



Exercise sheet 8

Exercise 1. Consider i.i.d. r.v.'s $(Y, Z), (Y_1, Z_1), (Y_2, Z_2), \dots$ obeying a non-parametric regression model $\mathbb{E}_f(Y|Z) = f(Z)$ and satisfying the Assumptions §5.3.1. Denote by \mathbb{F} the c.d.f. of Z and assume that \mathbb{F} is continuous and admits an inverse denoted by \mathbb{F}^{-1} . We set $\ell := f \circ \mathbb{F}^{-1}(z)$ and note, that $f = \ell \circ \mathbb{F}$. Given a kernel K and a bandwidth h consider the kernel estimator $\widehat{\ell}_h(z) = \frac{1}{nh} \sum_{i=1}^n Y_i K\left(\frac{\mathbb{F}(Z_i) - z}{h}\right)$ of f .

- Derive an upper bound for $\text{bias}(z) = \mathbb{E}(\widehat{\ell}_h(z)) - \ell(z)$ if f belongs to an Hölder class and K is a kernel of appropriate order.
- Derive an upper bound for $\text{Var}(\widehat{\ell}_h(z))$ assuming that $\|L^\infty\| f < \infty$ and $\|K\|_{L^2} < \infty$.
- Find an upper bound for $\text{MSE}(z) = \mathbb{E}|\widehat{\ell}_h(z) - \ell(z)|^2$ depending on the bandwidth. Select an optimal value for the bandwidth and derive the associated upper bound.
- Propose an estimator of f if \mathbb{F} is known and if it isn't. (4 points)

Exercise 2. Consider i.i.d. r.v.'s $(X, U), (X_1, U_1), (X_2, U_2), \dots$ where U is uniformly distributed on the interval $[0, 1]$, i.e., $U \sim \mathcal{U}([0, 1])$ and X is non-negative with unknown density \mathbb{p} . Moreover, X and U are independent. Let \mathbb{p}^y denote the common density of the r.v.'s $Y := XU, Y_1 = X_1U_1, \dots$. Given a kernel K with derivative \dot{K} and a bandwidth h consider the kernel estimator $\widehat{\mathbb{p}}_h(z) = \frac{1}{nh} \sum_{i=1}^n \left\{ \frac{Y_i}{h} \dot{K}\left(\frac{Y_i - x}{h}\right) + K\left(\frac{Y_i - x}{h}\right) \right\}$ of \mathbb{p} .

- Let g be a function with derivative \dot{g} such that $g, y \mapsto \text{Id}(y)g(y) := yg(y)$ and $\text{Id} \dot{g}$ are bounded. Show that, $\mathbb{E}(Y \dot{g}(Y) + g(Y)) = \mathbb{E}(g(X))$.
Hint: First show $\mathbb{E}(g(Y)) = \int_0^\infty g(v) \int_v^\infty \frac{\mathbb{p}(x)}{x} dx dv$ and conclude $\mathbb{p}^y(y) = \int_y^\infty \frac{\mathbb{p}(x)}{x} dx$ and $\dot{\mathbb{p}}^y(y) = -\frac{\mathbb{p}(y)}{y}$.
- Derive an upper bound for $\text{bias}(x)$ if \mathbb{p} is three-times differentiable with bounded third derivative and the kernel is of order 2 such that $\int |u|^3 |K(u)| du < \infty$.
- Derive an upper bound for $\text{Var}(\widehat{\mathbb{p}}(x))$ assuming that $\|\mathbb{p}^y\|_{L^\infty} < \infty$, $\|K\|_{L^2} < \infty$, $\|\text{Id}^2 \mathbb{p}^y\|_{L^\infty} < \infty$, $\|\dot{K}\|_{L^2} < \infty$.
- Find an upper bound for the $\text{MSE}(x)$ depending on the bandwidth. Select an optimal value for the bandwidth and derive the associated upper bound of the $\text{MSE}(x)$. What do you notice? (4 points)

Exercise 3. Consider r.v.'s $Y_i = f(x_i) + \varepsilon_i, i \in \llbracket 1, n \rrbracket$, where x_1, \dots, x_n are \mathbb{R}^d -valued deterministic covariates, $\varepsilon_1, \dots, \varepsilon_n$ are i.i.d. real-valued centred r.v.'s with finite variance

σ^2 , and $f : \mathbb{R}^d \rightarrow \mathbb{R}$ is an unknown regression function. Denote by $\|\cdot\|$ the Euclidean norm on \mathbb{R}^d . Given a bandwidth $h > 0$ and the kernel $K := \mathbb{1}_{[0,1]}$ for each $x \in \mathbb{R}^d$ such that $\sum_{i=1}^n K\left(\frac{\|x_i - x\|}{h}\right) > 0$, define a locally constant estimator of $f(x)$ by:

$$\hat{f}_h(x) = \arg \min_{a \in \mathbb{R}} \sum_{i=1}^n (Y_i - a)^2 K\left(\frac{\|x_i - x\|}{h}\right).$$

- Give an explicit form for $\hat{f}_h(x)$.
- Let f be Lipschitz with constant $L > 0$, i.e. $|f(x_1) - f(x_2)| \leq L \|x_1 - x_2\|$, for all $x_1, x_2 \in \mathbb{R}^d$. Show that $|\mathbb{E}[\hat{f}_h(x)] - f(x)| \leq Lh$, for all $x \in \mathbb{R}^d$.
- Given a ball $B_h := \{u \in \mathbb{R}^d : \|u\| \leq h\}$ in \mathbb{R}^d and denoting by $\text{Vol}(B_h)$ its volume suppose that there exist a constant $C > 0$ such that $\sum_{i=1}^n \mathbb{1}_{B_h}(x_i - x) \geq C n \text{Vol}(B_h)$. Show that there is D depending on C and d such that $\text{Var}[\hat{f}_h(x)] \leq (nh^d)^{-1} D \sigma^2$.
- Deduce from (b) and (c) an upper bound for the $\text{MSE}(x)$ depending on the bandwidth. Select an optimal value for the bandwidth and compute the value of the associated $\text{MSE}(x)$. How does d influences this bound? Give an interpretation for this.

Hint : you may show $\{\mathbb{E}[\hat{f}_h(x)] - f(x)\} \sum_{i=1}^n K\left(\frac{\|x_i - x\|}{h}\right) = \sum_{i=1}^n \{f(x_i) - f(x)\} K\left(\frac{\|x_i - x\|}{h}\right)$ and $\text{Var}[\hat{f}_h(x)] \sum_{i=1}^n K\left(\frac{\|x_i - x\|}{h}\right) \leq \sigma^2$. (4 points)

Exercise 4. Consider r.v.'s $Y_i = f(X_i) + \varepsilon_i$, $i \in \llbracket 1, n \rrbracket$, where X_1, \dots, X_n are \mathbb{R}^d -valued r.v.'s, $\varepsilon_1, \dots, \varepsilon_n$ are i.i.d. real-valued centred r.v.'s with finite variance σ^2 and $f : \mathbb{R}^d \rightarrow \mathbb{R}$ is an unknown regression function. Suppose that f admits at least l derivatives with Lipschitz property with constant $L > 0$. Given a bandwidth $h > 0$, a kernel K and $U(x) := (1, x, \dots, \frac{x^l}{l!})$ define a local polynomial estimator of degree l by $\hat{f}_h(x) := \hat{\theta}^t U(0)$ where

$$\hat{\theta} = \arg \min_{\theta \in \mathbb{R}^{l+1}} \sum_{i=1}^n |Y_i - \theta^t U\left(\frac{X_i - x}{h}\right)|^2 K\left(\frac{X_i - x}{h}\right).$$

- Give an explicit form for $W_i(x)$ such that $\hat{f}_h(x) = \sum_{i=1}^n Y_i W_i(x)$.
- Show that $\hat{f}_h(x)$ reproduces polynomials of order lower or equal to l , that is to say, if Q is a polynomial of order lower than l , then $\sum_{i=1}^n Q(X_i) W_i(x) = Q(x)$.
- Deduce from this that $\sum_{i=1}^n W_i(x) = 1$ and $\sum_{i=1}^n (X_i - x)^k W_i(x) = 0$ for all $k \in \llbracket 1, l \rrbracket$.
- Suggest an estimator of the k^{th} derivative of f depending on U , $\hat{\theta}$ and h . (4 points)