

## Appendix A. Proofs

### A.1. Proof of theorem 1

Let  $a_t$  denotes the arm with the highest index at time  $t$ , i.e.  $a_t = \arg \max_a \mathfrak{J}_{a,t}^{\text{BAYESIAN-CPD-TS}}$ . First note that at each time  $t$ , if the arm  $a$  is played, then the **BAYESIAN-CPD-TS** algorithm is either sampling a random arm or playing the arm with the highest index. So the probability that arm  $a$  is chosen at time  $t$  when  $a$  is not the optimal arm is written as:

$$\mathbb{P}(A_t = a \neq a_t^*) \leq \frac{\alpha}{A} + (1 - \alpha)\mathbb{P}(a_t = a \neq a_t^*)$$

Using the definition of  $\bar{N}_{a,T}$ , we have:

$$\begin{aligned} \mathbb{E}[\bar{N}_{a,T}] &\leq \sum_{t=1}^T \mathbb{P}(A_t = a \neq a_t^*) \\ &\leq \sum_{t=1}^T \left( \frac{\alpha}{A} + (1 - \alpha)\mathbb{P}(a_t = a \neq a_t^*) \right) \\ &\leq \frac{\alpha}{A}T + \underbrace{\sum_{t=1}^T \mathbb{P}(a_t = a \neq a_t^*)}_{(a)} \end{aligned}$$

Now, we need to upper bound the term (a). For this purpose, let us consider an experiment of the **BAYESIAN-CPD-TS** over  $T$  plays. Let  $F_a$  denote the number of false alarms up to time  $T$  and  $D_{a,k}$  denote the detection delay of  $k$ -th change-point on arm  $a$ , where  $a \leq \text{NC}_{a,T}$ . By the way, the total number of detection points, when the change detection algorithm **RBOCPD** signals an alarm on arm  $a$  is upper bounded by  $\text{NC}_{a,T} + F_a$ . Recall that  $\tau_a(t)$  is the latest detection time (which include also false alarms). For each arm  $a$ , we define  $\mathcal{T}_a$  as the set of times slots that no change-point occurs i.e.

$$\mathcal{T}_a = \{t \in [1, T] : \mu_{a,s} = \mu_{a,t} \text{ and } \tau_a(t) + 1 \leq s \leq t, t \geq \tau_a(t) + 1\}$$

Following this, we have:

$$(a) \leq \mathbb{E} \left[ \sum_{k=1}^{\text{NC}_{a,T}} D_{a,k} + \sum_{t \in \mathcal{T}_a} \mathbb{I}\{a_t = a \neq a_t^*\} \right]$$

Note that during a stationary period, we can easily use the regret upper control of Thompson Sampling to control the quantity  $\mathbb{I}\{a_t = a \neq a_t^*\}$ . Thus, following analysis in [Kaufmann et al. \(2012b\)](#), we have (in the case where  $\mathcal{T}_a$  is a deterministic set related to change-point  $k$ ):

$$\forall \varepsilon \in (0, 1), \exists C_{a,k} > 0 : \sum_{t \in \mathcal{T}_a} \mathbb{P}(a_t = a \neq a_t^*) \leq (1 + \varepsilon) \times \frac{\log |\mathcal{T}_a| + \log \log |\mathcal{T}_a|}{\mathbf{kl}(\theta_{a,[k]}, \theta_{[k]}^*)} + C_{a,k}$$

where  $|\mathcal{T}_a|$  denotes the length of the period  $\mathcal{T}_a$ .

Following this, since  $|\mathcal{T}_a| \leq T$  we have naturally :

$$\forall \varepsilon \in (0, 1), \exists C_{a,k} > 0 : \sum_{t \in \mathcal{T}_a} \mathbb{P}(a_t = a \neq a_t^*) \leq (1 + \varepsilon) \times \frac{\log T + \log \log T}{\mathbf{kl}(\theta_{a,[k]}, \theta_{[k]}^*)} + C_{a,k}$$

And then,

$$\forall \varepsilon \in (0, 1), \exists C_{a,k} > 0 : \sum_{t \in \mathcal{T}_a} \mathbb{P}(a_t = a \neq a_t^*) \leq (1 + \varepsilon) \times \frac{\log T + \log \log T}{\min_{k \in [1, K_T], a \neq a_k^*} \mathbf{kl}(\theta_{a,[k]}, \theta_{[k]}^*)} + C_{a,k}$$

Finally, by applying the expectation operator, we get:

$$\begin{aligned} \mathbb{E}[\bar{N}_{a,T}] &\leq \frac{\alpha}{A} T + \underbrace{\sum_{t=1}^T \mathbb{P}(a_t = a \neq a_t^*)}_{(a)} \\ &\leq \frac{\alpha}{A} T + \sum_{k=1}^{\text{NC}_{a,T}} \mathbb{E}[D_{a,k}] + (\text{NC}_{a,T} + \mathbb{E}[F_T]) \times (1 + \varepsilon) \times \frac{\log T + \log \log T}{\min_{k \in [1, K_T], a \neq a_k^*} \mathbf{kl}(\theta_{a,[k]}, \theta_{[k]}^*)} + C \end{aligned}$$

where  $\mathbb{E}[F_T]$  denotes the expected number of false alarm raised up to horizon  $T$  and  $C$  a problem dependant constant depending on all  $C_{a,k}$ .

## A.2. Proof of Theorem 2

Regarding the false alarm control, it comes directly from Theorem 1 in the analysis of the restarted Bayesian online changepoint detector in [Alami et al. \(2020\)](#).

Indeed, we have:

$$\begin{aligned} \forall \delta' \in (0, 1) : \mathbb{E}[F_T] &\leq \sum_{k=1}^{K_T} \mathbb{P}(\exists t \in [\tau_k + 1, \tau_{k+1} - 1] : \text{RBOCPD\_Restart}(Y_{A_t,1}, \dots, Y_{A_t, N_{A_t,t}}) = 1) \\ &\leq K_T \delta'. \end{aligned}$$

Thus, by choosing  $\delta' = \frac{\delta}{K_T}$ , we upper bound  $\mathbb{E}[F_T] \leq \delta$ .

Then, the control of the detection delay comes also from theorem 2 in the analysis of the restarted Bayesian online change-point detector in [Alami et al. \(2020\)](#).

Indeed we upper bound the detection delay of change point  $\tau_{a,k}$  related to arm  $a$  (with some  $\delta' \in (0, 1)$ )

$$\mathbb{E}[D_{a,k}] = \min \left\{ d \in \mathbb{N}^* : d > \frac{\left(1 - \frac{c_{\tau_{a,k}, d+\tau_{a,k}-1, \delta}}{\Lambda_{a,[k]}}\right)^{-2}}{2\Lambda_{a,[k]}^2} \times \frac{-\log \eta_{\tau_{a,k}, d+\tau_{a,k}-1} + f_{\tau_{a,k}, d+\tau_{a,k}-1}}{1 + \frac{\log \eta_{\tau_{a,k}, d+\tau_{a,k}-1} - f_{1, \tau_{a,k}, d+\tau_{a,k}-1}}{2n_{1:\tau_{a,k}-1} (\Lambda_{a,[k]} - c_{\tau_{a,k}, d+\tau_{a,k}-1, \delta})^2}} \right\}, \quad (5)$$

where:

$$c_{s,t,\delta} = \frac{\sqrt{2}}{2} \left( \sqrt{\frac{1 + \frac{1}{n_{1:s-1}}}{n_{1:s-1}} \log \left( \frac{2\sqrt{n_{1:s}}}{\delta'} \right)} + \sqrt{\frac{1 + \frac{1}{n_{s:t}}}{n_{s:t}} \log \left( \frac{2n_{1:t} \sqrt{n_{s:t} + 1} \log^2(n_{1:t})}{\log(2)\delta'} \right)} \right). \quad (6)$$

with  $f_{s,t} = \log n_{1:s} + \log n_{s:t+1} - \frac{1}{2} \log n_{1:t} + \frac{9}{8}$  and the decreasing function  $n_{i:j} = j - i + 1$  and  $\eta \in (0, 1)$ .

Indeed assuming that we collect enough samples between two consecutive change-points, we upper bound the detection delay of change point  $\tau_{a,k}$  related to arm  $a$  by its behavior in the asymptotic regime such that:

$$\mathbb{E}[D_{a,k}] = \mathcal{O} \left( \frac{o(\log \frac{1}{\delta'})}{2\alpha \times \Lambda_{a,[k]}^2} \right) \leq \mathcal{O} \left( \frac{o(\log \frac{1}{\delta'})}{2\alpha \times \min_{a: \Lambda_{a,[k]} \neq 0} \Lambda_{a,[k]}^2} \right)$$

Finally, by choosing  $\delta' = \frac{\delta}{K_T}$  we get the result of Theorem 2.

### A.3. Proof of Corollary 1

The result of corollary 1 comes directly by injecting the result of Theorem 2 into Theorem 1 after summing over all the arms.