



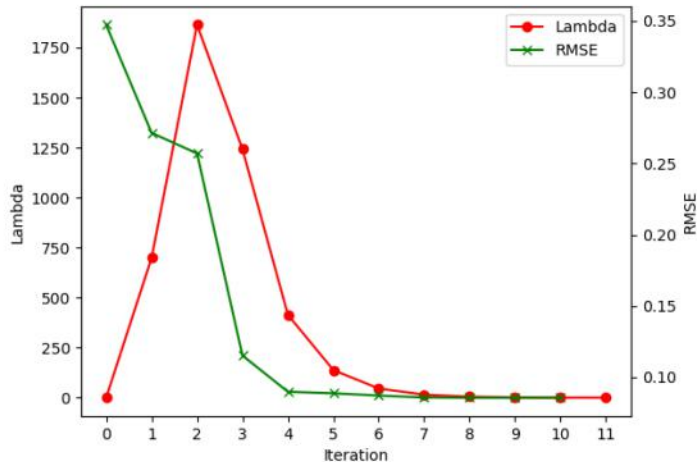
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## 第三章作业分享



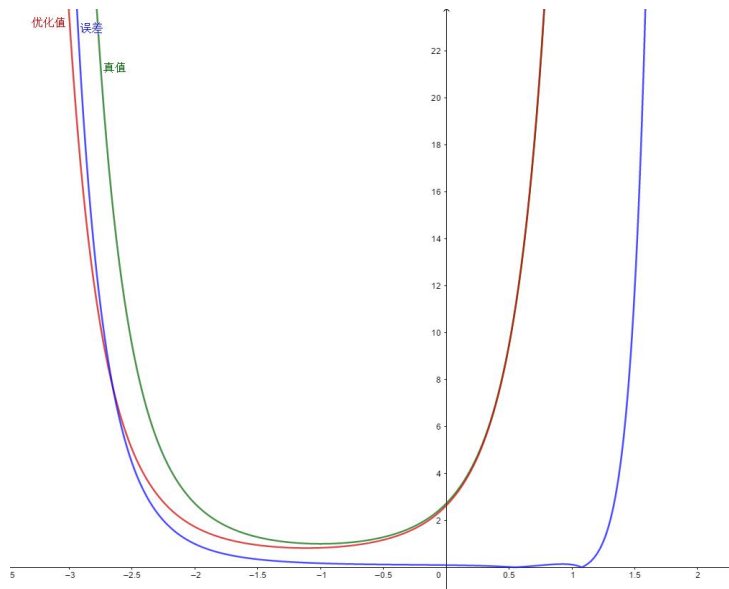
# 第一题

## 1.1 绘制阻尼因子随迭代的变化曲线图

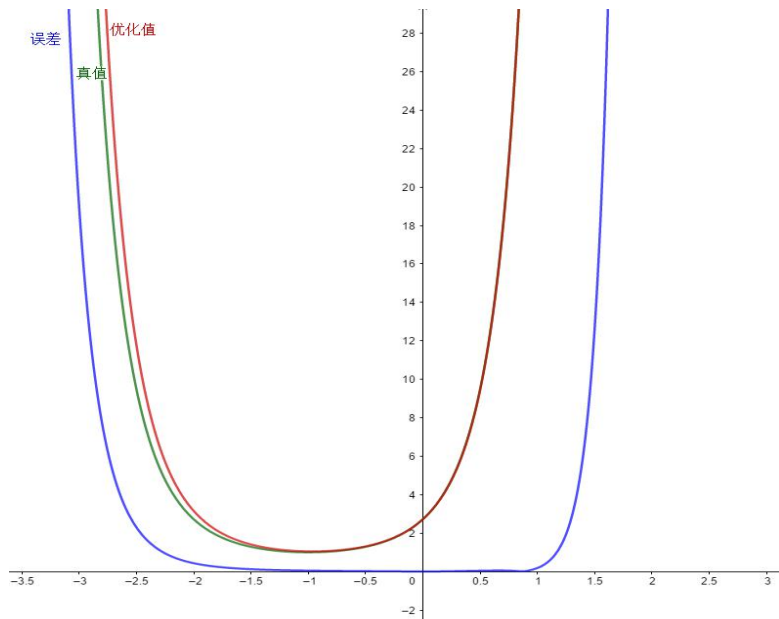


# 第一题

## 1.1 绘制阻尼因子随迭代的变化曲线图



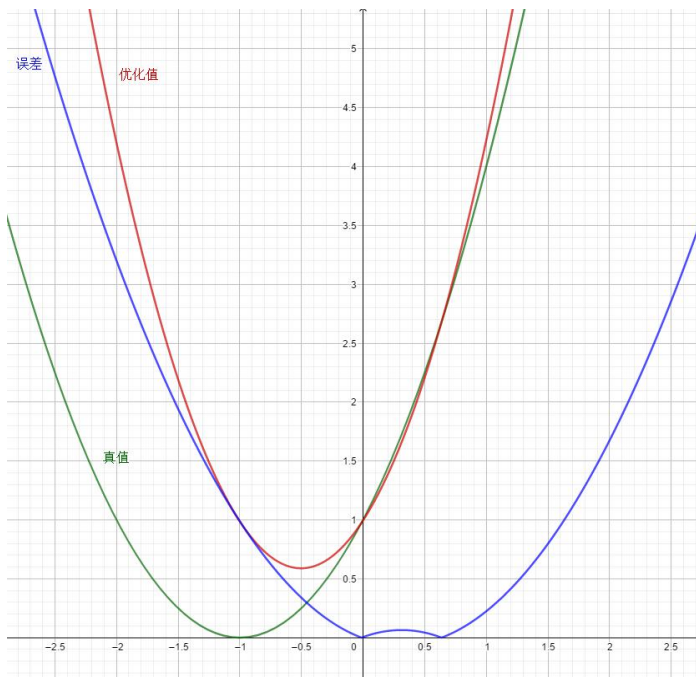
默认采样区间:  $[0, 1]$



扩大后的采样区间:  $[-1, 1]$

# 第一题

## 1.2 LM求解 $y = ax^2 + bx + c$



```
// 观测 y
// double y = std::exp( a*x*x + b*x + c ) + n;
double y = a*x*x + b*x + c + n;
// double y = std::exp( a*x*x + b*x + c );
```

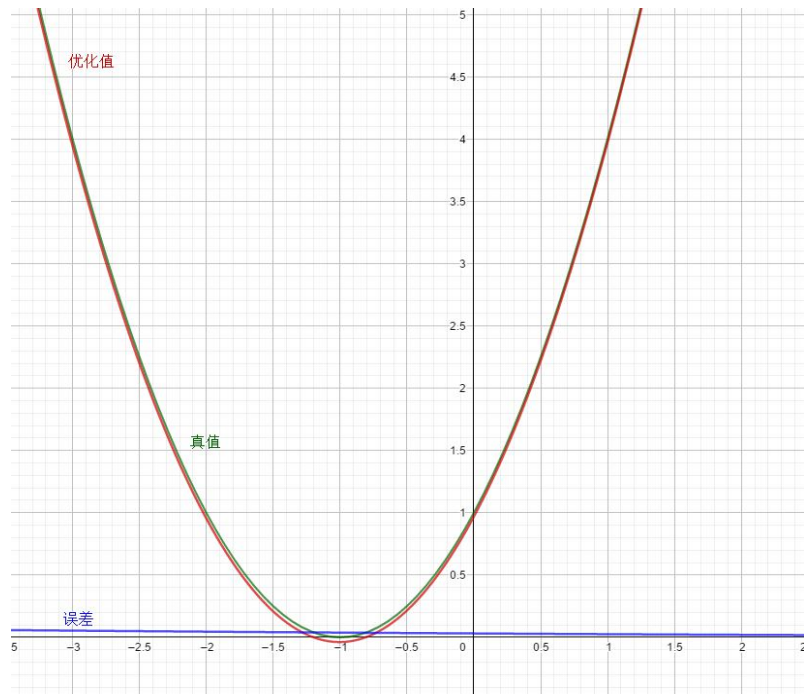
```
// 计算残差对变量的雅克比
virtual void ComputeJacobians() override
{
    Vec3 abc = vertices_[0]->Parameters();
    double exp_y = std::exp( x_abc(index:0)*x_ + abc(index:1)*x_ + abc(index:2) );

    Eigen::Matrix<double, 1, 3> jaco_abc; // 误差为1维, 状态量 3 个, 所以是 1x3 的雅克比矩阵
    // jaco_abc << x_ * x_ * exp_y, x_ * exp_y, 1 * exp_y;
    jaco_abc << x_ * x_, x_, 1;
    jacobians_[0] = jaco_abc;
}
```

```
// 计算曲线模型误差
virtual void ComputeResidual() override
{
    Vec3 abc = vertices_[0]->Parameters(); // 估计的参数
    // residual_[0] = std::exp( abc(0)*x_ + abc(1)*x_ + abc(2) ) - y_; // 构建残差
    residual_(index:0) = abc(index:0)*x_ + abc(index:1)*x_ + abc(index:2) - y_; // 构建残差
}
```

# 第一题

## ● 1.2 LM求解 $y = ax^2 + bx + c$



采样区间:  $[0, 10]$

# 第一题

## ● 1.3 实现更优秀的阻尼因子策略

论文 The Levenberg-Marquardt method for nonlinear least squares curve-fitting problems 4.1.1 节中提供了 3 种不同的阻尼因子更新策略。我的作业里主要实现了第2种。

策略摘要：

1. 选择一个合适的系数 $\tau$ （由经验确定），并设置初始阻尼因子 $\lambda_0 = \tau \max\{\text{diag}[\mathbf{J}^\top \mathbf{W} \mathbf{J}]\}$ （ $\mathbf{W}$ 为权重矩阵）。

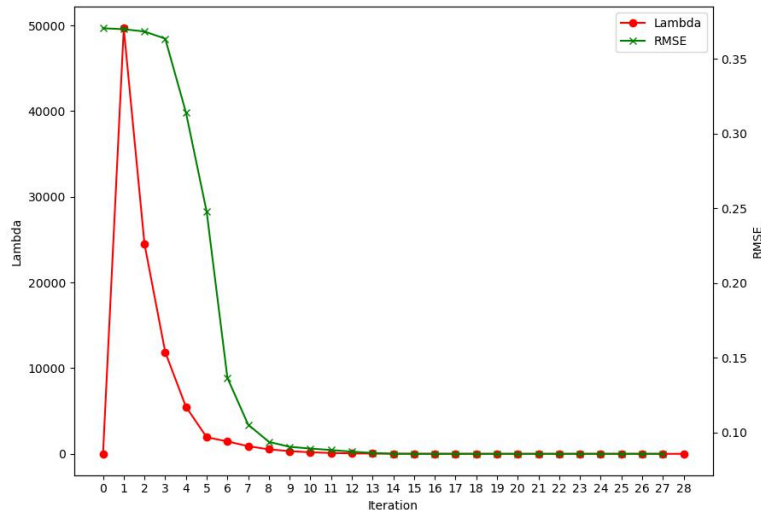
$$2. \text{ 计算 } \alpha = \frac{\left( (\mathbf{J}^\top \mathbf{W} (\mathbf{y} - \bar{\mathbf{y}}(\mathbf{p})))^\top \mathbf{h} \right)}{\left( \left( \chi^2(\mathbf{p} + \mathbf{h}) - \chi^2(\mathbf{p}) \right) /_{2+2} (\mathbf{J}^\top \mathbf{W} (\mathbf{y} - \bar{\mathbf{y}}(\mathbf{p})))^\top \mathbf{h} \right)}$$

3. 如果 $\rho(\alpha \mathbf{h})$ 大于阈值（经验确定，一般可设置为0），更新 $\lambda \leftarrow \max\{\lambda / (1 + \alpha), 10^{-7}\}$ ，更新 $\mathbf{p} \leftarrow \mathbf{p} + \alpha \mathbf{h}$

4. 否则，更新 $\lambda \leftarrow \lambda + |\chi^2(\mathbf{p} + \alpha \mathbf{h}) - \chi^2(\mathbf{p})| /_{2\alpha}$

# 第一题

## 1.3 实现更优秀的阻尼因子策略



同样的初始参数拟合 $e^{ax^2+bx+c}$

迭代数比Nielson策略多，RMSE达到同样数量级的迭代数量接近。

最终的RMSE接近，拟合得到的参数效果近似（区间内都能较好逼近，区间外偏差较大）

# 第二题

●  $f_{15}$

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

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

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

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



## 第二题

●  $g_{12}$

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

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

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

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

# 第三题

## ●证明式(9)

1. 所有损失函数 $f_i$ 都是实函数+ $J^T J$ 是半正定矩阵  $\Rightarrow J^T J$ 是实对称矩阵, 可对角正交化
2. 对角正交化形式:  $J^T J = V \Lambda V^T \Rightarrow V$ 是正交矩阵,  $V$ 满秩,  $\text{colspan } V = \mathbb{R}^n$
3.  $\Delta x_{lm}, -F'^T$  可被 $\{v_1, v_2, \dots, v_n\}$ 线性表示。 $\{v_1, v_2, \dots, v_n\}$ 是 $J^T J$ 的特征向量, 对应特征值 $\{\lambda_1, \lambda_2, \dots, \lambda_n\}$ 。

$$\begin{aligned}(J^T J + \mu I) \Delta x_{lm} &= J^T J \Delta x_{lm} + \mu I \Delta x_{lm} \\ &= J^T J \sum_{i=1}^n x_i v_i + \mu \sum_{i=1}^n x_i v_i \\ &= \sum_{i=1}^n x_i J^T J v_i + \mu x_i v_i \\ &= \sum_{i=1}^n x_i \lambda_i v_i + \mu x_i v_i \\ &= \sum_{i=1}^n x_i (\lambda_i + \mu) v_i\end{aligned}$$

$$\begin{aligned}-F'^T &= -\sum_{i=1}^n f_i v_i = \sum_{i=1}^n x_i (\lambda_i + \mu) v_i \\ x_i (\lambda_i + \mu) &= -f_i \\ x_i &= -\frac{f_i}{\lambda_i + \mu}\end{aligned}$$

$$\begin{aligned}f_i v_i &= \text{proj}_{v_i} F'^T = \frac{F'^T \cdot v_i}{v_i \cdot v_i} v_i \\ f_i v_i &= (F'^T \cdot v_i) v_i \\ f_i &= F'^T \cdot v_i\end{aligned}$$

$$\Delta x_{lm} = -\sum_{i=1}^n \frac{F'^T \cdot v_i}{\lambda_i + \mu} v_i = -\sum_{i=1}^n \frac{v_i^T F'^T}{\lambda_i + \mu} v_i$$

**感谢各位聆听 !**  
Thanks for Listening

