

# 0.1 Learning Objectives

By the end of this lecture, you will be able to:

- Understand why statistical tests are needed
- Define null and alternative hypotheses
- Calculate and interpret test statistics
- Interpret p-values correctly
- Distinguish one-tailed from two-tailed tests

# 1. Why Statistical Tests?

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## 1.1 Warm-Up

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***Try it yourself***

Talk to your neighbor and try to solve this problem.

## 1.2 Warm-Up: One Data Point

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Student A (bike): 12 minutes

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Can we conclude anything from a single observation per group?

## 1.3 Warm-Up: More Data

We survey six students and time their Monday morning commutes:

<b>Student</b>	<b>Commute (min)</b>	<b>Mode</b>
1	11	Bike
2	14	Bike
3	9	Bike
4	16	Car
5	22	Car
6	13	Car

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## 1.4 The Core Problem

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**Note:** “Random chance” collects the influence of *all other variables* we aren’t measuring: route chosen, time of departure, traffic lights, finding parking, etc.

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**Statistical tests** help us quantify how confident we should be in conclusions drawn from finite samples.

## 2. Sample vs. Population

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## 2.1 Population Statistics

### Definition: Population Parameters

For a population of size  $N$ :

**Population mean:**  $\mu = \frac{1}{N} \sum_{i=1}^N x_i$

**Population variance:**  $\sigma^2 = \frac{1}{N} \sum_{i=1}^N (x_i - \mu)^2$

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We rarely have access to the entire population.

## 2.2 Sample Statistics

### Definition: Sample Statistics

For a sample of size  $n$  drawn from the population:

**Sample mean:**  $\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$

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**Note:** Why  $n - 1$ ? Dividing by  $n - 1$  gives an **unbiased estimate** of the population variance:  $E(s^2) = \sigma^2$ . Dividing by  $n$  would systematically underestimate  $\sigma^2$ .

## 2.3 Sample vs. Population: Summary

	<b>Sample Statistic</b>	<b>Population Parameter</b>
Mean	$\bar{x} = \frac{1}{n} \sum x_i$	$\mu = \frac{1}{N} \sum X_i$
Variance	$s^2 = \frac{1}{n-1} \sum (x_i - \bar{x})^2$	$\sigma^2 = \frac{1}{N} \sum (X_i - \mu)^2$

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We use **sample statistics** to *estimate* population parameters.

# 3. Hypothesis Testing Framework

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## 3.1 Key Terminology

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The hypothesis that there is **no effect** or **no difference**. For example: “CS and CSEng majors have the same mean income.”

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### Definition: Alternative Hypothesis ( $H_1$ )

The hypothesis that the null is **not true**. For example: “CS and CSEng majors have different mean incomes.”

## 3.2 More Terminology

### Definition: Test Statistic

A number computed from the data that **summarizes the evidence** against  $H_0$ .

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### Definition: Null Distribution

The distribution of the test statistic **assuming  $H_0$  is true**.

If our observed test statistic is extreme relative to the null distribution, we have evidence against  $H_0$ .

## 3.3 The t-Test

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The idea: if both samples came from the *same* population, how likely is it to see a difference this large?

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A larger  $|t|$  indicates a greater difference relative to the variability in the data.

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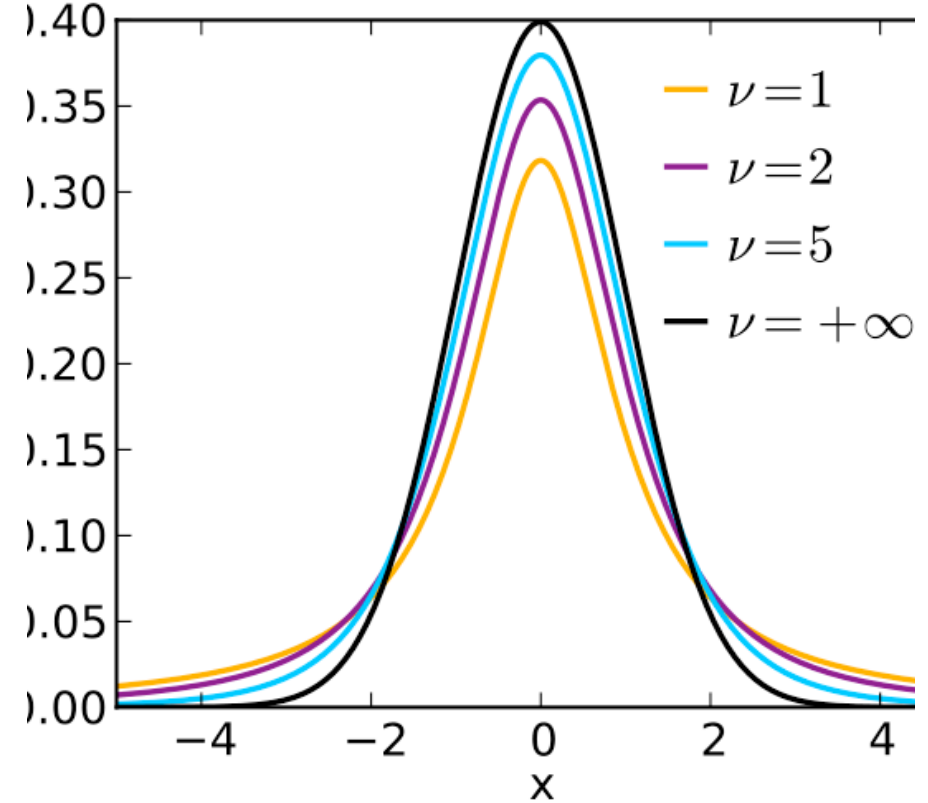
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Looks like the normal distribution, but with **fatter tails** (more probability in the extremes).

Named after William Sealy Gosset, who published under the pseudonym "Student".



## 3.6 Try It: Reading the t-Distribution

Given

$$t = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}$$

Where on the distribution is the region  
for  $t \geq 2.5$ ?

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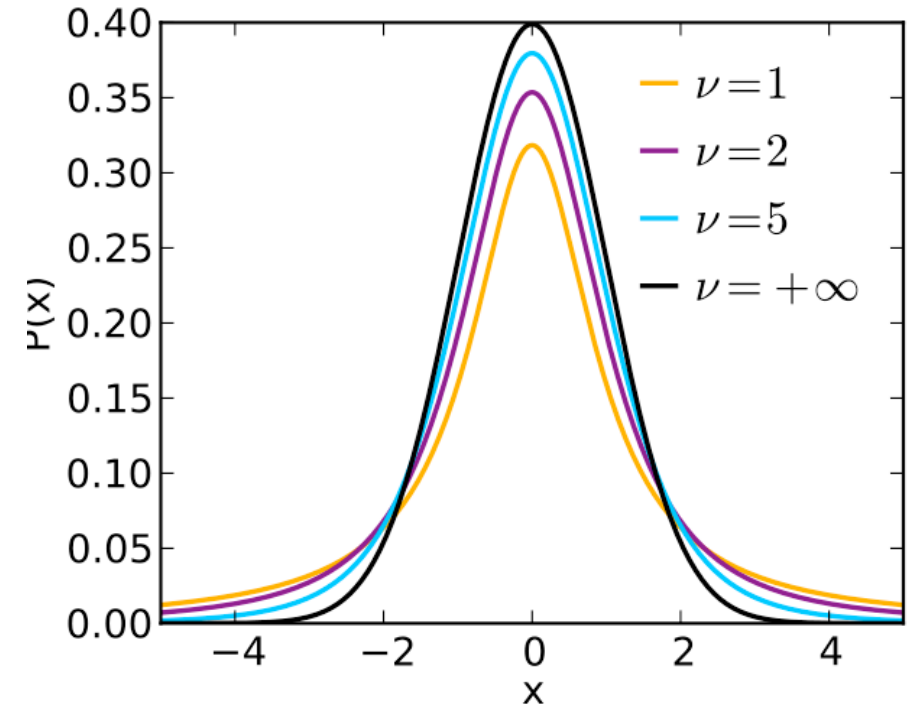
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## 4. p-Values

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## 4.1 Understanding p-Values

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### Definition: p-Value

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We say a result is **significant at the 5% level** if the p-value is less than 0.05.

This means: there is only a 5% chance of seeing such an extreme result if  $H_0$  is true.

## 4.2 One-Tailed vs. Two-Tailed Tests

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- $H_1: \mu_1 > \mu_2$  (or  $\mu_1 < \mu_2$ )

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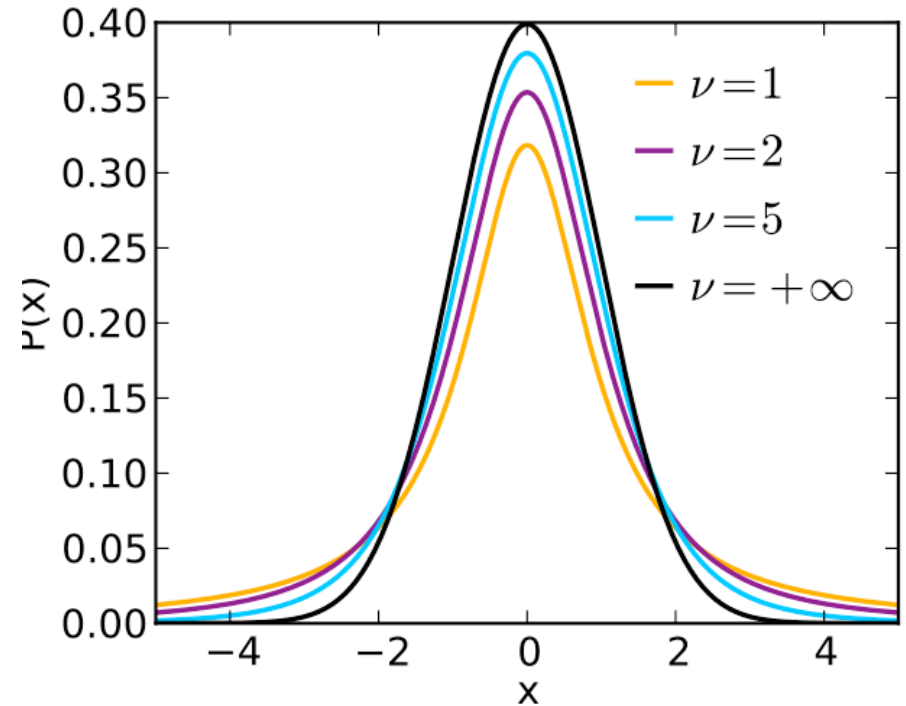
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- $H_1: \mu_1 \neq \mu_2$

Two-tailed is more conservative (harder to reject  $H_0$ ).



## 4.3 Try It: Interpreting a p-Value

### **Example:** Commute Study

“We performed a t-test comparing mean commute times of bikers and drivers at UC Davis. We found that drivers take 5.3 minutes longer on average, with a p-value of 0.043.”

**In your own words, what does this mean?**

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At the 1% significance level ( $\alpha = 0.01$ ): we **fail to reject**  $H_0$  since  $0.043 > 0.01$ .

**Note:** Rejecting  $H_0$  does **not** prove  $H_1$ . It means the data is unlikely under  $H_0$ .

# 5. Significance Levels and Errors

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### **Definition: Type I Error (False Positive)**

Rejecting  $H_0$  when it is actually true. Probability =  $\alpha$ .

### **Definition: Type II Error (False Negative)**

Failing to reject  $H_0$  when it is actually false. Probability =  $\beta$ .

## 5.2 The Error Trade-Off

	$H_0$ True	$H_0$ False
Reject $H_0$	Type I Error ( $\alpha$ )	Correct!
Fail to reject $H_0$	Correct!	Type II Error ( $\beta$ )

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	$H_0$ True	$H_0$ False
Reject $H_0$	Type I Error ( $\alpha$ )	Correct!
Fail to reject $H_0$	Correct!	Type II Error ( $\beta$ )

- Decreasing  $\alpha$  (stricter threshold)  $\rightarrow$  fewer false positives, but more false negatives
- Common choices:  $\alpha = 0.05$ ,  $\alpha = 0.01$ ,  $\alpha = 0.001$

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In this course, we focus on the **concepts**

## 5.3 Other Statistical Tests

the specific test depends on your data and question.

## 5.4 Recap

Today we covered:

- **Statistical tests** quantify uncertainty when drawing conclusions from finite samples
- **Null hypothesis** ( $H_0$ ): assume no effect; **alternative** ( $H_1$ ): there is an effect
- The **t-statistic** measures how different two means are, relative to variability
- The **p-value** is the probability of seeing data this extreme if  $H_0$  is true
- **Type I error** (false positive) rate is controlled by the significance level  $\alpha$