

# One Sample Hypothesis Testing for Means: Raise What They Raise In Ireland

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# Hypothesis Testing for Means: The Idea

We are going to:

1. form null and alternative hypotheses and gather data.
2. calculate a mean difference (effect).
3. calculate a standard error (sd of the sampling distribution)
4. divide the \_\_\_\_\_ by the \_\_\_\_\_ in order to obtain the test statistic.
5. check the probability of the statistic from #3 occurring.
6. choose to reject or not reject the \_\_\_\_\_ based on this fact.

# The Basic Form of Most Parametric Test Statistics

$$\frac{\textit{Mean Difference or Effect}}{\textit{Standard Error}}$$

I used a whole slide for this thing. You should probably remember it.

# The Research Question

The one-sample mean question often arises when you have previous expectations or a “norm” for comparison.

IO Psychology:

Suppose you are consulting for a factory making gloves for the U. S. Army. You know that the number of flaw-free pairs of gloves an employee can sew in a week is approximately normally distributed with a mean of 800 and a standard deviation of 50 pairs.

Suppose that we want to try to increase productivity by boosting morale. How do we test if the morale-boosting improves or hurts *mean individual productivity*?

# Setting Up the Hypotheses and Alpha

Null:

Alternative (experimental):

Choose a critical alpha level:

# The Central Limit Theorem

In order to answer the research question, we need to know the Central Limit Theorem (CLT).

The CLT states that, for almost any distribution:

If a distribution has a mean  $\mu$  and a standard deviation of  $\sigma$ , the mean of the sampling distribution of the mean for sample size  $N$  will be  $\mu$  with a standard deviation of  $\sigma/\sqrt{N}$ . As  $N$  becomes large, the sampling distribution of the mean will become normal.

The quantity  $\sigma/\sqrt{N}$  is called the \_\_\_\_\_.

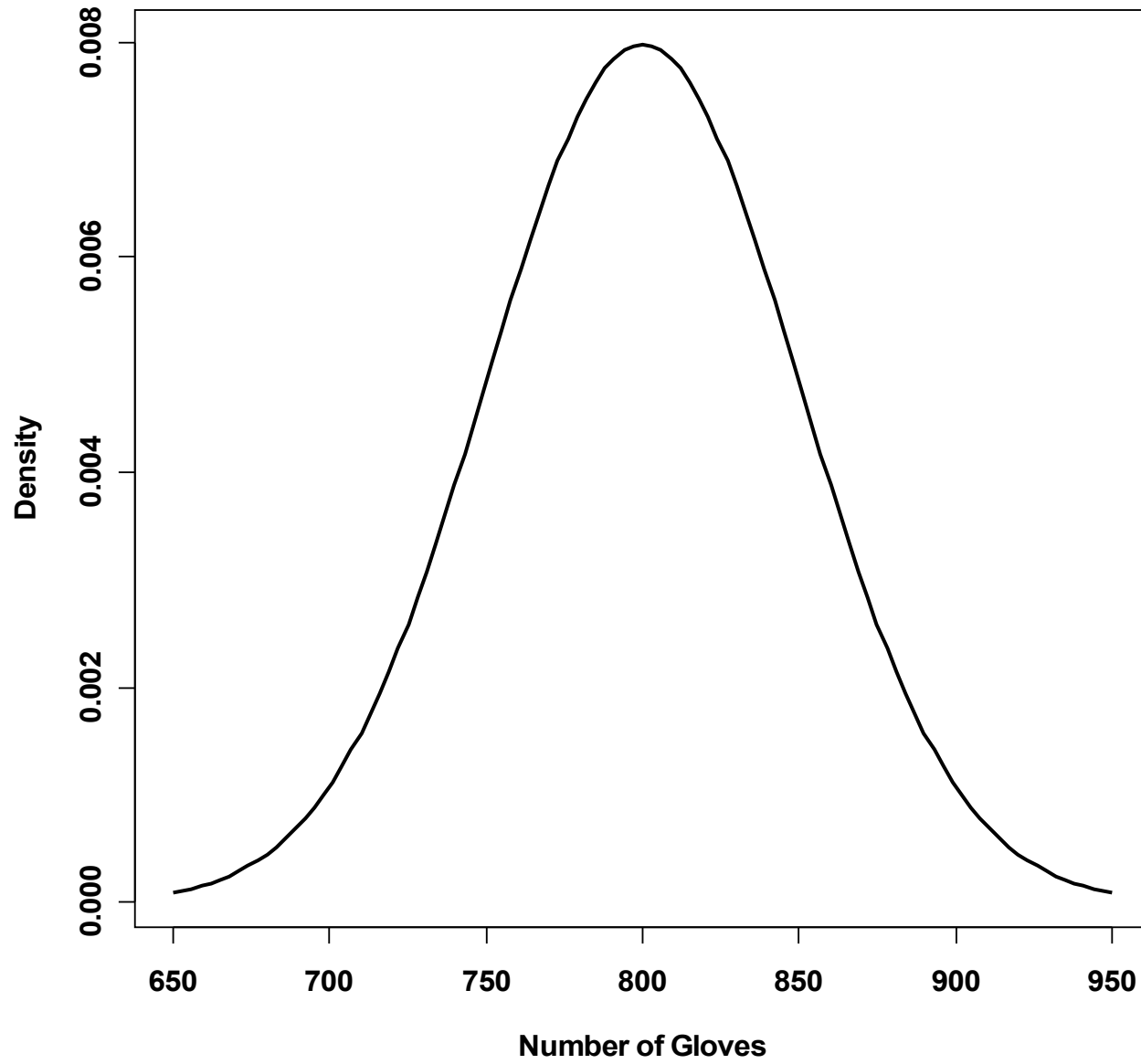
# Back to the Research Question

4 Things that we know:

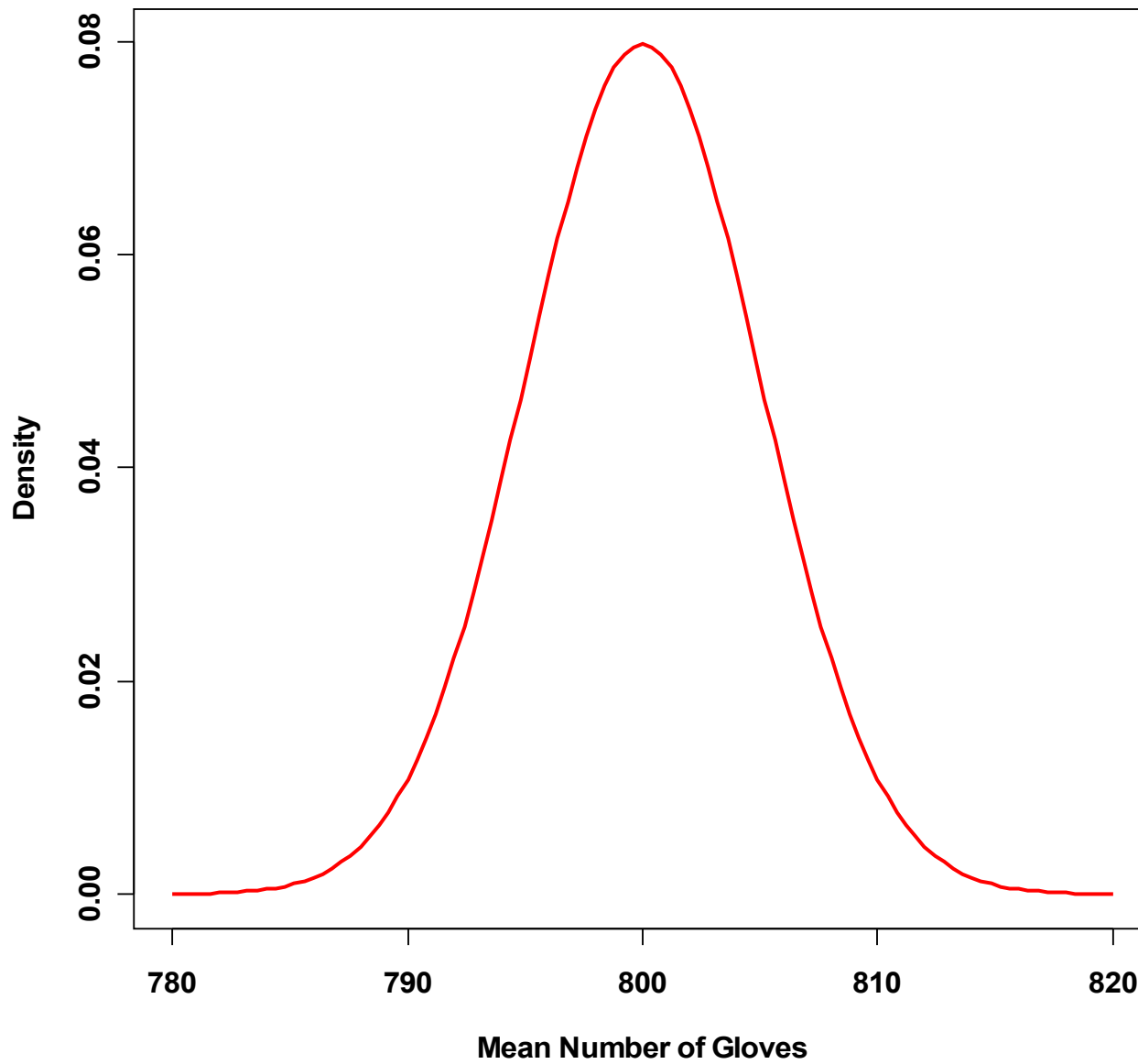
1.  $\mu$  gloves: 800
2.  $\sigma$  gloves: 50
3. The Central Limit Theorem
4. We used the morale-boosting technique on 100 people. They have a mean of 825 pairs with a standard deviation of 100.

How do we test to see if our data are rare given the null (null=population distribution)?

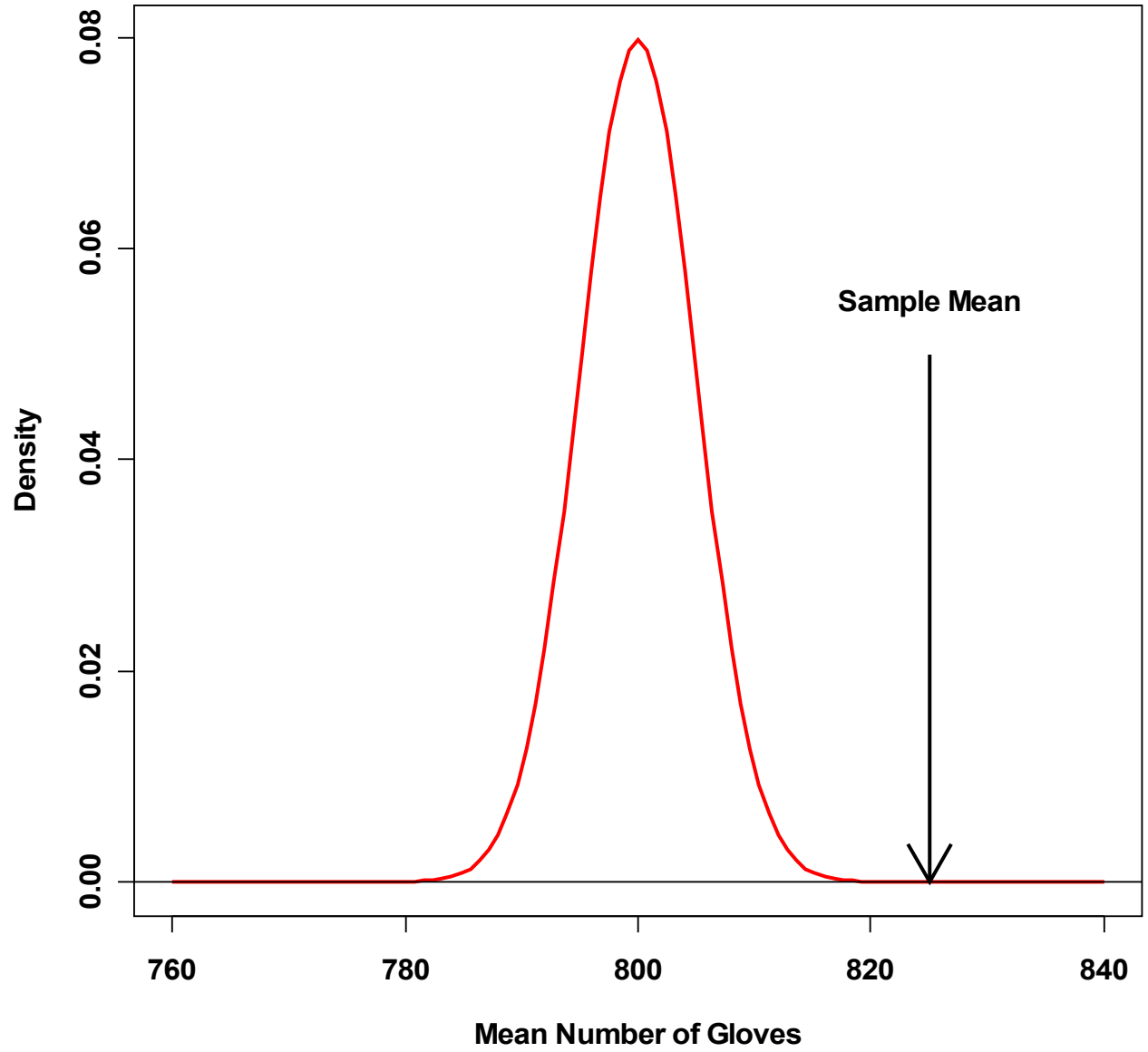
**Population Distribution of Individual Glove Production**



**Population Mean Sampling Distribution of Individual Glove Production, N=100**



### Population Mean Sampling Distribution of Individual Glove Production, N=100



# Back to the Research Question

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Remember the \_\_\_-score...

It's basic form was:

# The z-test

We have a population mean (800). We have a sample mean (825). We have a population standard error ( $50/100^{1/2}$ ). We have everything we need to produce a z-score. H, 286

$$z = \frac{\bar{X} - \mu}{\sigma / \sqrt{N}}$$

where  $\bar{X}$  is the sample mean,  
 $\mu$  and  $\sigma$  are the known population mean and standard deviation  
and  $N$  is sample size.

Calculations here:

*p*-value (area “more extreme” ):

Conclusion and interp. here:

# One-Sample $t$ -test: $\sigma$ Unknown

When you *do not* know  $\sigma$ , the statistic is nearly the same. We just use the \_\_\_\_\_ in place of  $\sigma$ . We also need something called “degrees of freedom”. H, 288 and 546

The one-sample  $t$  statistic ( $t$ ) is

$$t(df) = \frac{\bar{X} - \mu}{s_X / \sqrt{N}}$$

where  $s_X$  is the sample sd and  $df$  is the degrees of freedom.

What does this equation mean? Remember the basic form:

$$\frac{\text{Mean difference or effect}}{\text{Standard Error}}$$

# The $t$ -distribution: Similar to the $z$

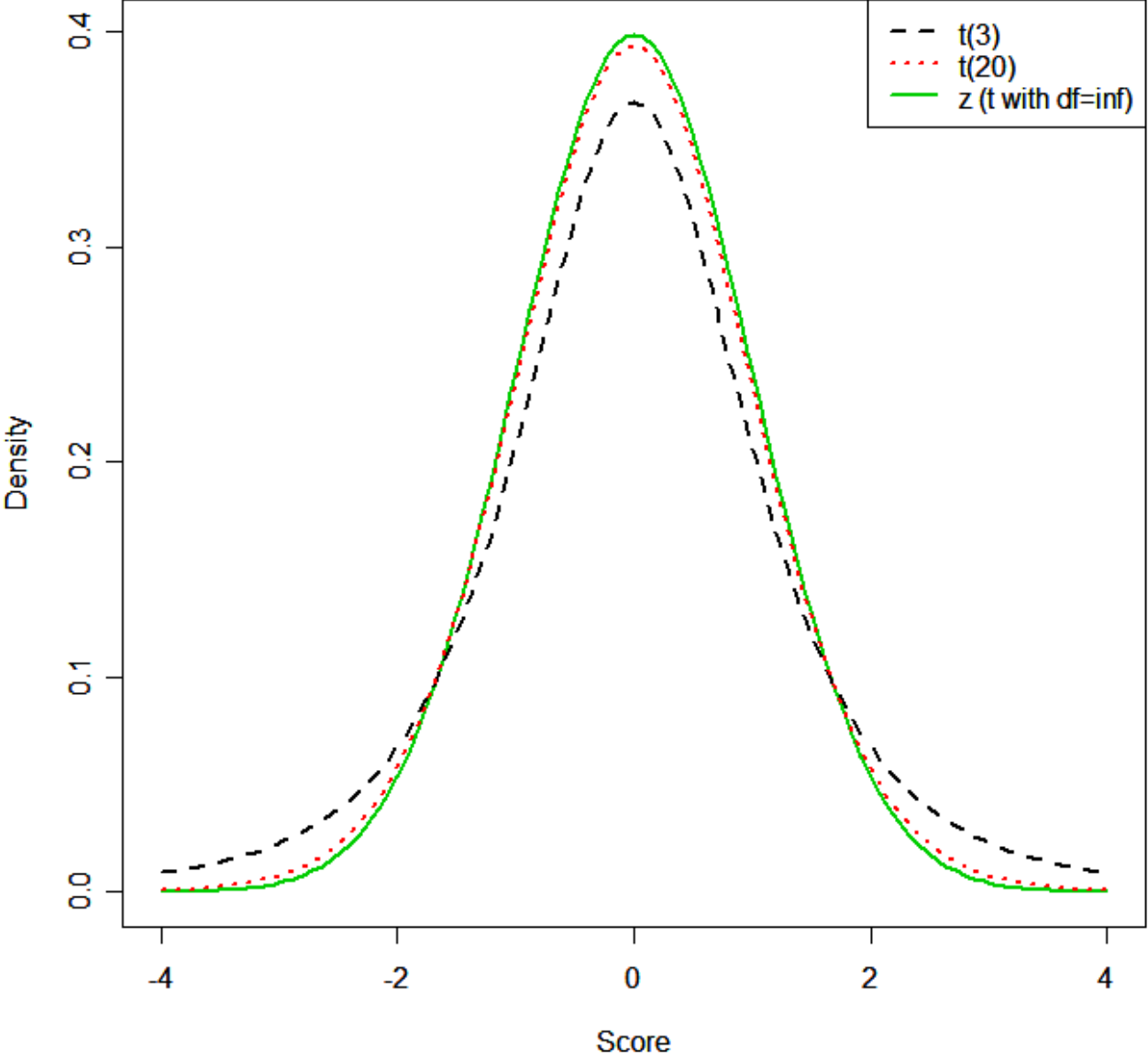
The  $t$ -distributions are like the  $z$ -distribution with \_\_\_\_\_ . This makes  $t$ -tests more conservative for sampling error.

William Gossett published the  $t$  family of distributions while working for Guinness<sup>®</sup> Brewing Company.

When you are working with the  $t$ -distribution, you must know your degrees of freedom (df).

The  $t$ -distribution is not one but *many* distributions. They depend on your sample size. The larger your sample size (df), the more the  $t$ -distribution \_\_\_\_\_ .

Plot of the z and Two t Distributions



# Degrees of Freedom

The df is an indicator of “independent pieces” of information you have when estimating a parameter.

It is generally the number of people that you have ( $N$ ) minus 1 or 2. For the one-sample  $t$ , it is \_\_\_\_\_.

H, 290

Example of degrees of freedom:

Suppose that we know the mean of the following 5 numbers is 3. The numbers are 2, 3, 4, 5, and  $x$ . What *must*  $x$  be?

We have \_\_\_\_\_ degrees of freedom in the estimation of the mean.

# One-Sample $t$ -test: $\sigma$ Unknown

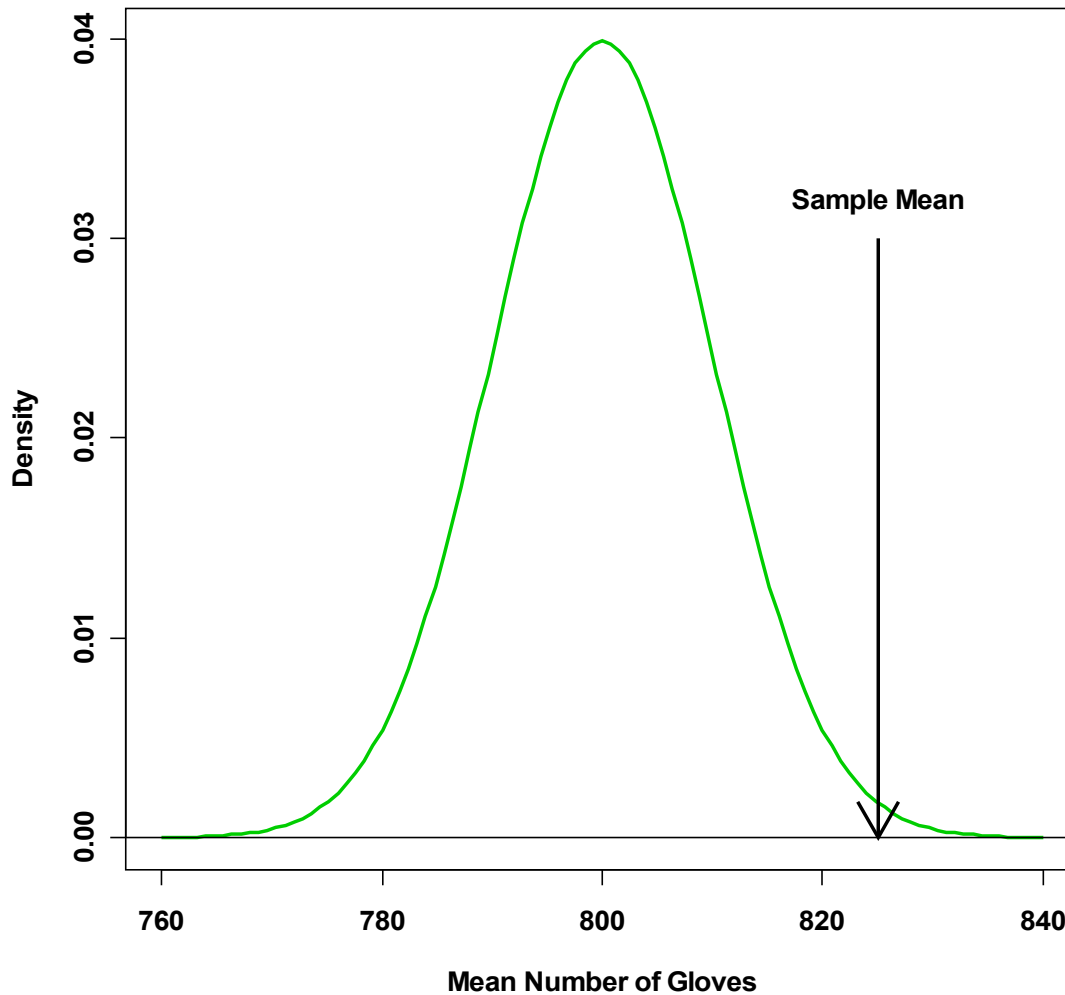
Previous question: You know that the number of pairs of flaw-free pairs of gloves an employee can sew in a week is approximately normally distributed with a mean of 800. **You do not know the population  $\sigma$ .** You do your morale thing, and the 100 lucky people have a mean of 825 with  $s_X = 100$ .

$$t(df) = \frac{\bar{X} - \mu}{s_X / \sqrt{N}}$$

Calculations:

Conclusion:

Mean Sampling Distribution of Glove Production  
Estimated from the Sample SD, N=100



The estimated sampling distribution of the mean is wider because the sample SD was greater than  $\sigma$  (when we knew it).

# Effect Size

There are two types of effect sizes in the  $t$ -test situation: unstandardized and standardized.

Standardized: Divide the mean difference by the standard deviation you use. It's similar to a  $z$ -score.

H, 295

Unstandardized: Simply the \_\_\_\_\_.

The unstandardized effect is good if your units of measurement are well known or meaningful in many contexts. What are some examples of well known units?

# Confidence Intervals

We need a *range* that is a reasonable guess for the value of a parameter. H, 296-297. Howell gives us b.s. on pages 298-299. Basic form of all confidence intervals:

$$C.I. = \textit{statistic} \pm \textit{crit. value} \times \textit{standard error}$$
$$\approx \textit{statistic} \pm 2 \times \textit{standard error}$$

95% Confidence Interval around a single mean using a *t*-value.

Sample Mean = 50    S. Dev = 12    N = 145    *df* =

Critical *t*-value = \_\_\_\_\_

Calculations go here:

Remember to always use the 2-tailed value. Confidence intervals are of VITAL IMPORTANCE to modern statistics!

# Applets to Visualize Concepts

## Confidence Intervals

[http://www.ruf.rice.edu/~lane/stat\\_sim/conf\\_interval/index.html](http://www.ruf.rice.edu/~lane/stat_sim/conf_interval/index.html)

## Sampling Distributions of the Mean

[http://wise.cgu.edu/sdmmod/sdm\\_applet.asp](http://wise.cgu.edu/sdmmod/sdm_applet.asp)

## Online $p$ -value calculator

<http://www.graphpad.com/quickcalcs/PValue1.cfm>

or just do a Google search for “ $p$ -value calculator”

Critical values from  $p$ -values (good for confidence intervals)

<http://www.graphpad.com/quickcalcs/Statratio1.cfm>