

s.t.

$$\max(e_T(\mu_*), e_T(\mu^{[a]})) \geq \frac{1}{4} e^{-\frac{2T}{H_1(\mu)}}$$

Proof: claim:  $\exists a \in \{2, \dots, k\}$  s.t.

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$$E_\mu[N_a(T)] \leq \frac{T}{H_1 \Delta_a^2}$$

Reason: If  $E_\mu[N_a(T)] > \frac{T}{H_1 \Delta_a^2}$  for all  $a \in \{2, \dots, k\}$

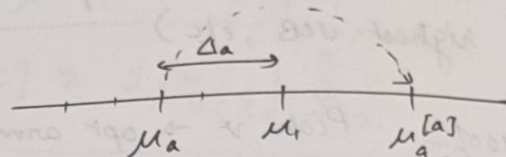
then

$$\sum_{a \geq 1} E[N_a(T)] > \frac{T}{H_1} \left( \sum \frac{1}{\Delta_a^2} \right)$$

$\Rightarrow$  Contradiction

$\rightarrow$  Pick such  $a$ , define  $\mu^{[a]}$  as;

$$\mu_i^{[a]} = \begin{cases} \mu_i & i \neq a \\ \mu_a + 2\Delta_a & i = a \end{cases}$$



Easy to see:  $H_1(\mu^{[a]}) < H_1(\mu)$

By B-H, Divergence decomposition,

$$\begin{aligned} \mathbb{P}_\mu(A) + \mathbb{P}_{\mu^{[a]}}(A^c) &\geq \frac{1}{2} e^{-D(\mu_a, \mu_a^{[a]})} \cdot \mathbb{E}_\mu[N_a(T)] \\ &\geq \frac{1}{2} e^{-\frac{(2\Delta_a)^2}{2}} \cdot \frac{T}{H_1 \Delta_a^2} \\ &= \frac{1}{2} e^{-2T/H_1} \end{aligned}$$

Since  $\mu_a^{[a]}$  is now the new opt arm, the subopt gap increases for all  $a$  (except  $\mu_a$  &  $\mu_i$ .)

$A = \{a_T = a\} \rightarrow$  Bad for  $\mu$   
and  $A^c$  bad for  $\mu^{[a]}$

$$e_T(\mu) \geq \mathbb{P}_\mu(A)$$

$$e_T(\mu^{[a]}) = \mathbb{P}_{\mu^{[a]}}(A^c)$$

$$\Rightarrow e_T(\mu) + e_T(\mu^{[a]}) \geq \frac{1}{2} e^{-2T/H_1}$$

$$\Rightarrow \max(e_T(\mu), e_T(\mu^{[a]})) \geq \frac{1}{4} e^{-2T/H_1}$$

$$\therefore \alpha(\text{any algo}) \leq \frac{2}{H_1} \leq \frac{4}{H_2} \quad (\text{using Lemma } \frac{H_2}{2} \leq H_1)$$

$$\text{And } \alpha(\text{SR}) \geq \frac{1}{8(\log k)H_2}$$

Thus, SR is already near-perfect.

Theorem: Consider algo s.t. for any instance  $v$ , for any  $a \neq 1$   
 $\mathbb{E}[N_a(T)] \leq C_a(v) \log(T)$

For this algo, prob. of error cannot decay exponentially in  $T$   $\forall v$ .

(Basically, for any algo, which gives log regret like VCB for all instances of  $v$ , we cannot get exponential decay (for BAI) for all instances)



→ This is irrespective of how we declare the best arm (highest mean, highest UCB, etc)

Proof: Pick  $v \rightarrow \text{opt arm 1}$   
Pick  $a \neq 1$ ,

Define  $v^{[a]}$  s.t. only arm  $a$  is perturbed;  $a$  is opt. in  $v^{[a]}$

By B-H, divergence decomp,

$$\mathbb{P}_v(A) + \mathbb{P}_{v^{[a]}}(A^c) \geq \frac{1}{2} e^{-D(v_a, v_a^{[a]})} \mathbb{E}_v[N_a(T)]$$

As before,  $(A = \{a_t = a\})$

$$\begin{aligned} e_T(v) + e_T(v^{[a]}) &\geq \frac{1}{2} e^{-D(v_a, v_a^{[a]})} \mathbb{E}_v[N_a(T)] \\ &\geq \frac{1}{2} e^{-DC \log T} \\ &= \frac{1}{2} T^{-DC} \end{aligned}$$

Powerlaw decay slower than exponentials.

$\Rightarrow$  Both  $e_T(v)$  and  $e_T(v^{[a]})$  cannot decay exponentially in  $T$ .

## FIXED CONFIDENCE BAI

Given: Error threshold  $\delta \in (0, 1)$        $\{\text{Prob. error} \leq \delta\}$

Algo keeps sampling until at stopping time  $\tau$ , it stops, and reports output  $\hat{a}_\tau$

Formally, we need,  $\mathbb{P}(\tau < \infty, \hat{a}_\tau \neq 1) \leq \delta$  ——— ①  
prob. that we stop & doesn't give right answer less than  $\delta$

Algo, that satisfies ① are called Sound /  $\delta$ -pc  
(prob. correct)

→ With prob.  $1-\delta$ , we give right ans (after stopping) or we don't stop.  
(For sound algo)

→ If we prove that we stop with prob. 1 then we give right answer with prob.  $1-\delta$ .

Goal: Minimize  $\mathbb{E}[\tau]$ , or high prob. upper bound on  $\tau$ .

Theorem : Consider 1-Gaussian instance  $\mu$  (arm 1 opt).

For any  $\delta$ -sound algo,

$$E[\tau] \geq 2 \log\left(\frac{1}{\delta}\right) \sum_{i=1}^k \frac{1}{\Delta_i^2}$$

Convention :  $\Delta_1 = \Delta_2$

$$\text{or } \Delta_i = \begin{cases} \mu_1 - \mu_2 & i=1 \\ \mu_1 - \mu_i & i \neq 1 \end{cases}$$

\* This is the first instance where we need that only one arm is optimal. If there are even 2 opt arms  $E[\tau]$  blows to  $\infty$ .

Earlier, we used only 1 optimal arm only for cosmetic reasons (not needed).

Here, the algo cannot differentiate whether there are 2 opt arms or the other arm is arbit. close to the first.