

# Parametric inference on proportions

# Overview

Quick review of Normal distributions

Calculating confidence intervals using normal distributions

Parametric inference on proportions

- Distribution of a sample proportion
- Confidence interval for a single proportion
- Tests for a single proportion

Announcement:  
NS fantastic  
Friday talk

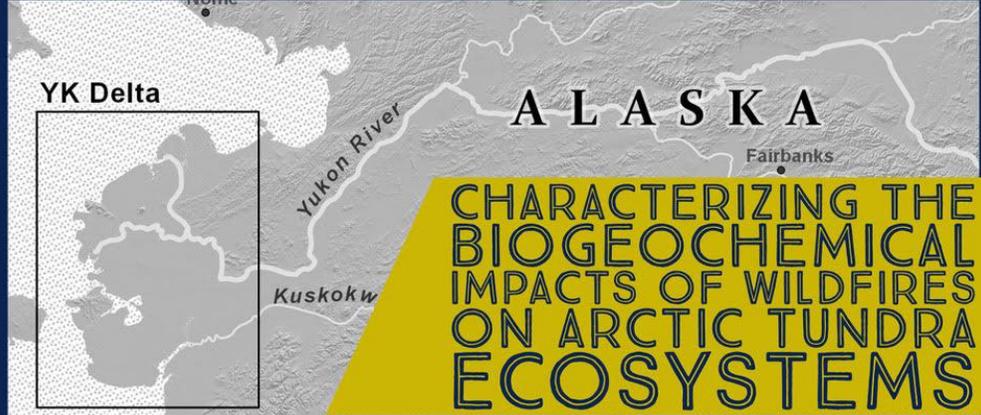
SCHOOL OF NATURAL SCIENCE FANTASTIC FRIDAY SEMINAR



NATALIE  
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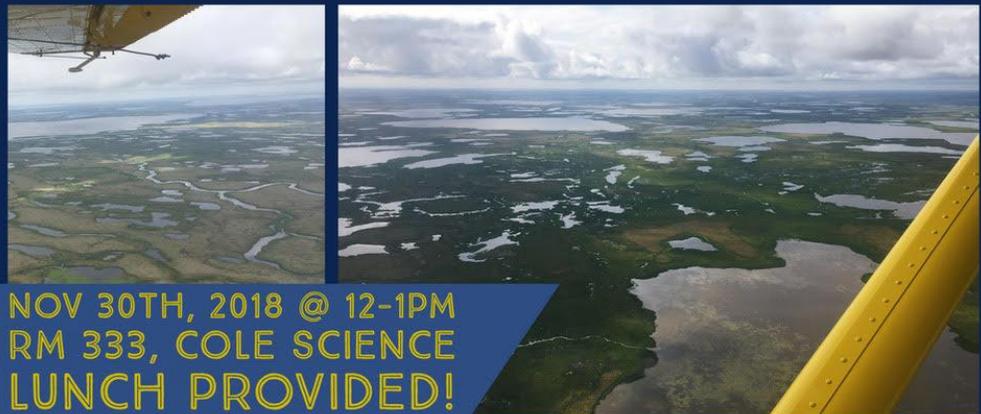


RHYS  
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YK Delta  
Yukon River  
Kuskokw  
ALASKA  
Fairbanks

CHARACTERIZING THE  
BIOGEOCHEMICAL  
IMPACTS OF WILDFIRES  
ON ARCTIC TUNDRA  
ECOSYSTEMS



NOV 30TH, 2018 @ 12-1PM  
RM 333, COLE SCIENCE  
LUNCH PROVIDED!

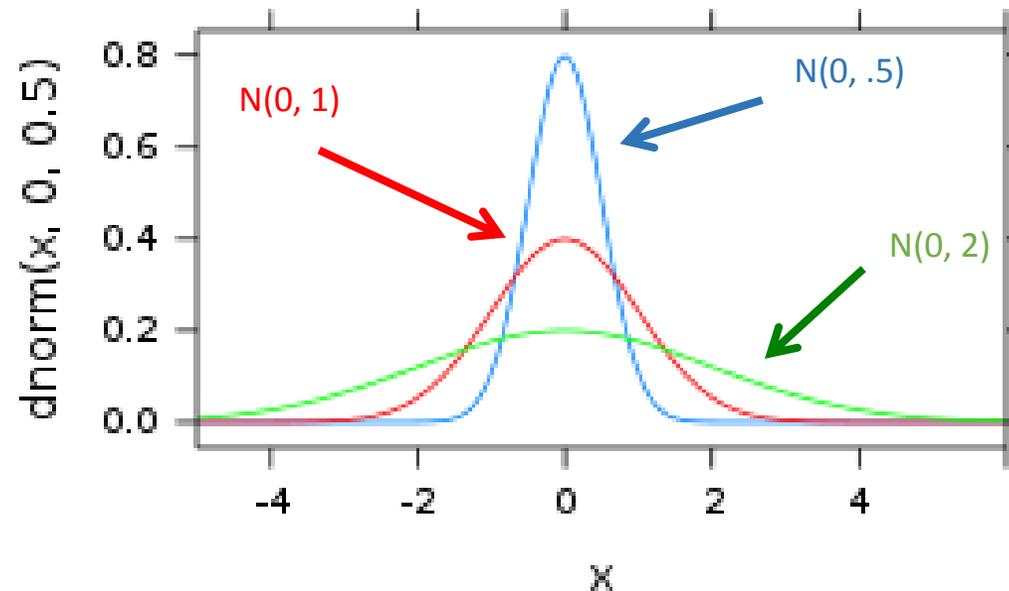


# Review of Normal distributions

# Normal Density Curve

Normal distributions  $N(\mu, \sigma)$  have two parameters:

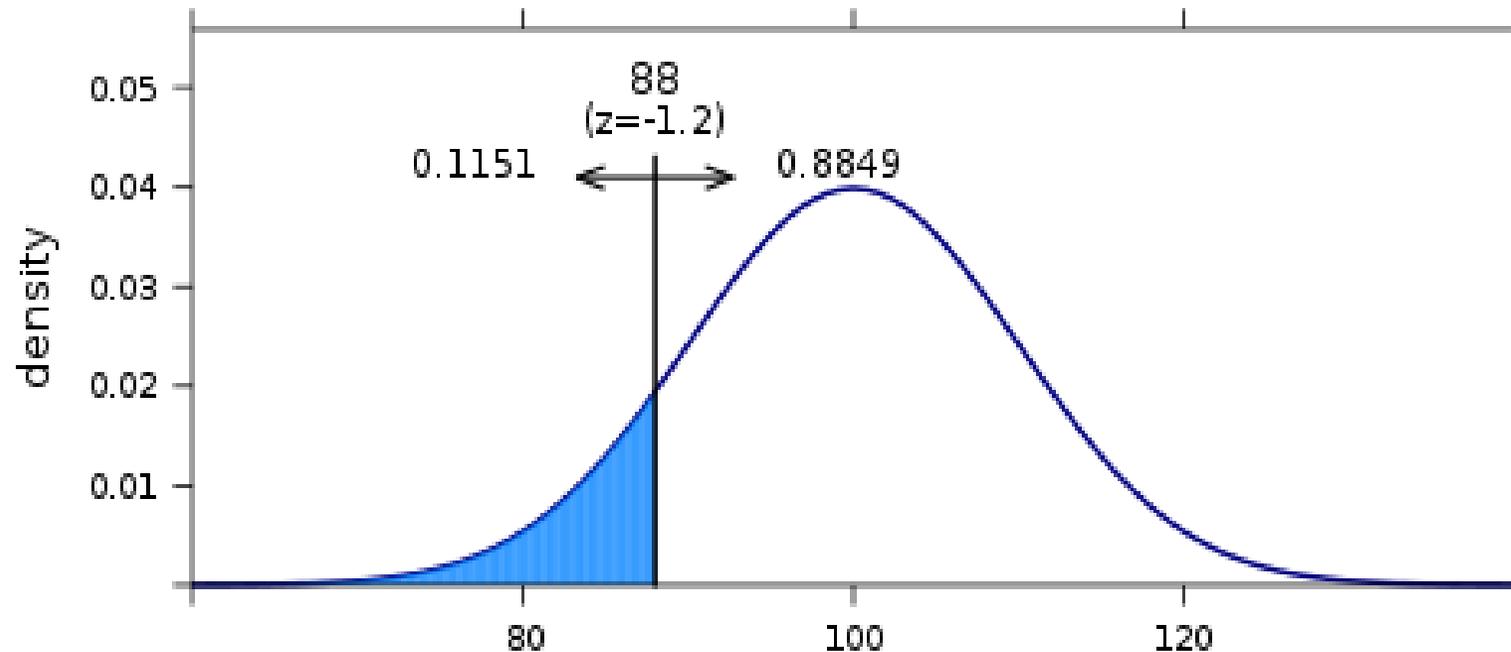
- The mean:  $\mu$
- The standard deviation:  $\sigma$



# Calculating probabilities from normal distributions

We can find the probability of getting a value less than or equal to  $x$ :

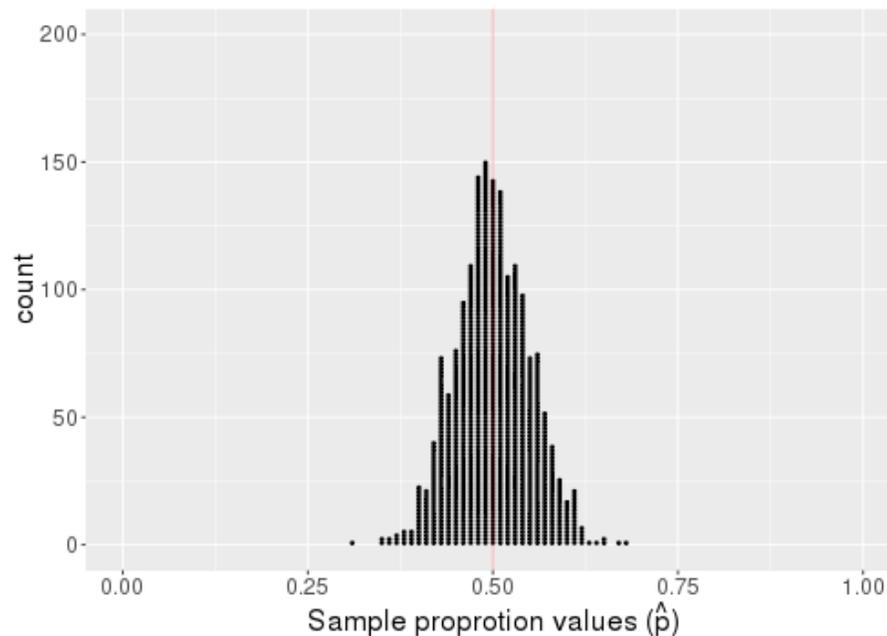
`pnorm(x, mu, sigma)`      #  $\Pr(X \leq x)$



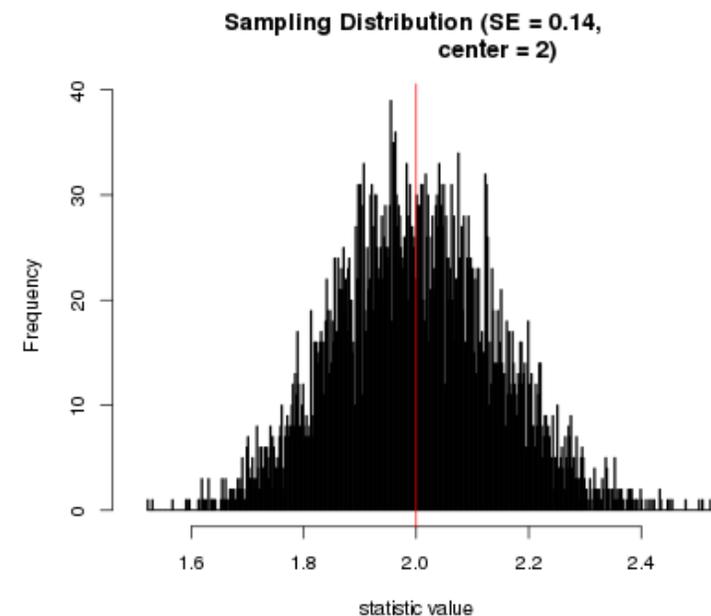
# Central limit theorem

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 and is centered at the value of the population parameter

proportion ( $\hat{p}$ )



mean ( $\bar{x}$ )



# Central limit theorem

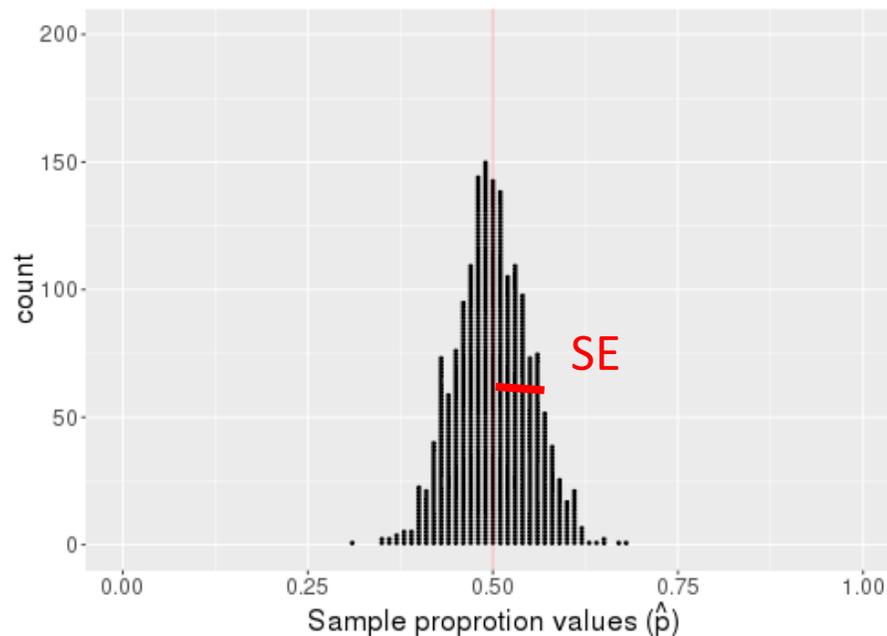
## Questions:

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?

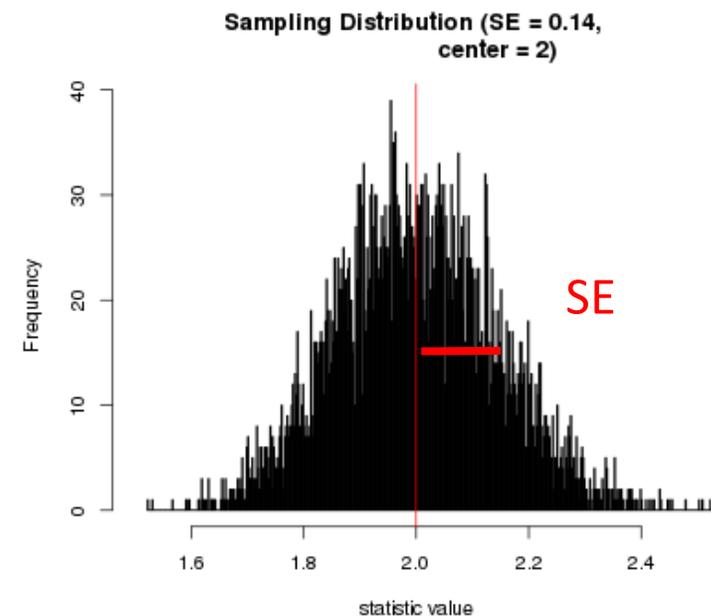
For a proportion  $\pi$ :  $CI_{95} = \hat{p} \pm 2 \cdot SE$

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

proportion ( $\hat{p}$ )

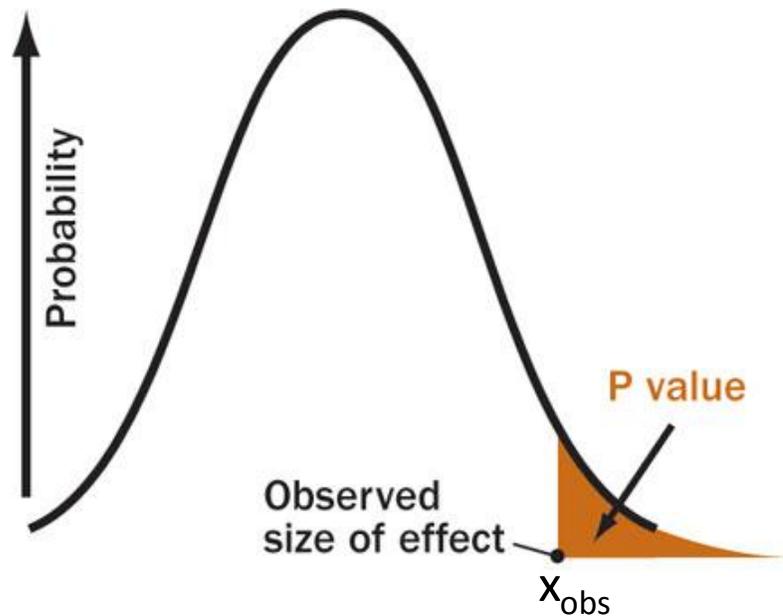


mean ( $\bar{x}$ )



# p-values based on a normal distribution

When a distribution under the **null hypothesis** is normal, we can use the normal density curve to compute p-values rather than a randomization distribution



$$\Pr( X \geq x_{obs} ; \mu, \sigma )$$

`pnorm(obs_stat, mu, sigma,  
lower.tail = FALSE)`

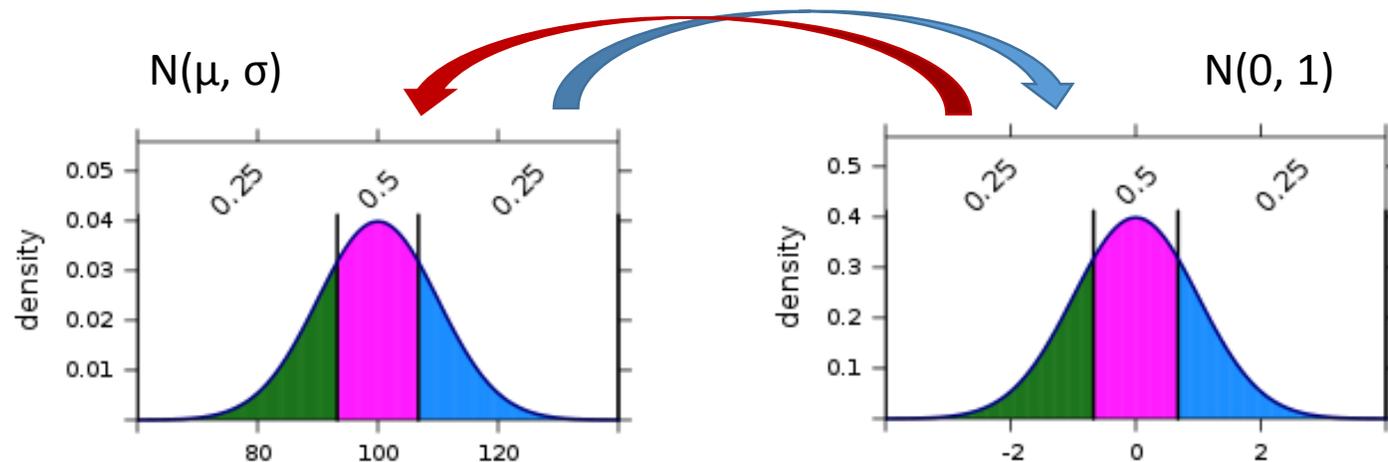
# Standard Normal $N(0, 1)$

We can scale any normal distribution value  $X \sim N(\mu, \sigma)$  to a **standard normal** distribution value  $Z \sim N(0, 1)$  using:

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

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

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



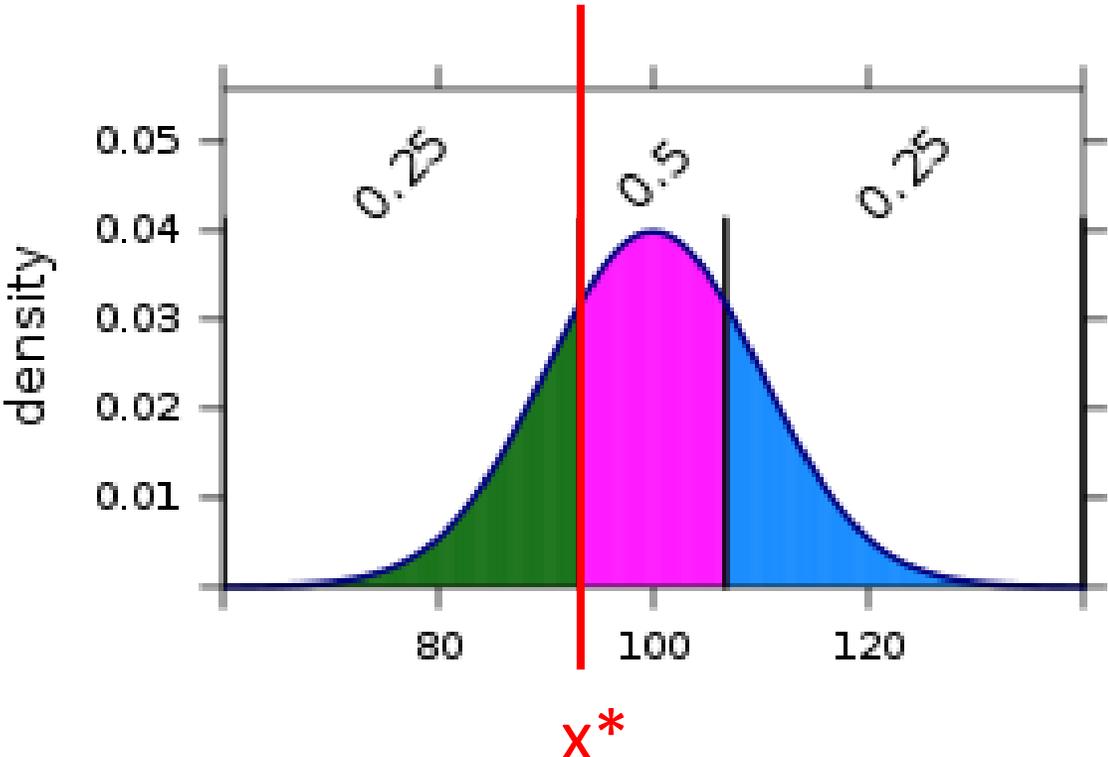
# Finding normal probabilities and percentiles

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

```
qnorm(q, mu, sigma)
```

The 'q' in qnorm stands for quantile

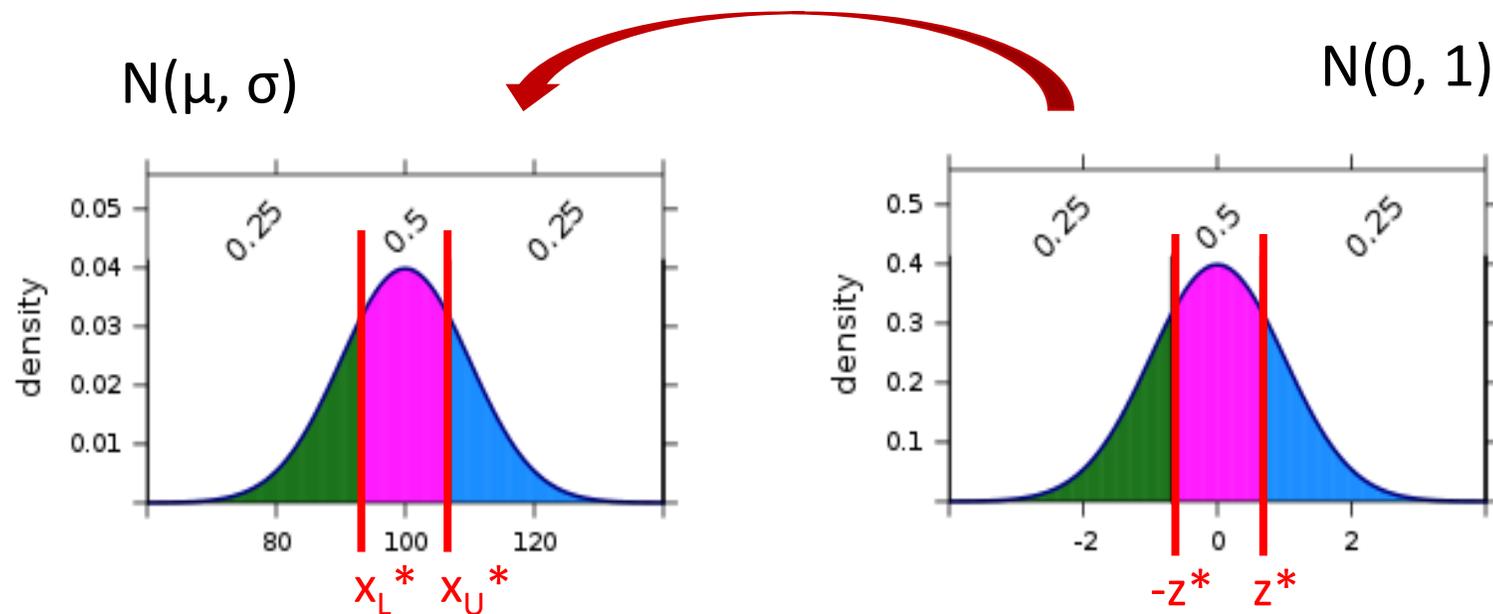
What is the max and min that q can be?



# 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 :

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



# 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:

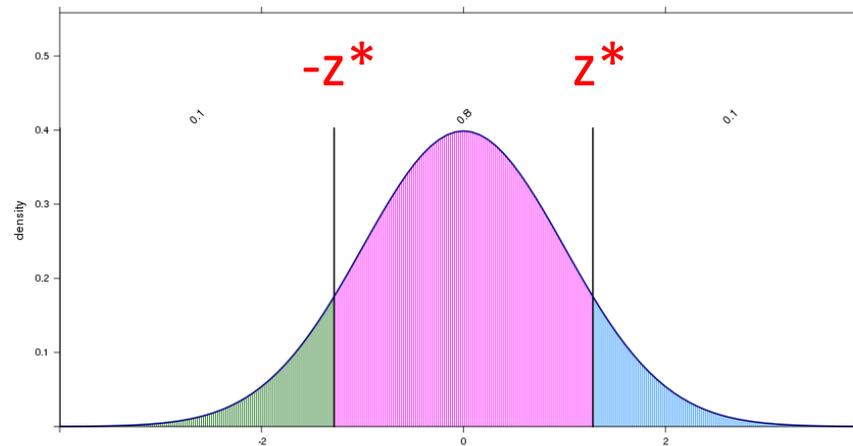
$$\text{sample statistic} \pm z^* \times \text{SE}$$

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 |

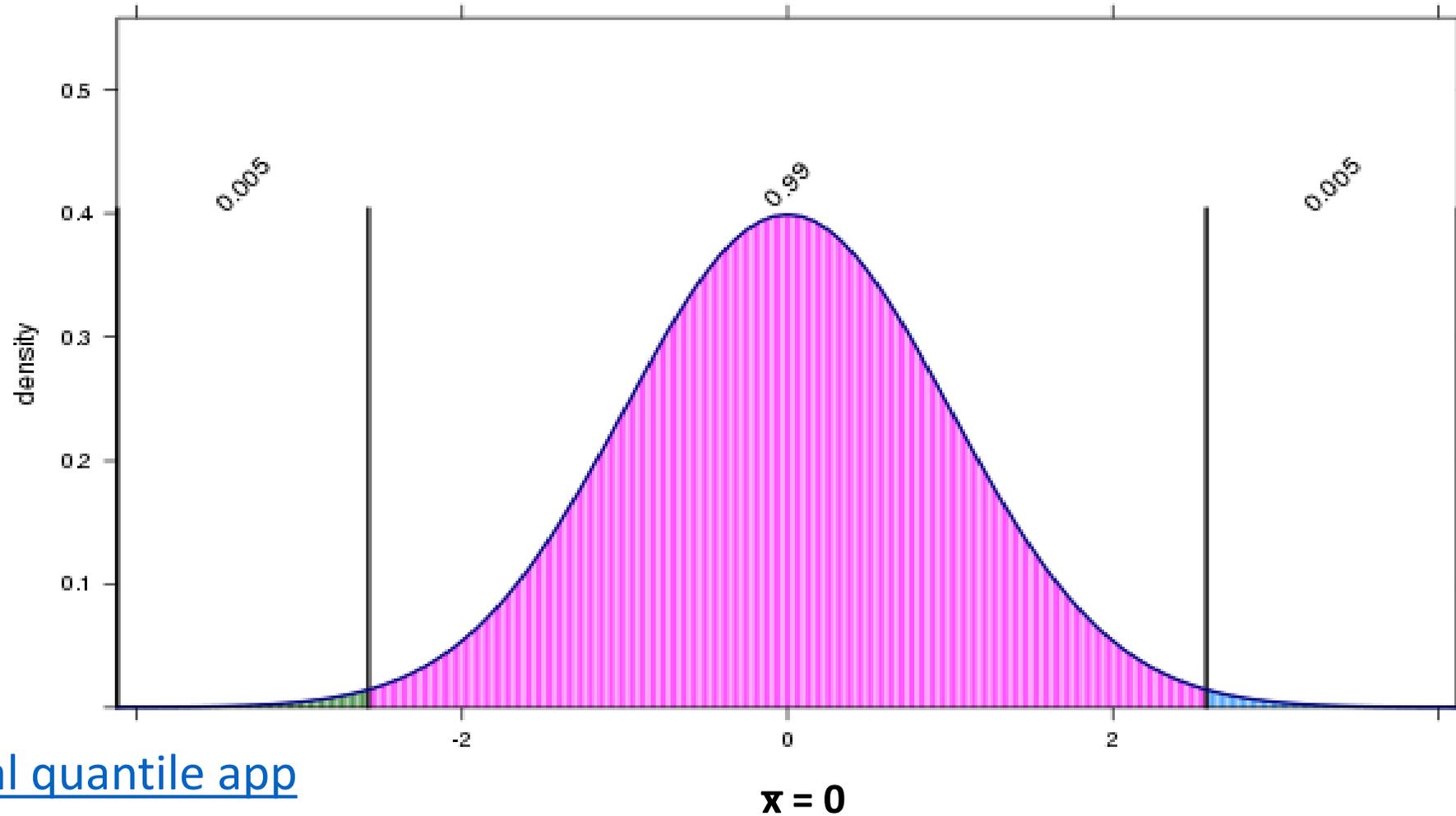
```
z_stars <- qnorm(c(.90, .95, .975, .99, .995), 0, 1)
```

[Normal quantile app](#)

# .99 quantile values

$\mu = 0$ ,  $SE = 1$

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 |

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# 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 |

# Parametric inference on proportions

# Review: questions about proportions

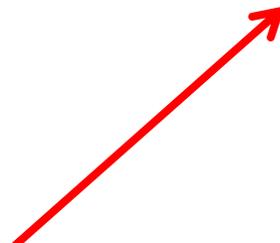
1. What symbols have we been using for the parameter and statistic for proportions?
  - What are examples of confidence intervals and hypotheses tests we've run for proportions?
2. What does the shape of a sampling distribution for a proportion look like?
3. Suppose  $\pi = .6$ , and  $n = 100$ , can you draw the sampling distribution for  $\hat{p}$ ?
  - If you were given the SE could you do it?

# Standard Error for Sampling Proportions

When choosing random samples of size  $n$  from a population with proportion  $\pi$ , the standard error (SE) of the sample proportions is given by:

$$SE = \sqrt{\frac{\pi(1-\pi)}{n}}$$

The larger the sample size ( $n$ ) the smaller the standard error (SE)



# Standard Error for Sampling Proportions

Note: we don't usually know  $\pi$ , so we can't compute the standard error exactly using the formula:

$$SE = \sqrt{\frac{\pi(1-\pi)}{n}}$$



However, we can substitute  $\hat{p}$  for  $\pi$  and then we can get an estimate of the standard error:

$$\hat{SE} = \sqrt{\frac{\hat{p}(1-\hat{p})}{n}}$$



# Comparing formula SE to the bootstrap SE

Q: How have we calculated SE in previous classes?

A: The bootstrap!

How could we do this for the green sprinkles?

```
bootstrap_dist <- NULL
for (i in 1:10000) {
  boot_sample <- sample(my_sprinkles, replace = TRUE)
  bootstrap_dist[i] <- sum(boot_sample == 'green')/100
}
```

```
bootstrap_SE <- sd(bootstrap_dist)
```

| Color |
|-------|
| White |
| Red   |
| Red   |
| White |
| Green |
| White |
| .     |
| .     |
| .     |
| White |
| Green |

n = 100 sprinkles

# Comparing formula SE to the bootstrap SE

For my green sprinkles I get:

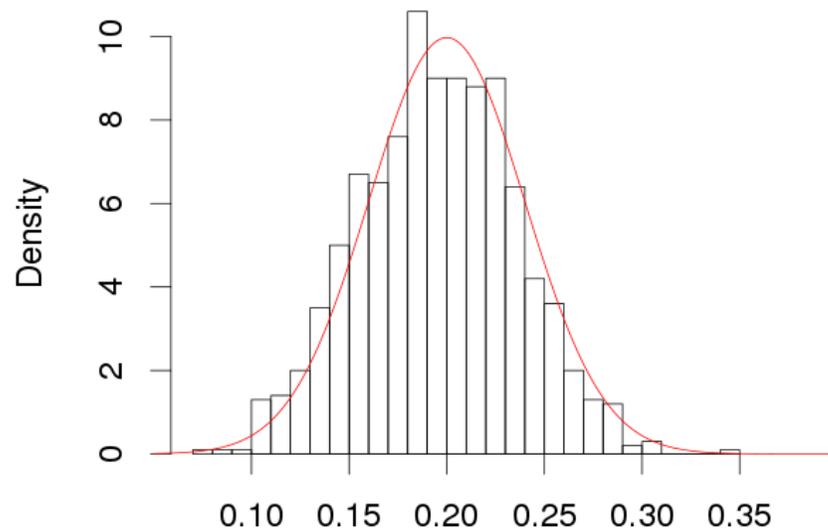
- Bootstrap SE = **0.039959**
- Formula SE = **0.04**

$$\hat{p} = 0.20$$

$$n = 100$$

$$\hat{SE} = \sqrt{\frac{\hat{p}(1-\hat{p})}{n}}$$

**Bootstrap Distribution**



```
SE <- sqrt( (.2 * (1 - .2))/100)
```

# SE for percentage of houses owned

65.1% of all houses are owned ( $\pi = .651$ )

If we randomly selected 50 houses...

- a) What would the SE of sampling distribution for the proportion of owned houses ( $\hat{p}$ ) be?
- b) What would this sampling distribution look like?

What if we randomly selected 200 houses?

$$SE = \sqrt{\frac{\pi(1-\pi)}{n}}$$

# SE for percentage of houses owned

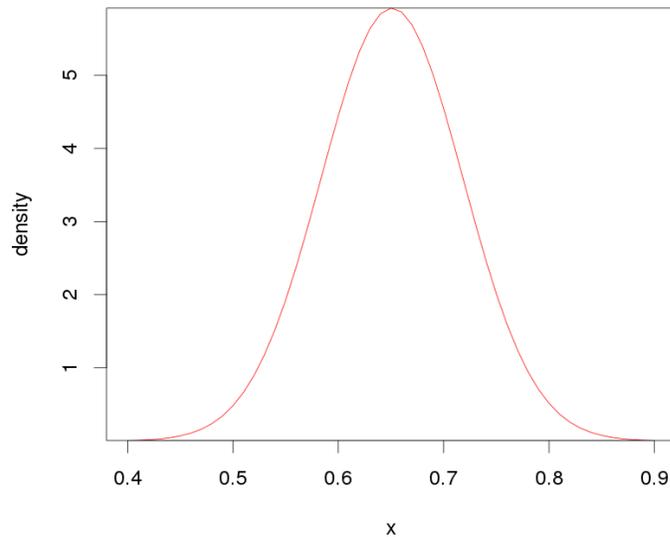
65.1% of all houses are owned

- $\pi = .651$
- When  $n = 50$ :  $SE = .0674$
- When  $n = 200$ :  $SE = .0337$

$$SE = \sqrt{\frac{\pi(1-\pi)}{n}}$$

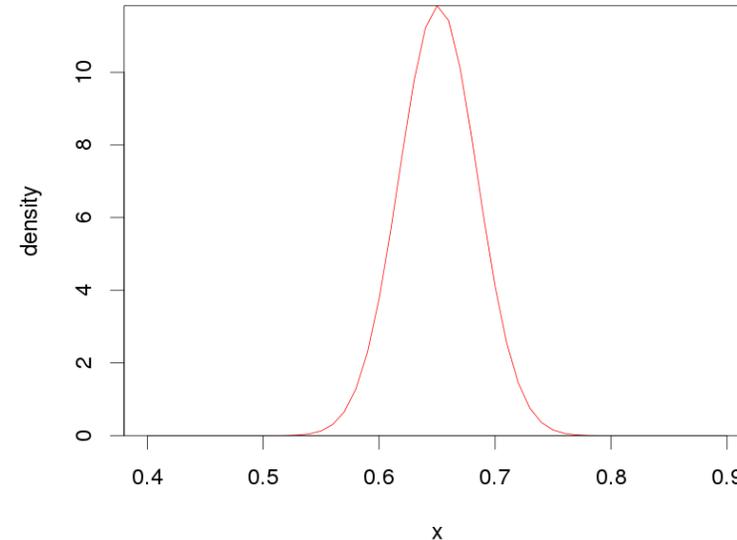
$N(.651, .0671)$

$n = 50$



$n = 200$

$N(.651, .0337)$



# How large of a sample is needed for the normal approximation?

$n = 50$

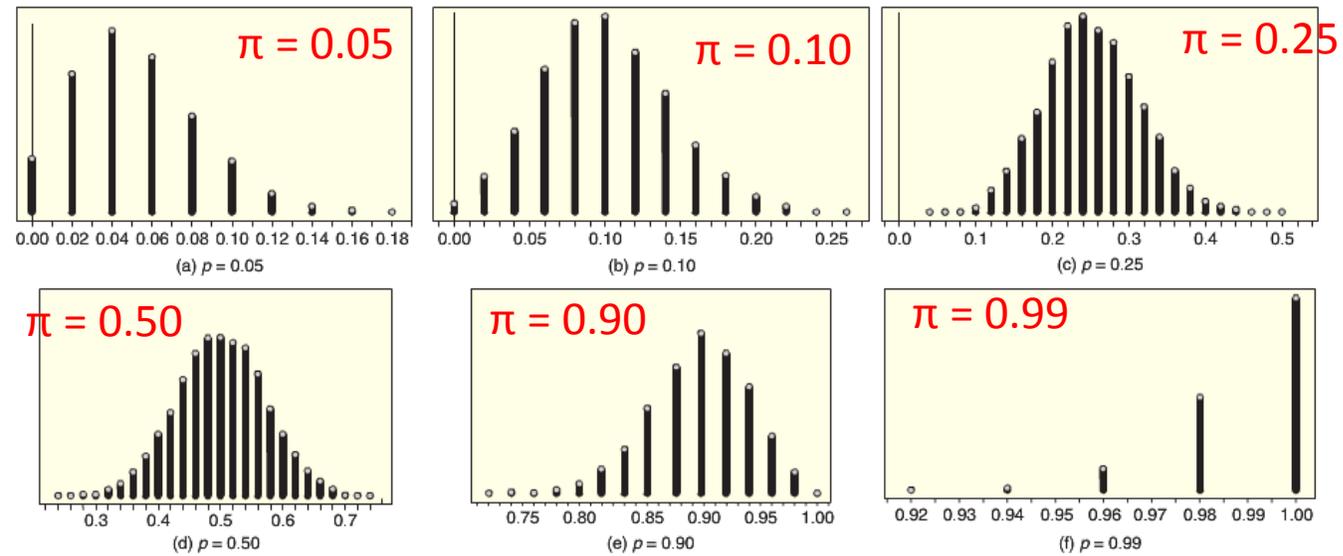


Figure 6.2 Distributions of sample proportions when  $n = 50$

# How large of a sample is needed for the normal approximation?

The normal approximation is reasonable good when we see 10 “positive” outcomes and 10 “negative” outcomes

$$n\pi \geq 10 \quad \text{and} \quad n(1 - \pi) \geq 10$$

# Summary: Central Limit Theorem for Sample Proportions

When choosing random samples of size  $n$  from a population with a proportion  $p$ , the distribution of the sample proportions has the following characteristics:

**Center:** The mean is equal to the population proportion,  $\pi$

**Spread:** The standard error is:  $SE = \sqrt{\frac{\pi(1-\pi)}{n}}$

**Shape:** If the sample size is sufficiently large, the distribution is reasonably normal.

The larger the sample size, the more like a normal distribution it becomes. A normal distribution is a good approximation as long as  $n\pi \geq 10$  and  $n(1 - \pi) \geq 10$

We can write this as:

$$\hat{p} \sim N\left(\pi, \sqrt{\frac{\pi(1-\pi)}{n}}\right)$$

# Confidence intervals for a single proportion

Provided the sample size is large enough so that  $n\pi \geq 10$  and  $n(1 - \pi) \geq 10$ , a confidence interval for a population proportion  $p$  can be computed based on a random sample of size  $n$  using:

$$\hat{p} \pm z^* \cdot \sqrt{\frac{\hat{p}(1-\hat{p})}{n}}$$

Note we are substituting  $\hat{p}$  for  $\pi$



Where  $\hat{p}$  is the sample proportion and  $z^*$  is a standard normal endpoint to give the desired confidence level

# My green sprinkles

I counted 100 sprinkles, 20 of which were green

What is a 95% confidence interval for the proportion of green sprinkles?

$$\hat{p} \pm z^* \cdot \sqrt{\frac{\hat{p}(1-\hat{p})}{n}}$$

# My green sprinkles

$$\hat{p} = .20$$

$$n = 100$$

$$z^* = 1.96$$

$$SE = .04$$

$$CI = 0.1216 \text{ to } 0.2784$$

$$\hat{p} \pm z^* \cdot \sqrt{\frac{\hat{p}(1-\hat{p})}{n}}$$

$$.20 \pm 1.96 \cdot \sqrt{\frac{.2 \cdot (1-.2)}{100}}$$

# Test for single proportions

To compute p-values when the null distribution is normal we use:

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

In the context of proportions we usually state  $H_0: \pi = \pi_0$ , and the formula for z becomes:

$$z = \frac{\hat{p} - \pi_0}{SE} \quad SE = \sqrt{\frac{\pi_0(1 - \pi_0)}{n}}$$

# Test for single proportions

To test for  $H_0: \pi = \pi_0$  vs  $H_A: \pi \neq \pi_0$  (or the one-tail alternative), we use the standardized test statistic:

$$z = \frac{\hat{p} - \pi_0}{\sqrt{\frac{\pi_0(1 - \pi_0)}{n}}}$$

Where  $\hat{p}$  is the proportion in a random sample of size  $n$ . Provided the sample size is reasonable large (usual conditions), the p-value of the test is computed using the standard normal distribution.

# Do more than 25% of US adults believe in ghosts?

A telephone survey of 1000 randomly selected US adults found that 31% of them say they believe in ghosts. Does this provide evidence that more than 1 in 4 US adults believe in ghosts?

1. State the null and alternative hypothesis
2. Calculate the statistic of interest
- 3-4. Calculate the p-value  
Hint: the `pnorm()` function will be useful
5. What do you conclude?

$$z = \frac{\hat{p} - \pi_0}{\sqrt{\frac{\pi_0(1 - \pi_0)}{n}}}$$

# Do more than 25% of US adults believe in ghosts?

$H_0: \pi = .25$  vs.  $H_A: \pi > .25$

$\hat{p} = .31$

$n = 1000$

$$z = \frac{\hat{p} - \pi_0}{\sqrt{\frac{\pi_0(1 - \pi_0)}{n}}}$$

```
SE <- sqrt( (.25 * (1 - .25))/1000)
```

```
z_val <- (.31 - .25)/SE
```

z\_val is 4.38

# Do more than 25% of US adults believe in ghosts?

$H_0: \pi = .25$  vs.  $H_A: \pi > .25$

$\hat{p} = .31$

$n = 1000$

$$z = \frac{\hat{p} - \pi_0}{\sqrt{\frac{\pi_0(1 - \pi_0)}{n}}}$$

p-value = `1 - pnorm(z_val, 0, 1)`

0.00000589

Indeed, very strong evidence!



# Worksheet 11

Lock 5 questions on computing areas/quantiles of normal distributions and doing parametric inference on proportions

```
> source('/home/shared/intro_stats_2016/cs206_functions.R')
```

```
> get_worksheet(11)
```