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# MINIMAX ADAPTIVE BOOSTING FOR ONLINE NONPARAMETRIC REGRESSION

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A PREPRINT

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## ABSTRACT

We study boosting for adversarial online nonparametric regression with general convex losses. We first introduce a parameter-free online gradient boosting (OGB) algorithm and show that its application to chaining trees achieves minimax optimal regret when competing against Lipschitz functions. While competing with nonparametric function classes can be challenging, the latter often exhibit local patterns, such as local Lipschitzness, that online algorithms can exploit to improve performance. By applying OGB over a core tree based on chaining trees, our proposed method effectively competes against all prunings that align with different Lipschitz profiles and demonstrates optimal dependence on the local regularities. As a result, we obtain the first computationally efficient algorithm with locally adaptive optimal rates for online regression in an adversarial setting.

**Keywords** Online Learning, Boosting, Nonparametric Regression

## 1 Introduction

Observing a stream of data  $x_1, x_2, \dots$ , an online regression algorithm predicts at each time  $t \geq 1$  a function  $\hat{f}_t$  of the current  $x_t \in \mathcal{X} \subset \mathbb{R}^d$ ,  $d \geq 1$ . The prediction's accuracy is assessed using a sequence of convex loss functions  $(\ell_t)_{t \geq 1}$ , each of which has a minimum within  $[-B, B]$  for some  $B > 0$ , e.g.  $\ell_t(\hat{y}) = |\hat{y} - y_t|$  or  $(\hat{y} - y_t)^2$  with  $|y_t| \leq B$ . We define the *regret* over a time horizon  $T \geq 1$  and against some function  $f$  belonging to a benchmark class of functions  $\mathcal{F} \subset \mathbb{R}^{\mathcal{X}}$  as

$$\text{Reg}_T(f) := \sum_{t=1}^T \ell_t(\hat{f}_t(x_t)) - \sum_{t=1}^T \ell_t(f(x_t)), \quad \forall f \in \mathcal{F}. \quad (1)$$

The set of functions  $\mathcal{F}$  is usually assumed to perform well on the data sequence (e.g. Lipschitz functions). Unlike traditional (*batch*) regression methods, which train some model using all available

data  $\{(x_s, \ell_s)\}_{s=1}^T$  at once, online regression algorithms (see [Cesa-Bianchi and Lugosi \[2006\]](#) for a reference textbook) update  $\hat{f}_t$  at each time  $t \geq 1$  using only the past observed data  $\{(x_s, \ell_s)\}_{s=1}^{t-1}$ . This adaptive learning process allows to capture complex and evolving patterns in the data without requiring strong assumptions about its structure (such as i.i.d.). Furthermore, optimal algorithms (in the minimax sense of [Rakhlin and Sridharan \[2014\]](#)) can be tailored to adapt to unknown regularities and systematically leverage these patterns. On the other hand, *boosting* is a powerful ensemble learning technique to solve the problem of nonparametric regression in batch learning. First introduced in [Freund et al. \[1999\]](#) for classification task, boosting was later analyzed by [Friedman \[2001\]](#) as a stagewise greedy numerical optimization strategy to improve the performances of the combination of weak learners, called strong learner.

Adaptation of boosting methods to online nonparametric regression presents unique challenges and opportunities. Recent efforts of [Beygelzimer et al. \[2015\]](#), [Hazan and Singh \[2021\]](#), [Chen et al. \[2012\]](#) have extended the efficiency of the gradient and classification boosting. We introduce in this paper a new interpretation of boosting in the context of online convex optimization. We design an algorithm that dynamically trains and optimizes weak learners based on the gradient step of a given strong learner. This new boosting algorithm holds promise for enhancing predictive performance and adaptability in chaining trees. In particular, we show that our online boosting procedure achieves optimal regret over Hölder function classes. Moreover, inspired by prior work [Kuzborskij and Cesa-Bianchi \[2020\]](#), we further boost the chaining trees in a core tree that adapts to local regularities of the competitor function.

## 1.1 Related work

### 1.1.1 Online nonparametric regression

[Vovk \[2006\]](#) introduced online nonparametric regression with general function classes. [Cesa-Bianchi and Lugosi \[2006\]](#) developed an algorithm exploiting losses with good curvature properties such as exp-concavity to achieve fast regret in adversarial settings. [Rakhlin and Sridharan \[2014\]](#) further developed the minimax theory and provided a non-polynomial algorithm that is optimal for the regret in cumulative squared errors of prediction. The extension of this theory to general convex losses was later developed in [Rakhlin and Sridharan \[2015\]](#). Finally [Gaillard and Gerchinovitz \[2015\]](#), [Cesa-Bianchi et al. \[2017\]](#) designed a chaining algorithm which is polynomial and minimax knowing the regularity of the competitor. They also noticed that the same algorithm with a different tuning is minimax for general convex losses.

In the statistical learning setting, the rate of convergence of aggregation of tree-based algorithms have been analyzed mainly in the context of random forest, see [Biau and Scornet \[2016\]](#) for a survey. Avoiding early-stopping and overfitting, the purely random forests of [Arlot and Genuer \[2014\]](#) are minimax for (batch) nonparametric regression of functions. Closer to our setting, [Mourtada et al. \[2017\]](#) aggregated Mondrian trees that are trained sequentially in a batch setting. This methods adapt to the regularity of the unknown regression function in a well-specified setting but not to an adversary.

### 1.1.2 Regret against Lipschitz competitors and local adaptivity

Considering  $\mathcal{F}$  as the set of Lipschitz functions for any constant  $L > 0$ , [Hazan and Megiddo \[2007\]](#) introduced the corresponding minimax regret. They proved that for  $d = 1$  the rate is  $O(\sqrt{LT})$  for any convex losses motivating the design of an algorithm that localizes at an optimal rate depending on  $L$ . The knowledge of  $L$  is crucial for their procedures to prevent from growing linearly with  $L$ .

Ref.	Assumptions	Upper bound
This paper	$(\ell_t)$ exp-concave, $L > 0$ unknown $(\ell_t)$ convex, $L > 0$ unknown	$\min \{\sqrt{LT}, L^{\frac{2}{3}} T^{\frac{1}{3}}\}$ $\sqrt{LT}$
KCB20	$(\ell_t)$ square loss, $L > 0$ unknown	$\sqrt{LT}$
HM07	$(\ell_t)$ absolute loss, $L > 0$ known $(\ell_t)$ square loss, $L > 0$ known	$L^{\frac{1}{3}} T^{\frac{2}{3}}$ $\sqrt{LT}$
GG15	$(\ell_t)$ square loss, $L = 1$ known	$T^{\frac{1}{3}}$
CB3G17	$(\ell_t)$ convex, $L = 1$ known	$\sqrt{T}$

Going one step further, [Kuzborskij and Cesa-Bianchi \[2020\]](#) proved the adaptability of tree-based online algorithms by introducing the oracle pruning given a core tree in the regret analysis. Tracking the best pruning goes back to [Helmbold and Schapire \[1995\]](#) and [Margineantu and Dietterich \[1997\]](#). [Kpotufe and Orabona \[2013\]](#) also designed adaptive pruning algorithm based on trees to partition optimally the instance space  $\mathcal{X}$ . Competing with an oracle pruning in nonparametric regression allows to adapt to the local regularities of Lipschitz functions. Indeed, the implicit multi-resolution aspect of a pruning allows to adapt the depth of the leaves to the local Lipschitz constants. The larger the constant the deeper the pruning because it is ready to pay to learn refined (potentially smaller) Lipschitz constants.

However the existing methods require the knowledge of the local Lipschitz constants and do not achieve the minimax regret rate in time. The question to design a polynomial minimax algorithm that adapts to the local regularities remained open. One solution of that problem relies in applying some online boosting approach on chaining trees.

### 1.1.3 (Online) Boosting algorithms

Proving the consistency of boosting algorithms in regression is a significant challenge. Earliest and seminal works, such as those by [Friedman \[2001\]](#) and [Collins et al. \[2002\]](#), often lack explicit convergence proofs. The minimax theory for boosting is sparse because of the importance of introducing an early-stopping rule, that is sensitive to tune even in the easiest regression problem of [Bühlmann and Yu \[2003\]](#). To our knowledge, [Zhang and Yu \[2005\]](#) were the first to offer a convergence bound for greedy boosting procedures in traditional statistical learning, without requiring strong assumptions on the base learners.

Subsequent research endeavors have sought to expand the application of boosting to online learning scenarios. In the framework of online boosting, as introduced in [Hazan and Singh \[2021\]](#) and [Beygelzimer et al. \[2015\]](#), the emphasis is on sequentially boosting a particular type of algorithm belonging to a specified class, known as weak online learners. These algorithms must satisfy specific assumptions, typically contingent upon their regret and the associated loss functions.

## 1.2 Contributions and outline of the paper

Our contributions are threefold: first, we present a novel and generic online gradient boosting method that employs sequential gradient based optimization to enhance strong learners that combine weak learners. Second, we apply this boosting procedure on specific Chaining Trees to achieve minimax regret over Hölder functions with global regularity. Finally, we introduce a core boosting algorithm that competes with the oracle pruning tree. We demonstrate that it achieves an optimal locally adaptive regret bound that scales with the local regularities of the competitor function. In particular, we also prove that our algorithm adapts to the curvature of the loss functions, and remains optimal with both general convex and exp-concave losses. Finally, we include numerical experiments in the supplementary materials (Appendix F) to illustrate our results on a synthetic dataset.

## 2 A new and generic online gradient boosting procedure

**Setting and notations.** We consider that data  $x_1, x_2, \dots \in \mathcal{X}$  arrive in a stream. At each time step  $t \geq 1$ , the algorithm updates  $\hat{f}_t$ , receives  $x_t \in \mathcal{X}$  and predicts  $\hat{f}_t(x_t) \in \mathbb{R}$ . Then, a loss function  $\ell_t : \mathbb{R} \rightarrow \mathbb{R}$  is disclosed. The learner incurs loss  $\ell_t(\hat{f}_t(x_t))$  and considers gradients to update strategies for time  $t + 1$ . We assume that  $(\ell_t)$  are convex and  $G$ -Lipschitz, and that  $\mathcal{X}$  is a bounded subspace of  $\mathbb{R}^d$ ,  $d \geq 1$ . We write  $|\mathcal{X}'| = \sup_{x, x' \in \mathcal{X}'} \|x - x'\|_\infty < \infty$  for any  $\mathcal{X}' \subset \mathcal{X}$  and  $[N] = \{1, \dots, N\}$  for  $N \geq 1$ .

We introduce a new and generic boosting procedure designed specifically to the online learning setting and some fundamental notions which are later used in our analysis.

Let  $\mathcal{W}$  be a set of real-valued functions  $\mathcal{X} \rightarrow \mathbb{R}$  and for some  $N \geq 1$

$$\text{span}_N(\mathcal{W}) = \left\{ \sum_{n=1}^N \beta_n h_n, h_n \in \mathcal{W}, \beta_n \in \mathbb{R} \right\} \quad (2)$$

which forms a linear function space based on  $N$  functions in  $\mathcal{W}$ . We want to find a sequence of function  $\hat{f}_t \in \text{span}_N(\mathcal{W})$ ,  $t \geq 1$ , such that it tends to minimize  $\text{Reg}_T(\mathcal{F})$  with  $\mathcal{F} = \text{span}_N(\mathcal{W})$  in (1). In Algorithm 1, we provide a generic form of the boosting procedure considered in the paper based on an abstract gradient step, along with a schematic diagram in Figure 1.

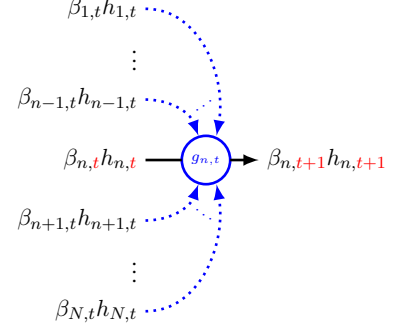


Figure 1: Boosting at time  $t$ .

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**Algorithm 1:** OGB - Boosting at time  $t$

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**Input** :  $(\beta_{n,t}, h_{n,t})_{n \in [N]}$  and gradients  $g_{n,t}, n \in [N]$  (later specified).

1 **for**  $n = 1$  **to**  $N$  **do**

2     Predict  $\hat{f}_t = \sum_{n=1}^N \beta_{n,t} h_{n,t}$

3     Find  $(\beta_{n,t+1}, h_{n,t+1}) \in \mathbb{R} \times \mathcal{W}$  to approximately minimize

$$(\beta_n, h_n) \mapsto \ell_t(\hat{f}_{-n,t}(x_t) + \beta_n h_n(x_t)) \quad \text{with} \quad \hat{f}_{-n,t}(x_t) = \hat{f}_t(x_t) - \beta_{n,t} h_{n,t}(x_t) \quad (3)$$

using gradient  $g_{n,t} = \left[ \nabla_{(\beta_n, h_n)} \ell_t(\hat{f}_{-n,t}(x_t) + \beta_n h_n(x_t)) \right]_{(\beta_n, h_n) = (\beta_{n,t}, h_{n,t})}$ .

**Output** :  $(\beta_{n,t+1}, h_{n,t+1})_{n \in [N]}$

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To keep things concise, the gradient minimization step in (3) is expressed as:

$$(\beta_{n,t+1}, h_{n,t+1}) \leftarrow \text{grad-step}((\beta_{n,t}, h_{n,t}), g_{n,t})$$

where the function  $\text{grad-step}((\beta, h), g)$  stands for *any* rule that updates  $(\beta, h) \in \mathbb{R} \times \mathcal{W}$  from time  $t$  to  $t + 1$  using some gradient  $g \in \mathbb{R}$ .

**Comparison with boosting in statistical learning.** In statistical (batch) learning, the boosting procedure would solve the greedy optimisation problem

$$(\beta_n, h_n) \in \arg \min_{(\beta, h) \in \mathbb{R} \times \mathcal{W}} \sum_{t=1}^T \ell_t(\sum_{l=1}^{n-1} \beta_l h_l(x_t) + \beta h(x_t)), \quad n \geq 1.$$

While classical gradient boosting relies on a *stagewise* strategy (Friedman [2001], Section 3.) introducing new terms as the number  $n \geq 1$  of boosts increase, our approach described in Algorithm 1 is *stepwise* with the sequential readjustment of the weak learners over time  $t \geq 1$ . It is worth noting that the risk of overfitting with boosting in online learning is not existing because the gradient step uses past observed data  $\{(x_s, \ell_s)\}_{s=1}^{t-1}$  only. This is because new data arrives over time in online learning, unlike in batch learning, where the risk of overfitting a given dataset is well-documented (e.g. Grove and Schuurmans [1998], Vezhnevets and Barinova [2007]). As a note, defining the update step according to the well-established online gradient descent method by Zinkevich [2003] is analogous to gradient boosting as described by Friedman [2001], but adapted for an online setting and without the risk of overfitting.

**Online Gradient Boosting (OGB).** From now on, we call OGB the procedure Algorithm 1 coupled with some gradient-step rule  $\text{grad-step}$ . Our definition of OGB differs from the previous one introduced in Beygelzimer et al. [2015]. We update sequentially the weak-learners using the gradient at the strong learner  $\hat{f}_t$  whereas Beygelzimer et al. [2015] use an online algorithms based on gradients evaluated at  $\sum_{l=1}^{n-1} \beta_{l,t} h_{l,t}(x_t)$ ,  $n = 1, \dots, N$ ,  $t \geq 1$ , stagewise combination of weak learners associated to basic online algorithms. Once the latter satisfies some regret properties, their approach apply to any type of weak learners. Our procedure can be applied to any weak learner  $\mathcal{W}$  for which the gradient step can be specified. The sequential update rule (3) can be defined properly

and efficiently introducing chaining tree as follows. In our algorithms, the gradient is evaluated at  $\sum_{l=1}^N \beta_{l,t} h_{l,t}(x_t)$  only, and the errors of the gradients at the stagewise functions  $\sum_{l=1}^{n-1} \beta_{l,t} h_{l,t}(x_t)$  for  $n$  small do not propagate at every step  $t \geq 1$  of our algorithm.

### 3 Online gradient boosting in a chaining tree

We detail in this section our online boosting procedure Algorithm 1 with specific decision trees, that we call chaining trees. In particular, we show that it achieves minimax regret in nonparametric regression over the class of Hölder functions.

#### 3.1 Chaining tree

Tree-based methods are conceptually simple yet powerful - see Breiman et al. [2017]. They consist in partitioning the feature space into small regions and then fitting a simple model in each one. Given  $\mathcal{X} \subset \mathbb{R}^d$ , a *regular decision tree*  $(\mathcal{T}, \bar{\mathcal{X}}, \bar{\mathcal{W}})$  is composed of the following components:

- a finite rooted ordered regular tree  $\mathcal{T}$  of degree  $\deg(\mathcal{T})$ , with nodes  $\mathcal{N}(\mathcal{T})$  and leaves or terminal nodes  $\mathcal{L}(\mathcal{T}) \subset \mathcal{N}(\mathcal{T})$ . The root and depth of  $\mathcal{T}$  are respectively denoted by  $\text{root}(\mathcal{T})$  and  $d(\mathcal{T})$ . Each interior node  $n \in \mathcal{N}(\mathcal{T}) \setminus \mathcal{L}(\mathcal{T})$  has  $\deg(\mathcal{T})$  childs. The parent of a node is referred to as  $\text{p}(n)$  and its depth as  $d(n)$ ;
- a family of sub-regions  $\bar{\mathcal{X}} = \{\mathcal{X}_n, n \in \mathcal{N}(\mathcal{T})\}$  consisting of subsets of  $\mathcal{X}$  such that for any interior node  $n$ ,  $\{\mathcal{X}_m : \text{p}(m) = n\}$  forms a partition of  $\mathcal{X}_n$ ;
- a family of weak prediction functions  $\bar{\mathcal{W}} = \{h_n : \mathcal{X} \rightarrow \mathbb{R}, n \in \mathcal{N}(\mathcal{T})\}$  associated to each node such that  $h_n(x) = 0$  for all  $x \notin \mathcal{X}_n$ .

The standard method of Breiman et al. [2017] for predicting with a decision tree is to use the partition induced by the leaves  $\sum_{n \in \mathcal{L}(\mathcal{T})} h_n(x)$ ,  $x \in \mathcal{X}$ . On the contrary, the chaining tree that we define below, performs multi-scale predictions by combining the predictions from all nodes.

**Definition 1** (Chaining-Tree). A *Chaining-Tree (CT) prediction function*  $\hat{f}$  is defined as

$$\hat{f}(x) = \sum_{n \in \mathcal{N}(\mathcal{T})} h_n(x), \quad x \in \mathcal{X} \subset \mathbb{R}^d,$$

where the regular prediction tree  $(\mathcal{T}, \bar{\mathcal{X}}, \bar{\mathcal{W}})$  satisfies:

- the weak prediction functions  $h_n$  are constant  $h_n(x) = \theta_n \mathbb{1}_{x \in \mathcal{X}_n}$ ,  $\theta_n \in \mathbb{R}$ . We denote them by  $\theta_n$  by abuse of notation;
- the degree  $\deg(\mathcal{T}) = 2^d$  and for any interior node  $n$ ,  $\{\mathcal{X}_m : \text{p}(m) = n\}$  forms a regular partition of  $\mathcal{X}_n$  in infinite norm. In particular, this implies  $|\mathcal{X}_m| = |\mathcal{X}_{\text{p}(m)}|/2$ .

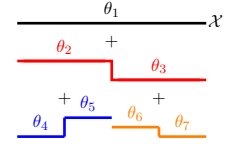


Figure 2: Prediction of a CT over  $\mathcal{X} \subset \mathbb{R}$ .

Chaining technique in Dudley [1967] is at the core of algorithms addressing function approximation tasks, and was first introduced to design concrete online learning algorithm with optimal rates by Gaillard and Gerchinovitz [2015]. This method involves a sequential refinement process, that is - roughly speaking - growing a sequence of refining approximations over a function space.

#### 3.2 Online boosting procedure in a chaining-tree

The goal is to use our boosting procedure (Alg. 1) for sequentially training CT by tuning the family  $\bar{\mathcal{W}}$  over time. In this section, we will make our OGB procedure explicit over CT, that corresponds to the class of weak learners:

$$\mathcal{W} = \{h_n : x \mapsto \theta_n \mathbb{1}_{x \in \mathcal{X}_n}, \theta_n \in \mathbb{R}, n \in \mathcal{N}(\mathcal{T})\}. \quad (4)$$

For such a class of weak learner  $\mathcal{W}$  we fix  $\beta_n = 1$  and  $N = |\mathcal{N}(\mathcal{T})|$ . Thus  $\text{span}(\mathcal{W}) = \{\sum_{n \in \mathcal{N}(\mathcal{T})} \theta_n \mathbb{1}_{x \in \mathcal{X}_n}, \theta_n \in \mathbb{R}\}$  and any CT prediction can be written as an additive model of weak learners in  $\mathcal{W}$ .

To sequentially learn a family  $\bar{\mathcal{W}}_t = \{h_{n,t} = \theta_{n,t} \mathbb{1}_{\mathcal{X}_n}, n \in \mathcal{N}(\mathcal{T})\} \subset \mathcal{W}$ , the gradient step in Equation (3) of the OGB procedure (Alg. 1) reduces to

$$\theta_{n,t+1} \leftarrow \text{grad-step}(\theta_{n,t}, g_{n,t}). \quad (5)$$

Here  $g_{n,t}$  is the subgradient of the last loss in  $\theta_{n,t}$ , i.e.,

$$g_{n,t} = \left[ \frac{\partial \ell_t(\hat{f}_{-n,t}(x_t) + \theta \mathbb{1}_{x_t \in \mathcal{X}_n})}{\partial \theta} \right]_{\theta=\theta_{n,t}} \quad \text{with} \quad \hat{f}_{-n,t} = \sum_{m \in \mathcal{N}(\mathcal{T}) \setminus \{n\}} h_{m,t}. \quad (6)$$

By the chain rule, we further simplify

$$g_{n,t} = \ell'_t(\hat{f}_t(x_t)) \mathbb{1}_{x_t \in \mathcal{X}_n}, \quad n \in \mathcal{N}(\mathcal{T}), \quad (7)$$

making the computation of subgradients extremely simple, as the dependence on  $n$  only involves the indicator function. More precisely, the subroutine `grad-step`, detailed below, will not perform any update (i.e.,  $\theta_{n,t+1} = \theta_{n,t}$ ) when the gradients are zero (i.e.,  $x_t \notin \mathcal{X}_n$ ). All non-zero updates use the same subgradient  $g_t = \ell'_t(\hat{f}_t(x_t))$  based on the derivative of the loss of the strong learner prediction.

**Online gradient optimization subroutine.** We now detail the subroutine `grad-step`, which, in our analysis, can be any online optimization algorithm satisfying the following regret upper-bound.

**Assumption 1.** Let  $g_{n,1}, \dots, g_{n,T} \in [-G, G]$  for  $T \geq 1$ ,  $G > 0$ , and  $n \in \mathcal{N}(\mathcal{T})$ . We assume that the parameters  $\theta_{n,t}$  starting at  $\theta_{n,1} \in \mathbb{R}$  and following the update (5) satisfy the linear regret bound:

$$\sum_{t \in T_n} g_{n,t}(\theta_{n,t} - \theta_n) \leq G|\theta_n - \theta_{n,1}|(C_1 \sqrt{|T_n|} + C_2), \quad \text{with} \quad T_n = \{1 \leq t \leq T, g_{n,t} \neq 0\},$$

for some  $C_1, C_2 > 0$  and every  $\theta_n \in \mathbb{R}$ .

Such an assumption is satisfied by so-called *parameter-free* online convex optimization algorithms, such as those described in Cutkosky and Orabona [2018], Mhammedi and Koolen [2020], Orabona and Pál [2016], by considering only the time steps where  $g_{n,t} \neq 0$  in their procedures. Note that the constants  $C_1, C_2$  often hide logarithmic factors in  $T, G$  or  $|\theta_n|$ . These algorithms require no parameter tuning (though some need prior knowledge of  $G$ ) and provide a regret upper bound that automatically scales with the parameter norm  $|\theta_n|$ . This property is crucial in analyzing our CT, where each node is tasked with correcting the errors of its ancestors in a more refined subregion of the input space. This multi-resolution aspect of the predictions leads us to consider  $\theta_n$  that approach zero as  $d(n)$  increases.

In the theorem below, we prove, when resorting to such a subroutine into Algorithm 1, a regret upper bound with respect to the class of Hölder functions over  $\mathcal{X}$  defined for any  $L > 0$  and  $\alpha \in (0, 1]$  as

$$\text{Lip}_L^\alpha(\mathcal{X}) = \{f : \mathcal{X} \rightarrow \mathbb{R} : |f(x) - f(x')| \leq L \|x - x'\|_\infty^\alpha \quad x, x' \in \mathcal{X}\}, \quad \text{and} \quad \sup_{x \in \mathcal{X}} |f(x)| \leq B,$$

with  $B > 0$  such that  $\ell_t$  has minimum lying in  $[-B, B]$ . We will refer to  $L$  as the Lipschitz constant.

**Theorem 1.** Let  $T \geq 1$ ,  $(\mathcal{T}, \bar{\mathcal{X}}, \bar{\mathcal{W}}_1)$  be a CT with  $\mathcal{X}_{\text{root}(\mathcal{T})} = \mathcal{X}$ ,  $\theta_{n,1} = 0$  for all  $n \in \mathcal{N}(\mathcal{T})$  and  $d(\mathcal{T}) = \frac{1}{d} \log_2 T$ . Then, Algorithm 1 applied with a `grad-step` procedure satisfying Assumption 1 achieves the regret upper bound

$$\sup_{f \in \text{Lip}_L^\alpha(\mathcal{X})} \text{Reg}_T(f) \leq GB(C_1 \sqrt{T} + C_2) + GL|\mathcal{X}|^\alpha \begin{cases} (\Phi(\frac{d}{2} - \alpha)C_1 + 4C_2 + 1)\sqrt{T} & \text{if } d < 2\alpha, \\ (\frac{C_1}{d} \log_2 T + 4C_2 + 1)\sqrt{T} & \text{if } d = 2\alpha, \\ (\Phi(\frac{d}{2} - \alpha)C_1 + 4C_2 + 1)T^{1-\frac{\alpha}{d}} & \text{if } d > 2\alpha, \end{cases}$$

for any  $L > 0$  and  $\alpha \in (0, 1]$ , where  $\Phi(u) = |2^u - 1|^{-1}$ .

The proof of Theorem 1 is postponed to Appendix A.



**Minimax optimality and adaptivity to  $L$  and  $\alpha$ .** Note that the above rates are minimax optimal for online nonparametric regression with convex losses over  $\text{Lip}_L^\alpha(\mathcal{X})$ , as shown by [Rakhlin and Sridharan \[2015\]](#) that provides a non-constructive minimax analysis for this problem (see also [Rakhlin and Sridharan \[2014\]](#)). For the case of low-dimensional settings, where  $d \leq 2\alpha$ , our bound is in  $O((B + L)\sqrt{T})$ . However, it has been demonstrated in [Rakhlin and Sridharan \[2015\]](#) that faster rates  $O(T^{\frac{1}{3}})$  can be attained when dealing with exp-concave losses. In the next section, we will address this by making our algorithm adaptive to the curvature of the loss functions. A similar chaining technique was applied by [Gaillard and Gerchinovitz \[2015\]](#) to design an algorithm with minimax rates for the square loss or [Cesa-Bianchi et al. \[2017\]](#) in the partial information setting. However, unlike these works, our Algorithm 1 over a CT does not require prior knowledge of neither  $L$  nor  $\alpha$  and automatically adapts to them. This is achieved through the use of *parameter-free* subroutines that satisfy Assumption 1 and automatically adapt to the norm of  $\theta_n$ .

**Complexity.** Although the formal definition of our algorithm requires constructing a decision tree with  $|\mathcal{N}(\mathcal{T})| = 2^{d(\mathcal{T})} = T$  nodes, it remains tractable, similar to the approach in [Gaillard and Gerchinovitz \[2015\]](#). At each round, the input  $x_t$  falls into one node per level of the tree constituting  $\text{path}(x_t)$ , since  $\{\mathcal{X}_n, d(n) = m\}$  forms a partition of  $\mathcal{X}$  for any depth  $1 \leq m \leq d(\mathcal{T})$ . Consequently, most subgradients in (6) are zero, and  $\text{grad-step}$  only needs to be called  $d(\mathcal{T}) = \frac{1}{d} \log_2 T$  times per round, each using the same gradient  $g_t$ . The overall space complexity is at most  $O(|\mathcal{N}(\mathcal{T})|) = O(T)$ . It can be improved noticing that nodes in the tree do not need to be created until at least one input falls into that node.

**Unknown input space.** In practice our procedure can be easily extended to the case where  $\mathcal{X}$  is unknown beforehand and is sequentially revealed through new inputs  $x_t \in \mathbb{R}^d$  (similarly to [Kuzborskij and Cesa-Bianchi \[2020\]](#)). This can be done either through a doubling trick (starting with  $\mathcal{X} = [-1, 1]^d$  and restarting the algorithm with an increased diameter by at least a factor of 2 each time an input falls outside of the current tree) or by creating a new CT around  $x_t$  that runs in parallel, whenever a new point  $x_t$  falls outside the existing trees.

### 3.3 Optimal and locally adaptive regret in online nonparametric regression

In the previous section, we demonstrated that our boosting procedure applied to CT achieves minimax regret  $O(LT^{(d-1)/d})$  compared to Hölder functions. This bound scales linearly with the constant  $L$ . This raises the question of whether our boosting-approximation method could be adapted to fit subregions with lower variation. Our second contribution is an algorithm that adapts on the local Hölder profile of the competitor. For any  $f \in \text{Lip}_L^\alpha(\mathcal{X})$ ,  $\alpha \in (0, 1]$ , and some subset  $\mathcal{X}_n \subset \mathcal{X}$ , the local Hölder constant  $L_n(f)$  satisfies

$$|f(x) - f(x')| \leq L_n(f) \|x - x'\|_\infty^\alpha, \quad x, x' \in \mathcal{X}_n. \quad (8)$$

Recall that we assume that for any  $f \in \text{Lip}_L^\alpha(\mathcal{X})$ ,  $\sup_{x \in \mathcal{X}} |f(x)| \leq B$ . We define  $[\cdot]_B := \min(B, \max(-B, \cdot))$  the clipping operator in  $[-B, B]$  and a uniform discretization grid with precision  $\varepsilon = T^{-\frac{1}{2}}$  as the set of  $K = \lceil 2B/\varepsilon \rceil$  constants

$$\Gamma := \{\gamma_k = -B + (k - 1)\varepsilon, k = 1, \dots, K\} \subset [-B, B].$$

**Locally adaptive boosting.** We base our predictions on a combination of several regular decision tree predictions (see Section 3.1). The latter are sitting in nodes of a *core tree*  $(\mathcal{T}_0, \mathcal{X}, \mathcal{W})$ , with  $\mathcal{W} = \{(\hat{f}_{n,k})_{k=1}^K, n \in \mathcal{N}(\mathcal{T}_0)\}$ . In our main Algorithm 2, referred to as *LocAdaBoost* for *Locally Adaptive Boosting*, the core tree  $\mathcal{T}_0$  provides an average prediction at each time step  $t \geq 1$  as follows:

$$\hat{f}_t(x_t) = \sum_{n \in \mathcal{N}(\mathcal{T}_0)} \sum_{k=1}^K w_{n,k,t} \hat{f}_{n,k,t}(x_t),$$

where, for each pair  $(n, k) \in \mathcal{N}(\mathcal{T}_0) \times [K]$



- $\hat{f}_{n,k,\cdot}$  is a clipped predictor associated with a CT  $\mathcal{T}_{n,k}$  (see Definition 1), rooted at  $\mathcal{X}_{\text{root}(\mathcal{T}_{n,k})} = \mathcal{X}_n \in \bar{\mathcal{X}}$  and with  $\theta_{\text{root}(\mathcal{T}_{n,k}),1} = \gamma_k \in \Gamma$ ,  $\theta_{n',1} = 0$  for  $n' \in \mathcal{N}(\mathcal{T}_{n,k}) \setminus \{\text{root}(\mathcal{T}_{n,k})\}$ ;
- the weight  $w_{n,k,t}$  adjust the contribution of the predictor  $\hat{f}_{n,k}$  such that the sum of all weights over the tree satisfies  $\sum_{n \in \mathcal{N}(\mathcal{T}_0)} \sum_{k \in [K]} w_{n,k,t} = 1$  at any time  $t \geq 1$ .

First, LocAdaBoost (Algorithm 2) leverages OGB (Algorithm 1) to sequentially train the weights  $(w_{n,k})_{(n,k) \in \mathcal{N}(\mathcal{T}_0) \times [K]}$  using a particular grad-step function combining two subroutines: `weight` and `sleeping`, both inspired by classical expert aggregation methods. Specifically, the `weight` subroutine refers to any general algorithm satisfying the following Assumption 2.

**Assumption 2.** Let  $\tilde{\mathbf{g}}_1, \dots, \tilde{\mathbf{g}}_T \in [-G, G]^{K \times |\mathcal{N}(\mathcal{T}_0)|}$ , for  $T \geq 1$  and  $G > 0$ . We assume that the weight vectors  $\tilde{\mathbf{w}}_t$ , initialized with a uniform distribution  $\tilde{\mathbf{w}}_1$  and updated via `weight` in line Alg. 2, satisfy the following linear regret bound:

$$\sum_{t=1}^T \tilde{\mathbf{g}}_t^\top \tilde{\mathbf{w}}_t - \tilde{g}_{n,k,t} \leq C_3 \sqrt{\log(K|\mathcal{N}(\mathcal{T}_0)|) \sum_{t=1}^T (\tilde{\mathbf{g}}_t^\top \tilde{\mathbf{w}}_t - \tilde{g}_{n,k,t})^2} + C_4 G,$$

for some constants  $C_3, C_4 > 0$  and for every  $n \in \mathcal{N}(\mathcal{T}_0)$ ,  $k \in [K]$ .

Well-established aggregation algorithms, such as those from Gaillard et al. [2014], Koolen and Van Erven [2015], and Wintenberger [2017], exhibit such second-order linear regret bounds.

Second, LocAdaBoost also employs the OGB procedure to independently train the CTs

$$\{\mathcal{T}_{n,k}, (n,k) \in \mathcal{N}(\mathcal{T}_0) \times [K]\}$$

that reside within  $\mathcal{T}_0$ . For each  $(n,k) \in \mathcal{N}(\mathcal{T}_0) \times [K]$ ,  $\mathcal{T}_{n,k}$  is initialized with  $\theta_{\text{root}(\mathcal{T}_{n,k}),1} = \gamma_k$  and  $\theta_{n',1} = 0$  for all  $n' \in \mathcal{N}(\mathcal{T}_{n,k}) \setminus \{\text{root}(\mathcal{T}_{n,k})\}$ , and is then boosted at each time  $t \geq 1$  via the `boosting` subroutine, line 10, in the same manner as described in Section 3.2.

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### Algorithm 2: LocAdaBoost

---

**Input** : A core regular tree  $(\mathcal{T}_0, \bar{\mathcal{X}}, \bar{\mathcal{W}})$  with root  $\mathcal{X}$ , bounds  $G, B > 0$ .

Initial prediction functions  $\hat{f}_{n,k,1} = \tilde{f}_{n,k,1} = \theta_{\text{root}(\mathcal{T}_{n,k}),1} \mathbb{1}_{x \in \mathcal{X}_n}$  associated to CT

$\mathcal{T}_{n,k}, k \in [K], n \in \mathcal{N}(\mathcal{T}_0)$ .

Initial uniform weights  $\tilde{\mathbf{w}}_1 = (\tilde{w}_{n,k,1})_{n \in \mathcal{N}(\mathcal{T}_0), k \in [K]}$ .

1 **for**  $t = 1$  **to**  $T$  **do**

2     Receive  $x_t$ ;

3      $\mathcal{N}_t \leftarrow \text{path}(x_t)$ ;

4      $\tilde{\mathbf{w}}_t \leftarrow \text{sleeping}(\tilde{\mathbf{w}}_t, \mathcal{N}_t)$ ;

5     Predict  $\hat{f}_t(x_t) = \sum_{n \in \mathcal{N}(\mathcal{T}_0)} \sum_{k=1}^K w_{n,k,t} \hat{f}_{n,k,t}(x_t)$ ;

6     Observe  $y_t$ ;

7     Udpate  $\tilde{\mathbf{w}}_{t+1} \leftarrow \text{weight}(\tilde{\mathbf{w}}_t, \tilde{\mathbf{g}}_t)$  with

$$\tilde{\mathbf{g}}_t = \nabla_{\tilde{\mathbf{w}}_t} \ell_t(\sum_{n \in \mathcal{N}_t} \sum_{k=1}^K \tilde{w}_{n,k,t} \hat{f}_{n,k,t}(x_t) + \sum_{n \notin \mathcal{N}_t} \sum_{k=1}^K \tilde{w}_{n,k,t} \hat{f}_t(x_t));$$

8     **for**  $n \in \mathcal{N}(\mathcal{T}_0), k \in [K]$  **do**

9         Reveal gradients  $g_{n,k,t} = \ell'_t(\tilde{f}_{n,k,t}(x_t))$ ;

10         Boost node expert as:  $(h_{l,t+1})_{l \in \mathcal{N}(\mathcal{T}_{n,k})} \leftarrow \text{boosting}((h_{l,t})_{l \in \mathcal{N}(\mathcal{T}_{n,k})}, g_{n,k,t})$ ;

11         Compute local predictors  $\tilde{f}_{n,k,t+1} = \sum_{l \in \mathcal{N}(\mathcal{T}_{n,k})} h_{l,t+1}$ ;

12         Clip local predictors  $\hat{f}_{n,k,t+1} = [\tilde{f}_{n,k,t+1}]_B$ ;

**Output** :  $\hat{f}_{T+1} = \sum_{n,k} w_{n,k,T+1} \hat{f}_{n,k,T+1}$

---

Since  $\mathcal{T}_0$  partitions the input space  $\mathcal{X}$ , only a subset  $\mathcal{N}_t$  of the nodes in  $\mathcal{N}(\mathcal{T}_0)$  contributes predictions at each round  $t \geq 1$ . The set of active nodes is determined by `path`( $x_t$ ), which maps the data point  $x_t$  to the nodes  $\{n \in \mathcal{N}(\mathcal{T}_0) : x_t \in \mathcal{X}_n\}$ . This structure mirrors the *sleeping experts* framework

introduced by Freund et al. [1997] and Gaillard et al. [2014], and we incorporate the sleeping subroutine in line 4. The weights are updated as follows, for each  $k \in [K]$ :

$$w_{n,k,t} = 0 \quad \text{if } n \notin \mathcal{N}_t, \quad w_{n,k,t} = \frac{\tilde{w}_{n,k,t}}{\sum_{n' \in \mathcal{N}_t} \sum_{k'=1}^K \tilde{w}_{n',k',t}} \quad \text{otherwise.} \quad (9)$$

This ensures that only the active nodes are boosting (by contributing to) the average prediction.

**Pruning as local adaptivity.** Pruning techniques are frequently employed in traditional statistical learning involving subtrees to reduce overfitting or simplify models. In this context, each pruned tree represents a localized profile corresponding to a partition of  $\mathcal{X}$ . Our Algorithm 2 strives to learn the oracle pruning strategy to compete effectively against any Hölder function.

**Definition 2 (Pruning).** Let  $(\mathcal{T}_0, \tilde{\mathcal{X}}, \tilde{\mathcal{W}})$  be some regular tree with  $\tilde{\mathcal{W}} = \{(\hat{f}_{n,k})_{k \in [K]}, n \in \mathcal{N}(\mathcal{T}_0)\}$ . A pruning or pruned regular decision tree  $(\mathcal{T}, \tilde{\mathcal{X}}, \tilde{\mathcal{W}})$  consists in a subtree, i.e.  $\mathcal{N}(\mathcal{T}) \subset \mathcal{N}(\mathcal{T}_0)$ , with root  $\mathcal{X}_{\text{root}(\mathcal{T})} = \mathcal{X}_{\text{root}(\mathcal{T}_0)}$  and prediction functions  $\tilde{\mathcal{W}} = \{\hat{f}_{n,k_n}, n \in \mathcal{N}(\mathcal{T}), k_n \in [K]\} \subset \tilde{\mathcal{W}}$ . It predicts, at each time  $t \geq 1$ ,

$$\hat{f}_{\mathcal{T},t}(x) = \sum_{n \in \mathcal{L}(\mathcal{T})} \hat{f}_{n,k_n,t}(x), \quad x \in \mathcal{X}.$$

We denote  $\mathcal{P}(\mathcal{T}_0)$  the set of all prunings of  $\mathcal{T}_0$ .

Note that a pruning is a decision tree whose predictions are induced by its leaves, contrary to the core tree  $\mathcal{T}_0$ . In particular, a prediction made by a leaf of a pruning is inherited from the associated node in  $\mathcal{T}_0$  before pruning. We provide some illustration in Figure 3.

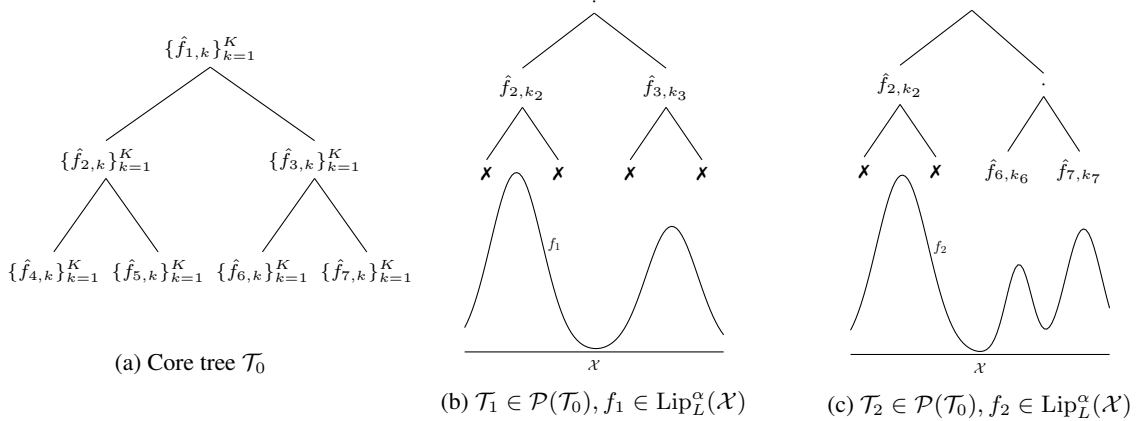


Figure 3: Example of a core tree  $\mathcal{T}_0$  with depth  $d(\mathcal{T}_0) = 3$ ,  $d = 1$ , in Fig. 3a. We give 2 pruned tree instances  $\mathcal{T}_1$  for a given Hölder function  $f_1$  in Fig. 3b and  $\mathcal{T}_2$  for a second profile  $f_2$  in Fig. 3c. In Fig. 3a all nodes  $\mathcal{N}(\mathcal{T}_0)$  are awakened and predictive while  $\mathcal{T}_1$  in Fig. 3b (resp.  $\mathcal{T}_2$  in Fig. 3c) predicts with  $\hat{f}_{2,k_2}, \hat{f}_{3,k_3}$  sitting in its leaves  $\mathcal{L}(\mathcal{T}_1)$  (resp. with  $\hat{f}_{2,k_2}, \hat{f}_{6,k_6}, \hat{f}_{7,k_7}$  sitting in its leaves  $\mathcal{L}(\mathcal{T}_2)$ ).  $\mathbf{X}$  represents a pruned node.

**Complexity.** Similar to before, even though our core tree  $\mathcal{T}_0$  involves at most  $O(|\mathcal{N}(\mathcal{T}_0)|) = O(\sqrt{T}2^{d(\mathcal{T}_0)d}) = O(T^{\frac{3}{2}})$  predictors after  $T$  iterations, our algorithm remains computationally feasible, since at a time  $t$ , only a subset of  $d(\mathcal{T}_0)$  nodes are active and boosted with the weight subroutine. The resulting overall complexity is of order  $\frac{1}{d^2} \sqrt{T} \log_2(T)^2$  per step.

**Main result.** In our main result (Theorem 2), we prove that Algorithm 2 achieves a locally adaptive regret with respect to any Hölder function. Indeed, we show an upper-bound regret that scales with the local regularities of the competitor. Meanwhile, we show that LocAdaBoost also adapts to the curvature of the losses: its regret performances improve when facing exp-concave losses (i.e., when  $y \mapsto e^{-\eta \ell_t(y)}$  are concave for some  $\eta > 0$ ), as shown in the second part of Theorem 2. Exp-concave losses include the squared, logistic or logarithmic losses. Note that for Assumption 2 to

hold, the gradients  $\tilde{\mathbf{g}}_t$  must be bounded by  $G$  in the sup-norm. The Hölder assumption on  $f$  and the boundedness condition on  $\mathcal{X}$  alone are not sufficient. It is also essential that all predictions  $\hat{f}_{n,k,t}(x_t)$  are bounded, which is achieved through clipping in Alg. 2 — see e.g., Gaillard and Gerchinovitz [2015], Cutkosky and Orabona [2018].” To simplify the presentation, we state the theorem here only for the case  $d = 1$  and  $\alpha > 1/2$ . The complete result, which covers more general cases, is available in Appendix B.

**Theorem 2.** *Let  $\alpha \in (\frac{1}{2}, 1]$ ,  $d = 1$ ,  $T \geq 1$  and  $(\mathcal{T}_0, \bar{\mathcal{X}}, \bar{\mathcal{W}})$  be a core regular tree with  $\mathcal{X}_{\text{root}(\mathcal{T}_0)} = \mathcal{X}$  and  $CT \{\mathcal{T}_{n,k} : (n, k) \in \mathcal{N}(\mathcal{T}_0) \times [K]\}$  satisfying the same assumptions as in Theorem 1 and whose nodes root are initialized as  $\theta_{\text{root}(\mathcal{T}_{n,k}),1} = \gamma_k \in \Gamma$ , for all  $(n, k) \in \mathcal{N}(\mathcal{T}_0) \times [K]$ . Then, Algorithm 2 with a weight subroutine as in Assumption 2, achieves the regret upper-bound with respect to any  $f \in \text{Lip}_L^\alpha(\mathcal{X})$ ,  $L > 0$ ,*

$$\text{Reg}_T(f) \lesssim \inf_{\mathcal{T} \in \mathcal{P}(\mathcal{T}_0)} \left\{ \sqrt{|\mathcal{L}(\mathcal{T})|T} + |\mathcal{L}(\mathcal{T})| + |\mathcal{X}|^\alpha \sum_{n \in \mathcal{L}(\mathcal{T})} L_n(f) 2^{-\alpha(d(n)-1)} \sqrt{|T_n|} \right\},$$

where  $\lesssim$  is a rough inequality depending on  $C_i, i = 1, \dots, 4, G$  and  $L_n(f) \leq L, n \in \mathcal{L}(\mathcal{T})$ , are the local Hölder constants (8) of  $f$ , and  $T_n = \{1 \leq t \leq T : x_t \in \mathcal{X}_n\}$ .

Moreover, if  $\ell_1, \dots, \ell_T$  are exp-concave, one has:

$$\text{Reg}_T(f) \lesssim \inf_{\mathcal{T} \in \mathcal{P}(\mathcal{T}_0)} \left\{ |\mathcal{L}(\mathcal{T})| + |\mathcal{X}|^\alpha \sum_{n \in \mathcal{L}(\mathcal{T})} L_n(f) 2^{-\alpha(d(n)-1)} \sqrt{|T_n|} \right\}$$

where  $\lesssim$  also depends on the exp-concavity constant.

We state and prove a complete version of Theorem 2 in Appendix B, for all  $\alpha \in (0, 1], d \geq 1$ . For a more practical interpretation of the results, refer to the experiments in Appendix F. As a remark, Algorithm 2 is not only adaptive to the local Hölderness of  $f$  (via  $L_n(f)$ ), but also to the smoothness rate  $\alpha \in (0, 1]$ . One could extend the previous results in Theorem 2 with some local constants ( $\alpha_n$ ) associated to the regularity of the function over the pruned leaves at the price of the interpretability of the bound in specific situations as below.

**Minimax optimality and adaptivity to the loss curvature.** Moreover, Theorem 2 yields the following corollary, which demonstrates that our algorithm simultaneously achieves optimal rates for generic convex losses (i.e., similar rates to Theorem 1) and for exp-concave losses, while also adapting locally to the Hölder profile of the functions  $f$ . Importantly, our algorithm does not require prior knowledge of the curvature of the losses.

**Corollary 1.** *Let  $d = 1$  and  $\alpha \in (\frac{1}{2}, 1]$ . Under assumptions of Theorem 2, Algorithm 2 achieves a regret with respect to any  $f \in \text{Lip}_L^\alpha(\mathcal{X})$ ,  $L > 0$ , and any pruning  $\mathcal{T} \in \mathcal{P}(\mathcal{T}_0)$ ,*

$$\text{Reg}_T(f) \lesssim \inf_{\mathcal{T} \in \mathcal{P}(\mathcal{T}_0)} \left\{ \sum_{n \in \mathcal{L}(\mathcal{T})} (L_n(f) |\mathcal{X}_n|^\alpha)^{\frac{1}{2\alpha}} \sqrt{|T_n|} \right\}.$$

Moreover, if  $\ell_1, \dots, \ell_T$  are exp-concave, one has:

$$\text{Reg}_T(f) \lesssim \inf_{\mathcal{T} \in \mathcal{P}(\mathcal{T}_0)} \left\{ \sum_{n \in \mathcal{L}(\mathcal{T})} (L_n(f) |\mathcal{X}_n|^\alpha)^{\frac{2}{2\alpha+1}} |T_n|^{\frac{1}{2\alpha+1}} \right\}.$$

The proof of Corollary 1 is postponed to Appendix C. In particular, upper-bounding the infimum over all prunings by the root, our regret becomes  $O(L^{2/(2\alpha+1)} T^{1/(2\alpha+1)})$  and  $O(L^{1/(2\alpha)} \sqrt{T})$  for the exp-concave and general case respectively. This achieves the same optimal regret to that obtained in Gaillard and Gerchinovitz [2015], for any sequence of exp-concave losses, without the prior-knowledge of the scale-parameter  $\gamma$  that they require, and adapting to the regularity while they consider  $L = 1$ . Our algorithm is also nearly minimax in term of the constants  $(L, \alpha)$  as shown by Tsybakov [2003], Hazan and Megiddo [2007] or Bach [2021]. We provide some experimental illustrations of the results from Corollary 1 in Appendix F.

We note that the fast rate in  $T$  obtained under exp-concavity is not optimal in  $L$ . Thus a compromise is made by our algorithm which competes with more complex oracle trees when  $L$  is large to improve and obtain the rate  $\sqrt{L}$  by decreasing the rate in  $T$ . Such trade-off is classical in parametric online learning as bearing resemblances with the comparison between first and second order algorithms, the first ones being optimal in the dimension, the second ones in  $T$ . Remarkably, our unique algorithm achieves both regret bounds which opens the door to a minimax theory on rates in  $L$  and  $T$  and not solely on fast rates in  $T$ .

**Adaptivity to local regularities.** Theorem 2 improves the optimal regret bound established in Theorem 1 by making it adaptive to the local regularities of the Hölder function  $f$ . To illustrate this better, applying Hölder's inequality entails - see Appendix D: for any pruning  $\mathcal{T}$

$$\text{Reg}_T(f) \lesssim \begin{cases} (|\mathcal{X}|^\alpha \bar{L}(f))^{\frac{2}{2\alpha+1}} T^{\frac{1}{2\alpha+1}} & \text{if } \ell_t \text{ are exp-concave,} \\ (|\mathcal{X}|^\alpha \bar{L}(f))^{\frac{1}{2\alpha}} \sqrt{T}, & \end{cases} \quad (10)$$

where  $\bar{L}(f) = \left(\frac{1}{|\mathcal{X}|} \sum_{n \in \mathcal{L}(\mathcal{T})} |\mathcal{X}_n| L_n(f)^{1/\alpha}\right)^\alpha$  is an averaged of the local Hölder constants  $L_n(f)$  weighted by the size of the sets  $\mathcal{X}_n$  over  $\mathcal{T}$ . This result is in the same spirit as that of Kuzborskij and Cesa-Bianchi [2020], that focus on adapting to tree-based local Hölder profiles. However, contrary to us, they need to assume the prior knowledge of bounds  $(M^{(k)})_{1 \leq k \leq d(\mathcal{T}_0)}$  such that  $M^{(k)} \geq L_n$  for any  $n \in \mathcal{N}(\mathcal{T}_0)$ ,  $d(n) = k$ . Doing so, for any pruning  $\mathcal{T}$ , when  $\alpha = 1$  and ignoring the dependence on  $\mathcal{X}$ , for the squared loss (which is exp-concave), they prove a bound of order

$$O\left(\bar{M}(f)T^{\frac{1}{2}} + \sum_k (M^{(k)}|T^{(k)}|)^{1/2}\right) \quad \text{where} \quad \bar{M}(f) = \sum_{k=1}^{d(\mathcal{T})} w^{(k)} M^{(k)},$$

where  $w^{(k)}$  is the proportion of leaves at depth  $k$  in the pruning; and  $T^{(k)}$  the number of rounds in which  $x_t$  belongs to a leaf at level  $k$ . By grouping our leaves  $n$  by their respective depths and applying Hölder's inequality, our results recover theirs with two key improvements - see Appendix E: 1) the prior-knowledge of the  $M^{(k)}$  is not required in our case and they are replaced with the true Hölder constants  $L_n(f)$  that are smaller; 2) the rate in  $T$  is improved from  $\sqrt{T}$  to  $T^{1/3}$ . Note that, similarly to us, the results of Kuzborskij and Cesa-Bianchi [2020] hold for general dimensions and convex losses as well.

## 4 Conclusion and future work

In this paper, we introduced a new and generic online boosting approach. We instantiated the procedure on chaining-trees and proved that we reach minimax regret for the Hölder nonparametric regression problem. We designed a general and computationally tractable algorithm based on a core tree that incorporates our boosting procedure to perform an optimal local approximation of Hölder functions. In addition, we showed that our algorithm also adapts to the curvature of losses revealed by the environment, while remaining optimal in a minimax sense.

The limitation of our approach is the non adaptivity of its tree structures to the data  $(x_t)_{1 \leq t \leq T}$ . Actually, tree structures can also be learned online as in Kuzborskij and Cesa-Bianchi [2020], Kpotufe and Orabona [2013]. Another point is that the smoothness parameter  $\alpha$  is restricted to be smaller than one. However combinations of trees such as the forests in Arlot and Genuer [2014] and Mourtada et al. [2020] can achieve minimax rates for  $\alpha \in (1, 2]$  as well. Their framework is batch i.i.d. and it is an open question whether combinations of trees can also be minimax in an adversarial setting for  $\alpha \in (1, 2]$ .

As future work, our boosting method could also be applied with alternative types of weak learners, such as shallow networks, which are recognized for their effectiveness in regression tasks. In particular, this could address a nonparametric regression problem with respect to richer classes of functions.

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## A Proof of Theorem 1

Let  $f^* \in \arg \min_{f \in \text{Lip}_L^\alpha} \sum_{t=1}^T \ell_t(f(x_t))$ . We define the function

$$f_{\mathcal{W}}^* = \sum_{n \in \mathcal{L}(\mathcal{T})} f^*(x_n) \mathbb{1}_{\mathcal{X}_n} \in \text{span}(\mathcal{W}), \quad (11)$$

where  $T_n = \{1 \leq t \leq T : x_t \in \mathcal{X}_n\}$ ,  $x_n$  the center of hyper region  $\mathcal{X}_n$  (i.e. for any  $x \in \mathcal{X}_n, \|x - x_n\| \leq 2^{-1}|\mathcal{X}_n|$ ) and  $\mathcal{W} = \{h_n : x \mapsto \theta_n \mathbb{1}_{x \in \mathcal{X}_n}, \theta_n \in \mathbb{R}, n \in \mathcal{N}(\mathcal{T})\}$  is the class of weak learners defined in Equation 4. The proof starts with the following regret decomposition

$$\text{Reg}_T(\text{Lip}_L^\alpha) = \underbrace{\sum_{t=1}^T \ell_t(\hat{f}_t(x_t)) - \ell_t(f_{\mathcal{W}}^*(x_t))}_{R_1} + \underbrace{\sum_{t=1}^T \ell_t(f_{\mathcal{W}}^*(x_t)) - \ell_t(f^*(x_t))}_{R_2}. \quad (12)$$

We will refer to  $R_1$  as the estimation error, which consists of the error incurred by sequentially learning the best Chaining-Tree.  $R_2$  will refer to the approximation error, which involves approximating Hölder functions in  $\text{Lip}_L^\alpha(\mathcal{X})$  by functions in  $\text{span}(\mathcal{W})$ .

**Step 1: Upper-bounding the approximation error  $R_2$ .** Note that by definition of the Chaining-Tree  $\mathcal{T}$  (see Definition 1),  $\{\mathcal{X}_n, n \in \mathcal{L}(\mathcal{T})\}$  forms a partition of  $\mathcal{X} = \mathcal{X}_{\text{root}(\mathcal{T})}$  and for any leaf  $n \in \mathcal{L}(\mathcal{T})$

$$|\mathcal{X}_n| = \frac{|\mathcal{X}_{\text{root}(\mathcal{T})}|}{2^{\text{d}(n)-1}} = \frac{|\mathcal{X}|}{2^{\text{d}(\mathcal{T})-1}}. \quad (13)$$

Then,

$$\begin{aligned} R_2 &= \sum_{t=1}^T \ell_t(f_{\mathcal{W}}^*(x_t)) - \ell_t(f^*(x_t)) \\ &\leq \sum_{t=1}^T G |f_{\mathcal{W}}^*(x_t) - f^*(x_t)| && \leftarrow \ell_t \text{ is } G\text{-Lipschitz} \\ &= G \sum_{t=1}^T \left| \sum_{n \in \mathcal{L}(\mathcal{T})} f^*(x_n) \mathbb{1}_{x_t \in \mathcal{X}_n} - f^*(x_t) \right| && \leftarrow \text{by (11)} \\ &= G \sum_{n \in \mathcal{L}(\mathcal{T})} \sum_{t \in T_n} |f^*(x_n) - f^*(x_t)| && \leftarrow \{\mathcal{X}_n, n \in \mathcal{L}(\mathcal{T})\} \text{ partitions } \mathcal{X} \\ &\leq G \sum_{n \in \mathcal{L}(\mathcal{T})} \sum_{t \in T_n} L \|x_n - x_t\|_\infty^\alpha && \leftarrow f^* \in \text{Lip}_L^\alpha \\ &\leq G \sum_{n \in \mathcal{L}(\mathcal{T})} L 2^{-\alpha} |\mathcal{X}_n|^\alpha |T_n| && \leftarrow x_n \text{ center of } \mathcal{X}_n \\ &\leq GL 2^{-\alpha \text{d}(\mathcal{T})} |\mathcal{X}|^\alpha T, \end{aligned} \quad (14)$$

where the last inequality is by (13) and because the leaves form a partition of  $\mathcal{X}$ , which implies  $\sum_{n \in \mathcal{L}(\mathcal{T})} |T_n| = T$ .

**Step 2: Upper-bounding the estimation error  $R_1$ .** We now turn to the bound of the estimation error, that is the regret with respect to  $f_{\mathcal{W}}^* \in \text{span}(\mathcal{W})$ .

*Step 2.1: Parametrization of  $f_{\mathcal{W}}^*$  in terms of  $\theta_n$ .* Note that the parametrization of  $f_{\mathcal{W}}^*$  in terms of  $\theta_n$  is non-unique. We design below a parametrization such that for any  $x \in \mathcal{X}$

$$f_{\mathcal{W}}^*(x) = \sum_{n \in \mathcal{N}(\mathcal{T})} \theta_n \mathbb{1}_{x \in \mathcal{X}_n}, \quad (15)$$

and which will allow us to leverage the chaining structure of our Chaining-Tree. We define,

$$\theta_{\text{root}(\mathcal{T})} = f^*(x_{\text{root}(\mathcal{T})}) \quad \text{and} \quad \theta_n = f^*(x_n) - f^*(x_{p(n)}), \quad \text{for } n \neq \text{root}(\mathcal{T}), \quad (16)$$

where  $T_n = \{1 \leq t \leq T : x_t \in \mathcal{X}_n\}$  and  $x_n$  stands for the center of subregion  $\mathcal{X}_n$  for any  $n \in \mathcal{N}(\mathcal{T})$ .

Let us show that the above construction (16) indeed satisfies (15). To do so, we fix  $x \in \mathcal{X}$  and proceed by induction on  $m = 1, \dots, d(\mathcal{T})$ , by proving that

$$\sum_{n \in \mathcal{N}(\mathcal{T})} \theta_n \mathbb{1}_{x \in \mathcal{X}_n} \mathbb{1}_{d(n) \leq m} = \sum_{n \in \mathcal{N}(\mathcal{T})} f^*(x_n) \mathbb{1}_{x \in \mathcal{X}_n} \mathbb{1}_{d(n) = m}. \quad (\mathcal{H}_m)$$

First, note that  $(\mathcal{H}_1)$  is true by definition of  $\theta_{\text{root}(\mathcal{T})}$ . Then, let  $m \geq 1$ , and assume that  $(\mathcal{H}_m)$  is satisfied, we have

$$\begin{aligned} & \sum_{n \in \mathcal{N}(\mathcal{T})} \theta_n \mathbb{1}_{x \in \mathcal{X}_n} \mathbb{1}_{d(n) \leq m+1} \\ &= \sum_{n \in \mathcal{N}(\mathcal{T})} \theta_n \mathbb{1}_{x \in \mathcal{X}_n} \mathbb{1}_{d(n) \leq m} + \sum_{n \in \mathcal{N}(\mathcal{T})} \theta_n \mathbb{1}_{x \in \mathcal{X}_n} \mathbb{1}_{d(n) = m+1} \\ &= \sum_{n \in \mathcal{N}(\mathcal{T})} f^*(x_n) \mathbb{1}_{x \in \mathcal{X}_n} \mathbb{1}_{d(n) = m} + \sum_{n \in \mathcal{N}(\mathcal{T})} \theta_n \mathbb{1}_{x \in \mathcal{X}_n} \mathbb{1}_{d(n) = m+1} \quad \leftarrow \text{by } (\mathcal{H}_m) \\ &= \sum_{n \in \mathcal{N}(\mathcal{T})} f^*(x_n) \mathbb{1}_{x \in \mathcal{X}_n} \mathbb{1}_{d(n) = m} \\ & \quad + \sum_{n \in \mathcal{N}(\mathcal{T})} (f^*(x_n) - f^*(x_{p(n)})) \mathbb{1}_{x \in \mathcal{X}_n} \mathbb{1}_{d(n) = m+1} \quad \leftarrow \text{by (16)} \\ &= \sum_{n \in \mathcal{N}(\mathcal{T})} f^*(x_n) \mathbb{1}_{x \in \mathcal{X}_n} \mathbb{1}_{d(n) = m+1}, \end{aligned}$$

which concludes the induction. In particular, for  $m = d(\mathcal{T})$ ,  $(\mathcal{H}_m)$  yields

$$\sum_{n \in \mathcal{N}(\mathcal{T})} \theta_n \mathbb{1}_{x \in \mathcal{X}_n} = \sum_{n \in \mathcal{L}(\mathcal{T})} f^*(x_n) \mathbb{1}_{x \in \mathcal{X}_n} = f_{\mathcal{W}}^*(x),$$

where the last equality is by definition of  $f_{\mathcal{W}}^*$  in (11).

*Step 2.2: Upper-bounding  $|\theta_n|$ .* The key advantage of the parametrization  $\theta_n$  in (16) is that it leverages the chaining structure of our tree. Each node aims to correct the error made by its parent, and as we show below, this error decreases significantly with the depth  $d(n)$  of the node  $n$ . Let  $n \in \mathcal{N}(\mathcal{T}) \setminus \{\text{root}(\mathcal{T})\}$ ,

$$|\theta_n| = |f^*(x_n) - f^*(x_{p(n)})| \leq L \|x_n - x_{p(n)}\|_{\infty}^{\alpha} = L 2^{-\alpha} |\mathcal{X}_n|^{\alpha} = L |\mathcal{X}|^{\alpha} 2^{-\alpha d(n)} \quad (17)$$

where the last equalities are because  $\mathcal{X}_n \subset \mathcal{X}_{p(n)}$  and  $|\mathcal{X}_n| = |\mathcal{X}| 2^{-(d(n)-1)}$ , from Definition 1. Furthermore, by definition of  $\text{Lip}_L^{\alpha}(\mathcal{X})$ ,  $|f^*(x)| \leq B$  for any  $x \in \mathcal{X}$ , hence  $|\theta_{\text{root}(\mathcal{T})}| = |f^*(x_{\text{root}(\mathcal{T})})| \leq B$ .

*Step 2.3: Proof of the regret upper bound.* We are now ready to upper bound the estimation error in (12). We have

$$\begin{aligned} R_1 &= \sum_{t=1}^T \ell_t(\hat{f}_t(x_t)) - \ell_t(f_{\mathcal{W}}^*(x_t)) \\ &= \sum_{t=1}^T \ell_t\left(\sum_{n \in \mathcal{N}(\mathcal{T})} \theta_{n,t} \mathbb{1}_{x_t \in \mathcal{X}_n}\right) - \ell_t\left(\sum_{n \in \mathcal{N}(\mathcal{T})} \theta_n \mathbb{1}_{x_t \in \mathcal{X}_n}\right) \\ &\leq \sum_{t=1}^T \sum_{n \in \mathcal{N}(\mathcal{T})} g_{n,t}(\theta_{n,t} - \theta_n) \end{aligned} \quad (18)$$

by convexity of  $\ell_t$ , where  $g_{n,t}$  is the partial subgradient in  $\theta_{n,t}$  as defined in Equation (6). Now, from Assumption 1 on the grad-step procedure to optimize  $\theta_{n,t}$  and with  $\theta_{n,1} = 0$ , we further have

$$\begin{aligned}
R_1 &\leq G \sum_{n \in \mathcal{N}(\mathcal{T})} |\theta_n| (C_1 \sqrt{|T_n|} + C_2) \\
&= G \sum_{m=1}^{d(\mathcal{T})} \sum_{n: d(n)=m} |\theta_n| (C_1 \sqrt{|T_n|} + C_2) \\
&\leq BG(C_1 \sqrt{T} + C_2) + LG|\mathcal{X}|^\alpha \sum_{m=2}^{d(\mathcal{T})} \sum_{n: d(n)=m} (C_1 \sqrt{|T_n|} + C_2) 2^{-\alpha m} \quad \leftarrow \text{by (17)} \\
\end{aligned} \tag{19}$$

Now, because in a  $d$ -regular decision tree, the number of nodes with depth  $m$  equals  $|\{n : d(n) = m\}| = 2^{d(m-1)}$  (recall that the depth of the root is 1), and because  $\{\mathcal{X}_n : d(n) = m\}$  forms a partition of  $\mathcal{X}$ , we have  $\sum_{n: d(n)=m} T_n = T$  and by Cauchy-Schwarz inequality

$$\sum_{n: d(n)=m} \sqrt{T_n} \leq \sqrt{2^{d(m-1)} \sum_{n: d(n)=m} T_n} = \sqrt{2^{d(m-1)} T},$$

which substituted into the previous upper bound entails

$$\begin{aligned}
R_1 &\leq BG(C_1 \sqrt{T} + C_2) + LG|\mathcal{X}|^\alpha \sum_{m=2}^{d(\mathcal{T})} \left( C_1 2^{\frac{d(m-1)}{2} - \alpha m} \sqrt{T} + C_2 2^{d(m-1) - \alpha m} \right) \\
&= BG(C_1 \sqrt{T} + C_2) + LG|\mathcal{X}|^\alpha \left( 2^{-\frac{d}{2}} C_1 \sqrt{T} \sum_{m=2}^{d(\mathcal{T})} 2^{m(\frac{d}{2} - \alpha)} + 2^{-d} C_2 \sum_{m=2}^{d(\mathcal{T})} 2^{m(d - \alpha)} \right). \tag{20}
\end{aligned}$$

**Step 3: Conclusion and optimization of  $d(\mathcal{T})$ .** To conclude the proof, we consider three cases according to the sign of  $d - 2\alpha$ :

• *Case 1: if  $d < 2\alpha$ .* Then

$$2^{-\frac{d}{2}} \sum_{m=2}^{d(\mathcal{T})} 2^{m(\frac{d}{2} - \alpha)} \leq \frac{1}{1 - 2^{\frac{d}{2} - \alpha}} \quad \text{and} \quad 2^{-d} \sum_{m=2}^{d(\mathcal{T})} 2^{m(d - \alpha)} \leq 2^{-d} \sum_{m=0}^{d(\mathcal{T})} 2^{m\alpha} \leq 2^{-d} \frac{2^{\alpha(d(\mathcal{T})+1)}}{2^\alpha - 1} \stackrel{(2\alpha \geq 1)}{\leq} 2^{\alpha d(\mathcal{T})+2},$$

and (20) yields

$$R_1 \leq BG(C_1 \sqrt{T} + C_2) + LG|\mathcal{X}|^\alpha \left( \frac{C_1 \sqrt{T}}{1 - 2^{\frac{d}{2} - \alpha}} + C_2 2^{\alpha d(\mathcal{T})+2} \right);$$

Therefore, combining with (12) and (14), the regret is upper-bounded as

$$\text{Reg}_T(\text{Lip}_L^\alpha) \leq BG(C_1 \sqrt{T} + C_2) + LG|\mathcal{X}|^\alpha \left( \frac{C_1 \sqrt{T}}{1 - 2^{\frac{d}{2} - \alpha}} + C_2 2^{\alpha d(\mathcal{T})+2} + T 2^{-\alpha d(\mathcal{T})} \right).$$

The choice  $d(\mathcal{T}) = \frac{1}{d} \log_2 T$  entails

$$\text{Reg}_T(\text{Lip}_L^\alpha) \leq BG(C_1 \sqrt{T} + C_2) + LG|\mathcal{X}|^\alpha \left( \frac{C_1}{1 - 2^{\frac{d}{2} - \alpha}} + 4C_2 + 1 \right) \sqrt{T}. \tag{21}$$

• *Case 2: if  $d = 2\alpha$ .* Then

$$2^{-\frac{d}{2}} \sum_{m=2}^{d(\mathcal{T})} 2^{m(\frac{d}{2} - \alpha)} \leq d(\mathcal{T}) \quad \text{and} \quad 2^{-d} \sum_{m=2}^{d(\mathcal{T})} 2^{m(d - \alpha)} = 2^{-d} \sum_{m=2}^{d(\mathcal{T})} 2^{m\alpha} \leq 2^{\alpha d(\mathcal{T})+2},$$

and (20) yields

$$R_1 \leq BG(C_1\sqrt{T} + C_2) + LG|\mathcal{X}|^\alpha \left( C_1\sqrt{T}d(\mathcal{T}) + C_22^{\alpha d(\mathcal{T})+2} \right);$$

Therefore, combining with (12) and (14), the regret is upper-bounded as

$$\text{Reg}_T(\text{Lip}_L^\alpha) \leq BG(C_1\sqrt{T} + C_2) + 2^\alpha LG|\mathcal{X}|^\alpha \left( C_1\sqrt{T}d(\mathcal{T}) + C_22^{\alpha d(\mathcal{T})+2} + T2^{-\alpha d(\mathcal{T})} \right).$$

The choice  $d(\mathcal{T}) = \frac{1}{d} \log_2 T$  entails

$$\text{Reg}_T(\text{Lip}_L^\alpha) \leq BG(C_1\sqrt{T} + C_2) + 2^\alpha LG|\mathcal{X}|^\alpha \left( \frac{C_1}{d} \log_2 T + 4C_2 + 1 \right) \sqrt{T}. \quad (22)$$

• *Case 3: if  $d > 2\alpha$ . Then*

$$2^{-\frac{d}{2}} \sum_{m=2}^{d(\mathcal{T})} 2^{m(\frac{d}{2}-\alpha)} \leq \frac{2^{(\frac{d}{2}-\alpha)d(\mathcal{T})}}{2^{\frac{d}{2}-\alpha} - 1} \quad \text{and} \quad 2^{-d} \sum_{m=2}^{d(\mathcal{T})} 2^{m(d-\alpha)} \leq \frac{2^{(d-\alpha)d(\mathcal{T})}}{2^{d-\alpha} - 1} \leq 2^{(d-\alpha)d(\mathcal{T})+2},$$

where the last inequality is because  $(2^{d-\alpha} - 1)^{-1} \leq (2^{d/2} - 1)^{-1} \leq (\sqrt{2} - 1)^{-1} \leq 4$ . And (20) yields

$$R_1 \leq BG(C_1\sqrt{T} + C_2) + LG|\mathcal{X}|^\alpha \left( C_1\sqrt{T} \frac{2^{(\frac{d}{2}-\alpha)d(\mathcal{T})}}{2^{\frac{d}{2}-\alpha} - 1} + C_22^{(d-\alpha)d(\mathcal{T})+2} \right).$$

Therefore, combining with (12) and (14), the regret is upper-bounded as

$$\text{Reg}_T(\text{Lip}_L^\alpha) \leq BG(C_1\sqrt{T} + C_2) + LG|\mathcal{X}|^\alpha \left( C_1\sqrt{T} \frac{2^{(\frac{d}{2}-\alpha)d(\mathcal{T})}}{2^{\frac{d}{2}-\alpha} - 1} + C_22^{(d-\alpha)d(\mathcal{T})+2} + T2^{-\alpha d(\mathcal{T})} \right).$$

The choice  $d(\mathcal{T}) = \frac{1}{d} \log_2 T$  entails

$$\text{Reg}_T(\text{Lip}_L^\alpha) \leq BG(C_1\sqrt{T} + C_2) + LG|\mathcal{X}|^\alpha \left( \frac{C_1}{2^{\frac{d}{2}-\alpha} - 1} + 4C_2 + 1 \right) T^{1-\frac{\alpha}{d}}. \quad (23)$$

*Conclusion.* Combining the three cases (21), (22), and (23) concludes the proof of the regret bound, which we summarize below

$$\text{Reg}_T(\text{Lip}_L^\alpha) \leq BG(C_1\sqrt{T} + C_2) + GL|\mathcal{X}|^\alpha \begin{cases} (\Phi(\frac{d}{2} - \alpha)C_1 + 4C_2 + 1)\sqrt{T} & \text{if } d < 2\alpha \\ (\frac{C_1}{d} \log_2 T + 4C_2 + 1)\sqrt{T} & \text{if } d = 2\alpha \\ (\Phi(\frac{d}{2} - \alpha)C_1 + 4C_2 + 1)T^{1-\frac{\alpha}{d}} & \text{if } d > 2\alpha, \end{cases}$$

where  $\Phi(u) = |2^u - 1|^{-1}$ .

## B Proof of Theorem 2

We state here the full version of Theorem 2 that we prove right after.

**Theorem 3.** *Let  $T, d \geq 1$  and  $(\mathcal{T}_0, \bar{\mathcal{X}}, \bar{\mathcal{W}})$  be a core regular tree with  $CT \{ \mathcal{T}_{n,k}, (n,k) \in \mathcal{N}(\mathcal{T}_0) \times [K] \}$  satisfying the same assumptions as in Theorem 1 and root nodes initialized as  $\theta_{\text{root}(\mathcal{T}_{n,k}),1} = \gamma_k \in \Gamma$ , for all  $(n,k) \in \mathcal{N}(\mathcal{T}_0) \times [K]$ . Then, Algorithm 2 with a weight subroutine as in Assumption 2, achieves the regret upper-bound with respect to any  $f \in \text{Lip}_L^\alpha(\mathcal{X})$ ,  $L > 0$ ,*

$$\text{Reg}_T(f) \leq \inf_{\mathcal{T} \in \mathcal{P}(\mathcal{T}_0)} \left\{ \beta_1 \sqrt{T|\mathcal{L}(\mathcal{T})|} + \beta_2 |\mathcal{L}(\mathcal{T})| \right. \\ \left. + G|\mathcal{X}|^\alpha \sum_{n \in \mathcal{L}(\mathcal{T})} L_n(f) 2^{-\alpha(d(n)-1)} \begin{cases} \psi_1 \sqrt{|T_n|} & \text{if } d < 2\alpha \\ \psi_2 \log_2 |T_n| \sqrt{|T_n|} & \text{if } d = 2\alpha \\ \psi_1 |T_n|^{1-\frac{\alpha}{d}} & \text{if } d > 2\alpha, \end{cases} \right\},$$

with  $\beta_1 = 2C_3 G \sqrt{\log(2BT|\mathcal{N}(\mathcal{T}_0)|)}$  and  $\beta_2 = G(2^{-1}C_1 + C_2 2^{-1}T^{-\frac{1}{2}} + C_4)$ , local Lipschitz constants  $L_n(f) \leq L$  as in (8),  $\psi_1 = \Phi(d/2 - \alpha)C_1 + 4C_2 + 1$ ,  $\psi_2 = C_1/d + 4C_2 + 1$ , and  $\Phi, C_1, C_2$  as in Theorem 1.

Moreover, if  $\ell_1, \dots, \ell_T$  are  $\eta$ -exp-concave with some  $\eta > 0$ , one has:

$$\text{Reg}_T(f) \leq \inf_{\mathcal{T} \in \mathcal{P}(\mathcal{T}_0)} \left\{ \beta_3 |\mathcal{L}(\mathcal{T})| + G|\mathcal{X}|^\alpha \sum_{n \in \mathcal{L}(\mathcal{T})} L_n(f) 2^{-\alpha(d(n)-1)} \begin{cases} \psi_1 \sqrt{|T_n|} & \text{if } d < 2\alpha \\ \psi_2 \log_2 |T_n| \sqrt{|T_n|} & \text{if } d = 2\alpha \\ \psi_1 |T_n|^{1-\frac{\alpha}{d}} & \text{if } d > 2\alpha, \end{cases} \right\}$$

with  $\beta_3 = \frac{C_3^2 \log(2BT|\mathcal{N}(\mathcal{T}_0)|)}{2\mu} + C_4 G + 2^{-1}G(C_1 + C_2 T^{-\frac{1}{2}})$  and  $0 < \mu \leq \min\{1/G, \eta\}$ .

**Proof.** Let  $L > 0$ ,  $\alpha \in (0, 1]$ ,  $f^* \in \text{Lip}_L^\alpha(\mathcal{X})$  and  $\varepsilon > 0$  be the precision of the grid  $\Gamma$ ,  $K = \lfloor 2B/\varepsilon \rfloor$  the number of experts in each node in  $\mathcal{N}(\mathcal{T}_0)$ . Let  $\mathcal{T} \in \mathcal{P}(\mathcal{T}_0)$  be some pruned tree from  $(\mathcal{T}_0, \bar{\mathcal{X}}, \bar{\mathcal{W}})$  with prediction functions  $\bar{\mathcal{W}} = \{(\hat{f}_{n,k})_{k \in [K]}, n \in \mathcal{N}(\mathcal{T}_0)\}$  on subsets  $\bar{\mathcal{X}} = \{\mathcal{X}_n, n \in \mathcal{N}(\mathcal{T}_0)\}$ . We call  $\hat{f}_{\mathcal{T}}$  the associated prediction function of pruning  $\mathcal{T}$  (see Definition 2) such that at any time  $t \geq 1$ ,

$$\hat{f}_{\mathcal{T},t}(x) = \sum_{n \in \mathcal{L}(\mathcal{T})} \hat{f}_{n,k_n,t}(x), \quad x \in \mathcal{X},$$

with  $k_n = \arg \min_{k \in [K]} |(-B + (k-1)\varepsilon) - f^*(x_n)|$  the best approximating constant of  $f^*(x_n)$  where  $x_n \in \mathcal{X}_n$  is the center of the sub-region  $\mathcal{X}_n$ , i.e. for any  $x \in \mathcal{X}_n$ ,  $\|x - x_n\|_\infty \leq 2^{-1}|\mathcal{X}_n|$ . We have a decomposition of regret as:

$$\text{Reg}_T(f) = \underbrace{\sum_{t=1}^T \ell_t(\hat{f}_t(x_t)) - \ell_t(\hat{f}_{\mathcal{T},t}(x_t))}_{=: R_1} + \underbrace{\sum_{t=1}^T \ell_t(\hat{f}_{\mathcal{T},t}(x_t)) - \ell_t(f^*(x_t))}_{=: R_2}, \quad (24)$$

$R_1$  is the regret related to the estimation error of the core expert tree  $\mathcal{T}_0$  compared to some pruning  $\mathcal{T}$  from it. On the other hand,  $R_2$  is related to the error of the pruning tree  $\mathcal{T}$  against some function  $f^*$ .

**Step 1: Upper-bounding  $R_2$  as local chaining tree regrets.** Recall that according to Definition 2, pruning subsets  $\{\mathcal{X}_n, n \in \mathcal{L}(\mathcal{T})\}$  form a partition of  $\mathcal{X} = \mathcal{X}_{\text{root}(\mathcal{T}_0)}$ . Hence, for any  $x_t \in \mathcal{X}$ , prediction from pruning  $\mathcal{T}$  at time  $t$  is  $\hat{f}_{\mathcal{T},t}(x_t) = \hat{f}_{n,k_n,t}(x_t)$  with  $n \in \mathcal{L}(\mathcal{T})$  the unique leaf such

that  $x_t \in \mathcal{X}_n$  at time  $t$ . Then,  $R_2$  can be written as follows:

$$\begin{aligned}
R_2 &= \sum_{t=1}^T \sum_{n \in \mathcal{L}(\mathcal{T})} (\ell_t(\hat{f}_{\mathcal{T},t}(x_t)) - \ell_t(f^*(x_t))) \mathbb{1}_{x_t \in \mathcal{X}_n} \\
&= \sum_{n \in \mathcal{L}(\mathcal{T})} \sum_{t \in T_n} \ell_t(\hat{f}_{n,k_n,t}(x_t)) - \ell_t(f^*(x_t)) \\
&\leq \sum_{n \in \mathcal{L}(\mathcal{T})} \sum_{t \in T_n} \ell_t(\tilde{f}_{n,k_n,t}(x_t)) - \ell_t(f^*(x_t)), \tag{25}
\end{aligned}$$

where we set  $T_n = \{1 \leq t \leq T : x_t \in \mathcal{X}_n\}$ ,  $n \in \mathcal{L}(\mathcal{T})$  and (25) is because  $\hat{f}_{n,k_n,t} = [\tilde{f}_{n,k_n,t}]_B \leq \tilde{f}_{n,k_n,t}$  and  $\ell_t$  is convex and has minimum in  $[-B, B]$ .

The decomposition in (25) represents a sum of *local* error approximations of the function  $f^*$  over the partition  $\{\mathcal{X}_n, n \in \mathcal{L}(\mathcal{T})\}$ , using predictors  $\tilde{f}_{n,k_n}$  located at the leaves of the pruned tree  $\mathcal{T}$ . Recall that for every  $n \in \mathcal{N}(\mathcal{T}_0)$ ,  $\tilde{f}_{n,k_n}$  is a prediction function associated with a CT  $\mathcal{T}_{n,k_n}$ , where the root node starts from  $\theta_{\text{root}(\mathcal{T}_{n,k_n}),1} = -B + (k_n - 1)\varepsilon \in \Gamma$  on  $\mathcal{X}_n$ . In proof of Theorem 1 (Appendix A) we study a regret bound (12) decomposed into two terms: estimation and approximation. In particular, we showed that any CT adapts to any regularity  $(L, \alpha) \in \mathbb{R}_+ \times (0, 1]$  of  $f^*$ . Thus, the approximation error of CT  $\tilde{f}_{n,k_n}$  with respect to  $f^*$  remains similar to that in (14), but now with regard to an Hölder function with a constant  $L_n(f^*) \geq 0$  over  $\mathcal{X}_n$ . Specifically, from (25), we get:

$$R_2 \leq \sum_{n \in \mathcal{L}(\mathcal{T})} \left[ \underbrace{G \sum_{m=1}^{d(\mathcal{T}_{n,k_n})} \sum_{n': d(n')=m} |\theta_{n'} - \theta_{n',1}| (C_1 \sqrt{|T_{n'}|} + C_2)}_{\text{estimation error as in (19)}} + \underbrace{GL_n(f^*) |\mathcal{X}_n|^\alpha |T_n| 2^{-\alpha d(\mathcal{T}_{n,k_n})}}_{\text{approximation error (14) over } \mathcal{X}_n} \right], \tag{26}$$

with  $C_1, C_2$  as in Assumption 1 and where we set in (16),

$$\theta_{\text{root}(\mathcal{T}_{n,k_n})} = f^*(x_{\text{root}(\mathcal{T}_{n,k_n})}) \quad \text{and} \quad \theta_{n'} = f^*(x_{n'}) - f^*(x_{\text{p}(n')}), \quad n' \in \mathcal{N}(\mathcal{T}_{n,k_n}) \setminus \{\text{root}(\mathcal{T}_{n,k_n})\}.$$

In particular, we have for  $n' = \text{root}(\mathcal{T}_{n,k_n})$ ,

$$|\theta_{n'} - \theta_{n',1}| = \left| f^*(x_{\text{root}(\mathcal{T}_{n,k_n})}) - (-B + (k_n - 1)\varepsilon) \right| \leq \frac{\varepsilon}{2}, \tag{27}$$

by definition of  $k_n$  and since  $\Gamma = \{-B + (k-1)\varepsilon\}_{k \in [K]}$  is an  $\varepsilon$ -discretization of the  $y$ -axis. Moreover, if  $n' \in \mathcal{N}(\mathcal{T}_{n,k_n})$ ,  $d(n') \geq 2$ , one has  $\theta_{n',1} = 0$  and

$$|\theta_{n'} - \theta_{n',1}| = |\theta_{n'}| \leq L_n(f^*) |\mathcal{X}_n|^\alpha 2^{-\alpha d(n')}, \tag{28}$$

according to (17) with  $f^* \in \text{Lip}_{L_n}^\alpha(\mathcal{X}_n)$ .

Then, following the same optimization steps as for Theorem 1, in each  $d(\mathcal{T}_{n,k_n})$ ,  $n \in \mathcal{L}(\mathcal{T})$  of (26), we get:

$$\begin{aligned}
R_2 &\leq G \sum_{n \in \mathcal{L}(\mathcal{T})} \frac{\varepsilon}{2} (C_1 \sqrt{|T_n|} + C_2) \\
&\quad + G |\mathcal{X}|^\alpha \sum_{n \in \mathcal{L}(\mathcal{T})} L_n(f^*) 2^{-\alpha(d(n)-1)} \begin{cases} \psi_1 \sqrt{|T_n|} & \text{if } d < 2\alpha \\ \psi_2 \log_2 |T_n| \sqrt{|T_n|} & \text{if } d = 2\alpha \\ \psi_1 |T_n|^{1-\frac{\alpha}{d}} & \text{if } d > 2\alpha \end{cases}
\end{aligned}$$



with  $\psi_1 = \Phi(d/2 - \alpha)C_1 + 4C_2 + 1$ ,  $\psi_2 = C_1/d + 4C_2 + 1$ , and  $\Phi$  defined in Theorem 1.

Cauchy-Schwarz inequality gives

$$\sum_{n \in \mathcal{L}(\mathcal{T})} (C_1 \sqrt{|T_n|} + C_2) \leq C_1 \sqrt{|\mathcal{L}(\mathcal{T})|T} + C_2 |\mathcal{L}(\mathcal{T})|$$

Finally,

$$R_2 \leq \frac{\varepsilon}{2} G \left( C_1 \sqrt{|\mathcal{L}(\mathcal{T})|T} + C_2 |\mathcal{L}(\mathcal{T})| \right) + G |\mathcal{X}|^\alpha \sum_{n \in \mathcal{L}(\mathcal{T})} L_n(f^*) 2^{-\alpha(d(n)-1)} \begin{cases} \psi_1 \sqrt{|T_n|} & \text{if } d < 2\alpha \\ \psi_2 \log_2 |T_n| \sqrt{|T_n|} & \text{if } d = 2\alpha \\ \psi_1 |T_n|^{1-\frac{\alpha}{d}} & \text{if } d > 2\alpha \end{cases} \quad (29)$$

**Step 2: Upper-bounding the pruning estimation error  $R_1$ .** We aim at bounding the estimation error  $R_1$  due to the error incurred by sequentially learning the best pruned tree prediction and the best root node in  $\Gamma$  inside each pruned leaves. Note that at each time  $t$ , only a subset of nodes of  $\mathcal{T}_0$  are active and output predictions: for any time  $t \geq 1$ , let us denote  $\mathcal{N}_t \subset \mathcal{N}(\mathcal{T}_0)$  the set of active nodes (i.e. making a prediction) at time  $t$ . Remark that

$$\hat{f}_t(x_t) = \sum_{n \in \mathcal{N}(\mathcal{T}_0)} \sum_{k=1}^K w_{n,k,t} \hat{f}_{n,k,t}(x_t) \quad (30)$$

$$= \sum_{n \in \mathcal{N}_t} \sum_{k=1}^K \tilde{w}_{n,k,t} \hat{f}'_{n',k',t}(x_t) + \sum_{n \notin \mathcal{N}_t} \sum_{k=1}^K \tilde{w}_{n,k,t} \hat{f}_t(x_t), \quad (31)$$

by definition of  $\hat{f}_t$  and the so called trick of prediction with sleeping experts, e.g. in Gaillard et al. [2014]. Recall that  $\tilde{\mathbf{g}}_t = \nabla_{\tilde{\mathbf{w}}_t} \ell_t \left( \sum_{n \in \mathcal{N}_t} \sum_{k=1}^K \tilde{w}_{n,k,t} \hat{f}_{n,k,t}(x_t) + \sum_{n \notin \mathcal{N}_t} \sum_{k=1}^K \tilde{w}_{n,k,t} \hat{f}_t(x_t) \right) \in \mathbb{R}^{|\mathcal{N}(\mathcal{T}_0)| \times K}$ , for all  $t \geq 1$ . Then, for all  $n \in \mathcal{N}(\mathcal{T}_0)$ ,  $k \in [K]$ ,

$$\tilde{g}_{n,k,t} = \begin{cases} \ell'_t(\hat{f}_t(x_t)) \hat{f}_{n,k,t}(x_t) & \text{if } n \in \mathcal{N}_t, \\ \ell'_t(\hat{f}_t(x_t)) \hat{f}_t(x_t) & \text{if } n \notin \mathcal{N}_t. \end{cases} \quad (32)$$

For any  $t \geq 1$ ,  $n \in \mathcal{L}(\mathcal{T})$  and  $k \in [K]$ , one has:

$$\begin{aligned} \tilde{\mathbf{g}}_t^\top \mathbf{w}_t - \tilde{g}_{n,k,t} &= \sum_{n' \in \mathcal{N}(\mathcal{T}_0)} \sum_{k'=1}^K w_{n',k',t} \tilde{g}_{n',k',t} - \tilde{g}_{n,k,t} \\ &= \ell'_t(\hat{f}_t(x_t)) \underbrace{\sum_{n' \in \mathcal{N}_t} \sum_{k'=1}^K w_{n',k',t} \hat{f}_{n',k',t}(x_t)}_{=\hat{f}_t(x_t)} - \tilde{g}_{n,k,t} \\ &= \ell'_t(\hat{f}_t(x_t)) \left( \sum_{n' \in \mathcal{N}_t} \sum_{k'=1}^K \tilde{w}_{n',k',t} \hat{f}'_{n',k',t}(x_t) + \sum_{n' \notin \mathcal{N}_t} \sum_{k'=1}^K \tilde{w}_{n',k',t} \hat{f}_t(x_t) \right) - \tilde{g}_{n,k,t} \\ &= \ell'_t(\hat{f}_t(x_t)) \\ &\quad \times \begin{cases} (\hat{f}_t(x_t) - \hat{f}_t(x_t)) & \text{if } n \notin \mathcal{N}_t, \\ \left( \sum_{n' \in \mathcal{N}_t} \sum_{k'=1}^K \tilde{w}_{n',k',t} \hat{f}'_{n',k',t}(x_t) + \sum_{n' \notin \mathcal{N}_t} \sum_{k'=1}^K \tilde{w}_{n',k',t} \hat{f}_t(x_t) - \hat{f}_{n,k,t}(x_t) \right) & \text{else,} \end{cases} \\ &= \begin{cases} 0 & \text{if } n \notin \mathcal{N}_t, \\ \tilde{\mathbf{g}}_t^\top \tilde{\mathbf{w}}_t - \tilde{g}_{n,k,t} & \text{else,} \end{cases} \\ &= (\tilde{\mathbf{g}}_t^\top \tilde{\mathbf{w}}_t - \tilde{g}_{n,k,t}) \mathbf{1}_{x_t \in \mathcal{X}_n}, \end{aligned} \quad (33)$$

where the second equality follows from (30), the third from (31), and the fourth from (32). Finally, we obtain

$$\begin{aligned}
(\ell_t(\hat{f}_t(x_t)) - \ell_t(\hat{f}_{n,k,t}(x_t)))\mathbb{1}_{x_t \in \mathcal{X}_n} &\leq \ell'_t(\hat{f}_t(x_t))(\hat{f}_t(x_t) - \hat{f}_{n,k,t}(x_t))\mathbb{1}_{x_t \in \mathcal{X}_n} \quad \leftarrow \text{by convexity of } \ell_t \\
&= (\tilde{\mathbf{g}}_t^\top \tilde{\mathbf{w}}_t - \tilde{g}_{n,k,t})\mathbb{1}_{x_t \in \mathcal{X}_n} \\
&= \tilde{\mathbf{g}}_t^\top \mathbf{w}_t - \tilde{g}_{n,k,t} \quad \leftarrow \text{by (33),} \\
&\quad (34)
\end{aligned}$$

and setting  $T_n = \{1 \leq t \leq T : x_t \in \mathcal{X}_n\}$ ,  $n \in \mathcal{L}(\mathcal{T})$ :

$$\begin{aligned}
R_1 &= \sum_{t=1}^T \sum_{n \in \mathcal{L}(\mathcal{T})} (\ell_t(\hat{f}_t(x_t)) - \ell_t(\hat{f}_{n,k,t}(x_t)))\mathbb{1}_{x_t \in \mathcal{X}_n} \quad \leftarrow \{\mathcal{X}_n, n \in \mathcal{L}(\mathcal{T})\} \text{ partition of } \mathcal{X} \\
&\leq \sum_{n \in \mathcal{L}(\mathcal{T})} \sum_{t=1}^T (\tilde{\mathbf{g}}_t^\top \mathbf{w}_t - \tilde{g}_{n,k,t}) \quad \leftarrow \text{by (34)} \\
&\leq \sum_{n \in \mathcal{L}(\mathcal{T})} \left( C_3 \sqrt{\log(K|\mathcal{N}(\mathcal{T}_0))} \sqrt{\sum_{t=1}^T (\tilde{\mathbf{g}}_t^\top \mathbf{w}_t - \tilde{g}_{n,k,t})^2} + C_4 G \right) \quad \leftarrow \text{by Assumption 2} \\
&= C_4 G |\mathcal{L}(\mathcal{T})| + C_3 \sqrt{\log(K|\mathcal{N}(\mathcal{T}_0))} \sum_{n \in \mathcal{L}(\mathcal{T})} \sqrt{\sum_{t \in T_n} (\tilde{\mathbf{g}}_t^\top \mathbf{w}_t - \tilde{g}_{n,k,t})^2}, \quad (35)
\end{aligned}$$

where last equality holds because for any  $n \in \mathcal{L}(\mathcal{T})$ ,  $\tilde{\mathbf{g}}_t^\top \mathbf{w}_t - \tilde{g}_{n,k,t} = 0$  if  $x_t \notin \mathcal{X}_n$ .

• *Case 1:  $(\ell_t)_{1 \leq t \leq T}$  convex.*

Since  $\|\tilde{\mathbf{g}}_t\|_\infty \leq G$ ,  $\|\mathbf{w}_t\|_\infty \leq 1$ ,  $t \in [T]$  by Assumption 2 and using Cauchy-Schwartz inequality we get from Equation (35):

$$\begin{aligned}
R_1 &\leq C_4 G |\mathcal{L}(\mathcal{T})| + 2C_3 \sqrt{\log(K|\mathcal{N}(\mathcal{T}_0))} G \sum_{n \in \mathcal{L}(\mathcal{T})} \sqrt{|T_n|} \\
&\leq C_4 G |\mathcal{L}(\mathcal{T})| + 2C_3 G \sqrt{\log(K|\mathcal{N}(\mathcal{T}_0)) |\mathcal{L}(\mathcal{T})| \sum_{n \in \mathcal{L}(\mathcal{T})} |T_n|} \\
&= C_4 G |\mathcal{L}(\mathcal{T})| + 2C_3 G \sqrt{\log(K|\mathcal{N}(\mathcal{T}_0)) |\mathcal{L}(\mathcal{T})| T}. \quad (36)
\end{aligned}$$

In case of convex losses, we finally have by (24), (29) and (36) :

$$\begin{aligned}
\text{Reg}_T(f) &\leq 2C_3 G \sqrt{\log(K|\mathcal{N}(\mathcal{T}_0)) |\mathcal{L}(\mathcal{T})| T} + \left( C_2 \frac{\varepsilon}{2} + C_4 \right) G |\mathcal{L}(\mathcal{T})| + \frac{\varepsilon}{2} G C_1 \sqrt{|\mathcal{L}(\mathcal{T})| T} \\
&\quad + G |\mathcal{X}|^\alpha \sum_{n \in \mathcal{L}(\mathcal{T})} L_n(f) 2^{-\alpha(d(n)-1)} \begin{cases} \psi_1 \sqrt{|T_n|} & \text{if } d < 2\alpha, \\ \psi_2 \log_2 |T_n| \sqrt{|T_n|} & \text{if } d = 2\alpha, \\ \psi_1 |T_n|^{1-\frac{\alpha}{d}} & \text{if } d > 2\alpha, \end{cases}
\end{aligned}$$

with  $\psi_1, \psi_2$  defined in (29). Taking  $\varepsilon = T^{-\frac{1}{2}}$ ,  $K = \lfloor 2BT^{\frac{1}{2}} \rfloor \leq 2BT$ , we get:

$$\begin{aligned}
\text{Reg}_T(f) &\leq 2C_3 G \sqrt{\log(2BT|\mathcal{N}(\mathcal{T}_0))} \sqrt{|\mathcal{L}(\mathcal{T})| T} + (2^{-1}C_1 + C_2 2^{-1} T^{-\frac{1}{2}} + C_4) G |\mathcal{L}(\mathcal{T})| \\
&\quad + G |\mathcal{X}|^\alpha \sum_{n \in \mathcal{L}(\mathcal{T})} L_n(f) 2^{-\alpha(d(n)-1)} \begin{cases} \psi_1 \sqrt{|T_n|} & \text{if } d < 2\alpha, \\ \psi_2 \log_2 |T_n| \sqrt{|T_n|} & \text{if } d = 2\alpha, \\ \psi_1 |T_n|^{1-\frac{\alpha}{d}} & \text{if } d > 2\alpha, \end{cases}
\end{aligned}$$

Since this inequality holds for all pruning  $\mathcal{T} \in \overline{\mathcal{P}(\mathcal{T}_0)}$ , one can take the infimum over all pruning in  $\mathcal{P}(\mathcal{T}_0)$  to get the desired upper-bound:

$$\text{Reg}_T(f) \leq \inf_{\mathcal{T} \in \mathcal{P}(\mathcal{T}_0)} \left\{ \beta_1 \sqrt{|\mathcal{L}(\mathcal{T})|T} + \beta_2 |\mathcal{L}(\mathcal{T})| \right. \\ \left. + G|\mathcal{X}|^\alpha \sum_{n \in \mathcal{L}(\mathcal{T})} L_n(f) 2^{-\alpha(d(n)-1)} \begin{cases} \psi_1 \sqrt{|T_n|} & \text{if } d < 2\alpha, \\ \psi_2 \log_2 |T_n| \sqrt{|T_n|} & \text{if } d = 2\alpha, \\ \psi_1 |T_n|^{1-\frac{\alpha}{d}} & \text{if } d > 2\alpha, \end{cases} \right\},$$

with  $\beta_1 = 2C_3 G \sqrt{\log(2BT|\mathcal{N}(\mathcal{T}_0)|)}$  and  $\beta_2 = G(2^{-1}C_1 + C_2 2^{-1}T^{-\frac{1}{2}} + C_4)$ .

• *Case 2:  $(\ell_t)_{1 \leq t \leq T}$   $\eta$ -exp-concave.*

If the sequence of loss functions  $(\ell_t)$  is  $\eta$ -exp-concave for some  $\eta > 0$ , then thanks to a Lemma in Hazan et al. [2016] we have for any  $0 < \mu \leq \frac{1}{2} \min\{\frac{1}{G}, \eta\}$  and all  $t \geq 1, n \in \mathcal{L}(\mathcal{T}), k \in [K]$ :

$$(\ell_t(\hat{f}_t(x_t)) - \ell_t(\hat{f}_{n,k,t}(x_t))) \mathbb{1}_{x_t \in \mathcal{X}_n} \leq (\tilde{\mathbf{g}}_t^\top \tilde{\mathbf{w}}_t - \tilde{g}_{n,k,t} - \frac{\mu}{2} (\tilde{\mathbf{g}}_t^\top \tilde{\mathbf{w}}_t - \tilde{g}_{n,k,t})^2) \mathbb{1}_{x_t \in \mathcal{X}_n} \\ = \tilde{\mathbf{g}}_t^\top \mathbf{w}_t - \tilde{g}_{n,k,t} - \frac{\mu}{2} (\tilde{\mathbf{g}}_t^\top \mathbf{w}_t - \tilde{g}_{n,k,t})^2 \quad \leftarrow \text{by (33)}. \quad (37)$$

Summing (37) over  $t \in [T]$  and  $n \in \mathcal{L}(\mathcal{T})$ , we get:

$$R_1 \leq \sum_{n \in \mathcal{L}(\mathcal{T})} \sum_{t \in T_n} \tilde{\mathbf{g}}_t^\top \tilde{\mathbf{w}}_t - \tilde{g}_{n,k,t} - \frac{\mu}{2} \sum_{n \in \mathcal{N}(\mathcal{P})} \sum_{t \in T_n} (\tilde{\mathbf{g}}_t^\top \mathbf{w}_t - \tilde{g}_{n,k,t})^2 \\ \leq C_4 G |\mathcal{L}(\mathcal{T})| + \tilde{C}_3 \sum_{n \in \mathcal{L}(\mathcal{T})} \sqrt{\sum_{t \in T_n} (\tilde{\mathbf{g}}_t^\top \mathbf{w}_t - \tilde{g}_{n,k,t})^2} - \frac{\mu}{2} \sum_{n \in \mathcal{L}(\mathcal{T})} \sum_{t \in T_n} (\tilde{\mathbf{g}}_t^\top \mathbf{w}_t - \tilde{g}_{n,k,t})^2 \quad \leftarrow \text{by (35)}, \quad (38)$$

where we set  $\tilde{C}_3 = C_3 \sqrt{\log(K|\mathcal{N}(\mathcal{T}_0)|)}$ . Young's inequality gives, for any  $\nu > 0$ , the following upper-bound:

$$\sqrt{\sum_{t \in T_n} (\tilde{\mathbf{g}}_t^\top \mathbf{w}_t - \tilde{g}_{n,k,t})^2} \leq \frac{1}{2\nu} + \frac{\nu}{2} \sum_{t \in T_n} (\tilde{\mathbf{g}}_t^\top \mathbf{w}_t - \tilde{g}_{n,k,t})^2. \quad (39)$$

Finally, plugging (39) with  $\nu = \mu/\tilde{C}_3 > 0$  in (38), we get

$$R_1 \leq C_4 G |\mathcal{L}(\mathcal{T})| + \tilde{C}_3 \sum_{n \in \mathcal{L}(\mathcal{T})} \left( \frac{\tilde{C}_3}{2\mu} + \frac{\mu}{2\tilde{C}_3} \sum_{t \in T_n} (\tilde{\mathbf{g}}_t^\top \mathbf{w}_t - \tilde{g}_{n,k,t})^2 \right) - \frac{\mu}{2} \sum_{n \in \mathcal{L}(\mathcal{T})} \sum_{t \in T_n} (\tilde{\mathbf{g}}_t^\top \mathbf{w}_t - \tilde{g}_{n,k,t})^2 \\ = \left( \frac{C_3^2 \log(K|\mathcal{N}(\mathcal{T}_0)|)}{2\mu} + C_4 G \right) |\mathcal{L}(\mathcal{T})|. \quad (40)$$

To conclude, if  $(\ell_t)$  are  $\eta$ -exp-concave, one has via (24), (29) and (40)

$$\text{Reg}_T(f) \leq \beta_3 |\mathcal{L}(\mathcal{T})| + G|\mathcal{X}|^\alpha \sum_{n \in \mathcal{L}(\mathcal{T})} L_n(f) 2^{-\alpha(d(n)-1)} \begin{cases} \psi_1 \sqrt{|T_n|} & \text{if } d < 2\alpha, \\ \psi_2 \log_2 |T_n| \sqrt{|T_n|} & \text{if } d = 2\alpha, \\ \psi_1 |T_n|^{1-\frac{\alpha}{d}} & \text{if } d > 2\alpha, \end{cases}$$

with  $\beta_3 = \frac{C_3^2 \log(2BT|\mathcal{N}(\mathcal{T}_0)|)}{2\mu} + C_4 G + 2^{-1}G(C_1 + C_2 T^{-\frac{1}{2}})$ ,  $0 < \mu < \frac{1}{2} \min\{\frac{1}{G}, \eta\}$  and  $\psi_1, \psi_2$  defined in (29). Again, taking infimum over  $\mathcal{T} \in \mathcal{P}(\mathcal{T}_0)$  gives the result.

**Worst case regret bound** Note that since we assume that  $\|f\|_\infty \leq B$ , and that all local predictors  $\hat{f}_{n,k}, n \in \mathcal{N}(\mathcal{T}_0), k \in [K]$  in Algorithm 2 are clipped in  $[-B, B]$ , we first have for any  $x \in \mathcal{X}$ ,

$$|\hat{f}_t(x)| = \sum_{n \in \mathcal{N}(\mathcal{T}_0)} \sum_{k=1}^K w_{n,k,t} |\hat{f}_{n,k,t}(x)| \leq B \sum_{n \in \mathcal{N}(\mathcal{T}_0)} \sum_{k=1}^K w_{n,k,t} = B.$$

Thus,

$$\begin{aligned} \text{Reg}_T(f) &= \sum_{t=1}^T \ell_t(\hat{f}_t(x_t)) - \ell_t(f^*(x_t)) \\ &\leq \sum_{t=1}^T G |\hat{f}_t(x_t) - f^*(x_t)| && \leftarrow \ell_t \text{ is } G\text{-Lipschitz} \\ &\leq G \sum_{t=1}^T (|\hat{f}_t(x_t)| + |f^*(x_t)|) \\ &= 2BGT \end{aligned} \tag{41}$$

□

## C Proof of Corollary 1

We state here a complete version of Corollary 1.

**Corollary 2.** *Let  $\alpha \in (0, 1]$ ,  $1 \leq d \leq 2\alpha$ . Under the same assumptions as in Theorem 2, Algorithm 2 achieves a regret with respect to any  $f \in \text{Lip}_L^\alpha(\mathcal{X})$ ,  $L > 0$ :*

$$\text{Reg}_T(f) \lesssim \inf_{\mathcal{T} \in \mathcal{P}(\mathcal{T}_0)} \left\{ \sum_{n \in \mathcal{L}(\mathcal{T})} \min \left( 1 + L_n(f)|\mathcal{X}_n|^\alpha, \left( L_n(f)|\mathcal{X}_n|^\alpha \right)^{\frac{1}{2\alpha}} \right) \sqrt{|T_n|} \right\},$$

where  $\lesssim$  is a rough inequality that depends on  $C_i$ ,  $i = 1, \dots, 4$  but is independent of  $L, X, T$ . Moreover, if  $(\ell_t)$  are exp-concave:

$$\text{Reg}_T(f) \lesssim \inf_{\mathcal{T} \in \mathcal{P}(\mathcal{T}_0)} \left\{ \sum_{n \in \mathcal{L}(\mathcal{T})} \min \left( L_n(f)|\mathcal{X}_n|^\alpha \sqrt{|T_n|}, \left( L_n(f)|\mathcal{X}_n|^\alpha \right)^{\frac{2}{2\alpha+1}} |T_n|^{\frac{1}{2\alpha+1}} \right) \right\},$$

where  $\lesssim$  also depends on the exp-concavity constant.

### Proof.

We consider 2 cases:

1. Case  $d < 2\alpha$  (i.e.  $d = 1, \alpha \in (\frac{1}{2}, 1]$ ).

Let  $f \in \text{Lip}_L^\alpha(\mathcal{X})$  and  $L > 0$  and fix any pruning  $\mathcal{T} \in \mathcal{P}(\mathcal{T}_0)$ . We will apply Theorem 2 to an extended pruning  $\mathcal{T}'$ , in which we extend each leaf  $n \in \mathcal{L}(\mathcal{T})$  by a regular tree of depth  $h_n \in \mathbb{N}$  to be optimized later in the proof. In particular, for each leaf  $n$  in the original pruning  $\mathcal{T}$ ,  $\mathcal{T}'$  has  $2^{h_n}$  leaves  $m$  at depth  $d(m) = d(n) + h_n \geq d(n)$  with  $L_m(f) \leq L_n(f)$ . In particular, when  $h_n = 0$ , the original pruning  $\mathcal{T}$  is recovered.

- (a) Case  $(\ell_t)$  convex:

Thanks to Theorem 2 (without applying Inequality (36) in the term depending on  $C_3$ ), one has for  $d = 1 < 2\alpha$ :

$$\begin{aligned} \text{Reg}_T(f) &\leq 2C_3 \sqrt{\log(K|\mathcal{N}(\mathcal{T}_0)|)} \sum_{m \in \mathcal{L}(\mathcal{T}')} \sqrt{|T_m|} + C_4 G |\mathcal{L}(\mathcal{T}_1)| \\ &\quad + G \psi_1 \sum_{m \in \mathcal{L}(\mathcal{T}')} L_m(f) |\mathcal{X}_m|^\alpha \sqrt{|T_m|}, \\ &\leq \min_{h_n \in \mathbb{N}} \left\{ C \sum_{n \in \mathcal{L}(\mathcal{T})} \left( \sqrt{2^{h_n} |T_n|} + 2^{h_n} + L_n(f) |\mathcal{X}_n|^\alpha 2^{-\alpha h_n} \sqrt{2^{h_n} |T_n|} \right) \right\} \end{aligned} \tag{42}$$

where  $C > 0$  is some constant that depends on  $C_3, C_4, G, X, \log(T), B$  and  $\psi_1$  (defined in Theorem 2) but independent of other quantities  $L_n(f), T, T_n$ , that is used to simplify the presentation and may change from a display to another along the proof. Then, optimizing over  $h_n$  so that

$$\sqrt{2^{h_n} |T_n|} = L_n(f) |\mathcal{X}_n|^\alpha 2^{-\alpha h_n} \sqrt{2^{h_n} |T_n|},$$

we set

$$h_n = \max \left\{ 0, \frac{1}{\alpha} \log_2 (L_n(f) |\mathcal{X}_n|^\alpha) \right\} \geq 0$$

which yields

$$\text{Reg}_T(f) \leq C \sum_{n \in \mathcal{L}(\mathcal{T})} \min \left\{ 1 + L_n(f) |\mathcal{X}_n|^\alpha, \left( L_n(f) |\mathcal{X}_n|^\alpha \right)^{\frac{1}{2\alpha}} \right\} \sqrt{|T_n|}.$$

(b) *Case  $(\ell_t)$  exp-concave:*

Since  $(\ell_t)$  are exp-concave, Theorem 2 (with Inequality (40)) gives, for  $d < 2\alpha$ , for any extension  $\mathcal{T}_1$  of pruning  $\mathcal{T} \in \mathcal{P}(\mathcal{T}_0)$ :

$$\text{Reg}_T(f) \leq C \left( |\mathcal{L}(\mathcal{T}_1)| + \sum_{m \in \mathcal{L}(\mathcal{T}_1)} L_m(f) |\mathcal{X}_m|^\alpha \sqrt{|T_m|} \right), \quad (43)$$

$$\leq C \sum_{n \in \mathcal{L}(\mathcal{T})} \left( 2^{h_n} + L_n(f) |\mathcal{X}_n|^\alpha 2^{-\alpha h_n} \sqrt{2^{h_n} |T_n|} \right), \quad (44)$$

where again  $C > 0$  is a constant independent of  $L$ ,  $L_n(f)$ ,  $|T_n|$  and  $h_n$  that may change from a display to another. Optimizing over  $h_n$  by equalizing the terms:

$$2^{h_n} = L_n(f) |\mathcal{X}_n|^\alpha 2^{-\alpha h_n} \sqrt{2^{h_n} |T_n|}$$

leads to

$$h_n = \max \left\{ 0, \frac{2}{2\alpha + 1} \log_2 (L_n(f) |\mathcal{X}_n|^\alpha |T_n|^{\frac{1}{2}}) \right\},$$

which yields and concludes the proof:

$$\text{Reg}_T(f) \leq C \sum_{n \in \mathcal{L}(\mathcal{T})} \min \left\{ L_n(f) |\mathcal{X}_n|^\alpha \sqrt{|T_n|}, (L_n(f) |\mathcal{X}_n|^\alpha)^{\frac{2}{2\alpha+1}} |T_n|^{\frac{1}{2\alpha+1}} \right\}$$

2. *Case  $d = 2\alpha$ .*

The proof is the same as for the case  $d < 2\alpha$  but with  $C$  now depending on  $\psi_2$  (also defined in Theorem 1) rather than  $\psi_1$ . We get the same result.

□



## D Proof of Equation (10)

One has, for any pruning  $\mathcal{T} \in \mathcal{P}(\mathcal{T}_0)$  and some  $f \in \text{Lip}_L^\alpha(\mathcal{X})$ :

$$\begin{aligned} \text{Reg}_{\mathcal{T}}(f) &\lesssim \sum_{n \in \mathcal{L}(\mathcal{T})} (L_n(f) |\mathcal{X}_n|^\alpha)^{\frac{2}{2\alpha+1}} |T_n|^{\frac{1}{2\alpha+1}} = \sum_{n \in \mathcal{L}(\mathcal{T})} (L_n(f)^{\frac{1}{\alpha}} |\mathcal{X}_n|)^{\frac{2\alpha}{2\alpha+1}} |T_n|^{\frac{1}{2\alpha+1}} \\ &\leq \left( \sum_{n \in \mathcal{L}(\mathcal{T})} L_n(f)^{\frac{1}{\alpha}} |\mathcal{X}_n| \right)^{\frac{2\alpha}{2\alpha+1}} \left| \sum_{n \in \mathcal{L}(\mathcal{T})} T_n \right|^{\frac{1}{2\alpha+1}} \\ &= \left( \sum_{n \in \mathcal{L}(\mathcal{T})} L_n(f)^{\frac{1}{\alpha}} |\mathcal{X}_n| \right)^{\frac{2\alpha}{2\alpha+1}} |T|^{\frac{1}{2\alpha+1}} \end{aligned}$$

where inequality is obtained with Hölder's inequality with  $p = (2\alpha + 1)/2\alpha$  and  $q = 2\alpha + 1$ .

One could also write:

$$\left( \sum_{n \in \mathcal{L}(\mathcal{T})} L_n(f)^{\frac{1}{\alpha}} |\mathcal{X}_n| \right)^{\frac{2\alpha}{2\alpha+1}} = \left( |\mathcal{X}| \sum_{n \in \mathcal{L}(\mathcal{T})} L_n(f)^{\frac{1}{\alpha}} \frac{|\mathcal{X}_n|}{|\mathcal{X}|} \right)^{\frac{2\alpha}{2\alpha+1}} := \left( |\mathcal{X}|^\alpha \|f\|_{\mathcal{L}(\mathcal{T}), \frac{1}{\alpha}} \right)^{\frac{2}{2\alpha+1}},$$

where  $f \mapsto \|f\|_{\mathcal{L}(\mathcal{T}), \frac{1}{\alpha}}$  is some  $\frac{1}{\alpha}$ -norm (or expectation) of  $f$  over leaves  $n \in \mathcal{L}(\mathcal{T})$  with probability  $|\mathcal{X}_n|/|\mathcal{X}| = 2^{-d(n)}$ ,  $n \in \mathcal{L}(\mathcal{T})$ .

## E Comparison with Kuzborskij and Cesa-Bianchi [2020]

Let  $f \in \text{Lip}_L^\alpha(\mathcal{X})$ ,  $(M^{(k)})_{1 \leq k \leq d(\mathcal{T}_0)}$  such that  $M^{(k)} \geq L_n(f)$  for any  $n \in \mathcal{N}(\mathcal{T}_0)$ ,  $d(n) = k$  and  $T^{(k)} = \{1 \leq t \leq T : x_t \in \mathcal{X}_n, d(n) = k\}$ . Let  $\mathcal{T}$  be any pruning and let  $\alpha = 1, d = 1$ . We have for the squared (exp-concave) loss, according to Corollary 1:

$$\begin{aligned} \text{Reg}_T(f) &\lesssim \sum_{n \in \mathcal{L}(\mathcal{T})} \min \left\{ \left( L_n(f) \frac{|\mathcal{X}_n|}{|\mathcal{X}|} \right)^{\frac{2}{3}} |T_n|^{\frac{1}{3}}, \left( L_n(f) \frac{|\mathcal{X}_n|}{|\mathcal{X}|} \right)^{\frac{1}{2}} |T_n|^{\frac{1}{2}} \right\} \\ &= \sum_{k=1}^{d(\mathcal{T})} \sum_{n \in \mathcal{L}(\mathcal{T}):d(n)=k} \min \left\{ \left( L_n(f) \frac{|\mathcal{X}_n|}{|\mathcal{X}|} \right)^{\frac{2}{3}} |T_n|^{\frac{1}{3}}, \left( L_n(f) \frac{|\mathcal{X}_n|}{|\mathcal{X}|} \right)^{\frac{1}{2}} |T_n|^{\frac{1}{2}} \right\} \\ &\leq \sum_{k=1}^{d(\mathcal{T})} \min \left\{ \left( \sum_{n \in \mathcal{L}(\mathcal{T}):d(n)=k} L_n(f) 2^{-k} \right)^{\frac{2}{3}} |T^{(k)}|^{\frac{1}{3}}, \left( \sum_{n \in \mathcal{L}(\mathcal{T}):d(n)=k} L_n(f) 2^{-k} \right)^{\frac{1}{2}} |T^{(k)}|^{\frac{1}{2}} \right\} \end{aligned} \quad (45)$$

$$\begin{aligned} &\leq \sum_{k=1}^{d(\mathcal{T})} \min \left\{ \left( M^{(k)} w^{(k)} \right)^{\frac{2}{3}} |T^{(k)}|^{\frac{1}{3}}, \left( M^{(k)} w^{(k)} \right)^{\frac{1}{2}} |T^{(k)}|^{\frac{1}{2}} \right\} \\ &\leq \min \left\{ (\bar{M}(f))^{\frac{2}{3}} T^{\frac{1}{3}}, (\bar{M}(f)T)^{\frac{1}{2}} \right\} \end{aligned} \quad (46)$$

where  $\bar{M}(f) = \sum_{k=1}^{d(\mathcal{T})} w^{(k)} M^{(k)}$  with  $w^{(k)} = \sum_{n \in \mathcal{L}(\mathcal{T}):d(n)=k} \frac{|\mathcal{X}_n|}{|\mathcal{X}|} = 2^{-k} |\{n \in \mathcal{L}(\mathcal{T}) : d(n) = k\}|$  proportion of leaves in  $\mathcal{L}(\mathcal{T})$  at level  $k$  in  $\mathcal{N}(\mathcal{T}_0)$  and where we applied Hölder's inequality to get (45) and (46). The last upper-bound recovers and improves the one of Kuzborskij and Cesa-Bianchi [2020] for dimension  $d = 1$ , as described in the main part of the paper. For higher dimension  $d \geq 2$ , both for exp-concave and convex losses, Theorem 2 gives for any pruning  $\mathcal{T}$  and any function  $f \in \text{Lip}_L^1(\mathcal{X})$  (ignoring the dependence on  $\mathcal{X}$ ):

$$\begin{aligned} \text{Reg}_T(f) &\lesssim \sum_{n \in \mathcal{L}(\mathcal{T})} L_n(f) |T_n|^{1-\frac{1}{d}} = \sum_{k=1}^{d(\mathcal{T})} \sum_{n \in \mathcal{L}(\mathcal{T}):d(n)=k} L_n(f) |T_n|^{\frac{d-1}{d}} \\ &\leq \sum_{k=1}^{d(\mathcal{T})} M^{(k)} |\{n : d(n) = k\}|^{\frac{1}{d}} |T^{(k)}|^{\frac{d-1}{d}}, \end{aligned}$$

which grows as  $O(\sum_k M^{(k)} |T^{(k)}|^{\frac{d-1}{d}})$  compared to  $O(\sum_k (M^{(k)} |T^{(k)}|)^{\frac{d}{d+1}})$  in Kuzborskij and Cesa-Bianchi [2020]. As a consequence, if for every level  $k = 1, \dots, d(\mathcal{T})$ ,  $M^{(k)} |T^{(k)}|^{\frac{d-1}{d}} \geq (M^{(k)} |T^{(k)}|)^{\frac{d}{d+1}}$  it turns out that  $M^{(k)} \geq |T^{(k)}|^{\frac{1}{d}}$  which leads to an equivalent bound  $O(\sum_k |T^{(k)}|) = O(T)$  which corresponds to the worst case regret bound (41). As a conclusion, our bound recovers and improves their results in particular with a dependence to lower constants  $L_n(f)$  and lower time rate  $|T_n|^{1-\frac{1}{d}}$ .

## F Experiments

The following presents experimental results in a synthetic regression setting for both the Chaining Tree method and LocAdaBoost. We consider the model  $y_t = f(x_t) + \varepsilon_t$ , where  $\varepsilon_t \sim \mathcal{N}(0, \sigma^2)$  with  $\sigma = 0.5$ ,  $f(x) = \sin(10x) + \cos(5x) + 5$ , for  $x \in \mathcal{X} = [0, 1]$  and  $\sup_x |f'(x)| \leq 15 =: L$ . Furthermore, we assume that  $x_t$  is independently drawn from the uniform distribution  $\mathcal{U}(\mathcal{X})$ .

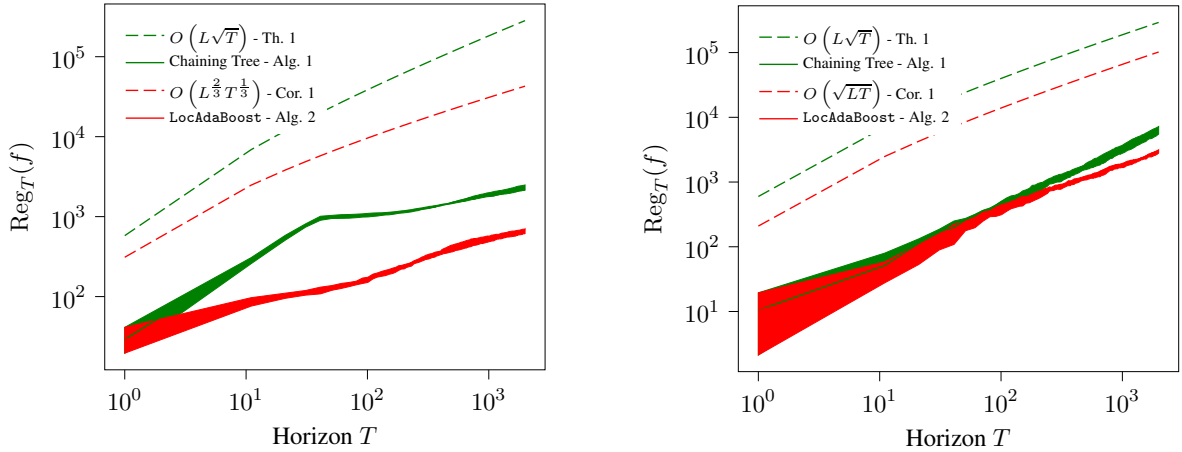
Refer to Theorem 1, Theorem 2 and Corollary 1 in the paper to compare experimental results to theoretical guarantees. Code will be available on Github for the final version.

*Key observations:*

- For the squared loss,  $\ell_t(\hat{y}) = (\hat{y} - y_t)^2$ , LocAdaBoost achieves a time rate of  $O(T^{\frac{1}{3}})$  compared to  $O(\sqrt{T})$  for Chaining Tree - see Figure 4a. However, the trade-off is an increased dependence on the smoothness  $L$ , shifting from  $O(L^{\frac{1}{2}})$  to  $O(L^{\frac{2}{3}})$ ;
- We observe in Figure 5 that LocAdaBoost reduces regret with respect to  $L$ : it achieves  $O(\sqrt{L})$  for absolute loss in Fig. 5b and  $O(L^{\frac{2}{3}})$  for square loss in Fig. 5a;
- In Figure 5a and Figure 5b, we observe that both the experimental and theoretical curves level off once  $L$  increases beyond a certain threshold  $L_0 \gtrsim BT$ . Indeed, we demonstrated that for any  $f \in \text{Lip}_L^\alpha$ ,

$$\text{Reg}_T(f) \lesssim \min \left\{ BT, \sum_n L_n(f) |T_n|^{1-\frac{1}{d}} \right\}.$$

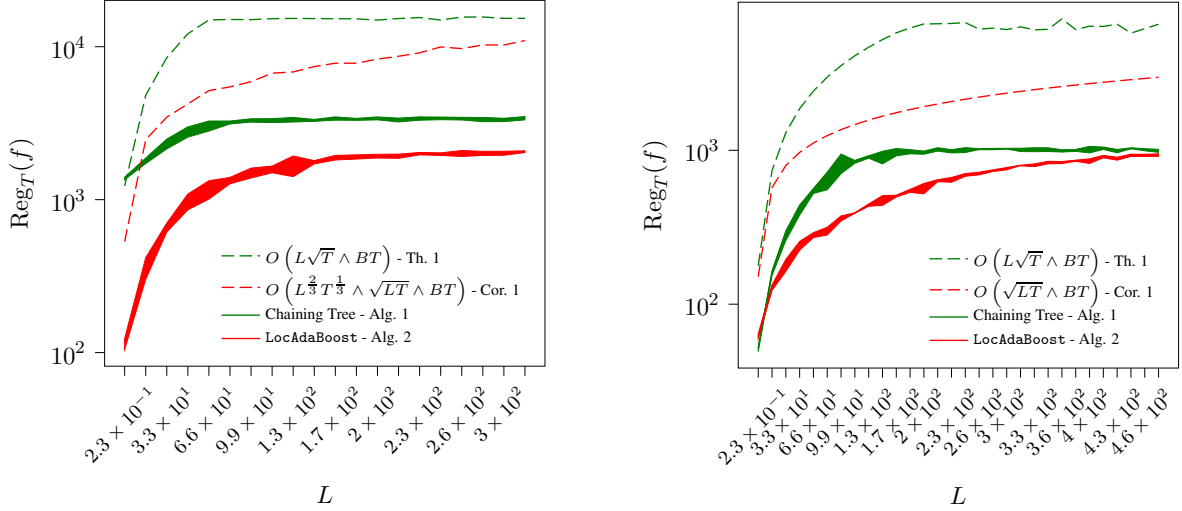
See Appendix B and Equation (41) for more details.



(a) Regret with  $\ell_t(\hat{y}) = (\hat{y} - y_t)^2$

(b) Regret with  $\ell_t(\hat{y}) = |\hat{y} - y_t|$

Figure 4: Comparison of regret as a function of  $T$  for square and absolute loss functions. The dotted lines represent the theoretical results (where  $O$  hides terms in  $\log T$ ), while the solid lines show the actual performance of our algorithms (averaged over 10 experiments).



(a) Regret with  $\ell_t(\hat{y}) = (\hat{y} - y_t)^2$

(b) Regret with  $\ell_t(\hat{y}) = |\hat{y} - y_t|$

Figure 5: Regret as a function of  $L$  for square and absolute loss functions, with a fixed horizon of  $T = 2000$ . The analysis uses 20 equally spaced constants  $l \in [2^{-6}, 2^5]$ , which define the different Lipschitz functions where we apply our algorithms, given by  $f_l(x) = f(lx)$  such that  $\sup_{x \in \mathcal{X}} |f'_l(x)| \leq 15l =: L$ .

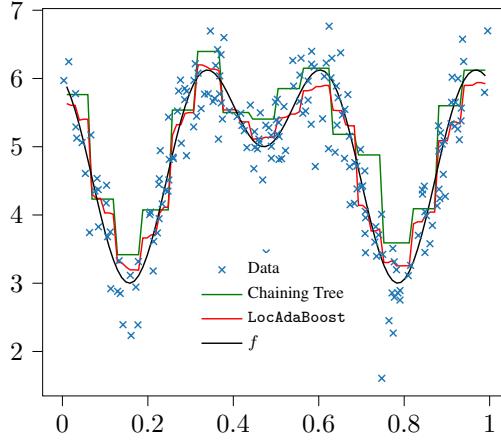


Figure 6: Predictions for Chaining Tree and LocAdaBoost after  $T = 1000$  data. For illustration purposes, we set the depth of the Chaining Trees to 5 and that of the Core Tree to 3.

*Note:* A minor adjustment has been made to the implementation of our LocAdaBoost (Algorithm 2). Rather than performing a grid search to determine the root nodes of the CT in Core Tree  $\mathcal{T}_0$ , we employ a *Follow the Leader* (or best expert) strategy. For squared losses, this method offers a similar benefit, that is reducing the regret for learning the root nodes from  $O(B\sqrt{T})$  to  $O(B \log(T))$  - see [Cesa-Bianchi and Lugosi \[2006, Chap 3.2\]](#). Consequently, the overall performance bound is improved, especially in low-dimensional cases (see Corollary 1, exp-concave case).