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ON THE WOLVERTON AND WAGNER'S ASYMPTOTICALLY OPTIMAL DISCRIMINANT FUNCTION

By

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1. Introduction

Suppose we have an observation \mathbf{x} , which may be a scalar or a vector, and we know apriori that it should have come from either of two populations π_1 and π_2 , which have the probability density functions $f_1(\mathbf{x})$ and $f_2(\mathbf{x})$ respectively and apriori probabilities q_1 and q_2 respectively. We assume that the losses due to two kinds of misclassification are same, where one misclassification is that if the observation is actually from π_1 we classify it as coming from π_2 and the other is that if the observation is actually from π_2 we classify it as coming from π_1 . Then according to the Bayes procedure, if

$$\frac{q_1 f_1(\mathbf{x})}{q_1 f_1(\mathbf{x}) + q_2 f_2(\mathbf{x})} \geq \frac{q_2 f_2(\mathbf{x})}{q_1 f_1(\mathbf{x}) + q_2 f_2(\mathbf{x})}$$

then we decide that the observation has come from π_1 , and otherwise we decide that the observation has come from π_2 . Equivalently if

$$D(\mathbf{x}) = q_1 f_1(\mathbf{x}) - q_2 f_2(\mathbf{x}) \geq 0$$

then we decide that it has come from π_1 and otherwise we decide that it has come from π_2 .

The purpose of this paper is to discuss the statistical properties of the estimate of $D(\mathbf{x})$ constructed by Wolverton and Wagner [6] by using the results in Yamato [7].

Let $X_1^1, X_2^1, X_3^1, \dots$ and $X_1^2, X_2^2, X_3^2, \dots$ be sequences of independent, identically distributed m -dimensional random vectors in the m -dimensional Euclidian space E_m , which have the probability density functions $f_1(\mathbf{x})$ and $f_2(\mathbf{x})$ respectively. Let $\rho_1, \rho_2, \rho_3, \dots$ be a sequence of independent identically distributed random variables with

$$\Pr(\rho_i=1)=q_1 \text{ and } \Pr(\rho_i=0)=q_2 \quad (i=1,2,3,\dots).$$

We assume that X_i^1, X_j^2, ρ_k are mutually independent for all $i=1, 2, \dots, j=1, 2, \dots$ and $k=1, 2, \dots$. In this paper we consider a sequential estimation of $D(\mathbf{x})$ with a scheme that we observe X_i^1 when $\rho_i=1$ and X_i^2 when $\rho_i=0$. Wolverton and Wagner [6] considered an estimate of $D(\mathbf{x})$ under the same sampling scheme given by

$$D_n(\mathbf{x}) = \frac{1}{n} \sum_{j=1}^n \left[\rho_j \frac{1}{h_j^m} K\left(\frac{\mathbf{x} - X_j^1}{h_j}\right) - (1 - \rho_j) \frac{1}{h_j^m} K\left(\frac{\mathbf{x} - X_j^2}{h_j}\right) \right]$$

and showed that under a certain condition on $f_1(\mathbf{x})$, $f_2(\mathbf{x})$, h_n , $k(\cdot)$

$$\int_{E_m} |D_n(\mathbf{x}) - D(\mathbf{x})|^2 d\mathbf{x}$$

converges to 0 in probability (with probability 1) and then $P_{D_n}(e)$ converges to $P_D(e)$ in probability (with probability 1), where $P_d(e)$ denote the probability of misclassification by using a discriminant function $d(\mathbf{x})$.

In the following sections we shall discuss the asymptotic unbiasedness, asymptotically uniform unbiasedness, consistency, uniform consistency and asymptotic normality of $D_n(\mathbf{x})$ by using Yamato[7]. Concerning its asymptotically uniform unbiasedness, Wolverton and Wagner[6] proved it in Lemma 2 under the assumption that $f_1(\mathbf{x})$ and $f_2(\mathbf{x})$ are uniformly continuous. In section 2 we shall, however, generalize it for continuous probability density functions $f_1(\mathbf{x})$ and $f_2(\mathbf{x})$ and moreover at the continuous point \mathbf{x} of $f_1(\mathbf{x})$ and $f_2(\mathbf{x})$.

In section 3 we shall treat the limits of the variance and the mean square error of $D_n(\mathbf{x})$ and the limit of $nh_n^m \text{Var} [D_n(\mathbf{x})]$.

In section 4 we shall treat the uniform consistency of $D_n(\mathbf{x})$.

In section 5 we shall treat the limit distribution of $D_n(\mathbf{x})$.

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2. Asymptotic unbiasedness

Theorem 1. *We suppose that the probability density functions $f_1(\mathbf{x})$ and $f_2(\mathbf{x})$ are continuous and that $\{h_n\}$ is a sequence of monotone decreasing positive numbers such that*

$$(2.1) \quad \lim_{n \rightarrow \infty} h_n = 0$$

Let $K(\mathbf{y})$ be a measurable function satisfying

$$(2.2) \quad \sup_{\mathbf{y} \in E_m} |K(\mathbf{y})| < \infty$$

$$(2.3) \quad \int_{E_m} K(\mathbf{y}) d\mathbf{y} = 1$$

$$(2.4) \quad \int_{E_m} |K(\mathbf{y})| d\mathbf{y} < \infty$$

where E_m denotes the m -dimensional Euclidian space and let $\{X_i^1\}$, $\{X_i^2\}$, $\{\rho_i\}$ be mutually independent sequences of random variables and vectors as described in section 1. Then

$$(2.5) \quad D_n(\mathbf{x}) = \frac{1}{n} \sum_{j=1}^n \left[\rho_j \frac{1}{h_j^m} K\left(\frac{\mathbf{x} - X_j^1}{h_j}\right) - (1 - \rho_j) \frac{1}{h_j^m} K\left(\frac{\mathbf{x} - X_j^2}{h_j}\right) \right]$$

is an asymptotically unbiased estimate of $D(\mathbf{x})$.

The following corollary can be found in Wolverton and Wagner [6], which we need to prove Theorem 5. In the following corollary, we assume the uniform continuity of the probability density function, which is satisfied when a population characteristic function is absolutely integrable.

Corollary 1. *If we assume the uniform continuity of the probability density functions $f_1(\mathbf{x})$ and $f_2(\mathbf{x})$ in Theorem 1, then we have*

$$(2.6) \quad \lim_{n \rightarrow \infty} \sup_{\mathbf{x} \in E_m} |E D_n(\mathbf{x}) - D(\mathbf{x})| = 0$$

Theorem 2. *We suppose that $\{h_n\}$ is a sequence of monotone decreasing positive numbers satisfying (2.1) and that the measurable function $K(\mathbf{y})$ satisfies (2.2), (2.3), (2.4) and*

$$(2.7) \quad \lim_{\mathbf{y} \rightarrow \infty} |\mathbf{y}|^m |K(\mathbf{y})| = 0$$

Let $\{\mathbf{X}_i^1\}$, $\{\mathbf{X}_i^2\}$, $\{\rho_i\}$ be mutually independent sequences of random variables and vectors as described in section 1. Then $D_n(\mathbf{x})$ is asymptotically unbiased at the point \mathbf{x} such that both $f_1(\mathbf{x})$ and $f_2(\mathbf{x})$ are continuous.

By applying Theorem 1, Corollary 1 and Theorem 2 in Yamato[7] on an inequality

$$(2.8) \quad |E D_n(\mathbf{x}) - D(\mathbf{x})| \leq q_1 |E \hat{f}_1(\mathbf{x}) - f_1(\mathbf{x})| + q_2 |E \hat{f}_2(\mathbf{x}) - f_2(\mathbf{x})|$$

we can easily obtain Theorem 1, Corollary 1 and Theorem 2, where

$$(2.9) \quad \hat{f}_1(\mathbf{x}) = \frac{1}{n} \sum_{j=1}^n \frac{1}{h_j^m} K\left(\frac{\mathbf{x} - \mathbf{X}_j^1}{h_j}\right)$$

$$(2.10) \quad \hat{f}_2(\mathbf{x}) = \frac{1}{n} \sum_{j=1}^n \frac{1}{h_j^m} K\left(\frac{\mathbf{x} - \mathbf{X}_j^2}{h_j}\right).$$

3. Consistency

Theorem 3. *We suppose that the probability density functions $f_1(\mathbf{x})$ and $f_2(\mathbf{x})$ are continuous and that $\{h_n\}$ is a sequence of monotone decreasing positive numbers satisfying (2.1) and*

$$(3.1) \quad \lim_{n \rightarrow \infty} n h_n^m = \infty.$$

Let the measurable function $K(\mathbf{y})$ satisfy (2.2) and (2.4) and let $\{\mathbf{X}_i^1\}$, $\{\mathbf{X}_i^2\}$, $\{\rho_i\}$ be mutually independent sequences of random vectors and variables as described in section 1. Then we have

$$(3.2) \quad \lim_{n \rightarrow \infty} \text{Var}[D_n(\mathbf{x})] = 0 \quad \text{at all points } \mathbf{x} \in E_m.$$

Furthermore if $K(\mathbf{y})$ satisfy (2.3), then we have

$$(3.3) \quad \lim_{n \rightarrow \infty} E |D_n(\mathbf{x}) - D(\mathbf{x})|^2 = 0.$$

Proof. We shall note at first that

$$(3.4) \quad \begin{aligned} \text{Var}[D_n(\mathbf{x})] \\ = E I_1^2 + E I_2^2 + E I_3^2 + E I_4^2 - 2 E I_2 I_4 \end{aligned}$$

where

$$(3.5) \quad \begin{aligned} I_1 &= \frac{1}{n} \sum_{j=1}^n \rho_j \frac{1}{h_j^m} \left[K\left(\frac{\mathbf{x} - \mathbf{X}_j^1}{h_j}\right) - E K\left(\frac{\mathbf{x} - \mathbf{X}_j^1}{h_j}\right) \right] \\ I_2 &= \frac{1}{n} \sum_{j=1}^n (\rho_j - q_1) \frac{1}{h_j^m} E K\left(\frac{\mathbf{x} - \mathbf{X}_j^1}{h_j}\right) \\ I_3 &= \frac{1}{n} \sum_{j=1}^n (1 - \rho_j) \frac{1}{h_j^m} \left[K\left(\frac{\mathbf{x} - \mathbf{X}_j^2}{h_j}\right) - E K\left(\frac{\mathbf{x} - \mathbf{X}_j^2}{h_j}\right) \right] \\ I_4 &= \frac{1}{n} \sum_{j=1}^n (1 - \rho_j - q_2) \frac{1}{h_j^m} E K\left(\frac{\mathbf{x} - \mathbf{X}_j^2}{h_j}\right). \end{aligned}$$

We can show easily that

$$(3.6) \quad \begin{aligned} E I_1^2 &= q_1 \text{Var}[\hat{f}_1(\mathbf{x})] \\ E I_2^2 &\leq \frac{1}{n} q_1 q_2 \|\mathbf{f}_1\| \left\{ \int_{E_m} |K(\mathbf{y})| d\mathbf{y} \right\}^2 \\ E I_3^2 &= q_2 \text{Var}[\hat{f}_2(\mathbf{x})] \\ E I_4^2 &\leq \frac{1}{n} q_1 q_2 \|\mathbf{f}_2\| \left\{ \int_{E_m} |K(\mathbf{y})| d\mathbf{y} \right\}^2. \end{aligned}$$

where $\|\mathbf{f}_1\| = \max \mathbf{f}_1(\mathbf{x})$ and $\|\mathbf{f}_2\| = \max \mathbf{f}_2(\mathbf{x})$, whose existence is secured by the continuity of $\mathbf{f}_1(\mathbf{x})$ and $\mathbf{f}_2(\mathbf{x})$. By applying (3.6) and the Schwarz's inequality on (3.4), we have

$$(3.7) \quad \text{Var}[D_n(\mathbf{x})] = q_1 \text{Var}[\hat{f}_1(\mathbf{x})] + q_2 \text{Var}[\hat{f}_2(\mathbf{x})] + O\left(\frac{1}{n}\right).$$

Theorem 3 in Yamato[7] implies that the right side of (3.7) tends to zero as n tends to ∞ . Thus (3.2) was established.

Next, it is obvious that

$$(3.8) \quad E |D_n(\mathbf{x}) - D(\mathbf{x})|^2 = \text{Var}[D_n(\mathbf{x})] + |E D_n(\mathbf{x}) - D(\mathbf{x})|^2.$$

The combination of (3.2), (3.8) and Theorem 1 leads us to (3.3), thus proving the theorem.

This theorem furnishes a sufficient condition for $D_n(\mathbf{x})$ to be consistent. In Theorem 3, if we assume furthermore that $K(\mathbf{y})$ satisfies (2.7), then we have that both $\text{Var}[D_n(\mathbf{x})]$ and $E|D_n(\mathbf{x}) - D(\mathbf{x})|^2$ converge to zero at all points \mathbf{x} at which both probability density functions $f_1(\mathbf{x})$ and $f_2(\mathbf{x})$ are continuous.

Theorem 4. *We suppose that the probability density functions $f_1(\mathbf{x})$ and $f_2(\mathbf{x})$ are continuous and that for the sequence of monotone decreasing positive numbers $\{h_n\}$ satisfying (2.1) there exists a limit with*

$$(3.9) \quad \lim_{n \rightarrow \infty} \frac{1}{n} \sum_{j=1}^n \frac{h_n^m}{h_j^m} = \alpha \quad (0 \leq \alpha \leq 1).$$

Let the measurable function $K(\mathbf{y})$ satisfy (2.2) and (2.4) and let $\{X_i^1\}$, $\{X_i^2\}$, $\{\rho_i\}$ be mutually independent sequences of random variables and vectors as described in section 1. Then for $D_n(\mathbf{x})$ defined by (2.5) we have

$$(3.10) \quad \lim_{n \rightarrow \infty} n h_n^m \text{Var}[D_n(\mathbf{x})] \\ = \alpha \{q_1 f_1(\mathbf{x}) + q_2 f_2(\mathbf{x})\} \int_{E_m} |K(\mathbf{y})|^2 d\mathbf{y}.$$

Proof. It follows from (3.7) that

$$(3.11) \quad n h_n^m \text{Var}[D_n(\mathbf{x})] = q_1 \cdot n h_n^m \text{Var}[\hat{f}_1(\mathbf{x})] \\ + q_2 n h_n^m \text{Var}[\hat{f}_2(\mathbf{x})] + 0(h_n^m).$$

Hence by applying Theorem 4 in Yamato[7] on (3.11) we have (3.10). Thus the theorem is proved.

4. Uniform consistency

Theorem 5. *We suppose that the probability density functions $f_1(\mathbf{x})$ and $f_2(\mathbf{x})$ are uniformly continuous and that a sequence of monotone decreasing positive numbers $\{h_n\}$ satisfy (2.1) and*

$$(4.1) \quad \lim_{n \rightarrow \infty} n^{1/2} h_n^m = \infty.$$

Let the measurable function $K(\mathbf{y})$ satisfy (2.3) and (2.4), its Fourier transform

$$(4.2) \quad k(\mathbf{u}) = \int_{E_m} e^{i\mathbf{u}'\mathbf{y}} K(\mathbf{y}) d\mathbf{y}$$

be absolutely integrable and $k(\mathbf{u})$ be nondecreasing in negative part and nonincreasing in positive part for each argument.

Let $\{X_i^1\}$, $\{X_i^2\}$, $\{\rho_i\}$ be mutually independent sequences of random variables and vectors as described in section 1. Then for $D_n(\mathbf{x})$ defined by (2.5) we have

$$(4.3) \quad \sup_x |D_n(\mathbf{x}) - D(\mathbf{x})| \xrightarrow{P} 0$$

where (4.2) denotes that $\sup |D_n(\mathbf{x}) - D(\mathbf{x})|$ converges to zero in probability as n tends to ∞ .

Proof. In terms of $k(\mathbf{u})$, the Fourier transform of $K(\mathbf{y})$, we have

$$(4.4) \quad \begin{aligned} D_n(\mathbf{x}) - E D_n(\mathbf{x}) &= \frac{1}{(2\pi)^m} \int_{E_m} \left\{ \frac{1}{n} \sum_{j=1}^n [\rho_j e^{iu'x_j^1} - q_1 \varphi_1(\mathbf{u})] k(h_j \mathbf{u}) \right\} e^{-iu'x} d\mathbf{u} \\ &\quad - \frac{1}{(2\pi)^m} \int_{E_m} \left\{ \frac{1}{n} \sum_{j=1}^n [(1 - \rho_j) e^{iu'x_j^2} - q_2 \varphi_2(\mathbf{u})] k(h_j \mathbf{u}) \right\} e^{-iu'x} d\mathbf{u} \end{aligned}$$

where $\varphi_1(\mathbf{u})$ and $\varphi_2(\mathbf{u})$ are the characteristic functions of $f_1(\mathbf{x})$ and $f_2(\mathbf{x})$ respectively. Therefore we have

$$(4.5) \quad \begin{aligned} \sup_x |D_n(\mathbf{x}) - E D_n(\mathbf{x})| &\leq \frac{1}{(2\pi)^m} \int_{E_m} \left| \frac{1}{n} \sum_{j=1}^n [\rho_j e^{iu'x_j^1} - q_1 \varphi_1(\mathbf{u})] k(h_j \mathbf{u}) \right| d\mathbf{u} \\ &\quad + \frac{1}{(2\pi)^m} \int_{E_m} \left| \frac{1}{n} \sum_{j=1}^n [(1 - \rho_j) e^{iu'x_j^2} - q_2 \varphi_2(\mathbf{u})] k(h_j \mathbf{u}) \right| d\mathbf{u}. \end{aligned}$$

By applying the Schwartz's inequality on (4.5)

$$(4.6) \quad \begin{aligned} E \sup_x |D_n(\mathbf{x}) - E D_n(\mathbf{x})| &\leq \frac{1}{(2\pi)^m} \int_{E_m} \left\{ \frac{1}{n^2} \sum_{j=1}^n E |\rho_j e^{iu'x_j^1} - q_1 \varphi_1(\mathbf{u})|^2 \cdot |k(h_j \mathbf{u})|^2 \right\}^{1/2} d\mathbf{u} \\ &\quad + \frac{1}{(2\pi)^m} \int_{E_m} \left\{ \frac{1}{n^2} \sum_{j=1}^n E |(1 - \rho_j) e^{iu'x_j^2} - q_2 \varphi_2(\mathbf{u})|^2 \cdot |k(h_j \mathbf{u})|^2 \right\}^{1/2} d\mathbf{u}. \end{aligned}$$

Since

$$E |\rho_j e^{iu'x_j^1} - q_1 \varphi_1(\mathbf{u})|^2 \leq 1,$$

$$E |(1 - \rho_j) e^{iu'x_j^2} - q_2 \varphi_2(\mathbf{u})|^2 \leq 1,$$

$\{h_n\}$ is the sequence of monotone decreasing positive numbers and $k(\mathbf{u})$ is nondecreasing in negative part and nonincreasing in positive part for each argument, by (4.5) we have

$$(4.6) \quad \begin{aligned} E \sup_x |D_n(\mathbf{x}) - E D_n(\mathbf{x})| &\leq \frac{1}{(2\pi)^m n} \int_{E_m} \left\{ n |k(h_n \mathbf{u})|^2 \right\}^{1/2} d\mathbf{u} \end{aligned}$$

$$\begin{aligned}
 & + \frac{1}{(2\pi)^m n} \int_{E_m} \left\{ n |k(h_n \mathbf{u})|^2 \right\}^{1/2} d\mathbf{u} \\
 & = \frac{2}{n^{1/2} h_n^m (2\pi)^m} \int_{E_m} |k(\mathbf{u})| d\mathbf{u}.
 \end{aligned}$$

By applying (4.1) on (4.6), we have

$$(4.7) \quad \lim_{n \rightarrow \infty} E \sup_{\mathbf{x}} |D_n(\mathbf{x}) - E D_n(\mathbf{x})| = 0.$$

It follows from (4.7) and Markov's inequality that

$$(4.8) \quad \sup_{\mathbf{x}} |D_n(\mathbf{x}) - E D_n(\mathbf{x})| \xrightarrow{P} 0.$$

Finally we remark the inequality

$$(4.9) \quad \begin{aligned}
 \sup_{\mathbf{x}} |D_n(\mathbf{x}) - D(\mathbf{x})| \\
 \leq \sup_{\mathbf{x}} |D_n(\mathbf{x}) - E D_n(\mathbf{x})| + \sup_{\mathbf{x}} |E D_n(\mathbf{x}) - D(\mathbf{x})|.
 \end{aligned}$$

By applying Corollay 1 and (4.8) on (4.9), we have (4.3). Thus the theorem is proved.

5. Asymptotic normality

Theorem 6. *We suppose that the probability density functions $f_1(\mathbf{x})$ and $f_2(\mathbf{x})$ are continuous and that for the sequence of monotone decreasing positive numbers $\{h_n\}$ satisfying (2.1) and (3.1) there exists a non zero limit with (3.9). Let the measurable function $K(\mathbf{y})$ satisfy (2.2) and (2.4) and let $\{X_i^1\}$, $\{X_i^2\}$, $\{\rho_i\}$ be mutually independent sequences of random variables and vectors as described in section 1. Then for $D_n(\mathbf{x})$ defined by (2.5) the distribution function of*

$$(5.1) \quad \frac{D_n(\mathbf{x}) - E D_n(\mathbf{x})}{\sqrt{\text{Var}[D_n(\mathbf{x})]}}$$

converges to the standardized normal distribution function at all points \mathbf{x} .

$h_n = 1/n^{r/m}$ ($0 < r < 1/2$) and $h_n = 1/(\log n)^{1/m}$ are examples of sequences of monotone decreasing positive numbers satisfying (2.1), (3.1), (4.1) and (3.9) with $\alpha = 1/(r + 1)$ and $\alpha = 1$ respectively.

Proof. If we put for any fixed \mathbf{x}

$$(5.2) \quad V_j^1 = \frac{1}{h_j^m} K\left(\frac{\mathbf{x} - X_j^1}{h_j}\right) \quad (j = 1, 2, 3, \dots)$$

$$V_j^2 = \frac{1}{h_j^m} K\left(\frac{\mathbf{x} - X_j^2}{h_j}\right) \quad (j = 1, 2, 3, \dots)$$

then $\{\rho_j V_j^1 - (1 - \rho_j) V_j^2\}$ ($j=1, 2, 3, \dots$) is a sequence of independent random variables and we have

$$(5.3) \quad \frac{D_n(\mathbf{x}) - ED_n(\mathbf{x})}{\sqrt{\text{Var}[D_n(\mathbf{x})]}} \\ = \frac{\sum_{j=1}^n \{\rho_j V_j^1 - (1 - \rho_j) V_j^2 - q_1 EV_j^1 + q_2 EV_j^2\}}{\sqrt{\text{Var} \left[\sum_{j=1}^n \{\rho_j V_j^1 - (1 - \rho_j) V_j^2\} \right]}}$$

Therefore by virtue of Lyapunov's condition it is enough to show that

$$(5.4) \quad \lim_{n \rightarrow \infty} \frac{\sum_{j=1}^n E |\rho_j V_j^1 - (1 - \rho_j) V_j^2 - q_1 EV_j^1 + q_2 EV_j^2|^3}{\left(\text{Var} \left[\sum_{j=1}^n \{\rho_j V_j^1 - (1 - \rho_j) V_j^2\} \right] \right)^{3/2}} = 0.$$

From Theorem 4 we have

$$(5.5) \quad \frac{h_n^m}{n} \text{Var} \left[\sum_{j=1}^n \{\rho_j V_j^1 - (1 - \rho_j) V_j^2\} \right] \\ = n h_n^m \text{Var} [D_n(\mathbf{x})] \\ \rightarrow \alpha \{q_1 f_1(\mathbf{x}) + q_2 f_2(\mathbf{x})\} \int_{E_m} K^2(\mathbf{y}) d\mathbf{y} (n \rightarrow \infty).$$

On the other hand, by an inequality

$$(5.6) \quad (a + b + c + d)^3 \leq 16 (a^3 + b^3 + c^3 + d^3) \text{ for } a, b, c, d \geq 0$$

we have

$$(5.7) \quad \sum_{j=1}^n E |\rho_j V_j^1 - (1 - \rho_j) V_j^2 - q_1 EV_j^1 + q_2 EV_j^2|^3 \\ \leq \sum_{j=1}^n E \{ |\rho_j (V_j^1 - EV_j^1)| + |(\rho_j - q_1) EV_j^1| \\ + |(1 - \rho_j) (V_j^2 - EV_j^2)| + |(1 - \rho_j - q_2) EV_j^2| \}^3 \\ \leq 16 \left\{ q_1 \sum_{j=1}^n E |V_j^1 - EV_j^1|^3 + q_2 \sum_{j=1}^n E |V_j^2 - EV_j^2|^3 \right. \\ \left. + q_1 q_2 (q_1^2 + q_2^2) \left(\sum_{j=1}^n E |V_j^1|^3 + \sum_{j=1}^n E |V_j^2|^3 \right) \right\}.$$

By (5.6) and (5.9) in Yamato[7], it turns out that the right hand side of (5.7) is smaller than

$$\begin{aligned}
 & 64\{q_1\|f_1\| + q_2\|f_2\|\} \frac{n}{h_n^{2m}} \int_{E_m} |K(z)|^3 dz \\
 & + 64n\{q_1\|f_1\|^3 + q_2\|f_2\|^3\} \left\{ \int_{E_m} |K(z)| dz \right\}^3 \\
 & + 16q_1 q_2 (q_1^2 + q_2^2) \cdot n \cdot \{\|f_1\|^3 + \|f_2\|^3\} \left\{ \int_{E_m} |K(z)| dz \right\}^3.
 \end{aligned}$$

Hence we have

$$\begin{aligned}
 (5.9) \quad & \lim_{n \rightarrow \infty} \frac{\sum_{j=1}^n E|\rho_j V_j^2 - (1-\rho_j)V_j^2 - q_1 E V_j^1 + q_2 E V_j^2|^3}{\left(\text{Var} \left[\sum_{j=1}^n \{\rho_j V_j^1 - (1-\rho_j) V_j^2\} \right] \right)^{3/2}} \\
 & \leq \lim_{n \rightarrow \infty} \frac{1}{\left(\frac{h_n^m}{n} \text{Var} \left[\sum_{j=1}^n \{\rho_j V_j^1 - (1-\rho_j) V_j^2\} \right] \right)^{3/2}} \\
 & \times \left(64\{q_1\|f_1\| + q_2\|f_2\|\} \frac{1}{(n h_n^m)^{1/2}} \int_{E_m} |K(z)|^3 dz \right. \\
 & + 64 \frac{h_n^{3m/2}}{n^{1/2}} \{q_1\|f_1\|^3 + q_2\|f_2\|^3\} \left\{ \int_{E_m} |K(z)| dz \right\}^3 \\
 & \left. + 16 q_1 q_2 (q_1^2 + q_2^2) \frac{h_n^{3m/2}}{n^{1/2}} \{\|f_1\|^3 + \|f_2\|^3\} \left\{ \int_{E_m} |K(z)| dz \right\}^3 \right).
 \end{aligned}$$

By applying (2.1), (2.2), (2.4), (3.1) and (5.5) on (5.9) we have (5.4), which leads us to the completion of the theorem.

Thus we have obtained the asymptotic normality of $D_n(x)$. We considered its property under the assumption that for $\{h_n\}$ there exists a non zero limit with (3.9) and the auther wishes to develop the asymptotic normality of $D_n(x)$ without this assumption on another occasion.

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Errata

Page	Line	Wrong	Corrected
13	↑9	pifferentiable	differentiable