

# Mathematical Statistics II

## Maximum Likelihood Estimation

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# Introduction

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- The next approach we will discuss is Maximum Likelihood Estimation (MLE).
- As we will see, the MLE has several desirable properties, and as a result is often favored over approaches like the method of moments.
- The material for this section largely comes from Chapter 8.5 of Rice (2007), and various sections in Pawitan (2001).

## **Likelihood: an introduction**

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# What is likelihood?

- The term “likelihood” is often used colloquially to mean something analogous to probability. E.g., “What is the likelihood that it rains tomorrow?”
- When we use this term in statistics / mathematics, we mean something specific that isn’t the same thing as probability.
- The use of the term “likelihood” was first made by R. A. Fisher, who was the architect and primary proponent of “likelihood-based-inference”.
- We will start with the treatment of likelihood in the text “In all Likelihood” (Pawitan, 2001), which is a fantastic resource on the subject. (This will lead to some review...)

## What is likelihood? II

### Coin Flips

We will revisit this example, as it is a great starting point to connect with existing understanding.

Consider flipping a coin  $N = 10$  times.

## What is likelihood? III

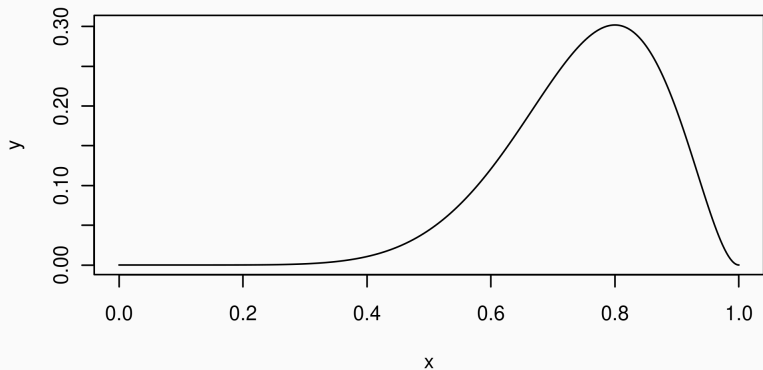
- For our specific coin-flipping example with  $N = 10$ ,  $X = 8$ , the likelihood function is

$$L(\theta) = P_{\theta}(X = 8).$$

- This is plotted in the following way:

```
x <- seq(1e-8, 1-1e-8, length.out = 1000)
y <- dbinom(8, 10, x)
plot(x = x, y = y, type = 'l')
```

## What is likelihood? IV





## What is likelihood? V

- From the figure, we see that  $p$  is unlikely to be less than 0.5, or greater than 0.95.
- Given the data alone (no prior), we should prefer a value somewhere in the middle of these values.
- We still have some uncertainty about the value of  $p$ , but the likelihood gives us a numerical way to compare values of  $\theta$ . Stochastic uncertainty as a result of sampling is captured in the likelihood function  $L(\theta)$ .

## What is likelihood? VI

- **The likelihood is not a probability.** Though it came from a probability, the likelihood function (a function of  $\theta$ ) does not satisfy the requirements to be a probability. In our previous example, we have:

$$\int_0^1 L(\theta) d\theta = 1/11 \neq 1.$$

## What is likelihood? VII

- The idea behind maximum likelihood estimation (MLE) is simple: our estimate is the value of  $\theta$  that maximizes the likelihood function  $L(\theta)$ .
- The MLE is considered a *frequentist* approach. Why? It quantifies a maximum belief about a parameter, which is more Bayesian in nature than Frequentist.
- As we'll see later, the MLE has nice theoretical Frequentist *properties*, and as a result can be justified via the frequentist paradigm.
- Still, it has close connection to Bayesian estimation and interpretation. In fact, we'll discuss connections between the MLE and Bayesian statistics later.

## What is likelihood? VIII

- Often, maximizing the likelihood directly is challenging, so we maximize the log-likelihood instead.
- Other times, the likelihood has to be maximized numerically.

### MLE of coin toss problem

Suppose we have  $N = 10$  total tosses, and  $n$  total heads. Find the MLE of  $p$ , the probability of heads.

# Continuous models

- The interpretation of the likelihood function as the “the probability of the observed data  $x^*$ , considered as a function of  $\theta$ ” makes perfect sense in the discrete model case.
- For continuous models, the technical issue arises that the probability of any point value  $x$  is zero.
- We resolve the problem similar to what was done in Math 4450 and the John Rice text: approximate the probability by discretizing into small, discrete intervals:

$$x^* \in (x^* - \epsilon/2, x^* + \epsilon/2),$$

## Continuous models II

thus, the probability of observing something  $\epsilon$ -close to the data is:

$$\begin{aligned} L(\theta) &= P_{\theta}(X \in (x^* - \epsilon/2, x^* + \epsilon/2)) \\ &= \int_{x^* - \epsilon/2}^{x^* + \epsilon/2} f(x; \theta) d\theta \approx \epsilon f(x^*; \theta). \end{aligned}$$

- Then, since the likelihood is only meaningful up to a constant (we will discuss likelihood ratios later), then this has the same behavior as  $L(\theta) = f(x^*; \theta)$ .
- There are more advanced approaches to this problem, but this simple argument justifies the use of the pdf of a continuous random variable as the likelihood  $L(\theta)$ .

## Continuous models III

- **Going forward:** we once again will generalize a model  $f(x; \theta)$  to mean either the pmf or pdf of a random variable. I will often say “density” as a blanket term, even if this corresponds to a pmf, not a density.
- Further, when we “integrate” a density, this means either:

$$\int f(x; \theta) dx, \quad \text{If continuous}$$

or

$$\sum_x f(x; \theta), \quad \text{If discrete.}$$

# Joint Probabilities

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## Likelihood with multiple observations

- Often the data we observe is multi-dimensional, rather than summarized as a single observation.
- In this case, the likelihood  $\theta$  is still determined via the joint model:

$$L(\theta) = f(x^*; \theta) = f_{X_{1:N}}(x_1^*, x_2^*, \dots, x_N^*; \theta).$$

- We are mostly focused in this class in the case where the observations are independent, meaning the likelihood factors:

$$L(\theta) = \prod_{i=1}^N f_{X_i}(x_i^*; \theta).$$

## Likelihood with multiple observations II

- We often further simplify this by assuming the data are identically distributed:

$$L(\theta) = \prod_{i=1}^N f_{X_1}(x_i^*; \theta).$$

- As we've seen, it's generally easier to maximize the log-likelihood. In the IID case:

$$\ell(\theta) = \log \prod_{i=1}^N f_{X_1}(x_i^*; \theta) = \sum_{i=1}^n \log f_{X_1}(x_i^*; \theta).$$

## Likelihood with multiple observations III

### Traffic data: Poisson Model

Returning to a motivating example, suppose we model traffic accidents in a given week as  $X_1, X_2, \dots, X_N$ , where the data are iid  $\text{Poisson}(\lambda)$ . Obtain the MLE for  $\lambda$ .

## References and Acknowledgements

Pawitan Y (2001). *In all likelihood: statistical modelling and inference using likelihood*. Oxford University Press.

Rice JA (2007). *Mathematical statistics and data analysis*, volume 371. 3 edition. Thomson/Brooks/Cole Belmont, CA.

- Compiled on January 16, 2026 using R version 4.5.2.
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## References and Acknowledgements II

- We acknowledge [students and instructors for previous versions of this course / slides](#).