Gradient methods for conditional problems. Projected Gradient Descent. Frank-Wolfe method. Idea of Mirror Descent algorithm

Daniil Merkulov

Optimization methods. MIPT

Conditional methods

Constrained optimization

Unconstrained optimization

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- Any point $x_0 \in \mathbb{R}^n$ is feasible and could be a solution.

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Gradient Descent is a great way to solve unconstrained problem

$$x_{k+1} = x_k - \alpha_k \nabla f(x_k) \tag{GD}$$

Is it possible to tune GD to fit constrained problem?

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Is it possible to tune GD to fit constrained problem?

Yes. We need to use projections to ensure feasibility on every iteration.
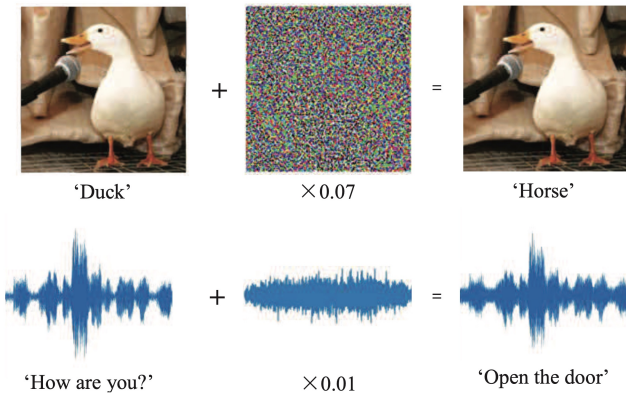
Example: White-box Adversarial Attacks

'Duck' $\times 0.07$ 'Horse'

'How are you?' $\times 0.01$ 'Open the door'

Figure 1: Source

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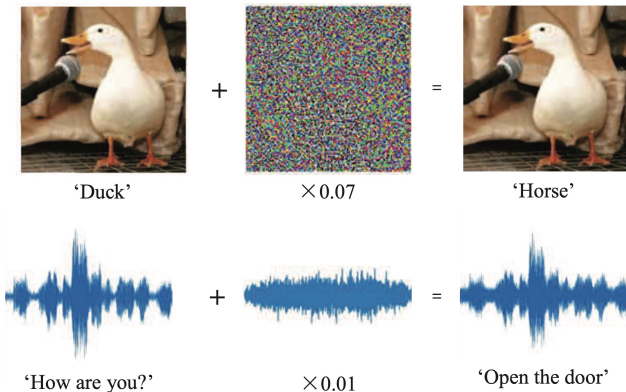
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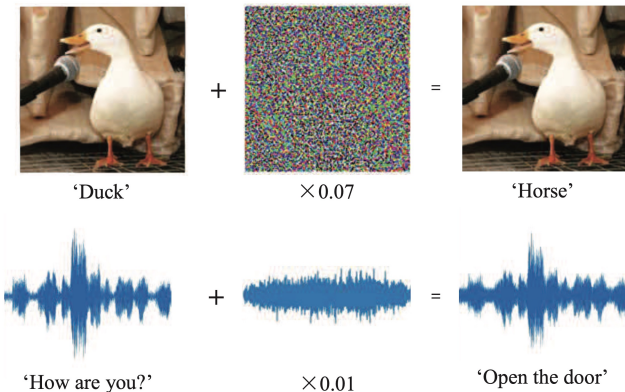
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- Mathematically, a neural network is a function $f(w; x)$
- Typically, input x is given and network weights w optimized
- Could also freeze weights w and optimize x, adversarially!

$$\min_{\delta} \mathsf{size}(\delta) \quad \mathsf{s.t.} \quad \mathsf{pred}[f(w; x + \delta)] \neq y$$

or

$$\max_{\delta} l(w; x + \delta, y) \ \mathsf{s.t.} \ \mathsf{size}(\delta) \leq \epsilon, \ 0 \leq x + \delta \leq 1$$
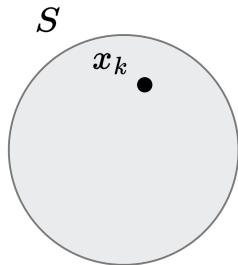
Idea of Projected Gradient Descent

Figure 2: Suppose, we start from a point x_k.

Idea of Projected Gradient Descent

Figure 3: And go in the direction of $-\nabla f(x_k)$.

Idea of Projected Gradient Descent

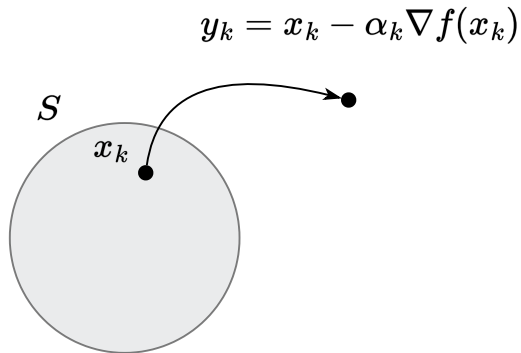$$y_k = x_k - \alpha_k \nabla f(x_k)$$

Figure 4: Occasionally, we can end up outside the feasible set.

Idea of Projected Gradient Descent
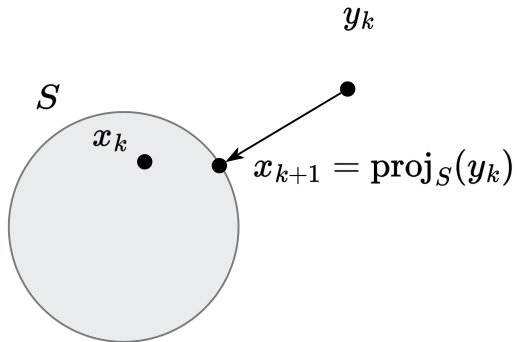

Figure 5: Solve this little problem with projection!

Idea of Projected Gradient Descent

$$x_{k+1} = \mathsf{proj}_S \left(x_k - \alpha_k \nabla f(x_k) \right) \qquad \Leftrightarrow \qquad \begin{aligned} y_k &= x_k - \alpha_k \nabla f(x_k) \\ x_{k+1} &= \mathsf{proj}_S \left(y_k \right) \end{aligned}$$
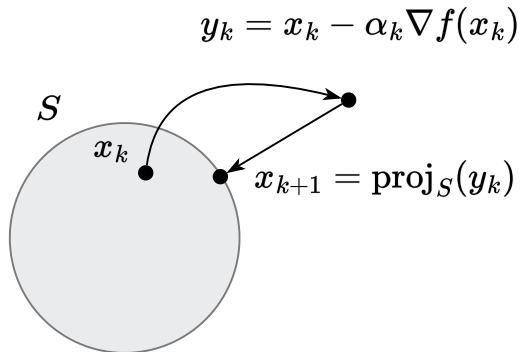

Figure 6: Illustration of Projected Gradient Descent algorithm

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$$d(\mathbf{y}, S, \|\cdot\|) = \inf\{\|x - y\| \mid x \in S\}$$

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We will focus on Euclidean projection (other options are possible) of a point $\mathbf{y} \in \mathbb{R}^n$ on set $S \subseteq \mathbb{R}^n$ is a point $\mathsf{proj}_S(\mathbf{y}) \in S$:

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- **Sufficient conditions of existence of a projection**. If $S \subseteq \mathbb{R}^n$ - closed set, then the projection on set S exists for any point.

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- **Sufficient conditions of uniqueness of a projection**. If $S \subseteq \mathbb{R}^n$ - closed convex set, then the projection on set S is unique for any point.

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Projection criterion (Bourbaki-Cheney-Goldstein inequality)

> **i** Theorem
>
> Let $S \subseteq \mathbb{R}^n$ be closed and convex, $\forall x \in S, y \in \mathbb{R}^n$. Then
>
> $$\langle y - \mathsf{proj}_S(y), \mathbf{x} - \mathsf{proj}_S(y) \rangle \leq 0 \qquad (1)$$
>
> $$\|x - \mathsf{proj}_S(y)\|^2 + \|y - \mathsf{proj}_S(y)\|^2 \leq \|x - y\|^2 \qquad (2)$$
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> **Proof**
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> 1. $\mathsf{proj}_S(y)$ is minimizer of differentiable convex function
> $d(y, S, \|\cdot\|) = \|x - y\|^2$ over S. By first-order characterization of
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Figure 7: Obtuse or straight angle should be for any point $x \in S$

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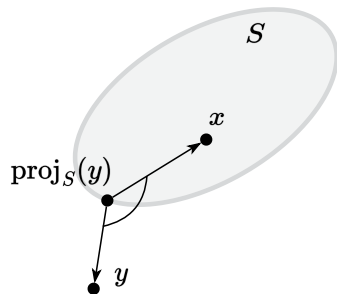   optimality.

   $$\nabla d(\mathsf{proj}_S(y))^T (x - \mathsf{proj}_S(y)) \geq 0$$

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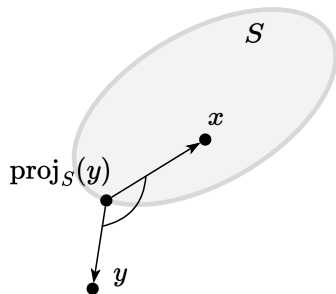

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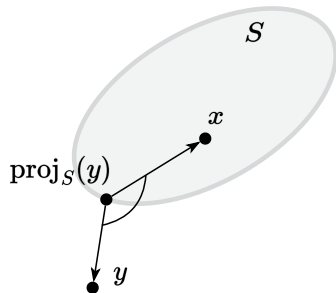

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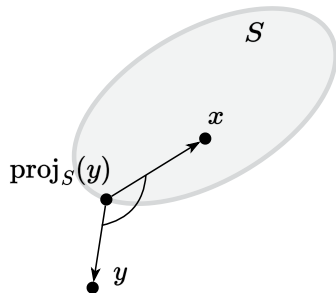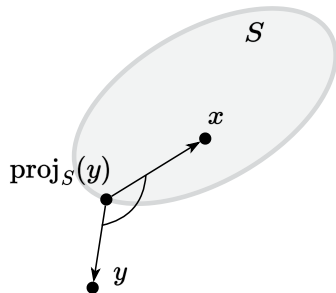   theorem:

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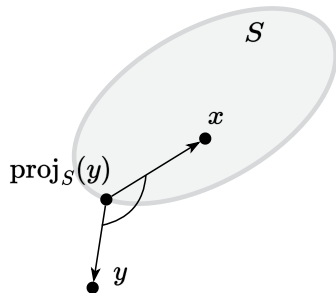>
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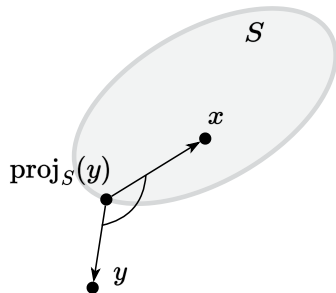

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Projection operator is non-expansive

- A function f is called non-expansive if f is L-Lipschitz with $L \leq 1$ [1]. That is, for any two points $x, y \in \text{dom} f$,

$$\|f(x) - f(y)\| \leq L\|x - y\|, \text{ where } L \leq 1.$$

It means the distance between the mapped points is possibly smaller than that of the unmapped points.

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- Next: variational characterization implies non-expansiveness. i.e.,

$$\langle y - \text{proj}(y), x - \text{proj}(y) \rangle \leq 0 \quad \forall x \in S \qquad \Rightarrow \qquad \|\text{proj}(x) - \text{proj}(y)\|_2 \leq \|x - y\|_2.$$

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Begins with the variational characterization / obtuse angle inequality

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Replace x by $\pi(x)$ in Equation 3

$$\langle y - \pi(y), \pi(x) - \pi(y) \rangle \leq 0. \tag{4}$$

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Replace x by $\pi(x)$ in Equation 3 $\qquad$ Replace y by x and x by $\pi(y)$ in Equation 3

$$\langle y - \pi(y), \pi(x) - \pi(y) \rangle \leq 0. \tag{4} \qquad \langle x - \pi(x), \pi(y) - \pi(x) \rangle \leq 0. \tag{5}$$

(Equation 4)+(Equation 5) will cancel $\pi(y) - \pi(x)$, not good. So flip the sign of (Equation 5) gives

$$\langle \pi(x) - x, \pi(x) - \pi(y) \rangle \leq 0. \tag{6}$$

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Shorthand notation: let $\pi = $ proj and $\pi(x)$ denotes proj(x).

Begins with the variational characterization / obtuse angle inequality

$$\langle y - \pi(y), x - \pi(y) \rangle \leq 0 \quad \forall x \in S. \tag{3}$$

Replace x by $\pi(x)$ in Equation 3   Replace y by x and x by $\pi(y)$ in Equation 3

$$\langle y - \pi(y), \pi(x) - \pi(y) \rangle \leq 0. \tag{4} \qquad \langle x - \pi(x), \pi(y) - \pi(x) \rangle \leq 0. \tag{5}$$

(Equation 4)+(Equation 5) will cancel $\pi(y) - \pi(x)$, not good. So flip the sign of (Equation 5) gives

$$\langle \pi(x) - x, \pi(x) - \pi(y) \rangle \leq 0. \tag{6}$$

$$\langle y - \pi(y) + \pi(x) - x, \pi(x) - \pi(y) \rangle \leq 0$$
$$\langle y - x, \pi(x) - \pi(y) \rangle \leq -\langle \pi(x) - \pi(y), \pi(x) - \pi(y) \rangle$$
$$\langle y - x, \pi(y) - \pi(x) \rangle \geq \|\pi(x) - \pi(y)\|_2^2$$
$$\|(y - x)^\top (\pi(y) - \pi(x))\|_2 \geq \|\pi(x) - \pi(y)\|_2^2$$

Projection operator is non-expansive

Shorthand notation: let $\pi = $ proj and $\pi(x)$ denotes proj(x).

Begins with the variational characterization / obtuse angle inequality

$$\langle y - \pi(y), x - \pi(y) \rangle \leq 0 \quad \forall x \in S. \tag{3}$$

Replace x by $\pi(x)$ in Equation 3 $\qquad\qquad$ Replace y by x and x by $\pi(y)$ in Equation 3

$$\langle y - \pi(y), \pi(x) - \pi(y) \rangle \leq 0. \tag{4} \qquad\qquad \langle x - \pi(x), \pi(y) - \pi(x) \rangle \leq 0. \tag{5}$$

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$\langle y - \pi(y) + \pi(x) - x, \pi(x) - \pi(y) \rangle \leq 0$

$\qquad \langle y - x, \pi(x) - \pi(y) \rangle \leq -\langle \pi(x) - \pi(y), \pi(x) - \pi(y) \rangle$

$\qquad \langle y - x, \pi(y) - \pi(x) \rangle \geq \|\pi(x) - \pi(y)\|_2^2$

$\qquad \|(y - x)^\top (\pi(y) - \pi(x))\|_2 \geq \|\pi(x) - \pi(y)\|_2^2$

By Cauchy-Schwarz inequality, the left-hand-side is upper bounded by $\|y - x\|_2 \|\pi(y) - \pi(x)\|_2$, we get $\|y - x\|_2 \|\pi(y) - \pi(x)\|_2 \geq \|\pi(x) - \pi(y)\|_2^2$. Cancels $\|\pi(x) - \pi(y)\|_2$ finishes the proof.

Example: projection on the ball

Find $\pi_S(y) = \pi$, if $S = \{x \in \mathbb{R}^n \mid \|x - x_0\| \le R\}$, $y \notin S$

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$$\left(x_0 - y + R\frac{y - x_0}{\|y - x_0\|} \right)^T \left(x - x_0 - R\frac{y - x_0}{\|y - x_0\|} \right) =$$

$$\left(\frac{(y - x_0)(R - \|y - x_0\|)}{\|y - x_0\|} \right)^T \left(\frac{(x - x_0)\|y - x_0\| - R(y - x_0)}{\|y - x_0\|} \right) =$$

$$\frac{R - \|y - x_0\|}{\|y - x_0\|^2} (y - x_0)^T \left((x - x_0)\|y - x_0\| - R(y - x_0) \right) =$$

$$\frac{R - \|y - x_0\|}{\|y - x_0\|} \left((y - x_0)^T (x - x_0) - R\|y - x_0\| \right) =$$

$$(R - \|y - x_0\|) \left(\frac{(y - x_0)^T (x - x_0)}{\|y - x_0\|} - R \right)$$

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The first factor is negative for point selection y. The second factor is also negative, which follows from the Cauchy-Bunyakovsky inequality:

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Example: projection on the ball

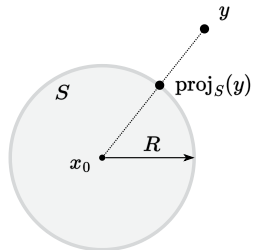Find $\pi_S(y) = \pi$, if $S = \{x \in \mathbb{R}^n \mid \|x - x_0\| \leq R\}$, $y \notin S$

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$$\frac{(y - x_0)^T (x - x_0)}{\|y - x_0\|} - R \leq \frac{\|y - x_0\|\|x - x_0\|}{\|y - x_0\|}$$

Example: projection on the halfspace

Find $\pi_S(y) = \pi$, if $S = \{x \in \mathbb{R}^n \mid c^T x = b\}$, $y \notin S$. Build a hypothesis from the figure: $\pi = y + \alpha c$. Coefficient α is chosen so that $\pi \in S$: $c^T \pi = b$, so:

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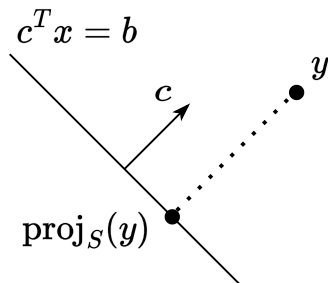

Figure 9: Hyperplane

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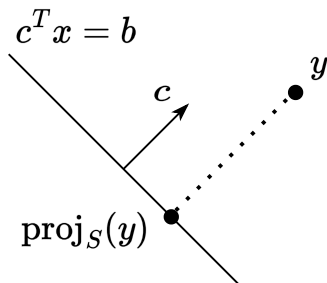

Figure 9: Hyperplane

$$c^T(y + \alpha c) = b$$
$$c^T y + \alpha c^T c = b$$
$$c^T y = b - \alpha c^T c$$

Check the inequality for a convex closed set:
$(\pi - y)^T(x - \pi) \geq 0$

$$(y + \alpha c - y)^T(x - y - \alpha c) =$$
$$\alpha c^T(x - y - \alpha c) =$$
$$\alpha(c^T x) - \alpha(c^T y) - \alpha^2(c^T c) =$$
$$\alpha b - \alpha(b - \alpha c^T c) - \alpha^2 c^T c =$$
$$\alpha b - \alpha b + \alpha^2 c^T c - \alpha^2 c^T c = 0 \geq 0$$

Projected Gradient Descent (PGD)

Idea

$$x_{k+1} = \mathsf{proj}_S \left(x_k - \alpha_k \nabla f(x_k) \right) \qquad \Leftrightarrow \qquad \begin{aligned} y_k &= x_k - \alpha_k \nabla f(x_k) \\ x_{k+1} &= \mathsf{proj}_S \left(y_k \right) \end{aligned}$$
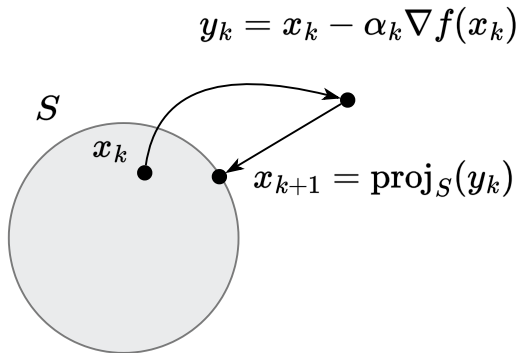

Figure 10: Illustration of Projected Gradient Descent algorithm

Convergence rate for smooth and convex case

> **i** Theorem
>
> Let $f : \mathbb{R}^n \to \mathbb{R}$ be convex and differentiable. Let $S \subseteq \mathbb{R}^n$d be a closed convex set, and assume that there is a minimizer x^* of f over S; furthermore, suppose that f is smooth over S with parameter L. The Projected Gradient Descent algorithm with stepsize $\frac{1}{L}$ achieves the following convergence after iteration $k > 0$:
>
> $$f(x_k) - f^* \leq \frac{L\|x_0 - x^*\|_2^2}{2k}$$

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Proof

1. Let's prove sufficient decrease lemma, assuming, that $y_k = x_k - \frac{1}{L}\nabla f(x_k)$ and cosine rule $2x^T y = \|x\|^2 + \|y\|^2 - \|x - y\|^2$:

(7)

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   Smoothness: $f(x_{k+1}) \leq f(x_k) + \langle \nabla f(x_k), x_{k+1} - x_k \rangle + \dfrac{L}{2}\|x_{k+1} - x_k\|^2$

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   Method: $\qquad\qquad = f(x_k) - L\langle y_k - x_k, x_{k+1} - x_k \rangle + \frac{L}{2}\|x_{k+1} - x_k\|^2$

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   Cosine rule: $\qquad = f(x_k) - \frac{L}{2}\left(\|y_k - x_k\|^2 + \|x_{k+1} - x_k\|^2 - \|y_k - x_{k+1}\|^2\right) + \frac{L}{2}\|x_{k+1} - x_k\|^2$ (7)

Convergence rate for smooth and convex case

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   Method: $\qquad\qquad = f(x_k) - L\langle y_k - x_k, x_{k+1} - x_k \rangle + \dfrac{L}{2}\|x_{k+1} - x_k\|^2$

   Cosine rule: $\qquad = f(x_k) - \dfrac{L}{2}\left(\|y_k - x_k\|^2 + \|x_{k+1} - x_k\|^2 - \|y_k - x_{k+1}\|^2\right) + \dfrac{L}{2}\|x_{k+1} - x_k\|^2$ (7)

   $\qquad\qquad\qquad = f(x_k) - \dfrac{1}{2L}\|\nabla f(x_k)\|^2 + \dfrac{L}{2}\|y_k - x_{k+1}\|^2$

Convergence rate for smooth and convex case

2. Now we do not immediately have progress at each step. Let's use again cosine rule:

$$\left\langle \frac{1}{L}\nabla f(x_k), x_k - x^* \right\rangle = \frac{1}{2}\left(\frac{1}{L^2}\|\nabla f(x_k)\|^2 + \|x_k - x^*\|^2 - \left\|x_k - x^* - \frac{1}{L}\nabla f(x_k)\right\|^2 \right)$$

$$\langle \nabla f(x_k), x_k - x^* \rangle = \frac{L}{2}\left(\frac{1}{L^2}\|\nabla f(x_k)\|^2 + \|x_k - x^*\|^2 - \|y_k - x^*\|^2 \right)$$

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3. We will use now projection property: $\|x - \mathsf{proj}_S(y)\|^2 + \|y - \mathsf{proj}_S(y)\|^2 \leq \|x - y\|^2$ with $x = x^*, y = y_k$:

$$\|x^* - \mathsf{proj}_S(y_k)\|^2 + \|y_k - \mathsf{proj}_S(y_k)\|^2 \leq \|x^* - y_k\|^2$$

$$\|y_k - x^*\|^2 \geq \|x^* - x_{k+1}\|^2 + \|y_k - x_{k+1}\|^2$$

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$$\langle \nabla f(x_k), x_k - x^* \rangle = \frac{L}{2}\left(\frac{1}{L^2}\|\nabla f(x_k)\|^2 + \|x_k - x^*\|^2 - \|y_k - x^*\|^2 \right)$$

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$$\|x^* - \mathsf{proj}_S(y_k)\|^2 + \|y_k - \mathsf{proj}_S(y_k)\|^2 \leq \|x^* - y_k\|^2$$

$$\|y_k - x^*\|^2 \geq \|x^* - x_{k+1}\|^2 + \|y_k - x_{k+1}\|^2$$

4. Now, using convexity and previous part:

Convexity:
$$f(x_k) - f^* \leq \langle \nabla f(x_k), x_k - x^* \rangle$$
$$\leq \frac{L}{2}\left(\frac{1}{L^2}\|\nabla f(x_k)\|^2 + \|x_k - x^*\|^2 - \|x_{k+1} - x^*\|^2 - \|y_k - x_{k+1}\|^2 \right)$$

Sum for $i = 0, k - 1$
$$\sum_{i=0}^{k-1}[f(x_i) - f^*] \leq \sum_{i=0}^{k-1}\frac{1}{2L}\|\nabla f(x_i)\|^2 + \frac{L}{2}\|x_0 - x^*\|^2 - \frac{L}{2}\sum_{i=0}^{i-1}\|y_i - x_{i+1}\|^2$$

Convergence rate for smooth and convex case

5. Bound gradients with sufficient decrease lemma 7:

$$\sum_{i=0}^{k-1} [f(x_i) - f^*] \leq \sum_{i=0}^{k-1} \left[f(x_i) - f(x_{i+1}) + \frac{L}{2} \|y_i - x_{i+1}\|^2 \right] + \frac{L}{2} \|x_0 - x^*\|^2 - \frac{L}{2} \sum_{i=0}^{i-1} \|y_i - x_{i+1}\|^2$$

$$\leq f(x_0) - f(x_k) + \frac{L}{2} \sum_{i=0}^{i-1} \|y_i - x_{i+1}\|^2 + \frac{L}{2} \|x_0 - x^*\|^2 - \frac{L}{2} \sum_{i=0}^{i-1} \|y_i - x_{i+1}\|^2$$

$$\leq f(x_0) - f(x_k) + \frac{L}{2} \|x_0 - x^*\|^2$$

$$\sum_{i=0}^{k-1} f(x_i) - kf^* \leq f(x_0) - f(x_k) + \frac{L}{2} \|x_0 - x^*\|^2$$

$$\sum_{i=1}^{k} [f(x_i) - f^*] \leq \frac{L}{2} \|x_0 - x^*\|^2$$

Convergence rate for smooth and convex case

6. From the sufficient decrease inequality

$$f(x_{k+1}) \leq f(x_k) - \frac{1}{2L}\|\nabla f(x_k)\|^2 + \frac{L}{2}\|y_k - x_{k+1}\|^2,$$

we use the fact that $x_{k+1} = \text{proj}_S(y_k)$. By definition of projection,

$$\|y_k - x_{k+1}\| \leq \|y_k - x_k\|,$$

and recall that $y_k = x_k - \frac{1}{L}\nabla f(x_k)$ implies $\|y_k - x_k\| = \frac{1}{L}\|\nabla f(x_k)\|$. Hence

$$\frac{L}{2}\|y_k - x_{k+1}\|^2 \leq \frac{L}{2}\|y_k - x_k\|^2 = \frac{L}{2}\frac{1}{L^2}\|\nabla f(x_k)\|^2 = \frac{1}{2L}\|\nabla f(x_k)\|^2.$$

Substitute back into $(*)$:

$$f(x_{k+1}) \leq f(x_k) - \frac{1}{2L}\|\nabla f(x_k)\|^2 + \frac{1}{2L}\|\nabla f(x_k)\|^2 = f(x_k).$$

Hence

$$f(x_{k+1}) \leq f(x_k) \quad \text{for each } k,$$

so $\{f(x_k)\}$ is a monotonically nonincreasing sequence.

Convergence rate for smooth and convex case

7. Final convergence bound From step 5, we have already established

$$\sum_{i=0}^{k-1} \big[f(x_i) - f^* \big] \leq \frac{L}{2} \|x_0 - x^*\|_2^2.$$

Since $f(x_i)$ decreases in i, in particular $f(x_k) \leq f(x_i)$ for all $i \leq k$. Therefore

$$k \big[f(x_k) - f^* \big] \leq \sum_{i=0}^{k-1} \big[f(x_i) - f^* \big] \leq \frac{L}{2} \|x_0 - x^*\|_2^2,$$

which immediately gives

$$f(x_k) - f^* \leq \frac{L \|x_0 - x^*\|_2^2}{2k}.$$

This completes the proof of the $\mathcal{O}(\frac{1}{k})$ convergence rate for convex and L-smooth f under projection constraints.
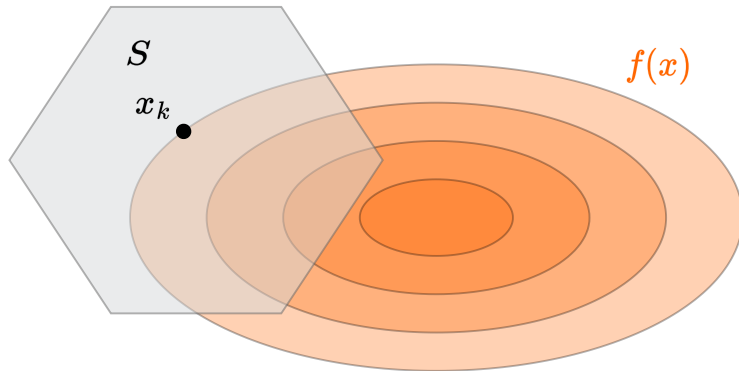
Frank-Wolfe Method

Idea

Figure 11: Illustration of Frank-Wolfe (conditional gradient) algorithm
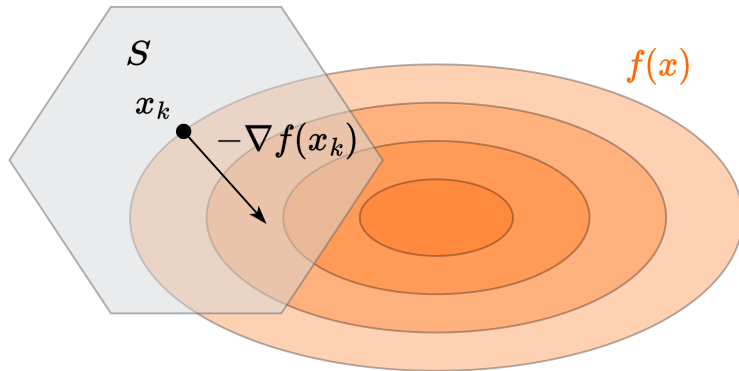
Idea

Figure 12: Illustration of Frank-Wolfe (conditional gradient) algorithm
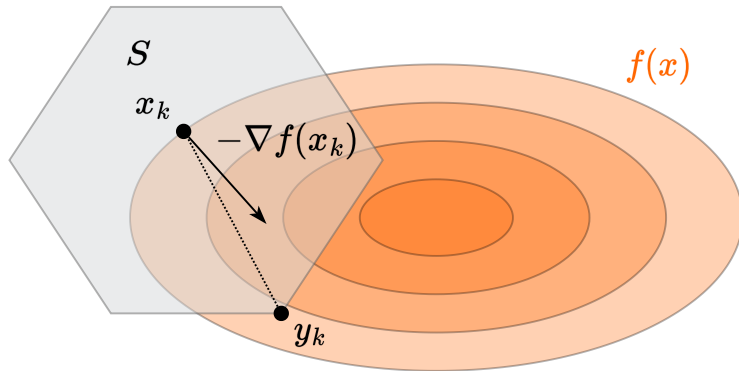
Idea

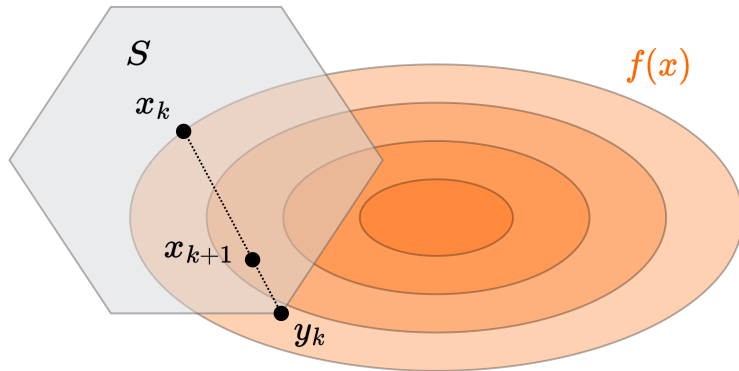Figure 13: Illustration of Frank-Wolfe (conditional gradient) algorithm

Idea

Figure 14: Illustration of Frank-Wolfe (conditional gradient) algorithm
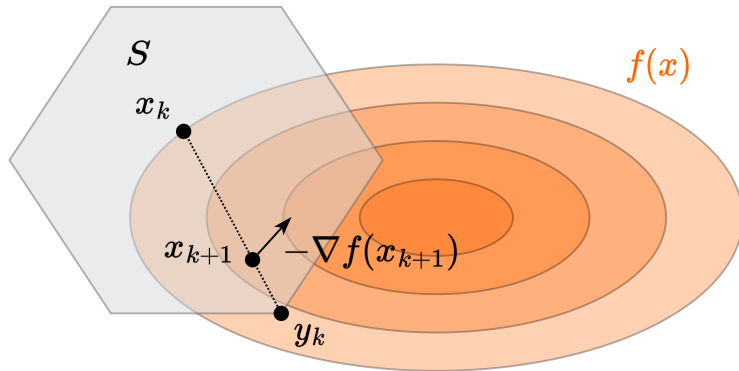
Idea

Figure 15: Illustration of Frank-Wolfe (conditional gradient) algorithm
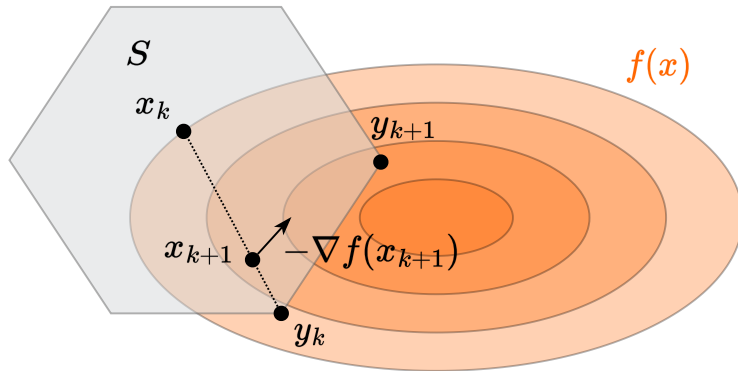
Idea

Figure 16: Illustration of Frank-Wolfe (conditional gradient) algorithm
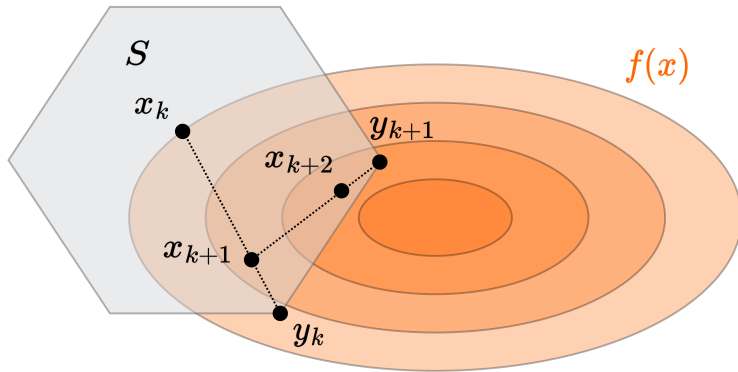
Idea

Figure 17: Illustration of Frank-Wolfe (conditional gradient) algorithm

Idea

$$y_k = \arg\min_{x \in S} f_{x_k}^I(x) = \arg\min_{x \in S} \langle \nabla f(x_k), x \rangle$$
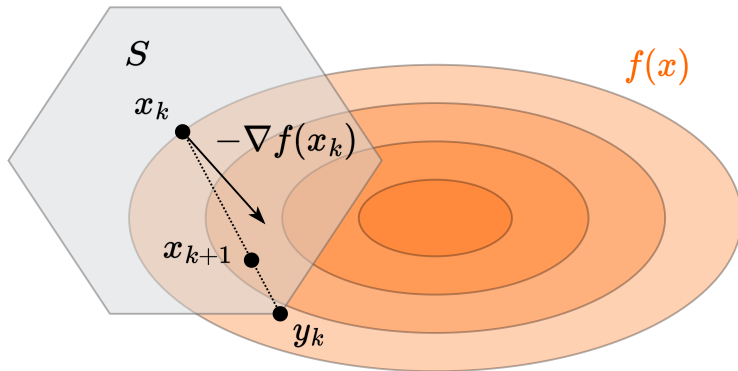
$$x_{k+1} = \gamma_k x_k + (1 - \gamma_k) y_k$$

Figure 18: Illustration of Frank-Wolfe (conditional gradient) algorithm

Convergence rate for smooth and convex case

> **i** Theorem
>
> Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ be convex and differentiable. Let $S \subseteq \mathbb{R}^n$ be a closed convex set, and assume that there is a minimizer x^* of f over S; furthermore, suppose that f is smooth over S with parameter L. The Frank-Wolfe algorithm with step size $\gamma_k = \frac{k-1}{k+1}$ achieves the following convergence after iteration $k > 0$:
>
> $$f(x_k) - f^* \leq \frac{2LR^2}{k+1}$$
>
> where $R = \max\limits_{x,y \in S} \|x - y\|$ is the diameter of the set S.

Convergence rate for smooth and convex case

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> $$f(x_k) - f^* \leq \frac{2LR^2}{k+1}$$
>
> where $R = \max\limits_{x,y \in S} \|x - y\|$ is the diameter of the set S.

Proof

1. By L-smoothness of f, we have:

$$f(x_{k+1}) - f(x_k) \leq \langle \nabla f(x_k), x_{k+1} - x_k \rangle + \frac{L}{2} \|x_{k+1} - x_k\|^2$$

$$= (1 - \gamma_k) \langle \nabla f(x_k), y_k - x_k \rangle + \frac{L(1 - \gamma_k)^2}{2} \|y_k - x_k\|^2$$

Convergence rate for smooth and convex case

2. By convexity of f, for any $x \in S$, including x^*:

$$\langle \nabla f(x_k), x - x_k \rangle \leq f(x) - f(x_k)$$

In particular, for $x = x^*$:

$$\langle \nabla f(x_k), x^* - x_k \rangle \leq f(x^*) - f(x_k)$$

Convergence rate for smooth and convex case

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In particular, for $x = x^*$:

$$\langle \nabla f(x_k), x^* - x_k \rangle \leq f(x^*) - f(x_k)$$

3. By definition of y_k, we have $\langle \nabla f(x_k), y_k \rangle \leq \langle \nabla f(x_k), x^* \rangle$, thus:

$$\langle \nabla f(x_k), y_k - x_k \rangle \leq \langle \nabla f(x_k), x^* - x_k \rangle \leq f(x^*) - f(x_k)$$

Convergence rate for smooth and convex case

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$$\langle \nabla f(x_k), y_k - x_k \rangle \le \langle \nabla f(x_k), x^* - x_k \rangle \le f(x^*) - f(x_k)$$

4. Combining the above inequalities:

$$f(x_{k+1}) - f(x_k) \le (1 - \gamma_k) \langle \nabla f(x_k), y_k - x_k \rangle + \frac{L(1-\gamma_k)^2}{2} \|y_k - x_k\|^2$$
$$\le (1 - \gamma_k)(f(x^*) - f(x_k)) + \frac{L(1-\gamma_k)^2}{2} R^2$$

Convergence rate for smooth and convex case

2. By convexity of f, for any $x \in S$, including x^*:

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$$f(x_{k+1}) - f(x_k) \leq (1 - \gamma_k) \langle \nabla f(x_k), y_k - x_k \rangle + \frac{L(1-\gamma_k)^2}{2} \|y_k - x_k\|^2$$
$$\leq (1 - \gamma_k)(f(x^*) - f(x_k)) + \frac{L(1-\gamma_k)^2}{2} R^2$$

5. Rearranging terms:

$$f(x_{k+1}) - f(x^*) \leq \gamma_k (f(x_k) - f(x^*)) + (1 - \gamma_k)^2 \frac{LR^2}{2}$$

Convergence rate for smooth and convex case

6. Denoting $\delta_k = \frac{f(x_k) - f(x^*)}{LR^2}$, we get:

$$\delta_{k+1} \leq \gamma_k \delta_k + \frac{(1 - \gamma_k)^2}{2} = \frac{k-1}{k+1}\delta_k + \frac{2}{(k+1)^2}$$

Convergence rate for smooth and convex case

6. Denoting $\delta_k = \frac{f(x_k) - f(x^*)}{LR^2}$, we get:

$$\delta_{k+1} \leq \gamma_k \delta_k + \frac{(1-\gamma_k)^2}{2} = \frac{k-1}{k+1}\delta_k + \frac{2}{(k+1)^2}$$

7. Starting from $\delta_2 \leq \frac{1}{2}$ and applying induction on k, we can show that:

$$\delta_k \leq \frac{2}{k+1}$$

which gives us the desired result:

$$f(x_k) - f^* \leq \frac{2LR^2}{k+1}$$

Convergence rate for strongly convex case

> **i** Theorem

Let $f : \mathbb{R}^n \to \mathbb{R}$ be μ-strongly convex and differentiable. Let $S \subseteq \mathbb{R}^n$ be a closed convex set, and assume that there is a minimizer x^* of f over S; furthermore, suppose that f is smooth over S with parameter L. The Frank-Wolfe algorithm with step size $\gamma_k = \frac{2}{k+2}$ achieves the following convergence after iteration $k > 0$:

$$f(x_k) - f^* \leq \frac{4LR^2}{(k+2)^2}$$

where $R = \max\limits_{x,y \in S} \|x - y\|$ is the diameter of the set S.

Convergence rate for strongly convex case

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> Let $f : \mathbb{R}^n \to \mathbb{R}$ be μ-strongly convex and differentiable. Let $S \subseteq \mathbb{R}^n$ be a closed convex set, and assume that there is a minimizer x^* of f over S; furthermore, suppose that f is smooth over S with parameter L. The Frank-Wolfe algorithm with step size $\gamma_k = \frac{2}{k+2}$ achieves the following convergence after iteration $k > 0$:
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> where $R = \max\limits_{x,y \in S} \|x - y\|$ is the diameter of the set S.

Proof

1. By μ-strong convexity of f, for any $x, y \in S$:

$$f(y) \geq f(x) + \langle \nabla f(x), y - x \rangle + \frac{\mu}{2} \|y - x\|^2$$

Convergence rate for strongly convex case

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Proof

1. By μ-strong convexity of f, for any $x, y \in S$:

   $$f(y) \geq f(x) + \langle \nabla f(x), y - x \rangle + \frac{\mu}{2} \|y - x\|^2$$

2. This gives us a stronger inequality than in the convex case:

   $$\langle \nabla f(x_k), x^* - x_k \rangle \leq f(x^*) - f(x_k) - \frac{\mu}{2} \|x^* - x_k\|^2$$

Convergence rate for strongly convex case

3. Following similar steps as in the convex case, but using the stronger inequality:

$$f\left(x_{k+1}\right) - f\left(x_k\right) \leq \left(1 - \gamma_k\right) \left\langle \nabla f\left(x_k\right), y_k - x_k \right\rangle + \frac{L(1 - \gamma_k)^2}{2} \left\| y_k - x_k \right\|^2$$

$$\leq \left(1 - \gamma_k\right) \left(f(x^*) - f(x_k) - \frac{\mu}{2} \|x^* - x_k\|^2 \right) + \frac{L(1 - \gamma_k)^2}{2} R^2$$

Convergence rate for strongly convex case

3. Following similar steps as in the convex case, but using the stronger inequality:

$$f\left(x_{k+1}\right) - f\left(x_k\right) \leq \left(1 - \gamma_k\right) \langle \nabla f\left(x_k\right), y_k - x_k \rangle + \frac{L(1 - \gamma_k)^2}{2} \|y_k - x_k\|^2$$

$$\leq \left(1 - \gamma_k\right) \left(f(x^*) - f(x_k) - \frac{\mu}{2}\|x^* - x_k\|^2\right) + \frac{L(1 - \gamma_k)^2}{2}R^2$$

4. Rearranging terms and using the fact that $\|x^* - x_k\|^2 \geq 0$:

$$f\left(x_{k+1}\right) - f(x^*) \leq \gamma_k \left(f(x_k) - f(x^*)\right) + (1 - \gamma_k)^2 \frac{LR^2}{2} - (1 - \gamma_k)\frac{\mu}{2}\|x^* - x_k\|^2$$

$$\leq \gamma_k \left(f(x_k) - f(x^*)\right) + (1 - \gamma_k)^2 \frac{LR^2}{2}$$

Convergence rate for strongly convex case

3. Following similar steps as in the convex case, but using the stronger inequality:

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$$\leq (1 - \gamma_k) \left(f(x^*) - f(x_k) - \frac{\mu}{2}\|x^* - x_k\|^2\right) + \frac{L(1 - \gamma_k)^2}{2} R^2$$

4. Rearranging terms and using the fact that $\|x^* - x_k\|^2 \geq 0$:

$$f\left(x_{k+1}\right) - f(x^*) \leq \gamma_k \left(f(x_k) - f(x^*)\right) + (1 - \gamma_k)^2 \frac{LR^2}{2} - (1 - \gamma_k)\frac{\mu}{2}\|x^* - x_k\|^2$$

$$\leq \gamma_k \left(f(x_k) - f(x^*)\right) + (1 - \gamma_k)^2 \frac{LR^2}{2}$$

5. With $\gamma_k = \frac{2}{k+2}$ and denoting $\delta_k = f(x_k) - f^*$, we get:

$$\delta_{k+1} \leq \frac{2}{k+2}\delta_k + \frac{LR^2}{2}\left(1 - \frac{2}{k+2}\right)^2$$

$$= \frac{2}{k+2}\delta_k + \frac{LR^2}{2}\frac{(k)^2}{(k+2)^2}$$

Convergence rate for strongly convex case

6. It can be shown by induction that:

$$\delta_k \leq \frac{4LR^2}{(k+2)^2}$$

Convergence rate for strongly convex case

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7. This gives us the improved convergence rate of $\mathcal{O}(\frac{1}{k^2})$ for the strongly convex case, compared to $\mathcal{O}(\frac{1}{k})$ for the convex case.