

Using the normal distribution for
inference

Overview

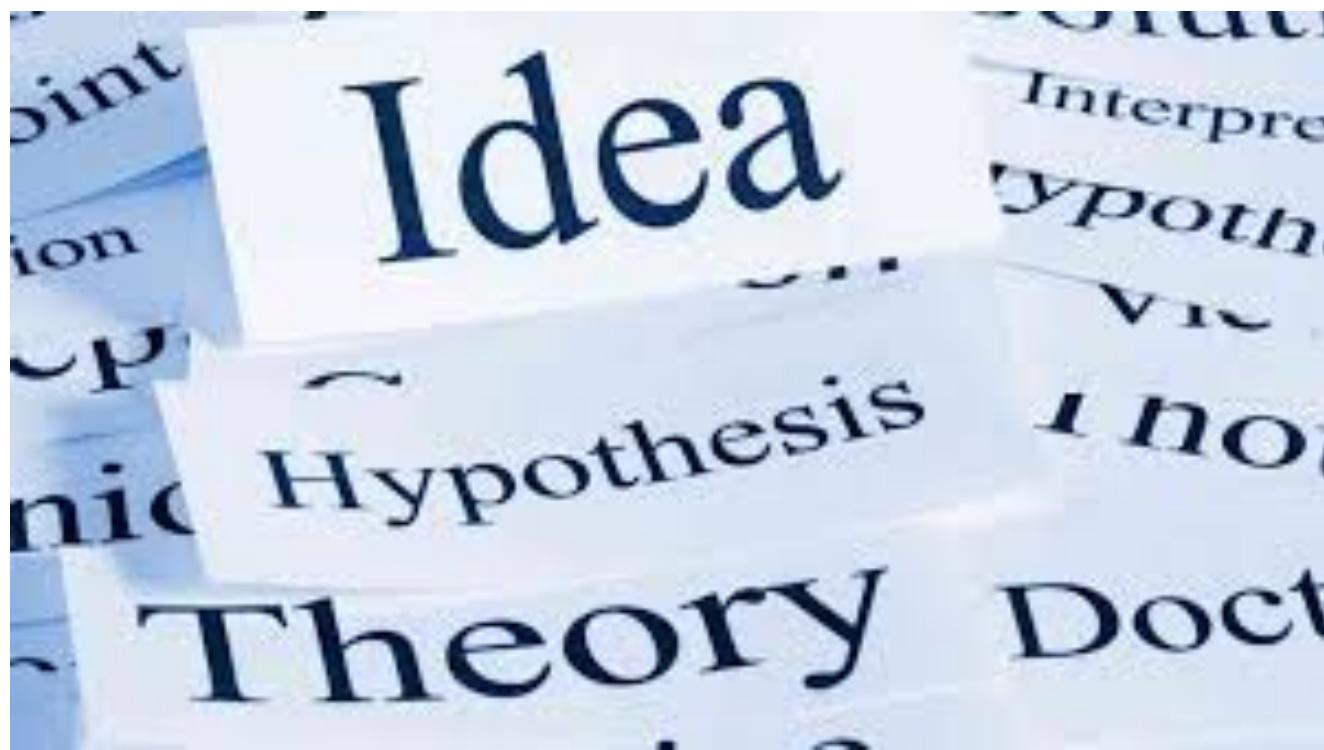
Quick review of theories/concepts in hypothesis testing

Review and continuation of the normal distribution

Using the normal distribution for inference

- Hypothesis tests
- Confidence intervals

Quick review of theories of hypothesis tests



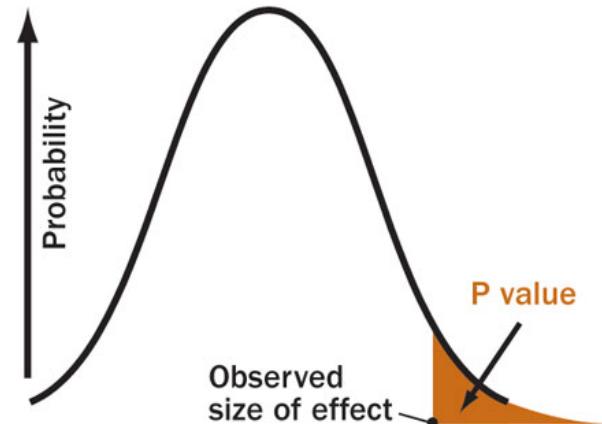
Two theories of hypothesis testing

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 α value)

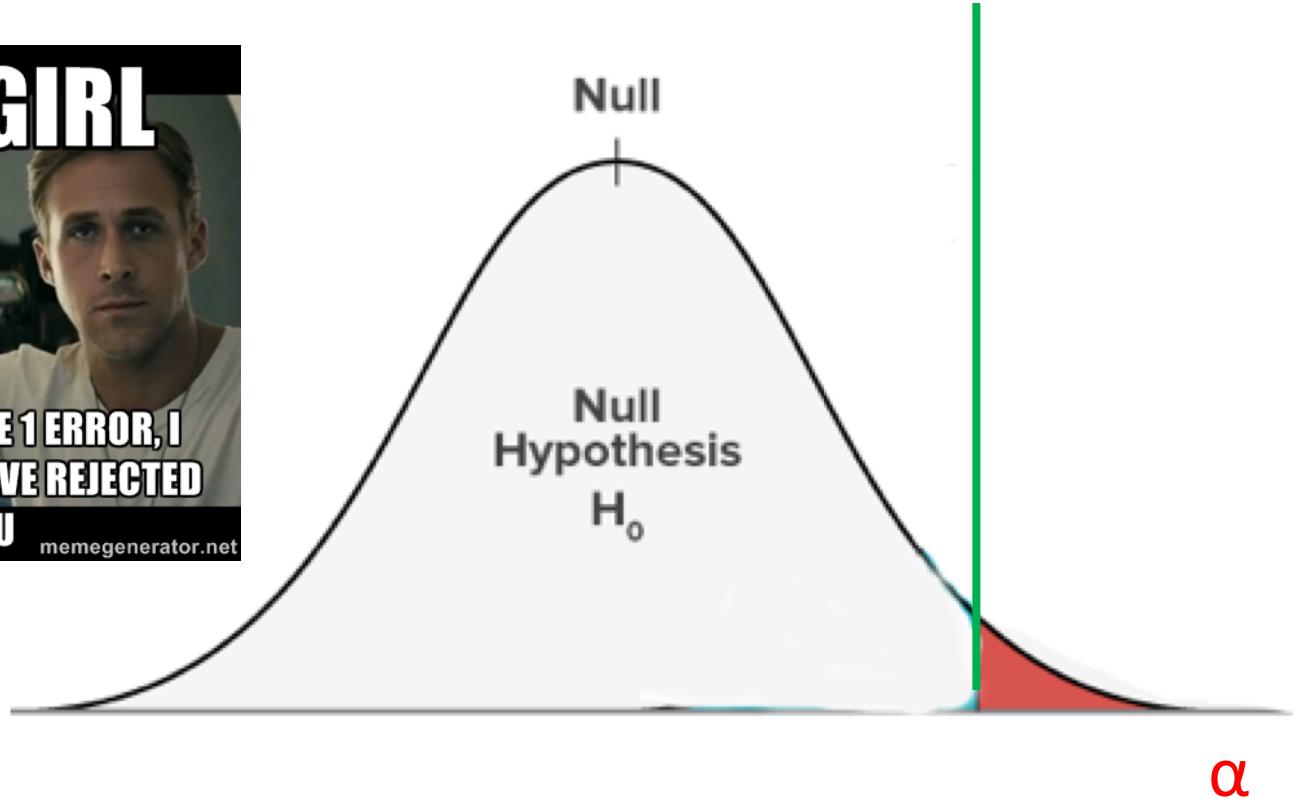
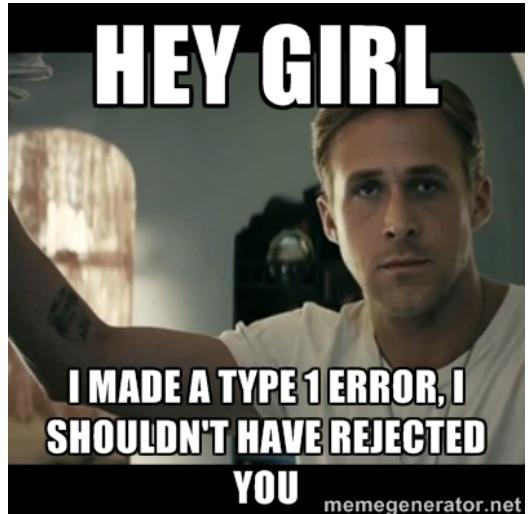


Significance testing



Hypothesis testing

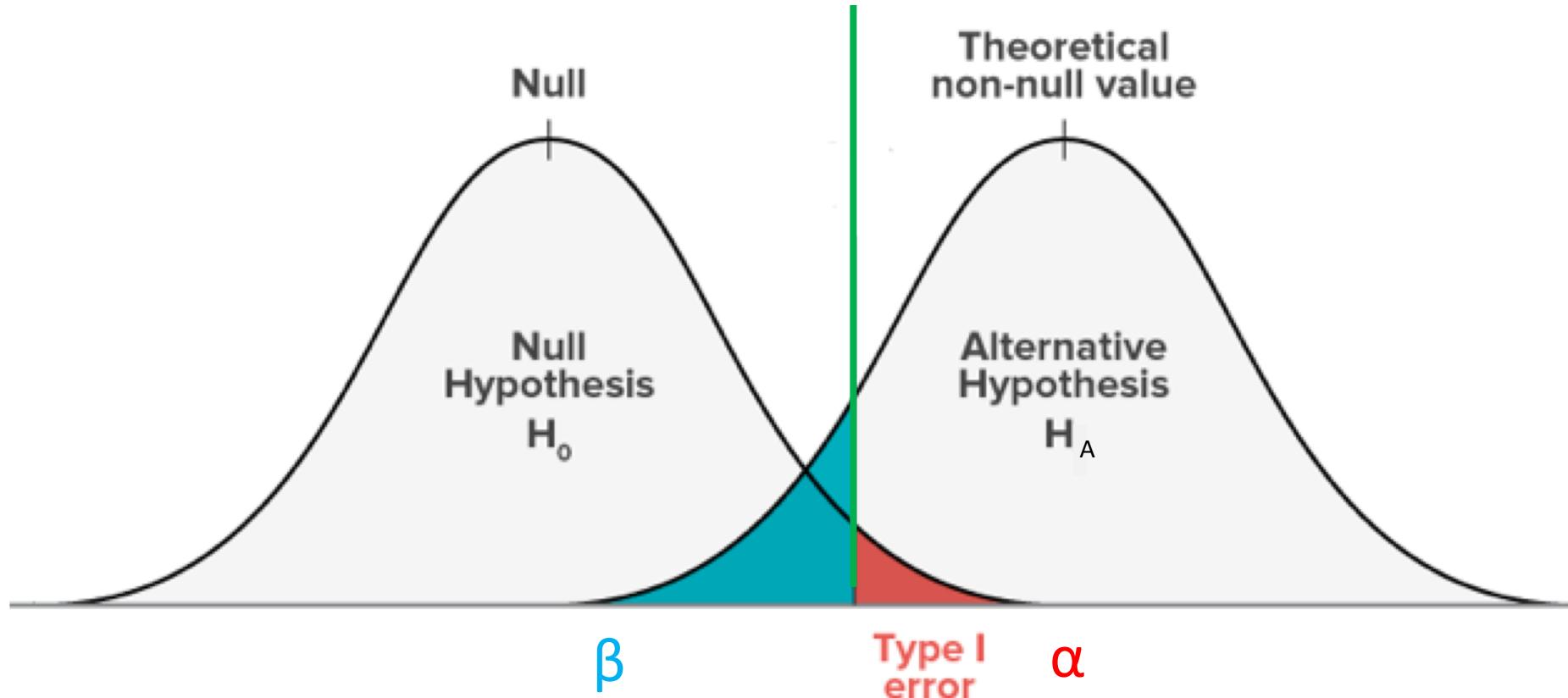
Neyman-Pearson Frequentist logic



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

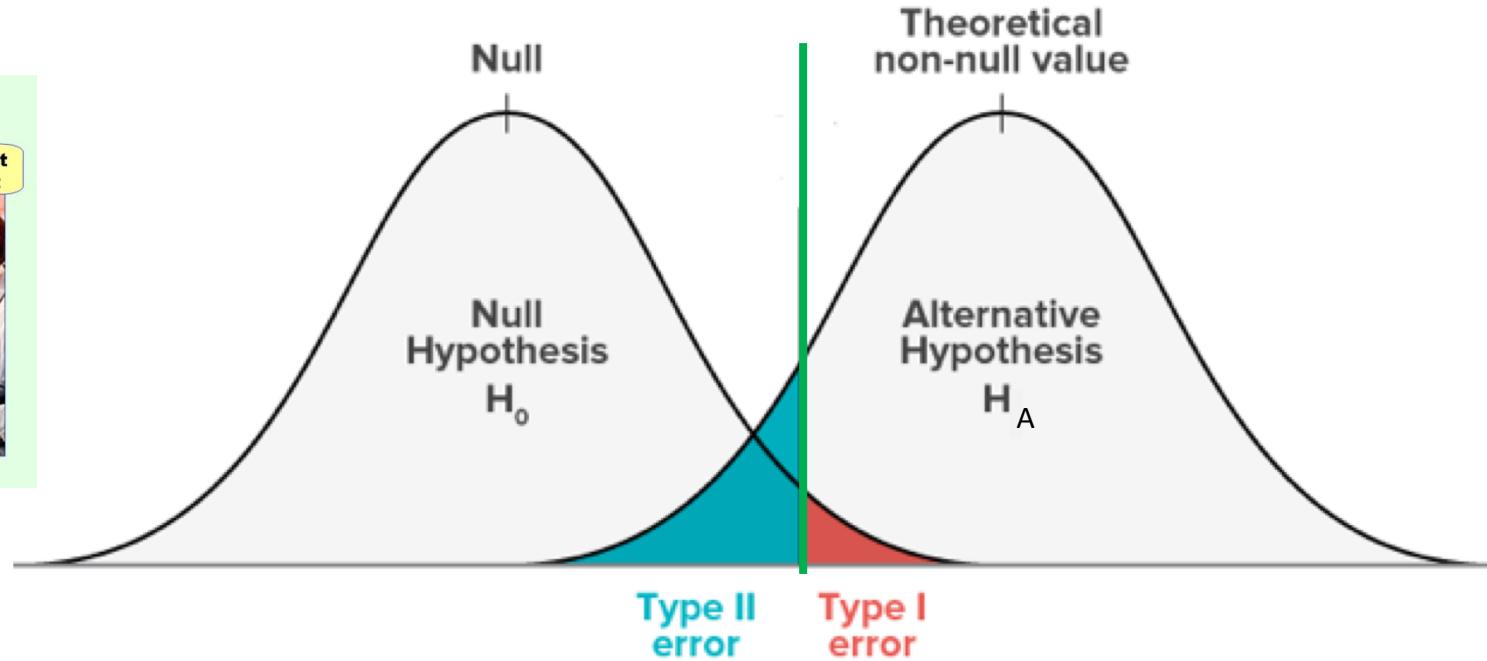
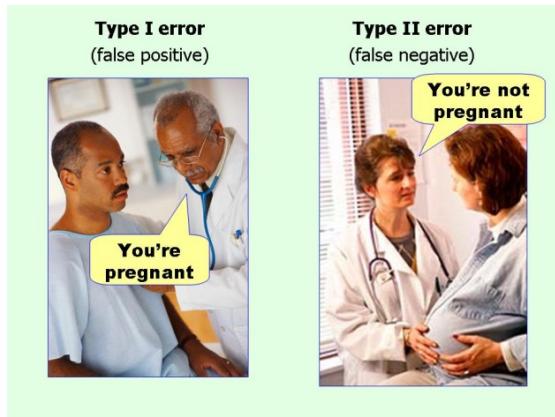
Type I error: incorrectly rejecting the null hypothesis when it is true

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 (α) (false positive)	No error

Problems with the NP hypothesis tests

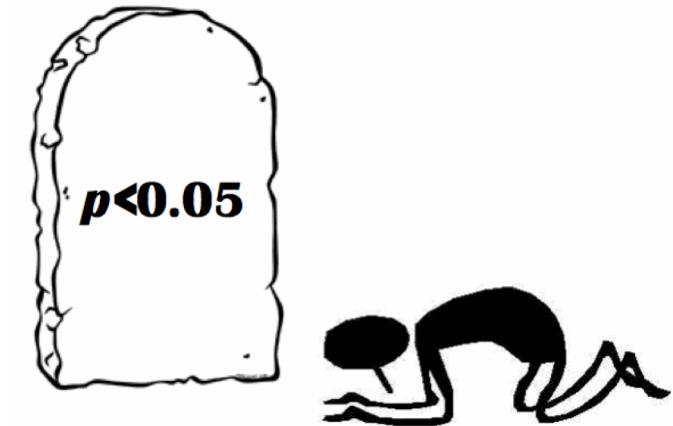
Problem 1: we are interested in the results of a specific experiment, not whether we are right most of the time

- 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

...and this is where we put the non-significant results.



someecards
user card

[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.

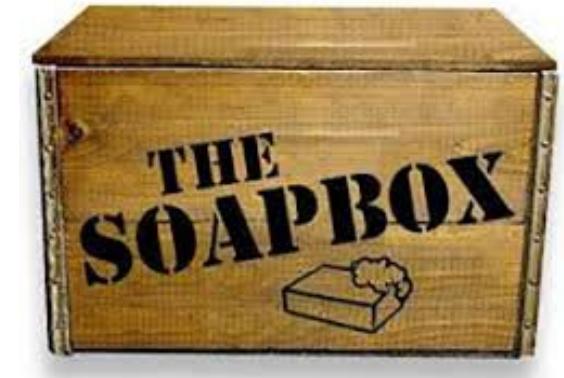
Report effect size in most cases – i.e., confidence intervals

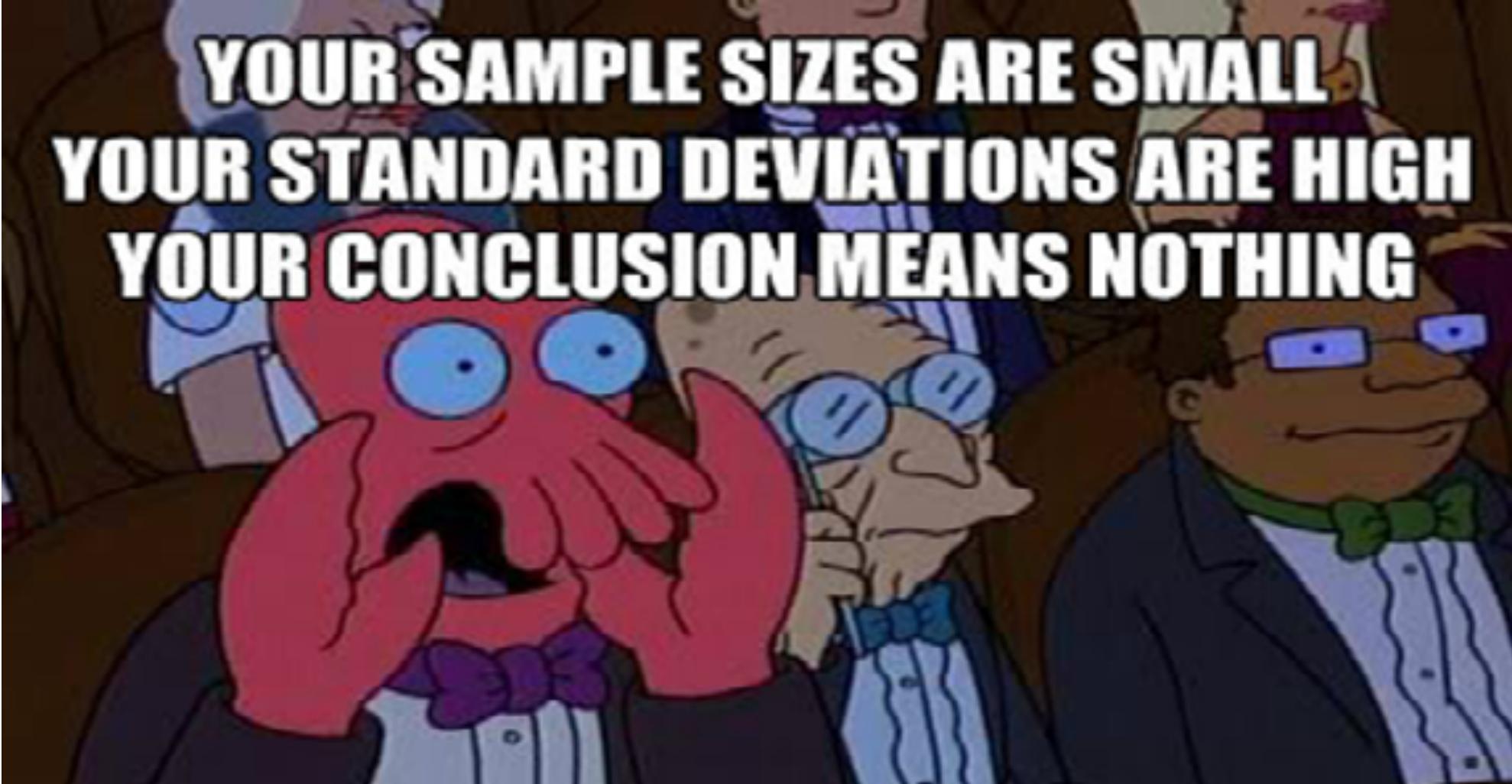
Report the p-values rather than accept/reject H_0

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

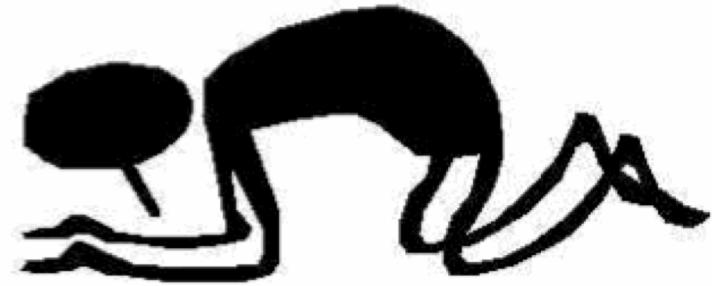
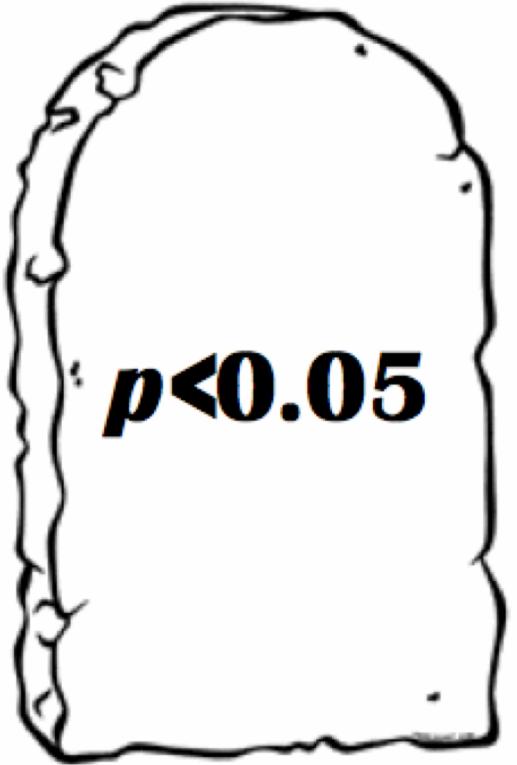
Replicate findings (perhaps in different contexts) to make sure you get the same results

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

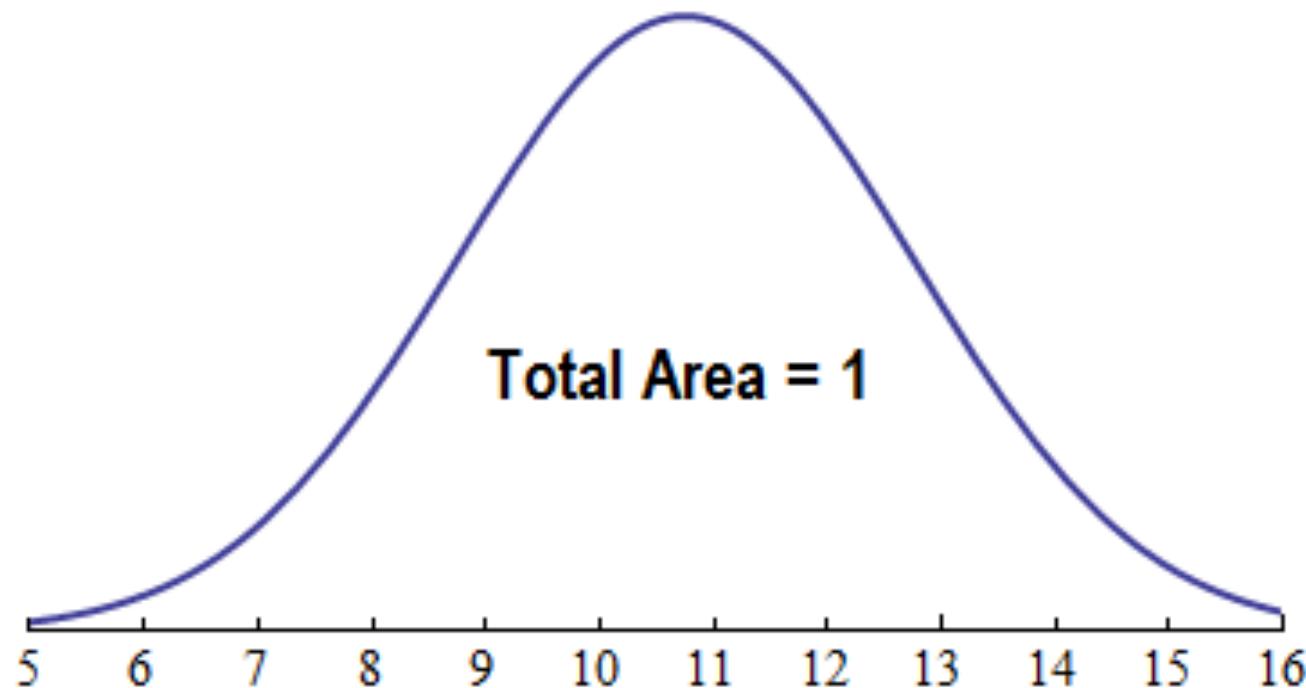


A cartoon image featuring three characters from the TV show Futurama. In the foreground, a large red, multi-eyed alien with a wide, toothy grin holds a black microphone. Behind him is an elderly man with a wrinkled face, wearing blue-rimmed glasses and a blue bow tie. To the right is a brown-skinned man with a mustache, wearing a dark suit jacket over a striped shirt and a green bow tie. They appear to be at a formal event or press conference.

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



Inference using parametric probability distributions



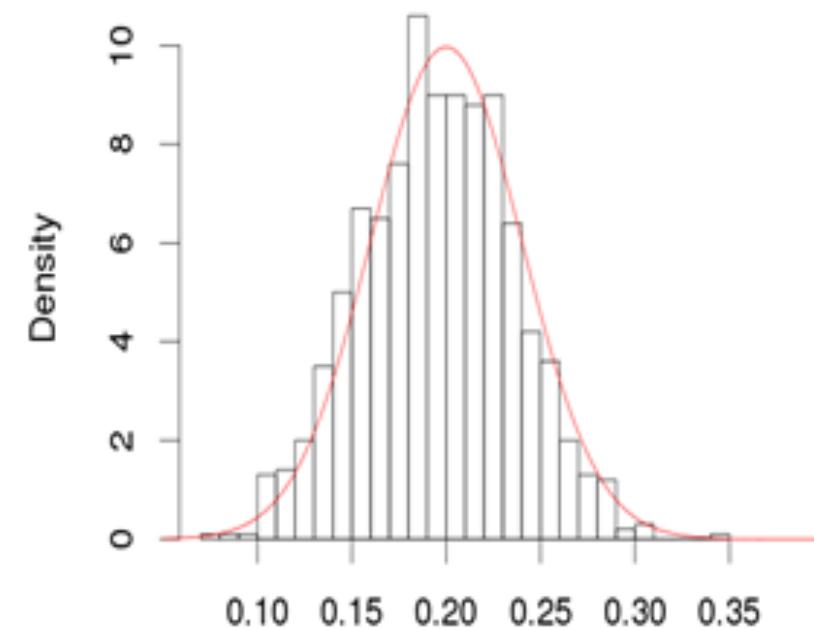
Inference using parametric probability distributions

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 mathematical probability distributions

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

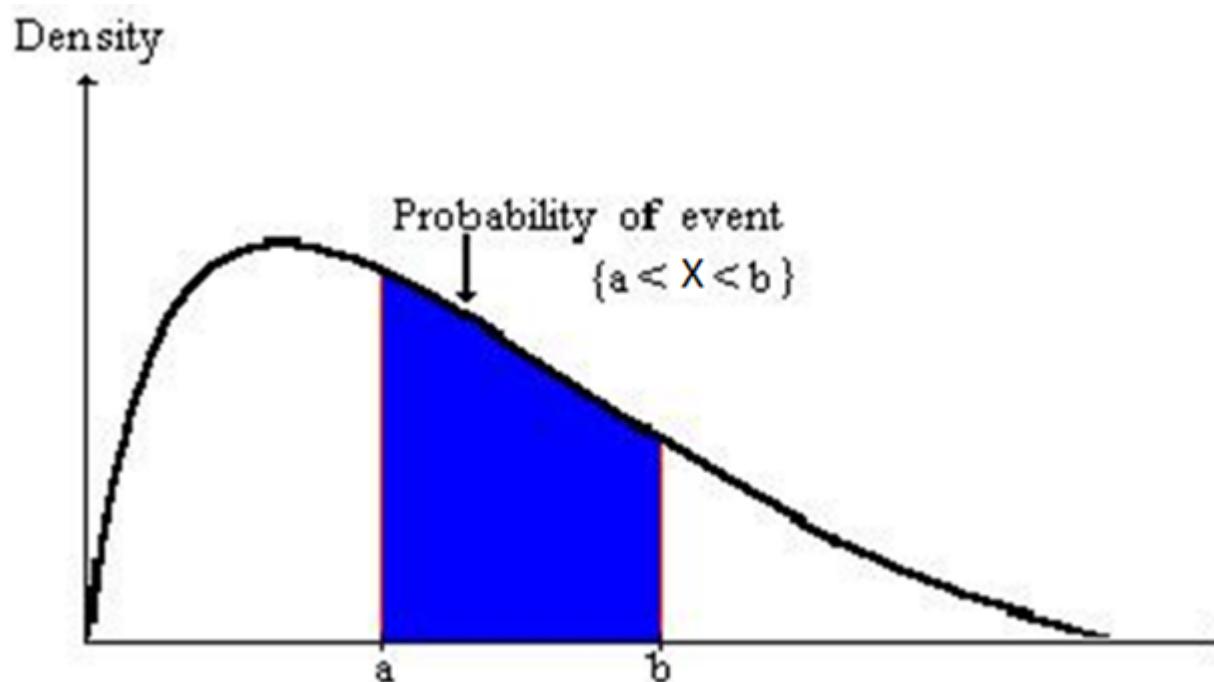
1. The total area under the curve $f(x)$ is equal to 1
2. The curve is always ≥ 0



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

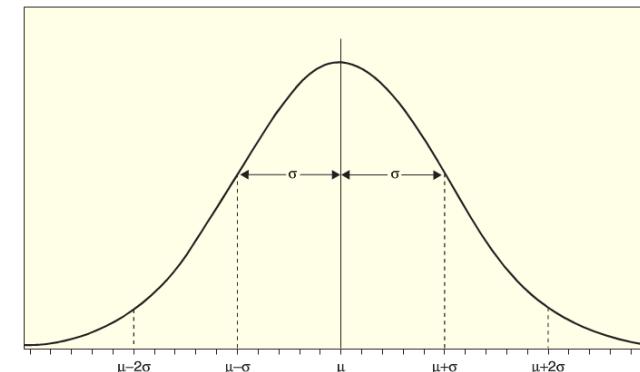


The Normal Density Curve

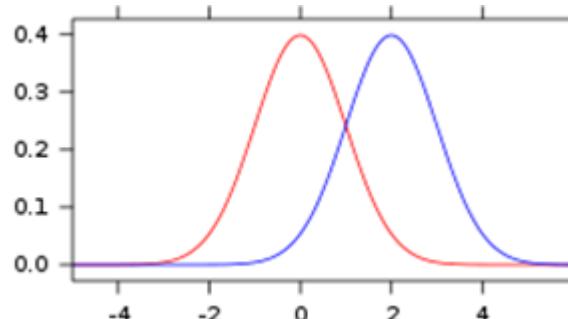
Normal distributions are a family of bell-shaped curves with two parameters

- The mean: μ
- The standard deviation: σ

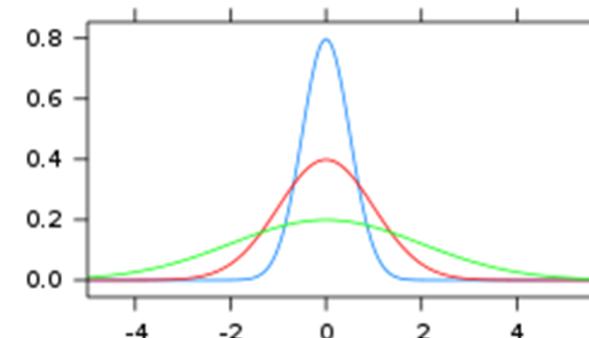
Notation: $X \sim N(\mu, \sigma)$



Changing μ



Changing σ

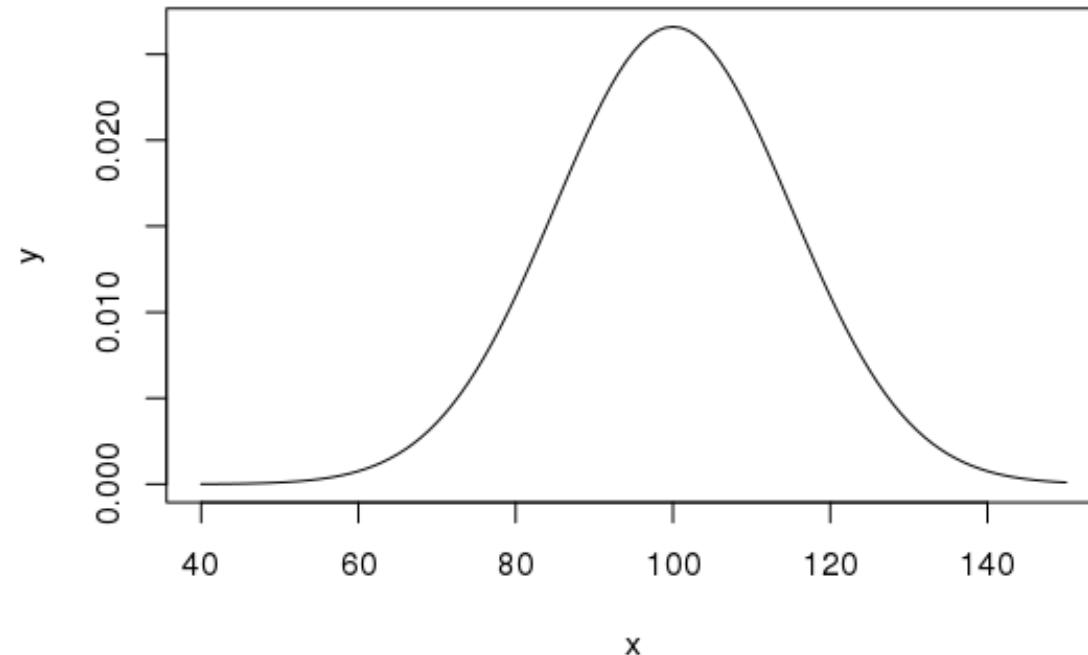
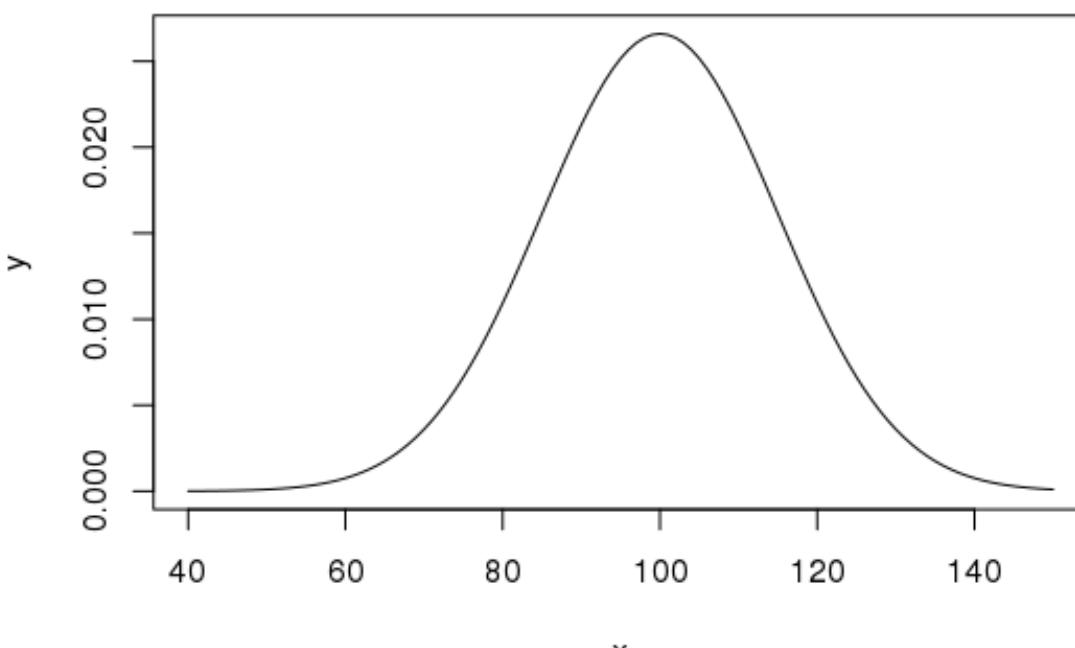


Graphing Normal Curves

Plotting IQ scores

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

μ σ



Finding normal probabilities of a normal curve

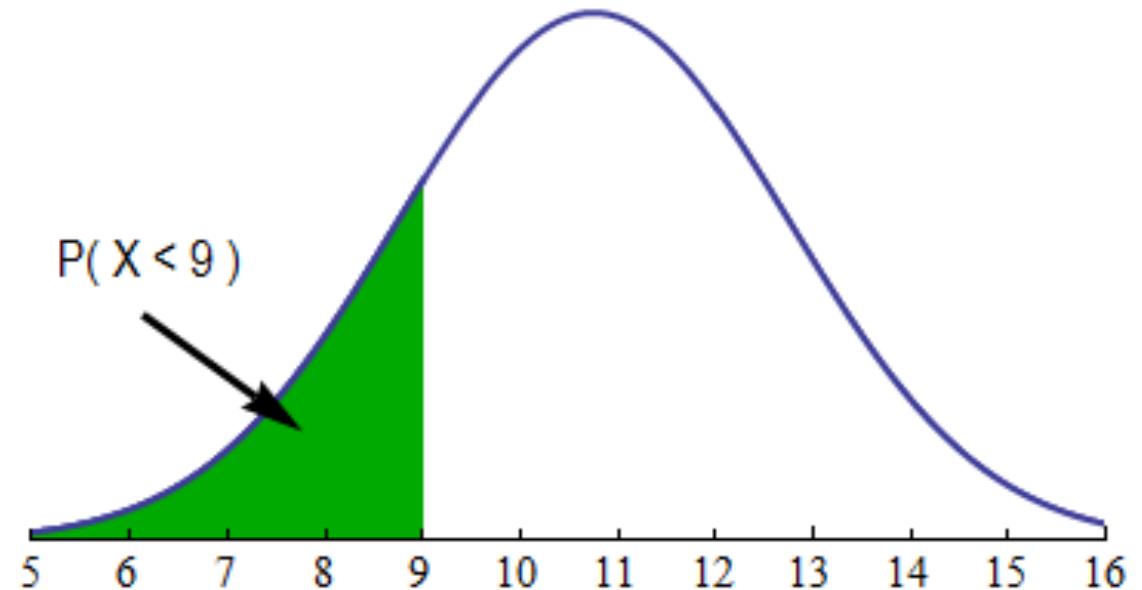
To get the probability (area) from a normal distribution we can use the **pnorm** function

`pnorm(x, mu, sigma)`

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

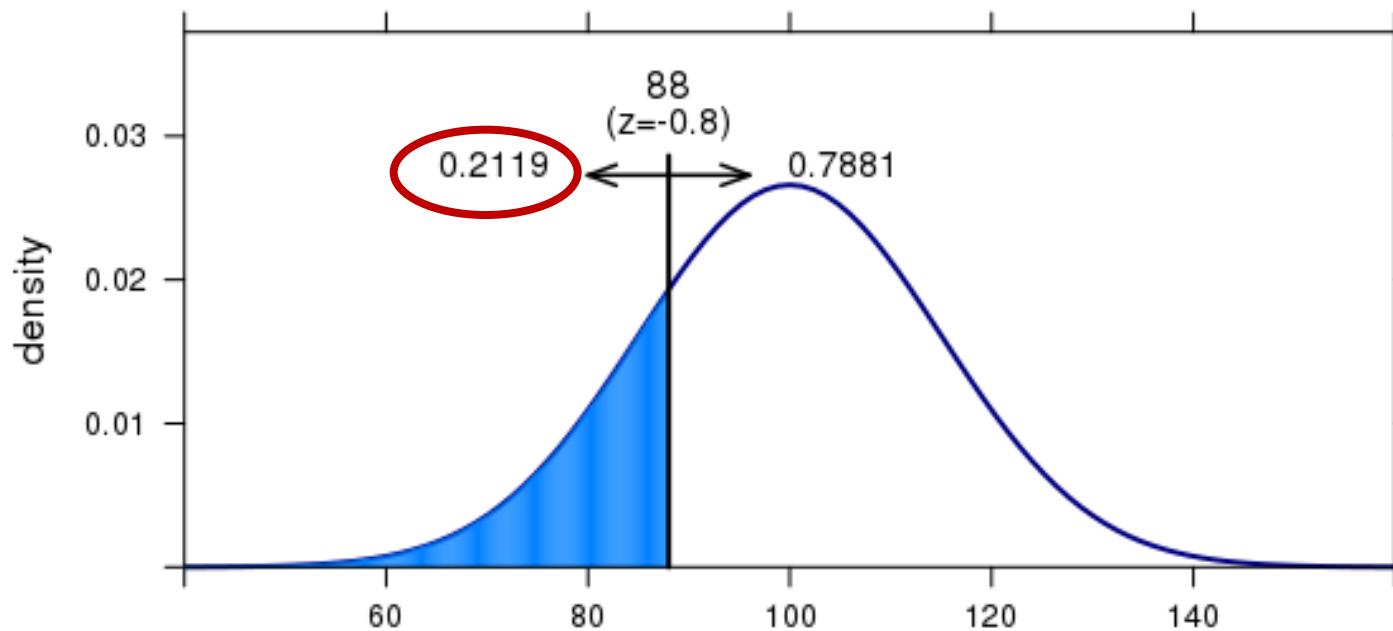
μ σ

`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?

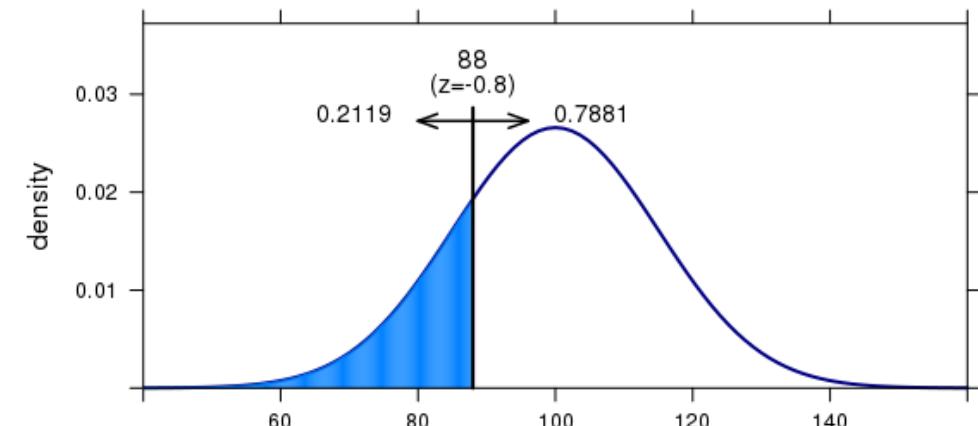
`pnorm(96, 100, 15, lower.tail = FALSE)`

- 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:

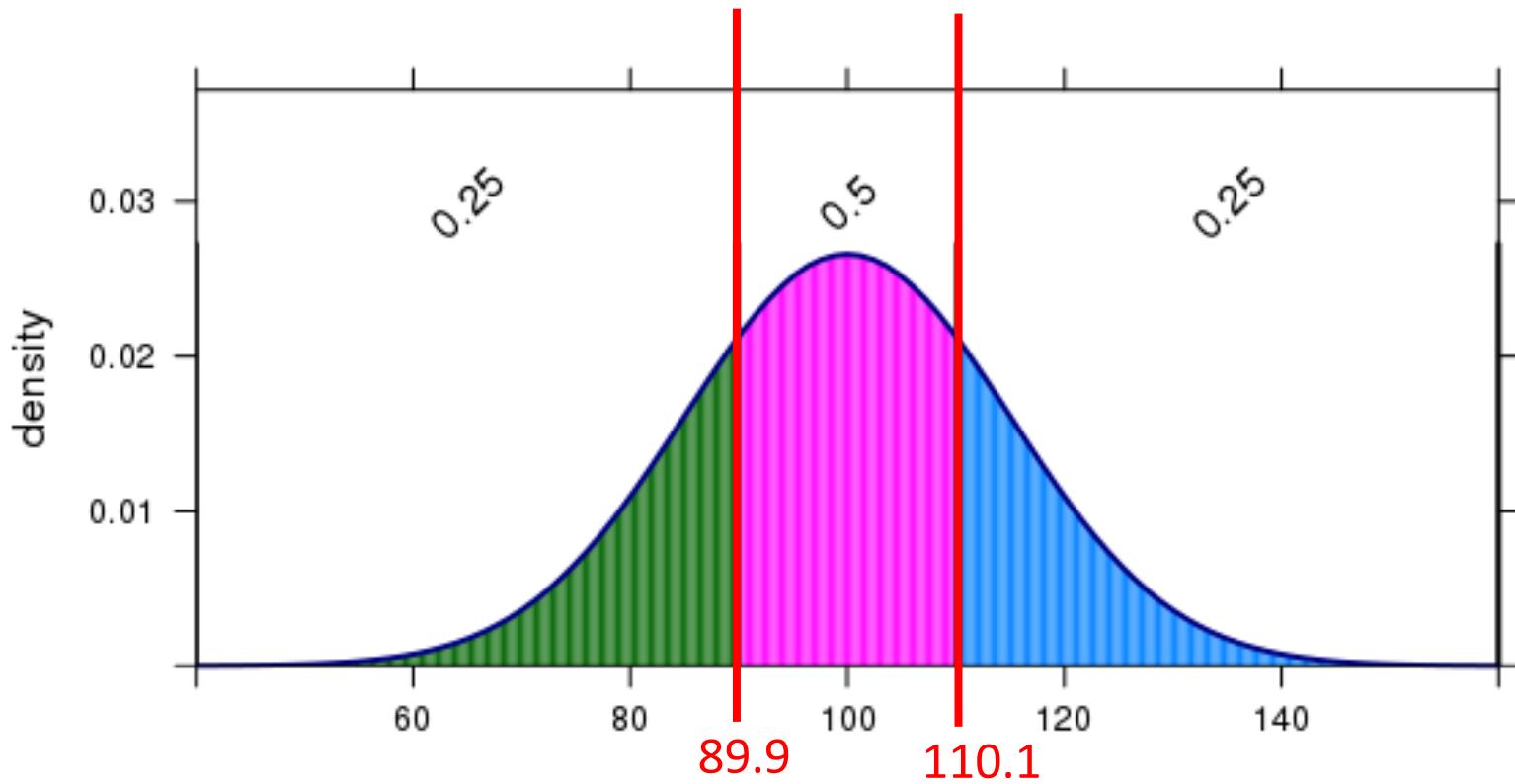
```
qnorm(quantile, mu, sigma)
```

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 actually 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

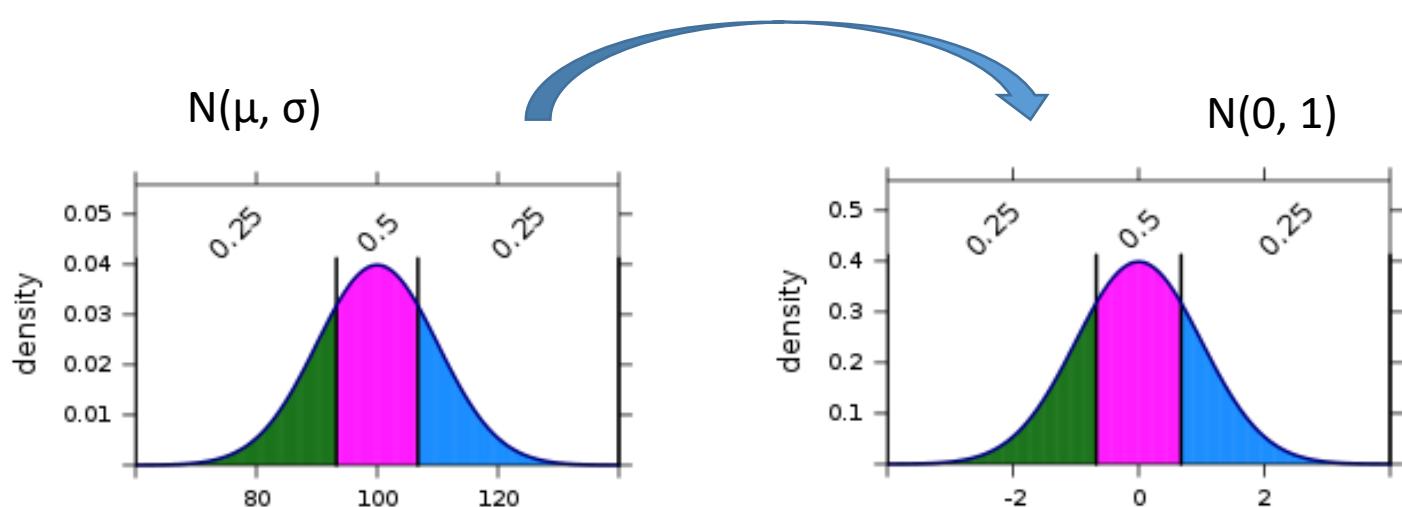
Standard Normal $N(0, 1)$

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: $IQ = 100 + 2.2 * 15 = 133$

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:

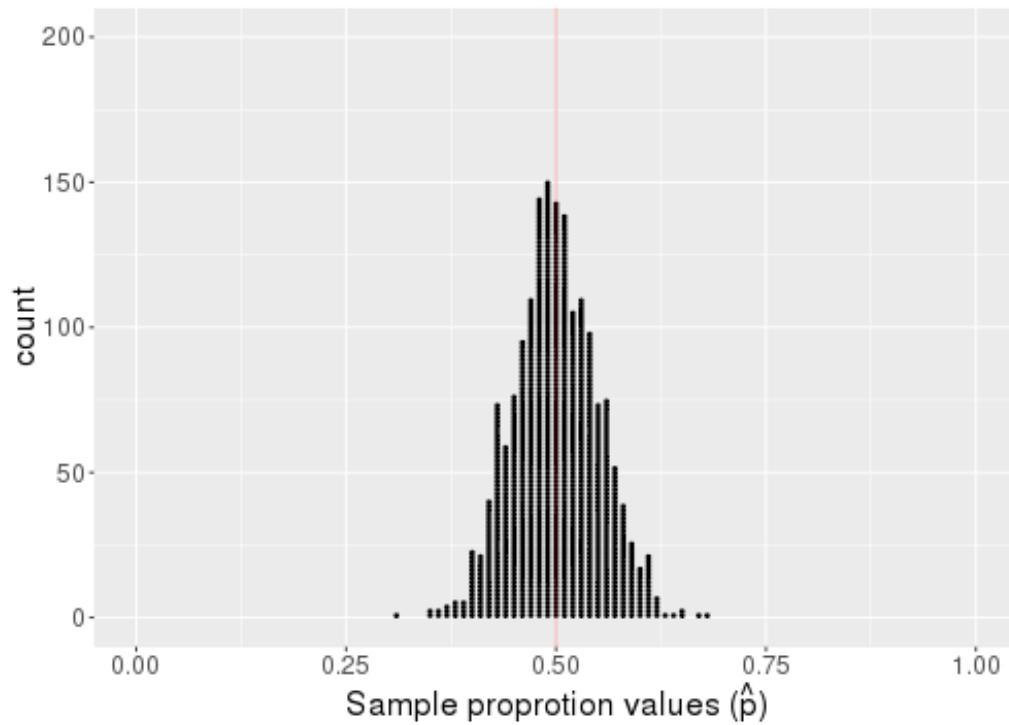
- normally distributed
- centered at the value of the population parameter

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!

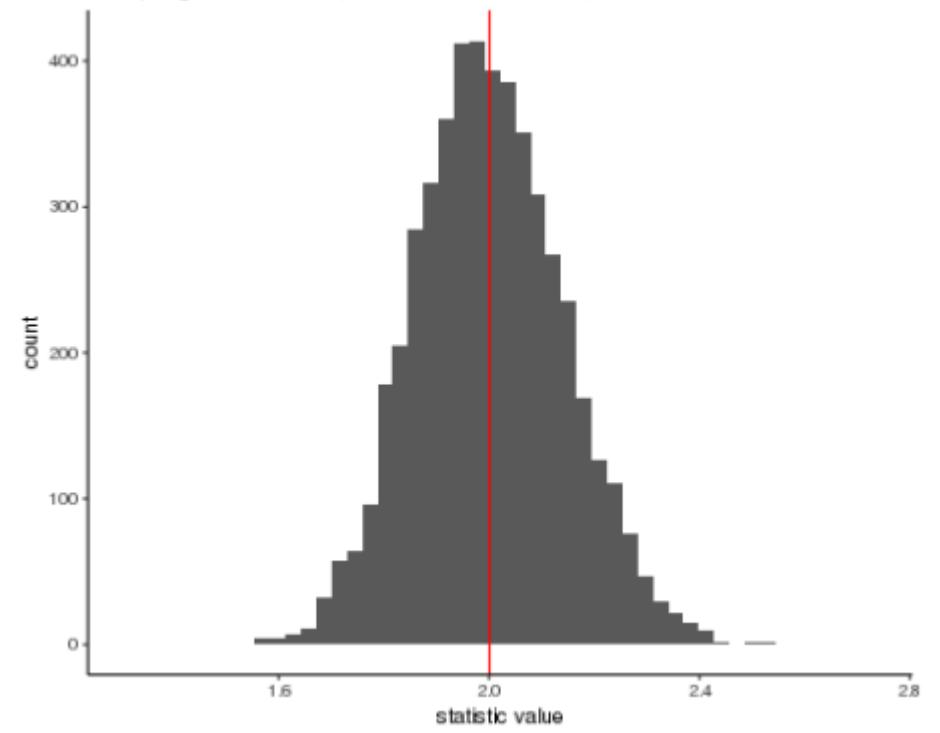
Central limit theorem

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

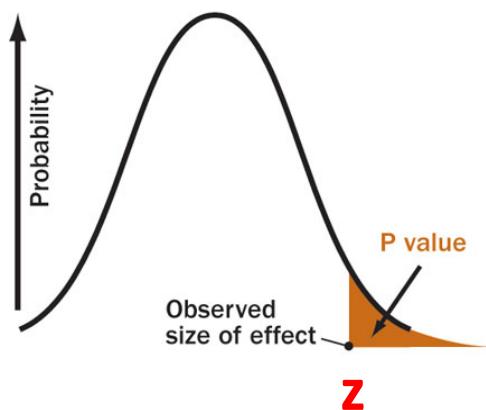
Hypothesis tests using a normal distribution

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)`

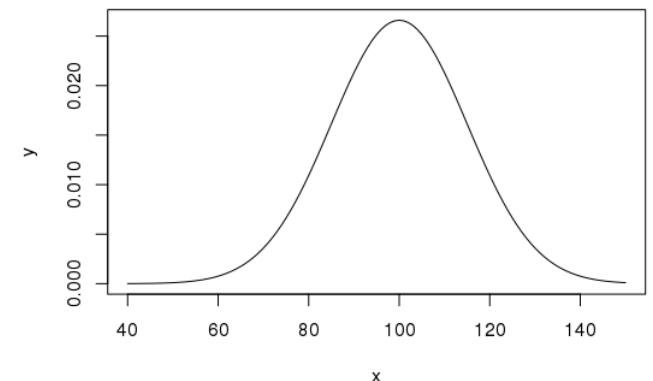
Hypothesis tests based on a Normal Distribution

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

<code>> pnorm(z, 0, 1)</code>	if $H_A: \mu < param_0$
<code>> 1 - pnorm(z, 0, 1)</code>	if $H_A: \mu > param_0$
<code>> 2 * (1 - pnorm(abs(z), 0, 1))</code>	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?

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

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?

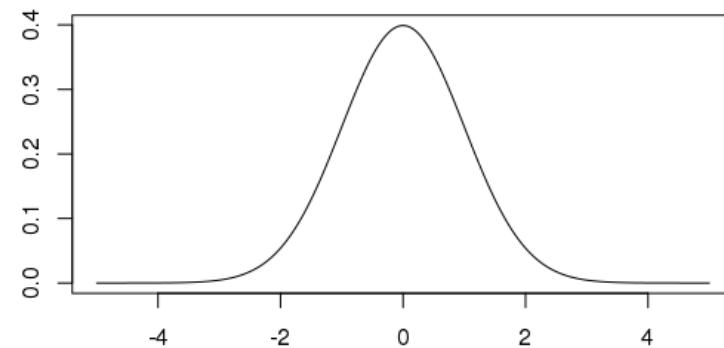
Steps: 3-4. What is the probability one would get a z-statistic as larger or larger than 1.875 from a standard normal distribution?

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

p-value = .0304

Normal area app $\Pr(X \leq x)$

Standard normal null distribution



Step 5?



Confidence intervals using a normal distribution

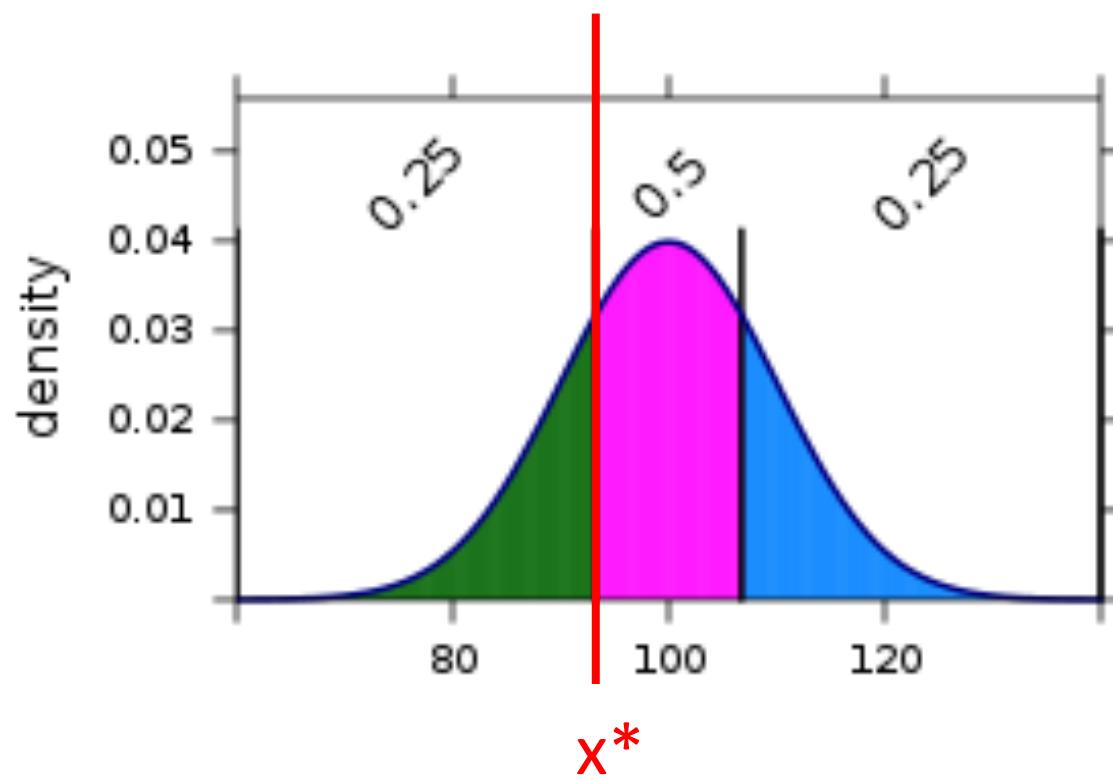
Finding quantile values

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

`qnorm(q, mu, sigma)`

The 'q' in qnorm stands for quantile

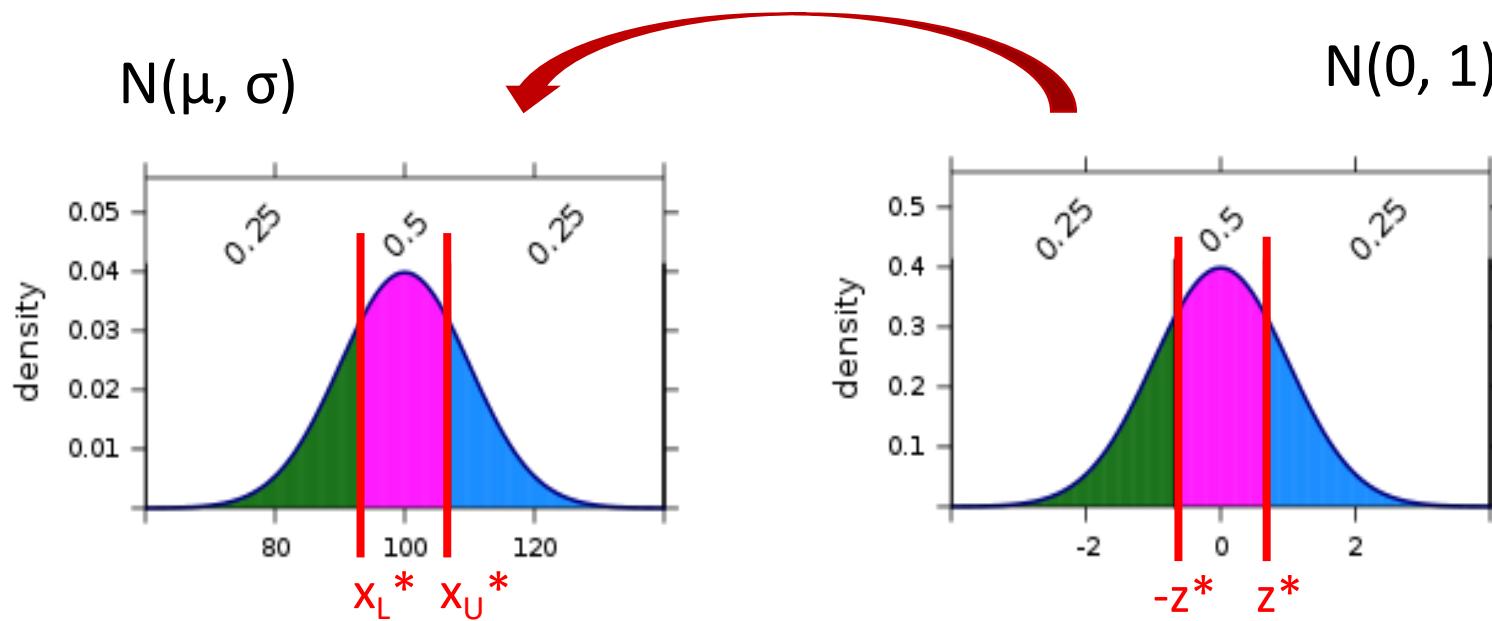
What is the max and min that q can be?



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

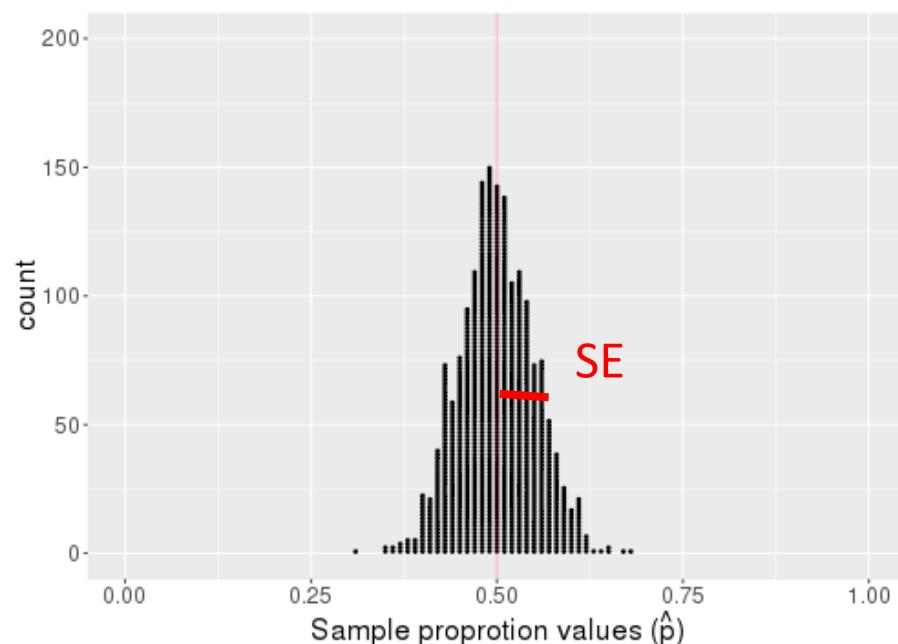
Questions:

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?

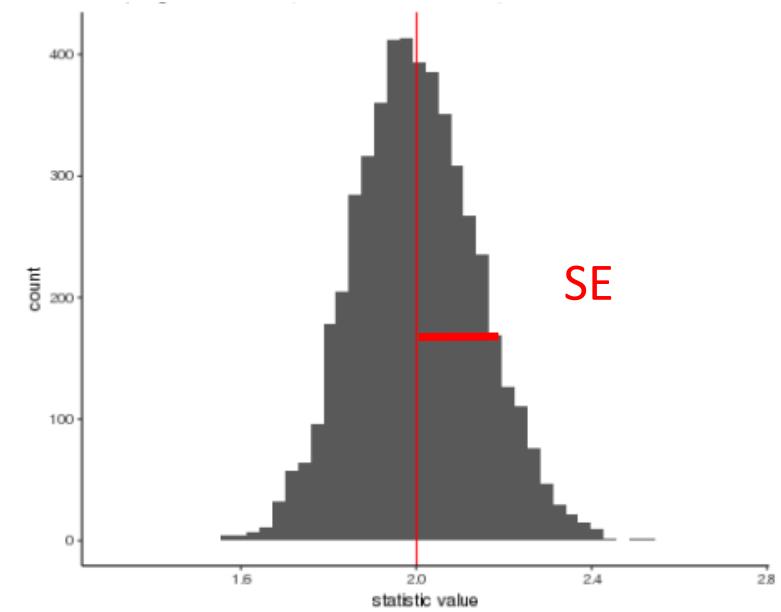
For a proportion π : $CI_{95} = \hat{p} \pm 2 \cdot SE$

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

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:

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

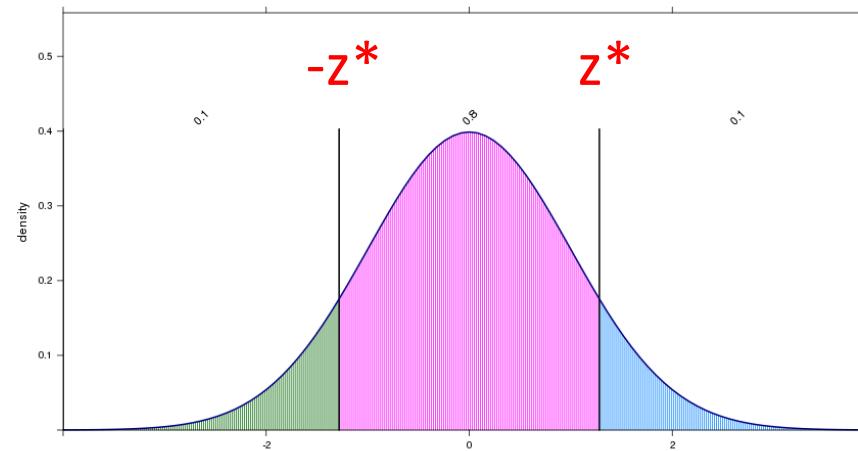
where z^* is chosen so that the area between $-z^*$ and $+z^*$ in the standard normal distribution is the desired confidence level

- 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 μ

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 μ . If we have an observed statistic from:

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

We can create an interval that will capture μ 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

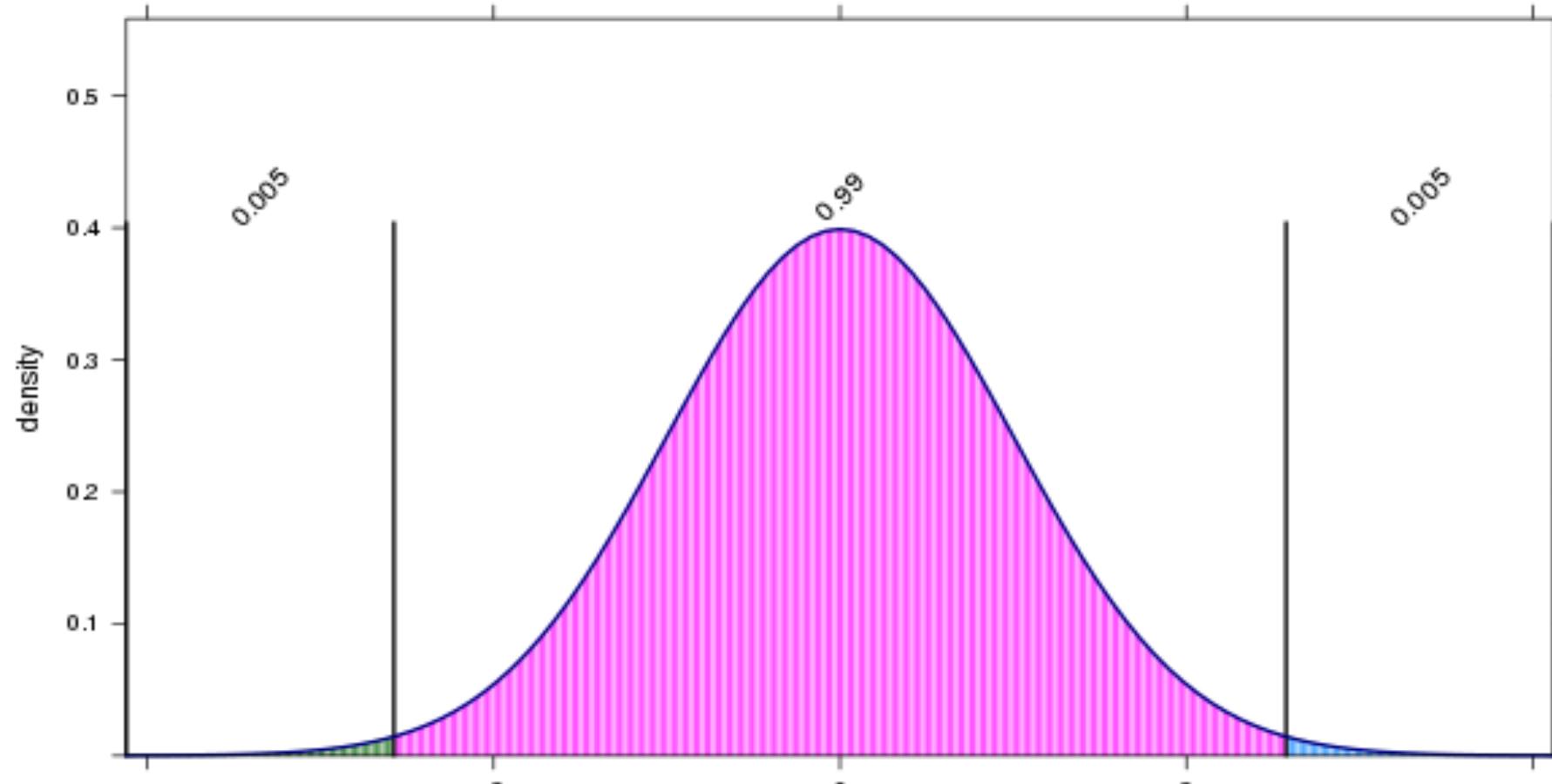
```
z_stars <- qnorm(c(.90, .95, .975, .99, .995), 0, 1)
```

[Normal quantile app](#)

.99 quantile values

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

Quantile values: [-2.576 2.576]



Normal quantile app

$\bar{x} = 0$

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

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

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 $SE = 0.015$.

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

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

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

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

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

Homework 8

Is on Canvas

Due Sunday April 5th at 11:30pm