

# ON CONVERGENCES OF ASYMPTOTICALLY OPTIMAL DISCRIMINANT FUNCTIONS FOR PATTERN CLASSIFICATION PROBLEMS

Watanabe, Masafumi  
Department of Mathematics, Kyushu University

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# ON CONVERGENCES OF ASYMPTOTICALLY OPTIMAL DISCRIMINANT FUNCTIONS FOR PATTERN CLASSIFICATION PROBLEMS

By

Masafumi WATANABE\*

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## § 1. Introduction and Summary.

This is a continuation of the paper [11] and is concerned with the pattern classification problem related to "learning with a teacher". In [11], in the case when the optimal discriminant function is assumed to belong to the  $L^2$  space and the case when that is assumed to be uniformly continuous, we gave algorithms, which were applications of the stochastic approximation method, for constructing the asymptotically optimal estimates, and investigated the convergence (mean convergence and almost sure convergence) of the algorithms. But we did not consider the rate of almost sure convergence. In this paper we shall discuss the convergence of the algorithm in the case when the "optimal discriminant function" (o.d.f.) is continuous and the rate of the almost sure convergence.

This paper consists of five sections. In Section 2, we shall give definition of the o.d.f. and of asymptotically optimal estimates to the o.d.f., and we shall prepare several lemmas to be used throughout subsequent sections. In Section 3, we shall treat the case when the o.d.f. is continuous, and give an algorithm which is more general than the form in [10]. And we shall discuss the almost sure convergence and the mean convergence of asymptotically optimal estimates. In Section 4, we shall give some inequalities concerning the rates of convergences.

## § 2. The formulation of the problem and Preliminaries.

We consider the two-categories classification problem. In this paper, we assume that a pattern space is equal to the  $N$ -dimensional Euclidian space  $R^N$ , and the set of categories is equal to  $\{A, B\}$ .

Let  $(q_A, q_B)$  denote a given priori distribution on  $\{A, B\}$ , where  $q_A, q_B > 0$  and  $q_A + q_B = 1$ , and let  $f(\cdot|A)(f(\cdot|B))$  denote the probability density function of the observed  $R^N$ -valued random vector  $X$  if  $X$  is drawn from the class  $A(B)$ .

Let's assume tentatively  $q_A, q_B, f(\cdot|A)$  and  $f(\cdot|B)$  are all known to us. Let's consider the discriminant function;

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\* Department of Mathematics, Kyushu University, Fukuoka.

$$(2.1) \quad D(x) = q_A \cdot f(x|A) - q_B \cdot f(x|B), \quad x \in R^N.$$

And let's consider the following decision rule based on (2.1); decide  $X$  to be from the class  $A$  if  $D(x) \geq 0$  for outcome  $x$  of  $X$ , and decide  $X$  from the class  $B$  if  $D(x) < 0$  for the outcome  $x$  of  $X$ . It is well known that this decision rule minimizes the probability of misclassification, and this rule has been called the Bayes decision rule. In this paper, we shall call (2.1) the optimal discriminant function (hereafter, abbreviated as o. d. f.).

In this paper we shall treat the case when none of  $q_A$ ,  $q_B$ ,  $f(\cdot|A)$  and  $f(\cdot|B)$  is known to us, consequently the o. d. f. is unknown to us. In this situation we are supposed to have a training sequence  $\{(X_n, \Theta_n)\}_{n=1}^{\infty}$  with the observed pattern  $X_n \in R^N$  and the category  $\Theta_n \in \{A, B\}$  from which  $X_n$  is actually drawn. It is assumed that the category from which an each observed pattern has been drawn is correctly indicated by a teacher at each instant  $n$ .

We assume the training sequence  $\{(X_n, \Theta_n)\}_{n=1}^{\infty}$  is independently and identically distributed, each  $X_n$  has probability density function  $f(\cdot|A)(f(\cdot|B))$  if  $\Theta_n = A(\Theta_n = B)$ , and each  $\Theta_n$  is distributed as  $q_A = P[\Theta_n = A]$  and  $q_B = P[\Theta_n = B]$ . Throughout this paper these assumptions remain valid.

Let  $D_n(x)$  be an estimate of the o. d. f.  $D(x)$  based on  $\{(X_k, \Theta_k)\}_{k=1}^n$ . Let  $P_g(e)$  be the probability of misclassification using a discriminant function  $g(\cdot)$  which is a realvalued function on  $R^N$ . Here to classify by using  $g(\cdot)$  means that we make use of the decision rule; decide  $x$  come from the class  $A$  if  $g(x) \geq 0$ , and  $x$  from  $B$  if  $g(x) < 0$ .

DEFINITION 1.  $\{D_n(\cdot)\}_{n=1}^{\infty}$  is said to be the asymptotically optimal sequence of type I (hereafter, abbreviated as AO(I)), if

$$(2.2) \quad \lim_{n \rightarrow \infty} E|P_{D_n}(e) - P_D(e)| = 0,$$

and  $\{D_n(\cdot)\}_{n=1}^{\infty}$  is said to be the asymptotically optimal sequence of type II (hereafter, abbreviated as AO(II)), if

$$(2.3) \quad \lim_{n \rightarrow \infty} |P_{D_n}(e) - P_D(e)| = 0 \quad \text{with pr. 1.}$$

DEFINITION 2. Let  $\{\alpha_n\}_{n=1}^{\infty}$  be a sequence of positive numbers such that  $\lim_{n \rightarrow \infty} \alpha_n = 0$ . Then,  $\{D_n(\cdot)\}_{n=1}^{\infty}$  is said to be the asymptotically optimal sequence of order  $\{\alpha_n\}$  of Type I (AO-I( $\{\alpha_n\}$ )), if there exists a constant  $C > 0$  such that

$$(2.4) \quad E|P_{D_n}(e) - P_D(e)| \leq C \cdot \alpha_n \quad \text{for all } n \geq 1,$$

and  $\{D_n(\cdot)\}_{n=1}^{\infty}$  is said to be asymptotically optimal sequence of order  $\{\alpha_n\}$  of type II (AO-II( $\{\alpha_n\}$ )), if for any  $\delta > 0$  there exists a constant  $C(\delta) > 0$  such that

$$(2.5) \quad P[|P_{D_n}(e) - P_D(e)| \leq C(\delta) \cdot \alpha_n \quad \text{for all } n \geq 1] > 1 - \delta.$$

The following lemma was essentially proved in [11].

LEMMA 2.1. Let  $\{A_n\}_{n=1}^{\infty}$  be a sequence of non-negative numbers.

Suppose that there exist three sequences of non-negative numbers  $\{a_n\}_{n=1}^{\infty}$ ,  $\{b_n\}_{n=1}^{\infty}$  and  $\{K_n\}_{n=1}^{\infty}$  such that

$$(2.6) \quad A_{n+1} \leq (1 - a_{n+1})A_n + a_{n+1} \cdot b_{n+1} + K_{n+1} \quad \text{for all } n \geq 1,$$

$$(2.7) \quad \sum_{n=1}^{\infty} a_n = \infty \quad \text{and} \quad \lim_{n \rightarrow \infty} a_n = 0,$$

$$(2.8) \quad \lim_{n \rightarrow \infty} b_n = 0,$$

$$(2.9) \quad \sum_{n=1}^{\infty} K_n < \infty.$$

Then, it holds that  $\lim_{n \rightarrow \infty} A_n = 0$ .

And if  $K_n \equiv 0$  for all  $n \geq 1$  in (2.6) and there exist a constant  $\alpha_0 > 0$  and some positive integer  $n_0$  such that

$$(2.10) \quad (1 - a_{n+1}) \cdot \frac{b_n}{b_{n+1}} \leq (1 - \alpha_0 a_{n+1}) \quad \text{for all } n \geq n_0,$$

where  $\{b_n\}_{n=1}^{\infty}$  need not satisfy the condition (2.8), then there exists a constant  $C > 0$  such that

$$(2.11) \quad A_n \leq C \cdot b_n \quad \text{for all } n \geq 1.$$

The following lemma is a direct application of Theorem III in [2] and Lemma 2.1.

LEMMA 2.2. Let  $\{U_n\}_{n=1}^{\infty}$  and  $\{V_n\}_{n=1}^{\infty}$  be two sequences of random variables on a probability space  $(\Omega, \mathcal{F}, P)$ . Let  $\{\mathcal{F}_n\}_{n=1}^{\infty}$  be a sequence of  $\sigma$ -fields,  $\mathcal{F}_n \subset \mathcal{F}_{n+1} \subset \mathcal{F}$ , where  $U_n$  and  $V_n$  are measurable with respect to  $\mathcal{F}_n$  for each  $n$ . And let  $\{a_n\}_{n=1}^{\infty}$  be a sequence of real numbers. Suppose that the following conditions be satisfied

- (i)  $0 \leq U_n$  a.s. for all  $n \geq 1$
- (ii)  $E[U_1] < \infty$
- (iii)  $E[U_{n+1} | \mathcal{F}_n] \leq (1 - a_{n+1})U_n + V_n$  a.s. for all  $n \geq 1$ .
- (iv)  $\sum_{n=1}^{\infty} E|V_n| < \infty$
- (v)  $a_n \geq 0$  ( $n = 1, 2, \dots$ ),  $\lim_{n \rightarrow \infty} a_n = 0$  and  $\sum_{n=1}^{\infty} a_n = \infty$ .

Then,  $\lim_{n \rightarrow \infty} U_n = 0$  a.s. and  $\lim_{n \rightarrow \infty} E[U_n] = 0$ .

LEMMA 2.3. Let  $\{U_n\}_{n=1}^{\infty}$  be a sequence of random variables on a probability space  $(\Omega, \mathcal{F}, P)$ . Let  $\{\mathcal{F}_n\}_{n=1}^{\infty}$  be a sequence of  $\sigma$ -fields,  $\mathcal{F}_n \subset \mathcal{F}_{n+1} \subset \mathcal{F}$ , where  $U_n$  is measurable with respect to  $\mathcal{F}_n$  for each  $n$ . And let  $\{a_n\}_{n=1}^{\infty}$  and  $\{v_n\}_{n=1}^{\infty}$  be two sequences of positive numbers. Suppose that there exist a positive integer  $n_0$  and two positive numbers  $0 < M < \infty$  and  $0 < \lambda < 1$  satisfying

$$(2.12) \quad U_n \geq 0 \quad \text{a.s. for all } n \geq n_0,$$

$$(2.13) \quad M \geq U_{n_0} \quad \text{a.s.}$$

$$(2.14) \quad E[U_{n+1} | \mathcal{F}_n] \leq (1 - a_{n+1})U_n + v_{n+1} \quad \text{a.s. for all } n \geq n_0.$$

$$(2.15) \quad (1 - a_{n+1}) \left( \frac{v_n}{v_{n+1}} \right)^{\lambda} \leq 1 \quad \text{for all } n \geq n_0,$$

and

$$(2.16) \quad \sum_{n=1}^{\infty} v_n^{1-\lambda} < \infty.$$

Then for any  $\delta > 0$  there exists a constant  $C(\delta)$  such that

$$P[U_n \leq C(\delta) \cdot v_n^\lambda \quad \text{for all } n \geq n_0] > 1 - \delta.$$

PROOF. Let  $A_n$  be the event such that

$$(2.17) \quad A_n = [U_k \leq C \cdot v_k^\lambda \quad \text{for } k = n_0, n_0+1, \dots, n]$$

for  $n \geq n_0$ , where  $C$  is a positive constant. It is easily seen that  $A_n \in \mathcal{F}_n$ . And for  $n = n_0+1, n_0+2, \dots$ , we put

$$(2.18) \quad P_n = P[U_k \leq C \cdot v_k^\lambda \quad \text{for } k = n_0, \dots, n-1 \text{ and } U_n > C \cdot v_n^\lambda].$$

Since

$$P_n = P[A_{n-1}] - P[A_n] \quad \text{for } n \geq n_0+1,$$

we have

$$(2.19) \quad P[A_n] = P[A_{n_0}] - \sum_{k=n_0+1}^n P_k \quad n \geq n_0+1.$$

We put

$$(2.20) \quad E_1[U_{n+1}] = \int_{A_n} E[U_{n+1} | \mathcal{F}_n] dP \quad \text{for } n \geq n_0$$

$$(2.21) \quad E_2[U_n] = \int_{A_n} U_n dP \quad \text{for } n \geq n_0.$$

By the definition of the conditional expectation, we have

$$(2.22) \quad E_1[U_{n+1}] = \int_{A_n} U_{n+1} dP \quad \text{for } n \geq n_0.$$

From (2.14) we have

$$(2.23) \quad E_1[U_{n+1}] \leq (1 - a_{n+1}) E_2[U_n] + v_{n+1} \quad \text{for } n \geq n_0.$$

And from (2.21) and (2.22), we have

$$(2.24) \quad \begin{aligned} E_1[U_{n+1}] &= \int_{A_{n+1}} U_{n+1} dP + \int_{A_n - A_{n+1}} U_n dP \\ &\geq E_2[U_{n+1}] + C \cdot v_{n+1}^\lambda \cdot P_{n+1} \quad \text{for } n \geq n_0. \end{aligned}$$

Therefore from (2.23) and (2.24), we have

$$(2.25) \quad E_2[U_{n+1}] + C \cdot v_{n+1}^\lambda \cdot P_{n+1} \leq E_2[U_n] \cdot (1 - a_{n+1}) + v_{n+1} \quad \text{for } n \geq n_0.$$

In (2.25) we put  $z_n = E_2[U_n] / v_n^\lambda$  for each  $n \geq n_0$ . Then we have

$$(2.26) \quad z_{n+1} + C \cdot P_{n+1} \leq \left( \frac{v_n}{v_{n+1}} \right)^\lambda (1 - a_{n+1}) z_n + v_{n+1}^{1-\lambda} \quad \text{for } n \geq n_0.$$

Noting (2.15), we have

$$(2.27) \quad z_{n+1} + C \cdot P_{n+1} \leq z_n + v_{n+1}^{1-\lambda} \quad \text{for } n \geq n_0.$$

Summing the both side of (2.27) from  $n = n_0$  to  $n = \infty$  and note that (2.16), we have

$$(2.28) \quad C \cdot \sum_{n=n_0+1}^{\infty} P_n \leq z_{n_0} + \sum_{n=n_0+1}^{\infty} v_n^{1-\lambda}.$$

Note that  $z_{n_0} \leq E[U_{n_0}] \cdot v_{n_0}^{-\lambda} \leq M \cdot v_{n_0}^{-\lambda}$  and  $P[A_{n_0}] = 1$  if  $C \geq M \cdot v_{n_0}^{-\lambda}$ , choosing  $C$  according  $C > \max \{M \cdot v_{n_0}^{-\lambda}, (M \cdot v_{n_0}^{-\lambda} + \sum_{n=n_0+1}^{\infty} v_n^{1-\lambda})/\delta\}$  we obtain

$$(2.29) \quad \lim_{n \rightarrow \infty} P[A_n] = 1 - \sum_{n=n_0+1}^{\infty} P_n > 1 - \delta.$$

Thus the proof of the lemma is completed.

The following lemma can be found in [7].

LEMMA 2.4. Let  $\{f_n(\cdot)\}_{n=1}^{\infty}$  and  $f(\cdot)$  be a sequence of density functions on  $R^N$  and a density function on  $R^N$ , respectively. If  $\lim_{n \rightarrow \infty} f_n(x) = f(x)$  for almost all  $x \in R^N$ , then  $\lim_{n \rightarrow \infty} \int_S |f_n(y) - f(y)| dy = 0$  uniformly for all Borel sets  $S$  in  $R^N$ .

### § 3. Convergences.

Let  $K(\cdot)$  be a real-valued Borel function on  $R^N$  satisfying

$$(K1) \quad K(y) \geq 0 \quad \text{for all } y \in R^N,$$

$$(K2) \quad \sup_y K(y) = K < \infty,$$

$$(K3) \quad \int_{R^N} K(y) dy = 1,$$

$$(K4) \quad \lim_{\|y\| \rightarrow \infty} \|y\| \cdot K(y) = 0 \quad \text{where } \|y\| = \left(\sum_{i=1}^N y_i^2\right)^{1/2} \text{ for } y = (y_1, \dots, y_N) \in R^N,$$

and let  $\{h_n\}_{n=1}^{\infty}$  be a sequence of real numbers satisfying

$$(H1) \quad 1 \geq h_n > 0 \quad \text{for all } n \geq 1,$$

$$(H2) \quad \lim_{n \rightarrow \infty} h_n = 0.$$

Then we can define the sequence  $\{K_n(x, y)\}_{n=1}^{\infty}$  for  $x, y \in R^N$ ,

$$(3.1) \quad K_n(x, y) = h_n^{-N} \cdot K[h_n^{-1}(x - y)] \quad \text{for } n = 1, 2, \dots.$$

The following lemma can be found in [5].

LEMMA 3.1. Let  $g(\cdot)$  be a continuous and bounded function on  $R^N$  and  $\int_{R^N} |g(x)| dx < \infty$ . Then, it holds that  $\lim_{n \rightarrow \infty} \left| \int_{R^N} K_n(x, y) g(y) dy - g(x) \right| = 0$  at all  $x \in R^N$ , where  $K_n(x, y)$  is defined by (3.1).

If  $f(\cdot|A)$  and  $f(\cdot|B)$  are continuous density function on  $R^N$  then o.d.f.  $D(\cdot)$  is also continuous and bounded function on  $R^N$ .

And for  $x \in R^N$ , we have

$$(3.2) \quad \begin{aligned} E[\rho(\theta_n) \cdot K_n(x, X_n) | (X_1, \theta_1) \cdots (X_{n-1}, \theta_{n-1})] \\ = E[\rho(\theta_n) \cdot K_n(x, X_n)] = \int_{R^N} K_n(x, y) D(y) dy \quad \text{for } n = 1, 2, \dots \end{aligned}$$

where

$$(3.3) \quad \begin{aligned} \rho(\Theta_n) &= 1 && \text{if } \Theta_n = A \\ &= -1 && \text{if } \Theta_n = B. \end{aligned}$$

In this paper, we put

$$(3.4) \quad D_n^*(x) = E[\rho(\Theta_n) \cdot K_n(x, X_n)] \quad \text{for } n = 1, 2, \dots.$$

In view of the above arguments, we shall construct the following algorithm which is an application of stochastic approximation methods.

LEARNING ALGORITHM. Let  $\{a_n\}_{n=1}^\infty$  be a sequence of real numbers satisfying

$$(A1) \quad a_n > 0 \ (n = 1, 2, \dots) \text{ and } \sum_{n=1}^\infty a_n = \infty,$$

$$(A2) \quad \lim_{n \rightarrow \infty} a_n = 0.$$

Then  $D_n(x)$  is given by the recursive relation as follows

$$(3.5) \quad \begin{aligned} D_0(x) &\equiv 0, \quad x \in R^N \\ D_{n+1}(x) &= D_n(x) + a_{n+1}(\rho(\Theta_{n+1})K_{n+1}(x, X_{n+1}) - D_n(x)) \end{aligned}$$

for  $n \geq 0$  and  $x \in R^N$ .

The above algorithm is transformed to the following one

$$(3.6) \quad D_n(x) = \sum_{i=1}^n \prod_{j=i+1}^n (1 - a_j) a_i \cdot \rho(\Theta_i) \cdot K_i(x, X_i), \quad \text{where } \prod_{j=n+1}^\infty (1 - a_j) = 1.$$

THEOREM 3.1. Let  $f(\cdot|A)$  and  $f(\cdot|B)$  be continuous on  $R^N$ .

(i) If  $\lim_{n \rightarrow \infty} a_n h_n^{-N} = 0$ , then it holds that

$$(3.7) \quad \lim_{n \rightarrow \infty} E \left[ \int_{R^N} (D_n(x) - D(x))^2 dx \right] = 0.$$

(ii) If  $\sum_{n=1}^\infty a_n^2 h_n^{-N} < \infty$ , then it holds that

$$(3.8) \quad \lim_{n \rightarrow \infty} \int_{R^N} (D_n(x) - D(x))^2 dx = 0 \quad \text{with pr. 1 and (3.7).}$$

PROOF. For each  $n \geq 1$ , we put

$$(3.9) \quad A_n = \int_{R^N} (E[D_n(x)] - D(x))^2 dx,$$

$$(3.10) \quad U_n = \int_{R^N} (D_n(x) - E[D_n(x)])^2 dx$$

and

$$M = \sup_x |D(x)|.$$

First, we shall prove that  $\lim_{n \rightarrow \infty} A_n = 0$ . From the construction of  $D_n(x)$ , (3.2) and (3.4), we have

$$(3.11) \quad \begin{aligned} \sup_x |E[D_n(x)] - D(x)| &\leq (1 - a_{n+1}) \cdot \sup_x |E[D_n(x)] - D(x)| \\ &\quad + a_{n+1} \cdot |D_{n+1}^*(x) - D(x)| \\ &\leq (1 - a_{n+1}) \sup_x |E[D_n(x)] - D(x)| + 2M \cdot a_{n+1} \end{aligned}$$

for all  $n \geq n_0$ , where  $n_0$  is a positive integer such that  $0 < a_n \leq 1$  for all  $n \geq n_0$ . Therefore, from Lemma 2.1, we have

$$(3.12) \quad \sup_x |E[D_n(x)] - D(x)| \leq M_1 \quad \text{for all } n \geq 1,$$

where  $M_1$  is some positive constant. By the same arguments similar to (3.11), we have

$$(3.13) \quad A'_{n+1} \leq (1 - a_{n+1})A'_n + a_{n+1} \int_{R^N} |D_{n+1}^*(x) - D(x)| dx$$

for all  $n \geq n_0$ , where

$$(3.14) \quad A'_n = \int_{R^N} |E[D_n(x)] - D(x)| dx \quad \text{for } n = 1, 2, \dots.$$

In (3.13), noting that

$$(3.15) \quad |D_n^*(x) - D(x)| \leq q_A \cdot \left| \int_{R^N} K_n(x, y) f(y|A) dy - f(x|A) \right| \\ + q_B \cdot \left| \int_{R^N} K_n(x, y) f(y|B) dy - f(x|B) \right|$$

for all  $n \geq 1$  and from Lemma 2.4 and Lemma 3.1, we have

$$(3.16) \quad \lim_{n \rightarrow \infty} \int_{R^N} |D_n^*(x) - D(x)| dx = 0.$$

Therefore, from Lemma 2.1, we have

$$(3.17) \quad \lim_{n \rightarrow \infty} A'_n = 0.$$

And noting that

$$(3.18) \quad A_n \leq \sup_x |E[D_n(x)] - D(x)| \cdot A'_n \\ \leq M_1 \cdot A'_n \quad \text{for all } n \geq 1.$$

Thus, we have  $\lim_{n \rightarrow \infty} A_n = 0$ .

Noting that  $\{(X_n, \Theta_n)\}_{n=1}^\infty$  is a sequence of independent random vectors, we have

$$(3.19) \quad E[U_{n+1} | (X_1, \Theta_1), \dots, (X_n, \Theta_n)] \\ \leq (1 - a_{n+1})U_n + a_{n+1}^2 \cdot E \left[ \int_{R^N} (\rho(\Theta_{n+1})K_{n+1}(x, X_{n+1}) - D_{n+1}^*(x))^2 dx \right]$$

with *pr.* 1 for all  $n \geq n_0$ . From (K2) and  $\sup_x |D(x)| = M$ , we have

$$(3.20) \quad E \left[ \int_{R^N} (\rho(\Theta_n)K_n(x, X_n) - D_n^*(x))^2 dx \right] \leq 2h_n^{-N} \cdot K + 2M \quad \text{for all } n \geq 1.$$

Therefore, from Lemma 2.2, if  $\sum_{n=1}^\infty a_n^2 h_n^{-N} < \infty$  then  $\lim_{n \rightarrow \infty} E[U_n] = 0$ , and  $\lim_{n \rightarrow \infty} U_n = 0$  with *pr.* 1. And taking the expectation on the both side (3.19) and by (3.20), we have

$$(3.21) \quad E[U_{n+1}] \leq (1 - a_{n+1})E[U_n] + 2K \cdot a_{n+1}^2 h_{n+1}^{-N} + 2Ma_{n+1}^2 \quad \text{for all}$$

$n \geq n_0$ . Therefore, from Lemma 2.1, if  $\lim_{n \rightarrow \infty} a_n h_n^{-N} = 0$  then  $\lim_{n \rightarrow \infty} E[U_n] = 0$ .

Thus the proof of the theorem is completed.

It is easily seen that for any  $\varepsilon > 0$  there exists a bounded Borel set  $S_\varepsilon$  in  $R^N$  such that

$$(3.22) \quad |P_{D_n}(e) - P_D(e)| \leq \int_{R^N} |D_n(x) - D(x)| \cdot I_{S_\varepsilon}(x) dx + \varepsilon$$

for all  $n \geq 1$ , where  $I_S(\cdot)$  is the indicator function of  $S$  (see [10]).

By the above argument and Theorem 3.1, we have the following corollary.

COROLLARY 3.1.1. *Let  $f(\cdot|A)$  and  $f(\cdot|B)$  be continuous densities on  $R^N$ .*

(i) *If  $\lim_{n \rightarrow \infty} a_n h_n^{-N} = 0$ , then  $\{D_n(\cdot)\}_{n=1}^\infty$  is AO(I).*

(ii) *If  $\sum_{n=1}^\infty a_n^2 h_n^{-N} < \infty$ , then  $\{D_n(\cdot)\}_{n=1}^\infty$  is AO(I) and AO(II).*

NOTE ON DENSITY ESTIMATION. Consider a sequence  $X_1, X_2, \dots$  of independent identically distributed  $N$ -dimensional random vectors having a probability density function  $f(\cdot)$ .

H. Yamato [9] proposed the recursive estimator of the form

$$(3.23) \quad \hat{f}_n(x) = n^{-1} \sum_{j=1}^n K_j(x, X_j) \quad \text{for all } n \geq 1 \text{ and } x \in R^N,$$

where  $K_j(x, y)$  is defined by (3.1), and he showed  $\lim_{n \rightarrow \infty} E|\hat{f}_n(x) - f(x)|^2 = 0$  at all points  $x \in R^N$  if  $f(\cdot)$  is continuous and  $\lim_{n \rightarrow \infty} n h_n^N = \infty$ .

In this problem, we consider a following modified algorithm

$$(3.24) \quad \begin{aligned} f_0(x) &= 0 & \text{for all } x \in R^N \\ f_{n+1}(x) &= f_n(x) + a_{n+1}(K_{n+1}(x, X_{n+1})) & \text{for } n \geq 0, x \in R^N. \end{aligned}$$

If we put  $a_n = \frac{1}{n}$  ( $n = 1, 2, \dots$ ) then (3.24) is same as (3.23).

And in this case, by the same arguments similar to Theorem 3.1, it is easily seen that  $\lim_{n \rightarrow \infty} E(f_n(x) - f(x))^2 = 0$  at all  $x \in R^N$  if  $\lim_{n \rightarrow \infty} a_n h_n^{-N} = 0$  and  $\lim_{n \rightarrow \infty} (f_n(x) - f(x))^2 = 0$  with *pr. 1* at all  $x \in R^N$  if  $\sum_{n=1}^\infty a_n^2 h_n^{-N} < \infty$ .

#### § 4. Rates of Convergences.

Let  $K(\cdot)$  be a real-valued Borel function on  $R^N$  satisfying (K1), (K2), (K3), (K4) and

$$(K5) \quad \int_{R^N} \|y\| K(y) dy = K_0 < \infty.$$

And let  $\{a_n\}_{n=1}^\infty$  and  $\{h_n\}_{n=1}^\infty$  be two sequences of real numbers satisfying the conditions in § 3 ((A1), (A2) and (H1), (H2), respectively). In this section, we assume that the above conditions are always satisfied.

ASSUMPTION 1.  $f(\cdot|A)$  and  $f(\cdot|B)$  are continuous functions on  $R^N$ . And there exists a constant  $0 < C_0 < \infty$  such that

$$(4.1) \quad \max_{\theta \in \{A, B\}} \int_{R^N} |f(x+y|\theta) - f(y|\theta)| dy \leq C_0 \cdot \|x\|$$

for all  $x \in R^N$ .

ASSUMPTION 2.  $f(\cdot|A)$  and  $f(\cdot|B)$  satisfy uniform Lipschitz conditions with positive constants  $C_A$  and  $C_B$ , respectively. And we put  $C_f = \max\{C_A, C_B\}$ .

THEOREM 4.1. Let Assumption 1 or Assumption 2 be satisfied. And if there exist two positive constant  $0 < \alpha_1, \alpha_2 \leq 1$  and some positive integer  $n_0$  such that

$$(4.2) \quad (1 - a_{n+1}) \frac{h_n}{h_{n+1}} \leq (1 - \alpha_1 a_{n+1}) \quad \text{for all } n \geq n_0,$$

$$(4.3) \quad (1 - a_{n+1}) \frac{a_n h_n^{-N}}{a_{n+1} h_{n+1}^{-N}} \leq (1 - \alpha_2 a_{n+1}) \quad \text{for all } n \geq n_0,$$

then there exists a constant  $0 < C < \infty$  such that

$$(4.4) \quad E \left[ \int_{R^N} (D_n(x) - D(x))^2 dx \right] \leq C \cdot b_n \quad \text{for all } n \geq 1$$

where

$$(4.5) \quad b_n = \max\{h_n, a_n h_n^{-N}\} \quad \text{for each } n \geq 1.$$

PROOF. Let  $A_n, A'_n$  and  $U_n$  be defined by (3.9), (3.14) and (3.10), respectively.

First, if Assumption 1 holds then

$$(4.6) \quad \begin{aligned} \int_{R^N} |D_n^*(x) - D(x)| dx &= \int_{R^N} \left| \int_{R^N} K(z) \cdot D(x - h_n z) dz - D(x) \right| dx \\ &\leq \int_{R^N} \int_{R^N} K(z) |f(x - h_n z|A) - f(x|A)| dz dx \\ &\quad + \int_{R^N} \int_{R^N} K(z) |f(x - h_n z|B) - f(x|B)| dz dx \\ &\leq 2K_0 \cdot C_0 \cdot h_n \quad \text{for all } n \geq 1. \end{aligned}$$

We apply Lemma 2.1 to (3.13). Then we have

$$(4.7) \quad A'_n \leq C_1 \cdot h_n \quad \text{for all } n \geq 1$$

and for some positive constant  $C_1$ . Therefore, by (3.18) we have

$$(4.8) \quad A_n \leq M_1 \cdot C_1 \cdot h_n \quad \text{for all } n \geq 1.$$

In (3.21), by the some argument similar to (4.7) we have

$$(4.9) \quad E[U^n] \leq C_2 \cdot a_n h_n^{-N} \quad \text{for all } n \geq 1$$

and for some positive constant  $C_2$ . Therefore from (4.8) and (4.9) we have (4.5).

Next, if Assumption 2 holds then we have

$$(4.10) \quad \sup_x |D_n^*(x) - D(x)| \leq C_f \cdot K_0 \cdot h_n \quad \text{for all } n \geq 1.$$

And note that

$$(4.11) \quad A_n \leq \sup_x |E[D_n(x)] - D(x)| \cdot A'_n.$$

and

$$\begin{aligned}
(4.12) \quad \sup_x |E[D_{n+1}(x)] - D(x)| &\leq (1 - a_{n+1}) \sup_x |E[D_n(x)] - D(x)| \\
&\quad + a_{n+1} \cdot \sup_x |D_{n+1}^*(x) - D(x)| \\
&\leq (1 - a_{n+1}) \sup_x |E[D_n(x)] - D(x)| + C_f \cdot K_0 \cdot h_{n+1} a_{n+1}.
\end{aligned}$$

for all  $n \geq 1$ .

We apply Lemma 2.1 to (4.12). Then we have

$$(4.13) \quad \sup_x |E[D_n(x)] - D(x)| \leq C_3 \cdot h_n \quad \text{for all } n \geq 1$$

and for some positive constant  $C_3$ . From (4.11) and  $\lim_{n \rightarrow \infty} A'_n = 0$ , we have

$$(4.14) \quad A_n \leq C_4 \cdot h_n \quad \text{for all } n \geq 1$$

and for some positive constant  $C_4$ . And (4.9) also holds. Therefore from (4.14) and (4.9), we have (4.5). Thus the proof of the theorem is completed.

**THEOREM 4.2.** *Let Assumption 1 or Assumption 2 be satisfied. And if there exist two positive constant  $0 < \alpha_1 \leq 1$ ,  $0 < \lambda < 1$  and same positive integer  $n_0$  such that (4.2) holds and*

$$(4.15) \quad (1 - a_{n+1}) \left( \frac{a_n^2 h_n^{-N}}{a_{n+1}^2 h_{n+1}^{-N}} \right)^\lambda \leq 1 \quad \text{for all } n \geq n_0$$

and

$$(4.16) \quad \sum_{n=1}^{\infty} (a_{n+1}^2 h_{n+1}^{-N})^{1-\lambda} < \infty,$$

then for any  $\delta > 0$  there exists a constant  $C(\delta) > 0$  such that

$$(4.17) \quad P \left[ \int_{\mathbb{R}^N} (D_n(x) - D(x))^2 dx \leq C(\delta) \cdot b'_n \quad \text{for all } n \geq 1 \right] > 1 - \delta,$$

where

$$(4.18) \quad b'_n = \max \{h_n, (a_n^2 h_n^{-N})^\lambda\} \quad \text{for all } n \geq 1.$$

**PROOF.** From (3.19), (3.20) and (H1), we have

$$\begin{aligned}
(4.19) \quad E[U_{n+1} | (X_1, \Theta_1), \dots, (X_n, \Theta_n)] \\
\leq (1 - a_{n+1}) U_n + 2(M + K) a_{n+1}^2 h_{n+1}^{-N} \quad \text{with pr. 1}
\end{aligned}$$

for all  $n \geq n_1$ , where  $n_1$  is some positive integer. Noting (3.6), (K2) and (K3) and applying Lemma 2.3 to (4.19), it holds that for any  $\delta > 0$  there exists a constant  $C'(\delta)$  such that

$$(4.20) \quad P[U_n \leq C'(\delta) (a_n^2 h_n^{-N})^\lambda \quad \text{for all } n \geq 1] > 1 - \delta.$$

And from the proof of Theorem 4.1 we have

$$(4.21) \quad A_n \leq C'' \cdot h_n \quad \text{for all } n \geq 1,$$

where  $C''$  is some positive constant. Therefore we put  $C(\delta) = \max \{C'', C'(\delta)\}$ , then (4.17) holds. Thus the proof of the theorem is completed.

If  $f(\cdot | A)$  and  $f(\cdot | B)$  have bounded supports, then we have

$$(4.22) \quad |P_{D_n}(e) - P_D(e)| \leq \int_{R^N} |D_n(x) - D(x)| I_S(x) dx \quad \text{for all } n \geq 1$$

where  $S$  is the bounded support of  $f(\cdot|A) + f(\cdot|B)$ . From (4.22), we have

$$(4.23) \quad |P_{D_n}(e) - P_D(e)| \leq \int_{R^N} |E[D_n(x)] - D(x)| dx \\ + \left[ \int_{R^N} (E[D_n(x)] - D_n(x))^2 dx \cdot \int_{R^N} I_S(x) dx \right]^{\frac{1}{2}}$$

for all  $n \geq 1$ . And noting the proof of Theorem 4.1 and Theorem 4.2 we have the following theorem.

**THEOREM 4.3.** *Let Assumption 1 or Assumption 2 be satisfied. And let  $f(\cdot|A)$  and  $f(\cdot|B)$  have bounded supports and  $\lim_{n \rightarrow \infty} a_n h_n^{-N} = 0$ .*

(i) *If the conditions in Theorem 4.1 hold, then  $\{D_n(\cdot)\}_{n+1}^\infty$  is AO-I $\{\beta_n\}$  where*

$$(4.24) \quad \beta_n = \max \{h_n, (a_n h_n^{-N})^{\frac{1}{2}}\} \quad \text{for each } n \geq 1.$$

(ii) *If the conditions in Theorem 4.2 hold, then  $\{D_n(\cdot)\}_{n+1}^\infty$  is AO-II $\{\beta'_n\}$  where*

$$(4.25) \quad \beta'_n = \max \{h_n, (a_n^2 h_n^{-N})^{\frac{1}{2}}\} \quad \text{for each } n \geq 1.$$

**EXAMPLES.** We put  $a_n = n^{-\alpha}$  and  $h_n = n^{-t}$  for each  $n \geq 1$ . And suppose that

$$(4.26) \quad \frac{1}{2} < \alpha \leq 1 \quad \text{and} \quad 0 < t < \frac{2\alpha - 1}{N}.$$

In this case, the conditions (4.2) and (4.3) in Theorem 4.1 are satisfied and the conditions (4.15) and (4.16) in Theorem 4.2 are also satisfied by  $\lambda$  such that

$$(4.27) \quad \frac{2\alpha - Nt - 1}{2\alpha - Nt} > \lambda > 0,$$

moreover (A1), (A2), (H1) and (H2) be satisfied.

And if we put  $\alpha = 1$  and  $t = \frac{1}{N+1}$  then we have

$$(4.28) \quad E \left[ \int_{R^N} (D_n(x) - D(x))^2 dx \right] \leq C \cdot n^{\frac{-1}{N+1}} \quad \text{for all } n \geq 1$$

and for some constant  $C > 0$ , and for any  $\delta > 0$  there exists a constant  $C(\delta)$  such that

$$(4.29) \quad P \left[ \int_{R^N} (D_n(x) - D(x))^2 dx \leq C(\delta) \cdot n^{-(1 + \frac{1}{N+1})\lambda} \quad \text{for all } n \geq 1 \right] > 1 - \delta$$

for any  $\lambda$  such that  $0 < \lambda < \frac{1}{N+2}$ .

Moreover, if  $f(\cdot|A)$  and  $f(\cdot|B)$  have bounded supports then  $\{D_n(\cdot)\}_{n+1}^\infty$  is AO-I $\{n^{\frac{-1}{2(N+1)}}\}$  and AO-II $\{n^{\frac{\lambda(N+2)}{2(N+1)}}\}$  for any  $0 < \lambda < \frac{1}{N+2}$ .

If we put  $\alpha = 1$  and  $t = \frac{1}{N+1}$ , then  $\{D_n(\cdot)\}_{n+1}^\infty$  is AO-I $\{n^{\frac{-1}{N+2}}\}$  and AO-II $\{n^{\frac{-\lambda(N+4)}{N+2}}\}$  for any  $0 < \lambda < \frac{1}{N+1}$ .

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