STATISTICAL PATTERN RECOGNITION ASSIGNMENT 3

Ali Gholami

Department of Computer Engineering & Information Technology Amirkabir University of Technology

> https://aligholamee.github.io aligholami7596@gmail.com

Abstract

In this paper, we'll review the parametric techniques to estimate the unknown parameters of data distributions. We'll use, MLE and Bayesian estimation for parameter estimation. Also, we'll delve into the non-parametric techniques to estimate the unknown density of data distribution. We'll use Kernel Density Estimation methods such as Parzen Windows and other techniques such as Histogram and k-NN density estimation.

Keywords. Parameter Estimation, Density Estimation, Non-parametric Methods, Parametric Methods, Kernel Density Estimation, Maximum Likelihood Estimation, Bayesian Estimation, Histogram Density Estimation, K-NN Density Estimation.

1 Parameter Estimation

Let x_k , k = 1, 2, ..., N denote independent training samples from one of the following densities. Obtain the Maximum Likelihood estimate of θ in each case.

(a)
$$f(x_k; \theta) = \frac{x_k}{\theta^2} \exp(\frac{-x_k^2}{2\theta^2})$$
 where $x_k \ge 0$ and $\theta \ge 0$

(b)
$$f(x_k; \theta) = \sqrt{\theta} x_k^{\sqrt{\theta}-1}$$
 where $0 \le x_k \le 1$ and $\theta \ge 0$

Solution

(a) Substituting the given density inside the *MLE* equation yields the following results.

$$\hat{\theta} = \arg \max_{\theta} \{P(D|\theta)\} = \arg \max_{\theta} \{\sum_{k=1}^{n} \ln P(x_k|\theta)\}$$

$$\hat{\theta} = \arg \max_{\theta} \{\sum_{k=1}^{n} \ln \frac{x_k}{\theta^2} \exp(\frac{-x_k^2}{2\theta^2})\}$$

$$\nabla_{\theta} l(\theta) = 0$$

$$(1.1)$$

where $l(\theta)$ is $\sum_{k=1}^{n} \ln \frac{x_k}{\theta^2} \exp(\frac{-x_k^2}{2\theta^2})$ in this case. Performing the gradient on the given equation yields the following results.

$$\sum_{k=1}^{n} (\frac{-2}{\theta} + \frac{x_k^2}{\theta^3}) = 0$$

The simplified estimate of unknown θ is given below.

$$\hat{\theta} = \sqrt{\frac{\sum_{k=1}^{n} x_k^2}{2N}}$$