

## Hypothesis Testing

We want to assess the validity of a claim about the population against a counter-claim using sample data. The two claims are:

**Null Hypothesis**  $H_0$  is the claim of “no difference.”

**Alternative Hypothesis**  $H_1$  is the claim we are trying to prove.

Example (Vaccine Trial)

Let  $P_1$  be the fraction of the control group population who get polio.

$P_2$  is the fraction of the treatment population who get polio.

$H_0$  is the claim that the vaccine is not effective.  $P_1 = P_2$ .

$H_1$  is the claim that the vaccine is effective.  $P_1 > P_2$ .

The main idea: assume  $H_0$  is true. Does the data contradict the assumption beyond a reasonable doubt?

If yes: accept  $H_1$  and reject  $H_0$ .

If no:  $H_0$  can't be ruled out as an explanation for the data. *In this case we can't accept any hypothesis.*

Analogy: Presumed innocent until proven guilty

$H_0$ : not guilty

$H_1$ : guilty

Does the data contradict  $H_0$ ? If yes, then rule as guilty. If no, it doesn't mean the person is innocent but evidence is insufficient to establish guilt, it gives the person the benefit of the doubt.

We can think of a hypothesis test as a method to weigh evidence against  $H_0$  (rather than a decision procedure between  $H_0$  and  $H_1$ ).

Usually  $H_0$  is chosen to represent a hypothesis of “no difference” between the new and existing methods, just chance alone. If we can reject this sort of hypothesis then we have a **statistically significant** proof of claim  $H_1$ . In this case, the hypothesis test is a **significance test**.

Again, the hypothesis test is not a decision procedure between  $H_0$  and  $H_1$ . If  $H_1$  is not accepted, it does not mean we can accept  $H_0$ . I never want to hear you say: “therefore we accept the null hypothesis”.

A **type I error** is made when a test rejects  $H_0$  in favor of  $H_1$  when  $H_0$  is actually true (false positive).

E.g. person does not have the disease but test is positive.

A **type II error** is made when the test fails to reject  $H_0$  when  $H_1$  is true. (false negative).

E.g. person has the disease but test is negative.

|                | Decision            |                  |
|----------------|---------------------|------------------|
|                | Do not reject $H_0$ | Reject $H_0$     |
| $H_0$ is true  | Correct Decision    | Type I Error     |
| $H_0$ is false | Type II Error       | Correct Decision |

The probability of a type I error is called the  **$\alpha$ -risk**.

The probability of a type II error is called the  **$\beta$ -risk**.

That is:

$$\alpha = P(\text{type I error}) = P(\text{reject } H_0 \mid H_0)$$

$$\beta = P(\text{type II error}) = P(\text{fail to reject } H_0 \mid H_1).$$

Type I error is sometimes more serious than Type II, e.g., Type I is like convicting an innocent person and Type II is letting a guilty person go free due to lack of evidence.

Here we create a test that is required to satisfy  $P(\text{type I error}) \leq \alpha$ . In this case,  $\alpha$  is called the **level of significance**, and the test is a  **$\alpha$ -level test**.

Usually we choose  $\alpha = 0.05$  (or 0.10 or 0.01). This says that most of the time, we accept less than 5% probability of Type I error.

E.g., if we are checking whether:  $P(\text{type I error}) = P(\text{test rejects } H_0 \mid H_0) \leq 0.10$ , then the test is a 0.10-level test.

The **p-value** is the probability of observing a sample statistic *as extreme or more extreme* than the one observed under the assumption that the null hypothesis is true. It is the “observed level of significance.”

*When testing a hypothesis, state  $\alpha$ . Calculate the p-value and if the p-value  $\leq \alpha$ , then reject  $H_0$ . Otherwise do not reject  $H_0$ .*

Note: in order to compute the  $\alpha$ -risk, you need  $H_0$  and a decision rule (such as “reject if  $X > a$ ”). For computing  $\beta$ -risk, you need  $H_1$  and a decision rule.

Example: Let’s say we reject a shipment from a vendor if we find more than 1 defective item in a shipment of 100. (That’s our decision rule for determining whether the probability of error is 1%). The number of defective items in a shipment obeys the binomial distribution. If the true probability of error really is 1%, then:

$$\alpha = P(\text{type I error}) = P(\text{reject } H_0 \mid H_0) \\ \mathbb{P}(2 \text{ or more defective} \mid p=0.01) = 0.264 .$$

(We can compute this using the first 2 terms of the binomial distribution.)

Define  $\pi = 1 - \beta$  to be the **power** of the test,

$$\pi = 1 - \beta = P(\text{reject } H_0 \mid H_1).$$

The higher the power, the better the test. The power is useful for assessing whether the test has sufficiently high probability to reject  $H_0$  when  $H_1$  is true.

### Misuse of Hypothesis Tests

- Data in practice are not always a random sample from a distribution.
- It is possible to have a highly statistically significant result that is practically insignificant
  - E.g. an SAT coaching program that has an average improvement of 15.5 points with  $p$ -value  $< 0.001$ , but the average retest gain is already 15 points.
- “If you torture data long enough it will confess” – testing so many hypotheses that you will likely find at least one significant result – and then you only report that one. This is commonly done yet highly incorrect! There are methods (e.g., Bonferroni) that lower the acceptable significance levels when there are multiple tests.

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