Recall that the mean of a random sample of size *n* from a $N(\mu, \sigma)$ population also has a normal distribution:

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More often than not, in practice we cannot assume that we know σ .

Since we need to come up with some estimate of the population standard deviation, one approach is to simply use the sample standard deviation s in place of the population standard deviation σ .

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While this seems innocent enough, the situation is much more complicated because s is a random variable while σ is a constant.

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Recall that a sum of the squares of standard normal random variables has a distribution called *Chi-square* with a parameter called the "degrees of freedom" that is the number of independent random variables squared and summed.

As it turns out, s^2/n has a Chi-square distribution with n-1 degrees of freedom.

This means that the random variable T is the ratio of a normal random variable to the square root of an (independent) Chi-square random variable:

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$$\Gamma = \frac{\overline{x} - \mu}{s/\sqrt{n}}$$

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The t distribution was known for many years as "student's t distribution".

The *t* distribution appears in Table A5 in the text, although we will generally use a computer.

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Directions for obtaining thresholds for the t distribution for two-tailed and one-tailed regions are documented in the technology pages (linked from the web page).

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Note carefully that spreadsheets implement the *t* distribution functions *TDIST* and *TINV* differently from *NORMDIST* and *NORMINV*.

The t distribution values can also be obtained using R.

Unlike spreadsheets, R is consistent in its implementation across distributions.

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Numerical values for a t distribution with n degrees of freedom:

 $P(X \le x) \qquad \qquad pt(x, n)$

x such that $P(X \le x) = q)$ qt(x, n)

The two-sided $100(1 - \alpha)\%$ confidence interval when both the mean and standard deviation are estimated from the sample is based on:

- the sample mean \overline{x}
- \bullet the sample standard deviation s
- then sample size n
- the value of α

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The lower and upper limits of the two-sided confidence interval are:

Lower limit
$$\overline{x} + qt(\alpha/2, n-1) \cdot s/\sqrt{n}$$

Upper limit $\overline{x} + qt(1 - \alpha/2, n-1) \cdot s/\sqrt{n}$

The upper one-sided $100(1 - \alpha)\%$ confidence interval when both the mean and standard deviation are estimated from the sample is:

Lower limit $-\infty$ Upper limit $\overline{x} + qt(1 - \alpha, n - 1) \cdot s/\sqrt{n}$

The upper one-sided $100(1 - \alpha)\%$ confidence interval when both the mean and standard deviation are estimated from the sample is:

Lower limit $-\infty$ Upper limit $\overline{x} + qt(1 - \alpha, n - 1) \cdot s/\sqrt{n}$

The lower one-sided $100(1 - \alpha)\%$ confidence interval when both the mean and standard deviation are estimated from the sample is:

Lower limit $\overline{x} + qt(\alpha, n-1) \cdot s/\sqrt{n}$ Upper limit ∞

A random sample of 100 students have their heights measured. If the average score is 69.3 inches with a sample standard deviation of 3.4, construct a two-sided 95%confidence interval for the mean height of students.

A random sample of 100 students have their heights measured. If the average score is 69.3 inches with a sample standard deviation of 3.4, construct a two-sided 95%confidence interval for the mean height of students.

In this case, $\alpha = .05$, n = 100, $\overline{x} = 69.3$ and s = 3.4. Since we have no reason to assume we know the standard deviation of heights, we will use a *t* distribution to construct the confidence interval.

A random sample of 100 students have their heights measured. If the average score is 69.3 inches with a sample standard deviation of 3.4, construct a two-sided 95%confidence interval for the mean height of students.

In this case, $\alpha = .05$, n = 100, $\overline{x} = 69.3$ and s = 3.4. Since we have no reason to assume we know the standard deviation of heights, we will use a *t* distribution to construct the confidence interval.

Lower limit $\overline{x} + qt(\alpha/2, n-1) \cdot s/\sqrt{n}$ Lower limit 69.3 + qt(.025, 99) * 3.4/10 = 68.625Upper limit $\overline{x} + qt(1 - \alpha/2, n-1) \cdot s/\sqrt{n}$ Upper limit 69.3 + qt(0.975, 99) * 3.4/10 = 69.975

The speed of 250 cars in the right hand lane of an interstate highway is measured with radar. If the average speed is 60.2mph and the sample standard deviation is 5.3, construct a 99% confidence interval for the mean vehicle speed.

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In this case, $\alpha = .01$, n = 250, $\overline{x} = 60.2$ and s = 5.3. Since we have no reason to assume we know the true standard deviation of speeds, we will use a *t* distribution to construct the confidence interval.

The speed of 250 cars in the right hand lane of an interstate highway is measured with radar. If the average speed is 60.2mph and the sample standard deviation is 5.3, construct a 99% confidence interval for the mean vehicle speed.

In this case, $\alpha = .01$, n = 250, $\overline{x} = 60.2$ and s = 5.3. Since we have no reason to assume we know the true standard deviation of speeds, we will use a *t* distribution to construct the confidence interval.

Lower limit $\overline{x} + qt(\alpha/2, n-1) \cdot s/\sqrt{n}$ Lower limit $60.2 + qt(.005, 249) * 5.3/\sqrt{250}=59.330$ Upper limit $\overline{x} + qt(1 - \alpha/2, n-1) \cdot s/\sqrt{n}$ Upper limit $60.2 + qt(0.995, 99) * 5.3/\sqrt{250}=61.070$

Viscosity of oil from 50 test vehicles after 10,000 miles of driving averaged 43.1 with a standard deviation of 10.3. Find a two-sided 95% confidence interval for the mean viscosity of oil after 10,000 miles.

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Download the spreadsheet from the Technology Page in the section:

- Confidence Intervals for Population Means
- Sigma unknown

A sample of 80 lobsters caught in Narragansett Bay averaged 12.4 ounces in weight with a standard deviation of 3.1. Find a two-sided 99% confidence interval for the mean weight of lobsters in Narragansett Bay.

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Download the spreadsheet from the Technology Page in the section:

- Confidence Intervals for Population Means
- Sigma unknown

Now we will perform a simulation experiment in which we:

- generate random samples of size 10 from a normal population with known mean and standard deviation
- construct $100(1 \alpha)\%$ confidence intervals for each sample as if we knew sigma
- use the sample standard deviation in place of the true population standard deviation
- determine the proportion of these intervals that contain the true population mean

Now we will perform a simulation experiment in which we:

- generate random samples of size 10 from a normal population with known mean and standard deviation
- construct $100(1 \alpha)\%$ confidence intervals for each sample as if we knew sigma
- use the sample standard deviation in place of the true population standard deviation
- determine the proportion of these intervals that contain the true population mean

Naturally, we expect that approximately $100(1 - \alpha)$ percent of the intervals will contain the true mean.

Starting with a blank spreadsheet, enter the following values:

| Value | Cell Address |
|-------|--------------|
| ALPHA | A1 |
| 0.05 | B1 |
| MU | C1 |
| 10 | D1 |
| SIGMA | E1 |
| 3 | F1 |

Starting with a blank spreadsheet, enter the following values:

Value Cell Address

| ALPHA | A1 |
|-------|----|
| 0.05 | B1 |
| MU | C1 |
| 10 | D1 |
| SIGMA | E1 |
| 3 | F1 |

Now carefully enter the following in cell H3:

```
=NORMINV(RAND(),$D$1,$F$1)
```

Starting with a blank spreadsheet, enter the following values:

| Value C | Cell Address |
|---------|--------------|
|---------|--------------|

| ALPHA | A1 |
|-------|----|
| 0.05 | B1 |
| MU | C1 |
| 10 | D1 |
| SIGMA | E1 |
| 3 | F1 |

Now carefully enter the following in cell H3:

```
=NORMINV(RAND(),$D$1,$F$1)
```

This generates a $N(\mu, \sigma)$ random variable.

Now replicate cell H3 horizontally 9 times, filling cells I3-Q3.

This gives us a simulated random sample of size n = 10 from a $N(\mu, \sigma)$ population.

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This gives us a simulated random sample of size n = 10 from a $N(\mu, \sigma)$ population.

Now carefully enter the following in cell G_3 :

=AVERAGE(H3:Q3)

This computes the sample mean \overline{x} .

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This gives us a simulated random sample of size n = 10 from a $N(\mu, \sigma)$ population.

Now carefully enter the following in cell G_3 :

=AVERAGE(H3:Q3)

This computes the sample mean \overline{x} .

Now carefully enter the following in cell *F*3: =STDEV(H3:Q3)

Now carefully enter the following in cell *B*3:

=NORMINV(\$B\$1/2,G3,F3/SQRT(10))

This gives us the lower limit of the $100(1 - \alpha)\%$ confidence interval for μ .

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=NORMINV(\$B\$1/2,G3,F3/SQRT(10))

This gives us the lower limit of the $100(1 - \alpha)\%$ confidence interval for μ .

Now carefully enter the following in cell C3:

=NORMINV(1-\$B\$1/2,G3,F3/SQRT(10))

This gives us the upper limit of the $100(1 - \alpha)\%$ confidence interval for μ .

All that remains is to set up a counter. Enter the following in cell A3:

```
=IF(AND(B3<$D$1,$D$1<C3),1,0)
```

This will code a value of one if the true population mean, in cell D1, lies in the confidence interval, and a value of zero if it does not.

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```
=IF(AND(B3<$D$1,$D$1<C3),1,0)
```

This will code a value of one if the true population mean, in cell D1, lies in the confidence interval, and a value of zero if it does not.

Of course we need more than one trial. Replicate cells A3 - N3 down to row 1003.

Finally, set up a count of the number of ones in column A: In cell A2, enter:

=SUM(A3:A1002)

Finally, set up a count of the number of ones in column A: In cell A2, enter:

```
=SUM(A3:A1002)
```

The result should be **lower** than the expected $1000(1 - \alpha)$

This illustrates that we need to use the t distribution when the sample size is small and the standard deviation is estimated from the sample.