

## Lec 18

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Recap: last time: Various first-order optimization algos  
that is, algos that use gradient info  
i.e. only first deriv

Fitting NNs w/ Gradient Descent:

Back propagation

$$R(\theta) = \sum_i \sum_k L(y_{ik}, f_k(x_i; \theta))$$

e.g. regression  $L(y, \hat{y}) = (y - \hat{y})^2$

classification  $L(y, \hat{p}) = -y \log \hat{p}$

$\theta = \{ \text{all the weights } w_{0k}, w_{1k}, \beta_{0k}, \beta_k$   
parameterizing our vanilla neural net }

Want  $\theta$  to min  $R(\theta)$

Use first-order methods

So need to compute  $\nabla R(\theta)$

The key: chain rule

$$\frac{\partial z}{\partial x} = \frac{\partial z}{\partial y} \cdot \frac{\partial y}{\partial x}$$

Focus on  $L(y, \hat{y}) = (y - \hat{y})^2$

$\frac{\partial}{\partial x} (x - y)^2 = 2(x - y) \cdot \frac{\partial}{\partial x} (x - y) = 2(x - y) \cdot 1 = 2(x - y)$

$$f(x_i; \theta) = \beta_k x_i + \beta_0 \quad (g_k = \text{identity})$$

$$R(\theta) = \sum_i \underbrace{\sum_k (y_{ik} - f_k(x_i; \theta))^2}_{R_i(\theta)}$$

Want  $\frac{\partial R_i}{\partial \beta_{km}}$ ,  $\frac{\partial R_i}{\partial d_{ml}}$  for all  $k, m, l$

$$\frac{\partial R_i}{\partial \beta_{km}} = \sum_{k'} \frac{\partial R_i}{\partial f_{k'}(x_i)} \cdot \underbrace{\frac{\partial f_{k'}(x_i)}{\partial \beta_{km}}}_{=0 \text{ whenever } k \neq k'}$$

$$= \frac{\partial R_i}{\partial f_k(x_i)} \cdot \frac{\partial f_k(x_i)}{\partial \beta_{km}}$$

$$= \underbrace{-2(y_{ik} - f_k(x_i))}_{\delta_{ki}} z_{mi} \quad \left. \begin{array}{l} \text{convention} \\ z_{0i} = 1 \end{array} \right\}$$

$$\frac{\partial R_i}{\partial d_{ml}} = \sum_k \frac{\partial R_i}{\partial f_k(x_i)} \sum_{m'} \frac{\partial f_k(x_i)}{\partial z_{m'l}} \underbrace{\frac{\partial z_{m'l}}{\partial d_{ml}}}_{=0 \text{ whenever } m \neq m'}$$

$$= \sum_k \frac{\partial R_i}{\partial f_k(x_i)} \frac{\partial f_k(x_i)}{\partial z_{ml}} \frac{\partial z_{ml}}{\partial d_{ml}}$$

$$= \sum_k \underbrace{(-2(y_{ik} - f_k(x_i)) \beta_{km} \sigma'(z_m) x_{il})}_{\delta_{ki}}$$

$$S_{mi} = \sum_k \delta_{ki} \cdot \beta_{km} \sigma(\beta_{km}) \quad \text{back prop}$$

$$\frac{\partial R_i}{\partial \beta_{km}} = \sum_k \delta_{ki} z_{mi}$$

$$\frac{\partial R_i}{\partial \alpha_{ml}} = S_{mi} x_{il}$$

"errors"