

# ON THE CONVERGENCE OF OPTIMUM STRATIFICATIONS FOR EMPIRIC DISTRIBUTION FUNCTION IN UNIVARIATE CASE

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## Summary

Let  $\{X_n\}$ ,  $n=1, 2, \dots$ , be a sequence of independent random variables distributed according to a distribution function  $F(x)$  with finite variance,  $F_n(x)$  be the empiric distribution function of  $X_1, \dots, X_n$  for each  $n$ , and  $\phi_{(n)}^*$  and  $\phi^*$  be optimum stratifications corresponding to  $F_n(x)$  and  $F(x)$  respectively.

It is shown in this paper that  $\phi_{(n)}^*$  tends almost surely to  $\phi^*$  under a suitable criterion.

## 1. Introduction

Let  $X$  be an univariate stratification variable with a marginal distribution function  $F(x)$ , and  $Y$  be an univariate objective variable with finite mean  $\mu_0$  and variance  $\sigma_0^2$ , and  $\eta(x)$  be the regression function of  $Y$  on  $X$ .

Let us suppose that stratification operation should be made only using the stratification variable  $X$  for estimating the mean  $\mu_0$  of  $Y$ , and that the number  $l$  of strata, the total sample size  $m$  and the sample allocation  $\{m_i, 1 \leq i \leq l\}$  are preassigned.

Such a stratification may be expressed by a decomposition  $\{F_i, 1 \leq i \leq l\}$  of the marginal distribution function  $F(x)$  of  $X$ , i.e.

$$\sum_{i=1}^l F_i(x) = F(x) \quad \text{for all } x,$$

where  $F_i(x)$  is non-negative and non-decreasing in  $x$ .

Since each measure  $F_i$  corresponding to the function  $F_i(x)$  is absolutely continuous with respect to the measure  $F$  corresponding to  $F(x)$ , there exists a vector-valued measurable function  $\phi(x) = (\phi_1(x), \dots, \phi_l(x))$  for each decomposition  $\{F_i\}$  of  $F$  such that

$$\sum_{i=1}^l \phi_i(x) = 1 \quad \text{a.e. } (F), \quad \phi_i(x) \geq 0 \quad (1 \leq i \leq l),$$

and the correspondence between  $\{F_i\}$  and  $\phi$  may be regarded as one to one (see the section 3 in [1]).

In case of proportionate allocation ( $m_i = w_i m$ ) the variance of an unbiased estimator  $\bar{Y} = \sum_{i=1}^l w_i \bar{Y}_i$  of  $\mu_0$ , based on the random sample under a stratification  $\phi$ , may be expressed as

$$(1.1) \quad V(\bar{Y} | \phi) = \frac{1}{m} \left\{ \sigma_0^2 (1 - \rho^2) + \sum_{i=1}^l \int_{-\infty}^{\infty} [\eta(x) - \mu_{0i}]^2 \phi_i(x) dF(x) \right\},$$

where  $w_i = F_i(+\infty)$  is the weight of the  $i$ th stratum,  $\sigma_0^2$  is the total variance of  $Y$ ,  $\mu_{0i}$  is the mean of  $Y$  in the  $i$ th stratum and  $\rho$  is the correlation ratio of  $Y$  on  $X$  (see the section 4 in [1]).

It is easily seen from (1.1) that  $V(\bar{Y} | \phi)$  takes the minimum value at  $\phi = \phi^*$  if and only if  $\phi^*$  attains the infimum of the second term in the bracket of the right-hand side of (1.1) which is rewritten as

$$(1.2) \quad \sum_{i=1}^l \int_{-\infty}^{\infty} [\eta(x) - \mu_{0i}]^2 \phi_i(x) dF(x) = \int_{-\infty}^{\infty} \eta^2(x) dF(x) - \sum_{i=1}^l w_i \mu_{0i}^2.$$

Further if the regression function is linear, i.e.  $\eta(x) = \beta_0 + \beta_1 x$ , then (1.2) reduces to

$$(1.3) \quad \sum_{i=1}^l \int_{-\infty}^{\infty} [\eta(x) - \mu_{0i}]^2 \phi_i(x) dF(x) = \beta_1^2 \left\{ \int_{-\infty}^{\infty} x^2 dF(x) - \sum_{i=1}^l w_i \mu_i^2 \right\},$$

where  $\mu_i = \frac{1}{w_i} \int_{-\infty}^{\infty} x \phi_i(x) dF(x)$  is the mean of  $X$  in the  $i$ th stratum.

Therefore the optimum stratification  $\phi^*$  attains the infimum of the function

$$(1.4) \quad G_1(w(\phi), u(\phi)) = - \sum_{i=1}^l \frac{[u_i(\phi)]^2}{w_i(\phi)},$$

where  $w_i(\phi) = \int_{-\infty}^{\infty} \phi_i(x) dF(x)$  and  $u_i(\phi) = \int_{-\infty}^{\infty} x \phi_i(x) dF(x)$ . (see example i in [1], p. 123).

This fact shows that  $\phi^*$  is identical to an optimum stratification for the marginal distribution function  $F(x)$  of the stratification variable  $X$  in the case of proportionate allocation and linear regression.

If  $F(x)$  is unknown but a simple random sample of size  $n$  ( $X_1, \dots, X_n$ ) is given under the above situation in advance of stratification operation, it is necessary to make an estimate  $\phi_{(n)}^*$  of  $\phi^*$  using the given sample ( $X_1, \dots, X_n$ ) and investigate its probabilistic behavior.

One way of doing this is to obtain  $\phi_{(n)}^*$  as an optimum stratification for the empiric distribution function  $F_n(x)$  of ( $X_1, \dots, X_n$ ), and to examine whether  $G_1(w(\phi_{(n)}^*), u(\phi_{(n)}^*))$  converges almost surely to  $G_1(w(\phi^*), u(\phi^*))$

or not as  $n \rightarrow \infty$ .

It is noted here that there exists an optimum  $\phi^*$  for any  $F(x)$  (discrete or continuous) such that

$$\phi_i^*(x) = \begin{cases} 1 & \text{if } x_{i-1}^* \leq x < x_i^* \quad (1 \leq i \leq l) \\ 0 & \text{otherwise,} \end{cases}$$

where  $w_i^* = \int_{-\infty}^{\infty} \phi_i^*(x) dF(x)$ ,  $\mu_i^* = \int_{-\infty}^{\infty} x \phi_i^*(x) dF(x)$ ,  $(1 \leq i \leq l)$   $\mu_1^* < \mu_2^* < \dots < \mu_l^*$ ,  $x_i^* = (\mu_i^* + \mu_{i+1}^*)/2$  with no probability mass on it  $(1 \leq i \leq l)$ ,  $x_0^* = -\infty$  and  $x_l^* = +\infty$ , if the support of  $F(x)$  contains at least  $l$  points (see also [1]).

In case of Neyman allocation  $(n_i = \frac{w_i \sigma_i}{\sum_j w_j \sigma_j} n)$  there exists an optimum stratification  $\phi^{**}$  for  $F(x)$  which minimizes the function

$$(1.5) \quad G_2(w(\phi), u(\phi), v(\phi)) = \sum_{i=1}^l [w_i(\phi)v_i(\phi) - u_i^2(\phi)]^{1/2},$$

where  $w(\phi) = \int_{-\infty}^{\infty} \phi(x) dF(x)$ ,  $u(\phi) = \int_{-\infty}^{\infty} x \phi(x) dF(x)$  and  $v(\phi) = \int_{-\infty}^{\infty} x^2 \phi(x) \cdot dF(x)$  (see [2]).

It is also of interest to investigate the probabilistic behavior of an optimum stratification  $\phi_{(n)}^{**}$  for  $F_n(x)$ , i.e. to examine whether  $G_2(w(\phi_{(n)}^{**}), u(\phi_{(n)}^{**}), v(\phi_{(n)}^{**}))$  converges almost surely to  $G_2(w(\phi^{**}), u(\phi^{**}), v(\phi^{**}))$  or not as  $n \rightarrow \infty$ .

## 2. Preparatory lemmas

In this section we state two lemmas useful for deriving main theorems in the following sections.

**LEMMA 1.** *Let  $F(x)$  be a distribution function having finite mean  $\mu$  and variance  $\sigma^2$  and  $F_n(x)$  be the empiric distribution function of random variables distributed independently according to  $F(x)$ . If  $g(x)$  is a continuous and integrable function with respect to  $F$ , then*

$$(2.1) \quad P \left\{ \lim_{n \rightarrow \infty} \sup_{x \in \mathcal{I}} \left| \int_I g(x) dF_n - \int_I g(x) dF \right| = 0 \right\} = 1$$

holds, where  $\mathcal{I}$  is the family of all intervals on the real line.

**PROOF.** Since  $g$  is integrable with respect to  $F$ , for any positive  $\epsilon$  there exists a positive constant  $K_\epsilon$  such that

$$\int_{|x|>K_\epsilon} |g(x)| dF(x) < \epsilon$$

holds.

By the strong law of large numbers there exists a positive integer  $n_1(\epsilon)$  depending only on  $\epsilon$  such that

$$(2.2) \quad \int_{|x|>K_\epsilon} |g(x)| dF_n(x) < \int_{|x|>K_\epsilon} |g(x)| dF(x) + \epsilon < 2\epsilon$$

holds with probability one for all  $n > n_1(\epsilon)$ .

Let us divide the interval  $[-K_\epsilon, K_\epsilon]$  into  $\nu_\epsilon$  intervals  $\{I_j\}$  with equal length such that

$$|g(x) - g(x')| < \epsilon \quad \text{for } |x - x'| < \delta_\epsilon, \quad x \text{ and } x' \in [-K_\epsilon, K_\epsilon]$$

and

$$\nu_\epsilon = \left[ \frac{2K_\epsilon}{\delta_\epsilon} \right] + 1, \quad I_j = \left( -K_\epsilon + (j-1) \frac{2K_\epsilon}{\nu_\epsilon}, -K_\epsilon + j \frac{2K_\epsilon}{\nu_\epsilon} \right], \quad (2 \leq j \leq \nu_\epsilon),$$

and

$$I_1 = \left[ -K_\epsilon, -K_\epsilon + \frac{2K_\epsilon}{\nu_\epsilon} \right).$$

Let us take any fixed point  $x_j$  in each  $I_j$  ( $1 \leq j \leq \nu_\epsilon$ ). Then the following relations hold:

$$(2.3) \quad \left| \int_{I \cap (-K_\epsilon, K_\epsilon)} g(x) dF(x) - \sum_{j=1}^{\nu_\epsilon} g(x_j) F(I \cap I_j) \right| < \epsilon,$$

$$(2.4) \quad \left| \int_{I \cap (-K_\epsilon, K_\epsilon)} g(x) dF_n(x) - \sum_{j=1}^{\nu_\epsilon} g(x_j) F_n(I \cap I_j) \right| < \epsilon,$$

and then for any  $\eta > 0$

$$(2.5) \quad \left| \int_{I \cap (-K_\epsilon, K_\epsilon)} g(x) dF_n(x) - \int_{I \cap (-K_\epsilon, K_\epsilon)} g(x) dF(x) \right| < 2\epsilon + M_\epsilon \sum_{j=1}^{\nu_\epsilon} |F_n(I \cap I_j) - F(I \cap I_j)| < 2\epsilon + M_\epsilon \nu_\epsilon \eta$$

uniformly in  $I$  with probability one for all  $n > n_2(\eta)$  by the theorem of Glivenko-Cantelli where  $M_\epsilon = \sup_{|x| \leq K_\epsilon} |g(x)|$ . If we take  $\eta$  for  $\eta_\epsilon$  such that  $M_\epsilon \nu_\epsilon \eta_\epsilon < \epsilon$ , then from (2.5)

$$(2.6) \quad \left| \int_{I \cap [-K_\epsilon, K_\epsilon]} g(x) dF(x) - \int_{I \cap [-K_\epsilon, K_\epsilon]} g(x) dF(x) \right| < 3\epsilon$$

holds uniformly in  $I$  with probability one for all  $n > n_2(\eta_\epsilon)$ .

Therefore from (2.2) and (2.6) we can find a positive integer  $n_0(\epsilon) =$

max  $(n_1(\epsilon), n_2(\eta_\epsilon))$  such that the inequality

$$(2.7) \quad \left| \int_I g(x) dF_n(x) - \int_I g(x) dF(x) \right| < 6\epsilon$$

holds uniformly in  $I$  with probability 1 for all  $n > n_0(\epsilon)$ . This result shows that (2.1) holds. Thus the proof is completed.

COROLLARY. *If  $F(x)$  has the finite  $r$ th moment, then the relation*

$$(2.8) \quad P \left\{ \limsup_{n \rightarrow \infty} \sup_{I \in \mathcal{I}} \left| \int_I x^k dF_n(x) - \int_I x^k dF(x) \right| = 0 \right\} = 1$$

holds for  $0 \leq k \leq r$ .

Remark. In the case  $k=0$  (2.8) is identical to the theorem of Glivenko-Cantelli.

LEMMA 2. *Under the same assumptions in Lemma 1 and the assumption that  $0 < \tau = \int [g(x)]^4 dF(x) < \infty$ ,*

$$(2.9) \quad P \left\{ \limsup_{n \rightarrow \infty} \sup_{I \in \mathcal{I}} \left| \frac{\left[ \int_I g(x) dF_n(x) \right]^2}{\int_I dF_n(x)} - \frac{\left[ \int_I g(x) dF(x) \right]^2}{\int_I dF(x)} \right| = 0 \right\} = 1.$$

holds, where both terms in the bracket in the left-hand side of (2.9) should be taken to be zero if

$$\int_I dF_n(x) = 0 \quad \text{or} \quad \int_I dF(x) = 0 \quad \text{respectively.}$$

PROOF. Let  $\mathcal{I}$  be the family of all intervals on the real line, and let us divide it into two sets  $\mathcal{I}_\epsilon$  and  $\mathcal{I}'_\epsilon$  for any positive  $\epsilon$  such that

$$\mathcal{I}_\epsilon = \left\{ I; \int_I dF(x) < \frac{\epsilon^2}{9\tau} \right\} \quad \text{and} \quad \mathcal{I}'_\epsilon = \mathcal{I} - \mathcal{I}_\epsilon.$$

Then it is easily seen by the Schwarz's inequality

$$(2.10) \quad \frac{\left[ \int_I g dF \right]^2}{\int_I dF} \leq \int_I g^2 dF \leq \sqrt{\int_I g^4 dF} \sqrt{\int_I dF} < \frac{\epsilon}{3}$$

holds for any  $I \in \mathcal{I}_\epsilon$ . In the same way

$$(2.11) \quad \frac{\left[ \int_I g dF_n \right]^2}{\int_I dF_n} \leq \int_I g^2 dF_n$$

holds for any possible  $F_n$ . By Lemma 1 there exists a positive integer  $n_1(\varepsilon)$  such that

$$(2.12) \quad \int_I g^2 dF_n < \int_I g^2 dF + \frac{\varepsilon}{3} < \frac{2}{3} \varepsilon$$

holds with probability 1 for any  $I \in \mathcal{I}_\varepsilon$  for  $n > n_1(\varepsilon)$ .

Therefore from (2.10) and (2.12)

$$(2.13) \quad \sup_{I \in \mathcal{I}_\varepsilon} \left| \frac{\left[ \int_I g dF_n \right]^2}{\int_I dF_n} - \frac{\left[ \int_I g dF \right]^2}{\int_I dF} \right| < \varepsilon$$

holds with probability 1 for any  $I \in \mathcal{I}_\varepsilon$  for  $n > n_1(\varepsilon)$ .

On the other hand the inequality

$$\int_I dF(x) \geq \frac{\varepsilon^2}{9\tau}$$

holds for any  $I \in \mathcal{I}'_\varepsilon$ . Let us put

$$\eta_{1n} = \int_I g dF_n - \int_I g dF \quad \text{and} \quad \eta_{2n} = \int_I dF_n - \int_I dF.$$

For any  $\delta > 0$  there exists a positive integer  $n_2(\delta)$  by Lemma 1 such that

$$|\eta_{1n}| < \delta \quad \text{and} \quad |\eta_{2n}| < \delta$$

hold with probability 1 uniformly in  $I \in \mathcal{I}'_\varepsilon$  for all  $n > n_2(\delta)$ .

Therefore it is easily seen that for  $\delta < 9\tau\varepsilon^{-2}$

$$(2.14) \quad \sup_{I \in \mathcal{I}'_\varepsilon} \left| \frac{\left[ \int_I g dF_n \right]^2}{\int_I dF_n} - \frac{\left[ \int_I g dF \right]^2}{\int_I dF} \right| \leq \frac{\delta}{\varepsilon^2/9\tau - \delta} \left( 2\rho + \delta + \frac{9\tau\rho^2}{\varepsilon^2} \delta \right)$$

holds with probability 1 if  $n > n_2(\delta)$ , where  $\rho = \int_{-\infty}^{\infty} |g(x)| dF(x)$ . The right-hand side of (2.14) may be smaller than  $\varepsilon$  for sufficiently small  $\delta = \delta_\varepsilon$ .

Hence from (2.13) and (2.14)

$$(2.15) \quad \sup_{I \in \mathcal{I}} \left| \frac{\left[ \int_I g dF_n \right]^2}{\int_I dF_n} - \frac{\left[ \int_I g dF \right]^2}{\int_I dF} \right| < \varepsilon$$

holds with probability 1 if  $n > n_0(\varepsilon) = \max(n_1(\varepsilon), n_2(\delta_\varepsilon))$ , and the proof is completed.

### 3. Main theorems

In this section we shall state two main theorems which shows the optimum stratifications  $\phi_{(n)}^*$  and  $\phi_{(n)}^{**}$  for the empiric distribution function  $F_n$  in cases of proportionate and Neyman allocations converge almost surely in the following sense to optimum ones  $\phi^*$  and  $\phi^{**}$  for the true distribution function  $F$  respectively.

As stated in Section 1, the optimum stratifications  $\phi^*$  and  $\phi^{**}$  for the true  $F$  attain the minimum values of the functions

$$(3.1) \quad G_1(y(\phi)) = - \sum_{i=1}^l \frac{[u_i(\phi)]^2}{w_i(\phi)}$$

and

$$(3.2) \quad G_2(y(\phi)) = \sum_{i=1}^l \sqrt{w_i(\phi)v_i(\phi) - [u_i(\phi)]^2}$$

in cases of proportionate and Neyman allocations respectively.

Let  $\phi_{(n)}^*$  and  $\phi_{(n)}^{**}$  be optimum stratifications, corresponding to  $\phi^*$  and  $\phi^{**}$ , for the empiric distribution function  $F_n(x)$  based on the simple random sample of size  $n$  which is given to us in advance of stratification operation.

Further let us define

$$(3.3) \quad \begin{aligned} y^{(n)} &= (w^{(n)}(\phi), u^{(n)}(\phi), v^{(n)}(\phi)), \\ w^{(n)}(\phi) &= \int \phi dF_n, \quad u^{(n)}(\phi) = \int x \phi dF_n \\ \text{and} \quad v^{(n)}(\phi) &= \int x^2 \phi dF_n. \end{aligned}$$

Then  $\phi_{(n)}^* = (\phi_{(n)1}^*, \dots, \phi_{(n)l}^*)$  may be represented by a partition of the real line consisting of  $l$  disjoint intervals each of which has no sample point on its end points as shown in Section 1.

**THEOREM 1.** *Let  $F(x)$  be a distribution function which has a finite fourth moment and contains at least  $l$  points in its support. Then*

$$(3.4) \quad P\{\lim_{n \rightarrow \infty} G_1(y(\phi_{(n)}^*)) = G_1(y(\phi^*))\} = 1$$

holds, where  $G_1$  is defined by (3.1) or (1.4),  $\phi^*$  and  $\phi_{(n)}^*$  are optimum stratifications in case of proportionate allocation for  $F$  and  $F_n$  respectively and  $y(\phi) = (w(\phi), u(\phi))$ . That is,  $\phi_{(n)}^*$  converges almost surely to  $\phi^*$  in the above sense.

**PROOF.** Let  $T$  be the set of all possible partitions of the real line

consisting of  $l$  disjoint interval, i.e.

$$T = \{J = (J_1, \dots, J_l)\}, \quad \bigcup_{i=1}^l J_i = (-\infty, \infty)$$

and

$$J_i \cap J_k = 0 \text{ (empty)} \quad \text{for } i \neq k.$$

Then it is easily seen by Lemma 2 that

$$(3.5) \quad P \left\{ \lim_{n \rightarrow \infty} \sup_{J \in T} \left| \frac{\sum_{i=1}^l \left[ \int_{J_i} x dF_n(x) \right]^2}{\int_{J_i} dF_n(x)} - \frac{\sum_{i=1}^l \left[ \int_{J_i} x dF(x) \right]^2}{\int_{J_i} dF(x)} \right| = 0 \right\} = 1$$

holds. This means that for any positive  $\epsilon$  there exists a positive integer  $n_0(\epsilon)$  such that

$$(3.6) \quad |G_1[y^{(n)}(\phi_J)] - G_1[y(\phi_J)]| < \epsilon$$

holds almost surely for any  $J \in T$  and any  $n > n_0(\epsilon)$ , where the  $i$ th component  $\phi_{J_i}(x)$  of  $\phi_J(x)$  denotes the indicator function of the interval  $J_i$ .

Since the optimum  $\phi_{(n)}^*$  for  $F_n$  may be represented as  $\phi_{J^{(n)}}$  using a partition  $J^{(n)}$  in  $T$ , then the inequality (3.6) holds almost surely for  $\phi_{J^{(n)}}$  if  $n > n_0(\epsilon)$ . Therefore

$$(3.7) \quad G_1[y^{(n)}(\phi_{J^{(n)}})] < G_1[y(\phi_{J^{(n)}})] + \epsilon$$

holds almost surely for any  $n > n_0(\epsilon)$ .

On the other hand

$$(3.8) \quad G_1[y(\phi^*)] - \epsilon < G_1[y^{(n)}(\phi^*)] \leq G_1[y^{(n)}(\phi_{J^{(n)}})]$$

holds almost surely for any  $n > n_0(\epsilon)$  by (3.6) and the optimality of  $\phi_{J^{(n)}}$  for  $F_n$ .

From (3.7) and (3.8) it is easily seen that

$$(3.9) \quad G_1[y(\phi^*)] - \epsilon < G_1[y(\phi_{J^{(n)}})] + \epsilon \leq G_1[y(\phi^*)] + \epsilon$$

hold almost surely for any  $n > n_0(\epsilon)$ . This is equivalent to (3.4), and the proof is completed.

**THEOREM 2.** *Let  $F(x)$  be a distribution function which has a finite second moment and contains at least  $l$  points in its support. Then*

$$(3.10) \quad P\{\lim_{n \rightarrow \infty} G_2(y_{(n)}^{**}) = G_2[y(\phi^{**})]\} = 1$$

where  $G_2$  is defined in (3.2) or (1.5),  $\phi^{**}$  and  $\phi_{(n)}^{**}$  are optimum stratifications in case of Neyman allocation for  $F$  and  $F_n$  respectively, and  $y(\phi) = (w(\phi), u(\phi), v(\phi))$ .



PROOF. Let us first note that the image  $S$  and  $S^{(n)}$  of the  $\Phi$  of all stratifications by the linear mapping  $y(\phi)$  and  $y^{(n)}(\phi)$  are compact sets in  $R^{3l}$ . Further it is easily seen by the strong law of large numbers that for any positive  $\varepsilon$

$$|w_i^{(n)}(\phi)| \leq \int_{-\infty}^{\infty} |x| dF_n(x) < \int_{-\infty}^{\infty} |x| dF(x) + \varepsilon$$

and

$$|v_i^{(n)}(\phi)| \leq \int_{-\infty}^{\infty} x^2 dF_n(x) < \int_{-\infty}^{\infty} x^2 dF(x) + \varepsilon$$

hold almost surely for  $n > n_0(\varepsilon)$ . This means the set  $S^{(n)}$  is included in  $S_\varepsilon = \{y'; y' = y \pm \varepsilon, y \in S\}$  for  $n > n_0(\varepsilon)$ .

Since  $G_2(\cdot)$  is continuous on the compact set  $S_\varepsilon$ , it is uniformly continuous on  $S_\varepsilon$ . Besides it is easily seen by Lemma 1 that  $y^{(n)}(\phi_J) = (w^{(n)}(\phi_J), v^{(n)}(\phi_J))$  converges almost surely to  $y(\phi_J)$  uniformly in  $J \in T$ .

Therefore

$$(3.11) \quad P\{\lim_{n \rightarrow \infty} \sup_{J \in T} |G_2[y^{(n)}(\phi_J)] - G_2[y(\phi_J)]| = 0\} = 1$$

holds, and hence the rest of the proof goes on in the same way as shown in Theorem 1.

#### 4. Conclusion

We have shown in this paper that the optimum stratifications  $\phi_{(n)}^*$  and  $\phi_{(n)}^{**}$  for the empiric distribution function  $F_n(x)$  converge to the optimum stratifications  $\phi^*$  and  $\phi^{**}$  for a univariate distribution function  $F(x)$  respectively, both in cases of proportionate and Neyman allocation.

There still remain the following problems:

- 1) It is possible to extend these results to the multivariate distribution function  $F(x)$ ?
- 2) May we find some useful algorithm to find out  $\phi_{(n)}^*$  and  $\phi_{(n)}^{**}$  for a finite  $n$ ?

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