MA3227 Numerical Analysis II

Lecture 6: GMRES

Simon Etter

2019/2020

GMRES

Introduction

LU factorisation is an all-or-nothing algorithm: we must run the full algorithm to extract any meaningful information, but when we do we get a result which is accurate up to machine precision.

Such an algorithm is called *direct*.

Over the next few weeks, we will look at methods which proceed in iterations. After each iteration, we get an approximation $x_k \approx x$, and we may terminate the algorithm if we are happy with x_k.

Such an algorithm is called *iterative*.

Iterative algorithms may perform better than LU factorisation when used correctly, but doing so can be challenging.

GMRES

Problem statement

Given invertible $A \in \mathbb{R}^{N \times N}$ and $b \in \mathbb{R}^N$, find $x \in \mathbb{R}^N$ such that $Ax = b$.

Subspace method

Given $V_k \in \mathbb{R}^{N \times k}$, approximate x by

$$x_k = V_k y_k \qquad \text{where} \qquad y_k = \arg\min \|AV_k y_k - b\|.$$

Terminology: $r = b - Ax_k$ is called the *residual* of x_k.

Krylov subspace method

Choose $V_k = \begin{pmatrix} b & Ab & \dots & A^{k-1}b \end{pmatrix}$.

The approximate solution x_k is then given by

$$x_k = p_{k-1}(A)\, b \qquad \text{where} \qquad p_{k-1} = \underset{p_{k-1} \in \mathcal{P}_{k-1}}{\arg\min} \left\| \left(A p_{k-1}(A) - I \right) b \right\|.$$

$\mathcal{P}_k = \left\{ p(x) \mid p(x) = \sum_{\ell=0}^{k} c_\ell x^\ell \right\}$ denotes the space of polynomials of degree $\leq k$.

GMRES

Remarks on Krylov subspace methods

- Terminology: Krylov subspace $= \text{span}\{b, Ab, \ldots, A^{k-1}b\}$.
- We will discuss pros and cons of Krylov subspaces later.
  For now, let us focus on the *how* rather than the *why*.
- There are several distinct but related Krylov subspace methods.
  In this lecture, we will focus on the Generalised Minimal Residual (GMRES) method, which solves

$$x_k = p_{k-1}(A)\, b \qquad \text{where} \qquad p_{k-1} = \underset{p_{k-1} \in \mathcal{P}_{k-1}}{\arg\min} \left\| \left(A p_{k-1}(A) - I \right) b \right\|_2 .$$

Note that this formula uses $\| \cdot \|_2$ while formula on previous slide uses $\| \cdot \|$.

GMRES

Implementing GMRES, the bad way

1. Assemble $V_k = \begin{pmatrix} b & Ab & \dots & A^{k-1}b \end{pmatrix}$.
2. Solve least squares problem $y_k = \arg\min \|AV_k y_k - b\|_2$.
3. Set $x_k = V_k y_k$.

See `gmres_unstable()` and `test()`.

Observation

Algorithm breaks down for $k \gtrsim 8$!

The following slides will explain why.

GMRES

Breakdown of naive GMRES

Notation and assumptions:

- Let λ_ℓ, u_ℓ be the eigenvalues and -vectors of A sorted such that $|\lambda_1| \geq |\lambda_2| \geq \ldots \geq |\lambda_N|$.
  We will always assume that there are N distinct eigenvectors. Argument is similar but more technical otherwise.
- Let $c \in \mathbb{R}^N$ be such that $b = \sum_{\ell=1}^{N} c_\ell u_\ell$.
- Assume $|\lambda_1| > |\lambda_2|$ (argument is similar but more technical otherwise).

We observe:

- $A^k b = \sum_{\ell=1}^{N} c_\ell A^k u_\ell = \sum_{\ell=1}^{N} c_\ell \lambda_\ell^k u_\ell$.
- $\frac{|\lambda_\ell|^k}{|\lambda_1|^k} \to 0$ for $k \to \infty$ and all $\ell > 1$.

Hence we conclude that $\boxed{A^k b / \lambda_1^k \to c_1 u_1}$ for $k \to \infty$.

GMRES

Breakdown of naive GMRES (continued)

- $A^k b / \lambda_1^k \to c_1 u_1$ implies that the right-most columns of

$$V_k = \begin{pmatrix} b & Ab & \dots & A^{k-1}b \end{pmatrix}$$

  are almost collinear. See `normalised_krylov_vectors()`.
- We have seen in Lecture 5 (least squares) that computing $QR = AV_k$ is ill-conditioned if columns of AV_k are almost linearly dependent, i.e. rounding errors will be amplified in this case.

Armed with the above, we can now explain why `gmres_unstable()` breaks down for $k \gtrsim 8$:

- For $k \lesssim 8$, the columns of V_k are independent enough that the rounding errors remain small.
- For $k \gtrsim 8$, rounding errors are amplified to the extent that they spoil the accuracy of the result.

Question: Can we modify the GMRES algorithm to avoid excessive growth of rounding errors?

GMRES

Stabilising GMRES

Observations:

- The matrix $V_k = \begin{pmatrix} b & Ab & \dots & A^{k-1}b \end{pmatrix}$ is a bad representation for the subspace $K_k = \text{range}(V_k)$ because the columns of V_k are almost linearly dependent.
- GMRES solution x_k depends on subspace K_k but not on the matrix V_k which represents this subspace.
- The ideal representation of K_k would be an orthogonal matrix $Q_k \in \mathbb{R}^{N \times k}$ such that $K_k = \text{span}(Q_k)$ since orthogonality is the most extreme form of linear independence.
- Such a Q_k could be computed by first assembling V_k and then computing the QR factorisation of V_k, but of course this would run into the same conditioning problem as before.
- To get a numerically stable algorithm, we must interleave the steps "add column to Q_k" and "orthogonalise Q_k" as demonstrated on the next slide.

GMRES

Stabilising GMRES (continued)

Algorithm 1 Arnoldi iteration

1: $Q_1 = b/\|b\|_2$.
2: **for** $\ell = 1, \ldots, k$ **do**
3: $\quad \tilde{q}_{\ell+1} = AQ_\ell[:, \ell]$.
4: $\quad$ **for** $m = 1, \ldots, \ell$ **do**
5: $\quad\quad H[m, \ell] = Q_\ell[:, m]^T \tilde{q}_{\ell+1}$
6: $\quad\quad \tilde{q}_{\ell+1} = \tilde{q}_{\ell+1} - Q_\ell[:, m]\, H[m, \ell]$
7: $\quad$ **end for**
8: $\quad H[\ell + 1, \ell] = \|\tilde{q}_{k+1}\|_2$
9: $\quad Q_{\ell+1} = \begin{pmatrix} Q_\ell & | & \frac{\tilde{q}_{\ell+1}}{H[\ell+1,\ell]} \end{pmatrix}$
10: **end for**

This algorithm is almost the same as modified Gram-Schmidt from Lecture 5. The only substantial difference is that above we initialise $\tilde{q}_{\ell+1} = AQ_\ell[:, \ell]$ while for Gram-Schmidt we had $\tilde{q}_\ell = A[:, \ell]$.

The following slides list the key properties of this algorithm.

GMRES

Lemma

Let $Q = Q_k$ be the matrix computed by the Arnoldi iteration. Then,

$$\text{range}(Q) = \text{span}\{b, Ab, \ldots, A^{k-1}b\}$$

Proof (not examinable).

We will show by induction that for all $\ell = 1, \ldots, k$ we have

$$Q[:, \ell] = \sum_{m=0}^{\ell-1} c_m^{(\ell)} A^m b \qquad \text{with} \qquad c_{\ell-1}^{(\ell)} \neq 0.$$

The first part implies $\text{range}(Q) \subset \text{span}\{b, Ab, \ldots, A^{k-1}b\}$.

The second part guarantees that

$$A^{\ell-1}b = \frac{1}{c_{\ell-1}^{(\ell)}} \left(Q[:, \ell] - \sum_{m=0}^{\ell-2} c_m^{(\ell)} A^m b \right)$$

which can be used to inductively show that $A^{\ell-1}b \in \text{range}(Q)$.

The details are easy to work out, so I omit them here.

GMRES

Proof (continued).

Base: $Q[:,1] = b/\|b\|_2 = c_0^{(1)} A^0 b$ with $c_0^{(1)} = 1/\|b\|_2$.

Induction: We can rewrite lines 3, 6, 9 of the Arnolid iteration in the form

$$H[\ell+1,\ell]\, Q[:,\ell+1] = AQ[:,\ell] - \sum_{m=1}^{\ell} Q[:,m]\, H[m,\ell].$$

By induction hypothesis, the highest power of A in $AQ[:,\ell]$ is A^ℓ while all the green terms only go up to at most $A^{\ell-1}$.

This implies that $Q[:,\ell+1]$ can be written in the form

$$Q[:,\ell+1] = \sum_{m=0}^{\ell} c_m^{(\ell+1)} A^m b \qquad \text{with} \qquad c_\ell^{(\ell+1)} = \frac{c_{\ell-1}^{(\ell)}}{H[\ell+1,\ell]} \neq 0$$

as claimed.

GMRES

Lemma

Let Q_ℓ be the matrices computed by the Arnoldi iteration. Then,

$$Q_\ell^T Q_\ell = I$$

Proof. This follows straightforwardly from the discussion of the Gram-Schmidt orthogonalisation procedure in Lecture 5.

Corollary

The columns of Q_k are an orthogonal basis for $\text{span}\{b, Ab, \ldots, A^{k-1}b\}$.

Implementing GMRES, the stable way

1. Run Arnoldi iteration to obtain Q_k, H_k.
2. Solve least squares problem $y_k = \arg\min \|AQ_k y_k - b\|_2$
3. Set $x_k = Q_k\, y_k$.

See `gmres_slow()`.

GMRES

Discussion

Assembling AQ_k in the above algorithm is expensive.

The next result shows that it is also unnecessary.

Lemma (Arnoldi relations)

$$AQ_\ell = Q_{\ell+1} H_\ell$$

where Q_ℓ are the matrices computed by the Arnoldi iteration and $H_\ell = H[1:\ell+1, 1:\ell]$.

Proof (not examinable). As before, we rewrite lines 3, 6, 9 of the Arnoldi iteration in the form

$$H[\ell+1,\ell]\, Q[:,\ell+1] = AQ[:,\ell] - \sum_{m=1}^{\ell} Q[:,m]\, H[m,\ell].$$

Rearranging yields

$$AQ[:,\ell] = \sum_{m=1}^{\ell} Q[:,m]\, H[m,\ell] + Q[:,\ell+1]\, H[\ell+1,\ell] = Q_{\ell+1}\, H[:,\ell].$$

GMRES

Discussion

Arnoldi relations allow to rewrite the GMRES least squares problem as

$$\begin{aligned} y_k &= \arg\min \|AQ_k y_k - b\|_2 \\ &= \arg\min \|Q_{k+1} H_k y - b\|_2 \\ &= \arg\min \left\| \hat{Q}\left(H_k y_k - \hat{Q}^T b\right) \right\|_2 \\ &= \arg\min \left\| H_k y_k - \hat{Q}^T b \right\|_2 \\ &= \arg\min \left\| H_k y_k - \|b\|_2 \, e_1 \right\|_2. \end{aligned}$$

- On the third line, I introduced a new matrix

$$\hat{Q} = \begin{pmatrix} Q_{k+1} & Q_\perp \end{pmatrix} \in \mathbb{R}^{N \times N}$$

  with $Q_\perp \in \mathbb{R}^{N \times (N-k)}$ such that $\hat{Q}$ is orthogonal (i.e. $\hat{Q}^T Q = I$). Such a $\hat{Q}$ always exists. Because $\hat{Q}$ is square, orthogonality also implies $\hat{Q}\hat{Q}^T = I$ which is what I used here.
- On the fourth line, I used that $\|\hat{Q}v\|_2 = \|v\|_2$ for any $v \in \mathbb{R}^N$.
- On the last line, I used that $Q_{k+1}[:, 1] = b/\|b\|_2$.

GMRES

Discussion (continued)

Advantages of rewriting

$$y_k = \arg\min \|AQ_k y_k - b\|_2 = \arg\min \left\| H_k y_k - \|b\|_2 \, e_1 \right\|_2.$$

- No more matrix products to assemble least squares matrix.
- $H_k \in \mathbb{R}^{(k+1)\times k}$ is much smaller than $AQ_k \in \mathbb{R}^{N\times k}$.
- H_k has special structure: $H_k[i,j] = 0$ if $i > j+1$, i.e.

$$H_k = \begin{pmatrix} x & x & x & x \\ x & x & x & x \\ & x & x & x \\ & & x & x \\ & & & x \end{pmatrix}.$$

  Matrices of this form are called *Hessenberg*.
  QR factorisation of such H_k can be computed in $\mathcal{O}\left(k^2\right)$ operations.
  See literature for details.

See `gmres()` for final implementation of GMRES algorithm.

GMRES

Runtime of Arnoldi iteration

- Line 3: k matrix-vector products.
- Lines 5, 6: $\mathcal{O}\left(Nk^2\right)$ FLOP.
  - $\mathcal{O}(N)$ FLOP per execution of either line.
  - Number of executions: $\sum_{\ell=1}^{k} \sum_{m=1}^{\ell} 1 = \sum_{\ell=1}^{k} \ell = \frac{k\,(k+1)}{2}$.
- Lines 8, 9: $\mathcal{O}(Nk)$ FLOP.

Summary: k matrix-vector products, $\mathcal{O}\left(Nk^2\right)$ other FLOP.

Runtime of Arnoldi-based GMRES

- Arnoldi: k matrix-vector products, $\mathcal{O}\left(Nk^2\right)$ other FLOP.
- Least squares: $\mathcal{O}(k^2)$ FLOP.
- $x_k = Q_k y_k$: $\mathcal{O}\left(Nk\right)$ FLOP.

Summary: k matrix-vector products, $\mathcal{O}\left(Nk^2\right)$ other FLOP.

GMRES

Discussion

GMRES runtime (copied from above):

$$k \text{ matrix-vector products, } \mathcal{O}\left(Nk^2\right) \text{ other FLOP.}$$

- GMRES runtime is $\mathcal{O}(N)$ if
  - runtime of matrix-vector product is $\mathcal{O}(N)$, and
  - sufficient accuracy can be achieve for $k = \mathcal{O}(1)$.

  The first condition is the case e.g. for sparse matrices like $\Delta_n^{(d)}$.

  We will return to the second condition in a later lecture.
- GMRES becomes expensive for large k due to the $\mathcal{O}(Nk^2)$ operations for orthogonalisation.
- Good news: orthogonalisation simplifies for symmetric matrices! See next lecture.

GMRES

Summary GMRES

- Core idea of GMRES: approximate $x = A^{-1}b$ by

$$x_k := p_{k-1}(A)\, b \qquad \text{where} \qquad p_{k-1} := \operatorname*{arg\,min}_{p_{k-1} \in \mathcal{P}_{k-1}} \left\| \left(A p_{k-1}(A) - I \right) b \right\|_2 .$$

- The above optimisation problem can be solved using linear algebra techniques. The resulting runtime is

$$k \text{ matrix-vector products}, \qquad \mathcal{O}\left(Nk^2\right) \text{ other FLOP}.$$