Unit 4: Inference for numerical data

1. Inference using the *t*-distribution

GOVT 3990 - Spring 2018

Cornell University

Outline

1. Main ideas

- 1. T corrects for uncertainty introduced by plugging in s for σ
- 2. When comparing means of two groups, details depend on paired or independent
 - 3. All other details of the inferential framework is the same...

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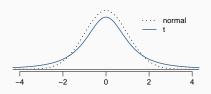
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 - We make up for this by using a more "conservative" distribution than the normal distribution.
- ► *t*-distribution also has a bell shape, but its tails are *thicker* than the normal model's
 - Observations are more likely to fall beyond two SDs from the mean than under the normal distribution.
 - Extra thick tails help mitigate the effect of a less reliable estimate for the standard error of the sampling distribution.



1

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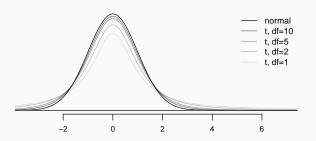
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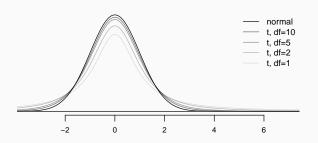
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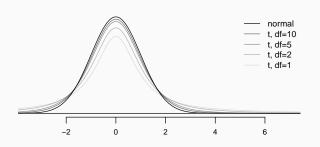
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Why?

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Example 1: Zinc in water

Trace metals in drinking water affect the flavor and an unusually high concentration can pose a health hazard. Ten pairs of data were taken measuring zinc concentration in bottom water and surface water at 10 randomly sampled locations.

Location	bottom	surface
1	0.43	0.415
2	0.266	0.238
3	0.567	0.39
4	0.531	0.41
5	0.707	0.605
6	0.716	0.609
7	0.651	0.632
8	0.589	0.523
9	0.469	0.411
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Water samples collected at the same location, on the surface and in the bottom, cannot be assumed to be independent of each other, hence we need to use a *paired* analysis.

Source: https://onlinecourses.science.psu.edu/stat500/node/51

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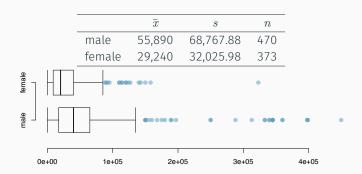
The Beginning of the End of the Census?

"This is a program that intrudes on people's lives, just like the Environmental Protection Agency or the bank regulators," said Daniel Webster, a first-term Republican congressman from Florida who sponsored the relevant legislation.

"We're spending \$70 per person to fill this out. That's just not cost effective," he continued, "especially since in the end this is not a scientific survey. It's a random survey."

In fact, the randomness of the survey is precisely what makes the survey scientific, statistical experts say.

Since 2005, the American Community Survey polls \sim 3.5 million households yearly. The following summarizes distribution of salaries of males and females from a random sample of individuals who responded to the 2012 ACS:



How are the two examples different from each other? How are they similar to each other?

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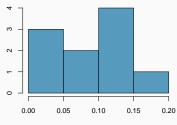
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Location	bottom	surface	difference
1	0.43	0.415	0.015
2	0.266	0.238	0.028
3	0.567	0.39	0.177
4	0.531	0.41	0.121
5	0.707	0.605	0.102
6	0.716	0.609	0.107
7	0.651	0.632	0.019
8	0.589	0.523	0.066
9	0.469	0.411	0.058
10	0.723	0.612	0.111



difference in zinc concentrations (bottom - surface)

Parameter and point estimate for paired data

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► Point estimate: Average difference between the bottom and surface zinc measurements of drinking water from the sampled locations.

 \bar{x}_{diff}

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► Point estimate: Average difference between the average salaries of sampled males and females in the US.

$$\bar{x}_m - \bar{x}_f$$

Standard errors

▶ Dependent (paired) groups (e.g. pre/post weights of subjects in a weight loss study, twin studies, etc.)

$$SE_{\bar{x}_{diff}} = \frac{s_{diff}}{\sqrt{n_{diff}}}$$

► Independent groups (e.g. grades of students across two sections)

$$SE_{\bar{x}_1 - \bar{x}_2} = \sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}$$

ightharpoonup For the same data, $SE_{paired} < SE_{independent}$, so be careful about calling data paired

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One mean:

$$df = n - 1$$

HT:

$$H_0: \mu = \mu_0$$

$$T_{df} = \frac{\bar{x} - \mu}{\frac{s}{\sqrt{x}}}$$

CI:

$$\bar{x} \pm t_{df}^{\star} \frac{s}{\sqrt{n}}$$

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$$df = n - 1$$

$$df = n_{diff} - 1$$

$$\begin{array}{ll} H_0: \mu = \mu_0 & H_0: \mu_{diff} = 0 \\ T_{df} = \frac{\bar{x} - \mu}{\frac{s}{\sqrt{n}}} & T_{df} = \frac{\bar{x}_{diff} - 0}{\frac{s}{\sqrt{n}_{diff}}} \end{array}$$

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$$\bar{\mathbf{x}} \pm \, t_{df}^{\star} \tfrac{s}{\sqrt{n}}$$

$$H_0: \mu_{diff} = 0$$

$$T_{df} = \frac{\bar{x}_{diff} - 0}{\frac{\bar{x}_{diff}}{\sqrt{n_{diff}}}}$$

CI:

$$\bar{x}_{diff} \pm t_{df}^{\star} \frac{s_{diff}}{\sqrt{n_{diff}}}$$

Independent means:

$$df = min(n_1 - 1, n_2 - 1)$$

$$H_0: \mu_1 - \mu_2 = 0$$

$$T_{df} = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}$$

$$\bar{x}_1 - \bar{x}_2 \pm t_{df}^{\star} \sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}$$