

# **Q & A: Linear Regression**

Lecture Series „Machine Learning“

Niels Landwehr

Research Group „Data Science“  
Institute of Computer Science  
University of Hildesheim

# Quiz: Linear Regression

- Assume we want to learn a linear regression model  $f: \mathbb{R}^2 \rightarrow \mathbb{R}$  of the form

$$f(\mathbf{x}) = \theta_0 + \theta_1 x_1 + \theta_2 x_2$$

where  $\mathbf{x} = (x_1, x_2)^T \in \mathbb{R}^2$  is the input and  $\boldsymbol{\theta} = (\theta_0, \theta_1, \theta_2)^T \in \mathbb{R}^3$  is the parameter vector

- Assume a data set of three training examples  $\mathcal{D} = \{(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), (\mathbf{x}_3, y_3)\}$  given by

$$\mathbf{X} = \begin{pmatrix} 1 & 1 & 1 \\ 1 & -1 & 1 \\ 1 & 1 & 2 \end{pmatrix} \begin{matrix} \mathbf{x}_1 \\ \mathbf{x}_2 \\ \mathbf{x}_3 \end{matrix} \quad \mathbf{y} = \begin{pmatrix} 2 \\ -2 \\ 3 \end{pmatrix}$$

$x_0 \quad x_1 \quad x_2$

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- Consider the following parameter vectors  $\boldsymbol{\theta}_1, \boldsymbol{\theta}_2, \boldsymbol{\theta}_3$ . Which of the parameter vectors has the lowest squared loss?

$$\boldsymbol{\theta}_1 = \begin{pmatrix} 1 \\ 2 \\ -1 \end{pmatrix} \quad \boldsymbol{\theta}_2 = \begin{pmatrix} 1 \\ -2 \\ 1 \end{pmatrix} \quad \boldsymbol{\theta}_3 = \begin{pmatrix} -1 \\ 2 \\ 1 \end{pmatrix}$$

# Quiz: Linear Regression

- **Solution:** The predictions for the three different parameter vectors  $\theta_1, \theta_2, \theta_3$  are:

$$\hat{y}_1 = \mathbf{X}\theta_1 = \begin{pmatrix} 1 & 1 & 1 \\ 1 & -1 & 1 \\ 1 & 1 & 2 \end{pmatrix} \begin{pmatrix} 1 \\ 2 \\ -1 \end{pmatrix} = \begin{pmatrix} 2 \\ -2 \\ 1 \end{pmatrix} \rightarrow \text{Loss is } \frac{1}{3} \left\| \begin{pmatrix} 2 \\ -2 \\ 1 \end{pmatrix} - \begin{pmatrix} 2 \\ -2 \\ 3 \end{pmatrix} \right\|_2^2 = \frac{1}{3}(0 + 0 + 4) = \frac{4}{3}$$

$$\hat{y}_2 = \mathbf{X}\theta_2 = \begin{pmatrix} 1 & 1 & 1 \\ 1 & -1 & 1 \\ 1 & 1 & 2 \end{pmatrix} \begin{pmatrix} 1 \\ -2 \\ 1 \end{pmatrix} = \begin{pmatrix} 0 \\ 4 \\ 1 \end{pmatrix} \rightarrow \text{Loss is } \frac{1}{3} \left\| \begin{pmatrix} 0 \\ 4 \\ 1 \end{pmatrix} - \begin{pmatrix} 2 \\ -2 \\ 3 \end{pmatrix} \right\|_2^2 = \frac{1}{3}(4 + 36 + 4) = \frac{44}{3}$$

$$\hat{y}_3 = \mathbf{X}\theta_3 = \begin{pmatrix} 1 & 1 & 1 \\ 1 & -1 & 1 \\ 1 & 1 & 2 \end{pmatrix} \begin{pmatrix} -1 \\ 2 \\ 1 \end{pmatrix} = \begin{pmatrix} 2 \\ -2 \\ 3 \end{pmatrix} \rightarrow \text{Loss is } \frac{1}{3} \left\| \begin{pmatrix} 2 \\ -2 \\ 3 \end{pmatrix} - \begin{pmatrix} 2 \\ -2 \\ 3 \end{pmatrix} \right\|_2^2 = 0$$

# Quiz: Convexity

- Is the function  $f : \mathbb{R}_{>0} \rightarrow \mathbb{R}$  given by  $f(x) = x^2 + x - \log x$  convex?

↑  
natural logarithm
- A1: Yes, it is convex everywhere where the function is defined
- A2: It is convex only for  $x > 1$
- A3: It is not convex

# Quiz: Convexity

- Is the function  $f : \mathbb{R}_{>0} \rightarrow \mathbb{R}$  given by  $f(x) = x^2 + x - \log x$  convex?
- **Solution:** Yes, it is convex everywhere where it is defined. We use the criterion that the second derivative of the function is positive everywhere.

Compute derivatives:

$$f'(x) = 2x + 1 - x^{-1} \quad \text{Note: } \frac{\partial}{\partial x} \log x = \frac{1}{x}$$
$$f''(x) = 2 + x^{-2}$$
$$= 2 + \frac{1}{x^2}$$

- The second derivative  $f''(x)$  is positive everywhere. Therefore the function is convex (special case of Hessian criterion mentioned in the lecture)

# Quiz: Gradient Descent

- We want to minimize the function  $L : \mathbb{R} \rightarrow \mathbb{R}$ ,  $L(\theta) = \theta^2$  using gradient descent with a learning rate  $\eta \in \mathbb{R}$
- Question 1: Which of the following is the correct update rule?
  1.  $\theta_{i+1} = \theta_i - \eta\theta_i^2$
  2.  $\theta_{i+1} = \theta_i + 2\eta\theta_i$
  3.  $\theta_{i+1} = \theta_i - 2\eta\theta_i$
  4.  $\theta_{i+1} = \theta_i - \theta_i$
- Question 2: We initialize the gradient descent procedure with  $\theta_0 = 1$ . For which learning rates  $\eta$  will gradient descent find the correct minimum?
  - 1. For all learning rates  $\eta \in \mathbb{R}$
  - 2. For all learning rates  $\eta \in \mathbb{R}_{>0}$
  - 3. For all learning rates  $\eta \in (0,1]$
  - 4. For all learning rates  $\eta \in (0,1)$
  - 5. Only for learning rates  $\eta < 0.01$

# Quiz: Gradient Descent

- **Solution update rule:** The correct update rule is

$$\begin{aligned}\theta_{i+1} &= \theta_i - \eta \nabla L(\theta_i) \\ &= \theta_i - 2\eta \theta_i\end{aligned}$$

# Quiz: Gradient Descent

- **Solution update rule:** The correct update rule is

$$\begin{aligned}\theta_{i+1} &= \theta_i - \eta \nabla L(\theta_i) \\ &= \theta_i - 2\eta \theta_i\end{aligned}$$

- **Solution convergence:** we first note that the minimum is at  $\theta = 0$

- Let's try  $\eta = 1$ :

$$\left. \begin{aligned}\theta_0 &= 1 \\ \theta_1 &= \theta_0 - 2\theta_0 = -1 \\ \theta_2 &= \theta_1 - 2\theta_1 = 1 \\ \theta_3 &= \theta_2 - 2\theta_2 = -1\end{aligned} \right\} \rightarrow \text{This is not converging}$$

- Basically,  $\eta < 1$  is needed such that  $|\theta|$  is reduced in every iteration:

$$|\theta_{i+1}| = |\theta_i - 2\eta\theta_i| = |(1 - 2\eta)\theta_i| = \underbrace{|1 - 2\eta|}_{< 1, \text{ so } \eta < 1} |\theta_i|$$

- Of course,  $\eta$  also needs to be positive. Therefore  $\eta \in (0, 1)$  is the right solution.