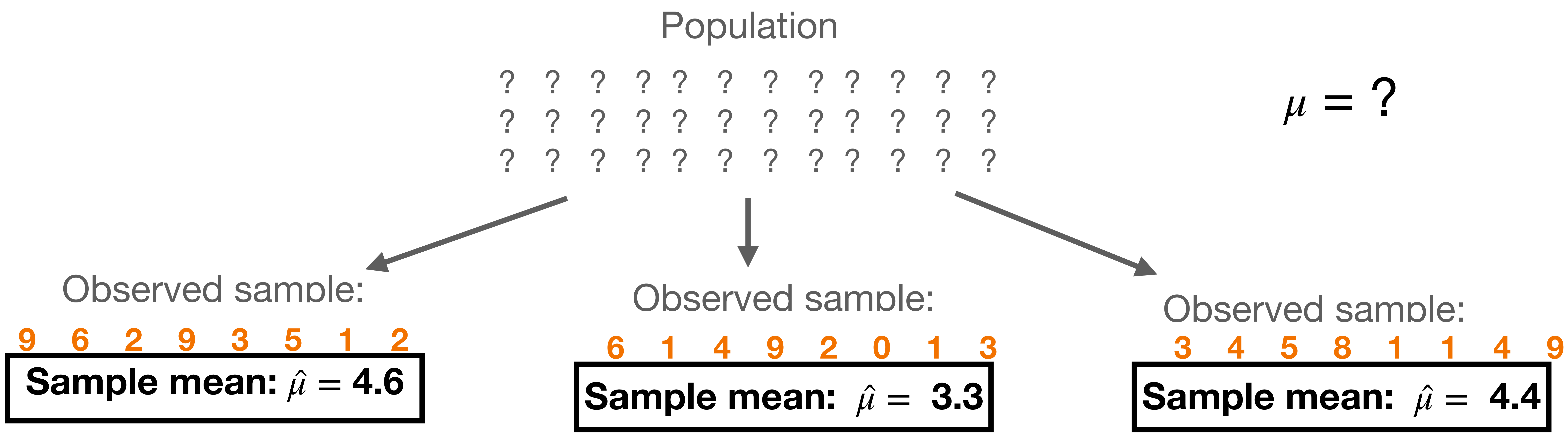
$$E\left[\frac{1}{\boldsymbol{n-1}}\sum_{i=1}^{n}(X_i - \bar{X})^2\right] = \sigma^2$$

Theoretical evaluations of parameter estimates:

1. Bias
2. **Variance**

Parameter variance

The **variance** of a parameter estimate tells you how much it generally changes across alternative equivalent versions of the data



The **variance** of an estimate, $\hat{\theta}$, of population parameter, θ, is:

$$Var(\hat{\theta}) = E\left[\left(\hat{\theta} - E[\hat{\theta}]\right)^2\right] = E\left[\hat{\theta}^2\right] - E[\hat{\theta}]^2$$

The variance of the sample mean

Theorem: when the observations in a sample are IID from a population with mean μ and standard deviation σ, the sample mean, $\hat{\mu} = \frac{1}{n}\sum_{i=1}^{n} X_i$, has variance $\frac{\sigma^2}{n}$

Proof: $$Var(\hat{\mu}) = Var\left(\frac{1}{n}\sum_{i=1}^{n} X_i\right) = \frac{1}{n^2}\sum_{i=1}^{n} Var(X_i)$$ *(Since the X_is are IID)*

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

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

This means that the variance *decreases* as the sample size increases

Theoretical evaluations of parameter estimates:

1. Bias
2. Variance
3. **MSE**

Mean Squared Error

The Mean Squared Error (MSE) is a measure of how "good" an estimate $\hat{\theta}$ is. The MSE is equal to:

$$MSE(\hat{\theta}) = E\left[(\hat{\theta} - \theta)^2\right]$$

Mean Squared Error

Theorem: The Mean Squared Error (MSE) can be decomposed into the sum of the squared bias and the variance of $\hat{\theta}$:

$$MSE(\hat{\theta}) = Bias(\hat{\theta})^2 + Var(\hat{\theta})$$

Proof: $MSE(\hat{\theta}) = E\left[(\hat{\theta} - \theta)^2\right] = E\left[(\hat{\theta}^2 - 2\hat{\theta}\theta + \theta^2)\right]$

$= E[\hat{\theta}^2] - 2\theta E[\hat{\theta}] + \theta^2$ (Since θ is not a random variable, $E[\theta] = \theta$)

$= Var(\hat{\theta}) + E[\hat{\theta}]^2 - 2\theta E[\hat{\theta}] + \theta^2$ (Since $Var(\hat{\theta}) = E[\hat{\theta}^2] - E[\hat{\theta}]^2$)

$= Var(\hat{\theta}) + \left(E[\hat{\theta}] - \theta\right)^2$

$= Var(\hat{\theta}) + Bias(\hat{\theta})^2$

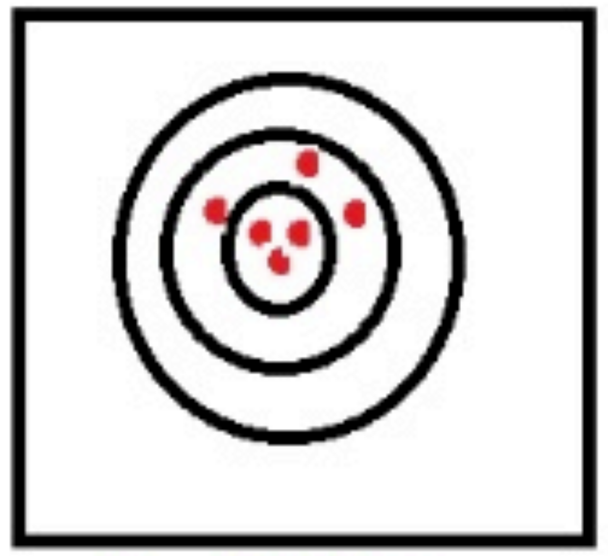
Note that this is true for all general parameter estimates $\hat{\theta}$

The bias-variance tradeoff

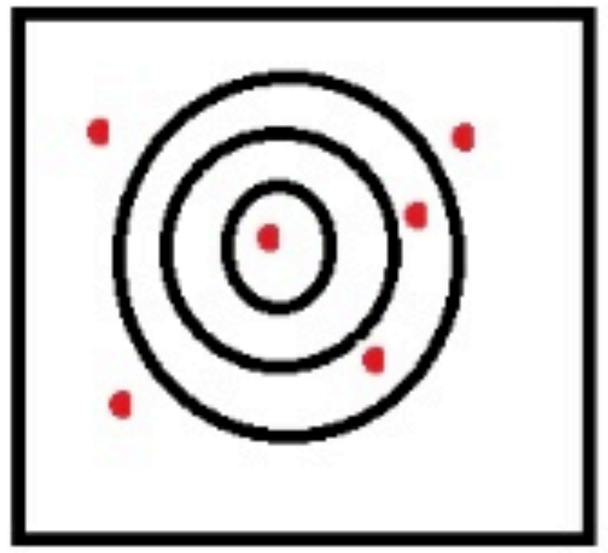
The bias-variance tradeoff

In general:

- Low variance (good) corresponds to high bias (bad)
- Low bias (good) corresponds to high variance (bad)

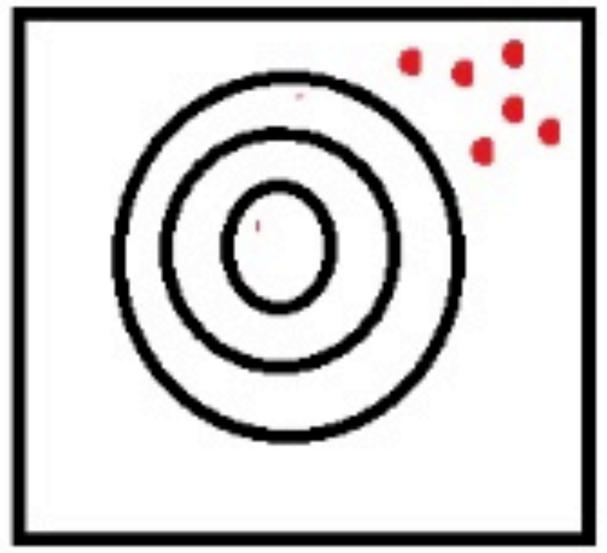


Small Variance -
Small Bias



Large Variance -
Small Bias

Small Variance -
Large Bias



Small Variance -
Huge Bias

More Bias, Variance, and MSE examples

Binomial example

If $X_1, ..., X_n$ are an IID sample from a $Binomial(n, p)$ distribution, and we decide estimate p using $\hat{p} = \dfrac{\bar{X}}{n}$

What is the **bias** of $\hat{p}$?

$$\begin{aligned} Bias(\hat{p}) &= E(\hat{p}) - p \\ &= E\left[\overline{X}/n\right] - p \\ &= \frac{1}{n}E\left[\frac{1}{n}\sum_{i=1}^{n} X_i\right] - p \\ &= \frac{1}{n^2}\sum_{i=1}^{n} E(X_i) - p = \frac{n}{n^2}np - p = 0 \end{aligned}$$

Binomial example

If $X_1, \ldots, X_n$ are an IID sample from a $Binomial(n, p)$ distribution, and

we decide estimate p using $\hat{p} = \dfrac{\bar{X}}{n}$

What is the **variance** of $\hat{p}$?

$$Var(\hat{p}) = E(\hat{p}^2) - E(\hat{p})^2 = E\left[\overline{X}^2/n^2\right] - E(\overline{X}/n)^2$$

$$= \frac{1}{n^2}E(\overline{X}^2) - \frac{1}{n^2}E(\overline{X})^2$$

$$= \frac{1}{n^2}[Var(\overline{X}) + E(\overline{X})^2] - \frac{(np)^2}{n^2}$$

$$= \frac{1}{n^2}[np(1-p) + (np)^2] - p^2$$

$$= \frac{1}{n^2}[np - np^2 + (np)^2] - p^2$$

$$= \frac{1}{n}[p - p^2] + p^2 - p^2$$

$$= \frac{1}{n}[p - p^2]$$

$$= \frac{p(1-p)}{n} \quad \to 0 \text{ as } n \to \infty$$

Recall:
$E(X_i) = E(\overline{X}) = np,$
$Var(X_i) = np(1-p),$

The problem…

There's a catch:

How can we compute the **bias of the estimator** when we don't know the value of the true parameter estimate?

$$Bias(\hat{\theta}) = E(\hat{\theta}) - \theta$$

We don't know what this is equal to

How can we compute the **Variance of the (mean) estimator** when we don't know the value of the population standard deviation?

$$Var(\hat{\mu}) = \frac{\sigma^2}{n}$$

We don't know what this is equal to

Techniques for estimating bias, variance, and MSE from a single data sample:

1. Non-parametric bootstrap

Non-parametric bootstrap

Note that we are focusing on the mean parameter, but this could be any parameter of interest

Suppose our data corresponds to a random sample

While we usually *can't* draw another sample from the **original population**…

We *can* draw samples from our ***sample***

Since we want our "new" samples to be the same size as our original sample, we must sample ***with replacement***

A sample with replacement is considered a representative sample from the population*

Population:

? ? ? ? ? ? ? ? ? ? ? ?
? ? ? ? ? ? ? ? ? ? ? ?
? ? ? ? ? ? ? ? ? ? ? ?

$\mu = ?$

Observed sample: (Sample mean: $\hat{\mu} = 3.3$)

6 1 4 9 2 0 1 3

6 6 4 2 2 0 1 3
Bootstrap sample mean:
$\hat{\mu}_1^* = 3$

1 1 4 4 9 0 0 1
Bootstrap sample mean:
$\hat{\mu}_2^* = 2.5$

6 1 9 9 2 1 1 3
Bootstrap sample mean:
$\hat{\mu}_3^* = 4$

*Assuming the original sample is representative of the population

Estimating <u>bias</u> of an estimator using non-parametric bootstrap

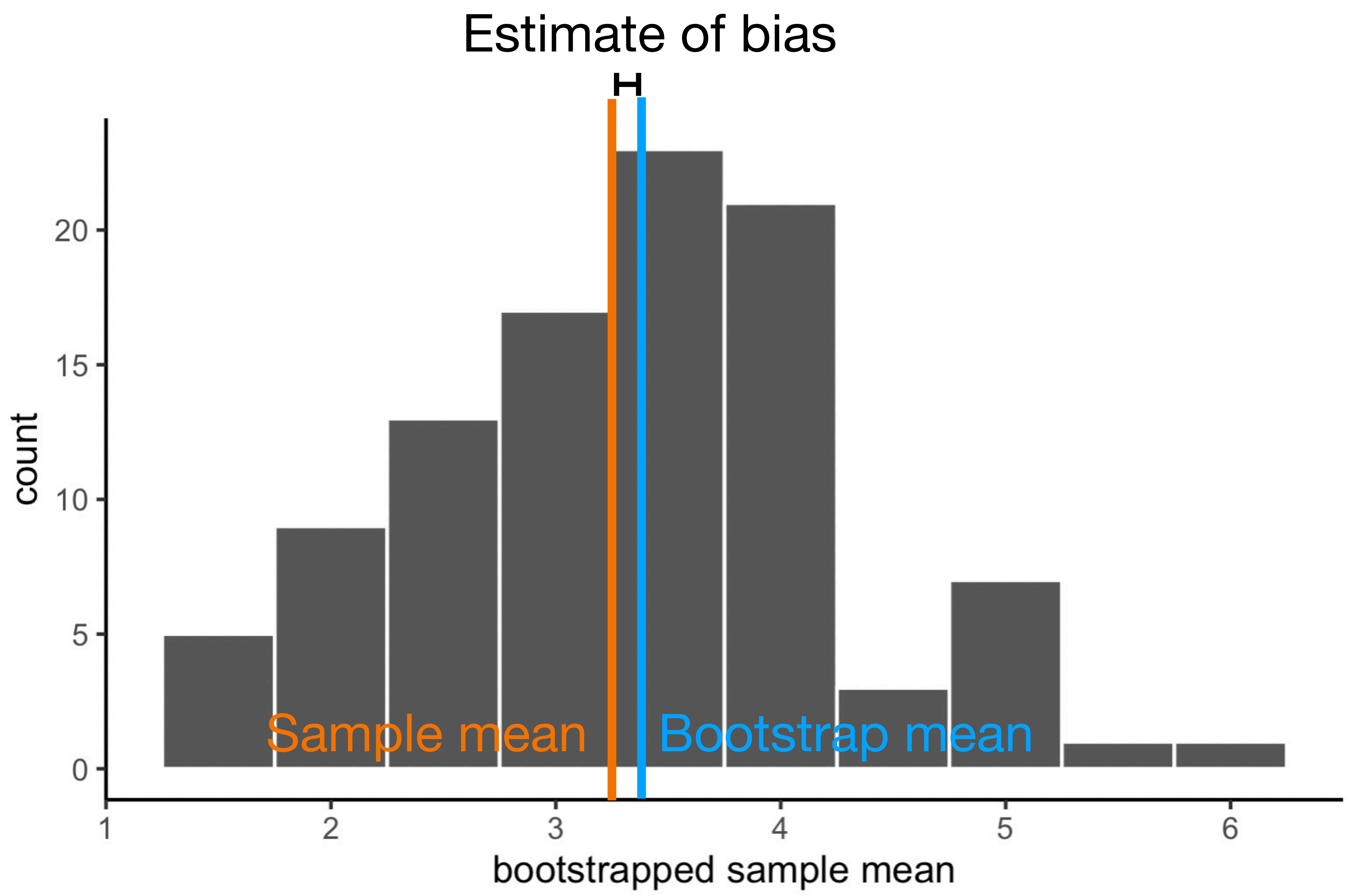
Observed sample:

6 1 4 9 2 0 1 3

6 6 4 2 2 0 1 3
Bootstrap sample mean:
$\hat{\mu}_1^* = 3$

1 1 4 4 9 0 0 1
Bootstrap sample mean:
$\hat{\mu}_2^* = 2.5$

6 1 9 9 2 1 1 3
Bootstrap sample mean:
$\hat{\mu}_3^* = 4$



Idea:

- treat the original sample as the population
- treat the bootstrapped sample as the sample

Use these to estimate the bias

NP Bootstrap bias estimate:

$$Bias(\hat{\mu}) \approx \frac{1}{N}\sum_{k=1}^{N} \hat{\mu}_k^* - \hat{\mu}$$

See bootstrap_mean.R for code for this example

Estimating <u>variance</u> of an estimator using non-parametric bootstrap

Observed sample:

6 1 4 9 2 0 1 3

6 6 4 2 2 0 1 3
Bootstrap sample mean:
$\hat{\mu}^*_1 = 3$

1 1 4 4 9 0 0 1
Bootstrap sample mean:
$\hat{\mu}^*_2 = 2.5$

6 1 9 9 2 1 1 3
Bootstrap sample mean:
$\hat{\mu}^*_3 = 4$

NP Bootstrap variance estimate:

$$Var(\hat{\mu}) \approx = \frac{1}{N}\sum_{k=1}^{N}(\hat{\mu}^*_k - \overline{\hat{\mu}^*})^2$$

Idea:

- treat the sample as the population
- treat the bootstrapped sample as the sample

Use these to estimate the bias

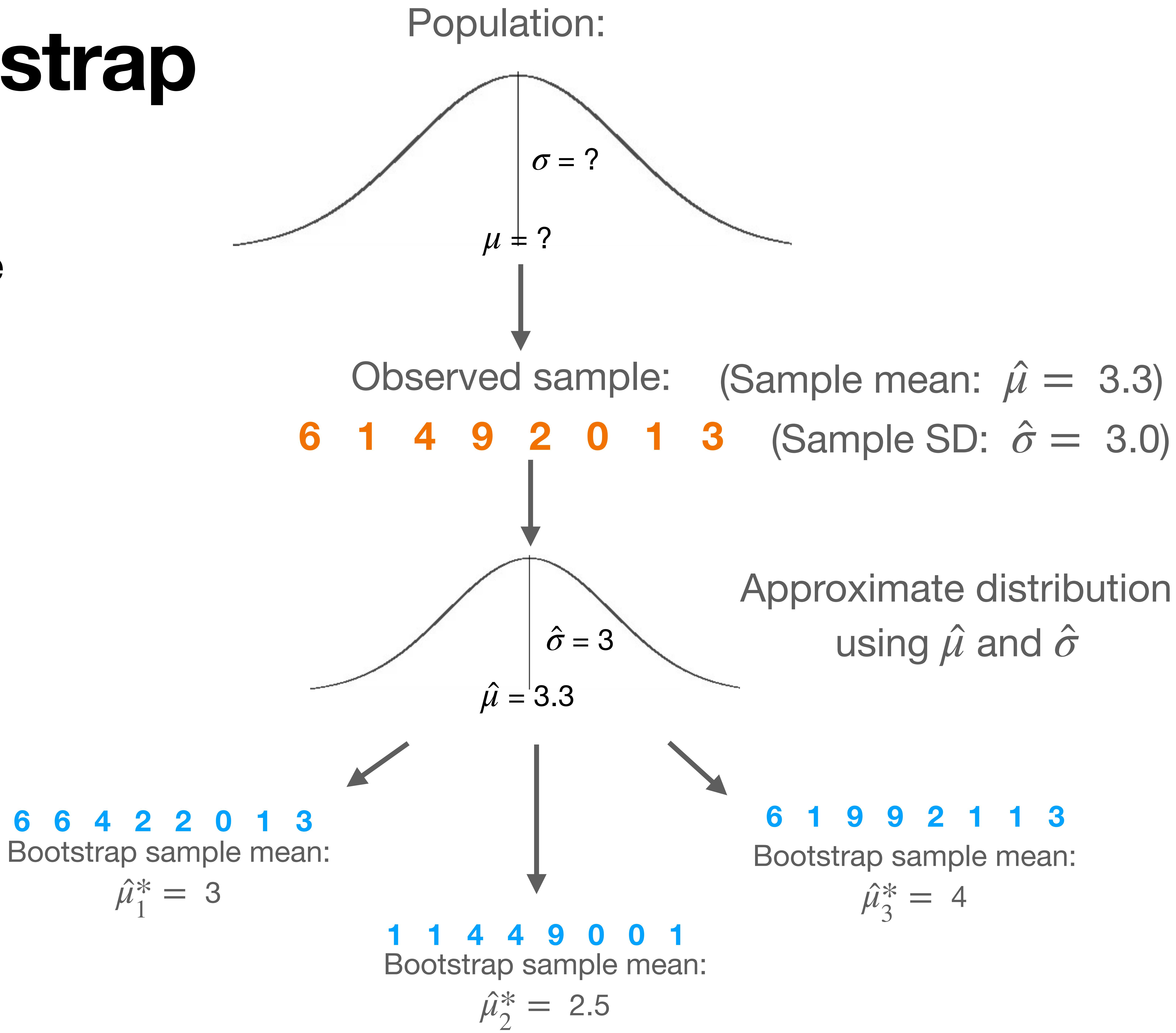
Techniques for estimating bias, variance, and MSE from a single data sample:

1. Non-parametric bootstrap
2. Parametric bootstrap

Parametric bootstrap

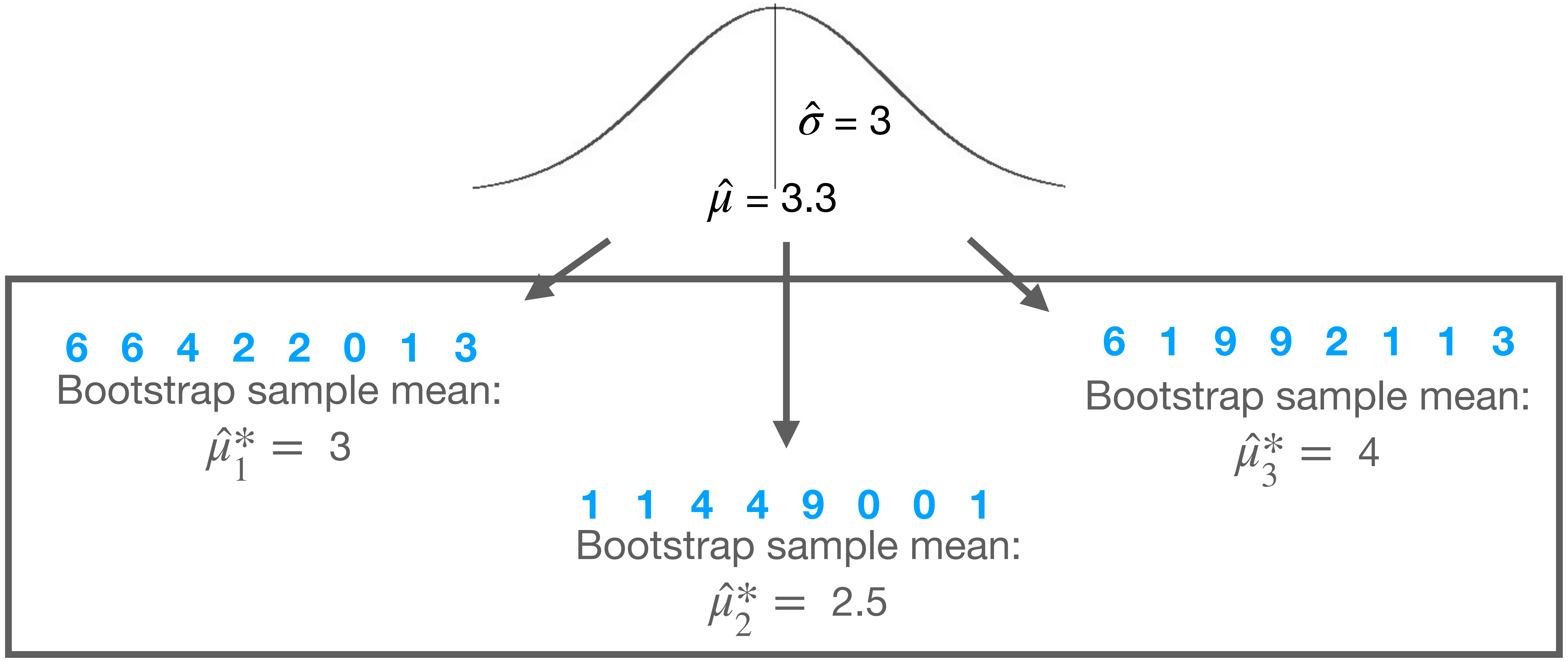
If you know that your data came from a particular distribution, e.g., a normal distribution

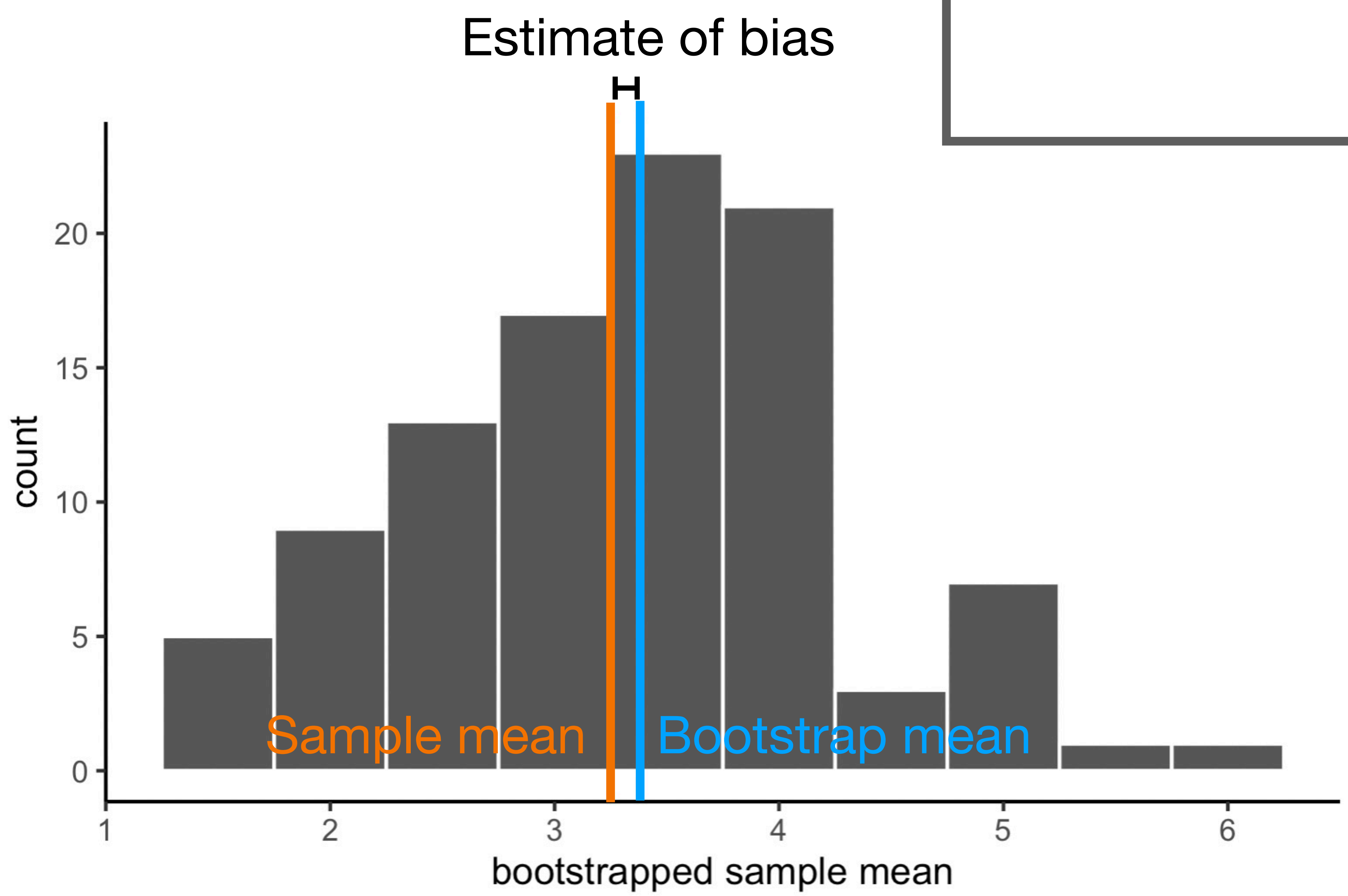
Then use the distribution with the estimated parameters to *draw* many "parametric bootstrap" samples



Estimating <u>bias</u> of an estimator using parametric bootstrap

Once you have the bootstrap parameter estimates, estimating the bias and variance is then the same as in the non-parametric bootstrap case





Parametric bootstrap bias estimate:

$$Bias(\hat{\mu}) \approx \frac{1}{N}\sum_{k=1}^{N} \hat{\mu}_k^* - \hat{\mu}$$

See bootstrap_mean.R for code for this example

Asymptotic properties of the sample mean

The Central Limit Theorem (CLT)

Theorem: if $X_1, X_2, \ldots, X_n$ is an IID sample from a population with mean μ and standard deviation σ, then:

$$\overline{X} = \frac{1}{n}\sum_{i=1}^{n} X_i \to N\left(\mu, \frac{\sigma^2}{n}\right), \quad \text{as } n \to \infty$$

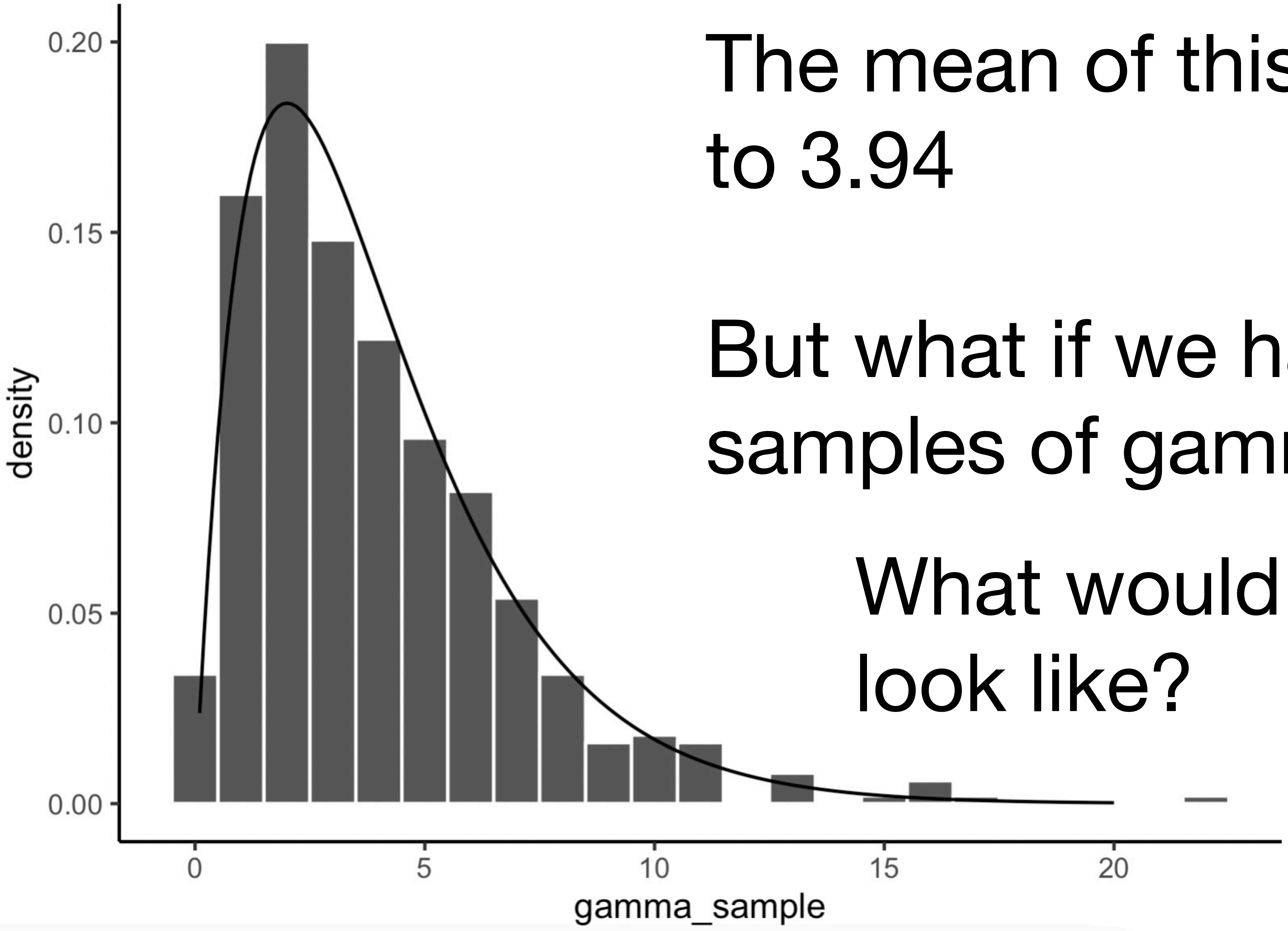
Regardless of the original distribution of the X_i.
("as the sample size increases, the sample mean behaves as if it is from a Normal distribution with mean μ and standard deviation $\frac{\sigma}{\sqrt{n}}$)

Note: We had already shown that $E(\bar{X}) = \mu$ and $Var(\bar{X}) = \dfrac{\sigma^2}{n}$, but the CLT also says that the *distribution* of $\overline{X}$ is *Normal* when the sample size is large enough

Empirical CLT example

If $X_1, X_2, \ldots, X_n$ correspond to an IID sample from a *Gamma*($\alpha =$ *2*, $\beta =$ *0.5*) distribution.

The distribution of a *single sample* of size n = 500 looks like:



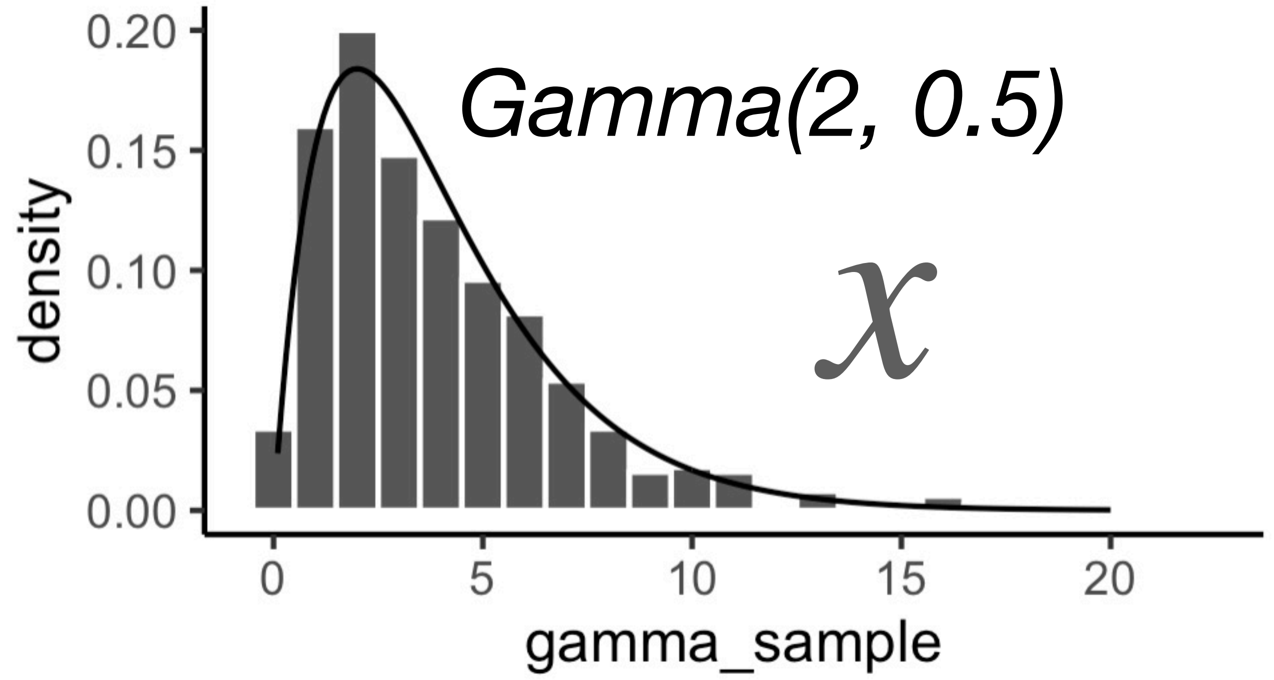
The mean of this sample specific sample is equal to 3.94

But what if we had produced many different samples of gamma-distributed numbers?

What would the distribution of the sample *means* look like?

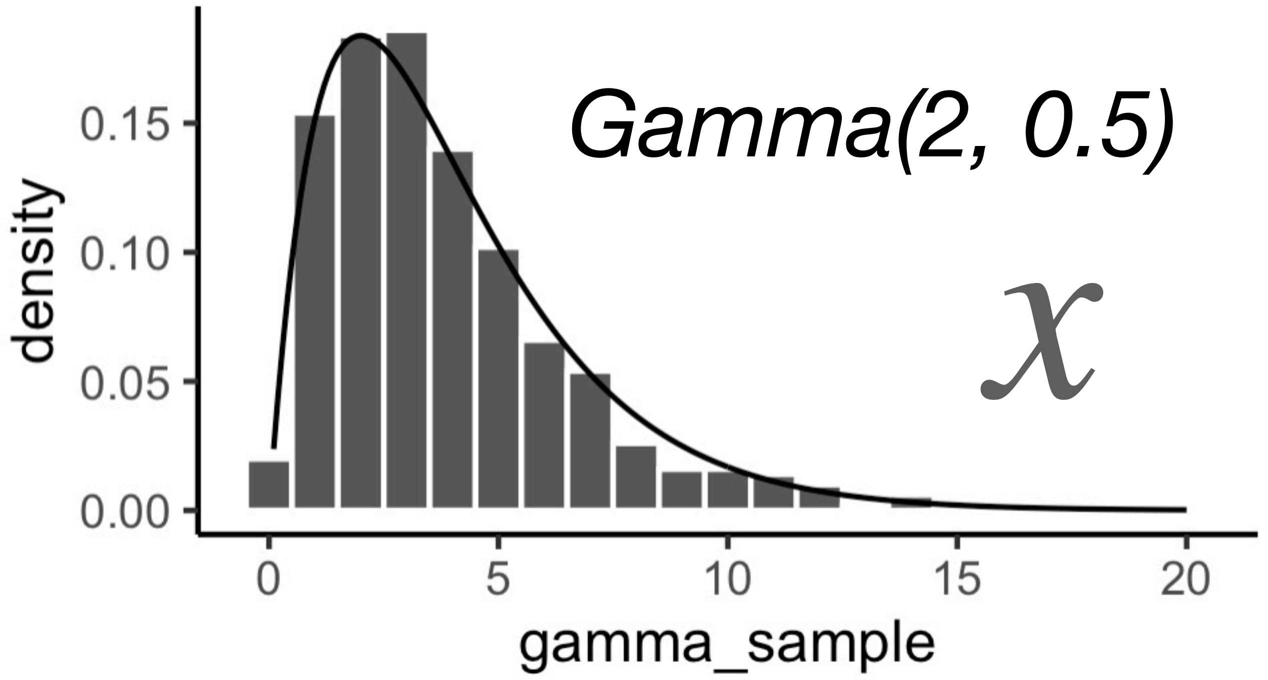
Empirical CLT example

Sample 1



Sample mean: 3.94

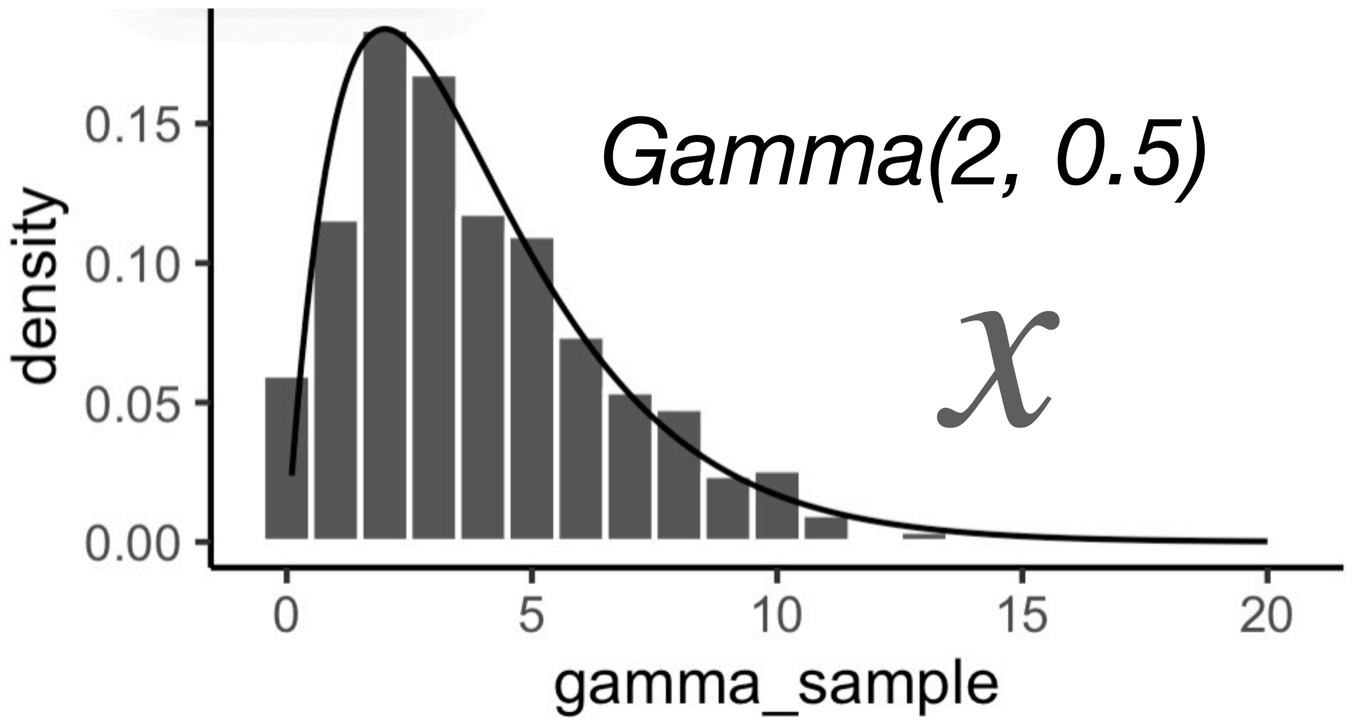
Sample 2



Sample mean: 3.89

…

Sample 1000



Sample mean: 3.92

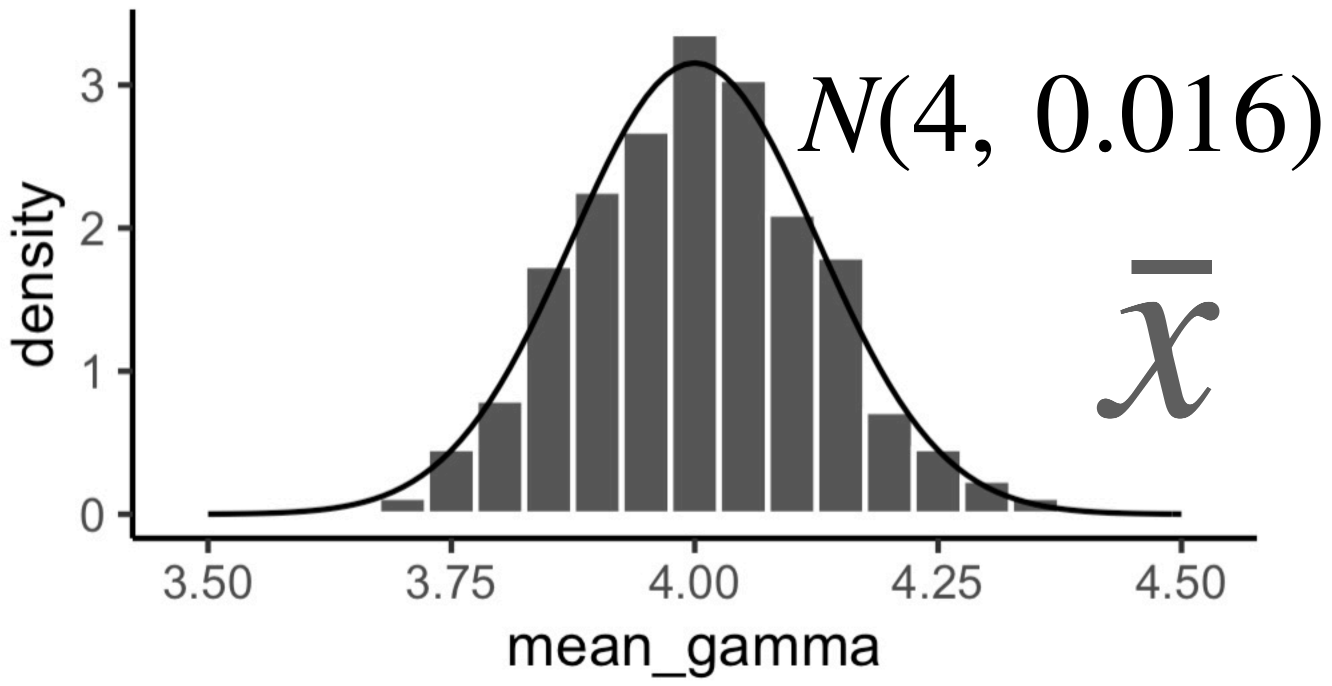
Since:

$\mu = E(X) = \frac{\alpha}{\beta}$, and

$\sigma^2 = Var(X_i) = \frac{\alpha}{\beta^2}$

The CLT implies that:

$$\frac{1}{n}\sum_{i=1}^{n} X_i \to N\left(\frac{\alpha}{\beta}, \frac{\alpha}{n\beta^2}\right), \quad \text{as } n \to \infty$$



Even though the original data itself isn't Normal, the distribution of the sample means is!

See clt.R for code for this example

General useful result for CLT

Corollary: if $X_1, X_2, \ldots, X_n$ is an IID sample from a population with mean μ and standard deviation σ, then if $\overline{X} = \frac{1}{n}\sum_{i=1}^{n} X_i$:

$$\frac{\overline{X} - \mu}{\sigma/\sqrt{n}} = \rightarrow N(0,1), \quad \text{as } n \rightarrow \infty$$

Regardless of the form of the original distribution of the X_i.

General useful result for CLT

Corollary: if $X_1, X_2, \ldots, X_n$ is an IID sample from a population with mean μ and standard deviation σ, then if $\overline{X} = \frac{1}{n}\sum_{i=1}^{n} X_i$:

$$P\left(\frac{\overline{X} - \mu}{\sigma/\sqrt{n}} \leq z\right) \to \Phi(z), \quad \text{as } n \to \infty$$

Where Φ is the CDF of the standard normal distribution

General useful result for CLT

Theorem: if $X_1, X_2, \ldots, X_n$ is an IID sample from a population with mean μ and standard deviation σ, then:

$$P\left(|\bar{X} - \mu| \leq \delta\right) \approx 2\Phi\left(\frac{\sqrt{n}\delta}{\sigma}\right) - 1$$

Regardless of the original distribution of the X_i.

Proof:

$$P(|\bar{X} - \mu| \leq \delta) = P\left(\left|\frac{\bar{X} - \mu}{\sigma/\sqrt{n}}\right| \leq \frac{\delta\sqrt{n}}{\sigma}\right) \overset{Z \sim N(0,1)}{\approx} P\left(|Z| \leq \frac{\delta\sqrt{n}}{\sigma}\right)$$

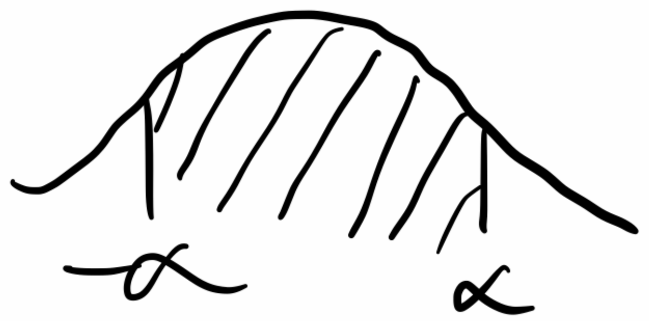
Divide both sides by $\sigma/\sqrt{n}$

$$= 2\Phi\left(\frac{\delta\sqrt{n}}{\sigma}\right) - 1$$

Since
$P(|Z| < \alpha) = 2\Phi(\alpha) - 1$

General useful result for CLT

Visual proof that: $P(|Z| < \alpha) = 2\Phi(\alpha) - 1$

$P(|Z| \leq \alpha) =$ 

$=$ 

$-$ 

$= \Phi(\alpha) - [1 -$ 

$]$

$= \Phi(\alpha) - [1 -$ 

$]$

$= \Phi(\alpha) - [1 - \Phi(\alpha)]$

$= 2\Phi(\alpha) - 1$

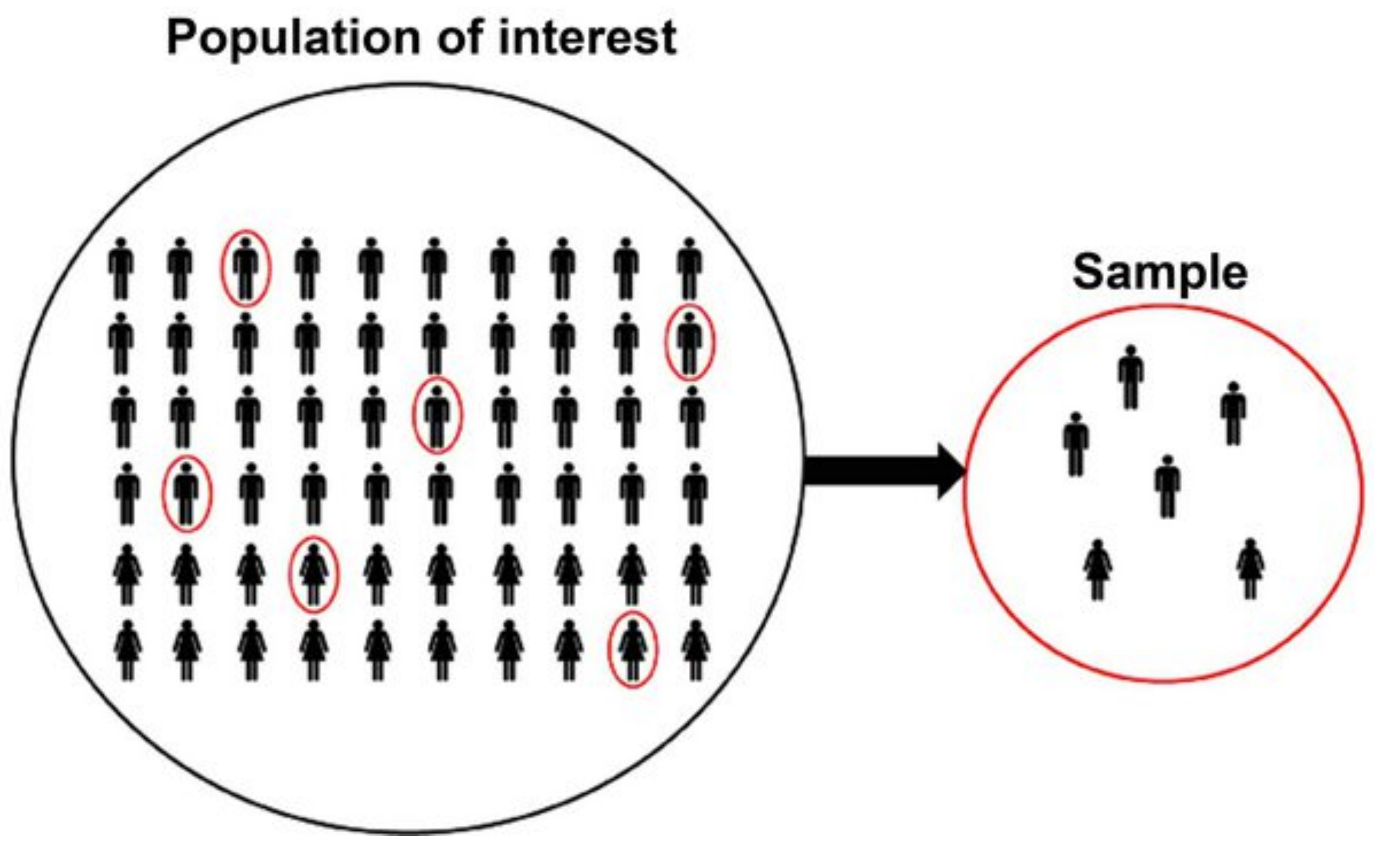
Recap

What we've covered so far

A **parameter** is an unknown feature of a population (such as a mean or proportion).

Data that comes from the population can be used to generate **estimates** of the parameters if the data is ***representative of the population***.

Random samples tend to be representative of the population



Random variables represent the hypothetical versions of the random samples that can be drawn from the population

What we've covered so far

An estimate of a parameter can be assessed in terms of its **bias, variance and MSE**

$$Bias(\hat{\theta}) = E(\hat{\theta}) - \theta$$

$$Var(\hat{\theta}) = E\left[\left(\hat{\theta} - E(\hat{\theta})\right)^2\right] = E(\hat{\theta}^2) - E(\hat{\theta})^2$$

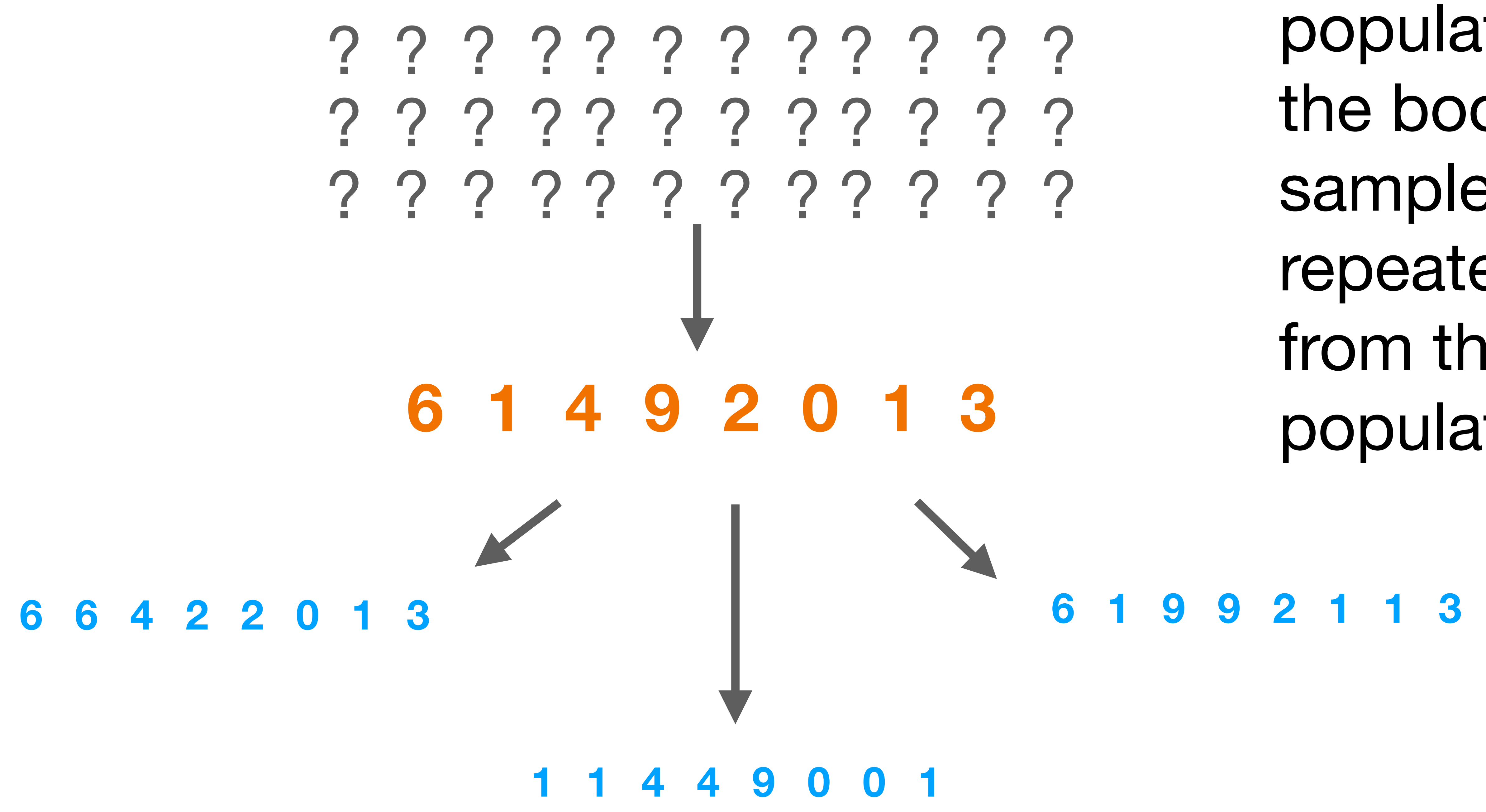
$$MSE(\hat{\theta}) = E\left[\left(\hat{\theta} - \theta\right)^2\right] = Bias(\hat{\theta})^2 + Var(\hat{\theta})$$

But these quantities cannot be estimated from the data alone because they require knowledge of the original population parameters

What we’ve covered so far

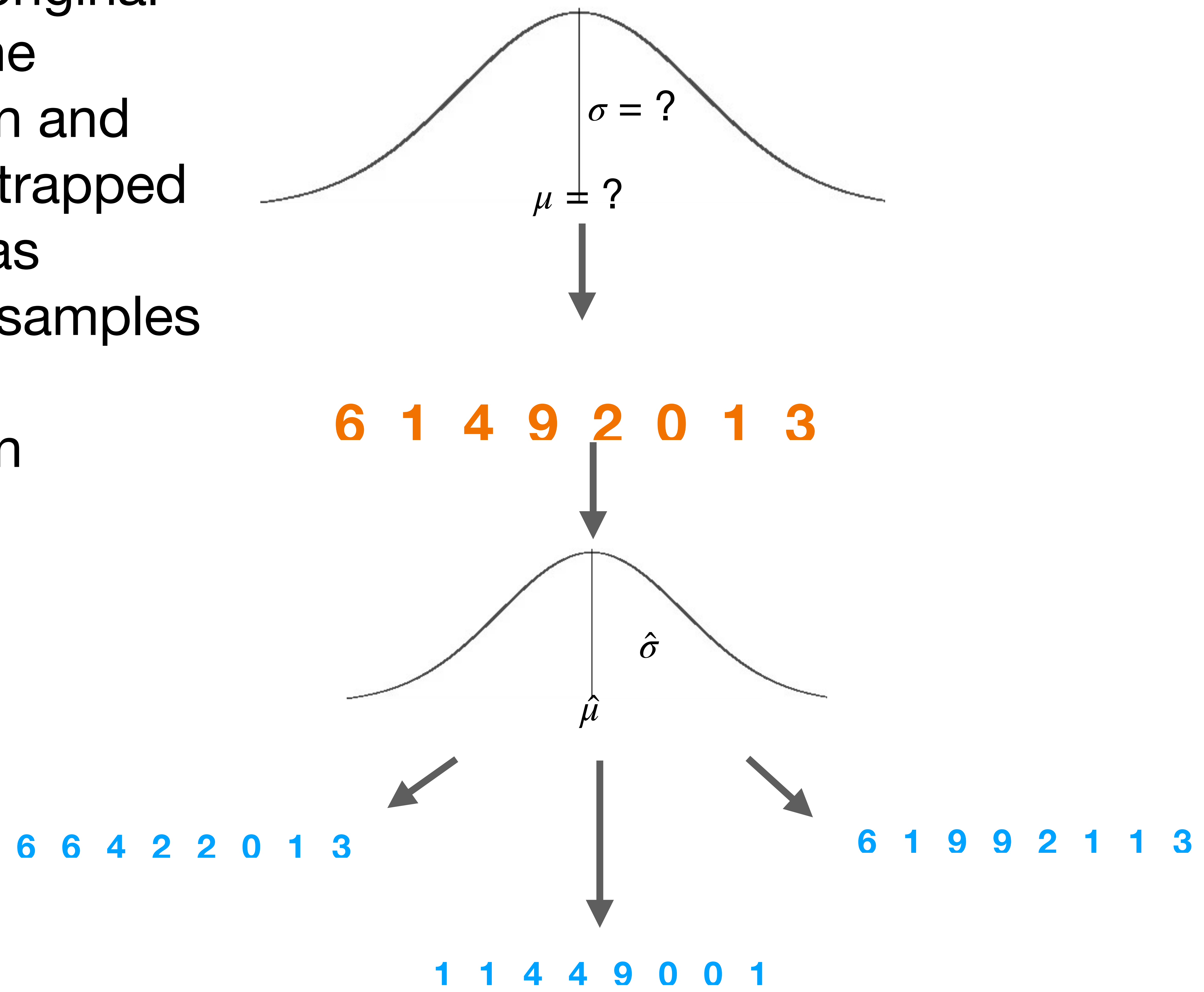
We can estimate the **bias, variance and MSE** using a bootstrapping technique, which can be:

Non-parametric



The idea is to treat the original data as the population and the bootstrapped samples as repeated samples from the population

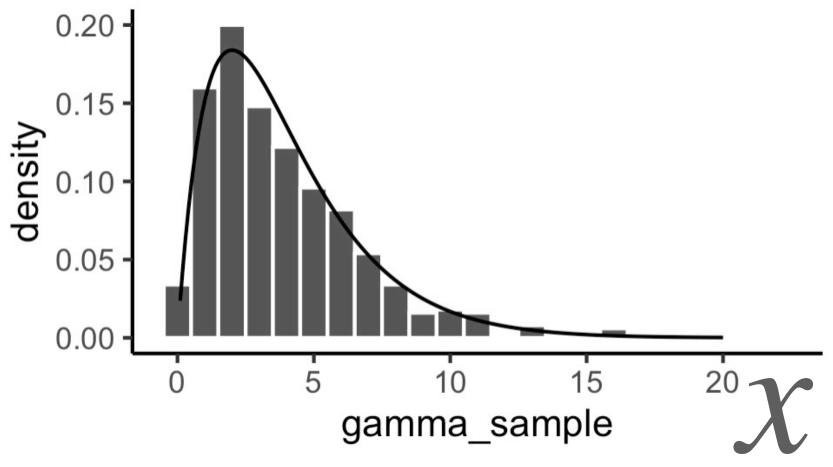
Parametric



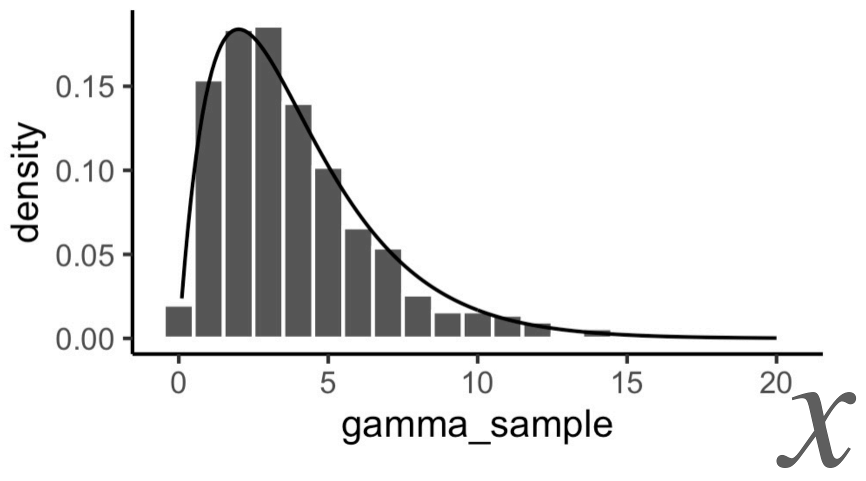
What we've covered so far

The **Central Limit Theorem** tells us that if our data are IID, the sample mean tends to wards a normal distribution whose mean is equal to the population mean and whose variance is equal to the population variance divided by n (sample size)

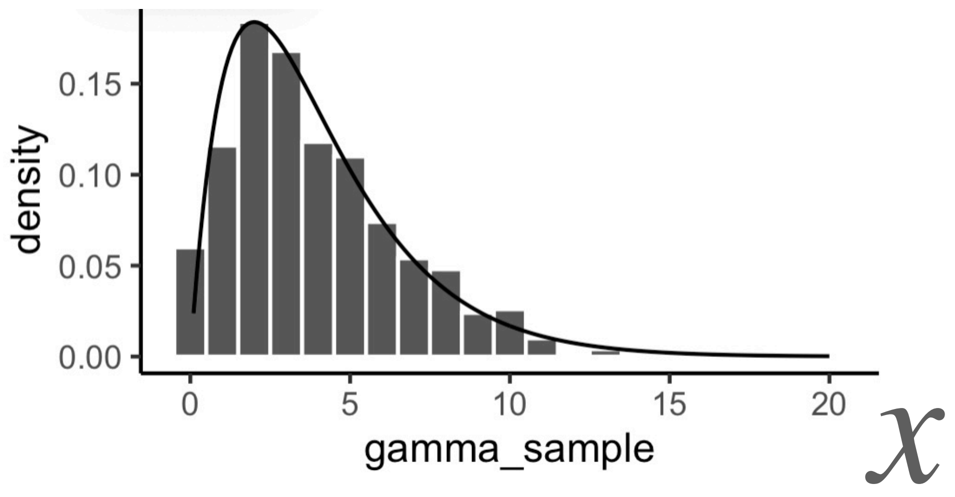
$$\bar{X} = \frac{1}{n}\sum_{i=1}^{n} X_i \to N\left(\mu, \frac{\sigma^2}{n}\right), \quad \text{as } n \to \infty$$



Sample mean: 3.94



Sample mean: 3.89



Sample mean: 3.92