

# Lecture 0: Foundations

## What Statistics Is and Why It's Hard

## How much should you trust a number?

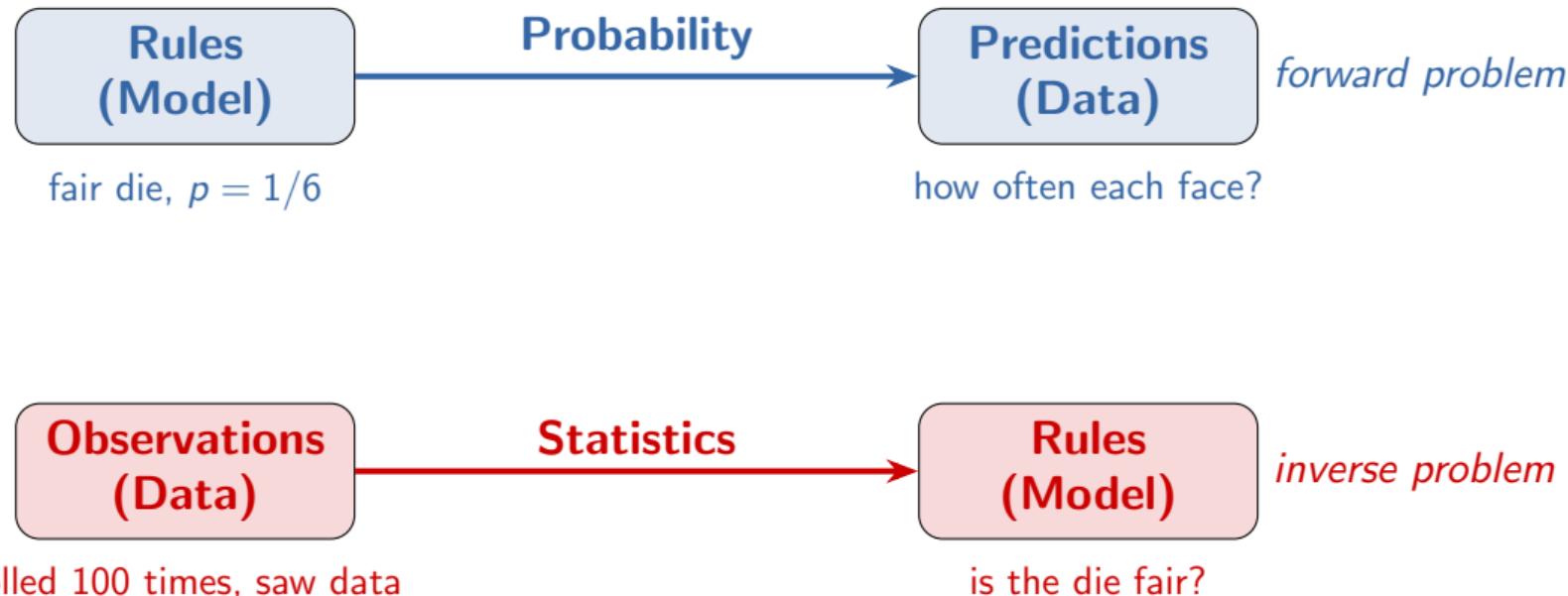
**A poll says:** “52% support candidate A” ( $n = 1,000$ )

**A clinical trial says:** “Drug B reduces symptoms by 15%” ( $n = 200$ )

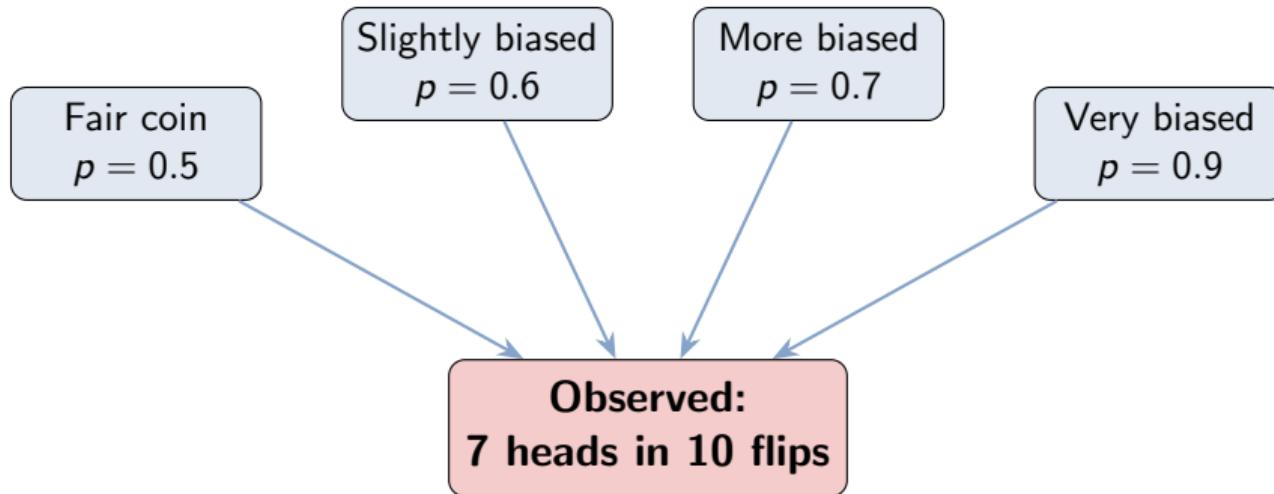
## How confident should we be?

This entire course is about answering this question rigorously.

# Probability vs Statistics



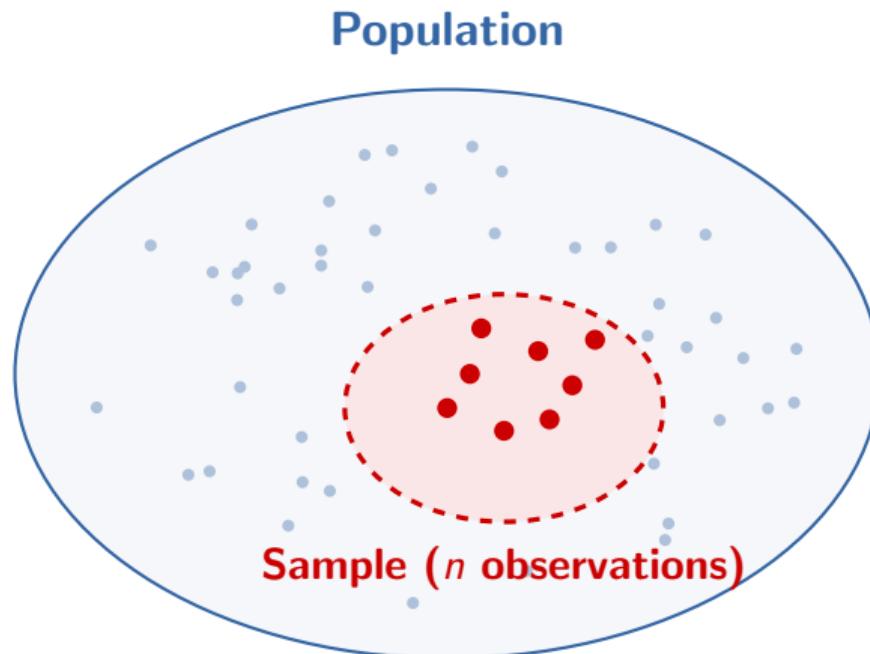
## Why the inverse problem is harder



Many different models could have produced this data!

The inverse problem is **ill-posed** — statistics gives us tools to navigate this.

# Population vs Sample



**Population:**

All units of interest

Can be finite or

conceptually infinite

**Sample:**

The subset we  
actually observe

# Parameter vs Statistic

## Parameter $\theta$

Fixed, unknown number  
Describes the **population**

Examples:

$\mu$  = true mean lifetime  
 $p$  = true approval rate  
 $\sigma^2$  = true variance

we estimate this  
using this

## Statistic $T(X_1, \dots, X_n)$

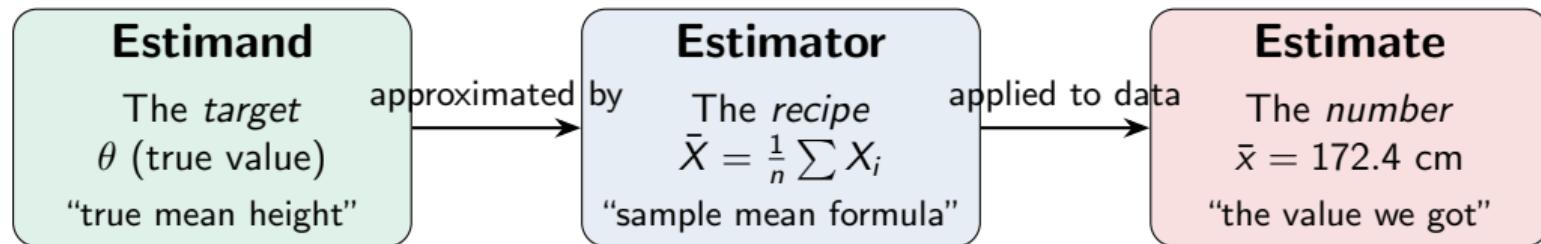
Random variable, computable  
Computed from the **sample**

Examples:

$\bar{X}$  = sample mean  
 $\hat{p}$  = sample proportion  
 $S^2$  = sample variance

A **parameter** is a fixed number. A **statistic** is a random variable.  
Confusing these is the source of most beginner mistakes.

# The Triple: Estimand / Estimator / Estimate



## Discussion

**A polling agency surveys 1,000 people and reports:**  
**“62% support policy X”**

Identify each:

1. What is the **population**?
2. What is the **parameter**?
3. What is the **sample**?
4. What is the **statistic**?
5. What is the **estimate**?

# The i.i.d. Assumption

Classical statistics assumes our sample  $X_1, X_2, \dots, X_n$  is **i.i.d.**:

## Independent

Knowing  $X_1$  tells you  
nothing about  $X_2$

Each observation is a fresh draw

## Identically Distributed

Every  $X_i$  comes from the  
same distribution  $F$

Same process generates each one

## When does i.i.d. hold?

- ✓ Random sampling from a large population
- ✓ Repeated independent measurements of the same quantity
- ✓ Controlled experiments with proper randomization

i.i.d. is an **idealization** — it's approximately true in many practical settings, and most of what we'll do this course assumes it.

# When does i.i.d. break?

## Time dependence

stock prices, weather

## Non-response bias

who refuses the survey?

## Spatial correlation

neighboring sensors

## Distribution shift

training data  $\neq$  deployment

## Selection bias

hospital-only patients

## Clustering

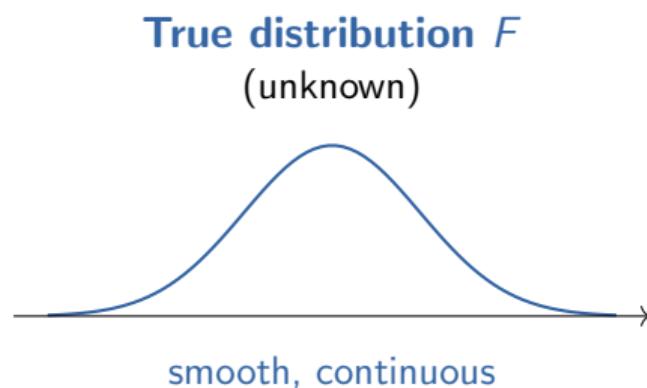
students within schools

Not a disaster — just means you need different tools.

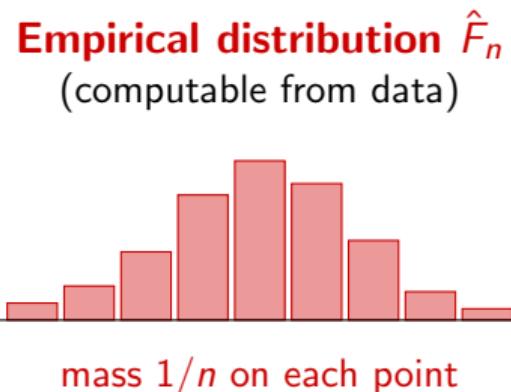
But if you *pretend* non-i.i.d. data is i.i.d.,  
your conclusions can be **wildly wrong**.

# The Plug-in Principle

**Idea:** We don't know the true distribution  $F$ , so replace it with the **empirical distribution**  $\hat{F}_n$ .



replace with  
→



## Plug-in in Action

Replace the **population quantity** with its **sample analogue**:

Want	Population	Plug-in
Mean	$\mu = \mathbb{E}_F[X]$	$\hat{\mu} = \bar{X} = \frac{1}{n} \sum X_i$
Variance	$\sigma^2 = \text{Var}_F(X)$	$\hat{\sigma}^2 = \frac{1}{n} \sum (X_i - \bar{X})^2$
CDF	$F(t) = P(X \leq t)$	$\hat{F}_n(t) = \frac{\#\{X_i \leq t\}}{n}$

**Glivenko–Cantelli theorem:**  $\hat{F}_n \rightarrow F$  uniformly as  $n \rightarrow \infty$ .

(The “fundamental theorem of statistics” — connects to LLN from Module 20.)

# The Summarization Problem

You must summarize a distribution with a **single number**  $a$ .

How do you choose?

It depends on what “error” means to you.

This is formalized by a **loss function**  $L(\theta, a)$ .

# Three Losses, Three Optimal Summaries

## Squared Error

$$L = (\theta - a)^2$$

Penalizes large errors heavily



Mean

## Absolute Error

$$L = |\theta - a|$$

Linear penalty,  
robust to outliers



Median

## 0–1 Loss

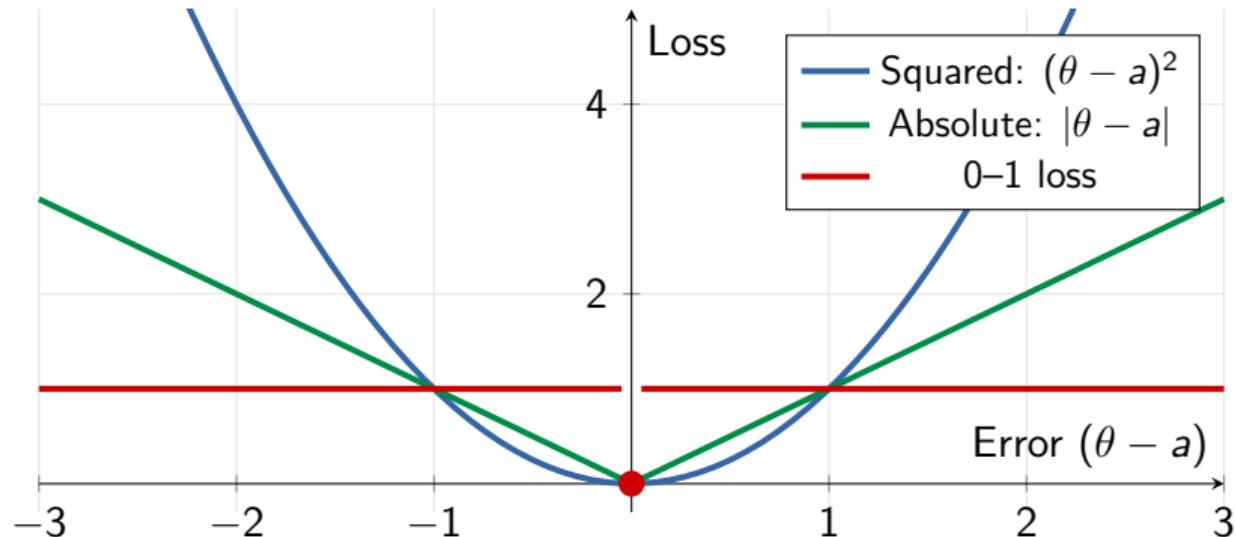
$$L = \mathbf{1}[\theta \neq a]$$

Wrong or right,  
nothing in between



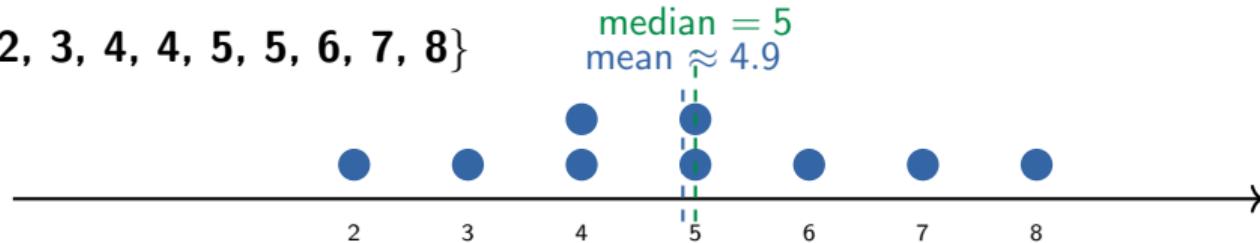
Mode

## Visualizing the Losses

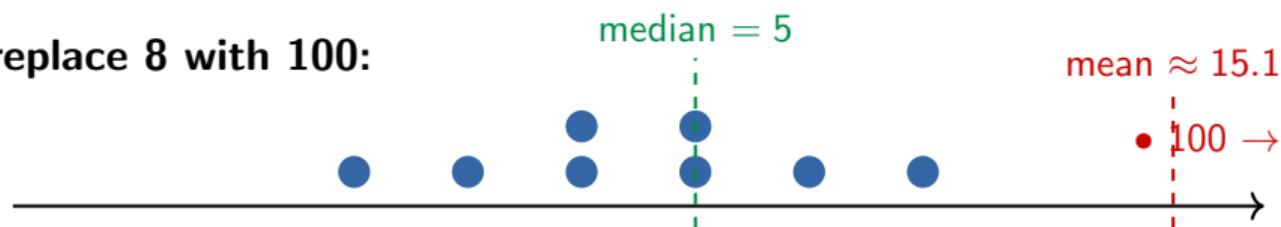


## Mean vs Median: Sensitivity to Outliers

Dataset:  $\{2, 3, 4, 4, 5, 5, 6, 7, 8\}$



Now replace 8 with 100:



One outlier moved the mean from 4.9 to 15.1.  
The median didn't budge.

# Risk and Empirical Risk

## Risk (theoretical)

$$R(\theta, \hat{\theta}) = \mathbb{E}[L(\theta, \hat{\theta})]$$

Average loss over  
all possible samples

(unknown — depends on  $F$ )

approximate  
→

## Empirical Risk

$$\hat{R} = \frac{1}{n} \sum_{i=1}^n L(X_i, a)$$

Average loss on the  
data we actually have

(computable!)

**Empirical Risk Minimization (ERM):** choose the estimator that minimizes  $\hat{R}$ .  
This principle unifies least squares, maximum likelihood, and most learning algorithms.

# The Choice of Loss Reflects Your Values

## Medical dosing

Overdose vs underdose have very different consequences  
⇒ asymmetric loss

## House prices

Mansions in the data?  
 $MAE \neq MSE$  answer  
⇒ median vs mean

## Spam filter

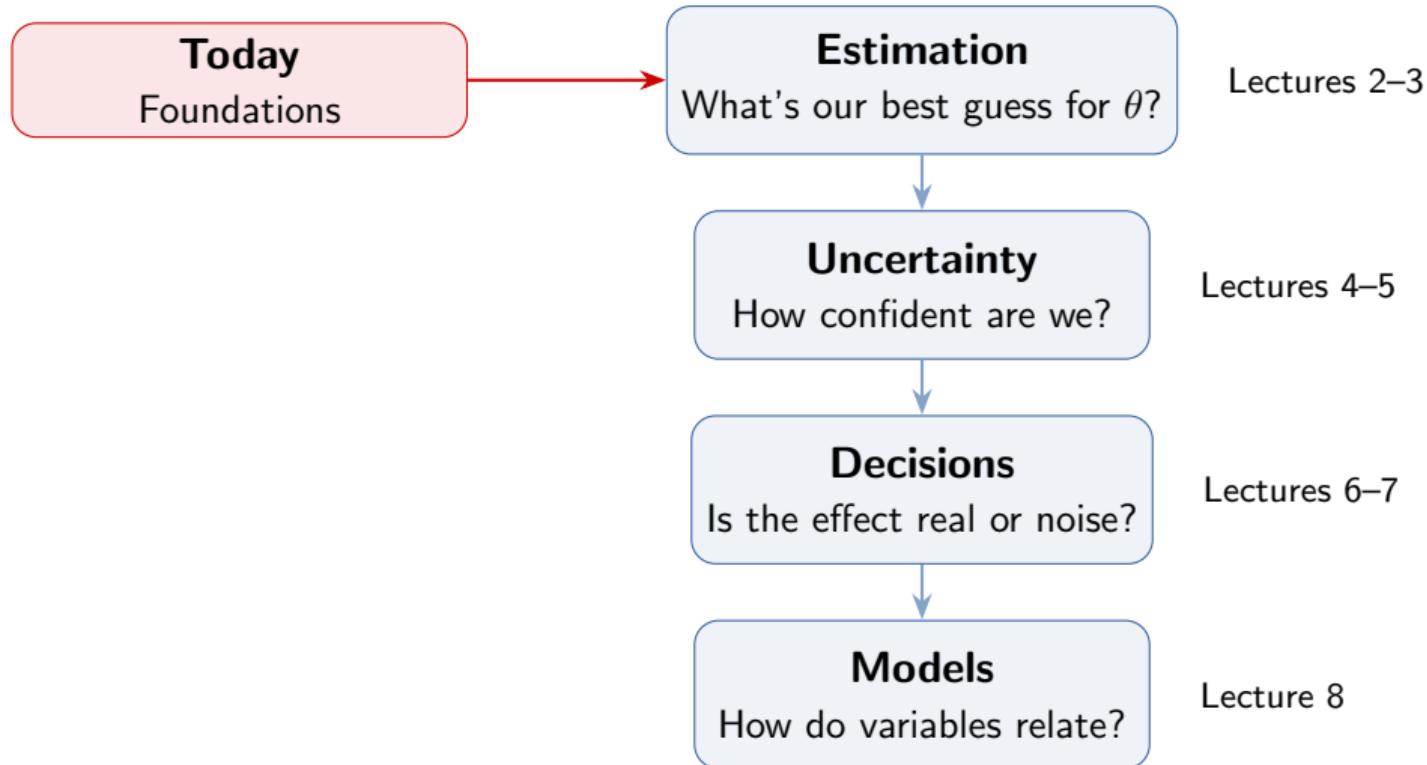
Blocking real email vs letting spam through  
⇒ different error costs

## Flood planning

Under-predicting flood level is catastrophic  
⇒ conservative (high quantile)

**There is no “correct” loss — it depends on context.**

# What Statistics Will Give Us



## Practical: Loss, Risk, and Robustness

Given a dataset (e.g., city temperatures, exam scores, household incomes):

1. Compute the sample **mean**, **median**, and **mode**
2. Compute empirical risk under each loss for each summary
3. Verify: mean minimizes squared-error risk, median minimizes absolute-error risk
4. Add one extreme outlier and repeat
5. Observe: how much does each summary move?

**Discuss:** Which summary would you report, and why?

Does the answer depend on context?

# Questions?

Next lecture: Descriptive Statistics & Empirical Distributions