

Tests of hypotheses

Confidence interval: Form an interval (on the basis of data) of plausible values for a population parameter.

Test of hypothesis: Answer a yes or no question regarding a population parameter.

- Examples:**
- Do the two strains have the same average response?
 - Is the concentration of substance X in the water supply above the safe limit?
 - Does the treatment have an effect?

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Example

We have a quantitative assay for the concentration of antibodies against a certain virus in blood from a mouse.

We apply our assay to a set of **ten** mice **before and after** the injection of a vaccine. (This is called a “paired” experiment.)

Let X_i denote the differences between the measurements (“after” minus “before”) for mouse i .

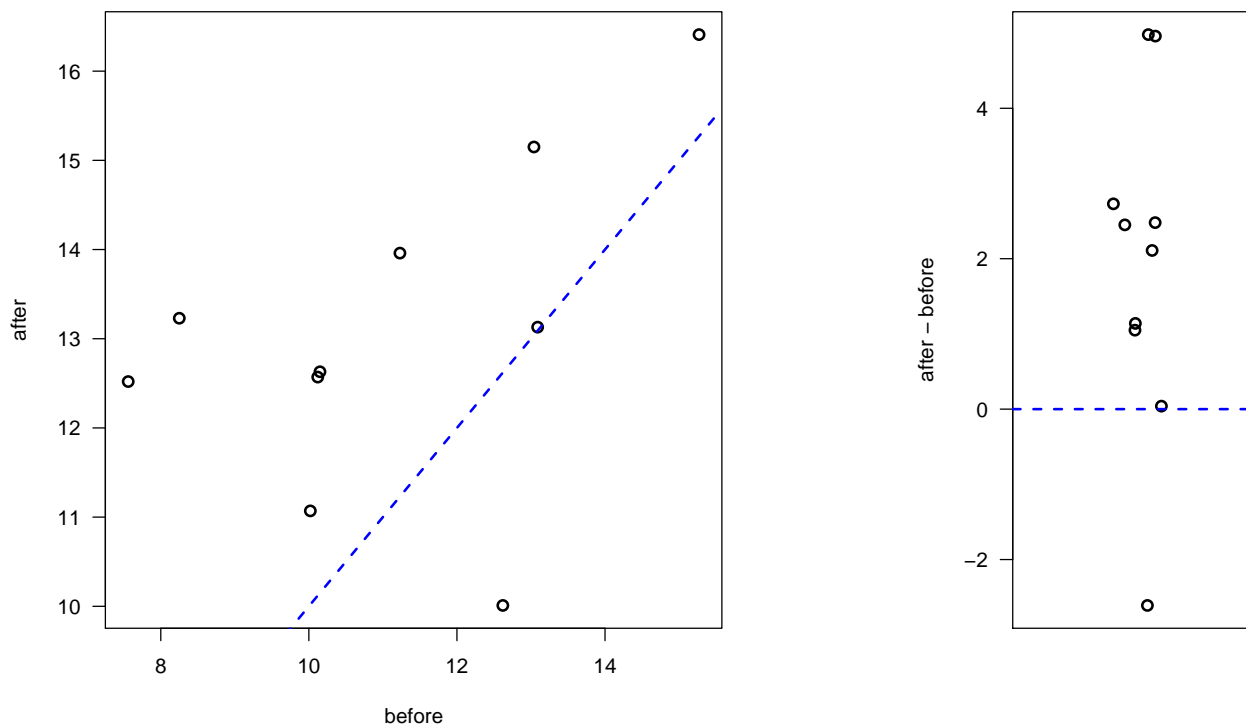
We imagine that the X_i are independent and identically distributed $\text{normal}(\mu, \sigma)$.

Does the vaccine have an effect?

In other words: **Is $\mu \neq 0$?**

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The data



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Hypothesis testing

We consider two hypotheses:

Null hypothesis, $H_0: \mu = 0$

Alt. hypothesis, $H_a: \mu \neq 0$

Type I error: Reject H_0 when it is true. (false positive)

Type II error: Fail to reject H_0 when it is false. (false negative)

We set things up so that a Type I error is a worse error (and so that we are seeking to prove the alternative hypothesis). We want to control the rate (the significance level, α) of such errors.

Test statistic: $T = (\bar{X} - 0)/(s/\sqrt{10})$

We reject H_0 if $|T| > t^*$, where t^* is chosen so that

$$\Pr(\text{Reject } H_0 \mid H_0 \text{ is true}) = \Pr(|T| > t^* \mid \mu = 0) = \alpha.$$

(generally $\alpha = 5\%$)

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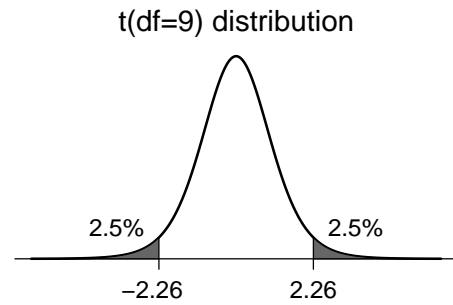
Example (continued)

Under H_0 (i.e., when $\mu = 0$),

$$T = (\bar{X} - 0) / (s / \sqrt{10}) \sim t(df = 9)$$

We reject H_0 if $|T| > 2.26$.

As a result, if H_0 is true, there's a 5% chance that you'll reject it.



For the observed data:

$$\bar{X} = 1.93, s = 2.24, n = 10$$

$$T = (1.93 - 0) / (2.24 / \sqrt{10}) = 2.72$$

Thus we **reject** H_0 .

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The goal

We seek to **prove** the **alternative** hypothesis.

We are **happy** if we **reject** H_0 .

In the case that we reject H_0 , we might say,

“Either H_0 is false, or a rare event occurred.”

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Another example

Question: is the concentration of substance X in the water supply above the safe level?

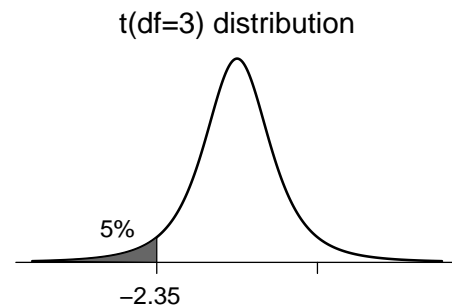
$X_1, X_2, \dots, X_4 \sim \text{iid normal}(\mu, \sigma)$.

Null hyp., $H_0: \mu \geq 6$ (unsafe)

Alt. hyp., $H_a: \mu < 6$ (safe)

Test statistic: $T = \frac{\bar{X} - 6}{s/\sqrt{4}}$

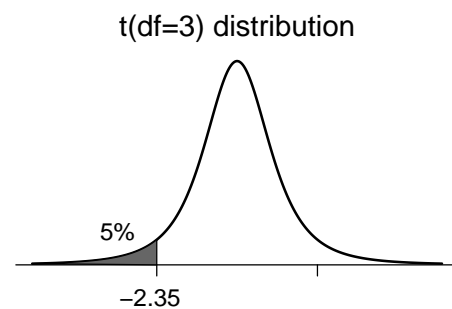
If we wish to have the significance level $\alpha = 5\%$, the rejection region is $T < t^* = -2.35$.



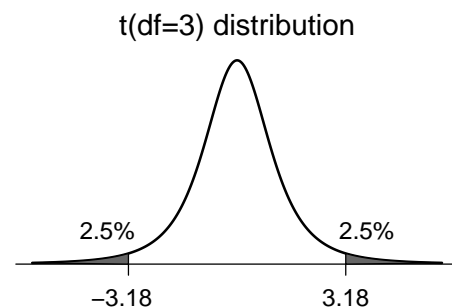
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One-tailed vs two-tailed tests

If you are trying to prove that a treatment **improves** things, you want a **one-tailed** (or one-sided) test. (You'll reject H_0 only if $T < t^*$.)



If you are just looking for a **difference**, use a **two-tailed** (or two-sided) test. (You'll reject H_0 if $T < t^*$ or $T > t^*$.)



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P-values

P-value: smallest significance level (α) for which you would fail to reject H_0 with the observed data.

probability, if H_0 was true, of receiving data as extreme as what was observed.

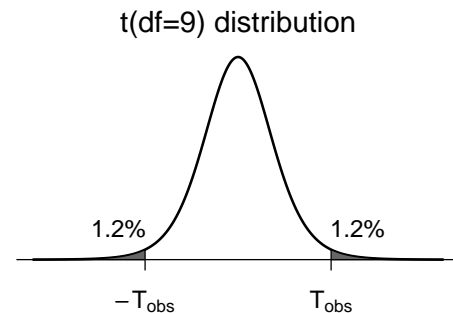
$$X_1, \dots, X_{10} \sim \text{iid normal}(\mu, \sigma)$$

$$H_0: \mu = 0; H_a: \mu \neq 0.$$

Observe: $\bar{X} = 1.93$; $s = 2.24$

$$\text{so } T_{\text{obs}} = \frac{1.93 - 0}{2.24/\sqrt{10}} = 2.72$$

$$\begin{aligned} \text{P-value} &= \Pr(|T| > T_{\text{obs}}) \\ &= 2 * \text{pt}(-2.72, 9) \\ &= 2.4\%. \end{aligned}$$



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Another example

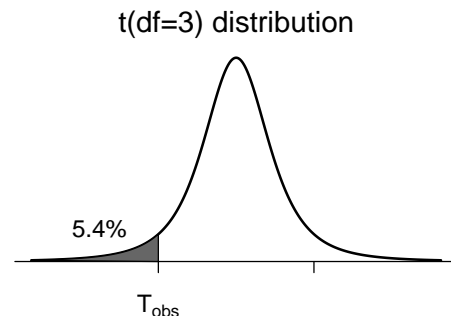
$$X_1, \dots, X_4 \sim \text{normal}(\mu, \sigma)$$

$$H_0: \mu \geq 6; H_a: \mu < 6.$$

Observe: $\bar{X} = 5.51$; $s = 0.43$

$$T_{\text{obs}} = \frac{5.51 - 6}{0.43/\sqrt{4}} = -2.28$$

$$\begin{aligned} \text{P-value} &= \Pr(T < T_{\text{obs}} \mid \mu = 4) \\ &= \text{pt}(-2.28, 3) = 5.4\%. \end{aligned}$$



The P-value is (roughly) a measure of evidence against the null hypothesis.

Recall: We want to prove the alternative hypothesis (i.e., reject H_0 ; i.e., receive a small P-value)

Hypothesis tests and confidence intervals

The 95% confidence interval for μ is the set of values, μ_0 , such that the null hypothesis $H_0 : \mu = \mu_0$ **would not be rejected** (by a two-sided test with $\alpha = 5\%$).

The 95% CI for μ is the set of plausible values of μ .

If a value of μ is plausible, then as a null hypothesis, it would not be rejected.

For example: 9.98 9.87 10.05 10.08 9.99 9.90

(assumed iid normal(μ, σ).)

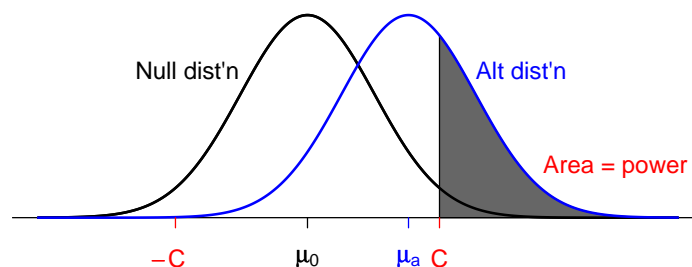
$$\bar{X} = 9.98; s = 0.082; n = 6 \quad \text{qt}(0.975, 5) = 2.57$$

$$\begin{aligned} 95\% \text{ CI for } \mu &= 9.98 \pm 2.57 \cdot 0.082 / \sqrt{6} \\ &= \mathbf{9.98 \pm 0.086 = (9.89, 10.06)} \end{aligned}$$

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Power

The **power** of a test = $\Pr(\text{reject } H_0 \mid H_0 \text{ is false})$.



The power depends on:

- The null hypothesis and test statistic
- The sample size
- The true value of μ
- The true value of σ

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Why “fail to reject”?

If the data are insufficient to reject H_0 , we say,

“The data are insufficient to reject H_0 .”

We shouldn't say, “We have **proven** H_0 .”

Why? We have very low power to detect similar alternatives. We may have low power to detect anything but extreme differences.

We control the rate of **type I errors** (“false positives”) at 5% (or whatever), but we have little or no control over the rate of **type II errors**.

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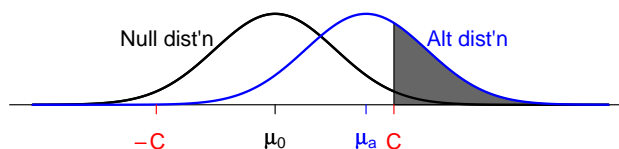
The effect of sample size

Let X_1, \dots, X_n be iid normal(μ, σ).

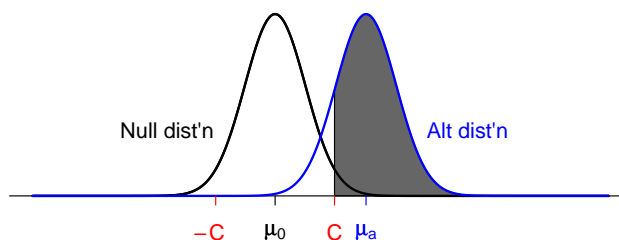
We wish to test $H_0 : \mu = \mu_0$ vs $H_a : \mu \neq \mu_0$.

Imagine $\mu = \mu_a$.

$n = 4$



$n = 16$



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Testing the difference between two means

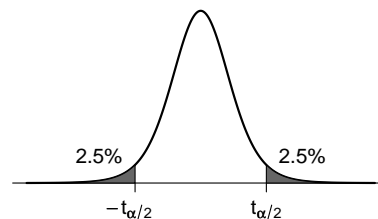
Strain A: $X_1, \dots, X_n \sim \text{iid normal}(\mu_A, \sigma_A)$

Strain B: $Y_1, \dots, Y_m \sim \text{iid normal}(\mu_B, \sigma_B)$

Test $H_0 : \mu_A = \mu_B$ vs $H_a : \mu_A \neq \mu_B$

Test statistic: $T = \frac{\bar{X} - \bar{Y}}{\sqrt{\frac{s_A^2}{n} + \frac{s_B^2}{m}}}$

Reject H_0 if $|T| > t_{\alpha/2}$



If H_0 is true, then T follows (approximately) a **t distr'n with k d.f.**
(k according to the nasty formula from the last lecture)

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Example

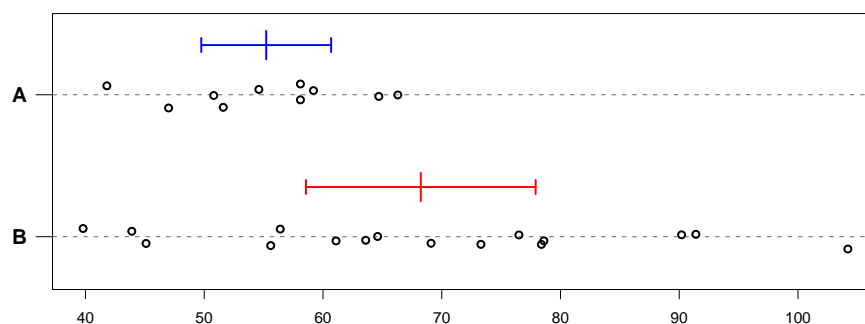
Strain A: $n=10$; $\bar{X}=55.2$; $s_A=7.64$

Strain B: $m=16$; $\bar{Y}=68.2$; $s_B=18.14$

$$\bar{X} - \bar{Y} = -13.0 \quad \widehat{SD}(\bar{X} - \bar{Y}) = \sqrt{7.64^2/10 + 18.1^2/16} = 5.14$$

$$T = -13.0 / 5.14 = -2.53 \quad k = \dots = 21.8$$

$$\text{P-value} = 2 * \text{pt}(-2.53, 21.8) = 1.9\%.$$



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Cite CIs as well as P-values

Example 1: 95% CI for $\mu_A - \mu_B = (-23.7, -2.4)$

P-value for test of $\mu_A = \mu_B = 1.9\%$.

Example 2: 95% CI for $\mu_A - \mu_B = (-1.84, -0.16)$

P-value for test of $\mu_A = \mu_B = 2.2\%$.

The P-value is just one number, and only says so much.

The confidence interval contains much more information.

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Summary

- **Tests of hypotheses** = answering yes/no questions regarding population parameters
- Two kinds of errors:
 - Type I: Reject H_0 when it is true
 - Type II: Fail to reject H_0 when it is false
- We seek to **reject** the null hypothesis
- If we fail to reject H_0 , we **don't** “accept H_0 .”
- **P-value** = probability, if H_0 is true, of obtaining data as extreme as was observed: **Pr(data | no effect) rather than** Pr(no effect | data)
- **Power** = probability of rejecting H_0 when it is false.
- Always look at the **confidence interval** as well as the P-value

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