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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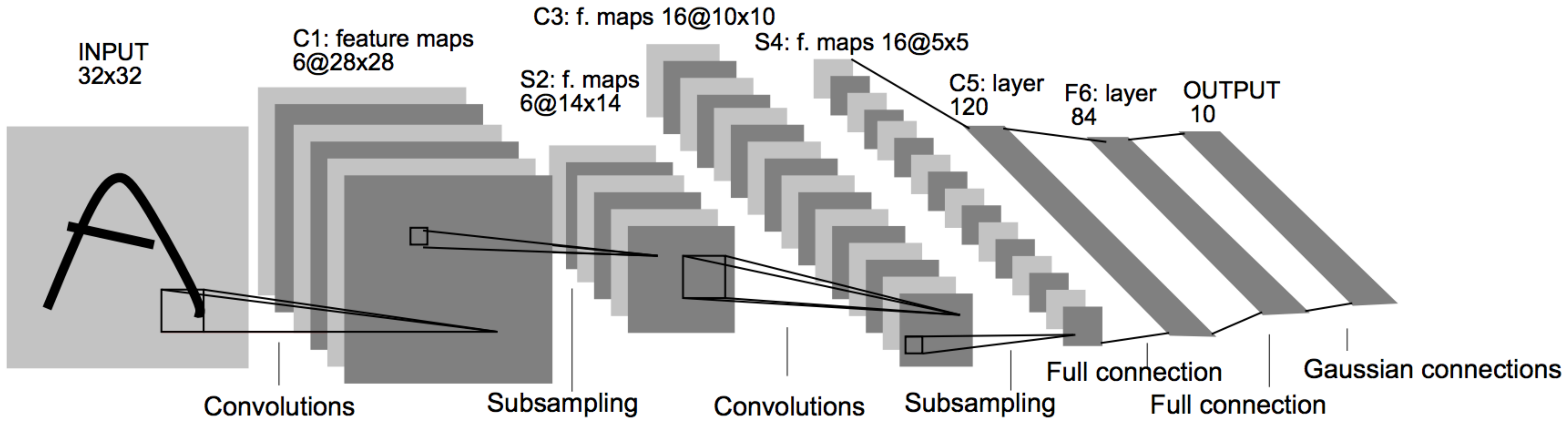
- Convnets: applied to MNIST by LeCun in 1998



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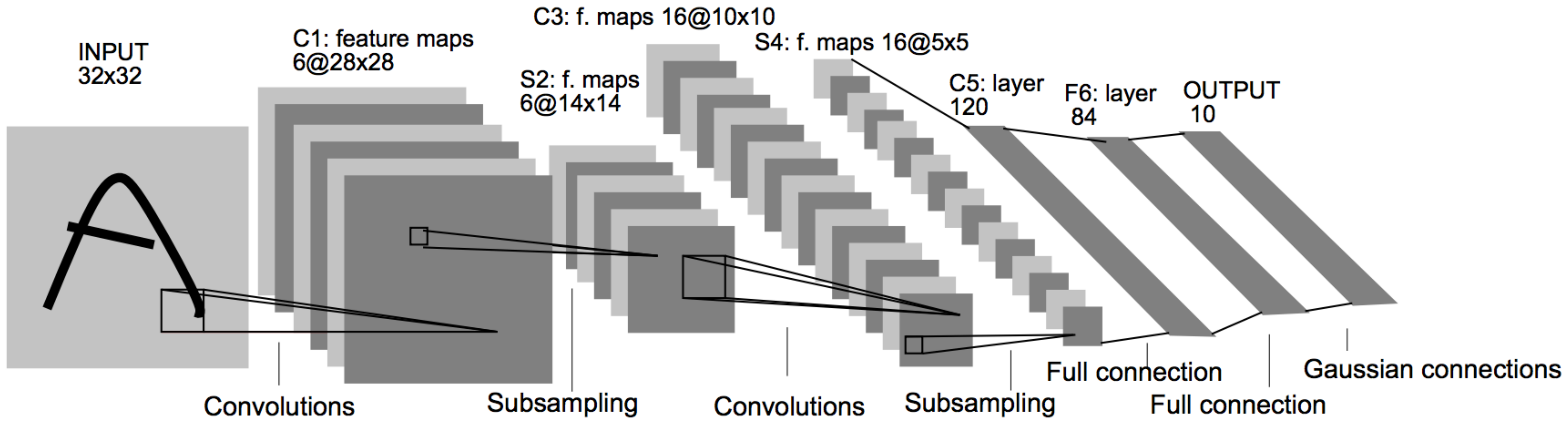

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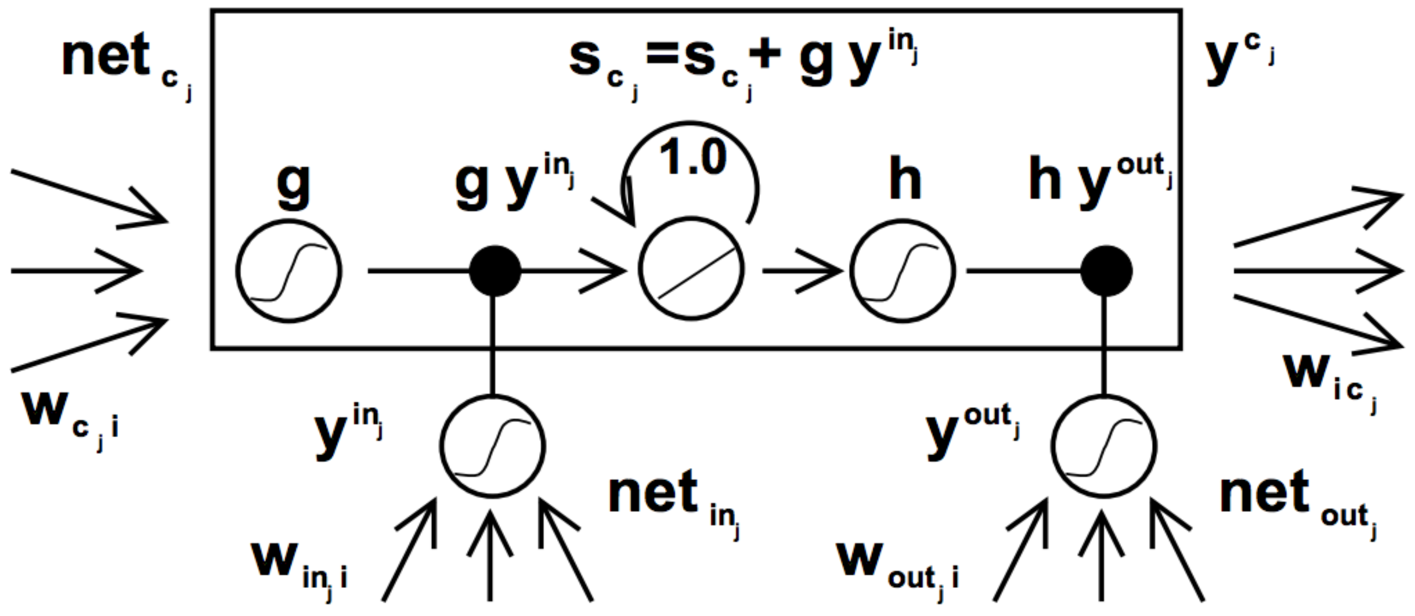

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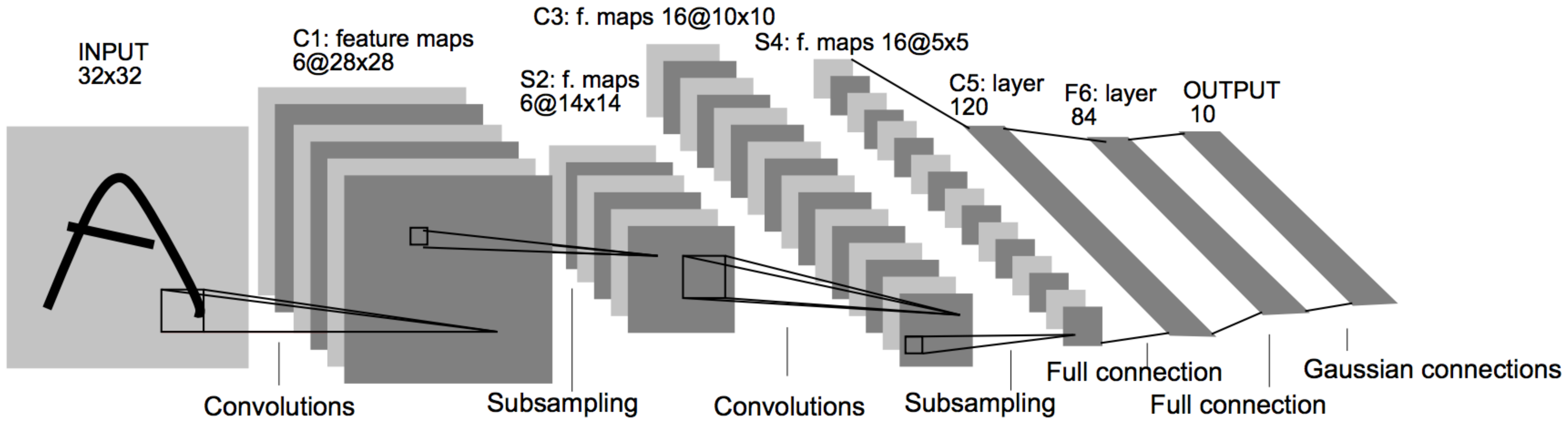

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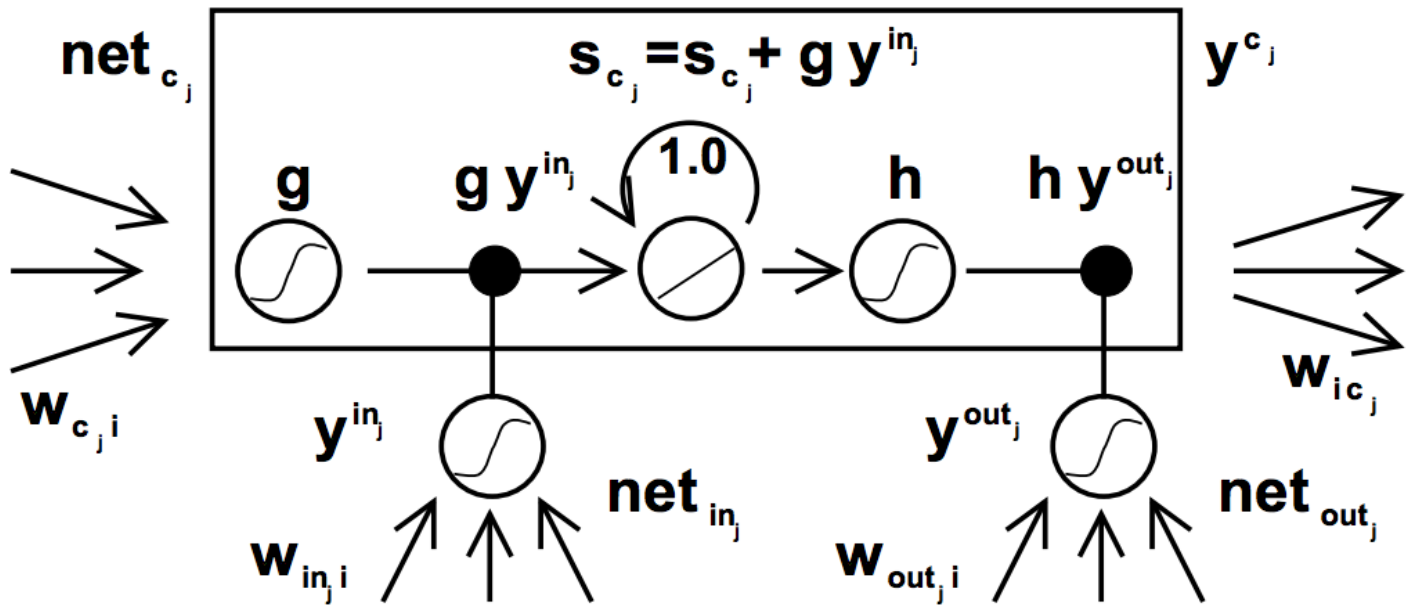

- Henderson (2003): neural shift-reduce parser, not SOTA

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  - Feedforward neural nets induce features for sequential CRFs ("neural CRF")
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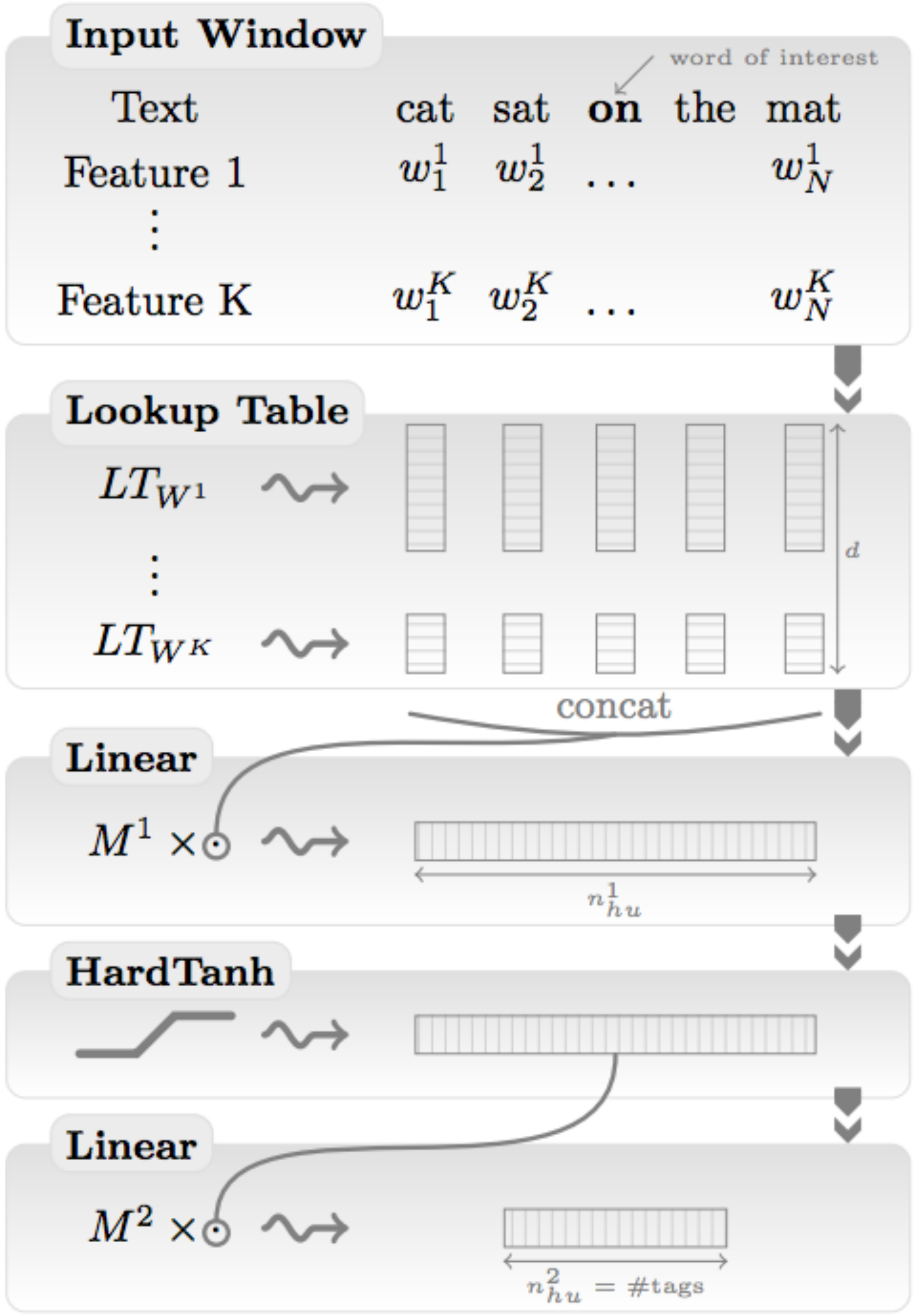

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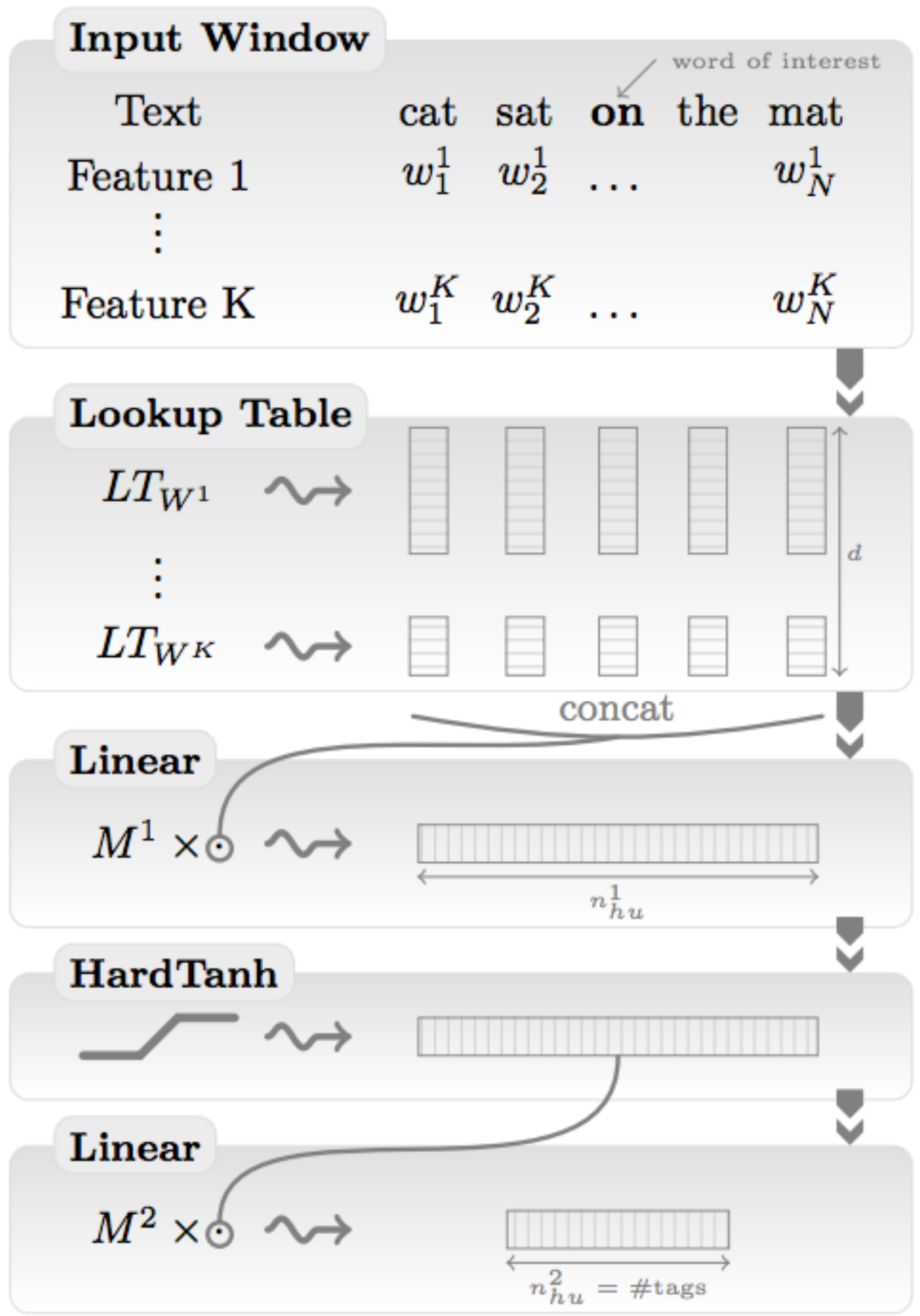

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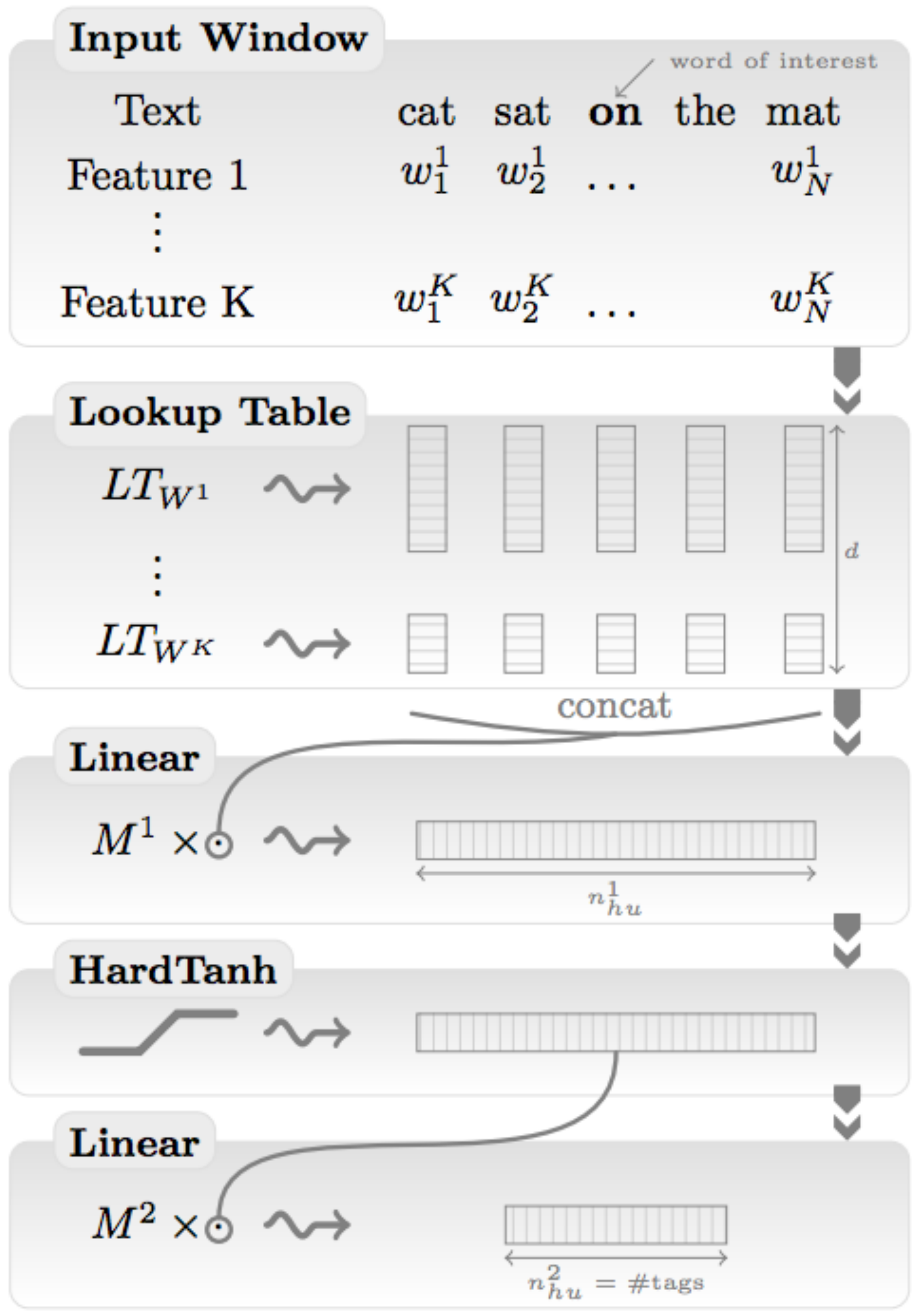

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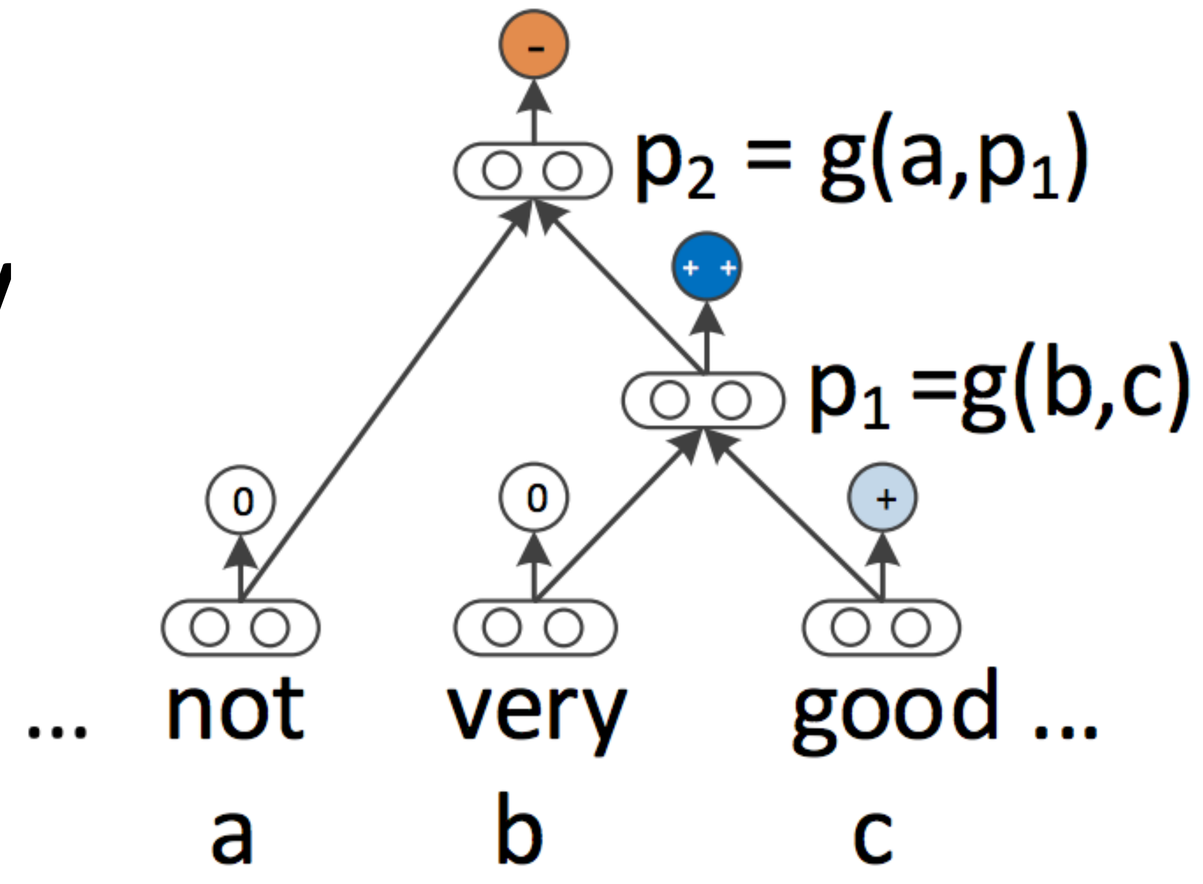
- Socher 2011-2014: tree-structured RNNs working okay



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- 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

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

Neural Networks: XOR

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- Inputs
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- Inputs $x_1, \; x_2$

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x_1	x_2	$y = x_1 \text{ XOR } x_2$
0	0	
0	1	
1	0	
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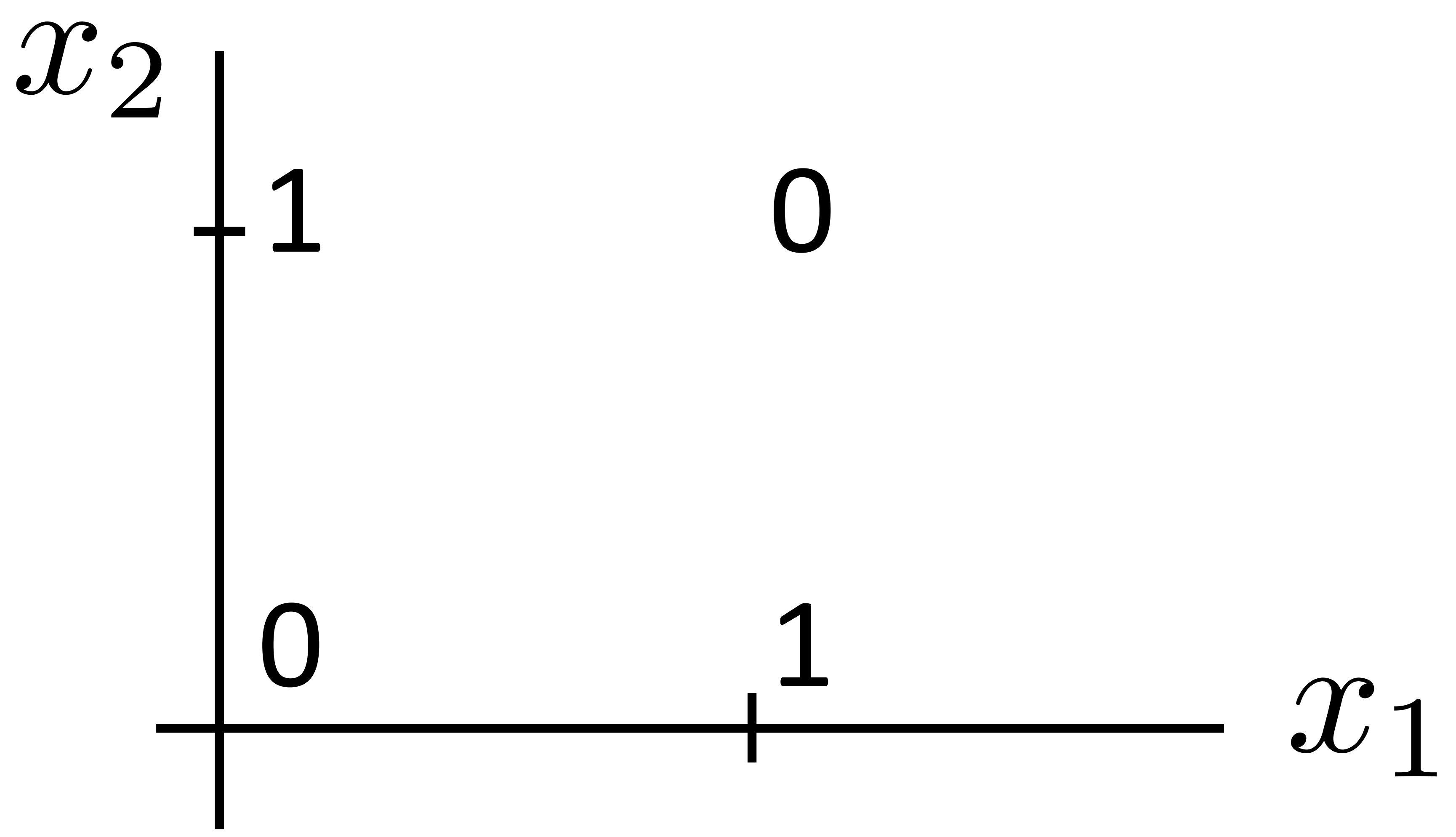

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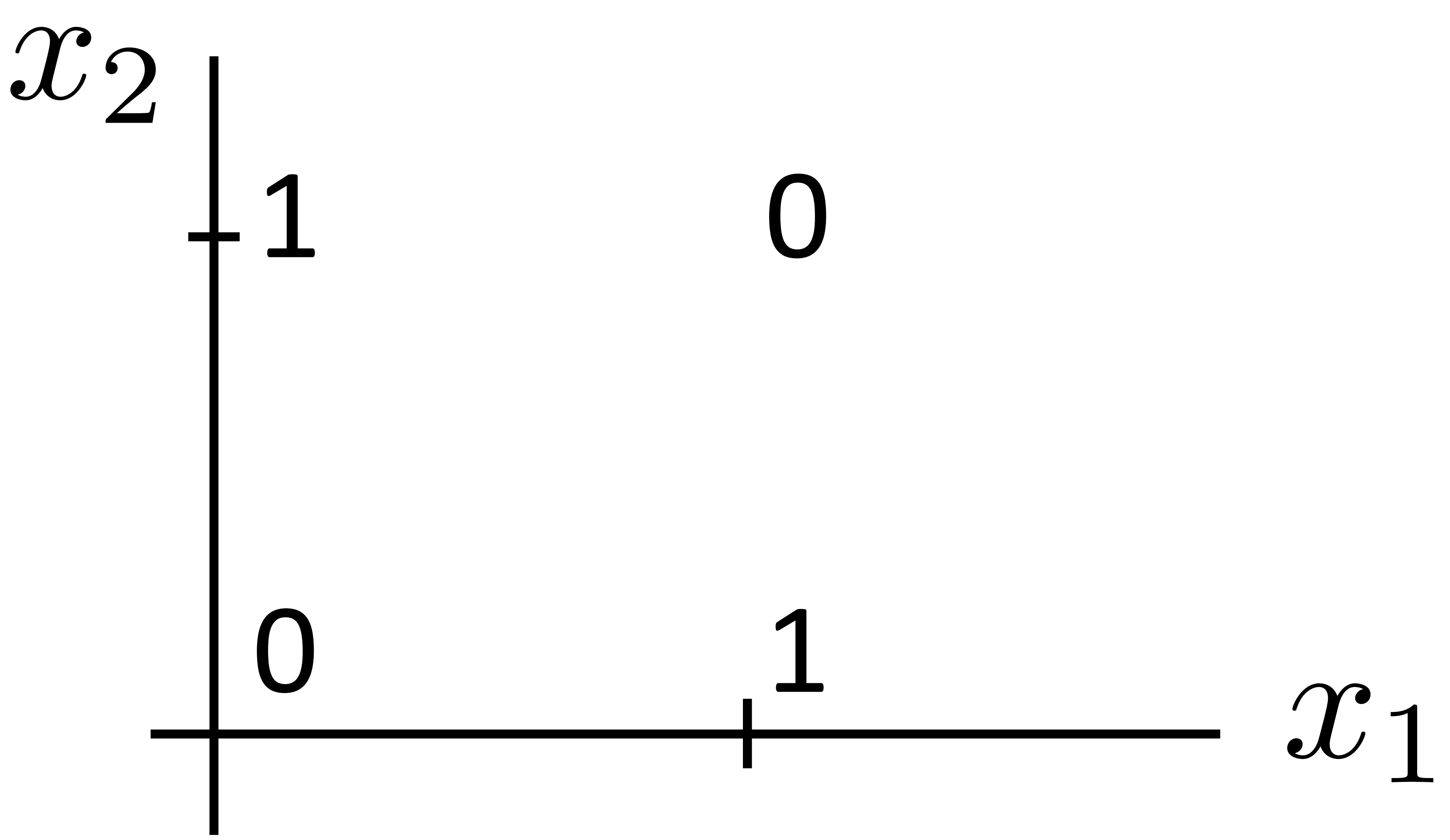

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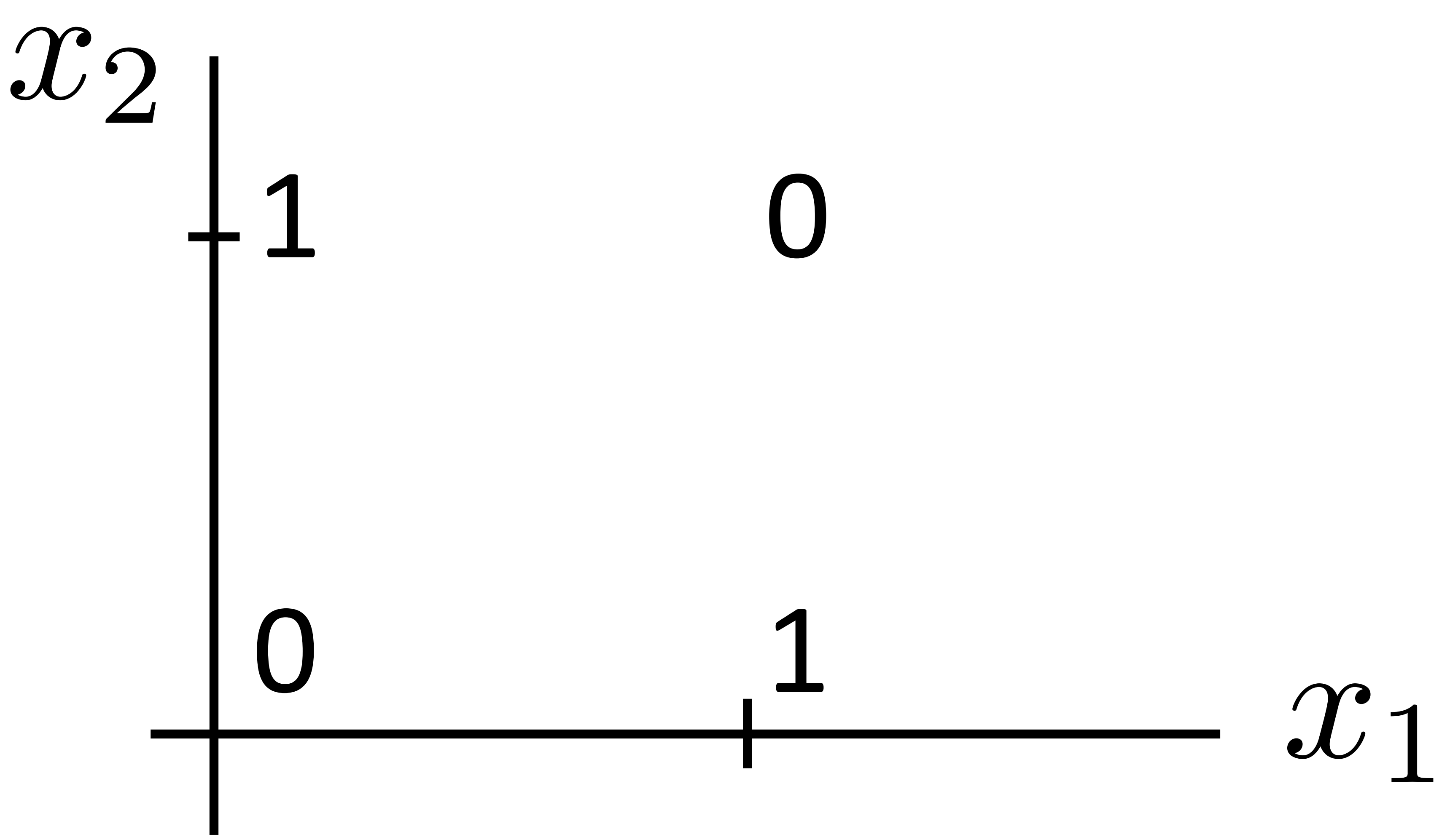

$$y = a_1 x_1 + a_2 x_2$$

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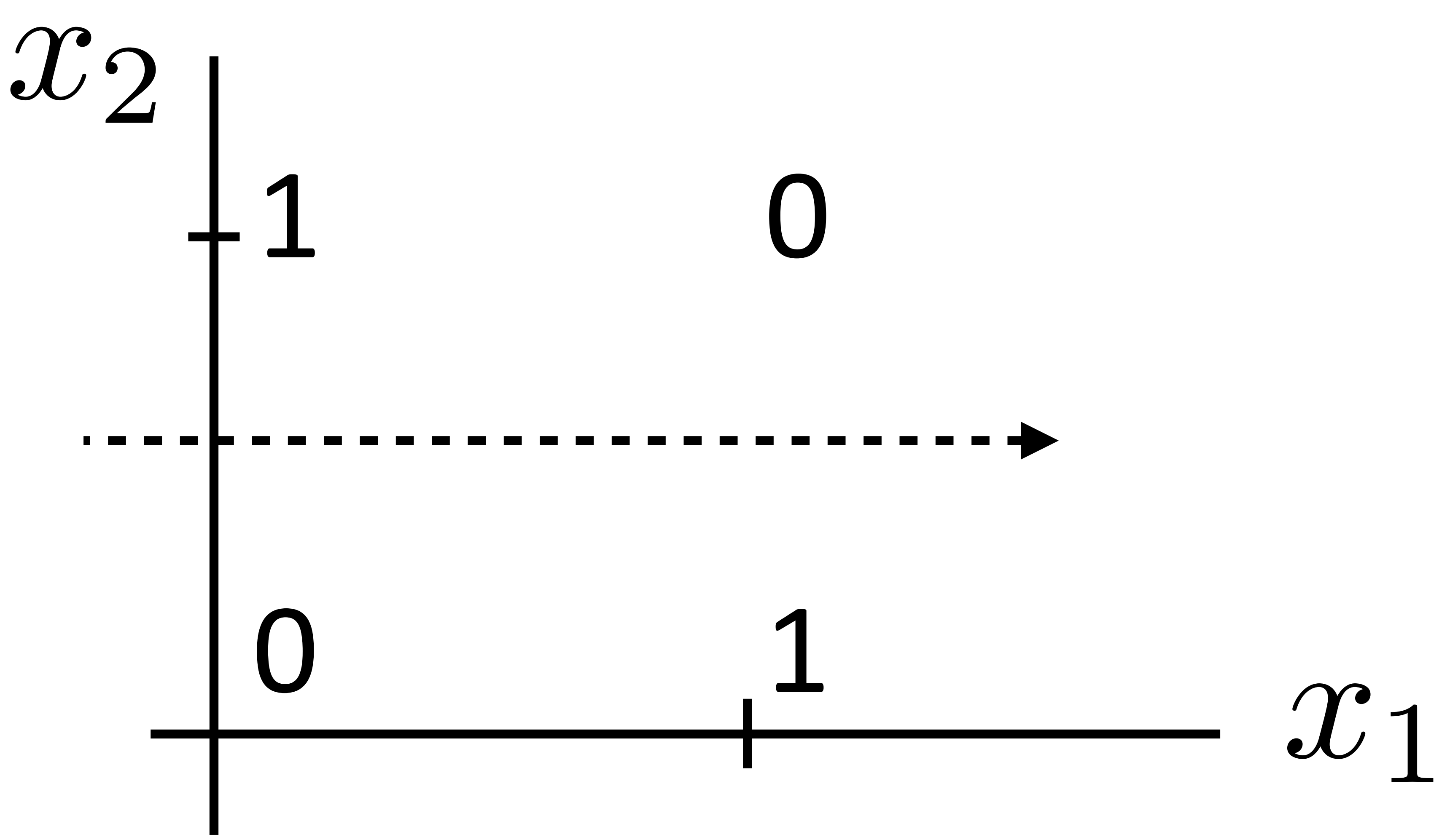

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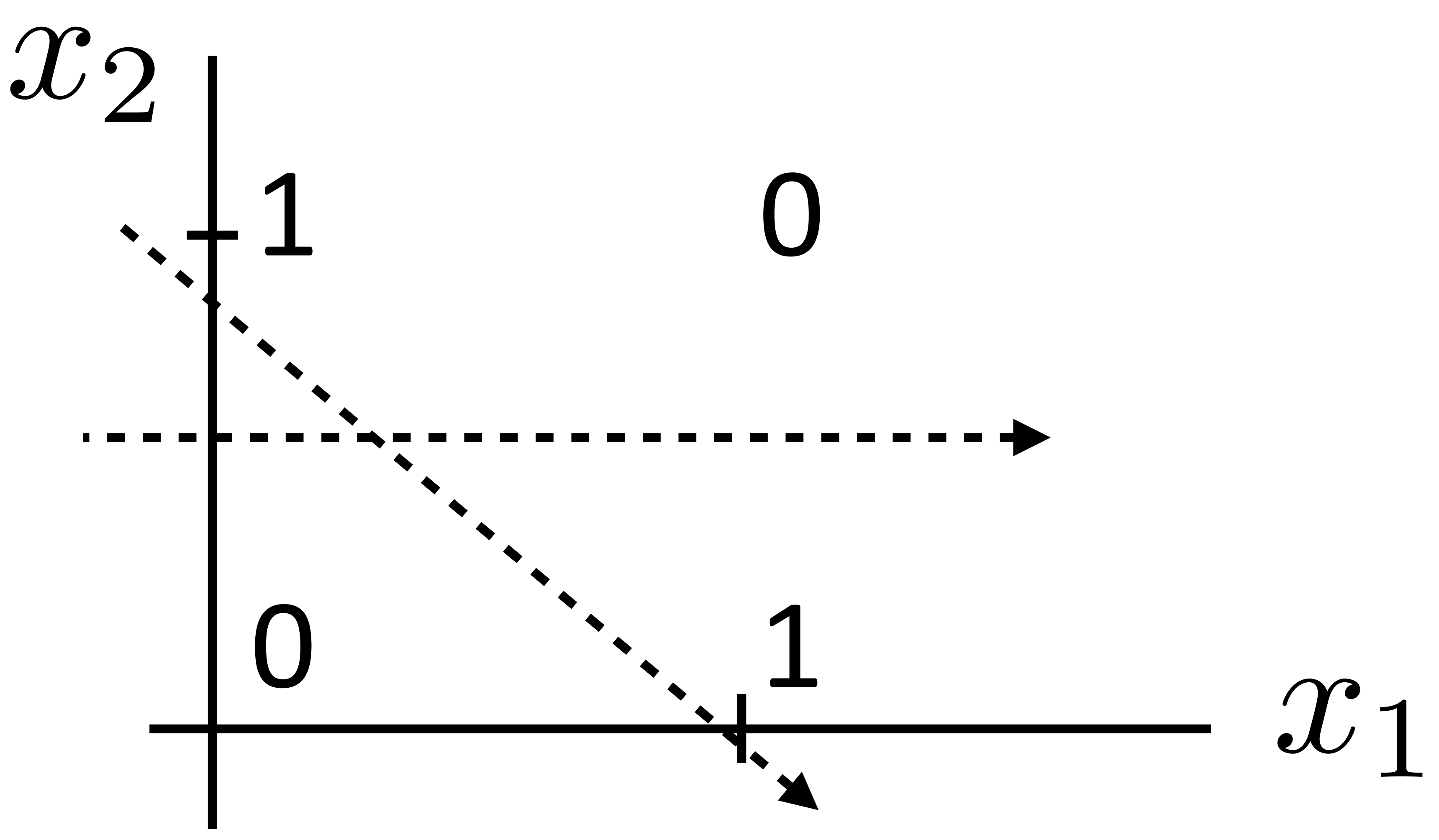

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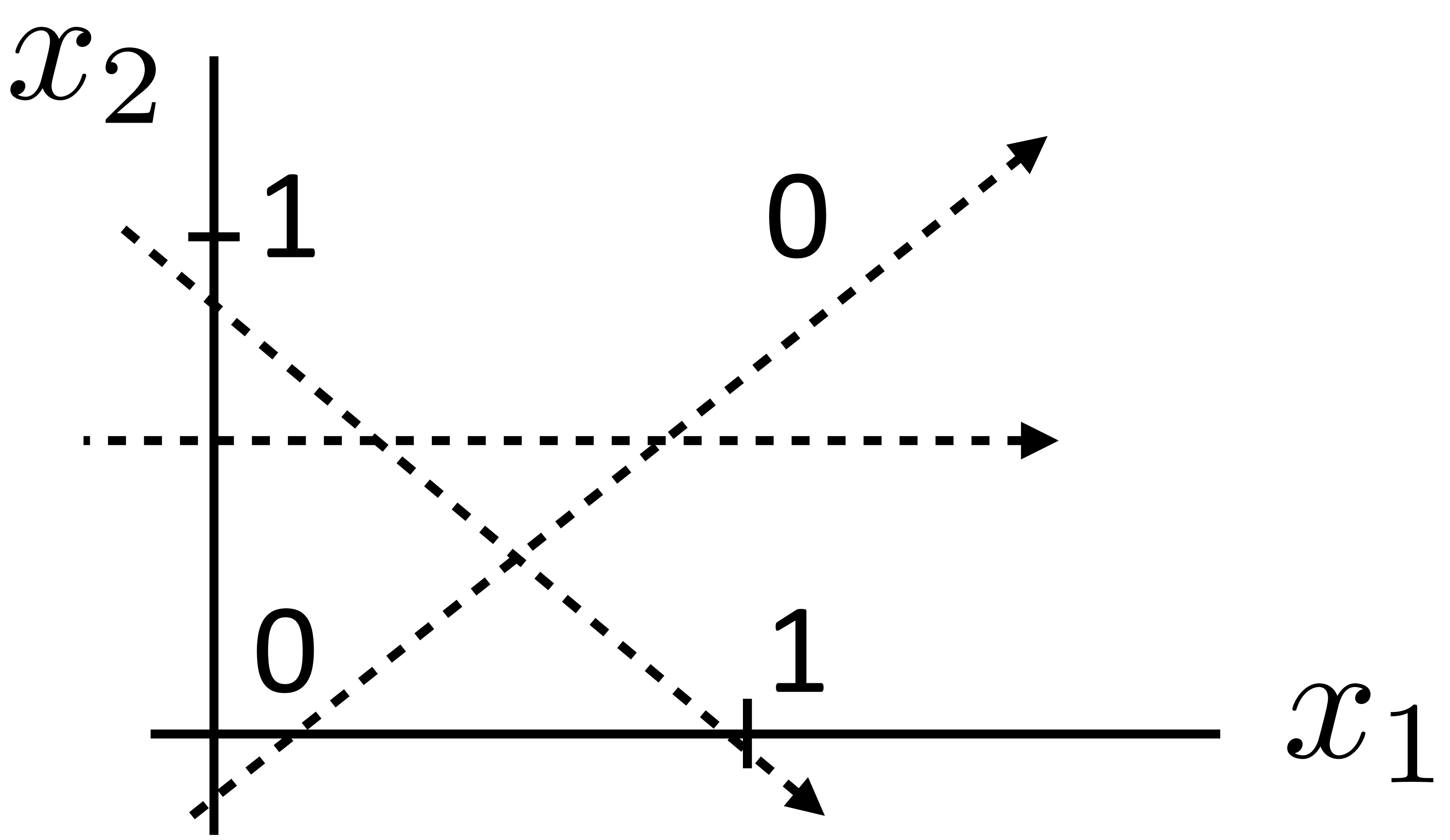

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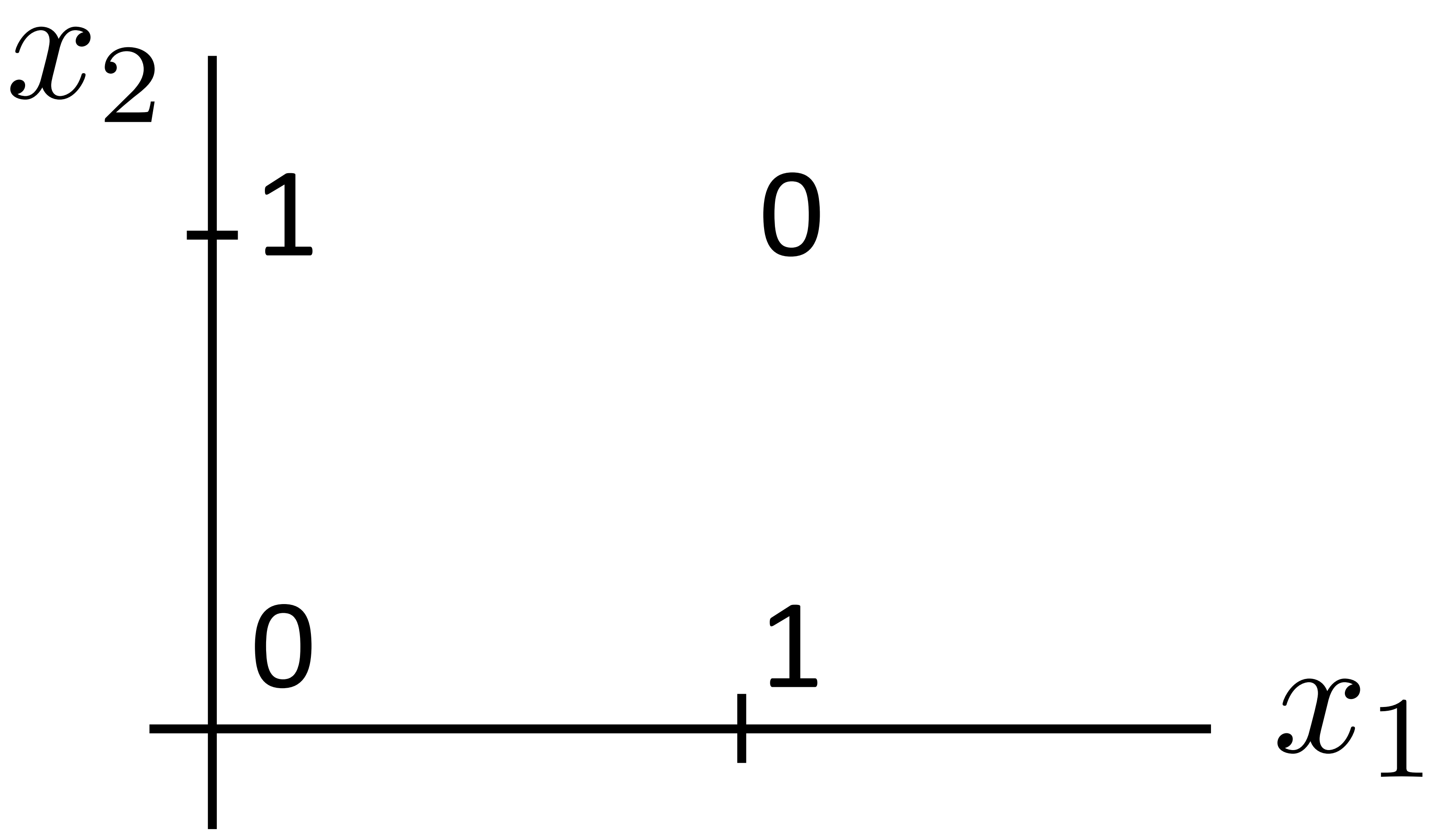

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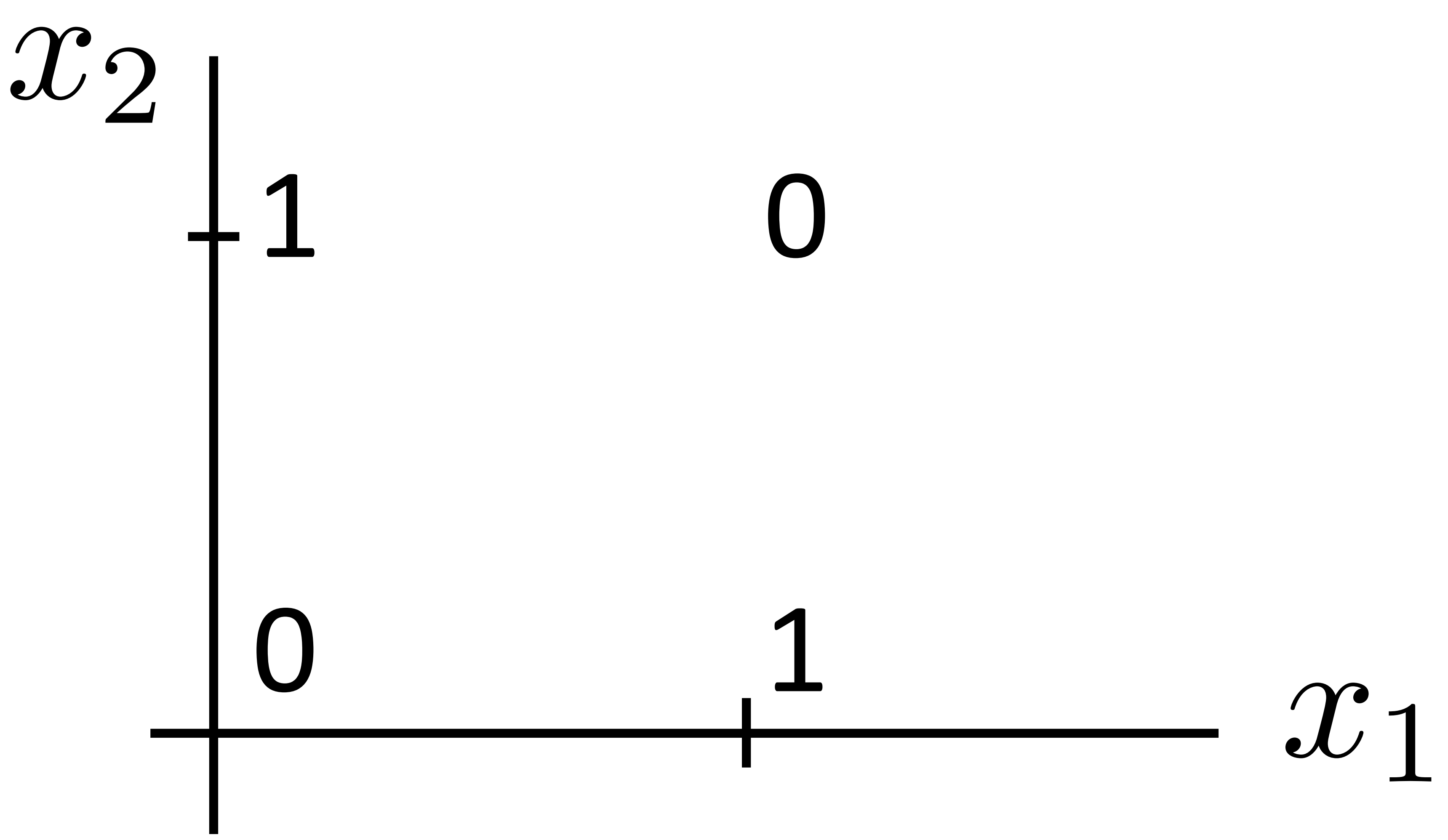

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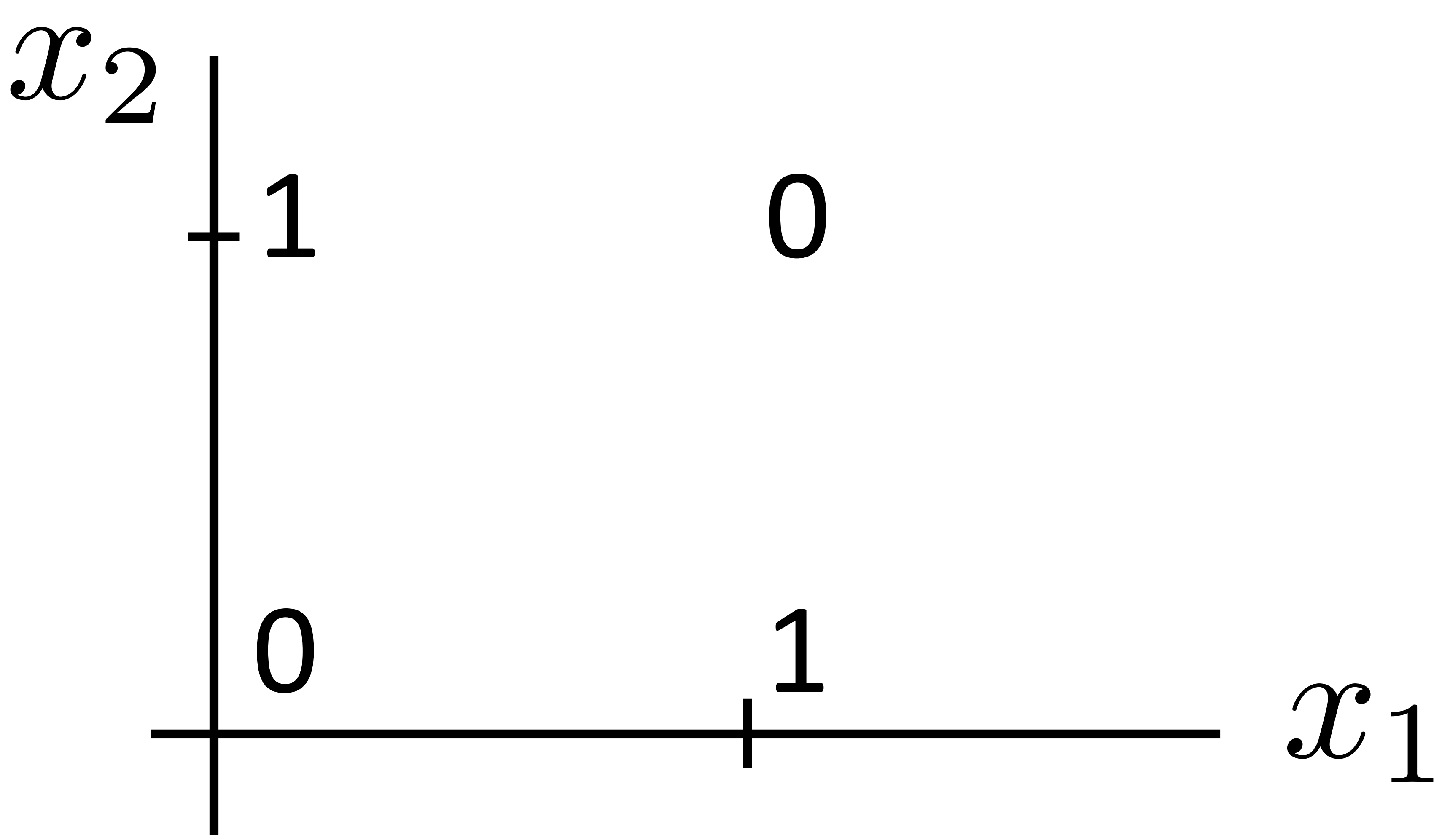

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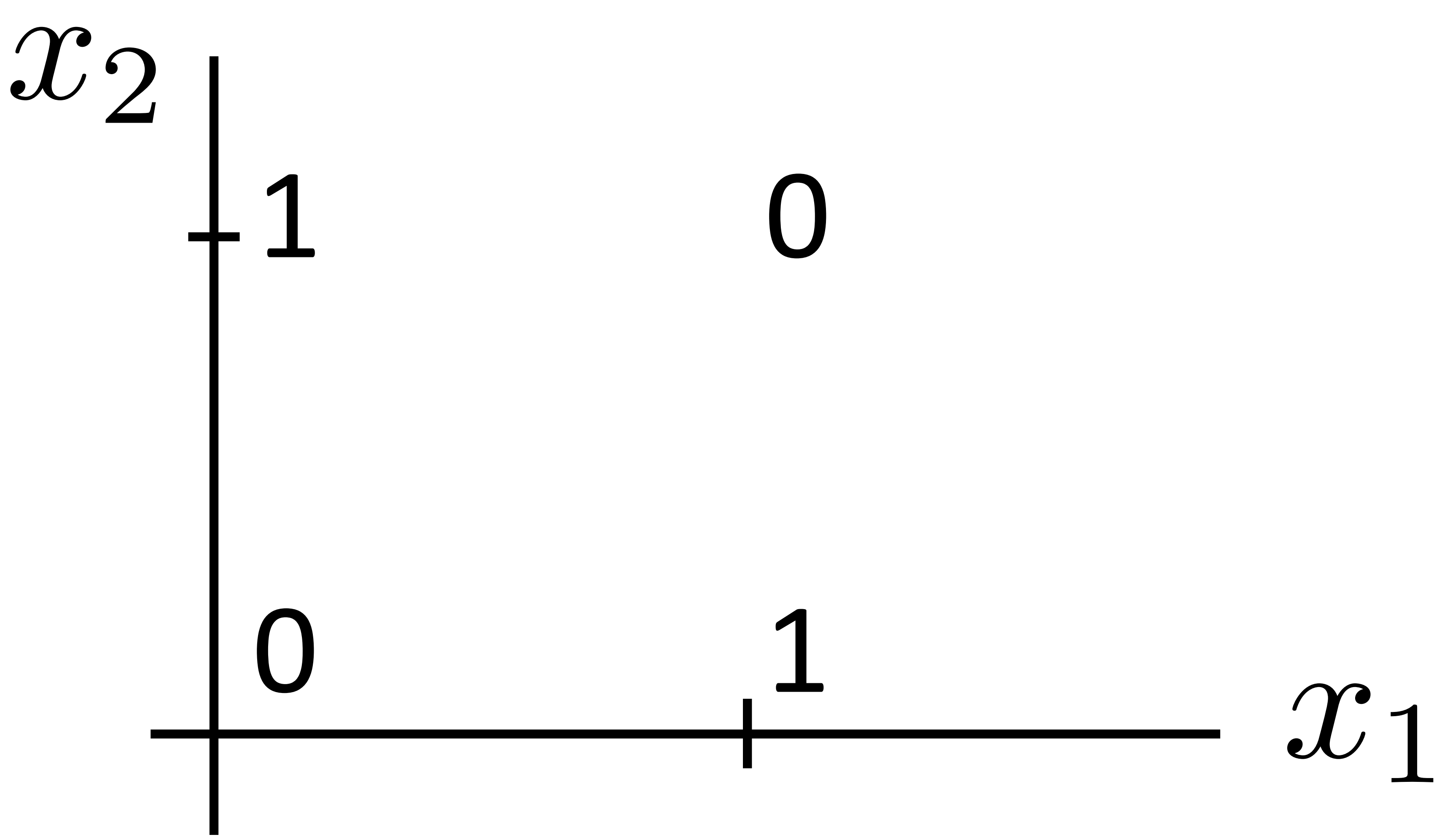
$$y = a_1 x_1 + a_2 x_2$$ X

$$y = a_1 x_1 + a_2 x_2 + a_3 \tanh(x_1 + x_2)$$ ✓

Neural Networks: XOR



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"or"

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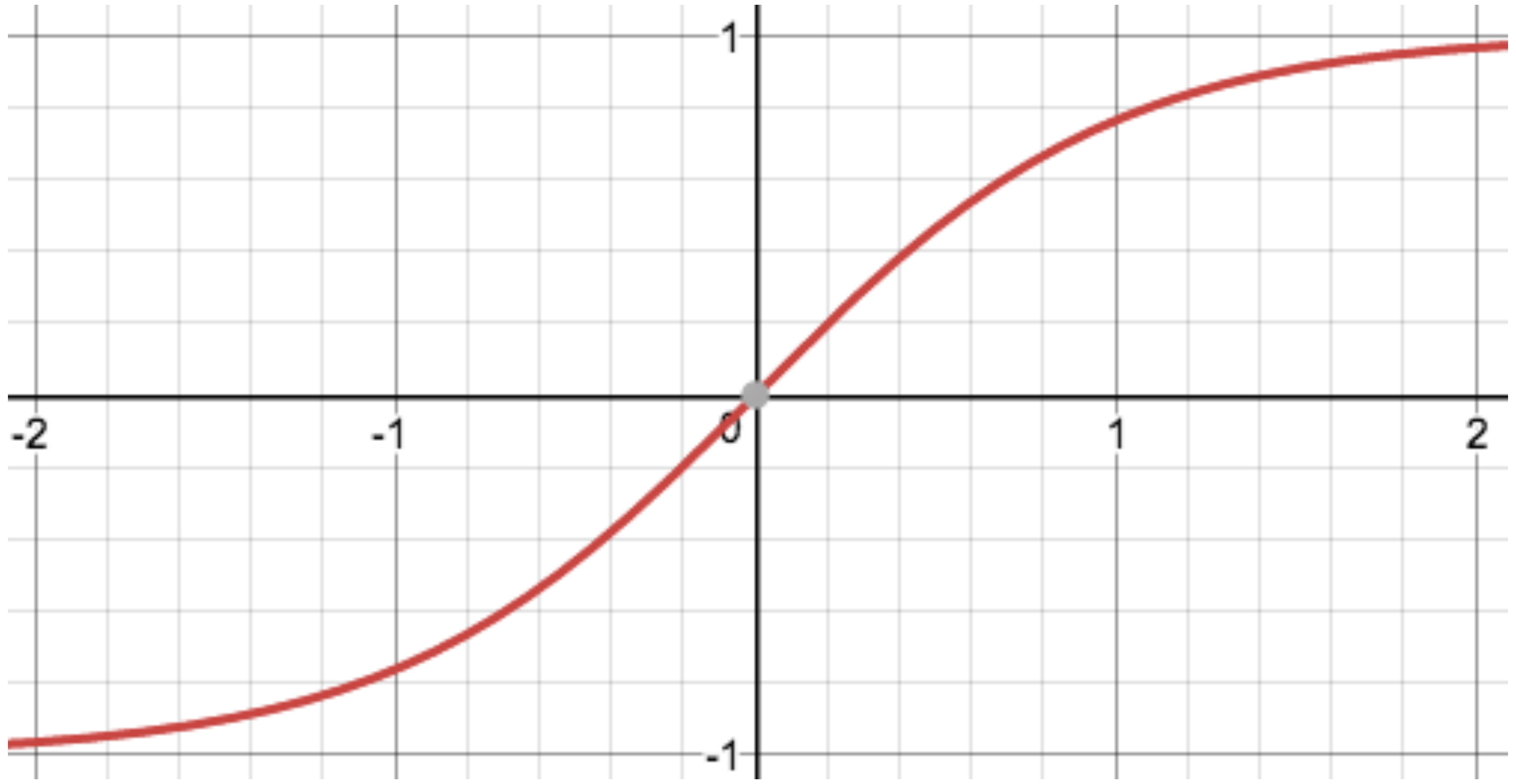

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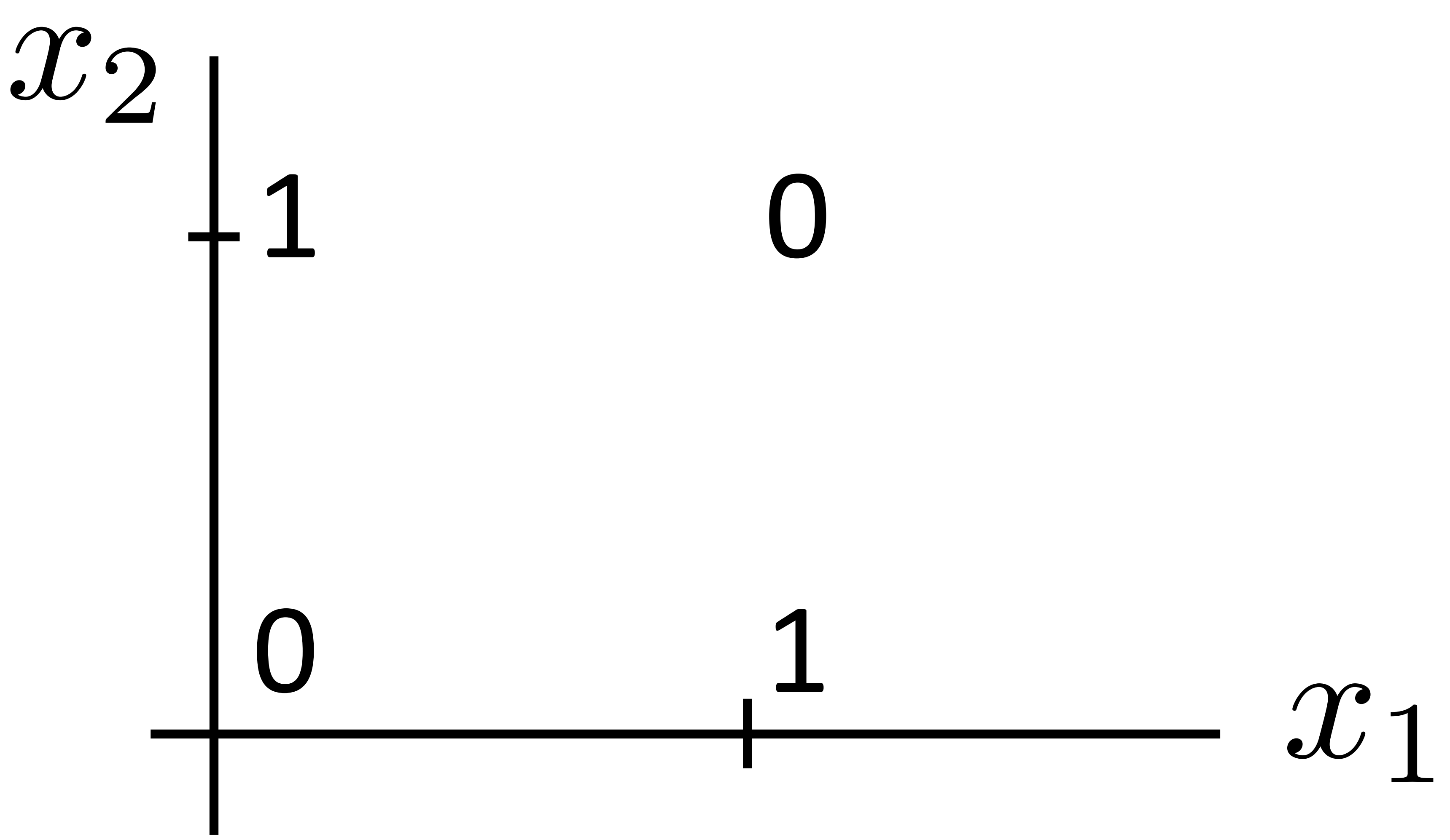

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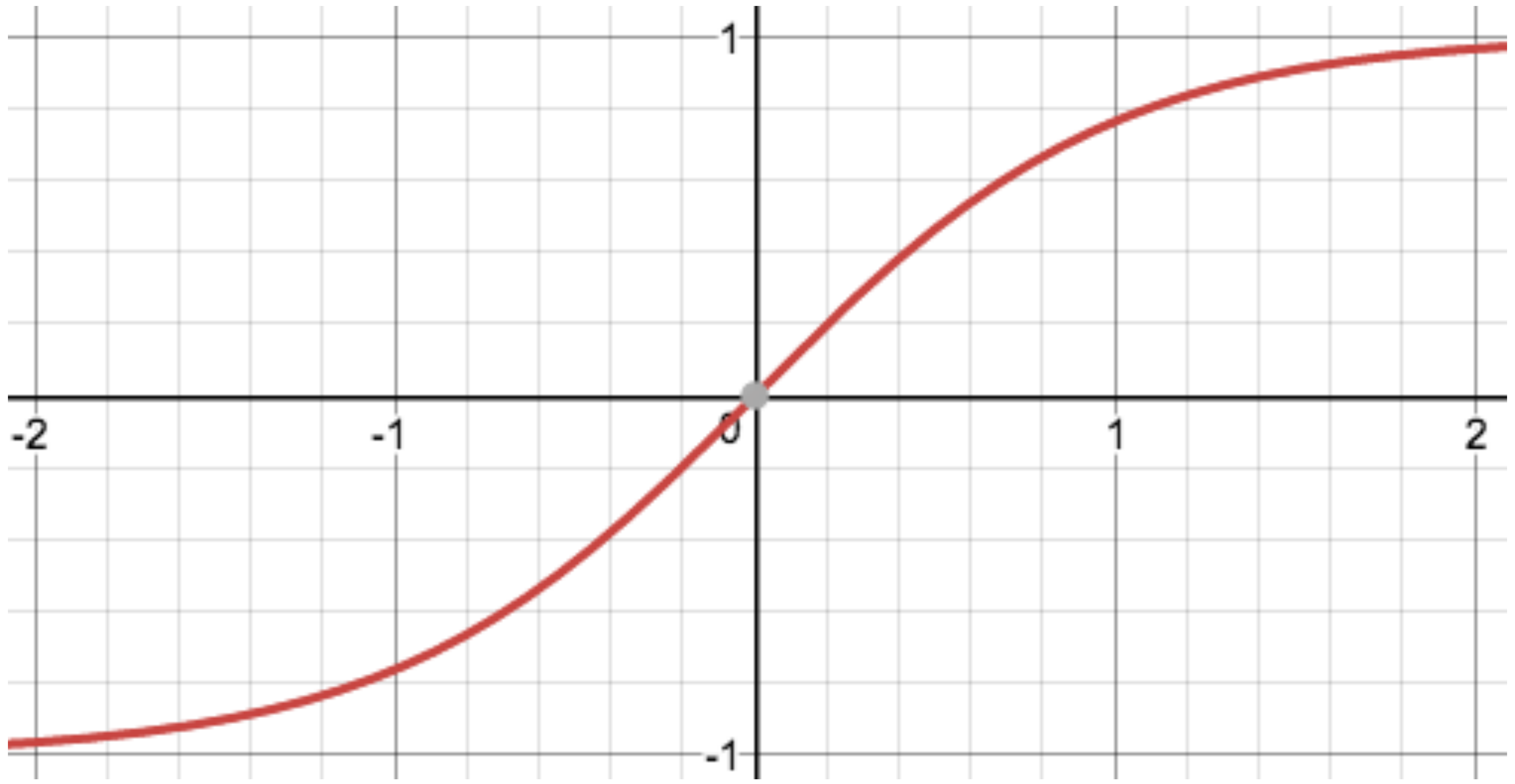
(looks like action potential in neuron)



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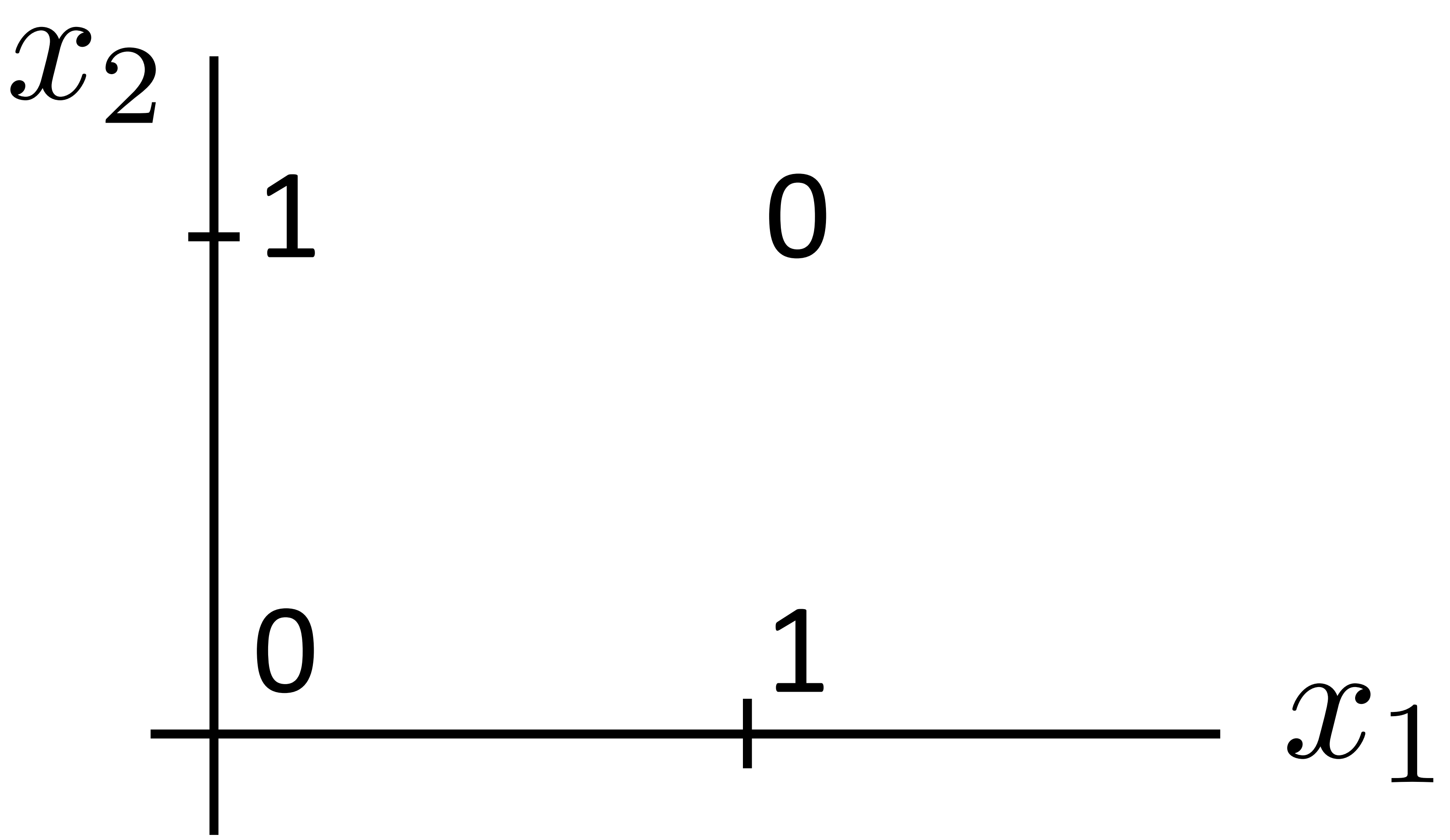

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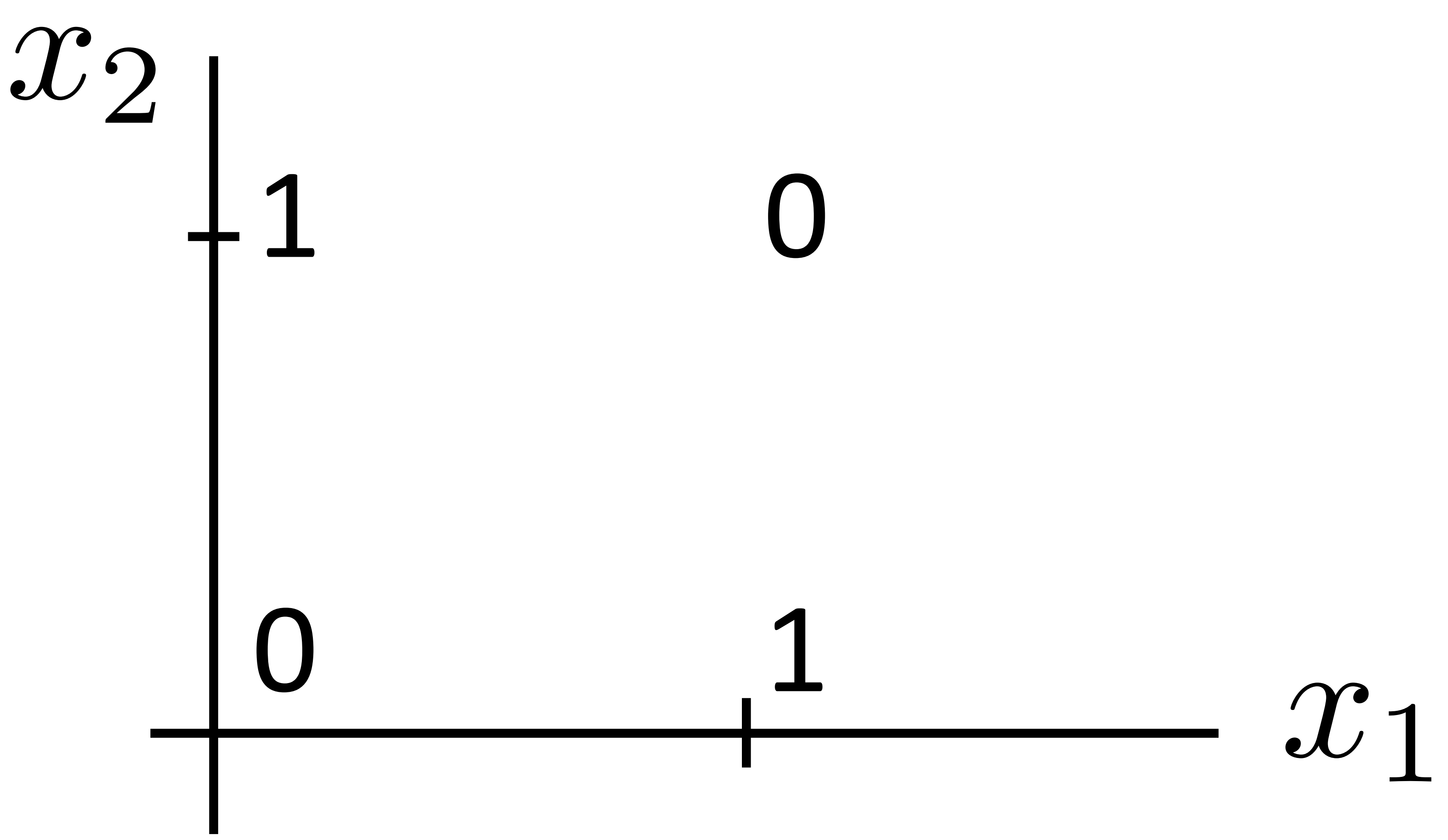

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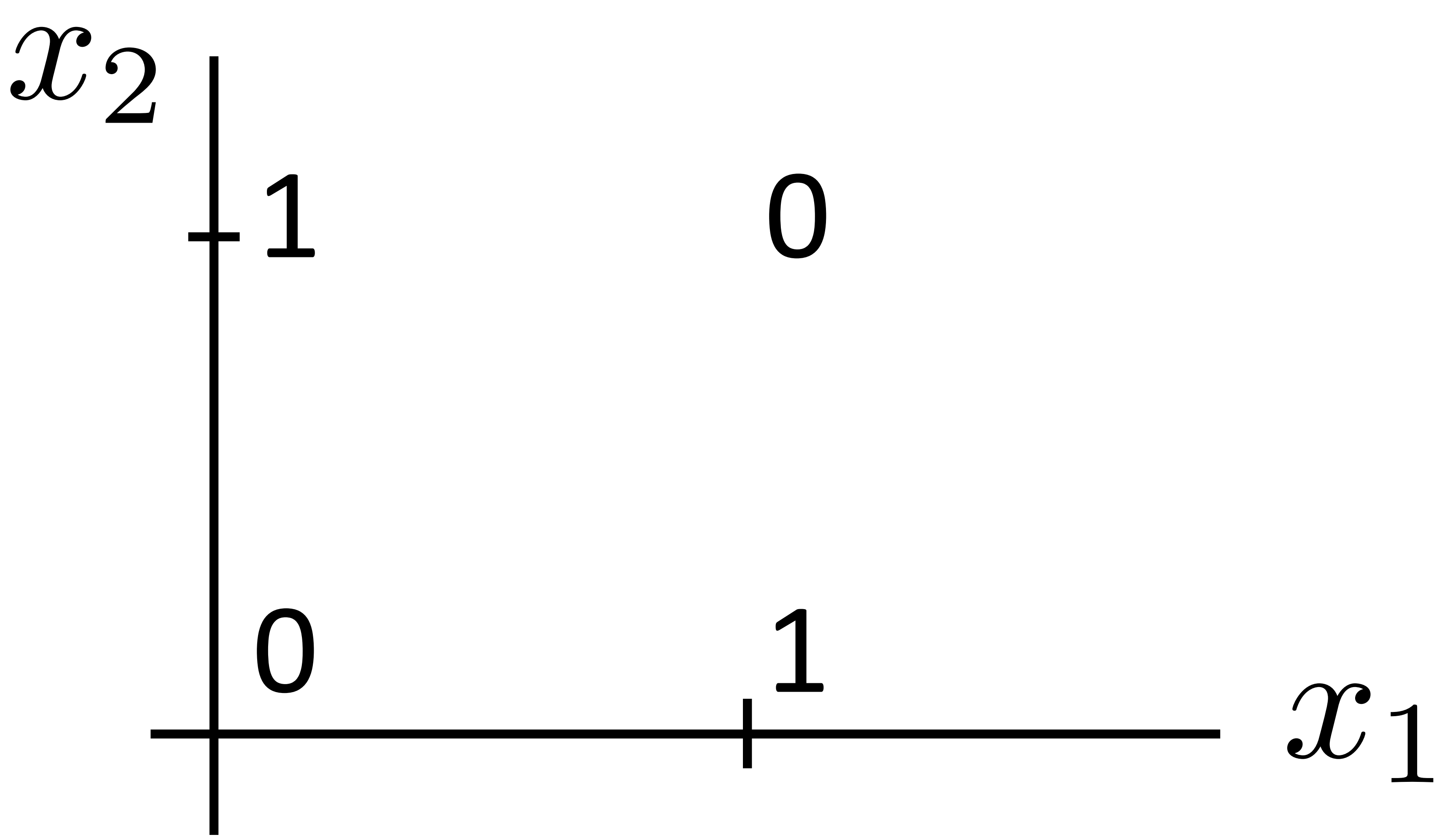

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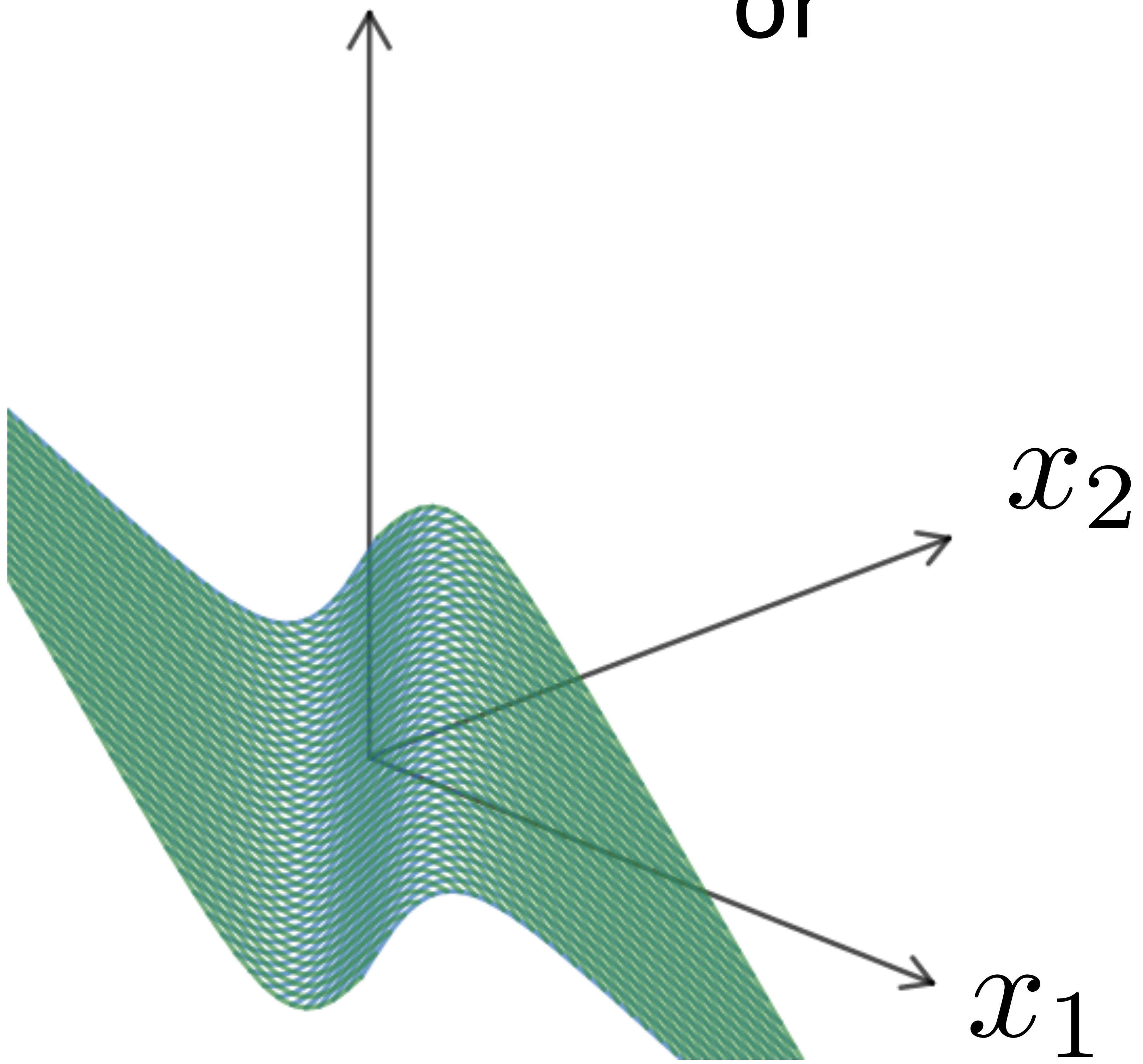

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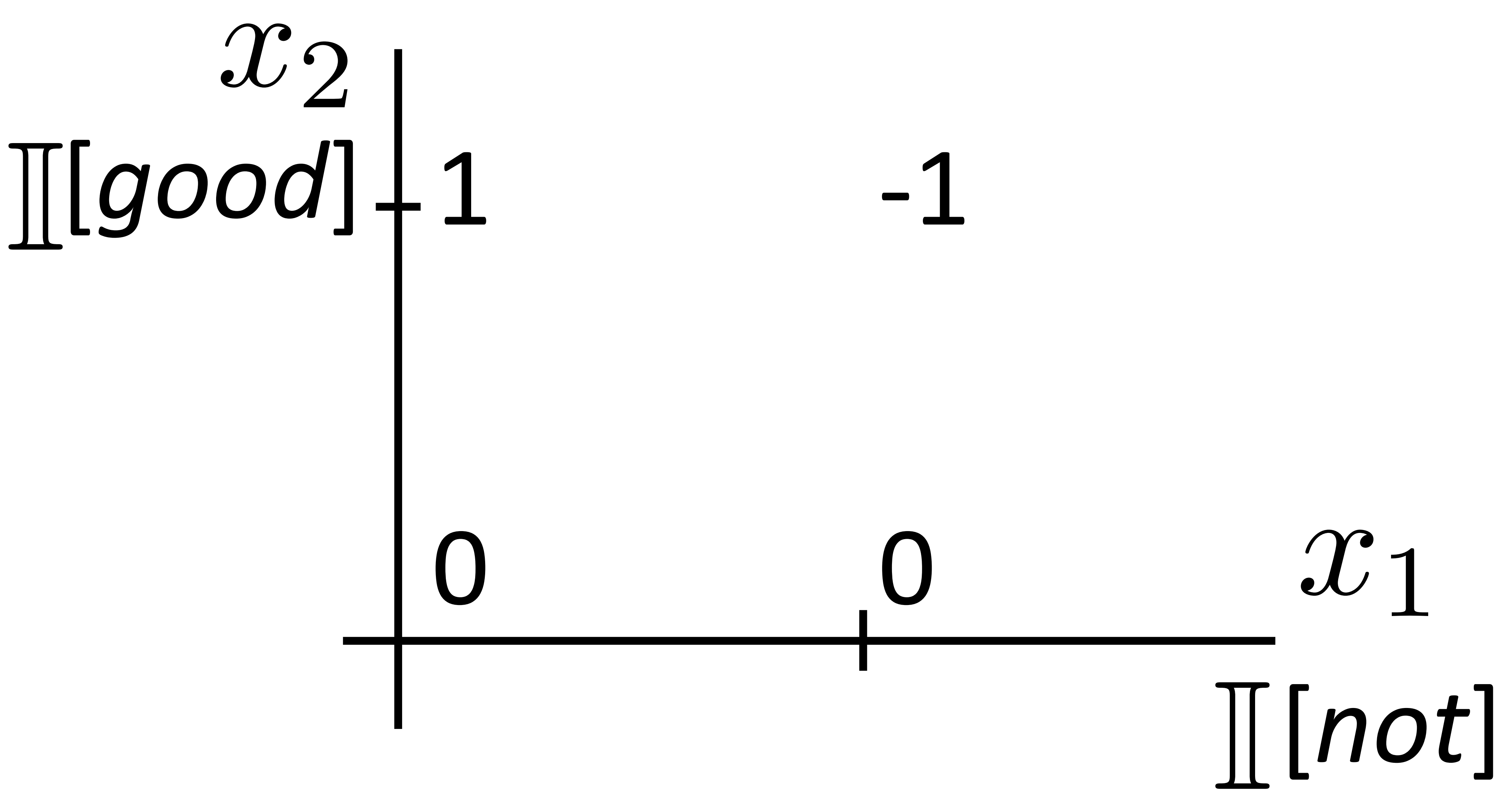

*the movie was **not** all that **good***

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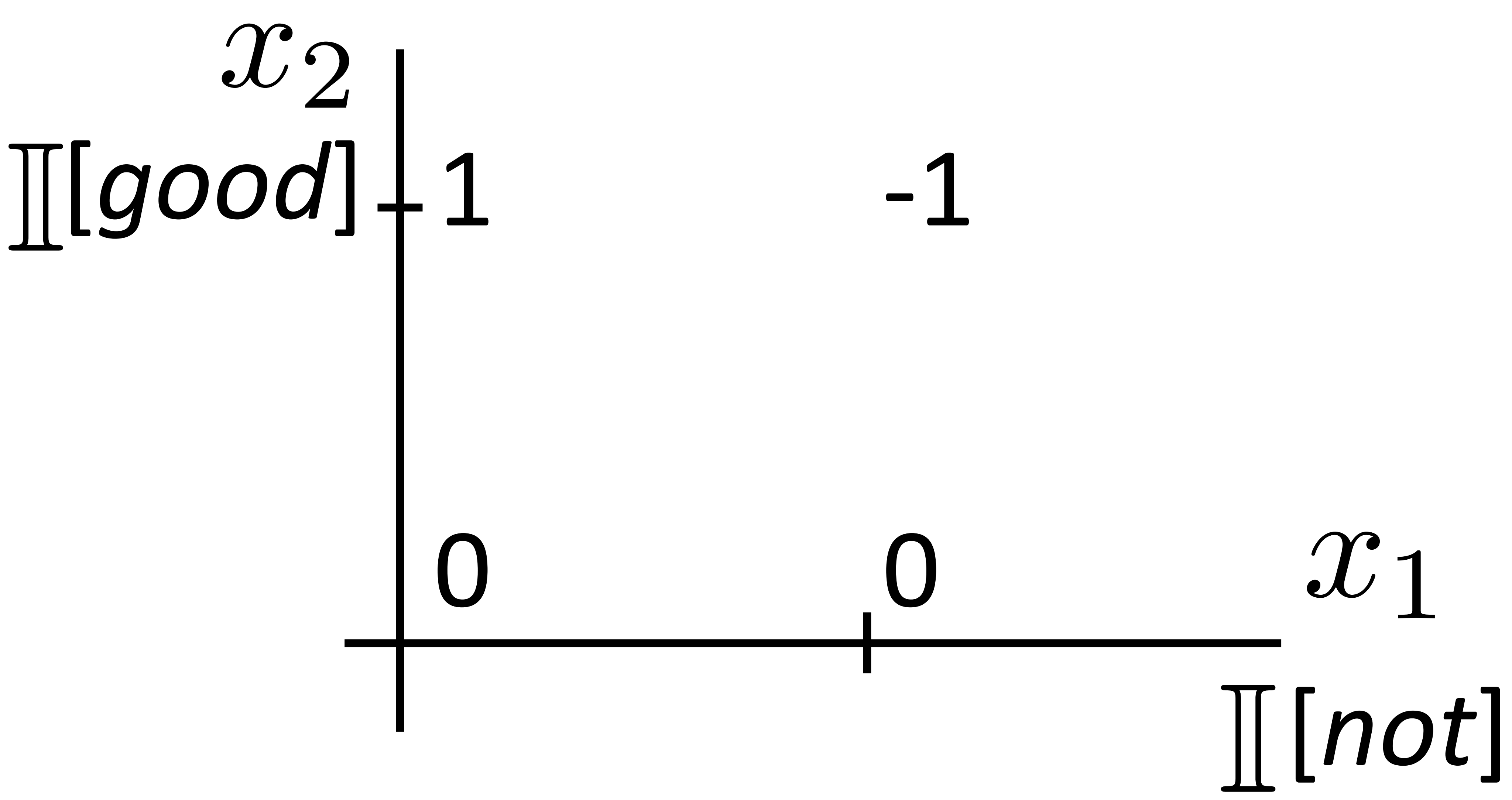

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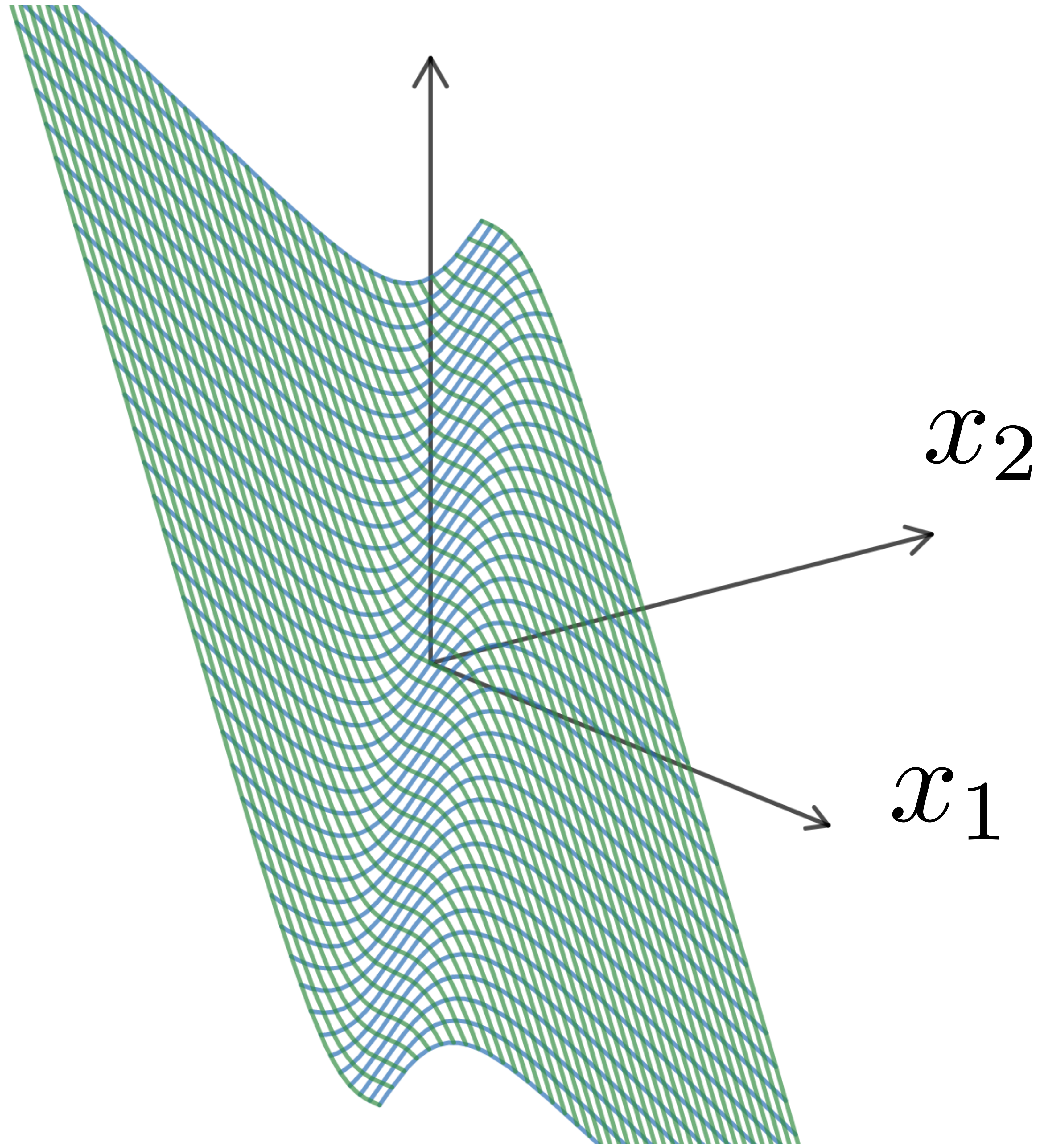

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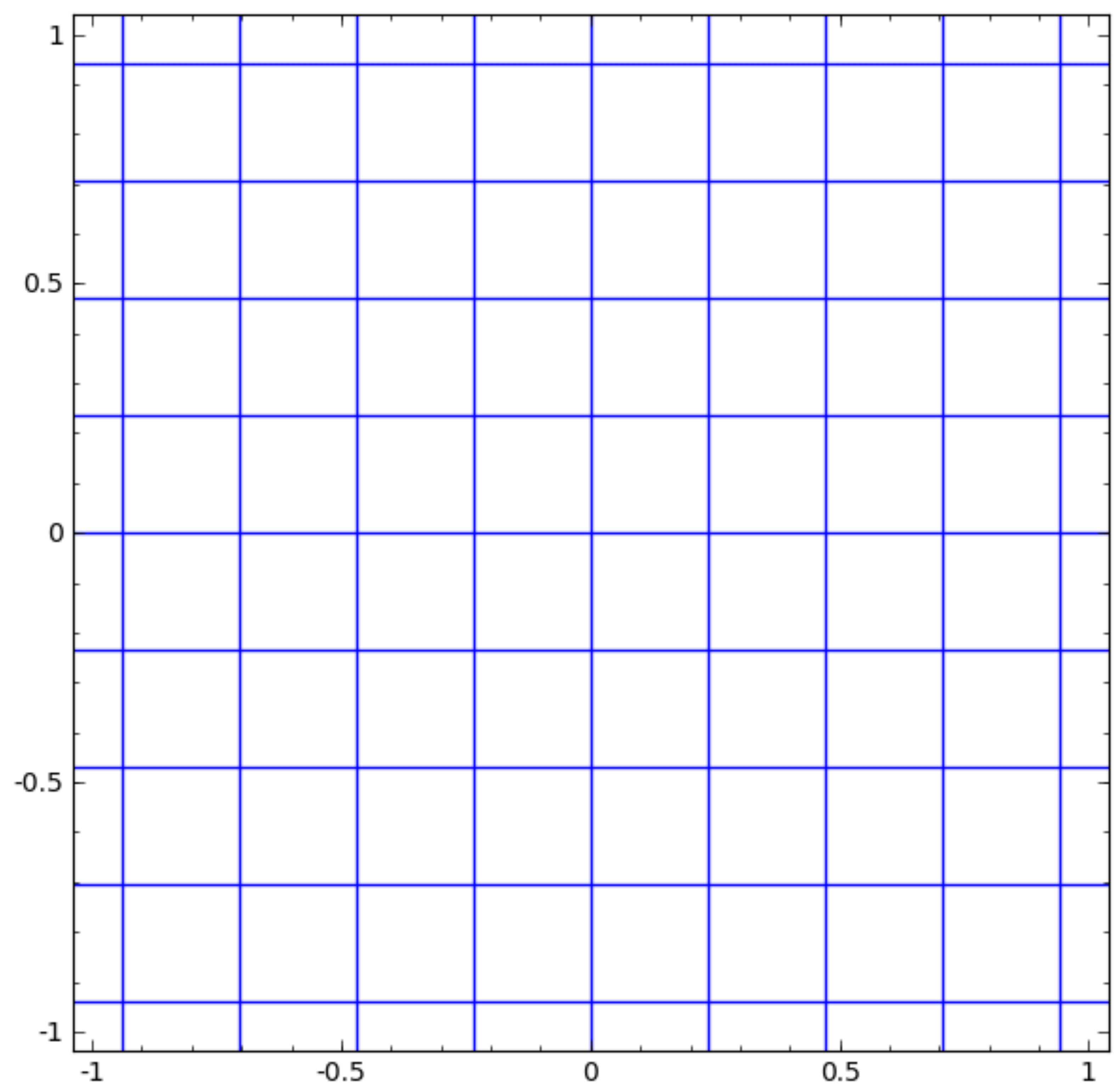
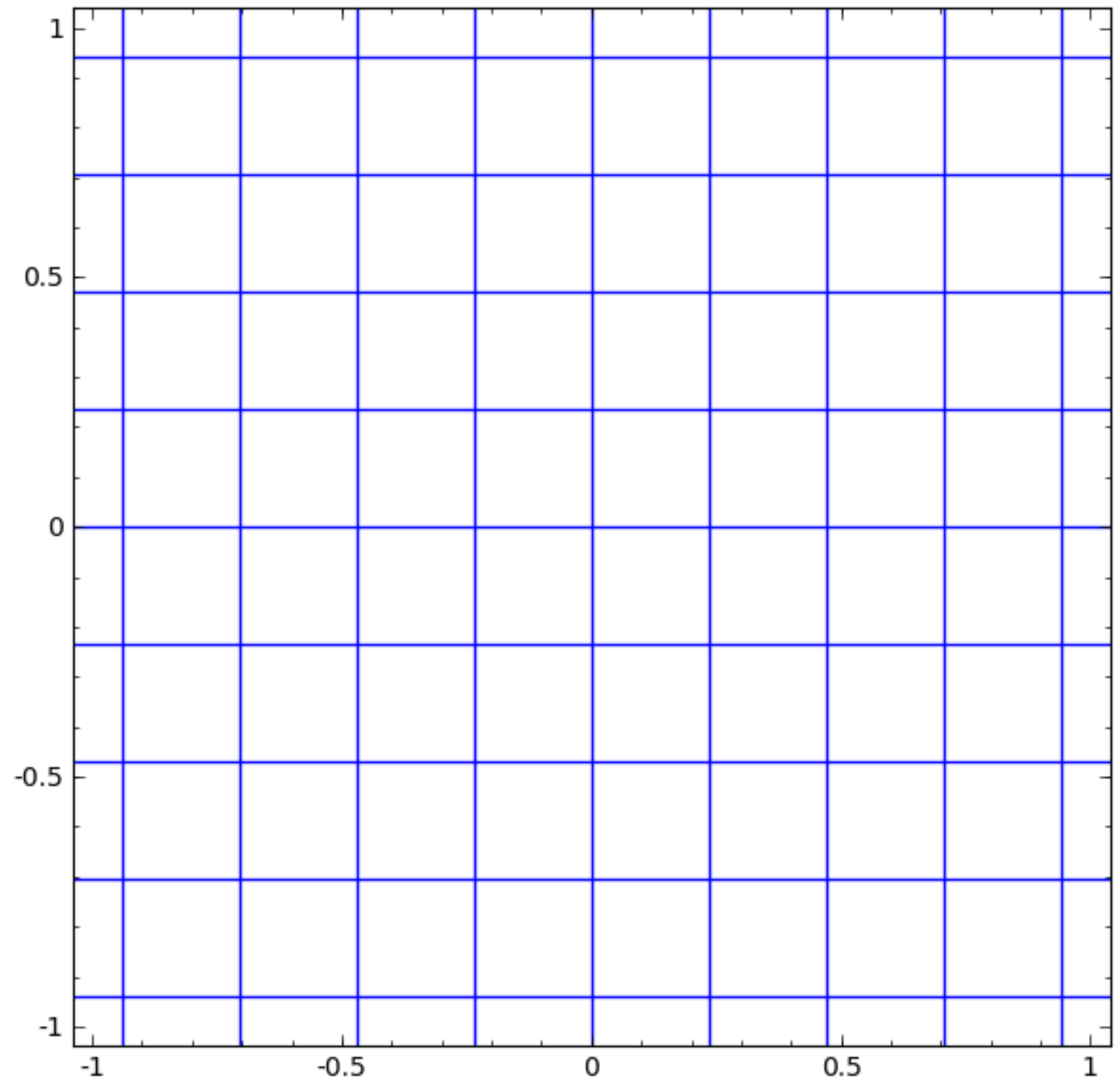
Neural Networks



Neural Networks

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



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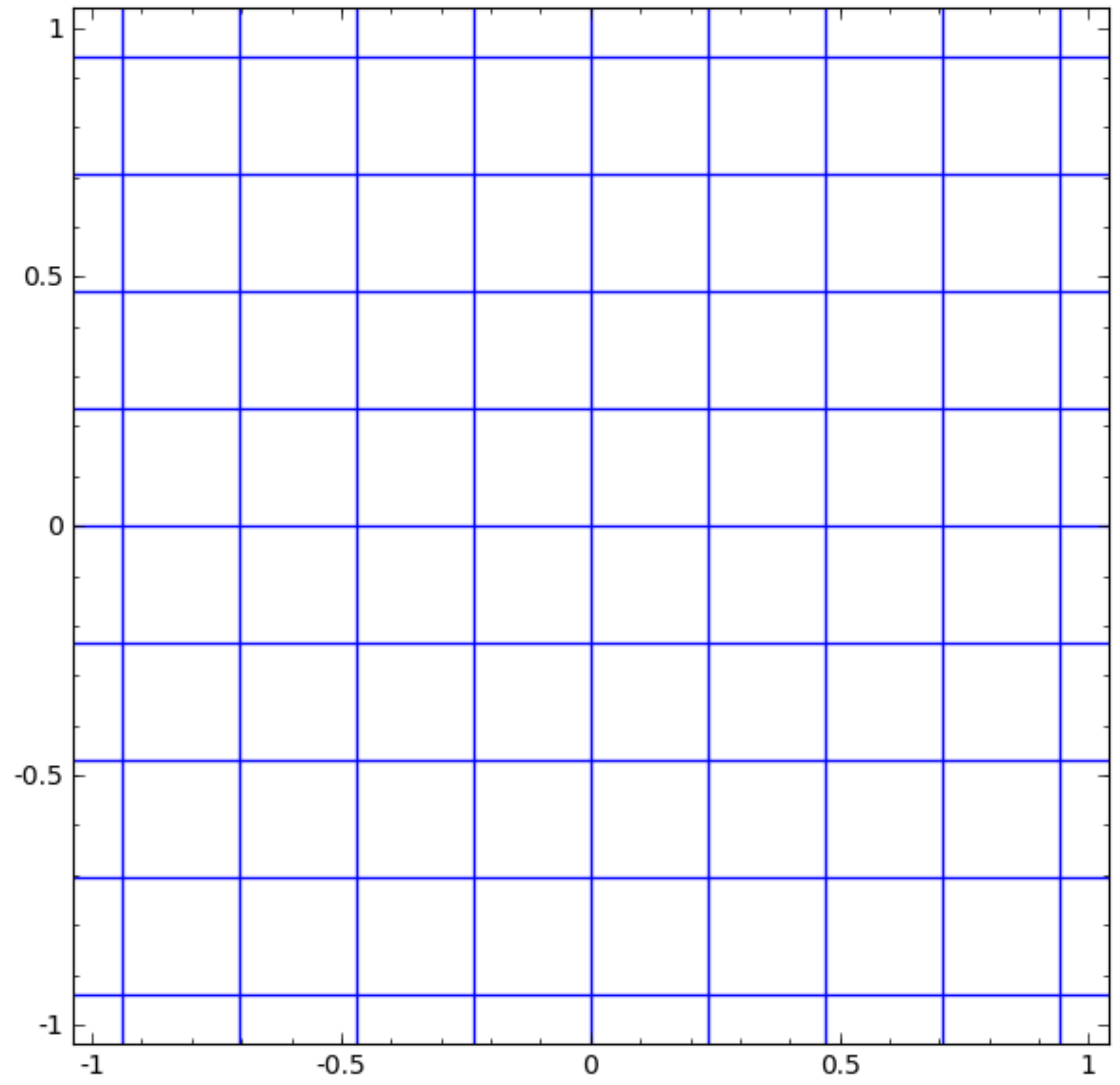
Nonlinear transformation



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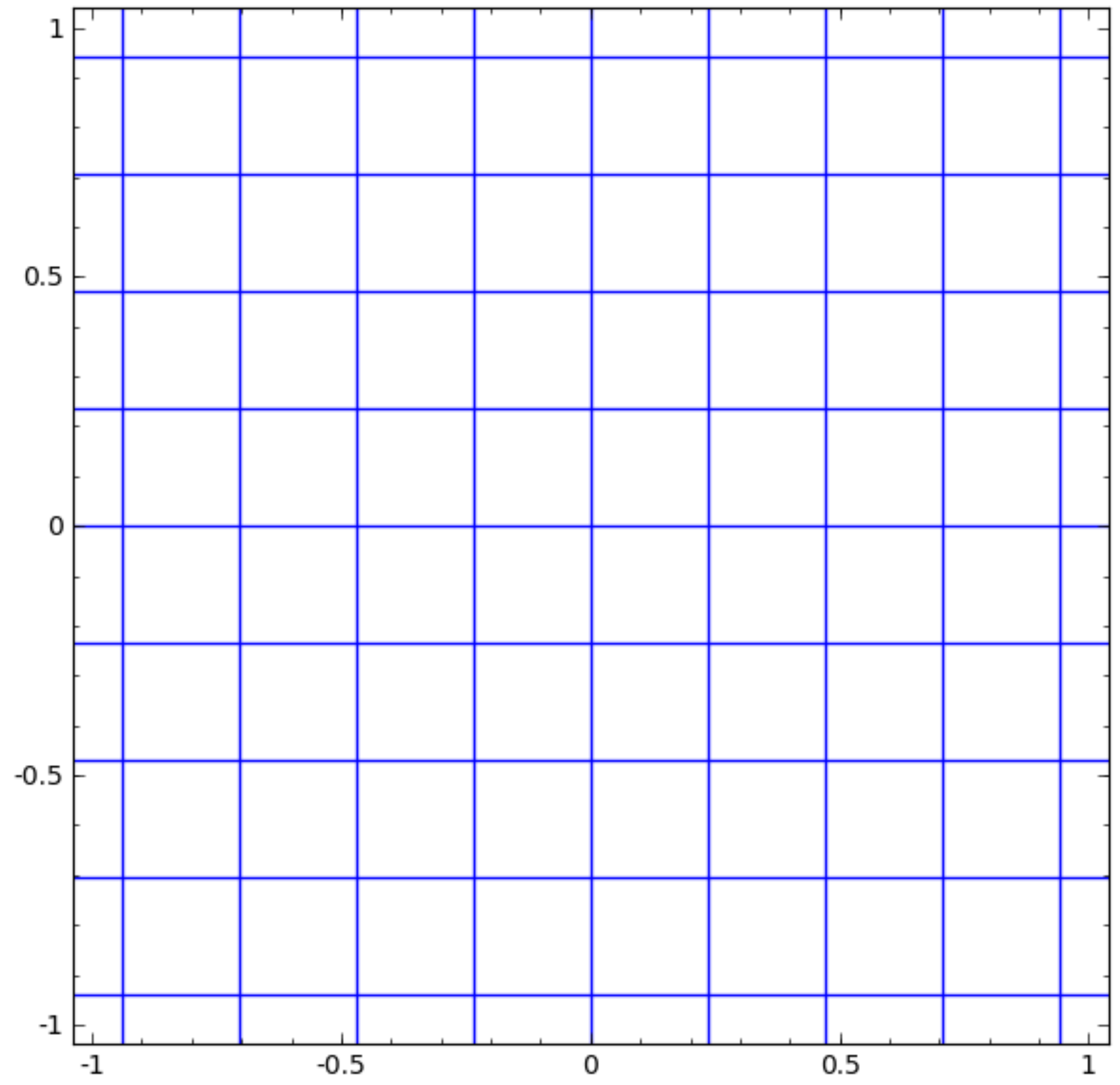
Nonlinear transformation

Warp space



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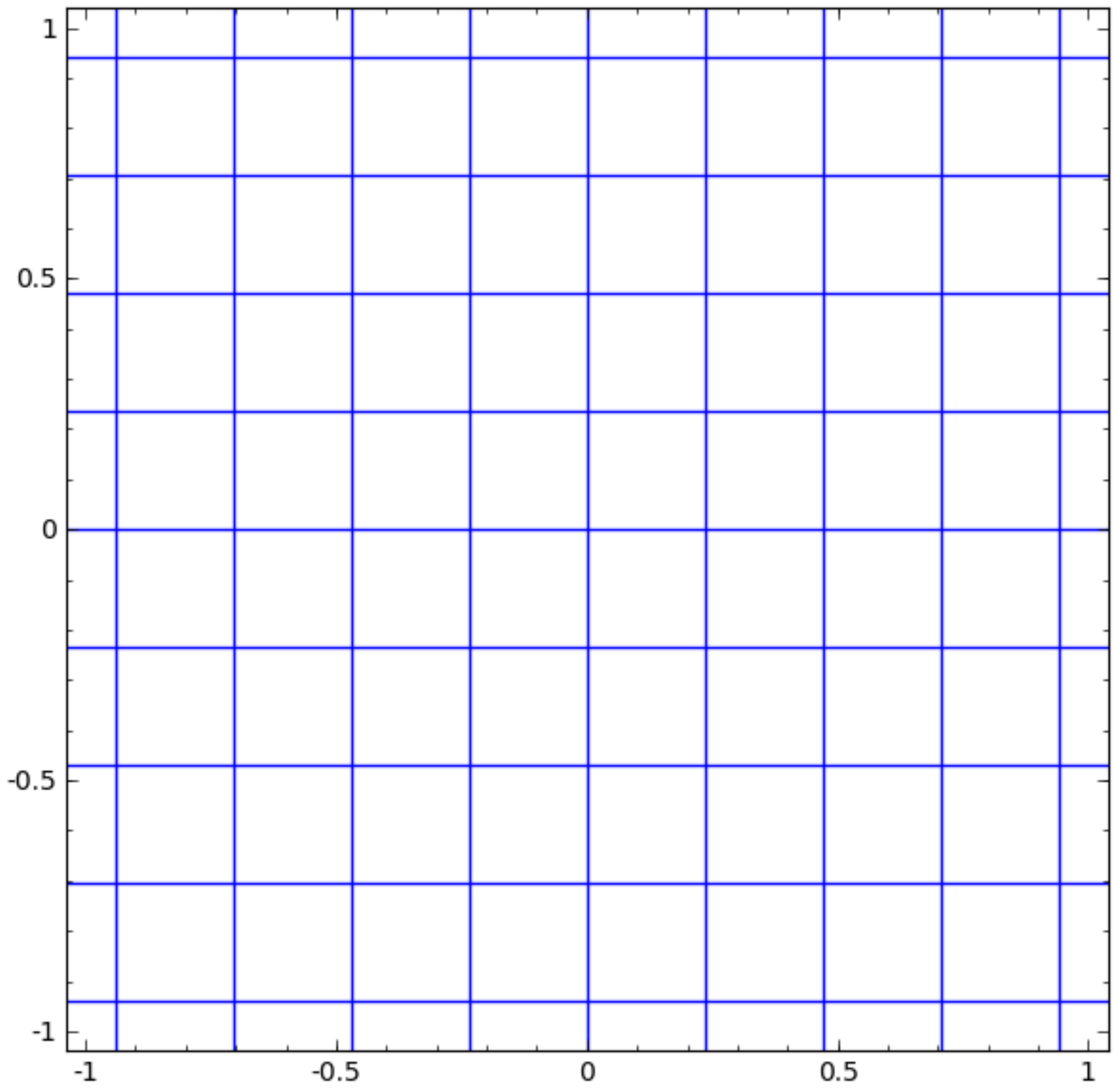
Nonlinear transformation

Warp space

Shift



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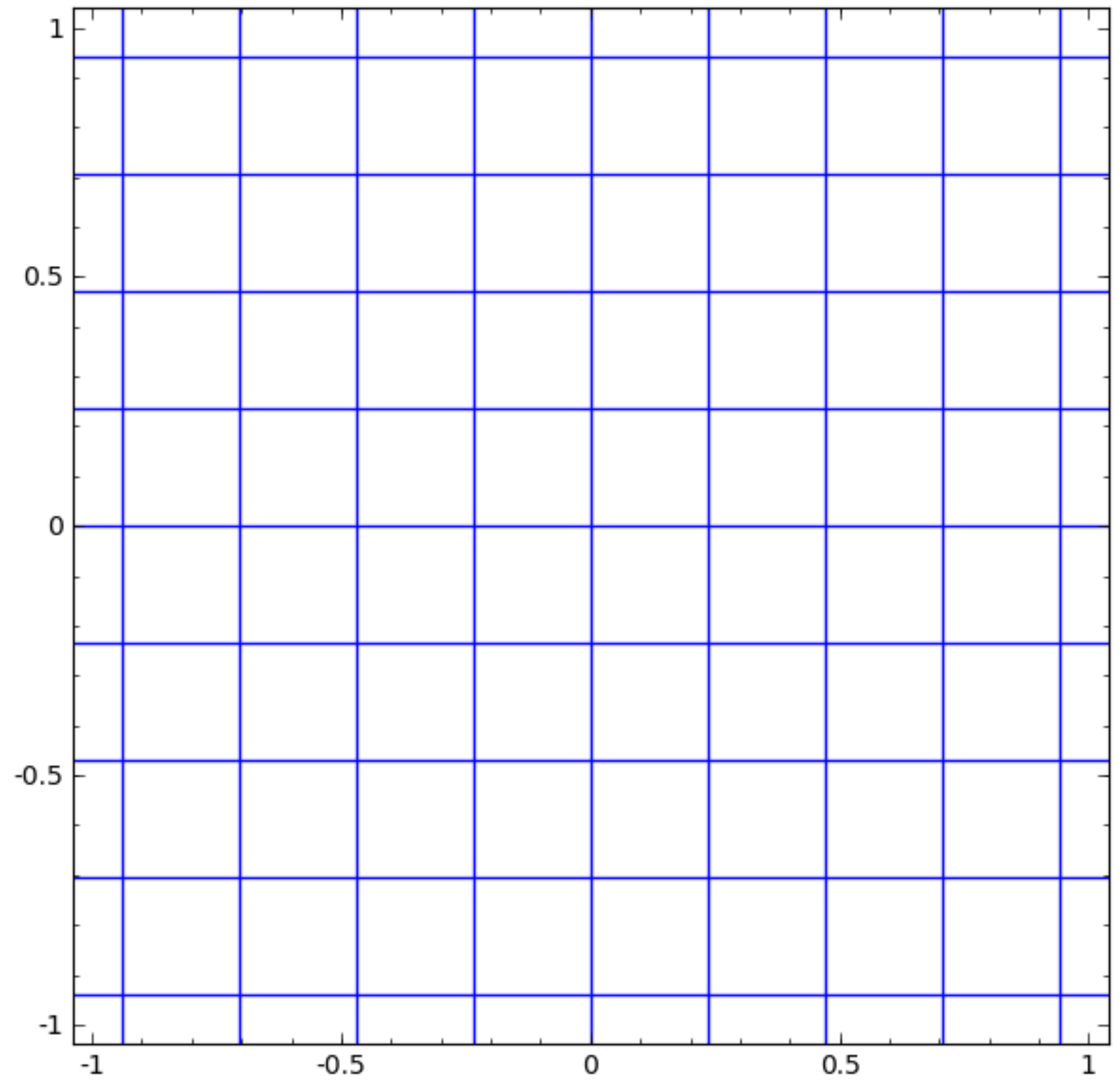

Taken from http://colah.github.io/posts/2014-03-NN-Manifolds-Topology/

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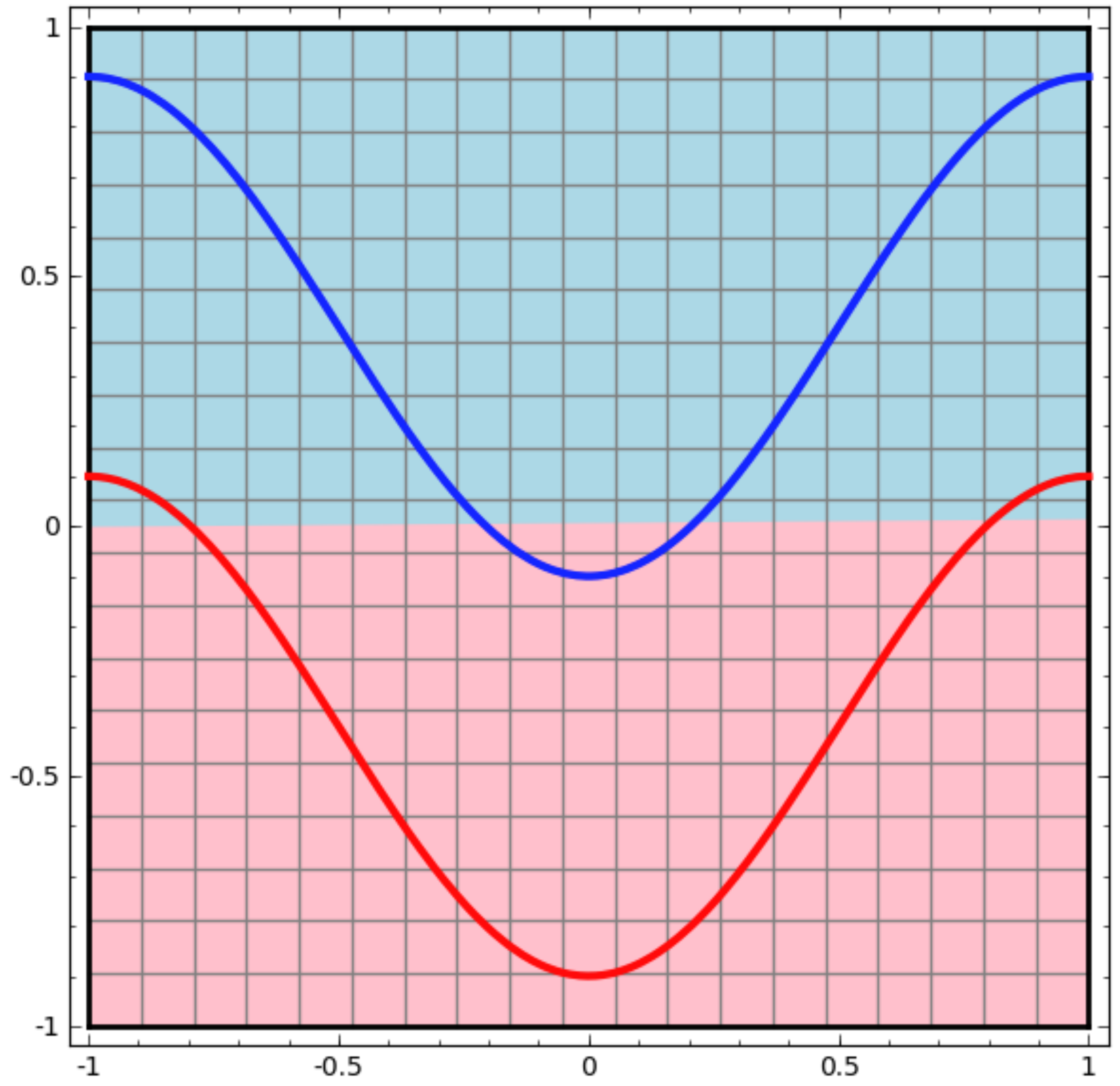
Neural Networks

Linear classifier



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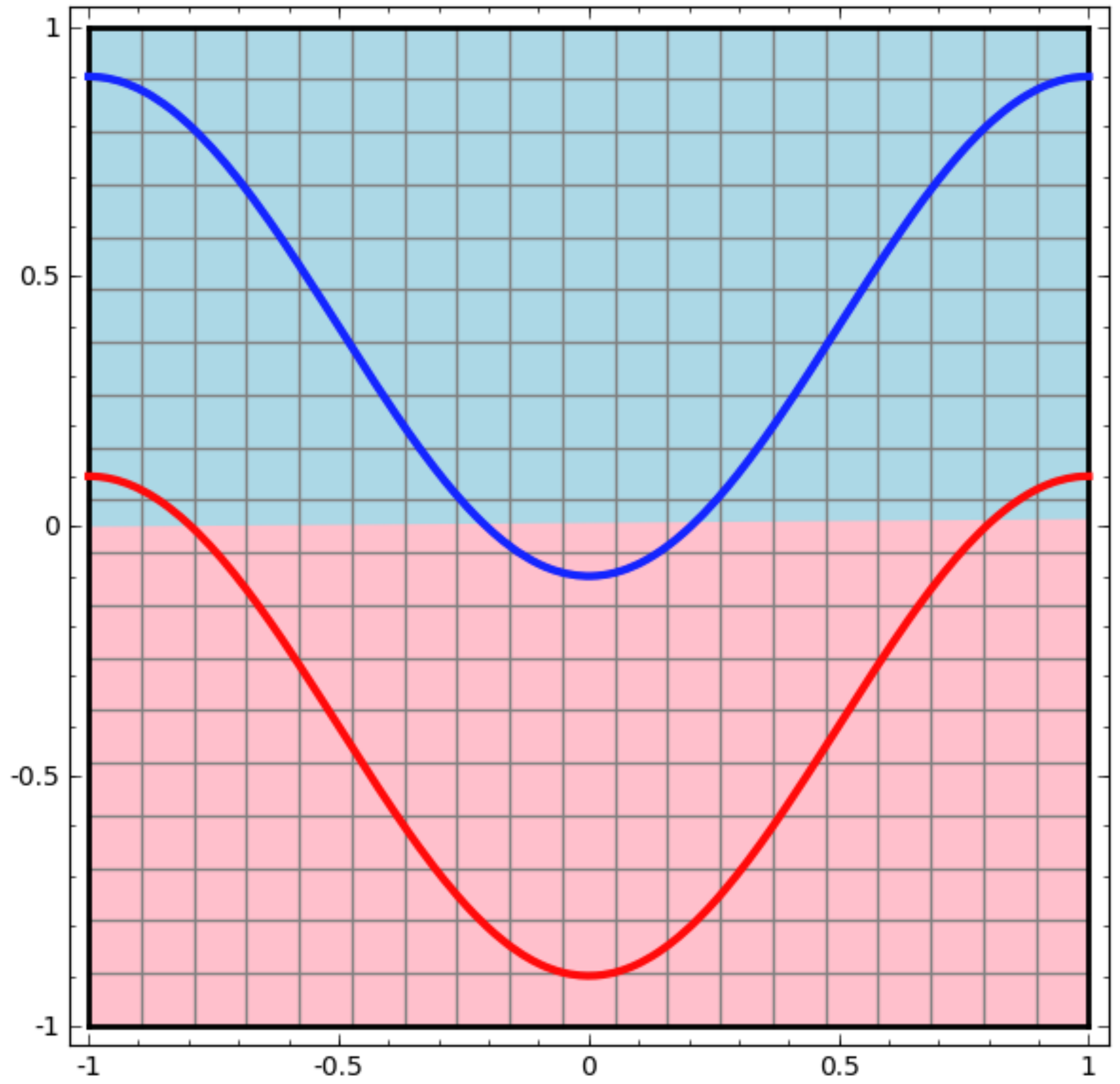
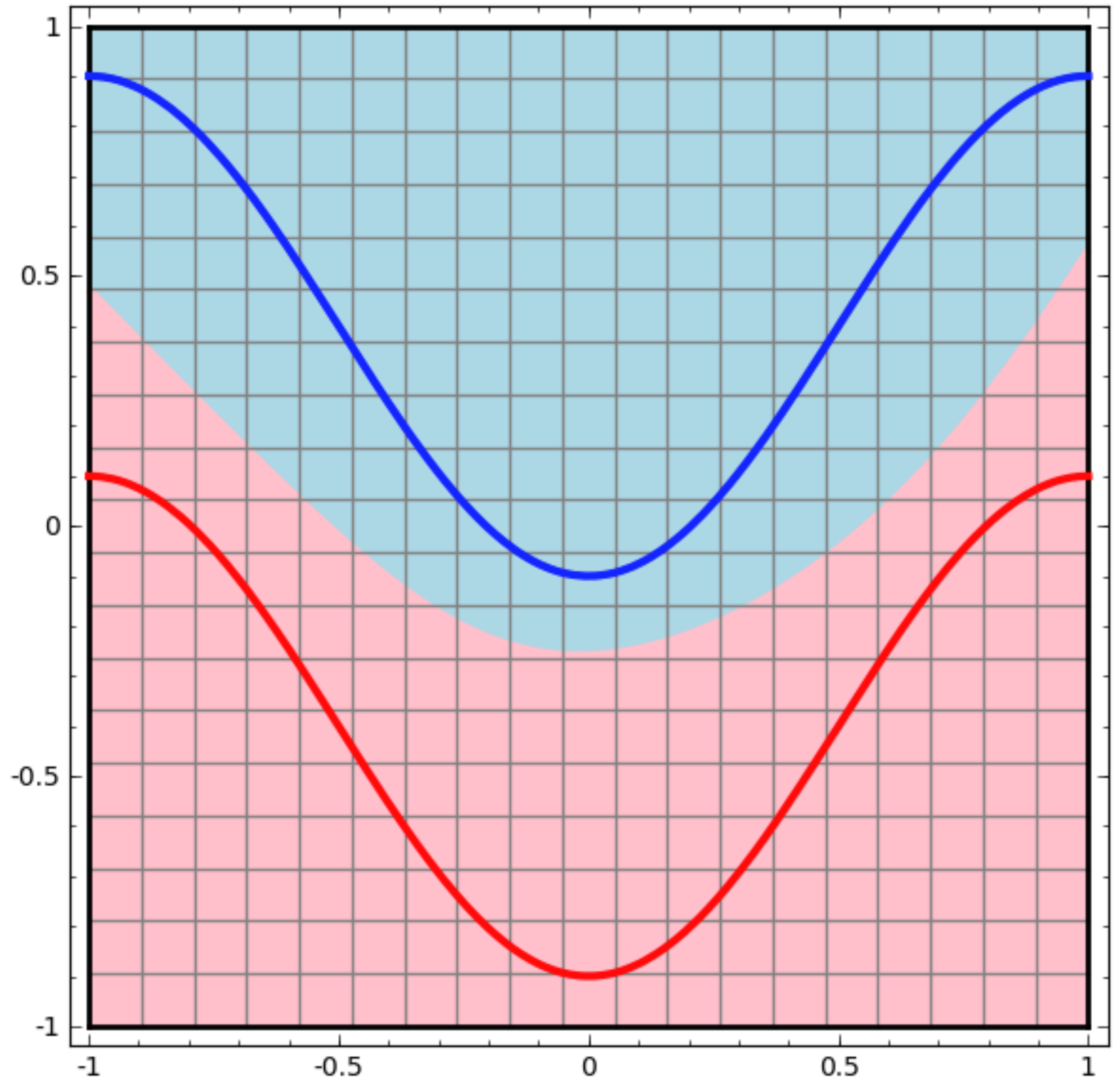


Neural network



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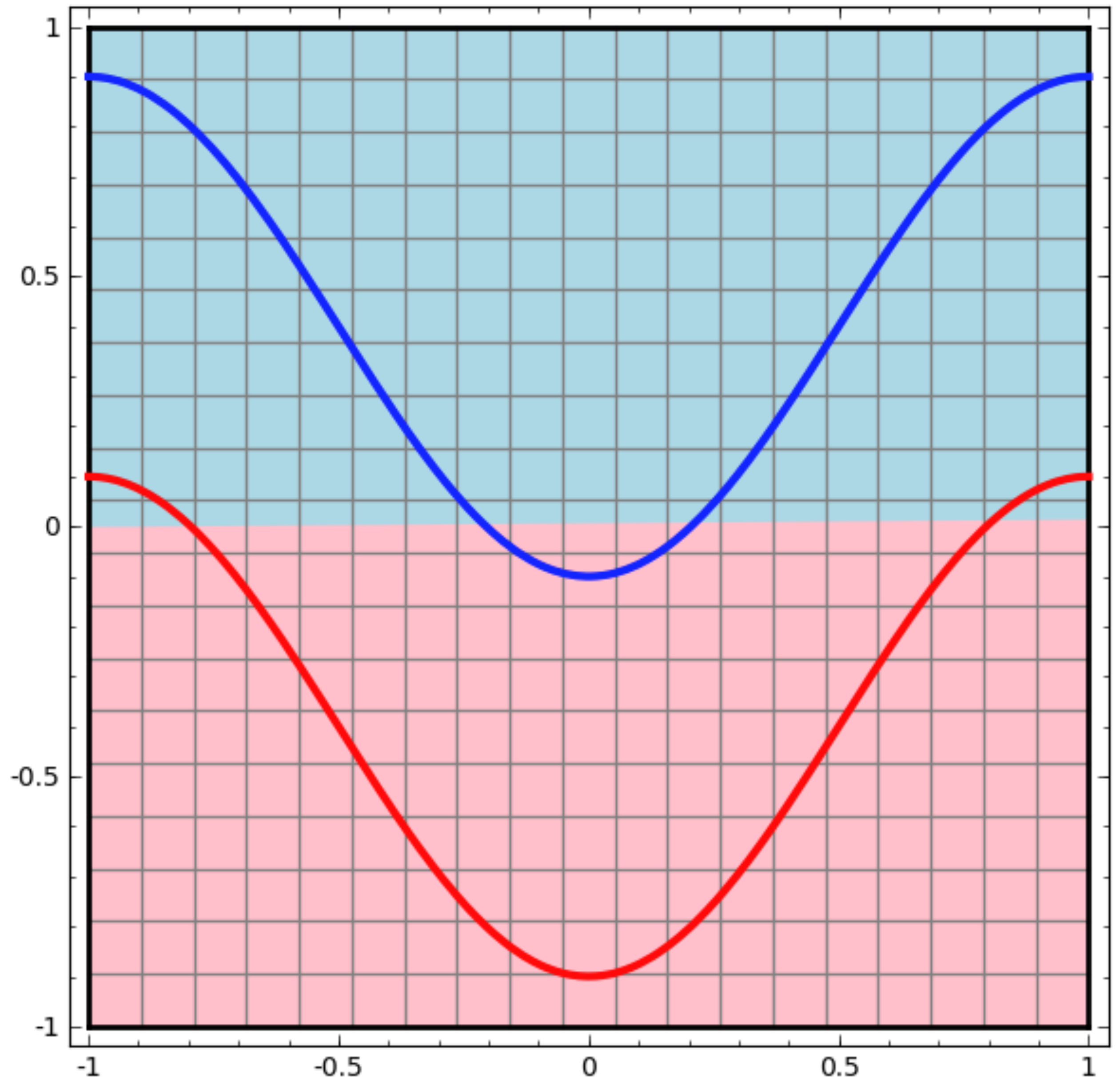
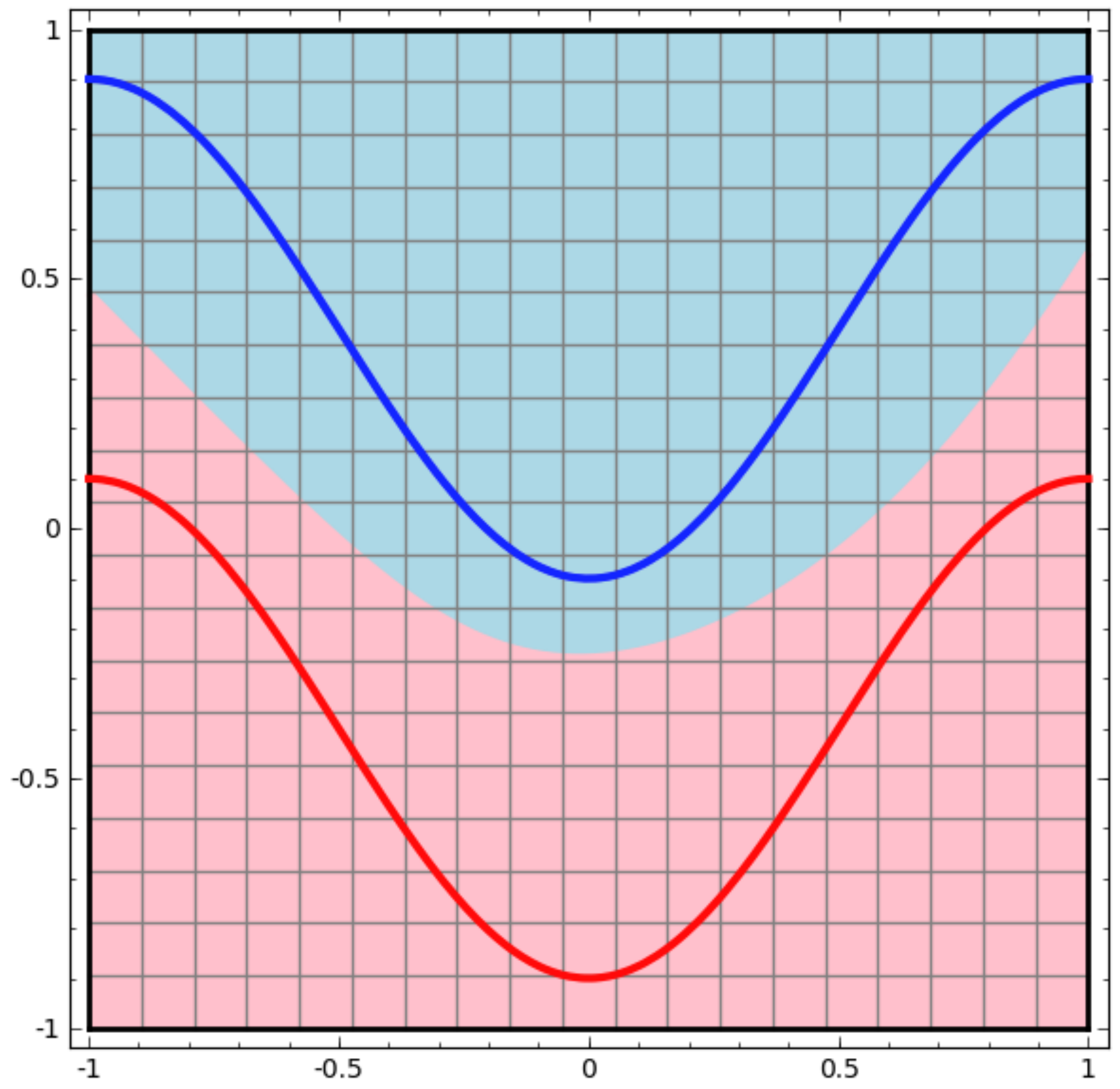
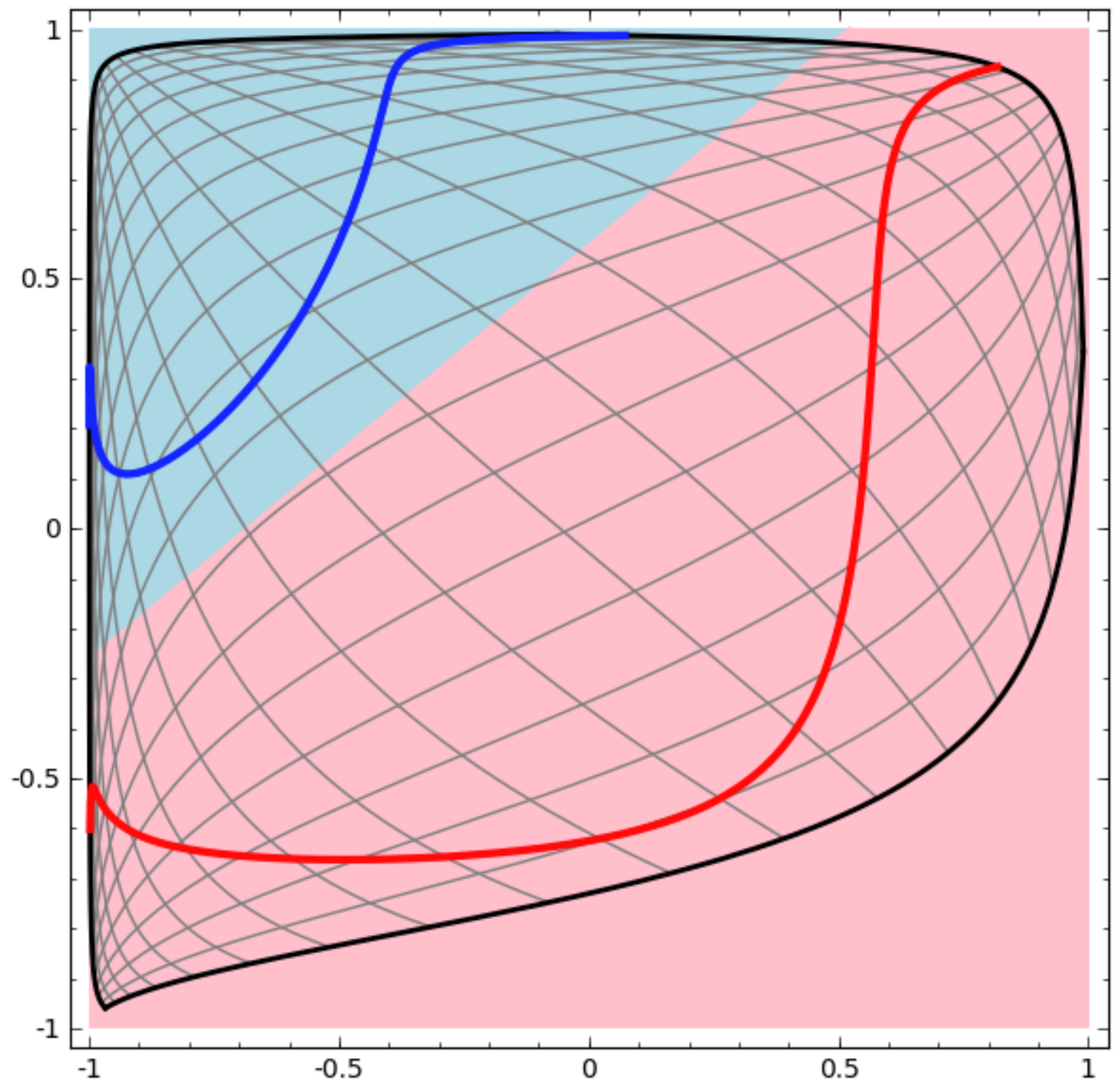


Neural network

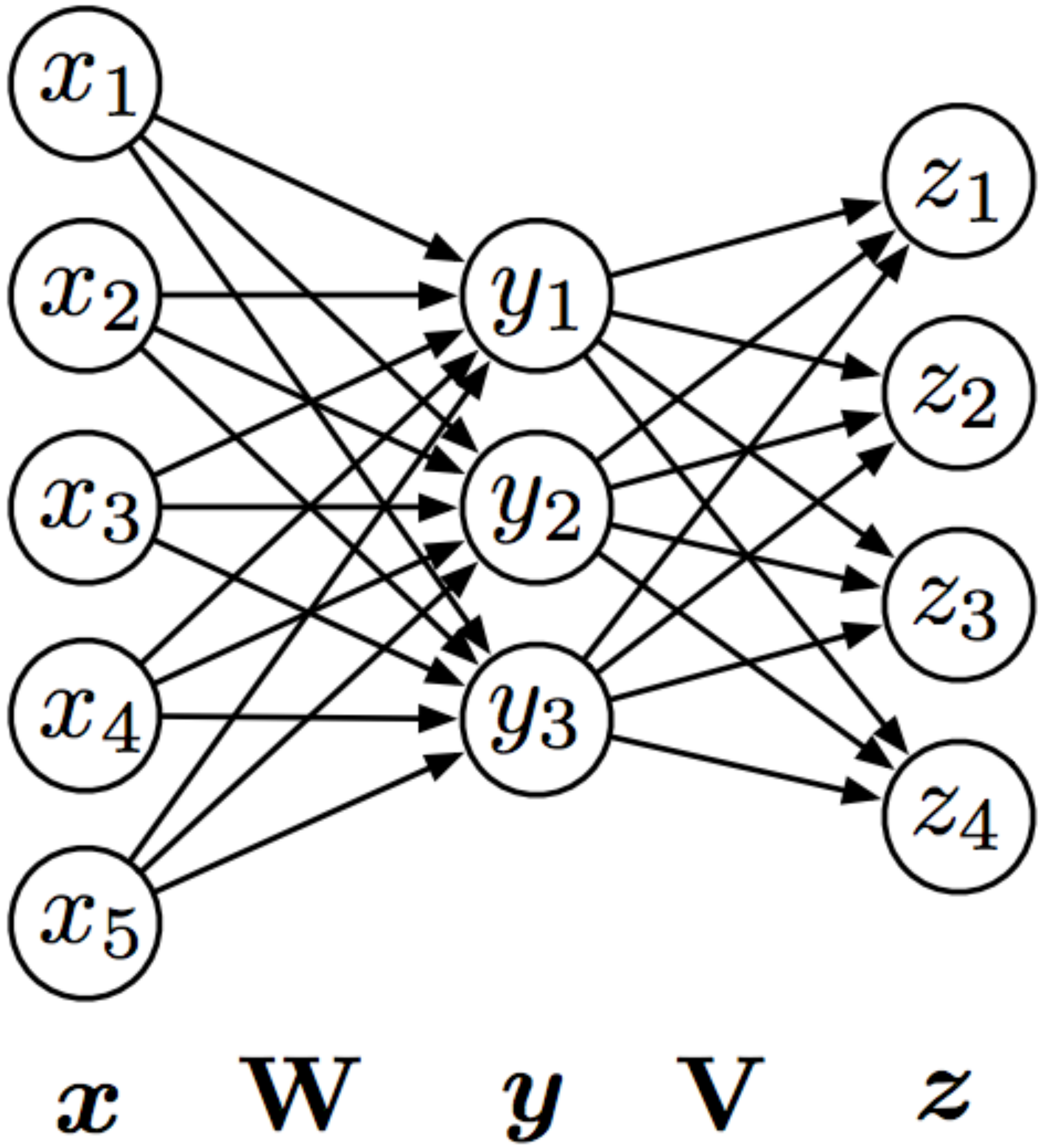


…possible because we transformed the space!



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

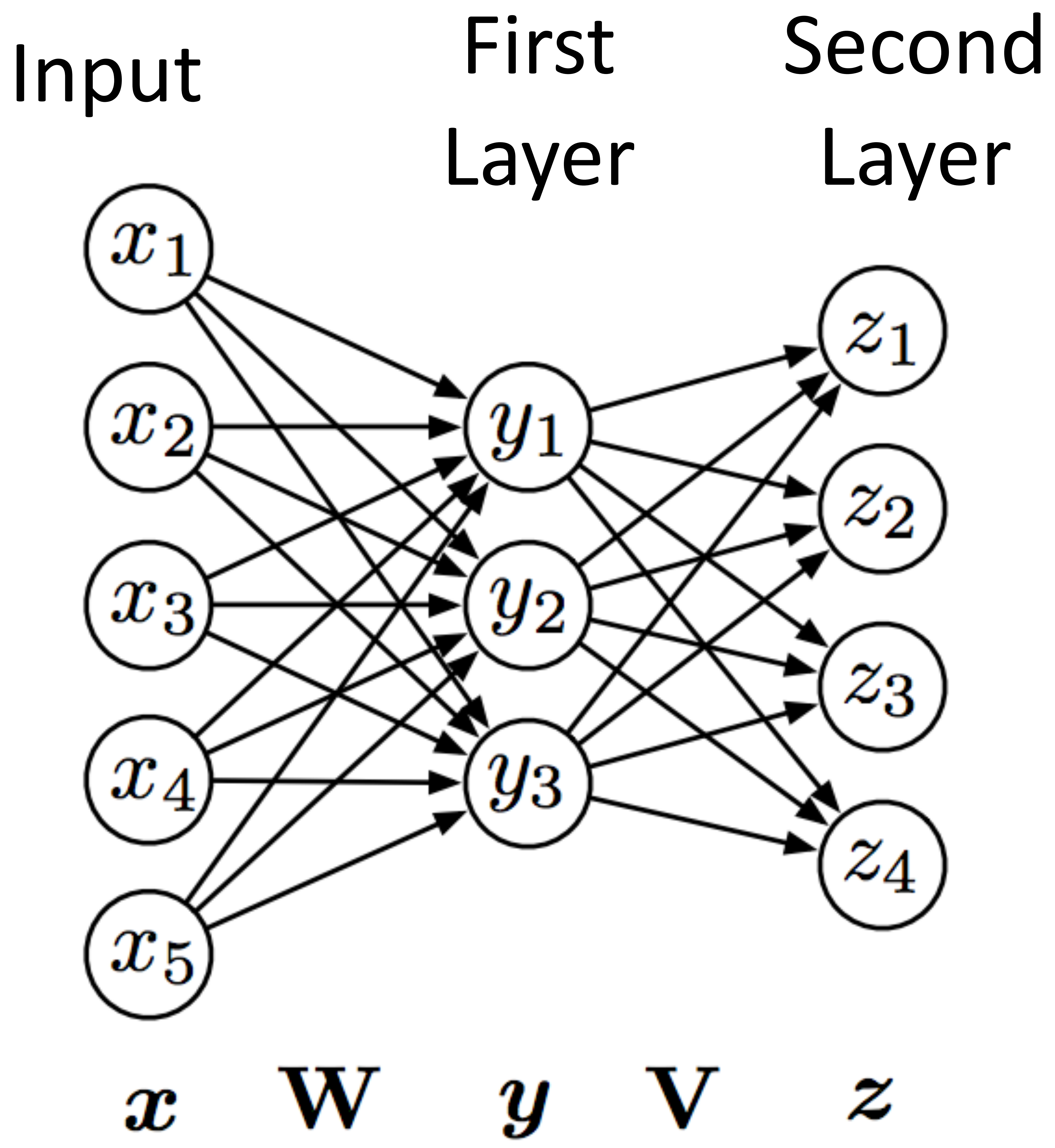
Deep Neural Networks



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

Adopted from Chris Dyer

Deep Neural Networks



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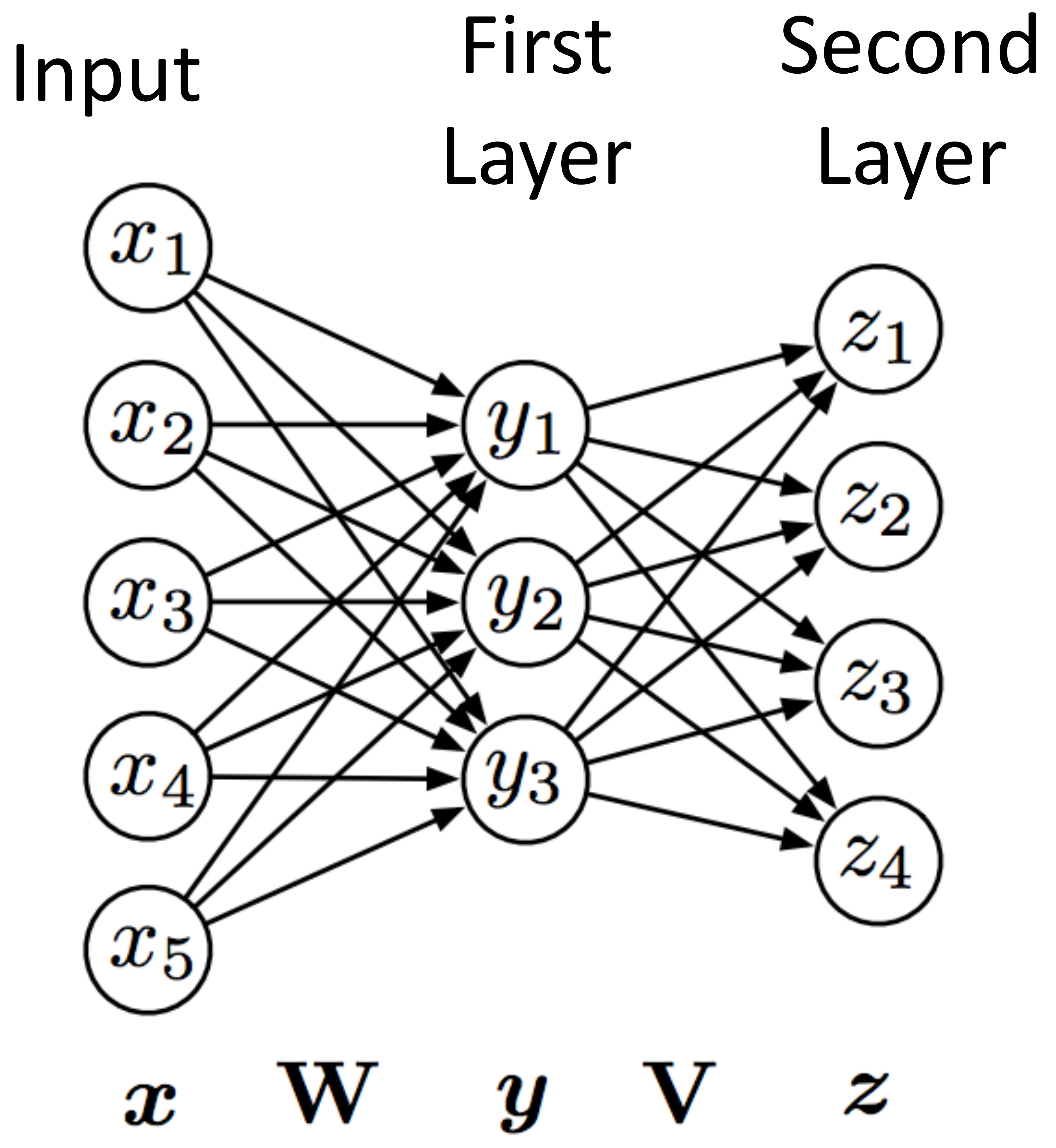

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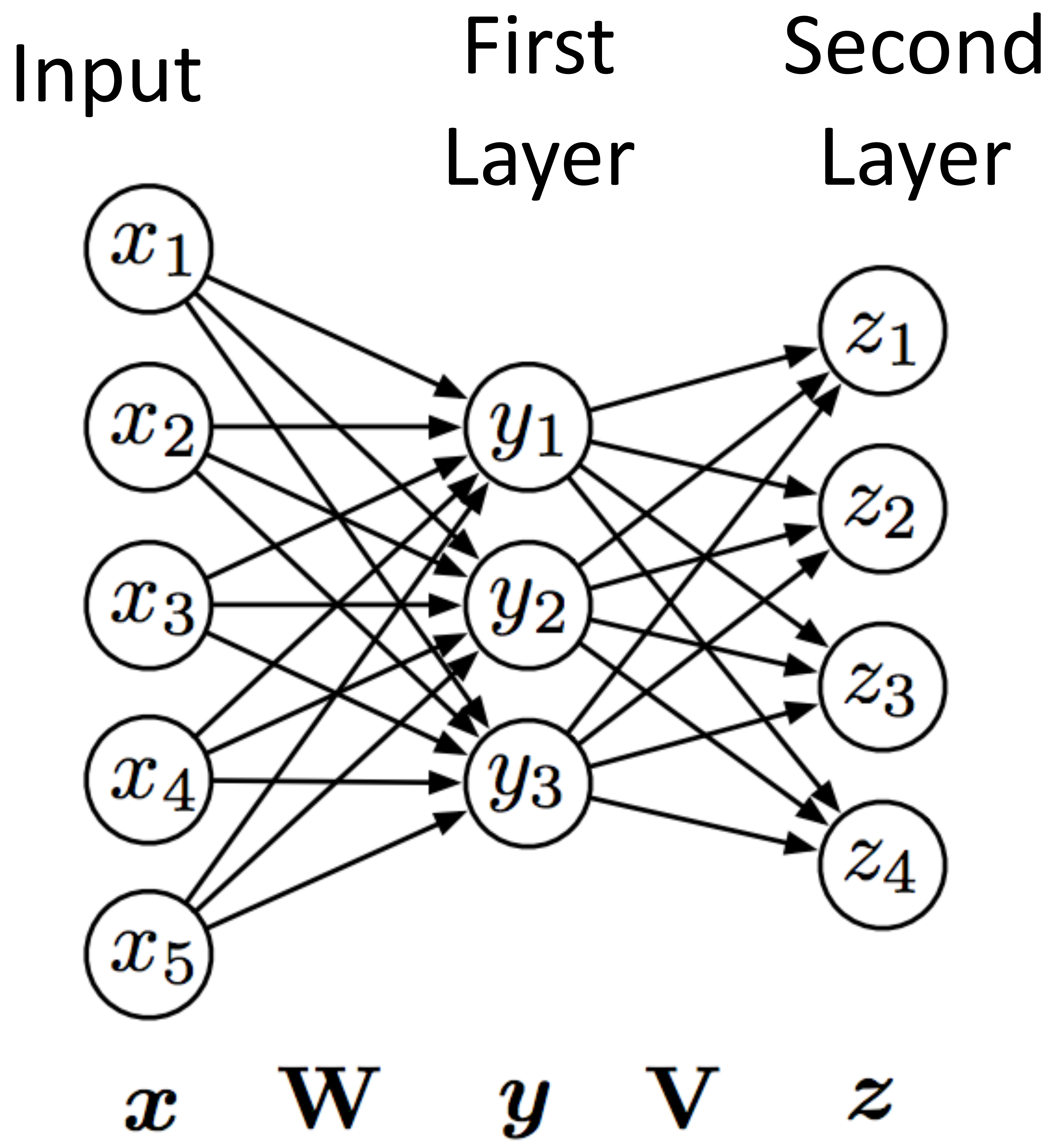

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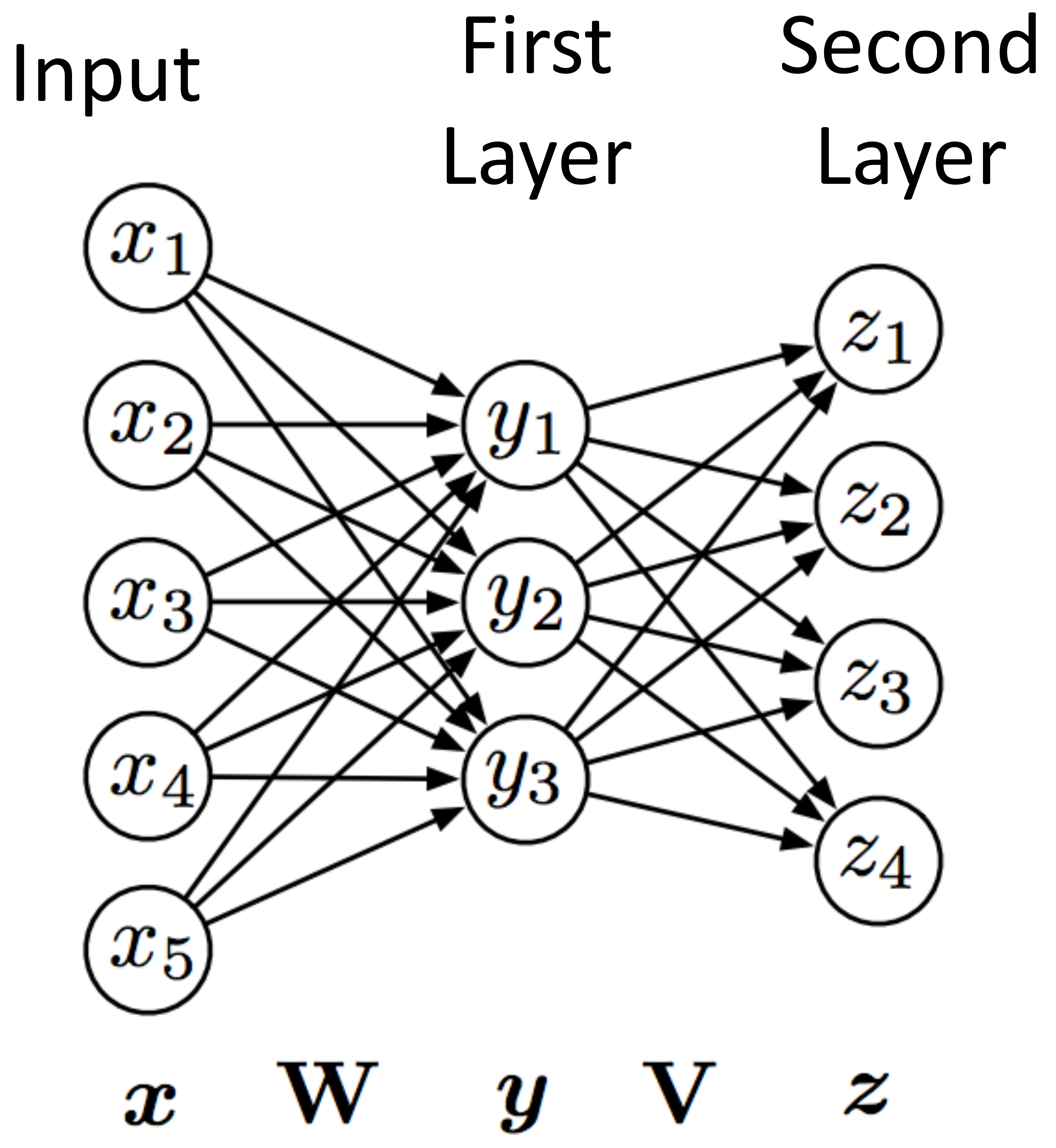

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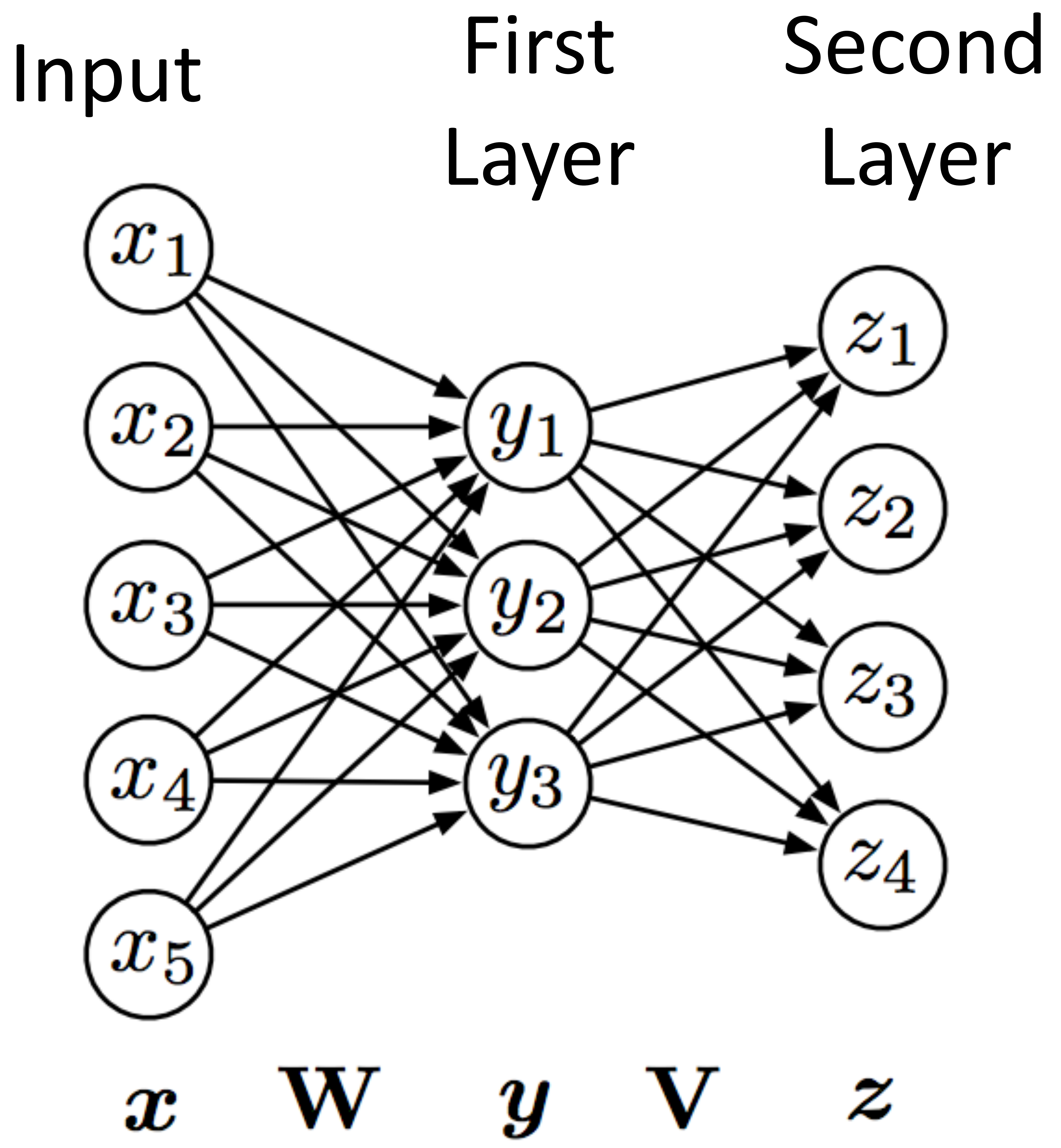
"Feedforward" computation (not recurrent)

Adopted from Chris Dyer

Deep Neural Networks



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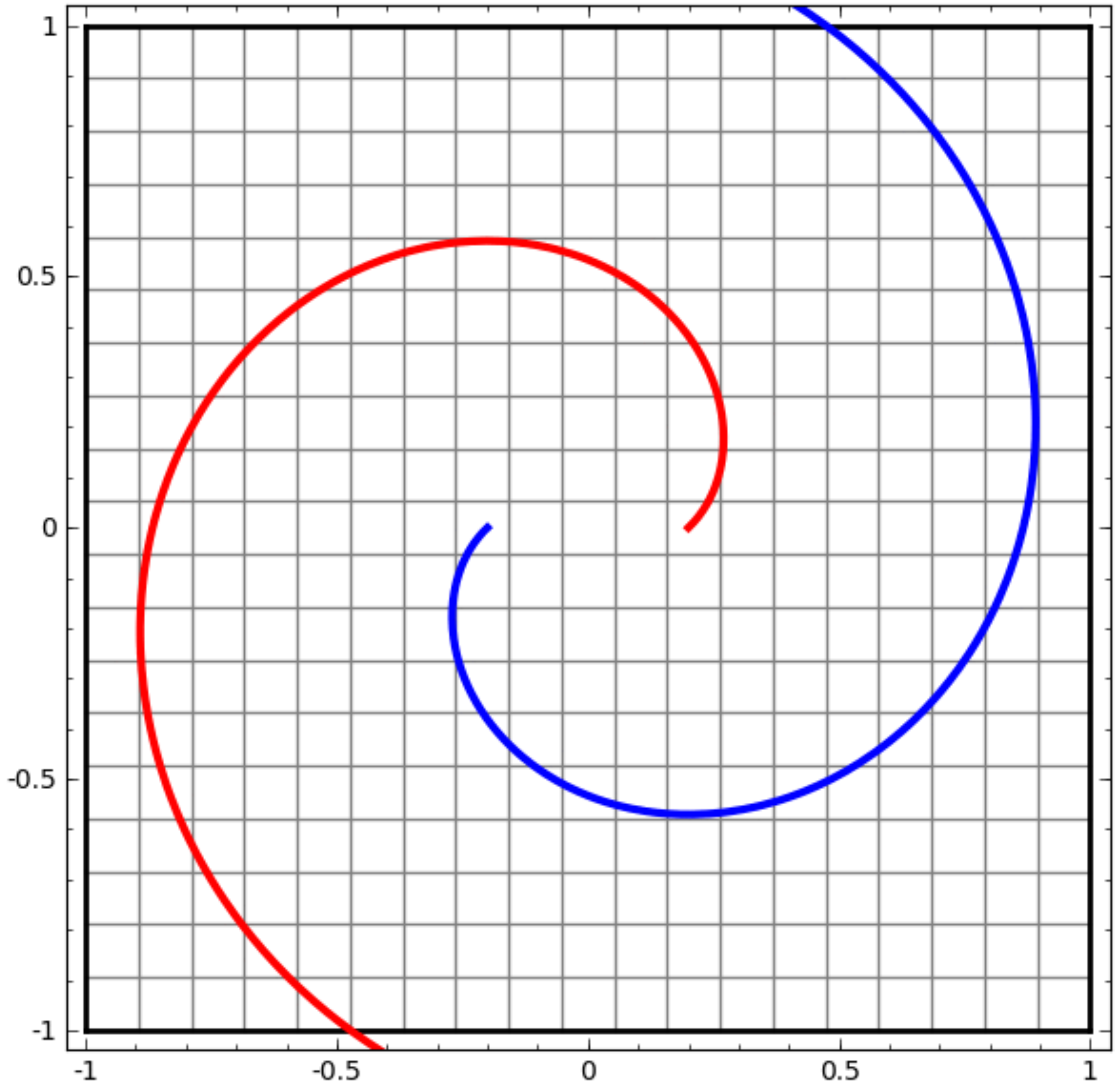
"Feedforward" computation (not recurrent)

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

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

Adopted from Chris Dyer

Deep Neural Networks



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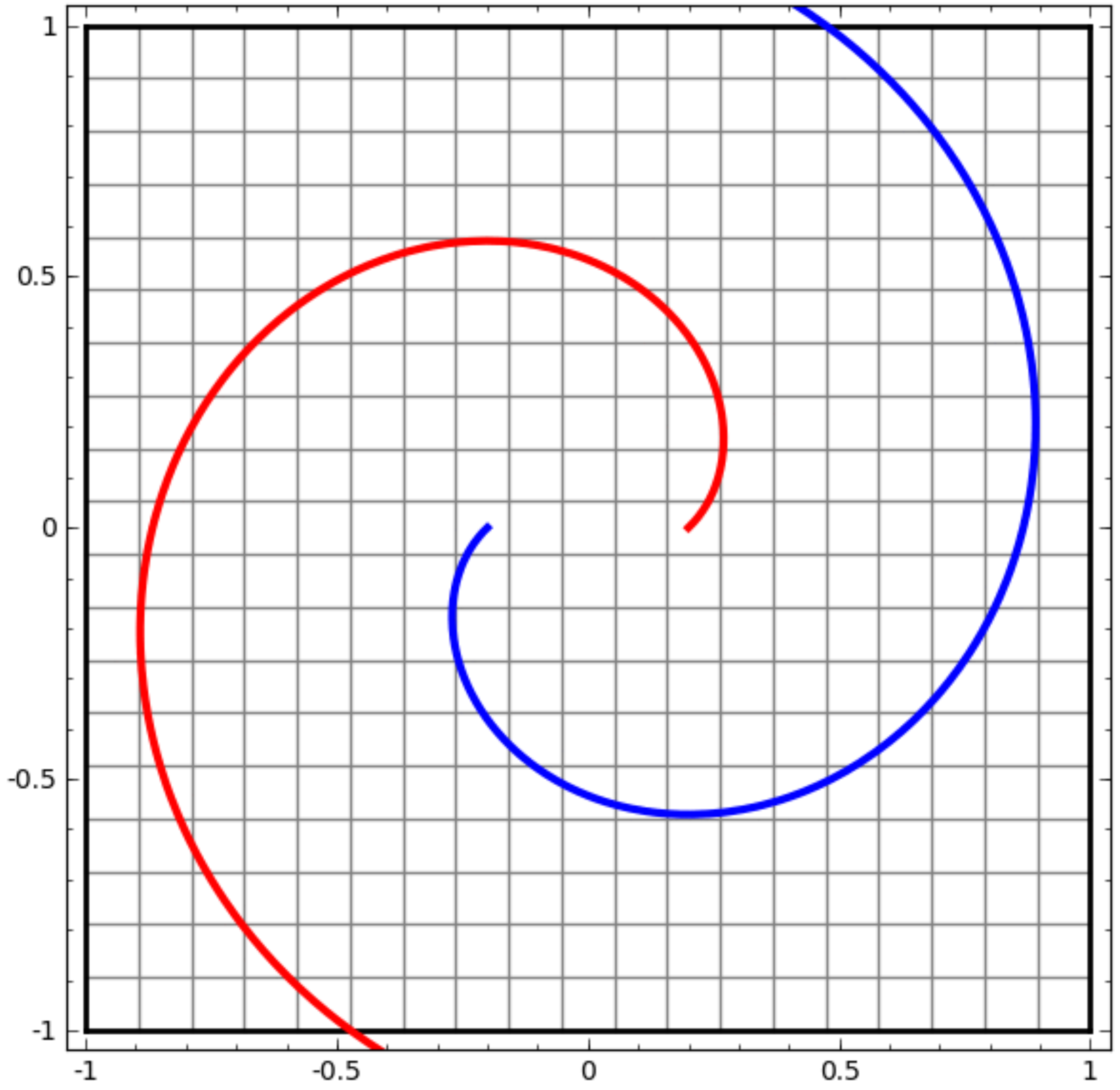

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Feedforward Networks, Backpropagation

Logistic Regression with NNs

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

- Single scalar probability

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  W is [num classes x num feats]

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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

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

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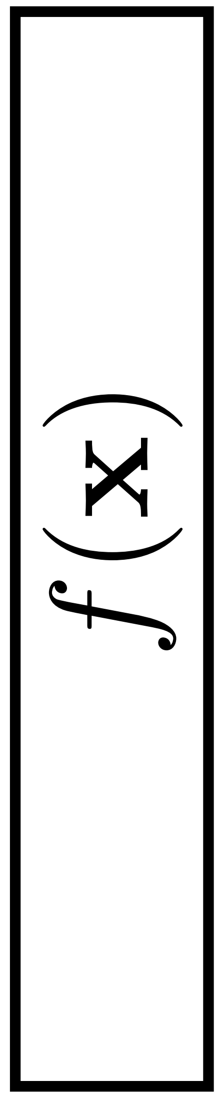

n features

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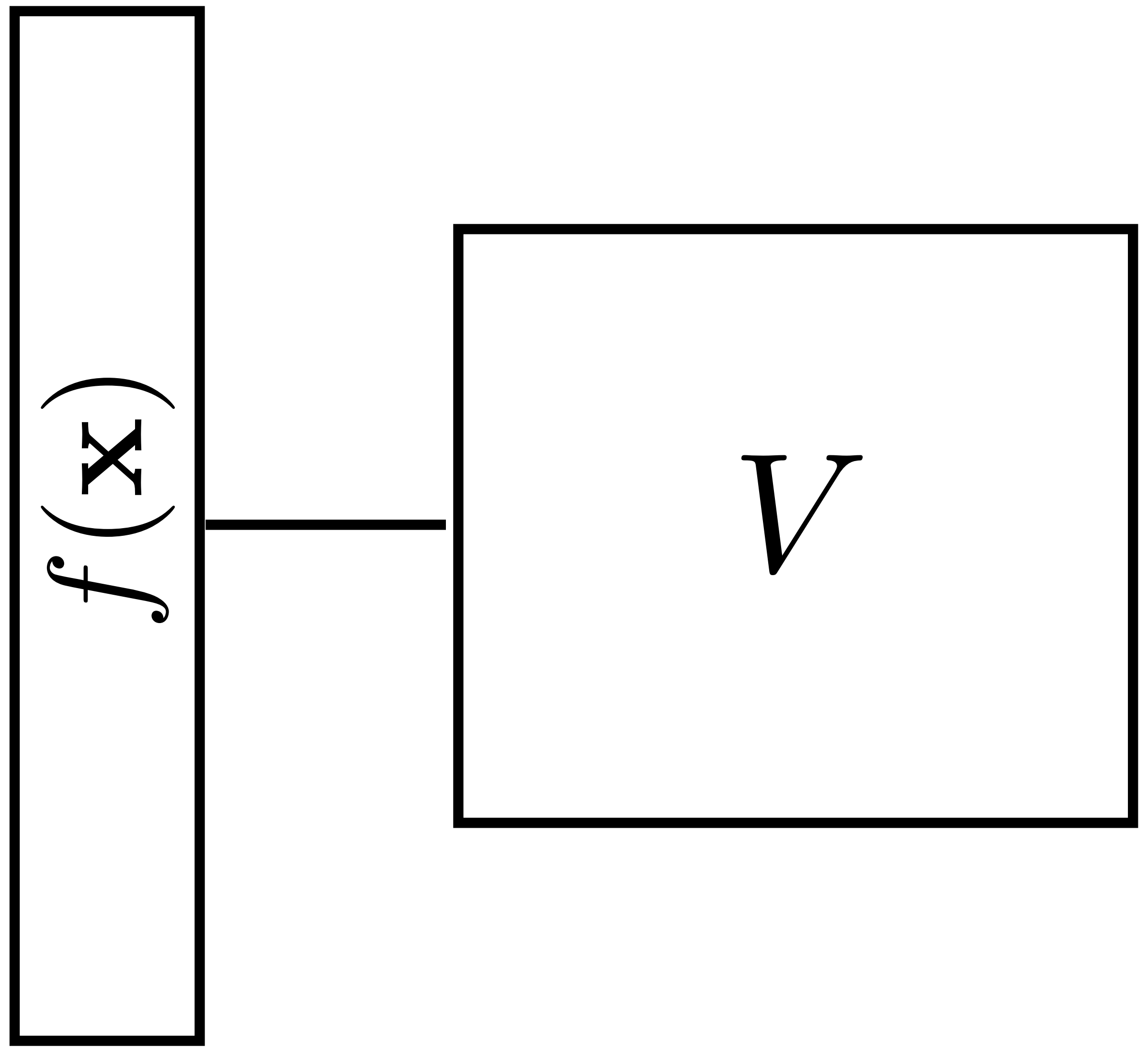

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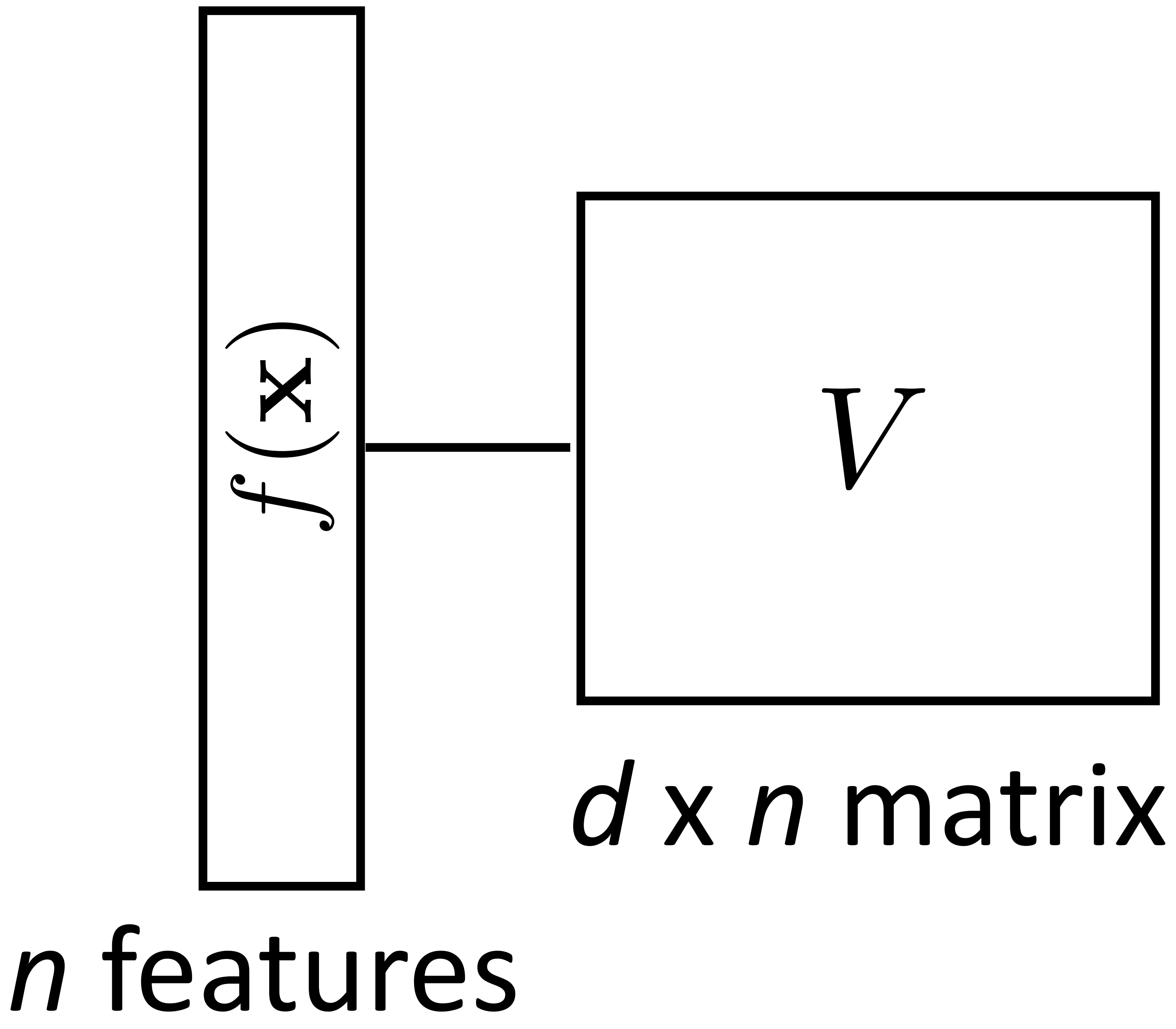

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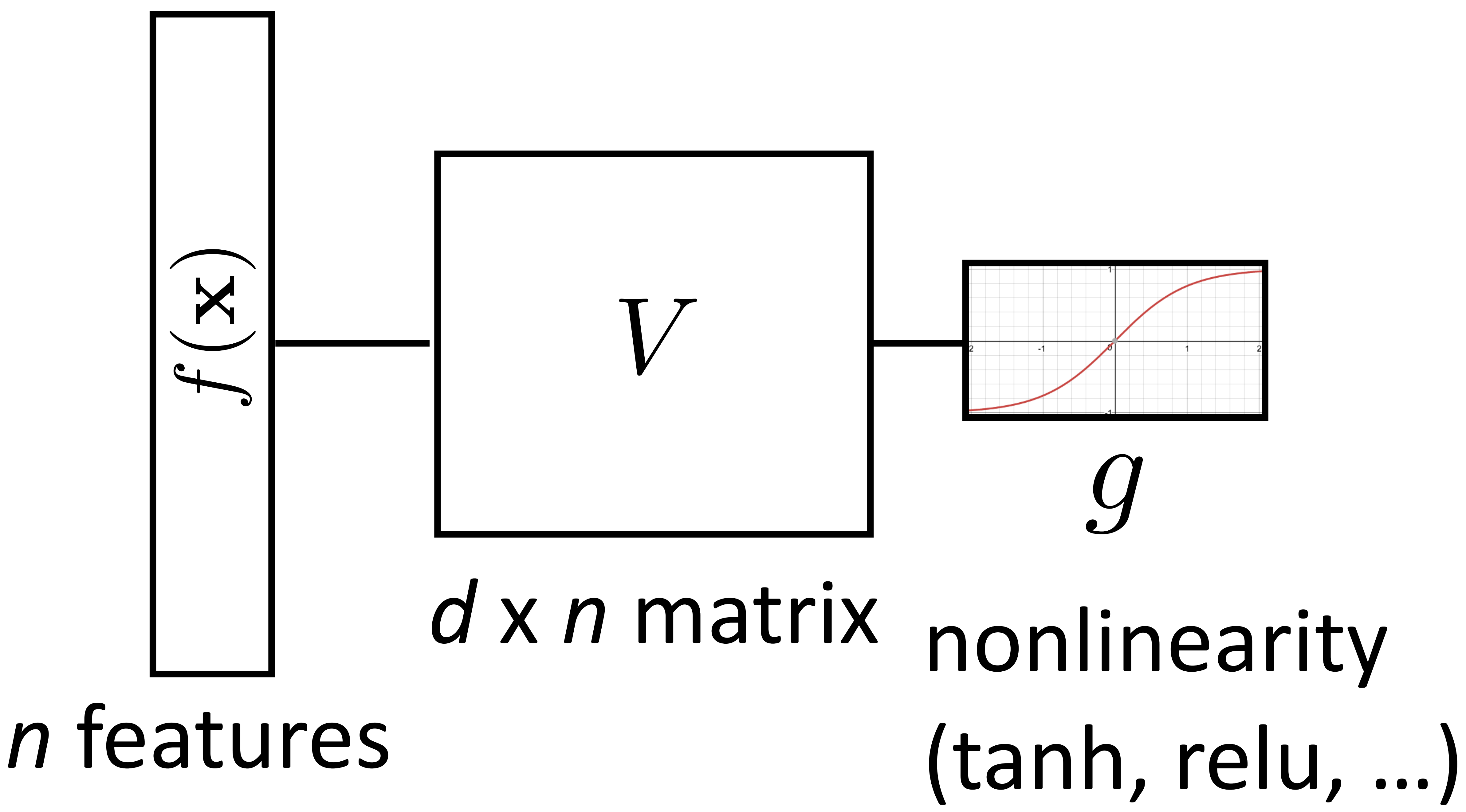

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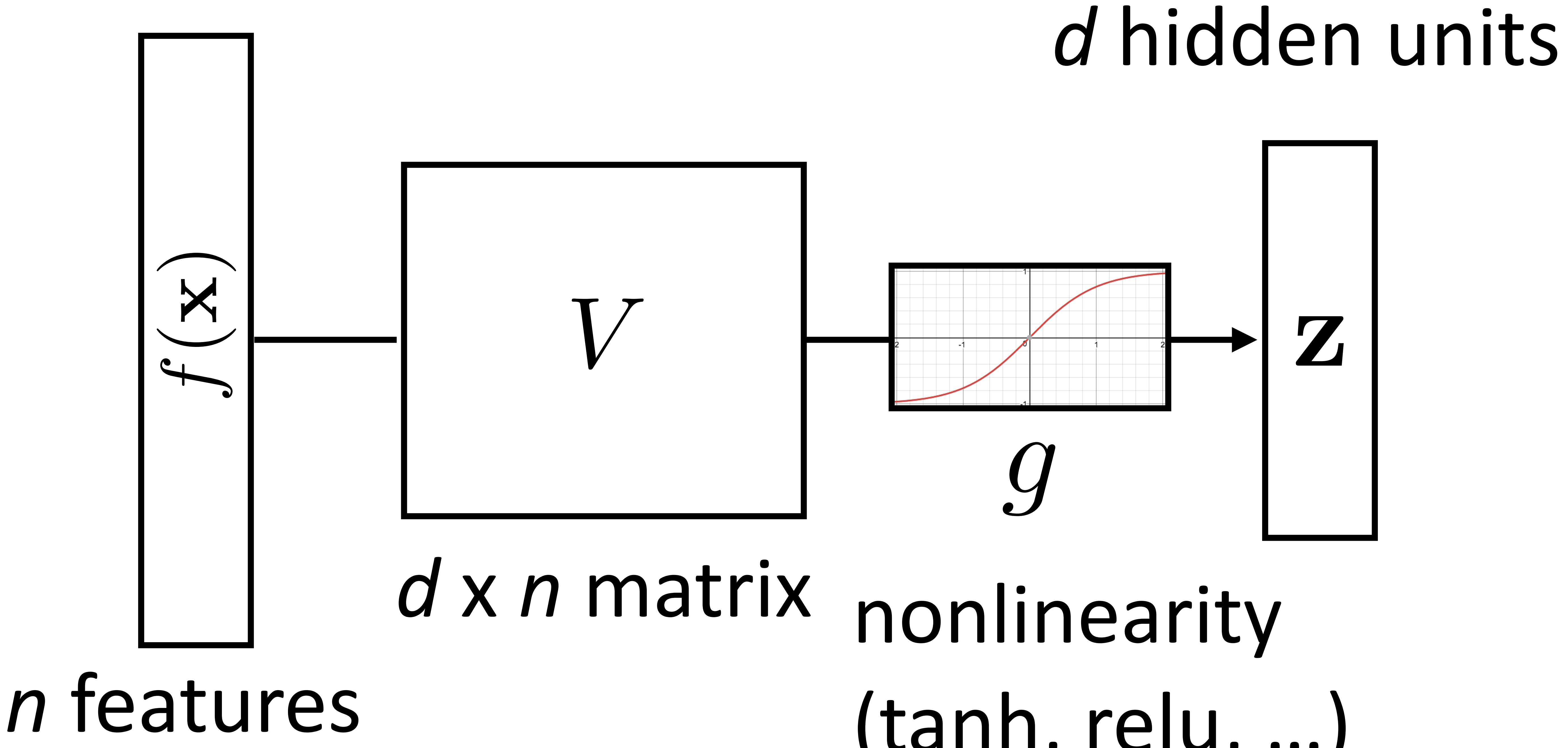

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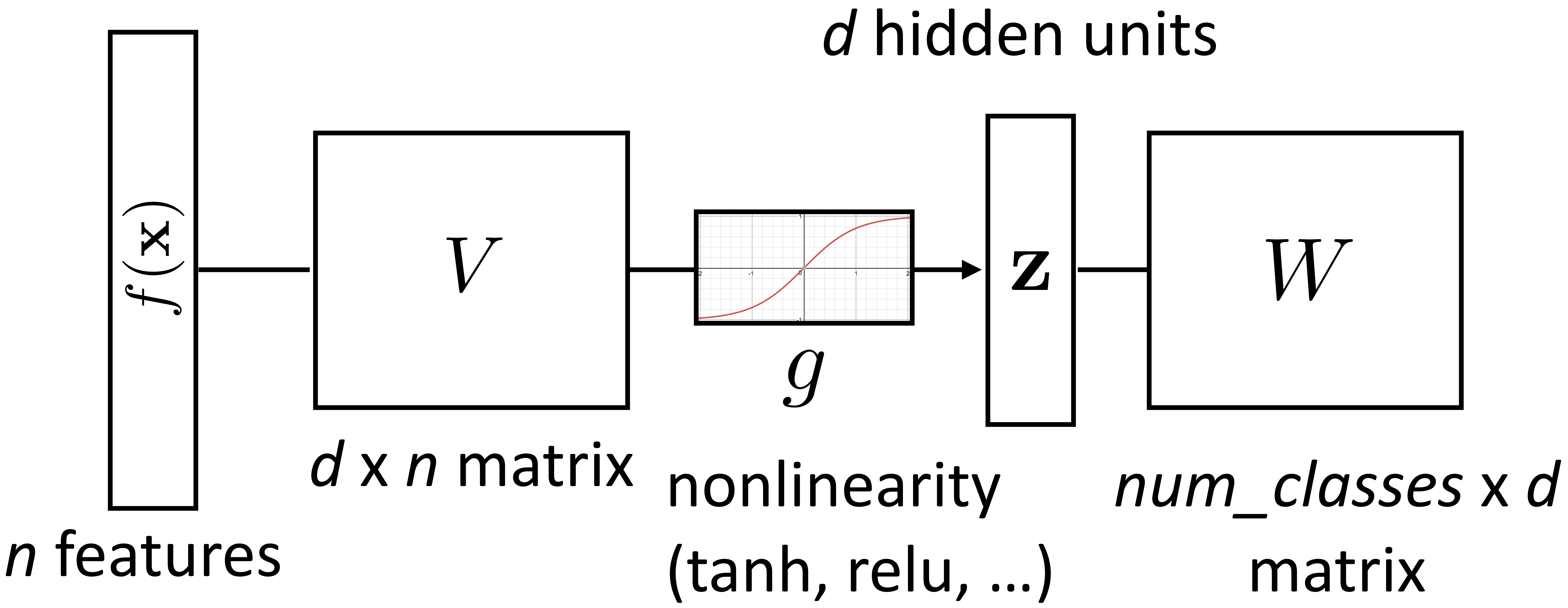

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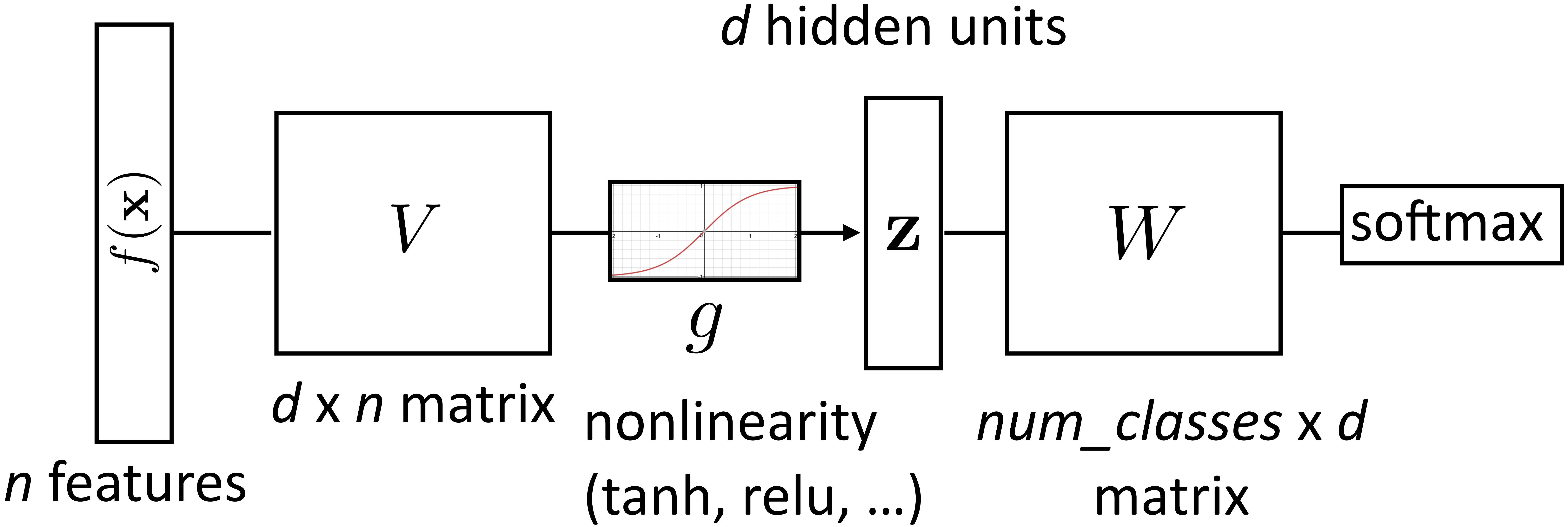

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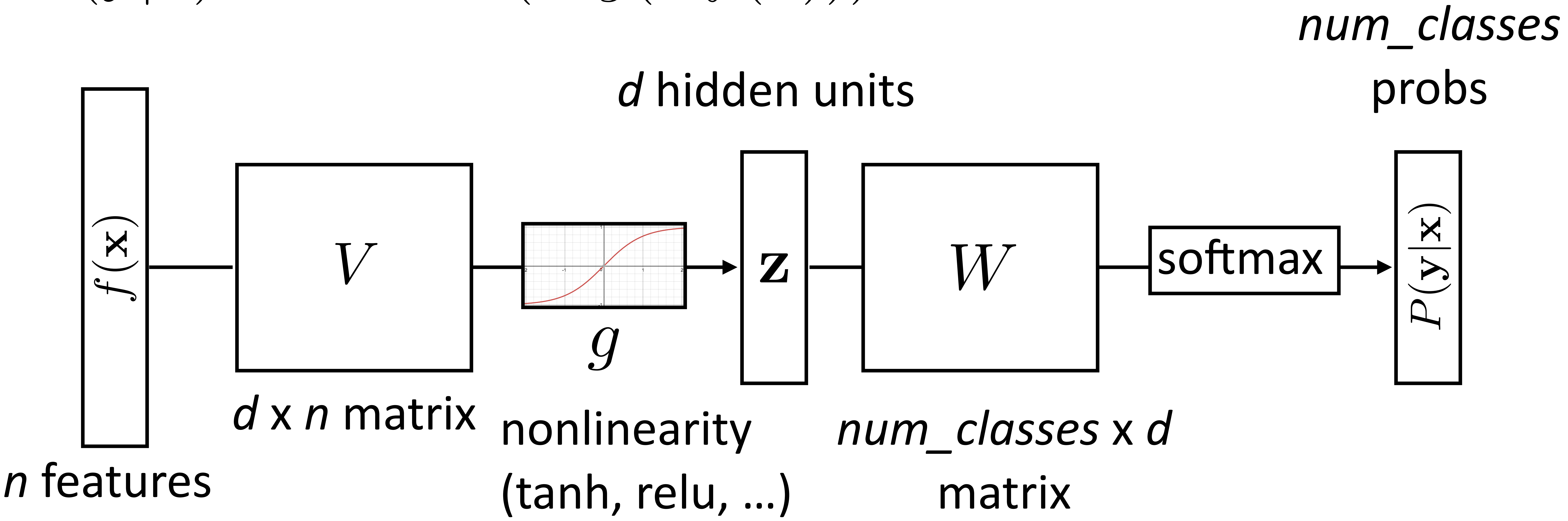

Training Neural Networks

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

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- *i**: index of the gold label

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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

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

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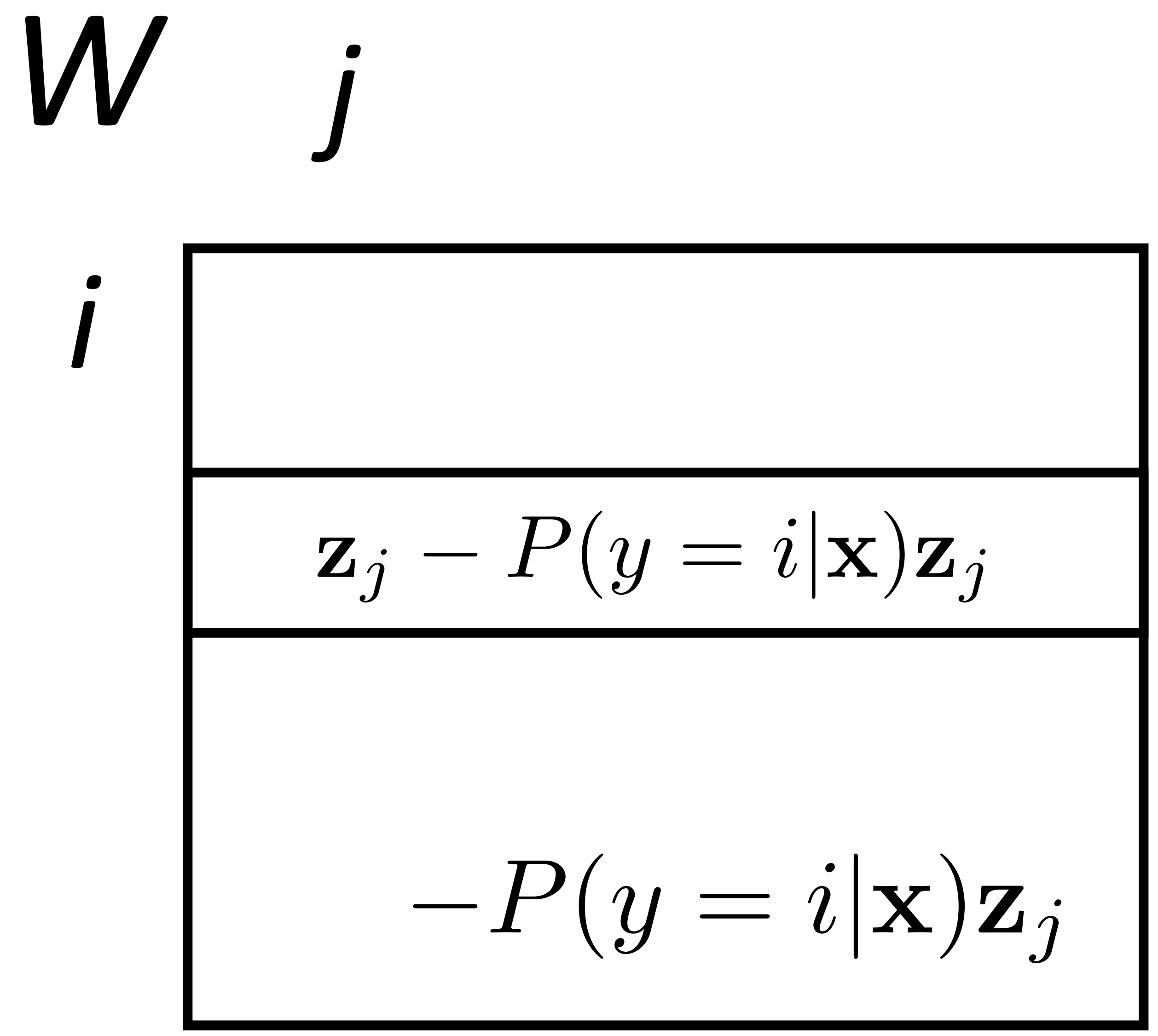

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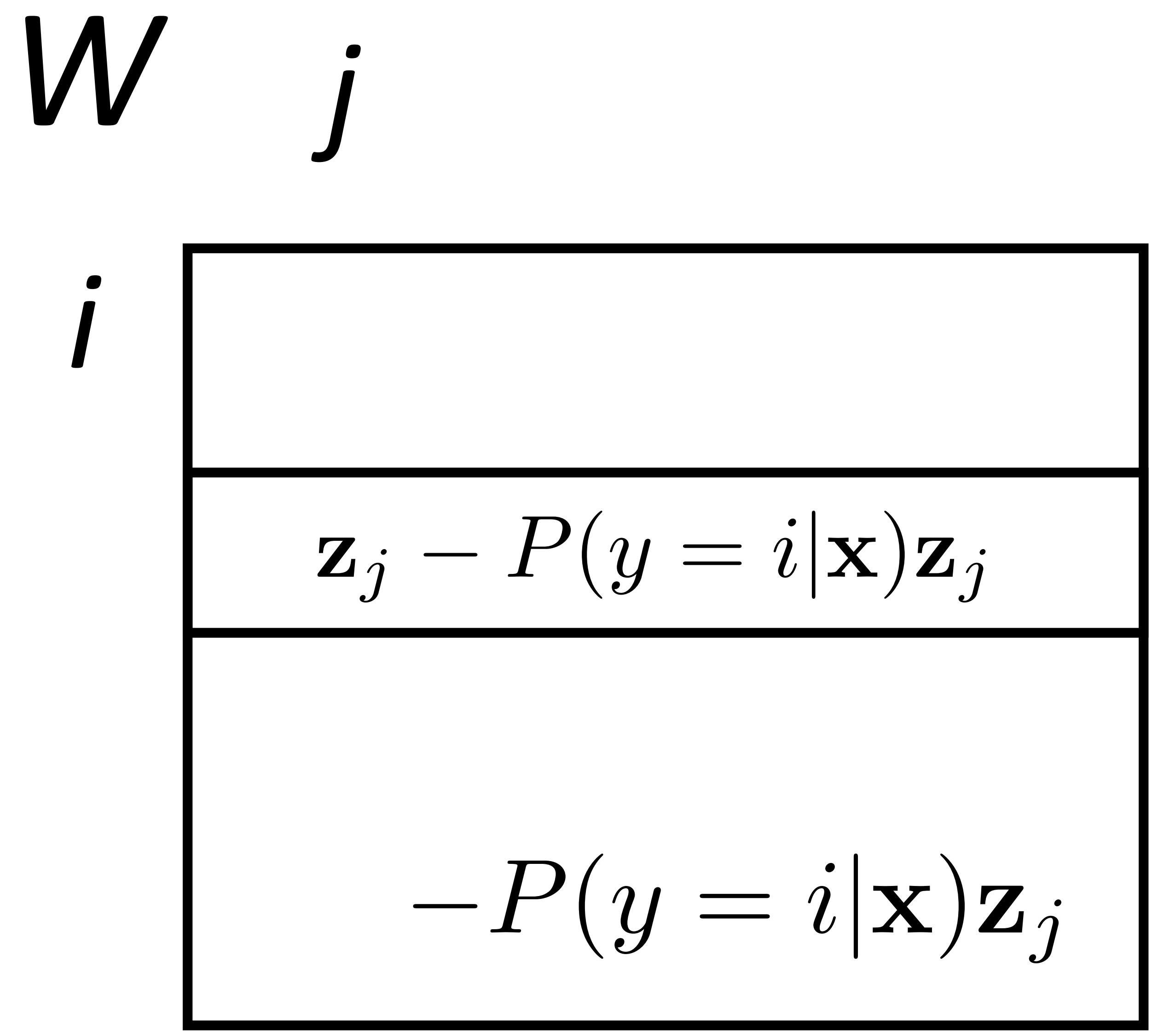
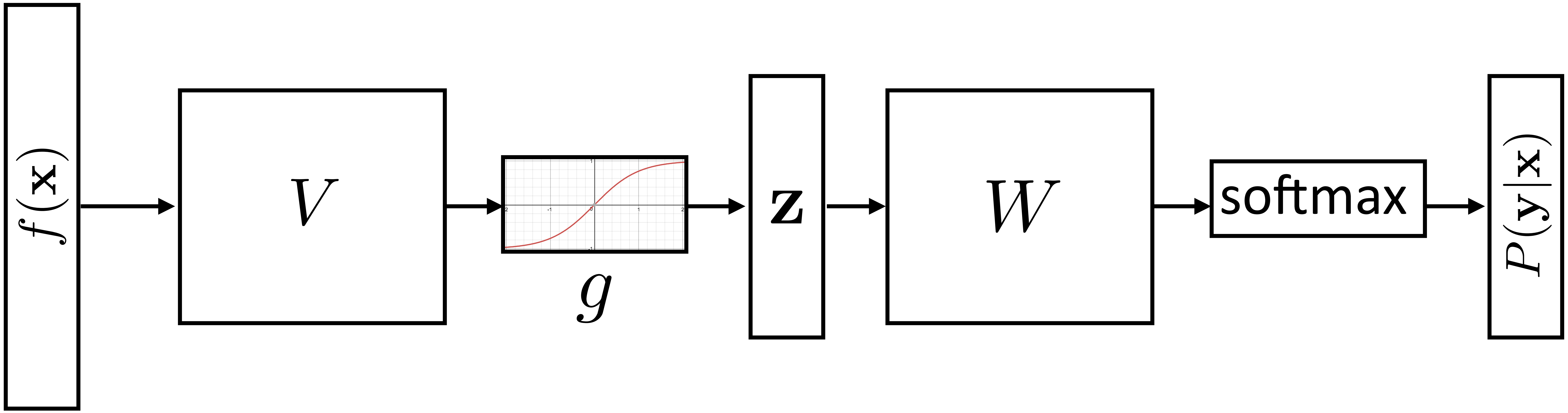


- Looks like logistic regression with ***z*** as the features!

Neural Networks for Classification

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



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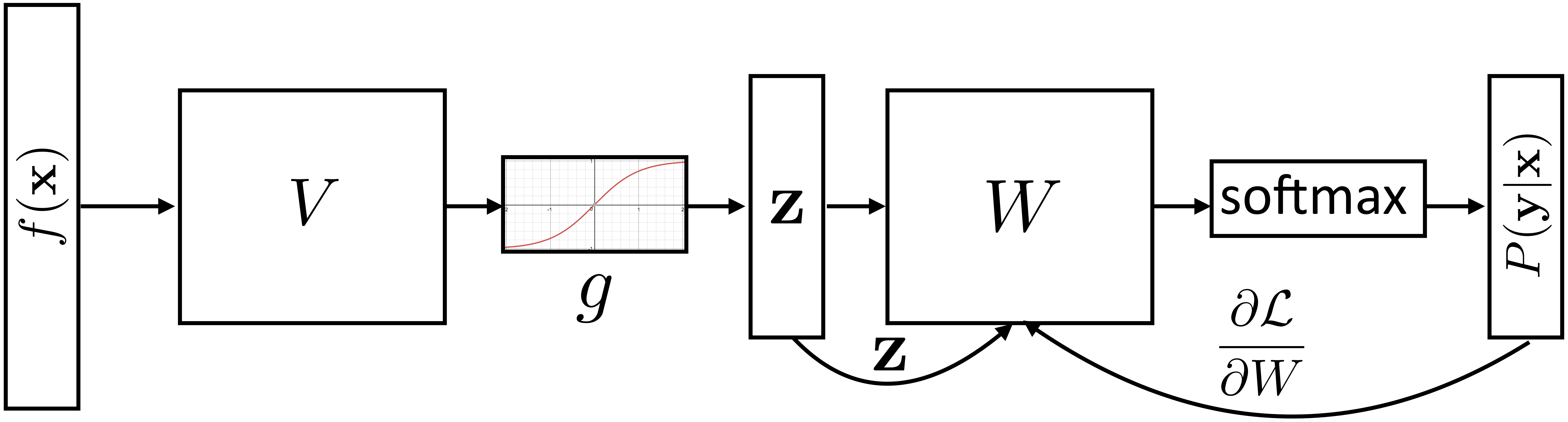

Computing Gradients: Backpropagation

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

$$\mathbf{z} = g(Vf(\mathbf{x}))$$

Activations at hidden layer

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Activations at hidden layer

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

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

Computing Gradients: Backpropagation

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Activations at hidden layer

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

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

Computing Gradients: Backpropagation

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$\mathbf{z} = g(Vf(\mathbf{x}))$

Activations at hidden layer

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

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

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

dim = num_classes

Computing Gradients: Backpropagation

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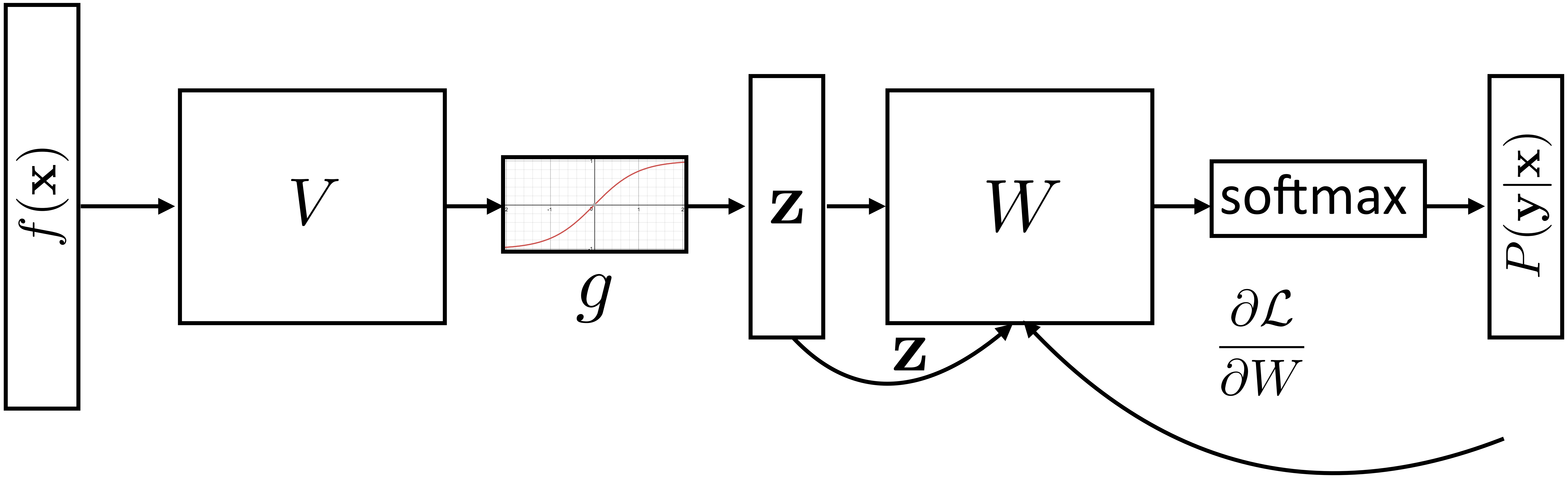
[some math…]

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

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

Backpropagation: Picture

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



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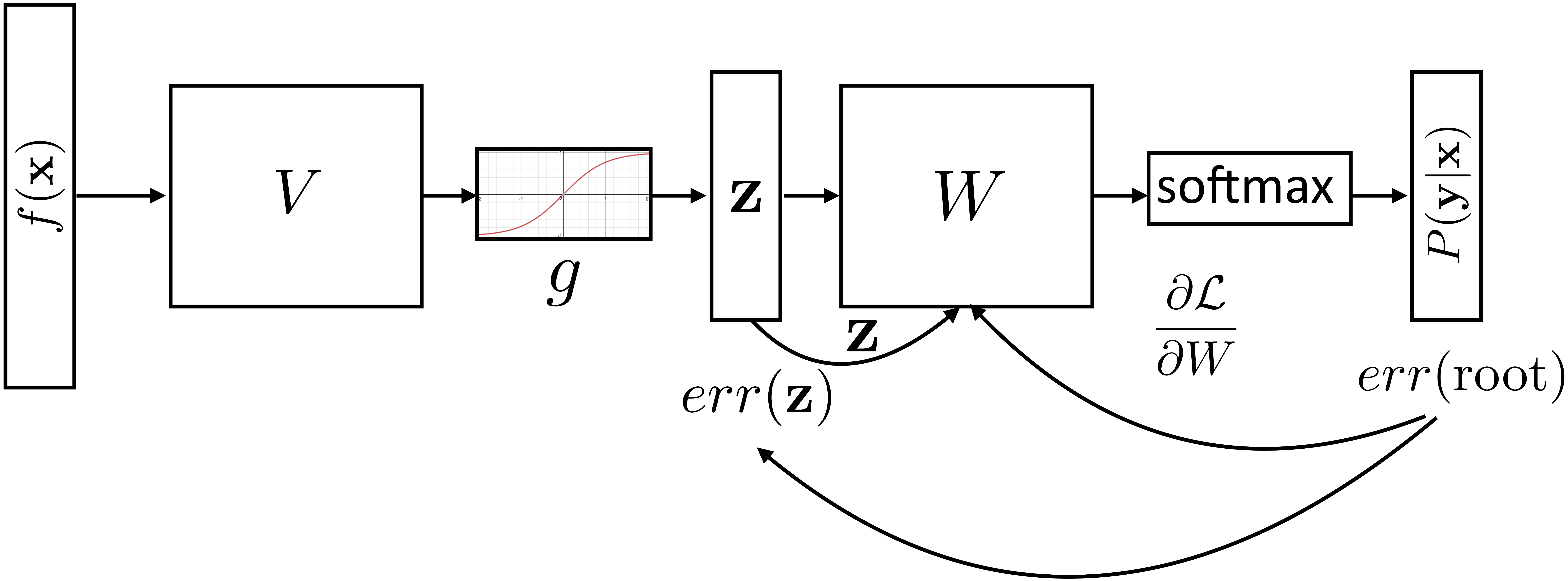

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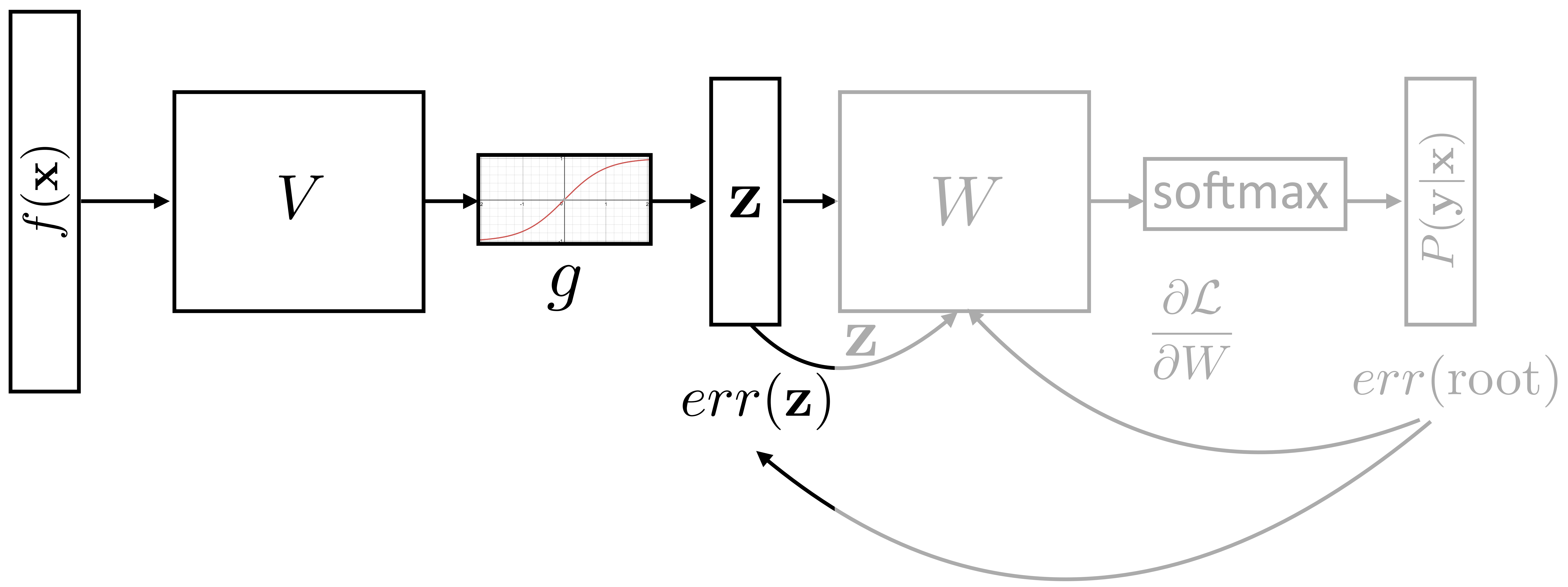

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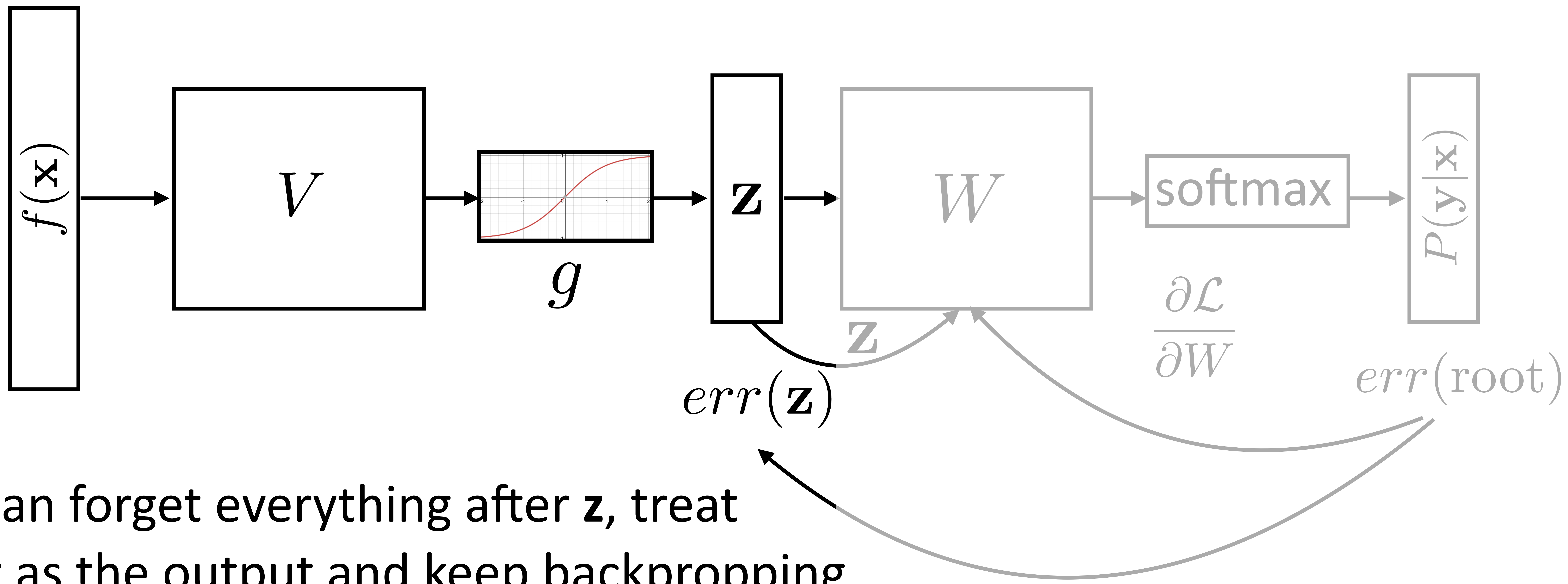

- Can forget everything after **z**, treat it as the output and keep backpropping

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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$$\frac{\partial \mathbf{z}}{V_{ij}} = \frac{\partial g(\mathbf{a})}{\partial \mathbf{a}} \frac{\partial \mathbf{a}}{\partial V_{ij}}$$

$$\mathbf{a} = Vf(\mathbf{x})$$

Computing Gradients: Backpropagation

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

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Activations at hidden layer

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

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

$\mathbf{a} = Vf(\mathbf{x})$

- First term: gradient of nonlinear activation function at ***a*** (depends on current value)

Computing Gradients: Backpropagation

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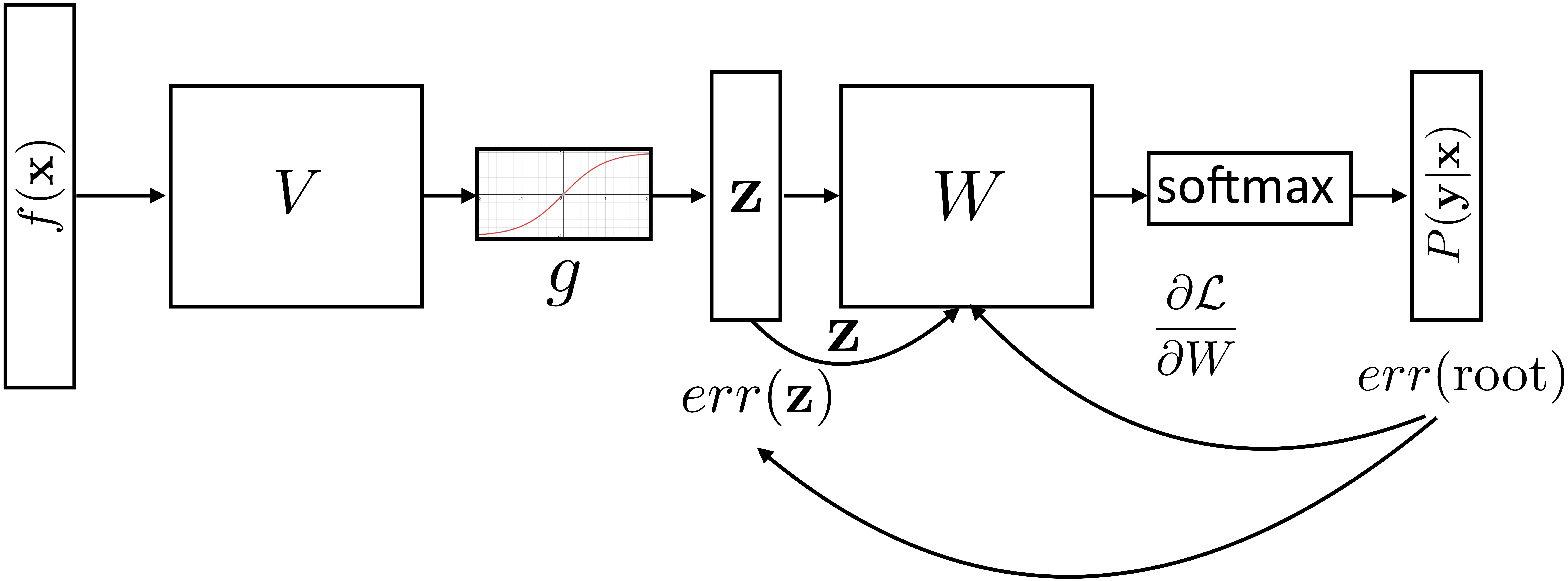
- Straightforward computation once we have *err*(**z**)

Backpropagation: Picture

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



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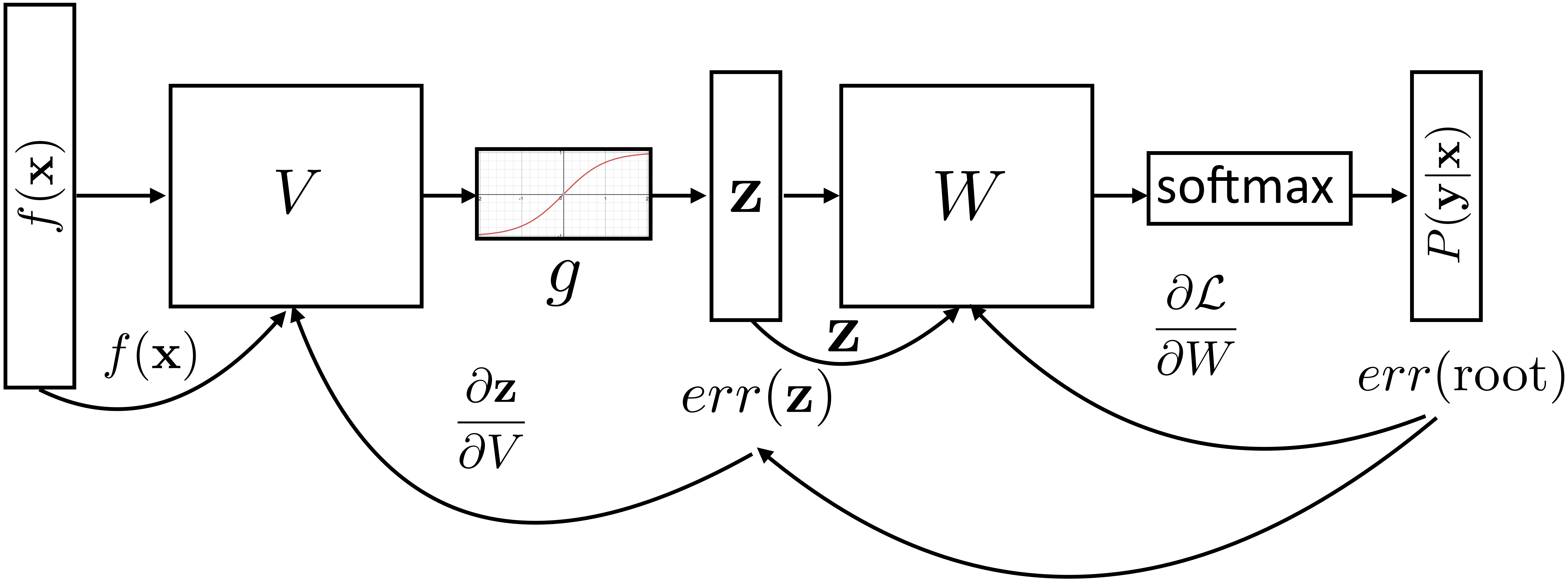

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- Step 4: compute derivatives of *V* using *err*(**z**) (matrix)
- Step 5+: continue backpropagation (compute err(*f*(**x**)) if necessary…)

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- Need to remember the values from the forward computation

Applications

NLP with Feedforward Networks

- Part-of-speech tagging with FFNNs

Botha et al. (2017)

NLP with Feedforward Networks

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??

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

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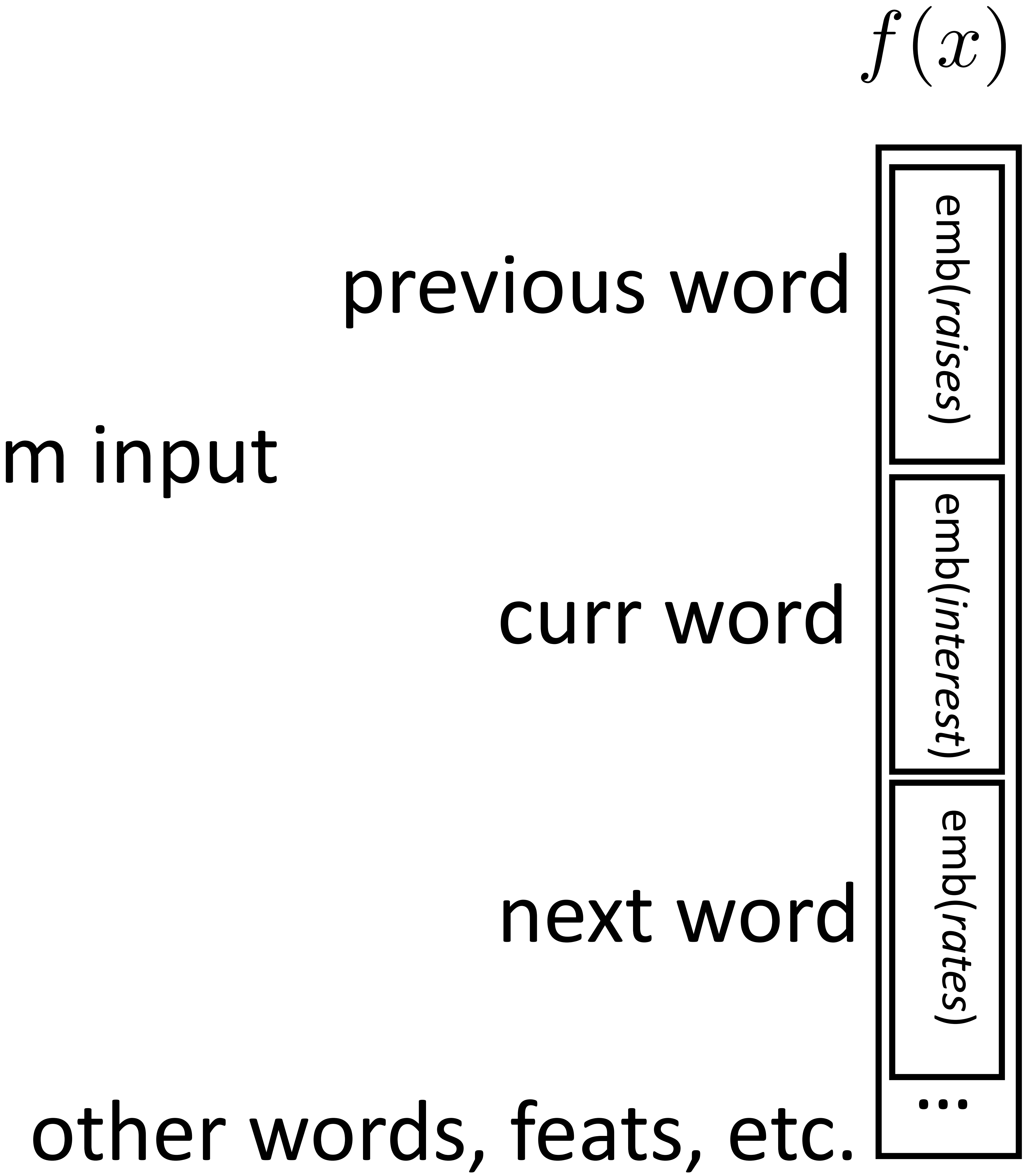

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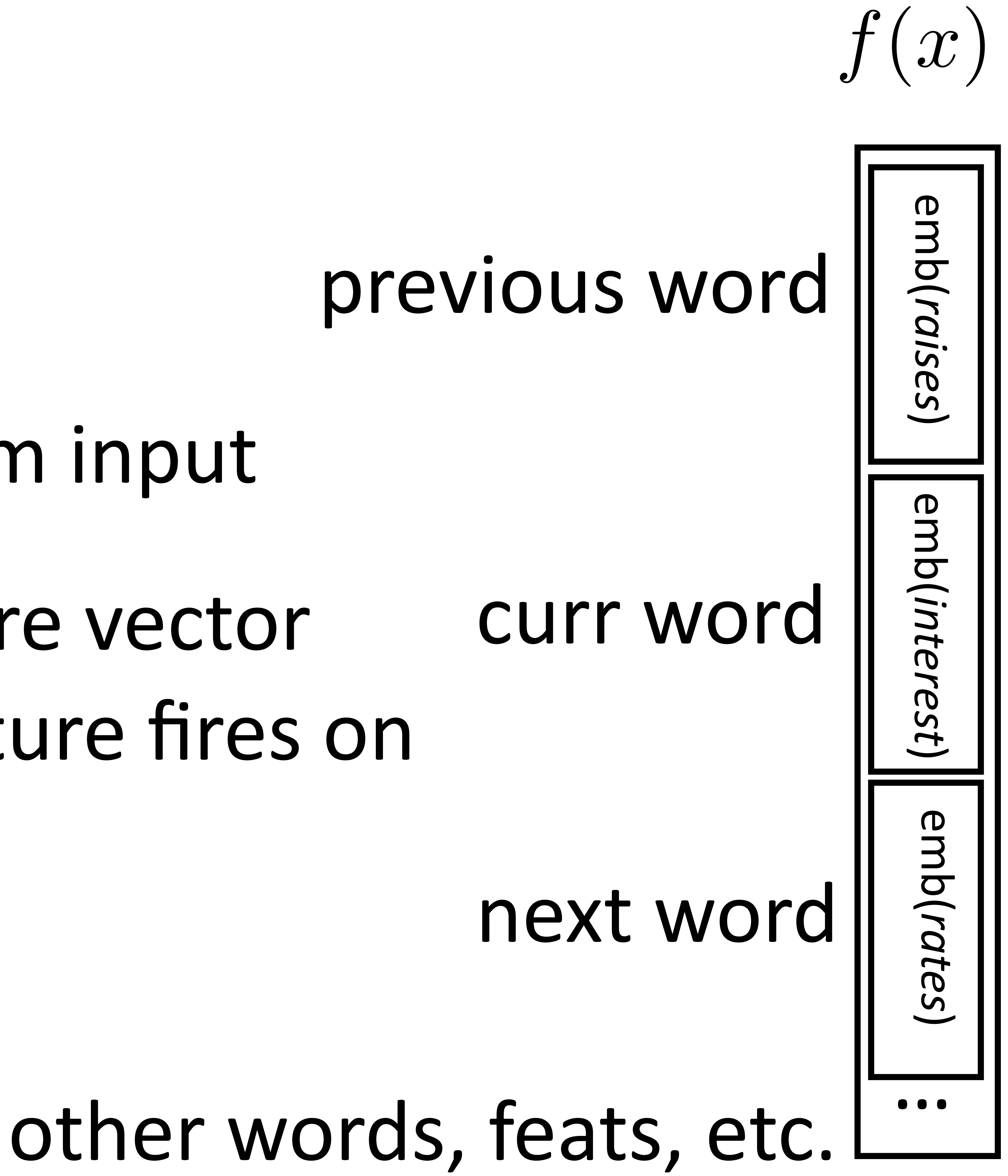

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- Word embeddings for each word form input

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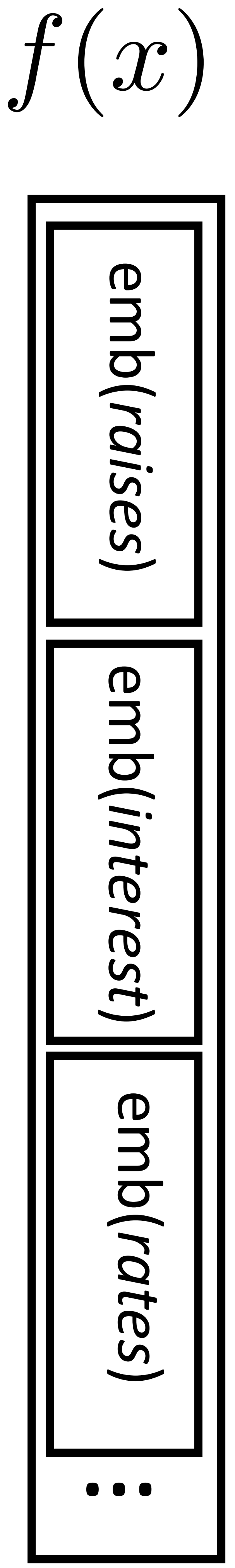
- Weight matrix learns position-dependent processing of the words

previous word

curr word

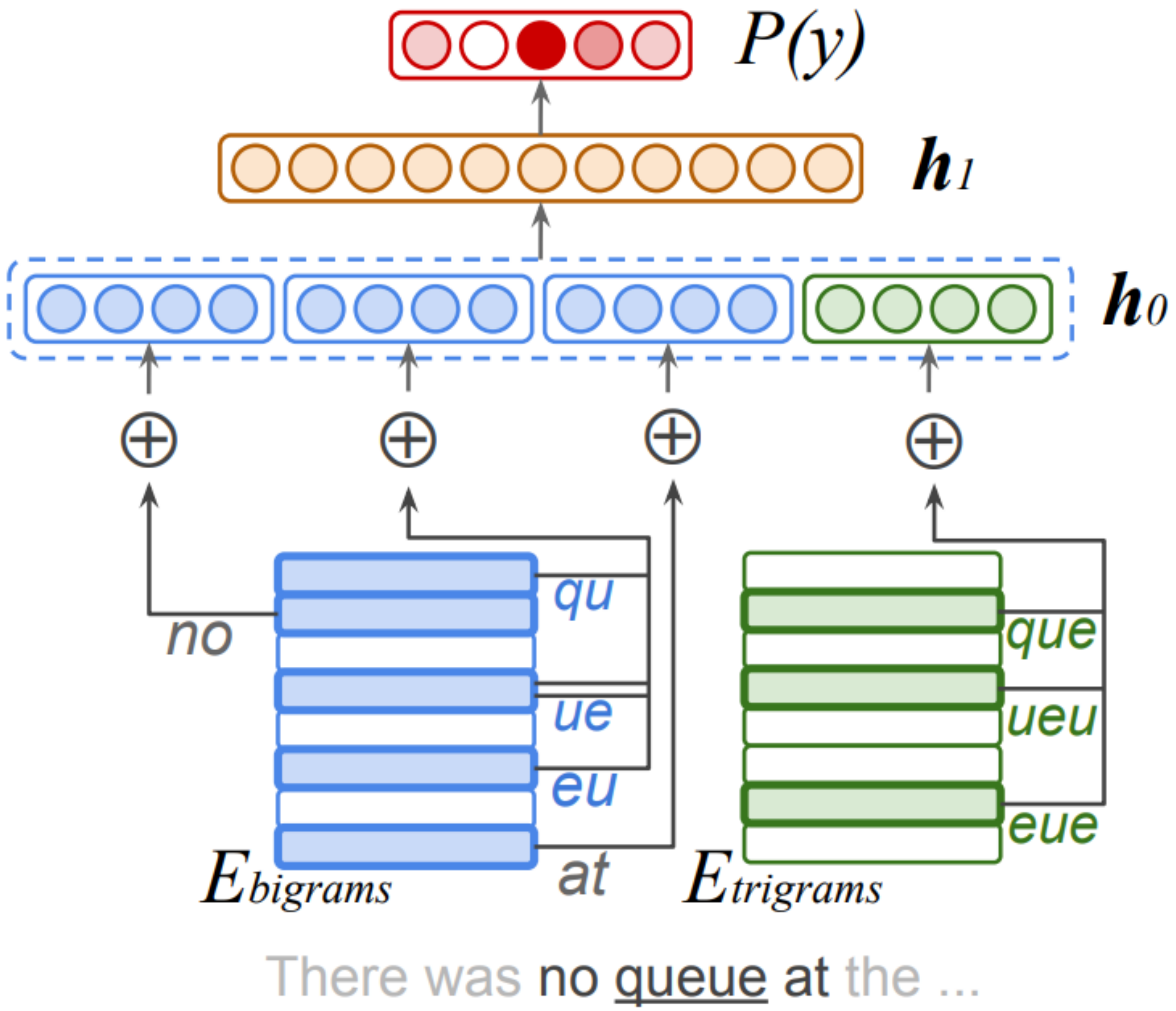
next word

other words, feats, etc.



Botha et al. (2017)

NLP with Feedforward Networks



- Hidden layer mixes these different signals and learns feature conjunctions

Botha et al. (2017)

NLP with Feedforward Networks

- Multilingual tagging results:

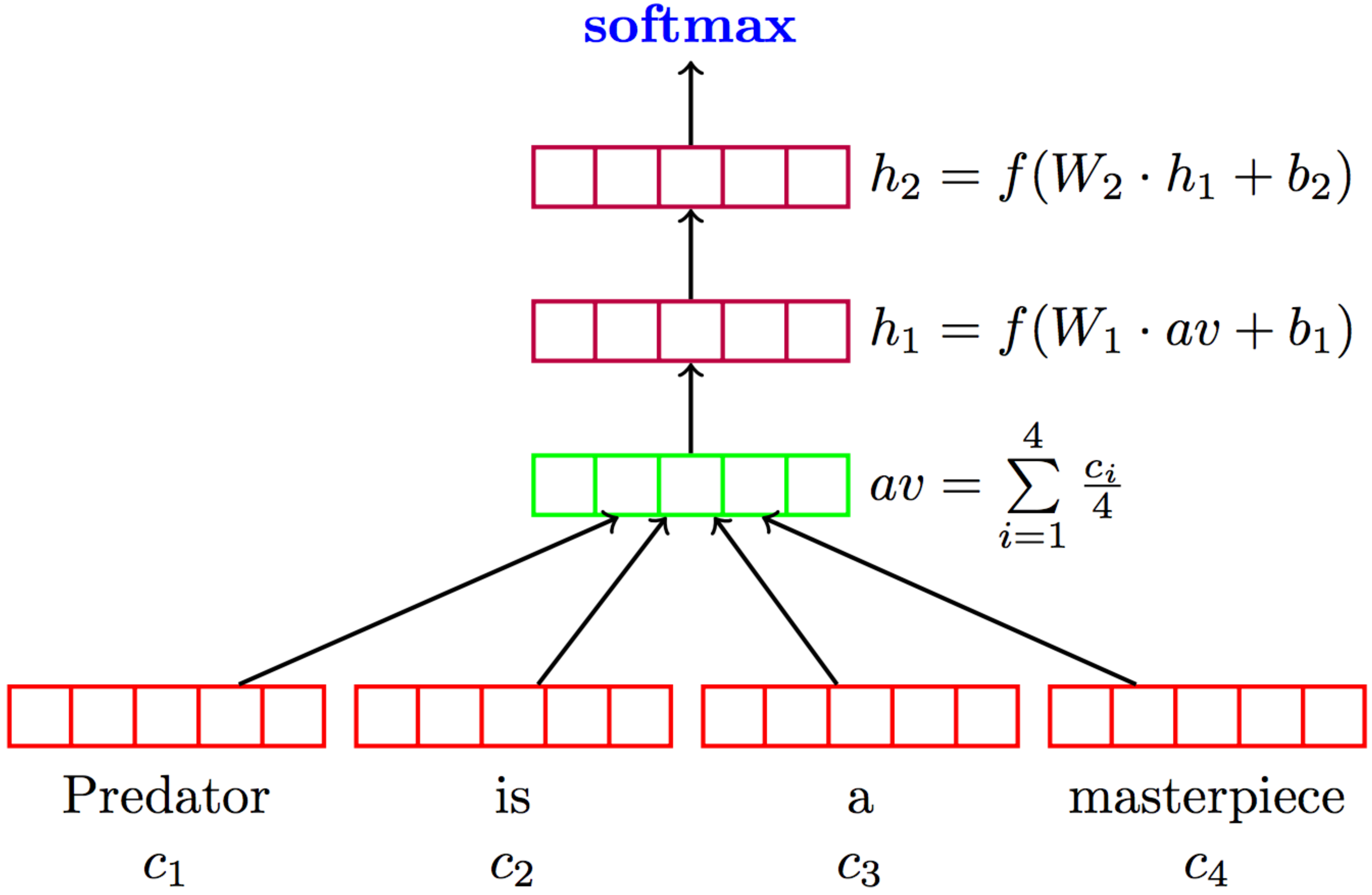
Model	Acc.	Wts.	MB	Ops.
Gillick et al. (2016)	95.06	900k	-	6.63m
Small FF	94.76	241k	0.6	0.27m
+Clusters	95.56	261k	1.0	0.31m
$\frac{1}{2}$ Dim.	95.39	143k	0.7	0.18m

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

Botha et al. (2017)

Sentiment Analysis

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



Iyyer et al. (2015)

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
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	—
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
WRRBM*	—	—	—	89.2	—

Iyyer et al. (2015)

Bag-of-words

Wang and Manning (2012)

Tree RNNs / CNNS / LSTMS

Kim (2014)

Coreference Resolution

- Feedforward networks identify coreference arcs

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

Coreference Resolution

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President Obama signed…

?

He later gave a speech…

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

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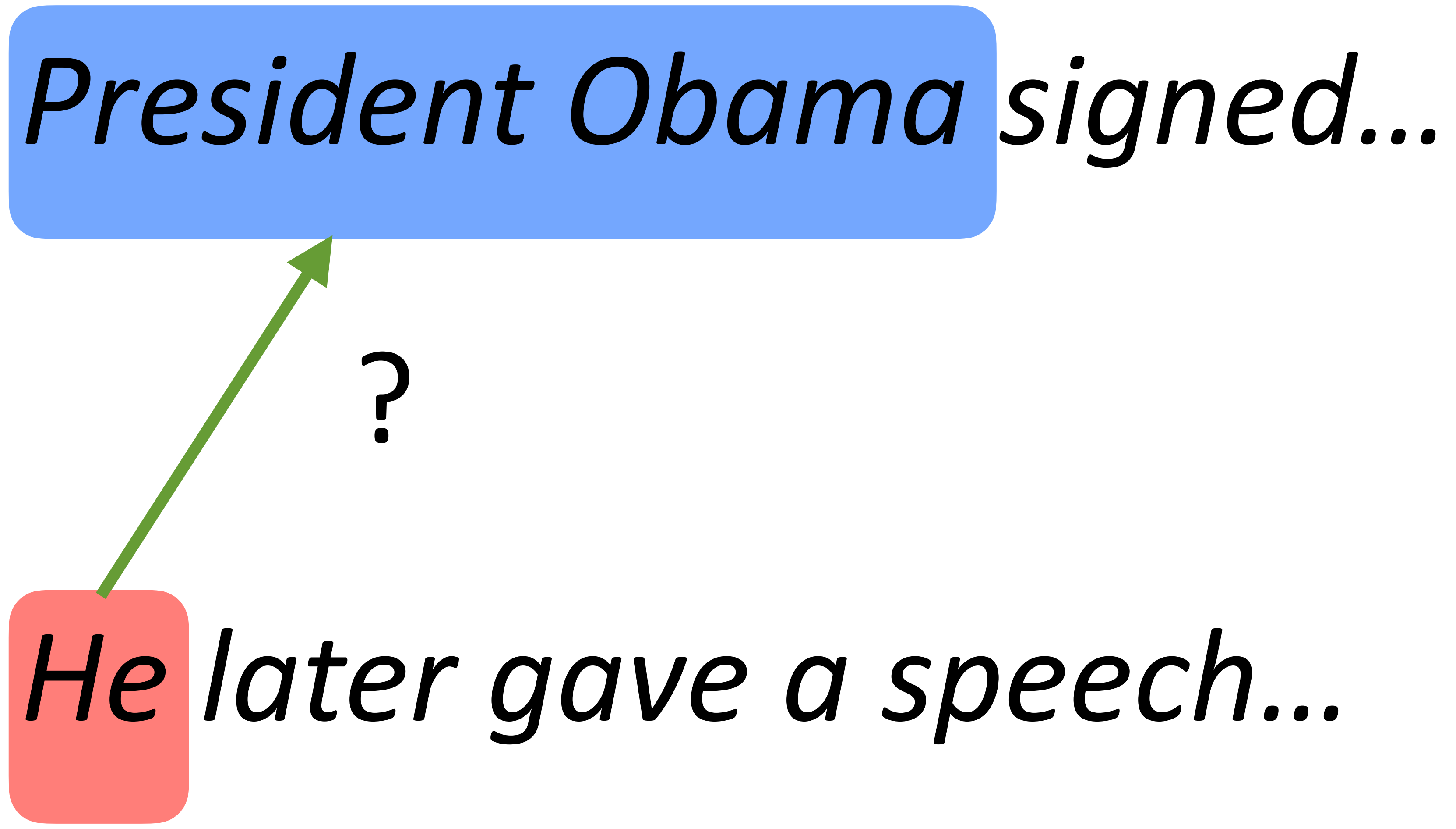

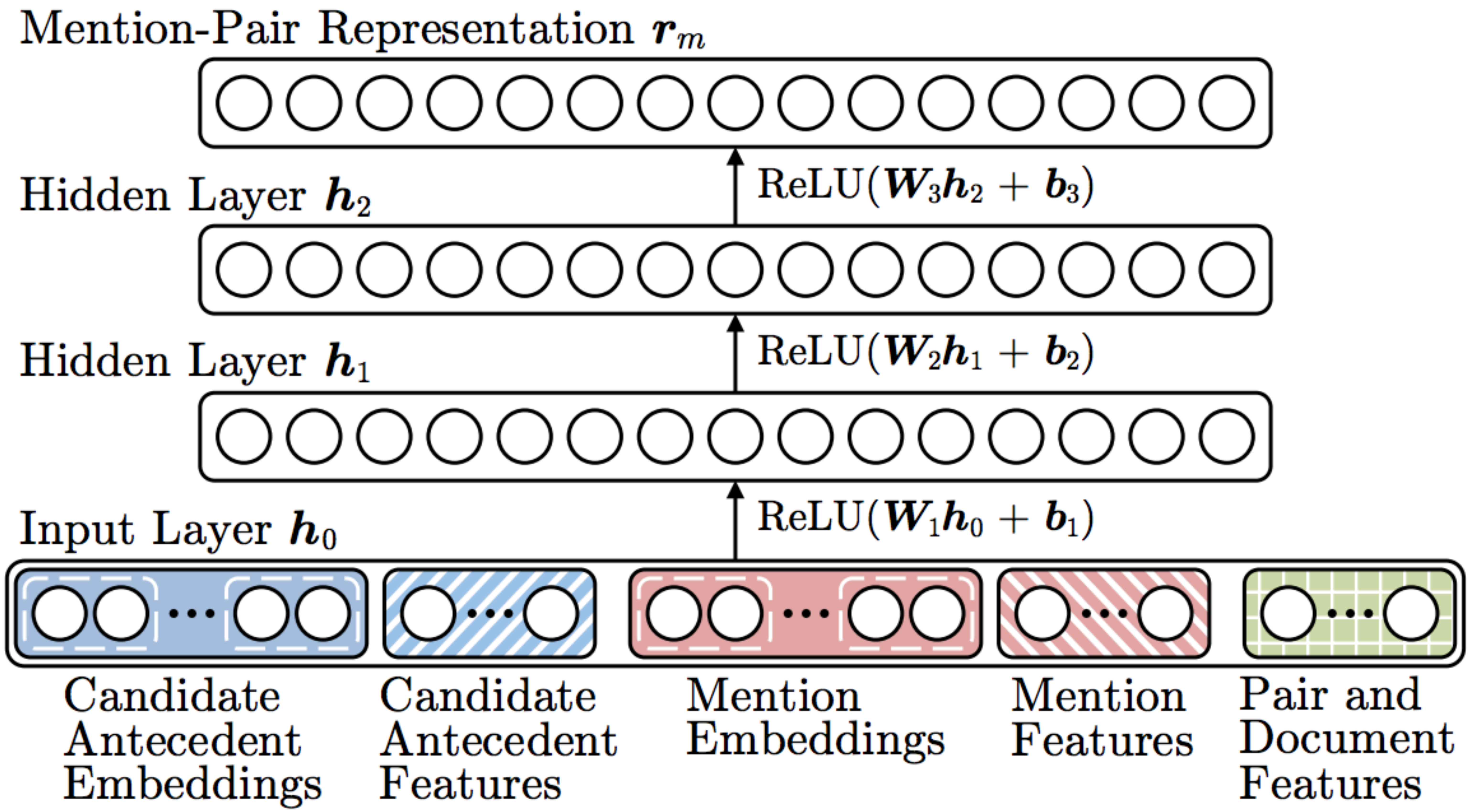

Clark and Manning (2015), Wiseman et al. (2015)

Implementation Details

Computation Graphs

- Computing gradients is hard!

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- Automatic differentiation: instrument code to keep track of derivatives

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Computation Graphs

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y = x * x      ──codegen──▶      (y,dy) = (x * x, 2 * x * dx)
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- Computation is now something we need to reason about symbolically

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- 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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   loss.backward()
   optimizer.step()
```

Training a Model

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Define a computation graph

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For each epoch:

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For each batch of data:

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Decode test set

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```

- Batch sizes from 1-100 often work well