

ON L_p -CONVERGENCE RATES FOR STATISTICAL FUNCTIONS WITH APPLICATION TO L -ESTIMATES

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Summary

A parameter which may be represented as a functional $T(F)$ of a distribution function F may be estimated by the "statistical function" $T(F_n)$, where F_n is the empirical distribution function. Recently, Boos and Serfling (1979, Florida State University Statistics Report No. M 499) obtained sufficient conditions for the Berry-Esseen theorem to hold for $T(F_n)-T(F)$ and applied the results to derive rates of convergence in L_∞ for L -estimates. The present note complements their work by obtaining the L_p -rates of convergence, $1 \leq p < \infty$ for $T(F_n)-T(F)$ and its application to L -estimates.

1. Introduction and a portmanteau theorem

Let a parameter θ of a distribution function (d.f.) F be represented as a functional $T(F)$. If X_1, \dots, X_n is a random sample from F , then θ may be estimated by $T(F_n)$, where $F_n(x)$ denote the empirical d.f. For many instances the random variable $n^{1/2}(T(F_n)-T(F))/\sigma(T, F)$ is asymptotically standard normal, for some positive constant $\sigma(T, F)$. Using von Mises [6] expansion of $T(F_n)-T(F)$ as a sum of two terms; a U -statistic and a remainder term, i.e. $T(F_n)-T(F)=U_n+R_n$, Boos and Serfling [2] prove that under some conditions, $\sup_x |P[n^{1/2}(T(F_n)-T(F)) \leq x\sigma(T, F)] - \Phi(x)| = O(n^{-1/2})$, $n \rightarrow \infty$, where $\Phi(\cdot)$ denote the d.f. of the standard normal variate, see Theorem 2.1 (i) below. Then, they use this result to establish rates of convergence for L -estimate, i.e., $T(F) = \int_0^1 F^{-1}(u)J(u)du$.

The purpose of the present note is to show that one can obtain L_p -rates of convergence for $T(F_n)-T(F)$ for $1 \leq p < \infty$, thus when combining these rates with those of Boos and Serfling [2] we can list rates

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of convergence for L_p , $1 \leq p \leq \infty$.

For any function ϕ , define $\|\phi\|_p = \left(\int |\phi(t)|^p dt \right)^{1/p}$, $1 \leq p < \infty$ and $\|\phi\|_\infty = \sup_t |\phi(t)|$. Denote by G_n the d.f. of $n^{1/2}(T(F_n) - T(F))/\sigma(T, F)$. Then we state and prove the following portmanteau theorem.

THEOREM 1.1. *Suppose that $T(F_n) - T(F)$ can be written as $V_n + R_n$ where*

$$(1.1) \quad V_n = n^{-2} \sum_i \sum_j h(X_i, X_j),$$

with $h(\cdot, \cdot)$ a symmetric function, such that $E h(X_1, X_2) = 0$, $E |h(X_1, X_2)|^2 < \infty$, and $E |h(X_1, X_1)|^2 < \infty$. Let $\{\varepsilon_n\}$ be a sequence of real numbers such that $\varepsilon_n \geq n^{-1}$ for all $n \geq 1$ and $\varepsilon_n \rightarrow 0$ as $n \rightarrow \infty$.

(i) *If for some $C > 0$, $P[|R_n| > C\varepsilon_n] = O(\varepsilon_n^{1/2})$ and putting $\sigma(T, F) = 4 \text{Var} g(X_1)$, with $g(x) = E_F[h(X_1, X_2) | X_1 = x]$, then*

$$(1.2) \quad \|G_n - \Phi\|_\infty = O(\varepsilon_n^{1/2}).$$

(ii) *If in addition $E(R_n^2) = O(\varepsilon_n^2)$, then for any $1 \leq p < \infty$*

$$(1.3) \quad \|G_n - \Phi\|_p = O(\varepsilon_n^{1/2}).$$

PROOF. (i) Follows exactly that of Theorem 1.1 of Boos and Serfling [2] with obvious modifications and hence is not repeated here.

(ii) Let $H_n(\cdot)$ denote the d.f. of the random variable $\sqrt{n} V_n / \sigma(T, F)$. We use the following inequalities:

$$(1.4) \quad \|G_n - \Phi\|_p^2 \leq \|G_n - \Phi\|_\infty^{p-1} \|G_n - \Phi\|_1$$

and

$$(1.5) \quad \|G_n - \Phi\|_1 \leq \|H_n - \Phi\|_1 + \sqrt{n} E^{1/2}(R_n^2) / \sigma(T, F).$$

A proof of (1.5) is given in the appendix. Now, from Part (i) it follows that $\|G_n - \Phi\|_\infty^{p-1} = O(\varepsilon_n^{(p-1)/2})$.

Also we have

$$(1.6) \quad \|H_n - \Phi\|_1 \leq \|K_n - \Phi\|_1 + \sqrt{n} E^{1/2}(U_n - V_n)^2 / \sigma(T, F),$$

where $K_n(\cdot)$ denote the d.f. of $\sqrt{n} U_n / \sigma(T, F)$, with $U_n = \binom{n}{2}^{-1} \sum_{1 \leq i < j \leq n} h(X_i, X_j)$. Note that if $W_n = n^{-1} \sum_{i=1}^n h(X_i, X_i)$, then $U_n - V_n = n^{-1}(U_n - W_n)$.

Hence

$$\begin{aligned} \sqrt{n} E^{1/2}(U_n - V_n)^2 &= n^{-1/2} E^{1/2}(U_n - W_n)^2 \\ &\leq 2n^{-1/2} \{[\text{Var}(U_n)] + [\text{Var}(W_n)]\}^{1/2} \\ &= 2n^{-1/2} \{O(n^{-1/2})\} = O(n^{-1}) = O(\varepsilon_n). \end{aligned}$$

All that is remained is to show that $\|K_n - \Phi\|_1 = O(\varepsilon_n^{1/2})$. It suffices, cf. Callaert and Janssen [3], to consider \hat{K}_n , the d.f. of $\sqrt{n} U_n / 2\sigma_g$. Write $U_n = \hat{U}_n + \hat{A}_n$, where $\hat{U}_n = 2n^{-1} \sum_{j=1}^n g(X_j)$ with $g(X_1) = E[h(X_1, X_2) | X_1]$, and $\hat{A}_n = \binom{n}{2}^{-1} \sum_{1 \leq i < j \leq n} [h(X_i, X_j) - g(X_i) - g(X_j)]$. Let L_n denote the d.f. of $\sqrt{n} \hat{U}_n / 2\sigma_g$. Then

$$(1.7) \quad \|\hat{K}_n - \Phi\|_1 \leq \|L_n - \Phi\|_1 + \sqrt{n} E^{1/2}(\hat{A}_n^2) / 4\sigma_g^2 = O(n^{-1/2}) + O(n^{-1/2}),$$

where the first term in the last upper bound is obtained from Theorem 4.3 of Ibragimov [5], and the second from the well-known result that $E \hat{A}_n^2 = O(n^{-1})$. Thus $\|\hat{K}_n - \Phi\|_1 = O(\varepsilon_n^{1/2})$ and the theorem is now proved.

Remark 1.1. Note that listing the rate in Theorem 1.1 in terms of ε_n allows the accommodation of the cases when $P[|R_n| > Cn^{-1}]$ and $E(R_n^2)$ do not attain the optimum rate. Note also that if we assume that $E|h(X_1, X_2)|^{2+\delta} < \infty$ and $E|h(X_1, X_1)|^{(2+\delta)/2} < \infty$ for some $0 < \delta \leq 1$, then $\|G_n - \Phi\|_\infty = O(\varepsilon_n^{\delta/2})$ if $P[|R_n| > Cn^{-1}] = O(\varepsilon_n^{\delta/2})$ and if further $E(R_n^2) = O(\varepsilon_n^{1+\delta})$, then $\|G_n - \Phi\|_p = O(\varepsilon_n^{\delta/2})$ $1 \leq p < \infty$. All the ingredients needed for the proof of this extension are in the proof of Theorem 1.1 above except that in this case $\|\hat{K}_n - \Phi\|_\infty = O(\varepsilon_n^{\delta/2})$, $0 < \delta \leq 1$. This latter results is obtained by altering the proof of Callaert and Janssen [3], for details see Ahmad [1], Theorem 2.1.

Remark 1.2. Another rate of convergence is possible to establish namely, if $\varepsilon_n = O(n^{-1})$, if $E|h(X_1, X_2)|^{2+\delta} < \infty$, $E|h(X_1, X_1)|^{(2+\delta)/2} < \infty$, $0 < \delta < 1$, or $Eh^2(X_1, X_2) \ln(1 + |h(x_1, x_2)|) < \infty$, $\delta = 0$ and if for some $C > 0$, $\sum_{n=1}^\infty \varepsilon_n^{1-\delta/2} P[|R_n| > C\varepsilon_n] < \infty$, then $\sum_{n=1}^\infty \varepsilon_n^{1-\delta/2} \|G_n - \Phi\|_\infty < \infty$. If further, $\sum_{n=1}^\infty \varepsilon_n^{(1-\delta)} E^{1/2}(R_n^2) < \infty$, then $\sum_{n=1}^\infty \varepsilon_n^{1-\delta/2} \|G_n - \Phi\|_p < \infty$, $1 \leq p < \infty$, $0 \leq \delta < 1$. Again the main points in the proof of this result is to show that $\sum_{n=1}^\infty n^{-1+\delta/2} \|H_n - \Phi\|_\infty < \infty$ which is proved in Theorem 2.2 of Ahmad [1], and that $\sum_{n=1}^\infty n^{-1+\delta/2} \|L_n - \Phi\|_1 < \infty$ which is proved by Heyde [4], Corollary 2.

2. Application to L -estimates

Consider the functional defined by $T(F) = \int_0^1 F^{-1}(u) J(u) du$ and the corresponding L -estimate $T(F_n)$. As shown by Boos and Serfling [2] it is possible to write

$$(2.1) \quad T(F_n) - T(F) = V_n + R_n,$$

where $V_n = n^{-2} \sum_{i=1}^n \sum_{j=1}^n h(X_i, X_j)$ with $h(x, y) = (1/2)[\alpha(x) + \alpha(y) + \beta(x, y)]$ where $\alpha(x) = -\int_{-\infty}^{\infty} [I(x \leq t) - F(t)] J \circ F(t) dt$, and $\beta(x, y) = -\int_{-\infty}^{\infty} [I(x \leq t) - F(t)][I(y \leq t) - F(t)] J^{(1)} \circ F(t) dt$, with $J^{(1)}(\cdot)$ the first derivative of J . Note also that $R_n = T(F_n) - T(F) - V_n$ may be written as $-\int_{-\infty}^{\infty} W_{F_n, F}(x) dx$ with $W_{G, F} = K \circ G - K \circ F - J \circ F(G - F) - (1/2)(J^{(1)} \circ F)(F - G)^2$ and $K(u) = \int_{-0}^u J(v) dv$. Further in this case $\sigma^2(J, F) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} J \circ F(x) J \circ F(y) \cdot [F(\min(x, y)) - F(x)F(y)] dx dy$.

Boos and Serfling [2] established the Berry-Esseen bound of $\sqrt{n} \cdot (T(F_n) - T(F)) / \sigma(J, F)$ under two sets of conditions on J and F , viz.:

CONDITION A: Assume that J vanishes outside a closed interval $[a, b]$, $0 < a < b < 1$ and that $J^{(1)}$ exists and is such that $|J^{(1)}(x) - J^{(1)}(y)| \leq D|x - y|^\gamma$ for some $D > 0$, $\gamma > 0$ for all x, y defined on an open interval containing $[a, b]$, i.e., $J^{(1)}$ is Lipschitz of order $\gamma > 0$.

Or

CONDITION B: Suppose that $J^{(1)}$ exists and is such that $|J^{(1)}(x) - J^{(1)}(y)| \leq D|x - y|^\gamma$, for some $D > 0$, $\gamma > 1/3$ and all $x, y \in (0, 1)$. Assume also that $E|X_i|^\beta < \infty$.

Using Theorem 1.1 we shall establish L_p -rate of convergence of the order $n^{-1/2}$ for $\sqrt{n} (T(F_n) - T(F)) / \sigma(J, F)$ assuming that either Condition A or B is satisfied and that $\sigma^2(J, F) > 0$.

THEOREM 2.1. Assume that $\sigma^2(J, F) > 0$ and that either Condition A or B is satisfied. Let G_n denote the d.f. of $n^{1/2}(T(F_n) - T(F)) / \sigma(J, F)$. Then

$$(2.2) \quad \|G_n - \Phi\|_p = O(n^{-1/2}), \quad 1 \leq p \leq \infty.$$

PROOF. We need to establish that under either Condition A or B, $P[|R_n| > Cn^{-1}] = O(n^{-1/2})$ for some $C > 0$ and $E(R_n)^2 = O(n^{-2})$. But the first assertion is a consequence of Theorems 2.1 and 2.2 of Boos and Serfling [2]. Thus we shall prove the second. Since $J^{(1)}$ is Lipschitz of order γ we obtain

$$(2.3) \quad |R_n| \leq (D/2) \int |F_n(x) - F(x)|^{2+\gamma} dx \leq (D/2) \|F_n - F\|_\infty^\gamma \cdot \|F_n - F\|_2^2.$$

Hence

$$(2.4) \quad E R_n^2 \leq (D^2/4) E \|F_n - F\|_\infty^\gamma \cdot \|F_n - F\|_2^4 \leq (D^2/4) E \|F_n - F\|_2^4 \leq O(n^{-2}),$$

where $E \|F_n - F\|_2^4 = O(n^{-2})$ follows from Lemma 2.1 of Boos and Serfling [2].

Remark 2.1. Since under Condition A, or Condition B, $P[|R_n| > Cn^{-1}] = O(n^{-1/2})$ and that $E|R_n^2| = O(n^{-2})$ it follows that $\sum_{n=1}^{\infty} n^{-1+\delta/2} P[|R_n| > Cn^{-1}] < \infty$, and $\sum_{n=1}^{\infty} n^{-1+\delta/2} E^{1/2}(R_n^2) < \infty$, and hence it follows that for any $0 \leq \delta < 1$, $\sum_{n=1}^{\infty} n^{-1+\delta/2} \|G_n - \Phi\|_p < \infty$, $1 \leq p < \infty$, from Remark 1.2. It appears that this is the first attempt at series rate of convergence for L -estimates. Also analogous rates are obtainable for linear combinations of order statistics. $T_n = n^{-1} \sum_{i=1}^n J(i/(n+1))X_{(i)}$, where $X_{(1)} \leq \dots \leq X_{(n)}$ denote the order statistics corresponding to X_1, \dots, X_n .

Remark 2.2. Boos and Serfling indicate how the Berry-Esseen rate can be obtained for the class of M -estimates (we refer the reader to Boos and Serfling [2] for definition). Their representation $T(F_n) - T(F) = V_n + R_n$ leads to R_n satisfying $|R_n| < D_1 \|F_n - F\|_{\infty}^3$ under certain conditions, but it can be shown that $E \|F_n - F\|_{\infty}^{2k} = O(n^{-k})$, $k=1, 2, \dots$, and thus $E R_n^2 = O(n^{-2})$ and thus we can obtain the rate $n^{-1/2}$ for L_p -convergence in light of Theorem 1.1.

Appendix

PROOF OF (1.5). Note that

$$\|G_n - \Phi\|_1 \leq \|G_n - H_n\|_1 + \|H_n - \Phi\|_1.$$

But

$$\begin{aligned} \|G_n - H_n\|_1 &= \int_{-\infty}^{\infty} |E I(X_n > x) - E I(Y_n > x)| dx \\ &\leq E \int |I(X_n > x) - I(Y_n > x)| dx \\ &= E |X_n - Y_n| \leq E^{1/2} |X_n - Y_n|^2, \end{aligned}$$

where $X_n = n^{1/2} \{T(F_n) - T(F)\} / \sigma(T, F)$ and $Y_n = n^{1/2} V_n / \sigma(T, F)$ with V_n defined in (1.1).

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