## Normal Distribution, Known $\sigma$ , Any Sample Size

▶ Under these assumptions, a  $100(1 - \alpha)\%$  CI of sample mean  $\mu$  is given by

$$(\bar{x} - z_{\alpha/2} \cdot \frac{\sigma}{\sqrt{n}}, \bar{x} + z_{\alpha/2} \cdot \frac{\sigma}{\sqrt{n}})$$

## General Distribution, Unknown $\sigma$ , Large Sample

▶ Under these assumptions, an approximate  $100(1 - \alpha)\%$  CI of sample mean  $\mu$  is given by

$$(\bar{x} - z_{\alpha/2} \cdot \frac{\hat{\sigma}}{\sqrt{n}}, \bar{x} + z_{\alpha/2} \cdot \frac{\hat{\sigma}}{\sqrt{n}})$$

Notice a special case if the distribution is Bernoulli, we have a more accurate but very complicated formula.

# Normal Distribution, Unknown $\sigma$ , Any Sample Size

▶ Under these assumptions, a  $100(1 - \alpha)\%$  CI of sample mean  $\mu$  is given by

$$(\bar{x}-t_{\alpha/2,n-1}\cdot\frac{\hat{\sigma}}{\sqrt{n}},\bar{x}+t_{\alpha/2,n-1}\cdot\frac{\hat{\sigma}}{\sqrt{n}})$$

▶ Here we utilize the *t* distribution.

### **Hypothesis Testing**

- A statistical hypothesis, or just hypothesis, is a claim or assertion either about the value of a single parameter (population characteristic or characteristic of a probability distribution), about the values of several parameters, or about the form of an entire probability distribution.
- A testing problem usually contains two hypotheses: the null hypothesis, denoted by H<sub>0</sub>, is the claim that is initially assumed to be true (the "prior belief" claim). The alternative hypothesis, denoted by H<sub>a</sub>, is the assertion that is contradictory to H<sub>0</sub>.
- The null hypothesis will be rejected in favor of the alternative only if sample evidence suggests that H<sub>0</sub> is false. If the sample does not strongly contradict H<sub>0</sub>, we will continue to believe in the truth of the null hypothesis. The two possible conclusions from a testing analysis are then reject H<sub>0</sub> or fail to reject H<sub>0</sub>.

### **Examples**

Ex. A factory claims that less than 10% of the components they produce are defective. A consumer group is skeptical of the claim and checks a random sample of 300 components and finds that 39 are defective. Is there evidence that more than 10% of all components made at the factory are defective?

$$H_0: p \le 0.10$$
  $H_a: p > 0.10$ 

Ex. We are interested in height of all Columbia students. In a sample of 12 students, the sample mean is 66.30 inches, and the sample s.d. is 4.35 inches. Should we reject the null hypothesis  $H_0$ :  $\mu$  = 68 vs  $H_a$ :  $\mu \neq$  68?

#### Remarks

- In our treatment of hypothesis testing,  $H_0$  will always be stated as an equality claim. If  $\theta$  denotes the parameter of interest, the null hypothesis will have the form  $H_0$ :  $\theta = \theta_0$ .
- The alternative to the null hypothesis  $H_0$ :  $\theta = \theta_0$  will usually look like one of the following three forms:
- 1.  $H_a$ :  $\theta > \theta_0$  (in which case the implicit null hypothesis is  $\theta \le \theta_0$ ).
- 2.  $H_a$ :  $\theta < \theta_0$  (in which case the implicit null hypothesis is  $\theta \ge \theta_0$ ).
- 3.  $H_a$ :  $\theta \neq \theta_0$ .
- 4.  $H_a$ :  $\theta = \theta_1 \neq \theta_0$  (simple alternative).
- The value  $\theta_0$  separates the alternative from the null and is called the null value. The null and alternative are not treated equivalently, once a statement is in the null hypothesis, we will not easily reject it unless we have enough evidence.

### **Motivating example**

Ex. Suppose we have a biased coin, we believe that it has probability 95% of having a head in a flip. Alternatively, it could also have probability 5% of having a head. Can you design a simple test to see if the coin has probability 95% of having heads?

Simple alternative:  $H_0$ : p = 0.95  $H_a$ : p = 0.05

#### **Test Procedures**

A test procedure is specified by the following:

- 1. Find a test statistic, a function of the sample data on which the decision (reject  $H_0$  or do not reject  $H_0$ ).
- 2. Construct a rejection region, the set of all test statistic values for which  $H_0$  will be rejected.

The null hypothesis will then be rejected if and only if the observed or computed test Statistic value falls in the rejection region.

Can you construct a test procedure for the previous example?

### **Example cont.**

Ex. (Biased coin cont.) In order to test if p = 0.95 we decide to conduct one experiment. We are going to flip this biased coin once, if it comes out a head, we will accept the null hypothesis, if it comes out a tail, we will reject the null hypothesis.

Test statistic: X = outcome of the first flip (Bernoulli rv.)

Rejection region: {X: X = 0}

Any other test statistics?

What are the odds that we'll make a mistake in our decision?

## Two types of errors

#### Definition

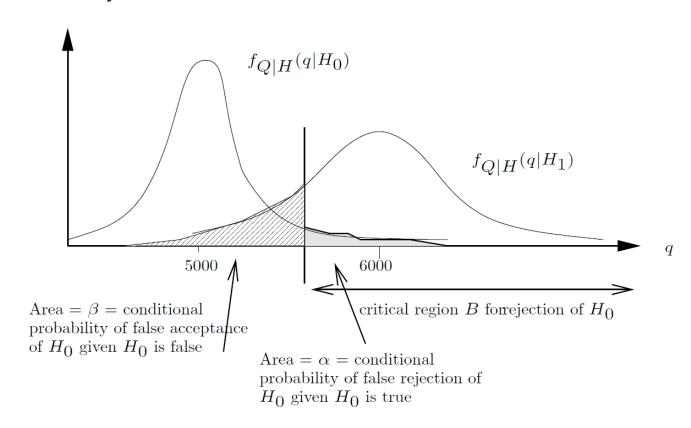
A type I error  $\alpha$  consists of rejecting the null hypothesis  $H_0$  when it is true.

A type II error  $\beta$  involves not rejecting  $H_0$  when  $H_0$  is false.

	Decide to accept	Decide to reject
Null is true	Right	Type I
Alternative is true	Type II	Right

### **Errors**

• Choice of  $\alpha$  is subjective. As move threshold to left, increase  $\alpha$  and decrease  $\beta$ .



### **Example cont.**

Ex. (Biased coin cont.) In order to test if p = 0.95 we decide to conduct one experiment. We are going to flip this biased coin once, if it comes out a head, we will accept the null hypothesis, if it comes out a tail, we will reject the null hypothesis. What are the two types of errors associated with this test procedure?

#### Criteria

- A good test will be aimed to make two types of errors, both  $\alpha$  and  $\beta$ , as small as possible.
- Unfortunately, there is no rejection region that will simultaneously make both  $\alpha$  and  $\beta$  small once the test statistic and sample size are fixed. Thus, a region must be chosen to effect a compromise between  $\alpha$  and  $\beta$ .
- Because of the suggested guidelines for specifying and . A type I error is usually more serious than a type II error (we don't want to reject the null easily).
- In practice, people specify to the largest value that  $\alpha$  can be tolerated and find a rejection region having that value of  $\alpha$ . The resulting value of  $\alpha$  is often referred to as the significance level of the test (0.1, 0.05, 0.01). The corresponding test procedure is called an  $\alpha$  level test. The previous example was an exact 0.05-level test.