

Fiche TD N =° 03(b) : Estimation NP de la fonction densité de probabilité

Exercice 01:

In the case when the true density is Uniform(0,1) calculate the exact bias of the histogram.

Exercice 02:

Prove that if $\hat{f}_X(x)$ is the Kernel density estimator, then

$$\text{var}(\hat{f}_X(x)) = \frac{1}{n} ((K_h^2 * f_X)(x) - (K_h * f_X)^2(x))$$

where $(f * g)(x) = \int f(x - y)g(y)dy$

Exercice 03:

Let (X_1, \dots, X_n) be a random sample from a distribution on \mathbb{R} with Lebesgue density $2^{-1}(1 - \theta^2)e^{\theta x - |x|}$, where $\theta \in (-1, 1)$ is unknown.

1. Show The cumulative distribution function ?
2. Show that the median of the distribution of X_1 is given by $m(\theta) = (1 - \theta)^{-1} \log(1 + \theta)$ when $\theta > 0$ and $m(\theta) = -m(-\theta)$ when $\theta < 0$.
3. Show that the mean of the distribution of X_1 is $\mu(\theta) = 2\theta/(1 - \theta^2)$.

Exercice 04:

1. If $K(t) = \frac{15}{16}(1 - t^2)^2$; $|t| \leq 1$ Find $\int K^{(2)}(x)dx$ and $\int x^2 K(x)dx$? if $f''(x) = -1$ find h^* ?
2. The efficiency of a kernel $K(\cdot)$ is defined as:

$$\text{eff}(K) = \frac{3}{5\sqrt{5}} \left(\int t^2 K(t)dt \right)^{(-1/2)} \left(\int K(t)^2 dt \right)^{(-1)}$$

Determine the efficiencies for the following kernels:

- a. Biweight: $K(t) = \frac{15}{16}(1 - t^2)^2$; $|t| \leq 1$.
- b. Triangular: $K(t) = (1 - |t|)$; $|t| \leq 1$.
- c. Normal: $K(t) = \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}}$; $t \in \mathbb{R}$
- d. Rectangular: $K(t) = \frac{1}{2}$; $|t| \leq 1$.

Exercice 05:

Which of the following serve as kernel functions for a density estimator?

Prove your assertion one way or the other.

- a. $K(x) = \mathbf{1}_{(-1 < x < 1)/2}$,
- b. $K(x) = \mathbf{1}_{(0 < x < 1)}$,

- c. $K(x) = 1/x$,
- d. $K(x) = \frac{3}{2}(2x+1)(1-2x)\mathbf{1}_{-\frac{1}{2} < x < \frac{1}{2}}$,
- e. $K(x) = 0.75(1-x^2)\mathbf{1}_{(-1 < x < 1)}$,

Exercise 06:

A natural estimate of the derivative of a density $f'(x)$ is the derivative of a kernel estimate of the density; that is,

$$\hat{f}'(x) = \frac{1}{nh^2} \sum_{i=1}^n K' \left(\frac{x - X_i}{h} \right)$$

(assuming differentiability of K). Calculations similar to those leading to h^* of \hat{f} imply that the optimal bandwidth is $O(n^{-1/7})$, with optimal AMISE of order $O(n^{-1/7})$. Compare "reasonable" choices of h for estimation of f' . Are the density derivative estimates less precisely determined than the density estimates, as the asymptotics would suggest?

Exercise 06: Calculate the exact values of $\int K^2(u)du$ and $\int u^2 K(u)du$ for the Gaussian, Epanechnikov and Quartic kernels.

Exercise 07: Multivariate Density Estimation

Kernel density estimation can be easily generalized from univariate to multivariate data, in theory if not always in practice. The general form of the estimator is

$$\hat{f}(x) = \frac{1}{n|H|} \sum_{i=1}^n K_d \left(\frac{x - X_i}{H^{-1}} \right)$$

where $|H|$ is the absolute value of the determinant of the matrix H . Here $K_d : \mathbb{R} \rightarrow \mathbb{R}$ is the kernel function, often taken to be a d -variate probability density function, and if is a nonsingular $d \times d$ bandwidth matrix A . A popular technique for generating K_d from a univariate kernel K is by using a product kernel,

$$K_d(u) = \prod_{i=1}^n K(u_j).$$

using multivariate Taylor Series expansions. Assume that all second partial derivatives of f are piecewise continuous and square integrable, and that the kernel K_d satisfies the usual conditions.

Define $h > 0$ and the $d \times d$ matrix A to satisfy $H = hA$, where A has unit determinant. Then, if $h \rightarrow 0$ and $nh_d \rightarrow \infty$ as $n \rightarrow \infty$, show that the AMISE has the form

where $\nabla^2 f(u)$ is the $d \times d$ Hessian matrix,

$$\nabla^2 f(u) = \frac{\partial^2 f(u)}{\partial u_i \partial u_j}$$

The optimal H is not generally available in closed form, but AMISE shows that h should be taken to be $O(n^{-1/(d+4)})$,