Online Optimization of Smoothed Piecewise Constant Functions

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Abstract

We study online optimization of *smoothed* piecewise constant functions over the domain $[0, 1)$. This is motivated by the problem of adaptively picking parameters of learning algorithms as in the recently introduced framework by Gupta and Roughgarden (2016). Majority of the machine learning literature has focused on Lipschitz-continuous functions or functions with bounded gradients.[1] This is with good reason—any learning algorithm suffers linear regret even against piecewise constant functions that are chosen adversarially, arguably the simplest of non-Lipschitz continuous functions. The *smoothed* setting we consider is inspired by the seminal work of Spielman and Teng (2004) and the recent work of Gupta and Roughgarden (2016)—in this setting, the sequence of functions may be chosen by an adversary, however, with some uncertainty in the location of discontinuities. We give algorithms that achieve sublinear regret in the full information and bandit settings.

1 Introduction

In this paper, we study the problem of online optimization of piecewise constant functions. This is motivated by the question of selecting *optimal parameters* for learning algorithms. Recently, Gupta and Roughgarden (2016) introduced a *probably approximately correct* (PAC) framework for choosing parameters of algorithms. Imagine a situation, when a website wishes to provide personalized results to a user. To respond to a user's query, the service provider may need to implement a learning (or some other type of) algorithm which involves choosing parameters. The choice of parameters affects the quality of solution and ideally we would like to design a mechanism where the service provider learns from past instances, or at least employs a strategy that has low regret with respect to the *single* optimal solution in hindsight. In many learning problems, the goal is to find parameters by optimizing a continuous function (of the parameters); however, ever so often one encounters problems with discrete solutions, such as k-means or independent set, which result in objective functions that have discontinuities.

Concretely, we consider the problem of online optimization of piecewise constant functions over the domain $[0, 1)$. At each round the learning algorithm plays a point $x_t \in [0, 1)$, receives payoff $f_t(x_t)$, where f_t is a piecewise constant function. The aim of the learning algorithm is to achieve *no-regret* with respect to the best single point $x^* \in [0, 1)$ in hindsight.[2] As is standard, by *no regret* we mean, regret that grows sublinearly with T, the number of rounds played. If we make no assumptions about how the piecewise linear functions f_t are chosen then, it is easy to construct instances where the algorithm would suffer regret that is linear in T.

We take the view that real-world problems, while not entirely stochastic are rarely truly adversarial.[3] In this work, we consider a *smoothed* adversary; rather than defining a piecewise constant function f over $[0, 1)$ by defining the intervals $[0, a_1), \ldots [a_{k-1}, 1)$ exactly, the adversary may only define distributions to pick the

[1] These functions are typically called *smooth* in the machine learning literature. We avoid this usage here, since we use *smoothed* and *smoothness* in the sense of Spielman and Teng (2004).

[2] Unfortunately, the confusing terminology *no-regret* is common in the literature and is used to denote that the regret grows sublinearly in T, the number of rounds for which the online algorithm is run.

[3] There may be settings where assumption of a malicious adversary is justified, *e.g.,* when spammers, google bombers, *etc.* are actively seeking to compromise systems.

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points a_i, with the added constraint that the density of these distributions is upper bounded by some parameter σ. It is very natural to assume that there is uncertainty in defining real-world problems, either due to noise or imperfect information; indeed this was also the motivation of the original work by Spielman and Teng (2004) where they showed that the smoothed time complexity of (a variant of) the simplex algorithm is polynomial. This uncertainty in defining the intervals (or the points of discontinuity) is precisely what we exploit in designing no-regret algorithms.

Machine learning research has primarily focused on optimizing functions with bounded (first few) derivatives. For example, there exists substantial literature on online optimization of Lipschitz continuous functions, both in the full information and the bandit setting (see *e.g.,* (Kleinberg, 2004; Kleinberg et al., 2008; Bubeck et al., 2009)). However, any sort of combinatorial structure typically introduces discontinuities in the objective function. Thus, most of the existing methods for online optimization are no longer applicable.

The *smoothness* formulation we use in the paper restricts an adversary from being able to define too narrow an interval in which *optimal solutions* may lie. In particular, if we consider the refinement of all the intervals we get over T rounds of the (smoothed) adversary choosing piecewise constant functions, the smallest interval is still polynomially small in T (and the bound σ on the density and the number of pieces k). This ensures that the problem is not that of finding a needle in a haystack, but a rather hefty iron rod. Under these conditions, in principle, one could simply draw a large enough (but still polynomial in T) number of points uniformly in the interval $[0, 1)$, and consider the problem as the standard experts setting. The bandit setting is a bit more delicate, but still could be handled using ideas similar to the Exp4 algorithm (Auer et al., 2002). The difficulty is *computational*—we would rather design algorithms that at time step t, run in time polynomial in $\log(t)$ and other problem-dependent factors, than in time polynomial in t. With carefully designed algorithms and data-structures, we can indeed achieve this goal. We summarize our contributions below, describe related work, and then discuss how our work fits in a broader context. (All missing details and complete proofs are provided in the long version (Cohen-Addad and Kanade, 2016).)

1.1 Our Results

We show that against a *smoothed* adversary, one can design algorithms that achieve the almost optimal regret of $\tilde{O}(\sqrt{T})$ (the $\tilde{O}(\cdot)$ notation hides poly-logarithmic factors) in the expert setting, *i.e.,* when we observe the entire function f_t at the end of the round. Our algorithm is based on a continuous version of the exponentially-weighted forecaster. A naïve implementation of the algorithm we propose would result in a running time that grows polynomially in t. We design a data structure based on *interval trees* or *red-black trees* (see Section 3.3 for the full description) that allows us to implement our algorithm extremely efficiently—the running time of our algorithm is $O(k \log(kt))$ at any given timestep, where k is the number of pieces of the piecewise constant function at each round. We remark that at least logarithmic dependence in t is required in the sense that even keeping track of time requires time at least $\log(t)$.

We also consider the *bandit setting*: here the algorithm does not observe the entire function f_t, but only the value $f_t(x_t)$ for the point chosen. In order to estimate the function f_t elsewhere, we optimistically assume that it is constant in some (suitably chosen) small interval around x_t. Of course, sometimes the point x_t chosen by the algorithm may lie very close to a point of discontinuity of the function f_t. However, this cannot happen very often because of the *smoothness* constraint on the adversary. With a somewhat delicate analysis we obtain a regret bound of $\tilde{O}(\text{poly}(k, \sigma)T^{2/3})$ in the bandit setting. As in the full information (or expert) setting, our algorithm is very efficient, *i.e.,* polynomial in $\log(t)$ and other parameters such as k and σ.

In Section 5, we consider a few different problems in this setting—knapsack, weighted independent set, and weighted k-means. The first two of these problems were already considered by Gupta and Roughgarden (2016), however they do not provide *true* regret bounds in their paper, *i.e.,* bounds where the average regret approaches 0 as $T \to \infty$.[4] The combinatorial nature of these problems means that as we vary the algorithm parameters, there may be discontinuities in the objective function. Our preliminary experiments indicate that the behavior does indeed correspond to that predicted by theoretical bounds, albeit with slightly better rates of convergence (possibly since we generate instances randomly).

1.2 Related Work

The work most closely related to ours is that of Gupta and Roughgarden (2016). In the context of online learning, our work improves upon theirs in providing bounds for online learning of algorithm parameters that are *true regret* bounds; in their paper they

[4] We remark that their algorithm will be a "true" no-regret algorithm with suitably chosen parameters, but in that regime the running time is polynomial in T.

only provide ϵ-regret bounds, in that one can guarantee that for any given ϵ the algorithm will achieve average regret of ϵ. The algorithms we present in this paper are more natural and achieve a significant improvement in running time. We also give results in the *bandit* setting, which is in many ways more appropriate for the applications under consideration. The approach considered in their paper does not yield a bandit algorithm. With some effort, one may be able to adapt ideas from the Exp.4 algorithm of Auer et al. (2002) to achieve a non-trivial regret bound in the *bandit* case; however, the resulting algorithm would be computationally expensive.

There is a substantial body of work that seeks to use learning mechanisms to choose the parameters or *hyperparameters* of algorithms. Snoek et al. (2014, 2012) suggest using Bayesian optimization techniques to choose hyperparameters effectively. Yet other papers (see *e.g.,* (Fink, 1998; Huang et al., 2010; Kotthoff et al., 2012; Hutter et al., 2015; Jamieson and Talwalkar, 2016)) suggest various techniques to choose parameters for algorithms (not necessarily in the context of learning). However, except for the work of Gupta and Roughgarden (2016) and Jamieson and Talwalkar (2016), most work is not theoretical in nature.

1.3 Discussion

The notion of *smoothness* considered in this paper is inspired by the seminal work of Spielman and Teng (2004). In theoretical computer science, this notion allows us to look beyond worst-case analysis without making extremely strong assumptions required for average-case analyses. This approach seems particularly relevant to machine learning, a field in which worst-case results or those using strong distributional assumptions typically have little bearing in practice. The smoothness considered here is on the instances themselves rather than on the functions being optimized as is common in machine learning. Combinatorial problems arise naturally in several online and offline learning settings; in these cases the notion of *smoothness* à la Spielman and Teng may be more appropriate than the traditional notion of Lipschitz continuity. It would be interesting to explore if this notion of smoothness is applicable in other settings, *e.g.,* sleeping combinatorial experts and bandit settings—where it is known that *stochastic instances* are often tractable, while adversarial ones are *computationally hard* (see *e.g.,* (Kanade and Steinke, 2014; Neu and Valko, 2014; Kale et al., 2016)).

A natural open question is whether our work could be extended to more general functions with discontinuities, such as piecewise linear or piecewise Lipschitz functions. If computational cost were not a concern, we believe this could be achieved (at least in the full-information setting) by choosing a fine enough grid of $[0, 1)$ as experts. However, whether efficient algorithms such as ours for the case of piecewise constant functions can be designed is an open question.

2 Setting

We consider the online optimization setting where the decision space is $[0, 1)$. At each time step t, the learning algorithm must pick a point $x_t \in [0, 1)$ to play. A *smoothed oblivious adversary* picks a function $f_t : [0, 1) \to [0, 1]$ that is piecewise constant as follows:

1. Adversary defines distributions $D_{t,1}, \ldots, D_{t,k-1}$ where the support of each $D_{t,i}$ is contained in $(0, 1)$ and the density functions are bounded by σ.
2. Adversary defines values $v_{t,1}, \ldots, v_{t,k} \in [0, 1]$
3. Nature draws $a'_{t,i} \sim D_{t,i}$ independently for $i = 1, \ldots, k-1$. Let $0 = a_{t,0}, a_{t,1}, \ldots, a_{t,k-1}, a_{t,k} = 1$ be in non-decreasing order, where $a_{t,1}, \ldots, a_{t,k-1}$ are just $a'_{t,1}, \ldots, a'_{t,k-1}$ sorted.[5]
4. The piecewise constant function f_t is defined as $f_t(x) = v_{t,i}$ for $x \in [a_{t,i-1}, a_{t,i})$.

For a known time horizon T, let $x_1, \ldots, x_T$ be the choices made by the learning algorithm.[6] Then the regret is defined as:

$$\text{Regret(Alg)} = \max_{x \in [0,1)} \sum_{t=1}^{T} f_t(x) - \sum_{t=1}^{T} f_t(x_t)$$

We consider the full information (or *experts*) setting, where at the end of each round the full function f_t is revealed to the learning algorithm. We also look at the *bandit* setting, where the learning algorithm only sees the value $f_t(x_t)$. All results in this paper are stated in terms of expected regret; we believe that bounds that hold with high probability can be obtained using standard techniques.

All the results in this paper can easily be generalized to the setting where the decision space is $[0, 1]^d$ and the adversary chooses functions that are constant on sub-hypercubes. In the full-information setting, the regret guarantees will be worse by a factor that is polynomial in d and the running time worse by a factor exponential in d. In the bandit setting, both the regret and the

[5] Under the smoothness assumptions, the $a'_{t,i}$ will be distinct with probability 1.

[6] We assume that the time horizon T is known, otherwise, the standard doubling trick may be applied.

running time will be worse by a factor exponential in d. For simplicity we only discuss the one dimensional setting and defer the general case to the full version of the paper.

We first state some useful observation that we will use repeatedly in this paper. These are by no means original and already appear in some form in the work of Gupta and Roughgarden (2016) for example.

Observation 2.1. *Let $x_1, \ldots, x_m$ be independently drawn from any distributions (possibly different) whose density functions are bounded by σ. Then the probability that there exist $x_i < x_j$ such that $x_j - x_i < \epsilon$ is at most $m^2\sigma\epsilon$.*

Proof. The proof is just an application of the union bound over all $\binom{m}{2}$ pairs. □

Observation 2.2. *Let $0 = x_0 < x_1 < \cdots < x_m = 1$ be any points in $[0, 1]$ such that $x_i - x_{i-1} > \epsilon$ for all i. Let $y_1, \ldots, y_N$ be drawn uniformly at random from $[0, 1)$. Then if $N \geq \frac{1}{\epsilon}(\ln(\epsilon^{-1}) + \ln(\delta^{-1}))$, the probability that there exists i such that there is no y_j in the interval (x_{i-1}, x_i) is at most δ.*

Proof. This is basically a balls into bins argument with at most ϵ^{-1} bins and the probability of throwing a ball into each bin is at least ϵ. □

3 Full Information Setting

First in Section 3.1, we explain why it is necessary to look at *smoothed adversaries*; without this, one can easily construct a relatively benign instance that suffers a regret of $\Omega(T)$. Then, we give an exponentially-weighted forecaster that achieves expected regret that is $O(\sqrt{\log(T)T})$. We show that in fact this can be implemented very efficiently; at time t the running time of our algorithm is polynomial in k and $\log(t)$, where k is the number of pieces of the functions.

3.1 Lower Bound for Worst-Case Adversaries

Here, we show that unless one adds a smoothness assumption the worst-case regret bound is linear in T. This is unsurprising and in a way already follows from Theorem 4.2 in the extended version of the paper by Gupta and Roughgarden (2016). However, in the more general setting considered in this paper, the bad instance is simpler to describe and we provide it for completeness.

We describe a simple adversary that chooses functions that are piecewise constant with at most 3 pieces and each piece being of length at least 1/5; but for allowing the adversary to choose the points of discontinuity arbitrarily, the freedom given to the adversary is limited. For round 1 the adversary chooses f_1 such that $f_1(x) = 1$ for $x \in [2/5, 3/5)$ and 0 otherwise. On round 2 the adversary chooses f_2 to be 1 on either the interval $[3/10, 1/2)$ or $[1/2, 7/10)$ uniformly at random. Thus, any learning algorithm can get expected payoff at most 1/2, but either the entire interval $[2/5, 1/2)$ or $[1/2, 3/5)$ would have got payoff of 1 on both rounds. In general if after t rounds, if there is an interval $[l_t, u_t)$ such that $f_s(x) = 1$ for all $x \in [l_t, u_t)$ for all $s \leq t$, then if $m_t = (l_t + u_t)/2$, the adversary picks f_{t+1} to take value on either $[m_t - 1/5, m_t)$ or $[m_t, m_t + 1/5)$. It is clear that after T rounds the expected payoff of any learning algorithm is at most $T/2$, however there exists a point $x^* \in [0, 1)$ that would receive a payoff of T.

3.2 No-Regret Algorithm for Smoothed Adversaries

Algorithm 1 is a fairly standard exponentially-weighted forecaster that is used to make predictions in the non-stochastic setting. We describe the efficient implementation using *modified* interval trees in Section 3.3. If one were merely concerned with achieving a running time that was polynomial in T at each round, there is a rather easy solution. Using the fact that the distributions used to define points of discontinuity have a bound on the density, we can argue that even after a full refinement of intervals that appear in the functions $f_1, \ldots, f_T$, with high probability the smallest interval is of length at least $1/(kT)^3$. Then by picking $(kT)^3 \log(kT)$ points uniformly at random, we get a set of points that would hit every interval in the refinement. Thus, we could pick these points to begin with and apply a standard expert algorithm, such as Hedge (Freund and Schapire, 1995). Since the regret depends only logarithmically on the number of experts, we would still achieve a regret bound of $O(\sqrt{\log(kT)T})$. In a way, this is what Gupta and Roughgarden (2016) do to obtain their "low-regret" bound. However, this solution is inelegant and suffers significantly in terms of computational cost. Our algorithm runs in time polynomial in k and $\log(t)$ at time t; note that dependence on $\log(t)$ is required even just to keep track of time! The proof of the following theorem is fairly standard and appears in the long version (Cohen-Addad and Kanade, 2016).

Theorem 3.1. *The expected regret of Algorithm 1 is bounded by $2\sqrt{(e-2)\log(k^2T^3\sigma)T} + 1$. The expectation is with respect to the random choices of the algorithm as well as nature.*

Remark 3.2. *Rather than considering a smoothed adversary, one may consider a slightly different notion of regret. For example, one can consider the best "small"*

Algorithm 1 No-regret algorithm

input: η

set $F_1(x) = 0$ to be the constant 0 function over $[0, 1)$

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

1. Define $p_t(x) = \frac{\exp(\eta F_t(x))}{\int_0^1 \exp(\eta F_t(x))dx}$
2. Pick $x_t \sim p_t$
3. Observe function f_t and receive payoff $f_t(x_t)$
4. Set $F_{t+1} = F_t + f_t$

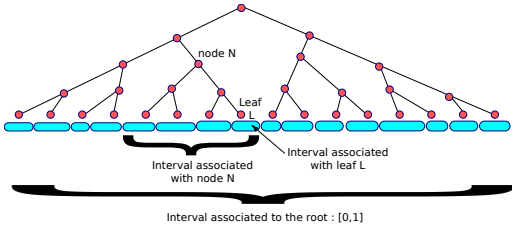

Figure 1: Example of an interval tree over the interval $[0, 1]$.

enough interval, but the comparison point is chosen to be the worst point in that interval (in other words some kind of a minimax criterion). Obviously, choosing the best point is impossible as discussed in the example in Section 3.1. Our algorithm and proof technique work essentially unchanged in this setting. The only change is that in Step (4) *we will use this interval instead. The regret bound depends on the inverse of the length of the interval, but only logarithmically.*

Running Time. A naïve implementation of Algorithm 1 would result in running time that is polynomial in t at time t (apart from also being polynomial in k and σ). This is because the number of intervals in the refinement increase linearly in T. However, by using an *augmented* interval tree data structure to store the past functions and using *messages* to perform updates lazily, we can guarantee that the running time of the algorithm is polynomial in $\log(t)$. The sampling required in Step 2 of the algorithm can also be implemented efficiently by storing auxiliary information about the *weights* of intervals. The next subsection explains this data structure at a high level (full details appear in the long version (Cohen-Addad and Kanade, 2016)).

3.3 An Efficient Data-Structure

In this section, we describe a data structure that ensures that the *selection* and *update* steps (steps 2, 4) of Algorithm 1 have a running time of $O(k \log(tk))$ at time t.

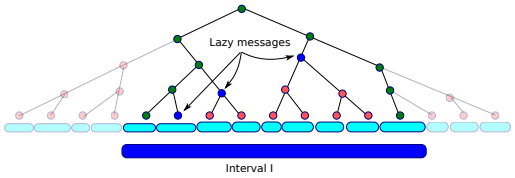

Figure 2: Example of a call to the update procedure. The interval to update is the interval I. Messages are left along the path connecting the two extremities (smallest and highest intervals) of I. In green are the nodes that get their messages updated ($m(N) = 1$ for those nodes). In blue are the nodes that get a new message corresponding to $\exp(\eta f_t(I))$ ($m(N) \leftarrow m(N) \cdot \exp(\eta f_t(I))$ for those nodes). This update should be propagated to all the descendants of the green nodes (the red nodes), but will only be done lazily when required. The lazy approach and the structure of the tree allows to bound the number of green and blue vertices by $O(\log T)$. Indeed, observe that not all the nodes of the subtrees corresponding to interval I are updated at this step.

Here, we describe the high level idea. In order to have an efficient implementation, we exploit the fact that the function is piecewise constant with k pieces. We build upon a data structure called *interval trees* (see (Cormen et al., 2009) for more details), that for any partition P of the interval $[0, 1)$ into n parts, maintains a binary tree with n leaves that has the following properties:

(i) The leaves are the parts of P.

(ii) Any level of the tree corresponds to a coarsening of the partition. More precisely, for any internal node N, there is an interval associated with N which corresponds to the interval that is the union of the intervals associated with the children of N (see Figure 1).

With such a data-structure, it is possible to refine the partition (split existing intervals), and establish membership in time $O(\log n)$, where n is the number of leaves in the tree. In our setting, n will be $O(tk)$ after t steps.

Here, we extend this data structure to support additional operations. Note that F_t is piecewise constant, in particular F_t is constant over $I(\ell)$, the interval defined at leaf ℓ; by abuse of notation let $F_t(I(\ell))$ denote this constant value. For each leaf ℓ of the tree we will maintain a variable $w(\ell)$ whose value is $|I(\ell)| \exp(\eta F_t(I(\ell)))$, where $I(\ell)$ is the length of the interval corresponding to leaf ℓ. Then, for each internal node N of the tree, whose associated interval is

$I = [a, b)$, we will maintain

$$w(N) = \sum_{\substack{\ell \text{ leaf of the subtree} \\ \text{rooted at } N}} |I(\ell)| \exp(\eta F_t(I(\ell))) = \int_a^b \exp(\eta F_t(x))dx.$$

This allows us to encode the cumulative distribution function of p_t defined at Step 1 of Algorithm 1. Thus, starting from the root and moving toward the leaves, it is possible to draw from this distribution in time $O(\log(kt))$ (see Fig 3 and the description of the Draw procedure in the long version (Cohen-Addad and Kanade, 2016)).

Then, at Step 4 of Algorithm 1, we know that the function f_t is piecewise constant with k pieces. For each such *piece* I, we need to set $F_{t+1}(I') = F_t(I') + f_t(I)$ for each interval $I' \subseteq I$ on which F_t is constant. We proceed in two steps. First, we ensure that I is the disjoint union of intervals corresponding to subtrees by splitting at most two existing intervals, those that contain the endpoints of I. This operation can be implemented in interval trees of size n in time $O(\log(n))$. Then, we need to update $w(N)$ for each node N of the subtrees. Since f_t is constant on the interval I, we want to set $w(N) \leftarrow w(N) \cdot \exp(\eta f_t(I))$ for each such node N. However the number of such intervals may be $\Omega(tk)$ at time t and doing so naïvely would result in a time complexity of $\Omega(tk)$. Here we are aiming at time complexity $O(k \log(kT))$. To achieve this, we make the updates in a lazy fashion. For any interval I on which f_t is constant, we consider the leaves l and h of the tree that contain the extremities of I (recall that membership can be computed in time $O(\log n)$ for a tree of size n). We then update the values of the variables w for all the nodes along the path joining l to h. For each child of these nodes, we leave a *message*, that contains the value of the update for the subtree rooted at this child. The message at a node will be applied to the node and propagated to its children only when it is needed in the future (see Figure 2). Thanks to the structure of the tree and since f_t is piecewise constant, we show that no information is lost through this process.

4 Bandit Setting

In the bandit setting, we only observe the value $f_t(x_t)$. Thus, we need to estimate f_t elsewhere. This is made difficult by the fact that f_t may have discontinuities. We construct an estimator $\hat{f}_t$ which takes an appropriately re-scaled value on a small interval around x_t and is 0 elsewhere. If this chosen interval is too large, then it is quite likely that a point of discontinuity of f_t lies in this interval. If it is small and no point of discontinuity of f_t lies in the interval, then $\hat{f}_t$ is an unbiased estimator of f_t; however, choosing too small an interval may make $\hat{f}_t(x_t)$ very large. Tuning the length of the interval and a careful analysis gives us a regret bound of $\tilde{O}(T^{2/3})$.

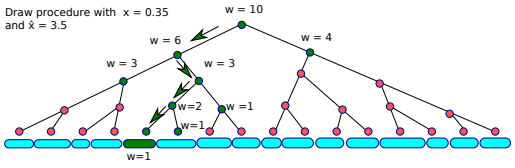

Figure 3: Example of call to the draw procedure. Assuming the value of x is 0.35, the procedure moves along the tree based on the values of the $w(N)$ to find the interval corresponding to $p_t(x)$. The vertices in green are the vertices whose pending messages are updated by the procedure (i.e.: the value of $m(N)$ for each node N is 1 after the call).

Algorithm 2 Bandit Algorithm

input: η, μ, γ all positive and satisfying $1/\mu \in \mathbb{N}$, $\gamma \leq \frac{1}{2}$, $\eta \leq \gamma\mu$

set $\mathcal{I} = \langle [(i-1)\mu, i\mu) \rangle_{i=1}^{1/\mu}$ be a family of intervals.

set $w_1(x) = 1$ to be the constant 1 function over $[0, 1)$

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

1. Define $p_t(x) = (1-\gamma)\frac{w_t(x)}{\int_0^1 w_t(x)dx} + \gamma$
2. Pick $x_t \sim p_t$
3. Let I_t be the interval of $\mathcal{I}$ that contains x_t.
4. Observe function $f_t(x_t)$. Receive payoff $f_t(x_t)$.
5. Set $\hat{f}_t(x) = \frac{f_t(x)}{p_t(I_t)}$ for all $x \in I_t$ and $\hat{f}_t(x) = 0$ for all $x \in [0, 1) \setminus I_t$,
   Here for interval I, $p_t(I) = \Pr_{x \sim p_t}(x \in I)$.
6. Set $w_{t+1}(x) = w_t(x) \cdot \exp(\eta \hat{f}_t(x))$ for all $x \in [0, 1)$.

Theorem 4.1. *The expected regret of Algorithm 2 is bounded by*

$$2\gamma T + 2\frac{\eta}{\mu}T + \frac{1}{\eta}\ln\left(\mu^{-1}\right) + k\sigma\mu T$$

The expectation is taken with respect to the random choices made by the algorithm as well as those by the adversary/nature. For suitable choices of μ, γ, and, η, this gives a regret bound of $O(\text{poly}(k, \sigma, \log(T))T^{2/3})$.

Proof Idea: The complete proof is a bit delicate. We give a very high level sketch here. Note that at any

time t, $\hat{f}_t$ is going to be non-zero on at most an interval of length μ, elsewhere it will be 0.

This interval is determined by the choice of x_t. If the interval $[(i-1)\mu, i\mu)$ containing x_t is entirely contained in one of the pieces on which f_t is constant, then $\mathbb{E}_{p_t}[\hat{f}_t(x)] = f_t(x)$, giving us an unbiased estimator. However, in order to guarantee this with very high probability would require a very small value of μ, which could make $\hat{f}_t(x_t)$ very large. We show that it is possible to tune the value of μ so that these two competing requirements can be traded off to get a reasonable bound on the regret.

Running Time. As in the full-information setting, the running time of our algorithm can be made polynomial in $\log(t)$ by using the *augmented* interval trees defined in Section 3.3.

5 Applications and Experiments

This section illustrates our framework with concrete examples. We describe three problems for which greedy approaches (also called *priority algorithms* by Borodin et al. (2003)) are often used in practice. We provide experimental results that highlight the efficiency of our approach.

We focus on three well-know optimization problems for which standard greedy methods works well in practice: the weighted k-means, knapsack and maximum independent set problems. Gupta and Roughgarden (2016) show that the objective as a function of the parameters of the greedy heuristics on an instance of size n is a piecewise constant function with a number of pieces that is polynomial in the size of the input. Therefore we propose to apply our approach to the following problems.

The Knapsack problem: The input is a set of n pairs value and size, (v_i, s_i), and a capacity C. The objective is to output a subset $S \subseteq [n]$ such that $\sum_{j\in S} s_j \leq C$ and $\sum_{j\in S} v_j$ is maximum.

A family of greedy heuristics for Knapsack: Given a parameter ρ the greedy heuristic performs the following computations. It first orders the elements by non-decreasing values of $v_i/(s_i)^\rho$. Then the heuristic greedily (subject to feasibility) adds objects to the solution in this order. Note that the cases $\rho = 0$ and $\rho = 1$ are classical heuristics for knapsack.

The Maximum Weighted Independent Set problem (MWIS): The input is a graph $G = (V, E)$, and weights w_i for each of the n vertices. The objective is to output a subset $S \subseteq [n]$ such that for any $i, j \in S$, $(i, j) \notin E$ and $\sum_{j\in S} w_j$ is maximum.

A family of greedy heuristics for MWIS: Denote by $N(i)$ the set of neighbors of i in G. Given a parameter ρ, we consider the *adaptive* greedy heuristic. It adds all the degree 0 vertices to the solution and adds the vertex maximizing $w_i/|N(i)|^\rho$, then removes vertex i and all the vertices of $N(i)$ from the graph, updates $N(j)$ for the remaining vertices j, and repeats until there are no more vertices in the graph.

The Knapsack and MWIS problems were studied by Gupta and Roughgarden (2016). Here, we also consider the weighted k-means problem.

The weighted k-means problem : The input is a set of n points, a metric $d : [n] \times [n] \to \mathbb{R}_+$, and a set of weights $\{w_1, \ldots, w_n\}$. The objective is to output a subset $S \subseteq [n]$ of size k such that $\sum_{i\in[n]} \min_{j\in S} w_i \cdot d(i, j)^2$ is minimized.

A family of greedy heuristics for k-means: Given a parameter ρ and a metric d, we consider the *adaptive* greedy heuristic, which can be seen as a generalization of Gonzalez' algorithm (Gonzalez, 1985) for the k-center problem (when $\rho = \infty$).

Algorithm 3 Adaptive Greedy for weighted k-means.

input: k, ρ, $d : n \times n \mapsto R_+$
set $S \leftarrow \emptyset$
for $t = 1, 2, \ldots, k$ **do**

1. Add to S the point p that maximizes $\max_{i\in S} w_p/d(p, i)^{1/\rho}$.

Return S

Figures 4a,4b and 4c show that the per-round regret of Algorithm 1 decreases quickly and that the algorithm has significantly better performances on random instances than in the worst-case scenario. In all the cases, the variance introduced by the internal randomness of the No-Regret Algorithm is very small.

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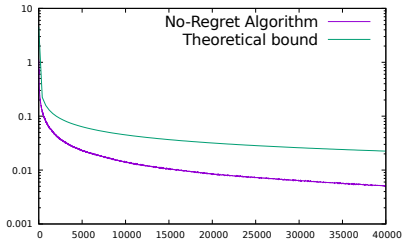
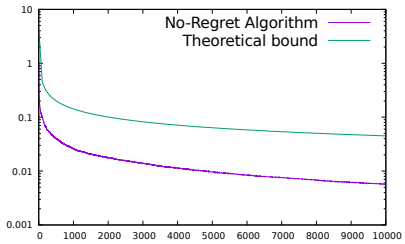
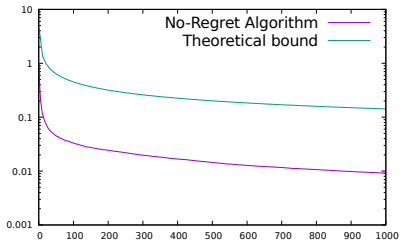


(a) Knapsack



(b) MWIS



(c) Weighted k-means

Figure 4: Average per-round regret of Algorithm 1 for Knapsack, MWIS and weighted k-Means, and the theoretical bound of 2η. The x-axis represents the timesteps. The y-axis represents the per-round regret.

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