

# Exact Passive-Aggressive Algorithms for Multiclass Classification Using Bandit Feedbacks

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## 1. EPABF Step Size $\lambda_r^t$ Derivation

EPABF updates the parameters by solving the following optimization problem.

$$\begin{aligned} \mathbf{w}_1^{t+1} \dots \mathbf{w}_K^{t+1} &= \arg \min_{\mathbf{w}_1, \dots, \mathbf{w}_K} \frac{1}{2} \sum_{v=1}^K \|\mathbf{w}_v - \mathbf{w}_v^t\|^2 \quad \text{s.t.} \quad \sum_{r=1}^K \tilde{l}_r = 0 \\ &= \arg \min_{\mathbf{w}_1, \dots, \mathbf{w}_K} \frac{1}{2} \sum_{v=1}^K \|\mathbf{w}_v - \mathbf{w}_v^t\|^2 \quad \text{s.t.} \quad a_t \mathbf{w}_{\tilde{y}^t} \cdot \mathbf{x}^t - \mathbf{w}_r \cdot \mathbf{x}^t \geq 1, \forall r \in [K] \end{aligned}$$

This is a quadratic optimization problem with  $K$  linear constraints. KKT conditions (Bertsekas (1999)) for optimal solution are as follows.

$$\begin{cases} \mathbf{w}_r = \mathbf{w}_r^t - \lambda_r^t \mathbf{x}^t + a_t \mathbb{I}_{\{\tilde{y}^t=r\}} \sum_r \lambda_r^t \mathbf{x}^t, & \forall r \\ \lambda_r^t (1 + \mathbf{w}_r \cdot \mathbf{x}^t - a_t \mathbf{w}_{\tilde{y}^t} \cdot \mathbf{x}^t) = 0, & \forall r \\ (1 + \mathbf{w}_r \cdot \mathbf{x}^t - a_t \mathbf{w}_{\tilde{y}^t} \cdot \mathbf{x}^t) \leq 0; \lambda_r^t \geq 0, & \forall r \end{cases} \quad (1)$$

where the Lagrange multipliers,  $\lambda_r^t$ , turn out to be the step sizes of the updates for each class. Using these equations, the weight vector could potentially be updated for every class. To complete the update rule, we need to determine the values of  $\lambda_r^t$ . Those with positive  $\lambda_r^t$  should satisfy

$$a_t \mathbf{w}_{\tilde{y}^t}^{t+1} \cdot \mathbf{x}^t - \mathbf{w}_r^{t+1} \cdot \mathbf{x}^t = 1 \quad (2)$$

The classes for which  $\lambda_r^t > 0$  are called support classes. Let the support class set is denoted by  $S^t$ . We assume that  $S^t$  is known. Plugging values of  $\mathbf{w}_{\tilde{y}^t}^t$  and  $\mathbf{w}_r^t$  in Eq. (2) we get the following.

$$a_t^2 \sum_i \lambda_i^t - a_t \lambda_{\tilde{y}^t}^t + \lambda_r^t = \frac{1 + \mathbf{w}_r^t \cdot \mathbf{x}^t - a_t \mathbf{w}_{\tilde{y}^t}^t \cdot \mathbf{x}^t}{\|\mathbf{x}^t\|^2} = \frac{\tilde{l}_r^t}{\|\mathbf{x}^t\|^2} \quad (3)$$

Summing the above equation over all  $r \in S^t$ , we get

$$(a_t^2 |S^t| + 1) \sum_{r \in S^t} \lambda_r^t - a_t |S^t| \lambda_{\tilde{y}^t}^t = \frac{\sum_{r \in S^t} \tilde{l}_r^t}{\|\mathbf{x}^t\|^2} \quad (4)$$

We have two cases.

- **Case 1:**  $\tilde{y}^t \in S^t$ : In this case we have, Taking  $r = \tilde{y}^t$  in Eq.(3), we get,

$$a_t^2 \sum_{r \in S^t} \lambda_r^t - a_t \lambda_{\tilde{y}^t}^t + \lambda_{\tilde{y}^t}^t = \frac{\tilde{l}_{\tilde{y}^t}^t}{\|\mathbf{x}^t\|^2} \quad (5)$$

Using Eq.(4) and (5), we find the values of  $\lambda_{\tilde{y}^t}^t$  and  $\sum_{r \in S^t} \lambda_r^t$  as follows.

$$\begin{aligned} \lambda_{\tilde{y}^t}^t &= \frac{1 + |S^t| a_t^2}{(1 + |S^t| a_t^2 - a_t) \|\mathbf{x}^t\|^2} \left( \tilde{l}_{\tilde{y}^t}^t - \frac{a_t^2}{1 + |S^t| a_t^2} \sum_{r \in S^t} \tilde{l}_r^t \right) \\ \sum_{r \in S^t} \lambda_r^t &= \frac{(1 - a_t) \sum_{r \in S^t} \tilde{l}_r^t + a_t |S^t| \tilde{l}_{\tilde{y}^t}^t}{(1 + |S^t| a_t^2 - a_t) \|\mathbf{x}^t\|^2} \end{aligned}$$

Putting the values of  $\lambda_{\tilde{y}^t}^t$  and  $\sum_{r \in S^t} \lambda_r^t$  in Eq.(3), we get,

$$\lambda_r^t = \frac{1}{\|\mathbf{x}^t\|^2} \left( \tilde{l}_r^t + \frac{a_t \tilde{l}_{\tilde{y}^t}^t}{1 + |S^t| a_t^2 - a_t} - \frac{a_t^2 \sum_{i \in S^t} \tilde{l}_i^t}{1 + |S^t| a_t^2 - a_t} \right) \quad (6)$$

- **Case 2:**  $\tilde{y}^t \notin S^t$ : In this case  $\lambda_{\tilde{y}^t}^t = 0$ . Using Eq.(3) and (4), we will get,

$$\begin{aligned} \sum_{r \in S^t} \lambda_r^t &= \frac{1}{(\|\mathbf{x}^t\|^2)(a_t^2 |S^t| + 1)} \sum_{r \in S^t} \tilde{l}_r^t \\ \lambda_r^t &= \frac{1}{\|\mathbf{x}^t\|^2} \left( \tilde{l}_r^t - \frac{a_t^2}{a_t^2 |S^t| + 1} \sum_{i \in S^t} \tilde{l}_i^t \right) \end{aligned} \quad (7)$$

## 2. Proof of Theorem 1

**Proof** We will have 2 cases:

- **Case 1:** If  $\tilde{y}^t \in S^t$

Using the KKT conditions, we see that for any  $r \notin S^t$ , we have,

$$a_t (\mathbf{w}_{\tilde{y}^t}^t - \lambda_{\tilde{y}^t}^t \mathbf{x}^t + a_t \sum_i \lambda_i^t \mathbf{x}^t) \cdot \mathbf{x}^t - (\mathbf{w}_r^t - \lambda_r^t \mathbf{x}^t) \cdot \mathbf{x}^t \geq 1$$

Since  $\lambda_r^t = 0$  for  $r \notin S^t$ , the above equation reduces to,

$$a_t^2 \sum_i \lambda_i^t - a_t \lambda_{\tilde{y}^t}^t \geq \frac{1 + \mathbf{w}_r^t \cdot \mathbf{x}^t - a_t \mathbf{w}_{\tilde{y}^t}^t \cdot \mathbf{x}^t}{\|\mathbf{x}^t\|^2} = \frac{\tilde{l}_r^t}{\|\mathbf{x}^t\|^2} \quad (8)$$

We know that,

$$\lambda_{\tilde{y}^t}^t = \frac{1 + |S^t|a_t^2}{(1 + |S^t|a_t^2 - a_t)\|\mathbf{x}^t\|^2} \left( \tilde{l}_{\tilde{y}^t}^t - \frac{a_t^2}{1 + |S^t|a_t^2} \sum_{r \in S^t} \tilde{l}_r^t \right) \quad (9)$$

$$\sum_{r \in S^t} \lambda_r^t = \frac{1}{(1 + |S^t|a_t^2 - a_t)\|\mathbf{x}^t\|^2} \left( (1 - a_t) \sum_{r \in S^t} \tilde{l}_r^t + a_t |S^t| \tilde{l}_{\tilde{y}^t}^t \right) \quad (10)$$

Using Eq.(9) and Eq.(10), we can rewrite the equation Eq.(8) as,

$$\frac{a_t^2 \sum_{j \in S^t} \tilde{l}_j^t}{1 + |S^t|a_t^2 - a_t} \geq \tilde{l}_r^t + \frac{a_t \tilde{l}_{\tilde{y}^t}^t}{1 + |S^t|a_t^2 - a_t}, \quad \forall r \notin S^t \quad (11)$$

Also we have,

$$\lambda_r^t = \frac{1}{\|\mathbf{x}^t\|^2} \left( \tilde{l}_r^t + \frac{a_t \tilde{l}_{\tilde{y}^t}^t}{1 + |S^t|a_t^2 - a_t} - \frac{a_t^2 \sum_{i \in S^t} \tilde{l}_i^t}{1 + |S^t|a_t^2 - a_t} \right) \quad (12)$$

To get support class,  $\lambda_r^t$  should be positive, so by Eq.(12), we get

$$\frac{a_t^2 \sum_{j \in S^t} \tilde{l}_j^t}{1 + |S^t|a_t^2 - a_t} < \tilde{l}_r^t + \frac{a_t \tilde{l}_{\tilde{y}^t}^t}{1 + |S^t|a_t^2 - a_t}, \quad \forall r \in S^t \quad (13)$$

Let  $\sigma(k)$  be the  $k$ -th class when sorted in descending order of  $\tilde{l}_r^t$ .

(*Sufficiency*) Assume that  $\tilde{l}_{\sigma(k)}^t$  satisfies the theorem, then we have,

$$\begin{aligned} \sum_{j=1}^{k-1} \tilde{l}_{\sigma(j)}^t &< \frac{1 + (k-1)a_t^2 - a_t \tilde{l}_{\sigma(k)}^t}{a_t^2} \tilde{l}_{\sigma(k)}^t + \frac{1}{a_t} \tilde{l}_{\tilde{y}^t}^t \\ \Rightarrow \sum_{j=1}^{|S^t|} \tilde{l}_{\sigma(j)}^t &< \frac{1 + |S^t|a_t^2 - a_t \tilde{l}_{\sigma(k)}^t}{a_t^2} \tilde{l}_{\sigma(k)}^t + \frac{1}{a_t} \tilde{l}_{\tilde{y}^t}^t \\ \Rightarrow \frac{a_t^2}{1 + |S^t|a_t^2 - a_t} \sum_{j=1}^{|S^t|} \tilde{l}_{\sigma(j)}^t &< \tilde{l}_{\sigma(k)}^t + \frac{a_t}{1 + |S^t|a_t^2 - a_t} \tilde{l}_{\tilde{y}^t}^t \end{aligned}$$

The second inequality is justified as the losses  $\tilde{l}_{\sigma(j)}^t$  are in decreasing order. This means  $\sigma(k)$  corresponds to a label of some support classes (Eq.(13)).

(*Necessity*) Assume that  $\tilde{l}_{\sigma(k)}^t$  does not satisfy theorem, then

$$\begin{aligned} \sum_{j=1}^{k-1} \tilde{l}_{\sigma(j)}^t &\geq \frac{1 + (k-1)a_t^2 - a_t \tilde{l}_{\sigma(k)}^t}{a_t^2} \tilde{l}_{\sigma(k)}^t + \frac{1}{a_t} \tilde{l}_{\tilde{y}^t}^t \\ \sum_{j=1}^k \tilde{l}_{\sigma(j)}^t &\geq \frac{1 + (k)a_t^2 - a_t \tilde{l}_{\sigma(k)}^t}{a_t^2} \tilde{l}_{\sigma(k)}^t + \frac{1}{a_t} \tilde{l}_{\tilde{y}^t}^t \end{aligned}$$

$$\frac{a_t^2}{1 + ka_t^2 - a_t} \sum_{j=1}^k \tilde{l}_{\sigma(j)}^t - \frac{a_t}{1 + ka_t^2 - a_t} \tilde{l}_{\tilde{y}^t}^t \geq \tilde{l}_{\sigma(k)}^t \geq \tilde{l}_{\sigma(k+1)}^t$$

Therefore, any  $j$  larger than  $\sigma(k)$  does not satisfy Eq.(13). It means  $|S^t| < k$  and thus  $\sigma(k)$  does not correspond to a label of a support class.

- **Case 2:** If  $\tilde{y}^t \notin S^t$

Using the KKT conditions, we see that for any  $r \notin S^t$ , we have,

$$a_t(\mathbf{w}_{\tilde{y}^t}^t + a_t \sum_i \lambda_i^t \mathbf{x}^t) \cdot \mathbf{x}^t - (\mathbf{w}_r^t - \lambda_r^t \mathbf{x}^t) \cdot \mathbf{x}^t \geq 1$$

Since  $\lambda_r^t = 0$  for  $r \notin S^t$ , the above equation reduces to,

$$a_t^2 \sum_i \lambda_i^t \geq \frac{1 + \mathbf{w}_r^t \cdot \mathbf{x}^t - a_t \mathbf{w}_{\tilde{y}^t}^t \cdot \mathbf{x}^t}{\|\mathbf{x}^t\|^2} = \frac{\tilde{l}_r^t}{\|\mathbf{x}^t\|^2}$$

We know that,

$$\sum_{r \in S^t} \lambda_r^t = \frac{1}{(1 + |S^t|a_t^2)\|\mathbf{x}^t\|^2} \left( \sum_{r \in S^t} \tilde{l}_r^t \right) \quad (14)$$

Using Eq.(14), we can rewrite this equation as,

$$\frac{a_t^2 \sum_{j \in S^t} \tilde{l}_{\sigma(j)}^t}{1 + |S^t|a_t^2} \geq \tilde{l}_{\sigma(r)}^t, \quad \forall r \notin S^t \quad (15)$$

Also we have,

$$\lambda_r^t = \frac{1}{\|\mathbf{x}^t\|^2} \left( \tilde{l}_r^t - \frac{a_t^2 \sum_{i \in S^t} \tilde{l}_i^t}{1 + |S^t|a_t^2} \right) \quad (16)$$

To get support class,  $\lambda_r^t$  should be positive, so by Eq.(16), we get

$$\frac{a_t^2 \sum_{j \in S^t} \tilde{l}_{\sigma(j)}^t}{1 + |S^t|a_t^2} < \tilde{l}_{\sigma(r)}^t, \quad \forall r \in S^t \quad (17)$$

Let  $\sigma(k)$  be the  $k$ -th class when sorted in descending order of  $\tilde{l}_r^t$ .  
(Sufficiency) Assume that  $\tilde{l}_{\sigma(k)}^t$  satisfies the theorem, then we have,

$$\begin{aligned} \sum_{j=1}^{k-1} \tilde{l}_{\sigma(j)}^t &< \frac{1 + (k-1)a_t^2}{a_t^2} \tilde{l}_{\sigma(k)}^t \\ \Rightarrow \sum_{j=1}^{|S^t|} \tilde{l}_{\sigma(j)}^t &< \frac{1 + |S^t|a_t^2}{a_t^2} \tilde{l}_{\sigma(k)}^t \\ \Rightarrow \frac{a_t^2}{1 + |S^t|a_t^2} \sum_{j=1}^{|S^t|} \tilde{l}_{\sigma(j)}^t &< \tilde{l}_{\sigma(k)}^t \end{aligned}$$

The second inequality is justified as the losses  $\tilde{l}_{\sigma(j)}^t$  are in decreasing order. This means  $\sigma(k)$  corresponds to a label of some support classes Eq. (17).

(*Necessity*) Assume that  $\tilde{l}_{\sigma(k)}^t$  does not satisfy theorem, then

$$\begin{aligned} \sum_{j=1}^{k-1} \tilde{l}_{\sigma(j)}^t &\geq \frac{1 + (k-1)a_t^2}{a_t^2} \tilde{l}_{\sigma(k)}^t \\ \sum_{j=1}^k \tilde{l}_{\sigma(j)}^t &\geq \frac{1 + (k)a_t^2}{a_t^2} \tilde{l}_{\sigma(k)}^t \\ \frac{a_t^2}{1 + ka_t^2} \sum_{j=1}^k \tilde{l}_{\sigma(j)}^t &\geq \tilde{l}_{\sigma(k)}^t \geq \tilde{l}_{\sigma(k+1)}^t \end{aligned}$$

Therefore, any  $j$  larger than  $\sigma(k)$  does not satisfy Eq. (17). It means  $|S^t| < k$  and thus  $\sigma(k)$  does not correspond to a label of a support class. ■

### 3. Proof of Theorem 2: EPABF bound

#### Proof

- **Case 1:** If  $\tilde{y}^t \in S^t$

We define  $\Delta_t$  as the following,

$$\Delta_t = \sum_{v=1}^K \|\mathbf{w}_v^t - \mathbf{u}_v\|^2 - \sum_{v=1}^K \|\mathbf{w}_v^{t+1} - \mathbf{u}_v\|^2$$

We can write it as,

$$\begin{aligned} \Delta_t &= \sum_{v=1}^K \|\mathbf{w}_v^t - \mathbf{u}_v\|^2 - \sum_{v=1}^K \|\mathbf{w}_v^t - \mathbf{u}_v - \lambda_v^t \mathbf{x}^t + \mathbb{I}_{\{\tilde{y}^t=v\}} \frac{\mathbb{I}_{\{\tilde{y}^t=y^t\}}}{P(\tilde{y}^t)} \sum_i \lambda_i^t \mathbf{x}^t\|^2 \\ &= 2 \sum_{v=1}^K \left( \lambda_v^t - \mathbb{I}_{\{\tilde{y}^t=v\}} \frac{\mathbb{I}_{\{\tilde{y}^t=y^t\}}}{P(\tilde{y}^t)} \sum_i \lambda_i^t \right) (\mathbf{w}_v^t - \mathbf{u}_v) \cdot \mathbf{x}^t - \sum_{v=1}^K \left( \lambda_v^t - \mathbb{I}_{\{\tilde{y}^t=v\}} \frac{\mathbb{I}_{\{\tilde{y}^t=y^t\}}}{P(\tilde{y}^t)} \sum_i \lambda_i^t \right)^2 \|\mathbf{x}^t\|^2 \\ &= 2 \sum_{v \in S} \lambda_v^t (\mathbf{w}_v^t - \mathbf{u}_v) \cdot \mathbf{x}^t - 2a_t \sum_i \lambda_i (\mathbf{w}_{\tilde{y}^t}^t - \mathbf{u}_{\tilde{y}^t}) \cdot \mathbf{x}^t - \sum_{v \in S^t} (\lambda_v^t)^2 \|\mathbf{x}^t\|^2 \\ &\quad - a_t^2 \left( \sum_v \lambda_v^t \right)^2 \|\mathbf{x}^t\|^2 + 2a_t \lambda_{\tilde{y}^t}^t \sum_v \lambda_v^t \|\mathbf{x}^t\|^2 \end{aligned}$$

We know that  $\tilde{l}_v^t = 1 - a_t \mathbf{w}_{\tilde{y}^t}^t \cdot \mathbf{x}^t + \mathbf{w}_v^t \cdot \mathbf{x}^t$ ,  $\forall v \in S^t$  and  $\tilde{l}_v^{*t} \geq 1 - a_t \mathbf{u}_{\tilde{y}^t} \cdot \mathbf{x}^t + \mathbf{u}_v \cdot \mathbf{x}^t$ ,  $\forall v \in [K]$ . Thus,  $(\mathbf{w}_v^t - \mathbf{u}_v) \cdot \mathbf{x}^t \geq \tilde{l}_v^t - \tilde{l}_v^{*t} + a(\mathbf{w}_{\tilde{y}^t}^t - \mathbf{u}_{\tilde{y}^t}) \cdot \mathbf{x}^t$ . So, we get the following.

$$\Delta_t \geq 2 \sum_{v \in S^t} \lambda_v^t (\tilde{l}_v^t - \tilde{l}_v^{*t}) - \sum_{v \in S^t} (\lambda_v^t)^2 \|\mathbf{x}^t\|^2 - a_t^2 \left( \sum_v \lambda_v^t \right)^2 \|\mathbf{x}^t\|^2 + 2a_t \lambda_{\tilde{y}^t}^t \sum_v \lambda_v^t \|\mathbf{x}^t\|^2$$

We use the following in the above equation.

$$\begin{aligned}\lambda_{\tilde{y}^t}^t &= \frac{1 + |S^t|a_t^2}{(1 + |S^t|a_t^2 - a_t)\|\mathbf{x}^t\|^2} \left( \tilde{l}_{\tilde{y}^t}^t - \frac{a_t^2}{1 + |S^t|a_t^2} \sum_{r \in S^t} \tilde{l}_r^t \right) \\ \sum_{r \in S^t} \lambda_r^t &= \frac{(1 - a_t) \sum_{r \in S^t} \tilde{l}_r^t + a_t |S^t| \tilde{l}_{\tilde{y}^t}^t}{(1 + |S^t|a_t^2 - a_t)\|\mathbf{x}^t\|^2} \\ \lambda_r^t &= \frac{1}{\|\mathbf{x}^t\|^2} \left( \tilde{l}_r^t + \frac{a_t \tilde{l}_{\tilde{y}^t}^t}{1 + |S^t|a_t^2 - a_t} - \frac{a_t^2 \sum_{i \in S^t} \tilde{l}_i^t}{1 + |S^t|a_t^2 - a_t} \right)\end{aligned}$$

Using the above values to get,

$$\begin{aligned}\Delta_t &\geq \frac{1}{\|\mathbf{x}^t\|^2} \sum_{v \in S^t} \left( \tilde{l}_v^t \right)^2 - \frac{2}{\|\mathbf{x}^t\|^2} \sum_{v \in S^t} \tilde{l}_v^t \tilde{l}_v^{*t} - 2 \left( \frac{a_t}{\|\mathbf{x}^t\|^2 (a_t^2 |S^t| + 1 - a_t)} \right) \tilde{l}_{\tilde{y}^t}^t \sum_{v \in S^t} \tilde{l}_v^{*t} \\ &\quad + 2 \left( \frac{a_t^2}{\|\mathbf{x}^t\|^2 (a_t^2 |S^t| + 1 - a_t)} \right) \sum_{v \in S^t} \tilde{l}_v^t \sum_{v \in S^t} \tilde{l}_v^{*t} + \left( \frac{a_t^2 |S^t| (a_t^2 |S^t| + 1)}{\|\mathbf{x}^t\|^2 (a_t^2 |S^t| + 1 - a_t)^2} \right) \left( \tilde{l}_{\tilde{y}^t}^t \right)^2 \\ &\quad + \left( \frac{a_t^2 (a_t^2 |S^t| + 1 - a_t)}{\|\mathbf{x}^t\|^2 (a_t^2 |S^t| + 1 - a_t)^2} \right) \left( \sum_{v \in S^t} \tilde{l}_v^t \right)^2 + \left( \frac{2a_t (a_t^4 |S^t|^2 + 1 - a_t + a_t^3 |S^t|)}{\|\mathbf{x}^t\|^2 (a_t^2 |S^t| + 1 - a_t)^2} \right) \tilde{l}_{\tilde{y}^t}^t \sum_{v \in S^t} \tilde{l}_v^t\end{aligned}$$

We observe the following.

$$\begin{aligned}2 \left( \frac{a_t^2}{\|\mathbf{x}^t\|^2 (a_t^2 |S^t| + 1 - a_t)} \right) \sum_{v \in S^t} \tilde{l}_v^t \sum_{v \in S^t} \tilde{l}_v^{*t} &\geq 0 \\ \frac{a_t^2 (a_t^2 |S^t|^2 - |S^t| + 2)}{\|\mathbf{x}^t\|^2 (a_t^2 |S^t| + 1 - a_t)^2} \left( \tilde{l}_{\tilde{y}^t}^t \right)^2 &\geq 0 \\ \frac{a_t^2 (a_t^2 |S^t| + 1 - a_t)}{\|\mathbf{x}^t\|^2 (a_t^2 |S^t| + 1 - a_t)^2} \left( \sum_{v \in S^t} \tilde{l}_v^t \right)^2 &\geq 0 \\ \left( \frac{2a_t (a_t^4 |S^t|^2 + 1 - a_t + a_t^3 |S^t|)}{\|\mathbf{x}^t\|^2 (a_t^2 |S^t| + 1 - a_t)^2} \right) \tilde{l}_{\tilde{y}^t}^t \sum_{v \in S^t} \tilde{l}_v^t &\geq 0\end{aligned}$$

Using these, we get,

$$\Delta_t \geq \frac{1}{\|\mathbf{x}^t\|^2} \sum_{v \in S^t} \left( \tilde{l}_v^t \right)^2 - \frac{2}{\|\mathbf{x}^t\|^2} \sum_{v \in S^t} \tilde{l}_v^t \tilde{l}_v^{*t} - 2 \left( \frac{a_t}{\|\mathbf{x}^t\|^2 (a_t^2 |S^t| + 1 - a_t)} \right) \tilde{l}_{\tilde{y}^t}^t \sum_{v \in S^t} \tilde{l}_v^{*t}.$$

Also,

$$2 \left( \frac{a_t}{\|\mathbf{x}^t\|^2 (a_t^2 |S^t| + 1 - a_t)} \right) \tilde{l}_{\tilde{y}^t}^t \sum_{v \in S^t} \tilde{l}_v^{*t} \leq \frac{2}{\|\mathbf{x}^t\|^2} \tilde{l}_{\tilde{y}^t}^t \sum_{v \in S^t} \tilde{l}_v^{*t}.$$

Using the above approximation, the expression becomes,

$$\begin{aligned}\Delta_t &\geq \frac{1}{\|\mathbf{x}^t\|^2} \sum_{v \in S^t} \left( \tilde{l}_v^t \right)^2 - \frac{2}{\|\mathbf{x}^t\|^2} \sum_{v \in S^t} \tilde{l}_v^t \tilde{l}_v^{*t} - \frac{2}{\|\mathbf{x}^t\|^2} \tilde{l}_{\tilde{y}^t}^t \sum_{v \in S^t} \tilde{l}_v^{*t} \\ &\geq \frac{1}{\|\mathbf{x}^t\|^2} \sum_{v \in S^t} \left( \tilde{l}_v^t \right)^2 - \frac{4}{\|\mathbf{x}^t\|^2} \sum_{v \in S^t} \tilde{l}_v^t \tilde{l}_v^{*t}.\end{aligned}$$

Taking expectation on both sides with respect to  $\tilde{y}^t$ .

$$\mathbb{E}[\Delta_t] \geq \frac{1}{\|\mathbf{x}^t\|^2} \mathbb{E}\left[\sum_{v \in S^t} \left(\tilde{l}_v^t\right)^2\right] - \frac{4}{\|\mathbf{x}^t\|^2} \mathbb{E}\left[\sum_{v \in S^t} \tilde{l}_v^t \tilde{l}_v^{*t}\right]$$

But,  $\mathbb{E}[\sum_{v \in S^t} \tilde{l}_v^t \tilde{l}_v^{*t}] \leq \mathbb{E}[\sqrt{\sum_{v \in S^t} (\tilde{l}_v^t)^2 \sum_{v \in S^t} (\tilde{l}_v^{*t})^2}]$ . Now using Cauchy Schwarz inequality  $\mathbb{E}[xy] \leq \sqrt{\mathbb{E}[x^2] \mathbb{E}[y^2]}$ , we get,  $\mathbb{E}[\sum_{v \in S^t} \tilde{l}_v^t \tilde{l}_v^{*t}] \leq \sqrt{\mathbb{E}[\sum_{v \in S^t} (\tilde{l}_v^t)^2]} \sqrt{\mathbb{E}[\sum_{v \in S^t} (\tilde{l}_v^{*t})^2]}$ . Using this and  $\|\mathbf{x}^t\| \leq R$ , we get the following.

$$\mathbb{E}[\Delta_t] \geq \frac{1}{R^2} \mathbb{E}\left[\sum_{v \in S^t} \left(\tilde{l}_v^t\right)^2\right] - \frac{4}{R^2} \sqrt{\mathbb{E}\left[\sum_{v \in S^t} \left(\tilde{l}_v^t\right)^2\right]} \sqrt{\mathbb{E}\left[\sum_{v \in S^t} \left(\tilde{l}_v^{*t}\right)^2\right]} \quad (18)$$

- **Case 2:** If  $\tilde{y}^t \notin S^t$

We define  $\Delta_t$  as the following,

$$\Delta_t = \sum_{v=1}^K \|\mathbf{w}_v^t - \mathbf{u}_v\|^2 - \sum_{v=1}^K \|\mathbf{w}_v^{t+1} - \mathbf{u}_v\|^2$$

We can write it as,

$$\begin{aligned} \Delta_t &= \sum_{v \neq \tilde{y}^t} \|\mathbf{w}_v^t - \mathbf{u}_v\|^2 + \|\mathbf{w}_{\tilde{y}^t}^t - \mathbf{u}_{\tilde{y}^t}\|^2 - \sum_{v \neq \tilde{y}^t} \|\mathbf{w}_v^{t+1} - \mathbf{u}_v\|^2 - \|\mathbf{w}_{\tilde{y}^t}^{t+1} - \mathbf{u}_{\tilde{y}^t}\|^2 \\ &= \sum_{v \neq \tilde{y}^t} \|\mathbf{w}_v^t - \mathbf{u}_v\|^2 + \|\mathbf{w}_{\tilde{y}^t}^t - \mathbf{u}_{\tilde{y}^t}\|^2 - \sum_{v \neq \tilde{y}^t} \|\mathbf{w}_v^t - \lambda_v^t \mathbf{x}^t - \mathbf{u}_v\|^2 - \|\mathbf{w}_{\tilde{y}^t}^t + a \sum_{i \neq \tilde{y}^t} \lambda_i^t \mathbf{x}^t - \mathbf{u}_{\tilde{y}^t}\|^2 \\ &= \sum_{v \neq \tilde{y}^t} \|\mathbf{w}_v^t - \mathbf{u}_v\|^2 + \|\mathbf{w}_{\tilde{y}^t}^t - \mathbf{u}_{\tilde{y}^t}\|^2 - \sum_{v \neq \tilde{y}^t} \|\mathbf{w}_v^t - \mathbf{u}_v\|^2 - \sum_{v \neq \tilde{y}^t} (\lambda_v^t)^2 \|\mathbf{x}^t\|^2 + 2 \sum_{v \neq \tilde{y}^t} \lambda_v^t (\mathbf{w}_v^t - \mathbf{u}_v) \cdot \mathbf{x}^t \\ &\quad - \|\mathbf{w}_{\tilde{y}^t}^t - \mathbf{u}_{\tilde{y}^t}\|^2 - a^2 \left(\sum_{i \neq \tilde{y}^t} \lambda_i^t\right)^2 \|\mathbf{x}^t\|^2 - 2a \sum_{i \neq \tilde{y}^t} \lambda_i^t (\mathbf{w}_{\tilde{y}^t}^t - \mathbf{u}_{\tilde{y}^t}) \cdot \mathbf{x}^t \\ &= 2 \sum_{v \neq \tilde{y}^t} \lambda_v^t (\mathbf{w}_v^t - \mathbf{u}_v) \cdot \mathbf{x}^t - 2a \sum_{i \neq \tilde{y}^t} (\mathbf{w}_{\tilde{y}^t}^t - \mathbf{u}_{\tilde{y}^t}) \cdot \mathbf{x}^t - \sum_{v \neq \tilde{y}^t} (\lambda_v^t)^2 \|\mathbf{x}^t\|^2 - a^2 \left(\sum_{i \neq \tilde{y}^t} \lambda_i^t\right)^2 \|\mathbf{x}^t\|^2 \\ &= 2 \sum_{v \neq \tilde{y}^t} \lambda_v^t (\mathbf{w}_v^t - a \mathbf{w}_{\tilde{y}^t}^t - \mathbf{u}_v + a \mathbf{u}_{\tilde{y}^t}) \cdot \mathbf{x}^t - \sum_{v \neq \tilde{y}^t} (\lambda_v^t)^2 \|\mathbf{x}^t\|^2 - a^2 \left(\sum_{v \neq \tilde{y}^t} \lambda_v^t\right)^2 \|\mathbf{x}^t\|^2 \end{aligned}$$

We know that  $\tilde{l}_v^t = 1 - a \mathbb{1}_{\{\tilde{y}^t=v\}} - a \mathbf{w}_{\tilde{y}^t}^t \cdot \mathbf{x}^t + \mathbf{w}_v^t \cdot \mathbf{x}^t$ ,  $\forall v \in S^t$  and  $\tilde{l}_v^{*t} \geq 1 - a \mathbb{1}_{\{\tilde{y}^t=v\}} - a \mathbf{u}_{\tilde{y}^t} \cdot \mathbf{x}^t + \mathbf{u}_v \cdot \mathbf{x}^t$ ,  $\forall v \in [K]$ . Thus,  $(\mathbf{w}_v^t - \mathbf{u}_v) \cdot \mathbf{x}^t - a(\mathbf{w}_{\tilde{y}^t}^t - \mathbf{u}_{\tilde{y}^t}) \cdot \mathbf{x}^t \geq \tilde{l}_v^t - \tilde{l}_v^{*t}$ . Thus, we get the following.

$$\Delta_t \geq 2 \sum_{v \neq \tilde{y}^t} \lambda_v^t (\tilde{l}_v^t - \tilde{l}_v^{*t}) - \sum_{v \neq \tilde{y}^t} (\lambda_v^t)^2 \|\mathbf{x}^t\|^2 - a^2 \left(\sum_{v \neq \tilde{y}^t} \lambda_v^t\right)^2 \|\mathbf{x}^t\|^2$$

Let  $S^t$  be the set of support classes in  $t^{\text{th}}$  trial. For all  $v \in S^t$ , we can see that

$$\begin{aligned}\|\mathbf{x}^t\|^2 \lambda_v^t &= \tilde{l}_v^t - \frac{a^2}{a^2|S^t|+1} \sum_{j \in S^t} \tilde{l}_j^t \\ \|\mathbf{x}^t\|^2 \sum_{v \in S^t} \lambda_v^t &= \frac{1}{(a^2|S^t|+1)} \sum_{v \in S^t} \tilde{l}_v^t\end{aligned}$$

We can ignore all  $v \notin S^t$  in the sum for the last representation of  $\Delta_t$  and substituting the above values in that to get,

$$\begin{aligned}\Delta_t &\geq \sum_{v \in S} \lambda_v^t \left( 2\tilde{l}_v^t - 2\tilde{l}_v^{*t} - \|\mathbf{x}^t\|^2 \lambda_v^t \right) - \|\mathbf{x}^t\|^2 a^2 \left( \sum_{v \in S} \lambda_v^t \right)^2 \\ &= \frac{1}{\|\mathbf{x}^t\|^2} \sum_{v \in S^t} \left( \tilde{l}_v^t - \frac{a^2}{a^2|S^t|+1} \sum_{j \in S^t} \tilde{l}_j^t \right) \left( \tilde{l}_v^t - 2\tilde{l}_v^{*t} + \frac{a^2}{a^2|S^t|+1} \sum_{j \in S^t} \tilde{l}_j^t \right) - \frac{1}{\|\mathbf{x}^t\|^2} \frac{a^2}{(a^2|S^t|+1)^2} \left( \sum_{v \in S^t} \tilde{l}_v^t \right)^2 \\ &= \frac{1}{\|\mathbf{x}^t\|^2} \sum_{v \in S^t} \left( \tilde{l}_v^t - \frac{a^2}{a^2|S^t|+1} \sum_{j \in S^t} \tilde{l}_j^t \right) \left( \tilde{l}_v^t + \frac{a^2}{a^2|S^t|+1} \sum_{j \in S^t} \tilde{l}_j^t \right) - \frac{1}{\|\mathbf{x}^t\|^2} \frac{a^2}{(a^2|S^t|+1)^2} \left( \sum_{v \in S^t} \tilde{l}_v^t \right)^2 \\ &\quad - \frac{2}{\|\mathbf{x}^t\|^2} \sum_{v \in S^t} \tilde{l}_v^{*t} \tilde{l}_v^t + \frac{2a_t^2}{a_t^2|S^t|+1} \sum_{v \in S^t} \tilde{l}_v^{*t} \sum_{j \in S^t} \tilde{l}_j^t\end{aligned}$$

We see that  $\frac{2a_t^2}{a_t^2|S^t|+1} \sum_{v \in S^t} \tilde{l}_v^{*t} \sum_{j \in S^t} \tilde{l}_j^t \geq 0$ . Thus, we get the following.

$$\begin{aligned}\Delta_t &\geq \frac{1}{\|\mathbf{x}^t\|^2} \sum_{v \in S^t} \left( \tilde{l}_v^t \right)^2 - \left( \frac{a^4|S|}{(a^2|S^t|+1)^2} \right) \left( \sum_{j \in S^t} \tilde{l}_j^t \right)^2 - \frac{1}{\|\mathbf{x}^t\|^2} \frac{a^2}{(a^2|S^t|+1)^2} \left( \sum_{v \in S^t} \tilde{l}_v^t \right)^2 - \frac{2}{\|\mathbf{x}^t\|^2} \sum_{v \in S^t} \tilde{l}_v^{*t} \tilde{l}_v^t \\ &\geq \frac{1}{\|\mathbf{x}^t\|^2} \sum_{v \in S^t} \left( \tilde{l}_v^t \right)^2 - \left( \frac{a^2}{(a^2|S^t|+1)} \right) \left( \sum_{j \in S^t} \tilde{l}_j^t \right)^2 - \frac{2}{\|\mathbf{x}^t\|^2} \sum_{v \in S^t} \tilde{l}_v^{*t} \tilde{l}_v^t \\ &= \frac{1}{\|\mathbf{x}^t\|^2 (a^2|S^t|+1)} \sum_{v \in S^t} \left( \tilde{l}_v^t \right)^2 + \frac{a^2}{\|\mathbf{x}^t\|^2 (a^2|S^t|+1)} \left( |S^t| \sum_{v \in S^t} \left( \tilde{l}_v^t \right)^2 - \left( \sum_{v \in S^t} \tilde{l}_v^t \right)^2 \right) \\ &\quad - \frac{2}{\|\mathbf{x}^t\|^2} \sum_{v \in S^t} \tilde{l}_v^{*t} \tilde{l}_v^t\end{aligned}$$

We observe that  $n \sum_{i=1}^n m_i^2 - \left( \sum_{i=1}^n m_i \right)^2 = (n-1) \sum_{i=1}^n m_i^2 - 2 \sum_{i=1}^n \sum_{j=i+1}^n m_i m_j = \sum_{i=1}^n \sum_{j=i+1}^n (m_i - m_j)^2 \geq 0$ . Thus,

$$\Delta_t \geq \frac{1}{\|\mathbf{x}^t\|^2 (a^2|S^t|+1)} \sum_{v \in S^t} \left( \tilde{l}_v^t \right)^2 - \frac{2}{\|\mathbf{x}^t\|^2} \sum_{v \in S^t} \tilde{l}_v^{*t} \tilde{l}_v^t$$



Taking expectation on both side with respect to  $\tilde{y}^t$ .

$$\begin{aligned}\mathbb{E}[\Delta_t] &\geq \frac{1}{\|\mathbf{x}^t\|^2} \mathbb{E} \left[ \frac{1}{(a^2|S^t|+1)} \sum_{v \in S^t} (\tilde{l}_v^t)^2 - 2 \sum_{v \in S^t} \tilde{l}_v^{*t} \tilde{l}_v^t \right] \\ &= \frac{1}{\|\mathbf{x}^t\|^2} \left( \mathbb{E} \left[ \frac{1}{(a^2|S^t|+1)} \sum_{v \in S^t} (\tilde{l}_v^t)^2 \right] - 2 \mathbb{E} \left[ \sum_{v \in S^t} \tilde{l}_v^{*t} \tilde{l}_v^t \right] \right)\end{aligned}$$

But,  $\mathbb{E}[\sum_{v \in S^t} \tilde{l}_v^t \tilde{l}_v^{*t}] \leq \mathbb{E}[\sqrt{\sum_{v \in S^t} (\tilde{l}_v^t)^2 \sum_{v \in S^t} (\tilde{l}_v^{*t})^2}]$ . Now using Cauchy Schwartz inequality  $\mathbb{E}[xy] \leq \sqrt{\mathbb{E}[x^2] \mathbb{E}[y^2]}$ , we get,  $\mathbb{E}[\sum_{v \in S^t} \tilde{l}_v^t \tilde{l}_v^{*t}] \leq \sqrt{\mathbb{E}[\sum_{v \in S^t} (\tilde{l}_v^t)^2]} \sqrt{\mathbb{E}[\sum_{v \in S^t} (\tilde{l}_v^{*t})^2]}$  Using this we get the following.

$$\mathbb{E}[\Delta_t] \geq \frac{1}{\|\mathbf{x}^t\|^2} \mathbb{E} \left[ \frac{1}{(a^2|S^t|+1)} \sum_{v \in S^t} (\tilde{l}_v^t)^2 \right] - \frac{2}{\|\mathbf{x}^t\|^2} \sqrt{\mathbb{E} \left[ \sum_{v \in S^t} (\tilde{l}_v^t)^2 \right]} \sqrt{\mathbb{E} \left[ \sum_{v \in S^t} (\tilde{l}_v^{*t})^2 \right]}$$

Since  $\|\mathbf{x}^t\|^2 \leq R^2$ ,  $a \leq \frac{K}{\gamma}$  and  $|S^t| \leq K$ , so  $a^2|S^t|+1 \leq \frac{K^3}{\gamma^2}+1$ , therefore  $\frac{1}{\|\mathbf{x}^t\|^2} \frac{1}{a^2|S^t|+1} \geq \frac{1}{R^2} \frac{\gamma}{\left(\frac{K^3}{\gamma^2}+1\right)}$  Using the above approximations to get,

$$\mathbb{E}[\Delta_t] \geq \frac{1}{R^2} \frac{1}{\left(\frac{K^3}{\gamma^2}+1\right)} \mathbb{E} \left[ \sum_{v \in S^t} (\tilde{l}_v^t)^2 \right] - \frac{2}{R^2} \sqrt{\mathbb{E} \left[ \sum_{v \in S^t} (\tilde{l}_v^t)^2 \right]} \sqrt{\mathbb{E} \left[ \sum_{v \in S^t} (\tilde{l}_v^{*t})^2 \right]} \quad (19)$$

Combining the lower bounds in (18) and (19), we can get the following lower bound on  $\mathbb{E}[\Delta_t]$ .

$$\mathbb{E}[\Delta_t] \geq \frac{1}{R^2} \frac{1}{\left(\frac{K^3}{\gamma^2}+1\right)} \mathbb{E} \left[ \sum_{v \in S^t} (\tilde{l}_v^t)^2 \right] - \frac{4}{R^2} \sqrt{\mathbb{E} \left[ \sum_{v \in S^t} (\tilde{l}_v^t)^2 \right]} \sqrt{\mathbb{E} \left[ \sum_{v \in S^t} (\tilde{l}_v^{*t})^2 \right]}$$

Summing  $\Delta_t = \sum_{v=1}^K \|\mathbf{w}_v^t - \mathbf{u}_v\|^2 - \sum_{v=1}^K \|\mathbf{w}_v^{t+1} - \mathbf{u}_v\|^2$  from  $t = 1$  to  $T$ .

$$\sum_{t=1}^T \Delta_t = \sum_{v=1}^K \|\mathbf{w}_v^1 - \mathbf{u}_v\|^2 - \sum_{v=1}^K \|\mathbf{w}_v^{T+1} - \mathbf{u}_v\|^2$$

Since  $\mathbf{w}^1 = 0$  and  $\|\mathbf{w}_v^{T+1} - \mathbf{u}_v\|^2 \geq 0$ , we get  $\sum_{t=1}^T \Delta_t \leq \sum_{v=1}^K \|\mathbf{u}_v\|^2$ . Let  $\alpha = \left(\frac{K^3}{\gamma^2}+1\right)$ , then comparing the upper and lower bounds on  $\sum_{t=1}^T \mathbb{E}[\Delta_t]$ , we get

$$\sum_{t=1}^T \mathbb{E} \left[ \sum_{v \in S^t} (\tilde{l}_v^t)^2 \right] \leq R^2 \alpha \sum_{v=1}^K \|\mathbf{u}_v\|^2 + 4\alpha \sum_{t=1}^T \sqrt{\mathbb{E} \left[ \sum_{v \in S^t} (\tilde{l}_v^t)^2 \right]} \sqrt{\mathbb{E} \left[ \sum_{v \in S^t} (\tilde{l}_v^{*t})^2 \right]}.$$

Using Cauchy-Shwartz Inequality, we get

$$\sum_{t=1}^T \sqrt{\mathbb{E}[\sum_{v \in S^t} (\tilde{l}_v^t)^2]} \sqrt{\mathbb{E}[\sum_{v \in S^t} (\tilde{l}_v^{*t})^2]} \leq \sqrt{\sum_{t=1}^T \mathbb{E}[\sum_{v \in S^t} (\tilde{l}_v^t)^2]} \sqrt{\sum_{t=1}^T \mathbb{E}[\sum_{v \in S^t} (\tilde{l}_v^{*t})^2]}.$$

Let  $L_T = \sqrt{\sum_{t=1}^T \mathbb{E}[\sum_{v \in S^t} (\tilde{l}_v^t)^2]}$  and  $U_T = \sqrt{\sum_{t=1}^T \mathbb{E}[\sum_{v \in S^t} (\tilde{l}_v^{*t})^2]}$ . So, we get

$$L_T^2 \leq R^2 \alpha \sum_{v=1}^K \|\mathbf{u}_v\|^2 + 4\alpha L_T U_T.$$

The upper bound is bounded by largest root of the polynomial  $L_T^2 - 4\alpha L_T U_T - R^2 \alpha \sum_{v=1}^K \|\mathbf{u}_v\|^2$  which is  $2\alpha U_T + \sqrt{4\alpha^2 U_T^2 + R^2 \alpha \sum_{v=1}^K \|\mathbf{u}_v\|^2}$ . Using the inequality that  $\sqrt{a+b} \leq \sqrt{a} + \sqrt{b}$ , we get,  $L_T \leq 4\alpha U_T + R\sqrt{\alpha \sum_{v=1}^K \|\mathbf{u}_v\|^2}$ . As  $\tilde{l}_v^t = 0, \forall v \notin S_t$ , we get,  $\sum_{v \in S^t} (\tilde{l}_v^t)^2 = \sum_{v=1}^K (\tilde{l}_v^t)^2$ . Thus, we get,

$$\begin{aligned} \sum_{t=1}^T \mathbb{E}[\sum_{v=1}^K (\tilde{l}_v^t)^2] &\leq \left( R \sqrt{\alpha \sum_{v=1}^K \|\mathbf{u}_v\|^2} + 4\alpha \sqrt{\sum_{t=1}^T \mathbb{E}[\sum_{v \in S^t} (\tilde{l}_v^{*t})^2]} \right)^2 \\ &\leq \left( R \sqrt{\alpha \sum_{v=1}^K \|\mathbf{u}_v\|^2} + 4\alpha \sqrt{\sum_{t=1}^T \mathbb{E}[\sum_{v=1}^K (\tilde{l}_v^{*t})^2]} \right)^2. \end{aligned}$$

■

#### 4. Derivation Of EPABF-I Updates

EPABF-I updates the parameter by solving the following optimization problem.

$$\begin{aligned} \mathbf{w}_1^{t+1} \dots \mathbf{w}_K^{t+1} &= \arg \min_{\mathbf{w}_1, \dots, \mathbf{w}_K} \frac{1}{2} \sum_{v=1}^K \|\mathbf{w}_v - \mathbf{w}_v^t\|^2 + C \sum_{v=1}^K \tilde{l}_v \\ &= \arg \min_{\mathbf{w}_1, \dots, \mathbf{w}_K} \frac{1}{2} \sum_{v=1}^K \|\mathbf{w}_v - \mathbf{w}_v^t\|^2 + C \sum_{v=1}^K \xi_v \\ s.t. &\begin{cases} a_t \mathbf{w}_{\tilde{y}^t} \cdot \mathbf{x}^t - \mathbf{w}_r \cdot \mathbf{x}^t \geq 1 - \xi_r, r \in [K] \\ \xi_r \geq 0, r \in [K] \end{cases} \end{aligned} \quad (20)$$

KKT conditions for the optimal solution of the optimization problem (20) are as follows.

$$\begin{cases} \lambda_v^t (1 - \xi_v + \mathbf{w}_v \cdot \mathbf{x}^t - a_t \mathbf{w}_{\tilde{y}^t} \cdot \mathbf{x}^t) = 0, \forall v \\ \lambda_v^t \geq 0; 1 - \xi_v + \mathbf{w}_v \cdot \mathbf{x}^t - a_t \mathbf{w}_{\tilde{y}^t} \cdot \mathbf{x}^t \leq 0, \forall v \\ \beta_v^t \geq 0; \xi_v \geq 0, \forall v \\ \mathbf{w}_v = \mathbf{w}_v^t - \lambda_v^t \mathbf{x}^t + \mathbb{I}_{\{\tilde{y}^t=v\}} a_t \sum_{i=1}^K \lambda_i^t \mathbf{x}^t, \forall v \\ C = \lambda_v^t + \beta_v^t, \forall v \end{cases}$$

We now determine  $\lambda_r^t$  for the support classes. When  $\lambda_r^t > 0$ , we see that

$$\mathbf{w}_{\tilde{y}^t}^{t+1} \cdot \mathbf{x}^t a_t - \mathbf{w}_r^{t+1} \cdot \mathbf{x}^t = 1 - \xi_r$$

Using the corresponding values of  $\mathbf{w}_{\tilde{y}^t}^{t+1}$  and  $\mathbf{w}_r^{t+1}$ , we get

$$\frac{\xi_r}{\|\mathbf{x}^t\|^2} + a_t^2 \sum_i \lambda_i^t - a_t \lambda_{\tilde{y}^t}^t + \lambda_r^t = \frac{\tilde{l}_r^t}{\|\mathbf{x}^t\|^2} \quad (21)$$

Summing the above for  $\forall r \in S^t$ , we get,

$$\sum_{r \in S^t} \frac{\xi_r}{\|\mathbf{x}^t\|^2} + (a_t^2 |S^t| + 1) \sum_{r \in S^t} \lambda_r^t - a_t |S^t| \lambda_{\tilde{y}^t}^t = \frac{\sum_{r \in S^t} \tilde{l}_r^t}{\|\mathbf{x}^t\|^2} \quad (22)$$

Now, we have two cases:

- **Case 1:**  $\tilde{y}^t \in S^t$ : Using  $r = \tilde{y}^t$  in Eq.(21) we get,

$$\frac{\xi_{\tilde{y}^t}}{\|\mathbf{x}^t\|^2} + a_t^2 \sum_{r \in S^t} \lambda_r^t + (1 - a_t) \lambda_{\tilde{y}^t}^t = \frac{\tilde{l}_{\tilde{y}^t}^t}{\|\mathbf{x}^t\|^2} \quad (23)$$

Using (22) and (23), we solve for  $\lambda_{\tilde{y}^t}^t$  and  $\sum_{v \in S^t} \lambda_v^t$ .

$$\begin{aligned} \sum_{r \in S^t} \lambda_r^t &= \frac{(1 - a_t) \sum_{r \in S^t} \tilde{l}_r^t + a_t |S^t| \tilde{l}_{\tilde{y}^t}^t}{\|\mathbf{x}^t\|^2 (a_t^2 |S^t| + 1 - a_t)} - \frac{(a_t |S^t| \xi_{\tilde{y}^t} + (1 - a_t) \sum_{r \in S^t} \xi_r)}{\|\mathbf{x}^t\|^2 (a_t^2 |S^t| + 1 - a_t)} \\ \lambda_{\tilde{y}^t}^t &= \frac{(a_t^2 |S^t| + 1) \tilde{l}_{\tilde{y}^t}^t - a_t^2 \sum_{r \in S^t} \tilde{l}_r^t + a_t^2 \sum_{r \in S^t} \xi_r}{\|\mathbf{x}^t\|^2 (a_t^2 |S^t| + 1 - a_t)} - \frac{(a_t^2 |S^t| + 1) \xi_{\tilde{y}^t}}{\|\mathbf{x}^t\|^2 (a_t^2 |S^t| + 1 - a_t)} \end{aligned}$$

Plugging the values of  $\lambda_{\tilde{y}^t}^t$  and  $\sum_{r \in S^t} \lambda_r^t$  in Eq.(21), to get  $\lambda_r^t$  as follows.

$$\begin{aligned} \lambda_r^t &= \frac{1}{\|\mathbf{x}^t\|^2} \left( \tilde{l}_r^t + \frac{a_t \tilde{l}_{\tilde{y}^t}^t}{a_t^2 |S^t| + 1 - a_t} - \frac{a_t^2 \sum_{v \in S^t} \tilde{l}_v^t}{a_t^2 |S^t| + 1 - a_t} \right) - \\ &\quad \frac{1}{\|\mathbf{x}^t\|^2} \left( \xi_r - \frac{a_t \xi_{\tilde{y}^t}}{a_t^2 |S^t| + 1 - a_t} + \frac{a_t^2 \sum_{v \in S^t} \xi_v}{a_t^2 |S^t| + 1 - a_t} \right) \end{aligned}$$

Since  $\left( \xi_r - \frac{a_t \xi_{\tilde{y}^t}}{a_t^2 |S^t| + 1 - a_t} + \frac{a_t^2 \sum_{v \in S^t} \xi_v}{a_t^2 |S^t| + 1 - a_t} \right) \geq 0$ , so we have,

$$\lambda_r^t \leq \frac{1}{\|\mathbf{x}^t\|^2} \left( \tilde{l}_r^t + \frac{a_t \tilde{l}_{\tilde{y}^t}^t}{a_t^2 |S^t| + 1 - a_t} - \frac{a_t^2 \sum_{v \in S^t} \tilde{l}_v^t}{a_t^2 |S^t| + 1 - a_t} \right)$$

From the KKT conditions we know that  $\lambda_r \leq C$ . Thus,

$$\lambda_r^t = \min \left( C, \frac{1}{\|\mathbf{x}^t\|^2} \left( \tilde{l}_r^t + \frac{a_t \tilde{l}_{\tilde{y}^t}^t}{a_t^2 |S^t| + 1 - a_t} - \frac{a_t^2 \sum_{v \in S^t} \tilde{l}_v^t}{a_t^2 |S^t| + 1 - a_t} \right) \right)$$

- **Case 2:**  $\tilde{y}^t \notin S^t$ : In this case  $\lambda_{\tilde{y}^t}^t = 0$ . Using Eq.(21) and (22) , we will get,

$$\lambda_r^t = \min \left( C, \frac{1}{\|\mathbf{x}^t\|^2} \left( \tilde{l}_r^t - \frac{a_t^2 \sum_{v \in S^t} \tilde{l}_v^t}{a_t^2 |S^t| + 1} \right) \right) \quad (24)$$

## 5. Proof of Theorem 3: EPABF-I bound

**Proof** In the previous proof, we had

$$\Delta_t \geq 2 \sum_{v \in S^t} \lambda_v^t (\tilde{l}_v^t - \tilde{l}_v^{*t}) - \sum_{v \in S^t} (\lambda_v^t)^2 \|\mathbf{x}_t\|^2 - a_t^2 \left( \sum_v \lambda_v^t \right)^2 \|\mathbf{x}_t\|^2 + 2a_t \lambda_{\tilde{y}^t}^t \sum_v \lambda_v^t \|\mathbf{x}_t\|^2$$

- **Case 1:** If  $\tilde{y}^t \in S^t$  The step size for EPA-I is

$$\lambda_v^t = \min \left( C, \frac{1}{\|\mathbf{x}^t\|^2} \left( \tilde{l}_v^t + \frac{a_t}{1 + |S^t| a_t^2 - a_t} \tilde{l}_{\tilde{y}^t}^t - \frac{a_t^2}{1 + |S^t| a_t^2 - a_t} \sum_{i \in S} \tilde{l}_i^t \right) \right)$$

- **Case 2:** If  $\tilde{y}^t \notin S^t$  The step size for EPA-I is

$$\lambda_v^t = \min \left( C, \frac{1}{\|\mathbf{x}^t\|^2} \left( \tilde{l}_v^t - \frac{a_t^2}{1 + |S^t| a_t^2} \sum_{i \in S} \tilde{l}_i^t \right) \right)$$

So in both the cases we have  $\lambda_v^t \leq C, \lambda_v^t \tilde{l}_v^{*t} \leq C \tilde{l}_v^{*t}, \sum_{v \in S^t} \lambda_v^t \tilde{l}_v^{*t} \leq C \sum_{v \in S^t} \tilde{l}_v^{*t}, (\lambda_v^t)^2 \leq C^2, \sum_{v \in S^t} (\lambda_v^t)^2 \leq C^2 |S^t|$   
So,

$$\Delta_t \geq 2 \sum_{v \in S^t} \lambda_v^t \tilde{l}_v^t - 2 \sum_{v \in S^t} \lambda_v^t \tilde{l}_v^{*t} - \sum_{v \in S^t} (\lambda_v^t)^2 \|\mathbf{x}_t\|^2 - a_t^2 \left( \sum_v \lambda_v^t \right)^2 \|\mathbf{x}_t\|^2 + 2a_t \lambda_{\tilde{y}^t}^t \sum_v \lambda_v^t \|\mathbf{x}_t\|^2$$

By using the above mentioned approximations, we get,

$$\Delta_t \geq 2 \sum_{v \in S^t} \lambda_v^t \tilde{l}_v^t - 2C \sum_{v \in S^t} \tilde{l}_v^{*t} - C^2 |S^t| R^2 - \frac{C^2 K^2 |S^t|^2 R^2}{\gamma^2}$$

Since  $|S^t| \leq K$ , we get,

$$\Delta_t \geq 2 \sum_{v \in S^t} \lambda_v^t \tilde{l}_v^t - 2C \sum_{v \in S^t} \tilde{l}_v^{*t} - C^2 K R^2 - \frac{C^2 K^4 R^2}{\gamma^2}$$

$$\mathbb{E} [\Delta_t] \geq 2 \mathbb{E} \left[ \sum_{v \in S^t} \lambda_v^t \tilde{l}_v^t \right] - 2C \mathbb{E} \left[ \sum_{v \in S^t} \tilde{l}_v^{*t} \right] - C^2 K R^2 - \frac{C^2 K^4 R^2}{\gamma^2}$$

If we consider Case 1:

$$\begin{aligned} & \text{Adding and subtracting } 2\mathbb{E} \left[ \sum_{v \in S^t} \lambda_v^t \frac{a_t \tilde{l}_v^t}{a_t^2 |S^t| + 1 - a_t} \right] \\ & - 2\mathbb{E} \left[ \sum_{v \in S^t} \lambda_v^t \frac{a_t^2 \sum_{j \in S^t} \tilde{l}_j^t}{a_t^2 |S^t| + 1 - a_t} \right], \text{ and } \mathbb{E} [\sum_{v \in S^t} (\lambda_v^t)^2] \text{ and using the fact that } \sum_{v \in S^t} \lambda_v^t \frac{a_t^2 \sum_{j \in S^t} \tilde{l}_j^t}{a_t^2 |S^t| + 1 - a_t} - \\ & \sum_{v \in S^t} \lambda_v^t \frac{a_t \tilde{l}_v^t}{a_t^2 |S^t| + 1 - a_t} \geq 0 \text{ and } \sum_{v \in S^t} (\lambda_v^t)^2 \geq 0 \text{ and simplifying to get,} \end{aligned}$$

$$\mathbb{E} [\Delta_t] \geq 2\mathbb{E} \left[ \sum_{v \in S^t} \lambda_v^t \left( \tilde{l}_v^t + \frac{a_t \tilde{l}_v^t}{a_t^2 |S^t| + 1 - a_t} - \frac{a_t^2 \sum_{j \in S^t} \tilde{l}_j^t}{a_t^2 |S^t| + 1 - a_t} - \frac{\lambda_v^t}{2} \right) \right] - 2C\mathbb{E} \left[ \sum_{v \in S^t} \tilde{l}_v^{*t} \right] - C^2 K R^2 - \frac{C^2 K^4 R^2}{\gamma^2}$$

If we consider Case 2:

$$\begin{aligned} & \text{Adding and subtracting } -2\mathbb{E} \left[ \sum_{v \in S^t} \lambda_v^t \frac{a_t^2 \sum_{j \in S^t} \tilde{l}_j^t}{a_t^2 |S^t| + 1} \right], \text{ and } \mathbb{E} [\sum_{v \in S^t} (\lambda_v^t)^2] \text{ and using the} \\ & \text{fact that } \sum_{v \in S^t} \lambda_v^t \frac{a_t^2 \sum_{j \in S^t} \tilde{l}_j^t}{a_t^2 |S^t| + 1} \text{ and } \sum_{v \in S^t} (\lambda_v^t)^2 \geq 0 \text{ and simplifying to get,} \end{aligned}$$

$$\mathbb{E} [\Delta_t] \geq 2\mathbb{E} \left[ \sum_{v \in S^t} \lambda_v^t \left( \tilde{l}_v^t - \frac{a_t^2 \sum_{j \in S^t} \tilde{l}_j^t}{a_t^2 |S^t| + 1} - \frac{\lambda_v^t}{2} \right) \right] - 2C\mathbb{E} \left[ \sum_{v \in S^t} \tilde{l}_v^{*t} \right] - C^2 K R^2 - \frac{C^2 K^4 R^2}{\gamma^2}$$

Combining the two cases we get,

$$\begin{aligned} \mathbb{E} [\Delta_t] & \geq 2\mathbb{E} \left[ \sum_{v \in S^t} \lambda_v^t \left( \tilde{l}_v^t - \frac{a_t^2 \sum_{j \in S^t} \tilde{l}_j^t}{a_t^2 |S^t| + 1} - \frac{\lambda_v^t}{2} \right) \right] - 2C\mathbb{E} \left[ \sum_{v \in S^t} \tilde{l}_v^{*t} \right] - C^2 K R^2 - \frac{C^2 K^4 R^2}{\gamma^2} \\ & \geq 2\mathbb{E} \left[ \sum_{v \in S^t} \lambda_v^t \left( \frac{1}{\|\mathbf{x}^t\|^2} \left( \tilde{l}_v^t - \frac{a_t^2 \sum_{j \in S^t} \tilde{l}_j^t}{a_t^2 |S^t| + 1} \right) - \frac{\lambda_v^t}{2} \right) \right] - 2C\mathbb{E} \left[ \sum_{v \in S^t} \tilde{l}_v^{*t} \right] - C^2 K R^2 - \frac{C^2 K^4 R^2}{\gamma^2} \end{aligned}$$

Now the above expression becomes,

$$\mathbb{E} [\Delta_t] \geq 2C\mathbb{E} \left[ \sum_{v=1}^K \phi \left( \frac{1}{\|\mathbf{x}^t\|^2} \left( \tilde{l}_v^t - \frac{a_t^2 \sum_{j \in S^t} \tilde{l}_j^t}{a_t^2 |S^t| + 1} \right) \right) \right] - 2C\mathbb{E} \left[ \sum_{v=1}^K \tilde{l}_v^{*t} \right] - C^2 K R^2 - \frac{C^2 K^4 R^2}{\gamma^2}$$

where  $\phi(z) = \frac{1}{C} \left( \min(z, C) \left( z - \frac{1}{2} \min(z, C) \right) \right)$ , [Shalev-Shwartz and Singer \(2007\)](#). Summing the above from  $t=1$  to  $T$  to get,

$$\begin{aligned} \sum_{t=1}^T \mathbb{E} [\Delta_t] & \geq 2C \sum_{t=1}^T \left( \mathbb{E} \left[ \sum_{v=1}^K \phi \left( \frac{1}{\|\mathbf{x}^t\|^2} \left( \tilde{l}_v^t - \frac{a_t^2 \sum_{j \in S^t} \tilde{l}_j^t}{a_t^2 |S^t| + 1} \right) \right) \right] \right) - 2C \sum_{t=1}^T \left( \mathbb{E} \left[ \sum_{v=1}^K \tilde{l}_v^{*t} \right] \right) - TC^2 K R^2 \\ & \quad - \frac{TC^2 K^4 R^2}{\gamma^2} \end{aligned}$$

Also  $\phi(\cdot)$  is a convex function, so we get,

$$\begin{aligned} \sum_{t=1}^T \mathbb{E} [\Delta_t] &\geq \frac{2CT}{R^2} \phi \left( \frac{1}{T} \left( \sum_{t=1}^T \left( \mathbb{E} \left[ \sum_{v=1}^K \tilde{l}_v^t - \frac{a_t^2 \sum_{j \in S^t} \tilde{l}_j^t}{a_t^2 |S^t| + 1} \right] \right) \right) \right) - 2C \sum_{t=1}^T \left( \mathbb{E} \left[ \sum_{v=1}^K \tilde{l}_v^{*t} \right] \right) - TC^2KR^2 \\ &\quad - \frac{TC^2K^4R^2}{\gamma^2} \end{aligned}$$

We had,

$$\begin{aligned} \sum_{t=1}^T \Delta_t &\leq \sum_{v=1}^K \|\mathbf{u}_v\|^2 \\ \sum_{t=1}^T \mathbb{E} [\Delta_t] &\leq \sum_{v=1}^K \|\mathbf{u}_v\|^2 \end{aligned}$$

On comparing the lower and upper bounds we get,

$$\begin{aligned} \frac{2CT}{R^2} \phi \left( \frac{1}{T} \left( \sum_{t=1}^T \left( \mathbb{E} \left[ \sum_{v=1}^K \tilde{l}_v^t - \frac{a_t^2 \sum_{j \in S^t} \tilde{l}_j^t}{a_t^2 |S^t| + 1} \right] \right) \right) \right) &\leq \sum_{v=1}^K \|\mathbf{u}_v\|^2 + 2C \sum_{t=1}^T \left( \mathbb{E} \left[ \sum_{v=1}^K \tilde{l}_v^{*t} \right] \right) + TC^2KR^2 \\ &\quad + \frac{TC^2K^4R^2}{\gamma^2} \end{aligned}$$

Simplifying it to get,

$$\frac{1}{TR^2} \left( \sum_{t=1}^T \left( \mathbb{E} \left[ \sum_{v=1}^K \tilde{l}_v^t - \frac{a_t^2 \sum_{j \in S^t} \tilde{l}_j^t}{a_t^2 |S^t| + 1} \right] \right) \right) \leq \phi^{-1} \left( \frac{1}{2CT} \sum_{v=1}^K \|\mathbf{u}_v\|^2 + \frac{1}{T} \sum_{t=1}^T \left( \mathbb{E} \left[ \sum_{v=1}^K \tilde{l}_v^{*t} \right] \right) + \frac{CKR^2}{2} + \frac{CK^4R^2}{2\gamma^2} \right)$$

Notice that,

$$\begin{aligned} \frac{1}{TR^2} \left( \sum_{t=1}^T \left( \mathbb{E} \left[ \sum_{v=1}^K \tilde{l}_v^t - \frac{a_t^2 \sum_{j \in S^t} \tilde{l}_j^t}{a_t^2 |S^t| + 1} \right] \right) \right) &\geq \frac{1}{TR^2} \left( \sum_{t=1}^T \left( \mathbb{E} \left[ \sum_{v=1}^K \tilde{l}_v^t - \frac{1}{a_t |S^t|} \sum_{j \in S^t} \tilde{l}_j^t \right] \right) \right) \\ &= \frac{1}{TR^2} \left( \sum_{t=1}^T \left( \mathbb{E} \left[ \sum_{v=1}^K \tilde{l}_v^t - \frac{1}{a_t} \tilde{l}_v^t \right] \right) \right) \\ &\geq \frac{1}{TR^2} \left( 1 - \frac{\gamma}{K} \right) \left( \sum_{t=1}^T \left( \mathbb{E} \left[ \sum_{v=1}^K \tilde{l}_v^t \right] \right) \right) \end{aligned}$$

we know that  $\phi^{-1}(z) \leq z + \frac{C}{2}$ , [Shalev-Shwartz and Singer \(2007\)](#). Hence we get,

$$\begin{aligned} \phi^{-1} \left( \frac{1}{2CT} \sum_{v=1}^K \|\mathbf{u}_v\|^2 + \frac{1}{T} \sum_{t=1}^T \left( \mathbb{E} \left[ \sum_{v=1}^K \tilde{l}_v^{*t} \right] \right) + \frac{CKR^2}{2} + \frac{CK^4R^2}{2\gamma^2} \right) &\leq \frac{1}{2CT} \sum_{v=1}^K \|\mathbf{u}_v\|^2 + \frac{1}{T} \sum_{t=1}^T \left( \mathbb{E} \left[ \sum_{v=1}^K \tilde{l}_v^{*t} \right] \right) \\ &\quad + \frac{CKR^2}{2} + \frac{CK^4R^2}{2\gamma^2} + \frac{C}{2} \end{aligned}$$

Combining the last two inequalities we get,

$$\frac{1}{R^2} \left(1 - \frac{\gamma}{K}\right) \left( \sum_{t=1}^T \left( \mathbb{E} \left[ \sum_{v=1}^K \tilde{l}_v^t \right] \right) \right) \leq \frac{1}{2C} \sum_{v=1}^K \|\mathbf{u}_v\|^2 + \sum_{t=1}^T \left( \mathbb{E} \left[ \sum_{v=1}^K \tilde{l}_v^{*t} \right] \right) + \frac{TKR^2}{2} + \frac{TK^4R^2}{2\gamma^2} + \frac{CT}{2}$$

We use  $C = \frac{\sqrt{\sum_{v=1}^K \|\mathbf{u}_v\|^2}}{\sqrt{TKR^2 + \frac{TK^4R^2}{\gamma^2} + T}}$  as it minimizes the upper bound. Using that we get,

$$\frac{1}{R^2} \left(1 - \frac{\gamma}{K}\right) \sum_{t=1}^T \mathbb{E} \left[ \sum_{v=1}^K \tilde{l}_v^t \right] \leq \frac{1}{2} \sqrt{\sum_{v=1}^K \|\mathbf{u}_v\|^2} \sqrt{TKR^2 + \frac{TK^4R^2}{\gamma^2} + T} + \sum_{t=1}^T \mathbb{E} \left[ \sum_{v=1}^K \tilde{l}_v^{*t} \right]$$

■

## 6. Derivation of EPABF-II Updates

The optimization problem associated to the EPABF-II is as follows.

$$\begin{aligned} \mathbf{w}_1^{t+1} \dots \mathbf{w}_K^{t+1} &= \arg \min_{\mathbf{w}_1 \dots \mathbf{w}_K} \frac{1}{2} \sum_{v=1}^K \|\mathbf{w}_v - \mathbf{w}_v^t\|^2 + C \sum_{v=1}^K (\tilde{l}_v)^2 \\ &= \arg \min_{\mathbf{w}_1 \dots \mathbf{w}_K} \frac{1}{2} \sum_{v=1}^K \|\mathbf{w}_v - \mathbf{w}_v^t\|^2 + C \sum_{v=1}^K \xi_v^2 \\ &\text{s.t. } a_t \mathbf{w}_{\tilde{y}^t} \cdot \mathbf{x}^t - \mathbf{w}_r \cdot \mathbf{x}^t \geq 1 - \xi_v, \quad v \in [K] \end{aligned}$$

The optimal solution satisfies the following KKT conditions.

$$\begin{cases} \lambda_r^t (1 - \xi_r + \mathbf{w}_r \cdot \mathbf{x}^t - a_t \mathbf{w}_{\tilde{y}^t} \cdot \mathbf{x}^t) = 0, \quad \forall r \\ \lambda_r^t \geq 0; \quad (1 - \xi_r + \mathbf{w}_r \cdot \mathbf{x}^t - a_t \mathbf{w}_{\tilde{y}^t} \cdot \mathbf{x}^t) \leq 0, \quad \forall r \\ \mathbf{w}_r = \mathbf{w}_r^t - \lambda_r^t \mathbf{x}^t + \mathbb{I}_{\{\tilde{y}^t=r\}} a_t \sum_i \lambda_i^t \mathbf{x}^t, \quad \forall r \\ \xi_r = \frac{\lambda_r^t}{2C}, \quad \forall r \end{cases}$$

Now we determine  $\lambda_r^t$  for the support classes.

$$\begin{aligned} &a_t \left( \mathbf{w}_{\tilde{y}^t}^t - \lambda_{\tilde{y}^t}^t \mathbf{x}^t + a_t \sum_i \lambda_i^t \mathbf{x}^t \right) \cdot \mathbf{x}^t - (\mathbf{w}_r^t - \lambda_r^t \mathbf{x}^t) \cdot \mathbf{x}^t = 1 - \xi_r \\ \Rightarrow &a_t \mathbf{w}_{\tilde{y}^t}^t \cdot \mathbf{x}^t - a_t \lambda_{\tilde{y}^t}^t \|\mathbf{x}^t\|^2 + a_t^2 \|\mathbf{x}^t\|^2 \sum_i \lambda_i^t - \mathbf{w}_r^t \cdot \mathbf{x}^t + \lambda_r^t \|\mathbf{x}^t\|^2 = 1 - \xi_r \\ \Rightarrow &\xi_r + (a_t^2 \sum_i \lambda_i^t - a_t \lambda_{\tilde{y}^t}^t + \lambda_r^t) \|\mathbf{x}^t\|^2 = 1 - a_t \mathbf{w}_{\tilde{y}^t}^t \cdot \mathbf{x}^t + \mathbf{w}_r^t \cdot \mathbf{x}^t \end{aligned}$$

Using value of  $\xi_r$  and rearrange to get,

$$\frac{1}{2C\|\mathbf{x}^t\|^2}\lambda_r^t + a_t^2 \sum_i \lambda_i^t - a_t \lambda_{\tilde{y}^t}^t + \lambda_r^t = \frac{\tilde{l}_r^t}{\|\mathbf{x}^t\|^2} \quad (25)$$

Summing the above for  $\forall r \in S^t$ , we get,

$$\left( a_t^2 |S^t| + 1 + \frac{1}{2C\|\mathbf{x}^t\|^2} \right) \sum_{r \in S^t} \lambda_r^t - a_t |S^t| \lambda_{\tilde{y}^t}^t = \frac{\sum_{r \in S^t} \tilde{l}_r^t}{\|\mathbf{x}^t\|^2} \quad (26)$$

Now, we have two cases:

- **Case 1** :  $\tilde{y}^t \in S^t$ : Taking  $r = \tilde{y}^t$ , the Eq.(25) becomes,

$$a_t^2 \sum_{r \in S^t} \lambda_r^t + \left( 1 + \frac{1}{2C\|\mathbf{x}^t\|^2} - a_t \right) \lambda_{\tilde{y}^t}^t = \frac{\tilde{l}_{\tilde{y}^t}^t}{\|\mathbf{x}^t\|^2} \quad (27)$$

Using Eq.(26) and (27), we get the following.

$$\sum_{r \in S^t} \lambda_r^t = \frac{a_t |S^t| \tilde{l}_{\tilde{y}^t}^t + \left( 1 + \frac{1}{2C\|\mathbf{x}^t\|^2} - a_t \right) \sum_{r \in S^t} \tilde{l}_r^t}{\|\mathbf{x}^t\|^2 \left( a_t^2 |S^t| + 1 + \frac{1}{2C\|\mathbf{x}^t\|^2} - a_t \right) \left( 1 + \frac{1}{2C\|\mathbf{x}^t\|^2} \right)} \quad (28)$$

$$\lambda_{\tilde{y}^t}^t = \frac{\left( a_t^2 |S^t| + 1 + \frac{1}{2C\|\mathbf{x}^t\|^2} \right) \tilde{l}_{\tilde{y}^t}^t - a_t^2 \sum_{r \in S^t} \tilde{l}_r^t}{\|\mathbf{x}^t\|^2 \left( a_t^2 |S^t| + 1 + \frac{1}{2C\|\mathbf{x}^t\|^2} - a_t \right) \left( 1 + \frac{1}{2C\|\mathbf{x}^t\|^2} \right)} \quad (29)$$

Using Eq.(28) and Eq.(29) in Eq.(25), we can find  $\lambda_r^t$  as follows.

$$\lambda_r^t = \frac{1}{\|\mathbf{x}^t\|^2 \left( 1 + \frac{1}{2C\|\mathbf{x}^t\|^2} \right)} \left( \tilde{l}_r^t + \frac{a_t \tilde{l}_{\tilde{y}^t}^t - a_t^2 \sum_{j \in S^t} \tilde{l}_j^t}{a_t^2 |S^t| + 1 + \frac{1}{2C\|\mathbf{x}^t\|^2} - a_t} \right) \quad (30)$$

- $\tilde{y}^t \notin S^t$ : In this case  $\lambda_{\tilde{y}^t}^t = 0$ . Using Eq.(25) and (26), we will get,

$$\lambda_r^t = \frac{1}{\|\mathbf{x}^t\|^2 \left( 1 + \frac{1}{2C\|\mathbf{x}^t\|^2} \right)} \left( \tilde{l}_r^t - \frac{a_t^2 \sum_{j \in S^t} \tilde{l}_j^t}{a_t^2 |S^t| + 1 + \frac{1}{2C\|\mathbf{x}^t\|^2}} \right)$$



## 7. Proof of Theorem 4

**Proof** We will have 2 cases:

- **Case 1:** If  $\tilde{y}^t \in S^t$

Using the KKT conditions, we see that for any  $r \notin S^t$ , we have,

$$a_t(\mathbf{w}_{\tilde{y}^t}^t - \lambda_{\tilde{y}^t}^t \mathbf{x}^t + a_t \sum_i \lambda_i^t \mathbf{x}^t) \cdot \mathbf{x}^t - (\mathbf{w}_r^t - \lambda_r^t \mathbf{x}^t) \cdot \mathbf{x}^t \geq 1 - \xi_r^t$$

Since  $\xi_r^t = \frac{\lambda_r^t}{2C}$ ,  $\lambda_r^t = 0$  for  $r \notin S^t$ , the above equation reduces to,

$$a_t^2 \sum_i \lambda_i^t - a_t \lambda_{\tilde{y}^t}^t \geq \frac{1 + \mathbf{w}_r^t \cdot \mathbf{x}^t - a_t \mathbf{w}_{\tilde{y}^t}^t \cdot \mathbf{x}^t}{\|\mathbf{x}^t\|^2} = \frac{\tilde{l}_r^t}{\|\mathbf{x}^t\|^2} \quad (31)$$

We know that,

$$\sum_{r \in S^t} \lambda_r^t = \frac{a_t |S^t| \tilde{l}_{\tilde{y}^t}^t + \left(1 + \frac{1}{2C \|\mathbf{x}^t\|^2} - a_t\right) \sum_{r \in S^t} \tilde{l}_r^t}{\|\mathbf{x}^t\|^2 \left(a_t^2 |S^t| + 1 + \frac{1}{2C \|\mathbf{x}^t\|^2} - a_t\right) \left(1 + \frac{1}{2C \|\mathbf{x}^t\|^2}\right)} \quad (32)$$

$$\lambda_{\tilde{y}^t}^t = \frac{\left(a_t^2 |S^t| + 1 + \frac{1}{2C \|\mathbf{x}^t\|^2}\right) \tilde{l}_{\tilde{y}^t}^t - a_t^2 \sum_{r \in S^t} \tilde{l}_r^t}{\|\mathbf{x}^t\|^2 \left(a_t^2 |S^t| + 1 + \frac{1}{2C \|\mathbf{x}^t\|^2} - a_t\right) \left(1 + \frac{1}{2C \|\mathbf{x}^t\|^2}\right)} \quad (33)$$

Using Eq.(33) and (32) in Eq.(31), we get

$$\frac{a_t^2 \sum_{j \in S^t} \tilde{l}_j^t}{|S^t| a_t^2 + 1 - a_t + \frac{1}{2C \|\mathbf{x}^t\|^2}} \geq \tilde{l}_r^t + \frac{a_t \tilde{l}_{\tilde{y}^t}^t}{|S^t| a_t^2 + 1 - a_t + \frac{1}{2C \|\mathbf{x}^t\|^2}}, \quad \forall r \notin S^t$$

On the other hand, if  $r$  lies in the support set  $S^t$ , we have  $\lambda_r^t > 0$ . Using Eq.(30), we get the following condition for  $r \in S^t$ .

$$\frac{a_t^2 \sum_{j \in S^t} \tilde{l}_{\sigma(j)}^t}{|S^t| a_t^2 + 1 - a_t + \frac{1}{2C \|\mathbf{x}^t\|^2}} < \tilde{l}_{\sigma(r)}^t + \frac{a_t \tilde{l}_{\tilde{y}^t}^t}{|S^t| a_t^2 + 1 - a_t + \frac{1}{2C \|\mathbf{x}^t\|^2}}, \quad \forall r \in S^t \quad (34)$$

Let  $\sigma(k)$  be the  $k$ -th class when sorted in descending order of  $\tilde{l}_r^t$ .

(*Sufficiency*) Assume that  $\tilde{l}_{\sigma(k)}^t$  satisfies the theorem, then we have,

$$\begin{aligned} \sum_{j=1}^{k-1} \tilde{l}_{\sigma(j)}^t &< \frac{\left(1 + (k-1)a_t^2 - a_t + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)}{a_t^2} \tilde{l}_{\sigma(k)}^t + \frac{1}{a_t} \tilde{l}_{\tilde{y}^t}^t \\ \Rightarrow \sum_{j=1}^{|S^t|} \tilde{l}_{\sigma(j)}^t &< \frac{\left(1 + |S^t|a_t^2 - a_t + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)}{a_t^2} \tilde{l}_{\sigma(k)}^t + \frac{1}{a_t} \tilde{l}_{\tilde{y}^t}^t \\ \Rightarrow \frac{a_t^2}{\left(1 + |S^t|a_t^2 - a_t + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)} \sum_{j=1}^{|S^t|} \tilde{l}_{\sigma(j)}^t &< \tilde{l}_{\sigma(k)}^t + \frac{a_t}{\left(1 + |S^t|a_t^2 - a_t + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)} \tilde{l}_{\tilde{y}^t}^t \end{aligned}$$

The second inequality is justified as the losses  $\tilde{l}_{\sigma(j)}^t$  are in decreasing order. This means  $\sigma(k)$  belongs to the support set  $S^t$ .

(*Necessity*) Assume that  $\tilde{l}_{\sigma(k)}$  does not satisfy theorem, then

$$\begin{aligned} \sum_{j=1}^{k-1} \tilde{l}_{\sigma(j)}^t &\geq \frac{\left(1 + (k-1)a_t^2 - a_t + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)}{a_t^2} \tilde{l}_{\sigma(k)}^t + \frac{1}{a_t} \tilde{l}_{\tilde{y}^t}^t \\ \sum_{j=1}^k \tilde{l}_{\sigma(j)}^t &\geq \frac{\left(1 + (k)a_t^2 - a_t + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)}{a_t^2} \tilde{l}_{\sigma(k)}^t + \frac{1}{a_t} \tilde{l}_{\tilde{y}^t}^t \\ \frac{a_t^2}{\left(1 + ka_t^2 - a_t + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)} \sum_{j=1}^k \tilde{l}_{\sigma(j)}^t - \frac{a_t}{\left(1 + ka_t^2 - a_t + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)} \tilde{l}_{\tilde{y}^t}^t &\geq \tilde{l}_{\sigma(k)}^t \geq \tilde{l}_{\sigma(k+1)}^t \end{aligned}$$

Therefore, any  $j$  larger than  $\sigma(k)$  does not satisfy Eq.(34). It means  $|S^t| < k$  and thus  $k$  does not correspond to a label of a support class.

- **Case 2:** If  $\tilde{y}^t \notin S^t$

Using the KKT conditions, we see that for any  $r \notin S^t$ , we have,

$$a_t(\mathbf{w}_{\tilde{y}^t}^t + a_t \sum_i \lambda_i^t \mathbf{x}^t) \cdot \mathbf{x}^t - (\mathbf{w}_r^t - \lambda_r^t \mathbf{x}^t) \cdot \mathbf{x}^t \geq 1 - \xi_r^t$$

Since  $\xi_r^t = \frac{\lambda_r^t}{2C}$ ,  $\lambda_r^t = 0$  for  $r \notin S^t$ , the above equation reduces to,

$$a_t^2 \sum_i \lambda_i^t \geq \frac{1 + \mathbf{w}_r^t \cdot \mathbf{x}^t - a_t \mathbf{w}_{\tilde{y}^t}^t \cdot \mathbf{x}^t}{\|\mathbf{x}^t\|^2} = \frac{\tilde{l}_r^t}{\|\mathbf{x}^t\|^2}$$

We know that,

$$\sum_{r \in S^t} \lambda_r^t = \frac{1}{\left(1 + \frac{1}{2C\|\mathbf{x}^t\|^2} + |S^t|a_t^2\right)\|\mathbf{x}^t\|^2} \left( \sum_{r \in S^t} \tilde{l}_r^t \right) \quad (35)$$

Using Eq.(35), we can rewrite this equation as,

$$\frac{a_t^2 \sum_{j \in S^t} \tilde{l}_{\sigma(j)}^t}{1 + \frac{1}{2C\|\mathbf{x}^t\|^2} + |S^t|a_t^2} \geq \tilde{l}_{\sigma(r)}^t, \quad \forall r \notin S^t \quad (36)$$

Also we have,

$$\lambda_r^t = \frac{1}{\|\mathbf{x}^t\|^2 \left(1 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)} \left( \tilde{l}_r^t - \frac{a_t^2 \sum_{j \in S^t} \tilde{l}_j^t}{\left(a_t^2 |S^t| + 1 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)} \right) \quad (37)$$

To get support class,  $\lambda_r^t$  should be positive, so by Eq.(37), we get

$$\frac{a_t^2 \sum_{j \in S^t} \tilde{l}_{\sigma(j)}^t}{1 + \frac{1}{2C\|\mathbf{x}^t\|^2} + |S^t|a_t^2} < \tilde{l}_{\sigma(r)}^t, \quad \forall r \in S^t \quad (38)$$

Let  $\sigma(k)$  be the  $k$ -th class when sorted in descending order of  $\tilde{l}_r^t$ .  
*(Sufficiency)* Assume that  $\tilde{l}_{\sigma(k)}^t$  satisfies the theorem, then we have,

$$\begin{aligned} \sum_{j=1}^{k-1} \tilde{l}_{\sigma(j)}^t &< \frac{1 + \frac{1}{2C\|\mathbf{x}^t\|^2} + (k-1)a_t^2}{a_t^2} \tilde{l}_{\sigma(k)}^t \\ \Rightarrow \sum_{j=1}^{|S^t|} \tilde{l}_{\sigma(j)}^t &< \frac{1 + \frac{1}{2C\|\mathbf{x}^t\|^2} + |S^t|a_t^2}{a_t^2} \tilde{l}_{\sigma(k)}^t \\ \Rightarrow \frac{a_t^2}{1 + \frac{1}{2C\|\mathbf{x}^t\|^2} + |S^t|a_t^2} \sum_{j=1}^{|S^t|} \tilde{l}_{\sigma(j)}^t &< \tilde{l}_{\sigma(k)}^t \end{aligned}$$

The second inequality is justified as the losses  $\tilde{l}_{\sigma(j)}^t$  are in decreasing order. This means  $\sigma(k)$  corresponds to a label of some support classes Eq. (38).

*(Necessity)* Assume that  $\tilde{l}_r^t$  does not satisfy theorem, then

$$\sum_{j=1}^{k-1} \tilde{l}_{\sigma(j)}^t \geq \frac{1 + \frac{1}{2C\|\mathbf{x}^t\|^2} + (k-1)a_t^2}{a_t^2} \tilde{l}_{\sigma(k)}^t$$

$$\sum_{j=1}^k \tilde{l}_{\sigma(j)}^t \geq \frac{1 + \frac{1}{2C\|\mathbf{x}^t\|^2} + (k)a_t^2}{a_t^2} \tilde{l}_{\sigma(k)}^t$$

$$\frac{a_t^2}{1 + \frac{1}{2C\|\mathbf{x}^t\|^2} + ka_t^2} \sum_{j=1}^k \tilde{l}_{\sigma(j)}^t \geq \tilde{l}_{\sigma(k)}^t \geq \tilde{l}_{\sigma(k+1)}^t$$

Therefore, any  $j$  larger than  $\sigma(k)$  does not satisfy Eq. (38). It means  $|S^t| < k$  and thus  $\sigma(k)$  does not correspond to a label of a support class. ■

## 8. Proof of Theorem 5: EPABF-II bound

### Proof

- **Case 1:** If  $\tilde{y}^t \in S^t$  We had

$$\mathbb{E} [\Delta_t] \geq 2\mathbb{E} \left[ \sum_{v \in S^t} \lambda_v^t (\tilde{l}_v^t - \tilde{l}_v^{*t}) \right] - \mathbb{E} \left[ \sum_{v \in S^t} (\lambda_v^t)^2 \|\mathbf{x}_t\|^2 \right] - \mathbb{E} \left[ a_t^2 \left( \sum_v \lambda_v^t \right)^2 \|\mathbf{x}_t\|^2 \right]$$

$$+ \mathbb{E} \left[ 2a_t \lambda_{\tilde{y}^t}^t \sum_v \lambda_v^t \|\mathbf{x}_t\|^2 \right]$$

And the step sizes for EPABF-II are as follows,

$$\sum_{r \in S^t} \lambda_r^t = \frac{a_t |S^t| \tilde{l}_{\tilde{y}^t}^t + \left(1 + \frac{1}{2C\|\mathbf{x}^t\|^2} - a_t\right) \sum_{r \in S^t} \tilde{l}_r^t}{\|\mathbf{x}^t\|^2 \left( a_t^2 |S^t| + 1 + \frac{1}{2C\|\mathbf{x}^t\|^2} - a_t \right) \left(1 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)}$$

$$\lambda_{\tilde{y}^t}^t = \frac{\left( a_t^2 |S^t| + 1 + \frac{1}{2C\|\mathbf{x}^t\|^2} \right) \tilde{l}_{\tilde{y}^t}^t - a_t^2 \sum_{r \in S^t} \tilde{l}_r^t}{\|\mathbf{x}^t\|^2 \left( a_t^2 |S^t| + 1 + \frac{1}{2C\|\mathbf{x}^t\|^2} - a_t \right) \left(1 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)}$$

$$\lambda_r^t = \frac{1}{\|\mathbf{x}^t\|^2 \left(1 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)} \left( \tilde{l}_r^t + \frac{a_t \tilde{l}_{\tilde{y}^t}^t - a_t^2 \sum_{j \in S^t} \tilde{l}_j^t}{\left( a_t^2 |S^t| + 1 - a_t + \frac{1}{2C\|\mathbf{x}^t\|^2} \right)} \right)$$

The Inequality is true even if we subtract  $\mathbb{E} \left[ \sum_{v \in S^t} \left( \alpha \lambda_v^t - \frac{\tilde{l}_v^{*t}}{\alpha} \right)^2 \right]$  from it. Here,

$$\alpha = \frac{1}{\sqrt{2C\|\mathbf{x}^t\|^2}}$$

$$\begin{aligned}
 \mathbb{E}[\Delta_t] &\geq 2\mathbb{E}\left[\sum_{v \in S^t} \lambda_v^t (\tilde{l}_v^t - \tilde{l}_v^{*t})\right] - \mathbb{E}\left[\sum_{v \in S^t} (\lambda_v^t)^2 \|\mathbf{x}_t\|^2\right] - \mathbb{E}\left[a_t^2 \left(\sum_v \lambda_v^t\right)^2 \|\mathbf{x}_t\|^2\right] \\
 &+ \mathbb{E}\left[2a_t \lambda_{\tilde{y}^t}^t \sum_v \lambda_v^t \|\mathbf{x}_t\|^2\right] - \mathbb{E}\left[\sum_{v \in S^t} \left(\alpha \lambda_v^t - \frac{\tilde{l}_v^{*t}}{\alpha}\right)^2\right] \\
 &= 2\mathbb{E}\left[\sum_{v \in S^t} \lambda_v^t \tilde{l}_v^t\right] - (\|\mathbf{x}_t\|^2 + \alpha^2) \mathbb{E}\left[\sum_{v \in S^t} (\lambda_v^t)^2\right] - \mathbb{E}\left[a_t^2 \left(\sum_v \lambda_v^t\right)^2 \|\mathbf{x}_t\|^2\right] \\
 &+ \mathbb{E}\left[2a_t \lambda_{\tilde{y}^t}^t \sum_v \lambda_v^t \|\mathbf{x}_t\|^2\right] - \frac{1}{\alpha^2} \mathbb{E}\left[\sum_{v \in S^t} (\tilde{l}_v^{*t})^2\right] \\
 &= \frac{2}{\|\mathbf{x}_t\|^2 \left(1 + \frac{1}{2C\|\mathbf{x}_t\|^2}\right)} \mathbb{E}\left[\sum_{v \in S^t} \left(\tilde{l}_v^t + \frac{a_t \tilde{l}_{\tilde{y}^t}^t - a_t^2 \sum_{j \in S^t} \tilde{l}_j^t}{\left(a_t^2 |S^t| + 1 - a_t + \frac{1}{2C\|\mathbf{x}_t\|^2}\right)}\right) \tilde{l}_v^t\right] \\
 &- \frac{(\|\mathbf{x}_t\|^2 + \alpha^2)}{\|\mathbf{x}_t\|^4 \left(1 + \frac{1}{2C\|\mathbf{x}_t\|^2}\right)^2} \mathbb{E}\left[\sum_{v \in S^t} \left(\tilde{l}_v^t + \frac{a_t \tilde{l}_{\tilde{y}^t}^t - a_t^2 \sum_{j \in S^t} \tilde{l}_j^t}{\left(a_t^2 |S^t| + 1 - a_t + \frac{1}{2C\|\mathbf{x}_t\|^2}\right)}\right)^2\right] \\
 &- \mathbb{E}\left[a_t^2 \left(\frac{a_t |S^t| \tilde{l}_{\tilde{y}^t}^t}{\|\mathbf{x}_t\|^2 \left(a_t^2 |S^t| + 1 + \frac{1}{2C\|\mathbf{x}_t\|^2} - a_t\right) \left(1 + \frac{1}{2C\|\mathbf{x}_t\|^2}\right)}\right.\right. \\
 &\quad \left.\left. + \frac{\left(1 + \frac{1}{2C\|\mathbf{x}_t\|^2} - a_t\right) \sum_{r \in S^t} \tilde{l}_r^t}{\left(a_t^2 |S^t| + 1 + \frac{1}{2C\|\mathbf{x}_t\|^2} - a_t\right) \left(1 + \frac{1}{2C\|\mathbf{x}_t\|^2}\right)}\right)^2 \|\mathbf{x}_t\|^2\right] \\
 &+ \mathbb{E}\left[2a_t \left(\frac{\left(a_t^2 |S^t| + 1 + \frac{1}{2C\|\mathbf{x}_t\|^2}\right) \tilde{l}_{\tilde{y}^t}^t - a_t^2 \sum_{r \in S^t} \tilde{l}_r^t}{\|\mathbf{x}_t\|^2 \left(a_t^2 |S^t| + 1 + \frac{1}{2C\|\mathbf{x}_t\|^2} - a_t\right) \left(1 + \frac{1}{2C\|\mathbf{x}_t\|^2}\right)}\right)\right. \\
 &\quad \left.\left(\frac{a_t |S^t| \tilde{l}_{\tilde{y}^t}^t + \left(1 + \frac{1}{2C\|\mathbf{x}_t\|^2} - a_t\right) \sum_{r \in S^t} \tilde{l}_r^t}{\|\mathbf{x}_t\|^2 \left(a_t^2 |S^t| + 1 + \frac{1}{2C\|\mathbf{x}_t\|^2} - a_t\right) \left(1 + \frac{1}{2C\|\mathbf{x}_t\|^2}\right)}\right) \|\mathbf{x}_t\|^2\right] - \frac{1}{\alpha^2} \mathbb{E}\left[\sum_{v \in S^t} (\tilde{l}_v^{*t})^2\right]
 \end{aligned}$$

$$\begin{aligned}
&\geq \left( \frac{2}{\|\mathbf{x}^t\|^2 \left(1 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)} - \frac{\|\mathbf{x}^t\|^2 + \alpha^2}{\|\mathbf{x}^t\|^4 \left(1 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)^2} \right) \mathbb{E} \left[ \sum_{v \in S^t} (\tilde{l}_v^t)^2 \right] \\
&\quad - \frac{1}{\|\mathbf{x}^t\|^2 \left(1 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)^2} \mathbb{E} \left[ \tilde{l}_{\tilde{y}^t}^t \sum_{v \in S^t} \tilde{l}_v^t \right] - \frac{1}{\|\mathbf{x}^t\|^2 \left(1 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)^2} \mathbb{E} \left[ \left( \sum_{v \in S^t} \tilde{l}_v^t \right)^2 \right] \\
&\quad + \frac{1}{\|\mathbf{x}^t\|^2 \left(1 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)^2} \mathbb{E} \left[ (\tilde{l}_{\tilde{y}^t}^t)^2 \right] - \frac{1}{\alpha^2} \mathbb{E} \left[ \sum_{v \in S^t} (\tilde{l}_v^{*t})^2 \right] \\
&= \left( \frac{2}{\|\mathbf{x}^t\|^2 \left(1 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)} - \frac{\|\mathbf{x}^t\|^2 + \alpha^2}{\|\mathbf{x}^t\|^4 \left(1 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)^2} \right) \mathbb{E} \left[ \sum_{v \in S^t} (\tilde{l}_v^t)^2 \right] \\
&\quad + \frac{1}{\|\mathbf{x}^t\|^2 \left(1 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)^2} \mathbb{E} \left[ \left( \sum_{v \in S^t} \tilde{l}_v^t - \tilde{l}_{\tilde{y}^t}^t \right)^2 \right] - \frac{2}{\|\mathbf{x}^t\|^2 \left(1 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)^2} \mathbb{E} \left[ \left( \sum_{v \in S^t} \tilde{l}_v^t \right)^2 \right] \\
&\quad + \frac{1}{\|\mathbf{x}^t\|^2 \left(1 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)^2} \mathbb{E} \left[ \tilde{l}_{\tilde{y}^t}^t \sum_{v \in S^t} \tilde{l}_v^t \right] - \frac{1}{\alpha^2} \mathbb{E} \left[ \sum_{v \in S^t} (\tilde{l}_v^{*t})^2 \right] \\
&= \left( \frac{2}{\|\mathbf{x}^t\|^2 \left(1 + \frac{1}{2C}\right)} - \frac{\|\mathbf{x}^t\|^2 + \alpha^2}{\|\mathbf{x}^t\|^4 \left(1 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)^2} \right) \mathbb{E} \left[ \sum_{v \in S^t} (\tilde{l}_v^t)^2 \right] \\
&\quad + \frac{1}{\|\mathbf{x}^t\|^2 \left(1 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)^2} \mathbb{E} \left[ \left( \sum_{v \in S^t} \tilde{l}_v^t - \tilde{l}_{\tilde{y}^t}^t \right)^2 - 2 \left( \sum_{v \in S^t} \tilde{l}_v^t \right)^2 + \tilde{l}_{\tilde{y}^t}^t \sum_{v \in S^t} \tilde{l}_v^t \right] - \frac{1}{\alpha^2} \mathbb{E} \left[ \sum_{v \in S^t} (\tilde{l}_v^{*t})^2 \right]
\end{aligned}$$

Since  $(x - y)^2 + xy = \frac{x^2}{2} + \frac{y^2}{2} + \frac{(x - y)^2}{2} \geq \frac{x^2}{2} + \frac{y^2}{2}$

$$\begin{aligned}
&\geq \left( \frac{2}{\|\mathbf{x}^t\|^2 \left(1 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)} - \frac{\|\mathbf{x}^t\|^2 + \alpha^2}{\|\mathbf{x}^t\|^4 \left(1 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)^2} \right) \mathbb{E} \left[ \sum_{v \in S^t} (\tilde{l}_v^t)^2 \right] \\
&\quad - \left( \frac{3}{2} \right) \frac{1}{\|\mathbf{x}^t\|^2 \left(1 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)^2} \mathbb{E} \left[ \left( \sum_{v \in S^t} \tilde{l}_v^t \right)^2 \right] - \frac{1}{\alpha^2} \mathbb{E} \left[ \sum_{v \in S^t} (\tilde{l}_v^{*t})^2 \right]
\end{aligned}$$

$$\begin{aligned}
 &= \left( \frac{1 + \frac{1}{C\|\mathbf{x}^t\|^2}}{\|\mathbf{x}^t\|^2 \left(1 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)^2} - \frac{\alpha^2}{\|\mathbf{x}^t\|^4 \left(1 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)^2} \right) \mathbb{E} \left[ \sum_{v \in S^t} (\tilde{l}_v^t)^2 \right] \\
 &\quad - \left( \frac{3}{2} \right) \frac{1}{\|\mathbf{x}^t\|^2 \left(1 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)^2} \mathbb{E} \left[ \left( \sum_{v \in S^t} \tilde{l}_v^t \right)^2 \right] - \frac{1}{\alpha^2} \mathbb{E} \left[ \sum_{v \in S^t} (\tilde{l}_v^{*t})^2 \right] \\
 &\geq \left( \frac{1 + \frac{1}{C\|\mathbf{x}^t\|^2}}{\|\mathbf{x}^t\|^2 \left(1 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)^2} - \frac{1}{\|\mathbf{x}^t\|^4 \left(1 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)^2} - \left( \frac{3}{2} \right) \frac{K}{\|\mathbf{x}^t\|^2 \left(1 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)^2} \right) \mathbb{E} \left[ \sum_{v \in S^t} (\tilde{l}_v^t)^2 \right] \\
 &\quad - \frac{1}{\alpha^2} \mathbb{E} \left[ \sum_{v \in S^t} (\tilde{l}_v^{*t})^2 \right]
 \end{aligned}$$

We have used  $\mathbb{E} \left[ \left( \sum_{v \in S^t} \tilde{l}_v^t \right)^2 \right] \leq K \mathbb{E} \left[ \sum_{v \in S^t} (\tilde{l}_v^t)^2 \right]$  in the last inequality

- **Case 2:** If  $\tilde{y}^t \notin S^t, \lambda_{\tilde{y}^t} = 0$ , then we had

$$\mathbb{E} [\Delta_t] \geq 2\mathbb{E} \left[ \sum_{v \in S^t} \lambda_v^t (\tilde{l}_v^t - \tilde{l}_v^{*t}) \right] - \mathbb{E} \left[ \sum_{v \in S^t} (\lambda_v^t)^2 \|\mathbf{x}_t\|^2 \right] - \mathbb{E} \left[ a_t^2 \left( \sum_v \lambda_v^t \right)^2 \|\mathbf{x}_t\|^2 \right]$$

And the step sizes for EPABF-II are as follows,

$$\begin{aligned}
 \sum_{r \in S^t} \lambda_r^t &= \frac{\sum_{r \in S^t} \tilde{l}_r^t}{\|\mathbf{x}^t\|^2 \left( a_t^2 |S^t| + 1 + \frac{1}{2C\|\mathbf{x}^t\|^2} \right)} \\
 \lambda_r^t &= \frac{1}{\|\mathbf{x}^t\|^2 \left( 1 + \frac{1}{2C\|\mathbf{x}^t\|^2} \right)} \left( \tilde{l}_r^t - \frac{a_t^2 \sum_{j \in S^t} \tilde{l}_j^t}{\left( a_t^2 |S^t| + 1 + \frac{1}{2C\|\mathbf{x}^t\|^2} \right)} \right)
 \end{aligned}$$

The Inequality is true even if we subtract  $\mathbb{E} \left[ \sum_{v \in S^t} \left( \alpha \lambda_v^t - \frac{\tilde{l}_v^{*t}}{\alpha} \right)^2 \right]$  from it. Here,

$$\alpha = \frac{1}{\sqrt{2C\|\mathbf{x}^t\|^2}}$$

$$\begin{aligned}
\mathbb{E}[\Delta_t] &\geq 2\mathbb{E}\left[\sum_{v \in S^t} \lambda_v^t (\tilde{l}_v^t - \tilde{l}_v^{*t})\right] - \mathbb{E}\left[\sum_{v \in S^t} (\lambda_v^t)^2 \|\mathbf{x}_t\|^2\right] - \mathbb{E}\left[a_t^2 \left(\sum_v \lambda_v^t\right)^2 \|\mathbf{x}_t\|^2\right] \\
&\quad - \mathbb{E}\left[\sum_{v \in S^t} \left(\alpha \lambda_v^t - \frac{\tilde{l}_v^{*t}}{\alpha}\right)^2\right] \\
&= 2\mathbb{E}\left[\sum_{v \in S^t} \lambda_v^t \tilde{l}_v^t\right] - (\|\mathbf{x}_t\|^2 + \alpha^2)\mathbb{E}\left[\sum_{v \in S^t} (\lambda_v^t)^2\right] - \mathbb{E}\left[a_t^2 \left(\sum_v \lambda_v^t\right)^2 \|\mathbf{x}_t\|^2\right] - \frac{1}{\alpha^2}\mathbb{E}\left[\sum_{v \in S^t} (\tilde{l}_v^{*t})^2\right] \\
&= \frac{2}{\|\mathbf{x}^t\|^2 \left(1 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)} \mathbb{E}\left[\sum_{v \in S^t} \left(\tilde{l}_v^t - \frac{a_t^2 \sum_{j \in S^t} \tilde{l}_j^t}{\left(a_t^2 |S^t| + 1 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)}\right) \tilde{l}_v^t\right] \\
&\quad - \frac{(\|\mathbf{x}_t\|^2 + \alpha^2)}{\|\mathbf{x}^t\|^4 \left(1 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)^2} \mathbb{E}\left[\sum_{v \in S^t} \left(\tilde{l}_v^t - \frac{a_t^2 \sum_{j \in S^t} \tilde{l}_j^t}{\left(a_t^2 |S^t| + 1 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)}\right)^2\right] \\
&\quad - \mathbb{E}\left[a_t^2 \left(\frac{\sum_{r \in S^t} \tilde{l}_r^t}{\|\mathbf{x}^t\|^2 \left(a_t^2 |S^t| + 1 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)}\right)^2 \|\mathbf{x}_t\|^2\right] - \frac{1}{\alpha^2} \mathbb{E}\left[\sum_{v \in S^t} (\tilde{l}_v^{*t})^2\right] \\
&\geq \left(\frac{1 + \frac{1}{C\|\mathbf{x}^t\|^2}}{\|\mathbf{x}^t\|^2 \left(1 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)^2} - \frac{1}{\|\mathbf{x}^t\|^4 \left(1 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)^2} - \left(\frac{\left(3 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)K}{\|\mathbf{x}^t\|^2 \left(1 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)}\right)\right) \times \\
&\quad \mathbb{E}\left[\sum_{v \in S^t} (\tilde{l}_v^t)^2\right] - \frac{1}{\alpha^2} \mathbb{E}\left[\sum_{v \in S^t} (\tilde{l}_v^{*t})^2\right]
\end{aligned}$$

We have used  $\mathbb{E}\left[\left(\sum_{v \in S^t} \tilde{l}_v^t\right)^2\right] \leq K\mathbb{E}\left[\sum_{v \in S^t} (\tilde{l}_v^t)^2\right]$  in the last inequality



Combining the two cases we get,

$$\begin{aligned} \mathbb{E}[\Delta_t] &\geq \min \left( \left( \frac{1 + \frac{1}{C\|\mathbf{x}^t\|^2}}{\|\mathbf{x}^t\|^2 \left(1 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)^2} - \frac{\frac{1}{2C\|\mathbf{x}^t\|^2}}{\|\mathbf{x}^t\|^4 \left(1 + \frac{1}{2CR^2}\right)^2} - \left(\frac{3}{2}\right) \frac{K}{\|\mathbf{x}^t\|^2 \left(1 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)^2} \right) \times \right. \\ &\quad \mathbb{E} \left[ \sum_{v \in S^t} (\tilde{l}_v^t)^2 \right] - \frac{1}{\alpha^2} \mathbb{E} \left[ \sum_{v \in S^t} (\tilde{l}_v^{*t})^2 \right], \\ &\quad \left( \frac{1 + \frac{1}{C\|\mathbf{x}^t\|^2}}{\|\mathbf{x}^t\|^2 \left(1 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)^2} - \frac{\frac{1}{2C\|\mathbf{x}^t\|^2}}{\|\mathbf{x}^t\|^4 \left(1 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)^2} - \left( \frac{\left(3 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right) K}{\|\mathbf{x}^t\|^2 \left(1 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)} \right) \right) \times \\ &\quad \left. \mathbb{E} \left[ \sum_{v \in S^t} (\tilde{l}_v^t)^2 \right] - \frac{1}{\alpha^2} \mathbb{E} \left[ \sum_{v \in S^t} (\tilde{l}_v^{*t})^2 \right] \right) \end{aligned}$$

So we can write,

$$\begin{aligned} \mathbb{E}[\Delta_t] &\geq \left( \frac{1 + \frac{1}{C\|\mathbf{x}^t\|^2}}{\|\mathbf{x}^t\|^2 \left(1 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)^2} - \frac{\frac{1}{2C\|\mathbf{x}^t\|^2}}{\|\mathbf{x}^t\|^4 \left(1 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)^2} - \left( \frac{\left(3 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right) K}{\|\mathbf{x}^t\|^2 \left(1 + \frac{1}{2C\|\mathbf{x}^t\|^2}\right)} \right) \right) \times \\ &\quad \mathbb{E} \left[ \sum_{v \in S^t} (\tilde{l}_v^t)^2 \right] - \frac{1}{\alpha^2} \mathbb{E} \left[ \sum_{v \in S^t} (\tilde{l}_v^{*t})^2 \right] \end{aligned}$$

Since, we have

$$\Delta_t = \mathbb{E} \left[ \sum_{v=1}^K \|\mathbf{w}_v^t - \mathbf{u}_v\|^2 \right] - \mathbb{E} \left[ \sum_{v=1}^K \|\mathbf{w}_v^{t+1} - \mathbf{u}_v\|^2 \right]$$

Summing it over t to get,

$$\sum_{t=1}^T \Delta_t = \mathbb{E} \left[ \sum_{v=1}^K \|\mathbf{w}_v^1 - \mathbf{u}_v\|^2 \right] - \mathbb{E} \left[ \sum_{v=1}^K \|\mathbf{w}_v^{T+1} - \mathbf{u}_v\|^2 \right]$$

Since  $\mathbf{w}^1 = 0$  and  $\|\mathbf{w}_v^{T+1} - \mathbf{u}_v\|^2$  is a positive quantity, we will get

$$\sum_{t=1}^T \Delta_t \leq \mathbb{E} \left[ \sum_{v=1}^K \|\mathbf{u}_v\|^2 \right]$$

which is same as

$$\sum_{t=1}^T \Delta_t \leq \sum_{v=1}^K \|\mathbf{u}_v\|^2$$

Comparing the upper and lower bounds on  $\sum_{t=1}^T \Delta_t$ , we get

$$\sum_{t=1}^T \mathbb{E} \left[ \sum_{v=1}^K (\tilde{l}_v^t)^2 \right] \leq \frac{\left(R^2 + \frac{1}{2C}\right)^2}{\left(2K + \frac{1}{C}\right)} \left( \sum_{v=1}^K \|\mathbf{u}_v\|^2 + 2CR^2 \sum_{t=1}^T \mathbb{E} \left[ \sum_{v=1}^K (\tilde{l}_v^{*t})^2 \right] \right)$$

■

## References

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