

## NONPARAMETRIC ESTIMATION OF MATUSITA'S MEASURE OF AFFINITY BETWEEN ABSOLUTELY CONTINUOUS DISTRIBUTIONS

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(Received Dec. 14, 1977; revised July 26, 1979)

### Abstract

Let  $F$  and  $G$  be two distribution functions defined on the same probability space which are absolutely continuous with respect to the Lebesgue measure with probability densities  $f$  and  $g$ , respectively. Matusita [3] defines a measure of the closeness, affinity, between  $F$  and  $G$  as:  $\rho = \rho(F, G) = \int [f(x)g(x)]^{1/2} dx$ . Based on two independent samples from  $F$  and  $G$  we propose to estimate  $\rho$  by  $\hat{\rho} = \int [\hat{f}(x)\hat{g}(x)]^{1/2} dx$ , where  $\hat{f}(x)$  and  $\hat{g}(x)$  are taken to be the kernel estimates of  $f(x)$  and  $g(x)$ , respectively, as given by Parzen [5].

In this note sufficient conditions are given such that

(i)  $E(\hat{\rho} - \rho)^2 \rightarrow 0$  as  $n \rightarrow \infty$  and (ii)  $\hat{\rho} \rightarrow \rho$  with probability one, as  $n \rightarrow \infty$ .

### 1. Introduction

Let  $F$  and  $G$  be two distribution functions (d.f.'s) defined on the same probability space. Assume that  $F$  and  $G$  admit densities  $f$  and  $g$ , respectively, with respect to a measure  $\mu$ . Matusita [3] defines a measure of the closeness between  $F$  and  $G$  as:

$$(1.1) \quad \rho = \rho(F, G) = \int [f(x)g(x)]^{1/2} d\mu(x).$$

Matusita [3] studies certain decision problems based on estimates of  $\rho$  when  $\mu$  is the counting measure, while Matusita [4] gives an extensive account of the mathematical properties of  $\rho$ . In several other papers, Matusita applied  $\rho$  to various inferential problems such as classification,

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\* Research supported in part by the National Research Council of Canada and by McMaster University Science and Engineering Research Board.

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independence, among others. He also furthered his mathematical studies of  $\rho$  in other publication, see Ahmad [2] for a list of references. Ahmad and Van Belle [1] introduced another measure of affinity when  $f$  and  $g$  are square integrable, viz.,

$$(1.2) \quad \lambda = \lambda(F, G) = 2 \int f(x)g(x)d\mu(x) / \left\{ \int f^2(x)d\mu(x) + \int g^2(x)d\mu(x) \right\}.$$

When  $\mu$  is the counting measure, Ahmad and Van Belle [1] propose certain test statistics based on estimates of  $\rho$  and  $\lambda$ , while when  $\mu$  is the Lebesgue measure, Ahmad [2] proposes a nonparametric estimate of  $\lambda$  using the kernel estimates of  $f(x)$  and  $g(x)$  and present its large sample properties and its applications in hypothesis testing. Note that  $\lambda$  is defined only when  $f$  and  $g$  are square integrable. This restriction motivates the development of inference about  $\rho$ . In this note a large class of nonparametric estimates of  $\rho$  is shown to be, under certain conditions, consistent in the second mean, and under a bit stronger conditions it is strongly consistent.

Let  $X_1, \dots, X_n$  and  $Y_1, \dots, Y_n$  be two independent random samples from  $F$  and  $G$  respectively. Assume that  $F$  and  $G$  admit probability density functions (p.d.f.'s)  $f$  and  $g$ , respectively, thus

$$(1.3) \quad \rho = \rho(F, G) = \int [f(x)g(x)]^{1/2} dx.$$

Furthermore, let  $k$  be a known p.d.f. satisfying the following conditions:

$$(1.4) \quad \sup_x k(u) < \infty \quad \text{and} \quad |u|k(u) \rightarrow 0 \quad \text{as} \quad |u| \rightarrow \infty,$$

and let  $\{a_n\}$  be a sequence of nonnegative real numbers such that  $a_n \rightarrow 0$  as  $n \rightarrow \infty$ . The kernel estimates of  $f(x)$  and  $g(x)$  are given by:

$$(1.5) \quad \hat{f}(x) = a_n^{-1} \int k[(x-u)/a_n] dF_n(u) = (na_n)^{-1} \sum_{i=1}^n k[(x-X_i)/a_n],$$

and

$$(1.6) \quad \hat{g}(x) = a_n^{-1} \int k[(x-u)/a_n] dG_n(u) = (na_n)^{-1} \sum_{i=1}^n k[(x-Y_i)/a_n].$$

The estimates (1.5) and (1.6) are due to Rosenblatt [6] and Parzen [5], and are called the kernel estimates. Thus a nonparametric estimate of  $\rho$  may be given by:

$$(1.7) \quad \hat{\rho} = \int [\hat{f}(x)\hat{g}(x)]^{1/2} dx.$$

It should be mentioned here that the results of this note are readily

extendable to affinity of several distribution, cf, Matusita [4].

Throughout this note we shall assume that the set of discontinuity points of  $f$  and  $g$  are, respectively, null sets.

## 2. Main results

**THEOREM 2.1.** *If  $na_n \rightarrow \infty$ , then*

$$(2.1) \quad E (\hat{\rho} - \rho)^2 \rightarrow 0 \quad \text{as } n \rightarrow \infty .$$

**PROOF.** Note that

$$(2.2) \quad E (\hat{\rho} - \rho)^2 \leq 2 E \left\{ \int (\hat{f}(x))^{1/2} [(\hat{g}(x))^{1/2} - (g(x))^{1/2}] dx \right\}^2 \\ + 2 E \left\{ \int (g(x))^{1/2} [(\hat{f}(x))^{1/2} - (f(x))^{1/2}] dx \right\}^2 .$$

It suffices to show that one term in the above right-hand side converges to 0 as  $n \rightarrow \infty$ . The second term may be shown to converge similarly. But using Fubini's theorem,

$$(2.3) \quad E \left\{ \int (\hat{f}(x))^{1/2} [(\hat{g}(x))^{1/2} - (g(x))^{1/2}] dx \right\}^2 \\ = \int \int E [\hat{f}(x)\hat{f}(y)]^{1/2} E [(\hat{g}(x))^{1/2} - (g(x))^{1/2}] [(\hat{g}(y))^{1/2} - (g(y))^{1/2}] dx dy \\ \leq \int \int [E \hat{f}(x)]^{1/2} [E \hat{f}(y)]^{1/2} E^{1/2} [(\hat{g}(x))^{1/2} - (g(x))^{1/2}]^2 \\ \cdot E^{1/2} [(\hat{g}(y))^{1/2} - (g(y))^{1/2}]^2 dx dy \\ = \left\{ \int [E \hat{f}(x)]^{1/2} E^{1/2} [(\hat{g}(x))^{1/2} - (g(x))^{1/2}]^2 dx \right\}^2 \\ \leq \int [E \hat{f}(x)] dx \cdot \int E [(\hat{g}(x))^{1/2} - (g(x))^{1/2}]^2 dx \\ = \int E [(\hat{g}(x))^{1/2} - (g(x))^{1/2}]^2 dx \\ \leq \int E |\hat{g}(x) - g(x)| dx ,$$

where the first equality follows since  $\hat{f}$  and  $\hat{g}$  are independent, the first and the second inequalities follow from Schwarz's inequality while the last inequality follows since  $\int E \hat{f}(x) dx = 1$  for all  $n \geq 1$  and since for all  $a, b \geq 0$ ,  $(a-b)^2 \leq |a^2 - b^2|$ . Since  $E |\hat{g}(x) - g(x)| \leq E^{1/2} [\hat{g}(x) - g(x)]^2 \leq \{\text{Var } \hat{g}(x) + [E \hat{g}(x) - g(x)]^2\}^{1/2}$ , it follows from Theorems 1A and 2A of Parzen [5] that for each continuity point of  $g$ ,  $E |\hat{g}(x) - g(x)| \rightarrow 0$  and  $n \rightarrow \infty$ , but  $E |\hat{g}(x) - g(x)| \leq E \hat{g}(x) + g(x)$  which is integrable for all  $n \geq 1$  and converges to  $2g(x)$  as  $n \rightarrow \infty$ , again an integrable function. Hence

the extended Lebesgue dominated convergence theorem, Royden [7] p. 89, applies and we have  $\int E |\hat{g}(x) - g(x)| dx \rightarrow 0$  as  $n \rightarrow \infty$ . Similarly we have

$$(2.4) \quad E \left\{ \int (g(x))^{1/2} [(\hat{f}(x))^{1/2} - (f(x))^{1/2}] dx \right\}^2 \leq \int E |\hat{f}(x) - f(x)| dx \rightarrow 0$$

as  $n \rightarrow \infty$ .

**THEOREM 2.2.** *If  $k$  is a continuous functions of bounded variation, if for any  $\gamma > 0$ ,  $\sum_{n=1}^{\infty} \exp(-\gamma n a_n^2) < \infty$ , if  $\inf_x f(x) > 0$  and  $\inf_x g(x) > 0$ , and if  $\int f(x)g(x)dx < \infty$ , then*

$$(2.5) \quad \hat{\rho} \rightarrow \rho \quad \text{with probability one as } n \rightarrow \infty.$$

**PROOF.** Note that,

$$(2.6) \quad |\hat{\rho} - \rho| = \left| \int [\hat{f}(x)\hat{g}(x)]^{1/2} dx - \int [f(x)g(x)]^{1/2} dx \right|$$

$$= \left| \int [|\hat{f}(x)\hat{g}(x) - f(x)g(x)|] \cdot \{[\hat{f}(x)\hat{g}(x)]^{1/2} + [f(x)g(x)]^{1/2}\}^{-1} dx \right|$$

$$\leq [\inf f(x) \inf g(x)]^{-1/2} \int |\hat{f}(x)\hat{g}(x) - f(x)g(x)| dx$$

$$\leq C \left\{ \int \hat{f}(x)|\hat{g}(x) - g(x)| dx + \int g(x)|\hat{f}(x) - f(x)| dx \right\}$$

$$\leq C \left\{ \sup_x |\hat{g}(x) - E \hat{g}(x)| + \int \hat{f}(x)|E \hat{g}(x) - g(x)| dx \right.$$

$$\left. + \sup_x |\hat{f}(x) - E \hat{f}(x)| + \int g(x)|E \hat{f}(x) - f(x)| dx \right\}.$$

Under the condition of the theorem it follows as in Lemma 2.2 (iii) of Ahmad [2] that the first and third terms above converge to 0 with probability one as  $n \rightarrow \infty$ . The second term is majorized by

$$\sup_x |\hat{f}(x) - E \hat{f}(x)| \int |E \hat{g}(x) - g(x)| dx + \int E \hat{f}(x) |E \hat{g}(x) - g(x)| dx,$$

where the first term converge to 0 with probability one as  $n \rightarrow \infty$ , since as seen in the proof of Theorem 2.1,  $\int |E \hat{f}(x) - f(x)| dx \rightarrow 0$ , as  $n \rightarrow \infty$ .

Also since  $E \hat{f}(x) |E \hat{g}(x) - g(x)| \rightarrow 0$  as  $n \rightarrow \infty$  at all continuity points  $x$  of  $f$  and  $g$  and since  $E \hat{f}(x) |E \hat{g}(x) - g(x)| \leq E \hat{f}(x) |E \hat{g}(x) + g(x)|$  which is integrable and converges to  $2f(x)g(x)$  again and integrable function, thus the extended Lebesgue dominated convergence theorem applies and  $\int E \hat{f}(x) |E \hat{g}(x) - g(x)| dx \rightarrow 0$  as  $n \rightarrow \infty$ . The fourth term in the right-

hand side of (2.6) also converge to 0 as  $n \rightarrow \infty$ .

*Remark 2.1.* An interesting and open question would be to discuss the limiting distribution of  $\hat{\rho}$ .

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