CSC 665: Online convex optimization

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1 Background

1.1 Norms

Definition 1. *A function $\|\cdot\| : \mathbb{R}^d \to \mathbb{R}_+$ (that maps x to $\|x\|$) is called a norm, if the following holds:*

1. *(Homogeneity) $\forall a \in \mathbb{R}$, $\|ax\| = |a|\|x\|$.*
2. *(Triangle inequality) $\forall x, y \in \mathbb{R}^d$, $\|x + y\| \le \|x\| + \|y\|$.*
3. *(Point separation) If $\|v\| = 0$, then $v = \vec{0}$. In other words, all nonzero vectors have nonzero norms.*

Definition 2. *For a norm $\|\cdot\|$, define its dual norm as follows:*

$$\|z\|_\star = \sup_{x:\|x\|\le 1} \langle x, z \rangle .$$

(It can be checked that $\|\cdot\|_\star$ also satisfies the requirements of a norm.)

Example 1.

1. *$\|\cdot\|_2$ has dual norm $\|\cdot\|_2$.*
2. *In general, for $p, q \in [1, \infty]$ being conjugate exponents, that is $\frac{1}{p} + \frac{1}{q} = 1$, $\|\cdot\|_p$ has dual norm $\|\cdot\|_q$.*
3. *Given a positive definite matrix A, define $\|x\|_A = \sqrt{x^\top A x}$. It has dual norm $\|\cdot\|_{A^{-1}}$.*

Fact 1 ("Cauchy-Schwarz" for general norms)**.** *For any norm $\|\|$ and its dual norm $\|\|_\star$, and any two points $x, z \in \mathbb{R}^d$,*

$$\langle x, z \rangle \le \|x\|\|z\|_\star.$$

The fact simply follows from the definition of dual norm.

One might wonder, $\|\cdot\|$ has dual norm $\|\cdot\|_\star$, but what is the dual norm of $\|\cdot\|_\star$? It turns out that under mild assumptions, the dual of $\|\cdot\|_\star$ is $\|\cdot\|$.

1.2 Convexity

Definition 3. *Define convex sets and convex functions as follows:*

1. *For any u, v and any $\alpha \in [0, 1]$, the* convex combination *between u and v with coefficient α is defined as $\alpha u + (1 - \alpha)v$.*
2. *A set $\mathcal{C} \subset \mathbb{R}^d$ is* convex, *if for u and v in $\mathcal{C}$, and any coefficient $\alpha \in [0, 1]$, their convex combination with coefficient α is in $\mathcal{C}$.*
3. *A function $f : \mathcal{C} \to \mathbb{R}$ is* convex, *if (1) its domain $\mathcal{C}$ is convex, (2) for any u, v in $\mathcal{C}$, and any $\alpha \in [0, 1]$, $f(\alpha u + (1 - \alpha)v) \le \alpha f(u) + (1 - \alpha)f(v)$.*

If we have a convex function f on a convex domain $\mathcal{C}$, we define its extension to $\mathbb{R}^d$ as

$$\bar{f}(x) = \begin{cases} f(x) & x \in \mathcal{C} \\ +\infty & x \notin \mathcal{C} \end{cases}. \tag{1}$$

Sometimes we will use $f : \mathcal{C} \to \mathbb{R}$ and $\bar{f} : \mathbb{R}^d \to \mathbb{R} \cup \{+\infty\}$ interchangably.

Fact 2 (Local minimum vs. global minimum)**.** *Suppose f is a convex function. If x is a local minimum of f, in that there exists a radius $r > 0$ such that for all y such that $\|y - x\| \le r$, $f(x) \le f(y)$, then x is also a global minimum f.*

Definition 4 (Subgradient)**.** *Given a convex function $f : \mathcal{C} \to \mathbb{R}$ and a point $v \in \mathcal{C}$, define $\partial f(v)$ as the set of $g \in \mathbb{R}^d$'s such that:*

$$\forall u \in \mathcal{C}, \quad f(u) \ge f(v) + \langle g, u - v \rangle .$$

Therefore, for convex f, if $0 \in \partial f(x^\star)$, then $x^\star$ is the global minimum of f. However for $f : \mathcal{C} \to \mathbb{R}$, a global minimum of f in $\mathcal{C}$ may not necessarily have zero subgradient: for example, suppose $\mathcal{C} = [-1, +1]$ and $f(x) = x$, then the global minimum $x^\star = -1$, but f has subgradient 1 on $x^\star$. Nevertheless, we have the following first order optimality condition.

Fact 3 (First order optimality condition)**.** *For a convex set $\mathcal{C}$ and $f : \mathcal{C} \to \mathbb{R}$. Suppose $x^\star \in \mathcal{C}$ is the global minimum of f, then we have that there exists $g \in \partial f(x^\star)$:*

$$\forall x \in \mathcal{C}, \quad \langle g, x - x^\star \rangle \ge 0. \tag{2}$$

The proof of this fact is not trivial and can be found at [1, Proposition 4.7.2]. We make the following two remarks:

1. The "exists $g \in \partial f(x^\star)$" cannot be replaced with "for any $g \in \partial f(x^\star)$": for example, if $f(x) = |x|$ over $\mathcal{C} = [-1, +1]$, $x^\star = 0$, but we can only take $g = 0 \in \partial f(0)$ such that Equation (2) is true.
2. If f is differentiable, then the above fact is not hard to show: indeed, we only need to check that $\forall x \in \mathcal{C}, \quad \left\langle \nabla f(x^\star), x - x^\star \right\rangle \ge 0$. If this were not true, i.e. $\left\langle \nabla f(x^\star), x - x^\star \right\rangle < 0$, then it can be seen that
$$f(x^\star + \alpha(x - x^\star)) = f(x^\star) + \alpha \cdot \left\langle \nabla f(x^\star), x - x^\star \right\rangle + o(\alpha),$$
and is smaller than $f(x^\star)$ when α is small enough; contradiction.

Fact 4. *For any convex $f : \mathcal{C} \to \mathbb{R}$ and a point $v \in \mathcal{C}$, $\partial f(v) \ne \emptyset$, i.e. subgradient always exists. If f is differentiable at v, then $\partial f(v) = \left\{ \nabla f(v) \right\}$.*

Example 2. *For function $f(x) = |x|$,*

$$\partial f(x) = \begin{cases} +1 & x > 0, \\ [-1, +1] & x = 0, \\ -1 & x < 0. \end{cases}$$

Definition 5 (Bregman divergence)**.** *For a differentiable convex function f, define its induced Bregman divergence on points u and v as:*

$$D_f(u, v) = f(u) - f(v) - \left\langle \nabla f(v), u - v \right\rangle .$$

In words, $D_f(u, v)$ is the gap between f and its first order approximation (using v) at location u. By convexity of f, $D_f(u, v)$ is always nonnegative. Interestingly, $D_f(u, v)$ may not agree with $D_f(v, u)$, as can be seen in the second example below.

Example 3. 1. *If* $f(x) = \frac{\lambda}{2}\|x\|^2$*, then* $D_f(u,v) = \frac{\lambda}{2}\|u-v\|_2^2$.

2. *If* $f(x) = \sum_{i=1}^d x_i \ln x_i$*, then* $D_f(u,v) = \sum_{i=1}^d (u_i \ln \frac{u_i}{v_i} - u_i + v_i)$*. This is the* unnormalized relative entropy *between* u *and* v*; if both* u *and* v *are in* Δ^{d-1}*, then* $D_f(u,v)$ *is the* relative entropy *between these two probability vectors.*

Fact 5 (Building convex functions from simple ones)**.** *Suppose* $f_1, \dots, f_n$ *is a collection of convex functions.*

1. *If* $w_1, \dots, w_n \geq 0$*, then* $\sum_{i=1}^n w_i f_i(x)$ *is convex.*
2. *Let* $f(x) = \max(f_1(x), \dots, f_n(x))$*. Then* f *is convex. Moreover, given an* x*,* $\partial f(x)$ *contains elements of* $\partial f_i(x)$*, where* $i \in \arg\max_{i=1}^n f_i(x)$.

Definition 6. f *is* L*-Lipschitz with respect to norm* $\|\cdot\|$ *if for any* u, v*,* $f(u) - f(v) \leq L\|u - v\|$.

Fact 6. *For any convex* $f : \mathcal{C} \to \mathbb{R}$*,*

$$f \text{ is } L-\text{Lipschitz} \Leftrightarrow \forall v, \forall g \in \partial f(v), \|g\|_\star \leq L.$$

Therefore, for differentiable functions, to check Lipschitzness, it suffices to check that the gradients at all locations have uniformly-bounded norms.

1.3 Strong convexity

Definition 7 (Strong convexity)**.** *A function* $f : \mathcal{C} \to \mathbb{R}$ *is* λ*-strongly convex with respect to norm* $\|\cdot\|$*, if for any two points* $u, v \in \mathcal{C}$*, and* $\alpha \in [0,1]$*,*

$$f(\alpha u + (1-\alpha)v) \leq \alpha f(u) + (1-\alpha) f(v) - \frac{\lambda}{2}\alpha(1-\alpha)\|u-v\|^2.$$

Strong convexity requires that the gap between interpolated function values and the function value of the interpolated input to have a quadratic lower bound. Clearly, if f is λ-strongly convex, then f is λ'-strongly convex for $\lambda' < \lambda$. Moreover, a function f is 0-strongly convex iff f is convex.

We have the following simple additivity property on strong convexity simply by definition:

Lemma 1. *If* f_1 *and* f_2 *are* λ_1*- and* λ_2*- strongly convex with respect to* $\|\cdot\|$ *respectively, then* $f_1 + f_2$ *is* $\lambda_1 + \lambda_2$*-strongly convex. Specifically, a* λ*-strongly convex function plus a convex function is still* λ*-strongly convex.*

Fact 7. *The following are equivalent:*

1. f *is* λ*-strongly convex.*
2. *For any* v *in* $\mathcal{C}$*, and* $g \in \partial f(v)$*,*

$$f(u) \geq f(v) + \langle g, u - v\rangle + \frac{\lambda}{2}\|u - v\|^2, \forall u \in \mathcal{C}\,.$$

3. *For any* v *in* $\mathcal{C}$*, there exists a vector* g *such that:*

$$f(u) \geq f(v) + \langle g, u - v\rangle + \frac{\lambda}{2}\|u - v\|^2, \forall u \in \mathcal{C}\,.$$

Properties 2 or 3 are sometimes easier to check than the original strong convexity definition. Specifically, if f is differentiable, using the equivalence between items 1 and 2, strong convexity is equivalent to a quadratic lower bound on Bregman divergence: $D_f(u,v) \geq \frac{\lambda}{2}\|u-v\|^2$.

Example 4. 1. *If $f(x) = \frac{\lambda}{2}\|x\|^2$, then $D_f(u,v) = \frac{\lambda}{2}\|u-v\|_2^2$. Therefore f is λ-strongly convex with respect to $\|\cdot\|_2$.*

2. *If $f(x) = \sum_{i=1}^d x_i \ln x_i, x \in \left\{x \in \mathbb{R}^d : x_i > 0, \forall i, \text{ and } \sum_{i=1}^d x_i \le B_1\right\}$, then it can be checked by second-order Taylor's Theorem that $D_f(u,v) \ge \frac{1}{2B_1}\|u-v\|_1^2$, in other words, f is $\frac{1}{B_1}$-strongly convex with respect to $\|\cdot\|_1$.*

Strongly convex functions have unique global minima, as given by the following fact:

Fact 8. *If $f : \mathcal{C} \to \mathbb{R}$ is λ-strongly convex, and $x^\star$ is a global minimum of f in $\mathcal{C}$, then $f(x) - f(x^\star) \ge \frac{\lambda}{2}\|x - x^\star\|^2$. Consequently, if $x \in \mathcal{C}$ is such that $f(x) \le f(x^\star)$, then $x = x^\star$.*

Proof. Note that for all $g \in \partial f(x^\star)$, we have that for all $x \in \mathcal{C}$,

$$f(x) - f(x^\star) \ge \langle g, x - x^\star \rangle + \frac{\lambda}{2}\|x - x^\star\|^2.$$

Now, by first order optimality condition (Fact 3), we also have that there exists $g_0 \in \partial f(x^\star)$, such that for all $x \in \mathcal{C}$,

$$\langle g_0, x - x^\star \rangle \ge 0.$$

Combining the above two inequalities, we immediately conclude that

$$f(x) - f(x^\star) \ge \frac{\lambda}{2}\|x - x^\star\|^2.$$

The second statement directly follows from the point separation property of norms. □

For twice-differentiable f, strong convexity with respect to $\|\cdot\|_2$ reduces to the following simple criterion.

Fact 9. *Suppose f is twice differentiable. f is λ-strongly convex with respect to $\|\cdot\|_2$ iff for any x, $\nabla^2 f(x) \succeq \lambda I$.*

1.4 Smoothness

Definition 8 (Smoothness)**.** *A differentiable function f is called β-smooth with respect to norm $\|\cdot\|$, if for any u, v, $\|\nabla f(u) - \nabla f(v)\|_\star \le \beta\|u - v\|$. In other words, ∇f is β-Lipschitz with respect to $\|\cdot\|$.*

Fact 10. *The following are equivalent:*

1. *f is β-smooth with respect to norm $\|\cdot\|$.*
2. *For any u, v, $f(u) \le f(v) + \langle \nabla f(v), u - v \rangle + \frac{\beta}{2}\|u - v\|^2$.*
3. *For any u, v, $f(u) \ge f(v) + \langle \nabla f(v), u - v \rangle + \frac{1}{2\beta}\|\nabla f(u) - \nabla f(v)\|^2$.*

It can be seen that, smoothness is opposite to strong convexity: it asks for a function f, $D_f(u,v) \le \frac{\beta}{2}\|u - v\|^2$ for any u, v. Therefore, if f is both λ-strongly convex and β-smooth, then $\lambda \le \beta$.

Again for twice-differentiable function f and ℓ_2 norm, we have a simpler way to check smoothness:

Fact 11. *Suppose f is twice differentiable. f is β-smooth with respect to $\|\cdot\|_2$ iff for any x, $\nabla^2 f(x) \preceq \beta I$.*

1.5 Legendre-Fenchel duality

Main idea: given convex function $f : \mathcal{C} \to \mathbb{R}$, use all its tangents to charaterize it.

Fix a slope s, we would like find a tangent of f with slope s. One charaterization of the tangent is that, go over all x's, look at the gaps between $f(x)$ and $\langle s, x\rangle$, and find the location with the smallest gap. This smallest gap is the offset b, such that $\langle s, x\rangle + b$ is the tangent of f with slope s.

As discussed above, the offeset can be written as:

$$b(s) = \min_{x\in\mathcal{C}} \left(f(x) - \langle s, x\rangle \right).$$

We define the Legendre-Fenchel conjugate of f as $-b(s)$, denoted as $f^\star(s)$.

Definition 9. *Given convex function $f : \mathcal{C} \to \mathbb{R}$, its Legendre-Fenchel conjugate (dual), $f^\star$, is defined as*

$$f^\star(s) = \max_{x\in\mathcal{C}} \left(\langle s, x\rangle - f(x) \right).$$

Remark. Alternatively, if we extend f to domain $\mathbb{R}^d$ using the definition of $\bar{f}$ in Equation 1, and taking the Legendre-Fenchel dual, we get the same $f^\star$. Namely,

$$\max_{x\in\mathcal{C}} \left(\langle s, x\rangle - f(x) \right) = \max_{x\in\mathbb{R}^d} \left(\langle s, x\rangle - \bar{f}(x) \right).$$

This can be easily seen by noting that if $x \notin \mathcal{C}$, then it must not achieve the maximum on the function of x on the right hand side, as $\langle s, x\rangle - \bar{f}(x) = -\infty$.

As $f^\star$ is the pointwise maximum of a collection of convex functions, $f^\star$ is convex. Can we give a characterization of the subgradient of $f^\star$? Using a generalization of Fact 5, and the facts that $h_x(s) = \langle s, x\rangle - f(x)$ has subgradient x, and $f^\star(s) = \max_x h_x(s)$, we can see that

$$\operatorname*{argmax}_{x\in\mathcal{C}} \left(\langle s, x\rangle - f(x) \right) \in \partial f^\star(s).$$

Let us look at the dual of $f^\star$, that is $f^{\star\star}(x) = \max_s \left(\langle x, s\rangle - f^\star(s) \right)$. This equation has a nice geometric interpretation. Recall that for each s, $\langle x, s\rangle - f^\star(s)$ is the tangent of f of slope s; therefore, by varying s in $\mathbb{R}$, we get a collection of lines below f. $f^{\star\star}$ is an upper envelope of these lines. Curiously, under mild assumptions, $f^{\star\star}$ is exactly the original function f.

Fact 12. *Suppose f is closed (in that $\left\{(x, t) \in \mathbb{R}^{d+1} : f(x) \le t\right\}$ is a closed set) and convex, then $f^{\star\star} = f$. In words, the dual of the dual is the original function.*

The following simple fact is by the definition of Legendre-Fenchel conjugate function:

Fact 13 (Fenchel-Young's Inequality)**.** *For any pairs of x and s in $\mathbb{R}^d$,*

$$f(x) + f^\star(s) \ge \langle x, s\rangle.$$

Example 5.

1. *For conjugate exponents $p, q \in (1, \infty)$ such that $\frac{1}{p} + \frac{1}{q} = 1$, if $f(x) = \frac{x^p}{p}$, then $f^\star(s) = \frac{s^q}{q}$. This is the classical Young's inequality.*
2. *For any norm $\|\cdot\|$, if $f(x) = \frac{\lambda}{2}\|x\|^2$, then $f^\star(s) = \frac{1}{2\lambda}\|s\|_\star^2$.*
3. *If $f(x) = \begin{cases} \sum_{i=1}^d x_i \ln x_i, & x \in \Delta^{d-1} \\ +\infty, & x \notin \Delta^{d-1} \end{cases}$, then $f^\star(s) = \ln \sum_{s=1}^d e^{s_i}$.*
4. *If $f(x) = \begin{cases} \sum_{i=1}^d x_i \ln x_i, & x \succ 0 \\ +\infty, & x \not\succ 0 \end{cases}$, then $f^\star(s) = \sum_{i=1}^d e^{s_i - 1}$.*

If $f \geq g$, then by the definition of conjugate function, $f^\star \leq g^\star$.

It can be shown that for a strongly convex f, $f^\star$ is differentiable. Specifically,

$$\nabla f^\star(s) = \operatorname*{argmax}_{x \in \mathcal{C}} \left(\langle s, x \rangle - f(x) \right),$$

as f is strongly convex, the right hand side has unique element and the equality is thus well-defined.

Fact 14. *f is λ-strongly convex with respect to $\|\cdot\|$ iff $f^\star$ is $\frac{1}{\lambda}$-smooth with respect to $\|\cdot\|_\star$.*

Proof. We only show the "only if" here. The proof of the "if" statement can be found at [7, Theorem 3]. Our goal is to show that for u, v,

$$\|x_u - x_v\|_\star \leq \frac{1}{\lambda}\|u - v\|,$$

where

$$x_u = \nabla f^\star(u) = \operatorname*{argmin}_{x \in \mathcal{C}} h_u(x), \text{ where } h_u(x) = \left(f(x) - \langle u, x \rangle \right),$$
$$x_v = \nabla f^\star(v) = \operatorname*{argmin}_{x \in \mathcal{C}} h_v(x), \text{ where } h_v(x) = \left(f(x) - \langle v, x \rangle \right).$$

Note that h_u and h_v are close to each other when u and v are close: but close functions may not necessarily imply that their optimal points are close to each other; for example, $f(x) = 0.01x$ has minimum at $-\infty$, and $f(x) = -0.01x$ has minimum at $+\infty$; luckily, for strongly convex functions that differ by a small linear function, we show that their minimum points are close.

By the strong convexity of $h_u(x)$ (resp. $h_v(x)$) and the optimality of x_u (resp. x_v), and Fact 8, we have:

$$h_u(x_v) \geq h_u(x_u) + \frac{\lambda}{2}\|x_u - x_v\|^2,$$
$$h_v(x_u) \geq h_v(x_v) + \frac{\lambda}{2}\|x_u - x_v\|^2.$$

Summing the two inequalities up,

$$\langle u - v, x_u - x_v \rangle \geq \lambda \|x_u - x_v\|^2.$$

By the generalized Cauchy-Schwarz, we have

$$\lambda \|x_u - x_v\|^2 \leq \|u - v\| \|x_u - x_v\|,$$

implying

$$\|x_u - x_v\|_\star \leq \frac{1}{\lambda}\|u - v\|. \qquad \square$$

The above fact shows that, if f is more "curved", then $f^\star$ is more "flat", and vice versa.

2 Online convex optimization

Setup [5, 12]: see Framework 1.

Equivalent goal: minimize regret against *the best fixed point in hindsight*:

$$\mathrm{Reg}(T, \mathcal{C}) = \max_{w^\star \in \mathcal{C}} \mathrm{Reg}(T, w^\star) = \sum_{t=1}^T f_t(w_t) - \min_{w^\star \in \mathcal{C}} \sum_{t=1}^T f_t(w^\star),$$

where

$$\mathrm{Reg}(T, w^\star) = \sum_{t=1}^T f_t(w_t) - \sum_{t=1}^T f_t(w^\star).$$

Definition 10. *Suppose for every f_t, $f_t(w) = \langle g_t, w \rangle$ for some vector g_t, then the OCO problem is called an online linear optimization (OLO) problem.*

Algorithm 1 Online convex optimization (OCO)

Require: Convex decision set $\mathcal{C}$.

for timesteps $t = 1, 2, \dots, T$: **do**

Learner chooses $w_t \in \mathcal{C}$,

Learner receives a convex loss f_t.

end for

Goal: minimize cumulative loss $\sum_{t=1}^{T} f_t(w_t)$.

2.1 Follow the regularized leader (FTRL) for OLO

Given a λ-strongly convex regularization function Φ, set

$$\begin{aligned} w_t &= \operatorname*{argmin}_w \sum_{s=1}^{t-1} \langle g_s, w \rangle + \Phi(w) \\ &= \operatorname*{argmax}_w \langle -G_{t-1}, w \rangle - \Phi(w) \\ &= \nabla \Phi^\star(-G_{t-1}), \end{aligned}$$

where $G_t = \sum_{s=1}^{t} g_s$ is the cumulative gradients. the mapping $\nabla\Phi^\star$ is called the *mirror map* or *link function*, that "transports" the cumulative negative gradient to a point in the decision space.

Example 6. *We give a few instantiations of FTRL:*

1. *Hedge as FTRL: let $g_t = \ell_t$ for every t, and let $\Phi(w) = \begin{cases} \frac{1}{\eta}\sum_{i=1}^{d} w_i \ln w_i, & w \in \Delta^{d-1} \\ +\infty, & w \notin \Delta^{d-1} \end{cases}$, then it can be checked that*
$$w_{t,i} = \exp\left(-\eta \sum_{s=1}^{t-1} \ell_{s,i}\right).$$
2. *Online gradient descent: let $\Phi(w) = \frac{1}{2\eta}\|w\|_2^2$, then $R^\star(G) = \frac{\eta}{2}\|G\|_2^2$, and $\nabla R^\star(G) = \eta G$. Therefore, $w_t = -\eta G_{t-1} = -\sum_{s=1}^{t-1} \eta g_s$. This is the cumulative sum of negative gradients, times a stepsize of η.*
3. *Online gradient descent with lazy projections: let $\Phi(w) = \begin{cases} \frac{1}{2\eta}\|w\|^2, & w \in \mathcal{C}, \\ +\infty, & w \notin \mathcal{C} \end{cases}$, then it can be shown that,*
$$w_t = \operatorname*{argmin}_{w \in \mathcal{C}} \|w - (-\eta G_{t-1})\|_2,$$
which is the ℓ_2-projection of the point returned by online gradient descent to the convex set $\mathcal{C}$.

In this theoreom below, we will show that FTRL has a small regret given an appropriately-tuned step size η.

Theorem 1. *If R is λ-strongly convex with respect to $\|\cdot\|$, then FTRL has the following regret agains benchmark $w^\star$:*
$$\mathrm{Reg}(T, w^\star) = \sum_{t=1}^{T} \langle g_t, w_t - w \rangle \le \Phi(w^\star) - \min_{w'} \Phi(w') + \frac{1}{\lambda}\sum_{t=1}^{T} \|g_t\|_\star^2.$$

Proof. Recall that $f_t(w) = \langle g_t, w \rangle$. We break the proof into two steps:

1. Consider a 'look-ahead' prediction strategy named the "be-the-regularized leader" (BTRL), that is, at time t, w_{t+1}'s are selected as the decision point. We will show that BTRL has a small regret.

2. Note that BTRL cannot be implemented as a real algorithm: w_{t+1} relies on information on g_t, which is unavailable at the beginning of round t. Nevertheless, we will show that w_t, the decision point selected by FTRL, is close to w_{t+1}, therefore the regret of FTRL can be bounded in terms of that of BTRL.

Step 1: Analysis of BTRL. Denote by $f_0(w) = \Phi(w)$. Consider a modification of the original OCO game: there is an extra round of online convex optimization at the beginning, namely round 0. Therefore, algorithmically, BTRL is equivalent to Be-the-leader (BTL) on $\{f_0, f_1, \ldots, f_T\}$. We will show that BTL has nonpositive regret on this modified OCO game, and relate this regret guarantee to that of the original OCO game.

Lemma 2 (Be the leader)**.** *For any $w^\star$,*

$$\sum_{t=0}^{T} f_t(w_{t+1}) \leq \sum_{t=0}^{T} f_t(w^\star).$$

Proof. This is best illustrated by iteratively relaxing the right hand side; as $w_{T+1} = \operatorname{argmin}_w \sum_{t=0}^{T} f_t(w)$, we have that

$$\sum_{t=0}^{T} f_t(w_{T+1}) \leq \sum_{t=0}^{T} f_t(w^\star).$$

Now let us focus on all but the last term in the left hand side, that is, $\sum_{t=0}^{T-1} f_t(w_{t+1})$. As as $w_T = \operatorname{argmin}_w \sum_{t=0}^{T-1} f_t(w)$, we have that

$$\left(\sum_{t=0}^{T-1} f_t(w_T)\right) + f_T(w_{T+1}) \leq \sum_{t=0}^{T} f_t(w_{T+1}) \leq \sum_{t=0}^{T} f_t(w^\star).$$

By iteratively using the fact that $w_\tau = \operatorname{argmin}_w \sum_{t=0}^{\tau-1} f_t(w)$, we have that

$$\left(\sum_{t=0}^{\tau-1} f_t(w_\tau)\right) + f_\tau(w_{\tau+1}) + \ldots + f_T(w_{T+1}) \leq \sum_{t=0}^{T} f_t(w^\star).$$

The lemma is a direct consequence of the above inequality in the case of $\tau = 1$. □

Lemma 2 immediately implies that:

$$\sum_{t=1}^{T} \langle g_t, w_{t+1} - w^\star \rangle \leq \Phi(w^\star) - \Phi(w_1). \tag{3}$$

Step 2: relating BTRL to FTRL. Our next task will be to upper bound $\sum_{t=1}^{T} \langle g_t, w_t - w_{t+1} \rangle$, the difference of the cumulative losses of FTRL and BTRL.

Lemma 3 (Stability)**.**

$$\sum_{t=1}^{T} \langle g_t, w_t - w_{t+1} \rangle \leq \frac{1}{\lambda} \sum_{t=1}^{T} \|g_t\|_\star^2. \tag{4}$$

Proof. We will show that for every t, $\langle g_t, w_t - w_{t+1} \rangle \le \frac{1}{\lambda}\|g_t\|_\star^2$. To show this, by generalized Cauchy-Schwarz, it suffices to show that

$$\|w_t - w_{t+1}\| \le \frac{1}{\lambda}\|g_t\|_\star.$$

By definition of $w_t = \nabla\Phi^\star(-G_{t-1})$ and $w_{t+1} = \nabla\Phi^\star(-G_t)$, we see that

$$\|w_t - w_{t+1}\| = \|\nabla\Phi^\star(-G_{t-1}) - \nabla\Phi^\star(-G_t)\|.$$

Recall that Φ is λ-strongly convex, by Fact 14, $\Phi^\star$ is $\frac{1}{\lambda}$-smooth. Therefore the right hand side is indeed at most $\frac{1}{\lambda}\| - G_{t-1} - (-G_t)\| = \frac{1}{\lambda}\|g_t\|_\star$. □

The theorem is proved by summing Equations (3) and (4) together. □

2.2 FTRL for general OCO

It turns out that a low-regret algorithm for OLO immediately yields an algorithm for OCO. To see this, suppose that at every iteration t, f_t is a general convex function. Now, suppose that $g_t \in \partial f_t(w_t)$ is a subgradient of f_t at location x_t. We have that for any $w^\star$,

$$f_t(w_t) - f_t(w^\star) \le \langle g_t, w_t - w^\star \rangle .$$

Therefore, if we let $\tilde{f}_t(w) = \langle g_t, w \rangle$, and run FTRL on $\tilde{f}_t$'s, we get that

$$\sum_{t=1}^{T} \langle g_t, w_t - w^\star \rangle \le \mathrm{R}(T)$$

for some regret function $\mathrm{R}(T)$. This implies that

$$\mathrm{Reg}(T, w^\star) = \sum_{t=1}^{T} f_t(w_t) - f_t(w^\star) \le \sum_{t=1}^{T} \langle g_t, w_t - w^\star \rangle \le \mathrm{R}(T).$$

2.3 Instantiations of FTRL: theoretical guarantees

1. Online gradient descent (OGD) [12]: $\Phi(w) = \frac{1}{2\eta}\|w\|_2^2$, which is $\frac{1}{\eta}$-strongly convex wrt $\|\cdot\|_2$. FTRL with Φ has regret

   $$\mathrm{Reg}(T, w^\star) \le \frac{\|w^\star\|_2^2}{2\eta} + \eta\sum_{t=1}^{T}\|g_t\|_2^2,$$

   for all benchmark $w^\star \in \mathbb{R}^d$.

   Suppose we would like to guarantee $\mathrm{Reg}(T, \mathcal{C})$ with $\mathcal{C} \subset \{w : \|w\| \le B_2\}$. If in addition, it is known apriori that $\|g_t\| \le R_2$, then

   $$\mathrm{Reg}(T, \mathcal{C}) \le \frac{B_2^2}{2\eta} + \eta T R_2^2.$$

   We can setting $\eta = \frac{B_2}{R_2\sqrt{2T}}$ that minimize the regret bound, which gives $B_2 R_2\sqrt{2T}$.

2. OGD with lazy projections:

   $$\Phi(w) = \begin{cases} \frac{1}{2\eta}\|w\|_2^2 & w \in \mathcal{C} \\ +\infty & w \notin \mathcal{C} \end{cases},$$

which is also $\frac{1}{\eta}$-strongly convex wrt $\|\cdot\|_2$. Note that FTRL in this case ensures $w_t \in \mathcal{C}$ at every round. This is useful in error or safety critical settings (for exmaple, taking actions in $\mathcal{C}$ prevents self-driving cars from falling off cliffs). FTRL with Φ has regret:

$$\mathrm{Reg}(T, w^\star) \leq \frac{\|w^\star\|_2^2}{2\eta} + \eta \sum_{t=1}^T \|g_t\|_2^2,$$

for all benchmark $w^\star \in \mathcal{C}$. Again, setting $\eta = \frac{B_2}{R_2\sqrt{2T}}$ guarantees $\mathrm{Reg}(T, \mathcal{C}) \leq B_2 R_2 \sqrt{2T}$.

3. p-norm algorithms ($p \in (1, 2]$) [6, 4]: It is known that $\Phi(w) = \frac{1}{2\eta}\|w\|_p^2$ is $\frac{p-1}{\eta}$-strongly convex wrt $\|\cdot\|_p$. FTRL with R has regret:

$$\mathrm{Reg}(T, w) \leq \frac{\|w\|_p^2}{2\eta} + \frac{\eta}{p-1} \sum_{t=1}^T \|g_t\|_q^2.$$

If $\mathcal{C} \subset \left\{w : \|w\|_p \leq B_p\right\}$, and for all t, $\|g_t\|_q \leq R_q$, setting $\eta = \frac{B_p}{R_q\sqrt{2(p-1)T}}$ implies that

$$\mathrm{Reg}(T, \mathcal{C}) \leq B_p R_q \sqrt{\frac{2T}{p-1}}.$$

4. Exponentiated gradient (Hedge) [3, 8]: consider the negative entropy regularizer

$$\Phi(w) = \begin{cases} \frac{1}{\eta}\sum_{i=1}^d w_i \ln x_i, & w \in \Delta^{d-1}, \\ +\infty, & \text{otherwise}. \end{cases}$$

Recall that by the calibration exercise, $\Phi(w)$ is 1-strongly convex with respect to $\|\cdot\|_1$. Therefore, FTRL with R has regret:

$$\mathrm{Reg}(T, w^\star) \leq \frac{\sum_{i=1}^d w_i^\star \ln w_i^\star - \min_{w' \in \Delta^{d-1}} \sum_{i=1}^d w_i' \ln w_i'}{\eta} + \eta \sum_{t=1}^T \|g_t\|_\infty^2.$$

It can be seen that $\sum_{i=1}^d w_i^\star \ln w_i^\star \leq 0$, on the other hand, $\min_{w' \in \Delta^{d-1}} \sum_{i=1}^d w_i' \ln w_i' = -\max_{w' \in \Delta^{d-1}} H(w)$, where $H(w)$ is the entropy of probability vector w. Therefore, it is $-\ln d$. This implies that the first term is at most $\frac{\ln d}{\eta}$. Now suppose we know that all t is such that $\|g_t\|_\infty \leq R_\infty$, we have

$$\mathrm{Reg}(T, w) \leq \frac{\ln d}{\eta} + \eta T R_\infty^2.$$

Setting $\eta = \frac{\sqrt{\ln d}}{R_\infty \sqrt{T}}$ gives that

$$\mathrm{Reg}(T, \Delta^{d-1}) \leq 2R_\infty \sqrt{T \ln d}.$$

(The above regularizer can also be used to deal with a scaled version of probability simplex:

$$\left\{ w : \forall i, w_i > 0, \sum_{i=1}^d w_i = B_1 \right\},$$

for general $B_1 > 0$; we skip the discussion for brevity.)

Algorithm 2 Online linear classification (with FTRL)

Require: Regularizer R, stepsize η.

for timesteps $t = 1, 2, \ldots, T$: **do**

Learner chooses $w_t = \operatorname{argmin}_w \left(\frac{1}{\eta}\Phi(w) + \sum_{s=1}^{t-1} \langle g_s, w\rangle \right) = \nabla(\frac{1}{\eta}\Phi)^\star(-\sum_{s=1}^{t-1} g_s) \in \mathbb{R}^d$,

Learner receives an example (x_t, y_t).

Learner suffers from zero-one loss $M_t = \mathbf{1}(\langle w_t, y_t x_t\rangle \leq 0)$.

Induced loss $f_t(w) = \mathbf{1}(\langle w_t, y_t x_t\rangle \leq 0)(1 - \langle w, y_t x_t\rangle)$.

Let $g_t = \nabla f_t(w)|_{w=w_t} = \begin{cases} 0 & M_t = 0 \\ -y_t x_t & M_t = 1 \end{cases} \in \partial f_t(w_t)$.

end for

Goal: minimize cumulative zero-one loss $\sum_{t=1}^T M_t$.

2.4 Applications of FTRL to online linear classification

Theorem 2. *Suppose R is 1-strongly convex defined on $\mathcal{C}$ with with respect to $\|\cdot\|$, and for all x_t, $\|x_t\|_\star \leq R$. Moreover, suppose for all w, $\Phi(w) \geq \Phi_{\min}$. Then, for any $w^\star \in \mathcal{C}$,*

$$\sum_{t=1}^T M_t \leq \frac{1}{1-\eta R^2}\left(L_T(w^\star) + \frac{\Phi(w^\star) - \Phi_{\min}}{\eta}\right),$$

where $L_T(w) = \sum_{t=1}^T (1 - \langle w, y_t x_t\rangle)_+$ is the cumulative hinge loss of w. Specifically, if there exists $w^\star \in \mathcal{C}$ such that the data is separable by a margin of 1: $\forall t, \langle w^\star, y_t x_t\rangle \geq 1$, then setting $\eta = \frac{1}{2R^2}$ implies that

$$\sum_{t=1}^T M_t \leq 2R^2 \cdot (\Phi(w^\star) - \Phi_{\min}),$$

in other words, the algorithm has a finite mistake bound.

Proof. As R is 1-strongly convex wrt $\|\cdot\|$, $\frac{\Phi}{\eta}$ is $\frac{1}{\eta}$-strongly convex wrt $\|\cdot\|$. By the guarantees of OCO with respect to $\{f_t(\cdot)\}$'s, we have that for all $w^\star$,

$$\sum_{t=1}^T f_t(w_t) - \sum_{t=1}^T f_t(w^\star) \leq \frac{\Phi(w^\star) - \min_{w'} \Phi(w')}{\eta} + \sum_{t=1}^T \eta \|g_t\|^2 \leq \frac{\Phi(w^\star) - \Phi_{\min}}{\eta} + \sum_{t=1}^T \eta\|g_t\|^2,$$

where the second inequality uses the uniform lower bound of Φ.

We have the following observations:

1. $g_t = 0$ if $M_t = 0$; therefore, the second term on the right hand side is at most $\eta R^2(\sum_{t=1}^T M_t)$.
2. Moreover, $f_t(w_t) = \mathbf{1}(\langle w_t, y_t x_t\rangle \leq 0)(1 - \langle w_t, y_t x_t\rangle)$. Observe that $f_t(w_t) \geq 0$. Moreover, if $M_t = 1$, then $f_t(w_t) \geq 1$. Therefore, $\sum_{t=1}^T M_t \leq \sum_{t=1}^T f_t(w_t)$.
3. $f_t(w) \leq \mathbf{1}(\langle w_t, y_t x_t\rangle \leq 0)(1 - \langle w, y_t x_t\rangle)_+ \leq (1 - \langle w, y_t x_t\rangle)_+$, which is the instantaneous hinge loss of w.

Combining the above insights, we get

$$\sum_{t=1}^T M_t \cdot (1 - \eta R^2) \leq L_t(w^\star) + \frac{\Phi(w^\star) - \Phi_{\min}}{\eta},$$

that is,

$$\sum_{t=1}^{T} M_t \leq \frac{1}{1-\eta R^2}(L_t(w^\star) + \frac{\Phi(w^\star) - \Phi_{\min}}{\eta}).$$

The second claim of the theorem follows simply from algebra and the fact that $L_t(w^\star) = 0$. $\square$

Instantiations. We consider two settings of Φ:

1. Let $\Phi(w) = \frac{1}{2}\|w\|^2$. This gives the well-known Perceptron algorithm [11]:

$$w_t = \operatorname*{argmin}_w \left(\frac{1}{2\eta}\|w\|_2^2 + \sum_{s=1}^{t-1} \langle g_s, w \rangle \right) = -\eta \cdot \sum_{s=1}^{t-1} g_s.$$

Suppose all examples lies in $\left\{x : \|x\|_2 \leq R_2\right\}$. By Theorem 2, Perceptron has a mistake bound of

$$\sum_{t=1}^{T} M_t \leq \frac{1}{1-\eta R_2^2}\left(L_T(w^\star) + \eta\|w^\star\|^2\right),$$

for any $w^\star \in \mathbb{R}^d$.

Now, if the data is linearly separable by margin 1 by classifier w such that $\|w\|_2 \leq B_2$, then setting $\eta = \frac{1}{2R_2^2}$ gives that

$$\sum_{t=1}^{T} M_t \leq 2R_2^2 B_2^2.$$

This is a variant of the well-known Percetron convergence theorem by Novikoff [11].

2. Let $\Phi(w) = \begin{cases} \sum_{i=1}^{d} w_i \ln w_i, & w \in \Delta^{d-1}, \\ +\infty, & \text{otherwise.} \end{cases}$. This gives the Winnow [9] algorithm:

$$w_{t,i} = \exp\left\{ -\eta \sum_{s=1}^{t=1} g_{s,i} \right\}, \forall i \in \{1, \ldots, d\}.$$

Suppose all examples lies in $\left\{x : \|x\|_\infty \leq R_\infty\right\}$. Also, as discussed before, we can set $\Phi_{\min} = -\ln d$ and $\Phi(w) - \Phi_{\min} \leq \ln d$ for all $w^\star \in \Delta^{d-1}$. Therefore, FTRL with Φ has a mistake bound of

$$\sum_{t=1}^{T} M_t \leq \frac{1}{1-\eta R_\infty^2}\left(L_T(w^\star) + \eta \ln d\right).$$

for all $w^\star \in \Delta^{d-1}$.

If the data is linearly separable by margin 1 by classifier $w^\star$ in Δ^{d-1}, then setting $\eta = \frac{1}{2R_\infty^2}$ gives that

$$\sum_{t=1}^{T} M_t \leq 2R_\infty^2 \ln d.$$

This mistake bound is in general incomparable with the Perceptron mistake bound (see our discussions on ℓ_2-ℓ_2 vs. ℓ_1-ℓ_∞ margin bounds before.)

2.5 FTRL with adaptive regularization

As we have seen before, the choice of regularizer is crucial to obtain good online prediction performance. However, if we are faced with a stream of data, it is difficult to know which regularizer to choose ahead of the time. In this section, we will look at FTRL with adaptive regularization, which is a systematic way to achieve online performance guarantees that adapts to the geometry of the data on the fly.

Our starting point is to consider the following algorithm:

$$x_t = \nabla R_{t-1}^\star(-G_{t-1}),$$

recall that $G_{t-1} = \sum_{s=1}^{t-1} g_s$ is the sum of the gradients up to time $t-1$. We called the above algorithm FTRL-AR. Specifically, we will be looking at a sequence of monotonically increasing regularizers $\{R_t\}$'s, where R_t's are generated on the fly, and can thus carry over information on the past g_t's.

Theorem 3 (Modified from [10])**.** *Suppose FTRL-AR uses R_t that are 1-strongly convex with respect to $\|\cdot\|_t$. Then it has the following upper bound on its cumulative loss guarantee:*

$$\sum_{t=1}^T \langle g_t, x_t\rangle \leq R_0^\star(0) - R_T^\star(-G_T) + \sum_{t=1}^T \|g_t\|_{\star,t-1}^2.$$

Consequently,

$$\mathrm{Reg}(T, x^\star) = \sum_{t=1}^T \langle g_t, x_t - x^\star\rangle \leq R_T(x^\star) + R_0^\star(0) + \sum_{t=1}^T \|g_t\|_{\star,t-1}^2.$$

Note that the above theorem supercedes Theorem 1, as it is a direct consequence of the above theorem by taking $R_t \equiv R_0$ and observing that $R_0^\star(0) = -\min_{x'} R_0(x')$.

Proof. It suffices to show that

$$\langle g_t, x_t\rangle \leq R_{t-1}^\star(-G_{t-1}) - R_t^\star(-G_t) + \|g_t\|_{\star,t-1}^2,$$

as the theorem concludes by summing this inequality up over all t's.

To show the above inequality, it suffices for us to show that

$$R_t^\star(-G_t) - R_{t-1}^\star(-G_{t-1}) + \langle g_t, x_t\rangle \leq \|g_t\|_{\star,t-1}^2.$$

The above inequality is true by the following observations: first, as $R_t \geq R_{t-1}$, $R_t^\star \leq R_{t-1}^\star$; second, $x_t = \nabla R_{t-1}^\star(-G_{t-1})$, therefore, the left hand side of the inequality is at most

$$R_{t-1}^\star(-G_t) - R_{t-1}^\star(-G_{t-1}) - \left\langle \nabla R_{t-1}^\star(-G_{t-1}), -g_t \right\rangle = D_{R_{t-1}^\star}(-G_t, -G_{t-1}).$$

third, as R_{t-1} is 1-strongly convex wrt $\|\cdot\|_{t-1}$, $R_{t-1}^\star$ is 1-smooth wrt $\|\cdot\|_{\star,t-1}$, implying that the right hand side is at most $\frac{1}{2}\|-G_t - (-G_{t-1})\|_{\star,t-1}^2 = \frac{1}{2}\|g_t\|_{\star,t-1}^2$. $\square$

Using the above meta-theorem, we can instantiate with different adpative regularizers and get online learning algorithms with different degrees of adaptivity.

Online gradient descent with adaptive step-sizes [12]. One instantiation of the above result is to let

$$R_t(x) = \frac{\sqrt{t+1}}{\eta_0}\|x\|_2^2.$$

This implies that

$$\mathrm{Reg}(T, x^\star) \leq \frac{\sqrt{T+1}}{\eta_0}\|x^\star\|_2^2 + \sum_{t=1}^T \eta_0 \cdot \frac{\|g_t\|^2}{\sqrt{t}}.$$

Note that if $\eta =$, then this algorithm automatically achieves a $O(\sqrt{T})$ regret for all timesteps T.

There is a variant of the above ℓ_2 regularization scheme with another setting of the regularization strength:

$$R_t(x) = \frac{\sqrt{\sigma + \sum_{s=1}^{t} \|g_s\|^2}}{2\eta_0} \|x\|^2.$$

for some $\sigma > 0$.

Adaptive subgradient methods (Adagrad) [2]. More generally we can allow adaptive Mahalanobis norm-based regularization. Specifically, we can let

$$R_t(x) = \frac{1}{2}\|x\|_{A_t}^2,$$

for some adaptively generated A_t.

Specifically, one can let

$$A_t = \frac{1}{\eta}(\sigma I + \mathrm{diag}(\sum_{s=1}^{t} g_s g_s^\top))^{\frac{1}{2}}$$

be an "diagonal" adaptive regularizer.

Alternatively, one can let

$$A_t = \frac{1}{\eta}(\sigma I + \sum_{s=1}^{t} g_s g_s^\top)^{\frac{1}{2}}$$

be an "nondiagnoal" adaptive regularizer.

3 OCO for strongly convex functions

Motivating example: SVM optimization:

$$\min_w \sum_{t=1}^{T} \left(\frac{\lambda}{2}\|w\|_2^2 + (1 - \langle w, y_t x_t \rangle)_+ \right).$$

Here $f_t(w) = \frac{\lambda}{2}\|w\|_2^2 + (1 - \langle w, y_t x_t \rangle)_+$. If one can get a low regret $R(T)$, then one can use online-to-batch conversion to get a f that has excess expected regularized loss $\frac{R(T)}{T}$.

One can show that if all f_t's are λ-strongly convex, one can design a better OCO algorithm with regret bound much better than $O(\sqrt{T})$, that is, $O(\ln T)$.

How to achieve this? We will use the adaptive regularization method developed in the last section. Recall that AR-FTRL has the following regret guarantee:

$$\sum_{t=1}^{T} \langle g_t, x_t - x^\star \rangle \leq R_0^\star(0) + R_T(x^\star) + \sum_{t=1}^{T} \|g_t\|_{\star,t-1}^2.$$

How can the above regret relate to $\mathrm{Reg}(T, x^\star) = \sum_{t=1}^{T} f_t(x_t) - f_t(x^\star)$? Now because f_t is λ-strongly convex, we have a tighter bound on it. Specifically,

$$\mathrm{Reg}(T, x^\star) \leq \sum_{t=1}^{T} \langle g_t, x_t - x^\star \rangle - \sum_{t=1}^{T} \frac{\lambda}{2}\|x_t - x^\star\|^2.$$

This motivates us to define $R_t(x) = \frac{\lambda}{2}\|x\|^2 + \sum_{s=1}^{t} \frac{\lambda}{2}\|x_s - x\|^2$ so that $R_T(x^\star)$ cancels out the negative terms induced by linear approximation. Observe that R_t is 1-strongly convex with respect to $\| \cdot \|_{\lambda(t+1)I}$. We therefore get:

$$\mathrm{Reg}(T, x^\star) \leq \frac{\lambda}{2}\|x\|^2 + \sum_{t=1}^{T} \frac{\|g_t\|^2}{\lambda t}.$$

4 OCO for exp-concave functions

Motivating example 1: sequential investing. There are d stocks, with different growth rates every day.

$W_1 \leftarrow 1$.
For $t = 1, 2, \ldots, T$:

1. Given the current wealth W_t, allocate $p_t \in \Delta^{d-1}$ (spend $p_{t,i}$ fraction of current wealth to stock i)
2. Receive loss $f_t(p_t) = -\ln\big(\langle c_t, p_t\rangle\big)$, where $c_t \in \mathbb{R}_+^d$, and $c_{t,i}$ is the ratio of the stock i at the .
3. Sell all stocks, get new wealth W_{t+1}. Observe that
$$W_{t+1} = W_t \left(\sum_{t=1}^{T} p_{t,i} c_{t,i}\right),$$
i.e. $\ln(W_{t+1}) = \ln(W_t) - f_t(p_t)$. Therefore, maximizing W_{T+1} amounts to minimizing the cumulative loss $\sum_{t=1}^T f_t(p_t)$.

Goal: compete with the best constant rebalanced portfolio in hindsight (abbrev. CRP; that is, at the beginning of every day, allocate a constant fraction $q \in \Delta^{d-1}$ to all stocks.) Concretely,

$$\mathrm{Reg}(T, q) = \sum_{t=1}^{T} f_t(p_t) - \sum_{t=1}^{T} f_t(q).$$

Motivating example 2: online least squares regression. For $t = 1, 2, \ldots, T$:

1. Output a linear predictor $w_t \in \mathbb{R}^d$.
2. Receive example $(x_t, y_t) \in \mathbb{R}^d \times \mathbb{R}$.
3. Suffer loss $f_t(w_t)$, where $f_t(w) = \frac{1}{2}(\langle w, x_t\rangle - y_t)^2$.

$$\mathrm{Reg}(T, w^\star) = \sum_{t=1}^{T} f_t(w_t) - \sum_{t=1}^{T} f_t(w^\star).$$

The common characteristic of the above two OCO problems are that the f_t's are structured: they are compositions of a univariate "strongly convex" function and a linear function. It turns out that they both belong to the family called *exp-concave* functions.

Definition 11. *f is called α-exp-concave, if $\exp\big(-\alpha f(x)\big)$ is a concave function.*

Clearly, $f(x) = -\ln\big(\langle c, x\rangle\big)$ is 1-exp-concave.

Lemma 4. *f is α-exp-concave, iff for every x,*

$$\nabla^2 f(x) \succeq \alpha \nabla f(x) \cdot \nabla f(x)^\top.$$

Proof. $h = \exp\big(-\alpha f(x)\big)$ is concave iff for every x, the hessian of h is negative semidefinite. Observe that

$$\nabla^2 h(x) = \alpha^2 \nabla f(x) \nabla f(x)^\top \exp\big(-\alpha f(x)\big) - \alpha \nabla^2 f(x) \exp\big(-\alpha f(x)\big) \preceq 0.$$

□

It can be readily seen that for $\alpha < \gamma$, if f is γ-exp-concave, then f is α-exp-concave.

Lemma 5. *Suppose h is λ-strongly convex and has gradient at most G. Then for any sw, $h(\langle w, x\rangle)$ is $\frac{\lambda}{G^2}$-exp-concave.*

For online least-square regression with domain $\{w : \|w\|_2 \le B\}$ and all $x \in \{x : \|x\|_2 \le R\}$ and $y \in [-Y, Y]$, one can take $h(z) = \frac{1}{2}(z-y)^2$, which is 1-strongly convex, and has gradient norm at most $RB + Y$. Therefore, $\frac{1}{2}(\langle w, x\rangle - y)^2$ is $\frac{1}{(RB+Y)^2}$-exp-concave.

For exp-concave functions, one can have a more refined lower bound than linear approximation.

Lemma 6. *If f is α-exp-concave and G-Lipschitz, then for any two points $u, v \in \{x : \|x\|_2 \le B\}$, we have*

$$f(u) \ge f(v) + \langle \nabla f(v), u - v\rangle + \frac{\tilde{\alpha}}{2}(u-v)^\top \nabla f(v) \nabla f(v)^\top (u-v),$$

where $\tilde{\alpha} = \min(\frac{1}{8BR}, \frac{1}{2\alpha})$.

Algorithm with logarithmic regret: adaptive regularization. We will be using Lemma 6 and the insights similar to OCO for strongly-convex optimization to develop an algorithm with a $O(\log T)$ regret.

Recall that AR-FTRL has the following regret guarantee:

$$\sum_{t=1}^T \langle g_t, x_t - x^\star\rangle \le R_0^\star(0) + R_T(x^\star) + \sum_{t=1}^T \|g_t\|^2_{\star, t-1}.$$

In addition, by Lemma 6, we have that

$$\sum_{t=1}^T f_t(x_t) - f_t(x^\star) \le \sum_{t=1}^T \langle g_t, x_t - x^\star\rangle - \sum_{t=1}^T \frac{\tilde{\alpha}}{2}(x^\star - x_t)^\top \nabla f(x_t) \nabla f(x_t)^\top (x^\star - x_t)$$

This motivates us to set $R_T(x) = \frac{\sigma}{2}\|x\|_2^2 + \sum_{t=1}^T \frac{\tilde{\alpha}}{2}(x - x_t)^\top \nabla f(x_t) \nabla f(x_t)^\top (x - x_t)$. Observe that for every t, $R_t(x)$ is σ-strongly convex with respect to $\|\cdot\|_t = \|\cdot\|_{A_t}$, where $A_t = \sigma I + \sum_{t=1}^T \nabla f(x_t) \nabla f(x_t)^\top$.

This gives that

$$\mathrm{Reg}(T, x^\star) \le \frac{\sigma}{2}\|x^\star\|_2^2 + \sum_{t=1}^T \|g_t\|^2_{A_{t-1}^{-1}}.$$

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