

Lecture 23a. Fundamental Concepts of Modern Statistical Inference

March 29, 2013

Agenda

- Statistical Models
- Point Estimates
- Confidence Intervals
- Hypothesis Testing
- Summary

Statistical Inference

Statistical inference, or “learning”, is the process of using data to infer the distribution that generated the data. The basic statistical inference problem is the following:

Basic Problem

We observe $X_1, \dots, X_n \sim \pi$. We want to infer (or estimate, or learn) π or some features of π such as its mean.

Definition

A **statistical model** is a set of distributions or a set of densities \mathcal{F} .

- A **parametric model** is a set \mathcal{F} that can be parameterized by a finite number of parameters.
- A **nonparametric model** is a set \mathcal{F} that cannot be parameterized by a finite set of parameters.

Examples of Statistical Models

Examples:

- If we **assume** that the data come from a **normal distribution**, then the model is

$$\mathcal{F} = \left\{ \pi(x|\mu, \sigma^2) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right), \quad \mu, \sigma^2 \in \mathbb{R} \right\}$$

This is a **two-parameter model**. In $\pi(x|\mu, \sigma^2)$, x is a value of the random variable, whereas μ and σ^2 are parameters.

- A **nonparametric model**:

$$\mathcal{F}_{\text{all}} = \{\text{all PDFs}\}$$

We will focus on **parametric models**.

In general, a parametric model takes the form

$$\boxed{\mathcal{F} = \{\pi(x|\theta), \quad \theta \in \Theta\}}$$

where θ is an **unknown parameter** and Θ is the **parameter space**.

Remark: θ can be a vector, for instance, $\theta = (\mu, \sigma^2)$

Point Estimation

Given a **parametric model**, $\mathcal{F} = \{\pi(x|\theta), \theta \in \Theta\}$, the problem of inference is then to **estimate (to learn) the parameter θ** from the data.

Almost all problems in statistical inference can be identified as being one of three types: **point estimates**, **confidence intervals**, and **hypothesis testing**.

- **Point Estimation** refers to providing a single “best guess.”

Suppose $X_1, \dots, X_n \sim \pi(x|\theta)$, where $\pi(x|\theta) \in \mathcal{F}$.

A **point estimator** $\hat{\theta}_n$ of a parameter θ is some function of X_1, \dots, X_n :

$$\hat{\theta}_n = f(X_1, \dots, X_n)$$

Remember: θ is **fixed but unknown**, $\hat{\theta}_n$ is **random** since depends on X_1, \dots, X_n . We say that $\hat{\theta}_n$ is **unbiased** if

$$\mathbb{E}[\hat{\theta}_n] = \theta$$

Confidence Intervals and Hypothesis Testing

- A $100(1 - \alpha)\%$ **Confidence Interval** for a parameter θ is a **random** interval $I_n = (a, b)$ where $a = a(X_1, \dots, X_n)$ and $b = b(X_1, \dots, X_n)$ such that

$$\mathbb{P}(\theta \in I_n) = 1 - \alpha$$

In words: (a, b) traps θ with probability $1 - \alpha$.

$(1 - \alpha)$ is called **coverage** of the confidence interval.

In practice, $\alpha = 0.05$ is often used.

- In **Hypothesis Testing**, we start with some default theory, called a **null hypothesis**, and we ask if the data provide sufficient evidence to **reject** the theory. If not, we **accept** the null hypothesis.

Example:

$X_1, \dots, X_n \sim \text{Bernoulli}(p)$: n independent coin flips.

We want to test if the coin is fair \Rightarrow the **null hypothesis** $H_0 : p = 1/2$

The **alternative hypothesis** is then: $H_1 : p \neq 1/2$

It seems **reasonable to reject** H_0 if

$$\left| \frac{1}{n} \sum_{i=1}^n X_i - \frac{1}{2} \right| \quad \text{is large}$$

Summary

- A **parametric model** is a set \mathcal{F} that can be parameterized by a finite number of parameters.

- ▶ General parametric model:

$$\mathcal{F} = \{\pi(x|\theta), \theta \in \Theta\}$$

- A **nonparametric model** is a set \mathcal{F} that cannot be parameterized by a finite set of parameters.
- Almost all problems in statistical inference can be identified as being one of **three types**:
 - ▶ Point Estimates
 - ▶ Confidence Intervals
 - ▶ Hypothesis Testing