Kernel Density Estimation

Jiuzhou Miao

October 11, 2024

The first topic of this seminar is on *nonparametric estimation theories*, including *kernel density estimation*, *nonparametric local kernel and spline regression* and their asymptotic properties. Perhaps, more interesting topics (such as *minimax lower bounds* and *reproducing kernel Hilbert spaces*) will also be included. Throughout the whole topic, I will use the following notations:

For a function $\varphi(x), x \in \mathcal{D}$, use the notation $\|\varphi\|_\infty$ to denote $\sup_{x\in\mathcal{D}}\big|\varphi(x)\big|$. The notation $\varphi^{(p)}(\cdot)$ denotes the derivative of order p of the function $\varphi^{(p)}(\cdot)$ for some positive integer p and $\varphi^{(0)}(\cdot) = \varphi(\cdot)$. The notation $C^p(\mathcal{D})$ denotes the function space whose elements defined on $\mathcal{D}$ have continuous derivatives of order p for some positive integer p and $C^0(\mathcal{D}) = C(\mathcal{D})$. For a stochastic function $\xi(x), x \in \mathcal{D}$, the notation $\mathcal{L}\big\{\xi(x), x \in \mathcal{D}\big\}$ denotes its distribution. For two positive sequences $\{a_n\}_{n=1}^\infty$ and $\{b_n\}_{n=1}^\infty$, $a_n = o(b_n)$ means that $\lim_{n\to} a_n/b_n = 0$ and $a_n = \mathcal{O}(b_n)$ or $a_n \lesssim b_n$ means that a_n/b_n is bounded by a positive constant. The notation $a_n \gtrsim b_n$ means that $b_n \lesssim a_n$ and $a_n \asymp b_n$ means that $a_n \lesssim b_n$ and $a_n \gtrsim b_n$. For a random variable sequence $\{X_n\}_{n=1}^\infty$, $X_n = o_p(1)$ [or $X_n = o_{a.s.}(1)$] means that X_n converges to zero in probability [or almost surely] as $n \to \infty$ and $X_n = \mathcal{O}_p(1)$ [or $X_n = \mathcal{O}_{a.s.}(1)$] means that X_n is bounded in probability [or almost surely]. For a non-stochastic function sequence $\big\{f_n(x), x \in \mathcal{D}\big\}_{n=1}^\infty$, the notation $f_n(x) = u(1)$ [or $f_n(x) = \mathcal{U}(1)$] means that $\sup_{x\in\mathcal{D}}\big|f_n(x)\big| = o(1)$ [or $\sup_{x\in\mathcal{D}}\big|f_n(x)\big| = \mathcal{O}(1)$]. For a stochastic function sequence, notations u_p, $u_{a.s.}$, $\mathcal{U}_p$ and $\mathcal{U}_{a.s.}$ can be defined similarly.

1 Introduction

Let $\{X_i\}_{i=1}^n$ be independent random variables which have the same distribution with the random variable X. The distribution function and density function of X are $F(x) = \mathbb{P}(X \le x)$ and $f(x) = F^{(1)}(x)$. We are interested in estimating the probability density function with nonparametric methods.

Note that the density function $f(\cdot)$ is the derivative of the distribution function $F(\cdot)$, one can obtain the approximation

$$f(x) \approx \big\{F(x+h) - F(x-h)\big\}/(2h) = \mathbb{P}(x - h < X \le x + h)/(2h)$$

for some small h. A natural estimator of the distribution function $F(\cdot)$ is the well known empirical distribution function

$$\hat{F}_n(x) = n^{-1}\sum_{i=1}^{n}\mathbb{I}\big(X_i \le x\big),$$

then one can use

$$\hat{F}_n(x+h) - \hat{F}_n(x-h) = n^{-1}\sum_{i=1}^{n}\mathbb{I}\big(x-h < X_i \le x+h\big)$$

to estimate the probability $\mathbb{P}(x-h < X \le x+h)$. Hence, one can use the estimator

$$\begin{aligned}\hat{f}^{\dagger}(x) &= (2nh)^{-1}\sum_{i=1}^{n}\mathbb{I}\big(x-h < X_i \le x+h\big)\\ &= (nh)^{-1}\sum_{i=1}^{n}\mathbb{I}\Big(-1 < h^{-1}(X_i - x) \le 1\Big)/2\\ &= (nh)^{-1}\sum_{i=1}^{n}K^{\dagger}\Big(h^{-1}(X_i - x)\Big).\end{aligned}$$

to estimate $f(x)$.

Definition 1.1. (Kernel function) The function $K(\cdot)$ is called as *kernel function* if $K(\cdot)$ is a symmetrical probability density function, i.e.,

- $K(-x) = K(x)$;
- $\int_{-\infty}^{\infty} K(x)\mathrm{d}x = 1$.

Example 1.2. (Some kernel functions)

(1) Rectangular kernel:
$$K(x) = 2^{-1}\mathbb{I}\big(|x| \le 1\big);$$

(2) Gaussian kernel:
$$K(x) = (2\pi)^{-1/2}\exp\left(-x^2/2\right);$$

(3) Epanechnikov kernel:
$$K(x) = 3(1-x^2)\mathbb{I}\big(|x| \le 1\big)/4;$$

(4) Biweight kernel:
$$K(x) = 15(1-x^2)^2\mathbb{I}\big(|x| \le 1\big)/16.$$

Definition 1.3. (Kernel density estimation) The estimation

$$\hat{f}(x) = n^{-1}\sum_{i=1}^{n}K_h(X_i - x)$$

is called as *kernel density estimation*. In which h is a smooth parameter called as *bandwidth* and $K_h(\cdot) = K(\cdot/h)/h$ is a *rescaled kernel function* with $K(\cdot)$ by the bandwidth h.

In the following, we will establish the asymptotic properties of the estimator $\hat{f}(x)$, including derive the uniform convergence rate, pointwise and global asymptotic distribution. For convenience, assume that the support of X is $\mathcal{X} = [0, 1]$. The following assumption will be used throughout the whole notes.

(A) $f \in C^2(\mathcal{X})$, $K \in C^2[-1, 1]$ and $\inf_{x\in\mathcal{X}} f(x) > 0$.

Denote $\mathcal{I}_h = [h, 1-h]$. We introduce the error decomposition of $\hat{f}(x) - f(x)$ by

$$\hat{f}(x) - f(x) = \underbrace{\hat{f}(x) - \mathbb{E}\big\{\hat{f}(x)\big\}}_{\text{Noise term}} + \underbrace{\mathbb{E}\big\{\hat{f}(x)\big\} - f(x)}_{\text{Bias term}}.$$

2 Uniform convergence

In this section, we will derive the uniform convergence rate of $\sup_{x\in\mathcal{I}_h}\big|\hat{f}(x) - f(x)\big|$ under some mild conditions. We start from the bias term.

Proposition 2.1. *(Uniform convergence of bias term) Under Assumption (A), as $n \to \infty$, if $h = h_n \to 0$, one has that*

$$\sup_{x\in\mathcal{I}_h}\Big|\mathbb{E}\big\{\hat{f}(x)\big\} - f(x) - 2^{-1}f^{(2)}(x)h^2\int_{-1}^{1} v^2K(v)\mathrm{d}v\Big| = o(h^2)$$

and

$$\sup_{x\in\mathcal{I}_h}\Big|\mathbb{E}\big\{\hat{f}(x)\big\} - f(x)\Big| = \mathcal{O}(h^2).$$

Proof. We only need to calculate the expectation of $\hat{f}(x)$.

$$\begin{aligned}
\mathbb{E}\big\{\hat{f}(x)\big\} &= \mathbb{E}\big\{K_h(X_1 - x)\big\} \\
&= \int_{\mathcal{X}} h^{-1}K\big(h^{-1}(u-x)\big)f(u)\mathrm{d}u \\
&= \int_{-1}^{1} K(v)f(x+hv)\mathrm{d}v \\
&= \int_{-1}^{1} K(v)\big\{f(x) + f^{(1)}(x)hv + 2^{-1}f^{(2)}(x)(hv)^2 + u(h^2)\big\}\mathrm{d}v \\
&= f(x) + 2^{-1}f^{(2)}(x)h^2\int_{-1}^{1} v^2K(v)\mathrm{d}v + u(h^2),
\end{aligned}$$

then one can obtain the first equation. The second equation can be obtained from

$$\begin{aligned}
\sup_{x\in\mathcal{I}_h}\Big|\mathbb{E}\big\{\hat{f}(x)\big\} - f(x)\Big| &\le \sup_{x\in\mathcal{I}_h}\Big|\mathbb{E}\big\{\hat{f}(x)\big\} - f(x) - 2^{-1}f^{(2)}(x)h^2\int_{-1}^{1} v^2K(v)\mathrm{d}v\Big| \\
&\quad + 2^{-1}h^2\int_{-1}^{1} v^2K(v)\mathrm{d}v \times \sup_{x\in\mathcal{I}_h}\big|f^{(2)}(x)\big| \\
&= \mathcal{O}(h^2).
\end{aligned}$$

□

Then we deal with the noise term. The following useful Bernstein's inequality is a quite powerful weapon in estimating the uniform convergence rate of the summation of independent random variables.

Lemma 2.2. *(Bosq (1998), Theorem 1.2) Let $\{\eta_i\}_{i=1}^n$ be independent random variables with mean zero. If there exists $r > 0$ such that (Cramér's conditions)*

$$\mathbb{E}\big(|\eta_i|^k\big) \le r^{k-2}k!\mathbb{E}(\eta_i^2) < \infty, 1 \le i \le n, k \ge 3,$$

then for any $t > 0$,

$$\mathbb{P}\left\{\left|\sum_{i=1}^n \eta_i\right| > t\right\} \le 2\exp\left\{-\frac{t^2}{4\sum_{i=1}^n \mathbb{E}(\eta_i^2) + 2rt}\right\}.$$

Proposition 2.3. *(Uniform convergence of noise term) Under Assumption (A), as $n \to \infty$, if $h = h_n$ satisfies that $h \to 0$ and $n^{-1/2}h^{-1/2}\log^{1/2} n \to 0$, one has that*

$$\sup_{x\in\mathcal{I}_h}\left|\hat{f}(x) - \mathbb{E}\big\{\hat{f}(x)\big\}\right| = \mathcal{O}_{a.s.}(n^{-1/2}h^{-1/2}\log^{1/2} n).$$

Proof. Let $\xi_{in}(x) = n^{-1}K_h(X_i - x)$ and $\check{\xi}_{in}(x) = \xi_{in}(x) - \mathbb{E}\big\{\xi_{in}(x)\big\}$, then one has that

$$\hat{f}(x) - \mathbb{E}\big\{\hat{f}(x)\big\} = \sum_{i=1}^n \check{\xi}_{in}(x).$$

One can obtain that $\mathbb{E}\big\{\xi_{in}(x)\big\} \asymp n^{-1}$ and

$$\begin{aligned}
\mathbb{E}\big\{\xi_{in}^2(x)\big\} &= \int_{\mathcal{X}} n^{-2}h^{-2}K^2\big(h^{-1}(u-x)\big)f(u)\mathrm{d}u \\
&= \int_{-1}^1 n^{-2}h^{-1}K^2(v)f(x+hv)\mathrm{d}v \\
&= \int_{-1}^1 n^{-2}h^{-1}K^2(v)\big\{f(x) + f^{(1)}(x)hv + 2^{-1}f^{(2)}(x)(hv)^2 + u(h^2)\big\}\mathrm{d}v \\
&= n^{-2}h^{-1}f(x)\int_{-1}^1 K^2(v)\mathrm{d}v + 2^{-1}n^{-2}hf^{(2)}(x)\int_{-1}^1 v^2K^2(v)\mathrm{d}v + u(n^{-2}h) \\
&= n^{-2}h^{-1}f(x)\int_{-1}^1 K^2(v)\mathrm{d}v\big\{1 + \mathcal{U}(h^2)\big\} \\
&\asymp n^{-2}h^{-1}.
\end{aligned}$$

Then, one has that $\mathbb{E}\big\{\check{\xi}_{in}(x)\big\} = 0$, $\mathbb{E}\big\{\check{\xi}_{in}^2(x)\big\} \asymp n^{-2}h^{-1}$. Note that

$$\big|\check{\xi}_{in}(x)\big| \le \big|\xi_{in}(x)\big| + \mathbb{E}\Big\{\big|\xi_{in}(x)\big|\Big\} \le 2\|K\|_\infty n^{-1}h^{-1},$$

then one has that for $k = 3, 4, \ldots,$

$$\mathbb{E}\Big\{\big|\check{\xi}_{in}(x)\big|^k\Big\} = \mathbb{E}\Big\{\big|\check{\xi}_{in}(x)\big|^{k-2}\check{\xi}_{in}^2(x)\Big\} \le k!\big(2\|K\|_\infty n^{-1}h^{-1}\big)^{k-2}\mathbb{E}\big\{\check{\xi}_{in}^2(x)\big\},$$

which implies that Cramér's conditions hold with $r = 2\|K\|_\infty n^{-1}h^{-1}$. Then by the Bernstein's inequality in Lemma 2.2, for some $\delta > 0$, one has that

$$\begin{aligned}
&\mathbb{P}\left\{\left|\sum_{i=1}^{n} \check{\xi}_{in}(x)\right| > \delta n^{-1/2}h^{-1/2}\log^{1/2} n\right\}\\
&\leq 2\exp\left\{\frac{-\delta^2 n^{-1}h^{-1}\log n}{4\sum_{i=1}^{n}\mathbb{E}\{\check{\xi}_{in}^2(x)\} + 4\|K\|_\infty n^{-1}h^{-1}\delta n^{-1/2}h^{-1/2}\log^{1/2} n}\right\}\\
&= 2\exp\left\{\frac{-\delta^2 \log n}{4nh\sum_{i=1}^{n}\mathbb{E}\{\check{\xi}_{in}^2(x)\} + 4\|K\|_\infty \delta n^{-1/2}h^{-1/2}\log^{1/2} n}\right\}\\
&\leq 2n^{-10}.
\end{aligned}$$

In the following, we discretize $\mathcal{I}_h$ by $h = x_0 < x_1 < \cdots < x_{n^4-1} = 1-h$. By the subadditivity of probability, one has that

$$\begin{aligned}
&\sum_{n=1}^{\infty}\mathbb{P}\left\{\max_{0\leq l\leq n^4-1}\left|\sum_{i=1}^{n}\check{\xi}_{in}(x_l)\right| > \delta n^{-1/2}h^{-1/2}\log^{1/2} n\right\}\\
&\leq \sum_{n=1}^{\infty}\sum_{l=0}^{n^4-1}\mathbb{P}\left\{\left|\sum_{i=1}^{n}\check{\xi}_{in}(x_l)\right| > \delta n^{-1/2}h^{-1/2}\log^{1/2} n\right\}\\
&\leq \sum_{n=1}^{\infty} 2n^{-6} < \infty,
\end{aligned}$$

By Borel-Cantellis lemma, one obtains that

$$\max_{0\leq l\leq n^4-1}\left|\sum_{i=1}^{n}\check{\xi}_{in}(x_l)\right| = \mathcal{O}_{a.s.}(n^{-1/2}h^{-1/2}\log^{1/2} n).$$

For $x \in [x_l, x_{l+1}]$, $l = 0, \ldots, n^4-2$, one has that

$$\left|\xi_{in}(x) - \xi_{in}(x_l)\right| \leq n^{-1}h^{-2}\|K^{(1)}\|_\infty |x - x_l| \leq n^{-5}h^{-2}\|K^{(1)}\|_\infty(1-2h)$$

and

$$\begin{aligned}
\max_{0\leq l\leq n^4-2}\sup_{x\in[x_l,x_{l+1}]}\left|\sum_{i=1}^{n}\check{\xi}_{in}(x) - \check{\xi}_{in}(x_l)\right| &\leq 2n^{-4}h^{-2}\|K^{(1)}\|_\infty(1-2h)\\
&= \mathcal{O}_p(n^{-4}h^{-2}).
\end{aligned}$$

Hence, one has that

$$\begin{aligned}
\sup_{x\in\mathcal{I}_h}\left|\hat{f}(x) - \mathbb{E}\{\hat{f}(x)\}\right| &= \sup_{x\in\mathcal{I}_h}\left|\sum_{i=1}^{n}\check{\xi}_{in}(x)\right|\\
&\leq \max_{0\leq l\leq n^4-1}\left|\sum_{i=1}^{n}\check{\xi}_{in}(x_l)\right| + \max_{0\leq l\leq n^4-2}\sup_{x\in[x_l,x_{l+1}]}\left|\sum_{i=1}^{n}\check{\xi}_{in}(x) - \check{\xi}_{in}(x_l)\right|\\
&= \mathcal{O}_{a.s.}(n^{-1/2}h^{-1/2}\log^{1/2} n) + \mathcal{O}_p(n^{-4}h^{-2})\\
&= \mathcal{O}_{a.s.}(n^{-1/2}h^{-1/2}\log^{1/2} n).
\end{aligned}$$

□

Put Proposition 2.1 and 2.3 together, one can obtain the following theorem.

Theorem 2.4. *(Uniform convergence of kernel density estimation) Under the assumptions of Proposition 2.3, one has that*

$$\sup_{x\in\mathcal{I}_h}\Big|\hat{f}(x)-f(x)-2^{-1}f^{(2)}(x)h^2\int_{-1}^{1}v^2K(v)\mathrm{d}v\Big| = o(h^2)+\mathcal{O}_{a.s.}(n^{-1/2}h^{-1/2}\log^{1/2}n)$$

and

$$\sup_{x\in\mathcal{I}_h}\Big|\hat{f}(x)-f(x)\Big| = \mathcal{O}(h^2)+\mathcal{O}_{a.s.}(n^{-1/2}h^{-1/2}\log^{1/2}n).$$

Furthermore, assume that $h \asymp n^{-1/5}\log^{1/5}n$, one has that

$$\sup_{x\in\mathcal{I}_h}\Big|\hat{f}(x)-f(x)\Big| = \mathcal{O}_{a.s.}(n^{-2/5}\log^{2/5}n)$$

which is the optimal convergence rate of kernel density estimation.

3 Pointwise asymptotic distribution

In this section, we will derive the pointwise asymptotic distribution of $\hat{f}(x)-f(x)$ for any $x\in\mathcal{I}_h$ under some mild conditions. The following Lindeberg–Feller's CLT is a powerful tool to obtain the asymptotic normality of $\hat{f}(x)-\mathbb{E}\{\hat{f}(x)\}$.

Lemma 3.1. *(Lindeberg–Feller's CLT) Let $\{\eta_{in}\}_{i=1}^{k_n}$, $n\geq 1$ be independent random variables with mean zero, $\mathbb{E}(\eta_{in}^2)=\sigma_{in}^2$. Denote $S_n=\sum_{i=1}^{k_n}\eta_{in}$ and $V_n^2=\sum_{i=1}^{k_n}\sigma_{in}^2$. Then $V_n^{-1}S_n\xrightarrow{d}\mathcal{N}(0,1)$ if either of the following conditions holds:*

- *(Lindeberg's condition) for any $\varepsilon>0$,*

$$\lim_{n\to\infty}V_n^{-2}\sum_{i=1}^{k_n}\mathbb{E}\Big\{\eta_{in}^2\mathbb{I}\big(|\eta_{in}|\geq\varepsilon V_n\big)\Big\}=0.$$

- *(Lyapunov's condition) for some $\delta>0$,*

$$\lim_{n\to\infty}V_n^{-(2+\delta)}\sum_{i=1}^{k_n}\mathbb{E}\big(|\eta_{in}|^{2+\delta}\big)=0.$$

Proposition 3.2. *(Asymptotic normality of noise term) Under Assumption (A), as $n\to\infty$, if $h=h_n$ satisfies that $nh\to\infty$, one has that for a fixed $x\in\mathcal{I}_h$,*

$$\sqrt{nh}\Big[\hat{f}(x)-\mathbb{E}\{\hat{f}(x)\}\Big]\xrightarrow{d}\mathcal{N}\big(0,f(x)\int_{-1}^{1}K^2(v)\mathrm{d}v\big).$$

Proof. Note that

$$\mathbb{E}\{\check{\xi}_{in}^2(x)\}=n^{-2}h^{-1}f(x)\int_{-1}^{1}K^2(v)\mathrm{d}v\{1+\mathcal{U}(h^2)\},$$

then one has that

$$V_n^2(x) = n^{-1}h^{-1}f(x)\int_{-1}^{1} K^2(v)\mathrm{d}v\big\{1+\mathcal{U}(h^2)\big\} \asymp n^{-1}h^{-1}.$$

and $V_n^{-(2+\delta)}(x) \asymp (nh)^{1+\delta/2}$. Use the inequality $(a+b)^p \le 2^{p-1}(a^p+b^p)$, $a,b>0$ and $p \ge 1$, one has that

$$\mathbb{E}\Big\{\big|\check{\xi}_{in}(x)\big|^{2+\delta}\Big\} \le 2^{1+\delta}\Big[\mathbb{E}\Big\{\big|\xi_{in}(x)\big|^{2+\delta}\Big\} + \Big|\mathbb{E}\{\xi_{in}(x)\}\Big|^{2+\delta}\Big].$$

Note that

$$\begin{aligned}
\mathbb{E}\Big\{\big|\xi_{in}(x)\big|^{2+\delta}\Big\} &= \int_{\mathcal{X}} n^{-(2+\delta)}h^{-(2+\delta)}K^{2+\delta}\big(h^{-1}(u-x)\big)f(u)\mathrm{d}u \\
&= \int_{-1}^{1} n^{-(2+\delta)}h^{-(1+\delta)}K^{2+\delta}(v)f(x+hv)\mathrm{d}v \\
&\le n^{-(2+\delta)}h^{-(1+\delta)}\sup_{x\in\mathcal{X}} f(x)\int_{-1}^{1} K^{2+\delta}(v)\mathrm{d}v \\
&= \mathcal{U}(n^{-(2+\delta)}h^{-(1+\delta)})
\end{aligned}$$

and $\Big|\mathbb{E}\{\xi_{in}(x)\}\Big|^{2+\delta} = \mathcal{U}(n^{-(2+\delta)})$, then

$$\mathbb{E}\Big\{\big|\check{\xi}_{in}(x)\big|^{2+\delta}\Big\} \le 2^{1+\delta}\Big[\mathbb{E}\Big\{\big|\xi_{in}(x)\big|^{2+\delta}\Big\} + \Big|\mathbb{E}\{\xi_{in}(x)\}\Big|^{2+\delta}\Big] = \mathcal{U}(n^{-(2+\delta)}h^{-(1+\delta)}).$$

Hence, one has that

$$V_n^{-(2+\delta)}(x)\sum_{i=1}^{n}\mathbb{E}\Big\{\big|\check{\xi}_{in}(x)\big|^{2+\delta}\Big\} = \mathcal{O}(n^{-\delta/2}h^{-\delta/2}) = o(1),$$

and Lyapunov's condition holds. By using Lemma 3.1, one has that

$$V_n^{-1}(x)\sum_{i=1}^{n}\check{\xi}_{in}(x) \xrightarrow{d} \mathcal{N}(0,1)$$

and by using Slutsky's theorem, one has that

$$\begin{aligned}
\frac{\sqrt{nh}\Big[\hat{f}(x) - \mathbb{E}\{\hat{f}(x)\}\Big]}{\sqrt{f(x)\int_{-1}^{1} K^2(v)\mathrm{d}v}} &= \frac{\sum_{i=1}^{n}\check{\xi}_{in}(x)}{\sqrt{n^{-1}h^{-1}f(x)\int_{-1}^{1} K^2(v)\mathrm{d}v}} \\
&= V_n^{-1}(x)\sum_{i=1}^{n}\check{\xi}_{in}(x) \times \frac{V_n(x)}{\sqrt{n^{-1}h^{-1}f(x)\int_{-1}^{1} K^2(v)\mathrm{d}v}} \\
&\xrightarrow{d} \mathcal{N}(0,1).
\end{aligned}$$

□

Note that if $nh^5 = \mathcal{O}(1)$, then

$$\sqrt{nh} \sup_{x \in \mathcal{I}_h} \left| \mathbb{E}\{\hat{f}(x)\} - f(x) - 2^{-1} f^{(2)}(x) h^2 \int_{-1}^{1} v^2 K(v) \mathrm{d}v \right| = o(n^{1/2} h^{5/2}) = o(1),$$

by using Slutsky's theorem, one can obtain the asymptotic normality of kernel density estimation.

Theorem 3.3. *(Asymptotic normality of kernel density estimation) Under Assumption (A), as $n \to \infty$, if $h = h_n$ satisfies that $nh \to \infty$ and $nh^5 = \mathcal{O}(1)$, one has that for a fixed $x \in \mathcal{I}_h$,*

$$\sqrt{nh} \Big\{ \hat{f}(x) - f(x) - 2^{-1} f^{(2)}(x) h^2 \int_{-1}^{1} v^2 K(v) \mathrm{d}v \Big\} \xrightarrow{d} \mathcal{N}\big(0, f(x) \int_{-1}^{1} K^2(v) \mathrm{d}v\big).$$

Furthermore, assume that $nh^5 \to 0$, one has that for a fixed $x \in \mathcal{I}_h$,

$$\sqrt{nh} \big\{ \hat{f}(x) - f(x) \big\} \xrightarrow{d} \mathcal{N}\big(0, f(x) \int_{-1}^{1} K^2(v) \mathrm{d}v\big).$$

4 Uniform asymptotic distribution

In this section, we will derive the uniform asymptotic distribution of $\hat{f}(x) - f(x)$ over the whole $x \in \mathcal{I}_h$ under some mild conditions, i.e., derive the asymptotic distribution of $\sup_{x \in \mathcal{I}_h} \left| \hat{f}(x) - f(x) \right|$. By using the uniform asymptotic distribution, one can construct $100\%(1-\alpha)$ simultaneous confidence band for the density function $f(x), x \in \mathcal{I}_h$, which is more difficult in techniques but more useful in practice. The research on constructing simultaneous confidence band for the density function is firstly studied by Bickel and Rosenblatt (1973), while the proofs given in this section mainly refer to the notes written by Prof. Lijian Yang in 2011 which is a simplified version of Bickel and Rosenblatt (1973).

Recall Proposition 2.1, one knows that under Assumption (A)

$$\sup_{x \in \mathcal{I}_h} \left| \mathbb{E}\{\hat{f}(x)\} - f(x) \right| = \mathcal{O}(h^2),$$

if $h = h_n \to 0$ as $n \to \infty$. Then we only need to derive the asymptotic distribution of $\sup_{x \in \mathcal{I}_h} \left| \hat{f}(x) - \mathbb{E}\{\hat{f}(x)\} \right|$. The technical tool required for this section is the strong approximation theorem proposed by Komlós et al. (1975)

Lemma 4.1. *(Komlós et al. (1975), Theorem 3) For a fixed n, let $\{\eta_i\}_{i=1}^n$ be i.i.d. random variables with*

$$\mathbb{P}(\eta_1 \le t) = \begin{cases} 0, & t < 0 \\ t, & 0 \le t \le 1 \\ 1, & t > 1 \end{cases},$$

let $F_n(t)$ be the empirical distribution function based on the sample $\{\eta_i\}_{i=1}^n$ and let $B_n(t)$ be a Brownian bridge. There is a version of $F_n(t)$ and $B_n(t)$ such that

$$\mathbb{P}\left[\sup_{t \in [0,1]} \left| n\big\{F_n(t) - t\big\} - \sqrt{n} B_n(t) \right| > C \log n + x \right] < k e^{-\lambda x}$$

for all x, where C, K, λ are positive absolute constants.

Denote the empirical process $Z_n(t) = \sqrt{n}\{\hat{F}_n(t) - F(t)\}$. Here, $\hat{F}_n(t)$ and $F(t)$ are empirical distribution function and distribution function based on $\{X_i\}_{i=1}^n$. By using Lemma 4.1, one can easily obtain that

$$\sup_{t\in[0,1]}\Big|Z_n(t) - B_n\big(F(t)\big)\Big| = \mathcal{O}_{a.s.}(n^{-1/2}\log n).$$

Define the standardized stochastic process

$$\begin{aligned}
\Xi_n(x) &= n^{1/2}h^{1/2}f^{-1/2}(x)\Big[\hat{f}(x) - \mathbb{E}\big\{\hat{f}(x)\big\}\Big] \\
&= n^{1/2}h^{1/2}f^{-1/2}(x)\int_{\mathcal{X}} K_h(u-x)\mathrm{d}\big\{\hat{F}_n(u) - F(u)\big\} \\
&= h^{1/2}f^{-1/2}(x)\int_{\mathcal{X}} K_h(u-x)\mathrm{d}Z_n(u) \\
&= h^{-1/2}f^{-1/2}(x)\int_{\mathcal{X}} K\big(h^{-1}(u-x)\big)\mathrm{d}Z_n(u)
\end{aligned}$$

and stochastic processes

$$\begin{aligned}
\Xi_{n,0}(x) &= h^{-1/2}f^{-1/2}(x)\int_{\mathcal{X}} K\big(h^{-1}(u-x)\big)\mathrm{d}B_n\big(F(u)\big) \\
\Xi_{n,1}(x) &= h^{-1/2}f^{-1/2}(x)\int_{\mathcal{X}} K\big(h^{-1}(u-x)\big)\mathrm{d}W_n\big(F(u)\big) \\
\Xi_{n,2}(x) &= h^{-1/2}f^{-1/2}(x)\int_{\mathcal{X}} K\big(h^{-1}(u-x)\big)f^{1/2}(u)\mathrm{d}W_n(u) \\
\Xi_{n,3}(x) &= h^{-1/2}\int_{\mathcal{X}} K\big(h^{-1}(u-x)\big)\mathrm{d}W_n(u).
\end{aligned}$$

We will prove that $\Xi_n(x)$ can be uniformly approximated by $\Xi_{n,3}(x)$ over $x \in \mathcal{I}_h$ in Proposition 4.2–4.5 and $\Xi_{n,3}(x)$ is asymptotically Gumbel in Proposition 4.7.

Proposition 4.2. *Under Assumption (A), as $n \to \infty$, if $h = h_n \to 0$, one has that*

$$\sup_{x\in\mathcal{I}_h}\big|\Xi_n(x) - \Xi_{n,0}(x)\big| = \mathcal{O}_{a.s.}(n^{-1/2}h^{-1/2}\log n).$$

Proof. Note that

$$\begin{aligned}
\Xi_n(x) - \Xi_{n,0}(x) &= h^{-1/2}f^{-1/2}(x)\int_{\mathcal{X}} K\big(h^{-1}(u-x)\big)\mathrm{d}\Big\{Z_n(u) - B_n\big(F(u)\big)\Big\} \\
&= h^{-1/2}f^{-1/2}(x)K\big(h^{-1}(u-x)\big)\Big\{Z_n(u) - B_n\big(F(u)\big)\Big\}\Big|_{\mathcal{X}} \\
&\quad - h^{-1/2}f^{-1/2}(x)\int_{\mathcal{X}}\Big\{Z_n(u) - B_n\big(F(u)\big)\Big\}\mathrm{d}\Big\{K\big(h^{-1}(u-x)\big)\Big\} \\
&= -h^{-3/2}f^{-1/2}(x)\int_{\mathcal{X}}\Big\{Z_n(u) - B_n\big(F(u)\big)\Big\}K^{(1)}\big(h^{-1}(u-x)\big)\mathrm{d}u,
\end{aligned}$$

one has that

$$\begin{aligned}
\sup_{x\in\mathcal{I}_h}\big|\Xi_n(x) - \Xi_{n,0}(x)\big| &\lesssim h^{-3/2}\times\mathcal{O}_{a.s.}(n^{-1/2}\log n)\times h\int_{-1}^{1}\big|K^{(1)}(v)\big|\mathrm{d}v \\
&= \mathcal{O}_{a.s.}(n^{-1/2}h^{-1/2}\log n).
\end{aligned}$$

□

Proposition 4.3. *Under Assumption (A), as $n \to \infty$, if $h = h_n \to 0$, one has that*

$$\sup_{x\in\mathcal{I}_h} \big|\Xi_{n,0}(x) - \Xi_{n,1}(x)\big| = \mathcal{O}_p(h^{1/2}).$$

Proof. By the definition of Brownian bridge, one has that $B_n\big(F(u)\big) - W_n\big(F(u)\big) = -F(u)W_n(1)$. Hence, one has that

$$\begin{aligned}
\Xi_{n,0}(x) - \Xi_{n,1}(x) &= -W_n(1)h^{-1/2}f^{-1/2}(x)\int_{\mathcal{X}} K\big(h^{-1}(u-x)\big)f(u)\mathrm{d}u \\
&= -W_n(1)h^{1/2}f^{-1/2}(x)\int_{-1}^{1} K(v)f(x+hv)\mathrm{d}v \\
&= -W_n(1)h^{1/2}f^{-1/2}(x)\int_{-1}^{1} K(v)f(x+hv)\mathrm{d}v
\end{aligned}$$

and

$$\begin{aligned}
\sup_{x\in\mathcal{I}_h} \big|\Xi_{n,0}(x) - \Xi_{n,1}(x)\big| &\lesssim \big|W_n(1)\big| \times h^{1/2}\int_{-1}^{1} K(v)\mathrm{d}v \\
&= \mathcal{O}_p(h^{1/2}).
\end{aligned}$$

□

Proposition 4.4. *Under Assumption (A), as $n \to \infty$, if $h = h_n \to 0$, one has that*

$$\mathcal{L}\big\{\Xi_{n,1}(x), x\in\mathcal{I}_h\big\} = \mathcal{L}\big\{\Xi_{n,2}(x), x\in\mathcal{I}_h\big\}.$$

Proof. Note that $\Xi_{n,1}(x)$ and $\Xi_{n,2}(x)$ are two Gaussian process with zero mean function, we only need to verify that they have same covariance function. By Itô's isometric, one has that

$$\begin{aligned}
\mathbb{E}\big\{\Xi_{n,1}(x)\Xi_{n,1}(x')\big\} &= h^{-1}f^{-1/2}(x)f^{-1/2}(x')\int_{\mathcal{X}} K\big(h^{-1}(u-x)\big)K\big(h^{-1}(u-x')\big)\mathrm{d}F(u) \\
&= h^{-1}f^{-1/2}(x)f^{-1/2}(x')\int_{\mathcal{X}} K\big(h^{-1}(u-x)\big)K\big(h^{-1}(u-x')\big)f(u)\mathrm{d}u
\end{aligned}$$

and

$$\mathbb{E}\big\{\Xi_{n,2}(x)\Xi_{n,2}(x')\big\} = h^{-1}f^{-1/2}(x)f^{-1/2}(x')\int_{\mathcal{X}} K\big(h^{-1}(u-x)\big)K\big(h^{-1}(u-x')\big)f(u)\mathrm{d}u$$

□

Proposition 4.5. *Under Assumption (A), as $n \to \infty$, if $h = h_n \to 0$, one has that*

$$\sup_{x\in\mathcal{I}_h} \big|\Xi_{n,2}(x) - \Xi_{n,3}(x)\big| = \mathcal{O}_p(h^{1/2}).$$

Proof. Note that

$$\begin{aligned}
\Xi_{n,2}(x) - \Xi_{n,3}(x) &= h^{-1/2} \int_{\mathcal{X}} K\big(h^{-1}(u-x)\big)\big\{f^{1/2}(u) f^{-1/2}(x) - 1\big\} \mathrm{d}W_n(u) \\
&= -h^{-1/2} \int_{\mathcal{X}} W_n(u) \mathrm{d}\Big[K\big(h^{-1}(u-x)\big)\big\{f^{1/2}(u) f^{-1/2}(x) - 1\big\}\Big] \\
&= -h^{-3/2} \int_{\mathcal{X}} W_n(u) K^{(1)}\big(h^{-1}(u-x)\big)\big\{f^{1/2}(u) f^{-1/2}(x) - 1\big\} \mathrm{d}u \\
&\quad - 2^{-1} h^{-1/2} \int_{\mathcal{X}} W_n(u) K\big(h^{-1}(u-x)\big) f^{-1/2}(u) f^{-1/2}(x) f^{(1)}(u) \mathrm{d}u \\
&= -h^{-1/2} \int_{-1}^{1} W_n(x+hv) K^{(1)}(v)\big\{f^{1/2}(x+hv) f^{-1/2}(x) - 1\big\} \mathrm{d}v \\
&\quad - 2^{-1} h^{1/2} \int_{-1}^{1} W_n(x+hv) K(v) f^{-1/2}(x+hv) f^{-1/2}(x) f^{(1)}(x+hv) \mathrm{d}v,
\end{aligned}$$

and

$$\begin{aligned}
\sup_{x \in \mathcal{I}_h, v \in [-1,1]} \big|f^{1/2}(x+hv) f^{-1/2}(x) - 1\big| &\lesssim \sup_{x \in \mathcal{I}_h, v \in [-1,1]} \big|f(x+hv) - f(x)\big| \\
&= \mathcal{O}(h),
\end{aligned}$$

then one has that

$$\begin{aligned}
& h^{-1/2} \sup_{x \in \mathcal{I}_h} \Big| \int_{-1}^{1} W_n(x+hv) K^{(1)}(v)\big\{f^{1/2}(x+hv) f^{-1/2}(x) - 1\big\} \mathrm{d}v \Big| \\
\leq\ & h^{-1/2} \sup_{x \in \mathcal{I}_h, v \in [-1,1]} \big|f^{1/2}(x+hv) f^{-1/2}(x) - 1\big| \sup_{x \in \mathcal{I}_h, v \in [-1,1]} \big|W_n(x+hv)\big| \int_{-1}^{1} \big|K^{(1)}(v)\big| \mathrm{d}v \\
=\ & \mathcal{O}_p(h^{1/2}),
\end{aligned}$$

and

$$\begin{aligned}
& h^{1/2} \sup_{x \in \mathcal{I}_h} \Big| \int_{-1}^{1} W_n(x+hv) K(v) f^{-1/2}(x+hv) f^{-1/2}(x) f^{(1)}(x+hv) \mathrm{d}v \Big| \\
\lesssim\ & h^{1/2} \sup_{x \in \mathcal{I}_h, v \in [-1,1]} \big|W_n(x+hv)\big| \\
=\ & \mathcal{O}_p(h^{1/2}).
\end{aligned}$$

□

The following is a reformulation of Theorem 11.1.5 and Theorem 12.3.5 of Leadbetter et al. (1983)

Lemma 4.6. *(Leadbetter et al. (1983), Theorem 11.1.5 and Theorem 12.3.5) If the Gaussian process $\zeta(s), 0 \leq t \leq T$ is stationary with mean zero and variance one, and correlation function satisfying for some constant $C > 0$,*

$$\mathbb{E}\big\{\zeta(s)\zeta(s+t)\big\} = 1 - C|t|^{\alpha} + o(|t|^{\alpha})$$

as $t \to 0$, then as $T \to \infty$,

$$a_T\Big(\sup_{s \in [0,T]} \big|\zeta(s)\big| - b_T\Big) \xrightarrow{d} Z,$$

where the random variable Z satisfies $\mathbb{P}(Z \leq z) = \exp\{-2\exp(-z)\}$ for all $z \in \mathbb{R}$, and

$$\begin{aligned} a_T &= (2\log T)^{1/2}, \\ b_T &= a_T + a_T^{-1}\Big[(\alpha^{-1} - 2^{-1})\log(a_T^2/2) + \log\big\{C^{1/\alpha}H_\alpha(2\pi)^{-1/2}2^{(\alpha^{-1}-2^{-1})}\big\}\Big] \end{aligned}$$

with $H_1 = 1$ and $H_2 = \pi^{-1/2}$.

Proposition 4.7. *Under Assumption (A), as $n \to \infty$, if $h = h_n \to 0$, one has that*

$$a_h\Big(\sup_{x\in\mathcal{I}_h}\big|\Xi_{n,3}(x)/\Lambda\big| - b_h\Big) \xrightarrow{d} Z,$$

in which

$$a_h = (2\log h^{-1})^{1/2},\ b_h = a_h + 2^{-1}a_h^{-1}\log\Big(\frac{C}{2\pi^2}\Big),$$
$$C = 2^{-1}\Lambda^{-1}\int_{-1}^{-1}\big\{K^{(1)}(v)\big\}^2\mathrm{d}v,\ \Lambda = \sqrt{\int_{-1}^{1}K^2(v)\mathrm{d}v}$$

Proof. Note that

$$\begin{aligned} \mathcal{L}\big\{\Xi_{n,3}(x), x\in\mathcal{I}_h\big\} &= \mathcal{L}\Big\{h^{-1/2}\int_{\mathcal{X}}K\big(h^{-1}(u-x)\big)\mathrm{d}W_n(u), x\in\mathcal{I}_h\Big\} \\ &= \mathcal{L}\Big\{h^{-1/2}\int_{\mathcal{X}}K(h^{-1}u-x)\mathrm{d}W_n(u), x\in[1,h^{-1}-1]\Big\} \\ &= \mathcal{L}\Big\{\int_0^{h^{-1}}K(u-x)\mathrm{d}W_n(u), x\in[1,h^{-1}-1]\Big\} \\ &= \mathcal{L}\Big\{\int_0^{h^{-1}}K(u-1-x)\mathrm{d}W_n(u), x\in[0,h^{-1}-2]\Big\} \end{aligned}$$

denote $\xi(x) = \int_0^{h^{-1}}K(u-1-x)\mathrm{d}W_n(u), x\in[0,h^{-1}-2]$, one has that

$$\begin{aligned} \mathbb{E}\big\{\xi(x)\xi(x')\big\} &= \int_0^{h^{-1}}K(u-1-x)K(u-1-x')\mathrm{d}u \\ &= \int_{-1}^{1}K(v)K(v+x-x')\mathrm{d}v \end{aligned}$$

and $\mathbb{E}\big\{\xi^2(x)\big\} = \int_{-1}^{1}K^2(v)\mathrm{d}v$. Then

$$\begin{aligned} r(x-x') &= \frac{\mathbb{E}\big\{\xi(x)\xi(x')\big\}}{\sqrt{\mathbb{E}\big\{\xi^2(x)\big\}\mathbb{E}\big\{\xi^2(x')\big\}}} \\ &= \frac{\int_{-1}^{-1}K(v)K(v+x-x')\mathrm{d}v}{\int_{-1}^{-1}K^2(v)\mathrm{d}v} \end{aligned}$$

and

$$\begin{aligned}
r(t)-1 &= \frac{\int_{-1}^{-1} K(v)K(v+t)\mathrm{d}v}{\int_{-1}^{-1} K^2(v)\mathrm{d}v} - 1 \\
&= \frac{\int_{-1}^{-1} K(v)\big\{K(v+t)-K(v)\big\}\mathrm{d}v}{\int_{-1}^{-1} K^2(v)\mathrm{d}v} \\
&= \frac{\int_{-1}^{-1} K(v)\big\{K^{(1)}(v)t + 2^{-1}K^{(2)}(v)t^2 + o(t^2)\big\}\mathrm{d}v}{\int_{-1}^{-1} K^2(v)\mathrm{d}v} \\
&= \frac{\int_{-1}^{-1} K(v)K^{(2)}(v)\mathrm{d}v}{2\int_{-1}^{-1} K^2(v)\mathrm{d}v} t^2 + o(t^2) \\
&= \frac{\int_{-1}^{-1} K(v)\mathrm{d}K^{(1)}(v)}{2\int_{-1}^{-1} K^2(v)\mathrm{d}v} t^2 + o(t^2) \\
&= -\frac{\int_{-1}^{-1} \big\{K^{(1)}(v)\big\}^2\mathrm{d}v}{2\int_{-1}^{-1} K^2(v)\mathrm{d}v} t^2 + o(t^2)
\end{aligned}$$

Then the conditions of Lemma 4.6 holds with $\alpha = 2$, $C = 2^{-1}\Lambda^{-1}\int_{-1}^{-1}\big\{K^{(1)}(v)\big\}^2\mathrm{d}v$ in which $\Lambda = \sqrt{\int_{-1}^{1} K^2(v)\mathrm{d}v}$, $T = h^{-1}-2$, $a_T = (2\log T)^{1/2}$ and $b_T = a_T + 2^{-1}a_T^{-1}\log\left(\frac{C}{2\pi^2}\right)$, then one has that

$$a_T\Big(\sup_{x\in[0,T]}\big|\xi(x)/\Lambda\big| - b_T\Big) \xrightarrow{d} Z.$$

as $T\to\infty$. Besides, one can easily obtain that

$$a_h a_T^{-1} \to 1,\ a_h(b_T - b_h) \to 0.$$

Therefore, by using Slutsky's theorem, one can obtain that as $n\to\infty$,

$$\begin{aligned}
a_h\Big(\sup_{x\in\mathcal{I}_h}\big|\Xi_{n,3}(x)/\Lambda\big| - b_h\Big) &= a_h\Big(\sup_{x\in[0,T]}\big|\xi(x)/\Lambda\big| - b_h\Big) \\
&= a_h a_T^{-1} a_T\Big(\sup_{x\in[0,T]}\big|\xi(x)/\Lambda\big| - b_T\Big) + a_h(b_T - b_h) \xrightarrow{d} Z.
\end{aligned}$$

□

Proposition 4.8. *(Uniform asymptotic distribution of noise term) Under Assumption (A), as $n\to\infty$, if $h = h_n$ satisfies that $h\log n \to 0$ and $n^{-1/2}h^{-1/2}\log^{3/2} n \to 0$ and $\log h^{-1} = \mathcal{O}(\log n)$, one has that*

$$a_h\Big[\sqrt{nh}\Lambda^{-1}\sup_{x\in\mathcal{I}_h} f^{-1/2}(x)\Big|\hat{f}(x) - \mathbb{E}\big\{\hat{f}(x)\big\}\Big| - b_h\Big] \xrightarrow{d} Z.$$

Proof. Note that $a_h = (2\log h^{-1})^{1/2} = \mathcal{O}(\log^{1/2} n)$,

$$\begin{aligned}
\left| a_h\Big(\sup_{x\in\mathcal{I}_h}\big|\Xi_{n,2}(x)/\Lambda\big| - b_h\Big) - a_h\Big(\sup_{x\in\mathcal{I}_h}\big|\Xi_{n,3}(x)/\Lambda\big| - b_h\Big)\right| &\lesssim a_h \sup_{x\in\mathcal{I}_h}\big|\Xi_{n,2}(x) - \Xi_{n,3}(x)\big| \\
&= \mathcal{O}_p(a_h h^{1/2}) \\
&= \mathcal{O}_p(h^{1/2}\log^{1/2} n) \\
&= o_p(1), \\
\left| a_h\Big(\sup_{x\in\mathcal{I}_h}\big|\Xi_{n,0}(x)/\Lambda\big| - b_h\Big) - a_h\Big(\sup_{x\in\mathcal{I}_h}\big|\Xi_{n,1}(x)/\Lambda\big| - b_h\Big)\right| &\lesssim a_h \sup_{x\in\mathcal{I}_h}\big|\Xi_{n,0}(x) - \Xi_{n,1}(x)\big| \\
&= \mathcal{O}_p(a_h h^{1/2}) \\
&= \mathcal{O}_p(h^{1/2}\log^{1/2} n) \\
&= o_p(1), \\
\left| a_h\Big(\sup_{x\in\mathcal{I}_h}\big|\Xi_{n}(x)/\Lambda\big| - b_h\Big) - a_h\Big(\sup_{x\in\mathcal{I}_h}\big|\Xi_{n,0}(x)/\Lambda\big| - b_h\Big)\right| &\lesssim a_h \sup_{x\in\mathcal{I}_h}\big|\Xi_{n}(x) - \Xi_{n,0}(x)\big| \\
&= \mathcal{O}_{a.s.}(a_h n^{-1/2}h^{-1/2}\log n) \\
&= \mathcal{O}_{a.s.}(n^{-1/2}h^{-1/2}\log^{3/2} n) \\
&= o_{a.s.}(1),
\end{aligned}$$

and

$$\mathcal{L}\big\{\Xi_{n,1}(x), x\in\mathcal{I}_h\big\} = \mathcal{L}\big\{\Xi_{n,2}(x), x\in\mathcal{I}_h\big\},$$

then one has that

$$a_h\Big(\sup_{x\in\mathcal{I}_h}\big|\Xi_n(x)/\Lambda\big| - b_h\Big) \xrightarrow{d} Z,$$

i.e.,

$$a_h\left[\sqrt{nh}\Lambda^{-1}\sup_{x\in\mathcal{I}_h} f^{-1/2}(x)\Big|\hat f(x) - \mathbb{E}\{\hat f(x)\}\Big| - b_h\right] \xrightarrow{d} Z.$$

□

Put Proposition 4.8 and Proposition 2.1 together, one can obtain the uniform asymptotic distribution of kernel density estimation.

Theorem 4.9. *(Uniform asymptotic distribution of kernel density estimation) Under Assumptions (A), as* $n\to\infty$*, if* $h = h_n$ *satisfies that* $nh^5\log n \to 0$, $n^{-1/2}h^{-1/2}\log^{3/2} n \to 0$ *and* $\log h^{-1} = \mathcal{O}(\log n)$*, one has that*

$$a_h\Big\{\sqrt{nh}\Lambda^{-1}\sup_{x\in\mathcal{I}_h} f^{-1/2}(x)\big|\hat f(x) - f(x)\big| - b_h\Big\} \xrightarrow{d} Z$$

Proof. Note that

$$\begin{aligned}
&\Bigg| a_h \Big\{ \sqrt{nh}\Lambda^{-1} \sup_{x\in\mathcal{I}_h} f^{-1/2}(x) \big| \hat{f}(x) - f(x) \big| - b_h \Big\} \\
&\quad - a_h \Big[\sqrt{nh}\Lambda^{-1} \sup_{x\in\mathcal{I}_h} f^{-1/2}(x) \Big| \hat{f}(x) - \mathbb{E}\big\{\hat{f}(x)\big\} \Big| - b_h \Big] \Bigg| \\
&\lesssim a_h \sqrt{nh} \sup_{x\in\mathcal{I}_h} \Big| \mathbb{E}\big\{\hat{f}(x)\big\} - f(x) \Big| \\
&= \mathcal{O}(n^{1/2} h^{5/2} \log^{1/2} n) \\
&= o(1),
\end{aligned}$$

then Theorem 4.9 can be obtained by using Slutsky's theorem. □

Bibliography

Bickel, P. J. and Rosenblatt, M. (1973). On some global measures of the deviations of density function estimates. *Ann Stat*, 1:1071–1095.

Bosq, D. (1998). *Nonparametric statistics for stochastic processes: estimation and prediction*. Springer, New York.

Komlós, J., Major, P., and Tusnády, G. (1975). An approximation of partial sums of independent rv's, and the sample df. i. *Probab Theory Rel*, 32:111–131.

Leadbetter, M. R., Lindgren, G., and Rootzén, H. (1983). *Extremes and related properties of random sequences and processes*. Springer, New York.