

## Slides 11: t-tests

- t-distributions
- Exact confidence interval for  $\mu$
- Exact confidence interval for  $\sigma$
- One sample t-test
- Two sample t-test

**The risk to a quality  
test result comes from  
very small samples;  
not from a sample  
that's too large.**

## Exact confidence interval for the mean

In this special case, when a random sample  $(x_1, \dots, x_n)$  is taken from a normal distribution  $N(\mu, \sigma)$ ,

$$\frac{\bar{X} - \mu}{S/\sqrt{n}} \sim t_{n-1}$$

has the so-called t-distribution with  $n - 1$  degrees of freedom. This implies an exact  $100(1 - \alpha)\%$  confidence interval

$$I_\mu = \bar{x} \pm t_{n-1}\left(\frac{\alpha}{2}\right) \cdot \frac{s}{\sqrt{n}}$$

For example,

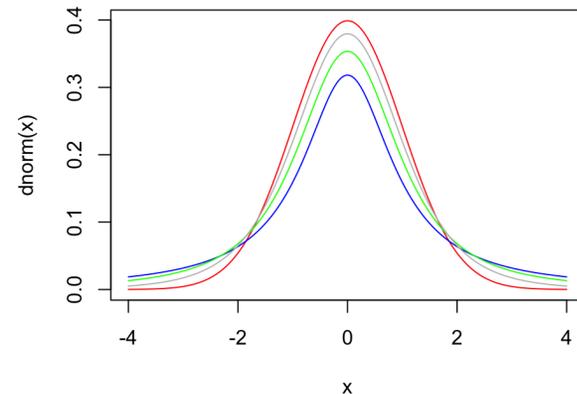
$$t_{10}(0.025) = 2.23,$$

$$t_{20}(0.025) = 2.09,$$

$$t_{30}(0.025) = 2.04$$

A  $t_k$ -distribution curve looks similar to  $N(0,1)$ -curve being symmetric around zero.

If  $k \geq 3$ , then the variance is  $\frac{k}{k-2}$ .



t-distribution curves with  $df = 1, 2, 5, \infty$

## Exact confidence interval for $\sigma$

If  $Z, Z_1, \dots, Z_k$  are  $N(0,1)$  and independent, then

$$\frac{Z}{\sqrt{(Z_1^2 + \dots + Z_k^2)/k}} \sim t_k.$$

Moreover, in the  $N(\mu, \sigma)$  case we get access to an exact confidence interval formula for the variance thanks to the following result.

Exact distribution  $\frac{(n-1)S^2}{\sigma^2} \sim \chi_{n-1}^2$

Exact  $100(1 - \alpha)\%$  confidence interval

$$I_\sigma = \left( c\left(\frac{\alpha}{2}\right)s, c\left(1 - \frac{\alpha}{2}\right)s \right)$$

where  $c^2(p) = \frac{n-1}{\chi_{n-1}^2(p)}$ . Examples of 95% confidence intervals

$$I_\sigma = (0.69s, 1.82s) \text{ for } n = 10,$$

$$I_\sigma = (0.74s, 1.55s) \text{ for } n = 16,$$

$$I_\sigma = (0.78s, 1.39s) \text{ for } n = 25,$$

$$I_\sigma = (0.85s, 1.22s) \text{ for } n = 60.$$

For the normal model,  $\text{Var}(S^2) = \frac{2\sigma^4}{n-1}$ , standard error for  $s^2$  is  $\sqrt{\frac{2}{n-1}}s^2$ .

## One sample t-test

We wish to test  $H_0: \mu = \mu_0$  against either the two-sided or a one-sided alternative. One-sample t-test is used for small  $n$ , under the assumption that the population distribution is normal. The t-test statistic

$$t = \frac{\bar{x} - \mu_0}{s/\sqrt{n}}, \quad T \stackrel{H_0}{\sim} t_{n-1}.$$

### Example: Smoking and platelet aggregation

$n = 11$  paired observations  $(x_i, y_i)$  before and after smoking

(25, 27); (25, 29); (27, 37); (28, 43); (30, 46); (44, 56); (52, 61); (53, 57); (53, 80); (60, 59); (67, 82)

Assuming that the population distribution for the differences  $d_i = x_i - y_i$  is normal, we test

$$H_0: \mu_1 - \mu_2 = 0 \text{ against } H_1: \mu_1 - \mu_2 \neq 0.$$

using the one-sample t-test. The observed test statistic value

$$t_{\text{obs}} = \frac{\bar{d}}{s_d/\sqrt{n}} = \frac{10.27}{2.40} = 4.28$$

gives two-sided p-value  $2 * (1 - \text{pt}(4.28, 10)) = 0.0016$ .

## Two sample t-test

Two independent random samples  $(x_1, \dots, x_n)$  and  $(y_1, \dots, y_m)$  from two populations. The key assumption for the two-sample t-test:

Two normal population distributions  $X \sim N(\mu_1, \sigma)$ ,  $Y \sim N(\mu_2, \sigma)$ .

In other words, there is a two level main factor plus noise  $N(0, \sigma)$ . The two levels of the main factor are quantified by  $\mu_1$  and  $\mu_2$ .

Define the pooled sample variance by

$$s_p^2 = \frac{\sum_{i=1}^n (x_i - \bar{x})^2 + \sum_{i=1}^m (y_i - \bar{y})^2}{n + m - 2}$$

Note that

$$s_p^2 = \frac{n-1}{n+m-2} \cdot s_1^2 + \frac{m-1}{n+m-2} \cdot s_2^2$$

The pooled sample variance is an unbiased estimate of the variance  $\sigma^2$ :

$$E(S_p^2) = \frac{n-1}{n+m-2} E(S_1^2) + \frac{m-1}{n+m-2} E(S_2^2) = \sigma^2.$$

**Question.** There are  $n + m$  terms in the numerator of  $s_p^2$  but the denominator is  $n + m - 2$ . Why?

## Two sample t-test

In the case of equal variances,

$$\text{Var}(\bar{X} - \bar{Y}) = \text{Var}(\bar{X}) + \text{Var}(\bar{Y}) = \frac{\sigma^2}{n} + \frac{\sigma^2}{m} = \sigma^2 \frac{n+m}{nm},$$

which yields the following expression for the standard error

$$s_{\bar{x}-\bar{y}} = s_p \sqrt{\frac{n+m}{nm}}.$$

Exact distribution  $\frac{(\bar{X}-\bar{Y})-(\mu_1-\mu_2)}{S_p} \cdot \sqrt{\frac{nm}{n+m}} \sim t_{n+m-2}$

Exact confidence interval formula

$$I_{\mu_1-\mu_2} = \bar{x} - \bar{y} \pm t_{n+m-2}\left(\frac{\alpha}{2}\right) \cdot s_p \cdot \sqrt{\frac{n+m}{nm}}.$$

Two sample t-test uses the test statistic  $t = \frac{\bar{x}-\bar{y}}{s_p} \cdot \sqrt{\frac{nm}{n+m}}$  for testing  $H_0: \mu_1 = \mu_2$ . The null distribution of the test statistic is

$$T \sim t_{n+m-2}$$

## Example: iron retention

The data on percentage of iron retained by mice

$$\text{Fe}^{2+}: n = 18, \bar{x} = 9.63, s_1 = 6.69, s_{\bar{x}} = 1.58$$

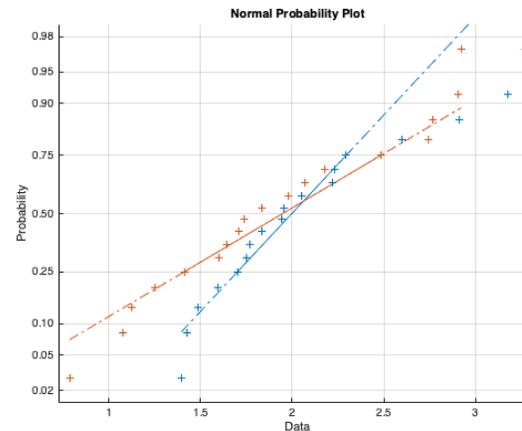
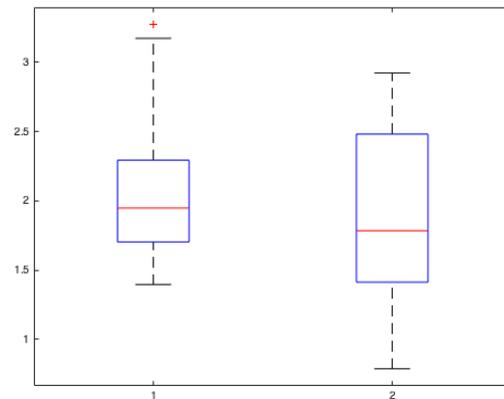
$$\text{Fe}^{3+}: m = 18, \bar{y} = 8.20, s_2 = 5.45, s_{\bar{y}} = 1.28$$

has "iron form" as the main factor with two levels  $\text{Fe}^{2+}$  and  $\text{Fe}^{3+}$ .

The boxplots and normal probability plots show that the distributions are not normal. After the log transformation the data look more like normally distributed

$$\bar{x}' = 2.09, s_1' = 0.659, s_{\bar{x}'} = 0.155,$$

$$\bar{y}' = 1.90, s_2' = 0.574, s_{\bar{y}'} = 0.135.$$



For the log-transformed data we get  $t_{\text{obs}} = 0.917$ ,  $df = 34$ , so that the two-sided p-value = 36.6%.