

Mathematical Tripos Part II: Michaelmas Term 2015

Numerical Analysis – Lecture 20

Algorithm 4.23 (The conjugate gradient method) Here it is.

- (A) For any initial vector $\mathbf{x}^{(0)}$, set $\mathbf{d}^{(0)} = -\mathbf{g}^{(0)} = -(A\mathbf{x}^{(0)} - \mathbf{b})$;
 (B) For $k \geq 0$, calculate $\mathbf{x}^{(k+1)} = \mathbf{x}^{(k)} + \omega^{(k)}\mathbf{d}^{(k)}$ and the residual

$$\mathbf{g}^{(k+1)} = \mathbf{g}^{(k)} + \omega^{(k)}A\mathbf{d}^{(k)}, \quad \text{with} \quad \omega^{(k)} = \{\mathbf{g}^{(k+1)} \perp \mathbf{d}^{(k)}\} = -\frac{\mathbf{d}^{(k)T}\mathbf{g}^{(k)}}{\mathbf{d}^{(k)T}A\mathbf{d}^{(k)}}, \quad k \geq 0. \quad (4.9)$$

- (C) For the same k , the next search direction is the vector

$$\mathbf{d}^{(k+1)} = -\mathbf{g}^{(k+1)} + \beta^{(k)}\mathbf{d}^{(k)}, \quad \text{with} \quad \beta^{(k)} = \{\mathbf{d}^{(k+1)} \perp A\mathbf{d}^{(k)}\} = \frac{\mathbf{g}^{(k+1)T}A\mathbf{d}^{(k)}}{\mathbf{d}^{(k)T}A\mathbf{d}^{(k)}}, \quad k \geq 0. \quad (4.10)$$

Theorem 4.24 (Properties of Algorithm 4.23) For every integer $m \geq 0$, the conjugate gradient method enjoys the following properties.

- (1) The linear space spanned by the gradients $\{\mathbf{g}^{(i)} : i = 0 \dots m\}$
 - (a) is the same as the linear space spanned by the search directions $\{\mathbf{d}^{(i)} : i = 0 \dots m\}$
 - (b) it coincides with the space $K_{m+1} = \text{span}\{A^i\mathbf{g}^{(0)} : i = 0 \dots m\}$.
- (2) The gradients satisfy the orthogonality conditions: $\mathbf{g}^{(m)T}\mathbf{g}^{(i)} = \mathbf{g}^{(m)T}\mathbf{d}^{(i)} = 0$, for $i < m$.
- (3) The search directions are conjugate: $\mathbf{d}^{(m)T}A\mathbf{d}^{(i)} = 0$, for $i < m$.

Proof. We use induction on $m \geq 0$, the assertions being trivial for $m = 0$, since $\mathbf{d}^{(0)} = -\mathbf{g}^{(0)}$, and (2)-(3) are void. Therefore, assuming that the assertions are true for some $m = k$, we ask if they remain true when $m = k + 1$.

(1) Formula $\mathbf{d}^{(k+1)} = -\mathbf{g}^{(k+1)} + \beta^{(k)}\mathbf{d}^{(k)}$ in (4.10) readily implies that (1a), i.e. equivalence of the spaces spanned by $(\mathbf{g}^{(i)})_0^k$ and $(\mathbf{d}^{(i)})_0^k$, is preserved when k is increased to $k + 1$. Similarly, it follows from $\mathbf{g}^{(k+1)} = \mathbf{g}^{(k)} + \omega^{(k)}A\mathbf{d}^{(k)}$ in (4.9), that (1b) holds for $m = k + 1$ as well.

(2) Turning to assertion (2), we need $\mathbf{g}^{(k+1)} \perp \mathbf{g}^{(i)}$ for $i \leq k$, which is equivalent to $\mathbf{g}^{(k+1)} \perp \mathbf{d}^{(i)}$ for $i \leq k$ because of (1a). The latter follows from (4.9): for $i = k$ by definition of $\omega^{(k)}$, and for $i < k$ by the inductive assumptions $\mathbf{g}^{(k)} \perp \mathbf{d}^{(i)}$ and $A\mathbf{d}^{(k)} \perp \mathbf{d}^{(i)}$.

(3) It remains to justify (3), namely that $\mathbf{d}^{(k+1)} \perp A\mathbf{d}^{(i)}$ in (4.10). The value of $\beta^{(k)}$ in (4.10) is defined to give $\mathbf{d}^{(k+1)} \perp A\mathbf{d}^{(k)}$, so we need $\mathbf{d}^{(k+1)} \perp A\mathbf{d}^{(i)}$ for $i < k$. By the inductive hypothesis $\mathbf{d}^{(k)} \perp A\mathbf{d}^{(i)}$, hence it is sufficient to establish that $\mathbf{g}^{(k+1)} \perp A\mathbf{d}^{(i)}$ for $i < k$. Now, the formula (4.9) yields $A\mathbf{d}^{(i)} = (\mathbf{g}^{(i+1)} - \mathbf{g}^{(i)})/\omega^{(i)}$, therefore we require the conditions $\mathbf{g}^{(k+1)} \perp (\mathbf{g}^{(i+1)} - \mathbf{g}^{(i)})$ for $i < k$, and they are a consequence of the assertion (2) for $m = k + 1$ obtained previously. \square

Corollary 4.25 (A termination property) If Algorithm 4.23 is applied in exact arithmetic, then, for any $\mathbf{x}^{(0)} \in \mathbb{R}^n$, termination occurs after at most n iterations.

Proof. Assertion (2) of Theorem 4.24 states that residuals $(\mathbf{g}^{(k)})_{k \geq 0}$ form a sequence of mutually orthogonal vectors in \mathbb{R}^n . Therefore at most n of them can be nonzero. \square

Standard Form 4.26 (Reformulation of the conjugate gradient method) We now simplify and reformulate Algorithm 4.23. Specifically, we write the parameters $\omega^{(k)}$ and $\beta^{(k)}$ in (4.9)-(4.10) as

$$\omega^{(k)} = -\frac{\mathbf{d}^{(k)T} \mathbf{g}^{(k)}}{\mathbf{d}^{(k)T} A \mathbf{d}^{(k)}} = \frac{\|\mathbf{g}^{(k)}\|^2}{\mathbf{d}^{(k)T} A \mathbf{d}^{(k)}} > 0, \quad \beta^{(k)} = \frac{\mathbf{g}^{(k+1)T} (\mathbf{g}^{(k+1)} - \mathbf{g}^{(k)})}{\mathbf{d}^{(k)T} (\mathbf{g}^{(k+1)} - \mathbf{g}^{(k)})} = \frac{\|\mathbf{g}^{(k+1)}\|^2}{\|\mathbf{g}^{(k)}\|^2} > 0.$$

Here we used (for β) the fact that $A \mathbf{d}^{(k)}$ is a multiple of $\mathbf{g}^{(k+1)} - \mathbf{g}^{(k)}$ and orthogonality of $\mathbf{g}^{(k+1)}$ to both $\mathbf{g}^{(k)}$, $\mathbf{d}^{(k)}$ proved above, and (for both β and ω) the property $\mathbf{d}^{(k)T} \mathbf{g}^{(k)} = -\|\mathbf{g}^{(k)}\|^2$ which follows from (4.10) with index $k + 1$. Furthermore, we let $\mathbf{x}^{(0)}$ be the zero vector and we write $-\mathbf{r}^{(k)}$ instead of $\mathbf{g}^{(k)}$, where $\mathbf{r}^{(k)}$ is the (sign reversed) residual $\mathbf{b} - A \mathbf{x}^{(k)}$.

Thus, Algorithm 4.23 takes the following form.

- (1) Set $k = 0$, $\mathbf{x}^{(0)} = 0$, $\mathbf{r}^{(0)} = \mathbf{b}$, and $\mathbf{d}^{(0)} = \mathbf{r}^{(0)}$;
- (2) Calculate the matrix vector product $\mathbf{v}^{(k)} = A \mathbf{d}^{(k)}$ and $\omega^{(k)} = \|\mathbf{r}^{(k)}\|^2 / \mathbf{d}^{(k)T} \mathbf{v}^{(k)} > 0$;
- (3) Apply the formulae $\mathbf{x}^{(k+1)} = \mathbf{x}^{(k)} + \omega^{(k)} \mathbf{d}^{(k)}$ and $\mathbf{r}^{(k+1)} = \mathbf{r}^{(k)} - \omega^{(k)} \mathbf{v}^{(k)}$;
- (4) Stop if $\|\mathbf{r}^{(k+1)}\|$ is acceptably small;
- (5) Set $\mathbf{d}^{(k+1)} = \mathbf{r}^{(k+1)} + \beta^{(k)} \mathbf{d}^{(k)}$, where $\beta^{(k)} = \|\mathbf{r}^{(k+1)}\|^2 / \|\mathbf{r}^{(k)}\|^2 > 0$;
- (6) Increase k by one, and then go back to (2).

The total work is usually dominated by the number of iterations, multiplied by the time it takes to compute $\mathbf{v}^{(k)} = A \mathbf{d}^{(k)}$. It follows from Corollary 4.25 that the conjugate gradient algorithm is highly suitable when most of the elements of A are zero, i.e. when A is *sparse*.

Definition 4.27 (Krylov subspace) Let A be an $n \times n$ matrix, $\mathbf{v} \in \mathbb{R}^n$ nonzero, and $m \in \mathbb{N}$. The linear space $K_m(A, \mathbf{v}) = \text{Sp}\{A^j \mathbf{v} : j = 0 \dots m-1\}$ is said to be the m th Krylov subspace of \mathbb{R}^n .

Remark 4.28 (The Krylov subspaces of the conjugate gradient method) In the standard form of the method, we set $\mathbf{d}^{(0)} = -\mathbf{g}^{(0)} = \mathbf{b} \in K_1(A, \mathbf{b})$, and from the formulas

$$\mathbf{g}^{(k+1)} = \mathbf{g}^{(k)} + \omega^{(k)} A \mathbf{d}^{(k)}, \quad \mathbf{d}^{(k+1)} = -\mathbf{g}^{(k+1)} + \beta^{(k)} \mathbf{d}^{(k)}$$

we deduced by induction that

$$\text{Sp}\{\mathbf{g}^{(0)}, \mathbf{g}^{(1)}, \dots, \mathbf{g}^{(m)}\} = \text{Sp}\{\mathbf{g}^{(0)}, A \mathbf{g}^{(0)}, \dots, A^m \mathbf{g}^{(0)}\} = K_{m+1}(A, \mathbf{b}).$$

By Theorem 4.24, the residuals $\mathbf{g}^{(i)}$ are orthogonal to each other, thus, the number of nonzero residuals (and hence the number of iterations) is bounded from above by the largest dimension of the subspaces $K_m(A, \mathbf{b})$. The latter is n at most, but it can be smaller as the following consideration shows.

Lemma 4.29 (Properties of Krylov subspaces) Given A and \mathbf{v} , let δ_m be the dimension of the Krylov subspace $K_m(A, \mathbf{v})$. Then the sequence $\{\delta_m\}_1^n$ increases monotonically and has the following properties.

- 1) There exists a positive integer $s \leq n$ such that $\delta_m = m$ for $m \leq s$ and $\delta_m = s$ for $m > s$.
- 2) If we can express \mathbf{v} as $\mathbf{v} = \sum_{i=1}^{s'} c_i \mathbf{w}_i$, where (\mathbf{w}_i) are eigenvectors of A corresponding to distinct eigenvalues and all (c_i) are nonzero, then $s = s'$.