

# Union Averaged Operators with Applications to Proximal Algorithms for Min-Convex Functions

MINH N. DAO

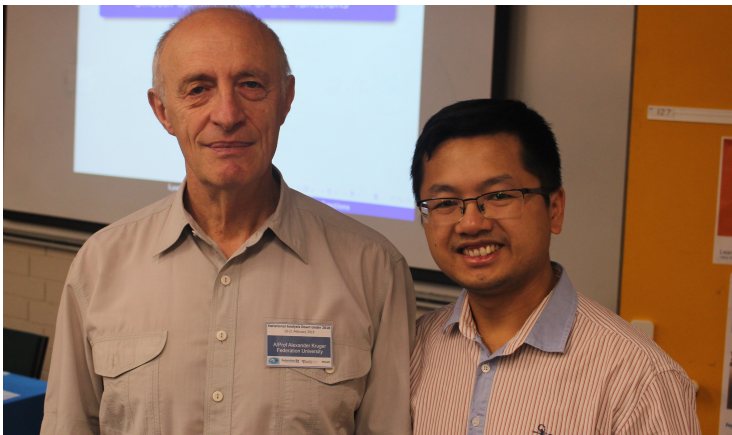
Priority Research Centre for Computer-Assisted Research Mathematics and its Applications  
(CARMA)



WoMBaT 2018 – Third Workshop on Metric Bounds and Transversality  
Deakin University, Melbourne Burwood Campus, 29 November – 1 December 2018

Joint work with [Matthew K. Tam](#) (Universität Göttingen, Germany)

# *Happy Birthday, Alex!*



Ballarat, February 2018

# Outline

- 1 Union averaged operators
- 2 Convergence of fixed point algorithms
- 3 Proximal algorithms for min-convex minimization

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# Projectors and reflectors

Throughout this talk,

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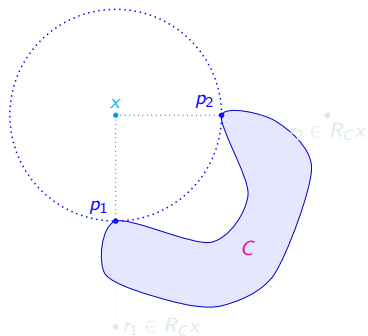
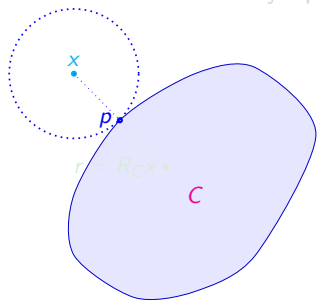
Given a nonempty closed subset  $C$  of  $X$ , the **projector** onto  $C$  is defined by

$$P_C: X \rightrightarrows C: x \mapsto P_C x := \operatorname{argmin}_{c \in C} \|x - c\|$$

and **reflector** across  $C$  is

$$R_C := 2P_C - \operatorname{Id},$$

where  $\operatorname{Id}$  is the identity operator on  $X$ .



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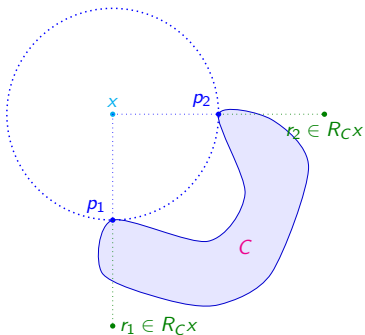
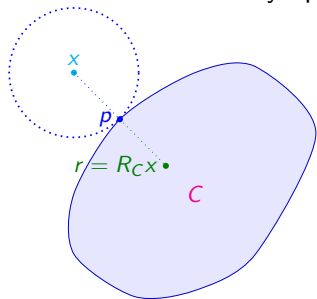
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## Alternating projections (AP) and Douglas–Rachford (DR) algorithm

Let  $A$  and  $B$  are closed sets with  $A \cap B \neq \emptyset$ . The **feasibility problem** is to  
find  $x \in A \cap B$ .

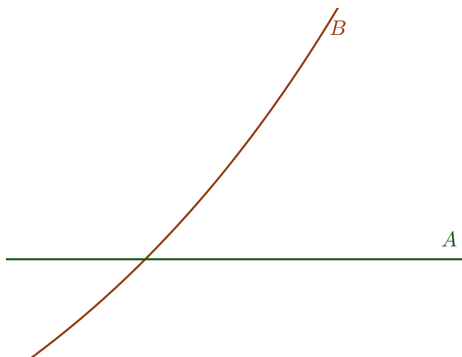
▶ AP operator:  $P_B P_A$ .

▶ DR operator:  $T_{A,B} := \frac{1}{2}(\text{Id} + R_B R_A)$  (a.k.a. reflect-reflect-average).

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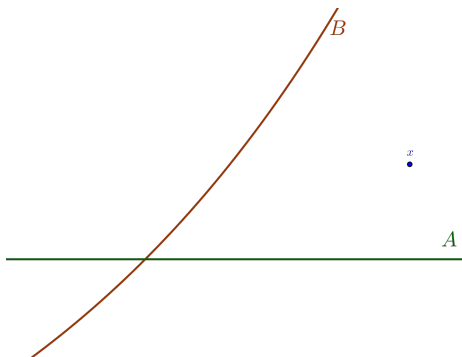
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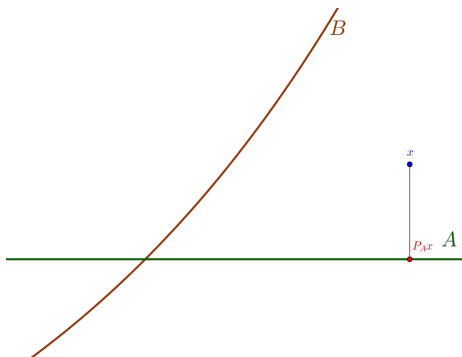


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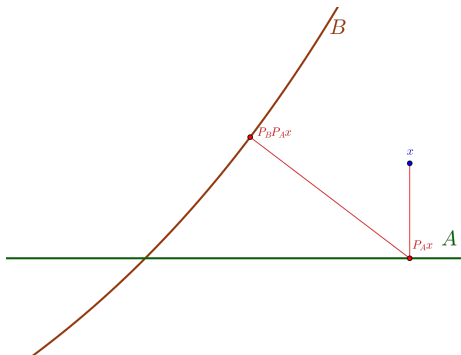


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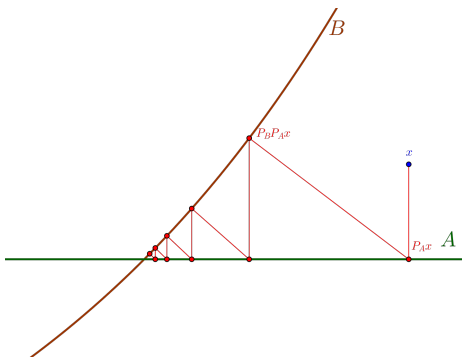


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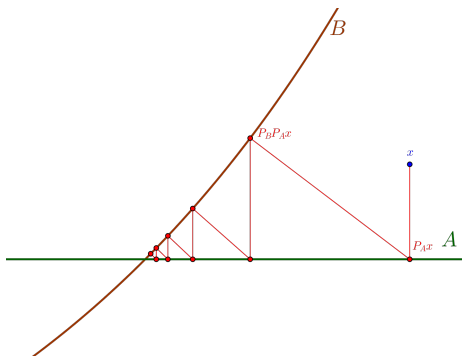


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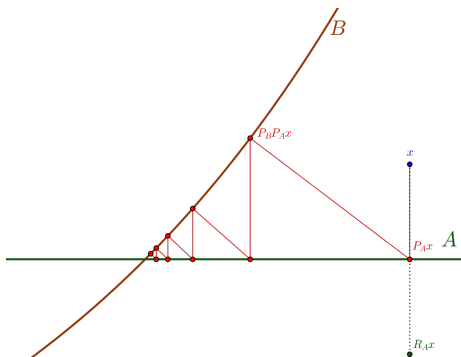


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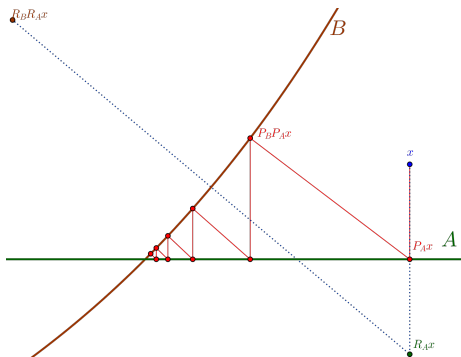


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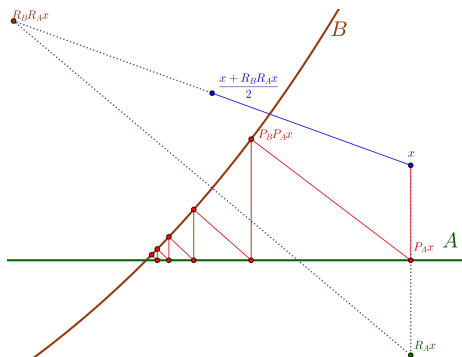


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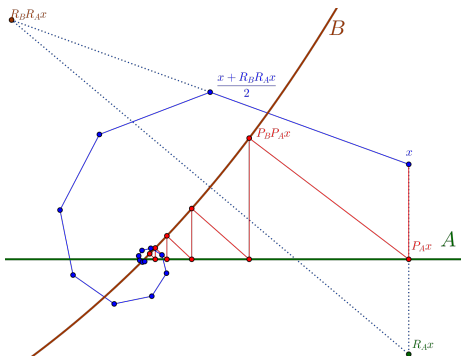
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# Convergence of AP and DR algorithms

When  $A$  and  $B$  are convex,

- ▶ the AP algorithm is globally convergent to a point in the intersection (Bregman, 1965);
- ▶ the DR algorithm is globally convergent to a **fixed point** (Lions–Mercier, 1979).

When  $A = \cup_{i \in I} A_i$  and  $B = \cup_{j \in J} B_j$  are finite unions of closed convex sets,

- ▶ the DR algorithm is locally convergent around **strong fixed points** (Bauschke–Noll, 2014);
- ▶ **is the AP algorithm locally convergent?**

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For a set-valued operator  $T: X \rightrightarrows X$ , the **fixed point set** is  $\text{Fix } T := \{x : x \in T(x)\}$ , and the **strong fixed point set** is  $\mathbf{Fix } T := \{x : \{x\} = T(x)\}$ . Both notions coincide for single-valued operators.

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# Averaged operators

Recall that a single-valued operator  $T: X \rightarrow X$  is **nonexpansive** if

$$\forall x, y \in X, \quad \|Tx - Ty\| \leq \|x - y\|,$$

and  **$\alpha$ -averaged** if  $\alpha \in (0, 1)$  and

$$\forall x, y \in X, \quad \|Tx - Ty\|^2 + \frac{1 - \alpha}{\alpha} \|(\text{Id} - T)x - (\text{Id} - T)y\|^2 \leq \|x - y\|^2.$$

- ▶  $T$  is  $\alpha$ -averaged if and only if  $T = (1 - \alpha)\text{Id} + \alpha R$  for some nonexpansive operator  $R: X \rightarrow X$ .
- ▶ The classes of nonexpansive and averaged operators are both closed under taking convex combination and under compositions.

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# Union averaged operators

## Definition

A set-valued operator  $T: X \rightrightarrows X$  is said to be **union  $\alpha$ -averaged** (resp. **union nonexpansive**) if  $T$  can be expressed in the form

$$\forall x \in X, \quad T(x) = \{T_i(x) : i \in \varphi(x)\},$$

where

- ▶  $I$  is a **finite** index set,
- ▶  $\{T_i\}_{i \in I}$  is a collection of  **$\alpha$ -averaged** (resp. **nonexpansive**) operators,
- ▶  $\varphi: X \rightrightarrows I$ , called an **active selector**, is nonempty-valued and **outer semicontinuous (osc)**:

$$\varphi(x) \supseteq \text{Limsup}_{y \rightarrow x} \varphi(y) := \{i \in I : \exists (x_n, i_n) \rightarrow (x, i) \text{ with } i_n \in \varphi(x_n)\}.$$

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# Unions, combinations and compositions

## Proposition

Let  $J := \{1, \dots, m\}$  and let  $T_j: X \rightrightarrows X$  be *union  $\alpha_j$ -averaged* (resp. *union nonexpansive*) for each  $j \in J$ . Then

- ①  $T: X \rightrightarrows X$  defined by  $x \mapsto T(x) := \cup_{j \in J} T_j(x)$  is *union  $\alpha$ -averaged* with  $\alpha := \max_{j \in J} \alpha_j$  (resp. *union nonexpansive*).
- ②  $\sum_{j \in J} \omega_j T_j$  is *union  $\alpha$ -averaged* with  $\alpha := \sum_{j \in J} \omega_j \alpha_j$  (resp. *union nonexpansive*) whenever  $(\omega_j)_{j \in J} \subseteq \mathbb{R}_{++}$  with  $\sum_{j \in J} \omega_j = 1$ .
- ③  $T_m \circ \dots \circ T_2 \circ T_1$  is *union  $\alpha$ -averaged* with

$$\alpha := \left( 1 + \left( \sum_{j \in J} \frac{\alpha_j}{1 - \alpha_j} \right)^{-1} \right)^{-1}$$

(resp. *union nonexpansive*).



# Min-convex functions

## Definition

A function  $f: X \rightarrow (-\infty, +\infty]$  is said to be **min-convex** if

$$\forall x \in X, \quad f(x) := \min_{i \in I} f_i(x),$$

where  $I$  is a finite index set and the  $f_i: X \rightarrow (-\infty, +\infty]$  are proper lsc convex functions.

If  $\{C_i\}_{i \in I}$  is a finite collection of nonempty closed convex subsets of  $X$ , then

$$\iota_C = \min_{i \in I} \iota_{C_i}$$

is a min-convex function.

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The **indicator function**  $\iota_C$  of  $C$  is defined by  $\iota_C(x) := 0$  if  $x \in C$  and  $\iota_C(x) := +\infty$  otherwise.

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# Proximity operator of min-convex functions

Given  $f: X \rightarrow (-\infty, +\infty]$  and  $\gamma > 0$ , the **Moreau envelope** of  $f$  is the function  $\gamma f: X \rightarrow (-\infty, +\infty]$  given by

$$\gamma f(x) := \inf_{y \in X} \left( f(y) + \frac{1}{2\gamma} \|x - y\|^2 \right)$$

and the **proximity operator** of  $f$  is the mapping  $\text{prox}_{\gamma f}: X \rightrightarrows X$  given by

$$\text{prox}_{\gamma f}(x) = \left\{ y \in X : f(y) + \frac{1}{2\gamma} \|x - y\|^2 = \gamma f(x) \right\}.$$

## Proposition

Let  $f = \min_{i \in I} f_i: X \rightarrow (-\infty, +\infty]$  be **min-convex**, and  $\gamma > 0$ . Then

- ① Every **fixed point of  $\text{prox}_{\gamma f}$**  is a **local minimum of  $f$** .
- ②  $\text{prox}_{\gamma f}$  is **union 1/2-averaged**. In particular,

$$\text{prox}_{\gamma f}(x) = \{ \text{prox}_{\gamma f_i}(x) : i \in \varphi(x) \}$$

with  $\varphi: X \rightrightarrows I$  given by  $\varphi(x) = \{ i \in I : \gamma f(x) = \gamma f_i(x) \}$ .

# Projection operators on union convex sets

## Corollary

Let  $A = \cup_{i \in I} A_i$  and  $B = \cup_{j \in J} B_j$  be finite unions of nonempty closed convex sets in  $X$ . Then

- ① The projector  $P_A$  is union 1/2-averaged with

$$P_A(x) = \{P_{A_i}(x) : i \in I, d(x, A_i) = d(x, A)\}$$

and the reflector  $R_A := 2P_A - \text{Id}$  is union nonexpansive.

- ② The DR operator  $T_{A,B}$  is union 1/2-averaged.

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$d(x, C) := \inf_{c \in C} \|x - c\|$  is the **distance** from  $x$  to  $C$ .

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## Krasnosel'skiĭ–Mann iterations with admissible control

## Definition (Admissible sequences)

A sequence  $(i_n)_{n \in \mathbb{N}} \subseteq I$  is **admissible** in  $I^* \subseteq I$  if every element of  $I^*$  appears infinitely often in  $(i_n)_{n \in \mathbb{N}}$ .

## Theorem

Let  $\{T_i\}_{i \in I}$  be a finite collection of *nonexpansive operators* on  $X$  with a common fixed point. Given  $x_0 \in X$ , define  $(x_n)_{n \in \mathbb{N}}$  according to

$$\forall n \in \mathbb{N}, \quad x_{n+1} := (1 - \lambda_n)x_n + \lambda_n T_{i_n}(x_n),$$

where  $(i_n)_{n \in \mathbb{N}}$  is *admissible* in  $I$ , and  $(\lambda_n)_{n \in \mathbb{N}}$  is in  $(0, 1]$  with  $\liminf_{n \rightarrow \infty} \lambda_n(1 - \lambda_n) > 0$ . Then  $x_n \rightarrow \bar{x} \in \bigcap_{i \in I} \text{Fix } T_i$ .

- ▶ The  $T_i$  are  $\alpha_i$ -averaged  
 $\longrightarrow \lambda_n \in (0, 1/\alpha_{i_n}]$  and  $\liminf_{n \rightarrow \infty} \lambda_n(1 - \alpha_{i_n} \lambda_n) > 0$ .

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# Local convergence of union nonexpansive iterations

Let  $T: X \rightrightarrows X$  be a **union nonexpansive** operator with representation

$$T(x) = \{T_i(x) : i \in \varphi(x)\}.$$

The **radius of attraction** of  $T$  at a point  $x^* \in X$  is defined as

$$r(x^*; T) := \sup\{\delta > 0 : \forall x \in \mathbb{B}(x^*; \delta), \varphi(x) \subseteq \varphi(x^*)\} \in (0, +\infty].$$

## Theorem

Let  $x^* \in \mathbf{Fix} T$ , set  $r := r(x^*; T)$ , and consider a sequence  $(x_n)_{n \in \mathbb{N}}$  with  $x_0 \in \mathbf{int} \mathbb{B}(x^*; r)$  satisfying

$$\forall n \in \mathbb{N}, \quad x_{n+1} \in (1 - \lambda_n)x_n + \lambda_n T(x_n),$$

where  $(\lambda_n)_{n \in \mathbb{N}} \subseteq (0, 1]$  with  $\liminf_{n \rightarrow \infty} \lambda_n(1 - \lambda_n) > 0$ . Then

$$x_n \rightarrow \bar{x} \in \mathbf{Fix} T \cap \mathbb{B}(x^*; r).$$

- ▶  $T$  is union  $\alpha$ -averaged:  $\lambda_n \in (0, 1/\alpha]$  &  $\liminf_{n \rightarrow \infty} \lambda_n(1/\alpha - \lambda_n) > 0$ .
- ▶  $\varphi(x^*) = I \implies r(x^*; T) = +\infty \implies$  global convergence.

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Let  $T: X \rightrightarrows X$  be a **union nonexpansive** operator with representation

$$T(x) = \{T_i(x) : i \in \varphi(x)\}.$$

The **radius of attraction** of  $T$  at a point  $x^* \in X$  is defined as

$$r(x^*; T) := \sup\{\delta > 0 : \forall x \in \mathbb{B}(x^*; \delta), \varphi(x) \subseteq \varphi(x^*)\} \in (0, +\infty].$$

## Theorem

Let  $x^* \in \mathbf{Fix} T$ , set  $r := r(x^*; T)$ , and consider a sequence  $(x_n)_{n \in \mathbb{N}}$  with  $x_0 \in \mathbf{int} \mathbb{B}(x^*; r)$  satisfying

$$\forall n \in \mathbb{N}, \quad x_{n+1} \in (1 - \lambda_n)x_n + \lambda_n T(x_n),$$

where  $(\lambda_n)_{n \in \mathbb{N}} \subseteq (0, 1]$  with  $\liminf_{n \rightarrow \infty} \lambda_n(1 - \lambda_n) > 0$ . Then

$$x_n \rightarrow \bar{x} \in \mathbf{Fix} T \cap \mathbb{B}(x^*; r).$$

- ▶  $T$  is union  $\alpha$ -averaged:  $\lambda_n \in (0, 1/\alpha]$  &  $\liminf_{n \rightarrow \infty} \lambda_n(1/\alpha - \lambda_n) > 0$ .
- ▶  $\varphi(x^*) = I \implies r(x^*; T) = +\infty \longrightarrow$  **global convergence**.

# Outline

- 1 Union averaged operators
- 2 Convergence of fixed point algorithms
- 3 Proximal algorithms for min-convex minimization

# Projection algorithms

## Theorem

Let  $J := \{1, \dots, m\}$  and let  $\{C_j\}_{j \in J}$  be a collection of union convex sets. Given  $x_0 \in X$ , define  $x_{n+1} \in T(x_n)$  for all  $n \in \mathbb{N}$  in one of the following:

- ① (*method of cyclic projections*)  $T = P_{C_m} \circ \dots \circ P_{C_2} \circ P_{C_1}$ .
- ② (*cyclic DR method*)  $T = T_{C_m, C_1} \circ \dots \circ T_{C_2, C_3} \circ T_{C_1, C_2}$ .
- ③ (*cyclically anchored DR method*)  $T = T_{C_1, C_m} \circ \dots \circ T_{C_1, C_3} \circ T_{C_1, C_2}$ .

Then  $\bigcap_{j \in J} C_j \subseteq \mathbf{Fix} T$ . Moreover, if  $x^* \in \mathbf{Fix} T$ , then

$$\exists r > 0, \forall x_0 \in \text{int } \mathbb{B}(x^*; r), \quad x_n \rightarrow \bar{x} \in \mathbf{Fix} T \cap \mathbb{B}(x^*; r).$$

# Cyclically anchored DR method

## Theorem

Let  $J := \{1, \dots, m\}$  and let  $\{C_j\}_{j \in J}$  be a collection of union convex sets with  $x^* \in \bigcap_{j \in J \setminus \{1\}} C_j$ . **Fix**  $T_{C_1, C_j}$ . Given  $x_0 \in X$ , define  $(x_n)_{n \in \mathbb{N}}$  according to

$$\forall n \in \mathbb{N}, \quad x_{n+1} \in T_{C_1, C_{i_n}}(x_n) \quad \text{where } i_n = (n \bmod (m-1)) + 2.$$

Then  $\exists r > 0, \forall x_0 \in \text{int } \mathbb{B}(x^*; r), x_n \rightarrow \bar{x} \in \bigcap_{j \in J \setminus \{1\}} C_j$ .

Moreover, if the set  $C_1$  is convex, then  $P_{C_1}(\bar{x}) \in \bigcap_{j \in J} C_j$ .

- ▶  $m = 2$ : Result by Bauschke–Noll (2014).
- ▶ Apply to  $\{X, C_1, \dots, C_m\}$ : Result for the method of cyclic projections.

# Cyclically anchored DR method

## Theorem

Let  $J := \{1, \dots, m\}$  and let  $\{C_j\}_{j \in J}$  be a collection of union convex sets with  $x^* \in \bigcap_{j \in J \setminus \{1\}} C_j$ . Given  $x_0 \in X$ , define  $(x_n)_{n \in \mathbb{N}}$  according to

$$\forall n \in \mathbb{N}, \quad x_{n+1} \in T_{C_1, C_{i_n}}(x_n) \quad \text{where } i_n = (n \bmod (m-1)) + 2.$$

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Moreover, if the set  $C_1$  is convex, then  $P_{C_1}(\bar{x}) \in \bigcap_{j \in J} C_j$ .

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# Proximal algorithms

Let  $f: X \rightarrow \mathbb{R}$  be convex,  $g := \min_{i \in I} g_i: X \rightarrow (-\infty, +\infty]$  be min-convex, and  $\gamma > 0$ .





- ▶ Proximal point algorithm (PPA):  $T_{\text{PPA}} := \text{prox}_{\gamma g}$ .
- ▶ Forward–backward splitting (FBS):  $T_{\text{FB}} := \text{prox}_{\gamma g}(\text{Id} - \gamma \nabla f)$ .
- ▶ Douglas–Rachford splitting (DRS):

$$T_{\text{DR}} := \frac{1}{2} (\text{Id} + (2 \text{prox}_{\gamma g} - \text{Id}) \circ (2 \text{prox}_{\gamma f} - \text{Id})).$$

## Theorem

- ▶ *The PPA is locally convergent to a **local minimum of  $g$** .*
- ▶ *The DRS is locally convergent to a fixed point  $\bar{x}$  such that  $\text{prox}_{\gamma f}(\bar{x})$  is a **local minimum of  $f + g$** .*
- ▶ *If  $f$  has Lipschitz continuous gradient, then FBS is locally convergent to a **local minimum of  $f + g$** .*

# Some key references

-  H.H. Bauschke and D. Noll, On the local convergence of the Douglas–Rachford algorithm, *Arch. Math.* **102**(6), 589–600 (2014).
-  M.N. Dao and M.K. Tam, Union averaged operators with applications to proximal algorithms for min-convex functions, *J. Optim. Theory Appl.* (2018). DOI:10.1007/s10957-018-1443-x
-  L. Elsner, I. Koltracht, and M. Neumann, Convergence of sequential and asynchronous nonlinear paracontractions, *Numer. Math.* **62**(3), 305–319 (1992).
-  M.K. Tam, Algorithms based on unions of nonexpansive maps, *Optim. Lett.* **12**(5), 1019–1027 (2018).

THANK YOU VERY MUCH!