CS532100 Numerical Optimization Homework 2

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1. Consider the linear least square problem:

$$min_{\vec{x}\in\mathbb{R}^2}||A\vec{x}-\vec{b}||^2,$$

where

$$A = \begin{bmatrix} 4 & 8 \\ 2 & 4 \\ 1 & 2 \end{bmatrix}, \vec{b} = \begin{pmatrix} 21/4 \\ 0 \\ 0 \end{pmatrix}$$

(a) (10%) Write its normal equation.

$$A^T A\vec{x} = A^T\vec{b} \tag{1}$$

$$\begin{bmatrix} 4 & 2 & 1 \\ 8 & 4 & 2 \end{bmatrix}\begin{bmatrix} 4 & 8 \\ 2 & 4 \\ 1 & 2 \end{bmatrix}\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 4 & 2 & 1 \\ 8 & 4 & 2 \end{bmatrix}\begin{bmatrix} 21/4 \\ 0 \\ 0 \end{bmatrix} \tag{2}$$

(b) (10%) Express $\vec{b} = \vec{b}_1 + \vec{b}_2$ such that $\vec{b}_1$ is in the subspace spanned by A's column vectors, and $\vec{b}_2$ is orthogonal to A's column vectors. From matrix A, we know that its basis is its first column which is $\begin{bmatrix} 4 & 2 & 1 \end{bmatrix}^T$. From its basis column, we can express $\vec{b}$ in $\vec{b}_1 + \vec{b}_2$. Let,

$$\vec{b}_1 = \begin{bmatrix} 4s \\ 2s \\ s \end{bmatrix}, \vec{b}_2 = \begin{bmatrix} t_1 \\ t_2 \\ t_3 \end{bmatrix} \tag{3}$$

Then we can express $\vec{b}$ such as

$$\vec{b} = \vec{b}_1 + \vec{b}_2 \tag{4}$$

$$\begin{bmatrix} 21/4 \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 4s + t_1 \\ 2s + t_2 \\ s + t_3 \end{bmatrix} \tag{5}$$

Since $\vec{b}_1$ is a column space of A, and $\vec{b}_2$ is orthogonal to $\vec{b}_1$, then

$$\begin{bmatrix} 4s \\ 2s \\ s \end{bmatrix}\begin{bmatrix} t_1 & t_2 & t_3 \end{bmatrix} = 0 \tag{6}$$

$$4s \cdot t_1 + 2s \cdot t_2 + s \cdot t_3 = 0 \tag{7}$$

We can add $4s \cdot t_1 + 2s \cdot t_2 + s \cdot t_3 = 0$ at the last index of our matrix equality. Then

$$\begin{bmatrix} 4s + t_1 \\ 2s + t_2 \\ s + t_3 \\ 4s \cdot t_1 + 2s \cdot t_2 + s \cdot t_3 \end{bmatrix} = \begin{bmatrix} 21/4 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

Solving the equality above, we then have $s = 1$, $t_1 = 5/4$, $t_2 = -2$, and $t_3 = -1$. Thus,

$$\vec{b}_1 = \begin{bmatrix} 4s \\ 2s \\ s \end{bmatrix}, \vec{b}_2 = \begin{bmatrix} 5/4 \\ -2 \\ -1 \end{bmatrix} \tag{8}$$

$$\begin{bmatrix} 21/4 \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 4 \\ 2 \\ 1 \end{bmatrix} + \begin{bmatrix} 5/4 \\ -2 \\ -1 \end{bmatrix} \tag{9}$$

(c) (10%) Show that $\vec{z} \in \mathbb{R}^2$ is a least square solution for $A\vec{x} = \vec{b}$ if and only if $\vec{z}$ is part of a solution to the larger linear system:

$$\begin{bmatrix} 0 & A^T \\ A & I \end{bmatrix} \begin{bmatrix} \vec{z} \\ \vec{y} \end{bmatrix} = \begin{bmatrix} 0 \\ \vec{b} \end{bmatrix}$$

2. In Note05 (Page 16), memoryless BFGS iteration matrix H_{k+1} can be derived from considering the Hestenes–Stiefel form of the nonlinear conjugate gradient method. Recalling that $\vec{s}_k = \alpha_k \vec{p}_k$, we have that the search direction for this method is given by

$$\begin{aligned} \vec{p}_{k+1} &= -\nabla f_{k+1} + \frac{\nabla f_{k+1}^T \vec{y}_k}{\vec{y}^T \vec{p}_k} \vec{p}_k \\ &= -\nabla f_{k+1} + \frac{\nabla f_{k+1}^T \vec{y}_k}{\vec{y}^T \vec{s}_k} \vec{s}_k \\ &= -(I - \frac{\vec{s}_k \vec{y}_k^T}{\vec{y}^T \vec{s}_k}) \nabla f_{k+1} \\ &= -\hat{H}_{k+1} \nabla f_{k+1} \end{aligned}$$

However, the matrix $\hat{H}_{k+1}$ is neither symmetric nor positive definite.

(a) (10%) Please show that the matrix $\hat{H}_{k+1}$ is singular.
(You can only prove it for the case $\nabla f_k, \vec{p}_k, \vec{y}_k, \vec{s}_k \in \mathbb{R}^2$ for all $k \in \mathbb{N}$.)
asd

(b) (0%) Please read the reference book (Page 180) to understand the derivation of the inverse hessian formula in Note05 (Page 16).
(you don't need to write anything in this subproblem.)

$$H_{k+1} = (I - \frac{\vec{s}_k \vec{y}_k^T}{\vec{y}_k^T \vec{s}_k})(I - \frac{\vec{y}_k \vec{s}_k^T}{\vec{y}_k^T \vec{s}_k}) + \frac{\vec{s}_k \vec{s}_k^T}{\vec{y}_k^T \vec{s}_k}$$

3. (10%) The total least square problem is to solve the following problem

$$\min_{\vec{x}, \|\vec{x}\|=1} \vec{x}^T A^T A \vec{x}$$

where A is an $m \times n$ matrix. Here we assume $m > n$. Let $A = U\Sigma V^T$ be the SVD of A, where U is the matrix of left singular vectors, V is the matrix of right singular vectors, and Σ is a diagonal matrix with diagonal elements $\sigma_1, \sigma_2, \ldots, \sigma_n$. Moreover, U and V are orthogonal matrices, and $\sigma_1 \geq \sigma_2 \geq \cdots \geq \sigma_n$. Show the solution of the above problem is the σ^2.

4. Consider the following linear programming problem:

$$\begin{array}{ll} \max_{x_1, x_2} & z = x_1 + x_2 \\ \text{s.t.} & x_1 + 2x_2 \leq 4 \\ & 4x_1 + 2x_2 \leq 12 \\ & -x_1 + x_2 \leq 1 \\ & x_1, x_2 \geq 0 \end{array}$$

   (a) (10%) Please refer Note08 (Page 2) to draw the figure of the constraints by any means, and use that to solve the problem.

   (b) (10%) Derive its dual problem and solve the dual problem by any means. Compare the solutions of the primal and the dual problems.

   (c) (10%) Verify the complementarity slackness condition.

   (d) (10%) Transform the problem to the standard form.

   (e) (10%) Solve it by the simplex method, as provided in Figure 1, using $\vec{x}_0 = (0, 0)$. Indicate $B_k, N_k, \vec{s}_k, \vec{d}_k, p_k, q_k, \gamma_k$ in each step.

(1) Given a basic feasible point $\vec{x}_0$ and the corresponding index set $\mathcal{B}_0$ and $\mathcal{N}_0$.

(2) For $k = 0, 1, \ldots$

(3) Let $B_k = A(:, \mathcal{B}_k), N_k = A(:, \mathcal{N}_k)$, $\vec{x}_B = \vec{x}_k(\mathcal{B}_k), \vec{x}_N = \vec{x}_k(\mathcal{N}_k)$, and $\vec{c}_B = \vec{c}_k(\mathcal{B}_k), \vec{c}_N = \vec{c}_k(\mathcal{N}_k)$.

(4) Compute $\vec{s}_k = \vec{c}_N - N_k^T (B_k^{-1})^T \vec{c}_B$ (pricing)

(5) If $\vec{s}_k \geq 0$, return the solution $\vec{x}_k$. (found optimal solution)

(6) Select $q_k \in \mathcal{N}_k$ such that $\vec{s}_k(i_q) < 0$, where i_q is the index of q_k in $\mathcal{N}_k$

(7) Compute $\vec{d}_k = B_k^{-1} A_k(:, q_k)$. (search direction)

(8) If $\vec{d}_k \leq 0$, return `unbounded`. (unbounded case)

(9) Compute $[\gamma_k, i_p] = \min\limits_{i, \vec{d}_k(i) > 0} \dfrac{\vec{x}_B(i)}{\vec{d}_k(i)}$ (ratio test)

(The first return value is the minimum ratio;
the second return value is the index of the minimum ratio.)

(10) $x_{k+1} \begin{pmatrix} \mathcal{B} \\ \mathcal{N} \end{pmatrix} = \begin{pmatrix} \vec{x}_B \\ \vec{x}_N \end{pmatrix} + \gamma_k \begin{pmatrix} -\vec{d}_k \\ \vec{e}_{i_q} \end{pmatrix}$

($\vec{e}_{i_q} = (0, \ldots, 1, \ldots, 0)^T$ is a unit vector with i_qth element 1.)

(11) Let the i_pth element in $\mathcal{B}$ be p_k. (pivoting)

$\mathcal{B}_{k+1} = (\mathcal{B}_k - \{p_k\}) \cup \{q_k\}$, $\mathcal{N}_{k+1} = (\mathcal{N}_k - \{q_k\}) \cup \{p_k\}$

Figure 1: The simplex method for solving (minimization) linear programming