

CSE 312

Foundations of Computing II

Lecture 24: Maximum Likelihood Estimation (MLE)



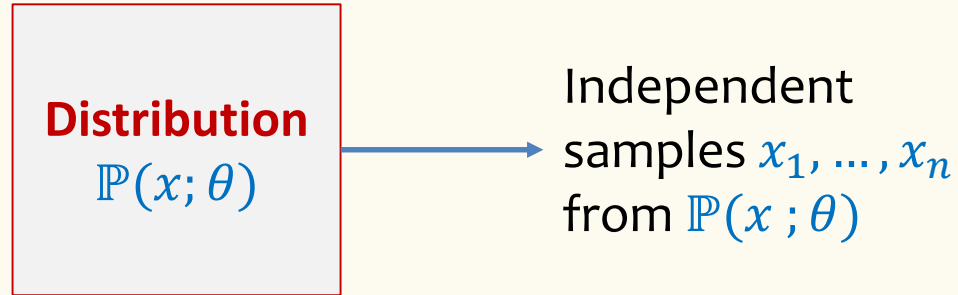
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Slide Credit: Based on Stefano Tessaro's slides for 312 19au incorporating ideas from Alex Tsun's and Anna Karlin's slides for 312 20su and 20au

Agenda

- Idea: Estimation ◀
- Maximum Likelihood Estimation (example: mystery coin)
- Continuous random variables
- General Steps

Probability: View Point up to Now

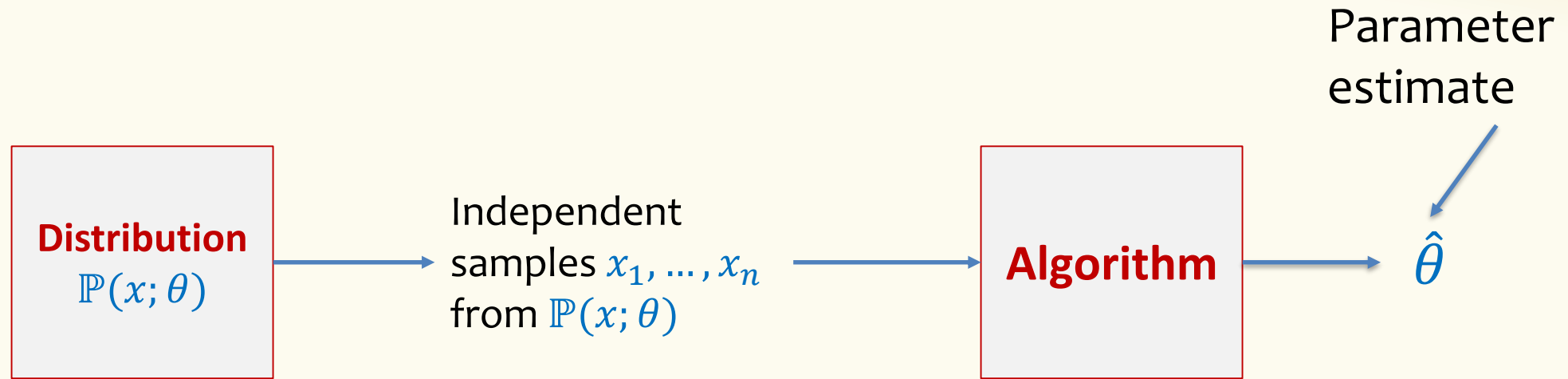


θ = known parameter

θ tells us how samples are distributed.

$\mathbb{P}(x; \theta)$ viewed as a function of x (fixed θ)

Statistics: Parameter Estimation – Workflow



$\theta =$ unknown parameter

Don't know how samples are distributed.

$\mathcal{L}(x|\theta)$ viewed as a function of θ (fixed x)

Example: $\mathcal{L}(x|\theta)$ = coin flip distribution with unknown θ = probability of heads

Observation: HTTHHHTHTHTTTTHTHTTTTHT

Goal: Estimate θ

Example

Suppose we have a mystery coin with some probability p of coming up heads. We flip the coin 8 times, independent of other flips and see the following sequence flips

TTHTHTTH

Given this data, what would you estimate p is?

Poll: pollev.com/hunter312

- a.* $1/2$
- b.* $5/8$
- c.* $3/8$
- d.* $1/4$

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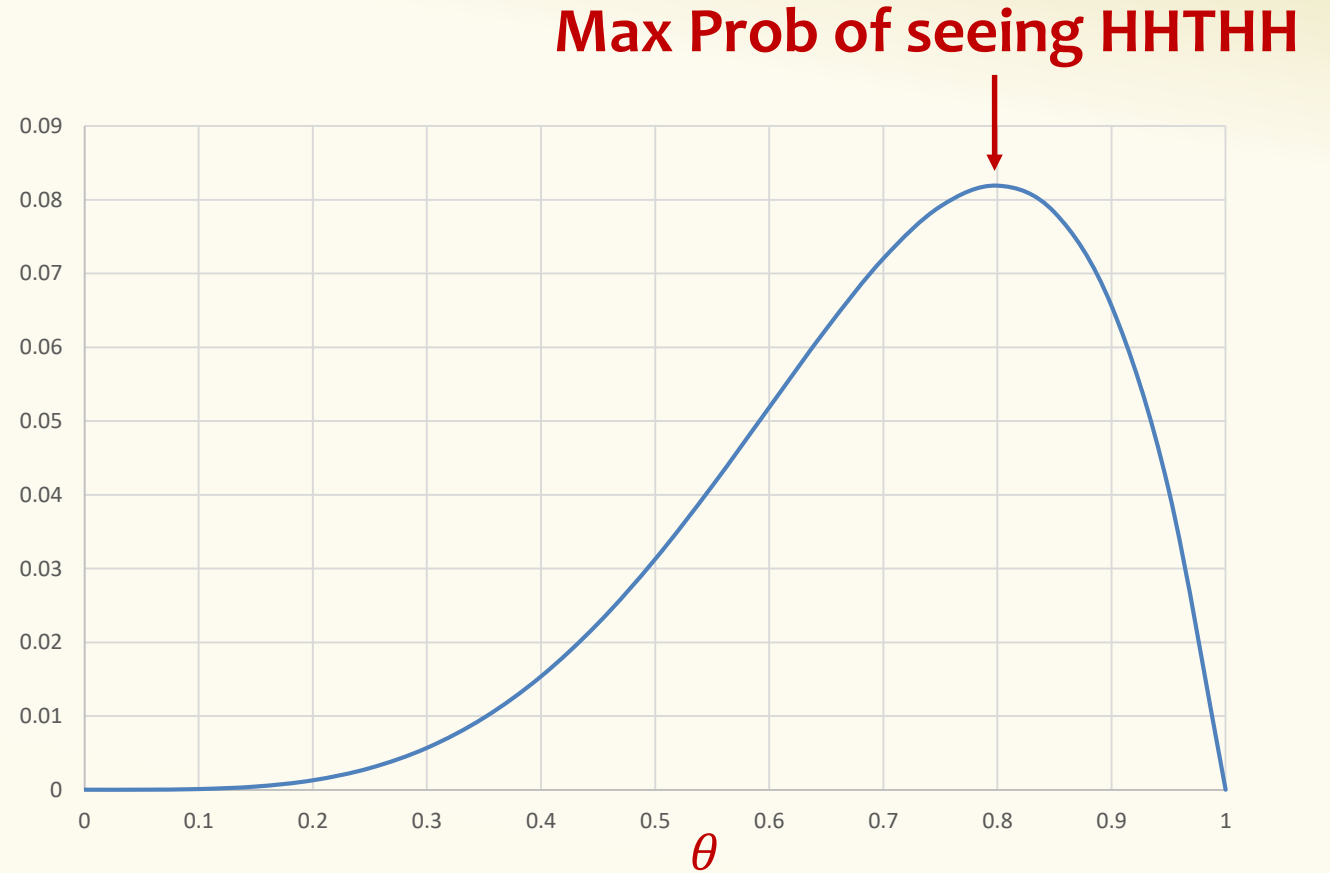
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Likelihood

Say we see outcome **HHTHH**.

$$\mathcal{L}(\text{HHTHH} \mid \theta) = \theta^4(1 - \theta)$$

Probability of observing the outcome **HHTHH** if $\theta =$ prob. of heads. This is a function of θ .



Likelihood of Different Observations

(Discrete case)

Definition. The **likelihood** of independent observations x_1, \dots, x_n is

$$\mathcal{L}(x_1, \dots, x_n | \theta) = \prod_{i=1}^n \mathbb{P}(x_i; \theta)$$

Maximum Likelihood Estimation (MLE). Given data x_1, \dots, x_n , find $\hat{\theta}$ (“the MLE”) of model such that $L(x_1, \dots, x_n | \hat{\theta})$ is maximized!

$$\hat{\theta} = \operatorname{argmax}_{\theta} \mathcal{L}(x_1, \dots, x_n | \theta)$$

Usually: Solve $\frac{\partial L(x_1, \dots, x_n | \theta)}{\partial \theta} = 0$ or $\frac{\partial \ln L(x_1, \dots, x_n | \theta)}{\partial \theta} = 0$ [+check it's a max!]

Likelihood vs. Probability

A **probability function** $\Pr(x ; \theta)$ is a function with input being an event x for some fixed probability model (w/ param θ).

$$\sum_x \Pr(x ; \theta) = 1$$

A **likelihood function** $\mathcal{L}(x | \theta)$ is a function with input being θ (the param of the prob. Model) for some fixed dataset x .

These notions are very closely connected, but answer different questions. We are trying to find the θ that maximizes likelihood, thus we are looking for the **maximum likelihood estimator**.

Example – Coin Flips

Observe: Coin-flip outcomes x_1, \dots, x_n , with n_H heads, n_T tails

– i.e., $n_H + n_T = n$

Goal: estimate θ = prob. heads.

$$L(x_1, \dots, x_n | \theta) = \theta^{n_H} (1 - \theta)^{n_T}$$

$$\frac{\partial}{\partial \theta} L(x_1, \dots, x_n | \theta) = ???$$

While it is possible to compute this derivative, it's not always nice since we are working with products.

Log-Likelihood

We can save some work if we work with the **log-likelihood** instead of the likelihood directly.

Definition. The **log-likelihood** of independent observations x_1, \dots, x_n is

$$\begin{aligned}\mathcal{LL}(x_1, \dots, x_n | \theta) &= \ln \mathcal{L}(x_1, \dots, x_n | \theta) \\ &= \ln \prod_{i=1}^n \mathbb{P}(x_i; \theta) = \sum_{i=1}^n \ln \mathbb{P}(x_i; \theta)\end{aligned}$$

Useful log properties

$$\begin{aligned}\log(ab) &= \log(a) + \log(b) \\ \log(a/b) &= \log(a) - \log(b) \\ \log(a^b) &= b \log(a)\end{aligned}$$

Example – Coin Flips

Observe: Coin-flip outcomes x_1, \dots, x_n , with n_H heads, n_T tails

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Goal: estimate θ = prob. heads.

$$\mathcal{L}(x_1, \dots, x_n | \theta) = \theta^{n_H} (1 - \theta)^{n_T}$$

$$\ln \mathcal{L}(x_1, \dots, x_n | \theta) = n_H \ln \theta + n_T \ln(1 - \theta)$$

$$\frac{\partial}{\partial \theta} \ln \mathcal{L}(x_1, \dots, x_n | \theta) = n_H \cdot \frac{1}{\theta} - n_T \cdot \frac{1}{1 - \theta}$$

$$\text{Solve } n_H \cdot \frac{1}{\hat{\theta}} - n_T \cdot \frac{1}{1 - \hat{\theta}} = 0$$

$$\hat{\theta} = \frac{n_H}{n}$$

Brain Break



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The Continuous Case

Given n samples x_1, \dots, x_n from a Gaussian $\mathcal{N}(\mu, \sigma^2)$, estimate $\theta = (\mu, \sigma^2)$

Definition. The **likelihood** of independent observations x_1, \dots, x_n is

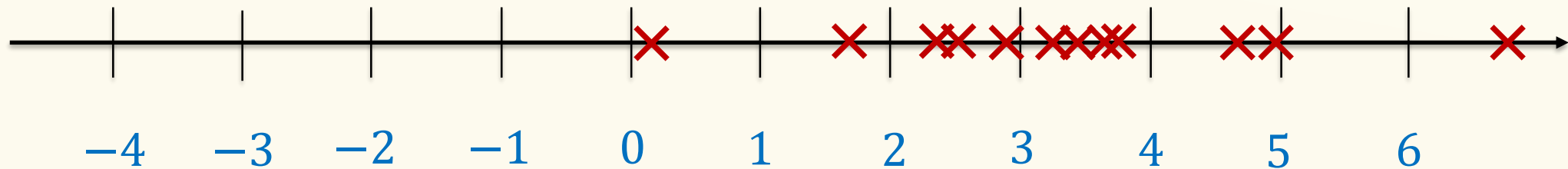
$$\mathcal{L}(x_1, \dots, x_n | \theta) = \prod_{i=1}^n f(x_i; \theta)$$

Density function! (Why?)

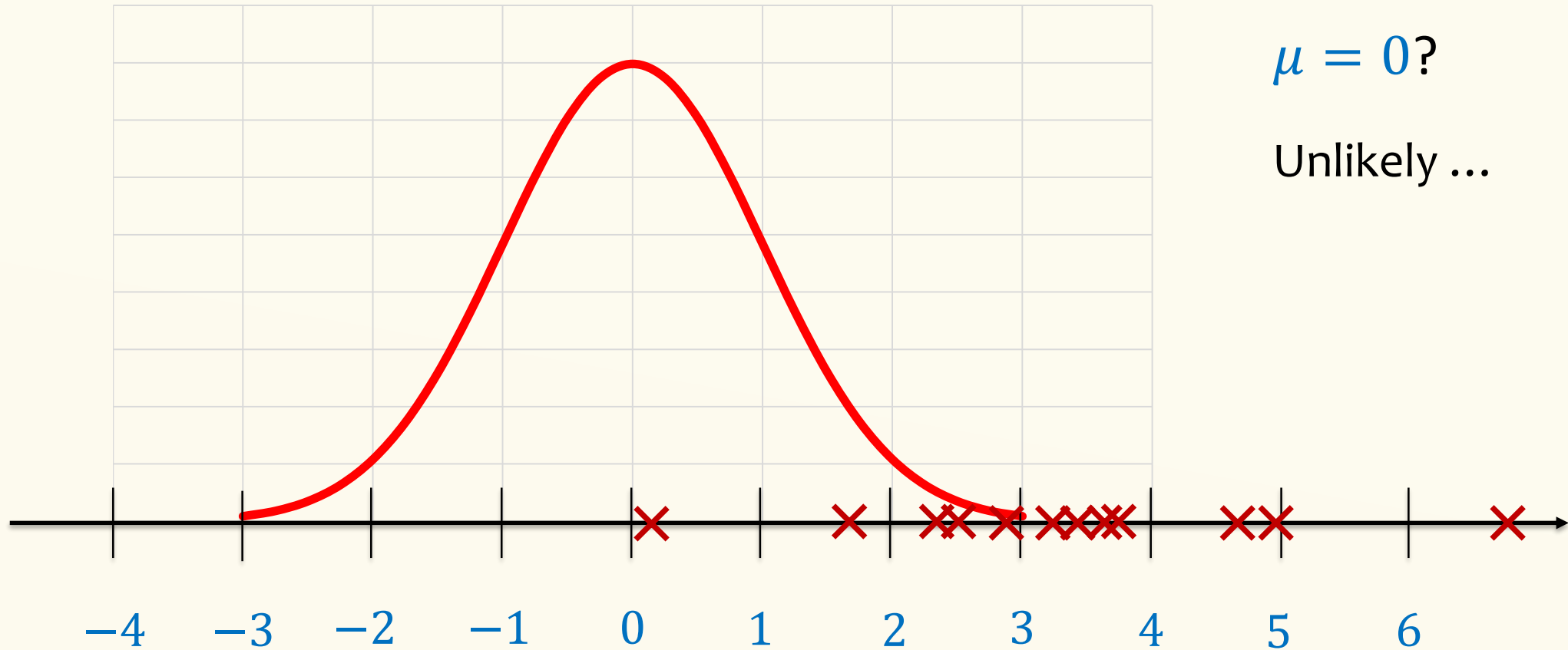
Why density?

- Density \neq probability, but:
 - For maximizing likelihood, **we really only care about relative likelihoods**, and density captures that
 - has desired property that likelihood increases with better fit to the model

n samples $x_1, \dots, x_n \in \mathbb{R}$ from Gaussian $\mathcal{N}(\mu, 1)$. Most likely μ ?
[i.e., we are given the promise that the variance is one]



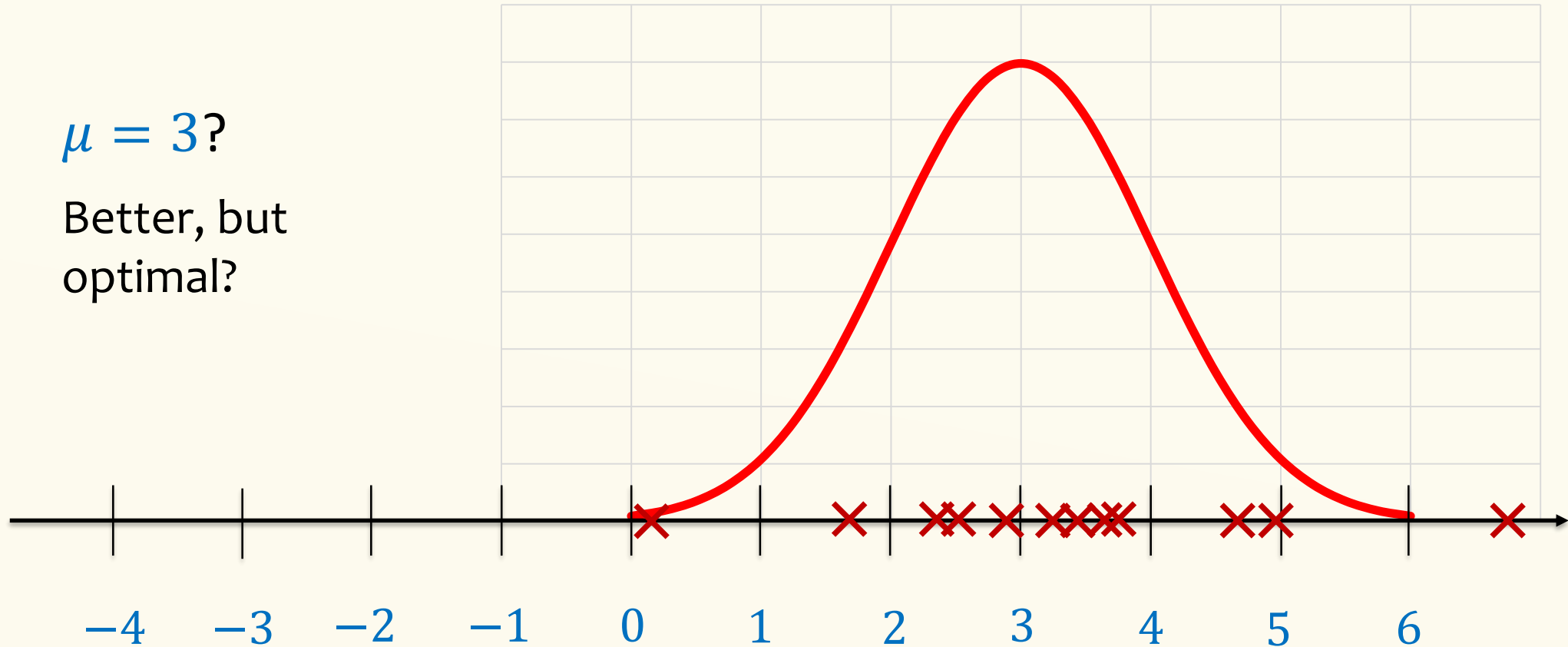
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n samples $x_1, \dots, x_n \in \mathbb{R}$ from Gaussian $\mathcal{N}(\mu, 1)$. Most likely μ ?

$\mu = 3$?

Better, but
optimal?



Example – Gaussian Parameters

Normal outcomes x_1, \dots, x_n , known variance $\sigma^2 = 1$

Goal: estimate θ expectation

$$\mathcal{L}(x_1, \dots, x_n | \theta) = \prod_{i=1}^n \frac{1}{\sqrt{2\pi}} e^{-\frac{(x_i - \theta)^2}{2}} = \left(\frac{1}{\sqrt{2\pi}} \right)^n \prod_{i=1}^n e^{-\frac{(x_i - \theta)^2}{2}}$$

$$\ln \mathcal{L}(x_1, \dots, x_n | \theta) = -n \frac{\ln 2\pi}{2} - \sum_{i=1}^n \frac{(x_i - \theta)^2}{2}$$

Example – Gaussian Parameters

Goal: estimate θ = expectation

Normal outcomes x_1, \dots, x_n , known variance $\sigma^2 = 1$

$$\ln \mathcal{L}(x_1, \dots, x_n | \theta) = -n \frac{\ln 2\pi}{2} - \sum_{i=1}^n \frac{(x_i - \theta)^2}{2}$$

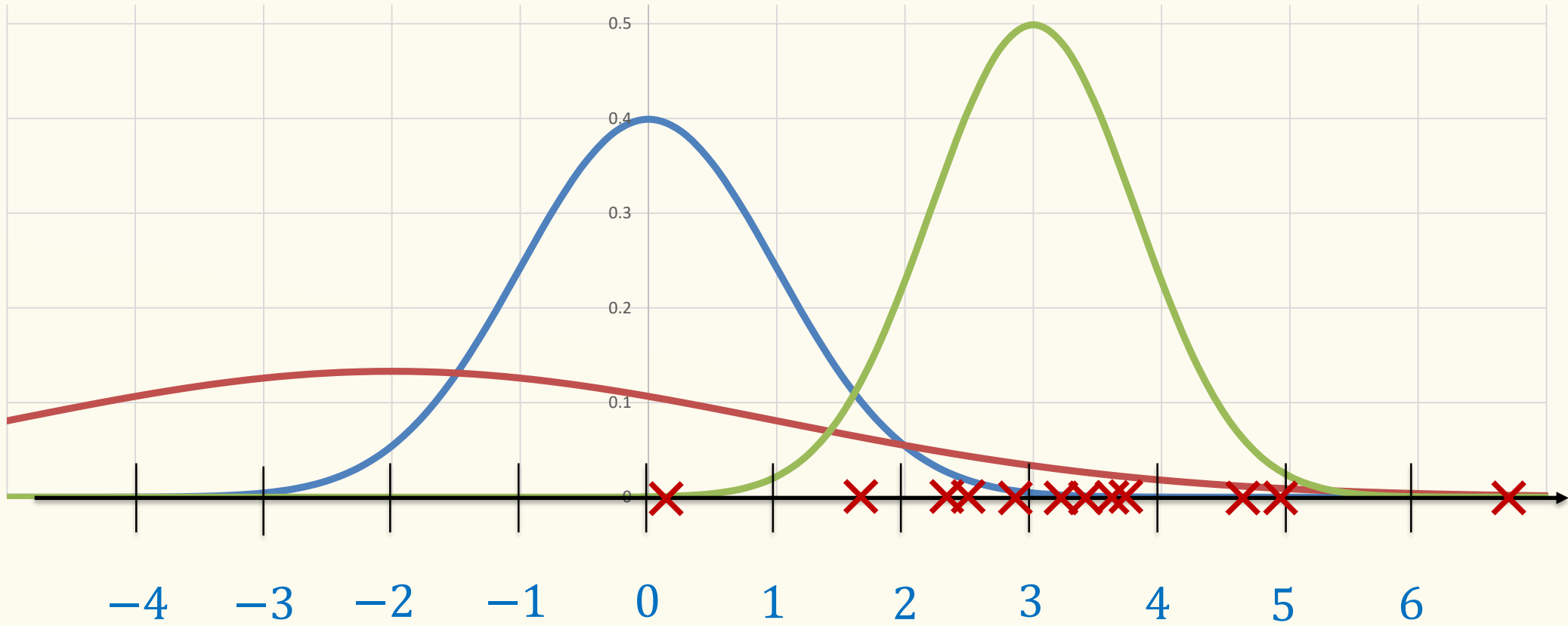
Note: $\frac{\partial}{\partial \theta} \frac{(x_i - \theta)^2}{2} = \frac{1}{2} \cdot 2 \cdot (x_i - \theta) \cdot (-1) = \theta - x_i$

$$\frac{\partial}{\partial \theta} \ln \mathcal{L}(x_1, \dots, x_n | \theta) = \sum_{i=1}^n (x_i - \theta) = \sum_{i=1}^n x_i - n\theta = 0$$

$$\hat{\theta} = \frac{\sum_{i=1}^n x_i}{n}$$

In other words, MLE is the *sample mean* of the data.

Next: n samples $x_1, \dots, x_n \in \mathbb{R}$ from Gaussian $\mathcal{N}(\mu, \sigma^2)$. Most likely μ and σ^2 ?



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General Recipe

1. **Input** Given n iid samples x_1, \dots, x_n from parametric model with parameters θ .
2. **Likelihood** Define your likelihood $\mathcal{L}(x_1, \dots, x_n | \theta)$.
 - For discrete $\mathcal{L}(x_1, \dots, x_n | \theta) = \prod_{i=1}^n \text{Pr}(x_i ; \theta)$
 - For continuous $\mathcal{L}(x_1, \dots, x_n | \theta) = \prod_{i=1}^n f(x_i ; \theta)$
3. **Log** Compute $\ln \mathcal{L}(x_1, \dots, x_n | \theta)$
4. **Differentiate** Compute $\frac{\partial}{\partial \theta} \ln \mathcal{L}(x_1, \dots, x_n | \theta)$
5. **Solve for $\hat{\theta}$** by setting derivative to 0 and solving for max.

Generally, you need to do a second derivative test to verify it is a maximum, but we won't ask you to do that in CSE 312.