

# Generalized Minimal Residual Method (GMRES)

## History:

In 1986, GMRES was developed by Yousef Saad and Martin H. Schultz. It is a generalization and improvement of the MINRES method. Shockingly, for how early it was developed, it is a very powerful tool still used today. Over the last 38 years, there have been many refinements to the algorithm for different use cases. Still further developments are begin made.

Given a linear system  $Ax = b$ , where  $A$  is an invertible matrix, consider the sequence of vectors:

$$b, Ab, A^2b, \dots, A^n b, \dots$$

Among these vectors,  $n + 1$  vectors can be written as:

$$\alpha_0 b + \alpha_1 Ab + \alpha_2 A^2 b + \dots + \alpha_n A^n b = 0$$

for some nonzero coefficients  $\{\alpha_i\}$ . Since  $n + 1$   $n$ -dimensional vectors are linearly dependent, let  $k$  ( $k \leq n$ ) be the smallest integer such that  $\alpha_k \neq 0$ .

The inverse of  $A$  acting on  $b$  can be written as:

$$A^{-1}b = -\frac{1}{\alpha_k}(\alpha_{k+1}b + \dots + \alpha_n A^{n-k-1}b),$$

which is known as the **Weak-Cayley Hamilton Theorem**.

The inverse of  $A$  acting on  $b$  can be computed using only matrix-vector products. The vectors  $b, Ab, A^2b, \dots, A^n b$  form a subspace for the solution.

## Krylov Subspace

For a matrix  $A$  and vector  $b$ , the  $r$ -th Krylov subspace is defined as:

$$K_r(A, b) := \text{span}\{b, Ab, \dots, A^{r-1}b\}.$$

## Arnoldi Process

The Arnoldi process is an algorithm, similar to the Gram-Schmidt algorithm, that constructs an orthonormal basis for the Krylov subspace  $K_r(A, b) := \text{span}\{b, Ab, \dots, A^{r-1}b\}$ .

## Algorithm:

- Choose a  $v_1$  such that  $\|v_1\| = 1$ .
- For  $j = 1, 2, \dots$ 
  - $h_{i,j} = (Av_j)^T v_i, \quad i = 1, 2, \dots, j$  (forming  $H_k$ )
  - $\hat{v}_{j+1} = Av_j - \sum_{i=1}^j h_{i,j} v_i$
  - $h_{j+1,j} = \|\hat{v}_{j+1}\|$
  - $v_{j+1} = \frac{\hat{v}_{j+1}}{h_{j+1,j}}$  (forming  $V_k$ )

This algorithm produces matrices  $V_k$  and  $H_k$ , where:

- $V_k$  contains the orthonormal basis for the Krylov subspace.
- $H_k$  is an upper Hessenberg matrix.

## Solving $Ax = f$ Using GMRES

1. Choose an initial guess  $x_0$  and compute the residual  $r_0 = f - Ax_0$ .
2. Set  $v_1 = \frac{r_0}{\|r_0\|}$ .
3. Apply the Arnoldi process to compute  $V_k$  and  $H_k$ .
4. Update the solution as:

$$x_k = x_0 + z_k, \quad z_k = V_k y_k,$$

where  $y_k$  minimizes:

$$\| \|r_0\| e_1 - H_k y \|,$$

with  $e_1$  being the first column of the  $(k+1) \times (k+1)$  identity matrix.

This is a simple version of GMRES. Many refined versions, such as GMRES( $m$ ), exist.

## GMRES Further Developments

### GMRES( $m$ )

In GMRES( $m$ ), the algorithm restarts after every  $m$  iterations, preventing the memory and computational cost from growing indefinitely. This makes it more efficient for problems where  $m$  is chosen to balance accuracy and computational expense.

### Preconditioned GMRES (PGMRES)

To improve convergence, preconditioners can be applied. These modify the system as  $M^{-1}Ax = M^{-1}b$ , where  $M$  is a preconditioner matrix chosen such that  $M^{-1}A$  has better spectral properties, leading to faster convergence. Examples include ILU (Incomplete LU), Jacobi, and SSOR.

### Flexible GMRES (FGMRES)

Flexible GMRES allows for changing preconditioners or using nonlinear preconditioning during iterations. This is particularly useful for complex systems where the preconditioning strategy evolves.

### Generalized Block GMRES (BGMRES)

Block GMRES simultaneously solves systems with multiple right-hand sides  $Ax = B$  by building Krylov subspaces for all right-hand vectors in parallel.

### Recycling GMRES

Recycling GMRES methods reuse Krylov subspaces across multiple linear systems (e.g., when solving parameter-dependent systems or in time-stepping schemes). This reduces computational effort.

**Complexity:** The computational complexity is generally less than  $O(n^2)$ . Different variants offer trade-offs between computational cost, memory usage, and convergence rate.

## Applications

GMRES is widely used in various fields, including:

- Engineering and Computational Fluid Dynamics
- Financial Engineering and Risk Analysis
- Physics and Material Science
- Environmental Modeling
- Weather Prediction and Geophysical Exploration
- Machine Learning Optimization

- Biomedical Engineering
- Robotics and Control Systems