

6 - Fixed point algorithms

\mathcal{X} $2^{\mathcal{X}}$ is the power of \mathcal{X} i.e. the family of all subsets of \mathcal{X}

\times Let $\phi: \mathcal{X} \rightarrow 2^{\mathcal{X}}$

- Set of fixed points of ϕ : $\text{Fix } \phi = \{x \in \mathcal{X} \mid x \in \phi x\}$
- Set of zeros of ϕ : $\text{Zer } \phi = \{x \in \mathcal{X} \mid 0 \in \phi x\}$

\times Convergence of a sequence $(x_n)_{n \in \mathbb{N}}$ in \mathcal{X} and $\hat{x} \in \mathcal{X}$

- Strong convergence of $(x_n)_{n \in \mathbb{N}}$ to \hat{x} if

$$x_n \rightarrow \hat{x} \quad \lim_{n \rightarrow \infty} \|x_n - \hat{x}\| = 0$$

- Weak convergence

$$x_n \rightharpoonup \hat{x} \quad (\forall y \in \mathcal{X}) \quad \lim_{n \rightarrow \infty} \langle y | x_n - \hat{x} \rangle = 0$$

Remark : In finite dim. Hilbert space, strong and weak convergences are equivalent.

\times Lipschitz continuous operator

- $\phi: \mathcal{X} \rightarrow \mathcal{X}$ is ω -Lipschitz continuous for some $\omega \in [0, 1[$ if $(\forall x \in \mathcal{X})(\forall y \in \mathcal{X}) \quad \|\phi x - \phi y\| \leq \omega \|x - y\|$
- ϕ nonexpansive if 1-Lipschitz continuous.

\times Banach - Picard Theorem

(Hyp) Let $\omega \in [0, 1[$. $\phi: \mathcal{X} \rightarrow \mathcal{X}$ be a ω -Lipschitz continuous operator
Let $x_0 \in \mathcal{X}$.
Set $(\forall k) \quad x_{k+1} = \phi x_k$.

Then $\text{Fix } \phi = \{\hat{x}\}$ for some $\hat{x} \in \mathcal{X}$ and we have $\|x_k - \hat{x}\| \leq \omega^k \|x_0 - \hat{x}\|$
Moreover, $(x_k)_{k \in \mathbb{N}}$ converges strongly to \hat{x} with linear convergence rate ω .

* Class $C_{\xi}^{1,1}(\mathcal{H})$

- Def: For every $\xi \geq 0$, the class $C_{\xi}^{1,1}(\mathcal{H})$ of functions $f: \mathcal{H} \rightarrow \mathbb{R}$ satisfying
 - * f is Gateaux differentiable in \mathcal{H}
 - * $\nabla f: \mathcal{H} \rightarrow \mathcal{H}$ is ξ -Lipschitz continuous

• Prop $f \in C_{\xi}^{1,1}(\mathcal{H}) \iff \left\{ \begin{array}{l} f \text{ Fréchet diff} \\ \langle x-y, \nabla f(x) - \nabla f(y) \rangle \leq \xi \|x-y\|^2 \end{array} \right\} \forall x, y$

* Cocoercive operators

For every $\eta > 0$, we define the class \mathcal{E}_{η} of η -cocoercive op \mathcal{M} satisfying,

$$\forall x, y \in \mathcal{H} \quad \eta \| \mathcal{M}x - \mathcal{M}y \|^2 \leq \langle x-y, \mathcal{M}x - \mathcal{M}y \rangle$$

Prop: $f \in C_{\xi}^{1,1}(\mathcal{H}) \iff \left\{ \begin{array}{l} f \text{ Fréchet diff.} \\ \nabla f \in \mathcal{E}_{1/\xi} \end{array} \right.$

Prop: If $\mathcal{M} \in \mathcal{E}_{\eta}$ then \mathcal{M} is η^{-1} -Lipschitz continuous

• Averaged nonexpansive operator

x $\phi: \mathcal{H} \rightarrow \mathcal{H}$ is μ -averaged non-expansive for some $\mu \in]0, 1[$ if
 $(\forall x \in \mathcal{H})(\forall y \in \mathcal{H}) \|\phi x - \phi y\|^2 \leq \|x - y\|^2 - \left(\frac{1-\mu}{\mu}\right) \|(\text{Id} - \phi)x - (\text{Id} - \phi)y\|^2$

x ϕ firmly nonexpansive if it is $\frac{1}{2}$ -averaged

x ϕ nonexpansive $\iff \phi$ is $\frac{1}{2}$ -averaged

x Theorem

Hyp: $\mu \in]0, 1[$

$\phi: \mathcal{H} \rightarrow \mathcal{H}$ be a μ -averaged nonexpansive operator such that $\text{Fix} \phi \neq \emptyset$

Let $x_0 \in \mathcal{H}$.

Set $x_{k+1} = \phi x_k$.

Then $(x_k)_{k \in \mathbb{N}}$ converges weakly to a point in $\text{Fix} \phi$.

x M is γ -coerive $\iff \text{Id} - \gamma M$ is $\frac{\gamma}{2\gamma}$ -averaged.

Examples. $F \in C_{\xi}^{1,1}$

• $\phi = I - \nabla F$ α -averaged. |||

- Recall descent lemma

$\forall (x, y) \in \mathcal{H}$ and $t \in \mathbb{R}$

Let $\varphi(t) = f(x + t(y-x))$

$\rightarrow \varphi$ diff and $\varphi'(t) = \langle y-x, \nabla f(x + t(y-x)) \rangle$

$\rightarrow \varphi(1) - \varphi(0) = \int_0^1 \varphi'(t) dt$

$$\Leftrightarrow f(y) - f(x) = \int_0^1 \langle y-x, \nabla f(x + t(y-x)) \rangle dt$$

$$\Leftrightarrow f(y) - f(x) - \langle y-x, \nabla f(x) \rangle = \int_0^1 \langle y-x, \nabla f(x + t(y-x)) - \nabla f(x) \rangle dt$$

\rightarrow According to Cauchy-Schwarz inequality

$$\langle y-x, \nabla f(x + t(y-x)) - \nabla f(x) \rangle$$

$$\leq \|y-x\| \|\nabla f(x + t(y-x)) - \nabla f(x)\|$$

$$\leq \xi \|y-x\| \|t(y-x)\|$$

$$= \xi t \|y-x\|^2$$

$$\Rightarrow f(y) \leq f(x) + \langle y-x, \nabla f(x) \rangle + \frac{\xi}{2} \|y-x\|^2$$

Descent lemma.

∇f ξ
Lipschitz
constant

\downarrow

Conjugate $f^*(u) = \sup_x \langle x, u \rangle - f(x)$

$$\forall (x, y, z) \in \mathbb{R}^3, f^*(\nabla f(y)) \geq \langle z, \nabla f(y) \rangle - f(z)$$

$$\geq \langle z, \nabla f(y) \rangle - f(x) - \langle z - x, \nabla f(x) \rangle - \frac{1}{2} \|z - x\|^2$$

$$= \langle z, \nabla f(y) - \nabla f(x) \rangle + \langle x, \nabla f(x) \rangle - f(x) - \frac{1}{2} \|z - x\|^2$$

→ Fenchel-Young inequality
 $\langle x, \nabla f(x) \rangle - f(x) = f^*(\nabla f(x))$

$$= \langle z, \nabla f(y) - \nabla f(x) \rangle + f^*(\nabla f(x)) - \frac{1}{2} \|z - x\|^2$$

$$= f^*(\nabla f(x)) + \langle x, \nabla f(y) - \nabla f(x) \rangle + \langle z - x, \nabla f(y) - \nabla f(x) \rangle - \frac{1}{2} \|z - x\|^2$$

* $f^*(\frac{\nabla f(x)}{\frac{1}{2}\|x\|}) = \frac{1}{2} f^*(\frac{\nabla f(x)}{\|x\|})$
 for $z = \frac{1}{2} \nabla f(x)$ + Fenchel Young inequality.

for $z = \frac{1}{2} \nabla f(x)$ + Fenchel Young inequality.

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

Then $f^*(\nabla f(y)) \geq f^*(\nabla f(x)) + \langle x, \nabla f(y) - \nabla f(x) \rangle + \frac{1}{2} \|\nabla f(y) - \nabla f(x)\|^2$

$$f^*(\nabla f(x)) \geq f^*(\nabla f(y)) + \langle y, \nabla f(x) - \nabla f(y) \rangle + \frac{1}{2} \|\nabla f(y) - \nabla f(x)\|^2$$

$$\langle x - y, \nabla f(y) - \nabla f(x) \rangle + \frac{1}{2} \|\nabla f(y) - \nabla f(x)\|^2 \leq 0$$

$$\frac{1}{2} \|(\mathbb{I} - \nabla f)x - (\mathbb{I} - \nabla f)y\|^2 - \frac{1}{2} \|x - y\|^2 - \frac{1}{2} \|\nabla f(y) - \nabla f(x)\|^2$$

$$+ \frac{1}{2} \|\nabla f(y) - \nabla f(x)\|^2 \leq 0$$

$$\|(\mathbb{I} - \nabla f)x - (\mathbb{I} - \nabla f)y\|^2 + \frac{(1 - \nu_2)}{\frac{1}{2}} \|\nabla f(x) - \nabla f(y)\|^2 \leq \|x - y\|^2$$

⇒ $\frac{1}{2}$ - averaged.

* $\text{prox}_{\frac{1}{2}f}$ is $\frac{1}{2}$ averaged.

Recall: def Subdifferential

$$\partial F(x) = \{u \mid \langle y-x, u \rangle + f(x) \leq f(y)\}$$

, Let $u_1 \in \partial f(x_1)$ and $u_2 \in \partial f(x_2)$

$$(1) \langle x_2 - x_1, u_1 \rangle + f(x_1) \leq f(x_2)$$

$$(2) \langle x_1 - x_2, u_2 \rangle + f(x_2) \leq f(x_1)$$

$$(1+2) \Rightarrow 0 \geq \langle x_2 - x_1, u_1 - u_2 \rangle$$

f is monotone $\leftarrow 0 \leq \langle x_1 - x_2, u_1 - u_2 \rangle$



$$\|x_1 - x_2\|^2 \leq \langle x_1 - x_2, u_1 - u_2 + x_1 - x_2 \rangle$$

, Let $u_1' \in (\text{Id} + \partial f)x_1$
 $u_2' \in (\text{Id} + \partial f)x_2$

$$\langle x_1 - x_2, u_1' - u_2' \rangle \geq \|x_1 - x_2\|^2$$

By def of the prox. $x_1 = \text{prox}_f(u_1')$

$$x_2 = \text{prox}_f(u_2')$$

$$\begin{aligned} & \langle \text{prox}_f(u_1') - \text{prox}_f(u_2'), u_1' - u_2' \rangle \geq \|\text{prox}_f(u_1') - \text{prox}_f(u_2')\|^2 \\ & \Rightarrow \frac{1}{2} \|(\text{Id} - \text{prox}_f)(u_1') - (\text{Id} - \text{prox}_f)(u_2')\|^2 + \frac{1}{2} \|\text{prox}_f(u_1') - \text{prox}_f(u_2')\|^2 + \frac{1}{2} \|u_1' - u_2'\|^2 \end{aligned}$$

$$\frac{1}{2} \|u_1' - u_2'\|^2 \geq \frac{1}{2} \|\text{prox}_f(u_1') - \text{prox}_f(u_2')\|^2 + \frac{1}{2} \|(\text{Id} - \text{prox}_f)u_1' - (\text{Id} - \text{prox}_f)u_2'\|^2$$

2/ Gradient method

Hyp $f \in \Gamma_0(\mathbb{H})$

$$f \in C_{\lambda}^{1,1}$$

$$\boxed{\Phi = I - \alpha \nabla f}$$

Iterations $(\forall n \in \mathbb{N}) \quad x_{n+1} = x_n - \alpha \nabla f(x_n)$

Theorem The sequence $(x_n)_{n \in \mathbb{N}}$ converges weakly to $\bar{x} \in \text{zer} \nabla f$ ($\Leftrightarrow \bar{x} \in \text{Argmin} f$)

• $\text{Fix} \Phi = \{x \mid x \in \Phi x\}$

$$x \in (I - \alpha \nabla f)x \Leftrightarrow 0 \in \nabla f(x) \\ \Leftrightarrow x \in \text{zer} \nabla f$$

$$\boxed{\text{zer} \nabla f = \text{Fix} \Phi}$$

• Φ averaged nonexpansive

$$\Phi \text{ is } \frac{\alpha \lambda}{2} \text{-averaged.}$$

$\Rightarrow (x_n)_{n \in \mathbb{N}}$ weakly converge to a point in $\text{Fix} T$

3/ Forward-backward

[Bauschke - Combettes 2017]

Hyp $g \in C_{\frac{1}{2}}^{1,1}(\mathcal{H})$ et $\Gamma_0(\mathcal{H})$

Th. 26.14

$f \in \Gamma_0(\mathcal{H})$

$$\Phi = \text{prox}_{\partial f} \circ (I - \sigma \nabla g)$$

Iterations $x_{n+1} = \text{prox}_{\partial f}(x_n - \sigma \nabla g(x_n))$

Theorem The sequence $(x_n)_{n \in \mathbb{N}}$ generated by FB converges weakly to a point in $\text{zer}(\nabla g + \partial f)$.

$$\begin{aligned} x &\stackrel{\text{def}}{=} (I + \sigma \partial f)^{-1} (I - \sigma \nabla g) \\ &\Leftrightarrow (I + \sigma \partial f)x \ni I - \sigma \nabla g \\ &\Leftrightarrow 0 \in \nabla g + \partial f \\ &\quad \nabla g(x) + \partial f(x) = 0 \end{aligned}$$

α $\text{prox}_{\partial f}$ is $\frac{1}{2}$ -averaged
 $(I - \sigma \nabla g)$ is $\frac{\sigma \zeta}{2}$ -averaged.

Prop: Let \mathcal{D} be a nonempty subset of \mathcal{H} , let $\alpha_1 \in]0, 1[$, let $\alpha_2 \in]0, 1[$, let $T_1: \mathcal{D} \rightarrow \mathcal{D}$ α_1 -averaged and $T_2: \mathcal{D} \rightarrow \mathcal{D}$ α_2 -averaged.

Then $T = T_1 T_2$ is α -averaged with $\alpha = \frac{\alpha_1 + \alpha_2 - 2\alpha_1 \alpha_2}{1 - \alpha_1 \alpha_2} \in]0, 1[$

$$\begin{aligned} \alpha &= \frac{\frac{1}{2} + \frac{\sigma \zeta}{2} - \frac{\sigma \zeta}{2}}{1 - \frac{\sigma \zeta}{4}} = \frac{1}{2} \left(\frac{4}{4 - \sigma \zeta} \right) \\ &= \frac{2}{4 - \sigma \zeta} \\ &= \frac{1}{2 - \frac{\sigma \zeta}{2}} \in]0, 1[\end{aligned}$$

$$1 < 2 - \frac{\sigma \zeta}{2} \Leftrightarrow \frac{\sigma \zeta}{2} < 1$$

$$\Leftrightarrow \sigma < \frac{2}{\zeta}$$

4/ Douglas-Rachford

$$\begin{cases} y_k = \text{prox}_{\partial f}(x_k) \\ x_{k+1} = \text{prox}_{\partial g}(2y_k - x_k) + x_k - y_k \end{cases}$$

$$\forall \delta > 0 \quad \text{zer}(\nabla f + \partial g) = \text{prox}_{\partial f}(F_{\tau, \phi})$$

Weak convergence [Lions-Mercier 1979]

Linear convergence [Giselsson 2017]

$$a + b \leq$$

$$a - b \leq a$$

5/ Convergence rate

- A function $h \in C^1_{\frac{1}{\gamma}}(\mathcal{H})$ is p -strongly convex for some $p > 0$
if $h - \frac{p}{2} \|\cdot\|_2^2$ is convex

- A function $h \in C^1_{\frac{1}{\gamma}}(\mathcal{H})$ is p -strongly convex for some $p > 0$
if

$$\langle \nabla h(x) - \nabla h(y), x - y \rangle \geq p \|x - y\|^2$$

• Linear convergence of gradient descent.

✓ Since $f \in C^1_{\xi}(\mathcal{H})$ ρ strongly convex then

$$\phi = f - \frac{\rho}{2} \|\cdot\|_2^2 \text{ is convex and Fréchet diff.}$$

If function $h \in C^1_{\xi}(\mathcal{H})$ is ρ -strongly convex for some $\rho > 0$

$$\langle \nabla h(x) - \nabla h(y) | x - y \rangle \geq \rho \|x - y\|^2$$

• Prop $f \in C^1_{\xi}(\mathcal{H}) \iff \begin{cases} \text{Fréchet diff} \\ \langle x - y | \nabla f(x) - \nabla f(y) \rangle \leq \xi \|x - y\|^2 \end{cases} \forall x, y$

For every $\eta > 0$, we define the class \mathcal{B}_{η} of η -coercive op. \mathcal{M} satisfying,

$$\forall x, y \in \mathcal{H} \quad \eta \|x - y\|^2 \leq \langle x - y, \mathcal{M}x - \mathcal{M}y \rangle$$

✓ Since ∇f is ξ -Lipschitz continuous

Since $\xi > \rho$

$$\begin{aligned} \langle x - y | \nabla \phi(x) - \nabla \phi(y) \rangle &\leq \xi \|x - y\|^2 \\ &= \langle x - y | \nabla f(x) - \nabla f(y) - \rho x + \rho y \rangle \\ &\leq \xi \|x - y\|^2 - \rho \|x - y\|^2 \\ &= (\xi - \rho) \|x - y\|^2 \end{aligned}$$

Then $\phi \in C^1_{(\xi-\rho)}(\mathcal{H})$

✓ $\rho \leq \xi$

✓ $\langle x - y | \nabla \phi(x) - \nabla \phi(y) \rangle$

$$= \langle x - y | \nabla f(x) - \rho x - \nabla f(y) + \rho y \rangle$$

$$= \langle x - y | \nabla f(x) - \nabla f(y) \rangle - \rho \|x - y\|^2$$

$$= (\xi - \rho) \|x - y\|^2 \quad (+ \text{Fréchet diff}) \Rightarrow \phi \in C^1_{(\xi-\rho)}(\mathcal{H})$$

$$\nabla \phi \in \mathcal{B}_{\frac{\rho}{\xi-\rho}}$$

\Downarrow

✓ $G_{\tau \nabla f} = I - \tau \nabla f = I - \tau \nabla \phi - \tau \rho I = (1 - \tau \rho) \text{Id} - \tau \nabla \phi$

$$\left(\text{let } \tau \in]0, \frac{2}{\xi}[\right) \text{ and } \begin{cases} p = G_{\tau} \nabla \phi x \\ q = G_{\tau} \nabla \phi y \end{cases}$$

$$\|p - q\|^2 = \|(1 - \tau p)(x - y) - \tau \nabla \phi(x - y)\|^2$$

$$= (1 - \tau p)^2 \|x - y\|^2 + \tau^2 \|\nabla \phi(x) - \nabla \phi(y)\|^2$$

$$- 2(1 - \tau p)\tau \langle x - y | \nabla \phi(x) - \nabla \phi(y) \rangle$$

$$\leq (1 - \tau p)^2 \|x - y\|^2 + \tau^2 (\xi - p) \langle x - y | \nabla \phi(x) - \nabla \phi(y) \rangle$$

$$- 2(1 - \tau p)\tau \langle x - y | \nabla \phi(x) - \nabla \phi(y) \rangle$$

$$\leq (1 - \tau p)^2 \|x - y\|^2 + \tau(\tau(\xi + p) - 2) \langle x - y | \nabla \phi(x) - \nabla \phi(y) \rangle$$

$$= \tau(\tau(\xi + p) - 2) \leq (1 - \tau p)^2 \|x - y\|^2 + \max\{0, (\tau(\tau(\xi + p) - 2))\} (\xi - p) \|x - y\|^2$$

$$\leq \max\{(1 - \tau p)^2, (1 - \tau \xi)^2\} \|x - y\|^2$$

$$\underbrace{\hspace{10em}}_{\omega^2}$$

$$\omega = \max\{|1 - \tau p|, |1 - \tau \xi|\} \in]0, 1[$$

$\phi \in \mathcal{C}^1$
 $\frac{1}{\xi - p}$

$$\begin{aligned} & \tau^2 \xi - \tau^2 p \\ & - 2\tau + 2\tau p \\ & = \tau^2 \xi + \tau^2 p \\ & \quad - 2\tau \end{aligned}$$

Theorem Let $\tau > 0$, $\xi > 0$, $\rho > 0$, $f \in C_{\xi}^{1,1}(\mathbb{R}^n)$
and f strongly convex.

Suppose that $\tau \in]0, 2/\xi[$

Then $\Phi = (\text{Id} - \tau \nabla f)$ is ω -Lipschitz continuous

where $\omega(\tau) = \max_{\rho \in]0, 1[} \{ |1 - \tau\rho|, |1 - \tau\xi| \}$

→ Same rate for Forward-backward.

$$\begin{cases} \tilde{p} = \text{prox}_{\tau f} \circ (\text{Id} - \tau \nabla g) x \\ \tilde{q} = \text{prox}_{\tau f} \circ (\text{Id} - \tau \nabla g) y \end{cases}$$

$$\|\tilde{p} - \tilde{q}\| \leq \|p - q\|$$



nonexpansive prox.

Reminder

f Gateaux diff if there exists $\nabla f(x) \in \mathcal{H}$ s.t. $x \in \text{dom } F$
 $(\forall y \in \mathcal{H}) \quad \langle \nabla f(x) | y \rangle = \lim_{\substack{\alpha \rightarrow 0 \\ \alpha \neq 0}} \frac{f(x+\alpha y) - f(x)}{\alpha}$

f convex iff $f(y) \geq f(x) + \langle \nabla f(x), y-x \rangle$

(\Rightarrow) f convex thus by def.

$$\alpha f(x) + (1-\alpha) f(y) \geq f(\alpha x + (1-\alpha) y)$$

$$f(x) \geq \frac{f(\alpha x + (1-\alpha) y) - (1-\alpha)f(y)}{\alpha}$$

$$\alpha (f(x) - f(y)) \geq \frac{f(y + \alpha(x-y)) - f(y)}{\alpha} \quad \left\{ \begin{array}{l} \lim \\ \alpha \rightarrow 0 \\ \alpha \neq 0 \end{array} \right.$$

$$f(x) - f(y) \geq \langle \nabla f(y), x-y \rangle$$

$$f(x) \geq f(y) + \langle \nabla f(y), x-y \rangle$$

(\Leftarrow) $(x, y) \in \text{dom } f \times \text{dom } f$
 $\alpha \in [0, 1] \quad \alpha x + (1-\alpha) y \in \text{dom } f$

$$(1) \quad f(x) \geq f(\alpha x + (1-\alpha) y) + \langle \nabla f(\alpha x + (1-\alpha) y), \underbrace{x - \alpha x - (1-\alpha) y}_{(1-\alpha)(x-y)} \rangle$$

$$(2) \quad f(y) \geq f(\alpha x + (1-\alpha) y) + \langle \nabla f(\alpha x + (1-\alpha) y), \underbrace{y - \alpha x - (1-\alpha) y}_{\alpha(y-x)} \rangle$$

$\alpha f(x) + (1-\alpha) f(y) \geq f(\alpha x + (1-\alpha) y)$
 \Rightarrow convexity

①

ISTA

Goal: $\min \Psi(x) := f(x) + g(y)$

where $f, g \in \Gamma_0(\mathbb{R}^n)$

g β -Lipschitz diff $\beta > 0$.

- Fundamental property for a smooth function in $C^{1,1}$
 g continuously diff. with Lipschitz gradient and Lipschitz constant β

$$\forall \beta > \bar{\beta} \quad g(x) \leq g(y) + \langle x-y, \nabla g(y) \rangle + \frac{\beta}{2} \|x-y\|^2$$

- Quadratic approximation of Ψ

$$Q_\beta(x, y) = g(y) + \langle x-y, \nabla g(y) \rangle + \frac{\beta}{2} \|x-y\|^2 + f(x)$$

$\forall \beta > \bar{\beta}$

$$\Psi(x) \leq Q(x, y)$$

- Forward-backward iterations

$$\forall k \quad x_{n+1} = \text{prox}_{\delta F}(x_n - \delta \nabla g(x_n)) \quad \delta < \frac{2}{\beta}$$

$$x_{n+1} = \arg \min_x \frac{1}{2} \|x - x_n + \delta \nabla g(x_n)\|^2 + \delta F(x)$$

$$\text{IF } \delta = \frac{1}{\beta} \quad x_{n+1} = \arg \min_x \frac{\beta}{2} \|x - x_n + \frac{1}{\beta} \nabla g(x_n)\|^2 + F(x) \\ = P_\beta(x_n)$$

- Preliminary result

Hyp $\forall y \in \mathbb{R}^n \quad \Psi(P_\beta(y)) \leq Q(P_\beta(y), y)$

Prove that $(\forall x \in \mathbb{R}^n)$

$$\Psi(x) - \Psi(P_\beta(y)) \geq \frac{\beta}{2} \|P_\beta(y) - y\|^2 + \beta \langle y - x, P_\beta(y) - y \rangle$$

Condition toujours
satisfait
pour $\beta > \bar{\beta}$

x Proj hyp. $\Psi(p_B(y)) \leq Q(p_B(y), y)$

done

$$\Psi(x) - \Psi(p_B(y)) \geq \Psi(x) - Q(p_B(y), y) \quad (3)$$

x Proj prop. de convexité

$$\forall y \quad g(x) \geq g(y) + \langle x - y, \nabla g(y) \rangle \quad (1)$$

$$\forall y \quad f(x) \geq f(y) + \langle x - y, \mu \rangle \quad \text{avec } \mu \in \partial f(y)$$

et donc

$$(1) \quad f(x) \geq f(p_B(y)) + \langle x - p_B(y), \tilde{\mu} \rangle \quad \text{avec } \tilde{\mu} \in \partial f(p_B(y))$$

$$(1) + (2) \quad \Psi(x) \geq g(y) + f(p_B(y)) + \langle x - y, \nabla g(y) \rangle \quad (4)$$

$$+ \langle x - p_B(y), \tilde{\mu} \rangle$$

(3) + (4) + def $Q(p_B(y), y)$

$$\Psi(x) - \Psi(p_B(y)) \geq \Psi(x) - Q(p_B(y), y)$$

$$\geq g(y) + f(p_B(y)) + \langle x - y, \nabla g(y) \rangle + \langle x - p_B(y), \tilde{\mu} \rangle$$

$$- g(y) = \langle p_B(y) - y, \nabla g(y) \rangle$$

$$- \frac{\beta}{2} \|p_B(y) - y\|^2 + f(p_B(y))$$

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

$$= \langle x - p_B(y), \nabla g(y) + \tilde{\mu} \rangle + \frac{\beta}{2} \|p_B(y) - y\|^2 \quad \tilde{\mu} \in \partial f(p_B(y))$$

By definition of $p_B(y)$ and characterization of prox :

$$z = p_B(y) = \operatorname{argmin}_x \frac{\beta}{2} \|x - y + \frac{1}{\beta} \nabla g(y)\|^2 + F(x)$$

$$\beta \left(z - y + \frac{1}{\beta} \nabla g(y) \right) + \tilde{\mu} = 0 \quad \tilde{\mu} \in \partial F(z)$$

$$\beta (p_B(y) - y) + \nabla g(y) + \tilde{\mu} = 0 \quad \tilde{\mu} \in \partial F(p_B(y))$$

$$\Psi(x) - \Psi(p_B(y)) \geq \beta \langle x - p_B(y), y - p_B(y) \rangle - \frac{\beta}{2} \|p_B(y) - y\|^2$$

$$\geq \beta \langle x - y, y - p_B(y) \rangle + \frac{\beta}{2} \|p_B(y) - y\|^2$$

Theorem: Let $\{x_n\}$ be a sequence generated by ISTA.

Then, for any $K \geq 1$

$$F(x_K) - F(x^*) \leq \frac{\beta \|x_0 - x^*\|^2}{2K}$$

← ISTA has a worst case complexity result of $O\left(\frac{1}{K}\right)$

Proof

* From previous lemma:

$$\begin{aligned} \frac{2}{\beta} (\Psi(x^*) - \Psi(x_{k+1})) &\geq \|x_{k+1} - x_k\|^2 + 2 \langle x_k - x^*, x_{k+1} - x_k \rangle \\ &= \|x_{k+1} - x_k\|^2 + \|x_{k+1} - x^*\|^2 - \|x_k - x^*\|^2 - \|x_{k+1} - x_k\|^2 \\ &= \|x_{k+1} - x^*\|^2 - \|x_k - x^*\|^2 \end{aligned}$$

→ Summing this inequality over $k=0, \dots, K-1$

$$(1) \quad \frac{2}{\beta} (K\Psi(x^*) - \sum_{k=0}^{K-1} \Psi(x_{k+1})) \geq \|x_K - x^*\|^2 - \|x_0 - x^*\|^2$$

* From previous lemma

$$\frac{2}{\beta} (\Psi(x_k) - \Psi(x_{k+1})) \geq \|x_{k+1} - x_k\|^2$$

→ multiply by k and summing over $k=0, \dots, K-1$

$$\frac{2}{\beta} \sum_{k=0}^{K-1} \{ k\Psi(x_k) - (k+1)\Psi(x_{k+1}) + \Psi(x_{k+1}) \} \geq \sum_{k=0}^{K-1} k \|x_k - x_{k+1}\|^2$$

$$\begin{aligned} &\rightarrow -\cancel{\Psi(x_0)} + \cancel{\Psi(x_1)} + \Psi(x_1) - 2\cancel{\Psi(x_2)} + \Psi(x_2) \\ &\quad + \cancel{\Psi(x_2)} - 3\cancel{\Psi(x_3)} + \Psi(x_3) \end{aligned}$$

$$(2) \quad \frac{2}{\beta} \sum_{k=0}^{K-1} \Psi(x_{k+1}) - K\Psi(x_K) \geq \sum_{k=0}^{K-1} k \|x_k - x_{k+1}\|^2$$

$$(1+2) \quad \frac{2}{\beta} K (\Psi(x^*) - \Psi(x_K)) \geq \|x_K - x^*\|^2 - \|x_0 - x^*\|^2 + \sum_{k=0}^{K-1} k \|x_k - x_{k+1}\|^2$$

$$\Rightarrow \Psi(x_K) - \Psi(x^*) \leq \frac{\beta}{2K} \|x_0 - x^*\|^2$$

② FISTA

• Iterations

$$\text{Set } y_1 = x_0 \in \mathbb{R}^N$$

$$\text{Set } t_1 = 1$$

$$\left\{ \begin{array}{l} x_k = \text{P}_\beta(y_k) \quad \text{avec } \beta \geq \bar{\beta} \\ t_{k+1} = \frac{1 + \sqrt{1 + 4t_k^2}}{2} \\ y_{k+1} = x_k + \frac{t_k - 1}{t_{k+1}} (x_k - x_{k-1}) \end{array} \right.$$

• Theorem [Beck - Teboulle 2009]

For any $k \geq 1$

$$\Psi(x_k) - \Psi(x^*) \leq \frac{2\alpha\beta \|x_0 - x^*\|^2}{(k+1)^2}$$

→ FISTA has a worst case complexity of $O\left(\frac{1}{k^2}\right)$

→ Convergence of the sequence $(x_n)_{n \geq 1}$ not proved theoretically.

③ [Chambolle & Dossal, 2015]

• Iterations

$$\text{Set } y_1 = x_0 \in \mathbb{R}^N$$

$$\text{Set } t_1 = 1, \quad a > 2$$

$$\left\{ \begin{array}{l} x_k = \text{P}_\beta(y_k) \quad \text{avec } \beta \geq \bar{\beta} \\ \alpha_k = \frac{m-1}{m+a} \\ y_{k+1} = x_k + \alpha_k (x_k - x_{k-1}) \end{array} \right.$$

→ Same rate as FISTA

→ convergence of the iterates.