Stochastic bandits with arm-dependent delays

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Abstract

Significant work has been recently dedicated to the stochastic delayed bandit setting because of its relevance in applications. The applicability of existing algorithms is however restricted by the fact that strong assumptions are often made on the delay distributions, such as full observability, restrictive shape constraints, or uniformity over arms. In this work, we weaken them significantly and only assume that there is a bound on the tail of the delay. In particular, we cover the important case where the delay distributions vary across arms, and the case where the delays are heavy-tailed. Addressing these difficulties, we propose a simple but efficient UCB-based algorithm called the PatientBandits. We provide both problems-dependent and problems-independent bounds on the regret as well as performance lower bounds.

1. Introduction

In realistic applications of reinforcement learning (RL), rewards come delayed. In a game, for instance, the consequences of the agent’s actions are only observed at the end. This issue at the core of challenges in RL (Garcia et al., 1966), when the horizon is finite or geometrically discounted. Even much simpler (state-less) bandit setups, such as online advertising suffer from delayed feedback (Chapelle and Li, 2011; Chapelle, 2014). In particular, most systems do not optimize for clicks but for conversions, which are events implying a stronger commitment from the customer. However, different ads trigger different customer response time. Typically, more expensive—and rewarding—products require more time to convert on customers’ side, and the system needs to be tuned to be robust to the delays.

As a result, we study stochastic delayed bandits for which the delay distributions are arm-dependent and possibly heavy-tailed. We consider the realistic model for delayed conversions of (Chapelle, 2014) and (Vernade et al., 2017) in which delays are only partially observable. Conversions are binary events that represent a strong commitment (buying, subscribing, . . . ). If a conversion happens, it is sent with some delay to the learner who observes both its reward and the corresponding delay. Otherwise, the reward is null by default but it has no specific delay, only the current waiting time. This models a typical e-commerce application: if a customer does not buy the recommended product, the recommendation system will not be informed. The nature of this setup brings two main challenges (1) the censoring due to partially observed delays, which forces the learner to deal with an unknown amount of missing feedback; and (2) the identifiability1 issue due to arm-dependent delays.

Prior work for delayed bandits have bypassed the challenges above by assuming that the delays are observed (Joulani et al., 2013; Dudík et al., 2011), which removes the ambiguity, or bounded by a fixed quantity (Pike-Burke et al., 2018; Garg and Akash, 2019; Cesa-Bianchi et al., 2018), which gives other possibilities to deal with them. Another approach that has been proposed by (Vernade et al., 2017) is to drop the artificial requirement of observability of delays, and instead impose that all delays have the same distribution across arms and that this distribution is known. We further discuss the relevant related work in Section 3. While the known approaches yield good results under their strong assumptions on delays, none of them provides a solution to the realistic problem that we are tackling.

Contributions This work is the first to consider a stochastic bandit setting with arm-dependent, unbounded, and possibly heavy-tailed delays with partially observable delays. We jointly address the challenges of (Vernade et al., 2017), (Zhou et al., 2019) and (Thune et al., 2019). Unlike (Vernade et al., 2017; Zhou et al., 2019), we make only mild assumptions on the delays. Furthermore, we give a precise characterization of the impact of the delays on the regret than that given in the more difficult, non-stochastic setting of (Thune et al., 2019). Our algorithmic solution is PatientBandits, the right calibration of upper confidence.

1Ex: Consider two instances for : (1) reward follows a Bernoulli(1) and delay is a Dirac in $\infty$ and (2) reward follows a Bernoulli(0) and delay is a Dirac in 0. Both instances produce the same data but have strictly different parameters.
bounds and prove that it attains problem-dependent and minimax regret upper bounds. In particular, we prove that:

- In the asymptotic regime, the presence of delays does not affect the regret by more than a constant factor with respect to what is achieved in standard bandits. In other words, the loss of information due to the delays does not lead to a significant increase of the regret with respect to standards bandits. Our algorithm attains the problem-dependent upper bound of the standard bandits up to a constant multiplicative factor in many cases, e.g. in the homoscedastic Gaussian case.

- On the other hand, we prove that there is a drop in performance with respect to problem-independent guarantees as compared to standard bandits. This is unavoidable and we prove a lower bound to support it.

- Finally, we study the impact of imperfect prior knowledge for PatientBandits. Our algorithm takes a parameter that is related to an upper bound on the heaviness of the tails of the delay distributions. We provide a comprehensive study in which respect the precise knowledge of this parameter can be avoided.

2. Bandits with delayed feedback

We define our stochastic delayed bandit setting. Consider a sequential game of $T \in \mathbb{N}^*$ rounds where an agent is interacting with an environment characterized by a finite set of $K \in \mathbb{N}^*$ arms which we denote $[K] \triangleq \{1, \ldots, K\}$. An instance is characterized by a tuple $((\mathcal{V}_i, \mathcal{D}_i)_{i \in [K]})$, where each arm $i \in [K]$ is associated with both

- an unknown reward distribution $\mathcal{V}_i$ whose support is in $[0, 1]$, and with mean $\mu_i$,
- and an unknown delay distribution $\mathcal{D}_i$ with cumulative distribution function (CDF) $\tau_i$ and support in $\mathbb{N}$, such that for any $d \geq 0$, $t \leq T$, if $D_t \sim \mathcal{D}_i$, then we have $\mathbb{P}(D_t \leq d) = \tau_i(d)$.

At each round $t \leq T$, the learner chooses (pulls) an arm $I_t \in [K]$. A reward $C_t \sim \mathcal{V}_{I_t}$ and a delay $D_t \sim \mathcal{D}_{I_t}$ are generated independently from each other. Neither the reward nor the delay is necessarily displayed at the current round $t$. However, at each upcoming round $t + u$ for $1 \leq u \leq T - t$, the learner observes the updated quantity

$$X_{t,u} \triangleq C_t 1\{D_t \leq u\}, \quad (1)$$

corresponding to her pull at time $t$. Note that, conversely, at time $t$, the learner only observes the updated quantities corresponding to its past actions: $(X_{s,t-s})_{s \leq t} \triangleq (C_s 1\{D_s \leq t-s\})_{s \leq t}$. And therefore at round $t$, it disposes of the entire history information

$$\mathcal{H}_t \triangleq (X_{u,v})_{u \leq t, v \leq t-u}. \quad (2)$$

This setting is summarized in Figure 1.

Note that delays are only partially observable: at round $t$ and for some $s \leq t$, if the learner observes $X_{s,t-s} = 0$, there is an ambiguity. Either the reward $C_s$ is actually 0, or the delay is not yet passed, i.e., $t - s < D_s$. This ambiguity is due to the multiplicative noise induced by the delays. Indeed, conditionally on the action taken at time $u < t$, $I_u \in [K]$, the expected observable payoff at round $t$ is scaled by some delay and action dependent factor

$$\mathbb{E}[X_{u,t-u} \mid I_u = i] = \tau_i(t - u)\mu_i.$$

In other words, the delays induce temporarily missing data among the observations, but the learner cannot know exactly how much feedback is missing.

Indeed, the heavier the tail of the delay distribution of an arm, the longer it takes for the learner to be able estimate its mean well. This creates dramatic identifiability issues: if the best arm is more delayed than the others, its apparent value might seem lower for a while and only a learner that is patient enough shall rightfully identify it as the optimal action. To mitigate this issue and to give a chance to a learner to tune its patience level, we rely on the following assumption.

**Assumption 1** ($\alpha$-polynomial tails for the delay distributions). Let $\alpha > 0$ be some fixed quantity. We assume that $\forall m \in \mathbb{N}^*$ and $\forall i \in \{1, \ldots, K\}$, it holds that

$$|1 - \tau_i(m)| \leq m^{-\alpha}.$$

The smaller $\alpha$, the more heavy-tailed the delay distribution, and the more difficult the setting. This assumption needs to hold uniformly across arms but does not impose they all have the same distribution, unlike required by (Vernade et al., 2017). This is an important weakening of the restricted setting of the prior work, which we generalize.
For $i \in [K]$, we denote by $T_i(t) \triangleq \sum_{s=1}^{t} 1\{I_s = i\}$ the number of times that the arm $i$ has been drawn up to round $t$. As $\mu^* \triangleq \max_{i} \mu_i$ denotes the mean of the best arm(s), $\Delta_i \triangleq \mu^* - \mu_i$ is the gap between the mean of the optimal arm(s) and the mean of arm $i$. The goal of the agent is to maximize its expected cumulative reward (i.e., $E[\sum_{i=1}^{K} C_i]$) after $T$ rounds and therefore to minimize the expected regret,

$$ R_T = T\mu^* - E\sum_{t=1}^{T} C_t = \sum_{i=1}^{K} \Delta_i E[T_i(T)]. \tag{3} $$

Remark 1. In this paper, we consider the same concept of regret as for standard bandits, unlike what is done by (Vernade et al., 2017). We believe it is a more relevant approach that allows for comparison with the vast existing prior work on the topic (see Section 3).

3. Related work

The problem of learning with delayed feedback is ubiquitous in a wide range of applications, including universal portfolios in finance (Cover, 2011), online advertising (Chapelle, 2014) and e-commerce (Yoshikawa and Imai, 2018). Therefore, there is a large body of theoretical results designed under different scenarios and assumptions on the delays. We review the contributions of prior works distinguishing between the full information setting and the bandit setting.

Full-information In online (convex) optimization, as opposed to our setting, the learner must perform gradient descent by estimating the gradient on the fly using the available information. Thus, delayed feedback forces the learner to make decisions in the face of additional uncertainty. This problem has been considered by (Weinberger and Ordentlich, 2002) in the cadre of prediction of individual sequences under the assumption that the delays were fixed and known. The study of online gradient type of algorithms under possibly random or adversarial delays is made under various hypotheses by (Langford et al., 2009; Quanrud and Khashabi, 2015; Joulani et al., 2016). In distributed learning, communication time between servers naturally induces delays, and this particular setting was studied by (Agarwal and Duchi, 2011; McMahan and Streeter, 2014; Sra et al., 2015) who all proposed asynchronous or delay-tolerant versions of AdaGrad. And an attempt to reduce the impact of delays was made by (Mann et al., 2018) by allowing the learner to observe intermediate signals.

Bandits with observed delays. (Joulani et al., 2013) provide a clear overview of the impact of the delays for both the stochastic and adversarial setting. Using a method based on a non-delayed algorithm called Base, he will succeed in extending the work of (Weinberger and Ordentlich, 2002) to the non-constant delays case. Following up in this work, (Mandel et al., 2015) argued in favor of more randomization to improve exploration in delayed environments, although the guarantees remained unchanged. Taking a different path, closer to ours, the recent work of (Zhou et al., 2019) relies on a biased estimator of the mean and corrects for it in the UCB using an estimator of the amount of missing information. They consider the contextual bandit setting and make a strong assumption on the delay distribution, imposing that 1) delays are fully observable, and 2) the delay distribution is the same for all arms and should concentrate nicely (bounded expectation). Due to these assumptions, their algorithm cannot be used in our setting and cannot be compared to ours. (Thune et al., 2019) considered the adversarial bandit setting, where delays are observed right after (or before) sampling an arm. Unfortunately their results and algorithms do not apply in our setting since we do not observe the delays before or right after sampling an arm.

Bandits with partially observed delays. The delayed bandits with censored observations was introduced by (Vernade et al., 2017), who builds on the real-data analysis of (Chapelle and Li, 2011). They rely on the major assumption that delays are the same across arms and have a finite expectation. In this setting they prove an asymptotic problem-dependent lower bound that recovers the standard Lai & Robbins’ lower bound. They propose an algorithm that uses as input the CDF of the delay distribution and matches this asymptotic lower bound. In other words, they prove that asymptotically, well-behaved delays have no impact on the regret. Following up in this work, (Vernade et al., 2018; Arya and Yang, 2019) extend this setting to the linear and contextual stochastic setting. Two other papers consider the case where the delays are not observed at all - but are bounded by a constant $D > 0$. (Garg and Akash, 2019) analyze the stochastic setting, and (Cesa-Bianchi et al., 2018) the adversarial setting and achieve a regret of order $\sqrt{TK \log K + KD \log T}$ and $\sqrt{DTK}$ respectively. (Pike-Burke et al., 2018) when further considering unbounded delays in adversarial setting but time under the assumption that only their expectation is bounded. Again these results do not apply in our context as we do not assume that the delays are bounded - and under Assumption 1 with $\alpha < 1$, the delays can even have infinite means.

4. The PatientBandits algorithm

In this section we describe an optimistic algorithm (Auer et al., 2002) that is able to cope with partially observed and potentially heavy-tailed delays. The PatientBandits algorithm estimates high-probability upper confidence bounds on the parameter of each arm. As opposed to the standard UCB approach, it is hopeless to design conditionally unbiased estimators in this delayed setting, so the algorithm also needs to properly bound the bias for each arm.
A delay-corrected, high-probability UCB. Delays being partially observable, the learner must build its estimators with an unknown number of observations. Indeed, since rewards are delayed, a certain proportion of the feedback of each arm is missing but it is impossible to know exactly how much because the zeros are ambiguous. Nonetheless, we show that it is possible to prove high-probability confidence bounds for the parameters of the problem, provided that we correctly handle this extra bias due to the delays. For this purpose, we rely on Assumption 1, that gives us a loose global bound on the tails of the distributions of the delays.

At a time \( t \geq K + 1 \), given the history of pulls and observed rewards \( \mathcal{H}_t \), we define the mean estimator:

\[
\hat{\mu}_i(t) = \frac{1}{T_i(t)} \sum_{u=1}^{t} X_{u,t-u} 1\{I_u = i\},
\]

where \( T_i(t) = \sum_{u=1}^{t} 1\{I_u = i\} \). The key ingredient for our algorithm is the upper confidence bound. The following theorem is our first major contribution and provides the required high-probability bound.

**Theorem 1.** Let \( i \in [K] \) and \( \alpha > 0 \) satisfy Assumption 1. Then for any \( t > K \) and \( \delta > 0 \), with probability \( 1 - \delta \)

\[
|\hat{\mu}_i(t) - \mu_i| \leq \left( \frac{2 \log \frac{2}{\delta}}{T_i(t)} \right)^{1/2} + 2T_i(t)^{-\alpha} \langle 1/2 \rangle.
\]

**Proof.** The full proof of this result is provided in Appendix A. It relies on the following decomposition

\[
|\hat{\mu}_i(t) - \mu_i| \leq \left| \hat{\mu}_i(t) - \frac{1}{T_i(t)} \sum_{u=1}^{t} \tau_i(t-u) \mu_i 1\{I_u = i\} \right| + \left| \frac{1}{T_i(t)} \sum_{u=1}^{t} \tau_i(t-u) \mu_i 1\{I_u = i\} - \mu_i \right|.
\]

On the right-hand side, the first term is a usual deviation term. The probability that it’s larger than \( \left( \frac{2 \log(2\delta)}{T_i(t)} \right)^{1/2} \) is uniformly bounded by \( \delta/2 \). The second term corresponds to the bias and is bounded by \( 2T_i(t)^{-\alpha} \langle 1/2 \rangle \), which comes from simply summing the \( \tau_i(t-u) \) in the worst case, i.e., when all pulls of arm \( i \) are made in the last \( T_i(t) \) rounds. \( \square \)

A clear benefit of the above result is a simple and easy-to-compute adaptive upper bound on the parameter \( \mu_i \) for our estimator. This UCB is similar to the standard UCB2 (Auer et al., 2002) except for the extra bias term that goes to zero with the number of pulls. In fact, it adaptively trades off bias and variance as a function of \( \alpha \): it is the largest for small values of \( \alpha \approx 1/2 \), that is when delays have very large tails. Indeed, \( \alpha \) plays an important role in our algorithm presented in details below.

**Algorithm 1 PatientBandits**

**Input:** \( \alpha > 0 \), horizon \( T \), number of arms \( K \).

**Initialisation:** Pull each arm once and set for all \( i \in [K] \):

\( T_i(1) = 1 \) and initialise \( \hat{\mu}_i(t) \) according to Eq. 4.

for \( t = K + 1 \ldots T \) do

Pull arm \( I_t \in \arg\max_{i \in [K]} UCB_i(t) \)

Observe all feedback updates \((X_{s,t-s})_{s \leq t}\)

end for

**PatientBandits is described in Algorithm 1.** It receives as input the parameter \( \alpha > 0 \), the horizon \( T \), and the number of arms \( K \) which we assume to be smaller than \( T \). In the first phase of the game, all arms are pulled once. The player then pulls the arm from \([K]\) that has the highest UCB as defined in Theorem 1,

\[
UCB_i(t) = \hat{\mu}_i(t) + \left( \frac{2 \log(2KT^3)}{T_i(t)} \right)^{1/2} + 2T_i(t)^{-\alpha} \langle 1/2 \rangle.
\]

The algorithm then pulls an arm \( I_t \) that maximises \( UCB_i(t) \).

**5. Analysis of PatientBandits**

We present the analysis of PatientBandits. We also provide a non-asymptotic lower-bound for delayed bandits. We provide first the following problem-dependent upper bound on the regret of PatientBandits. Its proof is deferred to Appendix B and follows the lines of the usual analysis of UCB by (Auer et al., 2002), see also (Lattimore and Szepesvári, 2019, §7).

**Theorem 2.** Let \( T > K \geq 1 \) and \( \alpha > 0 \). Let \((\mathcal{V}_i, \mathcal{D}_i)_{i \in [K]}\) be the problem as defined in Section 2 such that Assumption 1 holds. If PatientBandits is run with parameters \( \mathcal{P} = (\alpha, T, K) \), it achieves

\[
\mathcal{R}_T \leq \sum_{i: \Delta_i > 0} \left[ \frac{64 \log(2T)}{\Delta_i} \vee \left( \frac{8}{\Delta_i} \right)^{1/2} \right] + 2K.
\]

The only term that depends on \( T \) in Theorem 2 is of the order of \( \sum_{i: \Delta_i > 0} \log(T)/\Delta_i \). It is of the same order as the classical bound for UCB which is asymptotically optimal, see (Lai and Robbins, 1985). Note that this was expected, since (Vernade et al., 2017) showed that delays should not have an asymptotic impact on the regret\(^2\). Our bound has an additional term of order \( \sum_{i: \Delta_i > 0} \left( \frac{8}{\Delta_i} \right)^{1/2} \vee 1 \). This term

\(^2\)Their result is stated for delays with finite expectation but remains valid in our setting.
we now provide a problem-independent upper bound.

**Theorem 3.** Let $T > K \geq 1$ and $\alpha > 0$. If PatientBandits is run with parameters $P = (\alpha, T, K)$, for any stochastic delayed problem such that Assumption 1 holds, it achieves

$$R_T \leq 2 \times 64^{(1-\alpha)} \sqrt{\frac{1}{T}} \sqrt{\frac{1}{\sqrt{T}}} (K \log(2T))^{1/2} + 2K.$$ 

Up to logarithmic terms and multiplicative constants, the order of magnitude of this bound is $\max\left(\sqrt{\frac{K}{T}}, K^{\alpha} T^{1-\alpha}\right)$. Whenever $\alpha \geq 1/2$, the order of the bound is $\sqrt{\frac{K}{T}}$ - as is the case for UCB (up to logarithmic terms) and for more refined algorithms like MOSS in (Audibert and Bubeck, 2007) in the classical stochastic bandit setting (without delays). However, if the delays are allowed to be more heavy-tailed, i.e., $\alpha < 1/2$, then the regret starts degrading with $\alpha$ as the upper bound is of order $K^{\alpha} T^{1-\alpha}$. We prove that this degradation of the (problem-independent) regret is unavoidable.

**Theorem 4.** Consider $K = 2$ and $T \geq K$, and $\alpha > 0$. There exists a Bernoulli stochastic delayed bandit problem satisfying Assumption 1, such that the expected regret of any algorithm $\mathcal{R}_T$ on this problem is larger than $T^{1-\alpha}/8$.

Combining this theorem with the classical problem independent lower bound in classical stochastic bandits — see e.g., the book of (Lattimore and Szepesvári, 2018) — one obtains that the order of magnitude of the worst case regret (for bandit problems satisfying Assumption 1) of any algorithm is larger than $\max\left(\sqrt{\frac{K}{T}}, T^{1-\alpha}\right)$. This matches (up to logarithmic terms) the upper bound in Theorem 3 with respect to $T$ (not to $K$ whenever $\alpha < 1/2$).

### 6. Adaptation to $\alpha$

PatientBandits requires (a lower bound on ) $\alpha$ as input. It is indeed natural to ask whether this prior information on the delays is necessary. In other words, can we design an algorithm that learns $\alpha$ as well or adapts to the delays on-the-fly? And how much would the regret be impacted? In this section we give a detailed answer to those questions, both in the asymptotic and non-asymptotic regime. In the latter, we prove a negative result in the general case. However, we propose a new assumption under which adaptivity is achievable.

#### 6.1. Adaptation of the problem dependent regret to $\alpha$

We first study possibilities of adaptation in the asymptotic regime. An immediate corollary of Theorem 2 is as follows.

**Corollary 1.** Let $T > K \geq 1$ and consider a bandit problem with minimum gap $\Delta = \min_{k: \Delta_k > 0} \Delta_k$, and where each arm satisfies Assumption 1 for $\alpha_k$. Consider $T > e^c$ large enough so that $a) \log(T)/\log(T) \leq \min_i \alpha_i$, $b) 8\Delta^{-1} \leq \log(T)$. If PatientBandits is run with parameters $(\log \log(t)/\log(t))_{t \geq T}, T, K)$, it achieves:

$$R_T \leq \sum_{i: \Delta_i > 0} \left[ \frac{128 \log(2T)}{\Delta_i} \vee \left( \frac{8}{\Delta_i} \right)^{1/\alpha} \right] - 2K.$$ 

So for $T$ large enough depending on problem dependent quantities, it is possible to run a slight variant of PatientBandits that takes as input the sequence $(\alpha_t = \log \log(t)/\log(t))_{t \geq T}$ instead of a fixed $\bar{\alpha}$. So, for a fixed problem, asymptotically, knowing $\alpha$ is not necessary.

#### 6.2. Impossibility result under Assumption 1 for adapting the problem independent regret to $\alpha$

For a fixed horizon $T < \infty$, however, it is a different story. Our second lower bound below states that if you give a ‘too small’ input parameter $\alpha$ to a ‘good’ algorithm, then it has a suboptimal regret, even in the simpler case where $K = 2$.

Specifically, we define the class of $\alpha$-optimal algorithms $\mathcal{A}_\alpha$, as the algorithms whose expected regret is smaller than $T^{1-\alpha}/8$ for all bandit instances satisfying Assumption 1 for a fixed $\alpha$.

**Theorem 5.** Consider $K = 2$, $T \geq K$, and fix $\alpha > 0$. For any $\beta \geq \alpha$, there exists a Bernoulli bandit instance satisfying Assumption 1 for $\beta$ such that the expected regret $\mathcal{R}_T$ of any $\alpha$-optimal algorithm is larger than $T^{1-\alpha}/8 > T^{1-\beta}/8$.

In other words, an algorithm that performs optimally uniformly under Assumption 1 for a given $\alpha$ cannot at all adapt to $\beta \geq \alpha$.

#### 6.3. New algorithm for adapting the problem independent regret to $\alpha$ under more restrictive assumptions

Yet, is adaptivity a lost cause? Under the weak Assumption 1, Theorem 5 above is quite disheartening. A structural reason for this is that it is impossible to estimate $\alpha$ under this assumption. We show that under a slightly more restrictive assumption this becomes possible.

**Assumption 2.** Assume that there exists $0 < c \leq 1$ and $\bar{\mu} > 0$, such that $\min_k \mu_k > \bar{\mu}$ and for all $i \in [K]$, $cm^{-\alpha} \leq |1 - \tau_i(m)| \leq m^{-\alpha}$.


Assume also that $\alpha \geq \alpha$ for some $\alpha > 0$.

This assumption does not mean that the delay distributions of the arms are all the same. It means that the parameter $\alpha$ now globally characterizes the tails of the delay distributions. The challenge for estimating it is that delays are only partially observable. To further explain Assumption 2, let’s consider small and a large delay $d$ and $D$, such that $D > d > 0$. The conditional expectation of the difference of the same reward after respectively $d$ and $D$ time steps have passed is:

$$E[I_t, X_{t,D} - X_{t,d}] = \mu_t \tau_1(D) - \mu_t \tau_1(d) \in [\mu_t D^{-\alpha}, \mu_t d^{-\alpha}, \mu_t D^{-\alpha}, \mu_t d^{-\alpha}]$$

where $E[I_t]$ is the conditional expectation with respect to the arm $I_t$ pulled at time $t$, and where $c \geq 0$ comes from Assumption 2. Therefore, if $d \leq (c/2)^{1/\alpha}D$, we now have that

$$E[I_t, X_{t,D} - X_{t,d}] \in [c\mu_t d^{-\alpha} - \mu_t, D^{-\alpha}, \mu_t d^{-\alpha}]$$

where $\mu, D > 0$ are defined in Assumption 2. So we can now see that it is possible to estimate $\alpha$ up to a logarithmic factor using the logarithm of an estimator of $\mu_t \tau_1(D) - \mu_t \tau_1(d)$, if we properly choose $d$ and $D$ from some arm $i$ sampled often enough. We now formalize this idea, introducing all the necessary quantities.

In all this section, we denote $\tilde{T}_t = \arg \max_k T_k(t)$. We only use the samples of this arm to estimate $\alpha$ at each round. To simplify the notation let $\tilde{T}_k(t) = T_{\tilde{T}_k}(t)$ and for some delay $D$, let

$$\bar{m}_{t,D} \triangleq \frac{1}{T_{t-D}} \sum_{s=1}^{t-D} X_{s,D} \mathbf{1}\{I_s = \tilde{T}_s\}$$

be the sample mean after waiting $D$ steps. We set $D_t \triangleq \lceil \tilde{T}_t/2 \rceil$ and $d_t \triangleq \lceil (c/2)^{1/\alpha} D_t \rceil$. Subsequently, we define the estimator of $\alpha$ at round $t$ as

$$\hat{\alpha}_t \triangleq \min \left( \frac{\log(\bar{m}_{t,D_t} - \bar{m}_{t,d_t})}{\log(T_t)}, \frac{1}{2} \right)$$

Such an estimator is related to quantile or CDF-based estimators used in extreme value theory (De Haan and Ferreira, 2007; Carpentier and Kim, 2015). We define set the lower confidence bound on it as

$$\bar{\alpha}_t \triangleq \left[ \hat{\alpha}_t - \frac{\log(\bar{m}_{t,D_t} - \bar{m}_{t,d_t})}{\log(T_t)} \right] \vee 0.$$

Adapt-PatientBandits simply uses $\bar{\alpha}_t$ for the computation the upper confidence bounds as in Eq. 5. The algorithm therefore does not need to know for which parameter $\alpha$ Assumption 2 is satisfied. We summarize Adapt-PatientBandits in Algorithm 2.

### Algorithm 2: Adapt-PatientBandits

**Input:** $c, \alpha, \bar{\mu}, T, K$

**Initialisation:** Pull each arm twice.

**for** $t = 2K + 1, \ldots, T$ **do**

1. Pull the arm $I_t \in \arg \sup_i UCB_i(t - 1)$ when using the parameter $\bar{\alpha}_t$ in the UCB.
2. Observe all individual feedback $(X_{s,t-s})_{s \leq t}$.

**end for**

The expected regret of the Adapt-PatientBandits is bounded by the following theorem.

**Theorem 6.** Let $T > K \geq 1$ and $\alpha, \alpha, c, \bar{\mu} > 0$, such that Assumption 2 holds. The expected regret of Adapt-PatientBandits is bounded as

$$R_T = \bar{O}(K^{\alpha} T^{1-\alpha^{1/2}}).$$

And so Adapt-PatientBandits achieves a regret that depends on the unknown parameter $\alpha$ and is of the same order as the upper bound of Theorem 3 up to logarithmic term. This algorithm is therefore minimax optimal up to logarithmic terms relatively to the lower bound defined in Section 5.

### 7. Discussion

**Comparison to bandits without delays.** As discussed in the Section 4, the major difference between PatientBandits and the classical UCB algorithm is the extra bias term. In the classical bandit setting, we have strictly more information than in our setting. When rewards are delayed, the algorithm always has to deal with temporarily missing data: some actions have been taken but their rewards are missing until the delay has passed. In particular, when $\alpha < 1$, the delays are heavy-tailed, so their expectation is infinite, and this buffer of missing data always keeps growing in size with $T$, creating a non-negligible bias in the estimators. This difference is even more important when $\alpha < 1/2$, which corresponds to the situation where the bias term is larger than the usual deviation term. For such a problem, it is clear that a classical UCB would have a linear regret, see Section 8.

We now discuss optimality of PatientBandits by commenting both our problem-dependent (Th. 2) and problem-independent (Th. 3) bounds.

- The problem-dependent bound for our problem is of the order $\sum_{k, \Delta_k > 0} \log(T)/\Delta_k$. Up to a term that de-
pends only on the \((\Delta_k)_k\) (and not on \(T\), see Section 5), this is of the same order than the problem-dependent bound in classical stochastic bandits (Lai and Robbins, 1985) - and it does not depend on the delay distributions (e.g. it does not depend on \(\alpha\)).

- On the other hand, the problem-independent bound, is of order \(T^{1-\alpha \wedge (1/2)}K^{\alpha \wedge (1/2)}\) up to logarithmic terms. It differs widely from the problem-independent bound from classical stochastic bandits, which is of order \(\sqrt{KT}\) – see e.g. (Lattimore and Szepesvári, 2019, Chapter 7). It is of same order when \(\alpha \geq 1/2\), and is larger when \(\alpha < 1/2\). However, Theorem 4 ensures that this rate is minimax optimal with respect to \(T\), up to a multiplicative term \(K^{\alpha \wedge (1/2)}\) and some logarithmic terms. This means that this gap is the price to pay for having delays that are potentially long, and can therefore pose strong bias problems.

**Parameters of the algorithms.** Our algorithm needs as input a parameter \(\alpha\), which is the only external prior information on the delays given as input. It is a more delicate question to decide whether this prior information is necessary. We discuss it extensively in Section 6. In a nutshell, from an asymptotic perspective, the knowledge of \(\alpha\) is not necessary, but from a non-asymptotic perspective it is. Nonetheless, under a slightly stronger hypothesis on the delay distribution, see Assumption 2, there exists a fully adaptive algorithm \(\text{Adapt-PatientBandits}\). Its regret is sublinear, see Theorem 6, and matches that of \(\text{PatientBandits}\) up to a logarithmic term.

### 8. Experiments

In this section, we evaluate the empirical performance of \(\text{PatientBandits}\). Throughout this section, we will provide experiments where the delays of each arm \(i\) follows the Pareto Type I distribution with tail index \(\alpha_i\), and where the rewards of each arm \(i\) follows a Bernoulli distribution with parameter \(\mu_i\).

First, we investigate the performances of \(\text{PatientBandits}\) with respect to the parameters of the problem, \((\alpha_i, \Delta_i)_{i \in [K]}\), and to the hyperparameter of the algorithm \(\alpha\) - which we write \(\overline{\alpha}\) here to avoid confusion.

Second, we compare it to the state of art baseline, which is the censored version of D-UCB of (Vernade et al., 2017) with various threshold windows. This algorithm takes two parameters, the threshold \(m\) and the CDF \(\tau\) of the delays\(^4\). The threshold \(m\) calibrates the time that the algorithm waits before updating reward. To the best of our knowledge, D-UCB is the strongest baseline that deals with partially observed delays.

\(^4\) (Vernade et al., 2017) assumed that the delay distributions are known and homogeneous across arms.

#### 8.1. Influence of the parameters of the problem

**Study of the hyperparameter \(\overline{\alpha}\).** \(\text{PatientBandits}\) takes \(\overline{\alpha}\) as a parameter. The choice of this parameter is a key point for the implementation of \(\text{PatientBandits}\). Ideally we would like to take \(\overline{\alpha} = \min_i \alpha_i\), but in the absence of information on the delay distributions we cannot do this. We therefore illustrate the sensitivity of our method to the mis-calibration of \(\overline{\alpha}\). We consider a 2-arm setting with horizon \(T = 3000\), with arm means \(\mu = (0.5, 0.55)\) and with tail index \(\alpha_1 = 1, \alpha_2 = 0.3\) respectively. We consider \(\overline{\alpha} \in [0.02, 0.5]\) and display in Figure 2 the regret in function of \(\overline{\alpha}\). It can be seen that the regret first decreases with \(\overline{\alpha}\) and then increases after approximately \(\overline{\alpha} = 0.3\). This is precisely what is expected For small \(\overline{\alpha}\) the algorithm is consistent but explores too much and this induces a large regret. For \(\overline{\alpha}\) larger than \(\min_i \alpha_i\), the regret starts to increase again, since the bias coming from the delays are not sufficiently taken into account by the UCB.

**Study of the impact of \((\alpha_i, \Delta_i)_{i \in [K]}\).** We now investigate the dependency of the regret of \(\text{PatientBandits}\) on the delay parameters and arm gaps \((\alpha_i, \Delta_i)_{i \in [K]}\). We consider the following two armed problems where we set \(\mu = (0.4, 0.4 + \Delta)\) where we take \(\Delta \in \{0.02, \ldots, 0.6\}\) - fixing the horizon to \(T = 3000\). For each problem, we respectively choose \(\alpha_1 = 1\) and \(\alpha_2 \in \{0.2, 0.3, 0.4, 0.5, 0.8\}\) and run the \(\text{PatientBandits}\) policy with optimal parameter \(\overline{\alpha} = \alpha_2\), so that we can see the impact of \(\alpha_2\) and \(\Delta\) independently from calibration issues. The results represented in the Figure 3 display the influence of the arm gap \(\Delta\) on the regret, for various values of \(\alpha_2\).

Figure 2 illustrates a standard phenomenon in stochastic bandits, and which also holds for delayed bandits: for small values of the arm gap \(\Delta\), the regret increases with \(\Delta\). This corresponds to the fact that for small \(\Delta\), the algorithm explores and is not able to focus on the most promising arms since the arms means are too close. Then at some point for
Figure 3. Regret of PatientBandits in function of the arm gap $\Delta \in [0.02, 0.6]$ where the bandit problem is characterized by $\mu = (0.5, 0.5 + \Delta)$ and $\alpha_1 = 1$ and where $\alpha_2 \in \{0.2, 0.3, 0.4, 0.5, 0.8\}$ - each curve corresponds to a different value of $\alpha_2$. For each problem, PatientBandits was run with horizon $T = 3000$ and with parameter $\overline{\alpha} = \alpha_2$ and the results are averaged over 300 runs.

larger values of $\Delta$ the regret starts decreasing, as predicted by the bound in Theorem 2. A phenomenon that is specific to delayed bandits is that the smaller $\alpha_2$, the larger the regret. This is expected from Theorem 3, since the smaller $\alpha_2$, the more delayed the rewards, and the harder the problem. A more subtle phenomenon, also illustrating Theorem 3, is that the smaller $\alpha_2$, the larger the value and the position of the maximum of each curve - the maximum or the regret being bounded by the problem independent bound that depends here on $\overline{\alpha} = \alpha_2$.

8.2. Comparing with D-UCB.

We compare here the regret of PatientBandits with the one of D-UCB as a function of the horizon $T$, for different values of the parameters - respectively $\overline{\alpha}$ and $m$. Since D-UCB was designed for the context where the distribution of the delays is the same for all arms, i.e. $\alpha_i$ identical over arms, we consider that scenario as well as the more general case with heterogeneous $\alpha_i$’s.

Homogeneous delay distributions across arms. In the first scenario, we consider a two armed bandit problem with means $\mu = (0.6, 0.8)$. We set the same tail index for both arms, i.e. $\alpha_1 = 0.2 = 0.7$. We run PatientBandits for $\overline{\alpha} \in \{0.1, 0.5\}$. For D-UCB we consider various threshold parameters $m \in \{10, 50, 100, 200\}$, and feed D-UCB with the exact delay distribution of the arms - which gives D-UCB an important edge over our algorithm. The results are displayed in Figure 4 (regret as a function of time).

The performances of D-UCB and PatientBandits are comparable, in particular in the case of good calibration of the parameters, i.e. respectively $\overline{\alpha} = 0.5$, and $m = 50$. PatientBandits performs slightly worse in the best case, but note that D-UCB is tuned with the full knowledge of the

Figure 4. Regret of the D-UCB and PatientBandits for $\mu = (0.6, 0.8)$ and with homogeneous delay distributions characterised by $\alpha_1 = \alpha_2 = 0.7$. We plot results for PatientBandits with parameters $\overline{\alpha} = (0.1, 0.5)$, and for D-UCB with parameters $m = (10, 50, 100, 200)$. The results are averaged over 400 runs. CDF of the delays. An observation coming from Figure 4 is the presence of long lasting linear phases at the initial stage of learning of D-UCB for large $m$ which tend to be caught up over time. This comes from the structure of the algorithm, and from the fact that it has to wait until $m + K$ time steps before it starts exploiting the observations - which is not the case for our strategy.

Non-homogeneous delay distributions. In the second scenario we still consider a two-armed bandit problem with means $\mu = (0.6, 0.8)$, and we set the parameters of the tail distribution of the delays as $\alpha_1 = 1$, $\alpha_2 = 0.3$. This is a 'difficult' scenario, since arm 2 which has the highest mean has also the lowest delay parameter. This means that its delays are more heavy tailed. We consider as before PatientBandits with parameters $\overline{\alpha} \in \{0.1, 0.5\}$, and the D-UCB for threshold parameters $m \in \{10, 50, 100, 200\}$. Regarding the CDF parameter of D-UCB, we provide a Pareto distribution with parameter $0.7$. The results for all policies are displayed on Figure 5 (regret in function of horizon $T$). We observe that D-UCB has a very high regret, increasing linearly with $T$. This can be explained by the fact that D-UCB cannot adapt to delay distributions varying across arms. In other words, it does not take the heterogeneity of the delays into account and can be confused by this difficult situation where the best arm also corresponds to the longest delays. Consequently, D-UCB focuses only on observations that are substantially biased and misidentifies the best arm. On the other hand, PatientBandits adapts to the heterogeneous delays and manages to identify the best arm, leading to a sub-linear regret.

9. Conclusion

In this paper, we extend the problem of learning with bandit feedback and partially observable delays to arm-dependent delay distributions with possibly unbounded expectations.
Figure 5. Regret of the D-UCB and PatientBandits for $\mu = (0.6, 0.8)$ and with delay distributions that vary across arms, characterized by $\alpha_1 = 1$ and $\alpha_2 = 0.3$. We plot results for PatientBandits with parameters $\sigma = (0.1, 0.5)$, and for D-UCB with parameters $m = (10, 50, 100, 200)$. The results are averaged over 400 runs.

We close many existing open problems left by (Vernade et al., 2017; 2018), either with positive answers (Theorem 2) or negative answers (Theorem 5). The major difficulty faced by the learner in this setting is the identifiability issue due to missing rewards which induce a bias in the estimator of the real payoff. Under the assumption that the tail distribution of the delays is bounded - although it might be very heavy tailed - we designed a very simple UCB-based algorithm, termed PatientBandits. We proved that PatientBandits performs almost as well as the standard UCB in the classical, non-delayed case, from a problem dependent point of view. We also studied the problem of adaptivity to the delay distributions and concluded that this is not possible (Theorem 5) unless a global bound on the tails hold (Assumption 2). Closing the gap between the problem-independent bound and the lower bound may constitute the object of future studies.

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A. Proof of Theorems 1

The aim of this section is to bound the deviation of the estimator $\hat{\mu}_i$ from the true mean $\mu_i$. For this purpose, we first begin by defining the favorable event, that is, the event for which all confidence intervals hold for all arms at all time steps. We then prove with Hoeffding’s inequality that this event occurs with high probability. And finally, we derive the desired results by bounding the bias incurred by $\hat{\mu}_i$ and leveraging the properties of this favorable event.

Step 1: the favorable event. First let us define the following quantities (for $i \leq K$ and $u \leq T_i(T)$):

$$\bar{t}_i(u) = \inf\{t \geq 0 : \sum_{u \leq t} 1\{I_u = i\} = u\},$$

$$\overline{C}_{i,u} = C_{\bar{t}_i(u)},$$

$$\overline{D}_{i,u} = D_{\bar{t}_i(u)}.$$ 

Here $\bar{t}_i(u)$ is the time where we pulled arm $i$ for the $u$-th time, $\overline{C}_{i,u}, \overline{D}_{i,u}$ are respectively the corresponding reward and delay. Note that

$$\sum_{u=1}^t X_{u,t-u} \overline{1\{I_u = i\}} = \sum_{u=1}^{T_i(t)} \overline{C}_{i,u} \overline{1\{\bar{t}_i(u) + \overline{D}_{i,u} \leq t\}}.$$

We define the event $\xi$ as follows;

$$\xi \triangleq \left\{ \forall i \in \{1, \ldots, K\}, \forall t \in \{1, \ldots, T\}, \forall s \in \{1, \ldots, T_i(t)\} : \left| \sum_{i=1}^s \overline{C}_{i,u} \overline{1\{\bar{t}_i(u) + \overline{D}_{i,u} \leq t\}} - \sum_{u=1}^s \tau_i(t - \bar{t}_i(u))\mu_i \right| \leq \sqrt{2 \log \frac{2}{\delta}} \right\}.$$

Note that for fixed $i \in \{1, \ldots, K\}, t \in \{1, \ldots, T\}, s \in \{1, \ldots, T_i(t)\}$, we have that

$$\left( \sum_{u \leq v} \left[ \overline{C}_{i,u} \overline{1\{\bar{t}_i(u) + \overline{D}_{i,u} \leq t\}} - \tau_i(t - \bar{t}_i(u))\mu_i \right] \right)_{v \leq s}$$

is a martingale adapted to the filtration $\sigma(\overline{C}_{i,v}, \overline{D}_{i,v}, \bar{t}_i(v))$. And since the martingale increments $\left[ \overline{C}_{i,u} \overline{1\{\bar{t}_i(u) + \overline{D}_{i,u} \leq t\}} - \tau_i(t - \bar{t}_i(u))\mu_i \right]$ belong to $[-1, 1]$ by assumption, it holds by Azuma-Hoeffding’s inequality that with probability larger than $1 - \delta$

$$\sum_{u \leq s} \left| \overline{C}_{i,u} \overline{1\{\bar{t}_i(u) + \overline{D}_{i,u} \leq t\}} - \tau_i(t - \bar{t}_i(u))\mu_i \right| \leq \sqrt{2 \log \frac{2}{\delta}}.$$

Since $T_i(t) \leq t$, it holds by a union bound that

$$\mathbb{P}(\xi) \geq 1 - KT^2 \delta. \tag{8}$$

Step 2: Bound on the $|\hat{\mu}_i(t) - \mu_i|$ on $\xi$. By Equation 7, it holds that

$$\xi \subset \left\{ \forall i \in \{1, \ldots, K\}, \forall t \in \{1, \ldots, T\}, \left| \hat{\mu}_i(t) - \frac{1}{T_i(t)} \sum_{u=1}^t \tau_i(t - u)\mu_i 1\{I_u = i\} \right| \leq \sqrt{\frac{2 \log \frac{2}{\delta}}{T_i(t)}} \right\}. \tag{9}$$

Note that we have

$$\frac{1}{T_i(t)} \sum_{u=1}^t \tau_i(t - u)\mu_i 1\{I_u = i\} - \mu_i \leq \frac{1}{T_i(t)} \sum_{u=1}^t |(1 - \tau_i(t - u))\mu_i 1\{I_u = i\}| \leq \frac{1}{T_i(t)} \sum_{u=1}^t 1\{I_u = i\} ((t - u) \land 1)^{-\alpha},$$
since $0 \leq \mu_i \leq 1$ and since by Assumption 1 it holds that $|\tau_i(m) - 1| \leq (m \lor 1)^{-\alpha}$. And since $\sum_{u=1}^{t} 1\{I_u = i\} = T_i(t)$, we have

$$\left| \frac{1}{T_i(t)} \sum_{u=1}^{t} \tau_i(t-u)\mu_i 1\{I_u = i\} - T_i(t)\mu_i \right| \leq \frac{1}{T_i(t)} \sum_{v=0}^{T_i(t)} (v \lor 1)^{-\alpha} \leq \frac{1}{T_i(t)} \left[ 2 + \int_{1}^{T_i(t)} v^{-\alpha} dv \right],$$

whenever $\alpha \leq 1/2$:

$$\frac{1}{T_i(t)} \left[ 2 + \int_{1}^{T_i(t)} v^{-\alpha} dv \right] = \frac{1}{T_i(t)} \left[ 2 + \left[ \frac{-1}{1 - \alpha} v^{1 - \alpha} \right]_{1}^{T_i(t)} \right]$$

$$= \frac{1}{T_i(t)} \left[ 2 + \frac{1}{1 - \alpha} [T_i(t)]^{1 - \alpha} - 1 \right]$$

$$= \frac{1}{T_i(t)} \left[ - \frac{2\alpha}{1 - \alpha} + \frac{1}{1 - \alpha} T_i(t)^{1 - \alpha} \right]$$

$$\leq \frac{1}{T_i(t)} \left[ 2T_i(t)^{1 - \alpha} \right]$$

$$\leq 2T_i(t)^{-\alpha} = 2T_i(t)^{-\alpha \land (1/2)}.$$

Now for $\alpha \geq 1/2$:

$$\frac{1}{T_i(t)} \left[ 2 + \int_{1}^{T_i(t)} v^{-\alpha} dv \right] \leq \frac{1}{T_i(t)} \left[ 2 + \int_{1}^{T_i(t)} v^{-1/2} dv \right]$$

$$= \frac{1}{T_i(t)} \left[ 2 + 2[T_i(t)]^{1/2} - 1 \right] = 2T_i(t)^{1/2} = 2T_i(t)^{-\alpha \land (1/2)}.$$

Note that we have

$$|\tilde{\mu}_i(t) - \mu_i| = |\tilde{\mu}_i(t) - \frac{1}{T_i(t)} \sum_{u=1}^{t} \tau_{t-u}\mu_i 1\{I_u = i\} + \frac{1}{T_i(t)} \sum_{u=1}^{t} \tau_{t-u}\mu_i 1\{I_u = i\} - \mu_i|$$

$$\leq |\tilde{\mu}_i(t) - \frac{1}{T_i(t)} \sum_{u=1}^{t} \tau_{t-u}\mu_i 1\{I_u = i\}| + \left| \frac{1}{T_i(t)} \sum_{u=1}^{t} \tau_{t-u}\mu_i 1\{I_u = i\} - \mu_i \right|.$$

Now from the definition of the favorable event $\xi$ in Equation (9) and from the bound of the bias in Equation (10), it holds on $\xi$ that:

$$|\tilde{\mu}_i(t) - \mu_i| \leq \left( \frac{2 \log \frac{2}{\delta}}{T_i(t)} \right)^{1/2} + 2T_i(t)^{-\alpha \land 1/2}. \quad (11)$$

**B. Proof of Theorems 2 and 3**

The proof of these theorems relies on the results obtained in Appendix A. Indeed, we will use the deviation results obtained on the event $\xi$ to bound the number of pulls of sub-optimal arms in order to derive the upper bounds on the regret.
Step 1: upper bound on the number of pulls of sub-optimal arms. Let’s assume that at some given time $t + 1 > K$ the algorithm pulls a sub-optimal arm $i$ (such that $\mu_i < \mu^*$). According to the algorithm’s rules, we have: $UCB_i(t + 1) \geq UCB_{k^*}(t + 1)$. And so on $\xi$, we have because of Equation (11)

$$\mu^* \leq UCB_{k^*}(t + 1) \leq UCB_i(t + 1) \leq \mu_i + 2 \left( \frac{2 \log \frac{2}{T_i(t)}}{T_i(t)} \right)^{1/2} + 4T_i(t)^{-\alpha^{1/2}}.$$ 

Rearranging the terms, we have on $\xi$:

$$\Delta_i = \mu^* - \mu_i \leq 2 \left( \frac{2 \log \frac{2}{T_i(t)}}{T_i(t)} \right)^{1/2} + 4T_i(t)^{-\alpha^{1/2}},$$

which implies that on $\xi$

$$T_i(t) \leq \frac{16 \log (2/\delta)}{\Delta_i^2} \vee \left( \frac{8}{\Delta_i} \right)^{-\frac{1}{v^2}} \vee 1,$$

and so on $\xi$, we have for any sub-optimal arm $i$

$$T_i(T) \leq \frac{16 \log (2/\delta)}{\Delta_i^2} \vee \left( \frac{8}{\Delta_i} \right)^{\frac{1}{v^2}} \vee 1. \quad (12)$$

Step 2: Conclusion. Consider a sub-optimal arm $i$ (such that $\mu_i < \mu^*$). Combining Equation (12) with Equation (8), and since $T_i(T) \leq T$ we have

$$E[T_i(T)] \leq \frac{16 \log (2/\delta)}{\Delta_i^2} \vee \left( \frac{8}{\Delta_i} \right)^{\frac{1}{v^2}} \vee 1 + KT^3 \delta$$

$$\leq \frac{16 \log (2KT^3)}{\Delta_i^2} \vee \left( \frac{8}{\Delta_i} \right)^{\frac{1}{v^2}} \vee 1 + 1,$$

for $\delta \triangleq (KT^3)^{-1}$. Let us now consider some value $\Delta > 0$. We have by definition of the regret and with this $\delta \triangleq (KT^3)^{-1}$ as above:

$$\mathcal{R}_T \leq \sum_{i: \Delta_i > \Delta} \Delta_i \left[ \frac{16 \log (2KT^3)}{\Delta_i^2} \vee \left( \frac{8}{\Delta_i} \right)^{\frac{1}{v^2}} \vee 1 + 1 \right] + \sum_{i: \Delta_i \leq \Delta} E[T_i(T)]. \quad (13)$$

Taking $\Delta = 0$ and recalling that $K \leq T$, we obtain the result of Theorem 2, namely

$$\mathcal{R}_T \leq \sum_{i: \Delta_i > 0} \left[ \frac{64 \log (2T)}{\Delta_i} \vee \left( \frac{8}{\Delta_i} \right)^{\frac{1-\alpha}{v^1}} \right] + 2K.$$ 

Now not that since the function $\Delta_i \left[ \frac{16 \log (2KT^3)}{\Delta_i} \vee \left( \frac{8}{\Delta_i} \right)^{\frac{1}{v^2}} \vee 1 + 1 \right]$ increases when $\Delta_i$ decreases, we have for any $\Delta > 0$

$$\mathcal{R}_T \leq K \left[ \frac{16 \log (2KT^3)}{\Delta} \vee \left( \frac{8}{\Delta} \right)^{\frac{1-\alpha}{v^1}} \right] + \Delta T + 2K$$

$$\leq K \log (2T) \left( \frac{64}{\Delta} \right)^{\frac{1-\alpha}{v^1}} + \Delta T + 2K.$$ 

And so for $\Delta = \left( \frac{K \log (2T)64^{1-\alpha}}{T} \right)^{v^{1/2}}$, we have

$$\mathcal{R}_T \leq 2 \times 64^{(1-\alpha)v^{1/2}} T^{1-\alpha^{1/2}} \left( K \log (2T) \right)^{\alpha^{1/2}} + 2K,$$

which concludes the proof of Theorem 3.
C. Proof of Theorem 4

In order to prove this result, we need to show that there exists a bandit problem in the family described in Section 2 such that the regret at $T$ is $\Omega(T^{1-\alpha})$. To do so, we construct two problems in that family and show that for at least one of them, the regret is larger than the desired quantity.

First, for ease of notation, define

$$p = T^{-\alpha} \quad \text{and} \quad q = \frac{p}{4 - 2p}.$$ \hspace{1cm} (14)

We construct two alternative problems with two arms, $K = 2$. In both cases, we fix arm 1 such that the distribution of the rewards $\nu_1$ is $B(1/2)$ and the distribution of the delays $D_1$ is $\delta_0$ (i.e. a Dirac mass in 0, no delays).

- Problem A: $\nu_2^{(A)}$ is $B(1/2 - q)$ and $D_2^{(A)}$ is $\delta_0$.
- Problem B: $\nu_2^{(B)}$ is $B(1/2 + q)$ and $D_2^{(B)}$ is $(1 - p)\delta_0 + p\delta_T$.

In Problem A, arm 1 is the best with gap $\Delta = q$ and there are no delays. In Problem B, arm 2 is the best, but delays are sending a proportion $p$ of the rewards to $t \geq T$ so they cannot be used for learning. Thus, the conditional distribution of $X_{s,u}|I_t = 2$ is in fact $B((1/2 + q)(1 - p))$. Note that

$$\left(\frac{1}{2} + q\right)(1 - p) = \frac{1}{2} - \left(\frac{p}{2} - q + pq\right) = \frac{1}{2} - \left(\frac{p}{2} - \frac{p}{4 - 2p} + \frac{p^2}{4 - 2p}\right) = \frac{1}{2} - \frac{p}{4 - 2p} = \frac{1}{2} - q.$$ 

So the effective mean of arm 2 is $1/2 - q$, meaning that arm 2 has the same distribution in both problems. This implies in particular that

$$E_AT_2(T) = E_BT_2(T),$$

where $E_a$ is the expectation in problem $a \in \{A, B\}$.

And so if we write $R_T^{(a)}$ for the regret in scenario $a \in \{A, B\}$:

$$\max_{a \in \{1, 2\}} R_T^{(a)} \geq q \max(T - E_BT_2(T), E_AT_2(T)) \geq qT/2.$$ 

This concludes the proof as $q = p/(4 - 2p) \geq p/4 = T^{-\alpha}/4$.

D. Proof of Theorem 5

The proof of this theorem relies on the same tools as for Theorem 4 above, but uses a slightly different reasoning. Namely, we now fix $\alpha > 0$ and we restrict the family of algorithms to those that have a regret smaller than $T^{1-\alpha}/8$ for any stochastic bandit problem satisfying Assumption 1 for $\alpha$. We denote this family $A_\alpha$.

We want to prove that there exists a bandit problem satisfying Assumption 1 for some $\alpha' > \alpha$ such that any algorithm in $A_\alpha$ has regret at least $T^{1-\alpha}/8 > T^{1-\alpha'}/8$. This proves that any algorithm minimax optimal for $\alpha$ is suboptimal for $\alpha' > \alpha$.

Similarly to the previous section, fix $p = T^\alpha$ and $q = p/(4 - 2p)$ as in Eq. (14), and consider the two problems,

- Problem A: $\nu_2^{(A)}$ is $B(1/2 - q)$ and $D_2^{(A)}$ is $\delta_0$.
- Problem B: $\nu_2^{(B)}$ is $B(1/2 + q)$ and $D_2^{(B)}$ is $(1 - p)\delta_0 + p\delta_T$.

Note that, Problem B satisfies Assumption 1 for $\alpha$, while Problem A satisfies it for any $\alpha' > 0$ so in particular for $\alpha' > \alpha$. So for any algorithm in $A_\alpha$, $qE_B[T_1(t)] < 3T^{1-\alpha}/16$. But, as we proved above, because of the delays, the algorithm cannot distinguish both problems and we have $E_AT_1(T) = E_BT_1(T)$, i.e. the average number of pulls of arm 1 is the same in both problems. Thus,

$$E_AT_1(T) = E_BT_1(T) < q^{-1}T^{1-\alpha}/8.$$
Using that \( q > p/4 \) as before,
\[
\max_{\alpha \in \{A,B\}} \mathcal{R}_T^{(a)} \geq q(T - \mathbb{E}_A T_1(T)) > \frac{T^\alpha - \alpha}{4} T - T^{1-\alpha}/8 = T^{1-\alpha}/8.
\]

**E. Proof of Theorem 6**

We start by stating the full version of the theorem that guarantees the performance of Adopt-PatientBandits.

**Theorem 7.** Let \( T > K \geq 1 \) and \( \alpha, \alpha, c, \mu > 0 \), such that Assumption 2 holds. The regret of Adopt-PatientBandits is bounded as
\[
\mathcal{R}_T \leq 8^{17} \left( \frac{1}{2c} \right)^4 \left( \frac{2}{c} \right)^{4(\alpha \wedge 1/2)/\alpha} \log(2T)^{13/2} T(K/T)^{\alpha \wedge (1/2)}.
\]

Before proving Theorem 6, we first provide the following proposition that bounds the error on our estimator of \( \alpha \).

**Proposition 1.** Let \( \delta \in (0, 1) \). There exists an event of probability larger than \( 1 - 2KT^2 \delta \) such that for any \( t \leq T \),
\[
\alpha \wedge 1/2 - \frac{\log \left( \frac{2\log(2/\delta)}{T^d} \right)}{\log(T)} \leq \hat{\alpha}_t \leq \alpha \wedge 1/2 + \frac{\log \left( \frac{2\log(2/\delta)}{T^d} \right)}{\log T^t},
\]
where \( B \triangleq B_\delta \triangleq \sqrt{2\log(2/\delta)} \).

**Proof of Proposition 1.** For a lighter notation we set \( \mu_t \triangleq \mu_t^T \). Similarly to the analysis of the subset of \( \xi \) in Equation 9, we can prove that the event
\[
\xi' \triangleq \left\{ \forall t \leq T, |m_t d_t - \mu_t^T (d_t)| \leq \sqrt{\frac{2\log(2/\delta)}{T(t - D_t)}} \right\}
\]
has probability larger than \( 1 - 2KT^2 \delta \). Let us set
\[
B \triangleq B_\delta \triangleq \sqrt{2\log(2/\delta)}.
\]

Since \( d_t \leq D_t \), by Assumption 2 we have that on \( \xi' \),
\[
\frac{c}{2} \mu_t d_t^{1/2} - \mu_t^T (d_t) \leq \frac{2B}{\sqrt{T(t - D_t)}} \leq \frac{2B}{\sqrt{T(t - D_t)}} \leq \frac{2B}{\sqrt{T(t - D_t)}}.
\]

We now chose \( d_t \triangleq \left( \frac{c}{2} \right)^{1/2} D_t \), for which we have that \( c \mu_t d_t^{1/2} - \mu_t^T (d_t) \geq c \mu_t d_t^{1/2} \) and therefore on \( \xi' \),
\[
\frac{c}{2} \mu_t d_t^{1/2} - \frac{2B}{\sqrt{T(t - D_t)}} \leq \frac{2B}{\sqrt{T(t - D_t)}} \leq \frac{2B}{\sqrt{T(t - D_t)}}.
\]

Here we have that \( D_t = \lfloor T_t/2 \rfloor \), and since \( T_t \geq 2 \), we obtain
\[
T_t^{-\alpha} \leq D_t^{-\alpha} \leq 2^{2\alpha} T_t^{-\alpha}.
\]

Moreover, since we chose \( d_t = \left[ \left( \frac{c}{2} \right)^{1/2} D_t \right] \), we infer that
\[
T_t^{-\alpha} \leq d_t^{-\alpha} \leq 2^{2\alpha} \left( \frac{2}{c} \right)^{\alpha/\alpha} T_t^{-\alpha}.
\]

Therefore, since \( T(t - D_t) \leq T_t \leq 2T(t - D_t) \), we have that on \( \xi' \),
\[
\frac{c}{2} \mu_t T_t^{-\alpha} - 2^{3/2} B T_t^{-1/2} \leq m_t d_t - m_t d_t \leq \left( 2^{3(\alpha \wedge 1/2)} \left( \frac{2}{c} \right)^{\alpha(1/2)/\alpha} + 2^{3/2} B \right) T_t^{-\alpha \wedge 1/2} \triangleq C^\alpha T_t^{-\alpha \wedge 1/2},
\]
where we use the fact that the \( \mu_k \) are in \( [\mu, 1] \).
First case — small $\alpha$ First, consider the case where \( \frac{c}{4} \mu T_t^{-\alpha} \geq 2^{3/2} B T_t^{-1/2} \). Then we have that on event $\xi'$

\[
\frac{c}{4} \mu T_t^{-\alpha} \leq m_{t,D_t} - m_{t,d_t} \leq C_{\alpha} T_t^{-\alpha \land 1/2},
\]

which implies that on $\xi'$,

\[
- \log \left( \frac{c}{4} \right) + \alpha \log(T_t) \geq - \log(m_{t,D_t} - m_{t,d_t}) \geq - \log(C_\alpha) + (\alpha \land 1/2) \log(T_t).
\]

Therefore, on $\xi'$,

\[
\alpha - \frac{\log \left( \frac{c}{4} \right)}{\log(T_t)} \geq \frac{\log(m_{t,D_t} - m_{t,d_t})}{\log(T_t)} \geq \alpha \land 1/2 - \frac{\log(C_\alpha)}{\log(T_t)},
\]

from which we finally get that on $\xi'$,

\[
\alpha \land 1/2 + \frac{\log \left( \frac{c}{4} \right)}{\log(T_t)} \geq \hat{\alpha}_t \geq \alpha \land 1/2 - \frac{\log(C_\alpha)}{\log(T_t)}.
\] (15)

Note that while the left hand side of the above inequality only true under the assumption of the first case that demands \( \frac{c}{4} \mu T_t^{-\alpha} \geq 2^{3/2} B T_t^{-1/2} \), the right hand side is also true when this assumption does not hold since we did not use it.

Second case — large $\alpha$ Now consider the case where \( \frac{c}{4} \mu T_t^{-\alpha} \leq 2^{3/2} B T_t^{-1/2} \). In this case it holds that

\[
T_t^{\alpha - 1/2} \geq \frac{c/4}{2^{7/2} B} \triangleq b^{-1},
\]

which means that

\[
\alpha - 1/2 \geq - \frac{\log(b)}{\log(T_t)},
\]

and therefore,

\[
\alpha \land 1/2 \geq 1/2 - \frac{\log(b)}{\log(T_t)}.
\]

Now by definition of $\hat{\alpha}_t$, we have

\[
\hat{\alpha}_t \leq 1/2 \leq \alpha \land 1/2 + \frac{\log(b)}{\log(T_t)}.
\]

Taking only the right hand side of the first case in Equation 15, which does not use the assumption of the first case, unlike the left hand side (cf. the remark under Equation 15), we have that on $\xi$,

\[
\hat{\alpha}_t \geq \alpha \land 1/2 - \frac{\log(C_\alpha)}{\log(T_t)}.
\]

combining the two sides of the bound, we get that on $\xi$,

\[
\alpha \land 1/2 + \frac{\log \left( \frac{2^{7/2} B}{c} \right)}{\log(T_t)} \geq \hat{\alpha}_t \geq \alpha \land 1/2 - \frac{\log(C_\alpha)}{\log(T_t)}.
\]

Notice that this inequality holds also in the first case (small $\alpha$) since \( 4/(c\mu) \leq \frac{2^{7/2} B}{c\mu} \). The final result follows immediately since we have that \( C_\alpha \leq 2^{3 \left( \frac{1}{2} \right)^{(\alpha \land 1/2)/\alpha} + B} \).

Now leveraging these concentration bounds obtained on the error of the estimation of $\alpha$ as well as the theoretical results from Theorem 3 we prove the main result.
Proof of Theorem 6. Recall that, from Proposition 1 with probability larger than \(1 - 2KT^2\delta\) we have that,

\[
\alpha \wedge 1/2 + \frac{\log \left( \frac{2^{7/2}B}{c^\alpha} \right)}{\log T} \geq \hat\alpha_t \geq \alpha \wedge 1/2 - \frac{\log \left( 2^3 \left( \frac{2^{7/2}}{2} \right)^{(\alpha \wedge 1/2)/\alpha} + B \right)}{\log(T_t)},
\]

where \(B \triangleq B_\delta = \sqrt{2 \log(2/\delta)}\).

Let \(L_\alpha \triangleq \log \left( \frac{2^{7/2}}{c^\alpha} \right) + \log \left( 2^3 \left( \frac{2^{7/2}}{2} \right)^{(\alpha \wedge 1/2)/\alpha} + 1 \right)\). With probability larger than \(1 - 2KT^2\delta\),

\[
U_t \triangleq \frac{\log \left( \frac{2^{7/2}B}{c^\alpha} \right) + \log \left( 2^3 \left( \frac{2^{7/2}}{2} \right)^{(\alpha \wedge 1/2)/\alpha} + B \right)}{\log(T_t)} \leq \frac{L_\alpha + \log(B)}{\log(T_t)}
\]

is a high probability lower deviation on the lower bound \(\bar{\pi}_t\) on \(\alpha\). Note that \(T_t\) is the number of pulls of the most pulled arm at time \(t\) and therefore \(T_t \geq t/K\). Furthermore, note that after the initialisation phase, we have guaranteed that \(t \geq 2K\) from which we get

\[
U_t \leq \frac{2L_\alpha + 2 \log(B)}{\log(t)}.
\]

Moreover, by Theorem 3, we have that conditionally on the event \(\xi\) from Proposition 1, the expected regret coming from the samples pulled after round \(t\) can be bounded as

\[
128 \sqrt{\log(2T)T(K/T)^{\alpha \wedge (1/2) - U_t}} + 2K.
\]

The above bound implies that conditional on the event \(\xi'\) from Proposition 1, the expected regret due to the samples obtained after round \(t = T^{1/2}\) can be bounded as

\[
128 \sqrt{\log(2T)T(K/T)^{\alpha \wedge (1/2) - 4(L_\alpha + \log B)/\log T}} + 2K.
\]

Now setting \(\delta \triangleq (KT^3)^{-1}\) in the algorithm - where \(\delta\) is used to define the event \(\xi'\) in Proposition 1 - we have on \(\xi'\) that,

\[
\bar{R}_T \leq T^{1/2} + 128 \sqrt{\log(2T)T(K/T)^{\alpha \wedge (1/2) - 4(L_\alpha + \sqrt{T \log(2KT^3)})/\log T}} + 4K,
\]

where the additional regret \(T^{1/2}\) comes from the first \(T^{1/2}\) samples to the bound computed above, and where the additional regret \(2K\) comes from the case when the event \(\xi'\) from Proposition 1 does not hold - leading to a supplementary term bounded by \(\mathbb{P}((\xi')^c)T \leq 2K\).

Notice that in the expression in the regret bound above,

\[
T^{4(\log(2T)\log(\log(2KT^3)))}}/\log T \leq e^{4L_\alpha(8 \log(2T))} \leq 8^{12} \left( \frac{1}{c \alpha} \right) 4 \left( \frac{2^{7/2}}{2} \right)^{4(\alpha \wedge 1/2)/\alpha} \log(2T)^6
\]

and therefore we can simplify our guarantee to finally obtain

\[
\bar{R}_T \leq T^{1/2} + 8^{16} \left( \frac{1}{c \alpha} \right) 4 \left( \frac{2^{7/2}}{2} \right)^{4(\alpha \wedge 1/2)/\alpha} \log(2T)^{13/2}T(K/T)^{\alpha \wedge (1/2)} + 4K.
\]