CSC 311: Introduction to Machine Learning

Tutorial 8 - Probabilistic Models

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University of Toronto, Fall 2022

Outline

- Maximum likelihood estimation
- Bayesian inference basics

Maximum Likelihood Estimation (MLE)

Review

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

$$\hat{\theta} = \text{argmax } L(\theta; x_1, \cdots, x_N)$$

Three steps for computing MLE

1. Write down the likelihood objective:

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

2. Transform to log likelihood:

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

3. Compute the critical point:

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

Example 1 - categorial 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 θ?

Step 1: Likelihood objective

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

Step 2: Log likelihood

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

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 random variable following the poisson distribution:
$$P(\mathbf{X}=x)=\frac{e^{-\lambda}\lambda^x}{x!}$$
- Suppose we observe N samples of $\mathbf{X}$: $\{x_1,\cdots,x_N\}$
- What is the MLE for λ?

Three steps

1. Likelihood objective:

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

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

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 [1]

- 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 θ is	unknown constant	random variable

[1] Han Liu and Larry Wasserman, Statistical Machine Learning, 2014

The Bayesian approach to machine learning [2]

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

[2] Radford M. Neal, Bayesian Methods for Machine Learning, NIPS 2004 tutorial

Computing the posterior

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

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

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

$$\text{posterior} \;\propto \text{prior} \;\times \text{likelihood}$$

Exercise

- Suppose you have a Beta(4, 4) prior distribution on the probability θ 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 θ and sketch it.

Questions?

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