

Chapter 9. Hypothesis Testing (Vocabulary and Procedure)

- A “**Statistical Hypothesis**” is a statement about a distribution, usually about a parameter
- H_0 “**Null Hypothesis**” is that nothing interesting or unusual is happening
- H_A “**Alternative Hypothesis**” is the opposite of the Null Hypothesis (includes your expected value)

Example. If $H_0: p = \frac{1}{2}$ then $H_A: p \neq \frac{1}{2}$.

If $H_0: \mu \leq 8$ then $H_A: \mu > 8$.

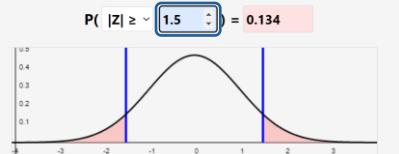
In practice, p -value is either a **one-tailed** or **two-tailed** probability of a z -score or t -score

Two-Tailed Test

$$H_0: \mu = 8 \text{ and } H_A: \mu \neq 8$$

- Statistic is $z = \frac{\bar{x} - 8}{\sigma/\sqrt{n}}$
- p -value is $P(|Z| \geq z)$

Standard Normal Quantiles and Probabilities



Usually tests are **two-tailed**.

- Note: p -values for two-tailed tests are $2 \times$ as big
- Use one-tailed test to show something is **bigger** than something else.

Goal of hypothesis testing is to show that data is incompatible with null hypothesis.

“Reject the null hypothesis”

1. Compute **statistic** estimating parameter
2. Compute **p -value** (probability of statistic if H_0 is true)
3. Compare p -value to chosen **significance level α**
4. If $p < \alpha$, then “Reject the Null Hypothesis”
If $p \geq \alpha$, then “Fail to Reject the Null Hypothesis”

Note: α is usually 1% or 5% and **cannot** be changed.

To get $p < \alpha$, we need **small** p -value.

- **Best way:** Use lots of data. Big n yields small p .
- **Alternate:** Decrease σ ? Partition data to subsets?

Note: If statistic \bar{x} is far from null hypothesis μ_0 , then p -value will be small even without much data!

The closer statistic is to null hypothesis, the more data will be needed to get **significance**!

Testing mean μ :

- **z -test** if σ **known** and either data is Normal or else number of samples $n > 30$
- **t -test** if σ **unknown** and data is Normal

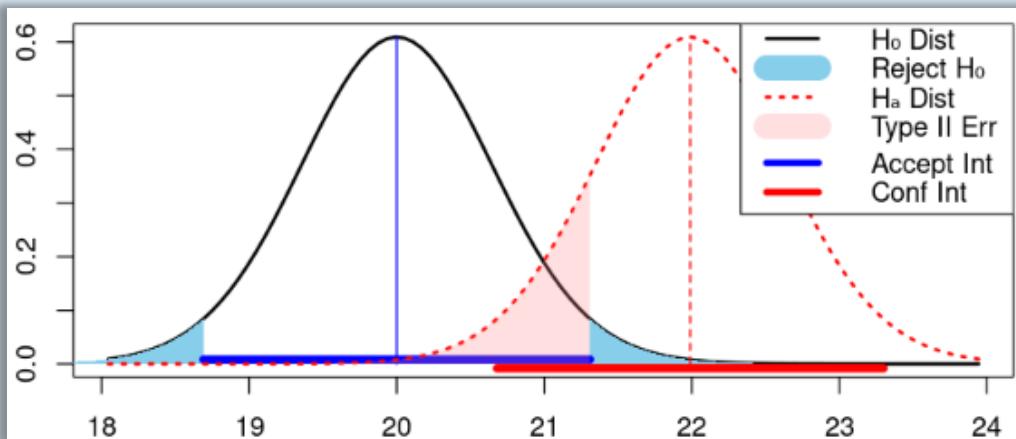
Testing population proportions:

- **Proportion test**

Chapter 9. Hypothesis Testing (Errors and Power)

| | Reject H_0 | Fail to reject H_0 |
|----------------|--------------|----------------------|
| H_0 is True | Type I Error | no error |
| H_0 is False | no error | Type II Error |

- **Type I Error** is when null hypothesis is **true**... but your data leads you to incorrectly **reject** it.
- **Type II Error** is when null hypothesis is **false**... but your data isn't significant enough to reject.



The **significance** cutoff α used for rejecting is equal to
Probability of Type I Error (blue area in plot above)

The complementary probability $(1 - \alpha)$ is called the
“Confidence Level”.

Confidence level is probability of correct conclusion if
the null hypothesis is **true**.

The **Probability of Type II Error** is written β .
(red shaded area in plot above)

The complementary probability $(1 - \beta)$ is called the
“Power”.

Power of test is the probability of correct conclusion if
the null hypothesis is **false**.

Goal: Design experiment to have **high confidence** and **high power** \iff error probabilities α and β **small**

Problem: Directly changing α to be **smaller** will make β **bigger**, and vice versa.

- Type I error is **WORSE** than Type II error
- Set α at a *small* value like 5% or 1%
- To get β small, use more data (bigger n)
(If statistic is far from null hypothesis, then β might be small even without much data!)

Note: “statistically significant” does not mean “important”.
If you have enough data, then even tiny, unimportant differences can be statistically significant.