

# Constraint relaxation algorithm

## Definitions

$$n \in \mathbb{N}$$

$$X = \mathbb{R}^n$$

$$Y = \{0, 1\}$$

$$L(r, \hat{y}) = -r\hat{y} + \log_p(1 + p^r)$$

$$f_\theta(x) : X \rightarrow \mathbb{R}, x \mapsto \langle \theta, x \rangle$$

$$S \subseteq X, S = \{x_1, x_2, \dots, x_{|S|}\}, k = |S|$$

$$\inf_{(\theta, \varphi) \in X \times Y^S} \frac{\lambda}{2} \|\theta\|_2^2 + \sum_{x_i \in S} L(f_\theta(x_i), \varphi_{x_i})$$

$$\theta := \begin{pmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{pmatrix}$$

## Derivatives

$$\frac{\partial R + L(f_\theta(x_i), \varphi_{x_i})}{\partial w_d} = \lambda w_d + x_{id} \left( -\varphi_{x_i} + \frac{1}{p^{-f_\theta(x_i)} + 1} \right)$$

$$\nabla_\theta R + L(f_\theta(x_i), \varphi_{x_i}) = \lambda \theta + \left( -\varphi_{x_i} + \frac{1}{p^{-f_\theta(x_i)} + 1} \right) x_i$$

$$\frac{\partial L(f_\theta(x_i), \varphi_{x_i})}{\partial \varphi_{x_i}} = -f_\theta(x_i)$$

$$G = \nabla \left( R + \sum_{x_i \in S} L(f_\theta(x_i), \varphi_{x_i}) \right) = \begin{pmatrix} \lambda w_1 + \sum_{x_i \in S} x_{i1} \left( -\varphi_{x_i} + \frac{1}{p^{-f_\theta(x_i)} + 1} \right) \\ \lambda w_2 + \sum_{x_i \in S} x_{i2} \left( -\varphi_{x_i} + \frac{1}{p^{-f_\theta(x_i)} + 1} \right) \\ \vdots \\ \lambda w_n + \sum_{x_i \in S} x_{in} \left( -\varphi_{x_i} + \frac{1}{p^{-f_\theta(x_i)} + 1} \right) \\ -f_\theta(x_1) \\ \vdots \\ -f_\theta(x_k) \end{pmatrix} = \begin{pmatrix} G_\theta \\ G_\varphi \end{pmatrix}$$