

ON THE INDIFFERENCE ZONE APPROACH TO SELECTION—A CONSISTENCY RESULT

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Summary

The problem of selecting the t best among k populations is considered. The concept of ψ -correct selection is defined and it is shown that the indifference zone approach is consistent in the following sense. The minimum probability of ψ -correct selection over the entire parameter space is no less than the minimum probability of correct selection over the preference zone.

1. Introduction

Consider the situation of k populations Π_1, \dots, Π_k and k random observations X_1, \dots, X_k , where each X_i is taken from Π_i with distribution function $F(\cdot; \theta_i)$. The problem of selection is to find those t populations with the largest θ -values (to be referred to as the t best populations). Suppose the family $\{F(\cdot; \theta): \theta \in \Theta\}$ is stochastically increasing, that is, $F(x; \cdot)$ is non-increasing for each fixed x (here Θ is a subset of the real line). A reasonable decision rule R , often used for this situation, is to select those t populations which give rise to the t largest X_i . Let the indices $[i]$ order the θ_i , that is

$$\theta_{[1]} \leq \theta_{[2]} \leq \dots \leq \theta_{[k]}.$$

Then a subset of t populations is a *correct selection* (CS) if it equals $\{\Pi_{[k-t+1]}, \dots, \Pi_{[k]}\}$.

Let $\Omega = \{\theta = (\theta_1, \dots, \theta_k): \theta_i \in \Theta\}$ be the parameter space. As θ varies over Ω , the probability of a correct selection $P_\theta\{CS|R\}$ may be as low as $1/\binom{k}{t}$. In the indifference zone approach of Bechhofer [2], the experimenter specifies a preference zone $M \subset \Omega$ and designs the experiment (e.g. if each X_i is a sample mean of size n , he may choose n) so that

$$(1.1) \quad p(M) = \inf_{\theta \in M} P_\theta\{CS|R\} \geq P^*$$

where $1/\binom{k}{t} < P^* < 1$. Following Barr and Rizvi [1], the preference zone is defined in terms of an increasing function ψ , $\psi(x) > x$ for all x , namely,

$$M \equiv \Omega_\psi = \{\theta: \psi(\theta_{[k-t]}) \leq \theta_{[k-t+1]}\}.$$

(For the classical cases of location or scale parameters $\psi(x) = x + d$ ($d > 0$) or $\psi(x) = cx$ ($c > 1$) respectively.)

The rationale for the indifference zone approach is that we want to control the minimum probability of correctly selecting the t best populations whenever they are really to be preferred (i.e. the t best are sufficiently far apart from the other $k-t$ populations). For this approach to be *consistent* we argue that any selection of t populations Π_i , for which $\psi(\theta_i) > \theta_{[k-t+1]}$, should be considered a correct selection (to be denoted ψ -CS) and that

$$(1.2) \quad p_\psi(\Omega) = \inf_{\theta \in \Omega} P_\theta\{\psi\text{-CS} | R\} \geq p(\Omega_\psi).$$

It is our purpose to prove the consistency of the indifference zone approach. Note however that CS always implies ψ -CS and on Ω_ψ both, CS and ψ -CS, are equivalent. Hence

$$(1.3) \quad p_\psi(\Omega) = \min \{p_\psi(\Omega_\psi^c), p(\Omega_\psi)\},$$

where $p_\psi(A) = \inf_{\theta \in A} P_\theta\{\psi\text{-CS} | R\}$. Thus consistency implies that the inequality in (1.2) is in fact equality. The consistency property will follow if we show that

$$(1.4) \quad P_\theta\{\psi\text{-CS} | R\} \geq p(\Omega_\psi) \quad \text{for all } \theta \in \Omega_\psi^c.$$

This is proved in Section 2. In Section 3 we have some general remarks.

2. The main result

For the proof of (1.4) we need a general result concerning stochastic monotonicity. Let $A \subseteq \{1, \dots, k\}$ and $A^c = \{1, \dots, k\} \setminus A$ and let $N(\xi) = \#\{i \in A: \xi_i > \bigvee_{j \in A^c} \xi_j\}$, $\xi = (\xi_1, \dots, \xi_k) \in R^k$.

LEMMA 1. *If $Y = (Y_1, \dots, Y_k)$ is a random vector with independent components, then $N(Y)$ is stochastically increasing in Y_i , $i \in A$ and stochastically decreasing in Y_j , $j \in A^c$.*

PROOF. We have to show that if $Y^* \in R^k$ is another random vector with independent components such that $Y_i^* \geq_{st} Y_i$, $i \in A$ and $Y_j^* \leq_{st} Y_j$, $j \in A^c$ then $N(Y) \leq_{st} N(Y^*)$. Clearly $N(\xi)$ (for non-random ξ) is a non-

decreasing function of ξ_i , $i \in A$ and non-increasing function of ξ_j , $j \in A^c$. The result follows from the fact that non-decreasing transformations preserve the stochastic ordering.

Now, assuming that the family $\{F(\cdot; \theta): \theta \in \Theta\}$ is stochastically increasing, for correct selection it is well known that

$$(2.1) \quad \inf_{\theta \in \Omega_{\psi}} P_{\theta} \left\{ \bigwedge_{i=k-t+1}^k X_{[i]} > \bigvee_{j=1}^{k-t} X_{[j]} \right\} \\ = \inf_{\theta \in \Theta} t \int_{-\infty}^{\infty} F^{k-t}(y; \theta) \{1 - F(y; \psi(\theta))\} dF(y; \psi(\theta)).$$

Let $A_u = \{k-u+1, \dots, k\}$ ($t \leq u \leq k$), $X = (X_{[1]}, \dots, X_{[k]})$ and let N_u and A_u play the role of N and A as above. Define the one-parameter subset $B = \{\theta = \theta(\theta): \theta_{[i]} = \theta, i \leq k-t; \theta_{[j]} = \psi(\theta), j > k-t; \theta \in \Theta\} \subset \Omega$. Then (2.1) can be written as

$$(2.2) \quad p(\Omega_{\psi}) = \inf_{\theta \in B} P_{\theta} \{N_t(X) \geq t\}$$

(note $0 \leq N_t \leq t$).

THEOREM 1. *If $\{F(\cdot; \theta): \theta \in \Theta\}$ is stochastically increasing then*

$$P_{\theta} \{\psi\text{-CS} | R\} \geq p(\Omega_{\psi}) \quad \text{for all } \theta \in \Omega_{\psi}^c.$$

PROOF. Suppose $\theta \in \Omega_{\psi}^c$. Then there exist a $\theta_0 \in \Theta$ and an integer u ($t < u \leq k$) such that

$$(2.3) \quad \theta_{[1]} \leq \dots \leq \theta_{[k-u]} \leq \theta_0 < \theta_{[k-u+1]} \leq \dots \leq \theta_{[k-t]} \leq \psi(\theta_0) \\ \psi(\theta_0) = \theta_{[k-t+1]} \leq \dots \leq \theta_{[k]}.$$

For this θ , a ψ -CS is any subset of size t of the populations $\{\pi_{[k-u+1]}, \dots, \pi_{[k]}\}$, hence

$$P_{\theta} \{\psi\text{-CS} | R\} = P_{\theta} \{N_u(X) \geq t\}.$$

It follows by Lemma 1 that for θ satisfying (2.3) we have

$$P_{\theta} \{N_u(X) \geq t\} \geq P_{\theta(\theta_0)} \{N_u(X) \geq t\} \\ \geq P_{\theta(\theta_0)} \{N_t(X) \geq t\} \geq \inf_{\theta(\theta) \in B} P_{\theta(\theta)} \{N_t(X) \geq t\} = p(\Omega_{\psi});$$

the second inequality follows from the fact that $N_t \leq N_u$ ($t < u$). This completes the proof.

3. Concluding remarks

Being " ψ -correct" in the subset selection approach is called *eliminating the non t -best* by Carroll, Gupta and Huang [3] (see also Gupta

and Panchapakesan [5]). If the experimenter is concerned with being " ψ -correct" in classifying the $k-t$ worst populations as well as the t best ones, he is led to the following definition, based on Fabian [4]. A selection of t populations is F -correct (F -CS) if $\psi(\theta_j) > \theta_i$ for every selected Π_j and nonselected Π_i . It is then easy to verify that

$$\begin{aligned} CS &\Rightarrow F\text{-}CS \Rightarrow \psi\text{-}CS && \text{on } \Omega \quad (1 \leq t < k), \\ CS &\Rightarrow F\text{-}CS \Leftrightarrow \psi\text{-}CS && \text{on } \Omega_\psi \quad (1 \leq t < k), \\ F\text{-}CS &\Leftrightarrow \psi\text{-}CS && \text{on } \Omega \quad (t=1). \end{aligned}$$

Thus Fabian's result

$$(3.1) \quad \inf_{\theta \in \Omega} P_\theta\{F\text{-}CS | R\} = p(\Omega_\psi) \quad (t=1)$$

is a special case of (1.2). It is still an open question whether (3.1) is true for general t .

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