

## A Supplementary Material

### A.1 Proof of Thm. 1

**Proof:** Fix  $n$  examples sequences,  $(\mathbf{x}_{i,1}, y_{i,1}), \dots, (\mathbf{x}_{i,n}, y_{i,n})$  for each of the  $K$  tasks. Let  $t$  be certain trial and  $i$  to be an update task on this trial, such that  $M_{i,t} = 1$  or  $A_{i,t} = 1$ . Denote this event by  $U_{i,t} = 1$ . We write,

$$\begin{aligned}
\gamma - \ell_{\gamma,i,t}(\mathbf{u}_i) &= \gamma - (\gamma - y_{i,t} \mathbf{u}_i^T \mathbf{x}_{i,t})_+ \\
&\leq y_{i,t} \mathbf{u}_i^T \mathbf{x}_{i,t} \\
&= y_{i,t} (\mathbf{u}_i + \mathbf{w}_{i,t-1} - \mathbf{w}_{i,t-1})^T \mathbf{x}_{i,t} \\
&= y_{i,t} \mathbf{w}_{i,t-1}^T \mathbf{x}_{i,t} + \frac{1}{2} \|\mathbf{u}_i - \mathbf{w}_{i,t-1}\|^2 \\
&\quad - \frac{1}{2} \|\mathbf{u}_i - \mathbf{w}_{i,t}\|^2 + \frac{1}{2} \|\mathbf{w}_{i,t-1} - \mathbf{w}_{i,t}\|^2 \\
&= y_{i,t} \hat{p}_{i,t} + \frac{1}{2} \|\mathbf{u}_i - \mathbf{w}_{i,t-1}\|^2 \\
&\quad - \frac{1}{2} \|\mathbf{u}_i - \mathbf{w}_{i,t}\|^2 + \frac{1}{2} \|\mathbf{w}_{i,t-1} - \mathbf{w}_{i,t}\|^2.
\end{aligned}$$

The last inequality holds for all  $\gamma > 0$  and for all  $\mathbf{u}_i \in \mathbb{R}^d$ , so we can replace  $\gamma$  and  $\mathbf{u}_i$  by their scaling  $\alpha\gamma$  and  $\alpha\mathbf{u}_i$  respectively, where  $\alpha > 0$  will be determined shortly and we get

$$\alpha\gamma + y_{i,t} \hat{p}_{i,t} \leq \alpha\ell_{\gamma,i,t}(\mathbf{u}_i) + \frac{1}{2} \|\alpha\mathbf{u}_i - \mathbf{w}_{i,t-1}\|^2 - \frac{1}{2} \|\alpha\mathbf{u}_i - \mathbf{w}_{i,t}\|^2 + \frac{1}{2} \|\mathbf{w}_{i,t-1} - \mathbf{w}_{i,t}\|^2.$$

In trials and task where there is no update, i.e.,  $U_{i,t} Z_{i,t} = 0$ , the equality  $\mathbf{w}_{i,t} = \mathbf{w}_{i,t-1}$  holds. Combining the last two observations, we have

$$U_{i,t} Z_{i,t} (\alpha\gamma + y_{i,t} \hat{p}_{i,t}) \leq U_{i,t} Z_{i,t} \alpha\ell_{\gamma,i,t}(\mathbf{u}_i) + \frac{1}{2} \|\alpha\mathbf{u}_i - \mathbf{w}_{i,t-1}\|^2 - \frac{1}{2} \|\alpha\mathbf{u}_i - \mathbf{w}_{i,t}\|^2 + \frac{1}{2} \|\mathbf{w}_{i,t-1} - \mathbf{w}_{i,t}\|^2.$$

Next, we sum the inequality above, over  $t$  and use the fact that  $\mathbf{w}_{i,0} = 0$  and  $\|\mathbf{w}_{i,t-1} - \mathbf{w}_{i,t}\|^2 \leq X^2$  to get,

$$\sum_{t=1}^n U_{i,t} Z_{i,t} \left( \alpha\gamma + y_{i,t} \hat{p}_{i,t} - \frac{X^2}{2} \right) \leq \alpha \sum_{t=1}^n U_{i,t} Z_{i,t} \ell_{\gamma,i,t}(\mathbf{u}_i) + \frac{\alpha^2}{2} \|\mathbf{u}_i\|^2. \quad (3)$$

Substituting  $\alpha = (2b + X^2)/2\gamma$  (where  $b \in \mathbb{R}$ ,  $b > 0$ ) in Eq. (3), we get

$$\sum_{t=1}^n U_{i,t} Z_{i,t} (b + y_{i,t} \hat{p}_{i,t}) \leq \frac{2b + X^2}{2\gamma} \sum_{t=1}^n U_{i,t} Z_{i,t} \ell_{\gamma,i,t}(\mathbf{u}_i) + \frac{(2b + X^2)^2}{8\gamma^2} \|\mathbf{u}_i\|^2.$$

We subtract a non negative quantity  $\sum_{t=1}^n U_{i,t} Z_{i,t} \min_j |\hat{p}_{j,t}|$  from the l.h.s. and get,

$$\sum_{t=1}^n U_{i,t} Z_{i,t} \left( b + y_{i,t} \hat{p}_{i,t} - \min_j |\hat{p}_{j,t}| \right) \leq \frac{2b + X^2}{2\gamma} \sum_{t=1}^n U_{i,t} Z_{i,t} \ell_{\gamma,i,t}(\mathbf{u}_i) + \frac{(2b + X^2)^2}{8\gamma^2} \|\mathbf{u}_i\|^2. \quad (4)$$

At this point we take the expectation of all the terms. Recall that the conditional expectation of  $Z_{i,t}$  is  $a_i(b + |\hat{p}_{i,t}| - \min_j |\hat{p}_{j,t}|)^{-1} / D_t$  and that  $U_{i,t} = M_{i,t} + A_{i,t}$  and  $\hat{p}_{i,t}$  are measurable with respect to the  $\sigma$ -algebra that generated by  $Z_1, \dots, Z_{t-1}$ . We start with the left term,

$$\begin{aligned}
&\mathbb{E} \left[ \sum_{t=1}^n U_{i,t} Z_{i,t} \left( b - y_{i,t} \hat{p}_{i,t} - \min_j |\hat{p}_{j,t}| \right) \right] \\
&= \mathbb{E} \left[ \mathbb{E}_{t-1} \left[ \sum_{t=1}^n U_{i,t} Z_{i,t} \left( b - y_{i,t} \hat{p}_{i,t} - \min_j |\hat{p}_{j,t}| \right) \right] \right] \\
&= \mathbb{E} \left[ \sum_{t=1}^n \frac{a_i}{D_t} \left( M_{i,t} + \frac{b - |\hat{p}_{j,t}| - \min_j |\hat{p}_{j,t}|}{b + |\hat{p}_{j,t}| - \min_j |\hat{p}_{j,t}|} A_{i,t} \right) \right].
\end{aligned}$$

We remind the reader that  $a_i \geq 1 \forall i$ . Thus we bound  $M_{i,t} \leq M_{i,t} a_i$  and get,

$$\mathbb{E} \left[ \sum_{t=1}^n \frac{1}{D_t} \left( M_{i,t} + \frac{b - |\hat{p}_{j,t}| - \min_j |\hat{p}_{j,t}|}{b + |\hat{p}_{j,t}| - \min_j |\hat{p}_{j,t}|} A_{i,t} a_i \right) \right] \leq \frac{2b + X^2}{2\gamma} \bar{L}_{\gamma,i,n}(u_i) + \frac{(2b + X^2)^2}{8\gamma^2} \|\mathbf{u}_i\|^2. \quad (5)$$

Next we bound the factor that multiplies  $a_i A_{i,t}$  as follows,

$$\left( 1 - 2\frac{\lambda}{b} \right) = \frac{b - 2\lambda}{b} \leq \frac{b - |\hat{p}_{j,t}| - \min_j |\hat{p}_{j,t}|}{b + |\hat{p}_{j,t}| - \min_j |\hat{p}_{j,t}|},$$

and plug it into the left side of the inequality,

$$\mathbb{E} \left[ \sum_{t=1}^n \frac{1}{D_t} \left( M_{i,t} + \frac{b - |\hat{p}_{j,t}| - \min_j |\hat{p}_{j,t}|}{b + |\hat{p}_{j,t}| - \min_j |\hat{p}_{j,t}|} A_{i,t} a_i \right) \right] \leq \mathbb{E} \left[ \sum_{t=1}^n \frac{1}{D_t} \left( M_{i,t} + \left( 1 - 2\frac{\lambda}{b} \right) A_{i,t} a_i \right) \right].$$

Since  $b/2 \geq \lambda$  we have that  $M_{i,t} + \left( 1 - 2\frac{\lambda}{b} \right) A_{i,t} a_i \geq 0$ , thus there exists  $\delta_i$  such that,

$$\mathbb{E} \left[ \sum_{t=1}^n \frac{1}{D_t} \left( M_{i,t} + \left( 1 - 2\frac{\lambda}{b} \right) A_{i,t} a_i \right) \right] = \frac{b}{\delta_i} \mathbb{E} \left[ \sum_{t=1}^n \left( M_{i,t} + \left( 1 - 2\frac{\lambda}{b} \right) A_{i,t} a_i \right) \right], \quad (6)$$

and

$$\frac{b}{\delta_i} \geq \min \frac{1}{D_t} = \frac{1}{\max D_t} \geq \frac{b}{\sum_{j=1}^K a_j},$$

where the last inequality follows from,

$$D_t = \sum_{j=1}^K \frac{a_j}{(b + |\hat{p}_{j,t}| - \min_{m=1}^K |\hat{p}_{m,t}|)} \leq \frac{\sum_{j=1}^K a_j}{b}. \quad (7)$$

The previous bound implies that  $0 < \delta_i \leq \sum_{i=1}^K a_i$ .

Combining Eq. (5) and Eq. (6),

$$\frac{b}{\delta_i} \mathbb{E} \left[ \sum_{t=1}^n M_{i,t} \right] \leq \frac{2b + X^2}{2\gamma} \bar{L}_{\gamma,i,n}(\mathbf{u}_i) + \frac{(2b + X^2)^2}{8\gamma^2} \|\mathbf{u}_i\|^2 + \frac{b}{\delta} \left( 2\frac{\lambda}{b} - 1 \right) a_i \mathbb{E} \left[ \sum_{t=1}^n A_{i,t} \right]. \quad (8)$$

Summing up the last inequality over all  $K$  tasks and setting  $\delta = \max_i \delta_i$  yields,

$$\mathbb{E} \left[ \sum_{i=1}^K \sum_{t=1}^n M_{i,t} \right] \leq \frac{\delta}{\gamma} \left[ \left( 1 + \frac{X^2}{2b} \right) \bar{L}_{\gamma,n} + \frac{(2b + X^2)^2}{8\gamma b} \sum_{i=1}^K \|\mathbf{u}_i\|^2 \right] + \left( 2\frac{\lambda}{b} - 1 \right) \mathbb{E} \left[ \sum_{i=1}^K \sum_{t=1}^n a_i A_{i,t} \right], \quad (9)$$

which concludes the proof.  $\blacksquare$

## A.2 Extension to $\kappa$ Queries per Round

We now allow the algorithm to query  $\kappa$  labels instead of one. On each iteration  $t$ , the modified algorithm samples without repetitions  $\kappa$  labels to be annotated, and perform the same update as of Eq. (2). Formally, on each round we have  $\sum_i Z_{i,t} = \kappa$  for  $Z_{i,t} \in \{0, 1\}$  where the first task-index to be queried is drawn according to Eq. (1). The second task is drawn from the same distribution, not allowing the first choice, and so on. Once  $\kappa$  tasks are drawn, the algorithm receives  $\kappa$  labels for the  $\kappa$  corresponding inputs, and updates the  $\kappa$  models according to Eq. (2).

**Corollary 4** *If SHAMPO algorithm gets feedback for  $\kappa$  tasks on each round, instead of only a single task, the expected cumulative weighted mistakes is bounded as follows*

$$\mathbb{E} \left[ \sum_{i=1}^K \sum_{t=1}^n M_{i,t} \right] \leq \frac{\delta}{\gamma \kappa} \left[ \left(1 + \frac{X^2}{2b}\right) \bar{L}_{\gamma,n}^\kappa + \kappa \frac{(2b + X^2)^2}{8\gamma^2 b} U^2 \right] + \left(2\frac{\lambda}{b} - 1\right) \mathbb{E} \left[ \sum_{i=1}^K \sum_{t=1}^n a_i A_{i,t} \right],$$

where  $\bar{L}_{\gamma,n}^\kappa$  is the expected loss of  $K$  models  $\{\mathbf{u}_i\}$  over the  $\kappa$  annotated instances per round  $t$ .

**Proof:** We follow the proof of Thm. 1 until the end of the proof. We repeat the process  $\kappa$  times, and get the equivalent inequality for sampling  $\kappa$  tasks without repetitions, where  $\delta_j$  is the per repetition quantity, and we have,  $\delta = \max_j \delta_j$ ,

$$\left( \sum_{j=1}^{\kappa} \frac{1}{\delta_j} \right) \mathbb{E} \left[ \sum_{i=1}^K \sum_{t=1}^n \left( M_{i,t} + \left(1 - 2\frac{\lambda}{b}\right) A_{i,t} a_i \right) \right] \leq \frac{1}{\gamma} \left[ \left(1 + \frac{X^2}{2b}\right) \bar{L}_{\gamma,n}^\kappa + \kappa \frac{(2b + X^2)^2}{8\gamma b} U^2 \right], \quad (10)$$

where all expectations are now with respect to the sampling with repetitions, and specifically  $\bar{L}_{\gamma,n}^\kappa$  is the expected loss of a set of linear models  $\{\mathbf{u}_i\}$  where  $\kappa$  tasks are sampled rather than a single one. For a choice of  $\kappa = 1$  we get the bound of Thm. 1, as expected.  $\blacksquare$