

Supplementary Material: Online Bandit Learning for a Special Class of Non-convex Losses

Lijun Zhang¹ and Tianbao Yang² and Rong Jin³ and Zhi-Hua Zhou¹

¹National Key Laboratory for Novel Software Technology, Nanjing University, Nanjing 210023, China

²Department of Computer Science, the University of Iowa, Iowa City, IA 52242, USA

³Department of Computer Science and Engineering, Michigan State University, East Lansing, MI 48824, USA
 {zhanglj, zhouzh}@lamda.nju.edu.cn, tianbao-yang@uiowa.edu, rongjin@cse.msu.edu

Proof of Proposition 1

The proof is similar to that of Lemma 4 in (Zhang, Yi, and Jin 2014). First, we have

$$\begin{aligned} & \mathbf{u}^\top \mathbb{E}_{t-1} \left[-\frac{Z_t C_t}{\|\mathbf{v}_t\|_2} \mathbf{v}_t \right] \\ \stackrel{(1)}{=} & -\mathbb{E}_{t-1} \left[f \left(\mathbf{u}^\top \frac{\mathbf{v}_t}{\|\mathbf{v}_t\|_2} \right) \mathbf{u}^\top \frac{\mathbf{v}_t}{\|\mathbf{v}_t\|_2} \right] \\ \stackrel{(3),(5)}{=} & 0; \end{aligned}$$

Then, consider any vector $\mathbf{u} \perp \mathbf{u}$. We have

$$\begin{aligned} & \mathbf{u}^\top \mathbb{E}_{t-1} \left[-\frac{Z_t C_t}{\|\mathbf{v}_t\|_2} \mathbf{v}_t \right] \\ \stackrel{(1)}{=} & -\mathbb{E}_{t-1} \left[f \left(\mathbf{u}^\top \frac{\mathbf{v}_t}{\|\mathbf{v}_t\|_2} \right) \mathbf{u}^\top \frac{\mathbf{v}_t}{\|\mathbf{v}_t\|_2} \right] \\ = & -\mathbb{E}_{t-1} \left[f \left(\frac{1}{\sqrt{\frac{1}{d} + \dots + \frac{1}{d}}} \right) \frac{\|\mathbf{u}\|_2}{\sqrt{\frac{1}{d} + \dots + \frac{1}{d}}} \right] \end{aligned}$$

where x_1, \dots, x_n are n independent standard Gaussian variables. Notice that $f \left(\frac{\alpha_1}{\sqrt{\alpha_1^2 + \dots + \alpha_d^2}} \right) \frac{\|\mathbf{u}\|_2 \alpha_2}{\sqrt{\alpha_1^2 + \dots + \alpha_d^2}}$ is an odd function of x_2 , so its expectation with respect to x_2 must be 0. Thus, we have

$$\mathbf{u}^\top \mathbb{E}_{t-1} \left[-\frac{Z_t C_t}{\|\mathbf{v}_t\|_2} \mathbf{v}_t \right] = 0;$$

Then, it is easy to prove Proposition 1 by contradiction.

Proof of Theorem 3

The following lemma extends Lemma 2 to the general case when each \mathbf{u}_t is a different vector.

Lemma 4. *We have*

$$\begin{aligned} & f(\mathbf{x}_t^\top \mathbf{u}_t) - \min_{\|\mathbf{x}\| \leq 1} f(\mathbf{x}^\top \mathbf{u}_t) \leq \\ & \begin{cases} 2B; & \text{if } t = 1; \\ \frac{2L}{\gamma \eta \rho_T^{(t-1)}} \left\| \sum_{i=1}^{t-1} \mathbf{u}_i \right\|_2 + 2L \|\mathbf{u}_t\|_2 & \text{if } t > 1; \end{cases} \end{aligned}$$

Following a simple geometric argument, we have

$$\left\| \frac{\mathbf{w}_t}{\|\mathbf{w}_t\|} - \frac{\mathbf{u}_{t-1}}{\|\mathbf{u}_{t-1}\|_2} \right\|_2 \leq \frac{2}{(t-1)\|\mathbf{u}_{t-1}\|_2} \left\| \sum_{i=1}^{t-1} \mathbf{i} \right\|_2;$$

implying

$$\begin{aligned} & f(\mathbf{x}_t^\top \mathbf{u}) - \min_{\|\mathbf{x}\| \leq 1} f(\mathbf{x}^\top \mathbf{u}) \\ & \stackrel{(18)}{\leq} \frac{2L}{(t-1)\|\mathbf{u}_{t-1}\|_2} \left\| \sum_{i=1}^{t-1} \mathbf{i} \right\|_2 + L \left\| \mathbf{u}_t - \frac{\mathbf{u}_{t-1}}{\|\mathbf{u}_{t-1}\|_2} \right\|_2 \\ & \leq \frac{2L}{T(t-1)} \left\| \sum_{i=1}^{t-1} \mathbf{i} \right\|_2 + 2L \|\mathbf{u}_t - \mathbf{u}_{t-1}\|_2. \end{aligned}$$

Proof of (7)

We provide the proof because our definition of \mathbf{u}_t is slightly different from the one in (Hazan and Kale 2010).

First, we have

$$\begin{aligned} & \sum_{t=2}^T \|\mathbf{u}_t - \mathbf{u}_{t-1}\|_2^2 - \sum_{t=2}^T \|\mathbf{u}_t - \mathbf{u}_t\|_2^2 \\ & \leq \sum_{t=2}^T 2 \langle \mathbf{u}_t - \mathbf{u}_{t-1}, \mathbf{u}_t - \mathbf{u}_{t-1} \rangle \\ & = \sum_{t=2}^T 2 \left\langle \mathbf{u}_t - \mathbf{u}_{t-1}, \frac{(t-1)\mathbf{u}_{t-1} + \mathbf{u}_t}{t} - \mathbf{u}_{t-1} \right\rangle \\ & = 2 \sum_{t=2}^T \frac{\|\mathbf{u}_t - \mathbf{u}_{t-1}\|_2^2}{t} \leq 4 \sum_{t=2}^T \frac{\|\mathbf{u}_t - \mathbf{u}_{t-1}\|_2}{t} \end{aligned} \quad (19)$$

where the first inequality is due to the property of convexity and the second inequality comes from our assumption that $\|\mathbf{u}_t\|_2 = 1, \forall t \in [T]$. We then bound $\sum_{t=2}^T \frac{\|\mathbf{u}_t - \mathbf{u}_{t-1}\|_2}{t}$ as follows.

$$\begin{aligned} & \sum_{t=2}^T \frac{\|\mathbf{u}_t - \mathbf{u}_{t-1}\|_2}{t} = \sum_{t=2}^T \frac{1}{t} \left\| \mathbf{u}_t - \frac{1}{t-1} \sum_{i=1}^{t-1} \mathbf{u}_i \right\|_2 \\ & = \sum_{t=2}^T \frac{1}{t} \left\| (\mathbf{u}_t - \mathbf{u}_T) - \frac{1}{t-1} \sum_{i=1}^{t-1} (\mathbf{u}_i - \mathbf{u}_T) \right\|_2 \\ & \leq \sum_{t=2}^T \frac{1}{t} \|\mathbf{u}_t - \mathbf{u}_T\|_2 + \sum_{t=1}^{T-1} \|\mathbf{u}_t - \mathbf{u}_T\|_2 \sum_{i=t}^{T-1} \frac{1}{i(i+1)} \\ & \leq \sum_{t=2}^T \frac{1}{t} \|\mathbf{u}_t - \mathbf{u}_T\|_2 + \sum_{t=1}^{T-1} \frac{1}{t} \|\mathbf{u}_t - \mathbf{u}_T\|_2 \\ & \leq 2 \sum_{t=1}^T \frac{1}{t} \|\mathbf{u}_t - \mathbf{u}_T\|_2 \\ & \leq 2 \sqrt{\sum_{t=1}^T \|\mathbf{u}_t - \mathbf{u}_T\|_2^2} \sqrt{\sum_{t=1}^T \frac{1}{t^2}} \leq 3 \sqrt{\sum_{t=1}^T \|\mathbf{u}_t - \mathbf{u}_T\|_2^2}. \end{aligned} \quad (20)$$

Combining (19) with (20), we have

$$\sum_{t=2}^T \|\mathbf{u}_t - \mathbf{u}_{t-1}\|_2^2 \leq \epsilon$$