

# A simple dynamic bandit algorithm for hyper-parameter tuning

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## Abstract

Hyper-parameter tuning is a major part of modern machine learning systems. The tuning itself can be seen as a sequential resource allocation problem. As such, methods for multi-armed bandits have been already applied. In this paper, we view hyper-parameter optimization as an instance of best-arm identification in infinitely many-armed bandits. We propose **D-TTTS**, a new adaptive algorithm inspired by Thompson sampling, which *dy-namically* balances between refining the estimate of the quality of hyper-parameter configurations previously explored and adding new hyper-parameter configurations to the pool of candidates. The algorithm is easy to implement and shows competitive performance compared to state-of-the-art algorithms for hyper-parameter tuning.

## 1. Introduction

Training a machine learning algorithm often requires to specify several parameters. For instance, for neural networks, it is the architecture of the network and also the parameters of the gradient algorithm used or the choice of regularization. These *hyper-parameters* are difficult to learn through the standard training process and are often manually specified.

When it is not feasible to design algorithms with a few hyper-parameters, we opt for *hyper-parameter optimization* (HPO). HPO can be viewed as a *black-box optimization* problem where the evaluation of the objective function is expensive as it is the accuracy of a learning algorithm for a given configuration of hyper-parameters. This vastly limits the number of evaluations that can be carried out, which calls for a design of efficient high-level algorithms that automate the tuning procedure.

Several naive but daily used HPO methods are grid search and random search. More sophisticated methods address HPO as a *sequential resource allocation problem*, by adaptively choosing the next hyper-parameter(s) to explore, based on the result obtained previously. For example, *evolutionary optimization* follows a process inspired by the biological concept of *evolution*, which repeatedly replaces the worst-performing hyper-parameter configurations from a randomly initialized population of solutions; see [Loshchilov and Hutter \(2016\)](#) for an example of using CMA-ES for hyper-parameter tuning. A major drawback of evolutionary optimization is its lack of theoretical understanding.

Bayesian optimization (BO) is another approach that leverages the sequential nature of the setting. BO depends on a prior belief for the target function, typically a Gaussian

process. This prior distribution can be updated to a posterior given a sequence of observations. Several algorithms exploiting this posterior distribution to decide where to sample next have been given (see [Shahriari et al., 2016](#), for a survey). [Snoek et al. \(2012\)](#) and [Klein et al. \(2017\)](#) provide Python packages called **Spear**mint and **RoBO** to perform hyper-parameter tuning with BO methods. Similar packages are available for PyTorch (**BoTorch**<sup>1</sup>) and TensorFlow (GPflowOpt by [Knudde et al. 2017](#)). Among BO algorithms, TPE ([Bergstra et al., 2011](#)) and SMAC ([Hutter et al., 2011](#)) were specifically proposed for HPO. A shortcoming of BO is that most algorithms select where to sample next based on optimizing some *acquisition function* computed from the posterior, e.g., the expected improvement ([Jones et al., 1998](#)). This auxiliary task cannot be solved analytically but needs to be performed itself by optimization procedures as L-BFGS that make the process slow.

Bandits are a simple model for sequential resource allocation (see [Lattimore and Szepesvari, 2019](#) for a recent book), and some bandit tools have already been explored for global optimization and HPO: First, in the field of Bayesian optimization, the GP-UCB algorithm ([Srinivas et al., 2010](#)) is a Gaussian process extension of the classical UCB bandit algorithm ([Auer et al., 2002](#)). Later, [Hoffman et al. \(2014\)](#) proposed to use *best-arm identification* (BAI) tools—still with a Bayesian flavor—for automated machine learning, where the goal is to smartly try hyper-parameters from a pre-specified *finite* grid.

However, in most cases, the number of hyper-parameter configurations to explore is infinite. In this paper, we investigate the use of bandit tools suited for an *infinite* number of arms. There are two lines of work for tackling a very large or infinite number of configurations (arms). The first combines standard bandit tools with a hierarchical partitioning of the arm space and aims at exploiting the (possibly unknown) smoothness of the black-box function to optimize ([Bubeck et al., 2010](#); [Grill et al., 2015](#); [Shang et al., 2019](#); [Bartlett et al., 2019](#)). To the best of our knowledge, these methods have never been investigated for HPO. The second line of work does not assume any smoothness: At each round, the learner may ask for a new arm from a *reservoir distribution*  $\nu_0$  (pick randomly a new hyper-parameter configuration) and add it to the current arm pool  $\mathcal{A}$ , or re-sample one of the previous arms (evaluate configuration already included in  $\mathcal{A}$ ), in order to find an arm with a good mean reward (i.e., a hyper-parameter configuration with a good validation accuracy). The *stochastic infinitely-many armed bandits* (SIAB) is studied by [Berry et al. \(1997\)](#); [Wang et al. \(2008\)](#) for the rewards maximization problem while [Carpentier and Valko \(2015\)](#); [Aziz et al. \(2018a\)](#) study the simple regret problem, which is related to BAI. While most proposed algorithms consist of querying an *adequate* number of arms from the reservoir before running a standard BAI algorithm, [Li et al. \(2017\)](#) propose a more robust approach called **Hyperband** that uses several such phases.

In this paper, we go even further and propose the first *dynamic* algorithm for BAI in SIAB, that at each round, may either query a new arm from the reservoir or re-sample arms previously queried. Our algorithm leverages a Bayesian model and builds on the top-two Thompson sampling (TTTS) algorithm by [Russo \(2016\)](#). We present an extensive numerical study in which we show that our algorithm is competitive with respect to state-of-the-art HPO methods.

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1. <https://botorch.org/>

## 2. Hyper-parameter optimization

In this paper, we view HPO as a particular *black-box optimization* setting, for which the target function  $f$  is a mapping from a hyper-parameter configuration to some measure of failure for the machine learning algorithm trained with these hyper-parameters. Formally, we aim at solving an optimization problem of the form  $\min\{f(\boldsymbol{\lambda}) : \boldsymbol{\lambda} \in \Omega\}$ , where  $\boldsymbol{\lambda}$  denotes a configuration of hyper-parameters chosen from a configuration space  $\Omega$ . A hyper-parameter optimizer is a sequential procedure, that at each round  $t$ , selects a configuration  $\boldsymbol{\lambda}_t$  to evaluate using some sampling rule, after which a (costly and *noisy*) evaluation of  $f(\boldsymbol{\lambda}_t)$  is observed. Besides, at round  $t$ , a hyper-parameter  $\boldsymbol{\lambda}_t^*$  configuration is recommended as a current guess for a close-to-optimal configuration. The hope is that  $f(\boldsymbol{\lambda}_t^*)$  is not far from the minimum of  $f$ .

We restrict our presentation to hyper-parameter tuning for supervised learning algorithms. Given a training dataset  $\mathcal{D}_{\text{train}}$  containing  $n$  labeled examples in  $\mathcal{X} \times \mathcal{Y}$  and a choice of hyper-parameter configuration  $\boldsymbol{\lambda}$ , a supervised learning algorithm (neural network, SVM, gradient boosting, ...) produces a predictor  $\hat{g}_{\boldsymbol{\lambda}}^{(n)} : \mathcal{X} \rightarrow \mathcal{Y}$ . Note that there can be some randomness in the training process (e.g., if stochastic gradient descent is used) so that  $\hat{g}_{\boldsymbol{\lambda}}^{(n)}$  may still be random for a given training set and hyper-parameters. The goal is to build a predictor that generalizes well. If we had access to the distribution  $\mathbf{P}$  that generated the data (i.e., assuming that data points in  $\mathcal{D}_{\text{train}}$  are i.i.d. from  $\mathbf{P}$ ), this generalization power would be measured by the risk  $f(\boldsymbol{\lambda}) \triangleq \mathbb{E} \left[ \ell \left( \mathbf{Y}, \hat{g}_{\boldsymbol{\lambda}}^{(n)}(\mathbf{X}) \right) \right]$ , where  $\ell$  is some loss function measuring the distance between two predictions and the expectation is taken on  $(\mathbf{X}, \mathbf{Y}) \sim \mathbf{P}$  and the possible randomness in the training process.

In practice, however, the explicit evaluation of  $f$  is impossible, but there are several methods for *noisy evaluations*. We can either compute the validation error of  $\hat{g}_{\boldsymbol{\lambda}}^{(n)}$  on a held-out validation set,  $1/|\mathcal{D}_{\text{valid}}| \sum_{i=1}^{|\mathcal{D}_{\text{valid}}|} \ell(\hat{g}_{\boldsymbol{\lambda}}^{(n)}(\mathbf{x}_i), \mathbf{y}_i)$ , or a cross validation error over the training set as an approximation of the objective.

## 3. Active Thompson sampling for HPO

HPO can be cast as a BAI in a bandits. However, standard algorithms are not directly applicable since the search space is often continuous. We thus turn our attention to BAI in an infinitely many armed bandits (see Appendix A for a detailed discussion).

In this section, we introduce a new algorithm for BAI in an infinite bandit model, that is an adaptation of Thompson sampling (Thompson, 1933). Thompson sampling can be seen as the very first bandit algorithm ever proposed, but has been used for the *rewards maximization* objective, which is quite different from BAI, as explained by Bubeck et al. (2009). Instead of using vanilla Thompson sampling, we build on the TTTS algorithm that is an adaptation of Thompson sampling for BAI in finite-arm bandits. Unlike the state-of-the-art algorithm SequentialHalving (SHA) that requires the knowledge of the total budget to operate, TTTS is particularly appealing as it does not need to have it. Such are algorithms are referred to as *anytime*. Besides, TTTS is known to be optimal in a Bayesian (asymptotic) sense, as it attains the best possible rate of decay of the posterior probability of the set of wrong models.

As a Bayesian algorithm, **TTTS** uses a prior distribution  $\Pi_0$  over the vector of means of the  $K$  arms,  $\boldsymbol{\mu} \triangleq (\mu_1, \dots, \mu_K)$ , which can be updated to a posterior distribution  $\Pi_t$  after  $t$  observations. Under the Bernoulli bandit model, arm  $i$  produces a reward  $Y_{t,i} = 1$  with probability  $\mu_i$ , and  $Y_{t,i} = 0$  with probability  $1 - \mu_i$  when sampled at round  $t$ . Given independent uniform prior for the mean of each arm, the posterior distribution on  $\boldsymbol{\mu}$  is a product of  $K$  Beta distributions:  $\Pi_t = \bigotimes_{i=1}^K \text{Beta}(1 + S_{t,i}, N_{t,i} - S_{t,i} + 1)$ , where  $N_{t,i}$  is the number of selections of arm  $i$  until round  $t$  and  $S_{t,i}$  is the sum of rewards obtained from that arm. At each round  $t$ , **TTTS** chooses one arm from the following two candidates to evaluate: (1) it first samples a parameter  $\boldsymbol{\theta}$  from  $\Pi_{t-1}$ , and the first candidate is defined as  $I_t^{(1)} \triangleq \arg \max_{i \in \mathcal{A}} \theta_i$ , (2) it repeatedly samples new  $\boldsymbol{\theta}'$  until  $I_t^{(2)} \triangleq \arg \max_{i \in \mathcal{A}} \theta'_i$  is different from  $I_t^{(1)}$ . **TTTS** depends on a parameter  $\beta \in (0, 1)$ . In particular, the algorithm selects  $I_t = I_t^{(1)}$  with probability  $\beta$  and  $I_t = I_t^{(2)}$  with probability  $1 - \beta$ .

**TTTS** can also be used for bandit settings in which the rewards are bounded in  $[0, 1]$  by using a binarization trick first proposed by [Agrawal and Goyal \(2012\)](#): When a reward  $Y_{t,i} \in [0, 1]$  is observed, the algorithm is updated with a fake reward  $Y'_{t,i} \sim \text{Ber}(Y_{t,i}) \in \{0, 1\}$ . **TTTS** can thus be used for BAI for a *finite* number of arms that with rewards in  $[0, 1]$ . We now present a simple way of extending **TTTS** to deal with an infinite number of arms.

**Dynamic TTTS** In an infinite bandit algorithm, at each round, we either query a new arm from the reservoir *and sample it*, or re-sample a previous arm. In a Bayesian setting, we can also imagine that at each round, an arm is queried from the reservoir and added with a *uniform prior* to the list of queried arms, *regardless of whether it is sampled or not*. Then, at round  $t$ , **D-TTTS** consists in running **TTTS** on these  $t$  arms, out of which several are endowed with a uniform prior and have never been sampled.

Leveraging the fact the the maximum of  $k$  uniform distribution has a  $\text{Beta}(k, 1)$  distribution and that **TTTS** only depends on the maxima of posterior samples, we give the following equivalent implementation for **D-TTTS** (Algorithm 1). Letting  $\mathcal{L}_t$  be the list of arms that have been queried from the reservoir and sampled *at least once* before round  $t$ , at round  $t$  we run **TTTS** on the set  $\mathcal{A}_t \triangleq \mathcal{L}_t \cup \{\mu_0\}$  where  $\mu_0$  is a pseudo-arm with posterior distribution  $\text{Beta}(t - k_t, 1)$ , where  $k_t \triangleq |\mathcal{L}_t|$ .

It remains to decide how to choose the arm to recommend as our best guess. The most natural recommendation strategy for Bayesian algorithms is the arm with the largest *posterior probability of being optimal*. Letting  $\Theta_i$  be the subset of the set  $\Theta$  of possible mean vectors such that arm  $i$  is optimal,  $\Theta_i \triangleq \{\boldsymbol{\theta} \in \Theta \mid \theta_i > \max_{j \neq i} \theta_j\}$ , the posterior probability that arm  $i$  is optimal after round  $n$  is defined as  $\Pi_n(\Theta_i)$ .

## 4. Experiments

We benchmark our bandit-based strategy against different types of HPO algorithms namely **TPE**, random search and **Hyperband** and a simple Thompson sampling variant of **Hyperband** (called **H-TTTS**) that we describe in Appendix B, for the tuning of classifiers (**SVM** and **MLP**) on four different classification task: Wine, Breast Cancer and Adult dataset from UCI Machine Learning Repository ([Dua and Taniskidou, 2017](#)); and the classical **MNIST** dataset.

For all those methods, a noisy evaluation of the black-box function  $f$  (see the terminology introduced in Section 2) for a hyper-parameter configuration  $\boldsymbol{\lambda}$  consists in performing

**Algorithm 1** Sampling rule of Dynamic TTTS (**D-TTTS**)

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**Input:**  $\beta$ ;  $B$  (total budget);  $\nu_0$   
**Initialization:**  $\mu_1 \sim \nu_0$ ;  $t = 0$ ;  $\mathcal{A} = \{\mu_0, \mu_1\}$ ;  $m = 1$ ;  $S_0, N_0 = 0$ ;  $S_1 \sim \text{Ber}(\mu_1)$ ,  $N_1 = 1$

- 1: **while**  $t < B$  **do**
- 2:    $\forall i = 0, \dots, m$ ,  $\theta_i \sim \text{Beta}(S_i + 1, N_i - S_i + 1)$ ;  $U \sim \mathcal{U}([0, 1])$
- 3:    $I^{(1)} = \arg \max_{i=0, \dots, m} \theta_i$
- 4:   **if**  $U > \beta$  **then**
- 5:     **while**  $I^{(2)} \neq I^{(1)}$  **do**
- 6:        $\forall i = 0, \dots, m$ ,  $\theta'_i \sim \text{Beta}(S_i + 1, N_i - S_i + 1)$
- 7:        $I^{(2)} \leftarrow \arg \max_{i=0, \dots, m} \theta'_i$
- 8:     **end while**
- 9:      $I^{(1)} \leftarrow I^{(2)}$
- 10:   **end if**
- 11:   **if**  $I^{(1)} \neq 0$  **then**
- 12:      $Y \leftarrow \text{evaluate arm } I^{(1)}$ ;  $X \sim \text{Ber}(Y)$
- 13:      $S_{I^{(1)}} \leftarrow S_{I^{(1)}} + X$ ;  $N_{I^{(1)}} \leftarrow N_{I^{(1)}} + 1$ ;  $S_0 \leftarrow S_0 + 1$
- 14:   **else**
- 15:      $\mu_{m+1} \sim \nu_0$ ;  $\mathcal{A} \leftarrow \mathcal{A} \cup \{\mu_{m+1}\}$ ;
- 16:      $Y \leftarrow \text{evaluate arm } m + 1$ ;  $X \sim \text{Ber}(Y)$
- 17:      $S_{m+1} \leftarrow X$ ;  $N_{m+1} \leftarrow 1$ ;  $m \leftarrow m + 1$
- 18:   **end if**
- 19:    $t = t + 1$
- 20: **end while**

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a shuffled 3-fold cross-validation on  $\mathcal{D}_{\text{train}}$ . More precisely, given a random partitioning  $\cup_{j=1}^3 \mathcal{D}_{\text{valid}}^j$  of  $\mathcal{D}_{\text{train}}$  where the folds have equal size, we train a classifier  $\hat{g}_{\lambda}^{(j)}$  on  $\mathcal{D}_{\text{train}} \setminus \mathcal{D}_{\text{valid}}^j$  for each fold  $j$  and the average validation error  $e = 1/|\mathcal{D}_{\text{train}}| \sum_{j=1}^3 \sum_{i \in \mathcal{D}_{\text{valid}}^j} \mathbb{1} \left\{ \hat{g}_{\lambda}^{(j)}(\mathbf{x}_i) \neq \mathbf{y}_i \right\}$  is reported as a noisy estimate of the risk  $f(\lambda) = \mathbf{P}(\hat{g}_{\lambda}^{(n)}(\mathbf{X}) \neq \mathbf{Y})$ .

Observe that both the noisy evaluation and the value of  $f$  belong to  $[0, 1]$ , so one can introduce an “arm” with rewards in  $[0, 1]$  for each hyper-parameter  $\lambda$ . Sampling the arm  $\lambda$  produces a reward  $r = 1 - e \in [0, 1]$  (with a different random partitioning and random seed for training for each selection), that is assumed to have mean  $1 - f(\lambda)$ . In an infinite setting, querying a new arm from the reservoir corresponds to selecting a new hyper-parameter at random from the search space. With these two notions (arm sampling and reservoir querying), our algorithm for infinite BAI can be readily applied to HPO.

For those experiments, we adapt the recommendation rule of **D-TTTS** to the HPO applications considered and always recommend the hyper-parameter configuration that has produced the smallest cross-validation error so far (which is the recommendation rule used by other approaches as well). For all methods, we then report as a function of time the cross-validation error for the recommended hyper-parameter configuration at this time. We stress again that, unlike in a classic bandit setting where we could use the simple regret as a performance metric, we do not have access to the ground truth generalization error in real classification tasks. Thus we only report a proxy of the error rate that we are interested in.

**Results** (code available at <https://bit.ly/2IDwuir>) We first benchmark our methods on some simple UCI datasets using **SVM** (from **scikit-learn**) as the classifier. We optimize over two hyper-parameters: the *penalty parameter*  $C$  and the *kernel coefficient*  $\gamma$  for a *rbf* kernel, for whom pre-defined search bounds are both  $[10^{-5}, 10^5]$ .

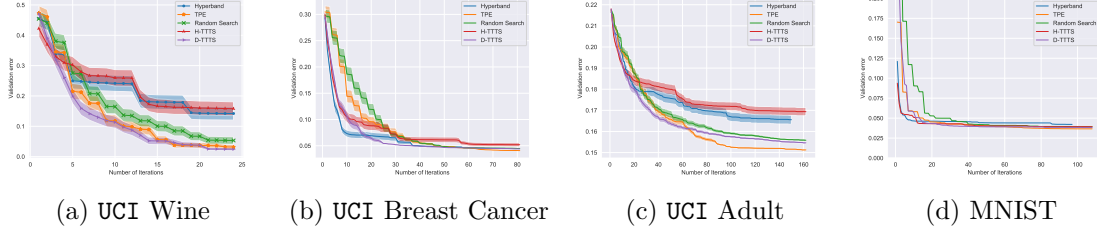


Fig. 1a shows the mean cross-validation error of **SVM** run on the UCI Wine dataset over 24 iterations averaged on 100 replications. The task is to predict the quality score (between 0 and 10) of a wine given 11 attributes. We recall that one iteration corresponds to one arm pull. In this experiment, **D-TTTS** improves over other benchmark algorithms. Fig. 1b is the same experiment run on the UCI Breast Cancer dataset over 81 iterations. The task is to predict whether a patient has breast cancer based on 32 attributes. We repeat the experiment for 100 times. This time, **D-TTTS** is slightly worse than **Hyperband** at the beginning, but improves later. Finally we optimize **SVM** on a relatively more complicated UCI Adult dataset over 162 iterations, for which the result is shown in Fig. 1c. The task is to tell whether the income of an individual is higher than 50k or not given 14 attributes. This experiment is also run over 100 replications. **D-TTTS** is better than other algorithms at the beginning, but is outperformed by **TPE** towards the end. We see that, although not always the best, **D-TTTS** shows a consistent, robust, and quite competitive performance in the 3 tasks.

We now carry out the classic MNIST digits classification task using multi-layer perceptron (MLP). We choose to optimize over three hyper-parameters: the *size of hidden layer* (an integer between 5 and 50), the *L2 penalty parameter*  $\alpha$  (between 0 and 0.9) and the *initial learning rate* (bounded in  $[10^{-5}, 10^{-1}]$ ). Fig. 1d shows the result of MLP run on MNIST over 108 iterations, this time averaged on 20 replications. **D-TTTS** is slightly slower than **Hyperband** and **H-TTTS** at the very beginning, but is performing well afterward.

## 5. Discussion

We presented a way to use Thompson sampling for BAI in an infinitely many-armed bandit model, and explained how to use it for HPO. We introduced the first fully dynamic algorithm for this problem and showed through an extensive empirical study that it is a promising approach for HPO. In the future, we would like to provide experiments on more datasets and establish theoretical guarantees to support the good performance of **D-TTTS**, with the hope to provide a finite-time upper bound on its error probability. We will also investigate variants of this algorithm for the non-stochastic bandit setting for which **Hyperband** can be used, and that allows to spend more time on training the more promising algorithms.



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## Appendix A. Best-arm identification for HPO

Hyper-parameter optimization can be modeled as a BAI task in a bandit model. Given a finite set of arms  $\mathcal{A} \triangleq \{1, \dots, K\}$ , when we select arm  $i$ , we get an independent observation from some unknown distribution  $\nu_i$  with mean  $\mu_i$ . A BAI algorithm sequentially selects arms in order to identify the arm with the largest mean,  $I^* \triangleq \arg \max_{i \in \mathcal{A}} \mu_i$ <sup>2</sup>. In the context of HPO, each arm models the quality of a given hyper-parameter configuration  $\lambda$ . When the arm is sampled, a noisy evaluation of  $f(\lambda)$  is received, which is the mean reward of that arm. A BAI (or pure-exploration) algorithm consists of a sequential arm selection strategy, indicating which arm  $I_t$  is selected at round  $t$ , coupled with *recommendation rule* that selects a candidate best arm  $I_t^*$  at round  $t$ . The goal is either to minimize the error probability  $\mathbf{P}(\mu_{I_t^*} \neq \mu_{I^*})$  (Audibert and Bubeck, 2010; Karnin et al., 2013) or the *simple regret* (Bubeck et al., 2009; Gabillon et al., 2012), defined as  $r_t = \mu_{I^*} - \mu_{I_t^*}$ , possibly after a total budget  $B$ , whose knowledge may be used by the algorithm. Note that the BAI problem can also be studied from a fixed-confidence point of view (Even-dar et al., 2003).

Standard BAI algorithms are however not straightforwardly applicable to HPO when the search space can be infinite and is often continuous. To handle those interesting cases, we rather turn our attention to BAI in a infinitely many armed bandit (Carpentier and Valko, 2015). In this context, there is an infinite pool of arms, whose means are assumed to be drawn from some *reservoir distribution*  $\nu_0$ . In such a model, a BAI algorithm maintains a list of arms (hyper-parameter configurations) that have been tried before. At each round it can either query a new arm from the reservoir (add a new hyper-parameter, selected at random, to the current pool), add it to the list and sample it (evaluate it), or sample an arm already in the list (re-evaluate a configuration tried before).

A natural way to perform BAI in an infinite-many armed bandit model consists in first querying a *well-chosen* number of arms from the reservoir and then running a standard BAI algorithm on those arms (Carpentier and Valko, 2015). However this ideal number may rely on the difficulty of the learning task, which is hardly known in practice. The Hyperband algorithm (Li et al., 2017) takes a step further and successively queries several batches of arms from the reservoir, including a decreasing number of arms in each batch, while increasing the budget dedicated to each of them. SHA (Karnin et al., 2013), a state-of-the-art BAI algorithm, is then run on each of these batches of arms. This approach seems more robust in that it trades off between *the number of arms that is needed to capture a good arm* and *how much measurement effort we should allocate to each of them*. However, a numerical study performed by Aziz et al. (2018b) seems to reveal that an infinite bandit algorithm based on SHA should always query the maximal number of arms from the reservoir<sup>3</sup>.

All the existing algorithms are still subject to a pre-defined scheduling of how many arms should be queried from the reservoir. The algorithm (D-TTTS) we proposed in this paper does not need to decide in advance how many arms will be queried, and is therefore fully *dynamic*.

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2. Here we present BAI problems in a standard way for which we search for an arm with the largest mean. For HPO, however, it is important to mention that we are searching for a hyper-parameter configuration that minimizes the validation error. One can easily see that it does not change the problem in principle.
  3. This reference is a preliminary draft that has been withdrawn due to technical issues in the proofs. Yet we believe the experimental section to be sound.

**Remark 1** *Hyperband* is proposed specifically for hyper-parameter tuning. Its original philosophy is to adaptively allocate resources to more promising configurations. Resources here can be time, dataset sub-sampling, feature sub-sampling, etc. In such a setting, the classifier is not always trained into completion given a parameter configuration, but is rather stopped early if it is shown to be bad so that we can allocate more resources to other configurations. In this case, different evaluations of a single configuration cannot be considered as i.i.d. anymore. Thus, HPO is stated as a non-stochastic infinitely-armed bandit problem. This idea of early stopping is also further investigated by combining Bayesian optimization with it (Falkner et al., 2018). However, this is out of the scope of this paper.

## Appendix B. Hyper TTTS

We present here another way of extending TTTS to deal with an infinite number of arms, namely Hyper-TTTS or H-TTTS, a variant of Hyperband in which SHA is replaced by TTTS. This algorithm, whose sampling rule is formally stated as Algorithm 2, runs  $s_{\max}$  batches of TTTS with different number of arms  $n$  and each batch with a same budget  $T = \lceil B/s_{\max} \rceil$  with  $B$  the total budget. The number of arms within each bracket is decreasing with an exponential rate of  $\gamma$ . One inconvenience of this algorithm is that  $s_{\max}$  and  $\gamma$  still need to be tuned (in practice, we use the same tuning as the one of Hyperband). D-TTTS is thus proposed to circumvent this issue.

## Appendix C. Some synthetic results

In this part, we give some synthetic experimental results comparing D-TTTS to Hyperband and to SHA, a state-of-the-art algorithm for finite BAI that can be adapted to the infinite setting. In those experiments, the arms are Bernoulli distributed and the reservoir distribution  $\nu_0$  is fixed to some Beta( $a, b$ ) distribution.

Infinite Sequential Halving (ISHA) consists in running SHA on a fixed number of arms drawn from the reservoir. Observe that for a total budget  $B$ , there exists a maximum number of arms  $K^*$  that can be processed by SHA, which satisfies  $B = \lceil K^* \log_2(K^*) \rceil$ . Following Aziz et al. (2018b), we run ISHA with  $K^*$  arms drawn from the reservoir.

We report in Fig. 2 the simple regret as a function of time for different algorithms and four Beta reservoir distributions. H-TTTS and D-TTTS are run with  $\beta = 1/2$  which is known to be a robust choice (Russo, 2016). Each point represents the expected simple regret  $\mathbb{E}[1 - \mu_{I_n^*}]$  estimated over 1000 replications for an algorithm run with budget  $n$ . D-TTTS is very competitive on 3 reservoirs and H-TTTS is sometimes better, sometimes worse than Hyperband. We also tried the SiRI algorithm (Carpentier and Valko, 2015) (with  $b$  as the tail parameter when  $\nu_0 = \text{Beta}(a, b)$ ) but obtained worse performance and therefore do not report the results.

Note that in the implementation of Hyperband for this *stochastic* infinite bandit setting, the elimination phase of the underlying SHA algorithm is carried out according to the averaged loss of previous samples (as samples from an arm are i.i.d. in this setting and not a converging sequence). In the next section, we apply our algorithm to some real hyper-parameter optimization tasks.

**Algorithm 2** Hyper TTTS (H-TTTS)**Input:**  $\beta; \gamma; B; s_{\max}; \nu_0$ **Initialization:**  $T = \lfloor B/s_{\max} \rfloor$ 


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```

1: for  $s \leftarrow s_{\max}$  to 0 do
2:    $K = \left\lceil \frac{s_{\max}+1}{s+1} \gamma^s \right\rceil$ 
3:    $\mathcal{A} \leftarrow \{i = 1, \dots, K : \mu_i \sim \nu_0\}; t = 0$ 
4:   while  $t < T$  do
5:     sample  $\theta \sim \Pi_t$ 
6:      $I^{(1)} \leftarrow \arg \max_{i \in \mathcal{A}} \theta_i$ 
7:     sample  $b \sim \text{Bernoulli}(\beta)$ 
8:     if  $b = 1$  then
9:        $Y \leftarrow \text{evaluate arm } I^{(1)}$ 
10:    else
11:      while  $I^{(2)} \neq I^{(1)}$  do
12:         $\forall i \in \mathcal{A}, \theta'_i \sim \text{Beta}(S_i + 1, N_i - S_i + 1)$ 
13:         $I^{(2)} \leftarrow \arg \max_{i \in \mathcal{A}} \theta'_i$ 
14:      end while
15:       $I^{(1)} \leftarrow I^{(2)}$ 
16:       $Y \leftarrow \text{evaluate arm } I^{(1)}$ 
17:    end if
18:     $X \sim \text{Bernoulli}(Y)$ 
19:     $S_{I^{(1)}} \leftarrow S_{I^{(1)}} + X; N_{I^{(1)}} \leftarrow N_{I^{(1)}} + 1$ 
20:     $t = t + 1$ 
21:  end while
22: end for

```

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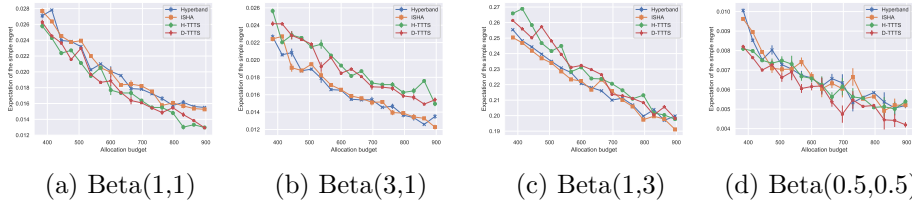


Figure 2: expected simple regret as a function of the number of arms evaluations for different Beta reservoir