

Follow the perturbed leader, online shortest path

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1 Oracle Regret

We begin by a lemma

Lemma 1.1. If

$$x_{t+1} = \arg \min_{x \in K} \eta \sum_{s=1}^t l_s(x) + R(x)$$

then for any $u \in K$

$$\sum_{t=1}^T l_t(x_{t+1}) \leq \sum_{t=1}^T l_t(u) + \eta^{-1}(R(u) - R(x_1)) \quad (1)$$

where $x_1 = \arg \min R(x)$.

This says that the hypothetical forecaster who knows l_t before having to predict x_t is almost perfect.

PROOF. Use induction.

$T = 0$ true, because $R(x_1) \leq R(u), \forall u \in K$.

Suppose statement holds for $T - 1$.

$$\sum_{t=1}^{T-1} l_t(x_{t+1}) + \eta^{-1}R(x_1) \leq \sum_{t=1}^{T-1} l_t(u) + \eta^{-1}R(u), \forall u \quad (2)$$

in particular, this holds for $u = x_{T+1}$.

$$\sum_{t=1}^{T-1} l_t(x_{t+1}) + \eta^{-1}R(x_1) \leq \sum_{t=1}^{T-1} l_t(x_{T+1}) + \eta^{-1}R(x_{T+1}) \quad (3)$$

Add $l_T(x_{T+1})$ to both sides

$$\sum_{t=1}^T l_t(x_{t+1}) + \eta^{-1}R(x_1) \leq \sum_{t=1}^T l_t(x_{T+1}) + \eta^{-1}R(x_{T+1}) \quad (4)$$

$$\sum_{t=1}^T l_t(x_{t+1}) + \eta^{-1}R(x_1) \leq \sum_{t=1}^T l_t(u) + \eta^{-1}R(u), \forall u \quad (5)$$

□

As a consequence, for $x^* = \arg \min_{x \in K} \sum_{t=1}^T l_t(x)$,

$$\sum_{t=1}^T l_t(x_t) - \sum_{t=1}^T l_t(x^*) \leq \sum_{t=1}^T (l_t(x_t) - l_t(x_{t+1})) + \eta^{-1}(R(x^*) - R(x_1)) \quad (6)$$

2 Regret Bounds for Follow the Perturbed Leader

Now we focus on linear $l_t(\cdot)$

Solve $x_{t+1} = \arg \min_{x \in K} \eta \sum_{s=1}^t l_s x + r x$, where r is drawn at the beginning of the game from distribution f .

Assume *oblivious adversary*: $l_1 \dots l_T$ are chosen by the adversary before the game.

Theorem 2.1 (A). Suppose $l_t \in \mathbb{R}_+^n$, $K \subset \mathbb{R}_+^n$, $f(r)$ has support on \mathbb{R}_+^n .

$$\forall u \in K, \mathbb{E} \sum_{t=1}^T l_t x_t \leq \sum_{t=1}^T l_t u + \sum_{t=1}^T l_t \int_{\{r: f(r) \geq f(r - \eta l_t)\}} x_t f(r) dr + \eta^{-1} \mathbb{E} \sup_{x \in K} r x \quad (7)$$

PROOF. Let $x^* = \arg \min \sum_{t=1}^T l_t x$.

$$\sum_{t=1}^T l_t x_t - \sum_{t=1}^T l_t x^* \leq \sum_{t=1}^T l_t (x_t - x_{t+1}) + \eta^{-1} (r x^* - r x_1) \quad (8)$$

and since $r x \geq 0$,

$$\sum_{t=1}^T l_t x_t - \sum_{t=1}^T l_t x^* \leq \sum_{t=1}^T l_t (x_t - x_{t+1}) + \eta^{-1} r x^* \quad (9)$$

Taking expectations, we have

$$\mathbb{E} \left(\sum_{t=1}^T l_t x_t - \sum_{t=1}^T l_t x^* \right) \leq \mathbb{E} \left(\sum_{t=1}^T (l_t x_t - l_t x_{t+1}) \right) + \eta^{-1} (r x^* - r x_1) \quad (10)$$

We want to have $\mathbb{E}(\sum_{t=1}^T (l_t x_t - l_t x_{t+1}))$ small.

$$\mathbb{E} l_t x_t = \int l_t \arg \min_x \left(\left(\eta \sum_{s=1}^{t-1} l_s + r \right) x \right) f(r) dr \quad (11)$$

$$\mathbb{E} l_t x_{t+1} = \int l_t \arg \min_x \left(\left(\eta \sum_{s=1}^t l_s + r \right) x \right) f(r) dr \quad (12)$$

Let $r' = r + l_t$

$$\mathbb{E} l_t x_t = \int l_t \arg \min_x \left(\left(\eta \sum_{s=1}^{T-1} l_s + r' \right) x \right) f(r' - \eta l_t) dr' \quad (13)$$

$$\mathbb{E} l_t (x_t - x_{t+1}) = \int l_t x_t (f(r) - f(r - \eta l_t)) dr = l_t \int x_t (f(r) - f(r - \eta l_t)) dr \quad (14)$$

$$\leq l_t \int_{\{r: f(r) > f(r - \eta l_t)\}} x_t f(r) dr = l_t \mathbb{E} x_t \mathbf{1}_{\{r: f(r) > f(r - \eta l_t)\}} \quad (15)$$

□

Now, we prove an analogous theorem where we relax the restriction to the positive orthant.

Theorem 2.2 (B).

$$\mathbb{E} \sum_{t=1}^T l_t x_t \leq \sup_{r,t} \frac{f(r)}{f(r-\eta l_t)} \left[\sum_{t=1}^T l_t + \eta^{-1} \mathbb{E} \sup_{x \in K} r \cdot x + \eta^{-1} \mathbb{E} \sup_{x \in K} -r \cdot x \right] \quad (16)$$

for any $u \in K$

PROOF.

$$\mathbb{E} l_t x_t = \int l_t \operatorname{argmin}_{x \in K} \left[\left(\eta \sum_{s=1}^{t-1} l_s + r \right) x \right] f(r) dr \quad (17)$$

$$\leq \sup_{r,t} \frac{f(r)}{f(r-\eta l_t)} \int l_t \operatorname{argmin}_{x \in K} \left[\left(\eta \sum_{s=1}^t l_s + r \right) x \right] f(r) dr \quad (18)$$

$$= \sup_{r,t} \frac{f(r)}{f(r-\eta l_t)} \mathbb{E} l_t x_{t+1} \quad (19)$$

By lemma 1.1,

$$\forall u \in K, \sum_{t=1}^T l_t x_{t+1} \leq \sum_{t=1}^T l_t \cdot u + \eta^{-1} \sup_{x \in K} (r \cdot x) + \eta^{-1} \sup_{x \in K} (-r \cdot x) \quad (20)$$

So,

$$\mathbb{E} \sum_{t=1}^T l_t x_t = \sup_{r,t} \frac{f(r)}{f(r-\eta l_t)} \mathbb{E} \left(\sum_{t=1}^T l_t \cdot u + \eta^{-1} \sup_{x \in K} (r \cdot x) + \eta^{-1} \sup_{x \in K} (-r \cdot x) \right) \quad (21)$$

□

3 Examples

3.1 Expert Setting

Here, K is the n -simplex. We will draw $r \sim \text{Unif}([0, 1]^N)$ and $l_t \in [0, 1]^N$

Applying Theorem A,

$$\mathbb{E} R_T \leq \sum_{t=1}^T l_t \int_{\{r: f(r) > f(r-\eta l_t)\}} x_t f(r) dr + \underbrace{\eta^{-1} \mathbb{E} \sup_{x \in K} r \cdot x}_{\leq 1} \quad (22)$$

$$\leq \sum_{t=1}^T \int_{\{r: f(r) > f(r-\eta l_t)\}} f(r) dr + \eta^{-1} \quad (23)$$

$$\leq \sum_{t=1}^T \text{Vol}(\{r : \exists i, r_i - \eta l_t(i) < 0\}) + \eta^{-1} \quad (24)$$

$$\leq \sum_{t=1}^T \eta \sum_{i=1}^N l_t(i) + \eta^{-1} \quad (25)$$

$$\leq \eta^{-1} + T\eta N \quad (26)$$

$$= 2\sqrt{TN} \text{ (with } \eta = \frac{1}{\sqrt{TN}}) \quad (27)$$

By using Theorem B, this result can be improved to replace the N term with $\log(N)$.

3.2 Online Shortest Path

In this setting, there is a fixed DAG with labeled vertices u and v such that v is reachable from u . At each time step, the player picks a path from u to v , and then the opponent reveals the cost of each edge. The loss is the cost of the chosen path.

Each path can be associated with some $x \in \{0, 1\}^{|E|}$, and the set of paths is $P \subseteq \{0, 1\}^{|E|}$.

The adversary picks $l_t \in \mathbb{R}_+^n$, so the loss can be written as $l_t \cdot x_t$ as usual.

To use the Follow the Perturbed Leader methodology, we draw $r \sim \text{Unif}([0, 1]^{|E|})$. Suppose, $l_t \in [0, 1]^{|E|}$ and the length of the longest path (number of edges) is ξ .

Then, applying Theorem A,

$$l_t \int_{\{r: f(r) > f(r - \eta l_t)\}} x_t f(r) dr \leq \|l_t\|_\infty \left\| \int_{\{r: f(r) > f(r - \eta l_t)\}} x_t f(r) dr \right\|_1 \quad (28)$$

$$\leq \xi \int_{\{r: f(r) > f(r - \eta l_t)\}} f(r) dr \quad (29)$$

$$\leq \xi |E| \eta \quad (30)$$

So,

$$\mathbb{E}R_T \leq \eta^{-1} \xi + \xi |E| \eta T \quad (31)$$

$$= 2\xi \sqrt{|E|T} \quad (\text{with } \eta = \frac{1}{\sqrt{|E|T}}) \quad (32)$$

By using Theorem B, this result can be improved to replace the $|E|$ term with $\log(|E|)$.