

**Lecture 7. Hypothesis testing: popular large-sample tests, choosing the sample size for a given β , p-value.
(Sections 10.3–10.7)**

1 Popular large-sample hypotheses tests

In this section, we consider a sample of i.i.d. Y_1, \dots, Y_n that is **not** necessarily normal, but we assume that n is large. As before, the distribution of Y_i depends on the unknown parameter θ .

Consider a null hyp. $H_0 = \{\theta = \theta_0\}$, where θ_0 is a known constant, and the alternative is (one of)

$$H_a = \{\theta < \theta_0\}, \{\theta > \theta_0\}, \{\theta \neq \theta_0\}.$$

As the sample is not normal, we have to relax the notion of significance level and consider the **asymptotic significance level** α , in the sense that

$$\lim_{n \rightarrow \infty} \mathbb{P}^0(U_n \in RR) \rightarrow \alpha,$$

where U_n is the test statistic for a sample size n , and RR is the rejection region.

To construct a test statistic U_n , we start by find an asymptotically normal estimator $\hat{\theta}_n$ of θ : i.e.,

$$\sqrt{n}(\hat{\theta}_n - \theta) \rightarrow N(0, \tilde{\sigma}^2),$$

as $n \rightarrow \infty$. If the value of $\tilde{\sigma}^2$ under H_0 is not known, we find a consistent estimator $\hat{\sigma}_n^2$ of $\tilde{\sigma}^2$: i.e.,

$$\hat{\sigma}_n^2 \rightarrow \tilde{\sigma}^2,$$

as $n \rightarrow \infty$. (If the value of $\tilde{\sigma}^2$ under H_0 is known, we set $\hat{\sigma}_n^2 = \tilde{\sigma}^2$.) Finally, we construct the test statistic

$$U_n = \frac{\sqrt{n}(\hat{\theta}_n - \theta_0)}{\hat{\sigma}_n}.$$

From Slutsky's theorem, we know that

$$U_n \rightarrow N(0, 1), \quad \text{under } H_0,$$

as $n \rightarrow \infty$, in the sense of distribution.

In addition, $\hat{\theta}_n$ and hence U_n are more likely to take large values if θ is large, U_n is more likely to take small values if θ is small, and U_n are more likely to take values far away from zero if θ is far away from θ_0 .

Thus, U_n is a reasonable choice of a test statistic.

The rejection region of asymptotic level α is chosen as (one of)

$$RR = (-\infty, z_{1-\alpha}], [z_\alpha, \infty), (-\infty, z_{1-\alpha/2}] \cup [z_{\alpha/2}, \infty),$$

corresponding to the alternative hypotheses.

Ex 1. A manager claims that each of his salespeople establishes, on average, no more than 15 contacts per week. He records the numbers of weekly contacts from $n = 36$ employees, the resulting sample mean is $\bar{y} = 17$ and the sample variance is $s^2 = 9$.

Q 1. At the asymptotic significance level 0.05, does the data contradict the manager's claim?

Y_i is the number of contacts established by the i -th employee per week, with $\mu = \mathbb{E}Y_i$. We test the null hypothesis

$$H_0 = \{\mu = 15\}$$

against the alternative

$$H_a = \{\mu > 15\}.$$

The values of relevant estimators are

$$\hat{\theta} = \bar{y} = 17, \quad \hat{\sigma}^2 = s^2 = 9,$$

and the test statistic takes the value

$$u = \frac{\sqrt{36}(17 - 15)}{\sqrt{9}} = 4.$$

The rejection region is

$$RR = [z_{0.05}, \infty) = [1.645, \infty).$$

Thus, we reject the null hyp. in favor of H_a .

Ex 2. A machine is in need of repair if more than 10% of items it produces are defective. A sample of size $n = 100$ is collected, resulting in 15 defective items. A supervisor claims that the machine must be repaired.

Q 2. Does the data support this claim, at the asymptotic significance level 0.01?

We are dealing with Bernoulli sample with an unknown success probability p (i.e., each Y_i equals one if the i -th item is defective, and zero otherwise), and

$$H_0 = \{p = 0.1\}, \quad H_a = \{p > 0.1\}, \quad \hat{p} = \bar{y} = 0.15, \quad \sqrt{n}(\bar{y} - p) \rightarrow N(0, \tilde{\sigma}^2), \quad \tilde{\sigma}^2 = p(1 - p).$$

Note that

$$\hat{\sigma}^2 = \bar{y}(1 - \bar{y})$$

is a consistent estimator of $\tilde{\sigma}^2$. However, under H_0 , we know the exact value of $\tilde{\sigma}^2$:

$$\tilde{\sigma}^2 = 0.1 \cdot (1 - 0.1) = 0.09.$$

Clearly, it is more efficient to use the above value than its estimate. Thus, we obtain the test statistic value:

$$u = \frac{\sqrt{100}(0.15 - 0.1)}{\sqrt{0.09}} = \frac{0.5}{0.3} \approx 1.67, \quad RR = [z_\alpha, \infty) = [2.33, \infty).$$

Thus, we accept (or, fail to reject) H_0 , which means that the data does not support the supervisor's claim at the given significance level.

Note that we could use $\hat{\sigma}^2$ as an approximation of $\tilde{\sigma}^2$. Strictly speaking it would be correct (and, in this case, would yield the same answer), but it is clearly less efficient.

Next, assume that we need to compare the means μ_1 and μ_2 of two independent samples $\{Y_i\}_{i=1}^{n_1}$ and $\{Z_i\}_{i=1}^{n_2}$, with the null hypothesis

$$H_0 = \{\mu_1 - \mu_2 = D_0\}$$

and with the alternatives $H_a = \{\mu_1 - \mu_2 < D_0\}, \{\mu_1 - \mu_2 > D_0\}, \{\mu_1 - \mu_2 \neq D_0\}$.

A natural choice of the test statistic is

$$U = \frac{\bar{Y} - \bar{Z} - D_0}{\sqrt{\hat{\sigma}_1^2/n_1 + \hat{\sigma}_2^2/n_2}} \rightarrow N(0, 1),$$

where the limit is taken as $n_1, n_2 \rightarrow \infty$, and where $\hat{\sigma}_1^2$ and $\hat{\sigma}_2^2$ are consistent estimators of $\sigma_1^2 = V(Y_i)$ and $\sigma_2^2 = V(Z_i)$.

We choose RR accordingly: $RR = (-\infty, -z_\alpha], [z_\alpha, \infty), (-\infty, -z_{\alpha/2}] \cup [z_{\alpha/2}, \infty)$.

Rem 1. Just remember that we also need to assume that

$$\frac{|n_1 - n_2|}{\sqrt{n_1} + \sqrt{n_2}}$$

remains bounded.

Ex 3. A study compares reaction times (in seconds) of men and women to a certain stimulus. Two samples $\{Y_i\}$ and $\{Z_i\}$ of sizes $n_1 = 50$ and $n_2 = 50$, of men and women respectively, are taken. The realized statistics' values are $\bar{y} = 3.6$, $s_1^2 = 0.18$, $\bar{z} = 3.8$, $s_2^2 = 0.14$.

Q 3. At the (asymptotic) level 0.05, does the data provide sufficient evidence that $\mu_1 \neq \mu_2$?

$$H_0 = \{\mu_1 - \mu_2 = 0\}, \quad H_a = \{\mu_1 - \mu_2 \neq 0\},$$

$$u = \frac{3.6 - 3.8}{\sqrt{0.18/50 + 0.14/50}} = -2.5, \quad RR = (-\infty, -z_{0.025}] \cup [z_{0.025}, \infty) = (-\infty, -1.96] \cup (1.96, \infty)$$

Thus, H_0 is rejected, which means that the data does provide sufficient evidence that $\mu_1 \neq \mu_2$ at the given significance level.

2 Choosing sample size for a given β

Recall that the type-I error, measured by the significance level α , is typically fixed. On the other hand, if H_a is simple, we may be interested in **decreasing the type-II error** β . One way to achieve this is by increasing the sample size n .

Consider $H_0 = \{\theta = \theta_0\}$ and $H_a = \{\theta = \theta_a\}$, where $\theta_0 < \theta_a$ are known constants. Let $\hat{\theta}_n$ be an asymptotically normal estimator of θ , with

$$\sqrt{n}(\hat{\theta}_n - \theta) \rightarrow N(0, \tilde{\sigma}^2).$$

Assume also that $\hat{\sigma}_n^2$ is a consistent estimator of $\tilde{\sigma}^2$. Then, we can use the test statistic U and the rejection region RR given by

$$U_n = \frac{\sqrt{n}(\hat{\theta}_n - \theta_0)}{\hat{\sigma}_n}, \quad RR = (z_\alpha, \infty).$$

Note that $U_n \rightarrow N(0, 1)$, hence the chosen test has asymptotic significance level (i.e., the type-I error) α .

On the other hand, as $n \rightarrow \infty$, the type-II error is

$$\begin{aligned}\beta &= \mathbb{P}^a(U_n \notin RR) = \mathbb{P}^a\left(\frac{\sqrt{n}(\hat{\theta}_n - \theta_0)}{\hat{\sigma}_n} \leq z_\alpha\right) = \mathbb{P}^a\left(\frac{\sqrt{n}(\hat{\theta}_n - \theta_a)}{\hat{\sigma}_n} \leq z_\alpha - \frac{\sqrt{n}(\theta_a - \theta_0)}{\hat{\sigma}_n}\right) \\ &= \mathbb{P}^a\left(U_n \leq z_\alpha - \frac{\sqrt{n}(\theta_a - \theta_0)}{\hat{\sigma}_n}\right) \approx \Phi\left(z_\alpha - \frac{\sqrt{n}(\theta_a - \theta_0)}{\hat{\sigma}_n}\right),\end{aligned}$$

where Φ is the cdf of $N(0, 1)$.

Rem 2. The above derivation is purely heuristic – it only holds under additional technical assumptions. But, in this course, we assume that these assumptions are always satisfied.

If we want to achieve a given value β of the type-II error, we need

$$\Phi\left(z_\alpha - \frac{\sqrt{n}(\theta_a - \theta_0)}{\hat{\sigma}_n}\right) = \beta,$$

which leads to

$$\begin{aligned}z_\alpha - \frac{\sqrt{n}(\theta_a - \theta_0)}{\hat{\sigma}_n} &= z_{1-\beta} = -z_\beta, \\ n &= \frac{(z_\alpha + z_\beta)^2 \hat{\sigma}_n^2}{(\theta_a - \theta_0)^2}.\end{aligned}$$

Rem 3. Note that $\hat{\sigma}_n^2$ still depends on n , so, strictly speaking, we haven't solved the equation for n . In practice, we cheat a bit: we run a preliminary estimate (on a possibly smaller sample), to compute $\hat{\sigma}^2$, then, use this estimate in the above formula to get n for the new sample.

Ex 4. A manager wants to test H_0 that his salespeople establish on average 15 contacts per week (each) against the alternative H_a of 16 contacts per week, with errors $\alpha = \beta = 0.05$. Assume that the true variance of the number of weekly contacts made by an employee, denoted σ^2 , has been approximated (via a consistent estimator) by 9.

Q 4. What is the size of the sample needed to achieve the desired accuracy of the test?

$$n = \frac{(z_\alpha + z_\beta)^2 \hat{\sigma}_n^2}{(\theta_a - \theta_0)^2} = \frac{(1.645 + 1.645)^2 \cdot 9}{(16 - 15)^2} = 97.4$$

3 p-value

What significance level α should be used for a test? This choice is somewhat arbitrary.

Instead of fixing α and searching for “acceptance/rejection” answer, let us search for the smallest α that gives us the “rejection” answer.

Def 1. Consider a test statistic $U(Y_1, \dots, Y_n)$ and a family of rejection regions $RR(\alpha)$, for all $\alpha \in (0, 1)$. Then, the *p-Value* of this test is the smallest α s.t.

$$u \in RR(\alpha),$$

where u is the realized value of U .

Note that p-Value contains more information than a simple “acceptance/rejection” answer for a given level. Indeed, p-value is the smallest significance level at which we can reject the null hypothesis: i.e., the null hyp. is rejected for any $\alpha \geq p$ and accepted for any $\alpha < p$.

If the null hyp. is rejected (i.e. if the test is conclusive), the smaller is the p-Value, the more compelling is the evidence for rejection. Heuristically, “one minus the p-value” is the confidence with which we can reject the null (although it is not a very precise statement).

Ex 5. Recall the example of a political poll, whose goal is to make a statistical inference about the unknown probability p that a randomly chosen voter is in favor of candidate Jones. In a sample of size $n = 15$ there are 3 people who are in favor of Jones.

Q 5. For the hypotheses $H_0 = \{p = 0.5\}$, $H_a = \{p < 0.5\}$, construct a test and find its p-value.

As before, the sample $\{Y_i\}$ consists of i.i.d. r.v.'s with Bernoulli(p) distribution ($Y_i = 1$ corresponds to the i -th person being in favor of Jones) we use

$$U = \sum_{i=1}^{15} Y_i$$

as a test statistic, and use the rejection region $RR(\alpha) = (0, b_{1-\alpha}]$, where $b_{1-\alpha}$ is the quantile of level α of $\text{Bin}(0.5, 15)$. Then, we compute

$$u = \sum_{i=1}^{15} y_i = 3, \quad RR(\alpha) = (0, b_{1-\alpha}].$$

To compute the p-value, we need to find the smallest $\alpha \in (0, 1)$ s.t.

$$3 \leq b_{1-\alpha}.$$

The above is equivalent to finding the smallest $\alpha \in (0, 1)$ s.t.

$$\mathbb{P} \left(\sum_{i=1}^{15} Y_i \leq 3 \right) \leq \mathbb{P} \left(\sum_{i=1}^{15} Y_i \leq b_{1-\alpha} \right) = \alpha,$$

which gives the p-value

$$p = \mathbb{P} \left(\sum_{i=1}^{15} Y_i \leq 3 \right) \approx 0.018.$$

Thus, according to the data, the null hyp. $H_0 = \{p = 0.5\}$ is rejected if our target significance level is at or above 0.018. In other words, this null hyp. can only be accepted if the significance level is below 0.018.

The above example motivates the following general method. Assume that $RR(\alpha)$ has the form

$$(-\infty, q_{1-\alpha}), (q_\alpha, \infty), (-\infty, q_{1-\alpha/2}) \cup (q_{\alpha/2}, \infty),$$

with q_α being the quantile of the test statistic U at level $1 - \alpha$, under H_0 . Then, the p-value is

$$p = F_U(u), 1 - F_U(u), 2 \min(F_U(u), 1 - F_U(u)),$$

where F_U is the cdf of U under H_0 , and u is the realized value of the test statistic.

Indeed, let us consider the first case, $RR = (-\infty, q_{1-\alpha})$. Then, the p-value is the smallest α s.t.

$$u \leq q_{1-\alpha}.$$

The above is equivalent to finding the smallest α s.t.

$$F_U(u) \leq F_U(q_{1-\alpha}) = \alpha.$$

Clearly, the smallest value of α that satisfies the above is $F_U(u)$, which is the desired p-value. The other cases are treated similarly.

If the sample and the unknown parameter are “nice” (e.g., the sample is normal), we may be able to find the distribution of U under H_0 explicitly.

If the sample is not normal, the test statistic U is typically chosen to be asymptotically normal under H_0 (e.g., via an asymptotically normal estimator of the unknown parameter). In such a case, F_U is replaced by the asymptotic (normal) distribution of U under H_0 .

Ex 6. A study compares the reaction times (measured in sec.) of men and women to a certain stimulus. Two samples (the first one of men, and the second one of women) are collected: $n_1 = 50$, $\bar{y} = 3.6$, $s_1^2 = 0.18$, $n_2 = 50$, $\bar{z} = 3.8$, $s_2^2 = 0.14$.

Q 6. Find a p-value for

$$H_0 = \{\mu_1 - \mu_2 = 0\}, \quad H_a = \{\mu_1 - \mu_2 \neq 0\},$$

with

$$U = \frac{\bar{Y} - \bar{Z}}{\sqrt{S_1^2/n_1 + S_2^2/n_2}}, \quad RR = (-\infty, -r) \cup (r, \infty).$$

Recall that, as $n_1, n_2 \rightarrow \infty$ (with n_1 and n_2 being not too different), we have:

$$\frac{\bar{Y} - \bar{Z} - (\mu_1 - \mu_2)}{\sqrt{S_1^2/n_1 + S_2^2/n_2}} \rightarrow N(0, 1).$$

Then, under H_0 , we have

$$U = \frac{\bar{Y} - \bar{Z}}{\sqrt{S_1^2/n_1 + S_2^2/n_2}} \rightarrow N(0, 1).$$

As the test statistic has a known (asymptotically) distribution under H_0 , and since the rejection interval is of the prescribed type, we can use the above general method to obtain

$$u = -2.5, \quad p = 2 \min(\Phi(-2.5), 1 - \Phi(-2.5)) = 2\Phi(-2.5) = 2 \cdot 0.0062 = 0.0124.$$

One has to have a very small significance level (below the above p-value) to accept the null hyp.

Rem 4. Two-sided tests and confidence intervals based on an asymptotically normal estimator $\hat{\theta}$ are closely related. Indeed, a confidence interval is centered around $\hat{\theta}$, while the acceptance region of the test has the same length and is centered around θ_0 (the value of θ under H_0). In the former case, we know that the true parameter value is in the confidence interval with high probability. In the latter case, under H_0 , the observed value of $\hat{\theta}$ must lie in the acceptance region with high probability.