

Sparsity pattern for a divergent IAD method

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Outline

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We assume an $N \times N$ irreducible acyclic column stochastic matrix B .

We compute the stationary probability distribution vector \hat{x} ,

$$B\hat{x} = \hat{x}.$$

We use a two - level iterative method:

the iterative aggregation - disaggregation (IAD) method

based on the aggregation groups of events, solving a smaller problem almost exactly, prolongation the solution to the original size and correction on the original level.

Basic notations

n is number of aggregation groups (G_i).

G_1, \dots, G_n are sets of indexes of events, disjoint, $\cup_{i=1}^n G_i = \{1, \dots, N\}$.

I is an identity matrix and e is a vector of ones.

R is a reduction matrix, $R_{ij} = 1$ if $j \in G_i$ and 0 otherwise.

$S(x)$ is a prolongation matrix, $S_{ji}(x) = x_j / \sum_{k \in G_i} x_k$ if $j \in G_i$ and 0 otherwise.

$P(x)$ is projection $P(x) = S(x)R$.

Five steps of IAD method, steps 2 - 5 are repeated:

- 1 Initial approximation $x^0 > 0$ is selected, k is set to 0.
- 2 Solving $RBS(x^k)z = z$.
- 3 Prolongation z to $y^k = S(x^k)z$.
- 4 Correction by some appropriate matrix T , T comes from weakly regular splitting, $I - B = M - W = M(I - T)$,

$$x^{k+1} = Ty^k.$$

- 5 Test for convergence.

Note.

In step 4, T can be taken as B which gives the power method, or it can correspond to block Jacobi or block Gauss-Seidel methods, etc.

We will consider $T = B$ in the following.

Then it holds

$$x^{k+1} - \hat{x} = J(x^k)(x^k - \hat{x}),$$

where

$$J(x) = B(I - P(x)Z)^{-1}(I - P(x)),$$

where Z comes from the spectral decomposition of B ,

$$B = P + Z, \quad P^2 = P, \quad PZ = ZP = 0,$$

P is the Perron projection of B .

Observing $J(x)$ we can find the sufficient local convergence condition.

Based on Mandel, Sekerka (83) and Marek, Mayer (98) we get

Theorem. *When B contains at least one positive row then the IAD method is locally convergent and the asymptotic rate of convergence is $\sqrt{1 - \alpha}$, where α is the minimum in this row.*

When $B > \alpha P$ then the IAD method is locally convergent and the asymptotic rate of convergence is $1 - \alpha$.

Analysing each step in the proof, we want to find some weaker conditions for local convergence. And we can come to the condition

$$P(\hat{x})Bv = 0 \quad \Rightarrow \quad (I - P(\hat{x}))Bv = 0$$

or equivalently

$$P(\hat{x})Bv = 0 \quad \Rightarrow \quad Bv = 0.$$

This is fulfilled for example when the assumptions of the following theorem hold.

Theorem. *Let in some IAD iteration there exist $b_i > 0$ such that*

$$x_{G_i}^k = b_i \hat{x}_{G_i}^k$$

for $i = 1, \dots, n$. Then $x^{k+1} = \hat{x}$.

We can call it the "rapid convergence", the exact solution is obtained after very small number of steps, which can be estimated in advance.

Example.

- a) Each set of rows of B corresponding to a particular aggregation group is a rank one matrix \Rightarrow IAD method yields the exact solution after at most 2 steps.
- b) $I - B = M - W$, M block diagonal and each set of rows of W corresponding to a particular aggregation group is a rank one matrix \Rightarrow IAD method results in the exact solution after at most 2 steps when using $T = M^{-1}W$.

Now we aim at finding the "boundary-line" between divergence and convergence (and rapid convergence) and we present here a small contribution to it.

We have discovered the sparsity pattern of B that leads to locally divergent IAD process when setting $T = B$ in step 2.

Theorem. *The approximations x^k , $k = 1, 2, \dots$ obtained by the IAD method fulfill*

$$BP(x^k)x^{k+1} = x^{k+1}.$$

Let us select an arbitrary aggregation group, say G_i . Then after a proper symmetric permutation, B can be partitioned into

$$B = \begin{pmatrix} B_{11} & B_{G_i}^C \\ B_{G_i}^R & B_{G_i} \end{pmatrix}.$$

Similarly, let us permute and partition $P(x^k)$ into the block diagonal matrix

$$P(x^k) = \begin{pmatrix} P(x^k)_1 & 0 \\ 0 & P(x^k)_{G_i} \end{pmatrix}.$$

Then the equation $BP(x^k)x^{k+1} = x^{k+1}$ can be rewritten to

$$x^{k+1} = \rho_{k+1} \tilde{B}_{G_i}(x^k)e,$$

where ρ_{k+1} is a scaling factor and

$$\tilde{B}_{G_i}(x^k) = \begin{pmatrix} 0 & (I - B_{11}P(x^k)_1)^{-1}B_{G_i}^C \\ 0 & S_{G_i}(x^k) \end{pmatrix} \begin{pmatrix} 0 \\ P(x^k)_{G_i} \end{pmatrix},$$

where S_{G_i} is a stochastic matrix,

$$S_{G_i}(x^k) = B_{G_i} + B_{G_i}^R P(x^k)_1 (I - B_{11}P(x^k)_1)^{-1} B_{G_i}^C.$$

Theorem. *When $P(x^k)_1(I - B_{11}P(x^k)_1)^{-1}$ is positive and $S_{G_i}(x)$ is cyclic for some x then it does not depend on x up to one block of cyclicity.*

Now we come to the two final theorems of this talk.

Theorem. *When $S_{G_i}(x)$ is cyclic of index m for some x then the sequence $\{x^k\}_{k=0}^{\infty}$ obtained by the IAD method can converge to the exact solution \hat{x} , only if the partial sums of part $x_{G_i}^0$ of the initial approximation x^0 corresponding to the block of cyclicity of $S_{G_i}(x)$ are equal.*

This immediately yields

Theorem. *When $S_{G_i}(x)$ is cyclic for some x then in each neighbourhood $U(\hat{x})$ of the exact solution \hat{x} there exist a zero measured set $\tilde{U}(\hat{x})$ such that $\{x^k\}_{k=0}^{\infty}$ obtained by the IAD algorithm doesn't converge to the exact solution \hat{x} for any $x^0 \in U(\hat{x}) \setminus \tilde{U}(\hat{x})$.*

Example 1.

$$B = \begin{pmatrix} 1/2 & 0 & 1/2 \\ 1/2 & 0 & 1/2 \\ 0 & 1 & 0 \end{pmatrix},$$

and $G_1 = \{1\}$ and $G_2 = \{2, 3\}$.

Example 2.

$$B = \left(\begin{array}{ccc|cccc} \times & \dots & \times & \times & 0 & \dots & 0 \\ \vdots & & \vdots & \vdots & \vdots & & \vdots \\ \times & \dots & \times & \times & 0 & \dots & 0 \\ \hline 0 & \dots & 0 & 0 & 0 & \dots & \times \\ \times & \dots & \times & \times & 0 & \dots & 0 \\ \vdots & & \vdots & \vdots & \vdots & & \vdots \\ 0 & \dots & 0 & 0 & \dots & \times & 0 \end{array} \right).$$

Conclusion.

- The local convergence of IAD method is not ensured for B irreducible a acyclic.
- The above results are valid only for $T = B$.
- Comparing to the two - groups case of Ipsen, Kirkland (2004).
- Open questions. Is $T = B^2$ sufficient for local convergence? Is $T = M^{-1}W$, where $I - B = M - W$ and M is block diagonal of $I - B$ corresponding to the aggregation groups, sufficient for local convergence?

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