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## SYSTEMATIC ESTIMATION AND PREDICTION FOR PROCESSES WITH BOUNDED SUM

A minimax  $n$ -estimator (see Section 1) of the parameter  $m = (m_1, \dots, m_r)$ ,  $m_i = E(X_i)$ , is determined for the loss function (2) in the case when the random variables  $X_1, \dots, X_r$  satisfy the conditions

$$X_1 \geq 0, \dots, X_r \geq 0, \quad X_1 + \dots + X_r \leq s.$$

The problem of minimax  $n$ -prediction for such a process is also solved.

1. Let  $X = (X_1, \dots, X_r)$  be a random variable satisfying the conditions

$$(1) \quad X_1 \geq 0, \dots, X_r \geq 0, \quad X_1 + \dots + X_r = s, \quad s > 0, \quad r \in \{2, 3, \dots\}.$$

Let  $X^{(1)}, \dots, X^{(n)}$ ,  $X^{(j)} = (X_1^{(j)}, \dots, X_r^{(j)})$ ,  $j = 1, \dots, n$ , be independent random variables having the same distribution as  $X$ . Let  $\hat{X}^{(k)} = (X^{(1)}, \dots, X^{(k)})$ ,  $k = 1, \dots, n$ ,  $m_i = E(X_i)$ ,  $i = 1, \dots, r$ . We consider the situation when the statistician estimates systematically the parameter  $m = (m_1, \dots, m_r)$  in steps  $1, \dots, n$  on the basis of  $\hat{X}^{(1)}, \dots, \hat{X}^{(n)}$ , respectively, and when the loss function is the sum of the losses at particular steps. The sequence

$$d(\hat{X}) = \{d^{(1)}(\hat{X}^{(1)}), \dots, d^{(n)}(\hat{X}^{(n)})\}, \quad \hat{X} = \hat{X}^{(n)},$$

where

$$d^{(k)}(\hat{X}^{(k)}) = (d_1^{(k)}(\hat{X}^{(k)}), \dots, d_r^{(k)}(\hat{X}^{(k)})),$$

is called an  $n$ -estimator.

Let the loss function be

$$(2) \quad L(m, d) = \sum_{k=1}^n c_k \sum_{i,j=1}^r c_{ij} (d_i^{(k)}(\hat{X}^{(k)}) - p_i)(d_j^{(k)}(\hat{X}^{(k)}) - p_j),$$

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where  $c_k \geq 0$ ,  $k = 1, \dots, n$ , at least one  $c_k > 0$ , and the matrix  $C = \|c_{ij}\|_1^r$  is symmetric and nonnegative definite.

The problem is to determine a minimax  $n$ -estimator for the above loss function.

Let

$$Y_i^{(k)} = \sum_{t=1}^k X_i^{(t)}, \quad k = 1, \dots, n, \quad Y^{(k)} = (Y_1^{(k)}, \dots, Y_r^{(k)}).$$

Consider the  $n$ -estimator  $d(\hat{X})$  for which

$$(3) \quad d_i^{(k)}(\hat{X}^{(k)}) = \frac{Y_i^{(k)} + \beta_i \alpha}{k + \alpha}, \quad i = 1, \dots, r, \quad k = 1, \dots, n,$$

where  $\beta_i \geq 0$ ,  $\sum_{i=1}^r \beta_i = s$ ,  $\alpha > 0$ . For this  $n$ -estimator the risk function is

$$\begin{aligned} R(m, d) &= E[L(m, d(X))] \\ &= \sum_{k=1}^n c_k \sum_{i,j=1}^r c_{ij} E \left[ \left( \frac{Y_i^{(k)} + \beta_i \alpha}{k + \alpha} - m_i \right) \left( \frac{Y_j^{(k)} + \beta_j \alpha}{k + \alpha} - m_j \right) \right] \\ &= \sum_{k=1}^n \frac{c_k}{(k + \alpha)^2} \\ &\quad \times \sum_{i,j=1}^r c_{ij} \{ E[(Y_i^{(k)} - m_i)(Y_j^{(k)} - m_j)] + \alpha^2 (\beta_i - m_i)(\beta_j - m_j) \} \\ &= \sum_{k=1}^n \frac{c_k}{(k + \alpha)^2} \sum_{i,j=1}^r c_{ij} [k E(X_i X_j) - k m_i m_j + \alpha^2 (\beta_i - m_i)(\beta_j - m_j)]. \end{aligned}$$

But

$$\begin{aligned} (4) \quad &\sum_{i,j=1}^r c_{ij} X_i X_j - s \sum_{i=1}^r c_{ii} X_i \\ &= \sum_{i,j=1}^r c_{ij} X_i X_j - \frac{1}{2} \sum_{i,j=1}^r c_{ii} X_i X_j - \frac{1}{2} \sum_{i,j=1}^r c_{jj} X_i X_j \\ &= -\frac{1}{2} \sum_{i,j=1}^r (c_{ii} + c_{jj} - 2c_{ij}) X_i X_j \leq 0, \end{aligned}$$

since the matrix  $C$  is nonnegative definite and  $X_i \geq 0$ . Hence

$$(5) \quad R(m, d) \leq \sum_{k=1}^n \frac{c_k}{(k + \alpha)^2}$$

$$\times \left\{ \sum_{i,j=1}^r c_{ij}[-km_i m_j + \alpha^2(\beta_i - m_i)(\beta_j - m_j)] + ks \sum_{i=1}^r c_{ii} m_i \right\}.$$

Suppose that

$$(6) \quad \sum_{k=1}^n \frac{c_k}{(k + \alpha)^2} (\alpha^2 - k) = 0.$$

For the parameter  $\alpha$  determined in this way we have from (5)

$$(7) \quad R(m, d) \leq \sum_{k=1}^r \frac{c_k}{(k + \alpha)^2} \left[ \sum_{i,j=1}^r c_{ij}(\beta_i \beta_j - 2\beta_j m_i) \alpha^2 + k \sum_{i,j=1}^r c_{ii} \beta_j m_i \right] \\ = \sum_{k=1}^r \frac{c_k \alpha^2}{(k + \alpha)^2} \left[ \sum_{i,j=1}^r c_{ij} \beta_i \beta_j + \sum_{i,j=1}^r (c_{ii} - 2c_{ij}) \beta_j m_i \right].$$

Let

$$(8) \quad P(X = e_i) = m_i / s \stackrel{\text{df}}{=} p_i,$$

where  $e_1 = (s, 0, \dots, 0)$ ,  $\dots$ ,  $e_r = (0, 0, \dots, s)$ . Then

$$E(X_i) = m_i, \quad E(X_i X_j) = 0 \quad \text{for } i \neq j, \quad E(X_i^2) = s m_i$$

and

$$(9) \quad R(m, d) = \sum_{k=1}^r \frac{c_k \alpha^2}{(k + \alpha)^2} \left\{ \sum_{i,j=1}^r c_{ij} \beta_i \beta_j + \sum_{i,j=1}^r (c_{ii} - 2c_{ij}) \beta_j m_i \right\}.$$

Suppose that there exist a set  $A \subset R = \{1, \dots, r\}$ ,  $|A| \geq 2$ , and constants  $\beta_1, \dots, \beta_r, v$  such that

$$(10) \quad \sum_{j \in A} (c_{ii} - 2c_{ij}) \beta_j = v \quad \text{if } i \in A,$$

$$(11) \quad \sum_{j \in A} (c_{ii} - 2c_{ij}) \beta_j \leq v \quad \text{if } i \in R - A,$$

$\beta_i > 0$  for  $i \in A$ ,  $\beta_i = 0$  for  $i \in R - A$ ,  $\sum_{i=1}^r \beta_i = s$ . From [5] it follows that either such a set  $A$  and constants  $\beta_1, \dots, \beta_r$  exist, or  $c_{ij} = \text{const}$ .

We prove that for  $\beta_1, \dots, \beta_r$  chosen in this way and  $\alpha$  determined from (6) the  $n$ -estimator (3) is minimax.

Let  $\beta_1, \dots, \beta_r, v$  be chosen according to (10) and (11). For  $\alpha$  being the solution of (6) we find from (7) and (9) that

$$R(m, d) = \sum_{k=1}^r \frac{c_k \alpha^2}{(k + \alpha)^2} \left( \sum_{i,j=1}^r c_{ij} \beta_i \beta_j + v s \right) \stackrel{\text{df}}{=} c$$

if  $X$  is distributed according to (8) and

$$R(m, d) \leq c$$

for any distribution of  $X$ .

One can view the problem of determining a minimax  $n$ -estimator of the parameter  $m = (m_1, \dots, m_r)$  as the problem of finding a minimax strategy in a game against nature: the nature chooses a distribution of the random variable  $X$ , the statistician chooses an  $n$ -estimator of  $m = E(X)$  and the payoff is a risk function  $R(m, d)$ . Choose a mixed strategy  $\tau$  for the nature in the following way:

First choose the parameter  $p = (p_1, \dots, p_r)$  according to the density

$$(12) \quad g(p_1, \dots, p_r) = \begin{cases} \frac{\Gamma(\sum_{j=1}^q \alpha_{i_j})}{\Gamma(\alpha_{i_1}) \dots \Gamma(\alpha_{i_q})} p_{i_1}^{\alpha_{i_1}-1} \dots p_{i_q}^{\alpha_{i_q}-1} & \text{if } p_{i_k} > 0, \sum_{k=1}^q p_{i_k} = 1, \\ 0 & \text{otherwise,} \end{cases}$$

$\{i_1, \dots, i_q\} = A$ ,  $\alpha_i = \beta_i \alpha / s$  ( $\alpha$  and  $\beta_i$  determined in (6), (10) and (11)), and later choose the distribution  $P$  of the random variable  $X$  according to (8).

It can be verified that the  $n$ -estimator  $d$  defined by (3), (6), (10) and (11) is Bayes with respect to such a mixed strategy of nature and thus it is minimax.

2. Let the random variable  $X = (X_1, \dots, X_r)$  satisfy the conditions

$$X_1 \geq 0, \dots, X_r \geq 0, \quad X_1 + \dots + X_r \leq s, \quad s > 0, \quad r \in \{1, 2, \dots\},$$

and let the loss function be given by (2). Define  $X_{r+1} = s - \sum_{i=1}^r X_i$  and  $c_{i,r+1} = 0$  for  $i = 1, \dots, r+1$ . Then we are in the situation considered in the previous section and a minimax  $n$ -estimator may be determined using the formulae (3), (6), (10) and (11) for  $R = \{1, \dots, r+1\}$ .

3. Let  $X = (X_1, \dots, X_r)$  be a random variable satisfying the conditions (1) and let  $X^{(1)}, \dots, X^{(n+1)}$ ,  $X^{(j)} = (X_1^{(j)}, \dots, X_r^{(j)})$ ,  $j = 1, \dots, n+1$ , be independent random variables having the same distribution as  $X$ . Define

$$\hat{X}^{(k)} = (X^{(1)}, \dots, X^{(k)}), \quad k = 1, \dots, n,$$

$$Y_i^{(k)} = \sum_{t=1}^k X_i^{(t)}, \quad Y_i^k = \sum_{t=k+1}^{n+1} X_i^{(t)}, \quad i = 1, \dots, r,$$

$$Y^k = (Y_1^k, \dots, Y_r^k), \quad \hat{Y} = (Y^1, \dots, Y^n), \quad \hat{X} = \hat{X}^{(n)}.$$

At the  $k$ th step we predict the random variable  $Y^0$  using  $\hat{X}^{(k)}$ . Since the random variables  $X^{(t)}$  in  $Y^0$  are known for  $t \leq k$  it is sufficient to predict at this step  $Y^k$  using  $\hat{X}^{(k)}$ . Then let

$$d(\hat{X}) = \{d^{(1)}(\hat{X}^{(1)}), \dots, d^{(n)}(\hat{X}^{(n)})\}, \quad \text{where}$$

$$d^{(k)}(\widehat{X}^{(k)}) = (d_1^{(k)}(\widehat{X}^{(k)}), \dots, d_r^{(k)}(\widehat{X}^{(k)})),$$

be an  $n$ -predictor of  $Y$ . Let the loss function be

$$L(\widehat{Y}, d) = \sum_{k=1}^n c_k \sum_{i,j=1}^r c_{ij} (d_i^{(k)}(\widehat{X}^{(k)}) - Y_i^k) (d_j^{(k)}(\widehat{X}^{(k)}) - Y_j^k),$$

where  $c_k$  and  $c_{ij}$  satisfy the same conditions as in Section 1. For this loss function the risk function can be represented in the form

$$\begin{aligned} R(m, d) &= E[L(\widehat{Y}, d(\widehat{X}))] \\ &= \sum_{k=1}^n c_k \sum_{i,j=1}^r c_{ij} \{ E[(d_i^{(k)}(\widehat{X}^{(k)}) - (n-k+1)m_i) \\ &\quad \times (d_j^{(k)}(\widehat{X}^{(k)}) - (n-k+1)m_j)] \\ &\quad + E[(Y_i^k - (n-k+1)m_i)(Y_j^k - (n-k+1)m_j)] \}. \end{aligned}$$

Notice that the second term does not depend on the  $n$ -predictor  $d$ .

Let us study the  $n$ -predictor for which

$$(13) \quad d_i^{(k)}(\widehat{X}^{(k)}) = (n-k+1) \frac{Y_i^{(k)} + \beta_i \alpha}{k + \alpha}, \quad i = 1, \dots, r, k = 1, \dots, n.$$

For this  $n$ -predictor the risk function is

$$\begin{aligned} (14) \quad R(m, d) &= \sum_{k=1}^n c_k \left\{ \sum_{i,j=1}^r c_{ij} \left\{ \left[ \left( \frac{n-k+1}{k+\alpha} \right)^2 k + n - k + 1 \right] E(X_i X_j) \right. \right. \\ &\quad + \left[ \left( \frac{n-k+1}{k+\alpha} \right)^2 (\alpha^2 - k) - (n-k+1) \right] m_i m_j \\ &\quad \left. \left. + \left( \frac{n-k+1}{k+\alpha} \right)^2 \alpha^2 (\beta_i \beta_j - 2m_i \beta_j) \right\} \right\} \\ &\leq \sum_{k=1}^n c_k \left\{ \sum_{i,j=1}^r c_{ij} \left\{ \left[ \left( \frac{n-k+1}{k+\alpha} \right)^2 (\alpha^2 - k) - (n-k+1) \right] m_i m_j \right. \right. \\ &\quad + \alpha^2 \left( \frac{n-k+1}{k+\alpha} \right)^2 (\beta_i \beta_j - 2m_i \beta_j) \left. \right\} \\ &\quad + \sum_{i,j=1}^r c_{ii} \left[ \left( \frac{n-k+1}{k+\alpha} \right)^2 k + n - k + 1 \right] m_i \beta_j \left. \right\} \end{aligned}$$

by (4).

Let  $\alpha > 0$  be a solution of the equation

$$(15) \quad \varphi(\alpha) = \sum_{k=1}^r c_k \left[ \left( \frac{n-k+1}{k+\alpha} \right)^2 (\alpha^2 - k) - (n-k+1) \right] = 0.$$

This solution always exists except for the case when

$$(16) \quad c_1 = \dots = c_{n-1}, \quad c_n > 0.$$

Under the condition given in (15) the inequality (14) takes the form

$$R(m, d) \leq \sum_{k=1}^r c_k \alpha^2 \left( \frac{n-k+1}{k+\alpha} \right)^2 \left[ \sum_{i,j=1}^r c_{ij} \beta_i \beta_j + \sum_{i,j=1}^r (c_{ii} - 2c_{ij}) m_i \beta_j \right].$$

Notice that the expression in square brackets is the same as that in (7). Moreover, the predictor  $d$  given by (13) is Bayes with respect to the strategy of nature  $\tau$  defined in (12) (with  $\alpha$  obtained from (15)). Then in the same way as in Section 1 one can prove that the  $n$ -predictor defined by (10), (11), (13) and (15) is minimax.

When conditions (16) hold there does not exist a solution  $\alpha > 0$  of the equation  $\varphi(\alpha) = 0$  but still  $\varphi(\alpha) \rightarrow 0$  as  $\alpha \rightarrow \infty$ . In this case one can prove that the  $n$ -predictor  $d$  for which  $d_i^{(n)}(\hat{X}^{(n)}) = \beta_i$ ,  $\beta_i$  determined by (10) and (11), is a Bayes predictor of  $\hat{Y}$  with respect to the strategy  $\tau_0$  for which the condition (8) holds and

$$P(m_i = \beta_i \text{ for } i \in A, m_i = 0 \text{ for } i \notin A) = 1.$$

Then this  $n$ -predictor is minimax.

4. Similarly to Section 3 one can solve the problem of minimax  $n$ -prediction when

$$X_1 \geq 0, \dots, X_r \geq 0, \quad X_1 + \dots + X_r \leq s, \quad r \in \{1, 2, \dots\}, \quad s > 0.$$

For related problems see [1]–[5].

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