Principles of Robot Autonomy II

Neural networks and Tensorflow tutorial

Stanford University

iliad

IPRL

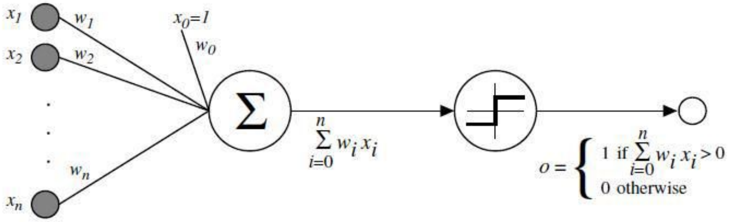
ASL
Autonomous Systems Lab

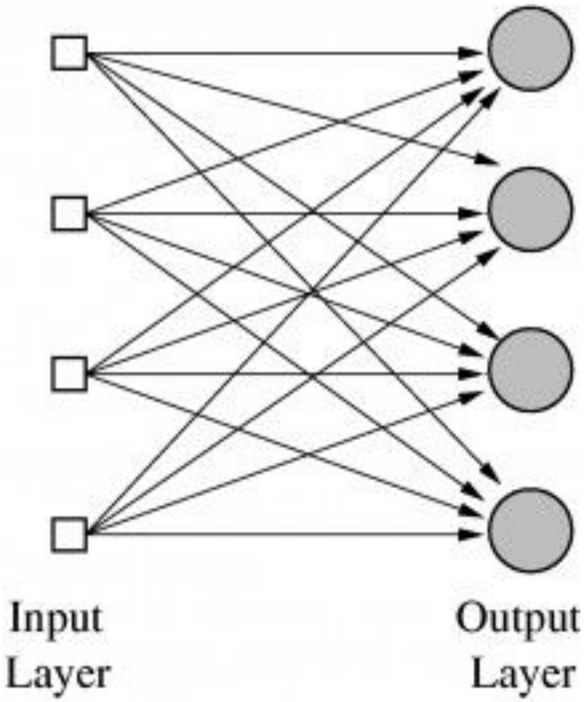
Overview

- Multi-Layer Perceptrons
- Activation Functions
- Backpropagation
- Regularization
- Tensorflow Tutorial

Single layer neural network

Original perceptron: binary inputs, binary output





$$y_1^i = f(x^i w_1 + b_1)$$

$$y_2^i = f(x^i w_2 + b_2)$$

$$y_3^i = f(x^i w_3 + b_3)$$

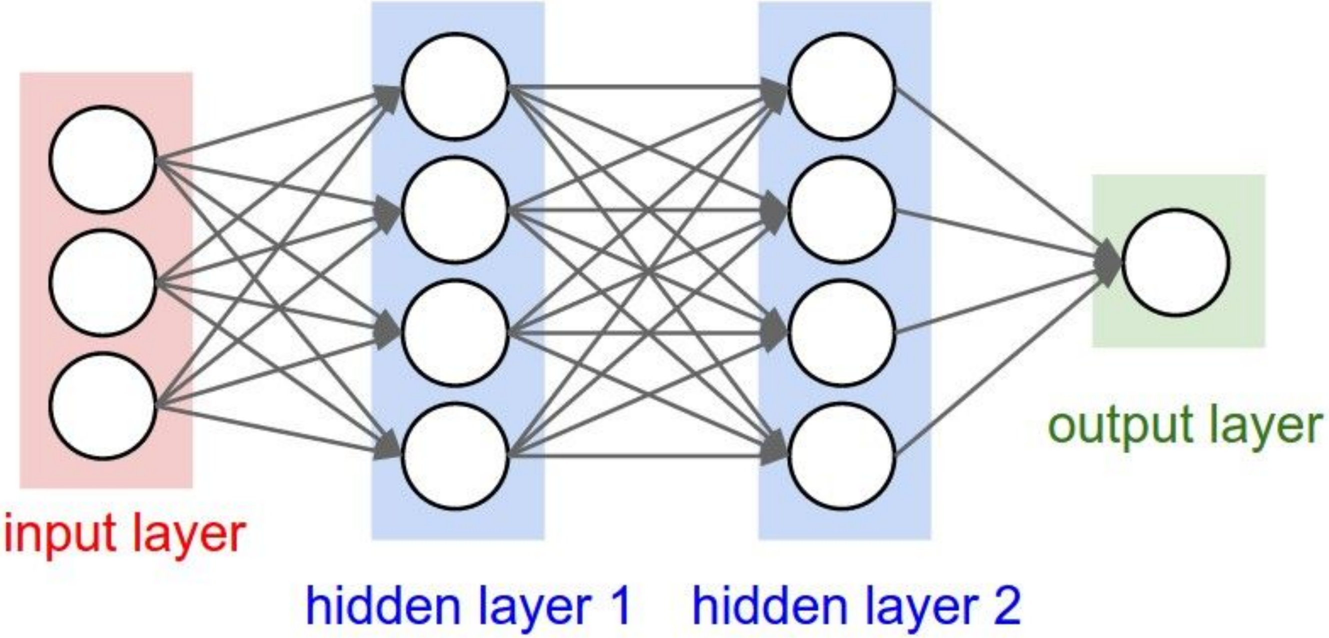
$$y_4^i = f(x^i w_4 + b_4)$$

$$\Rightarrow \quad y = f(xW + b)$$

Multi-layer neural network

Also known as the Multilayer Perceptron (MLP)

Also known as the foundations of DEEP LEARNING



$$h_1 = f_1(xW_1 + b_1)$$
$$h_2 = f_2(h_1W_2 + b_2)$$
$$y = f_3(h_2W_3 + b_3)$$

Other building blocks: convolutional layers, recurrent layers, …

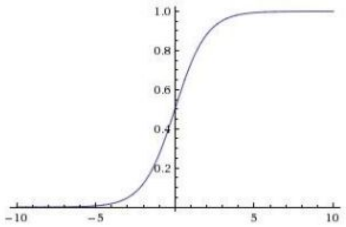
Activation functions

Can't go only linear: $y = ((xW_1 + b_1)W_2 + b_2)W_3 + b_3?$

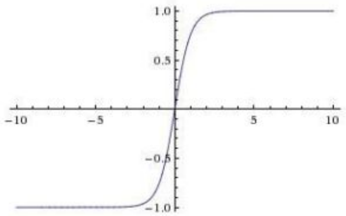
$$\implies y = xW_1W_2W_3 + (b_1W_2W_3 + b_2W_3 + b_3)$$

Sigmoid

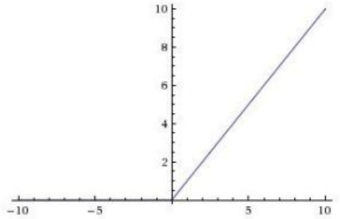
$\sigma(x) = 1/(1+e^{-x})$



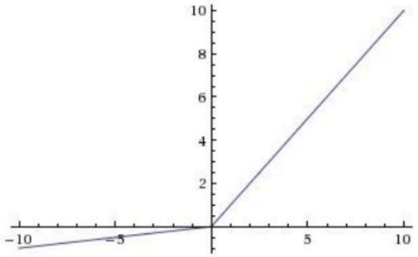
tanh tanh(x)



ReLU max(0,x)



Leaky ReLU
max(0.1x, x)



<u>Secret theme:</u>
All of these functions are super easy to differentiate

Training neural networks

We want to use some variant of gradient descent

How to compute gradients?

1. Sample a batch of data
2. Forward propagate it through the network to compute loss
3. Backpropagate to calculate the gradient of the loss with respect to the weights/biases
4. Update these parameters using SGD

The Chain Rule

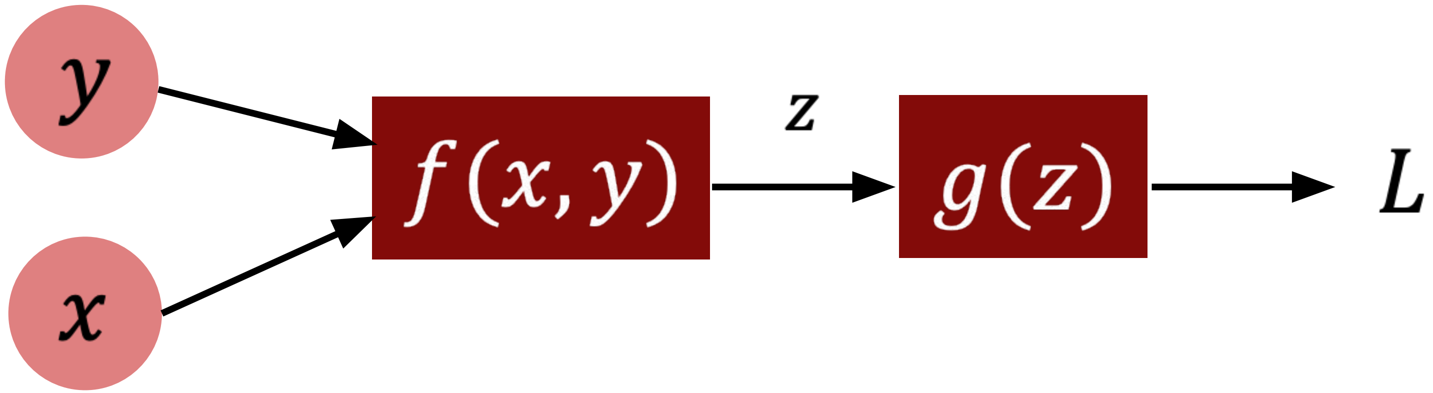
$$\nabla(f \circ g)(x) = ((Dg)(x))^T (\nabla f)(g(x))$$

Leveraging the intermediate results of forward propagation with "easy" to differentiate activation functions

 Gradient is a bunch of matrix multiplications

Backpropagation

Consider the function $L(x, y) = g(f(x, y))$



Backpropagation

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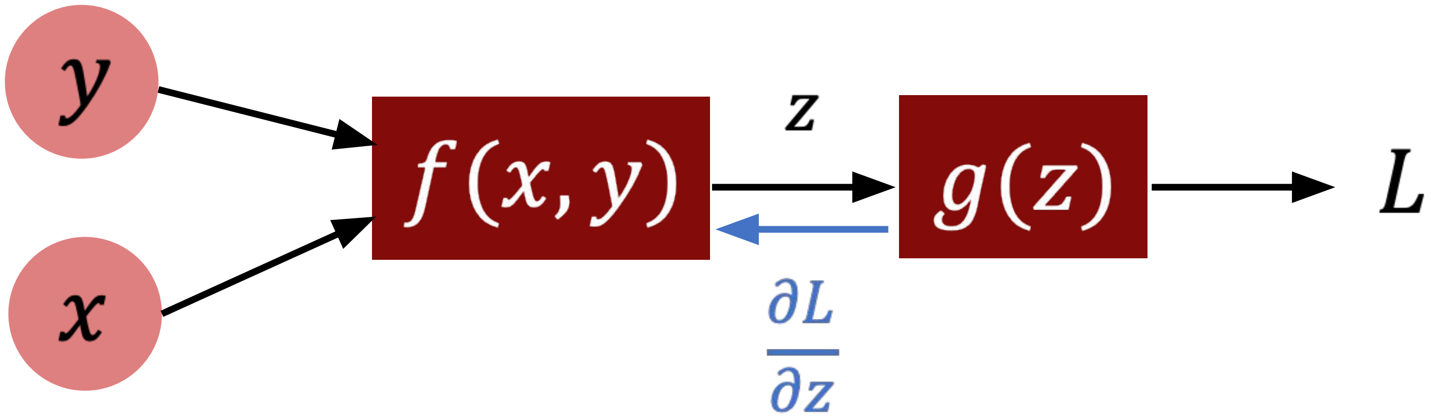

Backpropagation

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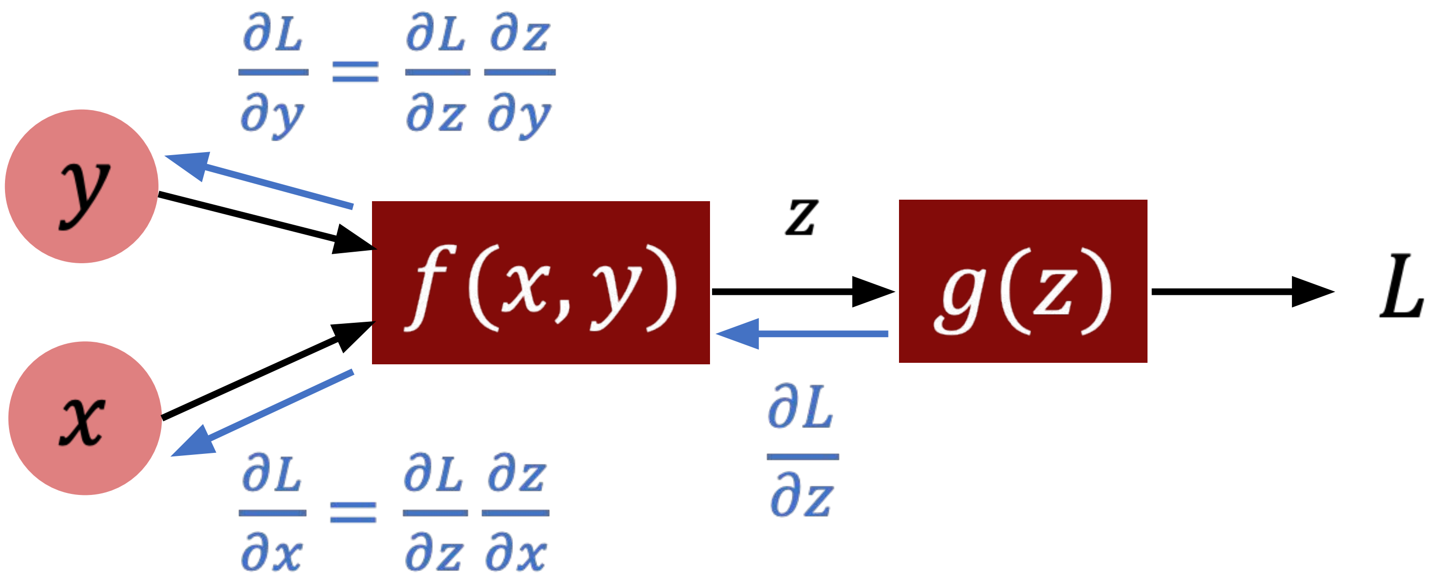

Training a simple model

- Consider the parametric model $f(x) = (x + a)(x + b)$ trained with L_2 loss $L_i = (y_i - f(x_i))^2$

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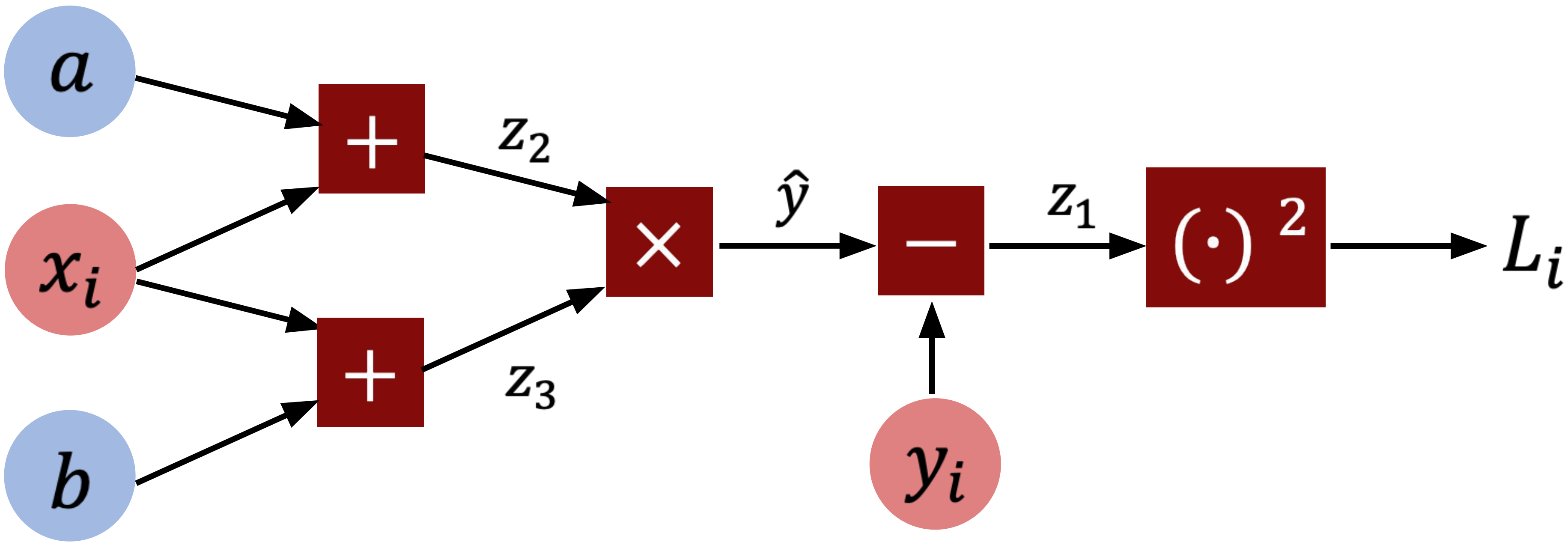
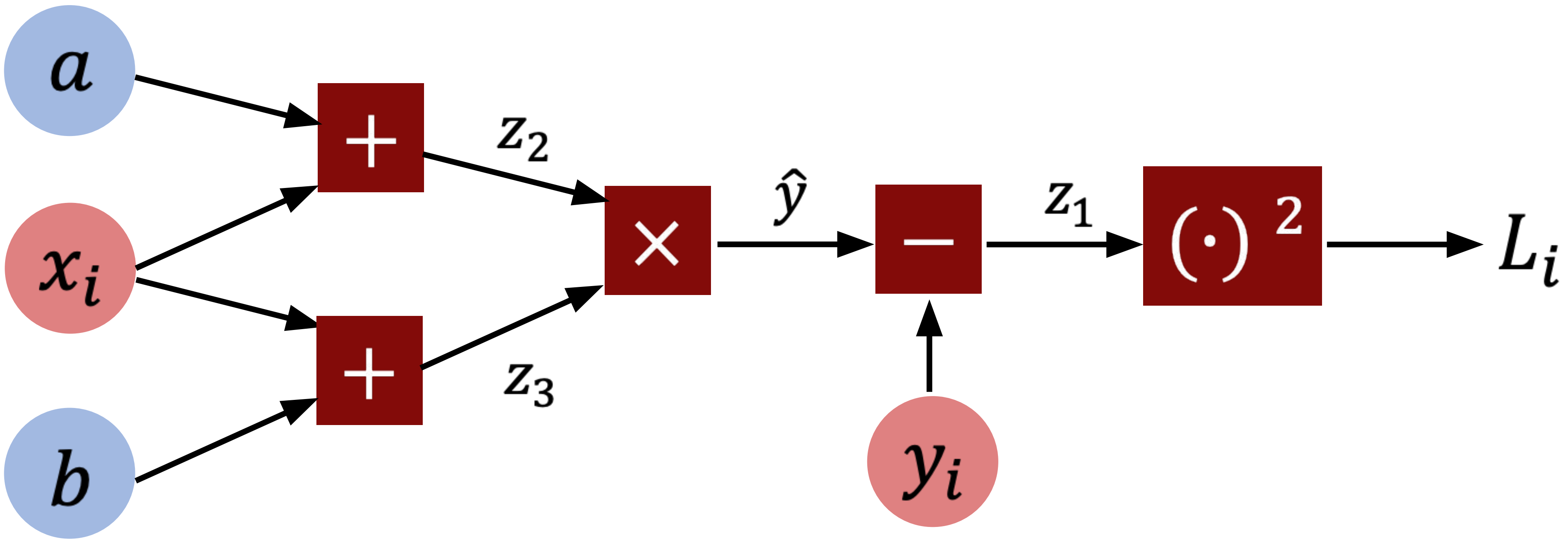


Training a simple model

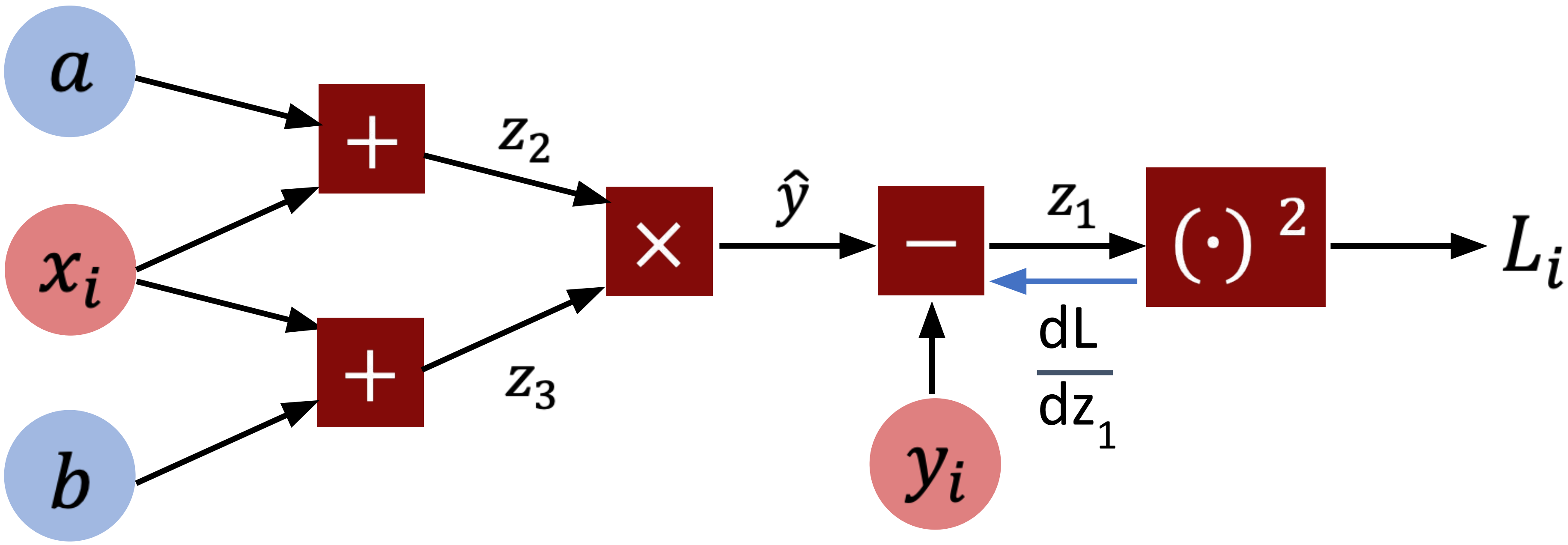
Consider a forward pass

5 total operations, corresponding to each node in the graph

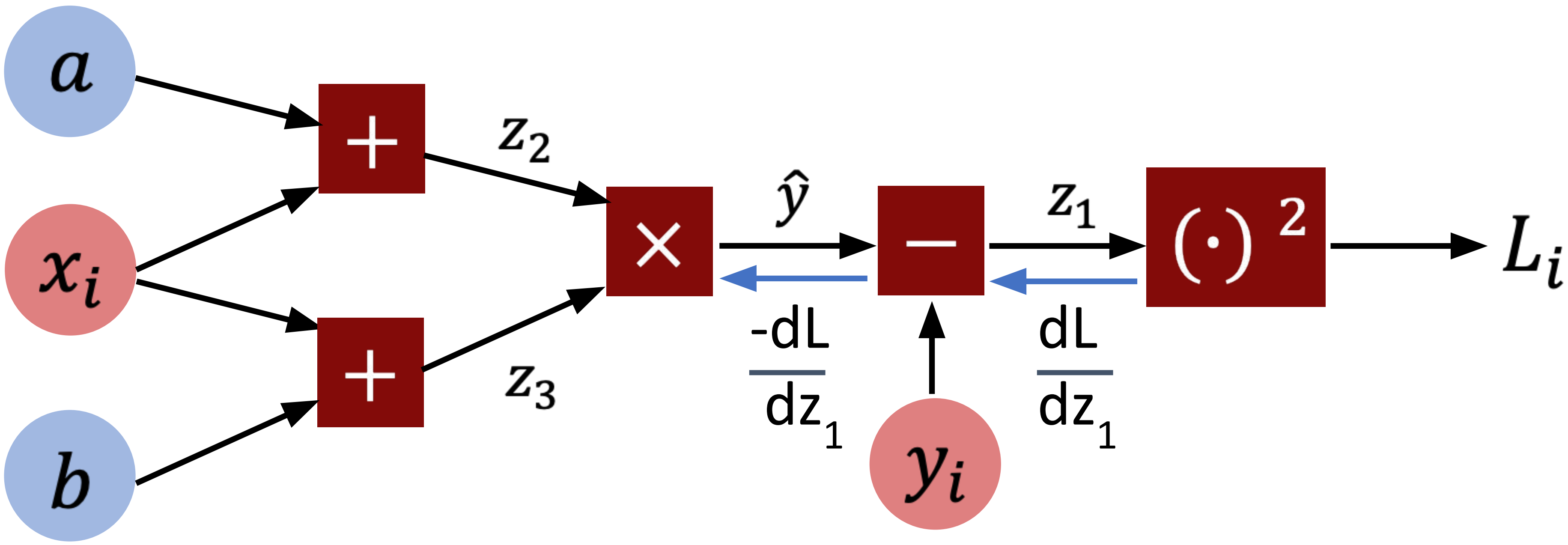


Training a simple model

Consider a backward pass



Training a simple model



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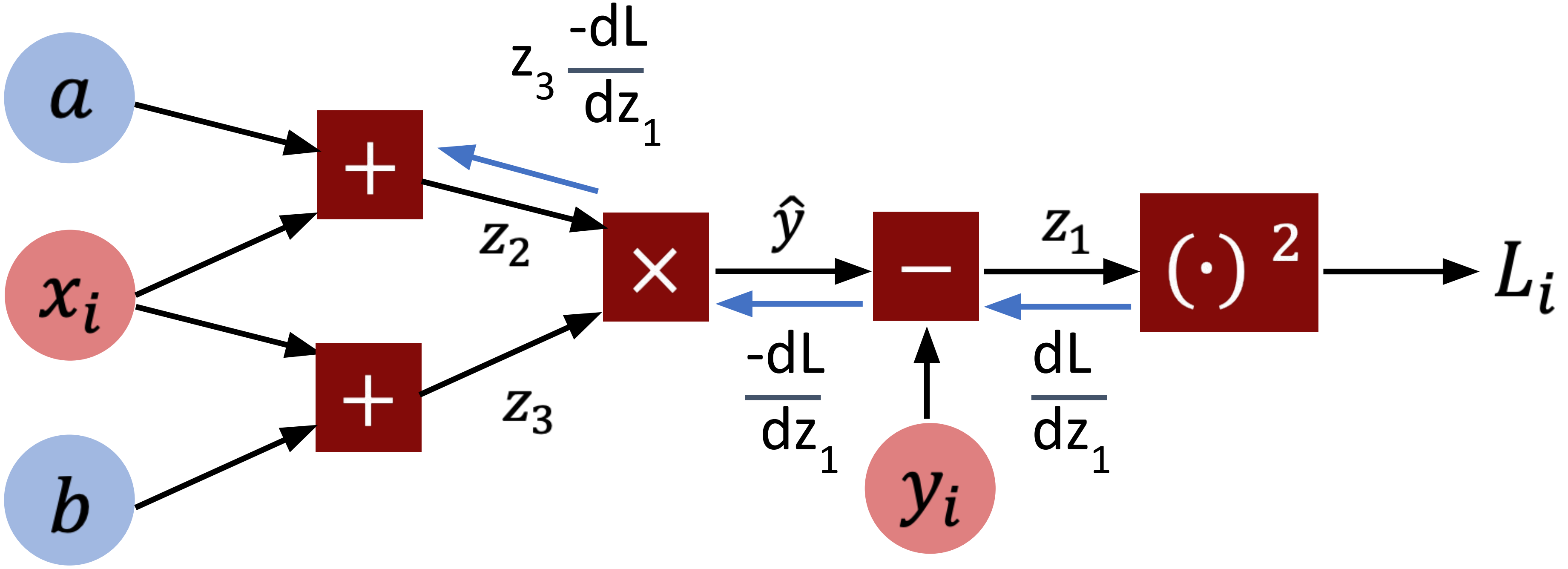

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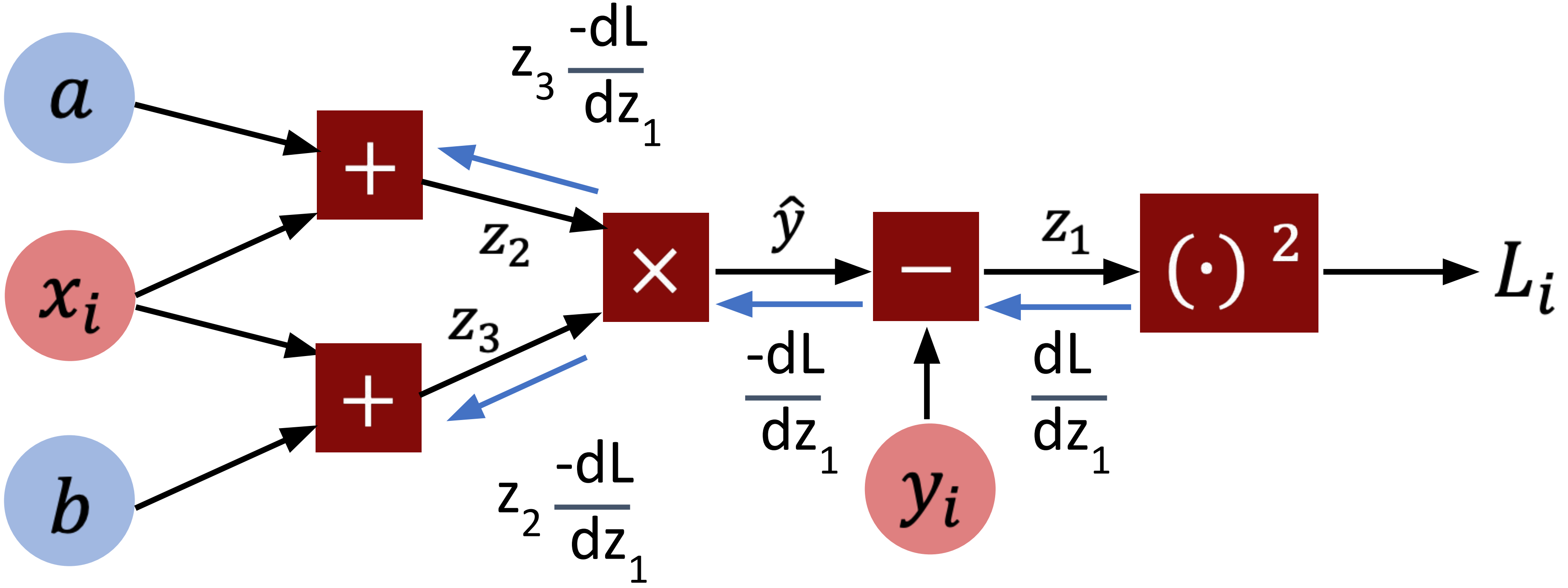

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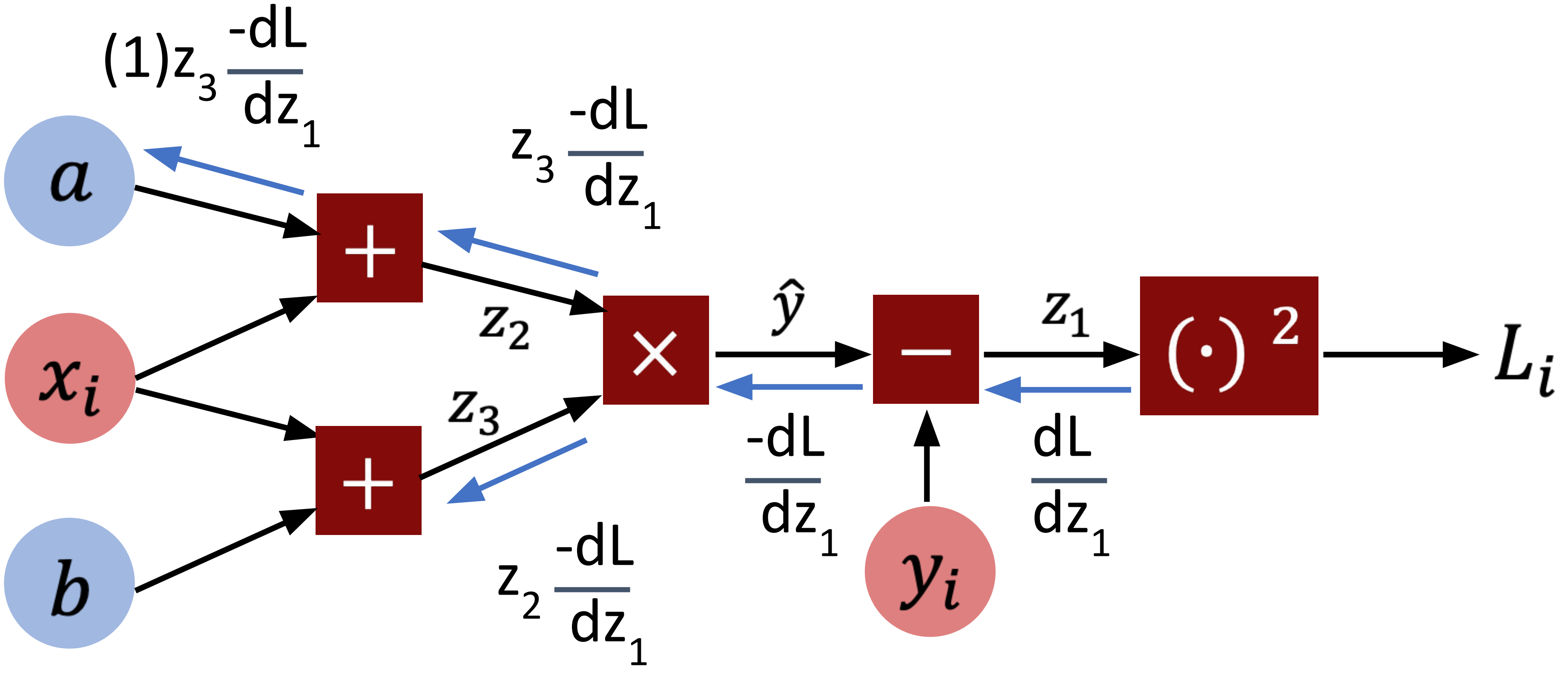

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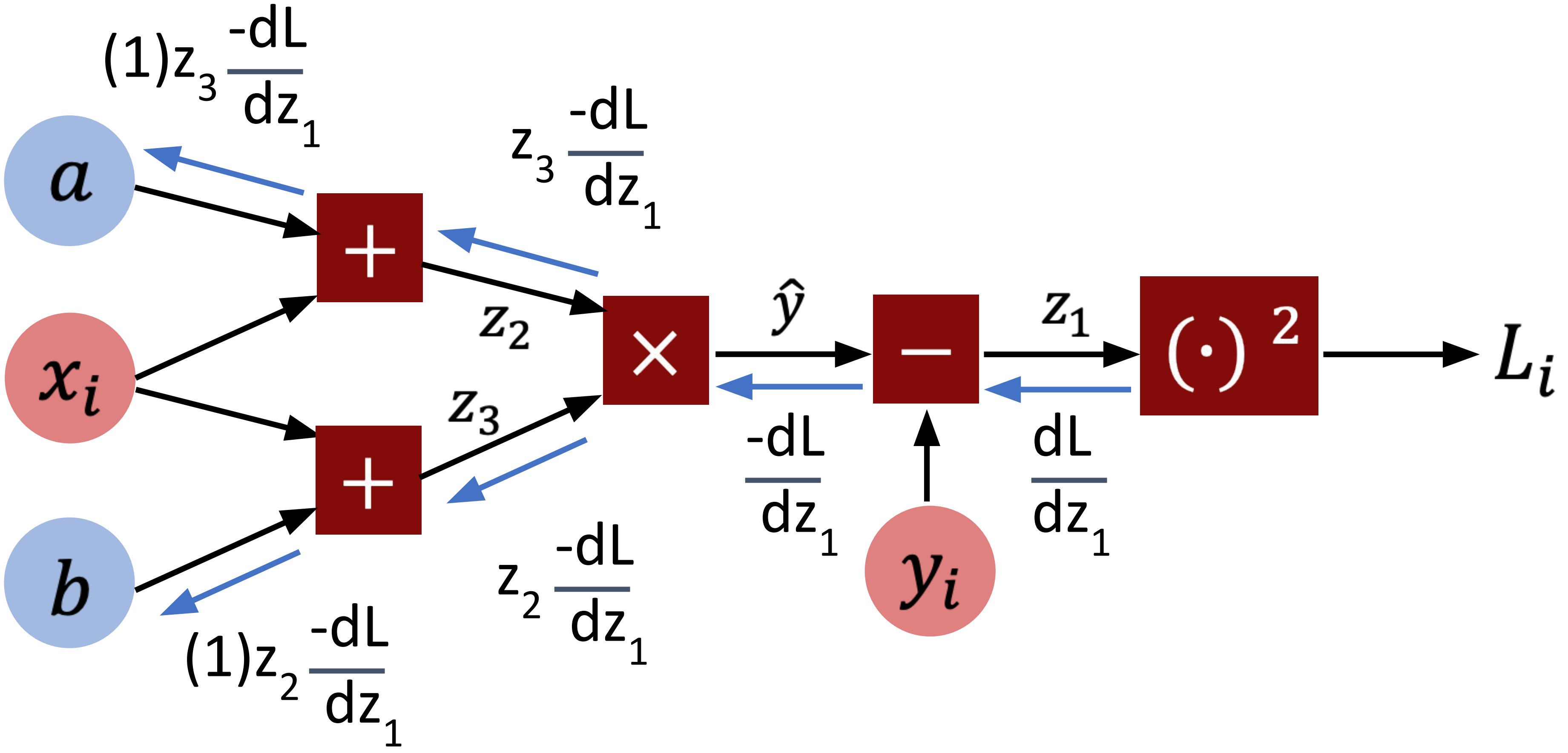
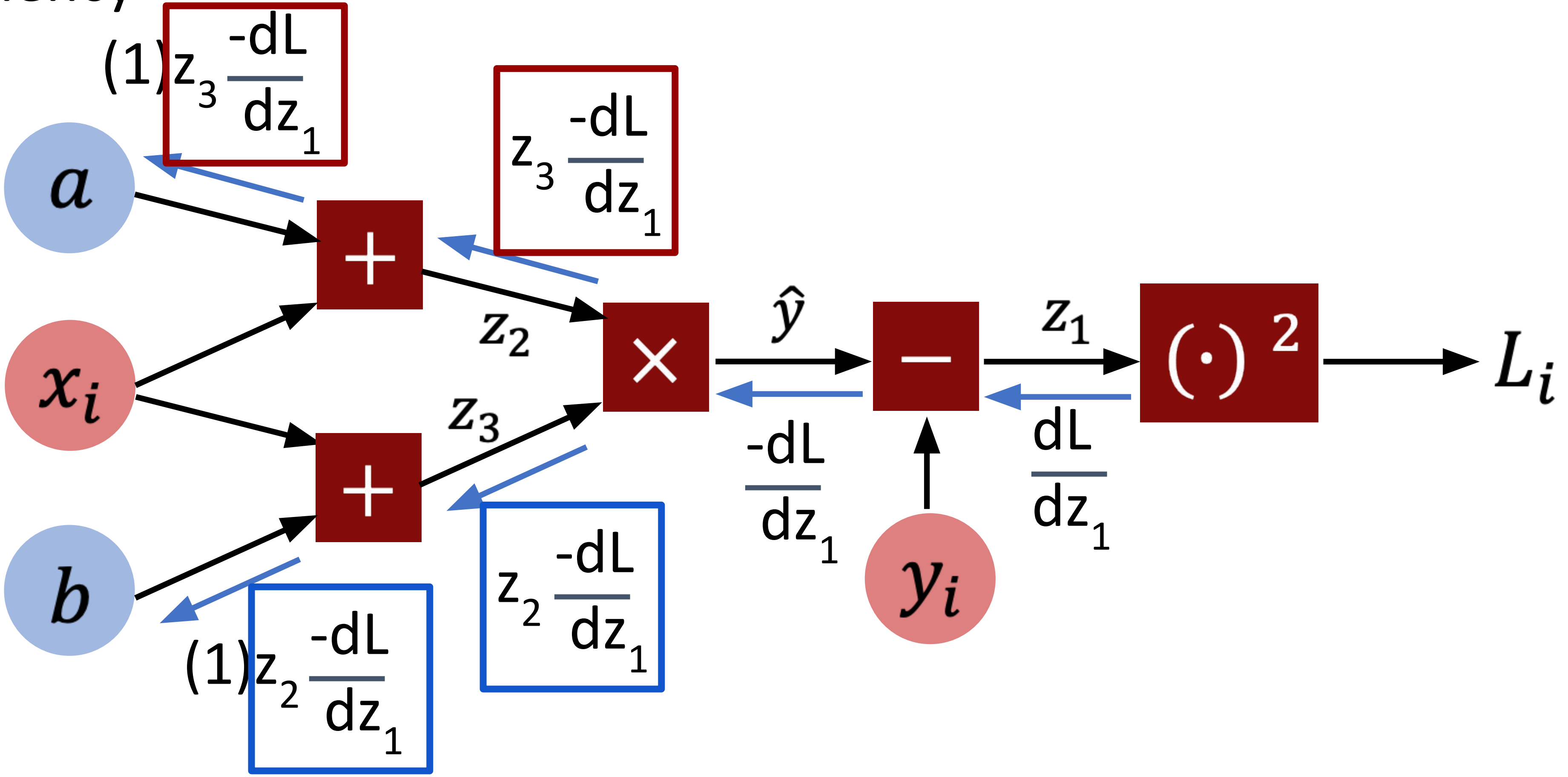


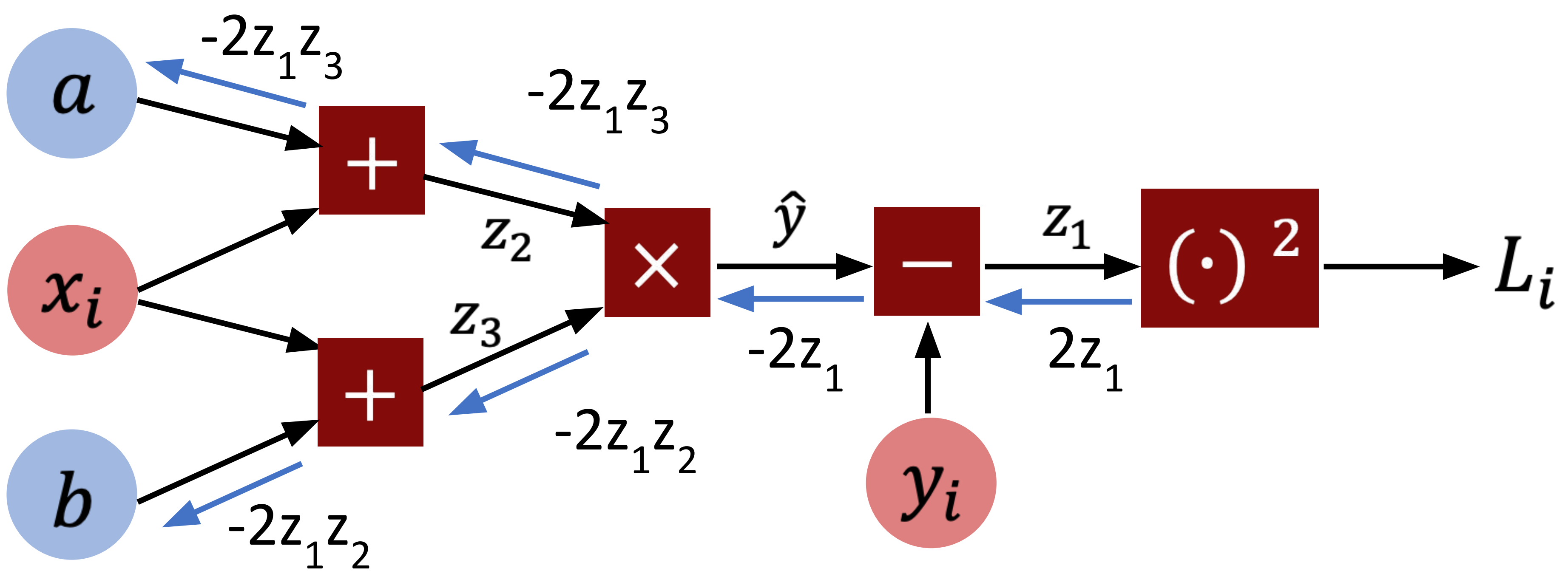
Training a simple model

Backpropagation allows for sharing values in computation, increasing efficiency



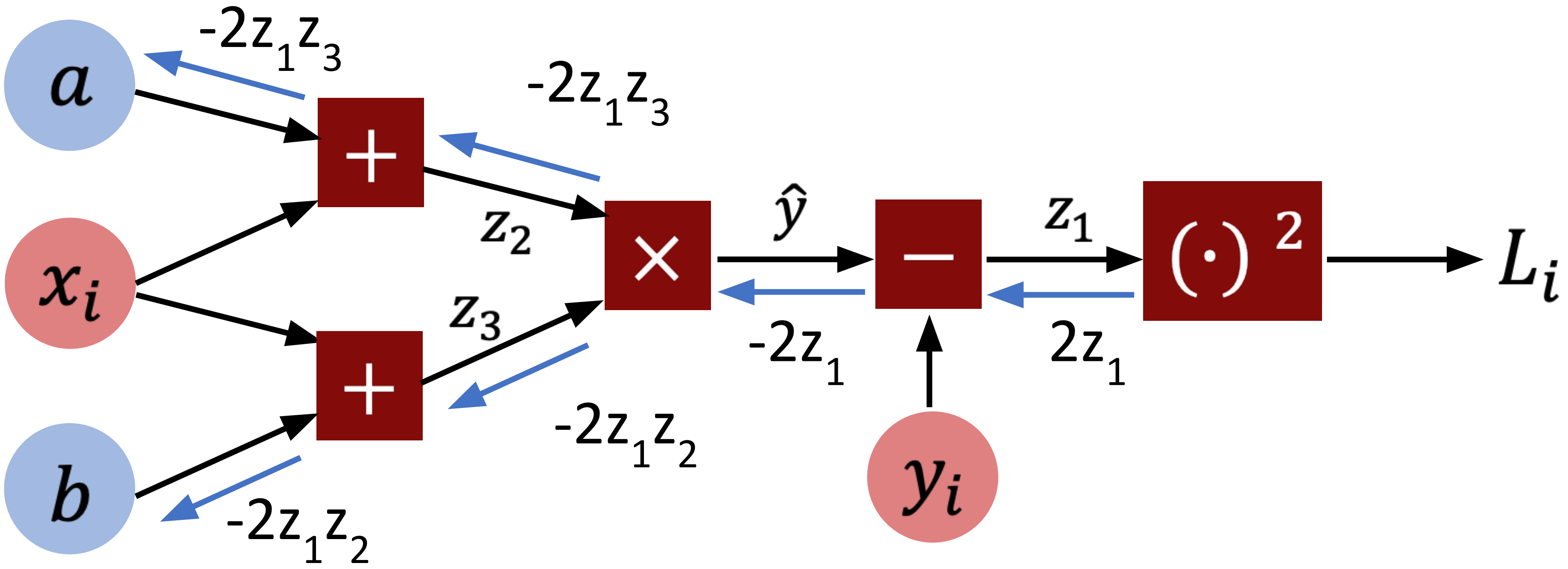
Training a simple model

How many operations in the forward and backward passes?
First sub, $dL/dz_1 = 2z_1$



Training a simple model

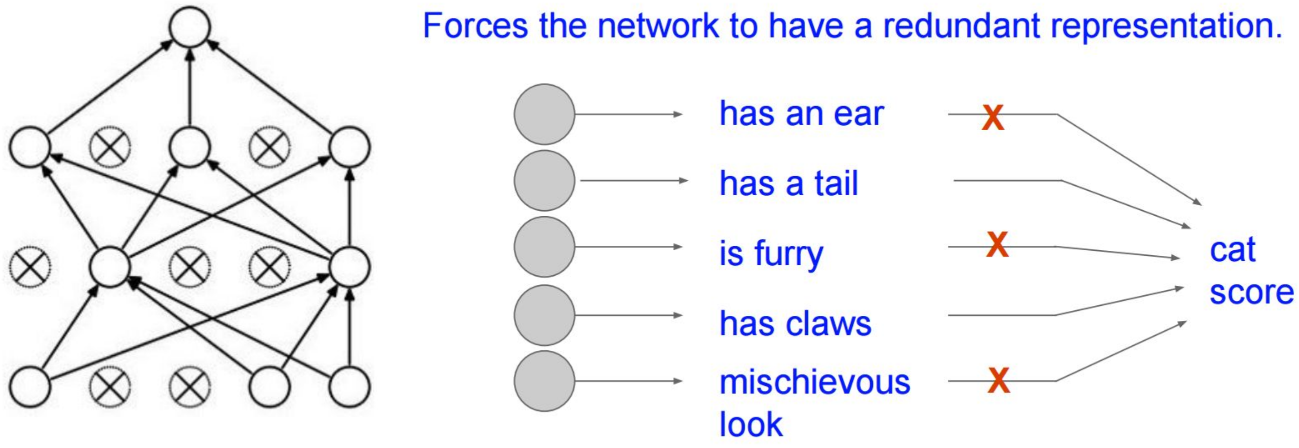
How many operations in the forward and backward passes?
5 in a Forward Pass, 4 in Backward



Training neural networks

Lots of regularization tricks:

Dropout:
(randomly zero out some neurons each pass)



Transform input data to artificially expand training set:

Tensorflow tutorial

- Tensorflow: software library that provides tools to train and evaluate deep learning models.

- Keras: high-level API written on top of Tensorflow that offers user-friendly interfaces to create neural networks.

- Link to Colab: https://colab.research.google.com/drive/1M1q-9YLSu_jLmTzjfoc2NWx-v9K0xE67?usp=sharing