



Outline

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- Preconditioning
- KS method in parallel

Overview

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- Motivation
- What is preconditioning
- What is its purpose
- Common preconditioners



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What is preconditioning?

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“a preconditioner is any form of implicit or explicit modification of an original linear system which makes it “easier” to solve by a given iterative method”

Y Saad, Iterative methods for Sparse Linear Systems

- Examples of preconditioners
 - Scaling all rows so that diagonal entries are equal to 1
 - Pre-multiplying the matrix by a given matrix, e.g. $A \rightarrow M^{-1} A$
 - Unlikely M or $M^{-1} A$ ever computed directly
 - M^{-1} may be complicated – e.g. result of some FFT transformations or integral calculations

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Motivation

- We would like Krylov subspace method to converge (smoothly)
- We would like KS method to converge in as few iterations as possible
 - reduce the effects of rounding error
 - make method more tractable for multiple righthand sides
- Number of iterations is affected by condition number, C , of matrix
 - a lower condition number implies fewer KS iterations

$$C = \frac{\lambda_{\max}}{\lambda_{\min}} \quad \text{Eigenvalue equation} \quad Ax = \lambda x$$

- Choose pre-conditioner which reduces the condition number

Preconditioning in linear systems

- Solving system

$$A\underline{u} = \underline{b}$$

is equivalent to solving

$$M^{-1}A\underline{u} = M^{-1}\underline{b}$$

where M is a SPD (for CG, at least).

- Idea is to choose M such that similar to A but easier to invert.
- Jacobi/Gauss-Seidel can be thought of as pre-conditioner, e.g.

$$A = L + D + U \rightarrow D^{-1}A = D^{-1}(L + U) + I$$

What is preconditioning? cont ...

- Two extremal cases:
 - choice $M=I$ is equivalent to no preconditioning
 - choice $M=A$ is equivalent to factorising the problem directly
- We seek an intermediate M which ensures that KS method will converge and reduces (minimises) the cost of solver.
- Idea to preserve structure of M (particularly symmetry!)

Incomplete LU factorisation

- A more powerful/expensive preconditioner is ILU factorisation
- Elements are computed as in LU factorisation, but those that fall outwith the sparsity pattern are discarded
$$A = LU - R$$
- This preserves sparsity pattern
- No guarantee of existence of non-singular ILU factors.
- Many modifications exist

Preconditioned CG algorithm

Choose \underline{v}_0 , compute $\underline{r}_0 = \underline{b} - \underline{A}\underline{v}_0$, $k=0$,
Solve $\underline{M}\underline{s}_0 = \underline{r}_0$ (using a direct method), $\underline{p}_0 = \underline{s}_0$
While ($k < \text{maxiter}$)
 $\alpha = \underline{r}_k \cdot \underline{s}_k / \underline{p}_k \cdot \underline{A}\underline{p}_k$
 $\underline{v}_{k+1} = \underline{v}_k + \alpha \underline{p}_k$
 $\underline{r}_{k+1} = \underline{r}_k - \alpha \underline{A}\underline{p}_k$
 if ($\|\underline{r}_{k+1}\|_2 / \|\underline{b}\|_2 < \text{tol}$) break
 Solve $\underline{M}\underline{s}_{k+1} = \underline{r}_{k+1}$
 $\beta = \underline{r}_{k+1} \cdot \underline{s}_{k+1} / \underline{r}_k \cdot \underline{s}_k$
 $\underline{p}_{k+1} = \underline{s}_{k+1} + \beta \underline{p}_k$
 $k = k + 1$
end while

Conclusions

- Preconditioning of linear system can improve reliability of KS method
- Preconditioning can also reduce iteration count and computational costs
- Simple preconditioners based on stationary splitting methods
- More complex methods such as ILU, or preconditioning using Fourier transforms are more effective but may not work at all.

Parallel KS methods

- How to decompose matrix across parallel machine?
 - Depends on how the matrix is stored
 - Depends on what the matrix is
- Block diagonal matrix MV routine is completely parallelisable

$$\begin{array}{c} P_1 \\ P_2 \\ P_3 \end{array} \begin{array}{|c|c|c|} \hline A_{11} & & \\ \hline & A_{22} & \\ \hline & & A_{33} \\ \hline \end{array} \begin{array}{|c|} \hline V_1 \\ \hline V_2 \\ \hline V_3 \\ \hline \end{array} = \begin{array}{c} P_1 \quad P_2 \quad P_3 \\ \begin{array}{|c|c|c|} \hline A_{11} \cdot V_1 & A_{22} \cdot V_2 & A_{33} \cdot V_3 \\ \hline \end{array} \end{array}$$

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General parallel matrix-vector

- More general approach is to decompose matrix by row
 - each processor has m rows of matrix
- Consider first processor

$$\begin{array}{c} P_1 \\ P_2 \\ P_3 \end{array} \begin{array}{|c|c|c|c|c|c|} \hline & & & & & \\ \hline & & & & & \\ \hline & & & & & \\ \hline & & & & & \\ \hline & & & & & \\ \hline & & & & & \\ \hline \end{array} \begin{array}{|c|} \hline \\ \hline \\ \hline \\ \hline \\ \hline \\ \hline \\ \hline \end{array} = \begin{array}{|c|} \hline \\ \hline \\ \hline \\ \hline \\ \hline \\ \hline \\ \hline \end{array}$$

- Could simply use replicated data for vector
 - i.e. all processors know about all data
 - Need to broadcast

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General parallel matrix-vector

- Replicated vector
 - extra memory requirement
 - Each processor has to broadcast result to populate result vector
- Distributed vector
 - efficient use of memory
 - accumulate locally matrix times vector block
 - processors exchange vector blocks
 - Answer ends up distributed
 - Sparse: may not need all processors to exchange blocks
- Smart implementations for specific matrix types
- Global sum required for scalar product

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Simple 2 processor 2x2 example

Distributed vector:

$$\begin{matrix} P_1 \\ P_2 \end{matrix} \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \begin{pmatrix} b_1 \\ b_2 \end{pmatrix} = \begin{pmatrix} a_{11}b_1 + a_{12}\textcircled{b_2} \\ a_{21}\textcircled{b_1} + a_{22}b_2 \end{pmatrix}$$

- Circled elements initially not available
- Calculate $a_{11}b_1$ on P_1 and $a_{22}b_2$ on P_2
- Then swap elements b_1 and b_2 between processors
- Then calculate $a_{12}b_2$ on P_1 and $a_{21}b_1$ on P_2
- Generalise to more processors (e.g. pass around a ring rather than simply “swap” elements)
- Can also generalise to bigger matrices
- Then deal with blocks instead

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