STAT 24400 Lecture 14
Section 8.3 Parameter Estimation
Section 8.4 The Method of Moments
Section 8.5 The Method of Maximum Likelihood

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Section 8.3 Parameter Estimation

Parameter Estimation

Suppose that we observe data $X_1, X_2, \dots, X_n$ generated from a known distribution with unknown parameter(s), e.g., the data is from

- $N(\mu, \sigma^2)$, with μ unknown (& σ^2 known)
- $N(\mu, \sigma^2)$, with μ & σ^2 unknown
- Exponential(λ), with λ unknown
- Binomial(n, p), with n known and p unknown

How can we estimate the unknown parameter(s)?
How can we perform inference on the unknown parameter(s)?

General Notation

- $X_1, \dots, X_n$ = data drawn i.i.d. from the distribution
- θ = the unknown parameter(s)
- θ lies in Θ = subspace of $\mathbb{R}$ (or $\mathbb{R}^2$ if two parameters, etc)

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- $X_1, \dots, X_n$ = data drawn i.i.d. from the distribution
- θ = the unknown parameter(s)
- θ lies in Θ = subspace of $\mathbb{R}$ (or $\mathbb{R}^2$ if two parameters, etc)
- We will write $f(x \mid \theta)$ for the PDF or PMF of the distribution, e.g.,
  - Exponential(λ) $\rightsquigarrow$ PDF $f(x \mid \lambda) = \lambda e^{-\lambda x}$
  - Poisson(λ) $\rightsquigarrow$ PMF $f(x \mid \lambda) = \dfrac{\lambda^x e^{-\lambda}}{x!}$

Parameter Estimation (Point Estimate)

Given data $X_1, \ldots, X_n$ i.i.d. $\sim f(x \mid \theta)$, would like to estimate the unknown θ

The *point estimate* or *estimator* of a parameter θ, is a function

$$\hat{\theta} = g(X_1, \ldots, X_n)$$

computed from the observed data $\{X_1, \ldots, X_n\}$ that is a sensible guess for the unknown θ.

Note: any estimator $\hat{\theta}$ must be a function of $X_1, \ldots, X_n$ only
it cannot involve any unknown parameter, e.g.,

$$\frac{\sum_{i=1}^{n}(X_i - \mu)^2}{n}$$

is not a estimator since it involves the unknown μ.

Examples of Point Estimates

Example 1: If $X_1, \dots, X_n$ are i.i.d. $N(\mu, \sigma^2)$, the point estimate for the population mean μ can be

- the sample mean $\overline{X} = \frac{1}{n}\sum_{i=1}^{n} X_i$
- the median of $X_1, \dots, X_n$
- the average of $X_1, \dots, X_n$ after excluding the minimum & maximum

The point estimate for the population variance σ^2 can be

- the sample variance $S^2 = \dfrac{\sum_{i=1}^{n}\left(X_i - \overline{X}\right)^2}{n-1}$
- an alternative estimator would result from using divisor n instead of $n-1$

$$\hat{\sigma}^2 = \frac{\sum_{i=1}^{n}\left(X_i - \overline{X}\right)^2}{n}$$

Examples of Point Estimates

Example 2: If $X \sim Bin(n, p)$ is Binomial, the point estimate for the success probability p can be

- the sample proportion $\hat{p} = \dfrac{X}{n}$
- Wilson's plus-four estimate $\tilde{p} = \dfrac{X+2}{n+4}$
  - adding two successes and two failures to the sample and then calculate the sample proportion of successes

Mean Squared Error

With many possible point estimates $\widehat{\theta}$'s for a parameter θ, how to choose a good one among them?

A population criterion is to compare their *Mean Squared Error (MSE)*, defined as

$$\text{Mean Squared Error (MSE)} = \mathrm{E}[(\widehat{\theta} - \theta)^2]$$

MSE $= (\text{Bias})^2 +$ Variance

Recall the shortcut formula for the variance of any variable Y

$$\text{Var}(Y) = \text{E}(Y^2) - (\text{E}(Y))^2,$$

Rearranging the terms, we get

$$\text{E}(Y^2) = (\text{E}(Y))^2 + \text{Var}(Y).$$

Plugging in $Y = \hat{\theta} - \theta$, then $\text{E}(\hat{\theta} - \theta) = \text{E}(\hat{\theta}) - \theta$, we get

$$\begin{array}{ccccc} \text{E}[(\hat{\theta} - \theta)^2] & = & [\text{E}(\hat{\theta}) - \theta]^2 & + & \text{Var}(\hat{\theta} - \theta) \\ \| & & \| & & \| \\ \text{MSE} & = & (\text{Bias}(\hat{\theta}))^2 & + & \text{Var}(\hat{\theta}) \end{array}$$

where the *bias* of an point estimate $\hat{\theta}$ for θ is defined to be the difference between the expected value of the estimate and the true value of the parameter

$$\text{Bias}(\hat{\theta}) = \text{E}(\hat{\theta}) - \theta$$

Unbiased Estimators

A point estimator $\hat{\theta}$ is said to be an *unbiased estimator* of θ if

$$\mathrm{E}(\hat{\theta}) = \theta$$

for every possible value of θ.

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For unbiased estimators, $\boxed{\text{MSE} = \text{Variance}}$.

Examples of MSE

If $X_1, \dots, X_n$ are i.i.d. with population mean μ and population variance σ^2, using the sample mean $\overline{X} = \frac{1}{n}\sum_{i=1}^{n} X_i$ the point estimate for the population mean μ

- the bias is $\mathrm{E}(\overline{X}) - \mu = \mu - \mu = 0$
- the variance is $\mathrm{Var}(\overline{X}) = \sigma^2/n$

The MSE for $\overline{X}$ is hence

$$\text{MSE} = (\text{Bias})^2 + \text{Variance} = 0^2 + \frac{\sigma^2}{n} = \frac{\sigma^2}{n}$$

MSE of Sample Variance S^2

In L13, we have shown that if $X_1, X_2, \dots, X_n$ are i.i.d. $\sim N(\mu, \sigma^2)$, then S^2 is an unbiased estimate for σ^2.

$$\mathrm{E}[S^2] = \sigma^2$$

To obtain the MSE, we need to calculate $\mathrm{Var}(S^2)$. From that

$$T = \frac{(n-1)S^2}{\sigma^2} \sim \chi^2_{n-1},$$

and the variance for $T \sim \chi^2_{n-1}$ is $2(n-1)$, it follows that

$$\mathrm{Var}(S^2) = \mathrm{Var}\left(\frac{\sigma^2 T}{n-1}\right) = \left(\frac{\sigma^2}{n-1}\right)^2 \underbrace{\mathrm{Var}(T)}_{=2(n-1)} = \frac{2\sigma^4}{n-1}.$$

The MSE of S^2 is hence

$$\text{MSE} = (\text{Bias})^2 + \text{Variance} = 0^2 + \frac{2\sigma^4}{n-1} = \frac{2\sigma^4}{n-1}$$

A Biased Estimator for σ^2 w/ a Smaller MSE

Consider an alternative estimator for σ^2 that using divisor $n+1$ instead of $n-1$

$$\hat{\sigma}^2 = \frac{\sum_{i=1}^{n}(X_i - \overline{X})^2}{n+1} = \frac{(n-1)S^2}{n+1}$$

The expected value and variance of $\hat{\sigma}^2$ are respectively

$$\mathrm{E}(\hat{\sigma}^2) = \frac{(n-1)\,\mathrm{E}(S^2)}{n+1} = \frac{(n-1)\sigma^2}{n+1},$$

$$\mathrm{Var}(\hat{\sigma}^2) = \left(\frac{n-1}{n+1}\right)^2 \mathrm{Var}(S^2) = \left(\frac{n-1}{n+1}\right)^2 \frac{2\sigma^4}{(n-1)} = \frac{2(n-1)\sigma^4}{(n+1)^2}$$

Hence, $\hat{\sigma}^2$ is a **biased** estimator for σ^2 with

$$\text{Bias} = \mathrm{E}(\hat{\sigma}^2) - \sigma^2 = \frac{(n-1)\sigma^2}{n+1} - \sigma^2 = \frac{-2\sigma^2}{n+1}.$$

The MSE of $\hat{\sigma}^2$ is

$$\begin{aligned} \text{MSE} &= (\text{Bias})^2 + \text{Variance} \\ &= \left(\frac{-2\sigma^2}{n+1}\right)^2 + \frac{2(n-1)\sigma^4}{(n+1)^2} = \frac{2n\sigma^4}{(n+1)^2} \end{aligned}$$

which is lower than the MSE of $\dfrac{2\sigma^4}{n-1}$ for the sample variance S^2.

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A biased estimator might have a smaller MSE if it has a smaller variance.

MSE of the Sample Proportion $\hat{p} = \dfrac{X}{n}$

If $X \sim Bin(n, p)$ is Binomial, a point estimate for the success probability p is the sample proportion $\hat{p} = \dfrac{X}{n}$. As X is Binomial,

$$\begin{aligned} \mathrm{E}(X) &= np & \Rightarrow \quad \mathrm{E}(\hat{p}) &= \frac{\mathrm{E}(X)}{n} = \frac{np}{n} = p \\ \mathrm{Var}(X) &= np(1-p) & \Rightarrow \quad \mathrm{Var}(\hat{p}) &= \frac{\mathrm{Var}(X)}{n^2} = \frac{np(1-p)}{n^2} = \frac{p(1-p)}{n} \end{aligned}$$

Thus the sample proportion $\hat{p}$ is **unbiased** with the MSE

$$\text{MSE} = (\text{Bias})^2 + \text{Variance} = 0^2 + \frac{p(1-p)}{n} = \frac{p(1-p)}{n}.$$

MSE for Wilson's "Plus-Four" Estimate for Proportions

Recall Wilson's plus-four estimate is

$$\tilde{p} = \frac{X + 2}{n + 4}.$$

It's expected value and variance are respectively,

$$\mathrm{E}(\tilde{p}) = \frac{\mathrm{E}(X) + 2}{n + 4} = \frac{np + 2}{n + 4}, \text{ and } \mathrm{Var}(\tilde{p}) = \frac{\mathrm{Var}(X)}{(n + 4)^2} = \frac{np(1 - p)}{(n + 4)^2}.$$

Its bias and MSE are respectively

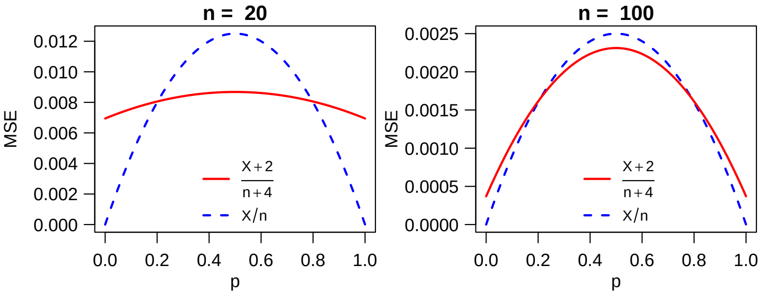
$$\text{Bias} = \mathrm{E}(\tilde{p}) - p = \frac{np + 2}{n + 4} - p = \frac{2 - 4p}{n + 4}$$

$$\text{MSE} = (\text{Bias})^2 + \text{Variance} = \left(\frac{2 - 4p}{n + 4}\right)^2 + \frac{np(1 - p)}{(n + 4)^2}$$

MSE's for Sample Proportion & Wilson's "Plus-Four"

Below are the graphs of the MSE for $\hat{p} = X/n$ and $\tilde{p} = \dfrac{X+2}{n+4}$

$$\text{MSE}(\hat{p}) = \frac{p(1-p)}{n}, \quad \text{MSE}(\tilde{p}) = \left(\frac{2-4p}{n+4}\right)^2 + \frac{np(1-p)}{(n+4)^2}$$



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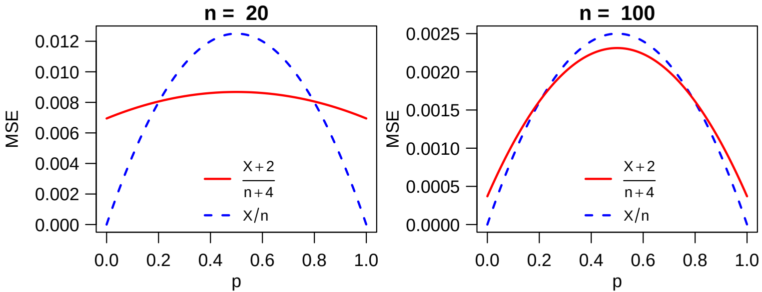


- $\hat{p} = X/n$ has a smaller MSE only when p is close to 0 or 1
- $\tilde{p} = \frac{X+2}{n+4}$ has a smaller MSE when p is NOT close to 0 or 1
- The two MSE's are close when n is large

Sampling Distributions

The *sampling distribution* of a point estimate $\widehat{\theta}$ is simply its probability distribution, e.g.,

Ex1. If $X_1, \dots, X_n$ are i.i.d. $\sim N(\mu, \sigma^2)$, the sampling distribution for $\hat{\mu} = \overline{X}$ is

$$\hat{\mu} = \overline{X} \sim N\left(\mu, \frac{\sigma^2}{n}\right)$$

and the sampling distribution for S^2 is that

$$S^2 = \frac{\sigma^2 T}{n-1}, \quad \text{where } T \sim \chi^2_{n-1}.$$

Note: The sampling distribution generally depends on some unknown parameter θ.

Ex2: If $X_1, \ldots, X_n$ are i.i.d. from some distribution with mean μ and variance σ^2 (not necessarily normal),

- the exact sampling distribution of $\hat{\mu} = \overline{X}$ would depend on the distribution of X_i
- CLT asserts that

$$\hat{\mu} = \overline{X} \text{ is approx. } \sim N\left(\mu, \frac{\sigma^2}{n}\right).$$

Standard Error

The *standard error (SE)* of a point estimate $\hat{\theta}$ refers to any estimate of the standard deviation of $\hat{\theta}$.

Ex1. If $X_1, \ldots, X_n$ are i.i.d. $\sim N(\mu, \sigma^2)$,

- the standard deviation for $\hat{\mu} = \overline{X}$ is

$$\mathrm{SD}(\overline{X}) = \sqrt{\mathrm{Var}(\overline{X})} = \sqrt{\frac{\sigma^2}{n}}$$

  which involves the unknown σ^2
- the standard error for $\overline{X}$ is

$$\mathrm{SE}(\overline{X}) = \sqrt{\frac{S^2}{n}}$$

  which replaces the unknown σ^2 by its estimate S^2.

Ex2. If $X \sim \text{Bin}(n, p)$,

- the standard deviation for $\hat{p} = X/n$ is

$$\mathrm{SD}(\hat{p}) = \sqrt{\mathrm{Var}(\hat{p})} = \sqrt{\frac{p(1-p)}{n}},$$ which involves the unknown p.

- the standard error for $\hat{p}$ is

$$\mathrm{SE}(\hat{p}) = \sqrt{\frac{\hat{p}(1-\hat{p})}{n}}$$

  which replaces the unknown p by its estimate $\hat{p}$.

Note: The true SD may depend on θ, while SE depends on the data but not on θ

Section 8.4 The Method of Moments

Sample Moments

Recall the kth moment of a random variable X is $\mathrm{E}[X^k]$.

If $X_1, \ldots, X_n$ are i.i.d. from some distribution $f(x \mid \theta)$, the *kth sample moment* is defined to be

$$\hat{\mu}_k = \frac{1}{n} \sum_{i=1}^{n} X_i^k$$

The Method of Moments (MME)

The *method of moments* is a strategy for finding an estimator $\hat{\theta}$.
If there is only **one parameter** θ,

1. compute $\mathrm{E}(X)$ as a function of θ
2. compute the sample mean $\overline{X} = \frac{1}{n}\sum_{i=1}^{n} X_i$
3. choose $\hat{\theta}$ as the value of θ so that $\mathrm{E}(X) = \overline{X}$

If there are k parameters $\theta_1, \dots, \theta_k$

1. compute $\mathrm{E}(X)$, $\mathrm{E}(X^2)$, ..., $\mathrm{E}(X^k)$ as functions of θ_i's
2. compute the sample moments
$$\hat{\mu}_1 = \frac{1}{n}\sum_{i=1}^{n} X_i, \quad \hat{\mu}_2 = \sum_{i=1}^{n} X_i^2, \dots, \hat{\mu}_k = \frac{1}{n}\sum_{i=1}^{n} X_i^k.$$
3. choose $(\hat{\theta}_1, \dots, \hat{\theta}_m)$ as the value of θ_i so that
$$\mathrm{E}(X^j) = \frac{1}{n}\sum_{i=1}^{n} X_i^j \quad \text{for } 1 \le j \le k.$$
(solving a system of k equations, for k unknowns)

Examples (1 Parameter)

Ex1: $X_1, \dots, X_n \overset{\text{iid}}{\sim}$ Poisson(λ) for unknown $\lambda > 0$

- PMF: $f(x \mid \lambda) = e^{-\lambda}\lambda^x/x!$, $x = 0, 1, 2, \dots$
- $\mathrm{E}(X) = \lambda$
- The method of moment estimate (MME) for λ is $\hat{\lambda} = \overline{X}$

Ex2: $X_1, \dots, X_n \overset{\text{iid}}{\sim}$ Geometric(p) for unknown p

- PMF: $f(x \mid p) = (1-p)^{x-1}p$, $x = 1, 2, 3, \dots$
- $\mathrm{E}(X) = 1/p$
- MME for p is $\hat{p} = 1/\overline{X}$

Ex3: $X_1, \dots, X_n \overset{\text{iid}}{\sim}$ Exponential(λ) for unknown $\lambda > 0$

- PDF: $f(x \mid \lambda) = \lambda e^{-\lambda x}$, $x > 0$
- $\mathrm{E}(X) = 1/\lambda$
- MME for λ is $\hat{\lambda} = 1/\overline{X}$.

Example 4 — Uniform$[0, \theta]$

$X_1, \ldots, X_n \overset{\text{iid}}{\sim}$ Uniform$[0, \theta]$ for unknown $\theta > 0$

- PDF: $f(x \mid \theta) = \frac{1}{\theta}$, $0 \leq x \leq \theta$
- $\mathrm{E}(X) = \theta/2$
- MME for θ is $\hat{\theta} = 2\overline{X}$.

Example 5 — MME for Gamma

$X_1, \dots, X_n \overset{\text{iid}}{\sim}$ Gamma(α, λ) for unknown $\alpha, \lambda > 0$

- $\mathrm{E}(X) = \alpha/\lambda$
- $\mathrm{Var}(X) = \alpha/\lambda^2 \;\Rightarrow\; \mathrm{E}[X^2] = \mathrm{Var}(X) + (\mathrm{E}(X))^2 = \dfrac{\alpha(\alpha+1)}{\lambda^2}$
- The MMEs for α and λ must satisfy

$$\overline{X} = \frac{\hat{\alpha}}{\hat{\lambda}}, \quad \hat{\mu}_2 = \frac{\hat{\alpha}(\hat{\alpha}+1)}{\hat{\lambda}^2} \qquad (\text{Recall } \hat{\mu}_2 = \frac{1}{n}\sum_{i=1}^{n} X_i^2)$$

First equation $\Rightarrow \hat{\alpha} = \hat{\lambda}\overline{X}$.
Plugging in $\hat{\alpha} = \hat{\lambda}\overline{X}$ into the 2nd equation, we get

$$\hat{\mu}_2 = \overline{X}^2 + \frac{\overline{X}}{\lambda} \;\Rightarrow\; \hat{\lambda} = \frac{\overline{X}}{\hat{\mu}_2 - \overline{X}^2} \;\Rightarrow\; \hat{\alpha} = \hat{\lambda}\overline{X} = \frac{\overline{X}^2}{\hat{\mu}_2 - \overline{X}^2}.$$

Section 8.5 Likelihood & Maximum Likelihood Estimation

A Probability Question

Let p be the proportion of US adults that are willing to get the latest flu shot.

A sample of 20 subjects are randomly selected. Let X be the number of them that are willing to get the latest flu shot. What is $P(X = 8)$?

Answer: X is Binomial ($n = 20$, p) (Why?)

$$P(X = x \mid p) = \binom{20}{x} p^x (1-p)^{n-x}.$$

If p is known to be 0.3, then

$$\mathrm{P}(X = 8 \mid p) = \binom{20}{8} (0.3)^8 (0.7)^{12} \approx 0.1144.$$

A Statistics Question

Suppose 8 of 20 randomly selected U.S. adults said they are willing to get the latest flu shot.

What can we infer about the value of

$$p = \text{proportion of U.S. adults that are willing to get a flu shot?}$$

The chance to observe $X = 8$ in a random sample of size $n = 20$ is

$$P(X = 8 \mid p) = \begin{cases} \binom{20}{8}(0.3)^8(0.7)^{12} \approx 0.1144 & \text{if } p = 0.3 \\ \binom{20}{8}(0.6)^8(0.4)^{12} \approx 0.0355 & \text{if } p = 0.6 \end{cases}$$

It appears that $p = 0.3$ is **more likely** to be true value p than $p = 0.6$, since the former gives a higher prob. to observe the outcome $X = 8$.

We say the *likelihood* of $p = 0.3$ is higher than that of $p = 0.6$.

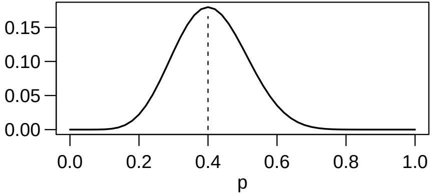
Maximum Likelihood Estimate (MLE)

The *maximum likelihood estimate* (*MLE*) of a parameter θ is the value at which the likelihood function is maximized.

Example. If 8 of 20 randomly selected U.S. adults are comfortable getting the flu shot, the likelihood function

$$L(p \mid x = 8) = \binom{20}{8} p^8 (1-p)^{12}$$

reaches its max at $p = 0.4$,
the MLE for p is $\hat{p} = 0.4$ given the data $X = 8$.



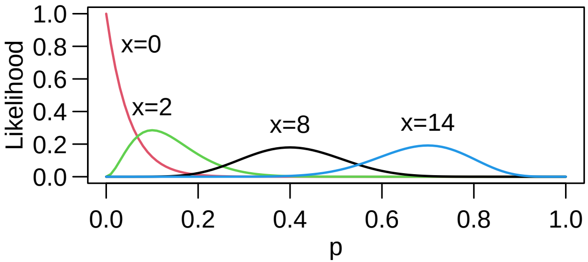
Maximum Likelihood Estimate (MLE)

The probability

$$P(X = x \mid p) = \binom{n}{x} p^x (1-p)^{n-x} = L(p \mid x)$$

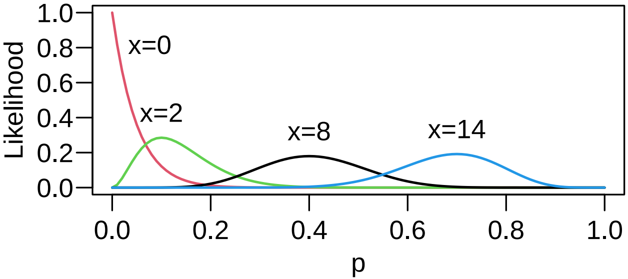
viewed as a function of p, is called the *likelihood function*,
(or just the **likelihood**) of p, denoted as $L(p \mid x)$.

It measure the "plausibility" of a value being the true value of p.

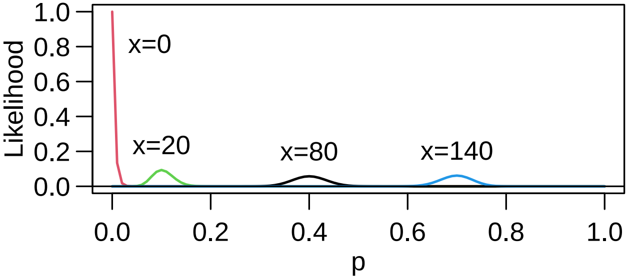


Likelihood functions $L(p \mid x)$ at different values of x for $n = 20$.

Likelihood functions $L(p \mid x)$ for various values of x when $n = 20$.



Likelihood functions $L(p \mid x)$ at various values of x when $n = 200$.



Likelihood in General

In general, suppose the observed data $(X_1, X_2, \ldots, X_n)$ have a joint PDF or PMF with some parameter(s) called θ

$$f(x_1, x_2, \ldots, x_n \mid \theta)$$

The *likelihood function* for the parameter θ is

$$L(\theta) = L(\theta \mid X_1, X_2, \ldots, X_n) = f(X_1, X_2, \ldots, X_n \mid \theta).$$

- Note the likelihood function regards the probability as a function of the parameter θ rather than as a function of the data $X_1, X_2, \ldots, X_n$.
- If

  $$L(\theta_1 \mid x_1, \ldots, x_n) > L(\theta_2 \mid x_1, \ldots, x_n),$$

  then θ_1 appears more plausible to be the true value of θ than θ_2 does, given the observed data $x_1, \ldots, x_n$.

Maximizing the Log-likelihood

Rather than maximizing the likelihood, it is often computationally easier to maximize its natural logarithm, called the *log-likelihood*, denoted as

$$\ell(\theta) = \log L(\theta)$$

which results in the same answer since logarithm is strictly increasing,

$$x_1 > x_2 \quad \Longleftrightarrow \quad \log(x_1) > \log(x_2).$$

So

$$L(\theta_1) > L(\theta_2) \quad \Longleftrightarrow \quad \log L(\theta_1) > \log L(\theta_2).$$

Here, $\log()$ is always the natural log.

Notation:

- **upper case** $L(\theta) =$ **likelihood**
- **lower case** $\ell(\theta) = \log L(\theta) =$ **log-likelihood**

Example (MLE for Binomial)

If the observed data $X \sim$ Binomial (n, p) but p is unknown, the likelihood of p is

$$L(p \mid x) = p(X = x \mid p) = \binom{n}{x} p^x (1-p)^{n-x}$$

and the *log-likelihood* is

$$\ell(p) = \log L(p \mid x) = \log \binom{n}{x} + x \log(p) + (n-x) \log(1-p).$$

From Calculus, we know a function $g(u)$ reaches its max at $u = u_0$ if

$$\frac{d}{\mathrm{d}u} g(u) = 0 \text{ at } u = u_0 \quad \text{and} \quad \frac{d^2}{du^2} g(u) < 0 \text{ at } u = u_0.$$

Example — MLE for Binomial

$$\frac{d}{dp}\ell(p \mid x) = \frac{x}{p} - \frac{n-x}{1-p} = \frac{x-np}{p(1-p)}.$$

equals 0 when

$$\frac{x-np}{p(1-p)} = 0$$

That is, when $x - np = 0$.

Solving for p gives the ML estimator (MLE) $\boxed{\hat{p} = \frac{x}{n}}$.

and $\frac{d^2}{dp^2}\ell(p \mid x) = -\frac{x}{p^2} - \frac{n-x}{(1-p)^2} < 0$ for any $0 < p < 1$

Thus, we know $\ell(p \mid x)$ reaches its max when $p = x/n$.

So MLE of p is $\hat{p} = \frac{X}{n}$ = sample proportion of successes.

Likelihood Based on i.i.d. Observations

Suppose $X_1, \ldots, X_n \overset{\text{iid}}{\sim} f(x \mid \theta)$ for an unknown parameter θ

The joint PDF or PMF of $(X_1, \ldots, X_n)$ is the product of the marginal PDF/PMF since they are i.i.d.

$$\prod_{i=1}^{n} f(x_i \mid \theta) = f(x_1 \mid \theta) f(x_2 \mid \theta) \times \cdots \times f(x_n \mid \theta)$$

The likelihood is then

$$L(\theta) = L(\theta \mid X_1, \ldots, X_n) = \prod_{i=1}^{n} f(X_i \mid \theta).$$

The log likelihood then has the summation form

$$\ell(\theta) = \log L(\theta \mid X_1, \ldots, X_n) = \log \left(\prod_{i=1}^{n} f(X_i \mid \theta) \right) = \sum_{i=1}^{n} \log \left(f(X_i \mid \theta) \right).$$

Example — MLE for Exponential

$X_1, \ldots, X_n \overset{\text{iid}}{\sim} \text{Exponential}(\lambda)$ for unknown $\lambda > 0$

- PDF: $f(x \mid \lambda) = \lambda e^{-\lambda x}$
- likelihood: $L(\lambda) = \prod_{i=1}^n f(X_i \mid \lambda) = \lambda^n \exp(\lambda \sum_{i=1}^n X_i)$
- log likelihood:

$$\ell(\lambda) = \log L(\lambda) = n \log(\lambda) - \lambda \sum_{i=1}^n X_i = n \log(\lambda) - n\lambda\overline{X}$$

- Solve for MLE:

$$0 = \frac{d}{d\lambda}\ell(\lambda) = \frac{n}{\lambda} - n\overline{X} \quad \Rightarrow \quad \hat{\lambda} = \frac{1}{\overline{X}} \quad \text{(same as MME)}$$

The likelihood indeed reaches its max at $\lambda = 1/\overline{X}$ since

$$\frac{d^2}{d\lambda^2}\ell(\lambda) = -\frac{n}{\lambda^2} < 0.$$

Example — MLE for Poisson

$X_1, \dots, X_n \overset{\text{iid}}{\sim} \text{Poisson}(\lambda)$ for unknown $\lambda > 0$

- PMF: $f(x \mid \lambda) = e^{-\lambda}\lambda^x / x!$
- likelihood: $L(\lambda) = \prod_{i=1}^n f(X_i \mid \lambda) = e^{-n\lambda}\lambda^{\sum_{i=1}^n X_i} \Big/ \prod_{i=1}^n X_i!$
- log likelihood:

$$\ell(\lambda) = \log L(\lambda) = -n\lambda + \sum_{i=1}^n X_i \log(\lambda) - \sum_{i=1}^n \log(X_i!)$$

- Solve for MLE:

$$0 = \frac{d}{d\lambda}\ell(\lambda) = -n + \frac{\sum_{i=1}^n X_i}{\lambda} = -n + \frac{n\overline{X}}{\lambda}$$

$$\Rightarrow \quad \hat{\lambda} = \overline{X} \quad \text{(same as MME)}$$

The likelihood indeed reaches its max at $\lambda = \overline{X}$ since

$$\frac{d^2}{d\lambda^2}\ell(\lambda) = -\frac{n\overline{X}}{\lambda^2} \leq 0.$$

Example — Negative Binomial

$X_1, \dots, X_n \overset{\text{iid}}{\sim} \text{NegBin}(r, p)$, r is known, but p is unknown

The PMF is $f(x \mid p) = \binom{x-1}{r-1} p^r (1-p)^{x-r}$.

$$\text{likelihood } L(p) = \prod_{i=1}^{n} f(X_i \mid p) = \left[\prod_{i=1}^{n} \binom{X_i - 1}{r - 1}\right] p^{nr} (1-p)^{(\sum_{i=1}^{n} X_i) - nr}$$

$$= \left[\prod_{i=1}^{n} \binom{X_i - 1}{r - 1}\right] p^{nr} (1-p)^{n\overline{X} - nr}$$

The log likelihood is

$$\ell(p) = \sum_{i=1}^{n} \log \binom{X_i - 1}{r - 1} + nr \log(p) + n(\overline{X} - r) \log(1-p)$$

Solve for MLE:

$$0 = \frac{d}{dp} \ell(p) = \frac{nr}{p} - \frac{n(\overline{X} - r)}{1 - p} = \frac{n(r - p\overline{X})}{p(1-p)} \quad \Rightarrow \quad \hat{p} = \frac{r}{\overline{X}}.$$

To see if log likelihood indeed reaches its max at $p = r/\overline{X}$, we check

$$\frac{d^2}{dp^2}\ell(p) = -\frac{nr}{p^2} - \frac{n(\overline{X} - r)}{(1-p)^2}$$

As $X_i \geq r$ and hence $\overline{X} \geq r$, the second derivative above is indeed ≤ 0.

This shows $\hat{p} = \dfrac{r}{\overline{X}}$ is indeed the MLE.

MLE for Two Parameters

From Calculus, we know a function $g(u, v)$ reaches its maximum at $(u, v) = (u_0, v_0)$ if the following 3 conditions are met

1. $\frac{\partial}{\partial u} g(u, v) = \frac{\partial}{\partial v} g(u, v) = 0$ at $(u, v) = (u_0, v_0)$;
2. $\frac{\partial^2}{\partial u^2} g(u, v) < 0$ at $(u, v) = (u_0, v_0)$;
3. the Hessian matrix

$$\begin{vmatrix} \frac{\partial^2}{\partial u^2} g(u, v) & \frac{\partial^2}{\partial uv} g(u, v) \\ \frac{\partial^2}{\partial vu} g(u, v) & \frac{\partial^2}{\partial v^2} g(u, v) \end{vmatrix}$$

has a *positive* determinant at $(u, v) = (u_0, v_0)$.

Example — MLE for Normal

$X_1, \ldots, X_n \overset{\text{iid}}{\sim} \mathrm{N}(\mu, \sigma^2)$ for unknown μ, σ^2

- PDF: $f(x \mid \mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(x-\mu)^2/2\sigma^2}$
- likelihood:

$$L(\mu, \sigma^2) = \prod_{i=1}^{n} f(X_i \mid \mu, \sigma^2) = (2\pi\sigma^2)^{-\frac{n}{2}} \exp\left(\frac{-1}{2\sigma^2} \sum_{i=1}^{n} (X_i - \mu)^2 \right)$$

- log likelihood:

$$\ell(\mu, \sigma^2) = -\frac{n}{2} \log(2\pi\sigma^2) - \frac{1}{2\sigma^2} \sum_{i=1}^{n} (X_i - \mu)^2$$

- Solve for MLE:

$$\begin{cases} 0 = \frac{\partial}{\partial \mu} \ell(\mu, \sigma^2) = \frac{1}{\sigma^2} \sum_{i=1}^{n} (X_i - \mu) = \frac{n}{\sigma^2} (\overline{X} - \mu) \\ 0 = \frac{\partial}{\partial \sigma^2} \ell(\mu, \sigma^2) = \frac{-n}{2\sigma^2} + \frac{1}{2(\sigma^2)^2} \sum_{i=1}^{n} (X_i - \mu)^2 \end{cases}$$

$$\begin{cases} 0 = \frac{\partial}{\partial \mu}\ell(\mu, \sigma^2) = \frac{n}{\sigma^2}(\overline{X} - \mu) \\ 0 = \frac{\partial}{\partial \sigma^2}\ell(\mu, \sigma^2) = \frac{-n}{2\sigma^2} + \frac{1}{2(\sigma^2)^2}\sum_{i=1}^{n}(X_i - \mu)^2 \end{cases}$$

The first equation immediately gives $\hat{\mu} = \overline{X}$.
Plugging $\mu = \overline{X}$ into the second equation, we get

$$0 = \frac{-n}{2\sigma^2} + \frac{1}{2(\sigma^2)^2}\sum_{i=1}^{n}(X_i - \overline{X})^2 \quad \Rightarrow \quad \hat{\sigma}^2 = \frac{\sum_{i=1}^{n}(X_i - \overline{X})^2}{n}.$$

Note the MLE for σ^2 is not $S^2 = \frac{\sum_{i=1}^{n}(X_i - \overline{X})^2}{n-1}$.

To check the log likelihood indeed reach its max when $\mu = \overline{X}$ and $\hat{\sigma}^2 = \frac{\sum_{i=1}^{n}(X_i - \overline{X})^2}{n}$, we calculate the second derivative of the log likelihood:

$$\frac{\partial^2}{\partial \mu^2}\ell(\mu, \sigma^2) = -\frac{n}{\sigma^2} < 0$$

$$\frac{\partial^2}{\partial \sigma^2 \mu}\ell(\mu, \sigma^2) = -\frac{n}{\sigma^4}(\overline{X} - \mu)$$

$$\frac{\partial^2}{\partial (\sigma^2)^2}\ell(\mu, \sigma^2) = \frac{n}{2(\sigma^2)^2} - \frac{1}{(\sigma^2)^3}\sum_{i=1}^{n}(X_i - \mu)^2$$

When $\mu = \overline{X}$ and $\sigma^2 = \hat{\sigma}^2 = \frac{\sum_{i=1}^{n}(X_i - \overline{X})^2}{n}$, the Hessian matrix is

$$\begin{vmatrix} -\frac{n}{\hat{\sigma}^2} & 0 \\ 0 & -\frac{n}{2(\hat{\sigma}^2)^2} \end{vmatrix}$$

which has a positive determinant. This shows the MLE for μ and σ^2 are

$$\mu = \overline{X} \quad \text{and} \quad \hat{\sigma}^2 = \frac{\sum_{i=1}^{n}(X_i - \overline{X})^2}{n}.$$

Example — MLE for Gamma

$X_1, \dots, X_n \overset{\text{iid}}{\sim} \text{Gamma}(\alpha, \lambda)$ for unknown α, λ

- PDF: $f(x \mid \alpha, \lambda) = \dfrac{\lambda^\alpha}{\Gamma(\alpha)} x^{\alpha-1} e^{-\lambda x}$, $x > 0$
- likelihood:
$$L(\alpha, \lambda) = \prod_{i=1}^n f(X_i \mid \alpha, \lambda) = \frac{\lambda^{n\alpha}}{(\Gamma(\alpha))^n} \left(\prod_{i=1}^n X_i\right)^{\alpha-1} e^{-\lambda \sum_{i=1}^n X_i}$$
- log likelihood:
$$\ell(\alpha, \lambda) = n\alpha \log \lambda - n \log \Gamma(\alpha) + (\alpha - 1) \sum_{i=1}^n \log X_i - \lambda \sum_{i=1}^n X_i$$
- Solve for MLE:
$$0 = \frac{\partial}{\partial \alpha} \ell(\alpha, \lambda) = n \log \lambda - n \frac{\Gamma'(\alpha)}{\Gamma(\alpha)} + \sum_{i=1}^n \log X_i$$
$$0 = \frac{\partial}{\partial \lambda} \ell(\alpha, \lambda) = \frac{n\alpha}{\lambda} - \sum_{i=1}^n X_i = \frac{n\alpha}{\lambda} - n\overline{X}$$

The second equation gives

$$\hat{\lambda} = \frac{\hat{\alpha}}{\overline{X}},$$

plugging it into the first equation we get

$$n\log(\hat{\alpha}) - n\log(\overline{X}) - n\frac{\Gamma'(\hat{\alpha})}{\Gamma(\hat{\alpha})} + \sum_{i=1}^{n} \log X_i = 0$$

This equation cannot be solved in closed form.
Numerical tools are required to compute the value of the MLE.

Example — Uniform$[0, \theta]$

$X_1, \ldots, X_n \overset{\text{iid}}{\sim}$ Uniform$[0, \theta]$ for unknown $\theta > 0$

- PDF: $f(x \mid \theta) = \frac{1}{\theta}$, $0 \le x \le \theta$
- Joint PDF:

$$\prod_{i=1}^{n} f(X_i \mid \theta) = \begin{cases} \theta^{-n} & \text{if } 0 \le X_i \le \theta \\ 0 & \text{otherwise} \end{cases}$$

  This means the joint PDF is non-zero only if $\theta \ge X_{(n)} = \max_{1 \le i \le n} X_i$.
- Likelihood: $L(\theta) = \theta^{-n}$
- Solve for MLE: Note the smaller the value of θ, the greater the likelihood, but θ cannot fall below $X_{(n)}$. Thus the MLE for θ is

$$\hat{\theta} = X_{(n)} \quad \text{(Different from MME} = 2\overline{X}.\text{)}$$

Comparison of MME and MLE for Uniform$[0, \theta]$

MME $\hat{\theta}_{\text{MME}} = 2\overline{X}$:

- For each X_i, $\mathrm{E}(X_i) = \frac{\theta}{2}$, $\mathrm{Var}(X_i) = \frac{\theta^2}{12}$
- $\mathrm{E}(\hat{\theta}_{\text{MME}}) = 2\,\mathrm{E}(\overline{X}) = 2 \cdot \frac{\theta}{2} = \theta$
- $\text{Bias}(\hat{\theta}_{\text{MME}}) = \mathrm{E}(\hat{\theta}_{\text{MME}}) - \theta = \theta - \theta = 0$
- Variance:

$$\mathrm{Var}(\hat{\theta}_{\text{MME}}) = \mathrm{Var}(2\overline{X}) = 2^2\,\mathrm{Var}(\overline{X}) = 2^2\frac{\mathrm{Var}(X_i)}{n} = \frac{\theta^2}{3n}$$

- $\text{MSE} = \text{bias}^2 + \mathrm{Var}(\hat{\theta}_{\text{MME}}) = \dfrac{\theta^2}{3n}$

Comparison of MME & MLE for Uniform$[0, \theta]$:

MLE $\hat{\theta}_{\text{MLE}} = X_{(n)}$:

- PDF of $X_{(n)}$ (from L07): $f(x) = \dfrac{nx^{n-1}}{\theta^n}, \quad 0 \le x \le \theta$
- Bias:
$$\mathrm{E}(\hat{\theta}_{\text{MLE}}) = \int_{x=0}^{\theta} x \cdot \frac{nx^{n-1}}{\theta^n}\,\mathrm{d}x = \frac{n\theta}{n+1} \;\Rightarrow\; \text{Bias} = -\frac{\theta}{n+1}$$
- Variance:
$$\mathrm{E}((\hat{\theta}_{\text{MLE}})^2) = \int_{x=0}^{\theta} x^2 \cdot \frac{nx^{n-1}}{\theta^n}\,\mathrm{d}x = \frac{n\theta^2}{n+2}$$
$$\Rightarrow \quad \mathrm{Var}(\hat{\theta}_{\text{MLE}}) = \frac{n\theta^2}{n+2} - \left(\frac{n\theta}{n+1}\right)^2 = \frac{n\theta^2}{(n+1)^2(n+2)}$$
- $\text{MSE}(\hat{\theta}_{\text{MLE}}) = \text{bias}^2 + \mathrm{Var}(\hat{\theta}_{\text{MLE}}) = \dfrac{2\theta^2}{(n+1)(n+2)}$
  - far smaller than $\text{MSE}(\hat{\theta}_{\text{MME}}) = \dfrac{\theta^2}{3n}$

Properties of MLE for Exponential

For $X_1, \dots, X_n \overset{\text{iid}}{\sim}$ Exponential(λ):

$$\text{PDF}: \; f(x \mid \lambda) = \lambda e^{-\lambda x}, \quad x > 0,$$

$$\text{MLE} = \text{MME for } \lambda \text{ is } \hat{\lambda} = 1/\overline{X}.$$

Since $Y = n\overline{X} = \sum_{i=1}^{n} X_i \sim$ Gamma(n, λ) has the PDF

$$f_Y(y) = \frac{\lambda^n}{\Gamma(n)} y^{n-1} e^{-\lambda y}, \quad y > 0,$$

we can find the expected value and variance for $\hat{\lambda} = 1/\overline{X} = n/Y$ as follows,

$$\mathrm{E}[\hat{\lambda}] = \mathrm{E}\left(\frac{n}{Y}\right) = \int_{y=0}^{\infty} \frac{n}{y} \cdot \frac{\lambda^n}{\Gamma(n)} y^{n-1} e^{-\lambda y} \mathrm{d}y = \frac{n\lambda}{n-1}$$

$$\mathrm{E}[\hat{\lambda}^2] = \mathrm{E}\left(\frac{n^2}{Y^2}\right) = \int_{y=0}^{\infty} \frac{n^2}{y^2} \cdot \frac{\lambda^n}{\Gamma(n)} y^{n-1} e^{-\lambda y} \mathrm{d}y = \frac{n^2\lambda^2}{(n-1)(n-2)}$$

$$\mathrm{Var}(\hat{\lambda}) = \mathrm{E}[\hat{\lambda}^2] - (\mathrm{E}[\hat{\lambda}])^2 = \frac{n^2\lambda^2}{(n-1)(n-2)} - \left(\frac{n\lambda}{n-1}\right)^2 = \frac{n^2\lambda^2}{(n-1)^2(n-2)}$$

The bias is

$$\text{Bias} = \mathrm{E}[\widehat{\lambda}] - \lambda = \frac{n\lambda}{n-1} - \lambda = \frac{\lambda}{n-1}.$$

The MSE of $\widehat{\lambda}$ is

$$\begin{aligned}\text{MSE} &= \text{Bias}^2 + \mathrm{Var}(\widehat{\lambda}) \\ &= \left(\frac{\lambda}{n-1}\right)^2 + \frac{n^2\lambda^2}{(n-1)^2(n-2)} = \frac{(n+2)\lambda^2}{(n-1)(n-2)}.\end{aligned}$$