CS 219: Sparse matrix algorithms: Homework 4

Assigned May 1, 2013

Due by class time Wednesday, May 8

Problem 1a. Find a 2-by-2 matrix A that is symmetric and nonsingular, but for which neither A nor $-A$ is positive definite. What are the eigenvalues of A? Find a 2-vector y such that $y^T Ay < 0$.

Problem 1b. For A as above, find a 2-vector b such that the conjugate gradient algorithm, when started with the zero vector as an initial guess, does not converge to the solution of $Ax = b$. Show what happens on the first two iterations of CG, as in the October 28 class slides. How do you know it won't converge to the right answer?

Problem 2. In this problem you'll actually prove that CG works in at most n steps, assuming that real numbers are represented exactly. (This is not a realistic assumption in floating-point arithmetic, or on any computer with a finite amount of hardware, but it gives a solid theoretical underpinning to CG.) Let A be an n-by-n symmetric, positive definite matrix, and let b be an n-vector.

We start with the idea of searching through n-dimensional space for the value of x that minimizes $f(x) = \frac{1}{2}x^T Ax - b^T x$, which is the x that satisfies $Ax = b$. We begin by picking a set of n linearly independent search directions, called d_0, d_1, …, d_{n-1}. (Actually we don't know them in advance, but that's a detail.) At each iteration we proceed along the next direction until we are "lined up" with the final answer, the value of x at which $Ax = b$. In n-space, once we are lined up with the answer from n independent directions, we will be exactly on the answer.

The **first magic of CG** is that for the right kind of search directions, there is a way to define "lined up" for which we can actually compute how far to go along each search direction. The key definition uses *A-conjugate* vectors. Then "lined up" means that the *error* $e_i = x_i - x$ is exactly crossways to the search direction d_{i-1}, not in the sense of being perpendicular (which would mean $e_i^T d_{i-1} = 0$), but in the sense of being A-conjugate: $e_i^T Ad_{i-1} = 0$.

An informal way to say that is, we proceed along the search direction until we are lined up with the solution as seen through A-glasses. The reason for lining up through A-glasses rather than bare eyes is that we can compute where to stop without knowing where the final answer is. We can't see and compute with x-space directly, but we can see the space where Ax and b live. And after lining up each of n independent directions in an n-dimensional space we are guaranteed to be sitting on top of the right answer, whether the independent directions are the conventional coordinate axes or the A-conjugate axes we see through our A-glasses.

To go along with this, we need to choose the search directions themselves to be mutually A-conjugate: we will require each d_i to be A-conjugate to all the earlier d_j's, so $d_i^T Ad_j = 0$ if $i \neq j$.

2(a) Suppose we are given i mutually A-conjugate vectors d_0, …, d_{i-1}. Suppose $x_0 = 0$, and for each $j < i$ we have $x_j = x_{j-1} + \alpha_j d_{j-1}$. Write down and prove correct an expression for a scalar α_i such that, if we take $x_i = x_{i-1} + \alpha_i d_{i-1}$, then the error $e_i = x_i - x$ is A-conjugate to d_{i-1}.

Now, how do we get a sequence of A-conjugate directions to search along? In fact, we can start with any sequence of linearly independent directions, and convert them to A-conjugate directions by projecting out all the earlier search directions from each one, using Gram-Schmidt orthogonalization, as follows.

2(b) Suppose we are given i mutually A-conjugate vectors $d_0, \ldots, d_{i-1}$, and one more vector u_i that does not lie in their span. Write down and prove correct an expression for scalars $\beta_{i,j}$ such that, if we take

$$d_i = u_i + \sum_{j=0}^{i-1} \beta_{i,j} d_j,$$

then d_i is A-conjugate to all the earlier d_j.

Finally, the **second magic of CG** is that there is a way to choose a particular sequence of directions for which the Gram-Schmidt orthogonalization is really easy. If we choose the right directions to start with, we only need to project out *one* earlier direction, not all i of them. This is why the cost of one CG iteration is only $O(n)$, not $O(n^2)$.

2(c) Suppose the vectors $d_0, \ldots, d_{i-1}$, the vectors $x_0, \ldots, x_{i-1}$, and the scalars α_j and $\beta_{i,j}$ are as above. Suppose in addition that at each stage we take $u_i = b - Ax_i$ (which is also known as r_i, the residual). First, prove that if this choice of u_i lies in the span of $d_0, \ldots, d_{i-1}$, the CG iteration can stop with $x_i = x$. Second, show that this direction u_i is already A-conjugate to all of the d_j except d_{i-1}, and therefore we can take $\beta_{i,j} = 0$ for $j < i - 1$.

2(d) One last detail: Prove that the CG code on the course slide does in fact compute the residual r_i correctly; that is, prove that $r_{i-1} - \alpha_i A d_{i-1}$ is in fact equal to $b - Ax_i$.