

Using the normal distribution for  
inference

# Overview

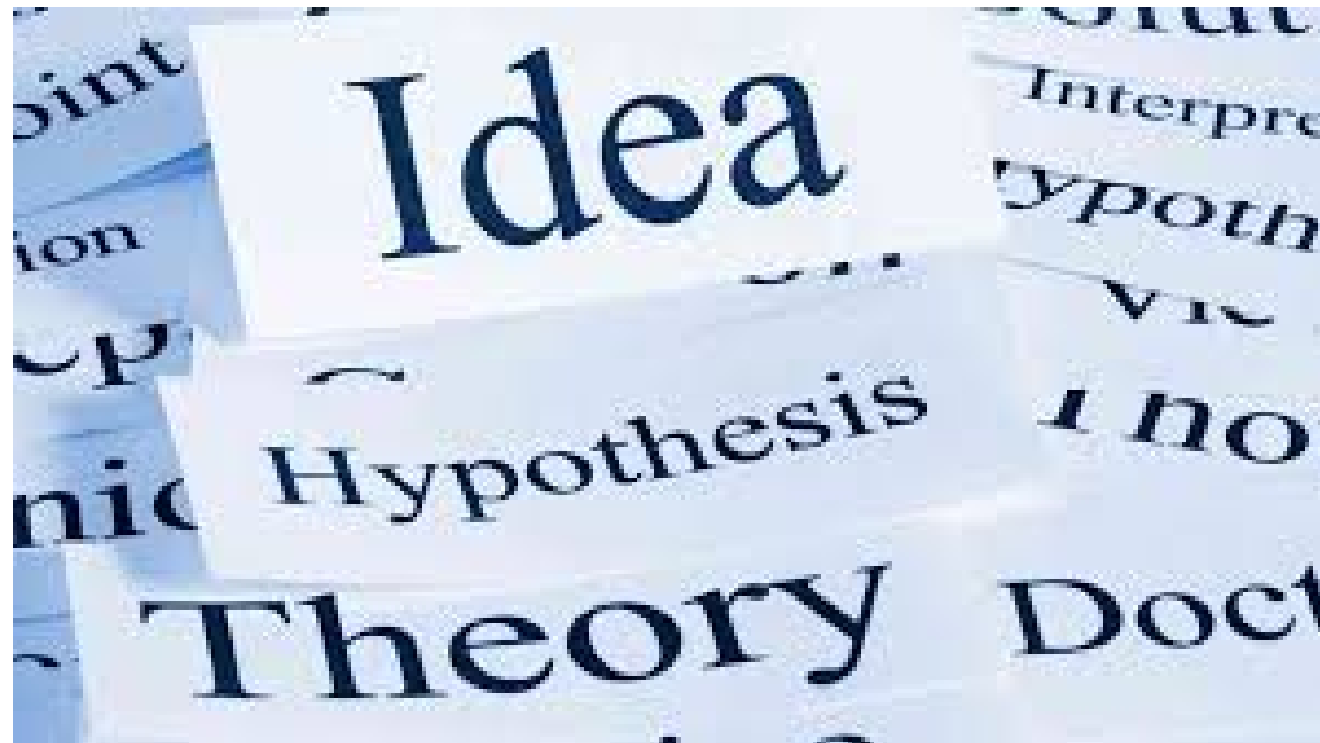
Quick review of theories/concepts in hypothesis testing

Review and continuation of the normal distribution

Using the normal distribution for inference

- Hypothesis tests
- Confidence intervals

# Quick review of theories of hypothesis tests



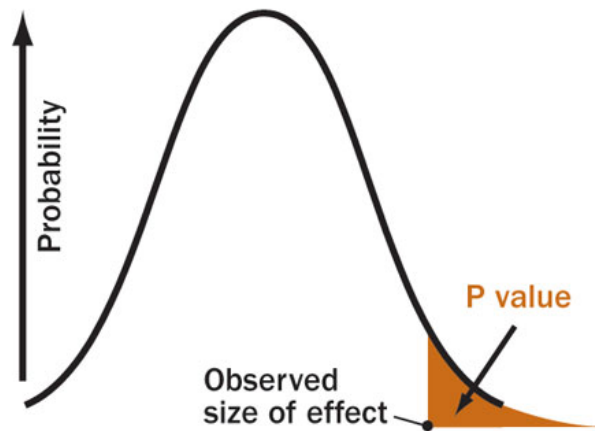
# Two theories of hypothesis testing

## 1. **Significance testing** of Ronald Fisher

- p-value as strength of evidence against the null hypothesis

## 2. **Hypothesis testing** of Jezy Neyman and Egon Pearson

- Make a formal decision of whether to reject  $H_0$  (if p-value < predefined  $\alpha$  value)

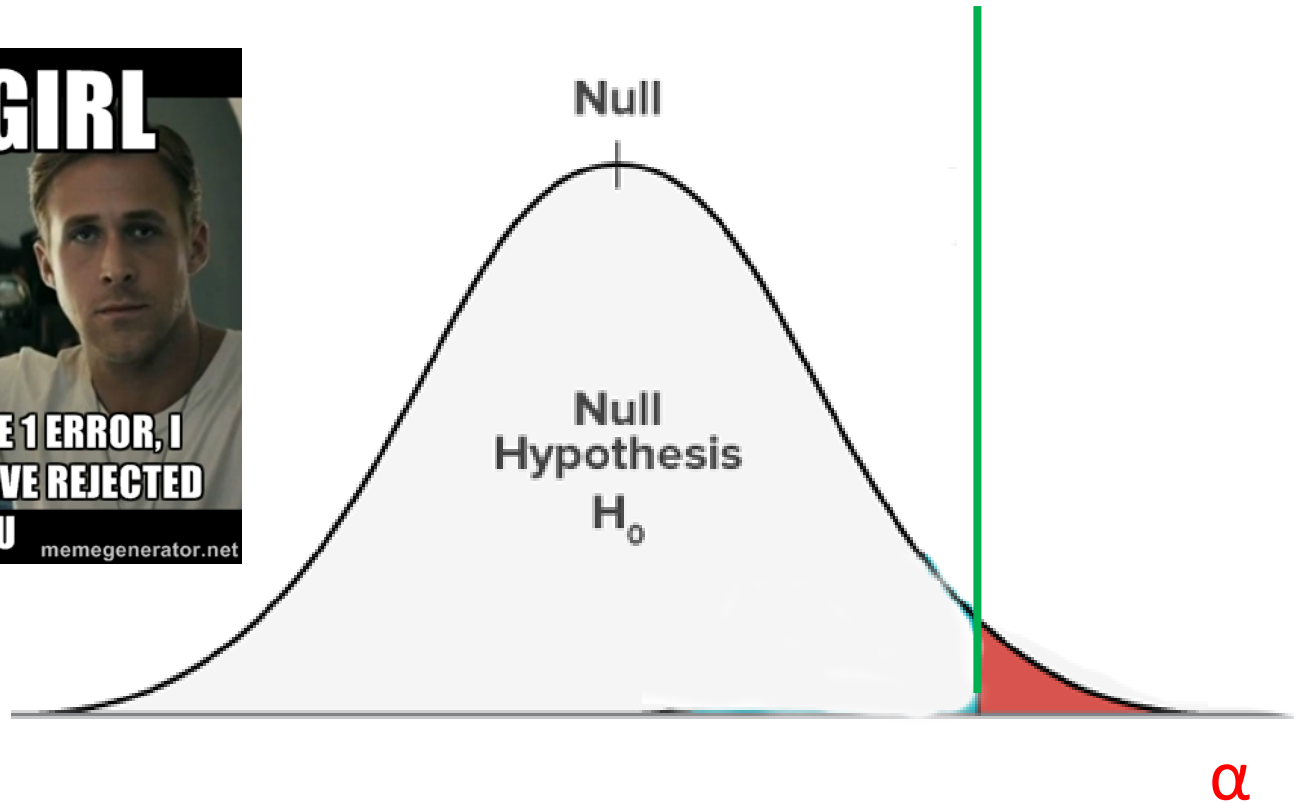
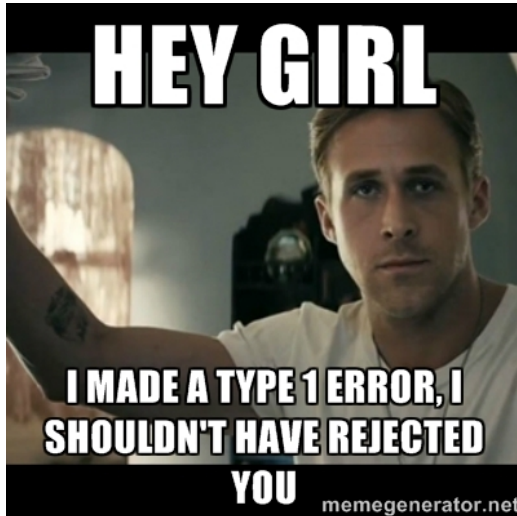


**Significance testing**



**Hypothesis testing**

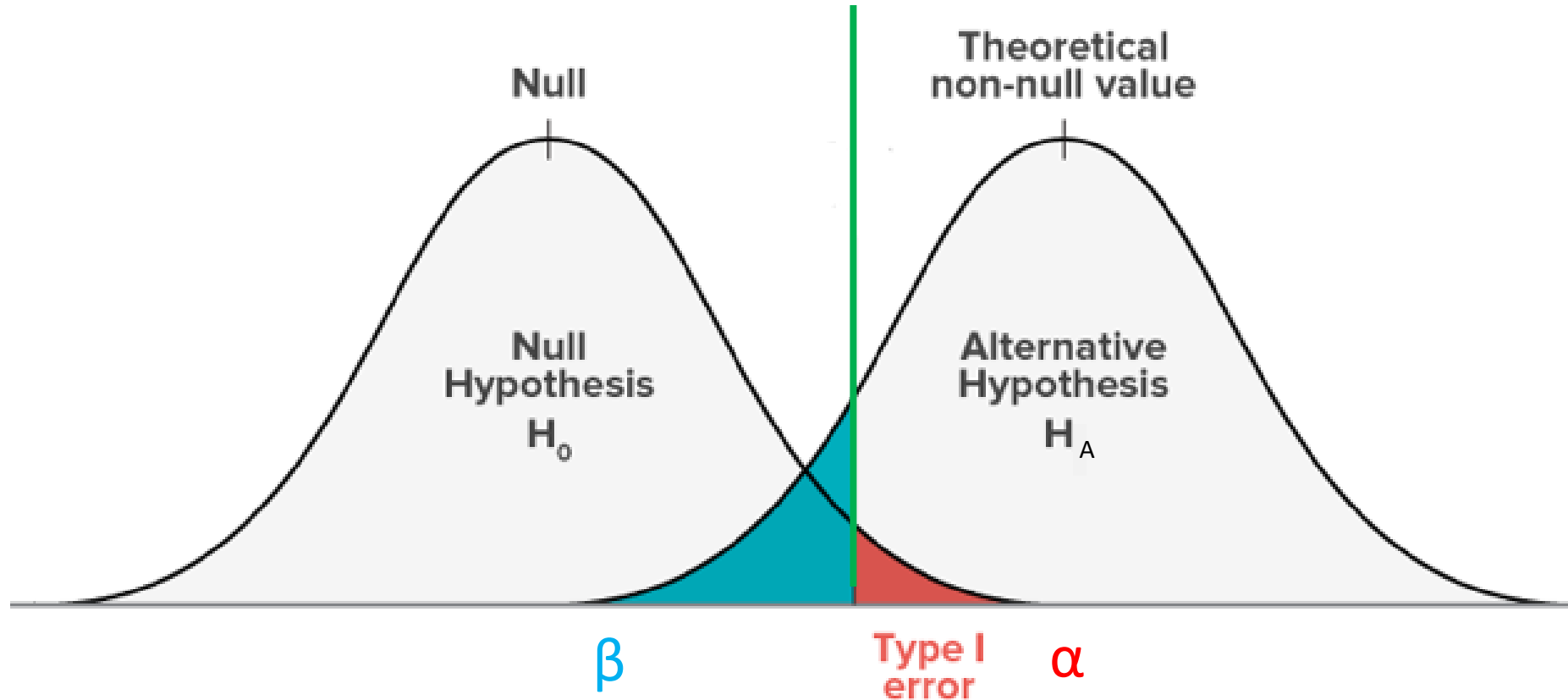
# Neyman-Pearson Frequentist logic



If Neyman-Pearson null hypothesis testing paradigm was followed perfectly, then only ~5% of all published research findings should be wrong (for  $\alpha = 0.05$ )

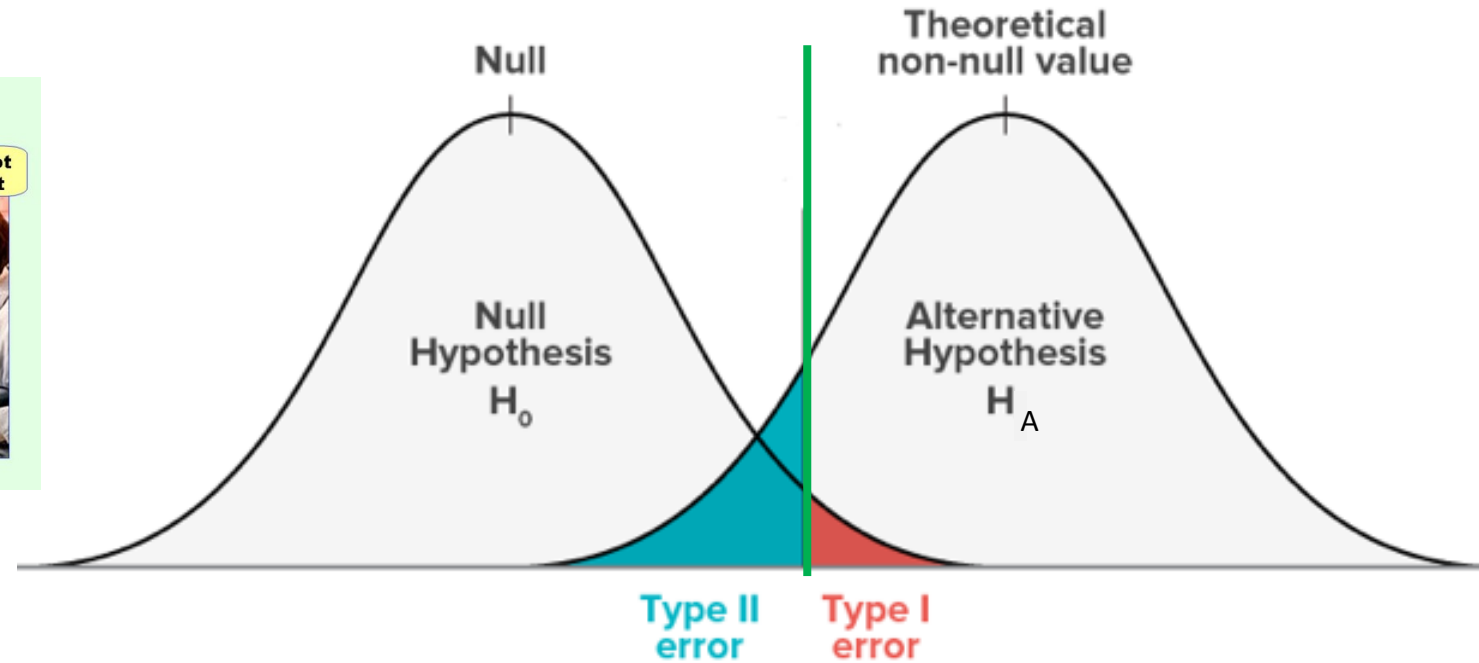
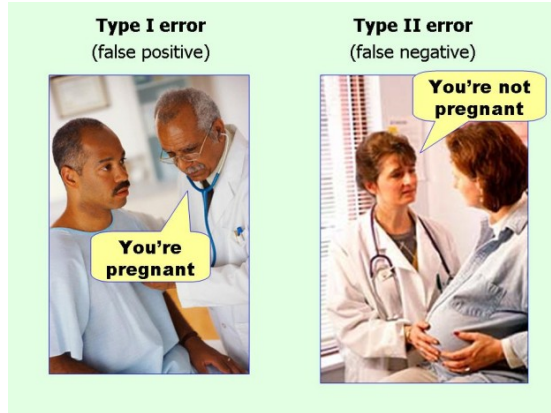
**Type I error:** incorrectly rejecting the null hypothesis when it is true

# Neyman-Pearson Frequentist logic



**Type 2 error:** incorrectly rejecting failing to reject  $H_0$  when it is false

# Type I and Type II Errors



	Reject $H_0$	Do not reject $H_0$
$H_0$ is true	Type I error ( $\alpha$ ) (false positive)	No error

# Problems with the NP hypothesis tests

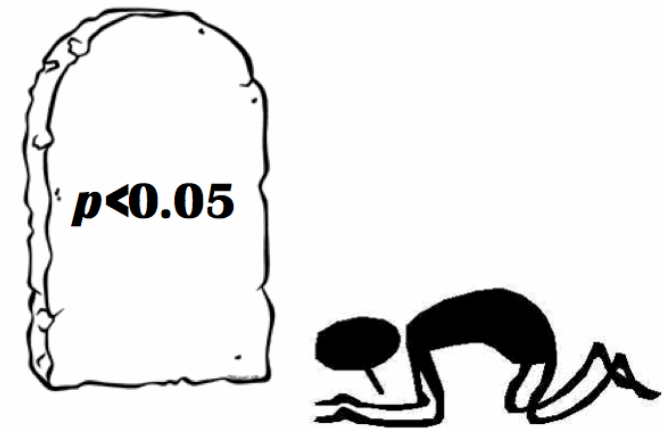
Problem 1: we are interested in the results of a specific experiment, not whether we are right most of the time

- E.g., 95% of these statements are true:
  - Calcium is good for your heart, Paul is psychic, Buzz and Doris can communicate, ...

Problem 2: Arbitrary thresholds for alpha levels

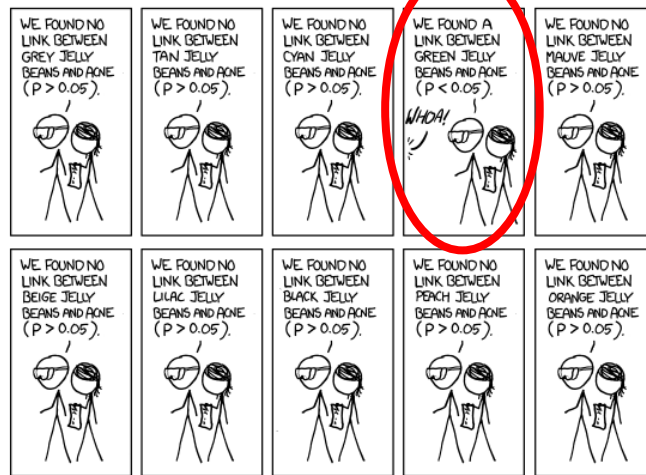
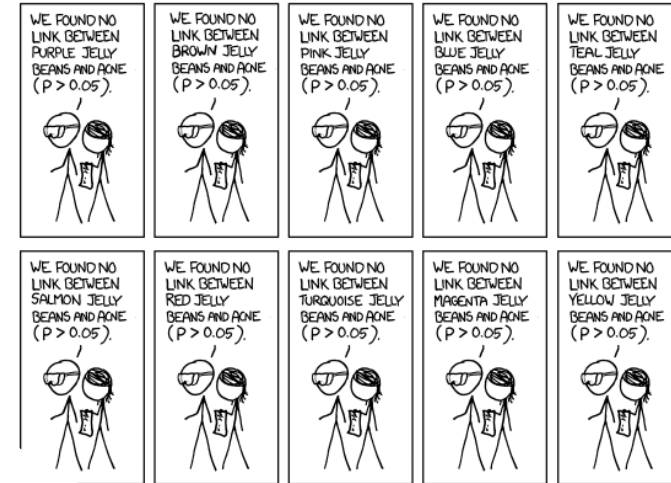
- P-value = 0.051, we don't reject  $H_0$ ?

Problem 3: running many tests can give rise to a high number of type 1 errors





# Multiple hypothesis tests



# Replication crisis

Essay

## Why Most Published Research Findings Are False

John P. A. Ioannidis

### The file drawer effect



[American Statistical Association's 'Statement on p-values'](#)

# Some thoughts...

Better to have hypothesis tests than none at all. Just need to think carefully and use your judgment.

Report effect size in most cases – i.e., confidence intervals

Report the p-values rather than accept/reject  $H_0$

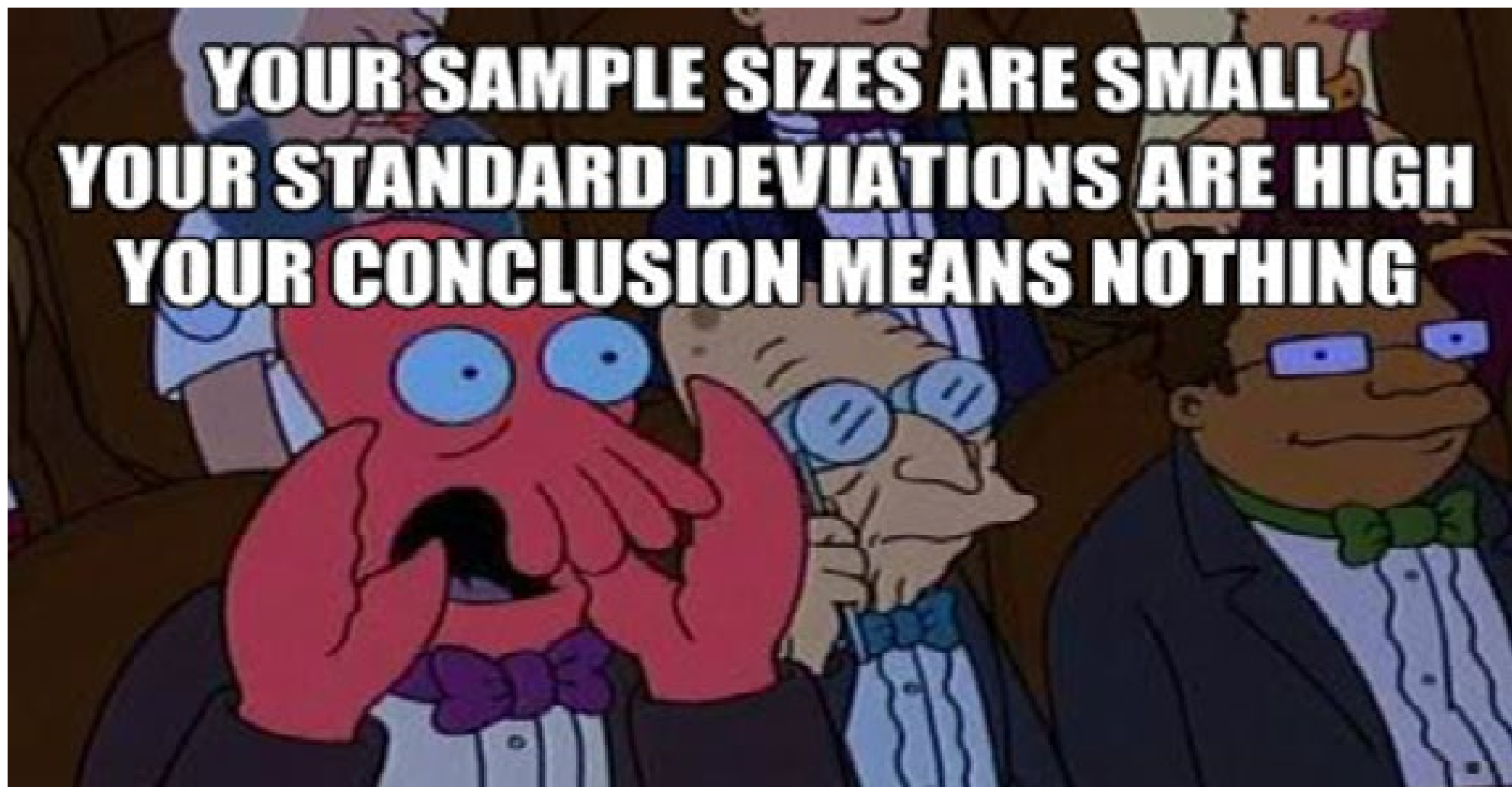
- i.e., report  $p = 0.023$  not  $p < 0.05$

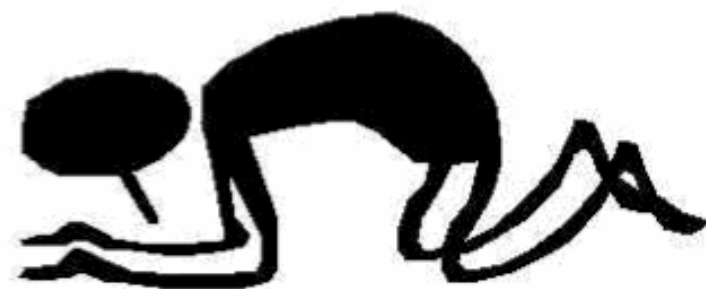
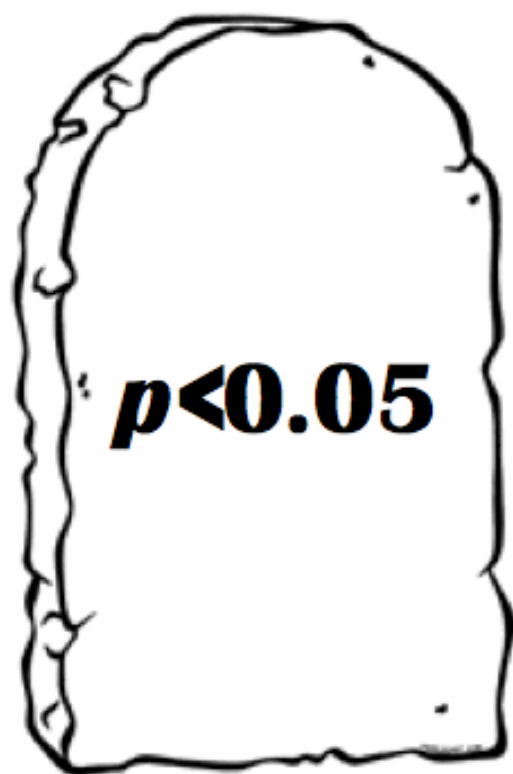
Replicate findings (perhaps in different contexts) to make sure you get the same results

Be a good/honest scientists and try to get at the Truth!

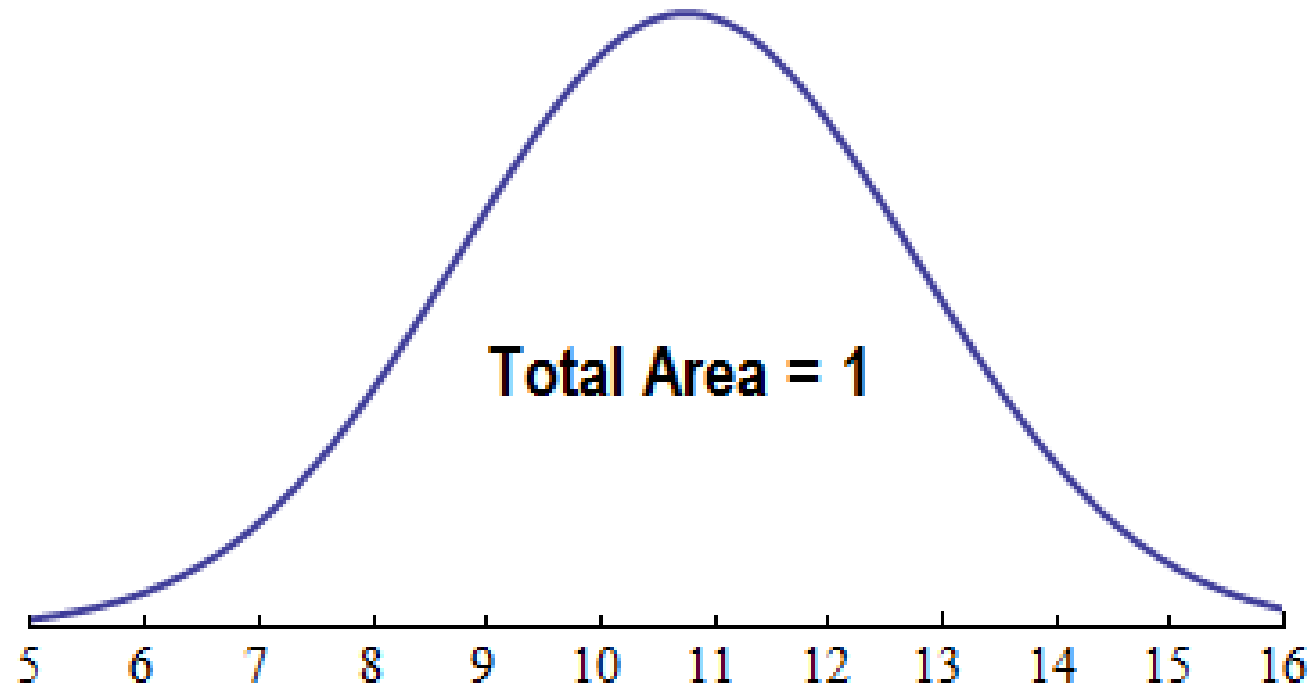


**YOUR SAMPLE SIZES ARE SMALL  
YOUR STANDARD DEVIATIONS ARE HIGH  
YOUR CONCLUSION MEANS NOTHING**





# Inference using parametric probability distributions



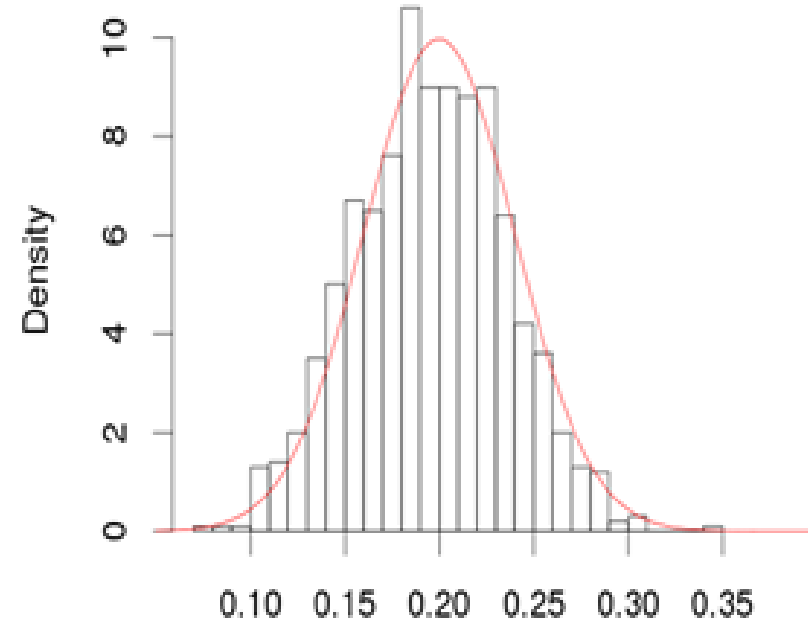
# Inference using parametric probability distributions

We can use mathematical functions called **probability distributions** to do inference

- e.g. instead of running computer simulations to create null distributions we can just use mathematical probability distributions

A **density curve** is a mathematical function  $f(x)$  that has two important properties:

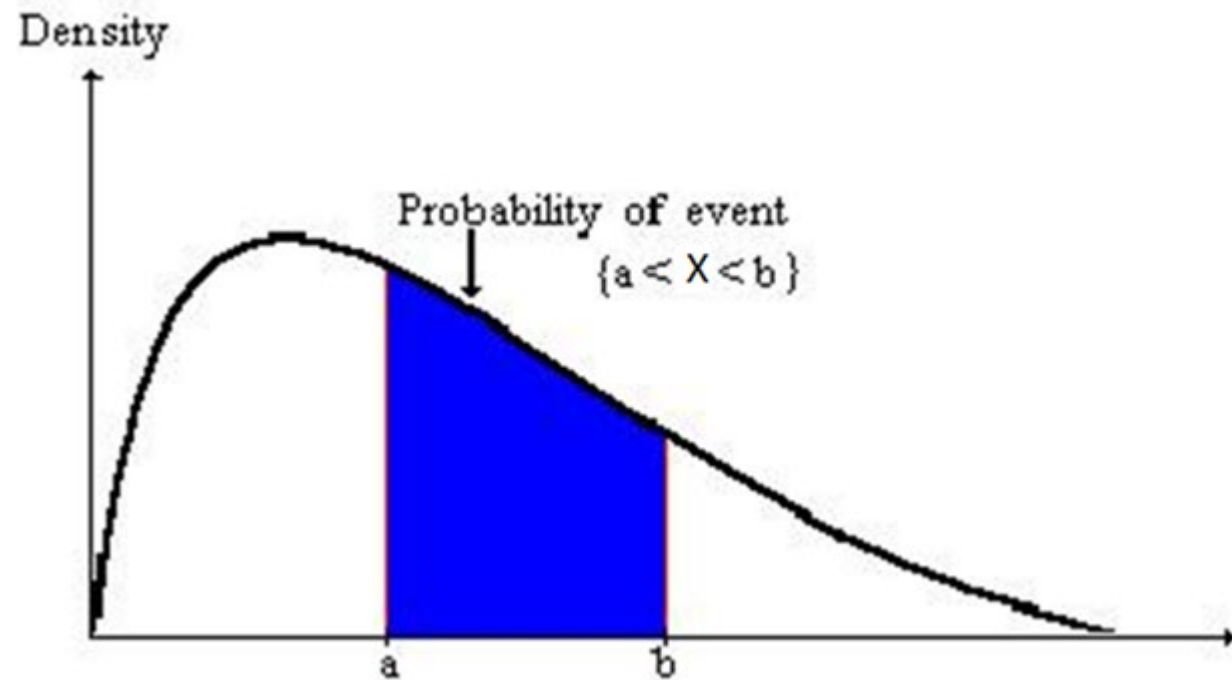
1. The total area under the curve  $f(x)$  is equal to 1
2. The curve is always  $\geq 0$



# Density Curves

The area under the curve in an interval  $[a, b]$  models the probability that a random number  $X$  will be in the interval

$\Pr(a < X < b)$  is the area under the curve from  $a$  to  $b$



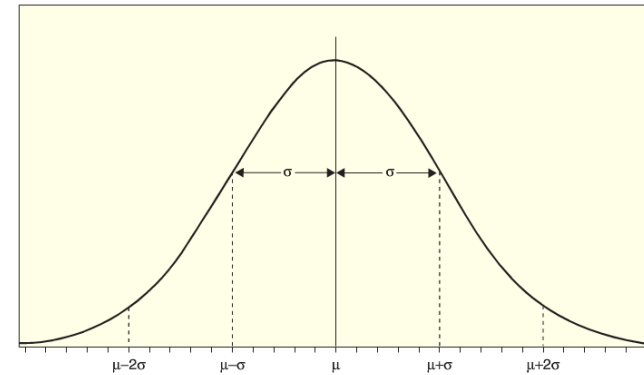


# The Normal Density Curve

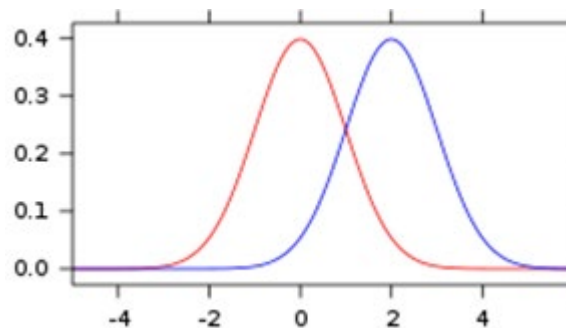
Normal distributions are a family of bell-shaped curves with two parameters

- The mean:  $\mu$
- The standard deviation:  $\sigma$

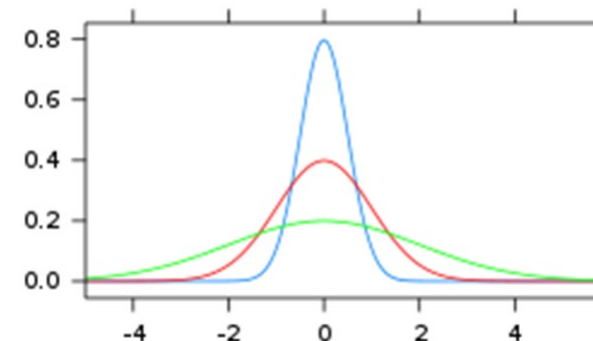
Notation:  $X \sim N(\mu, \sigma)$



**Changing  $\mu$**



**Changing  $\sigma$**



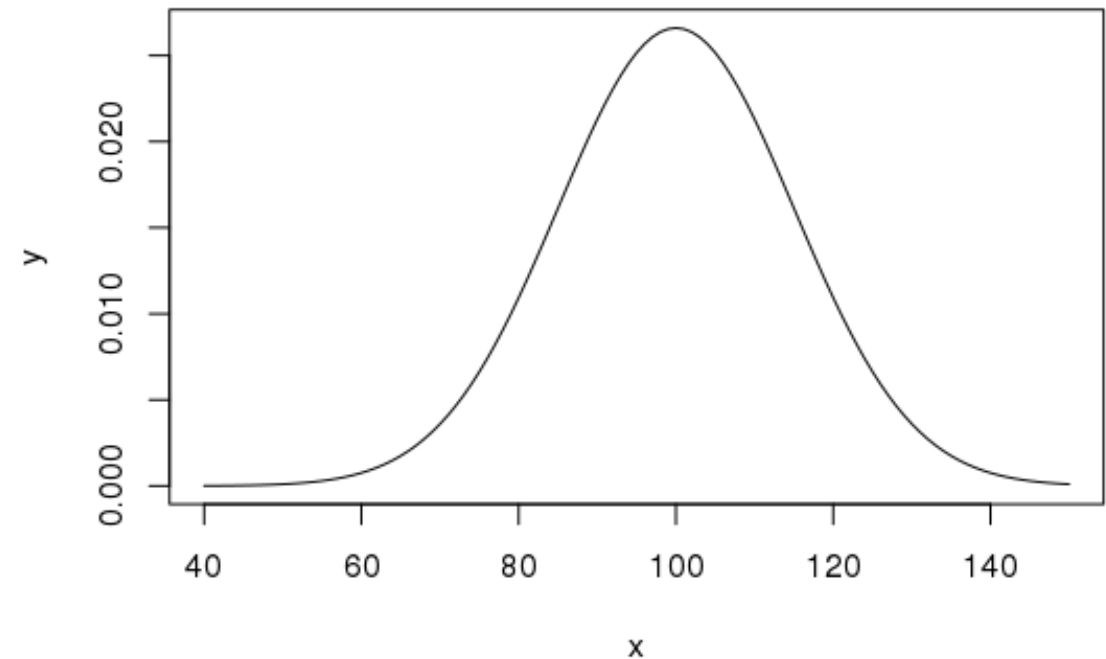
# Graphing Normal Curves

## Plotting IQ scores

```
x <- 40:150  
y <- dnorm(x, 100, 15)  
plot(x, y, type = "l")
```

Diagram illustrating the parameters of the normal distribution function `dnorm`:

- $\mu$  (mean) is 100, indicated by a red arrow pointing to the value 100 in the code.
- $\sigma$  (standard deviation) is 15, indicated by a red arrow pointing to the value 15 in the code.



# Finding normal probabilities of a normal curve

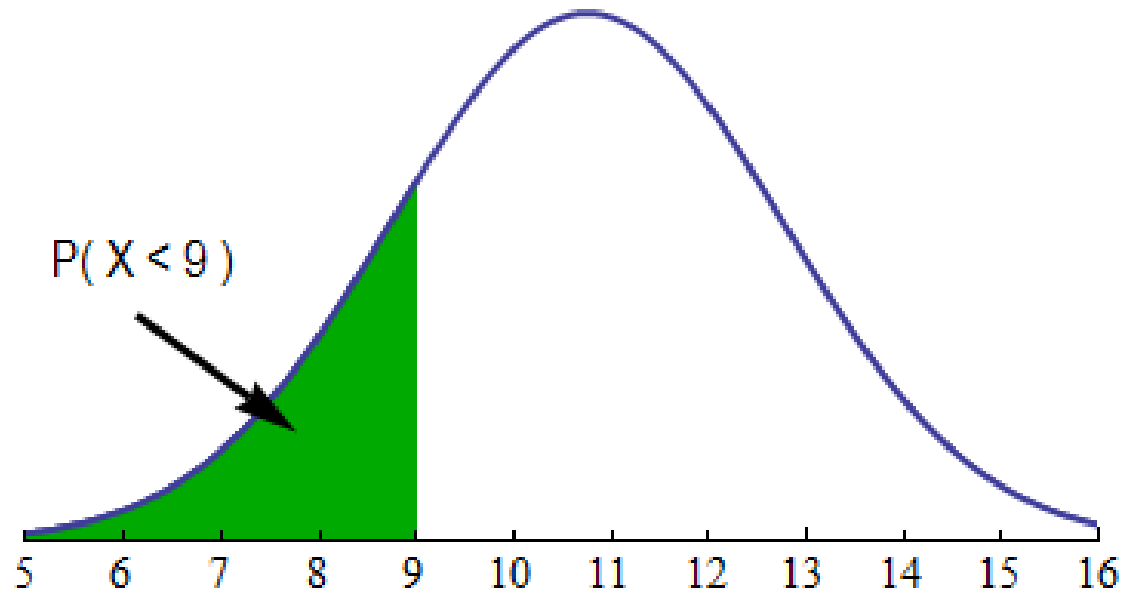
To get the probability (area) from a normal distribution we can use the **p**norm function

```
pnorm(x, mu, sigma)
```

$\Pr(X < 9; 11, 3)$

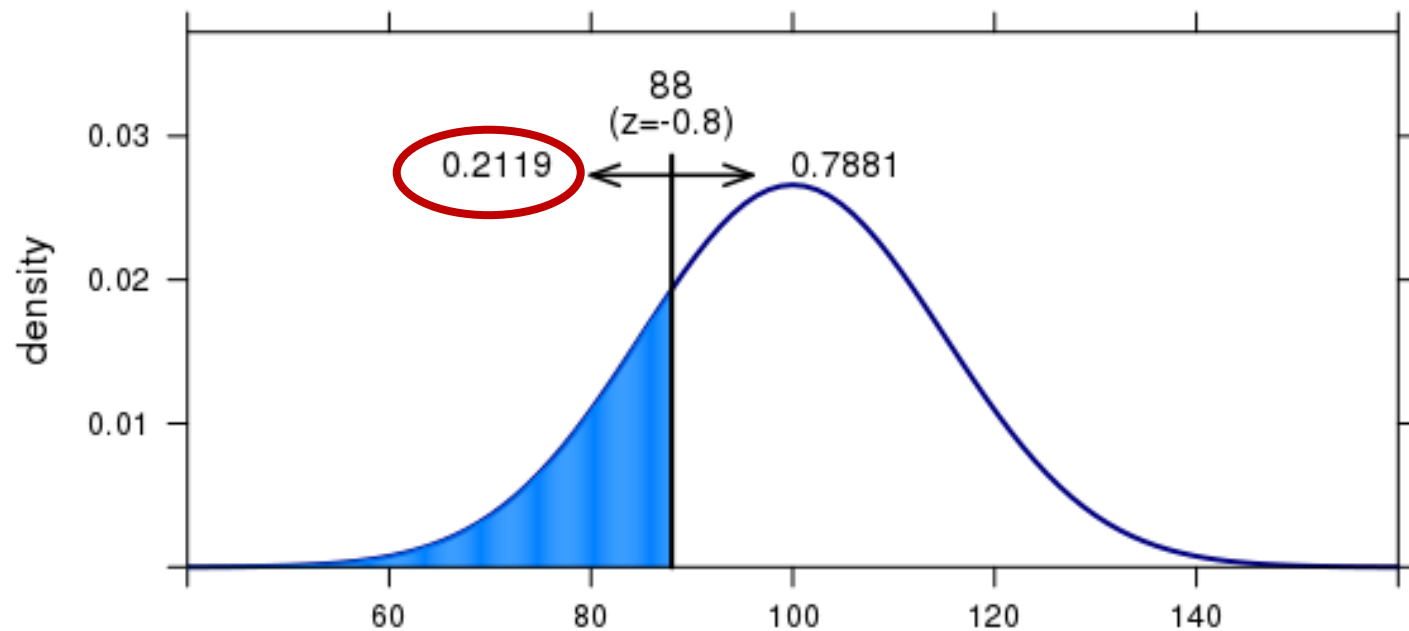
$\mu$   $\sigma$

```
pnorm(9, 11, 3)
```



Calculate the probability a random person you meet has an IQ less than 88

```
pnorm(88, 100, 15)
```



[Normal area  \$\Pr\(X \leq x\)\$  app](#)

[Normal area  \$\Pr\(a < X < b\)\$  app](#)

# Probability practice questions

1. What is probability a randomly chosen person will have an IQ greater than 96?

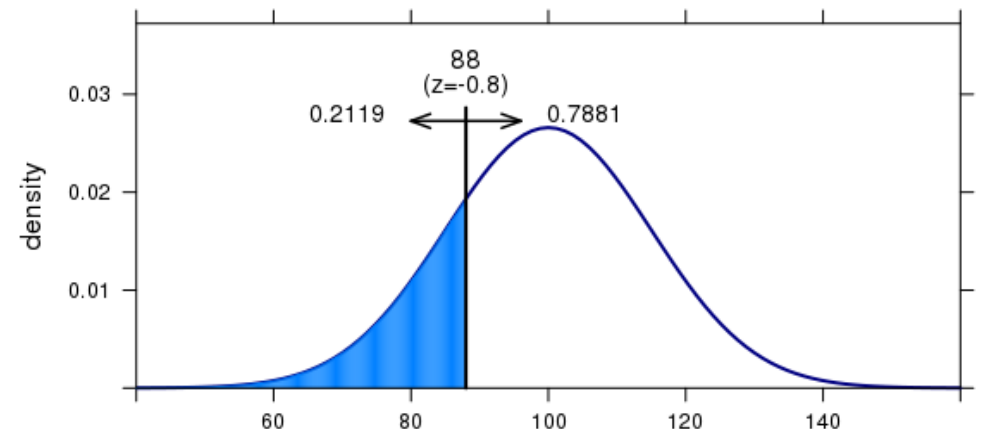
`pnorm(96, 100, 15, lower.tail = FALSE)`

- Answer: 0.605

2. What is the probability a randomly chosen person will have an IQ between 88 and 96?

`pnorm(96, 100, 15) - pnorm(88, 100, 15)`

- Answer: 0.183



# Calculating quantiles

To find quantiles of the normal distribution we can use the quantile function:

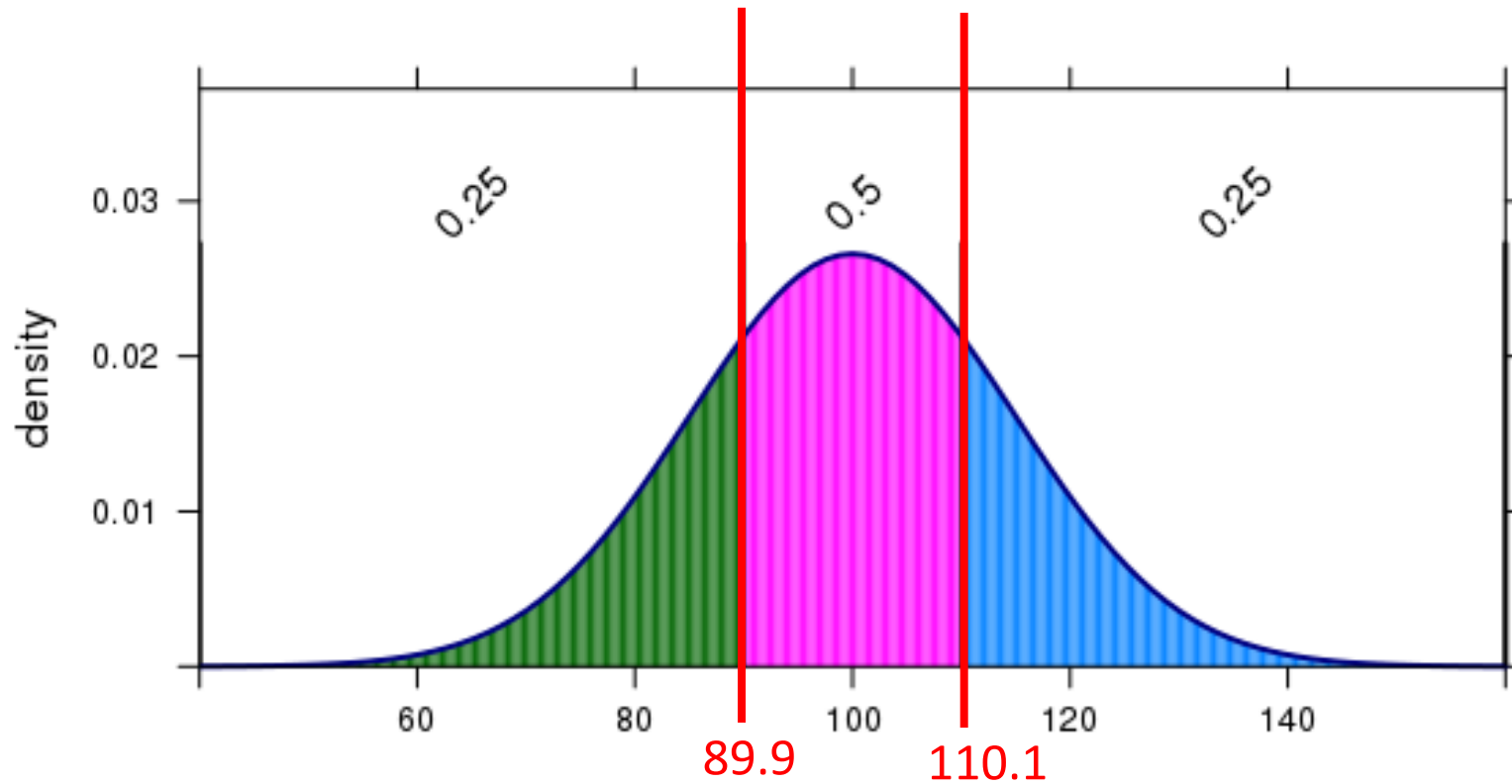
```
qnorm(quantile, mu, sigma)
```

What are the IQ scores (interval) that demark the middle 50% of the IQ range?

What about the middle 95%?

[Normal quantile app](#)

# Middle 50% of IQ scores



```
qnorm(c(.25, .75), 100, 15)
```

Middle 50%: 89.9 to 110.1

Middle 95%: 70.6 to 129.3

# Summary of R functions

Plot the actual density curve

- `dnorm(x_vec, mu, sigma)`

Get the probability that we would get a random value less than x

- `pnorm(x_vec, mu, sigma)`

Get the quantile value for a given proportion of the distribution

- `qnorm(area, mu, sigma)`

Note: `pnorm` and `qnorm` are inverses of each other

- `y = pnorm(x, mu, sigma)`
- `qnorm(y, mu, sigma)` # the output value here is x



# The Standard Normal distribution and the Central Limit Theorem

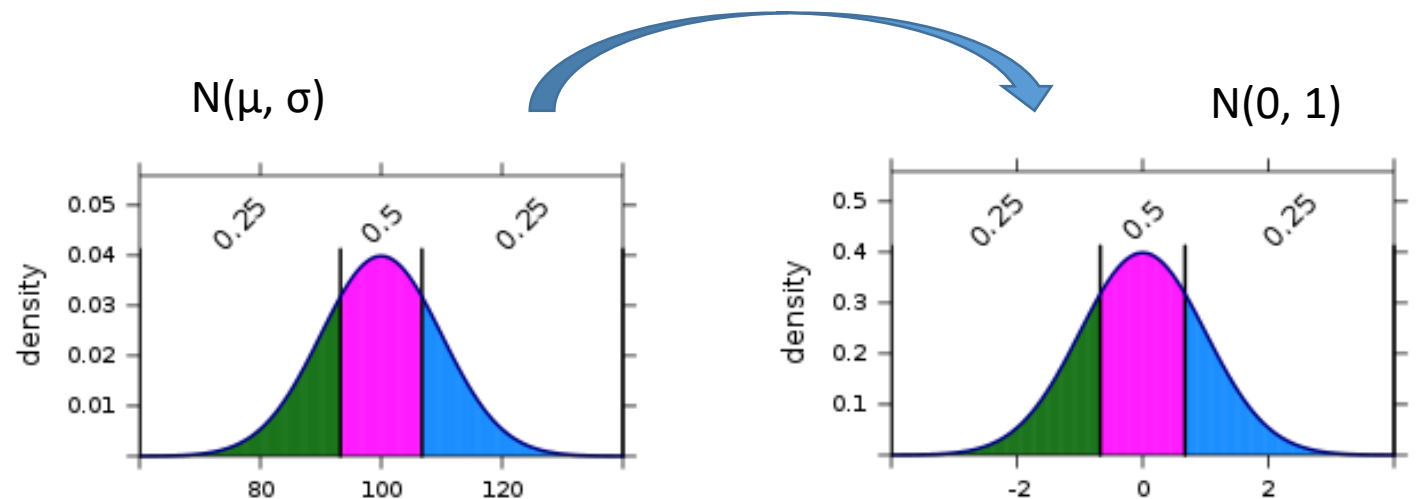
# Standard Normal $N(0, 1)$

Since all normal distributions have the same shape, it is convenient to convert them to a standard scale with:

$$\mu = 0, \quad \sigma = 1$$

This is called the **standard normal** distribution:

$$Z \sim N(0, 1)$$



# Converting to the standard normal distribution

We can use a z-score transformation to any normally distributed random variable  $X \sim N(\mu, \sigma)$  to the standard normal distribution  $Z \sim N(0, 1)$ :

$$Z = (X - \mu) / \sigma$$

To convert from  $Z \sim N(0, 1)$  to any  $X \sim N(\mu, \sigma)$ , we reverse the standardization with:

$$X = \mu + Z \cdot \sigma$$

# Converting to the standard normal distribution

1. What is the Z-score of someone who has an IQ score of 112?

$$Z = (X - \mu) / \sigma$$

2. What if someone has an Z-score of 2.2, what is their IQ score?

$$X = \mu + Z \cdot \sigma$$

**Answer 1:**  $Z = (112 - 100) / 15 = .8$

**Answer 2:**  $\text{IQ} = 100 + 2.2 * 15 = 133$

# Central limit theorem

For random samples with a sufficiently large sample size ( $n$ ), the distribution of sample statistics for a **mean** ( $\bar{x}$ ) or a **proportion** ( $\hat{p}$ ) is:

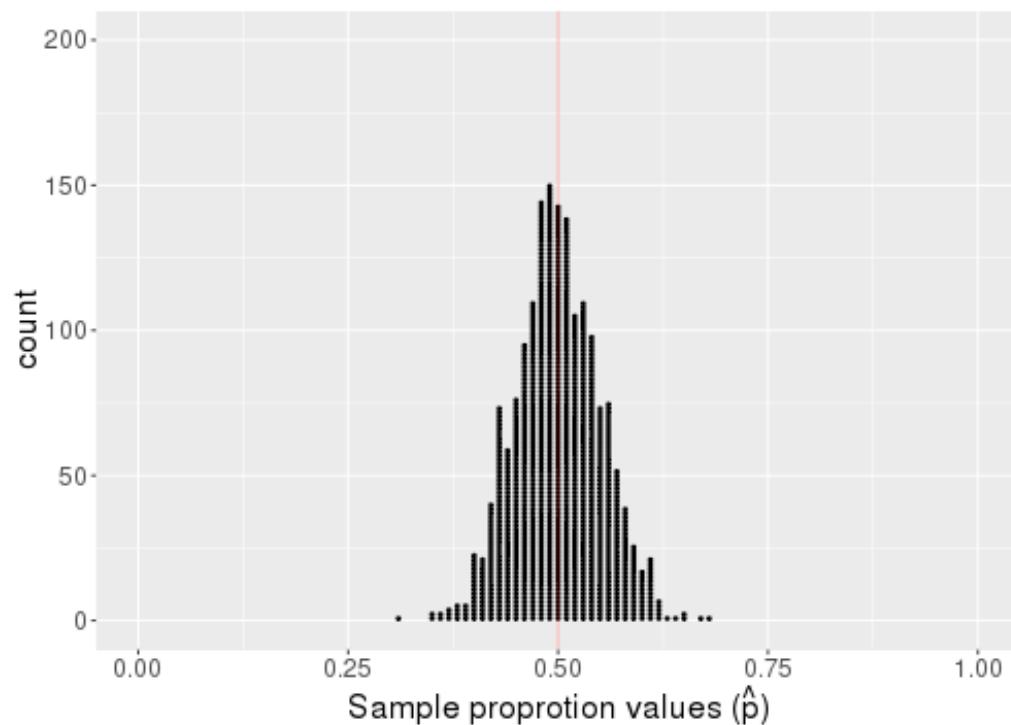
- normally distributed
- centered at the value of the population parameter

Stated again: the sampling distribution for means or proportions will be a normal distribution

- so we don't need to do resampling to get a bootstrap or null distribution!

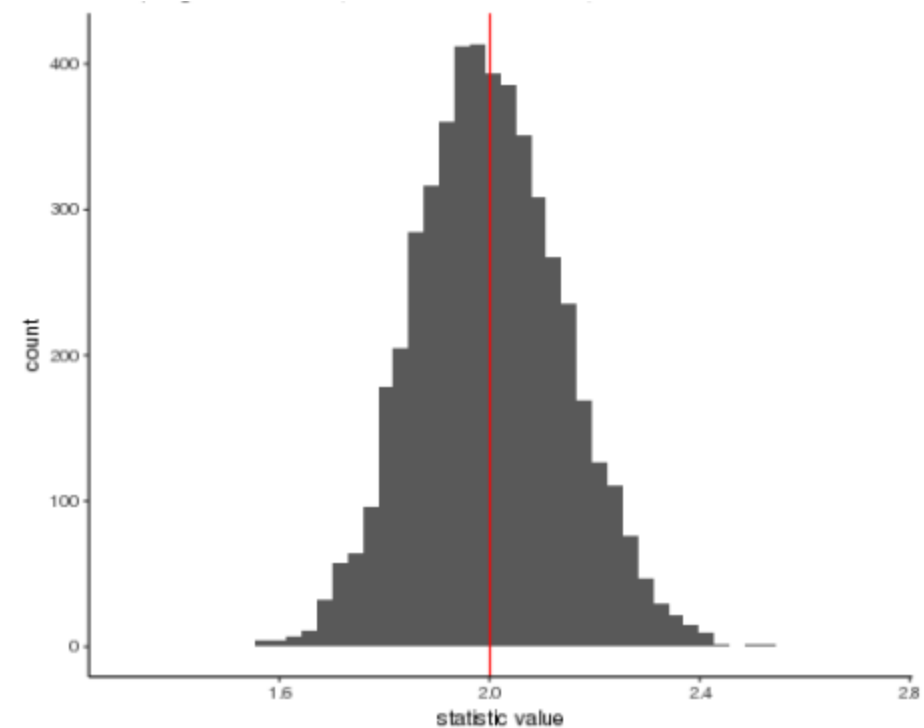
# Central limit theorem

proportion ( $\hat{p}$ )



[Proportion sampling distribution app](#)

mean ( $\bar{x}$ )



[Sampling/Bootstrap distribution app](#)

# Summary of standard normal and CLT

For large  $n$ , the sampling distributions of  $\bar{x}$  and  $\hat{p}$  are normal

We can convert any normal distribution  $N(\mu, \sigma)$ , into a standard normal distribution  $N(0, 1)$

We are now (almost) ready to run hypothesis tests and compute confidence intervals for  $\bar{x}$  and  $\hat{p}$  using normal distributions

# Hypothesis tests using a normal distribution

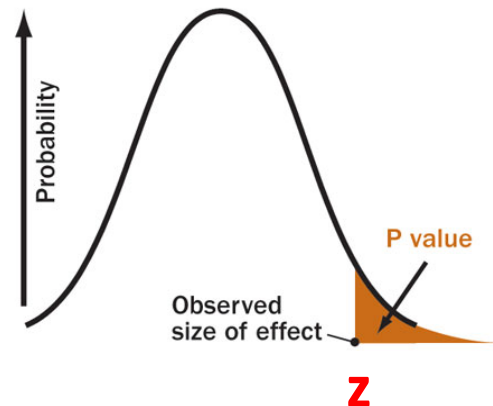


# Hypothesis tests based on a Normal Distribution

When the null distribution is normal, it is often convenient to use a standard normal test statistic using:

$$z = \frac{\text{Sample Statistic} - \text{Null Parameter}}{SE}$$

The p-value for the test is the probability a standard normal value is beyond this standardized test statistic



$$\Pr(Z \geq z_{\text{obs}} ; \mu = 0, \sigma = 1)$$

`pnorm(z, 0, 1, lower.tail = FALSE)`

# Hypothesis tests based on a Normal Distribution

To repeat what was on the last slide: we can transform our `obs_stat` to a z-statistic that comes from a standard normal distribution  $N(0, 1)$  using:

$$z = \frac{stat_{obs} - param_0}{SE}$$

The p-value is then the probability of obtaining a value from a standard normal distribution beyond this z statistic

> `pnorm(z, 0, 1)`

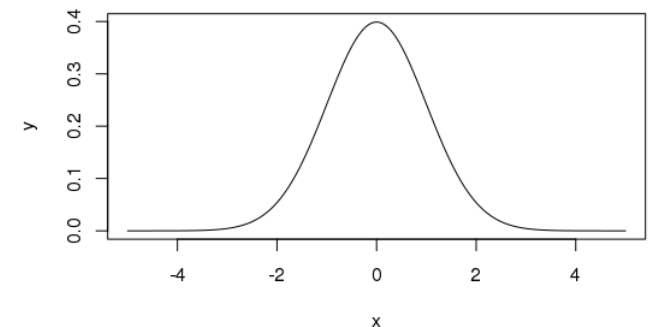
> `1 - pnorm(z, 0, 1)`

> `2 * (1 - pnorm(abs(z), 0, 1))`

if  $H_A: \mu < param_0$

if  $H_A: \mu > param_0$

if  $H_A: \mu \neq param_0$



# Do greater than 40% of Americans go without using cash in a typical week?

A survey of 1,000 Americans reported that 43% said they went an entire week without using cash, with a  $SE = 0.016$

Assuming the distribution of the statistic is normal, calculate whether the proportion of all Americans going a week without using cash is greater than 40%

**1. Start by stating  $H_0$  and  $H_A$**

$$H_0: \pi = .4$$

$$H_A: \pi > .4$$

# Do greater than 40% of Americans go without using cash in a typical week?

A survey of 1,000 Americans reported that 43% said they went an entire week without using cash, with a  $SE = 0.016$

Assuming the distribution of the statistic is normal, calculate whether the proportion of all Americans going a week without using cash is greater than 40%

**2. Can you compute the z statistic?**

$$z = \frac{\text{Sample Statistic} - \text{Null Parameter}}{SE}$$

# Do greater than 40% of Americans go without using cash in a typical week?

A survey of 1,000 Americans reported that 43% said they went an entire week without using cash, with a SE = 0.016

Assuming the distribution of the statistic is normal, calculate whether the proportion of all Americans going a week without using cash is greater than 40%

**2. Can you compute the z statistic?**

$$z = (.43 - .4)/.016 = 1.875$$

# Do greater than 40% of Americans go without using cash in a typical week?

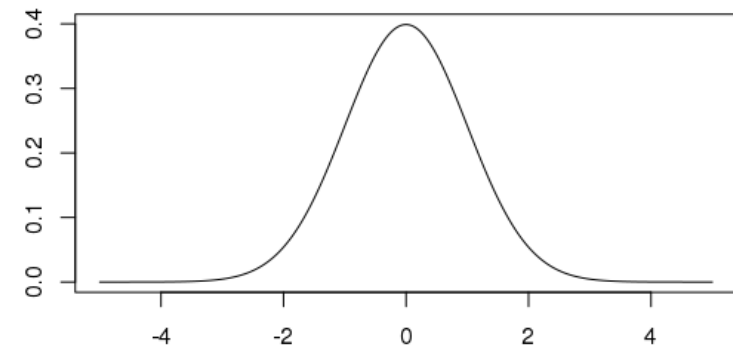
**Steps: 3-4.** What is the probability one would get a z-statistic as larger or larger than 1.875 from a standard normal distribution?

```
> pnorm(1.875, 0, 1, lower.tail = FALSE)
```

```
> 1 - pnorm(1.875, 0, 1)
```

p-value = .0304

Standard normal null distribution



**Step 5?**

[Normal area app](#)  $\Pr(X \leq x)$



# Confidence intervals using a normal distribution

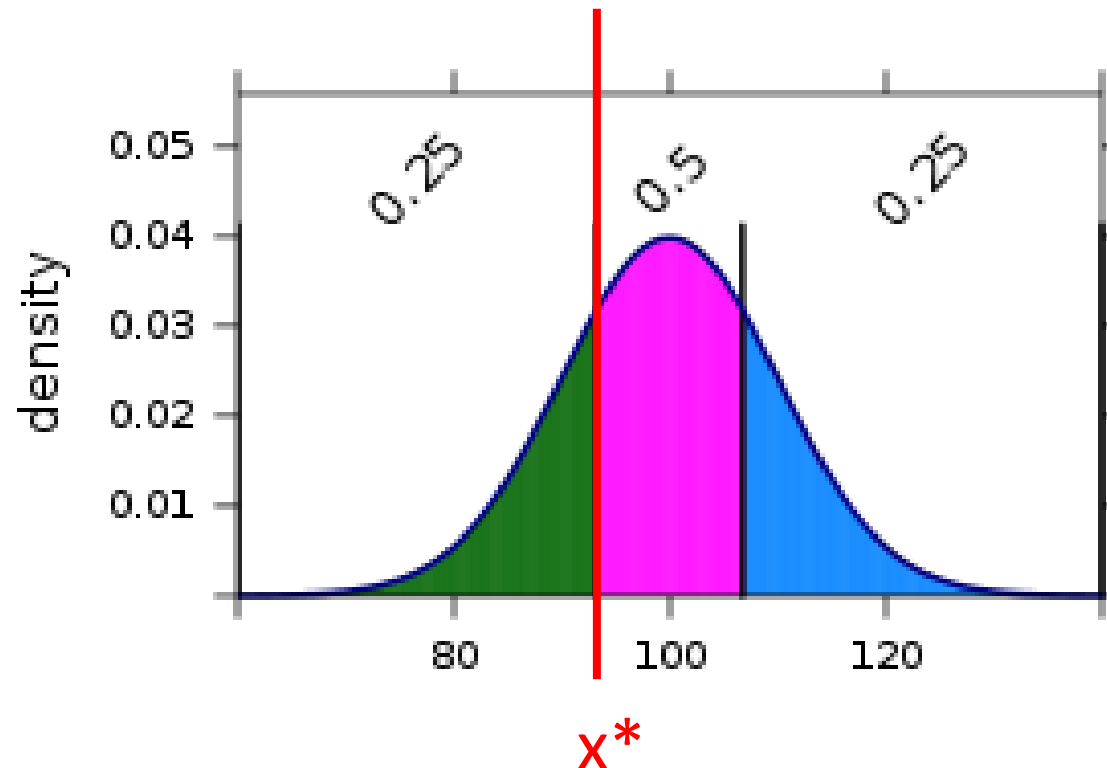
# Finding quantile values

We can find the quantile value from a normal distribution with:

`qnorm(q, mu, sigma)`

The 'q' in qnorm  
stands for quantile

What is the max and  
min that q can be?

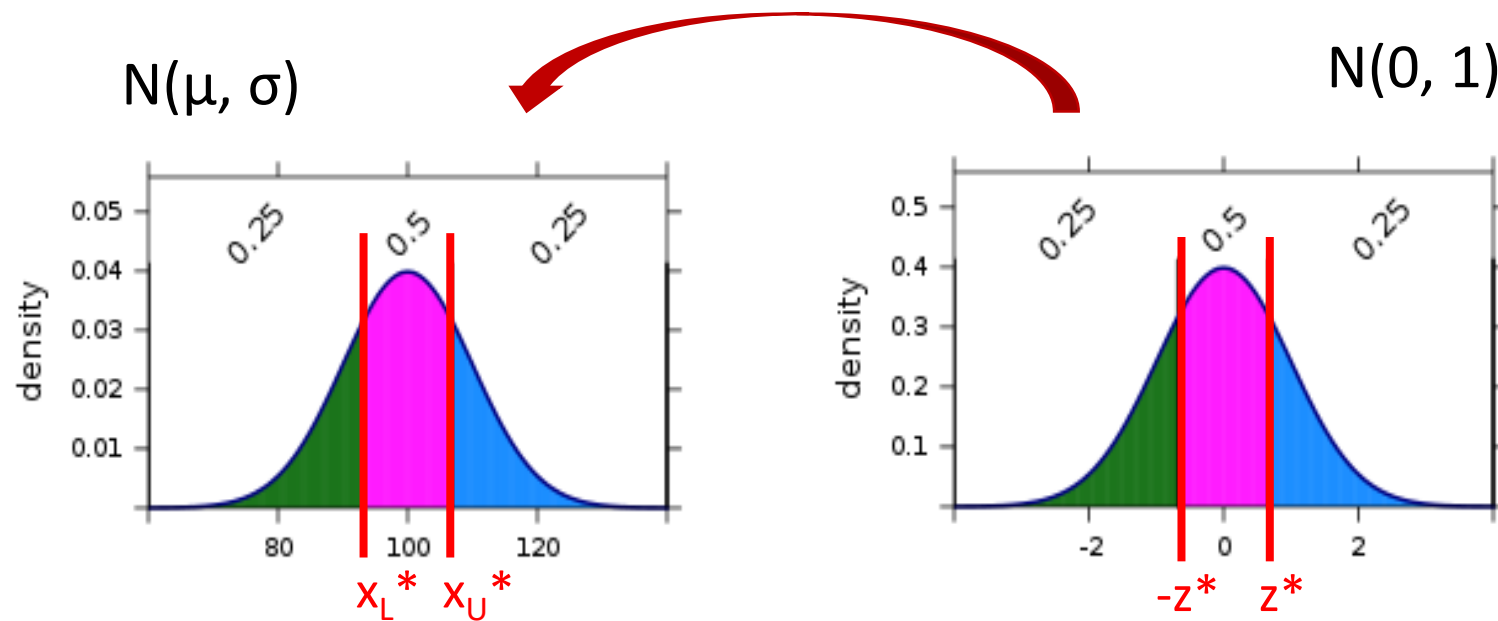




# Standard Normal $N(0, 1)$

It is often convenient to find quantiles on the standard normal distribution  $Z \sim N(0, 1)$  and then to transform them to an arbitrary normal distribution  $X \sim N(\mu, \sigma)$ , using :

$$X = \mu + Z \cdot \sigma$$



# Central limit theorem

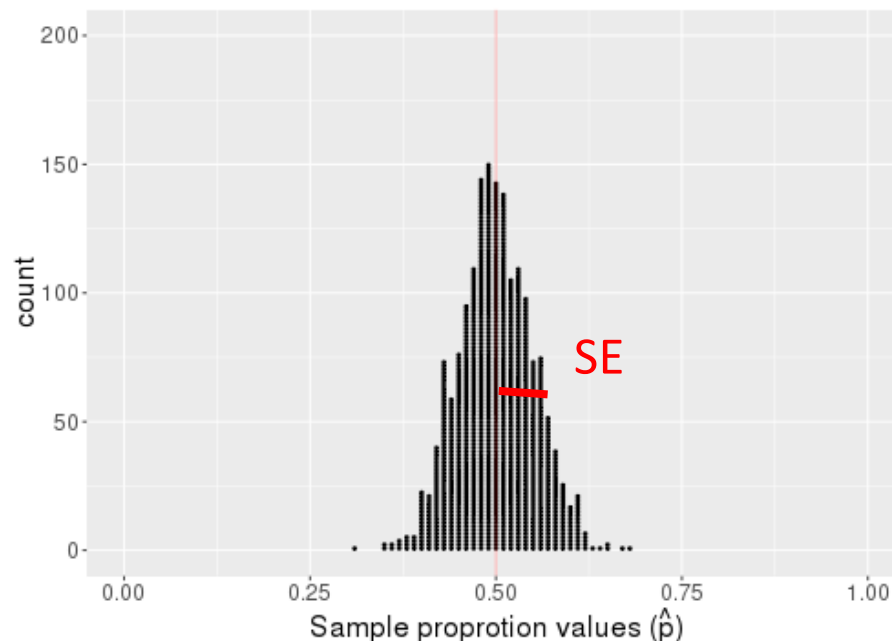
## Questions:

1. What is the standard deviation of these sampling distributions called?
2. Suppose we have a  $\hat{p}$  or  $\bar{x}$  and know the SE, how can we create a 95% CI?

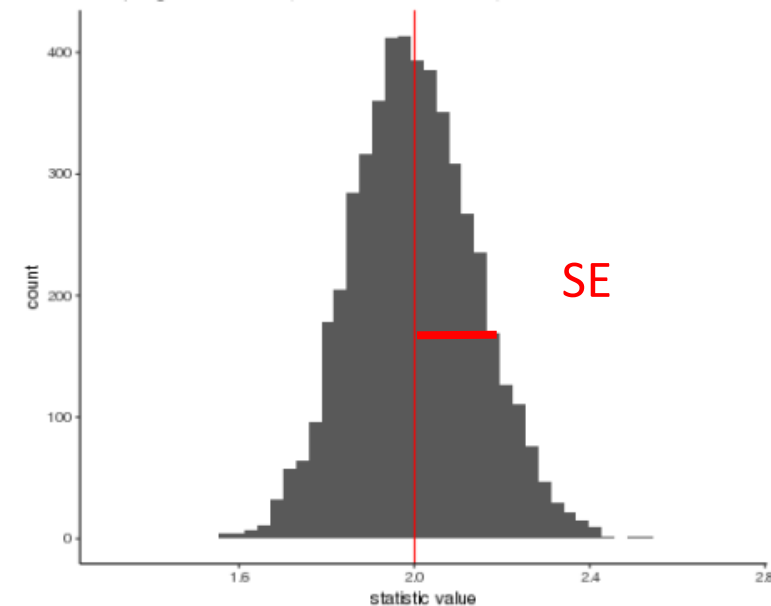
For a proportion  $\pi$ :  $CI_{95} = \hat{p} \pm 2 \cdot SE$

For a mean  $\mu$ :  $CI_{95} = \bar{x} \pm 2 \cdot SE$

proportion ( $\hat{p}$ )



mean ( $\bar{x}$ )



# Confidence intervals based on a Normal Distribution

If the distribution for a statistic is normal with a standard error SE, we can find a confidence interval for the parameter using:

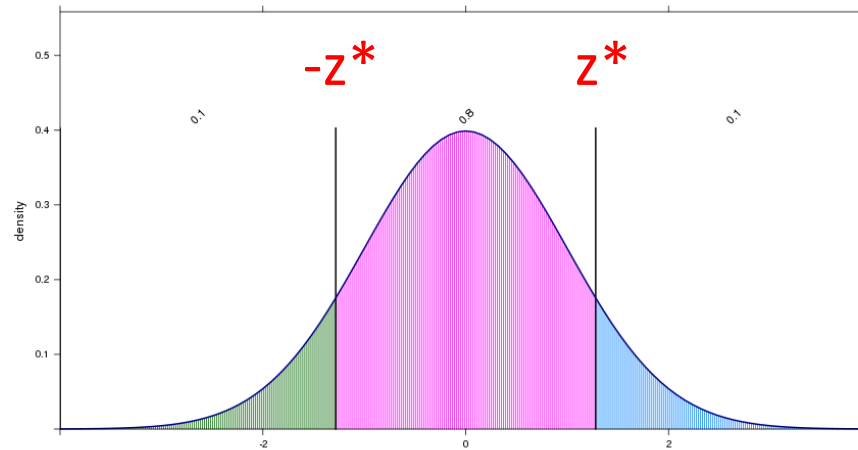
$$\text{sample statistic} \pm z^* \times \text{SE}$$

where  $z^*$  is chosen so that the area between  $-z^*$  and  $+z^*$  in the standard normal distribution is the desired confidence level

- i.e.,  $z^*$  is chosen such that say 95% of the distribution is between  $\pm z^*$

# Confidence intervals based on a Normal Distribution

Suppose we are interested in 80% confidence intervals for  $\mu$   
We calculate the  $\pm z_{80}$  that has 80% of the data on  $N(0, 1)$



Let's assume we know the SE but don't know  $\mu$ . If we have an observed statistic from:

$$x_{\text{obs}} \sim N(\mu, \text{SE})$$

We can create an interval that will capture  $\mu$  80% of the time using:

$$x_{\text{obs}} \pm z_{80} \cdot \text{SE}$$

# Normal percentiles for common confidence levels

Confidence level	80%	90%	95%	98%	99%
Z*	1.282	1.645	1.960	2.326	2.576

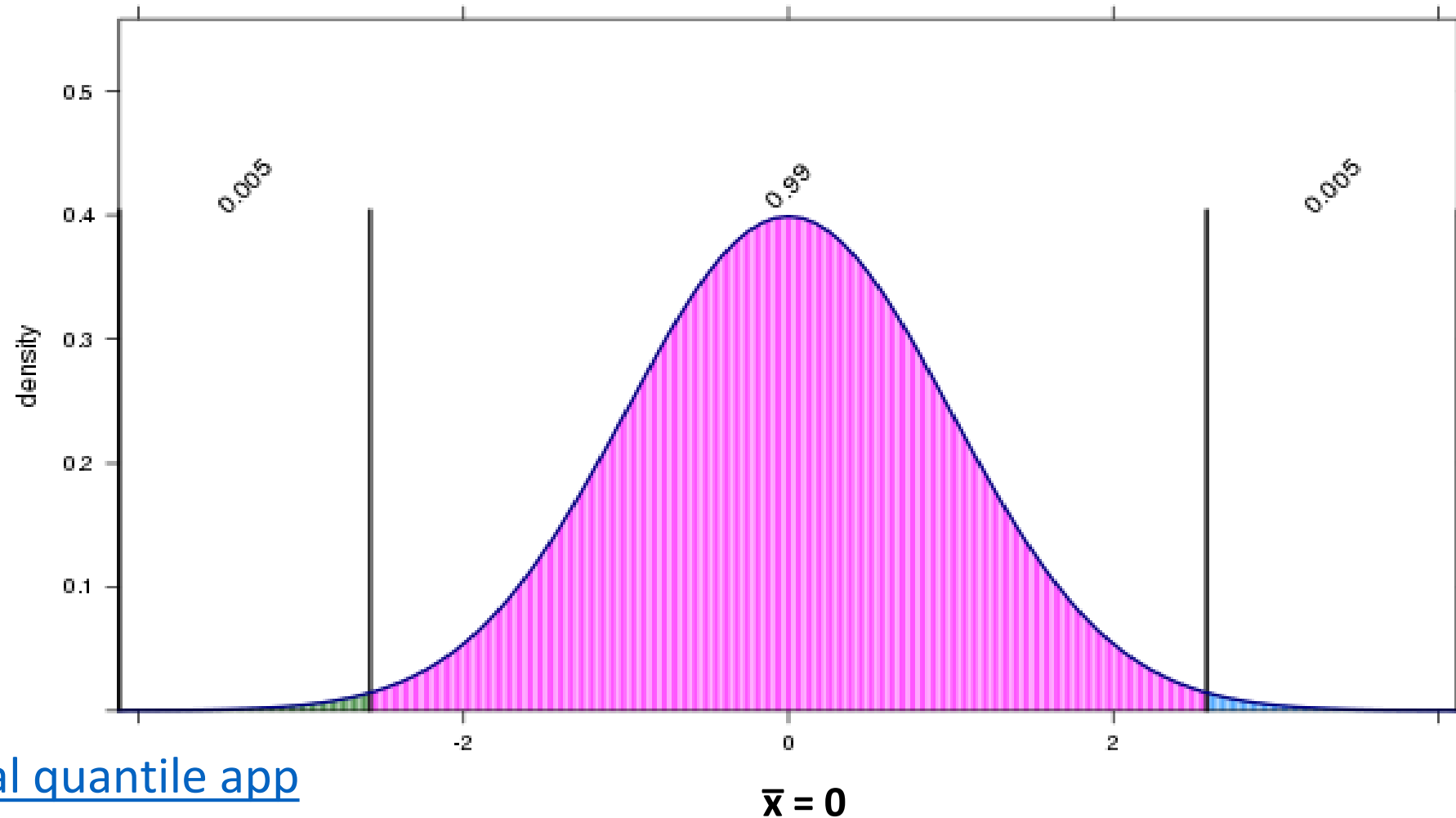
```
z_stars <- qnorm(c(.90, .95, .975, .99, .995), 0, 1)
```

[Normal quantile app](#)

# .99 quantile values

$\bar{x} = 0$ ,  $SE = 1$

Quantile values: [-2.576 2.576]



[Normal quantile app](#)

# What is the most preferred seat?

A survey of 1,000 air travelers found that 60% prefer a window seat, with a bootstrap standard error of  $SE = 0.015$

Use the normal distribution to compute a 90%, 95% and 99% CIs for the proportion of people who prefer a window seat

sample statistic  $\pm z^* \times SE$

Confidence level	80%	90%	95%	98%	99%
$z^*$	1.282	1.645	1.960	2.326	2.576

# What is the most preferred seat?

A survey of 1,000 air travelers found that 60% prefer a window seat, with a bootstrap standard error of  $SE = 0.015$ .

$$90\% \text{ CI} = .6 \pm 1.645 \times .015 = [.575 \ .625]$$

$$95\% \text{ CI} = .6 \pm 1.96 \times .015 = [.571 \ .629]$$

$$99\% \text{ CI} = .6 \pm 2.576 \times .015 = [.569 \ .638]$$

Sample statistics  $\pm z^* \times SE$

Confidence level	80%	90%	95%	98%	99%
$z^*$	1.282	1.645	1.960	2.326	2.576