1 February 25th, 2021

1.1 Gauss-Seidel Iteration

Recall that in Jacobi, $\xi_i^{(k+1)}$ are updated parallely in Algorithm ??.

Gauss-Seidel is just modifying Jacobi to be updated "successively". When we modify $\xi_i^{(k+1)}$ we can use $\xi_1^{(k+1)}, \ldots \xi_{i-1}^{(k+1)}$. This gives us Algorithm 1.

Algorithm 1 Gauss-Seidel Iteration

```
1: for k=0,1,2,\ldots do

2: for i=1,\ldots,n do

3: \xi_i^{(k+1)}=(\beta_i-\sum_{j>i}a_{ij}\xi_j^{(k)}-\sum_{j< i}a_{ij}\xi_j^{(k+1)})/a_{ii}

4: end for

5: end for
```

In the matrix reformulation, recalling that A = D - E - F, where E is lower triangular and F is upper triangular, we have:

$$x_{k+1} = D^{-1}(b + Fx_k + Ex_{k+1})$$

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

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

$$\iff x_{k+1} = \underbrace{(I - (D - E)^{-1}A)}_{G}x_x + \underbrace{(D - E)^{-1}}_{f}b.$$

which is in the stationary iteration form.

Remark 1.1 — In the algorithm above, we are updating $\xi_i^{(k+1)}$ in regular numerical order (from 1 to n). However, we can use other ordering, such as going from n to 1 in reverse order. Gauss-Seidel is sensitive to the ordering of updating of unknowns.

1.1.1 Convergence of Gauss-Seidel

Since Gauss-Seidel is a stationary iteration, we can use the same framework as the Jacobi iteration, with:

$$(x_k - x_*) = G^k(x_0 - x_*)$$

Theorem 1.2

Gauss-Seidel converges to x_* for any x_0 if and only if $\rho(G) < 1$.

The convergence speed is ||G||, as we have:

$$||x_{k+1} - x_*|| < ||G|| ||x_k - x_*||$$

In particular, we have:

$$||G|| = \begin{cases} \rho(G) & \text{if } G \text{ is symmetric and } ||\cdot|| = ||\cdot||_2 \\ \rho(G) + \epsilon & \text{otherwise} \end{cases}$$

with ϵ arbitrarily small.

Theorem 1.3

Let $A \in \mathbb{R}^{n \times n}$ be SPD. Then $\rho(G) < 1$.

Proof. Recall $G = I - (D - E)^{-1}A$. Let (λ, u) be an eigenpair of G (note that λ, u may be complex). We have:

$$Gu = \lambda u$$

$$(I - (D - E)^{-1}Au) = \lambda u$$

$$(D - E)^{-1}Fu = \lambda u$$

$$Fu = \lambda (D - E)^{-1}u.$$

Since A is symmetric, we have:

$$A = A^T \implies F = E^T$$
.

Thus, we have:

$$\lambda (D - E)u = E^{T}u$$
$$\lambda u^{*}(D - E)u = u^{*}E^{T}u.$$

by left-multiplying both side by $u^* = \overline{u}^T$

Let us set $u^*E^Tu=\alpha+i\beta\in\mathbb{C}$ and $u^*Du=\delta\in\mathbb{R}$, since D is real and symmetric. Then, we have:

$$u^*E^Tu = (u^*E^Tu)^T = u^TE(u^*)^T = \overline{u^*}\overline{E}\overline{u} = \overline{u^*Eu} = \alpha - i\beta$$

Since A is SPD, D is also SPD, giving us $\lambda = u^*Du > 0$.

Thus

$$\lambda(\delta - (\alpha + i\beta)) = \alpha - i\beta \implies \lambda = \frac{\alpha - i\beta}{(\delta - \alpha) - i\beta}$$

Giving us:

$$|\lambda|^2 = \frac{(\alpha^2 + \beta^2)}{(\delta - \alpha)^2 + \beta^2}$$

Because:

$$(\delta - \alpha)^2 + \beta^2 = \delta^2 + \alpha^2 + \beta^2 - 2\alpha\delta = (\alpha^2 + \beta^2) + \underbrace{\delta}_{>0} (\delta - 2\alpha)$$

we need to check the sign of $\delta - 2\alpha$.

Since A is SPD, $u^*Au>0 \implies u^*(D-E-E^T)u=\delta-(\alpha+i\beta)-(\alpha-i\beta)=\delta-2\alpha>0$. As such:

$$(\delta - \alpha)^2 + \beta^2 > \alpha^2 + \beta^2 \implies |\lambda|^2 < 1$$

Remark 1.4 — This is more general than Jacobi, which is convergent if and only if 2D - A is SPD.

Example 1.5

Recall that the 1D discrete Laplacian is SPD, meaning that Gauss-Seidel converges. Similarly for the 2D case.

Example 1.6

Gauss-Seidel converges for irriducible diagonally dominant matrices. This is used for laplacian on irregular domains.

1.2 Acceleration of G-S / and Jacobi (SOR)

Here we try to accelerate Gauss-Seidel and Jacobi by considering momentum acceleration. We can consider the iteration of x_k to x_{k+1} as a movement by the Gauss-Seidel iteration. The idea of SOR is to consider the momentum of the movement until some stage.

For Gauss-Seidel, the components are:

$$\bullet \ x_k : \xi_i^{(k)}$$

•
$$x_{k+1}: \xi_i^{(k+1)} = (\beta_i - \sum_{j>i} a_{ij} \xi_j^{(k)} - \sum_{j$$

To consider the momentum, we would have:

$$\begin{split} \xi_i^{(k+1)} &= \xi_i^{(k)} + \omega(\xi_i^{(k+1)} - \xi_i^{(k)}) \\ &= \xi_i^{(k)} + \omega \left((\beta_i - \sum_{j>i} a_{ij} \xi_j^{(k)} - \sum_{j$$

for some $\omega > 1$, giving us the Algorithm 2.

Algorithm 2 SOR Iteration

- 1: **for** $k = 0, 1, 2, \dots$ **do**
- 2: **for** i = 1, ..., n **do**

3:
$$\xi_i^{(k+1)} = \xi_i^{(k)} + \omega \left[(\beta_i - \sum_{j>i} a_{ij} \xi_j^{(k)} - \sum_{j$$

- 4: end for
- 5: end for

In the matrix reformulation, we have:

$$x_{k+1} = x_k + \omega \left[D^{-1}(b + Fx_k + Ex_{k+1}) - x_k \right]$$

Expressing this in its stationary form, we have:

$$x_{k+1} = \underbrace{(D - \omega E)^{-1} ((1 - \omega)D + \omega F)}_{G_{\omega}} x_k + \underbrace{\omega (D - \omega E)^{-1}}_{f_{\omega}} b$$

Now the question is finding a suitable ω .

1.2.1 Convergence of SOR

Theorem 1.7

If $\omega \notin (0,2)$, then $\rho(G_{\omega}) > 1$.

Proof. We have:

$$\det(G_{\omega}) = \det((D - \omega E)^{-1}) \cdot \det((1 - \omega)D + \omega F)$$

• Since $D - \omega E$ is lower triangular, $(D - \omega E)^{-1}$ is also lower triangular. Thus, $\det((D-\omega E)^{-1})$ is the product of its diagonals, which are the inverse of the diagonal of $D - \omega E$ which are $\frac{1}{a_{ii}}$. As such, we have:

$$\det((D - \omega E)^{-1}) = \prod_{i=1}^{n} a_{ii}^{-1}$$

• Since $(1 - \omega)D + \omega F$ is upper triangular, we have:

$$\det((1-\omega)D + \omega F) = \prod_{i=1}^{n} (1-\omega) \ a_{ii}$$

Thus, we have:

$$\det(G_{\omega}) = \prod_{i=1}^{n} (1 - \omega) \ a_{ii} \cdot a_{ii}^{-1} = (1 - \omega)^{n} = \prod_{i=1}^{n} \lambda_{i}$$

This gives us:

$$|1 - \omega|^n = |\lambda_1||\lambda_2|\dots|\lambda_n| \le (\rho(G_\omega))^n$$

$$\implies |1 - \omega| \le \rho(G_\omega).$$

Corollary 1.8

In order for SOR to converge, we must have $\omega < 2$.