



STATISTICS FOR DATA SCIENCE

Principles of Point Estimation

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Maximum Likelihood Estimation

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- ✓ The Method of Maximum Likelihood for Bernoulli, Binomial and Poisson Distributions.
- ✓ Pitfalls of Point Estimators

Let X_1, \dots, X_n be a random sample from the population with Bernoulli (p) distribution.

The probability mass function is given by,

$$P(X = x_i) = p^{x_i} (1 - p)^{1-x_i}$$

The likelihood function is,

$$L = f(p | x_1, \dots, x_n) = p^{x_1} (1 - p)^{1-x_1} * p^{x_2} (1 - p)^{1-x_2} * \dots * p^{x_n} (1 - p)^{1-x_n}$$

$$L = \prod_{i=1}^n p^{x_i} (1 - p)^{1-x_i} \sim p^{\sum x_i} (1 - p)^{n - \sum x_i}$$

Take log of the likelihood function,

$$\ln L = \sum x_i \ln p + \left(n - \sum x_i \right) \ln(1 - p)$$

Taking derivative with respect to p and set it to 0,

$$\frac{d \ln L}{dp} = 0 \rightarrow \sum x_i \frac{d \ln p}{dp} + \left(n - \sum x_i\right) \frac{d \ln(1-p)}{dp} = 0$$

$$\frac{\sum x_i}{p} + \left(n - \sum x_i\right) * \frac{-1}{1-p} = 0$$

$$\sum x_i - p \sum x_i + p \sum x_i = 0$$

$$\sum x_i - np = 0$$

$$p = \frac{\sum x_i}{n} = \bar{X}$$

The MLE of p is $\hat{p} = \bar{X}$

Let $X \sim \text{Bin}(n, p)$ where n is known and p is unknown

The probability mass function of X is $f(x; n, p) = \frac{n!}{x! (n-x)!} p^x (1-p)^{n-x}$

The likelihood function is given by,

$$L(p; n, x) = \frac{n!}{x! (n-x)!} p^x (1-p)^{n-x}$$

Take log of the likelihood function,

$$\begin{aligned} \ln L(p; n, x) &= \ln \left[\frac{n!}{x! (n-x)!} p^x (1-p)^{n-x} \right] \\ &= \ln \left(\frac{n!}{x! (n-x)!} \right) + x \ln p + (n-x) \ln(1-p) \end{aligned}$$

Taking derivative with respect to p and set it to 0,

$$\begin{aligned}\frac{d}{dp} L(p; n, x) &= \frac{d}{dp} (\ln n! - \ln x! - \ln(n-x)! + x \ln p + (n-x) \ln(1-p)) \\ &= 0 + \frac{x}{p} - \frac{x}{1-p} - \frac{n}{1-p}\end{aligned}$$

Apply chain rule,

Multiply both sides by $p(1-p)$

$$0 = x - xp + xp - np$$

$$p = \frac{x}{n}$$

The MLE of p is $\hat{p} = \frac{X}{n}$

Example – Binomial Distribution – Estimate Likelihood Function



Consider the following example,

$X \sim \text{Bin}(20, p)$, p is unknown

Suppose we observe $X = 7$. The probability mass function is,

$$f(7; p) = \frac{20!}{7!13!} p^7 (1 - p)^{13}$$

In the probability mass function it is as written $f(7; p)$ rather than $f(7)$. Here the data value 7 is constant.

When a probability mass function or probability density function is considered to be a function of parameters, it is called a **likelihood function**.

How can we maximise this likelihood function?

When \hat{p} is substituted for p , it maximizes the likelihood function

Let's compute maximum likelihood function for $f(7; p)$

We could maximize this function by taking the derivative with respect to p and setting it equal to 0.

$$\ln f(7; p) = \ln 20! - \ln 7! - \ln 13! + 7 \ln p + 13 \ln(1 - p)$$

We take the derivative with respect to p and set it equal to 0.

$$\frac{d}{dp} \ln f(7; p) = \frac{7}{p} - \frac{13}{1 - p} = 0$$

The maximizing value is $\frac{7}{20}$

Therefore the maximum likelihood estimate is $\hat{p} = \frac{7}{20}$

Let X_1, \dots, X_n be an independent random sample from an $\text{Exp}(\lambda)$, where λ is unknown.

The likelihood function is the joint probability density function of X_1, \dots, X_n considered as a function of the parameter λ .

The probability function is given by,

$$f(x_1, \dots, x_n; \lambda) = \prod_{i=1}^n e^{-\lambda} \frac{\lambda^{x_i}}{x_i!}$$

The likelihood function is,

$$L(x_i; \lambda) = \sum_{i=1}^n e^{-\lambda} \frac{\lambda^{x_i}}{x!}$$

Take log of the likelihood function,

$$\ln L(x_i; \lambda) = \sum_{i=1}^n \ln e^{-\lambda} + \sum_{i=1}^n x_i \ln \lambda - \sum_{i=1}^n \ln x_i$$

Taking derivative with respect to λ and set it to 0,

$$\frac{d}{d\lambda} L(x_i; \lambda) = 0$$

$$\frac{d}{d\lambda} \left(\sum_{i=1}^n (-\lambda) + \sum_{i=1}^n x_i \ln(\lambda) - \sum_{i=1}^n \ln x_i \right) = 0$$

$$= -n + \frac{1}{\lambda} \sum_{i=0}^n x_i + 0 = 0$$

$$\lambda = \frac{1}{\lambda} \sum_{i=1}^n x_i = \bar{X}$$

The MLE of λ is $\hat{\lambda} = \bar{X}$

Problem:

The following data are the observed frequencies of occurrence of domestic accidents: we have $n = 647$ data as follows

Number of Accidents	Frequency
0	447
1	132
2	42
3	21
4	3
5	2

Solution:

$$\lambda = \frac{1}{n} \sum_{i=1}^n x_i = \bar{X}$$

The MLE of λ is $\hat{\lambda} = \bar{X}$

$$\begin{aligned}\hat{\lambda} &= \frac{1}{n} \sum_{i=1}^n x_i = \bar{X} \\ &= \frac{(447 * 0) + (132 * 1) + (42 * 2) + (21 * 3) + (3 * 4) + (2 * 5)}{674} \\ &= 0.465\end{aligned}$$

Maximum likelihood is the most commonly used method of estimation.

The main reason for this is that in most cases that arise in practice, MLEs have two very desirable properties,

1. In most cases, as the sample size n increases, the bias of the MLE converges to 0.
2. In most cases, as the sample size n increases, the variance of the MLE converges to a theoretical minimum.

- A point estimator is a single number which may vary from sample to sample.
- Certainly the point estimators are slightly different from true population parameter .
- It cannot be confidently claimed to be close to the actual parameter.
- This can be solved by estimating population parameters in the given intervals of values where point estimator can be centered. This interval is called **confidence interval**.



THANK YOU

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