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# Empirical $L^2$ -distance between regression model and vector space

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**Abstract:** The paper is devoted to the estimation of the square distance between the regression function f and the subspace  $E_p$  spanned by the linearly independent functions  $g_1, \ldots, g_p$ . In order to estimate this measure of discreapancy, we propose an empirical  $L^2$ -distance between f and  $E_p$ , without weight and we show that it is invariant with respect to change of basis in  $E_p$ .

#### 1. Introduction

We consider the following regression model

(1.1) 
$$Y_{i,n} = f(t_{i,n}) + \varepsilon_{i,n}, \quad i = 1, \dots, n,$$

where f is a unknown real function, defined on the interval [0,1] and  $t_{1,n}=0 < t_{2,n} < \cdots < t_{n,n}=1$ , is a fixed sampling of the interval [0,1]. The errors  $\varepsilon_{i,n}$  form a triangular array of random variables with expectation zero and finite variance  $\sigma^2$ , and for any n, the random variables  $\varepsilon_{1,n}, \ldots, \varepsilon_{n,n}$  are independent.

Let  $g_1, \ldots, g_p$  be linearly independent functions defined on [0, 1] and let  $E_p$  be the vector space spanned by  $g_1, \ldots, g_p$ . We assume that the design  $\{t_{1,n}, \ldots, t_{n,n}\}$  is associated to a positive density function h in the interval [0, 1]. We denote  $L^2(d\mu)$ , where  $d\mu(t) = h(t) dt$ , the space of square integrable functions, equiped with the usual inner product  $\langle \ldots \rangle$ . As measure of discreapancy between the regression function f and the subspace  $E_p$ , we may use the square distance

(1.2) 
$$\mathcal{D}^{2}(f) = \min_{v \in E_{p}} \int_{0}^{1} |f(t) - v(t)|^{2} h(t) dt.$$

In this paper, we propose an empirical  $L^2$ -distance of  $\mathcal{D}^2(f)$ . We follow the procedure of Dette and Munk (1998), but without use of weights. Indeed Dette and Munk (1998) use weights satisfying particular conditions; this leads to a problem with the choice of weights. Generally, this empirical  $L^2$ -distance is used to test the null

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hypothesis  $H_0$ : " $f \in E_p$ " against the alternative hypothesis  $H_1$ : " $f \notin E_p$ ". The previous test has been the subject of several works: Dette and Munk (1998), Mohdeb and Mokkadem (2002, 2004) introduce a test statistic based on the estimation of the square of the distance of f to  $E_p$  with respect to a  $L^2$ -norm. Other related work includes that of Dette (1999), González-Manteiga and Cao (1993) and Stute (1997). We give the main result in the following section.

### 2. Main result

First, note that square distance  $\mathcal{D}^2(f)$  given in (1.2) may be expressed also as

(2.1) 
$$\mathcal{D}^{2}(f) = \frac{G(f, g_{1}, \dots, g_{p})}{G(g_{1}, \dots, g_{p})},$$

where  $G(v_1, \ldots, v_k)$  denotes the Gramian determinant  $|\langle v_i, v_j \rangle\rangle|_{i,j=1,\ldots,k}$  for  $v_1, \ldots, v_i$  in  $L^2(d\mu)$ . We need to estimate  $\mathcal{D}^2(f)$ ; for this, we use the observations  $Y = (Y_{1,n}, \ldots, Y_{n,n})'$  and we follow the procedure of Dette and Munk (1998), but without use of weights.

Let

$$\Delta_{i,n} = t_{i,n} - t_{i-1,n}, \quad i = 2, \dots, n, \quad \Delta_{1,n} = \Delta_{2,n},$$

$$W = \operatorname{diag}(\Delta_{i,n}h(t_{i,n}))_{i=1,\dots,n}$$

and let  $E_{p,n}$  be the vector space of  $\mathbb{R}^n$  spanned by  $(g_{1,n},\ldots,g_{n,n})$ , where

$$g_{k,n} = (g_k(t_{1,n}), \dots, g_k(t_{n,n}))', \quad k = 1, \dots, n.$$

Dette and Munk (1998) propose an estimator denoted  $\hat{M}^2$  of the distance  $\mathcal{D}^2(f)$  between f and the model  $E_p$ , and estimating the unknown inner products involved in the expression (2.1) by empirical expressions. To show the invariance of the estimator  $\hat{M}^2$  with respect to change of the basis in  $E_p$ , Dette and Munk (1998) are led to introduce suitable weights  $w_{i,n}, i, \ldots, n$  satisfying the following particular conditions:

$$\sum_{i=1}^{n} \Delta_{i,n} w_{i,n} h(t_{i,n}) = 1 \quad \forall n \ge 1$$

and

$$\langle g_k, g_l \rangle = \sum_{i=1}^n \Delta_{i,n} w_{i,n} h(t_{i,n}) g_k(t_{i,n}) g_l(t_{i,n}), \quad 1 \le k \le l \le p.$$

Weights  $w_{i,n}$ ,  $i, \ldots, n$  satisfying the previous conditions are generally not easy to obtainable (see the discussion on pages 783-784 in Dette and Munk (1998), and Theorem 2.1 therein).

In this paper, we define  $G_n(Y, g_1, \ldots, g_p)$  as the determinant obtained by replacing in (2.1) the inner product  $\langle f, f \rangle$  by

$$Y'WY = \sum_{i=1}^{n} \Delta_{i,n} h(t_{i,n}) Y_{i,n}^{2}$$

and  $\langle f, g_k \rangle$  by

$$Y'Wg_{k,n} = \sum_{i=1}^{n} \Delta_{i,n} h(t_{i,n}) g_k(t_{i,n}) Y_{i,n}, \quad k = 1, \dots, p.$$

We estimate  $\mathcal{D}^2(f)$  by

$$\mathcal{D}_n^2 = \frac{G_n(Y, g_1, \dots, g_p)}{G(g_1, \dots, g_p)}.$$

It is clear that  $\mathcal{D}^2(f)$  does not depend on the basis  $\{g_1,\ldots,g_p\}$  of  $E_p$ , since  $\mathcal{D}^2(f)$  is the square distance in  $L^2(d\mu)$  of f to  $E_p$ , but it is not obvious the same holds for  $\mathcal{D}_n^2(Y,g_1,\ldots,g_p)$ . The following result states that  $\mathcal{D}_n^2(Y,g_1,\ldots,g_p)$  does not depend on the choice of the basis  $\{g_1,\ldots,g_p\}$ .

**Theorem 2.1.** For any  $\Theta \in \mathbb{R}^n$ ,  $\mathcal{D}_n^2(\Theta, g_1, \dots, g_p)$  is invariant with respect to change of basis in  $E_p$ .

*Proof.* Let  $\mathcal{U} = \{u_1, \dots, u_p\}$  be an orthonormal basis of  $E_p$  and  $\mathcal{V} = \{v_1, \dots, v_p\}$  an arbitrary basis of  $E_p$ . It is sufficient to show that

$$\mathcal{D}_n^2(\Theta, u_1, \dots, u_p) = \mathcal{D}_n^2(\Theta, v_1, \dots, v_p).$$

We have for all  $f \in L^2(d\mu)$ ,

$$\mathcal{D}^{2}(f) = \langle f, f \rangle + P(\langle f, u_{1} \rangle, \dots, \langle f, u_{p} \rangle)$$

and

$$\mathcal{D}^{2}(f) = \langle f, f \rangle + Q(\langle f, v_{1} \rangle, \dots, \langle f, v_{p} \rangle),$$

where P (resp. Q) is a second degree polynomial whose coefficients depend only of the basis  $\mathcal{U}$  (resp.  $\mathcal{V}$ ).

Let  $A = (a_{ij})_{i,j=1,\dots,p}$  be the change-of-basis matrix, that is

(2.2) 
$$v_k = a_{k1}u_1 + \dots + a_{kp}u_p, \quad k = 1, \dots, p.$$

We have

$$\langle f, v_k \rangle = a_{k1} \langle f, u_1 \rangle + \dots + a_{kp} \langle f, u_p \rangle, \quad k = 1, \dots, p,$$

then

$$(\langle f, v_1 \rangle, \dots, \langle f, v_p \rangle) = H(\langle f, u_1 \rangle, \dots, \langle f, u_p \rangle),$$

where  $H: \mathbb{R}^p \longrightarrow \mathbb{R}^p$  is polynomial map, with  $H(c_1, \dots, c_p) = (c_1, \dots, c_p)A'$ .

Therefore

$$\mathcal{D}^{2}(f) = \langle f, f \rangle + Q \circ H(\langle f, u_{1} \rangle, \dots, \langle f, u_{p} \rangle),$$

whence

$$P(\langle f, u_1 \rangle, \dots, \langle f, u_p \rangle) = Q \circ H(\langle f, u_1 \rangle, \dots, \langle f, u_p \rangle), \quad \forall f \in L^2(d\mu).$$

Otherwise,  $\forall (z_1, \ldots, z_p) \in \mathbb{R}^p$ ,  $\exists f = \sum_{j=1}^p z_j u_j \in L^2(d\mu)$  such that  $z_j = \langle f, u_j \rangle$ ,  $j = 1, \ldots, p$ ; therefore

$$P(z_1,\ldots,z_p) = Q \circ H(z_1,\ldots,z_p), \quad \forall (z_1,\ldots,z_p) \in \mathbb{R}^p,$$

which leads to  $P \equiv Q \circ H$ .

Consider now  $\mathcal{D}_n^2(\Theta, u_1, \dots, u_p)$  and  $\mathcal{D}_n^2(\Theta, v_1, \dots, v_p)$ .

We have

$$\mathcal{D}_n^2(\Theta, u_1, \dots, u_p) = \Theta'W\Theta + P(\Theta'Wu_{1,n}, \dots, \Theta'Wu_{p,n})$$

and

$$\mathcal{D}_n^2(\Theta, v_1, \dots, v_p) = \Theta' W \Theta + Q \Big( \Theta' W v_{1,n}, \dots, \Theta' W v_{p,n} \Big),\,$$

where  $W = \operatorname{diag}(\Delta_{i,n}h(t_{i,n}))_{i=1,\dots,n}$ ,

$$u_{k,n} = (u_k(t_{1,n}), \dots, u_k(t_{n,n}))'$$

and

$$v_{k,n} = \left(v_k(t_{1,n}), \dots, v_k(t_{n,n})\right)'.$$

According to (2.2), we have also

$$v_{k,n} = a_{k1}u_{1,n} + \dots + a_{kp}u_{p,n}, \quad k = 1, \dots, p$$

and therefore

$$\Theta' W v_{k,n} = a_{k1} \Theta' W u_{1,n} + \dots + a_{kp} \Theta' W u_{p,n} \quad k = 1, \dots, p,$$

that is

$$(\Theta'Wv_{1,n},\ldots,\Theta'Wv_{p,n})=H(\Theta'Wu_{1,n},\ldots,\Theta'Wu_{p,n}).$$

Thus

$$\mathcal{D}_n^2(\Theta, v_1, \dots, v_p) = \Theta'W\Theta + Q \circ H(\Theta'Wu_{1,n}, \dots, \Theta'Wu_{p,n}),$$

as  $Q \circ H \equiv P$ , therefore

$$\mathcal{D}_n^2(\Theta, v_1, \dots, v_p) = \Theta'W\Theta + P\left(\Theta'Wu_{1,n}, \dots, \Theta'Wu_{p,n}\right)$$
$$= \mathcal{D}_n^2(\Theta, u_1, \dots, u_p).$$

The result is proved.

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