

ECE/MATH 520, Spring 2008

Homework Problems 4

Solutions (version: March 25, 2008, 11:13)

12.3 Suppose that we perform an experiment to calculate the gravitational constant g as follows. We drop a ball from a certain height, and measure its distance from the original point at certain time instants. The results of the experiment are shown in the following table:

Time (seconds)	1.00	2.00	3.00
Distance (meters)	5.00	19.5	44.0

The equation relating the distance s and the time t at which s is measured is given by

$$s = \frac{1}{2}gt^2.$$

- Find a least-squares estimate of g using the experimental results from the above table.
- Suppose that we take an additional measurement at time 4.00, and obtain a distance of 78.5. Use the recursive least-squares algorithm to calculate an updated least-squares estimate of g .

Ans.: a. We form

$$\mathbf{A} = \begin{bmatrix} 1^2/2 \\ 2^2/2 \\ 3^2/2 \end{bmatrix}, \quad \mathbf{b} = \begin{bmatrix} 5.00 \\ 19.5 \\ 44.0 \end{bmatrix}.$$

The least squares estimate of g is then given by

$$g = (\mathbf{A}^T \mathbf{A})^{-1} \mathbf{A}^T \mathbf{b} = 9.776.$$

b. We start with $\mathbf{P}_0 = 0.040816$, and $\mathbf{x}^{(0)} = 9.776$. We have $\mathbf{a}_1 = 4^2/2 = 8$, and $\mathbf{b}^{(1)} = 78.5$. Using the RLS formula, we get $\mathbf{x}^{(1)} = 9.802$, which is our updated estimate of g .

12.9 Suppose that we take measurements of a sinusoidal signal $y(t) = \sin(\omega t + \theta)$ at times t_1, \dots, t_p , and obtain values y_1, \dots, y_p , where $-\pi/2 \leq \omega t_i + \theta \leq \pi/2$, $i = 1, \dots, p$, and the t_i are not all equal. We wish to determine the values of the frequency ω and phase θ .

- Express the problem as a system of linear equations.

b. Find the least-squares estimate of ω and θ based on part a. Use the following notation:

$$\begin{aligned}\bar{T} &= \frac{1}{p} \sum_{i=1}^p t_i, \\ \overline{T^2} &= \frac{1}{p} \sum_{i=1}^p t_i^2, \\ \overline{TY} &= \frac{1}{p} \sum_{i=1}^p t_i \arcsin y_i, \\ \bar{Y} &= \frac{1}{p} \sum_{i=1}^p \arcsin y_i.\end{aligned}$$

Ans.: a. We wish to find ω and θ such that

$$\begin{aligned}\sin(\omega t_1 + \theta) &= y_1 \\ &\vdots \\ \sin(\omega t_p + \theta) &= y_p.\end{aligned}$$

Taking arcsin, we get the following system of linear equations:

$$\begin{aligned}\omega t_1 + \theta &= \arcsin y_1 \\ &\vdots \\ \omega t_p + \theta &= \arcsin y_p.\end{aligned}$$

b. We may write the system of linear equations in part a as $\mathbf{A}\mathbf{x} = \mathbf{b}$, where

$$\mathbf{A} = \begin{bmatrix} t_1 & 1 \\ \vdots & \vdots \\ t_p & 1 \end{bmatrix}, \quad \mathbf{x} = \begin{bmatrix} \omega \\ \theta \end{bmatrix}, \quad \mathbf{b} = \begin{bmatrix} \arcsin y_1 \\ \vdots \\ \arcsin y_p \end{bmatrix}.$$

Since the t_i are not all equal, the first column of \mathbf{A} is not a scalar multiple of the second column. Therefore, $\text{rank } \mathbf{A} = 2$. Hence, the least squares solution is

$$\begin{aligned}\mathbf{x} &= (\mathbf{A}^T \mathbf{A})^{-1} \mathbf{A}^T \mathbf{b} \\ &= \begin{bmatrix} \sum_{i=1}^p t_i^2 & \sum_{i=1}^p t_i \\ \sum_{i=1}^p t_i & p \end{bmatrix}^{-1} \begin{bmatrix} \sum_{i=1}^p t_i \arcsin y_i \\ \sum_{i=1}^p \arcsin y_i \end{bmatrix} \\ &= \begin{bmatrix} \overline{T^2} & \bar{T} \\ \bar{T} & 1 \end{bmatrix}^{-1} \begin{bmatrix} \overline{TY} \\ \bar{Y} \end{bmatrix} \\ &= \frac{1}{\overline{T^2} - (\bar{T})^2} \begin{bmatrix} 1 & -\bar{T} \\ -\bar{T} & \overline{T^2} \end{bmatrix} \begin{bmatrix} \overline{TY} \\ \bar{Y} \end{bmatrix} \\ &= \frac{1}{\overline{T^2} - (\bar{T})^2} \begin{bmatrix} \overline{TY} - (\bar{T})(\bar{Y}) \\ -(\bar{T})(\overline{TY}) + (\overline{T^2})(\bar{Y}) \end{bmatrix}.\end{aligned}$$

12.11 Consider the affine function $f : \mathbb{R}^n \rightarrow \mathbb{R}$ of the form $f(\mathbf{x}) = \mathbf{a}^T \mathbf{x} + c$, where $\mathbf{a} \in \mathbb{R}^n$ and $c \in \mathbb{R}$.

- a. We are given a set of p pairs $(\mathbf{x}_1, y_1), \dots, (\mathbf{x}_p, y_p)$, where $\mathbf{x}_i \in \mathbb{R}^n$, $y_i \in \mathbb{R}$, $i = 1, \dots, p$. We wish to find the affine function of best fit to these points, where “best” is in the sense of minimizing the total square error

$$\sum_{i=1}^p (f(\mathbf{x}_i) - y_i)^2.$$

Formulate the above as an optimization problem of the form: minimize $\|\mathbf{A}\mathbf{z} - \mathbf{b}\|^2$ with respect to \mathbf{z} . Specify the dimensions of \mathbf{A} , \mathbf{z} , and \mathbf{b} .

- b. Suppose that the points satisfy

$$\mathbf{x}_1 + \dots + \mathbf{x}_p = \mathbf{0}$$

and

$$y_1 \mathbf{x}_1 + \dots + y_p \mathbf{x}_p = \mathbf{0}.$$

Find the affine function of best fit in this case, assuming it exists and is unique.

Ans.: a. Write

$$\mathbf{A} = \begin{bmatrix} \mathbf{x}_1^T & 1 \\ \vdots & \vdots \\ \mathbf{x}_p^T & 1 \end{bmatrix} \in \mathbb{R}^{p \times (n+1)}, \quad \mathbf{z} = \begin{bmatrix} \mathbf{a} \\ c \end{bmatrix} \in \mathbb{R}^{n+1}, \quad \mathbf{b} = \begin{bmatrix} y_1 \\ \vdots \\ y_p \end{bmatrix} \in \mathbb{R}^p.$$

The objective function can then be written as $\|\mathbf{A}\mathbf{z} - \mathbf{b}\|^2$.

- b. Let $\mathbf{X} = [\mathbf{x}_1, \dots, \mathbf{x}_p]^T \in \mathbb{R}^{p \times n}$, and $\mathbf{e} = [1, \dots, 1]^T \in \mathbb{R}^p$. Then we may write $\mathbf{A} = [\mathbf{X} \ \mathbf{e}]$. The solution to the problem is $(\mathbf{A}^T \mathbf{A})^{-1} \mathbf{A}^T \mathbf{b}$. But

$$\mathbf{A}^T \mathbf{A} = \begin{bmatrix} \mathbf{X}^T \mathbf{X} & \mathbf{X}^T \mathbf{e} \\ \mathbf{e}^T \mathbf{X} & p \end{bmatrix} = \begin{bmatrix} \mathbf{X}^T \mathbf{X} & \mathbf{0} \\ \mathbf{0}^T & p \end{bmatrix}$$

since $\mathbf{X}^T \mathbf{e} = \mathbf{x}_1 + \dots + \mathbf{x}_p = \mathbf{0}$ by assumption. Also,

$$\mathbf{A}^T \mathbf{y} = \begin{bmatrix} \mathbf{X}^T \mathbf{y} \\ \mathbf{e}^T \mathbf{y} \end{bmatrix} = \begin{bmatrix} \mathbf{0} \\ \mathbf{e}^T \mathbf{y} \end{bmatrix}$$

since $\mathbf{X}^T \mathbf{y} = y_1 \mathbf{x}_1 + \dots + y_p \mathbf{x}_p = \mathbf{0}$ by assumption. Therefore, the solution is given by

$$\mathbf{z}^* = (\mathbf{A}^T \mathbf{A})^{-1} \mathbf{A}^T \mathbf{b} = \begin{bmatrix} (\mathbf{X}^T \mathbf{X})^{-1} & \mathbf{0} \\ \mathbf{0}^T & 1/p \end{bmatrix} \begin{bmatrix} \mathbf{0} \\ \mathbf{e}^T \mathbf{y} \end{bmatrix} = \begin{bmatrix} \mathbf{0} \\ \frac{1}{p} \mathbf{e}^T \mathbf{y} \end{bmatrix}.$$

The affine function of best fit is the constant function $f(\mathbf{x}) = c$, where

$$c = \frac{1}{p} \sum_{i=1}^p y_i.$$

12.13 Consider a discrete time linear system $x_{k+1} = ax_k + bu_k$, where u_k is the input at time k , x_k is the output at time k , and $a, b \in \mathbb{R}$ are system parameters. Suppose that we apply a constant input $u_k = 1$ for all $k \geq 0$, and measure the first 4 values of the output to be $x_0 = 0$, $x_1 = 1$, $x_2 = 2$, $x_3 = 8$. Find the least-squares estimate of a and b based on the above data.

Ans.: We pose the problem as a least squares problem: minimize $\|\mathbf{A}\mathbf{x} - \mathbf{b}\|^2$ where $\mathbf{x} = [a, b]^T$, and

$$\mathbf{A} = \begin{bmatrix} x_0 & 1 \\ x_1 & 1 \\ x_2 & 1 \end{bmatrix}, \quad \mathbf{b} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}.$$

We have

$$\mathbf{A}^T \mathbf{A} = \begin{bmatrix} \sum_{i=0}^2 x_i^2 & \sum_{i=0}^2 x_i \\ \sum_{i=0}^2 x_i & 3 \end{bmatrix}, \quad \mathbf{A}^T \mathbf{b} = \begin{bmatrix} \sum_{i=0}^2 x_i x_{i+1} \\ \sum_{i=0}^2 x_{i+1} \end{bmatrix}.$$

Therefore, the least squares solution is

$$\begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} \sum_{i=0}^2 x_i^2 & \sum_{i=0}^2 x_i \\ \sum_{i=0}^2 x_i & 3 \end{bmatrix}^{-1} \begin{bmatrix} \sum_{i=0}^2 x_i x_{i+1} \\ \sum_{i=0}^2 x_{i+1} \end{bmatrix} = \begin{bmatrix} 5 & 3 \\ 3 & 3 \end{bmatrix}^{-1} \begin{bmatrix} 18 \\ 11 \end{bmatrix} = \begin{bmatrix} 7/2 \\ 1/6 \end{bmatrix}.$$

12.14 Consider a discrete time linear system $x_{k+1} = ax_k + bu_k$, where u_k is the input at time k , x_k is the output at time k , and $a, b \in \mathbb{R}$ are system parameters. Given the first $n + 1$ values of the impulse response h_0, \dots, h_n , find the least squares estimate of a and b . You may assume that at least one h_k is nonzero. **Note:** The *impulse response* is the output sequence resulting from an input of $u_0 = 1$, $u_k = 0$ for $k \neq 0$, and zero initial condition $x_0 = 0$.

Ans.: We pose the problem as a least squares problem: minimize $\|\mathbf{A}\mathbf{x} - \mathbf{b}\|^2$ where $\mathbf{x} = [a, b]^T$, and

$$\mathbf{A} = \begin{bmatrix} 0 & 1 \\ h_1 & 0 \\ \vdots & \vdots \\ h_{n-1} & 0 \end{bmatrix}, \quad \mathbf{b} = \begin{bmatrix} h_1 \\ h_2 \\ \vdots \\ h_n \end{bmatrix}.$$

We have

$$\mathbf{A}^T \mathbf{A} = \begin{bmatrix} \sum_{i=1}^{n-1} h_i^2 & 0 \\ 0 & 1 \end{bmatrix}, \quad \mathbf{A}^T \mathbf{b} = \begin{bmatrix} \sum_{i=1}^{n-1} h_i h_{i+1} \\ h_1 \end{bmatrix}.$$

The matrix $\mathbf{A}^T \mathbf{A}$ is nonsingular because we assume that at least one h_k is nonzero. Therefore, the least squares solution is

$$\begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} \sum_{i=1}^{n-1} h_i^2 & 0 \\ 0 & 1 \end{bmatrix}^{-1} \begin{bmatrix} \sum_{i=1}^{n-1} h_i h_{i+1} \\ h_1 \end{bmatrix} = \begin{bmatrix} (\sum_{i=1}^{n-1} h_i h_{i+1}) / (\sum_{i=1}^{n-1} h_i^2) \\ h_1 \end{bmatrix}.$$

Optional Write MATLAB routines to implement the RLS algorithm and various random search algorithms (e.g., the genetic algorithm). Test your routines on various examples.

22.6a Consider the problem

$$\begin{aligned} & \text{minimize} && \frac{1}{2}\|\mathbf{x}\|^2 \\ & \text{subject to} && \mathbf{Ax} = \mathbf{b}, \end{aligned}$$

where $\mathbf{A} \in \mathbb{R}^{m \times n}$, $\mathbf{b} \in \mathbb{R}^m$, $m \leq n$, and $\text{rank } \mathbf{A} = m$. Let \mathbf{x}^* be the solution. Suppose we solve the problem using the penalty method, with the penalty function

$$P(\mathbf{x}) = \|\mathbf{Ax} - \mathbf{b}\|^2.$$

Let \mathbf{x}_γ^* be the solution to the associated unconstrained problem with the penalty parameter $\gamma > 0$, that is, \mathbf{x}_γ^* is the solution to

$$\text{minimize } \frac{1}{2}\|\mathbf{x}\|^2 + \gamma\|\mathbf{Ax} - \mathbf{b}\|^2.$$

a. Suppose

$$\mathbf{A} = \begin{bmatrix} 1 & 1 \end{bmatrix}, \quad \mathbf{b} = [1].$$

Verify that \mathbf{x}_γ^* converges to the solution \mathbf{x}^* of the original constrained problem as $\gamma \rightarrow \infty$.

Ans.: We have

$$\frac{1}{2}\|\mathbf{x}\|^2 + \gamma\|\mathbf{Ax} - \mathbf{b}\|^2 = \frac{1}{2}\mathbf{x}^T \begin{bmatrix} 1+2\gamma & 2\gamma \\ 2\gamma & 1+2\gamma \end{bmatrix} \mathbf{x} - \mathbf{x}^T \begin{bmatrix} 2\gamma \\ 2\gamma \end{bmatrix} + \gamma.$$

The above is a quadratic with positive definite Hessian. Therefore, the minimizer is

$$\begin{aligned} \mathbf{x}_\gamma^* &= \begin{bmatrix} 1+2\gamma & 2\gamma \\ 2\gamma & 1+2\gamma \end{bmatrix}^{-1} \begin{bmatrix} 2\gamma \\ 2\gamma \end{bmatrix} \\ &= \frac{1}{2+1/2\gamma} \begin{bmatrix} 1 \\ 1 \end{bmatrix}. \end{aligned}$$

Hence,

$$\lim_{\gamma \rightarrow \infty} \mathbf{x}_\gamma^* = \frac{1}{2} \begin{bmatrix} 1 \\ 1 \end{bmatrix}.$$

The solution to the original constrained problem is

$$\mathbf{x}^* = \mathbf{A}^T(\mathbf{AA}^T)^{-1}\mathbf{b} = \frac{1}{2} \begin{bmatrix} 1 \\ 1 \end{bmatrix}.$$