

Math 689

L#11

Oct 4, 2011
Tuesday

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The Conjugate Gradient Method for $Ax=b$

Steepest descent method suffers from one very unpleasant and potentially slowing down flaw: $r^{(k+1)} \perp r^{(k)}$, but often $r^{(k+1)}$ is the same as $r^{(k-1)}$, i.e. the search direction is repeated and often many times. Conjugate gradient is designed to avoid this. Here is how it does it.

Introduce the Krylov space

$$K_m(A, r) = \{r, Ar, A^2r, \dots, A^{m-1}r\}, \quad r \text{ given}$$

We assume that the vectors in $K_m(A, r)$ are linearly independent. ^{(often $r = r^{(0)}$ - the initial residual)} Therefore for $m=n$ $K_n(A, r) = \mathbb{R}^n$.

Then we minimize

$$(1) \quad J(y) = \frac{1}{2} (A(x-y), x-y) - \frac{1}{2} (Ax, x)$$

over the Krylov subspaces. Namely, for given $x^{(0)} \in \mathbb{R}^n$ we define $r^{(0)} = b - Ax^{(0)}$ and $K_m = K_m(A, r^{(0)})$. The k -th ^{CG} iterate $x^{(m)}$ has the form

$x^{(m)} = x^{(0)} + \theta^{(m)}$, where $\theta^{(m)} \in K_m$ is the minimizer or altogether

$$J(x^{(m)}) = \min_{y \in \{x^{(0)}\} + K_m} J(y)$$

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that is $J(x^{(m)}) \leq J(y)$ for any $y \in \{x^{(0)}\} + K_m$
 i.e. $y = x^{(0)} + \sum_{l=0}^{m-1} \alpha_l A^l r \equiv x^{(0)} + \theta^{(m)}$

Then making the computations we get

$$\frac{1}{2}(A(\underbrace{x - x^{(m)}}_{-e^{(m)}}), x - x^{(m)}) - \frac{1}{2}(Ax, x) \leq \frac{1}{2}(A(x - y), (x - y)) - \frac{1}{2}(Ax, x)$$

$$\boxed{e^{(m)} = x - x^{(m)}} \quad \text{for any } y = x^{(0)} + \theta^{(m)}$$

$$(Ae^{(m)}, e^{(m)}) \leq (A(\underbrace{x - x^{(0)}}_{e^{(0)}} - \theta^{(m)}), \underbrace{x - x^{(0)}}_{e^{(0)}} - \theta^{(m)})$$

$$\boxed{(Ae^{(m)}, e^{(m)}) \leq (A(e^{(0)} - \theta^{(m)}), e^{(0)} - \theta^{(m)})}$$

$$\text{for any } \theta^{(m)} \in K_m(A, r^{(0)})$$

The main question now is how to find the minimizer $A^{(m)} \in K_m$.

Make one more hypothetical move: what about if we have an A -orthogonal basis of $K_m(A, r^{(0)})$?

say

$$\text{span}\{r^{(0)}, Ar^{(0)}, \dots, A^{m-1}r^{(0)}\} = \text{span}\{p^{(0)}, p^{(1)}, \dots, p^{(m-1)}\}$$

$$\text{such that } (Ap^{(i)}, p^{(j)}) = 0 \quad i \neq j$$

(We can think of as an application of Gram-Schmidt orthogonalization procedure applied to $r^{(0)}, Ar^{(0)}, \dots$

The idea of CG from a point of view
minimization over a space spanned by the vectors

$\{p^{(0)}, p^{(1)}, \dots, p^{(n-1)}\} \in \mathbb{R}^n$
which are (by miracle) A -orthogonal, i.e.

$$(Ap^{(i)}, p^{(j)}) = 0 \quad i \neq j$$

Of course $(Ap^{(k)}, p^{(k)}) > 0$ since A is an SPD.

For an arbitrary given initial guess $x^{(0)}$
we can write the solution x of $Ax=b$ in the
form

$$(*) \quad x = x^{(0)} \oplus \sum_{l=0}^{n-1} \alpha_l p^{(l)} = x^{(0)} + t^n$$

this would be an exact
representation of the solution

Therefore we have

$$Ax = Ax^{(0)} \oplus \sum_{l=0}^{n-1} \alpha_l Ap^{(l)} = b$$

Since $p^{(l)}$ are A -orthogonal we have

$$\oplus \sum \alpha_l Ap^{(l)} = b - Ax^{(0)}$$

$$\oplus \alpha_l (Ap^{(l)}, p^{(l)}) = (b - Ax^{(0)}, p^{(l)})$$

$$\alpha_l = \frac{(Ax^{(0)} + b, p^{(l)})}{(Ap^{(l)}, p^{(l)})} \quad l = 0, 1, \dots, n-1$$

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By construction we shall define $x^{(m)}$ as a vector spanned by the first k vectors $p^{(m)}$, that is

$$x^{(m)} = x^0 + \sum_{l=0}^{m-1} \alpha_l p^l, \text{ i.e. } \theta^{(m)} = \sum_{l=0}^{m-1} \alpha_l p^l$$

By the same argument as before we have

$$x^{(m+1)} = x^{(m)} + \alpha_m p^{(m)}, \quad m = 0, 1, \dots, n-1$$

where $\alpha_m = \frac{-(Ax^0 - b, p^{(m)})}{(Ap^{(m)}, p^{(m)})}$

$$\alpha_m = - \frac{(Ax^0 - \sum_{l=0}^{m-1} \alpha_l p^{(l)} - b, p^{(m)})}{(Ap^{(m)}, p^{(m)})}$$

Note $\sum_{l=0}^{m-1} \alpha_l (Ap^{(l)}, p^{(m)}) = 0$

$$A \left(x^0 - \underbrace{\sum_{l=0}^{m-1} \alpha_l p^{(l)}}_{x^{(m)}} \right) \quad \boxed{r^{(m)} = b - Ax^{(m)}}$$

$$\boxed{\alpha_m = - \frac{(Ax^{(m)} - b, p^{(m)})}{(Ap^{(m)}, p^{(m)})} = \frac{(r^{(m)}, p^{(m)})}{(Ap^{(m)}, p^{(m)})}}$$

Also

$$r^{(m+1)} = b - Ax^{(m+1)} = b - Ax^{(m)} - \alpha_m Ap^{(m)} = r^{(m)} - \alpha_m Ap^{(m)}$$

$$\boxed{r^{(m+1)} = r^{(m)} - \alpha_m p^{(m)}}$$

The magic of CG is that we do not need $p^{(e)}$ from the very beginning and they are generated in the process of computing $x^{(m)}$. all

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The main point of CG is that for an approximation of x we need much less than n -terms of the exact representation.

The CG method for $Ax=b$

$$r^0 = b - Ax^{(0)} \quad x^0 - \text{given}$$

$$p^0 = r^0$$

for $m = 0, 1, \dots$ until convergence, compute

$$x^{m+1} = x^m + \alpha_m p^m \quad \alpha_m = \frac{(r^m, p^m)}{(Ap^m, p^m)} \stackrel{(1)}{=} \frac{(r^m, r^m)}{(Ap^m, p^m)}$$

$$r^{m+1} = r^m - \alpha_m Ap^m$$

$$p^{m+1} = r^{m+1} + \beta_m p^{(m)} \quad \beta_m = - \frac{(Ap^m, r^{m+1})}{(Ap^m, p^m)} \stackrel{(2)}{=} - \frac{(r^{m+1}, r^{m+1})}{(r^m, r^m)}$$

end m

The most important property of the vectors $p^0, p^1, \dots, p^m$ is that they are A -orthogonal. Indeed for $m+1 \neq m$ we have

$$(Ap^{m+1}, p^m) = (Ar^{m+1}, p^m) + \beta_m (Ap^m, p^m) = 0 \quad \text{because of the choice of } \beta_m.$$

It is valid for other pairs as well.

Steepest Descent Method

$$x^{(0)} - \text{given} \quad r^0 = b - Ax^0$$

$$x^{k+1} = x^k + \alpha_k r^k \quad \alpha_k = \frac{(r^k, r^k)}{(Ar^k, r^k)}$$

$$r^{k+1} = r^k - \alpha_k Ar^k$$

$$(r^{k+1}, r^k) = (r^k, r^k) - \alpha_k (Ar^k, r^k) = 0$$

$$r^{k+1} \perp r^k$$

but it could be parallel to r^{k-1}
so we have repetition of search
directions

Gram-Schmidt Method

$$\{r^0, r^1, r^2, \dots, r^{m-1}\} \rightarrow \{p^0, p^1, \dots, p^{m-1}\}$$

A-orthogonal

$$p^0 = r^0$$

$$p^{k+1} = r^{k+1} - \sum_{\ell=0}^k \beta_{k\ell} p^\ell \quad k=0, 1, \dots, m-2$$

where

$$\beta_{k\ell} = \frac{(Ar^{k+1}, p^\ell)}{(Ap^\ell, p^\ell)}$$

$$(Ap^\ell, p^j) = 0 \quad \ell \neq j$$

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We get the vectors $\{p^0, p^1, \dots, p^{m-1}\}$
 by Gram-Schmidt orthogonalization method
 from $\text{span}\{r^0, Ar^0, \dots, A^{m-1}r^0\}$
 $= \text{span}\{r^0, r^1, \dots, r^{m-1}\}$ our w^j are r^j !

$$p^0 = r^0$$

$$p^{m+1} = r^{m+1} - \sum_{l=0}^m \beta_{ml} p^l \quad \beta_{ml} = \frac{(Ar^{(m+1)}, p^{(l)})}{(Ap^{(l)}, p^{(l)})}$$

Gram-Schmidt

Obviously $x^{(1)} = x^{(0)} - \alpha_0 p^0 = r^0 - \alpha_0 r^0$

$$Ax^{(1)} - b = Ax^{(0)} - b - \alpha_0 Ar^0$$

$$-r^{(1)} = -r^{(0)} - \alpha_0 Ar^{(0)}$$

$$r^{(1)} \in \text{span}\{r^0, Ar^{(0)}\}$$

$$r^{(2)} = x^{(1)} - \alpha_1 p^{(1)}$$

$$p^{(1)} \in \text{span}\{r^0, Ar^{(0)}\}$$

$$-r^{(2)} = -r^{(1)} - \alpha_1 Ap^{(1)}$$

$$r^{(1)} \in \text{span}\{r^0, Ar^{(0)}\}$$

$$Ap^{(1)} \in \text{span}\{Ar^0, A^2r^{(0)}\}$$

$$r^{(2)} \in \text{span}\{r^0, Ar^{(0)}, A^2r^{(0)}\}$$

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Let us have a closer look at Gram-Schmidt and CG process defined above.

First, we prove that $r^{m+1} \perp p^l$ $l=0, 1, \dots, m$

Indeed

$$(r^{m+1}, p^m) = (r^m, p^m) - \alpha_m (Ap^m, p^m)$$

$$= (r^m, p^m) - \frac{(r^m, p^m)}{(Ap^m, p^m)} (Ap^m, p^m) = 0$$

What about (r^{m+1}, p^{m-1}) ?

$$(r^{m+1}, p^{m-1}) = \underbrace{(r^m, p^{m-1})}_{\text{by the previous}} - \alpha_m \underbrace{(Ap^m, p^{m-1})}_{\stackrel{=0}{\text{A-orthogonality}}}$$

$$\text{Thus } (r^{m+1}, p^l) = 0 \quad l=0, 1, \dots, m$$

Let us look at

$$(r^m, p^m) = (r^m, r^m) + \beta_m \underbrace{(r^m, p^{m-1})}_{=0} = (r^m, r^m)$$

$$\text{Therefore } \alpha_m = \frac{(r^m, r^m)}{(Ap^m, p^m)} > 0$$

$$\text{When } \alpha_m = 0? \quad r^m = 0 \Rightarrow Ax^m - b = 0$$

we have found the solution.

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Final consideration

$$r^{l+1} = r^l - \alpha_e' A p^e$$

$$A p^e = \frac{1}{\alpha_e'} (r^l - r^{l+1}) \quad e = 0, \dots, m$$

$$(r^{m+1}, A p^e) = \frac{1}{\alpha_e'} (r^{m+1}, r^e - r^{l+1})$$

$$(A r^{m+1}, p^e) = \begin{cases} -\frac{1}{\alpha_m} (r^{m+1}, r^{m+1}) & e = m \\ 0 & e < m \end{cases}$$

But remember from Gram-Schmidt $\beta_m = -\frac{(A r^{m+1}, p^e)}{(A p^e, p^e)} = \begin{cases} \beta_m & e = m \\ 0 & \end{cases}$

$\Downarrow$

$$p^{m+1} = r^{m+1} - \beta_m p^m$$

Moreover

$$\beta_m = -\frac{(A r^{m+1}, p^m)}{(A p^m, p^m)} = \frac{1}{\frac{(r^m, r^m)}{(A p^m, p^m)}} \frac{(r^{m+1}, r^{m+1})}{(A p^m, p^m)} = \frac{(r^{m+1}, r^{m+1})}{(r^m, r^m)}$$