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## **Supplementary Material of Revisiting Smoothed**

Thus, if  $\alpha \geq 2$ , we have

$$\begin{aligned}
& \sum_{t=1}^T f_t(\mathbf{x}_t) + k \sum_{t=1}^T \|\mathbf{x}_t\|^k \\
(8),(23) \quad & \frac{2}{\alpha} \sum_{t=1}^T f_t(\mathbf{u}_t) + \sum_{t=1}^T k \|\mathbf{u}_t\|^k + \sum_{t=1}^T \left(1 - \frac{2}{\alpha}\right) f_t(\mathbf{u}_t) \\
& \sum_{t=1}^T f_t(\mathbf{u}_t) + k \sum_{t=1}^T \|\mathbf{u}_t\|^k
\end{aligned} \tag{24}$$

which implies the naive algorithm is 1-competitive. Otherwise, we have

$$\begin{aligned}
& \sum_{t=1}^T f_t(\mathbf{x}_t) + k \sum_{t=1}^T \|\mathbf{x}_t\|^k \\
(23) \quad & \frac{2}{\alpha} \sum_{t=1}^T f_t(\mathbf{u}_t) + \sum_{t=1}^T k \|\mathbf{u}_t\|^k \geq \frac{2}{\alpha} \sum_{t=1}^T f_t(\mathbf{u}_t) + k \sum_{t=1}^T \|\mathbf{u}_t\|^k.
\end{aligned} \tag{25}$$

We complete the proof by combining (24) and (25).

## A.2 Proof of Theorem 2

We will make use of the following basic inequality of squared  $\ell_2$ -norm [Goel et al., 2019, Lemma 12].

$$\|\mathbf{kx} + \mathbf{y}\|^2 \leq (1 + \rho)k\|\mathbf{x}\|^2 + \left(1 + \frac{1}{\rho}\right)\|\mathbf{y}\|^2, \quad \rho > 0. \tag{26}$$

When  $t \geq 2$ , we have

$$\begin{aligned}
& f_t(\mathbf{x}_t) + \frac{1}{2}k\|\mathbf{x}_t\|^2 \\
(26) \quad & f_t(\mathbf{x}_t) + \frac{1 + \rho}{2}k\|\mathbf{u}_t - \mathbf{u}_{t-1}\|^2 + \frac{1}{2}\left(1 + \frac{1}{\rho}\right)\|\mathbf{kx}_t - \mathbf{x}_{t-1} - \mathbf{u}_t + \mathbf{u}_{t-1}\|^2 \\
(26) \quad & f_t(\mathbf{x}_t) + \frac{1 + \rho}{2}k\|\mathbf{u}_t - \mathbf{u}_{t-1}\|^2 + \left(1 + \frac{1}{\rho}\right)k\|\mathbf{u}_t - \mathbf{x}_t\|^2 + k\|\mathbf{u}_{t-1} - \mathbf{x}_t\|^2 \\
(9) \quad & f_t(\mathbf{x}_t) + \frac{1 + \rho}{2}k\|\mathbf{u}_t - \mathbf{u}_{t-1}\|^2 + \frac{2}{\lambda}\left(1 + \frac{1}{\rho}\right) f_t(\mathbf{u}_t) - f_t(\mathbf{x}_t) + f_{t-1}(\mathbf{u}_{t-1}) - f_{t-1}(\mathbf{x}_{t-1}).
\end{aligned}$$

For  $t = 1$ , we have

$$f_1(\mathbf{x}_1) + \frac{1}{2}k\|\mathbf{x}_1\|^2 \stackrel{(26),(9)}{\geq} f_1(\mathbf{x}_1) + \frac{1 + \rho}{2}k\|\mathbf{u}_1 - \mathbf{u}_0\|^2 + \frac{2}{\lambda}\left(1 + \frac{1}{\rho}\right) f_1(\mathbf{u}_1) - f_1(\mathbf{x}_1).$$

Summing over all the iterations, we have

$$\begin{aligned}
& \sum_{t=1}^T f_t(\mathbf{x}_t) + \frac{1}{2}k\sum_{t=1}^T \|\mathbf{x}_t\|^2 \\
& \sum_{t=1}^T f_t(\mathbf{x}_t) + \frac{1 + \rho}{2} \sum_{t=1}^T k\|\mathbf{u}_t - \mathbf{u}_{t-1}\|^2 + \frac{2}{\lambda}\left(1 + \frac{1}{\rho}\right) \sum_{t=1}^T f_t(\mathbf{u}_t) - \sum_{t=1}^T f_t(\mathbf{x}_t) \\
& + \frac{2}{\lambda}\left(1 + \frac{1}{\rho}\right) \sum_{t=2}^T f_{t-1}(\mathbf{u}_{t-1}) - \sum_{t=2}^T f_{t-1}(\mathbf{x}_{t-1}) \\
& \sum_{t=1}^T f_t(\mathbf{x}_t) + \frac{1 + \rho}{2} \sum_{t=1}^T k\|\mathbf{u}_t - \mathbf{u}_{t-1}\|^2 + \frac{4}{\lambda}\left(1 + \frac{1}{\rho}\right) \sum_{t=1}^T f_t(\mathbf{u}_t) - \sum_{t=1}^T f_t(\mathbf{x}_t) \\
= & \frac{4}{\lambda}\left(1 + \frac{1}{\rho}\right) \sum_{t=1}^T f_t(\mathbf{u}_t) + \frac{1 + \rho}{2} \sum_{t=1}^T k\|\mathbf{u}_t - \mathbf{u}_{t-1}\|^2 + \left(1 - \frac{4}{\lambda}\right)\left(1 + \frac{1}{\rho}\right) \sum_{t=1}^T f_t(\mathbf{x}_t).
\end{aligned} \tag{27}$$

First, we consider the case that

$$1 + \frac{4}{\lambda} \left(1 + \frac{1}{\rho}\right) \leq 0, \quad \frac{\lambda}{4} \left(1 + \frac{1}{\rho}\right) \geq 0 \quad (28)$$

and have

$$\begin{aligned} & \sum_{t=1}^T f_t(\mathbf{x}_t) + \frac{1}{2} k \sum_{t=1}^T \|\mathbf{x}_t\|^2 \\ (27),(28) \quad & \frac{4}{\lambda} \left(1 + \frac{1}{\rho}\right) \sum_{t=1}^T f_t(\mathbf{u}_t) + \frac{1+\rho}{2} \sum_{t=1}^T k \|\mathbf{u}_t\|^2 \\ \max \quad & \frac{4}{\lambda} \left(1 + \frac{1}{\rho}\right), 1 + \rho \sum_{t=1}^T f_t(\mathbf{u}_t) + \frac{1}{2} k \sum_{t=1}^T \|\mathbf{u}_t\|^2. \end{aligned}$$

To minimize the competitive ratio, we set

$$\frac{4}{\lambda} \left(1 + \frac{1}{\rho}\right) = 1 + \rho \implies \rho = \frac{4}{\lambda}$$

and obtain

$$\sum_{t=1}^T f_t(\mathbf{x}_t) + \frac{1}{2} k \sum_{t=1}^T \|\mathbf{x}_t\|^2 \leq \left(1 + \frac{4}{\lambda}\right) \sum_{t=1}^T f_t(\mathbf{u}_t) + \frac{1}{2} k \sum_{t=1}^T \|\mathbf{u}_t\|^2. \quad (29)$$

Next, we study the case that

$$1 + \frac{4}{\lambda} \left(1 + \frac{1}{\rho}\right) \leq 0, \quad \frac{\lambda}{4} \left(1 + \frac{1}{\rho}\right) \geq 0$$

which only happens when  $\lambda > 4$ . Then, we have

$$\sum_{t=1}^T f_t(\mathbf{x}_t) + \frac{1}{2} k \sum_{t=1}^T \|\mathbf{x}_t\|^2 \stackrel{(8),(27)}{\leq} \sum_{t=1}^T f_t(\mathbf{u}_t) + \frac{1+\rho}{2} \sum_{t=1}^T k \|\mathbf{u}_t\|^2.$$

To minimize the competitive ratio, we set  $\rho = \frac{4}{\lambda-4}$ , and obtain

$$\sum_{t=1}^T f_t(\mathbf{x}_t) + \frac{1}{2} k \sum_{t=1}^T \|\mathbf{x}_t\|^2 \leq \frac{\lambda}{\lambda-4} \sum_{t=1}^T f_t(\mathbf{u}_t) + \frac{1}{2} k \sum_{t=1}^T \|\mathbf{u}_t\|^2$$

which is worse than (29). So, we keep (29) as the final result.

### A.3 Proof of Theorem 3

Since  $f_t(\cdot)$  is convex, the objective function of (10) is  $\gamma$ -strongly convex. From the quadratic growth property of strongly convex functions [Hazan and Kale, 2011], we have

$$f_t(\mathbf{x}_t) + \frac{\gamma}{2} k \|\mathbf{x}_t\|^2 + \frac{\gamma}{2} k \|\mathbf{u}_t\|^2 \leq f_t(\mathbf{u}_t) + \frac{\gamma}{2} k \|\mathbf{x}_t\|^2, \quad \forall \mathbf{u}_t \in \mathcal{X}. \quad (30)$$

Similar to previous studies [Bansal et al., 2015], the analysis uses an amortized local competitiveness argument, using the potential function  $c k \|\mathbf{x}_t\|^2$ . We proceed to bound  $f_t(\mathbf{x}_t) + \frac{1}{2} k \|\mathbf{x}_t\|^2 + c k \|\mathbf{x}_t\|^2 \leq c k \|\mathbf{x}_t\|^2 + \frac{1}{2} k \|\mathbf{u}_t\|^2$ , and have

$$\begin{aligned} & f_t(\mathbf{x}_t) + \frac{1}{2} k \|\mathbf{x}_t\|^2 + c k \|\mathbf{x}_t\|^2 \leq c k \|\mathbf{x}_t\|^2 + \frac{1}{2} k \|\mathbf{u}_t\|^2 \\ (26) \quad & f_t(\mathbf{x}_t) + \frac{1}{2} k \|\mathbf{x}_t\|^2 + c k \|\mathbf{x}_t\|^2 + c k \|\mathbf{x}_t\|^2 \leq c k \|\mathbf{x}_t\|^2 + \frac{1}{2} k \|\mathbf{u}_t\|^2 \\ (9) \quad & 1 + \frac{4c}{\lambda} \left( f_t(\mathbf{x}_t) + \frac{1}{2} k \|\mathbf{x}_t\|^2 \right) + \frac{4c}{\lambda} f_t(\mathbf{u}_t) \leq c k \|\mathbf{x}_t\|^2 + \frac{1}{2} k \|\mathbf{u}_t\|^2 \\ & = 1 + \frac{4c}{\lambda} \left( f_t(\mathbf{x}_t) + \frac{\lambda}{2(\lambda+4c)} k \|\mathbf{x}_t\|^2 \right) + \frac{4c}{\lambda} f_t(\mathbf{u}_t) \leq c k \|\mathbf{x}_t\|^2 + \frac{1}{2} k \|\mathbf{u}_t\|^2. \end{aligned}$$

Suppose

$$\frac{\lambda}{\lambda + 4c} \leq \gamma, \quad (31)$$

we have

$$\begin{aligned} & f_t(\mathbf{x}_t) + \frac{1}{2}k\mathbf{x}_t \cdot \mathbf{x}_t - 1k^2 + c\mathbf{x}_t \cdot \mathbf{u}_t k^2 - c\mathbf{x}_t \cdot \mathbf{u}_t - 1k^2 \\ & 1 + \frac{4c}{\lambda} \left( f_t(\mathbf{x}_t) + \frac{\gamma}{2}k\mathbf{x}_t \cdot \mathbf{x}_t - 1k^2 + \frac{4c}{\lambda}f_t(\mathbf{u}_t) - c\mathbf{x}_t \cdot \mathbf{u}_t - 1k^2 \right) \\ (30) \quad & 1 + \frac{4c}{\lambda} \left( f_t(\mathbf{u}_t) + \frac{\gamma}{2}k\mathbf{u}_t \cdot \mathbf{x}_t - 1k^2 - \frac{\gamma}{2}k\mathbf{u}_t \cdot \mathbf{x}_t k^2 + \frac{4c}{\lambda}f_t(\mathbf{u}_t) - c\mathbf{x}_t \cdot \mathbf{u}_t - 1k^2 \right) \\ & = 1 + \frac{8c}{\lambda} \left( f_t(\mathbf{u}_t) + \frac{\gamma(\lambda + 4c)}{2\lambda}k\mathbf{u}_t \cdot \mathbf{x}_t - 1k^2 - \frac{\gamma(\lambda + 4c)}{2\lambda}k\mathbf{u}_t \cdot \mathbf{x}_t k^2 - c\mathbf{x}_t \cdot \mathbf{u}_t - 1k^2 \right). \end{aligned}$$

Summing over all the iterations and assuming  $\mathbf{x}_0 = \mathbf{u}_0$ , we have

$$\begin{aligned} & \sum_{t=1}^T \left( f_t(\mathbf{x}_t) + \frac{1}{2}k\mathbf{x}_t \cdot \mathbf{x}_t - 1k^2 + c\mathbf{x}_T \cdot \mathbf{u}_T k^2 \right) \\ & 1 + \frac{8c}{\lambda} \sum_{t=1}^T \left( f_t(\mathbf{u}_t) + \frac{\gamma(\lambda + 4c)}{2\lambda} \sum_{t=1}^T k\mathbf{u}_t \cdot \mathbf{x}_t - 1k^2 \right) \\ & \frac{\gamma(\lambda + 4c)}{2\lambda} \sum_{t=1}^T k\mathbf{u}_t \cdot \mathbf{x}_t k^2 - c \sum_{t=1}^T k\mathbf{x}_t \cdot \mathbf{u}_t - 1k^2 \\ (26) \quad & 1 + \frac{8c}{\lambda} \sum_{t=1}^T \left( f_t(\mathbf{u}_t) + \frac{\gamma(\lambda + 4c)}{2\lambda} \sum_{t=1}^T k\mathbf{u}_t \cdot \mathbf{x}_t - 1k^2 \right) - \frac{\gamma(\lambda + 4c)}{2\lambda} + c \sum_{t=1}^T k\mathbf{x}_t \cdot \mathbf{u}_t - 1k^2 \\ & 1 + \frac{8c}{\lambda} \sum_{t=1}^T \left( f_t(\mathbf{u}_t) + \frac{\gamma(\lambda + 4c)}{2\lambda} \sum_{t=1}^T k\mathbf{u}_t \cdot \mathbf{x}_t - 1k^2 \right) \\ & \frac{\gamma(\lambda + 4c)}{2\lambda} + c \sum_{t=1}^T \left( \frac{1}{1 + \rho} k\mathbf{x}_t \cdot \mathbf{u}_t k^2 - \frac{1}{\rho} k\mathbf{u}_t \cdot \mathbf{u}_t - 1k^2 \right) \\ & 1 + \frac{8c}{\lambda} \sum_{t=1}^T \left( f_t(\mathbf{u}_t) + \frac{\gamma(\lambda + 4c)}{2\lambda} + c \sum_{t=1}^T \left( \frac{1}{\rho} k\mathbf{u}_t \cdot \mathbf{u}_t - 1k^2 \right) \right) \\ \max & 1 + \frac{8c}{\lambda}, \frac{\gamma(\lambda + 4c)}{2\lambda} + c \sum_{t=1}^T \left( f_t(\mathbf{u}_t) + \frac{1}{2}k\mathbf{u}_t \cdot \mathbf{u}_t - 1k^2 \right) \end{aligned}$$

where in the penultimate inequality we assume

$$\frac{\gamma(\lambda + 4c)}{2\lambda} - \frac{\gamma(\lambda + 4c)}{2\lambda} + c \frac{1}{1 + \rho} \leq \frac{\gamma(\lambda + 4c)}{2\lambda} - \frac{c}{\rho}. \quad (32)$$

Next, we minimize the competitive ratio under the constraints in (31) and (32), which can be summarized as

$$\frac{\lambda}{\lambda + 4c} \leq \gamma \leq \frac{\lambda + 2c}{\lambda + 4c \rho}.$$

We first set  $c = \frac{\rho}{2}$  and  $\gamma = \frac{\lambda}{\lambda + 4c}$ , and obtain

$$\sum_{t=1}^T \left( f_t(\mathbf{x}_t) + \frac{1}{2}k\mathbf{x}_t \cdot \mathbf{x}_t - 1k^2 \right) \leq \max \left( 1 + \frac{4\rho}{\lambda}, 1 + \frac{1}{\rho} \sum_{t=1}^T \left( f_t(\mathbf{u}_t) + \frac{1}{2}k\mathbf{u}_t \cdot \mathbf{u}_t - 1k^2 \right) \right).$$

Then, we set

$$1 + \frac{4\rho}{\lambda} = 1 + \frac{1}{\rho} \Rightarrow \rho = \frac{\lambda}{2}.$$

As a result, the competitive ratio is

$$1 + \frac{1}{\rho} = 1 + \frac{2}{\lambda},$$

and the parameter is

$$\gamma = \frac{\lambda}{\lambda + 4c} = \frac{\lambda}{\lambda + 2\rho} = \frac{\lambda}{\lambda + \frac{2}{\lambda}}.$$

#### A.4 Proof of Theorem 4

The analysis is similar to the proof of Theorem 3 of Zhang et al. [2018a]. In the analysis, we need to specify the behavior of the meta-algorithm and expert-algorithm at  $t = 0$ . To simplify the presentation, we set

$$\mathbf{x}_0 = 0, \text{ and } \mathbf{x}_0^\eta = 0, \delta\eta \geq H. \quad (33)$$

First, we bound the dynamic regret with switching cost of the meta-algorithm w.r.t. all experts simultaneously.

**Lemma 1** Under Assumptions 2 and 3, and setting  $\eta = \frac{2}{(2G+1)D} \sqrt{\frac{2}{5T}}$ , we have

$$\sum_{t=1}^T s_t(\mathbf{x}_t) + k \sum_{t=1}^T \|\mathbf{x}_t - \mathbf{x}_{t-1}\| \leq \sum_{t=1}^T s_t(\mathbf{x}_t^\eta) + k \sum_{t=1}^T \|\mathbf{x}_t^\eta - \mathbf{x}_{t-1}^\eta\| + (2G+1)D \sqrt{\frac{5T}{8}} \ln \frac{1}{w_1^\eta} + 1 \quad (34)$$

for each  $\eta \geq H$ .

Next, we bound the dynamic regret with switching cost of each expert w.r.t. any comparator sequence  $\mathbf{u}_0, \mathbf{u}_1, \dots, \mathbf{u}_T \geq X$ .

**Lemma 2** Under Assumptions 2 and 3, we have

$$\sum_{t=1}^T s_t(\mathbf{x}_t^\eta) + k \sum_{t=1}^T \|\mathbf{x}_t^\eta - \mathbf{x}_{t-1}^\eta\| \leq \sum_{t=1}^T s_t(\mathbf{u}_t) + \frac{D^2}{2\eta} + \frac{D}{\eta} \sum_{t=1}^T \|\mathbf{u}_t - \mathbf{u}_{t-1}\| + \eta T \left( \frac{G^2}{2} + G \right). \quad (35)$$

Then, we show that for any sequence of comparators  $\mathbf{u}_0, \mathbf{u}_1, \dots, \mathbf{u}_T \geq X$  there exists an  $\eta_k \geq H$  such that the R.H.S. of (35) is almost minimal. If we minimize the R.H.S. of (35) exactly, the optimal step size is

$$\eta(P_T) = \frac{D^2 + 2DP_T}{T(G^2 + 2G)}. \quad (36)$$

From Assumption 3, we have the following bound of the path-length

$$\sum_{t=1}^T \|\mathbf{u}_t - \mathbf{u}_{t-1}\| \stackrel{(12)}{\leq} TD. \quad (37)$$

Thus

$$\frac{D^2}{T(G^2 + 2G)} \leq \eta(P_T) \leq \frac{D^2 + 2TD^2}{T(G^2 + 2G)}.$$

From our construction of  $H$  in (17), it is easy to verify that

$$\min H = \frac{D^2}{T(G^2 + 2G)}, \text{ and } \max H = \frac{D^2 + 2TD^2}{T(G^2 + 2G)}.$$

As a result, for any possible value of  $P_T$ , there exists a step size  $\eta_k \geq H$  with  $k$  defined in (19), such that

$$\eta_k = 2^{k-1} \frac{D^2}{T(G^2 + 2G)} \leq \eta(P_T) \leq 2\eta_k. \quad (38)$$

Plugging  $\eta_k$  into (35), the dynamic regret with switching cost of expert  $E^{\eta_k}$  is given by

$$\begin{aligned}
& \sum_{t=1}^T s_t(\mathbf{x}_t^{\eta_k}) + k \sum_{t=1}^T \|\mathbf{x}_t^{\eta_k} - \mathbf{x}_{t-1}^{\eta_k}\| + \sum_{t=1}^T s_t(\mathbf{u}_t) \\
& \frac{D^2}{2\eta_k} + \frac{D}{\eta_k} \sum_{t=1}^T \|\mathbf{u}_t - \mathbf{u}_{t-1}\| + \eta_k T \frac{G^2}{2} + G \\
(38) \quad & \frac{D^2}{\eta(P_T)} + \frac{2D}{\eta(P_T)} \sum_{t=1}^T \|\mathbf{u}_t - \mathbf{u}_{t-1}\| + \eta(P_T)T \frac{G^2}{2} + G \\
& \stackrel{(36)}{=} \frac{3}{2} \frac{D^2}{T(G^2 + 2G)(D^2 + 2DP_T)}.
\end{aligned} \tag{39}$$

From (13), we know the initial weight of expert  $E^{\eta_k}$  is

$$w_1^{\eta_k} = \frac{C}{k(k+1)} \frac{1}{k(k+1)} \frac{1}{(k+1)^2}.$$

Combining with (34), we obtain the relative performance of the meta-algorithm w.r.t. expert  $E^{\eta_k}$ :

$$\sum_{t=1}^T s_t(\mathbf{x}_t) + k \sum_{t=1}^T \|\mathbf{x}_t - \mathbf{x}_{t-1}\| \leq \sum_{t=1}^T s_t(\mathbf{x}_t^{\eta_k}) + k \sum_{t=1}^T \|\mathbf{x}_t^{\eta_k} - \mathbf{x}_{t-1}^{\eta_k}\| + (2G+1)D \frac{\sqrt{5T}}{8} [1 + 2 \ln(k+1)]. \tag{40}$$

From (39) and (40), we derive the following upper bound for dynamic regret with switching cost

$$\sum_{t=1}^T s_t(\mathbf{x}_t) + k \sum_{t=1}^T \|\mathbf{x}_t - \mathbf{x}_{t-1}\| \leq \sum_{t=1}^T s_t(\mathbf{u}_t) + \frac{3}{2} \frac{D^2}{T(G^2 + 2G)(D^2 + 2DP_T)} + (2G+1)D \frac{\sqrt{5T}}{8} [1 + 2 \ln(k+1)]. \tag{41}$$

Finally, from Assumption 1, we have

$$f_t(\mathbf{x}_t) - f_t(\mathbf{u}_t) \leq \eta \sum_{i=1}^k |f_t(\mathbf{x}_t) - f_t(\mathbf{u}_t)| \stackrel{(16)}{=} \eta \sum_{i=1}^k s_t(\mathbf{x}_t) - s_t(\mathbf{u}_t). \tag{42}$$

We complete the proof by combining (41) and (42).

## A.5 Proof of Theorem 5

The analysis is similar to that of Theorem 4. The difference is that we need to take into account the lookahead property of the meta-algorithm and the expert-algorithm.

First, we bound the dynamic regret with switching cost of the meta-algorithm w.r.t. all experts simultaneously.

**Lemma 3** Under Assumption 3, and setting  $\eta = \frac{1}{D} \frac{C}{\frac{2}{T}}$ , we have

$$\sum_{t=1}^T s_t(\mathbf{x}_t) + k \sum_{t=1}^T \|\mathbf{x}_t - \mathbf{x}_{t-1}\| \leq \sum_{t=1}^T s_t(\mathbf{x}_t^\eta) + k \sum_{t=1}^T \|\mathbf{x}_t^\eta - \mathbf{x}_{t-1}^\eta\| + D \frac{\sqrt{T}}{2} \ln \frac{1}{w_0^\eta} + 1 \tag{43}$$

for each  $\eta \geq H$ .

Combining Lemma 3 with Assumption 1, we have

$$\sum_{t=1}^T f_t(\mathbf{x}_t) + k \sum_{t=1}^T \|\mathbf{x}_t - \mathbf{x}_{t-1}\| \leq \sum_{t=1}^T f_t(\mathbf{x}_t^\eta) + k \sum_{t=1}^T \|\mathbf{x}_t^\eta - \mathbf{x}_{t-1}^\eta\| \stackrel{(42),(43)}{=} D \frac{\sqrt{T}}{2} \ln \frac{1}{w_0^\eta} + 1 \tag{44}$$

for each  $\eta \geq H$ .

Next, we bound the dynamic regret with switching cost of each expert w.r.t. any comparator sequence  $\mathbf{u}_0, \mathbf{u}_1, \dots, \mathbf{u}_T \in \mathcal{X}$ .

**Lemma 4** Under Assumptions 1 and 3, we have

$$\sum_{t=1}^T f_t(\mathbf{x}_t^\eta) + k \sum_{t=1}^T \|\mathbf{x}_t^\eta\|^2 \leq \sum_{t=1}^T f_t(\mathbf{u}_t) + \frac{D^2}{2\eta} + \frac{D}{\eta} \sum_{t=1}^T k \|\mathbf{u}_t\|^2 + \frac{\eta T}{2}. \quad (45)$$

The rest of the proof is almost identical to that of Theorem 4. We will show that for any sequence of comparators  $\mathbf{u}_0, \mathbf{u}_1, \dots, \mathbf{u}_T \in \mathcal{X}$  there exists an  $\eta_k \in H$  such that the R.H.S. of (45) is almost minimal. If we minimize the R.H.S. of (45) exactly, the optimal step size is

$$\eta(P_T) = \sqrt{\frac{D^2 + 2DP_T}{T}}. \quad (46)$$

From (37), we know that

$$\sqrt{\frac{D^2}{T}} \leq \eta(P_T) \leq \sqrt{\frac{D^2 + 2TD^2}{T}}.$$

From our construction of  $H$  in (22), it is easy to verify that

$$\min H = \sqrt{\frac{D^2}{T}}, \text{ and } \max H = \sqrt{\frac{D^2 + 2TD^2}{T}}.$$

As a result, for any possible value of  $P_T$ , there exists a step size  $\eta_k \in H$  with  $k$  defined in (19), such

1. the sum of the hitting cost and the switching cost is at least  $\frac{3\gamma d}{4} = \frac{3D^{\frac{D-d}{8}}}{8}$ ;
2. there exist a fixed point whose hitting cost is 0.

We consider two cases:  $\tau < D$  and  $\tau \geq D$ . When  $\tau < D$ , from Lemma 5 with  $d = T$ , we know that the dynamic regret with switching cost w.r.t. a fixed point  $\mathbf{u}$  is at least  $(D^{\frac{D-T}{8}})$ .

Next, we consider the case  $\tau \geq D$ . Without loss of generality, we assume  $b\tau/DC$  divides  $T$ . Then, we partition  $T$  into  $b\tau/DC$  successive stages, each of which contains  $T/b\tau/DC$  rounds. Applying Lemma 5 to each stage, we conclude that there exists a sequence of convex functions  $f_1(), \dots, f_T()$  over the domain  $[\frac{D}{2^d}, \frac{D}{2^{T-d}}]^d$  where  $d = T/b\tau/DC$  in the lookahead setting such that

1. the sum of the hitting cost and the switching cost of any online algorithm is at least

$$b\tau/DC \frac{3D}{8} \frac{S}{\frac{T}{b\tau/DC}} = \frac{3D}{8} \frac{T}{\tau} \frac{\tau}{D} = \left(\frac{D}{TD\tau}\right);$$

2. there exists a sequence of points  $\mathbf{u}_1, \dots, \mathbf{u}_T$  whose hitting cost is 0 and switching cost (i.e., path-length) is at most

$$D \frac{\tau}{D} \tau$$

since they switch at most  $b\tau/DC - 1$  times.

Thus, the dynamic regret with switching cost w.r.t.  $\mathbf{u}_1, \dots, \mathbf{u}_T$  is at least

$$\frac{3D}{8} \frac{T}{\tau} \frac{\tau}{D} = \left(\frac{D}{TD\tau}\right).$$

We complete the proof by combining the results of the above two cases.

## B Proof of supporting lemmas

We provide the proof of all the supporting lemmas.

### B.1 Proof of Lemma 1

Based on the prediction rule of the meta-algorithm, we upper bound the switching cost when  $t \geq 2$  as follows:

$$\begin{aligned}
\|\mathbf{x}_t - \mathbf{x}_{t-1}\| &= \sum_{\eta \geq H} w_t^\eta \|\mathbf{x}_t^\eta - \mathbf{x}_{t-1}^\eta\| = \sum_{\eta \geq H} w_t^\eta (\|\mathbf{x}_t^\eta - \mathbf{x}\| + \|\mathbf{x} - \mathbf{x}_{t-1}^\eta\|) \\
&= \sum_{\eta \geq H} w_t^\eta (\|\mathbf{x}_t^\eta - \mathbf{x}\|) + \sum_{\eta \geq H} w_t^\eta (\|\mathbf{x} - \mathbf{x}_{t-1}^\eta\|) \\
&= \sum_{\eta \geq H} w_t^\eta (\|\mathbf{x}_t^\eta - \mathbf{x}_{t-1}^\eta\|) + \sum_{\eta \geq H} (w_t^\eta - w_{t-1}^\eta) (\|\mathbf{x}_{t-1}^\eta - \mathbf{x}\|) \\
&\stackrel{(12)}{\leq} \sum_{\eta \geq H} w_t^\eta (\|\mathbf{x}_t^\eta - \mathbf{x}_{t-1}^\eta\|) + D \sum_{\eta \geq H} |w_t^\eta - w_{t-1}^\eta| \|\mathbf{x}_{t-1}^\eta - \mathbf{x}\| + D \|\mathbf{x}_t - \mathbf{x}_{t-1}\|
\end{aligned} \tag{50}$$

where  $\mathbf{x}$  is an arbitrary point in  $X$ , and  $\mathbf{w}_t = (w_t^\eta)_{\eta \geq H} \in \mathbb{R}^N$ . When  $t = 1$ , from (33), we have

$$\|\mathbf{x}_1 - \mathbf{x}_0\| = \|\mathbf{x}_1\| = \sum_{\eta \geq H} w_1^\eta \|\mathbf{x}_1^\eta\| = \sum_{\eta \geq H} w_1^\eta \|\mathbf{x}_1^\eta - \mathbf{x}_0^\eta\| + \sum_{\eta \geq H} w_1^\eta \|\mathbf{x}_0^\eta\|. \tag{51}$$



Then, the relative loss of the meta-algorithm w.r.t. expert  $E^\eta$  can be decomposed as

$$\begin{aligned}
& \sum_{t=1}^T s_t(\mathbf{x}_t) + k \sum_{t=1}^T \|\mathbf{x}_t\|_1 - \sum_{t=1}^T s_t(\mathbf{x}_t^\eta) + k \sum_{t=1}^T \|\mathbf{x}_t^\eta\|_1 \\
& \stackrel{(16),(50),(51)}{=} \sum_{t=1}^T \sum_{i=1}^N w_t^\eta \ell_t(\mathbf{x}_t^\eta) - \sum_{t=1}^T \sum_{i=1}^N w_t^\eta \ell_t(\mathbf{x}_t) + k \sum_{t=1}^T \|\mathbf{x}_t^\eta\|_1 - k \sum_{t=1}^T \|\mathbf{x}_t\|_1 \\
& \quad + D \sum_{t=2}^T \|k\mathbf{w}_t - \mathbf{w}_{t-1}\|_1 \\
& \stackrel{(15)}{=} \underbrace{\sum_{t=1}^T \sum_{i=1}^N w_t^\eta \ell_t(\mathbf{x}_t^\eta) - \sum_{t=1}^T \sum_{i=1}^N w_t^\eta \ell_t(\mathbf{x}_t)}_{:=A} + D \sum_{t=2}^T \|k\mathbf{w}_t - \mathbf{w}_{t-1}\|_1.
\end{aligned} \tag{52}$$

We proceed to bound  $A$  and  $k\mathbf{w}_t - \mathbf{w}_{t-1}$  in (52). Notice that  $A$  is the regret of the meta-algorithm w.r.t. expert  $E^\eta$ . From Assumptions 2 and 3, we have

$$\sum_{t=1}^T \sum_{i=1}^N w_t^\eta \ell_t(\mathbf{x}_t^\eta) - \sum_{t=1}^T \sum_{i=1}^N w_t^\eta \ell_t(\mathbf{x}_t) \leq k \sum_{t=1}^T \|\mathbf{x}_t^\eta - \mathbf{x}_t\|_1 \stackrel{(11),(12)}{\leq} GD.$$

Thus, we have

$$A \leq GD + \sum_{t=1}^T \sum_{i=1}^N w_t^\eta \ell_t(\mathbf{x}_t^\eta) - \sum_{t=1}^T \sum_{i=1}^N w_t^\eta \ell_t(\mathbf{x}_t) \leq (G+1)D, \quad \delta \eta \geq H. \tag{53}$$

According to the standard analysis of Hedge [Zhang et al., 2018a, Lemma 1] and (53), we have

$$\sum_{t=1}^T \sum_{i=1}^N w_t^\eta \ell_t(\mathbf{x}_t^\eta) - \sum_{t=1}^T \sum_{i=1}^N w_t^\eta \ell_t(\mathbf{x}_t) \leq \frac{1}{\beta} \ln \frac{1}{w_1^\eta} + \frac{\beta T(2G+1)^2 D^2}{8}. \tag{54}$$

Next, we bound  $k\mathbf{w}_t - \mathbf{w}_{t-1}$ , which measures the stability of the meta-algorithm, i.e., the change of coefficients between successive rounds. Because the Hedge algorithm is translation invariant, we can subtract  $D/2$  from  $\ell_t(\mathbf{x}_t^\eta)$  such that

$$\sum_{i=1}^N w_t^\eta \ell_t(\mathbf{x}_t^\eta) - D/2 \sum_{i=1}^N w_t^\eta \leq (G+1/2)D, \quad \delta \eta \geq H. \tag{55}$$

It is well-known that Hedge can be treated as a special case of ‘‘Follow-the-Regularized-Leader’’ with entropic regularization [Shalev-Shwartz, 2011]

$$R(\mathbf{w}) = \sum_{i=1}^N w_i \log w_i$$

over the probability simplex, and  $R(\cdot)$  is 1-strongly convex w.r.t. the  $\ell_1$ -norm. In other words, we have

$$\mathbf{w}_{t+1} = \underset{\mathbf{w} \in \mathcal{R}^N}{\operatorname{argmin}} \frac{1}{\beta} \log(w_1) + \sum_{i=1}^N \mathbf{g}_i \cdot \mathbf{w} + \frac{1}{\beta} R(\mathbf{w}), \quad \delta t \geq 1$$

where  $\mathcal{R}^N$  is the probability simplex, and  $\mathbf{g}_i = [\ell_i(\mathbf{x}_t^\eta) - D/2]_{1 \leq i \leq N} \in \mathcal{R}^N$ . From the stability property of Follow-the-Regularized-Leader [Duchi et al., 2012, Lemma 2], we have

$$\|k\mathbf{w}_t - \mathbf{w}_{t-1}\|_1 \leq \beta \|\mathbf{g}_t\|_1 \stackrel{(55)}{\leq} \beta(G+1/2)D, \quad \delta t \geq 2.$$

Then

$$\sum_{t=2}^T \|k\mathbf{w}_t - \mathbf{w}_{t-1}\|_1 \leq \frac{\beta(T-1)(2G+1)D}{2}. \tag{56}$$

Substituting (54) and (56) into (52), we have

$$\begin{aligned}
& \sum_{t=1}^T s_t(\mathbf{x}_t) + k \sum_{t=1}^T \|\mathbf{x}_t\|_1 - \sum_{t=1}^T s_t(\mathbf{x}_t^\eta) + k \sum_{t=1}^T \|\mathbf{x}_t^\eta\|_1 \\
& \leq \frac{1}{\beta} \ln \frac{1}{w_1^\eta} + \frac{\beta T(2G+1)^2 D^2}{8} + \frac{\beta(T-1)(2G+1)D^2}{2} + \frac{1}{\beta} \ln \frac{1}{w_1^\eta} + \frac{5\beta T(2G+1)^2 D^2}{8}.
\end{aligned}$$

We complete the proof by setting  $\beta = \frac{2}{(2G+1)D} \frac{2}{5T}$ .

## B.2 Proof of Lemma 2

First, we bound the dynamic regret of the expert-algorithm. Define

$$\mathbf{x}_{t+1}^\eta = \mathbf{x}_t^\eta - \eta \nabla f_t(\mathbf{x}_t).$$

Following the analysis of Ader [Zhang et al., 2018a, Theorems 1 and 6], we have

$$\begin{aligned} s_t(\mathbf{x}_t^\eta) - s_t(\mathbf{u}_t) &\stackrel{(16)}{=} \langle \nabla f_t(\mathbf{x}_t), \mathbf{x}_t^\eta - \mathbf{u}_t \rangle = \frac{1}{\eta} \langle \nabla f_t(\mathbf{x}_t), \mathbf{x}_t^\eta - \mathbf{x}_{t+1}^\eta + \mathbf{x}_{t+1}^\eta - \mathbf{u}_t \rangle \\ &= \frac{1}{2\eta} \|\nabla f_t(\mathbf{x}_t)\|_2^2 \|\mathbf{x}_t^\eta - \mathbf{u}_t\|_2^2 + \langle \nabla f_t(\mathbf{x}_t), \mathbf{x}_{t+1}^\eta - \mathbf{u}_t \rangle \\ &= \frac{1}{2\eta} \|\nabla f_t(\mathbf{x}_t)\|_2^2 \|\mathbf{x}_t^\eta - \mathbf{u}_t\|_2^2 + \frac{\eta}{2} \|\nabla f_t(\mathbf{x}_t)\|_2^2 \|\mathbf{x}_{t+1}^\eta - \mathbf{u}_t\|_2^2 \\ &\stackrel{(11)}{\leq} \frac{1}{2\eta} \|\nabla f_t(\mathbf{x}_t)\|_2^2 \|\mathbf{x}_t^\eta - \mathbf{u}_t\|_2^2 + \frac{\eta}{2} G^2 \|\mathbf{x}_{t+1}^\eta - \mathbf{u}_t\|_2^2 \\ &= \frac{1}{2\eta} \|\nabla f_t(\mathbf{x}_t)\|_2^2 \|\mathbf{x}_t^\eta - \mathbf{u}_t\|_2^2 + \|\nabla f_t(\mathbf{x}_t)\|_2^2 \|\mathbf{x}_{t+1}^\eta - \mathbf{u}_t\|_2^2 + \frac{\eta}{2} G^2 \\ &= \frac{1}{2\eta} \|\nabla f_t(\mathbf{x}_t)\|_2^2 \|\mathbf{x}_t^\eta - \mathbf{u}_t\|_2^2 + \|\nabla f_t(\mathbf{x}_t)\|_2^2 (\|\mathbf{x}_{t+1}^\eta - \mathbf{u}_t\|_2 + \|\mathbf{x}_{t+1}^\eta - \mathbf{x}_t^\eta\|_2) \|\mathbf{u}_t - \mathbf{u}_{t+1}\|_2 + \frac{\eta}{2} G^2 \\ &= \frac{1}{2\eta} \|\nabla f_t(\mathbf{x}_t)\|_2^2 \|\mathbf{x}_t^\eta - \mathbf{u}_t\|_2^2 + \|\nabla f_t(\mathbf{x}_t)\|_2^2 \|\mathbf{x}_{t+1}^\eta - \mathbf{u}_t\|_2 + \|\nabla f_t(\mathbf{x}_t)\|_2 \|\mathbf{u}_t - \mathbf{u}_{t+1}\|_2 + \frac{\eta}{2} G^2 \\ &\stackrel{(12)}{\leq} \frac{1}{2\eta} \|\nabla f_t(\mathbf{x}_t)\|_2^2 \|\mathbf{x}_t^\eta - \mathbf{u}_t\|_2^2 + \frac{D}{\eta} \|\mathbf{u}_t - \mathbf{u}_{t+1}\|_2 + \frac{\eta}{2} G^2. \end{aligned}$$

Summing the above inequality over all iterations, we have

$$\begin{aligned} \sum_{t=1}^T (s_t(\mathbf{x}_t^\eta) - s_t(\mathbf{u}_t)) &\leq \frac{1}{2\eta} \sum_{t=1}^T \|\nabla f_t(\mathbf{x}_t)\|_2^2 \|\mathbf{x}_t^\eta - \mathbf{u}_t\|_2^2 + \frac{D}{\eta} \sum_{t=1}^T \|\mathbf{u}_t - \mathbf{u}_{t+1}\|_2 + \frac{\eta T}{2} G^2 \\ &\stackrel{(12)}{\leq} \frac{1}{2\eta} D^2 + \frac{D}{\eta} \sum_{t=1}^T \|\mathbf{u}_t - \mathbf{u}_{t+1}\|_2 + \frac{\eta T}{2} G^2. \end{aligned} \quad (57)$$

Since (57) holds when  $\mathbf{u}_{T+1} = \mathbf{u}_T$ , we have

$$\sum_{t=1}^T (s_t(\mathbf{x}_t^\eta) - s_t(\mathbf{u}_t)) \leq \frac{1}{2\eta} D^2 + \frac{D}{\eta} \sum_{t=1}^T \|\mathbf{u}_t - \mathbf{u}_{t+1}\|_2 + \frac{\eta T}{2} G^2. \quad (58)$$

Next, we bound the switching cost of the expert-algorithm. To this end, we have

$$\sum_{t=1}^T \|\mathbf{x}_t^\eta - \mathbf{x}_{t-1}^\eta\|_2 = \sum_{t=0}^T \|\mathbf{x}_{t+1}^\eta - \mathbf{x}_t^\eta\|_2 = \sum_{t=0}^T \|\eta \nabla f_t(\mathbf{x}_t)\|_2 \stackrel{(11)}{\leq} \eta T G. \quad (59)$$

We complete the proof by combining (58) with (59).

## B.3 Proof of Lemma 3

We reuse the first part of the proof of Lemma 1, and start from (52). To bound  $A$ , we need to analyze the behavior of the lookahead Hedge. To this end, we prove the following lemma.

**Lemma 6** The meta-algorithm in Algorithm 3 satisfies

$$\sum_{t=1}^T \sum_{\eta \geq H} w_t^\eta \ell_t(\mathbf{x}_t^\eta) \leq \frac{1}{\beta} \ln \frac{1}{w_0^\eta} + \frac{1}{2\beta} \sum_{t=1}^T \|\mathbf{w}_t - \mathbf{w}_{t-1}\|_2^2 \quad (60)$$

for any  $\eta \geq H$ .

Substituting (60) into (52), we have

$$\begin{aligned}
& \sum_{t=1}^T s_t(\mathbf{x}_t) + k \sum_{t=1}^T \|\mathbf{x}_t\|_1^2 - \sum_{t=1}^T s_t(\mathbf{x}_t^\eta) + k \sum_{t=1}^T \|\mathbf{x}_t^\eta\|_1^2 \\
& \frac{1}{\beta} \ln \frac{1}{w_0^\eta} - \frac{1}{2\beta} \sum_{t=1}^T k \|\mathbf{w}_t\|_1^2 + D \sum_{t=2}^T k \|\mathbf{w}_t\|_1^2 \\
& \frac{1}{\beta} \ln \frac{1}{w_0^\eta} - \frac{1}{2\beta} \sum_{t=1}^T k \|\mathbf{w}_t\|_1^2 + \sum_{t=2}^T \frac{1}{2\beta} k \|\mathbf{w}_t\|_1^2 + \frac{\beta D^2}{2} \\
& \frac{1}{\beta} \ln \frac{1}{w_0^\eta} + \frac{\beta T D^2}{2} = D \frac{T}{2} \ln \frac{1}{w_0^\eta} + 1
\end{aligned} \tag{61}$$

where we set  $\beta = \frac{1}{D} \frac{1}{\frac{T}{2}}$ .

#### B.4 Proof of Lemma 6

To simplify the notation, we define

$$W_0 = \prod_{\eta \in 2H} w_0^\eta = 1, \quad L_t^\eta = \sum_{i=1}^t \ell_i(\mathbf{x}_i^\eta), \quad \text{and } W_t = \prod_{\eta \in 2H} w_0^\eta e^{\beta L_t^\eta}, \quad \forall t \geq 1.$$

From the updating rule in (20), it is easy to verify that

$$w_t^\eta = \frac{w_0^\eta e^{\beta L_t^\eta}}{W_t}, \quad \forall t \geq 1. \tag{62}$$

First, we have

$$\ln W_T = \ln \prod_{\eta \in 2H} w_0^\eta e^{\beta L_T^\eta} = \beta \min_{\eta \in 2H} L_T^\eta + \frac{1}{\beta} \ln \frac{1}{w_0^\eta}. \tag{63}$$

Next, we bound the related quantity  $\ln(W_t/W_{t-1})$  as follows. For any  $\eta \in 2H$ , we have

$$\ln \frac{W_t}{W_{t-1}} \stackrel{(62)}{=} \ln \frac{w_0^\eta e^{\beta L_t^\eta}}{w_t^\eta} \frac{w_{t-1}^\eta}{w_0^\eta e^{\beta L_{t-1}^\eta}} = \ln \frac{w_{t-1}^\eta}{w_t^\eta} - \beta \ell_t(\mathbf{x}_t^\eta). \tag{64}$$

Then, we have

$$\begin{aligned}
\ln \frac{W_t}{W_{t-1}} &= \ln \frac{W_t}{W_{t-1}} \prod_{\eta \in 2H} w_t^\eta = \sum_{\eta \in 2H} w_t^\eta \ln \frac{W_t}{W_{t-1}} \\
&\stackrel{(64)}{=} \sum_{\eta \in 2H} w_t^\eta \ln \frac{w_{t-1}^\eta}{w_t^\eta} - \beta \sum_{\eta \in 2H} w_t^\eta \ell_t(\mathbf{x}_t^\eta) - \frac{1}{2} k \|\mathbf{w}_t\|_1^2 + \beta \sum_{\eta \in 2H} w_t^\eta \ell_t(\mathbf{x}_t^\eta)
\end{aligned} \tag{65}$$

where the last inequality is due to Pinsker's inequality [Cover and Thomas, 2006, Lemma 11.6.1]. Thus

$$\ln W_T = \ln W_0 + \sum_{t=1}^T \ln \frac{W_t}{W_{t-1}} \stackrel{(65)}{\geq} \sum_{t=1}^T \left( \frac{1}{2} k \|\mathbf{w}_t\|_1^2 - \beta \sum_{\eta \in 2H} w_t^\eta \ell_t(\mathbf{x}_t^\eta) \right). \tag{66}$$

Combining (63) with (66), we obtain

$$\beta \min_{\eta \in 2H} L_T^\eta + \frac{1}{\beta} \ln \frac{1}{w_0^\eta} \geq \sum_{t=1}^T \left( \frac{1}{2} k \|\mathbf{w}_t\|_1^2 - \beta \sum_{\eta \in 2H} w_t^\eta \ell_t(\mathbf{x}_t^\eta) \right)$$

We complete the proof by rearranging the above inequality.

## B.5 Proof of Lemma 4

The analysis is similar to that of Theorem 10 of Chen et al. [2018], which relies on a strong condition

$$\mathbf{x}_t^\eta = \mathbf{x}_{t-1}^\eta - \eta \nabla f_t(\mathbf{x}_t^\eta).$$

Note that the above equation is essentially the vanishing gradient condition of  $\mathbf{x}_t^\eta$  when (21) is unconstrained. In contrast, we only make use of the first-order optimality criterion of  $\mathbf{x}_t^\eta$  [Boyd and Vandenberghe, 2004], i.e.,

$$\nabla f_t(\mathbf{x}_t^\eta) + \frac{1}{\eta}(\mathbf{x}_t^\eta - \mathbf{x}_{t-1}^\eta), \mathbf{y} - \mathbf{x}_t^\eta \leq 0, \forall \mathbf{y} \in \mathcal{X} \quad (67)$$

which is much weaker.

From the convexity of  $f_t(\cdot)$ , we have

$$\begin{aligned} & f_t(\mathbf{x}_t^\eta) - f_t(\mathbf{u}_t) \\ & \leq \langle \nabla f_t(\mathbf{x}_t^\eta), \mathbf{x}_t^\eta - \mathbf{u}_t \rangle \\ & \stackrel{(67)}{\leq} \frac{1}{\eta} \langle \mathbf{x}_t^\eta - \mathbf{x}_{t-1}^\eta, \mathbf{u}_t - \mathbf{x}_t^\eta \rangle = \frac{1}{2\eta} \|\mathbf{x}_t^\eta - \mathbf{u}_t\|^2 - \langle \mathbf{x}_t^\eta - \mathbf{u}_t, \mathbf{x}_{t-1}^\eta - \mathbf{u}_t \rangle \\ & = \frac{1}{2\eta} \|\mathbf{x}_t^\eta - \mathbf{u}_t\|^2 - \langle \mathbf{x}_t^\eta - \mathbf{u}_t, \mathbf{x}_{t-1}^\eta - \mathbf{u}_t \rangle + \langle \mathbf{x}_t^\eta - \mathbf{u}_t, \mathbf{x}_{t-1}^\eta - \mathbf{u}_t \rangle - \langle \mathbf{x}_t^\eta - \mathbf{u}_t, \mathbf{x}_{t-1}^\eta - \mathbf{u}_t \rangle \\ & = \frac{1}{2\eta} \|\mathbf{x}_t^\eta - \mathbf{u}_t\|^2 - \langle \mathbf{x}_t^\eta - \mathbf{u}_t, \mathbf{x}_{t-1}^\eta - \mathbf{u}_t \rangle + \langle \mathbf{x}_t^\eta - \mathbf{u}_t, \mathbf{x}_{t-1}^\eta - \mathbf{u}_t \rangle - \langle \mathbf{x}_t^\eta - \mathbf{u}_t, \mathbf{x}_{t-1}^\eta - \mathbf{u}_t \rangle \\ & \quad + \frac{1}{2\eta} \|\mathbf{x}_t^\eta - \mathbf{u}_t\|^2 - \langle \mathbf{x}_t^\eta - \mathbf{u}_t, \mathbf{x}_{t-1}^\eta - \mathbf{u}_t \rangle + \langle \mathbf{x}_t^\eta - \mathbf{u}_t, \mathbf{x}_{t-1}^\eta - \mathbf{u}_t \rangle - \langle \mathbf{x}_t^\eta - \mathbf{u}_t, \mathbf{x}_{t-1}^\eta - \mathbf{u}_t \rangle \\ & \quad + \frac{1}{2\eta} \|\mathbf{x}_t^\eta - \mathbf{u}_t\|^2 \\ & \stackrel{(12)}{\leq} \frac{1}{2\eta} \|\mathbf{x}_t^\eta - \mathbf{u}_t\|^2 - \langle \mathbf{x}_t^\eta - \mathbf{u}_t, \mathbf{x}_{t-1}^\eta - \mathbf{u}_t \rangle + \frac{D}{\eta} \|\mathbf{u}_t - \mathbf{x}_{t-1}^\eta\| + \frac{1}{2\eta} \|\mathbf{x}_t^\eta - \mathbf{x}_{t-1}^\eta\|^2. \end{aligned}$$

Summing the above inequality over all iterations, we have

$$\begin{aligned} & \sum_{t=1}^T (f_t(\mathbf{x}_t^\eta) - f_t(\mathbf{u}_t)) \leq \frac{1}{2\eta} \|\mathbf{x}_0^\eta - \mathbf{u}_0\|^2 + \frac{D}{\eta} \sum_{t=1}^T \|\mathbf{u}_t - \mathbf{x}_{t-1}^\eta\| + \frac{1}{2\eta} \sum_{t=1}^T \|\mathbf{x}_t^\eta - \mathbf{x}_{t-1}^\eta\|^2 \\ & \stackrel{(12)}{\leq} \frac{1}{2\eta} D^2 + \frac{D}{\eta} \sum_{t=1}^T \|\mathbf{u}_t - \mathbf{x}_{t-1}^\eta\| + \frac{1}{2\eta} \sum_{t=1}^T \|\mathbf{x}_t^\eta - \mathbf{x}_{t-1}^\eta\|^2. \end{aligned} \quad (68)$$

Then, the dynamic regret with switching cost can be upper bounded as follows

$$\begin{aligned} & \sum_{t=1}^T f_t(\mathbf{x}_t^\eta) + \sum_{t=1}^T \|\mathbf{x}_t^\eta - \mathbf{x}_{t-1}^\eta\| - \sum_{t=1}^T f_t(\mathbf{u}_t) \\ & \stackrel{(68)}{\leq} \frac{1}{2\eta} D^2 + \frac{D}{\eta} \sum_{t=1}^T \|\mathbf{u}_t - \mathbf{x}_{t-1}^\eta\| + \frac{1}{2\eta} \sum_{t=1}^T \|\mathbf{x}_t^\eta - \mathbf{x}_{t-1}^\eta\|^2 + \sum_{t=1}^T \|\mathbf{x}_t^\eta - \mathbf{x}_{t-1}^\eta\| \\ & = \frac{1}{2\eta} D^2 + \frac{D}{\eta} \sum_{t=1}^T \|\mathbf{u}_t - \mathbf{x}_{t-1}^\eta\| + \frac{1}{2\eta} \sum_{t=1}^T \|\mathbf{x}_t^\eta - \mathbf{x}_{t-1}^\eta\|^2 + \sum_{t=1}^T \|\mathbf{x}_t^\eta - \mathbf{x}_{t-1}^\eta\| + \frac{\eta T}{2}. \end{aligned}$$