

# Personal notes on computational mathematics

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## §1. Interpolation and data fitting

### 1.1. Least squares approximation

Let  $\{x_i\}$  be a mesh of points of a manifold  $M$ . Let  $\{\phi_\alpha : M \rightarrow \mathbb{C}\}$  be a set of complex (or real) valued functions on  $M$ . Any function  $f : M \rightarrow \mathbb{C}$  specified by its values  $f_i$  at the mesh points can be approximated by

$$f(x) = \sum_{\alpha} c_{\alpha} \phi_{\alpha}(x)$$

minimizing the sum of the absolute values of the residues,  $\sum_i w_i |f(x_i) - f_i|^2$ , where  $w_i$  are the weights. The vector of the optimal coefficients  $c_{\alpha}$  satisfies the linear equation  $Mc = V$ , where

$$M_{\alpha\beta} = \sum_i w_i \bar{\phi}_{\alpha}(x_i) \phi_{\beta}(x_i), \quad V_{\alpha} = \sum_i w_i \bar{\phi}_{\alpha}(x_i) f_i.$$

### 1.2. Least squares linear algebra

The least squares solution to the equation

$$\mathbf{A}\mathbf{X} = \mathbf{B} \tag{1.1}$$

minimizes the Frobenius norm of  $\mathbf{A}\mathbf{X} - \mathbf{B}$ . It is unique and is given by

$$\mathbf{X}_0 \equiv \arg \min_{\mathbf{X}} \|\mathbf{A}\mathbf{X} - \mathbf{B}\|_{\text{F}} = (\mathbf{A}^{\top} \mathbf{A})^{-1} \mathbf{A}^{\top} \mathbf{B}.$$

If  $\mathbf{X} = \mathbf{x}$  is a vector of size  $d$  and  $\mathbf{B} = \mathbf{b}$  is a vector of size  $n$  denoting sampling of a random variable, then  $\mathbf{x}_0 - \mathbf{x}$  is asymptotically normal with the covariance matrix  $\mathbf{\Sigma} = \sigma^2 (\mathbf{A}^{\top} \mathbf{A})^{-1}$ , where

$$\sigma^2 = \frac{1}{n} \|\mathbf{A}\mathbf{X}_0 - \mathbf{b}\|_{\text{F}}^2$$

is the standard deviation for the residuals, implying that the estimate  $\mathbf{b} = \mathbf{a}\mathbf{x}$  asymptotically has normal distribution with the mean value  $\mathbf{a}\mathbf{x}_0$  and the dispersion  $\mathbf{a}\mathbf{\Sigma}\mathbf{a}^{\top}$  (note that  $\text{tr} \mathbf{A}\mathbf{\Sigma}\mathbf{A}^{\top} = d$ ).

If  $\mathbf{A}$  and  $\mathbf{B}$  depend on some parameter then it is easy to show that

$$\|\mathbf{A}\mathbf{X}_0 - \mathbf{B}\|_{\text{F}}' = \|\mathbf{A}\mathbf{X}_0 - \mathbf{B}\|_{\text{F}}^{-1} \text{tr} \left[ (\mathbf{A}\mathbf{X}_0 - \mathbf{B})^{\top} (\mathbf{A}'\mathbf{X}_0 - \mathbf{B}') \right],$$

where prime means the derivative over this parameter.

In the so called orthogonal Procrustes problem the solution is constrained to orthogonal matrices only, i.e.  $\mathbf{X}^{\top} \mathbf{X} = \mathbf{1}$  condition is imposed. In this case the solution is given by

$$\mathbf{X}_0 = \mathbf{U}\mathbf{V}^{\top}, \quad \text{where } \mathbf{U}\mathbf{S}\mathbf{V}^{\top} \equiv \mathbf{A}^{\top} \mathbf{B}$$

is the singular value decomposition. If in 3D we additionally fix rotation axis  $\mathbf{n}$  then the angle

$$\alpha = \arctan \left[ 2 \sum_i \mathbf{n} (\mathbf{q}_i \times \mathbf{p}_i), \sum_i (|\mathbf{n} \times \mathbf{p}_i|^2 - |\mathbf{n} \times \mathbf{q}_i|^2) \right], \quad \text{where } \mathbf{p} = \mathbf{r}' + \mathbf{r}, \mathbf{q} = \mathbf{r}' - \mathbf{r},$$

gives the least squares rotation of set of points  $\mathbf{r}$  towards the set  $\mathbf{r}'$ , provided that both sets are centered that is  $\sum_i \mathbf{r}_i = 0$ .

### 1.3. Extrapolation

Extrapolation of a finite sequence of vectors can improve the convergence if these vectors are generated by some slowly converging (or diverging) iteration procedure. Here we consider the minimal polynomial extrapolation (MPE) method [2, 1]. Let  $x_1, \dots, x_m$  be a sequence of vectors generated by the formula  $x_{i+1} = Ax_i$ . We are looking for the best estimate of the solution of the equation  $\xi = A\xi$  in the form

$$x = \sum_{i=1}^m w_i x_i.$$

One of  $w_i$  can be chosen arbitrary, let it be  $w_m$ . The rest of  $w_i$  is chosen so as to minimize the norm  $\langle x - Ax | x - Ax \rangle$ , that results in the set of linear equations

$$\sum_{j=1}^m \langle \delta x_i | \delta x_j \rangle w_j = 0, \quad i = \overline{1, m-1}, \quad (1.2)$$

where  $\delta x_j = x_{j+1} - x_j$ . To fix  $w_m$  we imply the condition

$$\sum_{j=1}^m w_j = 1,$$

which asymptotically conserves the norm. Note that  $x_{m+1}$  is used in (1.2) through  $\delta x_m$ .

The minimum nontrivial extrapolation order is  $m = 2$ . In this case

$$w_2 = 1 - w_1 = \frac{\langle \delta x_1 | \delta x_1 \rangle}{\langle \delta x_1 | \delta x_1 - \delta x_2 \rangle},$$

reducing for a scalar sequence to Aitken's extrapolation formula.

### 1.4. Grid optimization (open problem)

Let  $f(x, \lambda)$  be a function smooth in  $x \in \mathbb{R}^d$  and "parametric" in  $\lambda$ . An example from computational chemistry:  $x$  are some molecular coordinates (e.g. dihedral, bond length, center of mass),  $f$  is potential energy, and  $\lambda$  is computational method. Different methods are compared according to the norm

$$\left( \int [f(x, \lambda_1) - f(x, \lambda_2)]^p \rho(x) dx \right)^{1/p}.$$

The weight function  $\rho$  is often given by Boltzmann distribution  $e^{-\beta f(x, \lambda_0)}$ , where  $\lambda_0$  is a hypothetical "exact" method.

The problem is to find a reasonably small grid in  $x$  (let say,  $< 10$  points) to benchmark different methods  $\lambda$ .

## References

- [1] Jbilou K, Sadok H, Vector extrapolation methods. Applications and numerical comparison, J Comp App Math 122, 149 (2000)
- [2] S Cabay, L W Jackson, A polynomial extrapolation method for finding limits and antilimits of vector sequences, SIAM J Numer Anal 13, 734 (1976)