

# Math 11

## Calculus-Based Introductory Probability and Statistics

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Today:

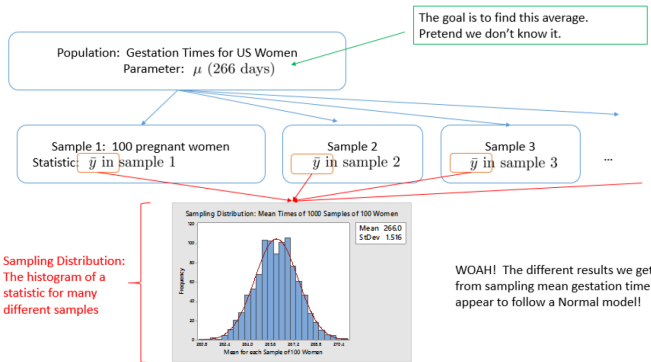
- Hypothesis Testing for Means ( $t$ -test)
- Better Understanding Errors Made in Hypothesis Tests

# Inference for Means

We want to do all the same inference for means that we did with proportions: understanding the sampling distribution, hypothesis testing, and confidence intervals

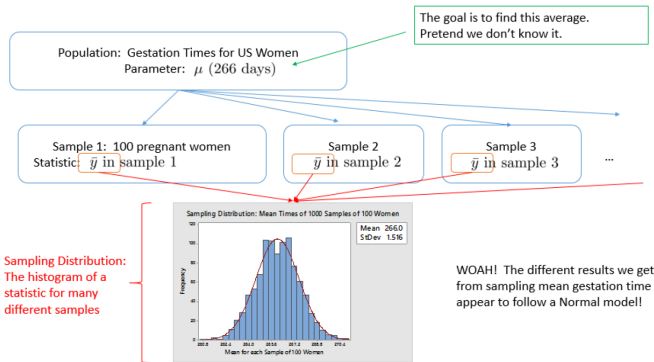
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In a previous class, we learned that the sampling distribution is approximately Normal with

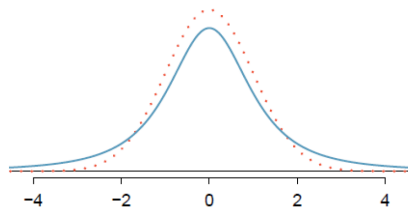
$$\mu_{model} = \mu_{population} \quad \text{and} \quad \sigma_{model} = \frac{\sigma_{model}}{\sqrt{n}}.$$

# Time for the Truth...

With smaller sample sizes (often  $n < 30$ ) or populations where you don't know  $\sigma$  (and must approximate it using  $s_x$ ), there is a better approximation of the sampling distribution than the Normal model.

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Solid line:  $t$ -distribution

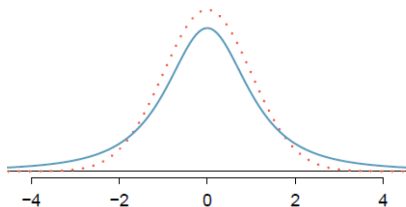
Dotted line: Normal ( $z$ ) distribution

Like the Normal distribution, the  $t$ -distribution is unimodal and symmetric.

Note, however, that the tails of the  $t$ -distribution are thicker, and this can change the area under the curve, and hence, the  $p$ -values that are based on it.

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Solid line: t-distribution

Dotted line: Normal (z) distribution

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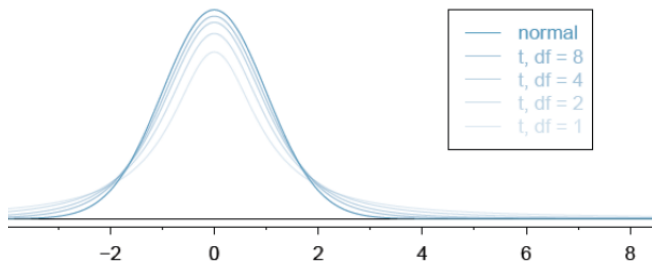
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## When Should I Use Z vs. T?

- If you know  $\sigma$  (almost never true): Use a  $z$ -distribution.
- In all other cases: Use a  $t$ -distribution.

## From $z$ to $t$

In practice, we tend **not** to use the Normal curve as the approximation of the sampling distribution because the  $t$ -distribution gives us more precise results.



There are many curves in the  $t$ -distribution family. You choose the appropriate one based on the size of your sample.

With  $n$  data points in the sample, you use the  $t$ -distribution with  
$$df = n - 1.$$

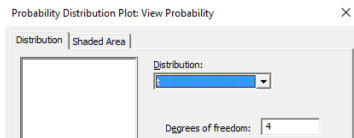
$df$  stands for “degrees of freedom” and as it gets bigger, the  $t$ -distribution morphs into a standard normal distribution.



# Welcome to the New World

How much area is to the right of  $-0.6$  on  $t_4$ ?

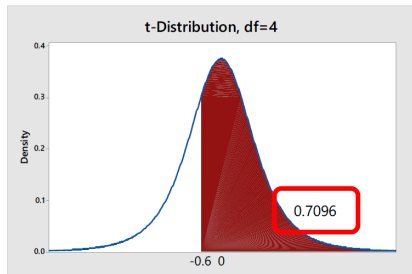
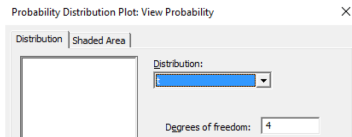
As before: Graph >> Probability Distribution Plot  
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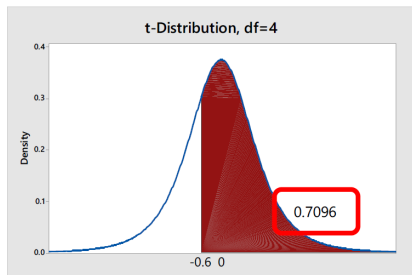
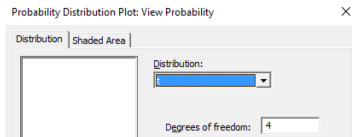
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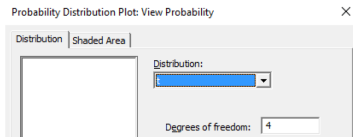


What percent of the  $t_6$  distribution is more than 2 units from 0?

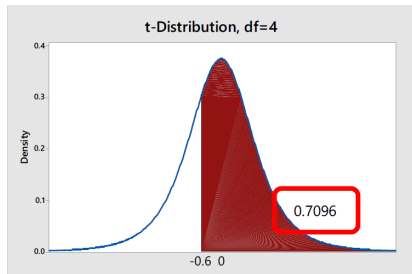
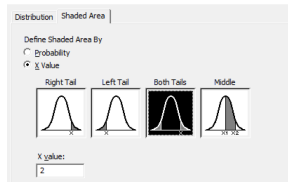
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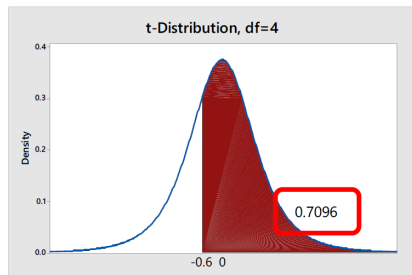
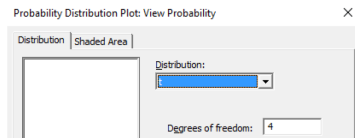
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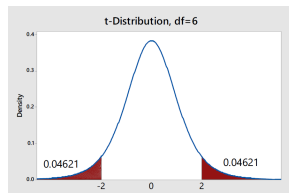
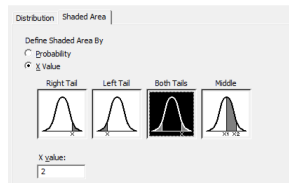
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What percent of the  $t_6$  distribution is more than 2 units from 0?



$$2 \times 0.046 = 0.092.$$

(On  $N(0, 1)$ , this answer would be about  $1 - 0.95 = 0.05$ )

# Using Tables with $t$ -Distributions

Since they don't want to print a new table for every possible  $df$  value, they print one table, but it is not as good as a  $z$ -table (standard Normal).

Also, a  $t$ -table is usually reversed (areas on outside, critical values in the table).

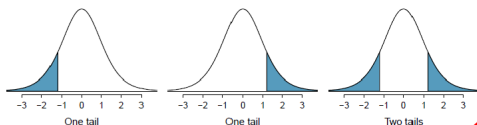


Figure B.1: Tails for the  $t$ -distribution.

(Redoing the last problem) Our critical value of 2 is between 1.94 and 2.45.

See back of your book

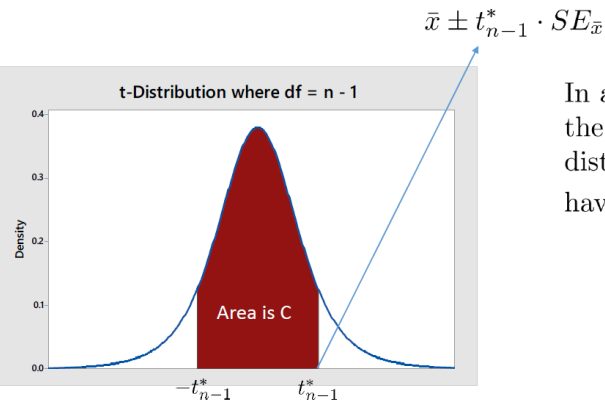
one tail	0.100	0.050	0.025	0.010	0.005
two tails	0.200	0.100	0.050	0.020	0.010
df	1	3.08	6.31	12.71	31.82
	2	1.89	2.92	4.30	6.96
	3	1.64	2.35	3.18	4.54
	4	1.53	2.13	2.78	3.75
	5	1.48	2.02	2.57	3.36
	6	1.44	1.94	2.45	3.14
	7	1.41	1.89	2.36	3.00
	8	1.40	1.86	2.31	2.90

So, the area we seek is somewhere between 0.05 and 0.10. (Technology gave an answer about 0.092.)

IMPORTANT: With a T-table, you will only be able to imprecisely find the area (i.e., find bounds on the area).

# New, Improved CIs for Means!

For means, our CIs will use the same setup as before, but we live on a  $t$ -distribution, not a  $z$ -distribution:



In a sample with  $n$  data points, the best model for the sampling distribution is  $t_{n-1}$ . We still have  $SE_{\bar{x}} = \frac{\sigma}{\sqrt{n}} \approx \frac{s_x}{\sqrt{n}}$

## First C.I. With the $t$ -Distribution

On average, how much do U.S. baby girls weigh? To find out, you sneak into random hospitals and collect illegally the weight of 12 random newborn babies. If  $\bar{x} = 7.3$  lbs and  $s_x = 2$ , find a 90% C.I. for  $\mu$ , the average weight of all U.S. female babies.



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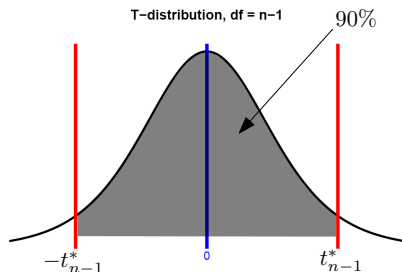
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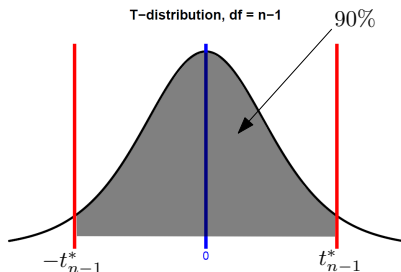


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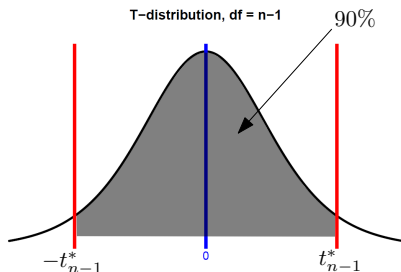
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	10	1.37	1.81	2.23	2.76	3.17
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We read  $t^* = 1.80$ .

2) Break out the C.I. formula.

$$\begin{aligned}\bar{x} \pm t_{n-1}^* \times SE_{\bar{x}} &\simeq 7.3 \pm 1.8 \times \frac{2}{\sqrt{12}} \\ &= (6.26, 8.34).\end{aligned}$$

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We are 90% confident that  $\mu$  is between 6.26 and 8.34 pounds.

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We are 90% confident that  $\mu$  is between 6.26 and 8.34 pounds.

**Remark:** The actual value for  $\mu$  is 7.5 pounds. Our C.I. was one of the lucky 90%.

# Your Turn!

You decide to build an 80% C.I. for some mean you are estimating.  
What is the critical value if your sample has size 15?

one tail		0.100	0.050	0.025	0.010	0.005
two tails		0.200	0.100	0.050	0.020	0.010
df	1	3.08	6.31	12.71	31.82	63.66
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	12	1.36	1.78	2.18	2.68	3.05
	13	1.35	1.77	2.16	2.65	3.01
	14	1.35	1.76	2.14	2.62	2.98
	15	1.34	1.75	2.13	2.60	2.95
	16	1.34	1.75	2.12	2.58	2.92
	17	1.33	1.74	2.11	2.57	2.90
	18	1.33	1.73	2.10	2.55	2.88
	19	1.33	1.73	2.09	2.54	2.86
	20	1.33	1.72	2.09	2.53	2.85
	21	1.32	1.72	2.08	2.52	2.83
	22	1.32	1.72	2.07	2.51	2.82
	23	1.32	1.71	2.07	2.50	2.81

- 1.34
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	18	1.33	1.73	2.10	2.55	2.88
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- 1.34

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- 1.76

Answer:  $t_{n-1}^* = t_{14}^* = 1.35$ .

# Your Turn!

About how much area is to the left of -2 on  $t_{15}$ ?

one tail		0.100	0.050	0.025	0.010	0.005
two tails		0.200	0.100	0.050	0.020	0.010
df	1	3.08	6.31	12.71	31.82	63.66
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	17	1.33	1.74	2.11	2.57	2.90
	18	1.33	1.73	2.10	2.55	2.88
	19	1.33	1.73	2.09	2.54	2.86
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- Between 0.1 and 0.2
- Between 0.05 and 0.1
- Between 0.025 and 0.05
- Between 0.001 and 0.025

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	18	1.33	1.73	2.10	2.55	2.88
	19	1.33	1.73	2.09	2.54	2.86
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- Between 0.1 and 0.2
- Between 0.05 and 0.1
- Between 0.025 and 0.05
- Between 0.001 and 0.025

Answer: Between 0.025 and 0.05

# Your Turn!

Suppose we want to do inference on a mean using a  $t$ -distribution. When does a  $t$ -distribution actually model the sample distribution?

1. It always does. It doesn't matter what the sample size is or what the population distribution looks like.
2. We only need the data points in our sample to be independent
3. If the data in the sample were chosen at random and are  $<10\%$  of the population
4. We need randomization,  $<10\%$  population, and the population to be reasonably normal looking (skew is ok with a larger  $n$ ).

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3. If the data in the sample were chosen at random and are  $<10\%$  of the population
4. We need randomization,  $<10\%$  population, and the population to be reasonably normal looking (skew is ok with a larger  $n$ ).

Answer: 4.

# Hypothesis Testing with $t$ -Distributions

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You collect data for 20 random runners in the current year, and get  $\bar{x} = 3.8$  with  $s_x = 0.5$ . Run a hypothesis test with  $\alpha = 0.05$ .



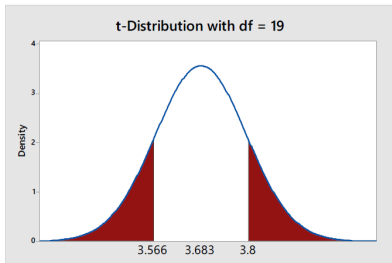
You should **always** convert to the standard  $t$ -distribution. To do so, you'll need the  $t$ -score:

$$\begin{aligned} T &= \frac{\text{point estimate} - \text{null value}}{SE} \\ &= \frac{3.8 - 3.683}{0.5/\sqrt{20}} \simeq 1.046. \end{aligned}$$

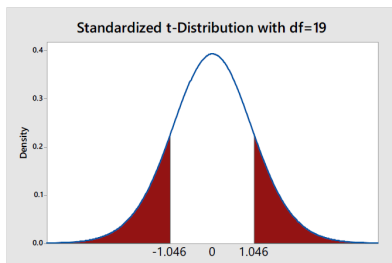
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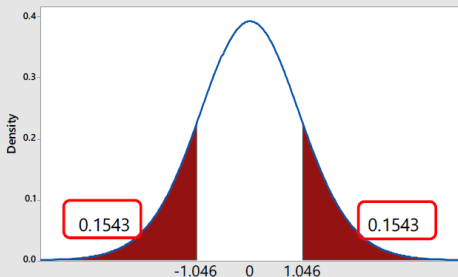
Original Setting



Standardized Setting



t-Distribution, df=19



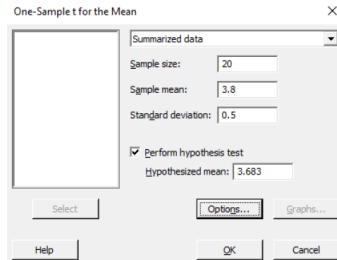
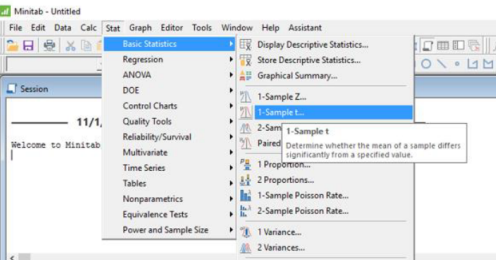
Technology says the area is  $0.154 + 0.154 = 0.308$

Since  $P = 0.31 > 0.05$ , we do not reject  $H_0$ . Our data are not strong enough to show a difference (if there is one).

In a table, our T-score of 1.046 is to the left of 1.33. So we have more area than the two-tails value of 0.2. So,  $P\text{-value} > 0.2 > 0.05$ , as before.

one tail	0.100	0.050	0.025	0.010	0.005
two tails	0.200	0.100	0.050	0.020	0.010
df	1	2	3	4	5
1	3.08	6.31	12.71	31.82	63.66
2	1.89	2.92	4.30	6.96	9.92
3	1.64	2.35	3.18	4.54	5.84
4	1.53	2.13	2.78	3.75	4.60
5	1.48	2.02	2.57	3.36	4.03
6	1.44	1.94	2.45	3.14	3.71
7	1.41	1.89	2.36	3.00	3.50
8	1.40	1.86	2.31	2.90	3.36
9	1.38	1.83	2.26	2.82	3.25
10	1.37	1.81	2.23	2.76	3.17
11	1.36	1.80	2.20	2.72	3.11
12	1.36	1.78	2.18	2.68	3.05
13	1.35	1.77	2.16	2.65	3.01
14	1.35	1.76	2.14	2.62	2.98
15	1.34	1.75	2.13	2.60	2.95
16	1.34	1.75	2.12	2.58	2.92
17	1.33	1.74	2.11	2.57	2.90
18	1.33	1.73	2.10	2.55	2.88
19	1.33	1.73	2.09	2.54	2.86
20	1.33	1.72	2.09	2.53	2.85

# The Last Example Done Easily

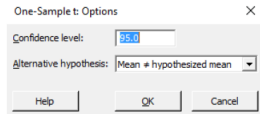


Under options, you need to tell Minitab what  $H_A$  is so it knows what area it is finding.

## One-Sample T

Test of  $\mu = 3.683$  vs  $\neq 3.683$

N	Mean	StDev	SE Mean	95% CI	T	P
20	3.800	0.500	0.112	(3.566, 4.034)	1.05	0.308



Set a one-sided  $H_A$  on this screen, if that is the case

# What Assumptions Must We Meet to Use $t$ -Distributions?

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When doing statistical inference (using CIs or hypothesis testing), you rely on the shape and SE of the sampling distribution. To get these to be correct, you must have:

**Independence of data:** Knowing one piece of data should not help you predict other data. Since this is hard to check, this is usually replaced with the:

- Randomization Condition
- $< 10\%$  Condition

**Population distribution must be nearly normal.** Since this is hard to check:

- Look for near normality in the histogram of your sample (or its qq-plot).
- More skew is OK as  $n$  gets larger.

# Beetle Study

We study beetle biodiversity in a pasture. For this, we collect a biodiversity index (Steinhaus index) in 12 parcels and get the following data:

$$\bar{x} = 0.2505 \text{ and } s_x = 0.0959.$$

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An environmental engineer, specialist of beetle populations, tells you that an average biodiversity index lower than 0.49 in the pasture would be worrying.

Build a test with level of confidence  $\alpha = 5\%$  for determining if the state of the pasture is worrying.



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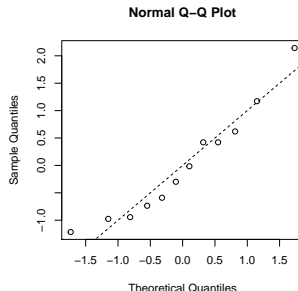
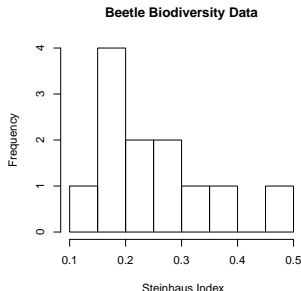
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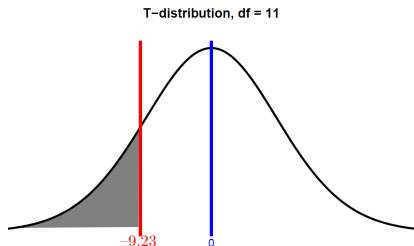
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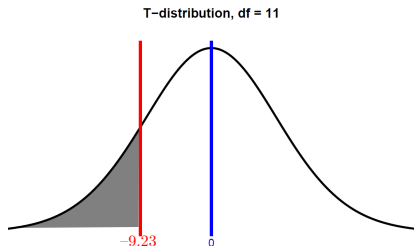


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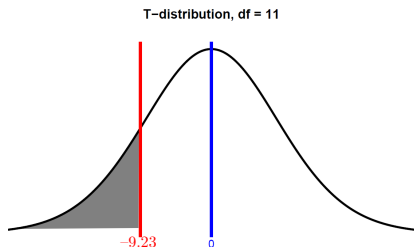
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With Minitab, you find the area under the curve is  $\simeq 8 \times 10^{-7}$ .

Since  $p \simeq 8 \cdot 10^{-7} \ll 0.05$ , we reject  $H_0$  and favor  $H_A$ .

There is (a very) strong evidence that the true average biodiversity index is smaller than 0.49.



# What Can Go Wrong?

There are Four possible scenarios we must think about related to hypothesis testing:

- We reject  $H_0$  when  $H_0$  is actually true
- We do not reject  $H_0$  when  $H_0$  is actually true
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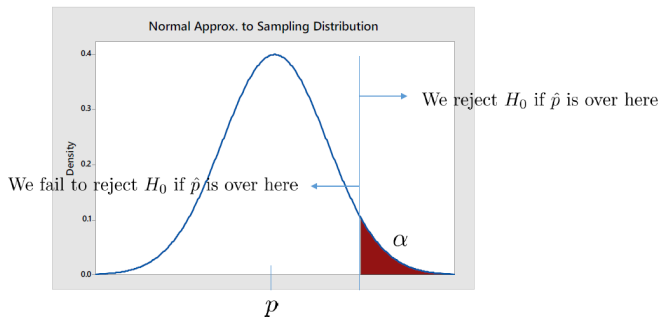
Truth \ Test Conclusion	Do not reject $H_0$	Reject $H_0$
$H_0$ true	OK	Type I Error
$H_A$ true	Type II Error	OK

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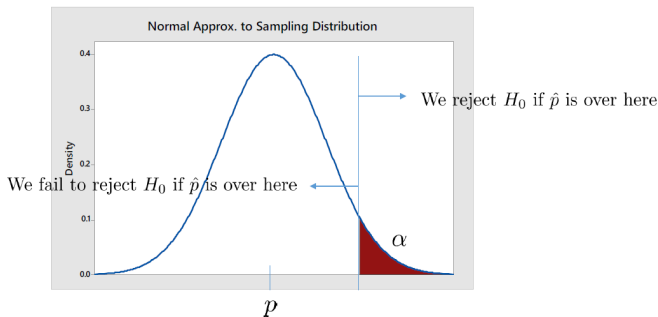
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$$P(\text{Type I error}) = \alpha$$

We reject the null when the  $p$ -value is  $< \alpha$  (say, 0.05). For this to happen,  $\hat{p}$  must be large enough to get the shaded area  $< \alpha$ . Said differently, we need  $\hat{p}$  to be in the top 5% of the data values. This happens with probability  $\alpha$ .

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The **power** of a test is

$$P(\text{Reject } H_0 | H_0 \text{ is false}) = 1 - \beta.$$

You'll learn how to deal with  $\beta$  in more advanced stat classes.

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**Moral:** For most actions,

Type I Error  $\searrow$  when Type II Error  $\nearrow$  (and vice versa).

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A Type I Error would mean the restaurant did meet regulations, but the inspector thought this was not true and shut it down.



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The restaurant owner dislikes Type I because the restaurant is shut down for no reason.

Diners dislike Type II because they are exposed to dangerous conditions.

# Reviewing the Framework: 21 Questions

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If the student has no powers, she will get the correct answer one-fourth of the time. We set  $H_0: p = 0.25$ .



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We eventually look at a sampling distribution, which will be normal if we have at least 10 successes and failures. We expect  $0.25 \times n$  successes, so we need at least  $n \geq 40$  to get adequate successes.

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We got  $\hat{p} = 0.32$ , but sampling variability exists. Some samples of 100 cards would yield results like this, other may not support her claim. We must sort out whether 32% is from sampling variation or not.

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Under the null,

$$\mu(\hat{p}) = p = 0.25 \text{ and } SE(\hat{p}) = \sqrt{pq/n} = \sqrt{0.75 \times 0.25/100} \simeq 0.0433.$$

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Under the null,

$$\mu(\hat{p}) = p = 0.25 \text{ and } SE(\hat{p}) = \sqrt{pq/n} = \sqrt{0.75 \times 0.25/100} \simeq 0.0433.$$

**10.** In words, what will be the  $p$ -value for this situation represent?

**8.** If we drew many samples of size 100, found the proportion of correct guesses of each and plotted these, we would get a sampling distribution (histogram). Why is it approximately normal in this case?

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It is the probability that sample variation gives us the result  $\hat{p} = 0.32$  (or something more extreme) if the null hypothesis is true (that is, if the student is just randomly guessing).



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**12.** Describe two ways to find this  $p$ -value.

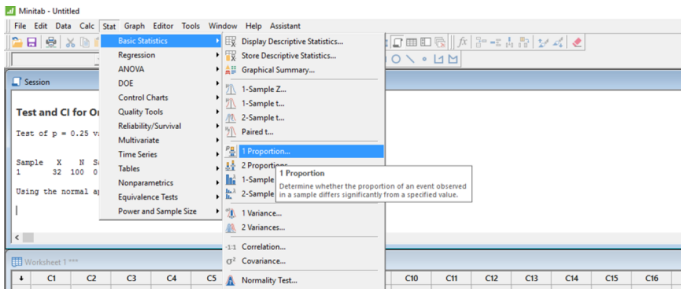
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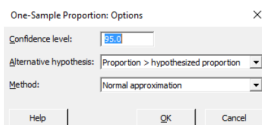
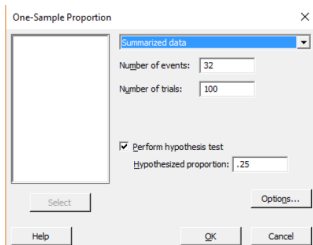
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- We can use Minitab to find the area on the sampling distribution itself,
- or we can convert  $\hat{p}$  to a  $z$ -score and use a table to find the area on the standard normal distribution.

Let's learn a new way to do this!



Minitab allows us to run tests and gives P-values (without drawing areas or showing any of the visual thinking behind the test).



### Test and CI for One Proportion

Test of  $p = 0.25$  vs  $p > 0.25$

Sample	X	N	Sample p	95% Lower Bound	Z-Value	P-Value
1	32	100	0.320000	0.243272	1.62	0.053

Using the normal approximation.

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**14.** This suggests that if we ran the experiment 20 times, one of those times we would expect to get a result like 0.32 (or wilder!). If there were 20 science labs in the country running this experiment, what would happen?

We expect one of them to get a result whose probability is very near the 0.05 significance threshold. They will probably publish a paper saying they found a student with special powers.

If we live in a society that only publishes results with  $p$ -values  $< 0.05$ , then for every published finding, we might expect 19 unpublished findings that found no interesting result.



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**16.** Give some reasons why a 0.05 cutoff is silly.

0.05 is a historical artifact derived from a 1931 book by Fisher (*The Design of Experiments*). He thought a 1 in 20 event might be surprising enough to toss out one's belief system ( $H_0$ ).

In some situations, you might be willing to reject the null hypothesis more or less readily.

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False. The cutoff, or  $\alpha$  level, is decided by the researcher. Values of  $\alpha = 0.05, 0.01, 0.001$  are common.

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True. The phrase “statistically significant” means that the  $p$ -value is less than the  $\alpha$  cutoff.

**Note:** Statistical significance is not the same as **practical significance**. For example, consider an SAT class that raises grades by 0.1% vs. a drug that cures 0.1% more people.

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Find a  $p$ -value! It equals

$$P(\text{our result or something more extreme} | H_0 \text{ is true}).$$

Here, this means  $P(\text{Heads} | H_0) = 0.15$ . We might reject  $H_0$ .

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### 4. What do Type I and Type II Errors mean in context?

	Heads Appears	Tails Appears
$H_0$ is true (unfair coin was flipped)	We think our coin is FAIR Type I Error	We think our coin is UNFAIR
$H_0$ is false (fair coin was flipped)	We think our coin is FAIR.	We think our coin is UNFAIR. Type 2 Error