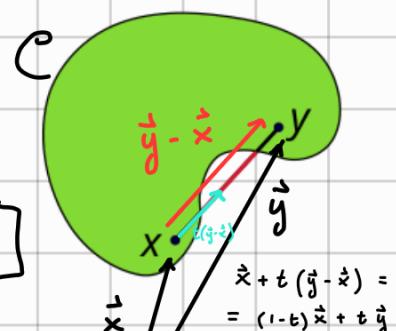


# DYKSTRA'S ALGORITHM

- A HILBERT SPACE  $H$  IS A VECTOR SPACE EQUIPPED WITH AN INNER PRODUCT THAT INDUCES A DISTANCE FUNCTION FOR WHICH THE SPACE IS A COMPLETE METRIC SPACE
- A CONVEX SET  $C$  IS A SET THAT SATISSES

$$\vec{x}\lambda + (1-\lambda)\vec{y} \in C$$

$$\forall \vec{x}, \vec{y} \in C \wedge \lambda \in [0, 1]$$



## PROJECTION ONTO CONVEX SETS

Let  $H$  BE A HILBERT SPACE, let  $C_1, C_2 \subset H$  BE TWO CONVEX SETS.

THE PROJECTION  $\vec{p}$  OF A POINT  $\vec{x}_0$  onto THE INTERSECTION OF  $C_1$  AND  $C_2$  IS GIVEN BY :

$$\vec{p} \in C_1 \cap C_2 : \|\vec{p} - \vec{x}_0\| \leq \|\vec{r} - \vec{x}_0\| \quad \forall \vec{r} \in C_1 \cup C_2$$

$\vec{p} = P_{C_1 \cap C_2}(\vec{x}_0)$  IS SOLVED RECURSIVELY BY :

$$\vec{p}_{n+1} = P_{C_1}(P_{C_2}(\vec{p}_n))$$

(ALTERNATING PROJECTIONS) WHERE :

$$P_C(\vec{x}) = \left[ \begin{smallmatrix} C & C^T \\ \vdash & \vdash \end{smallmatrix} \right]^{-1} \left[ \begin{smallmatrix} C^T \\ \vdash \end{smallmatrix} \right] \vec{x} \quad \in \text{Im}(C)$$

\* DERIVATION BELOW FROM A1

# PROJECTIONS DERIVATION ★

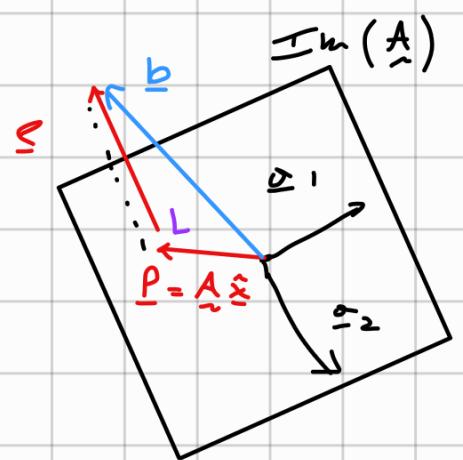
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• GIVEN :  $\underline{P} \in \text{Im}(\underline{A})$

WE CAN RE-WRITE  $\underline{P}$  AS :

$$\underline{P} = \underline{A} \hat{\underline{x}} - \underline{e} \quad (1)$$

WHERE  $\hat{\underline{x}}$  IS THE VECTOR FROM THE ORIGIN  
TO THE POINT WHERE  $\underline{b}$  IS PROJECTED  
ON  $\text{Im}(\underline{A})$



• WE CAN DEFINE THE VECTOR  $\underline{b}$  AS THE SUM OF VECTOR  $\underline{P}$  PLUS AN ERROR VECTOR  $\underline{e}$  :

$$\underline{b} = \underline{P} + \underline{e} \quad (2)$$

SUCH THAT  $\underline{e}$  IS  $\perp$  TO THE IMAGE OF  $\underline{A}$ .  
BUT, AS SEEN IN Q4(a), THIS IMPLIES  
THAT  $\underline{e}$  LIES IN THE LEFT NULLSET OF  $\underline{A}^T$

$$\underline{e} \perp \text{Im}(\underline{A}) \Rightarrow \underline{e} \in N(\underline{A}^T)$$

$$\therefore \underline{A}^T \underline{e} = \underline{0} \quad (3)$$

• COMBINE EQUATIONS (1) AND (2) :

$$\underline{e} = \underline{b} - \underline{P} = (\underline{b} - \underline{A} \hat{\underline{x}})$$

- COMBINE THIS RESULT WITH (3) :

$$\underset{\sim}{A^T} \underset{\sim}{e} = \underset{\sim}{A^T} (\underline{b} - \underset{\sim}{A} \hat{\underline{x}}) = \underline{0}$$

- SOLVE FOR VECTOR  $\hat{\underline{x}}$  :

$$\underset{\sim}{A^T} \underline{b} - \underset{\sim}{A^T} \underset{\sim}{A} \hat{\underline{x}} = \underline{0}$$

$$\therefore \hat{\underline{x}} = (\underset{\sim}{A^T} \underset{\sim}{A})^{-1} \underset{\sim}{A^T} \underline{b} //$$

- AND NOW SUBSTITUTE INTO EQ. (1) :

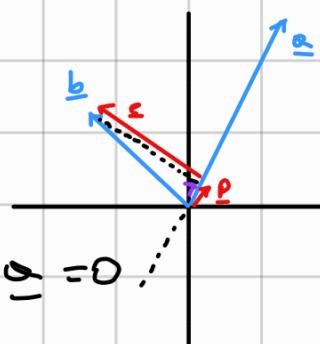
## PROJECTION onto A SUBSPACE

$$\underline{P} = \underset{\sim}{A} \hat{\underline{x}} = \left[ \underset{\sim}{A} (\underset{\sim}{A^T} \underset{\sim}{A})^{-1} \underset{\sim}{A^T} \right] \underline{b}$$

- SIMILARLY, BY A SIMILAR PROCEDURE, WE CAN OBTAIN THE 1D VERSION:

$\underline{P} \nearrow$  ↗ THIS IS CALLED PROJECTION MATRIX

$$\underline{b} = \underline{P} + \underline{e} = \hat{\underline{x}} \underline{\alpha} + \underline{e} \Rightarrow \underline{e} = \underline{b} - \hat{\underline{x}} \underline{\alpha}$$



$$\text{FOR MIN DISTANCE } \|\underline{e}\| : \underline{e} \cdot \underline{\alpha} = 0 \Rightarrow (\underline{b} - \hat{\underline{x}} \underline{\alpha}) \cdot \underline{\alpha} = 0$$

$$\therefore \hat{\underline{x}} (\underline{\alpha}^T \underline{\alpha}) = \underline{\alpha}^T \underline{b} \Rightarrow \hat{\underline{x}} = \frac{\underline{\alpha}^T \underline{b}}{\underline{\alpha}^T \underline{\alpha}} \text{ (SCALAR)}$$

## PROJECTION onto LINE

$$\underline{P} = \left[ \frac{\underline{\alpha} \underline{\alpha}^T}{\underline{\alpha}^T \underline{\alpha}} \right] \underline{b}$$

DO NOT FORM MATRIX:

- 1) OBTAIN SCALAR  $\underline{\alpha}^T \underline{b}$
- 2) DIVIDE BY SCALAR  $\underline{\alpha}^T \underline{\alpha}$
- 3) MULTIPLY BY VECTOR  $\underline{\alpha}$

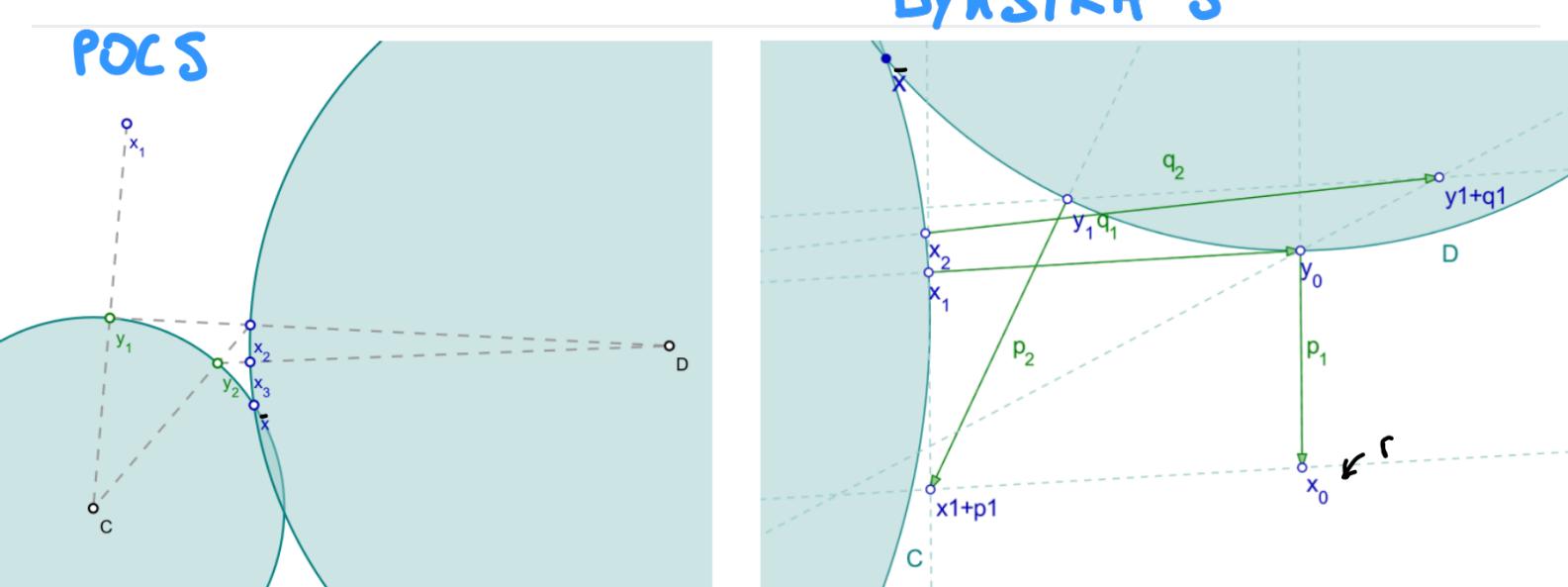
# Dykstra's projection algorithm

**Dykstra's algorithm** is a method that computes a point in the intersection of [convex sets](#), and is a variant of the [alternating projection](#) method (also called the [projections onto convex sets](#) method). In its simplest form, the method finds a point in the intersection of two convex sets by iteratively projecting onto each of the convex set; it differs from the alternating projection method in that there are intermediate steps. A parallel version of the algorithm was developed by Gaffke and Mathar.

The method is named after Richard L. Dykstra who proposed it in the 1980s.

A key difference between Dykstra's algorithm and the standard alternating projection method occurs when there is more than one point in the intersection of the two sets. In this case, the alternating projection method gives some arbitrary point in this intersection, whereas Dykstra's algorithm gives a specific point: the projection of  $r$  onto the intersection, where  $r$  is the initial point used in the algorithm,

## Algorithm



Dykstra's algorithm finds for each  $r$  the only  $\bar{x} \in C \cap D$  such that:

$$\|\bar{x} - r\|^2 \leq \|x - r\|^2, \text{ for all } x \in C \cap D,$$

where  $C, D$  are [convex sets](#). This problem is equivalent to finding the [projection](#) of  $r$  onto the set  $C \cap D$ , which we denote by  $\mathcal{P}_{C \cap D}$ .

To use Dykstra's algorithm, one must know how to project onto the sets  $C$  and  $D$  separately. SEE ABOVE

First, consider the basic [alternating projection](#) (aka POCS) method (first studied, in the case when the sets  $C, D$  were linear subspaces, by [John von Neumann](#)<sup>[1]</sup>), which initializes  $x_0 = r$  and then generates the sequence

$$x_{k+1} = \mathcal{P}_C(\mathcal{P}_D(x_k)).$$

Dykstra's algorithm is of a similar form, but uses additional auxiliary variables. Start with  $x_0 = r, p_0 = q_0 = 0$  and update by

$$y_k = \mathcal{P}_D(x_k + p_k)$$

$$p_{k+1} = x_k + p_k - y_k$$

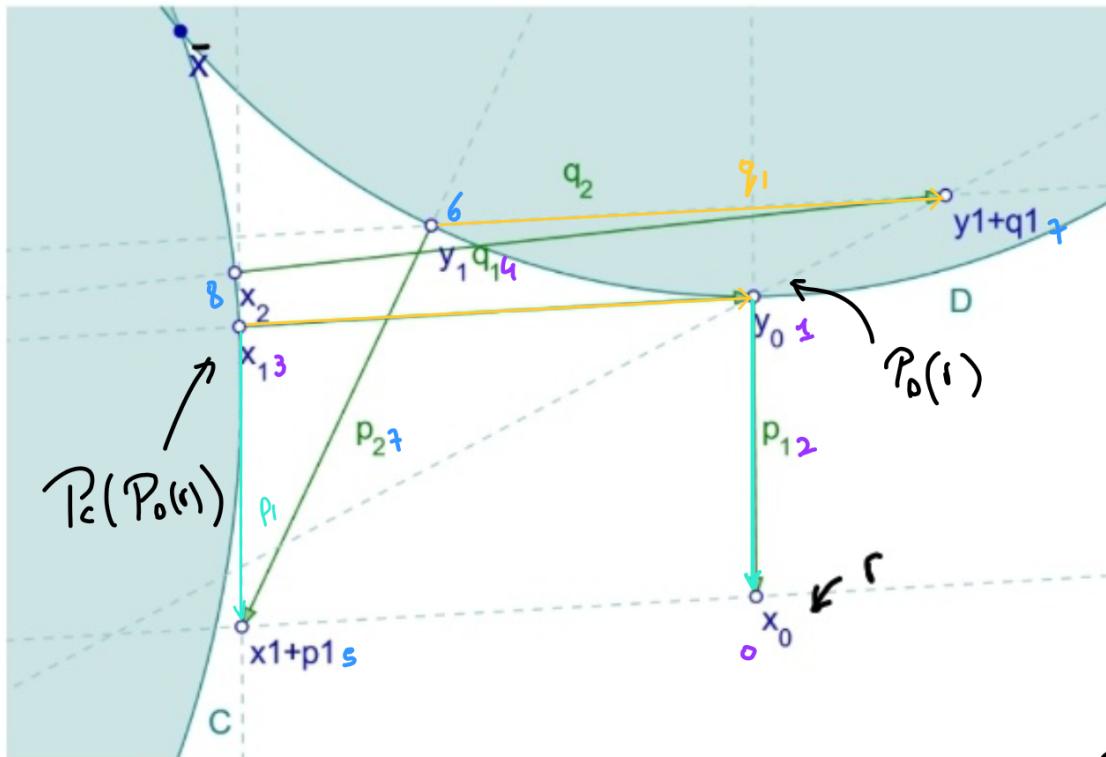
$$x_{k+1} = \mathcal{P}_C(y_k + q_k)$$

$$q_{k+1} = y_k + q_k - x_{k+1}$$

DISTANCE BETWEEN  $x_k + p_k$  AND NEWEST D PROJECTION ( $y_k$ )

Then the sequence  $(x_k)$  converges to the solution of the original problem. For convergence results and a modern perspective on the literature, see [2]

for example, here:



$$y_0 = \mathcal{P}_D(r)$$

$$p_1 = r - \mathcal{P}_D(r)$$

$$x_1 = \mathcal{P}_C(\mathcal{P}_D(r))$$

$$q_1 = \mathcal{P}_D(r) - \mathcal{P}_C(\mathcal{P}_D(r))$$

$$y_1 = \mathcal{P}_D\left(\mathcal{P}_C(\mathcal{P}_D(r)) + [r - \mathcal{P}_D(r)]\right)$$

$$p_2 = \mathcal{P}_C(\mathcal{P}_D(r)) + [r - \mathcal{P}_D(r)] - \dots$$

AND SO ON