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Regret Minimization for Online Buffering Problems Using the Weighted Majority Algorithm[*]

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Abstract

Suppose a decision maker has to purchase a commodity over time with varying prices and demands. In particular, the price per unit might depend on the amount purchased and this price function might vary from step to step. The decision maker has a buffer of bounded size for storing units of the commodity that can be used to satisfy demands at later points in time. We seek for an algorithm deciding at which time to buy which amount of the commodity so as to minimize the cost. This kind of problem arises in many technological and economical settings like, e.g., battery management in hybrid cars and economical caching policies for mobile devices. A simplified but illustrative example is a frugal car driver thinking about at which occasion to buy which amount of gasoline.

We study this problem within a regret analysis. In particular, we investigate the external regret obtained by the Weighted Majority Algorithm applied to our problem. We show that the algorithm does not achieve a reasonable regret bound if its random choices are independent from step to step, that is, the regret for T steps is $\Omega(T)$. However, one can achieve regret $O(\sqrt{T})$ when introducing dependencies in order to reduce the number of changes between the chosen experts. If price functions satisfy a convexity condition then one can even derive a deterministic, fractional variant of this algorithm achieving the same regret bound.

Our more detailed bounds on the regret depend on the buffer size and the number of available experts. The upper bounds are complemented by a matching lower bound on the best possible external regret.

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1 Introduction

We study online buffering problems dealing with the management of a storage for a commodity with varying prices and demands. Our setting is similar to the standard model for regret minimization. In particular, we assume that there is a number of experts corresponding to different policies for managing the buffer. An online algorithm observes the performance of the experts and combines their policies with the objective to achieve a performance close to the performance of the best expert. The difference to the standard setting of regret minimization is that the buffer makes it possible to defer actions from one point of time to another in order to reduce cost. This property is the major challenge in applying known learning algorithms like the Randomized Weighted Majority Algorithm to our problem.

The online buffering problem is defined as follows. A decision maker has to purchase a commodity over time. Time proceeds in steps. In step t, the decision maker needs to satisfy a demand of $d^t \in [0, 1]$ units of the commodity. The decision maker has a buffer of bounded size $B > 0$ for storing units of the commodity that can be used to satisfy demands at later points in time. In step t, it can purchase at most b^t units, where $b^t \in [d^t, B + d^t]$. The price per unit of the commodity varies over time and depends on the amount bought by the decision maker. It is described by a function $p^t : [0, b^t] \to [0, 1]$. So the price for buying x units in step t is given by $xp^t(x)$. We seek for an algorithm deciding at which time to buy which amount of the commodity so as to minimize the cost.

A simplified but illustrative example for the buffering problem is a frugal car driver thinking about at which occasion to buy which amount of gasoline. In this example the price per unit varies over time, but can be assumed to be constant in every step, as typically the price for gasoline at a gas station does not depend on the amount that is bought. Other examples are battery management in hybrid cars or economical caching policies for mobile devices. In these examples, the prices typically depend on the amount that is purchased (in this context, generated or used) and the price functions satisfy certain convexity assumptions. Some more information about these applications is given in Section 1.5.

1.1 Expert Problem and Weighted Majority Algorithm

In standard online learning the decision maker is equipped with N experts, numbered from 1 to N. The setup with respect to the cost is different from ours. (In particular, there is no buffer.) One might assume that an adversary chooses the cost for each expert in each step arbitrarily from $[0, 1]$. For expert i, we denote by c_i^t its cost in time step t and by $C_i^t = \sum_{k=1}^{t} c_i^k$ its accumulated cost until step t. In every step t, the decision maker selects an expert. The cost of the decision maker correspond to the cost of the expert chosen in that step. Afterwards, it observes the cost vector $c^t \in [0, 1]^N$ of the experts.

The decision maker aims at choosing the experts in such a way that its cost are close to the cost of the best expert, that is, it aims at minimizing its regret. The decision maker corresponds to a (possibly randomized) algorithm $\mathcal{A}$. Consider a sequence of length T. Let $C_{\mathcal{A}}^T$ denote the expected cost accumulated by $\mathcal{A}$ until step T. Formally, the *(external) regret* of $\mathcal{A}$ on this sequence is

$$C_{\mathcal{A}}^T - C_{\text{best}}^T \ .$$

Observe that there are no assumptions on the quality of the experts or the relation between the experts. In particular, regret minimization does not mean to be competitive to an optimal offline algorithm, as in competitive analysis [3, 17]. If the decisions of each expert are arbitrarily bad, online learning algorithms cannot achieve good solutions.

Algorithm 1 (`Randomized Weighted Majority (RWM)`)

```
1: $w_i = 1, q_i = \frac{1}{N}$ for all $i$
2: for $t = 1, \dots, T$ do
3:     choose expert depending on $Q = \{q_1, \dots, q_N\}$
4:     $w_i = w_i(1-\eta)^{c_i^t}$
5:     $q_i = \frac{w_i}{\sum_{i=1}^{N} w_i}$
6: end for
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The *Randomized Weighted Majority (RWM)* algorithm of Littlestone and Warmuth [16] guarantees a regret bound of $O(\sqrt{T \log N})$, see also [2]. It is known that this is the best possible bound in the standard setting. The idea of this algorithm is to give each expert a probability of being chosen which depends on the costs that the expert has experienced in the past. The probability q_i that the strategy of expert i is chosen in the next time step is controlled by the current weight w_i of the expert which itself depends only on the weights in the steps up to $t-1$. The calculation of the weights and of the probabilities used by the algorithm is described in Algorithm 1. In the rest of the paper the probability for choosing expert i in round t is denoted by q_i^t and the corresponding weight is denoted by w_i^t.

1.2 Extending the Online Learning Model towards the Buffering Problem

In the context of the buffering problem, we assume that there are N experts and each expert is equipped with a buffer of size B. The expert decides how much units to buy in which step. Recall that the price per unit in step t depends on the purchased amount and is defined by the price function p^t. Observe that the experts may buy up to $B+1$ units per step so that the total price for the purchased units can be as high as $B+1$.

In our analysis, we account for the purchased units not at the time when the expert (or the online algorithm) buys the units but when it uses them to satisfy the demand. To formalize this, assume that every amount purchased by the expert (or the online algorithm) is put into the buffer and all demands are satisfied from the buffer in first-in first-out (FIFO) manner. The cost accounted for satisfying a demand with units bought in previous steps is equal to the price at which the units were bought. This accounting trick ensures that the cost of the experts (and the online algorithm) is at most one per step and it only decreases the accumulated cost of the experts up to an additive value of at most B. The cost by expert i in time step t is termed c_i^t, its cost accumulated until step t is denoted by $C_i^t = \sum_{k=1}^{t} c_i^k$ like in the standard model.

In every step, an online algorithm $\mathcal{A}$ chooses (possibly at random) one of the experts (or a linear combination of experts). In step t this choice depends only on the demands and prices until step $t-1$, i.e. on $d^1, \cdots d^{t-1}, p^1, \cdots p^{t-1}$. The term *choosing an expert* needs further clarification. If $\mathcal{A}$ has chosen expert i in step t, then it purchases the same amount of the commodity as expert i in step t with the following two exceptions: If the amount purchased by the expert together with the units in $\mathcal{A}$'s buffer does not suffice to cover the demand in this step, then $\mathcal{A}$ purchases a minimal amount necessary to satisfy the demand. (After such a step the buffer is empty.) If the amount purchased by the expert exceeds the demand in this step and the excess does not fit completely into $\mathcal{A}$'s buffer, then it purchases only the amount needed to fill the buffer up to the capacity. (After such a step the buffer contains B units.) The (expected) cost of $\mathcal{A}$ in step t is termed $c_{\mathcal{A}}^t$ the cost that $\mathcal{A}$ accumulates until step t are denoted by $C_{\mathcal{A}}^t = \sum_{k=1}^{t} c_{\mathcal{A}}^k$.

1.3 Our Contribution

We investigate the regret achieved by the RWM algorithm and variations of this algorithm on the buffering problem.

When describing the RWM algorithm, we did not specify that the random experiments in different steps are independent. In fact, in the standard setting such dependencies do not effect the expected cost of the RWM algorithm.[1] This is different when applying the algorithm to the buffering problem. In particular, one does not obtain a reasonable bound on the regret if experts are chosen using an independent random experiment for every step.

To see this, consider the following input sequence with fixed per unit prices (i.e., the price functions p^t are constant):

$$\begin{pmatrix} p^t \\ d^t \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix} \begin{pmatrix} 0 & 1 & 0 & 1 \\ 1/4 & 1/4 & 1/4 & 1/4 \end{pmatrix}^{T'} .$$

Suppose the buffer size is 1 and a *round* consists of the 4 steps with request 1/4 each. Two experts are given:

1) The expert purchases 1/2 in the first time step and one unit in the third step of every round.

2) The expert purchases one unit in the first step of every round.

Both experts have cost 0 for the whole request sequence. We claim, however, that the RWM algorithm has cost $\Theta(T)$ for a request sequence of length $T = 4T' + 1$, that is, the regret of RWM is $\Theta(T)$.

The RWM algorithm assigns probability 1/2 to each of the experts in each step. If random experiments in different steps are independent, then in two consecutive rounds, with probability 1/16 the algorithm selects in each step an expert that does not purchase a unit in this step, which means that the buffer is empty in the second round so that the algorithm has cost 1/2 for serving the demands in this round. Thus, for each round the expected cost of RWM is at least 1/16.

A reason for the poor performance of the RWM algorithm is that it changes the experts frequently and the chosen experts might have completely different filling levels in their buffers. We present a variant of the RWM algorithm that uses dependencies in order to decrease the number of expert changes. The algorithm is called *Shrinking Dartboard (SD)* algorithm as the random experiments used by this algorithm are described in terms of a shrinking dartboard. We prove that the regret achieved by this algorithm is at most $O(\sqrt{BT \log N})$.

If the price functions in each step satisfy a convexity condition (e.g., if prices are constant) then we can derive even a deterministic variant of the Weighted Majority Algorithm with a good regret bound. The *Weighted Fractional (WF)* algorithm chooses linear combinations of experts rather than selecting experts at random. WF achieves a regret of at most $O(\sqrt{BT \log N})$, too. As this algorithm is deterministic, its regret guarantee holds even against an adaptive adversary.

Finally, we present a lower bound of $\Omega(\sqrt{BT \log N})$ for the regret showing that SD and WF achieve the optimal regret for the buffering problem up to constant factors. This lower bound holds even if prices are assumed to be constant.

[1] In the standard setting without buffer, the expected cost of the RWM algorithm are not effected by dependencies between different steps, unless the adversary who specifies the cost for the experts is *adaptive*, i.e., the cost vector presented for a step might depend on the random coin flips of the algorithm in previous steps.

1.4 Related Work

A special case of online buffering problems is the *economical caching* [7, 8] and the *one-way trading* problem [3, 6]. In one-way trading a price sequence is given, each price representing an exchange rate from dollar to yen. The task is to trade d dollars to a maximum number of yen. In economical caching, there is furthermore a previously unknown demand of yen at each time step which must be consumed from a buffer or bought for the current price. Economical caching was introduced in [7]. Englert et al. analyzed it in a worst case competitive analysis yielding general tight bounds for the competitive factor depending on the ratio between the lowest and highest exchange rate. [8] showed that if the price sequence is modeled by a random walk, a competitive factor which does not depend on this ratio can be achieved.

We study online buffering problems with online learning algorithms as described in Section 1.2. Online learning algorithms are used for regret minimization. A general introduction is given in [1, 2]. In this paper we use the external regret model [2, 4] with full information.

There are several algorithms for which the regret per time step converges against zero for a long time horizon. The following algorithms achieve a regret of $O(\sqrt{T \log N})$: The *Randomized Weighted Majority* (RWM) algorithm [16] weights each expert depending on its cost so far. In the randomized version the weights are used as probabilities for an expert to be chosen. It is known that RWM achieves the best possible bound for the standard setting. But this is no longer valid when applying the algorithm to the online buffering problem. A reason for this is that RWM changes the experts frequently.

[12] and [14] present the *Follow The Perturbed Leader* (FPL) algorithm that follows the expert which has achieved the lowest cost so far plus some perturbation. FPL reduces the number of expert changes to achieve good regret bounds. But in contrast to the Weighted Fractional (WF) algorithm presented in this paper FPL cannot achieve this bound against an adaptive adversary.

The WF algorithm can only achieve good regret bounds if the price functions satisfy a convexity property. This assumption is also made in [9, 18]. It is shown that if the cost of each expert is given by a convex function which may change over time, a gradient descent algorithm can be used to achieve good regret bounds. This algorithm cannot directly be used to achieve good regret bounds for online buffering problems, since the experts choose a fixed point of the convex function. In our model this would lead to very limited experts. An expert would then only be able to determine once the number units it wants to buy in every time step. This choice would be the same for all time steps. It could no longer depend on the current price or filling status of the buffer. This expert model is to limited and can therefore not be used to solve online buffering problems.

Online learning algorithms have been studied in many other research areas yielding a huge variety of results. Some of the possible applications for online learning are given in [10].

1.5 Applications

There are several applications for algorithms solving online buffering problems. One is the battery management for hybrid cars. In a hybrid car there are two engines a combustion engine and an electrical engine. In each time step, a demand for the torque is given by the driver which depends on the requested acceleration and the topology of the route. An algorithm has to decide how much power is produced by the combustion engine such that the total fuel consumption is minimized.

If more power is required than the combustion engine is producing, the remaining power must be used from the battery. On the other hand, if more power is produced than currently needed, the additional power is not given to the drive shaft, but saved into the battery for later usage. The price for producing the power depends on the amount of fuel used for the production, i.e., the efficiency to produce a given amount of power which itself depends on the given torque and gear. Consequently, the cost of filling the battery varies over time.

In engineering, decisions about which engine should produce which amount of power are often made based on engine operating maps [5] and possibly on knowledge of the route [13, 15] for which the fuel consumption should be optimized. Engine operating maps show the fuel consumption of the car for different operation states. They are often used in engineering since they simplify the production of a control unit for the car. The topology of the route can be given by an on-board navigation system. Both engine operating maps and the topology can be used as experts in online learning.

Another application is the *smart caching* problem [11] which arises from the area of mobile communication. A stream to a mobile device can be fetched over different communication standards, e.g., GSM, UMTS, WLAN, each for different costs, but not always and anywhere available. Therefore, the stream has to be buffered inside the mobile device to be able to provide the data intensive services at every point in time. Furthermore, in order to achieve that, the different communication standards may have to be combined.

The best strategy for combining those services depends on the users mobility and the availability of the services over time. Therefore, it is not possible to implement a fixed optimal strategy into the mobile device, but the strategy can better be learned over time with regard to the user needs. This can be done with online learning algorithms.

The experts for online learning in smart caching have to decide which standard to use at which time. Thereby it is also possible to combine the different communication standards by using each standard to download a certain amount of the data downloaded in a time step. The experts then decide which amount of data should be downloaded by which standard. It is possible to combine the experts by using a communication standard for that amount of data suggested by the combined experts. The objective of the online learning algorithm is to get the stream as cheaply as possible.

2 The Shrinking Dartboard Algorithm

We devise a variant of the Randomized Weighted Majority Algorithm that uses dependencies in order to reduce the number of expert changes. The selection of experts is controlled by a stochastic process described in terms of a dartboard shrinking over time. This algorithm is called *Shrinking Dartboard (SD)* algorithm.

The dartboard is a disc divided into N equally sized sectors, one for each expert. The total area covered by the disc has size N so that each sector has size 1. Initially, the *allowed region* for expert i is defined to be the area covered by sector i. Over time the allowed region of an expert shrinks, as illustrated in Figure 1. In particular, the allowed region of expert i in step $t > 1$ is assumed to be a subarea of its allowed region in step $t-1$ and the size of the allowed region of expert i in step t corresponds to the weight w_i^t of the RWM algorithm as specified in Algorithm 1.

In step 1, SD chooses an expert by *throwing a dart* to the board, that is, it picks a point from the disc uniformly at random and chooses that expert into which sector this point falls. In step $t > 1$, SD chooses an expert as follows: If the previously picked point is still in the allowed region, then SD does not change the expert. Otherwise, SD *throws a new dart*, that is, it picks a point uniformly at random from the allowed region (i.e., the union of the allowed regions over all experts) and chooses the expert into which sector this point falls. Let D denote the number of darts thrown by SD.

The number of expert changes is crucial for our analysis. This number (including the choice

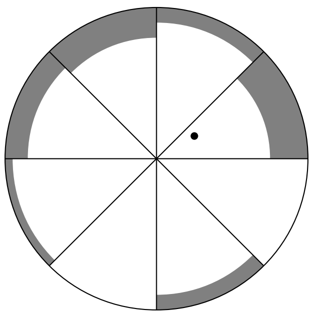

Figure 1: Probability distribution as a dartboard

of the first expert) is bounded from above by D, the number of darts thrown in the shrinking dartboard process. The following lemma bounds D in terms of the cost of the best expert.

Lemma 1 *The expected value of D is at most $2\eta C^T_{best} + \ln N + 1$.*

Proof. Let W^t be the sum of the weight over all experts in time step t, which is equal to the size of the allowed region in step t. In step t the dart corresponds to a point selected uniformly at random from this region. The probability that this point still belongs to the allowed region in the next step is W^{t+1}/W^t. Hence, the probability for throwing a new dart in step $t+1$ is $\alpha^{t+1} = (W^t - W^{t+1})/W^t$. Thus, $W^{t+1} = (1-\alpha^{t+1})W^t$. The total weight W^{T+1} after step T can hence be expressed in terms of these probabilities, that is,

$$W^{T+1} \;=\; W^1 \prod_{t=1}^{T}(1-\alpha^{t+1}) \;=\; N \prod_{t=1}^{T}(1-\alpha^{t+1}) \ .$$

On the other hand,

$$W^{T+1} \;\geq\; (1-\eta)^{C^T_{\text{best}}}$$

as the latter quantity corresponds to the weight of the best expert after step T. Combining these equations and applying the logarithm gives

$$C^T_{\text{best}} \ln(1-\eta) \leq \ln N + \sum_{t=1}^{T} \ln(1-\alpha^{t+1}) \ .$$

Using $\ln(1-\alpha^{t+1}) \leq -\alpha^{t+1}$ and $\ln(1-\eta) \geq -2\eta$, the expected number of thrown darts is thus

$$\sum_{t=1}^{T-1} \alpha^{t+1} \leq \ln N + 2\eta C^T_{\text{best}}$$

plus one for the dart thrown in the first step. ■

We exploit this lemma in the following regret analysis in which we compare the cost of SD, C^T_{SD} with the cost of the best expert C^T_{best}. As defined in the Introduction, C^t_i is the cost of the units expert i uses (rather than purchases) until step t, where we assume that units are removed from the expert's buffer in FIFO manner and valuated with the price at which they were bought. Recall that c^t_i denotes the cost accounted for expert i in step t.

Theorem 2 *For $\eta \leq 1/2$, the expected cost of SD satisfies*

$$C_{SD}^T \leq (1+\eta+2\eta B)C_{best}^T + \frac{\ln N}{\eta} + B(\ln N + 1) \ .$$

Setting $\eta = \min\{\sqrt{\ln N/(BT)}, 1/2\}$ yields $C_{SD}^T \leq C_{best}^T + O(\sqrt{BT\log N})$.

Proof. Let e^t denote the expert chosen by SD in step t. We claim that the cost of SD is bounded from above by

$$\sum_{t=1}^{T} c_{e^t}^t + DB \ .$$

In words, the cost of SD is bounded from above by the cost of the chosen experts plus DB. To see this, consider the cost in a time period beginning with a step in which a new expert is chosen and ending with the last step before the next expert is chosen or the sequence ends. The cost of SD in this period can be split into three contributions.

(1) Cost due to units used and bought in this period by both SD and the expert.

(2) Cost for using those units that are stored in SD's buffer at the beginning of the period.

(3) Cost for using units bought during the period by SD to ensure feasibility.

The cost in (1) is upper bounded by $\sum_{t=1}^{T} c_{e^t}^t$. Observe that the sum of units covered by (2) and (3) is at most B. Hence, the difference between cost of SD and the cost of the expert within such a period is at most B. This gives the stated upper bound on C_{SD}^T as the number of periods is D.

Next we claim that

$$E\left[\sum_{t=1}^{T} c_{e^t}^t\right] \ \leq \ (1+\eta)C_{\mathrm{best}}^T + \frac{\ln N}{\eta} \ .$$

This is because the probability that SD chooses expert i in step t is equal to the probability that the original RWM algorithm chooses expert i in step t. The left hand term describes the cost of the RWM algorithm assuming that the cost accounted for the learning algorithm in step t are $c_{e^t}^t$ (as in the standard setting of online learning). Thus, we can apply the well known upper bound on the cost of RWM holding for $\eta \leq 1/2$ (cf., e.g., [2]).

Together with the bound on the expected value of D in Lemma 1 this yields the first bound in the theorem.

Finally, assume $\eta \leq \sqrt{\ln N/(BT)}$. Combining the first bound of the theorem with the trivial bound $C_{\mathrm{SD}}^T - C_{\mathrm{best}}^T \leq T$, we obtain

$$\begin{aligned} C_{\mathrm{SD}}^T - C_{\mathrm{best}}^T &\leq (\eta + 2\eta B)T + \frac{\ln N}{\eta} + \min\{T, B(\ln N + 1)\} \\ &= O\left(\sqrt{BT\log N} + \min\{T, B\log N\}\right) \\ &= O\left(\sqrt{BT\log N}\right), \end{aligned}$$

which gives the second bound given in the theorem. ■

3 The Weighted Fractional Algorithm

The *Weighted Fractional (WF)* algorithm uses the same weights as algorithm RWM. However, instead of choosing an expert at random, it simulates the experts fractionally. That is, it purchases $x^t = \sum_{i=1}^N q_i^t x_i^t$ units in step t, where x_i^t is the amount purchased by expert i in the same step. Observe that this rule might lead to infeasibilities as the weights change over time: The amount of purchased units together with the units in the buffer might not be enough to satisfy the demand in a step or the buffer might overflow. In these cases, we ensure feasibility by purchasing as many as necessary additional units or by buying less units, respectively, in order to maintain feasibility.

The following theorem bounds the cost of WF assuming that the price functions satisfy a convexity property. In particular, the function $f^t(x) = xp^t(x)$ that describes the cost incurred for buying an amount of x needs to be convex.

Theorem 3 *Suppose the functions $f^t(x)$, $x \in [0, b^t]$ are convex, for $1 \le t \le T$. Then the cost of WF satisfies*

$$C_{WF}^T \le (1 + \eta + 2\eta B) C_{best}^T + \frac{\ln N}{\eta} + B(\ln N + 1) \ .$$

Setting $\eta = \min\{\sqrt{\ln N/(BT)}, 1/2\}$ yields $C_{WF}^T \le C_{best}^T + O(\sqrt{BT \log N})$.

Proof. We analyze WF by relating it to another algorithm called *k-SD*. This algorithm splits the buffer into $k \ge 1$ sub-buffers of size B/k each. For each of these sub-buffers, we simulate algorithm SD scaling down all demands as well as the amounts purchased by the experts by multiplying with $1/k$. Besides, we adapt the cost function, that is, when buying x_j^t units for sub-buffer j in step t, algorithm k-SD assumes that this incurs *virtual cost* of $f^t(kx_j^t)/k$.

For $1 \le j \le k$, let L_j^T denote the expected virtual cost for sub-buffer j accumulated until step T. As k-SD simulates SD for every sub-buffer using an appropriate scaling, it holds $L_j^T = C_{\mathrm{SD}}^T/k$ so that

$$\sum_{j=1}^k L_j^T = C_{\mathrm{SD}}^T \ .$$

Now let us compare the sum of the virtual cost of k-SD with the true cost of this algorithms. For every time step t, we have

$$f^t\left(\sum_{j=1}^k x_j^t\right) \le \frac{1}{k}\sum_{j=1}^k f^t(kx_j^t)$$

by Jensen's inequality. Thus, we observe that the true cost incurred for any step t is upper bounded by the sum of the virtual costs for this steps. Combining this observation with the equation above gives

$$C_{k\text{-SD}}^T \le C_{\mathrm{SD}}^T \ ,$$

for every $k \ge 1$.

Let us introduce a slight modification to k-SD. The resulting algorithm is called k-SD'. As k-SD simulates SD on each sub-buffer, it needs to buy additional units in some time steps in order to ensure feasibility. These are at most B/k units for every thrown dart (new expert) for each sub-storage. k-SD' does not need to buy these additional units when the respective sub-buffer is empty but can defer this until all sub-buffers are empty. This does not increase the number of units that need to be bought, but prices for these units might change. However, in the analysis of SD, we estimated the prices for these units with the worst possible price. Hence, we can apply Theorem 2 not only to k-SD, but also to k-SD' and obtain

$$C^T_{k\text{-SD'}} \le (1+\eta+2\eta B)C^T_{\text{best}} + \frac{\ln N}{\eta} + B(\ln N + 1) \ ,$$

for every $k \ge 1$.

Now we let k go to infinity. Consider a fixed step t. By the law of large numbers, the sum of the amounts purchased by the experts chosen for the sub-buffers converges to its expectation. That is, the sum of purchased amounts over all sub-buffers converges to $\sum_{i=1}^N q_i^t x_i^t$. As a consequence, k-SD (for $k \to \infty$) purchases the same amount per step as WF. Hence,

$$C^T_{\text{WF}} = \lim_{k\to\infty} C^T_{k\text{-SD'}} \ .$$

Combining the last two equations yields the theorem. ■

4 Lower Bound

The following theorem shows that our upper bounds on the external regret achieved by SD and WF are tight up to constant factors, that is, one cannot achieve significant further improvements. Let us remark that the lower bound given in the theorem holds even if we restrict the input sequences to fixed prices per unit and if the experts purchase at most one unit per step.

Theorem 4 *For every integer T, there exists a stochastically generated sequence of length T together with N experts such that every learning algorithm $\mathcal{A}$ with a buffer of size B suffers a regret of $\Omega(\sqrt{BT\log N})$.*

Proof. The sequence consists of T' consecutive *rounds*. Each round consists of 3 *phases* each of which has B steps so that the sequence has a total length of $T = 3BT'$ steps. Prices are defined by constant functions, i.e., there is a fixed price p^t per unit in every step t. For simplicity in notation, we assume that prices are chosen from the interval [0,4] instead of [0,1]. In particular, the sequence of prices and demands has the following structure

$$\binom{p^t}{d^t} = \left[\binom{2}{0}^B \binom{\{0,4\}}{0}^B \binom{4}{1}^B\right]^{T'} .$$

Prices in the second phase of each round are chosen at random from $\{0,4\}$. However, the choices within the same round are dependent, that is, for all steps within the second phase of the same round, we set the same price and this price is chosen uniformly at random from the set $\{0,4\}$. Prices for different rounds are selected independently.

The N experts for the problem are defined as follows: In each round, every expert chooses independently one of the following two strategies each with probability 1/2.

a) The expert purchases B units in the first phase.

b) The expert purchases B units in the second phase.

In both cases, no further units are bought. In particular, the buffer is empty at the end and the beginning of each round.

Let F_i^t denote the random variable defining the cost of expert i in round t. Depending on the outcome of the price for round t and the strategy chosen by the expert, this variable takes the following values.

F_i^t	0	1
a	$2B$	$2B$
b	0	$4B$

When analyzing this random variable, we can assume that, a *column player* (the designer of the sequence) selects a column of this matrix and a *row player* (the considered expert) selects a row. Both of these choices are made independently, uniformly at random. As every entry of the matrix is chosen with probability $1/4$, the expected value of F_i^t is $2B$. Thus, by linearity of expectation, the expected cost of an expert over the whole sequence is $2BT'$.

Next we analyze the expected cost of the *best* expert. Towards this end, let F^t be a random variable describing the average cost in the column chosen by the column player in round t, that is, if the column player chooses column 0 then $F^t = B$ and if the column player chooses column 1 then $F^t = 3B$. The expected value of this variable is $2B$ so that

$$E\left[\sum_{t=1}^{T'} F^t\right] = 2BT' = \frac{2}{3}T \ .$$

Now define $\Delta_i^t = F_i^t - F^t$. The values taken by the random variable Δ_i^t depend on the choices of the row and column players and are specified in the following matrix.

Δ_i^t	0	1
a	B	$-B$
b	$-B$	B

Observe that the random variables Δ_i^t, $1 \le i \le N$, $1 \le t \le T'$ are stochastically independent since each of these variables takes one of the value B or $-B$ with probability $1/2$ each, regardless of the outcome of the other variables. For $1 \le i \le N$, let $S_i = \sum_{t=1}^{T'} \Delta_i^t / B$. The random variables $S_1, \ldots, S_N$ are stochastically independent and each of them corresponds to the value of a fair random walk after T' steps. The expected minimum over N such variables is known to be $-\Theta(\sqrt{T' \log N})$, which gives

$$E\left[\min_i \left(\sum_{t=1}^{T'} \Delta_i^t\right)\right] = -\Theta(B\sqrt{T' \log N}) = -\Theta\left(\sqrt{BT \log N}\right) \ .$$

Hence, the expected cost of the best expert can be estimated by

$$\begin{aligned} E\left[\min_i \left(\sum_{t=1}^{T'} F_i^t\right)\right] &= E\left[\min_i \left(\sum_{t=1}^{T'} \left(F^t + \Delta_i^t\right)\right)\right] \\ &= E\left[\sum_{t=1}^{T'} F^t\right] + E\left[\min_i \left(\sum_{t=1}^{T'} \Delta_i^t\right)\right] \\ &= \frac{2}{3}T - \Theta\left(\sqrt{BT \log N}\right) \ . \end{aligned}$$

Finally, we show that any online learning algorithm $\mathcal{A}$ equipped with these experts cannot achieve an expected cost better than $2/3T$. W.l.o.g, $\mathcal{A}$ does not purchase any unit in the third phase of a round, but exactly B units during the first two phases of each round. In the first phase of a round, $\mathcal{A}$ does not have any information about the price in the second phase since the experts decisions (over the whole sequence) and costs (before entering the second phase) do not depend on this price and, hence, do not give any evidence about the price. Thus, $\mathcal{A}$'s decision about how many of the B units to purchase in the first and how many units to purchase in the second phase of a round is independent of the price selected for the second phase. As a consequence, the expected cost for each purchased unit is 2 and, hence, the expected cost per round is $2B$. Therefore, the expected cost of $\mathcal{A}$ for the whole sequence is $2BT' = 2/3\,T$ and, consequently, the regret is $\Theta\left(\sqrt{BT\log N}\right)$. ■

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