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Gains and Losses are Fundamentally Different in Regret Minimization: The Sparse Case

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Abstract

We demonstrate that, in the classical non-stochastic regret minimization problem with d decisions, gains and losses to be respectively maximized or minimized are fundamentally different. Indeed, by considering the additional sparsity assumption (at each stage, at most s decisions incur a nonzero outcome), we derive optimal regret bounds of different orders. Specifically, with gains, we obtain an optimal regret guarantee after T stages of order $\sqrt{T \log s}$, so the classical dependency in the dimension is replaced by the sparsity size. With losses, we provide matching upper and lower bounds of order $\sqrt{Ts \log(d)/d}$, which is decreasing in d. Eventually, we also study the bandit setting, and obtain an upper bound of order $\sqrt{Ts \log(d/s)}$ when outcomes are losses. This bound is proven to be optimal up to the logarithmic factor $\sqrt{\log(d/s)}$.

Keywords: regret minimization, bandit, sparsity

1. Introduction

We consider the classical problem of regret minimization (Hannan, 1957) that has been well developed during the last decade (Cesa-Bianchi and Lugosi, 2006; Rakhlin and Tewari, 2008; Bubeck, 2011; Shalev-Shwartz, 2011; Hazan, 2012; Bubeck and Cesa-Bianchi, 2012). We recall that in this sequential decision problem, a decision maker (or agent, player, algorithm, strategy, policy, depending on the context) chooses at each stage a decision in a finite set (that we write as $[d] := \{1, \dots, d\}$) and obtains as an *outcome* a real number in $[0, 1]$. We specifically chose the word *outcome*, as opposed to *gain* or *loss*, as our results show that there exists a fundamental discrepancy between these two concepts.

The criterion used to evaluate the policy of the decision maker is the *regret*, i.e., the difference between the cumulative performance of the best stationary policy (that always picks a given action $i \in [d]$) and the cumulative performance of the policy of the decision maker.

We focus here on the *non-stochastic* framework, where no assumption (apart from boundedness) is made on the sequence of possible outcomes. In particular, they are not i.i.d. and we can even assume, as usual, that they depend on the past choices of the decision maker. This broad setup, sometimes referred to as *individual sequences* (since a policy must be good against *any* sequence of possible outcomes) incorporates prediction with expert advice (Cesa-Bianchi and Lugosi, 2006), data with time-evolving laws, etc. Perhaps the most fundamental results in this setup are the upper bound of order $\sqrt{T \log d}$ achieved by the Exponential Weight Algorithm (Littlestone and Warmuth, 1994; Vovk, 1990; Cesa-Bianchi, 1997; Auer et al., 2002) and the asymptotic lower bound of the same order (Cesa-Bianchi et al., 1997). This general bound is the same whether outcomes are gains in $[0, 1]$ (in which case, the objective is to maximize the cumulative sum of gains) or losses in $[0, 1]$ (where the decision maker aims at minimizing the cumulative sum). Indeed, a loss ℓ can easily be turned into gain g by defining $g := 1 - \ell$, the regret being invariant under this transformation.

This idea does not apply anymore with structural assumption. For instance, consider the framework where the outcomes are limited to *s-sparse vectors*, i.e. vectors that have at most s nonzero coordinates. The coordinates which are nonzero may change arbitrarily over time. In this framework, the aforementioned transformation does not preserve the sparsity assumption. Indeed, if $(\ell_1, \dots, \ell_d)$ is a s-sparse loss vector, the corresponding gain vector $(1 - \ell_1, \dots, 1 - \ell_d)$ may even have full support. Consequently, results for loss vectors do not apply directly to sparse gains, and vice versa. It turns out that both setups are fundamentally different.

The sparsity assumption is actually quite natural in learning and have also received some attention in online learning (Gerchinovitz, 2013; Carpentier and Munos, 2012; Abbasi-Yadkori et al., 2012; Djolonga et al., 2013). In the case of gains, it reflects the fact that the problem has some hidden structure and that many options are irrelevant. For instance, in the canonical click-through-rate example, a website displays an ad and gets rewarded if the user clicks on it; we can safely assume that there are only a small number of ads on which a user would click.

The sparse scenario can also be seen through the scope of prediction with experts. Given a finite set of expert, we call the *winner of a stage* the expert with the highest revenue (or the smallest loss); ties are broken arbitrarily. And the objective would be to win as many stages as possible. The s-sparse setting would represent the case where s experts are designated as winners (or, non-loser) at each stage.

In the case of losses, the sparsity assumption is motivated by situations where rare failures might happen at each stage, and the decision maker wants to avoid them. For instance, in network routing problems, it could be assumed that only a small number of paths would lose packets as a result of a single, rare, server failure. Or a learner could have access to a finite number of classification algorithms that perform ideally most of the time; unfortunately, some of them makes mistakes on some examples and the learner would like to prevent that. The general setup is therefore a number of algorithms/experts/actions that mostly perform well (i.e., find the correct path, classify correctly, optimize correctly some target function, etc.); however, at each time instance, there are rare mistakes/accidents and the objective would be to find the action/algorithm that has the smallest number (or probability in the stochastic case) of failures.

	Full information		Bandit	
	Gains	Losses	Gains	Losses
Upper bound	$\sqrt{T \log s}$	$\sqrt{Ts \frac{\log d}{d}}$	$\sqrt{Td}$	$\sqrt{Ts \log \frac{d}{s}}$
Lower bound			$\sqrt{Ts}$	$\sqrt{Ts}$

Figure 1: Summary of upper and lower bounds.

1.1 Summary of Results

We investigate regret minimization scenarios both when outcomes are gains on the one hand, and losses on the other hand. We recall that our objectives are to prove that they are fundamentally different by exhibiting rates of convergence of different order.

When outcomes are gains, we construct an algorithm based on the Online Mirror Descent family (Shalev-Shwartz, 2007, 2011; Bubeck, 2011). By choosing a regularizer based on the ℓ^p norm, and then tuning the parameter p as a function of s, we get in Theorem 2 a regret bound of order $\sqrt{T \log s}$, which has the interesting property of being independent of the number of decisions d. This bound is trivially optimal, up to the constant.

If outcomes are losses instead of gains, although the previous analysis remains valid, a much better bound can be obtained. We build upon a regret bound for the Exponential Weight Algorithm (Littlestone and Warmuth, 1994; Freund and Schapire, 1997) and we manage to get in Theorem 4 a regret bound of order $\sqrt{\frac{Ts \log d}{d}}$, which is *decreasing* in d, for a given s. A nontrivial matching lower bound is established in Theorem 6.

Both of these algorithms need to be tuned as a function of s. In Theorem 9 and Theorem 10, we construct algorithms which essentially achieve the same regret bounds without prior knowledge of s, by adapting over time to the sparsity level of past outcome vectors, using an adapted version of the doubling trick.

Finally, we investigate the bandit setting, where the only feedback available to the decision maker is the outcome of his decisions (and, not the outcome of all possible decisions). In the case of losses we obtain in Theorem 11 an upper bound of order $\sqrt{Ts \log(d/s)}$, using the Greedy Online Mirror Descent family of algorithms (Audibert and Bubeck, 2009; Audibert et al., 2013; Bubeck, 2011). This bound is proven to be optimal up to a logarithmic factor, as Theorem 13 establishes a lower bound of order $\sqrt{Ts}$.

The rates of convergence achieved by our algorithms are summarized in Figure 1.

1.2 General Model and Notation

We recall the classical non-stochastic regret minimization problem. At each time instance $t \geqslant 1$, the decision maker chooses a decision d_t in the finite set $[d] = \{1, \ldots, d\}$, possibly at random, according to $x_t \in \Delta_d$, where

$$\Delta_d = \left\{ x = (x^{(1)}, \ldots, x^{(d)}) \in \mathbb{R}_+^d \;\middle|\; \sum_{i=1}^{d} x^{(i)} = 1 \right\}$$

is the the set of probability distributions over $[d]$. Nature then reveals an outcome vector $\omega_t \in [0,1]^d$ and the decision maker receives $\omega_t^{(d_t)} \in [0,1]$. As outcomes are bounded, we can easily replace $\omega_t^{(d_t)}$ by its expectation that we denote by $\langle \omega_t, x_t \rangle$. Indeed, Hoeffding-Azuma concentration inequality will imply that all the results we will state in expectation hold with high probability.

Given a time horizon $T \geqslant 1$, the objective of the decision maker is to minimize his regret, whose definition depends on whether outcomes are *gains* or *losses*. In the case of gains (resp. losses), the notation ω_t is then changed to g_t (resp. ℓ_t) and the regret is:

$$R_T = \max_{i\in[d]} \sum_{t=1}^{T} g_t^{(i)} - \sum_{t=1}^{T} \langle g_t, x_t \rangle \quad \left(\text{resp. } R_T = \sum_{t=1}^{T} \langle \ell_t, x_t \rangle - \min_{i\in[d]} \sum_{t=1}^{T} \ell_t^{(i)} \right).$$

In both cases, the well-known Exponential Weight Algorithm guarantees a bound on the regret of order $\sqrt{T \log d}$. Moreover, this bound cannot be improved in general as it matches a lower bound.

We shall consider an additional structural assumption on the outcomes, namely that ω_t is s-sparse in the sense that $\|\omega_t\|_0 \leqslant s$, i.e., the number of nonzero components of ω_t is less than s, where s is a fixed known parameter. The set of components which are nonzero is not fixed nor known, and may change arbitrarily over time.

We aim at proving that it is then possible to drastically improve the previously mentioned guarantee of order $\sqrt{T \log d}$ and that losses and gains are two fundamentally different settings with minimax regrets of different orders.

2. When Outcomes are Gains to be Maximized

2.1 Online Mirror Descent Algorithms

We quickly present the general Online Mirror Descent algorithm (Shalev-Shwartz, 2011; Bubeck, 2011; Bubeck and Cesa-Bianchi, 2012; Kwon and Mertikopoulos, 2014) and state the regret bound it incurs; it will be used as a key element in Theorem 2.

A convex function $h : \mathbb{R}^d \to \mathbb{R} \cup \{+\infty\}$ is called a *regularizer* on Δ_d if h is strictly convex and continuous on its domain Δ_d, and $h(x) = +\infty$ outside Δ_d. Denote $\delta_h = \max_{\Delta_d} h - \min_{\Delta_d} h$ and $h^* : \mathbb{R}^d \to \mathbb{R}^d$ the Legendre-Fenchel transform of h:

$$h^*(y) = \sup_{x\in\mathbb{R}^d} \{\langle y, x \rangle - h(x)\}, \quad y \in \mathbb{R}^d,$$

which is differentiable since h is strictly convex. For all $y \in \mathbb{R}^d$, it holds that $\nabla h^*(y) \in \Delta_d$.

Let $\eta \in \mathbb{R}$ be a parameter to be tuned. The Online Mirror Descent Algorithm associated with the regularizer h and parameter η is defined by:

$$x_t = \nabla h^* \left(\eta \sum_{k=1}^{t-1} \omega_k \right), \quad t \geqslant 1,$$

where $\omega_t \in [0,1]^d$ denote the vector of outcomes and x_t the probability distribution chosen at stage t. The specific choice $h(x) = \sum_{i=1}^{d} x^{(i)} \log x^{(i)}$ for $x = (x^{(1)}, \ldots, x^{(d)}) \in \Delta_d$ (and

$h(x) = +\infty$ otherwise) gives the celebrated Exponential Weight Algorithm, which can be written explicitly, component by component:

$$x_t^{(i)} = \frac{\exp\left(\eta \sum_{k=1}^{t-1} \omega_k^{(i)}\right)}{\sum_{j=1}^{d} \exp\left(\eta \sum_{k=1}^{t-1} \omega_k^{(j)}\right)}, \quad t \geqslant 1,\ i \in [d].$$

The following general regret guarantee for strongly convex regularizers is expressed in terms of the dual norm $\|\cdot\|_*$ of $\|\cdot\|$. Similar statements have appeared in e.g. (Shalev-Shwartz, 2011, Theorem 2.21), (Bubeck and Cesa-Bianchi, 2012, Theorem 5.6) and (Kwon and Mertikopoulos, 2014, Theorem 5.1).

Theorem 1 *Let $K > 0$ and assume h to be K-strongly convex with respect to a norm $\|\cdot\|$. Then, for any sequence of outcome vectors $(\omega_t)_{t\geqslant 1}$ in $\mathbb{R}^d$, the Online Mirror Descent strategy associated with h and η (with $\eta > 0$ in cases of gains and $\eta < 0$ in cases of losses) guarantees, for $T \geqslant 1$, the following regret bound:*

$$R_T \leqslant \frac{\delta_h}{|\eta|} + \frac{|\eta|}{2K} \sum_{t=1}^{T} \|\omega_t\|_*^2 .$$

2.2 Upper Bound on the Regret

We first assume $s \geqslant 2$. Let $p \in (1, 2]$ and define the following regularizer:

$$h_p(x) = \begin{cases} \frac{1}{2}\|x\|_p^2 & \text{if } x \in \Delta_d \\ +\infty & \text{otherwise.} \end{cases}$$

One can easily check that h_p is indeed a regularizer on Δ_d and that $\delta_{h_p} \leqslant 1/2$. Moreover, it is $(p-1)$-strongly convex with respect to $\|\cdot\|_p$: see (Bubeck, 2011, Lemma 5.7) or (Kakade et al., 2012, Lemma 9).

We can now state our first result, the general upper bound on regret when outcomes are s-sparse gains.

Theorem 2 *Let $\eta > 0$ and $s \geqslant 3$. Against all sequences of s-sparse gain vectors g_t, i.e., $g_t \in [0,1]^d$ and $\|g_t\|_0 \leqslant s$, the Online Mirror Descent algorithm associated with regularizer h_p and parameter η guarantees:*

$$R_T \leqslant \frac{1}{2\eta} + \frac{\eta T s^{2/q}}{2(p-1)},$$

where $1/p + 1/q = 1$. In particular, the choices $\eta = \sqrt{(p-1)/Ts^{2/q}}$ and $p = 1 + (2\log s - 1)^{-1}$ give:

$$R_T \leqslant \sqrt{2eT \log s}.$$

Proof h_p being $(p-1)$-strongly convex with respect to $\|\cdot\|_p$, and $\|\cdot\|_q$ being the dual norm of $\|\cdot\|_p$, Theorem 1 gives:

$$R_T \leqslant \frac{\delta_{h_p}}{\eta} + \frac{\eta}{2(p-1)} \sum_{t=1}^{T} \|g_t\|_q^2 .$$

For each $t \geqslant 1$, the norm of g_t can be bounded as follows:

$$\|g_t\|_q^2 = \left(\sum_{i=1}^{d} \left|g_t^{(i)}\right|^q\right)^{2/q} \leqslant \left(\sum_{s \text{ terms}} \left|g_t^{(i)}\right|^q\right)^{2/q} \leqslant s^{2/q},$$

which yields

$$R_T \leqslant \frac{1}{2\eta} + \frac{\eta T s^{2/q}}{2(p-1)}.$$

We can now balance both terms by choosing $\eta = \sqrt{(p-1)/(Ts^{2/q})}$ and get:

$$R_T \leqslant \sqrt{\frac{Ts^{2/q}}{p-1}}.$$

Finally, since $s \geqslant 3$, we have $2\log s > 1$ and we set $p = 1 + (2\log s - 1)^{-1} \in (1, 2]$, which gives:

$$\frac{1}{q} = 1 - \frac{1}{p} = \frac{p-1}{p} = \frac{(2\log s - 1)^{-1}}{1 + (2\log s - 1)^{-1}} = \frac{1}{2\log s},$$

and thus:

$$R_T \leqslant \sqrt{\frac{Ts^{2/q}}{p-1}} = \sqrt{2T\log s\, e^{2\log s/q}} = \sqrt{2e\, T\log s}.$$

■

We emphasize the fact that we obtain, up to a multiplicative constant, the exact same rate as when the decision maker only has a set of s decisions.

Theorem 2 was restricted to $s \geqslant 3$ to simplify the analysis. In the cases $s = 1, 2$, we can easily derive a bound of respectively $\sqrt{T}$ and $\sqrt{2T}$ using the same regularizer with $p = 2$.

2.3 Matching Lower Bound

For $s \in [d]$ and $T \geqslant 1$, we denote $v_T^{g,s,d}$ the minimax regret of the T-stage decision problem with outcome vectors restricted to s-sparse gains:

$$v_T^{g,s,d} = \min_{\text{strat.}} \max_{(g_t)_t} R_T$$

where the minimum is taken over all possible policies of the decision maker, and the maximum over all sequences of s-sparse gains vectors.

To establish a lower bound in the present setting, we can assume that only the s first coordinates of g_t may be positive (for all $t \geqslant 1$) and that the decision maker is aware of that. Therefore he has no interest in assigning positive probabilities to any decision but the first s ones. Indeed, for any mixed action x_t, the decision maker can construct alternative mixed action $x'_t = (x_t^{(1)}, \dots, x_t^{(s)} + \dots + x_t^{(d)}, 0, \dots, 0)$ which obviously give a higher payoff:

$$\langle g_t, x_t \rangle \leqslant \langle g_t, x'_t \rangle$$

and therefore a lower regret:

$$\max_{i\in[d]} \sum_{t=1}^{T} g_t^{(i)} - \sum_{t=1}^{T} \langle g_t, x'_t \rangle \leqslant \max_{i\in[d]} \sum_{t=1}^{T} g_t^{(i)} - \sum_{t=1}^{T} \langle g_t, x_t \rangle .$$

Therefore, we can restrict the strategies of the decision maker to those which assign positive probability to the s first components only. That setup, which is simpler for the decision maker than the original one, is obviously equivalent to the basic regret minimization problem with only s decisions. Therefore, the classical lower bound (Cesa-Bianchi et al., 1997, Theorem 3.2.3) holds and we obtain the following.

Theorem 3

$$\liminf_{\substack{s\to+\infty \\ d\geqslant s}} \liminf_{T\to+\infty} \frac{v_T^{g,s,d}}{\sqrt{T\log s}} \geqslant \frac{\sqrt{2}}{2}.$$

The same lower bound, up to the multiplicative constant actually holds non asymptotically, see (Cesa-Bianchi and Lugosi, 2006, Theorem 3.6).

An immediate consequence of Theorem 3 is that the regret bound derived in Theorem 2 is asymptotically minimax optimal, up to a multiplicative constant.

3. When Outcomes are Losses to be Minimized

3.1 Upper Bound on the Regret

We now consider the case of losses, and the regularizer shall no longer depend on s (as with gains), as we will always use the Exponential Weight Algorithm. Instead, it is the parameter η that will be tuned as a function of s.

Theorem 4 *Let $s \geqslant 1$. For any sequence of s-sparse loss vectors $(\ell_t)_{t\geqslant 1}$, i.e., $\ell_t \in [0,1]^d$ and $\|\ell_t\|_0 \leqslant s$, the Exponential Weight Algorithm with parameter $-\eta$ where*

$$\eta := \log\left(1 + \sqrt{2d\log d/sT}\right) > 0$$

guarantees, for $T \geqslant 1$:

$$R_T \leqslant \sqrt{\frac{2sT\log d}{d}} + \log d.$$

We build upon the following regret bound for losses which is written in terms of the performance of the best action. It is often called *improvement for small losses*: see e.g. (Littlestone and Warmuth, 1994) or (Cesa-Bianchi and Lugosi, 2006, Theorem 2.4).

Theorem 5 *Let $\eta > 0$. For any sequence of loss vectors $(\ell_t)_{t\geqslant 1}$ in $[0,1]^d$, the Exponential Weight Algorithm with parameter $-\eta$ guarantees, for all $T \geqslant 1$:*

$$R_T \leqslant \frac{\log d}{1-e^{-\eta}} + \left(\frac{\eta}{1-e^{-\eta}} - 1\right) L_T^* \ ,$$

where $L_T^* = \min_{i\in[d]} \sum_{t=1}^{T} \ell_t^{(i)}$ is the loss of the best stationary decision.

Proof Let $T \geqslant 1$ and $L_T^* = \min_{i\in[d]} \sum_{t=1}^T \ell_t^{(i)}$ be the loss of the best stationary policy. First note that since the loss vectors ℓ_t are s-sparse, we have $s \geqslant \sum_{i=1}^d \ell_t^{(i)}$. By summing over $1 \leqslant t \leqslant T$:

$$sT \geqslant \sum_{t=1}^T \sum_{i=1}^d \ell_t^{(i)} = \sum_{i=1}^d \left(\sum_{t=1}^T \ell_t^{(i)} \right) \geqslant d \left(\min_{i\in[d]} \sum_{t=1}^T \ell_t^{(i)} \right) = dL_T^*,$$

and therefore, we have $L_T^* \leqslant Ts/d$.

Then, by using the inequality $\eta \leqslant (e^\eta - e^{-\eta})/2$, the bound from Theorem 5 becomes:

$$R_T \leqslant \frac{\log d}{1-e^{-\eta}} + \left(\frac{e^\eta - e^{-\eta}}{2(1-e^{-\eta})} - 1 \right) L_T^* \ .$$

The factor of L_T^* in the second term can be transformed as follows:

$$\frac{e^\eta - e^{-\eta}}{2(1-e^{-\eta})} - 1 = \frac{(1+e^{-\eta})(e^\eta - e^{-\eta})}{2(1-e^{-2\eta})} - 1 = \frac{(1+e^{-\eta})e^\eta}{2} - 1 = \frac{e^\eta - 1}{2} \ ,$$

and therefore the bound on the regret becomes:

$$R_T \leqslant \frac{\log d}{1-e^{-\eta}} + \frac{e^\eta - 1}{2} L_T^* \leqslant \frac{\log d}{1-e^{-\eta}} + \frac{(e^\eta - 1)Ts}{2d} \ ,$$

where we have been able to use the upper-bound on L_T^* since $\frac{e^\eta - 1}{2} \geqslant 0$. Along with the choice $\eta = \log(1 + \sqrt{2d \log d / Ts})$ and standard computations, this yields:

$$R_T \leqslant \sqrt{\frac{2Ts \log d}{d}} + \log d \ .$$

■

Interestingly, the bound from Theorem 4 shows that $\sqrt{2sT \log d/d}$, the dominating term of the regret bound, is *decreasing* when the number of decisions d increases. This is due to the sparsity assumptions (as the regret increases with s, the maximal number of decision with positive losses). Indeed, when s is fixed and d increases, more and more decisions are optimal at each stage, a proportion $1 - s/d$ to be precise. As a consequence, it becomes *easier* to find an optimal decisions when d increases. However, this intuition will turn out not to be valid in the bandit framework.

On the other hand, if the proportion s/d of positive losses remains constant then the regret bound achieved is of the same order as in the usual case.

3.2 Matching Lower Bound

When outcomes are losses, the argument from Section 2.3 does not allow to derive a lower bound. Indeed, if we assume that only the first s coordinates of the loss vectors ℓ_t can be positive, and that the decision maker knows it, then he just has to take at each stage the decision $d_t = d$ which incurs a loss of 0. As a consequence, he trivially has a regret

$R_T = 0$. Choosing at random, but once and for all, a fixed subset of s coordinates does not provide any interesting lower bound either. Instead, the key idea of the following result is to choose at random and at each stage the s coordinates associated with positive losses. And we therefore use the following classical probabilistic argument. Assume that we have found a probability distribution on $(\ell_t)_t$ such that the expected regret can be bounded from below by a quantity which does not depend on the strategy of the decision maker. This would imply that for any algorithm, there exists a sequence of $(\ell_t)_t$ such that the regret is greater than the same quantity.

In the following statement, $v_T^{\ell,s,d}$ stands for the minimax regret in the case where outcomes are losses.

Theorem 6 *For all $s \geqslant 1$,*

$$\liminf_{d\to+\infty} \liminf_{T\to+\infty} \frac{v_T^{\ell,s,d}}{\sqrt{T\frac{s}{d}\log d}} \geqslant \frac{\sqrt{2}}{2}.$$

The main consequences of this theorem are that the algorithm described in Theorem 4 is asymptotically minimax optimal (up to a multiplicative constant) and that gains and losses are fundamentally different from the point of view of regret minimization.

Proof We define the sequence of i.i.d. loss vectors ℓ_t ($t \geqslant 1$) as follows. First, we draw a set $I_t \subset [d]$ of cardinality s uniformly among the $\binom{d}{s}$ possibilities. Then, if $i \in I_t$ set $\ell_t^{(i)} = 1$ with probability $1/2$ and $\ell_t^{(i)} = 0$ with probability $1/2$, independently for each component. If $i \notin I_t$, we set $\ell_t^{(i)} = 0$.

As a consequence, we always have that ℓ_t is s-sparse. Moreover, for each $t \geqslant 1$ and each coordinate $i \in [d]$, $\ell_t^{(i)}$ satisfies:

$$\mathbb{P}\left[\ell_t^{(i)} = 1\right] = \frac{s}{2d} \quad \text{and} \quad \mathbb{P}\left[\ell_t^{(i)} = 0\right] = 1 - \frac{s}{2d} \ ,$$

thus $\mathbb{E}\left[\ell_t^{(i)}\right] = s/2d$. Therefore we obtain that for any algorithm $(x_t)_{t\geqslant 1}$, $\mathbb{E}\left[\langle \ell_t, x_t\rangle\right] = s/2d$. This yields that

$$\begin{aligned}
\mathbb{E}\left[\frac{R_T}{\sqrt{T}}\right] &= \mathbb{E}\left[\frac{1}{\sqrt{T}}\left(\sum_{t=1}^T \langle \ell_t, x_t\rangle - \min_{i\in[d]} \sum_{t=1}^T \ell_t^{(i)}\right)\right] \\
&= \mathbb{E}\left[\max_{i\in[d]} \frac{1}{\sqrt{T}} \sum_{t=1}^T \left(\frac{s}{2d} - \ell_t^{(i)}\right)\right] \\
&= \mathbb{E}\left[\max_{i\in[d]} \frac{1}{\sqrt{T}} \sum_{t=1}^T X_t^{(i)}\right],
\end{aligned}$$

where $t \geqslant 1$, we have defined the random vector X_t by $X_t^{(i)} = s/2d - \ell_t^{(i)}$ for all $i \in [d]$. For $t \geqslant 1$, the X_t are i.i.d. zero-mean random vectors with values in $[-1,1]^d$. We can therefore apply the comparison Lemma 8 to get:

$$\liminf_{T\to+\infty} \mathbb{E}\left[\frac{R_T}{\sqrt{T}}\right] = \liminf_{T\to+\infty} \mathbb{E}\left[\max_{i\in[d]} \frac{1}{\sqrt{T}} \sum_{t=1}^T X_t^{(i)}\right] \geqslant \mathbb{E}\left[\max_{i\in[d]} Z^{(i)}\right] \ ,$$

where $Z \sim \mathcal{N}(0, \Sigma)$ with $\Sigma = (\mathrm{cov}(X_1^{(i)}, X_1^{(j)}))_{i,j}$.

We now make appeal to Slepian's lemma, recalled in Proposition 7 below. Therefore, we introduce the Gaussian vector $W \sim \mathcal{N}(0, \tilde{\Sigma})$ where

$$\tilde{\Sigma} = \mathrm{diag}\left(\mathrm{Var}\, X_1^{(1)}, \dots, \mathrm{Var}\, X_1^{(1)}\right).$$

As a consequence, the first two hypotheses of Proposition 7 follow from the definitions of Z and W. Let $i \neq j$, then

$$\mathbb{E}\left[Z^{(i)} Z^{(j)}\right] = \mathrm{cov}(Z^{(i)}, Z^{(j)}) = \mathrm{cov}(\ell_1^{(i)}, \ell_1^{(j)}) = \mathbb{E}\left[\ell_1^{(i)} \ell_1^{(j)}\right] - \mathbb{E}\left[\ell_1^{(i)}\right] \mathbb{E}\left[\ell_1^{(j)}\right].$$

By definition of ℓ_1, $\ell_1^{(i)}\ell_1^{(j)} = 1$ if and only if $\ell_1^{(i)} = \ell_1^{(j)} = 1$ and $\ell_1^{(i)}\ell_1^{(j)} = 0$ otherwise. Therefore, using the random subset I_1 that appears in the definition of ℓ_1:

$$\begin{aligned}
\mathbb{E}\left[Z^{(i)} Z^{(j)}\right] &= \mathbb{P}\left[\ell_1^{(i)} = \ell_1^{(j)} = 1\right] - \left(\frac{s}{2d}\right)^2 \\
&= \mathbb{P}\left[\ell_1^{(i)} = \ell_1^{(j)} = 1 \,\middle|\, \{i,j\} \subset I_1\right] \mathbb{P}\left[\{i,j\} \subset I_1\right] - \left(\frac{s}{2d}\right)^2 \\
&= \frac{1}{4} \cdot \frac{\binom{d-2}{s-2}}{\binom{d}{s}} - \left(\frac{s}{2d}\right)^2 \\
&= \frac{1}{4}\left(\frac{s(s-1)}{d(d-1)} - \frac{s^2}{d^2}\right) \leqslant 0,
\end{aligned}$$

and since $\mathbb{E}\left[W^{(i)} W^{(i)}\right] = 0$ by independence, the third hypothesis of Slepian's lemma is also satisfied. It yields that, for all $\theta \in \mathbb{R}$:

$$\begin{aligned}
\mathbb{P}\left[\max_{i\in[d]} Z^{(i)} \leqslant \theta\right] &= \mathbb{P}\left[Z^{(1)} \leqslant \theta, \dots, Z^{(d)} \leqslant \theta\right] \\
&\leqslant \mathbb{P}\left[W^{(1)} \leqslant \theta, \dots, W^{(d)} \leqslant \theta\right] = \mathbb{P}\left[\max_{i\in[d]} W^{(i)} \leqslant \theta\right].
\end{aligned}$$

This inequality between two cumulative distribution functions implies the reverse inequality on expectations:

$$\mathbb{E}\left[\max_{i\in[d]} Z^{(i)}\right] \geqslant \mathbb{E}\left[\max_{i\in[d]} W^{(i)}\right] \quad .$$

The components of the Gaussian vector W being independent, and of same variance $\mathrm{Var}\, \ell_1^{(1)}$, we have

$$\mathbb{E}\left[\max_{i\in[d]} W^{(i)}\right] = \kappa_d \sqrt{\mathrm{Var}\, \ell_1^{(1)}} = \kappa_d \sqrt{\frac{s}{2d}\left(1 - \frac{s}{2d}\right)} \geqslant \kappa_d \sqrt{\frac{s}{4d}} \ ,$$

where κ_d is the expectation of the maximum of d Gaussian variables. Combining everything gives:

$$\liminf_{T\to+\infty} \frac{v_T^{\ell,s,d}}{\sqrt{T}} \geqslant \liminf_{T\to+\infty} \mathbb{E}\left[\frac{R_T}{\sqrt{T}}\right] \geqslant \mathbb{E}\left[\max_{i\in[d]} Z^{(i)}\right] \geqslant \mathbb{E}\left[\max_{i\in[d]} W^{(i)}\right] \geqslant \kappa_d \sqrt{\frac{s}{4d}} \ .$$

And for large d, since κ_d is equivalent to $\sqrt{2\log d}$ (see e.g. Galambos, 1978),

$$\liminf_{d\to+\infty}\liminf_{T\to+\infty}\frac{v_T^{\ell,s,d}}{\sqrt{T\frac{s}{d}\log d}}\geqslant\frac{\sqrt{2}}{2}\ .$$

■

Proposition 7 (Slepian (1962)) *Let $Z=(Z^{(1)},\dots,Z^{(d)})$ and $W=(W^{(1)},\dots,W^{(d)})$ be Gaussian random vectors in $\mathbb{R}^d$ satisfying:*

(i) $\mathbb{E}[Z]=\mathbb{E}[W]=0$;

(ii) $\mathbb{E}\left[(Z^{(i)})^2\right]=\mathbb{E}\left[(W^{(i)})^2\right]$ *for* $i\in[d]$;

(iii) $\mathbb{E}\left[Z^{(i)}Z^{(j)}\right]\leqslant\mathbb{E}\left[W^{(i)}W^{(j)}\right]$ *for* $i\neq j\in[d]$.

Then, for all real numbers $\theta_1,\dots,\theta_d$, we have:

$$\mathbb{P}\left[Z^{(1)}\leqslant\theta_1,\dots,Z^{(d)}\leqslant\theta_d\right]\leqslant\mathbb{P}\left[W^{(1)}\leqslant\theta_1,\dots,W^{(d)}\leqslant\theta_d\right]\ .$$

The following lemma is an extension of e.g. (Cesa-Bianchi and Lugosi, 2006, Lemma A.11) to random vectors with correlated components.

Lemma 8 (Comparison lemma) *For $t\geqslant1$, let $(X_t)_{t\geqslant1}$ be i.i.d. zero-mean random vectors in $[-1,1]^d$, Σ be the covariance matrix of X_t and $Z\sim\mathcal{N}(0,\Sigma)$. Then,*

$$\liminf_{T\to+\infty}\mathbb{E}\left[\max_{i\in[d]}\frac{1}{\sqrt{T}}\sum_{t=1}^{T}X_t^{(i)}\right]\geqslant\mathbb{E}\left[\max_{i\in[d]}Z^{(i)}\right].$$

Proof Denote

$$Y_T=\max_{i\in[d]}\frac{1}{\sqrt{T}}\sum_{t=1}^{T}X_t^{(i)}.$$

Let $A\leqslant0$ and consider the function $\phi_A:\mathbb{R}\to\mathbb{R}$ defined by $\phi_A(x)=\max(x,A)$.

$$\begin{aligned}\mathbb{E}[Y_T]&=\mathbb{E}\left[Y_T\cdot\mathbb{1}_{\{Y_T\geqslant A\}}\right]+\mathbb{E}\left[Y_T\cdot\mathbb{1}_{\{Y_T<A\}}\right]\\&=\mathbb{E}\left[\phi_A(Y_T)\cdot\mathbb{1}_{\{Y_T\geqslant A\}}\right]+\mathbb{E}\left[Y_T\cdot\mathbb{1}_{\{Y_T<A\}}\right]\\&=\mathbb{E}\left[\phi_A(Y_T)\right]-\mathbb{E}\left[\phi_A(Y_T)\cdot\mathbb{1}_{\{Y_T<A\}}\right]+\mathbb{E}\left[Y_T\cdot\mathbb{1}_{\{Y_T<A\}}\right]\\&=\mathbb{E}\left[\phi_A(Y_T)\right]-\mathbb{E}\left[(A-Y_T)\cdot\mathbb{1}_{\{A-Y_T>0\}}\right].\end{aligned}$$

Let us estimate the second term. Denote $Z_T = (A - Y_T) \cdot \mathbb{1}_{A-Y_T>0}$. We clearly have, for all $u > 0$, $\mathbb{P}[Z_T > u] = \mathbb{P}[A - Y_T > u]$. And Z_T being nonnegative, we can write:

$$\begin{aligned}
0 \leqslant \mathbb{E}\left[(A - Y_T) \cdot \mathbb{1}_{\{A-Y_T\}>0}\right] &= \mathbb{E}[Z_T] \\
&= \int_0^{+\infty} \mathbb{P}[Z_T > u] \, \mathrm{d}u \\
&= \int_0^{+\infty} \mathbb{P}[A - Y_T > u] \, \mathrm{d}u \\
&= \int_{-A}^{+\infty} \mathbb{P}[Y_T < -u] \, \mathrm{d}u \\
&= \int_{-A}^{+\infty} \mathbb{P}\left[\max_{i\in[d]} \frac{1}{\sqrt{T}} \sum_{t=1}^{T} X_t^{(i)} < u\right] \mathrm{d}u \\
&\leqslant \int_{-A}^{+\infty} \mathbb{P}\left[\sum_{t=1}^{T} X_t^{(1)} < u\sqrt{T}\right] \mathrm{d}u.
\end{aligned}$$

For $u > 0$, using Hoeffding's inequality together with the assumptions $\mathbb{E}\left[X_t^{(1)}\right] = 0$ and $X_t^{(1)} \in [-1, 1]$, we can bound the last integrand:

$$\mathbb{P}\left[\sum_{t=1}^{T} X_t^{(1)} < u\sqrt{T}\right] \leqslant e^{-u^2/2},$$

Which gives:

$$0 \leqslant \mathbb{E}\left[(A - Y_T) \cdot \mathbb{1}_{\{A-Y_T\}>0}\right] \leqslant \int_{-A}^{+\infty} e^{-u^2/2} \, \mathrm{d}u \leqslant \frac{e^{-A^2/2}}{-A}.$$

Therefore:

$$\mathbb{E}[Y_T] \geqslant \mathbb{E}[\phi_A(Y_T)] + \frac{e^{-A^2/2}}{A}.$$

We now take the liminf on both sides as $t \to +\infty$. The left-hand side is the quantity that appears in the statement. We now focus on the second term of the right-hand side. The central limit theorem gives the following convergence in distribution:

$$\frac{1}{\sqrt{T}} \sum_{t=1}^{T} X_t \xrightarrow[T\to+\infty]{\mathcal{L}} X.$$

The application $(x^{(1)}, \ldots, x^{(d)}) \longmapsto \max_{i\in[d]} x^{(i)}$ being continuous, we can apply the continuous mapping theorem:

$$Y_T = \max_{i\in[d]} \frac{1}{\sqrt{T}} \sum_{t=1}^{T} X_t^{(i)} \xrightarrow[n\to+\infty]{\mathcal{L}} \max_{i\in[d]} X^{(i)}.$$

This convergence in distribution allows the use of the portmanteau lemma: ϕ_A being lower semi-continuous and bounded from below, we have:

$$\liminf_{t\to+\infty} \mathbb{E}\left[\phi_A(Y_T)\right] \geqslant \mathbb{E}\left[\phi_A\left(\max_{i\in[d]} X^{(i)}\right)\right],$$

and thus:

$$\liminf_{t\to+\infty} \mathbb{E}\left[Y_T\right] \geqslant \mathbb{E}\left[\phi_A\left(\max_{i\in[d]} X^{(i)}\right)\right] + \frac{e^{-A^2/2}}{A}.$$

We would now like to take the limit as $A \to -\infty$. By definition of ϕ_A, for $A \leqslant 0$, we have the following domination:

$$\left|\phi_A\left(\max_{i\in[d]} X^{(i)}\right)\right| \leqslant \left|\max_{i\in[d]} X^{(i)}\right| \leqslant \max_{i\in[d]} \left|X^{(i)}\right| \leqslant \sum_{i=1}^{d} \left|X^{(i)}\right|,$$

where each $X^{(i)}$ is L^1 since it is a normal random variable. We can therefore apply the dominated convergence theorem as $A \to -\infty$:

$$\mathbb{E}\left[\phi_A\left(\max_{i\in[d]} X^{(i)}\right)\right] \xrightarrow[A\to-\infty]{} \mathbb{E}\left[\max_{i\in[d]} X^{(i)}\right],$$

and eventually, we get the stated result:

$$\liminf_{t\to+\infty} \mathbb{E}\left[Y_T\right] \geqslant \mathbb{E}\left[\max_{i\in[d]} X^{(i)}\right].$$

■

4. When the Sparsity Level s is Unknown

We no longer assume in this section that the decision maker have the knowledge of the sparsity level s. We modify our algorithms to be adaptive over the sparsity level of the observed gain/loss vectors. The algorithms are proved to essentially achieve the same regret bounds as in the case where s is known. The constructions follow the same ideas behind the classical doubling trick. However, the latter cannot be directly applied here: the usual doubling trick involves time intervals whose lengths are always the same, whereas we here need to make the lengths on the sparsity levels of the payoff vectors.

Specifically, let $T \geqslant 1$ be the number of rounds and s^* the highest sparsity level of the gain/loss vectors chosen by Nature up to time T. In the following, we construct algorithms which achieve regret bounds of order $\sqrt{T \log s^*}$ and $\sqrt{T \frac{s^* \log d}{d}}$ for gains and losses respectively, without prior knowledge of s^*.

4.1 For Losses

Let $(\ell_t)_{t\geqslant 1}$ be the sequence of loss vectors in $[0,1]^d$ chosen by Nature, and $T \geqslant 1$ the number of rounds. We denote $s^* = \max_{1\leqslant t\leqslant T} \|\ell_t\|_0$ the higher sparsity level of the loss vectors up

to time T. The goal is to construct an algorithm which achieves a regret bound of order $\sqrt{\frac{Ts^* \log d}{d}}$ without any prior knowledge about the sparsity level of the loss vectors.

The time instances $\{1, \dots, T\}$ will be divided into several time intervals. On each of those, the previous loss vectors will be left aside, and a new instance of the Exponential Weight Algorithm with a specific parameter will be run. Let $M = \lceil \log_2 s^* \rceil$ and $\tau(0) = 0$. Then, for $1 \leqslant m < M$ we define

$$\tau(m) = \min \{1 \leqslant t \leqslant T \,|\, \|\ell_t\|_0 > 2^m\} \quad \text{and} \quad \tau(M) = T.$$

In other words, $\tau(m)$ is the first time instance at which the sparsity level of the loss vector exceeds 2^m. $(\tau(m))_{1 \leqslant m \leqslant M}$ is thus a nondecreasing sequence. We can then define the time intervals $I(m)$ as follows. For $1 \leqslant m \leqslant M$, let

$$I(m) = \begin{cases} \{\tau(m-1)+1, \dots, \tau(m)\} & \text{if } \tau(m-1) < \tau(m) \\ \varnothing & \text{if } \tau(m-1) = \tau(m). \end{cases}.$$

The sets $(I(m))_{1 \leqslant m \leqslant M}$ clearly form a partition of $\{1, \dots, T\}$ (some of the intervals may be empty). For $1 \leqslant t \leqslant T$, we define $m_t = \min \{m \geqslant 1 \,|\, \tau(m) \geqslant t\}$ which implies $t \in I(m_t)$. In other words, m_t is the index of the only interval t belongs to.

Let $C > 0$ be a constant to be chosen later and for $1 \leqslant m \leqslant M$, let

$$\eta(m) = \log \left(1 + C \sqrt{\frac{d \log d}{2^m T}}\right)$$

be the parameter of the Exponential Weight Algorithm to be used on interval $I(m)$. In this section, h will be entropic regularizer on the simplex $h(x) = \sum_{i=1}^d x^{(i)} \log x^{(i)}$, so that $y \longmapsto \nabla h^*(y)$ is the *logit map* used in the Exponential Weight Algorithm. We can then define the played actions to be:

$$x_t = \nabla h^* \left(-\eta(m_t) \sum_{\substack{t' < t \\ t' \in I(m_t)}} \ell_{t'} \right), \quad t = 1, \dots, T.$$

Theorem 9 *The above algorithm with $C = 2^{3/4}(\sqrt{2}+1)^{1/2}$ guarantees*

$$R_T \leqslant 4\sqrt{\frac{Ts^* \log d}{d}} + \frac{\lceil \log s^* \rceil \log d}{2} + 5s^* \sqrt{\frac{\log d}{dT}}.$$

Proof Let $1 \leqslant m \leqslant M$. On time interval $I(m)$, the Exponential Weight Algorithm is run with parameter $\eta(m)$ against loss vectors in $[0,1]^d$. Therefore, the following regret bound

Algorithm 1: For losses in full information without prior knowledge about sparsity

input: $T \geqslant 1$, $d \geqslant 1$ integers, and $C > 0$.
$\eta \leftarrow \log(1 + C\sqrt{d \log d / 2T})$;
$m \leftarrow 1$;
for $i \leftarrow 1$ **to** d **do**
  $w^{(i)} \leftarrow 1/d$;
end
for $t \leftarrow 1$ **to** T **do**
  draw and play decision i with probability $w^{(i)} / \sum_{j=1}^{d} w^{(j)}$;
  observe loss vector ℓ_t;
  if $\|\ell_t\|_0 \leqslant 2^m$ **then**
    for $i \leftarrow 1$ **to** d **do**
      $w^{(i)} \leftarrow w^{(i)} e^{-\eta \ell_t^{(i)}}$;
    end
  else
    $m \leftarrow \lceil \log_2 \|\ell_t\|_0 \rceil$;
    $\eta \leftarrow \log(1 + C\sqrt{d \log d / 2^m T})$;
    for $i \leftarrow 1$ **to** d **do**
      $w^{(i)} \leftarrow 1/d$;
    end
  end
end

derived in the proof of Theorem 4 applies:

$$\begin{aligned}
R(m) &:= \sum_{t\in I(m)} \langle \ell_t, x_t\rangle - \min_{i\in[d]} \sum_{t\in I(m)} \ell_t^{(i)} \\
&\leqslant \frac{\log d}{1-e^{-\eta(m)}} + \frac{e^{\eta(m)}-1}{2} \min_{i\in[d]} \sum_{t\in I(m)} \ell_t^{(i)} \\
&= \frac{1}{C}\sqrt{\frac{2^m T\log d}{d}} + \frac{\log d}{C} + \frac{C}{2}\sqrt{\frac{d\log d}{2^m T}} \cdot \min_{i\in[d]} \sum_{t\in I(m)} \ell_t^{(i)}.
\end{aligned}$$

We now bound the "best loss" quantity from above, using the fact that ℓ_t is 2^m-sparse for $t \in I(m) \setminus \{\tau(m)\}$ and that $\ell_{\tau(m)}$ is s^*-sparse:

$$\begin{aligned}
\sum_{i=1}^d \sum_{t\in I(m)} \ell_t^{(i)} = \sum_{t\in I(m)} \sum_{i=1}^d \ell_t^{(i)} &= \sum_{\substack{t<\tau(m)\\ t\in I(m)}} \sum_{i=1}^d \ell_t^{(i)} + \sum_{i=1}^d \ell_{\tau(m)}^{(i)} \\
&\leqslant (\tau(m)-\tau(m-1))2^m + s^*,
\end{aligned}$$

which implies:

$$\min_{i\in[d]} \sum_{t\in I(m)} \ell_t^{(i)} \leqslant \frac{(\tau(m)-\tau(m-1))2^m + s^*}{d}.$$

Therefore, the regret on interval $I(m)$, which we will denote $R(m)$, is bounded by:

$$\begin{aligned}
R(m) &:= \sum_{t\in I(m)} \langle \ell_t, x_t\rangle - \min_{i\in[d]} \sum_{t\in I(m)} \ell_t^{(i)} \\
&\leqslant \frac{1}{C}\sqrt{\frac{2^m T\log d}{d}} + \frac{\log d}{C} + \frac{C}{2}\sqrt{\frac{2^m \log d}{dT}}\,(\tau(m)-\tau(m-1)) + \frac{C}{2}\sqrt{\frac{\log d}{2^m dT}}\,s^* \\
&\leqslant \frac{1}{C}\sqrt{\frac{2^m T\log d}{d}} + \frac{\log d}{C} + \frac{C}{2}\sqrt{\frac{2s^* \log d}{dT}}\,(\tau(m)-\tau(m-1)) + \frac{C}{2}\sqrt{\frac{\log d}{2^m dT}}\,s^*,
\end{aligned}$$

where we used $2^m \leqslant 2^M = 2^{\lceil \log_2 s^*\rceil} \leqslant 2^{\log_2 s^*+1} = 2s^*$ for the third term of the last line.

We now turn the whole regret R_T from 1 to T. Since $(I(m))_{1\leqslant m\leqslant M}$ is a partition of $\{1,\dots,T\}$, we obtain

$$\begin{aligned}
R_T &= \sum_{t=1}^T \langle \ell_t, x_t\rangle - \min_{i\in[d]} \sum_{t=1}^T \ell_t^{(i)} \\
&\leqslant \sum_{m=1}^M \sum_{t\in I(m)} \langle \ell_t, x_t\rangle - \sum_{m=1}^M \min_{i\in[d]} \sum_{t\in I(m)} \ell_t^{(i)} \\
&= \sum_{m=1}^M R(m) \\
&\leqslant \frac{1}{C}\sqrt{\frac{T\log d}{d}} \sum_{m=1}^M \sqrt{2^m} + C\sqrt{\frac{s^* T\log d}{2d}} + \frac{M\log d}{C} + \frac{C}{2}\sqrt{\frac{\log d}{dT}}\,s^* \sum_{m=1}^M 2^{-m/2}.
\end{aligned}$$

The sum in the first term above can be bounded as follows

$$\sum_{m=1}^{M}\sqrt{2^m} \leqslant \sum_{m=1}^{M}\sqrt{2}^m = \sqrt{2}\frac{\sqrt{2}^M-1}{\sqrt{2}-1} \leqslant \sqrt{2}\frac{\sqrt{2^{\log_2 s^*+1}}}{\sqrt{2}-1} = 2\frac{\sqrt{s^*}}{\sqrt{2}-1} = 2(\sqrt{2}+1)\sqrt{s^*},$$

whereas the sum in the last term can be bounded by $\sqrt{2}+1$. Eventually, the choice $C = 2^{3/4}(\sqrt{2}+1)^{1/2}$ gives:

$$R_T \leqslant 2^{5/4}(\sqrt{2}+1)^{1/2}\sqrt{\frac{Ts^*\log d}{d}} + \frac{\lceil \log s^* \rceil \log d}{2^{3/4}(\sqrt{2}+1)^{1/2}} + 2^{1/4}(\sqrt{2}+1)^{3/2}s^*\sqrt{\frac{\log d}{dT}},$$

and the statement follows from numerical computation of the constant factors.

■

4.2 For Gains

The construction is similar to the case of losses, but the time intervals are slightly different. Let $(g_t)_{t\geqslant 1}$ be the sequence of gain vectors in $[0,1]^d$ chosen by Nature. We assume $s^* \geqslant 2$ and set $M = \lceil \log_2 \log_2 s^* \rceil$ and $\tau(0) = 0$. For $1 \leqslant m \leqslant M$ we define

$$\tau(m) = \min\left\{1 \leqslant t \leqslant T \,\middle|\, \|g_t\|_0 > 2^{2^m}\right\} \quad \text{and} \quad \tau(M) = T.$$

We now define the time intervals $I(m)$. For $1 \leqslant m \leqslant M$,

$$I(m) = \begin{cases} \{\tau(m-1)+1, \ldots, \tau(m)\} & \text{if } \tau(m-1) < \tau(m) \\ \varnothing & \text{if } \tau(m-1) = \tau(m). \end{cases}$$

Therefore, for $1 \leqslant m \leqslant M$ and $t < \tau(m)$, we have $\|g_t\|_0 \leqslant 2^{2^m}$. For $1 \leqslant t \leqslant T$, we denote $m_t = \min\{m \geqslant 1 \,|\, \tau(m) \geqslant t\}$. Let $C > 0$ be a constant to be chosen later and for $1 \leqslant m \leqslant M$, let

$$p(m) = 1 + \frac{1}{\log 2 \cdot 2^{m+1} - 1},$$
$$q(m) = \left(1 - \frac{1}{p(m)}\right)^{-1},$$
$$\eta(m) = C\sqrt{\frac{p(m)-1}{T2^{2^{m+1}/q(m)}}}.$$

As in Section 2.2, for $p \in (1,2]$, we denote h_p the regularizer on the simplex defined by:

$$h_p(x) = \begin{cases} \frac{1}{2}\|x\|_p^2 & \text{if } x \in \Delta_d \\ +\infty & \text{otherwise.} \end{cases}$$

The algorithm is then defined by:

$$x_t = \nabla h^*_{p(m_t)}\left(\eta(m_t) \sum_{\substack{t'<t \\ t' \in I(m_t)}} g_{t'}\right), \quad t = 1, \ldots, T.$$

Algorithm 2: For gains in full information without prior knowledge about sparsity.

input: $T \geqslant 1$, $d \geqslant 1$ integers, and $C > 0$.
$p \leftarrow 1 + (4 \log 2 - 1)^{-1}$;
$q \leftarrow (1 - 1/p)^{-1}$;
$\eta \leftarrow C\sqrt{(p-1)/2^{4/q}T}$;
$m \leftarrow 1$;
$y \leftarrow (0, \dots, 0) \in \mathbb{R}^d$;
for $t \leftarrow 1$ **to** T **do**
  draw and play decision $i \sim \nabla h_p^*(\eta \cdot y)$;
  observe gain vector g_t;
  if $\|g_t\|_0 \leqslant 2^{2^m}$ **then**
    $y \leftarrow y + g_t$;
  else
    $m \leftarrow \lceil \log_2 \log_2 \|g_t\|_0 \rceil$;
    $p \leftarrow 1 + (\log 2 \cdot 2^{m+1} - 1)^{-1}$;
    $q \leftarrow (1 - 1/p)^{-1}$;
    $\eta \leftarrow C\sqrt{(p-1)/2^{2^{m+1}/q}T}$;
    $y \leftarrow (0, \dots, 0)$;
  end
end

Theorem 10 *The above algorithm with* $C = (e\sqrt{2}(\sqrt{2}+1))^{1/2}$ *guarantees*

$$R_T \leqslant 7\sqrt{T \log s^*} + \frac{4s^*}{\sqrt{T}}.$$

Proof Let $1 \leqslant m \leqslant M$. On time interval $I(m)$, the algorithm boils down to an Online Mirror Descent algorithm with regularizer $h_{p(m)}$ and parameter $\eta(m)$. Therefore, using Theorem 1, the regret on this interval is bounded as follows.

$$\begin{aligned} R(m) &:= \max_{i \in [d]} \sum_{t \in I(m)} g_t^{(i)} - \sum_{t \in I(m)} \langle g_t, x_t \rangle \\ &\leqslant \frac{1}{2\eta(m)} + \frac{\eta(m)}{2(p(m)-1)} \sum_{t \in I(m)} \|g_t\|_{q(m)}^2 \\ &= \frac{1}{2\eta(m)} + \frac{\eta(m)}{2(p(m)-1)} \left(\sum_{\substack{t \in I(m) \\ t < \tau(m)}} \|g_t\|_{q(m)}^2 + \left\|g_{\tau(m)}\right\|_{q(m)}^2 \right). \end{aligned}$$

g_t being 2^{2^m}-sparse for $t < \tau(m)$ and $g_{\tau(m)}$ being s^*-sparse, the $q(m)$-norms can therefore bounded from above as follows:

$$\|g_t\|_{q(m)}^2 \leqslant 2^{2^{m+1}/q(m)} \quad \text{and} \quad \left\|g_{\tau(m)}\right\|_{q(m)}^2 \leqslant (s^*)^{2/q(m)}.$$

The bound on $R(m)$ then becomes

$$\begin{aligned}
R(m) &\leqslant \frac{1}{2\eta(m)} + \frac{\eta(m)(\tau(m)-\tau(m-1))2^{2^{m+1}/q(m)}}{2(p(m)-1)} + \frac{\eta(m)(s^*)^{2/q(m)}}{2(p(m)-1)} \\
&= \frac{1}{2C}\sqrt{Te(\log 2\cdot 2^{m+1}-1)} + \frac{C}{2}\sqrt{\frac{e(\log 2\cdot 2^{m+1}-1)}{T}}(\tau(m)-\tau(m-1)) \\
&\qquad + \frac{C}{2}(s^*)^{1/(\log 2\cdot 2^m)}\sqrt{\frac{e(\log 2\cdot 2^{m+1}-1)}{T}} \\
&\leqslant \frac{1}{2C}\sqrt{Te\log 2\cdot 2^{m+1}} + C\sqrt{\frac{e\log s^*}{T}}\,(\tau(m)-\tau(m-1)) \\
&\qquad + \frac{C}{2}s^*\sqrt{\frac{e\log 2\cdot 2^{m+1}}{T}},
\end{aligned}$$

where for the second term of the last expression we used:

$$\begin{aligned}
\log 2\cdot 2^{m+1}-1 &\leqslant \log 2\cdot 2^{M+1} = \log 2\cdot\exp\left(\log 2\left(\lceil \log_2\log_2 s^*\rceil + 1\right)\right) \\
&\leqslant \log 2\cdot\exp\left(\log 2\left(\log_2\log_2 s^* + 2\right)\right) \\
&= \log 2\cdot e^{2\log 2}\exp\left(\log 2\cdot\log_2\log_2 s^*\right) \\
&= 4\log 2\cdot\exp\left(\log\log_2 s^*\right) \\
&= 4\log 2\cdot\log_2 s^* \\
&= 4\log s^*.
\end{aligned}$$

Then, the whole regret R_T is bounded by the sum of the regrets on each interval:

$$\begin{aligned}
R_T &\leqslant \sum_{m=1}^{M} R(m) \leqslant \frac{1}{2C}\sqrt{Te\log 2}\sum_{m=1}^{M}\sqrt{2^{m+1}} + C\sqrt{\frac{e\log s^*}{T}}\sum_{m=1}^{M}(\tau(m)-\tau(m-1)) \\
&\qquad + \frac{Cs^*}{2}\sqrt{\frac{e\log 2}{T}}\sum_{m=1}^{M}2^{-(m+1)/2}.
\end{aligned}$$

The second sum is equal to T and the third sum is bounded from above by $(\sqrt{2}+1)/\sqrt{2}$. Let us bound the first sum from above:

$$\begin{aligned}
\sqrt{\log 2}\sum_{m=1}^{M}\sqrt{2^{m+1}} &= 2\sqrt{\log 2}\frac{2^{M/2}-1}{\sqrt{2}-1} \\
&\leqslant 2(\sqrt{2}+1)\sqrt{\log 2}\cdot\exp\left(\frac{\log 2}{2}\left(\log_2\log_2 s^*+1\right)\right) \\
&= 2(\sqrt{2}+1)\sqrt{\log 2}\cdot\sqrt{2e^{\log\log_2 s^*}} \\
&= 2\sqrt{2}(\sqrt{2}+1)\sqrt{\log 2\log_2 s^*} \\
&= 2\sqrt{2}(\sqrt{2}+1)\sqrt{\log s^*}.
\end{aligned}$$

Therefore,

$$R_T \leqslant \frac{\sqrt{2}(\sqrt{2}+1)}{C}\sqrt{Te\log s^*} + C\sqrt{Te\log s^*} + \frac{C(\sqrt{2}+1)s^*}{2}\sqrt{\frac{e\log 2}{2T}}.$$

Choosing $C = (e\sqrt{2}(\sqrt{2}+1))^{1/2}$ balances the first two term and gives:

$$\begin{aligned} R_T &\leqslant 2(e\sqrt{2}(\sqrt{2}+1))^{1/2}\sqrt{T\log s^*} + 2^{-5/4}e\sqrt{\log 2}(\sqrt{2}+1)^{3/2}\frac{s^*}{\sqrt{T}} \\ &\leqslant 7\sqrt{T\log s^*} + \frac{4s^*}{\sqrt{T}}. \end{aligned}$$

■

5. The Bandit Setting

We now turn to the bandit framework—see for instance (Bubeck and Cesa-Bianchi, 2012) for a recent survey. Recall that the minimax regret (Audibert and Bubeck, 2009) in the basic bandit framework (without sparsity) is of order $\sqrt{Td}$. In the case of losses, we manage to take advantage of the sparsity assumption and obtain in Theorem 11 an upper bound of order $\sqrt{Ts\log\frac{d}{s}}$, and a lower bound of order $\sqrt{Ts}$ in Theorem 13. This establishes the order of the minimax regret up to a logarithmic factor. In the case of gains, the argument from Section 2.3 can be adapted to get a lower bound of order $\sqrt{sT}$; but the upper bound techniques from losses do not seem to work; this difficulty is discussed below in Remark 12.

For simplicity, we shall assume that the sequence of outcome vectors $(\omega_t)_{t\geqslant 1}$ is chosen before stage 1 by the environment, which is called *oblivious* in that case. We refer to (Bubeck and Cesa-Bianchi, 2012, Section 3) for a detailed discussion on the difference between oblivious and non-oblivious opponent, and between regret and pseudo-regret.

As before, at stage t, the decision maker chooses $x_t \in \Delta_d$ and draws decision $d_t \in [d]$ according to x_t. The main difference with the previous framework is that the decision maker only observes his own outcome $\omega_t^{d_t}$ before choosing the next decision d_{t+1}.

5.1 Upper Bounds on the Regret with Sparse Losses

We shall focus in this section on s-sparse losses. The algorithm we consider belongs to the family of Greedy Online Mirror Descent. We follow (Bubeck and Cesa-Bianchi, 2012, Section 5) and refer to it for the detailed and rigorous construction. Let $F_q(x)$ be the Legendre function associated with the potential $\psi(x) = (-x)^{-q}$ $(q > 1)$, i.e.,

$$F_q(x) = -\frac{q}{q-1}\sum_{i=1}^{d}(x^i)^{1-1/q}.$$

The algorithm, which depends on a parameter $\eta > 0$ to be fixed later, is defined as follows. Set $x_1 = (\frac{1}{d},\dots,\frac{1}{d}) \in \Delta_d$. For all $t \geqslant 1$, we define the estimator $\hat{\ell}_t$ of ℓ_t as usual:

$$\hat{\ell}_t^{(i)} = \mathbb{1}_{\{d_t=i\}}\frac{\ell_t^{(i)}}{x_t^{(i)}}, \quad i \in [d],$$

which is then used to compute

$$z_{t+1} = \nabla F_q^*(\nabla F_q(x_t) - \eta\hat{\ell}_t) \quad \text{and} \quad x_{t+1} = \operatorname*{arg\,min}_{x\in\Delta_d} D_{F_q}(x, z_{t+1}),$$

where $D_{F_q} : \bar{\mathcal{D}} \times \mathcal{D} \to \mathbb{R}$ is the Bregman divergence associated with F_q:

$$D_{F_q}(x', x) = F_q(x') - F_q(x) - \left\langle \nabla F_q(x), x' - x \right\rangle.$$

Theorem 11 *Let $\eta > 0$ and $q > 1$. For any sequence of s-sparse loss vectors, the above strategy with parameter η guarantees, for $T \geqslant 1$:*

$$R_T \leqslant q \left(\frac{d^{1/q}}{\eta(q-1)} + \frac{\eta T s^{1-1/q}}{2} \right).$$

In particular, if $d/s \geqslant e^2$, the choices

$$\eta = \sqrt{\frac{2d^{1/q}}{(q-1)Ts^{1-1/q}}} \quad \text{and} \quad q = \log(d/s)$$

yield the following regret bound:

$$R_T \leqslant 2\sqrt{e}\sqrt{Ts \log \frac{d}{s}}.$$

Proof The general regret bound for Greedy Online Mirror Descent (Bubeck and Cesa-Bianchi, 2012, Theorem 5.10) gives:

$$R_T \leqslant \frac{\max_{x \in \Delta_d} F(x) - F(x_1)}{\eta} + \frac{\eta}{2} \sum_{t=1}^{T} \sum_{i=1}^{d} \mathbb{E}\left[\frac{(\hat{\ell}_t^{(i)})^2}{(\psi^{-1})'(x_t^{(i)})} \right],$$

with $(\psi^{-1})'(x) = (q\, x^{1+1/q})^{-1}$. Let us bound the first term.

$$\frac{1}{\eta} \max_{x \in \Delta_d} F_q(x) - F_q(x_1) \leqslant \frac{1}{\eta} \frac{q}{q-1} \left(0 + d\,(1/d)^{1-1/q} \right) = \frac{q d^{1/q}}{\eta(q-1)}.$$

We turn to the second term. Let $1 \leqslant t \leqslant T$.

$$\begin{aligned}
\sum_{i=1}^{d} \mathbb{E}\left[\frac{(\hat{\ell}_t^{(i)})^2}{(\psi^{-1})'(x_t^{(i)})} \right] &= q \sum_{i=1}^{d} \mathbb{E}\left[(\hat{\ell}_t^{(i)})^2 (x_t^{(i)})^{1+1/q} \right] \\
&= q \sum_{i=1}^{d} \mathbb{E}\left[\mathbb{E}\left[\mathbb{1}_{\{d_t = i\}} \frac{(\ell_t^{(i)})^2}{(x_t^i)^2} (x_t^i)^{1+1/q} \middle| x_t \right] \right] \\
&= q \sum_{i=1}^{d} \mathbb{E}\left[(\ell_t^{(i)})^2 (x_k^{(i)})^{1/q} \right] \\
&= q\, \mathbb{E}\left[\sum_{s \text{ terms}} (\ell_t^{(i)})^2 (x_t^{(i)})^{1/q} \right] \\
&\leqslant qs(1/s)^{1/q} = qs^{1-1/q},
\end{aligned}$$

where we used the assumption that ℓ_t has at most s nonzero components, and the fact that $x_t \in \Delta_d$. The first regret bound is thus proven. By choosing $\eta = \sqrt{\frac{2s^{1-1/q}}{(q-1)Td^{1/q}}}$, we balance both terms and get:

$$R_T \leqslant 2q\sqrt{\frac{Td^{1/q}s^{1-1/q}}{2(q-1)}} = \sqrt{2q}\sqrt{Ts\left(\frac{d}{s}\right)^{1/q}\left(\frac{q}{q-1}\right)}\ .$$

If $d/s \geqslant e^2$ and $q = \log(d/s)$, then $q/(q-1) \leqslant 2$ and finally:

$$R_T \leqslant 2\sqrt{e}\sqrt{Ts\log\frac{d}{s}}.$$

■

Remark 12 *The previous analysis cannot be carried in the case of gains because the bound from (Bubeck and Cesa-Bianchi, 2012, Theorem 5.10) that we use above only holds for nonnegative losses (and its proof strongly relies on this assumption). We are unaware of techniques which could provide a similar bound in the case of nonnegative gains.*

5.2 Matching Lower Bound

The following theorem establishes that the bound from Theorem 11 is optimal up to a logarithmic factor. We denote $\hat{v}_T^{\ell,s,d}$ the minimax regret in the bandit setting with losses.

Theorem 13 *For all $d \geqslant 2$, $s \in [d]$ and $T \geqslant d^2/4s$, the following lower bound holds:*

$$\hat{v}_T^{\ell,s,d} \geqslant \frac{1}{32}\sqrt{Ts}.$$

The intuition behind the proof is the following. Let us consider the case where $s = 1$ and assume that ℓ_t is a unit vector $e_{i_t} = (\mathbb{1}\{j = i_t\})_j$ where $\mathbb{P}(i_t = i) \simeq (1+\varepsilon)/d$ for all $i \in [d]$, except one fixed coordinate i^* where $\mathbb{P}(i_t = i^*) \simeq 1/d - \varepsilon$.

Since $1/d$ goes to 0 as d increases, the Kullback-Leibler divergence between two Bernoulli of parameters $(1+\varepsilon)/d$ and $1/d - \varepsilon$ is of order $d\varepsilon^2$. As a consequence, it would require approximately $1/d\varepsilon^2$ samples to distinguish between the two. The standard argument that one of the coordinates has not been chosen more than T/d times, yields that one should take $1/d\varepsilon^2 \simeq T/d$ so that the regret is of order $T\varepsilon$. This provides a lower bound of order $\sqrt{T}$. Similar arguments with $s > 1$ give a lower bound of order $\sqrt{sT}$.

We emphasize that one cannot simply assume that the s components with positive losses are chosen at the beginning once for all, and apply standard lower bound techniques. Indeed, with this additional information, the decision maker just has to choose, at each stage, a decision associated with a zero loss. His regret would then be uniformly bounded (or even possibly equal to zero).

5.3 Proof of Theorem 13

Let $d \geqslant 1$, $1 \leqslant s \leqslant d$, $T \geqslant 1$, and $\varepsilon \in (0, s/2d)$. Denote $\mathfrak{P}_s([d])$ the set of subsets of $[d]$ of cardinality s, δ_{ij} the Kronecker symbol, and $B(1,p)$ the Bernoulli distribution of parameter $p \in [0,1]$. If P, Q are two probability distributions on the same set, $D(P \,\|\, Q)$ will denote the relative entropy of P and Q.

5.3.1 Random s-Sparse Loss Vectors ℓ_t and ℓ'_t

For $t \geqslant 1$, define the random s-sparse loss vectors $(\ell_t)_{t\geqslant 1}$ as follows. Draw Z uniformly from $[d]$. We will denote $\mathbb{P}_i[\,\cdot\,] = \mathbb{P}[\,\cdot \mid Z = i]$ and $\mathbb{E}_i[\,\cdot\,] = \mathbb{E}[\,\cdot \mid Z = i]$. Knowing $Z = i$, the random vectors ℓ_t are i.i.d and defined as follows. Draw I_t uniformly from $\mathfrak{P}_s([d])$. If $j \in I_t$, define $\ell_t^{(j)}$ such that:

$$\mathbb{P}_i\left[\ell_t^{(j)} = 1\right] = 1 - \mathbb{P}_i\left[\ell_t^{(j)} = 0\right] = \frac{1}{2} - \frac{\varepsilon d}{s}\delta_{ij}.$$

If $j \notin I_t$, set $\ell_t^{(j)} = 0$. Therefore, one can check that for each component $j \in [d]$ and all $t \geqslant 1$,

$$\mathbb{E}_i\left[\ell_t^{(j)}\right] = \frac{s}{2d} - \varepsilon\delta_{ij}.$$

For $t \geqslant 1$, define the i.i.d. random s-sparse loss vectors $(\ell'_t)_{t\geqslant 1}$ as follows. Draw I'_t uniformly from $\mathfrak{P}_s([d])$. Then if $j \in I'_t$, set $(\ell'_t)^{(j)}$ such that:

$$\mathbb{P}\left[(\ell'_t)^{(j)} = 1\right] = \mathbb{P}\left[(\ell'_t)^{(j)} = 0\right] = 1/2.$$

And if $j \notin I'_t$, set $(\ell'_t)^{(j)} = 0$. Therefore, one can check that for each component $j \in [d]$ and all $t \geqslant 1$,

$$\mathbb{E}\left[(\ell'_t)^{(j)}\right] = \frac{s}{2d}.$$

By construction, ℓ_t and ℓ'_t are indeed random s-sparse loss vectors.

5.3.2 A Deterministic Strategy σ for the Player

We assume given a deterministic strategy $\sigma = (\sigma_t)_{t\geqslant 1}$ for the player:

$$\sigma_t : ([d] \times [0,1])^{t-1} \longrightarrow [d].$$

Therefore,

$$d_t = \sigma_t(d_1, \omega_1^{(d_1)}, \ldots, d_{t-1}, \omega_{t-1}^{(d_{t-1})}),$$

where d_t denotes the decision chosen by the strategy at stage t and ω_t the outcome vector of stage t. But since d_t is determined by previous decisions and outcomes, we can consider that σ_t only depends on the received outcomes:

$$\sigma_t : [0,1]^{t-1} \longrightarrow [d],$$

$$d_t = \sigma_t(\omega_1^{(d_1)}, \ldots, \omega_{t-1}^{(d_{t-1})}).$$

We define d_t and d'_t to be the (random) decisions played by deterministic strategy σ against the random loss vectors $(\ell_t)_{t\geqslant 1}$ and $(\ell'_t)_{t\geqslant 1}$ respectively:

$$\begin{aligned} d_t &= \sigma_t(\ell_1^{(d_1)}, \dots, \ell_{t-1}^{(d_{t-1})}), \\ d'_t &= \sigma_t((\ell'_1)^{(d'_1)}, \dots, (\ell'_{t-1})^{(d'_{t-1})}). \end{aligned}$$

For $t \geqslant 1$ and $i \in [d]$, define $A_t^{(i)}$ to be the set of sequences of outcomes in $\{0,1\}$ of the first $t-1$ stages for which strategy σ plays decision i at stage t:

$$A_t^{(i)} = \left\{ (u_1, \dots, u_{t-1}) \in \{0,1\}^{t-1} \,\middle|\, \sigma_t(u_1, \dots, u_{t-1}) = i \right\},$$

and $B_t^{(i)}$ the complement:

$$B_t^{(i)} = \{0,1\}^{t-1} \setminus A_t^{(i)}.$$

Note that for a given $t \geqslant 1$, $(A_t^{(i)})_{i\in[d]}$ is a partition of $\{0,1\}^{t-1}$ (with possibly some empty sets).

For $i \in [d]$, define $\tau_i(T)$ (resp. $\tau'_i(T)$) to be the number of times decision i is played by strategy σ against loss vectors $(\ell_t)_{t\geqslant 1}$ (resp. against $(\ell'_t)_{t\geqslant 1}$) between stages 1 and T:

$$\tau_i(T) = \sum_{t=1}^{T} \mathbb{1}_{\{d_t = i\}} \quad \text{and} \quad \tau'_i(T) = \sum_{t=1}^{T} \mathbb{1}_{\{d'_t = i\}}.$$

5.3.3 The Probability Distributions $\mathbb{Q}$ and $\mathbb{Q}_i$ ($i \in [d]$) on Binary Sequences

We consider binary sequences $\vec{u} = (u_1, \dots, u_T) \in \{0,1\}^T$. We define $\mathbb{Q}$ and $\mathbb{Q}_i$ ($i \in [d]$) to be probability distributions on $\{0,1\}^T$ as follows:

$$\begin{aligned} \mathbb{Q}_i\left[\vec{u}\right] &= \mathbb{P}_i\left[\ell_1^{(d_1)} = u_1, \dots, \ell_T^{(d_T)} = u_T\right], \\ \mathbb{Q}\left[\vec{u}\right] &= \mathbb{P}\left[(\ell'_1)^{(d'_1)} = u_1, \dots, (\ell'_T)^{(d'_T)} = u_T\right]. \end{aligned}$$

Fix $(u_1, \dots, u_{t-1}) \in \{0,1\}^t$. The applications

$$u_t \longmapsto \mathbb{Q}\left[u_t \,|\, u_1, \dots, u_{t-1}\right] \quad \text{and} \quad u_t \longmapsto \mathbb{Q}_i\left[u_t \,|\, u_1, \dots, u_{t-1}\right],$$

are probability distributions on $\{0,1\}$, which we now aim at identifying. The first one is Bernoulli of parameter $s/2d$. Indeed,

$$\begin{aligned} \mathbb{Q}\left[1 \,|\, u_1, \dots, u_{t-1}\right] &= \mathbb{P}\left[(\ell'_t)^{(d'_t)} = 1 \,\middle|\, (\ell'_1)^{(d'_1)} = u_1, \dots, (\ell'_{t-1})^{(d'_{t-1})} = u_{t-1}\right] \\ &= \mathbb{P}\left[(\ell'_t)^{(d'_t)} = 1\right] \\ &= \mathbb{P}\left[d'_t \in I'_t\right] \mathbb{P}\left[(\ell'_t)^{(d_t)} = 1 \,\middle|\, d'_t \in I'_t\right] \\ &= \frac{s}{d} \times \frac{1}{2} \\ &= \frac{s}{2d}, \end{aligned}$$

where we used the independence of the random vectors $(\ell'_t)_{t\geqslant 1}$ for the second inequality. We now turn to the second distribution, which depends on $(u_1, \dots, u_{t-1})$. If $(u_1, \dots, u_{t-1}) \in A_t^{(i)}$, it is a Bernoulli of parameter $s/2d - \varepsilon$:

$$\begin{aligned}
\mathbb{Q}_i\left[1 \,|\, u_1, \dots, u_{t-1}\right] &= \mathbb{P}_i\left[\ell_t^{(d_t)} = 1 \,\middle|\, \ell_1^{(d_1)} = u_1, \dots, \ell_{t-1}^{(d_{t-1})} = u_{t-1}\right] \\
&= \mathbb{P}_i\left[\ell_t^{(i)} = 1 \,\middle|\, \ell_1^{(d_1)} = u_1, \dots, \ell_{t-1}^{(d_{t-1})} = u_{t-1}\right] \\
&= \mathbb{P}_i\left[\ell_t^{(i)} = 1\right] \\
&= \mathbb{P}_i\left[i \in I_t\right] \mathbb{P}_i\left[\ell_t^{(i)} = 1 \,\middle|\, i \in I_t\right] \\
&= \frac{s}{d} \times \left(\frac{1}{2} - \frac{\varepsilon d}{s}\right) \\
&= \frac{s}{2d} - \varepsilon.
\end{aligned}$$

where for the third inequality, we used the assumption that the random vectors $(\ell_t)_{t\geqslant 1}$ are independent under $\mathbb{P}_i$, i.e. knowing $Z = i$. On the other hand, if $(u_1, \dots, u_{t-1}) \in B_t^{(i)}$, we can prove similarly that the distribution is a Bernoulli of parameter $s/2d$.

5.3.4 Computation the Relative Entropy of $\mathbb{Q}_i$ and $\mathbb{Q}$

We apply iteratively the chain rule to the relative entropy of $\mathbb{Q}[\vec{u}]$ and $\mathbb{Q}_i[\vec{u}]$. Using the short-hand $\mathbb{D}_i[\,\cdot\,] := D\left(\mathbb{Q}[\,\cdot\,] \,\|\, \mathbb{Q}_i[\,\cdot\,]\right)$,

$$\begin{aligned}
D\left(\mathbb{Q}\left[\vec{u}\right] \| \, \mathbb{Q}_i\left[\vec{u}\right]\right) &= \mathbb{D}_i[\vec{u}] \\
&= \mathbb{D}_i\left[u_1\right] + \mathbb{D}_i\left[u_2, \dots, u_T \,|\, u_1\right] \\
&= \mathbb{D}_i\left[u_1\right] + \mathbb{D}_i\left[u_2 \,|\, u_1\right] + \mathbb{D}_i\left[u_3, \dots, u_T \,|\, u_1, u_2\right] \\
&= \sum_{t=1}^{T} \mathbb{D}_i\left[u_t \,|\, u_1, \dots, u_{t-1}\right].
\end{aligned}$$

We now use the definition of the conditional relative entropy, and make the previously discussed Bernoulli distributions appear. For $1 \leqslant t \leqslant T$,

$$\begin{aligned}
\mathbb{D}_i\left[u_t \,|\, u_1, \dots, u_{t-1}\right] &= \sum_{u_1,\dots,u_{t-1}} \mathbb{Q}\left[u_1, \dots, u_{t-1}\right] \\
&\qquad \times \sum_{u_t} \mathbb{Q}\left[u_t \,|\, u_1, \dots, u_{t-1}\right] \log \frac{\mathbb{Q}\left[u_t \,|\, u_1, \dots, u_{t-1}\right]}{\mathbb{Q}_i\left[u_t \,|\, u_1, \dots, u_{t-1}\right]} \\
&= \frac{1}{2^{t-1}} \sum_{u_1,\dots,u_{t-1}} \sum_{u_t} \mathbb{Q}\left[u_t \,|\, u_1, \dots, u_{t-1}\right] \log \frac{\mathbb{Q}\left[u_t \,|\, u_1, \dots, u_{t-1}\right]}{\mathbb{Q}_i\left[u_t \,|\, u_1, \dots, u_{t-1}\right]} \\
&= \frac{1}{2^{t-1}} \sum_{(u_1,\dots,u_{t-1}) \in A_t^{(i)}} D\left(B\left(1, \frac{s}{2d}\right) \middle\| B\left(1, \frac{s}{2d} - \varepsilon\right)\right) \\
&\qquad + \frac{1}{2^{t-1}} \sum_{(u_1,\dots,u_{t-1}) \in B_t^{(i)}} D\left(B\left(1, \frac{s}{2d}\right) \middle\| B\left(1, \frac{s}{2d}\right)\right) \\
&= \frac{1}{2^{t-1}} \sum_{(u_1,\dots,u_{t-1}) \in A_t^{(i)}} \mathbb{B}\left(\frac{s}{2d}, \varepsilon\right),
\end{aligned}$$

where we used the short-hand $\mathbb{B}\left(\frac{s}{2d}, \varepsilon\right) := D\left(B\left(1, \frac{s}{2d}\right) \| B\left(1, \frac{s}{2d} - \varepsilon\right)\right)$. Eventually:

$$D\left(\mathbb{Q}[\vec{u}] \,\|\, \mathbb{Q}_i[\vec{u}]\right) = \mathbb{B}\left(\frac{s}{2d}, \varepsilon\right) \sum_{t=1}^{T} \frac{\left|A_t^{(i)}\right|}{2^{t-1}}.$$

5.3.5 Upper Bound on $\frac{1}{d}\sum_{i=1}^{d} \mathbb{E}_i\left[\tau_i(T)\right]$ Using Pinsker's Inequality

In this step, we will make use of Pinsker's inequality to make the relative entropy appear.

Proposition 14 (Pinsker's inequality) *Let X be a finite set, and P, Q probability distributions on X. Then,*

$$\frac{1}{2} \sum_{x \in X} |P(x) - Q(x)| \leqslant \sqrt{\frac{1}{2} D\left(P \,\|\, Q\right)}.$$

Immediate consequence:

$$\sum_{\substack{x \in X \\ P(x) > Q(x)}} (P(x) - Q(x)) \leqslant \sqrt{\frac{1}{2} D\left(P \,\|\, Q\right)}.$$

Let $i \in [d]$. If $(u_1, \dots, u_T) \in \{0,1\}^T$ is given, since the decisions d_t and d'_t are determined by the previous losses $\ell_t^{(d_t)}$ and $(\ell'_t)^{(d'_t)}$ respectively, we have in particular:

$$\mathbb{E}_i\left[\tau_i(T) \,\middle|\, \ell_1^{(d_1)} = u_1, \dots, \ell_T^{(d_T)} = u_T\right] = \mathbb{E}\left[\tau'_i(T) \,\middle|\, (\ell'_1)^{(d'_1)} = u_1, \dots, (\ell'_T)^{(d'_T)} = u_T\right].$$

Therefore,

$$\begin{aligned}
\mathbb{E}_i\left[\tau_i(T)\right] - \mathbb{E}\left[\tau_i'(T)\right] &= \sum_{\vec{u}} \mathbb{Q}_i[\vec{u}] \cdot \mathbb{E}_i\left[\tau_i(T) \,\middle|\, \forall t,\ \ell_t^{(d_t)} = u_t\right] \\
&\qquad - \sum_{\vec{u}} \mathbb{Q}[\vec{u}] \cdot \mathbb{E}\left[\tau_i'(T) \,\middle|\, \forall t,\ (\ell_t')^{d_t'} = u_t\right] \\
&= \sum_{\vec{u}} \left(\mathbb{Q}_i[\vec{u}] - \mathbb{Q}[\vec{u}]\right) \mathbb{E}_i\left[\tau_i(T) \,\middle|\, \forall t,\ \ell_t^{(d_t)} = u_t\right] \\
&\leqslant \sum_{\substack{\vec{u} \\ \mathbb{Q}_i[\vec{u}] > \mathbb{Q}[\vec{u}]}} \left(\mathbb{Q}_i[\vec{u}] - \mathbb{Q}[\vec{u}]\right) \mathbb{E}_i\left[\tau_i(T) \,\middle|\, \forall t,\ \ell_t^{(d_t)} = u_t\right] \\
&\leqslant T \sum_{\substack{\vec{u} \\ \mathbb{Q}_i[\vec{u}] > \mathbb{Q}[\vec{u}]}} \left(\mathbb{Q}_i[\vec{u}] - \mathbb{Q}[\vec{u}]\right) \\
&\leqslant T\sqrt{\frac{1}{2} D\left(\mathbb{Q}[\vec{u}] \,\|\, \mathbb{Q}_i[\vec{u}]\right)} \\
&= T\sqrt{\frac{\mathbb{B}(s/2d, \varepsilon)}{2}} \sqrt{\sum_{t=1}^{T} \frac{\left|A_t^{(i)}\right|}{2^{t-1}}},
\end{aligned}$$

where we used Pinsker's inequality in the fifth line. Moreover, we have:

$$\frac{1}{d}\sum_{i=1}^{d} \mathbb{E}\left[\tau_i'(T)\right] = \frac{1}{d}\mathbb{E}\left[\sum_{t=1}^{T}\sum_{i=1}^{d} \mathbb{1}_{\{d_t'=i\}}\right] = \frac{1}{d}\mathbb{E}\left[\sum_{t=1}^{T} 1\right] = \frac{T}{d}.$$

Combining this with the previous inequality gives:

$$\begin{aligned}
\frac{1}{d}\sum_{i=1}^{d} \mathbb{E}_i\left[\tau_i(T)\right] &\leqslant \frac{1}{d}\sum_{i=1}^{d} \mathbb{E}\left[\tau_i'(T)\right] + T\sqrt{\frac{\mathbb{B}(s/2d, \varepsilon)}{2}} \frac{1}{d}\sum_{i=1}^{d} \sqrt{\sum_{t=1}^{T} \frac{\left|A_t^{(i)}\right|}{2^{t-1}}} \\
&\leqslant \frac{T}{d} + T\sqrt{\frac{\mathbb{B}(s/2d, \varepsilon)}{2}} \sqrt{\frac{1}{d}\sum_{t=1}^{T}\sum_{i=1}^{d} \frac{\left|A_t^{(i)}\right|}{2^{t-1}}} \\
&= \frac{T}{d} + T\sqrt{\frac{\mathbb{B}(s/2d, \varepsilon)}{2}} \sqrt{\frac{1}{d}\sum_{t=1}^{T} \frac{\left|\{0,1\}^{t-1}\right|}{2^{t-1}}} \\
&= \frac{T}{d} + T\sqrt{\frac{\mathbb{B}(s/2d, \varepsilon)}{2}} \sqrt{\frac{T}{d}} \\
&= \frac{T}{d} + T^{3/2}\sqrt{\frac{\mathbb{B}(s/2d, \varepsilon)}{2d}}.
\end{aligned}$$

where we used Jensen for the second inequality, and for the third line, we remembered that $(A_t^{(i)})_{i\in[d]}$ is a partition of $\{0,1\}^{t-1}$.

5.3.6 An Upper Bound on $\mathbb{B}(s/2d,\varepsilon)$ for Small Enough ε

We first write $\mathbb{B}(s/2d,\varepsilon)$ explicitely.

$$\begin{aligned}\mathbb{B}\left(\frac{s}{2d},\varepsilon\right) &= D\left(B(1,s/2d)\,\|\,B(1,s/2d-\varepsilon)\right)\\ &= \frac{s}{2d}\log\frac{s/2d}{s/2d-\varepsilon}+\left(1-\frac{s}{2d}\right)\log\frac{1-s/2d}{1-s/2d+\varepsilon}\\ &= -\frac{s}{2d}\log\left(1-\frac{2d\varepsilon}{s}\right)+\left(\frac{s}{2d}-1\right)\log\left(1+\frac{\varepsilon}{1-m/2d}\right).\end{aligned}$$

We now bound the two logarithms from above using respectively the two following easy inequalities:

$$\begin{aligned}-\log(1-x) &\leqslant x+x^2, \quad \text{for } x\in[0,1/2]\\ -\log(1+x) &\leqslant -x+x^2, \quad \text{for } x\geqslant 0.\end{aligned}$$

This gives:

$$\begin{aligned}\mathbb{B}\left(\frac{s}{2d},\varepsilon\right) &\leqslant \frac{s}{2d}\left(\frac{2d\varepsilon}{s}+\frac{4d^2\varepsilon^2}{s^2}\right)+\left(1-\frac{s}{2d}\right)\left(-\frac{\varepsilon}{1-s/2d}+\frac{\varepsilon^2}{(1-s/2d)^2}\right)\\ &= \frac{4d^2\varepsilon^2}{s(2d-s)},\end{aligned}$$

which holds for $2d\varepsilon/s\leqslant 1/2$, in other words, for $\varepsilon\leqslant s/4d$.

5.3.7 Lower Bound on the Expectation of the Regret of σ Against ℓ_t

We can now bound from below the expected regret incurred when playing σ against loss vectors $(\ell_t)_{t\geqslant 1}$. For $\varepsilon \leqslant s/4d$,

$$\begin{aligned}
R_T &= \mathbb{E}\left[\sum_{t=1}^{T} \ell_t^{(d_t)} - \min_{j\in[d]} \sum_{t=1}^{T} \ell_t^{(j)}\right] \\
&= \frac{1}{d}\sum_{i=1}^{d} \mathbb{E}_i\left[\sum_{t=1}^{T} \ell_t^{(d_t)} - \min_{j\in[d]} \sum_{t=1}^{T} \ell_t^{(j)}\right] \\
&\geqslant \frac{1}{d}\sum_{i=1}^{d} \left(\mathbb{E}_i\left[\sum_{t=1}^{T} \ell_t^{(d_t)}\right] - \min_{j\in[d]} \sum_{t=1}^{T} \mathbb{E}_i\left[\ell_t^{(j)}\right]\right) \\
&= \frac{1}{d}\sum_{i=1}^{d} \left(\mathbb{E}_i\left[\sum_{t=1}^{T} \mathbb{E}_i\left[\ell_t^{(d_t)} \,\middle|\, d_t\right]\right] - T\min_{j\in[d]} \left(\frac{s}{2d} - \varepsilon\delta_{ij}\right)\right) \\
&= \frac{1}{d}\sum_{i=1}^{d} \left(\mathbb{E}_i\left[\sum_{t=1}^{T} \left(\frac{s}{2d} - \varepsilon\delta_{id_t}\right)\right] - T\left(\frac{s}{2d} - \varepsilon\right)\right) \\
&= \frac{1}{d}\sum_{i=1}^{d} \varepsilon\left(T - \mathbb{E}_i\left[\tau_i(T)\right]\right) \\
&= \varepsilon\left(T - \frac{1}{d}\sum_{i} \mathbb{E}_i\left[\tau_i(T)\right]\right).
\end{aligned}$$

We now use the upper bound derived in Section 5.3.5.

$$\begin{aligned}
R_T &\geqslant \varepsilon\left(T - \frac{T}{d} - T^{3/2}\sqrt{\frac{\mathbb{B}(s/2d,\varepsilon)}{2d}}\right) \\
&\geqslant \varepsilon\left(T - \frac{T}{d} - T^{3/2}\varepsilon\sqrt{\frac{2d}{s(2d-s)}}\right) \\
&\geqslant \varepsilon\left(T - \frac{T}{d} - 2T^{3/2}\varepsilon\frac{1}{\sqrt{s}}.\right),
\end{aligned}$$

where in the penultimate, we used the upper bound on $\mathbb{B}(s/2d,\varepsilon)$ that we established above, and in the last line, the fact that $s \leqslant d$. Let $C > 0$ and we choose $\varepsilon = C\sqrt{s/T}$. Then, for $\varepsilon \leqslant s/4d$,

$$\begin{aligned}
R_T &\geqslant \varepsilon T\left(1 - \frac{1}{d} - 2\varepsilon\sqrt{\frac{T}{s}}\right) \\
&= C\sqrt{sT}\left(1 - \frac{1}{d}\right) - 2\sqrt{sT}C^2 \\
&\geqslant \sqrt{sT}\left(\frac{C}{2} - 2C^2\right),
\end{aligned}$$

where in the last line, we used the assumption $d \geqslant 2$. The choice $C = 1/8$ give:

$$R_T \geqslant \frac{1}{32}\sqrt{sT},$$

which holds for $\varepsilon = C\sqrt{s/T} \leqslant s/4d$ i.e. for $T \geqslant d^2/4s$.

The above inequality does not depend on σ. As it is a classic that a randomized strategy is equivalent to some random choice of deterministic strategies, this lower bound holds for any strategy of the player. In other words, for $T \geqslant d^2/4s$,

$$\hat{v}_T^{\ell,s,d} \geqslant \frac{1}{32}\sqrt{sT}.$$

■

5.4 Discussion

If the outcomes are not losses but gains, then there is an important discrepancy between the upper and lower bounds we obtain. Indeed, obtaining small losses regret bound as in the first displayed equation of the proof of Theorem 11 is still open. An idea for circumventing this issue would be to enforce exploration by perturbing x_t into $(1-\gamma)x_t + \gamma\mathcal{U}$ where $\mathcal{U}$ is the uniform distribution over $[d]$, but usual computations show that the only obtainable upper bounds are of order of $\sqrt{dT}$. The aforementioned techniques used to bound the regret from below with losses would also work with gains, which would give a lower bound of order $\sqrt{sT}$. Therefore, finding the optimal dependency in the dimension and/or the sparsity level is still an open question in that specific case. We tend to believe that the upper bound could be improved: imagine the case $s = 1$, the restriction on the payoff vectors is huge, and we think that this could be taken advantage of. This would imply that there is no discrepancy between gains and losses, unlike the full information setting, which would be an interesting fact.

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References

Yasin Abbasi-Yadkori, David Pal, and Csaba Szepesvari. Online-to-confidence-set conversions and application to sparse stochastic bandits. In *JMLR: Workshop and Conference Proceedings (AISTATS)*, volume 22, pages 1–9, 2012.

Jean-Yves Audibert and Sébastien Bubeck. Minimax policies for adversarial and stochastic bandits. In *Proceedings of the 22nd Annual Conference on Learning Theory (COLT)*, pages 217–226, 2009.

Jean-Yves Audibert, Sébastien Bubeck, and Gábor Lugosi. Regret in online combinatorial optimization. *Mathematics of Operations Research*, 39(1):31–45, 2013.

Peter Auer, Nicolo Cesa-Bianchi, and Claudio Gentile. Adaptive and self-confident on-line learning algorithms. *Journal of Computer and System Sciences*, 64(1):48–75, 2002.

Sébastien Bubeck. *Introduction to Online Optimization: Lecture Notes*. Princeton University, 2011.

Sébastien Bubeck and Nicolo Cesa-Bianchi. Regret analysis of stochastic and nonstochastic multi-armed bandit problems. *Machine Learning*, 5(1):1–122, 2012.

Alexandra Carpentier and Rémi Munos. Bandit theory meets compressed sensing for high dimensional stochastic linear bandit. In *International Conference on Artificial Intelligence and Statistics*, pages 190–198, 2012.

Nicolo Cesa-Bianchi. Analysis of two gradient-based algorithms for on-line regression. In *Proceedings of the Tenth Annual Conference on Computational Learning Theory (COLT)*, pages 163–170. ACM, 1997.

Nicolo Cesa-Bianchi and Gábor Lugosi. *Prediction, learning, and games*. Cambridge University Press, 2006.

Nicolo Cesa-Bianchi, Yoav Freund, David Haussler, David P Helmbold, Robert E Schapire, and Manfred K Warmuth. How to use expert advice. *Journal of the ACM*, 44(3):427–485, 1997.

Josip Djolonga, Andreas Krause, and Volkan Cevher. High-dimensional gaussian process bandits. In *Advances in Neural Information Processing Systems (NIPS)*, volume 26, pages 1025–1033, 2013.

Yoav Freund and Robert E Schapire. A decision-theoretic generalization of on-line learning and an application to boosting. *Journal of computer and system sciences*, 55(1):119–139, 1997.

Janos Galambos. *The asymptotic theory of extreme order statistics*. John Wiley, New York, 1978.

Sébastien Gerchinovitz. Sparsity regret bounds for individual sequences in online linear regression. *The Journal of Machine Learning Research*, 14(1):729–769, 2013.

James Hannan. Approximation to bayes risk in repeated play. *Contributions to the Theory of Games*, 3(2):97–139, 1957.

Elad Hazan. The convex optimization approach to regret minimization. In S. Nowozin S. Sra and S. Wrigh, editors, *Optimization for Machine Learning*, pages 287–303. MIT press, 2012.

Sham M Kakade, Shai Shalev-Shwartz, and Ambuj Tewari. Regularization techniques for learning with matrices. *The Journal of Machine Learning Research*, 13(1):1865–1890, 2012.

Joon Kwon and Panayotis Mertikopoulos. A continuous-time approach to online optimization. *arXiv preprint arXiv:1401.6956*, 2014.

Nick Littlestone and Manfred K Warmuth. The weighted majority algorithm. *Information and computation*, 108(2):212–261, 1994.

Alexander Rakhlin and A Tewari. *Lecture notes on online learning.* University of Pennsylvania, 2008.

Shai Shalev-Shwartz. *Online learning: Theory, algorithms, and applications.* PhD thesis, The Hebrew University of Jerusalem, 2007.

Shai Shalev-Shwartz. Online learning and online convex optimization. *Foundations and Trends in Machine Learning*, 4(2):107–194, 2011.

David Slepian. The one-sided barrier problem for gaussian noise. *Bell System Technical Journal*, 41(2):463–501, 1962.

Volodimir G. Vovk. Aggregating strategies. In *Proceedings of the Third Workshop on Computational Learning Theory (COLT)*, pages 371–383. Morgan Kaufmann, 1990.