

Non linear Least Squares

Lectures for PHD course on
Numerical Optimization

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Notes

Outline

1 The Nonlinear Least Squares Problem

2 The Levemberg–Marquardt step



Notes

- An important class on minimization problem when $f : \mathbb{R}^n \mapsto \mathbb{R}$ is the **nonlinear least squares** and takes the form:

$$f(\mathbf{x}) = \frac{1}{2} \sum_{i=1}^m F_i(\mathbf{x})^2, \quad m \geq n$$

- When $n = m$ finding the minimum coincide to finding the solution of the non linear system $\mathbf{F}(\mathbf{x}) = \mathbf{0}$ where:

$$\mathbf{F}(\mathbf{x}) = (F_1(\mathbf{x}), F_2(\mathbf{x}), \dots, F_n(\mathbf{x}))^T$$

- Thus, special methods developed for the solution of nonlinear least squares can be used for the solution of nonlinear systems, but not the converse if $m > n$.



Notes

Example

Consider the the following **fitting model**

$$M(\mathbf{x}, t) = x_3 \exp(x_1 t) + x_4 \exp(x_3 t)$$

which can be used to fit some data. The model depend on the **parameters** $\mathbf{x} = (x_1, x_2, x_3, x_4)^T$. If we have a number of points

$$(t_k, y_k)^T, \quad k = 1, 2, \dots, m$$

we want to find the parameters \mathbf{x} such that $\frac{1}{2} \sum_{k=1}^m (M(\mathbf{x}, t_k) - y_k)^2$ is minimum. Defining

$$F_k(\mathbf{x}) = M(\mathbf{x}, t_k) - y_k, \quad k = 1, 2, \dots, m$$

then can be viewed as a non linear least squares problem.



Notes

- To solve nonlinear least squares problem, we can use any of the previously discussed method. For example BFGS or Newton method with globalization techniques.
- If for example we use Newton method we need to compute

$$\begin{aligned}
 \nabla^2 f(\mathbf{x}) &= \nabla^2 \frac{1}{2} \sum_{i=1}^m F_i(\mathbf{x})^2 = \frac{1}{2} \sum_{i=1}^m \nabla^2 F_i(\mathbf{x})^2 \\
 &= \frac{1}{2} \sum_{i=1}^m \nabla (2F_i(\mathbf{x}) \nabla F_i(\mathbf{x}))^T \\
 &= \sum_{i=1}^m \nabla F_i(\mathbf{x})^T \nabla F_i(\mathbf{x}) + \sum_{i=1}^m F_i(\mathbf{x}) \nabla^2 F_i(\mathbf{x})
 \end{aligned}$$



Notes

- If we define

$$\mathbf{J}(\mathbf{x}) = \begin{pmatrix} \nabla F_1(\mathbf{x}) \\ \nabla F_2(\mathbf{x}) \\ \vdots \\ \nabla F_m(\mathbf{x}) \end{pmatrix}$$

then we can write

$$\nabla^2 f(\mathbf{x}) = \mathbf{J}(\mathbf{x})^T \mathbf{J}(\mathbf{x}) + \sum_{i=1}^m F_i(\mathbf{x}) \nabla^2 F_i(\mathbf{x})$$

- However, in practical problem normally $\mathbf{J}(\mathbf{x})$ is known, while $\nabla^2 F_i(\mathbf{x})$ is not known or impractical to compute.



Notes

- A common approximation is given by neglecting the terms $\nabla^2 F_i(\mathbf{x})$ obtaining,

$$\nabla^2 f(\mathbf{x}) \approx \mathbf{J}(\mathbf{x})^T \mathbf{J}(\mathbf{x})$$

- This choice can be appropriate near the solution if $n = m$ in solving nonlinear system. In fact near the solution we have $F_i(\mathbf{x}) \approx 0$ so that the contribution of the neglected term is small.
- This choice is not good when near the minimum we have large residual (i.e. $\|\mathbf{F}(\mathbf{x})\|$ is large) because the contribution of $\nabla^2 F_i(\mathbf{x})$ can't be neglected.



Notes

1 The Nonlinear Least Squares Problem

2 The Levenberg–Marquardt step



Notes

References



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