

## Short review

Let us recall: we have a population characteristic  $X$ , whose pdf  $f(x; \theta)$  depends on  $\theta$ , the target parameter to be estimated. The estimation is done based on a sample of size  $n$ , i.e. sample variables  $X_1, X_2, \dots, X_n$  that are *iid*, with the same pdf as  $X$ .

We set up two hypotheses, the *null* hypothesis, always simple, i.e.

$$H_0 : \theta = \theta_0$$

and one of the *alternative* hypotheses

$$\begin{aligned} H_1 : \theta < \theta_0 & \text{ (left-tailed test),} \\ H_1 : \theta > \theta_0 & \text{ (right-tailed test),} \\ H_1 : \theta \neq \theta_0 & \text{ (two-tailed test).} \end{aligned} \tag{4.1}$$

We want to decide if  $H_0$  is *rejected* (in favor of  $H_1$ ) or *not rejected* (accepted). We use a *test statistic*  $TS$  (with the same properties as the pivot in CI's) and a *rejection (critical) region*  $RR$ , such that for a given *significance level*  $\alpha \in (0, 1)$ ,

$$P(\text{type I error}) = P(\text{reject } H_0 \mid H_0) = P(TS \in RR \mid H_0) = \alpha. \tag{4.2}$$

The probability of a *type II error* is

$$P(\text{type II error}) = P(\text{not reject } H_0 \mid H_1) = P(TS \notin RR \mid H_1) = \beta.$$

In general, the significance level  $\alpha$  is preset and a procedure is given for finding an appropriate rejection region, such that  $\beta$  is also reasonably small.

We considered the case where for a target parameter  $\theta$ ,  $\bar{\theta}$  is an unbiased estimator ( $E(\bar{\theta}) = \theta$ ), with standard error  $\sigma_{\bar{\theta}}$ , such that, under certain conditions, it is known that

$$Z = \frac{\bar{\theta} - \theta}{\sigma_{\bar{\theta}}} \left( = \frac{\bar{\theta} - E(\bar{\theta})}{\sigma(\bar{\theta})} \right) \tag{4.3}$$

has an approximately Standard Normal  $N(0, 1)$  distribution. Using  $Z$  as a test statistic, we found

the rejection regions for the three alternatives (4.1) as

$$RR : \begin{cases} \{Z_0 \leq z_\alpha\} \\ \{Z_0 \geq z_{1-\alpha}\} \\ \{Z_0 \leq z_{\frac{\alpha}{2}} \text{ or } Z_0 \geq z_{1-\frac{\alpha}{2}}\} = \{|Z_0| \geq z_{1-\frac{\alpha}{2}}\}. \end{cases} \quad (4.4)$$

### 4.3 Significance Testing, $P$ -Values

There is a problem that might occur in hypothesis testing: We preset  $\alpha$ , the probability of a type I error and henceforth determine a rejection region. We get a value of the test statistic that *does not belong* to it, so we cannot reject the null hypothesis  $H_0$ , i.e. we accept it as being true. However, when we compute the probability of getting that value of the test statistic under the assumption that  $H_0$  is true, we find it is *very small*, comparable with our preset  $\alpha$ . So, we accept  $H_0$ , yet considering it to be true, we find that it is *very unlikely* (very improbable) that the test statistic takes the observed value we found for it. That makes us wonder if we set our RR right and if we didn't "accept"  $H_0$  too easily, by hastily dismissing values of the test statistic that did not fall into our RR. So we should take a look at how "far-fetched" does the value of the test statistic seem, under the assumption that  $H_0$  is true. If it seems really implausible to occur by chance, i.e. if its probability is *small*, then maybe we should reject the null hypothesis  $H_0$ .

To avoid this situation, we perform what is called a **significance test**: for a given random sample (i.e. sample variables  $X_1, \dots, X_n$ ), we still set up  $H_0$  and  $H_1$  as before and we choose an appropriate test statistic. Then, we compute the probability of observing a value *at least as extreme* (in the sense of the test conducted) of the test statistic  $TS$  as the value observed from the sample,  $TS_0$ , under the assumption that  $H_0$  is true. This probability is called the critical value, the descriptive significance level, the probability of the test, or, simply the  **$P$ -value** of the test. If it is small, we reject  $H_0$ , otherwise we do not reject it. The  $P$ -value is a numerical value assigned to the test, it depends only on the sample data and its distribution, but *not* on  $\alpha$ .

In general, for the three alternatives (4.1), if  $TS_0$  is the value of the test statistic  $TS$  under the assumption that  $H_0$  is true and  $F$  is the cdf of  $TS$ , the  $P$ -value is computed by

$$P = \begin{cases} P(TS < TS_0 \mid H_0) & = F(TS_0) \\ P(TS > TS_0 \mid H_0) & = 1 - F(TS_0) \\ 2 \cdot \min\{P(TS < TS_0 \mid H_0), P(TS > TS_0 \mid H_0)\} & = 2 \cdot \min\{F(TS_0), 1 - F(TS_0)\}. \end{cases} \quad (4.5)$$

Then the decision will be

$$\begin{aligned} &\text{if } P \leq \alpha, \text{ reject } H_0, \\ &\text{if } P > \alpha, \text{ do not reject } H_0. \end{aligned} \tag{4.6}$$

So, more precisely, the  $P$ -value of a test is the smallest level at which we could have preset  $\alpha$  and still have been able to reject  $H_0$ , or the lowest significance level that *forces* rejection of  $H_0$ , i.e. the *minimum rejection level*.

**Remark 4.1.**

1. Thus, we can avoid the costly computation of the rejection region (costly because of the quantiles) and compute the  $P$ -value instead. Then, we simply compare it to the significance level  $\alpha$ . If  $\alpha$  is above the  $P$ -value, we reject  $H_0$ , but if it is below that minimum rejection level, we can no longer reject the null hypothesis.
2. Hypothesis testing (determining the rejection region) and significance testing (computing the  $P$ -value) are two methods for testing *the same* thing (the same two hypotheses), so, of course, the outcome (the decision of rejecting or not  $H_0$ ) will be *the same*, for the same data.

**Example 4.2.** Recall the problem in Example 4.4 (Lecture 10): The number of monthly sales at a firm is known to have a mean of 20 and a standard deviation of 4 and all salary, tax and bonus figures are based on these values. However, in times of economical recession, a sales manager fears that his employees do not average 20 sales per month, but less, which could seriously hurt the company. For a number of 36 randomly selected salespeople, it was found that in one month they averaged 19 sales. At the 5% significance level, does the data confirm or contradict the manager's suspicion? Now, let us perform a significance test.

**Solution.** We tested a left-tailed alternative for the mean

$$\begin{aligned} H_0 : \mu &= 20 \\ H_1 : \mu &< 20. \end{aligned}$$

The population standard deviation was given,  $\sigma = 4$ , and for a sample of size  $n = 36$ , the sample mean was  $\bar{X} = 19$ . For the test statistic

$$Z = \frac{\bar{X} - \mu}{\frac{\sigma}{\sqrt{n}}} \in N(0, 1),$$

the observed value was

$$Z_0 = \frac{\bar{X} - \mu_0}{\frac{\sigma}{\sqrt{n}}} = \frac{19 - 20}{\frac{4}{6}} = -1.5.$$

Now, we compute the  $P$ -value

$$P = P(Z < Z_0) = P(Z < -1.5) = 0.0668.$$

Since

$$\alpha = 0.05 < 0.0668 = P,$$

(is below the minimum rejection level), we do not reject  $H_0$ , so, at the 5% significance level, we conclude that the data contradicts the manager's suspicion. But, for example, at the 7% significance level, we would have rejected it. ■

## 4.4 Tests for the Parameters of One Population

Let  $X$  be a population characteristic, with pdf  $f(x; \theta)$ , mean  $E(X) = \mu$  and variance  $V(X) = \sigma^2$ . Let  $X_1, X_2, \dots, X_n$  be sample variables.

**Tests for the mean of a population,  $\theta = \mu$**

We test the hypotheses

$$\begin{aligned} H_0 : & \mu = \mu_0, \text{ versus one of} \\ H_1 : & \begin{cases} \mu < \mu_0 \\ \mu > \mu_0 \\ \mu \neq \mu_0, \end{cases} \end{aligned} \quad (4.7)$$

under the assumption that either  $X$  is approximately Normally  $N(\mu, \sigma)$  distributed or that the sample is large ( $n > 30$ ).

**Case  $\sigma$  known (ztest)**

We use the test statistic

$$TS = Z = \frac{\bar{X} - \mu}{\frac{\sigma}{\sqrt{n}}} \in N(0, 1), \quad (4.8)$$

with observed value

$$Z_0 = \frac{\bar{X} - \mu_0}{\frac{\sigma}{\sqrt{n}}}. \quad (4.9)$$

Then, as before, at the  $\alpha \in (0, 1)$  significance level, the rejection region for each test will be given by

$$RR : \begin{cases} \{Z_0 \leq z_\alpha\} \\ \{Z_0 \geq z_{1-\alpha}\} \\ \{|Z_0| \geq z_{1-\frac{\alpha}{2}}\} \end{cases} \quad (4.10)$$

and the  $P$ -value will be computed as

$$P = \begin{cases} P(Z < Z_0 | H_0) & = \Phi(Z_0) \\ P(Z > Z_0 | H_0) & = 1 - \Phi(Z_0) \\ P(|Z| > |Z_0| | H_0) & = 2(1 - \Phi(|Z_0|)), \end{cases} \quad (4.11)$$

since  $N(0, 1)$  is symmetric, where

$$\Phi(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-\frac{t^2}{2}} dt$$

is Laplace's function, the cdf for the Standard Normal  $N(0, 1)$  distribution.

### **Case $\sigma$ unknown (ttest)**

In this case, we use the test statistic

$$TS = T = \frac{\bar{X} - \mu}{\frac{s}{\sqrt{n}}} \in T(n-1), \quad (4.12)$$

with observed value

$$T_0 = \frac{\bar{X} - \mu_0}{\frac{s}{\sqrt{n}}}. \quad (4.13)$$

Similarly to the previous case, we find the rejection region for the three alternatives as

$$RR : \begin{cases} \{T_0 \leq t_\alpha\} \\ \{T_0 \geq t_{1-\alpha}\} \\ \{|T_0| \geq t_{1-\frac{\alpha}{2}}\}, \end{cases} \quad (4.14)$$

and compute the  $P$ -value will by

$$P = \begin{cases} P(T < T_0 | H_0) & = F(T_0) \\ P(T > T_0 | H_0) & = 1 - F(T_0) \\ P(|T| > |T_0| | H_0) & = 2(1 - F(|T_0|)), \end{cases} \quad (4.15)$$

where the cdf  $F$  and the quantiles refer to the  $T(n-1)$  distribution.

### Tests for the variance of a population, $\theta = \sigma^2$ (**vartest**)

Assuming that  $X$  has a Normal  $N(\mu, \sigma)$  distribution, we test the hypotheses

$$\begin{aligned} H_0 : \sigma^2 &= \sigma_0^2, & H_0 : \sigma &= \sigma_0, \\ H_1 : \begin{cases} \sigma^2 < \sigma_0^2 \\ \sigma^2 > \sigma_0^2 \\ \sigma^2 \neq \sigma_0^2, \end{cases} & \text{equivalent to} & H_1 : \begin{cases} \sigma < \sigma_0 \\ \sigma > \sigma_0 \\ \sigma \neq \sigma_0. \end{cases} \end{aligned} \quad (4.16)$$

The test statistic will be

$$TS = V = \frac{(n-1)s^2}{\sigma^2} \in \chi^2(n-1), \quad (4.17)$$

with observed value

$$V_0 = \frac{(n-1)s^2}{\sigma_0^2}. \quad (4.18)$$

Even though the  $\chi^2(n-1)$  distribution is not symmetric, we use the same line of reasoning and computations to find the rejection region for the three alternatives:

$$RR : \begin{cases} \{V_0 \leq \chi_\alpha^2\} \\ \{V_0 \geq \chi_{1-\alpha}^2\} \\ \{V_0 \leq \chi_{\frac{\alpha}{2}}^2 \text{ or } V_0 \geq \chi_{1-\frac{\alpha}{2}}^2\}. \end{cases} \quad (4.19)$$

Same goes for the computation of the  $P$ -values:

$$P = \begin{cases} P(V < V_0 | H_0) & = F(V_0) \\ P(V > V_0 | H_0) & = 1 - F(V_0) \\ 2 \cdot \min\{P(V < V_0 | H_0), P(V > V_0 | H_0)\} & = 2 \cdot \min\{F(V_0), 1 - F(V_0)\}, \end{cases} \quad (4.20)$$

where the cdf  $F$  and the quantiles refer to the  $\chi^2(n - 1)$  distribution.

**Example 4.3.** Let us consider again the problem in Example 4.2, where  $\sigma = 4$  was given. Suppose that for the sample considered, the standard deviation is found to be  $s = 4.5$ . Assuming that the number of monthly sales at that firm is Normally distributed, at the 5% significance level, does the assumption on  $\sigma$  seem to be correct?

**Solution.** We are now testing the variance. We want to know if the value  $\sigma = 4$  is correct *or not*, so, this will be a *two-tailed* test.

$$H_0 : \sigma = 4$$

$$H_1 : \sigma \neq 4,$$

i.e.,

$$H_0 : \sigma^2 = 16 = \sigma_0^2$$

$$H_1 : \sigma^2 \neq 16 = \sigma_0^2,$$

We have  $n = 36$  and  $s^2 = (4.5)^2 = 20.25$ . The observed value of the test statistic is

$$V_0 = \frac{(n - 1)s^2}{\sigma_0^2} = \frac{35 \cdot 20.25}{16} = 44.2969.$$

The significance level is  $\alpha = 0.05$  and the two quantiles for the  $\chi^2(35)$  distribution are

$$\chi_{0.025}^2 = 20.5694,$$

$$\chi_{0.975}^2 = 53.2033.$$

Then the rejection region is

$$RR = (-\infty, 20.5694] \cup [53.2033, \infty),$$

which *does not* include the value  $V_0$ . Therefore, the decision is to *not reject* the null hypothesis, i.e. to conclude that the assumption  $\sigma = 4$  is correct.

On the other hand, the  $P$ -value is

$$P = 2 \cdot \min\{P(V < V_0), P(V > V_0)\} = 2 \cdot \min\{0.8652, 0.1348\} = 0.2697.$$

Since

$$\alpha = 0.05 < 0.2697 = P,$$

the decision is to *not reject* the null hypothesis.

Notice that the significance test tells us more! Since the  $P$ -value is so large (remember, it is comparable to a probability of an *error*, so a *small* quantity), not only at the 5% significance level we decide to accept  $H_0$ , but at *any* reasonable significance level the decision would be the same. That means that the data *strongly* suggests that  $H_0$  is true and should not be rejected. Even though the *sample* standard deviation *is not* equal to 4, still, statistically, the data strongly suggests that the *population* standard deviation *is* 4. We should be careful not to extrapolate the property of one sample to the entire population (data from a sample may be misleading, if it is not used properly ...)

■

## 4.5 Tests for Comparing the Parameters of Two Populations

Assume we have two population characteristics  $X_{(1)}$  and  $X_{(2)}$ , with means and variances  $E(X_{(1)}) = \mu_1, V(X_{(1)}) = \sigma_1^2$  and  $E(X_{(2)}) = \mu_2, V(X_{(2)}) = \sigma_2^2$ , respectively. We draw two independent random samples  $X_{11}, \dots, X_{1n}$  and  $X_{21}, \dots, X_{2n}$ , with sample means  $\bar{X}_1, \bar{X}_2$ , sample variances  $s_1^2, s_2^2$ , respectively and *pooled* variance

$$s_p^2 = \frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{n_1 + n_2 - 2}.$$

**Tests for the difference of means,  $\theta = \mu_1 - \mu_2$**

We test the hypotheses

$$\begin{array}{ll} H_0 : \mu_1 - \mu_2 = 0, & H_0 : \mu_1 = \mu_2, \\ H_1 : \begin{cases} \mu_1 - \mu_2 < 0 \\ \mu_1 - \mu_2 > 0 \\ \mu_1 - \mu_2 \neq 0, \end{cases} & \text{equivalent to} \quad H_1 : \begin{cases} \mu_1 < \mu_2 \\ \mu_1 > \mu_2 \\ \mu_1 \neq \mu_2, \end{cases} \end{array} \quad (4.21)$$

under the assumption that either  $X_{(1)}$  and  $X_{(2)}$  have approximately Normal distributions or that the samples are large enough ( $n_1 + n_2 > 40$ ).

### Case $\sigma_1, \sigma_2$ known

We use the test statistic

$$TS = Z = \frac{(\bar{X}_1 - \bar{X}_2) - (\mu_1 - \mu_2)}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}} \in N(0, 1), \quad (4.22)$$



with observed value

$$Z_0 = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}}. \quad (4.23)$$

The rejection regions and  $P$ -values for the three alternatives are then given by equations (4.10)-(4.11), with  $Z_0$  from (4.23).

**Case  $\sigma_1 = \sigma_2$  unknown (ttest2)**

The test statistic is

$$TS = T = \frac{(\bar{X}_1 - \bar{X}_2) - (\mu_1 - \mu_2)}{s_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} \in T(n_1 + n_2 - 2), \quad (4.24)$$

with observed value

$$T_0 = \frac{\bar{X}_1 - \bar{X}_2}{s_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}}. \quad (4.25)$$

The rejection regions and  $P$ -values for the three alternatives are then given by equations (4.14)-(4.15), where  $T_0$  is given in (4.25) and the cdf  $F$  and the quantiles refer to the  $T(n_1 + n_2 - 2)$  distribution.

**Case  $\sigma_1, \sigma_2$  unknown (ttest2)**

We now use the test statistic

$$TS = T^* = \frac{(\bar{X}_1 - \bar{X}_2) - (\mu_1 - \mu_2)}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \in T(n), \quad (4.26)$$

where  $\frac{1}{n} = \frac{c^2}{n_1 - 1} + \frac{(1 - c)^2}{n_2 - 1}$  and  $c = \frac{\frac{s_1^2}{n_1}}{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}.$

The observed value of the test statistic is

$$T_0^* = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}. \quad (4.27)$$

The rejection regions and  $P$ -values for the three alternatives are again as in equations (4.14)-(4.15), with  $T_0$  replaced by  $T_0^*$  from (4.27). The cdf  $F$  and the quantiles refer to the  $T(n)$  distribution.

**Remark 4.4.** The same Matlab command **ttest2** performs a  $T$ -test for the difference of two population means, when the variances are *not* assumed equal, with the option *vartype* set on “unequal” (the default being “equal”, when it can be omitted).

**Tests for the ratio of variances,  $\theta = \frac{\sigma_1^2}{\sigma_2^2}$**  (**vartest2**)

Assuming that both  $X_{(1)}$  and  $X_{(2)}$  have Normal distributions, we test the hypotheses

$$\begin{aligned} H_0 : \frac{\sigma_1^2}{\sigma_2^2} = 1, \\ H_1 : \begin{cases} \frac{\sigma_1^2}{\sigma_2^2} < 1 \\ \frac{\sigma_1^2}{\sigma_2^2} > 1 \\ \frac{\sigma_1^2}{\sigma_2^2} \neq 1, \end{cases} & \Leftrightarrow \begin{aligned} H_0 : \sigma_1^2 = \sigma_2^2, \\ H_1 : \begin{cases} \sigma_1^2 < \sigma_2^2 \\ \sigma_1^2 > \sigma_2^2 \\ \sigma_1^2 \neq \sigma_2^2, \end{cases} \end{aligned} & \Leftrightarrow \begin{aligned} H_0 : \sigma_1 = \sigma_2, \\ H_1 : \begin{cases} \sigma_1 < \sigma_2 \\ \sigma_1 > \sigma_2 \\ \sigma_1 \neq \sigma_2. \end{cases} \end{aligned} \end{aligned} \quad (4.28)$$

The test statistic used is

$$TS = F = \frac{s_1^2/\sigma_1^2}{s_2^2/\sigma_2^2} \in F(n_1 - 1, n_2 - 1), \quad (4.29)$$

with observed value

$$F_0 = \frac{s_1^2}{s_2^2}. \quad (4.30)$$

Again, just like in the case of one population variance, the  $F(n_1 - 1, n_2 - 1)$  distribution is not symmetric, but proceeding as before, we find the rejection region for the three alternatives as

$$RR : \begin{cases} \{F_0 \leq f_\alpha\} \\ \{F_0 \geq f_{1-\alpha}\} \\ \{F_0 \leq f_{\frac{\alpha}{2}} \text{ or } F_0 \geq f_{1-\frac{\alpha}{2}}\}. \end{cases} \quad (4.31)$$

and the  $P$ -values given by

$$P = \begin{cases} P(F < F_0 | H_0) & = F(F_0) \\ P(F > F_0 | H_0) & = 1 - F(F_0) \\ 2 \cdot \min\{P(F < F_0 | H_0), P(F > F_0 | H_0)\} & = 2 \cdot \min\{F(F_0), 1 - F(F_0)\}, \end{cases} \quad (4.32)$$

where the cdf  $F$  and the quantiles refer to the  $F(n_1 - 1, n_2 - 1)$  distribution.

**Example 4.5.** Suppose the strengths to a certain load of two types of material,  $M1$  and  $M2$ , are studied, knowing that they are approximately Normally distributed. The more weight they can resist to, the stronger they are. Two independent random samples are drawn and they yield the following data.

$M1$	$M2$
$n_1 = 25$	$n_2 = 16$
$\bar{X}_1 = 380$	$\bar{X}_2 = 370$
$s_1^2 = 537$	$s_2^2 = 196$

- At the 5% significance level, do the variances of the two populations seem to be equal or not?
- At the same significance level, does the data suggest that on average,  $M1$  is stronger than  $M2$ ? (In both parts, perform both hypothesis and significance testing).

**Solution.**

a) First, we compare the variances of the two populations, so we know which way to proceed for comparing the means. We want to know if they are equal or not, so it is a two-tailed test. Hence, our hypotheses are

$$\begin{aligned} H_0 : \sigma_1^2 &= \sigma_2^2 \\ H_1 : \sigma_1^2 &\neq \sigma_2^2. \end{aligned}$$

The observed value of the test statistic is

$$F_0 = \frac{s_1^2}{s_2^2} = \frac{537}{196} = 2.7398.$$

For  $\alpha = 0.05$ ,  $n_1 = 25$  and  $n_2 = 16$ , the quantiles for the  $F(24, 15)$  distribution are

$$\begin{aligned} f_{\frac{\alpha}{2}} &= f_{0.025} = 0.4103 \\ f_{1-\frac{\alpha}{2}} &= f_{0.975} = 2.7006. \end{aligned}$$

Thus, the rejection region for our test is

$$RR = (-\infty, 0.4103] \cup [2.7006, \infty)$$

and clearly,  $F_0 \in RR$ . Thus we reject  $H_0$  in favor of  $H_1$ , i.e. we conclude that the data suggests that the population variances are *different*.

Let us also perform a significance test. The  $P$ -value of this (two-tailed) test is

$$P = 2 \cdot \min\{P(F < F_0), P(F > F_0)\} = 2 \cdot \min\{0.9765, 0.0235\} = 0.0469.$$

Since our  $\alpha > P$ , the “minimum rejection significance level”, we reject  $H_0$ .

**Note.** We now know that for instance, at 1% significance level (or any level less than 4.69%), we would have *not* rejected the null hypothesis. This goes to show that the data can be “misleading”. Simply comparing the values of the sample functions does not necessarily mean that the same thing will be true for the corresponding population parameters. Here,  $s_1^2$  is *much* larger than  $s_2^2$ , yet at 1% significance level, we would have concluded that the population variances seem to be equal.

b) Next we want to compare the population means. If  $M1$  is to be *stronger* than  $M2$  on average, then we must perform a *right*-tailed test:

$$H_0 : \mu_1 = \mu_2$$

$$H_1 : \mu_1 > \mu_2$$

Which one of the tests for the difference of means should we use? The answer is in part a). At this significance level, the variances are unknown and *different*.

Then the value of the test statistic is, by (4.27)

$$T_0^* = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} = \frac{380 - 370}{\sqrt{\frac{537}{25} + \frac{196}{16}}} = 1.7218.$$

To find the rejection region, we compute

$$c = 0.6368, \quad n = 38.9244 \approx 39$$

and the quantile for the  $T(39)$  distribution

$$t_{1-\alpha} = t_{0.95} = 1.6849.$$

Then the rejection region of the test is

$$RR = [1.6849, \infty),$$

which includes the value  $T_0^*$ , so we *reject*  $H_0$  in favor of  $H_1$ . So we conclude that yes, the data suggests that material  $M1$  is, on average, stronger than material  $M2$ .

On the other hand, the  $P$ -value of this test is

$$P = P(T^* > T_0^*) = 1 - F(T_0^*) = 1 - F(1.7218) = 0.0465,$$

where  $F$  is the cdf of the  $T(39)$  distribution. Again, the  $P$ -value is lower than  $\alpha = 0.05$ , which forces the rejection of  $H_0$ . ■

#### **Remark 4.6.**

1. As mentioned before, both hypothesis and significance testing lead to the same conclusion. From the implementation point of view, significance testing is more efficient, since it avoids the inversion of a cdf (i.e. computation of quantiles), which is often a complicated improper integral. This is the reason why, although the main tests *are* implemented in Matlab, the rejection regions *are not* computed.
2. Many tests (and formulas for CI's) work under the assumption of Normality of the population from which the sample was drawn. In practice, when there are outliers in the data, that is rarely the case. How important is this assumption of Normality and how affected are the results of these tests by small departures from model assumptions?  $Z$ -tests and  $T$ -tests work well even when the underlying population is not quite Normally distributed. From this point of view, they are called **robust** tests.  $\chi^2$ -tests and  $F$ -tests, however, are *not* robust, they perform very poorly when the assumption of Normality is breached. In modern Statistics there is an ongoing search for finding robust methods of estimation for variances.