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手写V10第三章作业讲解

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作业

1 样例代码给出了使用 LM 算法来估计曲线 $y = \exp(ax^2 + bx + c)$ 参数 a, b, c 的完整过程。

- ① 请绘制样例代码中 LM 阻尼因子 μ 随着迭代变化的曲线图
- ② 将曲线函数改成 $y = ax^2 + bx + c$, 请修改样例代码中残差计算, 雅克比计算等函数, 完成曲线参数估计。
- ③ 实现其他更优秀的阻尼因子策略, 并给出实验对比 (选做, 评优秀), 策略可参考论文^a 4.1.1 节。

2 公式推导, 根据课程知识, 完成 F, G 中如下两项的推导过程:

$$f_{15} = \frac{\partial \alpha_{b_i b_{k+1}}}{\partial \delta \mathbf{b}_k^g} = -\frac{1}{4}(\mathbf{R}_{b_i b_{k+1}}[(\mathbf{a}^{b_{k+1}} - \mathbf{b}_k^a)] \times \delta t^2)(-\delta t)$$

$$g_{12} = \frac{\partial \alpha_{b_i b_{k+1}}}{\partial \mathbf{n}_k^g} = -\frac{1}{4}(\mathbf{R}_{b_i b_{k+1}}[(\mathbf{a}^{b_{k+1}} - \mathbf{b}_k^a)] \times \delta t^2)(\frac{1}{2}\delta t)$$

3 证明式(9)。

^aHenri Gavin. "The Levenberg-Marquardt method for nonlinear least squares curve-fitting problems". In: Department of Civil and Environmental Engineering, Duke University (2011), pp. 1-15.

第一题

- 1.1 可以输出两种lambda, 分别是:
 - 确实在迭代过程中让误差下降的lambda, 在代码里对应让IsGoodStepInLM=true的lambda

```
while (!stop && (iter < iterations)) {  
    std::cout << "iter: " << iter << " , chi= " << currentChi_ << " , Lambda= " << currentLambda_  
    << std::endl;  
    outfile<< "iter: " << iter << " , chi= " << currentChi_ << " , Lambda= " << currentLambda_  
    << std::endl;
```

另一种是在while(!oneStepSuccess)中不断被尝试和更新的lambda, 可以选择在IsGoodStepInLM()中打印

第一题

残差和雅克比（优化变量是 a, b, c ）：

$$e_i = ax_i^2 + bx_i + c - y_i$$

$$J_i = [x_i^2, x_i, 1]$$

● 1.2

- 修改残差和雅克比，对应函数ComputeResidual(), ComputeJacobians()
- 原始数据拟合可能效果较差，大家可以尝试调整数据，比如数据点个数，噪声大小（方差），增大数据范围，直到得到一个满意的拟合结果

1.3 实现其他更新阻尼因子策略

策略1:

1. $\lambda_0 = \lambda_o$; λ_o is user ^{Δx} specified [8].
 use eq'n (13) for \mathbf{h}_{lm} and eq'n (16) for ρ
 if $\rho_i(\mathbf{h}) > \epsilon_4$: $\mathbf{p} \leftarrow \mathbf{p} + \mathbf{h}$; $\lambda_{i+1} = \max[\lambda_i/L_{\downarrow}, 10^{-7}]$;
 otherwise: $\lambda_{i+1} = \min[\lambda_i L_{\uparrow}, 10^7]$; μ

注意：算 Δx 和 ρ 与之前不一致

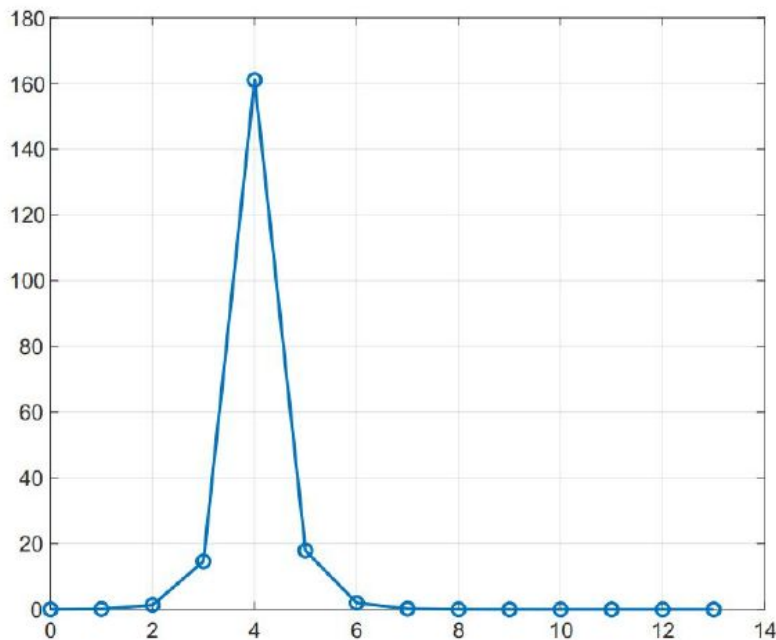
$$[J^T W J + \lambda \text{diag}(J^T W J)] \mathbf{h}_{lm} = J^T W (\mathbf{y} - \hat{\mathbf{y}})$$

$$\rho_i(\mathbf{h}_{lm}) = \frac{\chi^2(\mathbf{p}) - \chi^2(\mathbf{p} + \mathbf{h}_{lm})}{\mathbf{h}_{lm}^T (\lambda_i \text{diag}(J^T W J) \mathbf{h}_{lm} + J^T W (\mathbf{y} - \hat{\mathbf{y}}(\mathbf{p})))}$$

需要修改AddLambdatoHessianLM、RemoveLambdaHessianLM和IsGoodStepInLM。

1.3 实现其他更新阻尼因子策略

策略1阻尼因子变化（更少的迭代次数）：



1.3 实现其他更新阻尼因子策略

策略2:

2. $\lambda_0 = \lambda_o \max [\text{diag}[\mathbf{J}^\top \mathbf{W} \mathbf{J}]]$; λ_o is user-specified.
 use eq'n (12) for \mathbf{h}_{lm} and eq'n (15) for ρ

$$\alpha = \left(\left(\mathbf{J}^\top \mathbf{W} (\mathbf{y} - \hat{\mathbf{y}}(\mathbf{p})) \right)^\top \mathbf{h} \right) / \left((\chi^2(\mathbf{p} + \mathbf{h}) - \chi^2(\mathbf{p})) / 2 + 2 \left(\mathbf{J}^\top \mathbf{W} (\mathbf{y} - \hat{\mathbf{y}}(\mathbf{p})) \right)^\top \mathbf{h} \right);$$

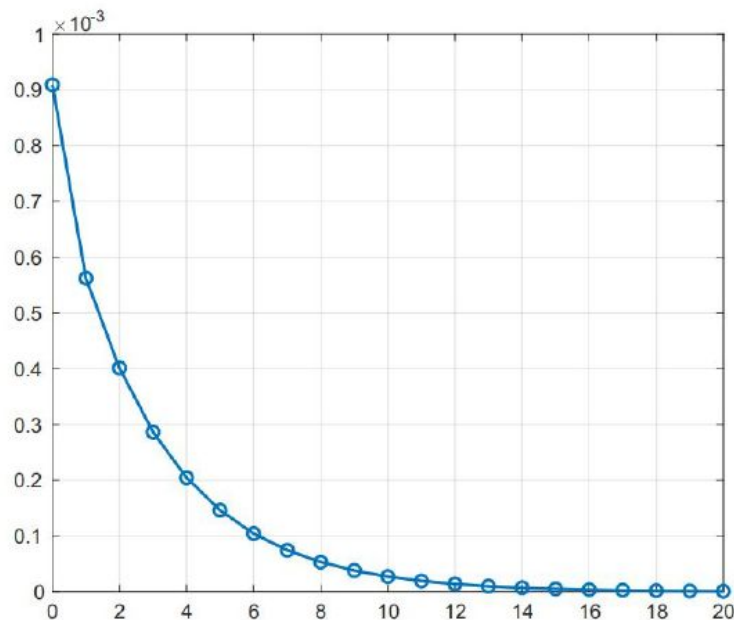
 if $\rho_i(\alpha \mathbf{h}) > \epsilon_4$: $\mathbf{p} \leftarrow \mathbf{p} + \alpha \mathbf{h}$; $\lambda_{i+1} = \max [\lambda_i / (1 + \alpha), 10^{-7}]$;
 otherwise: $\lambda_{i+1} = \lambda_i + |\chi^2(\mathbf{p} + \alpha \mathbf{h}) - \chi^2(\mathbf{p})| / (2\alpha)$; $F(x)$

算法流程:

- | | |
|--|--|
| <ol style="list-style-type: none"> 1、计算 $\Delta \mathbf{x}$ 2、计算 $F(\mathbf{x} + \Delta \mathbf{x})$ (累加edge的残差) 3、计算 $\alpha = \frac{-\mathbf{b}^\top \Delta \mathbf{x}}{\frac{F(\mathbf{x} + \Delta \mathbf{x}) - F(\mathbf{x})}{2} - 2\mathbf{b}^\top \Delta \mathbf{x}}$ | <ol style="list-style-type: none"> 4、计算 $\Delta \mathbf{x} \leftarrow \alpha \Delta \mathbf{x}$ (需要先RollbackStates) 5、计算 $\rho = \frac{F(\mathbf{x}) - F(\mathbf{x} + \Delta \mathbf{x})}{\frac{1}{2} \Delta \mathbf{x}^\top (\mu \Delta \mathbf{x} + \mathbf{b})}$ 6、根据5选择更新策略 |
|--|--|

1.3 实现其他更新阻尼因子策略

策略2阻尼因子变化：



三个策略（成功迭代次数/总迭代次数）

策略1： 9/13

策略2： 20/20

策略3： 11/18

可以发现策略2虽然增加了迭代次数，
但没有失败的迭代（每次迭代误差都在下降）。

2 公式推导 f_{15}

$$\alpha_{b_i b_{k+1}} = \alpha_{b_i b_k} + \beta_{b_i b_k} \delta t + \frac{1}{2} a \delta t^2$$

$$\begin{aligned} a \delta t^2 &= \frac{1}{2} \left(q_{b_i b_k} (a^{b_k} - b_k^a) + q_{b_i b_{k+1}} (a^{b_{k+1}} - b_k^a) \right) \delta t^2 \\ &= \frac{1}{2} \left(q_{b_i b_k} (a^{b_k} - b_k^a) + \left(q_{b_i b_k} \otimes \left(\frac{1}{2} \omega \delta t \right) \right) (a^{b_{k+1}} - b_k^a) \delta t^2 \right) \end{aligned}$$

$$\omega = \frac{1}{2} \left((\omega^{b_k} - b_k^g) + (\omega^{b_{k+1}} - b_k^g) \right) = \frac{1}{2} (\omega^{b_k} + \omega^{b_{k+1}}) - b_k^g$$

$$\begin{aligned} \frac{\partial \alpha_{b_i b_{k+1}}}{\partial \delta b_k^g} &= \frac{\partial \frac{1}{2} \cdot \frac{1}{2} \left(q_{b_i b_k} \otimes \left(\frac{1}{2} \omega \delta t \right) \right) (a^{b_{k+1}} - b_k^a) \delta t^2}{\partial \delta b_k^g} \\ &= \frac{\partial \frac{1}{4} \left(q_{b_i b_k} \otimes \left(\frac{1}{2} (\omega - \delta b_k^g) \delta t \right) \right) (a^{b_{k+1}} - b_k^a) \delta t^2}{\partial \delta b_k^g} \\ &= \frac{\partial \frac{1}{4} \left(R_{b_i b_k} e^{[(\omega - \delta b_k^g) \delta t]_{\times}} \right) (a^{b_{k+1}} - b_k^a) \delta t^2}{\partial \delta b_k^g} \\ &\approx \frac{\partial \frac{1}{4} \left(R_{b_i b_k} e^{[\omega \delta t]_{\times}} e^{[-J_r(\omega \delta t) \delta b_k^g \delta t]_{\times}} \right) (a^{b_{k+1}} - b_k^a) \delta t^2}{\partial \delta b_k^g} \\ &\approx \frac{\partial \frac{1}{4} \left(R_{b_i b_{k+1}} \left(I - [J_r(\omega \delta t) \delta b_k^g \delta t]_{\times} \right) \right) (a^{b_{k+1}} - b_k^a) \delta t^2}{\partial \delta b_k^g} \\ &= \frac{\partial \frac{1}{4} R_{b_i b_{k+1}} [-J_r(\omega \delta t) \delta b_k^g \delta t]_{\times} (a^{b_{k+1}} - b_k^a) \delta t^2}{\partial \delta b_k^g} \\ &= \frac{\partial -\frac{1}{4} R_{b_i b_{k+1}} [a^{b_{k+1}} - b_k^a]_{\times} (-J_r(\omega \delta t) \delta b_k^g \delta t) \delta t^2}{\partial \delta b_k^g} \\ &= -\frac{1}{4} R_{b_i b_{k+1}} [a^{b_{k+1}} - b_k^a]_{\times} (-J_r(\omega \delta t) \delta t) \delta t^2 \\ &\approx -\frac{1}{4} (R_{b_i b_{k+1}} [a^{b_{k+1}} - b_k^a]_{\times}) \delta t^2 (-\delta t) \end{aligned}$$

2 公式推导 g_{12}

$$\alpha_{b_i b_{k+1}} = \alpha_{b_i b_k} + \beta_{b_i b_k} \delta t + \frac{1}{2} a \delta t^2$$

$$\begin{aligned} a \delta t^2 &= \frac{1}{2} \left(q_{b_i b_k} (a^{b_k} - b_k^a) + q_{b_i b_{k+1}} (a^{b_{k+1}} - b_k^a) \right) \delta t^2 \\ &= \frac{1}{2} \left(q_{b_i b_k} (a^{b_k} - b_k^a) + \left(q_{b_i b_k} \otimes \left(\frac{1}{2} \omega \delta t \right) \right) \right) (a^{b_{k+1}} - b_k^a) \delta t^2 \end{aligned}$$

$$\begin{aligned} \omega &= \frac{1}{2} \left(((\omega^{b_k} + n_k^g) - b_k^g) + ((\omega^{b_{k+1}} + n_{k+1}^g) - b_k^g) \right) \\ &= \frac{1}{2} (\omega^{b_k} + \omega^{b_{k+1}}) - b_k^g + \frac{1}{2} n_{k+1}^g + \frac{1}{2} n_k^g \end{aligned}$$

$$\begin{aligned} \frac{\partial \alpha_{b_i b_{k+1}}}{\partial \delta n_{b_k}^g} &= \frac{\frac{\partial}{\partial} \frac{1}{2} \cdot \frac{1}{2} \left(q_{b_i b_k} \otimes \left(\frac{1}{2} \left(\omega + \frac{1}{2} n_{b_k}^g \right) \delta t \right) \right) (a^{b_{k+1}} - b_k^a) \delta t^2}{\partial \delta n_{b_k}^g} \\ &= \frac{\frac{\partial}{\partial} - \frac{1}{4} R_{b_i b_{k+1}} [a^{b_{k+1}} - b_k^a]_{\times} \left(J_r(\omega \delta t) \frac{1}{2} n_{b_k}^g \delta t \right) \delta t^2}{\partial \delta n_{b_k}^g} \\ &= -\frac{1}{4} R_{b_i b_{k+1}} [a^{b_{k+1}} - b_k^a]_{\times} \left(J_r(\omega \delta t) \frac{1}{2} \delta t \right) \delta t^2 \\ &\approx -\frac{1}{4} (R_{b_i b_{k+1}} [a^{b_{k+1}} - b_k^a]_{\times}) \delta t^2 \left(\frac{1}{2} \delta t \right) \end{aligned}$$

3 证明式(9)

$$\text{已知 } (J^T J + \mu I) \Delta x_{lm} = -F^{*T}$$

$$\text{对 } J^T J \text{ 做特征值分解: } J^T J = V \Sigma V^T = \begin{bmatrix} v_1 & v_2 & \dots & v_n \end{bmatrix} \begin{bmatrix} \lambda_1 & & & \\ & \lambda_2 & & \\ & & \ddots & \\ & & & \lambda_n \end{bmatrix} \begin{bmatrix} v_1^T \\ v_2^T \\ \vdots \\ v_n^T \end{bmatrix}$$

$$\Delta x_{lm} = \begin{bmatrix} v_1 & v_2 & \dots & v_n \end{bmatrix} \begin{bmatrix} (\lambda_1 + \mu)^{-1} & & & \\ & (\lambda_2 + \mu)^{-1} & & \\ & & \ddots & \\ & & & (\lambda_n + \mu)^{-1} \end{bmatrix} \begin{bmatrix} v_1^T \\ v_2^T \\ \vdots \\ v_n^T \end{bmatrix} (-F^{*T})$$

$$= - \sum_{i=1}^n \frac{v_i \cdot v_i^T F^{*T}}{\lambda_i + \mu} \quad \text{因为 } v_i^T F^{*T} \text{ 是一个数} = - \sum_{i=1}^n \frac{v_i^T F^{*T} v_i}{\lambda_i + \mu}$$

Q&A

感谢各位聆听 !

Thanks for Listening

