

Are We There Yet?

Iterative Methods for Solving Linear Systems

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- Theory on iterative methods for solving linear systems

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- Description and examples of Richardson, Jacobi, and Gauss-Seidel methods

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 - Example: finding solutions to linear systems (today's topic!)

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 - $\|x - x^{(k)}\| \rightarrow 0$ rapidly, and
 - $[x^{(k)}]$ is easy to compute
- Note: often the initial vector $x^{(0)}$ is an estimate of the solution or arbitrary ($x = 0$)

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$$\|x^{(k)} - x\| \leq \|I - Q^{-1}A\|^k \|x^{(0)} - x\|$$

- Thus, if $\|I - Q^{-1}A\| < 1$, then $\lim_{k \rightarrow \infty} \|x^{(k)} - x\| = 0$

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$$x^{(k)} = Gx^{(k-1)} + c.$$

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Corollary

The iteration formula

$$Qx^{(k)} = (Q - A)x^{(k-1)} + b$$

will produce a convergent sequence provided that $\rho(I - Q^{-1}A) < 1$.

Method	Q	Iteration Formula: $x^{(k)} = (I - Q^{-1}A)x^{(k-1)} + Q^{-1}b$
Richardson	I	$x^{(k)} = (I - A)x^{(k-1)} + b = x^{(k-1)} + r^{(k-1)}$
Jacobi	D	$x^{(k)} = (I - D^{-1}A)x^{(k-1)} + D^{-1}b$
Gauss-Seidel	L	$x^{(k)} = (I - L^{-1}A)x^{(k-1)} + L^{-1}b$

where

- D : diagonal matrix where $d_{ii} = a_{ii}$
- L : lower triangular matrix where $l_{ij} = a_{ij}, i \geq j$