Topic 3: Estimation

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Outline

1. Likelihoods

2. Maximum Likelihood Estimation

Likelihoods

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Leadup

- Last lecture, we began discussing the notion of a **likelihood**.

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- Recall that, computationally, a likelihood is just a joint PMF/PDF that we now treat as a function of one or more population parameters.

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Leadup

- Last lecture, we began discussing the notion of a **likelihood**.
- Recall that, computationally, a likelihood is just a joint PMF/PDF that we now treat as a function of one or more population parameters.
- Conceptually, the likelihood evaluated at a given set of observations represents how *likely* a given value of the parameter is.

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Likelihood

Definition (Likelihood)

Let $\vec{\boldsymbol{y}} := \{y_i\}_{i=1}^n$ be an observed instance of a random sample $\vec{\boldsymbol{Y}} := \{Y_i\}_{i=1}^n$, whose distribution depends on some parameter θ. The **likelihood** of the sample is simply the joint PMF/PDF of $\vec{\boldsymbol{Y}}$.

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- To avoid having to constantly separate the discrete and continuous cases, we adopt the notation

$$\mathcal{L}_{\vec{\mathbf{y}}}(\theta) \qquad \text{or} \qquad \mathcal{L}(y_1, \cdots, y_n; \theta)$$

to mean the likelihood.

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Notation

- A quick note on notation: I will use the notations $\mathcal{L}_{\vec{\mathbf{y}}}(\theta)$ and $\mathcal{L}(y_1, \cdots, y_n; \theta)$ interchangeably [though the second notation makes the sample values clearer, it is clunkier than the first].

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    - Technically the textbook writes $\mathcal{L}(y_1, \cdots, y_n \mid \theta)$, but so as to avoid confusion with conditional distributions I will avoid using this notation for the purposes of this class.

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    - Technically the textbook writes $\mathcal{L}(y_1, \cdots, y_n \mid \theta)$, but so as to avoid confusion with conditional distributions I will avoid using this notation for the purposes of this class.
- And, again, to reiterate - the likelihood is nothing more than the joint PMF/PDF of a random sample, evaluated at a particular observed instance $\vec{\boldsymbol{y}}$.

Simplification

- Now, if we assume an i.i.d. sample, we can expand things a bit.

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- For instance, if $Y_1, \cdots, Y_n$ are i.i.d. discrete random variables from a distribution with mass function $p(y; \theta)$, then

$$\mathcal{L}_{\vec{\mathbf{y}}}(\theta) = p_{X_1, X_2, \cdots, X_n}(x_1, x_2, \cdots, x_n)$$

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&= p_{X_1}(x_1; \theta) \times p_{X_2}(x_2; \theta) \times \cdots \times p_{X_n}(x_n; \theta)
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\end{aligned}$$

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Simplification

- Similarly, if $Y_1, \cdots, Y_n$ are i.i.d. continuous random variables from a distribution with density function $f(y; \theta)$, then

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\end{aligned}$$

Simplification

- Similarly, if $Y_1, \cdots, Y_n$ are i.i.d. continuous random variables from a distribution with density function $f(y;\theta)$, then

$$\begin{aligned}
\mathcal{L}_{\vec{\mathbf{y}}}(\theta) &= f_{X_1,X_2,\cdots,X_n}(x_1, x_2, \cdots, x_n) \\
&= f_{X_1}(x_1;\theta) \times f_{X_2}(x_2;\theta) \times \cdots \times f_{X_n}(x_n;\theta) = \prod_{i=1}^{n} f(x_i;\theta)
\end{aligned}$$

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Example

Example

The weight of a randomly-selected DSH cat is assumed to be normally distributed about some unknown mean μ and with some known standard deviation $\sigma = 2$ lbs. An i.i.d. random sample of 3 cats is taken; their weights are 8.2 lbs, 16.2 lbs, and 14.1 lbs. What is the likelihood of this sample? (Remember that this will be a function of μ!)

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Solution

- Let Y_i denote the weight of a randomly-selected DSH cat; then $Y_1, Y_2, \cdots \overset{\text{i.i.d.}}{\sim} \mathcal{N}(\mu, 4)$.

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Solution

- Let Y_i denote the weight of a randomly-selected DSH cat; then $Y_1, Y_2, \cdots \overset{\text{i.i.d.}}{\sim} \mathcal{N}(\mu, 4)$.
- Hence, the density of Y_i at a point y_i is given by the density of a $\mathcal{N}(\mu, 4)$ distribution, evaluated at y_i:

$$f(y_i; \mu) = \frac{1}{2\sqrt{2\pi}} e^{-\frac{1}{8}(y_i - \mu)^2}$$

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Solution

- Therefore,

$$\mathcal{L}_{(8.2, 16.2, 14.1)}(\mu) = f(8.2; \mu) \times f(16.2; \mu) \times f(14.1; \mu)$$

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Solution

- Therefore,

$$\begin{aligned}\mathcal{L}_{(8.2,16.2,14.1)}(\mu) &= f(8.2;\mu) \times f(16.2;\mu) \times f(14.1;\mu) \\ &= \left(\frac{1}{2\sqrt{2\pi}} e^{-\frac{1}{8}(8.2-\mu)^2} \right) \times \left(\frac{1}{2\sqrt{2\pi}} e^{-\frac{1}{8}(16.2-\mu)^2} \right) \times \\ &\qquad \left(\frac{1}{2\sqrt{2\pi}} e^{-\frac{1}{8}(14.1-\mu)^2} \right)\end{aligned}$$

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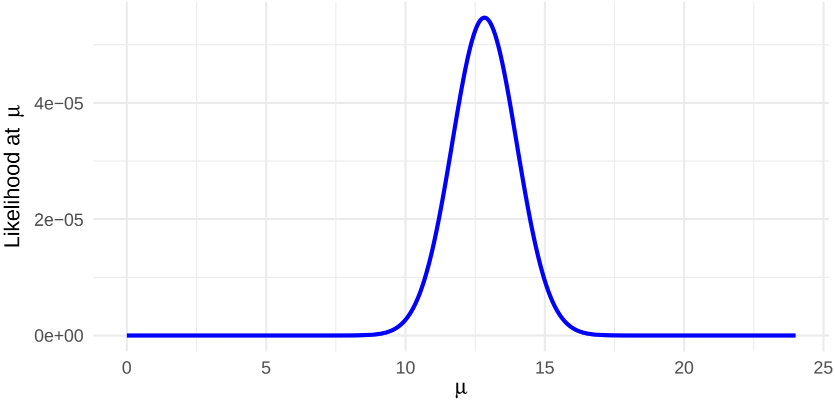
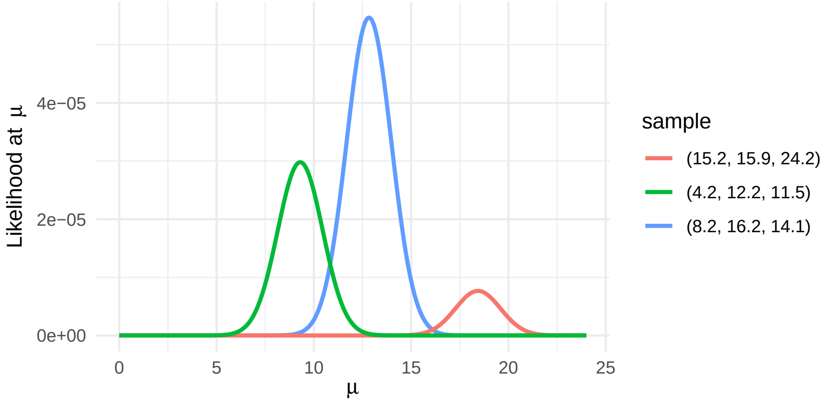
&\qquad \left(\frac{1}{2\sqrt{2\pi}} e^{-\frac{1}{8}(14.1-\mu)^2} \right) \\
&= \left(\frac{1}{2\pi} \right)^3 \exp\left\{ -\frac{1}{8}[(8.2-\mu)^2 + (16.2-\mu)^2 + (14.1-\mu)^2] \right\}
\end{aligned}$$

Example



Example



Likelihood at μ
4e−05
2e−05
0e+00
0
5
10
15
20
25
μ
sample
(15.2, 15.9, 24.2)
(4.2, 12.2, 11.5)
(8.2, 16.2, 14.1)

Example

Example

The wait time of a randomly-selected person at the DMV follows an exponential distribution with unknown parameter θ. Assuming an i.i.d. sample $\{Y_i\}_{i=1}^n$ of wait times and their corresponding observed instances $\{y_i\}_{i=1}^n$, what is the likelihood as a function of θ and $\{y_i\}_{i=1}^n$?

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- Let's do this one on the board.

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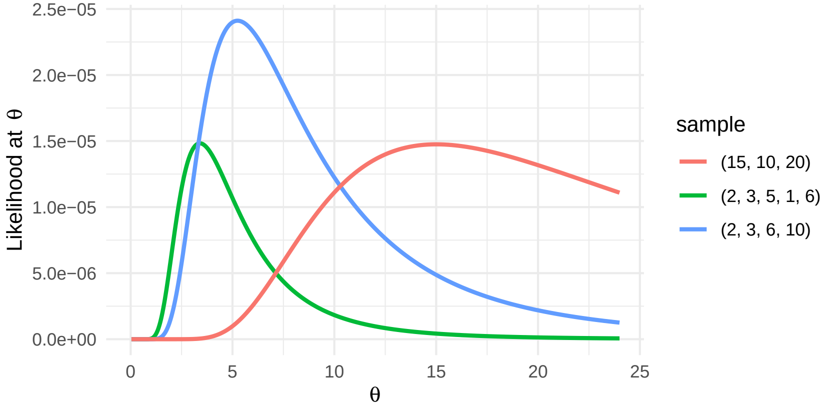
Example



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Leadup

- Alright, so that's what a likelihood is. Why do we care?

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- Again - I think of the likelihood as, well, the *likelihood* of a particular value of θ, given the data we observed.

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- Alright, so that's what a likelihood is. Why do we care?
- Again - I think of the likelihood as, well, the *likelihood* of a particular value of θ, given the data we observed.
  - Given that three randomly-selected cats weigh 8.2, 16.2, and 14.1 lbs, how likely is it that the true average weight of all cats is 10 lbs? 10.2 lbs? 11.4 lbs?

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- Again - I think of the likelihood as, well, the *likelihood* of a particular value of θ, given the data we observed.
  - Given that three randomly-selected cats weigh 8.2, 16.2, and 14.1 lbs, how likely is it that the true average weight of all cats is 10 lbs? 10.2 lbs? 11.4 lbs?
- So, here's the clever idea of how to leverage this to construct an estimator for θ - why don't we choose θ to maximize the likelihood of a particular sample!
- This is the idea behind **maximum likelihood estimation**.

Maximum Likelihood Estimation

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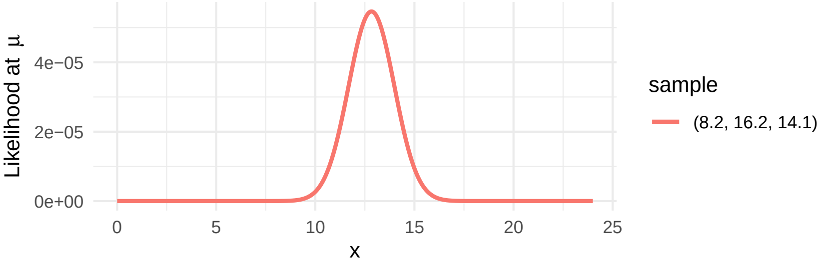
Intuition



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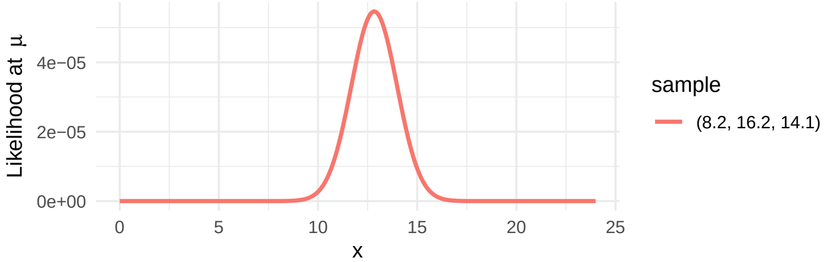
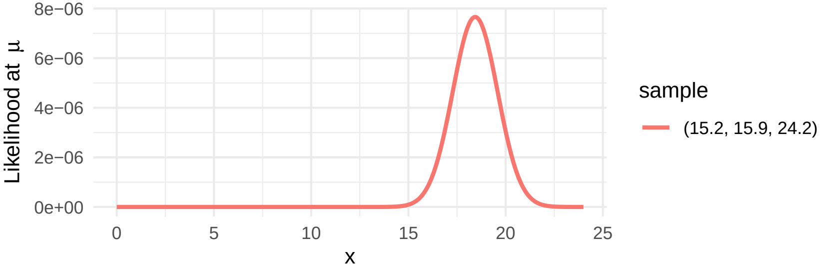
Intuition



- Given that we observed cat weights of 8.2, 16.2, and 14.1 lbs, the most plausible value for μ (i.e. the point corresponding to the highest likelihood) is around 13. Hence, a "good" estimate for μ, given the sample we observed, is around 13.

Intuition



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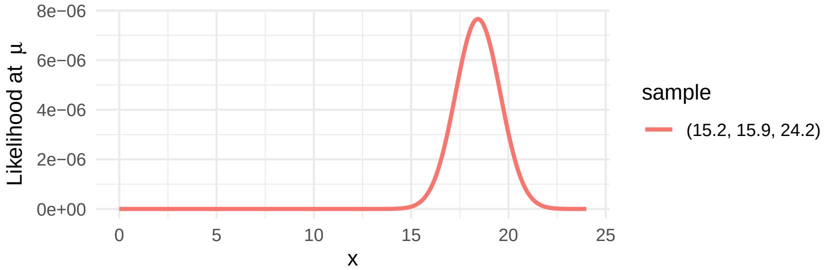
Intuition



- Given that we observed cat weights of 15.2, 15.9, and 24.2 lbs, the most plausible value for μ (i.e. the point corresponding to the highest likelihood) is around 18.5 Hence, a "good" estimate for μ, given the sample we observed, is around 18.5

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- Say we have a bucket containing 3 marbles, some of which are blue and some of which are gold.
- Suppose we take a sample of 2 marbles, and observe that they are both gold. What is a "good" guess for the total number of gold marbles in the bucket?

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- Say we have a bucket containing 3 marbles, some of which are blue and some of which are gold.
- Suppose we take a sample of 2 marbles, and observe that they are both gold. What is a "good" guess for the total number of gold marbles in the bucket?
- Let X denote the number of gold marbles in a sample of 2, taken at random and without replacement from a bucket containing 3 marbles, γ of which are gold. Then

$$X \sim \text{HyperGeom}(3, \gamma, 2)$$

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Intuition

- If there are only 2 gold marbles in the bucket, then the probability of observing the 2 gold marbles we did in our sample is given by

$$\mathbb{P}(X = 2) = \frac{\binom{2}{2}\binom{1}{0}}{\binom{3}{2}} = \frac{1}{3}$$

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- So, $\gamma = 3$ leads to a higher *likelihood* of having observed the 2 gold marbles we did than $\gamma = 2$.

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Maximum Likelihood Estimator

Definition (Maximum Likelihood Estimator)

Given a random sample $\vec{\mathbf{Y}} = \{Y_i\}_{i=1}^n$ from a population with unknown parameter θ, we define the **maximum likelihood estimator** for θ, denoted $\widehat{\theta}_{\mathrm{MLE}}$, as

$$\widehat{\theta}_{\mathrm{MLE}} = \arg\max_{\theta} \left\{ \mathcal{L}_{\vec{\mathbf{Y}}}(\theta) \right\}$$

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- Notice that when finding the MLE, we evaluate the likelihood at the *random* sample (so that we obtain a *random* estimator). More on that later.

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Leadup

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Leadup

- Now, recall that if our sample is i.i.d., then the likelihood becomes a product of several terms.
- Hence, maximizing the likelihood would require us to take the derivative of a function consisting of a product of a bunch of terms, which would therefore require several applications of the product rule (for derivatives).
- As such, the likelihood is somewhat rarely maximized directly. Instead, we make use of a clever fact: given a function $f(x)$ maximized at a point x' and a strictly increasing function $g(\cdot)$, then $(f \circ g)$ is also maximized at x'.

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Log-Likelihood

- Motivated by this, we define the following quantity:

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Log-Likelihood

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Definition (Log-Likelihood)

Given an observation $\vec{y}$ of a sample $\vec{Y}$ and the corresponding likelihood $\mathcal{L}_{\vec{\mathbf{y}}}(\theta)$, we define the **log likelihood**, notated $\ell_{\vec{\mathbf{y}}}(\theta)$, to be the natural logarithm of the likelihood. That is,

$$\ell_{\vec{\mathbf{y}}}(\theta) = \ln \mathcal{L}_{\vec{\mathbf{y}}}(\theta)$$

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Log-Likelihood

- Since the logarithm is a strictly increasing function, the value that maximizes the log-likelihood will be the same value that maximizes the likelihood.

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Log-Likelihood

- Since the logarithm is a strictly increasing function, the value that maximizes the log-likelihood will be the same value that maximizes the likelihood.
- That is, the MLE is equivalently given by the maximizing value of the log-likelihood.
- Furthermore, recall that logarithm of products are simply sums of logarithms!
- This is the guiding reason behind why we often maximize the *log*-likelihood, as opposed to the likelihood itself - maximizing the log-likelihood typically involves only taking the *sum* of several derivatives.

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Log-Likelihood

- More explicitly, suppose we have a continuous sample $\vec{\boldsymbol{Y}}$. Then

$$\mathcal{L}_{\vec{\mathbf{Y}}}(\theta) = \prod_{i=1}^{n} f(Y_i; \theta)$$

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Log-Likelihood

- More explicitly, suppose we have a continuous sample $\vec{\boldsymbol{Y}}$. Then

$$\mathcal{L}_{\vec{\mathbf{Y}}}(\theta) = \prod_{i=1}^{n} f(Y_i; \theta)$$

- Therefore,

$$\ell_{\vec{\mathbf{Y}}}(\theta) = \ln\left[\prod_{i=1}^{n} f(Y_i; \theta)\right] = \sum_{i=1}^{n} \ln f(Y_i; \theta)$$

which is much easier to differentiate than the original likelihood.

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Example

Example

Given $Y_1, \cdots, Y_n \overset{\text{i.i.d.}}{\sim} \text{Exp}(\theta)$, derive an expression for $\widehat{\theta}_{\text{MLE}}$, the maximum likelihood estimator for θ.

Solutions

- We've previously seen that

$$\mathcal{L}_{\vec{\mathbf{Y}}}(\theta) = \left(\frac{1}{\theta} \right)^n \cdot \exp\left\{ -\frac{1}{\theta} \sum_{i=1}^{n} Y_i \right\} \cdot \prod_{i=1}^{n} \mathbb{1}_{\{Y_i \geq 0\}}$$

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Solutions

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- The log-likelihood is therefore given by

$$\ell_{\vec{\mathbf{Y}}}(\theta) = -n \ln(\theta) - \frac{1}{\theta} \sum_{i=1}^{n} Y_i + \sum_{i=1}^{n} \ln \mathbb{1}_{\{Y_i \geq 0\}}$$

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Solutions

- The derivative of the log-likelihood wrt. θ is:

$$\frac{\partial}{\partial \theta} \ell_{\vec{\mathbf{Y}}}(\theta) = -\frac{n}{\theta} + \frac{1}{\theta^2} \sum_{i=1}^{n} Y_i$$

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Solutions

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- Therefore, $\widehat{\theta}_{\mathrm{MLE}}$ satisfies

$$-\frac{n}{\widehat{\theta}_{\mathrm{MLE}}} + \frac{1}{\widehat{\theta}^2_{\mathrm{MLE}}}\sum_{i=1}^{n} Y_i = 0$$

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Solutions

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- Solving and simplifying yields $\widehat{\theta}_{\mathrm{MLE}} = \overline{Y}_n$.

Multi-Parameter Case

- If the underlying population distribution has multiple parameters, we can still find maximum likelihood estimators for each by *jointly* maximizing the likelihood.

Multi-Parameter Case

- If the underlying population distribution has multiple parameters, we can still find maximum likelihood estimators for each by *jointly* maximizing the likelihood.
- In practice, this typically amounts to taking derivatives wrt. each of the parameters of interest, setting these derivatives equal to zero, and solving the resulting *system* of equations.

Example

Example

Given $Y_1, \cdots, Y_n \overset{\text{i.i.d.}}{\sim} \mathcal{N}(\mu, \sigma^2)$ where both $\mu \in \mathbb{R}$ and $\sigma^2 > 0$ are unknown parameters, find maximum likelihood estimators for both μ and σ^2.

- You'll work through this during Discussion Section.

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Example

Example

Given $Y_1, \cdots, Y_n \overset{\text{i.i.d.}}{\sim} \text{Unif}[0, \theta]$ where $\theta > 0$ is an unknown parameter, find $\widehat{\theta}_{\text{MLE}}$, the maximum likelihood estimator for θ.

Solution

- Let's begin as we did before, by first finding the likelihood:

$$\mathcal{L}_{\vec{\mathbf{Y}}}(\theta) = \prod_{i=1}^{n} f(Y_i; \theta) = \prod_{i=1}^{n} \left[\frac{1}{\theta} \cdot \mathbb{1}_{\{0 \leq Y_I \leq \theta\}} \right]$$

$$= \left(\frac{1}{\theta} \right)^n \cdot \prod_{i=1}^{n} \mathbb{1}_{\{0 \leq Y_i \leq \theta\}}$$

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- First note: the likelihood is **NOT** just equal to $(1/\theta)^n$!!! The product of indicators is **ABSOLUTELY** a part of the likelihood. In fact, let's focus on that product a bit.

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Solution

- The entire product (of indicators) is nonzero only when all of the constituent indicators are nonzero. This only happens when all of the Y_i's are greater than 0 and less than θ, which occurs when $Y_{(1)} \geq 0$ and $Y_{(n)} \leq \theta$. Therefore:

$$\prod_{i=1}^{n} \mathbb{1}_{\{0 \leq Y_i \leq \theta\}} = \mathbb{1}_{\{Y_{(1)} \geq 0\}} \cdot \mathbb{1}_{\{Y_{(n)} \leq \theta\}}$$

  and our likelihood can be written as

$$\mathcal{L}_{\vec{\mathbf{Y}}}(\theta) = \left(\frac{1}{\theta} \right)^{n} \cdot \mathbb{1}_{\{Y_{(1)} \geq 0\}} \cdot \mathbb{1}_{\{Y_{(n)} \leq \theta\}}$$

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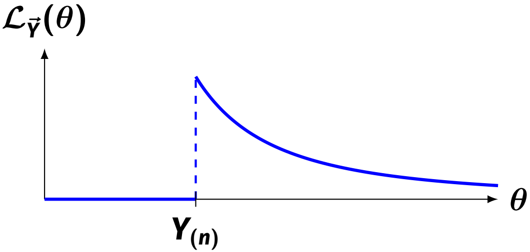

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- Of course, just because the likelihood is nondifferentiable doesn't mean that it doesn't have a maximizing value.

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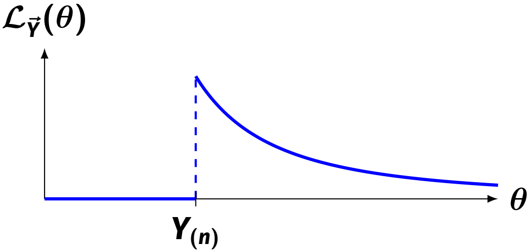
- Of course, just because the likelihood is nondifferentiable doesn't mean that it doesn't have a maximizing value.
- Indeed, just looking at the graph of $\mathcal{L}_{\vec{\mathbf{Y}}}(\theta)$, we can see that it is maximized when θ equals $Y_{(n)}$:



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- So, we find

$$\arg\max_{\theta} \{\mathcal{L}_{\vec{\mathbf{Y}}}(\theta)\} =: \boxed{\widehat{\theta}_{\mathrm{MLE}} = Y_{(n)}}$$

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- How could we have arrived at this conclusion without sketching the likelihood?

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Solution

- Here's how I like to think about things. Take a look again at the parts of the likelihood that depend on θ;

$$\mathcal{L}_{\vec{\mathbf{Y}}}(\theta) \propto \left(\frac{1}{\theta} \right)^n \cdot \mathbb{1}_{\{\theta \geq Y_{(n)}\}}$$

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- The term $(1/\theta)^n$ is a decreasing function in θ, meaning it is maximized by setting θ to be as small as possible. The term $\mathbb{1}_{\{\theta \geq Y_{(n)}\}}$ constrains θ to be no smaller than $Y_{(n)}$. Hence, combining these two facts, we see that the likelihood is maximized by setting θ to be $Y_{(n)}$, as we saw before.

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