# Operators

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# Today's lecture

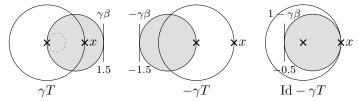
- forward step operators
- gradient step operators (subclass of forward step operators)
- resolvents
- proximal operators (subclass of resolvents)
- reflected resolvents
- reflected proximal operators (or proximal reflectors)

#### Forward step operator

- suppose that  $T: \mathbb{R}^n \to \mathbb{R}^n$  is single-valued
- the forward step operator is  $(\mathrm{Id} \gamma T)$

# Cocoercivity

- suppose that T is  $\frac{1}{\beta}$ -cocoercive with  $\beta = \frac{1}{2}$
- then  $\operatorname{Id} \gamma T$  with  $\gamma = 3$  is  $\alpha$ -averaged, decide  $\alpha$ :



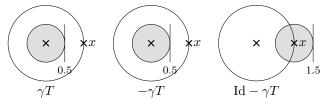
- T is 2-cocoercive  $\Leftrightarrow \gamma T$  is  $\frac{2}{3}$ -cocoercive  $\Leftrightarrow (\mathrm{Id} \gamma T)$  is  $\frac{3}{4}$ -averaged
- generally: suppose  $\gamma \in (0, \frac{2}{\beta})$
- then:  $\frac{1}{\beta}\text{-}\mathsf{cocoercivity}$  of  $T\Leftrightarrow \frac{\gamma\beta}{2}\text{-}\mathsf{averagedness}$  of  $(\mathrm{Id}-\gamma T)$

#### Iterating the forward step operator

- since  $\frac{1}{\beta}$ -cocoercivity of  $T \Leftrightarrow \frac{\gamma\beta}{2}$ -averagedness of  $(\mathrm{Id} \gamma T)$
- iterating  $x^{k+1} = (\mathrm{Id} \gamma T) x^k$  converges to fixed-point (if exists)
- (if  $\gamma \in (0, \frac{2}{\beta})$ )

# Lipschitz continuity

- suppose that T is  $\frac{1}{2}$ -Lipschitz and  $\gamma = 1$
- motivate that  $\mathrm{Id}-\gamma T$  is not averaged



- cannot make  $\mathrm{Id} \gamma T$  nonexpansive independent of  $\gamma$
- iterating forward step of Lipschitz  ${\cal T}$  not guaranteed to converge

### Gradient step operator

- suppose that  $f~:~\mathbb{R}^n \rightarrow \mathbb{R}$  is differentiable
- the forward step becomes the gradient step operator of  $\boldsymbol{f}$

$$I - \gamma \nabla f$$

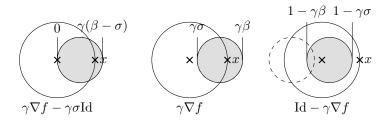
- if f (proper closed and) convex, then  $\frac{1}{\beta}$ -cocoercivity of  $\nabla f \Leftrightarrow \beta$ -Lipschitz continuity of  $\nabla f$  $\Leftrightarrow \beta$ -smoothness of f
- if f is  $\beta$ -smooth, the gradient method converges for  $\gamma \in (0, \frac{2}{\beta})$

$$x^{k+1} = (\mathrm{Id} - \gamma \nabla f) x^k$$

(since  $\nabla f \frac{1}{\beta}$ -cocoercive)

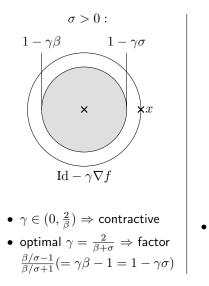
# Stronger properties

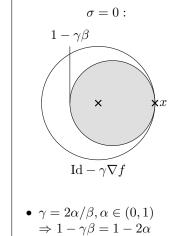
- assume f is  $\beta\text{-smooth}$  and  $\sigma\text{-strongly convex}$
- then  $\gamma f$  is  $\gamma\beta\text{-smooth}$  and  $\gamma\sigma\text{-strongly convex}$
- then  $\gamma f \frac{\gamma \sigma}{2} \| \cdot \|^2$  is  $\gamma(\beta \sigma)$ -smooth
- or  $\gamma \nabla f \gamma \sigma Id$  is  $\frac{1}{\gamma(\beta \sigma)}$ -cocoercive
- $(\mathrm{Id} \gamma \nabla f)$  is  $\delta$ -Lipschitz, decide  $\delta$



- $(\mathrm{Id} \gamma T)$  is  $\max(\gamma \beta 1, 1 \gamma \sigma)$ -Lipschitz
- contractive if  $1 \gamma \sigma < 1$  and  $\gamma \beta 1 < 1$ , i.e.,  $\gamma \in (0, \frac{2}{\beta})$
- gradient method  $x^{k+1} = (\mathrm{Id} \gamma T)x^k$  then converges linearly
- optimal  $\gamma$  (center circle) given by  $\gamma = \frac{2}{\beta + \sigma} \Rightarrow \delta = \frac{\beta/\sigma 1}{\beta/\sigma + 1}$

#### Summary: Gradient step operator





 $\Rightarrow (\mathrm{Id} - \gamma \nabla f) \ \alpha \text{-averaged}$ 

### Resolvent

• resolvent  $J_A : \mathcal{D} \to \mathbb{R}^n$  to monotone operator is defined as

$$J_A = (\mathrm{Id} + A)^{-1}$$

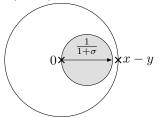
- due to Minty, if A maximally monotone, then  $\mathcal{D} = \mathbb{R}^n$  $(\operatorname{dom}(\operatorname{Id} + A^{-1}) = \operatorname{ran}(\operatorname{Id} + A) = \mathbb{R}^n$  iff A maximally monotone)
- this is important for algorithms involving resolvent
- we will consider resolvents to maximally monotone operators

### **Properties of resolvent**

- assume A is  $\sigma$ -strongly monotone ( $\sigma = 0$  implies monotone)
- Id + A is  $(1 + \sigma)$ -strongly monotone

 $\langle Ax - Ay + (x - y), x - y \rangle \ge \sigma \|x - y\|^2 + \|x - y\|^2 = (1 + \sigma)\|x - y\|^2$ 

- properties of  $J_A = (\mathrm{Id} + A)^{-1}$ ?
- $J_A = (\mathrm{Id} + A)^{-1}$  is  $(1 + \sigma)$ -cocoercive



- $\sigma = 0$ :  $J_A$  is  $\frac{1}{2}$ -averaged (or 1-cocoercive or firmly nonexpansive)
- $\sigma > 0$ :  $J_A$  is  $\frac{-1}{1+\sigma}$ -contractive
- (iteration of the resolvent converges to a fixed-point, if exists)
- note: resolvent is single-valued

# Lipschitz continuity

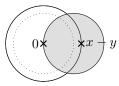
- assume A is  $\beta\text{-Lipschitz}$  continuous, then

 $2\langle J_A x - J_A y, x - y \rangle \ge \|x - y\|^2 + (1 - \beta^2) \|J_A x - J_A y\|^2$ 

(besides being 1-cocoercive)

proof sketch:

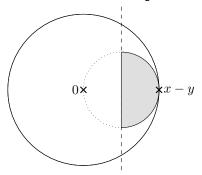
•  $A + \beta \text{Id is } \frac{1}{2\beta}$ -cocoercive



- dotted: Ax Ay
- gray:  $(\beta \operatorname{Id} + A)x (\beta \operatorname{Id} + A)y$
- using  $\beta Id = Id + (\beta 1)Id$ , the definition of a cocoercive operator, and the definition of the inverse, gives the result

### **Graphical representation**

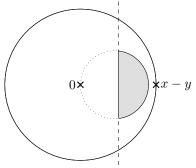
- assume A is 1-Lipschitz continuous
- then (besides being 1-cocoercive)  $J_A$  is  $\frac{1}{2}$ -strongly monotone



- 1-cocoercivity:  $J_A x J_A y$  in dotted region
- $\frac{1}{2}$ -strong monotonicity:  $J_A x J_A y$  to the right of dashed line

# Lipschitz continuity and strong monotonicity

- let A be 1-Lipschitz and  $\sigma$ -strongly monotone (with  $0 \le \sigma < 1$ )
- $\sigma$ -strong monotonicity of  $A \Rightarrow (1 + \sigma)$ -cocoercivity of  $J_A$
- 1-Lipschitz continuity of  $A \Rightarrow \frac{1}{2}$ -strong monotonicity of  $J_A$
- intersect regions to find region when both properties are present



- $J_A x J_A y$  ends up in gray region
- $(\sigma = \frac{1}{9} \text{ and } \beta = 1 \text{ in figure})$

### **Proximal operators**

- $\bullet\,$  assume f is proper closed and convex
- then  $\partial f$  maximally monotone
- let  $A = \partial f$ , then:

$$J_A(z) = \underset{x}{\operatorname{argmin}} \left\{ f(x) + \frac{1}{2} ||x - z||^2 \right\} =: \operatorname{prox}_f(z)$$

where  $prox_f$  is called prox operator

• proof:  $x = \text{prox}_f(z)$  if and only if

$$\begin{array}{ll} 0 \in \partial f(x) + x - z \\ \Leftrightarrow & z \in \partial f(x) + x \\ \Leftrightarrow & z \in (\mathrm{Id} + \partial f)x \\ \Leftrightarrow & x = (\mathrm{Id} + \partial f)^{-1}z \end{array}$$

### Proximal operator characterization

• the proximal operator satisfies

$$\operatorname{prox}_f = \nabla h^*$$

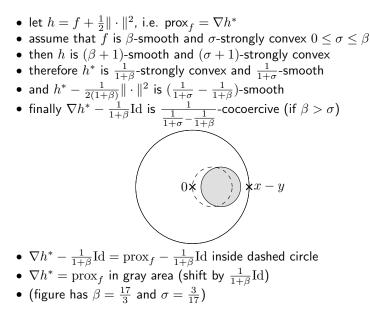
where 
$$h = f + \frac{1}{2} \| \cdot \|^2$$

- why?
  - h is proper closed and convex, and  $\partial h = \partial f + \mathrm{Id}$
  - therefore  $\nabla h^* = (\partial h)^{-1} = (\partial f + \mathrm{Id})^{-1} = J_{\partial f}$
- can this be used to derive tighter properties of  $J_{\partial f}$ ?

### Proximal operator properties

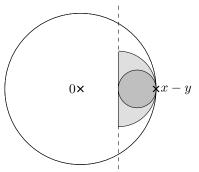
- we have  $\operatorname{prox}_f(z) = \nabla h^*(z)$  where  $h = f + \frac{1}{2} \| \cdot \|^2$
- recall equivalent dual properties
  - (i) f is  $\sigma$ -strongly convex
  - (ii)  $\partial f$  is  $\sigma$ -strongly monotone
  - (iii)  $\nabla f^*$  is  $\sigma$ -cocoercive
  - (iv)  $\nabla f^*$  is  $\frac{1}{\sigma}$ -Lipschitz continuous
  - (v)  $f^*$  is  $\frac{1}{\sigma}$ -smooth
- assume f is  $\sigma$ -strongly convex  $\Rightarrow h$  is  $(1 + \sigma)$ -strongly convex  $\Rightarrow \nabla h^* = \operatorname{prox}_f$  is  $(1 + \sigma)$ -cocoercive (same as in general case)

# Lipschitz continuity



# Comparison

- assume A is a maximal monotone operator and that f is PCC
- assume that A and  $\partial f$  are 1-Lipschitz
- $J_A$  and  $\operatorname{prox}_f$  end up in darker and lighter gray area respectively



• **conclusion**: under Lipschitz assumptions, the resolvent of subdifferentials are confined to smaller regions

#### Proximal operator for separable functions

- consider a separable function  $g(x) = \sum_{i=1}^{n} g_i(x_i)$
- the prox is also separable:

$$\begin{aligned} \operatorname{prox}_{g}(z) &= \operatorname*{argmin}_{x} \{g(x) + \frac{1}{2} \|x - z\|^{2} \} \\ &= \operatorname*{argmin}_{x} \{\sum_{i=1}^{n} g_{i}(x_{i}) + \frac{1}{2} \sum_{i=1}^{n} (x_{i} - z_{i})^{2} \} \\ &= \begin{bmatrix} \operatorname{argmin}_{x_{1}} \{g_{1}(x_{1}) + \frac{1}{2}(x_{1} - z_{1})^{2} \} \\ &\ddots \\ \operatorname{argmin}_{x_{n}} \{g_{n}(x_{n}) + \frac{1}{2}(x_{n} - z_{n})^{2} \} \end{bmatrix} \end{aligned}$$

- cheap evaluation  $\Rightarrow$  good to have in algorithms

### Separability and compositions

- assume that g is separable, i.e.,  $g(x) = \sum_{i=1}^n g_i(x_i)$
- let  $h = g \circ L$  where L is arbitrary linear operator
- the prox becomes

$$prox_h(z) = \underset{x}{\operatorname{argmin}} \{h(x) + \frac{1}{2} ||x - z||^2 \}$$
$$= \underset{x}{\operatorname{argmin}} \{g(Lx) + \frac{1}{2} ||x - z||^2 \}$$

• separability is lost in general

# Moreau's identity

- the following relation holds between the prox of f and  $f^{\ast}$ 

$$\operatorname{prox}_f + \operatorname{prox}_{f^*} = \operatorname{Id}$$

• when f scaled by  $\gamma$ , we have

$$\mathrm{prox}_{\gamma f} + \mathrm{prox}_{(\gamma f)^*} = \mathrm{prox}_{\gamma f} + \gamma \mathrm{prox}_{\gamma^{-1} f^*} \circ \gamma^{-1} \mathrm{Id} = \mathrm{Id}$$

• when f composed with L, we have

$$\mathrm{prox}_{\gamma(f\circ L)}(z)=z-\gamma L^*\mu^*$$

where

$$\mu^* \in \operatorname*{Argmin}_{\mu} \{ f^*(\mu) + \frac{\gamma}{2} \| L^* \mu - \gamma^{-1} z \|^2 \}$$

(assuming that the Argmin is nonempty)

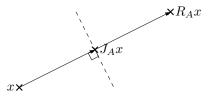
• these identities are very useful!

#### **Reflected resolvent**

• the reflected resolvent  $R_A$  to a monotone operator A is defined as

$$R_A := 2J_A - \mathrm{Id}$$

• it gives the reflection point (therefore its name)



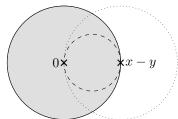
• if  $A = \partial f$  then *reflected proximal operator* given by

$$R_{\partial f} = 2 \operatorname{prox}_f - \operatorname{Id}$$

(sometimes denoted  $\operatorname{rprox}_f$  or  $R_f$ )

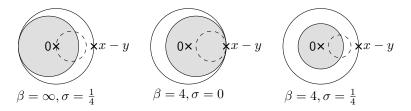
### Properties of reflected resolvent

- in the general case, A monotone
- reflected resolvent  $R_A$  is  $\beta$ -Lipschitz, what is  $\beta$ ?
- $\beta = 1$ , i.e.,  $R_A$  is nonexpansive "proof":
  - 1.  $J_A x J_A y$  within dashed region (since  $J_A$  1-cocoercive in general case)
  - 2.  $2J_Ax J_Ay$  within dotted region (multiply by 2)
  - 3.  $(2J_A \mathrm{Id})x (2J_A \mathrm{Id})y = (2J_Ax 2J_Ay) (x y)$  in gray area (shift by  $-\mathrm{Id}$ )



### Further properties of reflected resolvent

- properties of  $R_A$  obtained by multiplying resolvent  $(J_A)$  area by 2 (radially) and shifting with -Id
- examples:  $A = \partial f$  is  $\beta$ -smooth and  $\sigma$ -strongly monotone



- left: negatively averaged, middle: averaged, right: contractive
- (fairly easy to visualize, can be harder to prove)

# More properties of reflected proximal operator

• assume  $\nabla f$  is  $\sigma$ -strongly monotone and  $\beta$ -Lipschitz • then  $\operatorname{prox}_{\gamma f} - \frac{1}{1+\gamma\beta} \operatorname{Id}$  is  $\frac{1}{\frac{1}{1+\gamma\sigma} - \frac{1}{1+\gamma\beta}}$ -coccercive (if  $\beta > \sigma$ ) • it can be shown that  $R_{\gamma f}$  is  $\max\left(\frac{1-\gamma\sigma}{1+\gamma\sigma}, \frac{\gamma\beta-1}{1+\gamma\beta}\right)$ -contractive fix $R_{\gamma f} \times \begin{pmatrix} r \\ r \\ r \\ r \end{pmatrix} \times x \end{pmatrix}$ 

• contraction factor optimized for  $\gamma = \frac{1}{\sqrt{\sigma\beta}}$ (gives a contraction factor of  $\frac{\sqrt{\beta/\sigma}-1}{\sqrt{\beta/\sigma}+1}$ )

#### A reflected resolvent identity

- assume that A is a maximally monotone operator and  $\gamma \in (0,\infty)$
- then

$$R_{\gamma A}(\mathrm{Id} + \gamma A) = \mathrm{Id} - \gamma A$$

• proof

$$R_{\gamma A}(\mathrm{Id} + \gamma A) = 2(\mathrm{Id} + \gamma A)^{-1}(\mathrm{Id} + \gamma A) - (\mathrm{Id} + \gamma A)$$
$$= 2\mathrm{Id} - (\mathrm{Id} + \gamma A)$$
$$= (\mathrm{Id} - \gamma A)$$

where second step holds since  $(Id + \gamma A)^{-1} = J_{\gamma A}$  is single-valued