Lecture 6: Neural Networks

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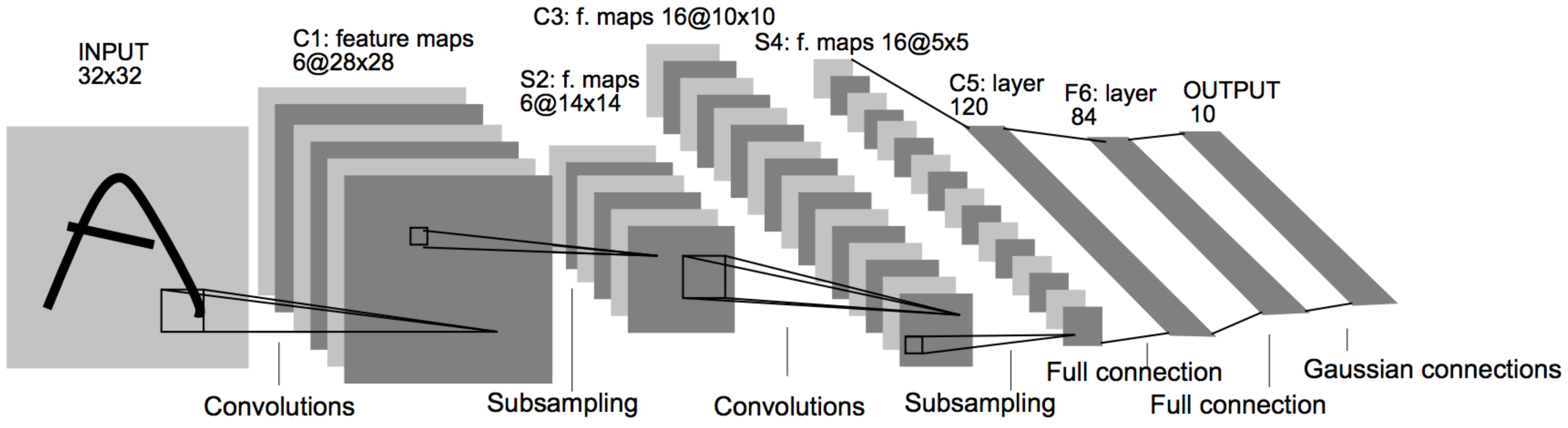
(many slides from Greg Durrett)

This Lecture

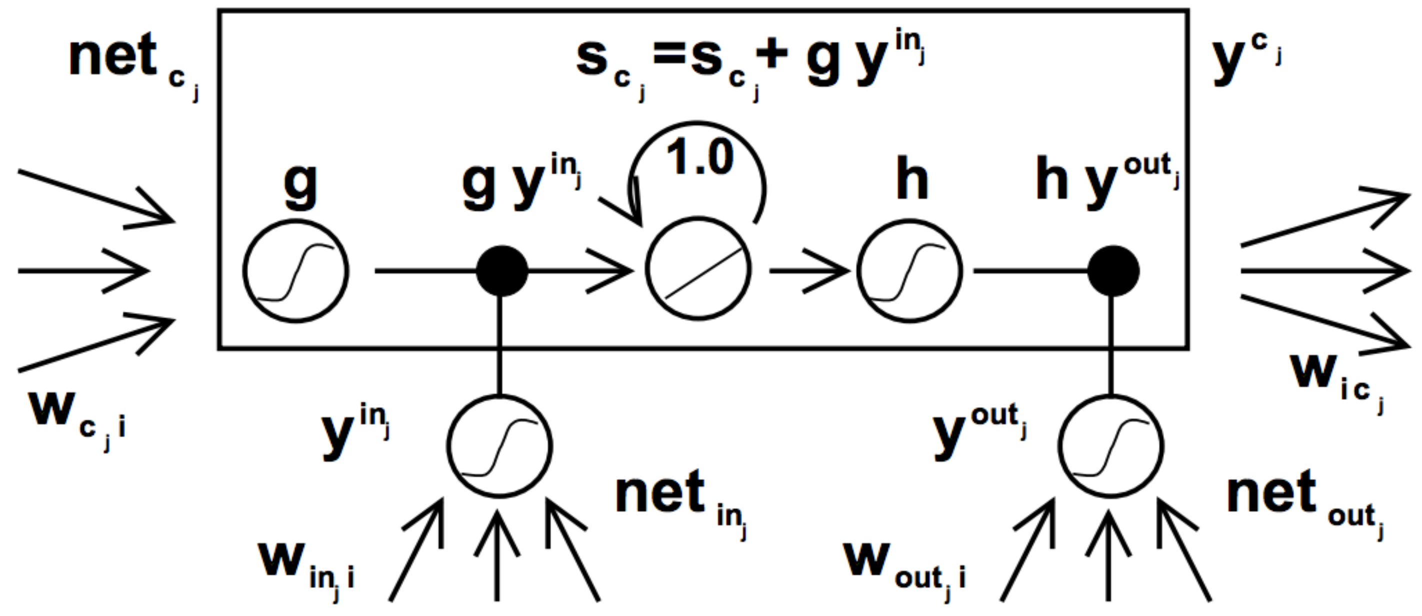
- Neural network history
- Neural network basics
- Feedforward neural networks + backpropagation
- Applications
- Implementing neural networks (if time)

History: NN “dark ages”

- Convnets: applied to MNIST by LeCun in 1998



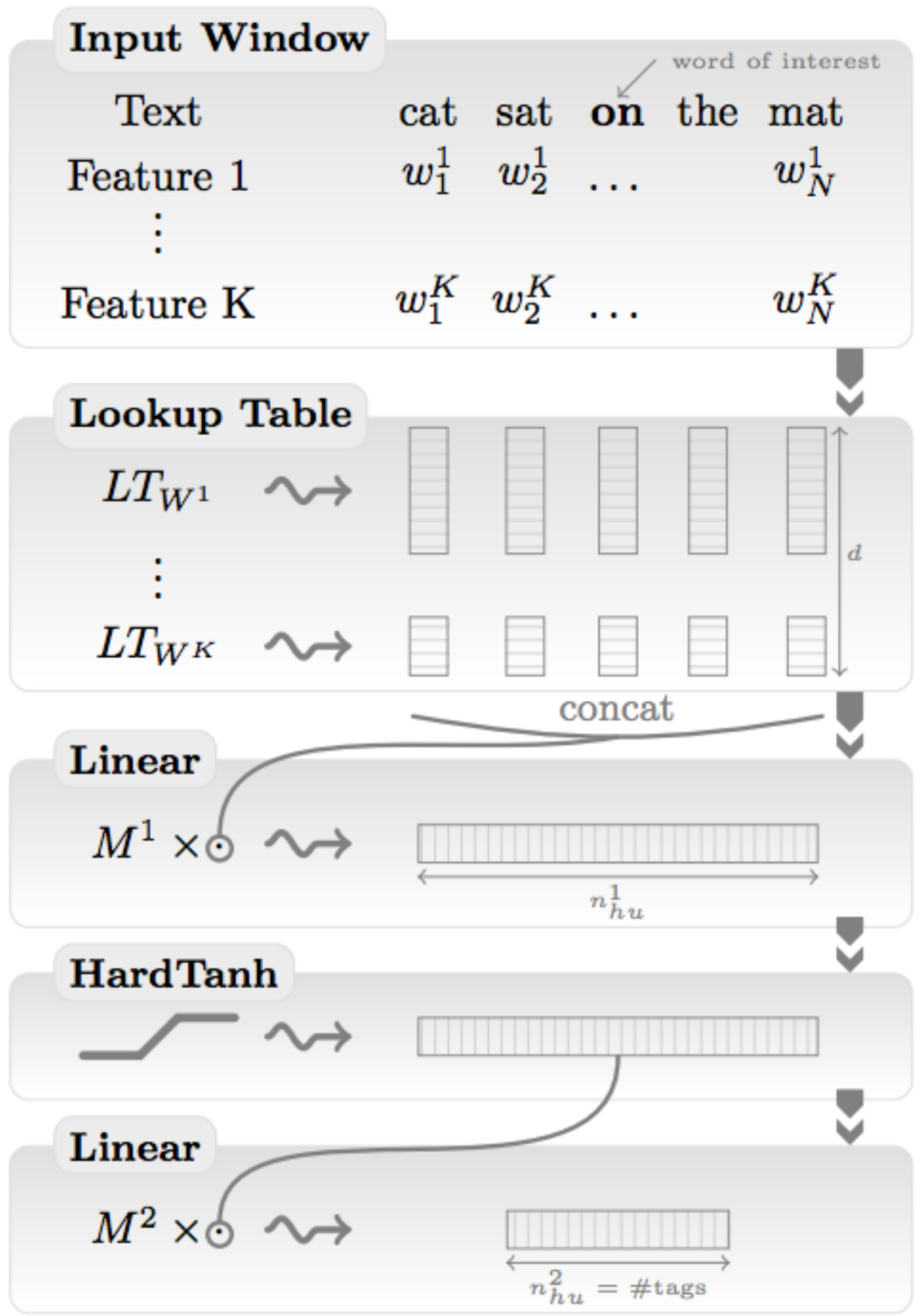
- LSTMs: Hochreiter and Schmidhuber (1997)

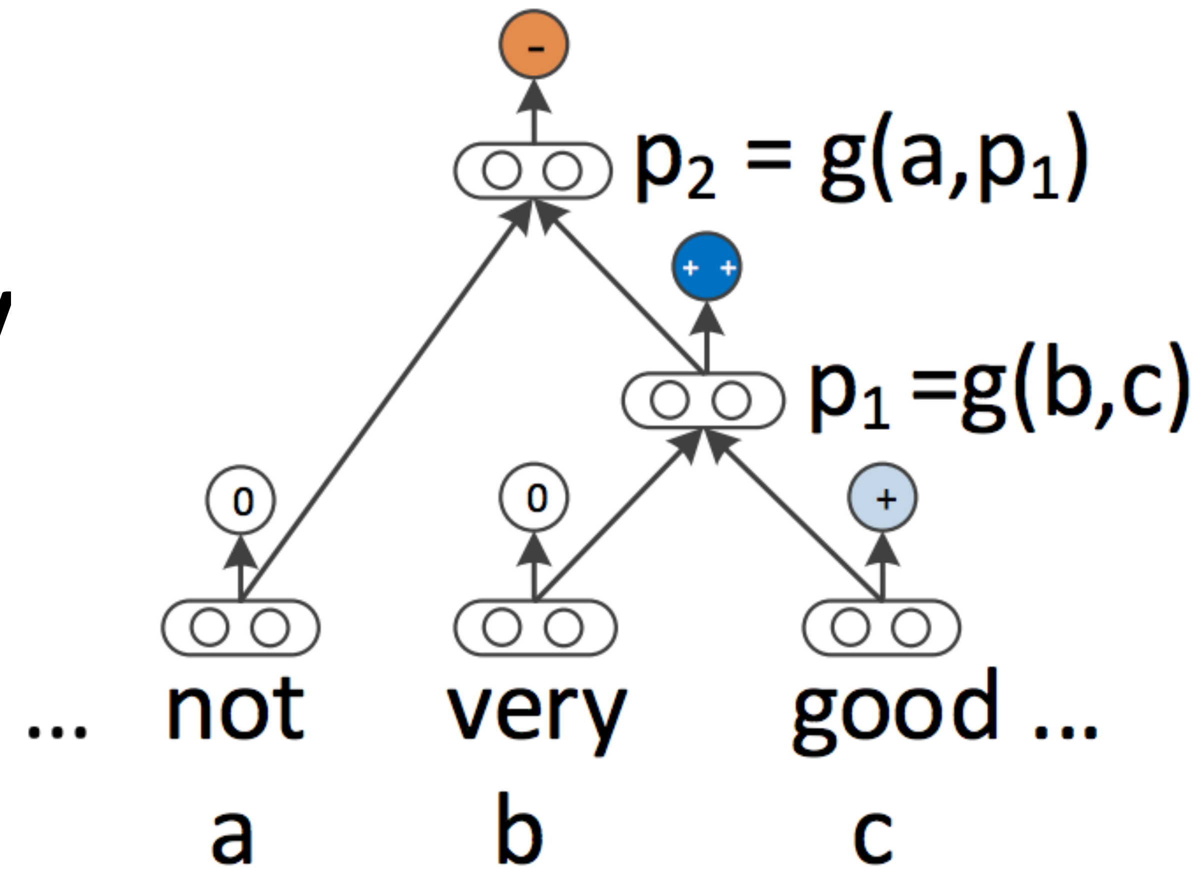


- Henderson (2003): neural shift-reduce parser, not SOTA

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
- Krizhevskey et al. (2012): AlexNet for vision
- Socher 2011-2014: tree-structured RNNs working okay





2014: Stuff starts working

- Kim (2014) + Kalchbrenner et al. (2014): sentence classification / sentiment (convnets work for NLP?)
- Sutskever et al. + Bahdanau et al.: seq2seq for neural MT (LSTMs work for NLP?)
- Chen and Manning transition-based dependency parser (even feedforward networks work well for NLP?)
- 2015: explosion of neural nets for everything under the sun

Why didn't they work before?

- **Datasets too small**: for MT, not really better until you have 1M+ parallel sentences (and really need a lot more)
- **Optimization not well understood**: good initialization, per-feature scaling + momentum (Adagrad / Adadelta / Adam) work best out-of-the-box
  - **Regularization**: dropout is pretty helpful
  - **Computers not big enough**: can't run for enough iterations
- **Inputs**: need word representations to have the right continuous semantics

Neural Net Basics

Neural Networks

- Linear classification: $\text{argmax}_y w^\top f(x, y)$
- How can we do nonlinear classification? Kernels are too slow…
- Want to learn intermediate conjunctive features of the input

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

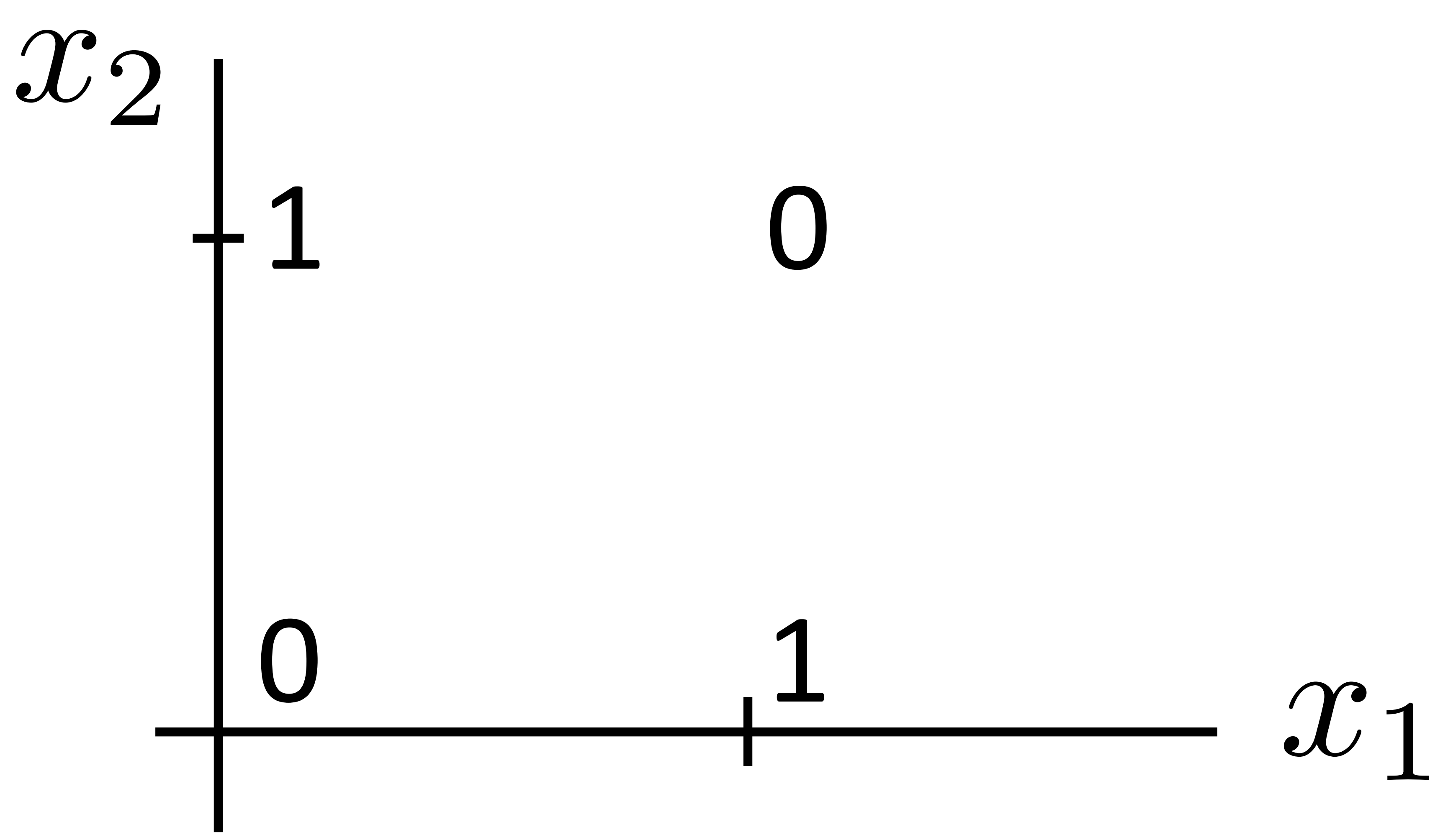
I[contains *not* & contains *good*]

Neural Networks: XOR

- Let's see how we can use neural nets to learn a simple nonlinear function
- Inputs $x_1, \; x_2$

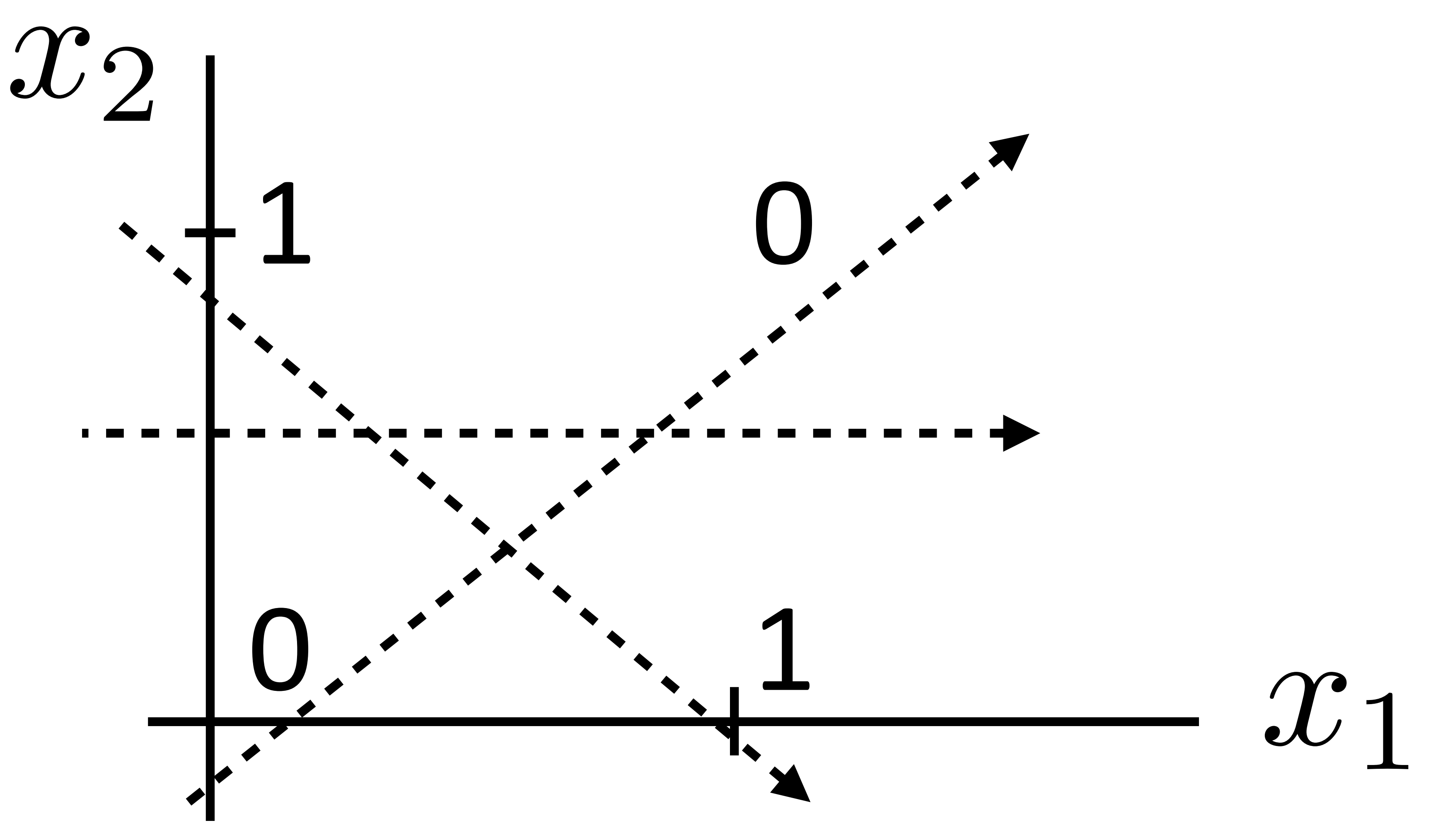
  $(\text{generally } \mathbf{x} = (x_1, \ldots, x_m))$
- Output y

  $(\text{generally } \mathbf{y} = (y_1, \ldots, y_n))$



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

Neural Networks: XOR



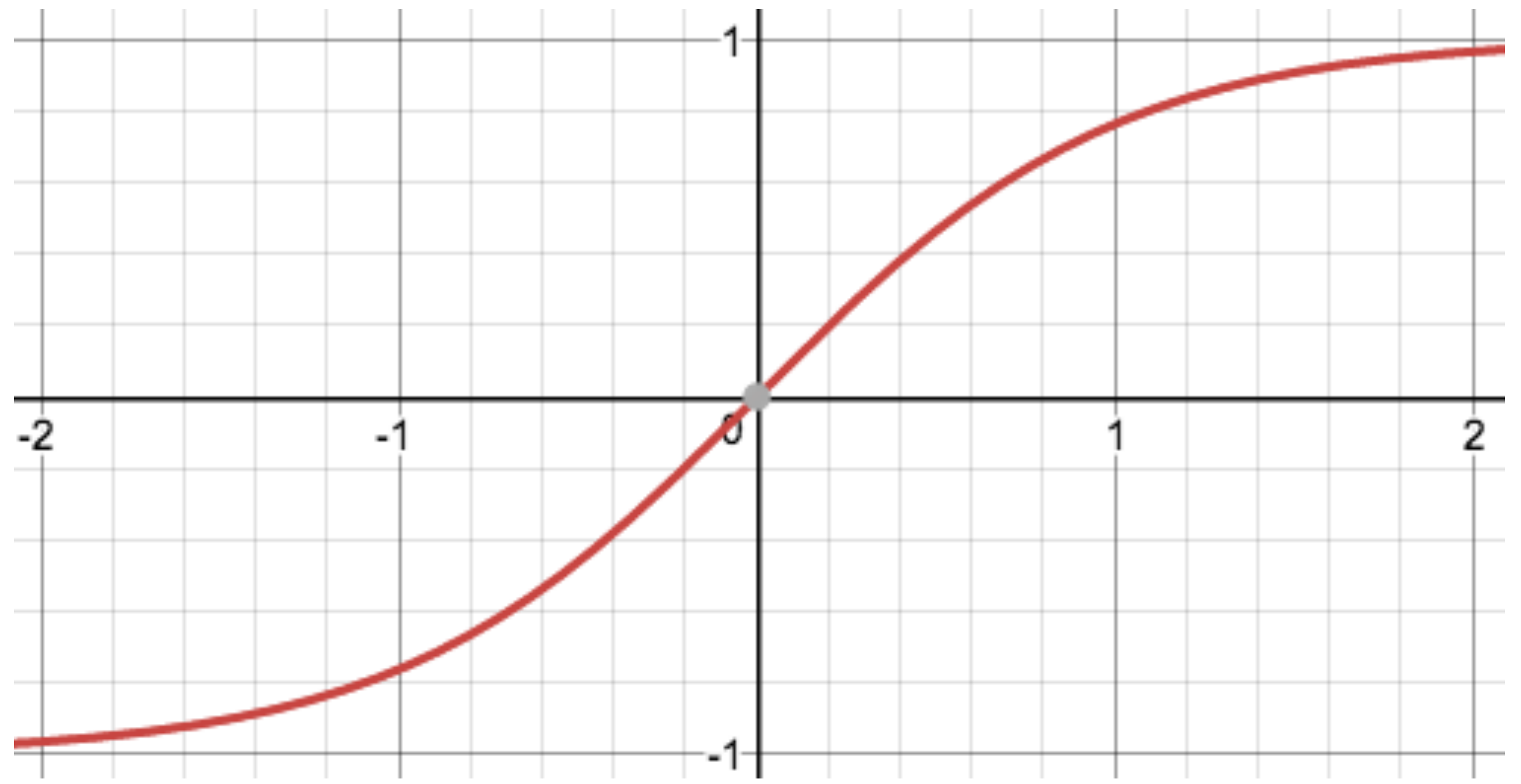
$$y = a_1 x_1 + a_2 x_2$$ ✗

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

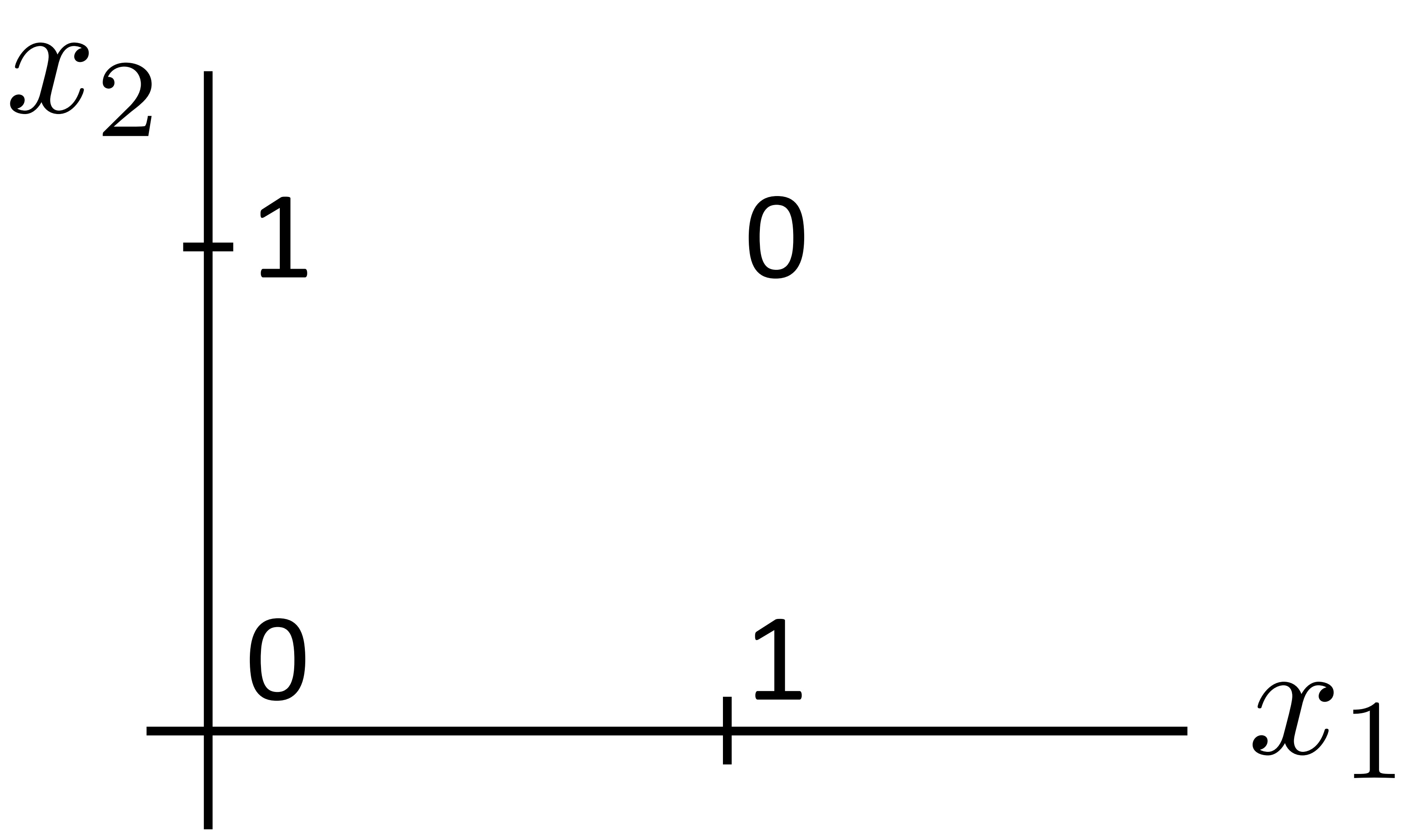
"or"

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

(looks like action potential in neuron)



Neural Networks: XOR



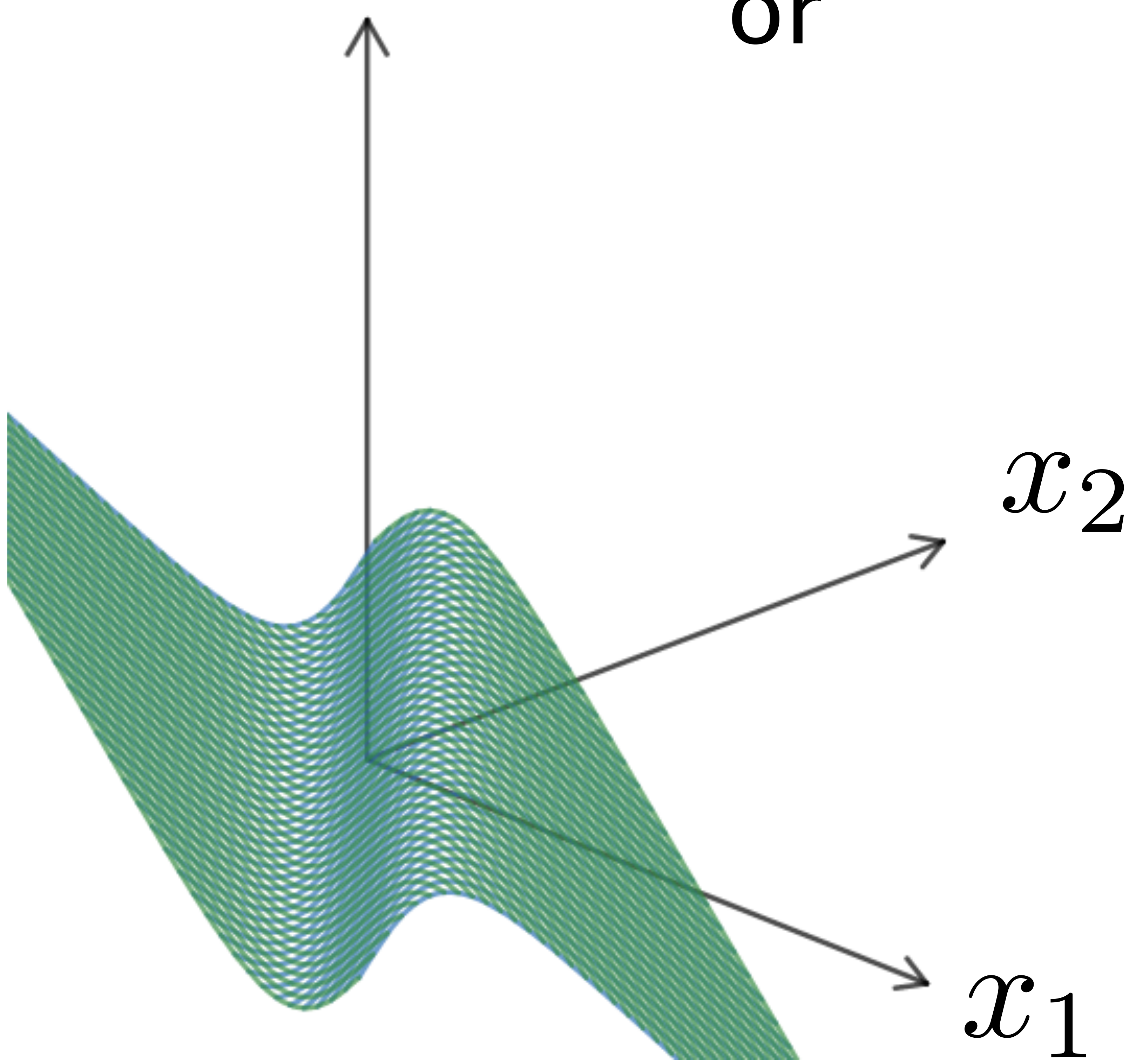
x_1	x_2	x_1 XOR x_2
0	0	0
0	1	1
1	0	1
1	1	0

$$y = a_1 x_1 + a_2 x_2$$ ✗

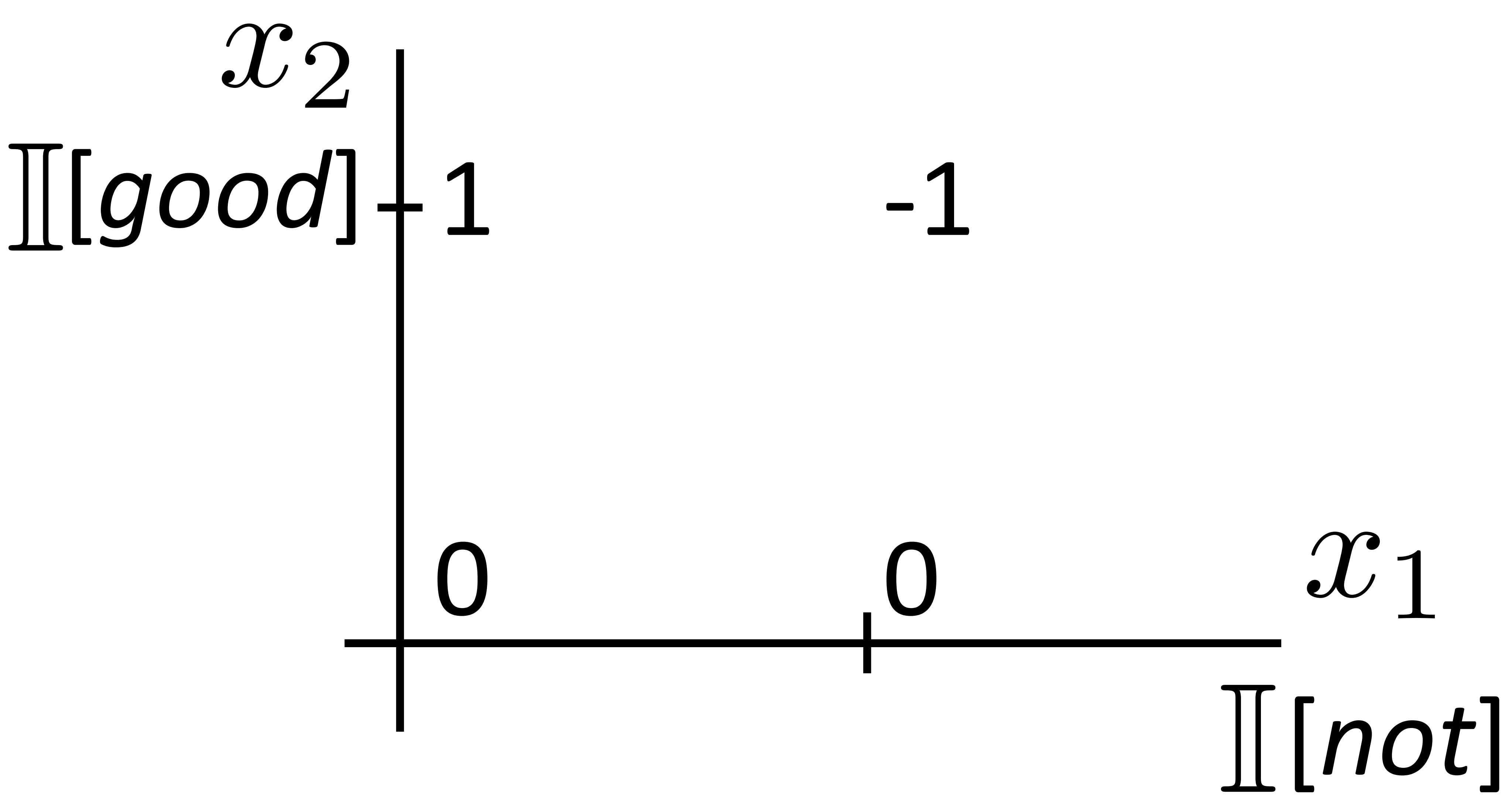
$$y = a_1 x_1 + a_2 x_2 + a_3 \tanh(x_1 + x_2)$$ ✓

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

“or”

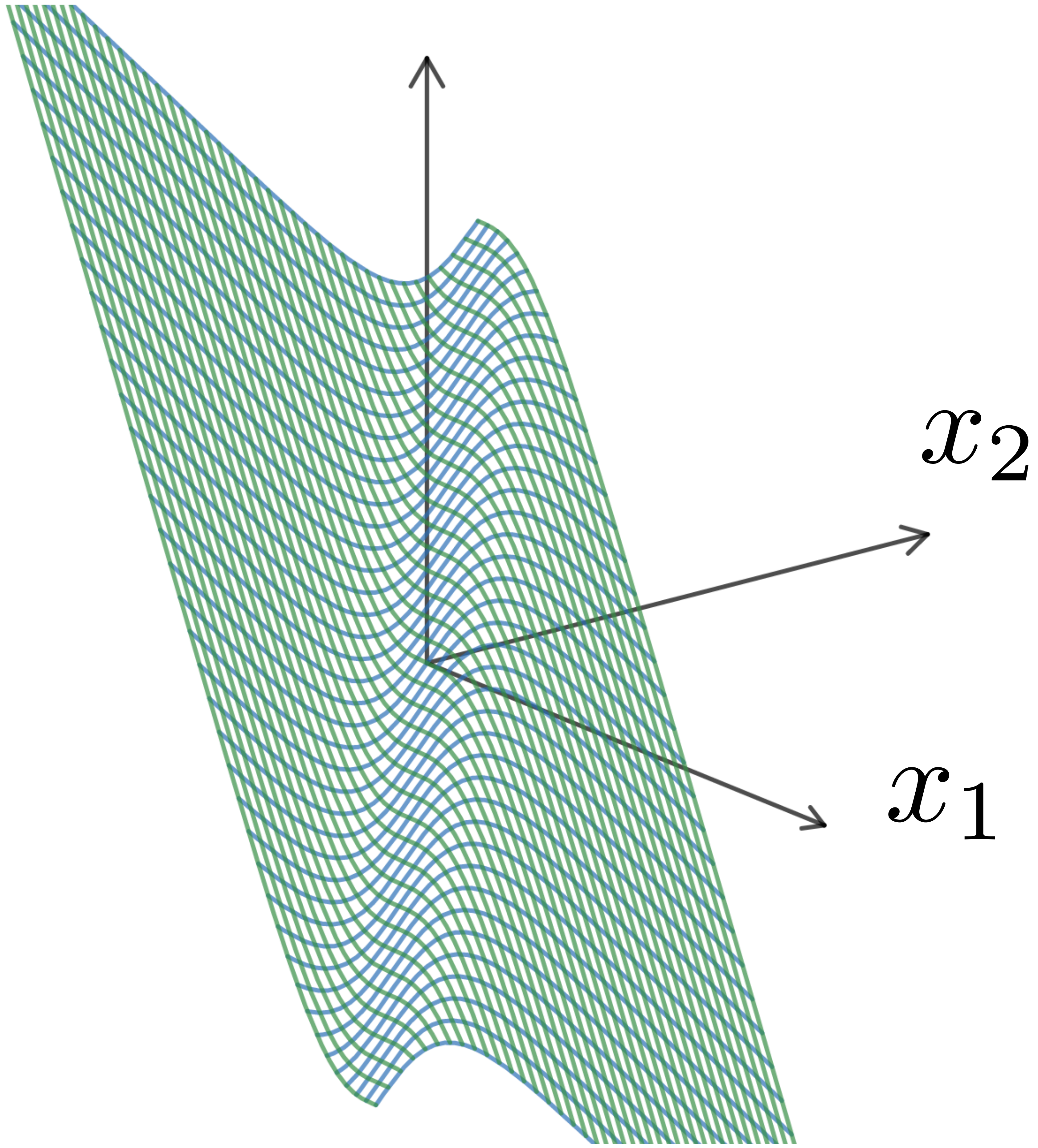


Neural Networks: XOR



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

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



Neural Networks

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

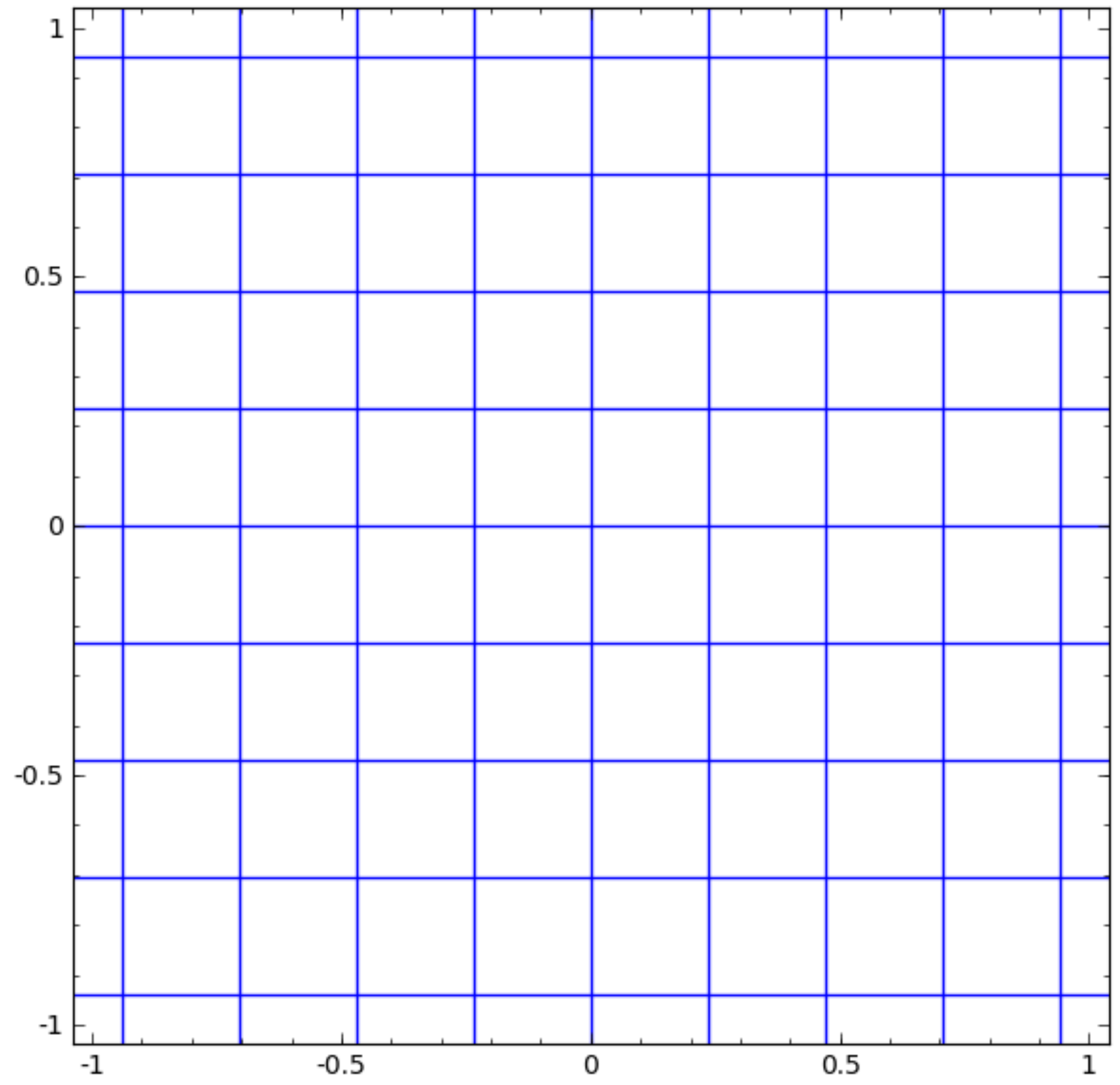
$$y = g(\mathbf{w} \cdot \mathbf{x} + b)$$

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

Nonlinear transformation → g

Warp space → $\mathbf{W}$

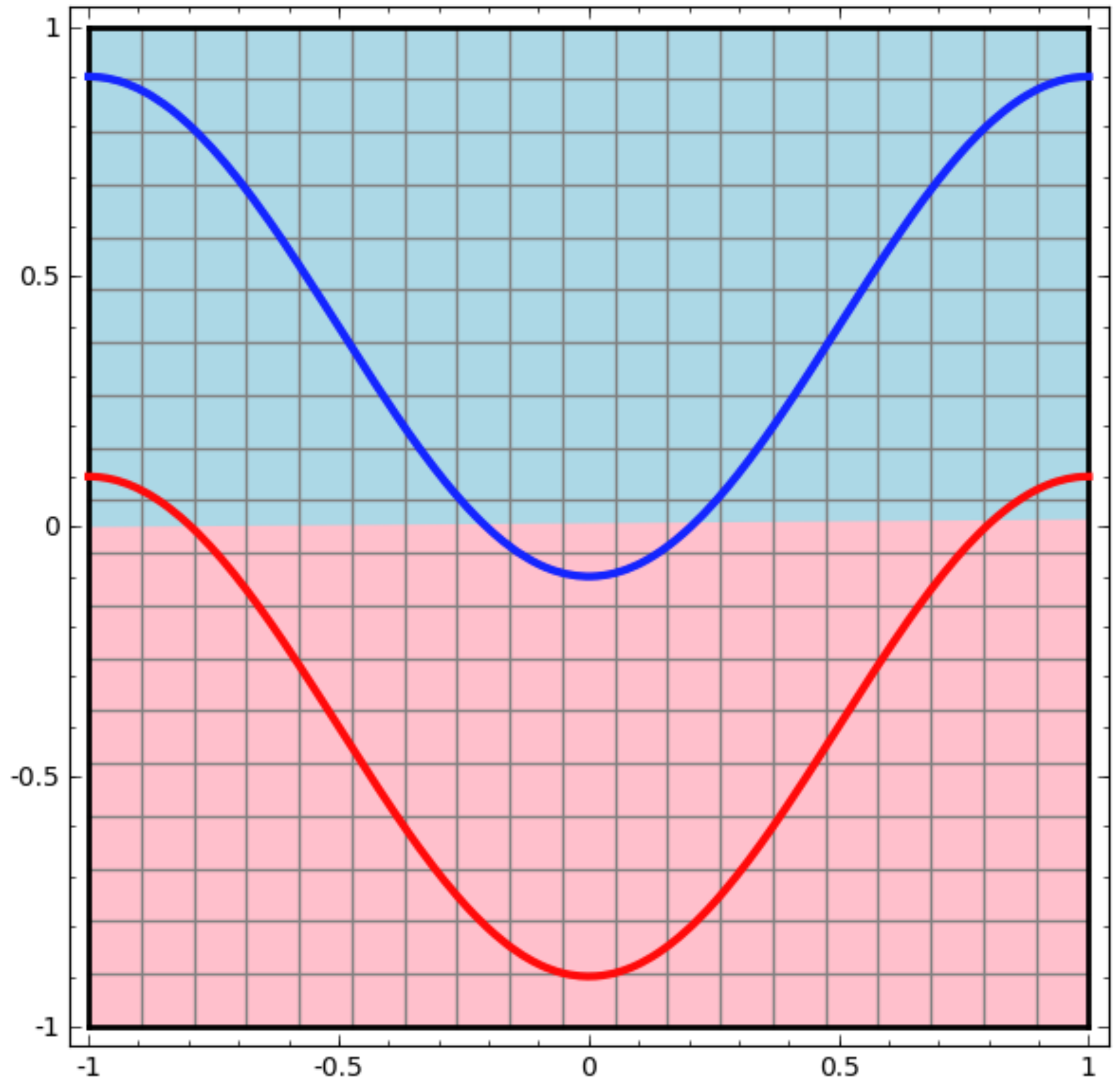
Shift → $\mathbf{b}$



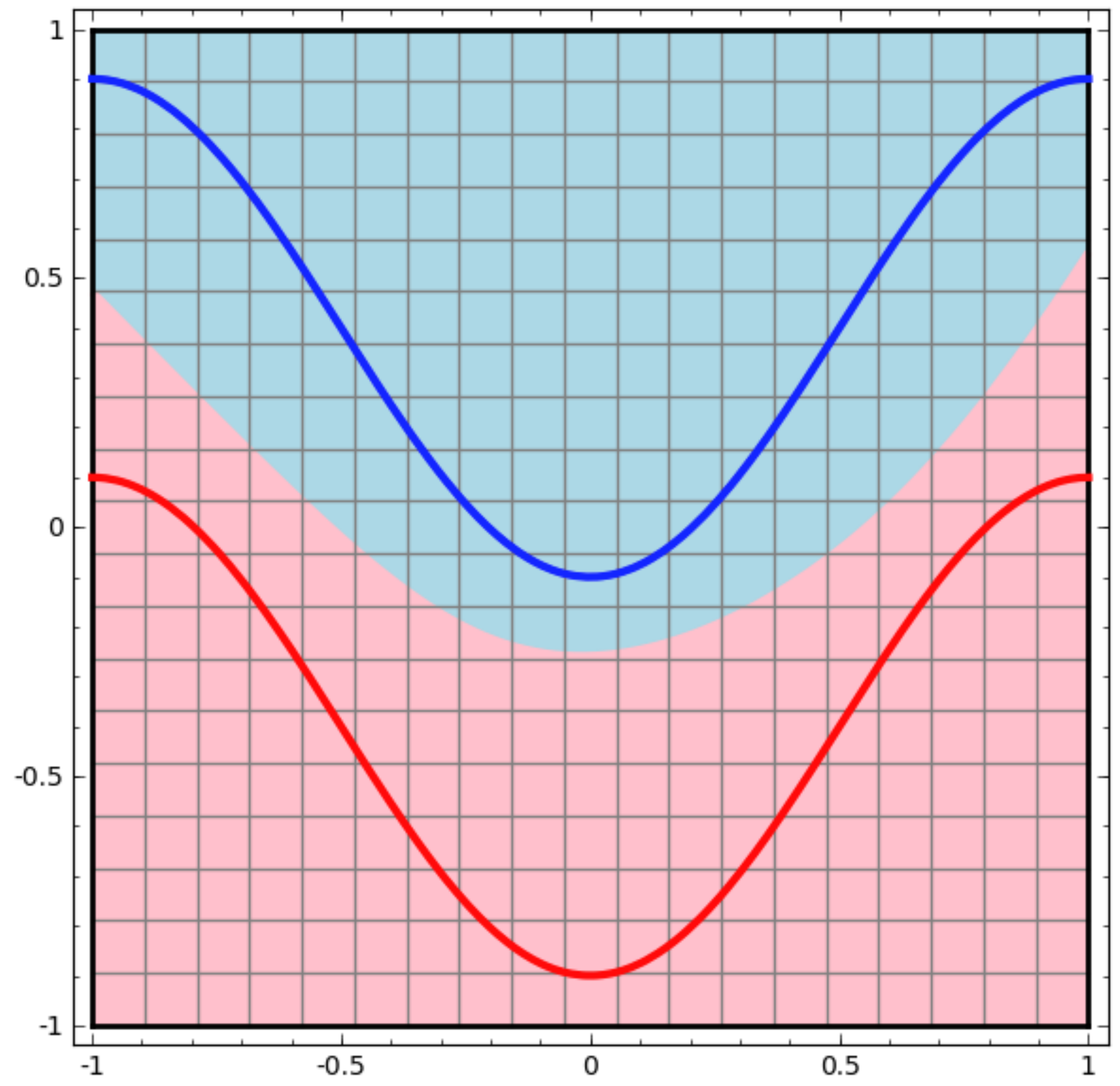
Taken from http://colah.github.io/posts/2014-03-NN-Manifolds-Topology/

Neural Networks

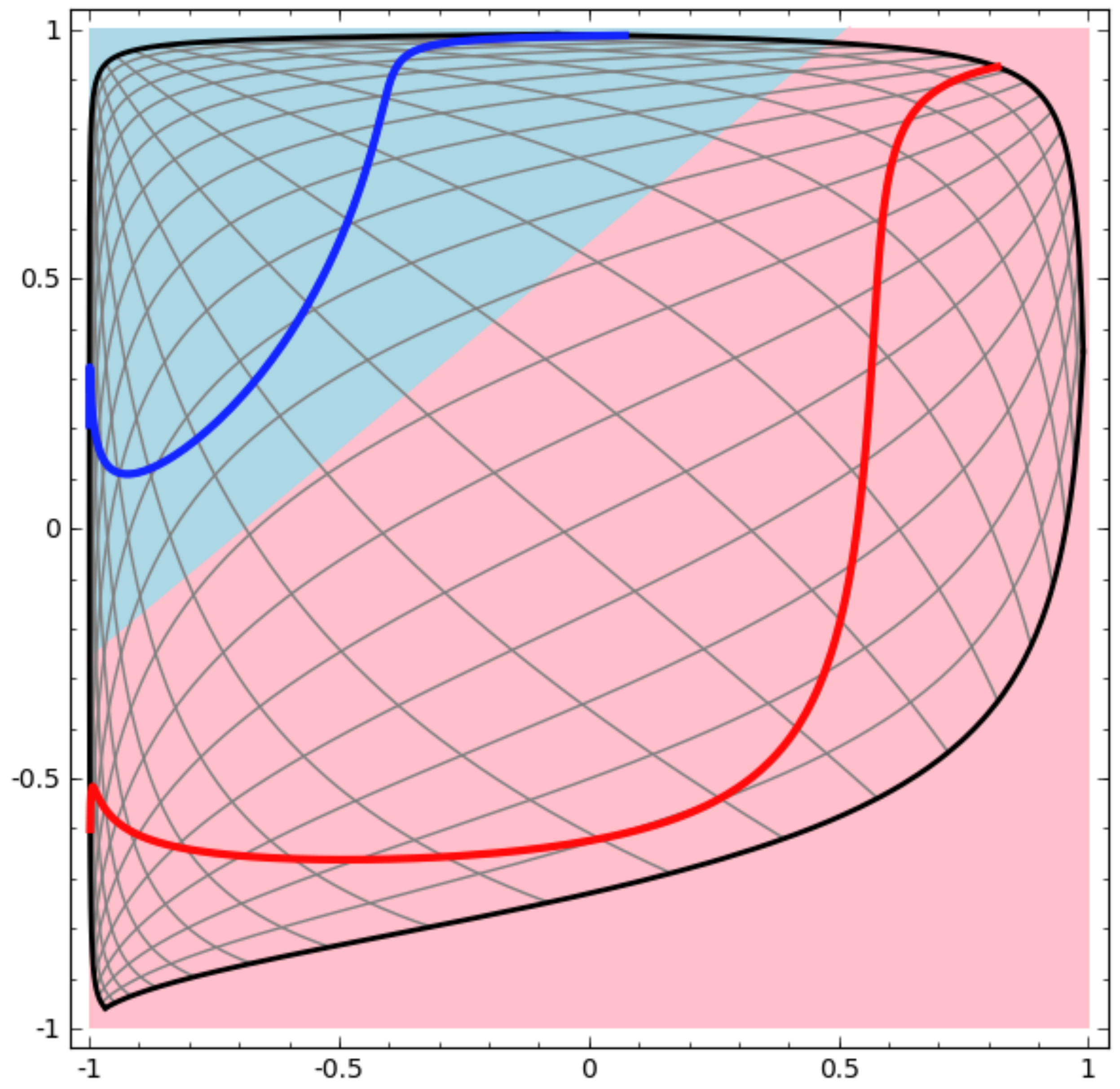
Linear classifier



Neural network



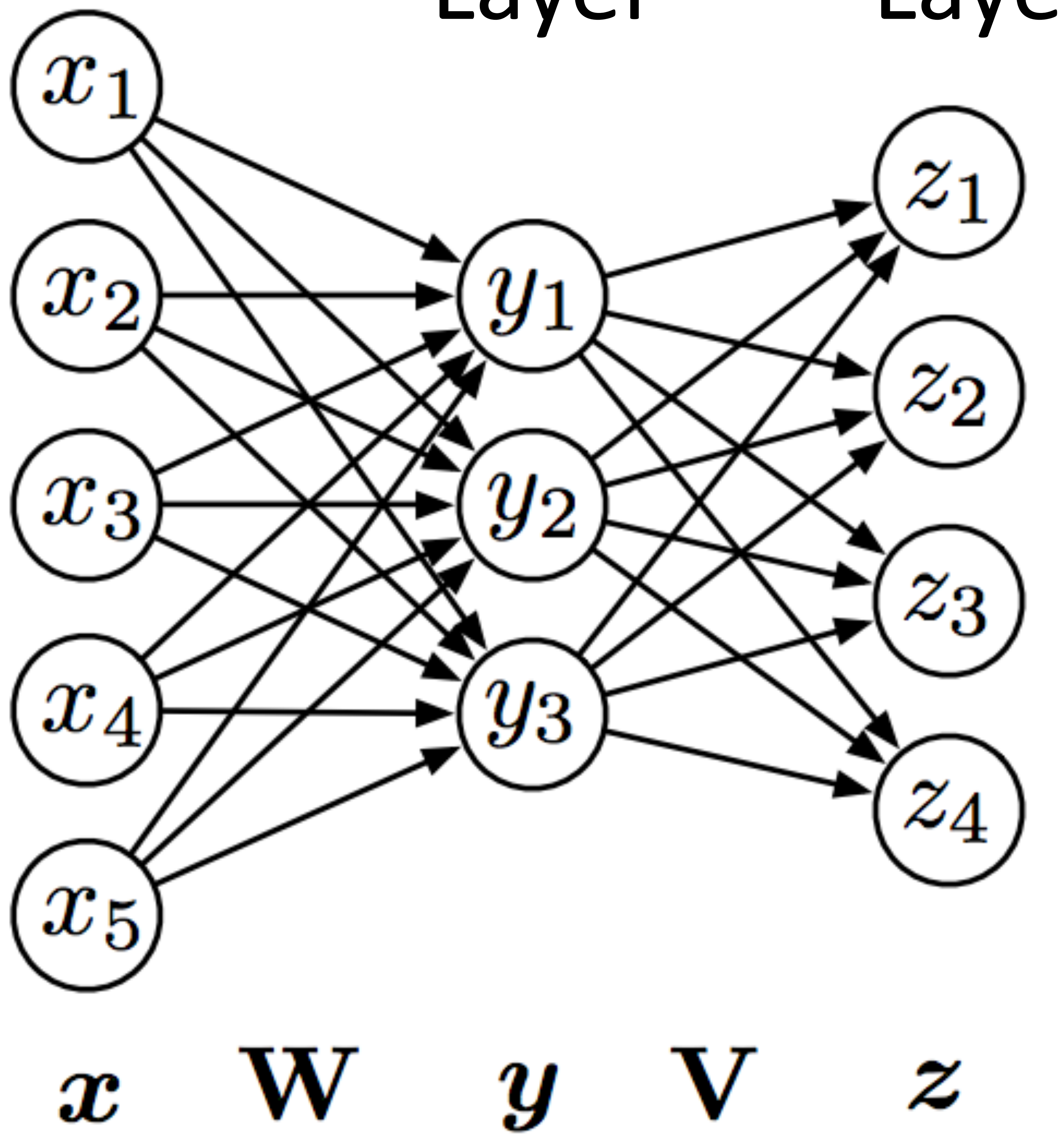
…possible because we transformed the space!



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

Deep Neural Networks

Input First Layer Second Layer



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

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

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

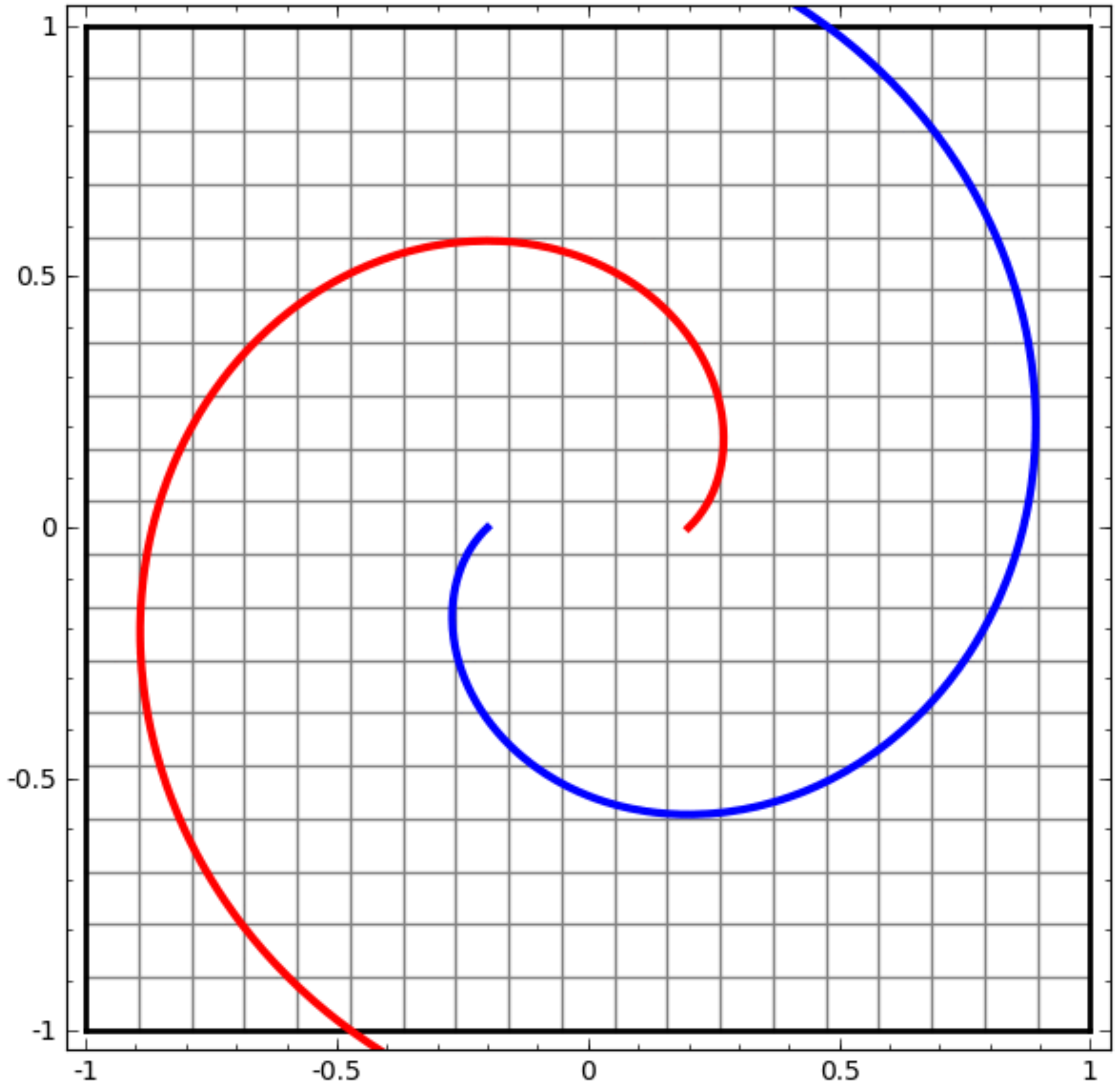
“Feedforward” computation (not recurrent)

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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Feedforward Networks, Backpropagation

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

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

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

$$\text{softmax}(p)_i = \frac{\exp(p_i)}{\sum_{i'} \exp(p_{i'})}$$

- softmax: exps and normalizes a given vector

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

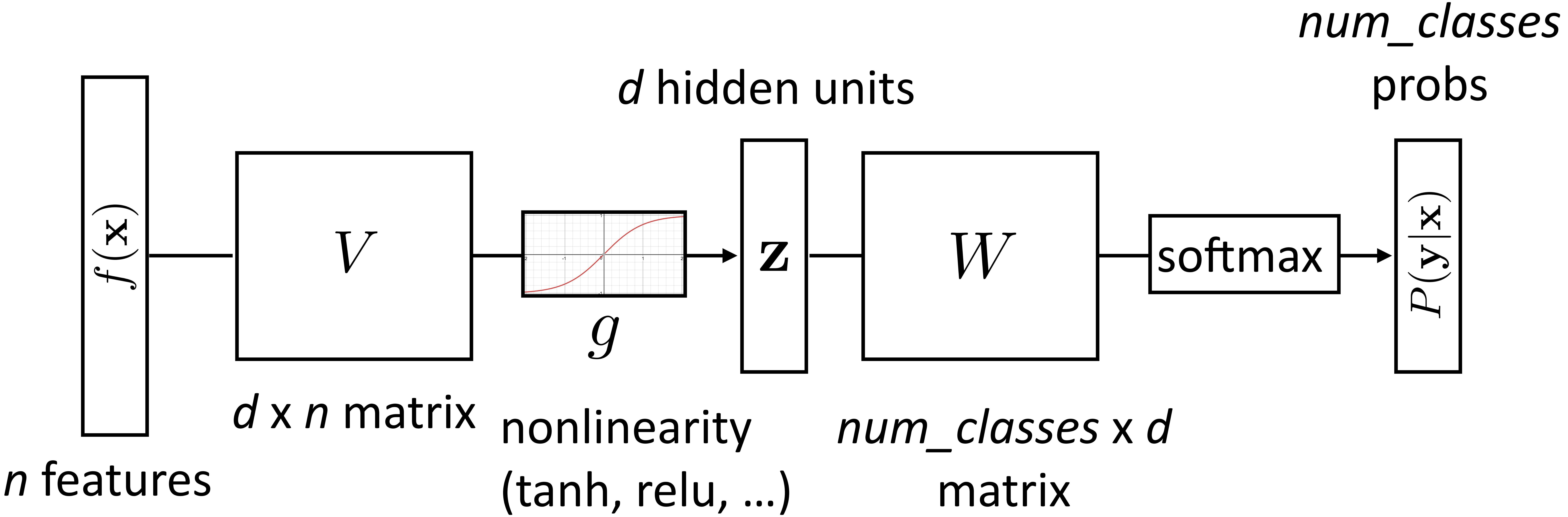
- Weight vector per class;
  W is [num classes x num feats]

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

- Now one hidden layer

Neural Networks for Classification

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



Training Neural Networks

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

- Maximize log likelihood of training data

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

- *i**: index of the gold label

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

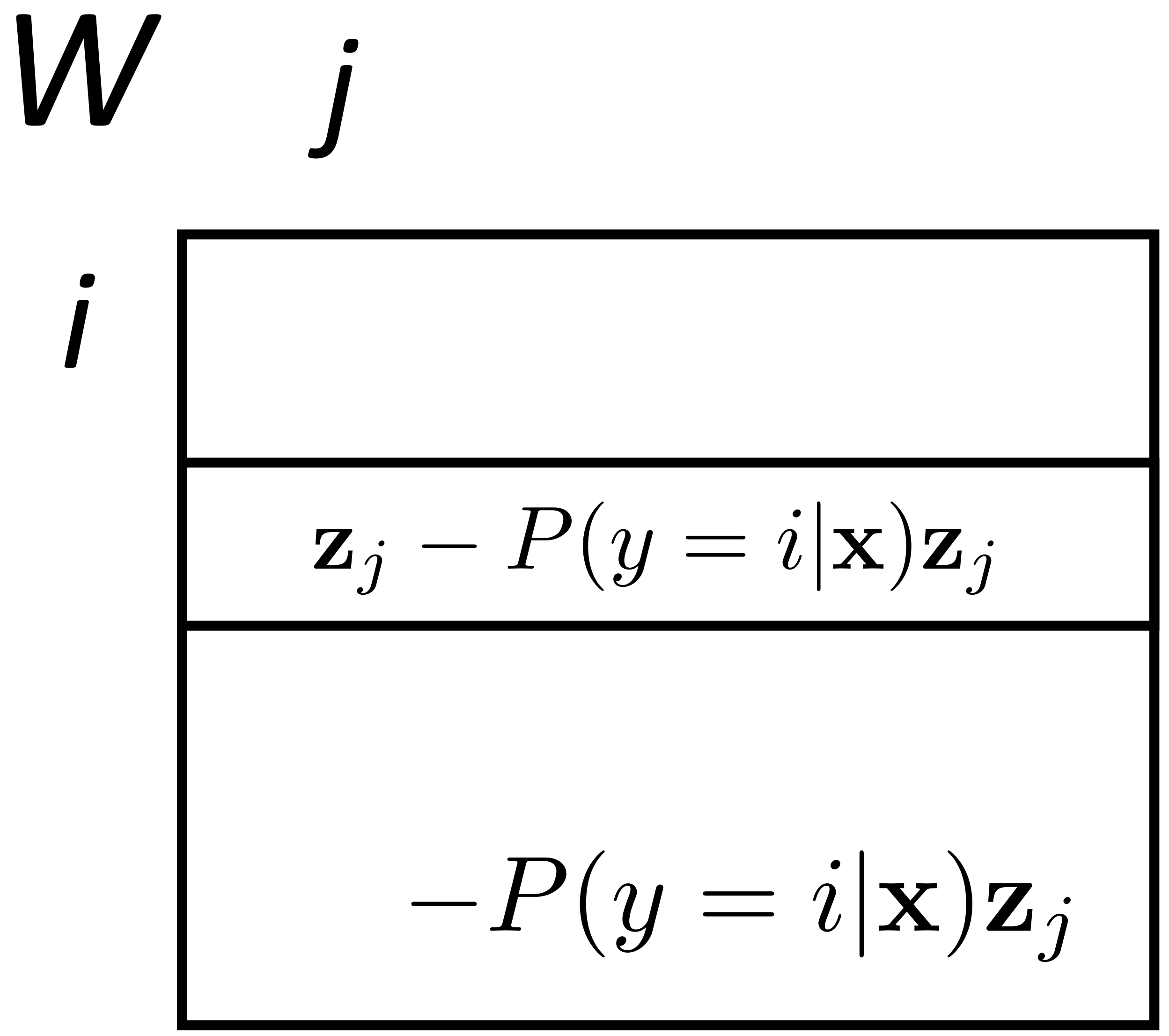
$$\mathcal{L}(\mathbf{x}, i^*) = W\mathbf{z} \cdot e_{i^*} - \log \sum_j \exp(W\mathbf{z}) \cdot e_j$$

Computing Gradients

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

- Gradient with respect to *W*

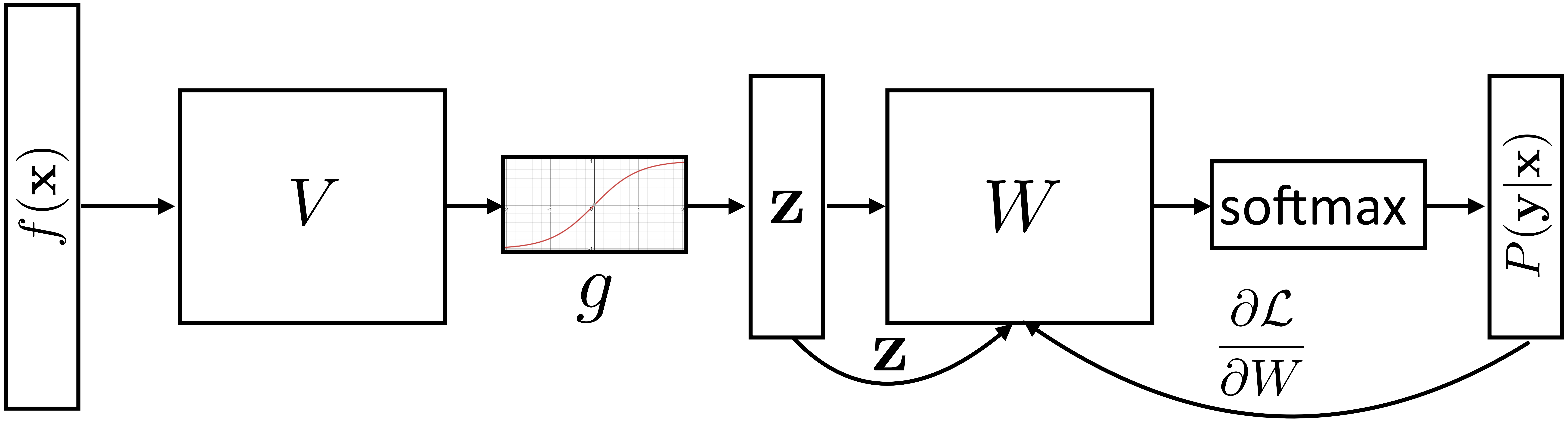
$$\frac{\partial}{\partial W_{ij}} \mathcal{L}(\mathbf{x}, i^*) = \begin{cases} \mathbf{z}_j - P(y = i|\mathbf{x})\mathbf{z}_j & \text{if } i = i^* \\ -P(y = i|\mathbf{x})\mathbf{z}_j & \text{otherwise} \end{cases}$$



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

Neural Networks for Classification

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



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

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

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

[some math…]

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

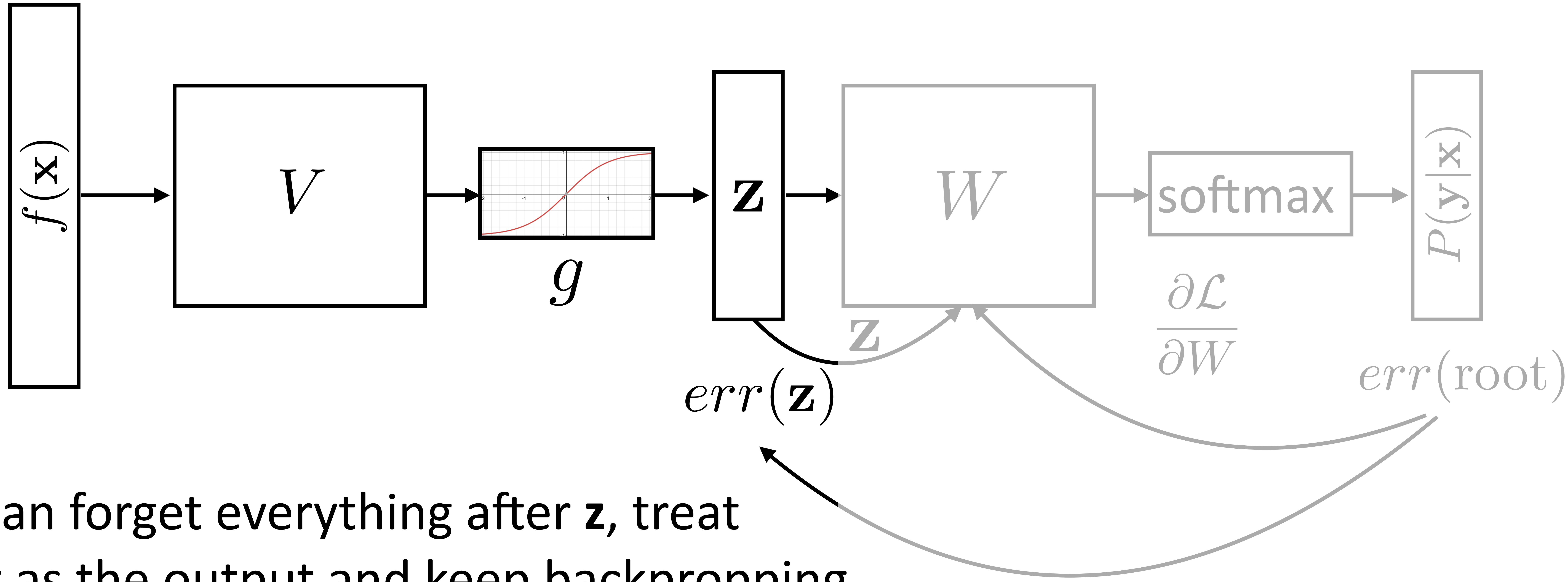
dim = m

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

dim = d

Backpropagation: Picture

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



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

Backpropagation: Takeaways

- Gradients of output weights W are easy to compute — looks like logistic regression with hidden layer $\mathbf{z}$ as feature vector

- Can compute derivative of loss with respect to $\mathbf{z}$ to form an "error signal" for backpropagation

- 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

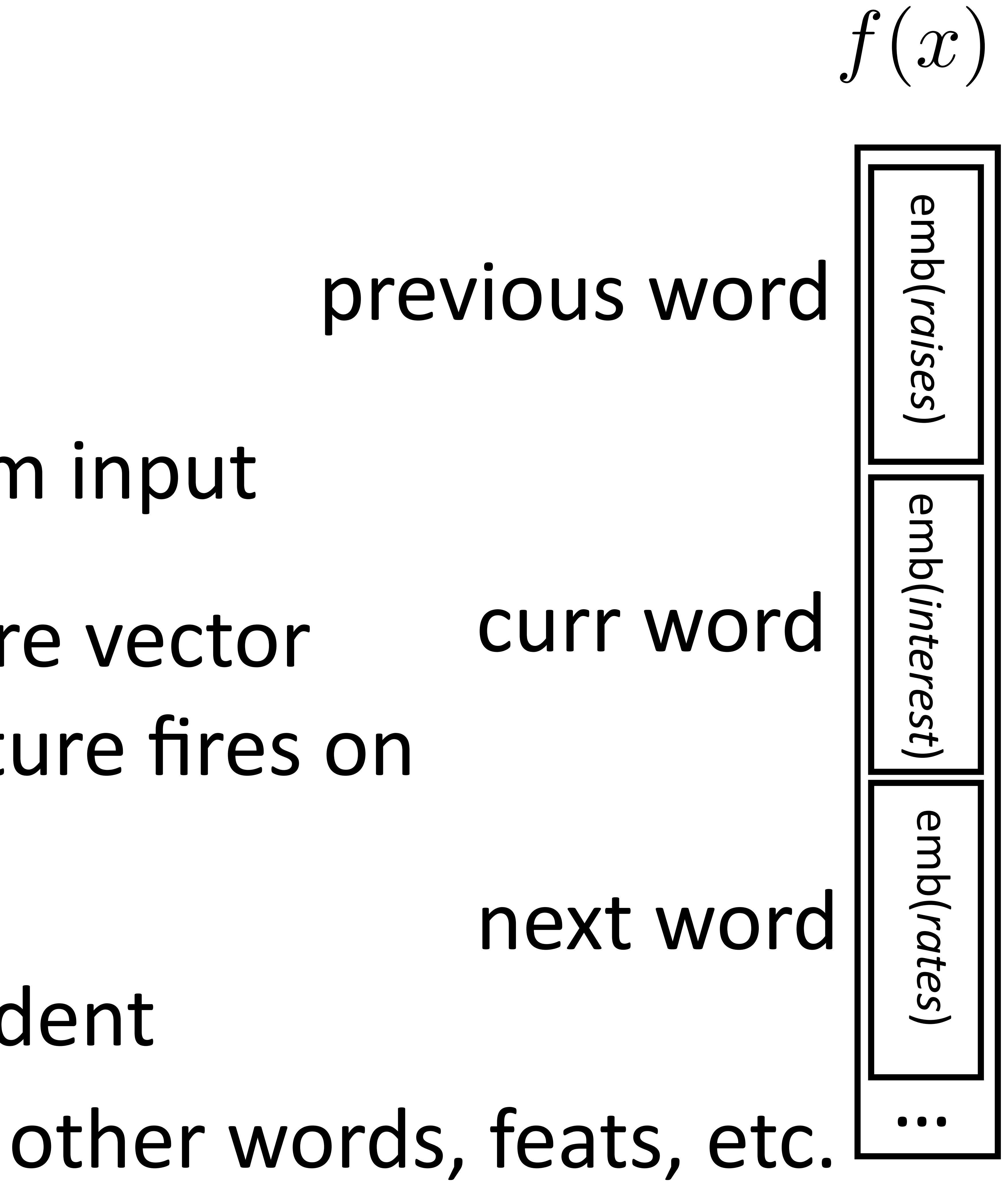
NLP with Feedforward Networks

- Part-of-speech tagging with FFNNs

??

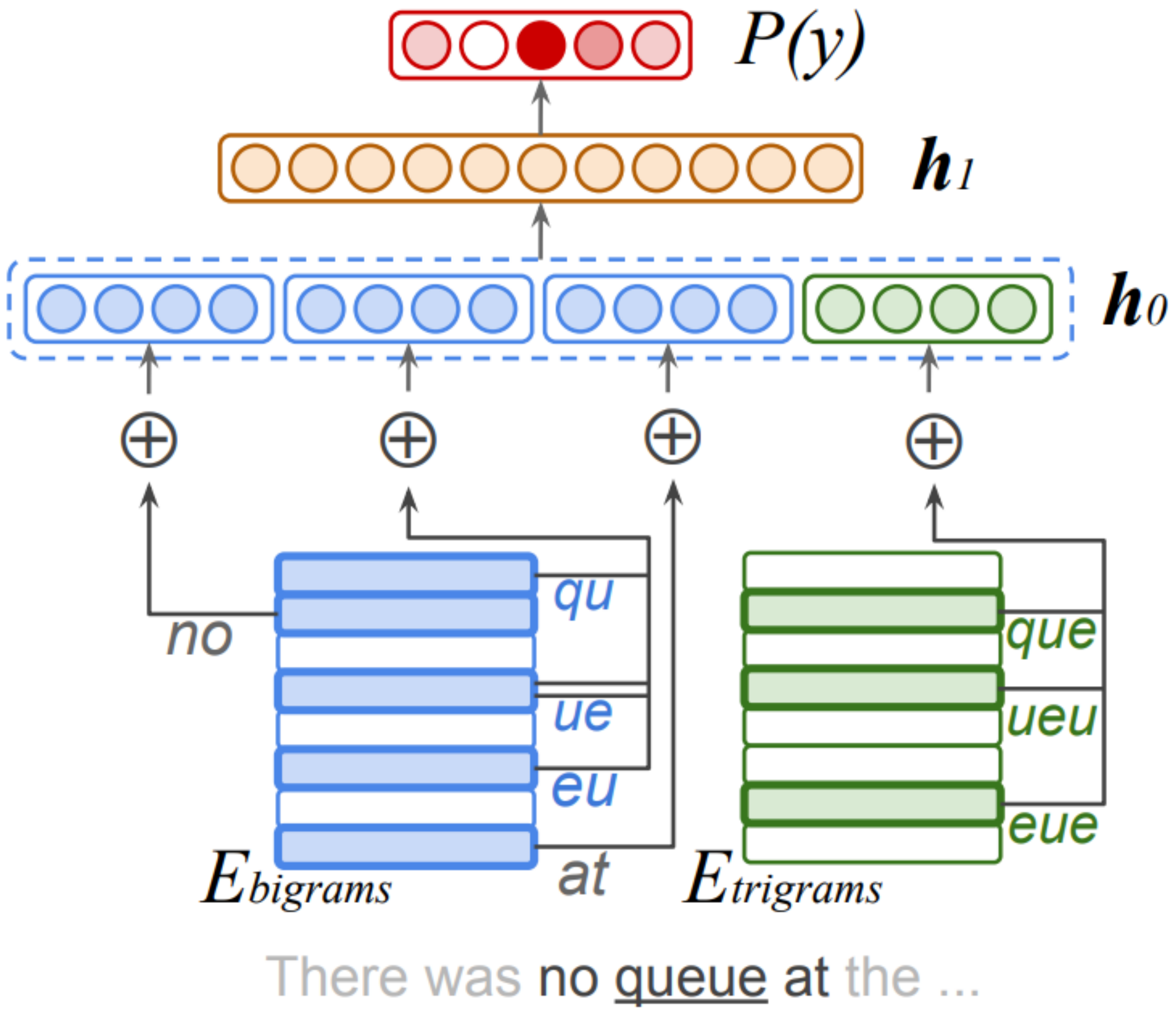
Fed raises ***interest*** *rates in order to …*

- 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



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:

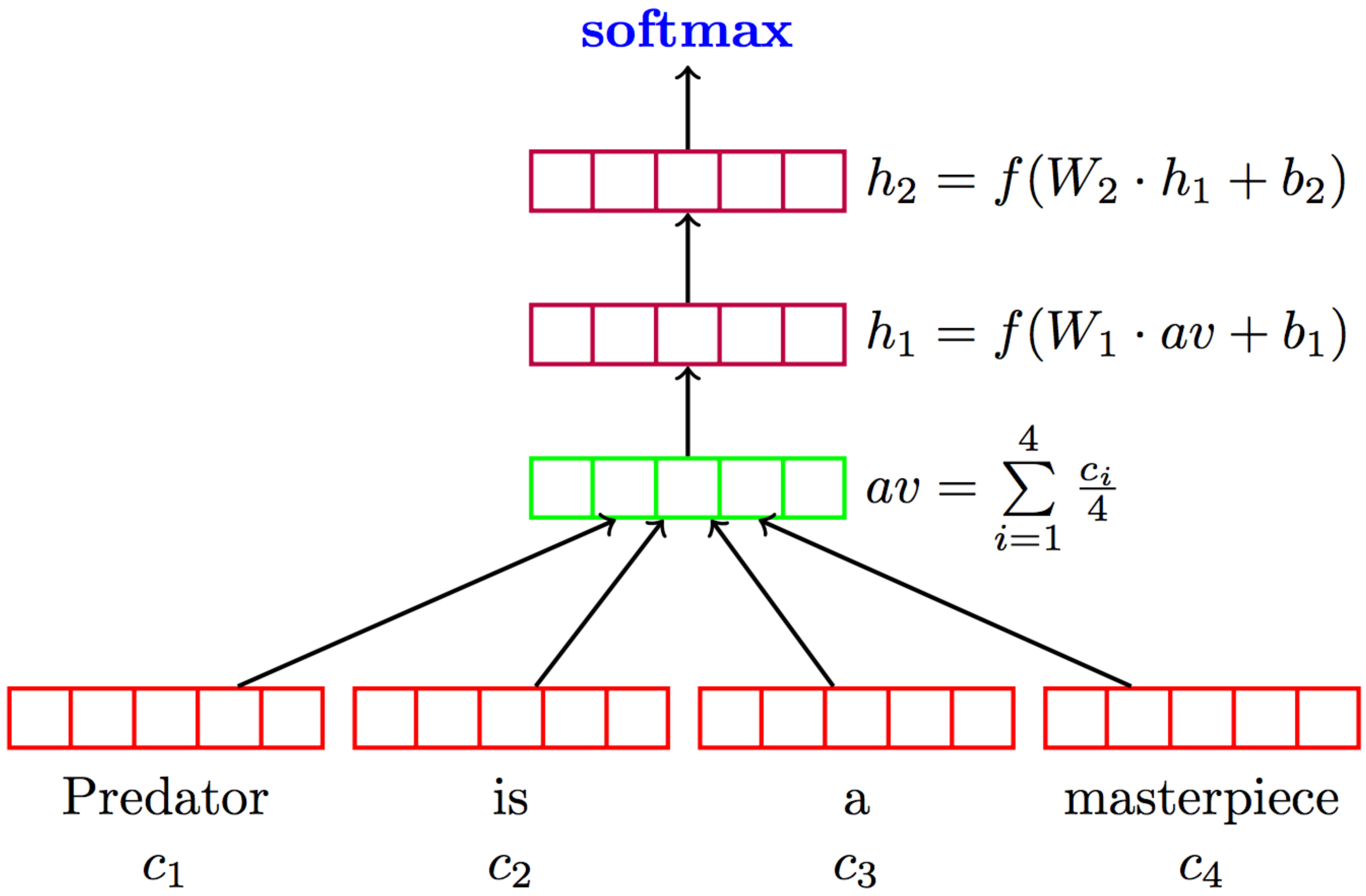
Model	Acc.	Wts.	MB	Ops.
Gillick et al. (2016)	95.06	900k	-	6.63m
Small FF	94.76	241k	0.6	0.27m
+Clusters	95.56	261k	1.0	0.31m
$\frac{1}{2}$ Dim.	95.39	143k	0.7	0.18m

- 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

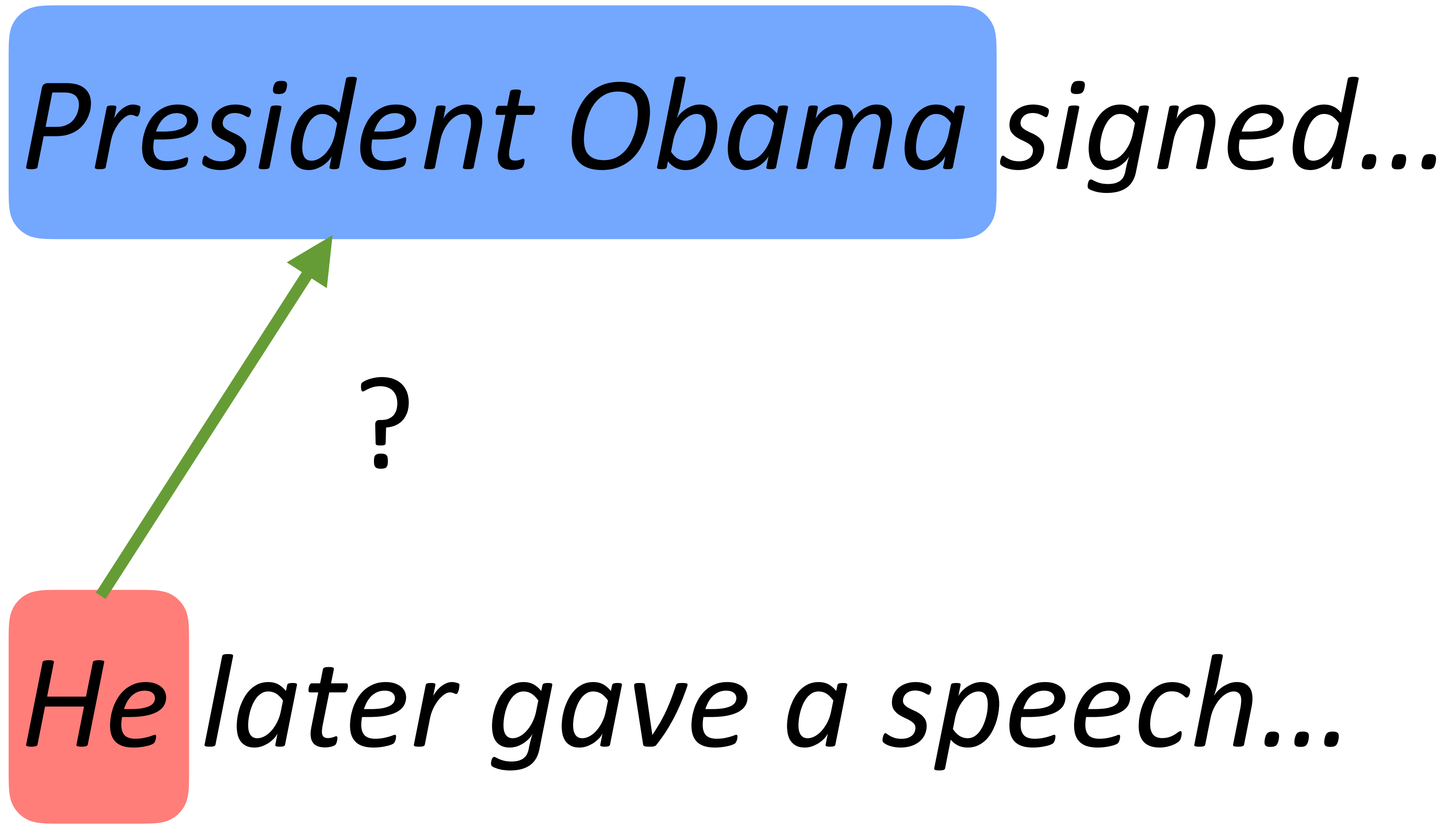
Wang and Manning (2012)

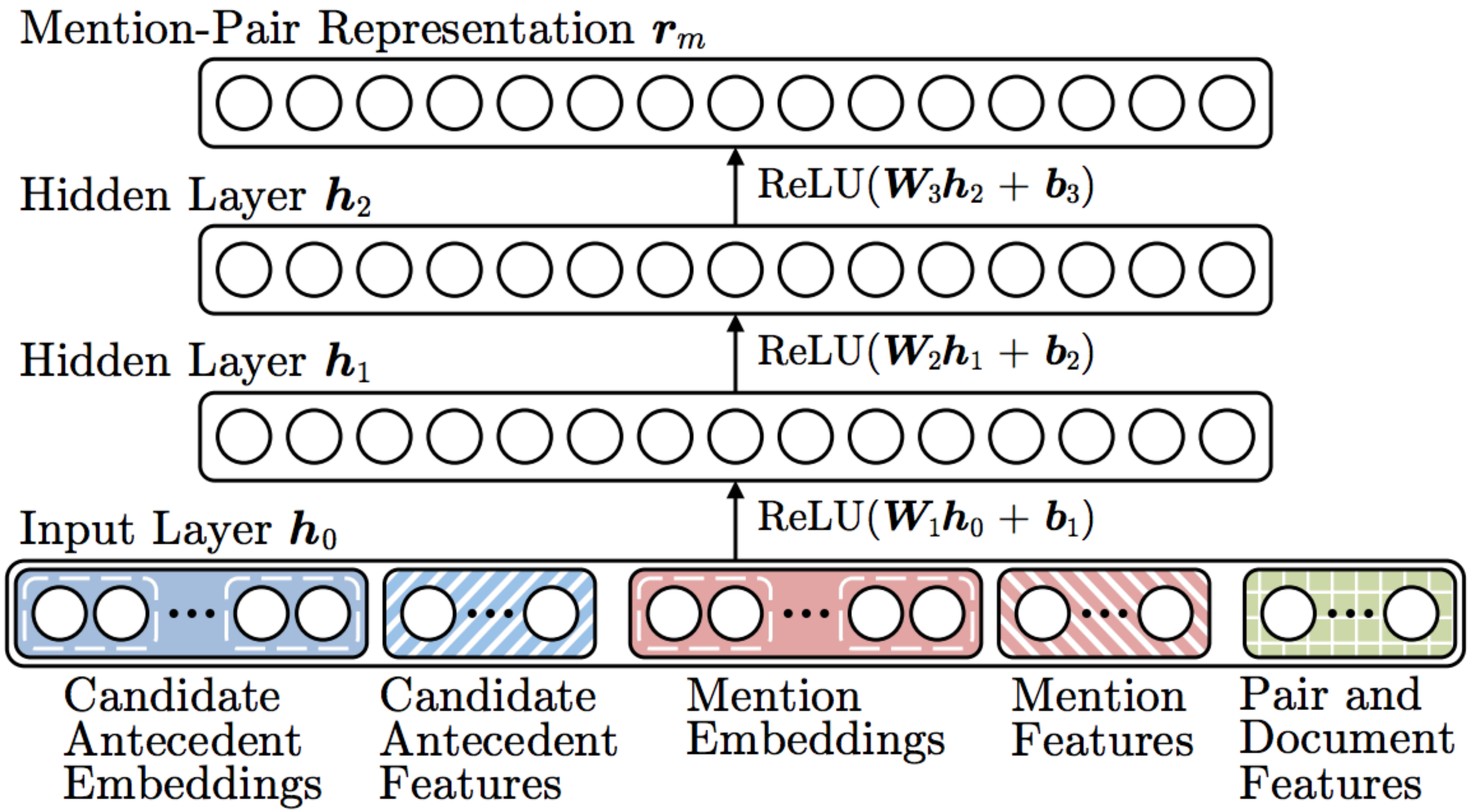
Tree RNNs / CNNS / LSTMS

Kim (2014)

Coreference Resolution

- Feedforward networks identify coreference arcs





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

Implementation Details

Computation Graphs

- Computing gradients is hard!

- Automatic differentiation: instrument code to keep track of derivatives

```
y = x * x   --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))))
```

Computation Graphs in Pytorch

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

```
ei*: one-hot vector
of the label
(e.g., [0, 1, 0])
```

```
ffnn = FFNN()
def make_update(input, gold_label):
   ffnn.zero_grad() # clear gradient variables
   probs = ffnn.forward(input)
   loss = torch.neg(torch.log(probs)).dot(gold_label)
   loss.backward()
   optimizer.step()
```

Training a Model

Define a computation graph

For each epoch:

  For each batch of data:

    Compute loss on batch

    Autograd to compute gradients and take step

Decode test set

Batching

- Batching data gives speedups due to more efficient matrix operations

- Need to make the computation graph process a batch at the same time

```
# input is [batch_size, num_feats]
# gold_label is [batch_size, num_classes]
def make_update(input, gold_label)
    ...
    probs = ffnn.forward(input) # [batch_size, num_classes]
    loss = torch.sum(torch.neg(torch.log(probs)).dot(gold_label))
    ...
```

- Batch sizes from 1-100 often work well

Next Time

- More implementation details: practical training techniques
- Word representations / word vectors
- word2vec, GloVe