Regularized Algorithms for Online Optimization and Learning

CS245: Online Optimization and Learning

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Review of Online Gradient Descent

Online Gradient Descent (OGD)

Initialization: $x_1 \in \mathcal{K}$ and $\{\eta_t\}$.
For $t = 1, \cdots, T$:

- **Learner:** Submit x_t.
- **Environment:** Observe the convex loss $f_t(\cdot)$.
- **Update:** $x_{t+1} = \prod_{\mathcal{K}}(x_t - \eta_t \nabla f_t(x_t))$.

The intuition of OGD is to solve "trust region optimization":

$$\min_{x \in \mathcal{K}} f_t(x_t) + \langle x - x_t, \nabla f_t(x_t) \rangle$$
$$\text{s.t. } \|x - x_t\| \leq \delta.$$

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The intuition of OGD is to minimize the first order approximation + regularization with ℓ_2 norm:

$$\hat{f}_{t+1}(x) = f_t(x_t) + \langle x - x_t, \nabla f_t(x_t) \rangle + \frac{1}{2\eta_t} \|x - x_t\|^2.$$

which is equavilent to

$$x_{t+1} = \arg\min_{x \in \mathcal{K}} \ \langle x, \nabla f_t(x_t) \rangle + \frac{1}{2\eta_t} \|x - x_t\|^2.$$

Bregman Divergence

Definition 1 (Bregman Divergence)

Let $\psi : X \to R$ be strongly convex and continuously differentiable function. The Bregman divergence w.r.t. ψ is B_ψ is defined as

$$B_\psi(x; y) = \psi(x) - \psi(y) - \langle x - y, \nabla\psi(y)\rangle.$$

If ψ is twice differentiable, and by Taylor theorem

$$B_\psi(x; y) = \langle x - y, \nabla^2\psi(z)(x - y)\rangle,$$

where z is a point between x and y.

Recall $\psi(\cdot)$ is α-strongly convex, we have a global property

$$B_\psi(x; y) \geq \frac{\alpha}{2}\|x - y\|^2.$$

Bregman Divergence - Examples

Let $\psi(x) = \frac{1}{2}\|x\|^2$, and the Bregman Divergence is

$$B_\psi(x; y) = ?$$

Let $\psi(x) = \sum_{i=1}^{d} x_i \log x_i$, with x being in a probability simplex, and the Bregman Divergence is

$$B_\psi(x; y) = ?.$$

Bregman Divergence - properties

The properties of Bregman divergence:

- Non-negative
$$B_\psi(x; y) \geq 0.$$
- "Non"-symmetric
$$B_\psi(x; y) \neq B_\psi(y; x).$$
- Three points identity:
$$B_\psi(z; x) + B_\psi(x; y) - B_\psi(z; y) = \langle \nabla\psi(y) - \nabla\psi(x), z - x \rangle.$$

Online Mirrored Descent

Online gradient descent is

$$x_{t+1} = \arg\min_{x \in \mathcal{K}} \langle x, \nabla f_t(x_t) \rangle + \frac{1}{2\eta_t} \|x - x_t\|^2.$$

Online Mirrored Descent

Online gradient descent is

$$x_{t+1} = \arg\min_{x \in \mathcal{K}} \ \langle x, \nabla f_t(x_t) \rangle + \frac{1}{2\eta_t} \|x - x_t\|^2.$$

Just change the "distance" metric to Bregman divergence w.r.t ψ, and we have

$$x_{t+1} = \arg\min_{x \in \mathcal{K}} \ \langle x, \nabla f_t(x_t) \rangle + \frac{1}{\eta_t} B_\psi(x; x_t).$$

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If $\mathcal{K}$ is $\mathbb{R}^d$, let $\psi(x) = \frac{1}{2}\|x\|^2$ gives us online gradient descent algorithm.

If $\mathcal{K}$ is a probability simplex, let $\psi(x) = \sum_{i=1}^{d} x_i \log x_i$ gives us any algorithm?

Online Mirrored Descent

Online Mirrored Descent (OMD)

Initialization: $x_1 \in \mathcal{K}$ and $\{\eta_t\}$.

For $t = 1, \cdots, T$:

- **Learner:** Submit x_t.
- **Environment:** Observe the convex loss $f_t(\cdot)$.
- **Update:** $x_{t+1} = \arg\min_{x \in \mathcal{K}} \ \langle x, \nabla f_t(x_t) \rangle + \frac{1}{\eta_t} B_\psi(x; x_t)$.

An alternative update is

$$
\begin{aligned}
y_{t+1} &= \arg\min_{x \in \mathbb{R}^d} \ \langle x, \nabla f_t(x_t) \rangle + \frac{1}{\eta_t} B_\psi(x; x_t) \\
x_{t+1} &= \arg\min_{x \in \mathcal{K}} B_\psi(x; y_{t+1})
\end{aligned}
$$

Online Mirrored Descent - Regret

Recall the regret of online gradient descent is $O(\sqrt{T})$. How about the regret of online mirrored descent?

Theorem 2

Let ψ be α-strongly convex function. Consider a fixed learning rate $\eta_t = \eta$. Online mirrored descent algorithm achieves

$$Regret(T) \leq \frac{B_\psi(x^*, x_1)}{\eta} + \frac{1}{2\alpha}\sum_{t=1}^{T} \eta \|\nabla f_t(x_t)\|^2.$$

OMD achieves $O(\sqrt{T})$ regret if:

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- The feasible set and gradients are bounded.

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OMD achieves $O(\sqrt{T})$ regret if:

- The feasible set and gradients are bounded.
- Learning rate is fixed with $O(1/\sqrt{T})$.

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OMD achieves $O(\sqrt{T})$ regret if:

- The feasible set and gradients are bounded.
- Learning rate is fixed with $O(1/\sqrt{T})$.
- Time varying learning rate $O(1/\sqrt{t})$ or adaptive learning rate also work (verify by yourself).

Online Mirrored Descent - Proof

We use a "potential/Lyapunov drift" style of analysis: define

$$\begin{aligned}\phi_t =& B_\psi(x^*; x_t)\\ =& \psi(x^*) - \psi(x_t) - \langle x^* - x_t, \nabla\psi(x_t)\rangle,\end{aligned}$$

and study the drift

$$\begin{aligned}\phi_{t+1} - \phi_t =& B_\psi(x^*; x_{t+1}) - B_\psi(x^*; x_t)\\ =& - B_\psi(x_{t+1}; x_t) + \langle \nabla\psi(x_t) - \nabla\psi(x_{t+1}), x^* - x_{t+1}\rangle\end{aligned}$$

Define $F_t(x) = \langle x, \nabla f_t(x_t)\rangle + \frac{1}{\eta} B(x; x_t)$

We have $x_{t+1} = \arg\min F_t(x)$, which implies

$\langle x^* - x_{t+1}, \nabla F_t(x_{t+1})\rangle \geq 0$ First-order optimality

Online Mirrored Descent - Proof

Substitude $\nabla F_t(x_{t+1})$ and we have

$$\langle x^* - x_{t+1}, \nabla f_t(x_t) + \frac{1}{\eta}\nabla\psi(x_{t+1}) - \frac{1}{\eta}\nabla\psi(x_t)\rangle \geq 0$$

$$\Rightarrow \quad \langle \nabla\psi(x_t) - \nabla\psi(x_{t+1}), x^* - x_{t+1}\rangle \leq \eta\langle x^* - x_{t+1}, \nabla f_t(x_t)\rangle$$

We finally have

$$\langle x_{t+1}, \nabla f_t(x_t)\rangle + \frac{1}{\eta}B(x_{t+1}; x_t)$$

$$\leq \langle x^*, \nabla f_t(x_t)\rangle + \frac{1}{\eta}B(x^*; x_t) - \frac{1}{\eta}B(x^*; x_{t+1})$$

which is exactly the push back lemma in the following alternative proof. the remaining proof can be found in the alternative proof next.

Online Mirrored Descent - An Alternative Proof

We have the following lemma that make our analysis simple[1]

Lemma 3 (A pushback lemma)

Suppose x_{t+1} minimizes the function $F(x)$ such that

$$F(x) := \langle x, \nabla f_t(x_t) \rangle + \frac{1}{\eta} B(x; x_t),$$

For any x, we have

$$F(x_{t+1}) \leq F(x) - \frac{1}{\eta} B(x; x_{t+1}).$$

[1] X. Wei, et al. Online Primal-Dual Mirror Descent under Stochastic Constraints. Sigmetrics 2020.

Online Mirrored Descent - An Alternative Proof

By Lemma 3, we have for any x such that

$$\langle x_{t+1}, \nabla f_t(x_t) \rangle + \frac{1}{\eta} B(x_{t+1}; x_t)$$

$$\leq \langle x, \nabla f_t(x_t) \rangle + \frac{1}{\eta} B(x; x_t) - \frac{1}{\eta} B(x; x_{t+1})$$

Let $x = x^*$, then we have

$$\langle x_{t+1} - x_t, \nabla f_t(x_t) \rangle + \frac{1}{\eta} B(x_{t+1}; x_t)$$

$$\leq \langle x^* - x_t, \nabla f_t(x_t) \rangle + \frac{1}{\eta} B(x^*; x_t) - \frac{1}{\eta} B(x^*; x_{t+1})$$

$$\leq f_t(x^*) - f_t(x_t) + \frac{1}{\eta} B(x^*; x_t) - \frac{1}{\eta} B(x^*; x_{t+1})$$

$$\Rightarrow \quad f(x_t) - f(x^*)$$

$$\leq -\langle x_{t+1} - x_t, \nabla f_t(x_t) \rangle - \frac{1}{\eta} B(x_{t+1}; x_t) + \frac{1}{\eta} B(x^*; x_t) - \frac{1}{\eta} B(x^*; x_{t+1})$$

$$\leq -\langle x_{t+1} - x_t, \nabla f_t(x_t) \rangle - \frac{\alpha}{2\eta} \|x_{t+1} - x_t\|^2 + \frac{1}{\eta} B(x^*; x_t) - \frac{1}{\eta} B(x^*; x_{t+1})$$

$$= -\langle x_{t+1} - x_t, \nabla f_t(x_t) \rangle - \frac{\alpha}{2\eta} \|x_{t+1} - x_t\|^2 - \frac{\eta}{2\alpha} \|\nabla f_t(x_t)\|^2 + \frac{\eta}{2\alpha} \|\nabla f_t(x_t)\|^2$$
$$+ \frac{1}{\eta} B(x^*; x_t) - \frac{1}{\eta} B(x^*; x_{t+1})$$

$$\leq \frac{\eta}{2\alpha} \|\nabla f_t(x_t)\|^2 + \frac{1}{\eta} B(x^*; x_t) - \frac{1}{\eta} B(x^*; x_{t+1})$$

therefore, we have

$$\sum_{t=1}^{T} f_t(x_t) - f_t(x^*) \leq \frac{1}{\eta} B(x^*; x_1) + \sum_{t=1}^{T} \frac{\eta}{2\alpha} \|\nabla f_t(x_t)\|^2$$

which proves the Theorem.

Why is called Mirrored descent?

Definition 4 (Fenchel Conjugate)

The Fenchel conjugate of a function f is

$$f^*(y) := \sup_{x \in \mathcal{K}} \langle y, x \rangle - f(x).$$

Theorem 5

The update of online mirrored descent

$$x_{t+1} = \arg\min_{x \in \mathcal{K}} \langle x, \nabla f_t(x_t) \rangle + \frac{1}{\eta_t} B_\psi(x; x_t)$$

is equivalent to

$$x_{t+1} = \nabla \psi^*_{\mathcal{K}}(\nabla \psi_{\mathcal{K}}(x_t) - \eta_t \nabla f_t(x_t)).$$

Let's consider the case of $\psi(x) = \frac{1}{2}\|x\|^2$, can we reduce it to online gradient descent?

Theorem 5 – Proof

By definition of online mirror descent, we have

$$
\begin{aligned}
x_{t+1} &= \arg\min_{x \in \mathcal{K}} \; \langle x, \nabla f_t(x_t) \rangle + \frac{1}{\eta_t} B_\psi(x; x_t) \\
&= \arg\min_{x \in \mathcal{K}} \; \eta_t \langle x, \nabla f_t(x_t) \rangle + B_\psi(x; x_t) \\
&= \arg\min_{x \in \mathcal{K}} \; \eta_t \langle x, \nabla f_t(x_t) \rangle + \psi(x) - \langle x, \nabla \psi(x_t) \rangle \\
&= \arg\min_{x \in \mathcal{K}} \; \langle x, \eta_t \nabla f_t(x_t) - \nabla \psi(x_t) \rangle + \psi(x) \\
&= \arg\max_{x \in \mathcal{K}} \; \langle x, \nabla \psi(x_t) - \eta_t \nabla f_t(x_t) \rangle - \psi(x)
\end{aligned}
$$

Let's define $y = \nabla \psi(x_t) - \eta_t \nabla f_t(x_t)$, and we have

$$
x_{t+1} = \arg\max_{x \in \mathcal{K}} \; \langle y, x \rangle - \psi(x).
$$

Theorem 5 – Proof

Let's first consider $\mathcal{K} = \mathbb{R}^d$. Note x_{t+1} is maximizing

$$\langle x, y \rangle - \psi(x),$$

we have

$$\begin{aligned}
\nabla \psi^*(y) =& \frac{\partial \left(\max_x \langle x, y \rangle - \psi(x)\right)}{\partial y}, \\
=& \frac{\partial \left(\langle x_{t+1}, y \rangle - \psi(x_{t+1})\right)}{\partial y} \\
=& x_{t+1},
\end{aligned}$$

which means

$$x_{t+1} = \nabla \psi^*(y) = \nabla \psi^*(\nabla \psi(x_t) - \eta_t \nabla f_t(x_t)).$$

We are done. Please verify the case of the general $\mathcal{K}$.

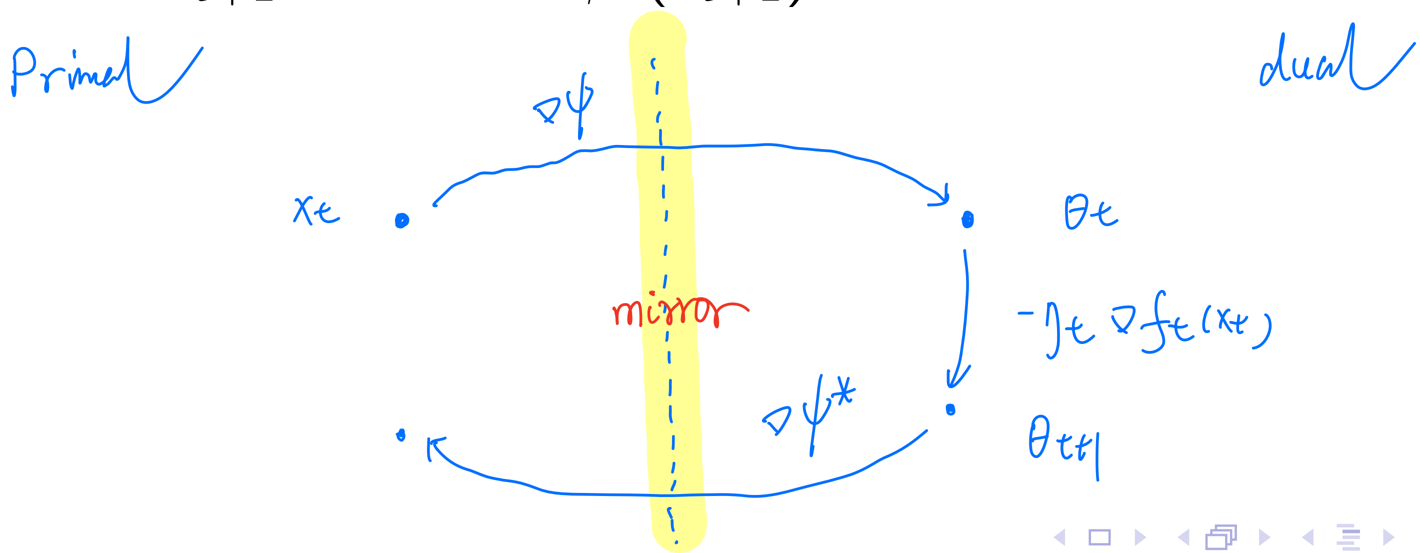
Why is called Mirrored descent?

Let's understand online mirrored descent ($\mathcal{K} = \mathbb{R}^d$)

$$x_{t+1} = \nabla\psi^*(\nabla\psi(x_t) - \eta_t \nabla f_t(x_t))$$

in three steps:

- Mirror x_t from primal space to dual $\theta_t = \nabla\psi(x_t)$.
- Take gradient descent in dual space
$$\theta_{t+1} = \theta_t - \eta_t \nabla f_t(x_t).$$
- Mirror θ_{t+1} back to $\nabla\psi^*(\theta_{t+1})$.



Review of Expert problem

Expert problem:

Initialization: N experts/models.

For each day $t = 1, \cdots, T$:

- **Learner:** Obtain predictions from N experts/models and sample an expert i from a probability simplex x_t.
- **Environment:** Observe the loss of each model $\ell_t \in [0,1]^N$.

Objective: Find the best expert in hindsight, which is equivalent to minimize regret:

$$\mathcal{R}(T) := \mathbb{E}\left[\sum_{t=1}^{T} \ell_t(i) - \sum_{t=1}^{T} \ell_t(i^*)\right] = \sum_{t=1}^{T} \langle x_t, \ell_t \rangle - \sum_{t=1}^{T} \langle x^*, \ell_t \rangle$$

Expert problem: Hedge

Hedge - "weighted" version:

Initialization: $w_1(i) = 1, \forall i \in [N]$.

For each day $t = 1, \cdots, T$:

- **Learner:** Sample an expert i : $p_t(i) = w_t(i)/\sum_i w_t(i)$.
- **Environment:** Observe the error $\ell_t \in [0,1]^N$.
- **Update:** $w_{t+1} = w_t \cdot e^{-\eta \ell_t(i)}, \forall i \in [N]$.

Hedge - "prob" version:

Initialization: $x_1 = [1/d, \cdots, 1/d]$ and η.

For each day $t = 1, \cdots, T$:

- **Learner:** Sample an expert i according to x_t.
- **Environment:** Observe the error $\ell_t \in [0,1]^N$.
- **Update:** $x_{t+1,i} = x_{t,i} e^{-\eta \ell_t(i)} / \sum_{i=1}^d x_{t,i} e^{-\eta \ell_t(i)}, \forall i \in [N]$.

Exponentiated Gradient – Hedge

Exponentiated Gradient:

Initialization: $x_1 = [1/d, \cdots, 1/d]$ and η.

For each day $t = 1, \cdots, T$:

- **Learner:** Submit x_t.
- **Environment:** Observe the loss $f_t(\cdot)$.
- **Update:** $x_{t+1,i} = x_{t,i} e^{-\eta \nabla f_{t,i}(x_t)} / \sum_{i=1}^{d} x_{t,i} e^{-\eta \nabla f_{t,i}(x_t)}$.

How it is related to Hedge - "prob" version?

- No sampling operator from x_t.
- The loss is $f_t(x_t) = \langle x_t, \ell_t \rangle$.
- Regret is equivalent to the "expected" regret of Hedge!

Online Mirrored Descent:

Initialization: $x_1 = [1/d, \cdots, 1/d]$ and η.

For each day $t = 1, \cdots, T$:

- **Learner:** submit x_t.
- **Environment:** Observe the loss $f_t(\cdot)$.
- **Update:** $x_{t+1} = \arg\min_{\mathcal{K}} \ \langle x, \nabla f_t(x_t)\rangle + \frac{1}{\eta} B_\psi(x; x_t)$.

Since x in the prob simplex, can we try $\psi(x) = \sum_{i=1}^{d} x_i \log x_i$ in the Bregman divergence and show x_{t+1} is equivalent to that in Exponentiated Gradient?

Exponentiated Gradient – Online Mirrored Descent

Online Mirrored Descent:

Initialization: $x_1 = [1/d, \cdots, 1/d]$ and η.
For each day $t = 1, \cdots, T$:

- **Learner:** submit x_t.
- **Environment:** Observe the loss $f_t(\cdot)$.
- **Update:** $x_{t+1} = \arg\min_{\mathcal{K}} \ \langle x, \nabla f_t(x_t) \rangle + \frac{1}{\eta} B_\psi(x; x_t)$.

Since x in the prob simplex, can we try $\psi(x) = \sum_{i=1}^{d} x_i \log x_i$ in the Bregman divergence and show x_{t+1} is equivalent to that in the Exponentiated Gradient:

$$x_{t+1,i} = \frac{x_{t,i} e^{-\eta \nabla f_{t,i}(x_t)}}{\sum_{i=1}^{d} x_{t,i} e^{-\eta \nabla f_{t,i}(x_t)}}.$$

Exponentiated Gradient as Online Mirrored Descent

The update of Bragman divergence

$$\min_{x \in \mathcal{K}} \eta \langle x, \nabla f_t(x_t) \rangle + \sum_{i=1}^{d} x_i \log \frac{x_i}{x_{t,i}}$$

$$\text{s.t.} \sum_{i=1}^{d} x_i = 1, \quad x_i \geq 0.$$

Let's consider (partial) Lagrangian function:

$$L(x, \lambda) = \eta \langle x, \nabla f_t(x_t) \rangle + \sum_{i=1}^{d} x_i \log \frac{x_i}{x_{t,i}} + \lambda(1 - \sum_{i=1}^{d} x_i)$$

$$\frac{\partial L(x,\lambda)}{\partial x_i} = \eta \nabla f_{t,i}(x_t) + \log \frac{x_i}{x_{t,i}} + 1 - \lambda = 0 \qquad (i)$$

$$\frac{\partial L(x,\lambda)}{\partial \lambda} = 1 - \sum_{i=1}^{d} x_i = 0 \qquad (ii)$$

Exponentiated Gradient as Online Mirrored Descent

From (i), we have

$$\log x_i = \log x_{t,i} - \eta \nabla f_{t,i}(x_t) + \lambda - 1$$

$$\Rightarrow \quad x_i = x_{t,i}\, e^{-\eta \nabla f_{t,i}(x_t)}\, e^{\lambda - 1}$$

Combine (ii), we normalize the x_i such that

$$x_i = \frac{x_{t,i}\, e^{-\eta \nabla f_{t,i}(x_t)}}{\sum_{i=1}^{d} x_{t,i}\, e^{-\eta \nabla f_{t,i}(x_t)}}$$

Hedge as Online Mirrored Descent

Hedge as Online Mirrored Descent:

Initialization: $x_1 = [1/d, \cdots, 1/d]$ and η_t.

For each day $t = 1, \cdots, T$:

- **Learner:** Sample an expert i from x_t.
- **Environment:** Observe the error $\ell_t(\cdot)$.
- **Update:** $x_{t+1} = \arg\min_{\mathcal{K}} \ \langle x, \ell_t \rangle + \frac{1}{\eta} B_\psi(x; x_t)$.

Hedge $\longrightarrow$ Exponentiated Gradient $\longrightarrow$ OMD!

OMD is a strong and general framework to design online algorithms!

Hedge as Online Mirrored Descent – Regret

Theorem 6 (Restate Theorem 2)

Let ψ be α-strongly convex function in B_ψ. Let fixed learning rate $\eta_t = \eta$. Online mirrored descent algorithm achieves

$$Regret(T) \leq \frac{B_\psi(x^*, x_1)}{\eta} + \frac{\eta}{2\alpha}\sum_{t=1}^{T} \|\nabla f_t(x_t)\|^2.$$

In Hedge, we have

- $\psi(x) = \sum_{i=1}^{d} x_i \log x_i$ is 1-strongly convex,
- $B_\psi(x^*, x_1) = \sum_{i=1}^{d} x_i^* \log \frac{x_i^*}{x_{1,i}} \leq \log N$,

which implies the regret of Hedge is

$$\text{Regret}(T) = O(\sqrt{T \log N}).$$

RLHF Finetuning as (Online) Mirrored Descent

RLHF[2] as (Online) Mirrored Descent:

Initialization: A pretrained reward model r and policy π_{ref}.
FineTuning: Find a policy such that

$$\pi_\theta^* = \arg\max \mathbb{E}_{c \sim \mathcal{D}, a \sim \pi_\theta(a|c)} \left[r(c, a) \right] - \frac{1}{\eta} \mathrm{KL}(\pi_\theta; \pi_{ref}).$$

[2] OpenAI. Training language models to follow instructions with human feedback. NeurIPS 2022.

Online Learning with Prediction

Consider a linear function

$$f_t(x) = \langle \ell_t, x \rangle.$$

Online Learning with Prediction

Initialization: $x_1 \in \mathcal{K}$ and $\{\eta_t\}$.

For $t = 1, \cdots, T$:

- **Learner:** Given a prediction $\hat{\ell}_t$ and submit x_t.
- **Environment:** Observe the cost ℓ_t.

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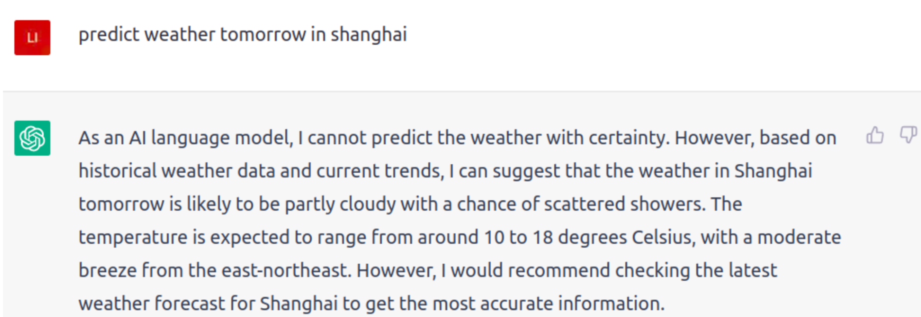

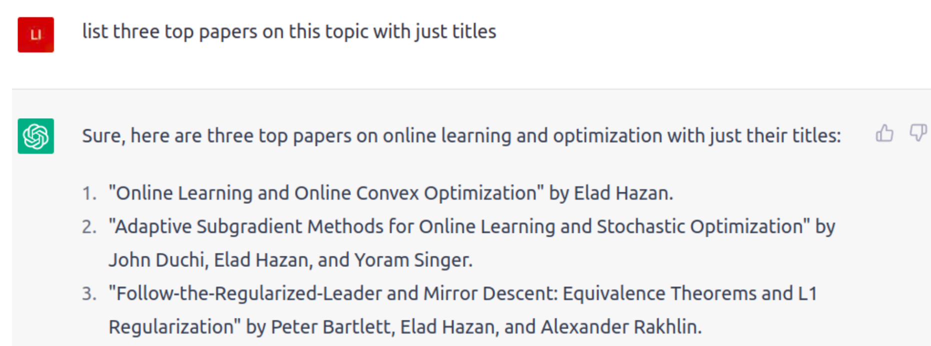

Online Learning with Prediction

Consider a linear function

$$f_t(x) = \langle \ell_t, x \rangle.$$

Online Learning with Prediction

Initialization: $x_1 \in \mathcal{K}$ and $\{\eta_t\}$.

For $t = 1, \cdots, T$:

- **Learner:** Given a prediction $\hat{\ell}_t$ and submit x_t.
- **Environment:** Observe the cost ℓ_t.

How to utilize the prediction to improve the online learning algorithms?

- For perfect predictions $\hat{\ell}_t = \ell_t$, the regret is smaller than $O(\sqrt{T})$?
- For bad predictions, the regret should not be worse than $O(\sqrt{T})$!

Online Learning with Prediction

Online Learning with Prediction

Initialization: $x_1 \in \mathcal{K}$ and $\{\eta\}$.

For $t = 1, \cdots, T$:

- **Learner:** Submit x_t.
- **Environment:** Observe the cost ℓ_t.
- **Prediction:** The cost $\hat{\ell}_{t+1}$.
- **Update:** $x_{t+1} = \text{Alg}(x_1, \cdots, x_t, \ell_1, \cdots, \ell_t, \hat{\ell}_{t+1})$.

$\text{Alg}(x_1, \cdots, x_t, \ell_1, \cdots, \ell_t, \hat{\ell}_{t+1})$ could be $\text{Alg}(x_t, \ell_t, \hat{\ell}_{t+1})$ like online gradient/mirrored descent:

$$x_{t+1} = \arg\min_{x \in \mathbb{R}^d} \ \langle x, \ell_t \rangle + \frac{1}{\eta} B_\psi(x; x_t)$$

How to incorporate the prediction $\hat{\ell}_{t+1}$?

Online Learning with Prediction

Online Learning with Prediction

Initialization: $x_1 \in \mathcal{K}$ and $\{\eta\}$.

For $t = 1, \cdots, T$:

- **Learner:** Submit x_t.
- **Environment:** Observe the cost ℓ_t.
- **Prediction:** The cost $\hat{\ell}_{t+1}$.
- **Update:** $x_{t+1} = \text{Alg}(x_1, \cdots, x_t, \ell_1, \cdots, \ell_t, \hat{\ell}_{t+1})$.

Online gradient/mirrored descent:

$$y_{t+1} = \arg\min_{y \in \mathbb{R}^d} \; \langle y, \ell_t \rangle + \frac{1}{\eta} B_\psi(y; y_t)$$

How to incorporate the prediction $\hat{\ell}_{t+1}$?

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Online gradient/mirrored descent with prediction:

$$y_{t+1} = \arg\min_{y \in \mathbb{R}^d} \ \langle y, \ell_t \rangle + \frac{1}{\eta} B_\psi(y; y_t)$$

$$x_{t+1} = \arg\min_{x \in \mathbb{R}^d} \ \langle x, \hat{\ell}_{t+1} \rangle + \frac{1}{\eta} B_\psi(x; y_{t+1})$$

Online Mirrored Descent with Prediction

Initialization: $x_1 \in \mathcal{K}$ and $\{\eta\}$.

For $t = 1, \cdots, T$:

- **Learner:** Submit x_t.
- **Environment:** Observe the loss ℓ_t.
- **Prediction:** The cost $\hat{\ell}_{t+1}$.
- **Update:** $y_{t+1} = \arg\min_{y \in \mathbb{R}^d} \ \langle y, \ell_t \rangle + \frac{1}{\eta} \ B_\psi(y; y_t)$

  $x_{t+1} = \arg\min_{x \in \mathbb{R}^d} \ \langle x, \hat{\ell}_{t+1} \rangle + \frac{1}{\eta} \ B_\psi(x; y_{t+1})$

Intuition:

- Online mirrored descent guarantees “not too bad” even with unreliable predictions.
- Decrease the cost further if $\hat{\ell}_{t+1}$ is reliable.

Online Mirrored Descent with Prediction – Regret

The regret of OMD with prediction is as follows. [3]

Theorem 7

Let ψ be 1-strongly convex function in B_ψ. Let fixed learning rate $\eta_t = \eta$. Given a prediction sequence of $\{\hat{\ell}_t\}$, online mirrored descent achieves

$$Regret(T) \leq \frac{B(x^*, x_1)}{\eta} + \frac{\eta}{2} \sum_{t=1}^{T} \|\hat{\ell}_t - \ell_t\|^2.$$

"Almost" the best of two worlds:

- If the predictions are "perfect", the regret is constant!
- If the predictions are "bad", the regret can be $O(\sqrt{T})$.
- If the predictions are "good", the regret can be $o(\sqrt{T})$.

[3] Alexander Rakhlin and Karthik Sridharan. Online learning with predictable sequences. COLT, 2013

Online Mirrored Descent with Prediction – Proof

According to the pushback lemma, suppose x_{t+1} minimizes the function $F(x)$ such that

$$F(x) := \langle x, \ell_t \rangle + \frac{1}{\eta} B(x; x_t).$$

For any x, we have

$$F(x_{t+1}) \leq F(x) - \frac{1}{\eta} B(x; x_{t+1}).$$

Therefore, we have

$$\eta \langle x_{t+1}, \ell_t \rangle + B(x_{t+1}; x_t) \leq \eta \langle x^*, \ell_t \rangle + B(x^*; x_t) - B(x^*; x_{t+1}).$$

which implies

$$\eta \langle x_t - x^*, \ell_t \rangle + \eta \langle x_{t+1} - x_t, \ell_t \rangle + B(x_{t+1}; x_t) \leq B(x^*; x_t) - B(x^*; x_{t+1}).$$

Online Mirrored Descent with Prediction – Proof

Step one:

$$y_{t+1} = \arg\min_{y \in \mathbb{R}^d} \; \langle y, \ell_t \rangle + \frac{1}{\eta} B_\psi(y; y_t).$$

By pushback lemma, we have

$$\eta\langle y_{t+1}, \ell_t \rangle + B(y_{t+1}; y_t) \leq \eta\langle x^*, \ell_t \rangle + B(x^*; y_t) - B(x^*; y_{t+1}).$$

Step two:

$$x_t = \arg\min_{x \in \mathbb{R}^d} \; \langle x, \hat{\ell}_t \rangle + \frac{1}{\eta} B_\psi(x; y_t).$$

By pushback lemma, we have

$$\eta\langle x_t, \hat{\ell}_t \rangle + B(x_t; y_t) \leq \eta\langle x, \hat{\ell}_t \rangle + B(x; y_t) - B(x; x_t).$$

Online Mirrored Descent with Prediction – Proof

From (i), we have

$$\eta \langle x_t - x^*, l_t \rangle + \eta \langle y_{t+1} - x_t, l_t \rangle$$

$$\leq \; - B(y_{t+1}; y_t) + B(x^*; y_t) - B(x^*; y_{t+1})$$

From (ii), we have

$$\eta \langle x_t - y_{t+1}, \hat{l}_t \rangle$$

$$\leq \; B(y_{t+1}; y_t) - B(y_{t+1}; x_t)$$

Sum two inequality above, we have

$$\eta \langle x_t - x^*, l_t \rangle + \eta \langle y_{t+1} - x_t, l_t - \hat{l}_t \rangle$$

$$\leq B(x^*; y_t) - B(x^*; y_{t+1}) - B(y_{t+1}; x_t)$$

$$\leq B(x^*; y_t) - B(x^*; y_{t+1}) - \frac{1}{2} \| y_{t+1} - x_t \|^2$$

We have got this type of inequality a few times.

please complete the remaining proof..

Why Online Gradient/Mirrored Descent?

Online Learning Algorithm

Initialization: $x_1 \in \mathcal{K}$.

For $t = 1, \cdots, T$:

- **Learner:** Submit x_t.
- **Environment:** Observe the cost ℓ_t.
- **Update:** $x_{t+1} = \text{Alg}(x_1, \cdots, x_t, \ell_1, \cdots, \ell_t)$.

We design online learning algorithms to achieve small regret:

- Online gradient/mirrored descent is based on the current x_t and ℓ_t as
$$\text{Alg}(x_t, \ell_t).$$
- Can we use all information to design online algorithms?
$$x_{t+1} = \text{Alg}(x_1, \cdots, x_t, \ell_1, \cdots, \ell_t).$$

Follow-The-Leader (FTL) Algorithm

Follow-The-Leader (FTL) Algorithm

Initialization: $x_1 \in \mathcal{K}$.

For $t = 1, \cdots, T$:

- **Learner:** Submit x_t.
- **Environment:** Observe the convex loss $f_t(\cdot)$.
- **Update:** $x_{t+1} = \arg\min_{x \in \mathcal{K}} \sum_{s=1}^{t} f_s(x)$.

Intuition of Follow-The-Leader (FTL) algorithm:

- A batch/offline learning problem to use all history info.
- Minimize the "regret" for the next round

$$\sum_{s=1}^{t} f_s(x_{t+1}) \leq \sum_{s=1}^{t} f_s(x^*).$$

Follow-The-Leader (FTL) Algorithm

Follow-The-Leader (FTL) Algorithm

Initialization: $x_1 \in \mathcal{K}$.

For $t = 1, \cdots, T$:

- **Learner:** Submit x_t.
- **Environment:** Observe the convex loss $f_t(\cdot)$.
- **Update:** $x_{t+1} = \arg\min_{x \in \mathcal{K}} \ \sum_{s=1}^{t} f_s(x)$.

Follow-The-Leader (FTL) algorithm seems to work!?

What is the regret of FTL algorithms?

$$\mathcal{R}(T) := \sum_{t=1}^{T} f_t(x_t) - \min_{x \in \mathcal{K}} \sum_{t=1}^{T} f_t(x).$$

Follow-The-Leader (FTL) Algorithm – Regret

Theorem 8

Under Follow-The-Leader algorithm, we have the sequence of actions $\{x_t\}$ which satisfies

$$\mathcal{R}(T) := \sum_{t=1}^{T} f_t(x_t) - \min_{x \in \mathcal{K}} \sum_{t=1}^{T} f_t(x) \\ \leq \sum_{t=1}^{T} f_t(x_t) - \sum_{t=1}^{T} f_t(x_{t+1}).$$

Intuitively, we have a small regret if it is "stable":

$$x_t \text{ is close to } x_{t+1}.$$

f_t is convex : $f_t(x_t) - f_t(x_{t+1}) \leq \langle \nabla f_t(x_t), x_t - x_{t+1} \rangle$

We want $\|x_t - x_{t+1}\| = O(\frac{1}{\sqrt{T}})$ to recover $O(\sqrt{T})$ regret!

Follow-The-Leader (FTL) Algorithm – Proof

We prove it by (informal) induction. Please finish the formal proof!

$$\text{FTL}: \quad x_{t+1} = \arg\min \sum_{s=1}^{t} f_s(x_s).$$

$t=2 \qquad f_1(x_2) \leq f_1(x^*)$

$\qquad\qquad \wedge|$

$t=3 \qquad f_1(x_3) + f_2(x_3) \leq f_1(x^*) + f_2(x^*)$

$\qquad\qquad \geq$

$t=4 \qquad f_1(x_4) + f_2(x_4) + f_3(x_4) \leq f_1(x^*) + f_2(x^*) + f_3(x^*)$

$\vdots$

$t=T \qquad f_1(x_2) + f_2(x_3) + \cdots + f_T(x_{T+1}) \leq \sum_{t=1}^{T} f_t(x^*)$

Follow-The-Leader (FTL) Algorithm – Caveat

Follow-The-Leader (FTL) Algorithm

Initialization: $x_1 \in \mathcal{K}$.

For $t = 1, \cdots, T$:

- **Learner:** Submit x_t.
- **Environment:** Observe the convex loss $f_t(\cdot)$.
- **Update:** $x_{t+1} = \arg\min_{x \in \mathcal{K}} \sum_{s=1}^{t} f_s(x)$.

Let's consider a counter example as follows

$$\mathcal{K} = [-1, 1],$$
$$\{f_1, f_2, f_3, f_4, f_5, \cdots, f_T\} = \{0.5x, -x, x, -x, x, \cdots, x\}.$$

What is the regret of FTL algorithms?

Follow-The-Leader (FTL) Algorithm – Caveat

t	1	2	3	4	.....	T
$f_t(x)$	$0.5x$	$-x$	x	$-x$		x
$\sum_{s=1}^{t} f_s(x)$	$0.5x$	$-0.5x$	$0.5x$	$-0.5x$	......	$0.5x$
x_t	0	-1	$+1$	-1	not stable !	
$f_t(x_t)$	0	$+1$	$+1$	$+1$		

Let's compute the regret:

$$\sum_{t=1}^{T} f_t(x_t) = T - 1$$

$$\min_x \sum_{t=1}^{T} f_t(x) = \min_x 0.5x = -0.5$$

$$R(T) = T - 0.5$$

Follow-The-Regularized-Leader (FTRL) Algorithm

We need to make FTL algorithm stable:

$$\text{FTL} + \text{Regularization} = \text{FTRL}.$$

Follow-The-Regularized-Leader (FTRL) Algorithm

Initialization: $x_1 \in \mathcal{K}$.

For $t = 1, \cdots, T$:

- **Learner:** Submit x_t.
- **Environment:** Observe the convex loss $f_t(\cdot)$.
- **Update:** $x_{t+1} = \arg\min_{x \in \mathcal{K}} \ \sum_{s=1}^{t} f_s(x) + R_{t+1}(x)$.

Intuition of Follow-The-Regularized-Leader:

- The regularization term $R_{t+1}(x)$ prevents x_{t+1} going too far from x_t.
- FTRL is FTL with the initial regularization $f_0(x) = R(x)$.

FTRL Algorithm – Regret

Let's consider the linear costs and the quadratic regularizar:

$$f_t(x) = \langle \ell_t, x \rangle, \forall t, \quad R(x) = \frac{1}{2\eta}\|x\|^2.$$

Theorem 9 (linear losses and quadratic regularizar)

Assume $\|x - y\| \leq D, \forall x, y \in \mathcal{K}$ $\|\nabla f_t(x)\| \leq G, \forall x \in \mathcal{K}$. *Under Follow-The-Regularized-Leader algorithm, we have the sequence of actions* $\{x_t\}$ *which satisfies*

$$\mathcal{R}(T) \leq DG\sqrt{2T}.$$

We recover the good result of $O(\sqrt{T})$, which is similar as online gradient descent.

We can also get similar result for a convex loss and other types of regulazizar.

FTRL Algorithm – Proof

Main idea : FTRL $\xRightarrow{\text{reduce to}}$ FTL

FTRL is FTL such that

$$
\begin{array}{ccccc}
f_0(x) & f_1(x) & f_2(x) & \cdots & f_T(x) \\
R(x) & f_1(x) & f_2(x) & \cdots & f_T(x)
\end{array}
$$

$$
\begin{aligned}
R^{FTL}(T) &= \sum_{t=0}^{T} f_t(x_t) - \sum_{t=0}^{T} f_t(x^*) \\
&\leq \sum_{t=0}^{T} f_t(x_t) - \sum_{t=0}^{T} f_t(x_{t+1})
\end{aligned}
$$

$$R^{FTRT}(T) = \sum_{t=1}^{T} f_t(x_t) - \sum_{t=1}^{T} f_t(x^*)$$

$$\leq f_0(x^*) - f_0(x_0) + \sum_{t=1}^{T} f_t(x_t) - \sum_{t=1}^{T} f_t(x_{t+1})$$

$$+ f_0(x_0) - f_0(x_1)$$

$$= R(x^*) - R(x_1) + \sum_{t=1}^{T} f_t(x_t) - f_t(x_{t+1})$$

$$\leq \frac{1}{2\eta}\|x^*\|^2 + \sum_{t=1}^{T} f_t(x_t) - f_t(x_{t+1})$$

Linear cost $f_t(x) = \langle l_t, x \rangle$ and we have

$$\sum_{t=1}^{T} f_t(x_t) - f_t(x_{t+1}) = \sum_{t=1}^{T} \langle l_t, x_t - x_{t+1} \rangle$$

By FTRL, we have

$$x_{t+1} = \arg\min_x \sum_{s=1}^{t} f_s(x) + R(x) \triangleq F_{t+1}(x)$$

$$= \arg\min_x \langle \sum_{s=1}^{t} l_s, x \rangle + \frac{1}{2\eta}\|x\|^2$$

$$\frac{\partial F_{t+1}(x)}{\partial x} = \sum_{s=1}^{t} l_s + \frac{1}{\eta} x = 0 \Rightarrow x_{t+1} = -\eta \sum_{s=1}^{t} l_s$$

Now $x_t - x_{t+1} = \eta l_t$, we finally have

$$R^{FTRT}(T) \leq \frac{1}{2\eta} D^2 + \sum_{t=1}^{T} \eta G^2$$

$$= GD\sqrt{T} \quad \text{when } \eta = \frac{D}{G}\sqrt{T}.$$

How about the convex losses ?

- We still need to bound $f_t(x_t) - f_t(x_{t+1})$ or $\|x_t - x_{t+1}\|$

Let's again come back to FTRL

$$x_{t+1} = \arg\min F_{t+1}(x)$$

By push back lemma :

$$F_{t+1}(x_{t+1}) \leq F_{t+1}(x) - \frac{1}{2\eta}\|x - x_{t+1}\|^2 \quad \forall x$$

$$\frac{1}{2\eta}\|x_t - x_{t+1}\|^2 \leq F_{t+1}(x_t) - F_{t+1}(x_{t+1})$$

$$= \sum_{s=1}^{t} f_s(x_t) + R(x_t) - \sum_{s=1}^{t} f_s(x_{t+1}) + R(x_{t+1})$$

$$= \sum_{s=1}^{t-1} f_s(x_t) + R(x_t) - \sum_{s=1}^{t-1} f_s(x_{t+1}) + R(x_{t+1})$$

$$+ f_t(x_t) - f_t(x_{t+1})$$

$$\Rightarrow \quad \frac{1}{2\eta} \| x_t - x_{t+1} \|^2 \le f_t(x_t) - f_t(x_{t+1})$$

$$\le G \| x_t - x_{t+1} \|$$

We have $\| x_t - x_{t+1} \| \le 2\eta G$ to recover the same regret

$$R^{FTRT}(T) \le \frac{1}{2\eta} D^2 + \sum_{t=1}^{T} \eta G^2$$

Reduction: from Linear to convex

$$R^{FTRL-Linear} = O(\sqrt{T})$$

$$R^{FTRL-convex}$$

$$= \sum_{t=1}^{T} f_t(x_t) - f_t(x^*) \le \sum_{t=1}^{T} \langle x_t - x^*, \nabla f_t(x_t) \rangle$$

$$= O(\sqrt{T})$$

FTRL and OMD Algorithms

Since FTRL and OMD both have regularization terms, any connection between these two algorithms?

- FTRL is

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

- OMD is

$$x_{t+1} = \arg\min_{x \in \mathcal{K}} \langle x, \nabla f_t(x) \rangle + \frac{1}{\eta} B_{\psi}(x; x_t).$$

Let's consider two examples corresponding to two type of gradient algorithms:

- Online gradient descent.
- Exponentiated gradient.

FTRL and OMD Algorithms

Let's consider the linear costs and the quadratic regularizar:

$$f_t(x) = \langle \ell_t, x \rangle, \forall t, \quad R(x) = \frac{1}{2\eta}\|x\|^2.$$

FTRL and OMD Algorithms

Let's consider the expert problem with linear costs and the negative entropy regularizar:

$$f_t(x) = \langle \ell_t, x \rangle, \forall t, \quad R(x) = \frac{1}{\eta} \sum_i x_i \log x_i.$$

$$x_{t+1} = \arg\min_{x \in P} \sum_{s=1}^{t} f_s(x) + \frac{1}{\eta} \sum_{i=1}^{d} x_i \log x_i$$

$$= \arg\min_{x \in P} \underbrace{\left\langle \sum_{s=1}^{t} \ell_s, x \right\rangle + \frac{1}{\eta} \sum_{i=1}^{d} x_i \log x_i}_{F_{t+1}(x)}$$

$$L(x,\lambda) = F_{t+1}(x) + \lambda\left(1 - \sum_{i=1}^{d} x_i\right)$$

$$\frac{\partial L(x,\lambda)}{\partial x_i} = \frac{\partial F_{t+1}(x)}{\partial x_i} - \lambda$$

$$= \sum_{s=1}^{t} l_{s,i} + \frac{1}{\eta} \frac{\partial x_i \log x_i}{\partial x_i} - \lambda$$

$$= \sum_{s=1}^{t} l_{s,i} + \frac{1}{\eta}(\log x_i + 1) - \lambda = 0$$

$$\Rightarrow \log x_i = \eta\lambda - 1 - \eta \sum_{s=1}^{t} l_{s,i}$$

$$\Rightarrow x_{t+1,i} = e^{-\eta \sum_{s=1}^{t} l_{s,i}} \Big/ \sum_{i=1}^{d} e^{-\eta \sum_{s=1}^{t} l_{s,i}}$$

OMD:

$$x_{t+1,i} = \frac{x_{t,i}\, e^{-\eta l_{t,i}}}{\sum_{i=1}^{d} x_{t,i}\, e^{-\eta l_{t,i}}}$$

FTRL and OMD Algorithms

FTRL with the linear losses and adaptive regularization are

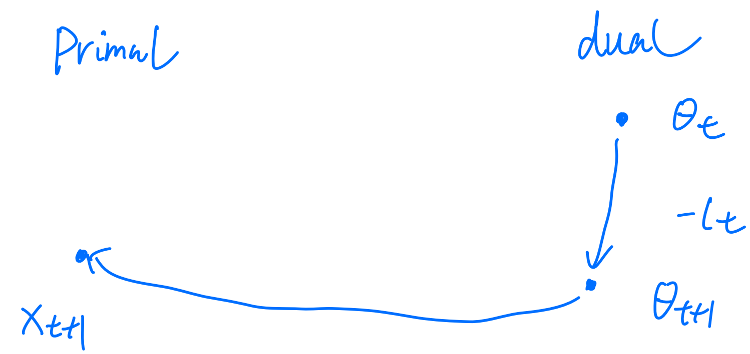
$$
\begin{aligned}
x_{t+1} &= \arg\min_{x\in\mathcal{K}} \sum_{s=1}^{t} f_s(x) + R_{t+1}(x) \\
&= \arg\min_{x\in\mathcal{K}} \langle \sum_{s=1}^{t} \ell_s, x\rangle + R_{t+1}(x) \\
&= \arg\max_{x\in\mathcal{K}} \langle -\sum_{s=1}^{t} \ell_s, x\rangle - R_{t+1}(x)
\end{aligned}
$$

Recall the conjugate definition $f^*(y) = \sup_x \ \langle y, x\rangle - f(x)$. Therefore, we have

$$
x_{t+1} = \nabla R_{t+1}^{*}\left(-\sum_{s=1}^{t} \ell_s\right)
$$

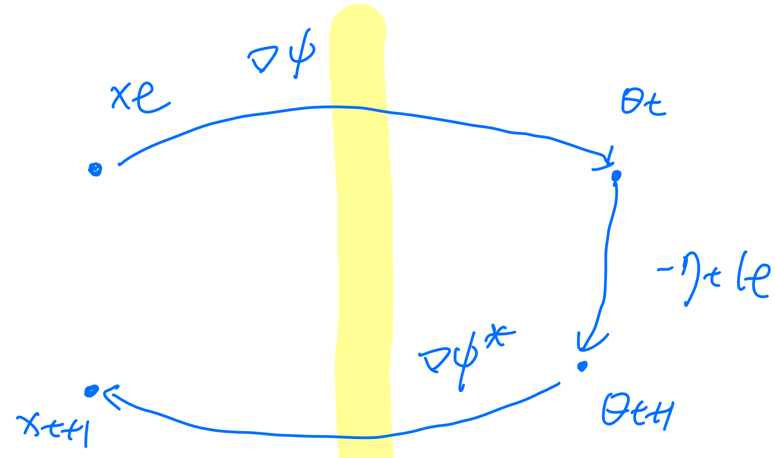
FTRL and OMD Algorithms

Let's define $\theta_{t+1} = -\sum_{s=1}^{t} \ell_s$ and $\theta_{t+1} = \theta_t - \ell_t$.
FTRL updates as



$$\theta_{t+1} = \theta_t - \ell_t$$
$$x_{t+1} = \nabla R_{t+1}^{*}\left(\theta_{t+1}\right)$$

Recall OMD updates as



$$\theta_{t+1} = \nabla\psi(x_t) - \eta_t \ell_t$$
$$x_{t+1} = \nabla\psi^{*}\left(\theta_{t+1}\right)$$

FTRL v.s. OMD:

- FTRL takes "gradient" directly in dual space. Unlike in OMD, it first "mirrors" from x_t to $\theta_t = \nabla\psi(x_t)$.
- FTRL treats losses equally & OMD weights losses by η_t.

Follow-The-Regularized-Leader (FTRL) Algorithm

Initialization: $x_1 \in \mathcal{K}$.

For $t = 1, \cdots, T$:

- **Learner:** Submit x_t.
- **Environment:** Observe the convex loss $f_t(\cdot)$.
- **Update:** $x_{t+1} = \arg\min_{x \in \mathcal{K}} \sum_{s=1}^{t} f_s(x) + R_{t+1}(x)$.

We have already got the intuition on how the regularization helps stabilize the algorithm.

FTRL is a powerful framework to design online algorithms and the adaptive regulazier plays an important role.

- $R_t(x) = \sqrt{t}\|x\|^2$.
- $R_t(x) = \sqrt{t}\sum_i x_i \log x_i$.

FTRL Algorithm – Regret

Let's consider the convex costs $f_t(x)$ and the adaptive regularizar $R_t(x)$ that is "increasing" as time t and α_t-strongly convex.

Theorem 10 (convex losses and adaptive regularizar)

Assume $\|x - y\| \leq D, \forall x, y \in \mathcal{K}$ $\|\nabla f_t(x)\| \leq G, \forall x \in \mathcal{K}$. *Under Follow-The-Regularized-Leader algorithm, we have the sequence of actions* $\{x_t\}$ *which satisfies*

$$\mathcal{R}(T) \leq R_{T+1}(x^*) - \min R_1(x) + \sum_{t=1}^{T} \frac{\|\nabla f_t\|^2}{2\alpha_t}.$$

We recover the good result of $O(\sqrt{T})$ (e.g., the regularizar $R_t(x) = \sqrt{t}\|x\|^2$). It is similar as FTRL with the fixed regularizar.

FTRL Algorithm – Proof

We want to study

$$\mathcal{R}(T) = \sum_{t=1}^{T} f_t(x_t) - \sum_{t=1}^{T} f_t(x^*).$$

Denote $F_t(x) = \sum_{s=1}^{t-1} f_s(x) + R_t(x)$ and we have

$$F_{T+1}(x^*) = \sum_{s=1}^{T} f_s(x^*) + R_{T+1}(x^*).$$

Therefore, we have

$$\mathcal{R}(T) = \sum_{t=1}^{T} f_t(x_t) - F_{T+1}(x^*) + R_{T+1}(x^*).$$

We need to connect $f_t(x_t)$ with $F_t(x_t)$.

FTRL Algorithm – Proof

We have

$$f_t(x_t) + F_t(x_t) = \sum_{s=1}^{t} f_s(x_t) + R_t(x_t)$$

$$F_{t+1}(x_{t+1}) = \sum_{s=1}^{t} f_s(x_{t+1}) + R_{t+1}(x_{t+1})$$

$$
\begin{aligned}
\mathcal{R}(T) &= \sum_{t=1}^{T} f_t(x_t) - F_{T+1}(x^*) + R_{T+1}(x^*) \\
&= \sum_{t=1}^{T} \left(F_t(x_t) - F_{t+1}(x_{t+1}) + f_t(x_t)\right) \\
&\quad + F_{T+1}(x_{T+1}) - F_1(x_1) - F_{T+1}(x^*) + R_{T+1}(x^*) \\
&= \sum_{t=1}^{T} \left(F_t(x_t) - F_{t+1}(x_{t+1}) + f_t(x_t)\right) \\
&\quad + \underbrace{F_{T+1}(x_{T+1}) - F_{T+1}(x^*)}_{\leq 0} + R_{T+1}(x^*) - \underbrace{\min R_1(x)}_{= 0}
\end{aligned}
$$

$$\sum_{t=1}^{T} F_t(x_t) - F_{t+1}(x_{t+1}) = F_1(x_1) - F_{T+1}(x_{T+1})$$

The key is to quantify $F_t(x_t) - F_{t+1}(x_{t+1}) + f_t(x_t)$.

FTRL Algorithm – Proof

Lemma 11 (One-step difference)

Let F_t be α_t-strongly convex function, FTRL algorithm has

$$F_t(x_t) - F_{t+1}(x_{t+1}) + f_t(x_t) \le \frac{\|\nabla f_t\|^2}{2\alpha_t} + R_t(x_{t+1}) - R_{t+1}(x_{t+1}).$$

Hint: pushback lemma!

FTRL Algorithm – Proof

Optimistic FTRL

Optimistic Follow-The-Regularized-Leader (FTRL)

Initialization: $x_1 \in \mathcal{K}$.

For $t = 1, \cdots, T$:

- **Learner:** Submit x_t.
- **Environment:** Observe the convex loss $f_t(\cdot)$.
- **Prediction:** The cost $\hat{f}_{t+1}(\cdot)$.
- **Update:**
  $x_{t+1} = \arg\min_{x \in \mathcal{K}} \ \sum_{s=1}^{t} f_s(x) + \hat{f}_{t+1}(x) + R_{t+1}(x)$.

Intuition:

- FTRL guarantees "not too bad" even with unreliable predictions.
- Decrease the cost further if $\hat{f}_{t+1}(\cdot)$ is reliable.

Optimistic FTRL – Regret

Theorem 12 (Optimistic FTRL)

Assume $\|x - y\| \leq D, \forall x, y \in \mathcal{K}$ $\|\nabla f_t(x)\| \leq G, \forall x \in \mathcal{K}$. $R_t(x)$ *that is "increasing" as time* t *and* α_t*-strongly convex. Under Optimistic Follow-The-Regularized-Leader algorithm, we have the sequence of actions* $\{x_t\}$ *which satisfies*

$$\mathcal{R}(T) \leq R_{T+1}(x^*) - \min R_1(x) + \sum_{t=1}^{T} \frac{\|\nabla f_t - \nabla \hat{f}_t\|^2}{2\alpha_t}.$$

As in OMD with prediction, we have a few observations:

- If the predictions are "perfect", the regret is constant!
- If the predictions are "bad", the regret can be $O(\sqrt{T})$.
- If the predictions are "good", the regret can be $o(\sqrt{T})$.

Optimistic FTRL – Proof

The idea is to do reduction to FTRL. Define F_t and $\tilde{F}_t$

$$F_t(x) = \sum_{s=1}^{t-1} f_s(x) + R_t(x) \qquad \tilde{F}_t(x) = \sum_{s=1}^{t-1} f_s(x) + \hat{f}_t(x) + R_t(x)$$

$$= F_t(x) + \hat{f}_t(x)$$

Recall in the proof Theorem 10, we have

$$h_t = F_t + f_t$$

$$R(T) \leq R_{T+1}(x^*) + \sum_{t=1}^{T} \frac{\|\nabla h_t(x)\|^2}{2\lambda_t}$$

$$= R_{T+1}(x^*) + \sum_{t=1}^{T} \frac{\|\nabla F_t(x_t) + \nabla f_t(x_t)\|^2}{2\lambda_t}$$

$$= R_{T+1}(x^*) + \sum_{t=1}^{T} \frac{\|\nabla f_t(x_t) - \nabla \hat{f}_t(x_t)\|^2}{2\lambda_t}$$

where the last equation holds because

$$x_t = \arg\min \tilde{F}_t(x) \qquad \nabla \tilde{F}_t(x_t) = \nabla F_t(x_t) + \hat{f}_t(x_t) = 0$$

Online Learning with Delayed Feedback

Initialization: $x_1 \in \mathcal{K}$.

For $t = 1, \cdots, T$:

- **Learner:** Submit x_t.
- **Environment:** Observe the convex loss $f_{t-d}(\cdot)$.
- **Update:** $x_{t+1} = \mathrm{Alg}(f_1, f_2, \cdots, f_{t-d})$.

A few examples:

- Subseasonal prediction: the prediction correct or not will be known in 2$\sim$6 weeks.
- Medical treatment: the treatment effective or not will be observed a few days or weeks.
- Dynamic pricing: the promotion working or not will be revealed a few days or weeks.

FTRL with Delayed Feedback

Initialization: $x_1 \in \mathcal{K}$.

For $t = 1, \cdots, T$:

- **Learner:** Submit x_t.
- **Environment:** Observe the convex loss $f_{t-d}(\cdot)$.
- **Update:** $x_{t+1} = \arg\min_{x \in \mathcal{K}} \sum_{s=1}^{t-d} f_s(x) + R_{t+1}(x)$.

Observations of FTRL with delayed feedback:

- Use all revealed feedback seen at time t.
- Large delay degrades the performance because of missing feedback $\sum_{s=t-d+1}^{t} f_s(x)$.

What is the regret of the algorithms?

Delay as Optimism in FTRL

Delay is "optimistism"!!!

Delay as Optimism in FTRL

Initialization: $x_1 \in \mathcal{K}$.

For $t = 1, \cdots, T$:

- **Learner:** Submit x_t.
- **Environment:** Observe the convex loss $f_t(\cdot)$.
- **Prediction:** The cost $\hat{f}_{t+1}(\cdot) = -\sum_{s=t-d+1}^{t} f_s(x)$.
- **Update:**
  $x_{t+1} = \arg\min_{x \in \mathcal{K}} \ \sum_{s=1}^{t} f_s(x) + \hat{f}_{t+1}(x) + R_{t+1}(x)$.

Delayed FTRL $\longrightarrow$ Optimistic FTRL.

Optimistic FTRL is a powerful framework that can handle the prediction and delay!

Delayed FTRL – Regret

Theorem 13 (Delayed FTRL)

Assume $\|x - y\| \leq D, \forall x, y \in \mathcal{K}$ $\|\nabla f_t(x)\| \leq G, \forall x \in \mathcal{K}$. $R_t(x)$ *that is "increasing" as time* t *and* α_t*-strongly convex. Under Follow-The-Regularized-Leader algorithm, we have the sequence of actions* $\{x_t\}$ *which satisfies*

$$\mathcal{R}(T) \leq R_{T+1}(x^*) - \min R_1(x) + \sum_{t=1}^{T} \frac{\|\nabla f_t - \nabla \hat{f}_t\|^2}{2\alpha_t},$$

where $\nabla \hat{f}_t = -\sum_{s=t-d+1}^{t} \nabla f_s$.

The effect caused by the delay:

$$\|\nabla f_t\|^2 \longrightarrow \|\nabla f_t + \textstyle\sum_{s=t-d+1}^{t} \nabla f_s\|^2.$$

Let $\alpha_t = O(1/d\sqrt{T})$. Delayed FTRL achieves the regret of $O(d\sqrt{T})$, where the delay hurts the regret!