

Hypothesis Testing

A statistical hypothesis is an assertion or conjecture concerning one or more populations.

To prove that a hypothesis is true with absolute certainty (or to prove that it is false with absolute certainty), we would have to examine the entire population.

Instead, take a random sample from the population and use it as ~~evidence~~ evidence that either supports or does not support ~~the~~ hypothesis.

H_0 = Null hypothesis. The hypothesis we wish to test.

The rejection of H_0 leads to the acceptance of an alternate hypothesis H_1 . 2 possible outcomes:

- ① reject H_0 : in favor of H_1 because of sufficient evidence in the sample.
- ② fail to reject H_0 : because of insufficient evidence

Note : There is no formal outcome that says accept H_0 . H_0 often represents "status quo" in opposition to a new idea H_1 .

Example : Jury Trial

H_0 : defendant is innocent

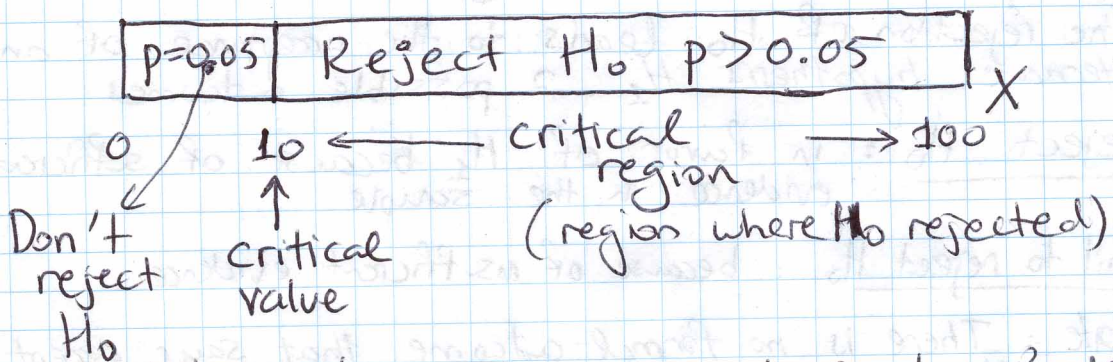
H_1 : " is guilty

H_0 is rejected if H_1 is supported by evidence beyond a reasonable doubt. Failure to reject H_0 doesn't imply innocence, only that the evidence was not sufficient to reject it. Therefore, failure to reject H_0 does not necessarily mean accept H_0 .

Example: A company manufacturing RAM chips claims the defective rate of the population is 5%. Let p denote the true defective probability

$$\begin{array}{l} H_0 : p = 0.05 \\ H_1 : p > 0.05 \end{array} \left\{ \begin{array}{l} \text{Take a sample of 100} \\ \text{RAM chips off the production} \\ \text{line and test. } \end{array} \right.$$

Let X denote the number of defectives in the sample of 100. Reject H_0 if $X \geq 10$ (Note 10 is chosen arbitrarily in this case)
 X is called the test statistic



Q: Why did we choose a critical value of 10 in this example?

A: Since we know this is a Bernoulli Process, the expected value of defectives is np . So if we believe that $p = 0.05$, we should expect $100 \times 0.05 = 5$ defectives in a sample of 100. Therefore, 10 defectives would be strong evidence that $p > 0.05$. Later we will learn how to choose the critical value based on the desired level of significance for the hypothesis test.

Possible situations

	H_0 is true	H_0 is false
Do not reject H_0	Correct decision	Type II error
Reject H_0	Type I error	Correct decision

Defn: Rejection of H_0 when it is true is called a Type I error.

Example: Convicting the defendant when he is innocent.

Defn: The probability of committing a type I error, denoted by α , is called the level of significance.

Example (RAM chips continued)

$$\alpha = P(\text{Type I error}) = P(X \geq 10 \text{ when } p = 0.05)$$

$\underbrace{\geq 10}_{\text{critical region}} \quad \underbrace{p = 0.05}_{H_0 \text{ is true.}}$

$$= \sum_{x=10}^{100} b(x; n=100, p=0.05) \quad \text{Binomial Distribution}$$

$$= \sum_{x=10}^{100} \binom{100}{x} 0.05^x 0.95^{100-x} = 0.0282$$

Level of significance is $\alpha = 0.0282$.

The lower the α , the less likely we are to commit a type I error. Would like small α values. (0.05 or smaller generally used)

Defn: Nonrejection of H_0 when it is false is called a type II error. The probability of committing a type II error is denoted β .

Note: β is impossible to compute unless we have a specific alternate hypothesis.

Example continued: Can't compute β for $H_1: p > 0.05$ but can compute it for testing $H_0: p = 0.05$ against the alternate hypothesis that $p = 0.1$ for instance.

$$\begin{aligned}\beta &= P(\text{Type II error}) = P(X < 10 \text{ when } p = 0.1) \\ &= \sum_{x=0}^9 b(x; n=100, p=0.1) = 0.4513\end{aligned}$$

↑
 H_1 (H_0 False)

This high probability suggests we are likely to fail to reject H_0 if the true p is 0.1.

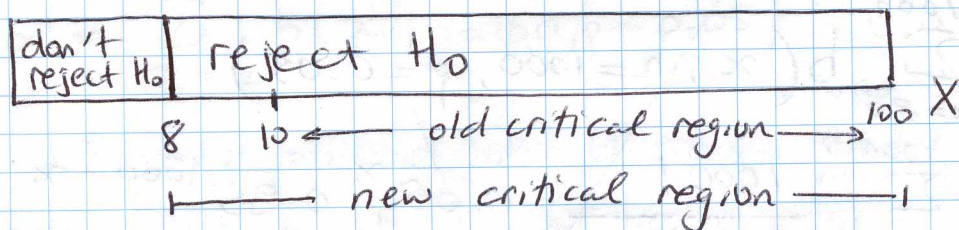
This might be OK if we only want to make sure we don't fail to reject if the true p is 0.15

$$\begin{aligned}\beta &= P(\text{Type II error}) = P(X < 10 \text{ when } p = 0.15) \\ &= \sum_{x=0}^9 b(x; n=100, p=0.15) = 0.0551\end{aligned}$$

Effect of critical value

Moving the critical value provides a trade-off between α and β . A reduction in β is always possible by ~~reducing~~ increasing the size of the critical region, but this increases α .

Example continued: Lets change the critical value from 10 to 8. So reject H_0 if $X \geq 8$.



$$\alpha = \sum_{x=8}^{100} b(x; n=100, p=0.05) \quad \text{Probability of rejecting } H_0 \text{ when it is true}$$
$$= 0.128 \quad (\text{note larger than before when the critical value was set at 10})$$

testing against alternate hypothesis $p=0.1$

$$\beta = \sum_{x=0}^7 b(x; n=100, p=0.1) \quad \text{Probability of not rejecting } H_0 \text{ when } p=0.1$$
$$= 0.206 \quad (\text{lower than before})$$

testing against alternate hypothesis $p=0.15$

$$\beta = \sum_{x=0}^7 b(x; n=100, p=0.15) \quad \text{Probability of not rejecting } H_0 \text{ when } p=0.15$$
$$= 0.012 \quad (\text{again lower than before})$$

Effect of sample size

Both α and β can be reduced simultaneously by increasing the sample size.

Example continued: Sample size $n=150$, critical value 12. Reject H_0 if $X \geq 12$ (X is the # of defectives in sample of 150)

$$\alpha = \sum_{x=12}^{150} b(x; n=150, p=0.05) = 0.074$$

(was 0.128 for $n=100$ and critical value 8)

testing against alternate hypothesis $p=0.1$

$$\beta = \sum_{x=0}^{11} b(x; n=150, p=0.1) = 0.171$$

(was 0.206 for $n=100$ and critical value 8)

Factorials of very large numbers problematic to compute accurately even with MATLAB. Thankfully, the Binomial Distribution can be approximated by the normal distribution - Details Section 6.5

Theorem: If X is a binomial random variable with n trials and probability of success of each trial p , then the limiting form of the distribution of $Z = \frac{X - np}{\sqrt{np(1-p)}}$ as $n \rightarrow \infty$ is the standard normal distribution.

Approximation is good when n is large and p is not extremely close to 0 or 1.

Lets recompute α with the normal approximation.

$$\alpha = P(\text{Type I error}) = \sum_{x=12}^{150} b(x; n=150, p=0.05)$$

$$\approx P\left(Z \geq \frac{12 - 150 \times 0.05}{\sqrt{150 \times 0.05 \times 0.95}}\right) = P(Z \geq 1.69)$$

$$= 1 - P(Z \leq 1.69) = 1 - 0.9545 = 0.0455$$

not too bad.

What if we increase the sample size to $n=500$ and the critical value to 40?

The normal approximation should be even better since n larger

$$\alpha \approx P\left(Z \geq \frac{40 - 500 \times 0.05}{\sqrt{500 \times 0.05 \times 0.95}}\right) = P(Z \geq 3.08)$$

$$= 1 - P(Z \leq 3.08) = 1 - 0.999 = 0.001$$

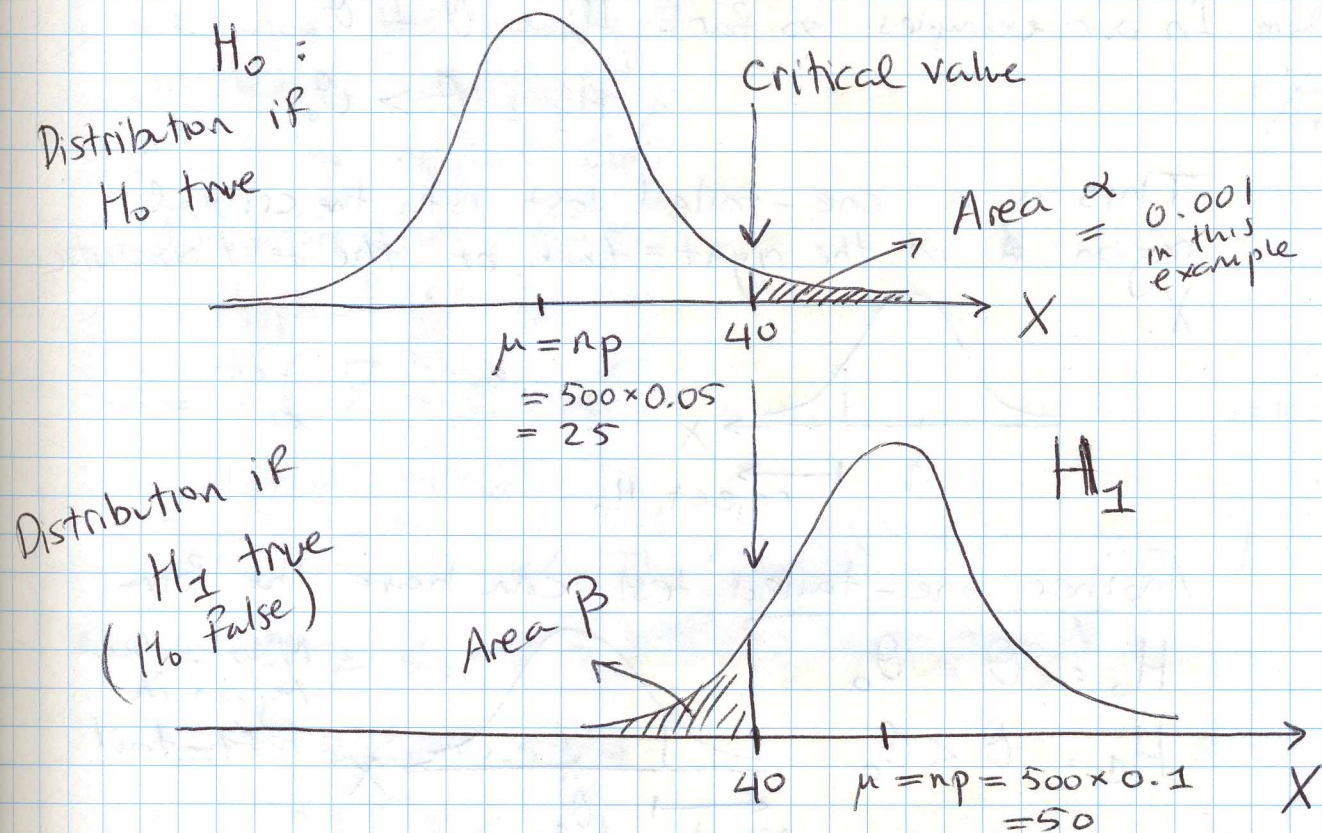
Very unlikely to commit type I error.

testing against alternate hypothesis $p=0.1$

$$\beta = \sum_{x=0}^{39} b(x; n=500, p=0.1)$$

$$\approx P\left(Z \leq \frac{39 - 500 \times 0.1}{\sqrt{500 \times 0.1 \times 0.9}}\right) = P(Z \leq -1.49)$$
$$= 0.0681$$

Visual interpretation with normal approximation



Defn: The power of a test is the probability of rejecting H_0 given that a specific alternate is true. Power = $1 - \beta$.

Properties of hypothesis testing

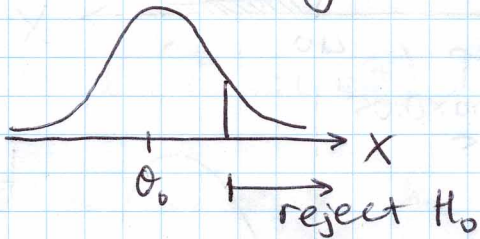
- ① α and β are related. Decreasing one generally increases the other
- ② α can be set to a desired value by adjusting the critical value. α typically set at 0.05 or 0.01
- ③ Increasing n decreases α and β both.
- ④ β decreases as the distance between the true value and hypothesized (H_1) value increases.

One-tailed vs. two-tailed tests

In an examples so far $H_0: \theta = \theta_0$

$H_1: \theta > \theta_0$

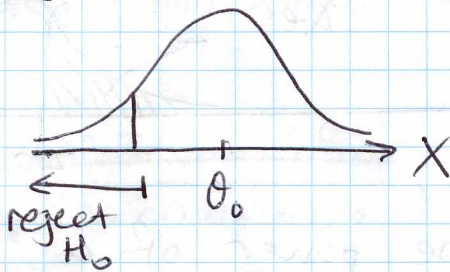
This is a one-tailed test with the critical region in the right-tail of the test statistic X .



Another one-tailed test can have the form

$H_0: \theta = \theta_0$

$H_1: \theta < \theta_0$

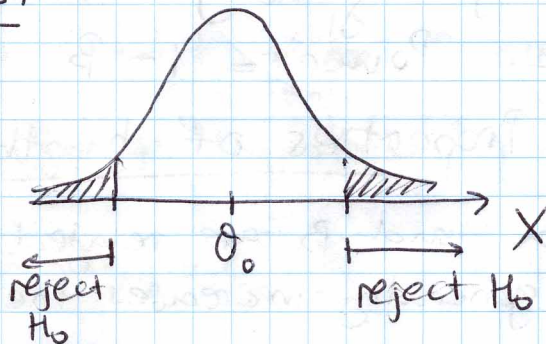


Now critical region in left-tail.

Two-sided test

$H_0: \theta = \theta_0$

$H_1: \theta \neq \theta_0$



Example: Production line of resistors that are supposed to be 100 ohms. Assume $\sigma = 8$

$H_0: \mu = 100$

Let \bar{X} be the sample mean for a sample of size $n = 100$

$H_1: \mu \neq 100$

Reject H_0	Do not reject H_0	Reject H_0
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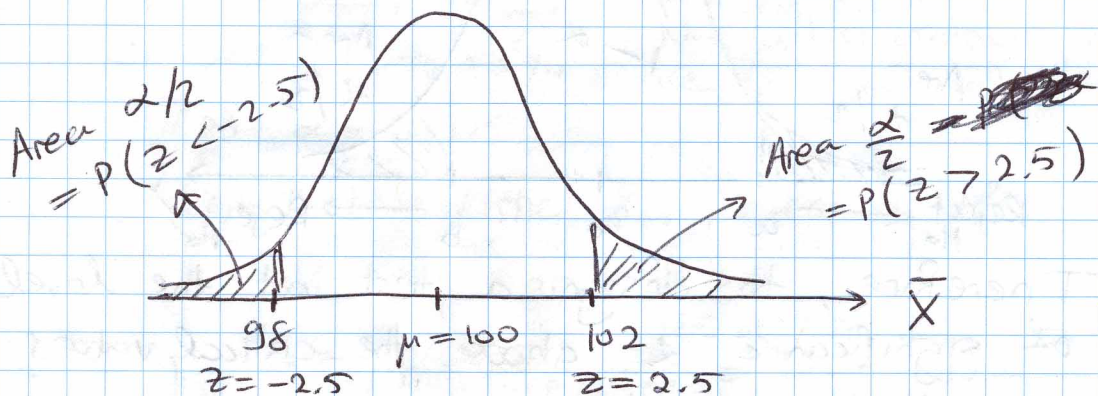
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The test statistic is the sample mean in this case.

We know the sampling distribution of \bar{X} is a normal distribution with mean μ and standard deviation $\frac{\sigma}{\sqrt{n}}$ due to the central limit theorem. ($n=100 > 30$)

Therefore we can compute the probability of a type I error as

$$\begin{aligned}\alpha &= P(\bar{X} < 98 \text{ when } \mu=100) + P(\bar{X} > 102 \text{ when } \mu=100) \\ &= P\left(Z < \frac{98-100}{8/\sqrt{100}}\right) + P\left(Z > \frac{102-100}{8/\sqrt{100}}\right) \\ &= P(Z < -2.5) + P(Z > 2.5) \\ &= P(Z < -2.5) + (1 - P(Z < 2.5)) \\ &= 2P(Z < -2.5) = 2 \times 0.0062 = 0.0124\end{aligned}$$



* Testing $H_0: \mu = \mu_0$ against $H_1: \mu \neq \mu_0$ at a significance level α is equivalent to computing a $100(1-\alpha)\%$ confidence interval for μ and rejecting H_0 if μ_0 is outside the confidence interval.