

# Cyclic Douglas–Rachford Iterations

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# Talk Outline

1 Preliminaries

2 Main Results

3 Computation Results

# Feasibility Problems

The  **$N$ -set convex feasibility problem** asks:

$$\text{Find } x \in \bigcap_{i=1}^N C_i \subseteq \mathcal{H}, \quad (\text{CFP})$$

where  $C_i$  are **closed** and **convex**,  $\mathcal{H}$  a Hilbert space.

A common approach is the use of **projection algorithms**.

- von Neumann's alternating projection method (cyclic projections).
- Dysktra's method.
- Douglas–Rachford method.
- Many variants exist!

# Projections, Reflections

Let  $S \subseteq \mathcal{H}$ . The (nearest point) **projection** of  $x$  onto  $S$  is the (set-valued) mapping defined by

$$P_S(x) := \arg \min_{s \in S} \|x - s\|.$$



## Variational Characterisation of Projections

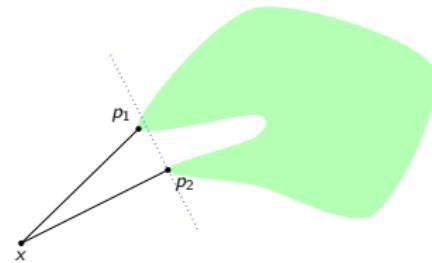
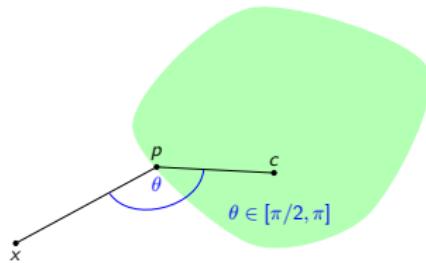
Let  $C \subseteq \mathcal{H}$  be **closed** and **convex**. Then  $P_C(x)$  exists uniquely  $\forall x \in \mathcal{H}$ , and

$$P_C(x) = p \iff \langle x - p, c - p \rangle \leq 0, \quad \forall c \in C.$$

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# Projections, Reflections

Let  $S \subseteq \mathcal{H}$ . The **reflection** of  $x$  onto  $S$  is the (set-valued) mapping defined by

$$R_S(x) := 2P_S(x) - x.$$



## Variational Characterisation of Reflections

Let  $C \subseteq \mathcal{H}$  be **closed** and **convex**. Then  $R_C(x)$  exists uniquely  $\forall x \in \mathcal{H}$ , and

$$R_C(x) = r \iff \langle x - r, c - r \rangle \leq \frac{1}{2} \|x - r\|^2, \quad \forall c \in C.$$

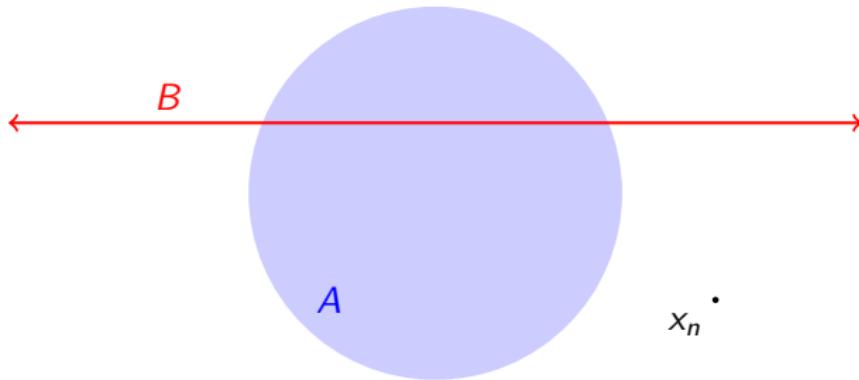
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Then  $(x_n)$  converges weakly to  $x$  such that  $P_Ax \in A \cap B$ .



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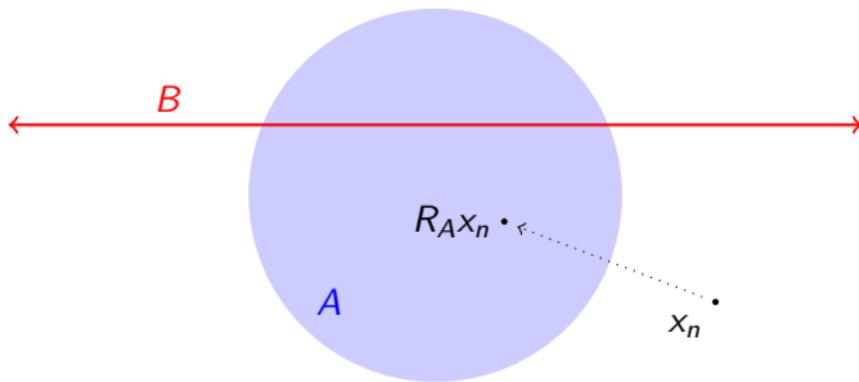
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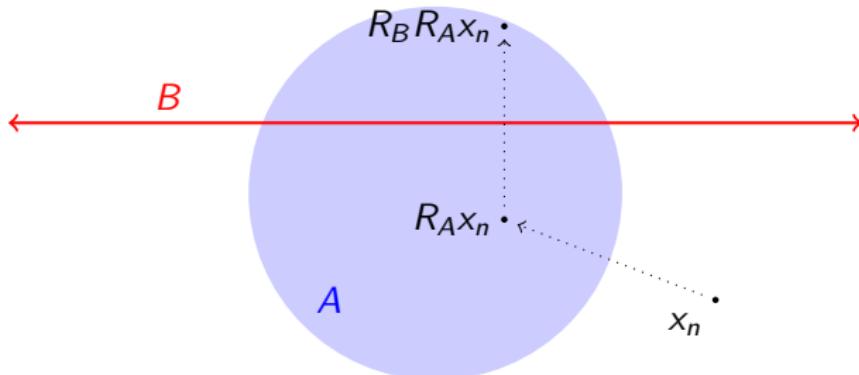
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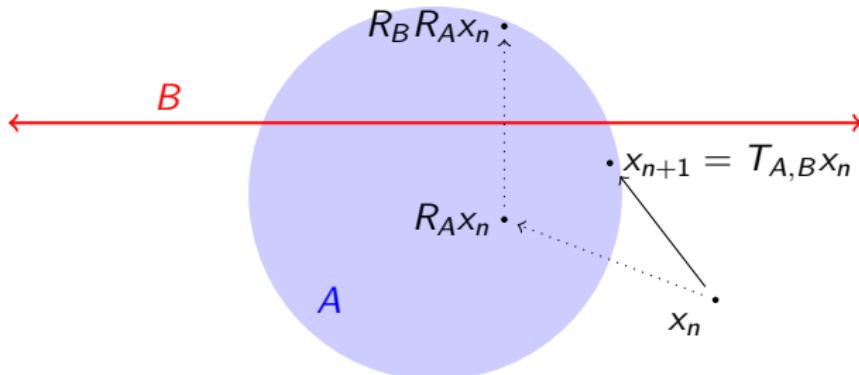
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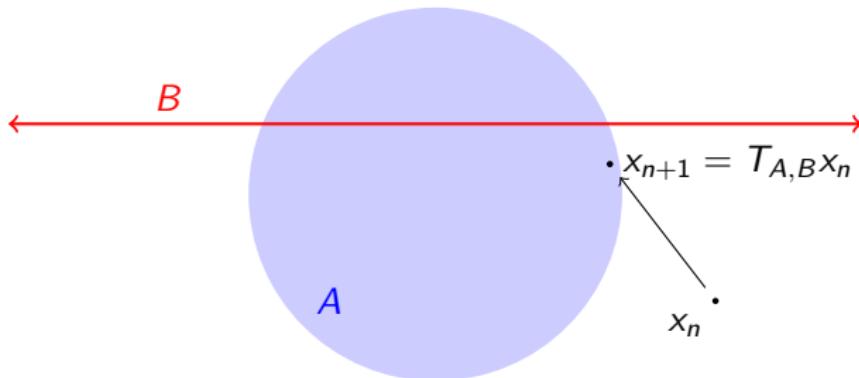
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# Some Tools

Let  $T : \mathcal{H} \rightarrow \mathcal{H}$ . Then  $T$  is:

- **nonexpansive** if

$$\|Tx - Ty\| \leq \|x - y\|, \quad \forall x, y \in \mathcal{H}.$$

- **firmly nonexpansive** if

$$\|Tx - Ty\|^2 + \|(I - T)x - (I - T)y\|^2 \leq \|x - y\|^2, \quad \forall x, y \in \mathcal{H}.$$

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## Proposition (Nonexpansive properties)

The following are equivalent.

- $T$  is firmly nonexpansive.
- $I - T$  is firmly nonexpansive.
- $2T - I$  is nonexpansive.
- $T = \alpha I + (1 - \alpha)R$ , for  $\alpha \in (0, 1/2]$  and some nonexpansive  $R$ .
- Many other characterisations.

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## Nonexpansive properties of projections

Let  $A, B \subseteq \mathcal{H}$  be closed and convex. Then

- $P_A := \arg \min_{s \in S} \|\cdot - s\|$  is firmly nonexpansive.
- $R_A := 2P_A - I$  is nonexpansive.
- $T_{A,B} := (I + R_B R_A)/2$  is firmly nonexpansive.

Nonexpansive maps are closed under composition, convex combinations, etc. Firmly nonexpansive maps need not be. E.g. Composition of two projections onto subspace in  $\mathbb{R}^2$  (Bauschke–Borwein–Lewis, 1997).

# Some Tools

- **asymptotically regular** if, for all  $x \in \mathcal{H}$ ,

$$\|T^{n+1}x - T^n x\| \rightarrow 0.$$

Any firmly nonexpansive mapping with at least one fixed point is asymptotically regular.

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## Theorem (Opial, 1967)

Let  $T : \mathcal{H} \rightarrow \mathcal{H}$  be **nonexpansive** and **asymptotically regular**. Set  $x_{n+1} = T^n x_n$ . Then  $(x_n)$  converges weakly to a point in  $\text{Fix } T$ .

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## Corollary

The Douglas–Rachford scheme converges weakly to a point  $x \in \text{Fix } T_{A,B}$ .

# Some Tools

What do fixed points of  $T_{A,B}$  look like?

$$\begin{aligned}x \in \text{Fix } T_{A,B} &\iff x = \frac{x + R_B R_A x}{2} \\&\iff x = 2P_B R_A x - R_A x \\&\iff x = 2P_B R_A x - 2P_A x + x \\&\iff P_A x = P_B R_A x\end{aligned}$$

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What if the feasibility problem has more than 2 sets? Can we generalise?

# Product Reformulation

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Moreover, the projections can be computed. If  $\mathbf{z} = (z_1, \dots, z_n) \in \mathcal{H}^N$ ,

$$P_C \mathbf{z} = \prod_{i=1}^N P_{C_i} z_i, \quad P_D \mathbf{z} = \left( \frac{1}{N} \sum_{i=1}^N z_i \right)^N.$$

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- $(x_n)$  converges weakly to a point  $x \in \text{Fix } T_{A,B,C}$ .
- Possible that  $P_Ax, P_Bx, P_Cx \notin A \cap B \cap C$ .

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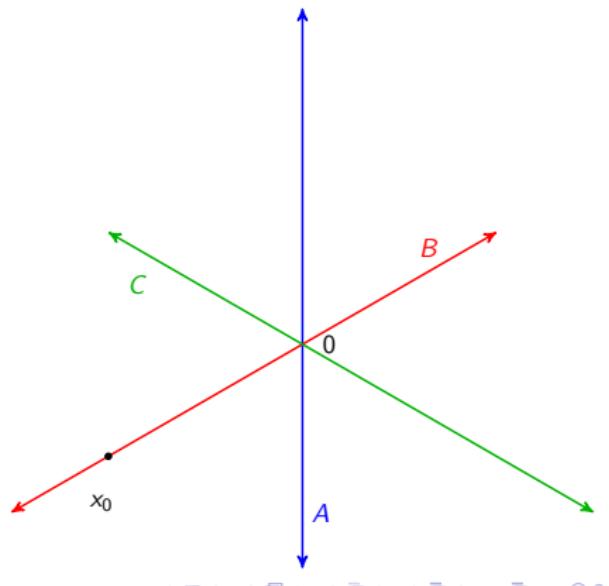
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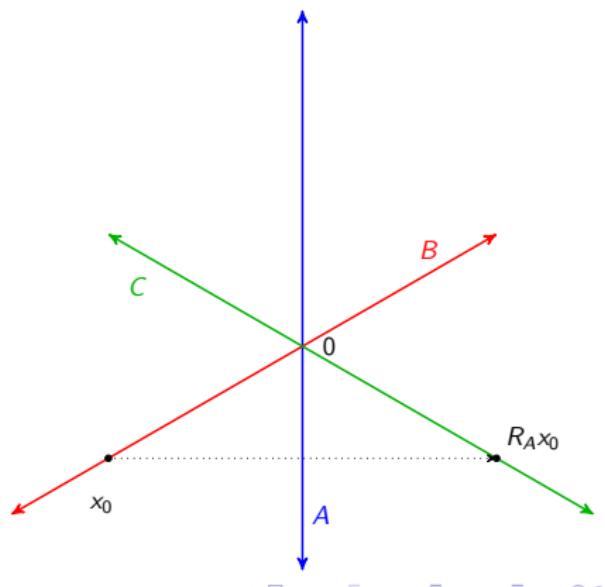
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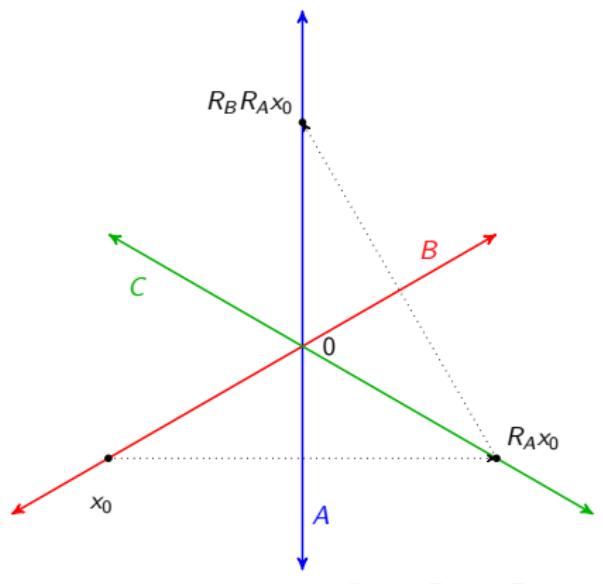
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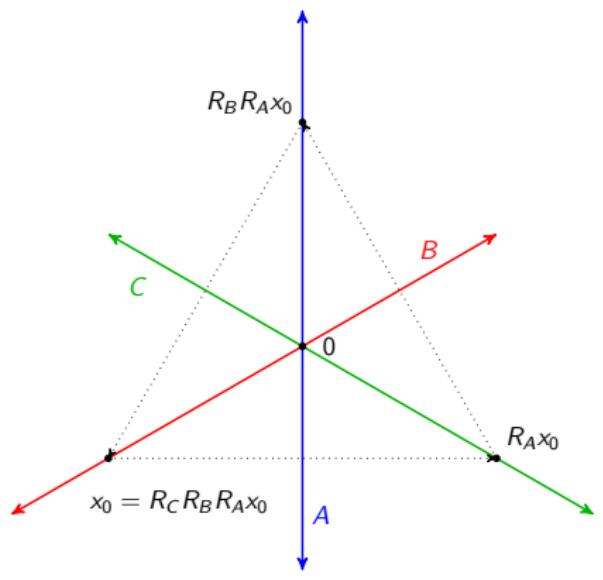
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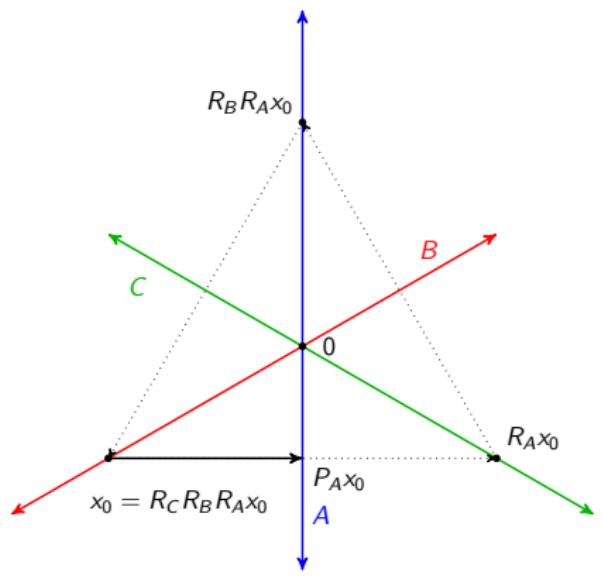
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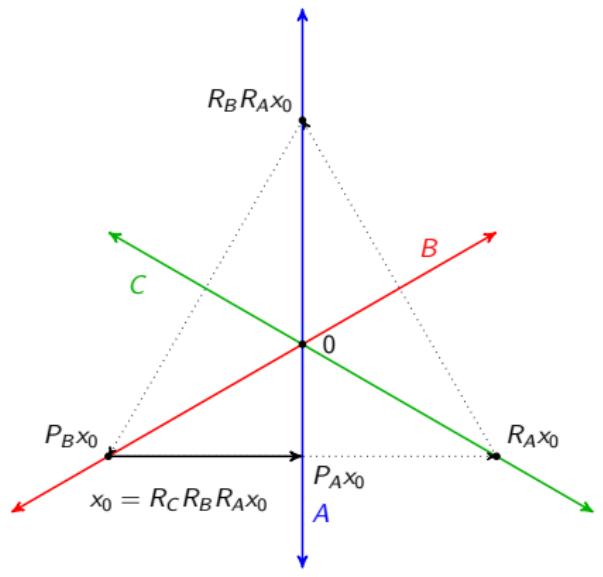
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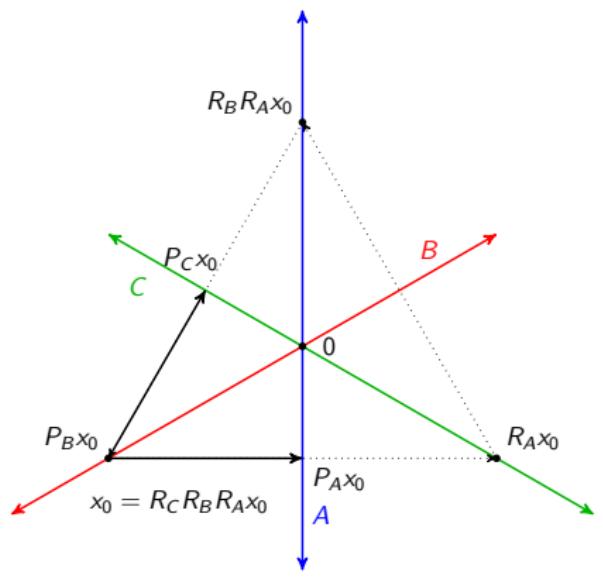
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For  $x_0 \in \mathcal{H}$ , define  $x_{n+1} := T_{[C_1 \ C_2 \dots \ C_N]} x_n$  where

$$T_{[C_1 \ C_2 \dots \ C_N]} := T_{C_1, C_N} T_{C_N, C_{N-1}} \dots T_{C_2, C_3} T_{C_1, C_2}.$$

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In the  $N = 2$  case, the mapping is:

$$T_{[A B]} = T_{B,A} T_{A,B} = \left( \frac{I + R_A R_B}{2} \right) \left( \frac{I + R_B R_A}{2} \right).$$

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Note: The iteration can be applied with or without the product space formulation.

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$$P_S(x) := \arg \min_{s \in S} \|x - s\|, \quad R_S = 2P_S - I, \quad T_{A,B} = \frac{I + R_B R_A}{2}.$$

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$$p = P_C x \iff \langle x - p, c - p \rangle \leq 0, \quad \forall c \in C.$$

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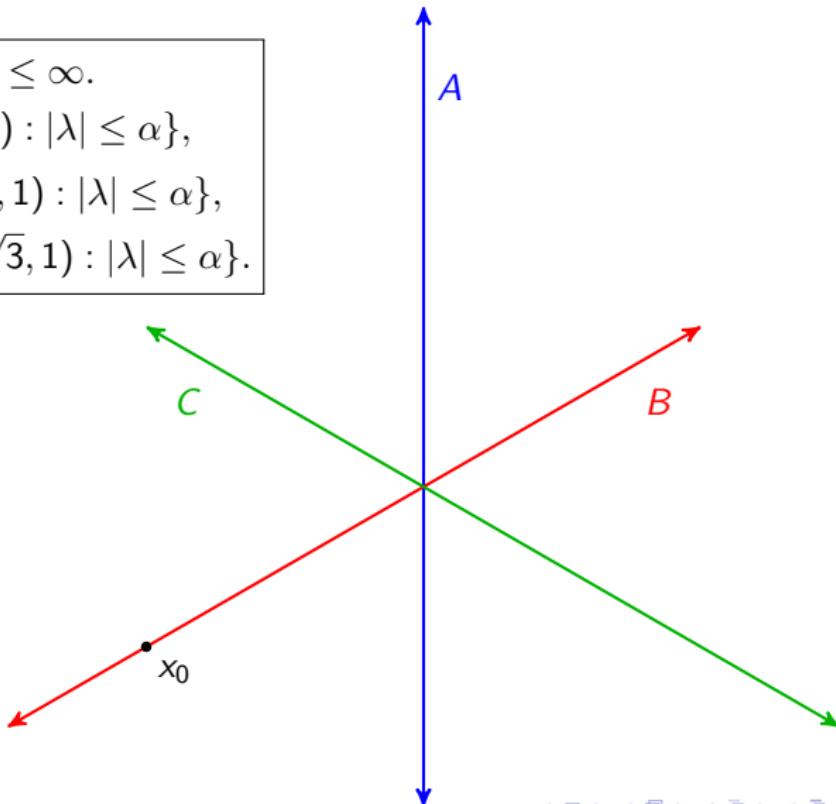
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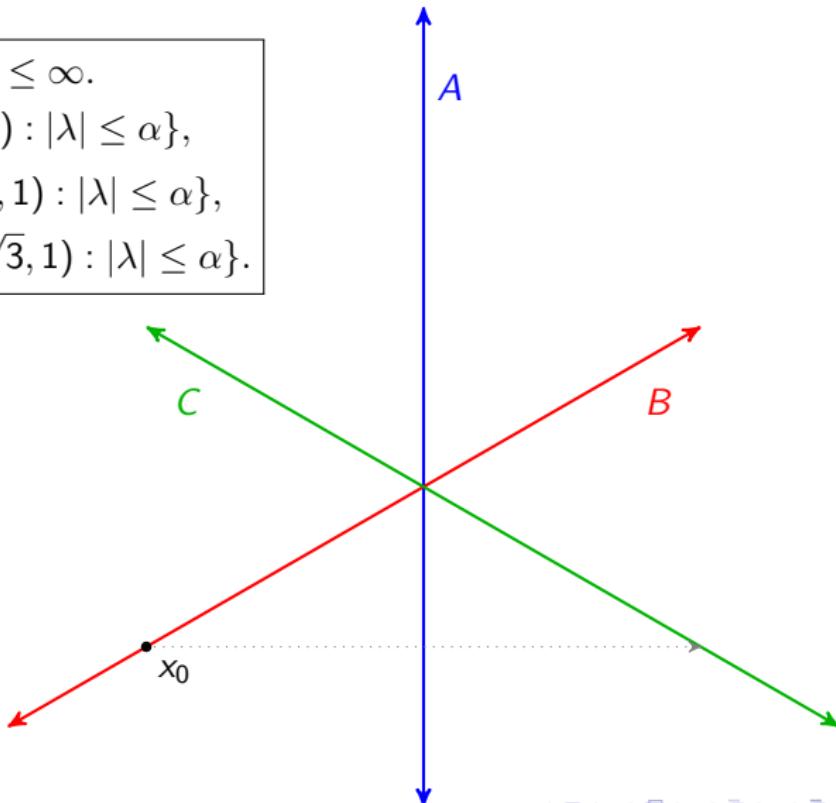
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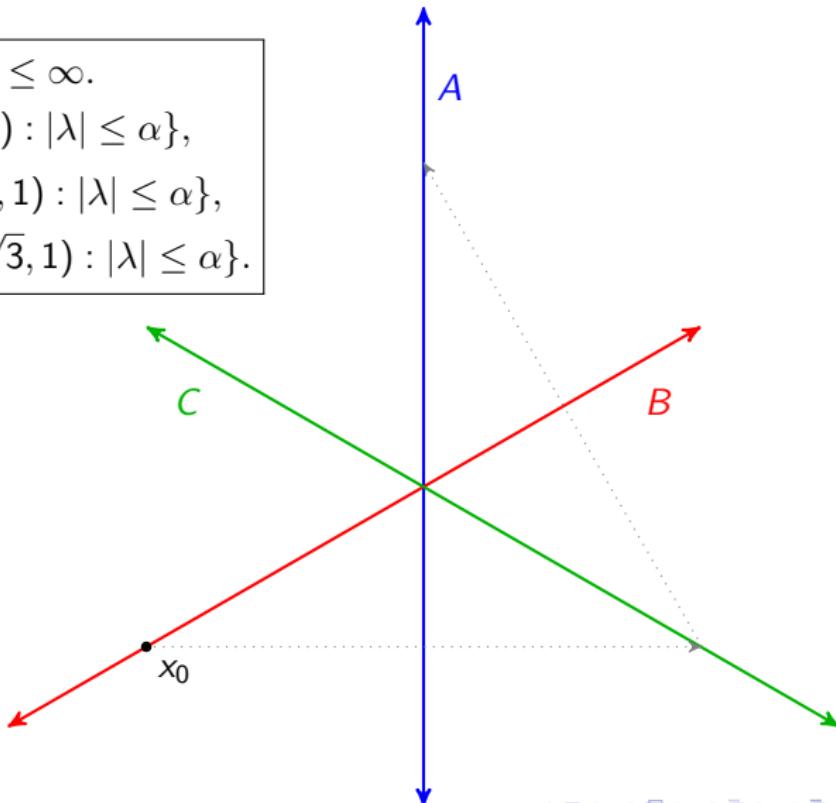
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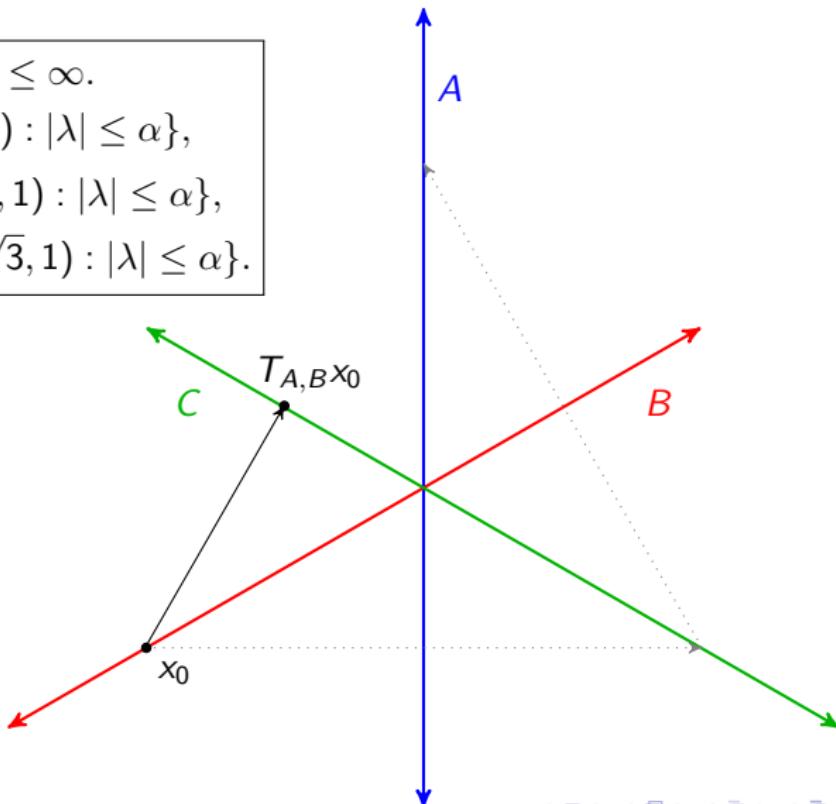
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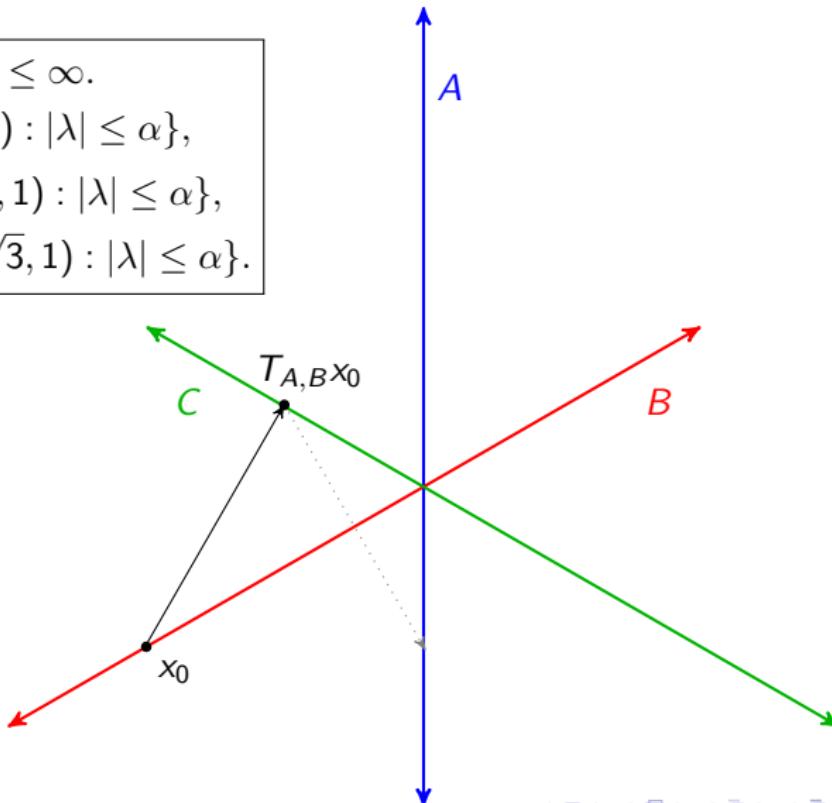
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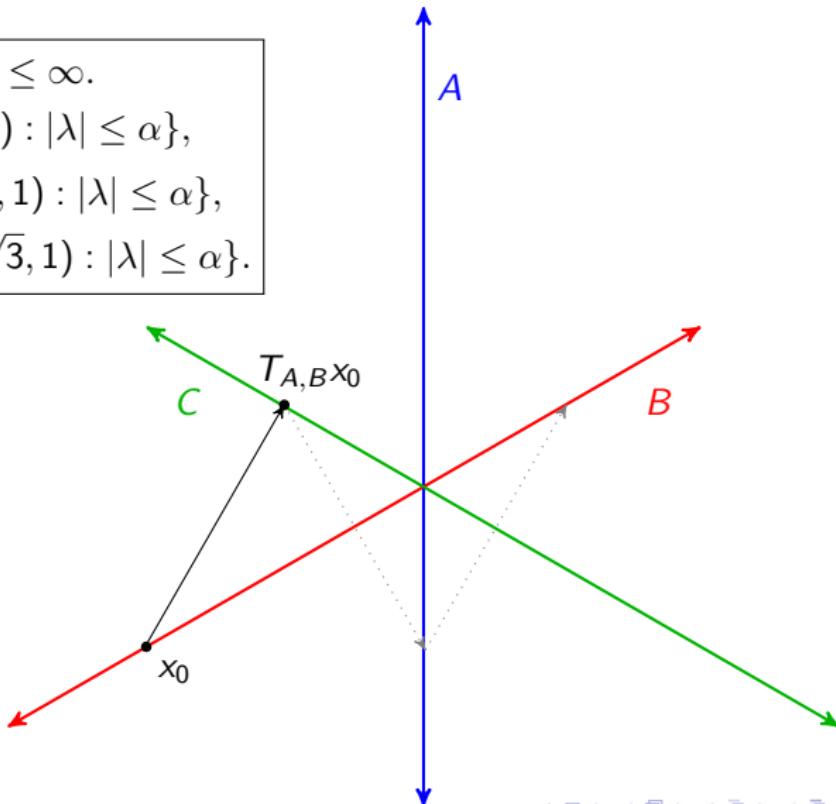
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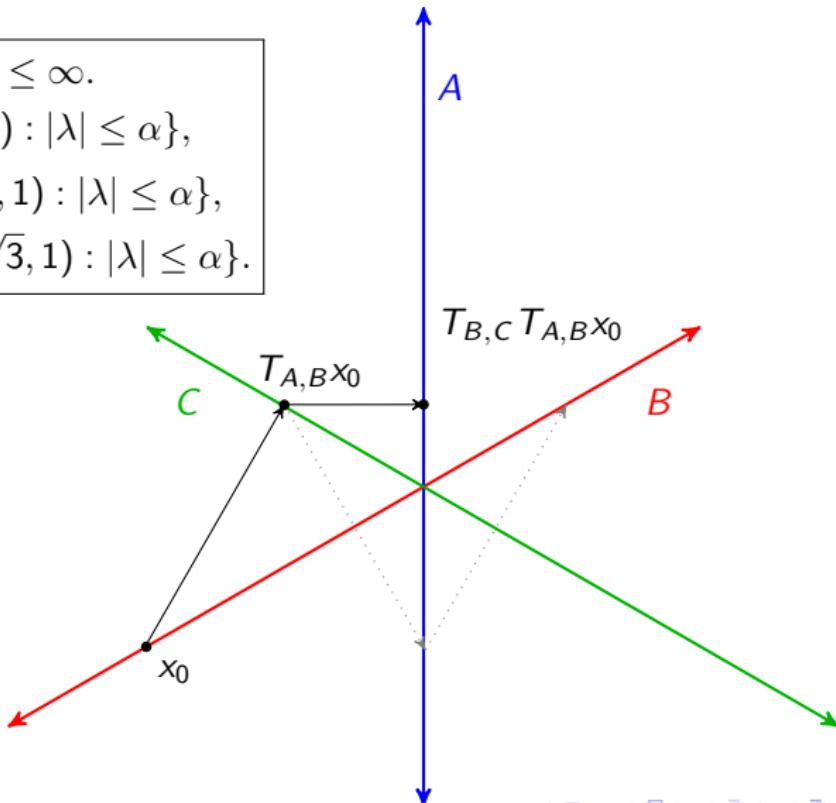
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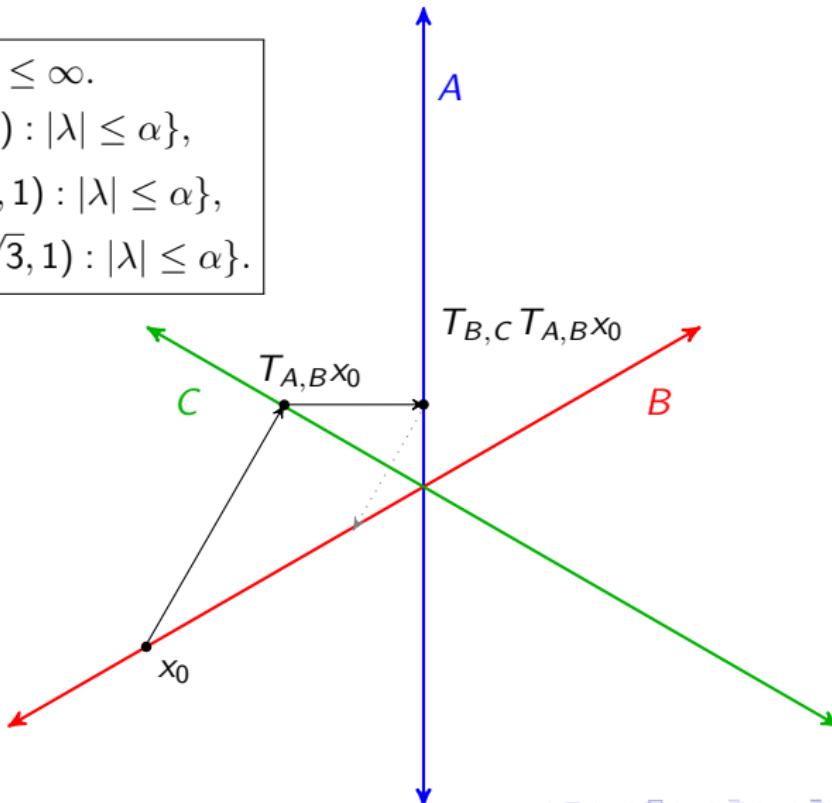
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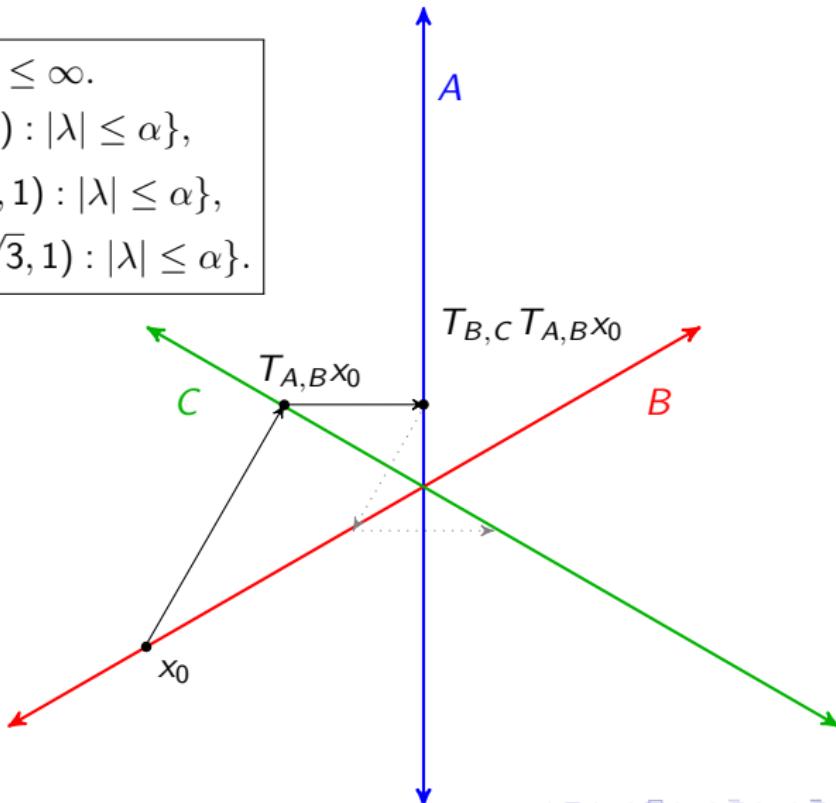
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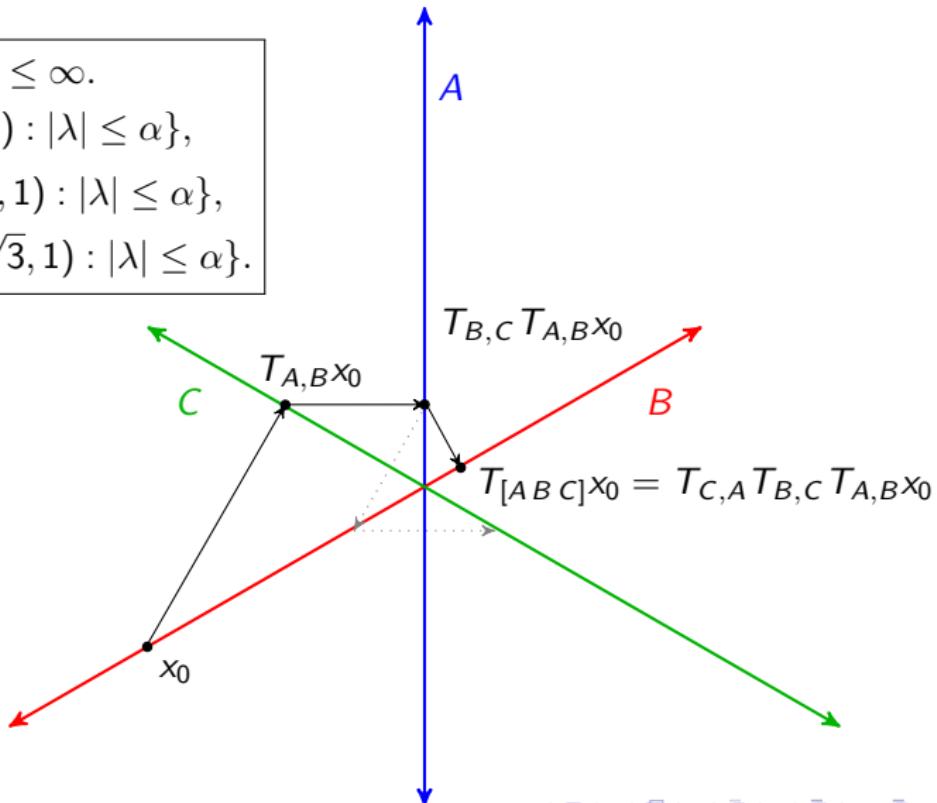
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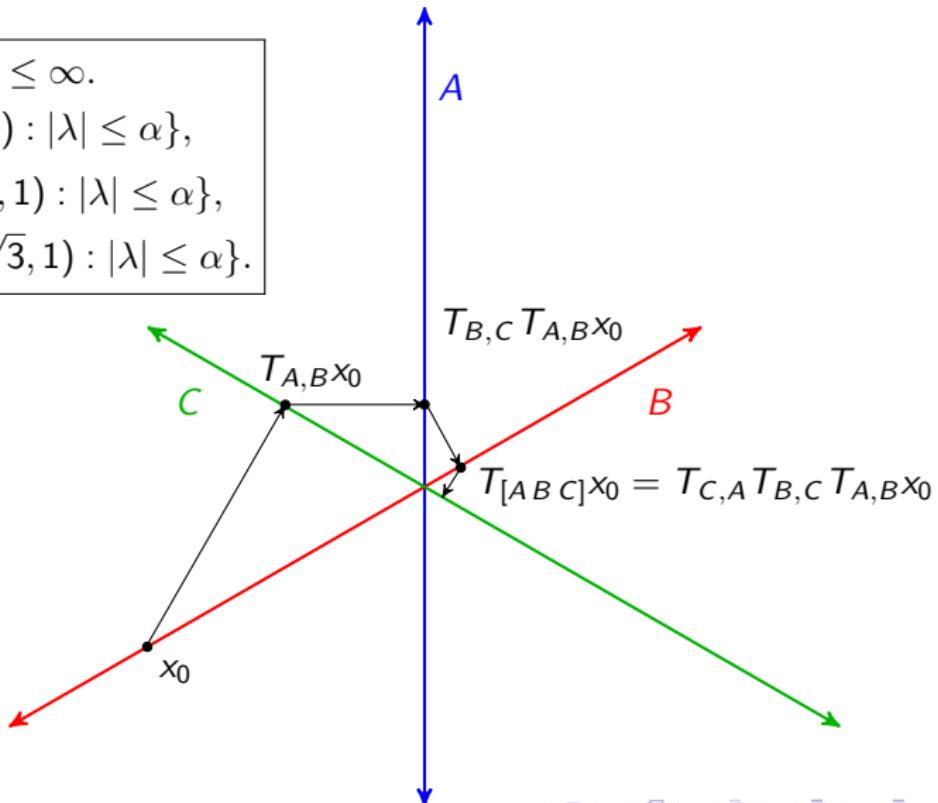
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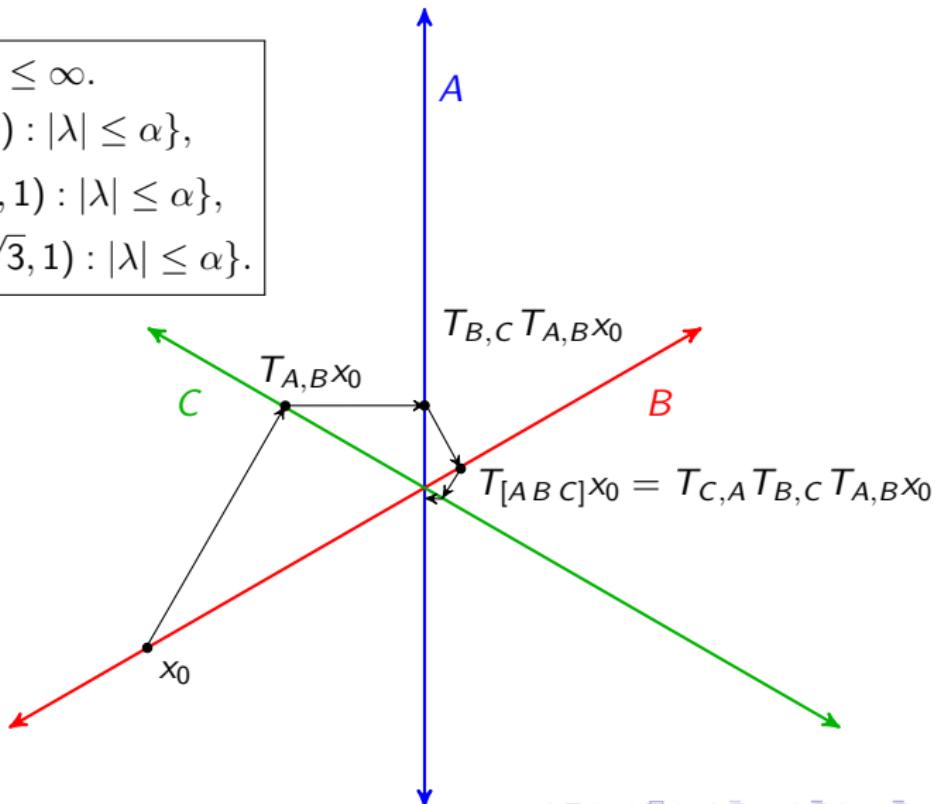
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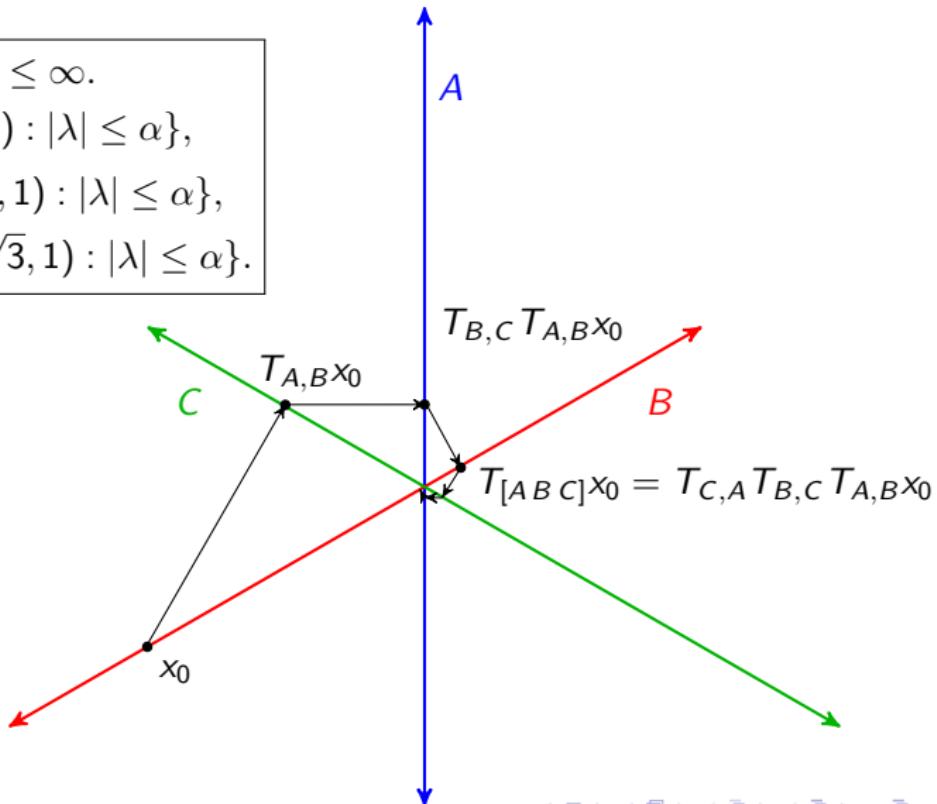
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## Failure of Norm Convergence (Hundal, 2004)

Let  $\mathcal{H} = \ell_2$  and  $\{e_i\}$  denote the standard basis vectors. Define

$$C_1 = \{x \in \mathcal{H} : \langle e_1, x \rangle \leq 0\}, \quad C_2 = \text{an "unnatural" cone.}$$

Then  $C_1 \cap C_2 = \{0\}$ . If  $x_0 = \exp(-100)e_1 + e_3$ , then

$$\lim_{n \rightarrow \infty} \|(P_{C_2}P_{C_1})^n x_0\| > 0.$$



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These are many other applicable variants. E.g. Krasnoselski–Mann iterations:

$$x_{n+1} = x_n + \lambda_n(Tx_n - x_n),$$

where  $\lambda_n \in [0, 1]$  such that  $\sum_{i=1}^{\infty} \lambda_n(1 - \lambda_n) = +\infty$ .

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**Proof.** For  $x_0 \in \mathcal{H}$ , set  $\mathbf{x}_0 = (x_0, \dots, x_0)$ . Now consider the (product space) iteration

$$\mathbf{x}_{n+1} = P_D \left( \prod_{i=1}^N T_{C_i, C_{i+1}} \right) \mathbf{x}_n.$$

# Numerical Experiments

Here we shall consider the  $N$ -set feasibly problem:

$$\text{Find } x \in \bigcap_{i=1}^N C_i, \text{ where } C_i = y_i + r_i \mathcal{B}_{\mathbb{R}^n} := \{x \in \mathbb{R}^n : \|x - y_i\| \leq r_i\}.$$

We have also consider the same problem replacing the ball constraints with (non-convex) spheres, and certain types of (convex) ellipsoids. Results are similar.

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- Initialise: Random  $x_0 \in [-5, 5]^n$ .
- Termination criterion:
  - $\|x_{n+1} - x_n\| < \epsilon$  where  $\epsilon = 10^{-3}, 10^{-6}$ .
  - Maximum of 1000 iterations.
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- Quality of solution was assessed by: error =  $\sum_{i=2}^N \|P_{C_i}x - P_{C_1}x\|^2$
- We compared:
  - Cyclic Douglas–Rachford, applied directly to the problem.
  - The classical Douglas–Rachford, in the product formulation.

# Numerical Results

**Table 1.** Mean (Max) results for  $N$  ball constraints in  $\mathbb{R}^n$  with  $\epsilon = 10^{-3}$ .

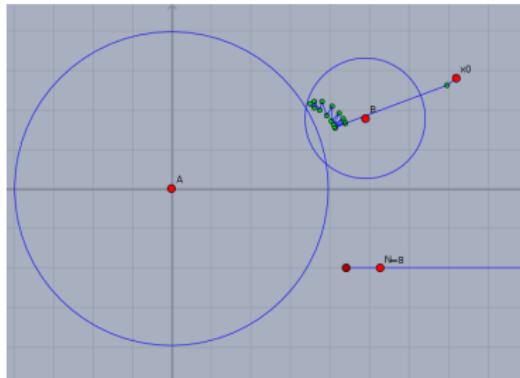
$n$	$N$	Iterations		Time (s)		Error	
		cycDR	DR	cycDR	DR	cycDR	DR
100	10	4.6 (5)	22.9 (45)	0.004 (0.005)	0.022 (0.041)	0 (0)	7.91e-34 (1.65e-33)
100	20	3.4 (4)	42.4 (113)	0.006 (0.007)	0.071 (0.183)	0 (0)	1.59e-33 (6.11e-33)
100	50	2.3 (3)	75.3 (241)	0.008 (0.011)	0.288 (0.907)	2.03e-14 (2.02e-13)	6.37e-08 (6.37e-07)
100	100	2.1 (3)	97.9 (151)	0.014 (0.019)	0.717 (1.096)	0 (0)	5.51e-33 (3.85e-32)
100	200	2.0 (2)	186.2 (329)	0.025 (0.025)	2.655 (4.656)	9.68e-15 (9.68e-14)	2.17e-08 (2.17e-07)
100	500	2.0 (2)	284.2 (372)	0.059 (0.060)	9.968 (12.989)	0 (0)	2.70e-07 (9.51e-07)
100	1000	2.0 (2)	383.0 (507)	0.118 (0.119)	26.656 (35.120)	0 (0)	4.30e-07 (9.42e-07)
100	1100	2.0 (2)	380.7 (471)	0.129 (0.130)	29.160 (36.001)	0 (0)	8.35e-07 (1.79e-06)
100	1200	2.0 (2)	372.3 (537)	0.141 (0.144)	31.140 (44.886)	0 (0)	8.08e-07 (1.79e-06)
100	1500	2.0 (2)	466.0 (631)	0.178 (0.181)	49.282 (66.533)	0 (0)	5.38e-05 (5.34e-04)
100	2000	2.0 (2)	529.3 (725)	0.232 (0.234)	74.878 (102.148)	9.31e-19 (5.29e-18)	4.79e-06 (4.00e-05)
1000	10	15.0 (16)	12.4 (26)	0.024 (0.026)	0.023 (0.048)	2.12e-19 (2.12e-18)	1.24e-32 (3.34e-32)
1000	20	8.2 (9)	20.4 (71)	0.024 (0.027)	0.069 (0.237)	0 (0)	3.02e-32 (6.98e-32)
1000	50	4.3 (5)	38.8 (112)	0.028 (0.031)	0.311 (0.884)	2.67e-19 (2.67e-18)	1.24e-31 (5.29e-31)
1000	100	3.3 (4)	80.8 (222)	0.037 (0.042)	1.260 (3.436)	0 (0)	2.15e-31 (6.84e-31)
1000	200	2.4 (3)	138.5 (270)	0.048 (0.058)	4.730 (9.446)	0 (0)	6.50e-31 (2.52e-30)
1000	500	2.0 (2)	201.3 (313)	0.085 (0.086)	20.356 (31.166)	3.90e-20 (3.90e-19)	2.10e-30 (6.11e-30)
1000	1000	2.0 (2)	348.8 (518)	0.162 (0.164)	73.420 (108.493)	0 (0)	1.36e-06 (1.20e-05)
1000	1100	2.1 (3)	334.4 (550)	0.183 (0.260)	77.174 (126.896)	0 (0)	1.10e-07 (7.62e-07)
1000	1200	2.0 (2)	353.8 (518)	0.190 (0.193)	89.153 (128.683)	0 (0)	1.74e-07 (9.63e-07)
1000	1500	2.1 (3)	403.9 (607)	0.245 (0.346)	126.707 (189.011)	1.33e-19 (1.33e-18)	3.17e-07 (8.94e-07)
1000	2000	2.0 (2)	487.0 (593)	0.307 (0.312)	239.210 (374.390)	0 (0)	3.58e-07 (1.11e-06)

# Numerical Results

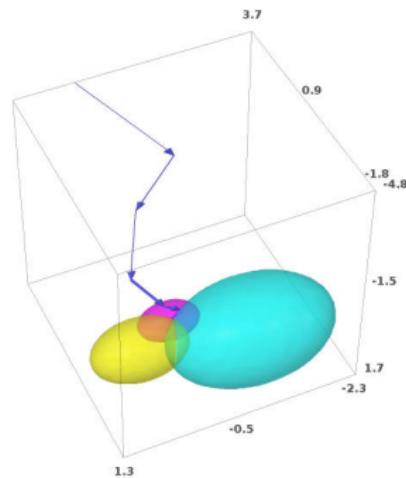
**Table 2.** Mean (Max) results for  $N$  ball constraints in  $\mathbb{R}^n$  with  $\epsilon = 10^{-6}$ .

$n$	$N$	Iterations		Time (s)		Error	
		cycDR	DR	cycDR	DR	cycDR	DR
100	10	4.7 (6)	22.9 (45)	0.005 (0.005)	0.023 (0.044)	0 (0)	7.91e-34 (1.65e-33)
100	20	3.6 (5)	42.4 (113)	0.006 (0.008)	0.077 (0.199)	0 (0)	1.59e-33 (6.11e-33)
100	50	2.6 (4)	77.4 (262)	0.010 (0.014)	0.320 (1.068)	0 (0)	1.24e-32 (5.96e-32)
100	100	2.1 (3)	97.9 (151)	0.015 (0.020)	0.781 (1.195)	0 (0)	5.51e-33 (3.85e-32)
100	200	2.3 (3)	187.1 (329)	0.029 (0.038)	2.909 (5.077)	0 (0)	5.89e-33 (2.30e-32)
100	500	2.3 (3)	329.6 (661)	0.071 (0.093)	12.554 (24.975)	0 (0)	1.81e-32 (6.37e-32)
100	1000	2.3 (3)	427.4 (635)	0.141 (0.184)	32.431 (47.903)	0 (0)	2.21e-32 (8.10e-32)
100	1100	2.3 (3)	467.4 (714)	0.153 (0.199)	38.936 (59.259)	0 (0)	3.92e-32 (3.17e-31)
100	1200	2.1 (3)	451.8 (698)	0.154 (0.218)	41.059 (63.259)	0 (0)	1.12e-31 (8.08e-31)
100	1500	2.1 (3)	507.2 (712)	0.193 (0.277)	58.578 (81.907)	0 (0)	2.66e-31 (8.15e-31)
100	2000	2.3 (3)	627.8 (808)	0.276 (0.361)	96.554 (124.880)	0 (0)	1.50e-31 (7.53e-31)
1000	10	15.1 (17)	12.4 (26)	0.024 (0.027)	0.030 (0.063)	0 (0)	1.24e-32 (3.34e-32)
1000	20	8.2 (9)	20.4 (71)	0.025 (0.027)	0.095 (0.330)	0 (0)	3.02e-32 (6.98e-32)
1000	50	4.5 (6)	38.8 (112)	0.029 (0.035)	0.434 (1.249)	0 (0)	1.24e-31 (5.29e-31)
1000	100	3.3 (4)	80.8 (222)	0.038 (0.043)	1.761 (4.730)	0 (0)	2.15e-31 (6.84e-31)
1000	200	2.5 (3)	138.5 (270)	0.051 (0.059)	6.224 (12.089)	0 (0)	6.50e-31 (2.52e-30)
1000	500	2.3 (3)	201.3 (313)	0.099 (0.125)	26.108 (40.534)	0 (0)	2.10e-30 (6.11e-30)
1000	1000	2.1 (3)	388.7 (905)	0.174 (0.241)	103.839 (243.085)	0 (0)	2.17e-30 (1.79e-29)
1000	1100	2.3 (3)	354.4 (660)	0.205 (0.264)	120.706 (220.612)	0 (0)	2.26e-30 (9.82e-30)
1000	1200	2.3 (3)	376.3 (620)	0.223 (0.288)	161.133 (260.857)	0 (0)	1.61e-30 (1.26e-29)
1000	1500	2.2 (3)	526.0 (1000)	0.265 (0.358)	276.095 (541.502)	2.68e-22 (2.68e-21)	1.08e-09 (5.98e-09)
1000	2000	2.1 (3)	595.0 (894)	0.332 (0.469)	427.933 (646.182)	0 (0)	4.48e-31 (1.97e-30)

# Interactive Geometry and Visualisations



**Figure 1.** Two circle constraints in  $\mathbb{R}^2$ , drawn in *Cinderella*.



**Figure 2.** Three ball constraints in  $\mathbb{R}^3$ , drawn in *Sage*.

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Let  $C_1, C_2 \in \mathcal{H}$  be closed and convex with empty intersection. Suppose best approximation pairs relative to  $(C_1, C_2)$  exists. Then the cyclic Douglas–Rachford scheme converges weakly to a point  $x$  such that  $(P_{C_1}x, P_{C_2}x)$  is a best approximation pair relative to  $(C_1, C_2)$ .

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- Further numerical experiments. e.g. arbitrary ellipsoids.

# References

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Many resources available at:

<http://carma.newcastle.edu.au/DRmethods>