

1 Derivation of conjugate gradient method

Lecture 14

(CG)

Now we'll derive a method, which uses the condition for nonzero diagonal entries of $P_n^T A P_n$ when A is pos. def. In this method, we'll also obtain recursions for residuals.

Consider the case, when A is sym. pos. def.

Search the approximate solution and the search direction in the form:

$$(1) \quad x_{j+1} = x_j + \alpha_j p_j$$

$$(2) \quad p_{j+1} = z_{j+1} + \beta_j p_j$$

Here α_j and β_j are unknown scalars to be found.

We'll use:

1) the orthogonality for residuals:

$$(z_i, z_j) = 0, \quad i \neq j$$

2) the conjugacy for search directions:

$$(A p_i, p_j) = \begin{cases} 0, & i \neq j \\ > 0, & i = j \end{cases}$$

1) let's find α_j using the first condition:

$$(z_i, z_j) = 0, \quad i \neq j$$

Consider z_j and z_{j+1}

$$(z_{j+1}, z_j) = 0$$

$$\downarrow z_{j+1} = b - A x_{j+1}$$

$$\downarrow z_j = b - A x_j$$

$$\begin{aligned}
 z_{j+1} - z_j &= b - Ax_{j+1} - b + Ax_j = \\
 &= -Ax_{j+1} + Ax_j = -A(x_j + \alpha_j p_j) + Ax_j = -\alpha_j A p_j \Rightarrow
 \end{aligned}$$

$$\boxed{z_{j+1} = z_j - \alpha_j A p_j} \quad (3) \text{ recursion for residuals}$$

$$\Rightarrow (z_{j+1}, z_j) = (z_j - \alpha_j A p_j, z_j) = 0$$

$$(z_j, z_j) - \alpha_j (A p_j, z_j) = 0 \Rightarrow$$

$$\boxed{\alpha_j = \frac{(z_j, z_j)}{(A p_j, z_j)}} \quad (4) \text{ we'll modify this formula later}$$

2) Now let's find β_j using the second condition:

$$(A p_i, p_j) = \begin{cases} 0, & i \neq j \\ > 0, & i = j \end{cases}$$

Consider p_j and p_{j+1} :

$$p_{j+1} = z_{j+1} + \beta_j p_j$$

$$(A p_j, p_{j+1}) = 0$$

$$(A p_j, z_{j+1} + \beta_j p_j) = 0$$

$$\underbrace{(A p_j, z_{j+1})} + \beta_j (A p_j, p_j) = 0 \quad (*)$$

$$(A p_j, z_{j+1}) = 0$$

$$z_{j+1} = z_j - \alpha_j A p_j \Rightarrow A p_j = -\frac{1}{\alpha_j} (z_{j+1} - z_j)$$

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$$\begin{aligned} \ominus \left(-\frac{1}{\alpha_j} (z_{j+1} - z_j), z_{j+1} \right) &= \\ &= -\frac{1}{\alpha_j} (z_{j+1}, z_{j+1}) + \frac{1}{\alpha_j} (z_j, z_{j+1}) \Rightarrow \end{aligned}$$

$$(AP_j, z_{j+1}) = -\frac{1}{\alpha_j} (z_{j+1}, z_{j+1}) \ominus \begin{matrix} \parallel \\ 0 \end{matrix}$$

$$\alpha_j = \frac{(z_j, z_j)}{(AP_j, z_j)}$$

$$\ominus - \frac{(AP_j, z_j)}{(z_j, z_j)} (z_{j+1}, z_{j+1})$$

Thus, in (*) we have

$$- \frac{(AP_j, z_j)}{(z_j, z_j)} (z_{j+1}, z_{j+1}) + \beta_j (AP_j, P_j) = 0 \Rightarrow$$

$$\beta_j = \frac{(AP_j, z_j) (z_{j+1}, z_{j+1})}{(z_j, z_j) (AP_j, P_j)}$$

$$\underbrace{(z_j, z_j)}_{\neq 0} \underbrace{(AP_j, P_j)}_{> 0 \text{ as } A \text{ is pos det.}}$$

As $P_{j+1} = z_{j+1} + \beta_j P_j$, then

$$z_{j+1} = P_{j+1} - \beta_j P_j$$

$$z_j = P_j - \beta_{j-1} P_{j-1}$$

$$\text{Consider } (AP_j, z_j) = (AP_j, P_j - \beta_{j-1} P_{j-1}) =$$

$$= (AP_j, P_j) - \beta_{j-1} (AP_j, P_{j-1}) = (AP_j, P_j)$$

$$\text{Hence, } \beta_j = \frac{\cancel{(AP_j, P_j)} (z_{j+1}, z_{j+1})}{(z_j, z_j) \cancel{(AP_j, P_j)}} = \frac{(z_{j+1}, z_{j+1})}{(z_j, z_j)}$$

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Thus,
$$\beta_j = \frac{(z_{j+1}, z_{j+1})}{(z_j, z_j)} \quad (5)$$

and
$$\alpha_j = \frac{(z_j, z_j)}{A p_j, p_j} \quad (4 \text{ new})$$

We have obtained 5 recursions:

- for approximate solution and residual

1)
$$\alpha_j = \frac{(z_j, z_j)}{(A p_j, p_j)} \quad (4)$$

2)
$$x_{j+1} = x_j + \alpha_j p_j \quad (1)$$

3)
$$z_{j+1} = z_j - \alpha_j A p_j \quad (3)$$

- for search direction

4)
$$\beta_j = \frac{(z_{j+1}, z_{j+1})}{(z_j, z_j)} \quad (5)$$

5)
$$p_{j+1} = z_{j+1} + \beta_j p_j \quad (2)$$

These five recursions give conjugate gradient method (CG)

Conjugate gradient method (CG)

A is sym. pos. def.

1. Take initial guess x_0 , compute initial residual $z_0 = b - A x_0$; $p_0 := z_0$

2. Start iterative process for $j = 0, 1, 2, \dots$
Do until convergence

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$$1) \alpha_j = \frac{(z_j, z_j)}{(Ap_j, p_j)}$$

$$2) x_{j+1} = x_j + \alpha_j p_j \leftarrow \text{check convergence of } x_{j+1}$$

$$3) z_{j+1} = z_j - \alpha_j Ap_j \leftarrow \text{check residual norm } \|z_{j+1}\|_2 < \epsilon$$

If not converged,

$$4) \beta_j = \frac{(z_{j+1}, z_{j+1})}{(z_j, z_j)}$$

$$5) p_{j+1} = z_{j+1} + \beta_j p_j$$

As it was in classic Lanczos and R-Lanczos, in CG method the residuals z_j are orthogonal and search directions p_j are conjugate. Vectors p_j in CG are called conjugate gradients

ⓧ In CG-method A is sym. pos. def. and

1) residuals z_j are orthogonal:

$$(z_i, z_j) = \begin{cases} 0, & i \neq j \\ > 0, & i = j \end{cases}$$

2) search directions p_j are A -conjugate:

$$(A p_i, p_j) = \begin{cases} 0, & i \neq j \\ > 0, & i = j \end{cases}$$

ⓧ || For $\text{cond}(A) \approx 1$ CG converges very fast