Indifference-zone Ranking and Selection with 10,000 or More Alternatives

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Ranking and Selection with Independent Normal Samples

- We have k alternative systems that can be simulated.
- Each time we simulate alternative x, we observe

  $$y \sim \mathrm{Normal}(\theta_x, \sigma_x^2) \qquad \text{(independent across } x \text{ and time)}$$

  where θ_x is unknown.
- We assume known constant $\sigma_x^2 = \sigma^2$ in this talk.
  Results can be generalized to known heterogeneous σ_x^2.
  Unknown σ_x^2 is ongoing work.
- **Goal**: Use simulation efficiently to find $\arg\max_x \theta_x$.

Definition: Probability of Correct Selection

- A **policy** is an adaptive rule for deciding which alternatives to sample.
- Given a system configuration $\theta = (\theta_1, \ldots, \theta_k)$, and a policy π,

$$\mathrm{PCS}(\pi, \theta) \qquad \textbf{(Probability of Correct Selection)}$$

is the probability that π selects an alternative in $\arg\max_x \theta_x$.

Definitions: Preference Zone, Indifference Zone, IZ Guarantee

- The **preference zone** is:

$$\mathrm{PZ}(\delta) = \left\{ \theta \in \mathbb{R}^k : \theta_{[1]} - \theta_{[2]} \geq \delta \right\},$$

  where $\theta_{[1]} \geq \theta_{[2]} \geq \ldots \geq \theta_{[k]}$, and $\delta > 0$ is fixed.
- The **indifference zone (IZ)** is the complement: $\mathbb{R}^k \setminus \mathrm{PZ}(\delta)$.
- We say a policy π has an **IZ guarantee** with parameters δ and P^* if

$$\mathrm{PCS}(\pi, \theta) \geq P^* \quad \text{for all } \theta \in \mathrm{PZ}(\delta).$$

- **Goal: Find a policy that satisfies the IZ guarantee, while taking as few samples as possible.**

There are Many Procedures with an IZ Guarantee

Lots of previous work has constructed policies that satisfy the IZ guarantee.

- Fixed sample size policies: [Bechhofer, 1954]
- Two-stage policies: [Dudewicz and Dalal, 1975, Rinott, 1978]
- Fully sequential policies [Paulson, 1964, Bechhofer and Goldsman, 1987, Hartmann, 1988, Hartmann, 1991, Paulson, 1994, Kim and Nelson, 2001, Nelson et al., 2001, Hong, 2006, Bechhofer et al., 1968]

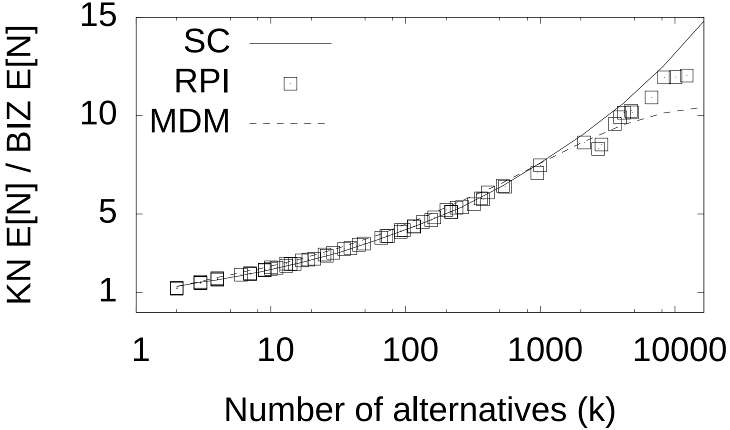
Overdelivery Leads To Oversampling (usually)

- Let π be a procedure with an IZ guarantee for a fixed P^* and δ.
- P^* is the PCS that π guarantees it will deliver.
- For any $\theta \in \mathrm{PZ}(\delta)$,
$$\mathrm{PCS}(\pi, \theta) - P^*$$
is the **overdelivery** on PCS.
- Overdelivery on PCS is inefficient: we could have taken fewer samples and achieved the guaranteed PCS faster.
- For existing policies and large k, this overdelivery causes the number of samples to be **significantly** larger than needed.

Contribution 1: We Have Tight PCS Bounds

- Given P^* and δ, we construct a fully sequential policy π for which
  1. We prove π has the IZ guarantee:
  $$\mathrm{PCS}(\pi, \theta) \geq P^*, \quad \text{for all } \theta \in \mathrm{PZ}(\delta).$$
  2. We prove the lower bound P^* on PCS is tight in continuous time:
  $$\inf_{\theta \in \mathrm{PZ}(\delta)} \mathrm{PCS}(\pi, \theta) = P^*$$
- This policy is inspired by a Bayesian analysis, and we call it the **Bayes-Inspired IZ (BIZ)** policy. (even though the theoretical results apply to non-Bayesian PCS).

Contribution 2: We Can Solve Larger Problems



- When the number of alternatives is large, this policy samples much less than existing IZ policies.
- For the largest problems, BIZ requires between 10 and 15 times fewer samples than KN.

We Construct BIZ with Bayesian Ideas

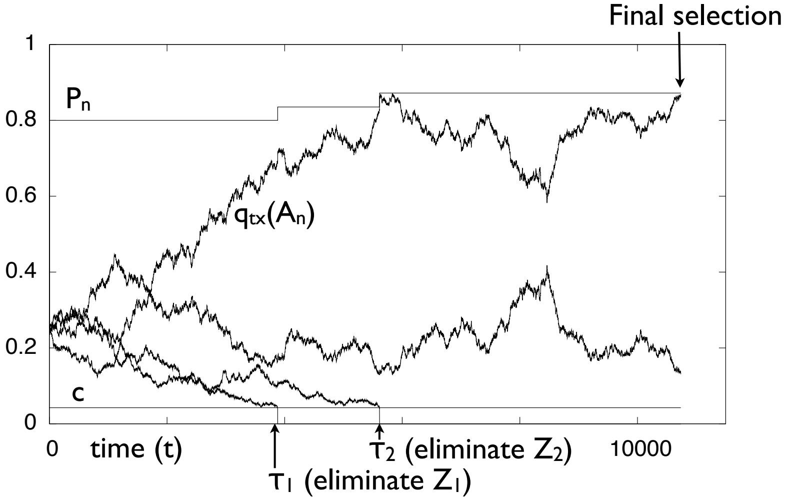
- Let Y_{tx} be the sum of all observations from alternative x by time t.
- Let Q be a probability measure concentrated on least-favorable configurations.
- For $A \subseteq \{1, \ldots, k\}$, define

$$q_{tx}(A) = Q\left\{x = X_* \mid X_* \in A, (Y_{tx'})_{x' \in A}\right\}.$$

  This can be interpreted as the **posterior probability that x is the best alternative**, given that the best is in the set A.
- One can show for $x \in A$:

$$q_{tx}(A) = \exp\left(\frac{\delta}{\sigma^2} Y_{tx}\right) \Big/ \sum_{x' \in A} \exp\left(\frac{\delta}{\sigma^2} Y_{tx'}\right).$$

Informal Definition of BIZ



Formal Definition of BIZ in Discrete or Continuous Time

- **Parameters**: $\mathbb{T} \in \{\mathbb{R}_+, \mathbb{Z}_+\}$, $c \leq 1 - (P^*)^{1/(k-1)}$, $\delta > 0$, $P^* > 1/k$.
- **Initalization**: $\tau_0 = 0$, $A_0 = \{1, \ldots, k\}$, $P_0 = P^*$.
- **Elimination Time**:

$$\tau_{n+1} = \inf \left\{ t \in \mathbb{T} \cap [\tau_n, \infty) : \min_{x \in A_n} q_{tx}(A_n) \leq c \text{ or } \max_{x \in A_n} q_{tx}(A_n) \geq P_n \right\}.$$

- **Eliminated Alternative and Contention Set**:

$$Z_{n+1} = \arg\min_{x \in A_n} q_{\tau_{n+1}}(A_n), \qquad A_{n+1} = A_n \setminus Z_{n+1}$$

- **Stopping Boundary**:

$$P_{n+1} = P_n \Big/ \left(1 - \min_{x \in A_n} q_{\tau_{n+1}}(A_n) \right).$$

- The **selected alternative** is the single alternative in A_{k-1}.

Implementing BIZ in Discrete Time is Easy

Fix parameters $c \leq 1-(P^*)^{1/(k-1)}$, $\delta > 0$, $P^* > 1/k$.

1. Let $A \leftarrow \{1,\dots,k\}$, $t \leftarrow 0$, $P \leftarrow P^*$.
2. While $\max_{x\in A} q_{tx}(A) < P$
   2a. While $\min_{x\in A} q_{tx}(A) \leq c$
      - Let $x \in \arg\min_x q_{tx}(A)$.
      - Let $P \leftarrow P/(1-q_{tx}(A))$.
      - Remove x from A.

   2b. Sample from each $x \in A$ to obtain $Y_{t+1,x}$. Then increment t.
3. Select $\hat{x} \in \arg\max_{x\in A} Y_{tx}$ as our estimate of the best.

Recall:

$$q_{tx}(A) = \exp\left(\frac{\delta}{\sigma^2} Y_{tx}\right) \Bigg/ \sum_{x'\in A} \exp\left(\frac{\delta}{\sigma^2} Y_{tx'}\right).$$

Main Theorem: Tight PCS Bounds

Theorem

Fix any $\delta > 0$, $P^* \in (1/k, 1)$, $\mathbb{T} \in \{\mathbb{Z}_+, \mathbb{R}_+\}$, $c \leq 1 - (P^*)^{1/(k-1)}$ and let π be the corresponding BIZ policy. Then,

$$\mathrm{PCS}(\pi, \theta) \geq P^* \quad \forall \theta \in \mathrm{PZ}(\delta)$$

Moreover, if $\mathbb{T} = \mathbb{R}_+$, then

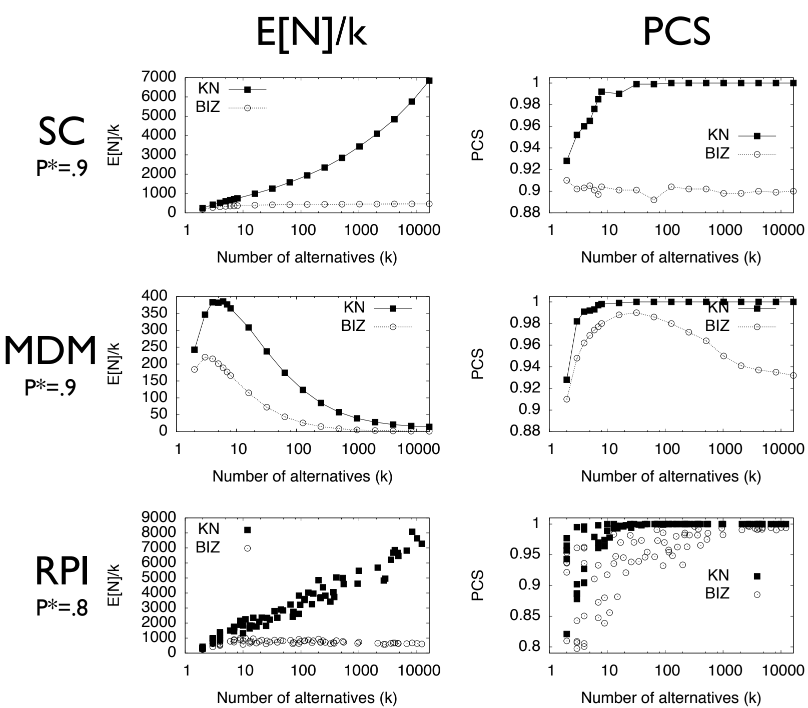
$$\inf_{\theta \in \mathrm{PZ}(\delta)} \mathrm{PCS}(\pi, \theta) = P^*$$

We construct BIZ with Bayesian ideas . . .
. . . but BIZ is a non-Bayesian Method

- BIZ is motived using Bayesian ideas, and manipulation of Bayesian PCS is critical in proofs of theoretical results.
- However, BIZ is a non-Bayesian method.
- You do not need to have a prior to use BIZ, and its IZ guarantee is non-Bayesian.

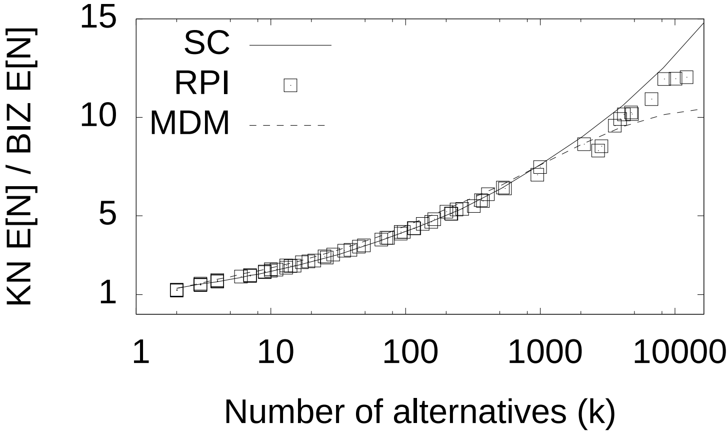
BIZ Generalizes [Bechhofer et al., 1968]

- Choosing $c = 0$ recovers the sequential ranking procedure $\mathscr{P}_B^*$ from [Bechhofer et al., 1968].
- In this special case, this policy does not eliminate.
- It was previously unknown that $\mathscr{P}_B^*$ is exact in continuous-time.



E[N]/k
PCS
SC
P*=.9
MDM
P*=.9
RPI
P*=.8
KN
BIZ
E[N]/k
PCS
Number of alternatives (k)

For the largest problems, BIZ requires 10 to 15 times fewer samples than KN.



Conclusion

- BIZ is a fully sequential IZ policy that delivers **exactly** P^*.
  (in continuous time, and under the worst θ in the preference zone).
- To my knowledge, this is the **first fully sequential elimination IZ policy with this property** for $k > 2$.
- This method of Bayesian analysis with least-favorable priors is a general theoretical tool.

Thank You!

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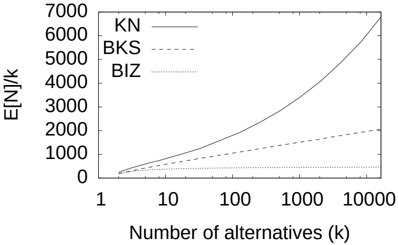
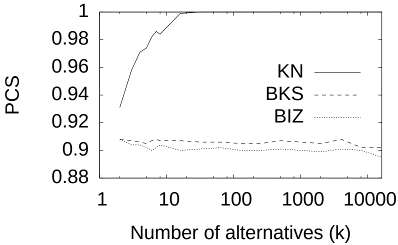
Heterogeneous Sampling Variance

- In continuous time, BIZ can be extended easily to the case where sampling variances are heterogeneous, and the main theoretical results are still true (IZ guarantee with a tight bound).
- In discrete time, the same technique can be applied, but the IZ guarantee no longer holds exactly. Ongoing work: does it hold in a limiting sense?

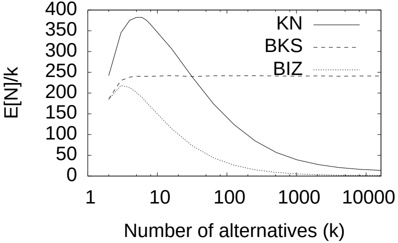
Numerical Comparisons: Slippage Configuration

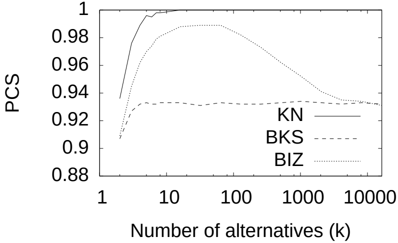




- $\theta = [0, \ldots, 0, \delta]$, $P^* = 0.9$, $\sigma = 10$, $\delta = 1$, estimated with $\geq 10,000$ independent replications.
- BIZ uses $c = 1 - (P^*)^{1/(k-1)}$ (eliminate aggressively).
- BKS is $\mathscr{P}_B^*$ $(c = 0)$ from [Bechhofer et al., 1968].

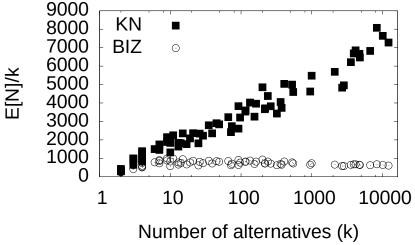
Numerical Comparisons: Monotone Decreasing Means

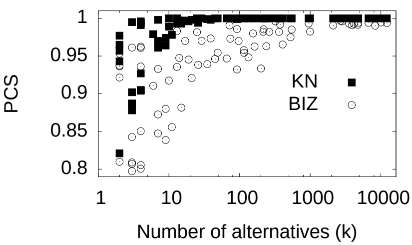




- Settings are the same as before: $\theta = [-\delta, -2\delta, \ldots, -k\delta]$, $P^* = 0.9$, $\sigma = 10$, $\delta = 1$, estimated with $\geq 10,000$ independent replications.
- BIZ uses $c = 1 - (P^*)^{1/(k-1)}$ (eliminate aggressively).
- BKS is $\mathscr{P}_B^*$ ($c = 0$) from [Bechhofer et al., 1968].

Numerical Comparisons: Random Problem Instances

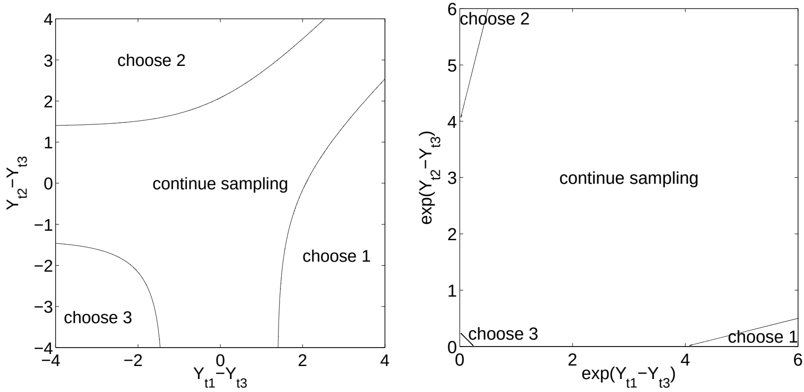




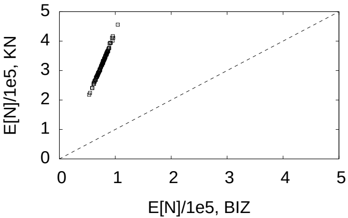
- $P^* = 0.8$, $\sigma = 10$, $\delta = 1$.
- Each set of sampling means μ was generated randomly from an independent normal prior and then adjusted to lie in $\mathrm{PZ}(\delta)$.
- BIZ uses $c = 1 - (P^*)^{1/(k-1)}$ (eliminate aggressively). BKS is $\mathscr{P}_B^*$ ($c = 0$) from [Bechhofer et al., 1968].

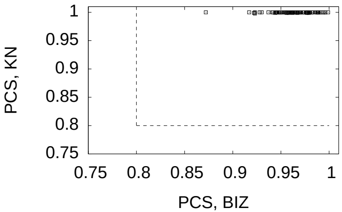
Continuation Region

- Images show continuation region for $k = 3$, in linear coordinates (left) and exponential coordinates (right).
- BKS (BIZ with $c = 0$) stops when Y_t exits the continuation region.



Numerical Comparisons: Random Problem Instances





- $k = 100$.
- $P^* = 0.8$.
- θ was generated randomly from an independent normal prior.
- It was then adjusted so that no alternative other than the best is within δ of the best, i.e., so that $\theta \in \mathrm{PZ}(\delta)$.

BIZ Construction: Elimination

Initialization: $(\tau_0 = 0,\ A_0 = \{1, 2, 3, 4\})$

t=1 1 2 3 4

t=2 1 2 3 4

t=3 1 2 3 4 $(\tau_1 = 3,\ Z_1 = 2,\ A_1 = \{1, 3, 4\})$

t=4 1 $\cancel{2}$ 3 4

t=5 1 $\cancel{2}$ 3 4 $(\tau_2 = 5,\ Z_2 = 4,\ A_2 = \{1, 3\})$

t=6 1 $\cancel{2}$ 3 $\cancel{4}$

t=7 1 $\cancel{2}$ 3 $\cancel{4}$ $(\tau_3 = 7,\ Z_3 = 1,\ A_3 = \{3\})$

Selection: Select alternative 3 as the best.

Heterogeneous Sampling Variance: Continuous Time

- In general, sampling variances σ_x^2 are heterogeneous and unknown.
- In continuous time, this problem is easily addressed:
  1. The sampling variance σ_x^2 can be estimated perfectly given $(Y_{tx} : 0 \leq t \leq \varepsilon)$ for any $\varepsilon > 0$.
  2. Replace $Y_{t,x} \sim \mathcal{N}(\theta_x, t\sigma_x^2)$ with $Y_{\sigma_x^2 t,x}/\sigma_x^2 \sim \mathcal{N}(\theta_x, t)$ and we obtain a ranking and selection problem with common sampling variance 1.
  3. Use BIZ for common sampling variance 1 on the transformed Y values.
- The IZ guarantee and the tightness of the bound remain true.

Heterogeneous Sampling Variance: Discrete Time

- In discrete time, the problem is harder:
- Idea: Replace $Y_{t,x}$ with $Y_{n_x(t),x}/\widehat{\sigma_x^2}$ where $n_x(t)$ rounds up $\widehat{\sigma_x^2}t$.
- The IZ guarantee no longer holds.
- Ongoing work: Does the IZ guarantee hold in a limiting sense?

Proof Sketch

Let CS be the event of correct selection.
For $\theta \in \mathbb{R}^d$, let Q_θ be a prior that is uniform on the permutations θ. In particular, $Q = Q_{[\delta,0,\ldots,0]}$.

Lemma (Symmetry)

$\mathrm{PCS}(\pi,\theta)$ *is invariant to permutations of* θ.
Moreover, $\mathrm{PCS}(\pi,\theta) = Q^\pi_\theta\{\mathrm{CS}\}$.

Lemma (Monotonicity)

For $\theta \in \mathrm{PZ}(\delta)$, $Q^\pi_\theta\{CS\} \geq Q^\pi_{[\delta,0,\ldots,0]}\{CS\}$.

Lemma (Bayes PCS of Least-favorable Configuration)

$Q^\pi_{[\delta,0,\ldots,0]}\{CS\} \geq P^*$, *with equality if* $\mathbb{T} = \mathbb{R}_+$.

BIZ Construction: Elimination

BIZ is an **elimination** procedure.

- It defines a sequence of stopping times, $0 = \tau_0 \leq \tau_1 \cdots \leq \tau_{k-1} < \infty$.
- For $n < k$,
  - τ_n is the time that the n^{th} alternative is eliminated.
  - $Z_n \in \arg\min_{x \in A_{n-1}} Y_{\tau_n, x}$ is the n^{th} alternative eliminated.
  - $A_n = \{1, \ldots, k\} \setminus \{Z_m : m \leq n\}$ are the remaining alternatives.
- At time τ_{k-1}, we stop sampling and select the single remaining alternative as best.

Elimination allows us to quickly eliminate very bad alternatives, reducing sampling effort.

Continuous-Time Observation Process

- In the original problem, we observe independent $\mathcal{N}(\theta_x, \sigma_x^2)$ values from alternative x.
  - The sum of all observations up to the current time is a random walk.
- In our continuous-time generalization, we let $(Y_{tx} : t \in \mathbb{R}_+)$ be a Brownian motion with drift θ_x and volatility $\sigma_x = \sigma$.
- Let $\mathbb{T} \in \{\mathbb{Z}_+, \mathbb{R}_+\}$. We restrict elimination and stopping decisions to be in $\mathbb{T}$.
- When $\mathbb{T} = \mathbb{Z}_+$, the resulting procedure can be implemented in discrete time.