

# Back Propagation and the Chain Rule

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December 19, 2017

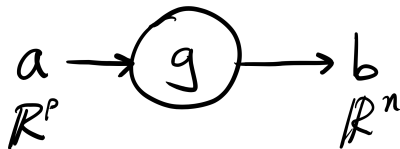
# Learning with Back-Propagation

- Back-propagation is an **algorithm** for computing the gradient
- With lots of chain rule, you could also work out the gradient by hand.
- Back-propagation is
  - a clean way to organize the computation of the gradient
  - an efficient way to compute the gradient

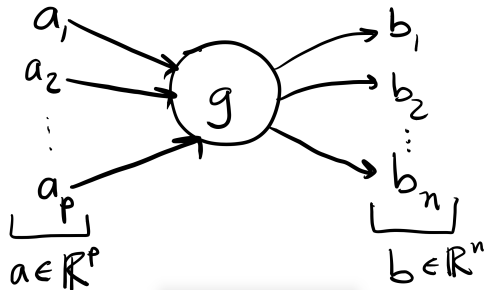
# Partial Derivatives

- Consider a function  $g: \mathbb{R}^p \rightarrow \mathbb{R}^n$ .

- Typical computation graph:

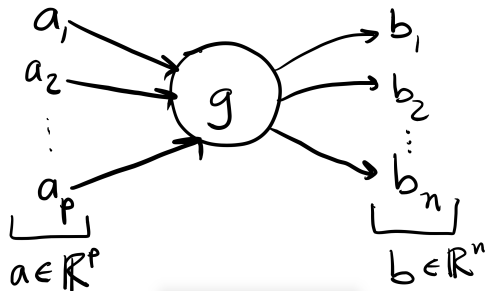


- Broken out into components:



# Partial Derivatives

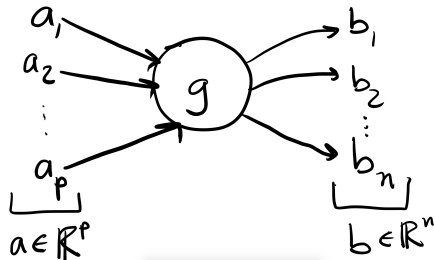
- Consider a function  $g : \mathbb{R}^p \rightarrow \mathbb{R}^n$ .



- Partial derivative  $\frac{\partial b_i}{\partial a_j}$  is the instantaneous rate of change of  $b_i$  as we change  $a_j$ .
- If we change  $a_j$  slightly to  $a_j + \delta$ ,
- Then (for small  $\delta$ ),  $b_i$  changes to approximately  $b_i + \frac{\partial b_i}{\partial a_j} \delta$ .

## Partial Derivatives of an Affine Function

- Define the affine function  $g(x) = Mx + c$ , for  $M \in \mathbf{R}^{n \times p}$  and  $c \in \mathbf{R}$ .



- If we let  $b = g(a)$ , then what is  $b_i$ ?
- $b_i$  depends on the  $i$ th row of  $M$ :

$$b_i = \sum_{k=1}^p M_{ik} a_k + c_i$$

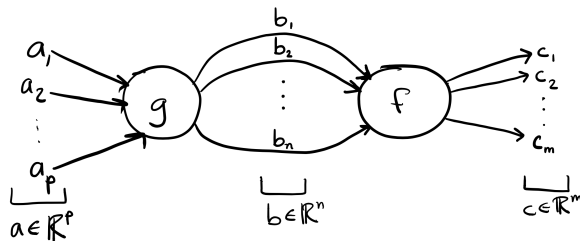
and

$$\frac{\partial b_i}{\partial a_j} = M_{ij}.$$

- So for an affine mapping, entries of matrix  $M$  directly tell us the rates of change.

## Chain Rule (in terms of partial derivatives)

- $g: \mathbb{R}^p \rightarrow \mathbb{R}^n$  and  $f: \mathbb{R}^n \rightarrow \mathbb{R}^m$ . Let  $b = g(a)$ . Let  $c = f(b)$ .



- Chain rule says that

$$\frac{\partial c_i}{\partial a_j} = \sum_{k=1}^n \frac{\partial c_i}{\partial b_k} \frac{\partial b_k}{\partial a_j}.$$

- Change in  $a_j$  may change each of  $b_1, \dots, b_n$ .
- Changes in  $b_1, \dots, b_n$  may each effect  $c_i$ .
- Chain rule tells us that, to first order, the net change in  $c_i$  is
  - the sum of the changes induced along each path from  $a_j$  to  $c_i$ .

## Example: Least Squares Regression

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## Review: Linear least squares

- Hypothesis space  $\{f(x) = w^T x + b \mid w \in \mathbf{R}^d, b \in \mathbf{R}\}$ .
- Data set  $(x_1, y_1), \dots, (x_n, y_n) \in \mathbf{R}^d \times \mathbf{R}$ .
- Define

$$\ell_i(w, b) = [(w^T x_i + b) - y_i]^2.$$

- In SGD, in each round we'd choose a random index  $i \in 1, \dots, n$  and take a gradient step

$$\begin{aligned} w_j &\leftarrow w_j - \eta \frac{\partial \ell_i(w, b)}{\partial w_j}, \text{ for } j = 1, \dots, d \\ b &\leftarrow b - \eta \frac{\partial \ell_i(w, b)}{\partial b}, \end{aligned}$$

for some step size  $\eta > 0$ .

- Let's revisit how to calculate these partial derivatives...



# Computation Graph and Intermediate Variables

- For a generic training point  $(x, y)$ , denote the loss by

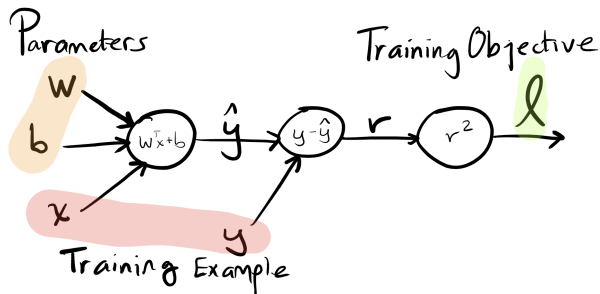
$$\ell(w, b) = [(w^T x + b) - y]^2.$$

- Let's break this down into some intermediate computations:

$$\text{(prediction)} \quad \hat{y} = \sum_{j=1}^d w_j x_j + b$$

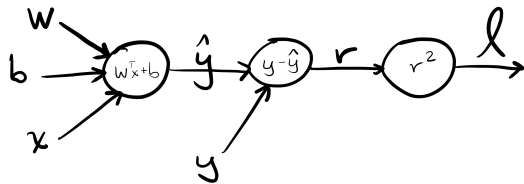
$$\text{(residual)} \quad r = y - \hat{y}$$

$$\text{(loss)} \quad \ell = r^2$$



# Partial Derivatives on Computation Graph

- We'll work our way from graph output  $\ell$  back to the parameters  $w$  and  $b$ :



$$\begin{aligned}\frac{\partial \ell}{\partial r} &= 2r \\ \frac{\partial \ell}{\partial \hat{y}} &= \frac{\partial \ell}{\partial r} \frac{\partial r}{\partial \hat{y}} = (2r)(-1) = -2r \\ \frac{\partial \ell}{\partial b} &= \frac{\partial \ell}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial b} = (-2r)(1) = -2r \\ \frac{\partial \ell}{\partial w_j} &= \frac{\partial \ell}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial w_j} = (-2r)x_j = -2rx_j\end{aligned}$$

## Example: Ridge Regression

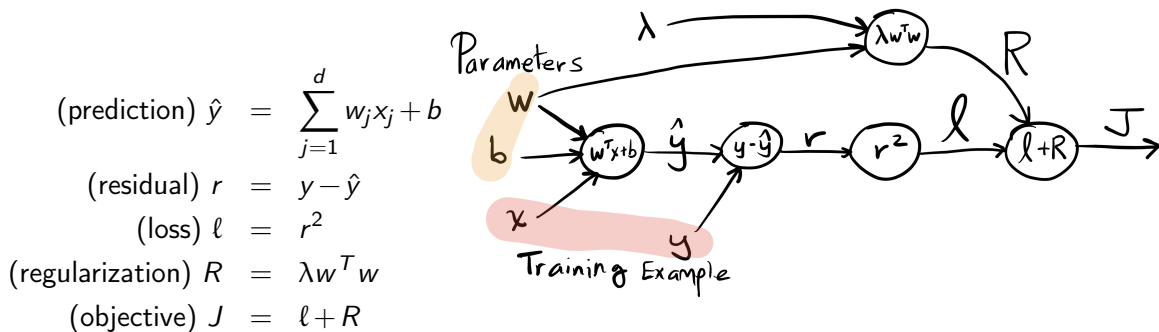
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# Ridge Regression: Computation Graph and Intermediate Variables

- For training point  $(x, y)$ , the  $\ell_2$ -regularized objective function is

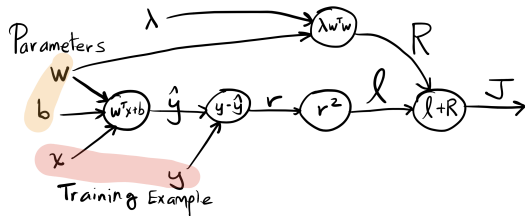
$$J(w, b) = [(w^T x + b) - y]^2 + \lambda w^T w.$$

- Let's break this down into some intermediate computations:



# Partial Derivatives on Computation Graph

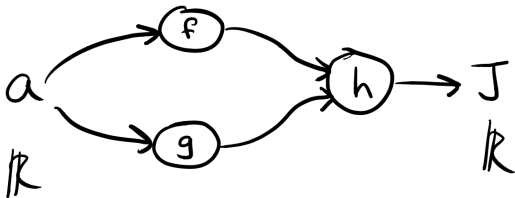
- We'll work our way from graph output  $\ell$  back to the parameters  $w$  and  $b$ :



$$\begin{aligned}\frac{\partial J}{\partial \ell} &= \frac{\partial J}{\partial R} = 1 \\ \frac{\partial J}{\partial \hat{y}} &= \frac{\partial J}{\partial \ell} \frac{\partial \ell}{\partial r} \frac{\partial r}{\partial \hat{y}} = (1)(2r)(-1) = -2r \\ \frac{\partial J}{\partial b} &= \frac{\partial J}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial b} = (-2r)(1) = -2r \\ \frac{\partial J}{\partial w_j} &= ?\end{aligned}$$

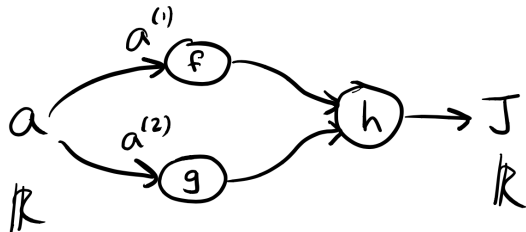
# Handling Nodes with Multiple Children

- Consider  $a \mapsto J = h(f(a), g(a))$ .



- It's helpful to think about having two independent copies of  $a$ , call them  $a^{(1)}$  and  $a^{(2)}$ ...

## Handling Nodes with Multiple Children

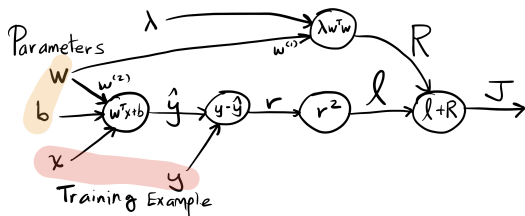


$$\begin{aligned}\frac{\partial J}{\partial a} &= \frac{\partial J}{\partial a^{(1)}} \frac{\partial a^{(1)}}{\partial a} + \frac{\partial J}{\partial a^{(2)}} \frac{\partial a^{(2)}}{\partial a} \\ &= \frac{\partial J}{\partial a^{(1)}} + \frac{\partial J}{\partial a^{(2)}}\end{aligned}$$

- Derivative w.r.t.  $a$  is the sum of derivatives w.r.t. each copy of  $a$ .

# Partial Derivatives on Computation Graph

- We'll work our way from graph output  $\ell$  back to the parameters  $w$  and  $b$ :



$$\begin{aligned} \frac{\partial J}{\partial \hat{y}} &= \frac{\partial J}{\partial \ell} \frac{\partial \ell}{\partial r} \frac{\partial r}{\partial \hat{y}} = (1)(2r)(-1) = -2r \\ \frac{\partial J}{\partial w_j^{(2)}} &= \frac{\partial J}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial w_j^{(2)}} = \frac{\partial J}{\partial \hat{y}} x_j \\ \frac{\partial J}{\partial w_j^{(1)}} &= \frac{\partial J}{\partial R} \frac{\partial R}{\partial w_j^{(1)}} = (1) \left( 2\lambda w_j^{(1)} \right) \\ \frac{\partial J}{\partial w_j} &= \frac{\partial J}{\partial w_j^{(1)}} + \frac{\partial J}{\partial w_j^{(2)}} \end{aligned}$$



# General Backpropagation

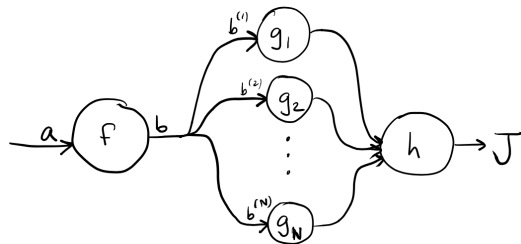
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# Backpropagation: Overview

- Backpropagation is a specific way to evaluate the partial derivatives of a computation graph output  $J$  w.r.t. the inputs and outputs of all nodes.
- Backpropagation works node-by-node.
- To run a “backward” step at a node  $f$ , we assume
  - we’ve already run “backward” for all of  $f$ ’s children.
- **Backward** at node  $f : a \mapsto b$  returns
  - Partial of objective value  $J$  w.r.t.  $f$ ’s output:  $\frac{\partial J}{\partial b}$
  - Partial of objective value  $J$  w.r.t  $f$ ’s input:  $\frac{\partial J}{\partial a}$

# Backpropagation: Simple Case

- Simple case: all nodes take a single scalar as input and have a single scalar output.

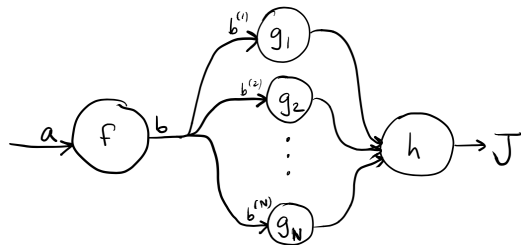


- Backprop for node  $f$ :
- Input:**  $\frac{\partial J}{\partial b^{(1)}}, \dots, \frac{\partial J}{\partial b^{(N)}}$   
(Partials w.r.t. inputs to all children)
- Output:**

$$\frac{\partial J}{\partial b} = \sum_{k=1}^N \frac{\partial J}{\partial b^{(k)}}$$
$$\frac{\partial J}{\partial a} = \frac{\partial J}{\partial b} \frac{\partial b}{\partial a}$$

# Backpropagation (General case)

- More generally, consider  $f : \mathbf{R}^d \rightarrow \mathbf{R}^n$ .



- **Input:**  $\frac{\partial J}{\partial b_j^{(i)}}$ ,  $i = 1, \dots, N$ ,  $j = 1, \dots, n$
- **Output:**

$$\frac{\partial J}{\partial b_j} = \sum_{k=1}^N \frac{\partial J}{\partial b_j^{(k)}}$$
$$\frac{\partial J}{\partial a_i} = \sum_{j=1}^n \frac{\partial J}{\partial b_j} \frac{\partial b_j}{\partial a_i}$$

# Running Backpropagation

- If we run “backward” on every node in our graph,
  - we’ll have the gradients of  $J$  w.r.t. all our parameters.
- To run backward on a particular node,
  - we assumed we already ran it on all children.
- A **topological sort** of the nodes in a directed [acyclic] graph
  - is an ordering which every node appears before its children.
- So we’ll evaluate backward on nodes in a **reverse topological ordering**.