

ECE/MATH 520, Spring 2008

Exam 2: Due Session 26

Solutions (version: April 29, 2008, 8:45)

75 mins.; Total 50 pts.

1. (16 pts.) The purpose of this question is to derive a recursive least-squares algorithm where we *remove* (instead of add) a data point. To formulate the algorithm, suppose we are given matrices \mathbf{A}_0 and \mathbf{A}_1 such that

$$\mathbf{A}_0 = \begin{bmatrix} \mathbf{A}_1 \\ \mathbf{a}_1^T \end{bmatrix},$$

where $\mathbf{a}_1 \in \mathbb{R}^n$. Similarly, suppose vectors $\mathbf{b}^{(0)}$ and $\mathbf{b}^{(1)}$ satisfy

$$\mathbf{b}^{(0)} = \begin{bmatrix} \mathbf{b}^{(1)} \\ b_1 \end{bmatrix},$$

where $b_1 \in \mathbb{R}$. Let $\mathbf{x}^{(0)}$ be the least-squares solution associated with $(\mathbf{A}_0, \mathbf{b}^{(0)})$, and $\mathbf{x}^{(1)}$ the least-squares solution associated with $(\mathbf{A}_1, \mathbf{b}^{(1)})$. Our goal is to write $\mathbf{x}^{(1)}$ in terms of $\mathbf{x}^{(0)}$ and the “removed” data point (\mathbf{a}_1, b_1) . As usual, let \mathbf{G}_0 and \mathbf{G}_1 be the Grammians associated with $\mathbf{x}^{(0)}$ and $\mathbf{x}^{(1)}$, respectively.

- a. Write down expressions for the least-squares solutions $\mathbf{x}^{(0)}$ and $\mathbf{x}^{(1)}$ in terms of \mathbf{A}_0 , $\mathbf{b}^{(0)}$, \mathbf{A}_1 , and $\mathbf{b}^{(1)}$.
- b. Derive a formula for \mathbf{G}_1 in terms of \mathbf{G}_0 and \mathbf{a}_1 .
- c. Let $\mathbf{P}_0 = \mathbf{G}_0^{-1}$ and $\mathbf{P}_1 = \mathbf{G}_1^{-1}$. Derive a formula for \mathbf{P}_1 in terms of \mathbf{P}_0 and \mathbf{a}_1 . (The formula must not contain any matrix inversions.)
- d. Derive a formula for $\mathbf{A}_0^T \mathbf{b}^{(0)}$ in terms of \mathbf{G}_1 , $\mathbf{x}^{(0)}$, and \mathbf{a}_1 .
- e. Finally, derive a formula for $\mathbf{x}^{(1)}$ in terms of $\mathbf{x}^{(0)}$, \mathbf{P}_1 , \mathbf{a}_1 , and b_1 . Use this and part c to write a recursive algorithm associated with successive removals of rows from $(\mathbf{A}_k, \mathbf{b}^{(k)})$.

Ans.: a. We have

$$\mathbf{x}^{(0)} = (\mathbf{A}_0^T \mathbf{A}_0)^{-1} \mathbf{A}_0^T \mathbf{b}^{(0)} = \mathbf{G}_0^{-1} \mathbf{A}_0^T \mathbf{b}^{(0)}.$$

Similarly,

$$\mathbf{x}^{(1)} = (\mathbf{A}_1^T \mathbf{A}_1)^{-1} \mathbf{A}_1^T \mathbf{b}^{(1)} = \mathbf{G}_1^{-1} \mathbf{A}_1^T \mathbf{b}^{(1)}.$$

b. Now,

$$\begin{aligned} \mathbf{G}_0 &= \begin{bmatrix} \mathbf{A}_1^T & \mathbf{a}_1 \end{bmatrix} \begin{bmatrix} \mathbf{A}_1 \\ \mathbf{a}_1^T \end{bmatrix} \\ &= \mathbf{A}_1^T \mathbf{A}_1 + \mathbf{a}_1 \mathbf{a}_1^T \\ &= \mathbf{G}_1 + \mathbf{a}_1 \mathbf{a}_1^T. \end{aligned}$$

Hence,

$$\mathbf{G}_1 = \mathbf{G}_0 - \mathbf{a}_1 \mathbf{a}_1^T.$$

c. Using the Sherman-Morrison formula,

$$\begin{aligned}
\mathbf{P}_1 &= \mathbf{G}_1^{-1} \\
&= (\mathbf{G}_0 - \mathbf{a}_1 \mathbf{a}_1^T)^{-1} \\
&= \mathbf{G}_0^{-1} - \frac{\mathbf{G}_0^{-1}(-\mathbf{a}_1) \mathbf{a}_1^T \mathbf{G}_0^{-1}}{1 + (-\mathbf{a}_1)^T \mathbf{G}_0^{-1} \mathbf{a}_1} \\
&= \mathbf{P}_0 + \frac{\mathbf{P}_0 \mathbf{a}_1 \mathbf{a}_1^T \mathbf{P}_0}{1 - \mathbf{a}_1^T \mathbf{P}_0 \mathbf{a}_1}.
\end{aligned}$$

d. We have

$$\begin{aligned}
\mathbf{A}_0^T \mathbf{b}^{(0)} &= \mathbf{G}_0 \mathbf{G}_0^{-1} \mathbf{A}_0^T \mathbf{b}^{(0)} \\
&= \mathbf{G}_0 \mathbf{x}^{(0)} \\
&= (\mathbf{G}_1 + \mathbf{a}_1 \mathbf{a}_1^T) \mathbf{x}^{(0)} \\
&= \mathbf{G}_1 \mathbf{x}^{(0)} + \mathbf{a}_1 \mathbf{a}_1^T \mathbf{x}^{(0)}.
\end{aligned}$$

e. Finally,

$$\begin{aligned}
\mathbf{x}^{(1)} &= \mathbf{G}_1^{-1} \mathbf{A}_1^T \mathbf{b}^{(1)} \\
&= \mathbf{G}_1^{-1} (\mathbf{A}_1^T \mathbf{b}^{(1)} + \mathbf{a}_1 b_1 - \mathbf{a}_1 b_1) \\
&= \mathbf{G}_1^{-1} (\mathbf{A}_0^T \mathbf{b}^{(0)} - \mathbf{a}_1 b_1) \\
&= \mathbf{G}_1^{-1} (\mathbf{G}_1 \mathbf{x}^{(0)} + \mathbf{a}_1 \mathbf{a}_1^T \mathbf{x}^{(0)} - \mathbf{a}_1 b_1) \\
&= \mathbf{x}^{(0)} - \mathbf{G}_1^{-1} \mathbf{a}_1 (b_1 - \mathbf{a}_1^T \mathbf{x}^{(0)}) \\
&= \mathbf{x}^{(0)} - \mathbf{P}_1 \mathbf{a}_1 (b_1 - \mathbf{a}_1^T \mathbf{x}^{(0)}).
\end{aligned}$$

The general RLS algorithm for removals of rows is:

$$\begin{aligned}
\mathbf{P}^{(k+1)} &= \mathbf{P}_k + \frac{\mathbf{P}_k \mathbf{a}_{k+1} \mathbf{a}_{k+1}^T \mathbf{P}_k}{1 - \mathbf{a}_{k+1}^T \mathbf{P}_k \mathbf{a}_{k+1}} \\
\mathbf{x}^{(k+1)} &= \mathbf{x}^{(k)} - \mathbf{P}_{k+1} \mathbf{a}_{k+1} (b_{k+1} - \mathbf{a}_{k+1}^T \mathbf{x}^{(k)}).
\end{aligned}$$

2. (10 pts.) Use the penalty method to solve the following problem analytically:

$$\begin{aligned}
&\text{minimize} && x_1^2 + 2x_2^2 \\
&\text{subject to} && x_1 + x_2 = 3.
\end{aligned}$$

Hint: Use the penalty function $P(x) = (x_1 + x_2 - 3)^2$. The solution you find must be exact, not approximate.

Ans.: First, we construct the unconstrained objective function with penalty parameter γ :

$$f(\mathbf{x}) = x_1^2 + 2x_2^2 + \gamma(x_1 + x_2 - 3)^2.$$

Because f is a quadratic with positive definite quadratic term, it is easy to find its minimizer:

$$\mathbf{x}_\gamma = \frac{1}{1 + 2/(3\gamma)} \begin{bmatrix} 2 \\ 1 \end{bmatrix}.$$

For example, we can obtain the above by solving the FONC:

$$\begin{aligned} 2(1 + \gamma)x_1 + 2\gamma x_2 - 6\gamma &= 0 \\ 2\gamma x_1 + 2(2 + \gamma)x_2 - 6\gamma &= 0. \end{aligned}$$

Now letting $\gamma \rightarrow \infty$, we obtain

$$\mathbf{x}^* = \begin{bmatrix} 2 \\ 1 \end{bmatrix}.$$

(It is easy to verify, using other means, that this is indeed the correct solution.)

3. (12 pts.) Consider a standard form LP problem. Suppose we start with an initial basic feasible solution $\mathbf{x}^{(0)}$ and we apply one iteration of the simplex algorithm to obtain $\mathbf{x}^{(1)}$.

As pointed out in class, it turns out that we can express $\mathbf{x}^{(1)}$ in terms of $\mathbf{x}^{(0)}$ as

$$\mathbf{x}^{(1)} = \mathbf{x}^{(0)} + \alpha_0 \mathbf{d}^{(0)},$$

where α_0 minimizes $\phi(\alpha) = f(\mathbf{x}^{(0)} + \alpha \mathbf{d}^{(0)})$ over all $\alpha > 0$ such that $\mathbf{x}^{(0)} + \alpha \mathbf{d}^{(0)}$ is feasible.

- Show that $\mathbf{d}^{(0)} \in \mathcal{N}(\mathbf{A})$.
- As usual, assume that the initial basis is the first m columns of \mathbf{A} , and the first iteration involves inserting \mathbf{a}_q into the basis, where $q > m$. Let the q th column of the canonical augmented matrix be $\mathbf{y}_q = [y_{1q}, \dots, y_{mq}]^T$. Express $\mathbf{d}^{(0)}$ in terms of \mathbf{y}_q .
- Show that $\mathbf{d}^{(0)}$ is a descent direction if and only if $r_q < 0$.

Ans.: a. We have

$$\mathbf{A}\mathbf{d}^{(0)} = \mathbf{A}(\mathbf{x}^{(1)} - \mathbf{x}^{(0)})/\alpha_0 = (\mathbf{b} - \mathbf{b})/\alpha_0 = 0.$$

Hence, $\mathbf{d}^{(0)} \in \mathcal{N}(\mathbf{A})$.

b. From our discussion of moving from one BFS to an adjacent BFS, we deduce that

$$\mathbf{d}^{(0)} = \begin{bmatrix} -\mathbf{y}_q \\ \mathbf{e}_{q-m} \end{bmatrix}.$$

In other words, the first m components of $\mathbf{d}^{(0)}$ are $-y_{1q}, \dots, -y_{mq}$, and all the other components are 0 except the q th component, which is 1.

c. Now, we know that $\mathbf{d}^{(0)}$ is a descent direction if and only if $\mathbf{c}^T \mathbf{d}^{(0)} < 0$. So it remains to show that $\mathbf{c}^T \mathbf{d}^{(0)} < 0$ if and only if $r_q < 0$. From part b, $\mathbf{c}^T \mathbf{d}^{(0)} = c_q - \sum_{i=1}^m c_i y_{iq} = r_q$, and the desired result follows.

4. (12 pts.) Suppose we are given a matrix $A \in \mathbb{R}^{m \times n}$ and a vector $b \in \mathbb{R}^m$ such that $b \geq 0$. We are interested in an algorithm that, given this A and b , is guaranteed to produce one of following two outputs: (1) If there exists x such that $Ax \geq b$, then the algorithm produces one such x . (2) If no such x exists, then the algorithm produces an output to declare so.

Describe in detail how to design this algorithm based on the simplex method.

Ans.: First, we convert the inequality constraint $Ax \geq b$ into standard form. To do this, we introduce a variable $w \in \mathbb{R}^m$ of surplus variables to convert the inequality constraint into the following equivalent constraint:

$$[A, -I] \begin{bmatrix} x \\ w \end{bmatrix} = b, \quad w \geq 0.$$

Next, we introduce variables $u, v \in \mathbb{R}^n$ to replace the free variable x by $u - v$. We then obtain the following equivalent constraint:

$$[A, -A, -I] \begin{bmatrix} u \\ v \\ w \end{bmatrix} = b, \quad u, v, w \geq 0.$$

This form of the constraint is now in standard form. So we can now use Phase I from the simplex method to implement an algorithm to find a vectors u, v , and w satisfying the above constraint, if one exists, or to declare that none exists. If one exists, we output $x = u - v$; otherwise, we declare that no x exists such that $Ax \geq b$. By construction, this algorithm is guaranteed to behave in the way specified by the question.