10-315 Introduction to ML

Neural Networks

Instructor: Pat Virtue

Poll 1

Logistic regression for 28x28=784 pixel hand-written digit images into 10 classes:

How many parameters (including bias terms)?

A. 10
B. 10+784
C. 10*784
D. 10*784 + 10
E. 10*784 + 784
F. I have no idea

Outline

Pre-reading: Neural Networks

- Network diagrams for linear and logistic regression
- Neuron and activation functions
- Three-neuron network
- Neural network structure (adding more neurons)

Today: Neural Networks

- Optimization (Backpropogation)

Next time: Neural Network

- Properties and Intuition

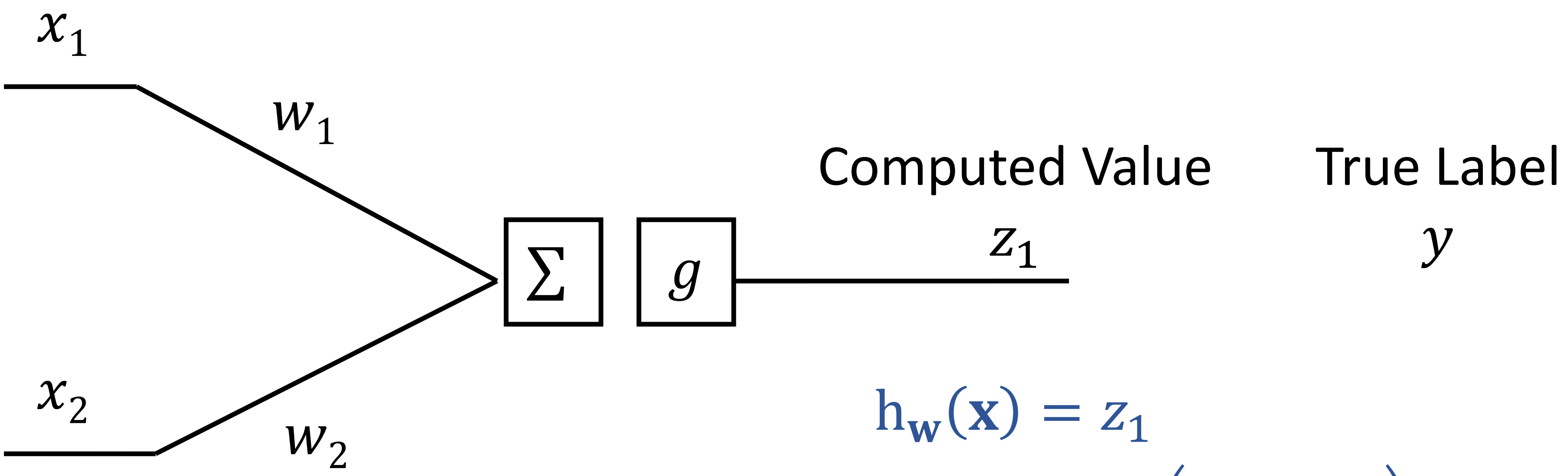
Neuron

Pre-reading

Single Neuron

Single neuron system

- Perceptron (if g is step function)
- Logistic regression (if g is sigmoid)
- Linear regression (if g is nothing)



$$\mathrm{h}_{\mathbf{w}}(\mathbf{x}) = z_1$$

$$h_{\mathbf{w}}(\mathbf{x}) = g\left(\sum_i w_i x_i\right)$$

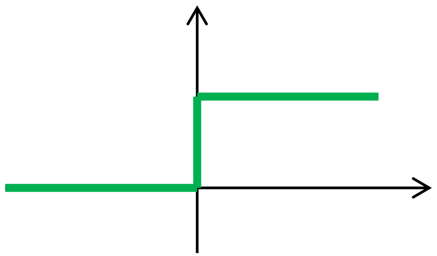
Activation Functions

Pre-reading

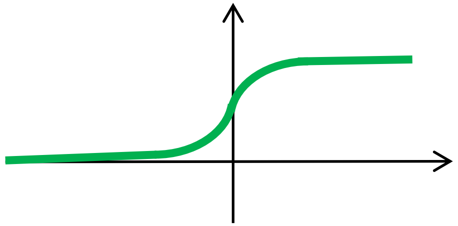
Activation Functions

It would be really helpful to have a g(z) that was nicely differentiable

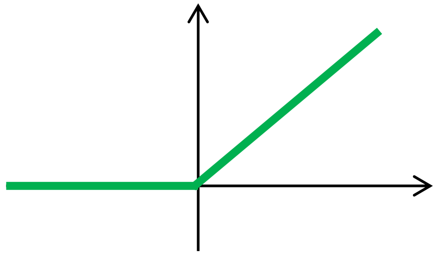
- Hard threshold: $g(z) = \begin{cases} 1 & z \geq 0 \\ 0 & z < 0 \end{cases}$ $\quad \frac{dg}{dz} = \begin{cases} 0 & z \geq 0 \\ 0 & z < 0 \end{cases}$



- Sigmoid: $g(z) = \frac{1}{1+e^{-z}}$ $\quad \frac{dg}{dz} = g(z)\big(1 - g(z)\big)$
- (Softmax)



- ReLU: $g(z) = max(0, z)$ $\quad \frac{dg}{dz} = \begin{cases} 1 & z \geq 0 \\ 0 & z < 0 \end{cases}$

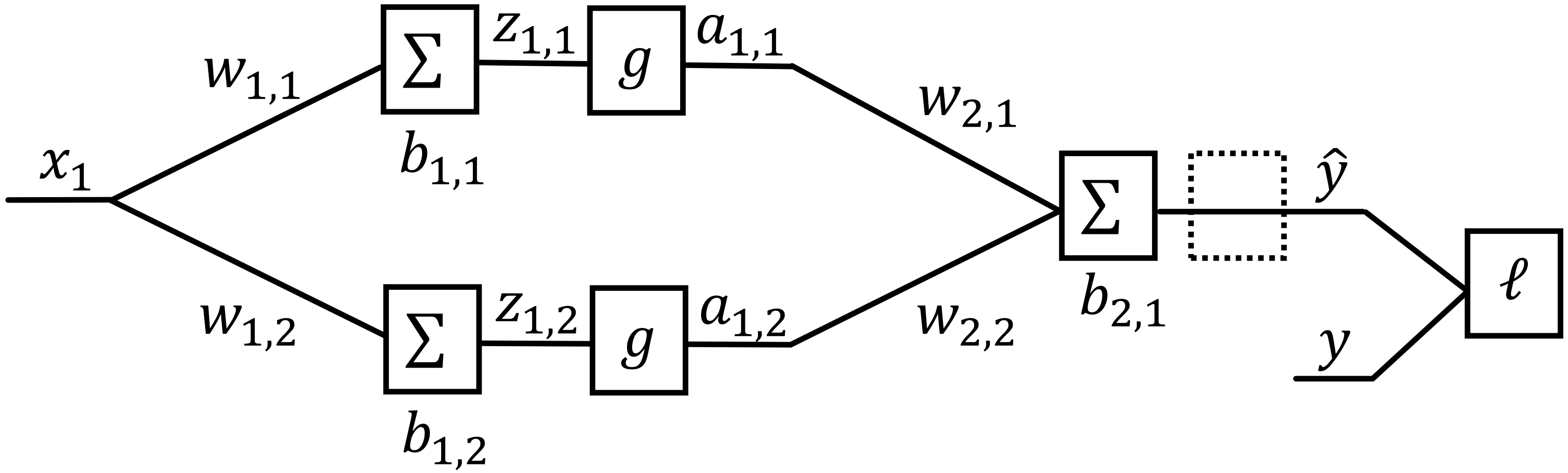


Three-neuron Network

Pre-reading

Three-neuron Network

Network diagram



$$\hat{y} = h_{\boldsymbol{\theta}}(\mathbf{x}) = b_2 + \sum_j w_{2,j}\, a_{1,j}$$

$$a_{1,j} = g_{ReLU}\left(b_{1,j} + w_{1,j}\, x_1\right)$$

Adding More Neurons

Pre-reading

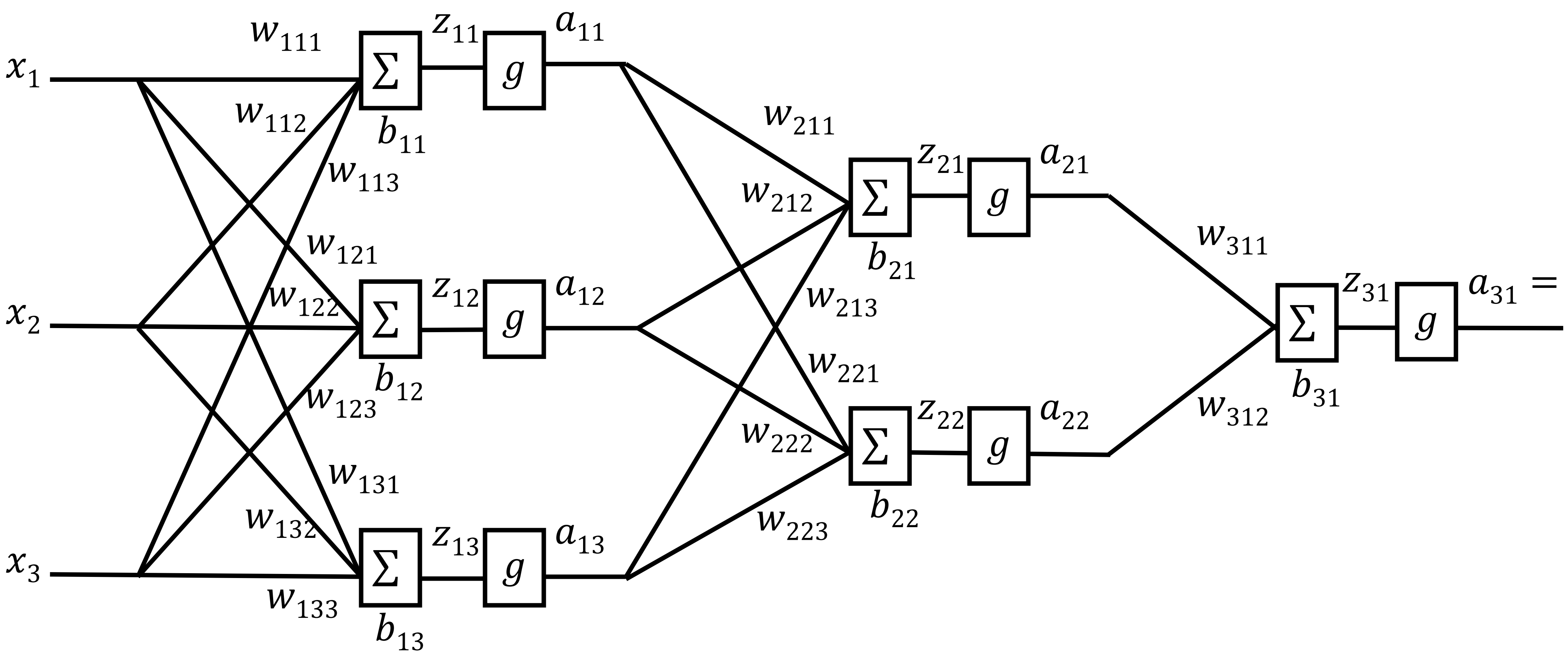
Three-layer Network

Parameter naming conventions

$w_{layer\ output\ input}$

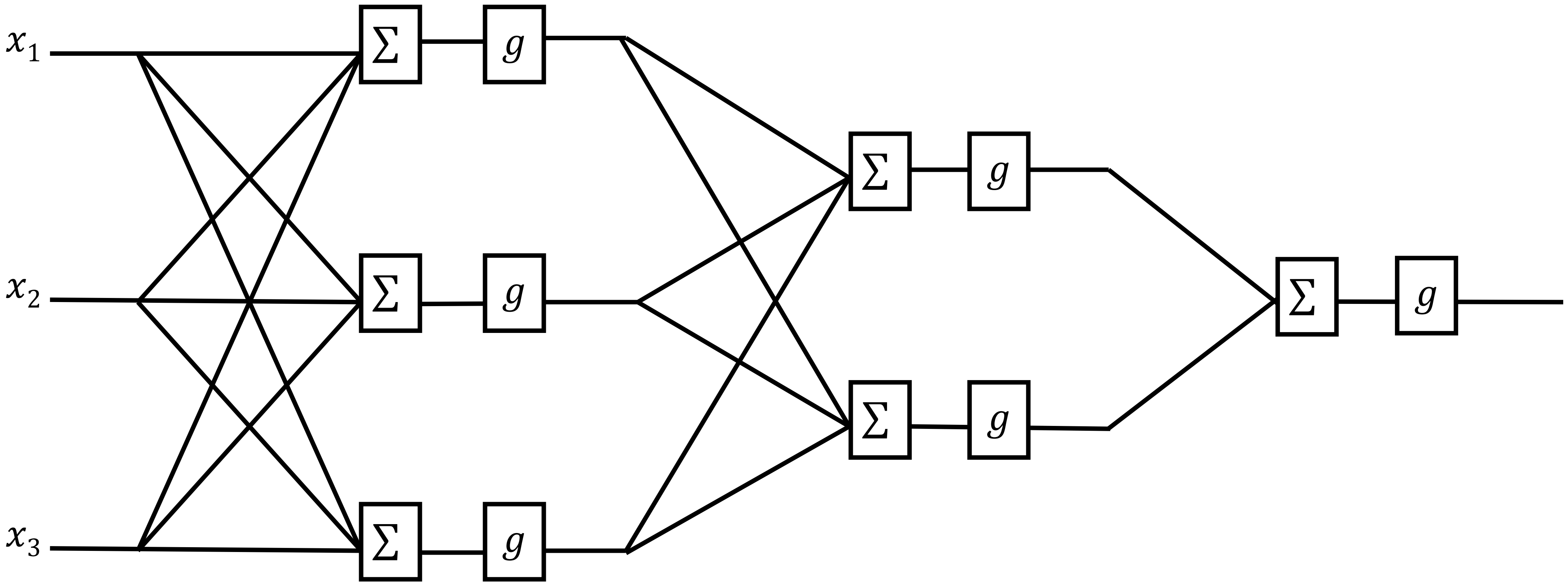
$b_{layer\ output}$

Network diagram



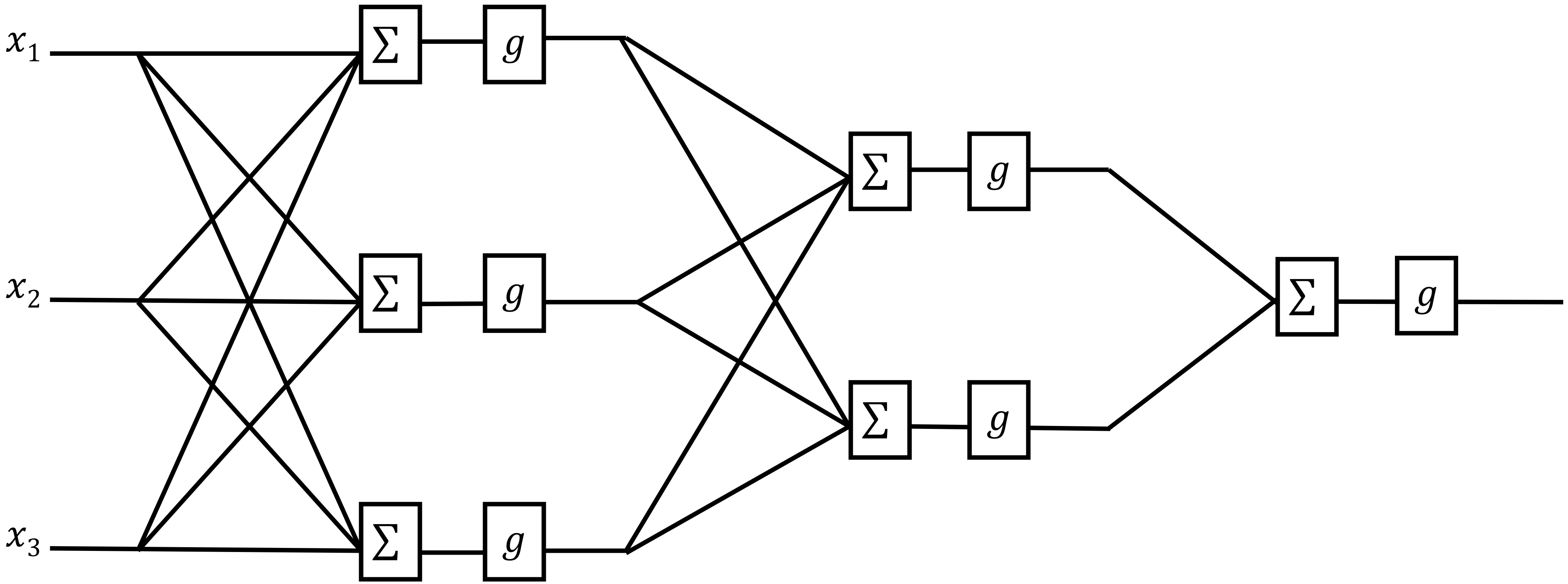
Three-layer Network

Different ways to define network layers: *Layers of functions*



Three-layer Network

Different ways to define network layers: *Layers of neurons*



Neural Network Optimization

Objective, Loss Functions, Gradient Descent

Objective

$$J(\theta) = \frac{1}{N}\sum_{i=1}^{N} J^{(i)}(\theta) \qquad J^{(i)}(\theta) = \ell\left(y^{(i)}, \hat{y}^{(i)}\right) \qquad \hat{y} = h(x;\theta)$$

Loss functions

- Regression → Squared error: $\ell(y, \hat{y}) = (y - \hat{y})^2$
- Classfication → Cross entropy: $\ell(\boldsymbol{y}, \hat{\boldsymbol{y}}) = -\sum_k y_k \log \hat{y}_k$

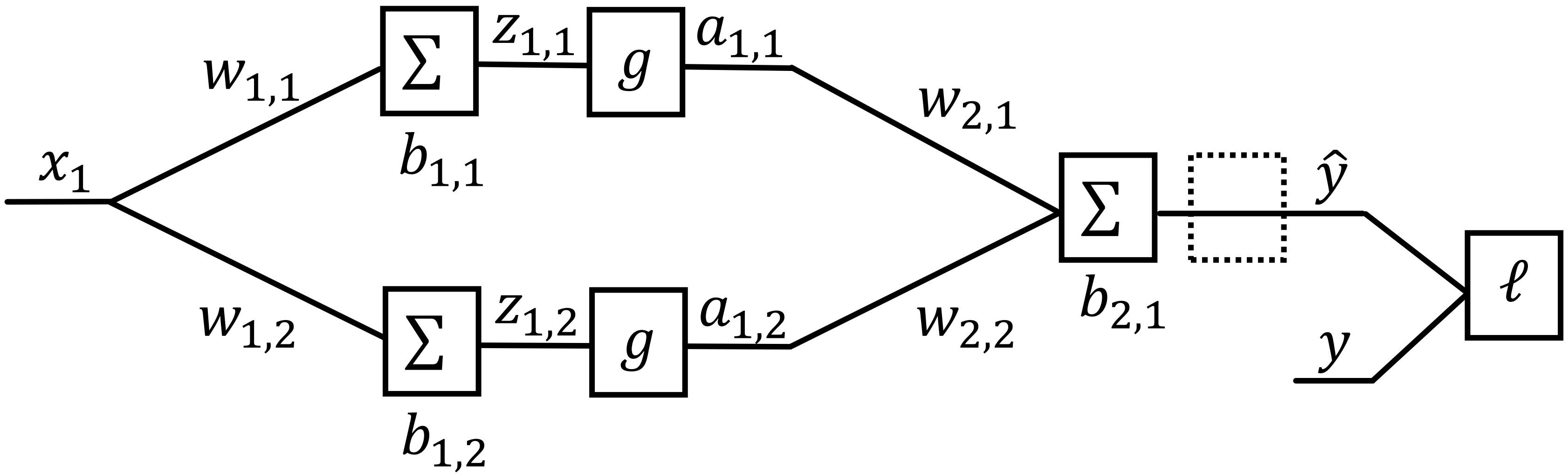
Gradient descent

while not converged

$$\theta \leftarrow \theta - \alpha\, \partial J / \partial \theta$$

Poll 2

How many total parameters?



Poll 3

Which of the following updates will we execute during gradient descent?

Select all that apply

A. $x \leftarrow x - \alpha \frac{\partial J}{\partial x}$

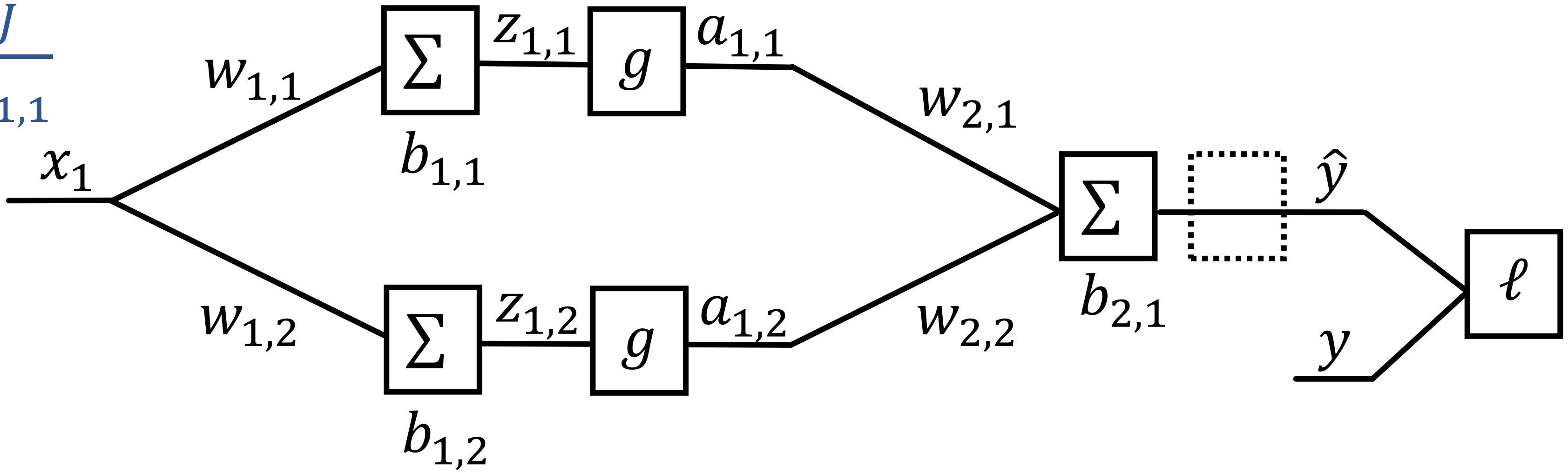
B. $w_{1,1} \leftarrow w_{1,1} - \alpha \frac{\partial J}{\partial w_{1,1}}$

C. $b_{1,1} \leftarrow b_{1,1} - \alpha \frac{\partial J}{\partial b_{1,1}}$

D. $a_{1,1} \leftarrow a_{1,1} - \alpha \frac{\partial J}{\partial a_{1,1}}$

E. $\hat{y} \leftarrow \hat{y} - \alpha \frac{\partial J}{\partial \hat{y}}$

F. $y \leftarrow y - \alpha \frac{\partial J}{\partial y}$

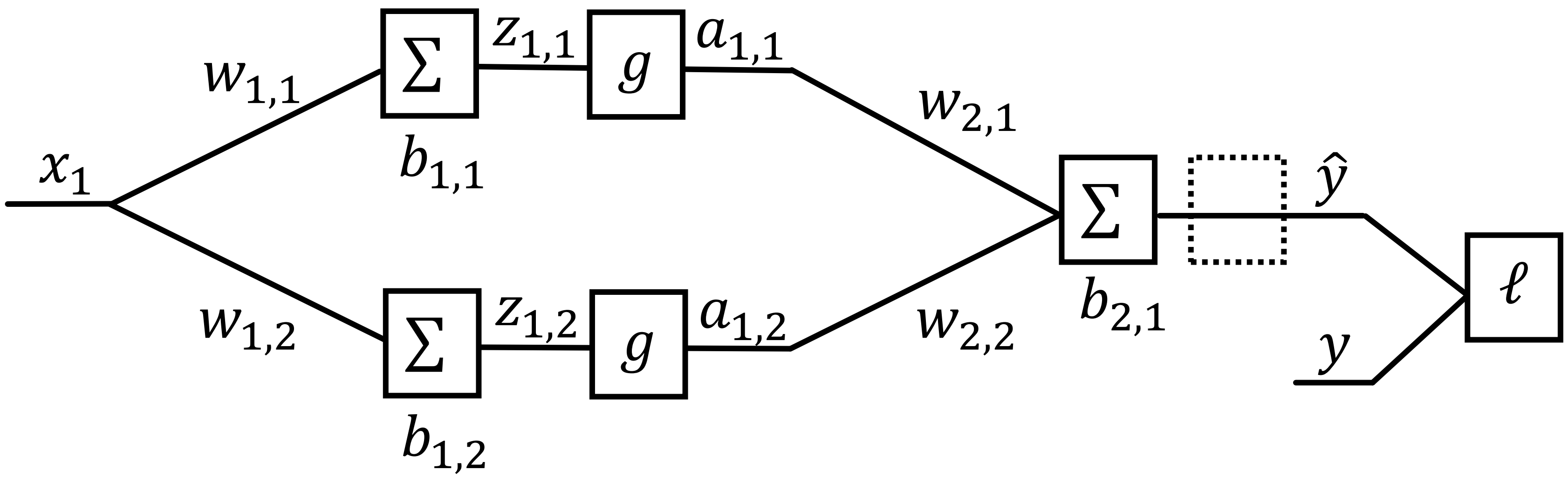


Optimization

Three-neuron network

$$\hat{y} = h_{\boldsymbol{\theta}}(\mathbf{x}) = b_2 + \sum_j w_{2,j}\, a_{1,j}$$

$$a_{1,j} = g\left(b_{1,j} + w_{1,j}\, x_1\right)$$



$$\frac{\partial J}{\partial w_{2,1}} =$$

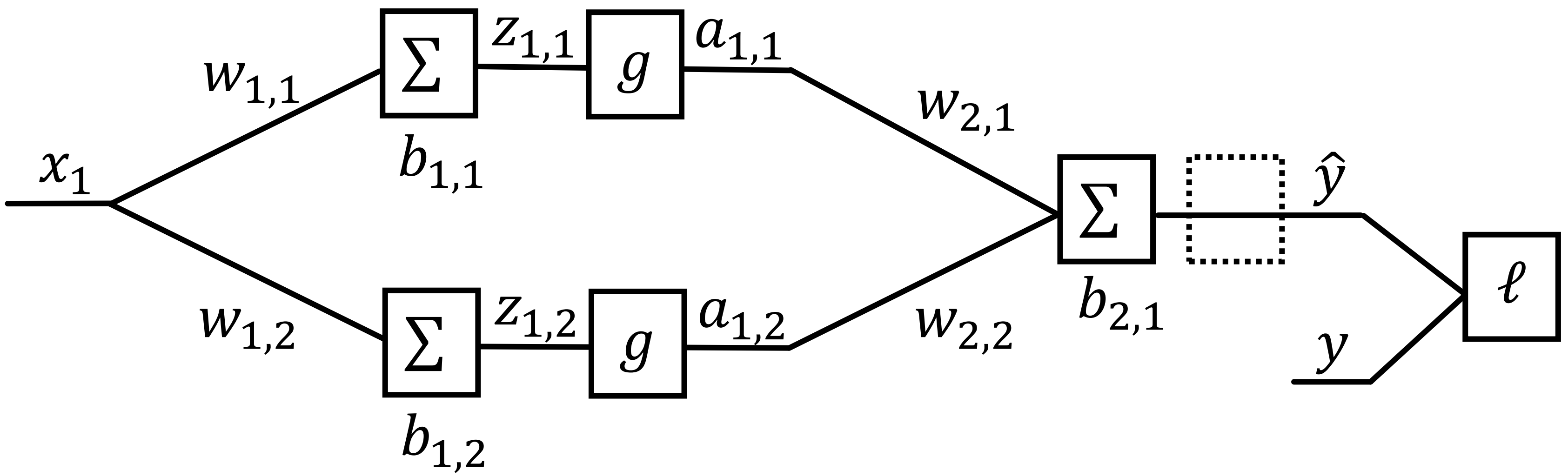
$$\frac{\partial J}{\partial b_{2,1}} =$$

Optimization

$$\hat{y} = h_{\boldsymbol{\theta}}(\mathbf{x}) = b_2 + \sum_j w_{2,j}\, a_{1,j}$$

$$a_{1,j} = g\left(b_{1,j} + w_{1,j}\, x_1\right)$$

Three-neuron network



$$\frac{\partial J}{\partial w_{1,1}} =$$

$$\frac{\partial J}{\partial b_{1,1}} =$$

$$\frac{\partial J}{\partial w_{2,1}} = \frac{\partial \ell}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial w_{2,1}}$$

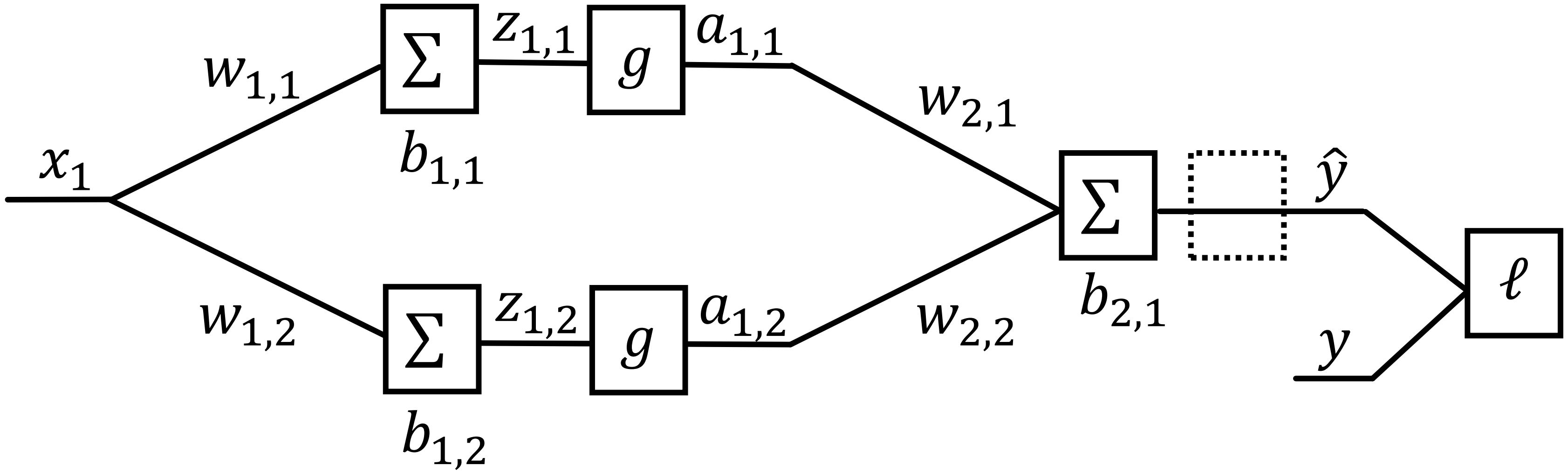
$$\frac{\partial J}{\partial b_{2,1}} = \frac{\partial \ell}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial b_{2,1}}$$

Optimization

$$\hat{y} = h_{\boldsymbol{\theta}}(\mathbf{x}) = b_2 + \sum_j w_{2,j}\, a_{1,j}$$

$$a_{1,j} = g\left(b_{1,j} + w_{1,j}\, x_1\right)$$

Three-neuron network



$$\frac{\partial J}{\partial w_{1,j}} = \frac{\partial \ell}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial a_{1,j}} \frac{\partial a_{1,j}}{\partial z_{1,j}} \frac{\partial z_{1,j}}{\partial w_{1,j}}$$

$$\frac{\partial J}{\partial w_{2,j}} = \frac{\partial \ell}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial w_{2,j}}$$

$$\frac{\partial J}{\partial b_{1,j}} = \frac{\partial \ell}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial a_{1,j}} \frac{\partial a_{1,j}}{\partial z_{1,j}} \frac{\partial z_{1,j}}{\partial b_{1,j}}$$

$$\frac{\partial J}{\partial b_{2,1}} = \frac{\partial \ell}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial b_{2,1}}$$

Neural Net Forward Pass and Backpropagation

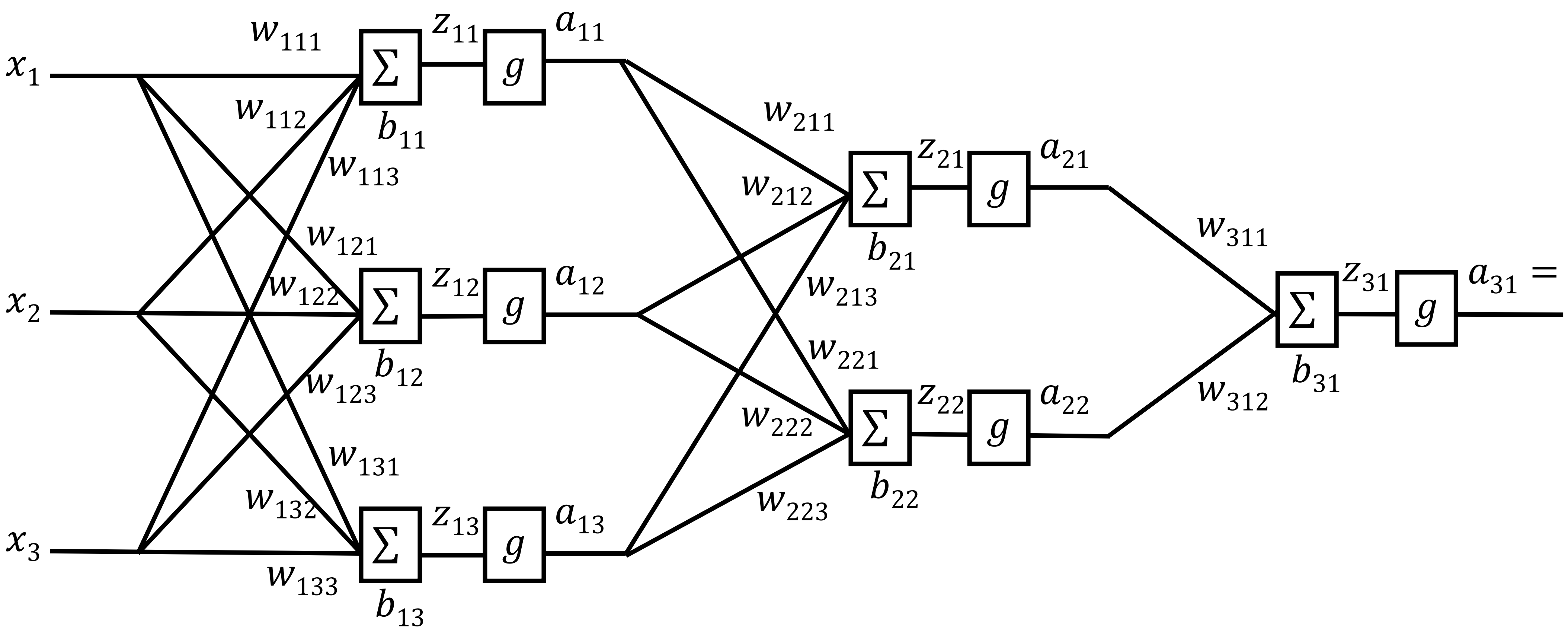
Forward pass

Predicting output from input

Parameter naming conventions

$w_{layer\ output\ input}$

$b_{layer\ output}$

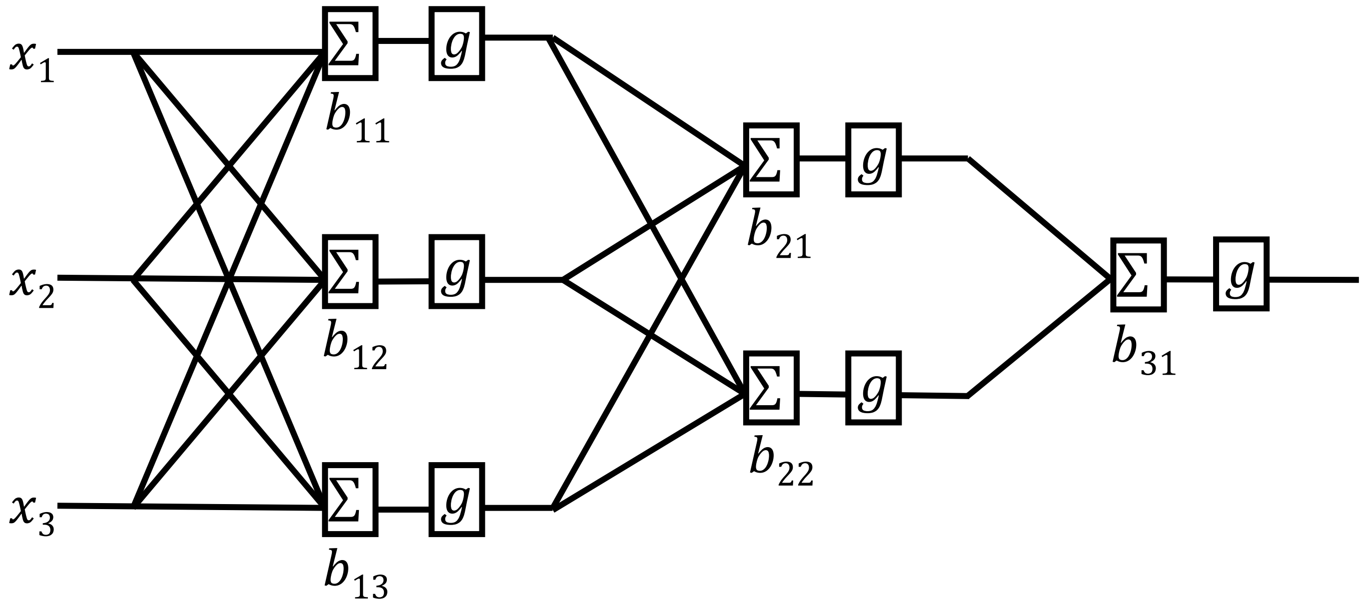


$$\hat{y} = h_{\boldsymbol{\theta}}(\mathbf{x}) = g\left(b_{3,1} + \sum_k w_{3,1,k}\ g\left(b_{2,k} + \sum_i w_{2,k,i}\ g\left(b_{1,i} + \sum_j w_{1,i,j}\ x_j\right)\right)\right)$$

Optimization

$$\hat{y} = h_{\boldsymbol{\theta}}(\mathbf{x}) = g\left(b_{3,1} + \sum_k w_{3,1,k}\ g\left(b_{2,k} + \sum_i w_{2,k,i}\ g\left(b_{1,i} + \sum_j w_{1,i,j}\ x_j\right)\right)\right)$$

Tons of repeated partial derivatives



$$\frac{\partial J}{\partial b_{3,1}} = \frac{\partial \ell}{\partial \hat{y}} \frac{\partial a_{3,1}}{\partial z_{3,1}} \frac{\partial z_{3,1}}{\partial b_{3,1}}$$

$$\frac{\partial J}{\partial b_{2,i}} = \frac{\partial \ell}{\partial \hat{y}} \frac{\partial a_{3,1}}{\partial z_{3,1}} \frac{\partial z_{3,1}}{\partial a_{2,i}} \frac{\partial a_{2,i}}{\partial z_{2,i}} \frac{\partial z_{2,i}}{\partial b_{2,i}}$$

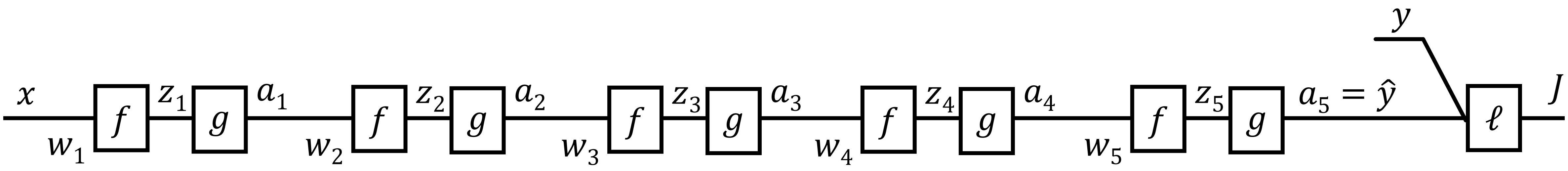
$$\frac{\partial J}{\partial b_{1,i}} = \frac{\partial \ell}{\partial \hat{y}} \frac{\partial a_{3,1}}{\partial z_{3,1}} \frac{\partial z_{3,1}}{\partial \mathbf{a}_2} \frac{\partial \mathbf{a}_2}{\partial \mathbf{z}_2} \frac{\partial \mathbf{z}_2}{\partial a_{1,i}} \frac{\partial a_{1,i}}{\partial z_{1,i}} \frac{\partial z_{1,i}}{\partial b_{1,i}}$$

Forward Pass and Backpropagation

Scalar's version

Forward Pass

Width 1 deep network (no bias) (dumb but will help with calculus)



$$z_\ell = f(w_\ell, a_{\ell-1}) = w_\ell \cdot a_{\ell-1}$$

$$a_\ell = g(z_\ell)$$

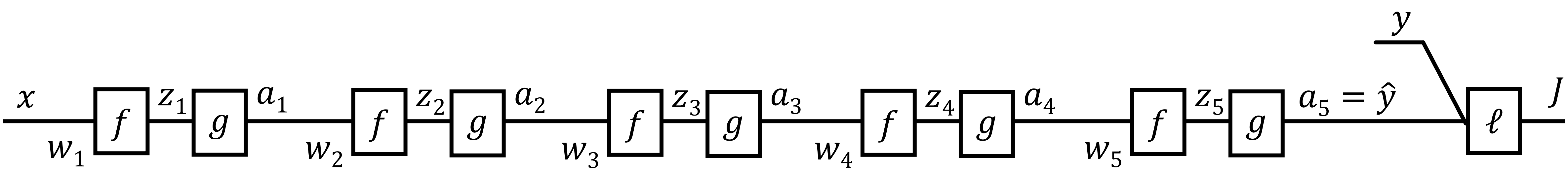
$$\hat{y} = h_{\boldsymbol{\theta}}(\mathbf{x}) = g\left(w_5 \cdot g\left(w_4 \cdot g\left(w_3 \cdot g\left(w_2 \cdot g(w_1 \cdot x)\right)\right)\right)\right)$$

$$= g\left(f\left(g\left(f\left(g\left(f\left(g\left(f\left(g\left(f(x)\right)\right)\right)\right)\right)\right)\right)\right)\right)$$

Forward Pass

$$\hat{y} = h_{\boldsymbol{\theta}}(\mathbf{x}) = g\left(w_5 \cdot g\left(w_4 \cdot g\left(w_3 \cdot g(w_2 \cdot g(w_1 \cdot x))\right)\right)\right)$$

Width 1 deep network (no bias) (dumb but will help with calculus)



With a new data point (x, y), we have our current weight values

but we don't $\hat{y}$ (or any of the intermediate values z_ℓ and a_ℓ)

or the value of our object function J

Forward Pass

$$\hat{y} = h_{\boldsymbol{\theta}}(\mathbf{x}) = g\left(w_5 \cdot g\left(w_4 \cdot g\left(w_3 \cdot g(w_2 \cdot g(w_1 \cdot x))\right)\right)\right)$$

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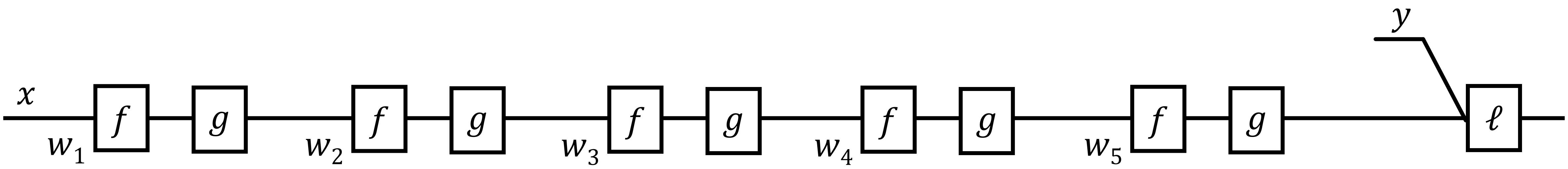

With a new data point (x, y), we have our current weight values

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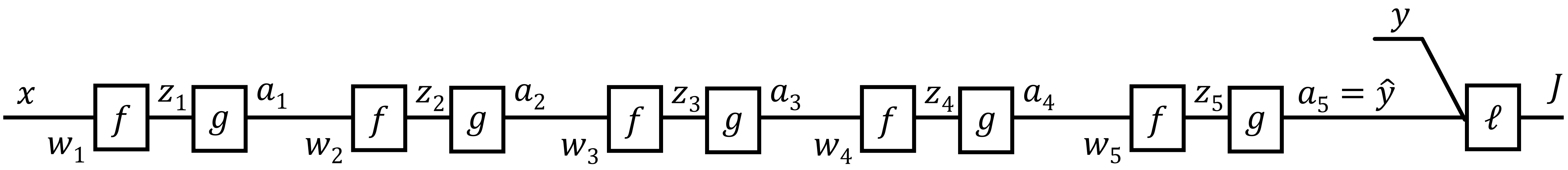
Forward Pass

$$\hat{y} = h_{\boldsymbol{\theta}}(\mathbf{x}) = g\left(w_5 \cdot g\left(w_4 \cdot g\left(w_3 \cdot g(w_2 \cdot g(w_1 \cdot x))\right)\right)\right)$$

Width 1 deep network (no bias) (dumb but will help with calculus)



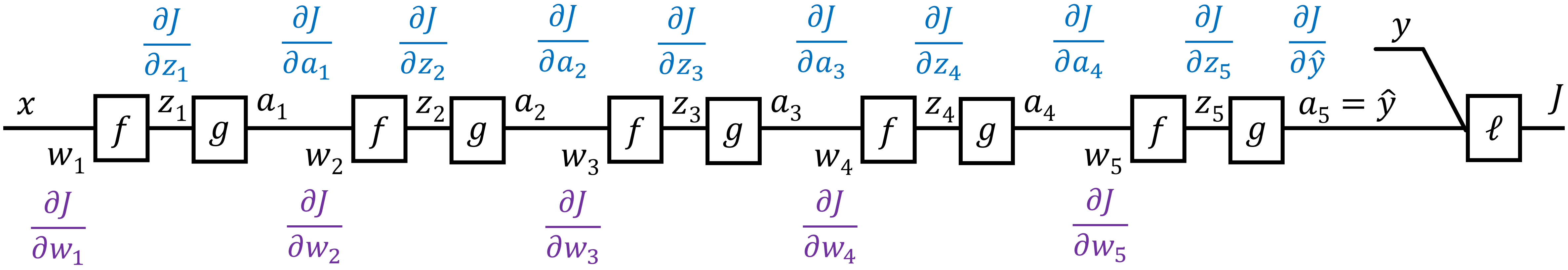
With a new data point (x, y), we have our current weight values but we don't have $\hat{y}$ (or any of the intermediate values z_ℓ and a_ℓ) or the value of our object function J

The forward pass propagates x (forward) through the network to give us these values

Backpropagation

$$\hat{y} = h_{\boldsymbol{\theta}}(\mathbf{x}) = g\left(w_5 \cdot g\left(w_4 \cdot g\left(w_3 \cdot g(w_2 \cdot g(w_1 \cdot x))\right)\right)\right)$$

Width 1 deep network (no bias) (dumb but will help with calculus)



To do gradient descent we need the partial derivative of the objective with respect to each parameter, $w_\ell \leftarrow w_\ell - \alpha\, \partial J / \partial w_\ell$

The backward pass propagates the change in the objective with respect to intermediate values ($\partial J / \partial z_\ell$ and $\partial J / \partial a_\ell$) back through the network to produce each $\partial J / \partial w_\ell$

Reminder: Calculus Chain Rule (scalar version)

Composite functions → chain rule

$$y = f\big(\mathrm{g}(\mathrm{x})\big)$$

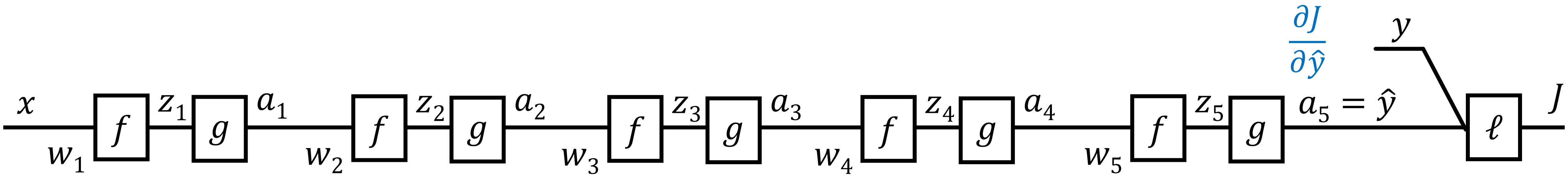
$$y = f(z)$$
$$z = g(x)$$

$$\frac{df}{dx} = \frac{df}{dz}\frac{dg}{dx}$$

Why backwards?

$$\hat{y} = h_{\boldsymbol{\theta}}(\mathbf{x}) = g\left(w_5 \cdot g\left(w_4 \cdot g\left(w_3 \cdot g(w_2 \cdot g(w_1 \cdot x))\right)\right)\right)$$

Width 1 deep network (no bias) (dumb but will help with calculus)

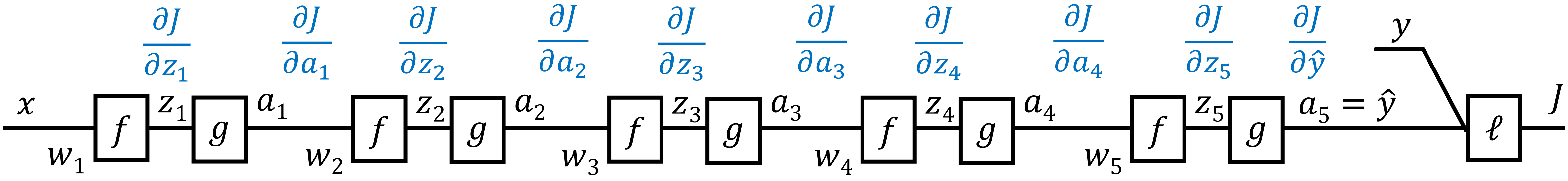


$$\frac{\partial J}{\partial w_1} =$$

Why backwards?

$$\hat{y} = h_{\boldsymbol{\theta}}(\mathbf{x}) = g\left(w_5 \cdot g\left(w_4 \cdot g\left(w_3 \cdot g(w_2 \cdot g(w_1 \cdot x))\right)\right)\right)$$

Width 1 deep network (no bias) (dumb but will help with calculus)



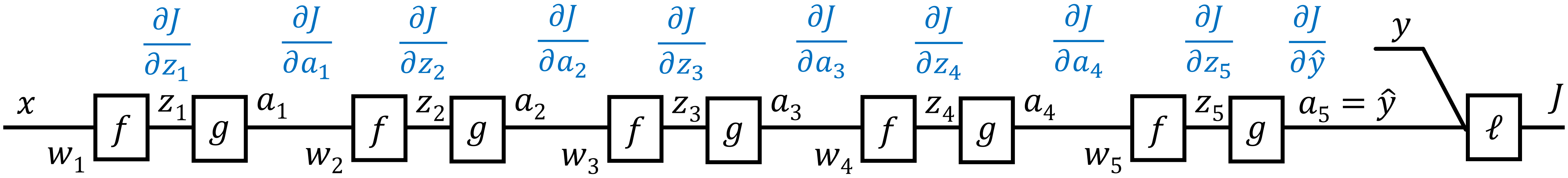
$$\frac{\partial J}{\partial w_1} = \frac{\partial J}{\partial \hat{y}} \frac{\partial g}{\partial z_5} \frac{\partial f}{\partial a_4} \frac{\partial g}{\partial z_4} \frac{\partial f}{\partial a_3} \frac{\partial g}{\partial z_3} \frac{\partial f}{\partial a_2} \frac{\partial g}{\partial z_2} \frac{\partial f}{\partial a_1} \frac{\partial g}{\partial z_1} \frac{\partial f}{\partial w_1}$$

$$\frac{\partial J}{\partial w_2} =$$

Why backwards?

$$\hat{y} = h_{\boldsymbol{\theta}}(\mathbf{x}) = g\left(w_5 \cdot g\left(w_4 \cdot g\left(w_3 \cdot g(w_2 \cdot g(w_1 \cdot x))\right)\right)\right)$$

Width 1 deep network (no bias) (dumb but will help with calculus)



$$\frac{\partial J}{\partial w_1} = \frac{\partial J}{\partial \hat{y}} \frac{\partial g}{\partial z_5} \frac{\partial f}{\partial a_4} \frac{\partial g}{\partial z_4} \frac{\partial f}{\partial a_3} \frac{\partial g}{\partial z_3} \frac{\partial f}{\partial a_2} \frac{\partial g}{\partial z_2} \frac{\partial f}{\partial a_1} \frac{\partial g}{\partial z_1} \frac{\partial f}{\partial w_1}$$

$$\frac{\partial J}{\partial w_2} = \frac{\partial J}{\partial \hat{y}} \frac{\partial g}{\partial z_5} \frac{\partial f}{\partial a_4} \frac{\partial g}{\partial z_4} \frac{\partial f}{\partial a_3} \frac{\partial g}{\partial z_3} \frac{\partial f}{\partial a_2} \frac{\partial g}{\partial z_2} \frac{\partial f}{\partial w_2}$$

$$\frac{\partial J}{\partial w_3} = \frac{\partial J}{\partial \hat{y}} \frac{\partial g}{\partial z_5} \frac{\partial f}{\partial a_4} \frac{\partial g}{\partial z_4} \frac{\partial f}{\partial a_3} \frac{\partial g}{\partial z_3} \frac{\partial f}{\partial w_3}$$

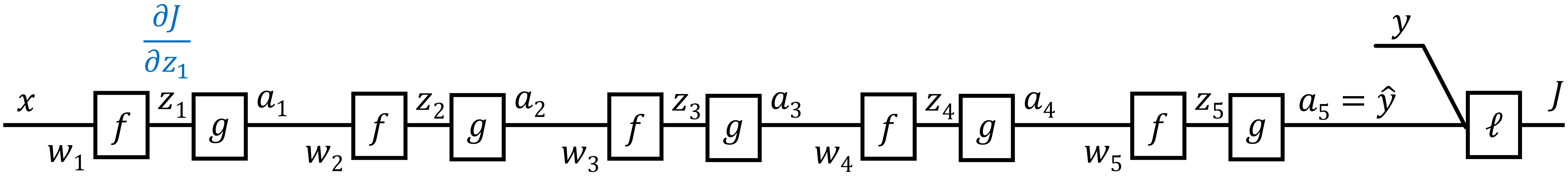
$$\frac{\partial J}{\partial w_4} = \frac{\partial J}{\partial \hat{y}} \frac{\partial g}{\partial z_5} \frac{\partial f}{\partial a_4} \frac{\partial g}{\partial z_4} \frac{\partial f}{\partial w_4}$$

$$\frac{\partial J}{\partial w_5} = \frac{\partial J}{\partial \hat{y}} \frac{\partial g}{\partial z_5} \frac{\partial f}{\partial w_5}$$

Why backwards?

$$\hat{y} = h_{\boldsymbol{\theta}}(\mathbf{x}) = g\left(w_5 \cdot g\left(w_4 \cdot g\left(w_3 \cdot g(w_2 \cdot g(w_1 \cdot x))\right)\right)\right)$$

Width 1 deep network (no bias) (dumb but will help with calculus)



$$\frac{\partial J}{\partial w_1} = \frac{\partial J}{\partial \hat{y}} \frac{\partial g}{\partial z_5} \frac{\partial f}{\partial a_4} \frac{\partial g}{\partial z_4} \frac{\partial f}{\partial a_3} \frac{\partial g}{\partial z_3} \frac{\partial f}{\partial a_2} \frac{\partial g}{\partial z_2} \frac{\partial f}{\partial a_1} \frac{\partial g}{\partial z_1} \frac{\partial f}{\partial w_1}$$

$$= \frac{\partial J}{\partial z_1} \frac{\partial f}{\partial w_1}$$

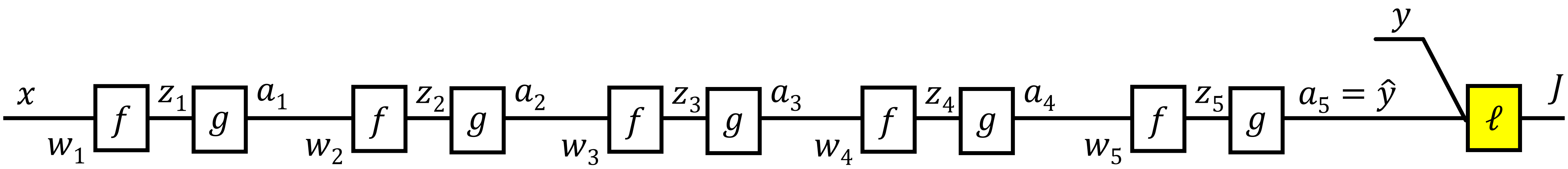
What if someone had already done all of the work to compute $\frac{\partial J}{\partial z_1}$?

Then we just need to do the local partial derivative for f with respect to the parameter w and then use that to compute the partial derivative for J with respect to the parameter w

Backpropagation

$$\hat{y} = h_{\boldsymbol{\theta}}(\mathbf{x}) = g\left(w_5 \cdot g\left(w_4 \cdot g\left(w_3 \cdot g(w_2 \cdot g(w_1 \cdot x))\right)\right)\right)$$

More efficient to start at the end and reuse values!

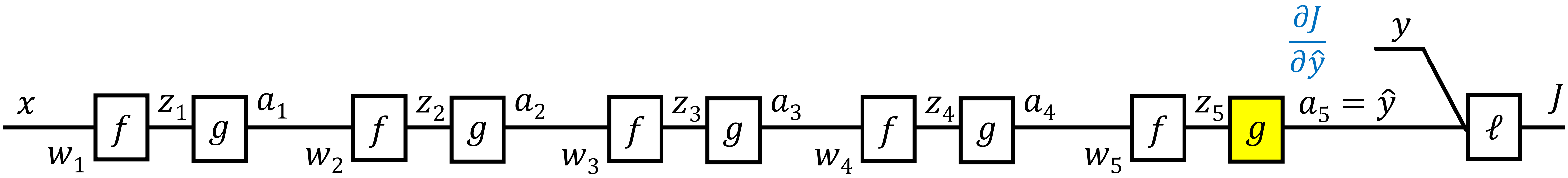


$$\frac{\partial J}{\partial \hat{y}} = \frac{\partial \ell}{\partial \hat{y}}$$

Backpropagation

$$\hat{y} = h_{\boldsymbol{\theta}}(\mathbf{x}) = g\Big(w_5 \cdot g\Big(w_4 \cdot g\Big(w_3 \cdot g\big(w_2 \cdot g(w_1 \cdot x)\big)\Big)\Big)\Big)$$

More efficient to start at the end and reuse values!

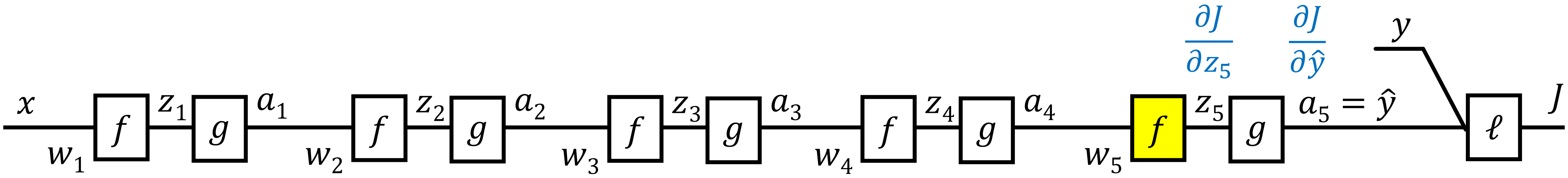


$$\frac{\partial \boldsymbol{J}}{\partial \boldsymbol{z_5}} = \frac{\partial J}{\partial \hat{y}} \frac{\partial g}{\partial z_5}$$

Backpropagation

$$\hat{y} = h_{\boldsymbol{\theta}}(\mathbf{x}) = g\left(w_5 \cdot g\left(w_4 \cdot g\left(w_3 \cdot g(w_2 \cdot g(w_1 \cdot x))\right)\right)\right)$$

More efficient to start at the end and reuse values!



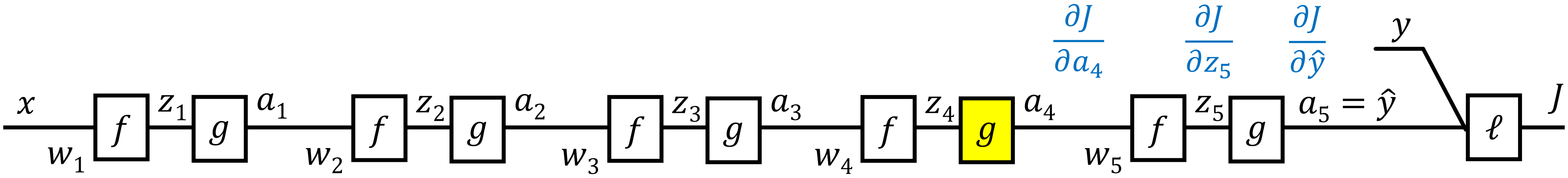
$$\frac{\partial J}{\partial a_4} = \frac{\partial J}{\partial z_5} \frac{\partial f}{\partial a_4}$$

$$\frac{\partial J}{\partial w_5} = \frac{\partial J}{\partial z_5} \frac{\partial f}{\partial w_5}$$

Backpropagation

$$\hat{y} = h_{\boldsymbol{\theta}}(\mathbf{x}) = g\left(w_5 \cdot g\left(w_4 \cdot g\left(w_3 \cdot g(w_2 \cdot g(w_1 \cdot x))\right)\right)\right)$$

More efficient to start at the end and reuse values!

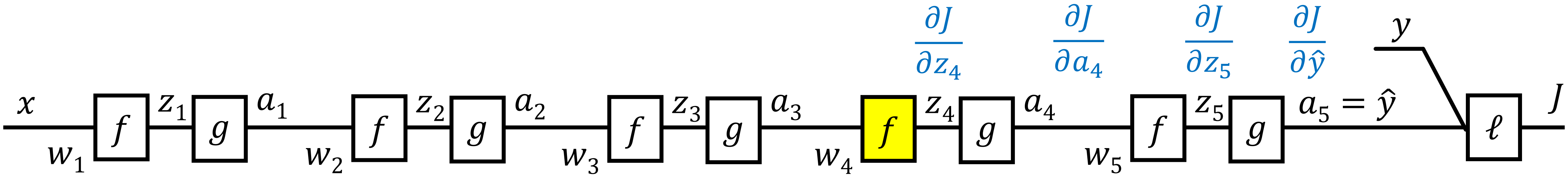


$$\boldsymbol{\frac{\partial J}{\partial z_4}} = \frac{\partial J}{\partial a_4} \frac{\partial g}{\partial z_4}$$

Backpropagation

$$\hat{y} = h_{\boldsymbol{\theta}}(\mathbf{x}) = g\left(w_5 \cdot g\left(w_4 \cdot g\left(w_3 \cdot g(w_2 \cdot g(w_1 \cdot x))\right)\right)\right)$$

More efficient to start at the end and reuse values!



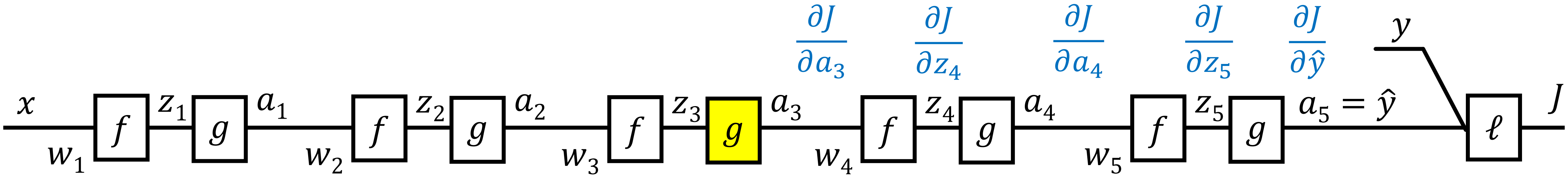
$$\frac{\partial J}{\partial a_3} = \frac{\partial J}{\partial z_4}\frac{\partial f}{\partial a_3}$$

$$\frac{\partial J}{\partial w_4} = \frac{\partial J}{\partial z_4}\frac{\partial f}{\partial w_4}$$

Backpropagation

$$\hat{y} = h_{\boldsymbol{\theta}}(\mathbf{x}) = g\left(w_5 \cdot g\left(w_4 \cdot g\left(w_3 \cdot g(w_2 \cdot g(w_1 \cdot x))\right)\right)\right)$$

More efficient to start at the end and reuse values!

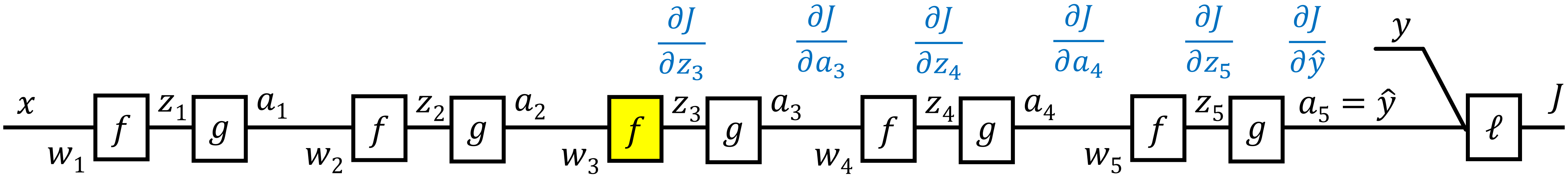


$$\frac{\partial J}{\partial z_3} = \frac{\partial J}{\partial a_3}\frac{\partial g}{\partial z_3}$$

Backpropagation

$$\hat{y} = h_{\boldsymbol{\theta}}(\mathbf{x}) = g\left(w_5 \cdot g\left(w_4 \cdot g\left(w_3 \cdot g(w_2 \cdot g(w_1 \cdot x))\right)\right)\right)$$

More efficient to start at the end and reuse values!



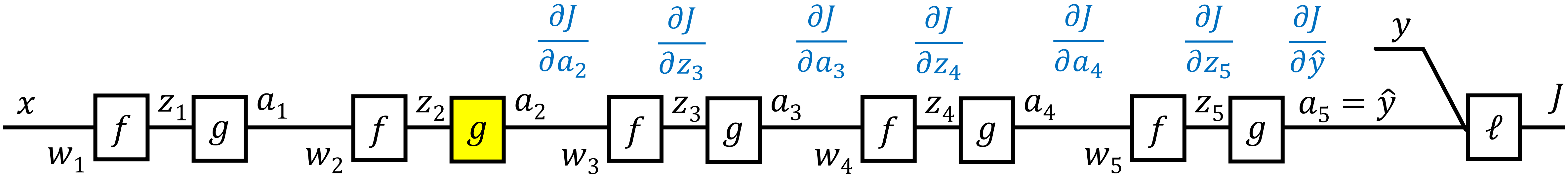
$$\frac{\partial J}{\partial a_2} = \frac{\partial J}{\partial z_3} \frac{\partial f}{\partial a_2}$$

$$\frac{\partial J}{\partial w_3} = \frac{\partial J}{\partial z_3} \frac{\partial f}{\partial w_3}$$

Backpropagation

$$\hat{y} = h_{\boldsymbol{\theta}}(\mathbf{x}) = g\left(w_5 \cdot g\left(w_4 \cdot g\left(w_3 \cdot g(w_2 \cdot g(w_1 \cdot x))\right)\right)\right)$$

More efficient to start at the end and reuse values!

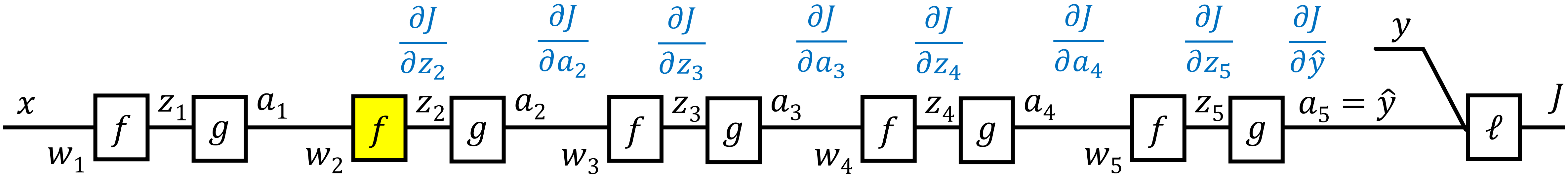


$$\frac{\partial J}{\partial z_2} = \frac{\partial J}{\partial a_2}\frac{\partial g}{\partial z_2}$$

Backpropagation

$$\hat{y} = h_{\boldsymbol{\theta}}(\mathbf{x}) = g\left(w_5 \cdot g\left(w_4 \cdot g\left(w_3 \cdot g(w_2 \cdot g(w_1 \cdot x))\right)\right)\right)$$

More efficient to start at the end and reuse values!



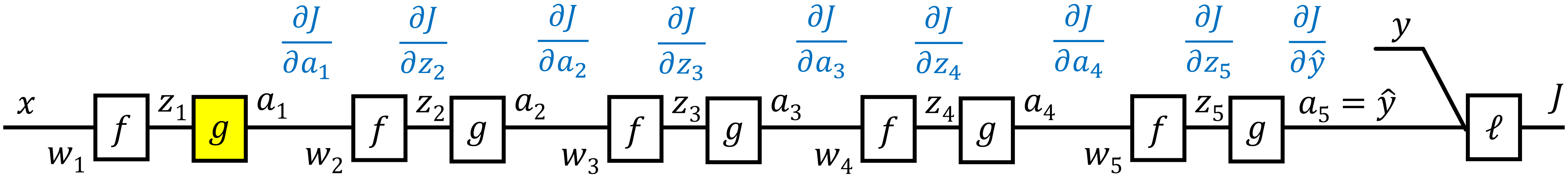
$$\frac{\partial J}{\partial a_1} = \frac{\partial J}{\partial z_2}\frac{\partial f}{\partial a_1}$$

$$\frac{\partial J}{\partial w_2} = \frac{\partial J}{\partial z_2}\frac{\partial f}{\partial w_2}$$

Backpropagation

$$\hat{y} = h_{\boldsymbol{\theta}}(\mathbf{x}) = g\left(w_5 \cdot g\left(w_4 \cdot g\left(w_3 \cdot g(w_2 \cdot g(w_1 \cdot x))\right)\right)\right)$$

More efficient to start at the end and reuse values!

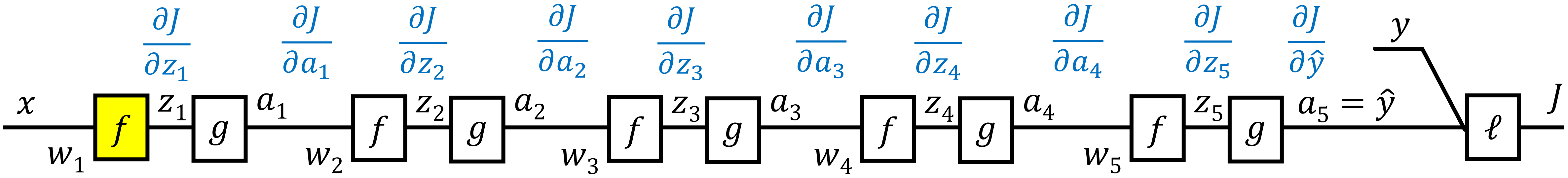


$$\frac{\partial J}{\partial z_1} = \frac{\partial J}{\partial a_1} \frac{\partial g}{\partial z_1}$$

Backpropagation

$$\hat{y} = h_{\boldsymbol{\theta}}(\mathbf{x}) = g\left(w_5 \cdot g\left(w_4 \cdot g\left(w_3 \cdot g(w_2 \cdot g(w_1 \cdot x))\right)\right)\right)$$

More efficient to start at the end and reuse values!

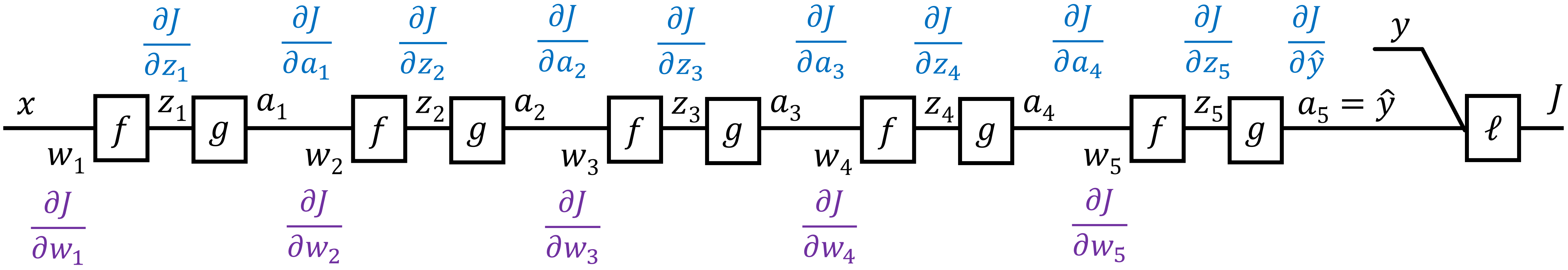


$$\frac{\partial J}{\partial w_1} = \frac{\partial J}{\partial z_1} \frac{\partial f}{\partial w_1}$$

Backpropagation

$$\hat{y} = h_{\boldsymbol{\theta}}(\mathbf{x}) = g\left(w_5 \cdot g\left(w_4 \cdot g\left(w_3 \cdot g(w_2 \cdot g(w_1 \cdot x))\right)\right)\right)$$

More efficient to start at the end and reuse values!



To do gradient descent we need the partial derivative of the objective with respect to each parameter, $w_\ell \leftarrow w_\ell - \alpha\, \partial J / \partial w_\ell$

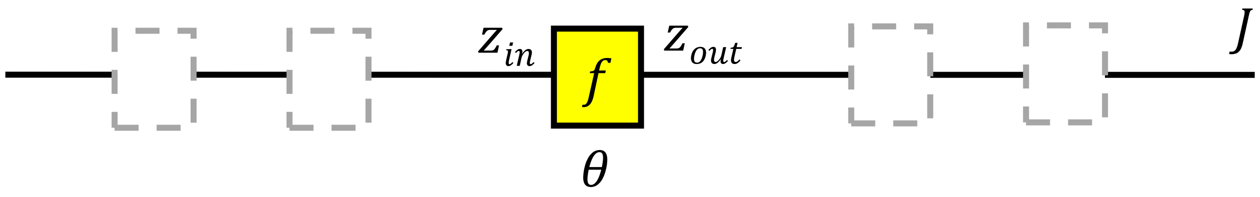
The backward pass propagates the change in the objective with respect to intermediate values ($\partial J / \partial z_\ell$ and $\partial J / \partial a_\ell$) back through the network to produce each $\partial J / \partial w_\ell$

Generic Layer Implementation (so-far)

Compute derivatives per layer, utilizing previous derivatives

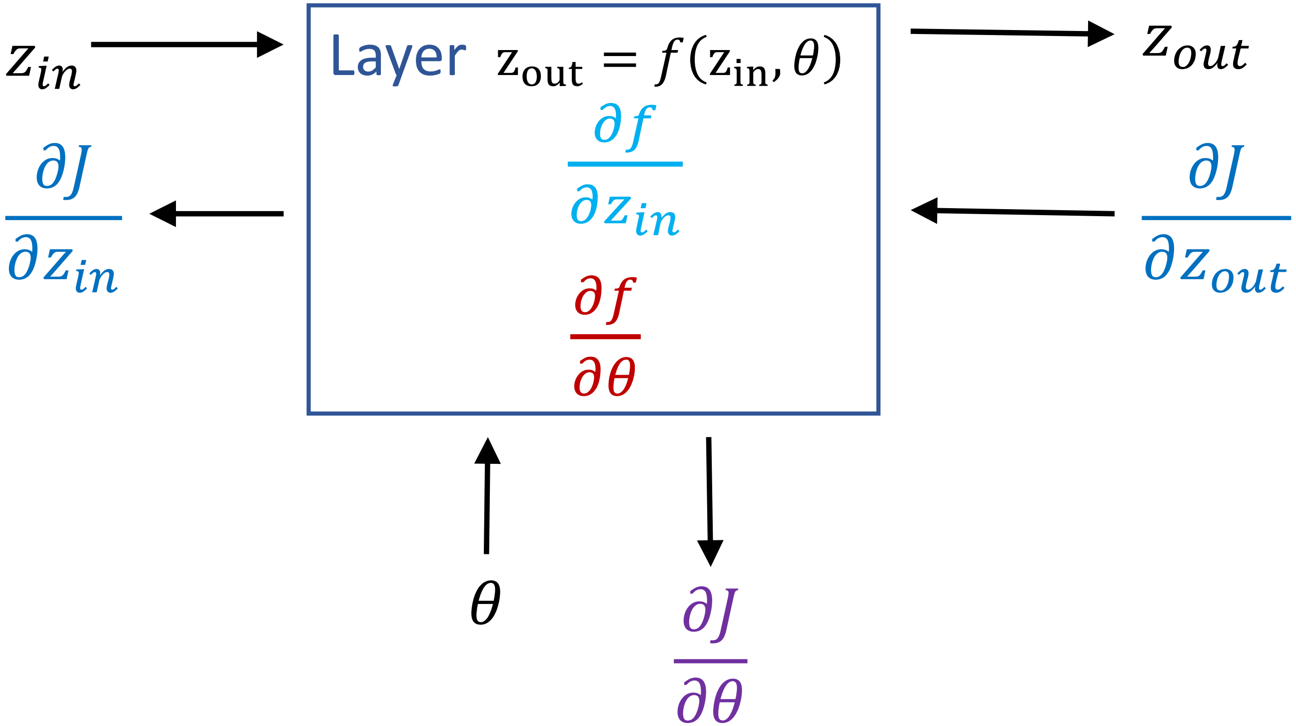
Objective: $J(\theta)$

Arbitrary layer: $\mathrm{z}_{\text{out}} = f(\mathrm{z}_{\text{in}}, \theta)$



Need:

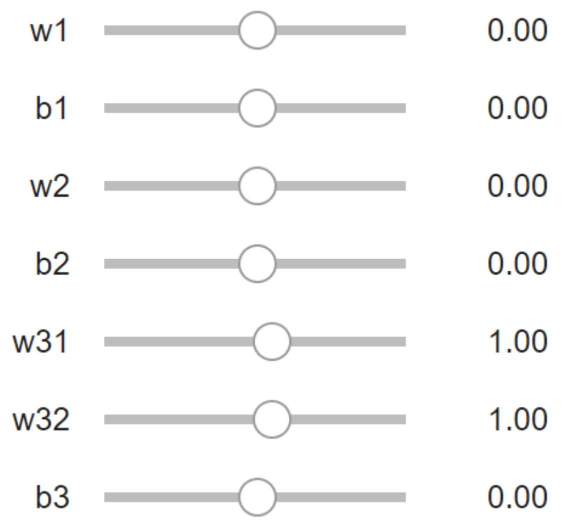
- $\dfrac{\partial J}{\partial z_{in}} = \dfrac{\partial J}{\partial z_{out}} \dfrac{\partial f}{\partial z_{in}}$
- $\dfrac{\partial J}{\partial \theta} = \dfrac{\partial J}{\partial z_{out}} \dfrac{\partial f}{\partial \theta}$

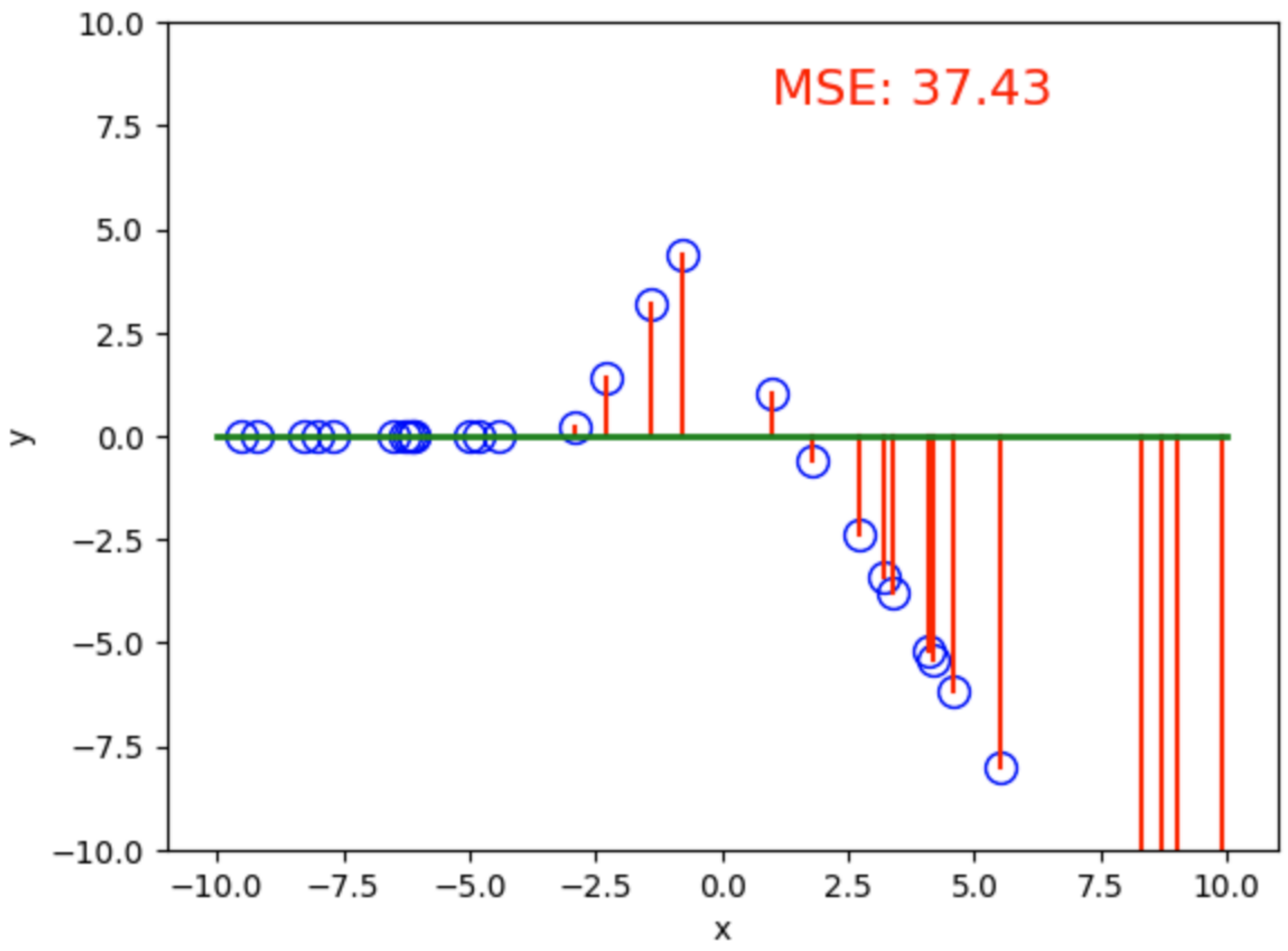


Additional Slides

Three-neuron network

Interactive demo: three_neuron_interactive.ipynb on course website

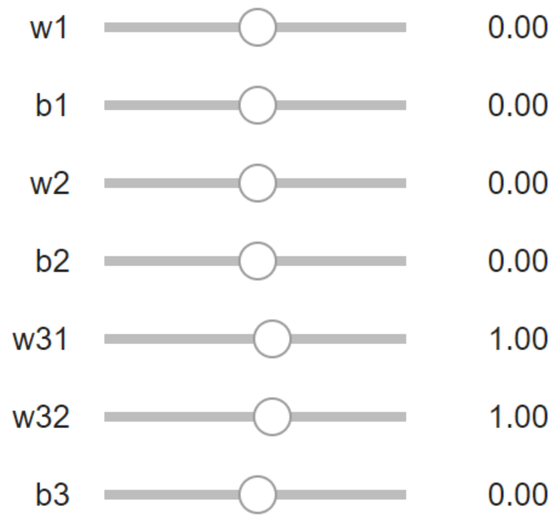


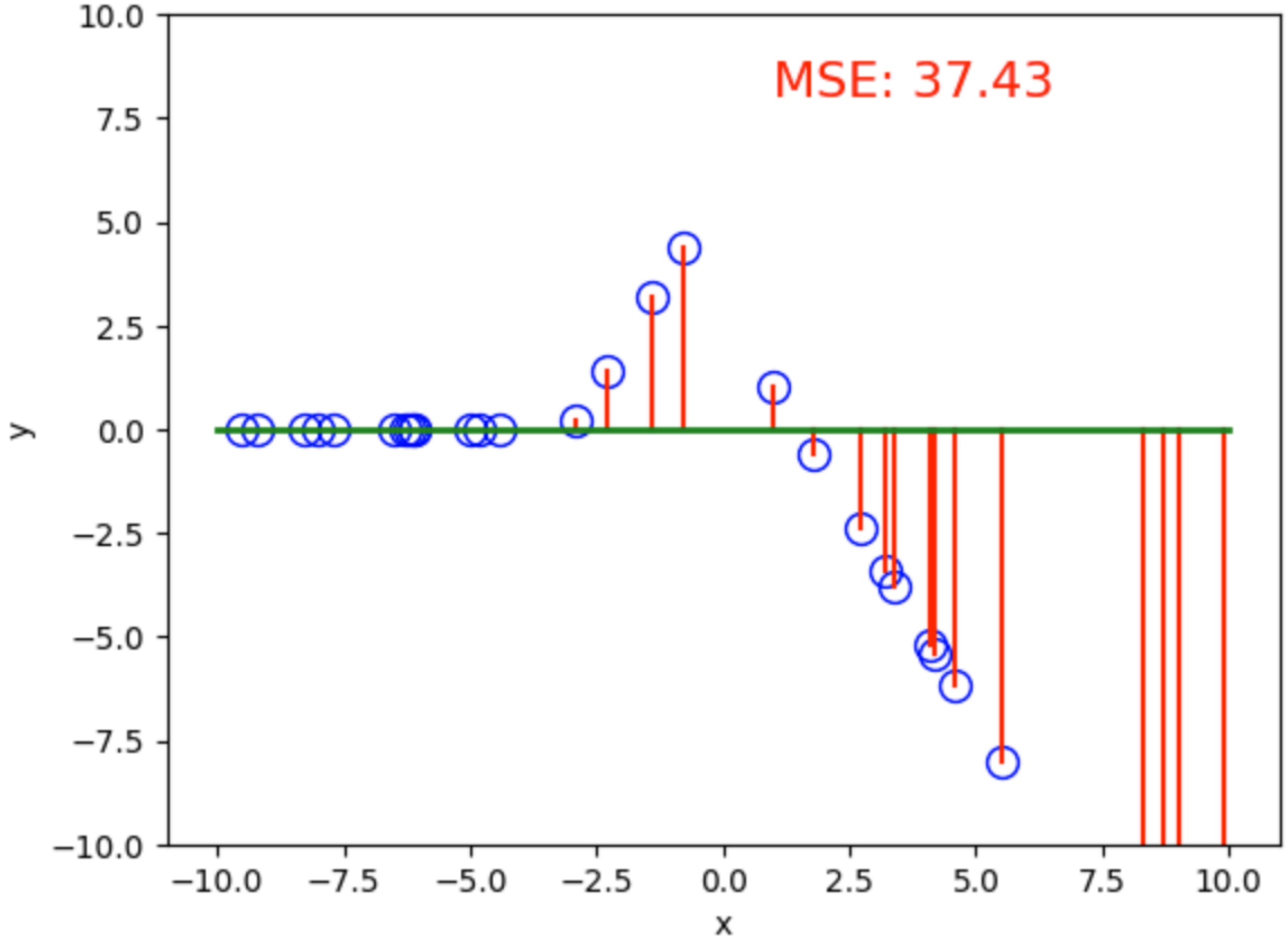


Poll

Interactive demo: [three_neuron_interactive.ipynb]() on course website

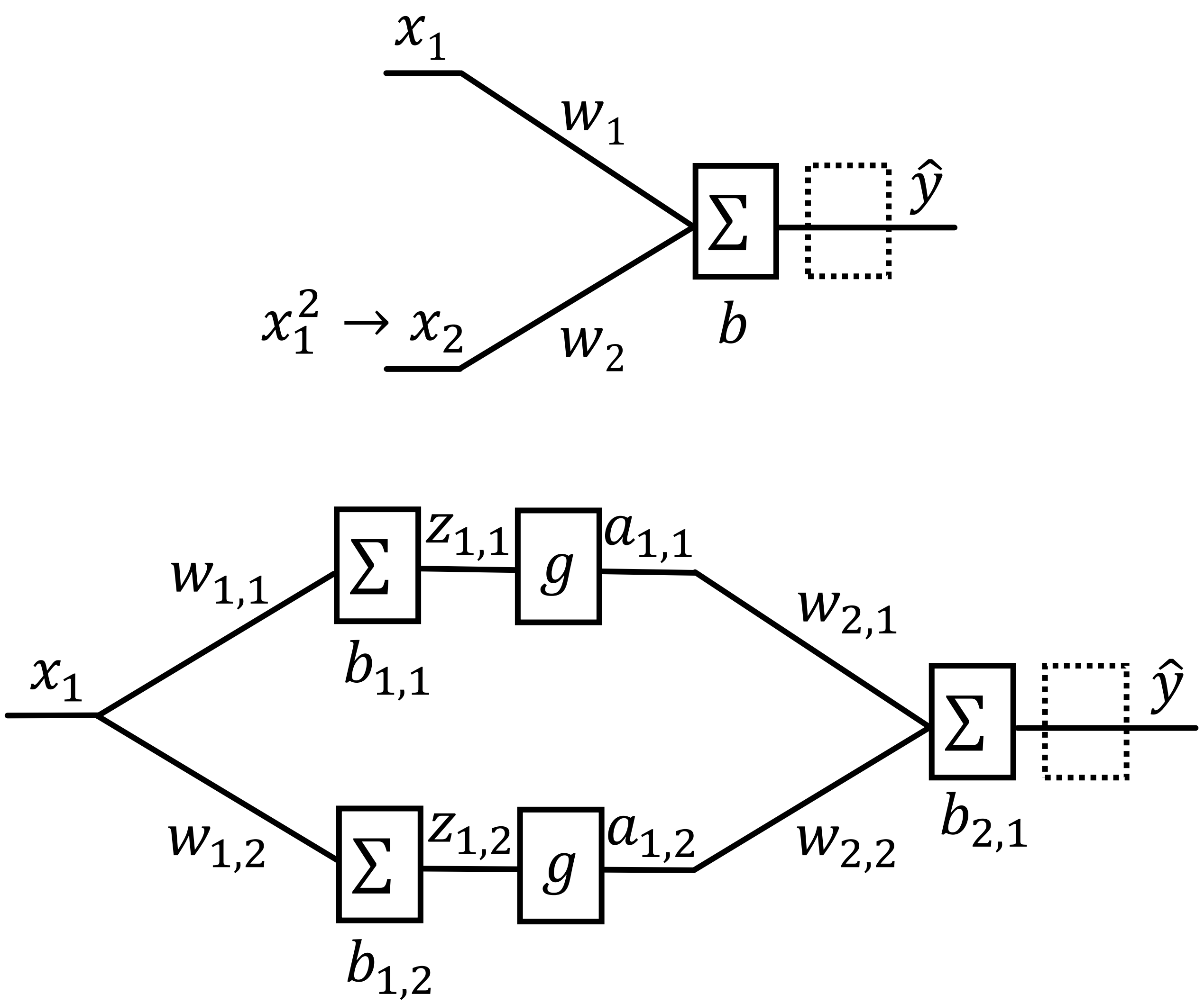
What's the smallest MSE that you can find?

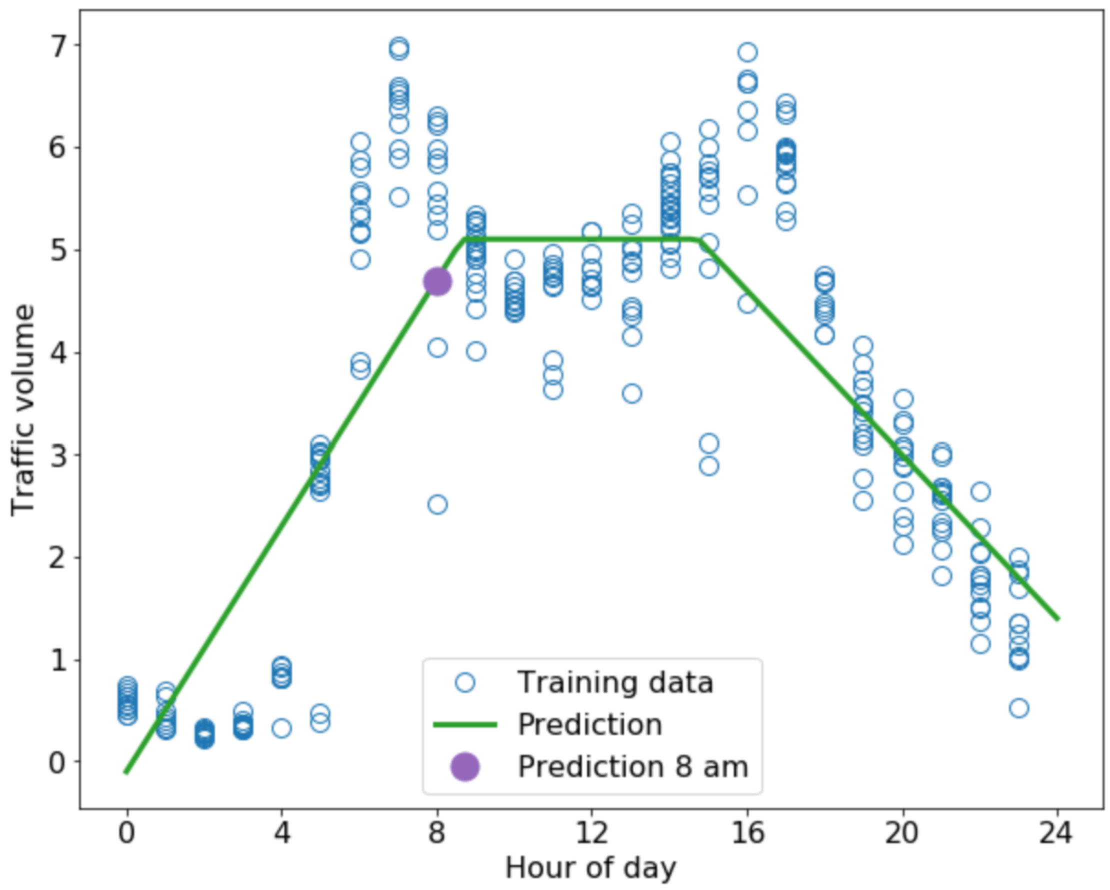




Traffic Data Example

Quadratic feature engineering vs three-neuron network





Traffic Data Example

Three-neuron network

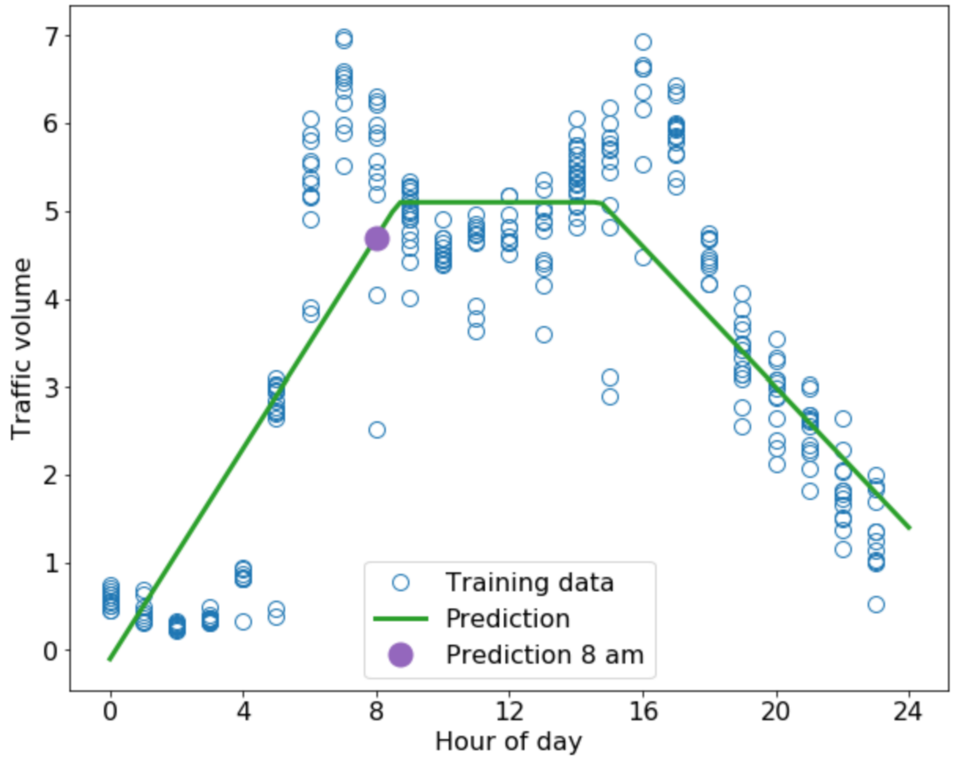
Parameters

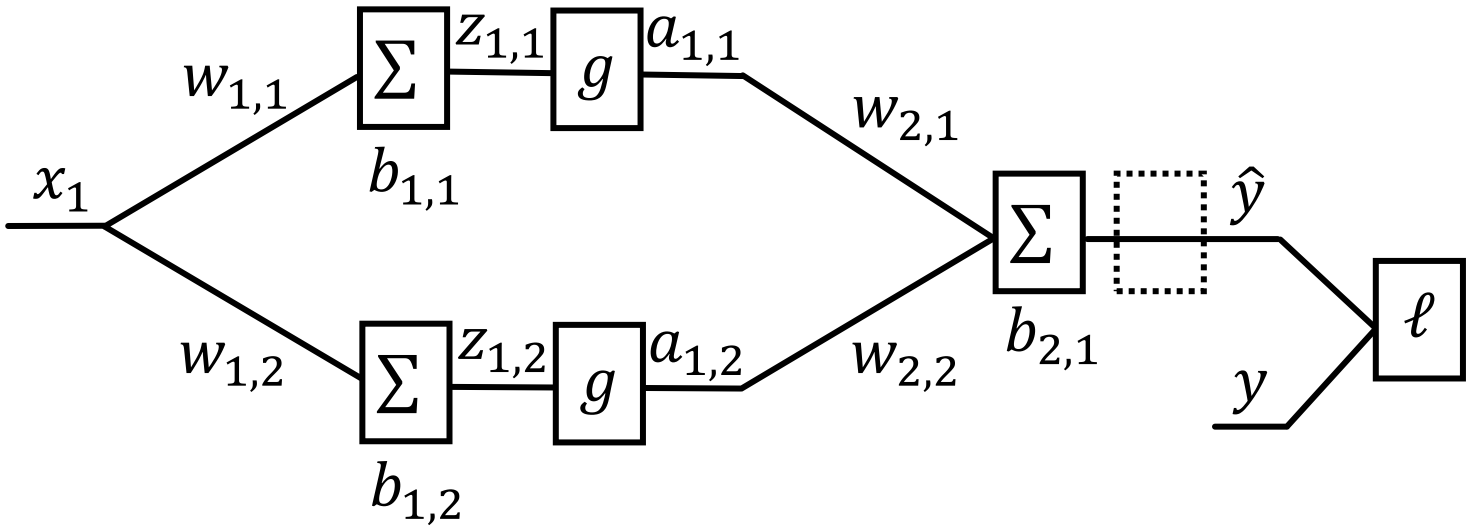
$w_{1,1}$: 0.4 $b_{1,1}$: -5.9

$w_{1,2}$: -0.6 $b_{1,2}$: 5.2

$w_{2,1}$: -1.0 $b_{2,1}$: 5.1

$w_{2,2}$: -1.0

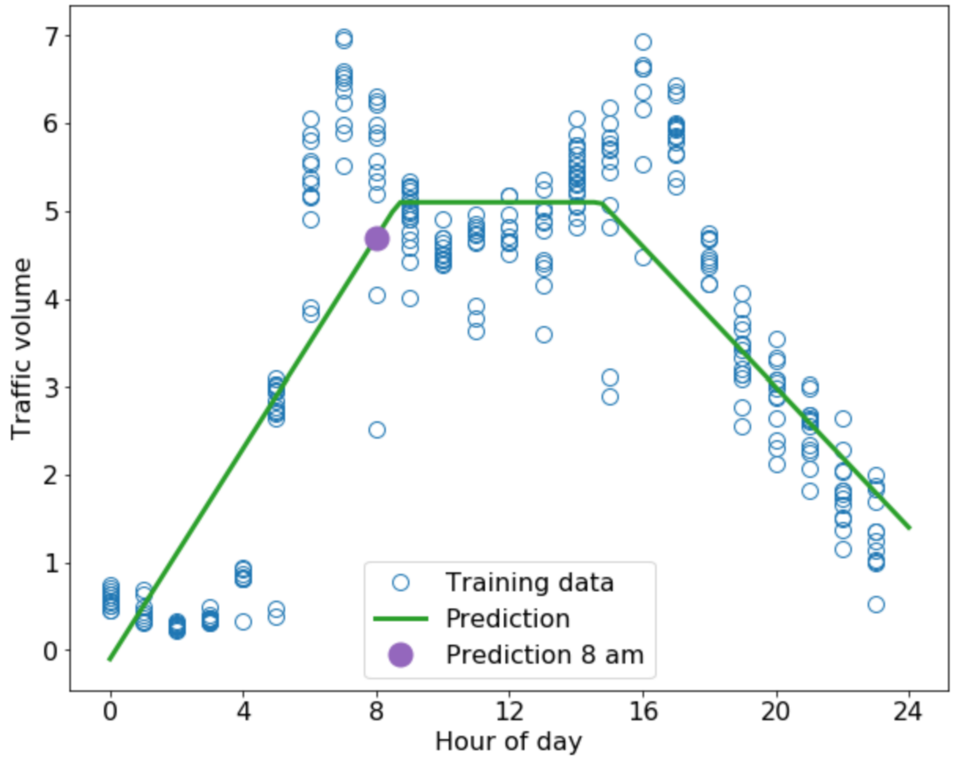


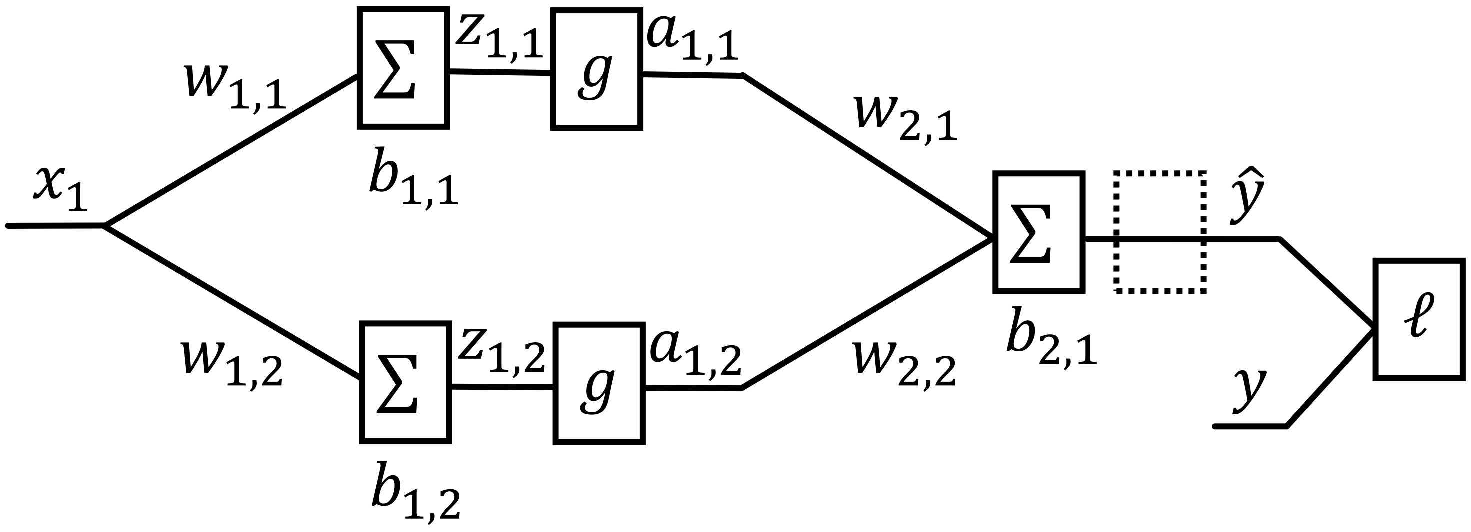


Traffic Data Example

Three-neuron network

Parameters	
$w_{1,1}$: 0.4	$b_{1,1}$: -5.9
$w_{1,2}$: -0.6	$b_{1,2}$: 5.2
$w_{2,1}$: -1.0	$b_{2,1}$: 5.1
$w_{2,2}$: -1.0	



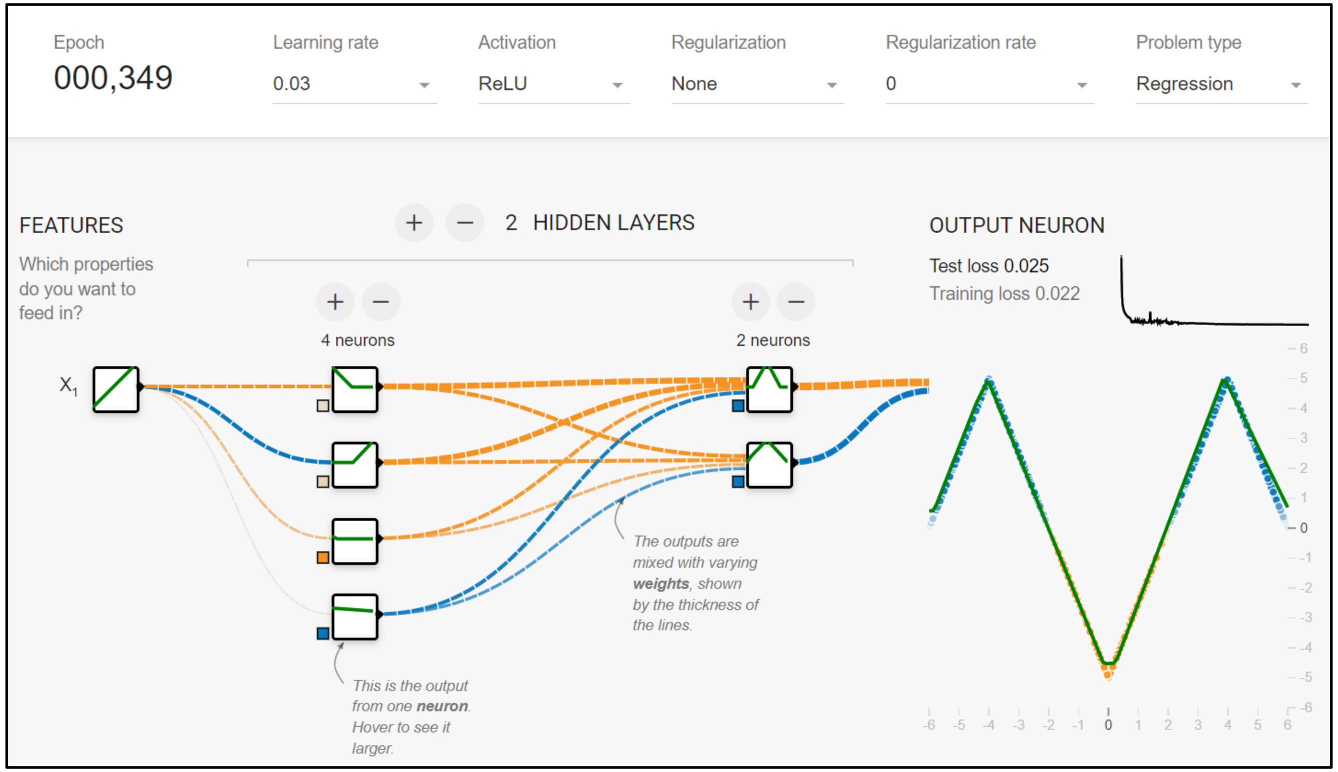


Simple Network

What do the colors of the lines represent?

A. Weight

B. Value from previous neuron



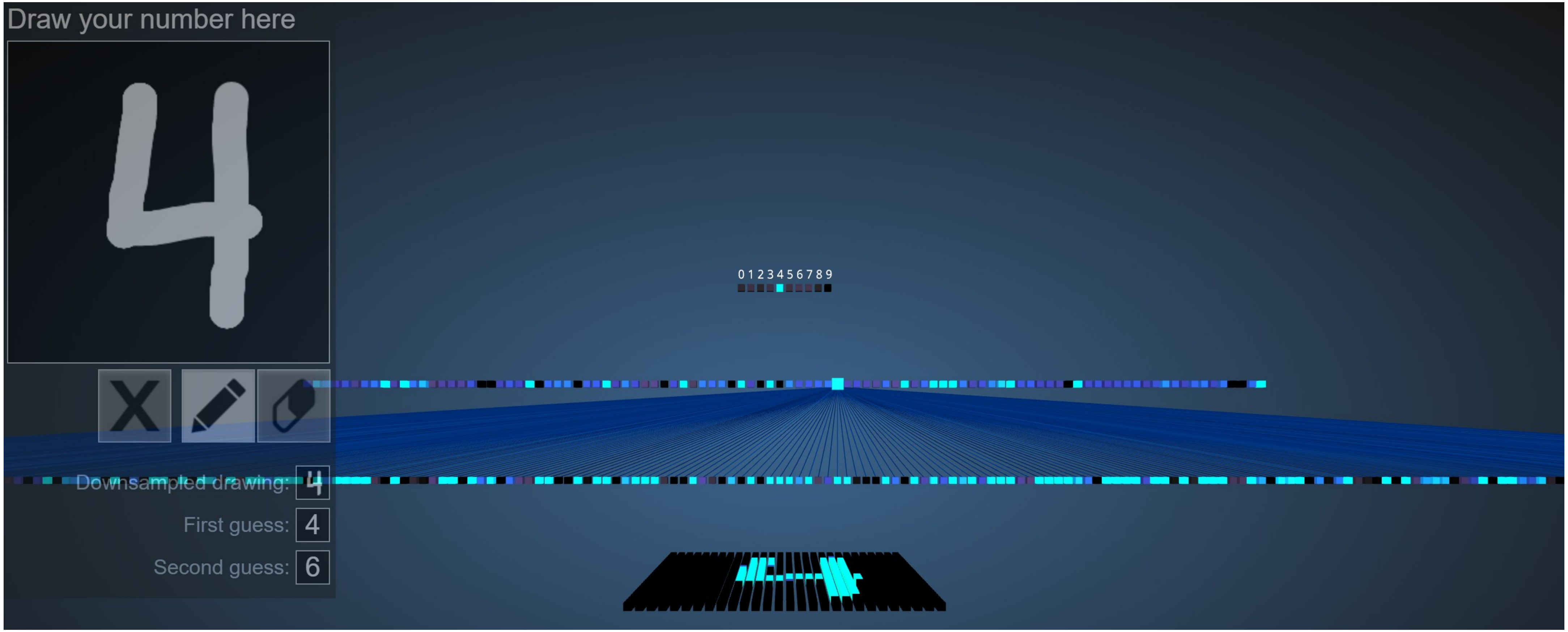
https://playground.tensorflow.org/

https://www.cs.cmu.edu/~pvirtue/tfp

Image Classification

Demo of (Fully-connected) neural network to classify images of hand-written digits

https://adamharley.com/nn_vis/mlp/3d.html



Reminder: Image Classification

Demo of (Fully-connected) neural network to classify images of hand-written digits

https://adamharley.com/nn_vis/mlp/3d.html

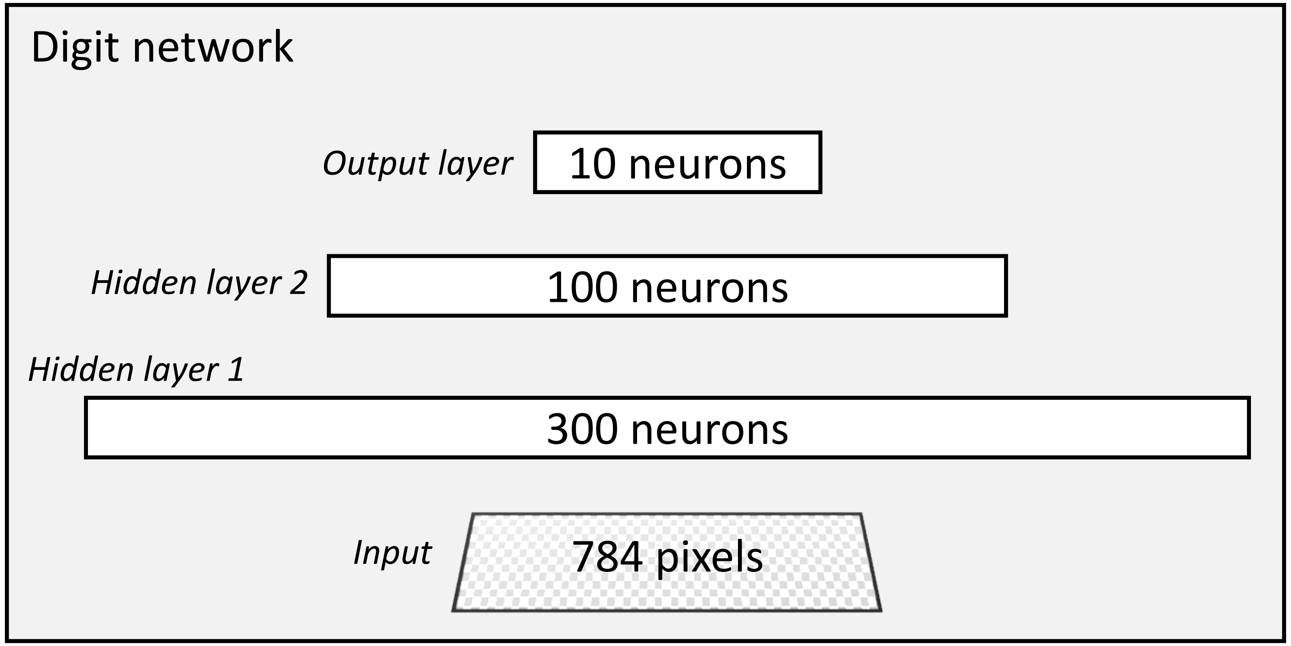


Image Classification

Demo of (Fully-connected) neural network to classify images of hand-written digits

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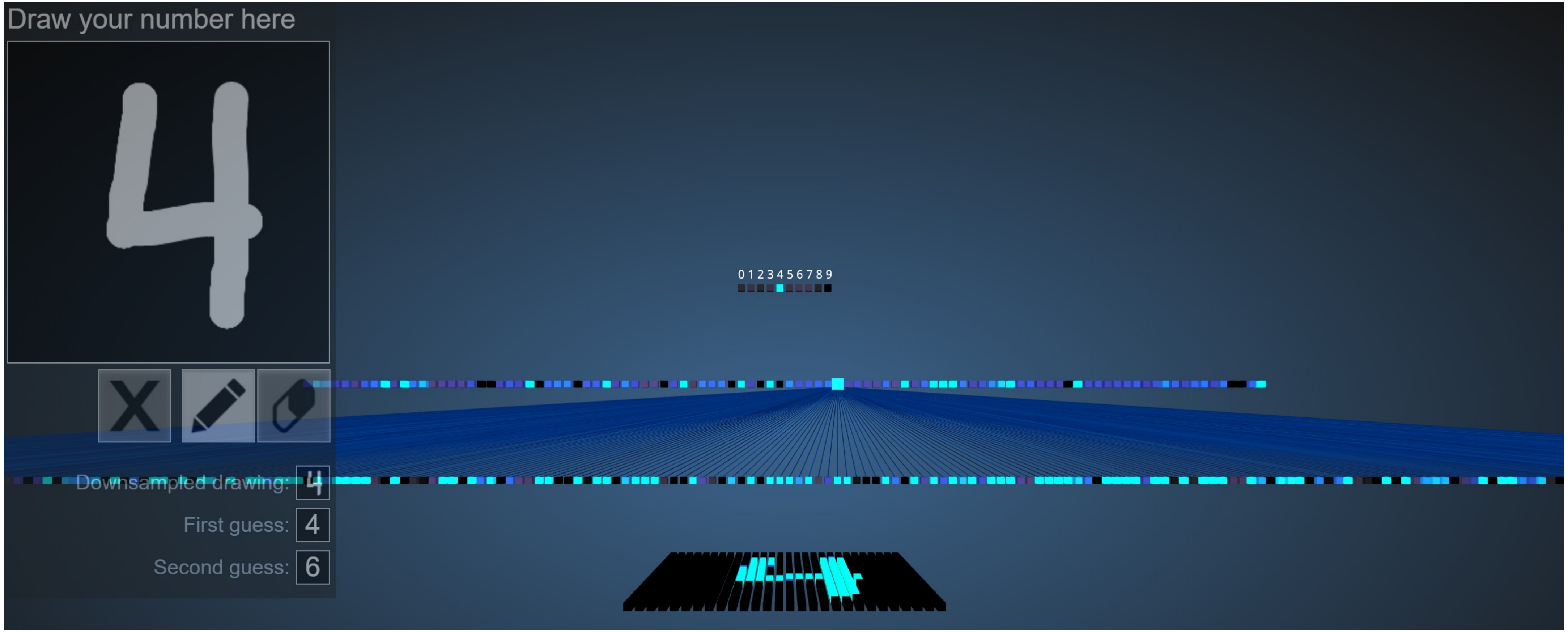
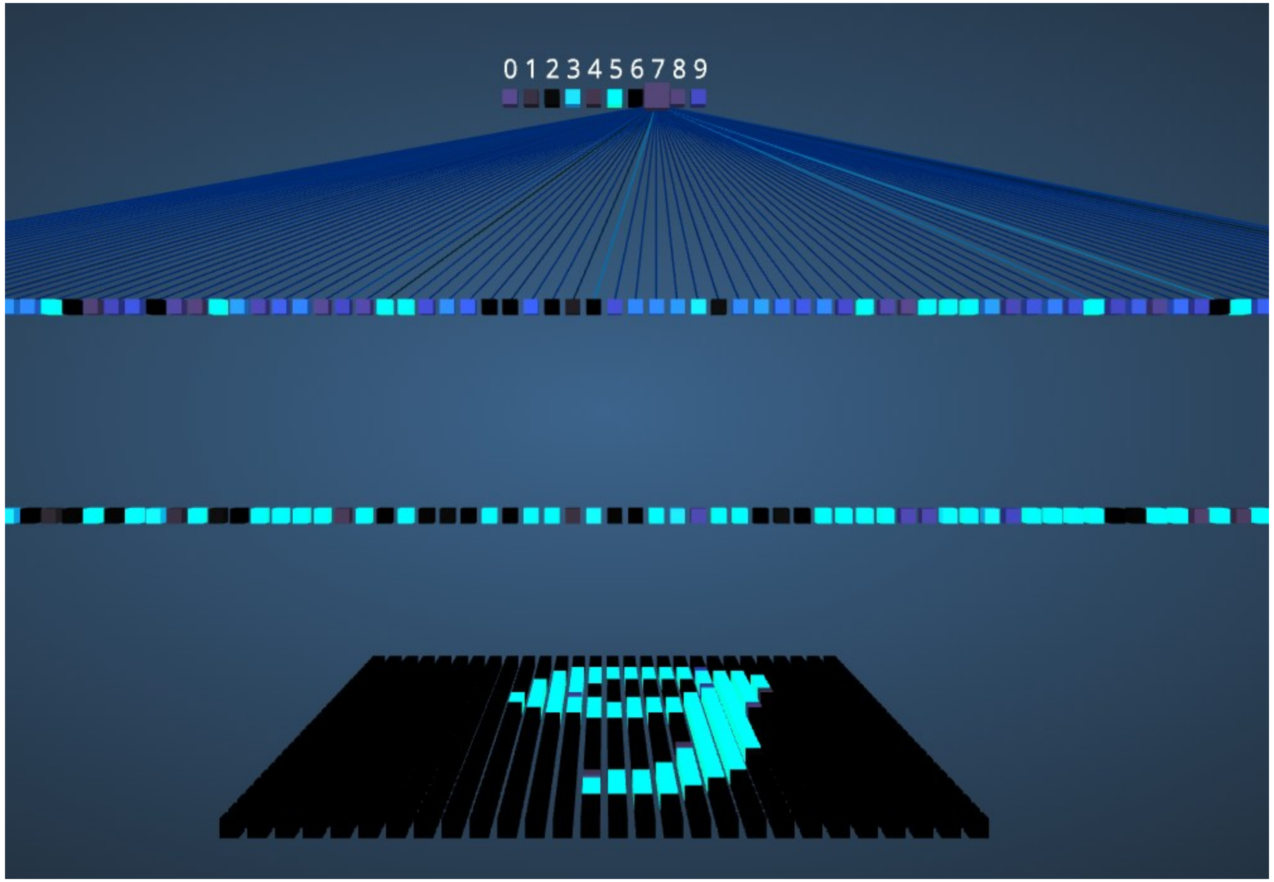


Poll

How many parameters does one neuron in the output layer have?

A. 1
B. 2
C. 10
D. 11
E. 100
F. 101



https://adamharley.com/nn_vis/mlp/3d.html

Poll

How many parameters does one neuron in the first hidden layer have?

A. 1

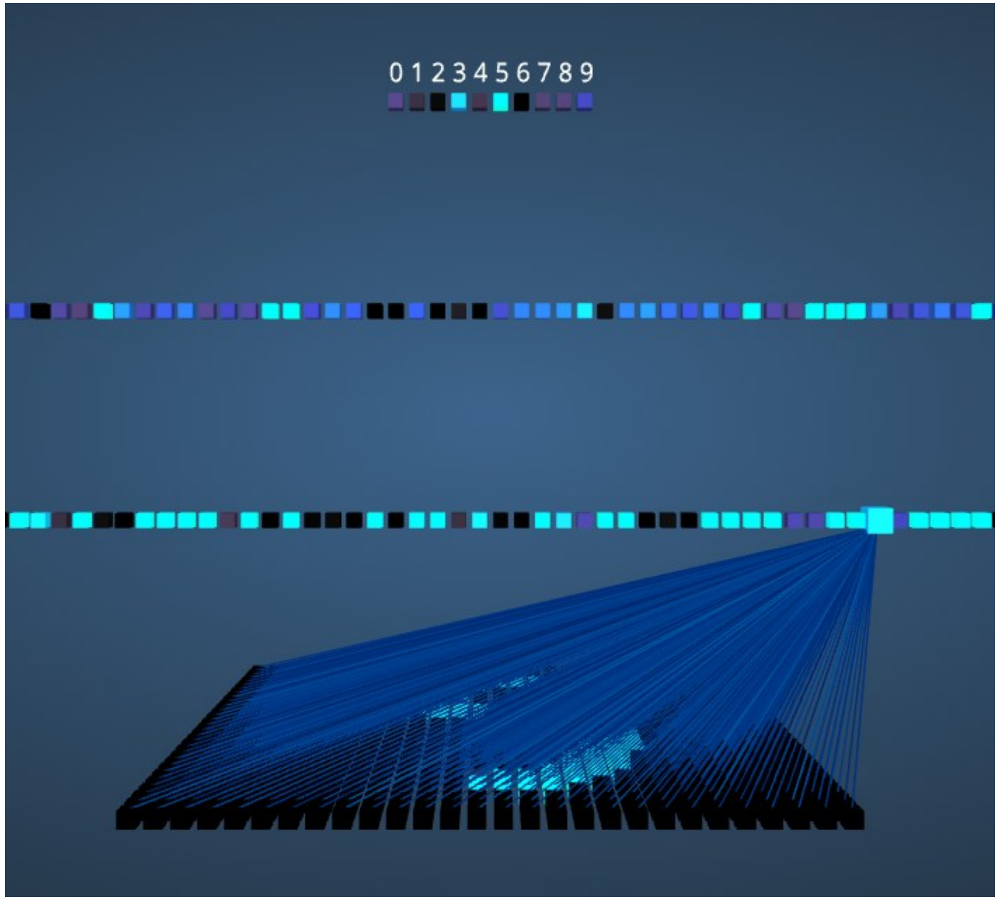
B. 2

C. 300

D. 301

E. 784

F. 785



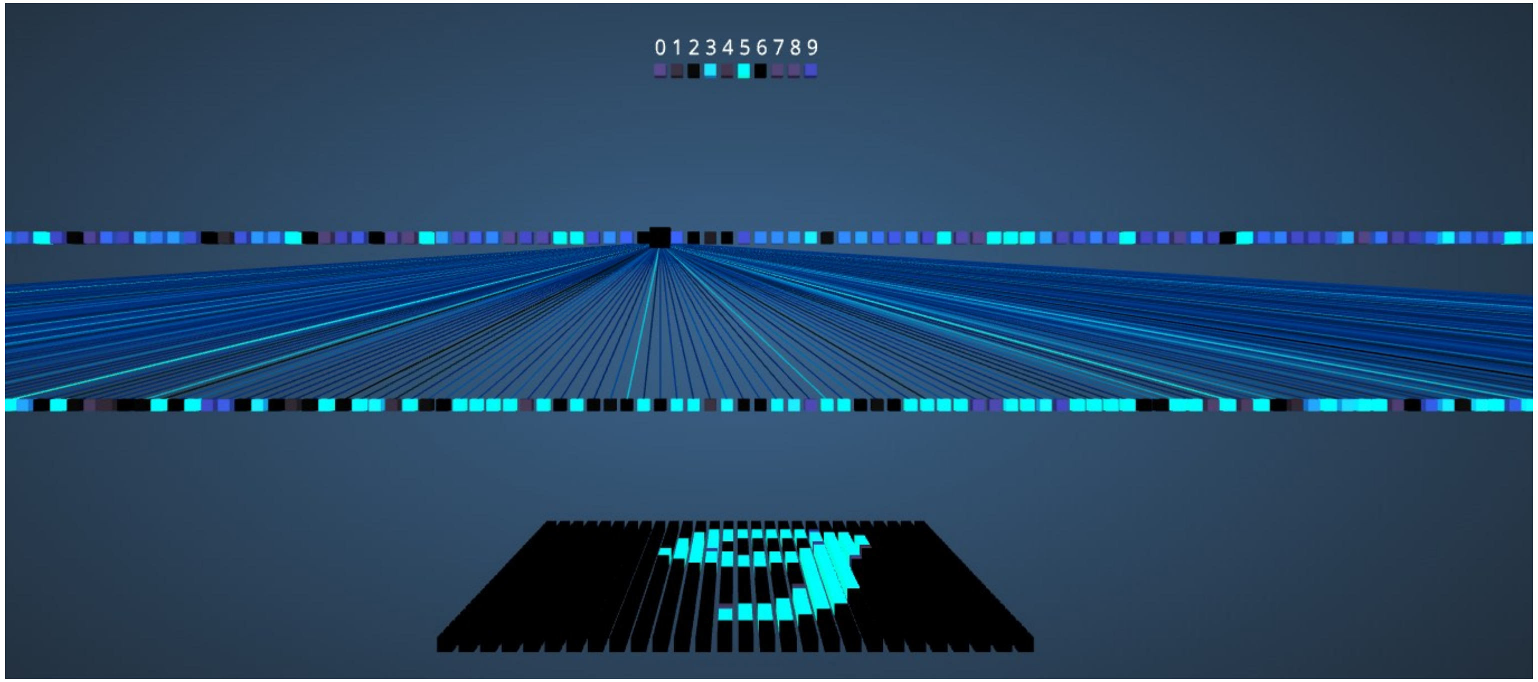
https://adamharley.com/nn_vis/mlp/3d.html

Poll

What do the colors of the lines represent?

A. Weight

B. Value from previous neuron



https://adamharley.com/nn_vis/mlp/3d.html

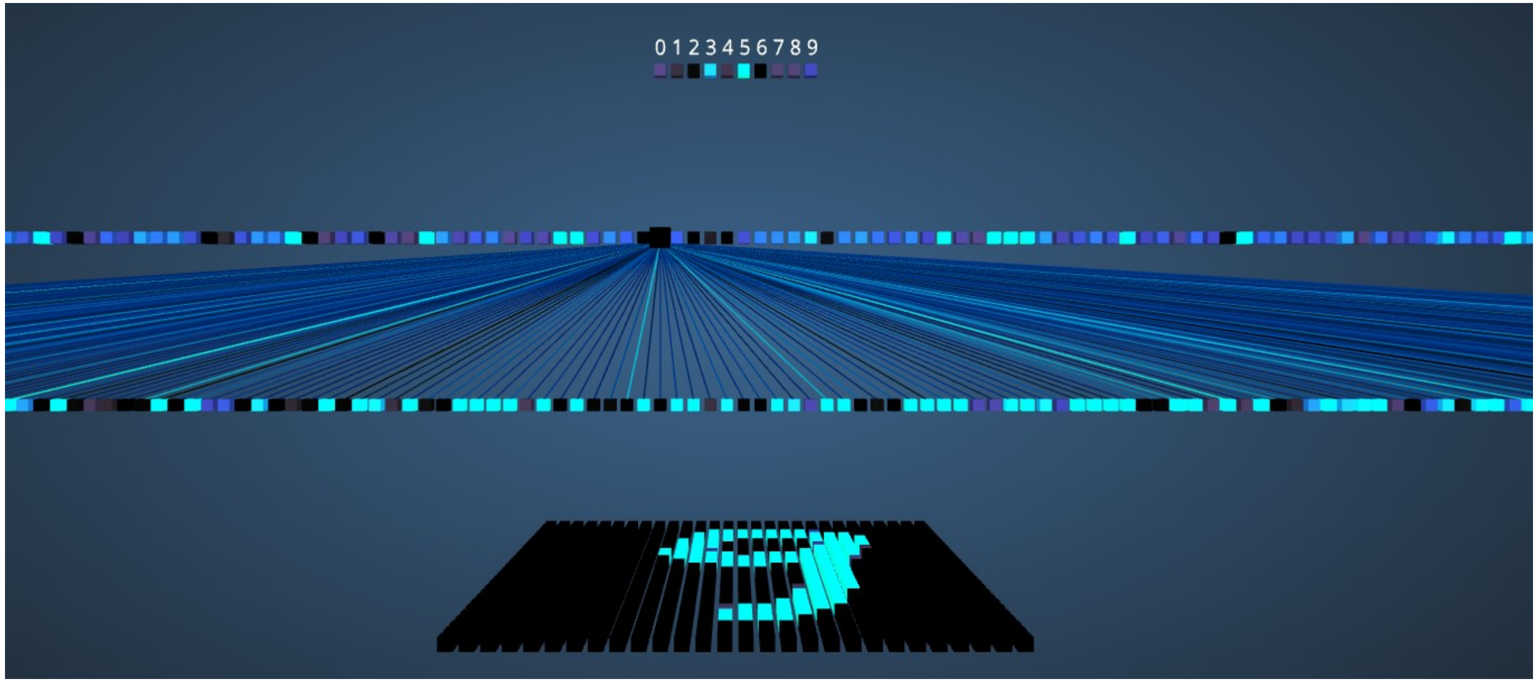
Poll

What do the colors of the neuron squares represent?

A. Weight

B. Output value of the neuron

C. Input value of the neuron



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