

BASIC ITERATIVE METHODS

For

$$A\vec{u} = \vec{f}$$

with

$$A = D - L - U$$

Jacobi:

$$\vec{v}^{n+1} = D^{-1}(L+U)\vec{v}^n + D^{-1}\vec{f}$$

Jacobi iteration matrix

$$G_J = D^{-1}(L+U)$$

$$\Rightarrow \boxed{\vec{v}^{n+1} = G_J \vec{v}^n + D^{-1}\vec{f}}$$

Jacobi with Relaxation:

$$\left. \begin{aligned} \vec{v}^* &= G_J \vec{v}^n + D^{-1}\vec{f} \\ \vec{v}^{n+1} &= \omega \vec{v}^* + (1-\omega)\vec{v}^n \end{aligned} \right\}$$

$$\boxed{\vec{v}^{n+1} = [(1-\omega)I + \omega G_J] \vec{v}^n + \omega D^{-1}\vec{f}}$$

$$G_{J\omega} = (1-\omega)I + \omega G_J$$

The same in Delta Formulation:

$$\vec{v}^{n+1} = (1-\omega)\vec{v}^n + \omega D^{-1}[(L+U)\vec{v}^n + \vec{f}] = \vec{v}^n + \omega D^{-1}[\underbrace{(-D+L+U)}_{r^2} \vec{v}^n + \vec{f}]$$

$$\Rightarrow \boxed{\vec{v}^{n+1} = \vec{v}^n + \omega D^{-1} r^2}$$

Gauss-Seidel:

$$(D-L) \vec{v}^{n+1} = U \vec{v}^n + \vec{f} \Rightarrow$$

$$\Rightarrow \boxed{\vec{v}^{n+1} = (D-L)^{-1} U \vec{v}^n + (D-L)^{-1} \vec{f}}$$

Gauss-Seidel with Relaxation:

you may develop it by yourself!

Comments:

Should we inverse $(D-L)^{-1}$?

Explicit & Point-Implicit variants

Parallelization (Jacobi or Gauss-Seidel?)

General Iterative Scheme:

$$\vec{v}^{n+1} = G\vec{v}^n + \vec{b}$$

⇔

$$M\vec{v}^{n+1} = N\vec{v}^n + \vec{f}$$

so:

$$G = M^{-1}N$$

$$, \quad \vec{b} = M^{-1}\vec{f}$$

$$, \quad \underline{\underline{A = M - N}}$$

Two Questions:

- (1) If the iterative scheme converges to any value, is this the real solution to the system of equations to be solved?
- (2) Under which conditions such an iterative scheme does converge?

Answering Question (1):

Assume that this converged to

\vec{u}

$$M\vec{u} = N\vec{u} + \vec{f} \Rightarrow$$

$$\Rightarrow (M-N)\vec{u} = \vec{f} \Rightarrow$$

$$\Rightarrow A\vec{u} = \vec{f}$$

so:

$$\vec{u} \equiv \vec{u}$$

Answering Question (2):

$$\left. \begin{array}{l} \vec{v}^{n+1} = G\vec{v}^n + \vec{b} \\ \vec{u} = G\vec{u} + \vec{b} \end{array} \right\} \boxed{\vec{e}^{n+1} = G\vec{e}^n}$$

$$\left. \begin{array}{l} \vec{e}^{n+1} = G\vec{e}^n \\ \vec{e}^n = G\vec{e}^{n-1} \\ \vdots \\ \vec{e}^1 = G\vec{e}^0 \end{array} \right\} \Rightarrow \boxed{\vec{e}^{n+1} = [G]^{n+1} \vec{e}^0}$$

Spectral Radius (G):

$$\rho(G) = \max(|\lambda|, \lambda \in \lambda(G))$$



If $\rho(G) < 1$ this iterative scheme converges to the right solution

Two Relevant Theorems:

Theorem 1:

Math. series G^n (i.e. (I, G, G^2, G^3, \dots))

converges to zero, if and only if: $\rho(G) < 1$

Theorem 2:

Sum

$$\sum_{k=0}^{\infty} G^k$$

converges if and only if

$\rho(G) < 1$

Under these conditions, the following

▣ $(I-G)$ is an invertible matrix

▣ $\sum_{k=0}^{\infty} G^k$ converges to $(I-G)^{-1}$.

Why Series G^n is of interest?

$$\vec{e}^{n+1} = [G]^{n+1} \vec{e}^0$$

Theorem 1: Proof of the Necessary Condition:

$$\text{as } G^n \rightarrow \emptyset \Rightarrow \rho(G) < 1$$

Let λ_1 = be the max. eigenvalue of G
 \vec{q}_1 = corresponding eigenvector (unit) } $G\vec{q}_1 = \lambda_1\vec{q}_1 \Rightarrow$

$$\Rightarrow G^2\vec{q}_1 = G\lambda_1\vec{q}_1 = \lambda_1 \underbrace{G\vec{q}_1}_{\lambda_1\vec{q}_1} = \lambda_1^2\vec{q}_1$$

$$G^n\vec{q}_1 = \lambda_1^n\vec{q}_1 \Rightarrow \|G^n\vec{q}_1\|_2 = \|\lambda_1^n\vec{q}_1\|_2 = |\lambda_1^n| \|\vec{q}_1\|_2 = |\lambda_1^n|$$

thus, for $\|G^n\| \rightarrow \emptyset$ it should $\rho(G) < 1$

From Theorem 2: only its second part

$$\text{OTL } \sum_{k=0}^{\infty} G^k \rightarrow (I-G)^{-1}$$

Identity:

$$(I-G^{k+1}) = (I-G)(I+G+G^2+\dots+G^k)$$

Since $\rho(G) < 1$ it is impossible that $G\vec{q} = \vec{q} \Leftrightarrow (I-G)\vec{q} = 0$ (else $\lambda=1!$)

$$\Rightarrow (I-G) = \text{invertible}$$

$$\Rightarrow (I-G)^{-1}(I-G^{k+1}) = I+G+G^2+\dots+G^k$$

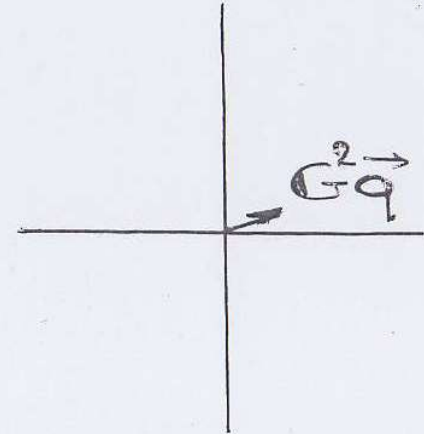
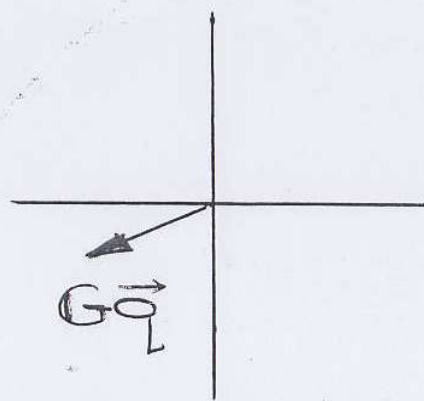
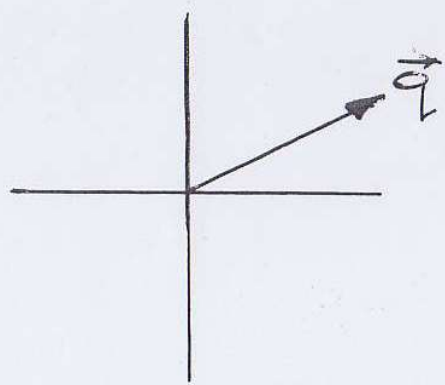
From Theorem 1, this converges to:

$$(I-G)^{-1}I = (I-G)^{-1}$$

Eigenproblem vs. Convergence:

\vec{q} = eigenvector of G
 λ = eigenvalue of G

$G\vec{q} = \lambda\vec{q}$



when $|\lambda| < 1$ $(\forall i)$ $G^n \vec{e}^0 = \lambda_i^n \vec{e}^0 \rightarrow \emptyset$ when $n \rightarrow \infty$

Apply G to any: \vec{v}

\vec{v} analysis in a vector basis $(\vec{q}_1, \vec{q}_2, \dots, \vec{q}_N)$
basis

If $|\lambda_i| < 1, \forall i$, then $G\vec{v} \rightarrow \emptyset$

Practically:

- Propose an Iterative scheme $\vec{v}^{n+1} = G\vec{v}^n + \vec{b}$
- Thus, I am proposing G, for a splitting $A = M - N$ with $G = M^{-1}N$.
- To converge, it should $\rho(G) < 1$
- The smaller, the faster to converge!!
- Converge does not depend on initialization \vec{v}_0

Asymptotic Convergence Factor

$$\rho(G)$$

this is the worst factor with which the error reduces from iteration to iteration

Asymptotic Convergence Rate

$$-\log_{10}(\rho(G))$$

It is $\vec{e}^n = [G]^n \vec{e}^0$ and $\|\vec{e}^n\| \leq \|G\|^n \cdot \|\vec{e}^0\| \Rightarrow \frac{\|\vec{e}^n\|}{\|\vec{e}^0\|} \leq \|G\|^n$

Assume that we want to reduce the error by d orders of magnitude:

$$\frac{\|\vec{e}^n\|}{\|\vec{e}^0\|} \leq 10^{-d}$$

Assume that we want to reduce the error by d orders of magnitude:

$$(\rho[G])^n \leq 10^{-d} \Rightarrow$$

$$n \geq \frac{d}{-\log_{10}(\rho(G))}$$

Application (Attention NEW Symbols)

We are solving

$$A\vec{x} = \vec{b}$$

using the iterative scheme

$$\vec{x}^{k+1} = \vec{x}^k + a(\vec{b} - A\vec{x}^k), \quad a \geq 0$$

or

$$\vec{x}^{k+1} = \underbrace{(I - aA)}_{\text{ITERATION MATRIX}} \vec{x}^k + a\vec{b}$$

ITERATION MATRIX $G_a = I - aA$

Convergence depends on

$$\rho(G_a) = \rho(I - aA)$$

Let

λ_i

be the real eigenvalues of A

$$\lambda_{\min} \leq \lambda_i \leq \lambda_{\max}$$

Then, the eigenvalues of

G_a (μ_i)

$$\underbrace{1 - a\lambda_{\max}}_{\text{SIGNED!}} \leq \mu_i \leq \underbrace{1 - a\lambda_{\min}}_{\text{SIGNED!}}$$

SIGNED!

SIGNED!

Cases

(a) $\lambda_{\min} < 0$, $\lambda_{\max} > 0$

$$\Rightarrow \max(\mu_i) = 1 - a\lambda_{\min} > 1$$

the method diverges $\forall a > 0$

(β) $\lambda_i > 0$, $\forall i$ $\Rightarrow \lambda_{\min} > 0$

To converge, it should

$$\left\{ \begin{array}{l} 1 - a\lambda_{\min} < 1 \ \& \ 1 - a\lambda_{\min} > -1 \\ 1 - a\lambda_{\max} > -1 \ \& \ 1 - a\lambda_{\max} < 1 \end{array} \right.$$

$$1 - a\lambda_{\min} < 1 \xrightarrow{\lambda_{\min} > 0} \Rightarrow a > 0 \quad \checkmark$$

or

$$\left. \begin{array}{l} 1 - a\lambda_{\min} > -1 \Rightarrow a < \frac{2}{\lambda_{\min}} \\ 1 - a\lambda_{\max} > -1 \Rightarrow a < \frac{2}{\lambda_{\max}} \end{array} \right\} \text{κυριαρχεί η } a < \frac{2}{\lambda_{\max}}$$

$$1 - a\lambda_{\max} < 1 \Rightarrow a > 0 \quad \checkmark$$

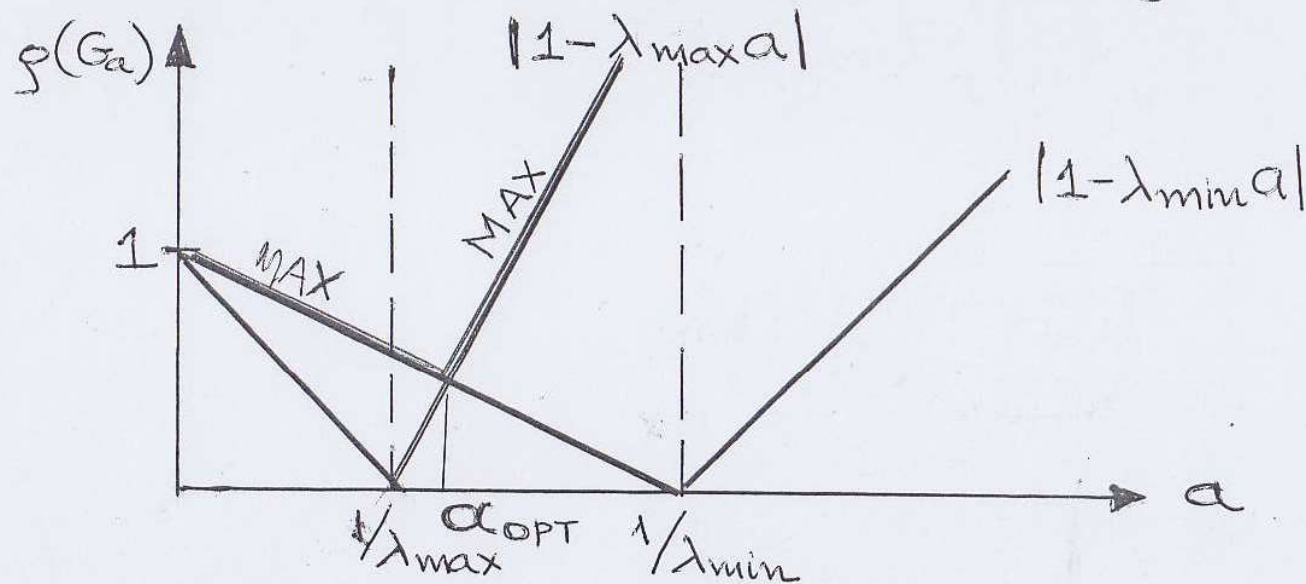
So, the method converges if

$$0 < a < \frac{2}{\lambda_{\max}}$$

Optimal value of a: (a_{OPT})

$$a_{\text{OPT}} = \arg \min_a \rho(G_a)$$

$$\rho(G_a) = \max \{ |1 - a\lambda_{\min}|, |1 - a\lambda_{\max}| \}$$



$$-1 + \lambda_{\max} a_{\text{OPT}} = 1 - \lambda_{\min} a_{\text{OPT}} \Rightarrow a_{\text{OPT}} = \frac{2}{\lambda_{\min} + \lambda_{\max}}$$

$$\rho_{\text{OPT}}(G_a) = 1 - \frac{2\lambda_{\min}}{\lambda_{\min} + \lambda_{\max}} = \frac{\lambda_{\max} - \lambda_{\min}}{\lambda_{\max} + \lambda_{\min}}$$

Useful Definitions

Non-Negative Matrix

$$(a) \quad A \geq 0, \text{ OTAN } \forall a_{ij} \geq 0$$

$$(b) \quad A \leq B \Rightarrow a_{ij} \leq b_{ij}, \forall (i,j).$$

$$(c) \quad \text{Positive Matrix } A > 0, \text{ iff } \forall a_{ij} > 0$$

Reduced Matrix

A is reduced matrix if there is a matrix P such as that

$$P A P^T = \text{upper-triangular}$$

Theorem 3:

If G is a non-negative matrix, a necessary and sufficient condition for $\rho(G) < 1$ is the following conditions:

$$(I - G) = \text{invertible}$$

$$(I - G)^{-1} = \text{non-negative}$$

Proof (of Sufficient condition):

$$\alpha \vee \rho(G) < 1, \text{ Θεώρημα 2} \Rightarrow$$

$$\Rightarrow (a) \quad I - G = \text{ομαλο}$$

$$(b) \quad (I - G)^{-1} = \lim_{k \rightarrow \infty} \sum_{k=0}^{\infty} G^k$$

$$\text{Οπως } G > 0 \Rightarrow \sum_k G^k > 0 \Rightarrow (I - G)^{-1} = \text{non-negative}$$

M-Matrix: Definition

A is an M-matrix if it satisfies the following conditions:

$$(a) \quad a_{i,i} > 0, \quad \forall i$$

$$(b) \quad a_{i,j} \leq 0, \quad \forall (i,j), i \neq j$$

$$(c) \quad A = \text{invertible}$$

$$(d) \quad A^{-1} \geq 0$$

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$$(a) \quad a_{i,i} > 0, \quad \forall i$$

$$(b) \quad a_{i,j} \leq 0, \quad \forall (i,j), i \neq j$$

$$(c) \quad \rho(B) < 1 \quad \text{where} \quad B = I - D^{-1}A$$

M-Matrix: Why these are of interest to us?

JACOBI

$$D \vec{v}^{n+1} = (D-A) \vec{v}^n + \vec{f}$$

$$\vec{v}^{n+1} = (I - D^{-1}A) \vec{v}^n + D^{-1} \vec{f}$$

$$\vec{v}^{n+1} = G \vec{v}^n + \vec{b}, \quad \underline{G = I - D^{-1}A}$$

It was shown that if $A=M$ -matrix

$$\Rightarrow \rho(G) < 1$$

- For the iterative scheme to converge for any initial condition, it should

$$\rho(G) < 1$$

which is ensured if $A=M$ -matrix
(A results from the discretization of the equation)

REGULAR SPLITTING OF A MATRIX

Definition: $A=M-N$ =regular splitting if M^{-1} and N are non-negative matrices

THEOREM 4: if M,N = a regular splitting of A , then $\rho(M^{-1}N)<1$, if and only if

$$A=\text{invertible} \quad \& \quad A^{-1}=\text{non-negative}$$

Lesson Learned:

$$M\vec{v}^{n+1} = N\vec{v}^n + \vec{f} \Rightarrow \vec{v}^{n+1} = M^{-1}N\vec{v}^n + M^{-1}\vec{f}$$

This iterative scheme converge always if M and N correspond to a regular splitting of A
& $A=M$ -matrix

PRECONDITIONING

$$\vec{v}^{n+1} = G \vec{v}^n + \vec{b}$$

$$G = M^{-1}N, \quad \vec{b} = M^{-1}\vec{f}$$

LEFT PRECONDITIONING:

$$P^{-1}A\vec{u} = P^{-1}\vec{f}$$

P = ΕΥΚΟΛΗ ΑΝΤΙΣΤΡΕΨΙΜΗ ΠΡΟΞΕΓΓΠΞΗ ΤΟΥ A

RIGHT PRECONDITIONING:

$$AQ(Q^{-1}\vec{u}) = \vec{f}$$

Real Residual....