# Introductory Course on Non-smooth Optimisation

Primal-Dual splitting

Lecture 06

Lecture 00

#### **Outline**

- 1 Problem
- 2 Primal-Dual splitting
- 3 Parallel sum
- 4 Composed optimisation
- 5 Acceleration

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## **Composed monotone inclusion**

#### **Problem**

Find 
$$x \in \mathbb{R}^n$$
 such that  $0 \in A(x) + L^* \circ C \circ L(x)$ .

#### **Assumptions**

- $A: \mathbb{R}^n \rightrightarrows \mathbb{R}^n$  is maximal monotone
- $L: \mathbb{R}^n \to \mathbb{R}^m$  is a linear mapping
- $C: \mathbb{R}^m \rightrightarrows \mathbb{R}^m$  is maximal monotone
- $\operatorname{zer}(A + L^* \circ C \circ L) \neq \emptyset$

## Saddle-point problem

Let 
$$x^*\in \operatorname{zer}(A+L^*\circ C\circ L)$$
, then  $\exists v^*\in C\circ Lx^*$  such that 
$$0\in A(x^*)+L^*v^*$$
 and  $Lx^*\in C^{-1}(v^*)$ .

# Saddle-point problem

Find 
$$v \in \mathbb{R}^m$$
 such that  $\exists x \in \mathbb{R}^n \begin{cases} 0 \in A(x) + L^*v \\ 0 \in C^{-1}(v) - Lx \end{cases}$ 

Denote  $\mathcal X$  and  $\mathcal V$  the set of primal and dual solutions.

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## Primal-Dual splitting

### Primal-Dual splitting

Let 
$$x_0 \in \mathbb{R}^n$$
,  $v_0 \in \mathbb{R}^n$  and  $\gamma_{_{\!A}}, \gamma_{_{\!C}} > 0$ ,  $\theta \in [-1,1]$ : 
$$\begin{cases} x_{k+1} = \mathcal{J}_{\gamma_{_{\!A}}A}(x_k - \gamma_{_{\!A}}L^*v_k), \\ \bar{x}_{k+1} = x_{k+1} + \theta(x_{k+1} - x_k), \\ v_{k+1} = \mathcal{J}_{\gamma_{_{\!C}}C^{-1}}(v_k + \gamma_{_{\!C}}L\bar{x}_{k+1}). \end{cases}$$

- Known as Chambolle-Pock Primal-Dual method in optimisation
- Douglas-Rachford is the limiting case of Primal-Dual
- · Moreau's identity

$$\mathsf{Id} = \mathcal{J}_{\gamma \mathsf{A}}(\cdot) + \gamma \mathcal{J}_{\mathsf{A}^{-1}/\gamma} \left( \frac{\cdot}{\gamma} \right).$$

## PPA structure of Primal-Dual splitting

· definition of resolvent

$$\begin{split} \frac{1}{\gamma_{A}}(x_{k}-x_{k+1})-L^{*}v_{k} \in A(x_{k+1}) \\ \frac{1}{\gamma_{C}}(v_{k}-v_{k+1})+L(x_{k+1}+\theta(x_{k+1}-x_{k})) \in C^{-1}(v_{k+1}) \end{split}$$

· arrange terms

$$\frac{1}{\gamma_{k}}(x_{k}-x_{k+1})-L^{*}(v_{k}-v_{k+1}) \in A(x_{k+1})+L^{*}v_{k+1}$$

$$\frac{1}{\gamma_{k}}(v_{k}-v_{k+1})+\theta L(x_{k+1}-x_{k}) \in C^{-1}(v_{k+1})-Lx_{k+1}$$

inclusion

$$\begin{pmatrix} 0 \\ 0 \end{pmatrix} \in \begin{bmatrix} A & L^* \\ -L & C^{-1} \end{bmatrix} \begin{pmatrix} x_{k+1} \\ v_{k+1} \end{pmatrix} + \begin{bmatrix} Id_n/\gamma_{_{\!A}} & -L^* \\ -\theta L & Id_m/\gamma_{_{\!C}} \end{bmatrix} \begin{pmatrix} x_{k+1} - x_k \\ v_{k+1} - v_k \end{pmatrix}$$

## PPA structure of Primal-Dual splitting

inclusion

$$\mathbf{z} = \begin{pmatrix} \mathbf{x} \\ \mathbf{v} \end{pmatrix}, \ \mathbf{A} = \begin{bmatrix} \mathbf{A} & L^* \\ -L & C^{-1} \end{bmatrix} \quad \text{and} \quad \mathbf{V} = \begin{bmatrix} \mathrm{Id}_n/\gamma_A & -L^* \\ -\theta L & \mathrm{Id}_m/\gamma_c \end{bmatrix}$$

- A is skew symmetric, hence maximal monotone
- **V** is symmetric if  $\theta = 1$  and moreover positive definite if  $\gamma_{A}\gamma_{C}\|L\|^{2} < 1$
- $Vz_k \in A(z_{k+1}) + Vz_{k+1}$ , hence

$$\mathbf{z}_{k+1} = (\mathbf{V} + \mathbf{A})^{-1} (\mathbf{V} \mathbf{z}_k)$$
$$= (\mathbf{Id} + \mathbf{V}^{-1} \mathbf{A})^{-1} (\mathbf{z}_k)$$

which is PPA under metrix V

## **Fixed-point equation**

### **Fixed-point formulation**

$$z_{k+1} = (\mathbf{Id} + \mathbf{V}^{-1}\mathbf{A})^{-1}(z_k)$$

**Property** space  $(\mathbb{R}^n \times \mathbb{R}^n)_V$ 

- $\mathcal{T}_{PD} = (\mathbf{Id} + \mathbf{V}^{-1}\mathbf{A})^{-1}$  is firmly non-expansive when  $\theta = 1$  and  $\gamma_A \gamma_C \|L\|^2 < 1$
- for  $\theta \in [-1, 1[$ , a correction step is needed
- Douglas-Rachford is the limiting case of Primal-Dual when

$$L = Id$$
 and  $\gamma_{A}\gamma_{C} = 1$ 

## Relation with Douglas-Rachford

- let  $\theta = 1$  and L = Id,  $\gamma_A \gamma_C = 1$
- change the order of updating variables,

$$\begin{vmatrix} \mathbf{v}_{k+1} = \mathcal{J}_{\gamma_c \mathbf{C}^{-1}}(\mathbf{v}_k + \gamma_c \bar{\mathbf{x}}_k) \\ \mathbf{x}_{k+1} = \mathcal{J}_{\gamma_A} \mathbf{A}(\mathbf{x}_k - \gamma_a \mathbf{v}_{k+1}) \\ \bar{\mathbf{x}}_{k+1} = 2\mathbf{x}_{k+1} - \mathbf{x}_k. \end{vmatrix}$$

• apply Moreau's identity to  $\mathcal{J}_{\gamma_{\mathbb{C}}\mathbb{C}^{-1}}$ ,

$$\mathbf{v}_{k+1} = \mathcal{J}_{\gamma_{c}C^{-1}}(\mathbf{v}_{k} + \gamma_{c}\bar{\mathbf{x}}_{k}) = \mathbf{v}_{k} + \gamma_{c}\bar{\mathbf{x}}_{k} - \gamma_{c}\mathcal{J}_{C/\gamma_{c}}\left(\frac{\mathbf{v}_{k} + \gamma_{c}\bar{\mathbf{x}}_{k}}{\gamma_{c}}\right)$$

• let  $\gamma_c = 1/\gamma_{A}$  and define  $z_{k+1} = x_k - \gamma_{A}v_{k+1}$ ,

$$\begin{vmatrix} u_{k+1} = \mathcal{J}_{\gamma_A} J(2x_k - z_k) \\ z_{k+1} = z_k + u_{k+1} - x_k \\ x_{k+1} = \mathcal{J}_{\gamma_A} R(z_{k+1}), \end{vmatrix}$$

### Convergence rate

• Let  $\mathcal{X}, \mathcal{Y}$  be two subspaces

$$\mathcal{X} = \{x : ax = 0\}, \ \mathcal{Y} = \{x : bx = 0\}$$

and assume

$$1 \leq p \stackrel{\text{def}}{=} \dim(\mathcal{X}) \leq q \stackrel{\text{def}}{=} \dim(\mathcal{Y}) \leq n-1.$$

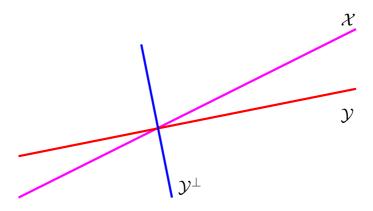
Projection onto subspace

$$\operatorname{proj}_{\mathcal{X}}(x) = x - a^{T}(aa^{T})^{-1}ax$$

Moreau identity

$$x = \operatorname{proj}_{\mathcal{X}}(x) + \operatorname{proj}_{\mathcal{X}^{\perp}}(x)$$

## **Convergence rate**



### Convergence rate

linearisation of PD

$$egin{align*} M_{ t PD} &= egin{bmatrix} \operatorname{Id}_n & -\gamma_{\!\scriptscriptstyle A} \operatorname{proj}_{\mathcal{X}} \operatorname{proj}_{\mathcal{Y}^\perp} \ \gamma_c \operatorname{proj}_{\mathcal{Y}^\perp} \operatorname{proj}_{\mathcal{X}} & \operatorname{Id}_n - 2\gamma_c \gamma_{\!\scriptscriptstyle A} \operatorname{proj}_{\mathcal{Y}^\perp} \operatorname{proj}_{\mathcal{X}} \operatorname{proj}_{\mathcal{Y}^\perp} \end{bmatrix} \end{aligned}$$

linearisation of DR

$$\mathbf{\textit{M}}_{\mathtt{DR}} = \begin{bmatrix} \mathsf{Id}_{n} & -\gamma_{\mathtt{\textit{A}}}\mathsf{proj}_{\mathcal{X}}\mathsf{proj}_{\mathcal{Y}^{\perp}} \\ \frac{1}{\gamma_{\mathtt{\textit{A}}}}\mathsf{proj}_{\mathcal{Y}^{\perp}}\mathsf{proj}_{\mathcal{X}} & \mathsf{Id}_{n} - 2\mathsf{proj}_{\mathcal{Y}^{\perp}}\mathsf{proj}_{\mathcal{X}}\mathsf{proj}_{\mathcal{Y}^{\perp}} \end{bmatrix}$$

- both  $M_{PD}$  and  $M_{DR}$  are convergent
- let  $\omega$  be the largest principal angle (yet smaller than  $\pi/2$ ) between  $\mathcal X$  and  $\mathcal Y^{\perp}$
- · spectral radius

$$\begin{split} \rho(\textit{\textit{M}}_{\scriptscriptstyle{PD}} - \textit{\textit{M}}_{\scriptscriptstyle{PD}}^{\infty}) &= \sqrt{1 - \gamma_{\scriptscriptstyle{C}} \gamma_{\scriptscriptstyle{A}} \mathrm{cos}^{2}(\omega)} \\ &\geq \sqrt{1 - \mathrm{cos}^{2}(\omega)} = \sin(\omega) = \cos(\pi/2 - \omega) = \rho(\textit{\textit{M}}_{\scriptscriptstyle{DR}} - \textit{\textit{M}}_{\scriptscriptstyle{DR}}^{\infty}) \end{split}$$

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#### Parallel sum

#### Parallel sum

Let  $C, D : \mathbb{R}^n \Rightarrow \mathbb{R}^n$  be two set-valued operators, the parallel sum of C and D is defined by

$$C\Box D \stackrel{\text{def}}{=} (C^{-1} + D^{-1})^{-1}.$$

- $(C\square D)x = \bigcup_{y\in\mathbb{R}^n}(A(x)\cap B(x-y))$
- if C and D are monotone, then  $C \square D$  is monotone

III: Parallel sur

## Monotone inclusion with parallel sum

### Primal problem

find 
$$x \in \mathbb{R}^n$$
 such that  $0 \in (A + B)(x) + L^*((C \square D)(Lx))$ 

### **Assumptions**

- $A:\mathbb{R}^n 
  ightrightarrows \mathbb{R}^n$  is maximal monotone,  $B:\mathbb{R}^n 
  ightarrow \mathbb{R}^n$  is  $eta_{\scriptscriptstyle B}$ -cocoercive for some  $eta_{\scriptscriptstyle B}>0$
- $L: \mathbb{R}^n \to \mathbb{R}^m$  is a linear operator
- $C, D : \mathbb{R}^m \rightrightarrows \mathbb{R}^m$  are maximal monotone, moreover D is  $\beta_{\scriptscriptstyle D}$ -strongly monotone for some  $\beta_{\scriptscriptstyle D} > 0$
- $0 \in \operatorname{ran}(A + B + L^*(C \square D)L)$

### Saddle-point problem

find 
$$v \in \mathbb{R}^m$$
 such that  $(\exists x \in \mathbb{R}^n)$  
$$\begin{cases} 0 \in (A+B)(x) + L^*v, \\ 0 \in (C^{-1} + D^{-1})(v) - Lx. \end{cases}$$

III: Parallel sum

## Primal-Dual splitting

#### Primal-Dual splitting

Let 
$$x_0 \in \mathbb{R}^n$$
,  $v_0 \in \mathbb{R}^n$  and  $\gamma_{\scriptscriptstyle A}, \gamma_{\scriptscriptstyle C} > 0$ ,  $\theta \in [-1,1]$ : 
$$\begin{cases} x_{k+1} = \mathcal{J}_{\gamma_{\scriptscriptstyle A} A}(x_k - \gamma_{\scriptscriptstyle A} B(x_k) - \gamma_{\scriptscriptstyle A} L^* v_k), \\ \bar{x}_{k+1} = x_{k+1} + \theta(x_{k+1} - x_k), \\ v_{k+1} = \mathcal{J}_{\gamma_{\scriptscriptstyle C} C^{-1}}(v_k - \gamma_{\scriptscriptstyle C} D^{-1}(v_k) + \gamma_{\scriptscriptstyle C} L \bar{x}_{k+1}). \end{cases}$$

• can be cast as Forward-Backward splitting

## FB structure of Primal-Dual splitting

Let  $\theta = 1$ ,

definition of resolvent

$$\frac{1}{\gamma_{k}}(x_{k}-x_{k+1})-B(x_{k})-L^{*}v_{k}\in A(x_{k+1})$$

$$\frac{1}{\gamma_{k}}(v_{k}-v_{k+1})-D^{-1}(v_{k})+L(x_{k+1}+(x_{k+1}-x_{k}))\in C^{-1}(v_{k+1})$$

arrange terms

$$\frac{1}{\gamma_{A}}(x_{k}-x_{k+1})-B(x_{k})-L^{*}(v_{k}-v_{k+1})\in A(x_{k+1})+L^{*}v_{k+1}$$

$$\frac{1}{\gamma_{C}}(v_{k}-v_{k+1})-D^{-1}(v_{k})+L(x_{k+1}-x_{k})\in C^{-1}(v_{k+1})-Lx_{k+1}$$

inclusion

$$-\begin{bmatrix}B&0\\0&D^{-1}\end{bmatrix}\begin{pmatrix}x_k\\v_k\end{pmatrix}\in\begin{bmatrix}A&L^*\\-L&C^{-1}\end{bmatrix}\begin{pmatrix}x_{k+1}\\v_{k+1}\end{pmatrix}+\begin{bmatrix}Id_n/\gamma_{_A}&-L^*\\-L&Id_m/\gamma_{_C}\end{bmatrix}\begin{pmatrix}x_{k+1}-x_k\\v_{k+1}-v_k\end{pmatrix}$$

III: Parallel sum

## FB structure of Primal-Dual splitting

inclusion

$$\boldsymbol{z} = \begin{pmatrix} \boldsymbol{x} \\ \boldsymbol{v} \end{pmatrix}, \ \boldsymbol{A} = \begin{bmatrix} \boldsymbol{A} & L^* \\ -L & C^{-1} \end{bmatrix}, \ \boldsymbol{B} = \begin{bmatrix} \boldsymbol{B} & \boldsymbol{0} \\ \boldsymbol{0} & D^{-1} \end{bmatrix} \ \text{and} \ \boldsymbol{V} = \begin{bmatrix} \mathrm{Id}_n/\gamma_{\scriptscriptstyle A} & -L^* \\ -L & \mathrm{Id}_m/\gamma_{\scriptscriptstyle C} \end{bmatrix}$$

- A is skew symmetric, hence maximal monotone
- **B** is min $\{\beta_{R}, \beta_{D}\}$ -cocoercive
- **V** is symmetric positive definite for  $\gamma_{A}\gamma_{c}\|L\|^{2}<1$
- $\mathbf{Vz}_k \mathbf{B}(z_k) \in \mathbf{A}(\mathbf{z}_{k+1}) + \mathbf{Vz}_{k+1}$ , hence

$$\mathbf{z}_{k+1} = (\mathbf{V} + \mathbf{A})^{-1} (\mathbf{V} - \mathbf{B}) (\mathbf{z}_k)$$
$$= (\mathbf{Id} + \mathbf{V}^{-1} \mathbf{A})^{-1} (\mathbf{Id} - \mathbf{V}^{-1} \mathbf{B}) (\mathbf{z}_k)$$

which is FB under metrix V

## **Fixed-point equation**

### **Fixed-point formulation**

$$z_{k+1} = (Id + V^{-1}A)^{-1}(Id - V^{-1}B)(z_k)$$

**Property** space  $(\mathbb{R}^n \times \mathbb{R}^n)_V$ 

- $(\mathbf{Id} + \mathbf{V}^{-1}\mathbf{A})^{-1}$  is firmly non-expansive when  $\gamma_{a}\gamma_{c}\|L\|^{2} < 1$
- Id  $V^{-1}B$  is  $\frac{1}{2\beta\nu}$ -averaged non-expansive with

$$\nu = \left(1 - \sqrt{\gamma_{_{A}}\gamma_{_{C}}\|L\|^{2}}\right)\min\left\{\frac{1}{\gamma_{_{A}}}, \frac{1}{\gamma_{_{C}}}\right\}$$

•  $\mathcal{T}_{PD}$  is  $\frac{2\beta\nu}{4\beta\nu-1}$ -averaged non-expansive

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#### Infimal convolution

Infimal convolution  $J, G \in \Gamma_0(\mathbb{R}^m)$ 

$$(J \stackrel{\scriptscriptstyle \mathsf{+}}{\lor} \mathsf{G})(\cdot) \stackrel{\scriptscriptstyle \mathsf{def}}{=} \inf_{\mathsf{v} \in \mathbb{R}^m} \mathsf{J}(\cdot) + \mathsf{G}(\cdot - \mathsf{v})$$

•  $\partial (J \stackrel{+}{\vee} G)(\cdot) = (\partial J \square \partial G)(\cdot)$ 

Example Moreau envelope

$$J \stackrel{\uparrow}{\vee} \frac{1}{2\gamma} \| \cdot \|^2 = \inf_{\mathbf{v} \in \mathbb{R}^m} J(\mathbf{v}) + \frac{1}{2\gamma} \| \cdot - \mathbf{v} \|^2$$

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## Conjugate

### Conjugate

Let  $F:\mathbb{R}^n\to]-\infty,+\infty]$ , the Fenchel conjugate of F is defined by

$$F^*(\mathbf{v}) \stackrel{\text{def}}{=} \sup_{\mathbf{x} \in \mathbb{R}^n} (\langle \mathbf{x}, \, \mathbf{v} \rangle - F(\mathbf{x})).$$

• F\* is closed and convex even F is not

Biconjugate 
$$F^{**} = (F^*)^*$$

IV: Composed optimisation 20/28

## Conjugate

**Example** Let  $S \subseteq \mathbb{R}^n$  be a non-empty convex set, the support function of S is defined by

$$\sigma_{\mathcal{S}}(\mathbf{V}) \stackrel{\text{def}}{=} \sup_{\mathbf{X} \in \mathcal{S}} \langle \mathbf{X}, \, \mathbf{V} \rangle = \iota_{\mathcal{S}}^*(\mathbf{Y}).$$

**Example** Let  $F = \frac{1}{2} \| \cdot \|^2$ ,

$$F^*(y) = \frac{1}{2} \|y\|^2$$

**Example** Let  $\|\cdot\|$  be a norm with dual norm  $\|\cdot\|$ . Let  $F = \|x\|$ , then

$$F^*(y) = \begin{cases} 0 & \|y\|_* \le 1 \\ +\infty & o.w. \end{cases}$$

i.e. the indicator function of the dual norm ball.

IV: Composed optimisation 20/28

## Conjugate

#### Informal convolution

$$(J \stackrel{+}{\vee} G)^* = J^* + G^*$$

**Fenchel–Moreau** Let  $F: \mathbb{R}^n \to ]-\infty, +\infty]$  be a proper function, then F is convex and lower semi-continuous if and only if  $F=F^{**}$ .

**Biconjugate** If  $F \in \Gamma_0(\mathbb{R}^n)$ , then  $F^* \in \Gamma_0(\mathbb{R}^n)$  and  $F^{**} = F$ .

**Subdifferential** If *F* is closed and convex, then

$$y \in \partial F(x) \iff x \in \partial F^*(y).$$

**Moreau's identify** Let function  $F \in \Gamma_0(\mathbb{R}^n)$  and  $\gamma > 0$ , then

$$\mathsf{Id} = \mathsf{prox}_{\gamma \mathsf{F}}(\cdot) + \gamma \, \mathsf{prox}_{\mathsf{F}^*/\gamma} \Big(\frac{\cdot}{\gamma}\Big).$$

**Strong convexity** Let *F* be closed and  $\alpha$ -strongly convex, then  $\nabla F^*$  is  $\frac{1}{\alpha}$ -Lipschitz.

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#### **Problem**

### Primal problem

$$\min_{\mathbf{x}\in\mathbb{R}^n}R(\mathbf{x})+F(\mathbf{x})+(J\stackrel{+}{\vee}G)(L\mathbf{x})$$

#### **Assumptions**

- $R, F \in \Gamma_0(\mathbb{R}^n)$ , and  $\nabla F$  is  $(1/\beta_F)$ -Lipschitz continuous for some  $\beta_F > 0$
- $J, G \in \Gamma_0(\mathbb{R}^m)$ , G is  $\beta_g$ -strongly convex for  $\beta_g > 0$
- $L: \mathbb{R}^n \to \mathbb{R}^m$  is a linear mapping
- The inclusion  $0 \in \text{ran}(\partial R + \nabla F + L^*(\partial J \Box \partial G)L)$  holds

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### **Dual problem**

### Saddle-point problem

$$\min_{x \in \mathbb{R}^n} \max_{v \in \mathbb{R}^m} R(x) + F(x) + \langle Lx, v \rangle - \left(J^*(v) + G^*(v)\right)$$

#### **Dual problem**

$$\min_{\mathbf{v} \in \mathbb{R}^m} J^*(\mathbf{v}) + \mathsf{G}^*(\mathbf{v}) + (\mathsf{R}^* \stackrel{\mathsf{\dagger}}{\vee} \mathsf{F}^*)(-L^*\mathbf{v})$$

Denote by  $\mathcal X$  and  $\mathcal V$  the sets of solutions of primal problem and dual problem, respectively.

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## Primal-Dual splitting

#### Primal-Dual splitting

$$\begin{split} \text{Let } x_0 \in \mathbb{R}^n, \, v_0 \in \mathbb{R}^n \text{ and } \gamma_{\scriptscriptstyle R}, \gamma_{\scriptscriptstyle J} > 0, \, \theta \in [-1,1] \text{:} \\ \begin{cases} x_{k+1} = \text{prox}_{\gamma_{\scriptscriptstyle R} R} (x_k - \gamma_{\scriptscriptstyle R} \nabla F(x_k) - \gamma_{\scriptscriptstyle R} L^* v_k), \\ \bar{x}_{k+1} = x_{k+1} + \theta(x_{k+1} - x_k), \\ v_{k+1} = \text{prox}_{\gamma_{\scriptscriptstyle J} J^*} (v_k - \gamma_{\scriptscriptstyle J} \nabla G^*(v_k) + \gamma_{\scriptscriptstyle J} L \bar{x}_{k+1}), \end{cases} \end{split}$$

- $A = \partial R$ ,  $B = \nabla F$
- $C^{-1} = \partial J^*, D^{-1} = \nabla G^*$

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#### **Problem**

## Primal problem

$$\min_{x\in\mathbb{R}^n}R(x)+J(Lx)$$

#### **Assumptions**

- $R \in \Gamma_0(\mathbb{R}^n)$
- $J \in \Gamma_0(\mathbb{R}^m)$
- $L: \mathbb{R}^n \to \mathbb{R}^m$  is a linear mapping
- The inclusion  $0 \in ran(\partial R + L^*\partial JL)$  holds

## **Dual problem**

$$\min_{\mathbf{v} \in \mathbb{R}^m} J^*(\mathbf{v}) + R^*(-L^*\mathbf{v})$$

### *R* or *J* is $\alpha$ -strongly convex

#### Primal-Dual splitting

Let  $x_0 \in \mathbb{R}^n$ ,  $v_0 \in \mathbb{R}^n$  and  $\gamma_{R,0}, \gamma_{J,0} > 0$  such that  $\gamma_{R,0}\gamma_{J,0}\|L\|^2 \le 1$ :

$$\begin{cases} v_{k+1} = \operatorname{prox}_{\gamma_{J,k}J^{*}}(v_{k} + \gamma_{J,k}L\bar{x}_{k+1}) \\ x_{k+1} = \operatorname{prox}_{\gamma_{R,k}R}(x_{k} - \gamma_{R,k}L^{*}v_{k}) \\ \theta_{k} = \frac{1}{\sqrt{1 + 2\alpha\gamma_{R,k}}}, \ \gamma_{R,k+1} = \theta_{k}\gamma_{R,k}, \ \gamma_{J,k+1} = \gamma_{J,k}/\theta_{k} \\ \bar{x}_{k+1} = x_{k+1} + \theta_{k}(x_{k+1} - x_{k}) \end{cases}$$

convergence rate

$$||x_k - x^*|| = O(1/k^2)$$

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## R and J are strongly convex

*R* is  $\alpha$ -strongly covnex and *J* is  $\kappa$ -strongly convex.

### Primal-Dual splitting

Let 
$$x_0 \in \mathbb{R}^n$$
,  $v_0 \in \mathbb{R}^n$ . Choose  $\mu = \frac{2\sqrt{\alpha\kappa}}{L}$ ,  $\gamma_R = \frac{\mu}{2\alpha}$ ,  $\gamma_J = \frac{\mu}{2\kappa}$  and  $\theta \in [1/(\mu+1), 1]$ : 
$$\begin{cases} v_{k+1} = \mathsf{prox}_{\gamma_J J^*}(v_k + \gamma_J L \bar{x}_{k+1}) \\ x_{k+1} = \mathsf{prox}_{\gamma_R R}(x_k - \gamma_R L^* v_k) \\ \bar{x}_{k+1} = x_{k+1} + \theta(x_{k+1} - x_k) \end{cases}$$

• convergence rate

$$\|\mathbf{x}_k - \mathbf{x}^\star\| = O(\eta^k)$$

with 
$$\eta = \frac{1+\theta}{2+\mu}$$

#### Reference

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