

## Lecture 14— Hypothesis Testing

Prof. Philippe Rigollet

Scribe: Anya Katsevich

Hypothesis testing answers binary questions, such as...

- Is a drug better than placebo?
- Is a plane boarding method faster than some reference method?
- Is the average waiting time in the ER  $> 30$  minutes?
- Is my data Gaussian?
- Our first example from class: do people turn their head to the right when kissing?

How do we formulate such a question using statistics?

Consider the ER question. Suppose we collect i.i.d. data  $X_1, \dots, X_n$ , the ER waiting times of different patients. Our parameter of interest is  $\mu = \mathbb{E}[X_1]$ . Is  $\mu > 30$ ? Equivalently, is  $\mu - 30 > 0$ ? (It helps to make 0 be the standard reference for comparison).

To answer this question, the first strategy that comes to mind is to compute  $\bar{X}_n$ , and check if  $\bar{X}_n - 30$  is large. But how large is large? We will learn to quantify “large” in a precise way.

## 1 Terminology

### Definition 1.1: Test & Rejection region

A *test* is a function  $\Psi : \text{data} \rightarrow \{0, 1\}$ . In particular, a test is an estimator. (Recall that an estimator is any function of the data).

The *rejection region* of a test is  $R = \{\text{datasets for which } \Psi(\text{data}) = 1\}$ .

Since  $\Psi$  only takes two values, zero or one, this means that the rejection region  $R$  fully characterizes  $\Psi$ . In fact, we can write  $\Psi$  in the equivalent form

$$\Psi(\text{data}) = \mathbb{1}\{\text{data} \in R\}.$$

### Example.

Going back to the ER example, a *test* might be  $\Psi(X_1, \dots, X_n) = \mathbb{1}(\bar{X}_n > 31)$ . The corresponding *rejection region* is  $R = \{(X_1, \dots, X_n) \mid \bar{X}_n > 31\}$ . In other words,  $R$  is given by all the datasets  $X_1, \dots, X_n$  whose sample mean is larger than 31.

### Definition 1.2: Test statistic

A test *statistic* is a function that summarizes the data and is sufficient to compute a test  $\Psi$ .

### Example.

$\bar{X}_n$  is a test statistic for the test  $\Psi(\text{data}) = \mathbb{1}(\bar{X}_n > 30)$ . Note that  $\bar{X}_n^3$  is also sufficient to compute  $\Psi$ , but we typically define the test statistic to be the most natural one.

## 2 The hypothesis testing problem

Let  $\Theta$  be the full parameter space, and let  $\Theta_0, \Theta_1$  split  $\Theta$  into two disjoint subsets. A hypothesis test takes the form

$$H_0 : \theta \in \Theta_0 \quad \text{vs} \quad H_1 : \theta \in \Theta_1.$$

### Example.

In the waiting room example,

$$H_0 : \mu \leq 30 \quad \text{vs} \quad H_1 : \mu \geq 30.$$

How do we choose which hypothesis to call  $H_0$  and which to call  $H_1$ ? The operating principles are

*innocent* ( $H_0$ ) until *proven guilty* ( $H_1$ ),

or

*status quo* ( $H_0$ ) vs *discovery* ( $H_1$ ).

### Example.

- Suppose someone is suing a hospital for falsely claiming that their waiting times are below 30 minutes . The default presumption is  $H_0 : \mu \leq 30$  (hospital is innocent). To prove the alternative hypothesis  $H_1 : \mu > 30$  (guilty), the person suing the hospital would need to bring data as evidence to reject the default assumption of innocence.
- A pharma company petitions the FDA to approve of the drug they developed. Then  $H_0$  : the placebo outperforms the drug (status quo),  $H_1$ : the drug outperforms the placebo (a scientific discovery).
- A scientist at the Broad claims she's discovered the gene for perfect GPA. Then  $H_0$  : GPA gene doesn't work,  $H_1$  : GPA gene does actually work (scientific discovery) .

## 2.1 Error types

We use a test to accept or reject the null hypothesis based on the value of the test statistic. There are two types of errors the test could make.

|            | test concludes $H_0$ ( $\Psi = 0$ ) | test concludes $H_1$ ( $\Psi = 1$ ) |
|------------|-------------------------------------|-------------------------------------|
| $H_0$ true | ✓                                   | Type I                              |
| $H_1$ true | Type II                             | ✓                                   |

By the “innocent until proven guilty” principle, Type I is the more serious error.

### Example.

A test commits a Type I error if it concludes a drug works better than the placebo when it actually doesn't. This is considered a more serious error than a Type II error, in which the test concludes the drug does not work better than placebo, when it actually does.

The probability of a test committing an error depends on the true value of the parameter. For example,  $\mathbb{P}_\theta(\Psi = 1)$  is the probability that the test commits a type I error when  $\theta \in \Theta_0$  is the ground truth. Similarly,  $\mathbb{P}_\theta(\Psi = 0)$  is the probability that the test commits a type II error when  $\theta \in \Theta_1$  is the ground truth.

### Example.

In the ER example, suppose the ground truth is some  $\mu \leq 30$ , and the test we are using has rejection region  $\{\bar{X}_n \geq 31\}$ . Then

$$\mathbb{P}_\mu(\Psi = 1) = \mathbb{P}_\mu(\bar{X}_n \geq 31)$$

is the probability of a type I error.

### Definition 2.1: Size and level of a set

The size of a test  $\Psi$  is

$$\text{size}(\Psi) = \max_{\theta \in \Theta_0} \mathbb{P}_\theta(\Psi = 1),$$

i.e. the maximum possible probability of a type I error. The test  $\Psi$  is said to have *level*  $\alpha$  (a number between 0 and 1) if  $\text{size}(\Psi) \leq \alpha$ . The typical levels used are  $\alpha = 5\%$  and  $\alpha = 1\%$

### Remark.

The maximum type I error probability  $\mathbb{P}_\theta(\Psi = 1)$  is always achieved for  $\theta$  on the boundary between  $\Theta_0$  and  $\Theta_1$ ; see Figure 2 (the function  $\beta(\theta)$  is introduced in Definition 2.2 below). Heuristically this makes sense since for  $\theta$ 's on the boundary between  $\Theta_0$  and  $\Theta_1$ , it is hardest to correctly decide whether to accept or reject the null hypothesis.

Note that a test which always accepts the null hypothesis has size 0 — it never commits a type I error! Such a test says “everyone is innocent no matter what”, or “no drug works better than placebo”. Clearly, such a test is not very useful. Therefore, given a certain allowable level  $\alpha$ , we try to max out the Type I error over all  $\theta \in \Theta_0$ , which means that for  $\theta$  on the boundary, we want  $\mathbb{P}_\theta(\Psi = 1)$  to equal  $\alpha$  exactly. This will help keep the Type II error low.

The *power* function helps us reason about Type I and Type II errors.

### Definition 2.2: Power

The *power* function is defined as

$$\beta(\theta) = \mathbb{P}_\theta(\Psi = 1).$$

For a perfect test  $\Psi$  (see Figure 1) the power function  $\beta$  is a step function: it is exactly zero when  $\theta \in \Theta_0$ , and exactly one when  $\theta \in \Theta_1$ .

The power functions in Figures 2 and 3 both correspond to tests with level  $\alpha$ . But the former is more efficient, because it maxes out the Type I error at exactly  $\alpha$  when crossing over from  $\Theta_0$  to  $\Theta_1$ .

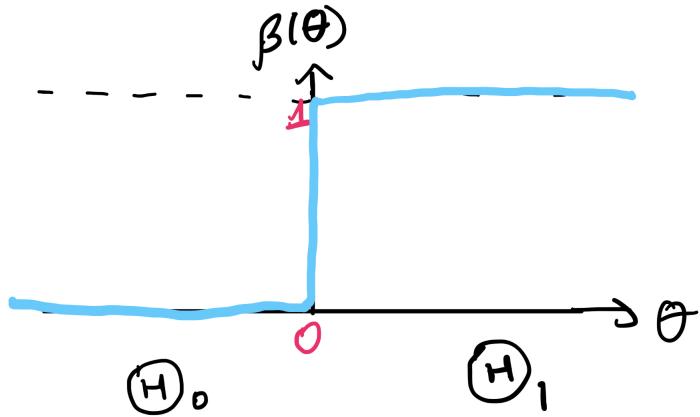


Figure 1: The power function for a perfect test, with zero type I error and zero type II error.

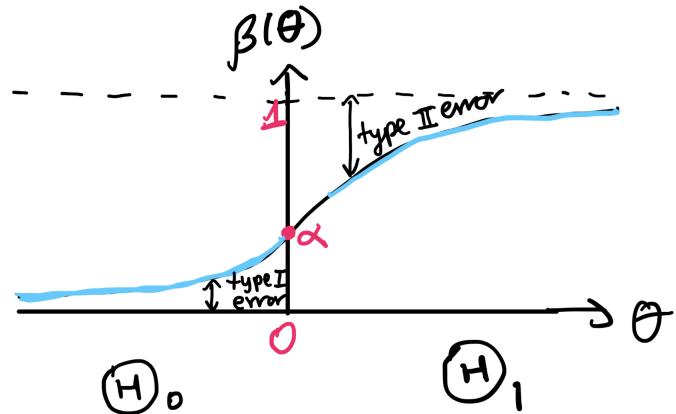


Figure 2: The power function for a test of size  $\alpha$  and level  $\alpha$ . Note the largest type I error is achieved at the boundary between  $\Theta_0$  and  $\Theta_1$ .

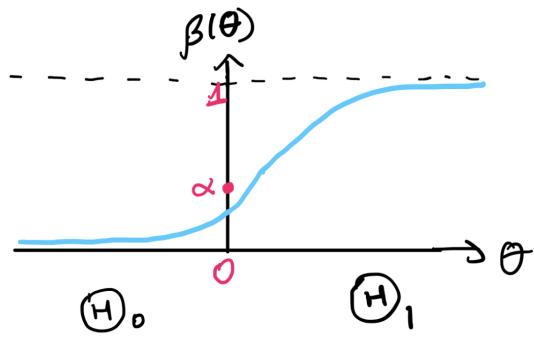


Figure 3: The power function for a test at level  $\alpha$ , but whose size is less than  $\alpha$ .