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# Math for Machine Learning

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## Probability and Statistics - Week 4

# W4 Lesson 1



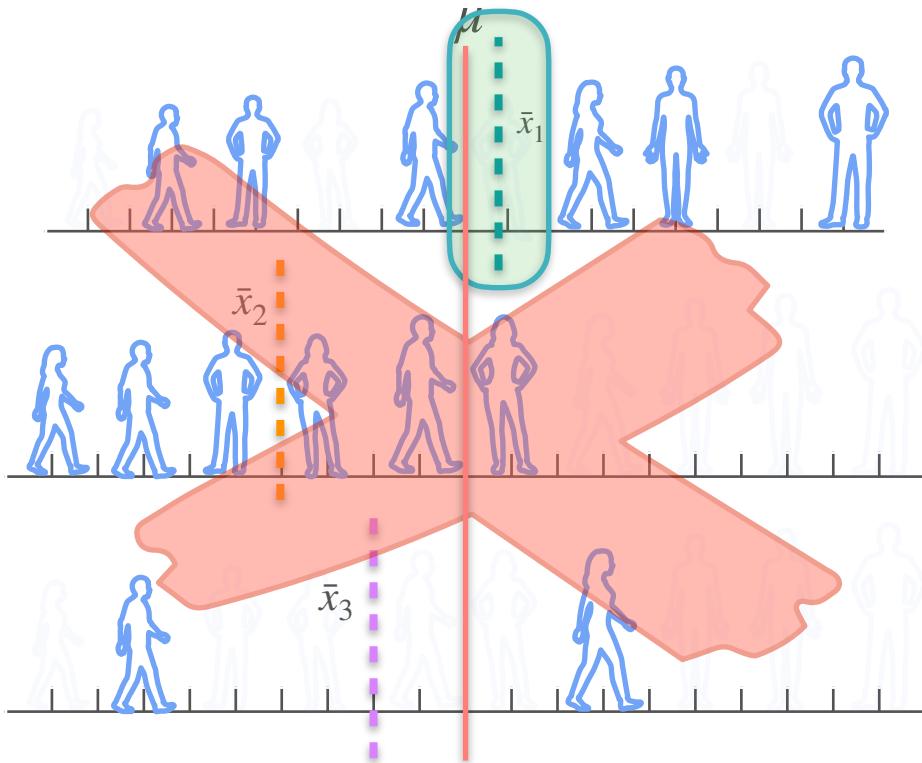
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## Confidence Interval

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**Confidence Interval  
(Known Standard Deviation)**

# Confidence Interval - Intuition



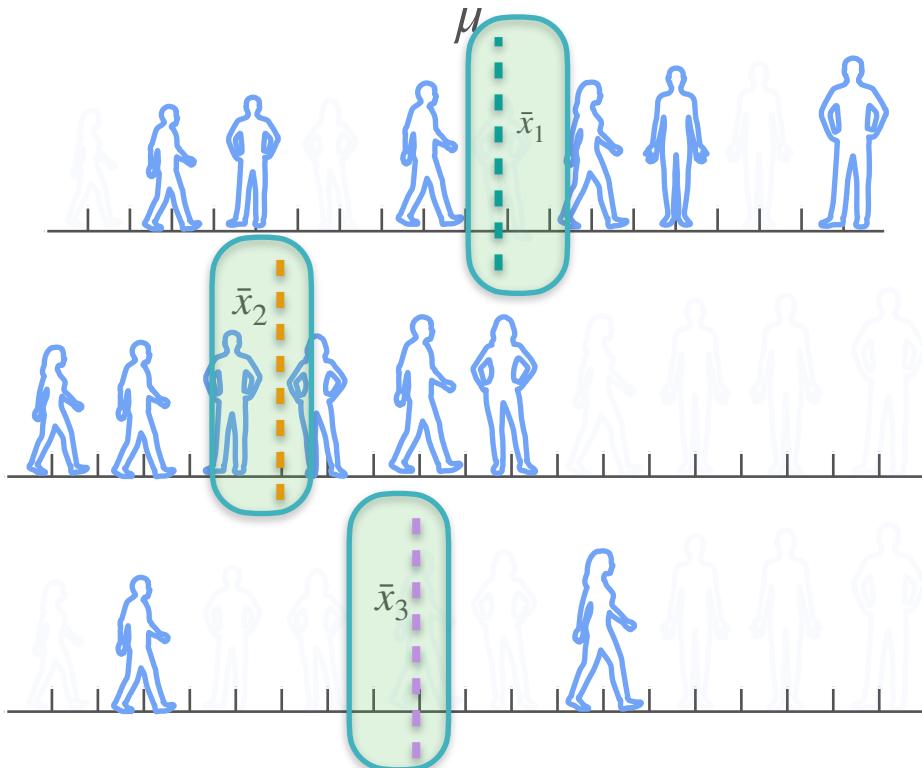
Statistopia

10,000 people

$\mu$   
(mean height of the population)

Can you use these sample means with  
some degree of certainty?

# Confidence Interval - Intuition



Can you use these sample means with some degree of certainty?

## Confidence Interval

lower limit  $< \mu <$  upper limit

# Confidence Interval - Intuition

$n = 1$



Confidence level



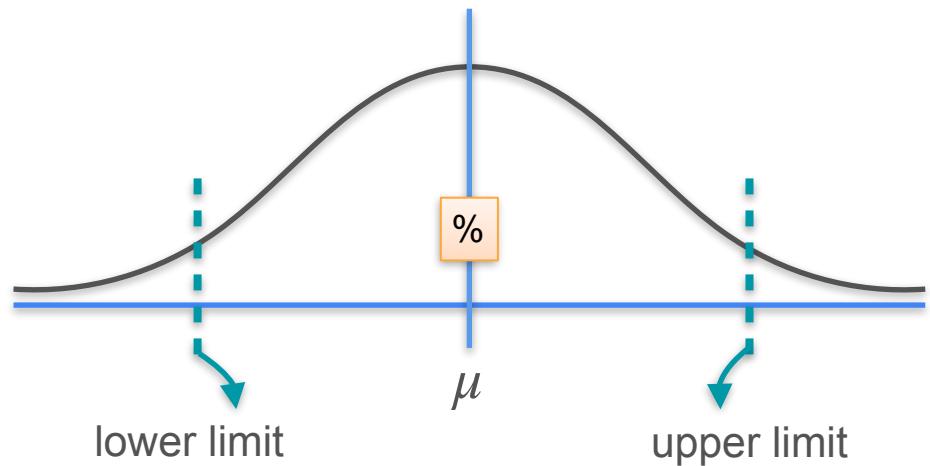
$\bar{x}$

$1 - \alpha$

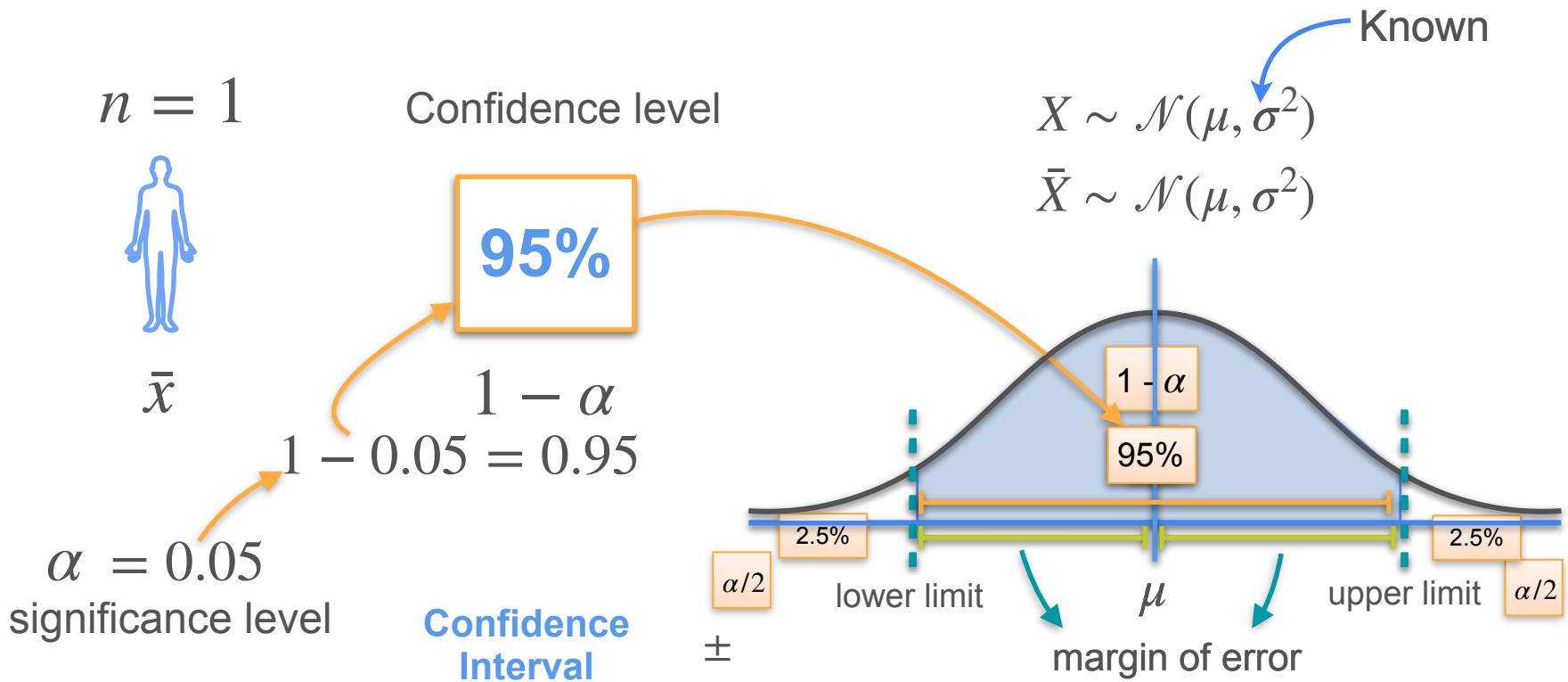
$\alpha$   
significance level

Known

$$X \sim \mathcal{N}(\mu, \sigma^2)$$
$$\bar{X} \sim \mathcal{N}(\mu, \sigma^2)$$



# Confidence Interval - Intuition



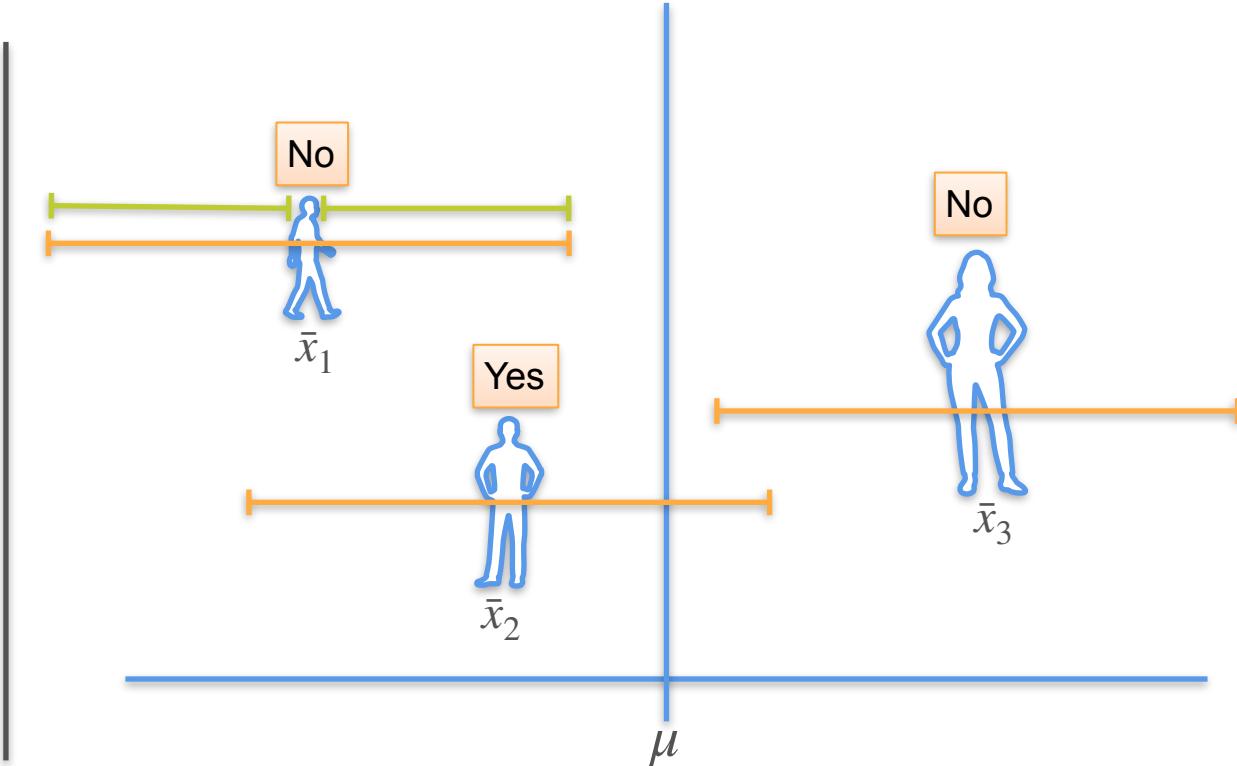
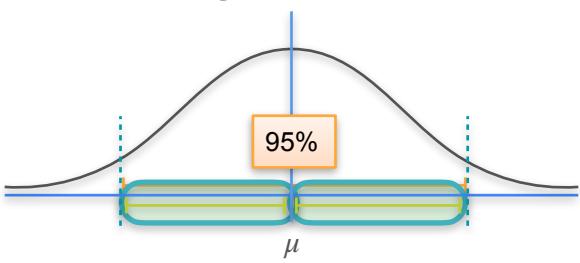
# Confidence Interval - Intuition

$n = 1$

Known  $\sigma$

95%

Margin of error



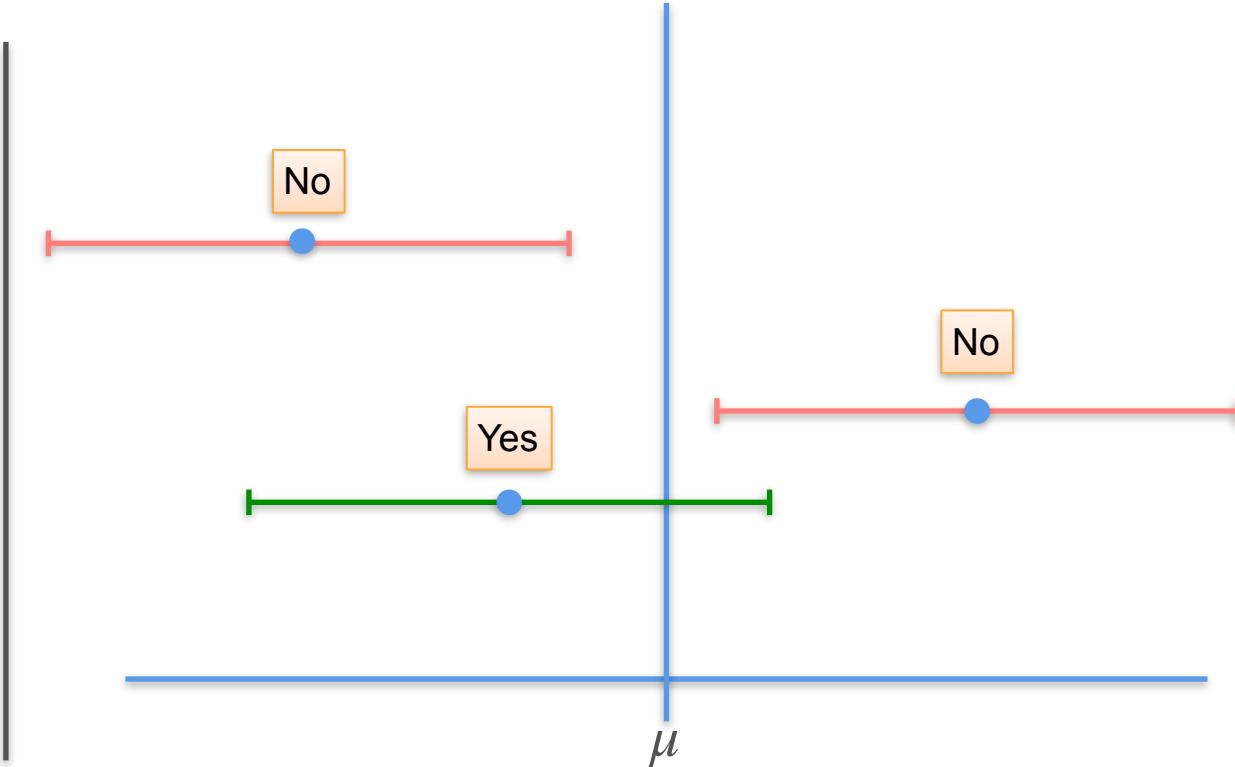
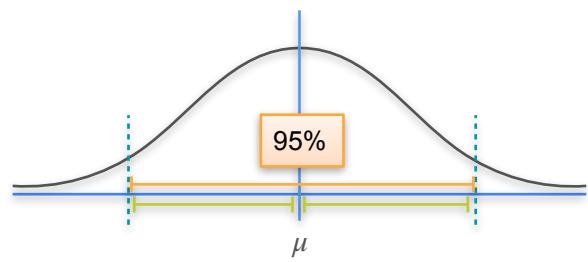
# Confidence Interval - Intuition

$n = 1$

Known  $\sigma$

95%

Margin of error



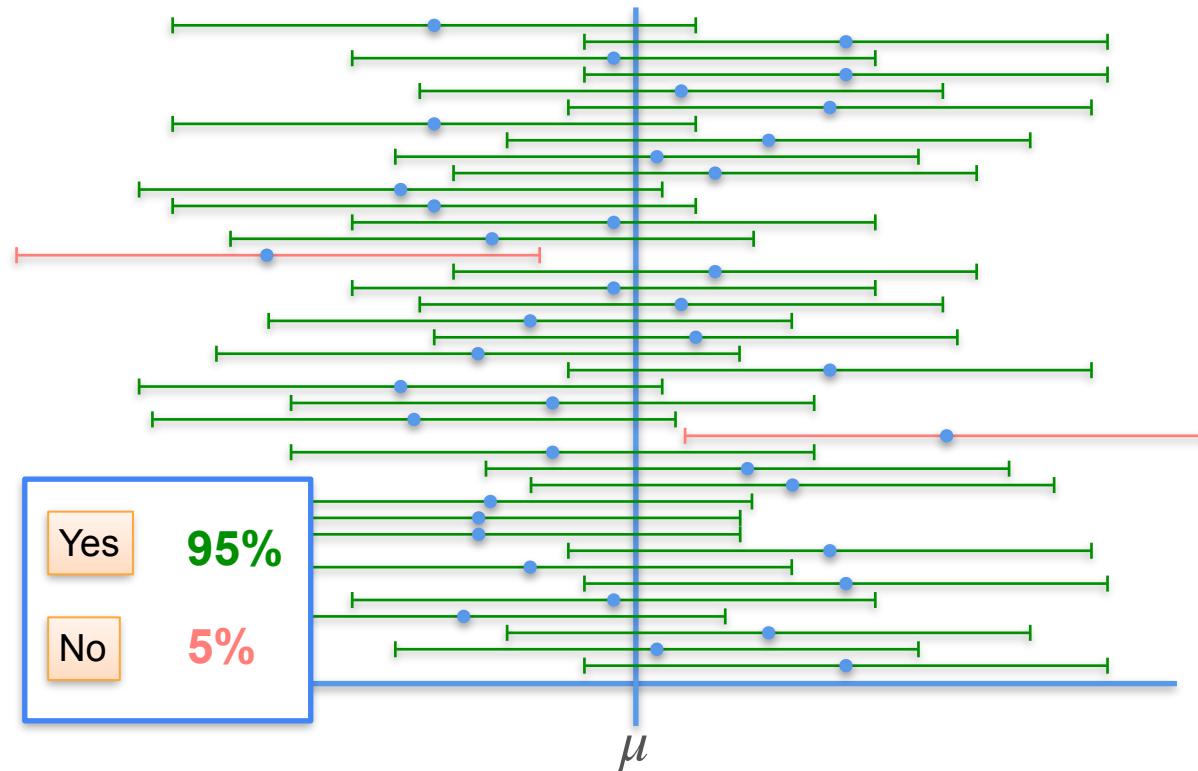
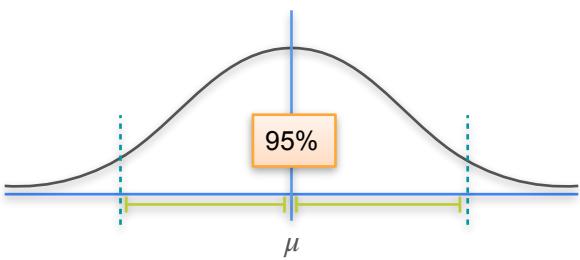
# Confidence Interval - Intuition

$n = 1$

Known  $\sigma$

95%

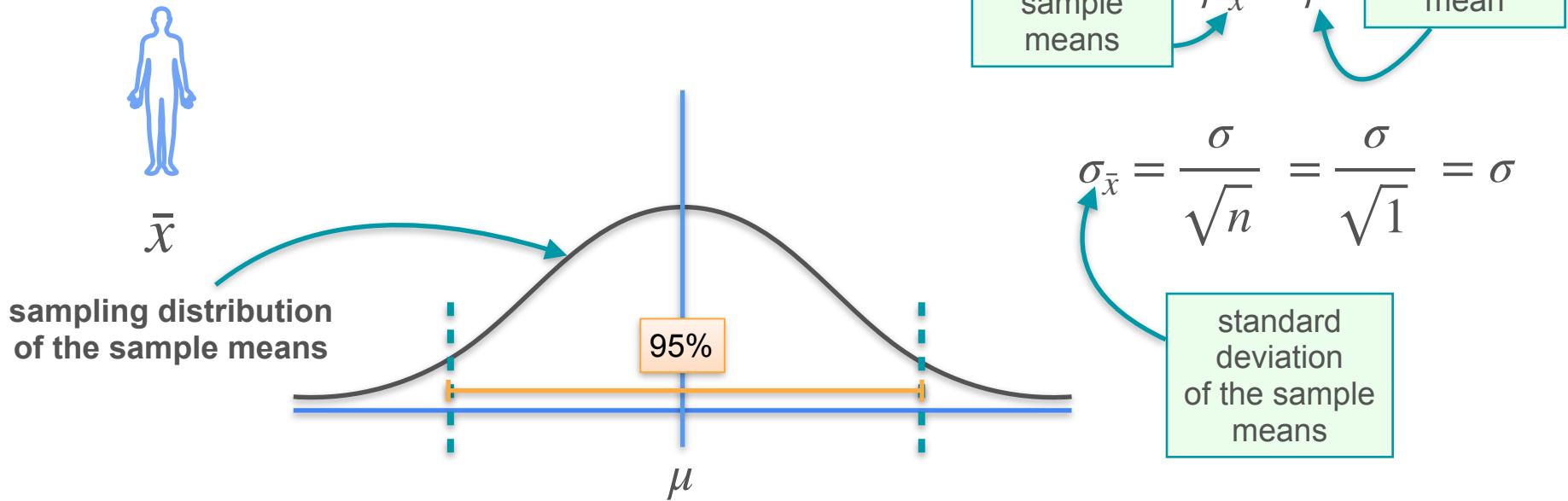
Margin of error



# Confidence Interval - Intuition

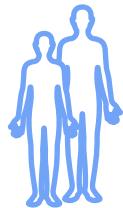
$$n = 1$$

$$\bar{X} \sim \mathcal{N}(\mu, \sigma^2)$$



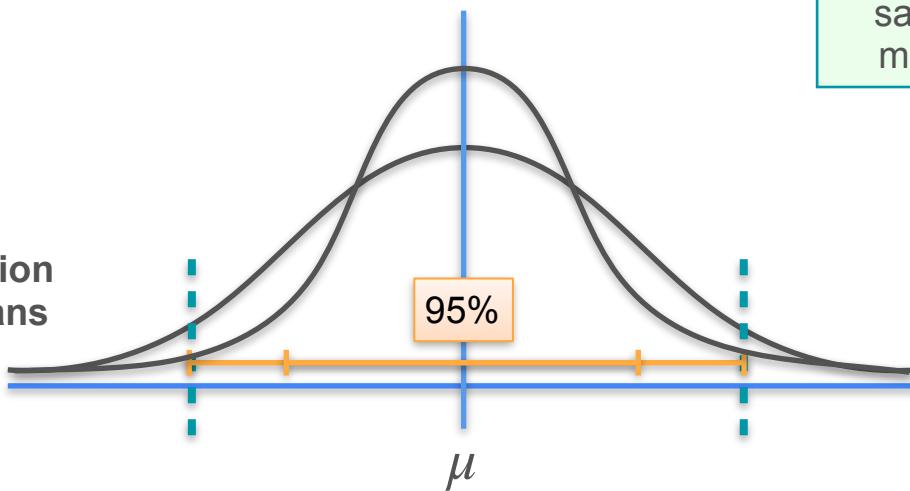
# Confidence Interval - Intuition

$$n = 2$$



$$\bar{X} \sim \mathcal{N}\left(\mu, \frac{\sigma^2}{2}\right)$$

sampling distribution  
of the sample means



Known population standard deviation ( $\sigma$ )

mean of the  
sample  
means

$$\mu_{\bar{x}} = \mu$$

population  
mean

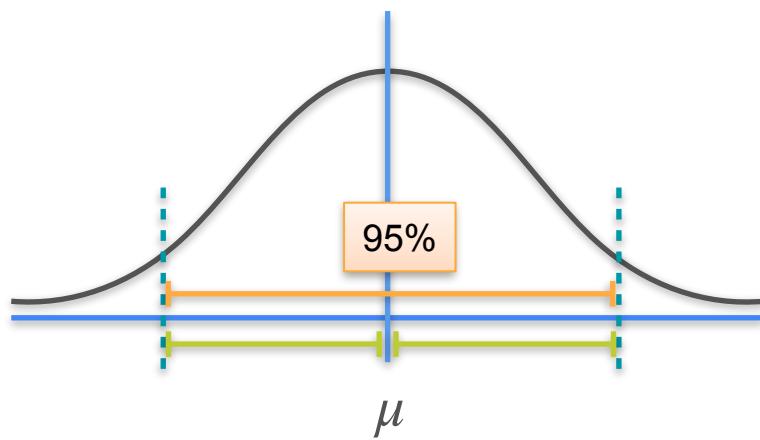
$$\sigma_{\bar{x}} = \frac{\sigma}{\sqrt{n}} = \frac{\sigma}{\sqrt{2}}$$

standard  
deviation  
of the sample  
means

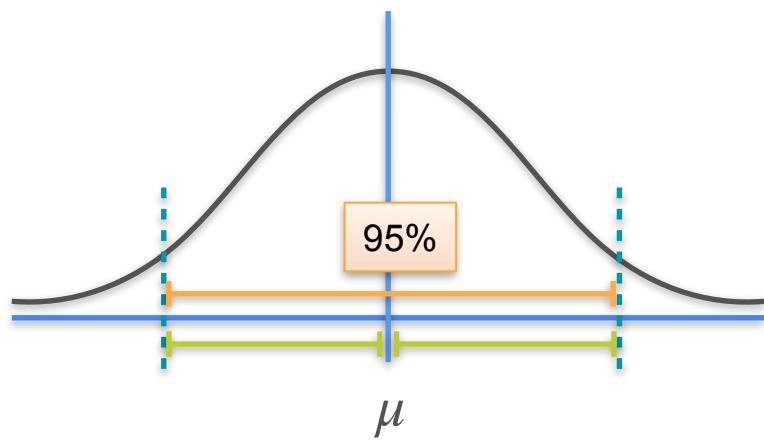
# Confidence Interval - Intuition

95%

$$n = 1$$
$$\mathcal{N}\left(\mu, \frac{\sigma^2}{1}\right)$$



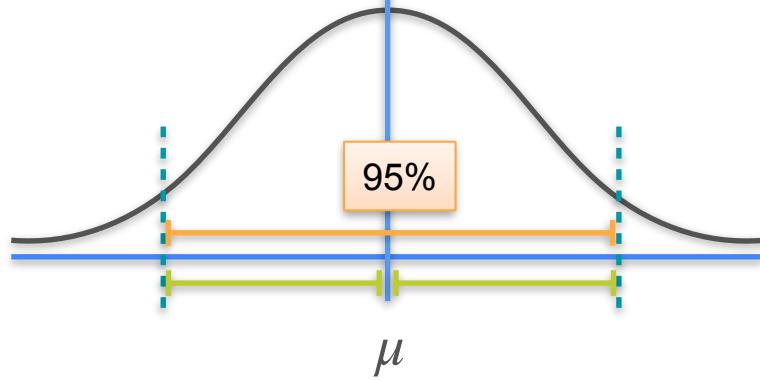
$n = 2$



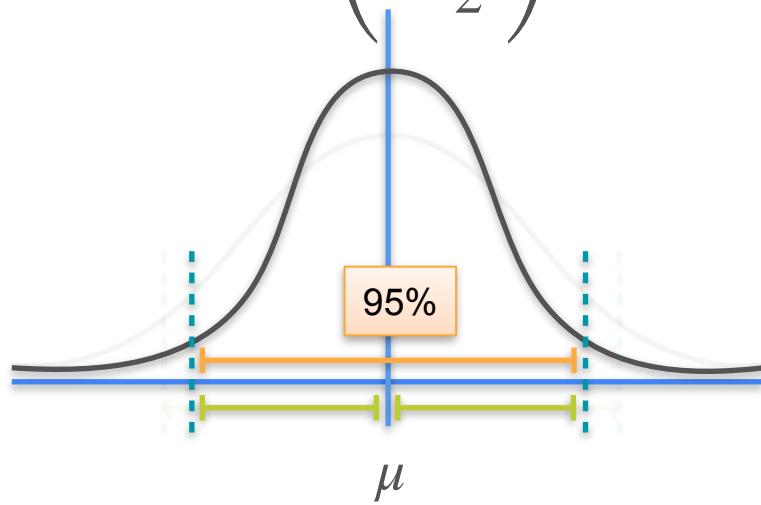
# Confidence Interval - Intuition

95%

$$n = 1$$
$$\mathcal{N}\left(\mu, \frac{\sigma^2}{1}\right)$$



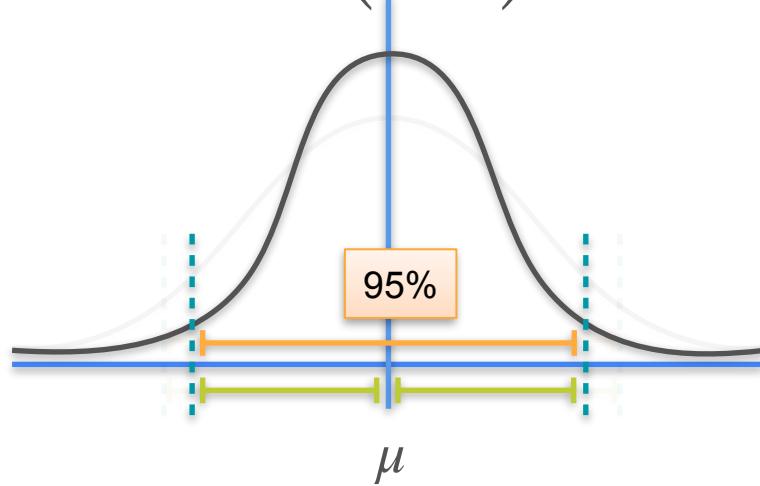
$$n = 2$$
$$\mathcal{N}\left(\mu, \frac{\sigma^2}{2}\right)$$



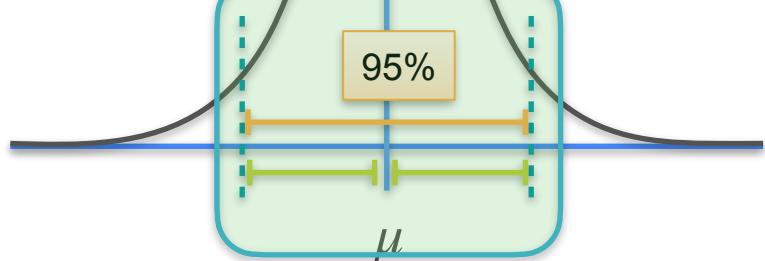
# Confidence Interval - Intuition

95%

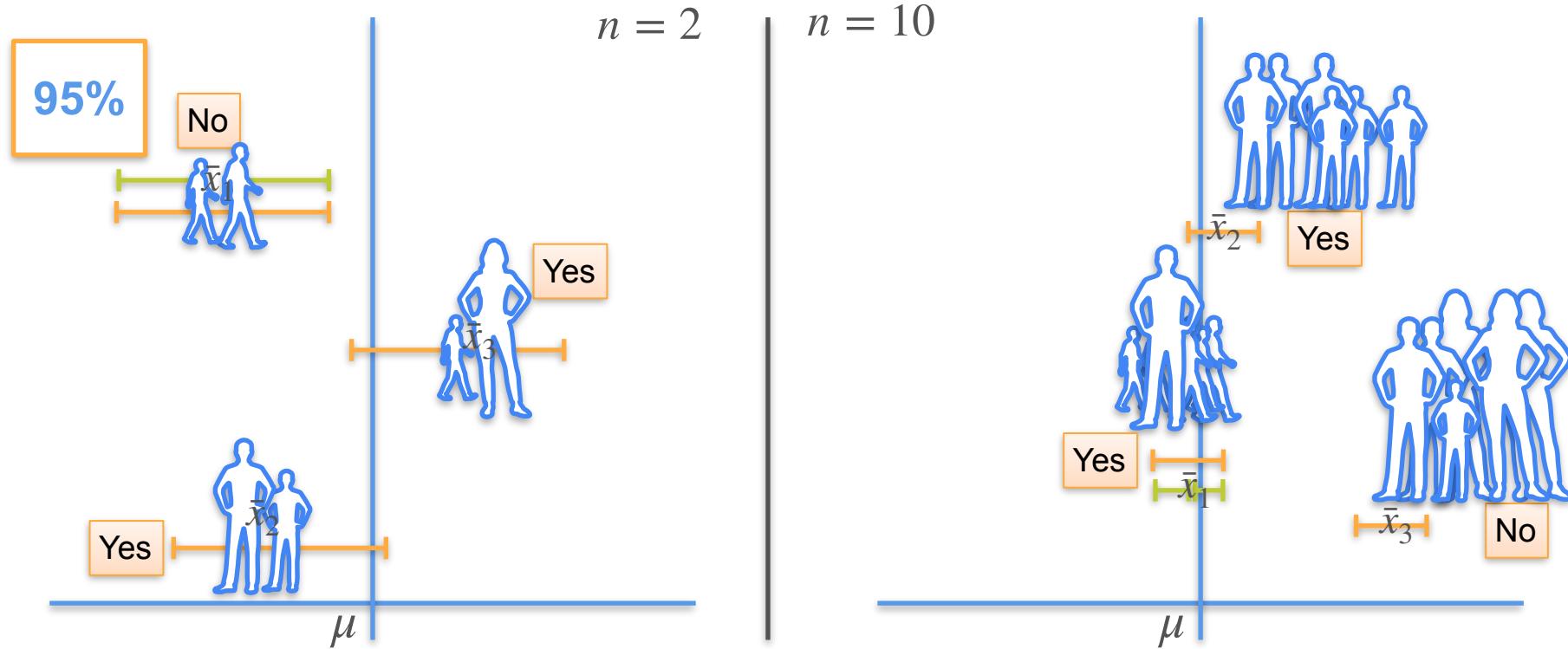
$$n = 2$$
$$\mathcal{N}\left(\mu, \frac{\sigma^2}{2}\right)$$



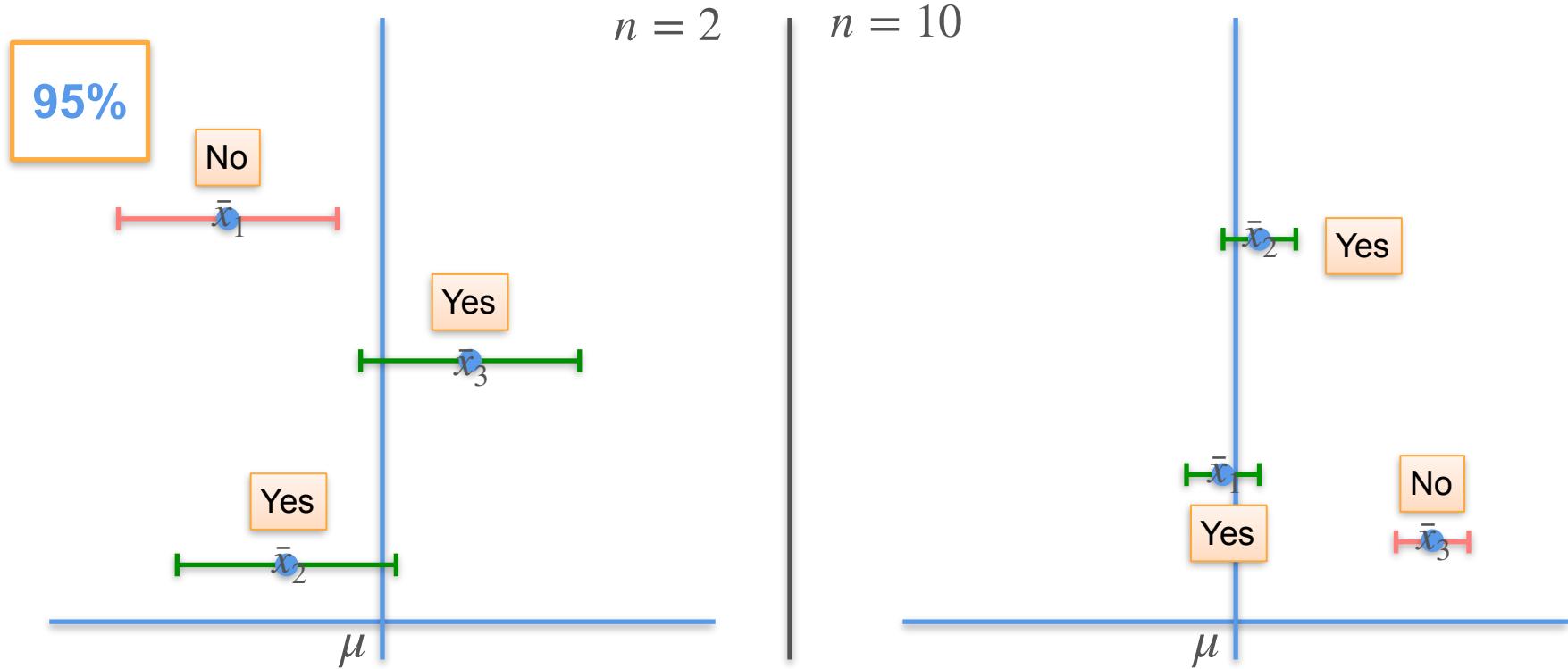
$$n = 10$$
$$\mathcal{N}\left(\mu, \frac{\sigma^2}{10}\right)$$



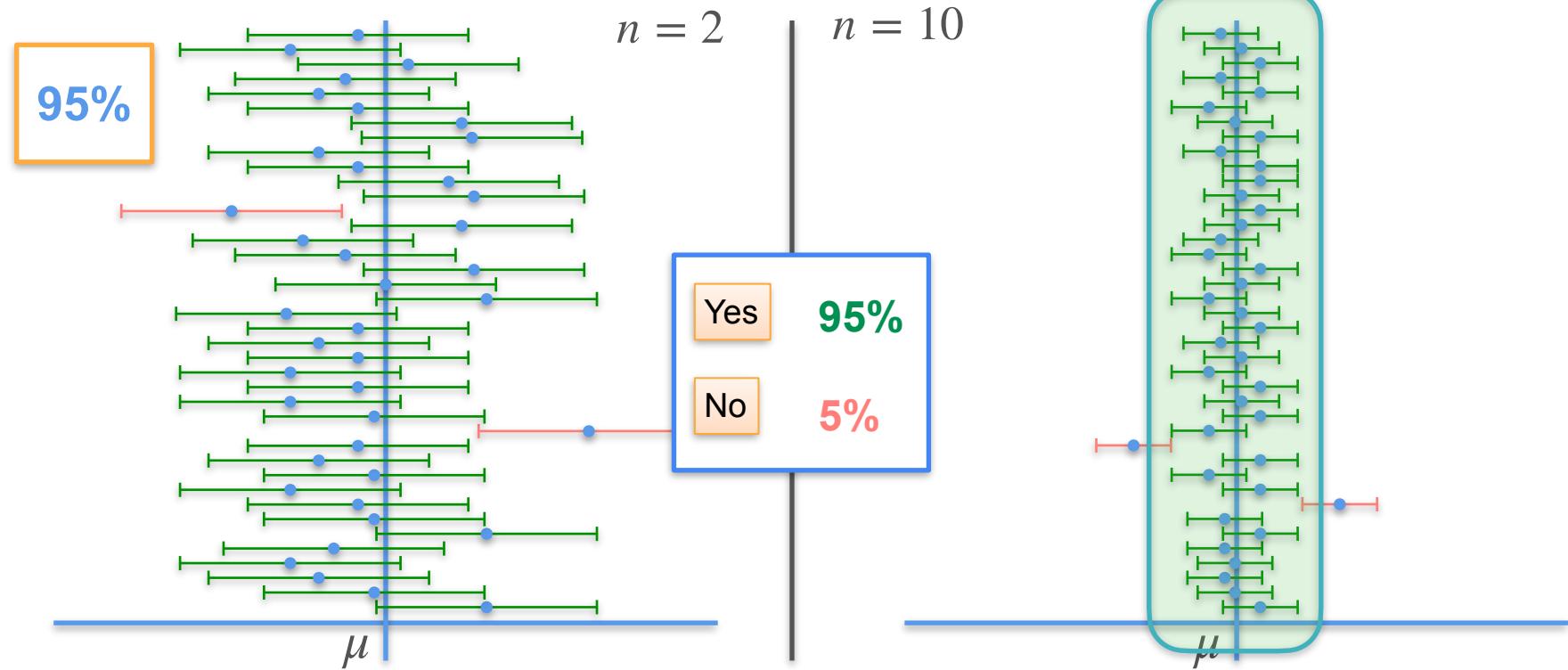
# Confidence Interval - Intuition



# Confidence Interval - Intuition

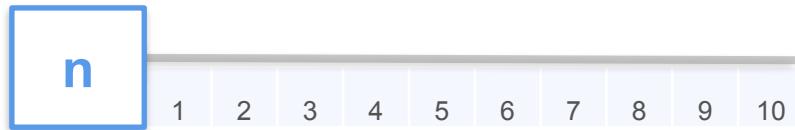


# Confidence Interval - Intuition

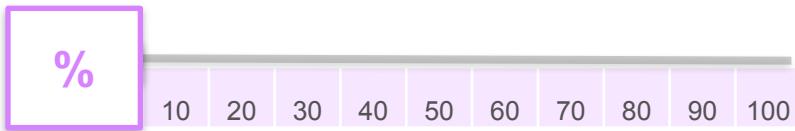


# Effect of the Sample Size

sample size

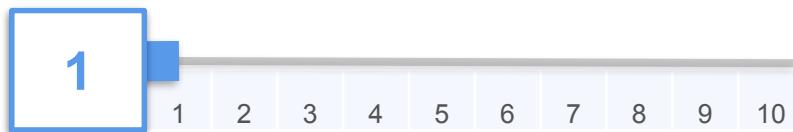


Confidence level

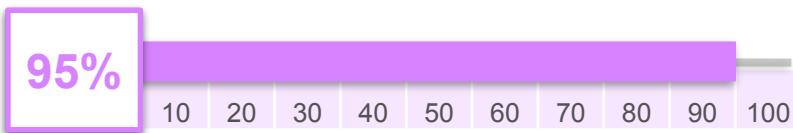


# Effect of the Sample Size

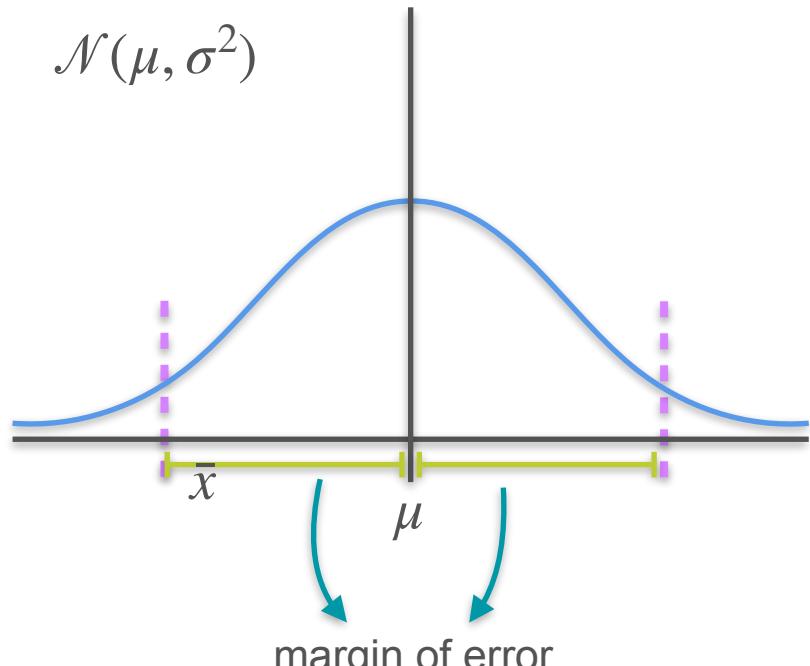
sample size



Confidence level

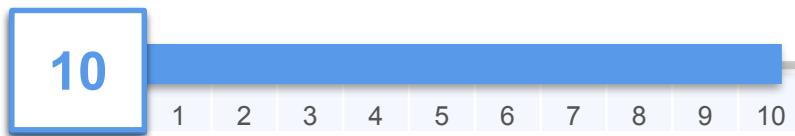


$$\mathcal{N}(\mu, \sigma^2)$$

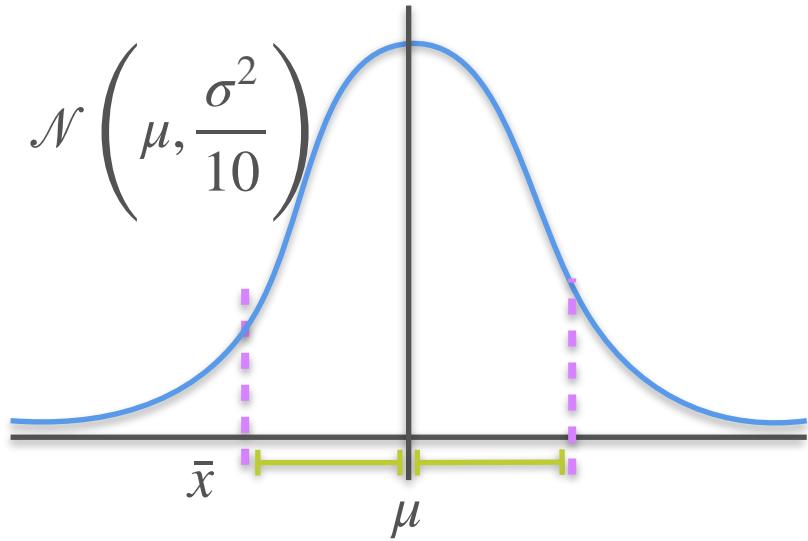
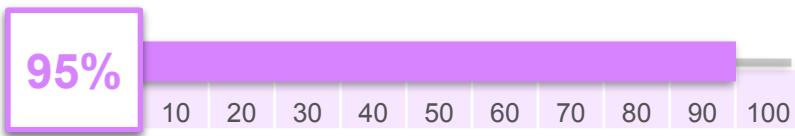


# Effect of the Sample Size

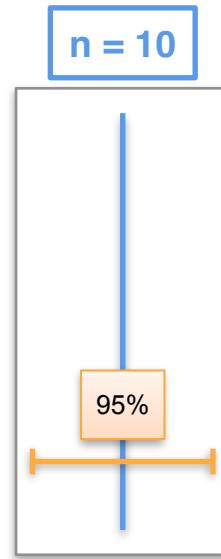
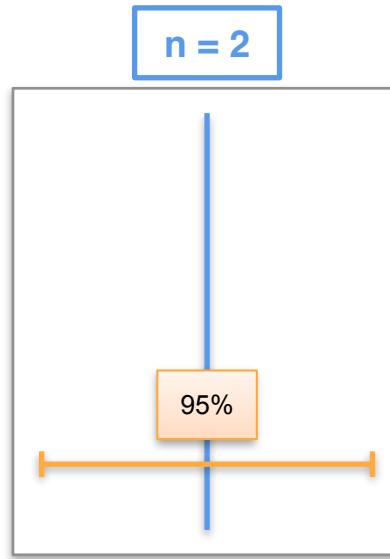
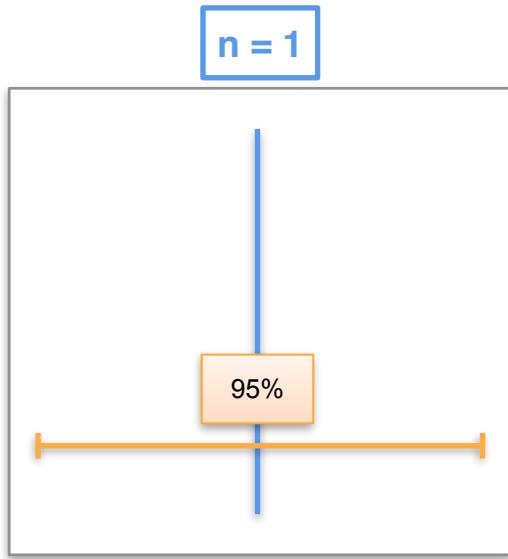
sample size



Confidence level



# Effect of the Sample Size

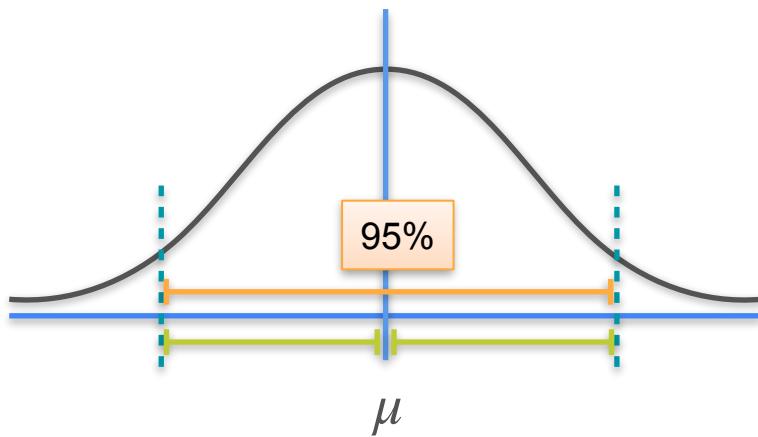


As  $n$  increases, the confidence interval shrinks

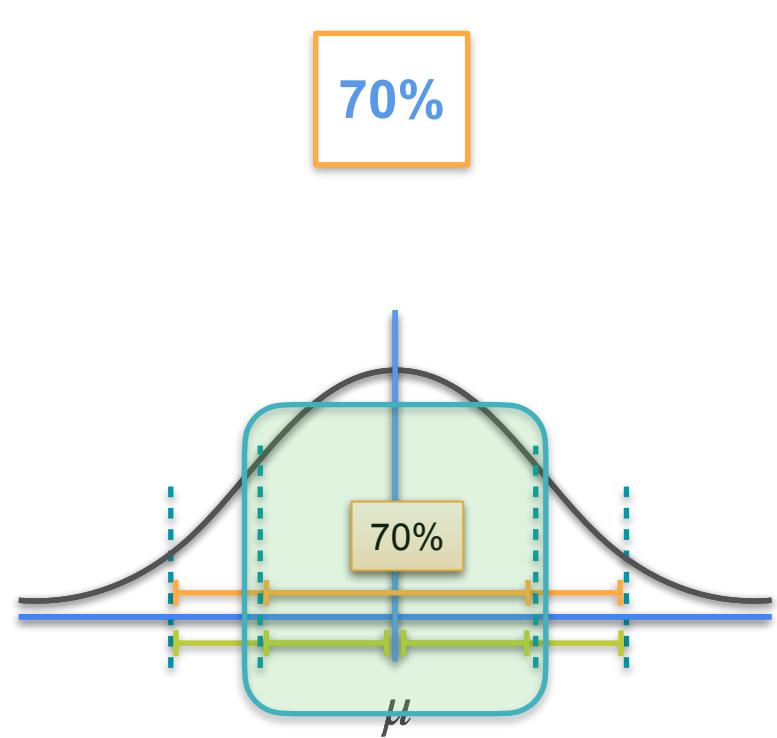
# Effect of the Confidence Level

$$n = 1$$

$$\mathcal{N}(\mu, \sigma^2)$$

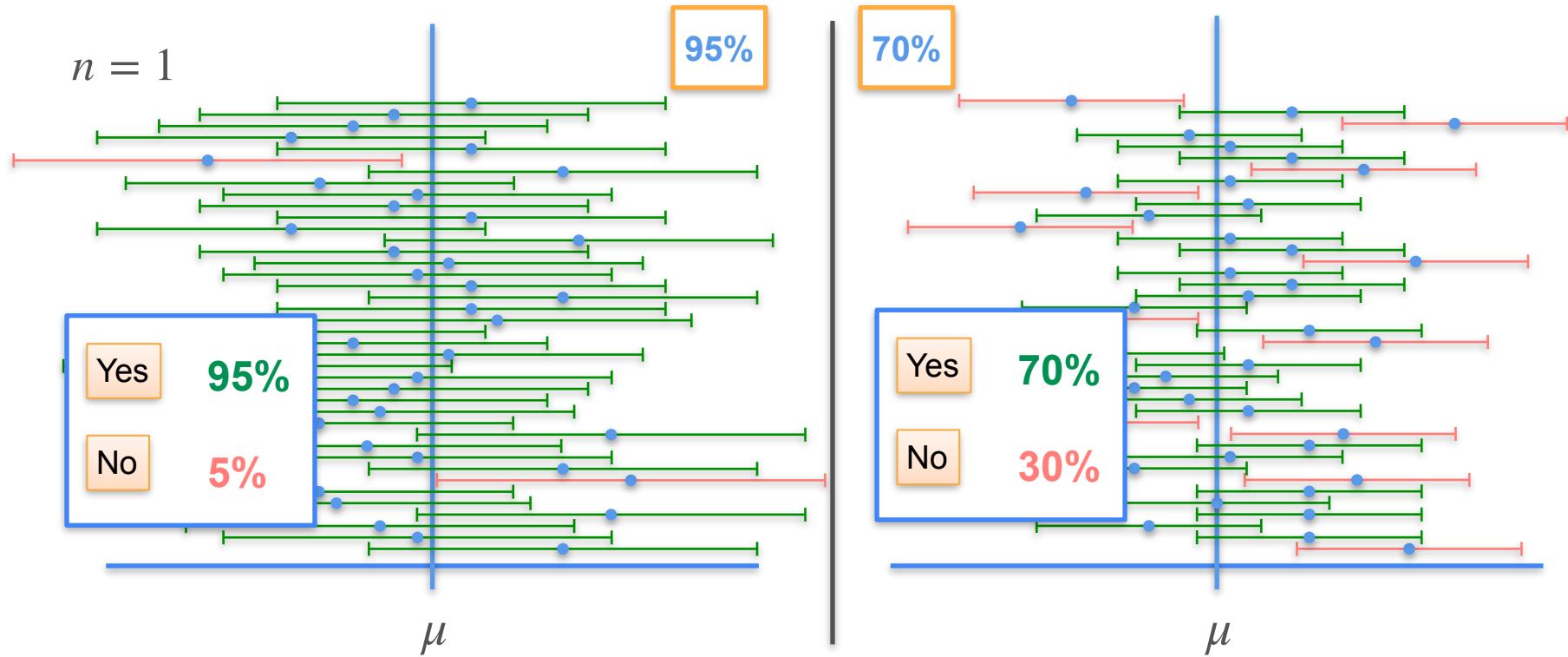


95%



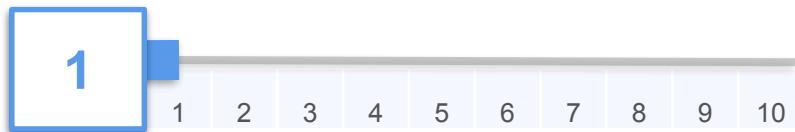
70%

# Effect of the Confidence Level

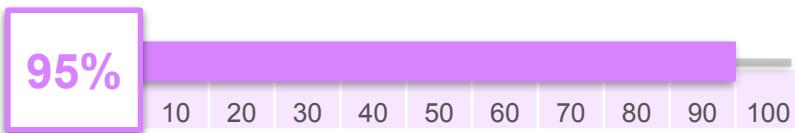


# Effect of the Confidence Level

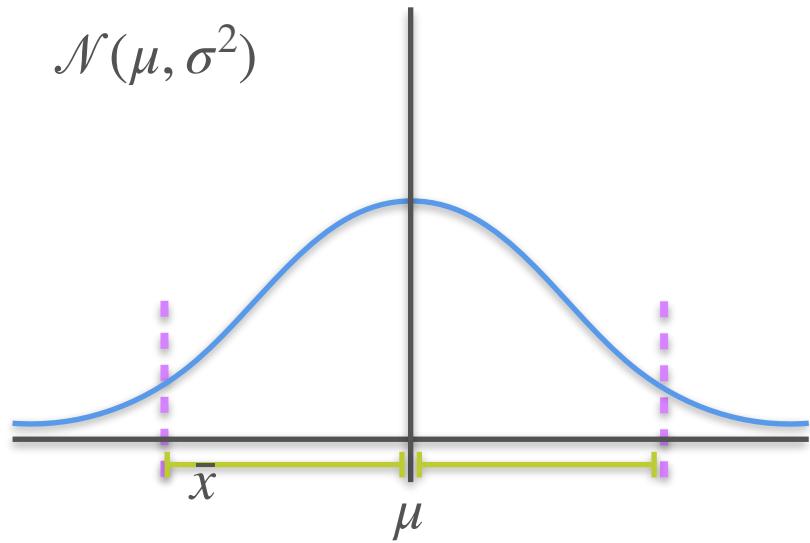
sample size



Confidence level

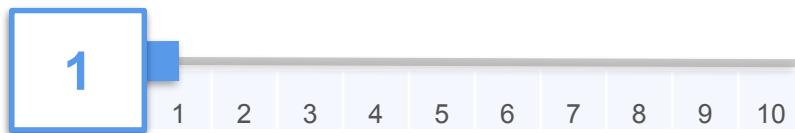


$$\mathcal{N}(\mu, \sigma^2)$$

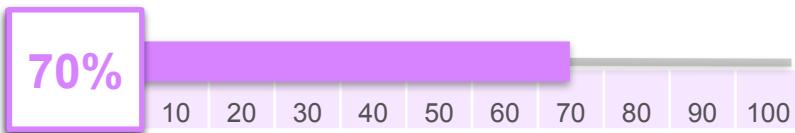


# Effect of the Confidence Level

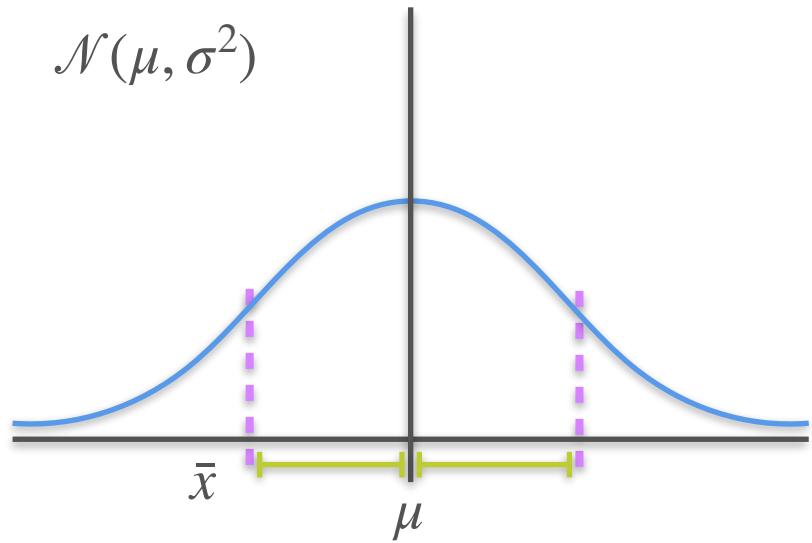
sample size



Confidence level

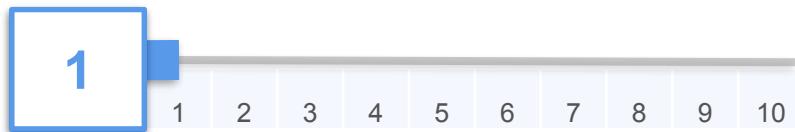


$$\mathcal{N}(\mu, \sigma^2)$$

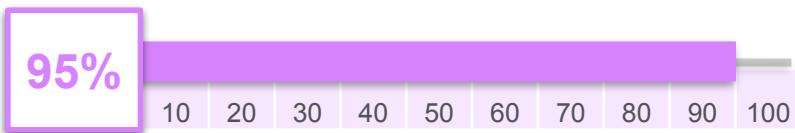


# Effect of the Confidence Level

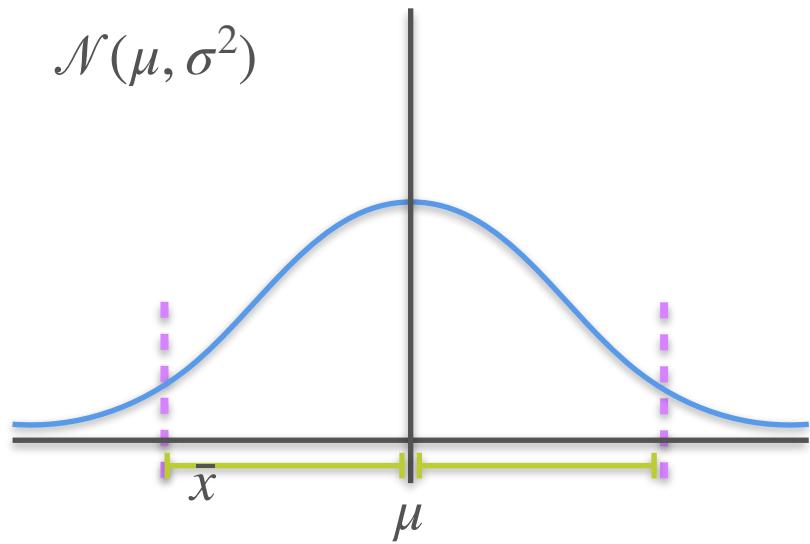
sample size



Confidence level



$$\mathcal{N}(\mu, \sigma^2)$$





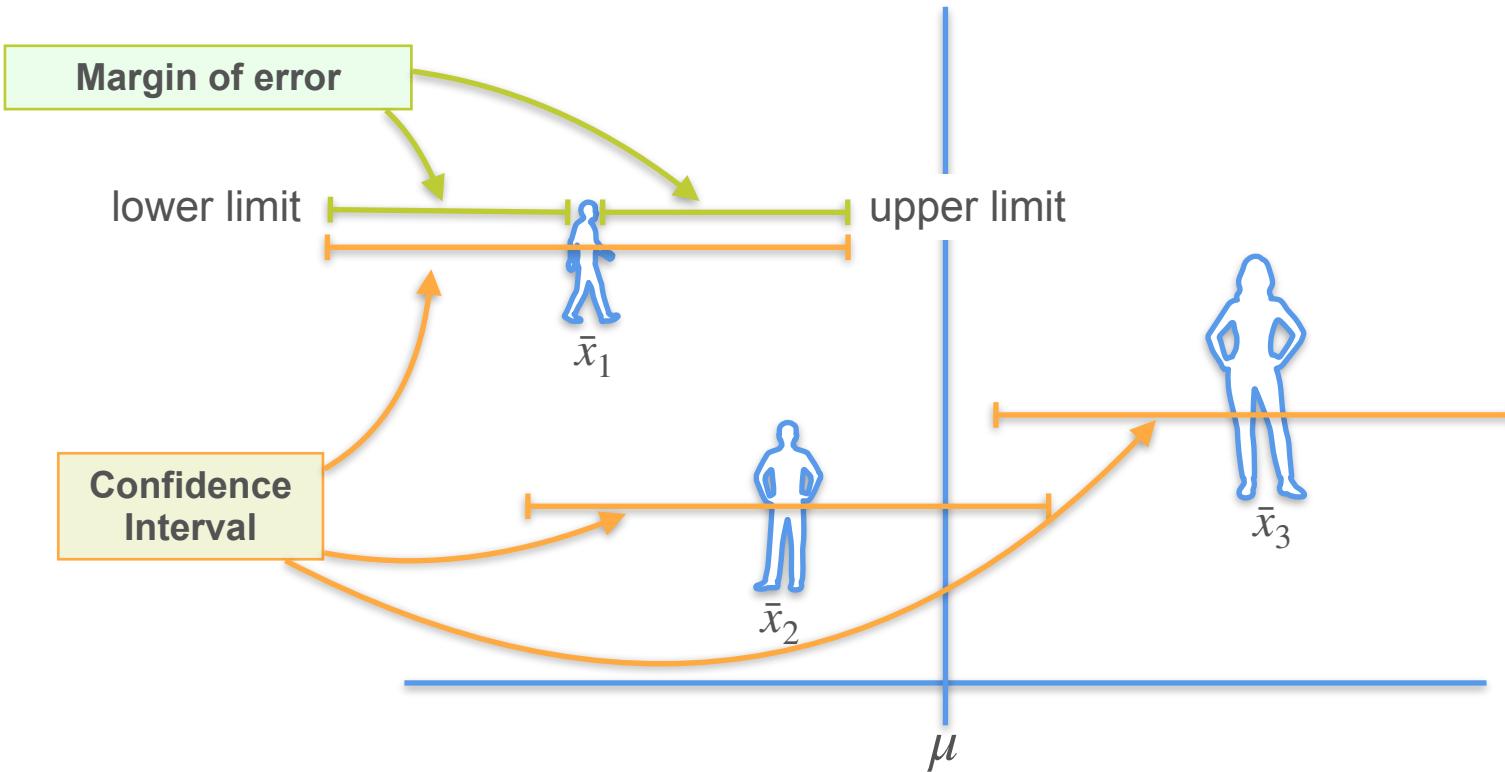
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# Confidence Interval

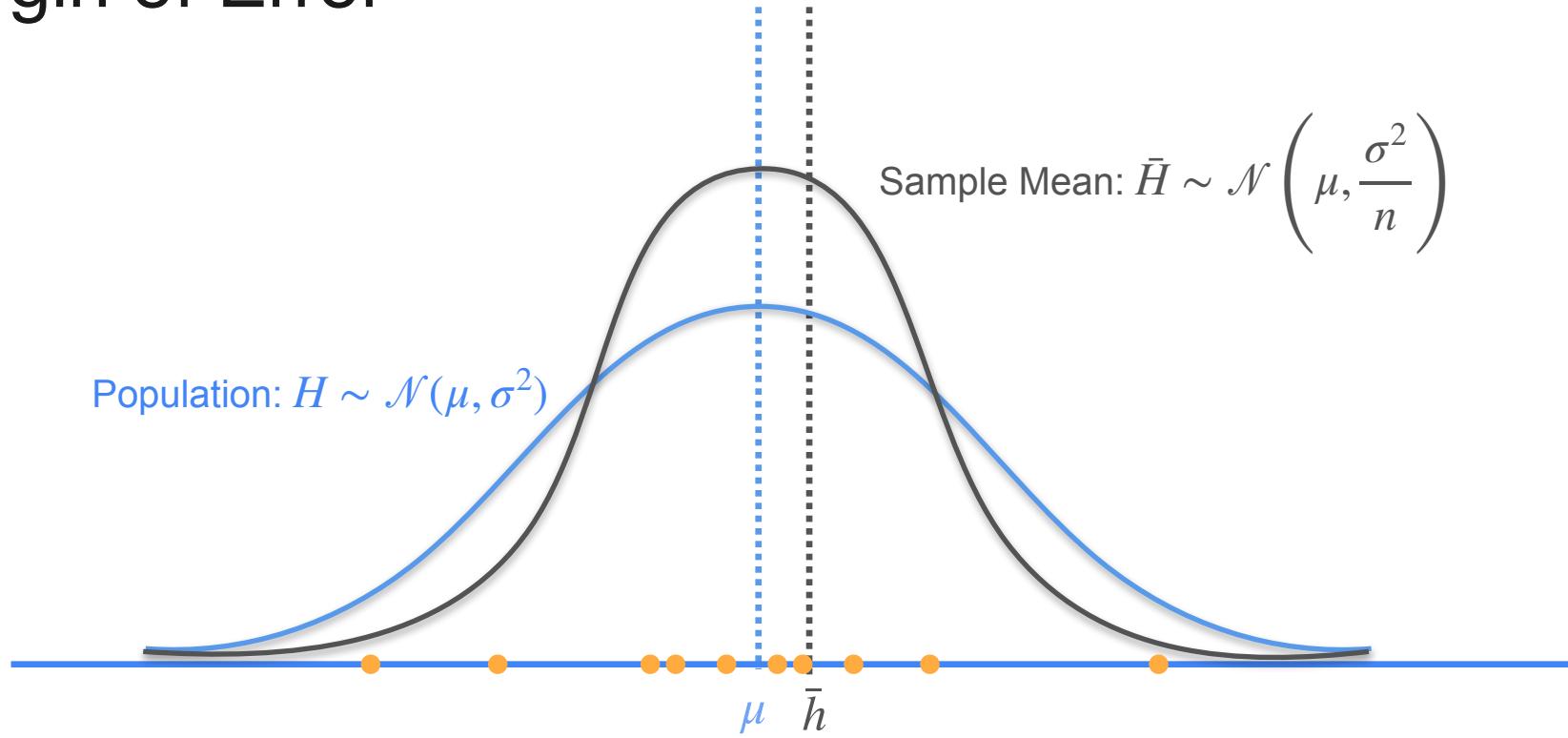
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## Margin of Error

# Margin of Error - Introduction

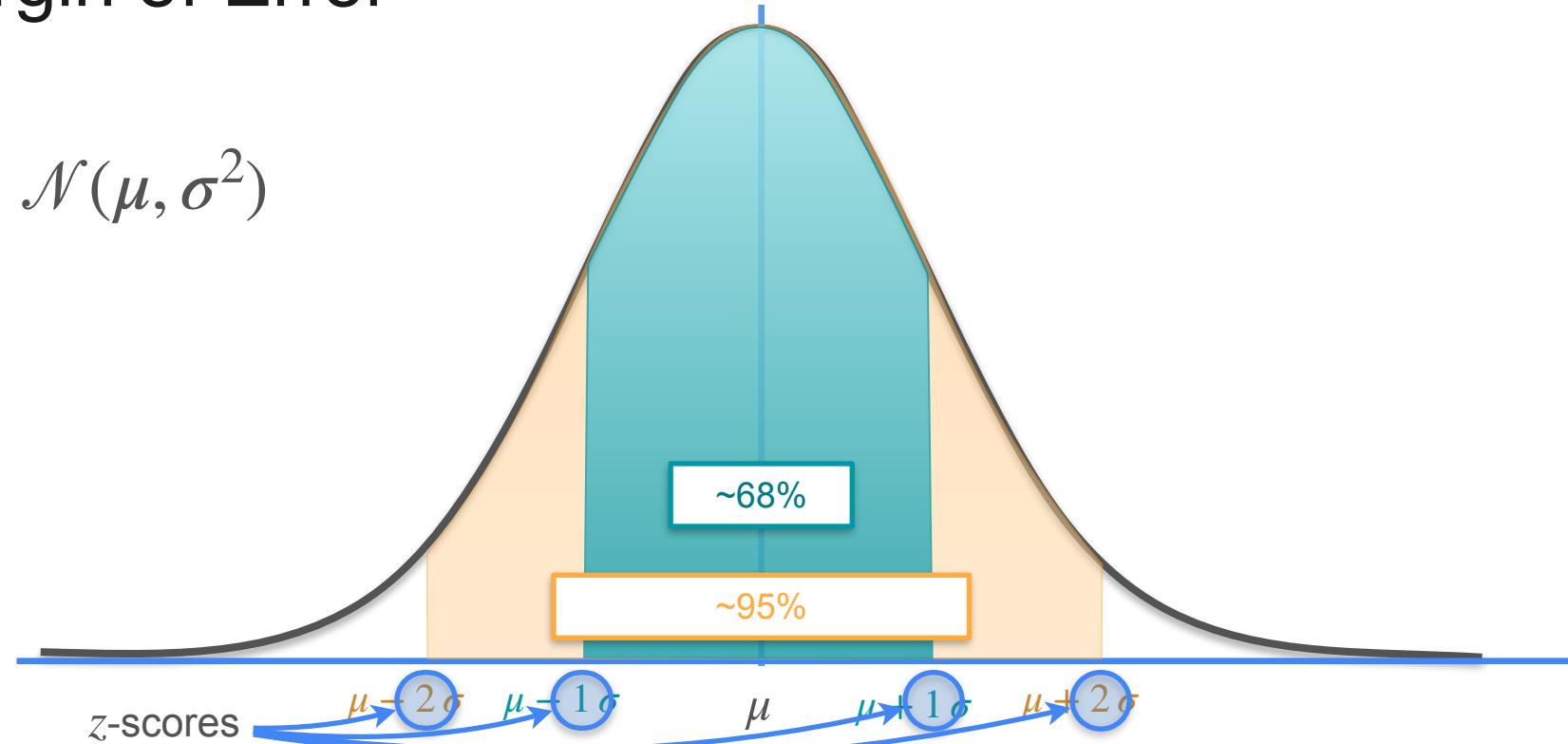


# Margin of Error



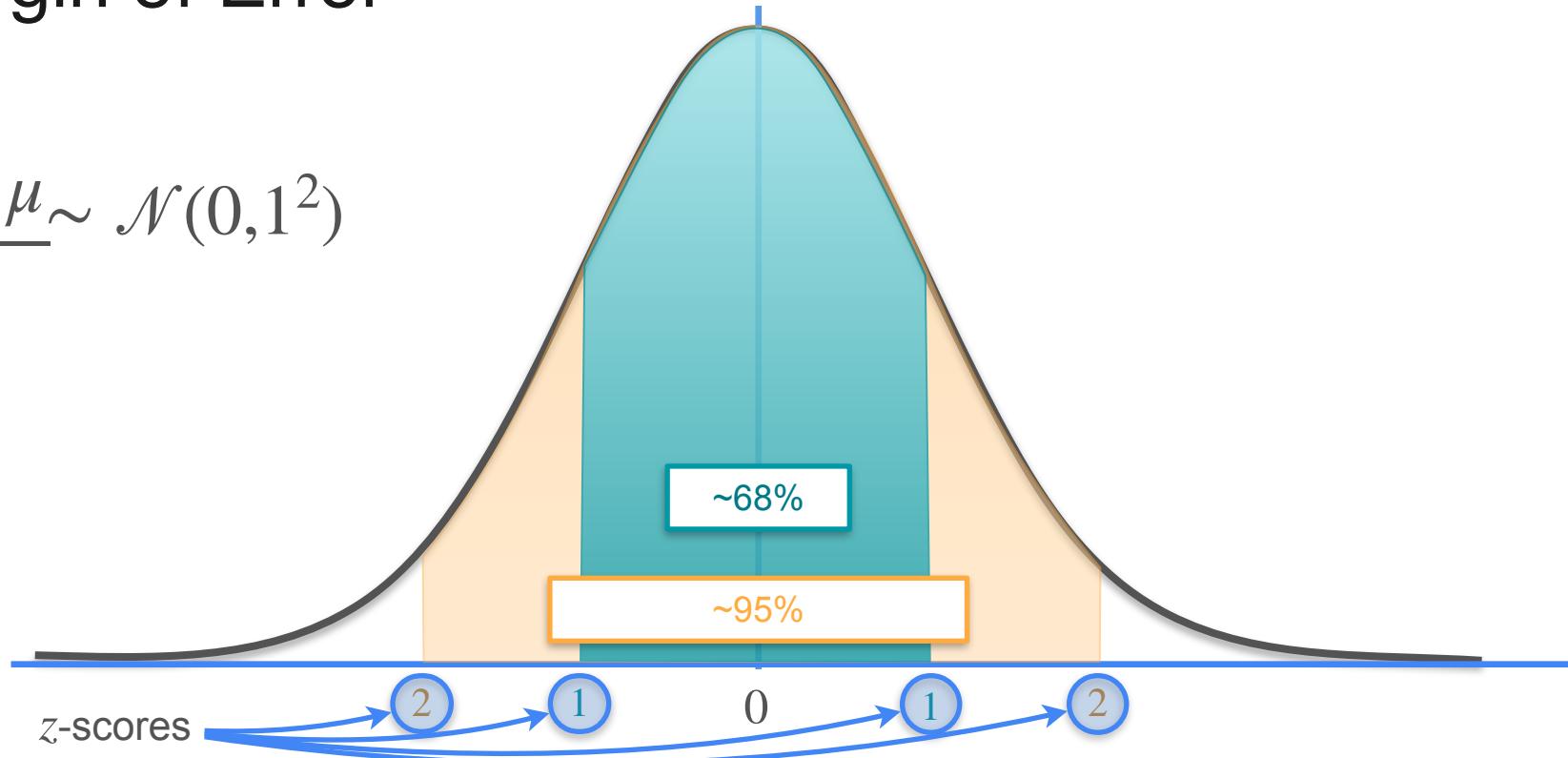
# Margin of Error

$$X \sim \mathcal{N}(\mu, \sigma^2)$$



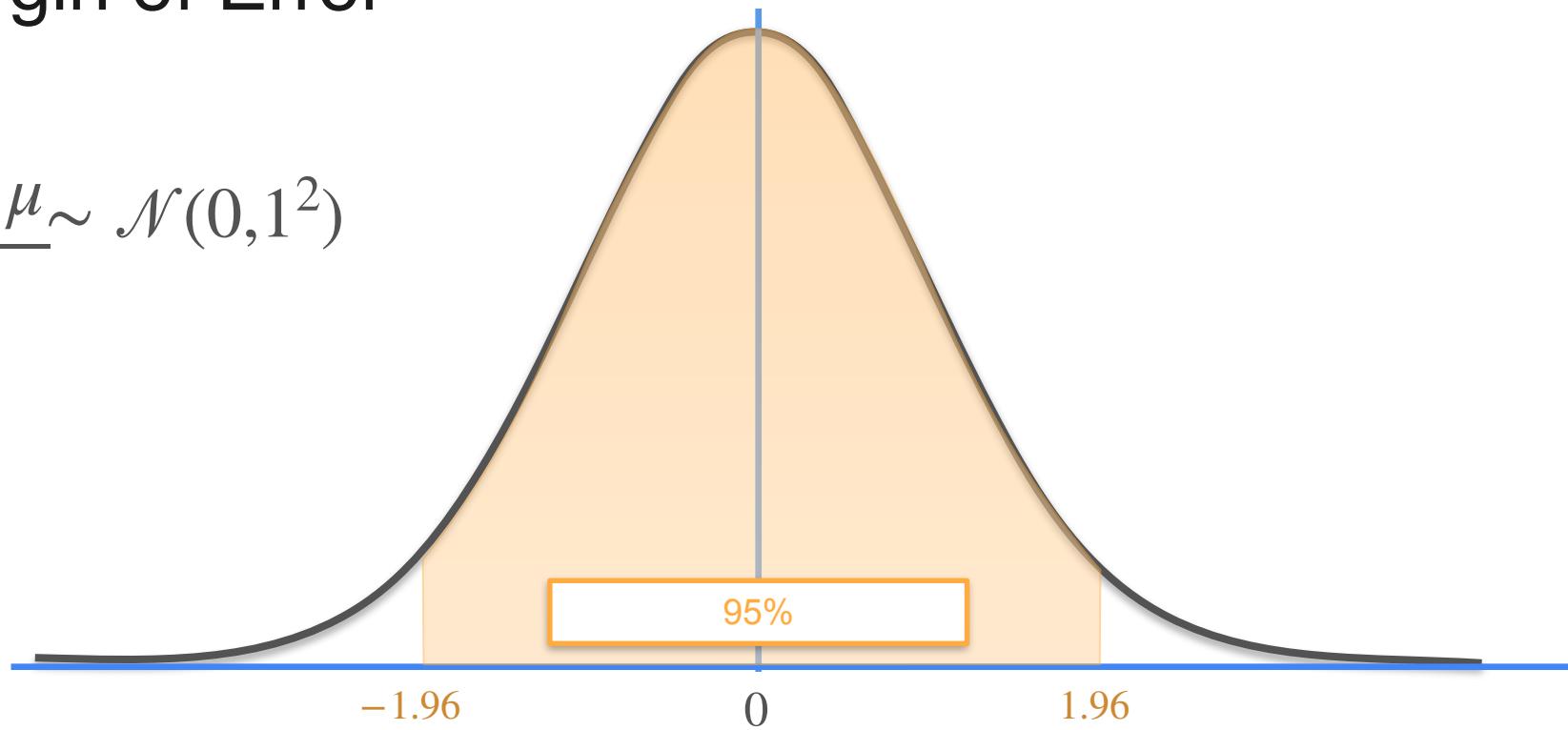
# Margin of Error

$$\frac{X - \mu}{\sigma} \sim \mathcal{N}(0, 1^2)$$



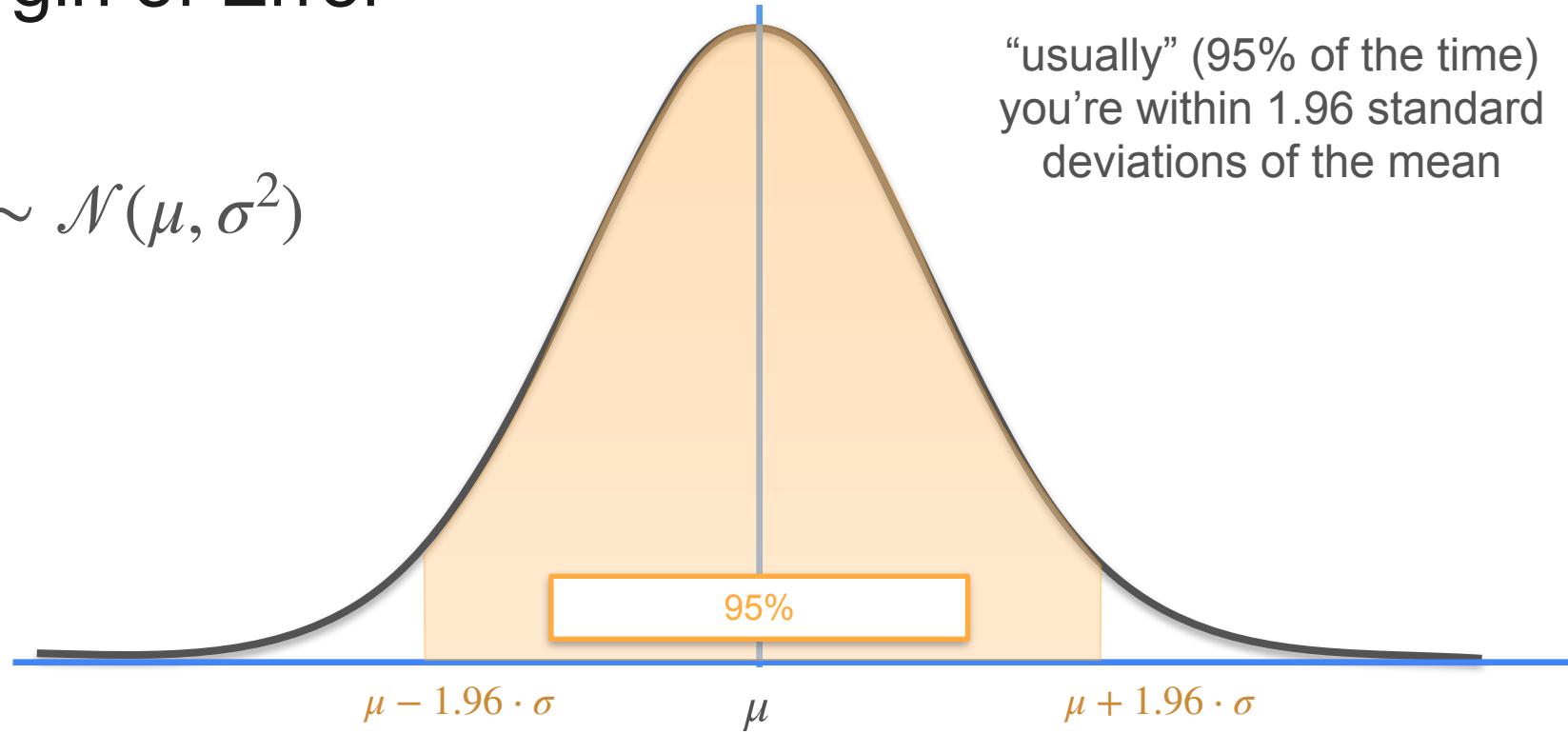
# Margin of Error

$$\frac{X - \mu}{\sigma} \sim \mathcal{N}(0, 1^2)$$



# Margin of Error

$$X \sim \mathcal{N}(\mu, \sigma^2)$$



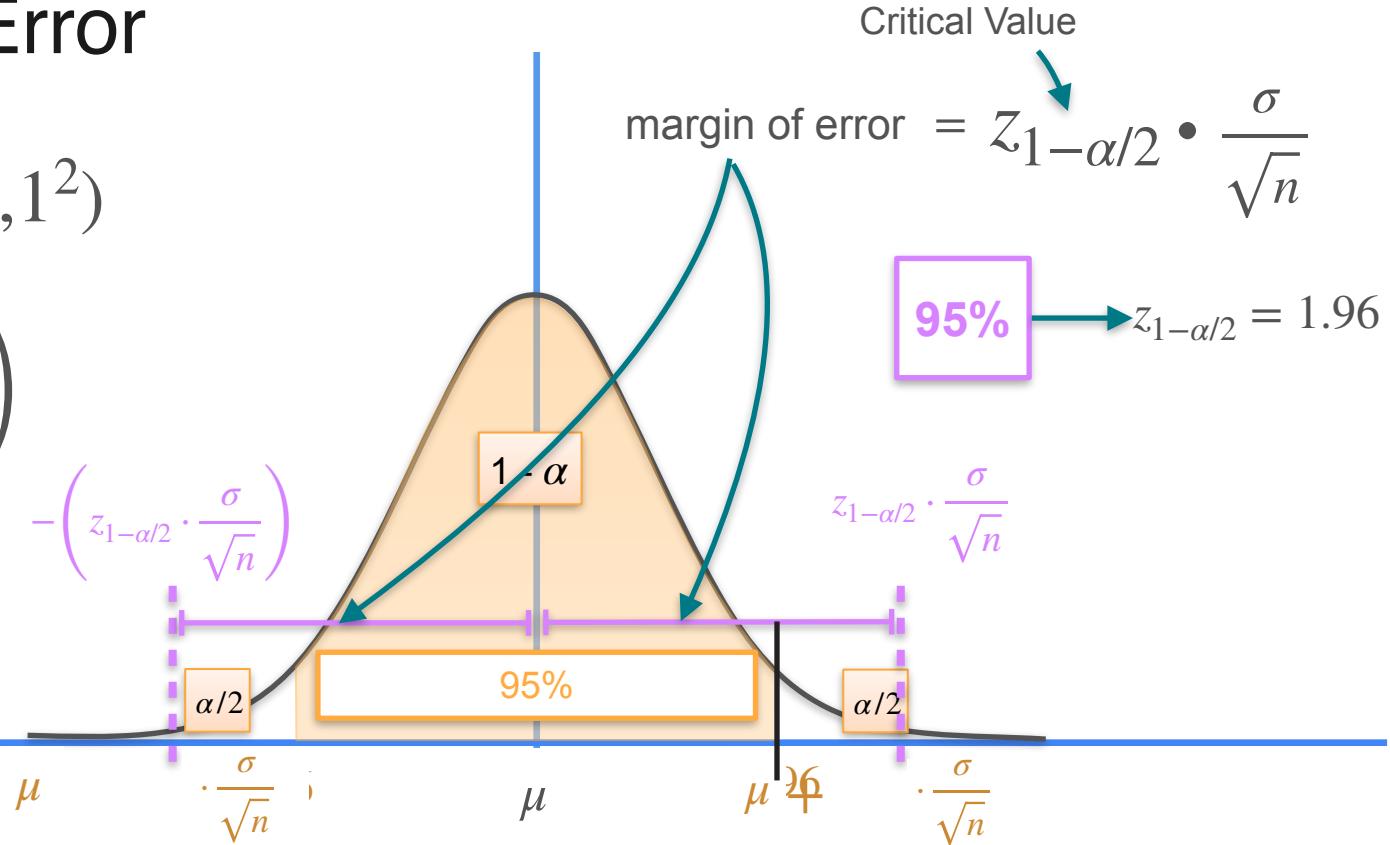
# Margin of Error

$$\bar{X} - \mu \sim \mathcal{N}(0, 1^2)$$

$$\bar{X} \sim \mathcal{N}\left(\mu_{\bar{x}}, \frac{\sigma^2}{n}\right)$$

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

Standard error





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# Confidence Interval

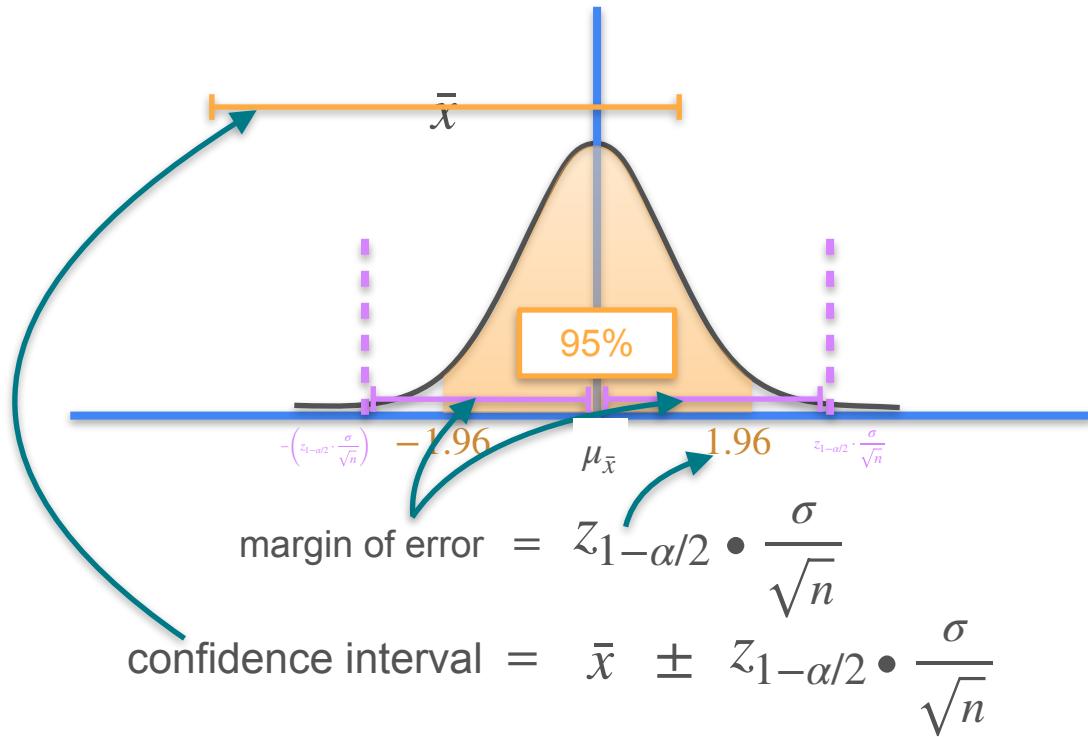
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**Confidence Interval -  
Calculation Steps**

# Confidence Interval - Calculation Steps

## STEPS:

- Find the sample mean
- Define a desired confidence level ( $1 - \alpha$ )
- Get the critical value ( $z_{1-\alpha/2}$ )
- Find the standard error ( $\frac{\sigma}{\sqrt{n}}$ )
- Find the margin of error
- Add/subtract the margin of error to the sample mean



# Confidence Interval - Calculation Steps

## STEPS:

- Find the sample mean
- Define a desired confidence level ( $1 - \alpha$ )
- Get the critical value ( $z_{1-\alpha/2}$ )
- Find the standard error ( $\frac{\sigma}{\sqrt{n}}$ )
- Find the margin of error
- Add/subtract the margin of error to the sample mean

$$\text{confidence interval} = \bar{x} \pm z_{1-\alpha/2} \cdot \frac{\sigma}{\sqrt{n}}$$

## Assumptions

- Simple random sample
- Sample size  $> 30$  or population is approximately normal



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## Confidence Interval

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**Confidence Interval -  
Example**

# Confidence Interval - Example

Statistopia

6,000 adults

Random Selection



$$\bar{x} = 170\text{cm}$$

$$\sigma = 25\text{cm}$$

95%

$$\rightarrow z_{1-\alpha/2} = 1.96$$

Calculate a 95% confidence interval for the average height of adults on Statistopia.

# Confidence Interval - Example

Random Selection



49

$\sigma = 25cm$

95%

$$z_{1-\alpha/2} = 1.96$$

Confidence Interval

$170cm \pm \text{margin of error}$

$$\text{margin of error} = z_{1-\alpha/2} \cdot \frac{\sigma}{\sqrt{n}}$$

$$= 1.96 \cdot \frac{25}{\sqrt{49}}$$

$$= 1.96 \cdot \frac{25}{7}$$

$$= 7$$

# Confidence Interval - Example

Random Selection

2500



$$\sigma = 10\text{cm}$$

95%

$$z_{1-\alpha/2} = 1.96$$

**Confidence Interval**

$$170\text{cm} \pm \text{margin of error}$$

$$\text{margin of error} = 7$$

**Confidence Interval**

$$170\text{cm} - 7 = 163\text{cm}$$

$$170\text{cm} + 7 = 177\text{cm}$$

$$163\text{cm} < \mu < 177\text{cm}$$



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## Confidence Interval

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## Calculating Sample Size

# Calculating Sample Size

6,000 adults

Random Selection

49

Margin of error: 7cm

$$\bar{x} \pm 7\text{cm}$$

$$163\text{cm} < \mu < 177\text{cm}$$



95% →  $z_{1-\alpha/2} = 1.96$

$$\bar{x} = 170\text{cm} \quad \sigma = 25\text{cm}$$

# Calculating Sample Size

6,000 adults

95%

$$z_{1-\alpha/2} = 1.96$$

$$\bar{x} = 170\text{cm}$$

$$\sigma$$

What is the smallest sample size to obtain the  
desired margin of error?

Random Selection



Margin of error: 7cm

$$\bar{x} \pm 7\text{cm}$$

$$163\text{cm} < \mu < 177\text{cm}$$

Margin of error: 3 cm

$$\bar{x} \pm 3\text{cm}$$

# Calculating Sample Size

6,000 adults

95%

$$z_{1-\alpha/2} = 1.96$$

$$\bar{x} = 170\text{cm} \quad \sigma = 25\text{cm}$$

Margin of error: 3 cm

$$\text{margin of error} = z_{1-\alpha/2} \cdot \frac{\sigma}{\sqrt{n}}$$

$$3 = z_{1-\alpha/2} \cdot \frac{\sigma}{\sqrt{n}}$$

$$3 \geq z_{1-\alpha/2} \cdot \frac{\sigma}{\sqrt{n}}$$

# Calculating Sample Size

6,000 adults

$$\text{margin of error} = z_{1-\alpha/2} \cdot \frac{\sigma}{\sqrt{n}}$$

95%

$$z_{1-\alpha/2} = 1.96$$

$$\bar{x} = 170\text{cm} \quad \sigma = 25\text{cm}$$

Margin of error: 3 cm

$$3 = z_{1-\alpha/2} \cdot \frac{\sigma}{\sqrt{n}}$$

$$3 \geq z_{1-\alpha/2} \cdot \frac{\sigma}{\sqrt{n}}$$

# Calculating Sample Size

6,000 adults

$$\text{margin of error} = z_{1-\alpha/2} \cdot \frac{\sigma}{\sqrt{n}}$$

95%

$$z_{1-\alpha/2} = 1.96$$

$$\bar{x} = 170\text{cm} \quad \sigma = 25\text{cm}$$

Margin of error: 3 cm

$$3 \geq z_{1-\alpha/2} \cdot \frac{\sigma}{\sqrt{n}}$$

$$3 \geq 1.96 \times \frac{25}{\sqrt{n}}$$

# Calculating Sample Size

6,000 adults

$$\text{margin of error} = z_{1-\alpha/2} \cdot \frac{\sigma}{\sqrt{n}}$$

95%

$$z_{1-\alpha/2} = 1.96$$

$$\bar{x} = 170\text{cm} \quad \sigma = 25\text{cm}$$

Margin of error: 3 cm

$$3 \geq z_{1-\alpha/2} \cdot \frac{\sigma}{\sqrt{n}}$$

$$\frac{3}{1.96} \geq \frac{25}{\sqrt{n}}$$

# Calculating Sample Size

6,000 adults

$$\text{margin of error} = z_{1-\alpha/2} \cdot \frac{\sigma}{\sqrt{n}}$$

95%

$$z_{1-\alpha/2} = 1.96$$

$$\bar{x} = 170\text{cm} \quad \sigma = 25\text{cm}$$

Margin of error: 3 cm

$$3 \geq z_{1-\alpha/2} \cdot \frac{\sigma}{\sqrt{n}}$$

$$\frac{3}{1.96 \times 25} \geq \frac{1}{\sqrt{n}}$$

# Calculating Sample Size

6,000 adults

$$\text{margin of error} = z_{1-\alpha/2} \cdot \frac{\sigma}{\sqrt{n}}$$

95%

$$z_{1-\alpha/2} = 1.96$$

$$\bar{x} = 170\text{cm} \quad \sigma = 25\text{cm}$$

Margin of error: 3 cm

$$3 \geq z_{1-\alpha/2} \cdot \frac{\sigma}{\sqrt{n}}$$

$$\frac{1.96 \times 25}{3} \leq \frac{\sqrt{n}}{1}$$

# Calculating Sample Size

6,000 adults

$$\text{margin of error} = z_{1-\alpha/2} \cdot \frac{\sigma}{\sqrt{n}}$$

95%

$$z_{1-\alpha/2} = 1.96$$

$$\bar{x} = 170\text{cm} \quad \sigma = 25\text{cm}$$

Margin of error: 3 cm

$$\frac{1.96 \times 25}{3} \leq \frac{\sqrt{n}}{1}$$

$$\left( \frac{1.96 \times 25}{3} \right)^2 \leq n$$

# Calculating Sample Size

6,000 adults

$$\text{margin of error} = z_{1-\alpha/2} \cdot \frac{\sigma}{\sqrt{n}}$$

95%   $z_{1-\alpha/2} = 1.96$

$$\bar{x} = 170\text{cm} \quad \sigma = 25\text{cm}$$

Margin of error: 3 cm

$$\frac{1.96 \times 25}{3} \leq \frac{\sqrt{n}}{1}$$

$$n \geq \left( \frac{1.96 \times 25}{3} \right)^2$$

# Calculating Sample Size

6,000 adults

$$\text{margin of error} = z_{1-\alpha/2} \cdot \frac{\sigma}{\sqrt{n}}$$

95%   $z_{1-\alpha/2} = 1.96$

$$n \geq \left( \frac{1.96 \times 25}{3} \right)^2$$

$$\bar{x} = 170\text{cm} \quad \sigma = 25\text{cm}$$

$$n \geq 266.78 \approx 267$$

Margin of error: 3 cm

# Calculating Sample Size

$$\text{margin of error} = z_{1-\alpha/2} \cdot \frac{\sigma}{\sqrt{n}}$$

$$n \geq \left( \frac{1.96 \times 25}{3} \right)^2$$

$$n \geq \left( \frac{z_{\alpha/2} \cdot \sigma}{MOE} \right)^2$$



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## Confidence Interval

---

**Difference Between  
Confidence and Probability**

# Difference Between Confidence and Probability

95%  
Confidence  
Level



The confidence interval contains the true population parameter approximately 95% of the time.

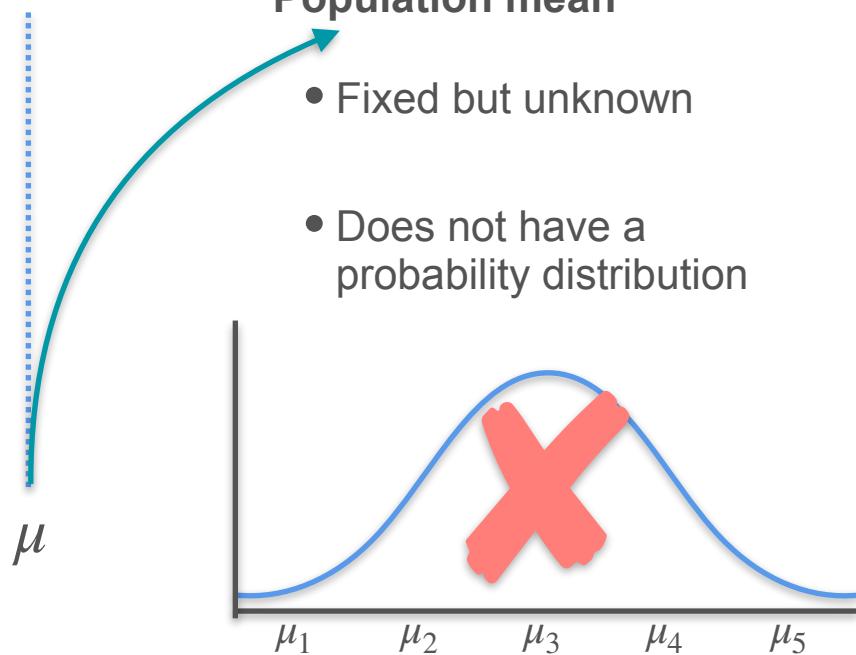


There's a 95% probability that the population parameter falls within the confidence interval.



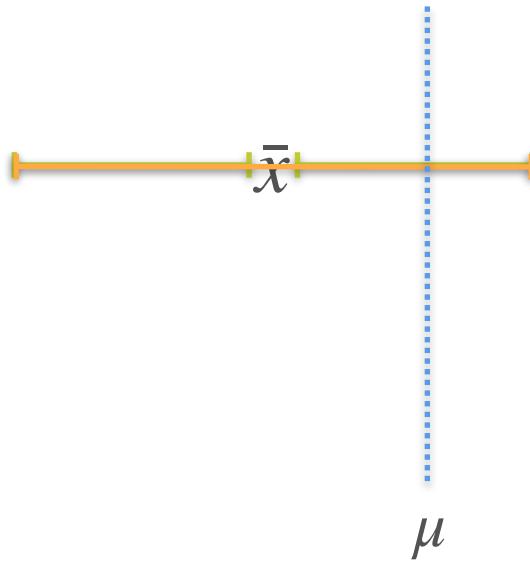
# Difference Between Confidence and Probability

95%  
Confidence  
Level



# Difference Between Confidence and Probability

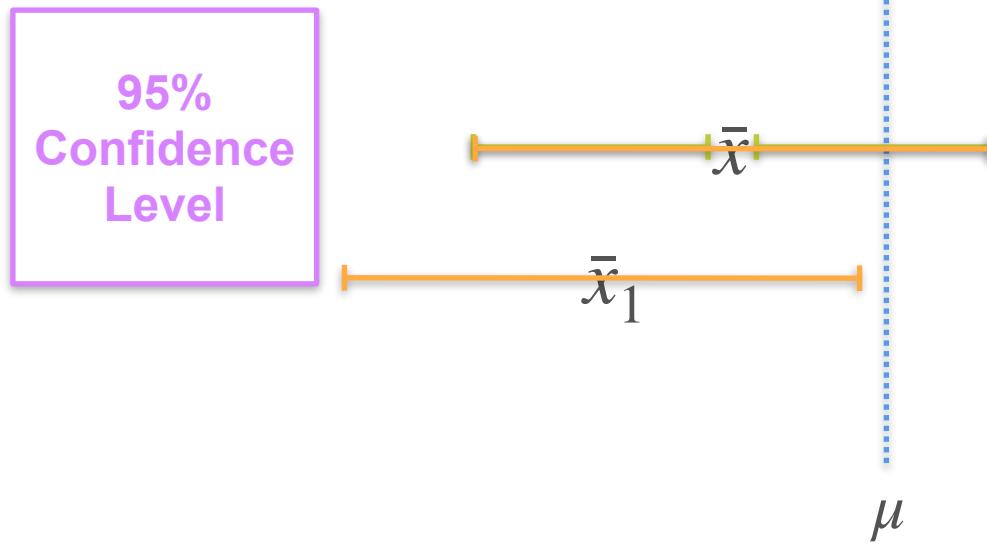
95%  
Confidence  
Level



## Population mean

- Fixed but unknown
- Does not have a probability distribution
- In the interval

# Difference Between Confidence and Probability

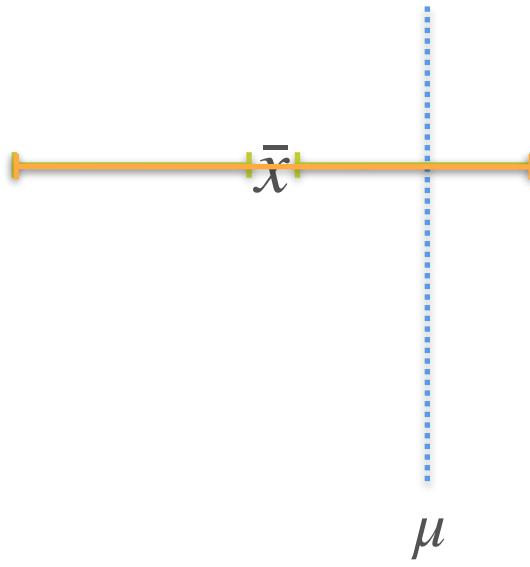


## Population mean

- Fixed but unknown
- Does not have a probability distribution
- In the interval or not

# Difference Between Confidence and Probability

95%  
Confidence  
Level



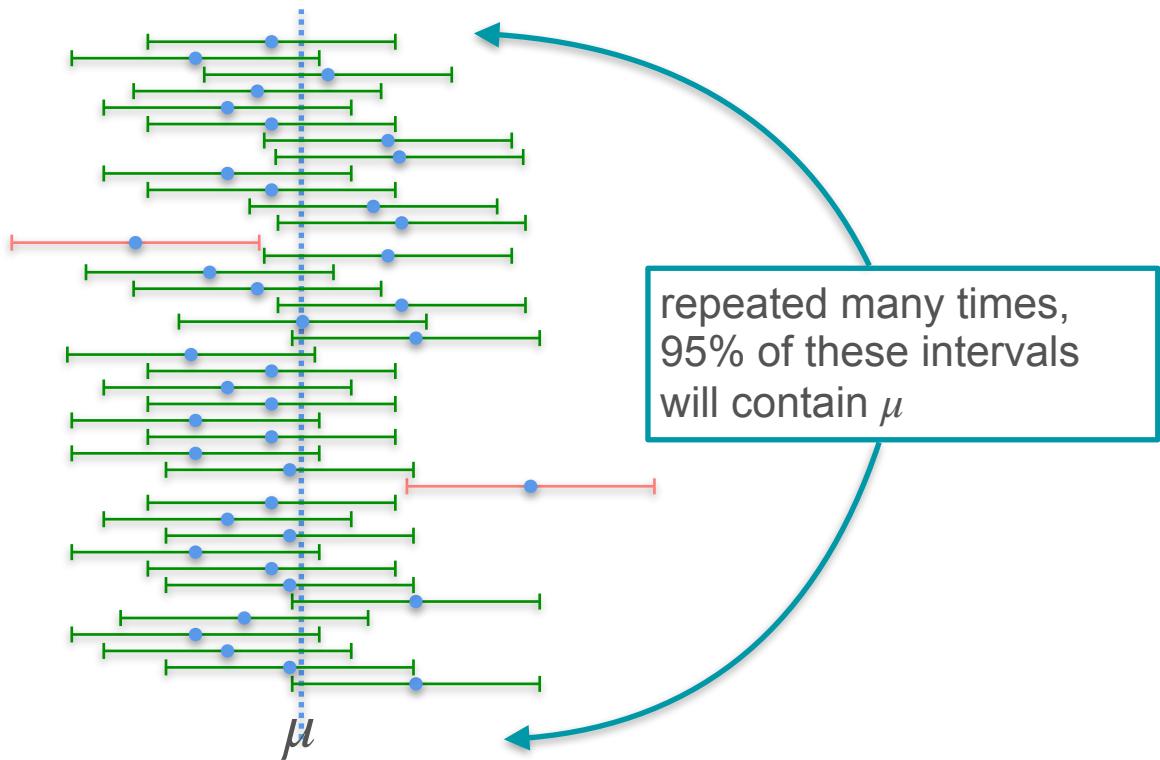
## Population mean

- Fixed but unknown
- Does not have a probability distribution
- In the interval or not
- Does not fall within a specific interval 95% of the time

# Difference Between Confidence and Probability

95%  
Confidence  
Level

success rate for constructing  
the confidence interval

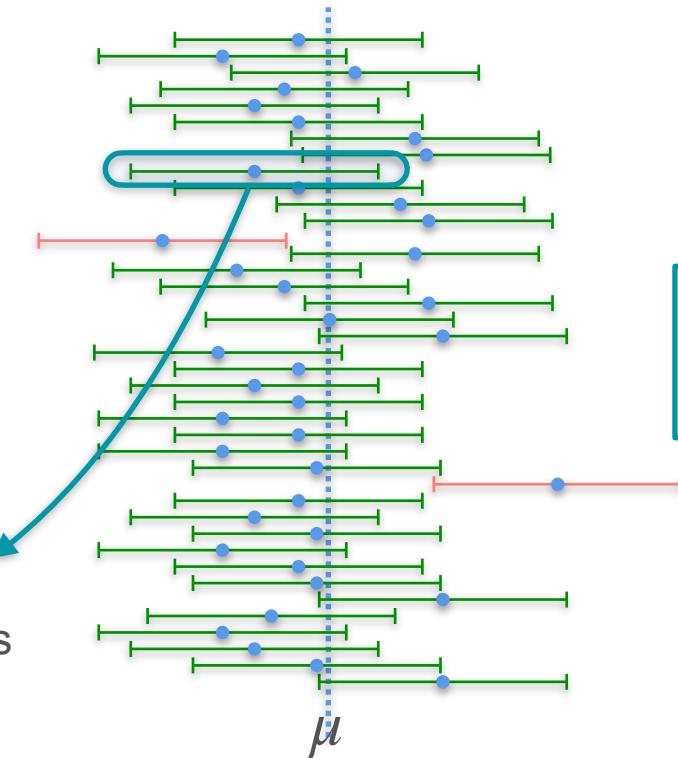


# Difference Between Confidence and Probability

95%  
Confidence  
Level

success rate for constructing  
the confidence interval

not the probability that  
one specific intervals contains  
the population mean



repeated many times,  
95% of these intervals  
will contain  $\mu$



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## Confidence Interval

---

# Unknown Standard Deviation

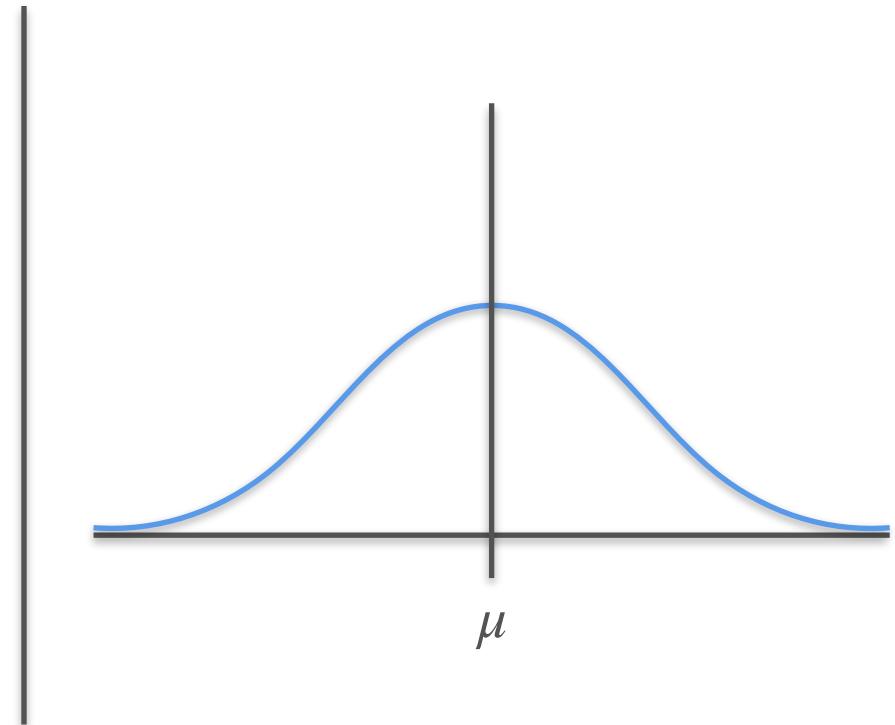
# Confidence Interval - $t$ Distribution

known  $\sigma$

$$\bar{x} \pm z_{1-\alpha/2} \cdot \frac{\sigma}{\sqrt{n}}$$

$$\frac{\bar{x} - \mu}{\frac{\sigma}{\sqrt{n}}}$$

normal  
distribution



# Confidence Interval - $t$ Distribution

known  $\sigma$  ?  $\rightarrow s$

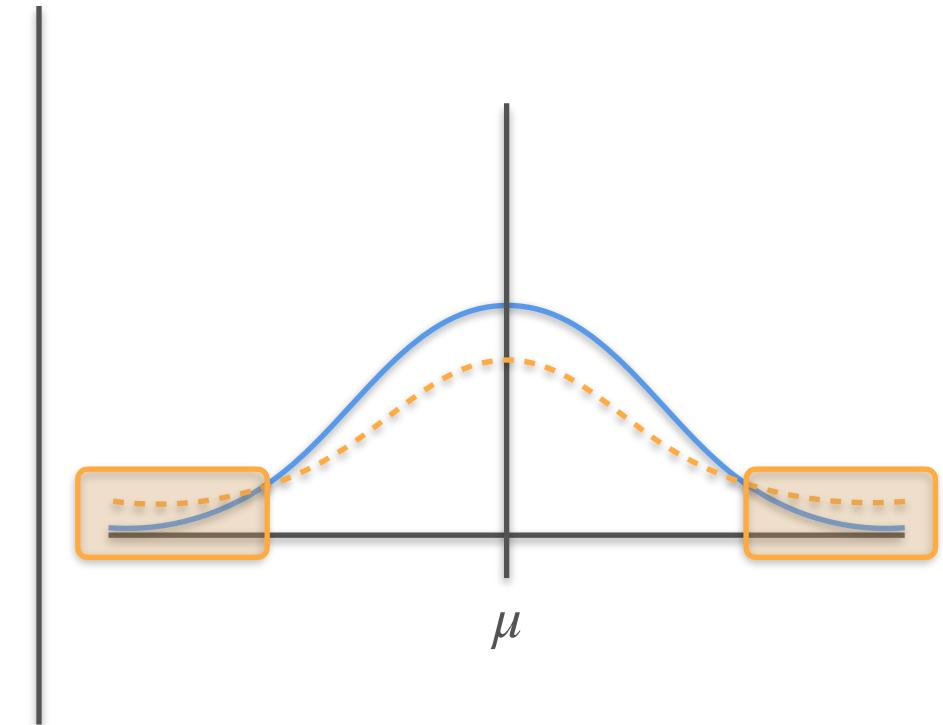
$$\bar{x} \pm z_{1-\alpha/2} \cdot \frac{\sigma}{\sqrt{n}}$$

$$\frac{\bar{x} - \mu}{\frac{\sigma}{\sqrt{n}}} \xrightarrow{\text{dotted arrow}} \frac{\bar{x} - \mu}{\frac{s}{\sqrt{n}}}$$

normal distribution

not a normal distribution

**student's t distribution**



# Confidence Interval - $t$ Distribution

known  $\sigma$

$$\frac{\bar{x} - \mu}{\frac{\sigma}{\sqrt{n}}}$$

normal distribution

$$\bar{x} \pm z_{1-\alpha/2} \cdot \frac{\sigma}{\sqrt{n}}$$



unknown  $\sigma$

replace with  $s$

$$\frac{\bar{x} - \mu}{\frac{s}{\sqrt{n}}}$$

student's t distribution

$$\bar{x} \pm z_{1-\alpha/2} \cdot \frac{s}{\sqrt{n}}$$



# Confidence Interval - $t$ Distribution

known  $\sigma$

$$\bar{x} \pm z_{1-\alpha/2} \cdot \frac{\sigma}{\sqrt{n}}$$



unknown  $\sigma$

$$\bar{x} \pm z_{1-\alpha/2} \cdot \frac{s}{\sqrt{n}}$$



$$\bar{x} \pm t_{1-\alpha/2} \cdot \frac{s}{\sqrt{n}}$$



# Confidence Interval - $t$ Distribution

known  $\sigma$

$$\bar{x} \pm z_{1-\alpha/2} \cdot \frac{\sigma}{\sqrt{n}}$$

unknown  $\sigma$

$$\bar{x} \pm t_{1-\alpha/2} \cdot \frac{s}{\sqrt{n}}$$

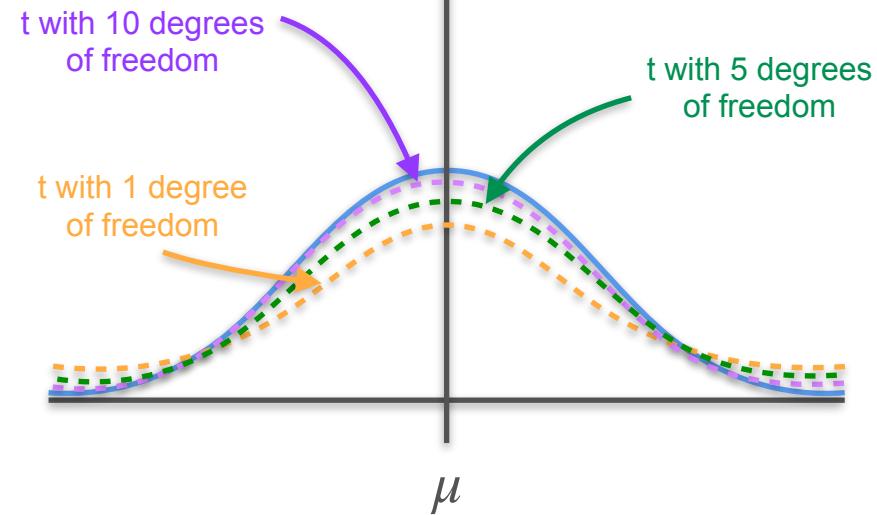
# Confidence Interval - $t$ Distribution

unknown  $\sigma$

$$\bar{x} \pm t_{1-\alpha/2} \cdot \frac{s}{\sqrt{n}}$$

degrees of freedom

$$n - 1$$





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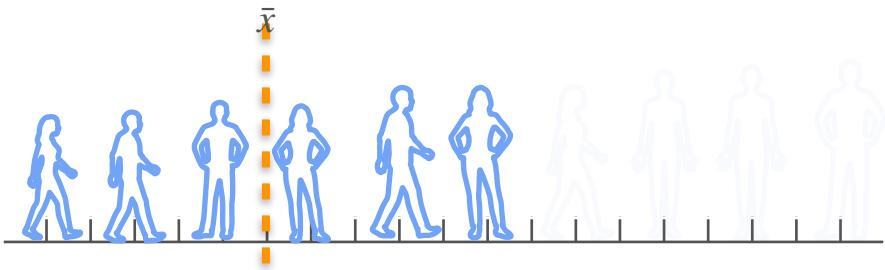
## Confidence Interval

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# Confidence Intervals for Proportion

# Confidence Interval for Proportions

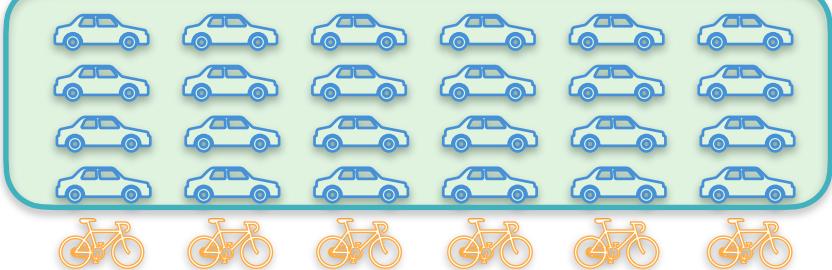
## Confidence Interval for Means



$$\text{confidence interval} = \bar{x} \pm \text{margin of error}$$

$$\text{margin of error} = z_{1-\alpha/2} \cdot \frac{\sigma}{\sqrt{n}}$$

## Confidence Interval for Proportions



$$x = 24$$

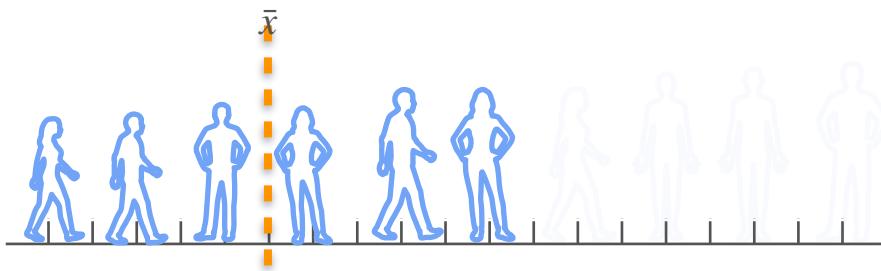
$$n = 30$$

$$\hat{p} = \frac{x}{n} = \frac{24}{30} = 80\%$$

How do you calculate a 95% confidence interval for this sample proportion?

# Confidence Interval for Proportions

## Confidence Interval for Means



$$\text{confidence interval} = \bar{x} \pm \text{margin of error}$$

$$\text{margin of error} = z_{1-\alpha/2} \cdot \frac{\sigma}{\sqrt{n}}$$

## Confidence Interval for Proportions

$$\hat{p} = \frac{x}{n} = \frac{24}{30} = 80\%$$

$$\text{confidence interval} = \hat{p} \pm \text{margin of error}$$

$$\text{margin of error} = z_{1-\alpha/2} \cdot \sqrt{\frac{\hat{p}(1 - \hat{p})}{n}}$$

**standard error**

# Confidence Interval for Proportions

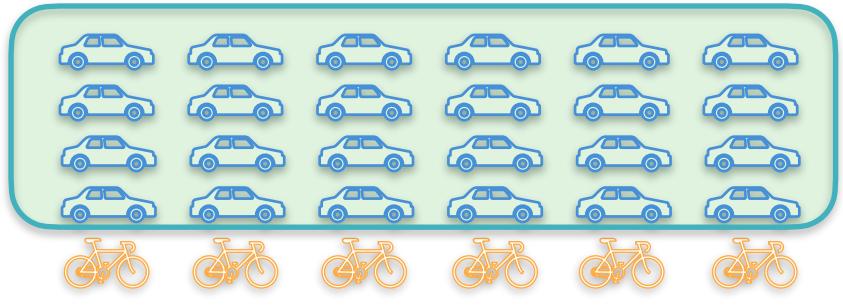
## Confidence Interval for Proportions

confidence interval =  $\hat{p} \pm$  margin of error

$$\text{margin of error} = z_{1-\alpha/2} \cdot \sqrt{\frac{\hat{p}(1 - \hat{p})}{n}}$$

$$\text{margin of error} = 1.96 \cdot \sqrt{\frac{0.8(1 - 0.8)}{30}}$$

$$\text{margin of error} = 0.14$$



$$n = 30 \quad \hat{p} = 80\% = 0.8$$

Calculate a 95% confidence interval for this sample proportion

$$95\% \rightarrow z_{1-\alpha/2} = 1.96$$

# Confidence Interval for Proportions

## Confidence Interval for Proportions

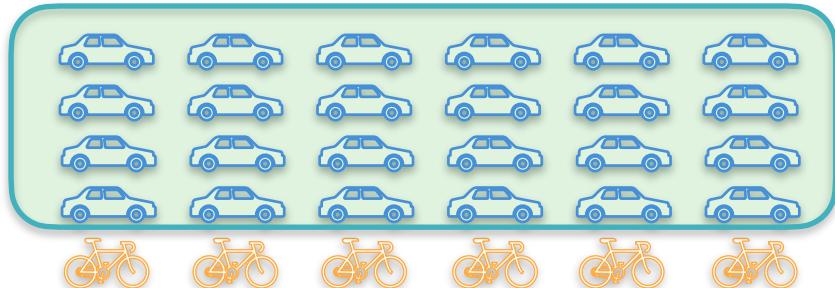
confidence interval =  $\hat{p} \pm$  margin of error

margin of error = 0.14

confidence interval =  $0.8 \pm 0.14$

$$0.66 < p < 0.94$$

$$66\% < p < 94\%$$



$$n = 30 \quad \hat{p} = 80\% = 0.8$$

Calculate a 95% confidence interval for this sample proportion

95%

$$\rightarrow z_{1-\alpha/2} = 1.96$$

# W4 Lesson 2



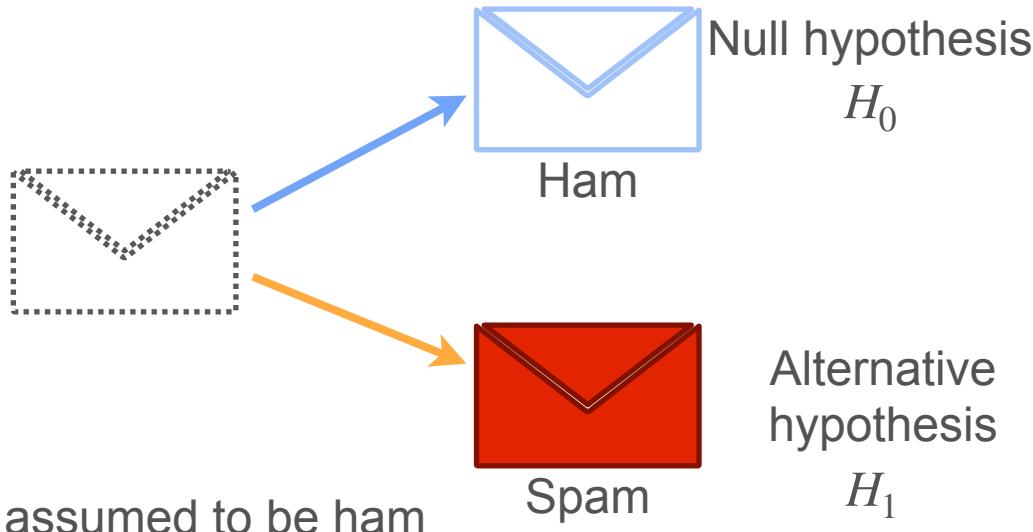
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# Hypothesis Testing

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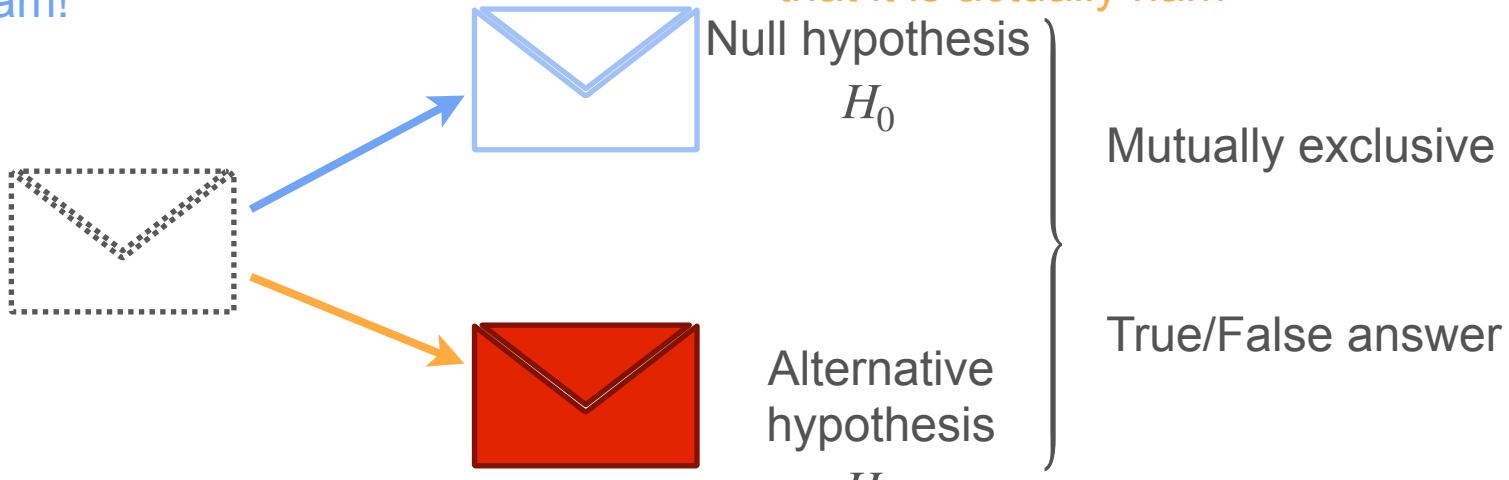
## Defining Hypotheses

# Motivation



# Motivation

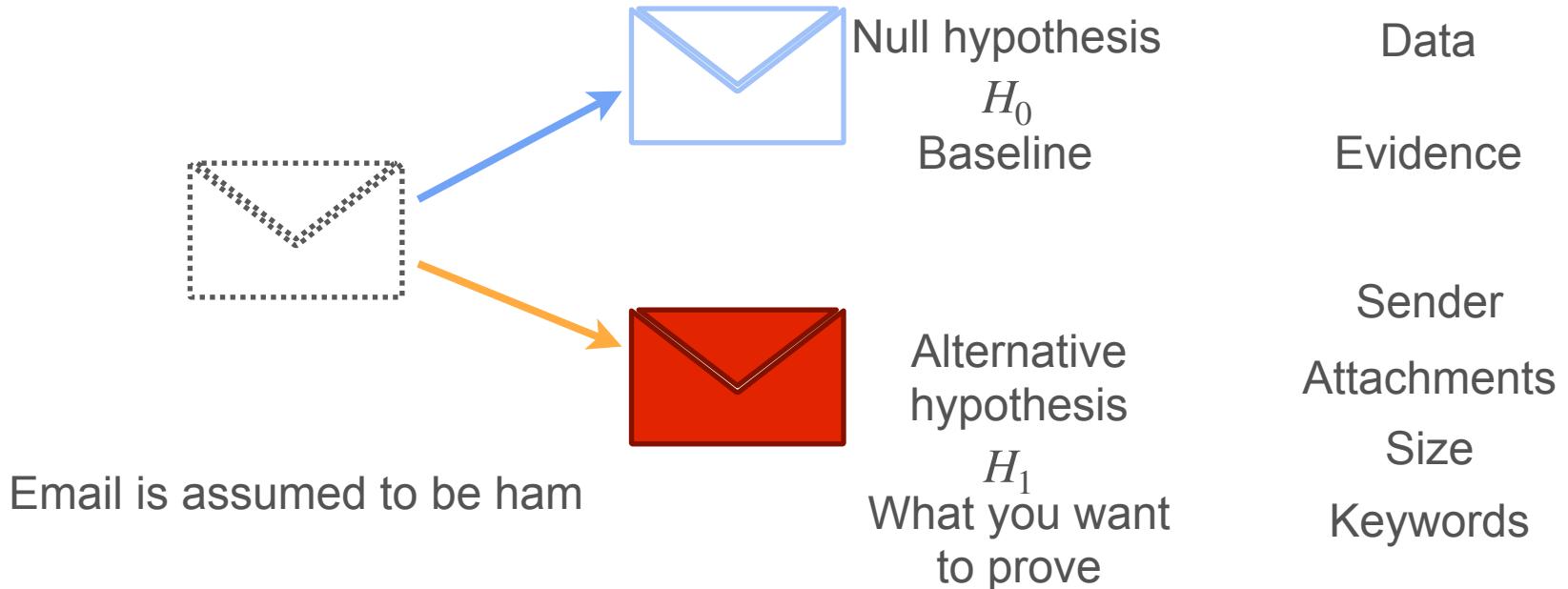
When rejecting that the email is not spam, you are accepting that the email is spam!



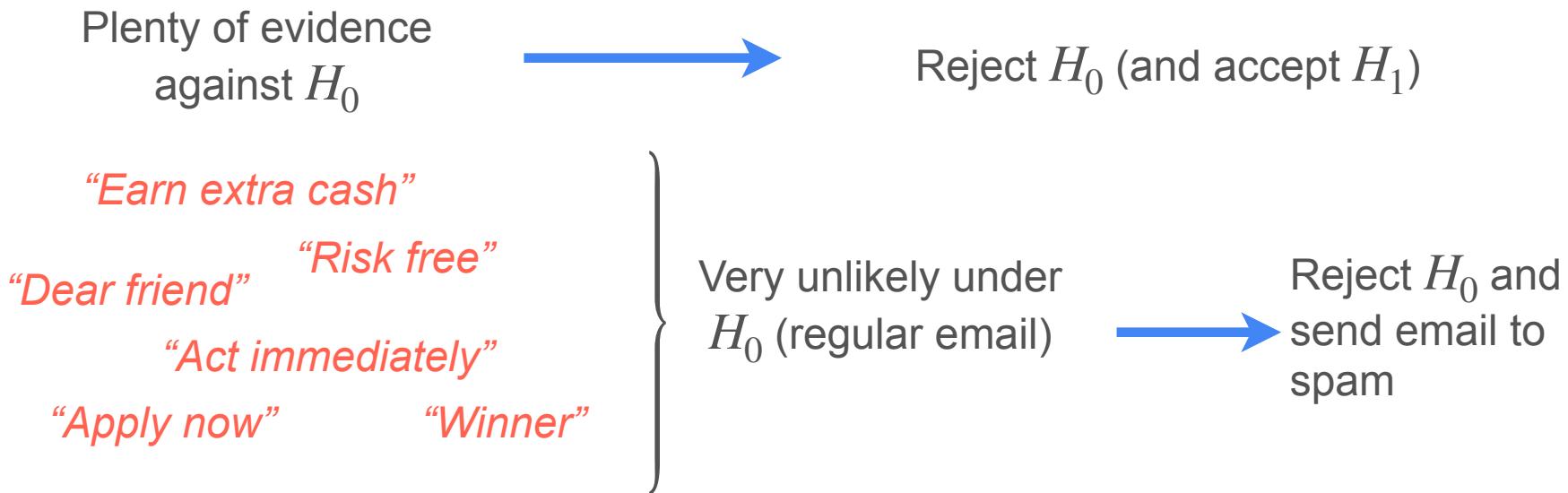
Email is assumed to be ham

# Motivation

Not labeling the email spam, doesn't mean the email is ham!



# How To Determine the Result of the Test





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# Hypothesis Testing

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## Type I and Type II errors

# Sometimes Things Go Wrong...

What if I make the wrong decision?



Type I error  
(False positive)



Type II error  
(False negative)

# Type I and Type II Errors

Decision	Reality	
	$H_0$ True (Innocent)	$H_0$ False (Guilty)
Reject $H_0$ (Decide Guilty)	Type I error	Correct
Don't reject $H_0$ (Decide not guilty)	Correct	Type II error

# Significance Level

Sending a regular email to spam is worse than sending a spam email to the regular inbox.

Type I error



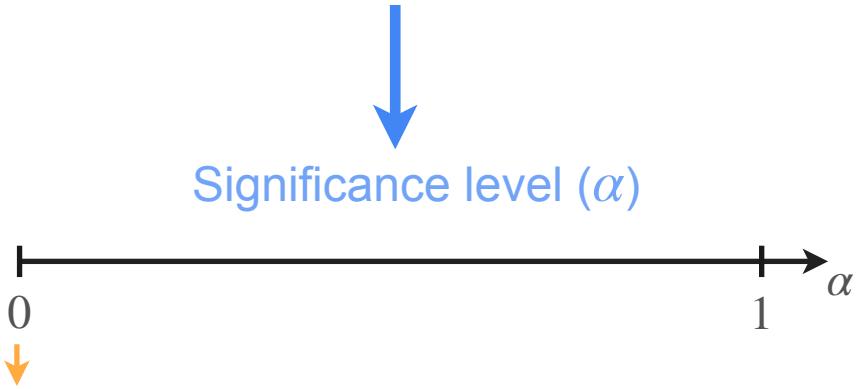
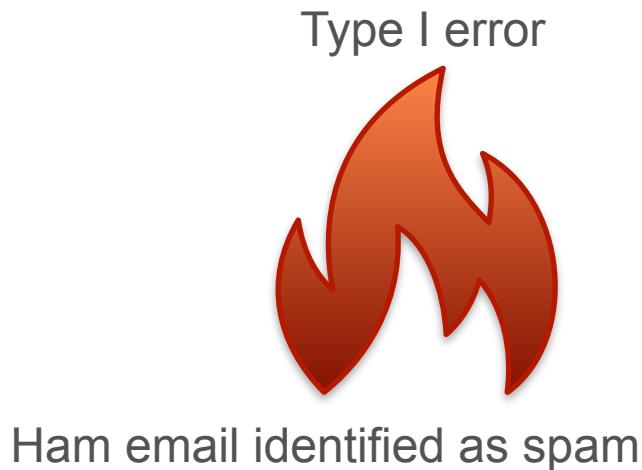
Type II error



What is the greatest probability of type I error you are willing to tolerate?

# Significance Level

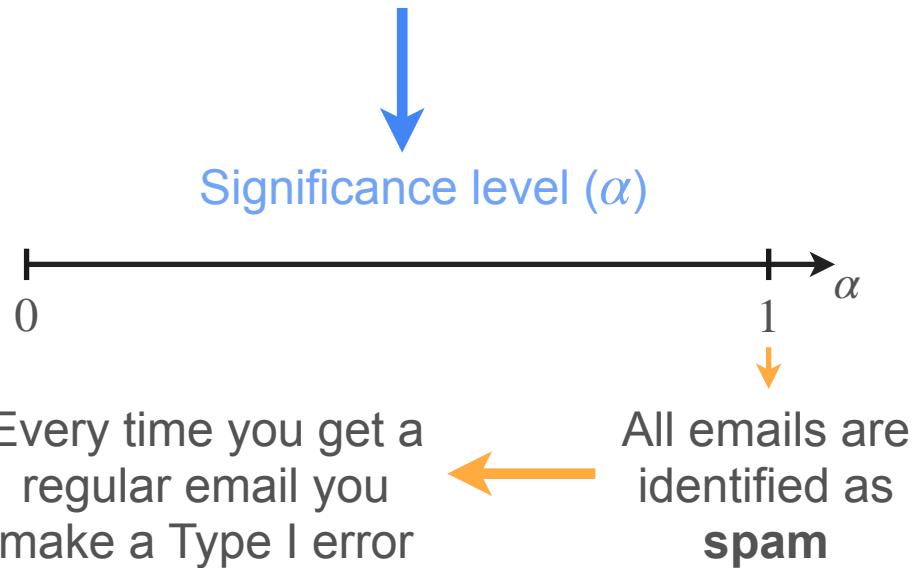
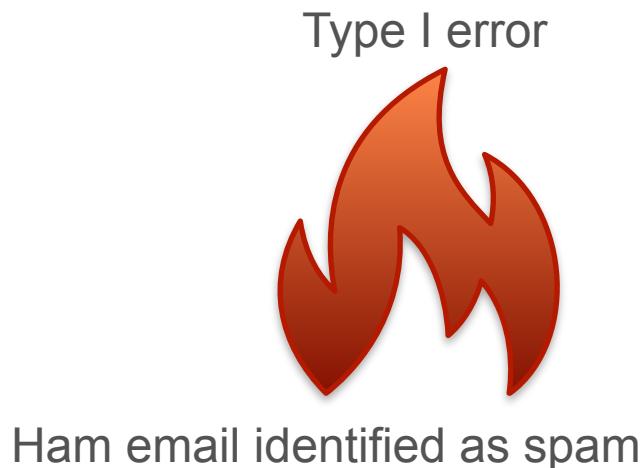
What is the greatest probability of type I error you are willing to tolerate?



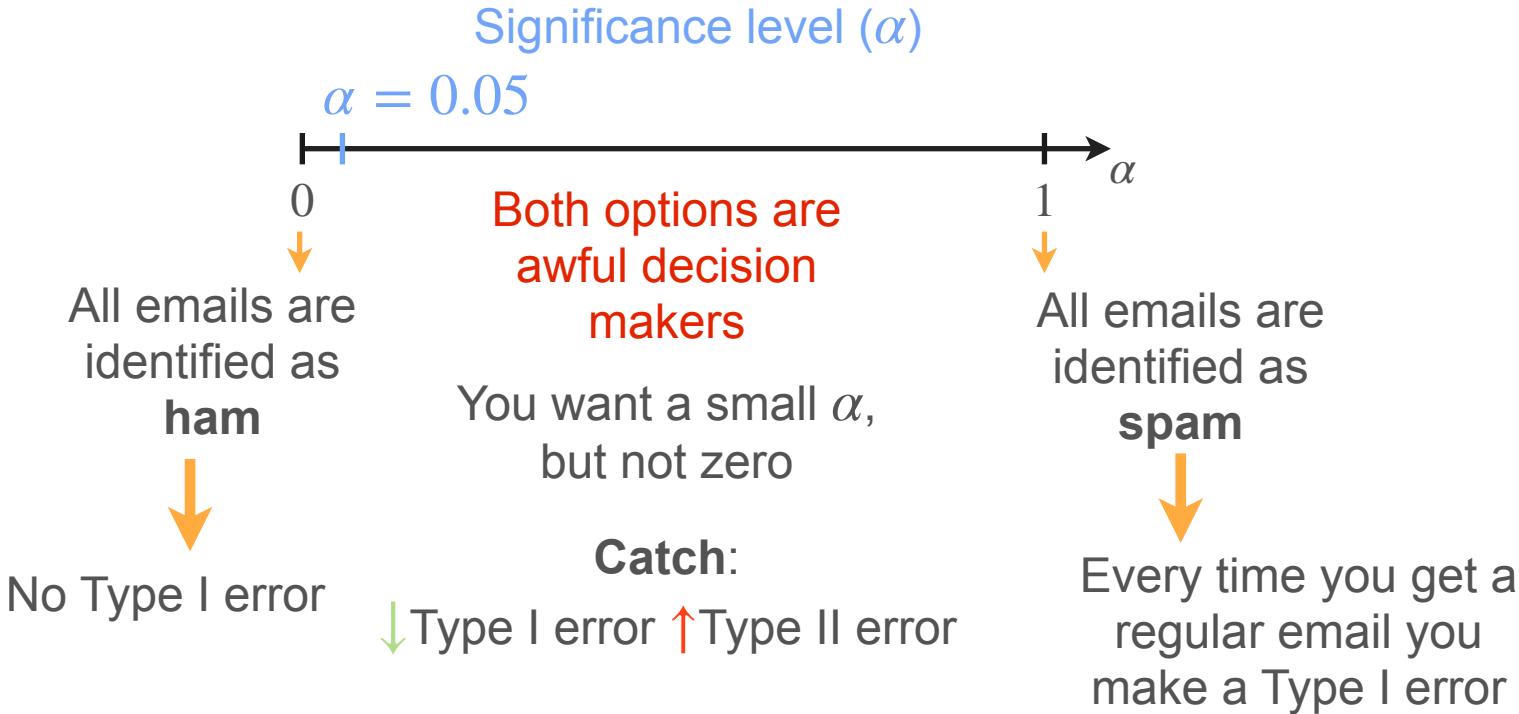
All emails are identified as **not spam**  $\longrightarrow$  No Type I error

# Significance Level

What is the greatest probability of type I error you are willing to tolerate?



# Significance Level



# Significance Level

Type I error



Ham email identified as spam

$$\begin{aligned}\alpha &= \max \mathbf{P}(\text{Type I error}) \\ &= \max \mathbf{P}(\text{Reject } H_0 | H_0)\end{aligned}$$

The value of  $\alpha$  is your criteria for designing your test

Given sample,  $\alpha$  will determine if you reject  $H_0$  or not



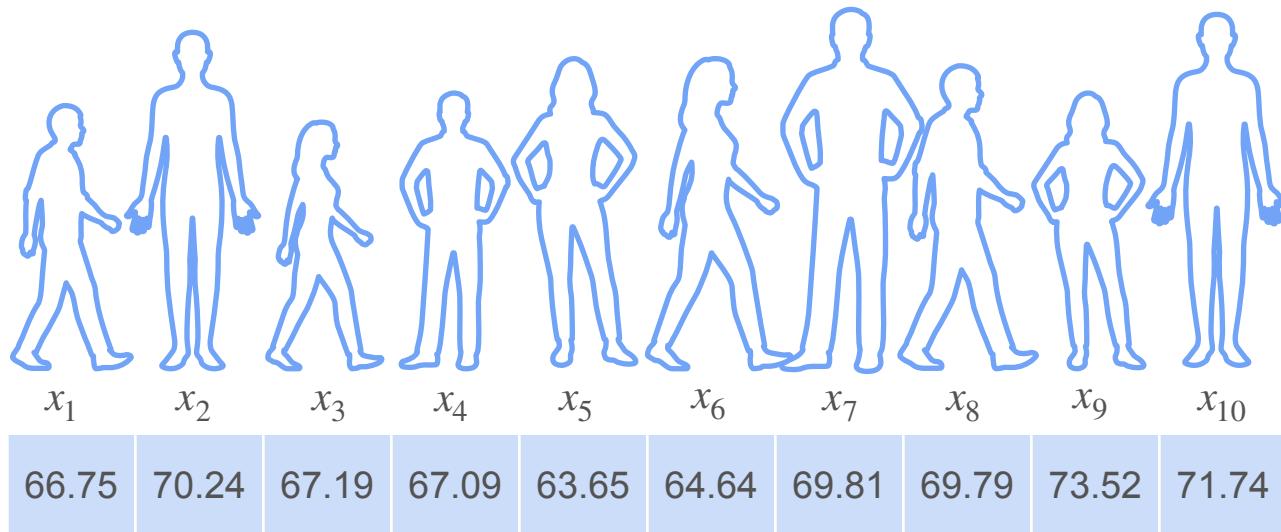
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# Hypothesis Testing

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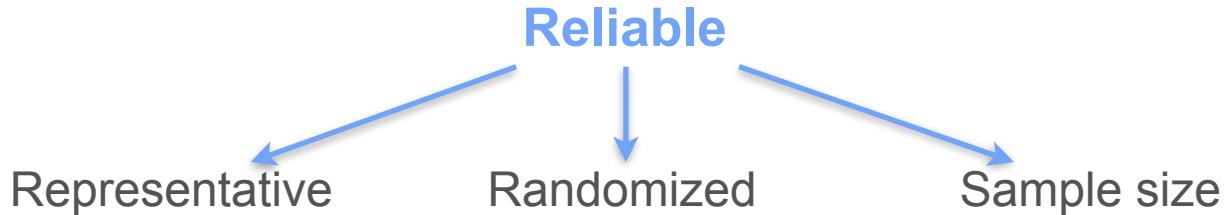
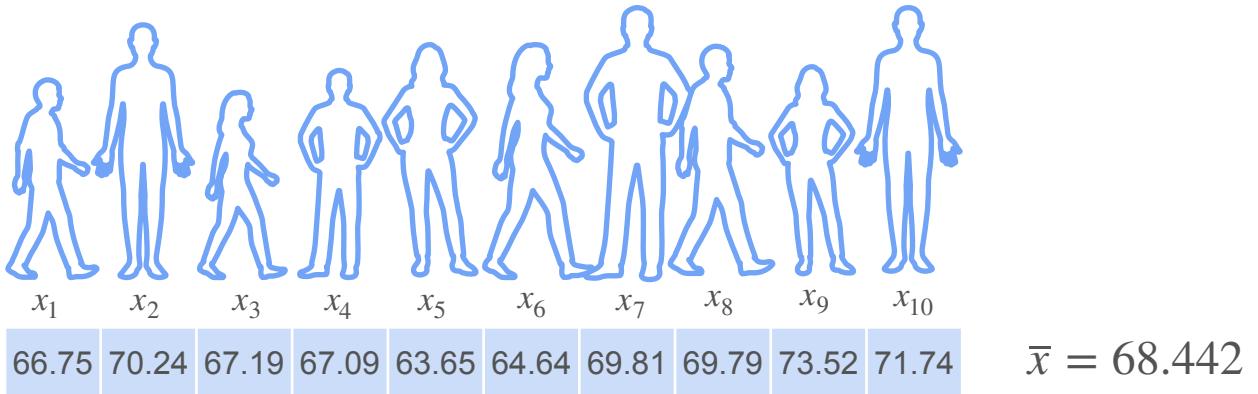
**Right-Tailed, Left-Tailed and  
Two-Tailed tests**

# Example: Heights

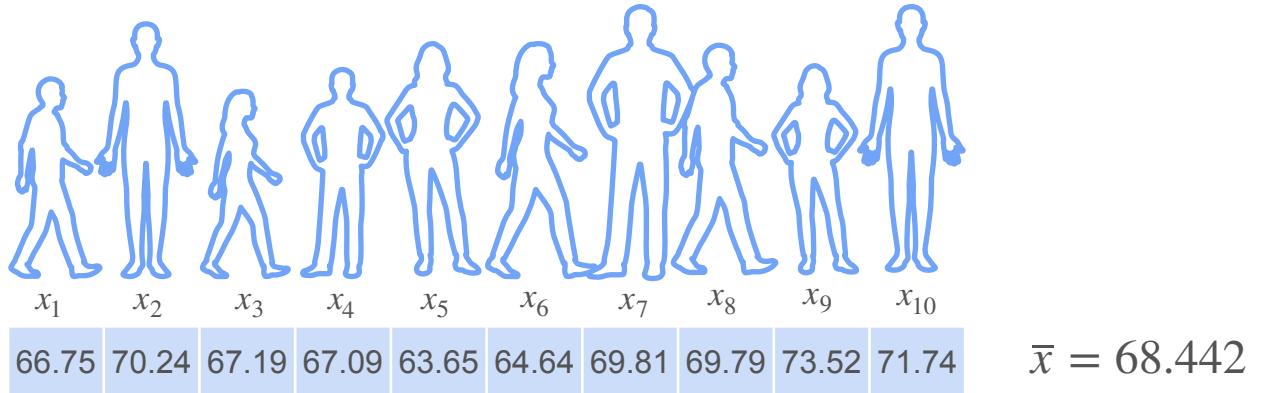


$$\bar{x} = 68.442$$

# Data Quality



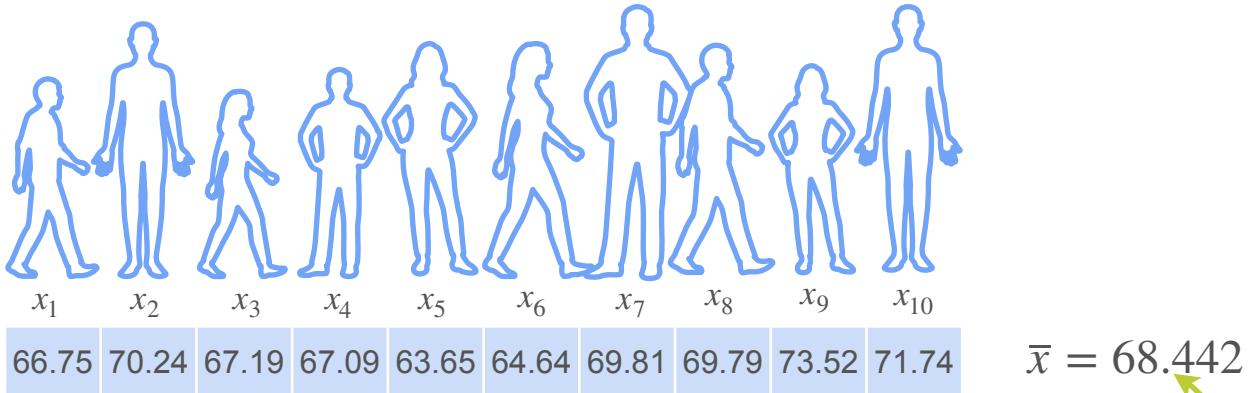
# Determining the Hypothesis



The **mean** height for 18 y/o in the US in the 70s was **66.7 in.**

Population  $H_0 : \mu = 66.7$  vs.  $H_1 : \mu > 66.7$

# Test Statistic



The **mean** height for 18 y/o in the US in the 70s was **66.7 in.**

$$H_0 : \mu = 66.7 \text{ vs. } H_1 : \mu > 66.7$$

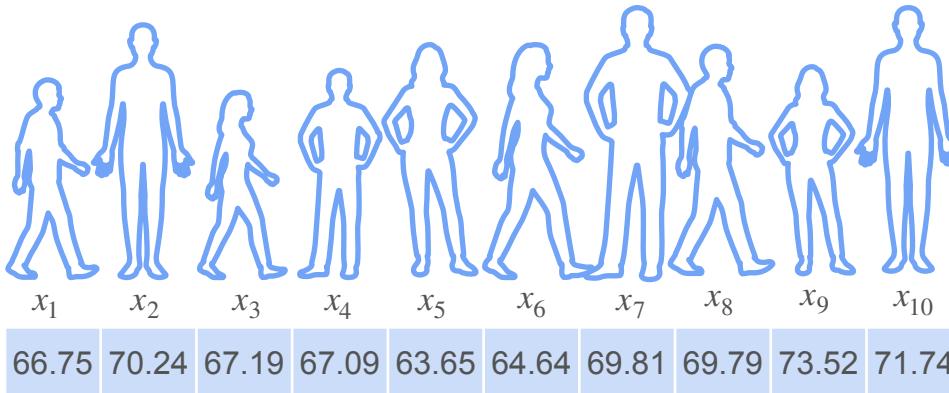
Observed statistic

Test statistic  $\longrightarrow \bar{X} = \frac{1}{10} \sum_{i=1}^{10} X_i$

# Test Statistic

Test statistic

$$\bar{X} = \frac{1}{10} \sum_{i=1}^{10} X_i$$



$$\bar{x} = 68.442$$

Test statistic:  $T(X)$      $X = (X_1, \dots, X_n)$

Information about the population parameter under study

$$\mu \rightarrow \bar{X}$$

$$p \rightarrow \bar{X}$$

Not unique!

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

# Example: Heights

The **mean** height for 18 y/o in the US in the 70s was **66.7 in.**

**3 questions**



**Right-Tailed Test**

**3 sets of hypothesis**

$$H_0 : \mu = 66.7 \text{ vs. } H_1 : \mu > 66.7$$



**Left Tailed Test**

$$H_0 : \mu = 66.7 \text{ vs. } H_1 : \mu < 66.7$$



**Two-Tailed Test**

$$H_0 : \mu = 66.7 \text{ vs. } H_1 : \mu \neq 66.7$$

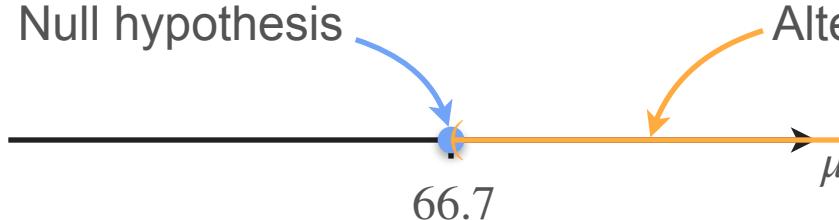
# Example: Heights

The mean height for 18 y/o in the US in the 70s was 66.7 in.

$\bar{X}$  Test statistic

Right-tailed test  $\longrightarrow H_0 : \mu \leq 66.7$  vs.  $H_1 : \mu > 66.7$

Null hypothesis



Type I error: Determine  $\mu > 66.7$ , when population mean did not change

If  $\bar{x} \gg 66.7 \Rightarrow$  Reject  $H_0$

Type II error: Do not reject that  $\mu = 66.7$  when in true  $\mu > 66.7$

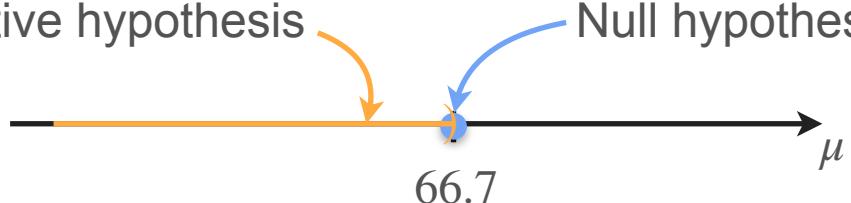
# Example: Heights

The mean height for 18 y/o in the US in the 70s was 66.7 in.

$\bar{X}$  Test statistic

Left tailed test  $\longrightarrow H_0 : \mu \geq 66.7$  vs.  $H_1 : \mu < 66.7$

Alternative hypothesis Null hypothesis



If  $\bar{x} \ll 66.7 \Rightarrow$  Reject  $H_0$

Type I error: Determine  $\mu < 66.7$ , when population mean did not change

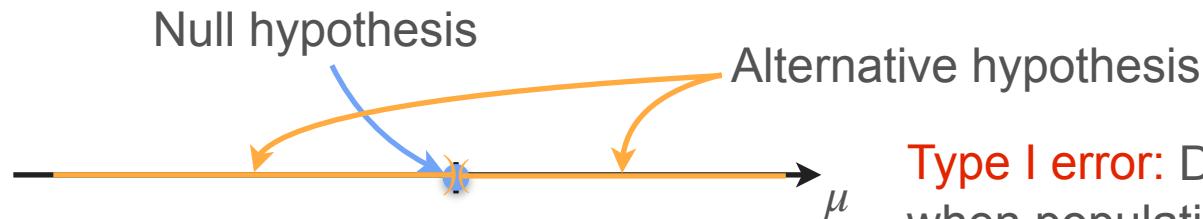
Type II error: Don't reject that  $\mu = 66.7$  when true  $\mu < 66.7$

# Example: Heights

The mean height for 18 y/o in the US in the 70s was **66.7 in.**

$\bar{X}$  Test statistic

Two tailed test  $\longrightarrow H_0 : \mu = 66.7$  vs.  $H_1 : \mu \neq 66.7$



$\bar{x} \gg 66.7$   
If or  $\Rightarrow$  Reject  $H_0$   
 $\bar{x} \ll 66.7$

Type I error: Determine  $\mu \neq 66.7$ , when population mean did not change

Type II error: Don't reject that  $\mu = 66.7$  when true  $\mu \neq 66.7$



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# Hypothesis Testing

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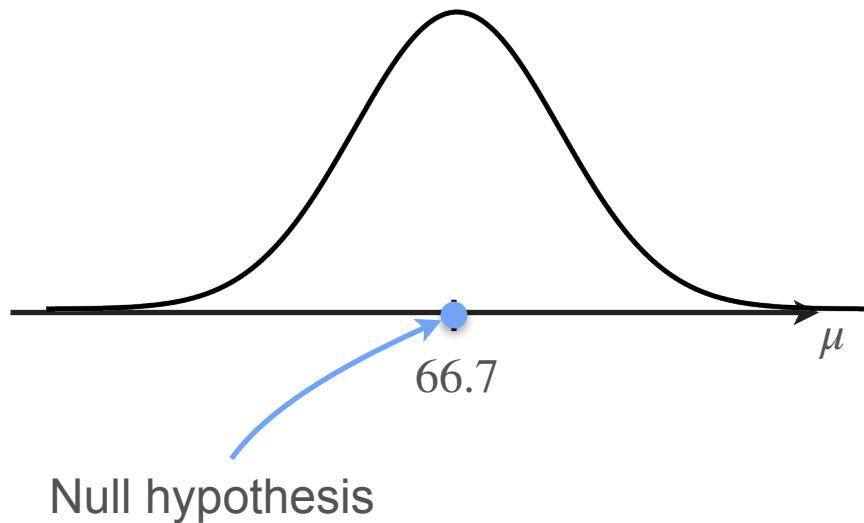
**$p$ -Value**

# Example: Heights

The mean height for 18 y/o in the US in the 70s was **66.7** in.

$$\begin{aligned}\sigma &= 3 \\ n &= 10\end{aligned}$$

If  $H_0$  is true:  $\bar{X} \sim \mathcal{N}\left(66.7, \frac{3^2}{10}\right)$



How likely was your sample if  $H_0$  is true?

If the answer is very unlikely, then reject  $H_0$

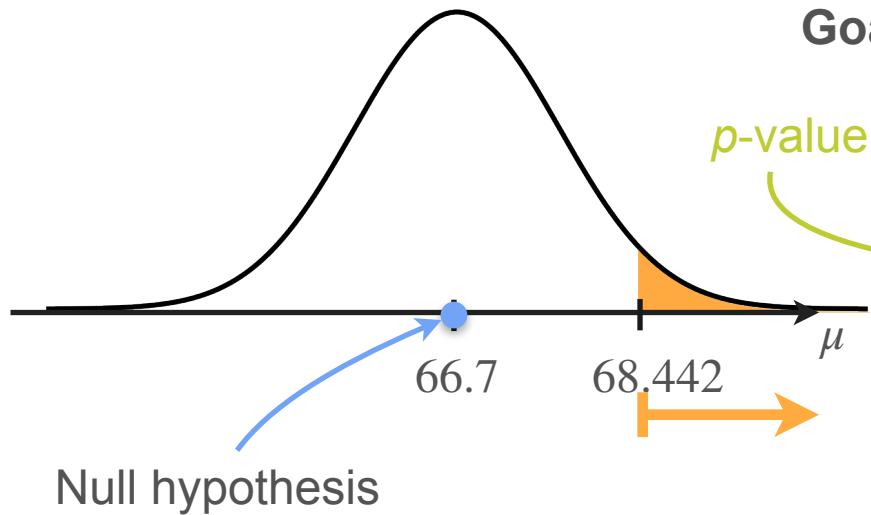
# Right-Tailed Test for Gaussian Data (Known $\sigma$ )

The mean height for 18 y/o in the US in the 70s was **66.7** in.

$$\begin{aligned}\sigma &= 3 \\ n &= 10\end{aligned}$$

$$\bar{x} = 68.442$$

$$H_0 : \mu = 66.7 \text{ vs. } H_1 : \mu > 66.7$$



**Goal:** Type I error probability  $< \alpha = 0.05$

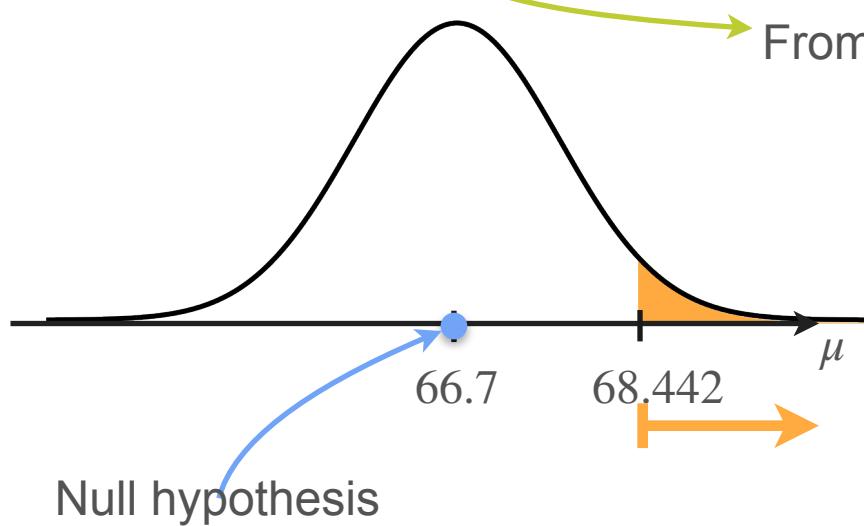
**Type I error:** Determine  $\mu > 66.7$ , when population mean did not change

$$\begin{aligned}P(\bar{X} > 68.442 \mid \mu = 66.7) \\ = 0.0332 < \alpha\end{aligned}$$

**Conclusion:** reject  $H_0$   
(with a 5% significance level)

# P-Values

A **p-value** is the probability, assuming  $H_0$  is true, that the test statistic takes on a value **as extreme as or more extreme than** the value observed



From the observed value to the direction of  $H_1$

$$H_0 : \mu = 66.7 \text{ vs. } H_1 : \mu > 66.7$$

Decision rule:

If  $p\text{-value} < \alpha$  reject  $H_0$  (and accept  $H_1$  as true)

If  $p\text{-value} > \alpha$  don't reject  $H_0$

# *p*-values

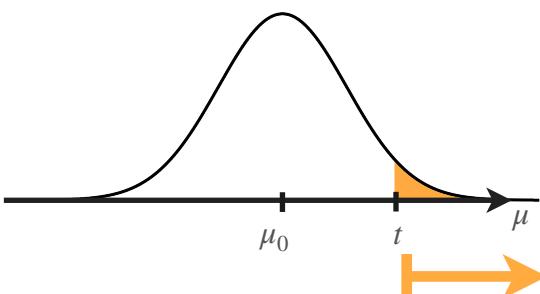
A ***p*-value** is the probability, assuming  $H_0$  is true, that the test statistic takes on a value as extreme as or more extreme than the value observed

$T(X)$ : test statistic

$t$ : observed statistic

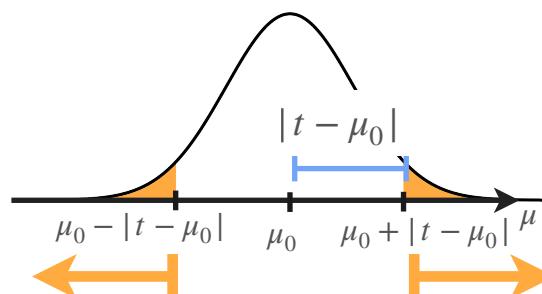
$H_0: \mu = \mu_0$

Right-tailed test



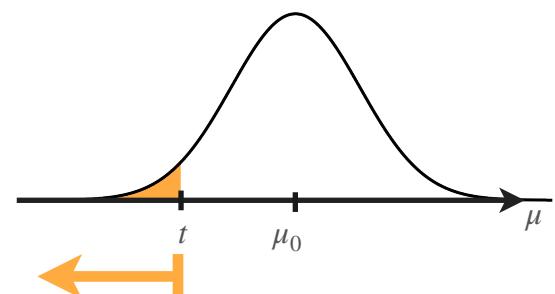
$$\mathbf{P}(T(X) > t | H_0)$$

Two-tailed test



$$\mathbf{P}(|T(X) - \mu_0| > |t - \mu_0| | H_0)$$

Left-tailed test



$$\mathbf{P}(T(X) < t | H_0)$$

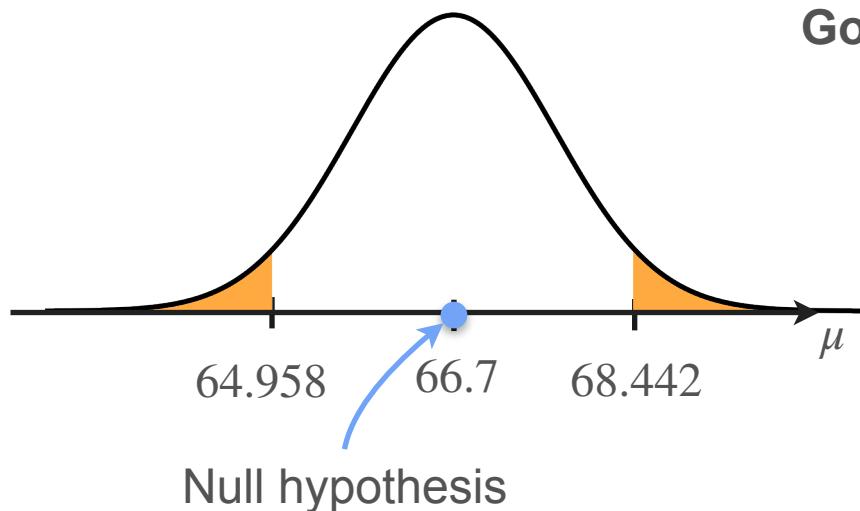
# Two-Tailed Test for Gaussian Data (Known $\sigma$ )

The mean height for 18 y/o in the US in the 70s was **66.7** in.

$$\begin{aligned}\sigma &= 3 \\ n &= 10\end{aligned}$$

$$\bar{x} = 68.442$$

$$H_0 : \mu = 66.7 \text{ vs. } H_1 : \mu \neq 66.7$$



**Goal:** Type I error probability  $< \alpha = 0.05$

**Type I error:** Determine  $\mu \neq 66.7$ ,  
when population mean did not change

$$\begin{aligned}P\left(\left|\bar{X} - 66.7\right| > |68.442 - 66.7| \mid \mu = 66.7\right) \\ = 0.0663 > \alpha\end{aligned}$$

**Conclusion:** Do not reject  $H_0$   
(with a 5% significance level)

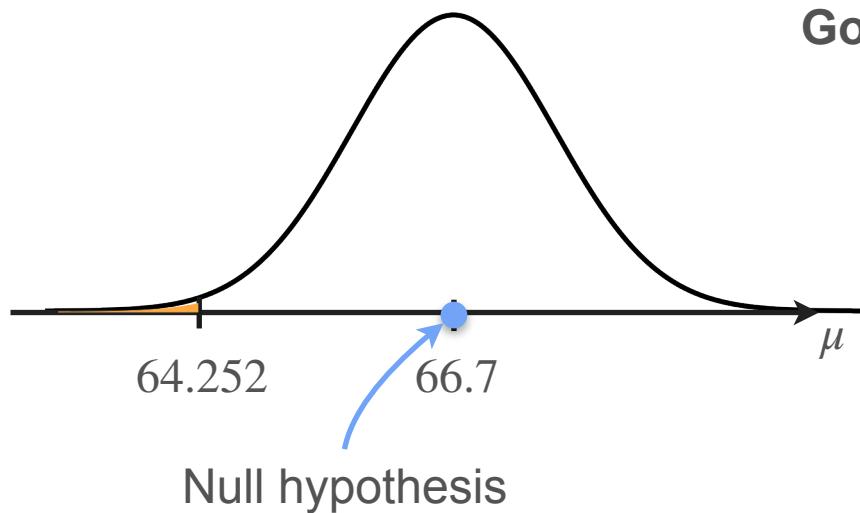
# Left-Tailed Test for Gaussian Data (Known $\sigma$ )

The mean height for 18 y/o in the US in the 70s was 66.7 in.

$$\begin{aligned}\sigma &= 3 \\ n &= 10\end{aligned}$$

$$\bar{x} = 64.252$$

$$H_0 : \mu = 66.7 \text{ vs. } H_1 : \mu < 66.7$$



Goal: Type I error probability  $< \alpha = 0.05$

Type I error: Determine  $\mu < 66.7$ , when population mean did not change

$$\begin{aligned}P(\bar{X} < 64.252 \mid \mu = 66.7) &: \\ &= 0.0049 < \alpha\end{aligned}$$

Conclusion: reject  $H_0$   
(with a 5% significance level)

# Tests Using the Z-Statistic

So far, you used the statistic  $\bar{X}$

$$\text{If } H_0 \text{ is true: } \bar{X} \sim \mathcal{N}\left(\mu_0, \frac{3^2}{10}\right)$$

Applying standardization, you can write equivalent tests using the

$$\text{Z-statistic } Z = \frac{\bar{X} - \mu_0}{3/\sqrt{10}}$$

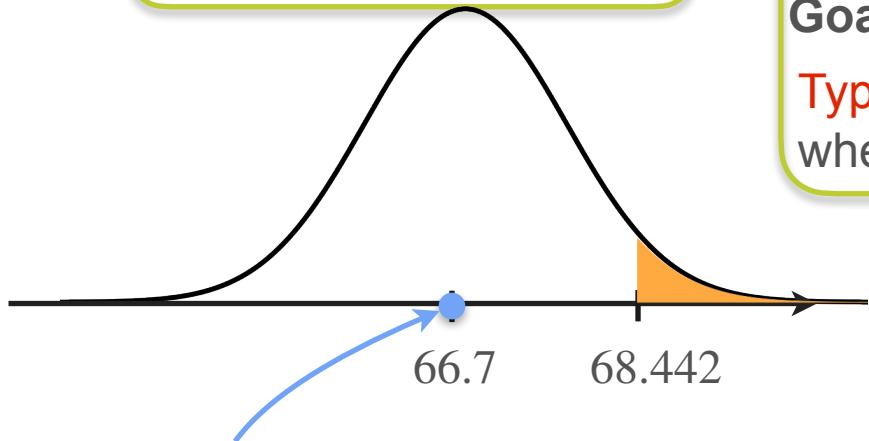
$$\text{If } H_0 \text{ is true, } Z = \frac{\bar{X} - \mu_0}{3/\sqrt{10}} \sim \mathcal{N}(0,1)$$

# Right-Tailed Test Using the Z Statistic

The mean height for 18 y/o in the US in the 70s was **66.7** in.

$$\sigma = 3 \\ n = 10$$

$$\bar{x} = 68.442$$



$$H_0 : \mu = 66.7 \text{ vs. } H_1 : \mu > 66.7$$

**Goal:** Type I error probability  $< \alpha = 0.05$

**Type I error:** Determine  $\mu > 66.7$ , when population mean did not change

$$P(\bar{X} > 68.442 \mid \mu = 66.7) \\ = 0.0332 < \alpha$$

**Conclusion:** reject  $H_0$   
(with a 5% significance level)

# Right-Tailed Test Using the Z Statistic

The mean height for 18 y/o in the US in the 70s was 66.7 in.

$$\sigma = 3$$
$$n = 10$$

$$\bar{x} = 68.442$$

$$H_0 : \mu = 66.7 \text{ vs. } H_1 : \mu > 66.7$$

**Goal:** Type I error probability  $< \alpha = 0.05$

**Type I error:** Determine  $\mu > 66.7$ ,  
when population mean did not change

$$Z = \frac{\bar{X} - \mu_0}{3/\sqrt{10}} \rightarrow z = \frac{68.442 - 66.7}{3/\sqrt{10}} = 1.837$$

$$P(\bar{X} > 68.442 \mid \mu = 66.7) = 0.0332 < \alpha$$

$$\frac{\bar{X} - 66.7}{3/\sqrt{10}} > \frac{68.442 - 66.7}{3/\sqrt{10}} =$$

Conclusion: reject  $H_0$   
(with a 5% significance level)

# Right-Tailed Test Using the Z Statistic

The mean height for 18 y/o in the US in the 70s was 66.7 in.

$$\begin{aligned}\sigma &= 3 \\ n &= 10\end{aligned}$$

$$\bar{x} = 68.442$$

$$H_0 : \mu = 66.7 \text{ vs. } H_1 : \mu > 66.7$$

**Goal:** Type I error probability  $< \alpha = 0.05$

**Type I error:** Determine  $\mu > 66.7$ ,  
when population mean did not change

$$Z = \frac{\bar{X} - \mu_0}{3/\sqrt{10}} \rightarrow z = \frac{68.442 - 66.7}{3/\sqrt{10}} = 1.837$$

$$\frac{\bar{X} - 66.7}{3/\sqrt{10}} > \frac{68.442 - 66.7}{3/\sqrt{10}} = 1.837$$

$$P\left( \frac{\bar{X} - 66.7}{3/\sqrt{10}} > 1.837 \mid \mu = 66.7 \right) = 0.0332 < \alpha$$

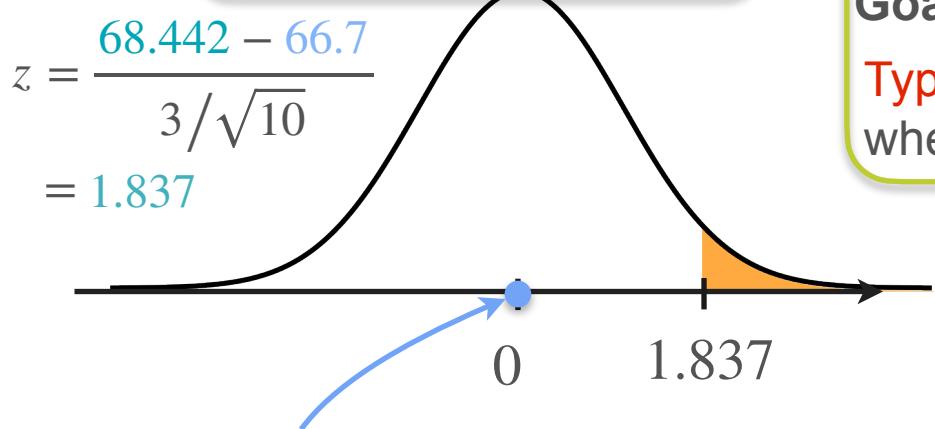
**Conclusion:** reject  $H_0$   
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# Right-Tailed Test Using the Z Statistic

The mean height for 18 y/o in the US in the 70s was 66.7 in.

$$\sigma = 3$$
$$n = 10$$

$$\bar{x} = 68.442$$



$$H_0 : \mu = 66.7 \text{ vs. } H_1 : \mu > 66.7$$

**Goal:** Type I error probability  $< \alpha = 0.05$

**Type I error:** Determine  $\mu > 66.7$ , when population mean did not change

$$P\left(\frac{\bar{X} - 66.7}{3/\sqrt{10}} > 1.837 \mid \mu = 66.7\right)$$

Conclusion: reject  $H_0$  if  $0.0332 < \alpha$   
(with a 5% significance level)



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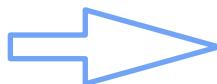
# Hypothesis Testing

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## Critical Values

# P-Values and Critical Values

If  $p\text{-value} < \alpha$

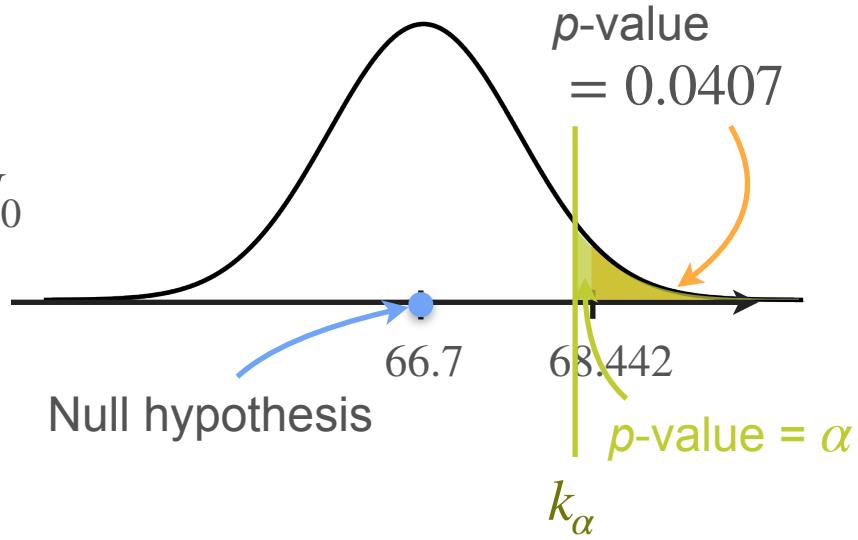


Reject  $H_0$

What is the least extreme sample you could get that you would still reject  $H_0$ ?

Sample that has  $p\text{-value} = \alpha$

Critical values



# Computing Critical Values

The mean height for 18 y/o in the US in the 70s was **66.7 in.**      **Reject  $H_0$**

$H_0 : \mu = 66.7$  vs.  $H_1 : \mu > 66.7$

$\alpha = 0.05$

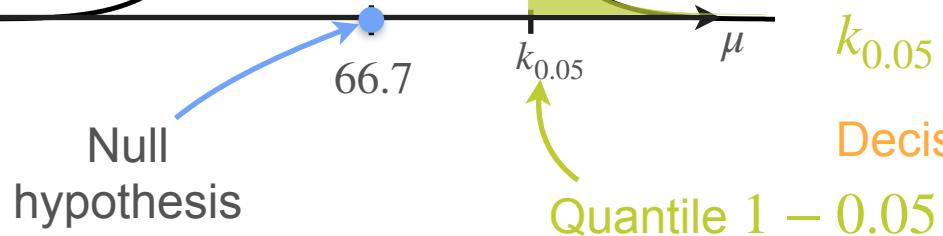
$n = 10 \quad \sigma = 3 \quad \bar{x} = 68.442$

$$0.05 = P(\bar{X} > k_{0.05} \mid \mu = 66.7)$$

If  $\mu = 66.7$   $\bar{X} \sim \mathcal{N}\left(66.7, \frac{3^2}{10}\right)$

$$k_{0.05} = 68.26$$

**Decision rule:** Reject  $H_0$  if  $\bar{x} > 68.26$



# Computing Critical Values

The mean height for 18 y/o in the US in the 70s was **66.7 in.**      **Reject  $H_0$**

$H_0 : \mu = 66.7$  vs.  $H_1 : \mu > 66.7$

$\alpha = 0.01$

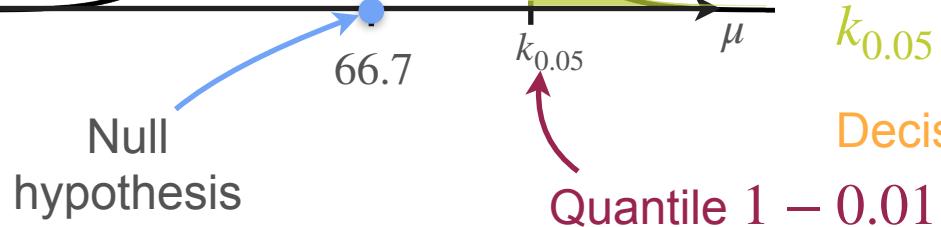
$$n = 10 \quad \sigma = 3 \quad \bar{x} = 68.442$$

$$0.05 = P(\bar{X} > k_{0.01} \mid \mu = 66.7)$$

If  $\mu = 66.7$   $\bar{X} \sim \mathcal{N}\left(66.7, \frac{3^2}{10}\right)$

$$k_{0.05} = 68.26$$

**Decision rule:** Reject  $H_0$  if  $\bar{x} > 68.26$



# Computing Critical Values

The mean height for 18 y/o in the US in the 70s was **66.7 in.**

Do not reject  $H_0$

$H_0 : \mu = 66.7$  vs.  $H_1 : \mu > 66.7$

$\alpha = 0.01$

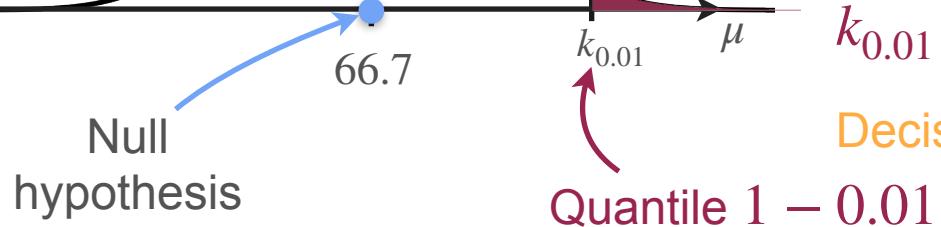
$$n = 10 \quad \sigma = 3 \quad \bar{x} = 68.442$$

$$0.01 = P(\bar{X} > k_{0.01} \mid \mu = 66.7)$$

If  $\mu = 66.7$   $\bar{X} \sim \mathcal{N}\left(66.7, \frac{3^2}{10}\right)$

$$k_{0.01} = 68.91$$

Decision rule: Reject  $H_0$  if  $\bar{x} > 68.91$



# Critical Values

$H_0 : \mu = \mu_0$  vs.  $H_1 : \mu > \mu_0$

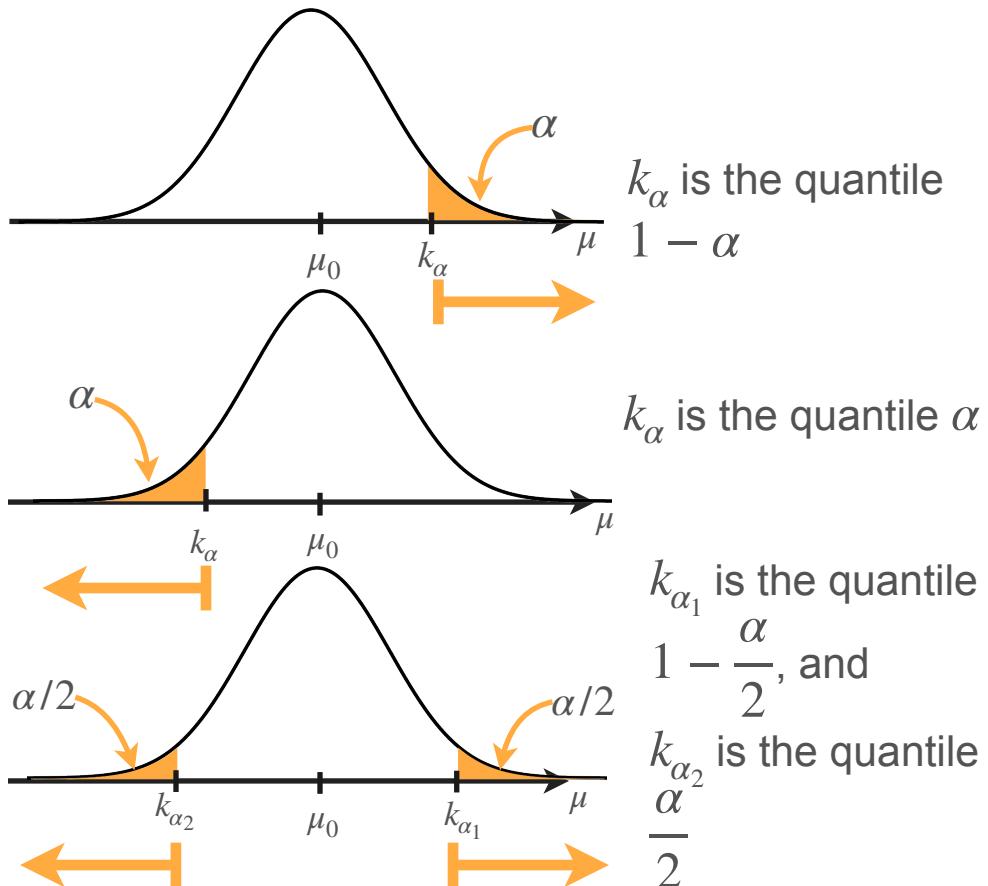
Decision rule: Reject  $H_0$  if  $t > k_\alpha$

$H_0 : \mu = \mu_0$  vs.  $H_1 : \mu < \mu_0$

Decision rule: Reject  $H_0$  if  $t < k_\alpha$

$H_0 : \mu = \mu_0$  vs.  $H_1 : \mu \neq \mu_0$

Decision rule: Reject  $H_0$  if  $t > k_{\alpha_1}$  or  
 $t < k_{\alpha_2}$



# Critical Values: Concluding Remarks

- You can define the critical value in advance
- For a given sample, using  $p$ -value and critical value will lead to the same conclusion
- Defining a test in terms of critical values makes determining Type II error probabilities for the decision rule.



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# Hypothesis Testing

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## Power of a Test

# Type I and Type II Errors

The **mean** height for 18 y/o in the US in the 70s was **66.7 in.**

$$H_0 : \mu = 66.7 \text{ vs. } H_1 : \mu > 66.7$$

Decision	Reality	
	$H_0$ True ( $\mu = 66.7$ )	$H_0$ False ( $\mu > 66.7$ )
Reject $H_0$ (Decide $\mu > 66.7$ )	Type I error	Correct
Don't reject $H_0$ (Decide $\mu = 66.7$ )	Correct	Type II error

# Finding the Type II Error Probabilities

The **mean** height for 18 y/o in the US in the 70s was **66.7 in.**

$$H_0 : \mu = 66.7 \text{ vs. } H_1 : \mu > 66.7 \quad n = 10 \quad \sigma = 3$$

For  $\alpha = 0.05$ :  $k_\alpha = 68.26$

Decision rule: Reject  $H_0$  if  $\bar{x} > 68.26$

What is the **Type II error probability** if the true value is  $\mu = 70$ ?

$$\mathbf{P}(\text{Do not reject } H_0 | \mu = 70) \longrightarrow \mathbf{P}(\bar{X} < 68.26 | \mu = 70)$$

# Finding the Type II Error Probabilities

The mean height for 18 y/o in the US in the 70s was **66.7** in.

$$H_0 : \mu = 66.7 \text{ vs. } H_1 : \mu > 66.7 \quad n = 10 \quad \sigma = 3$$

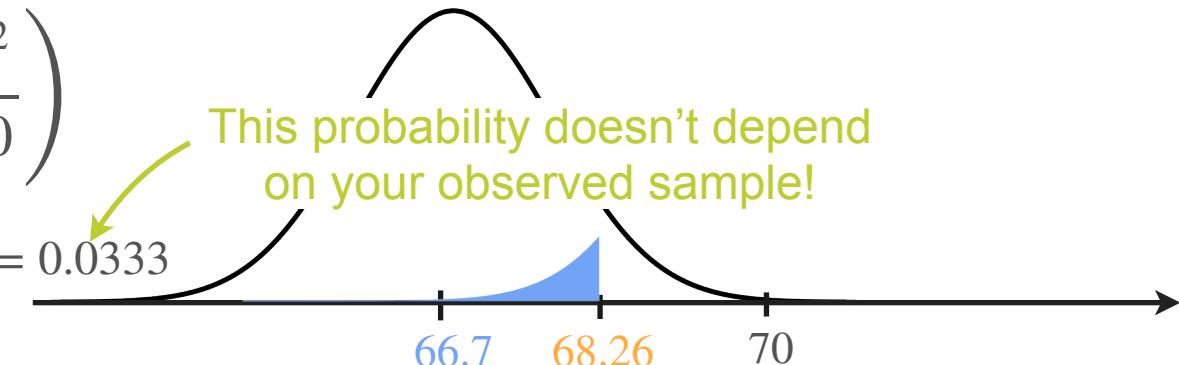
For  $\alpha = 0.05$ :  $k_\alpha = 68.2604$       Decision rule: Reject  $H_0$  if  $\bar{X} > 68.26$

What is the **Type II error probability** if the true value is  $\mu = 70$ ?

$$\text{If } \mu = 70 \quad \bar{X} \sim \mathcal{N}\left(70, \frac{3^2}{10}\right)$$

$$\beta = P(\bar{X} < 68.26 | \mu = 70) = 0.0333$$

This probability doesn't depend on your observed sample!



# Power of the Test

The **mean** height for 18 y/o in the US in the 70s was **66.7 in.**

$$H_0 : \mu = 66.7 \text{ vs. } H_1 : \mu > 66.7$$

Decision	Reality		Power of the test $P(\text{Reject } H_0   \mu \in H_1)$
	$H_0$ True ( $\mu = 66.7$ )	$H_0$ False ( $\mu > 66.7$ )	
Reject $H_0$ (Decide $\mu > 66.7$ )	Type I error	Correct	
Don't reject $H_0$ (Decide $\mu = 66.7$ )	Correct	Type II error	

# Power of the Test

$$\left. \begin{array}{l} \text{Type II error: } \mathbf{P} \left( \text{Do not reject } H_0 \mid \mu \in H_1 \right) \\ \text{Power of the test: } \mathbf{P} \left( \text{Reject } H_0 \mid \mu \in H_1 \right) \end{array} \right\} \begin{array}{l} \beta \\ 1 - \beta \end{array}$$

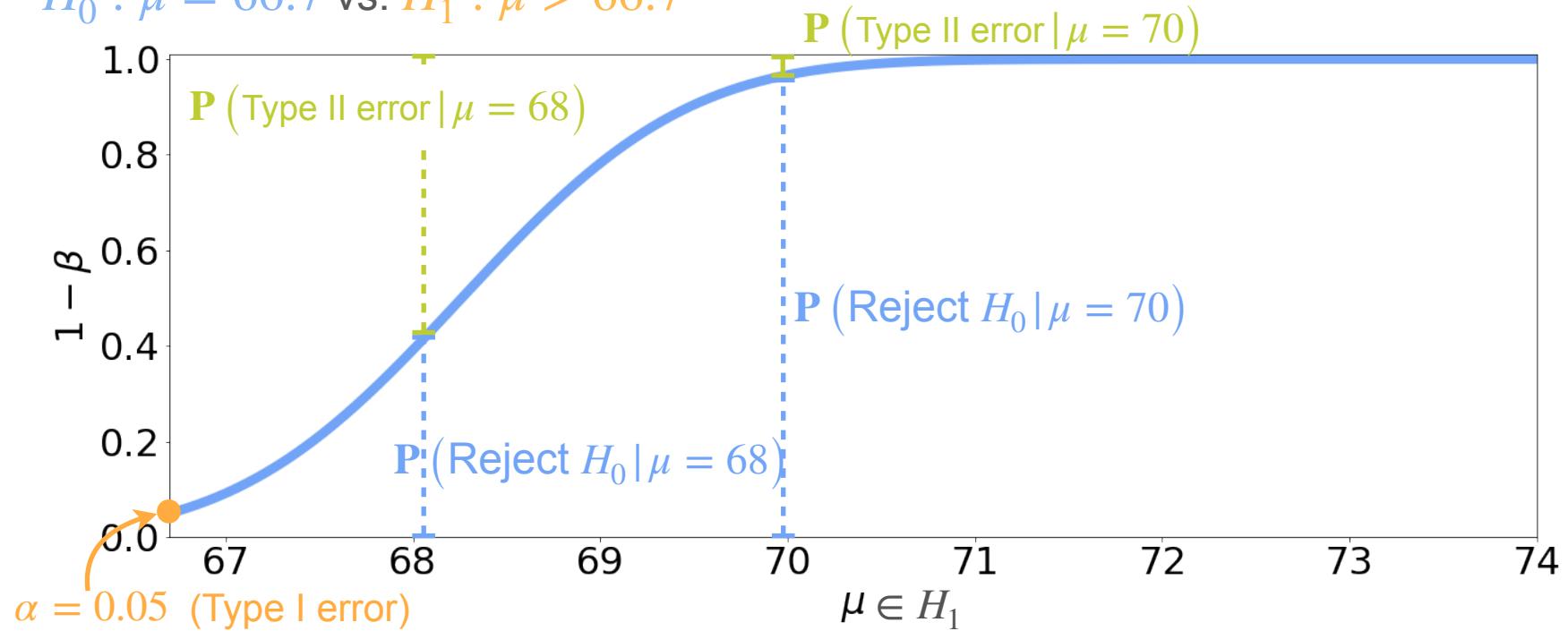
Complementary probabilities

Power of the test = 1 – Type II error probability

$$= 1 - \mathbf{P} \left( \text{Do not reject } H_0 \mid \mu \in H_1 \right)$$

# Power of the Test

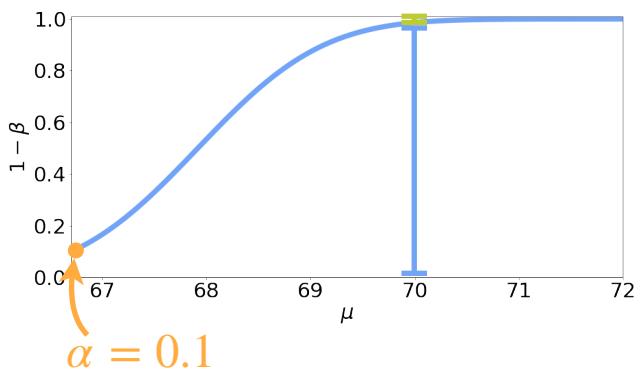
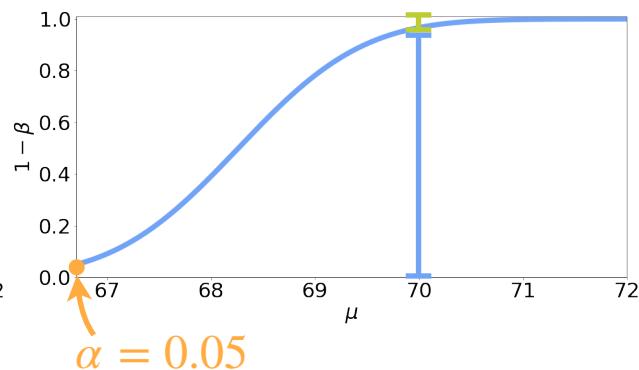
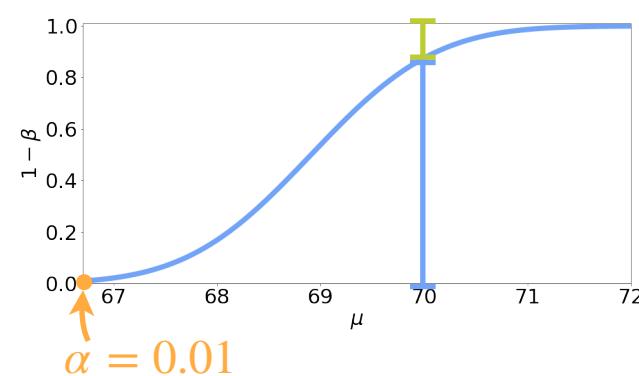
$H_0 : \mu = 66.7$  vs.  $H_1 : \mu > 66.7$



# Power of the Test

$$\mu = 70$$

Power

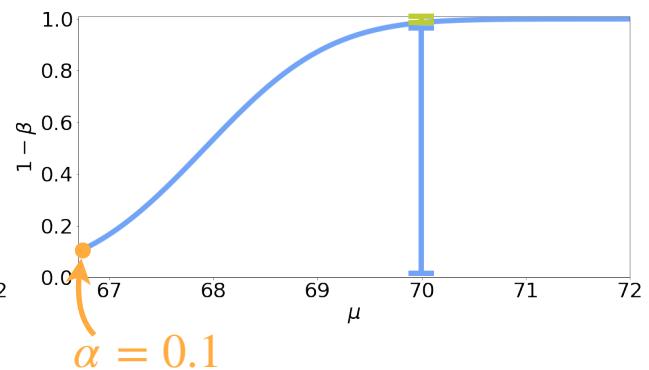
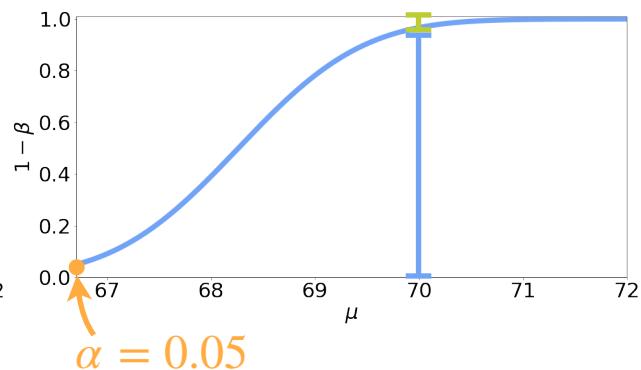
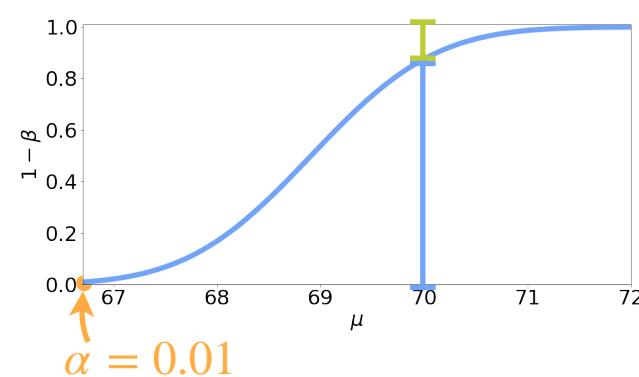


Type I error

# Power of the Test

$$\mu = 70$$

Type II error



Type I error



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# Hypothesis Testing

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## Interpreting results

# Steps for Performing Hypothesis Testing

## 1. State your hypotheses.

- Null hypothesis: the baseline  $\rightarrow H_0 : \mu = 66.7$
- Alternative hypothesis: the statement you want to prove  $\rightarrow H_1 : \mu > 66.7$

## 2. Design your test

- Decide the test statistic to work with.  $\rightarrow \bar{X}$
- Decide the significance level  $\rightarrow \alpha = 0.05$

## 3. Compute the observed statistic (based on your sample) $\rightarrow \bar{x} = 68.442$

## 4. Reach a conclusion:

- If the  $p$ -value is less than the significance level reject  $H_0$   
 $\rightarrow P(\bar{X} > 68.442 | \mu = 66.7) > ? 0.05$

# Important Remarks - Interpreting Tests

- Type I error:
  - Reject null hypothesis when it is true  $\rightarrow$  Reject  $H_0$  when  $\mu = 66.7$
- Type II error:
  - Do not reject null hypothesis, when it was false  $\rightarrow$  Do not reject  $H_0$  when  $\mu > 66.7$
- Significance level ( $\alpha$ ):
  - It is the maximum probability of incurring in a Type I error
- Errors:
  - $\downarrow \alpha \uparrow \beta$

# Important Remarks - Interpreting Tests

- *p*-values:

- If  $\mathbf{P}(\text{Reject } H_0 | H_0) < \alpha \longrightarrow \text{Reject } H_0 \text{ and then accept } H_1$
- The *p*-value represents the probability of  $H_0$  being true.

# Important Remarks - Interpreting Tests

- *p*-values:

- If  $\mathbf{P}(\text{Reject } H_0 | H_0) < \alpha \longrightarrow \text{Reject } H_0 \text{ and then accept } H_1$
- A small *p*-value indicates that the probability of seeing the observed data by chance is small

# Important Remarks - Interpreting Tests

- *p*-values:

- If  $\mathbf{P}(\text{Reject } H_0 | H_0) < \alpha \longrightarrow \text{Reject } H_0 \text{ and then accept } H_1$
- A small *p*-value indicates that the probability of seeing the observed data by chance is small

- Test conclusions

- Reject  $H_0 \rightarrow H_1$  true
- Do not reject  $H_0 \rightarrow H_0$  true



You can only say that there is not enough evidence



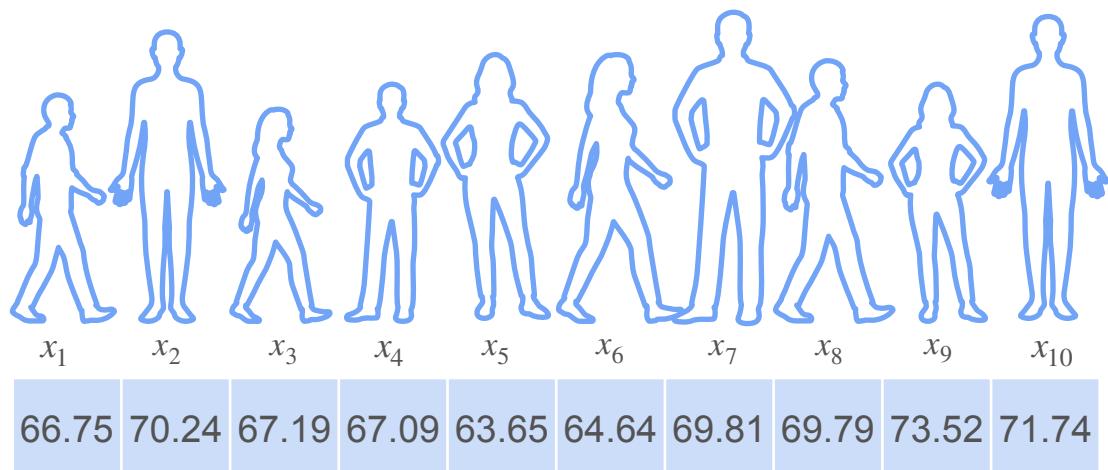
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# Hypothesis Testing

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## t-Distribution

# $t$ -Distribution: Motivation



$$X_i \stackrel{i.i.d}{\sim} \mathcal{N}(\mu, \sigma^2)$$

$$\bar{X} = \frac{1}{10} \sum_{i=1}^{10} X_i \sim \mathcal{N}\left(\mu, \frac{\sigma^2}{10}\right)$$

This is fine if you know  $\mu$  and  $\sigma$

What if  $\sigma$  is unknown?

# $t$ -Distribution: Motivation

$$X_i \stackrel{i.i.d}{\sim} \mathcal{N}(\mu, \sigma^2)$$

$$\bar{X} = \frac{1}{10} \sum_{i=1}^{10} X_i \sim \mathcal{N}\left(\mu, \frac{\sigma^2}{10}\right)$$

$$S = \sqrt{\frac{1}{10-1} \sum_{i=1}^{10} (X_i - \bar{X})^2}$$

If  $\mu, \sigma$  are known

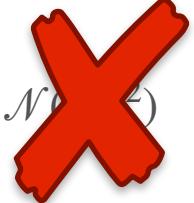
$$\frac{\bar{X} - \mu}{\sigma / \sqrt{10}} \sim \mathcal{N}(0, 1^2) \text{ (Standardization)}$$

Z statistic

What if  $\sigma$  is unknown?

Replace  $\sigma$  with its estimate

$$\frac{\bar{X} - \mu}{S / \sqrt{10}} \sim \mathcal{N}(0, 1^2)$$



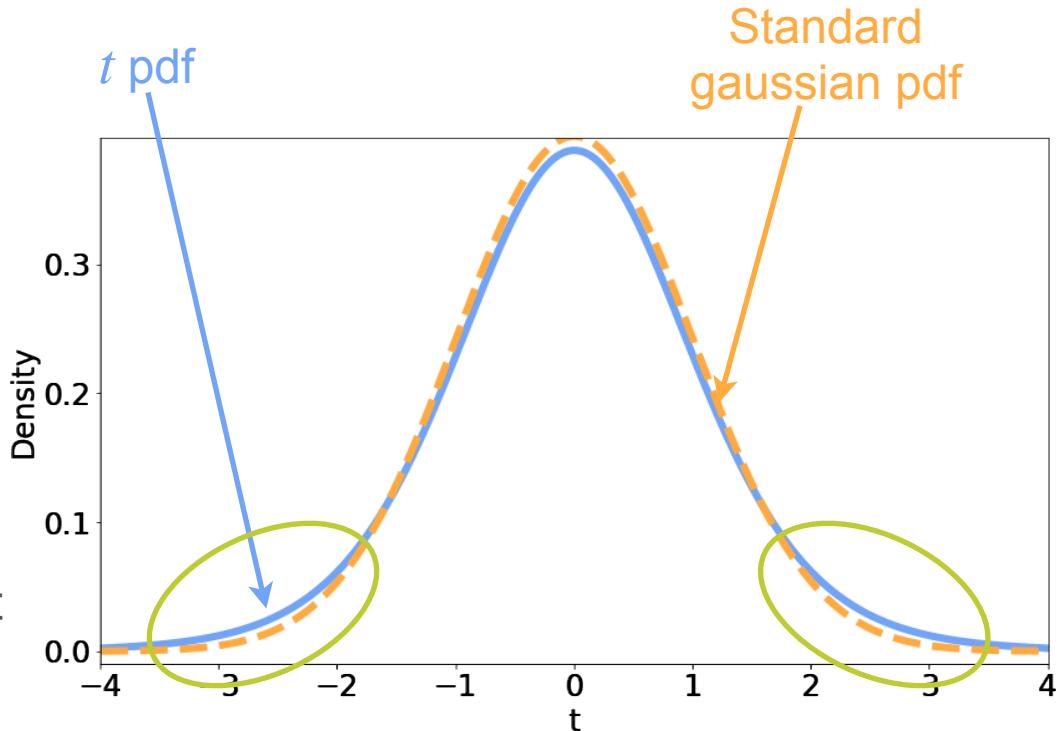
# $t$ -Distribution

$\frac{\bar{X} - \mu}{S/\sqrt{10}}$  follows a  $t$  distribution

What does it look like?

Still bell-shaped

It has heavier tails that account for the uncertainty introduced with the std estimation



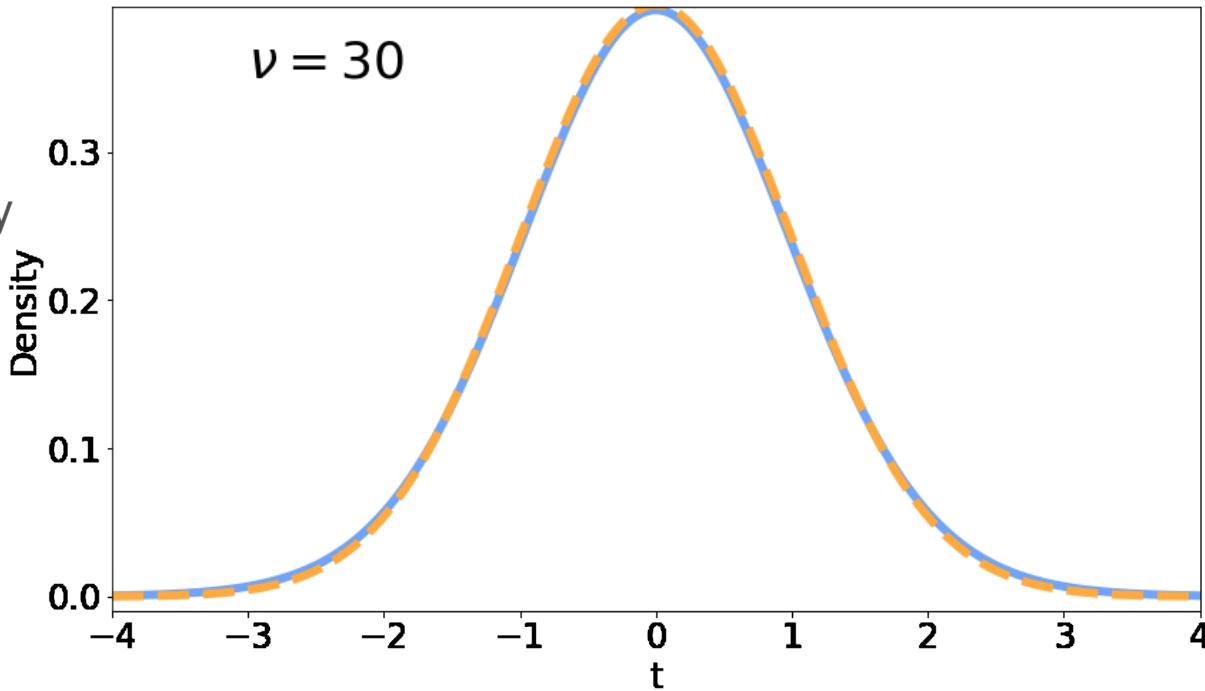
# $t$ -Distribution

## Parameters:

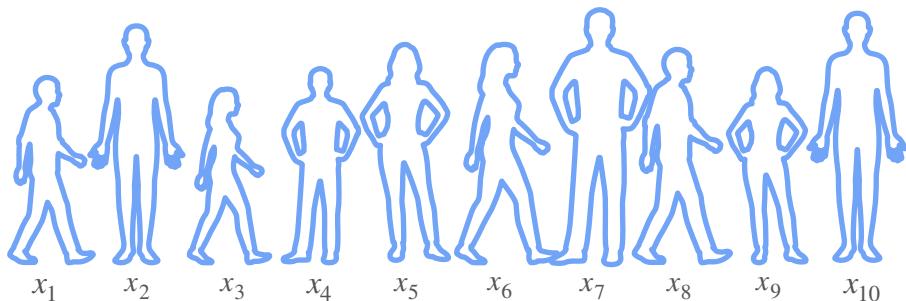
- Degrees of freedom ( $\nu$ )

Controls how heavy  
the tails are

$$X \sim t_{\nu}$$



# $t$ -Distribution and $T$ -Statistic



$$n = 10$$
$$T = \frac{\bar{X} - \mu}{S/\sqrt{10}} \sim t_9$$

$\nu = 10 - 1$

Degrees of freedom ( $\nu$ ) = sample size - 1  
=  $(n - 1)$

As  $n$  increases, this looks more like a  $\mathcal{N}(0, 1^2)$

$T$ -statistic is used when

- The population has a Gaussian distribution
- But you don't know the variance



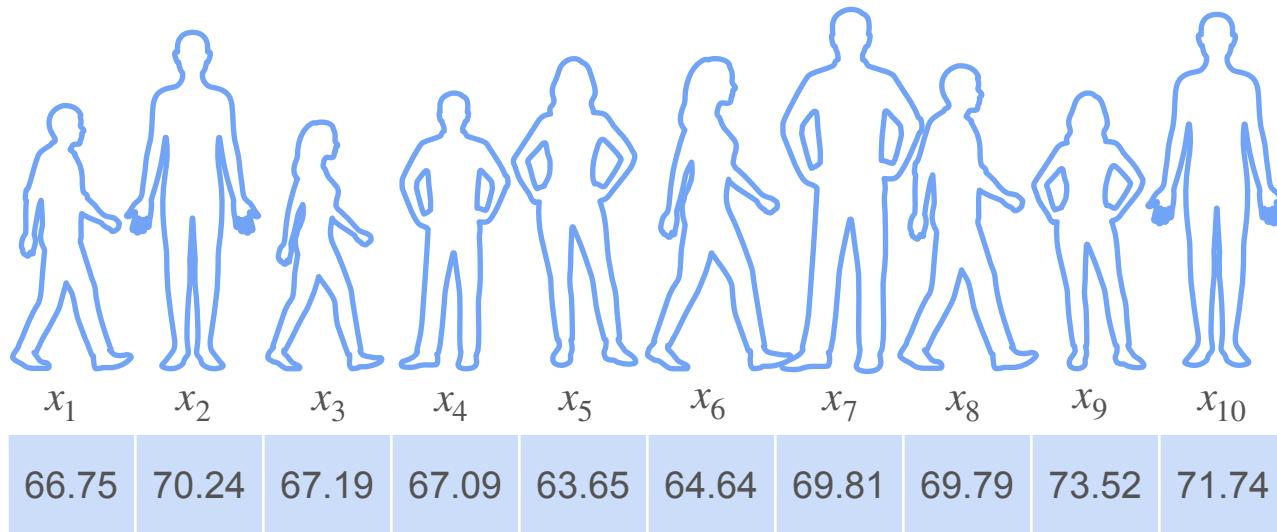
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# Hypothesis Testing

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## t-Tests

# Example: Heights

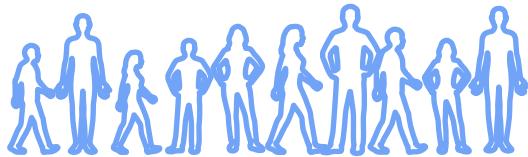


$$\bar{x} = 68.442$$

# Example: Heights

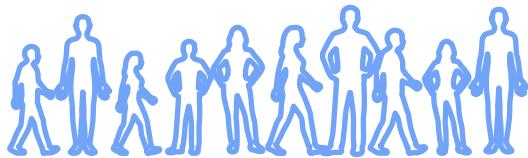
The **mean** height for 18 y/o in the US in the 70s was **66.7 in.**

**3 questions**

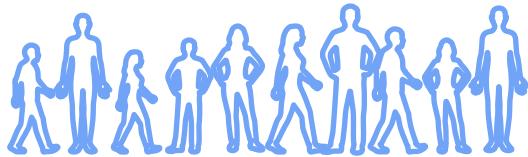


**3 sets of hypothesis**

$$H_0 : \mu = 66.7 \text{ vs. } H_1 : \mu > 66.7$$



$$H_0 : \mu = 66.7 \text{ vs. } H_1 : \mu < 66.7$$



$$H_0 : \mu = 66.7 \text{ vs. } H_1 : \mu \neq 66.7$$

# Example: Heights

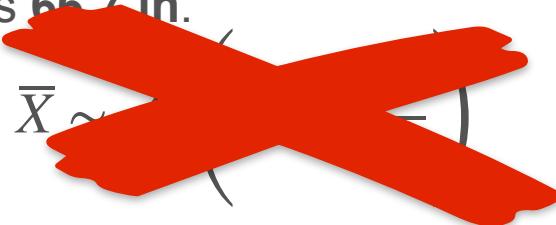
The **mean** height for 18 y/o in the US in the 70s was **66.7 in.**



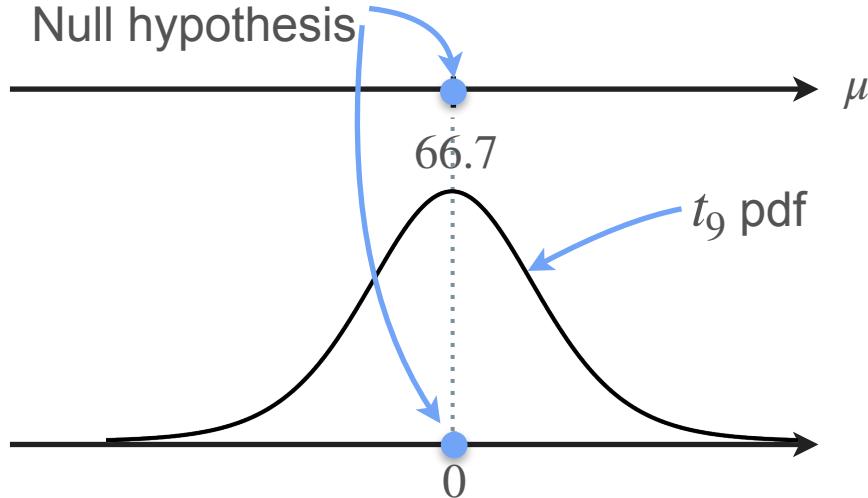
~~$n = 10$~~

$$H_0 : \mu = 66.7$$

If  $H_0$  is true:  $\bar{X} \sim$



Null hypothesis



$$\text{If } H_0 \text{ is true: } T = \frac{\bar{X} - 66.7}{S/\sqrt{10}} \sim t_9$$

# Right-Tailed Test for Gaussian Data (Unknown $\sigma$ )

The mean height for 18 y/o in the US in the 70s was **66.7** in.

$$H_0 : \mu = 66.7 \text{ vs. } H_1 : \mu > 66.7 \quad n = 10$$

$$\bar{x} = 68.442$$

$$s = 3.113$$

$$t = \frac{68.442 - 66.7}{3.113/\sqrt{10}} = 1.770$$

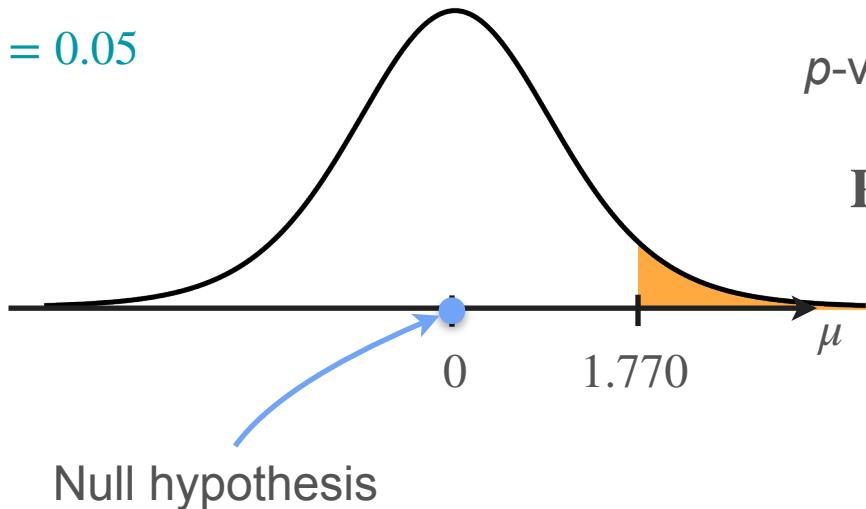
$$\alpha = 0.05$$

*p*-value:

$$P\left(\frac{\bar{X} - 66.7}{S/\sqrt{10}} > 1.770 \mid \mu = 66.7\right)$$

$$= 0.0552 > \alpha$$

Conclusion: do not reject  $H_0$   
(with a 5% significance level)



# Two-Tailed Test for Gaussian Data (Unknown $\sigma$ )

The mean height for 18 y/o in the US in the 70s was **66.7** in.

$$H_0 : \mu = 66.7 \text{ vs. } H_1 : \mu \neq 66.7$$

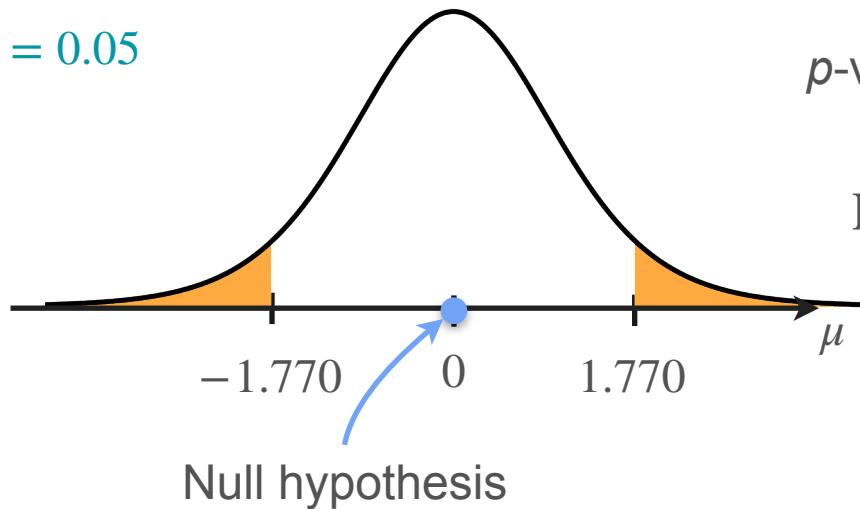
$$n = 10$$

$$\bar{x} = 68.442$$

$$s = 3.113$$

$$t = \frac{68.442 - 66.7}{3.113/\sqrt{10}} = 1.770$$

$$\alpha = 0.05$$



p-value:

$$P\left(\left|\frac{\bar{X} - 66.7}{S/\sqrt{10}}\right| > |1.770| \mid \mu = 66.7\right) = 0.1105 > \alpha$$

Conclusion: do not reject  $H_0$   
(with a 5% significance level)

# Left-Tailed Test for Gaussian Data (Unknown $\sigma$ )

The mean height for 18 y/o in the US in the 70s was **66.7** in.

$$H_0 : \mu = 66.7 \text{ vs. } H_1 : \mu < 66.7$$

$$n = 10$$

$$\bar{x} = 64.252$$

$$s = 3.113$$

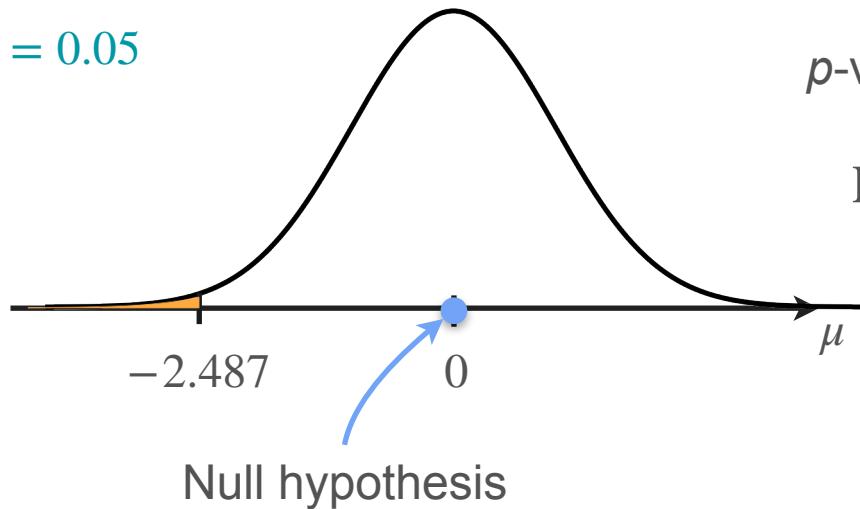
$$t = \frac{64.252 - 66.7}{3.113/\sqrt{10}} = -2.487$$

$$\alpha = 0.05$$

p-value:

$$P\left(\frac{\bar{X} - 66.7}{S/\sqrt{10}} < -2.487 \mid \mu = 66.7\right)$$

$$= 0.0173 < \alpha$$



Conclusion: reject  $H_0$   
(with a 5% significance level)



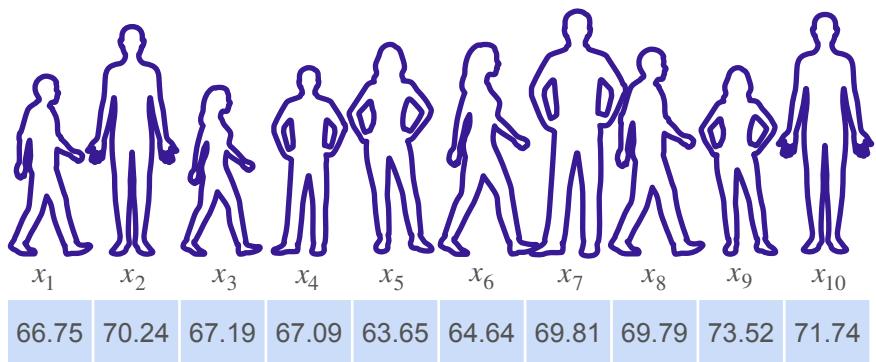
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# Hypothesis Testing

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## Two sample t-test

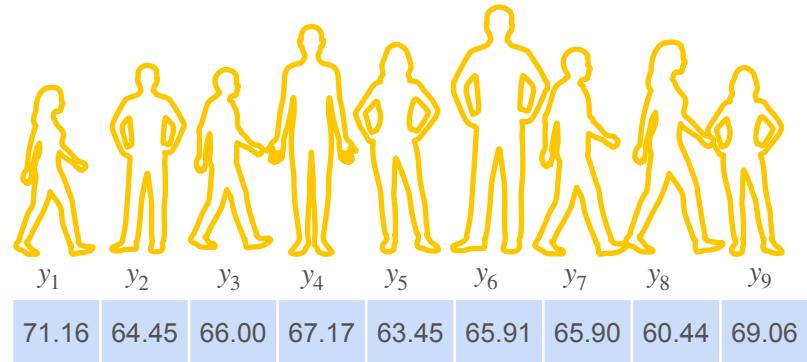
# Independent Two-Sample $t$ -Test



$$n_X = 10 \quad \bar{x} = 68.442$$
$$s_X = 3.113$$

Height of 18 y/o in the US

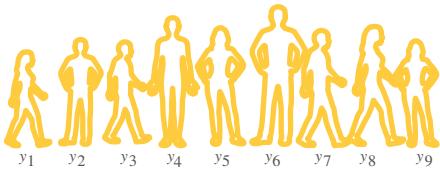
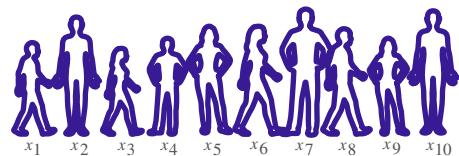
$$\mu_{US} \neq \mu_{Ar}$$



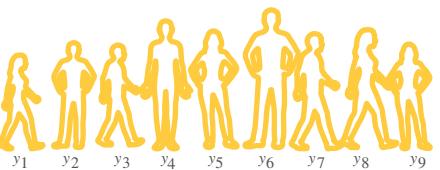
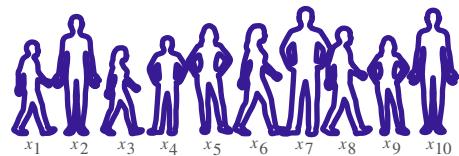
$$n_Y = 9 \quad \bar{y} = 65.949$$
$$s_Y = 3.106$$

Height of 18 y/o in Argentina

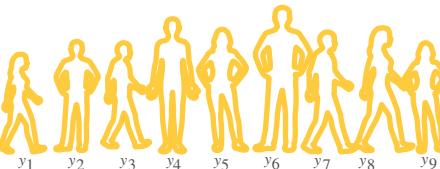
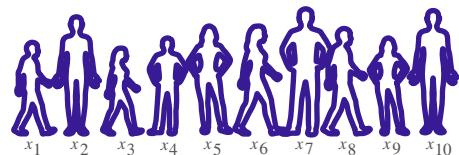
# Independent Two-Sample $t$ -Test: Hypothesis



$$H_0 : \mu_{US} - \mu_{Ar} = 0 \text{ vs. } H_1 : \mu_{US} - \mu_{Ar} > 0$$



$$H_0 : \mu_{US} - \mu_{Ar} = 0 \text{ vs. } H_1 : \mu_{US} - \mu_{Ar} < 0$$



$$H_0 : \mu_{US} - \mu_{Ar} = 0 \text{ vs. } H_1 : \mu_{US} - \mu_{Ar} \neq 0$$

# Independent Two-Sample $t$ -Test: Assumptions

- All people in the sample from the two groups are different
- Each person in both samples are independent
- Populations are normally distributed

$$X \sim \mathcal{N}(\mu_{US}, \sigma_{US}^2)$$

$$Y \sim \mathcal{N}(\mu_{Arg}, \sigma_{Arg}^2)$$

$$\bar{X} = \frac{1}{10} \sum_{i=1}^{10} X_i$$

$$\bar{X} - \bar{Y} \sim \mathcal{N}\left(\text{---, ---} + \text{---}\right)$$

$$\bar{Y} = \frac{1}{9} \sum_{i=1}^{9} Y_i$$

# Independent Two-Sample $t$ -Test: Assumptions

- All people in the sample from the two groups are different
- Each person in both samples are independent
- Populations are normally distributed

$$X \sim \mathcal{N}(\mu_{US}, \sigma_{US})$$

$$Y \sim \mathcal{N}(\mu_{Arg}, \sigma_{Arg})$$

$$\bar{X} = \frac{1}{10} \sum_{i=1}^{10} X_i$$

$$\bar{X} - \bar{Y} \sim \mathcal{N}\left(\mu_{US} - \mu_{Arg}, \sqrt{\frac{\sigma_{US}^2}{10} + \frac{\sigma_{Arg}^2}{9}}\right)$$

$$\bar{Y} = \frac{1}{9} \sum_{i=1}^9 Y_i$$

# Independent Two-Sample $t$ -Test: Statistic

$$X \sim \mathcal{N}(\mu_{US}, \sigma_{US}) \quad Y \sim \mathcal{N}(\mu_{Arg}, \sigma_{Arg})$$

$$\bar{X} - \bar{Y} \sim \mathcal{N}\left(\mu_{US} - \mu_{Arg}, \frac{\sigma_{US}^2}{10} + \frac{\sigma_{Arg}^2}{9}\right) \rightarrow \frac{(\bar{X} - \bar{Y}) - (\mu_{US} - \mu_{Arg})}{\sqrt{\frac{\sigma_{US}^2}{10} + \frac{\sigma_{Arg}^2}{9}}} \sim \mathcal{N}(0, 1^2)$$

You don't know  $\sigma_{US}$ ,  $\sigma_{Arg}$

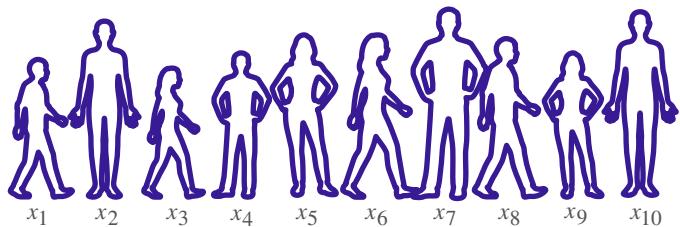


Replace it with the sample standard deviation

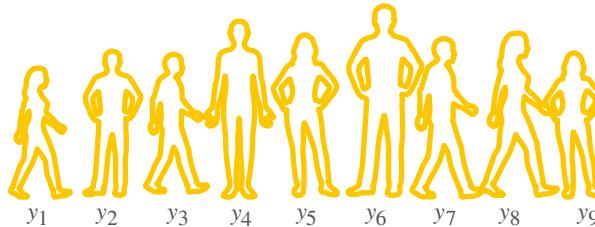
$$T = \frac{(\bar{X} - \bar{Y}) - (\mu_{US} - \mu_{Arg})}{\sqrt{\frac{s_X^2}{10} + \frac{s_Y^2}{9}}} \sim t_{\nu}$$

Degrees of freedom =  $\frac{\left(\frac{s_X^2}{n_X} + \frac{s_Y^2}{n_Y}\right)^2}{\frac{\left(\frac{s_X^2}{n_X}\right)^2}{n_X - 1} + \frac{\left(\frac{s_Y^2}{n_Y}\right)^2}{n_Y - 1}}$

# Independent Two-Sample $t$ -Test



$$n_X = 10 \quad \bar{x} = 68.442$$
$$s_X = 3.113$$



$$n_Y = 9 \quad \bar{y} = 65.949$$
$$s_Y = 3.106$$

Degrees of freedom =  $\frac{\overbrace{\left( \frac{16.8}{\left( \frac{-1}{2} + \frac{-1}{2} \right)^2} \right)^2}}{\left( \frac{-1}{2} \right)^2 + \left( \frac{-1}{2} \right)^2}$

# Independent Two-Sample $t$ -Test: Statistic

$$X \sim \mathcal{N}(\mu_{US}, \sigma_{US})$$

$$Y \sim \mathcal{N}(\mu_{Arg}, \sigma_{Arg})$$

$$\bar{X} - \bar{Y} \sim \mathcal{N}\left(\mu_{US} - \mu_{Arg}, \sqrt{\frac{\sigma_{US}^2}{10} + \frac{\sigma_{Arg}^2}{9}}\right) \rightarrow \frac{(\bar{X} - \bar{Y}) - (\mu_{US} - \mu_{Arg})}{\sqrt{\frac{\sigma_{US}^2}{10} + \frac{\sigma_{Arg}^2}{9}}} \sim \mathcal{N}(0,1)$$

You don't know  $\sigma_{US}$ ,  $\sigma_{Arg}$



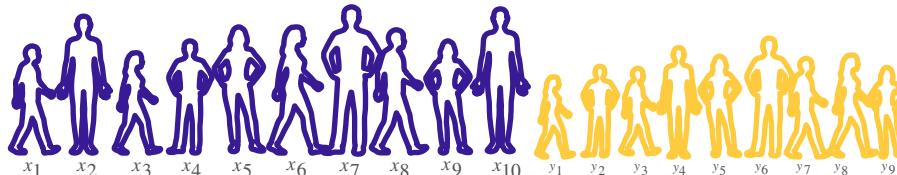
Replace it with the sample standard deviation

$$T = \frac{(\bar{X} - \bar{Y}) - (\mu_{US} - \mu_{Arg})}{\sqrt{\frac{s_X^2}{10} + \frac{s_Y^2}{9}}} \sim t_{16.8}$$

Degrees of freedom

$$\text{Degrees of freedom} = \frac{\left(\frac{s_X^2}{n_X} + \frac{s_Y^2}{n_Y}\right)^2}{\frac{\left(\frac{s_X^2}{n_X}\right)^2}{n_X - 1} + \frac{\left(\frac{s_Y^2}{n_Y}\right)^2}{n_Y - 1}}$$

# Independent Two-Sample $t$ -Test: Right Tailed Test



$$\bar{x} = 68.442$$

$$s_X = 3.113$$

$$n_X = 10$$

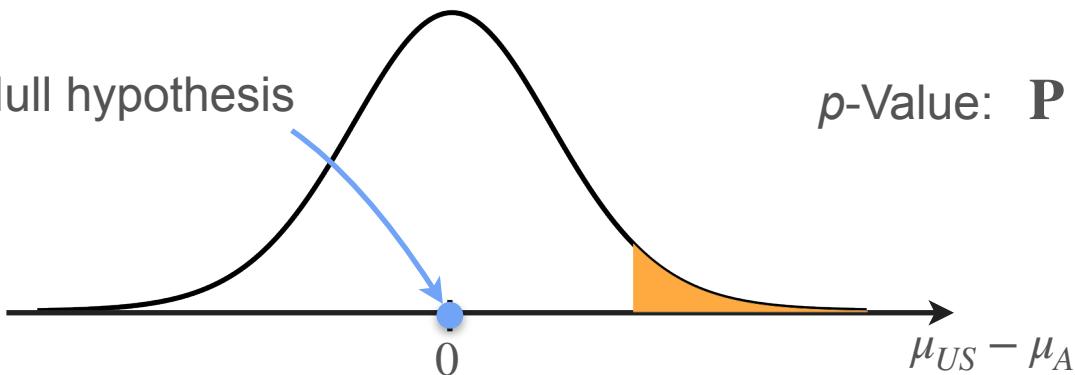
$$\bar{y} = 65.949$$

$$s_Y = 3.106$$

$$n_Y = 9$$

$$t = 1.7450$$

Null hypothesis



$$H_0 : \mu_{US} - \mu_{Ar} = 0 \text{ vs. } H_1 : \mu_{US} - \mu_{Ar} > 0$$

$$\alpha = 0.05$$

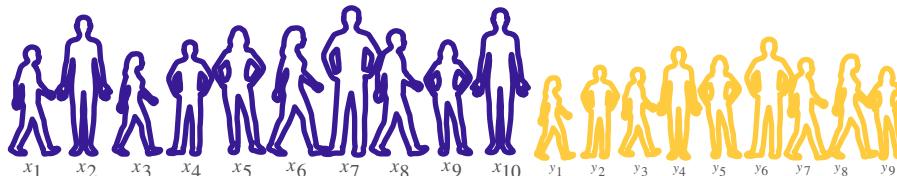
$$\text{If } H_0 \text{ is true: } T = \frac{(\bar{X} - \bar{Y}) - 0}{\sqrt{\frac{s_X^2}{10} + \frac{s_Y^2}{9}}} \sim t_{16.8}$$

$$p\text{-Value: } P(T > |\mu_{US} - \mu_{Ar}| = 0)$$

$$= 0.0495 < 0.05$$

$\Rightarrow$  Reject  $H_0$  (and accept  $H_1$ )  
(with a 5% significance level)

# Independent Two-Sample $t$ -Test: Two Tailed Test



$$\bar{x} = 68.442$$

$$s_x = 3.113$$

$$n_X = 10$$

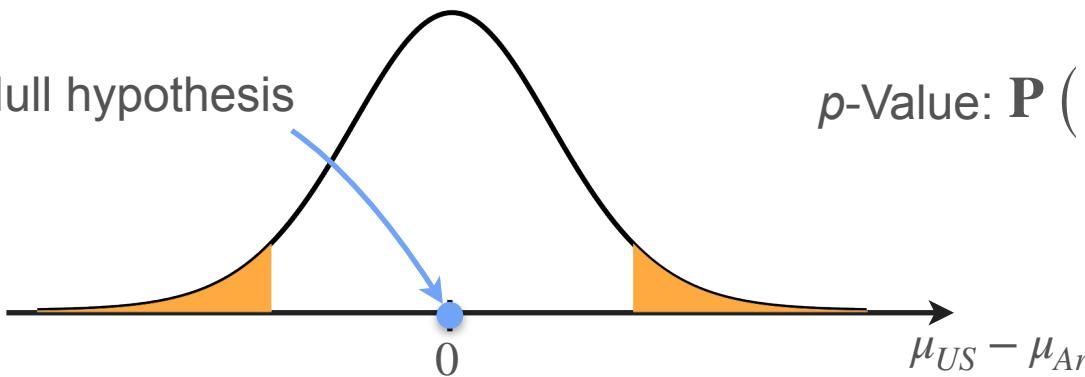
$$\bar{y} = 65.949$$

$$s_Y = 3.106$$

$$n_Y = 9$$

$$t = 1.7450$$

Null hypothesis



$$H_0 : \mu_{US} - \mu_{Ar} = 0 \text{ vs. } H_1 : \mu_{US} - \mu_{Ar} \neq 0$$

$$\alpha = 0.05$$

$$\text{If } H_0 \text{ is true: } T = \frac{(\bar{X} - \bar{Y}) - 0}{\sqrt{\frac{s_x^2}{10} + \frac{s_y^2}{9}}} \sim t_{16.8}$$

$$p\text{-Value: } \mathbf{P}(|T| > |\bar{X} - \bar{Y}| \mid \mu_{US} - \mu_{Ar} = 0)$$

$$= 0.0991 > 0.05$$

$\Rightarrow$  Do not reject  $H_0$   
(with a 5% significance level)



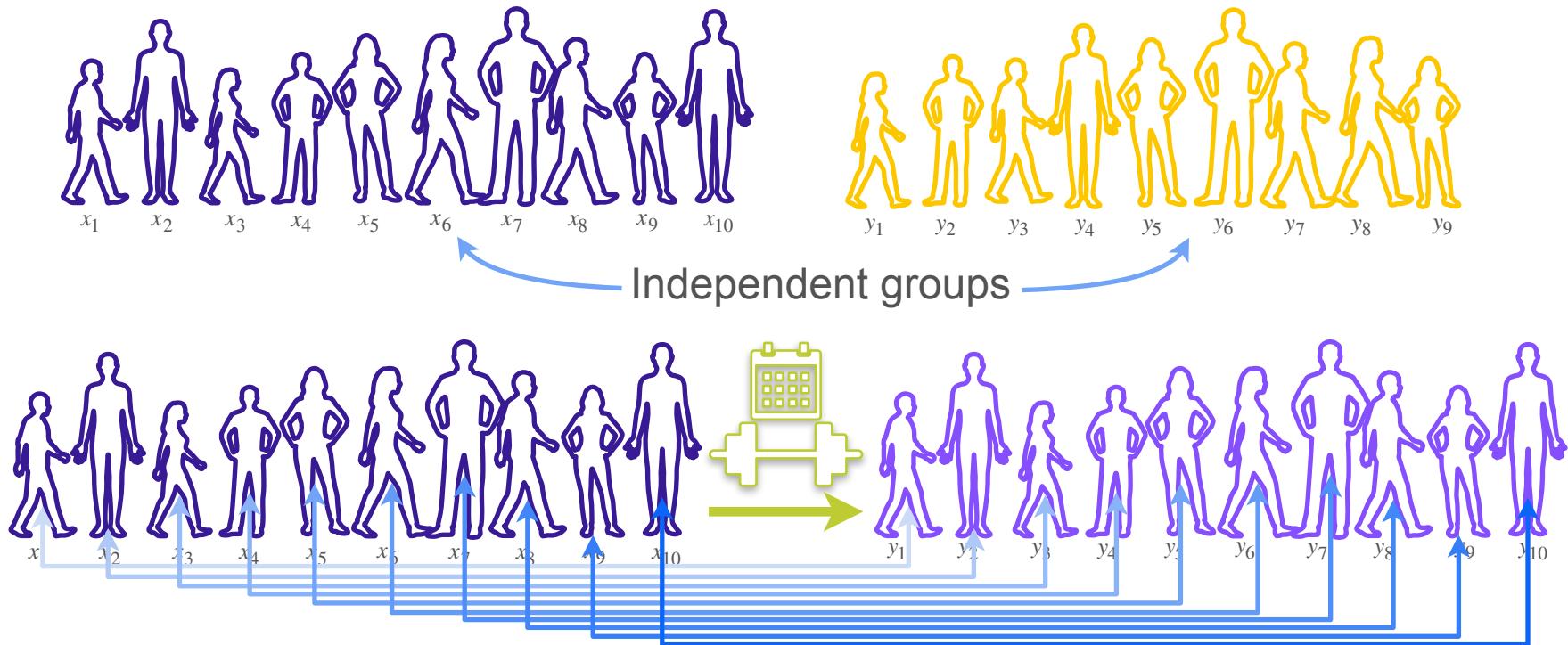
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# Hypothesis Testing

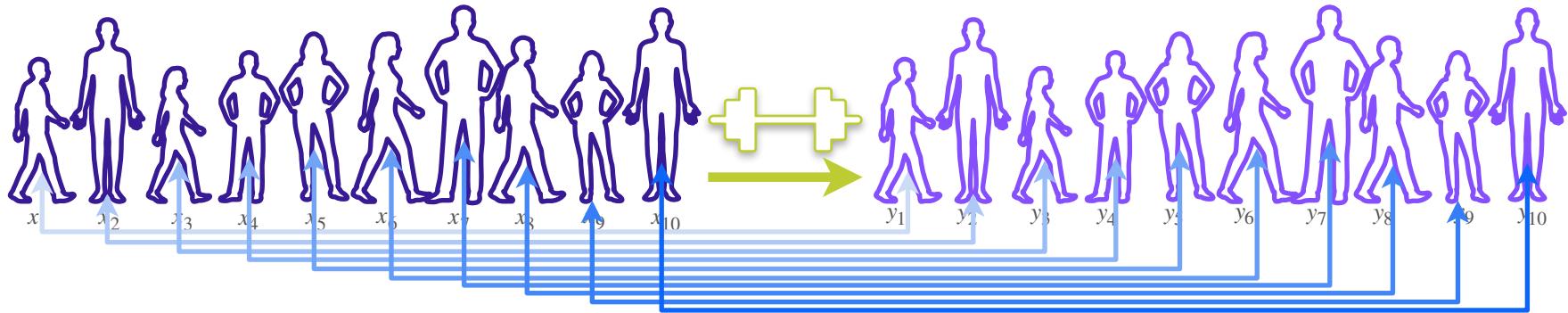
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## Paired t-test

# Paired $t$ -Test and Two-Sample $t$ -Test



# Paired $t$ -Test: Statistic



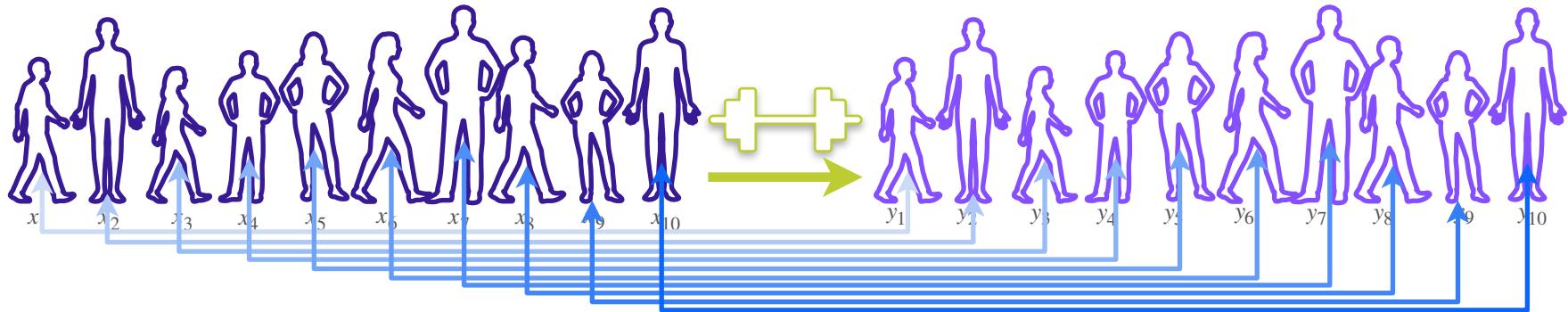
Now you're interested in the difference between pair of samples

$$\frac{(X_1 - Y_1) + (X_2 - Y_2) + (X_3 - Y_3) + (X_4 - Y_4) + (X_5 - Y_5) + (X_6 - Y_6) + (X_7 - Y_7) + (X_8 - Y_8) + (X_9 - Y_9) + (X_{10} - Y_{10})}{10}$$

---

$$\frac{D_1 + D_2 + D_3 + D_4 + D_5 + D_6 + D_7 + D_8 + D_9 + D_{10}}{10}$$

# Paired $t$ -Test: Statistic



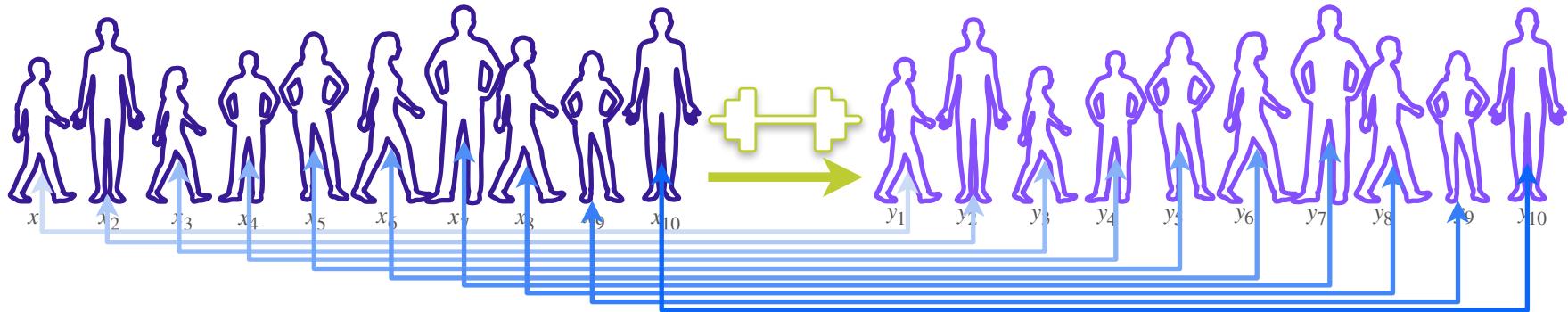
Now you're interested in the difference between pair of samples

$$(X_1 - Y_1) + (X_2 - Y_2) + (X_3 - Y_3) + (X_4 - Y_4) + (X_5 - Y_5) + (X_6 - Y_6) + (X_7 - Y_7) + (X_8 - Y_8) + (X_9 - Y_9) + (X_{10} - Y_{10})$$

10

$$\bar{D} = \frac{D_1 + D_2 + D_3 + D_4 + D_5 + D_6 + D_7 + D_8 + D_9 + D_{10}}{10}$$

# Paired $t$ -Test: Statistic



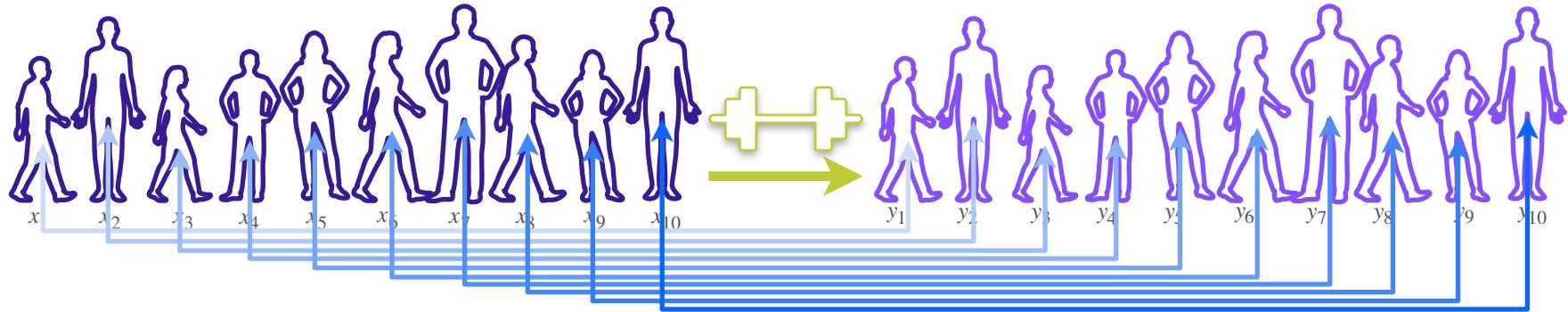
Now you're interested in the difference between pair of samples

$$\bar{D} = \frac{D_1 + D_2 + D_3 + D_4 + D_5 + D_6 + D_7 + D_8 + D_9 + D_{10}}{10}$$

If  $X_i, Y_i$  are gaussian  $\Rightarrow D_i = X_i - Y_i$  is gaussian.

$$D_i \stackrel{i.i.d}{\sim} \mathcal{N}(\mu_D, \sigma_D^2)$$

# Paired $t$ -Test: Statistic



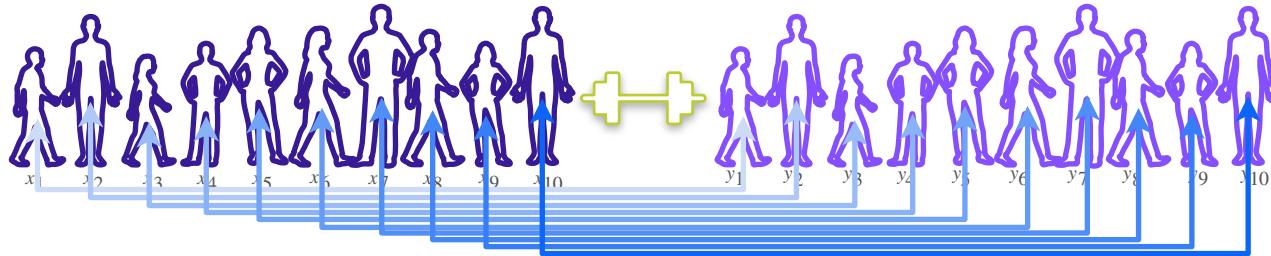
Now you're interested in the difference between pair of samples

$$\bar{D} = \frac{D_1 + D_2 + D_3 + D_4 + D_5 + D_6 + D_7 + D_8 + D_9 + D_{10}}{10}$$

If  $X_i, Y_i$  are gaussian  $\Rightarrow D_i = X_i - Y_i$  is gaussian.

$$D_i \stackrel{i.i.d}{\sim} \mathcal{N}(\mu_D, \sigma_D^2)$$

# Paired $t$ -Test: Statistic



Now you're interested in the difference between pair of samples

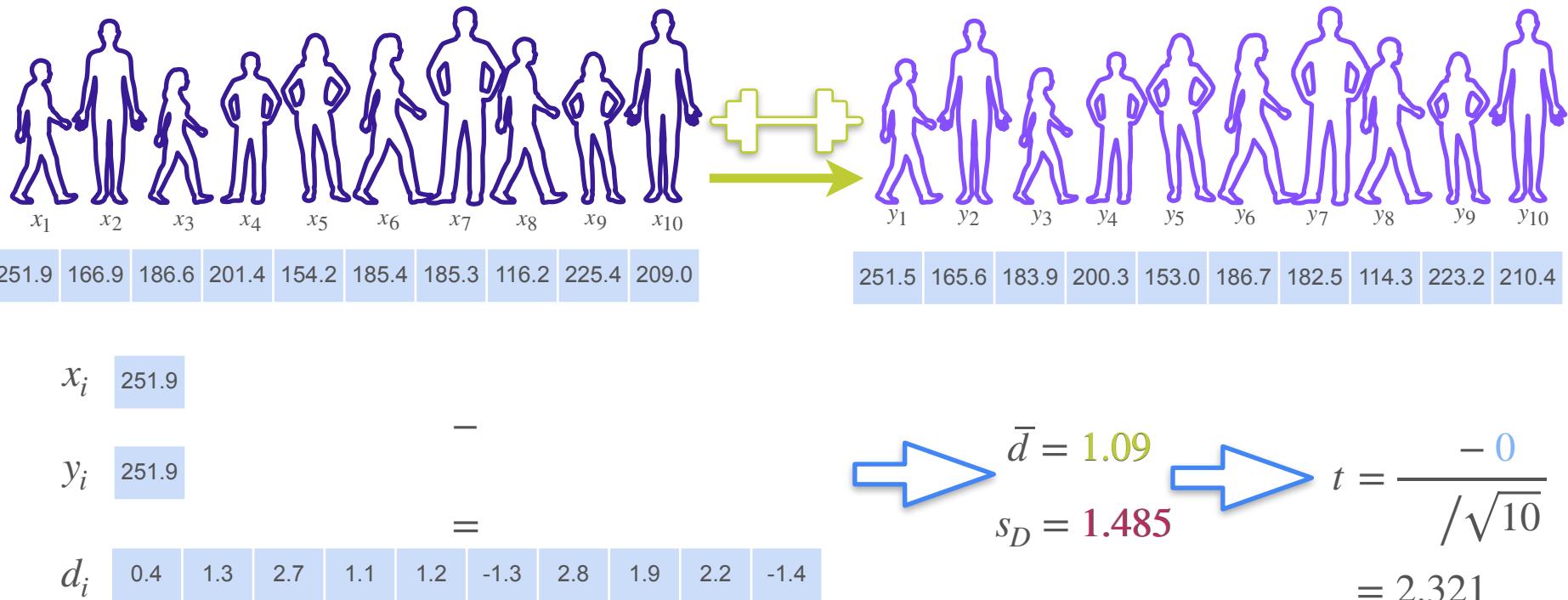
$$\bar{D} = \frac{D_1 + D_2 + D_3 + D_4 + D_5 + D_6 + D_7 + D_8 + D_9 + D_{10}}{10} \quad D_i = X_i - Y_i$$
$$D_i \stackrel{i.i.d}{\sim} \mathcal{N}(\mu_D, \sigma_D^2)$$

$$\frac{\bar{D} - \mu_D}{\sigma_D / \sqrt{10}} \sim \mathcal{N}(0, 1^2)$$

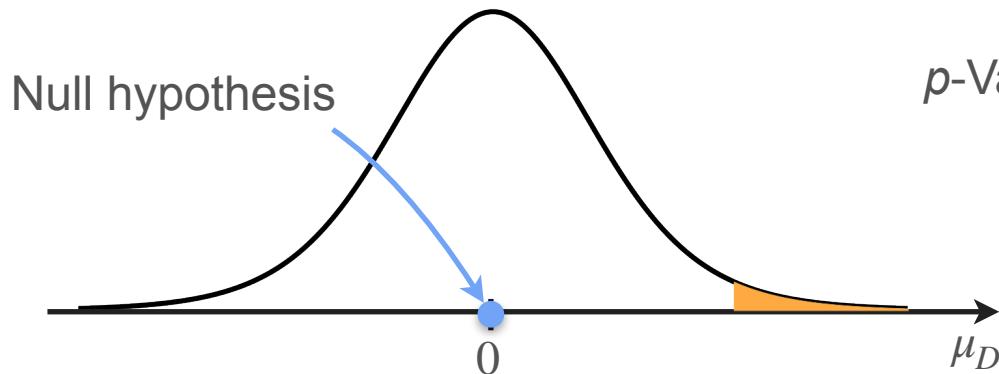
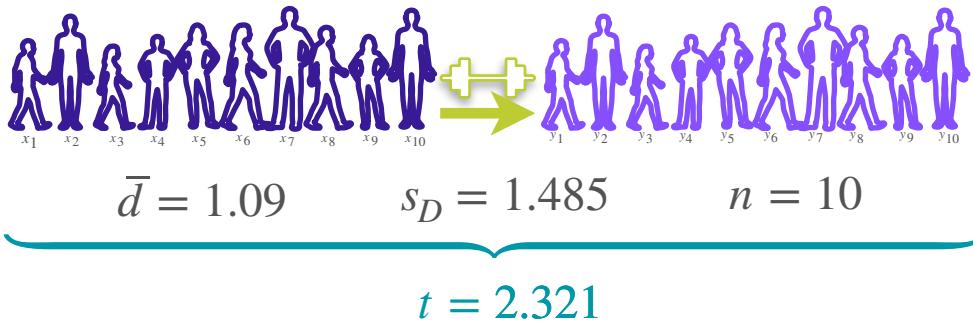
But  $\sigma_D$  is unknown  $\Rightarrow \sigma_D \rightarrow S_D = \sqrt{\frac{\sum_{i=1}^{10} (D_i - \bar{D})^2}{10 - 1}}$   $\Rightarrow T = \frac{\bar{D} - 0}{S_D / \sqrt{10}} \sim t_{10-1}$

$H_0 : \mu_D = 0$  Test statistic

# Paired $t$ -Test: Observations



# Paired Two-Sample $t$ -Test: Right Tailed Test



$$H_0 : \mu_D = 0 \text{ vs. } H_1 : \mu_D > 0$$

$$\alpha = 0.05$$

$$\text{If } H_0 \text{ is true: } T = \frac{\bar{D} - 0}{S_D / \sqrt{10}} \sim t_{10-1}$$

$$p\text{-Value: } P(T > \quad \quad \quad | \mu_D = 0)$$

$$= 0.0227 < 0.05$$

$\Rightarrow$  Reject  $H_0$  (and accept  $H_1$ )  
(with a 5% significance level)



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# Hypothesis Testing

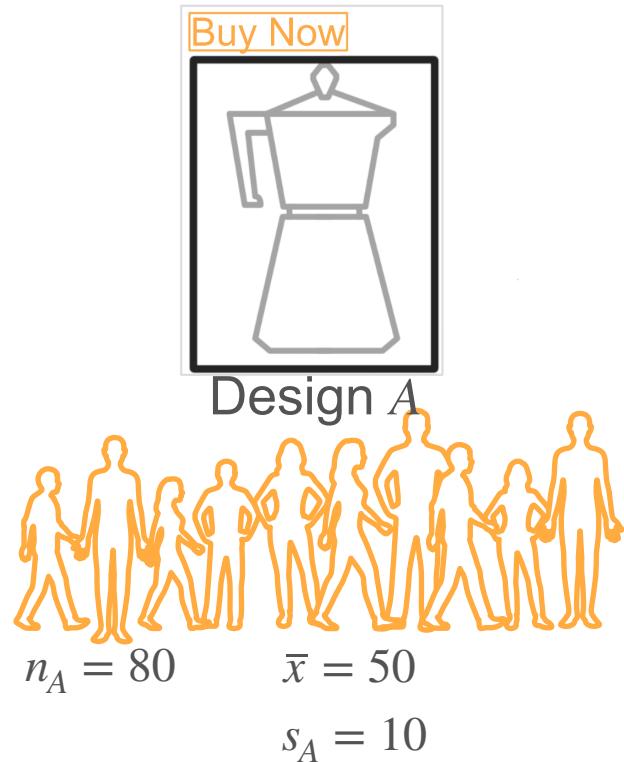
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**ML Application: A/B testing**

# A/B Testing: Purchase Amount



# A/B Testing: Purchase Amount



# A/B Testing: Purchase Amount



$$n_A = 80$$

$$\bar{x} = 50$$

$$s_A = 10$$

$$X \sim \mathcal{N}(\mu_A, \sigma_A^2)$$



$$n_B = 20$$

$$\bar{y} = 55$$

$$s_B = 15$$

$$Y \sim \mathcal{N}(\mu_B, \sigma_B^2)$$

$$H_0 : \mu_A - \mu_B = 0 \text{ vs. } H_1 : \mu_A - \mu_B < 0$$

$$\alpha = 0.05$$

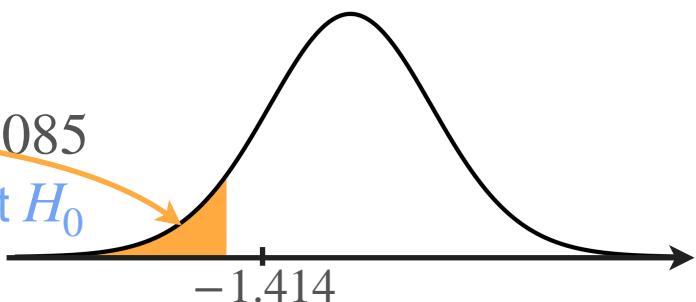
$$\text{If } H_0 \text{ is true: } T = \frac{(\bar{X} - \bar{Y}) - 0}{\sqrt{\frac{S_A^2}{n_A} + \frac{S_B^2}{n_B}}} \sim t_{23.38}$$

$$t = \frac{(-) - 0}{\sqrt{\frac{s_A^2}{n_A} + \frac{s_B^2}{n_B}}}$$

$$-1.414$$

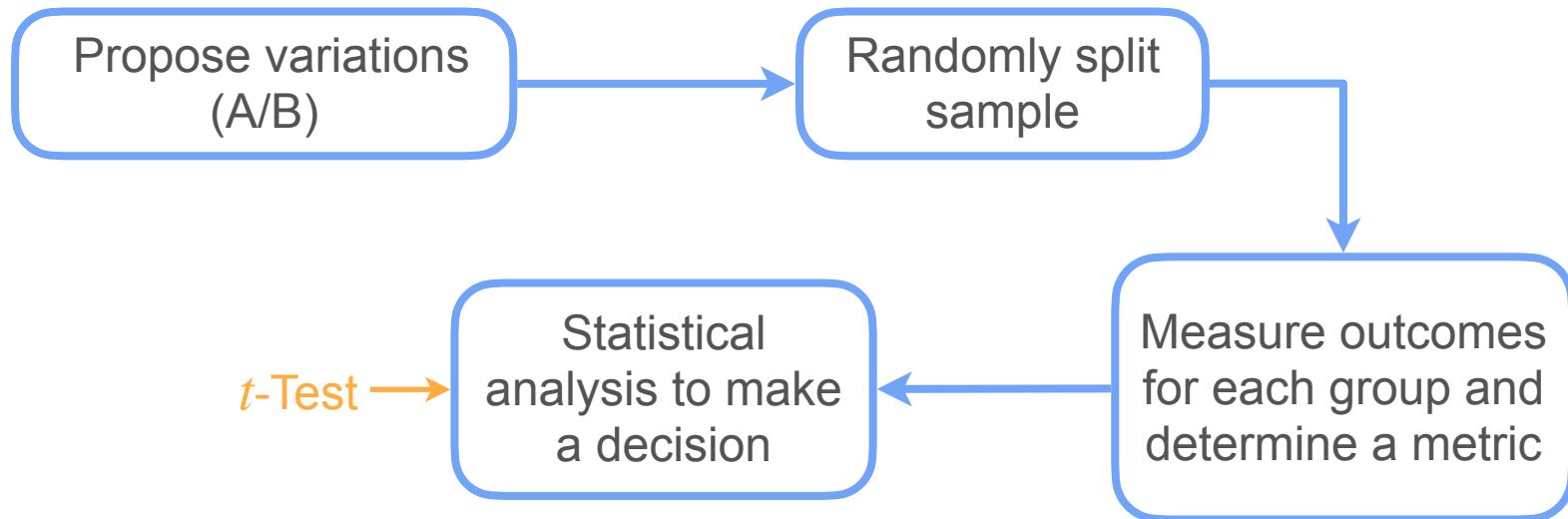
$$p\text{-Value: } 0.085$$

Don't reject  $H_0$

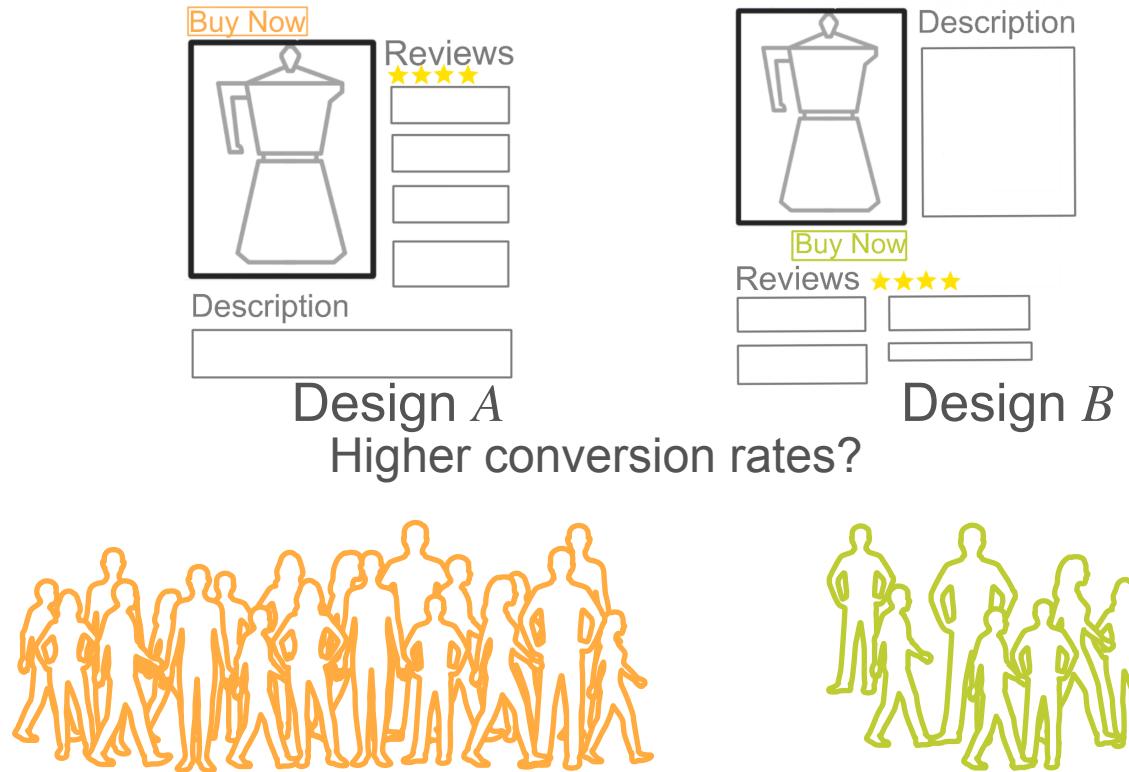


# A/B Testing and $t$ -Tests

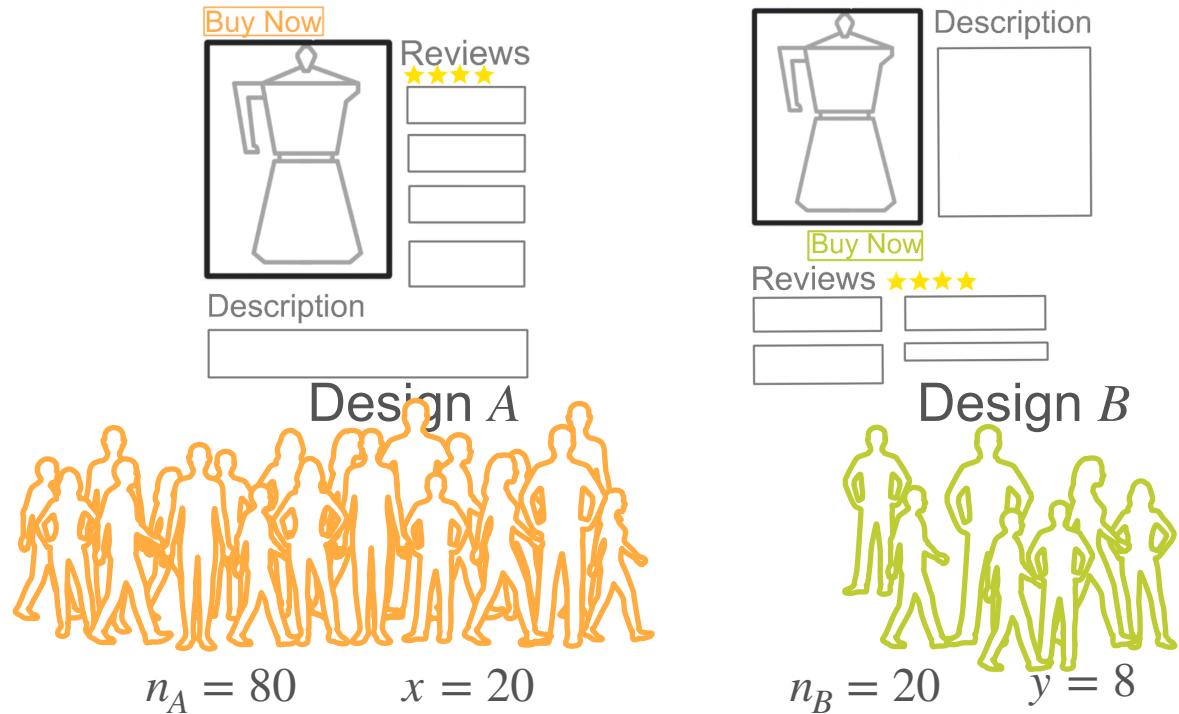
A/B testing is a methodology for comparing two variations (A/B)



# A/B Testing: Conversion Rates



# A/B Testing: Conversion Rates



# A/B Testing: Conversion Rates



$$n_A = 80$$

$$x = 20$$



$$n_B = 20$$

$$y = 8$$

$$X \sim \text{Binomial}(n_A, p_A) \quad Y \sim \text{Binomial}(n_B, p_B)$$

$$H_0 : p_A - p_B = 0 \text{ vs. } H_1 : p_A - p_B < 0$$

$p_A$  = Conversion rate from Design A

$p_B$  = Conversion rate from Design B

$$\alpha = 0.05$$

# A/B Testing: Conversion Rates

Statistic?

Law of large numbers

$$\frac{X}{n_A} \rightarrow p_A$$



$$\frac{X}{n_A} \sim \mathcal{N}\left(p_A, \frac{p_A(1-p_A)}{n_A}\right)$$

$$\frac{Y}{n_B} \rightarrow p_B$$

C.L.T.



$$\frac{Y}{n_B} \sim \mathcal{N}\left(p_B, \frac{p_B(1-p_B)}{n_B}\right)$$

# A/B Testing: Conversion Rates

Statistic?

$$\left. \begin{array}{l} \frac{X}{n_A} \stackrel{a}{\sim} \mathcal{N} \left( p_A, \frac{p_A(1-p_A)}{n_A} \right) \\ \frac{Y}{n_B} \stackrel{a}{\sim} \mathcal{N} \left( p_B, \frac{p_B(1-p_B)}{n_B} \right) \end{array} \right\} \quad \frac{X}{n_A} - \frac{Y}{n_B} \rightarrow p_A - p_B \quad \frac{\frac{X}{n_A} - \frac{Y}{n_B}}{\sqrt{\frac{p_A(1-p_A)}{n_A} + \frac{p_B(1-p_B)}{n_B}}} \stackrel{a}{\sim} \mathcal{N} (0, 1^2)$$

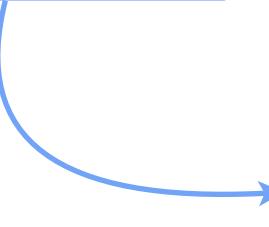
$\frac{X}{n_A} - \frac{Y}{n_B} \stackrel{a}{\sim} \mathcal{N} \left( p_A - p_B, \frac{p_A(1-p_A)}{n_A} + \frac{p_B(1-p_B)}{n_B} \right)$

↔

# A/B Testing: Conversion Rates

If  $H_0$  is true  $\Rightarrow p_A = p_B = p$

$$\frac{\left(\frac{X}{n_A} - \frac{Y}{n_B}\right) - (p - p)}{\sqrt{\frac{p(1-p)}{n_A} + \frac{p(1-p)}{n_B}}} \stackrel{a}{\sim} \mathcal{N}(0, 1^2)$$



$$= p(1-p) \left( \frac{1}{n_A} + \frac{1}{n_B} \right) = p(1-p)(n_A + n_B) \frac{1}{n_A n_B}$$

# A/B Testing: Conversion Rates

If  $H_0$  is true  $\Rightarrow p_A = p_B = p$

$$\frac{\left(\frac{X}{n_A} - \frac{Y}{n_B}\right) - (p - p)}{\sqrt{\frac{p(1-p)}{n_A} + \frac{p(1-p)}{n_B}}} \stackrel{a}{\sim} \mathcal{N}(0, 1^2) \longrightarrow \frac{\left(\frac{X}{n_A} - \frac{Y}{n_B}\right) - 0}{\sqrt{(n_A + n_B)p(1-p)}} \sqrt{n_A n_B} \stackrel{a}{\sim} \mathcal{N}(0, 1^2)$$

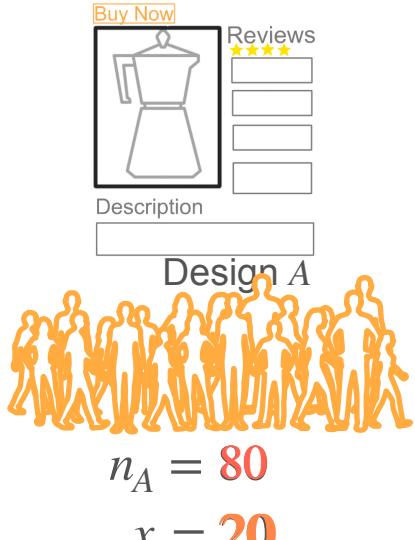
But you don't know  $p$

↓  
Replace it by estimation!  $\hat{p} = \frac{X + Y}{n_A + n_B}$

Test statistic

$$\frac{\left(\frac{X}{n_A} - \frac{Y}{n_B}\right) - 0}{\sqrt{(X + Y)\left(1 - \frac{X + Y}{n_A + n_B}\right)}} \sqrt{n_A n_B} \stackrel{a}{\sim} \mathcal{N}(0, 1^2)$$

# A/B Testing: Conversion Rates



$$X \sim \text{Binomial}(n_A, p_A) \quad Y \sim \text{Binomial}(n_B, p_B)$$

$$H_0 : p_A - p_B = 0 \text{ vs. } H_1 : p_A - p_B < 0$$

$\alpha = 0.05$     If  $H_0$  is true  $\Rightarrow p_A = p_B = p$

$$Z = \frac{\left( \frac{X}{n_A} - \frac{Y}{n_B} \right) - 0}{\sqrt{(X+Y)\left(1 - \frac{X+Y}{n_A+n_B}\right)}} \sqrt{n_A n_B} \sim \mathcal{N}(0, 1^2)$$

$$z = \frac{\left( \frac{x}{n_A} - \frac{y}{n_B} \right) - 0}{\sqrt{\left( \frac{x}{n_A} + \frac{y}{n_B} \right) \left( 1 - \frac{\frac{x}{n_A} + \frac{y}{n_B}}{n_A + n_B} \right)}} \sqrt{n_A n_B}$$

$$z = -1.336$$

# A/B Testing: Conversion Rates



$$n_A = 80$$

$$x = 20$$

$$X \sim \text{Binomial}(n_A, p_A) \quad Y \sim \text{Binomial}(n_B, p_B)$$



$$n_B = 20$$

$$y = 8$$

$$H_0 : p_A - p_B = 0 \text{ vs. } H_1 : p_A - p_B < 0$$

$$\alpha = 0.05 \quad \text{If } H_0 \text{ is true} \Rightarrow p_A = p_B = p$$

$$Z = \frac{\left( \frac{X}{n_A} - \frac{Y}{n_B} \right) - 0}{\sqrt{(X+Y)\left(1 - \frac{X+Y}{n_A+n_B}\right)}} \sqrt{n_A n_B} \sim \mathcal{N}(0, 1^2)$$

$$z = -1.336$$

$$p\text{-value} = 0.091$$

Do not reject  
 $H_0$

-1.336



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# Hypothesis Testing

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## Conclusion