

A title card for 'Section 9' featuring a light yellow background with a faint grid pattern. Two vertical purple lines extend from the top of the frame down to a white rectangular box with a purple border. Inside the box, the text 'SECTION 9' is written in a bold, purple, sans-serif font.

SECTION 9

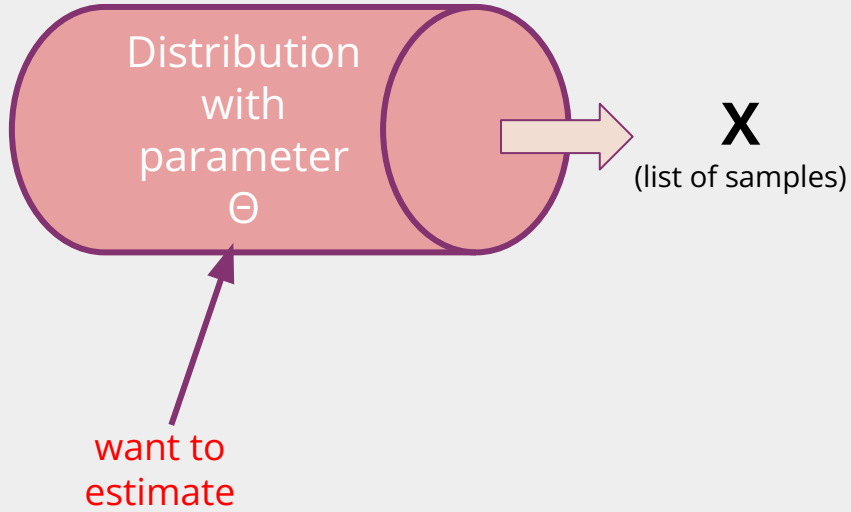
MLE

MLE

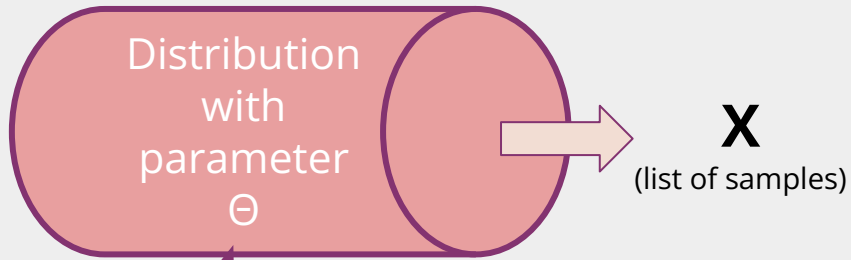
Sometimes, we don't know enough about a particular distribution, and we want to estimator a parameter to that distribution!

MLE helps us provide as estimate for some parameter(s) to a distribution based on some samples observed from that distribution

MLE



MLE



want to estimate

What value of Θ would make the most sense here? What value of Θ would have the greatest likelihood of producing this sample?

What value of Θ maximizes $L(X | \Theta)$?

MLE

Likelihood

Let x_1, \dots, x_n be iid samples from pmf $p_X(x; \theta)$ where θ are the distribution's parameters. The likelihood function is the probability of seeing the data given the parameters as

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

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multiplying bc we want the likelihood *all* of these are observed

in the *continuous* case, the PMF is replaced with the PDF

Represents the samples observed - can also just use X to represent the list of observations

MLE

MLE

MLE of θ is $\hat{\theta}$ - the value of θ that will **maximize** the likelihood function

$$\hat{\theta} = \arg \max_{\theta} \mathcal{L}(x_1, \dots, x_n; \theta)$$

We're given that there's a distribution with some unknown parameter(s) θ , and there are some observations x_1, \dots, x_n from this distribution

1. Write the likelihood function

*even if there are multiple parameters to the distribution, only one likelihood function
- remember to multiply (not sum) the probability of each of the observations!*

2. Take the log of the likelihood function (usually \ln , not \log)

we typically want to take natural log (\ln) of the likelihood function in order to make finding the derivative much easier (remember \ln of a product is a sum of the \ln 's)

3. Take the derivative of the log likelihood function

if you're finding an MLE where there are multiple parameters, in this step, take the partial derivative with respect to the parameter you're trying to solve for

4. Set the derivative of the log likelihood function to 0 and solve for θ

this step where you set the derivative equal to 0 is where you'll want to add the hat on top of the θ since at this step, we're solving for the maximum likelihood estimator

5. Verify the estimator is a maximizer via the 2nd derivative test (usually ignore for 312)

UNBIASED ESTIMATOR

Bias: The bias of an estimator $\hat{\theta}$ for a **true** parameter θ is defined as $E[\hat{\theta}] - \theta$. An estimator is unbiased iff $E[\hat{\theta}] = \theta$.