

MFDNN

Homework 12

24/06/15

1. (Workings)

$$L(\underline{\theta}, \underline{\phi}) = \frac{1}{N} \sum_{i=1}^N \log(1 + \exp(-\gamma_i (\mathbf{x}_i - \underline{\phi})^T \underline{\theta})) - \frac{\lambda}{2} \|\underline{\phi}\|^2$$

$$= \frac{1}{N} \sum_{i=1}^N \log(1 + \exp(-\gamma_i \sum_{k=1}^p ((\mathbf{x}_i)_k - \phi_k) \theta_k)) - \frac{\lambda}{2} \sum_{k=1}^p \phi_k^2$$

$$\nabla_{\underline{\phi}} L(\underline{\theta}, \underline{\phi}) = \frac{1}{N} \sum_{i=1}^N \frac{\gamma_i \underline{\theta} \exp(-\gamma_i (\mathbf{x}_i - \underline{\phi})^T \underline{\theta})}{1 + \exp(-\gamma_i (\mathbf{x}_i - \underline{\phi})^T \underline{\theta})} - \lambda \underline{\phi}$$

$$\nabla_{\underline{\theta}} L(\underline{\theta}, \underline{\phi}) = \frac{1}{N} \sum_{i=1}^N \frac{\gamma_i (\underline{\phi} - \mathbf{x}_i) \exp(-\gamma_i (\mathbf{x}_i - \underline{\phi})^T \underline{\theta})}{1 + \exp(-\gamma_i (\mathbf{x}_i - \underline{\phi})^T \underline{\theta})}$$

2. $f(u) = \begin{cases} u \log \frac{u}{\lambda+u} + \lambda \log \frac{\lambda}{\lambda+u} + (1+\lambda) \log(1+\lambda) - \lambda \log \lambda, & u \geq 0 \\ \infty, & \text{otherwise} \end{cases}$

$$\frac{\partial}{\partial u} (u(\lambda+u)^{-1}) = \frac{1}{\lambda+u} - \frac{u}{(\lambda+u)^2} \quad x(\lambda+u)$$

$$\frac{\partial}{\partial u} (\lambda(\lambda+u)^{-1}) = \frac{-\lambda}{(\lambda+u)^2} \quad x(\lambda+u)$$

$$\frac{\partial}{\partial u} (tu - f(u)) = t - \left(\log \frac{u}{\lambda+u} + \frac{\lambda}{\lambda+u} - \frac{\lambda}{\lambda+u} \right) = 0 \quad \text{when maximised}$$

$$\Leftrightarrow e^t = \frac{u}{\lambda+u} \Leftrightarrow \lambda e^t + u e^t = u \Leftrightarrow u(1-e^t) = \lambda e^t \Leftrightarrow u = \frac{\lambda}{e^{-t}-1}$$

$f^*(t) = \sup_{u \in \mathbb{R}} \{tu - f(u)\}$ \swarrow if $u \geq 0 \Leftrightarrow t < 0$

$$= \frac{t\lambda}{e^{-t}-1} - \frac{\lambda}{e^{-t}-1} \log \frac{1}{e^{-t}} - \lambda \log \frac{e^{-t}-1}{e^{-t}} - (1+\lambda) \log(1+\lambda) + \lambda \log \lambda$$

$$= \frac{t\lambda}{e^{-t}-1} - \frac{t\lambda}{e^{-t}-1} - \lambda \log(1-e^t) - (1+\lambda) \log(1+\lambda) + \lambda \log \lambda$$

$$= \lambda \log \lambda - (1+\lambda) \log(1+\lambda) - \lambda \log(1-e^t) \quad \text{for } t < 0, \text{ otherwise } f^*(t) = \infty$$

minimise $D_f(p_{true} \| p_\theta) = \underset{\theta}{\text{minimise}} \underset{\phi}{\text{maximise}} E_{\mathbf{x} \sim p_{true}} [\rho(D_\phi(\mathbf{x}))] - E_{\tilde{\mathbf{x}} \sim p_\theta} [f^*(\rho(D_\phi(\tilde{\mathbf{x}})))], \text{ by slide 131}$

\swarrow for infinitely expressive D_ϕ

With $\rho(r) = \log(r)$ to ensure $t < 0$ since $D_\phi: \mathbb{R}^n \rightarrow (0,1)$, (as on slide 134)

$$\underset{\theta}{\text{minimise}} D_f(p_{true} \| p_\theta) = \underset{\theta}{\text{minimise}} \underset{\phi}{\text{maximise}} E_{\mathbf{x} \sim p_{true}} [\log D_\phi(\mathbf{x})] + E_{\tilde{\mathbf{x}} \sim p_\theta} [\lambda \log(1 - D_\phi(\tilde{\mathbf{x}}))] - \lambda \log \lambda - (1+\lambda) \log(1+\lambda)$$

$$= \underset{\theta}{\text{minimise}} \underset{\phi}{\text{maximise}} E_{\mathbf{x} \sim p_{true}} [\log D_\phi(\mathbf{x})] + \lambda E_{\tilde{\mathbf{x}} \sim p_\theta} [\log(1 - D_\phi(\tilde{\mathbf{x}}))] \quad \blacksquare$$

