

# Strong Consistency of Kernel Regression Estimate

Wenquan Cui, Meng Wei

Department of Statistics and Finance, University of Science and Technology of China, Hefei, China  
 Email: wqcui@ustc.edu.cn

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## ABSTRACT

In this paper, regression function estimation from independent and identically distributed data is considered. We establish strong pointwise consistency of the famous Nadaraya-Watson estimator under weaker conditions which permit to apply kernels with unbounded support and even not integrable ones and provide a general approach for constructing strongly consistent kernel estimates of regression functions.

**Keywords:** Kernel Regression Estimator; Bandwidth; Strong Pointwise Consistency

## 1. Introduction

Let  $(X_1, Y_1), \dots, (X_n, Y_n)$  be independent observations of a  $R^d \times R$  valued random vector  $(X, Y)$  with  $E|Y| < \infty$ . We estimate the regression function  $m(x) = E(Y|X = x)$  by the following form of kernel estimates

$$m_n(x) = \frac{\sum_{i=1}^n Y_i K((X_i - x)/h)}{\sum_{j=1}^n Y_j K((X_j - x)/h)} \quad (1.1)$$

where  $h = h(n)$  is called the bandwidth and  $K$  is a given nonnegative Borel kernel. The estimator (1.1) was first introduced by Nadaraya ([1]) and Watson ([2]). The studies of  $m(x)$  can also refer to, for examples, Stone ([3]), Schuster and Yakowitz ([4]), Gasser and Muller ([5]), Mack and Müller ([6]), Greblicki and Pawlak ([7]), Kohler, Krzyżak and Walk ([8,9]), and Walk ([10]). When point  $x$  is near the boundary of their support, the kernel regression estimator (1.1) has suffered from a serious problem of boundary effects. Hereafter 0/0 is treated as 0. For the kernel function we assume that

$$c_1 H(\|x\|) \leq K(x) \leq c_2 H(\|x\|), \quad (1.2)$$

and

$$cI(\|x\| \leq r) \leq K(x), \quad (1.3)$$

where  $c_1, c_2, c$  and  $r$  are positive constants,  $\|\cdot\|$  is either always  $l_2$  or always  $l_\infty$  norm,  $I(\cdot)$  denotes the indicator function of a set, and  $H$  is a bounded decreasing Borel function in  $[0, \infty)$  such that

$$t^d H(t) \rightarrow 0, \text{ as } t \rightarrow \infty, \quad (1.4)$$

Through this paper we assume that

$$h = h(n) \rightarrow 0, \text{ as } n \rightarrow \infty, \quad (1.5)$$

One of the fundamental problems of asymptotic study on nonparametric regression is to find the conditions under which  $m_n(x)$  is a strongly consistent estimate of  $m(x)$  for almost all  $(\mu)x \in R^d$  ( $\mu$  probability distribution of  $X$ ). The first general result in this direction belongs to Devroye ([11]), who established strong pointwise consistency of  $m_n(x)$  for bounded  $Y$ . Zhao and Fang ([12]) establish its strong consistency under the weaker condition that  $E|Y|^p < \infty$  for some  $p > 1$ . However, the dominating function  $H(\|x\|)$  of (1.3) in the above literature is confined as  $I(\|x\| \leq r)$  for some  $r > 0$ . Greblicki, Krzyżak and Pawlak ([13]) establish the complete convergence of  $m_n(x)$  for bounded  $Y$  and rather general dominating function  $H$  of (1.3) for almost all  $(\mu)x \in R^d$ . This permits to apply kernels with unbounded support and even not integrable ones. In this paper, we establish the strong consistency of  $m_n(x)$  under the conditions of GKP ([13]) on the kernel and various moment conditions on  $Y$ , which provides a general approach for constructing strongly consistent kernel estimates of regression functions. We have

**Theorem 1.1** Assume that  $E|Y|^p < \infty$  for some  $p > 1$ , and (1.2)-(1.5) are satisfied, and that

$$nh^d / (n^{1/p} \log n) \rightarrow \infty, \text{ as } n \rightarrow \infty. \quad (1.6)$$

Then

$$m_n(x) \rightarrow m(x) \text{ a.s. for almost all } (\mu)x \in R^d, \quad (1.7)$$

as  $n \rightarrow \infty$ .

**Theorem 1.2** Assume that  $E \exp(t|Y|^\lambda) < \infty$  for some  $\lambda > 0$  and  $t > 0$ , and (1.2)-(1.5) are met, and that

$$nh^d / (\log n)^{1+\frac{1}{\lambda}} \rightarrow \infty, \text{ as } n \rightarrow \infty. \tag{1.8}$$

Then (1.7) is true.

It is worthwhile to point out that in the above theorems we do not impose any restriction on the probability distribution  $\mu$  of  $X$ .

**2. Proof of the Theorems**

For simplicity, denote by  $c$  a positive constant, by  $c(x)$  a positive constant depending on  $x$ . These constants may assume different values in different places, even within the same expression. We denote by  $S_r$  as a sphere of the radius  $r$  centered at  $x, x \in R^d$ .

**Lemma 2.1** Assume that  $\lim_{n \rightarrow \infty} h(n) = 0$ . For all  $c > 0$ , there exists a nonnegative function  $q(x)$  with  $q(x) < \infty$  such that for almost all  $(\mu)x \in R^d$ ,

$$h^d / \mu(S_{ch}) \rightarrow q(x), \text{ as } n \rightarrow \infty$$

Refer to Devroye ([11]).

**Lemma 2.2** Assume that (1.2)-(1.5) are satisfied. Let  $|f|^r$  be  $\mu$  integrable for some  $r > 0$ . Then

$$\int K\left(\frac{y-x}{h}\right) |f(y) - f(x)|^r \mu(dy) / \int K\left(\frac{y-x}{h}\right) \mu(dy) \rightarrow 0$$

as  $h \rightarrow 0$  for almost all  $(\mu)x \in R^d$ .

It is easily proved by using Lemma 1 of GKP ([13]).

**Lemma 2.3** Assume that (1.2)-(1.5) are met, and that

$$nh^d / \log n \rightarrow \infty, \text{ as } n \rightarrow \infty.$$

Then for almost all  $(\mu)x \in R^d$

$$B_{1n}(x) \equiv (nEK((X-x)/h))^{-1} \sum_{i=1}^n K((X_i-x)/h) \rightarrow 1$$

a.s. as  $n \rightarrow \infty$

Refer to GKP ([13]).

Now we are in a position to prove Theorems 1.1 and 1.2.

**Proof.** For simplicity, we write “for a.e.  $x$ ” instead of the longer phrase “for almost all  $(\mu)x \in R^d$ ”. Write

$$N = nEK((X-x)/h),$$

$$B_{2n}(x) = N^{-1} \sum_{i=1}^n (Y_i - m(x)) K((X_i - x)/h),$$

$$U_n(x) = N^{-1} \sum_{i=1}^n |m(X_i) - m(x)| K((X_i - x)/h),$$

$$T_n(x) = N^{-1} \sum_{i=1}^n (Y_i - m(X_i)) K((X_i - x)/h).$$

Since

$$m_n(x) = (B_{2n}(x) + m(x)B_{1n}(x)) / (1 + (B_{1n}(x) - 1)),$$

and by Lemma 2.3,  $B_{1n}(x) \rightarrow 1$  a.s. for a.e.  $x$ , it suffices to verify that  $B_{2n}(x) \rightarrow 0$  a.s. for a.e.  $x$ , or, to prove  $U_n(x) \rightarrow 0$  a.s. and  $T_n(x) \rightarrow 0$  a.s. for a.e.  $x$ .

Since  $|y|^p$  is convex in  $y$  for  $p > 1$ , and for fixed  $t > 0$  and  $\lambda > 0$ ,  $\exp(ty^\lambda)I(y > a)$  is convex in  $y \in (a, +\infty)$  for large  $a$ , it follows from Jensen’s inequality that  $E|m(X) - m(x)|^p < \infty$  and  $E|Y - m(x)|^p < \infty$  when  $E|Y|^p < \infty$ , and that

$$E \exp(s|m(X) - m(x)|^\lambda) < \infty \text{ and}$$

$$E \exp(s|Y - m(X)|^\lambda) < \infty \text{ for some } s > 0 \text{ and } \lambda > 0$$

when  $E \exp(|Y|^\lambda) < \infty$ .

Write  $g_j = G(X_j) = |m(X_j) - m(x)|$ ,  $c_j = j^{1/p}$  (in Theorem 1.1) or  $c_j = ((1/s)\log j)^{1/\lambda}$  (in Theorem 1.2). It follows that

$$\sum_j P(g_j > c_j) < \infty,$$

and

$$P(g_j > c_j, i.o.) = 0$$

by Borel-Cantelli’s lemma, and

$$\sum_j g_j^2 I(g_j > c_j) < \infty, \text{ a.s.} \tag{2.1}$$

Write  $a_n \gg b_n$ , if  $a_n/b_n \rightarrow \infty$  as  $n \rightarrow \infty$ . By (1.6) or (1.8),  $nh^d/c_n \gg \log n$ , we can take  $d_n$  such that

$$nh^d/c_n \gg d_n \gg \log n, \tag{2.2}$$

Put

$$g'_j = g_j I(g_j > c_j), U'_n(x) = N^{-1} \sum_{j=1}^n g'_j K((X_j - x)/h)$$

$$g''_j = g_j I(g_j \leq c_j), U''_n(x) = N^{-1} \sum_{j=1}^n g''_j K((X_j - x)/h),$$

$$\tilde{g}_{nj} = g_j I(N^{-1} K((X_j - x)/h) g_j \leq d_n^{-1}),$$

$$\tilde{U}_n(x) = N^{-1} \sum_{j=1}^n \tilde{g}_{nj} K((X_j - x)/h).$$

By (1.3) and Lemma 2.1, for a.e.  $x$ ,

$$N^{-1} = (nEK((X-x)/h))^{-1} \leq (cn\mu(S_{nh}))^{-1} \leq c(x)(nh^d)^{-1} \rightarrow 0. \tag{2.3}$$

By Lemma 2.3,

$$\begin{aligned}
 & N^{-1} \sum_{j=1}^n K^2 \left( (X_j - x)/h \right) \\
 & \leq c N^{-1} \sum_{j=1}^n K \left( (X_j - x)/h \right) \rightarrow c \quad (2.4)
 \end{aligned}$$

a.s. for a.e.  $x$

By Schwarz's inequality, (2.1), (2.3) and (2.4),

$$\begin{aligned}
 & (U'_n(x))^2 \\
 & \leq N^{-2} \sum_{j=1}^n K^2 \left( (X_j - x)/h \right) \sum_{j=1}^n g_j^2 I(g_j > c_j) \quad (2.5)
 \end{aligned}$$

$\rightarrow 0$

a.s. for a.e.  $x$

Write

$$Z_j = d_n N^{-1} \left( \tilde{g}_{nj} K \left( (X_j - x)/h \right) - E \tilde{g}_{nj} K \left( (X_j - x)/h \right) \right).$$

We have  $EZ_j = 0, Z_j \leq 1, j = 1, 2, \dots, n$ . Take  $b < p, 1 < b \leq 2$ . Since  $e^z \leq 1 + z + |z|^b$  for  $z \leq 1$ , we have

$$Ee^{Z_j} \leq 1 + E|Z_j|^b \leq \exp \left( E|Z_j|^b \right),$$

and

$$\begin{aligned}
 & E \exp \left( d_n (\tilde{U}_n(x) - E\tilde{U}_n(x)) \right) \\
 & \leq \exp \left( \sum_{j=1}^n |Z_j|^b \right) \leq \exp \left\{ cd_n^b N^{-b} n EK \left( (X_1 - x)/h \right) |g_1|^b \right\}.
 \end{aligned}$$

By Lemma 2.2,

$$\begin{aligned}
 & EK \left( (X_1 - x)/h \right) |g_1|^b / EK \left( (X - x)/h \right) \\
 & = \int K \left( \frac{y-x}{h} \right) |m(y) - m(x)|^b \mu(dy) / \int K \left( \frac{y-x}{h} \right) \mu(dy).
 \end{aligned}$$

$\rightarrow 0$

for a.e.  $x$ , as  $n \rightarrow \infty$

By (2.2) and (2.3),

$$(d_n/N)^{b-1} \ll c(x) \left( d_n / (nh^d) \right)^{b-1} \ll (1/c_n)^{b-1} \rightarrow 0$$

for a.e.  $x$ .

Given  $\varepsilon > 0$ , it follows that for a.e.  $x$  and for  $n$  large,

$$cd_n^b N^{-b} n EK \left( (X_1 - x)/h \right) |g_1|^b < d_n \varepsilon / 2, \quad (2.6)$$

and

$$\begin{aligned}
 & P \left\{ \tilde{U}_n(x) - E\tilde{U}_n(x) \geq \varepsilon \right\} \\
 & \leq e^{-d_n \varepsilon} E \exp \left\{ d_n (\tilde{U}_n(x) - E\tilde{U}_n(x)) \right\} \\
 & \leq e^{-d_n \varepsilon} \cdot e^{-d_n \varepsilon / 2} = e^{-3d_n \varepsilon / 2}.
 \end{aligned}$$

By Borel-Cantelli's lemma and for a.e.  $x$ ,

$$\sum_n P \left( \tilde{U}_n(x) - E\tilde{U}_n(x) \geq \varepsilon \right) < \infty \text{ for any } \varepsilon > 0,$$

we have

$$\tilde{U}_n(x) - E\tilde{U}_n(x) \rightarrow 0 \text{ a.s for a.e. } x$$

Since, by Lemma 2.2, for a.e.  $x$

$$\begin{aligned}
 & E\tilde{U}_n(x) \\
 & \leq E |m(X) - m(x)| K \left( (X - x)/h \right) / EK \left( (X - x)/h \right) \rightarrow 0,
 \end{aligned}$$

we have

$$\tilde{U}_n(x) \rightarrow 0 \text{ a.s for a.e. } x, \text{ as } n \rightarrow \infty. \quad (2.7)$$

By (2.2) and (2.3), when  $g_j \leq c_j$ , for a.e.  $x$ ,

$$N^{-1} K \left( (X_j - x)/h \right) g_j \leq c(x) (nh^d)^{-1} \cdot c \cdot c_n \ll d_n^{-1},$$

and for  $n$  large,  $g_j'' \leq \tilde{g}_{nj}, 1 \leq j \leq n$ , and

$$0 \leq U_n''(x) \leq \tilde{U}_n(x) \rightarrow 0 \text{ a.s for a.e. } x. \quad (2.8)$$

By (2.5) and (2.8), noticing that

$$U_n(x) = U_n'(x) + U_n''(x), \text{ we have}$$

$$U_n(x) \rightarrow 0 \text{ a.s for a.e. } x. \quad (2.9)$$

To prove  $T_n(x) \rightarrow 0$  a.s for a.e.  $x$ , we write  $e_j = Y_j - m(X_j)$ , and put

$$e'_j = e_j I(e_j > c_j), T'_n(x) = N^{-1} \sum_{j=1}^n e'_j K \left( (X_j - x)/h \right)$$

$$e''_j = e_j I(e_j \leq c_j), T''_n(x) = N^{-1} \sum_{j=1}^n e''_j K \left( (X_j - x)/h \right),$$

$$\tilde{e}_{nj} = e_j I \left( N^{-1} K \left( (X_j - x)/h \right) e_j \leq d_n^{-1} \right),$$

$$\tilde{T}_n(x) = N^{-1} \sum_{j=1}^n \tilde{e}_{nj} K \left( (X_j - x)/h \right).$$

By using the same argument as above,

$$\sum_j P \left( |e_j| > c_j \right) < \infty$$

$$P(e_j > c_j, i.o.) = 0 \text{ a.s.}$$

$$\sum_j e_j^2 I(e_j > c_j) < \infty$$

and for a.e.  $x$ ,

$$\begin{aligned}
 & (T'_n(x))^2 \\
 & \leq N^{-2} \sum_{j=1}^n K^2 \left( (X_j - x)/h \right) \sum_{j=1}^n e_j^2 I(e_j > c_j) \quad (2.10)
 \end{aligned}$$

$\rightarrow 0$

a.s.

Also, for a.e.  $x$  and for  $n$  large,

$$e''_j \leq \tilde{e}_{nj}, 1 \leq j \leq n \text{ and } T''_n(x) \leq \tilde{T}_n(x). \quad (2.11)$$

Write  $Z_j = d_n N^{-1} K \left( (X_j - x)/h \right) \tilde{e}_{nj}$ , then

$Z_j \leq 1, EZ_j \leq 0, j = 1, 2, \dots, n$ . Take  $1 < b \leq 2, b < p$ . Since  $e^z \leq 1 + z + |z|^b$  for  $z \leq 1$ , we have

$$Ee^{Z_j} \leq 1 + E|Z_j|^b \leq \exp\left(E|Z_j|^b\right),$$

and

$$\begin{aligned} E \exp\left(d_n \tilde{T}_n(x)\right) &\leq \exp\left(\sum_{j=1}^n |Z_j|^b\right) \\ &\leq \exp\left(cd_n^b N^{-b} n EK\left(\left|(X-x)/h\right| Y\right)^b\right). \end{aligned}$$

By Lemma 2.2, for a.e.  $x$ ,

$$\begin{aligned} EK\left(\left|(X-x)/h\right| Y\right)^b / EK\left(\left|(X-x)/h\right|\right) \\ = EK\left(\left|(X-x)/h\right| h_b(x)\right) / EK\left(\left|(X-x)/h\right|\right) \rightarrow h_b(x) \end{aligned}$$

Given  $\varepsilon > 0$ , similar to (2.6), for a.e.  $x$  and  $n$  large,  $cd_n^b N^{-b} n EK\left(\left|(X-x)/h\right| Y\right)^b < d_n \varepsilon / 2$ , and

$$\begin{aligned} P\left(\tilde{T}_n(x) \geq \varepsilon\right) &\leq e^{-d_n \varepsilon} E \exp\left(d_n \tilde{T}_n(x)\right) \\ &\leq e^{-d_n \varepsilon} \cdot e^{-d_n \varepsilon / 2} = e^{-3d_n \varepsilon / 2}, \end{aligned}$$

and it follows that

$$\limsup_{n \rightarrow \infty} \tilde{T}_n(x) \leq 0 \quad \text{a.s. for a.e. } x \quad (2.12)$$

from

$$\sum_n P\left(\tilde{T}_n(x) \geq \varepsilon\right) < \infty \quad \text{for a.e. } x \text{ and } \forall \varepsilon > 0$$

and Borel-Cantelli's lemma.

By (2.10)-(2.12),

$$\limsup_{n \rightarrow \infty} T_n''(x) \leq 0 \quad \text{a.s. for a.e. } x$$

and

$$\limsup_{n \rightarrow \infty} T_n(x) \leq 0 \quad \text{a.s. for a.e. } x \quad (2.13)$$

Replacing  $e_j$  by  $(-e_j)$ , it implies that

$$\liminf_{n \rightarrow \infty} T_n(x) \geq 0 \quad \text{a.s. for a.e. } x \quad (2.14)$$

(2.13) and (2.14) give

$$T_n(x) \rightarrow 0 \quad \text{a.s. for a.e. } x \quad (2.15)$$

The theorems follow from (2.9) and (2.15).

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