

Lecture 6: Neural Networks

Alan Ritter

(many slides from Greg Durrett)

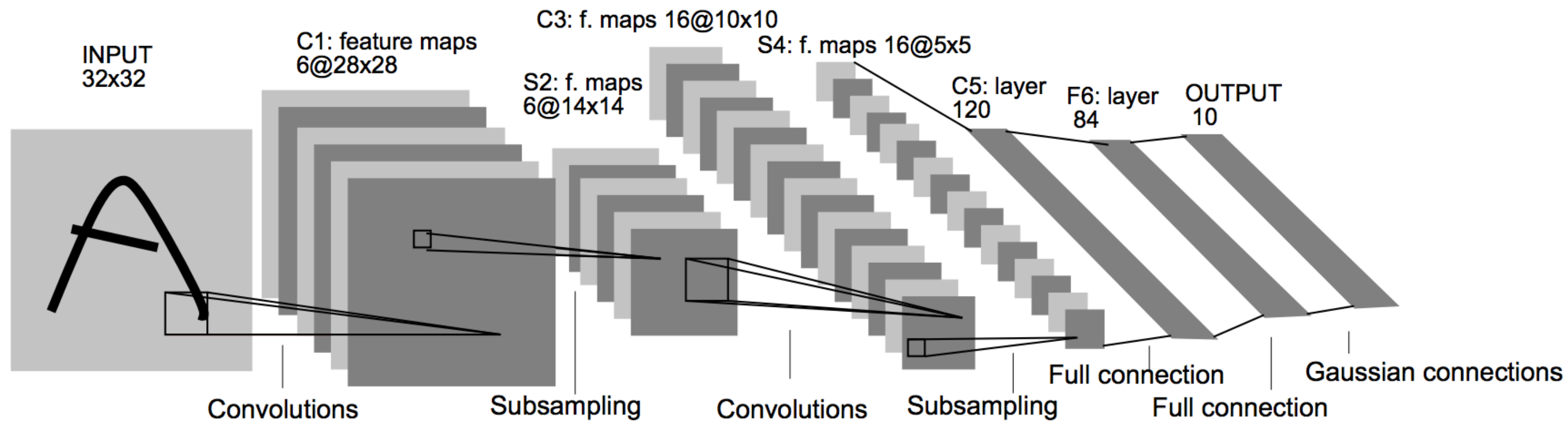
This Lecture

- ▶ Neural network history
- ▶ Neural network basics
- ▶ Feedforward neural networks + backpropagation
- ▶ Applications
- ▶ Implementing neural networks (if time)

History: NN “dark ages”

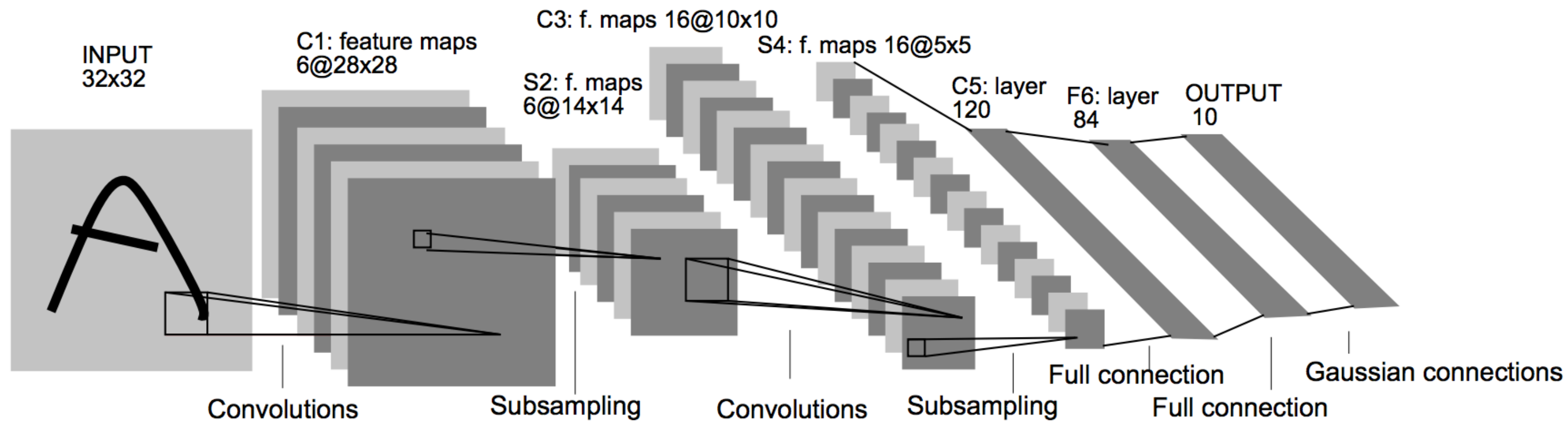
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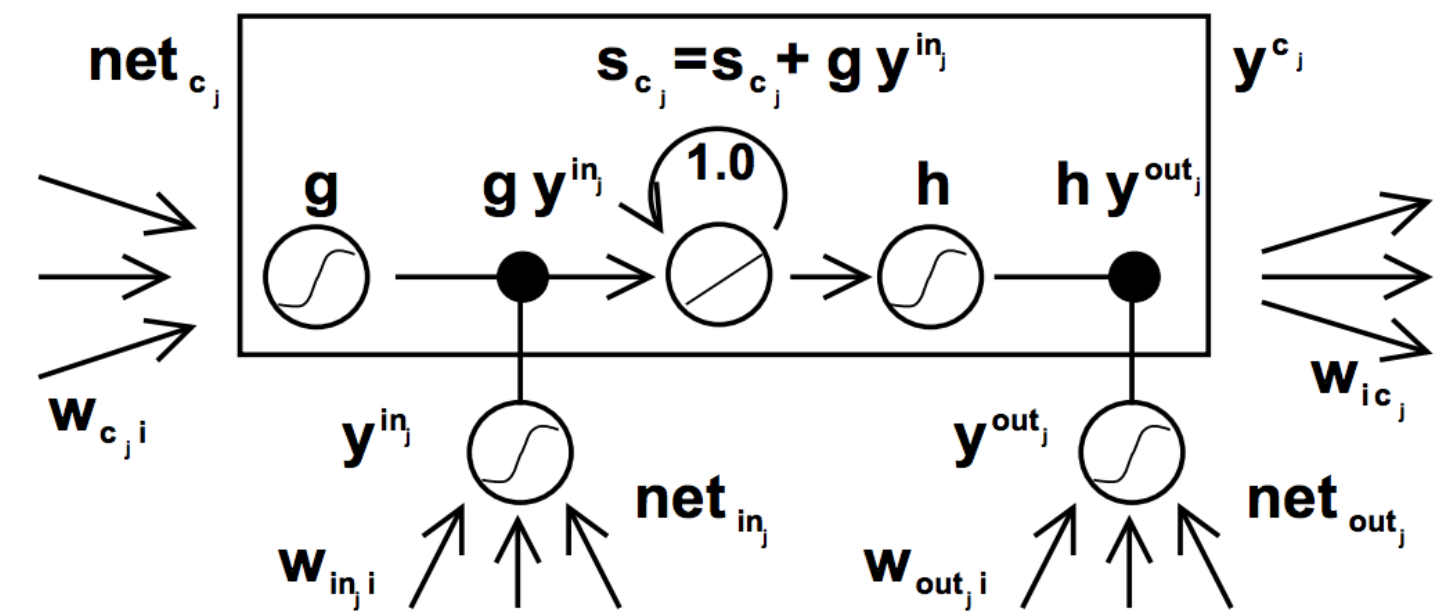


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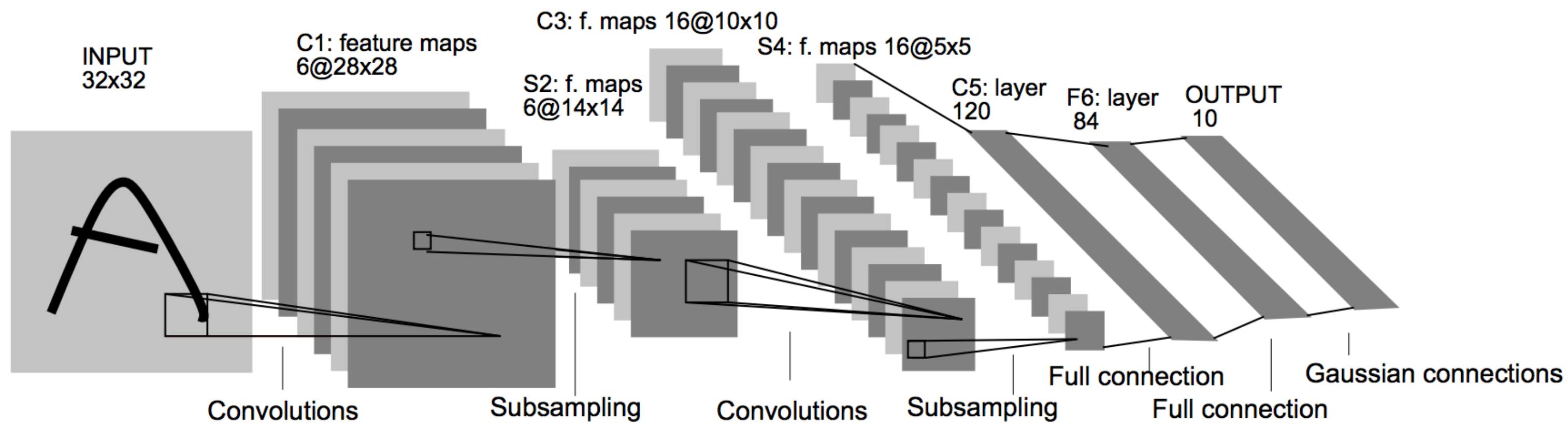


- ▶ LSTMs: Hochreiter and Schmidhuber (1997)

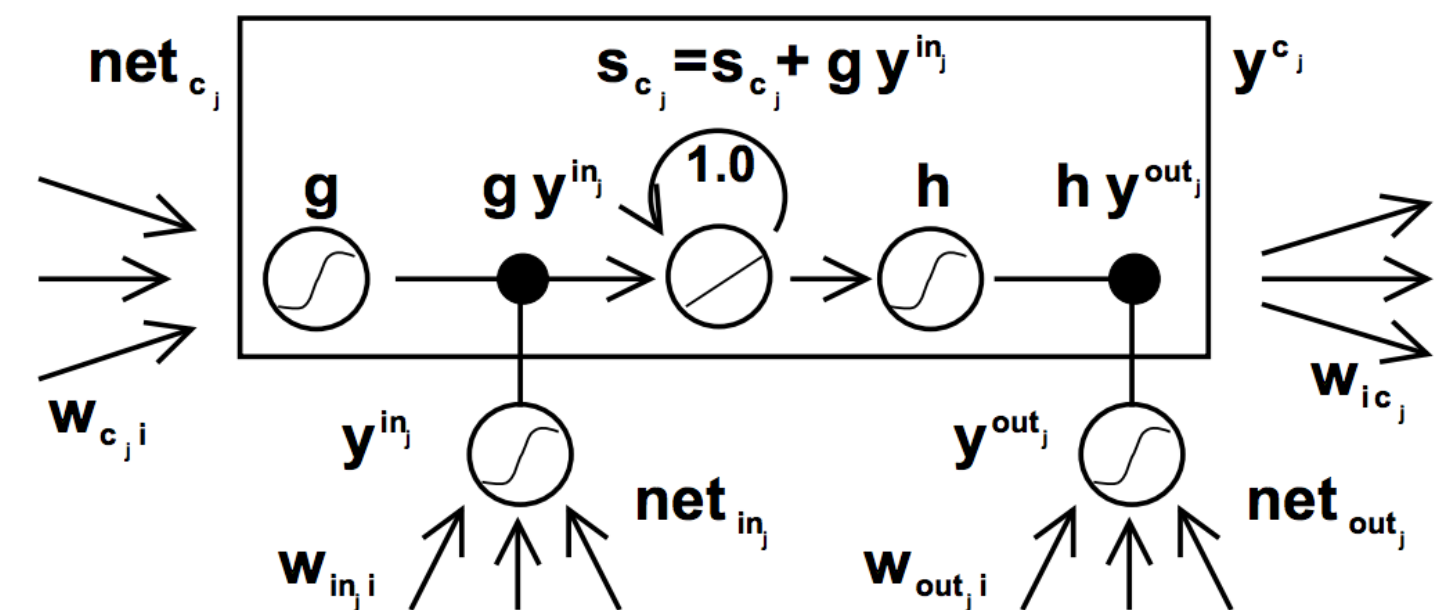


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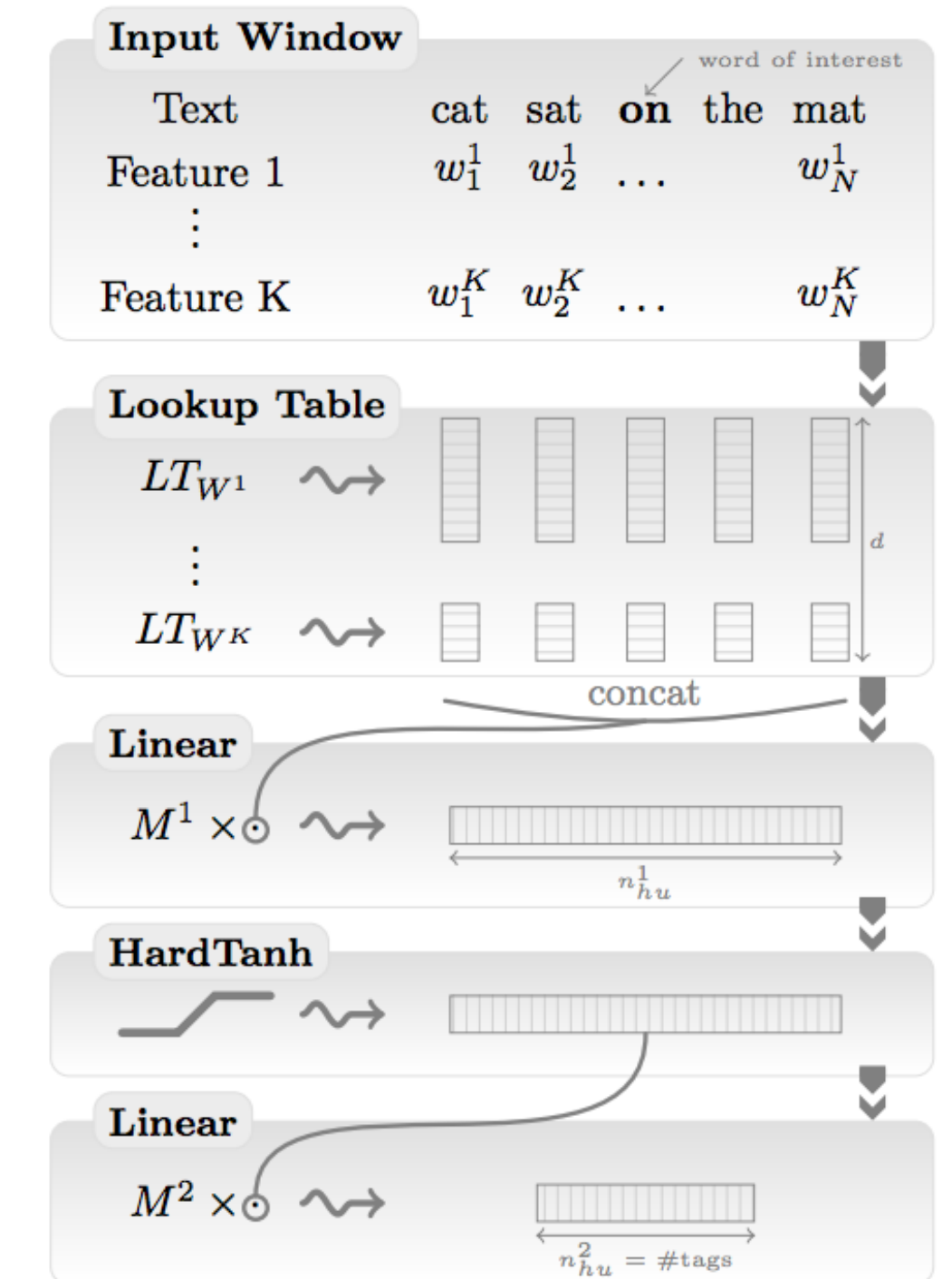


- ▶ Henderson (2003): neural shift-reduce parser, not SOTA

2008-2013: A glimmer of light...

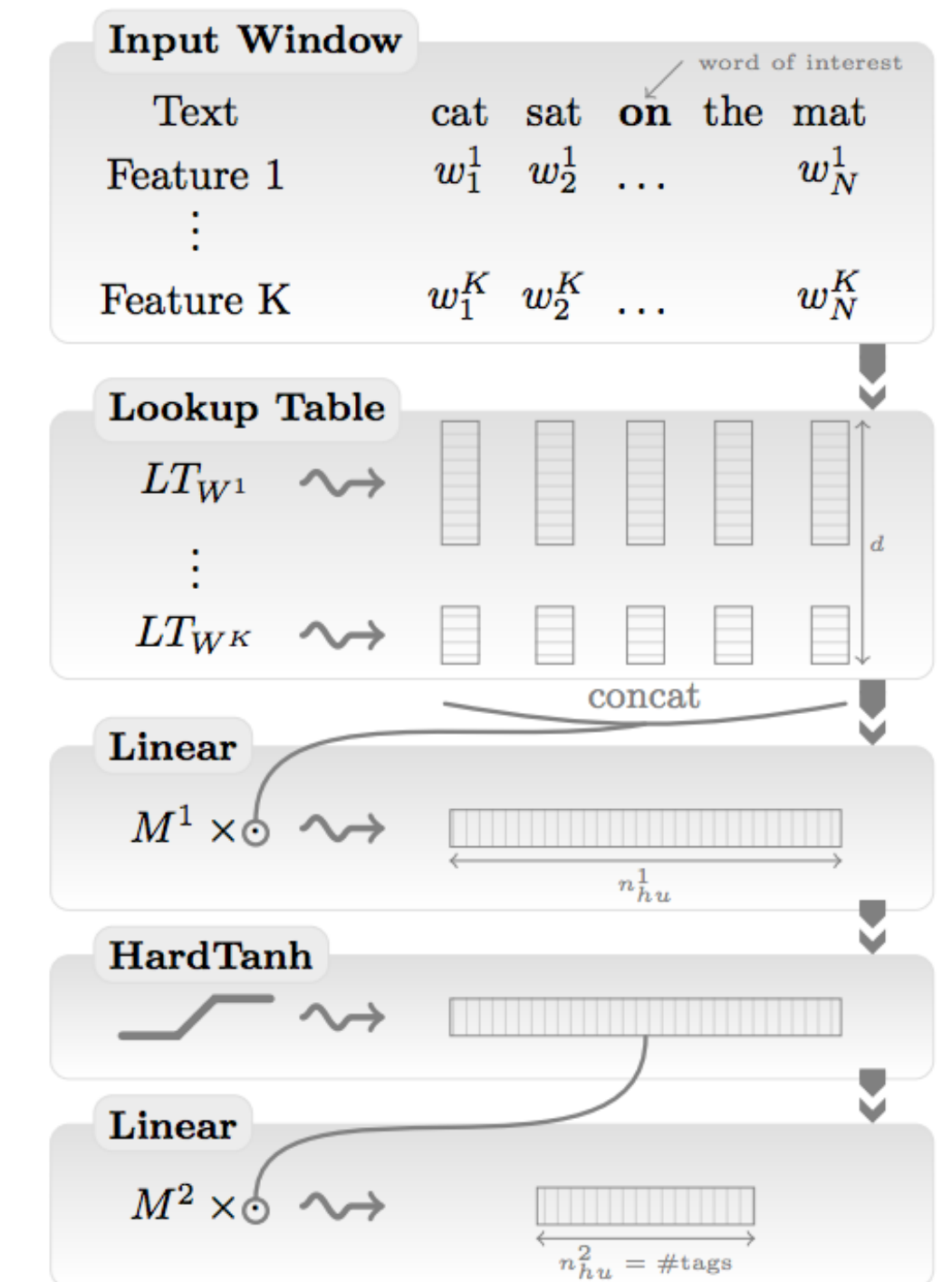
2008-2013: A glimmer of light...

- ▶ Collobert and Weston 2011: “NLP (almost) from scratch”
 - ▶ Feedforward neural nets induce features for sequential CRFs (“neural CRF”)
 - ▶ 2008 version was marred by bad experiments, claimed SOTA but wasn’t, 2011 version tied SOTA



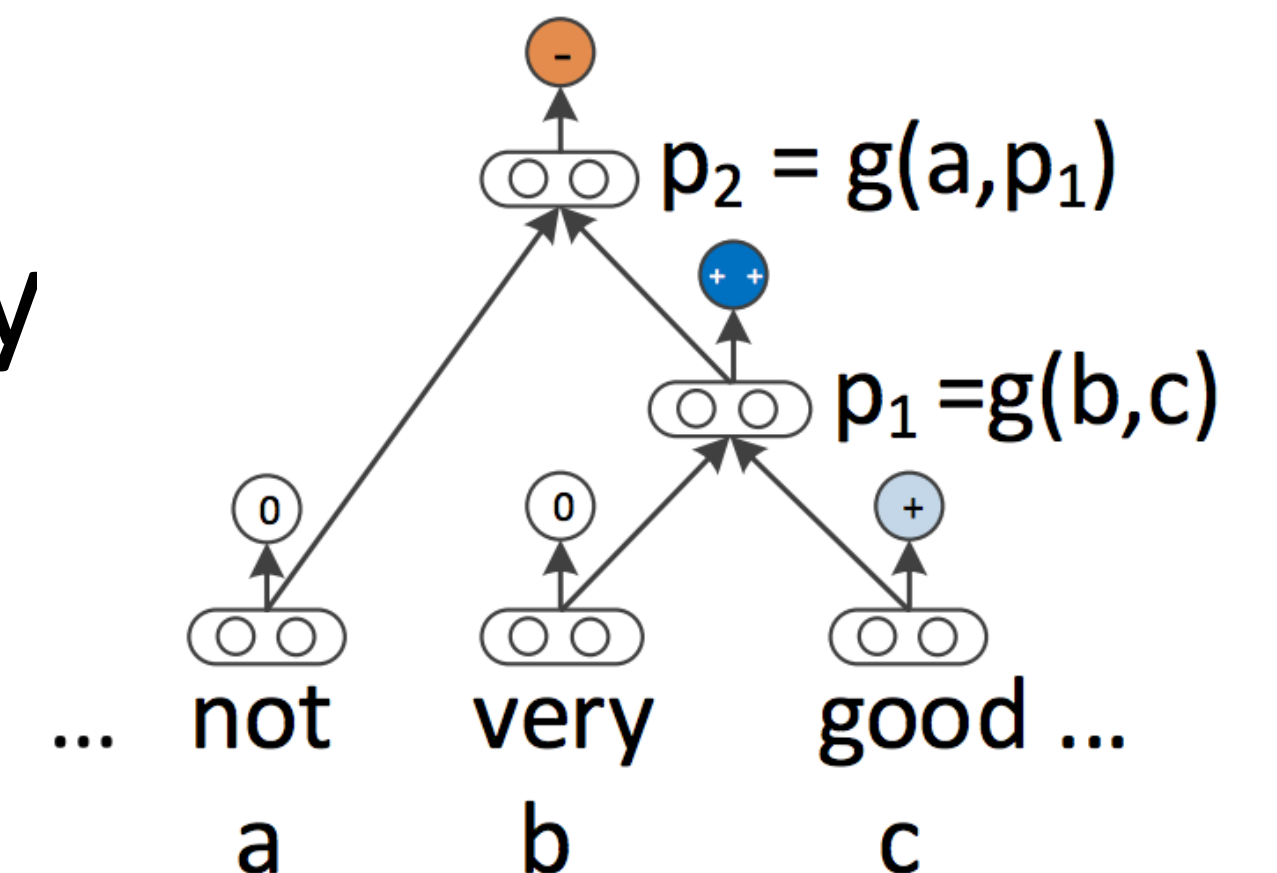
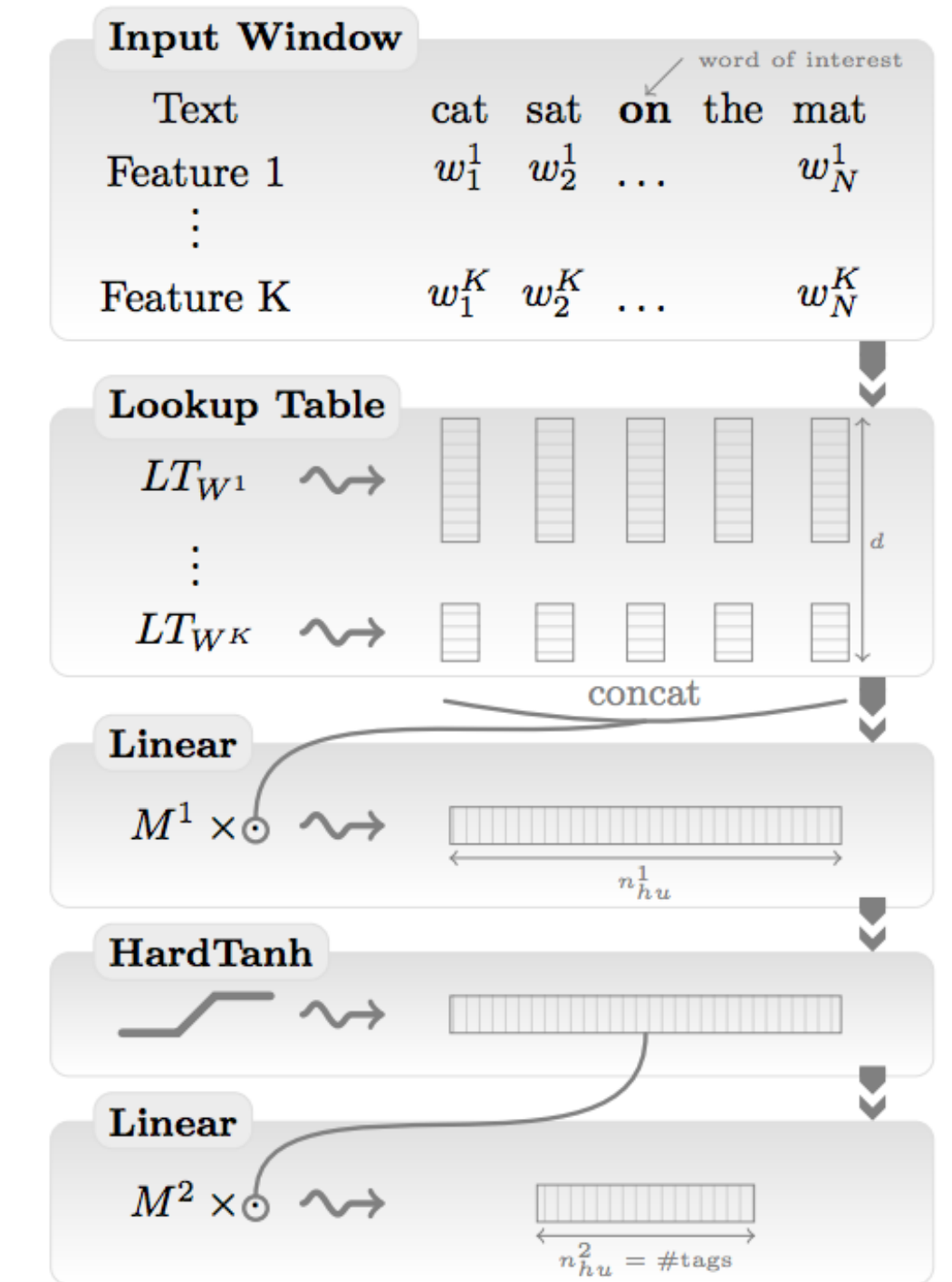
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- ▶ Socher 2011-2014: tree-structured RNNs working okay



2014: Stuff starts working

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- ▶ Chen and Manning transition-based dependency parser (even feedforward networks work well for NLP?)
- ▶ 2015: explosion of neural nets for everything under the sun

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- ▶ **Inputs:** need word representations to have the right continuous semantics

Neural Net Basics

Neural Networks

- ▶ Linear classification: $\operatorname{argmax}_y w^\top f(x, y)$

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I[contains *not* & contains *good*]

Neural Networks: XOR

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- ▶ Inputs
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(generally $\mathbf{x} = (x_1, \dots, x_m)$)
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x_1	x_2	$y = x_1 \text{ XOR } x_2$
0	0	0
0	1	1
1	0	1
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Neural Networks: XOR

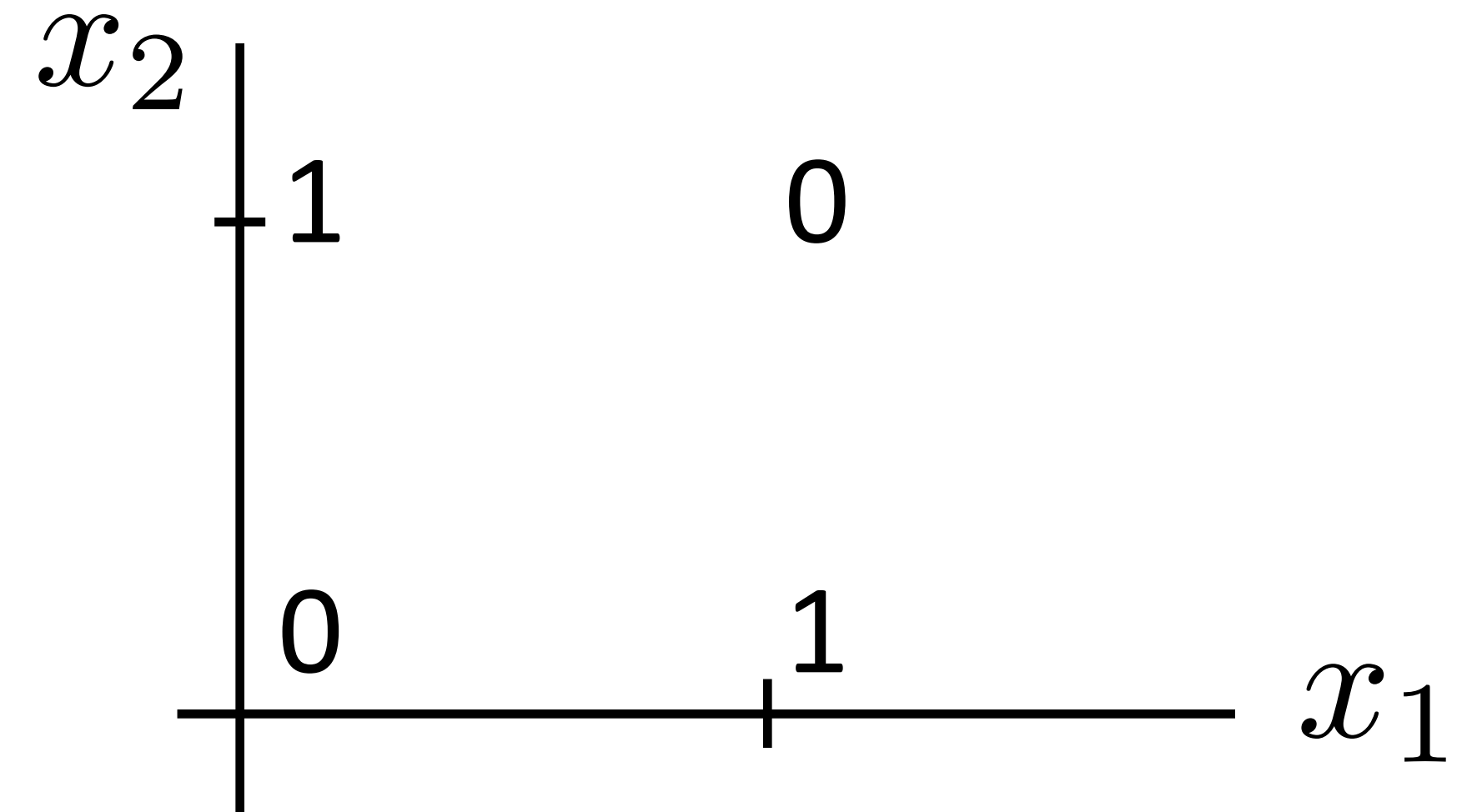
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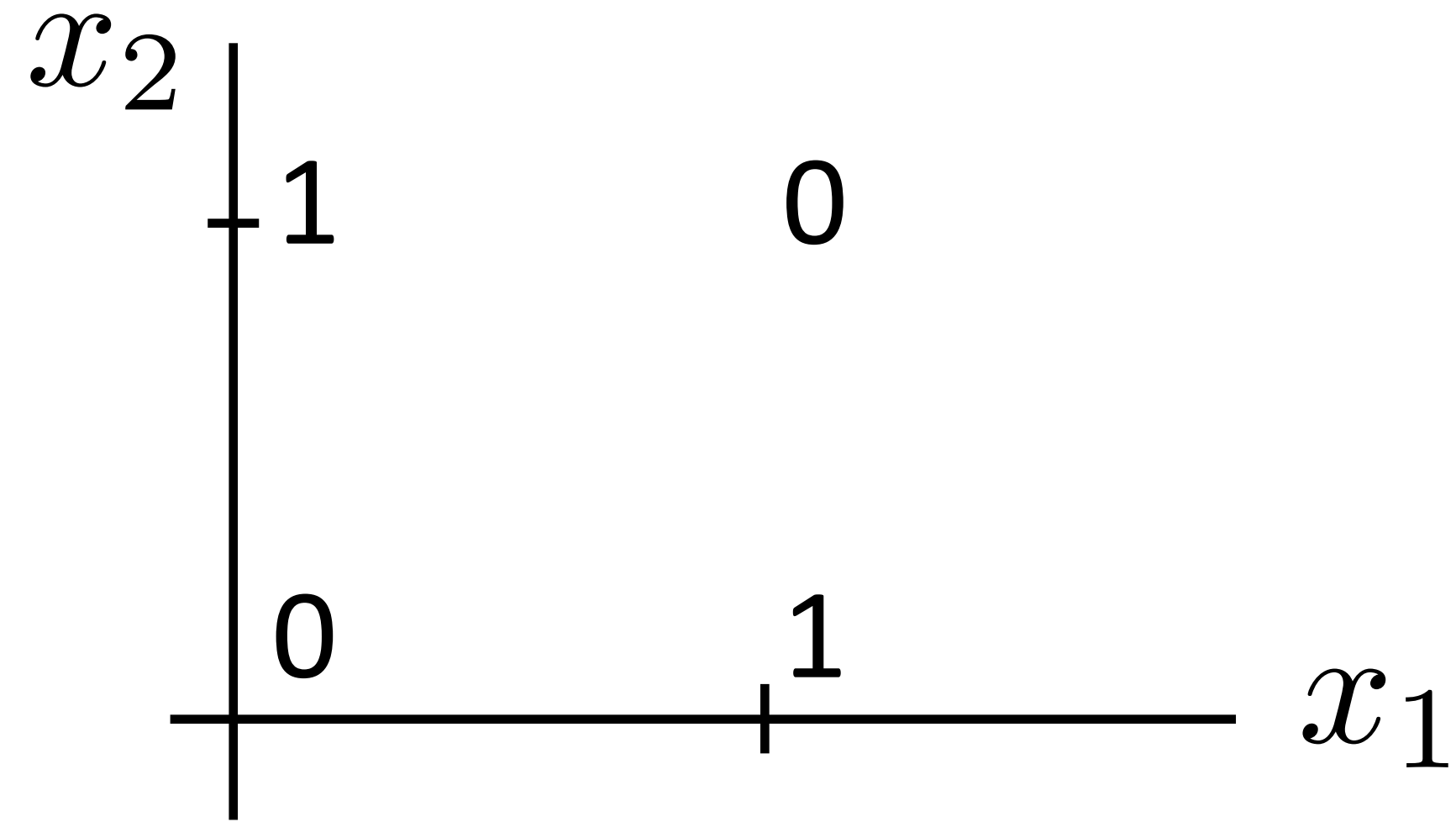
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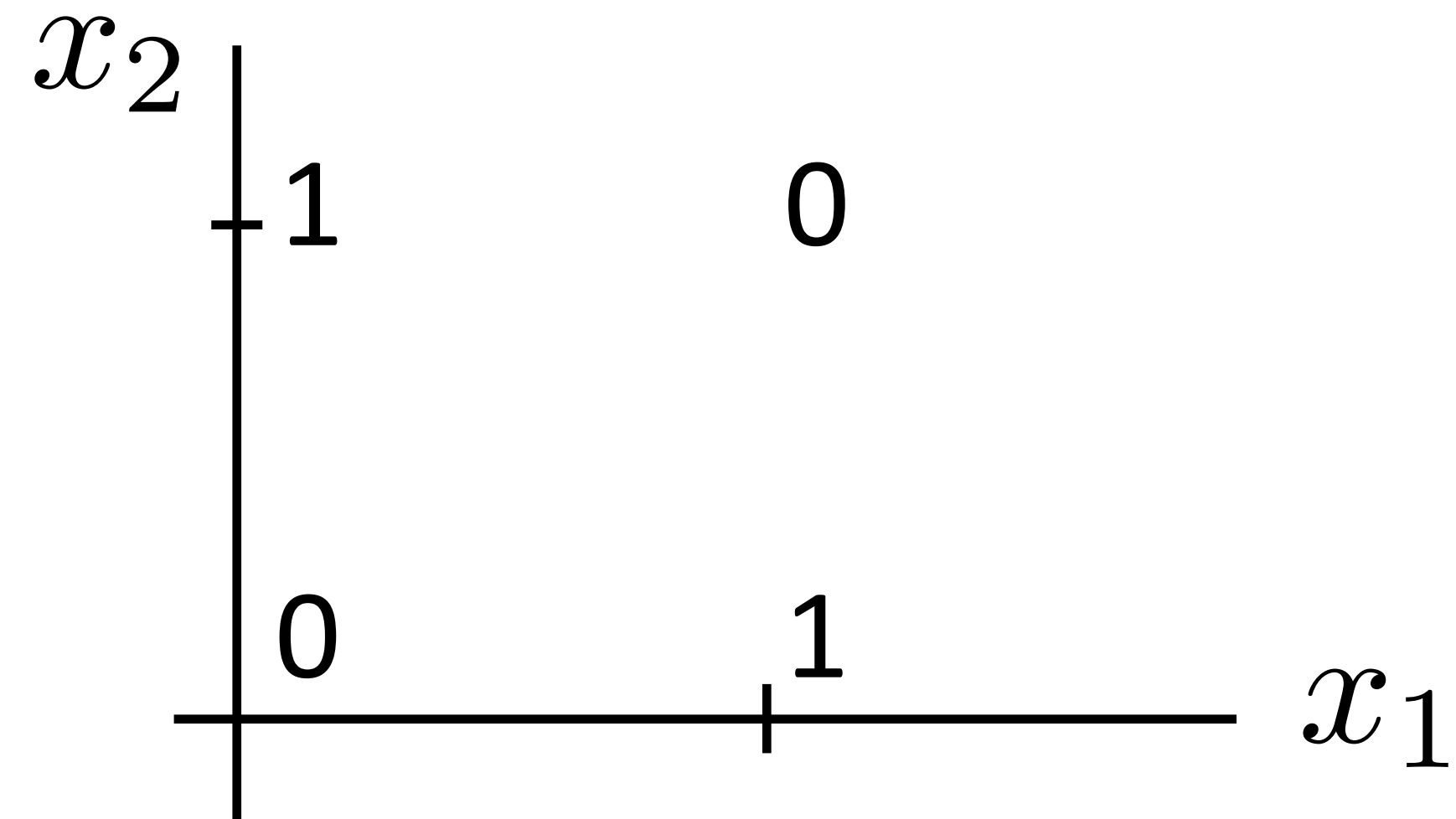
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Neural Networks: XOR



x_1	x_2	x_1	XOR	x_2
0	0		0	
0	1		1	
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1	1		0	

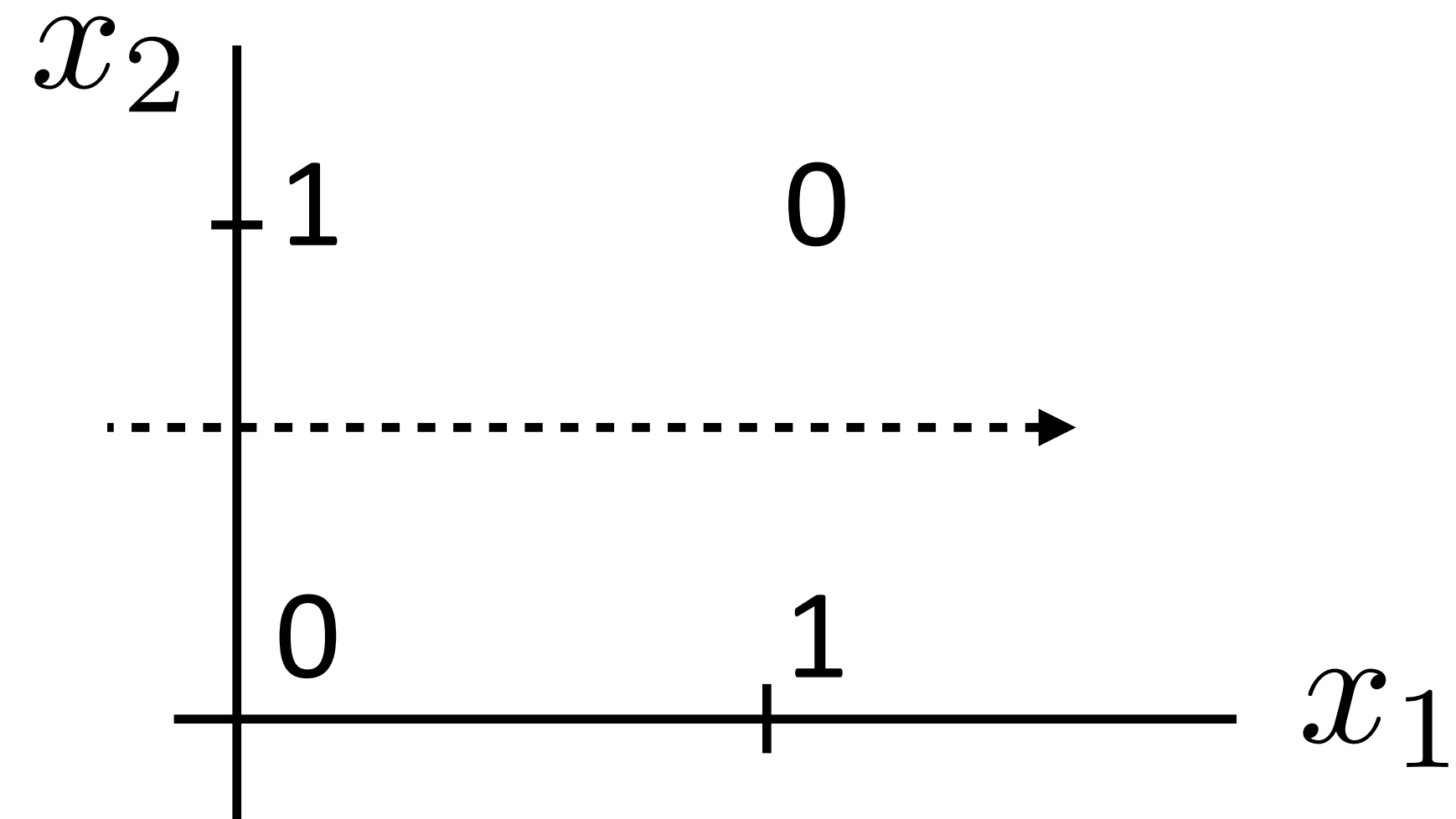
Neural Networks: XOR



$$y = a_1x_1 + a_2x_2$$

x_1	x_2	x_1	XOR	x_2
0	0		0	
0	1		1	
1	0		1	
1	1		0	

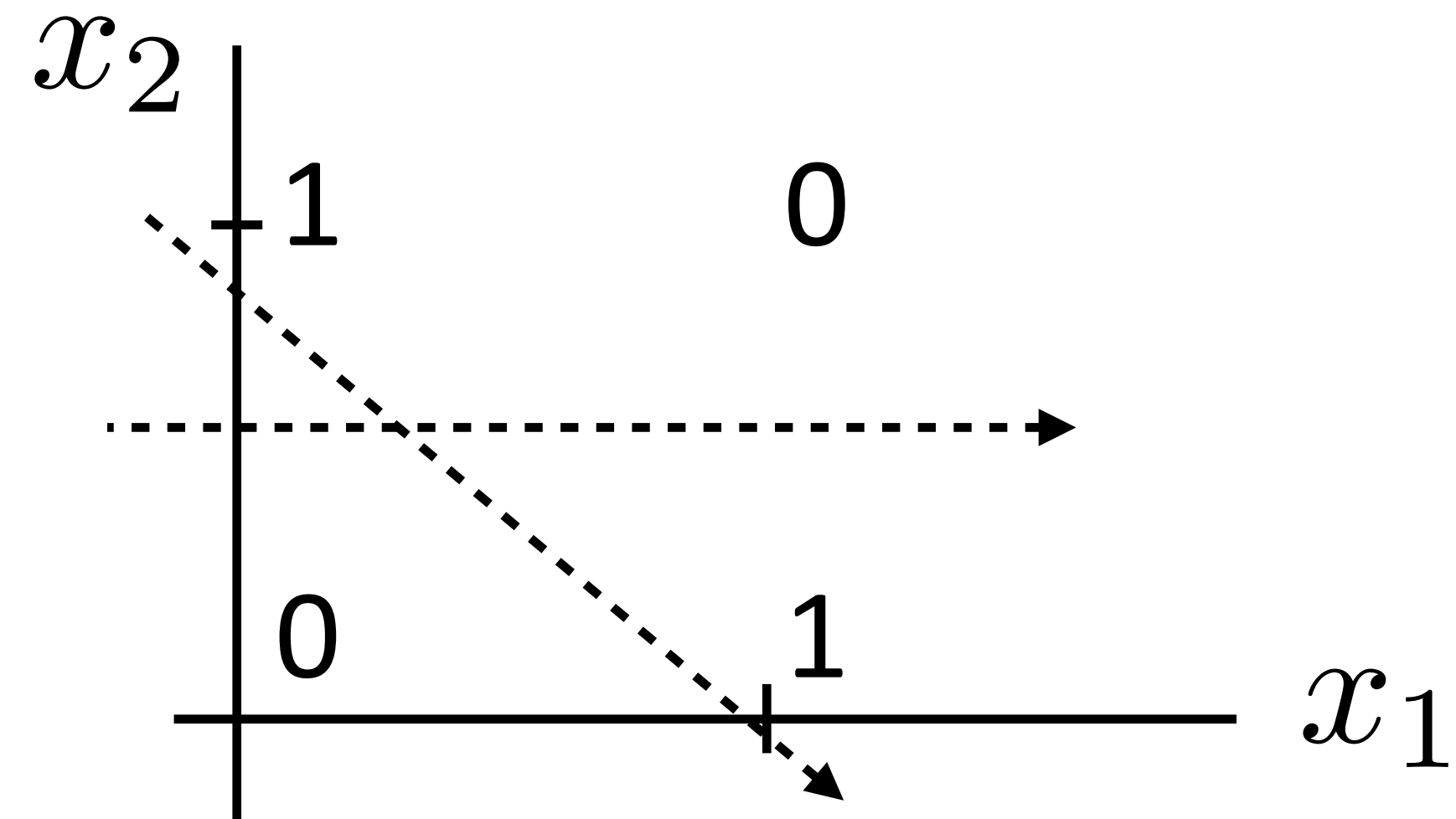
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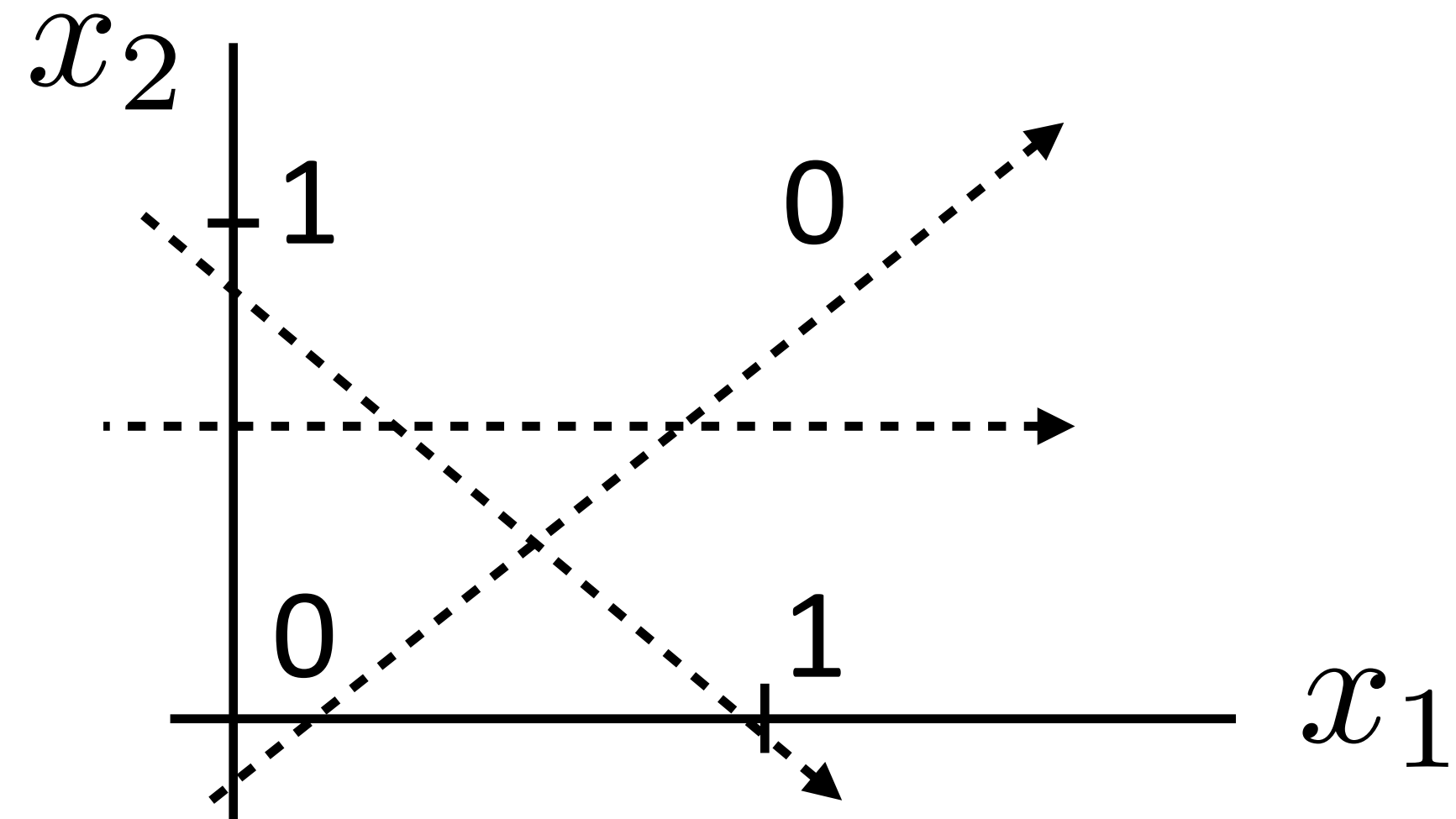
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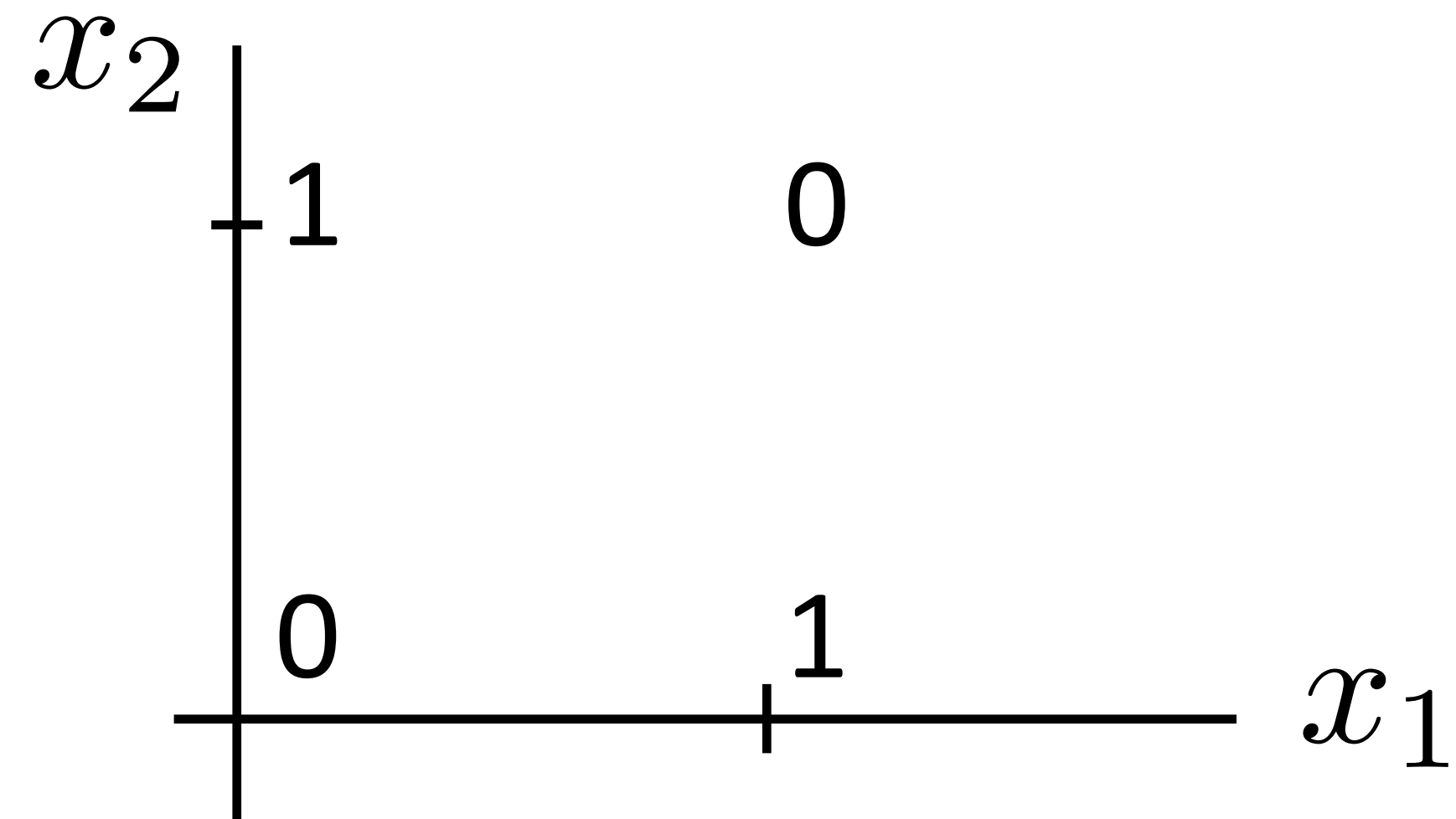
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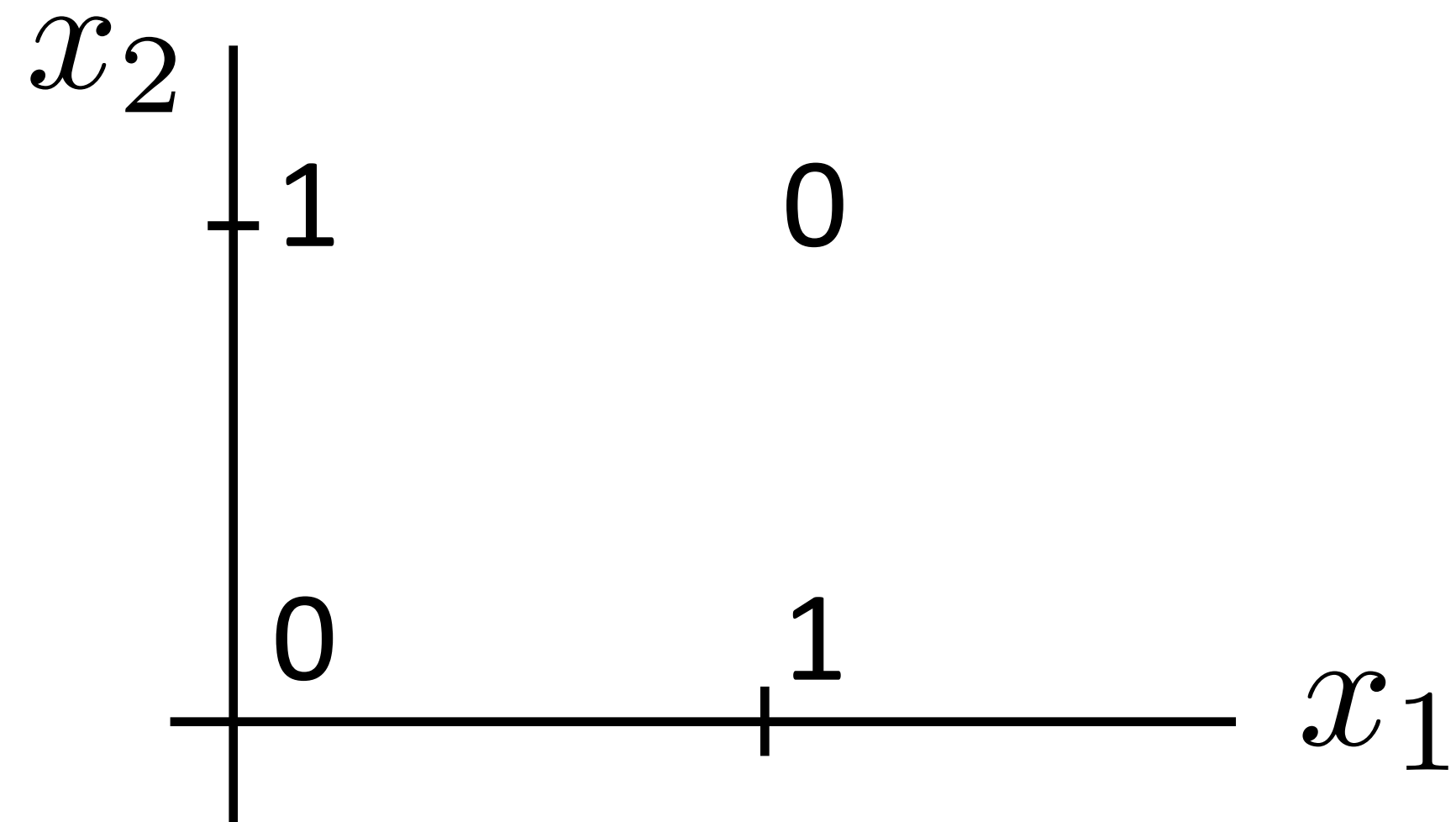
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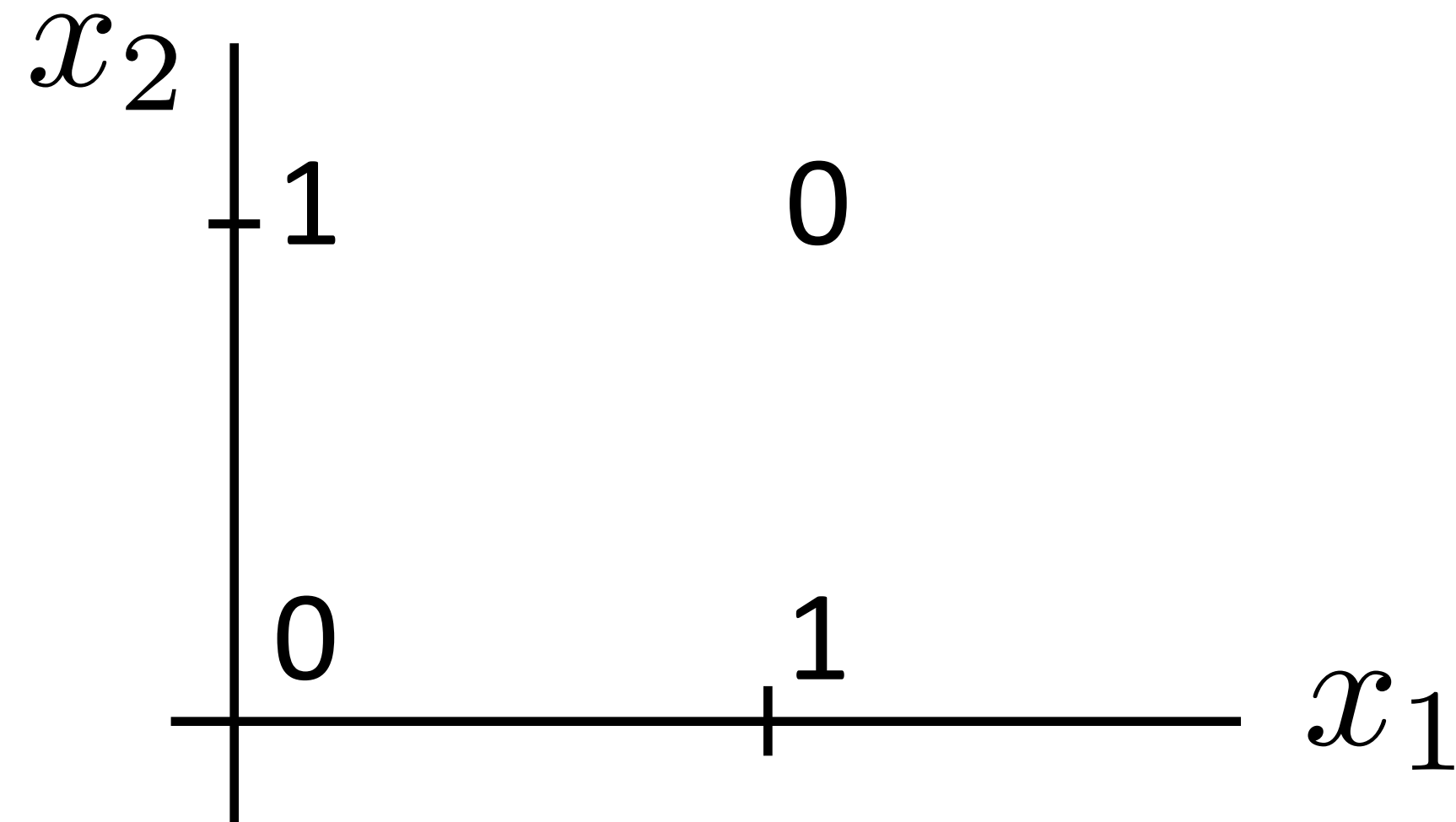


$$y = a_1x_1 + a_2x_2$$

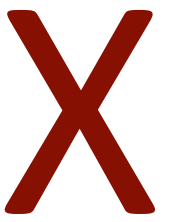
X

x_1	x_2	x_1	XOR	x_2
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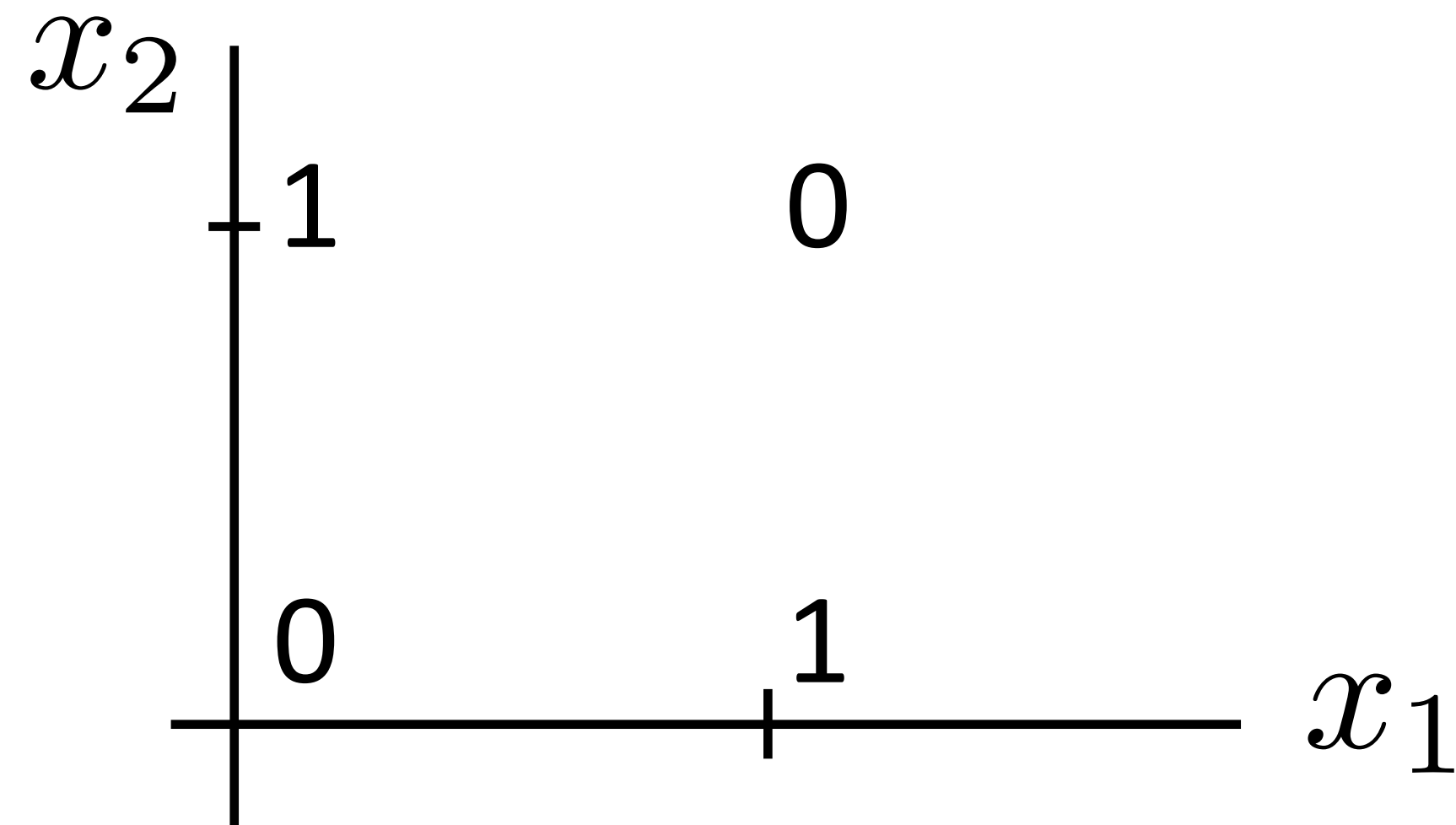


$$y = a_1x_1 + a_2x_2 + a_3 \tanh(x_1 + x_2)$$

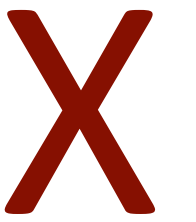


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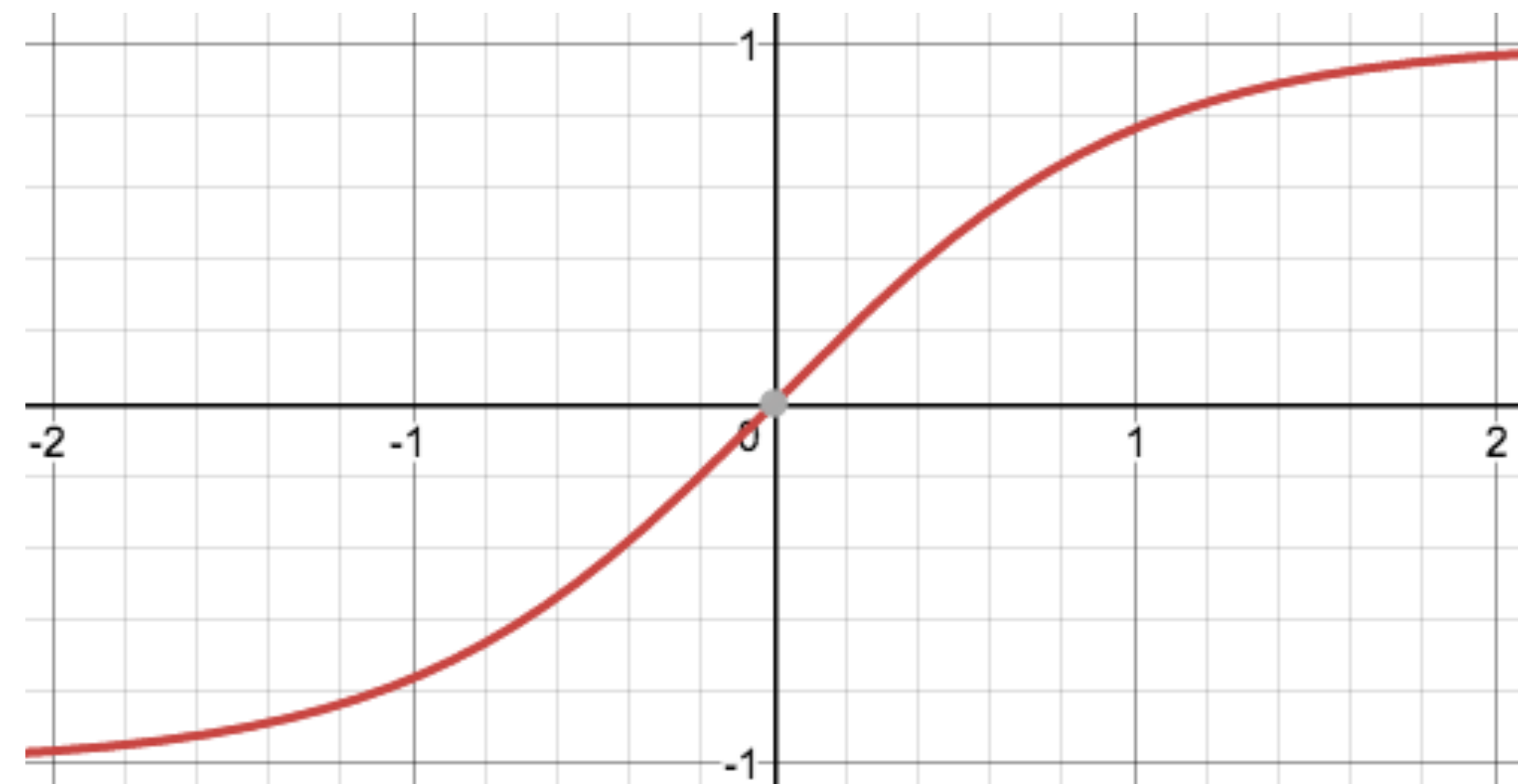


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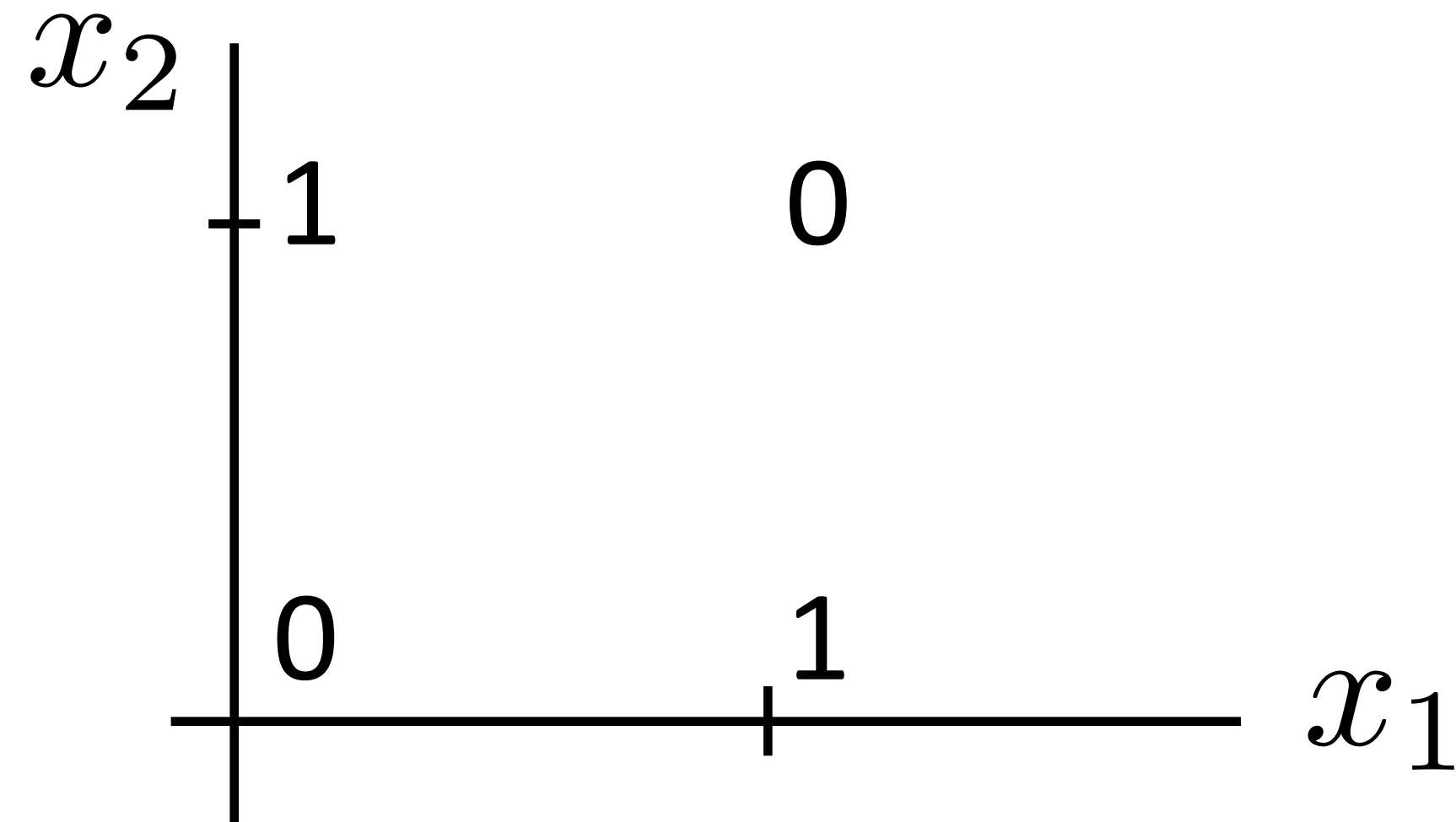
“or”



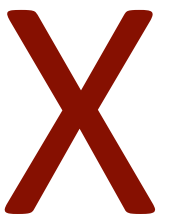
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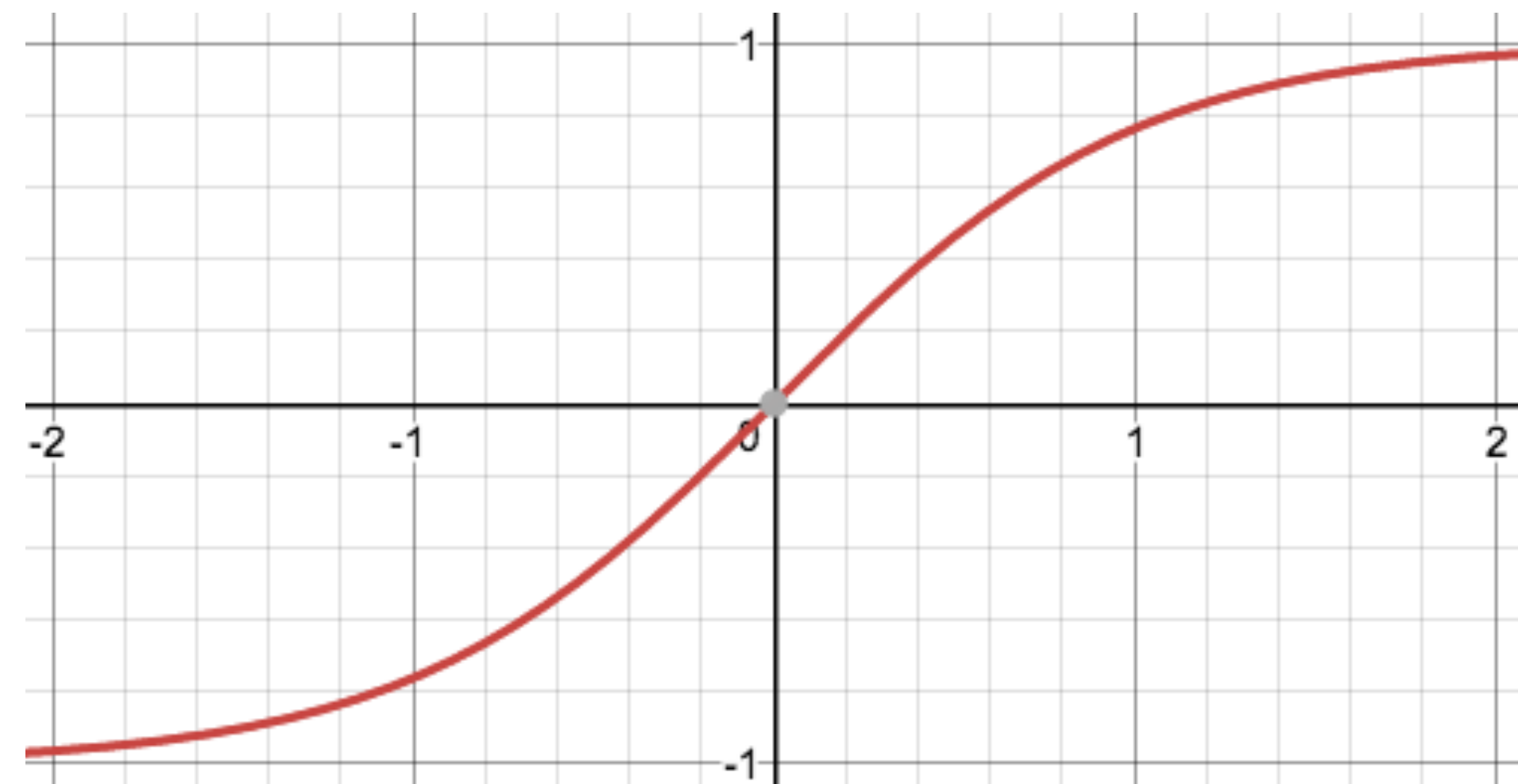
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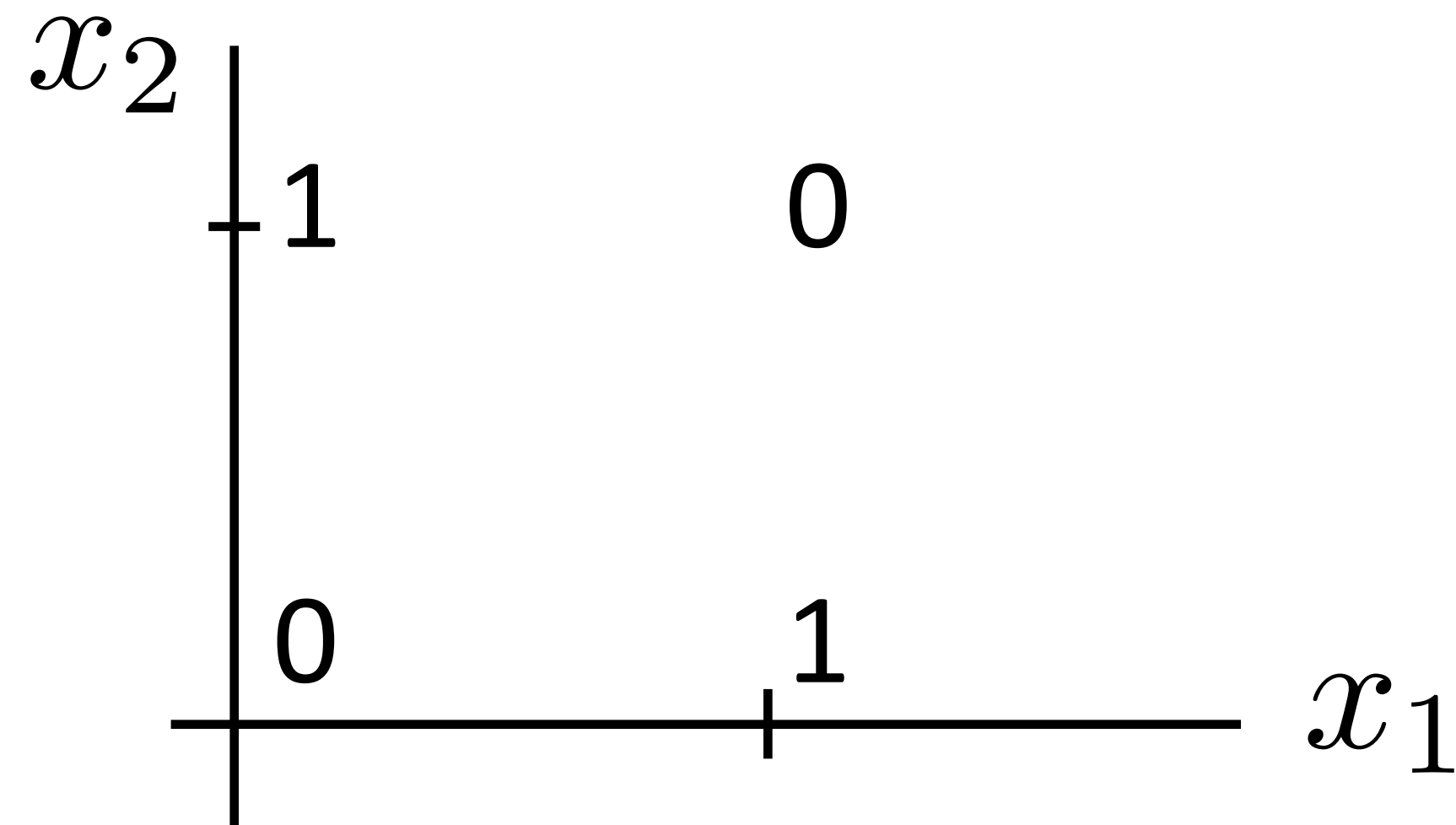


(looks like action potential in neuron)

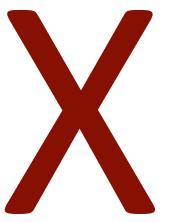
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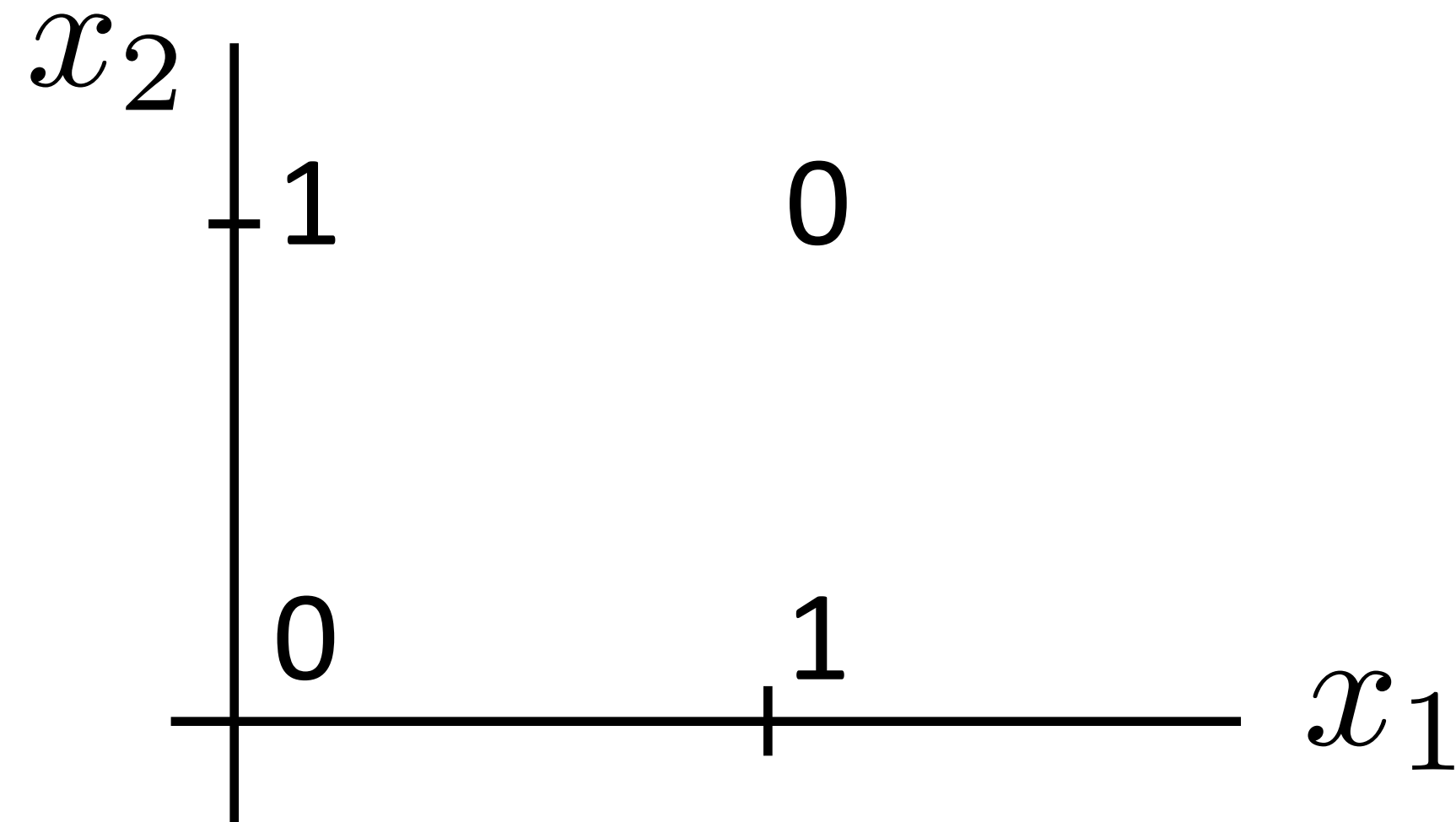


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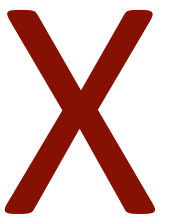


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Neural Networks: XOR



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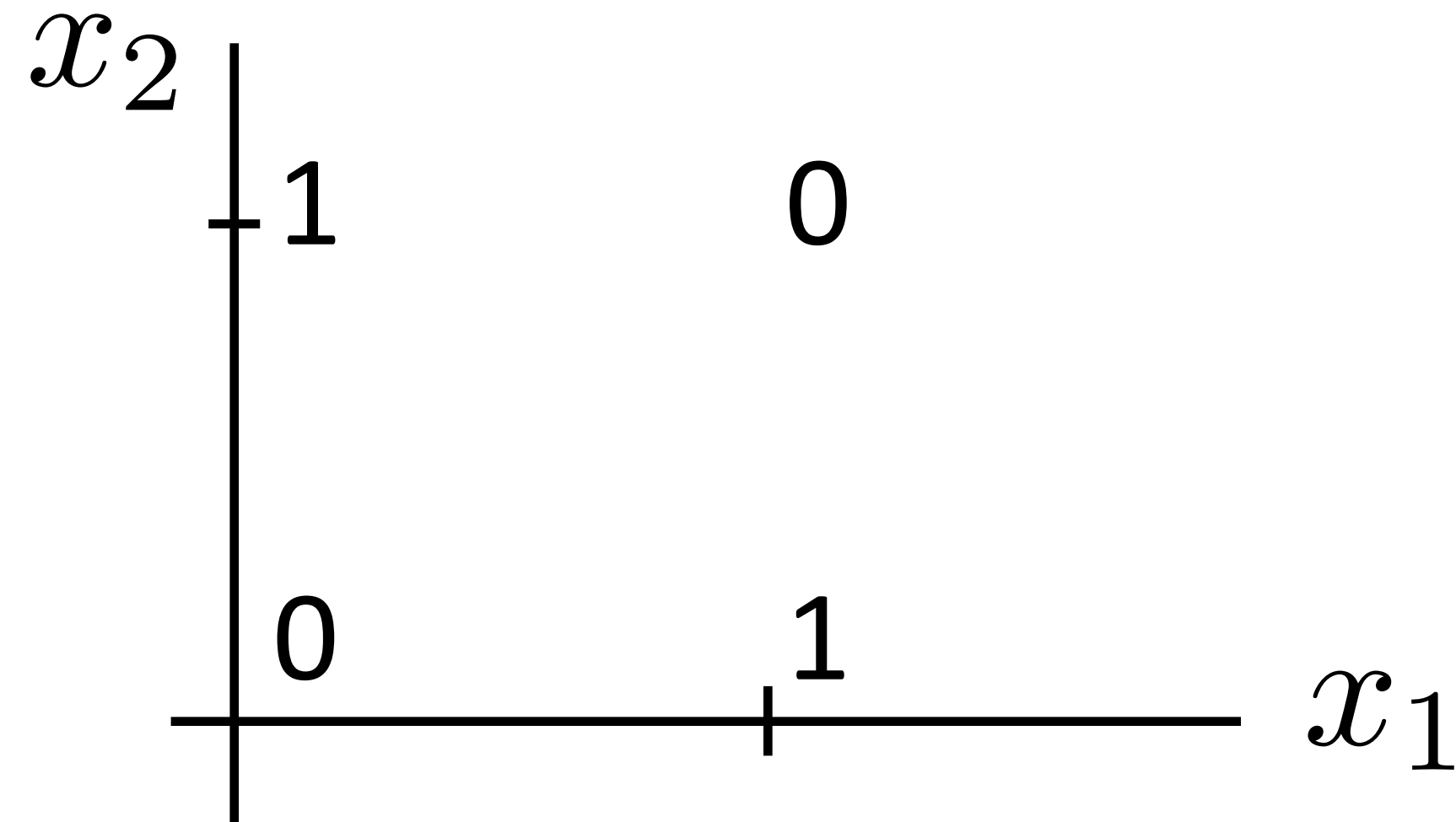


$$y = -x_1 - x_2 + 2 \tanh(x_1 + x_2)$$

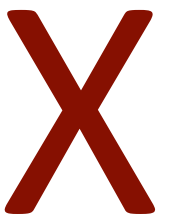
“or”

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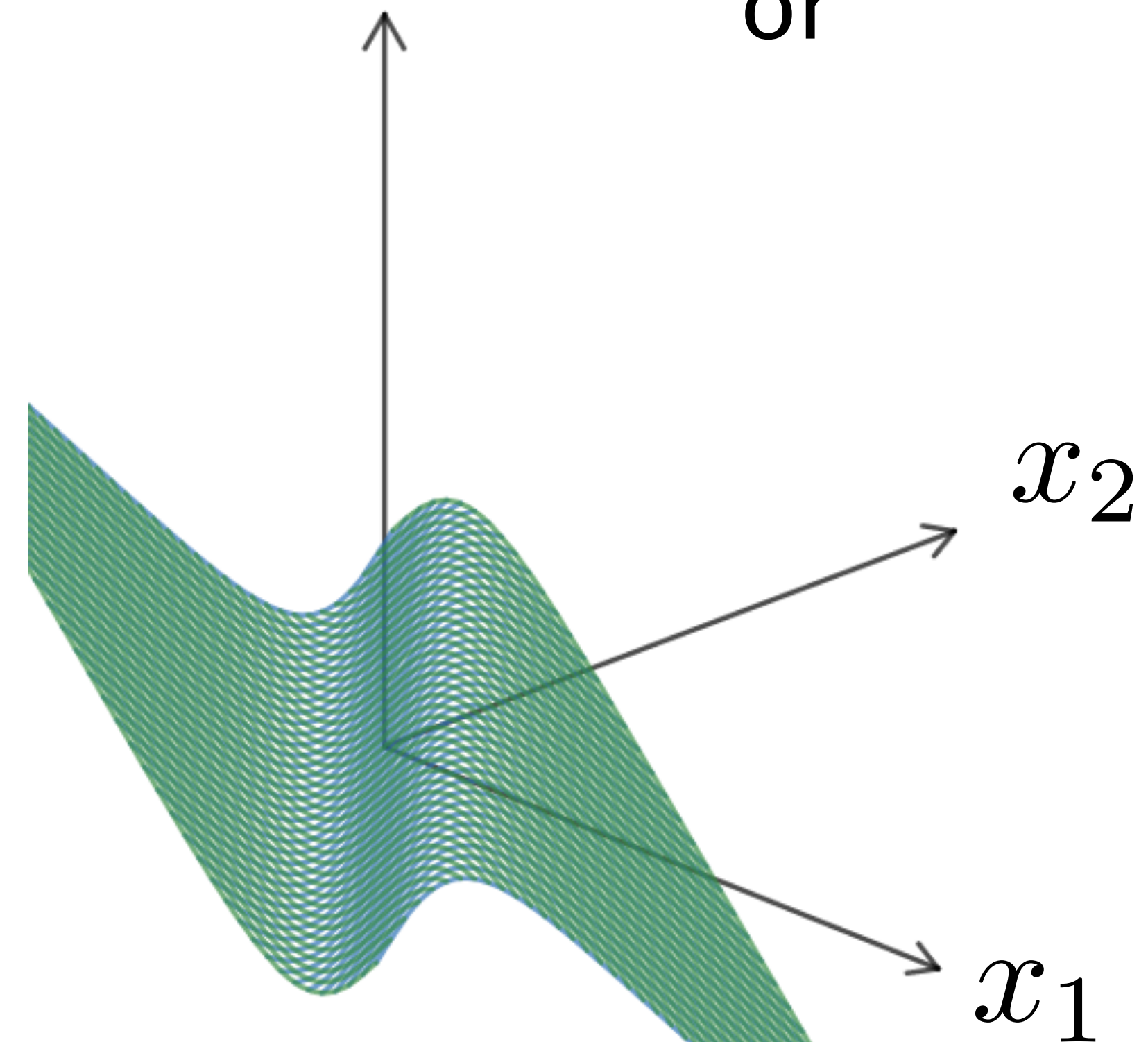
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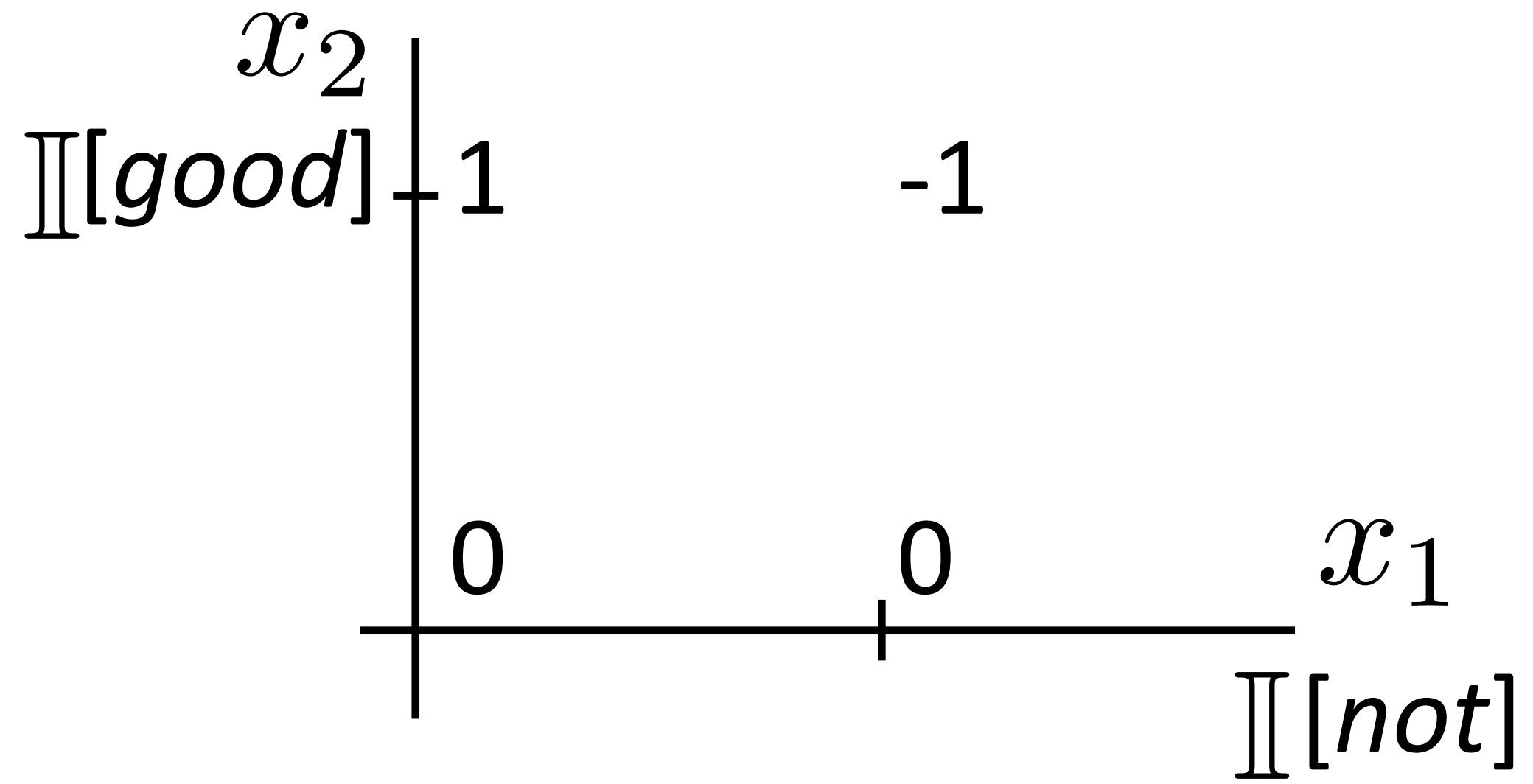
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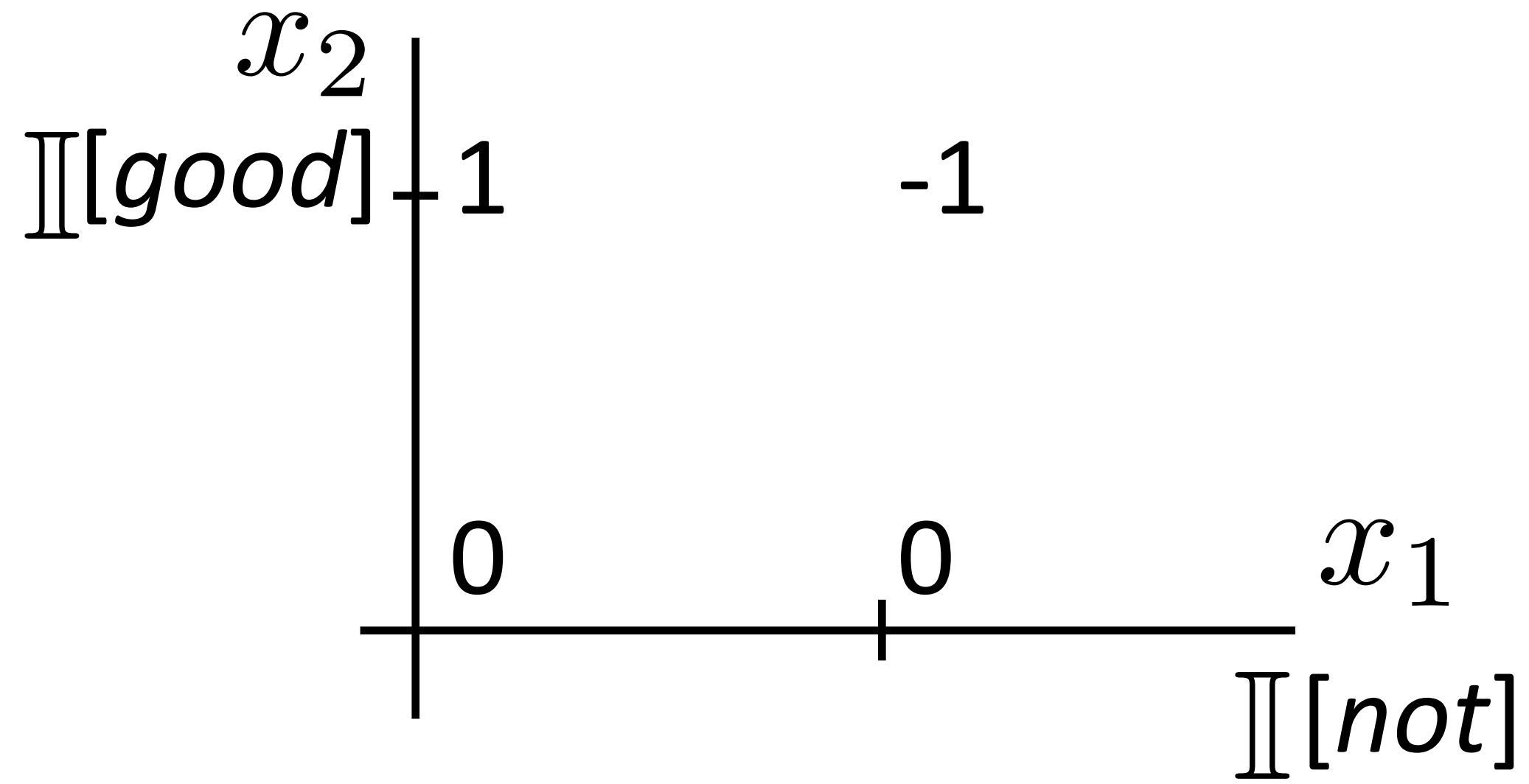
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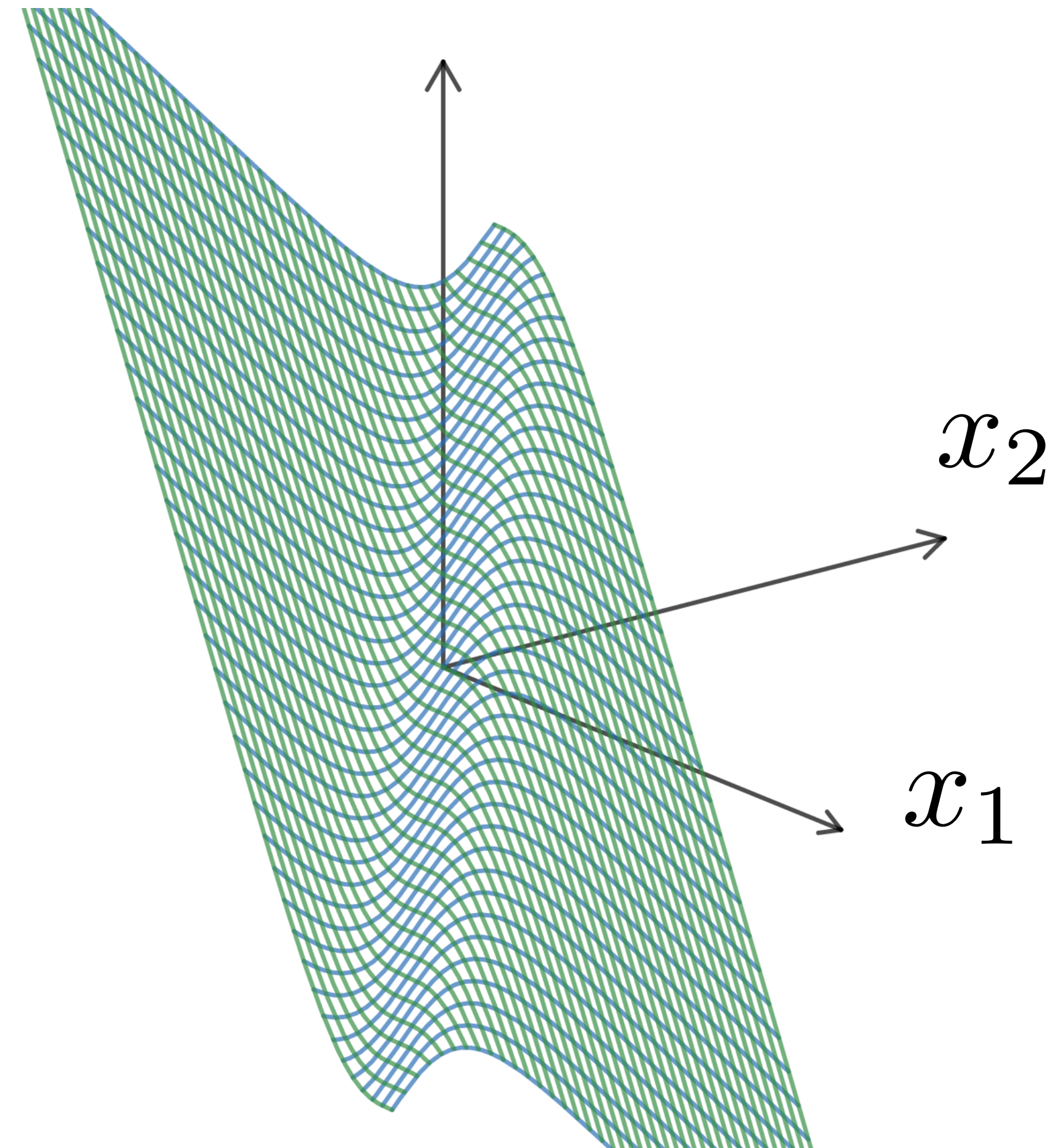


*the movie was **not** all that **good***

Neural Networks: XOR

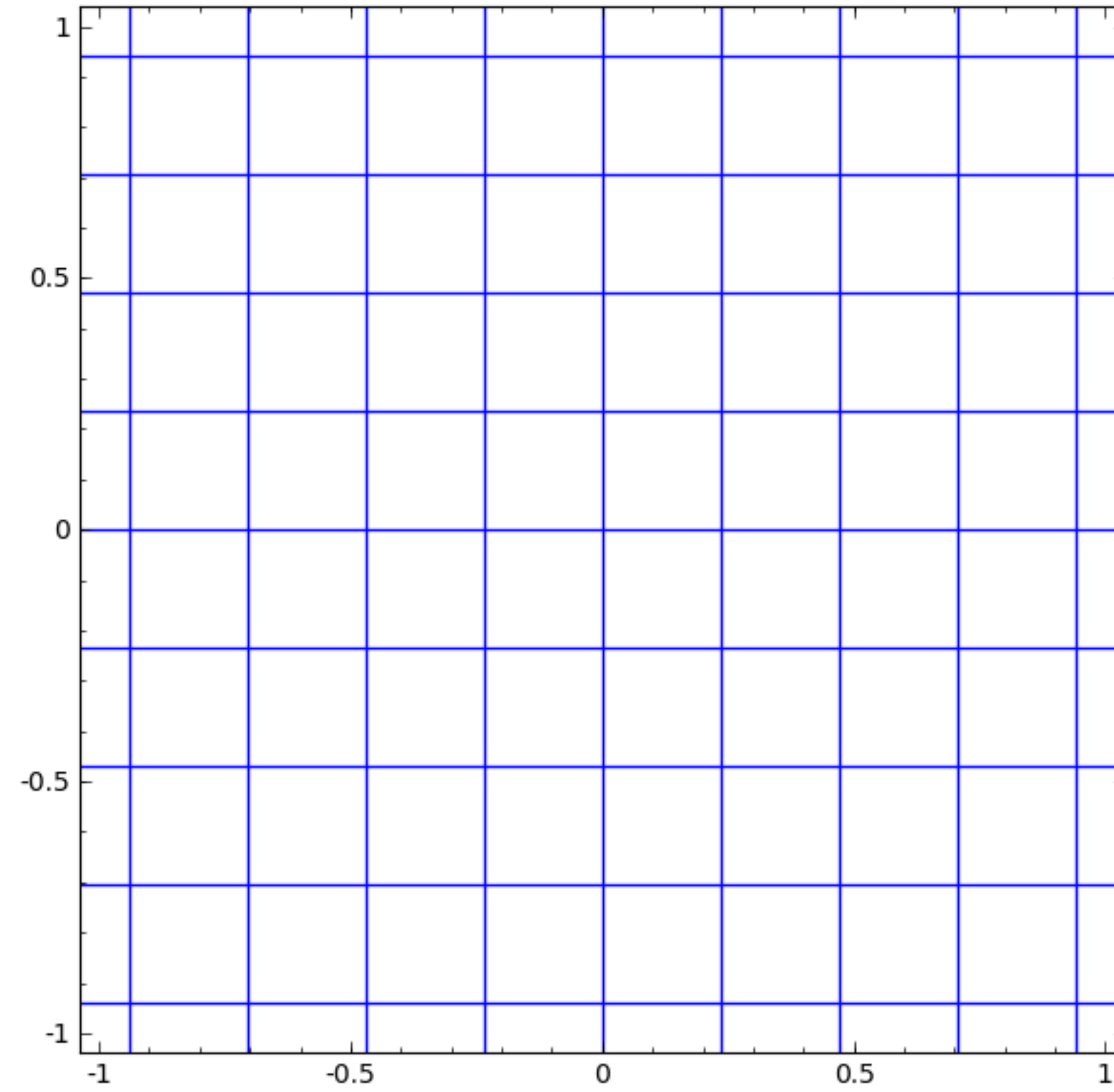


$$y = -2x_1 - x_2 + 2 \tanh(x_1 + x_2)$$



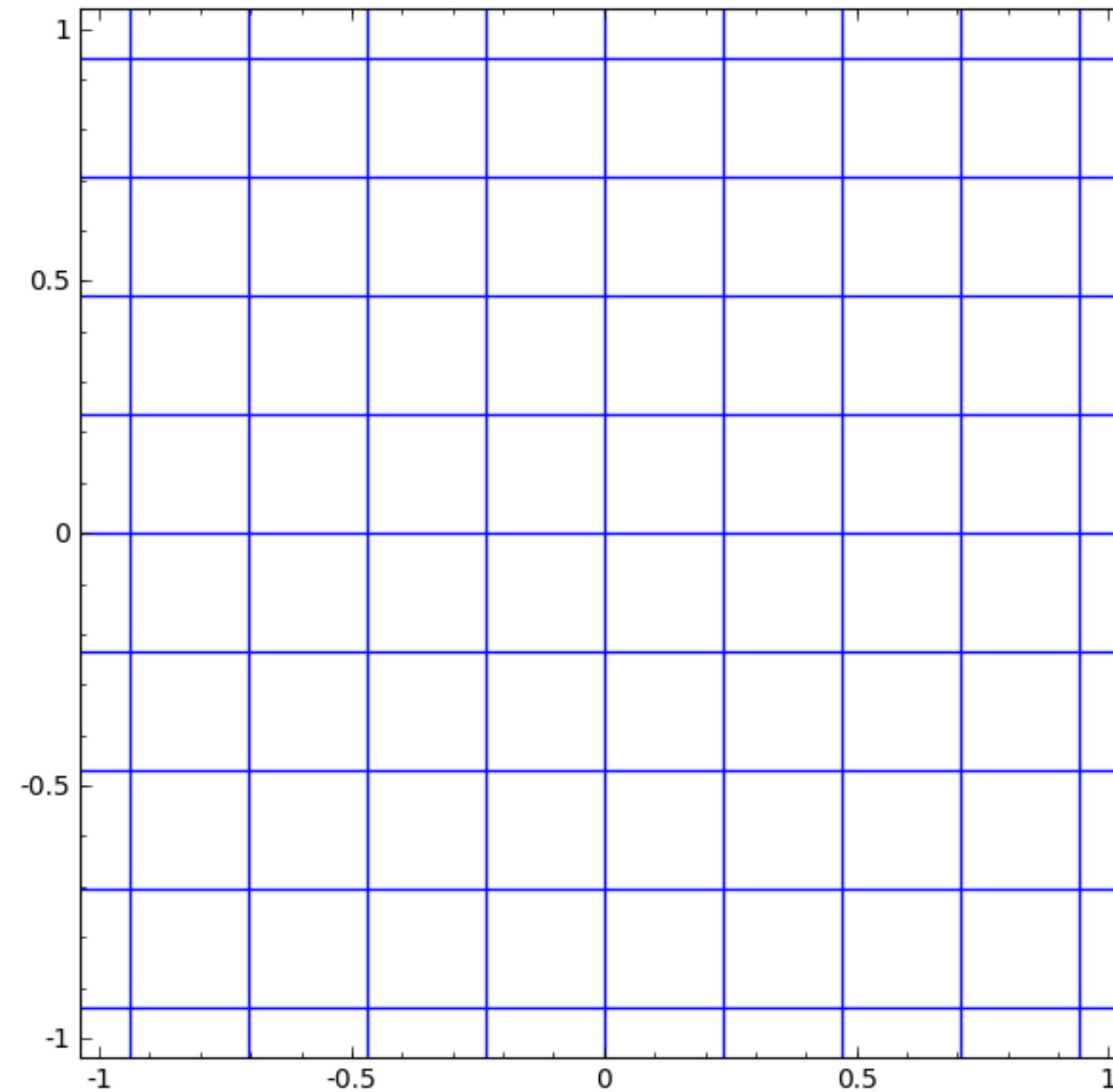
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Neural Networks



Neural Networks

Linear model: $y = \mathbf{w} \cdot \mathbf{x} + b$



Neural Networks

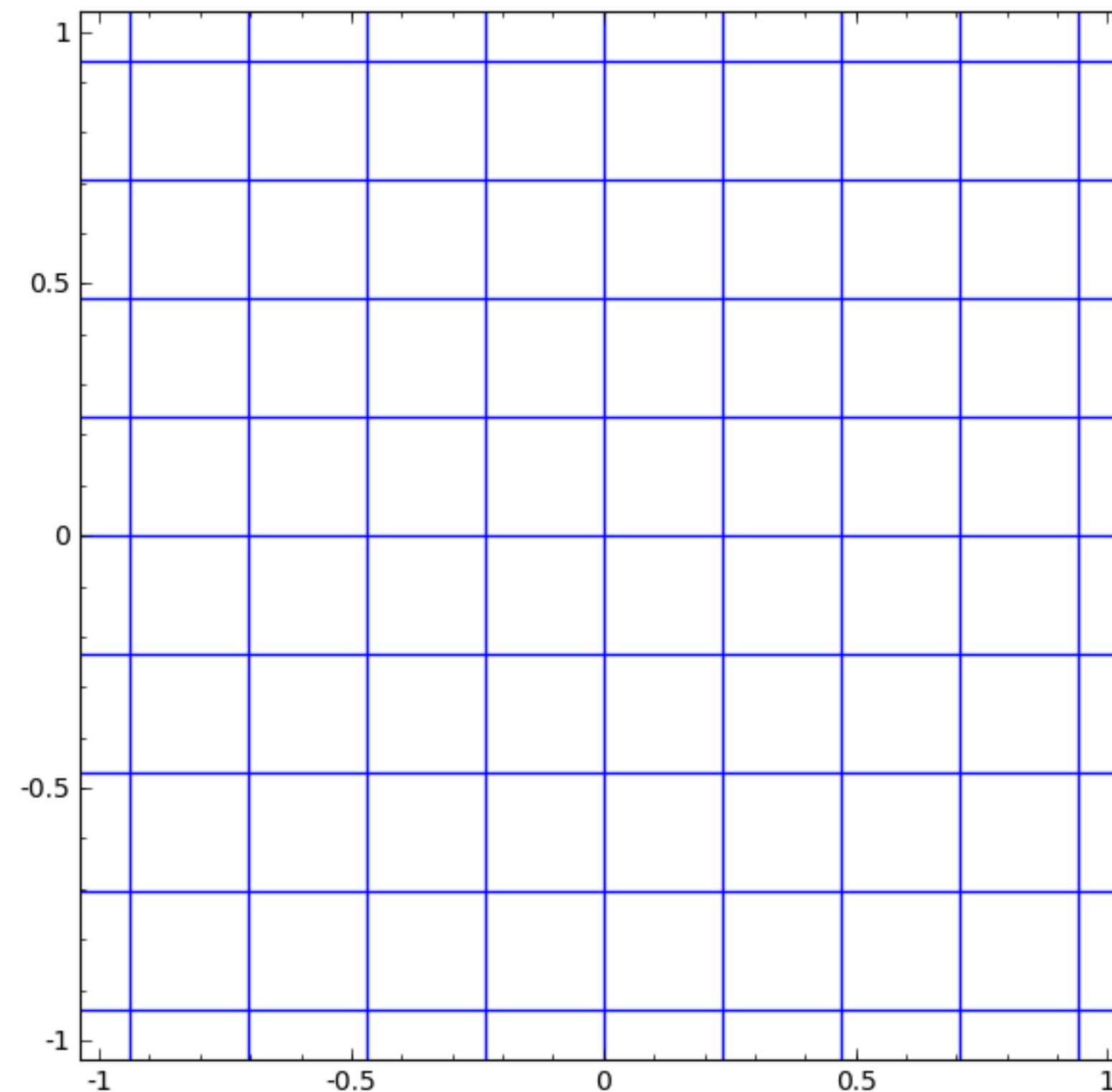
Linear model: $y = \mathbf{w} \cdot \mathbf{x} + b$

$$y = g(\mathbf{w} \cdot \mathbf{x} + b)$$

$$\mathbf{y} = g(\mathbf{W}\mathbf{x} + \mathbf{b})$$



Nonlinear
transformation



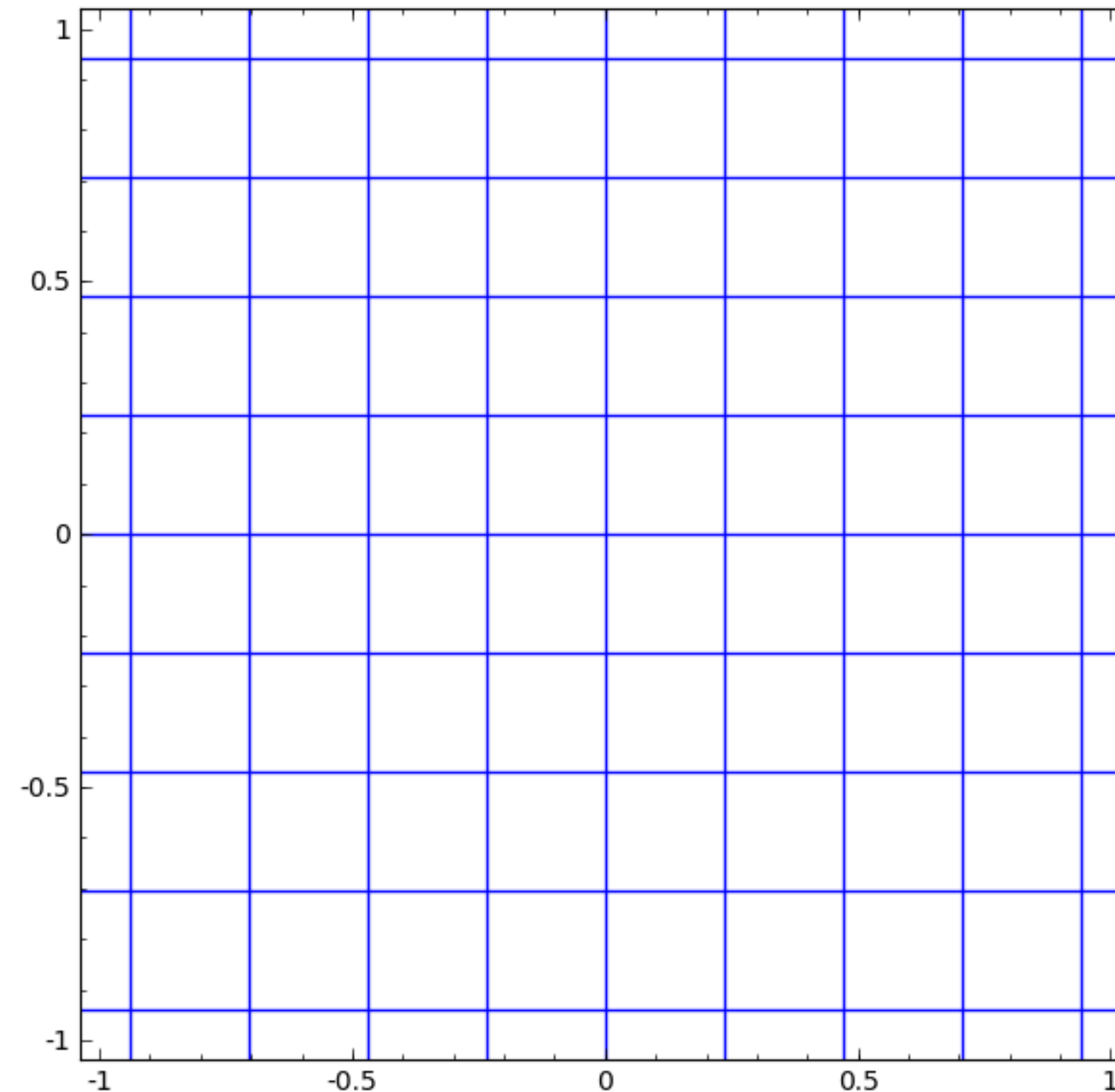
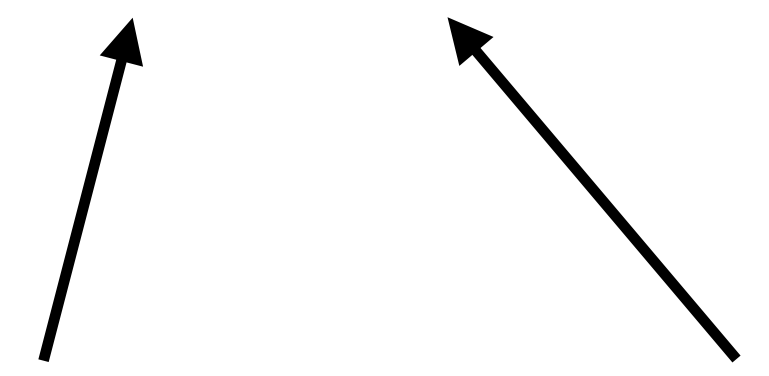
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Linear model: $y = \mathbf{w} \cdot \mathbf{x} + b$

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$$\mathbf{y} = g(\mathbf{W}\mathbf{x} + \mathbf{b})$$

Nonlinear transformation Warp space



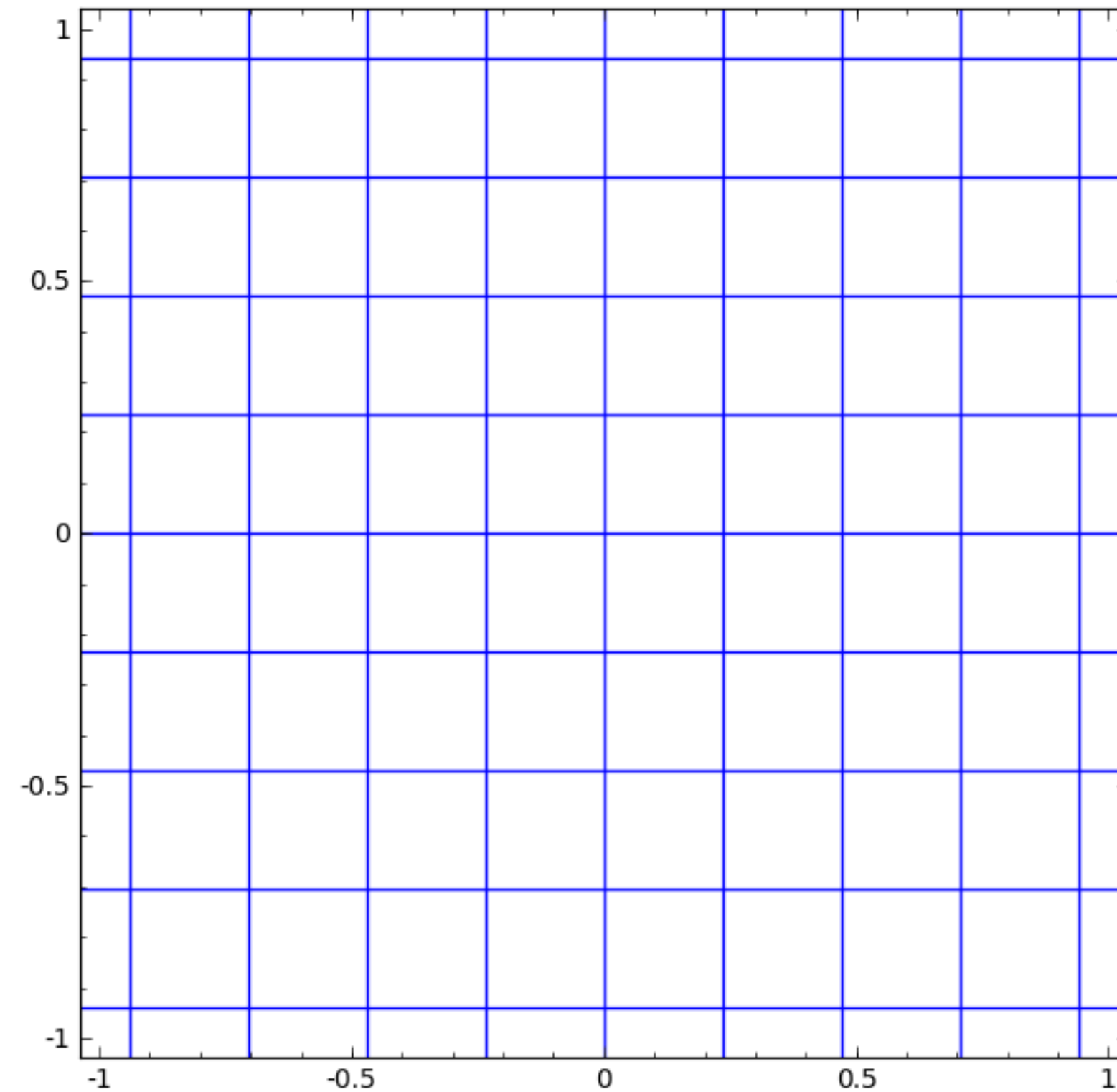
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Nonlinear transformation Warp space Shift

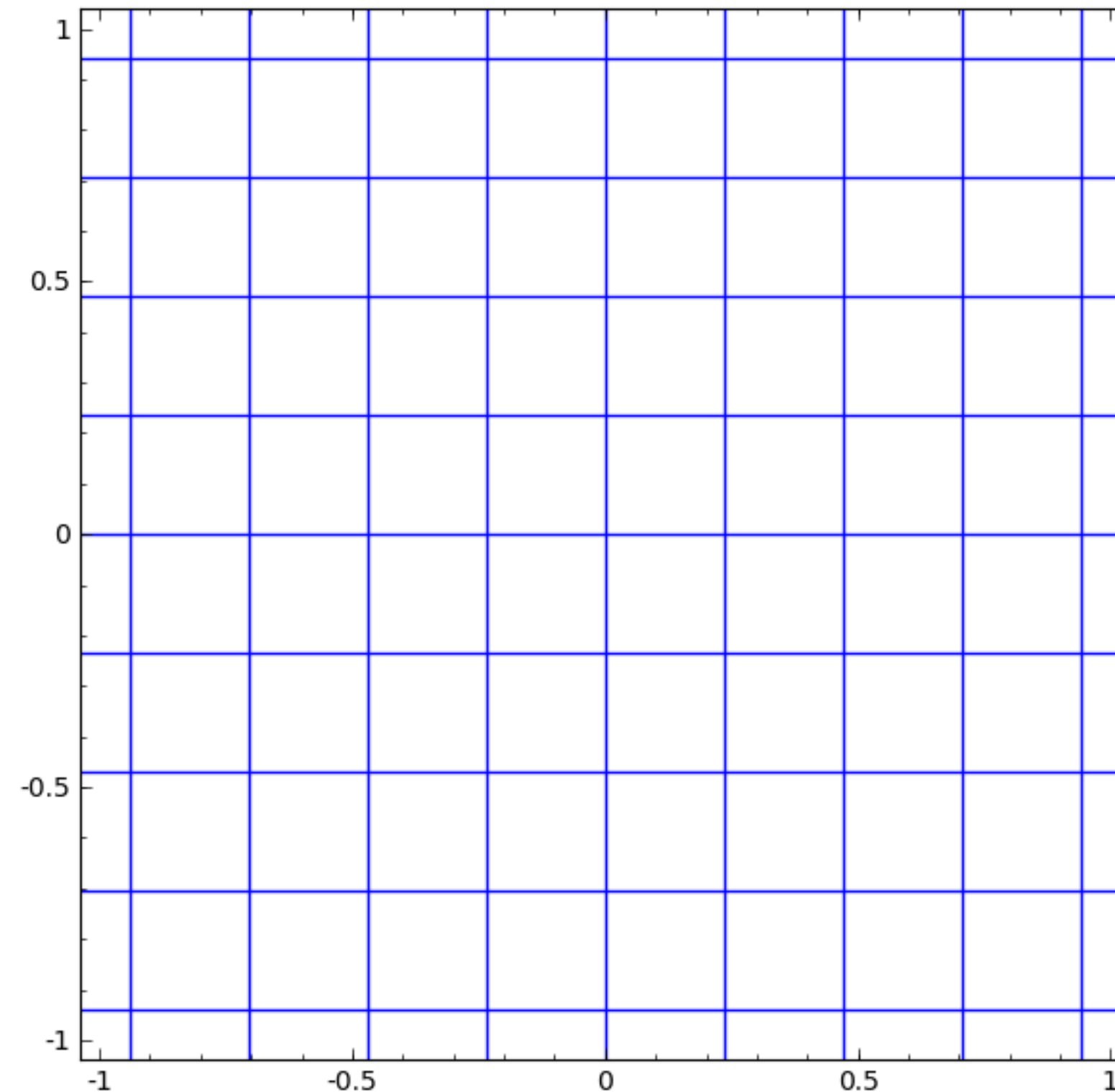
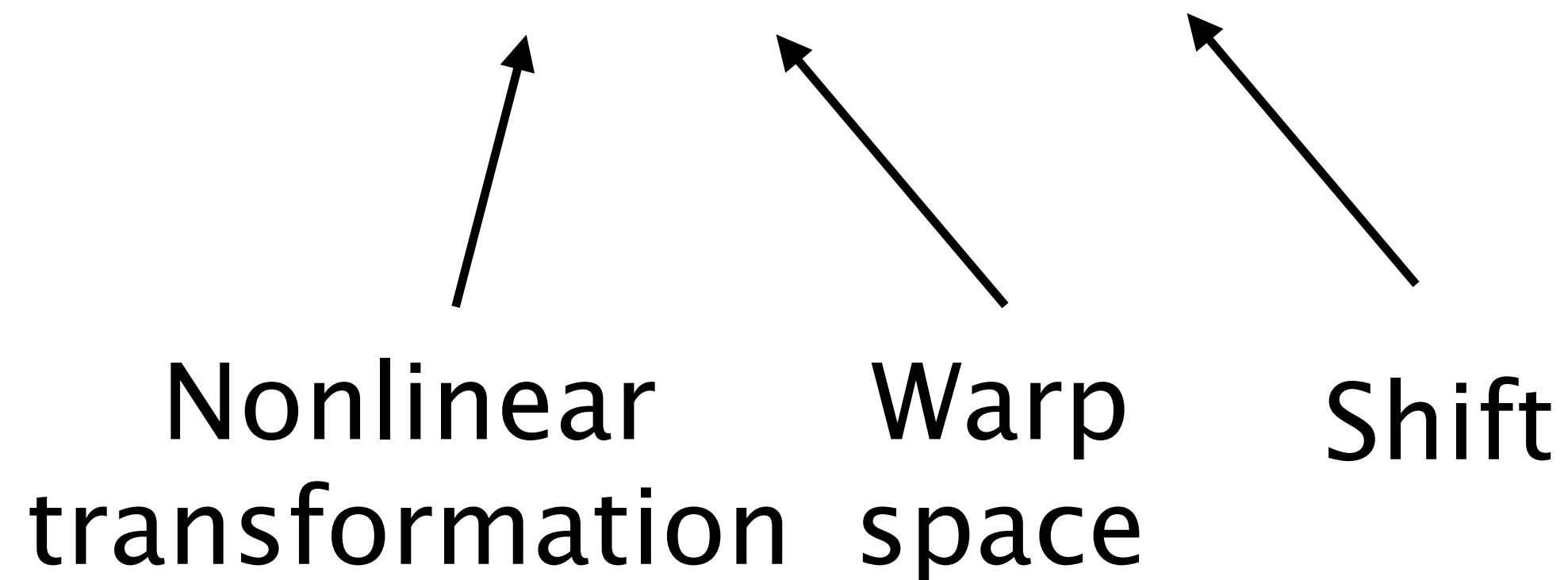


Neural Networks

Linear model: $y = \mathbf{w} \cdot \mathbf{x} + b$

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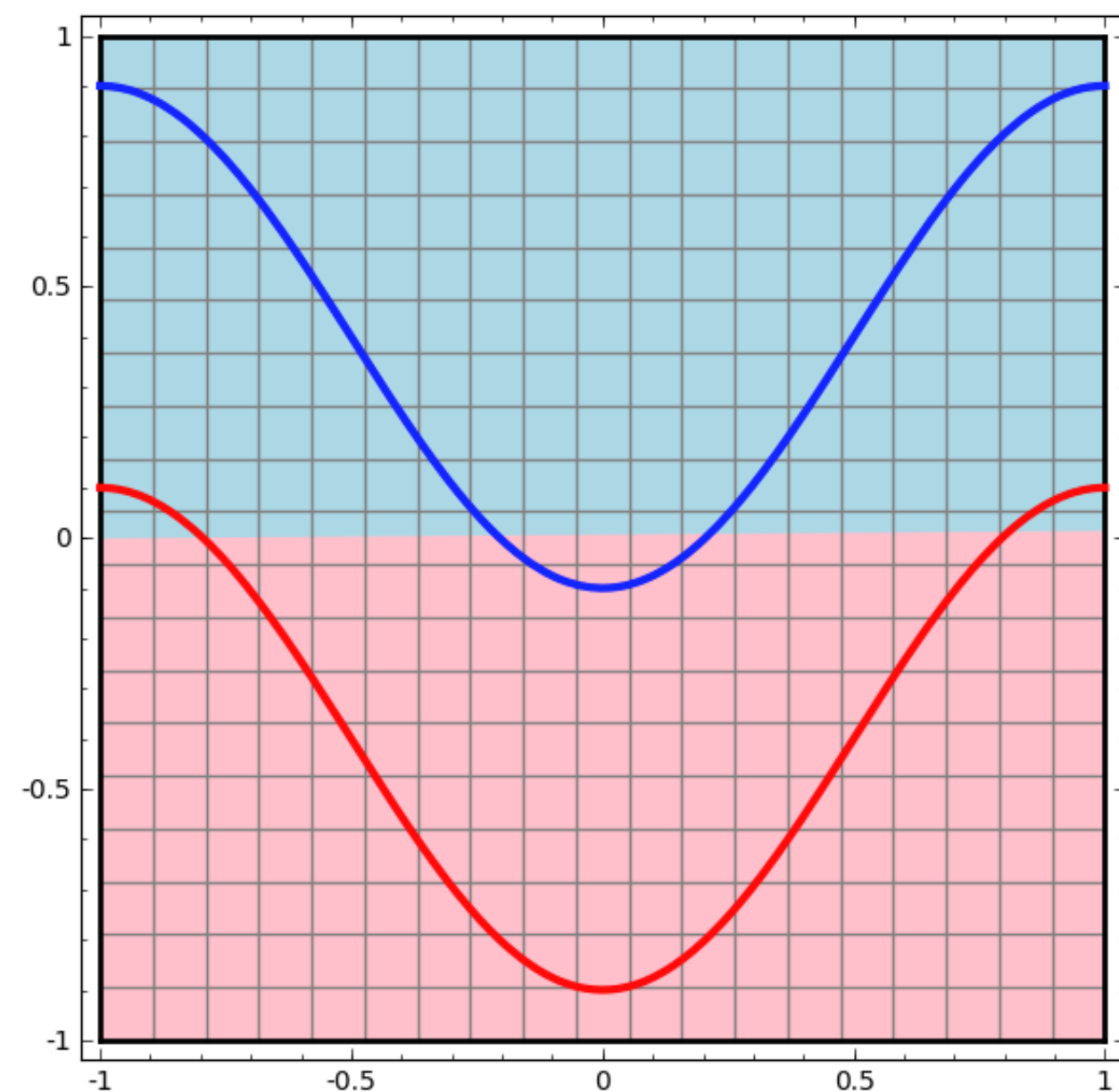
Neural Networks

Neural Networks

Taken from <http://colah.github.io/posts/2014-03-NN-Manifolds-Topology/>

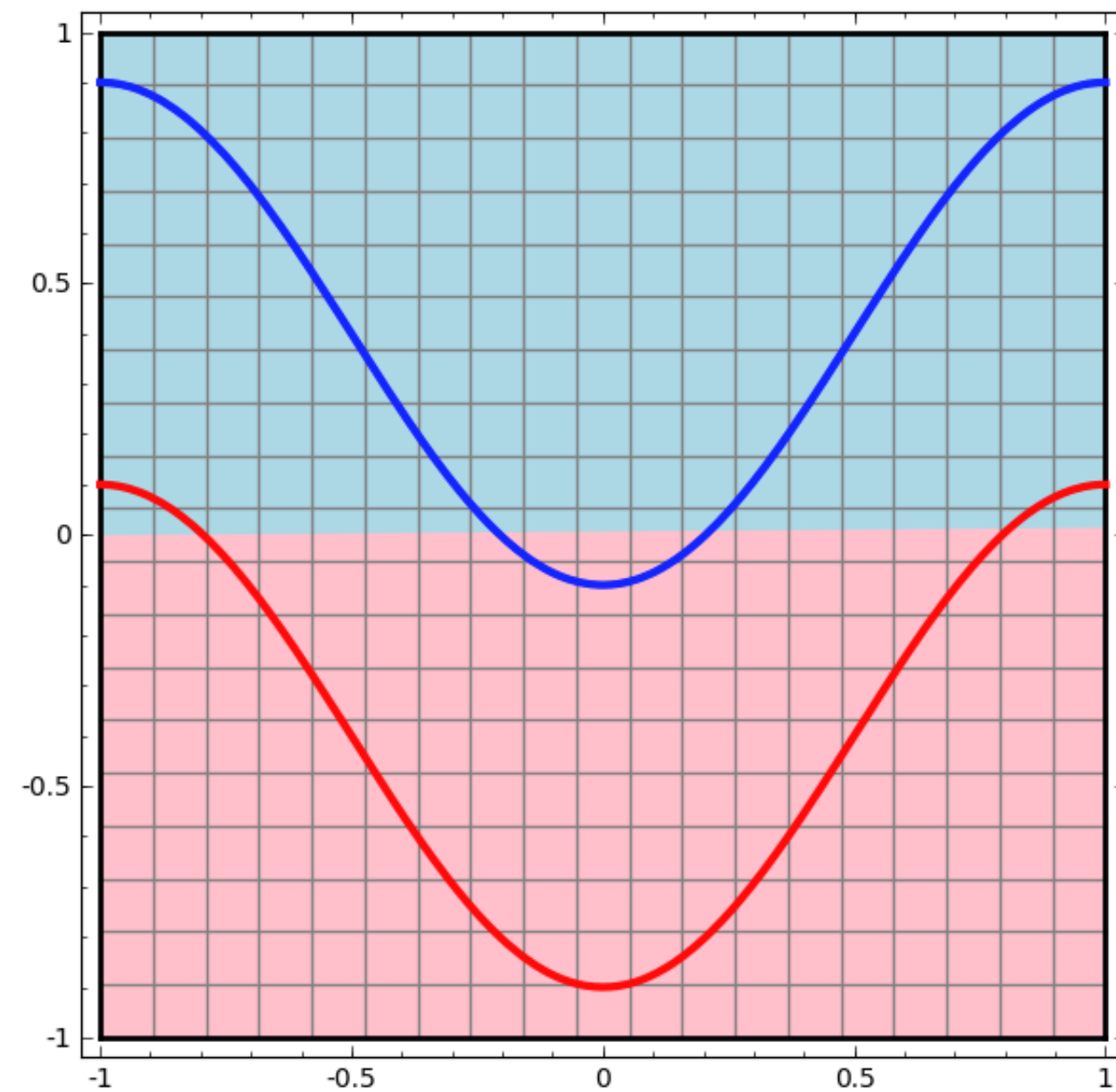
Neural Networks

Linear classifier

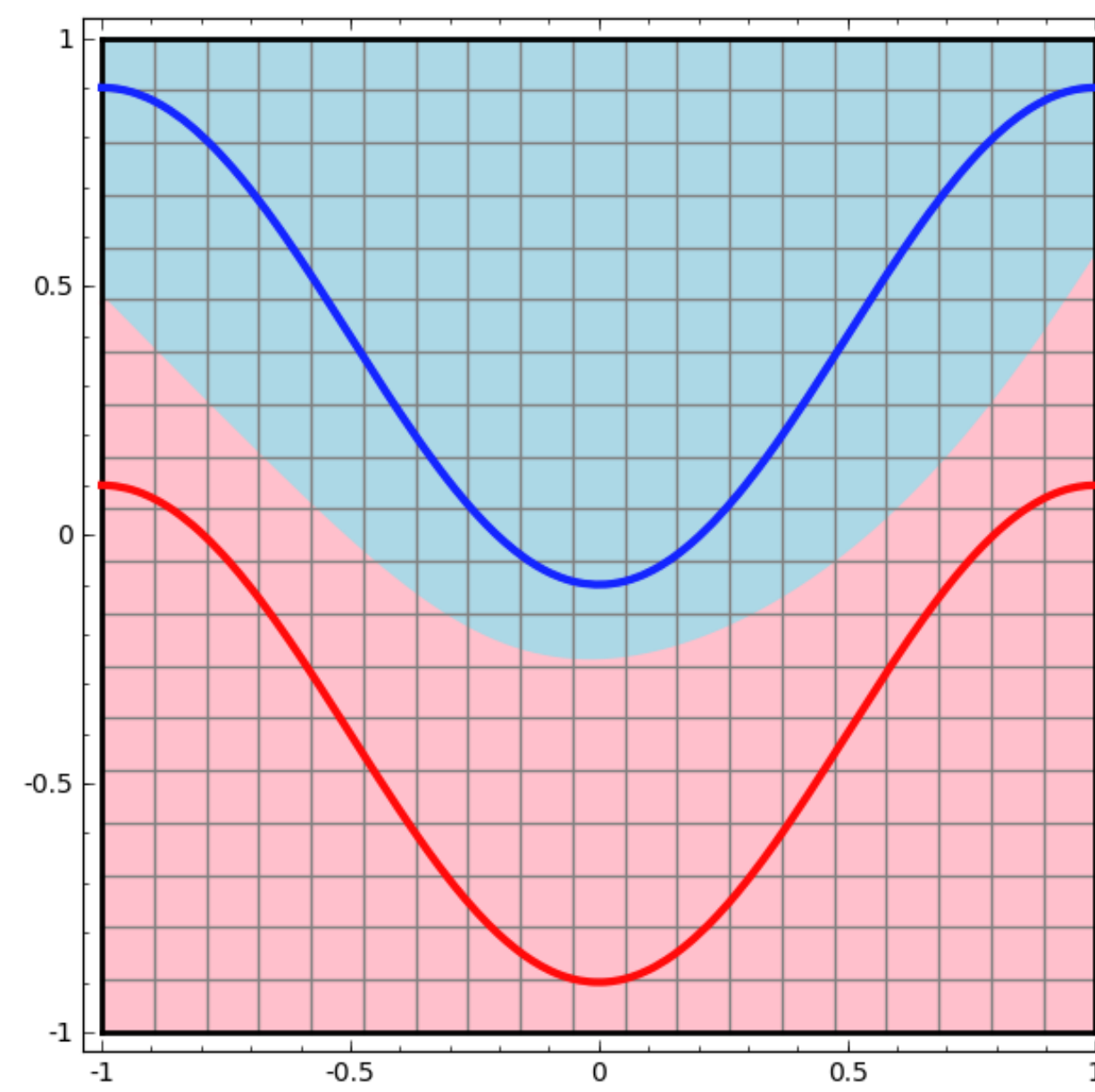


Neural Networks

Linear classifier

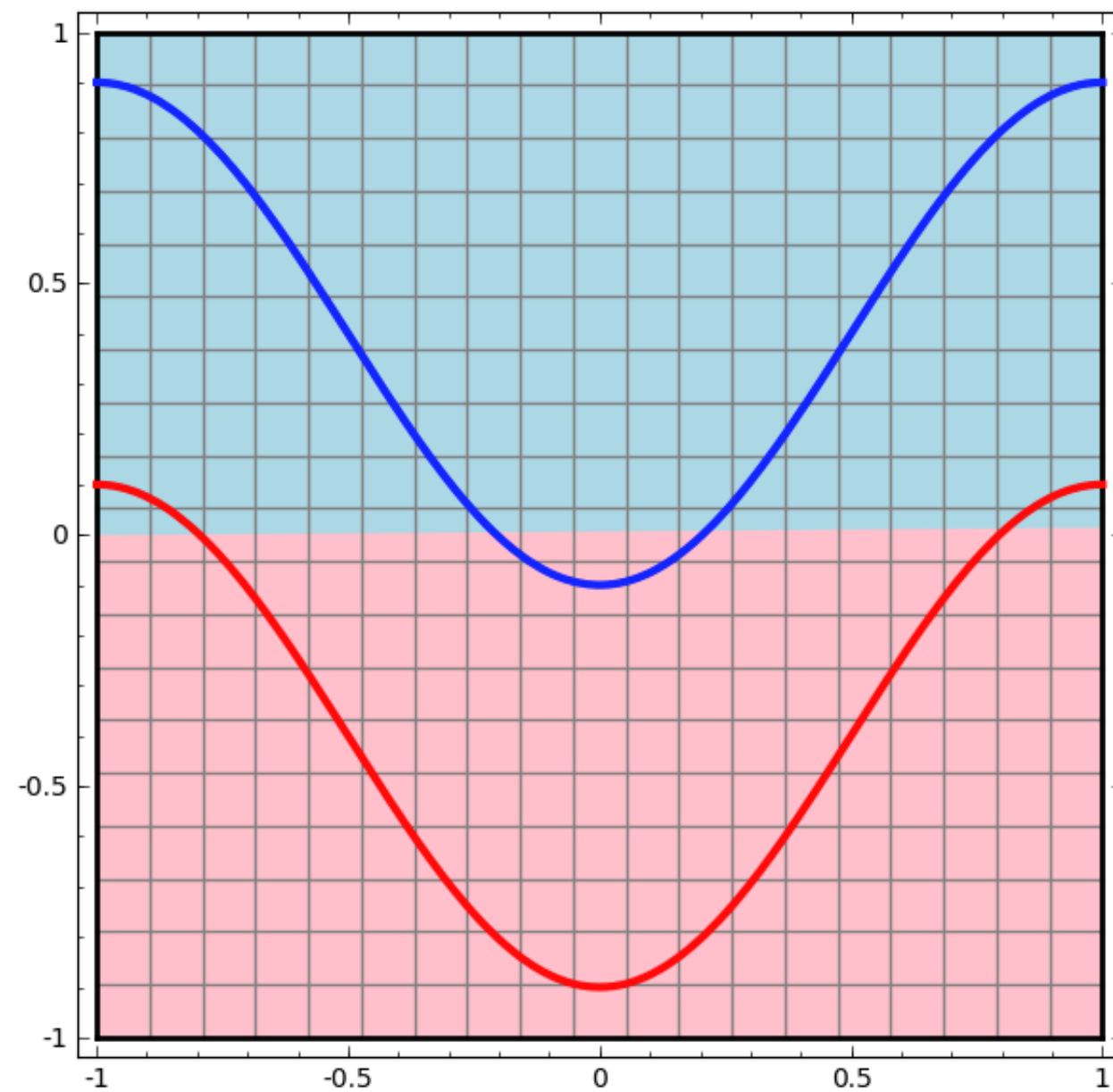


Neural network

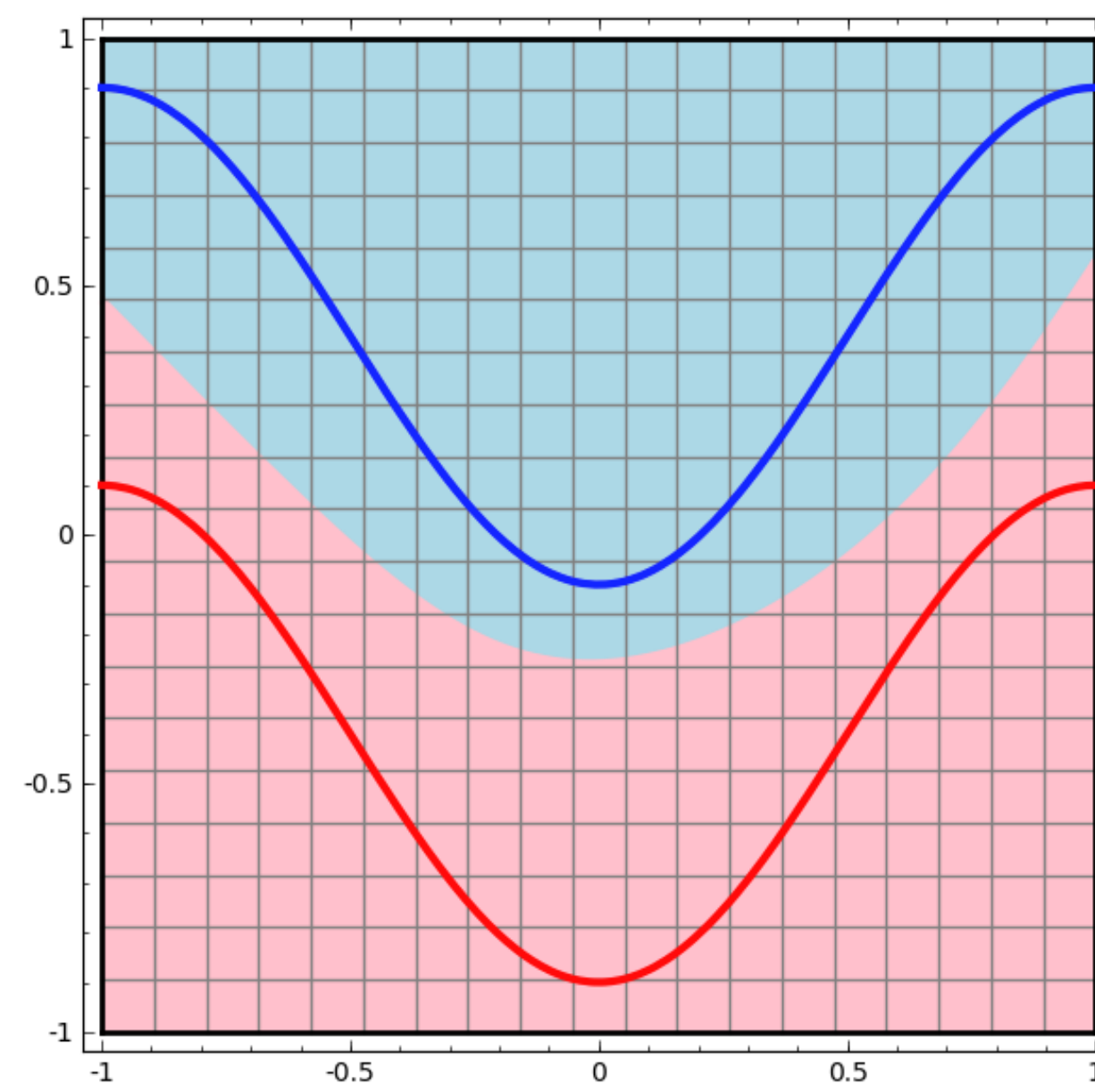


Neural Networks

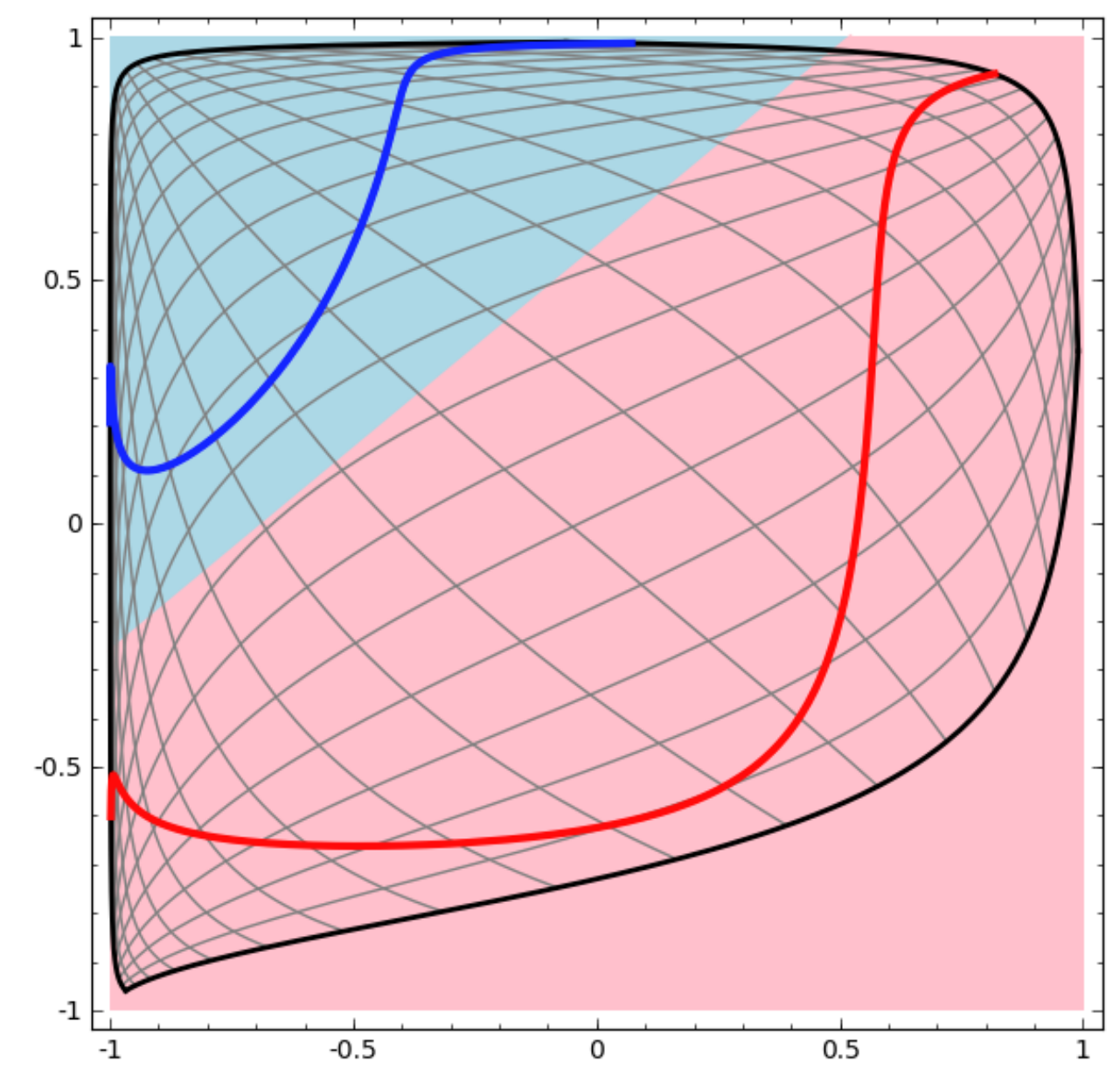
Linear classifier



Neural network

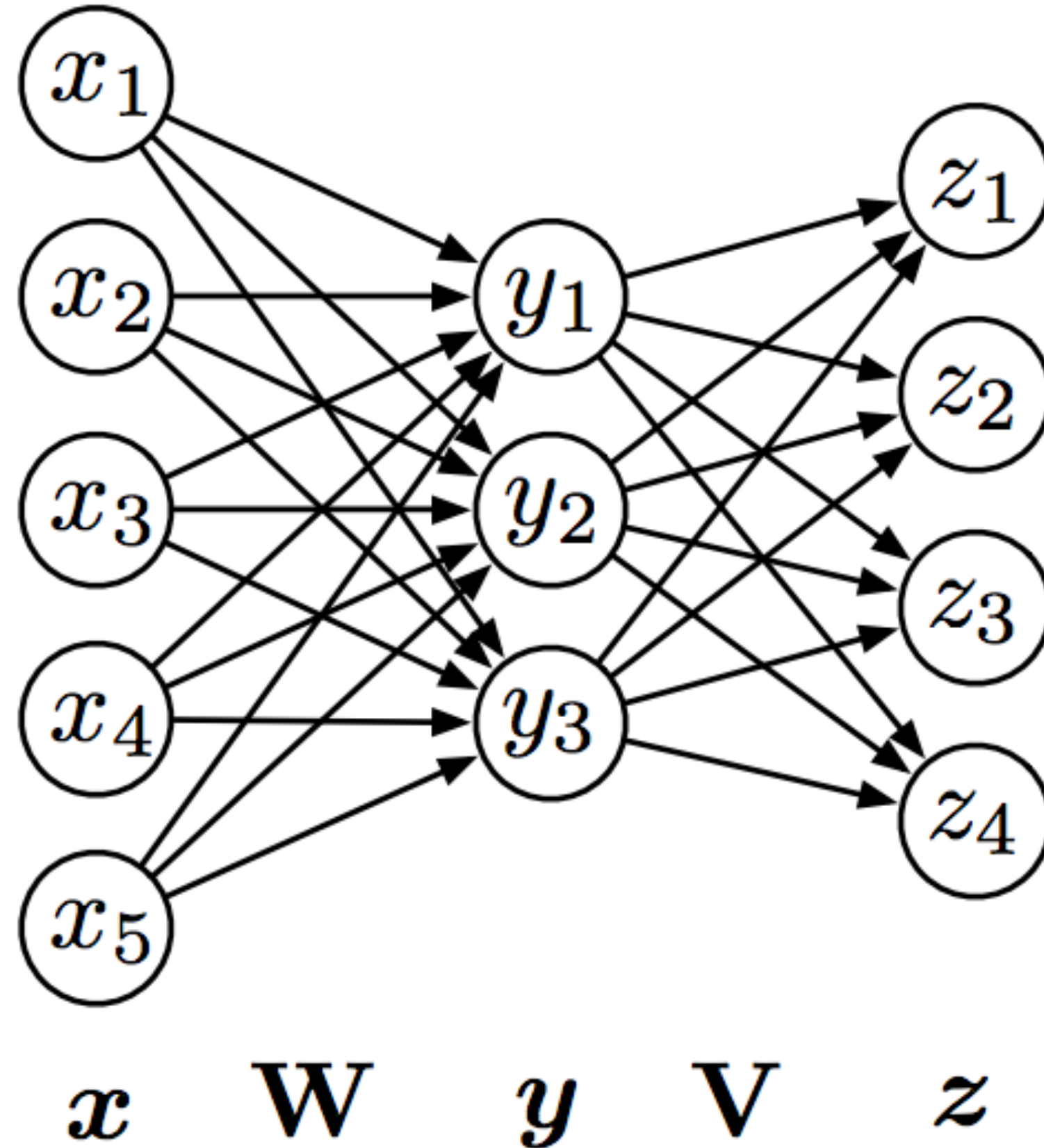


...possible because
we transformed the
space!



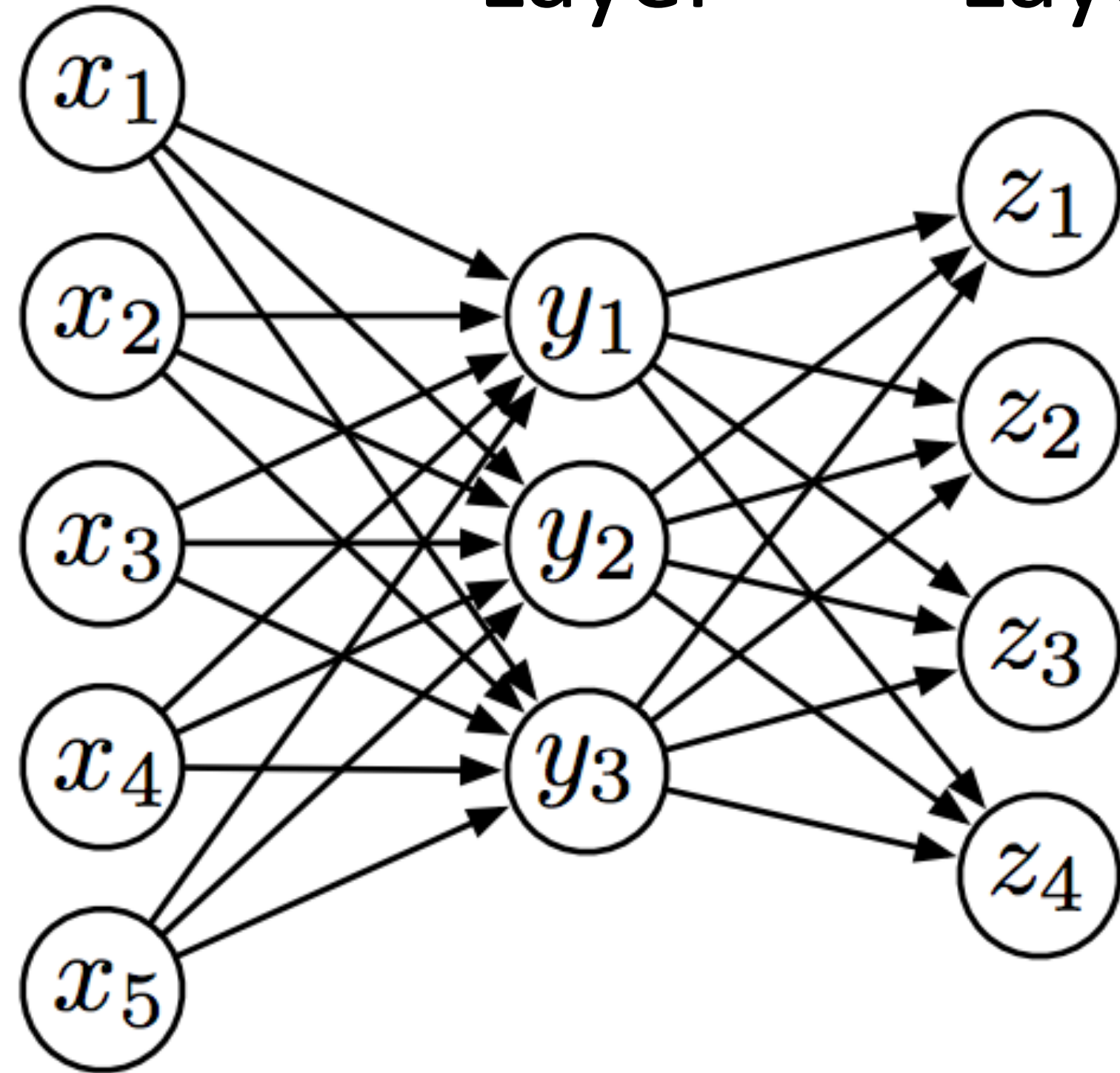
Deep Neural Networks

$$y = g(\mathbf{W}x + \mathbf{b})$$



Deep Neural Networks

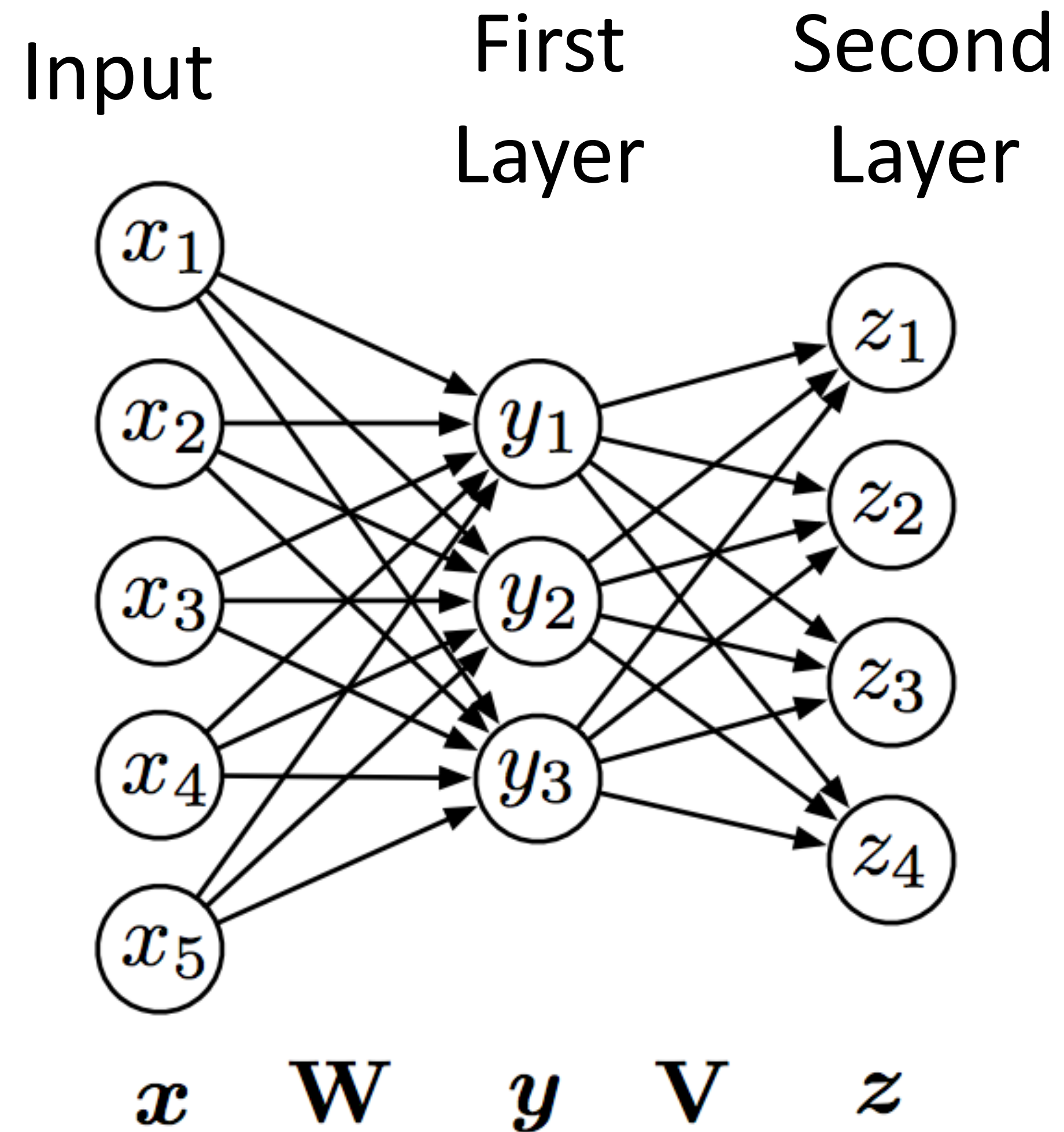
Input First Layer Second Layer



$$y = g(\mathbf{W}x + \mathbf{b})$$

x \mathbf{W} y \mathbf{V} z

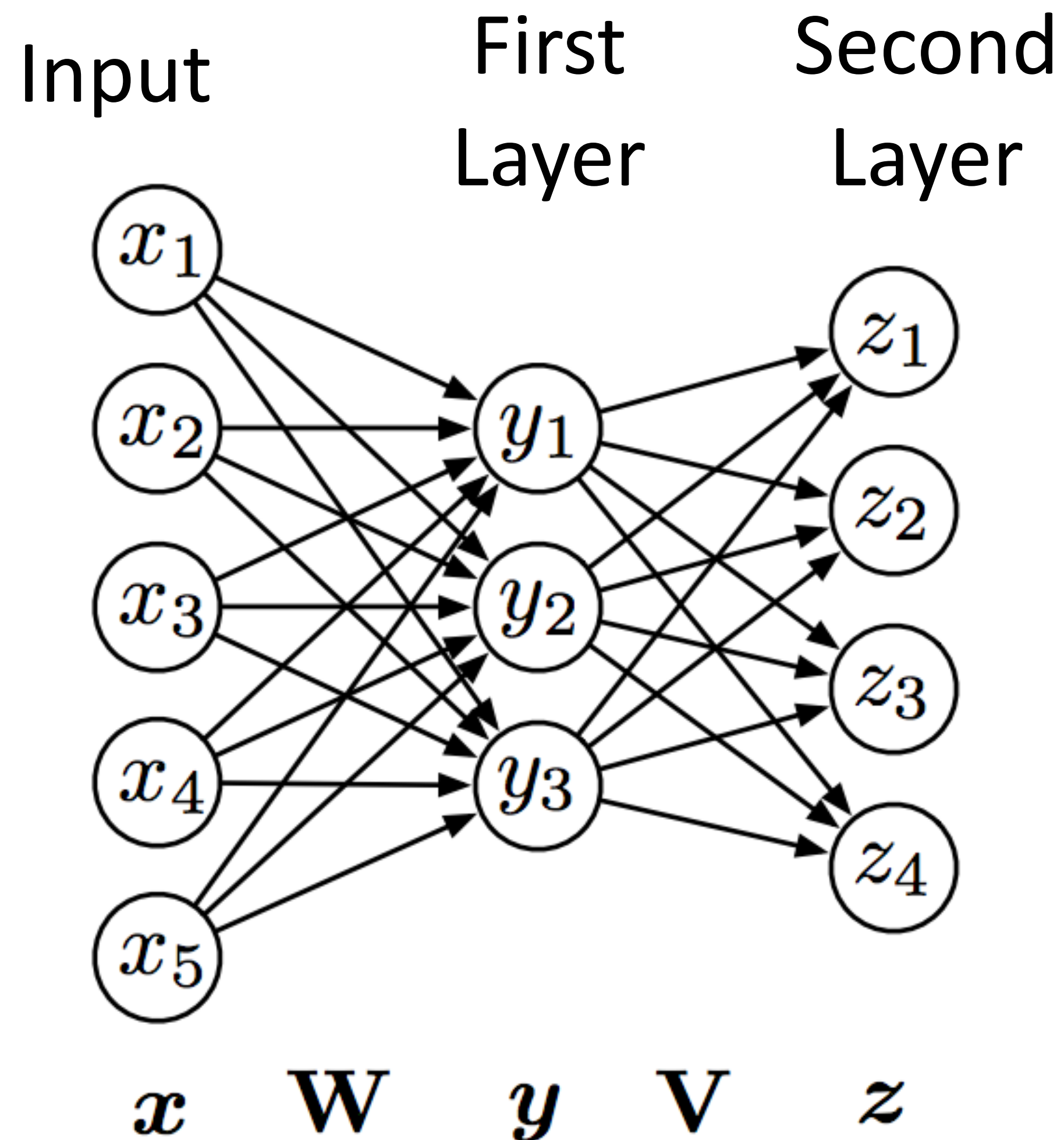
Deep Neural Networks



$$y = g(\mathbf{W}x + \mathbf{b})$$

$$z = g(\mathbf{V}y + \mathbf{c})$$

Deep Neural Networks



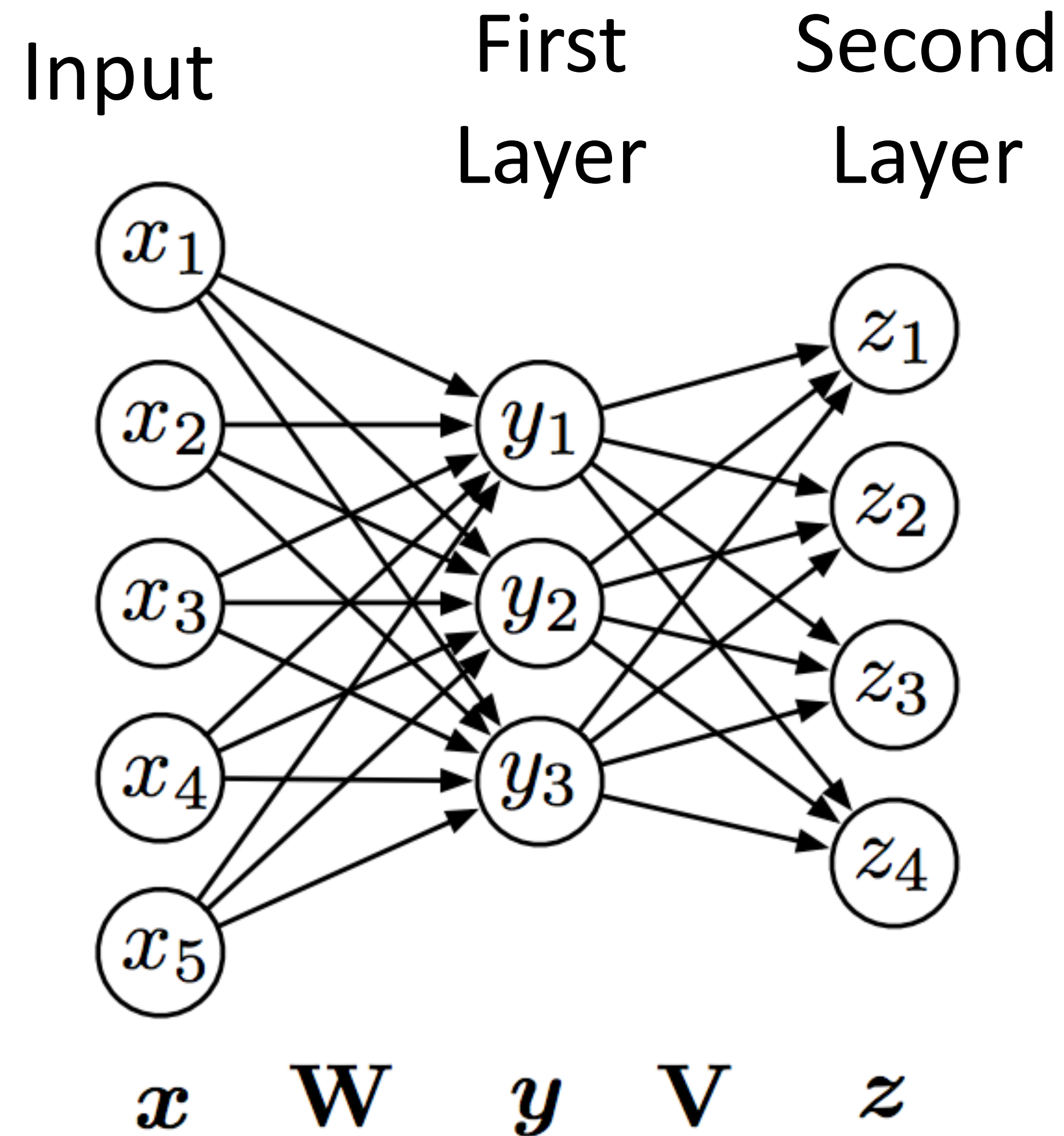
$$y = g(\mathbf{W}x + \mathbf{b})$$

$$z = g(\mathbf{V}y + \mathbf{c})$$

$$z = g(\mathbf{V} \underbrace{g(\mathbf{W}x + \mathbf{b})}_{\text{output of first layer}} + \mathbf{c})$$

output of first layer

Deep Neural Networks



$$y = g(\mathbf{W}x + \mathbf{b})$$

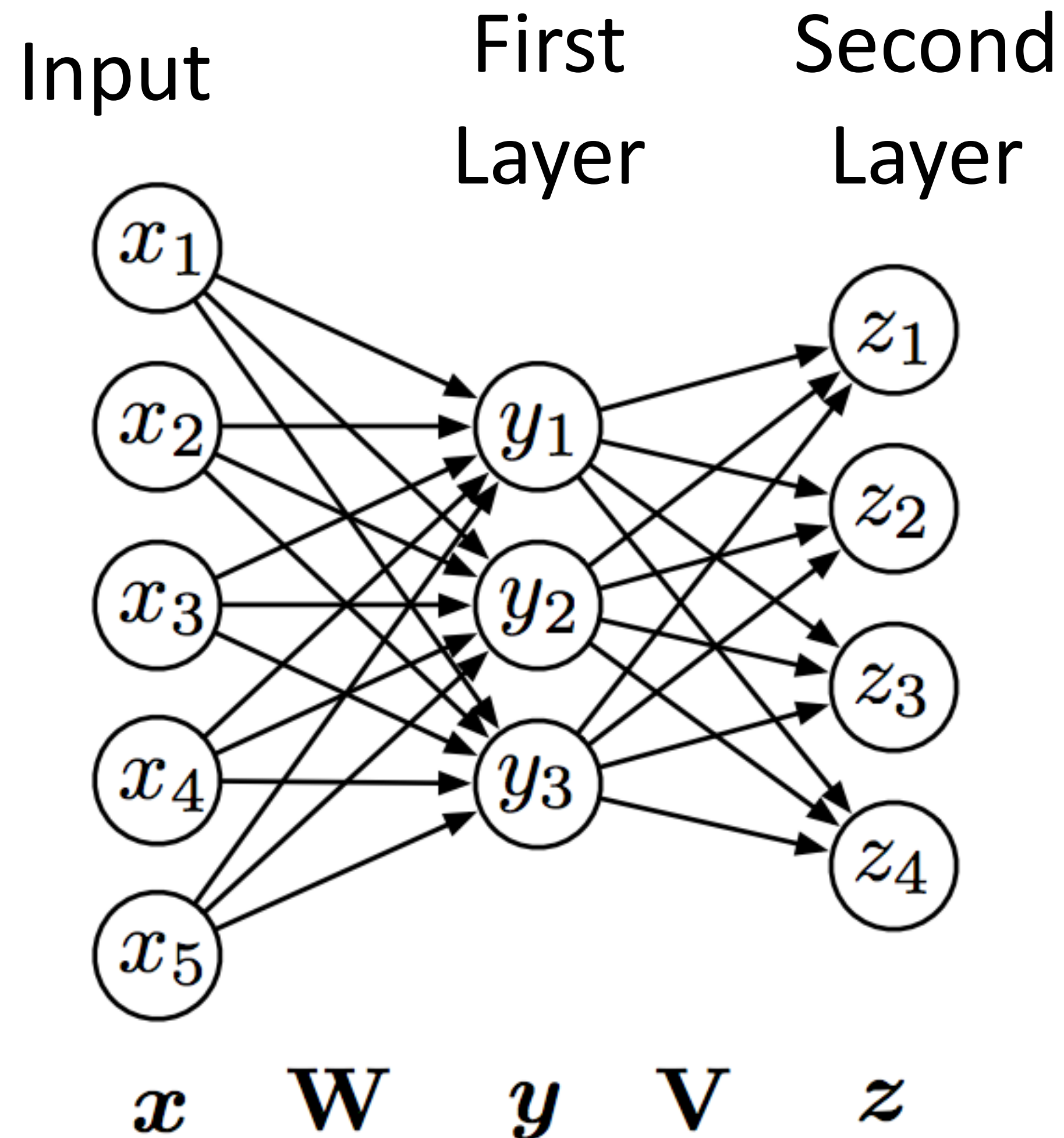
$$z = g(\mathbf{V}y + \mathbf{c})$$

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output of first layer

“Feedforward” computation (not recurrent)

Deep Neural Networks



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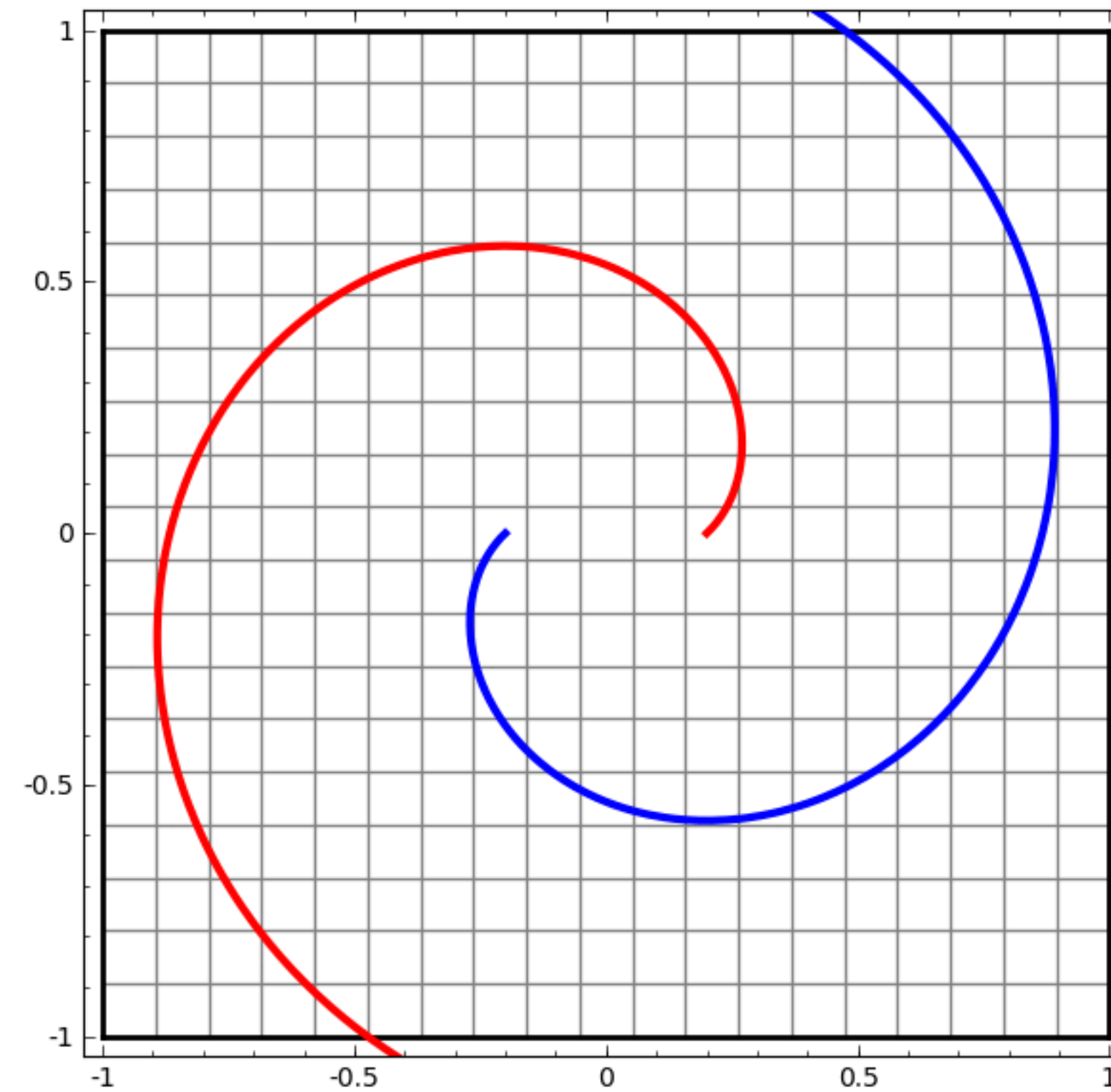
output of first layer

“Feedforward” computation (not recurrent)

Check: what happens if no nonlinearity?
More powerful than basic linear models?

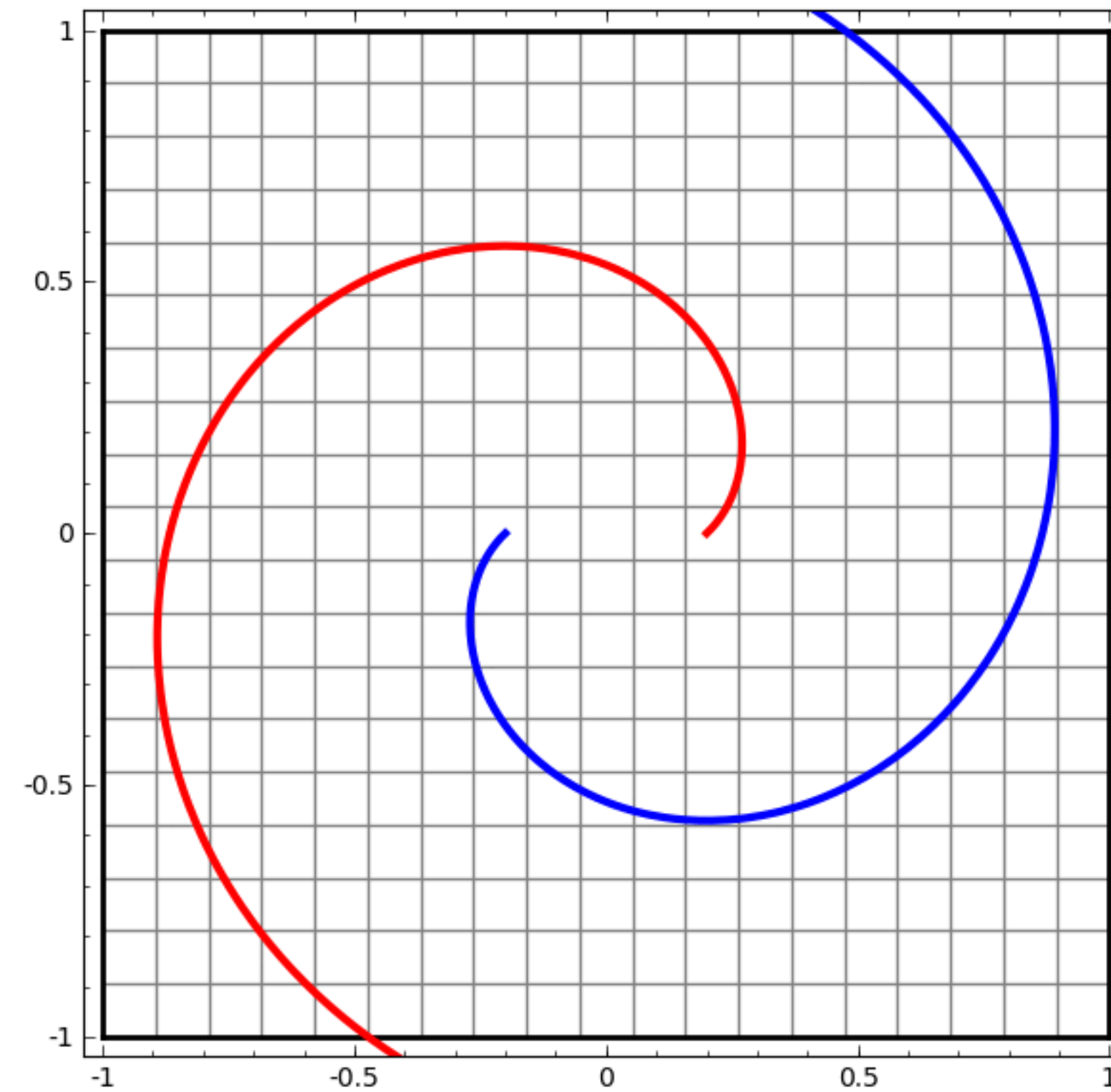
$$z = \mathbf{V}(\mathbf{W}x + \mathbf{b}) + \mathbf{c}$$

Deep Neural Networks



Taken from <http://colah.github.io/posts/2014-03-NN-Manifolds-Topology/>

Deep Neural Networks



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Feedforward Networks, Backpropagation

Logistic Regression with NNs

Logistic Regression with NNs

$$P(y|\mathbf{x}) = \frac{\exp(w^\top f(\mathbf{x}, y))}{\sum_{y'} \exp(w^\top f(\mathbf{x}, y'))}$$

- ▶ Single scalar probability

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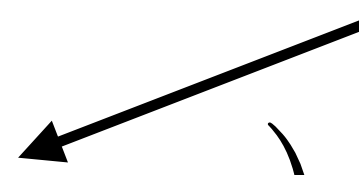
$$P(\mathbf{y}|\mathbf{x}) = \text{softmax}([w^\top f(\mathbf{x}, y)]_{y \in \mathcal{Y}})$$

▶ Compute scores for all possible labels at once (returns vector)

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- ▶ Weight vector per class; W is [num classes x num feats]

Logistic Regression with NNs

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$$P(\mathbf{y}|\mathbf{x}) = \text{softmax}(W g(V f(\mathbf{x})))$$

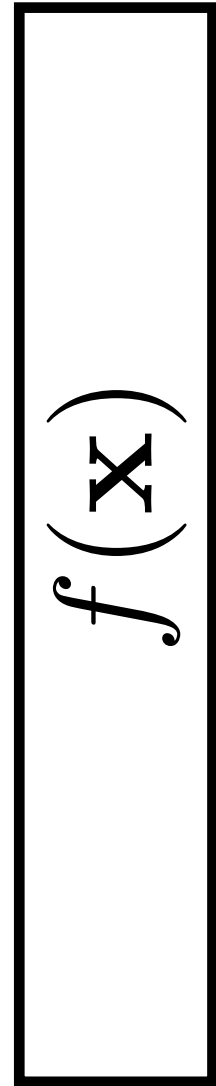
- ▶ Now one hidden layer

Neural Networks for Classification

$$P(\mathbf{y}|\mathbf{x}) = \text{softmax}(Wg(Vf(\mathbf{x})))$$

Neural Networks for Classification

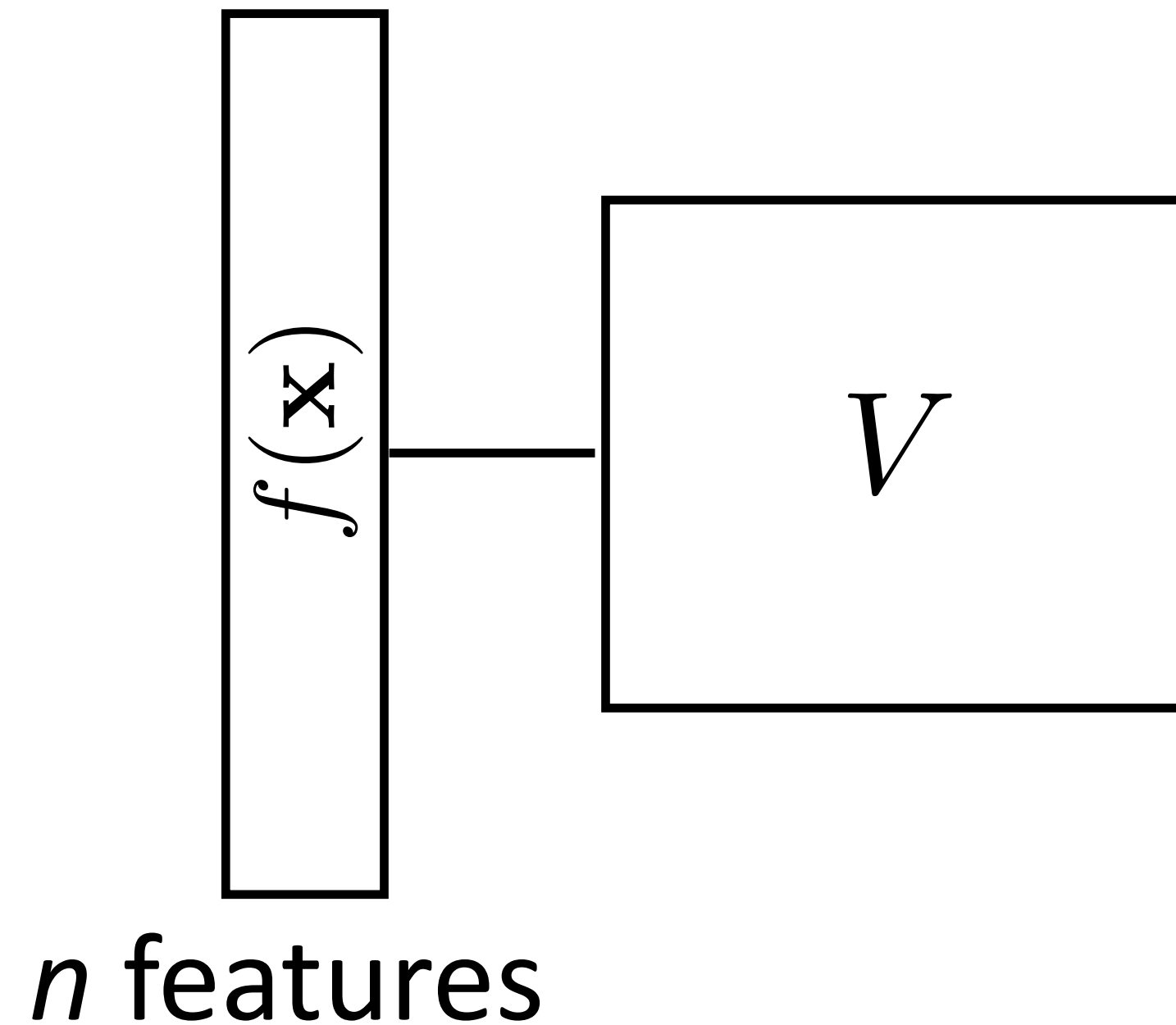
$$P(\mathbf{y}|\mathbf{x}) = \text{softmax}(Wg(Vf(\mathbf{x})))$$



n features

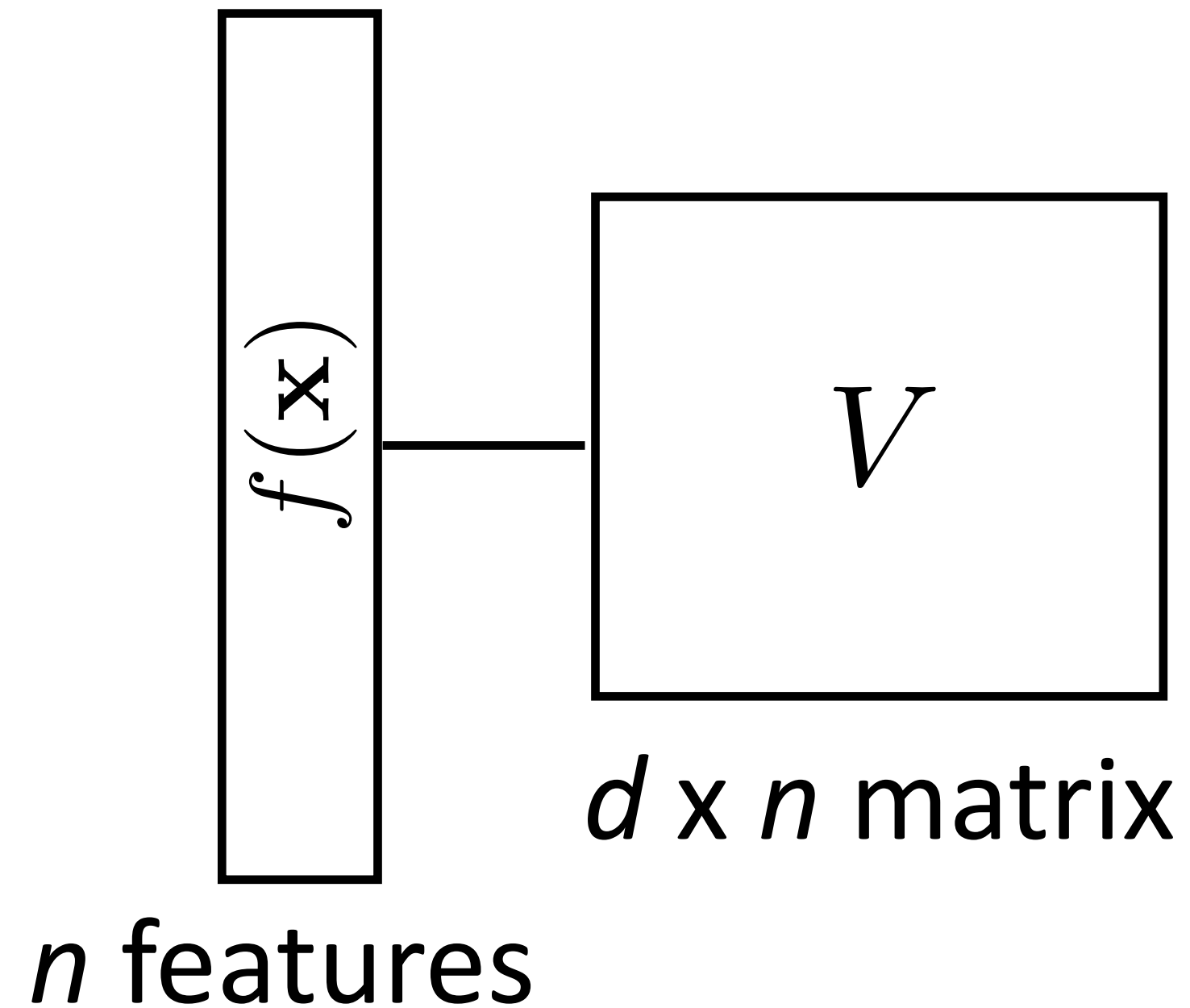
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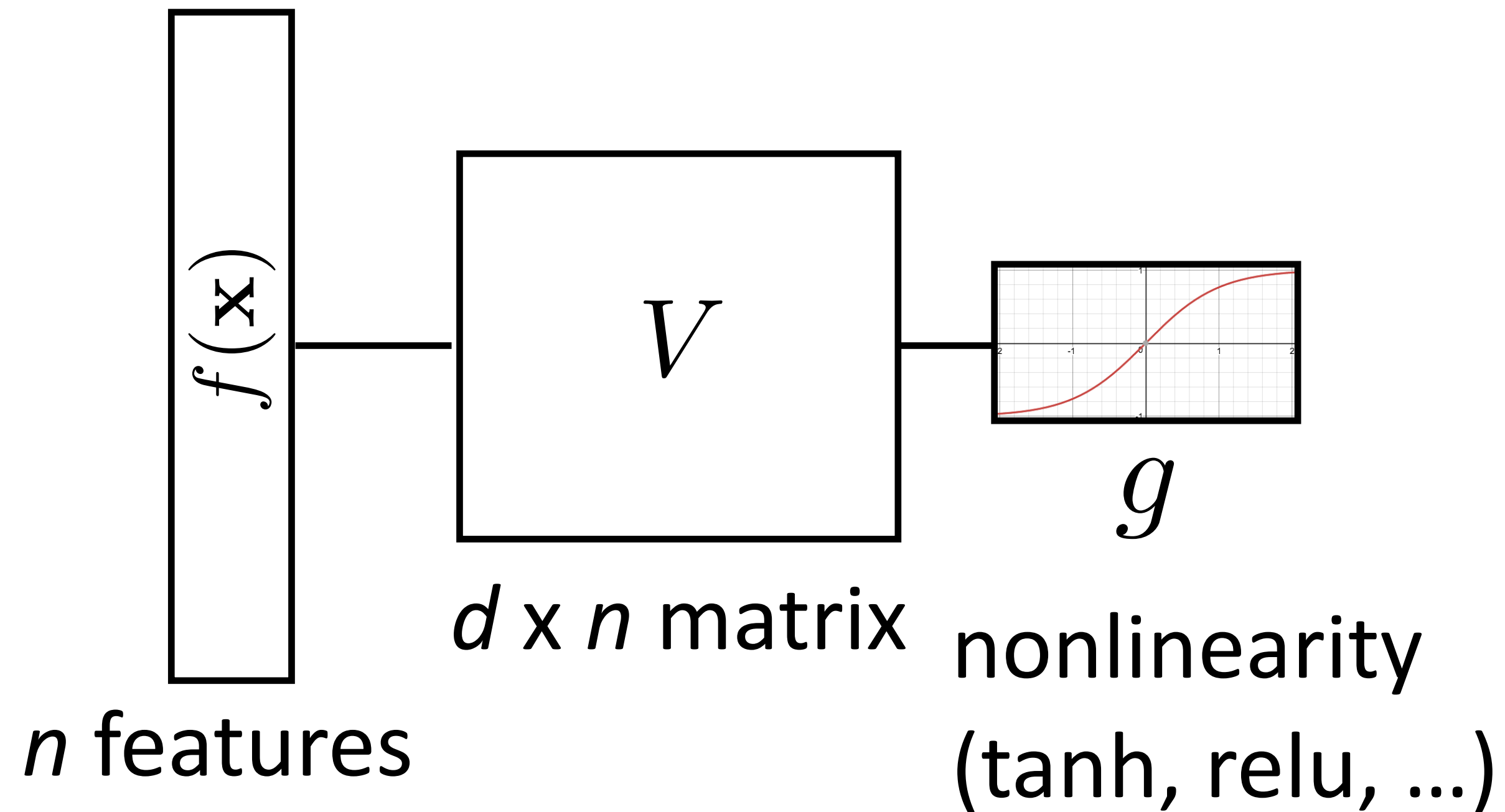
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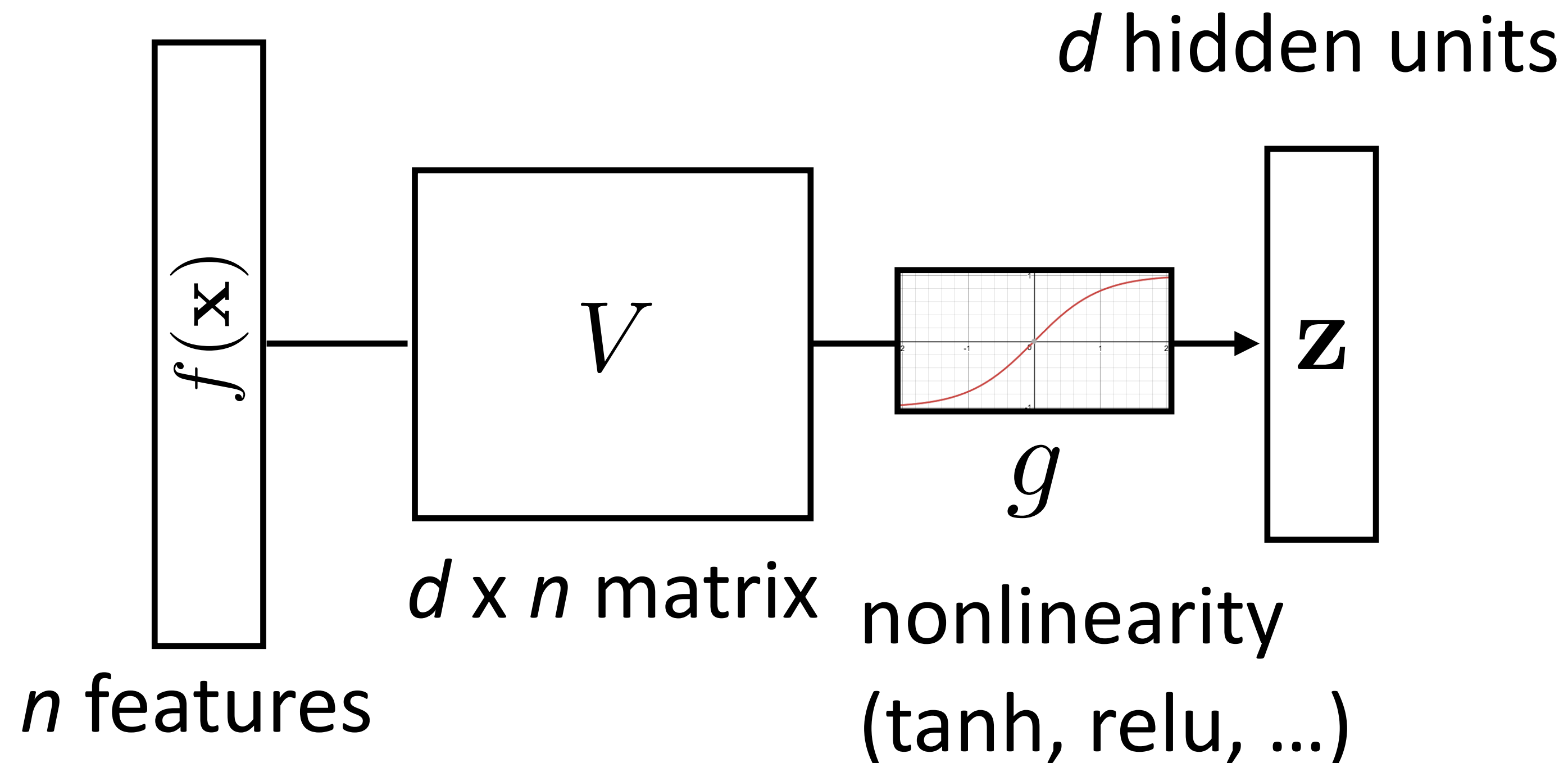
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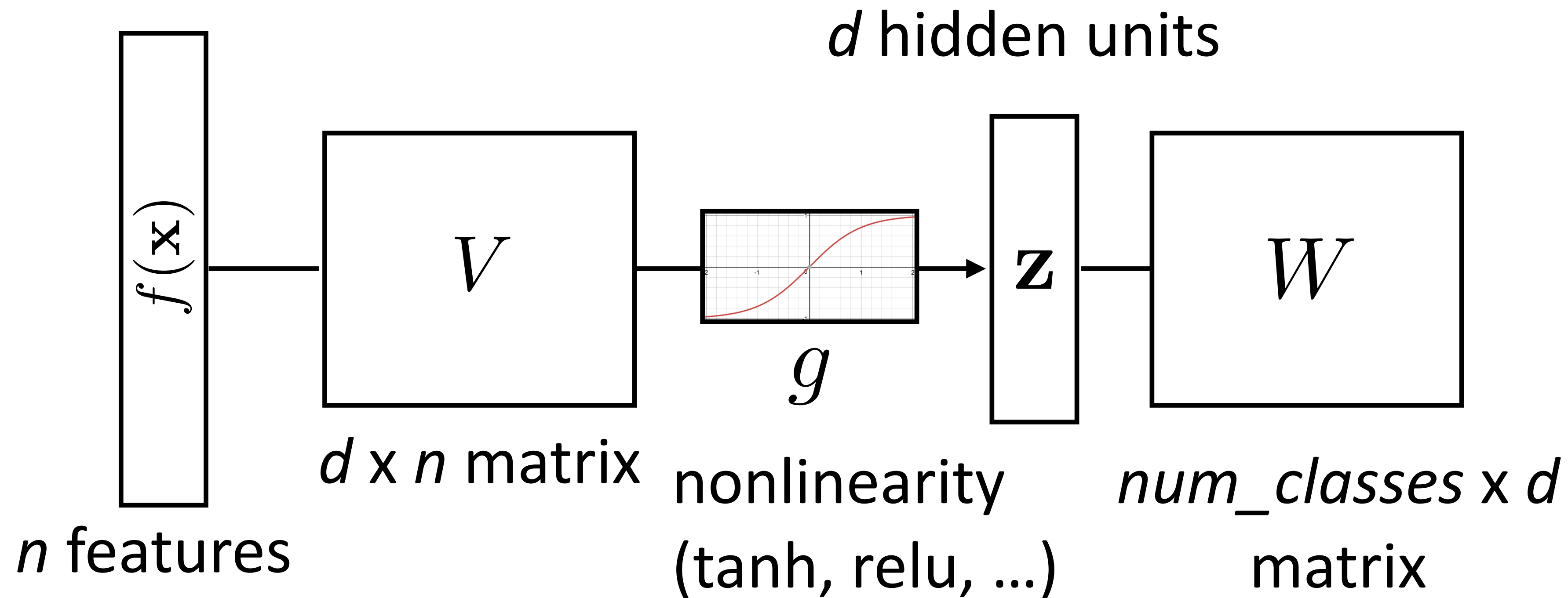
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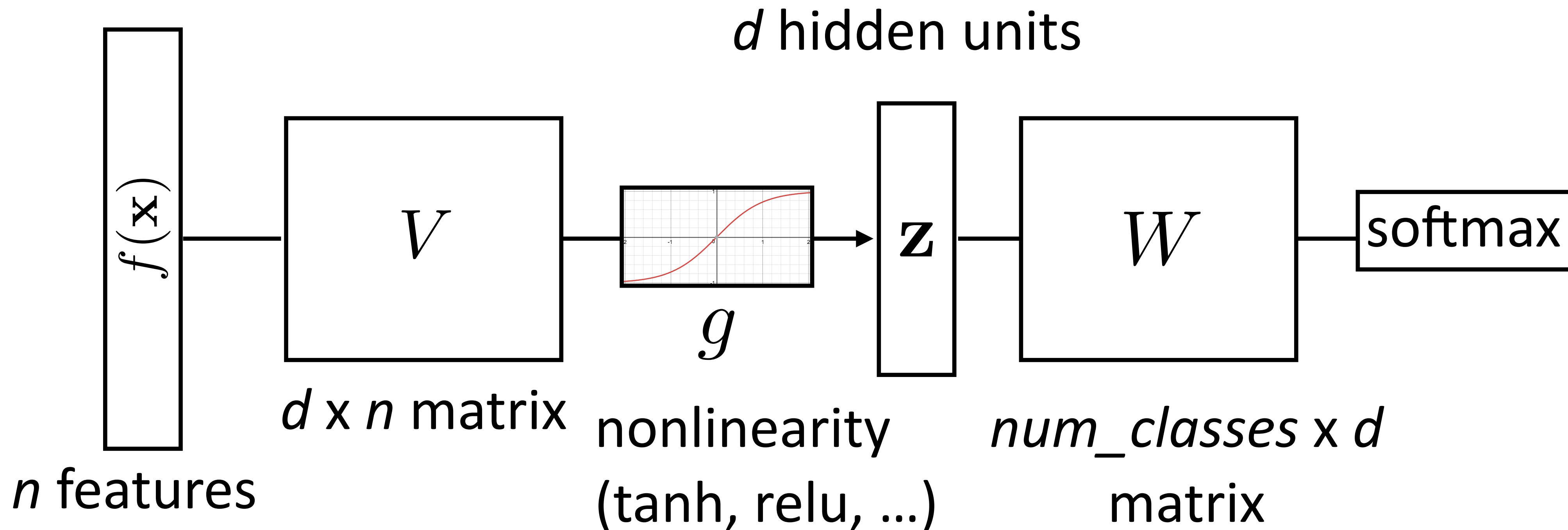
Neural Networks for Classification

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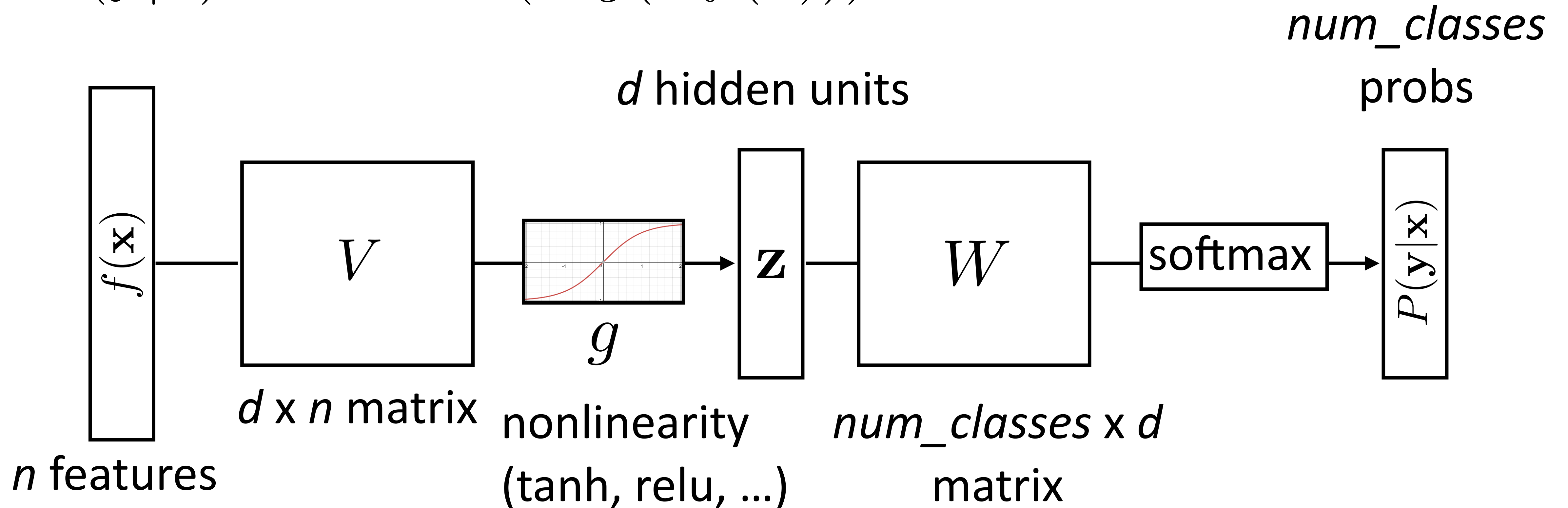
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Training Neural Networks

$$P(\mathbf{y}|\mathbf{x}) = \text{softmax}(W\mathbf{z}) \quad \mathbf{z} = g(Vf(\mathbf{x}))$$

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- ▶ Maximize log likelihood of training data

$$\mathcal{L}(\mathbf{x}, i^*) = \log P(y = i^* | \mathbf{x}) = \log (\text{softmax}(W\mathbf{z}) \cdot e_{i^*})$$

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- ▶ e_i : 1 in the i th row, zero elsewhere. Dot by this = select i th index

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$$\mathcal{L}(\mathbf{x}, i^*) = W\mathbf{z} \cdot e_{i^*} - \log \sum_j \exp(W\mathbf{z}) \cdot e_j$$

Computing Gradients

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- ▶ Gradient with respect to W

Computing Gradients

$$\mathcal{L}(\mathbf{x}, i^*) = W\mathbf{z} \cdot e_{i^*} - \log \sum_j \exp(W\mathbf{z}) \cdot e_j$$

- ▶ Gradient with respect to W

$$\frac{\partial}{\partial W_{ij}} \mathcal{L}(\mathbf{x}, i^*) = \begin{cases} \mathbf{z}_j - P(y = i|\mathbf{x})\mathbf{z}_j & \text{if } i = i^* \\ -P(y = i|\mathbf{x})\mathbf{z}_j & \text{otherwise} \end{cases}$$

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$$\mathcal{L}(\mathbf{x}, i^*) = W\mathbf{z} \cdot e_{i^*} - \log \sum_j \exp(W\mathbf{z}) \cdot e_j$$

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W j

i

$\mathbf{z}_j - P(y = i \mathbf{x})\mathbf{z}_j$
$-P(y = i \mathbf{x})\mathbf{z}_j$

Computing Gradients

$$\mathcal{L}(\mathbf{x}, i^*) = W\mathbf{z} \cdot e_{i^*} - \log \sum_j \exp(W\mathbf{z}) \cdot e_j$$

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W j

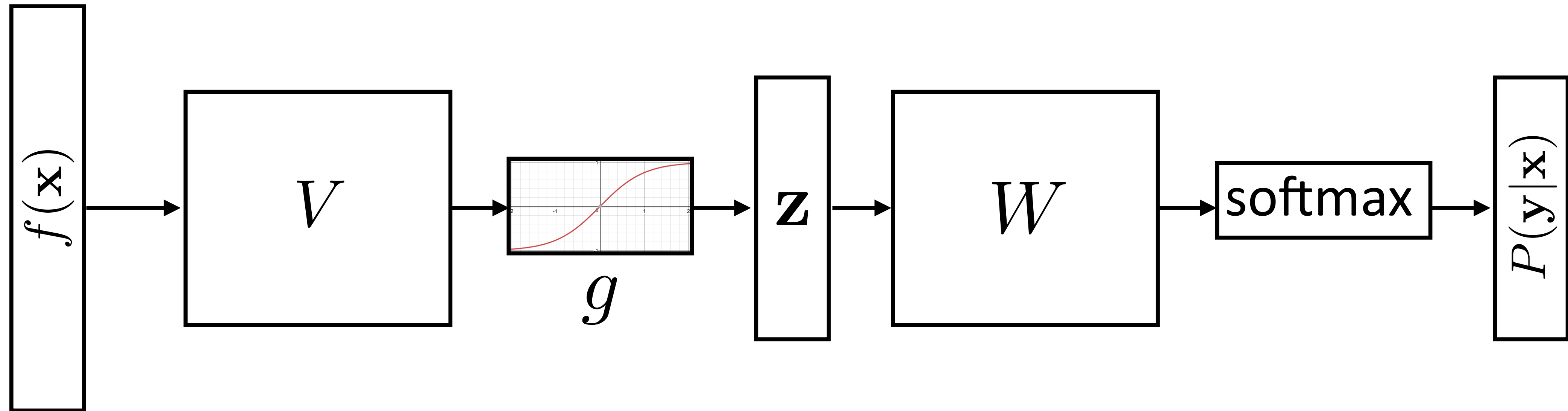
i

$\mathbf{z}_j - P(y = i \mathbf{x})\mathbf{z}_j$
$-P(y = i \mathbf{x})\mathbf{z}_j$

- ▶ Looks like logistic regression with \mathbf{z} as the features!

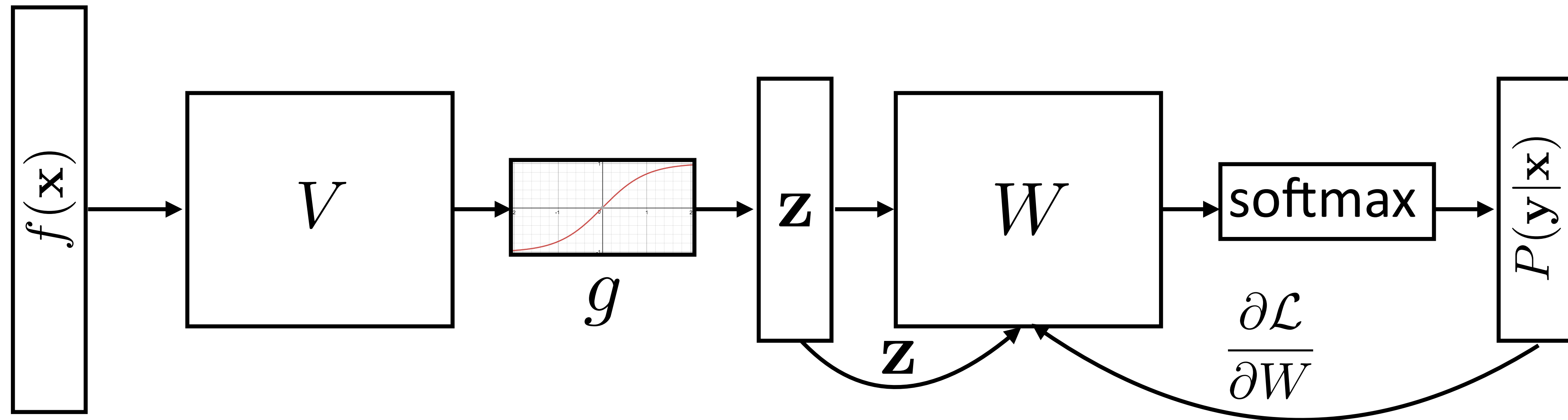
Neural Networks for Classification

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Computing Gradients: Backpropagation

$$\mathcal{L}(\mathbf{x}, i^*) = W\mathbf{z} \cdot e_{i^*} - \log \sum_j \exp(W\mathbf{z}) \cdot e_j$$

$\mathbf{z} = g(Vf(\mathbf{x}))$
Activations at
hidden layer

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Activations at hidden layer

- ▶ Gradient with respect to V : apply the chain rule

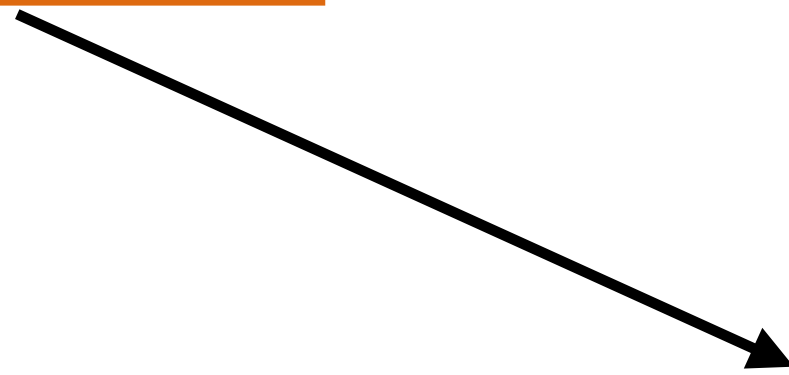
$$\frac{\partial \mathcal{L}(\mathbf{x}, i^*)}{\partial V_{ij}} = \frac{\partial \mathcal{L}(\mathbf{x}, i^*)}{\partial \mathbf{z}} \frac{\partial \mathbf{z}}{\partial V_{ij}}$$

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Activations at
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$$\frac{\partial \mathcal{L}(\mathbf{x}, i^*)}{\partial V_{ij}} = \boxed{\frac{\partial \mathcal{L}(\mathbf{x}, i^*)}{\partial \mathbf{z}}} \frac{\partial \mathbf{z}}{\partial V_{ij}}$$


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$$\frac{\partial \mathcal{L}(\mathbf{x}, i^*)}{\partial V_{ij}} = \boxed{\frac{\partial \mathcal{L}(\mathbf{x}, i^*)}{\partial \mathbf{z}}} \frac{\partial \mathbf{z}}{\partial V_{ij}}$$

$err(\text{root}) = e_{i^*} - P(\mathbf{y}|\mathbf{x})$
dim = num_classes

Computing Gradients: Backpropagation

$$\mathcal{L}(\mathbf{x}, i^*) = W\mathbf{z} \cdot e_{i^*} - \log \sum_j \exp(W\mathbf{z}) \cdot e_j \quad \mathbf{z} = g(Vf(\mathbf{x}))$$

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[some math...]

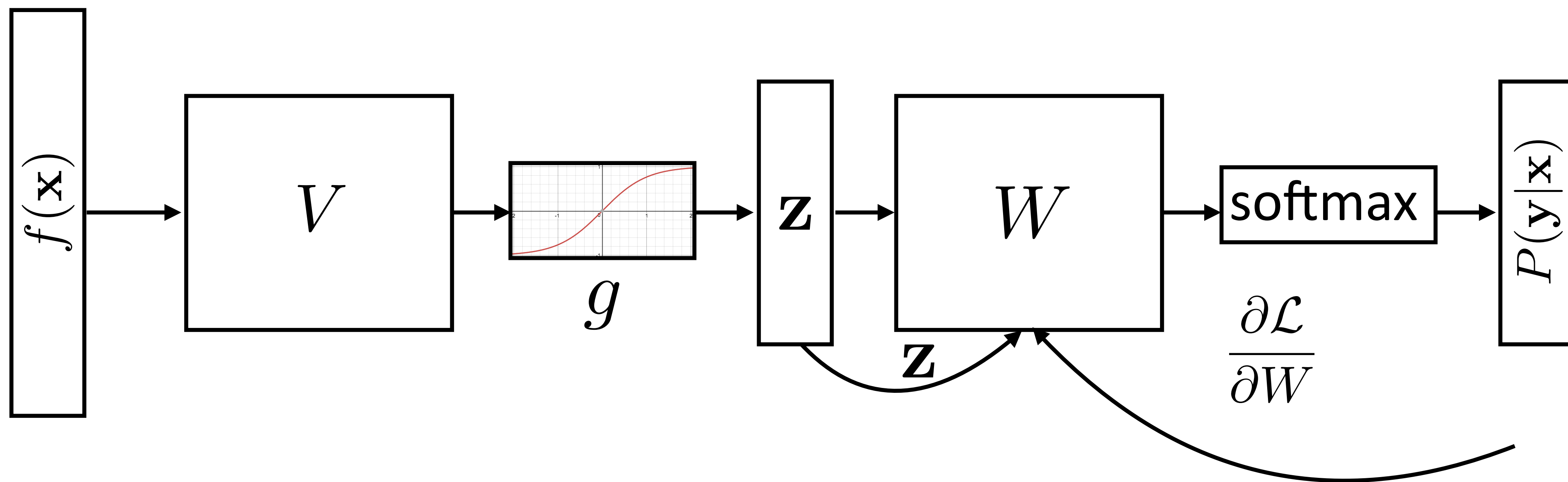
$$\begin{aligned} err(\text{root}) &= e_{i^*} - P(\mathbf{y}|\mathbf{x}) \\ \text{dim} &= \text{num_classes} \end{aligned}$$

$$\boxed{\frac{\partial \mathcal{L}(\mathbf{x}, i^*)}{\partial \mathbf{z}} = err(\mathbf{z}) = W^\top err(\text{root})}$$

dim = d

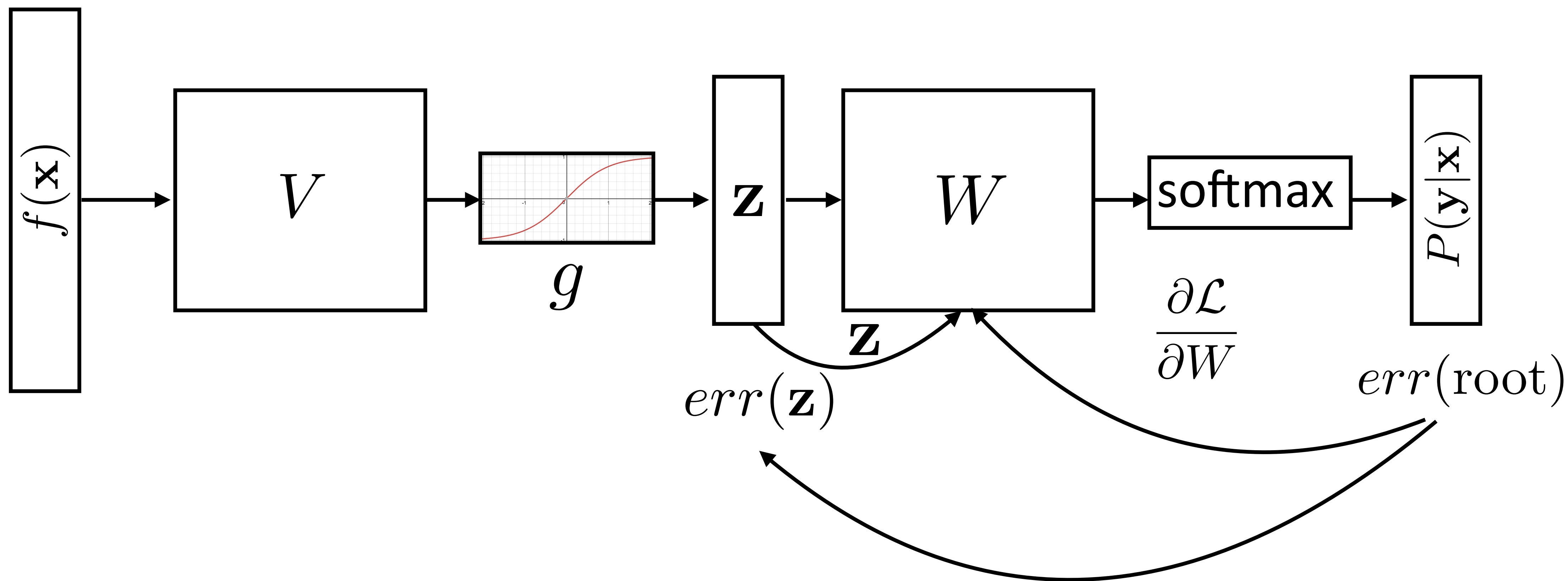
Backpropagation: Picture

$$P(\mathbf{y}|\mathbf{x}) = \text{softmax}(Wg(Vf(\mathbf{x})))$$



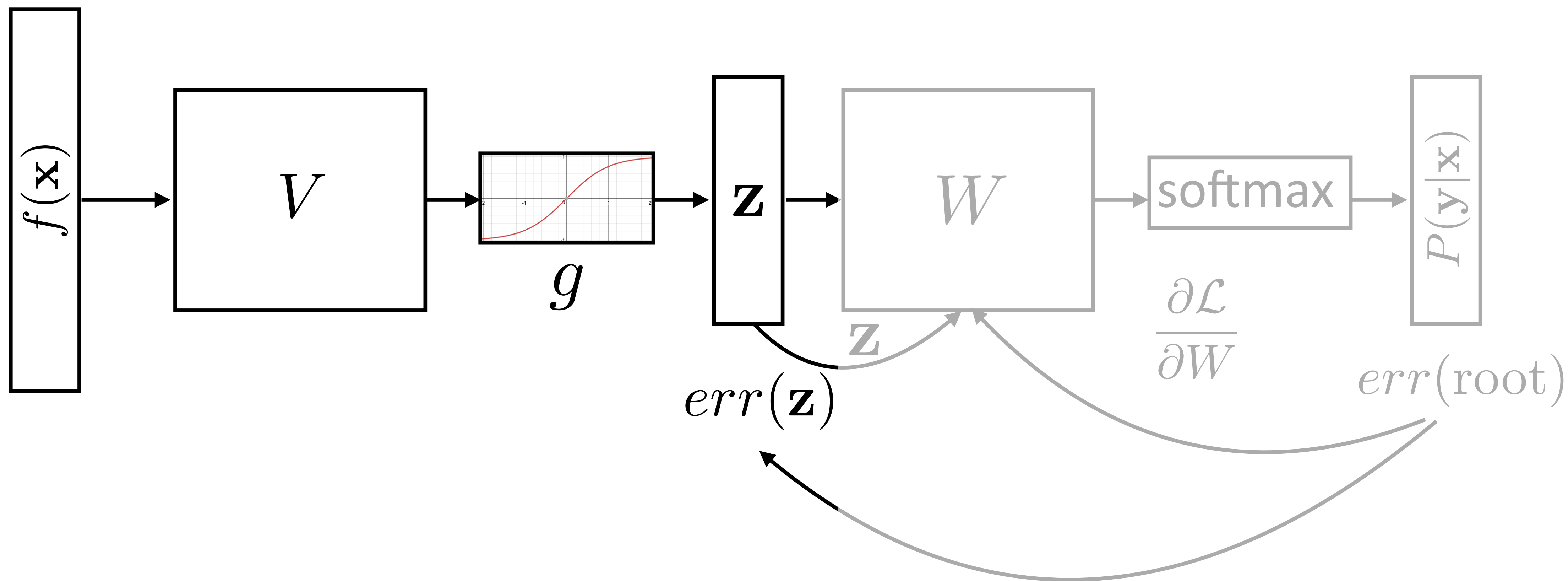
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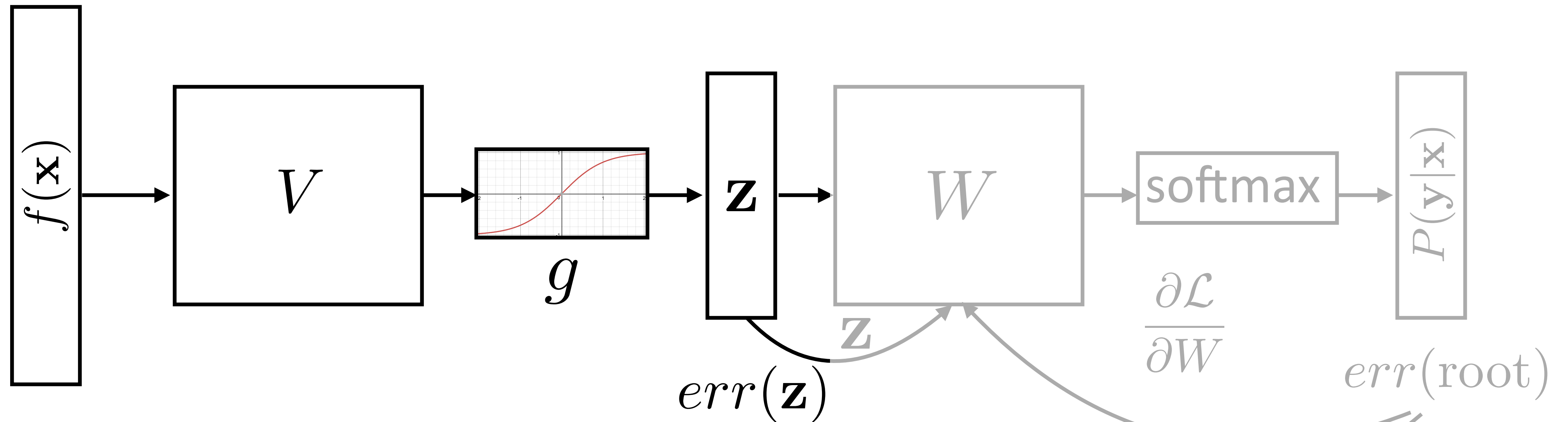
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Backpropagation: Picture

$$P(\mathbf{y}|\mathbf{x}) = \text{softmax}(Wg(Vf(\mathbf{x})))$$



- ▶ Can forget everything after \mathbf{z} , treat it as the output and keep backpropping

Computing Gradients: Backpropagation

$$\mathcal{L}(\mathbf{x}, i^*) = W\mathbf{z} \cdot e_{i^*} - \log \sum_{j=1}^m \exp(W\mathbf{z} \cdot e_j)$$

$\mathbf{z} = g(Vf(\mathbf{x}))$
Activations at
hidden layer

- ▶ Gradient with respect to V : apply the chain rule

$$\frac{\partial \mathcal{L}(\mathbf{x}, i^*)}{\partial V_{ij}} = \frac{\partial \mathcal{L}(\mathbf{x}, i^*)}{\partial \mathbf{z}} \frac{\partial \mathbf{z}}{V_{ij}}$$

Computing Gradients: Backpropagation

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Activations at hidden layer

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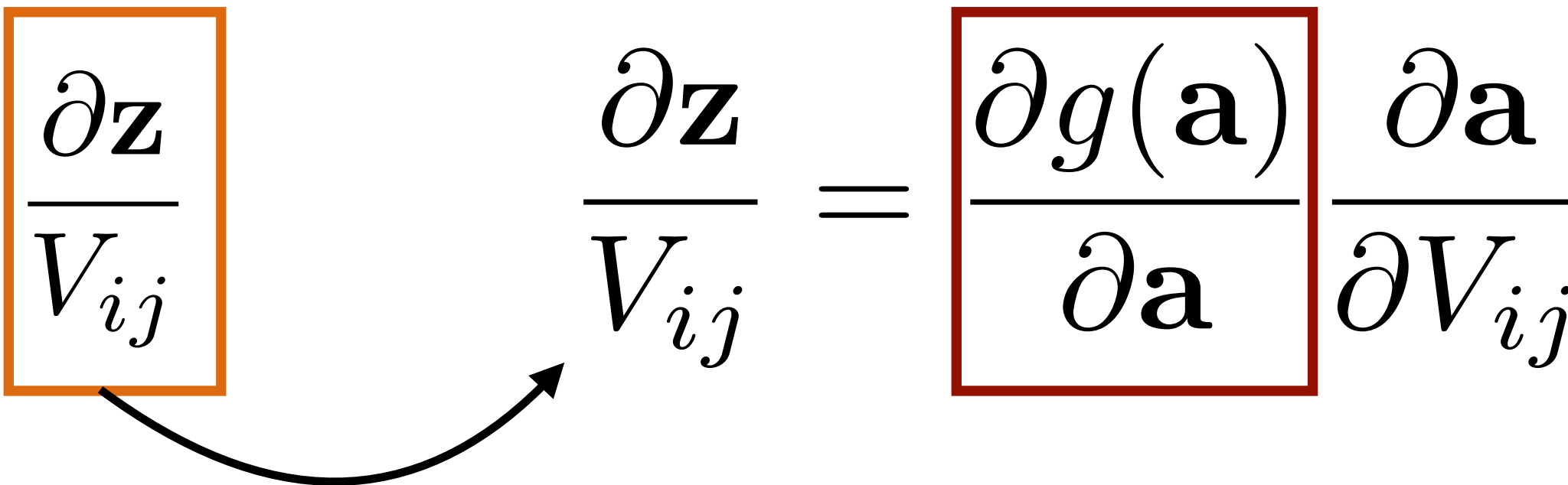
$$\frac{\partial \mathcal{L}(\mathbf{x}, i^*)}{\partial V_{ij}} = \frac{\partial \mathcal{L}(\mathbf{x}, i^*)}{\partial \mathbf{z}} \frac{\partial \mathbf{z}}{V_{ij}} = \frac{\partial \mathbf{z}}{V_{ij}} = \frac{\partial g(\mathbf{a})}{\partial \mathbf{a}} \frac{\partial \mathbf{a}}{\partial V_{ij}} \quad \mathbf{a} = V f(\mathbf{x})$$

Computing Gradients: Backpropagation

$$\mathcal{L}(\mathbf{x}, i^*) = W \mathbf{z} \cdot e_{i^*} - \log \sum_{j=1}^m \exp(W \mathbf{z} \cdot e_j) \quad \mathbf{z} = g(V f(\mathbf{x}))$$

Activations at hidden layer

- ▶ Gradient with respect to V : apply the chain rule

$$\frac{\partial \mathcal{L}(\mathbf{x}, i^*)}{\partial V_{ij}} = \frac{\partial \mathcal{L}(\mathbf{x}, i^*)}{\partial \mathbf{z}} \frac{\partial \mathbf{z}}{V_{ij}} = \frac{\partial \mathbf{z}}{V_{ij}} = \frac{\partial g(\mathbf{a})}{\partial \mathbf{a}} \frac{\partial \mathbf{a}}{\partial V_{ij}} \quad \mathbf{a} = V f(\mathbf{x})$$


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Activations at hidden layer

- ▶ Gradient with respect to V : apply the chain rule

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- ▶ First term: gradient of nonlinear activation function at \mathbf{a} (depends on current value)

Computing Gradients: Backpropagation

$$\mathcal{L}(\mathbf{x}, i^*) = W \mathbf{z} \cdot e_{i^*} - \log \sum_{j=1}^m \exp(W \mathbf{z} \cdot e_j) \quad \mathbf{z} = g(V f(\mathbf{x}))$$

Activations at hidden layer

- ▶ Gradient with respect to V : apply the chain rule

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- ▶ First term: gradient of nonlinear activation function at \mathbf{a} (depends on current value)
- ▶ Second term: gradient of linear function

Computing Gradients: Backpropagation

$$\mathcal{L}(\mathbf{x}, i^*) = W\mathbf{z} \cdot e_{i^*} - \log \sum_{j=1}^m \exp(W\mathbf{z} \cdot e_j) \quad \mathbf{z} = g(Vf(\mathbf{x}))$$

Activations at hidden layer

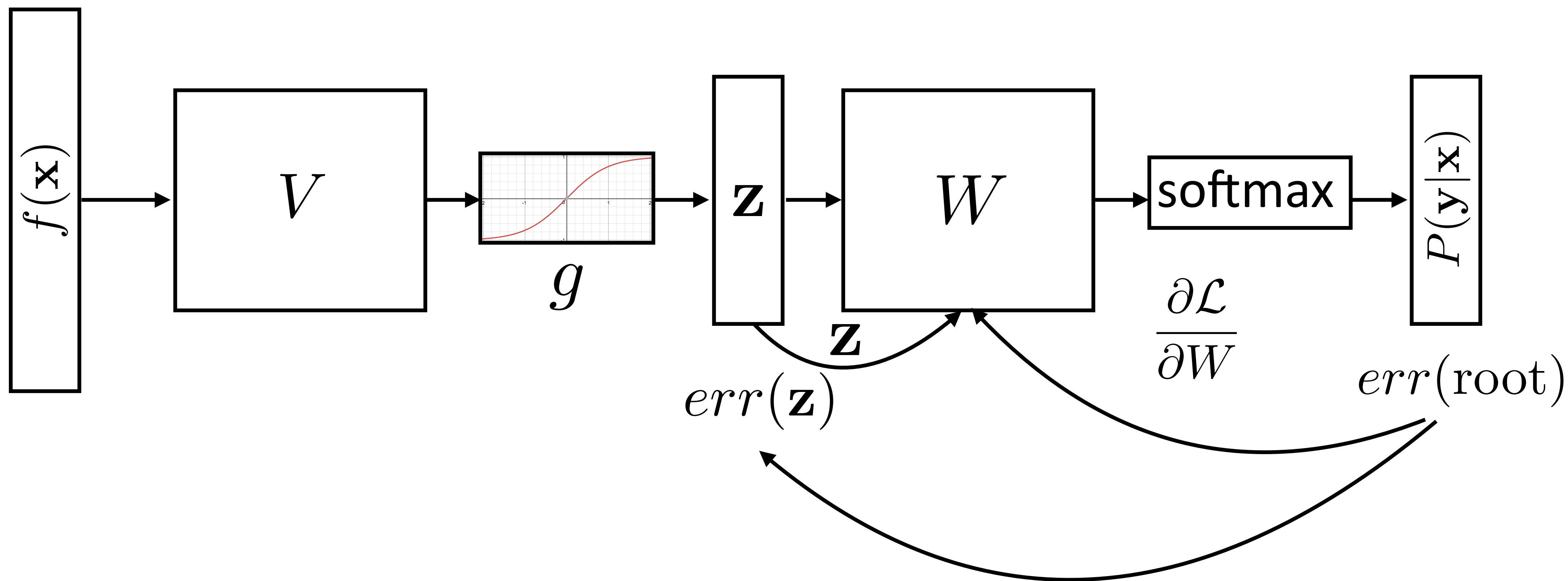
- ▶ Gradient with respect to V : apply the chain rule

$$\frac{\partial \mathcal{L}(\mathbf{x}, i^*)}{\partial V_{ij}} = \frac{\partial \mathcal{L}(\mathbf{x}, i^*)}{\partial \mathbf{z}} \frac{\partial \mathbf{z}}{V_{ij}} = \frac{\partial \mathbf{z}}{V_{ij}} = \frac{\partial g(\mathbf{a})}{\partial \mathbf{a}} \frac{\partial \mathbf{a}}{\partial V_{ij}} \quad \mathbf{a} = Vf(\mathbf{x})$$

- ▶ First term: gradient of nonlinear activation function at \mathbf{a} (depends on current value)
- ▶ Second term: gradient of linear function
- ▶ Straightforward computation once we have $err(\mathbf{z})$

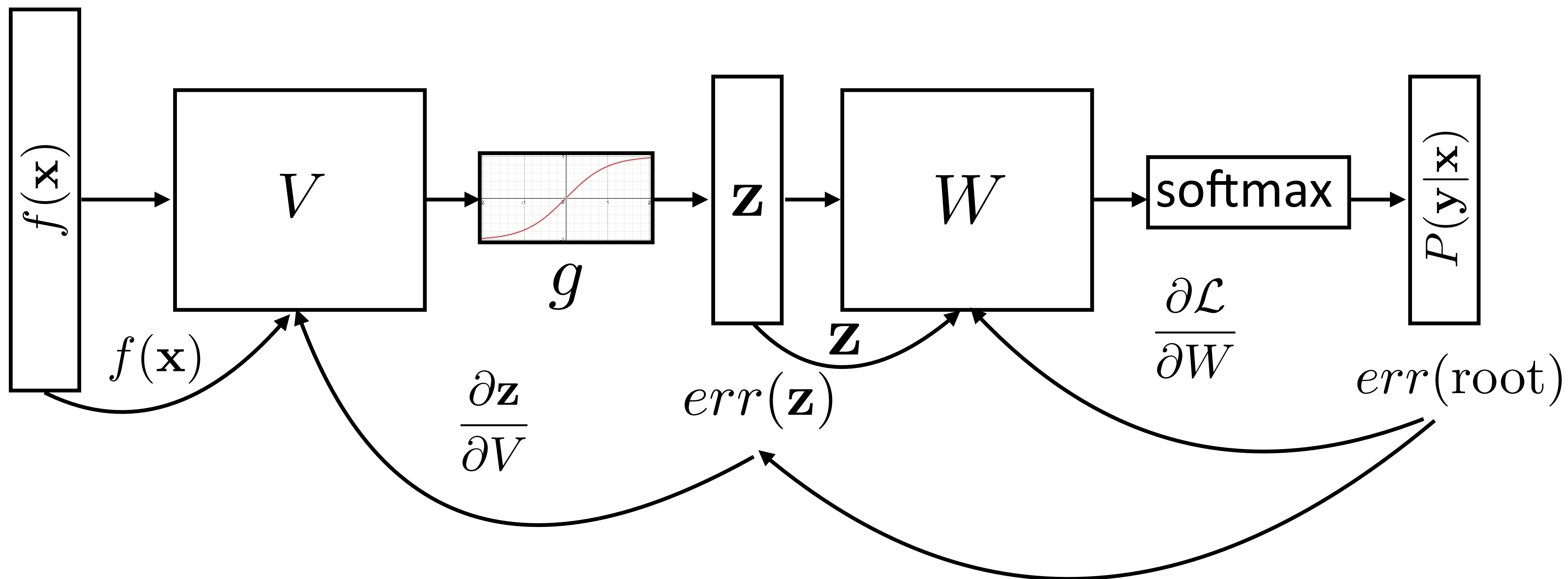
Backpropagation: Picture

$$P(\mathbf{y}|\mathbf{x}) = \text{softmax}(Wg(Vf(\mathbf{x})))$$



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Backpropagation

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- ▶ Step 4: compute derivatives of V using $err(\mathbf{z})$ (matrix)
- ▶ Step 5+: continue backpropagation (compute $err(f(\mathbf{x}))$ if necessary...)

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- ▶ Easy to update parameters based on “error signal” from next layer, keep pushing error signal back as backpropagation
- ▶ Need to remember the values from the forward computation

Applications

NLP with Feedforward Networks

- ▶ Part-of-speech tagging with FFNNs

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??

*Fed raises **interest** rates in order to ...*

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*Fed raises **interest rates** in order to ...*

- ▶ Word embeddings for each word form input

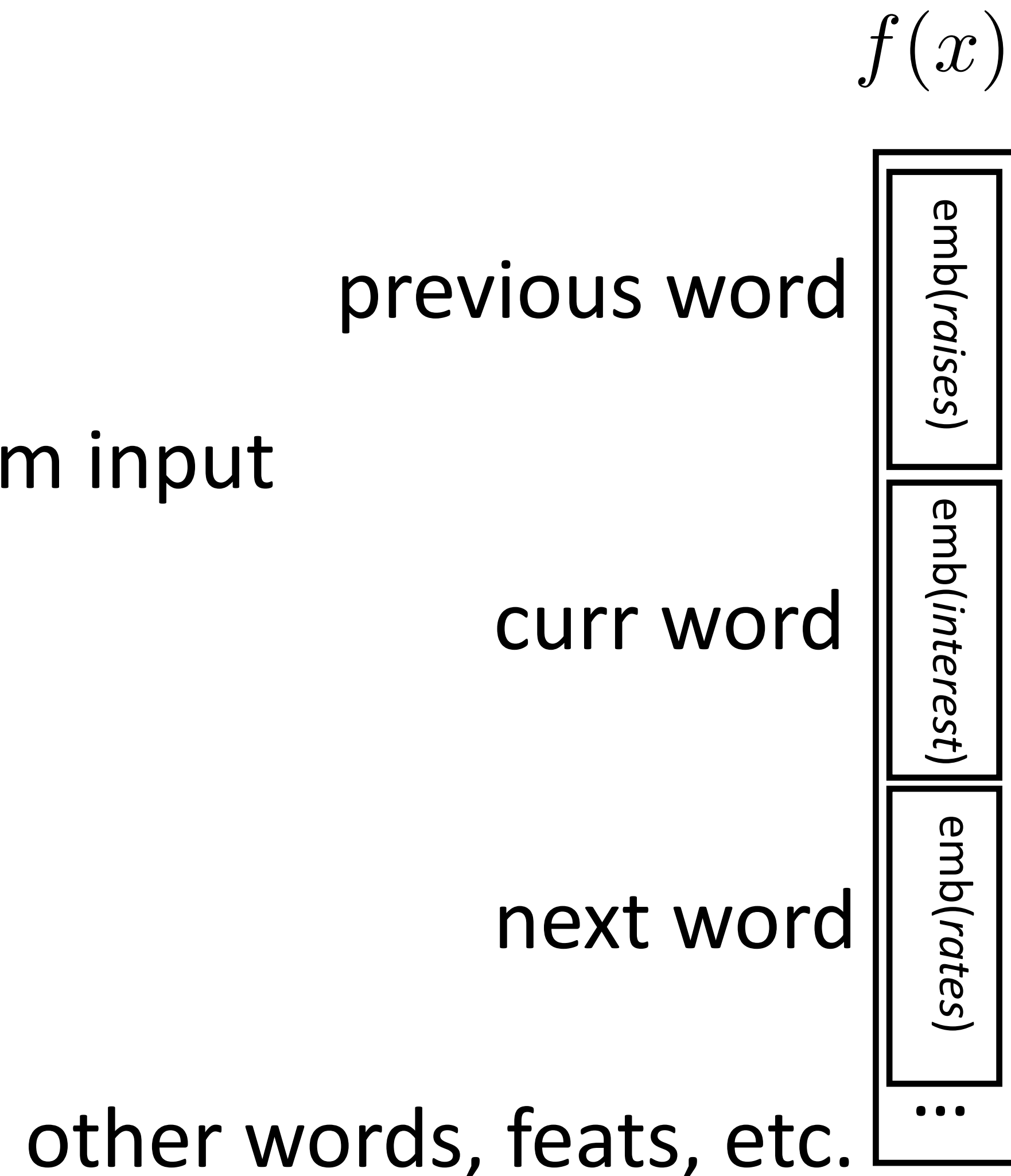
NLP with Feedforward Networks

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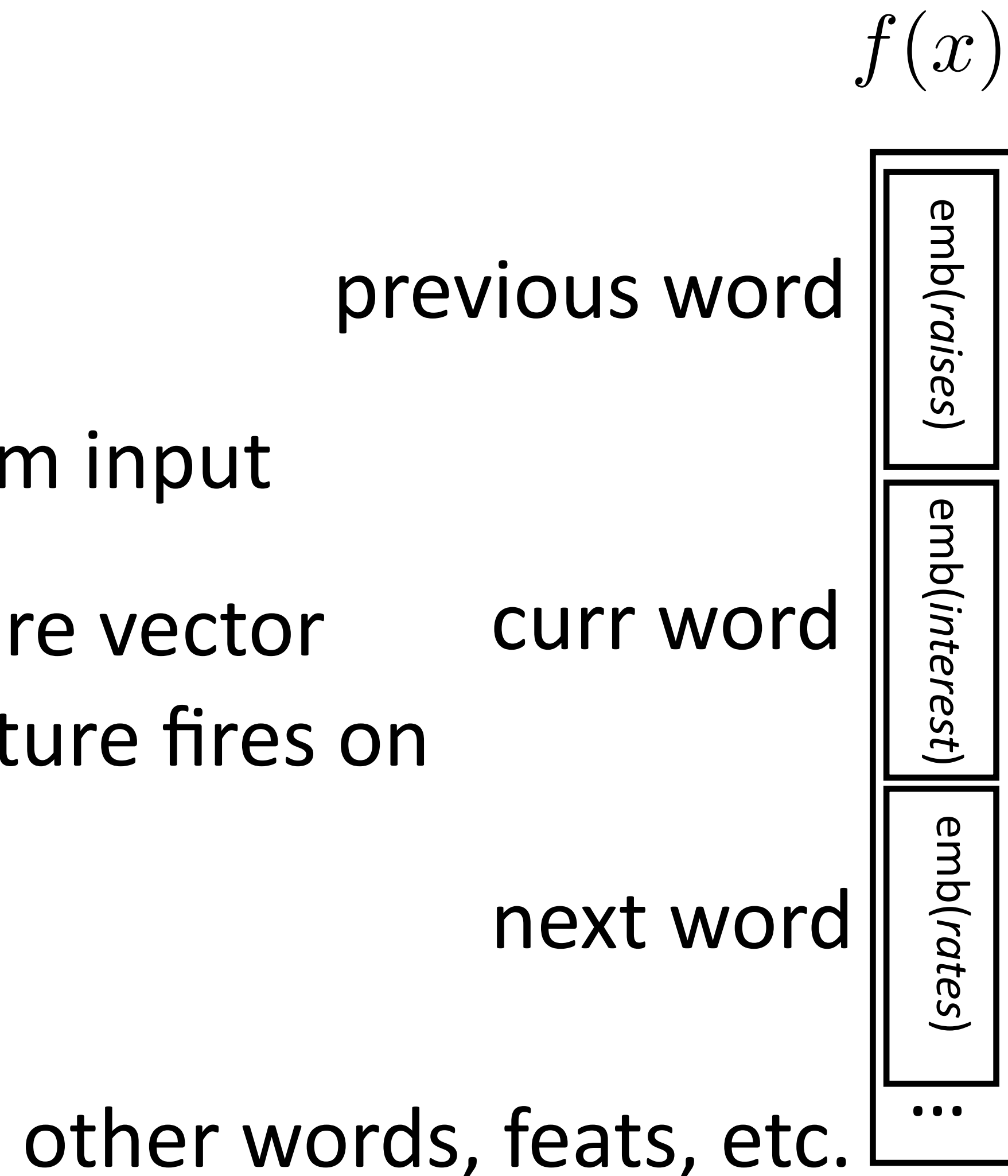
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*Fed raises **interest** rates in order to ...*

- ▶ Word embeddings for each word form input
- ▶ ~1000 features here — smaller feature vector than in sparse models, but every feature fires on every example
- ▶ Weight matrix learns position-dependent processing of the words

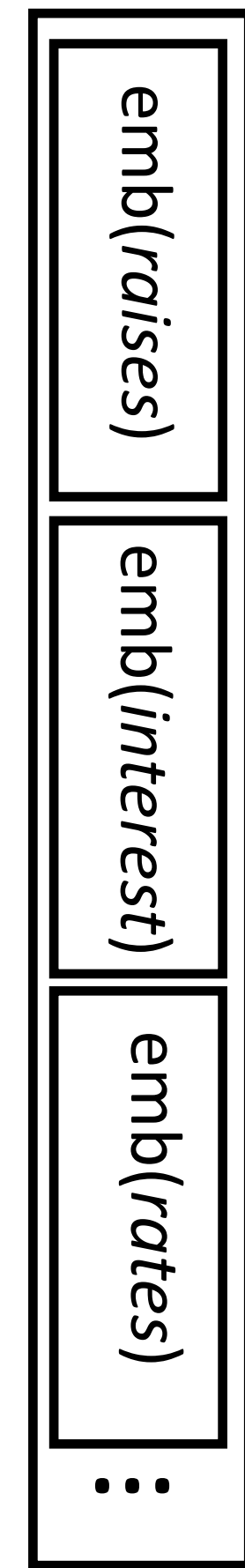
previous word

curr word

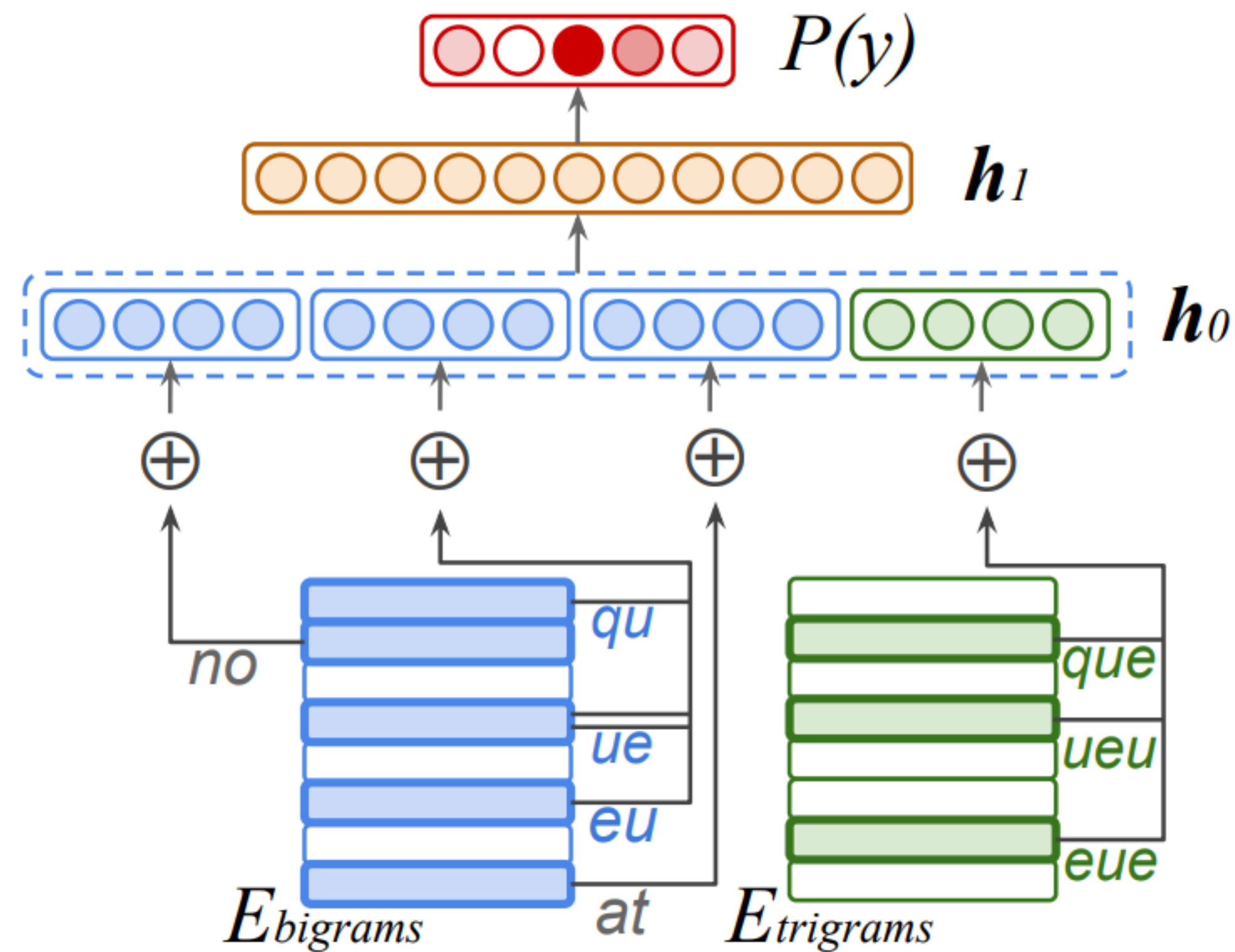
next word

other words, feats, etc.

$f(x)$



NLP with Feedforward Networks



- ▶ Hidden layer mixes these different signals and learns feature conjunctions

NLP with Feedforward Networks

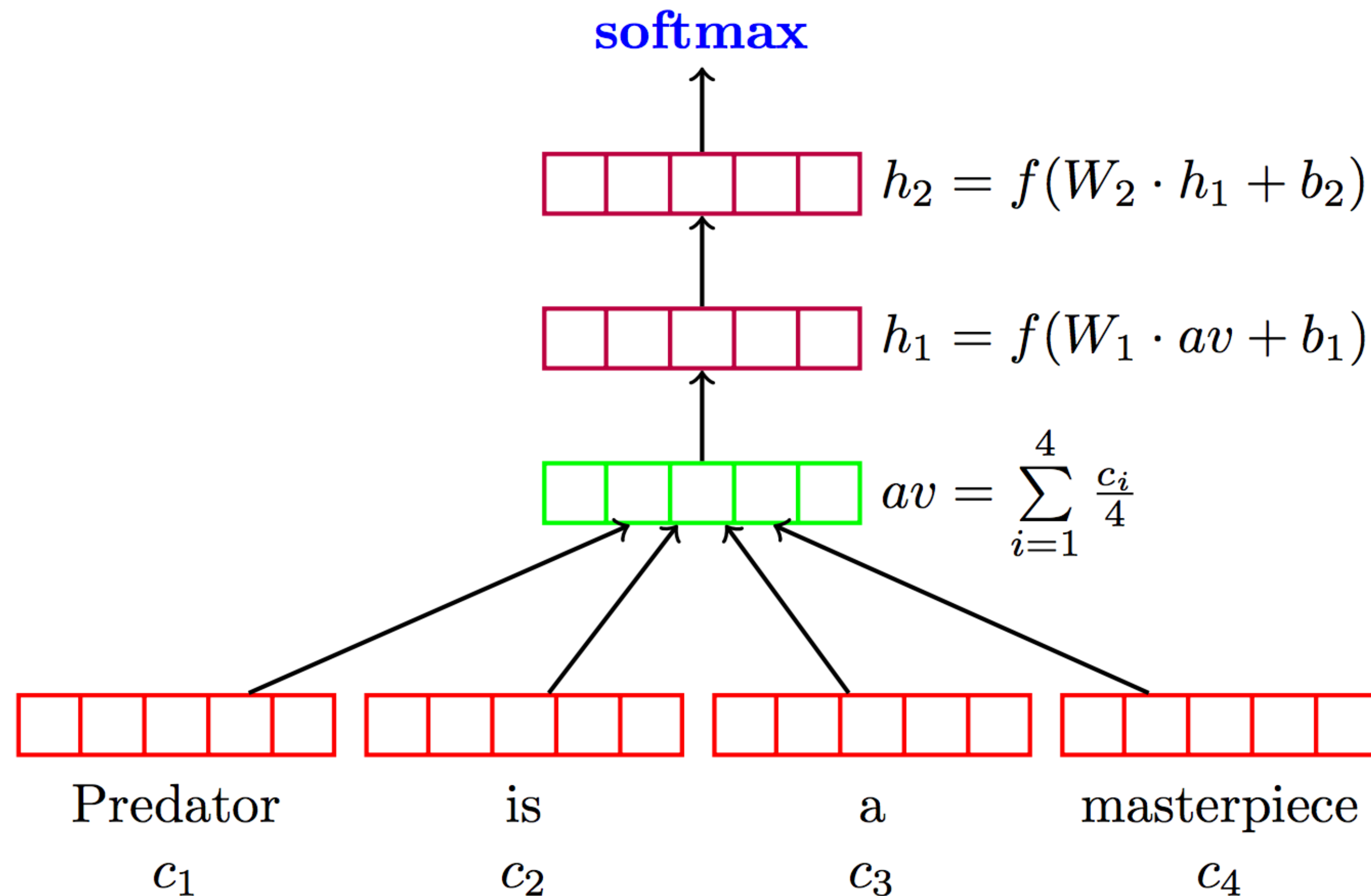
- ▶ Multilingual tagging results:

Model	Acc.	Wts.	MB	Ops.
Gillick et al. (2016)	95.06	900k	-	6.63m
Small FF	94.76	241k	0.6	0.27m
+Clusters	95.56	261k	1.0	0.31m
$\frac{1}{2}$ Dim.	95.39	143k	0.7	0.18m

- ▶ Gillick used LSTMs; this is smaller, faster, and better

Sentiment Analysis

- ▶ Deep Averaging Networks: feedforward neural network on average of word embeddings from input



Sentiment Analysis

	Model	RT	SST fine	SST bin	IMDB	Time (s)	
	DAN-ROOT	—	46.9	85.7	—	31	
	DAN-RAND	77.3	45.4	83.2	88.8	136	
	DAN	80.3	47.7	86.3	89.4	136	lyyer et al. (2015)
Bag-of-words	NBOW-RAND	76.2	42.3	81.4	88.9	91	
	NBOW	79.0	43.6	83.6	89.0	91	
	BiNB	—	41.9	83.1	—	—	
	NBSVM-bi	79.4	—	—	91.2	—	Wang and Manning (2012)
Tree RNNs / CNNS / LSTMS	RecNN*	77.7	43.2	82.4	—	—	
	RecNTN*	—	45.7	85.4	—	—	
	DRecNN	—	49.8	86.6	—	431	
	TreeLSTM	—	50.6	86.9	—	—	
	DCNN*	—	48.5	86.9	89.4	—	
	PVEC*	—	48.7	87.8	92.6	—	
	CNN-MC	81.1	47.4	88.1	—	2,452	Kim (2014)
WRRBM*	—	—	—	89.2	—		

Coreference Resolution

- ▶ Feedforward networks identify coreference arcs

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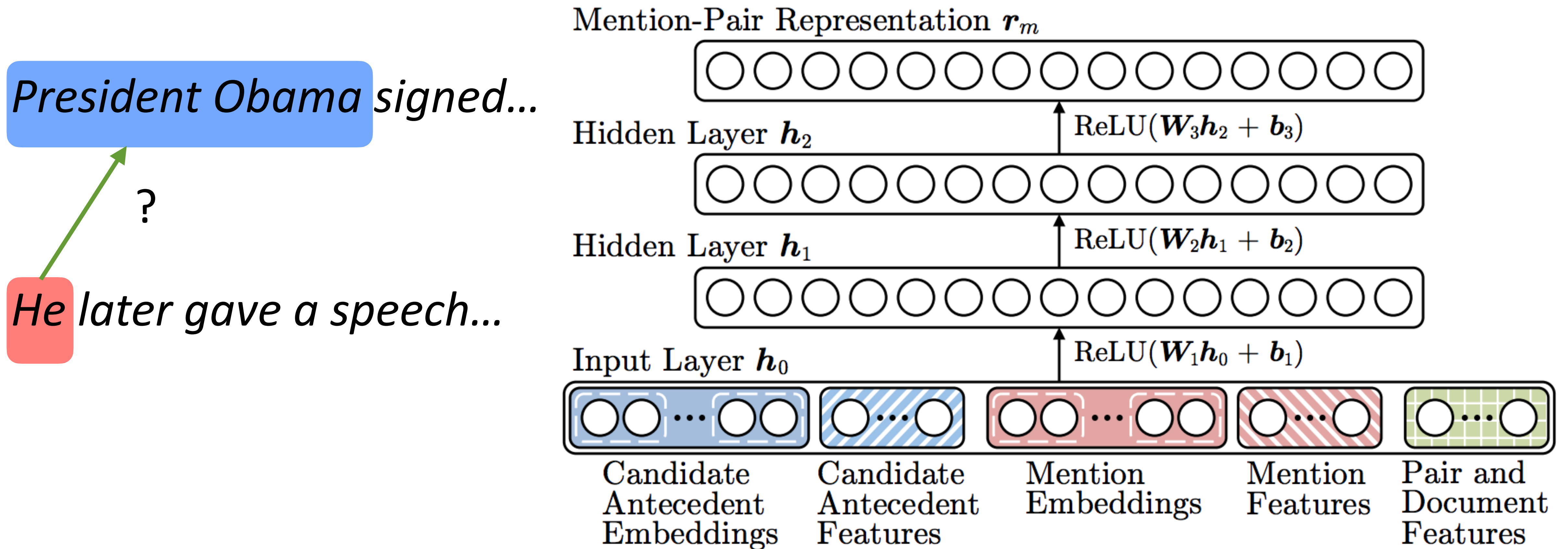
President Obama signed...

?

He later gave a speech...

Coreference Resolution

- ▶ Feedforward networks identify coreference arcs



Clark and Manning (2015), Wiseman et al. (2015)

Implementation Details

Computation Graphs

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$$y = x * x \xrightarrow{\text{codegen}} (y, dy) = (x * x, 2 * x * dx)$$

- ▶ Computation is now something we need to reason about symbolically
- ▶ Use a library like Pytorch or Tensorflow. This class: Pytorch

Computation Graphs in Pytorch

- ▶ Define forward pass for $P(\mathbf{y}|\mathbf{x}) = \text{softmax}(Wg(Vf(\mathbf{x})))$

```
class FFNN(nn.Module):
    def __init__(self, inp, hid, out):
        super(FFNN, self).__init__()
        self.V = nn.Linear(inp, hid)
        self.g = nn.Tanh()
        self.W = nn.Linear(hid, out)
        self.softmax = nn.Softmax(dim=0)

    def forward(self, x):
        return self.softmax(self.W(self.g(self.V(x))))
```

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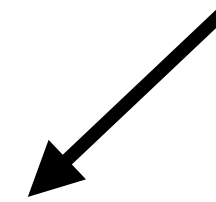
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def make_update(input, gold_label):
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Computation Graphs in Pytorch

$P(\mathbf{y}|\mathbf{x}) = \text{softmax}(Wg(Vf(\mathbf{x})))$ e_i^* : one-hot vector
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(e.g., [0, 1, 0])

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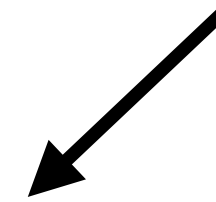
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```
    optimizer.step()
```

Training a Model

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For each epoch:

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Decode test set

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- ▶ Batch sizes from 1-100 often work well