

## Mathematical Tripos Part II: Michaelmas Term 2014

## 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  $\beta$ ) 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  $\beta$  and  $\omega$ ) 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 nonzero  $\mathbf{v}$ , let  $\delta_m$  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  $s = s'$ .