

## Problem Set 4: Solutions

**1a.** Use Lagrange multipliers to solve the overdetermined matrix equation  $\mathbf{G}\mathbf{m} = \mathbf{d}$ , subject to the constraint that the L2 norm of  $\mathbf{H}\mathbf{m} - \mathbf{f} = \mathbf{0}$  should be as close to zero as possible.

**b.** How does your solution to 1a above differ from the solution that you would obtain by augmenting the matrix  $\mathbf{G}$  with the matrix  $\mathbf{H}$  to create a revised matrix equation?

$$\begin{pmatrix} \mathbf{G} \\ \mathbf{H} \end{pmatrix} \mathbf{m} = \begin{pmatrix} \mathbf{d} \\ \mathbf{f} \end{pmatrix}$$

**Solution:**

**a.** In the first part of the problem, we use a Lagrange multiplier as a scalar and define a cost function:

$$\mathcal{L} = (\mathbf{G}\mathbf{m} - \mathbf{d})^T(\mathbf{G}\mathbf{m} - \mathbf{d}) + \lambda(\mathbf{H}\mathbf{m} - \mathbf{f})^T(\mathbf{H}\mathbf{m} - \mathbf{f})$$

Thus

$$\frac{\partial \mathcal{L}}{\partial \mathbf{m}} = 2\mathbf{G}^T(\mathbf{G}\mathbf{m} - \mathbf{d}) + 2\lambda\mathbf{H}^T(\mathbf{H}\mathbf{m} - \mathbf{f}) = \mathbf{0}.$$

Solving for  $\mathbf{m}$ ,

$$\mathbf{m} = (\mathbf{G}^T\mathbf{G} + \lambda\mathbf{H}^T\mathbf{H})^{-1}(\mathbf{G}^T\mathbf{d} + \lambda\mathbf{H}^T\mathbf{f})$$

**b.** In the second case, we define an augmented matrix:

$$\tilde{\mathbf{G}} = \begin{pmatrix} \mathbf{G} \\ \mathbf{H} \end{pmatrix} \text{ and } \tilde{\mathbf{d}} = \begin{pmatrix} \mathbf{d} \\ \mathbf{f} \end{pmatrix}.$$

Then the solution  $\mathbf{m}$  can be represented as:

$$\begin{aligned} \mathbf{m} &= (\tilde{\mathbf{G}}^T\tilde{\mathbf{G}})^{-1}\tilde{\mathbf{G}}^T\tilde{\mathbf{d}} \\ &= \left( \begin{bmatrix} \mathbf{G}^T & \mathbf{H}^T \end{bmatrix} \begin{bmatrix} \mathbf{G} \\ \mathbf{H} \end{bmatrix} \right)^{-1} \begin{bmatrix} \mathbf{G}^T & \mathbf{H}^T \end{bmatrix} \begin{bmatrix} \mathbf{d} \\ \mathbf{f} \end{bmatrix} \\ &= (\mathbf{G}^T\mathbf{G} + \mathbf{H}^T\mathbf{H})^{-1}(\mathbf{G}^T\mathbf{d} + \mathbf{H}^T\mathbf{f}) \end{aligned}$$

The solutions in parts a and b are the same when  $\lambda = 1$ .

**2.** Consider the standard matrix equation  $\mathbf{G}\mathbf{m} = \mathbf{d}$ , where:

$$\mathbf{G} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0.01 \end{pmatrix},$$

and

$$\mathbf{d} = \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}.$$

Uncertainties in the elements of  $\mathbf{d}$  are identified as  $\sigma_i$ .

- a. What is the least-squares solution for  $\mathbf{m}$  if  $\sigma_i = 0.1$  for all  $i$ ?
- b. What is the (row-weighted) least-squares solution for  $\mathbf{m}$  if  $\sigma_1 = \sigma_2 = 0.1$  and  $\sigma_3 = 10$ ?
- c. Comment on your results from cases a and b above? What would happen if  $\sigma_1 = \sigma_3 = 0.1$  and  $\sigma_2 = 10$ ?

**Solution:**

- a.  $\mathbf{m} = (\mathbf{G}^T \mathbf{G})^{-1} \mathbf{G}^T \mathbf{d}$ , so  $\mathbf{m}^T = [1 \ 1.01]$ .
- b. If the solution is row-weighted, then the 3rd row of  $\mathbf{G}$  has minimal impact on the solution and  $\mathbf{m}^T = [1 \ 1]$ .
- c. Alternatively, if  $\sigma$  is 0.1 for rows 1 and 3, and 10 for row 2, then the row weighted elements of  $\mathbf{G}$  are the same in rows 2 and 3, and both rows contribute equally to the solution. In this case,  $\mathbf{m}^T = [1 \ 50.5]$ .

**3.** Suppose that you have temperature data at fixed depths (such as CTD bottle depths) and you would like to find a functional form to describe the vertical temperature structure in the range between 150 and 900 m depth.

- a. Download the following profile data from the course web site:

[http://www-mae.ucsd.edu/~sgille/sio221b/ps4\\_profile.dat](http://www-mae.ucsd.edu/~sgille/sio221b/ps4_profile.dat)

and least-squares fit a linear profile of the form  $T = m_1 + m_2 z$  to the temperature data. In this data, column 3 contains depth, column 4 contains temperature, column 5 contains salinity, and column 6 is oxygen. The particular station was collected on 25 November 1972 at 35.32°W, 30.43°S.

- b. Assume that the observational error is 0.1°C at all depths. What are the estimated errors in your parameters  $m_i$ ? Is the functional misfit  $\langle (\mathbf{G}\mathbf{m} - \mathbf{T})^2 \rangle$  consistent with the assumed errors in  $T$ ? You can do this by computing the variable

$$\chi^2 = \frac{(\mathbf{G}\mathbf{m} - \mathbf{T})^T (\mathbf{G}\mathbf{m} - \mathbf{T})}{\sigma^2}$$

and checking whether  $\chi^2$  is equal to  $N - M$ . (More formal procedure would have you compute the complete gamma function to evaluate whether the observed value of  $\chi^2$  is plausible.)

- c. Verify that the formal error bars that you have derived are consistent with error bars that would be derived using a Monte Carlo simulation. To estimate alternate errors in  $m_i$  carry out a Monte Carlo simulation using the following procedure: 1. Generate 100 or more data

sets of normally distributed fake perturbations with a standard deviation equivalent to the observed data (using “randn” in Matlab, for example). 2. With each set of noise, randomly perturb the temperature data, and recompute the least-squares fit solution. 3. Compute the standard deviations of your estimates of  $m_i$ . Do your error bars differ from the error bars derived in part b?

**Solution:**

**a.** Least-squares fit from rows 9 through 25 of the data. This yields  $m_1 = 19.1343^\circ\text{C}$  and  $m_2 = 0.0169^\circ\text{C}/\text{m}$ .

**b.** The error covariance matrix is  $C_{mm} = 0.1^2(\mathbf{G}^T\mathbf{G})^{-1}$ . The formal errors in the solution are the square root of the diagonals of  $C_{mm}$ . Thus  $\sigma_1 = 0.065$  and  $\sigma_2 = 1.19 \times 10^{-4}$

In this case  $\chi^2$  is 218 and  $N - M$  is 10. This suggests that our estimated a priori error is too small compared with the typical misfit. This mismatch between  $\chi^2$  and  $N - M$  can occur when the a priori error bars are erroneous or when the model used to fit the data is a poor fit to the variability.

**c.** Using the Monte Carlo procedure discussed in the problem, I find that the error bars for  $m_1$  and  $m_2$  are the same as the theoretical error bars to 2 significant digits. This demonstrates that the formalism that we used to compute error bars in part b is consistent with error bars derived using a brute strength approach, but it does not guarantee that the true error bar is the same size as our estimate.