Online Stochastic Linear Optimization under One-bit Feedback

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Abstract

In this paper, we study a special bandit setting of online stochastic linear optimization, where only one-bit of information is revealed to the learner at each round. This problem has found many applications including online advertisement and online recommendation. We assume the binary feedback is a random variable generated from the logit model, and aim to minimize the regret defined by the unknown linear function. Although the existing method for generalized linear bandit can be applied to our problem, the high computational cost makes it impractical for real-world applications. To address this challenge, we develop an efficient online learning algorithm by exploiting particular structures of the observation model. Specifically, we adopt online Newton step to estimate the unknown parameter and derive a tight confidence region based on the exponential concavity of the logistic loss. Our analysis shows that the proposed algorithm achieves a regret bound of \(\tilde{O}(d\sqrt{T})\), which matches the optimal result of stochastic linear bandits.

1. Introduction

Online learning with bandit feedback plays an important role in several industrial domains, such as ad placement, website optimization, and packet routing (Bubeck & Cesa-Bianchi, 2012). A canonical framework for studying this problem is the multi-armed bandits (MAB), which models the situation that a gambler must choose which of \(K\) slot machines to play (Robbins, 1952). In the basic stochastic MAB, each arm is assumed to deliver rewards that are drawn from a fixed but unknown distribution. The goal of the gambler is to minimize the regret, namely the difference between his expected cumulative reward and that of the best single arm in hindsight (Auer et al., 2002).

Although MAB is a powerful framework for modeling online decision problems, it becomes intractable when the number of arms is very large or even infinite. To address this challenge, various algorithms have been designed to exploit different structure properties of the reward function, such as Lipschitz (Kleinberg et al., 2008) and convex (Flaxman et al., 2005; Agarwal et al., 2013). Among them, stochastic linear bandits (SLB) has received considerable attentions during the past decade (Auer, 2002; Dani et al., 2008; Abbasi-yadkori et al., 2011). In each round of SLB, the learner is asked to choose an action \(x_t\) from a decision set \(D \subseteq \mathbb{R}^d\), then he observes \(y_t\) such that

\[
E[y_t|x_t] = x_t^\top w^*.
\]

where \(w^* \in \mathbb{R}^d\) is a vector of unknown parameters. The goal of the learner is to minimize the (pseudo) regret

\[
T \max_{x \in D} x^\top w^* - \sum_{t=1}^T x_t^\top w_*.
\]

In this paper, we consider a special bandit setting of online linear optimization where the feedback \(y_t\) only contains one-bit of information. In particular, \(y_t \in \{\pm 1\}\). Our setting is motivated from the fact that in many real-world applications, such as online advertising and recommender
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The stochastic multi-armed bandits (MAB) (Robbins, 1952), has become the canonical formalism for studying systems, user feedback (e.g., click or not, like or dislike) is usually binary. Since the feedback is binary-valued, we assume it is generated according to the logit model (Hastie et al., 2009), i.e.,

$$\Pr[y_t = \pm 1|x_t] = \frac{1}{1 + \exp(-y_t x_t^\top w_*)}. \quad (3)$$

Without loss of generality, suppose 1 is the preferred outcome. Then, it is natural to define the regret in terms of the expected times that 1 is observed, i.e.,

$$T_{\max} \mathop{\times}^{x \in D} \frac{\exp(x^\top w_*)}{1 + \exp(x^\top w_*)} - \sum_{t=1}^{T} \frac{\exp(x_t^\top w_*)}{1 + \exp(x_t^\top w_*)}. \quad (4)$$

The observation model in (3) and the nonlinear regret in (4) can be treated as a special case of the Generalized Linear Bandit (GLB) (Filippi et al., 2010). However, the existing algorithm for GLB is inefficient in the sense that: i) it is not a truly online algorithm since the whole learning history is stored in memory and used to estimate $w_*$; and ii) it is limited to the case that the number of arms is finite because an upper bound for each arm needs to be calculated explicitly in each round.

The main contribution of this paper is an efficient online learning algorithm that effectively exploits particular structures of the logit model. Based on the analytical properties of the logistic function, we first show that the linear regret defined in (2) and the nonlinear regret in (4) only differs by a constant factor, and then focus on minimizing the former one due to its simplicity. Similar to previous studies (Bubeck & Cesa-Bianchi, 2012), we follow the principle of “optimism in face of uncertainty” to deal with the exploration-exploitation dilemma. The basic idea is to maintain a confidence region for $w_*$, and choose an estimate from the confidence region and an action so that the linear reward is maximized. Thus, the problem reduces to the construction of the confidence region from one-bit feedback that satisfies (3). Based on the exponential concavity of the logistic loss, we propose to use a variant of the online Newton step (Hazan et al., 2007) to find the center of the confidence region and derive its width by a rather technical analysis of the updating rule. Theoretical analysis shows that our algorithm achieves a regret bound of $\tilde{O}(d\sqrt{T})$,\(^1\) which matches the result for SLB (Dani et al., 2008). Furthermore, we provide several strategies to reduce the computational cost of the proposed algorithm.

2. Related Work

The stochastic multi-armed bandits (MAB) (Robbins, 1952), has become the canonical formalism for studying the problem of decision-making under uncertainty. A long line of successive problems have been extensively studied in statistics (Berry & Fristedt, 1985) and computer science (Bubeck & Cesa-Bianchi, 2012).

2.1. Stochastic Multi-armed Bandits (MAB)

In their seminal paper, Lai & Robbins (1985) establish an asymptotic lower bound of $O(K \log T)$ for the expected cumulative regret over $T$ periods, under the assumption that the expected rewards of the best and second best arms are well-separated. By making use of upper confidence bounds (UCB), they further construct policies which achieve the lower bound asymptotically. However, this initial algorithm is quite involved, because the computation of UCB relies on the entire sequence of rewards obtained so far. To address this limitation, Agrawal (1995) introduces a family of simpler policies that only needs to calculate the sample mean of rewards, and the regret retains the optimal logarithmic behavior. A finite time analysis of stochastic MAB is conducted by Auer et al. (2002). In particular, they propose an UCB-type algorithm based on the Chernoff-Hoeffding bound, and demonstrate it achieves the optimal logarithmic regret uniformly over time.

2.2. Stochastic Linear Bandits (SLB)

SLB is first studied by Auer (2002), who considers the case $D$ is finite. Although an elegant UCB-type algorithm named LinRel is developed, he fails to bound its regret due to independence issues. Instead, he designs a complicated master algorithm which uses LinRel as a subroutine, and achieves a regret bound of $\tilde{O}(\log |D|^{3/2}\sqrt{TD})$, where $|D|$ is the number of feasible decisions. In a subsequent work, Dani et al. (2008) generalize LinRel slightly so that it can be applied in settings where $D$ may be infinite. They refer to the new algorithm as ConfidenceBall2, and show it enjoys a bound of $\tilde{O}(d\sqrt{T})$, which does not depend on the cardinality of $D$. Later, Abbasi-yadkori et al. (2011) improve the theoretical analysis of ConfidenceBall2 by employing tools from the self-normalized processes. Specifically, the worst case bound is improved by a logarithmic factor and the constant is also improved.

2.3. Generalized Linear Bandit (GLB)

Filippi et al. (2010) extend SLB to the nonlinear case based on the Generalized Linear Model framework of statistics. In the so-called GLB model, $y_t$ is assumed to satisfy $E[y_t|x_t] = \mu(x_t^\top w_*)$ where $\mu: \mathbb{R} \mapsto \mathbb{R}$ is certain link function. The regret is also defined in terms of $\mu(\cdot)$ and given by

$$T_{\max} \mathop{\times}^{x \in D} \mu(x^\top w_*) - \sum_{t=1}^{T} \mu(x_t^\top w_*) \quad (5)$$

\(^1\)We use the $\tilde{O}$ notation to hide constant factors as well as polylogarithmic factors in $d$ and $T$.\n
Note that by setting $\mu(x) = \exp(x)/(1 + \exp(x))$, the problem considered in this paper becomes a special case of GLB. An UCB-type algorithm has been proposed for GLB and achieves a regret bound of $O(d\sqrt{T})$. Different from ConfidenceBall, which constructs a confidence region in the parameter space, the algorithm of Filippi et al. (2010) operates only in the reward space. However, the space and time complexities of that algorithm in the $t$-th iteration are $O(t)$ and $O(t + |D|)$, respectively. The $O(t)$ factor comes from the fact it needs to store the past action-feedback pairs $(x_1, y_1), \ldots, (x_t, y_t)$ and use all of them to estimate $w_*$. The $O(|D|)$ factor is due to the fact it needs to calculate an upper bound for each arm in order to decide the next action $x_t$.

Although we can reduce the computational cost of GLB by replacing the batch optimization with online algorithms, such as online gradient descent (Zinkevich, 2003), the theoretical guarantee of the new algorithm needs to be developed. Furthermore, it is also unclear how to extend GLB to the case of infinite number of arms.

### 2.4. Bandit Learning with One-bit Feedback

There are several new variants of bandit learning that also rely on one-bit feedback, such as multi-class bandits (Kakade et al., 2008; Chen et al., 2014) and $K$-armed dueling bandits (Yue et al., 2009; Ailon et al., 2014). For example, in multi-class bandits, the feedback is whether the predicted label is correct or not, and in $K$-armed dueling bandits, the feedback is the comparison between the rewards from two arms. However, none of them are designed for online linear optimization.

### 2.5. One-bit Compressive Sensing (CS)

Finally, we would like to discuss one closely related work in signal processing—one-bit Compressive Sensing (CS) (Boufounos & Baraniuk, 2008; Plan & Vershynin, 2013; Zhang et al., 2014). One-bit CS aims to recover a sparse vector $w_*$ from a set of one-bit measurements $\{y_i\}$ where $y_i$ is generated from $x_i^\top w_*$ according to certain observation model such as (3). The main difference is that one-bit CS is studied in batch setting with the goal to minimize the recovery error, while our problem is studied in online setting with the goal to minimize the regret. Another difference is that $w_*$ needs to be sparse in one-bit CS, but could be dense in our case.

### 3. Online Learning for Logit Model (OL2M)

We first describe the proposed algorithm for online stochastic linear optimization given one-bit feedback, next compare it with existing methods, then state its theoretical guarantees, and finally discuss implementation issues.

#### 3.1. The Algorithm

For a positive definite matrix $A \in \mathbb{R}^{d \times d}$, the weighted $\ell_2$-norm is defined by $\|x\|_A^2 = x^\top Ax$. Without loss of generality, we assume the decision space $D$ is contained in the unit ball, that is,

$$\|x\|_2 \leq 1, \forall x \in D. \quad (6)$$

We further assume the $\ell_2$-norm of $w_*$ is upper bounded by some constant $R$, which is known to the learner. Our first observation is that the linear regret in (2) and the nonlinear regret in (4) only differs by a constant factor as indicated below.

**Lemma 1.** Let $R_L$ and $R_N$ be the linear and nonlinear regrets in (2) and (4), respectively. We have

$$\frac{1}{2(1 + \exp(R))} R_L \leq R_N \leq \frac{1}{4} R_L \quad (7)$$

In the following, we will develop an efficient algorithm that minimizes the linear regret, which in turn minimizes the nonlinear regret as well.

The algorithm is motivated as follows. Suppose actions $x_1, \ldots, x_t$ have been submitted to the oracle, and let $y_1, \ldots, y_t$ be the one-bit feedback from the oracle. To approximate $w_*$, the most straightforward way is to find the maximum likelihood estimator by solving the following logistic regression problem

$$\min_{\|w\|_2 \leq R} \frac{1}{t} \sum_{i=1}^{t} \log \left(1 + \exp(-y_i x_i^\top w)\right).$$

However, this approach does not scale well since it requires the learner to store the entire learning history. Instead, we propose an online algorithm to find an approximate solution. The key observation is that the logistic loss

$$f_t(w) = \log \left(1 + \exp(-y_i x_i^\top w)\right)$$

is exponentially concave over bounded domain (Hazan et al., 2014), which motivates us to apply a variant of the online Newton step (Hazan et al., 2007). Specifically, we propose to find an approximate solution $w_{t+1}$ by solving the following problem

$$\min_{\|w\|_2 \leq R} \frac{\|w - w_t\|_2^2}{2 Z_{t+1}} + (w - w_t)^\top \nabla f_t(w_t) \quad (8)$$

where

$$Z_{t+1} = Z_t + \frac{\beta}{2} x_t x_t^\top, \quad (9)$$

and $\beta$ is defined in (14). Although our updating rule is similar to the method in (Hazan et al., 2007), there also exist some differences. As indicated by (9), in our case...
Since both ConfidenceBall and refer to as Online Learning for Logit Model (OLM). The above procedure is summarized in Algorithm 1, and is similar. The main difference lies in the construction of the confidence region, OLM resorts to online New- ton step. Due to the difference in the updating rule and the observation model, the self-normalized bound for vector-valued martingales (Abbasi-yadkori et al., 2011) can not be applied here.

Algorithm 1 Online Learning for Logit Model (OL^2M)

1: **Input:** Regularization Parameter \( \lambda \)
2: \( Z_1 = \lambda I, w_1 = 0 \)
3: for \( t = 1, 2, \ldots \) do
4: \( (x_t, \hat{w}_t) = \arg\max_{x \in D, w \in C_t} x^\top w \)
5: Submit \( x_t \) and observe \( y_t \in \{\pm 1\} \)
6: Solve the optimization problem in (8) to find \( w_{t+1} \)
7: end for

\( x_t x_t^\top \) is used to approximate the Hessian matrix, while in Hazan et al. (2007) \( \nabla f_t(w_t)[\nabla f_t(w_t)^\top] \) is used.

After a theoretical analysis, we are able to show that with a high probability
\[
\|w_{t+1} - w_*\|_{Z_{t+1}} \leq \sqrt{\gamma_{t+1}}, \quad \forall t > 0
\]
where the value of \( \gamma_{t+1} \) is given in (12). Given the confidence region, we adopt the principle of “optimism in face of uncertainty”, and the next action \( x_{t+1} \) is given by
\[
(x_{t+1}, \hat{w}_{t+1}) = \arg\max_{x \in D, w \in C_{t+1}} x^\top w.
\]

At the beginning, we set \( Z_1 = \lambda I \), and \( w_1 = 0 \).

The above procedure is summarized in Algorithm 1, and is refer to as Online Learning for Logit Model (OL^2M).

Since both ConfidenceBall (Dani et al., 2008) and our OL^2M are UCB-type algorithms, their overall framework are similar. The main difference lies in the construction of the confidence region and the related analysis. While ConfidenceBall uses online least square to update the center of the confidence region, OL^2M resorts to online Newton step. Due to the difference in the updating rule and the observation model, the self-normalized bound for vector-valued martingales (Abbasi-yadkori et al., 2011) can not be applied here.

Although our observation model in (3) can be handled by the Generalized Linear Bandit (GLB) (Filippi et al., 2010), this paper differs from GLB in the following aspects.

- To estimate \( w_* \), GLB needs to store the learning history and perform batch updating in each round. In contrast, the proposed OL^2M performs online updating.
- While GLB only considers a finite number of arms, we allow the number of arms to be infinite.
- Our algorithm follows the learning framework of SLB. Thus, existing techniques for speeding up SLB can also be used to accelerate our algorithm, which is discussed in Section 3.3.

3.2. Theoretical Guarantees

The main theoretical contribution of this paper is the following theorem regarding the confidence region of \( w_* \) at each round.

**Theorem 1.** With a probability at least \( 1 - \delta \), we have
\[
\|w_{t+1} - w_*\|_{Z_{t+1}} \leq \sqrt{\gamma_{t+1}}, \quad \forall t > 0
\]
where
\[
\gamma_{t+1} = \left[ 8R + \left( \frac{8}{\beta} + \frac{16}{3} R \right) \tau_t + \frac{2}{\beta^2} \log \left( \frac{\det(Z_{t+1})}{\det(Z_1)} \right) \right] + \lambda R^2,
\]
\[
\tau_t = \log \left( \frac{2 \beta t}{\delta} \right),
\]
\[
\beta = \frac{1}{2(1 + \exp(R))}.
\]

The main idea is to analyze the growth of \( \|w_{t+1} - w_*\|_{Z_{t+1}} \) by exploring the properties of the logistic loss (Lemmas 2 and 4) and concentration inequalities for martingales (Lemma 5). By a simple upper bound of \( \log \det(Z_{t+1})/\det(Z_1) \), we can show that the width of the confidence region is \( O(\sqrt{d \log t}) \).

**Corollary 2.** We have
\[
\log \frac{\det(Z_{t+1})}{\det(Z_1)} \leq d \log \left( 1 + \frac{\beta t}{2\lambda d} \right)
\]
and thus
\[
\gamma_{t+1} \leq O(d \log t), \quad \forall t > 0.
\]

Based on Theorem 1, we have the following regret bound for OL^2M.

**Theorem 3.** With a probability at least \( 1 - \delta \), we have
\[
\max_{x \in D} x^\top w_* - \sum_{t=1}^{T} x_t^\top w_* \leq 4 \max \left( 1, \sqrt{\frac{\beta}{2}} \right) \sqrt{\frac{\gamma_T T}{\beta} \log \left( \frac{\det(Z_{T+1})}{\det(Z_1)} \right)}
\]
holds for all \( T > 0 \).

Combining with the upper bound in Corollary 2, the above theorem implies our algorithm achieves a regret bound of \( O(d \sqrt{T}) \) which matches the bound for Stochastic Linear Bandits (Dani et al., 2008). One limitation of Theorem 3 is that the upper bound has an exponential dependence on \( R \), which is an upper bound of \( \|w_*\|_2 \). That is because our algorithm is built upon online Newton step (Hazan et al.,...
2007), the regret of which has such a undesirable dependence on $R$. From the recent studies on logistic regression (Bach & Moulinès, 2013; Bach, 2014; Hazan et al., 2014), we conjecture that it is possible to obtain a polynomial dependence on $R$, but with a higher dependence on $T$. We will investigate this issue in the future.

3.3. Implementation Issues
The main computational cost of OL$^2$M comes from (11) which is NP-hard in general (Dani et al., 2008). In the following, we discuss two strategies for reducing the computational cost. More results can be found in the supplementary material.

Finite Decision Set If the decision set $D$ is finite, (11) can be solved by computing an upper bound for each decision in $D$. Specifically, we have

$$x_{t+1} = \arg\max_{x \in D} \max_{\|w\|_2 \leq \sqrt{\gamma_{t+1}}} x^T w$$

$$= \arg\max_{x \in D} \max_{\|z\| \leq \sqrt{\gamma_{t+1}}} x^T (w_{t+1} + z)$$

$$= \arg\max_{x \in D} \left( x^T w_{t+1} + \sqrt{\gamma_{t+1}} \right).$$

Optimization Over Ball As mentioned by Dani et al. (2008), in the special case that $D$ is the unit ball, (11) could be solved in time $O(poly(d))$. Here, we provide an explanation using techniques from convex optimization. To this end, we rewrite the optimization problem in (11) as follows

$$\max_{\|x\|^2 \leq 1, \|w-w_{t+1}\| \leq \sqrt{\gamma_{t+1}}} x^T w$$

$$= \max_{\|w-w_{t+1}\| \leq \sqrt{\gamma_{t+1}}} \|w\|_2$$

which is equivalent to

$$\min_{\|w-w_{t+1}\| \leq \sqrt{\gamma_{t+1}}} -\|w\|_2^2.$$ 

The above problem is an optimization problem with a quadratic objective and one quadratic inequality constraint, it is well-known that strong duality holds provided there exists a strictly feasible point (Boyd & Vandenberghe, 2004). Thus, we can solve its dual problem which is convex and given by

$$\max_{\gamma} \gamma$$

s.t. $$\lambda \geq 0$$

$$\begin{bmatrix} -I + \lambda \gamma_{t+1} \nabla f_t(w_t) - \lambda Z_{t+1} \nabla f_t(w_t) \\
\lambda (\|w_{t+1}\|_2^2 - \gamma_{t+1} - \gamma_{t+1}) \end{bmatrix} \geq 0$$

After obtaining the dual solution, we can get the primal solution based on KKT conditions.

4. Analysis
Due to the limitation of space, we only prove Theorem 1. The omitted proofs are provided in the supplementary material.

4.1. Proof of Theorem 1
We begin with several lemmas that are central to our analysis.

Although the application of online Newton step (Hazan et al., 2007) in Algorithm 1 is motivated from the fact that $f_t(w)$ is exponentially concave over bounded domain, our analysis is built upon a related but different property that the logistic loss $\log(1 + \exp(x))$ is strongly convex over bounded domain, from which we obtain the following lemma.

Lemma 2. Denote the ball of radius $R$ by $B_R$, i.e.,

$$B_R = \{w : \|w\|_2 \leq R\}.$$ 

The following holds for $\beta \leq \frac{1}{2(1 + \exp(\beta))}$:

$$f_t(w_2) \geq f_t(w_1) + \|\nabla f_t(w_1)\|_2 (w_2 - w_1) + \frac{\beta}{2} (w_2 - w_1)^T x_t \geq \forall w_1, w_2 \in B_R.$$

Comparing Lemma 2 with Lemma 3 in (Hazan et al., 2007), we can see that the quadratic term in our inequality does not depend on $y_t$. This independence allows us to simplify the subsequent analysis involving martingales.

Our second lemma is devoted to analyzing the property of the updating rule in (8).

Lemma 3.

$$\langle w_t - w_*, \nabla f_t(w_t) \rangle - \frac{1}{2} \|\nabla f_t(w_t)\|_2^2 \leq \frac{\|w_t - w_*\|_{z_{t+1}}^2}{2} - \frac{\|w_{t+1} - w_*\|_{z_{t+1}}^2}{2}. \quad (15)$$

For each function $f_t(\cdot)$, we denote its conditional expectation over $y_t$ by $\bar{f}_t(w)$, i.e.,

$$\bar{f}_t(w) = E_{y_t} \log(1 + \exp(-y_t x_t^T w)). \quad (16)$$

According to the Leibniz integral rule, we have

$$\nabla \bar{f}_t(w) = E_{y_t} \nabla f_t(w). \quad (17)$$

Based the property of Kullback–Leibler divergence (Cover & Thomas, 2006), we obtain the following lemma.

Lemma 4. We have

$$\bar{f}_t(w) \geq f_t(w_*) \forall w \in \mathbb{R}^d.$$
Next, we introduce one inequality for bounding the weighted $\ell_2$-norm of the gradient
\[ \|\nabla f_t(w)\|_A^2 = \left(\frac{\exp(-yw_t^x)}{1 + \exp(-yw_t^x)}\right)^2 x_t^T A x_t \leq \|x_t\|_A^2, \quad \forall A \succeq 0, \ w \in \mathbb{R}^d. \] (18)

We continue the proof of Theorem 1 in the following. Our updating rule in (8) ensures $\|w_t\|_2 \leq R, \forall t > 0$. Combining with the assumption $\|w_*\|_2 \leq R$, Lemma 2 implies
\[ f_t(w_t) \leq f_t(w_*) + \|\nabla f_t(w_t)\|^T (w_t - w_*) - \frac{\beta}{2} \|w_* - w_t\|^2. \] (19)

By taking expectation over $y_t$, (19) becomes
\[ \tilde{f}_t(w_t) \leq \tilde{f}_t(w_*) + \|\tilde{\nabla} f_t(w_t)\|^T (w_t - w_*) - \frac{\beta}{2} \|w_* - w_t\|^2. \]

Combining with Lemma 4, we have
\[ 0 \leq \|\tilde{\nabla} f_t(w_t)\|^T (w_t - w_*) - \frac{\beta}{2} \|w_* - w_t\|^2. \]

We thus have
\[ \|w_{t+1} - w_*\|^2_{Z_{t+1}} \leq \|w_t - w_*\|^2_{Z_t} - \frac{\beta}{2} a_t + 2b_t + c_t \]

Summing the above inequality over iterations $1$ to $t$, we obtain
\[ \|w_{t+1} - w_*\|^2_{Z_{t+1}} + \frac{\beta}{2} \sum_{i=1}^{t} a_i \leq \lambda R^2 + 2 \sum_{i=1}^{t} b_i + \sum_{i=1}^{t} c_i. \] (20)

Next, we discuss how to bound the summation of martingale difference sequence $\sum_{i=1}^{t} b_i$. To this end, we prove the following lemma, which is built up the Bernstein’s inequality for martingales (Cesa-Bianchi & Lugosi, 2006) and the peeling technique (Bartlett et al., 2005).

**Lemma 5.** With a probability at least $1 - \delta$, we have
\[ \sum_{i=1}^{t} b_i \leq 4R + 2\sqrt{\tau_t \sum_{i=1}^{t} a_i + \frac{8}{3} R\tau_t}, \quad \forall t > 0 \]
where $\tau_t$ is defined in (13).

From Lemma 5 and the basic inequality
\[ 2 \sqrt{\tau_t \sum_{i=1}^{t} a_i} \leq \frac{\beta}{4} \sum_{i=1}^{t} a_i + \frac{4}{\beta} \tau_t, \]
with a probability at least $1 - \delta$, we have
\[ \sum_{i=1}^{t} b_i \leq 4R + \frac{\beta}{4} \sum_{i=1}^{t} a_i + \left(\frac{4}{\beta} + \frac{8}{3} R\right) \tau_t \] (21)
holds for all $t > 0$. Substituting (21) into (20), we obtain
\[ \|w_{t+1} - w_*\|^2_{Z_{t+1}} \leq \lambda R^2 + 2\left[4R + \left(\frac{4}{\beta} + \frac{8}{3} R\right) \tau_t\right] + \sum_{i=1}^{t} c_i. \] (22)

Finally, we show an upper bound for $\sum_{i=1}^{t} c_i$, which is a direct consequence of Lemma 12 in Hazan et al. (2007).

**Lemma 6.** We have
\[ \sum_{i=1}^{t} \|x_i\|^2_{Z_{t+1}} \leq \frac{2}{\beta} \log \frac{\det(Z_{t+1})}{\det(Z_t)}. \]
We complete the proof by combining (22) with the above lemma.
5. Experiments

In this section, we present experimental results to demonstrate the effectiveness of the proposed algorithm.

5.1. Experimental Setting

We sample a point uniformly at random from the \((d-1)\)-sphere as \(w_\ast\) and each time the learner submits an action \(x_t\), a one-bit feedback \(y_t \in \{\pm 1\}\) is generated according to the logit model in (3). To apply our algorithm, we need to determine the values of two parameters: \(\lambda\) and \(\gamma_t\). \(\lambda\) is introduced to make \(Z_t\) invertible, and the performance of our algorithm is insensitive to its value. Thus, we simply choose \(\lambda = 1\) in the following. \(\gamma_t\) is an essential parameter which is the width of the confidence region, and its value is tuned as \(c \log \frac{\det(Z_t)}{\det(Z_1)}\) according to (12), where \(c\) is searched in the range of \([1e^{-3}, 1]\).

5.2. Experimental Results

In the first experiment, we choose the unit ball as the decision set, i.e., \(D = \{x : \|x\|_2 \leq 1\} \subseteq \mathbb{R}^d\), which contains infinite number of actions. As discussed in Section 3.3, in this case, (11) can be cast as a convex optimization problem, which is then solved by the CVX package (Grant & Boyd, 2008; 2014). We first investigate how the instantaneous regret \(x_\ast^\top w_\ast - x_t^\top w_\ast\) varies with \(t\) during the learning process. The results for \(d = 10\) with different settings of \(c\) are shown in Fig. 1. As can be seen, the instantaneous regret decreases overall, although exhibits some local fluctuations. These fluctuations actually reflect the switches between exploitation and exploration. Generally speaking, valley and peak of the curve correspond to exploitation and exploration, respectively.

The value of \(c\) determines the width of the confidence region, which in turn controls the exploitation-exploration trade-off. A small value of \(c\) prefers exploitation, which may select an action which is not optimal because of too little exploration. For example, in Fig. 1(a) where \(c = 0.001\), after \(2 \times 10^4\) rounds, the learner always submits a suboptimal action and suffers a constant instantaneous regret. On the other hand, a larger value of \(c\) favors exploration, which might results in a large regret because too much exploration prevents the algorithm from playing the optimal action. This phenomenon can also be observed in Fig. 1(d) where \(c = 1\). From Fig. 1(b) and Fig. 1(c), we see that a good trade-off between exploitation-exploration is achieved when \(c = 0.02\) or \(0.2\), for which the instantaneous regret approaches 0 gradually. The behavior of the instantaneous regret for \(d = 100\) is similar and can be found in the supplementary.

Next, we examine the \(\tilde{O}(d\sqrt{T})\) regret bound indicated by Theorem 3. Let \(\text{Regret}(t)\) be the regret till round \(t\), i.e.,
Regret(t) = ∑_{i=1}^{t} x_i^T w_\ast - x_i^T w_* + x_i^T y_i. If the learner achieves an $\tilde{O}(d\sqrt{T})$ regret bound, the curve of Regret(t)/(d√t) should increase at most polylogarithmically. Fig. 2 plots the curve of Regret(t)/(d√t) with respect to t for $d = 10$ and 100. As can be seen, with a suitable choice of $c$, the curve indeed increases very slowly (e.g., $d = 10$ and $c = 0.02$), or even decreases slightly after certain rounds (e.g., $d = 10$ and $c = 0.2$).

In the last experiment, we study the case that $D$ is finite, so that the GLB algorithm (Filippi et al., 2010) can also be applied. In the experiments, the parameter of GLB is also manually tuned. The decision set $D \subseteq \mathbb{R}^d$ is constructed by sampling $10^d$ points uniformly at random from the $(d-1)$-sphere. In Fig. 3, we plot the regret of OL$^2$M and GLB with respect to t. Note that in each round, GLB solves a logistic regression problem that utilizes the whole learning history to estimate $w_*$. Thus, it is not surprising that the regret of GLB is smaller than OL$^2$M by a constant factor. On the other hand, OL$^2$M performs online updating, which is more efficient when $t$ is large.

## 6. Conclusions

In this paper, we consider the problem of online linear optimization under one-bit feedback. Under the assumption that the binary feedback is generated from the logit model, we develop a variant of the online Newton step to approximate the unknown vector, and discuss how to construct the confidence region theoretically. Given the confidence region, we choose the action that produces maximal reward in each round. Theoretical analysis reveals that our algorithm achieves a regret bound of $\tilde{O}(d\sqrt{T})$.

The current algorithm assumes that the one-bit feedback is generated from a logit model. In contrast, a much broader class of observation models are allowed in one-bit compressive sensing (Plan & Vershynin, 2013). In the future, we will investigate how to extend our algorithm to other observation models. Recently studies in online learning have shown that Thompson sampling is both competitive and efficient for addressing the exploration-exploitation dilemma (Chapelle & Li, 2011; Li, 2013). We leave the application of Thompson sampling to our problem for future work.
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