

On the Asymptotic Validity of a Fully Sequential Elimination Procedure for Indifference-Zone Ranking and Selection with Tight Bounds on Probability of Correct Selection

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We prove the validity of the sequential elimination IZ procedure proposed by Frazier [1] when δ goes to 0. Specifically, we analyze Algorithm 2, with known sampling variances, and $B_1 = \dots = B_k = 1$.

Asymptotic Validity when the Variances are Known

Without loss of generality, suppose that the true means of the systems are indexed so that $\mu_k \geq \mu_{k-1} \geq \dots \geq \mu_1$. We suppose that samples from system $x \in \{1, \dots, k\}$ are normally distributed and independent, over time and across alternatives. We also suppose that the algorithm ends in at most $R(\delta) \in \mathbb{N}$ iterations, and $R(\delta) \rightarrow \infty$ as $\delta \rightarrow 0$ with probability 1. To simplify notation, we write R in place of $R(\delta)$, and let the dependence on δ be implicit. Furthermore, $R^{1/2}\delta$ converges to a random variable Δ with probability 1 where $\infty > \Delta > 0$ with probability 1. We also define $\lambda_z^2 := \max_{i \in \{1, \dots, k\}} \lambda_i^2$.

Lemma 1. If $x \in \{1, \dots, k\}$ and $t \in [0, 1]$, then

$$C_x(\delta, t) := \frac{Y_{\text{ceil}\left(\frac{\lambda_x^2}{\lambda_z^2}(n_0 + tR)\right), x} - \frac{\lambda_x^2}{\lambda_z^2}(n_0 + tR)\mu_x}{\frac{\lambda_x^2}{\lambda_z^2}\sqrt{R}} \Rightarrow W_x(t)$$

where $Y_{n,x}$ is the sum of the first n samples and W_x is a standard Brownian motion.

Proof. Let $(a_n) \subset \mathbb{R}_+$ be a sequence, by the Lindeberg-Lévy central limit theorem and the fact that

$$\frac{\text{ceil}(a_n t)}{a_n} \rightarrow t, \text{ as } n \rightarrow \infty,$$

$$\frac{Y_{\text{ceil}(a_n t), x} - \text{ceil}(a_n t) (\mu_x)}{\lambda_x \sqrt{a_n}} \Rightarrow W_x(t).$$

Consequently, as $n \rightarrow \infty$,

$$\frac{Y_{\text{ceil}(a_n t), x} - a_n t (\mu_x)}{\lambda_x \sqrt{a_n}} \Rightarrow W_x(t)$$

because $\frac{nt - \text{ceil}(nt)}{\lambda_x \sqrt{n}} \rightarrow 0$. Thus, as $\delta \rightarrow 0$,

$$\frac{Y_{\text{ceil}\left(\frac{\lambda_x^2}{\lambda_z^2} t R\right), x} - \frac{\lambda_x^2}{\lambda_z^2} t R (\mu_x)}{\frac{\lambda_x^2}{\lambda_z} \sqrt{R}} \Rightarrow W_x(t),$$

and then

$$\frac{Y_{\text{ceil}\left(\frac{\lambda_x^2}{\lambda_z^2} (n_0 + tR)\right), x} - \frac{\lambda_x^2}{\lambda_z^2} (n_0 + tR) \mu_x}{\frac{\lambda_x^2}{\lambda_z} \sqrt{R}} \Rightarrow W_x(t).$$

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Now, we consider the set $D[0, 1]^k$ which is the set of functions from $[0, 1]$ to \mathbb{R}^k that are right-continuous and have left-hand limits. We'll use the Skorokhod metric d on $D[0, 1]^k$:

$$d(X, Y) = \inf_{\lambda \in \Lambda} \{ \|\lambda - I\| \vee \|X - Y \circ \lambda\| \}$$

where Λ is the set of strictly increasing, continuous mappings of $[0, 1]$ onto itself, and $\|\cdot\|$ is the uniform norm, and I is the identity map.

Suppose Δ is given. Let $Y \in D[0, 1]^k$ and $t \in [0, 1]$, we define

$$q_{tx}^{Y, \delta}(A) : = \exp \left(\delta \beta_{tR} \lambda_z \sqrt{R} \frac{Y_x(t)}{(n_0 + tR)} \right) / \sum_{x' \in A} \exp \left(\delta \beta_{tR} \lambda_z \sqrt{R} \frac{Y_{x'}(t)}{(n_0 + tR)} + \beta_{tR} \delta^2 I_{x', x} \right)$$

where $\beta_{tR} = \frac{(n_0 + tR)}{\lambda_z^2}$ and

$$I_{x', x} = \begin{cases} 0 & \text{if } x' = x \\ 1 & \text{if } x' > x \\ -1 & \text{if } x' < x \end{cases}.$$

We then define

$$\begin{aligned}
T_{Y,\delta}^0 &= 0 \\
A_0^{Y,\delta} &= \{1, \dots, k\} \\
P_0^{Y,\delta} &= P^* \\
T_{Y,\delta}^{n+1} &= \inf \left\{ t \in [T_{Y,\delta}^n, 1] : \min_{x \in A_n^{Y,\delta}} q_{tx}^{Y,\delta} (A_n^{Y,\delta}) \leq c \text{ or } \max_{x \in A_n^{Y,\delta}} q_{tx}^{Y,\delta} (A_n^{Y,\delta}) \geq P_n^{Y,\delta} \right\} \\
Z_{n+1}^{Y,\delta} &\in \arg \min_{x \in A_n^{Y,\delta}} q_{T_{Y,\delta}^{n+1},x}^{Y,\delta} (A_n^{Y,\delta}) \\
A_{n+1}^{Y,\delta} &= A_n - \left\{ Z_{n+1}^{Y,\delta} \right\} \\
P_{n+1}^{Y,\delta} &= P_n^{Y,\delta} / \left(1 - \min_{x \in A_n^{Y,\delta}} q_{T_{Y,\delta}^{n+1},x}^{Y,\delta} (A_n^{Y,\delta}) \right).
\end{aligned}$$

Now, let

$$M_{Y,\delta} = \inf \left\{ n = 1, \dots, k-1 : \max_{x \in A_{n-1}^{Y,\delta}} q_{T_{Y,\delta}^n,x}^{Y,\delta} (A_n^{Y,\delta}) \geq P_{n-1}^{Y,\delta} \right\}$$

and

$$f(Y, \delta) = \begin{cases} 1 & \text{if } k \in A_{M-1}^{Y,\delta} \text{ and } \frac{\lambda_k^2}{\lambda_z} \left(Y_k \left(T_{Y,\delta}^{M_{Y,\delta}} \right) \right) + \delta \frac{\lambda_k^2}{\lambda_z^2 \sqrt{R}} \left(n_0 + T_{Y,\delta}^{M_{Y,\delta}} R \right) \geq \frac{\lambda_x^2}{\lambda_z} \left(Y_x \left(T_{Y,\delta}^{M_{Y,\delta}} \right) \right) \quad \forall x \in A_{M-1}^{Y,\delta} \\ 0 & \text{otherwise} \end{cases}.$$

Now, we also define

$$q_{tx}^Y(A) := \exp \left(\Delta \frac{Y_x(t)}{\lambda_z} \right) / \sum_{x' \in A} \exp \left(\Delta \frac{Y_{x'}(t)}{\lambda_z} + t \frac{\Delta^2}{\lambda_z^2} I_{x',x} \right)$$

$$\begin{aligned}
T_Y^0 &= 0 \\
A_0^Y &= \{1, \dots, k\} \\
P_0^Y &= P^* \\
T_Y^{n+1} &= \inf \{t \in [T_Y^n, 1] : \min_{x \in A_n^Y} q_{tx}^Y(A_n^Y) \leq c \text{ or } \max_{x \in A_n^Y} q_{tx}^Y(A_n^Y) \geq P_n^Y\} \\
Z_{n+1}^Y &\in \arg \min_{x \in A_n^Y} q_{T_Y^{n+1}, x}^Y(A_n^Y) \\
A_{n+1}^Y &= A_n^Y - \{Z_{n+1}^Y\} \\
P_{n+1}^Y &= P_n^{Y, \delta} / \left(1 - \min_{x \in A_n^Y} q_{T_Y^{n+1}, x}^Y(A_n^Y)\right).
\end{aligned}$$

Now, let

$$M_Y = \inf \left\{ n = 1, \dots, k-1 : \max_{x \in A_{n-1}^Y} q_{T_Y^n, x}^Y(A_n^Y) \geq P_{n-1}^Y \right\}$$

and

$$g(Y) = \begin{cases} 1 & \text{if } k \in A_{M-1}^Y \text{ and } Y_k(T_Y^{M_Y}) + \Delta \frac{1}{\lambda_z} T_Y^{M_Y} \geq \frac{\lambda_x^2}{\lambda_k^2} (Y_x(T_Y^{M_Y})) \quad \forall x \in A_{M-1}^Y \\ 0 & \text{otherwise} \end{cases}.$$

Lemma 2. Let $D_s \equiv \{x \in D[0, 1]^k : \text{for some sequence } \{x_n\} \subset D[0, 1]^k \text{ with } \lim_n d(x_n, x) = 0, \text{ the sequence } \{f_n(x_n)\} \text{ does not converge to } \{g(x)\}\}$, then $\mathbb{P}(W \in D[0, 1]^k - D_s) = 1$.

Proof. Let $\{x_n\} \subset D[0, 1]^k$ such that $x_n \rightarrow W$. Then there exists $\lambda_n \in \Lambda$ such that $\sup_{t \in [0, 1]} \|\lambda_n(t) - t\| \leq d(x_n, W) + \frac{1}{n}$ and $\sup_{t \in [0, 1]} \|x_n(t) - W(\lambda_n(t))\| \leq d(x_n, W) + \frac{1}{n}$. Taking $g_n \equiv \sup_{t \in [0, 1]} \|W(t) - W(\lambda_n(t))\|$, we see from the uniform continuity of W on $[0, 1]^k$ and the definition of g_n that $\lim_{n \rightarrow \infty} g_n = 0$. Moreover, if we take $\epsilon_n = 3n^{-1} + 3\sup\{d(x_l, W) + g_l : l = n, n+1, \dots\}$, then $\{\epsilon_n\}$ is a monotonically decreasing sequence of positive numbers with limit zero.

From the definition of ϵ_n we have $d(x_n, W) < \epsilon_n/2$ and $g_n < \epsilon_n/2$ for $n = 1, 2, \dots$. Consequently, we

have

$$\begin{aligned}\|x_n(t) - W(t)\| &\leq \|x_n(t) - W(\lambda_n(t))\| + \|W(\lambda_n(t)) - W(t)\| \\ &< \epsilon_n\end{aligned}$$

Consequently,

$$\left\| W\left(T_{x_n, \delta_n}^{M_{x_n, \delta_n}}\right) - x_n\left(T_{x_n, \delta_n}^{M_{x_n, \delta_n}}\right) \right\| < \epsilon_n.$$

We will prove by induction that

$$\begin{aligned}T_{x_n, \delta_n}^m &\rightarrow T_W^m \\ Z_m^{x_n, \delta_n} &\rightarrow Z_m^W \\ A_m^{x_n, \delta_n} &\rightarrow A_m^W \\ P_m^{x_n, \delta_n} &\rightarrow P_m^W\end{aligned}$$

Suppose this is true for m . Observe that

$$T_{W - \epsilon_n e, \delta_n}^m \leq T_{x_n, \delta_n}^m \leq T_{W + \epsilon_n e, \delta_n}^m$$

We have that if $\hat{\tau}_M$ is the continuous version of $\frac{\tau_M}{R}$, then

$$f(C(\delta, t), \delta) = \begin{cases} 1 & \text{if } k \in \arg \max_{x \in A_{M-1}^{Y, \delta}} \frac{\lambda_x^2}{\lambda_z^2} \sqrt{R} \left(C_x(\delta, \hat{\tau}_M) + \frac{\lambda_x^2}{\lambda_z^2} (n_0 + \hat{\tau}_M R) \mu_x \right) \\ 0 & \text{otherwise} \end{cases}.$$

By lemma 1,

$$C(\delta, t) \Rightarrow W(t).$$

Now,

$$\begin{aligned}
\left| \frac{\lambda_x^2}{\lambda_z n_{tR,x}} \sqrt{R} \delta \beta_{tR} x_{n_x}(t) - \frac{\Delta}{\lambda_z} W_x(t) \right| &\leq \left| \frac{\lambda_x^2}{\lambda_z n_{tR,x}} \sqrt{R} \delta \beta_{tR} x_{n_x}(t) - \frac{\Delta}{\lambda_z} x_{n_x}(t) \right| \\
&\quad + \left| \frac{\Delta}{\lambda_z} W_x(t) - \frac{\Delta}{\lambda_z} x_{n_x}(t) \right| \\
&\leq \frac{\Delta}{\lambda_z} \epsilon_n + \epsilon |x_{n_x}(t)|,
\end{aligned}$$

furthermore

$$\begin{aligned}
\left| \frac{\lambda_x^2}{\lambda_z n_{tR,x}} \sqrt{R} \delta \beta_{tR} x_{n_x}(t) - \delta_n^2 \beta_{tR_n} - \frac{\Delta}{\lambda_z} W_x(t) + A(t) \right| &\leq \left| \frac{\lambda_x^2}{\lambda_z n_{tR,x}} \sqrt{R} \delta \beta_{tR} x_{n_x}(t) - \frac{\Delta}{\lambda_z} x_{n_x}(t) \right| \\
&\quad + \left| \frac{\Delta}{\lambda_z} W_x(t) - \frac{\Delta}{\lambda_z} x_{n_x}(t) \right| \\
&\quad + |A(t) - \delta_n^2 \beta_{tR_n}| \\
&\leq \frac{\Delta}{\lambda_z} \epsilon_n + \epsilon |x_{n_x}(t)| + \epsilon,
\end{aligned}$$

Now consider T_{x_n, δ_n} . Since $x_{n_i}(t) - W_i(t) < \epsilon_n$ and $W_i(t) - x_{n_i}(t) < \epsilon_n$, consequently

$$T_{W - \epsilon_n e, \delta_n} \leq T_{x_n, \delta_n} \leq T_{W + \epsilon_n e, \delta_n}$$

Observe that

$$t^* = \liminf_n T_{W - \epsilon_n e, \delta_n} \geq T_W$$

and

$$t_* = \limsup_n T_{W + \epsilon_n e, \delta_n} \leq T_W.$$

Then

$$t_* \leq T_W \leq t^* \leq \liminf_n T_{W + \epsilon_n e, \delta_n} \leq t_*$$

thus

$$t_* = t^* = T_W = \lim_n T_{W - \epsilon_n e, \delta_n} = \lim_n T_{W + \epsilon_n e, \delta_n}.$$

Then

$$\lim_n T_{x_n, \delta_n} = T_W$$

and so

$$\lim_n x_{n_i}(T_{x_n, \delta_n}) = \lim_n W_i(T_{x_n, \delta_n}) = W_i(T_W)$$

by the continuity of W_i .

Therefore

$$\lim_n f_n(x_n) = \lim_n f(x_n, \delta_n) = g(W).$$

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By the extension of the CMT (Theorem 5.5 of Billingsley 1968), we have the following corollary.

Corollary 1. We have that if $t \in [0, 1]$,

$$f(C(\delta, t), \delta) \Rightarrow g(W(t))$$

as $\delta \rightarrow 0$.

Theorem. If samples from system $x \in \{1 \dots, k\}$ are normally distributed and independent, over time and across alternatives, then $\lim_{\delta \rightarrow 0} Pr\{\text{BIZ selects } k\} \geq P^*$ provided $\mu_k \geq \mu_{k-1} + \delta$. We also suppose that the algorithm ends in at most $R(\delta) \in \mathbb{N}$ iterations, and $R(\delta) \rightarrow \infty$ as $\delta \rightarrow 0$ with probability 1. Furthermore, $\sqrt{R}\delta \rightarrow \Delta$ with probability 1 where $\infty > \Delta > 0$ with probability 1. We also suppose $B_1 = \dots = B_k = 1$.

Proof.

$$\begin{aligned}
\lim_{\delta \rightarrow 0} \mathbb{P}(CS) &\geq \lim_{\delta \rightarrow 0} \mathbb{P}(f(C(\delta, t), \delta) = 1) \\
&= \lim_{\delta \rightarrow 0} E(\mathbb{P}(f(C(\delta, t), \delta) = 1 \mid \Delta)) \\
&= E(\lim_{\delta \rightarrow 0} \mathbb{P}(f(C(\delta, t), \delta) = 1 \mid \Delta)) \\
&= E(\mathbb{P}(g(W) = 1 \mid \Delta)) \\
&= E\left(\mathbb{P}\left(W_k(\hat{\tau}_M) + \frac{1}{\lambda_z} \hat{\tau}_M \Delta \geq W_x(\hat{\tau}_M) \quad \forall x \in A_{M-1}^Y \mid \Delta\right)\right) \\
&\geq
\end{aligned}$$