

# Convex Optimization

(EE227A: UC Berkeley)

Lecture 17  
(Operator splitting)

19 March, 2013



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# Monotone operators

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**Def.** Set-valued map:  $R : \mathcal{X} \rightarrow 2^{\mathcal{X}}$ ; or view it as a subset of  $\mathcal{X} \times \mathcal{X}$

**Def.** The set valued operator  $R \subset \mathbb{R}^n \times \mathbb{R}^n$  is called **monotone** if

$$\langle R(x) - R(y), x - y \rangle \geq 0, \quad x, y \in \mathbb{R}^n.$$

**Exercise:** Verify that for convex  $f$ ,  $\nabla f$  is a monotone operator.

**Exercise:** Verify that for convex  $f$ ,  $\partial f$  is a monotone operator.

♠ Abstraction helps take our linear-algebra intuition to optimization

# Resolvents

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**Aim:** Solve generalized equation (inclusion problem):

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**Theorem** The solutions to the generalized equation coincide with **fixed-points** of the resolvent:  $x = (I + \alpha R)^{-1}(x)$

**Proof:**

$$0 \in R(x) \leftrightarrow 0 \in \alpha R(x) \leftrightarrow x \in (I + \alpha R)(x) \leftrightarrow x = (I + \alpha R)^{-1}(x)$$

# Prox-operators and Resolvents

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## The proximal-point algorithm

$$\begin{aligned} \min f(x) \\ x^{k+1} &= \text{prox}_{\alpha_k f}(x^k) \\ x^{k+1} &= (I + \alpha_k \partial f)^{-1}(x^k) \end{aligned}$$

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For suitable  $f$ , captures numerous algorithms!

**Theorem** If  $f$  admits minimizers, and  $\sum_k \alpha_k < \infty$ , then  $\{x^k\}$  converges to a minimizer.

# Proximal splitting

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$$\min f(x) + g(x)$$

- ▶ Proximal point algorithm directly usually not easy
- ▶ Requires computation of:  $\text{prox}_{\lambda(f+g)}$  (i.e.,  $(I + \lambda(\partial f + \partial g))^{-1}$ )



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## Example:

$$\min \frac{1}{2} \|x - y\|_2^2 + \underbrace{\lambda \|x\|_2}_{f(x)} + \underbrace{\mu \sum_{i=1}^{n-1} |x_{i+1} - x_i|}_{g(x)}.$$

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- ▶ But good feature:  $\text{prox}_f$  and  $\text{prox}_g$  separately easier
- ▶ Can we exploit that?

## Proximal splitting – operator notation

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- ▶ Let us derive a fixed-point equation that “splits” the operators!

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**Key idea: new variable!**

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# Proximal splitting

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$$\begin{aligned}0 &\in \partial f(x) + \partial g(x) \\ 2x &\in (I + \partial f)(x) + (I + \partial g)(x)\end{aligned}$$

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- ▶ We need another idea
- ▶ **Reflection operator:**

$$R_f(x) := 2 \operatorname{prox}_f(x) - x$$

# Douglas-Rachford splitting

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$$R_g(z) = (I + \partial f)(x) \implies x = \text{prox}_f(R_g(z))$$

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**optimality condition**

$$0 \in \partial f(x) + \partial g(x) \Leftrightarrow \begin{cases} x = \text{prox}_g(z) \\ z = R_f(R_g(z)) \end{cases}$$

# Douglas-Rachford method

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**DR method:** given  $z^0$ , iterate for  $k \geq 0$

$$x^k = \text{prox}_g(z^k)$$

$$v^k = \text{prox}_f(2x^k - z^k)$$

$$z^{k+1} = z^k + \gamma_k(v^k - x^k)$$

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$$\begin{aligned}x^k &= \text{prox}_g(z^k) \\v^k &= \text{prox}_f(2x^k - z^k) \\z^{k+1} &= z^k + \gamma_k(v^k - x^k)\end{aligned}$$

**Theorem** If  $f + g$  admits minimizers, and  $(\gamma_k)$  satisfy

$$\gamma_k \in [0, 2], \quad \sum_k \gamma_k(2 - \gamma_k) = \infty,$$

then the DR-iterations  $z^k$  converge to a minimizer.