

**Homework – 2**

**Exercise 1:**[Simulation experiments and KDE] Here is list of steps you have to perform with Python. At each step, you are expected to provide comments/explanations about the phenomenon of interest as well as graphs which illustrate your conclusions. Do not forget indicating legends and titles on the graph axes.

1. Draw one realization of  $n = 100$  *independent* random variables  $X_1, \dots, X_n$  from a standard Gaussian distribution  $\mathcal{N}(0, 1)$ .
  - (a) For a kernel  $K = \mathbf{1}_{[-1,1]}/2$ , compute and display the graph of the resulting KDE obtained with different bandwidth values  $h \in \mathcal{H} = \{10^{-5}, 10^{-3}, 10^{-1}, 10\}$ . What do you see?
  - (b) Repeat the same experiment with  $n = 10\,000$ . Is there a change? Comment.
  - (c) Let us now consider a Gaussian kernel  $K'(x) = 1/\sqrt{2\pi}e^{-x^2/2}$ ,  $x \in \mathbb{R}$ . Reproduce the same experiments as in the above two questions and make a “by eye” comparison regarding the quality of the approximation you get.
2. Using a Monte-Carlo (MC) strategy, compute (an approximation to) the  $MSE_h(x_0)$  criterion for the KDE built from  $K$ ,  $n = 100$ , and varying the bandwidth on the grid  $\mathcal{H}$ .
  - (a) Start with , with  $x_0 = -2$  Which value of  $h$  is the best?
  - (b) Repeat the experiments with  $x_0 = 0.1$ . Same question. Is there a difference? What conclusion could you draw?
  - (c) Let us now consider a somewhat different criterion denoted by  $DMSE(h)$  defined by

$$DMSE(h) = \frac{1}{T} \sum_{t=1}^T MSE_h(x_t),$$

with  $x_t = -3 + t \times 6/N$ , for  $1 \leq t \leq T$  and  $T = 200$ .

Display the graph of  $h \in \mathcal{H} \mapsto DMSE(h)$ . Which value of  $h$  is the best? Is there a change compared to what you observed for the  $MSE_h(x_0)$ ?

3. Draw now a realization of  $n = 1\,000$  independent random variables such that the first 200 ones are from a standard Gaussian and the remaining 800 ones are drawn from a  $\mathcal{N}(4, \sigma^2)$ , with  $\sigma^2 = 8$ .
  - (a) Draw the graphs of the KDE function obtained with  $K$  for  $h \in \mathcal{H}$ .
  - (b) Draw the graph of  $h \in \mathcal{H} \mapsto DMSE(h)$ , with  $x_t = -2 + t \times 10/N$ , for  $1 \leq t \leq T$  and  $T = 1000$ . Say which bandwidth value is the best one? Could you provide a tentative explanation?

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**Exercise 2:**[Bernstein’s condition and KDE] The purpose of the present exercise is to prove a concentration bound with high probability on the kernel density estimator (KDE) evaluated at  $x_0$ .

**Bernstein’s condition**  $BC(v, c)$ : We say that a real-valued random variable  $X$  satisfies the Bernstein condition ( $BC(v, c)$ ) for two constants  $v, c > 0$  if, for all integers  $k \geq 2$ ,

$$\mathbb{E} \left[ |X|^k \right] \leq \frac{k!}{2} v \cdot c^{k-2}.$$

**Fact:** For any sample of  $n$  real-valued random variables  $X_1, \dots, X_n$  such that each  $X_i$  satisfies  $BC(v, c)$ , it holds for every  $y > 0$  that

$$\mathbb{P} \left[ \frac{1}{n} \sum_{i=1}^n X_i > y \right] \vee \mathbb{P} \left[ \frac{1}{n} \sum_{i=1}^n X_i < -y \right] \leq e^{-\frac{ny^2}{2(v+cy)}}. \quad (\text{BCIneq})$$

Let  $D = \{X_1, \dots, X_n\}$  be  $n$  independent real-valued random variables from a probability distribution  $P$  with density  $f$  with respect to the Lebesgue measure on  $\mathbb{R}$ . We also recall that for a given non-negative kernel  $K$  (symmetric) and a bandwidth  $h > 0$ , the KDE is defined by

$$\hat{f}_h(x) = \frac{1}{n} \sum_{i=1}^n \frac{1}{h} K\left(\frac{X_i - x}{h}\right) = \frac{1}{n} \sum_{i=1}^n K_h(X_i - x), \quad \forall x \in \mathbb{R}.$$

Assume that the kernel  $K$  is bounded that is,  $\|K\|_\infty < +\infty$  and consider  $x_0 \in \mathbb{R}$  fixed.

1. Setting  $\zeta_1 = K_h(X_1 - x_0) - \mathbb{E}[K_h(X_1 - x_0)]$ , prove that, for any integer  $k \geq 2$ , we have

$$\mathbb{E}\left[|\zeta_1|^k\right] \leq \frac{k!}{2} v \cdot c^{k-2}.$$

where  $c = 2\|K\|_\infty/h$  and  $v = \text{Var}(K_h(X_1 - x_0))$ .

2. Deduce that, for every  $t > 0$ ,

$$\mathbb{P}\left[\left|\hat{f}_h(x_0) - \mathbb{E}_D[\hat{f}_h(x_0)]\right| > t\right] \leq 2e^{-\frac{nt^2}{2(v+ct)}}.$$

3. Prove that the next two statements are equivalent

- (a) For every  $y > 0$ ,

$$\mathbb{P}\left[\frac{1}{n} \sum_{i=1}^n X_i > y\right] \leq e^{-\frac{ny^2}{2(v+cy)}},$$

- (b) For every  $x > 0$ ,

$$\mathbb{P}\left[\frac{1}{n} \sum_{i=1}^n X_i > \sqrt{\frac{2vx}{n}} + \frac{cx}{n}\right] \leq e^{-x}.$$

4. Deduce that, for every  $x > 0$ ,

$$\mathbb{P}\left[\left(\hat{f}_h(x_0) - \mathbb{E}_D[\hat{f}_h(x_0)]\right)^2 > 2\frac{2vx}{n} + 2\left(\frac{cx}{n}\right)^2\right] \leq e^{-x},$$

where you can use that  $(a+b)^2 \leq 2(a^2 + b^2)$ , for all  $a, b \in \mathbb{R}$ .

5. Recalling that the kernel is bounded, justify why you could apply instead Hoeffding's inequality to  $\hat{f}_h$ .
6. After applying Hoeffding's inequality, compare the resulting upper bound to the former one derived from  $BC(v, c)$ . Which one is the tightest? Why?

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