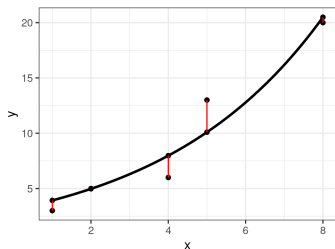
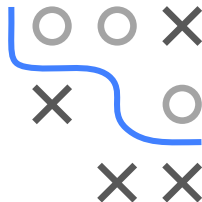


# Optimization in Machine Learning

## Second order methods

### Gauss-Newton



#### Learning goals

- Least squares
- Gauss-Newton
- Levenberg-Marquardt

# LEAST SQUARES PROBLEM

Consider the problem of minimizing a sum of squares

$$\min_{\theta} g(\theta),$$

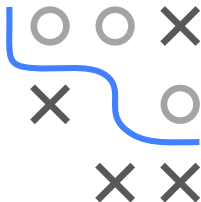
where

$$g(\theta) = r(\theta)^\top r(\theta) = \sum_{i=1}^n r_i(\theta)^2$$

and

$$\begin{aligned} r : \mathbb{R}^d &\rightarrow \mathbb{R}^n \\ \theta &\mapsto (r_1(\theta), \dots, r_n(\theta))^\top \end{aligned}$$

maps parameters  $\theta$  to residuals  $r(\theta)$



# LEAST SQUARES PROBLEM / 2

Risk minimization with squared loss  $L(y, f(\mathbf{x})) = (y - f(\mathbf{x}))^2$

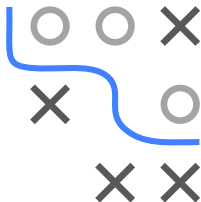
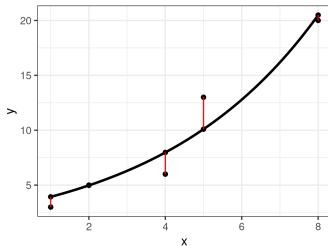
Least squares regression:

$$\mathcal{R}_{\text{emp}}(\theta) = \sum_{i=1}^n L(y^{(i)}, f(\mathbf{x}^{(i)} | \theta)) = \sum_{i=1}^n \underbrace{(y^{(i)} - f(\mathbf{x}^{(i)} | \theta))^2}_{r_i(\theta)^2}$$

- $f(\mathbf{x}^{(i)} | \theta)$  might be a function that is **nonlinear in  $\theta$**
- Residuals:  $r_i = y^{(i)} - f(\mathbf{x}^{(i)} | \theta)$

**Example:**

$$\begin{aligned}\mathcal{D} &= \left( (\mathbf{x}^{(i)}, y^{(i)}) \right)_{i=1, \dots, 5} \\ &= ((1, 3), (2, 7), (4, 12), (5, 13), (7, 20))\end{aligned}$$



# LEAST SQUARES PROBLEM / 3

Suppose, we suspect an *exponential* relationship between  $x \in \mathbb{R}$  and  $y$

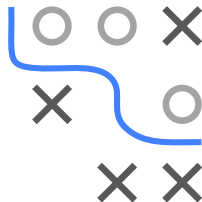
$$f(x | \theta) = \theta_1 \cdot \exp(\theta_2 \cdot x), \quad \theta_1, \theta_2 \in \mathbb{R}$$

**Residuals:**

$$r(\theta) = \begin{pmatrix} \theta_1 \exp(\theta_2 x^{(1)}) - y^{(1)} \\ \theta_1 \exp(\theta_2 x^{(2)}) - y^{(2)} \\ \theta_1 \exp(\theta_2 x^{(3)}) - y^{(3)} \\ \theta_1 \exp(\theta_2 x^{(4)}) - y^{(4)} \\ \theta_1 \exp(\theta_2 x^{(5)}) - y^{(5)} \end{pmatrix} = \begin{pmatrix} \theta_1 \exp(1\theta_2) - 3 \\ \theta_1 \exp(2\theta_2) - 7 \\ \theta_1 \exp(4\theta_2) - 12 \\ \theta_1 \exp(5\theta_2) - 13 \\ \theta_1 \exp(7\theta_2) - 20 \end{pmatrix}$$

**Least squares problem:**

$$\min_{\theta} g(\theta) = \min_{\theta} \sum_{i=1}^5 \left( y^{(i)} - \theta_1 \exp(\theta_2 x^{(i)}) \right)^2$$



# NEWTON-RAPHSON IDEA

**Approach:** Calculate Newton-Raphson update direction by solving:

$$\nabla^2 g(\theta^{[t]}) \mathbf{d}^{[t]} = -\nabla g(\theta^{[t]}).$$

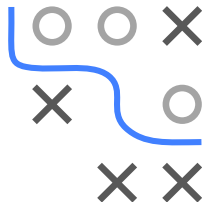
Gradient is calculated via chain rule

$$\nabla g(\theta) = \nabla(r(\theta)^\top r(\theta)) = 2 \cdot J_r(\theta)^\top r(\theta),$$

where  $J_r(\theta)$  is Jacobian of  $r(\theta)$ .

In our example:

$$J_r(\theta) = \begin{pmatrix} \frac{\partial r_1(\theta)}{\partial \theta_1} & \frac{\partial r_1(\theta)}{\partial \theta_2} \\ \frac{\partial r_2(\theta)}{\partial \theta_1} & \frac{\partial r_2(\theta)}{\partial \theta_2} \\ \vdots & \vdots \\ \frac{\partial r_5(\theta)}{\partial \theta_1} & \frac{\partial r_5(\theta)}{\partial \theta_2} \end{pmatrix} = \begin{pmatrix} \exp(\theta_2 x^{(1)}) & x^{(1)} \theta_1 \exp(\theta_2 x^{(1)}) \\ \exp(\theta_2 x^{(2)}) & x^{(2)} \theta_1 \exp(\theta_2 x^{(2)}) \\ \exp(\theta_2 x^{(3)}) & x^{(3)} \theta_1 \exp(\theta_2 x^{(3)}) \\ \exp(\theta_2 x^{(4)}) & x^{(4)} \theta_1 \exp(\theta_2 x^{(4)}) \\ \exp(\theta_2 x^{(5)}) & x^{(5)} \theta_1 \exp(\theta_2 x^{(5)}) \end{pmatrix}$$



## NEWTON-RAPHSON IDEA / 2

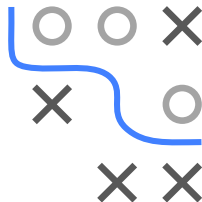
Hessian of  $g$ ,  $\mathbf{H}_g = (H_{jk})_{jk}$ , is obtained via product rule:

$$H_{jk} = 2 \sum_{i=1}^n \left( \frac{\partial r_i}{\partial \theta_j} \frac{\partial r_i}{\partial \theta_k} + r_i \frac{\partial^2 r_i}{\partial \theta_j \partial \theta_k} \right)$$

But:

**Main problem with Newton-Raphson:**

Second derivatives can be computationally expensive.



# GAUSS-NEWTON FOR LEAST SQUARES

Gauss-Newton approximates  $\mathbf{H}_g$  by dropping its second order part:

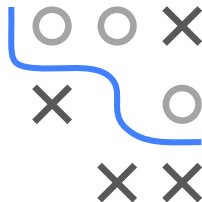
$$\begin{aligned} H_{jk} &= 2 \sum_{i=1}^n \left( \frac{\partial r_i}{\partial \theta_j} \frac{\partial r_i}{\partial \theta_k} + r_i \frac{\partial^2 r_i}{\partial \theta_j \partial \theta_k} \right) \\ &\approx 2 \sum_{i=1}^n \frac{\partial r_i}{\partial \theta_j} \frac{\partial r_i}{\partial \theta_k} \\ &= 2J_r(\boldsymbol{\theta})^\top J_r(\boldsymbol{\theta}) \end{aligned}$$

**Note:** We assume that

$$\left| \frac{\partial r_i}{\partial \theta_j} \frac{\partial r_i}{\partial \theta_k} \right| \gg \left| r_i \frac{\partial^2 r_i}{\partial \theta_j \partial \theta_k} \right|.$$

This assumption may be valid if:

- Residuals  $r_i$  are small in magnitude or
- Functions are only “mildly” nonlinear s.t.  $\frac{\partial^2 r_i}{\partial \theta_j \partial \theta_k}$  is small.



# GAUSS-NEWTON FOR LEAST SQUARES / 2

If  $J_r(\theta)^\top J_r(\theta)$  is invertible, Gauss-Newton update direction is

$$\begin{aligned}\mathbf{d}^{[t]} &= - \left[ \nabla^2 g(\theta^{[t]}) \right]^{-1} \nabla g(\theta^{[t]}) \\ &\approx - \left[ J_r(\theta^{[t]})^\top J_r(\theta^{[t]}) \right]^{-1} J_r(\theta^{[t]})^\top r(\theta) \\ &= -(J_r^\top J_r)^{-1} J_r^\top r(\theta)\end{aligned}$$

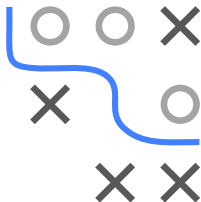
**Advantage:**

Reduced computational complexity since no Hessian necessary.

**Note:** Gauss-Newton can also be derived by starting with

$$r(\theta) \approx r(\theta^{[t]}) + J_r(\theta^{[t]})^\top (\theta - \theta^{[t]}) = \tilde{r}(\theta)$$

and  $\tilde{g}(\theta) = \tilde{r}(\theta)^\top \tilde{r}(\theta)$ . Then, set  $\nabla \tilde{g}(\theta)$  to zero.





# LEVENBERG-MARQUARDT ALGORITHM

- **Problem:** Gauss-Newton may not decrease  $g$  in every iteration but may diverge, especially if starting point is far from minimum
- **Solution:** Choose step size  $\alpha > 0$  s.t.

$$\mathbf{x}^{[t+1]} = \mathbf{x}^{[t]} + \alpha \mathbf{d}^{[t]}$$

decreases  $g$  (e.g., by satisfying Wolfe conditions)

- However, if  $\alpha$  gets too small, an **alternative** method is the

## Levenberg-Marquardt algorithm

$$(J_r^\top J_r + \lambda D) \mathbf{d}^{[t]} = -J_r^\top r(\theta)$$

- $D$  is a positive diagonal matrix
- $\lambda = \lambda^{[t]} > 0$  is the *Marquardt parameter* and chosen at each step

