

# CSC 311: Introduction to Machine Learning

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University of Toronto

# Outline

- Maximum likelihood estimation
- Bayesian inference basics

## Maximum Likelihood Estimation (MLE)

- Goal: estimate parameters  $\theta$  from observed data  $\{x_1, \dots, x_N\}$
- Main idea: We should choose parameters that assign high probability to the observed data:

$$\hat{\theta} = \operatorname{argmax} L(\theta; x_1, \dots, x_N)$$

# Three steps for computing MLE

1. Write down the likelihood objective:

$$L(\theta; x_1, \dots, x_N) = \prod_{i=1}^N L(\theta; x_i)$$

2. Transform to log likelihood:

$$l(\theta; x_1, \dots, x_N) = \sum_{i=1}^N \log L(\theta; x_i)$$

3. Compute the critical point:

$$\frac{\partial l}{\partial \theta} = 0$$

## Example 1 - categorical distribution

$\mathbf{X}$  is a discrete random variable with the following probability mass function ( $0 \leq \theta \leq 1$  is an unknown parameter):

$\mathbf{X}$	0	1	2	3
$P(\mathbf{X})$	$2\theta/3$	$\theta/3$	$2(1 - \theta)/3$	$(1 - \theta)/3$

- The following 10 independent observations were taken from  $\mathbf{X}$ :  $\{3, 0, 2, 1, 3, 2, 1, 0, 2, 1\}$ .
- What is the MLE for  $\theta$ ?

## Step 1: Likelihood objective

$$\begin{aligned} L(\theta) &= P(X = 3)P(X = 0)P(X = 2)P(X = 1)P(X = 3) \\ &\quad \times P(X = 2)P(X = 1)P(X = 0)P(X = 2)P(X = 1) \\ &= \left(\frac{2\theta}{3}\right)^2 \left(\frac{\theta}{3}\right)^3 \left(\frac{2(1-\theta)}{3}\right)^3 \left(\frac{(1-\theta)}{3}\right)^2 \end{aligned}$$

## Step 2: Log likelihood

$$\begin{aligned}l(\theta) &= \log L(\theta) \\&= 2(\log \frac{2}{3} + \log \theta) + 3(\log \frac{1}{3} + \log \theta) \\&\quad + 3(\log \frac{2}{3} + \log(1 - \theta)) + 2(\log \frac{2}{3} + \log(1 - \theta)) \\&= C + 5(\log \theta + \log(1 - \theta))\end{aligned}$$



### Step 3: critical points

$$\begin{aligned}\frac{\partial l}{\partial \theta} &= 0 \\ \rightarrow 5 \left( \frac{1}{\theta} - \frac{1}{1-\theta} \right) &= 0 \\ \rightarrow \hat{\theta} &= 0.5\end{aligned}$$

## Example 2 - Poisson distribution

- $\mathbf{X}$  is a discrete random variable following the poisson distribution:

$$P(\mathbf{X} = x) = \frac{e^{-\lambda} \lambda^x}{x!}$$

- Suppose we observe  $N$  samples of  $\mathbf{X}$ :  $\{x_1, \dots, x_N\}$
- What is the MLE for  $\lambda$ ?

# Three steps

1. Likelihood objective:

$$L(\lambda) = \prod_{i=1}^N \frac{e^{-\lambda} \lambda^{x_i}}{x_i!}$$

2. Log likelihood:

$$l(\lambda) = -N\lambda + \log \lambda \sum_{i=1}^N x_i - \sum_{i=1}^N \log(x_i!)$$

3. Critical point:

$$\frac{\partial l}{\partial \lambda} = 0 \rightarrow -N + \frac{1}{\lambda} \sum_{i=1}^N x_i \rightarrow \hat{\lambda} = \frac{\sum_{i=1}^N x_i}{N}$$

## Exercise

Suppose that  $X_1, \dots, X_n$  form a random sample from a uniform distribution on the interval  $(0, \theta)$ , where the parameter  $\theta > 0$  but is unknown. Please find MLE of  $\theta$ .

## Bayesian Inference Basics

# Bayesian Philosophy

- Bayesian interprets probability as degrees of beliefs.
- Bayesian treats parameters as random variables.
- Bayesian learning is updating our beliefs (probability distribution) based on observations.

# Bayesian versus Frequentist <sup>1</sup>

- MLE is the standard frequentist inference method.
- Bayesian and frequentist are the two main approaches in statistical machine learning. Some of their ideological differences can be summarized as:

	Frequentist	Bayesian
Probability is	relative frequency	degree of beliefs
Parameter $\theta$ is	unknown constant	random variable

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<sup>1</sup>Han Liu and Larry Wasserman, Statistical Machine Learning, 2014

# The Bayesian approach to machine learning<sup>2</sup>

1. We define a model that expresses qualitative aspects of our knowledge (eg, forms of *distributions*, independence assumptions). The model will have some unknown *parameters*.
2. We specify a *prior* probability distribution for these unknown parameters that expresses our beliefs about which values are more or less likely, before seeing the data.
3. We gather data.
4. We compute the *posterior* probability distribution for the parameters, given the observed data.
5. We use this posterior distribution to draw scientific conclusions and make predictions

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<sup>2</sup>Radford M. Neal, Bayesian Methods for Machine Learning, NIPS 2004 tutorial



# Computing the posterior

- The posterior distribution is computed by the Bayes' rule:

$$P(\textit{parameter}|\textit{data}) = \frac{P(\textit{parameter})P(\textit{data}|\textit{parameter})}{P(\textit{data})}$$

- The denominator is just the required normalizing constant. So as a proportionality, we can write:

$$\textit{posterior} \propto \textit{prior} \times \textit{likelihood}$$

## Exercise

- Suppose you have a  $\text{Beta}(4, 4)$  prior distribution on the probability  $\theta$  that a coin will yield a 'head' when spun in a specified manner.
- The coin is independently spun ten times, and 'heads' appear fewer than 3 times. You are not told how many heads were seen, only that the number is less than 3.
- Calculate your exact posterior density (up to a proportionality constant) for  $\theta$  and sketch it.

# Questions?

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