

# Sampling, Uncertainty, and Hypothesis Testing

## Mathematical Intuition for Seminar & Worksheet

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# Motivation: Why Do We Need Probability?

- In practice, we observe **samples**, not populations
- Samples vary due to **random chance**
- Statistics gives us tools to reason about this uncertainty

**Key question:** How confident should we be that an observed pattern reflects the population?

# Sampling and Central Tendency

Let  $Y_1, \dots, Y_n$  be a random sample from a population with mean  $\mu$ .

$$\bar{Y} = \frac{1}{n} \sum_{i=1}^n Y_i$$

- $\bar{Y}$  is our **best guess** of  $\mu$
- Different samples  $\Rightarrow$  different sample means

This variability across samples is called **sampling variation**.

# The Sampling Distribution

If we repeatedly draw samples and compute  $\bar{Y}$ :

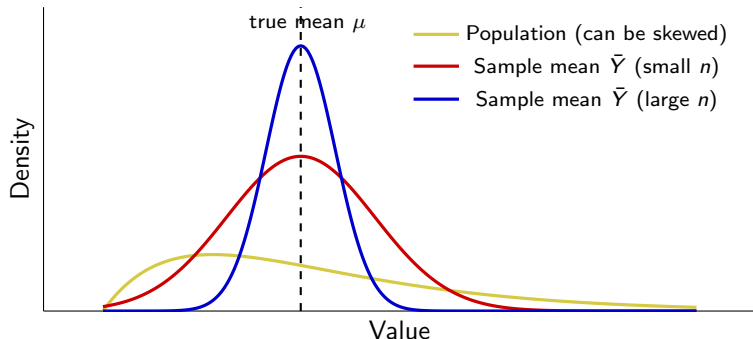
- The collection of sample means forms a distribution
- This is the **sampling distribution of the mean**

$$\bar{Y} \sim \mathcal{N}\left(\mu, \frac{\sigma^2}{n}\right)$$

- Centered at the true mean  $\mu$
- Spread shrinks as  $n$  increases

# Central Tendency + CLT

**Idea:** Individual observations can be skewed, but **averages** across many random samples cluster near the true mean.



**CLT (one line):** As sample size  $n$  increases, the distribution of  $\bar{Y}$  becomes more normal and more concentrated around  $\mu$  (since  $SE = \sigma/\sqrt{n}$  shrinks).

# Standard Error: Measuring Uncertainty

The standard deviation of the sampling distribution is the **standard error**:

$$SE(\bar{Y}) = \frac{\sigma}{\sqrt{n}}$$

- Larger  $n \Rightarrow$  smaller uncertainty
- Explains why large samples give more precise estimates

The same principle applies to:

- Differences in means
- Regression coefficients

# Hypothesis Testing: Formal Setup

We test claims about the population using two hypotheses:

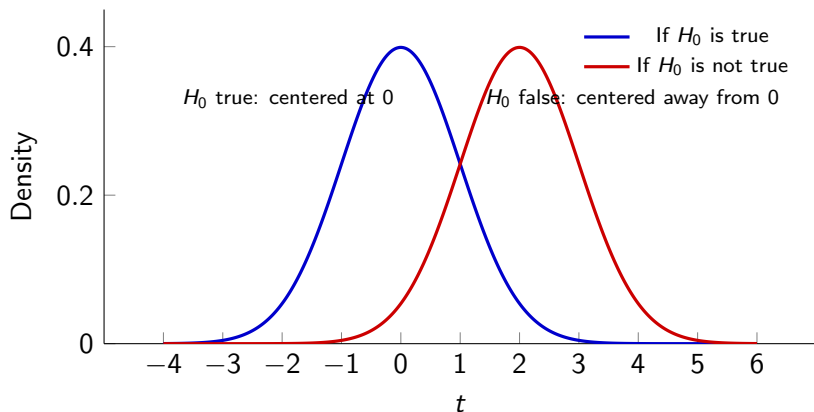
$$H_0 : \theta = \theta_0 \quad (\text{Null})$$

$$H_A : \theta \neq \theta_0 \quad (\text{Alternative})$$

- $H_0$  represents **no effect / no difference**
- $H_A$  represents the presence of an effect

We assume  $H_0$  is true and ask: *How surprising is our data?*

# Sampling Distributions: When $H_0$ is True vs Not True



- If  $H_0$  is true, repeated samples give test statistics clustered around 0.
- If  $H_0$  is not true (a real effect exists), the distribution shifts away from 0.

# Test Statistics and p-values

A generic test statistic:

$$z = \frac{\hat{\theta} - \theta_0}{SE(\hat{\theta})}$$

- Measures distance from the null in standard errors
- The **p-value** is:

$$P(|Z| \geq |z_{\text{obs}}| \mid H_0 \text{ true})$$

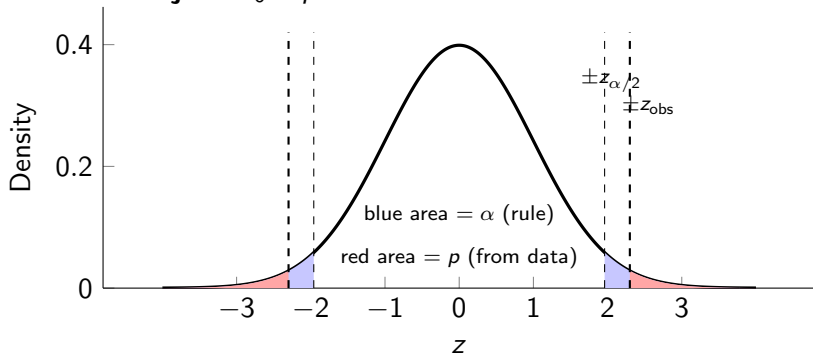
Small p-value  $\Rightarrow$  data unlikely under the null.

**Note:** Often software will use a t-distribution for the test statistic. For our purposes, this is immaterial.

# p-values vs Significance Level $\alpha$ (Two-Tailed Test)

Assume the null is true (e.g.  $H_0 : \mu = \mu_0$ ). The **p-value** is the probability of results at least this extreme under  $H_0$ :  $p = P(|Z| \geq |z_{\text{obs}}| \mid H_0)$ .

**Decision rule:** reject  $H_0$  if  $p < \alpha$



Two-tailed intuition: we count outcomes *too high or too low* relative to the null (both tails).

# What Is a p-value?

## The p-value answers:

*If the null were true, what fraction of the normal distribution lies at values at least this far from  $\mu_0$ ?*

- A p-value of 0.05 means **5% of the total area** of the distribution is more extreme than what we observed
- In a two-tailed test, this probability is split across **both tails**

**Key intuition:** small p-value  $\Rightarrow$  the observed sample mean lies in a low-probability region of the null distribution.

# Significance Levels and Decisions

Choose a significance level  $\alpha$  (e.g. 0.05 or 0.01).

- If  $p < \alpha$ : reject  $H_0$
- If  $p \geq \alpha$ : fail to reject  $H_0$

## Important:

- Rejecting  $H_0$  does *not* prove  $H_A$
- It means the data are inconsistent with  $H_0$

# Application: OLS Regression

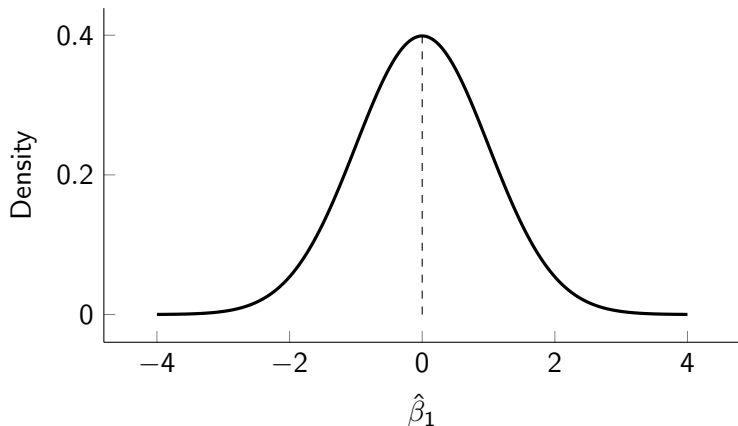
Simple regression model:

$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i$$

- $\beta_1$  measures the average change in  $Y$  for a 1-unit increase in  $X$
- We test:

$$H_0 : \beta_1 = 0 \quad \text{vs} \quad H_A : \beta_1 \neq 0$$

# Sampling Distribution of the OLS Slope



- Centered at 0 if  $H_0$  is true
- Observed slope far from 0  $\Rightarrow$  small p-value

In the worksheet you will:

- State null and alternative hypotheses
- Interpret t-statistics and p-values
- Compare results at 5% and 1% significance levels

**Always ask:**

- What is the parameter?
- What value does the null specify?
- How extreme is the observed estimate?