

Blatt 5

Aufgabe 1.

(a) $\psi = x^T A x + b^T x + \alpha$ $\frac{\partial \psi}{\partial x} = 0$
 mit chain rule and $\frac{\partial (x^T y)}{\partial x} = y$

$$\frac{d(f(x, y))}{dx} = \frac{\partial (f(x, y))}{\partial x} + \frac{d(y^T(x))}{dx} \cdot \frac{\partial (f(x, y))}{\partial y}$$

haben wir

$$① \frac{d(b^T x)}{dx} = \frac{d(x^T b)}{dx} = b$$

$$② \frac{d(x^T A x)}{dx} = \frac{\partial (x^T y)}{\partial x} + \frac{d(y^T(x))}{dx} \cdot \frac{\partial (x^T y)}{\partial y} \quad \text{mit } y = Ax$$

Dann

$$\begin{aligned} &= y + \frac{d(x^T A^T)}{dx} \cdot x \\ &= y + A^T x \\ &= (A + A^T)x \end{aligned}$$

Zusammen:

$$\frac{\partial \psi}{\partial x} = (A + A^T)x + b$$

$$(b) \tau = \sum_{i=1}^n (y_i - \beta(x_i^T w + b))^2 \quad \text{mit } \beta(\alpha) = \frac{1}{1 + \exp(-\alpha)}$$

$$1) \text{ wenn } y_i = 1, \text{ gilt } (1 - \beta(x_i^T w + b))^2 = 1 - 2\beta(x_i^T w + b) + \beta(x_i^T w + b)^2$$

$$\text{wenn } y_i = 0 \text{ gilt } (-\beta(x_i^T w + b))^2 = \beta(x_i^T w + b)^2$$

$$\text{Zusammen } \tau = 1 - 2\beta(x_i^T w + b) + 2\beta(x_i^T w + b)^2$$

$$2) \beta(\alpha) = \frac{1}{1 + \exp(-\alpha)} \quad \text{dann}$$

$$\beta(x_i^T w + b) = \frac{1}{1 + \exp(-x_i^T w + b)}$$

$$3) \frac{d}{dw} \cdot \frac{d}{db} (\tau) = \frac{d^2}{dw db} (-2\beta(x_i^T w + b) + 2\beta^2(x_i^T w + b))$$

$$= -2 \cdot \frac{d}{db} \cdot \left(-\frac{x_i^T e^{x_i^T w + b}}{(1 + e^{x_i^T w + b})^2} \right) + 2 \frac{d^2}{dw db} \beta^2(x_i^T w + b)$$

$$= -2 \cdot \left(-\frac{x_i^T e^{x_i^T w + b} \cdot (-e^{x_i^T w + b} + 1)}{(1 + e^{x_i^T w + b})^3} \right) + 2 \frac{d^2}{dw db} \beta^2(x_i^T w + b)$$

$$= \frac{2x_i^T \cdot e^{x_i^T w + b} \cdot (-e^{x_i^T w + b} + 1)}{(1 + e^{x_i^T w + b})^3} + 2 \frac{d}{db} \left(\frac{-2x_i^T e^{x_i^T w + b}}{(1 + e^{x_i^T w + b})^3} \right)$$

$$= \frac{2x_i^T \cdot e^{x_i^T w + b} \cdot (-e^{x_i^T w + b} + 1) \cdot (1 + e^{x_i^T w + b})}{(1 + e^{x_i^T w + b})^4} + \frac{(-4x_i^T e^{x_i^T w + b} \cdot (-2e^{x_i^T w + b} + 1))}{(1 + e^{x_i^T w + b})^4}$$

$$= \frac{2x_i^T \cdot e^{x_i^T w + b} (1 - e^{2x_i^T w + 2b} - 2 - 4e^{x_i^T w + b})}{(1 + e^{x_i^T w + b})^4}$$

c), $x, y \in \mathbb{R}^n$, $A, B \in \mathbb{R}^{m \times m}$

From $\|x\|_2^2 = x^T x$

sei $B(x) = c$

$$\begin{aligned} \text{Dann } \|y - Ac\|_2^2 &= (y - Ac)^T (y - Ac) \\ &= y^T y - (Ac)^T y - y^T Ac + c^T A^T A c \\ &= y^T y - 2(A^T y)^T c + c^T A^T A c \end{aligned}$$

$$\text{Dann } \nabla (\|y - Ac\|_2^2) = -2A^T y + (A^T A + (A^T A)^T) c$$

$$\text{mit } (A^T A)^T = A^T (A^T)^T = A^T A$$

$$\begin{aligned} \text{Dann } \nabla (\|y - Ac\|_2^2) &= 2(A^T A c - A^T y) \\ &= 2(A^T A B(x) - A^T y) \end{aligned}$$

d) $d(\phi^\alpha) = \alpha \phi^{\alpha-1} d\phi$ same as power rule $f(x) = x^n \rightarrow f'(x) = n x^{n-1}$

IA. (base case). $n=1$, $f(x) = x$, $f'(x) = (1)x^{1-1} = x^0 = 1$

IS. assume $[x^n]' = n x^{n-1}$, proof $[x^{n+1}]' = (n+1)x^n$
 $\Rightarrow f(x) = x^{n+1} = x^n \cdot x$, $f'(x) = (n x^{n-1})x + (x^n) \cdot (1) = n x^n + x^n = (n+1)x^n$

same

IA. $\alpha=1$ $d(\phi^1) = 1 \cdot \phi^0 d\phi = 1$. $1 = \phi^0$ ✓

IS. $\alpha=n$ assume $d(\phi^\alpha) = \alpha \phi^{\alpha-1} d\phi$. proof $d(\phi^{\alpha+1}) = (\alpha+1) \phi^\alpha d\phi$
 $\Rightarrow d(\phi^{\alpha+1}) = d(\phi^\alpha) * d(\phi^1) = \alpha \phi^{\alpha-1} d\phi \cdot 1 \cdot \phi^0 d\phi$
 $\quad \quad \quad = \alpha \phi^\alpha + \phi^\alpha$
 $\quad \quad \quad = (\alpha+1) \phi^\alpha$

Aufgabe 3. $p(y|x, w) = \mathcal{N}(y|xw, \sigma^2 I) = \frac{1}{\sigma \sqrt{2\pi} I} \exp\left(-\frac{(y-xw)^2}{2\sigma^2 I}\right)$

mit $\mathcal{D} = \{(x_1, y_1), \dots, (x_n, y_n)\}$

$$P_w(\mathcal{D}) = \prod_{i=1}^n P_w(y_i|x_i)$$

Dann

$$w^* = \arg \max_w P_w(\mathcal{D})$$

$$= \arg \max_{w \in \mathbb{R}^d} \sum_{i=1}^n \log P_w(y_i|x_i)$$

\Rightarrow mit log-likelihood.

$$\log P_w(\mathcal{D}) = \sum_{i=1}^n \log P_w(y_i|x_i)$$

$$= \sum_{i=1}^n \log \left[\frac{1}{\sigma \sqrt{2\pi} I} \exp\left(-\frac{(y_i - x_i w)^2}{2\sigma^2 I}\right) \right]$$

$$= \underbrace{\sum_{i=1}^n \log \left[\frac{1}{\sigma \sqrt{2\pi} I} \right]}_{\text{independent of } w} + \sum_{i=1}^n \left(-\frac{(y_i - x_i w)^2}{2\sigma^2 I} \right)$$

D.h. jetzt

$$w^* = \arg \min_{w \in \mathbb{R}^d} \sum_{i=1}^n (y_i - w^T x_i)^2 \quad \text{mit} \quad X = \begin{pmatrix} - & x_1 & - \\ & \vdots & \\ - & x_n & - \end{pmatrix}$$

$$y = (y_1, \dots, y_n)^T$$

$$\text{Dann } \sum_{i=1}^n (y_i - w^T x_i)^2 = (y - w^T X)^T (y - w^T X)$$

$$= y^T y - 2w^T X^T y + w^T X^T X w$$

\Leftrightarrow respect to w and equating to 0

$$2X^T X w - 2X^T y = 0$$

$$\Leftrightarrow X^T X w = X^T y$$

$$\Rightarrow w^* = (X^T X)^{-1} X^T y$$