Learning for vision II
Neural networks

Karel Zimmermann

http://cmp.felk.cvut.cz/~zimmerk/

Vision for Robotics and Autonomous Systems
https://cyber.felk.cvut.cz/vras/

Center for Machine Perception
https://cmp.felk.cvut.cz

Department for Cybernetics
Faculty of Electrical Engineering
Czech Technical University in Prague

Outline

- Neuron+ computational graph
- Fully connected neural network

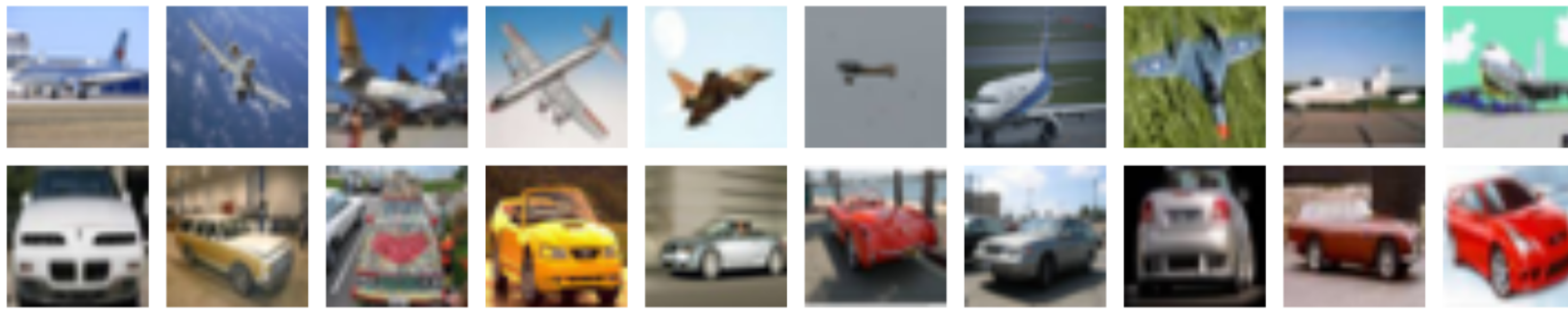
Linear classifier and neuron

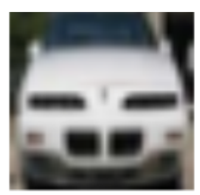
Labels

RGB images

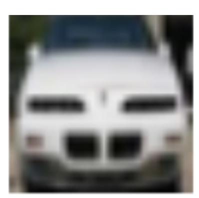
$+1$

-1



def classify():

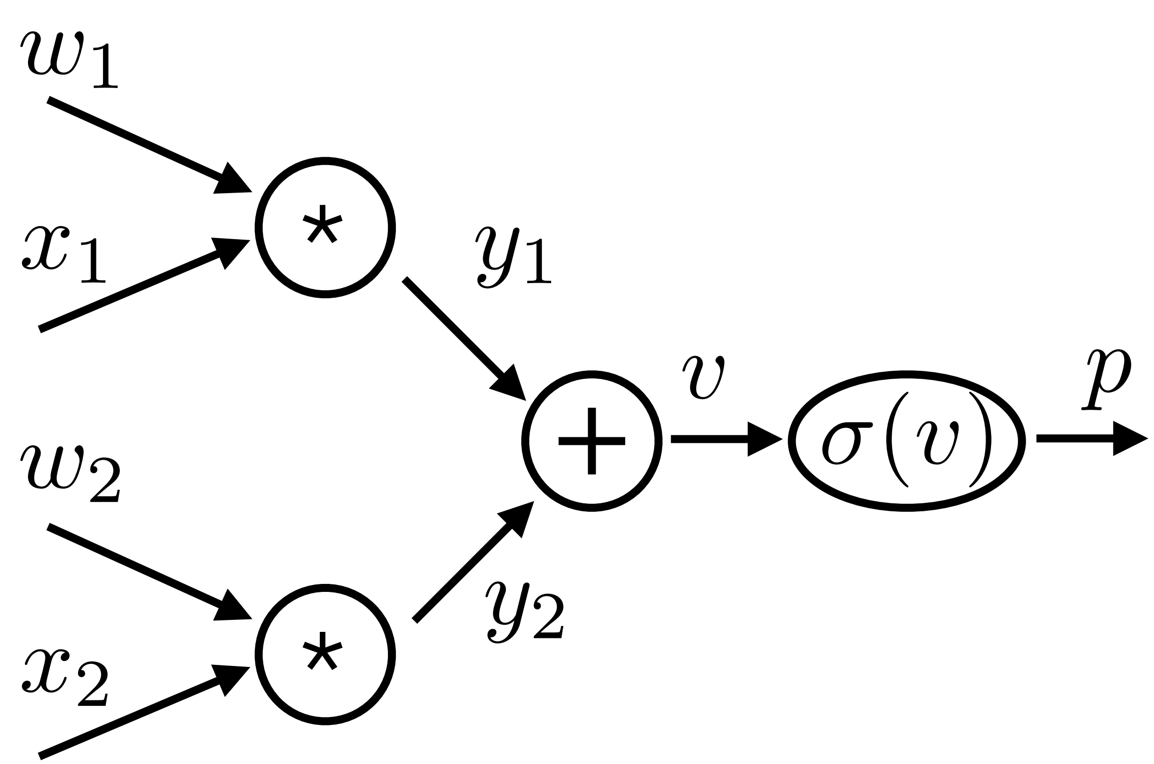
 # Linear classifier

$\mathbf{x} = \mathrm{vec}($  $)$

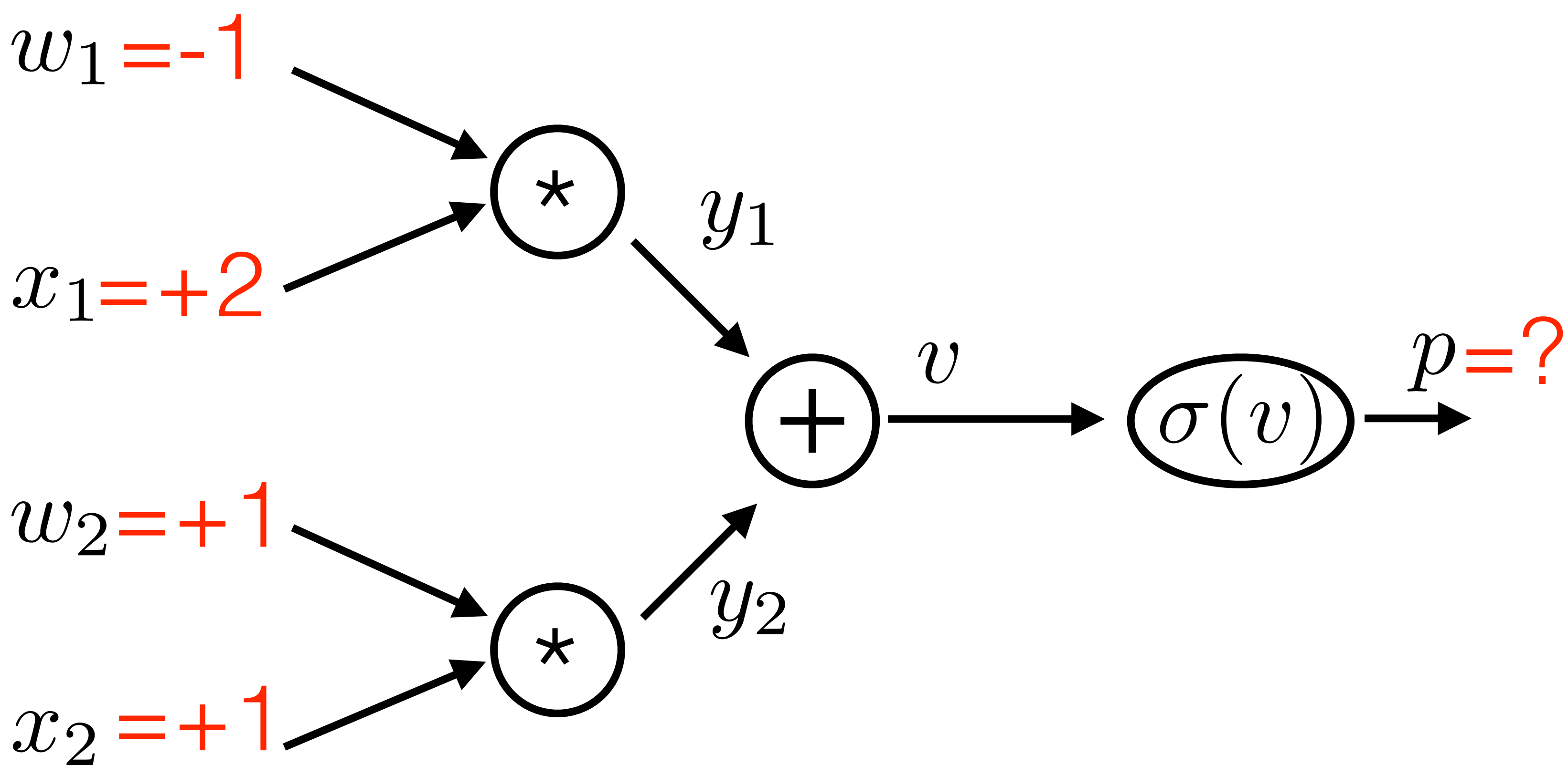
$p = \sigma\left(\mathbf{w}^\top \mathbf{x}\right)$

return p

Computational graph of linear classifier



Example I: given trained neuron, and input, what is output?



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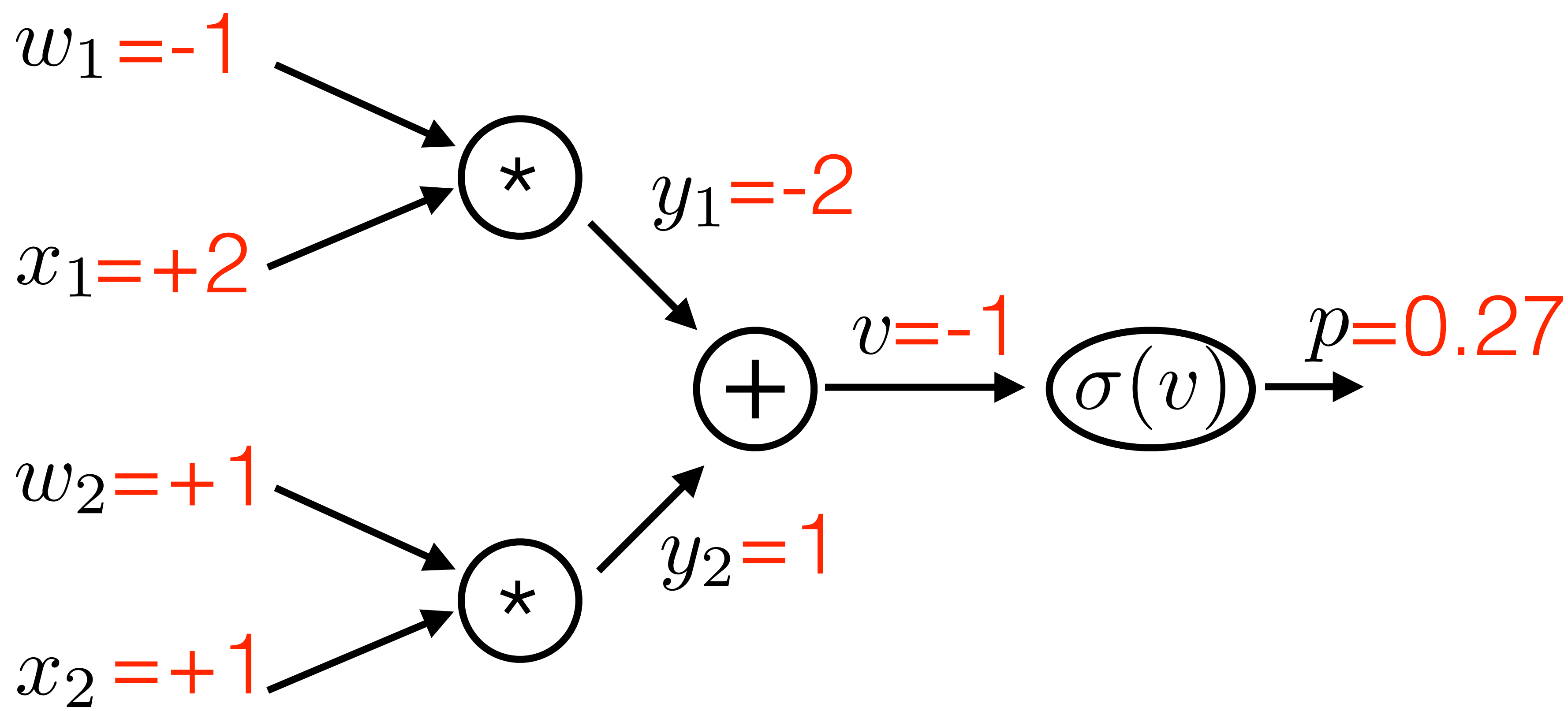
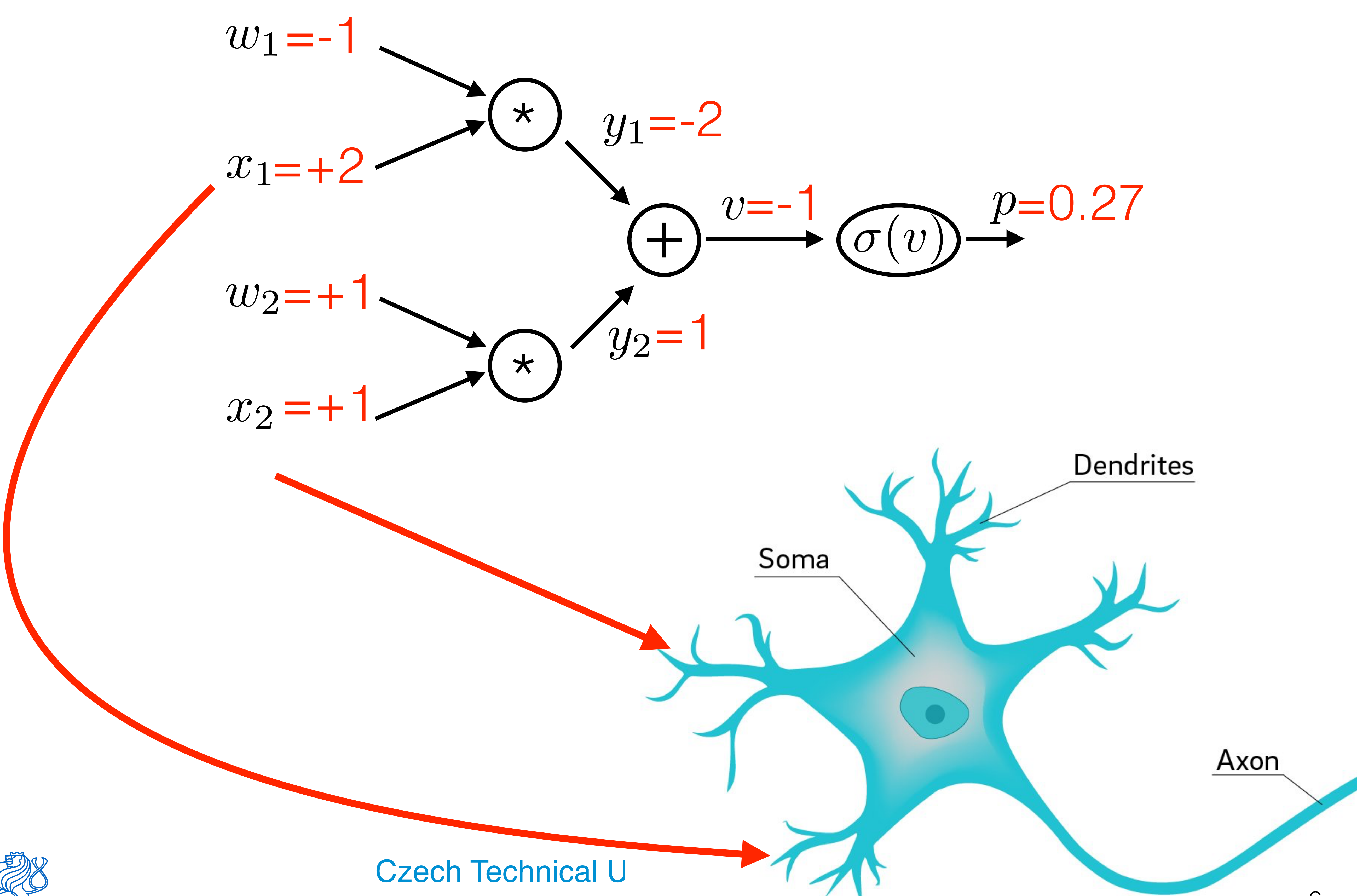


Relation to biological neuron



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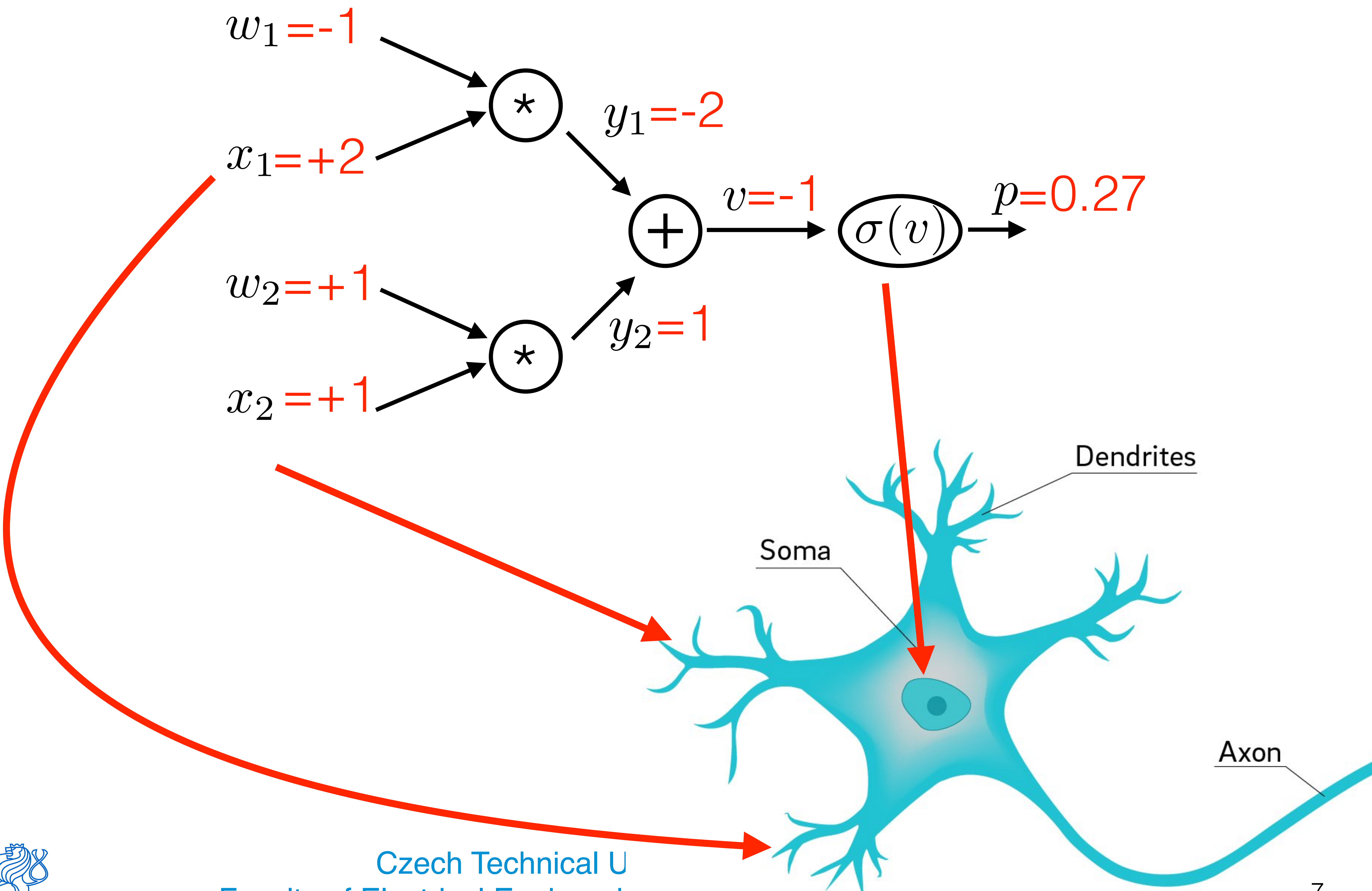

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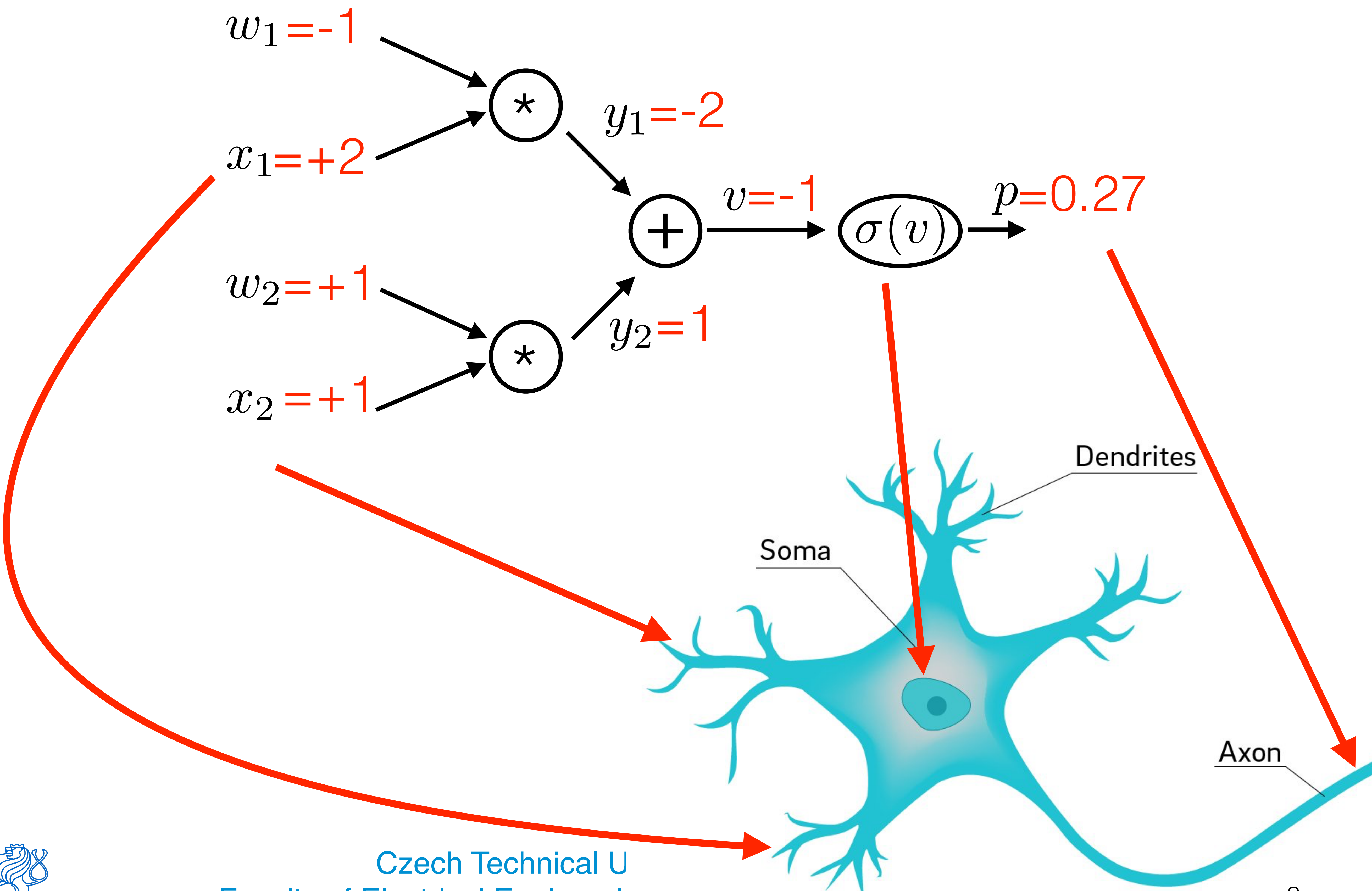
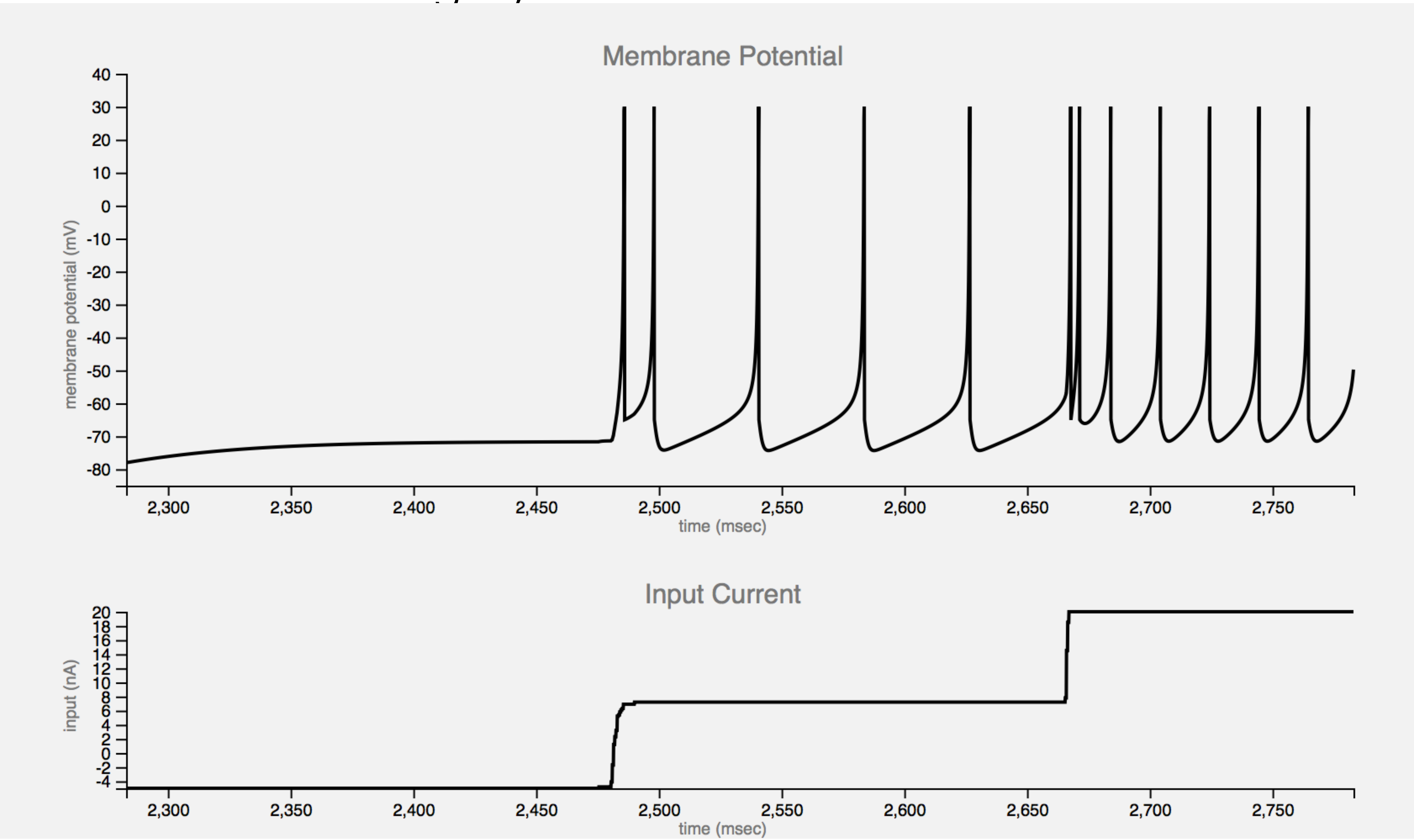


Modeling dynamic neuron behaviour



http://jackterwilliger.com/biological-neural-networks-part-i-spiking-neurons/

Linear classifier and neuron

Labels

RGB images

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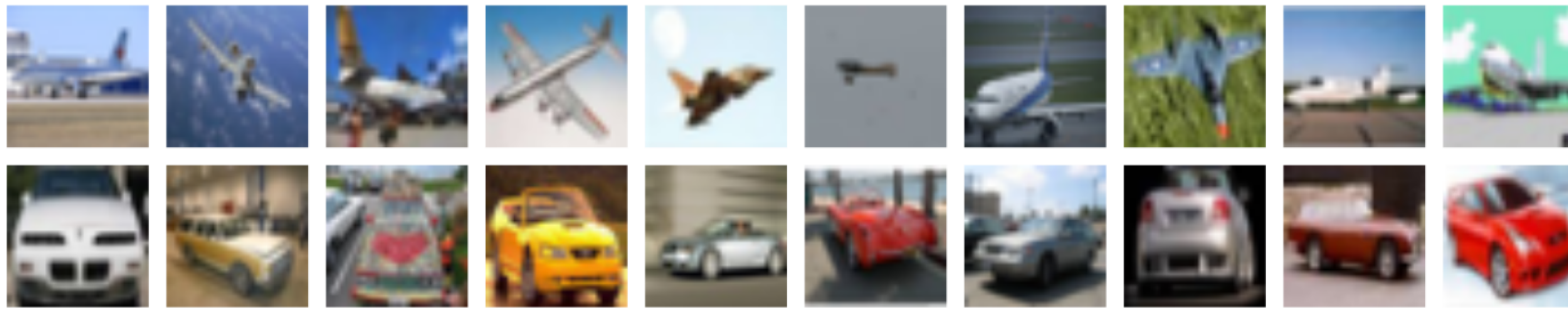
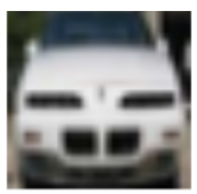


def classify():

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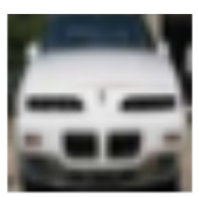
$\mathbf{x} = \mathrm{vec}($  $)$

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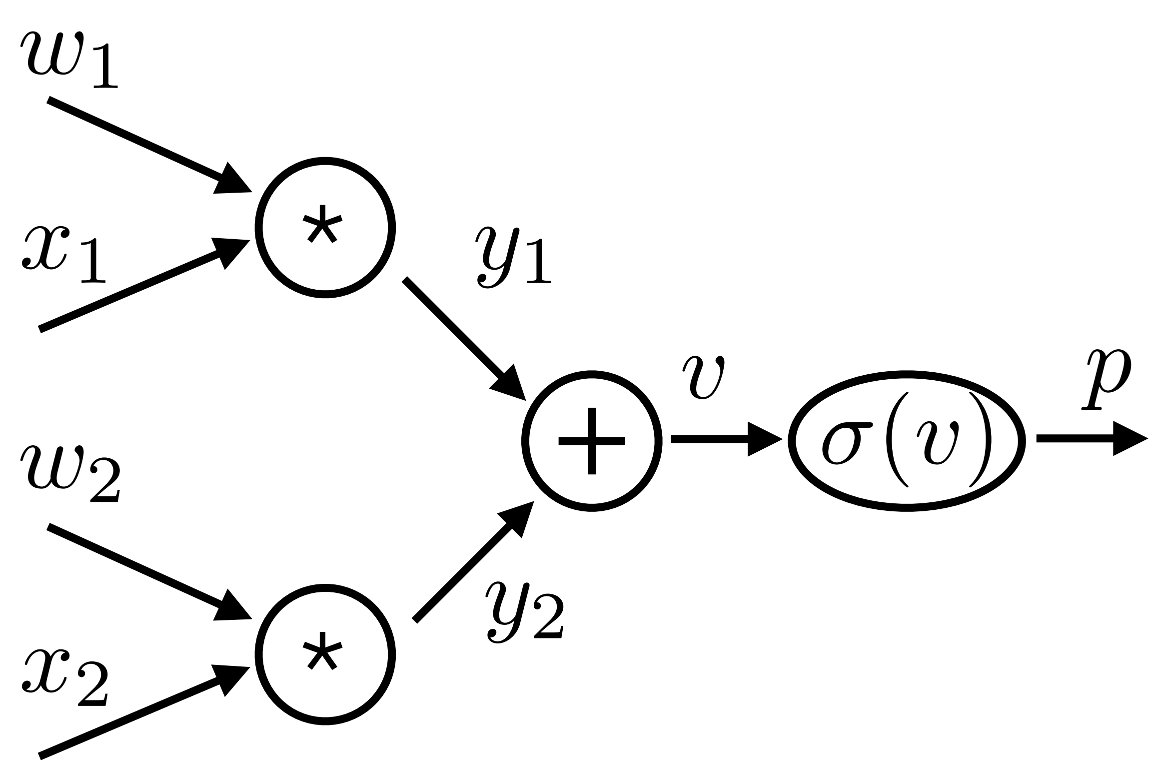

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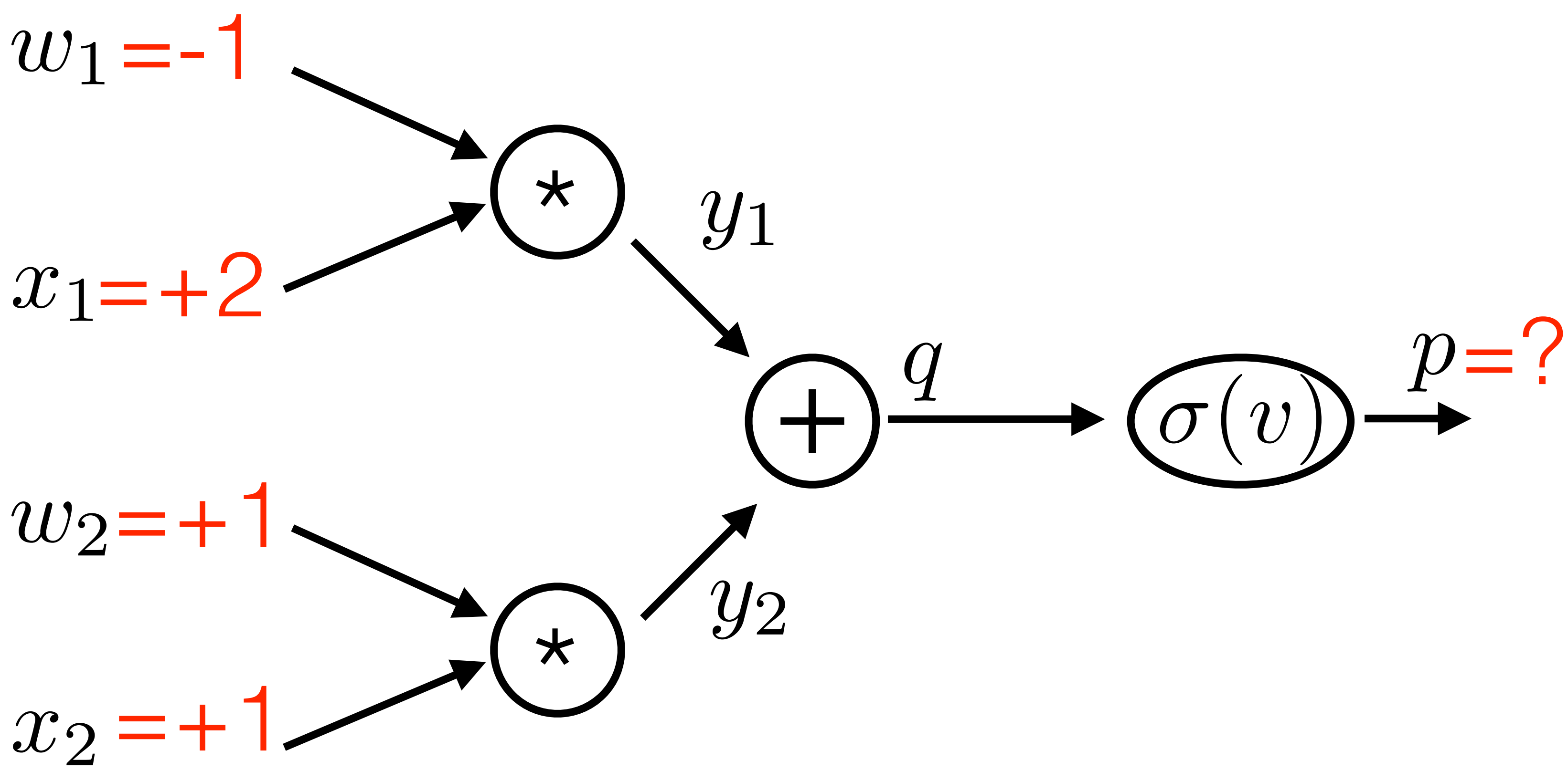
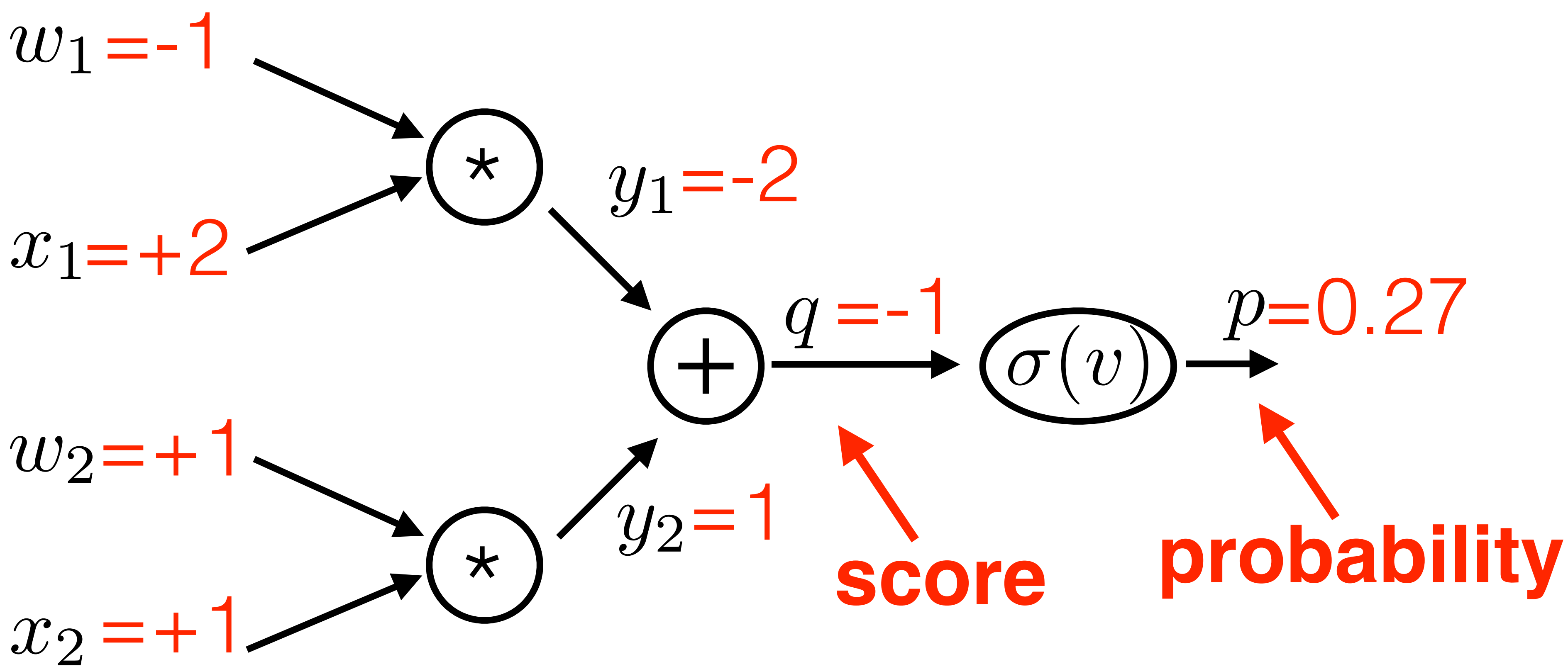
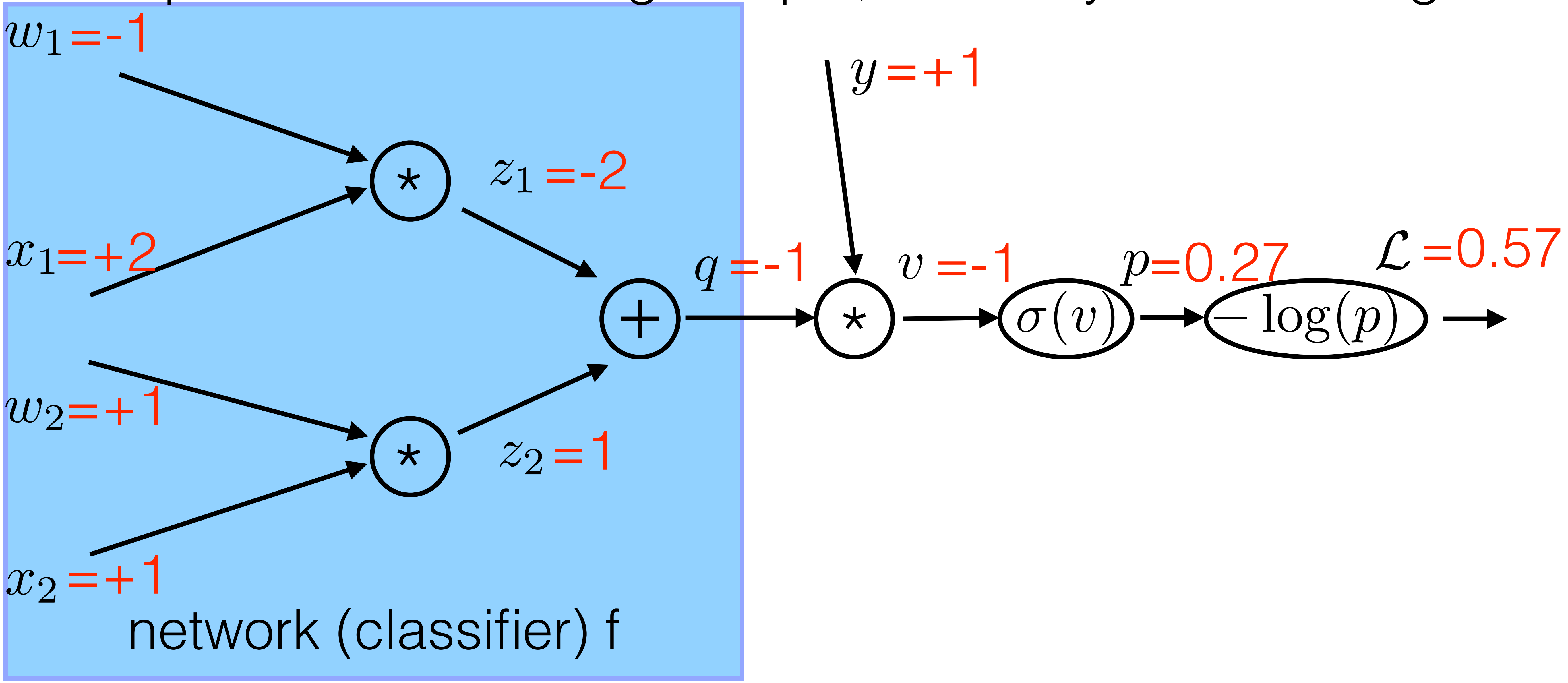


Example I: given trained classifier, and input, what is output?



Example II: Given training sample, how do you learn weights?



$$\arg\min_{\mathbf{w}} \Big(-\log\big[\sigma\big(y_i\, f(\mathbf{x}_i, \mathbf{w})\big)\big] \Big)$$

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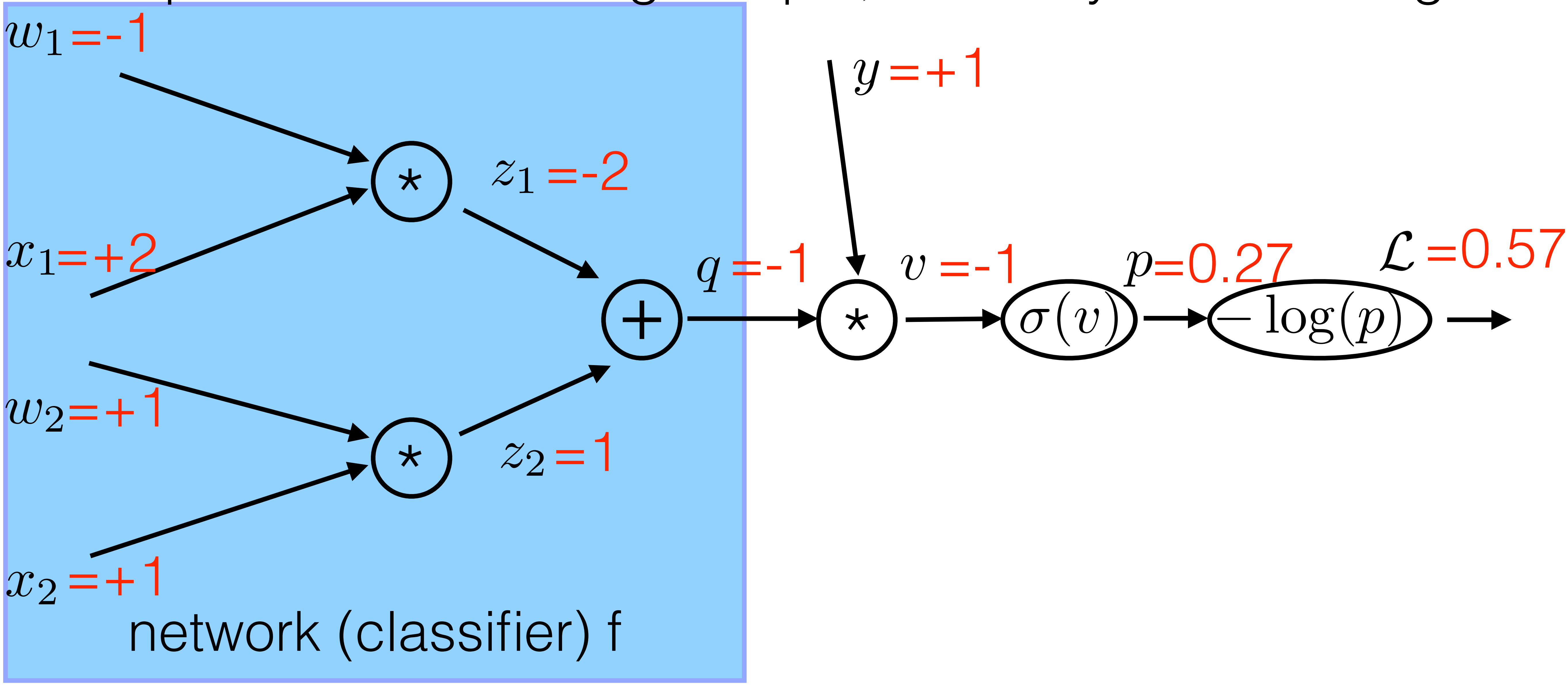

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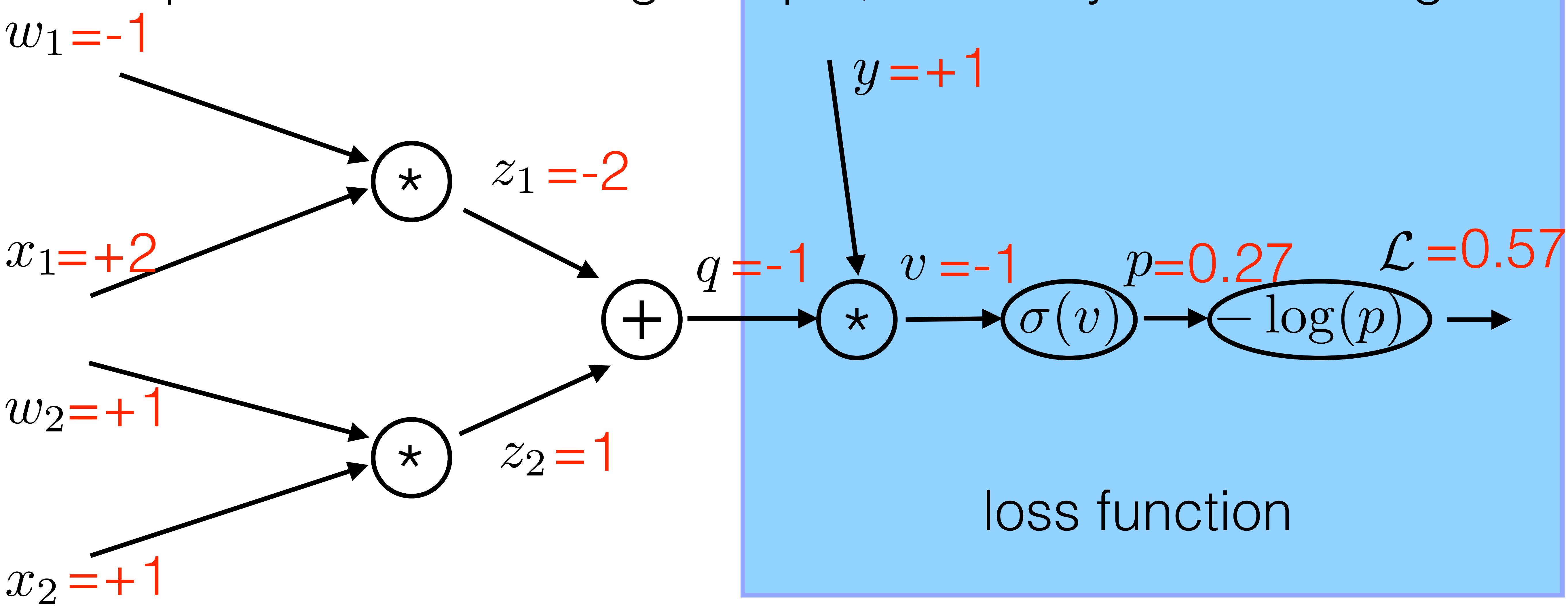

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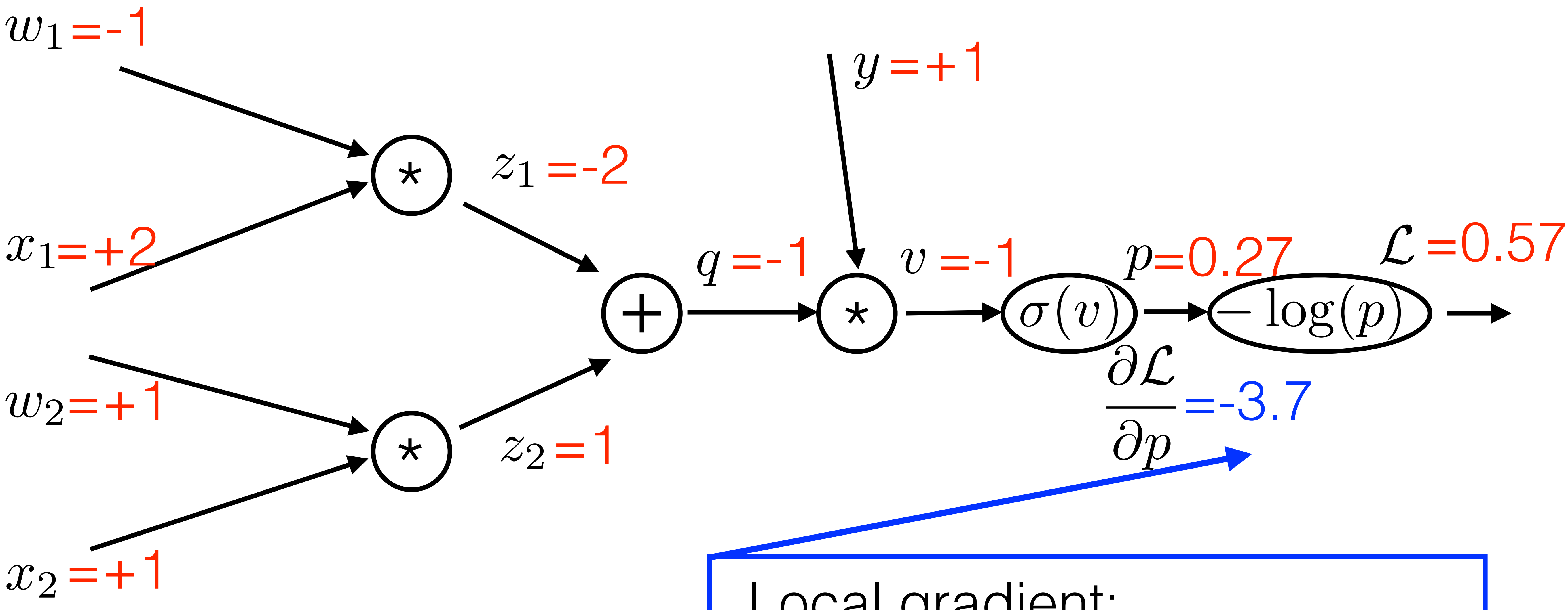

Local gradient:

$$\frac{\partial \mathcal{L}}{\partial p} = \frac{\partial(-\log(p))}{\partial p} = -\frac{1}{p}$$

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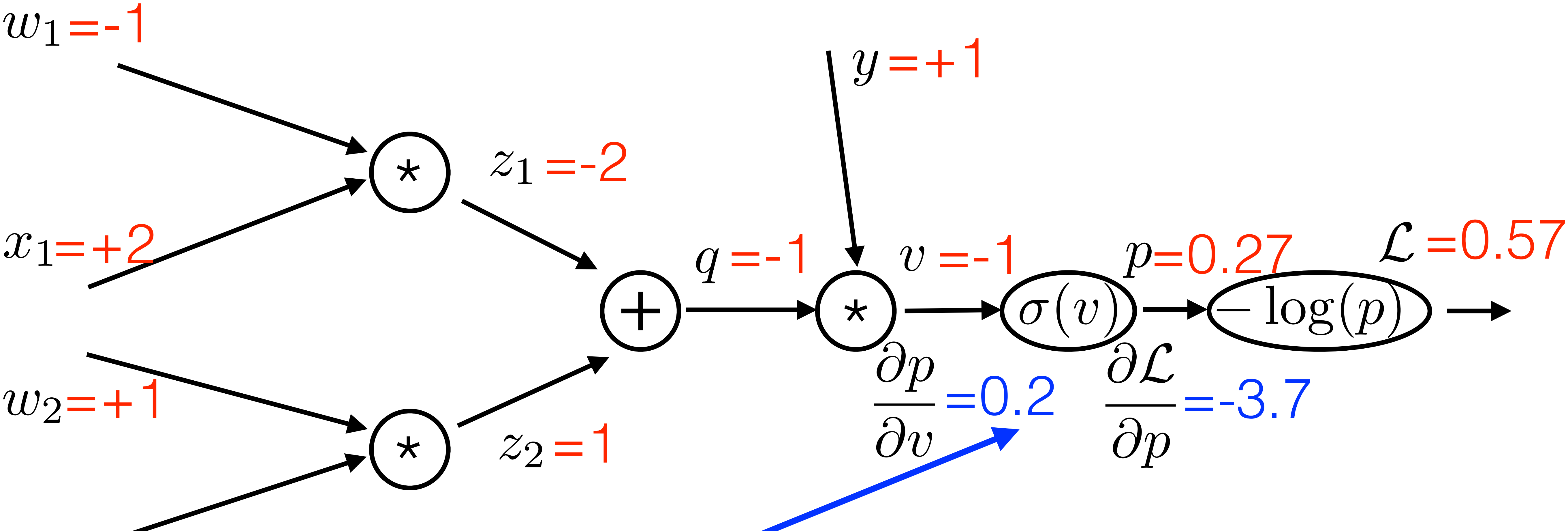

Local gradient:

$$\frac{\partial p}{\partial v} = \frac{\partial \sigma(v)}{\partial v} = \sigma(v)(1 - \sigma(v))$$

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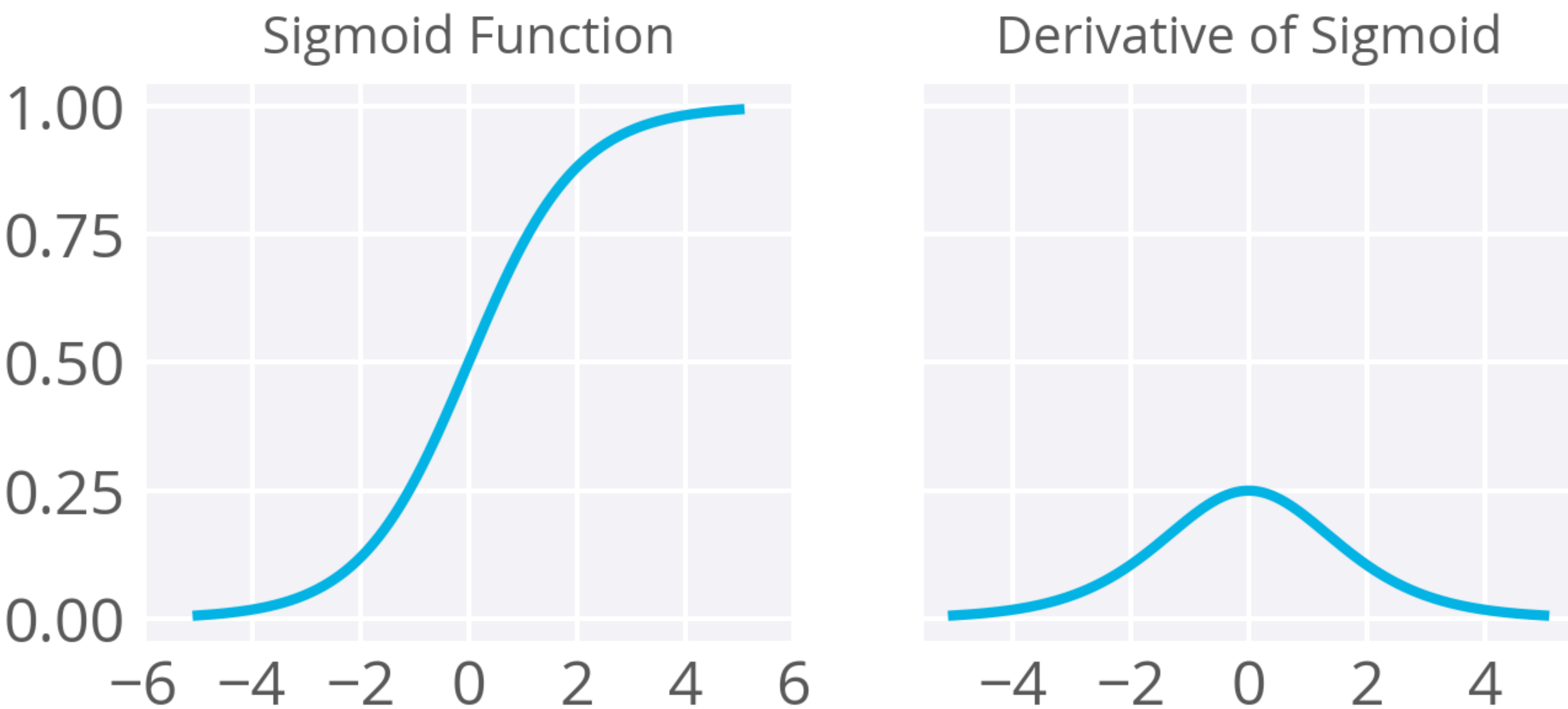

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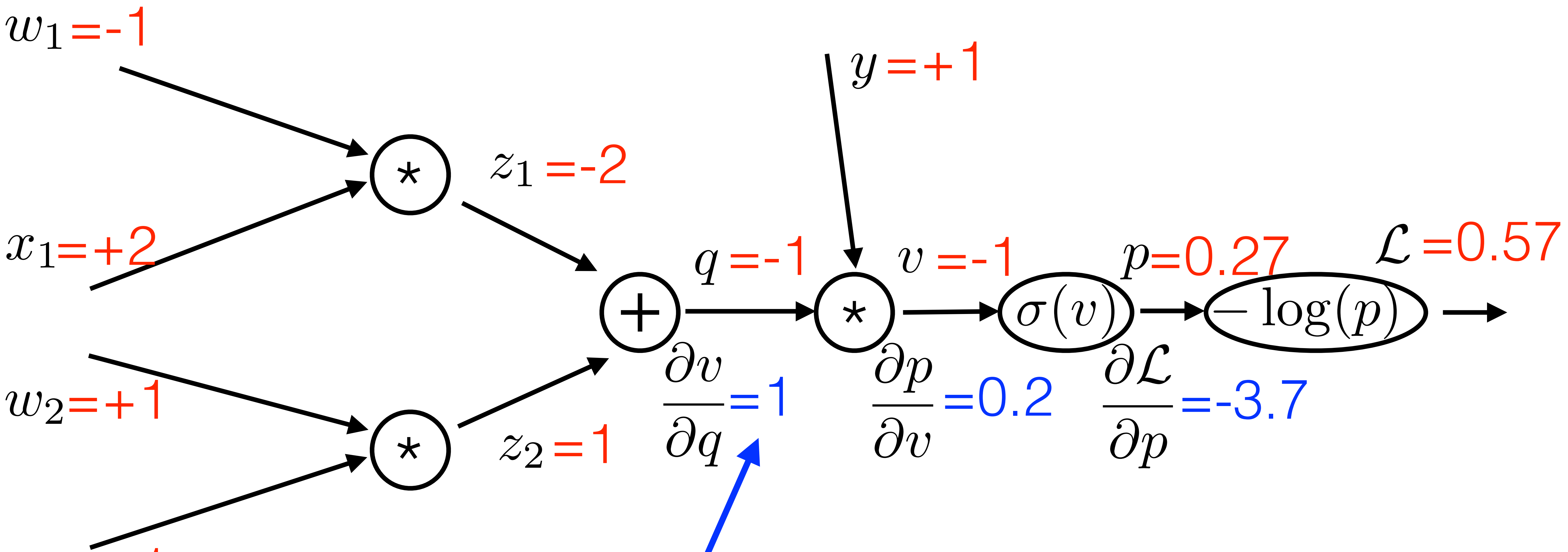

Local gradient:

$$\frac{\partial v}{\partial q} = \frac{\partial (yq)}{\partial q} = y$$

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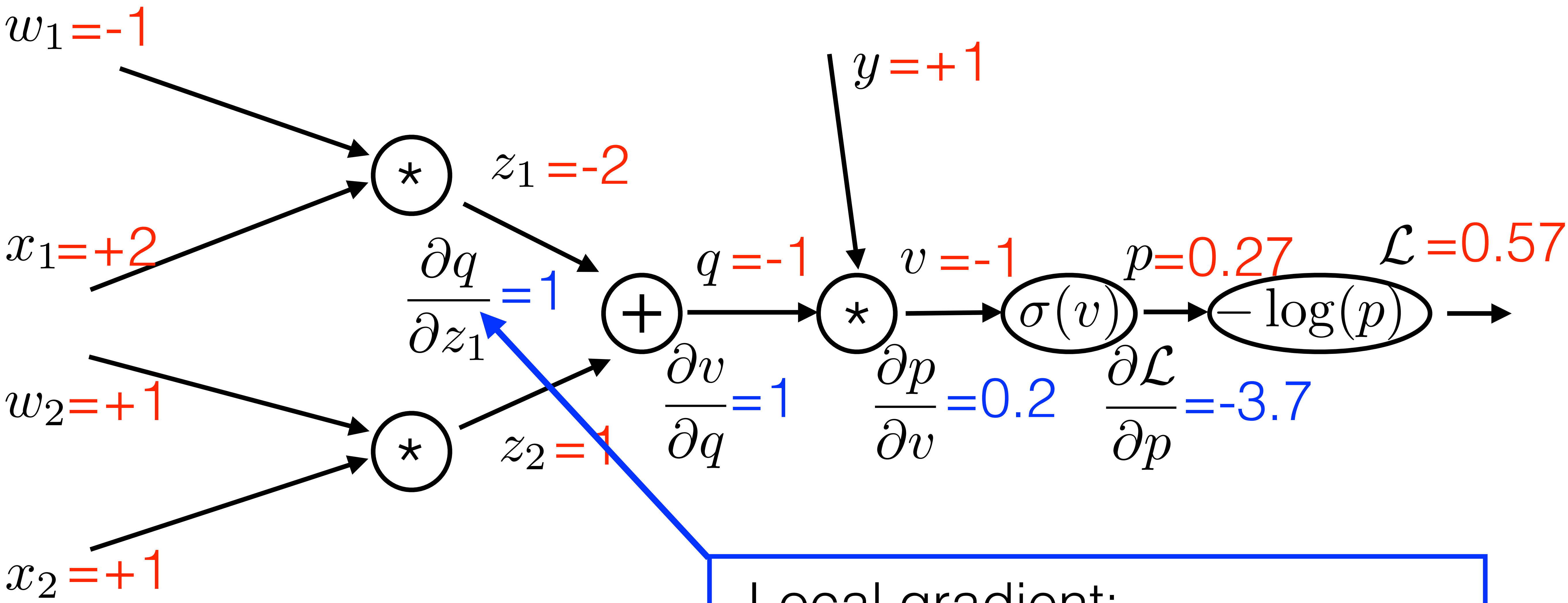

Local gradient:

$$\frac{\partial q}{\partial z_1} = \frac{\partial (z_1 + z_2)}{\partial z_1} = 1$$

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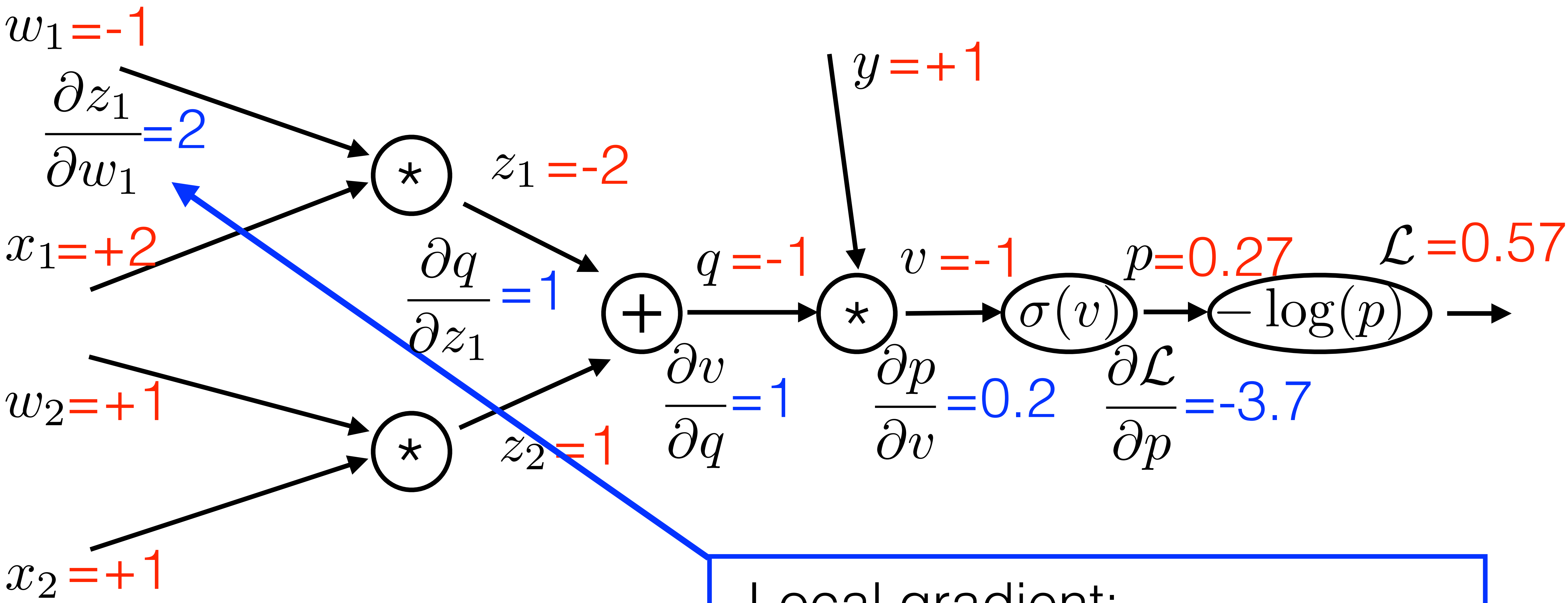

Local gradient:

$$\frac{\partial z_1}{\partial w_1} = \frac{\partial (w_1 x_1)}{\partial w_1} = x_1$$

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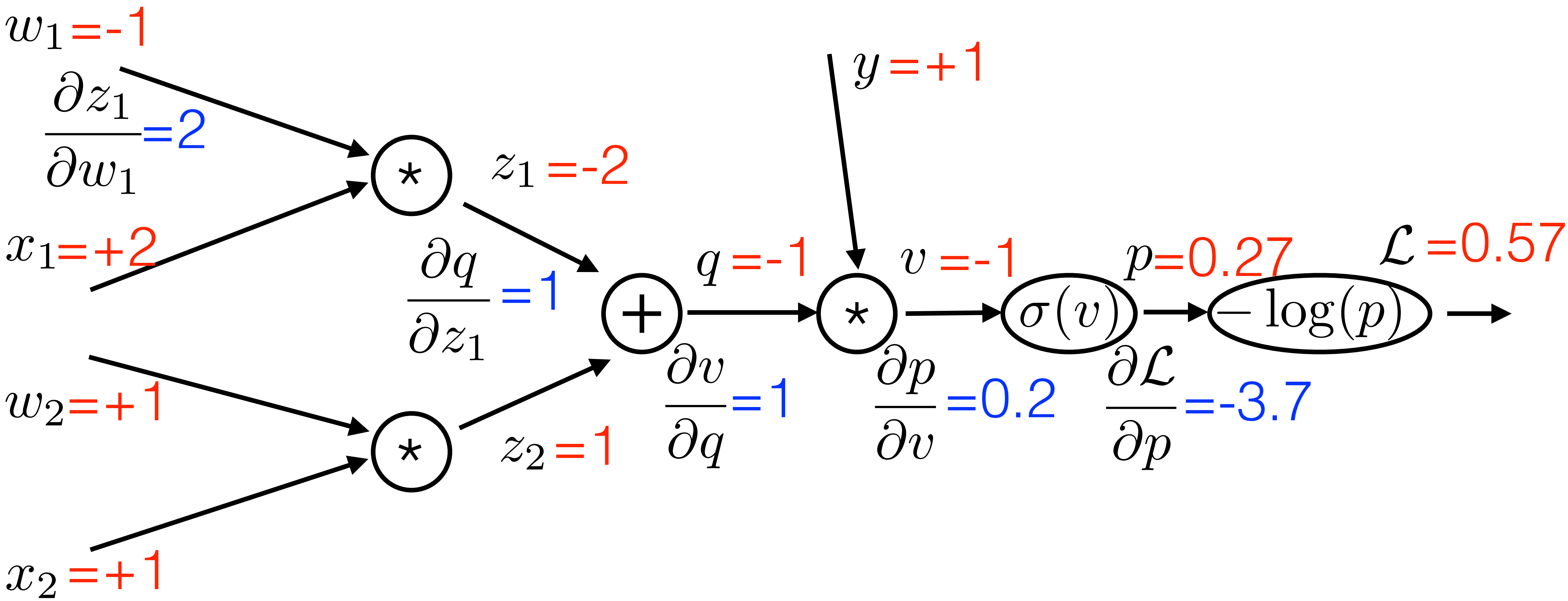
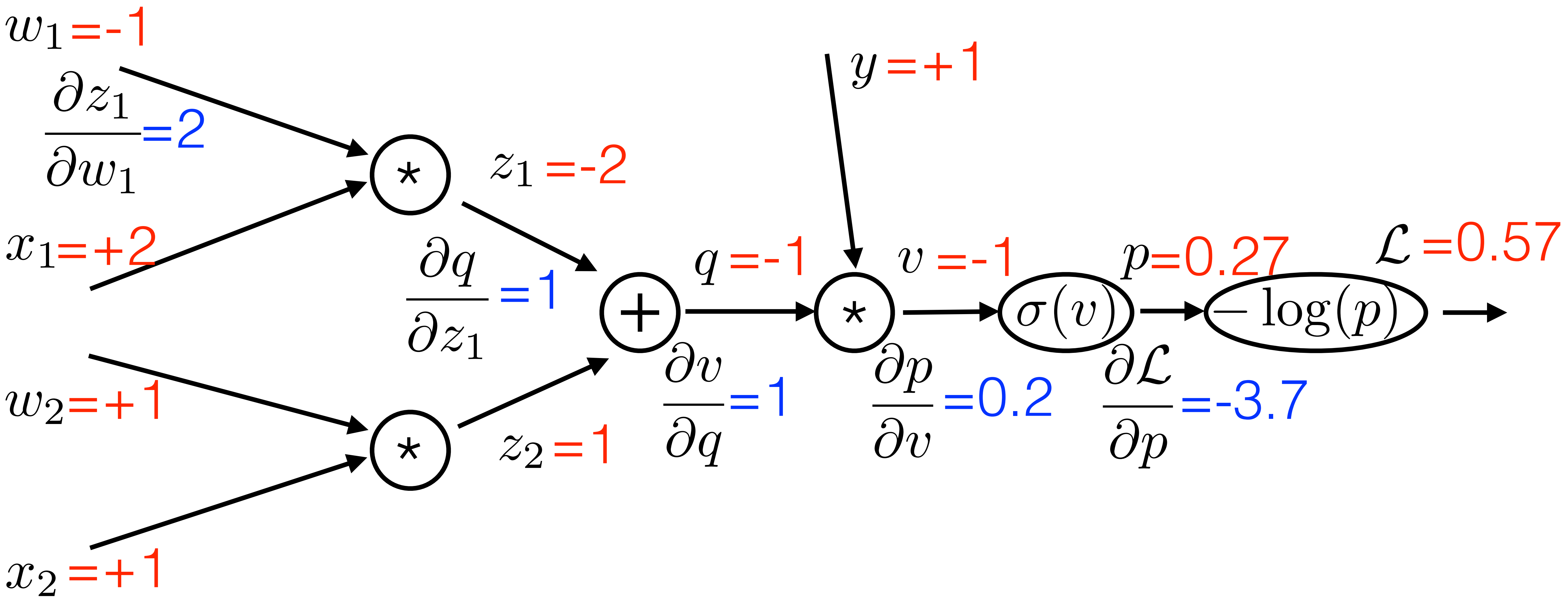


$$\frac{\partial \mathcal{L}}{\partial w_1} = \frac{\partial \mathcal{L}}{\partial p}\frac{\partial p}{\partial v}\frac{\partial v}{\partial q}\frac{\partial q}{\partial z_1}\frac{\partial z_1}{\partial w_1}$$ =-3.7*0.2*1*1*2 =-1.48

Example II: Given training sample, how do you learn weights?



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$$w_1 = w_1 - \alpha\frac{\partial \mathcal{L}}{\partial w1} = +0.48$$

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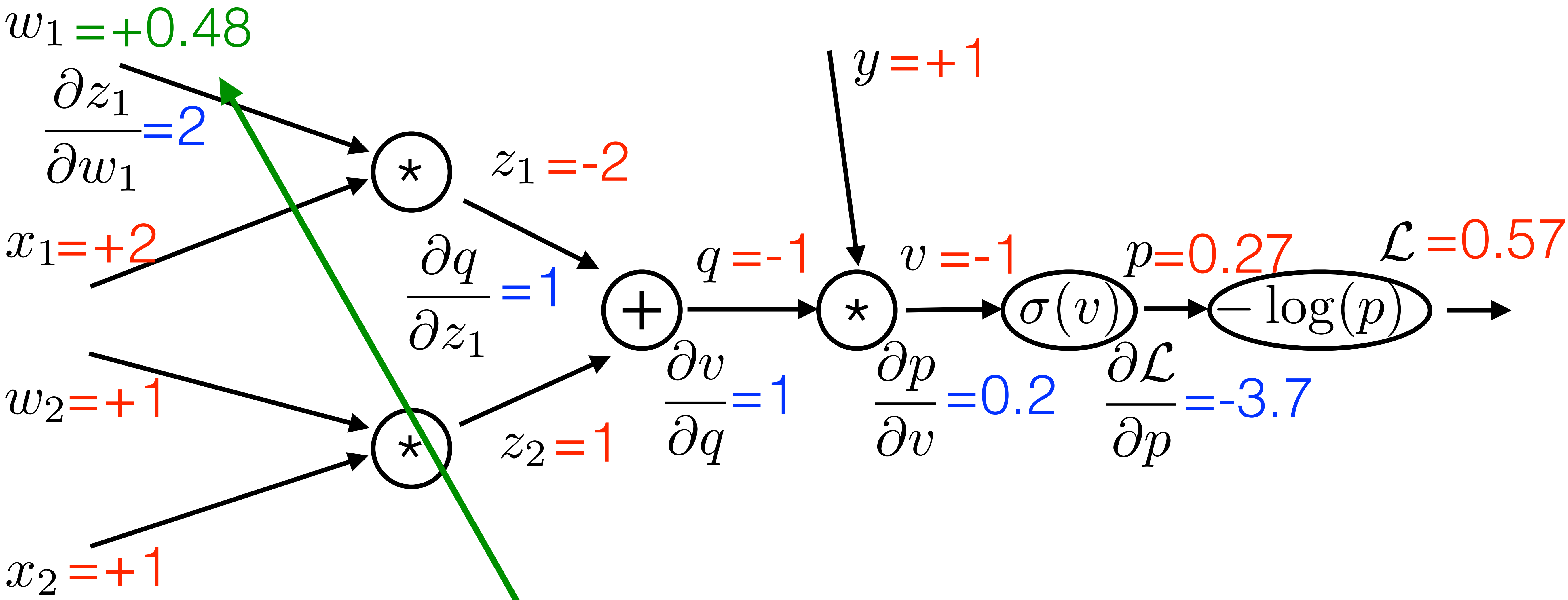

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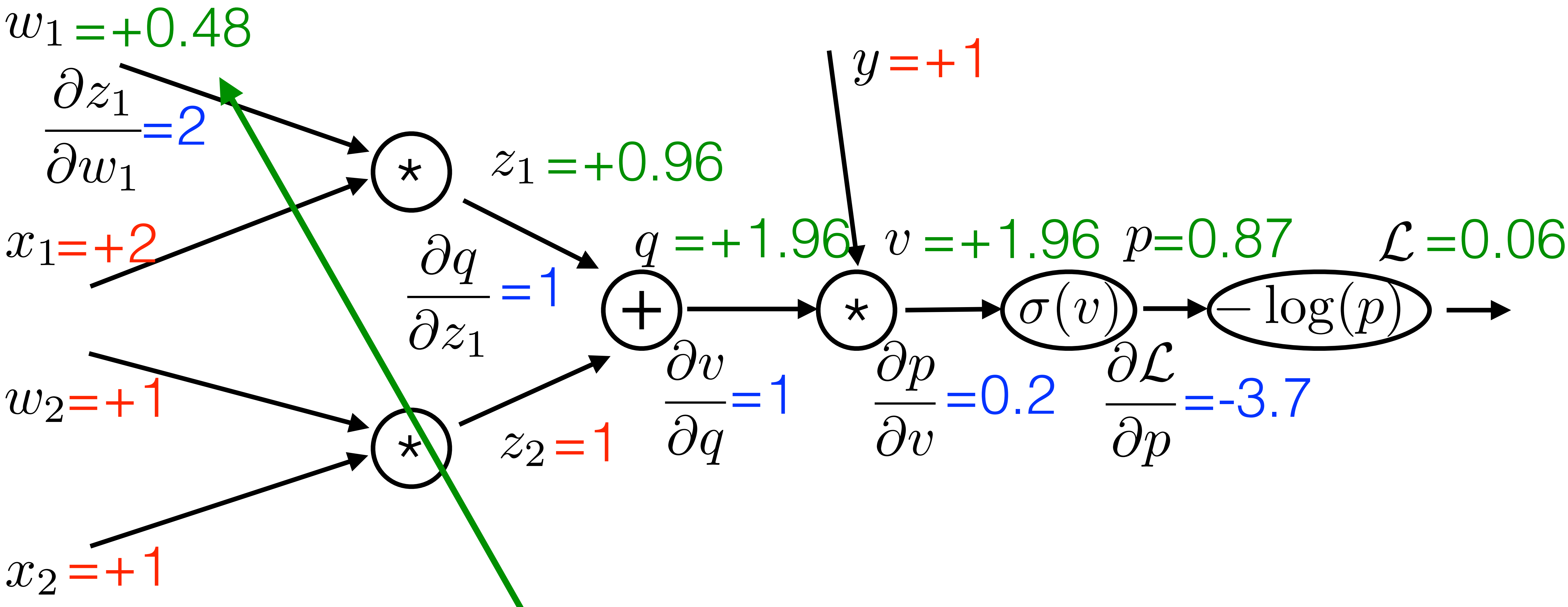

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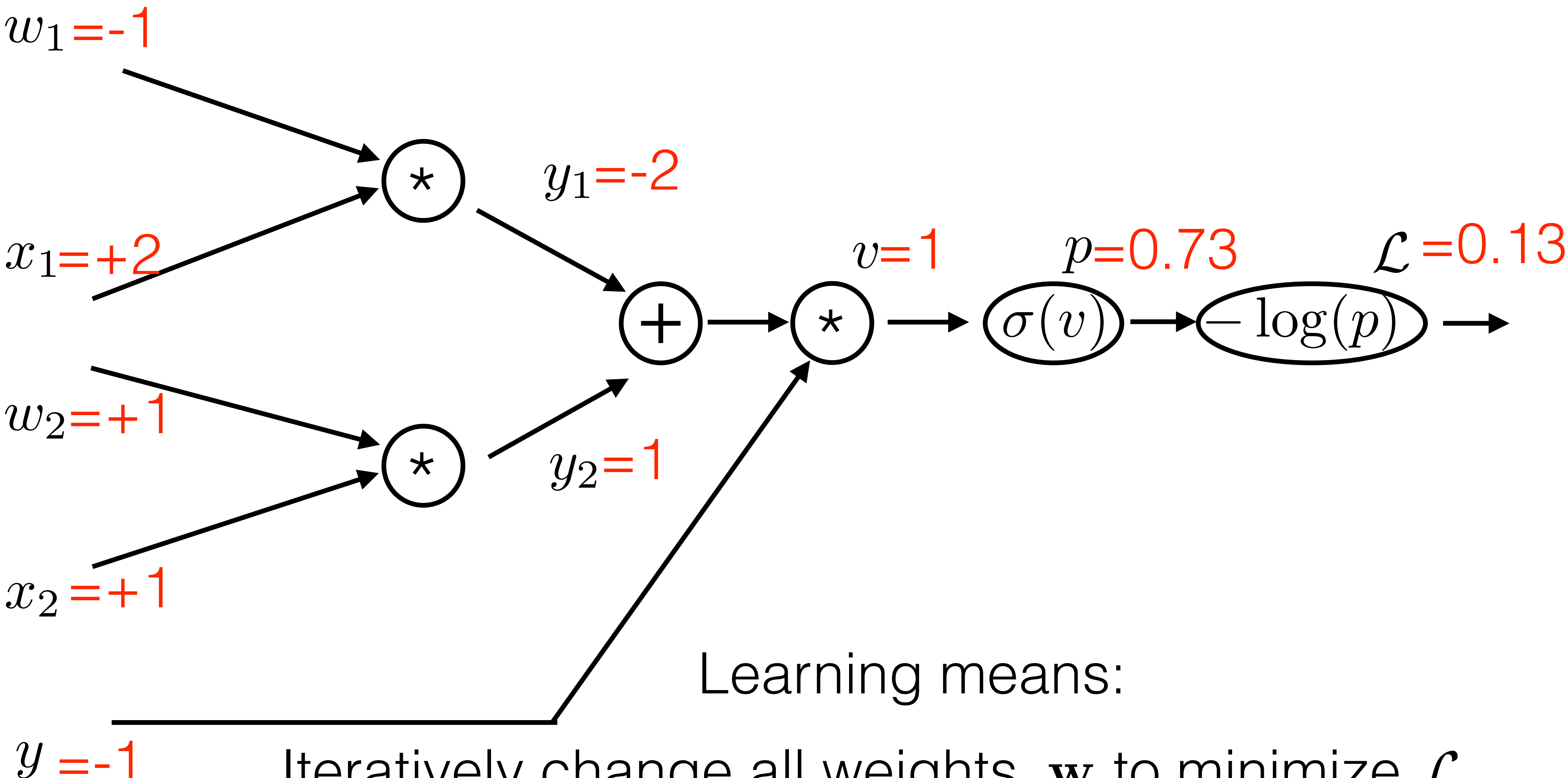
$$w_1 = w_1 - \alpha\frac{\partial \mathcal{L}}{\partial w1} = +0.48$$

Example III: vector representation

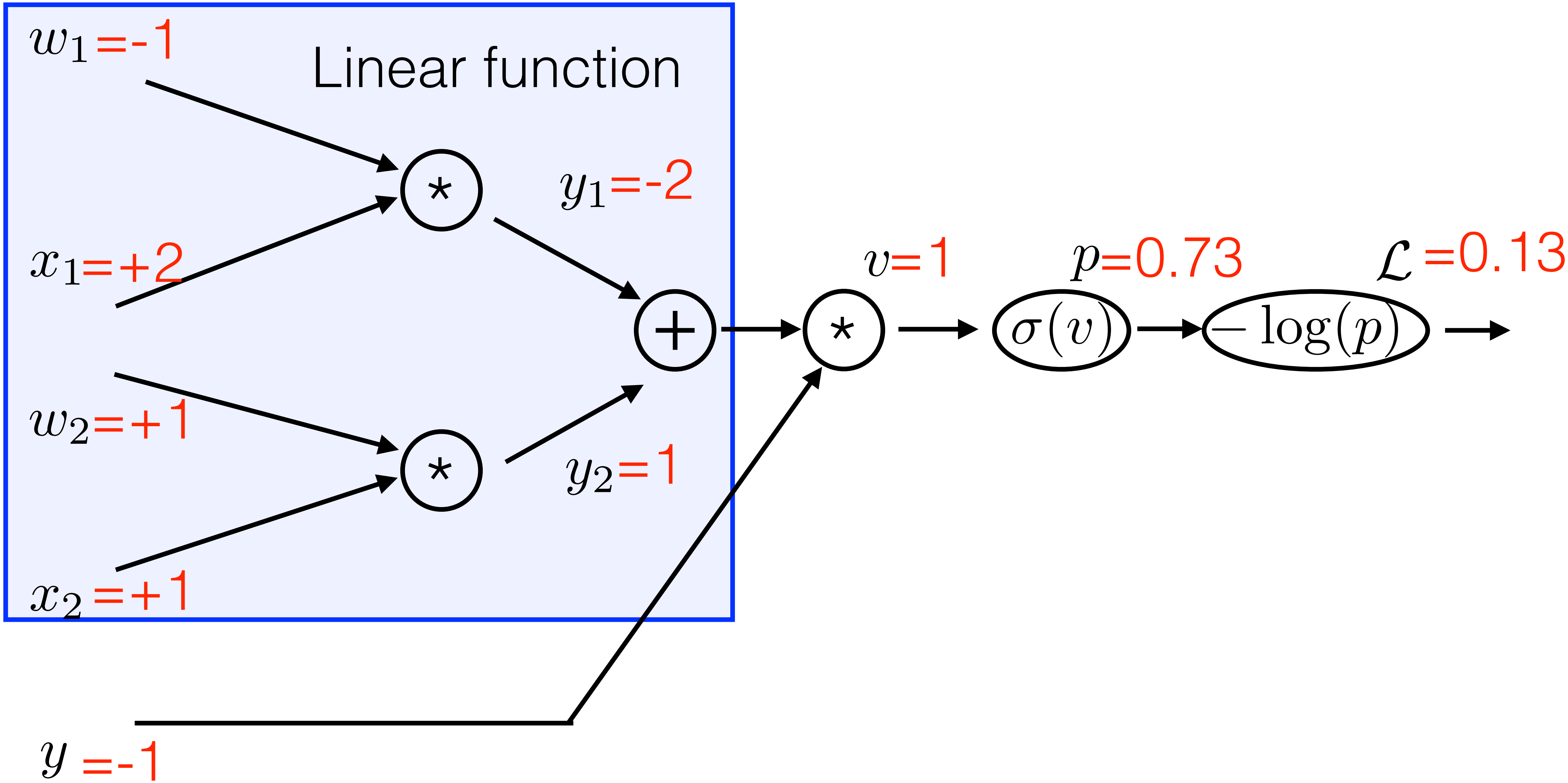


Learning means:

Iteratively change all weights $\mathbf{w}$ to minimize $\mathcal{L}$

$$\mathbf{w} = \mathbf{w} - \alpha \left[\frac{\partial \mathcal{L}(\mathbf{w})}{\partial \mathbf{w}} \right]^\top \quad \text{where} \quad \frac{\partial \mathcal{L}}{\partial \mathbf{w}} = \left[\frac{\partial \mathcal{L}}{\partial w_1}, \frac{\partial \mathcal{L}}{\partial w_2}, \ldots \right]$$

Computational graph of the learning



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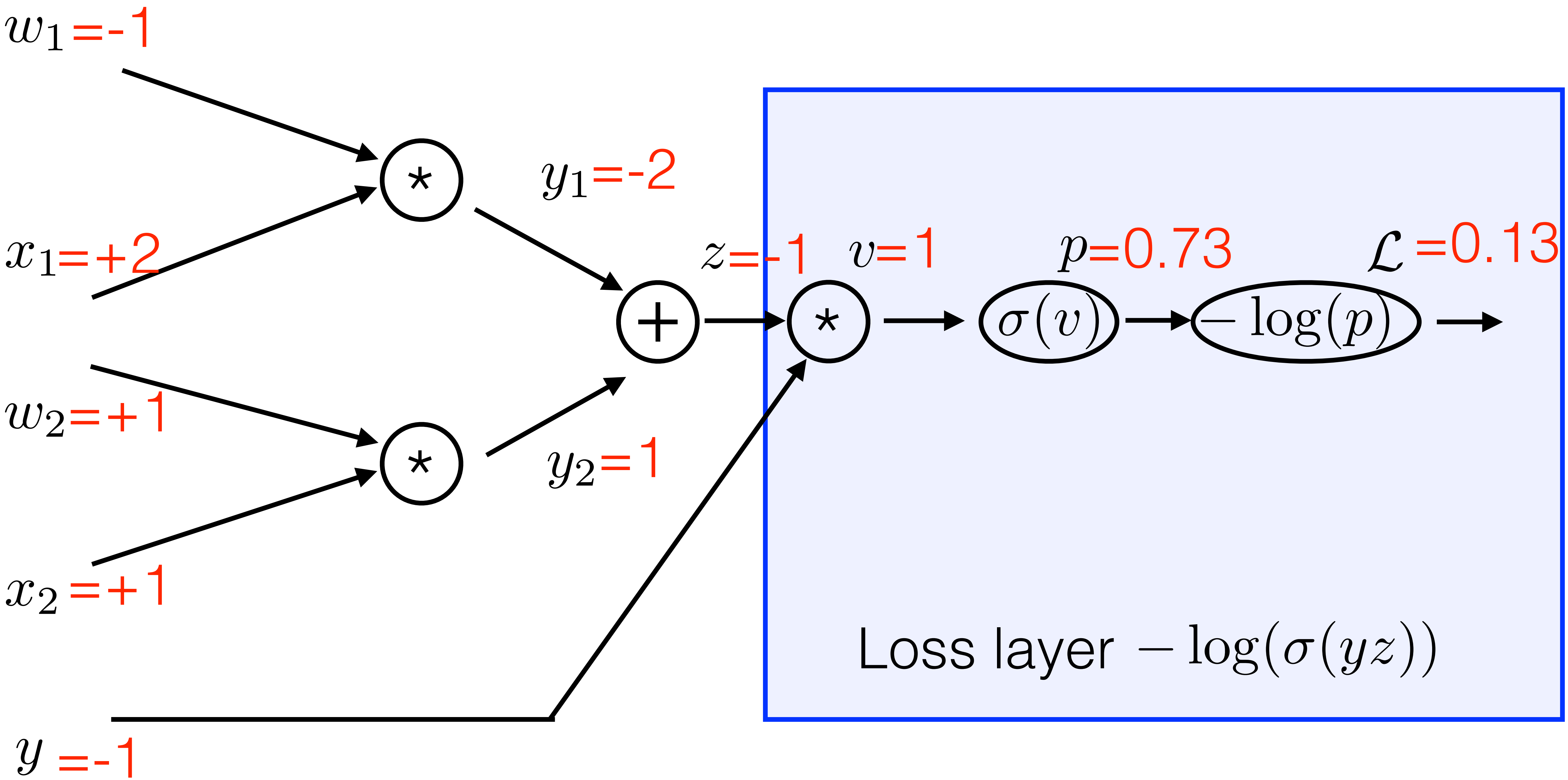
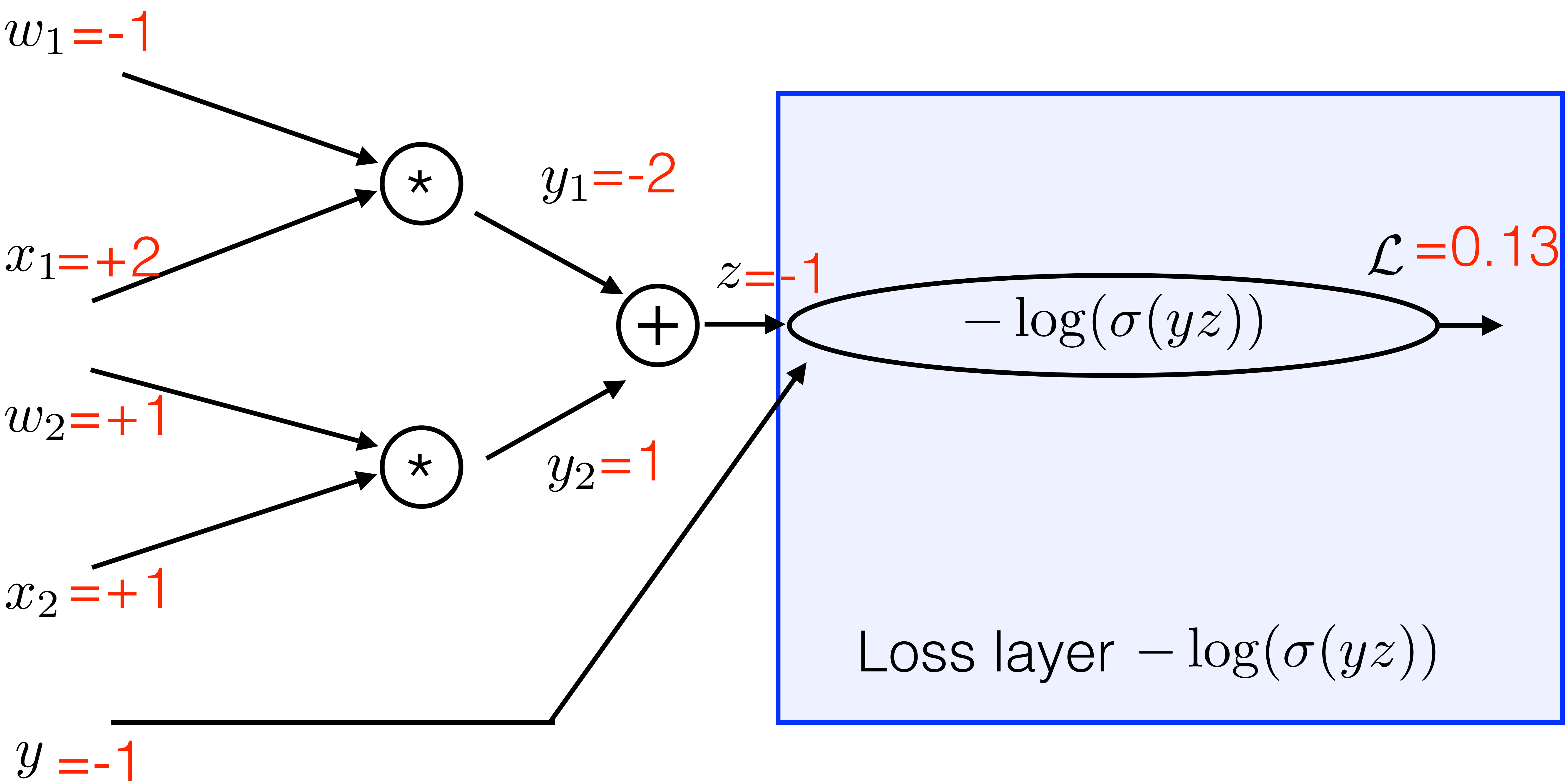


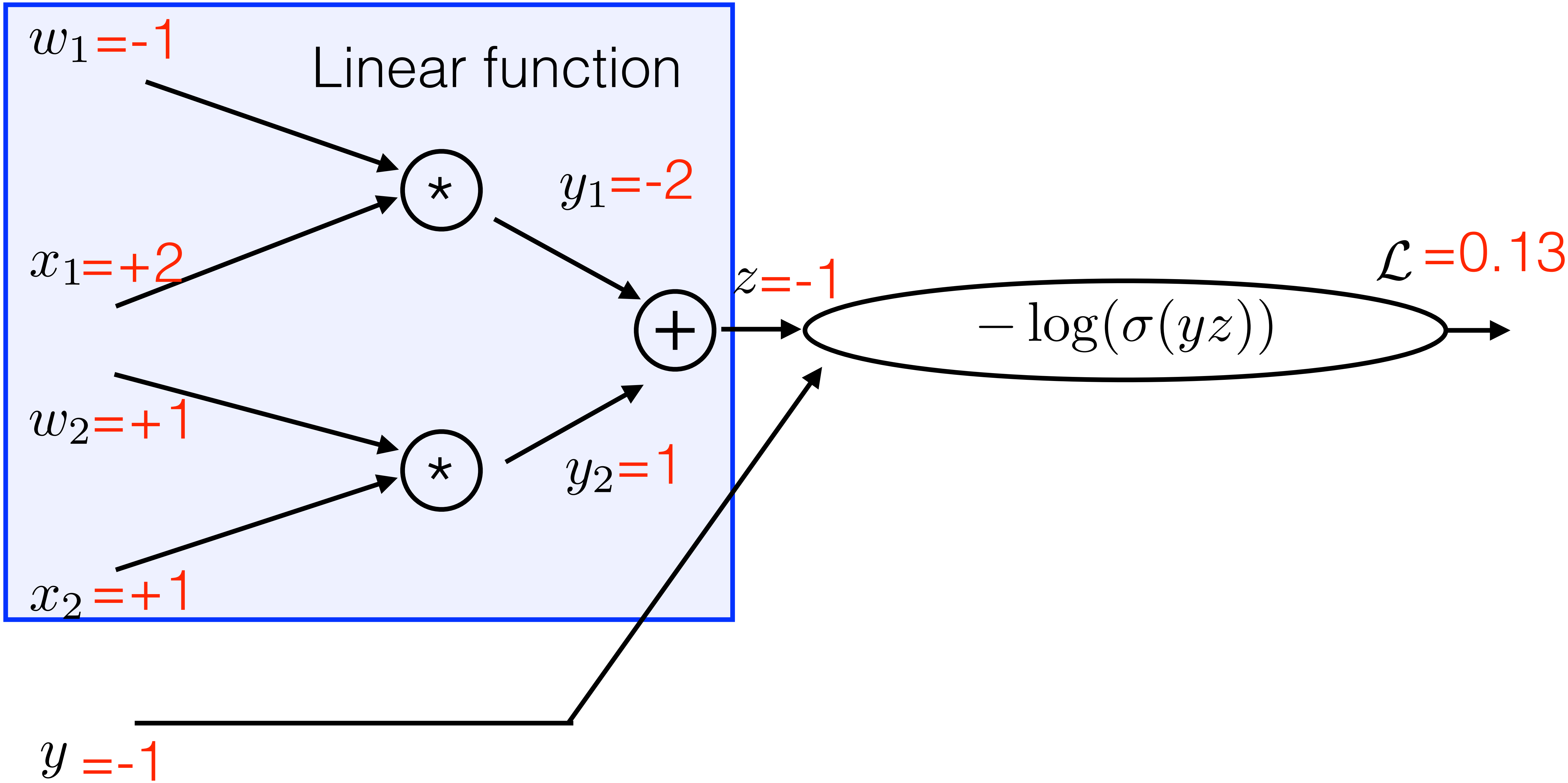
Backprop in vector representation



This is the logistic loss!

$$\mathcal{L}(y,z) = -\log(\sigma(yz)) = \log(1+\exp(-yz))$$

Backprop in vector representation



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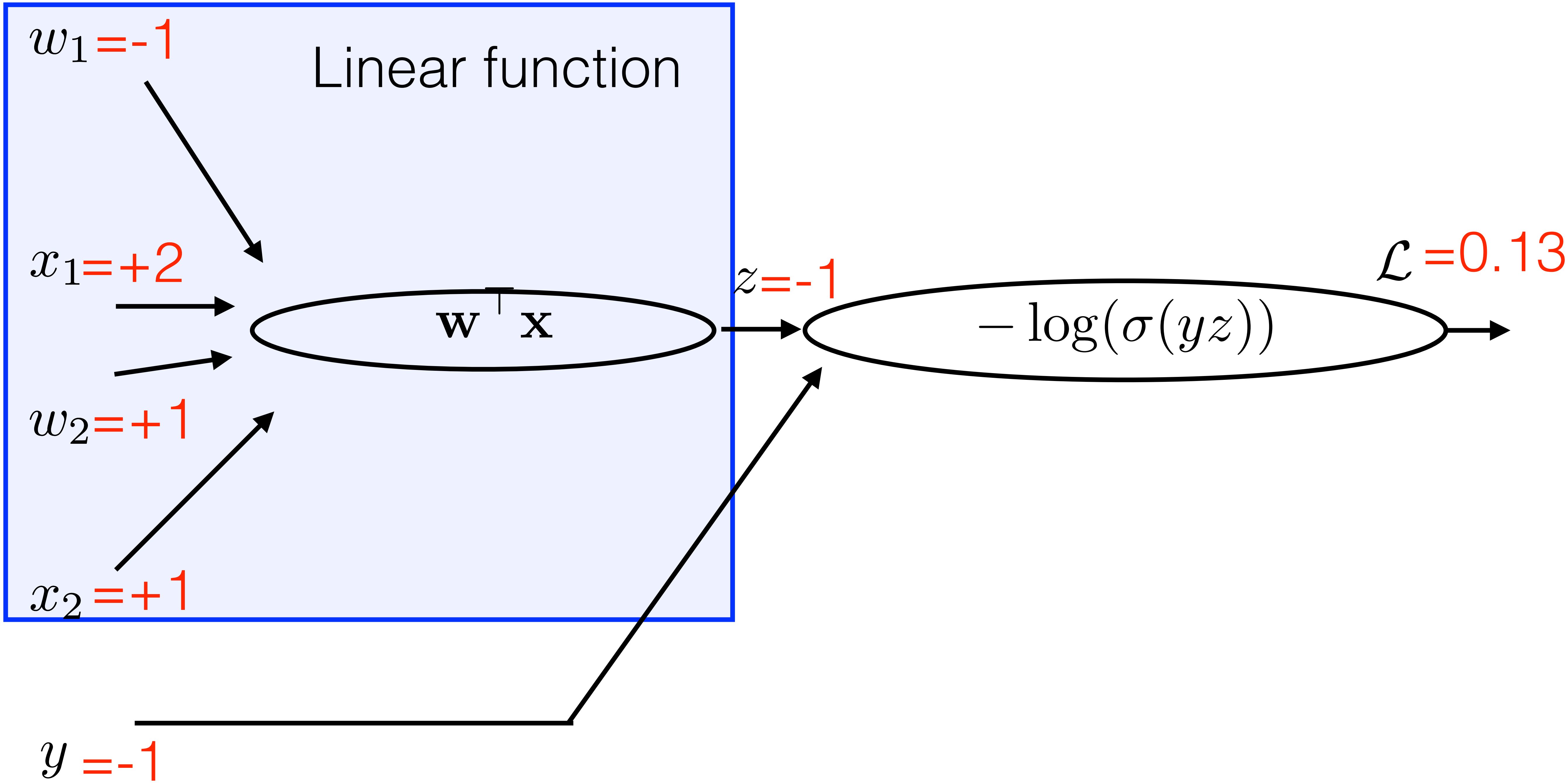

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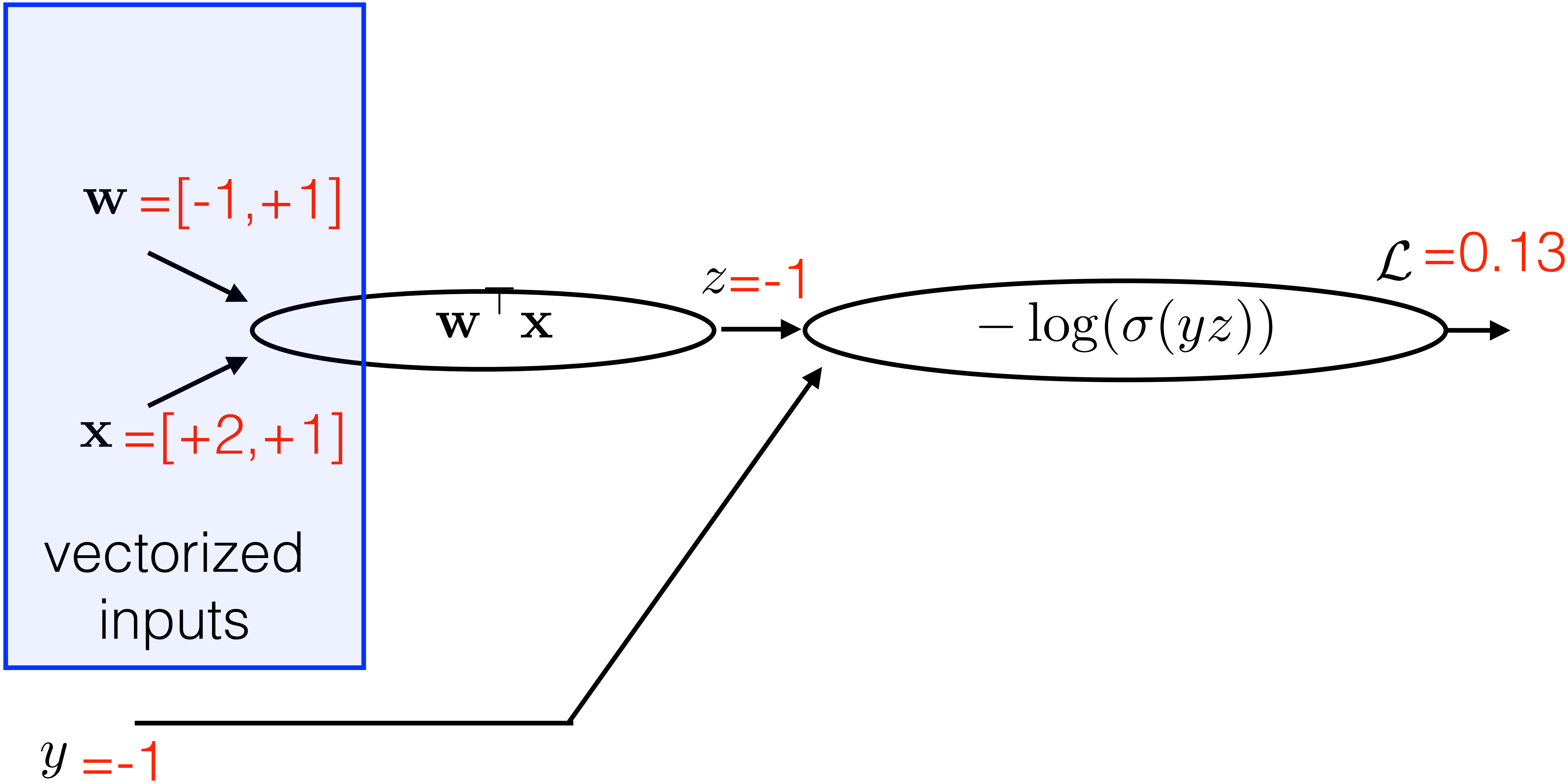

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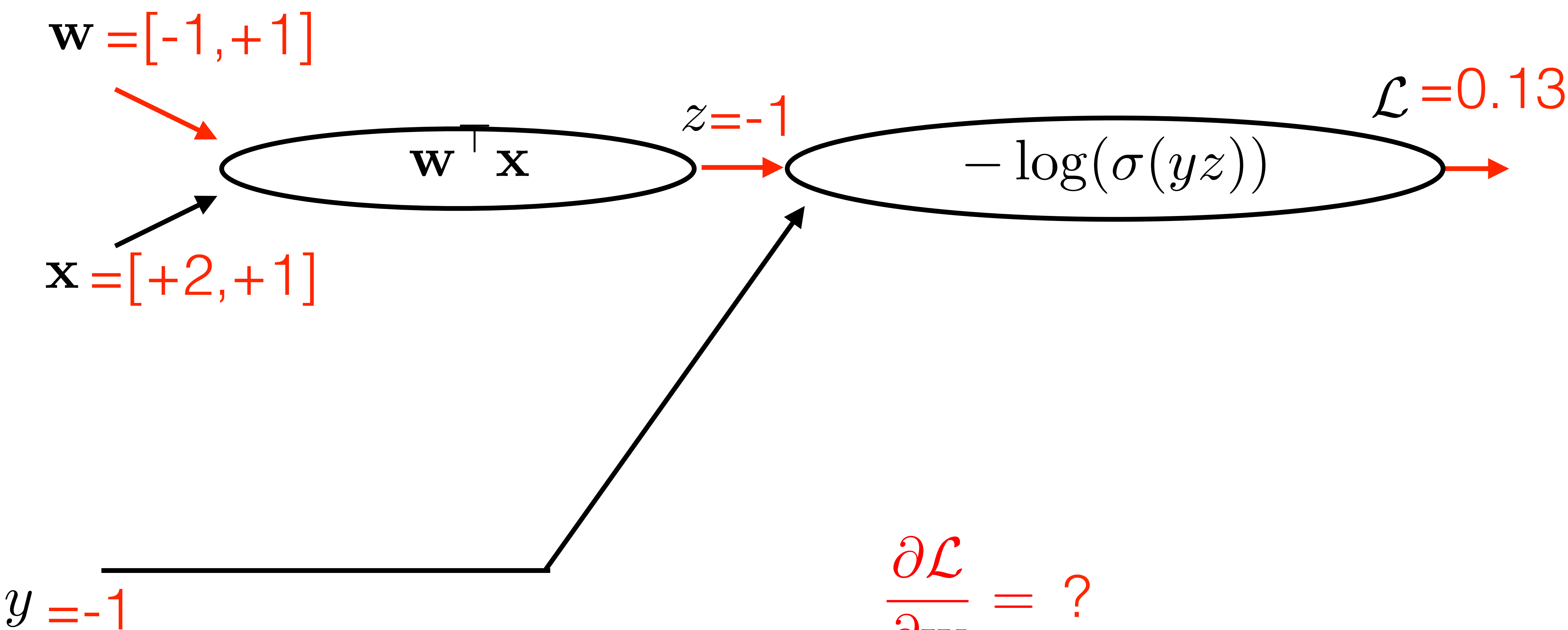

$$\frac{\partial \mathcal{L}}{\partial \mathbf{w}} = \ ?$$

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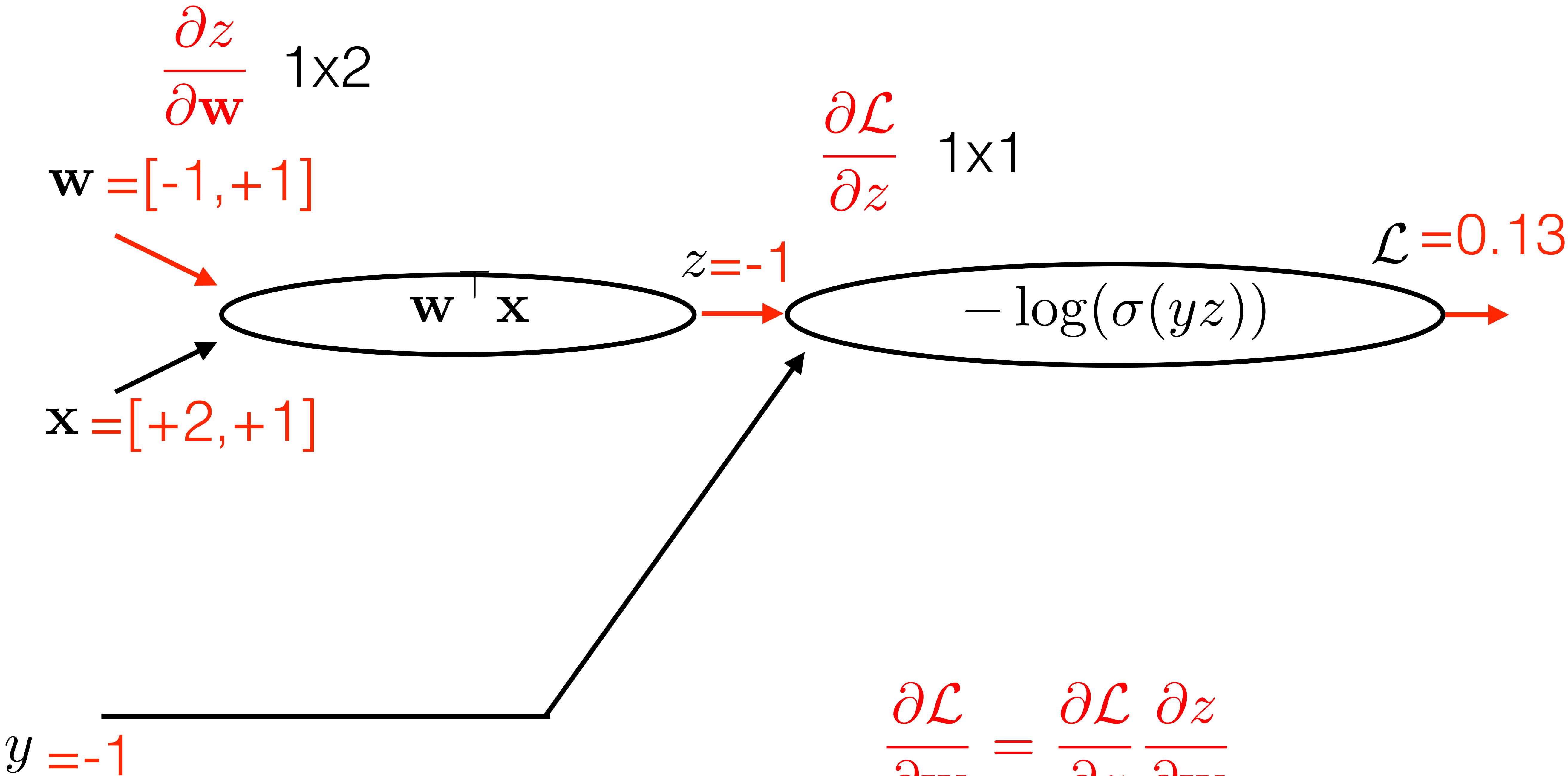
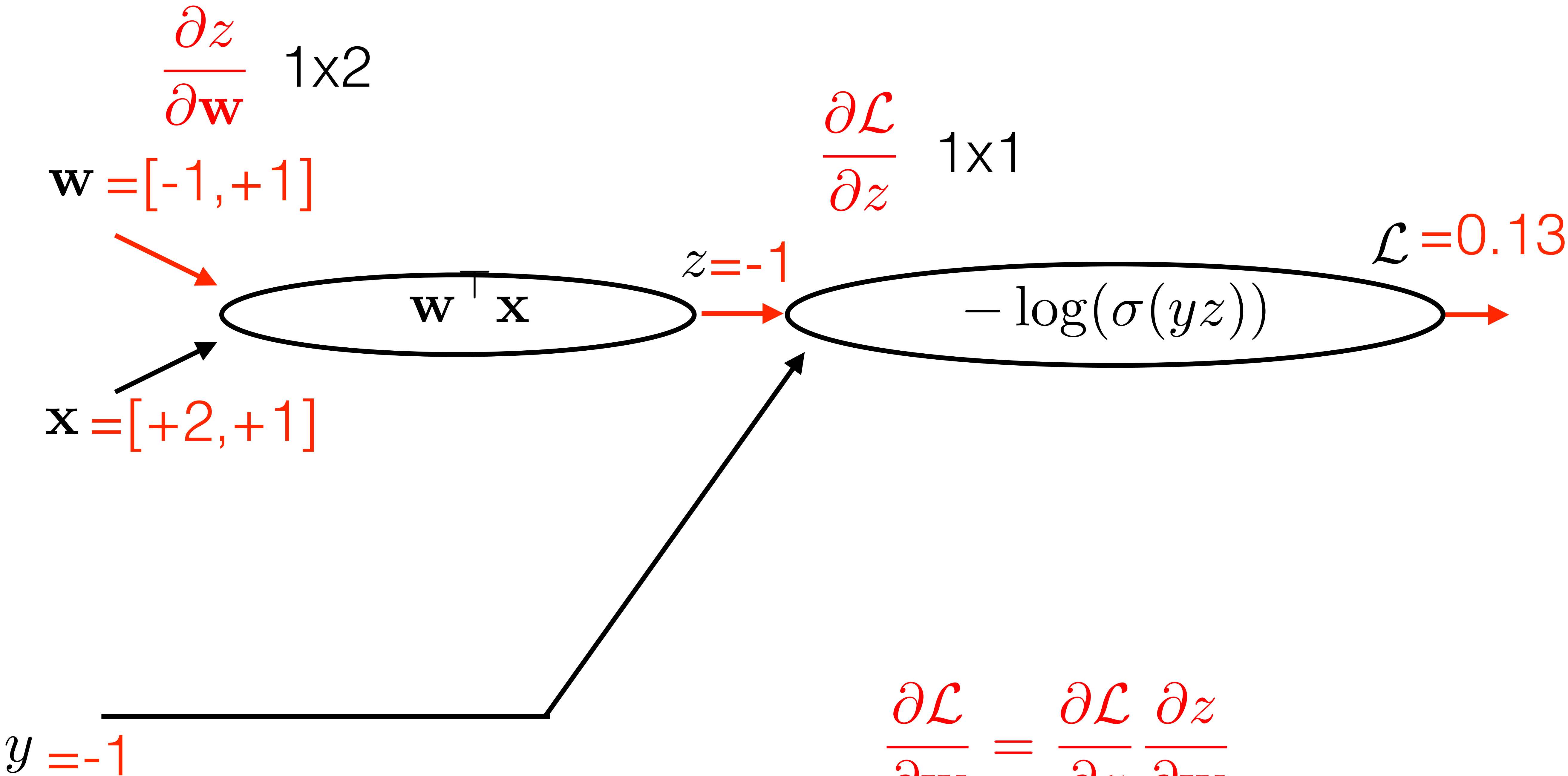


$$\frac{\partial \mathcal{L}}{\partial \mathbf{w}} = \frac{\partial \mathcal{L}}{\partial z} \frac{\partial z}{\partial \mathbf{w}}$$

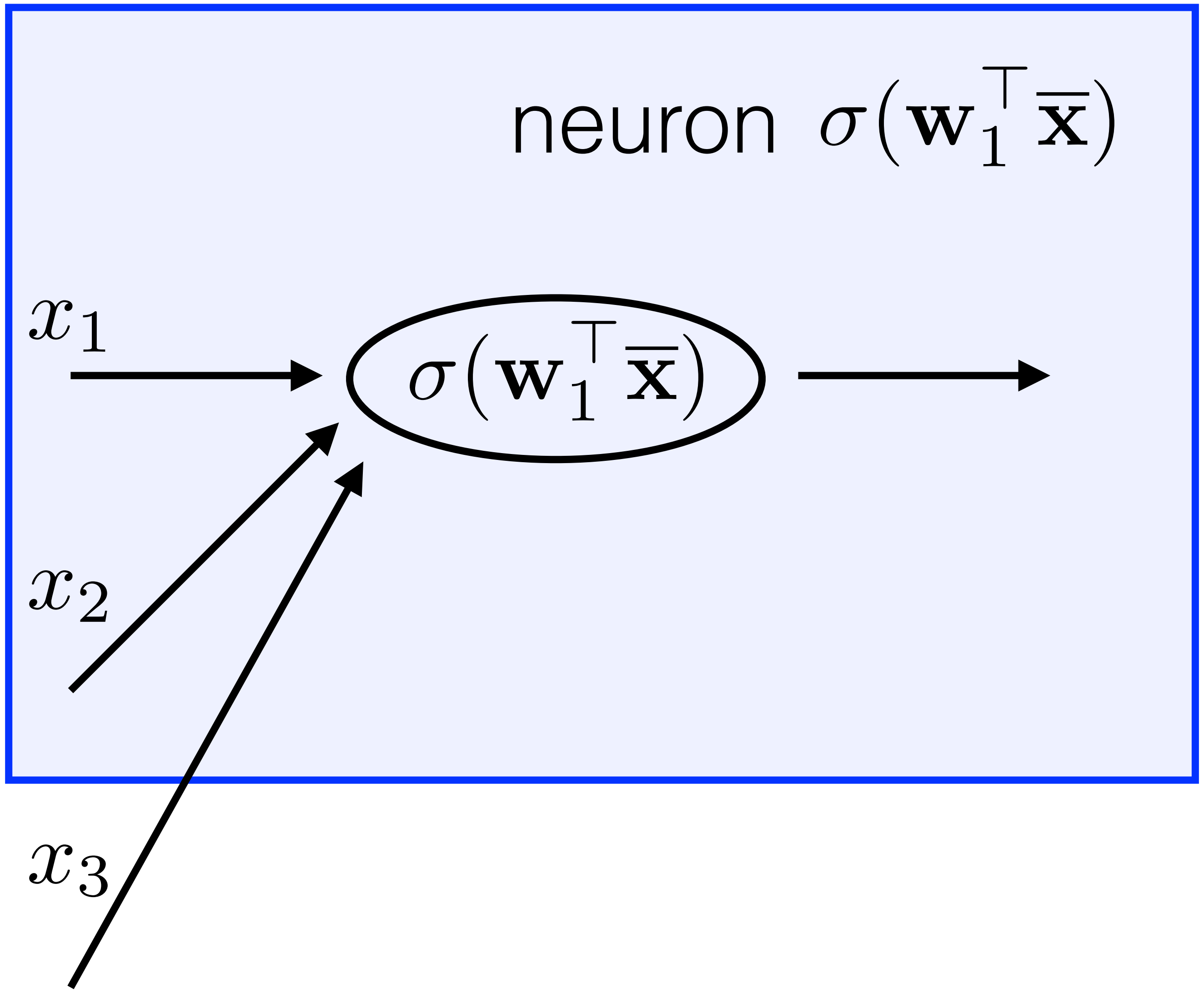
Backprop in vector representation



$$\frac{\partial \mathcal{L}}{\partial \mathbf{w}} = \frac{\partial \mathcal{L}}{\partial z}\frac{\partial z}{\partial \mathbf{w}}$$

Learning from multiple training samples means summing up the gradient over all samples

Fully connected neural network



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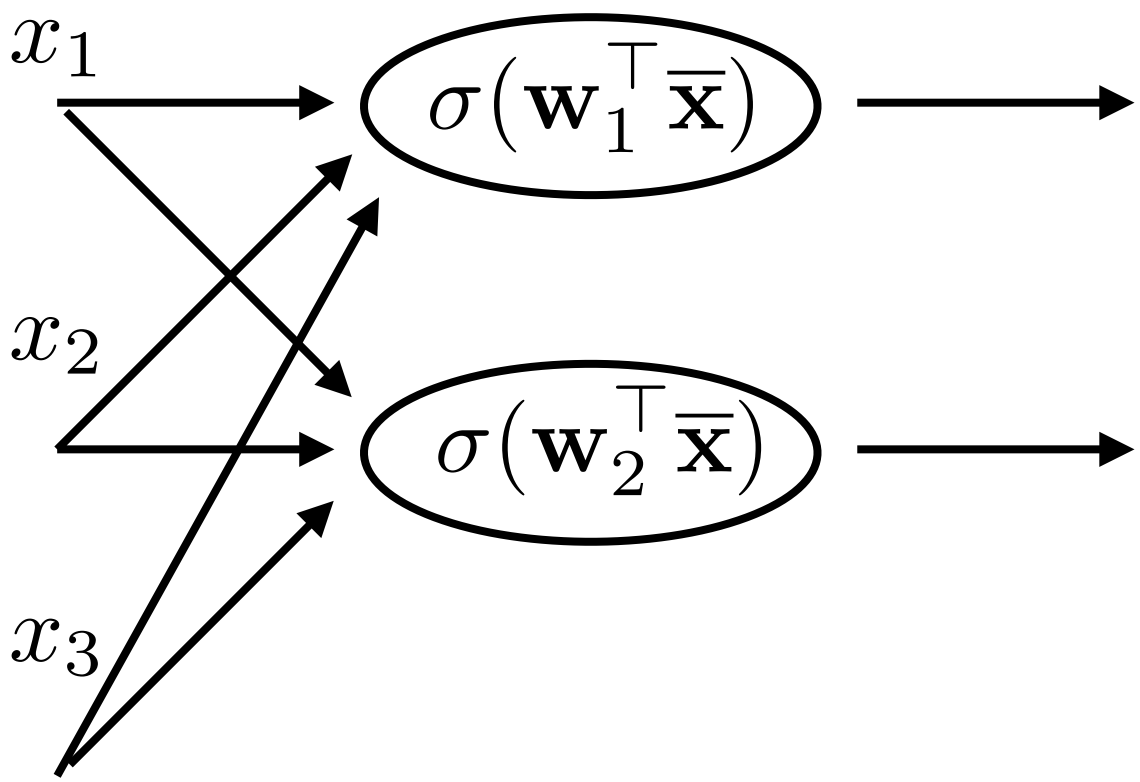

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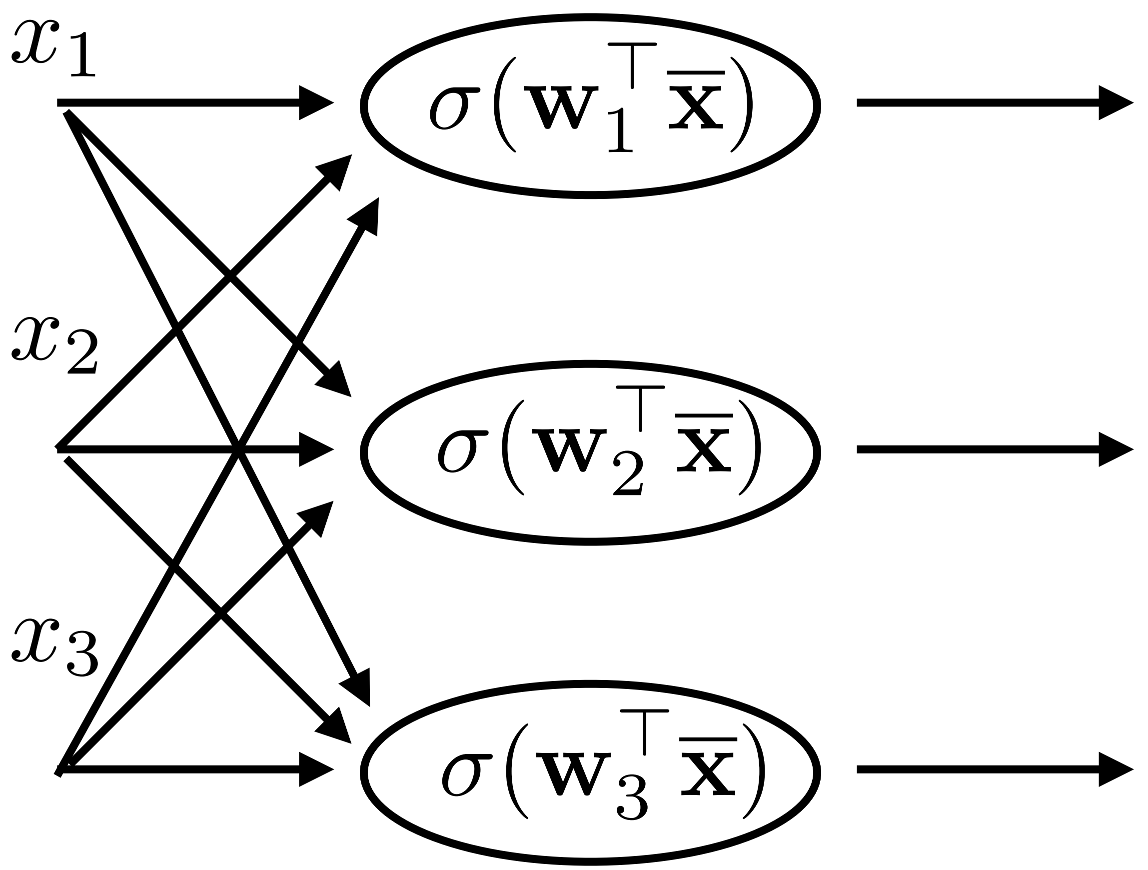

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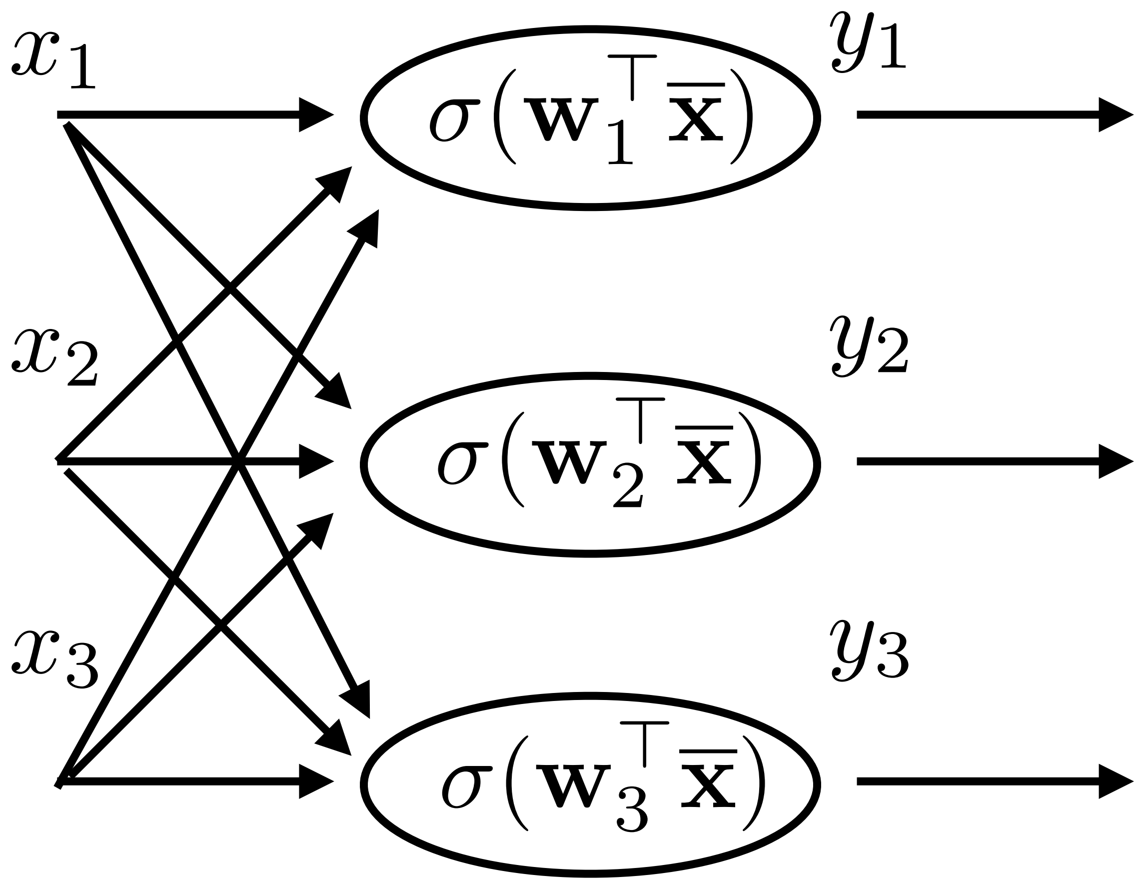

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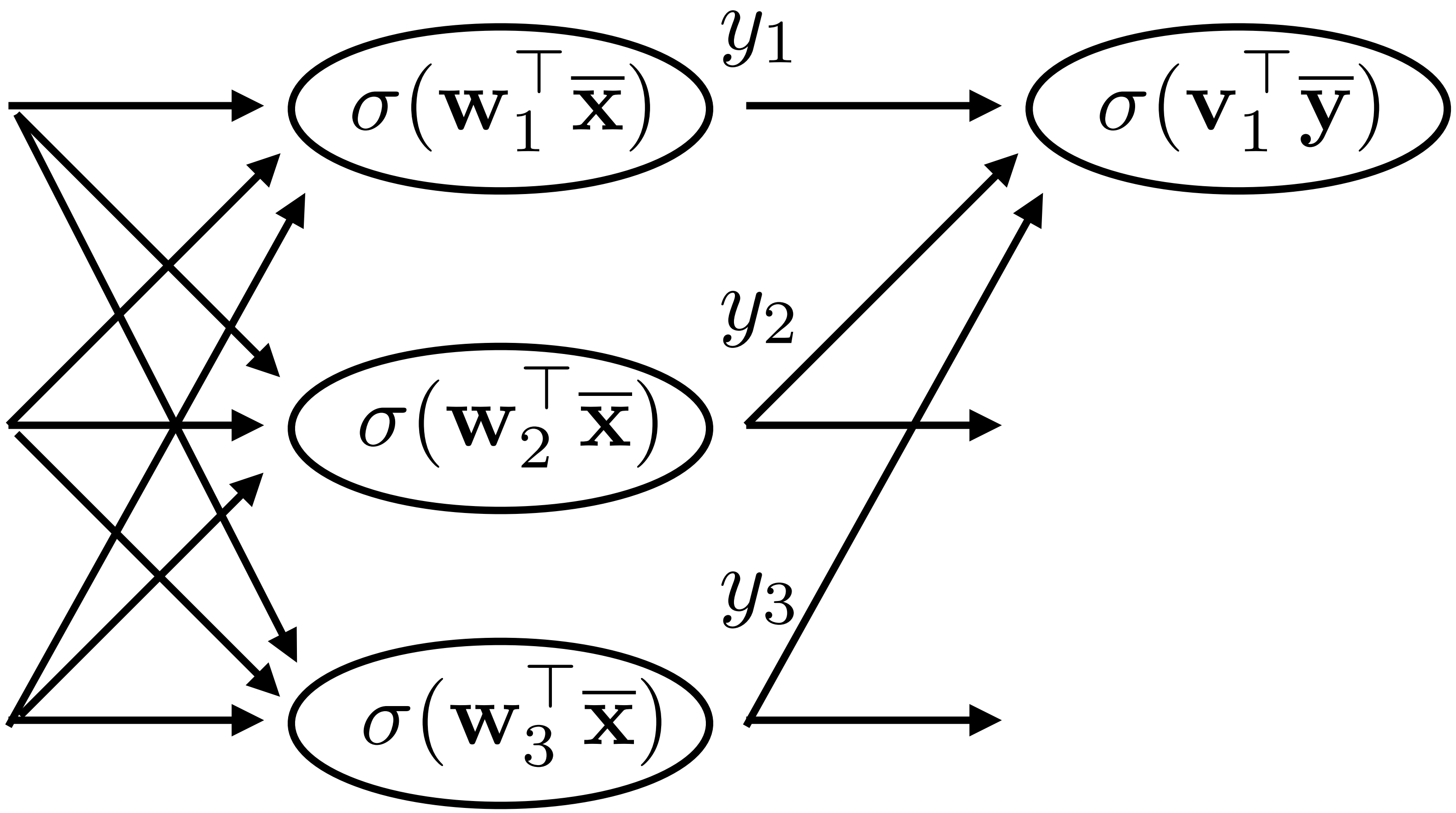

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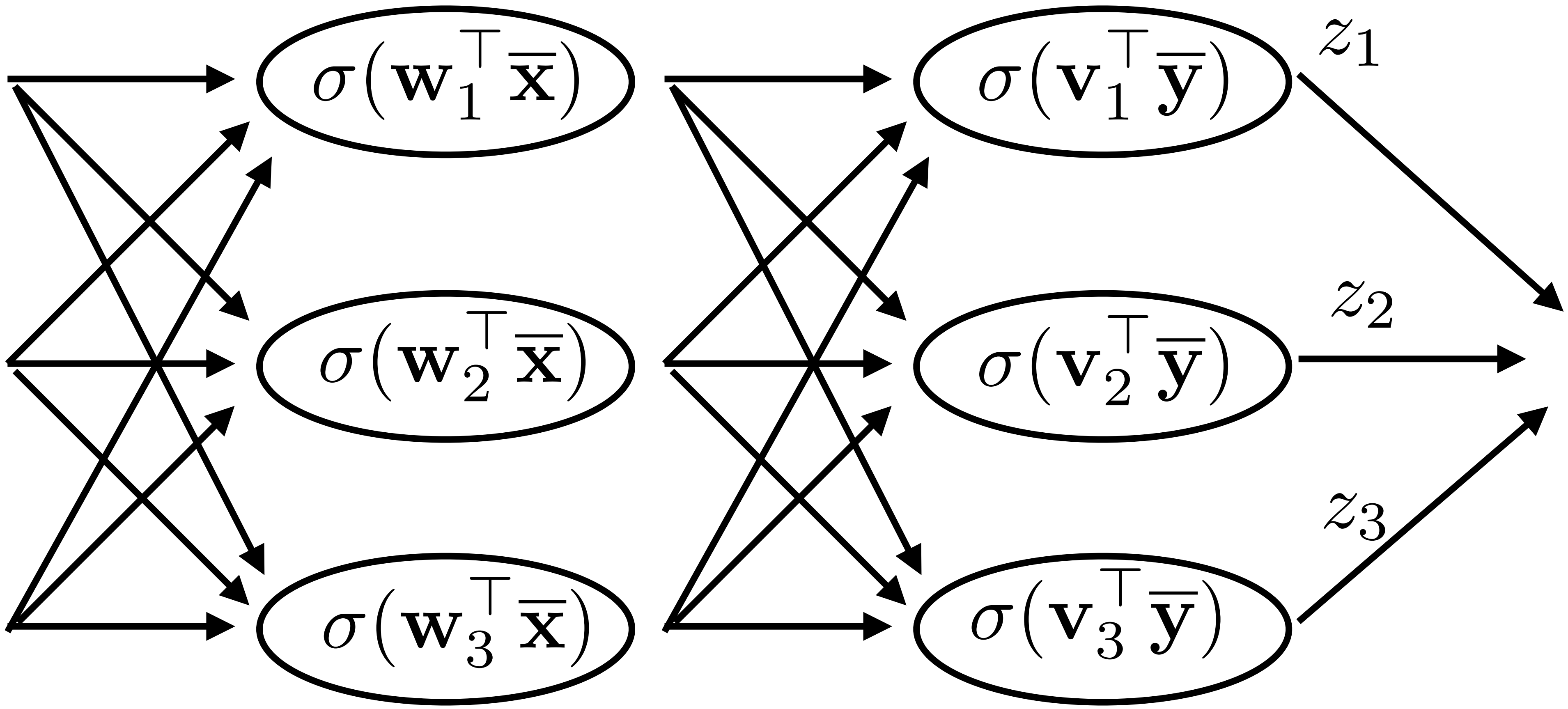

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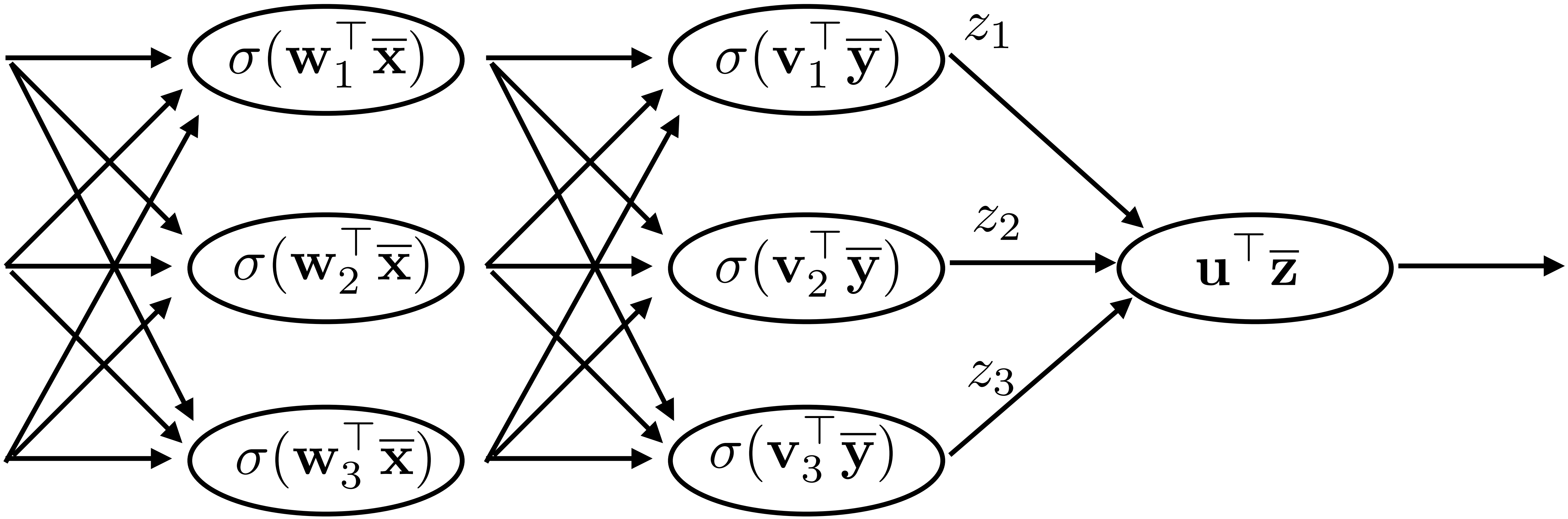

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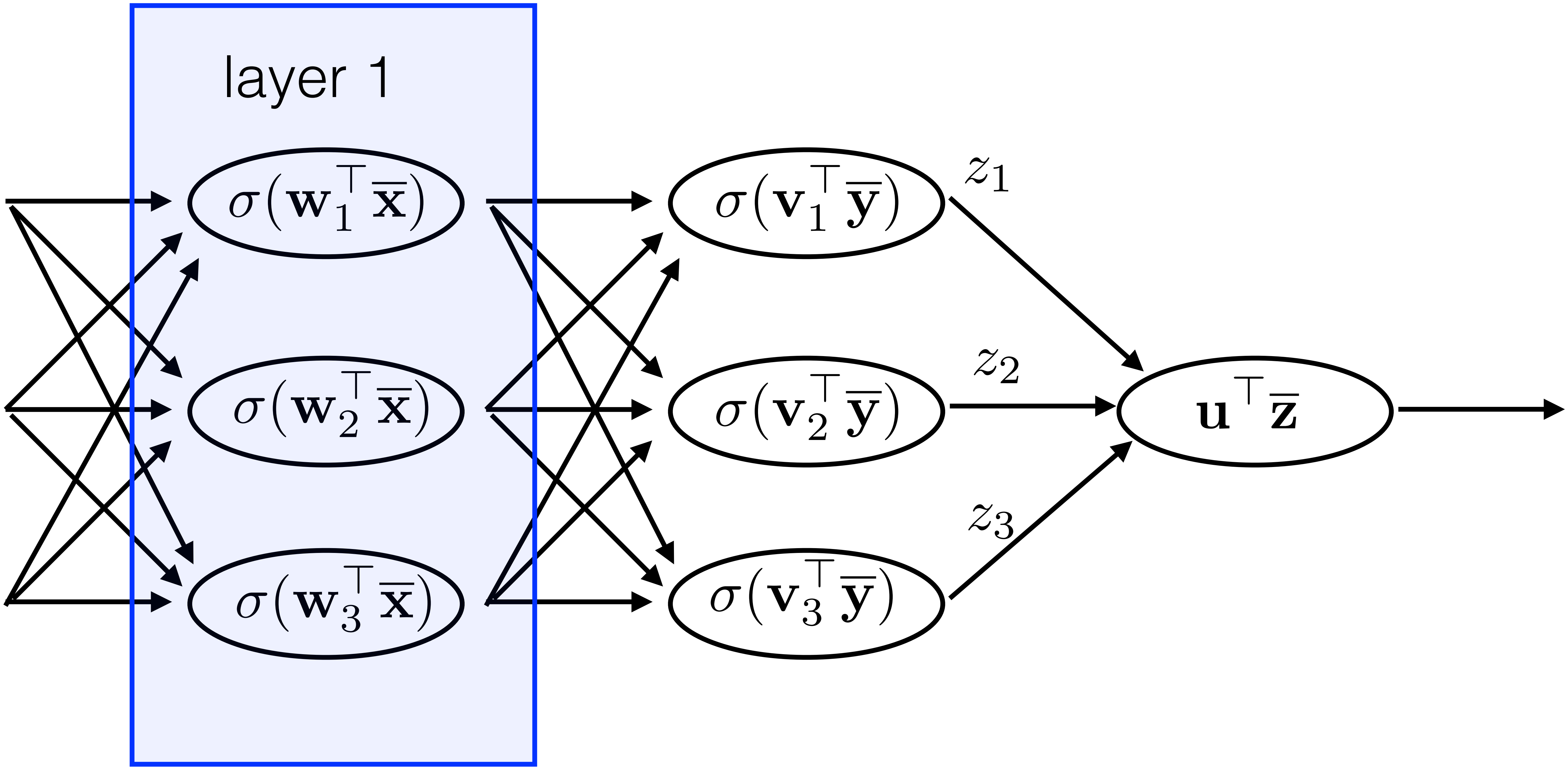

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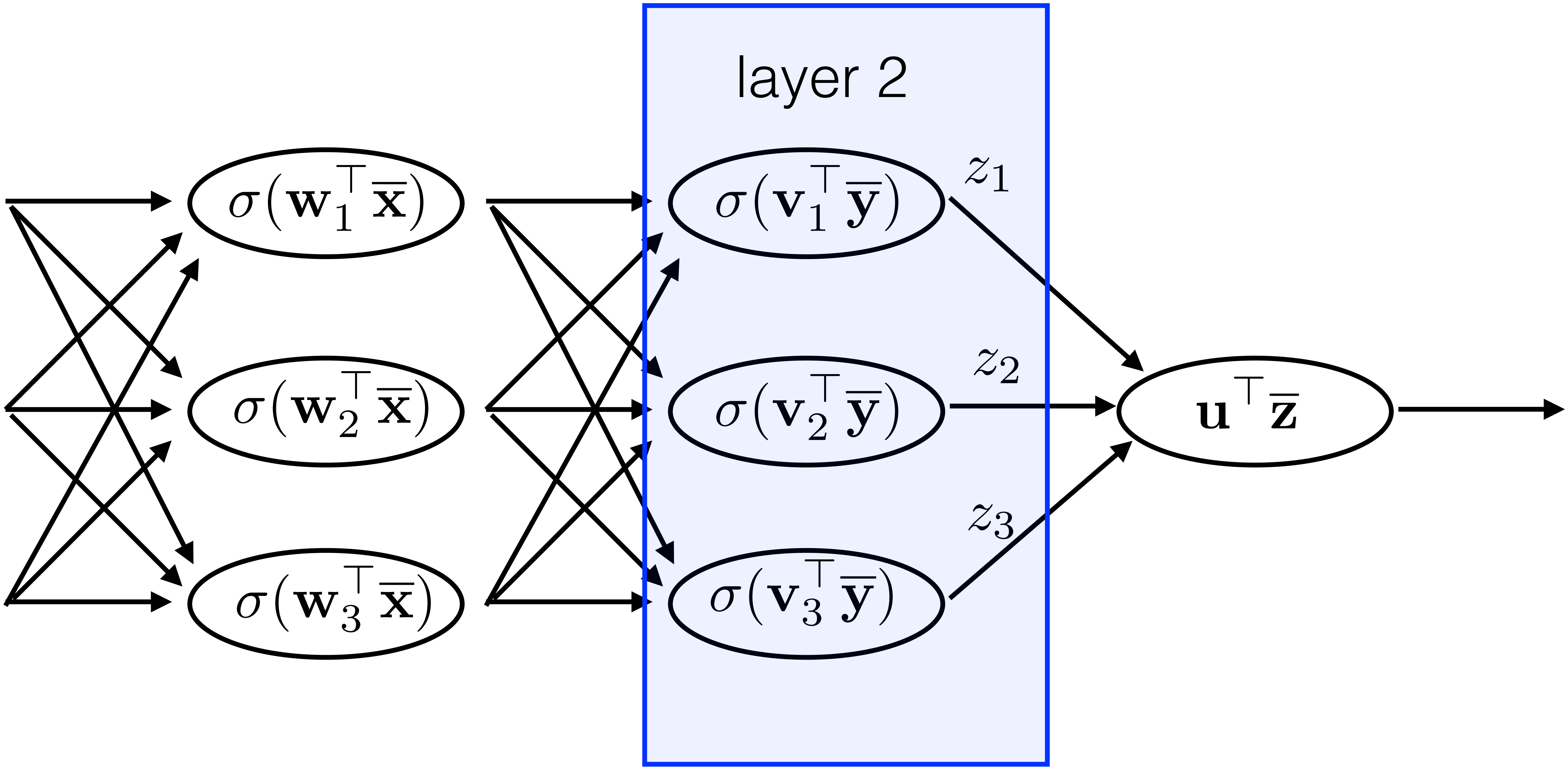

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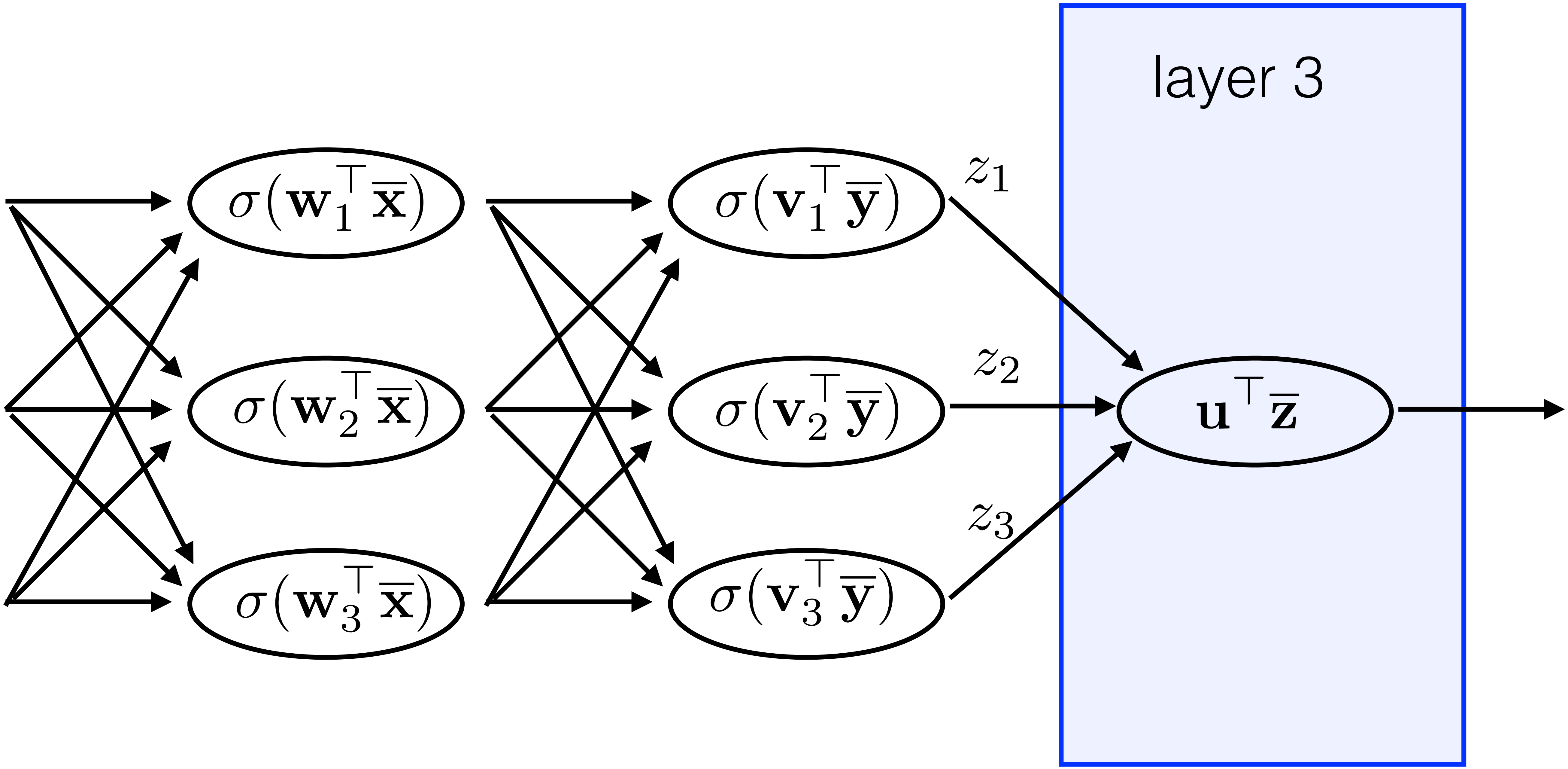

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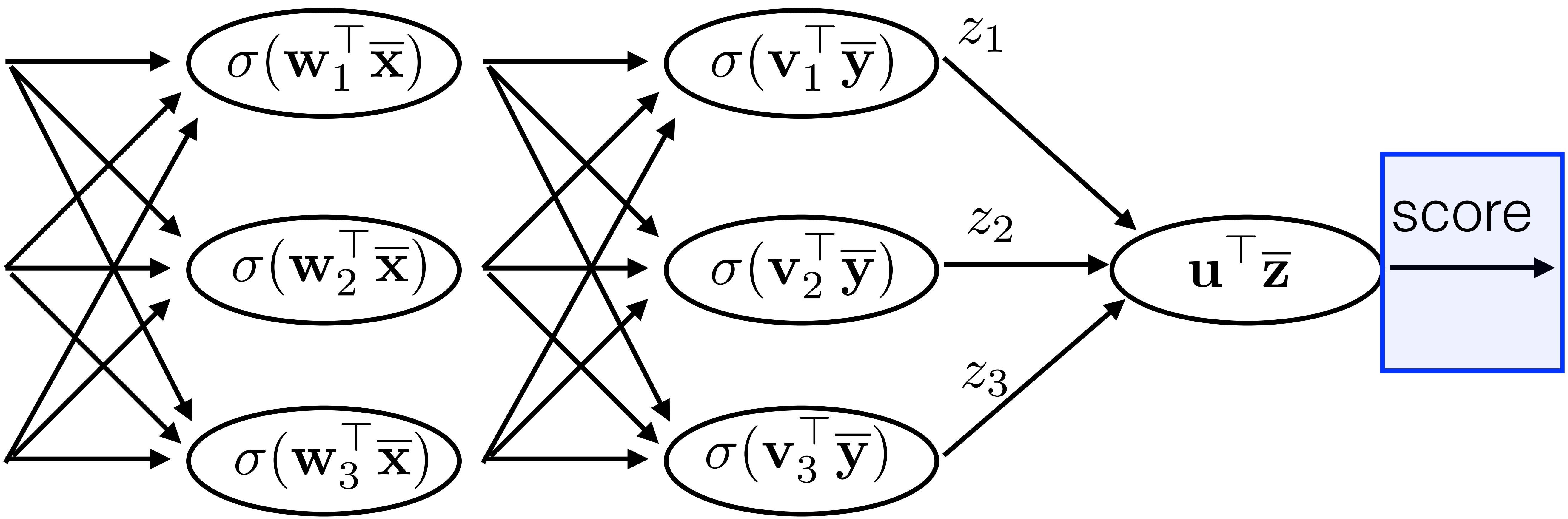

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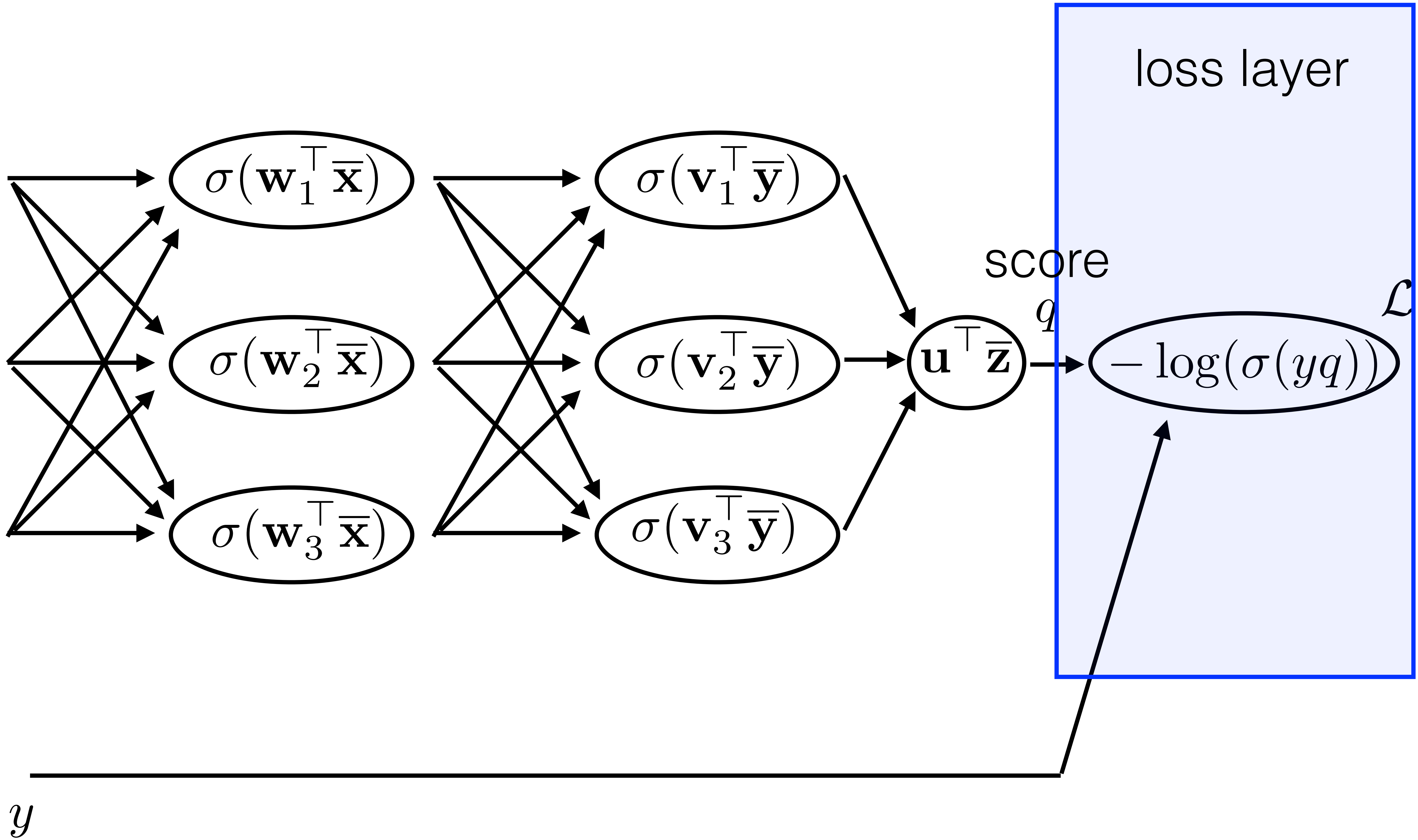

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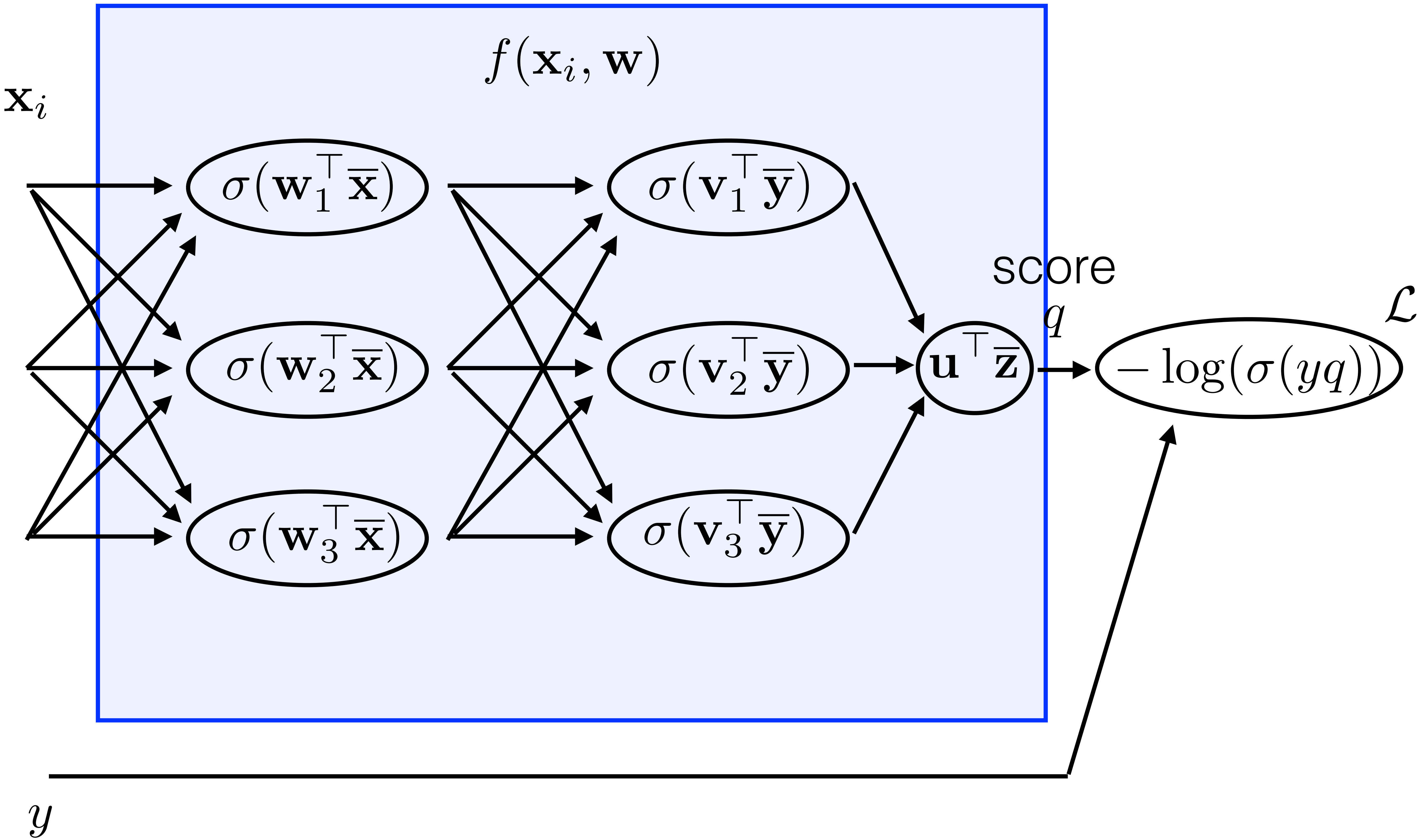

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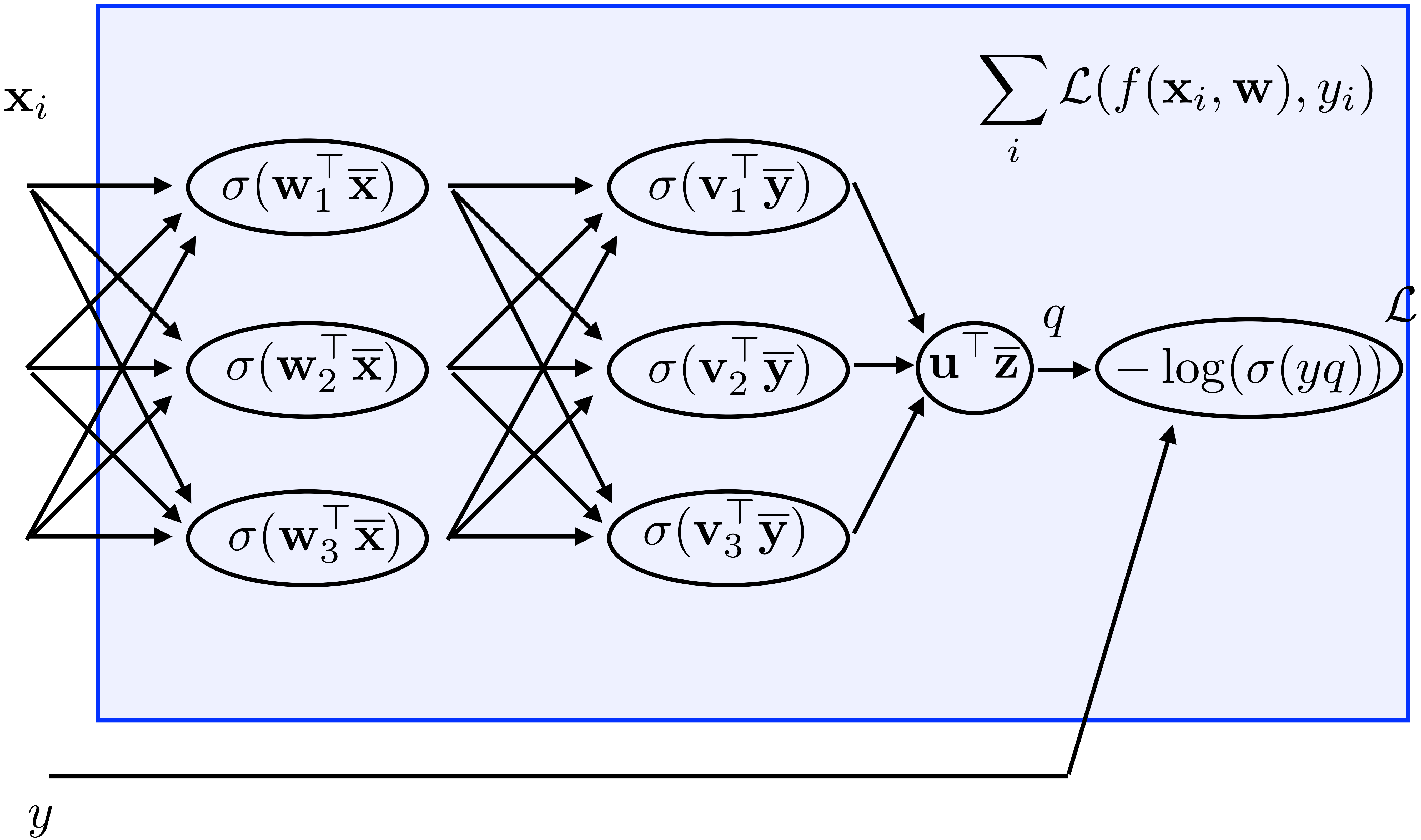


Learning of fully connected neural network

1. Estimate gradient

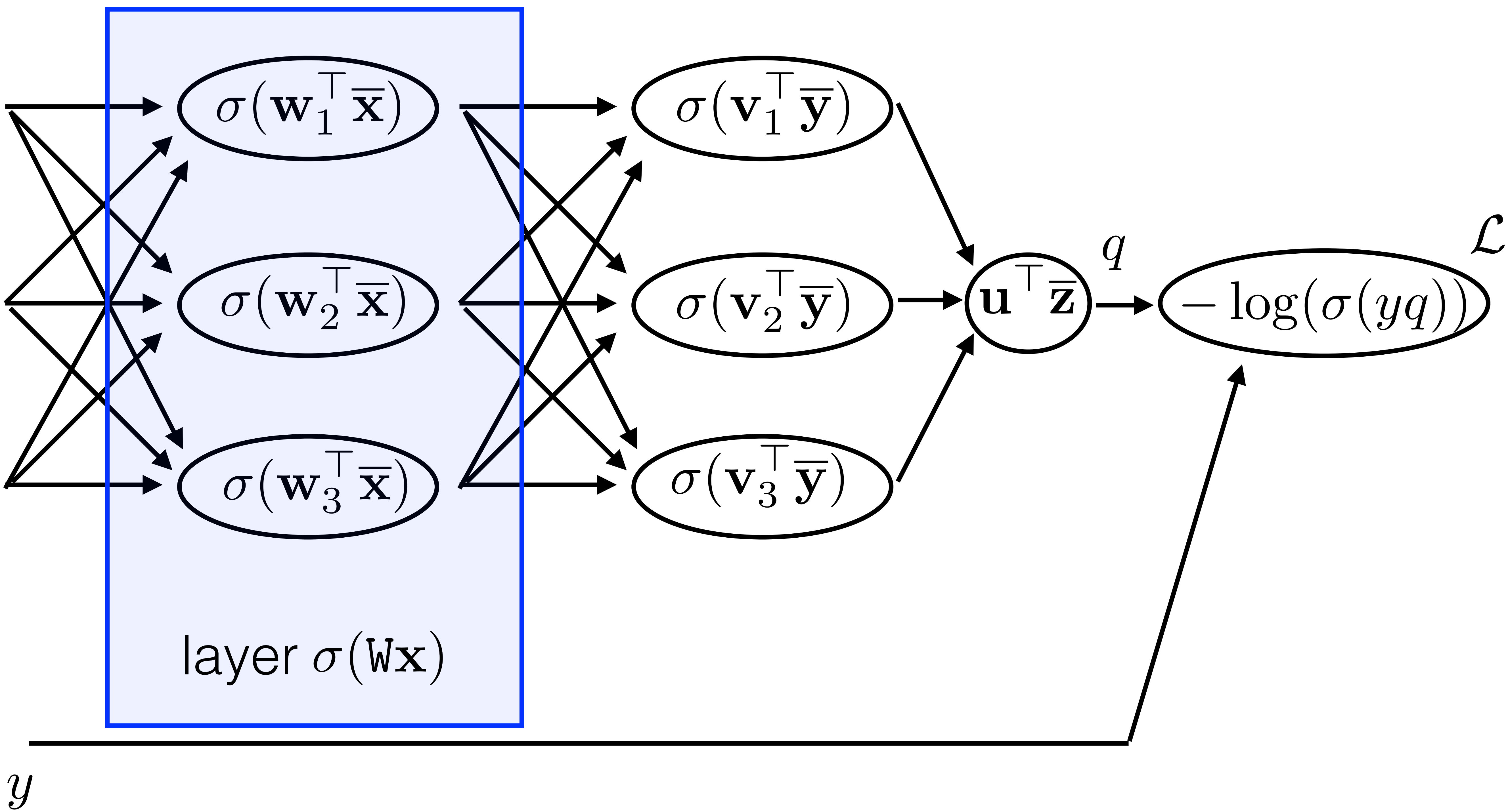
$$\sum_i \frac{\partial \mathcal{L}(f(\mathbf{x}_i, \mathbf{w}), y_i)}{\partial \mathbf{w}}$$

2. Update weights:

$$\mathbf{w} = \mathbf{w} - \alpha \sum_i \frac{\partial \mathcal{L}(f(\mathbf{x}_i, \mathbf{w}), y_i)}{\partial \mathbf{w}}$$

3. Optionally update learning rate α
4. Repeat until convergence

Learning of fully connected neural network



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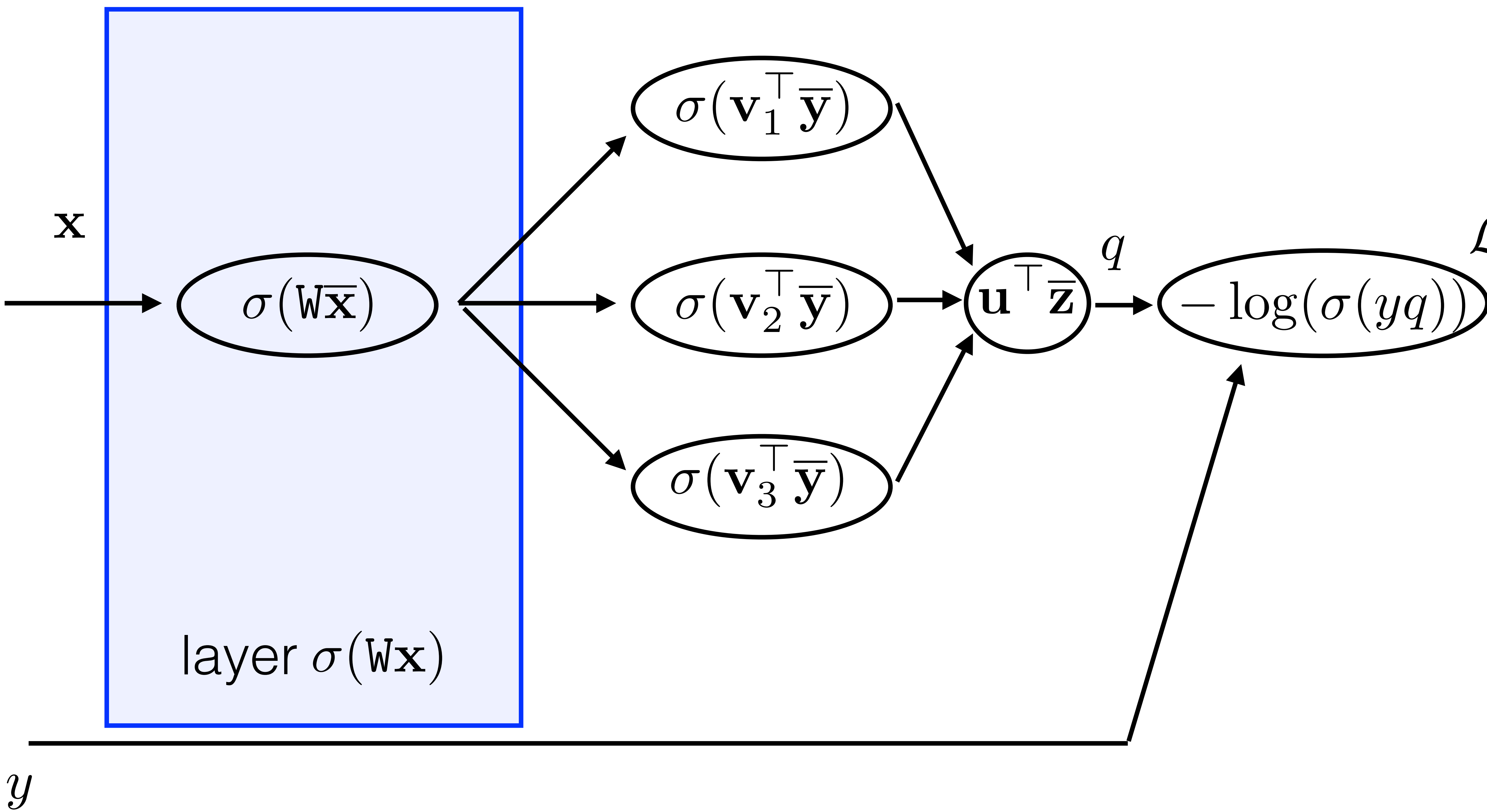

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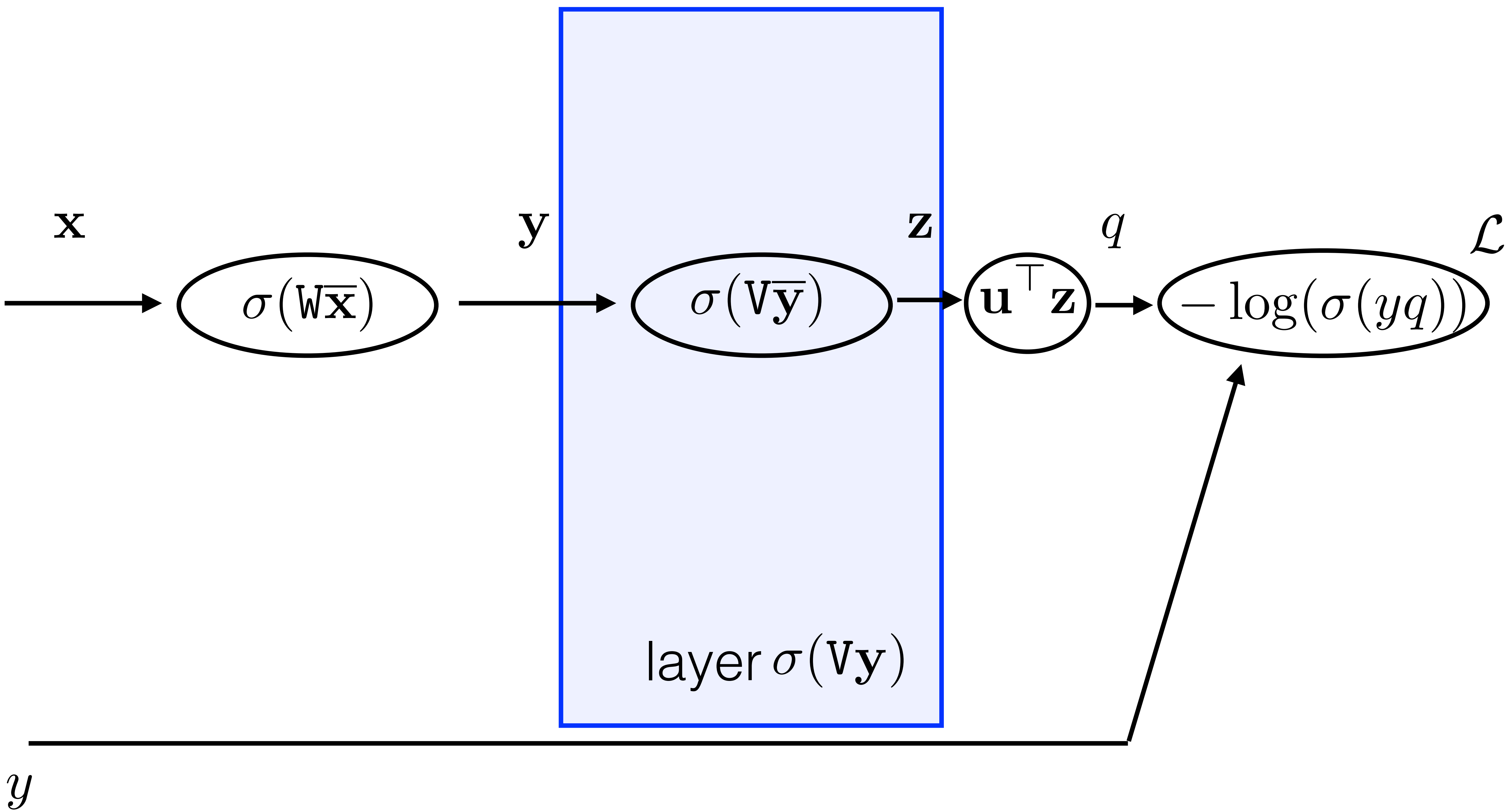
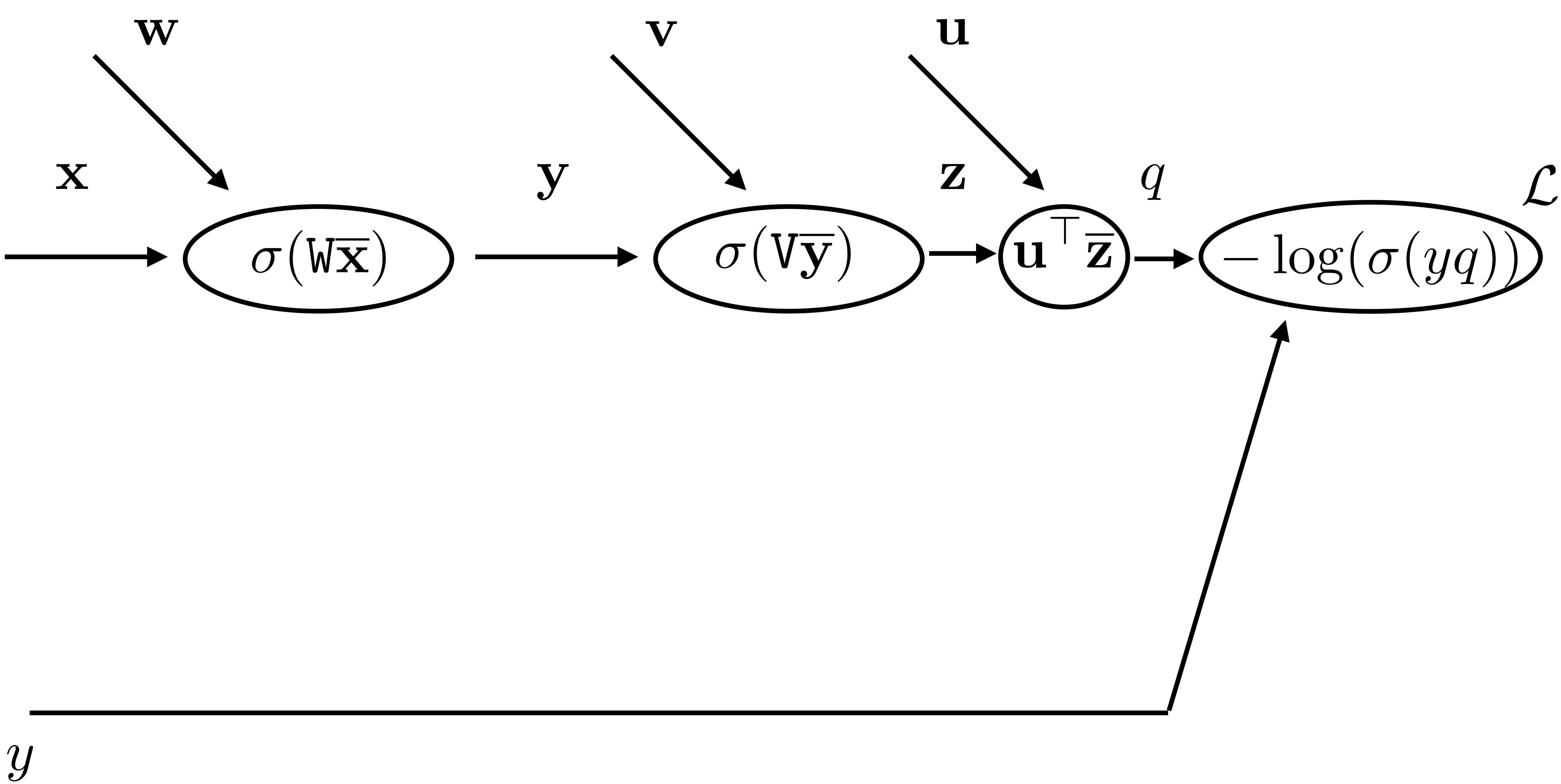


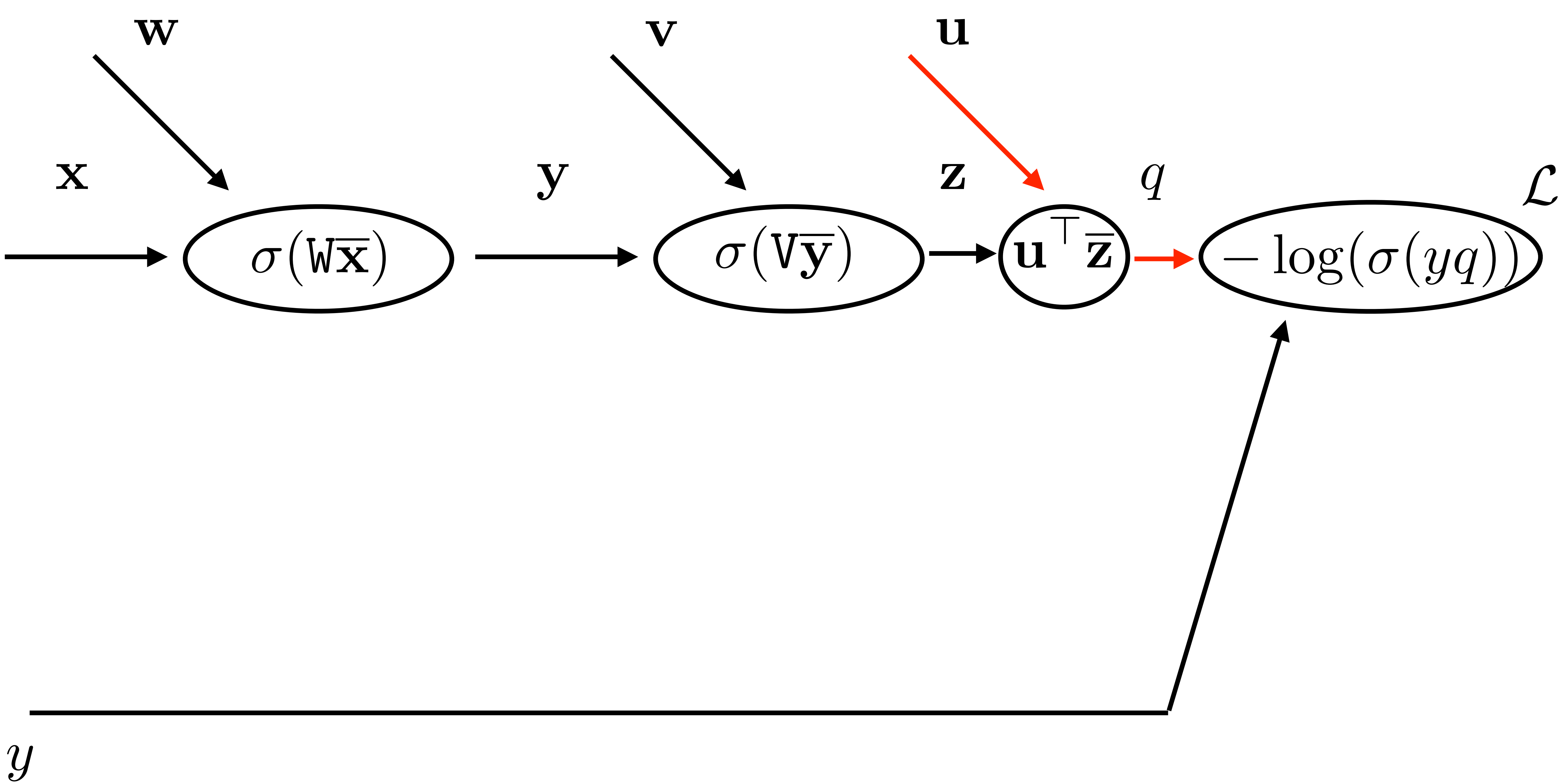
Learning of fully connected neural network

$\mathbf{w} = \mathrm{vec}(\mathtt{W}) \qquad \mathbf{v} = \mathrm{vec}(\mathtt{V})$



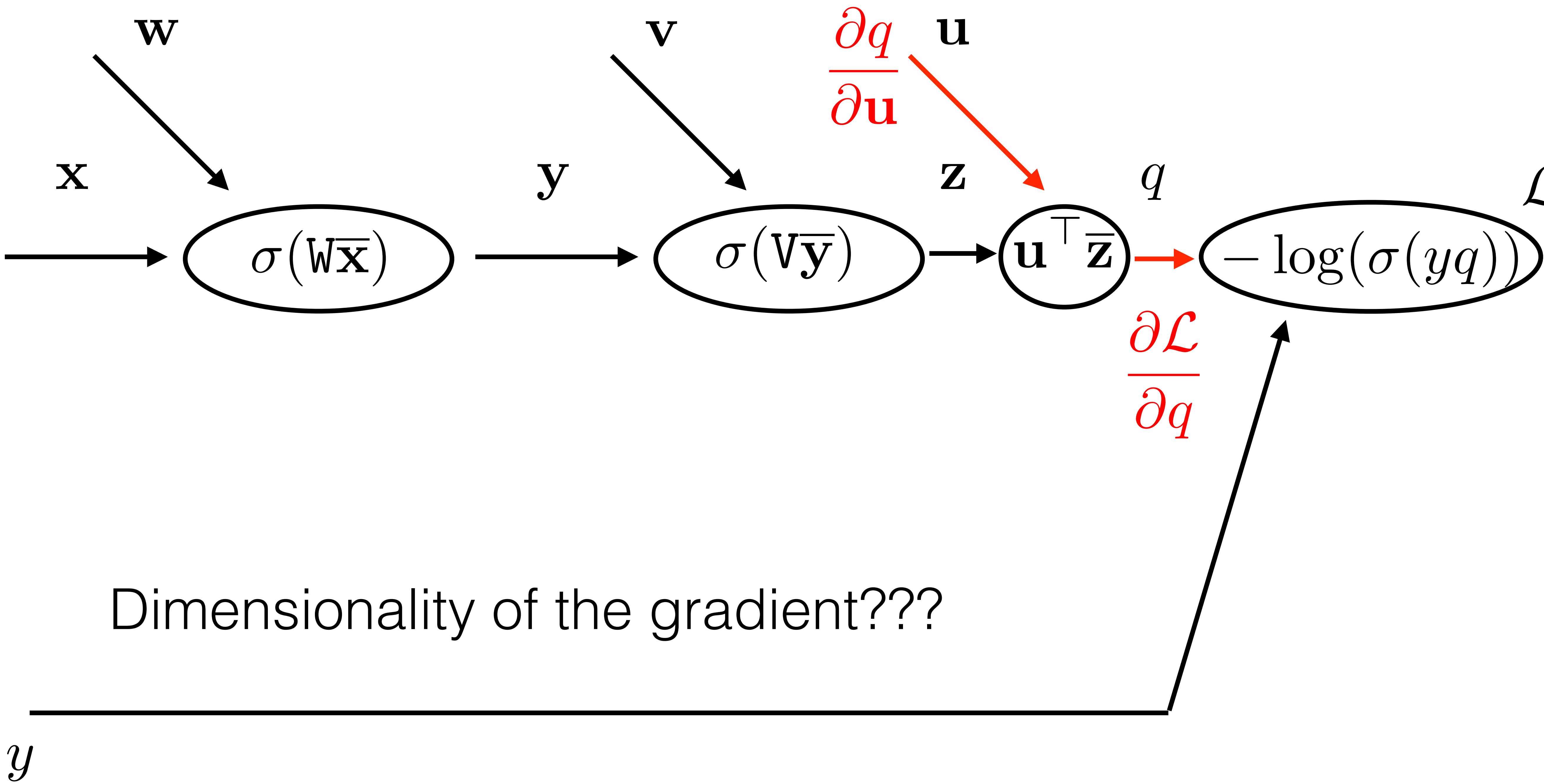
Learning of fully connected neural network

Derivative wrt $\mathbf{u}$: $\frac{\partial \mathcal{L}}{\partial \mathbf{u}} = ?$



Learning of fully connected neural network

Derivative wrt $\mathbf{u}$: $\dfrac{\partial \mathcal{L}}{\partial \mathbf{u}} = \dfrac{\partial \mathcal{L}}{\partial q}\dfrac{\partial q}{\partial \mathbf{u}}$



Dimensionality of the gradient???

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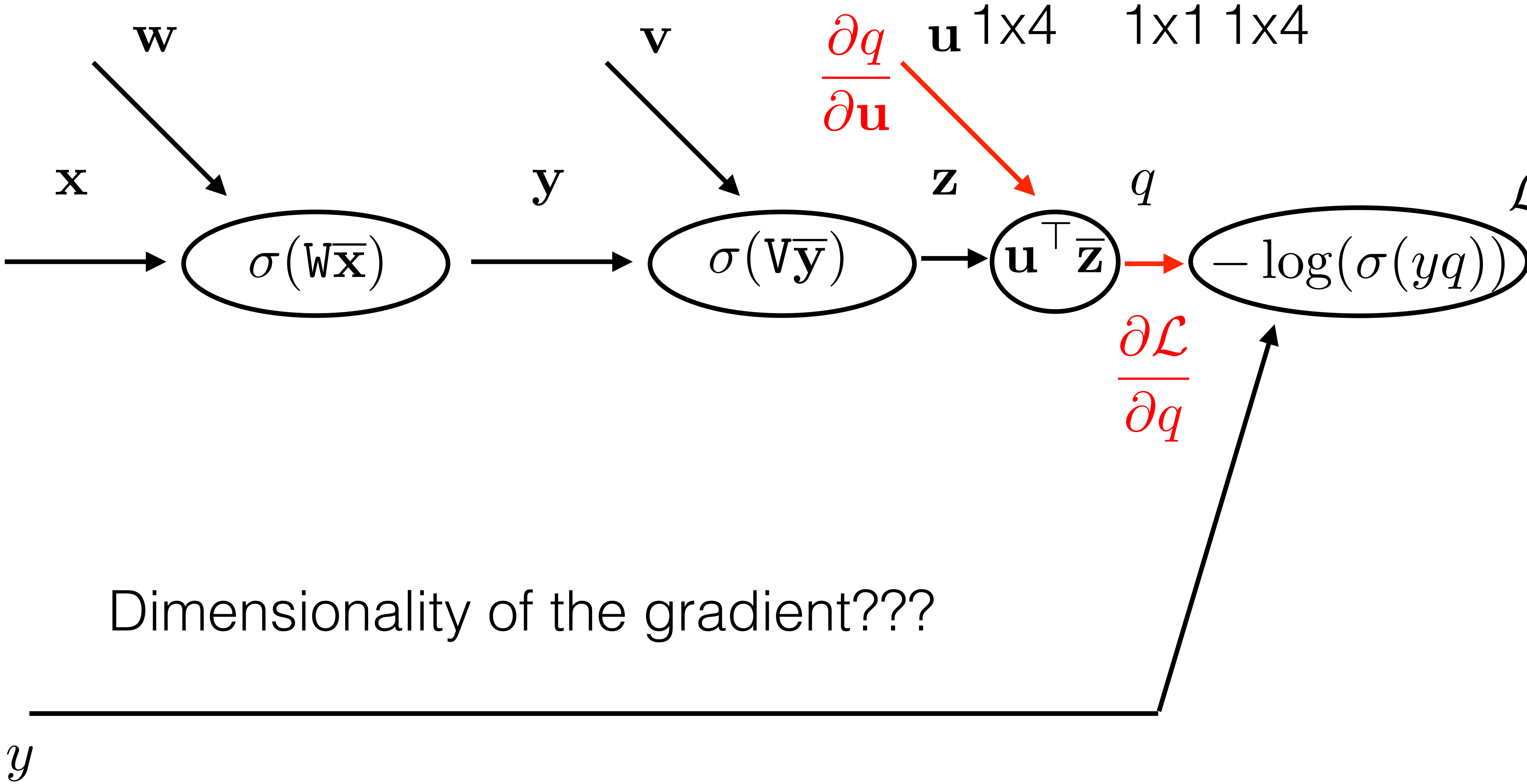
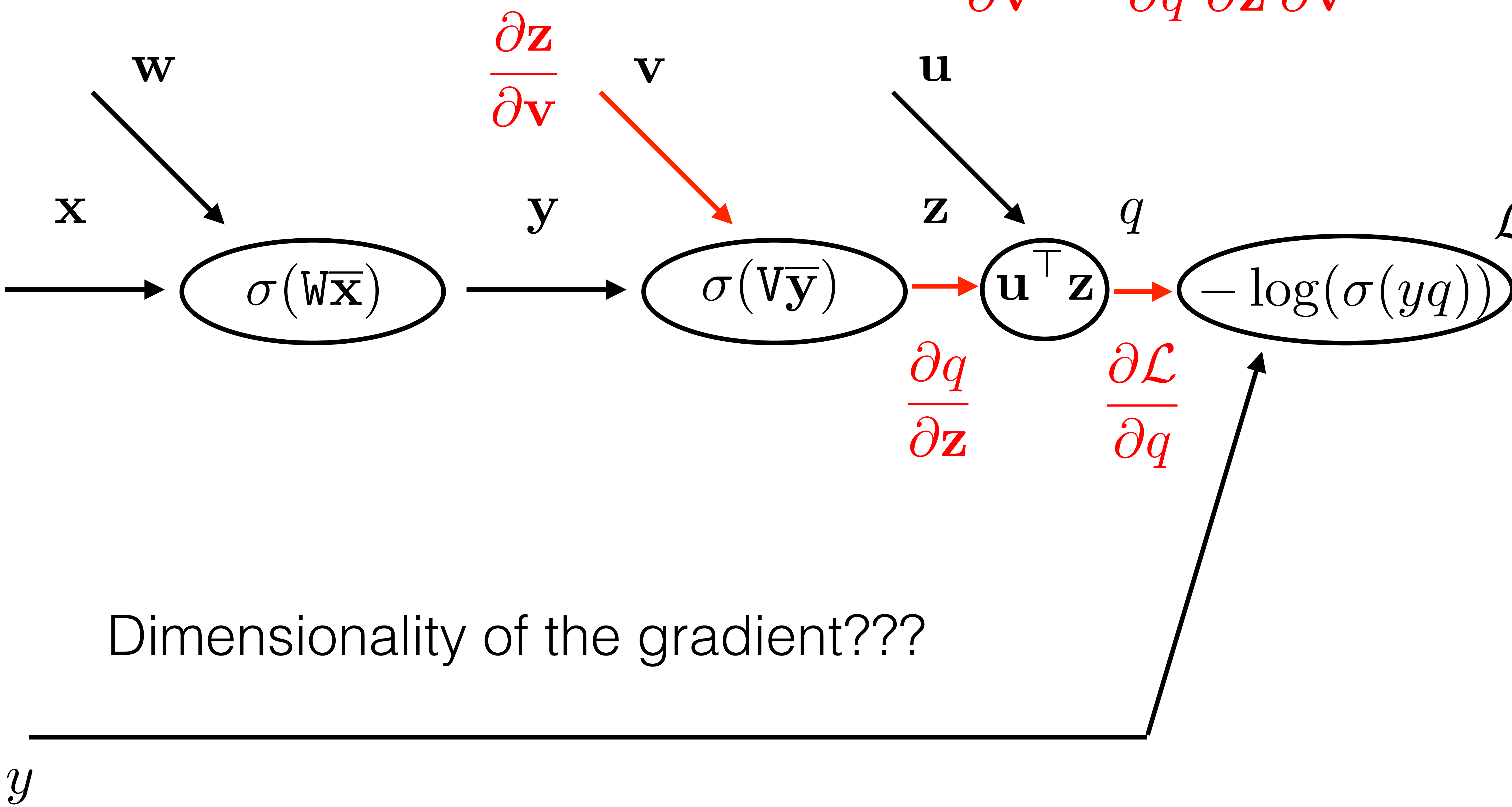


Dimensionality of the gradient???

Learning of fully connected neural network

Derivative wrt $\mathbf{v}$: $\frac{\partial \mathcal{L}}{\partial \mathbf{v}} = \frac{\partial \mathcal{L}}{\partial q}\frac{\partial q}{\partial \mathbf{z}}\frac{\partial \mathbf{z}}{\partial \mathbf{v}}$

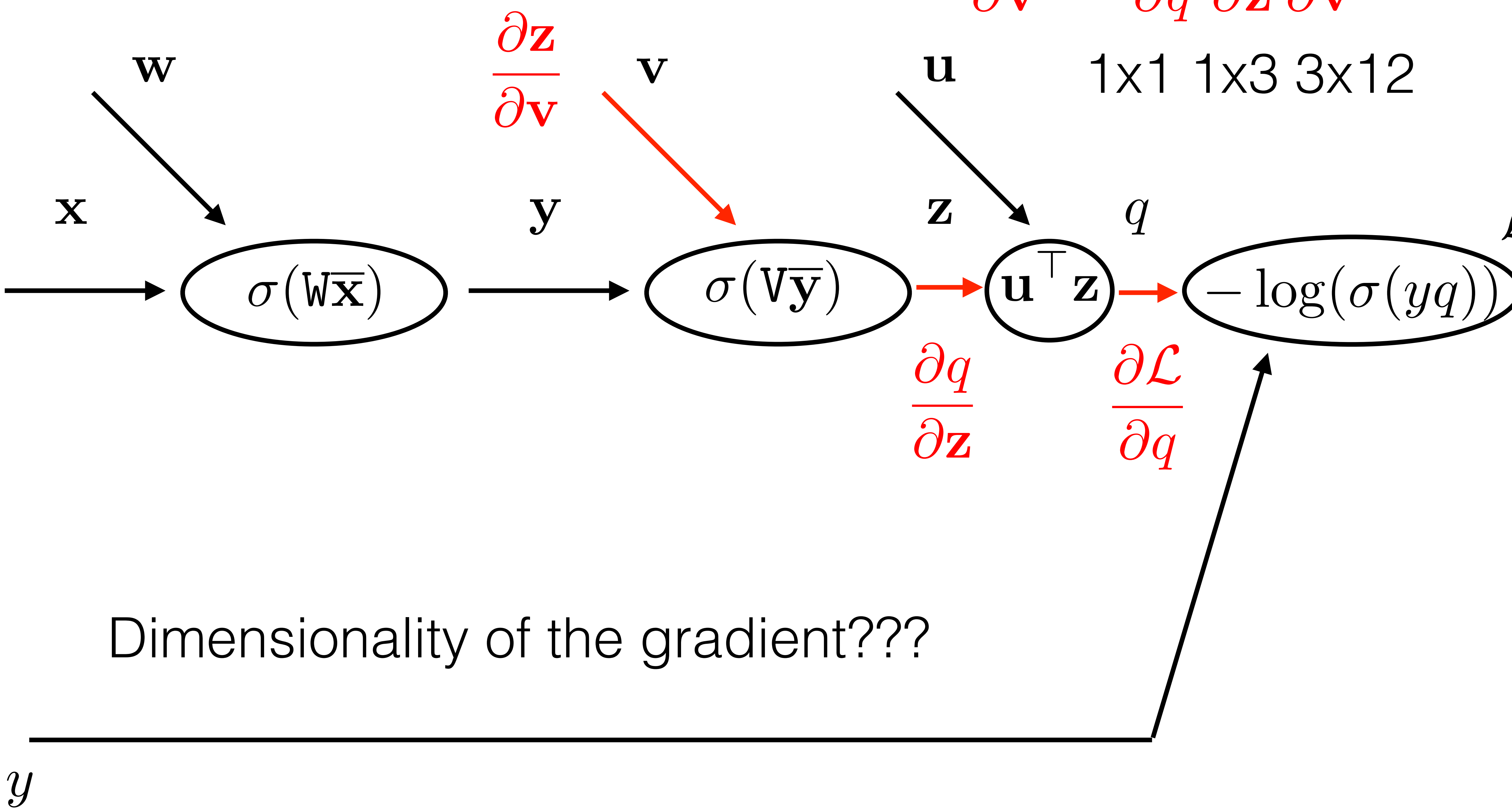


Dimensionality of the gradient???

Learning of fully connected neural network

Derivative wrt $\mathbf{v}$: $\dfrac{\partial \mathcal{L}}{\partial \mathbf{v}} = \dfrac{\partial \mathcal{L}}{\partial q} \dfrac{\partial q}{\partial \mathbf{z}} \dfrac{\partial \mathbf{z}}{\partial \mathbf{v}}$

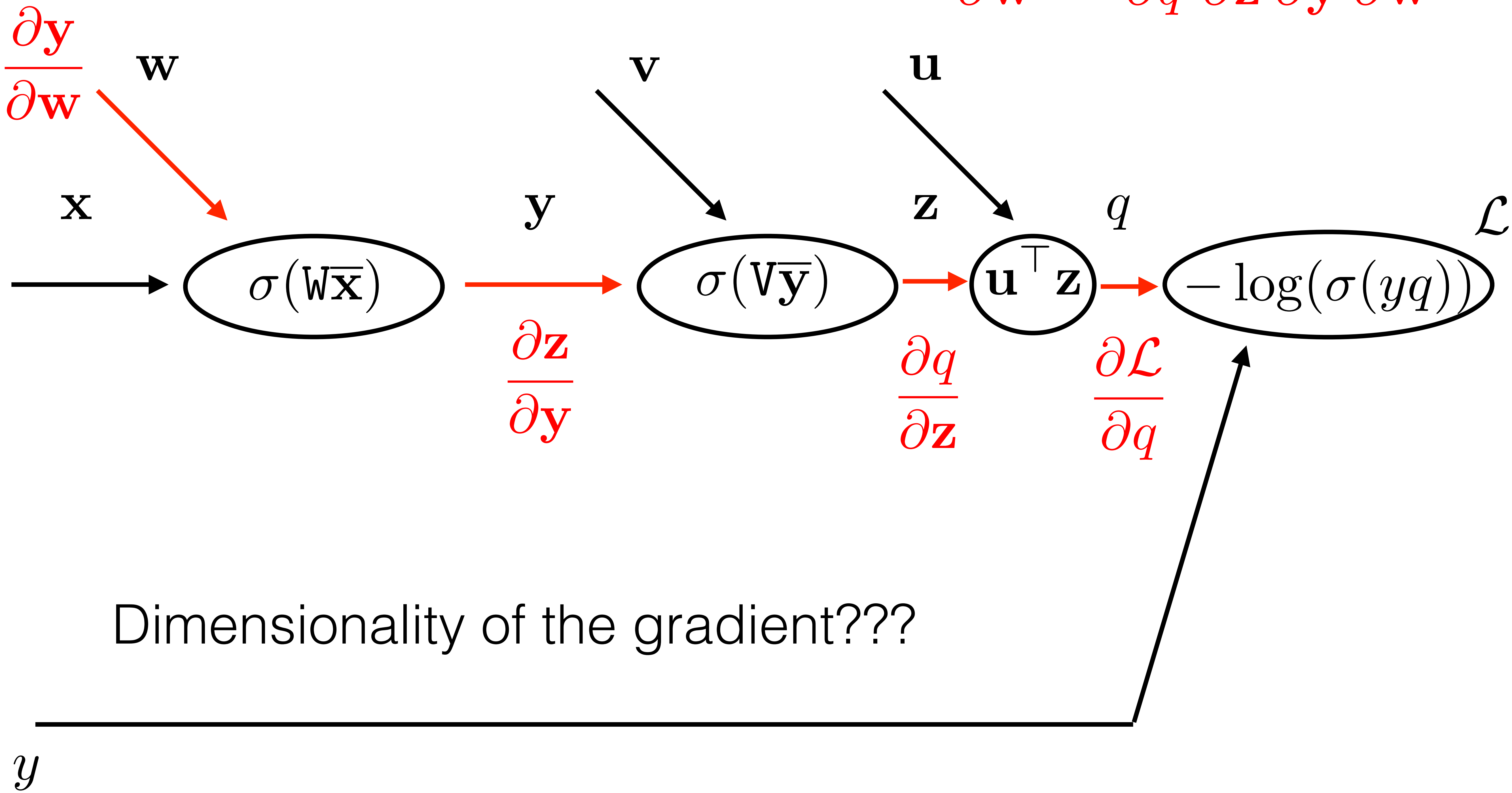
1x1 1x3 3x12



Dimensionality of the gradient???

Learning of fully connected neural network

Derivative wrt $\mathbf{w}$: $$\frac{\partial \mathcal{L}}{\partial \mathbf{w}} = \frac{\partial \mathcal{L}}{\partial q}\frac{\partial q}{\partial \mathbf{z}}\frac{\partial \mathbf{z}}{\partial \mathbf{y}}\frac{\partial \mathbf{y}}{\partial \mathbf{w}}$$

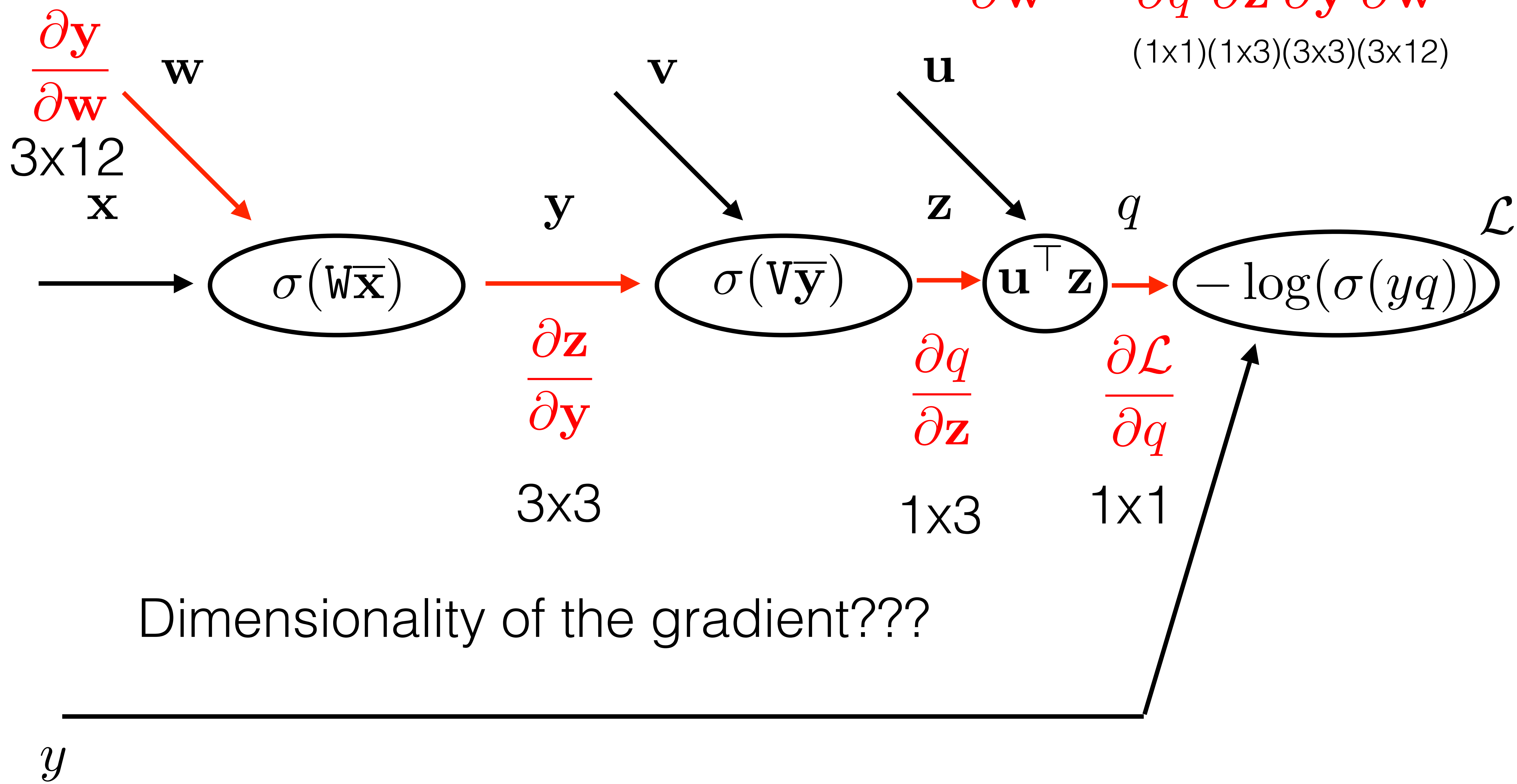


Dimensionality of the gradient???

Learning of fully connected neural network

Derivative wrt $\mathbf{w}$: $\frac{\partial \mathcal{L}}{\partial \mathbf{w}} = \frac{\partial \mathcal{L}}{\partial q} \frac{\partial q}{\partial \mathbf{z}} \frac{\partial \mathbf{z}}{\partial \mathbf{y}} \frac{\partial \mathbf{y}}{\partial \mathbf{w}}$

(1x1)(1x3)(3x3)(3x12)



Dimensionality of the gradient???

Learning of fully connected neural network

1. Estimate all required local gradients
2. Update weights:

$$\frac{\partial \mathcal{L}}{\partial \mathbf{u}} = \frac{\partial \mathcal{L}}{\partial q}\frac{\partial q}{\partial \mathbf{u}} \qquad \mathbf{u} = \mathbf{u} - \alpha \left[\frac{\partial \mathcal{L}}{\partial \mathbf{u}}\right]^\top$$

$$\frac{\partial \mathcal{L}}{\partial \mathbf{v}} = \frac{\partial \mathcal{L}}{\partial q}\frac{\partial q}{\partial \mathbf{z}}\frac{\partial \mathbf{z}}{\partial \mathbf{v}} \qquad \mathbf{v} = \mathbf{v} - \alpha \left[\frac{\partial \mathcal{L}}{\partial \mathbf{v}}\right]^\top$$

$$\frac{\partial \mathcal{L}}{\partial \mathbf{w}} = \frac{\partial \mathcal{L}}{\partial q}\frac{\partial q}{\partial \mathbf{z}}\frac{\partial \mathbf{z}}{\partial \mathbf{y}}\frac{\partial \mathbf{y}}{\partial \mathbf{w}} \qquad \mathbf{w} = \mathbf{w} - \alpha \left[\frac{\partial \mathcal{L}}{\partial \mathbf{w}}\right]^\top$$

3. Optionally update learning rate α
4. Repeat until convergence

Neural nets summary

- Neural net is a function created as concatenation of simplier functions (e.g. neurons or layers of neurons)
- Gradient optimization of the neural net is called backpropagation
- Neural net frameworks has many predefined layers
- **Spoiler alert:** It does not work (on images) at all - why?

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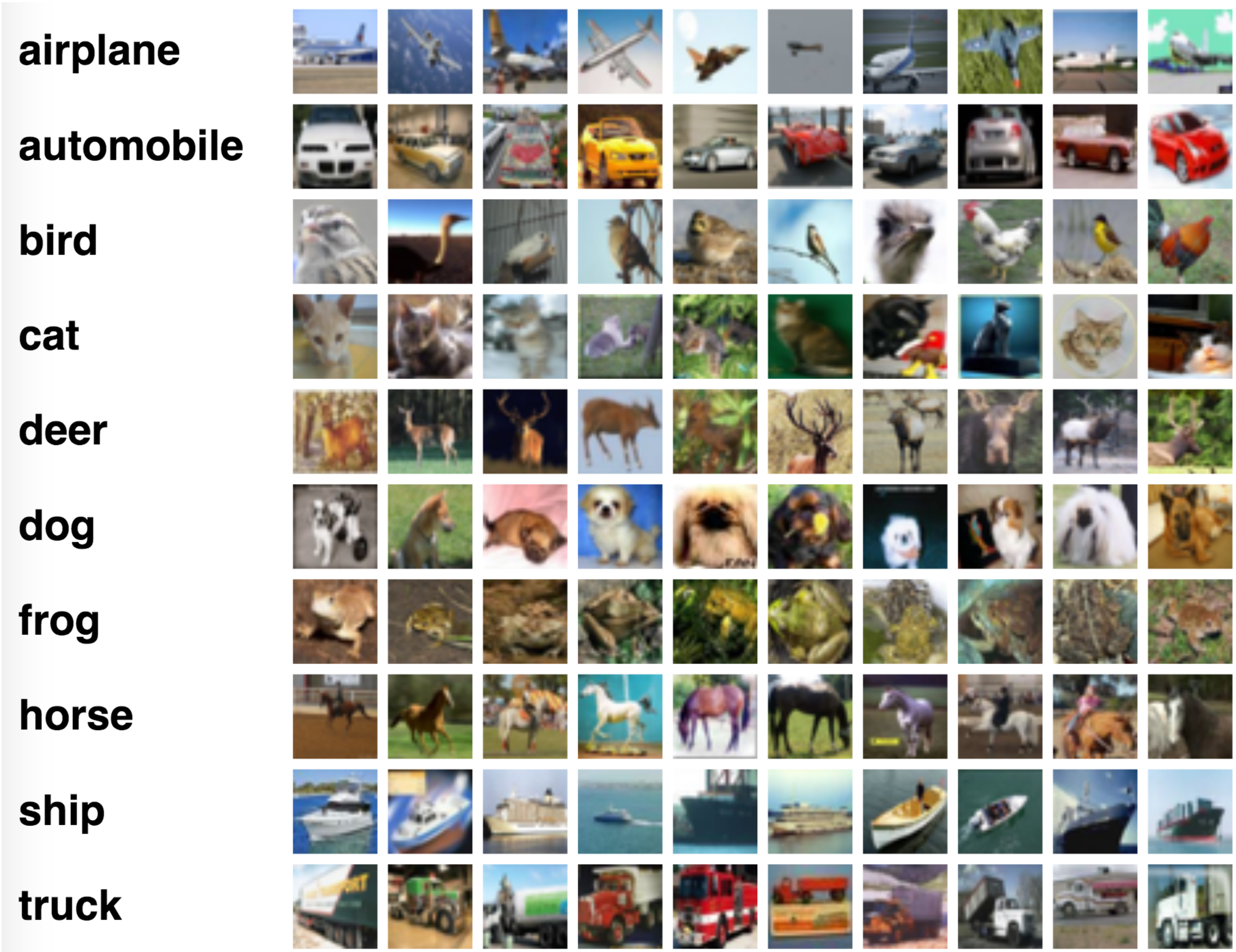
	Linear classifier	NN	convNet
MNIST			

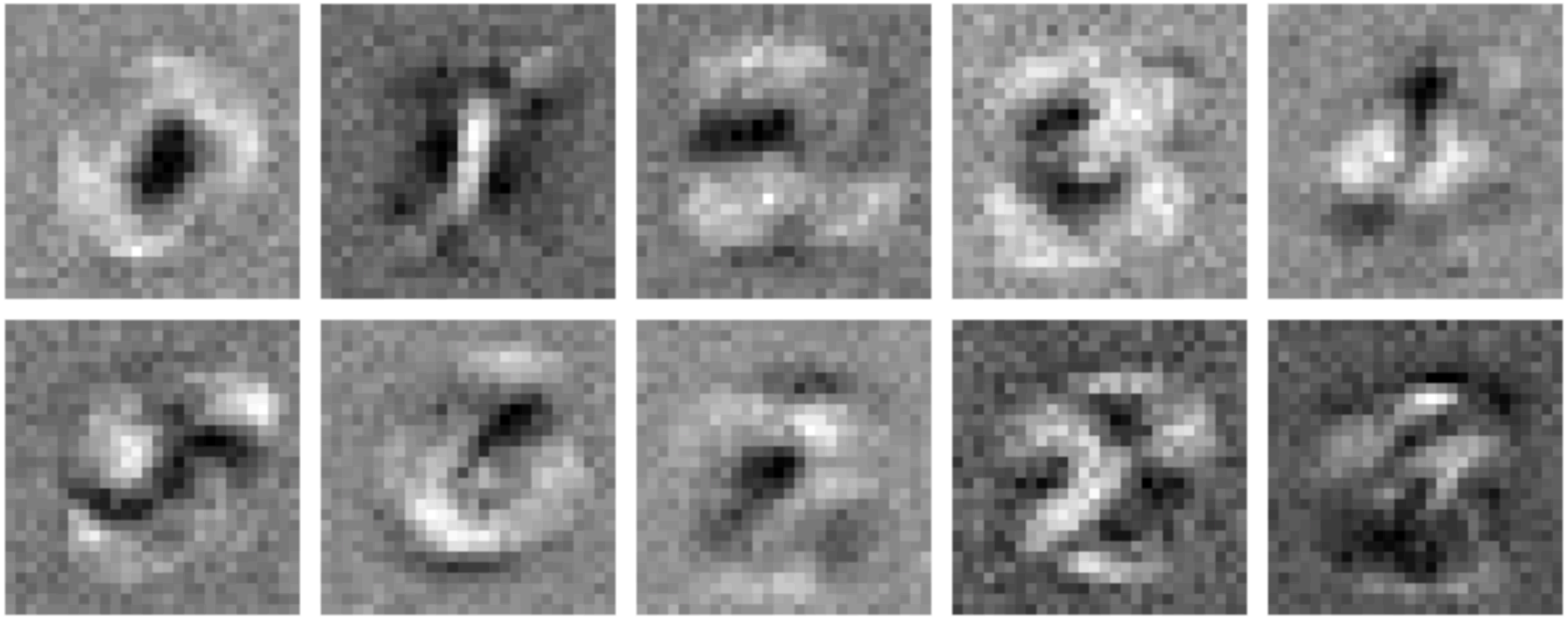
https://benchmarks.ai



CIFAR-10: classify 32x32 RGB images into 10 categories
https://www.cs.toronto.edu/~kriz/cifar.html

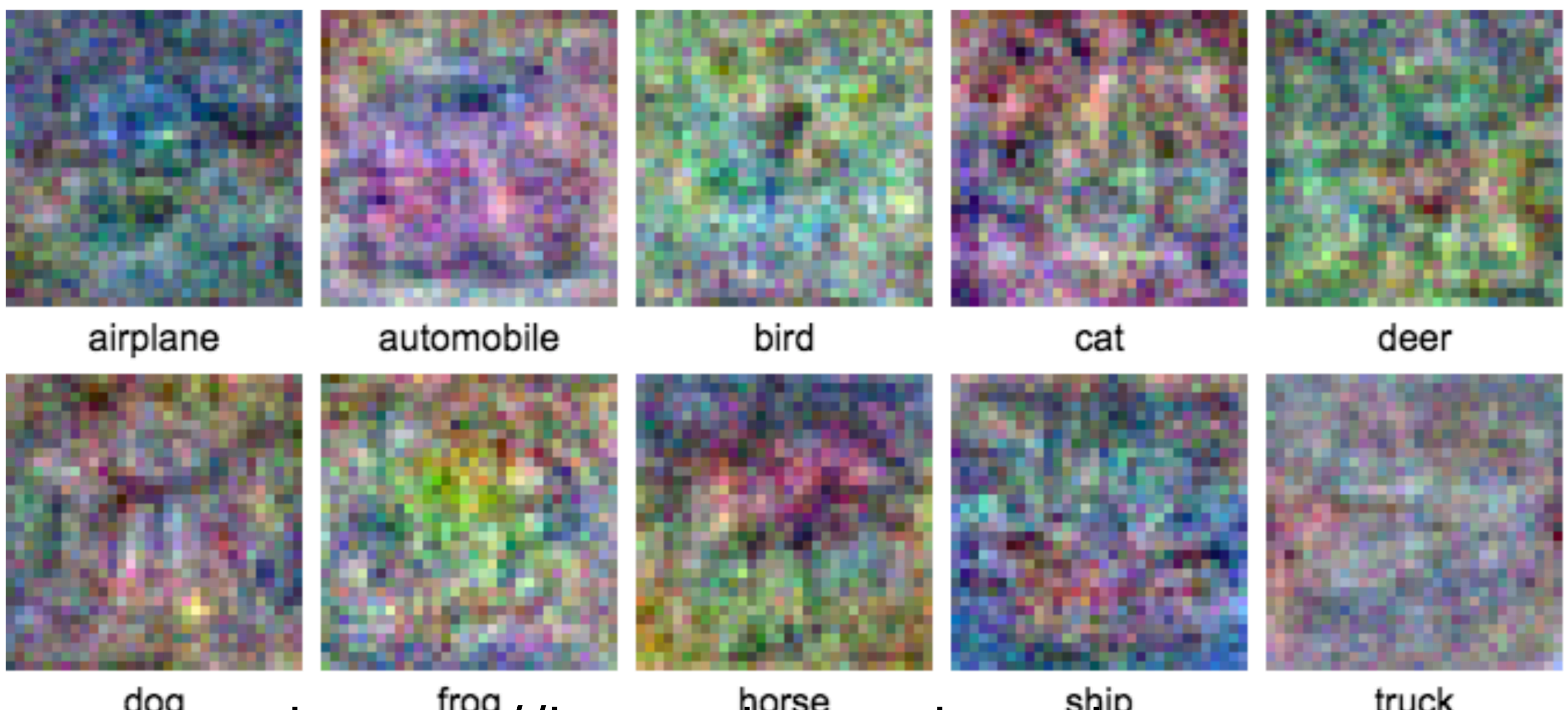
Dataset | Learned weights of linear classifier | Error

MNIST



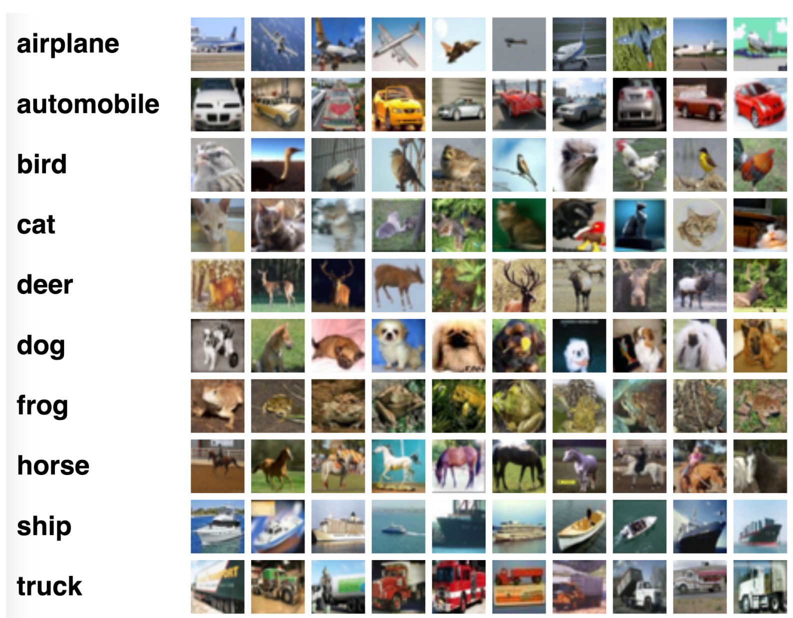
8%

CIFAR-10

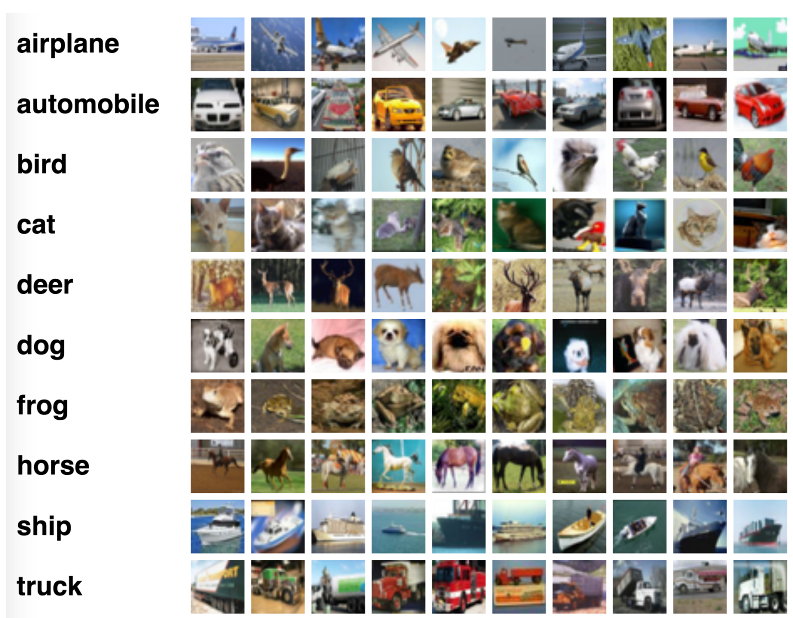


63%

https://benchmarks.ai

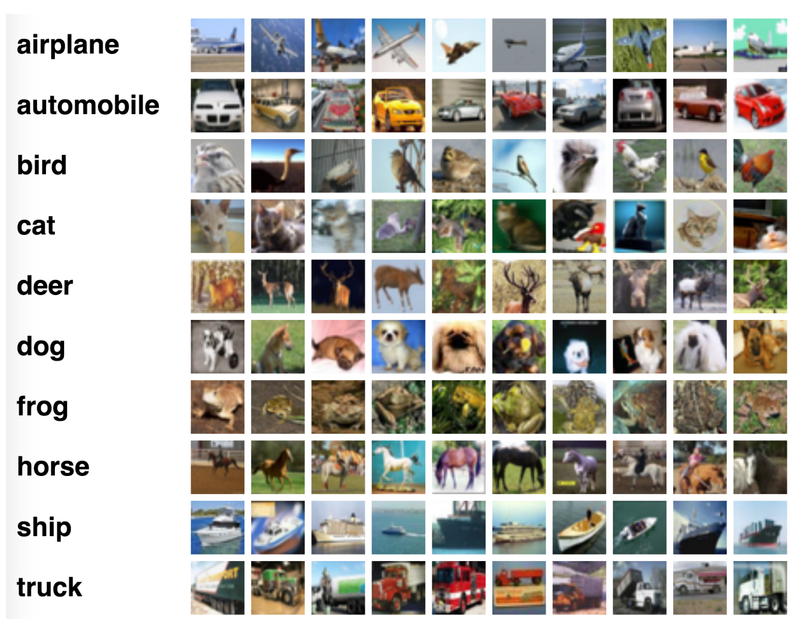
Dataset		Error
		Linear
MNIST		8%
CIFAR-10		63%

https://benchmarks.ai

Dataset		Error: Linear	Error: NN
MNIST		8%	2%
CIFAR-10		63%	55%

https://benchmarks.ai

Dataset	Error: Linear	Error: NN	Error: ConvNet
MNIST	8%	2%	0.2% [CVPR 2013]
CIFAR-10	63%	55%	1% [EfficientNet, 2018]



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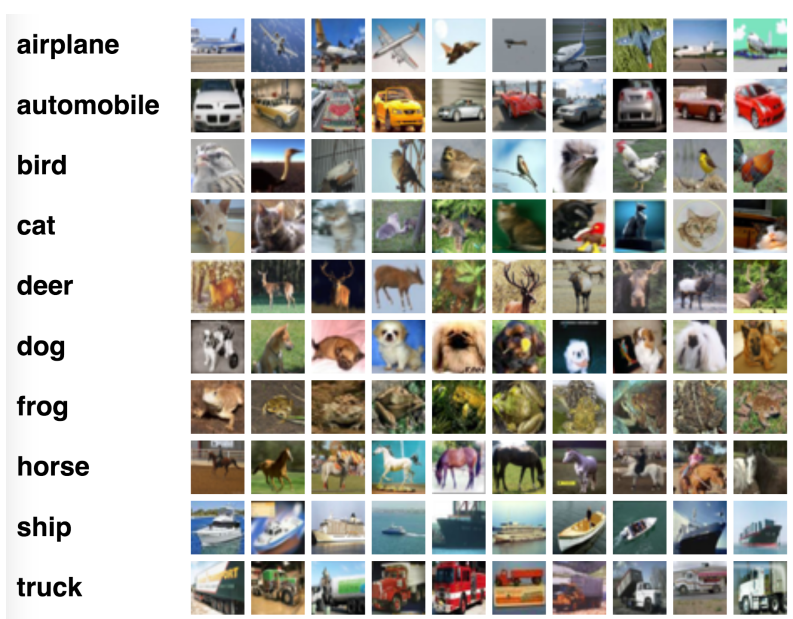
Dataset	Error: Linear	Error: NN	Error: ConvNet
MNIST	8%	2%	0.2% [CVPR 2013]
	underfit	overfit	cortex inspired structure
CIFAR-10	63%	55%	1% [EfficientNet, 2018]



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Competencies required for the test T1

- Ability to draw a computational graph.
- Compute edge gradients/jacobians.
- Perform one step of backpropagation in a vectorized form
-

$$\mathbf{w}^* = \arg\min_{\mathbf{w}} \left(\sum_i -\log(p(y_i|\mathbf{x}_i, \mathbf{w})) \right) + (-\log p(\mathbf{w}))$$

loss function prior/regulariser

- Class of function represented by a NN is too general.
- Naive regulariser helps a bit, but dimensionality/wildness is huge => curse-of-dimensionality, overfitting,…
- What is number of weights between two 1000-neuron layers?
- **Next lecture:** study animal cortex to find a stronger prior on the class of suitable functions.
- **Spoiler alert 2:** reduce very general class of functions "neuron layer" to very specific sub-class of functions "convolution layer"

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