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for supremum of empirical processes  
for  $\phi$ -mixing sequences

B. L. S. PRAKASA RAO

Indian Statistical Institute, Delhi Centre  
7, SJSS Marg, New Delhi-110 016, India



# MOMENT INEQUALITIES FOR SUPREMUM OF EMPIRICAL PROCESSES FOR $\phi$ -MIXING SEQUENCES

B.L.S. PRAKASA RAO  
Indian Statistical Institute, New Delhi

## Abstract

Let  $\{X_n, -\infty < n < \infty\}$  be a stationary  $\phi$ -mixing process with the one-dimensional marginal distribution function  $F$  and the density function  $f$ . Let  $F_n(x)$  be the empirical distribution function based on the observations  $\{X_i, 1 \leq i \leq n\}$  and  $W_n^* = \sup_{-\infty < x < \infty} \sqrt{n}|F_n(x) - F(x)|$ . We obtain upper bounds for  $E(W_n^*)$ . We give an application to get bounds on the expectation of the supremum of the deviation of a kernel density estimator  $\hat{f}_n(x)$  from true density function  $f(x)$ . Similar results were obtained for a kernel type estimator  $\hat{F}_n(x)$  for the true distribution function  $F(x)$ .

Mathematics Subject classification : Primary 62G07.

Keywords and Phrases :  $\phi$ -mixing sequence; Empirical process; Kernel type density estimation.

1

## 1 Introduction

Moment inequalities for the supremum of empirical processes with applications to kernel type estimation of a density function and a distribution function for identically distributed observations were investigated in Ahmad (2002). We obtain similar results for mixing processes.

## 2 Preliminaries

Let  $\{X_n, -\infty < n < \infty\}$  be a stationary  $\phi$ -mixing sequence defined on a probability space  $(\Omega, \mathcal{F}, P)$  with each  $X_i$  having a continuous distribution function  $F(x)$  and density function  $f(x)$ . Let  $Y_i = F(X_i)$ ,  $-\infty < i < \infty$ . Define  $G(t) = P(Y_i \leq t)$ . Let  $F_n(x)$  denote the empirical distribution function based on the observations  $\{X_i, 1 \leq i \leq n\}$  and  $G_n(t)$  denote the empirical distribution function based on the observations  $\{Y_i, 1 \leq i \leq n\}$ . It is easy to see that

$$\sup_{-\infty < x < \infty} |F_n(x) - F(x)| \leq \tilde{D}_n = \sup_{0 \leq t \leq 1} |G_n(t) - t|. \quad (2.1)$$

The following result is due to Kim (1999).

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<sup>1</sup>Corresponding address: Indian Statistical Institute, 7,S.J.S.Sansanwal Marg, New Delhi 110016, India; e-mail: blsp@isid.ac.in

**Theorem 2.1:** Let  $\{X_n, n \geq 1\}$  be a stationary and  $\phi$ -mixing sequence of random variables such that

$$\sum_{i=1}^{\infty} \phi_i < \infty. \quad (2. 2)$$

Then, for every positive integer  $k \geq 1$ , there corresponds a constant  $C_k > 0$  such that for any  $\lambda \geq 1$ ,

$$\sup_n P(\sqrt{n}\tilde{D}_n \geq \lambda) \leq C_k \lambda^{-2k}. \quad (2. 3)$$

Let

$$D_n = \sqrt{n}\tilde{D}_n. \quad (2. 4)$$

Note that for any positive integer  $k \geq 1$ ,

$$\begin{aligned} E(D_n) &= \int_0^{\infty} P(D_n > x) dx \\ &\leq 1 + \int_1^{\infty} P(D_n > x) dx \\ &\leq 1 + \int_1^{\infty} C_k x^{-2k} dx \\ &= 1 + C_k \left( \frac{1}{2k-1} \right) \end{aligned} \quad (2. 5)$$

and, in general, it is easy to see that for  $r \geq 1$  and positive integer  $k \geq \frac{r}{2}$ ,

$$E(D_n) \leq \left\{ 1 + C_k \left( \frac{r}{2k-r} \right) \right\}^{1/r}. \quad (2. 6)$$

### 3 Application to Density Estimation

Suppose a stationary  $\phi$ -mixing process  $\{X_i, i \geq 1\}$  is observed up to time  $n$  with the  $\phi$ -mixing sequence satisfying the condition (2.2) and with the one-dimensional probability density function  $f$ . The problem is to estimate the density function  $f$  based on the observations  $\{X_i, 1 \leq i \leq n\}$ .

Let  $J(\cdot)$  be a bounded symmetric probability density function with mean zero and finite variance  $\sigma_J^2$ . Further suppose that it is of bounded variation with total variation  $V_J$ . Let  $h_n$  be a sequence of positive numbers such that

$$h_n \rightarrow 0 \text{ and } nh_n \rightarrow \infty \text{ as } n \rightarrow \infty. \quad (3. 1)$$

Define, for any  $x$ ,

$$\hat{f}_n(x) = \frac{1}{nh_n} \sum_{i=1}^n J\left(\frac{x - X_i}{h_n}\right). \quad (3. 2)$$

The estimator  $\hat{f}_n(x)$  is a kernel type estimator of the probability density function  $f(x)$ . Properties of such estimators are discussed in Prakasa Rao (1983).

Suppose that the probability density function  $f$  has continuous and bounded second derivative with  $\sup_x |f''| = C_f < \infty$ . Let

$$W_n = \sup_{-\infty < x < \infty} |\hat{f}_n(x) - f(x)|. \quad (3.3)$$

Observe that

$$\begin{aligned} |\hat{f}_n(x) - f(x)| &\leq \left| \frac{1}{h_n} \int_{-\infty}^{\infty} J\left(\frac{x-y}{h_n}\right) dF_n(y) - \frac{1}{h_n} \int_{-\infty}^{\infty} J\left(\frac{x-y}{h_n}\right) dF(y) \right| \\ &\quad + \left| \frac{1}{h_n} \int_{-\infty}^{\infty} J\left(\frac{x-y}{h_n}\right) dF(y) - f(x) \right| \\ &\leq \frac{1}{h_n} \sup_{-\infty < y < \infty} |F_n(y) - F(y)| \int_{-\infty}^{\infty} dJ\left(\frac{x-y}{h_n}\right) + \frac{h_n^2}{2} \sigma_J^2 C_f \\ &= \frac{1}{h_n} \sup_{-\infty < y < \infty} |F_n(y) - F(y)| V_J + \frac{h_n^2}{2} \sigma_J^2 C_f \\ &\leq \frac{1}{h_n \sqrt{n}} D_n V_J + \frac{h_n^2}{2} \sigma_J^2 C_f. \end{aligned} \quad (3.4)$$

Hence

$$E(W_n) \leq \frac{1}{h_n \sqrt{n}} E(D_n) V_J + \frac{h_n^2}{2} \sigma_J^2 C_f. \quad (3.5)$$

Applying the bound on  $E(D_n)$  derived in the equation (2.5), we have

$$E(W_n) \leq \frac{1}{h_n \sqrt{n}} (1 + C_k \left(\frac{1}{2k-1}\right)) V_J + \frac{h_n^2}{2} \sigma_J^2 C_f \quad (3.6)$$

for any positive integer  $k \geq 1$ . Choosing  $h_n$  such that  $\frac{1}{h_n \sqrt{n}} = h_n^2$ , that is,  $h_n = n^{-1/6}$ , one can get an optimum bound on  $E(W_n)$  as far as the rate of convergence is concerned and

$$E(W_n) \leq n^{-1/3} [(1 + C_k \left(\frac{1}{2k-1}\right)) V_J + \frac{1}{2} \sigma_J^2 C_f]. \quad (3.7)$$

Let us now consider the problem of estimation of

$$I(f) = \int_{-\infty}^{\infty} f^2(x) dx. \quad (3.8)$$

An estimator of  $I(f)$  is  $I(\hat{f}_n)$ . Note that

$$\begin{aligned} |I(\hat{f}_n) - I(f)| &= \left| \int_{-\infty}^{\infty} (\hat{f}_n(x) - f(x)) (\hat{f}_n(x) + f(x)) dx \right| \\ &\leq \int_{-\infty}^{\infty} |(\hat{f}_n(x) - f(x))| |(\hat{f}_n(x) + f(x))| dx \\ &\leq 2 \sup_{-\infty < x < \infty} |\hat{f}_n(x) - f(x)| \\ &= 2W_n. \end{aligned}$$

Hence

$$E|I(\hat{f}_n) - I(f)| \leq 2\left[\frac{1}{h_n\sqrt{n}}(1 + C_k(\frac{1}{2k-1}))V_J + \frac{h_n^2}{2}\sigma_J^2 C_f\right]. \quad (3.9)$$

If  $h_n = n^{-1/6}$ , then the above bound reduces to

$$E|I(\hat{f}_n) - I(f)| \leq 2n^{-1/3}[(1 + C_k(\frac{1}{2k-1}))V_J + \frac{1}{2}\sigma_J^2 C_f]. \quad (3.10)$$

## 4 Application to Estimation of Distribution Function

Suppose a stationary  $\phi$ -mixing process  $\{X_i, i \geq 1\}$  is observed up to time  $n$  with the  $\phi$ -mixing sequence satisfying the condition (2.2) and with the one-dimensional probability distribution function  $F$ . The problem is to estimate the distribution function  $F$  based on the observations  $\{X_i, 1 \leq i \leq n\}$ .

Let  $R_n(x)$  be a sequence of distribution functions converging weakly to the distribution function  $R(x)$  degenerate at zero such that

$$\sup_{-\infty < x < \infty} |R_n(x) - R(x)| = o(\delta_n) \quad (4.1)$$

where  $\delta_n \rightarrow 0$  as  $n \rightarrow \infty$ . Define

$$\hat{F}_n(x) = \frac{1}{n} \sum_{i=1}^n R_n(x - X_i). \quad (4.2)$$

Let

$$\begin{aligned} Z_n &= \sup_{-\infty < x < \infty} |\hat{F}_n(x) - F(x)| \\ &\leq \sup_{-\infty < x < \infty} |\hat{F}_n(x) - E\hat{F}_n(x)| + \sup_{-\infty < x < \infty} |E\hat{F}_n(x) - F(x)|. \end{aligned} \quad (4.3)$$

But

$$\begin{aligned} \sup_{-\infty < x < \infty} |\hat{F}_n(x) - E\hat{F}_n(x)| &= \sup_{-\infty < x < \infty} \left| \int_{-\infty}^{\infty} R_n(x-y) dF_n(y) \right. \\ &\quad \left. - \int_{-\infty}^{\infty} R_n(x-y) dF(y) \right| \\ &= \sup_{-\infty < x < \infty} \left| \int_{-\infty}^{\infty} (F_n(y) - F(y)) dR_n(x-y) \right| \\ &\leq \frac{D_n}{\sqrt{n}}. \end{aligned} \quad (4.4)$$

Therefore

$$Z_n \leq \frac{D_n}{\sqrt{n}} + \sup_{-\infty < x < \infty} |E\hat{F}_n(x) - F(x)|. \quad (4.5)$$

It can be checked that

$$\begin{aligned}
\sup_{-\infty < x < \infty} |E\hat{F}_n(x) - F(x)| &\leq \sup_{-\infty < x < \infty} \left| \int_{-\infty}^{\infty} |R_n(x-y) - R(x-y)| f(y) dy \right| \quad (4.6) \\
&\leq \sup_{-\infty < x < \infty} |R_n(x) - R(x)| \int_{-\infty}^{\infty} f(y) dy \\
&\leq \delta_n.
\end{aligned}$$

Hence

$$E(Z_n) \leq \frac{E(D_n)}{\sqrt{n}} + \delta_n. \quad (4.7)$$

Applying the inequality (2.5), we get that

$$E(Z_n) \leq \frac{1 + C_k \left(\frac{1}{2k-1}\right)}{\sqrt{n}} + \delta_n. \quad (4.8)$$

## References

- Ahmad, Ibrahim A. (2002) On moment inequalities of the supremum of empirical processes with applications to kernel estimation, *Statist. Prob. Lett.*, **57**, 215-220.
- Kim, T.Y. (1999) On tail probabilities of Kolmogorov-Smirnov statistics based on uniform mixing processes, *Statist. Prob. Lett.*, **43**, 217-223.
- Prakasa Rao, B.L.S. (1983) *Nonparametric Functional Estimation*, Academic Press, New York.