

# Kaczmarz's Algorithm For Solving Large Linear Systems\*

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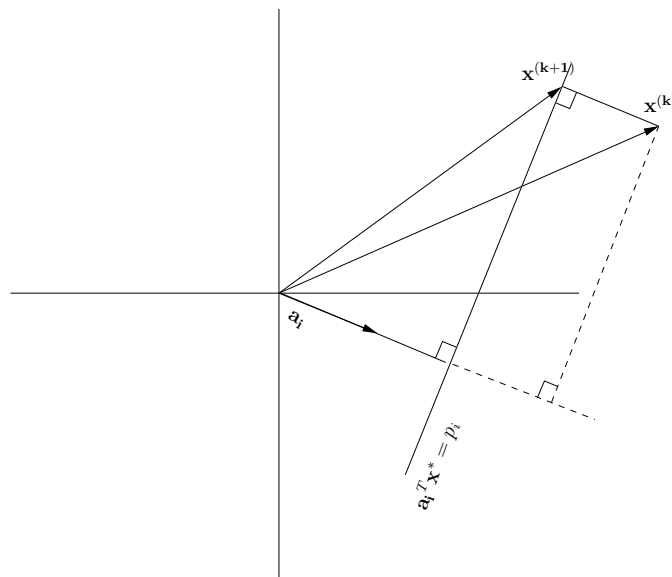


Figure 1: Hyper-plane representing one linear equation, with two consecutive approximate solutions. The plane's normal is given by  $\frac{\mathbf{a}_i}{\sqrt{\mathbf{a}_i^T \mathbf{a}_i}}$ , and the distance from the origin is given by  $\frac{p_i}{\sqrt{\mathbf{a}_i^T \mathbf{a}_i}}$ .

Given a large set of linear equations,  $A\mathbf{x} = \mathbf{p}$ , we seek a solution which does not require inversion of the matrix  $A$ . This summary describes Kaczmarz's [1] projection based approach for estimating this solution.

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\*Notation:

Matrices,  $A$ .

Column vectors,  $\mathbf{a}$ .

Scalars,  $a$ .

In expanded form we have:

$$\begin{aligned}
a_{1,1}x_1 + a_{1,2}x_2 + \cdots + a_{1,N}x_N &= p_1 \\
a_{2,1}x_1 + a_{2,2}x_2 + \cdots + a_{2,N}x_N &= p_2 \\
&\vdots \\
a_{M,1}x_1 + a_{M,2}x_2 + \cdots + a_{M,N}x_N &= p_M
\end{aligned}$$

Each of the equations defines a hyper-plane. If there exists a solution to the equation system, it is the intersection point of all planes. Figure 1 illustrates the projection based approach of Kaczmarz's algorithm.

Given an approximate solution  $\mathbf{x}^{(k)}$  we project it onto a hyper-plane to obtain our next approximation  $\mathbf{x}^{(k+1)}$ . Without prior knowledge, the initial approximation can be arbitrarily set to  $\mathbf{x}^{(0)} = \mathbf{0}$ .

*Note that the initialization allows explicit incorporation of prior knowledge, entries,  $x_i$ , that have known values.*<sup>1</sup>

We thus have:

$$\begin{aligned}
\mathbf{x}^{(k+1)} &= \mathbf{x}^{(k)} - \frac{\mathbf{a}_i^T \mathbf{x}^{(k)} - p_i}{\sqrt{\mathbf{a}_i^T \mathbf{a}_i}} \frac{\mathbf{a}_i}{\sqrt{\mathbf{a}_i^T \mathbf{a}_i}} \\
&= \mathbf{x}^{(k)} - \frac{\mathbf{a}_i^T \mathbf{x}^{(k)} - p_i}{\mathbf{a}_i^T \mathbf{a}_i} \mathbf{a}_i
\end{aligned} \tag{1}$$

We now show that this projection based method converges, and that it converges to the solution  $\mathbf{x}^*$ . This is done by analyzing the relationship between the residuals of successive approximations  $\mathbf{x}^{(k)}, \mathbf{x}^{(k+1)}$ .

$$\|\mathbf{x}^{(k+1)} - \mathbf{x}^*\|^2 = \|\mathbf{x}^{(k)} - \mathbf{x}^* - \frac{\mathbf{a}_i^T \mathbf{x}^{(k)} - p_i}{\mathbf{a}_i^T \mathbf{a}_i} \mathbf{a}_i\|^2$$

Using the identity  $\|\mathbf{x} + \mathbf{y}\|^2 = \|\mathbf{x}\|^2 + 2\mathbf{x}^T \mathbf{y} + \|\mathbf{y}\|^2$  we have:

$$\begin{aligned}
\|\mathbf{x}^{(k+1)} - \mathbf{x}^*\|^2 &= \|\mathbf{x}^{(k)} - \mathbf{x}^*\|^2 - 2 \frac{\mathbf{a}_i^T \mathbf{x}^{(k)} - p_i}{\mathbf{a}_i^T \mathbf{a}_i} \mathbf{a}_i^T (\mathbf{x}^{(k)} - \mathbf{x}^*) + \frac{(\mathbf{a}_i^T \mathbf{x}^{(k)} - p_i)^2}{\mathbf{a}_i^T \mathbf{a}_i} \\
&= \|\mathbf{x}^{(k)} - \mathbf{x}^*\|^2 - \frac{\mathbf{a}_i^T \mathbf{x}^{(k)} - p_i}{\mathbf{a}_i^T \mathbf{a}_i} (2\mathbf{a}_i^T \mathbf{x}^{(k)} - 2\mathbf{a}_i^T \mathbf{x}^* - \mathbf{a}_i^T \mathbf{x}^{(k)} + p_i)
\end{aligned}$$

Substituting  $\mathbf{a}_i^T \mathbf{x}^* = p_i$  into the equation above we get:

$$\begin{aligned}
\|\mathbf{x}^{(k+1)} - \mathbf{x}^*\|^2 &= \|\mathbf{x}^{(k)} - \mathbf{x}^*\|^2 - \frac{\mathbf{a}_i^T \mathbf{x}^{(k)} - p_i}{\mathbf{a}_i^T \mathbf{a}_i} (2\mathbf{a}_i^T \mathbf{x}^{(k)} - 2p_i - \mathbf{a}_i^T \mathbf{x}^{(k)} + p_i) \\
&= \|\mathbf{x}^{(k)} - \mathbf{x}^*\|^2 - \frac{(\mathbf{a}_i^T \mathbf{x}^{(k)} - p_i)^2}{\mathbf{a}_i^T \mathbf{a}_i}
\end{aligned}$$

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<sup>1</sup>In the case of computed tomography we may know which areas are empty space (air) and thus have a value of  $x_i = -1000\text{HU}$ .

The second term of the equation above is non-negative. We thus have:

$$\|\mathbf{x}^{(k+1)} - \mathbf{x}^*\|^2 \leq \|\mathbf{x}^{(k)} - \mathbf{x}^*\|^2$$

Therefore,  $\{\|\mathbf{x}^{(k)} - \mathbf{x}^*\|^2\}$  is a non-increasing sequence, bounded from below,  $\|\mathbf{x}^{(k)} - \mathbf{x}^*\|^2 \geq 0$ . Hence it converges.

We now observe that:

$$\|\mathbf{x}^{(k)} - \mathbf{x}^*\|^2 = \|\mathbf{x}^{(0)} - \mathbf{x}^*\|^2 - \sum_{i=0}^{k-1} \frac{(\mathbf{a}_{r(i)}^T \mathbf{x}^{(i)} - p_{r(i)})^2}{\mathbf{a}_{r(i)}^T \mathbf{a}_{r(i)}}$$

where  $r(i)$  is the index of the row used for projection of  $\mathbf{x}^{(i)}$ .  
as the sequence  $\{\|\mathbf{x}^{(k)} - \mathbf{x}^*\|^2\}$  converges we see that

$$\sum_{i=0}^{\infty} \frac{(\mathbf{a}_{r(i)}^T \mathbf{x}^{(i)} - p_{r(i)})^2}{\mathbf{a}_{r(i)}^T \mathbf{a}_{r(i)}} < \infty$$

consequentially (after setting  $p_i = \mathbf{a}_{r(i)}^T \mathbf{x}^*$ )

$$\lim_{k \rightarrow \infty} \mathbf{a}_{r(i)}^T (\mathbf{x}^{(k)} - \mathbf{x}^*) = 0$$

Giving us

$$\lim_{k \rightarrow \infty} \mathbf{x}^{(k)} = \mathbf{x}^*$$

## References

- [1] S. Kaczmarz, *Angenäherte Auflösung von Systemen linearer Gleichungen*, Bull. Acad. Polon. Sci. et Lettres A, vol. 35, pp. 355–357, 1937.