

Logistic regression:

$$P(y_1 | x) = \frac{P(y_1|x)P(x)}{P(y_1)} = \frac{P(y_1|x)P(x)}{P(y_1|x)P(x) + P(y_2|x)P(x)} = \frac{1}{1 + \frac{P(y_2|x)P(x)}{P(y_1|x)P(x)}} = \frac{1}{1 + \exp(-\alpha)}$$

mit

$$\alpha = -\ln \left(\frac{P(y_2|x)P(x)}{P(y_1|x)P(x)} \right)$$

Regression: berechne α als $\alpha = w_{k,0} + \sum_{d=1}^D w_{k,d}x_d = \sum_{d=0}^D w_{k,d}x_d$

Lernen: Minimiere Log Likelihood $-P(y_1 | w_0, w_1, \dots, w_N) - P(y_1 | w_0, w_1, \dots, w_N) = -\ln \prod_{n=1}^N \prod_{k=1}^K P(y_k | x_n)^{y_{nk}} = -\sum_{n=1}^N \sum_{k=1}^K y_{nk} \ln P(y_k | x_k)$

Nur 2 Klassen: $-P(y_1 | w_0, w_1, \dots, w_N) - P(y_1 | w_0, w_1, \dots, w_N) = -\ln \prod_{n=1}^N P(y_1 | x_n)^{y_{n1}} P(y_2 | x_n)^{y_{n2}} = -\sum_{n=1}^N y_{n1} \ln P(y_{1k} | x_k) + y_{n2} \ln P(y_{2k} | x_k)$

Einsetzen der oberen Definition:

$$\mathcal{L} = -P(y_1 | w_0, w_1, \dots, w_N) = -\sum_{n=1}^N \sum_{k=1}^D y_{nd} \ln \frac{1}{1 + \exp(\sum_{i=0}^D w_{nd}x_d)}$$

Ableitung der Log Likelihood:

$$\frac{\partial \mathcal{L}}{\partial w_{ml}} = -\sum_{n=1}^N \sum_{k=1}^K y_{nk} (1 + \exp(\sum_{d=0}^D w_{nd}x_d)) (-x_l \exp(-\sum_{d=0}^D w_{nd}x_d)) \frac{1}{(1 + \exp(\sum_{i=0}^D w_{nd}x_d))^2}$$

das ist gleich:

$$-\sum_{n=1}^N \sum_{k=1}^K y_{nk} (-x_l \exp(\sum_{d=0}^D w_{nd}x_d)) \frac{1}{(1 + \exp(\sum_{i=0}^D w_{nd}x_d))}$$

das ist gleich:

$$\sum_{n=1}^N \sum_{k=1}^K y_{nk} \frac{x_l}{(1 + \exp(-\sum_{i=0}^D w_{nd}x_d))}$$

$$P(y_1 | x) = \frac{1}{1 + \frac{P(y_2|x)P(x)}{P(y_1|x)P(x)}}$$

$$\mathcal{L}(w) = \prod_{i=1}^N P(y_i | x_i, w)$$

$$\begin{aligned}
\mathcal{L}(w) &= \prod_{i=1}^N P(y_i \mid x_i, w) \\
&= \prod_{i=1}^N P(y_i \mid x_i, w)^{y_i} + (1 - P(y_i \mid x_i, w))^{1-y_i}
\end{aligned} \tag{1}$$

$$\begin{aligned}
\ell(w) &= \ln(\mathcal{L}(w)) \\
&= \sum_{i=1}^N y_i P(y_i \mid x_i, w) + (1 - y_i)(1 - P(y_i \mid x_i, w))
\end{aligned} \tag{2}$$

$$P(y_1 \mid x_1, x_2) = P(y_1 \mid x)$$

$$P(y_2 \mid x) = 1 - P(y_1 \mid x)$$

Linear regression:
 $P(y \mid x, w) = \prod$