

Oct. 24, 2019

Pairs

samples

(x_i, y_i)

e.g. $y_i = [0010]$

k classes e.g. $k=4$

Reminder: $\sigma(x^T w) = \frac{\exp(x^T w)}{1 + \exp(x^T w)}$

Contrast (one-vs-rest): Separate log-regression predictor

$$\text{probs} = \begin{bmatrix} \sigma(x^T w_1) \\ \sigma(x^T w_2) \\ \vdots \\ \sigma(x^T w_k) \end{bmatrix} = \begin{bmatrix} \exp(x^T w_1) / (1 + \exp(x^T w_1)) \\ \vdots \\ \exp(x^T w_k) / (1 + \exp(x^T w_k)) \end{bmatrix}$$

$x \in \mathbb{R}^d$

$w_1 \in \mathbb{R}^d, \dots, w_k \in \mathbb{R}^d$

$$W = [w_1 \ w_2 \ \dots \ w_k]$$

Softmax for multinomial logistic regression

$$\text{probs} = \text{softmax}(x^T W) = \begin{bmatrix} \exp(x^T w_1) / \sum_{m=1}^k \exp(x^T w_m) \\ \vdots \\ \exp(x^T w_k) / \sum_{m=1}^k \exp(x^T w_m) \end{bmatrix}$$

Difference 1: probs for softmax sum to 1
but not for separate binary classifiers

e.g. $\exp(x^T w_1)$ is really big (1000) (for class 1)
what does this mean for prob of class 2

Modelling assumpt. $p(y|x)$ as a joint distribution

e.g. $p(y = \{0, 1, 0\} | x)$

Separate binary case: we use $\rightarrow [p(y_1=1|x), \dots, p(y_k=1|x)]$

Update: for each $m=1, \dots, k$ $(\text{softmax}(x^T w)_m - y_m) x$

generic: $(\underbrace{f(x^T w)}_{\hat{y}} - y) x$
for GLMs

Objective: $p(y|x) = p(y_1=1|x)^{y_1} p(y_2=1|x)^{y_2} \dots p(y_k=1|x)^{y_k}$

minimize $-\log\text{-likelihood}$

$$-\ln p(y|x) = - \sum_{m=1}^k \ln [p(y_m=1|x)^{y_m}] \quad \text{s.t. only one } y_m=1$$

$$= - \sum_{m=1}^k y_m \ln p(y_m=1|x)$$

$$\ln p(y_m = 1 | x) = \ln \frac{\exp(x^T w_m)}{\sum_{r=1}^k \exp(x^T w_r)}$$

$$\begin{aligned} \Rightarrow -\ln p(y|x) &= -\sum_{m=1}^k y_m \left[\ln \exp(x^T w_m) - \ln \sum_{r=1}^k \exp(x^T w_r) \right] \\ &= -\sum_{m=1}^k y_m \left[x^T w_m - \ln \sum_{r=1}^k \exp(x^T w_r) \right] \end{aligned}$$

Exercise: Show $\frac{\partial [-\ln p(y|x)]}{\partial \vec{w}_m} = \left[\frac{\exp(x^T w_m)}{\sum_{r=1}^k \exp(x^T w_r)} - y_m \right] x$

$$\nabla - \sum_{i=1}^n \ln p(y_i | x_i) \stackrel{!}{=} 0$$

Is there a closed form for W ?