

# Alternating Projections

- alternating projection algorithm
- convergence results
- example: PSD matrix completion
- example: relaxation method for linear inequalities

## Alternating projection algorithm

$C, D$  closed convex sets in  $\mathbf{R}^n$ ; goal is to find point in  $C \cap D$

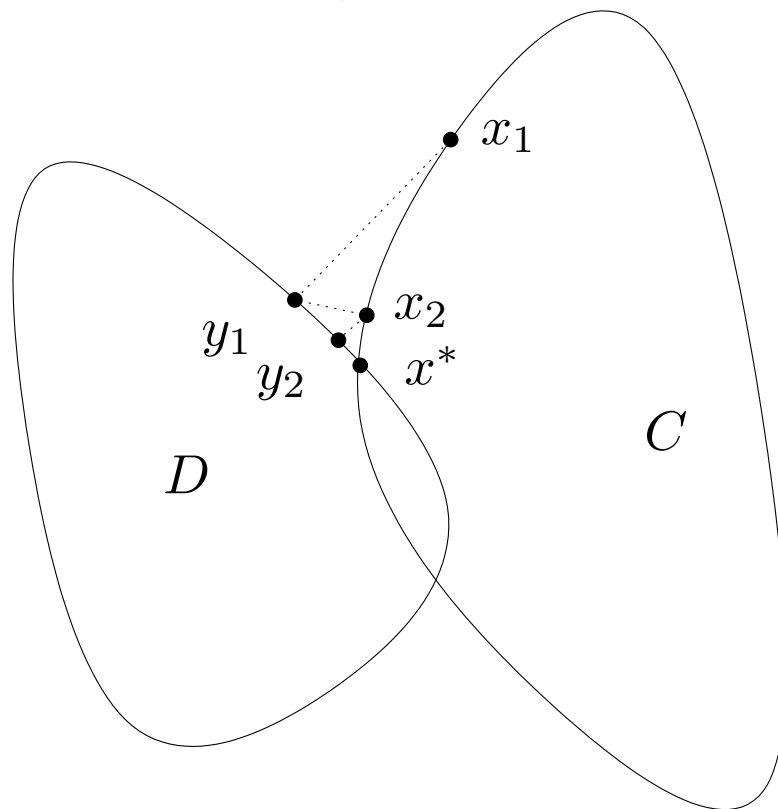
let  $P_C, P_D$  denote projection onto  $C$  and  $D$

- start with any  $x_0 \in C$
- alternately project onto  $C$  and  $D$ :

$$y_k = P_D(x_k), \quad x_{k+1} = P_C(y_k)$$

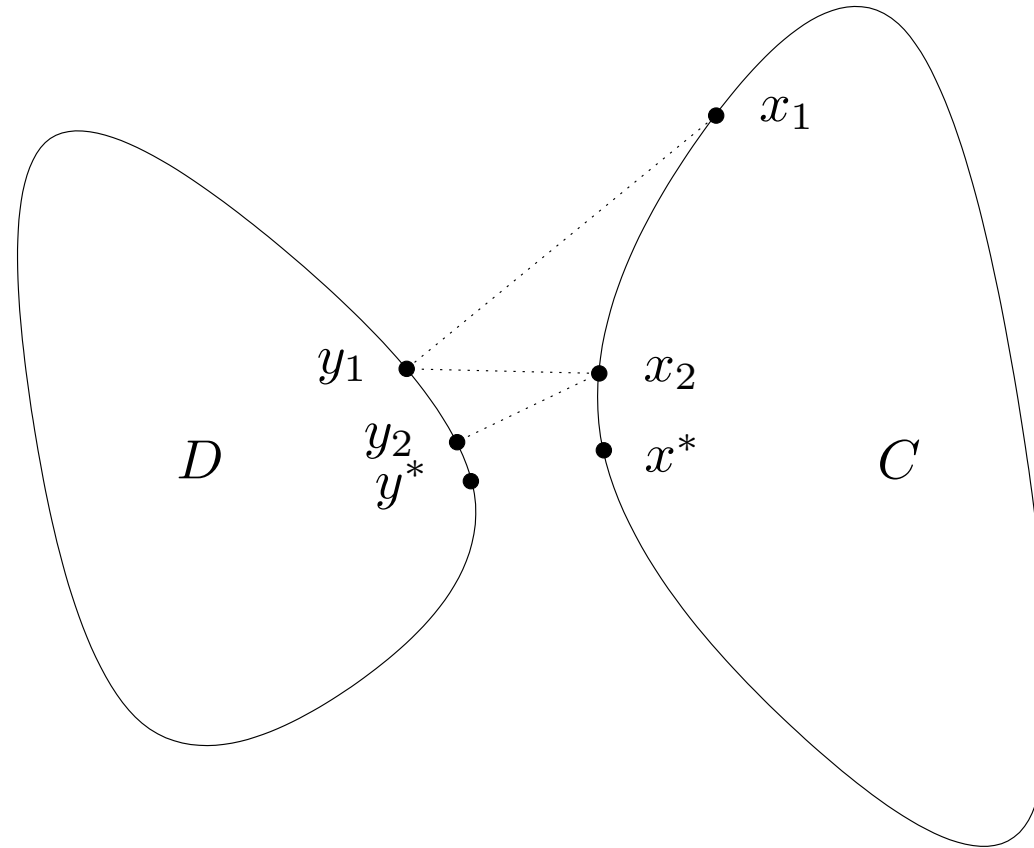
generates sequence  $x_k \in C, y_k \in D$

first few iterations for case  $C \cap D \neq \emptyset$ :



. . . suggests  $x_k, y_k$  converge to a point  $x^* \in C \cap D$

first few iterations for case  $C \cap D = \emptyset$ :



... suggests  $x_k \rightarrow x^*$ ,  $y_k \rightarrow y^*$ , with  $\|x^* - y^*\|_2 = \mathbf{dist}(C, D)$

## Convergence results

- if  $C \cap D \neq \emptyset$ ,  $x_k$  and  $y_k$  both converge to a point  $x^* \in C \cap D$  (Cheney and Goldstein, 1959)
- if  $C \cap D = \emptyset$  and  $\mathbf{dist}(C, D)$  is achieved, then  $x_k \rightarrow x^* \in C$ ,  $y_k \rightarrow y^* \in D$ , where  $\|x^* - y^*\|_2 = \mathbf{dist}(C, D)$

many generalizations, *e.g.*, sequential projection onto  $k > 2$  sets, . . .

## Example: Positive semidefinite matrix completion

- some entries of matrix in  $\mathbf{S}^n$  fixed; find values for others so completed matrix is PSD
- $C = \mathbf{S}_+^n$ ,  $D$  is (affine) set in  $\mathbf{S}^n$  with specified fixed entries
- projection onto  $C$  by eigenvalue decomposition, truncation: if  $Y_k = \sum_{i=1}^n \lambda_i q_i q_i^T$ ,

$$P_C(Y_k) = \sum_{i=1}^n \max\{0, \lambda_i\} q_i q_i^T$$

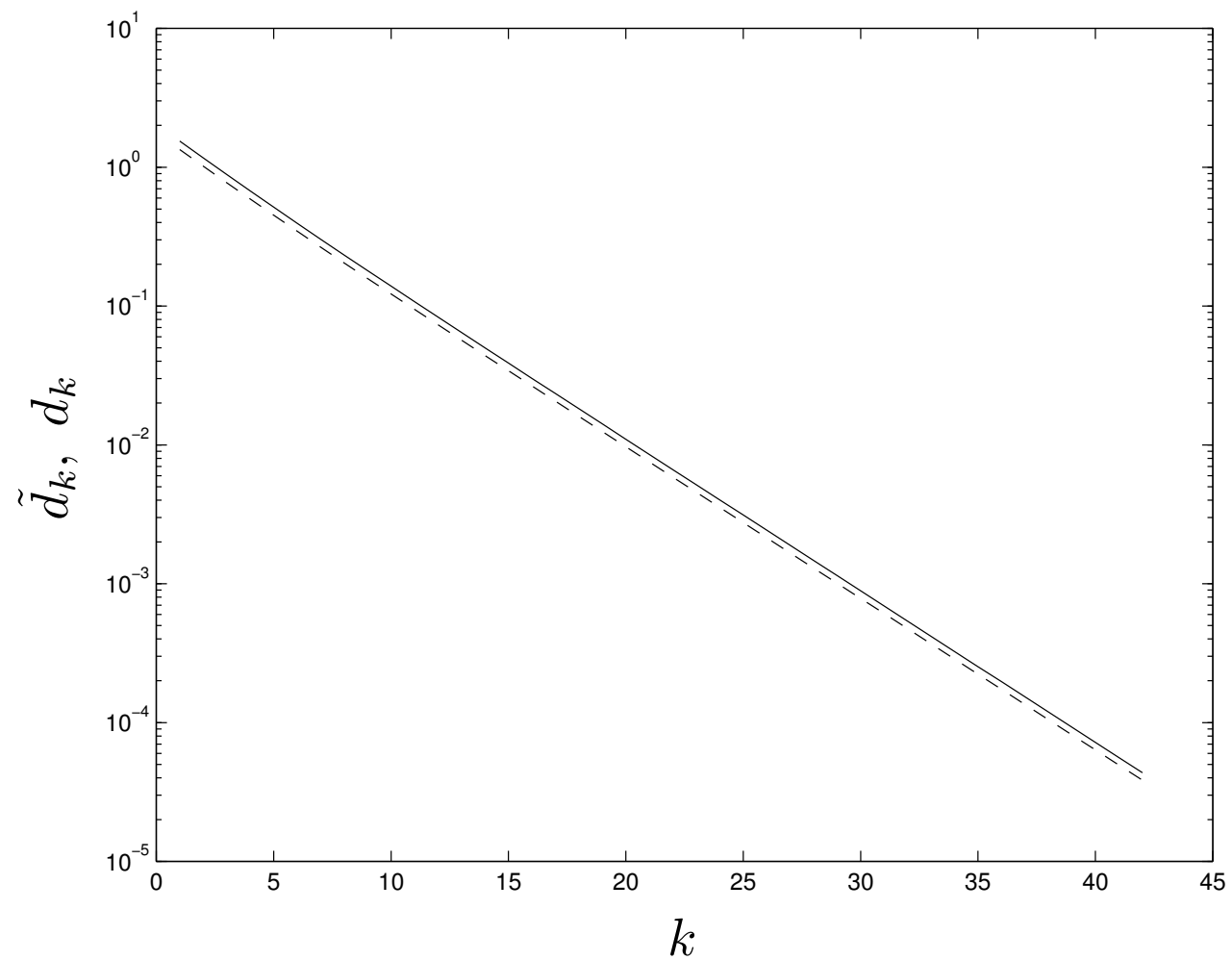
- projection of  $X_k$  onto  $D$  by re-setting specified entries to fixed values

specific example:

$$X = \begin{bmatrix} 4 & 3 & ? & 2 \\ 3 & 4 & 3 & ? \\ ? & 3 & 4 & 3 \\ 2 & ? & 3 & 4 \end{bmatrix}$$

- initialize with  $Y_0 = X$ , with ? entries set to 0
- $Y_k$  have correct fixed entries;  $X_k$  are PSD
- $d_k = \|X_k - Y_{k-1}\|_F$  is distance from  $Y_{k-1}$  to PSD cone
- $\tilde{d}_k = \|Y_k - X_k\|_F$  is norm of error in fixed entries

convergence is linear:





## Relaxation method for linear inequalities

(Agmon 1954) find a point in (non-empty) polyhedron

$$\mathcal{P} = \{x \mid a_i^T x \leq b_i, \quad i = 1, \dots, m\}$$

use sequential projection onto the  $m$  halfspaces  $a_i^T x \leq b_i$

- projection of  $z$  onto halfspace  $a_i^T x \leq b_i$  is

$$P_i(z) = \begin{cases} z & a_i^T z \leq b_i \\ z - (a_i^T z - b_i)a_i & a_i^T z > b_i \end{cases}$$

- cycle through these projections to find point in  $\mathcal{P}$

## Example

find point in  $\mathcal{P} \subseteq \mathbf{R}^{100}$ ,  $m = 1000$  inequalities,  $\|a_i\|_2 = 1$

maximum constraint violation:  $r_k = \max_{i=1, \dots, m} \max\{0, a_i^T x_k - b_i\}$

