

## EE364b Spring 2023 Homework 6

Due Sunday 5/21 at 11:59pm via Gradescope

- 6.1 (7 points) *Randomized preconditioners for conjugate gradient methods.* In this question, we explore the use of some randomization methods for solving overdetermined least-squares problems, focusing on conjugate gradient methods. Letting  $A \in \mathbf{R}^{m \times n}$  be a matrix (we assume that  $m \gg n$ ) and  $b \in \mathbf{R}^m$ , we wish to minimize

$$f(x) = \frac{1}{2} \|Ax - b\|_2^2 = \frac{1}{2} \sum_{i=1}^m (a_i^T x - b_i)^2,$$

where the  $a_i \in \mathbf{R}^n$  denote the rows of  $A$ .

Given  $m \in \{2^i, i = 1, 2, \dots\}$ , the (unnormalized) Hadamard matrix of order  $m$  is defined recursively as

$$H_2 = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \quad \text{and} \quad H_m = \begin{bmatrix} H_{m/2} & H_{m/2} \\ H_{m/2} & -H_{m/2} \end{bmatrix}.$$

The associated normalized Hadamard matrix is given by  $H_m^{(\text{norm})} = H_m / \sqrt{m}$ , which evidently satisfies  $H_m^{(\text{norm})T} H_m^{(\text{norm})} = I_{m \times m}$ . Moreover, via a recursive algorithm it is possible to compute  $H_m x$  in time  $O(m \log m)$ , which is much faster than  $m^2$  for a general matrix.

To solve the least squares minimization problem using conjugate gradients, we must solve  $A^T A x = A^T b$ . In class, we discussed that using a *preconditioner*  $M$  such that  $M \approx A^{-1}$  can give substantial speedup in computing solutions to large problems. Consider the following scheme to generate a randomized preconditioner, assuming that  $m = 2^i$  for some  $i$ :

1. Let  $S = \mathbf{diag}(S_{11}, \dots, S_{mm})$ , where  $S_{jj}$  are random  $\{-1, +1\}$  signs
2. Let  $p \in \mathbf{Z}_+$  be a small positive integer, say 20 for this problem.
3. Let  $R \in \{0, 1\}^{n+p \times m}$  be a *row selection matrix*, meaning that each row of  $R$  has only 1 non-zero entry, chosen uniformly at random. (The location of these non-zero columns is distinct.)<sup>1</sup>
4. Define  $\Phi = R H_m^{(\text{norm})} S \in \mathbf{R}^{n+p \times m}$

We then define the matrix  $M$  via its inverse  $M^{-1} = A^T \Phi^T \Phi A \in \mathbf{R}^{n \times n}$ .

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<sup>1</sup>*Hint.* To do this in Matlab, generate a random permutation `inds = randperm(m)`, then set `R = sparse(1:(n+p), inds(1:(n+p)), ones(n+p,1), n+p, m)`, in Julia, set `R = sparse(1:(n+p), inds[1:(n+p)], ones(n+p), n+p, m)`.

- (a) (1 point) How many FLOPs (floating point operations) are required to compute the matrices  $M^{-1}$  and  $M$ , respectively, assuming that you can compute the matrix-vector product  $H_m v$  in time  $m \log m$  for any vector  $v \in \mathbf{R}^m$ ?
- (b) (1 point) How many FLOPs are required to naïvely compute  $A^T A$ , assuming  $A$  is dense (using standard matrix algorithms)?
- (c) (1 point) How many FLOPs are required to compute  $A^T A v$  for a vector  $v \in \mathbf{R}^n$  by first computing  $u = Av$  and then computing  $A^T u$ ?
- (d) (1 point) Suppose that conjugate gradients runs for  $k$  iterations. Using the preconditioned conjugate gradient algorithm with  $M = (A^T \Phi^T \Phi A)^{-1}$ , how many total floating point operations have been performed? How many would be required to directly solve  $A^T A x = A^T b$ ? How large must  $k$  be to make the conjugate gradient method slower?
- (e) (3 points) Implement the conjugate gradient algorithm for solving the positive definite linear system  $A^T A x = A^T b$  both with and without the preconditioner  $M$ . To generate data for your problem, set  $m = 2^{12}$  and  $n = 400$ , then generate the matrix  $A$  by setting  $\mathbf{A} = \text{randn}(\mathbf{m}, \mathbf{n}) * \text{spdiags}(\text{linspace}(.001, 100, \mathbf{n}))$  (in Matlab) and  $\mathbf{A} = \text{randn}(\mathbf{m}, \mathbf{n}) * \text{spdiagam}(\text{linspace}(.001, 100, \mathbf{n}))$  (in Julia), and let  $\mathbf{b} = \text{randn}(\mathbf{m}, 1)$ . For simplicity in implementation, you may directly pass  $A^T A$  and  $A^T b$  into your conjugate gradient solver, as we only wish to explore how the methods work. (In Matlab, the `pcg` method may be useful.) Plot the norm of the residual  $r^k = A^T b - A^T A x^k$  (relative to  $\|A^T b\|_2$ ) as a function of iteration  $k$  for each of your conjugate gradient procedures. Additionally, compute and print the condition numbers  $\kappa(A^T A)$  and  $\kappa(M^{1/2} A^T A M^{1/2})$ . Include your code.