Computer Vision

Neural Networks

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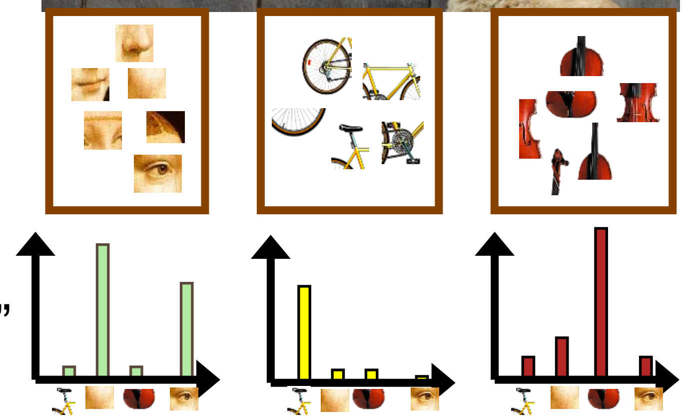
We have learned so for in this module

Image features and categorization

Choosing right features

Object, Scene, Action, etc.



Bag-of-visual-words

Extract local features

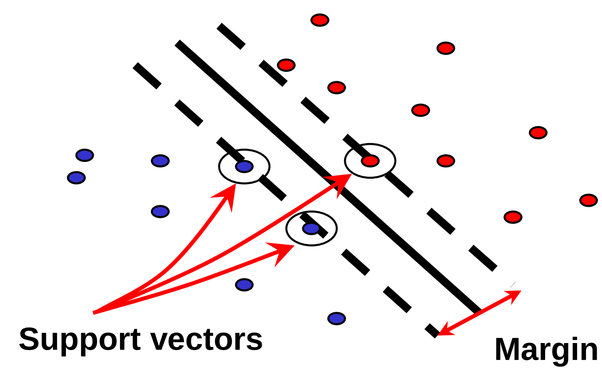
Learn “visual vocabulary”

Quantize features using visual vocabulary

Represent by frequencies of “visual words”

Classifiers

Nearest neighbor, KNN, Linear classifier, SVM, Non-linear SVM, Multi-class SVM, Softmax classifier



Previous Class

Two key components in context of the image classification

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Mapping the raw image pixels/features to class scores
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2. A loss function:

Measures the goodness of parameter values in terms of how well it performs over the training data
(e.g. Softmax/SVM)

Previous Class

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$$L_i = \sum_{j \neq y_i} \max(0, s_j - s_{y_i} + \Delta)$$

Softmax Loss:
Cross-entropy loss

$$L_i = -log\left(\frac{e^{s_{y_i}}}{\sum_j e^{s_j}}\right)$$

Today’s class

Optimization

Gradient Descent & Back propagation

Perceptron

Update rule

Neural networks

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Strategy #3: Following the gradients:

There is no need to randomly search for a good direction: this direction is related to the **gradient** of the loss function.

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The procedure of repeatedly evaluating the **gradient of loss function** and then performing a **parameter update**.

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Vanilla (Original) Gradient Descent:

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while True:
  weights_grad = evaluate_gradient(loss_fun, data, weights)
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  data_batch = sample_training_data(data, 256) # sample 256 examples
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***Stochastic Gradient Descent* (SGD):**

Special case of MGD when mini-batch contains only a single example

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Interpretation of the gradient

Interpretation. Derivatives indicate the rate of change of a function with respect to that variable surrounding an infinitesimally small region near a particular point:

$$\frac{df(x)}{dx} = \lim_{h \to 0} \frac{f(x+h) - f(x)}{h}$$

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Compound expressions with chain rule

$$f(x, y, z) = (x + y)z$$

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$$\Downarrow$$

$q = x + y$ and $f = qz$

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Chain rule: $\frac{\partial f}{\partial x} = \frac{\partial f}{\partial q} \frac{\partial q}{\partial x}$

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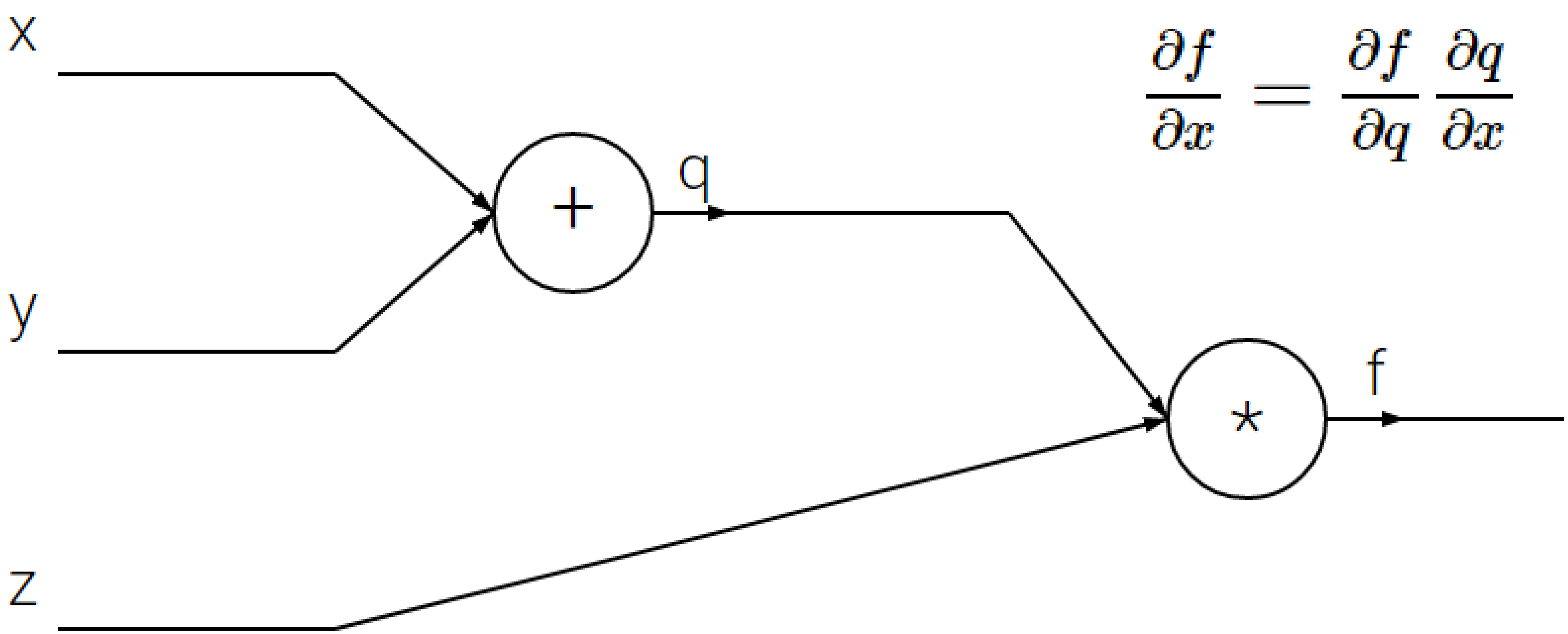

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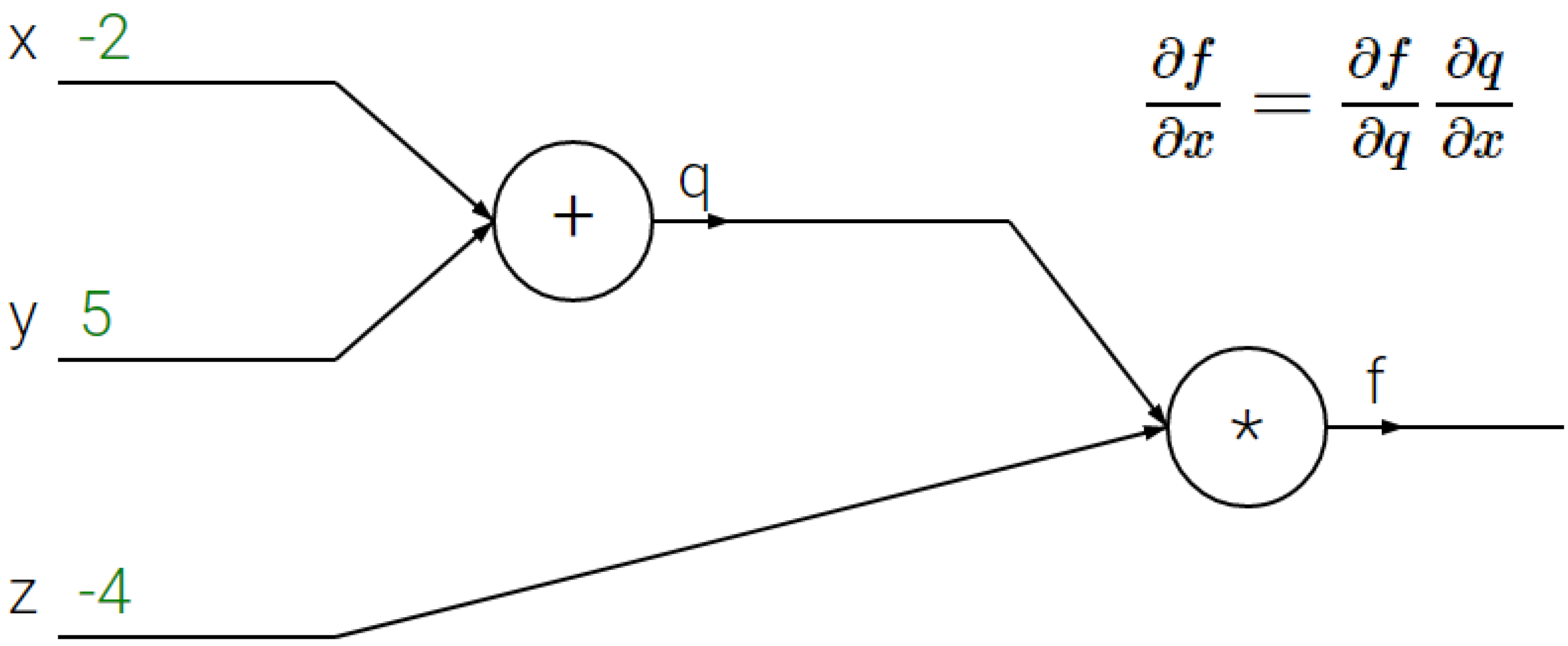

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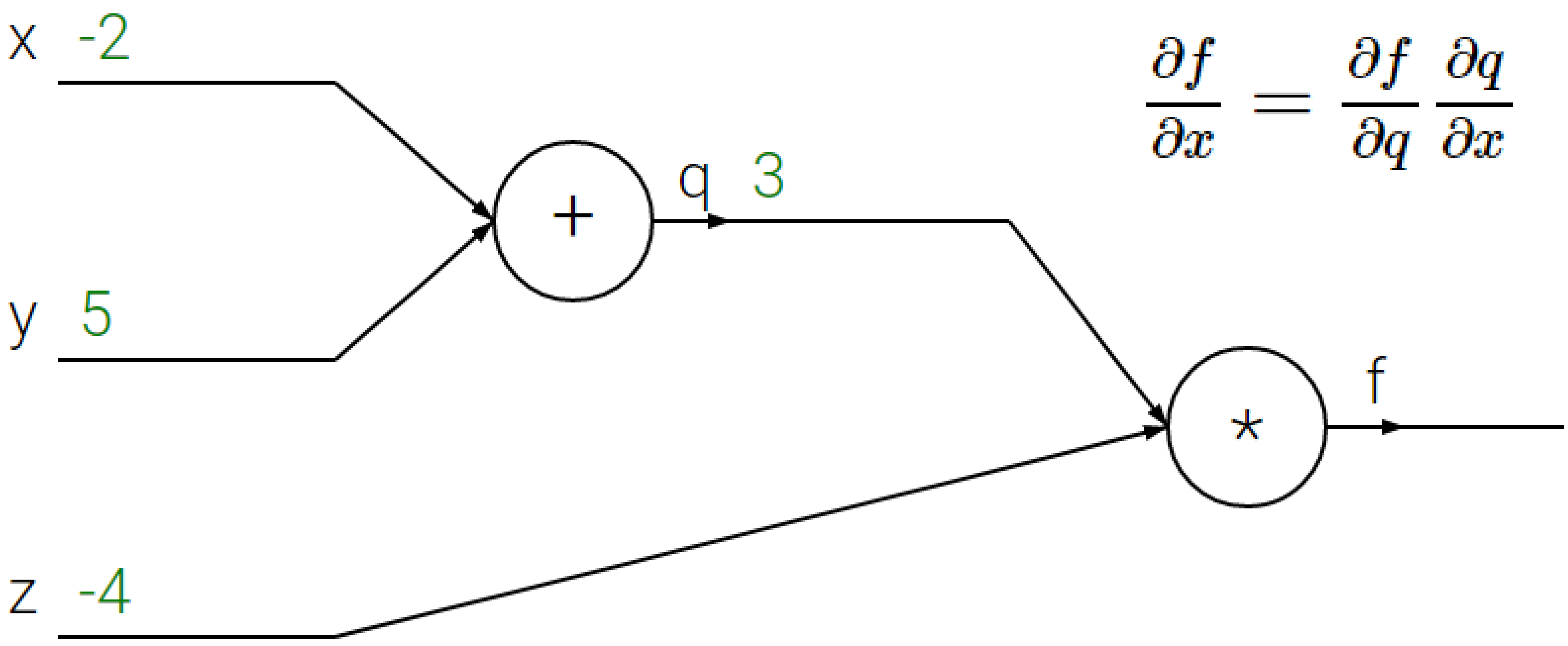

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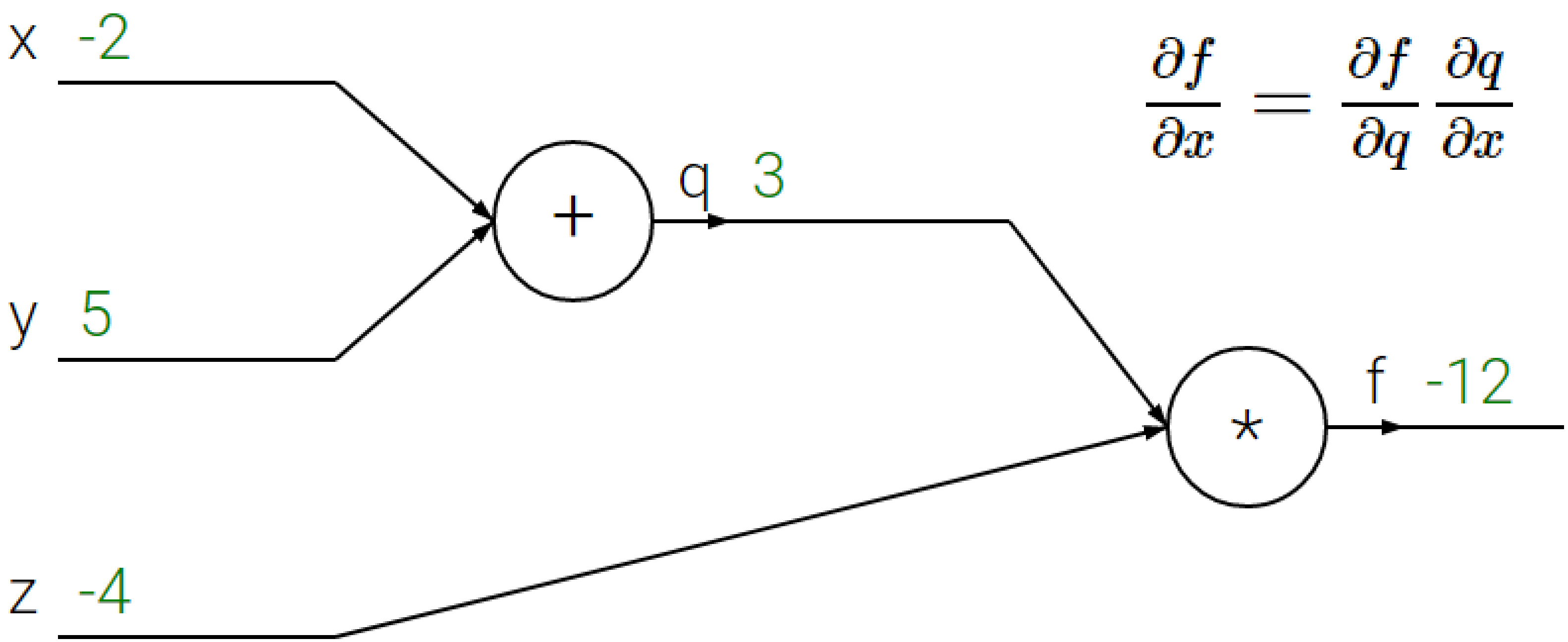

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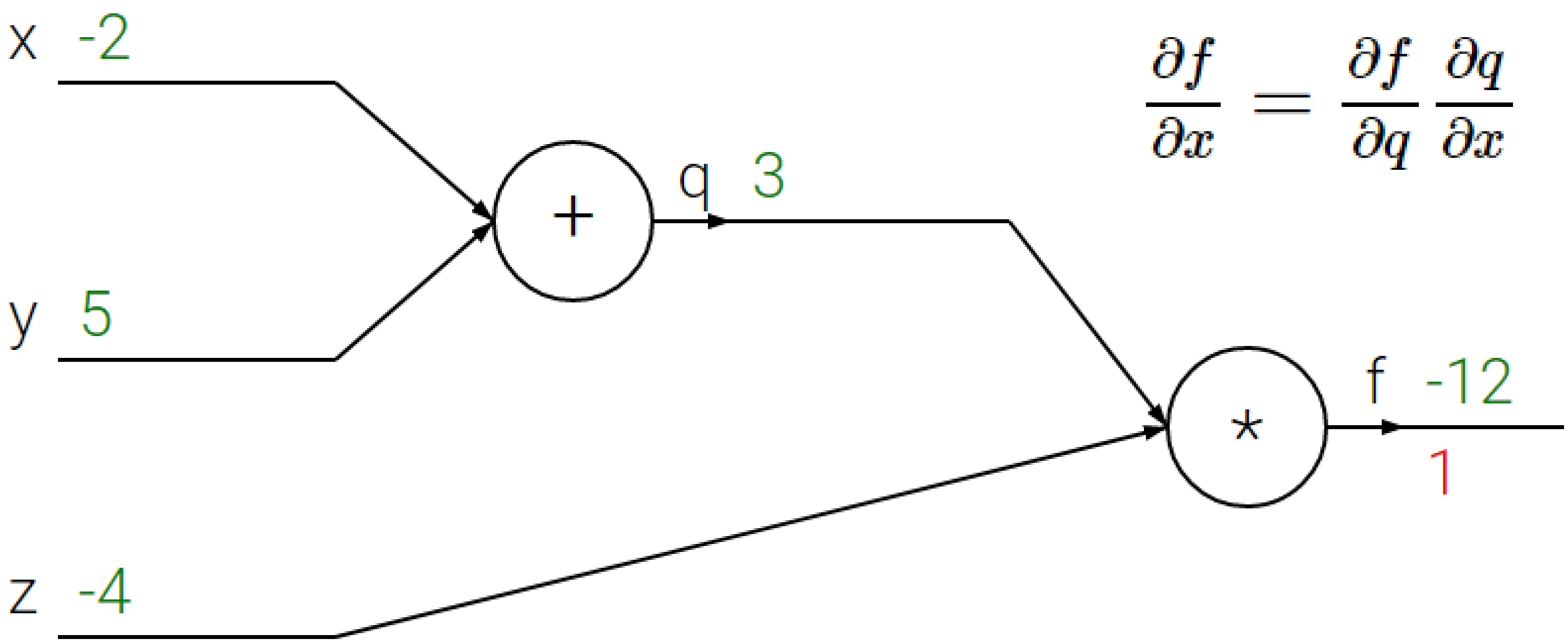

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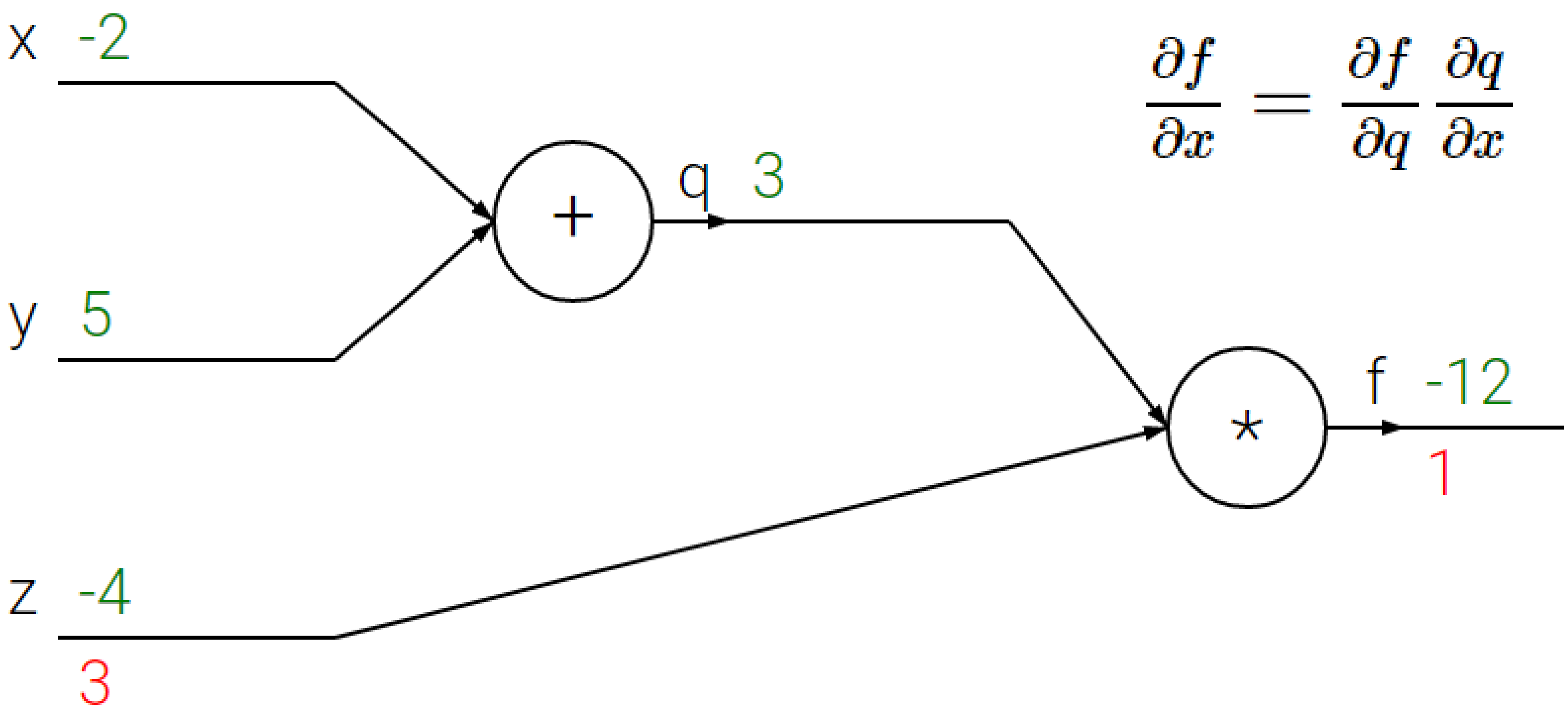

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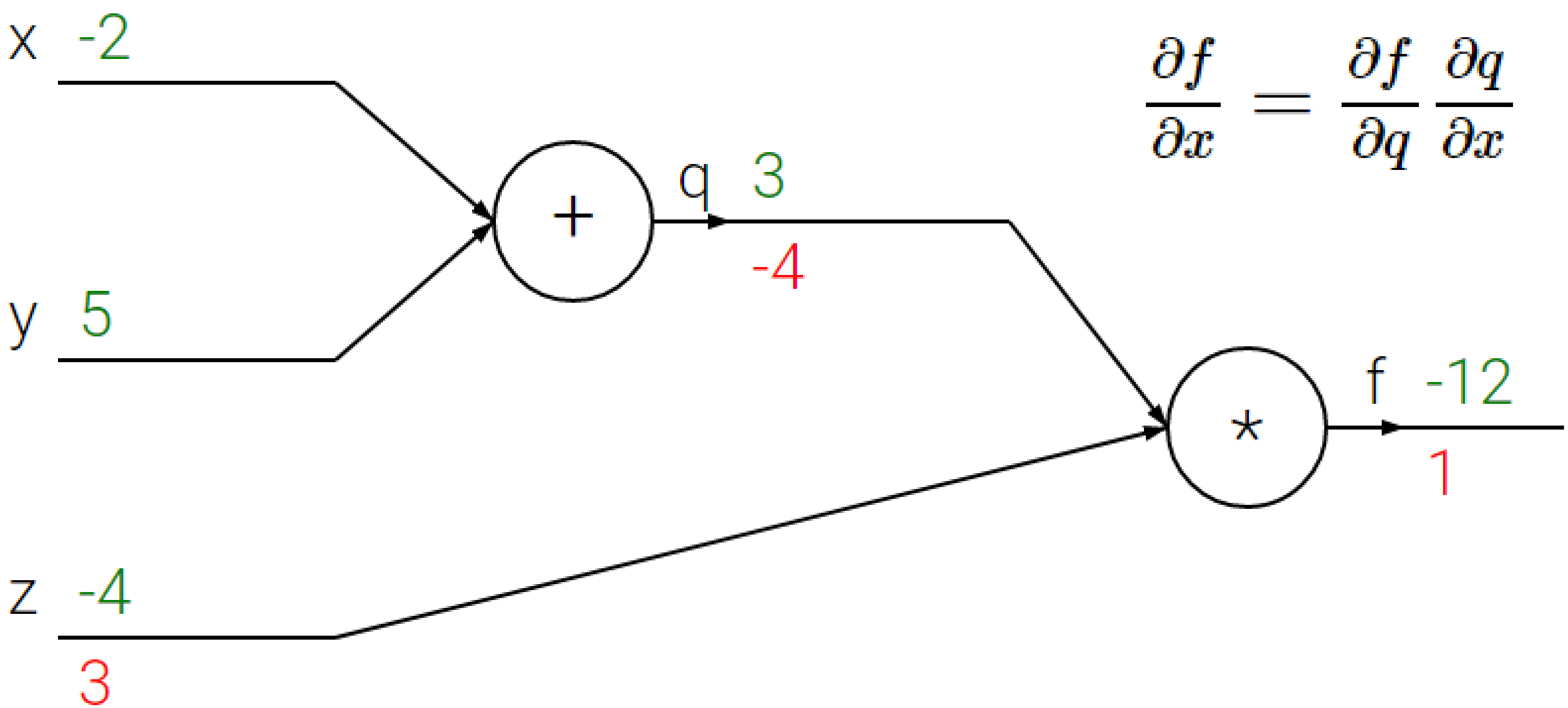

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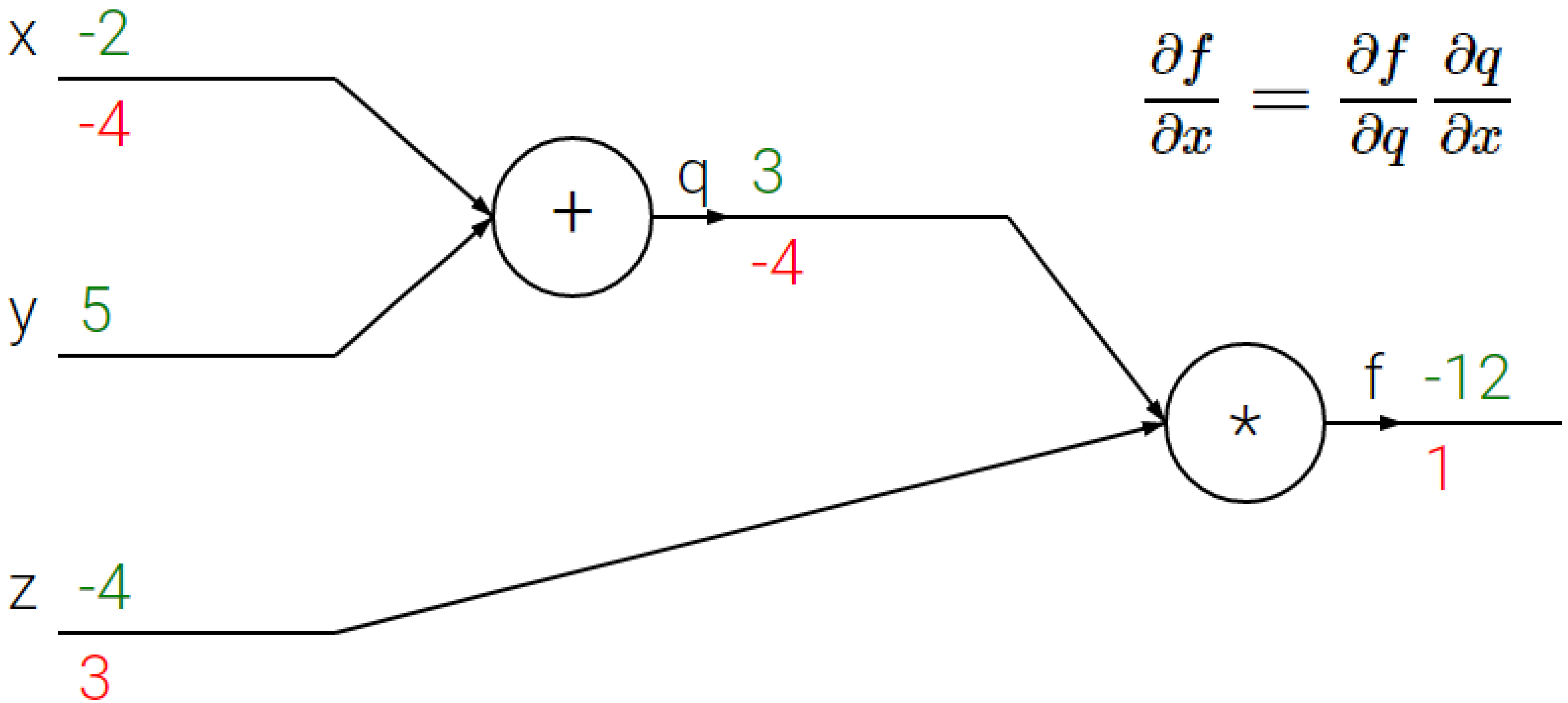

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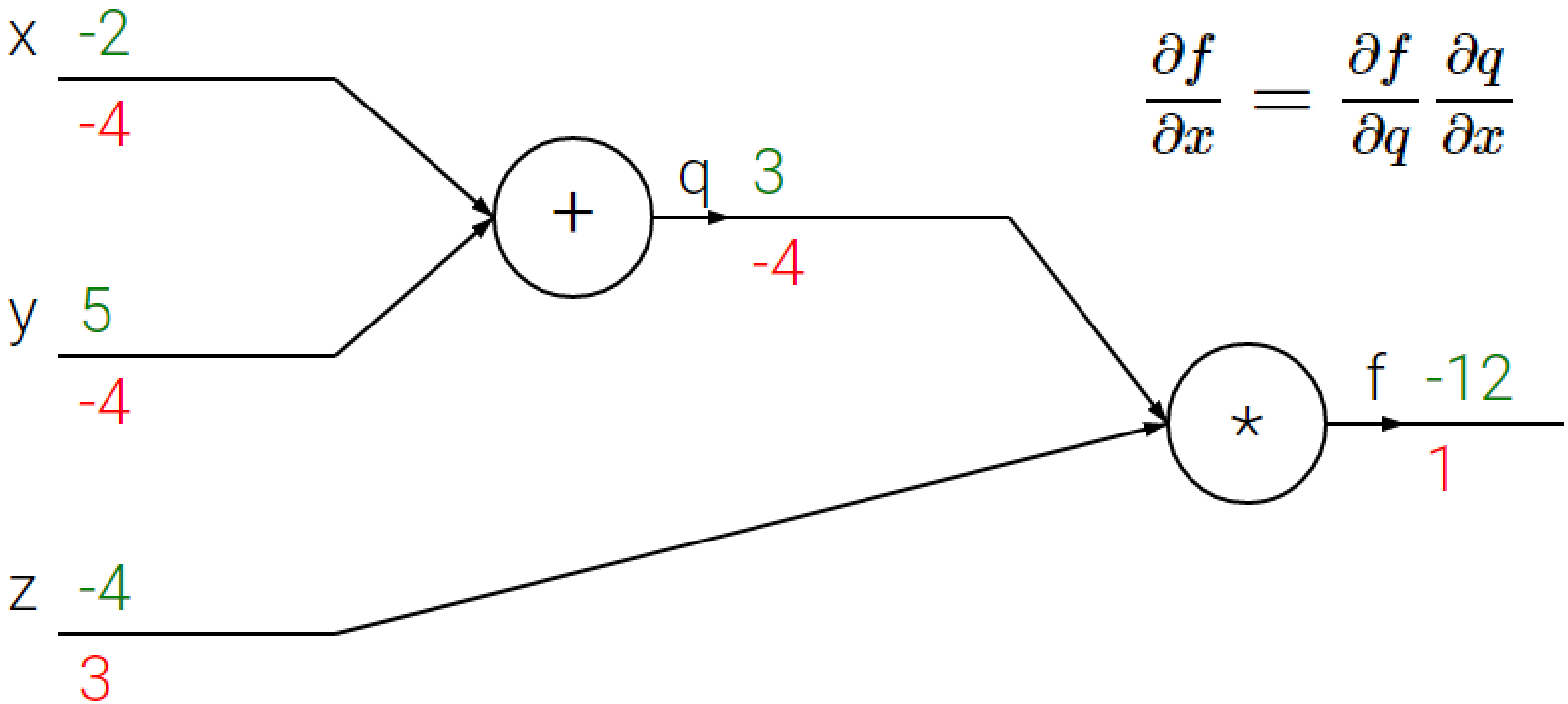

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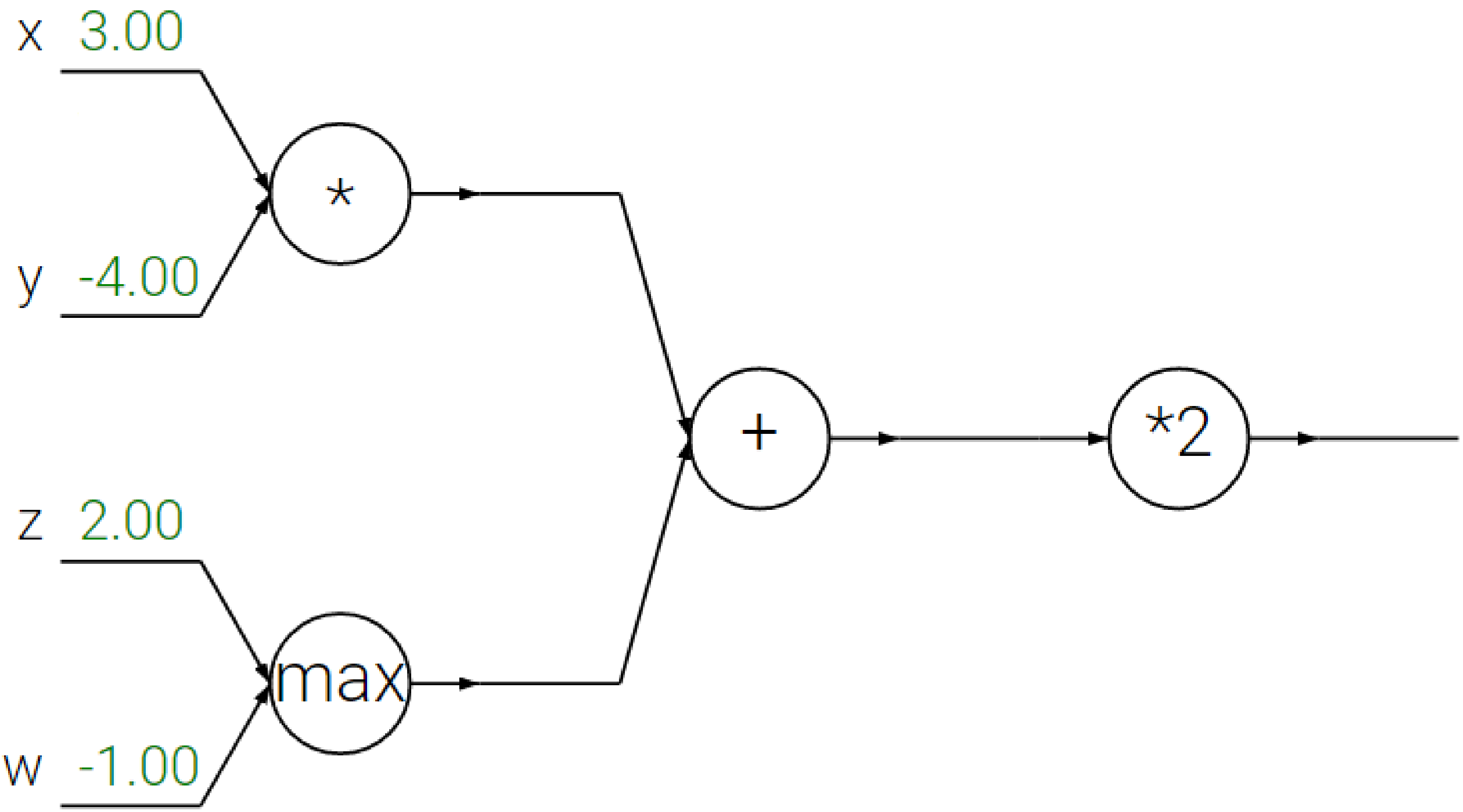
Forward and Backward Pass



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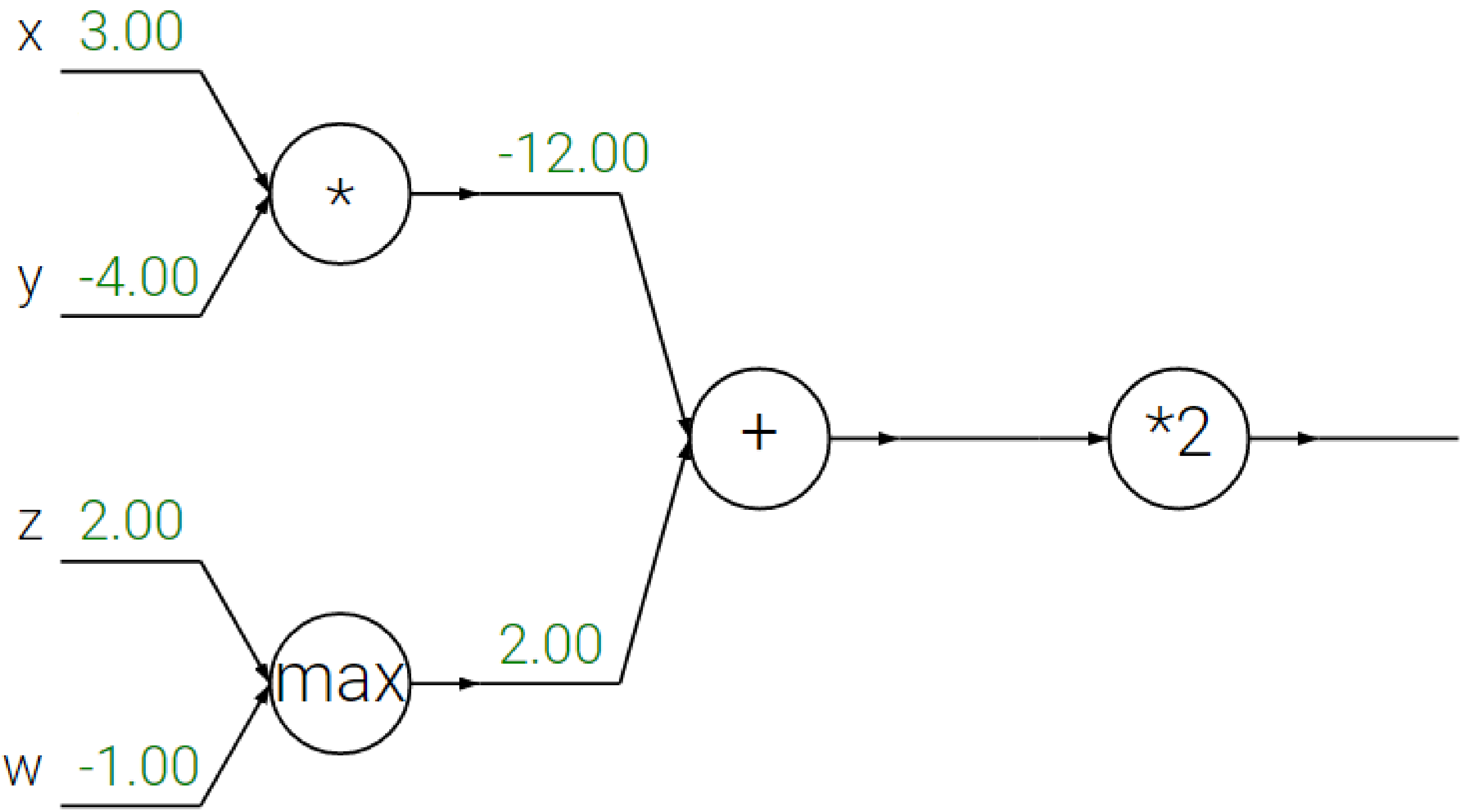

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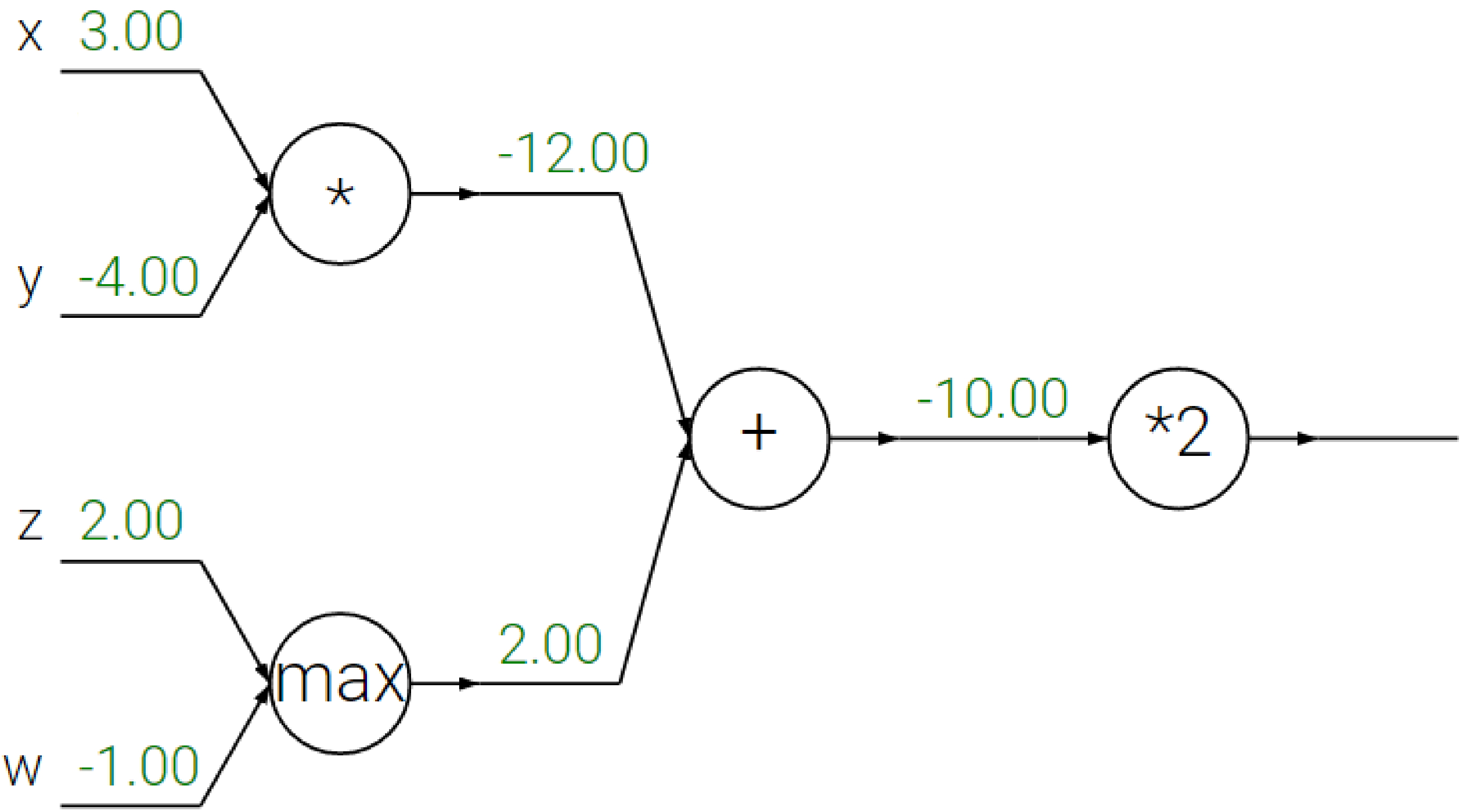

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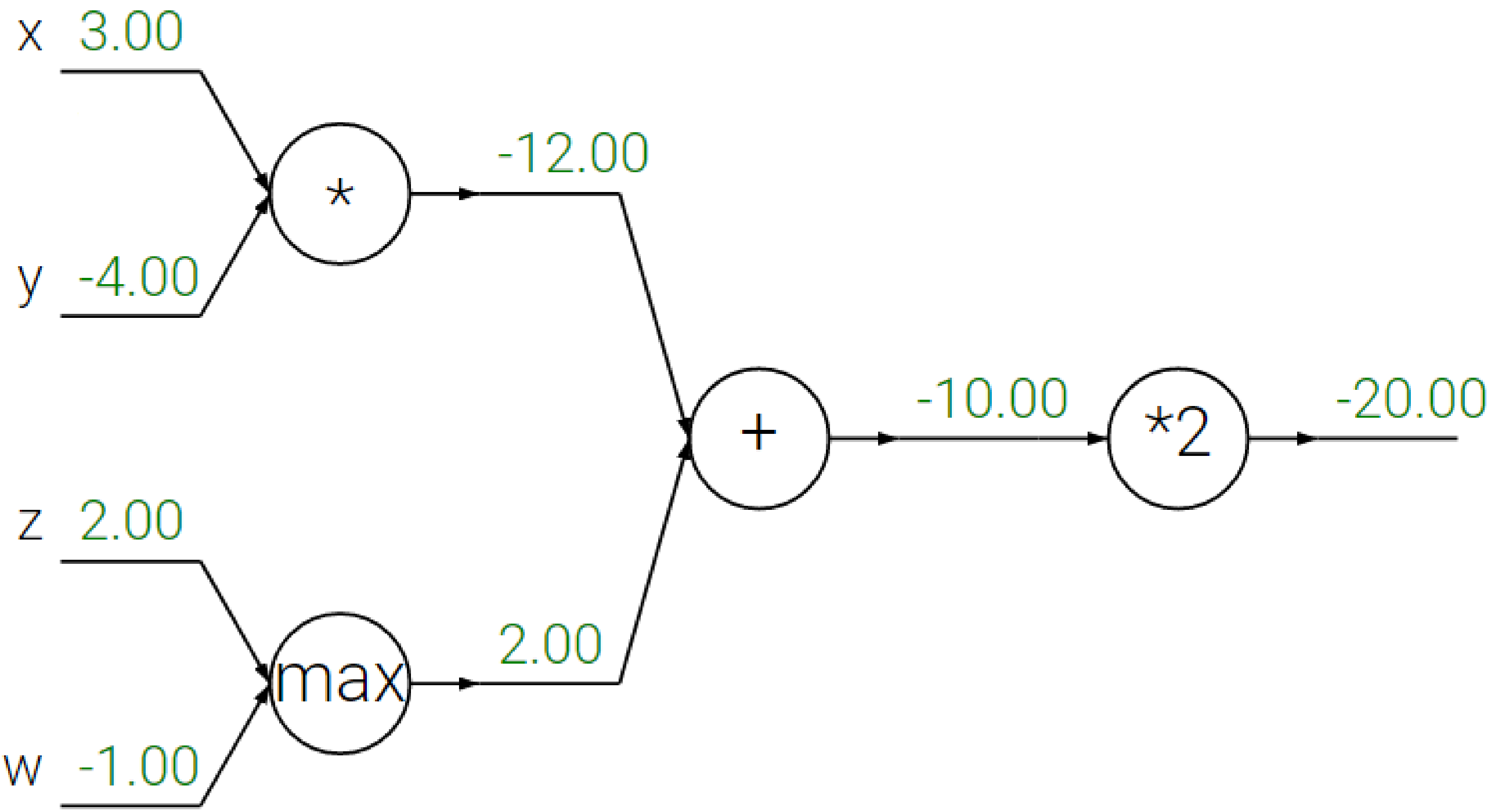

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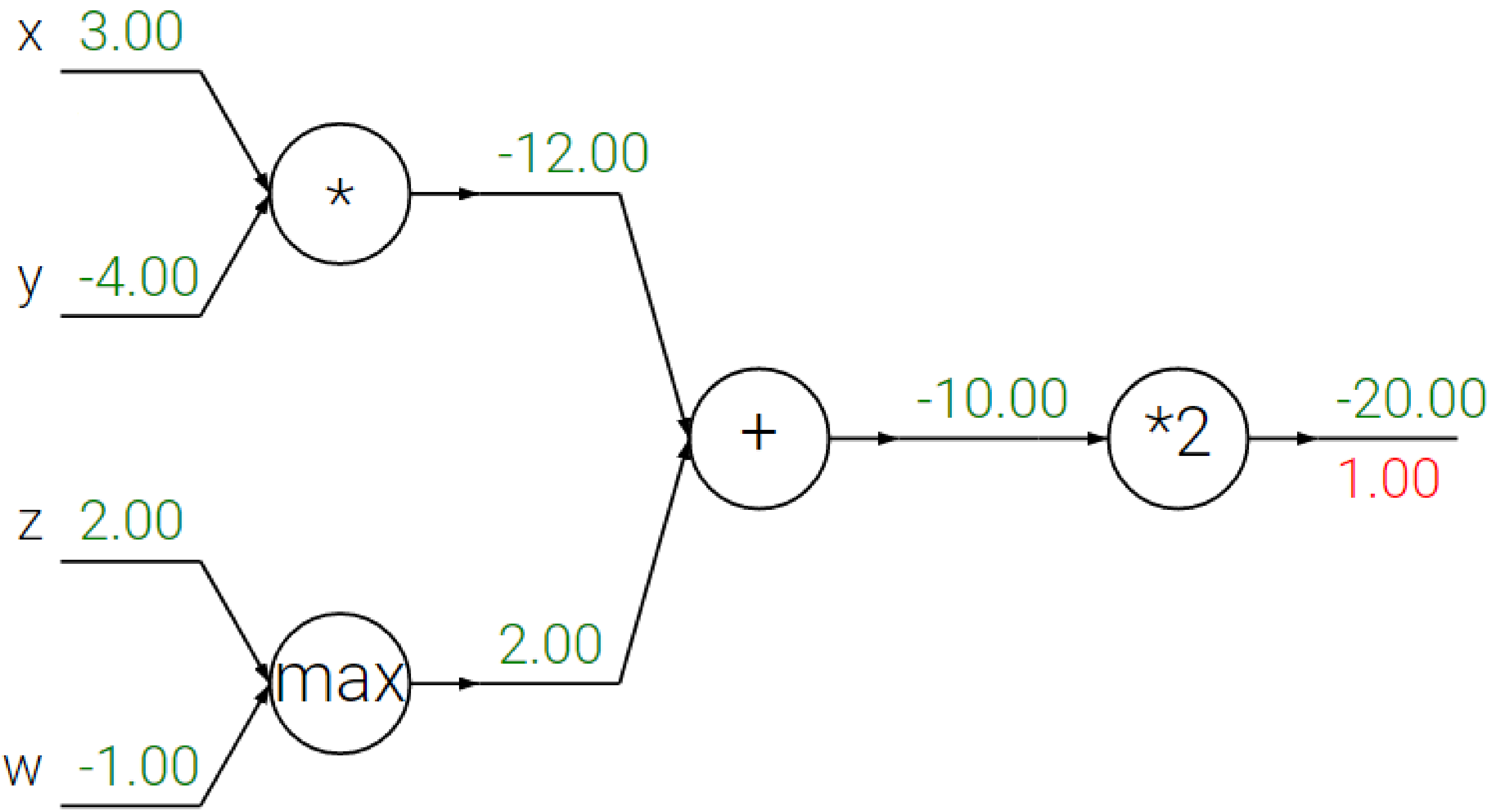

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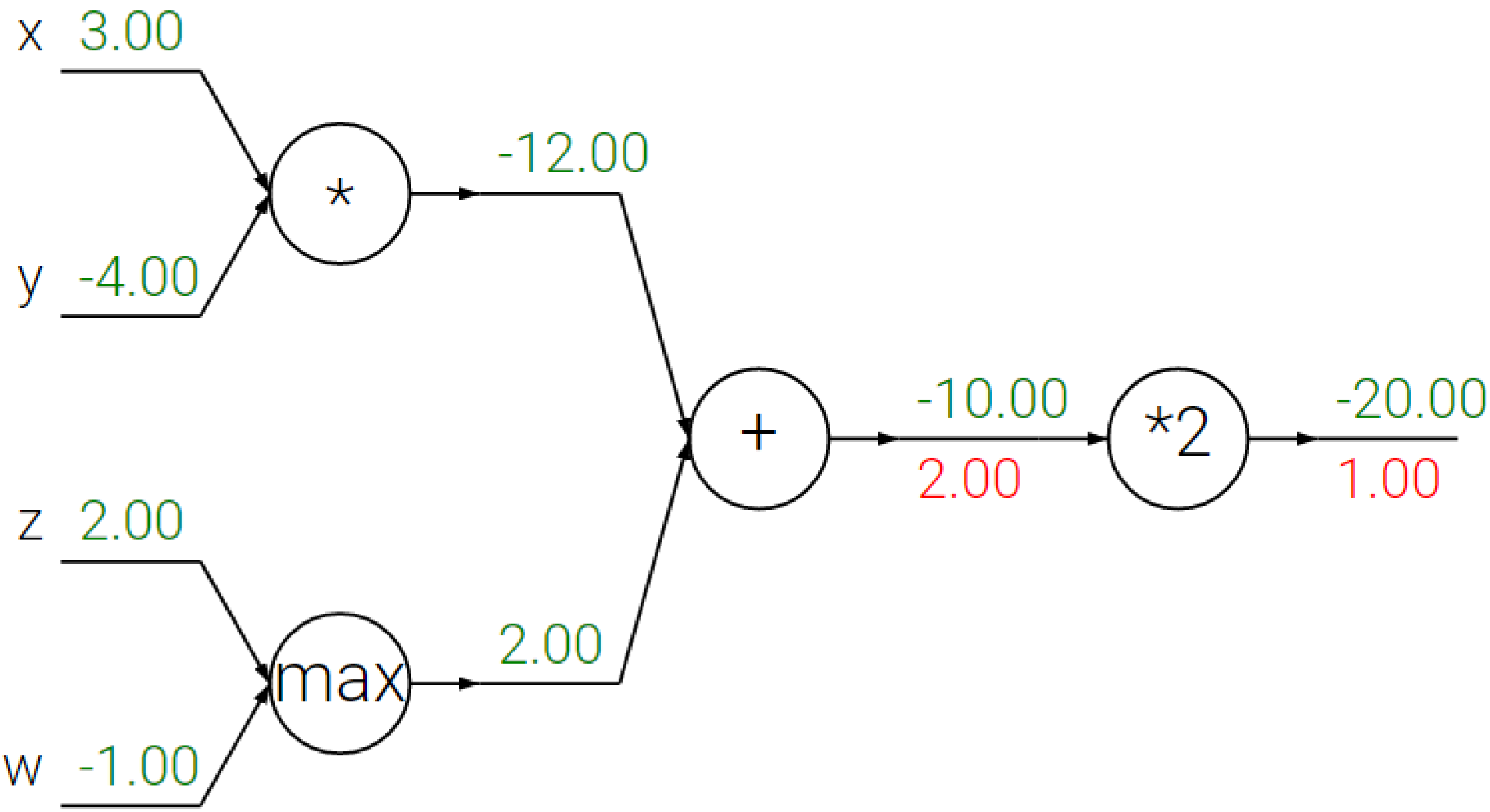

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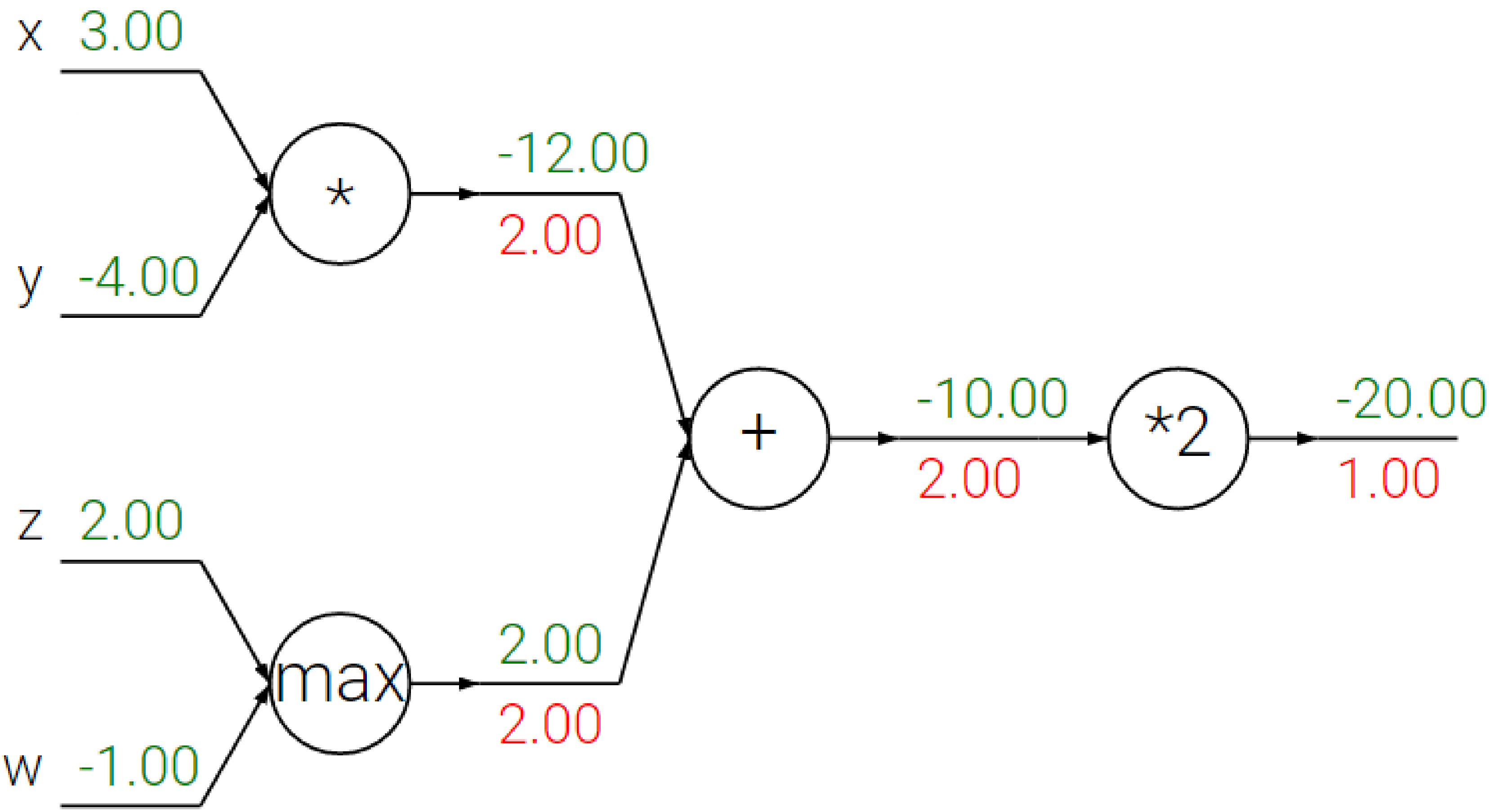

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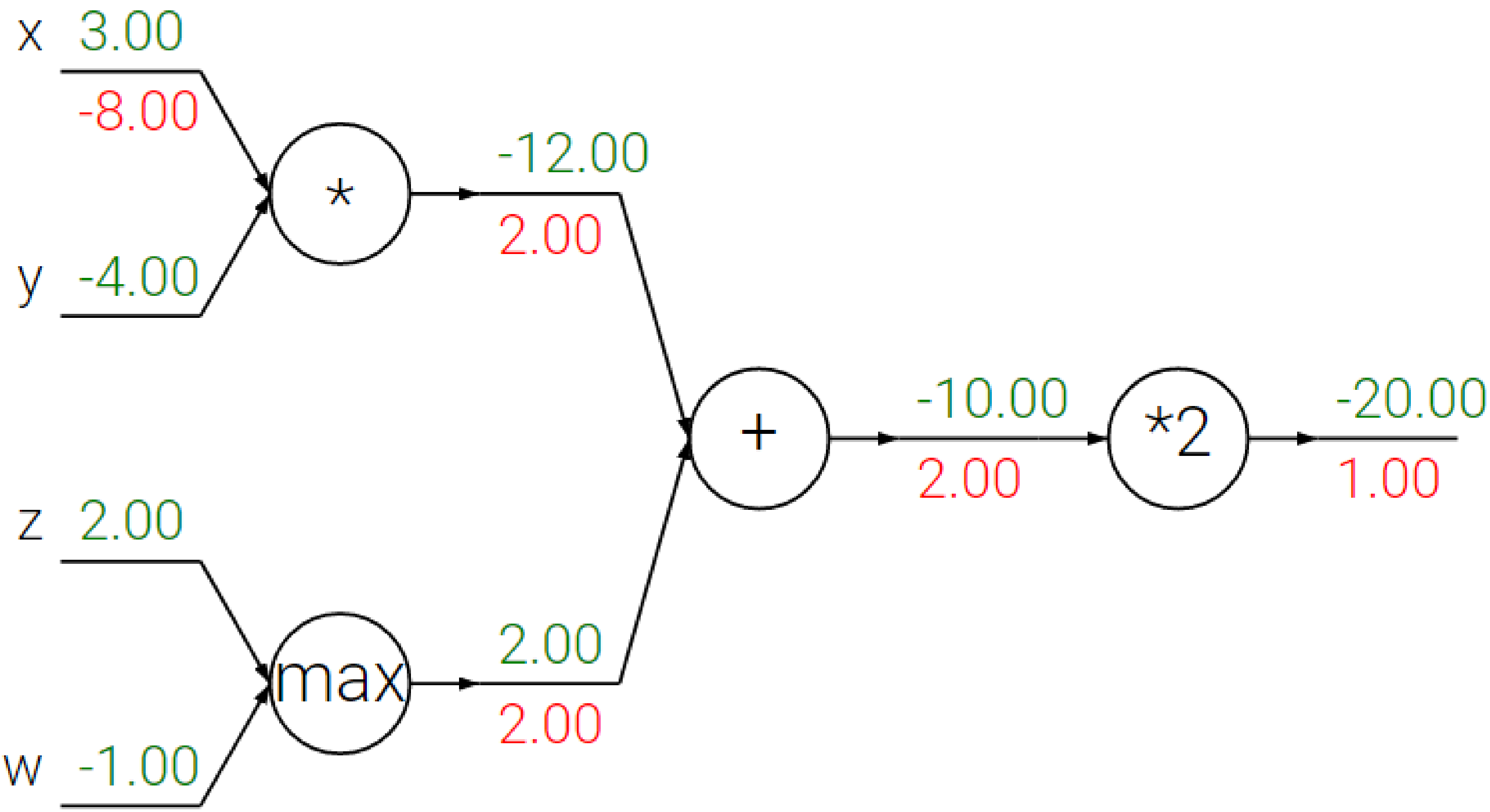

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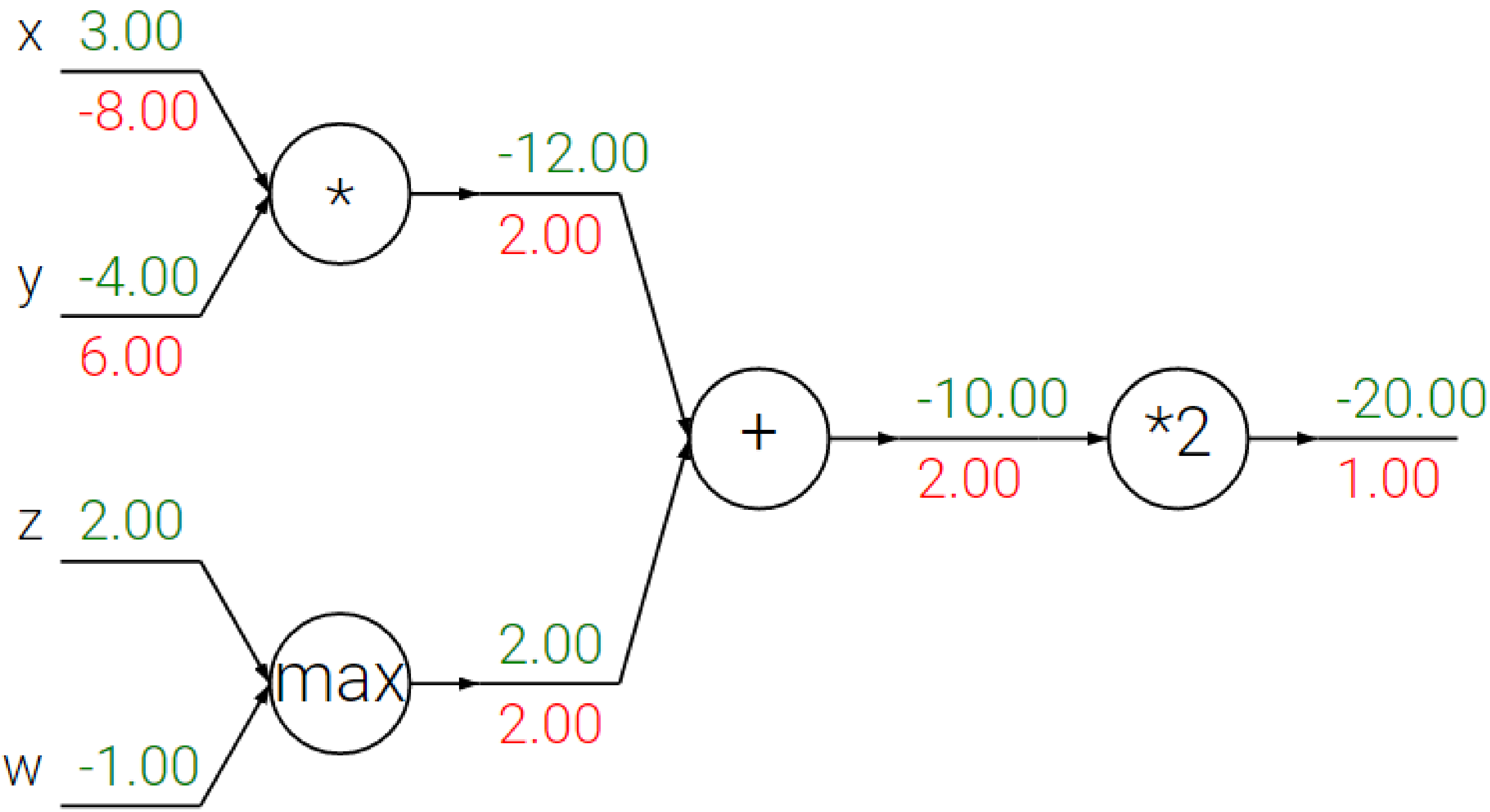

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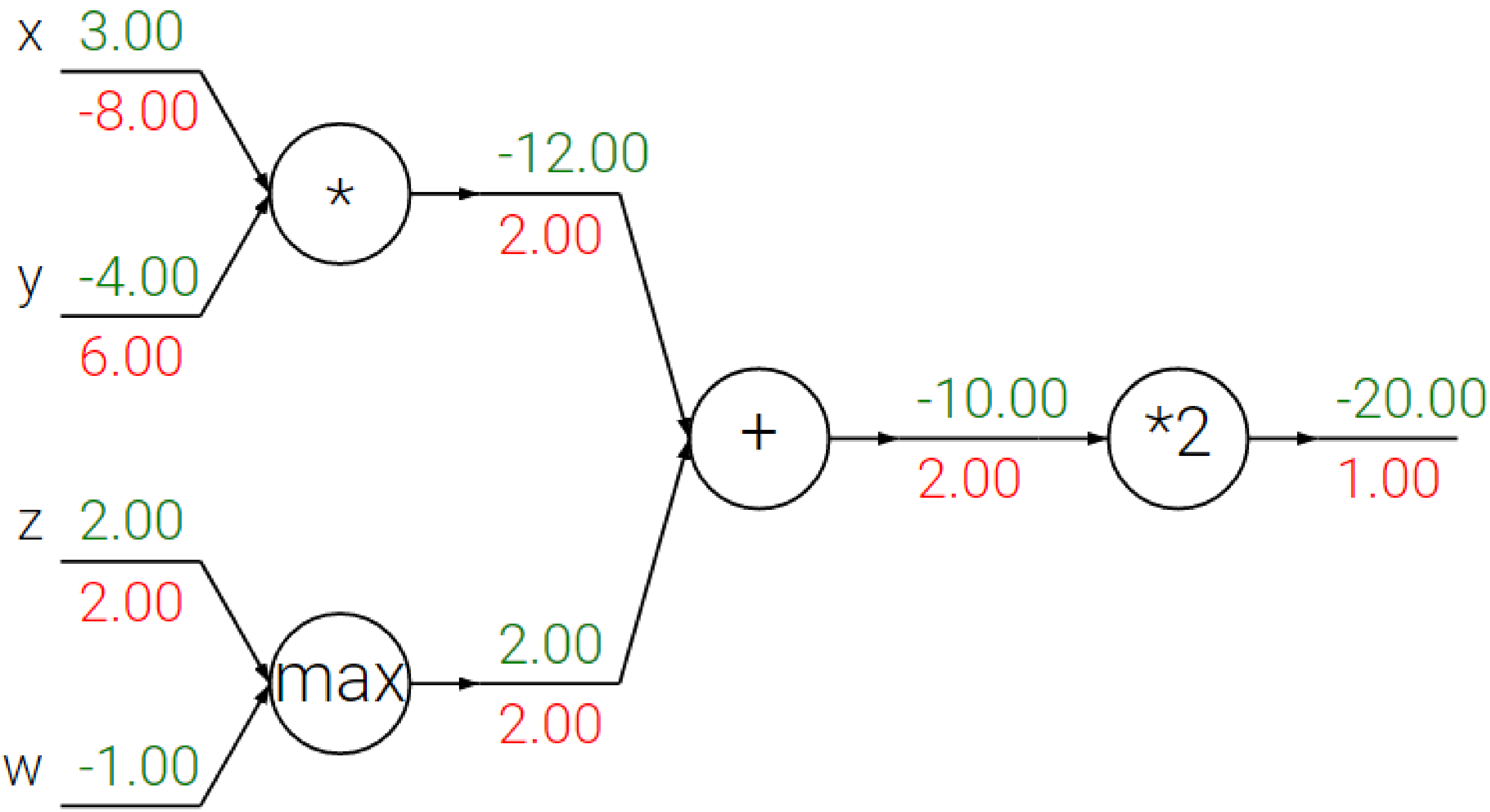

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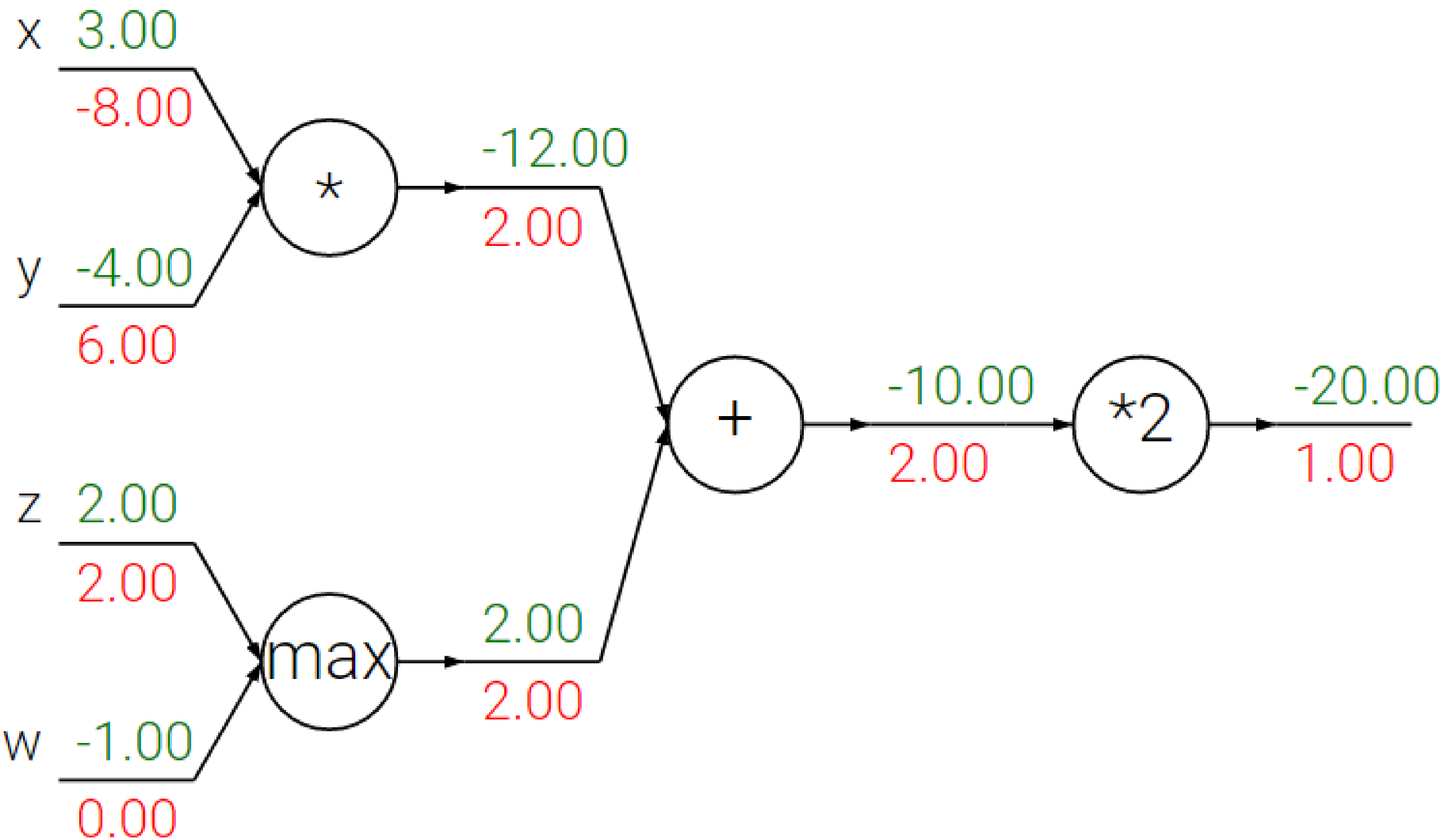

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Sigmoid example

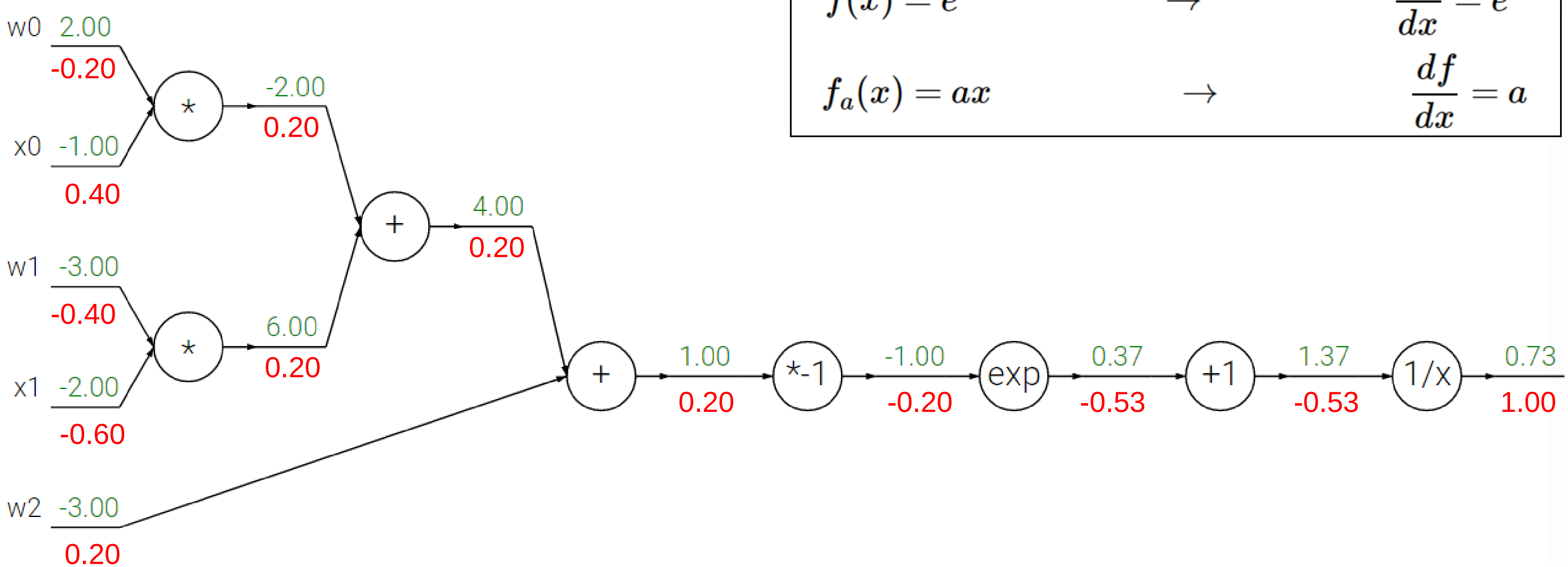
$$f(w,x) = \frac{1}{1+e^{-(w_0x_0+w_1x_1+w_2)}}$$

$$f(x) = \frac{1}{x} \quad \rightarrow \quad \frac{df}{dx} = -1/x^2$$

$$f_c(x) = c + x \quad \rightarrow \quad \frac{df}{dx} = 1$$

$$f(x) = e^x \quad \rightarrow \quad \frac{df}{dx} = e^x$$

$$f_a(x) = ax \quad \rightarrow \quad \frac{df}{dx} = a$$



Modified from: http://cs231n.github.io

SVM Loss: Gradient

SVM loss function for a single datapoint (without regularization):

$$L_i = \sum_{j \neq y_i} \left[\max(0, w_j^T x_i - w_{y_i}^T x_i + \Delta) \right]$$

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Gradient w.r.t. w_{y_i} :

$$\nabla_{w_{y_i}} L_i = - \left(\sum_{j \neq y_i} 1(w_j^T x_i - w_{y_i}^T x_i + \Delta > 0) \right) x_i$$

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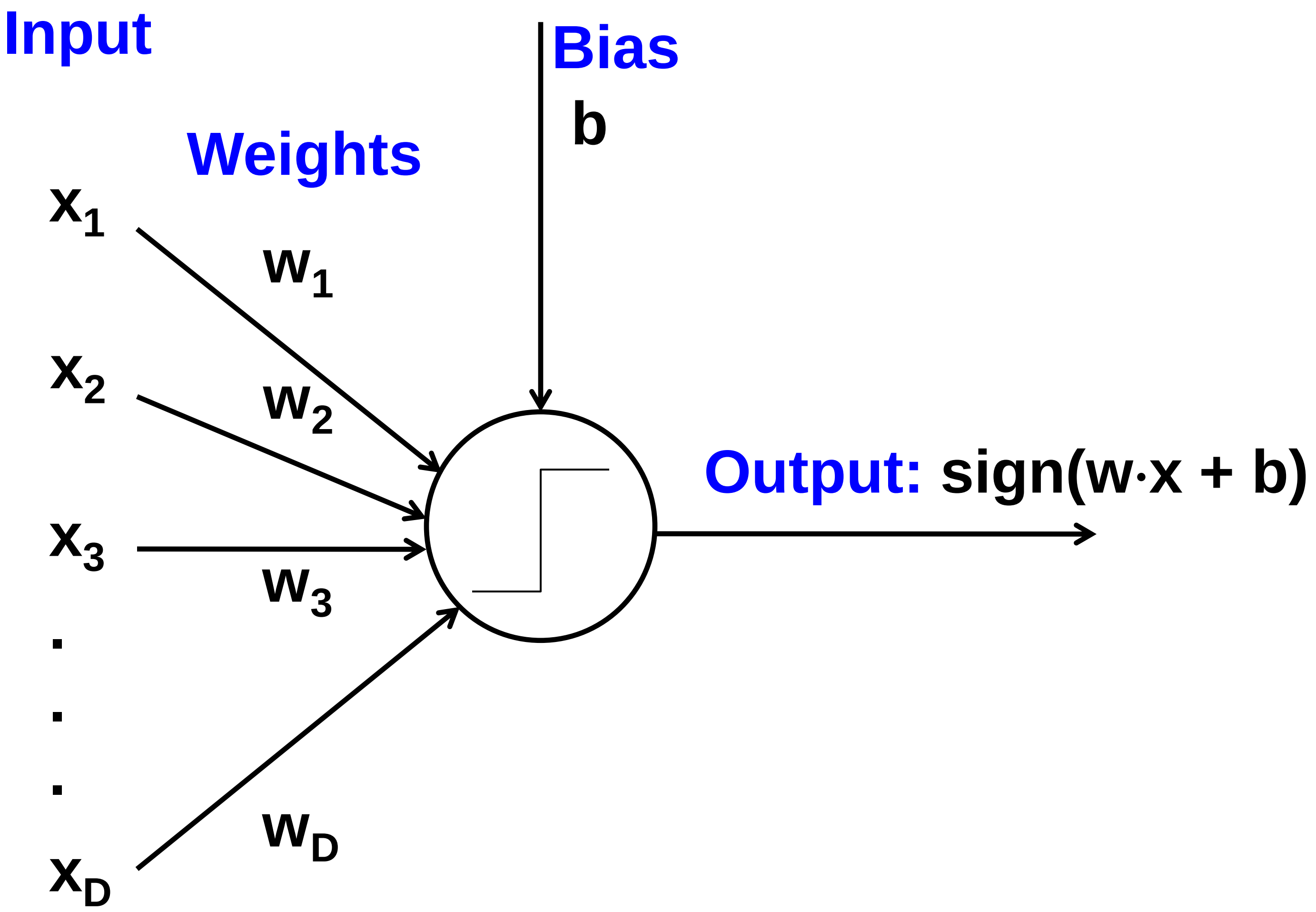
Gradient for the other rows where $j \neq y_i$:

$$\nabla_{w_j} L_i = 1(w_j^T x_i - w_{y_i}^T x_i + \Delta > 0) x_i$$

Source: http://cs231n.github.io

Perceptron

- Supervised learning of binary classifier



Perceptron

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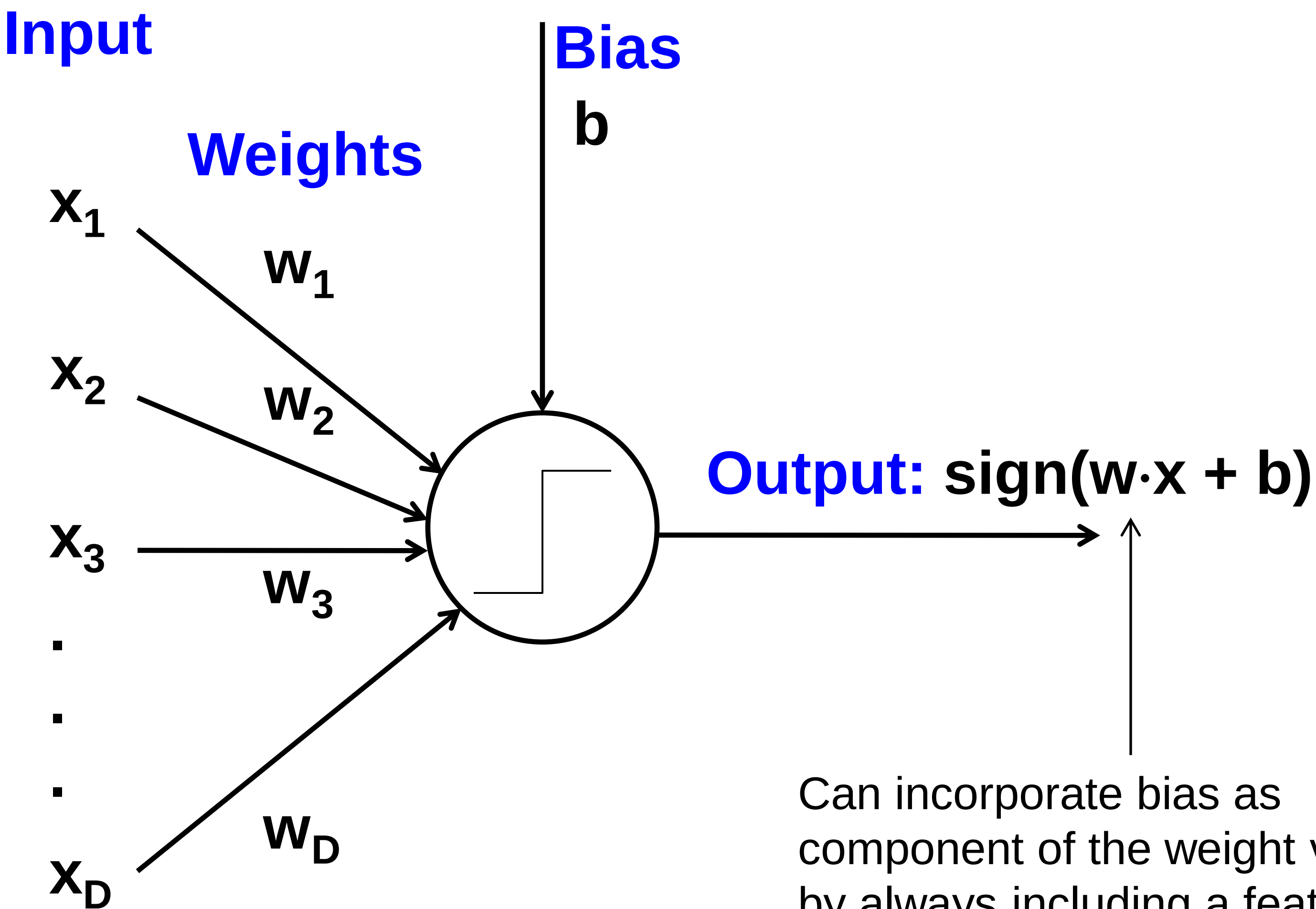

Can incorporate bias as component of the weight vector by always including a feature with value set to 1

Perceptron update rule

- Initialize weights randomly
- Cycle through training examples in multiple passes (*epochs*)

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  $w_i \leftarrow w_i + \alpha(y-y')x_i$

    – If y = 1 and y' = -1, w_i will be increased if x_i is positive or decreased if x_i is negative → $\mathbf{w} \cdot \mathbf{x}$ will get bigger

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  - **What happens if y' is correct?**
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    $w_i \leftarrow w_i + \alpha(y-y')x_i$
    - If $y = 1$ and $y' = -1$, w_i will be increased if x_i is positive or decreased if x_i is negative → $\mathbf{w}\cdot\mathbf{x}$ will get bigger
    - If $y = -1$ and $y' = 1$, w_i will be decreased if x_i is positive or increased if x_i is negative → $\mathbf{w}\cdot\mathbf{x}$ will get smaller

Single neuron as a linear classifier

Binary Softmax classifier (*Logistic Regression*)

$$\sigma(\sum_i w_i x_i + b)$$

Source: http://cs231n.github.io

Single neuron as a linear classifier

Binary Softmax classifier (*Logistic Regression*)

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$$\downarrow$$

Probability of one of the classes: $P(y_i = 1 \mid x_i; w)$

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Single neuron as a linear classifier

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Probability of the other class would be:

$$P(y_i = 0 \mid x_i; w) = 1 - P(y_i = 1 \mid x_i; w)$$

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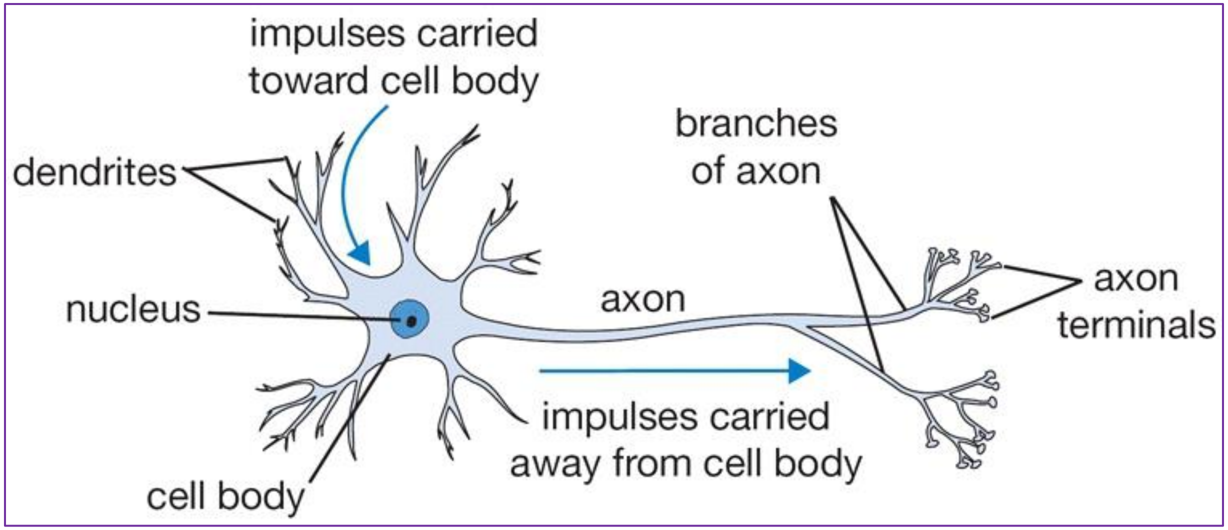
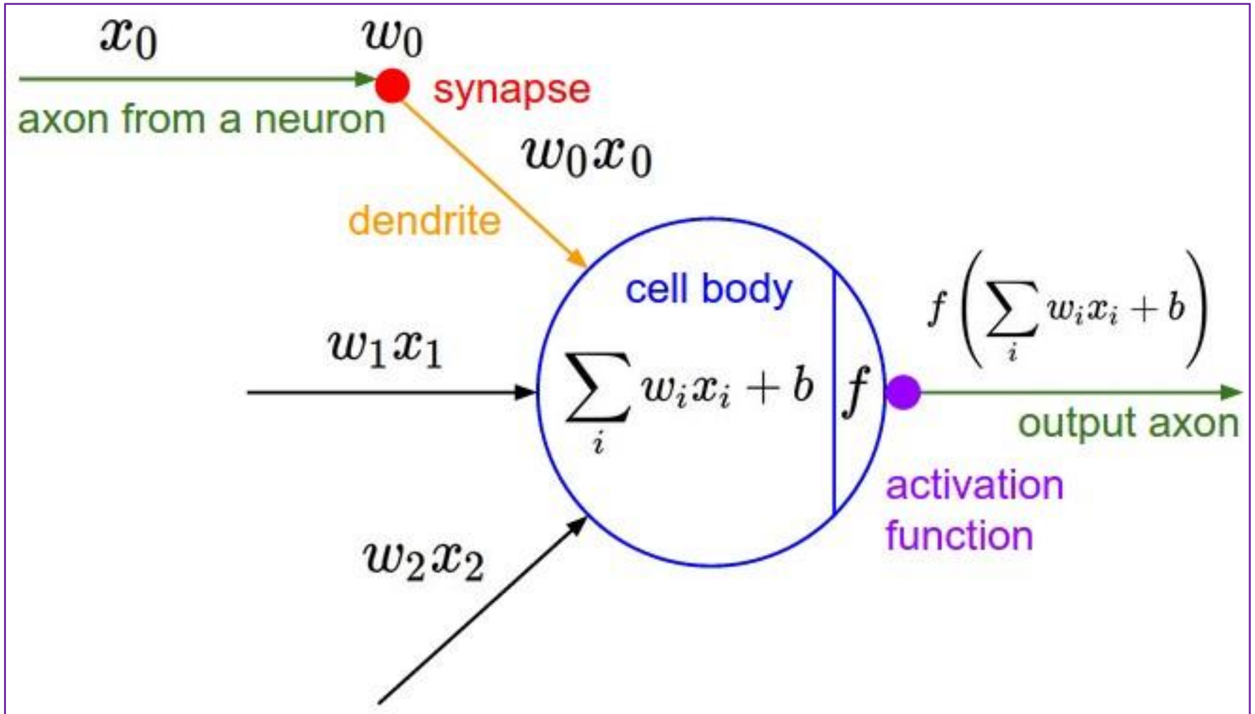
Binary SVM classifier.
Alternatively, we could attach a max-margin hinge loss to the output of the neuron and train it to become a binary Support Vector Machine.

Source: http://cs231n.github.io

Loose inspiration: Human neurons

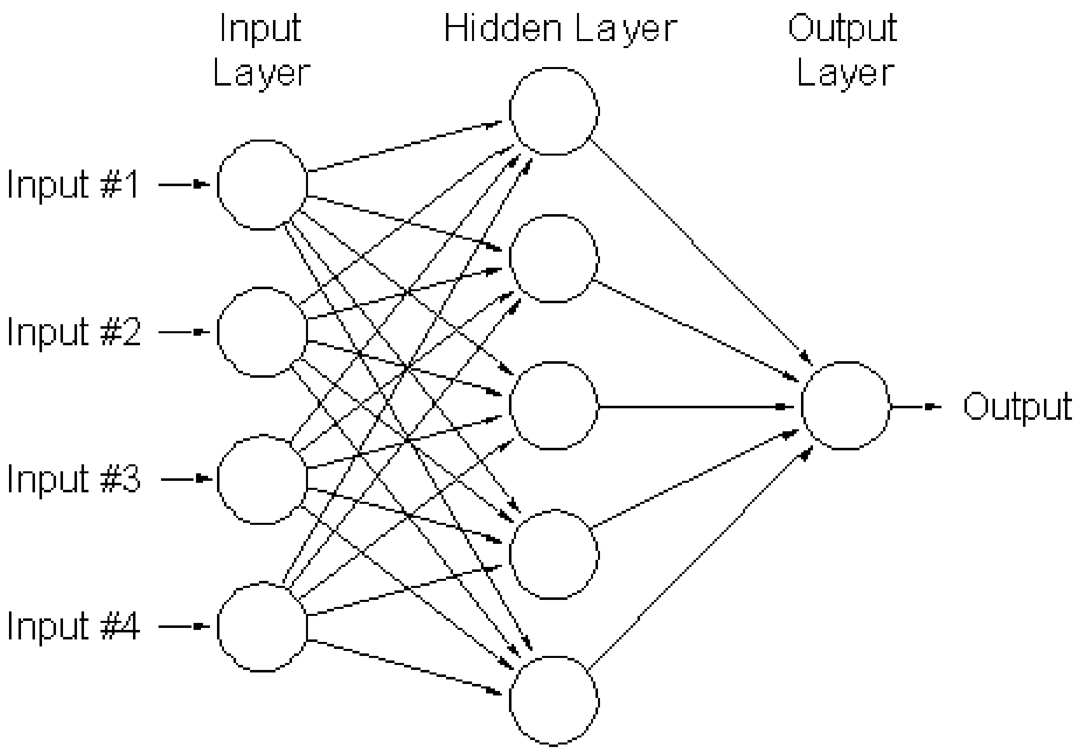




Source: http://cs231n.github.io

Multi-Layer Neural Networks

- Network with a hidden layer:



Multi-Layer Neural Networks

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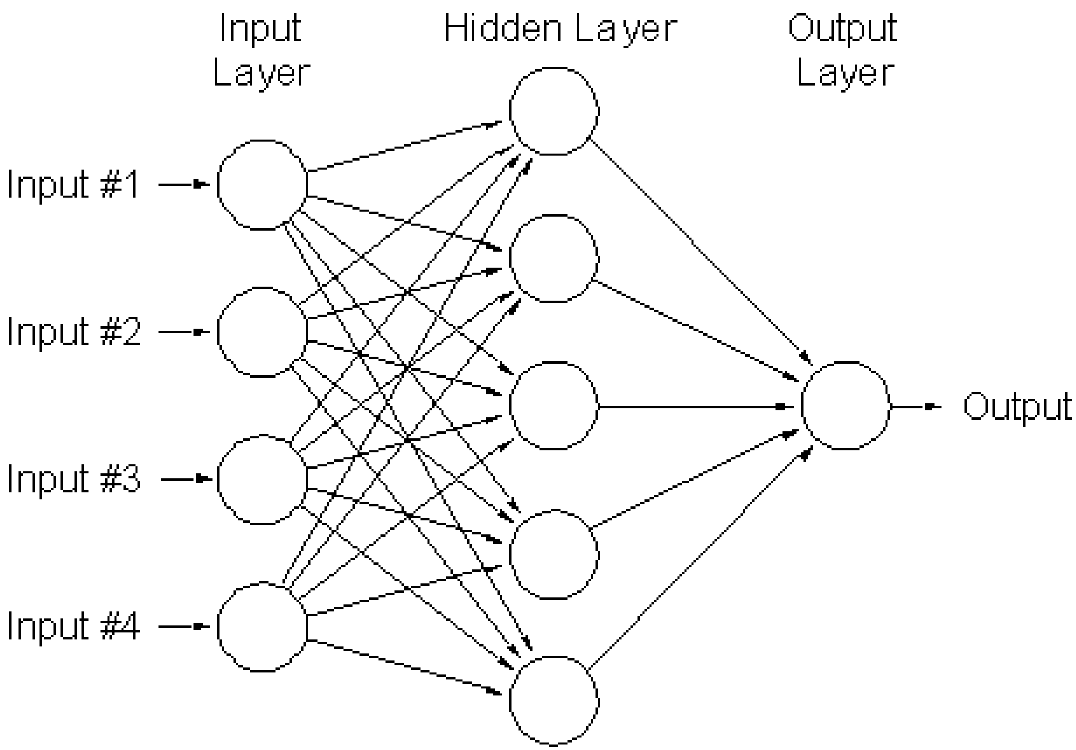
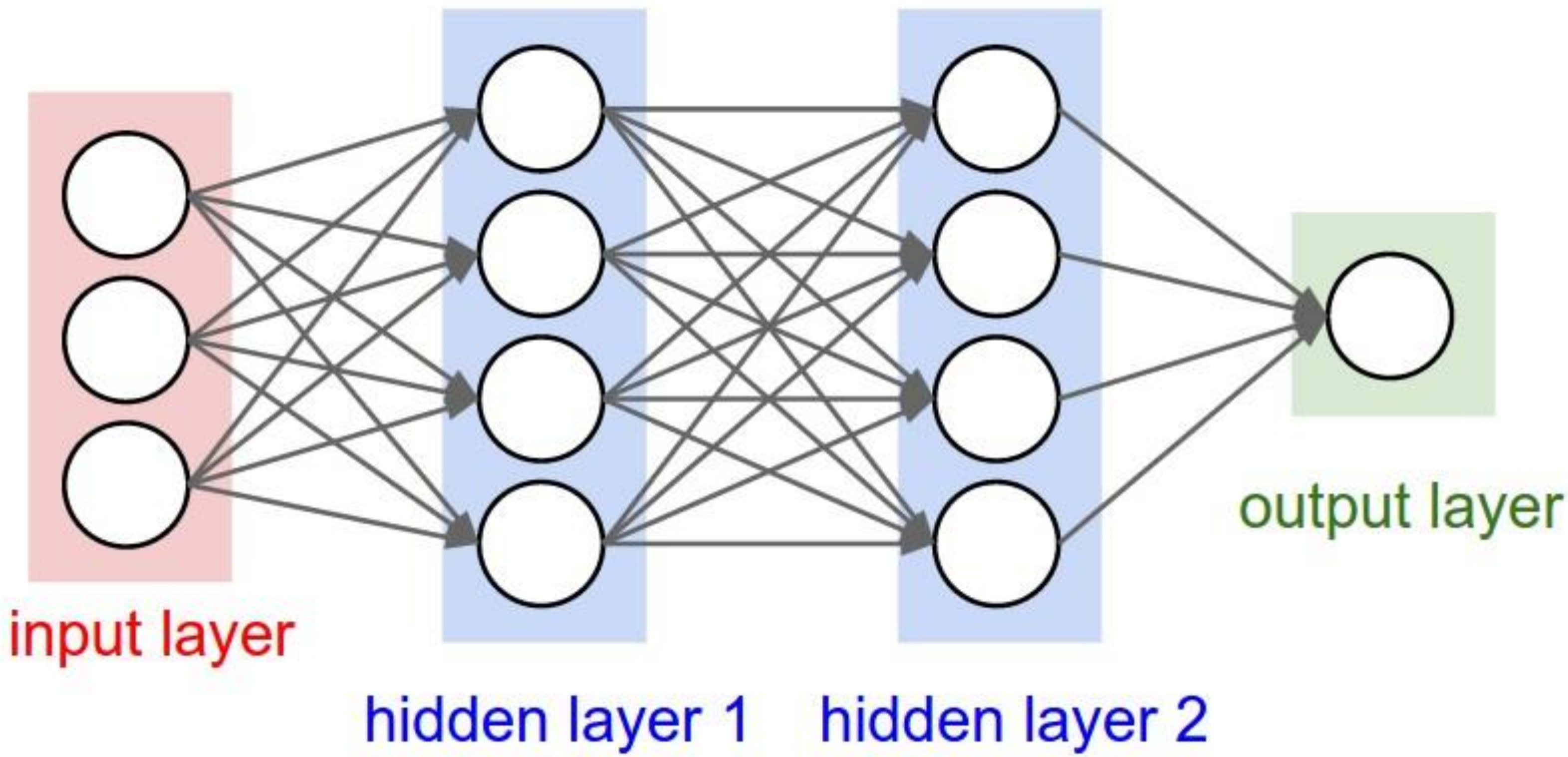


- Can represent nonlinear functions (provided each perceptron has a nonlinearity)

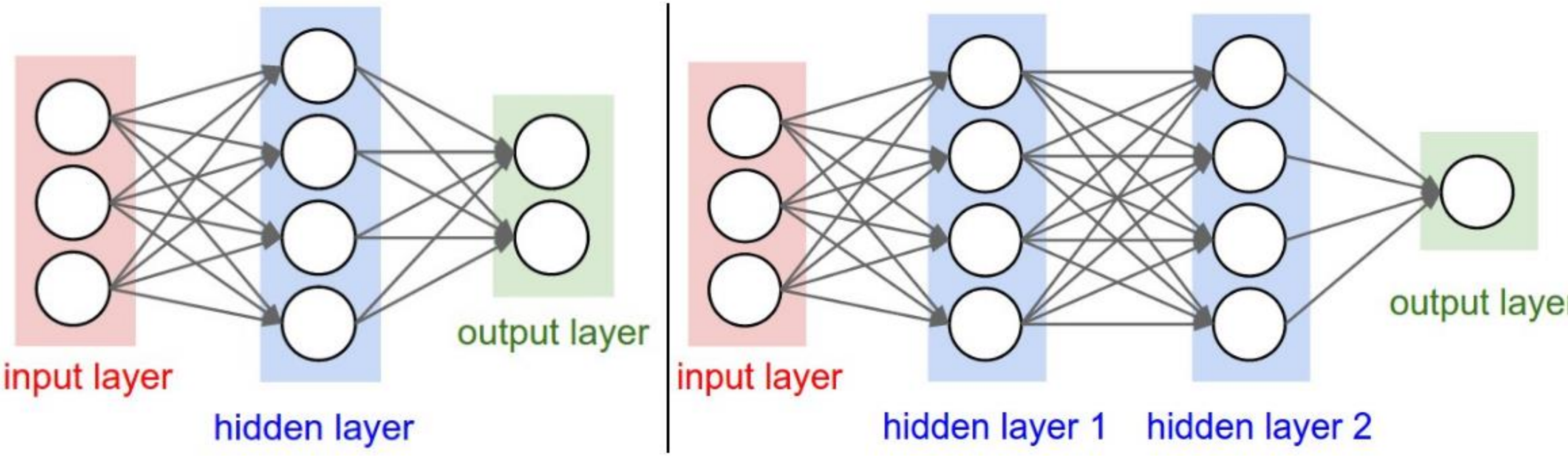
Multi-Layer Neural Networks

- Beyond a single hidden layer:



Source: http://cs231n.github.io

Sizing neural networks



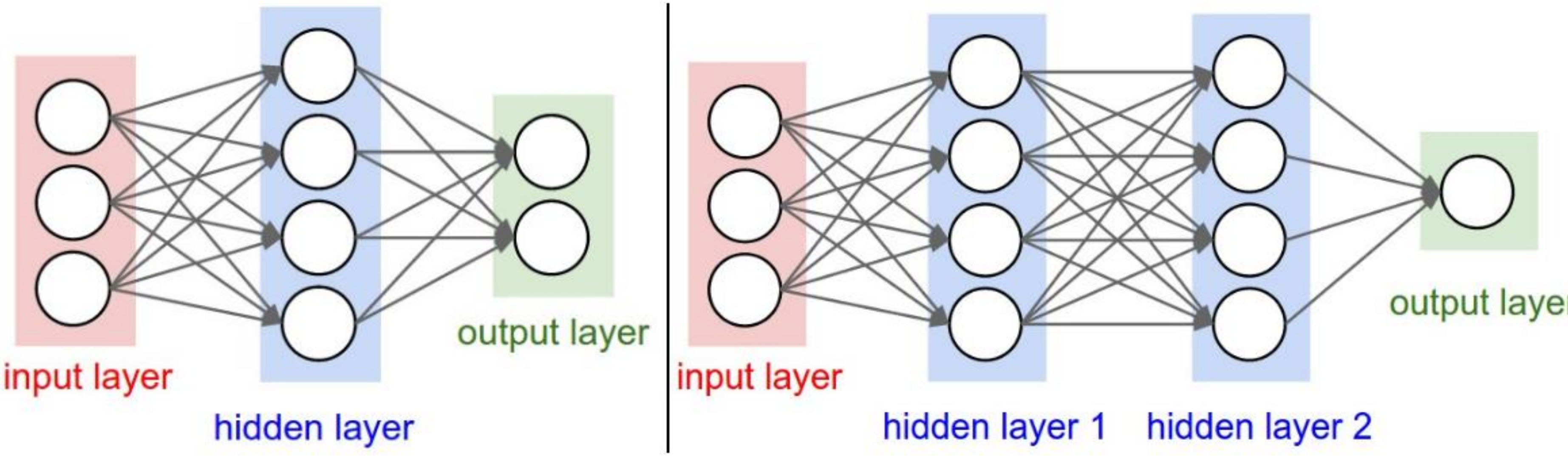
First network (left):

No. of neurons (not counting the inputs):

No. of learnable parameters:

Source: http://cs231n.github.io

Sizing neural networks



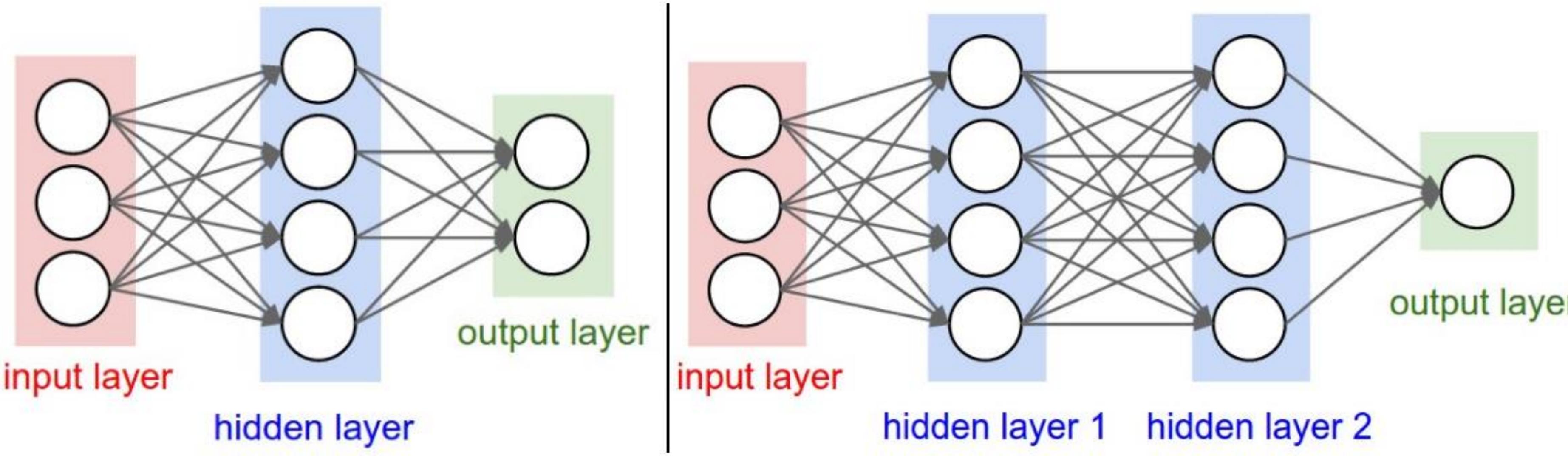
First network (left):

No. of neurons (not counting the inputs): 4 + 2 = 6

No. of learnable parameters:

Source: http://cs231n.github.io

Sizing neural networks



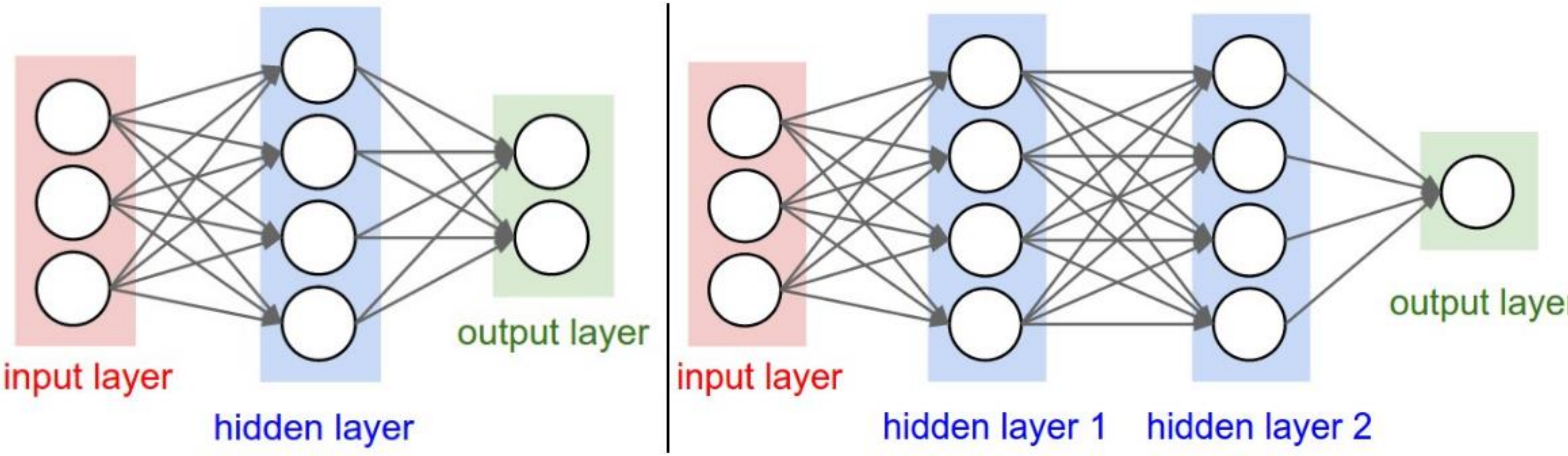
First network (left):

No. of neurons (not counting the inputs): 4 + 2 = 6

No. of learnable parameters: [3 x 4] + [4 x 2] = 20 weights + 4 + 2 = 6 biases = 26.

Source: http://cs231n.github.io

Sizing neural networks



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Second network (right):

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Source: http://cs231n.github.io

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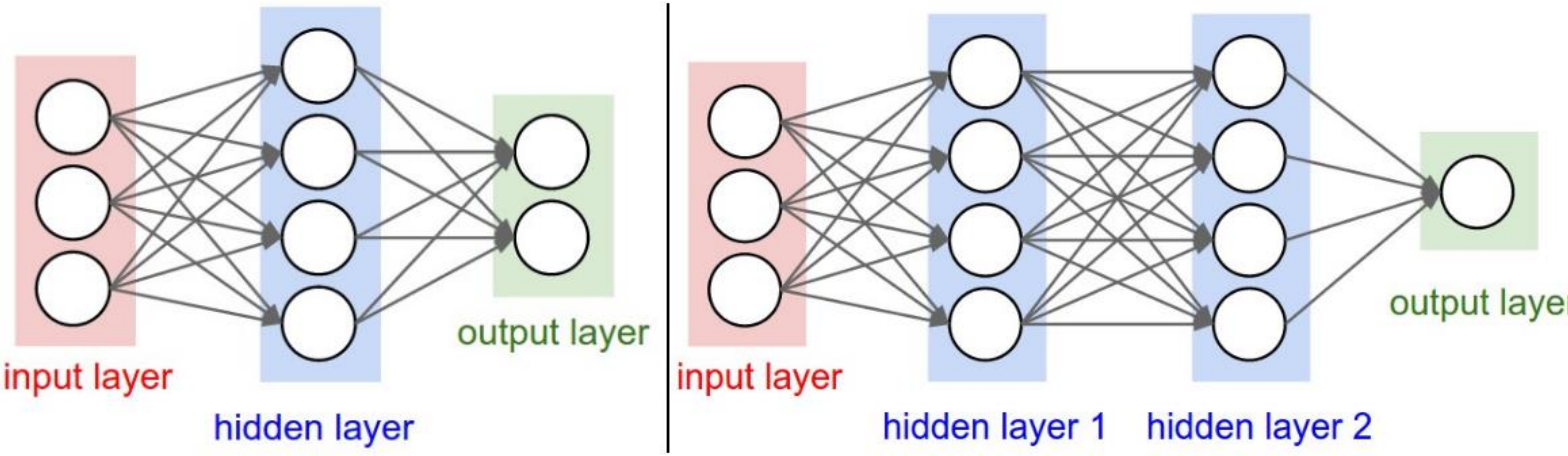

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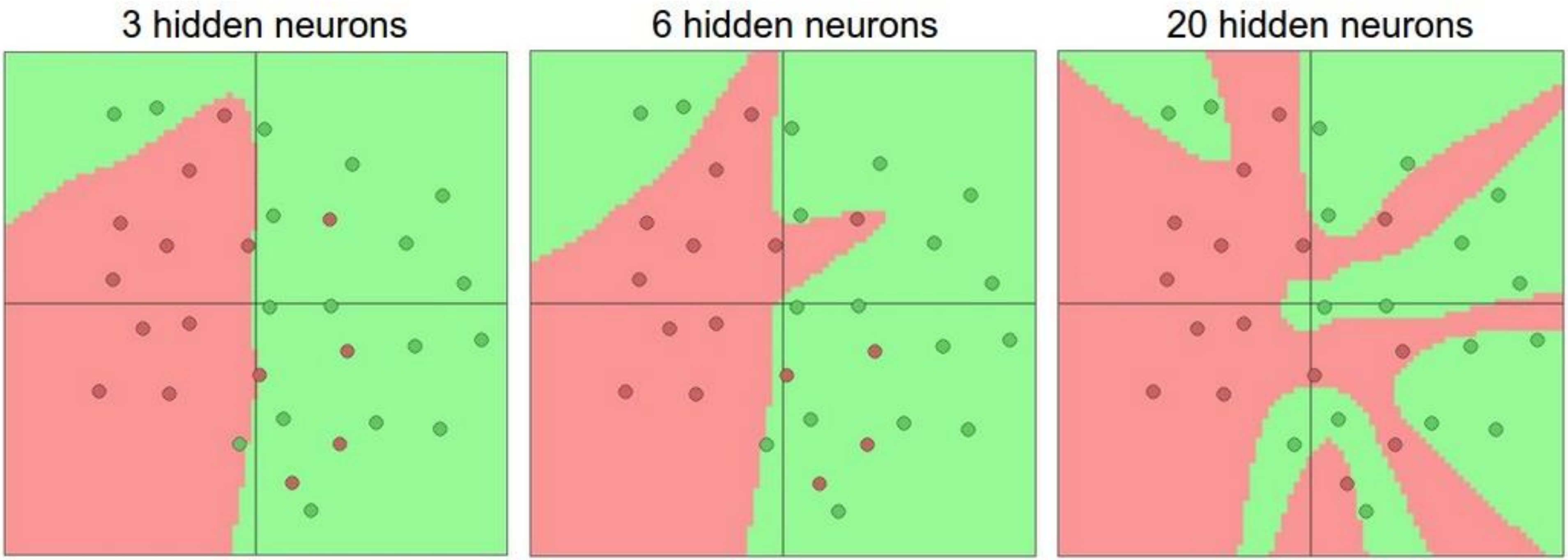
Second network (right):

No. of neurons (not counting the inputs): 4 + 4 + 1 = 9

No. of learnable parameters: [3x4]+[4x4]+[4x1] = 32 weights + 4 + 4 + 1 = 9 biases = 41.

Source: http://cs231n.github.io

Multi-Layer Neural Networks



Source: http://cs231n.github.io

Training of multi-layer networks

- Find network weights to minimize the error between true and estimated outputs of training examples:

$$E(\mathbf{w}) = \sum_{j=1}^{N} \left(y_j - f_{\mathbf{w}}(\mathbf{x}_j) \right)^2$$

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- **Back-propagation:** gradients are computed in the direction from output to input layers and combined using chain rule

Neural networks: Pros and cons

- Pros
  - Flexible and general function approximation framework
  - Can build extremely powerful models by adding more layers

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- Pros
  - Flexible and general function approximation framework
  - Can build extremely powerful models by adding more layers

- Cons
  - Hard to analyze theoretically (e.g., training is prone to local optima)
  - Huge amount of training data, computing power may be required to get good performance
  - The space of implementation choices are huge (network architectures, parameters)

Acknowledgements

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- Forsyth
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- R. Zaleski
- Antonio Torralba
- Rob Fergus
- Leibe
- And many more ………..

Next Lecture

Convolutional Neural Networks