



A proof of projection method about classical iterative methods

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Abstract Gauss-Siedel and Successive Over Relaxation (SOR) are two classical iterative methods to solve the large linear system $Ax = b$. In this paper, we prove that the two iterative methods are two orthogonal projection methods.

Keywords orthogonal projection, Gauss-Siedel, SOR

1. Introduction

Given an $n \times n$ real matrix A , and a real n -vector b , we consider to find x belonging to R^n such that

$$Ax = b, \quad (1.1)$$

where A is coefficient matrix and b is the right-hand side vector. Jacobi, Gauss-Seidel and SOR are three efficient methods suitable for solving the problem (1.1). They are all iterative methods by modifying one or a few components of an approximate vector solution at a time, and the criteria for modifying a component in order to improve an iterate is to annihilate some component of the residual vector $b - Ax$.

We split A into three parts

$$A = D - E - F$$

where D is the diagonal of A , $-E$ is the strict lower part and $-F$ its strict upper part. We let x_k be the k -th iterate. With the above notation, the Jacobi iteration in vector form can be written as

$$x_{k+1} = D^{-1}(E + F)x_k + D^{-1}b. \quad (1.2)$$

Similarly, the Gauss-Seidel iteration in vector form can be written as

$$x_{k+1} = (D - E)^{-1}Fx_k + (D - E)^{-1}b. \quad (1.3)$$

The difference between (1.2) and (1.3) is that the approximate solution of Gauss-Seidel is updated immediately after the new component is determined.

By introducing a parameter ω , the SOR iteration is based on the splitting

$$\omega A = (D - \omega E) - (\omega F + (1 - \omega)D),$$

and the SOR iteration in vector form can be written as

$$x_{k+1} = (D - \omega E)^{-1}[\omega F + (1 - \omega)D]x_k + (D - \omega E)^{-1}\omega b \quad (1.4)$$

A lot of application about these three iterative methods can be found in [2-4]

2. Projection Method

Most of the existing practical iterative techniques for solving large linear systems of equations utilize a projection process in one way or another.

Let κ and L be two m -dimensional subspaces of R^n . In general, κ is called search subspace and L the subspace of constraints. A projection technique onto the subspace κ and orthogonal to L is a process which



finds an approximate solution \tilde{x} to (1.1) by imposing the conditions that \tilde{x} belong to κ and that the new residual vector be orthogonal to L .

$$\text{Find } \tilde{x} \in \kappa, \text{ such that } b - A\tilde{x} \perp L.$$

If we exploit the knowledge of an initial guess x_0 to the solution, then the approximate problem should be refined as

$$\text{Find } \tilde{x} \in x_0 + \kappa, \text{ such that } b - A\tilde{x} \perp L.$$

Most standard techniques use a succession of such projections. Typically, a new projection step uses a new pair of subspaces κ and L , and an initial guess x_0 equal to the most recent approximation obtained from the previous projection step, see [1] for details.

Theorem 3.1 An elementary Gauss-Seidel step as defined by (1.3) is a projection step with $\kappa = L = \text{span}\{e_i\}$

Proof We rewrite (1.4) as

$$(D - E)x_{k+1} = Fx_k + b,$$

from the perspective of component updates, this iterate process is actually a n steps update, namely n steps projection. We assume that x_{k+1} has two components and $x_{k+1}(i)$ is the i -th component of x_{k+1} . The update equation of $x_{k+1}(i)$ is

$$\begin{aligned} a_{i1}x_{k+1}(1) + a_{i2}x_{k+1}(2) + \cdots + a_{i(i-1)}x_{k+1}(i-1) + a_{ii}x_{k+1}(i) \\ = -a_{i(i+1)}x_k(i+1) - a_{i(i+2)}x_k(i+2) - \cdots - a_{in}x_k(n) + b_i. \end{aligned}$$

This equation can be seen as the update from the vector

$$(x_{k+1}(1), x_{k+1}(2), \dots, x_k(i), x_k(i+1), \dots, x_k(n))$$

to the vector

$$(x_{k+1}(1), x_{k+1}(2), \dots, x_{k+1}(i), x_k(i+1), \dots, x_k(n)).$$

If i changes from 1 to n , all the components of the update is finished, i.e.

$$\begin{aligned} (x_{k+1}(1), x_{k+1}(2), \dots, x_{k+1}(i), x_k(i+1), \dots, x_k(n)) \\ = (x_{k+1}(1), x_{k+1}(2), \dots, x_k(i), x_k(i+1), \dots, x_k(n)) + t(0, 0, \dots, 0, 1, 0, \dots, 0)', \end{aligned} \quad (2.1)$$

here $(A)'$ represents the transpose of the matrix A . We denote the second vector $(0, 0, \dots, 0, 1, 0, \dots, 0)'$ on the right hand side of (2.1) as $e_{(i)}$, and the left vector on the left hand side as $x_{(k+1,i)}$. So (2.1) can be rewritten as

$$x_{(k+1,i)} = x_{(k+1,i-1)} + te_{(i)}.$$

The i -th component of the residual vector $b - Ax$ equal to zero, i.e.

$$(e_{(i)})'(b - Ax_{(k+1,i)}) = 0.$$

So Gauss-Seidel step is a projection step with $\kappa = L = \text{span}\{e_i\}$.

Theorem 3.2 An elementary SOR step as defined by (1.4) is a projection step with $\kappa = L = \text{span}\{e_i\}$.

Proof We rewrite (1.4) as

$$(D - \omega L)x_{k+1} = ((1 - \omega)D + \omega U)x_k + \omega b,$$

from the perspective of component updates, this iterate process is actually a n steps update, namely n steps projection. We assume that x_{k+1} has two components and $x_{k+1}(i)$ is the i -th component of x_{k+1} . The update equation of $x_{k+1}(i)$ is



$$\begin{aligned} & \omega a_{i1} x_{k+1}(1) + \omega a_{i2} x_{k+1}(2) + \cdots + \omega a_{i(i-1)} x_{k+1}(i-1) + a_{ii} x_{k+1}(i) \\ & = (1 - \omega) a_{ii} x_k(i) - \omega a_{i(i+1)} x_k(i+1) - a_{i(i+2)} x_k(i+2) - \cdots - \omega a_{in} x_n(k) + \omega b_i. \end{aligned}$$

This equation can be seen as the update from the vector

$$(x_{k+1}(1), x_{k+1}(2), \dots, x_k(i), x_k(i+1), \dots, x_k(n))$$

to the vector

$$(x_{k+1}(1), x_{k+1}(2), \dots, x_{k+1}(i), x_k(i+1), \dots, x_k(n)).$$

If i changes from 1 to n , all the components of the update is finished, i.e.

$$\begin{aligned} & (x_{k+1}(1), x_{k+1}(2), \dots, x_{k+1}(i), x_k(i+1), \dots, x_k(n)) \\ & = (x_{k+1}(1), x_{k+1}(2), \dots, x_k(i), x_k(i+1), \dots, x_k(n)) + t(0, 0, \dots, 0, 1, 0, \dots, 0)', \quad (2.2) \end{aligned}$$

(2.2) can be rewritten as

$$x_{(k+1,i)} = x_{(k+1,i-1)} + t e_{(i)}.$$

The i -th component of the residual vector $b - Ax$ equal to zero, i.e.

$$(e_{(i)})'(b - Ax_{(k+1,i)}) = 0.$$

So Gauss-Seidel step is a projection step with $\kappa = L = \text{span}\{e_i\}$.

References

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