

# Lab: Overdetermined Linear Systems

(Hints for Homework 6)

## Linear Least Squares: General Fitting Functions

**Objective.** Given data points  $\{(x_i, y_i) \mid i \in \mathbb{N}[1, m]\}$ , pick a form for the “fitting” function  $f(x)$  and minimize its total error in representing the data.

In lecture, we used a polynomial fitting function

$$p(x) = c_1 + c_2x + \cdots + c_nx^{n-1} \quad \text{with } n < m, \quad (1)$$

and looked for the coefficients  $c_1, \dots, c_n$  which minimize the 2-norm of the error<sup>1</sup>  $\mathbf{r} = \mathbf{y} - p(\mathbf{x})$ :

$$\|\mathbf{r}\|_2 = \sqrt{\sum_{i=1}^m r_i^2} = \sqrt{\sum_{i=1}^m (y_i - p(x_i))^2}. \quad (2)$$

The coefficients are found by solving the overdetermined system

$$\underbrace{\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{bmatrix}}_{\mathbf{y}} \text{ “=” } \underbrace{\begin{bmatrix} 1 & x_1 & x_1^2 & \cdots & x_1^{n-1} \\ 1 & x_2 & x_2^2 & \cdots & x_2^{n-1} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_m & x_m^2 & \cdots & x_m^{n-1} \end{bmatrix}}_V \underbrace{\begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_n \end{bmatrix}}_{\mathbf{c}}. \quad (3)$$

The solution  $\mathbf{c}$  of  $\mathbf{y} \text{ “=” } V\mathbf{c}$  turns out to be the solution of the normal equation

$$V^T V \mathbf{c} = V^T \mathbf{y}.$$

If the  $x$  and  $y$  data points are saved in MATLAB as column vectors `xdp` and `ydp`, respectively, one can solve the normal equation conveniently by

```
V = xdp.^(0:n-1)
c = V\ydp;
```

In the most general terms, the fitting function takes the form

$$f(x) = c_1 f_1(x) + \cdots + c_n f_n(x) \quad \text{with } n < m, \quad (4)$$

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<sup>1</sup>This difference is often called the *residual*.

where  $f_1, \dots, f_n$  are known functions while  $c_1, \dots, c_n$  are to be determined so that the 2-norm of the residual  $\mathbf{r} = \mathbf{y} - f(\mathbf{x})$  is minimized. This gives rise to an overdetermined system analogous to (3):

$$\underbrace{\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{bmatrix}}_{\mathbf{y}} \text{ "=" } \underbrace{\begin{bmatrix} f_1(x_1) & f_2(x_1) & f_3(x_1) & \cdots & f_n(x_1) \\ f_1(x_2) & f_2(x_2) & f_3(x_2) & \cdots & f_n(x_2) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ f_1(x_m) & f_2(x_m) & f_3(x_m) & \cdots & f_n(x_m) \end{bmatrix}}_V \underbrace{\begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_n \end{bmatrix}}_{\mathbf{c}}. \quad (5)$$

As in the case of polynomial fitting, this system is equivalent to the normal equation  $V^T V \mathbf{c} = V^T \mathbf{y}$ , which can be solved in MATLAB by

```
V = [f1(xdp) f2(xdp) ... fn(xdp)];
c = V\ydp;
```

where  $f_1, f_2, \dots, f_n$  are anonymous functions corresponding to  $f_1, f_2, \dots, f_n$ .

**Exercise 1 (FNC 3.1.4).**  Define the following data in MATLAB:

```
t = (0:.5:10)'; y = tanh(t);
```

- Fit the data to a cubic polynomial and plot the data together with the polynomial fit.
- Fit the data to the function  $c_1 + c_2 z + c_3 z^2 + c_4 z^3$ , where  $z = t^2/(1+t^2)$ . Plot the data together with the fit. What feature of  $z$  makes this fit much better than the original cubic?

## Gram-Schmidt and Thin QR Factorization

Consider the subspace  $S = \text{Span}\{\mathbf{a}_1, \mathbf{a}_2, \mathbf{a}_3\} \subset \mathbb{R}^4$  where

$$\mathbf{a}_1 = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}, \quad \mathbf{a}_2 = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 1 \end{bmatrix}, \quad \mathbf{a}_3 = \begin{bmatrix} 4 \\ 2 \\ -2 \\ 1 \end{bmatrix}.$$

By the *Gram-Schmidt procedure*, we can obtain an orthonormal basis for  $S$ :

$$\begin{aligned} \mathbf{q}_1 &= \frac{\mathbf{a}_1}{\|\mathbf{a}_1\|_2} = \frac{1}{2} \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}, \\ \mathbf{q}_2 &= \frac{\mathbf{v}_2}{\|\mathbf{v}_2\|_2} = \frac{1}{2} \begin{bmatrix} 1 \\ -1 \\ -1 \\ 1 \end{bmatrix}, \quad \text{where } \mathbf{v}_2 = \mathbf{a}_2 - (\mathbf{a}_2^T \mathbf{q}_1) \mathbf{q}_1, \\ \mathbf{q}_3 &= \frac{\mathbf{v}_3}{\|\mathbf{v}_3\|_2} = \frac{1}{5\sqrt{2}} \begin{bmatrix} 3 \\ 4 \\ -4 \\ -3 \end{bmatrix}, \quad \text{where } \mathbf{v}_3 = \mathbf{a}_3 - (\mathbf{a}_3^T \mathbf{q}_1) \mathbf{q}_1 - (\mathbf{a}_3^T \mathbf{q}_2) \mathbf{q}_2. \end{aligned}$$

The equations above can be re-arranged as

$$\begin{aligned} \mathbf{a}_1 &= \|\mathbf{a}_1\|_2 \mathbf{q}_1 \\ \mathbf{a}_2 &= (\mathbf{a}_1^T \mathbf{q}_1) \mathbf{q}_1 + \|\mathbf{v}_2\|_2 \mathbf{q}_2 \\ \mathbf{a}_3 &= (\mathbf{a}_3^T \mathbf{q}_1) \mathbf{q}_1 + (\mathbf{a}_3^T \mathbf{q}_2) \mathbf{q}_2 + \|\mathbf{v}_3\|_2 \mathbf{q}_3, \end{aligned}$$

which, in matrix form, is written as

$$\begin{bmatrix} \mathbf{a}_1 & \mathbf{a}_2 & \mathbf{a}_3 \end{bmatrix} = \begin{bmatrix} \mathbf{q}_1 & \mathbf{q}_2 & \mathbf{q}_3 \end{bmatrix} \begin{bmatrix} \|\mathbf{a}_1\|_2 & \mathbf{a}_2^T \mathbf{q}_1 & \mathbf{a}_3^T \mathbf{q}_1 \\ 0 & \|\mathbf{v}_2\|_2 & \mathbf{a}_3^T \mathbf{q}_2 \\ 0 & 0 & \|\mathbf{v}_3\|_2 \end{bmatrix},$$

or simply  $A = \hat{Q} \hat{R}$  (thin QR factorization).

The general Gram-Schmidt procedure can be summarized as

$$\begin{aligned} \mathbf{q}_1 &= \frac{\mathbf{a}_1}{r_{11}}, \\ \mathbf{q}_2 &= \frac{\mathbf{a}_2 - r_{12} \mathbf{q}_1}{r_{22}}, \\ \mathbf{q}_3 &= \frac{\mathbf{a}_3 - r_{13} \mathbf{q}_1 - r_{23} \mathbf{q}_2}{r_{33}}, \\ &\vdots \\ \mathbf{q}_n &= \frac{\mathbf{a}_n - \sum_{i=1}^{n-1} r_{in} \mathbf{q}_i}{r_{nn}}, \end{aligned} \quad \text{where } r_{ij} = \begin{cases} \mathbf{q}_i^T \mathbf{a}_j, & \text{if } i \neq j \\ \pm \left\| \mathbf{a}_j - \sum_{k=1}^{j-1} r_{kj} \mathbf{q}_k \right\|_2, & \text{if } i = j. \end{cases}$$

To turn these formulas into compute program, we first write down the logics in plain terms, not worrying about programming syntax; this is called a *pseudocode*.

```
Store the dimensions of  $A$  as  $m$  and  $n$ 
Initialize  $Q$  by making a copy of  $A$ . (This will be overwritten below.)
Initialize  $R$  as an  $n \times n$  zero matrix.
for  $j = 1$  to  $n$ 
    for  $i = 1$  to  $j - 1$ 
         $r_{ij} = \mathbf{q}_i^T \mathbf{a}_j$ 
         $\mathbf{q}_j = \mathbf{q}_j - r_{ij} \mathbf{q}_i$ 
     $r_{jj} = \|\mathbf{q}_j\|_2$ 
     $\mathbf{q}_j = \mathbf{q}_j / r_{jj}$ 
```

Even though the logic has been written using a nested for-loop, the inner loop can be vectorized resulting in a single loop for  $j$ . Either version will be okay for this homework.