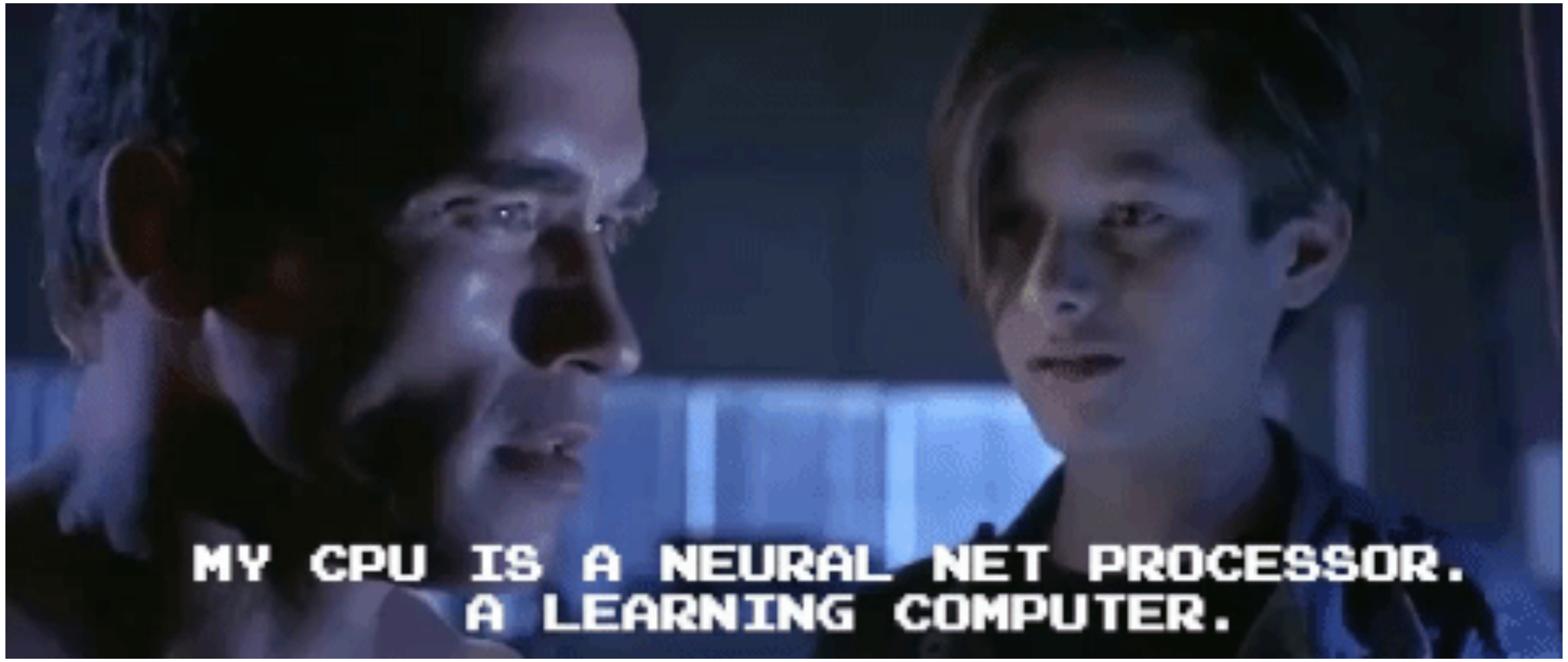
CS388: Natural Language Processing

Lecture 6: Neural Networks



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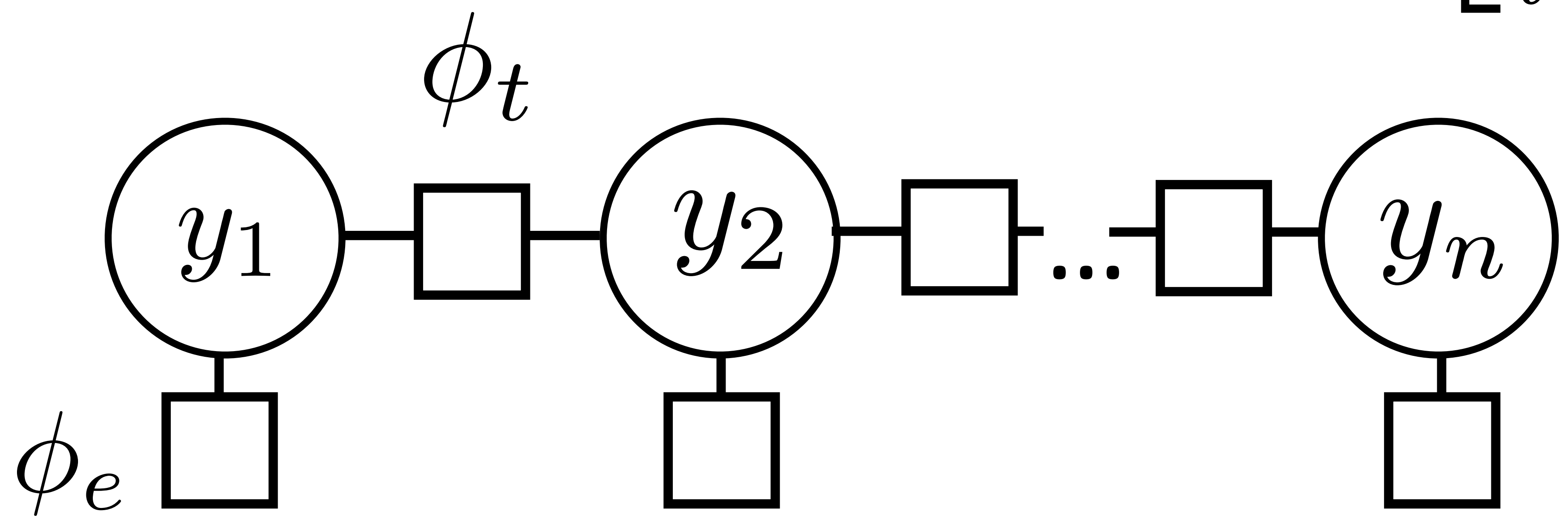
Administrivia

- Mini 1 graded by next week
- Project 1 due in a week

Recall: Sequential CRFs

- Model: $$P(\mathbf{y}|\mathbf{x}) \propto \exp w^\top \left[\sum_{i=2}^{n} f_t(y_{i-1}, y_i) + \sum_{i=1}^{n} f_e(y_i, i, \mathbf{x}) \right]$$



- Emission features capture word-level info, transitions enforce tag consistency

- Inference: argmax P(**y**|**x**) from Viterbi

- Learning: run forward-backward to compute posterior probabilities; then

$$\frac{\partial}{\partial w}\mathcal{L}(\mathbf{y}^*, \mathbf{x}) = \sum_{i=1}^{n} f_e(y_i^*, i, \mathbf{x}) - \sum_{i=1}^{n}\sum_{s} P(y_i = s|\mathbf{x}) f_e(s, i, \mathbf{x})$$

Recall: NER Feats Example

B-PER   I-PER   O   O

Barack Obama will travel

feats = $\mathbf{f}_e(\text{B-PER}, i{=}1, \mathbf{x}) + \mathbf{f}_e(\text{I-PER}, i{=}2, \mathbf{x}) + \mathbf{f}_e(\text{O}, i{=}3, \mathbf{x}) + \mathbf{f}_e(\text{O}, i{=}4, \mathbf{x})$

$+ \mathbf{f}_t(\text{B-PER}, \text{I-PER}, i{=}1, \mathbf{x}) + \mathbf{f}_t(\text{I-PER}, \text{O}, i{=}2, \mathbf{x}) + \mathbf{f}_t(\text{O}, \text{O}, i{=}3, \mathbf{x})$

B-PER   B-PER   O   O

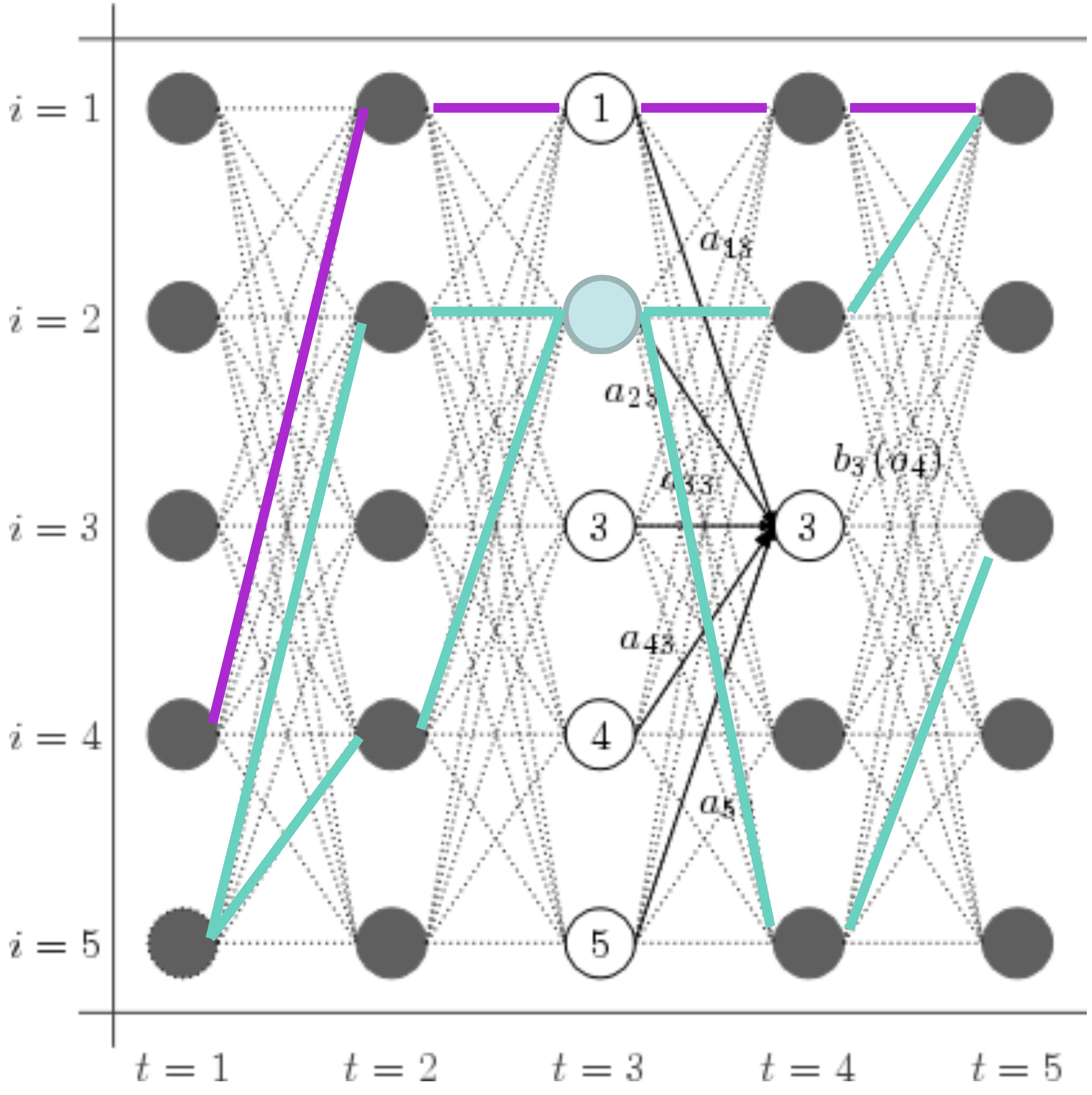
Barack Obama will travel

feats = $\mathbf{f}_e(\text{B-PER}, i{=}1, \mathbf{x}) + \mathbf{f}_e(\text{B-PER}, i{=}2, \mathbf{x}) + \mathbf{f}_e(\text{O}, i{=}3, \mathbf{x}) + \mathbf{f}_e(\text{O}, i{=}4, \mathbf{x})$

$+ \mathbf{f}_t(\text{B-PER}, \text{B-PER}, i{=}1, \mathbf{x}) + \mathbf{f}_t(\text{B-PER}, \text{O}, i{=}2, \mathbf{x}) + \mathbf{f}_t(\text{O}, \text{O}, i{=}3, \mathbf{x})$

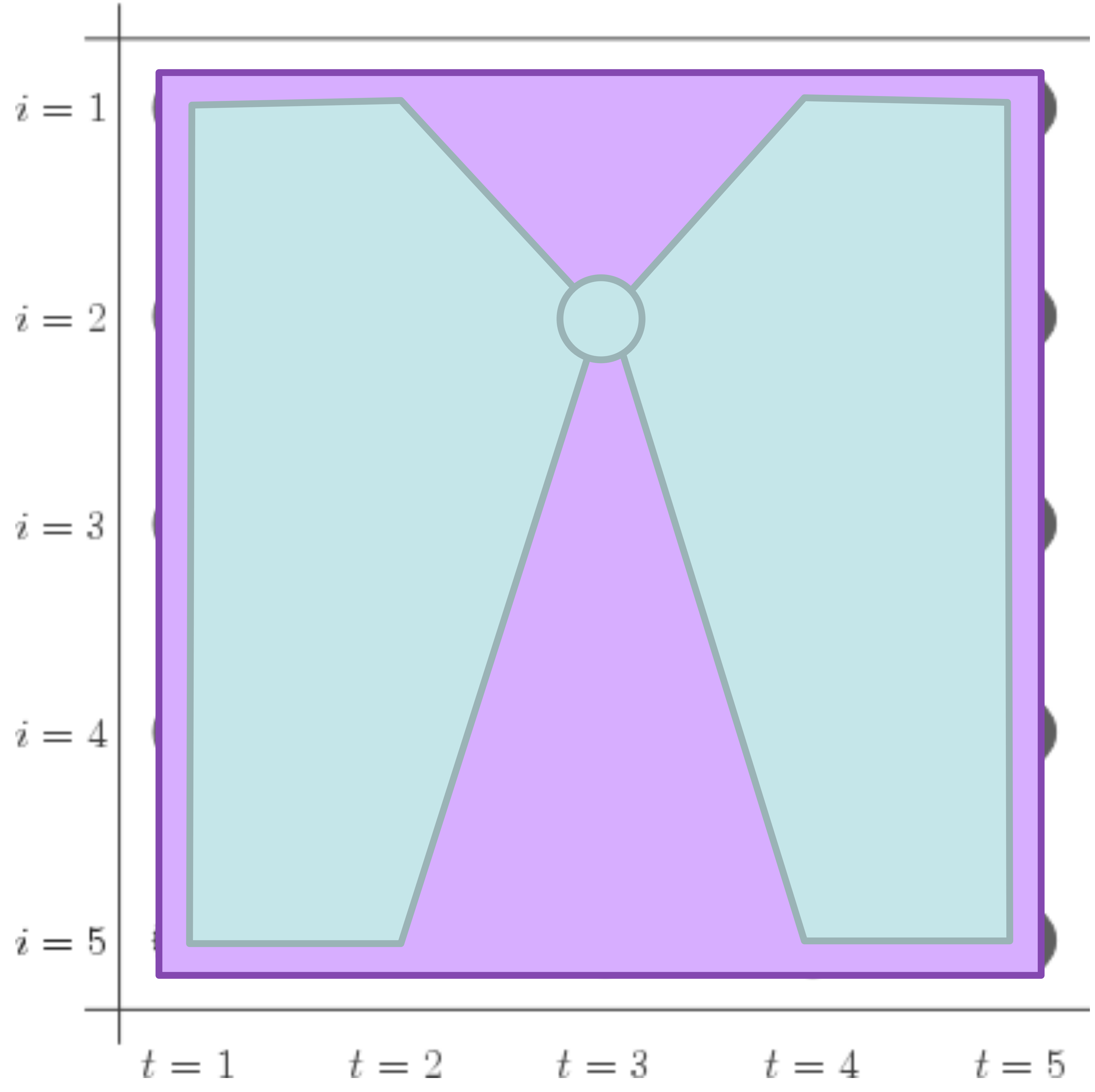
- *Obama* can start a new named entity (emission feats look okay), but we're not likely to have two PER entities in a row (transition feats)

Recall: Forward-Backward Algorithm

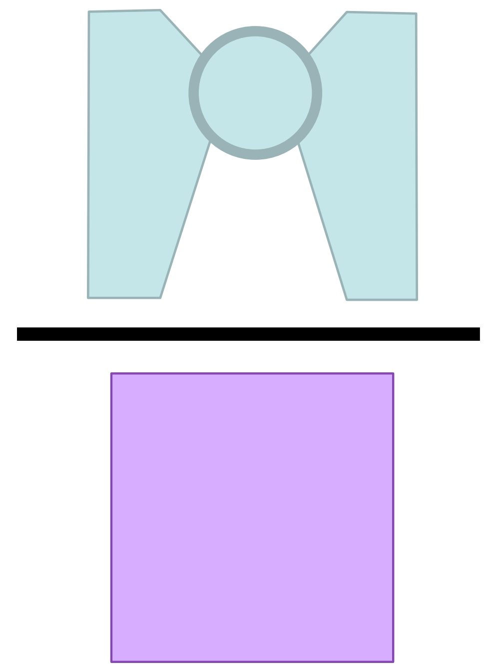


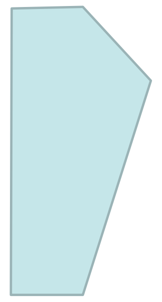
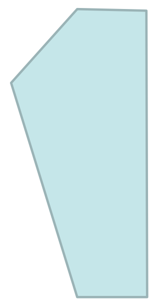
$$P(y_3 = 2|\mathbf{x}) = \frac{\text{sum of all paths through state 2 at time 3}}{\text{sum of all paths}}$$

Recall: Forward-Backward Algorithm



$$P(y_3 = 2|\mathbf{x}) = \frac{\text{sum of all paths through state 2 at time 3}}{\text{sum of all paths}}$$

= 

- Easiest and most flexible to do one pass to compute  and one to compute 

slide credit: Dan Klein

Recall: Implementation Tips for CRFs

- Caching is your friend! Cache feature vectors especially

- Do all dynamic program computation in log space to avoid underflow

- For transitions: there are various hardcoding schemes you can explore. Use log probabilities from HMM, use 0 or -infinity based on whether the transition is legal or not, …

This Lecture

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

NER

Evaluating NER

B-PER	I-PER	O	O	O	B-LOC	O	O	O	B-ORG	O	O
Barack	*Obama*	*will*	*travel*	*to*	*Hangzhou*	*today*	*for*	*the*	*G20*	*meeting*	*.*
PERSON					LOC				ORG		

- Prediction of all Os still gets 66% accuracy on this example!
- What we really want to know: how many named entity *chunk* predictions did we get right?
  - Precision: of the ones we predicted, how many are right?
  - Recall: of the gold named entities, how many did we find?
  - F-measure: harmonic mean of these two

NER

- CRF with lexical features can get around 85 F1 on CoNLL 2003: 4 classes (PER, ORG, LOC, MISC), newswire data
- Other pieces of information that many systems capture
- World knowledge:

The delegation met the president at the airport, Tanjug said.

Tanjug

From Wikipedia, the free encyclopedia

Tanjug (/ˈtʌnjʊɡ/) (Serbian Cyrillic: Тањуг) is a Serbian state news agency based in Belgrade.[2]

Nonlocal Features

The news agency Tanjug reported on the outcome of the meeting.

ORG?

PER?

The delegation met the president at the airport, Tanjug said.

- More complex factor graph structures can let you capture this, or just decode sentences in order and use features on previous sentences

Finkel and Manning (2008), Ratinov and Roth (2009)

How well do NER systems do?

	System	Resources Used	F_1
+	LBJ-NER	Wikipedia, Nonlocal Features, Word-class Model	90.80
-	(Suzuki and Isozaki, 2008)	Semi-supervised on 1G-word unlabeled data	89.92
-	(Ando and Zhang, 2005)	Semi-supervised on 27M-word unlabeled data	89.31
-	(Kazama and Torisawa, 2007a)	Wikipedia	88.02
-	(Krishnan and Manning, 2006)	Non-local Features	87.24
-	(Kazama and Torisawa, 2007b)	Non-local Features	87.17
+	(Finkel et al., 2005)	Non-local Features	86.86

Ratinov and Roth (2009)

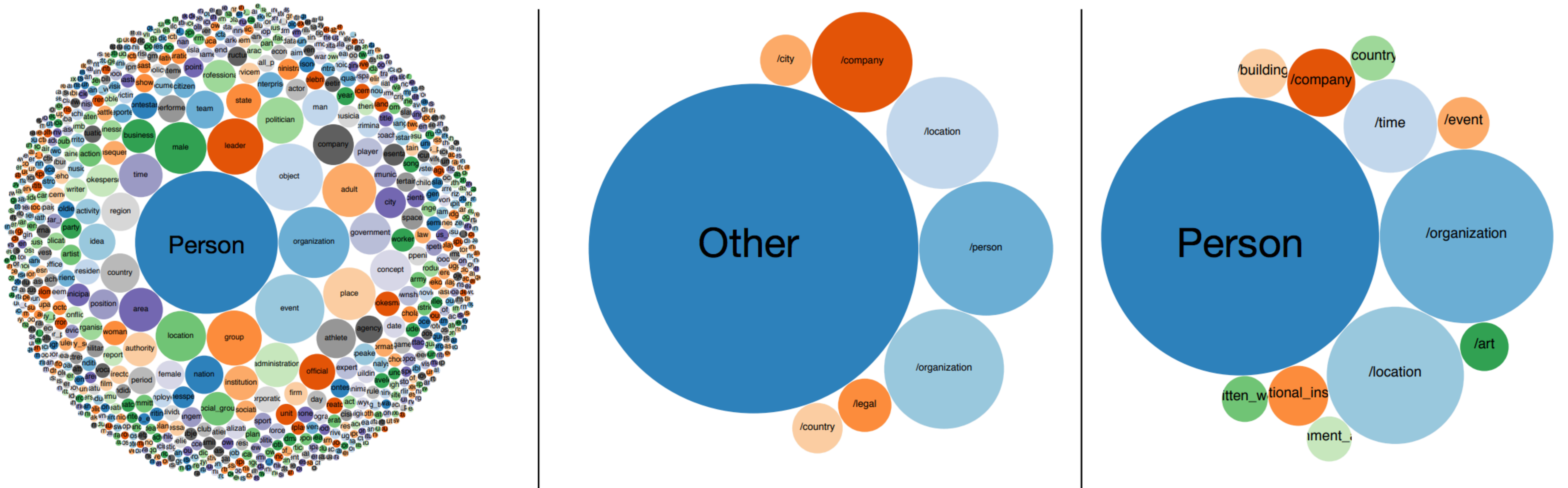
Lample et al. (2016)

LSTM-CRF (no char)	90.20
LSTM-CRF	**90.94**
S-LSTM (no char)	87.96
S-LSTM	90.33

BiLSTM-CRF + ELMo
Peters et al. (2018) **92.2**

BERT
Devlin et al. (2019) **92.8**

Modern Entity Typing



a) Our Dataset b) OntoNotes c) FIGER

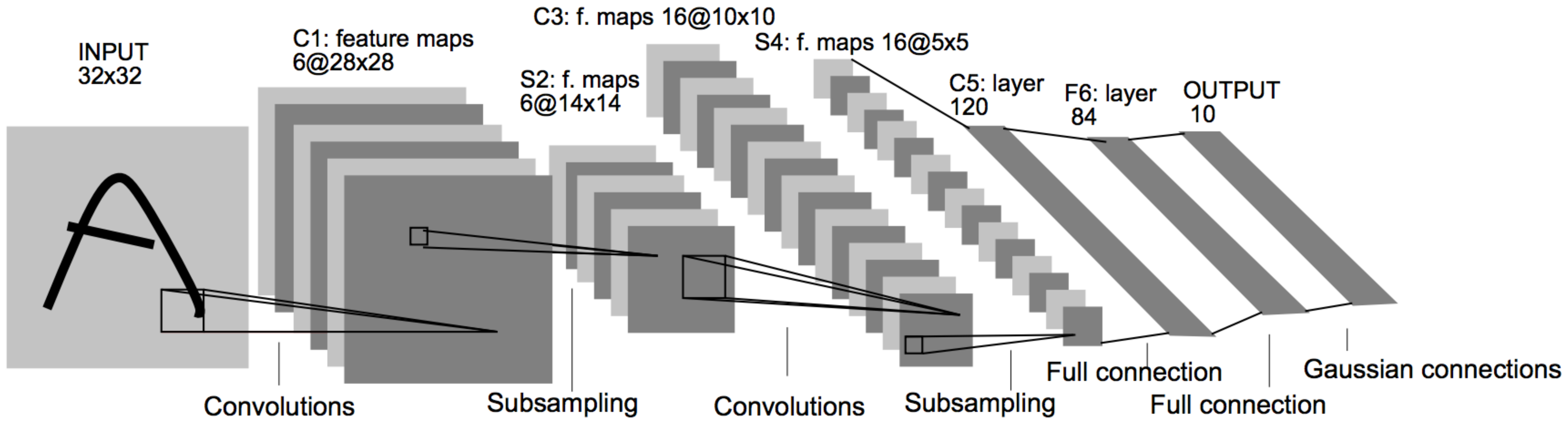
- More and more classes (17 -> 112 -> 10,000+)

Choi et al. (2018)

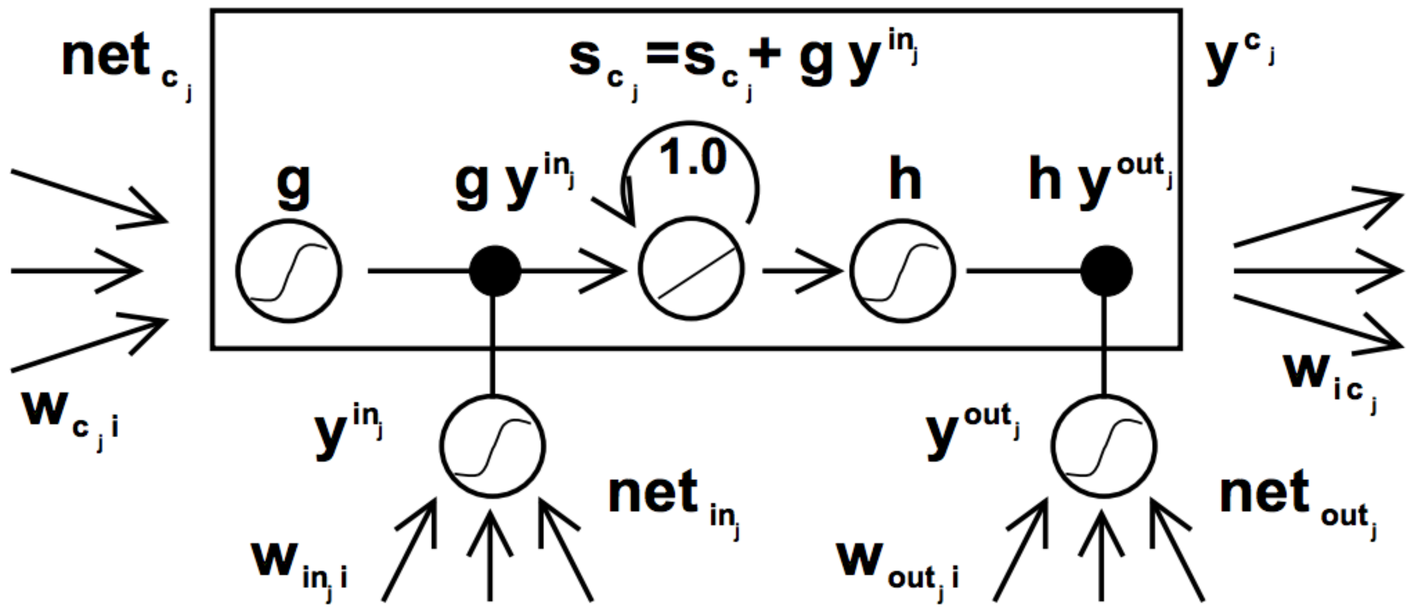
Neural Net History

History: NN “dark ages”

- Convnets: applied to MNIST by LeCun in 1998



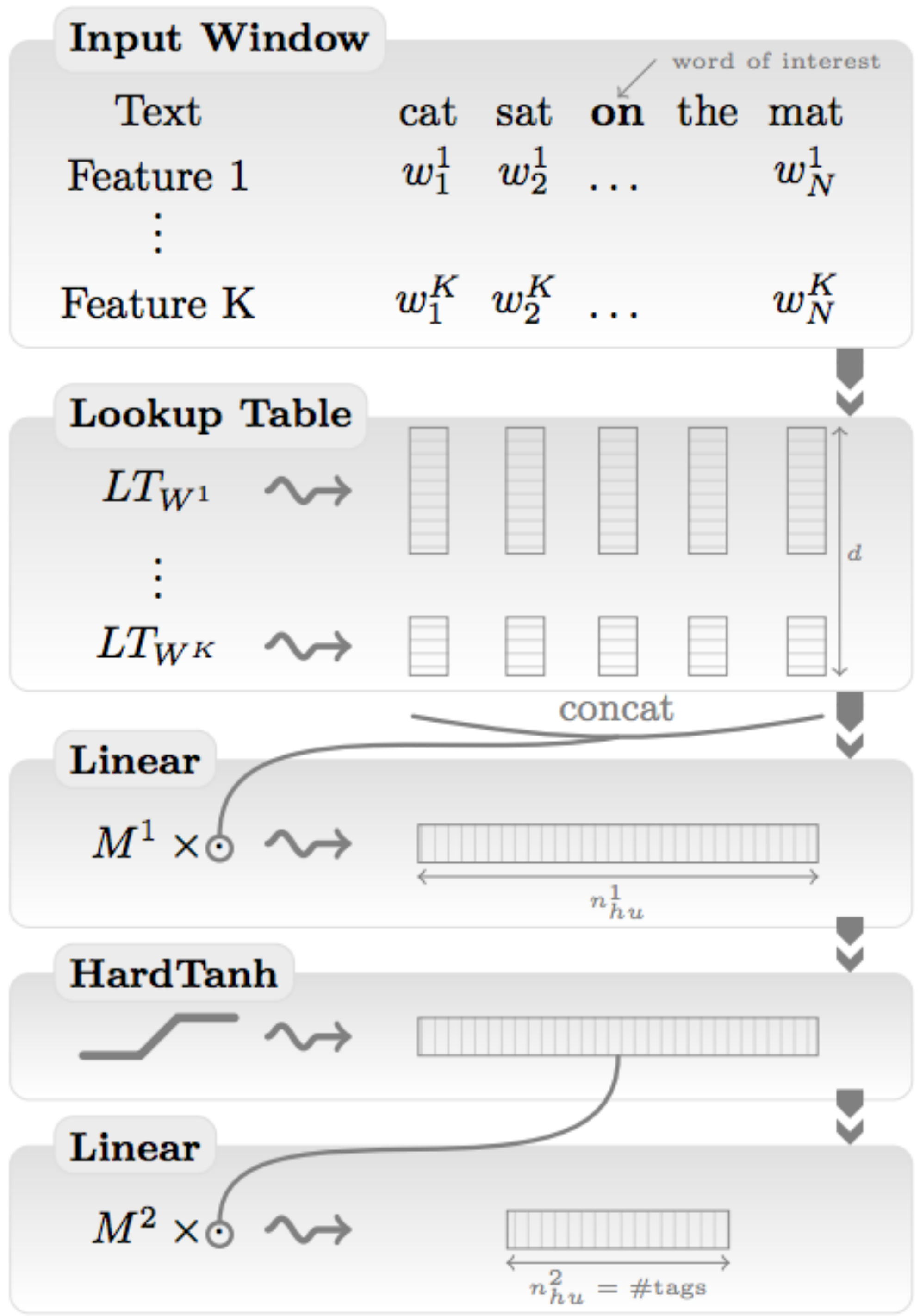
- LSTMs: Hochreiter and Schmidhuber (1997)



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

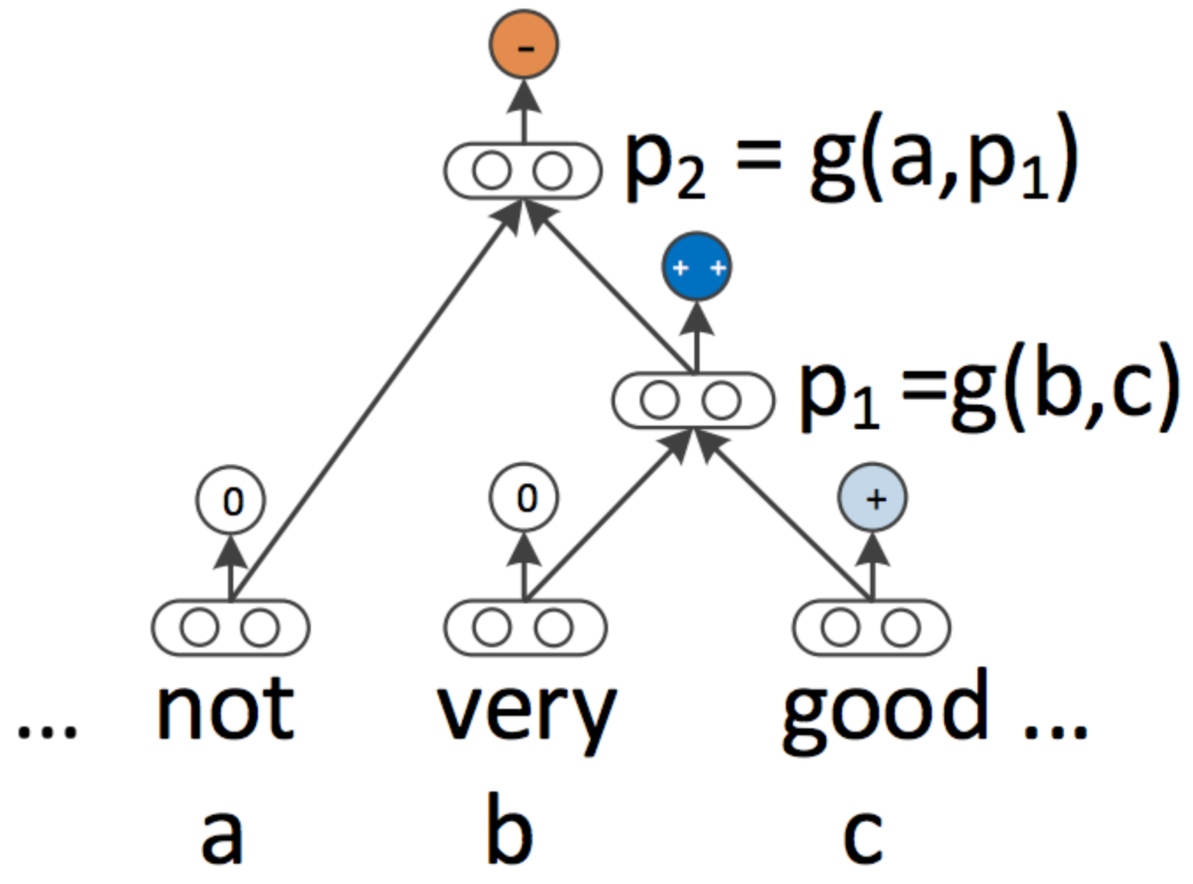
2008-2013: A glimmer of light…

- Collobert and Weston 2011: "NLP (almost) from scratch"
  - Feedforward neural nets induce features for sequential CRFs ("neural CRF")
  - Basically tied SOTA in 2011, but with lots of computation (two weeks of training embeddings)



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

- Krizhevskey et al. (2012): AlexNet for vision



2014: Stuff starts working

- Kim (2014) + Kalchbrenner et al. (2014): sentence classification / sentiment (convnets)

- Sutskever et al. + Bahdanau et al.: seq2seq for neural MT (LSTMs)

- Chen and Manning transition-based dependency parser (based on feedforward networks)

- What made these work? **Data**, **optimization** (initialization, adaptive optimizers), **representation** (good word embeddings)

Neural Net Basics

Neural Networks

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

- Want to learn intermediate conjunctive features of the input

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

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

- How do we learn this if our feature vector is just the unigram indicators?

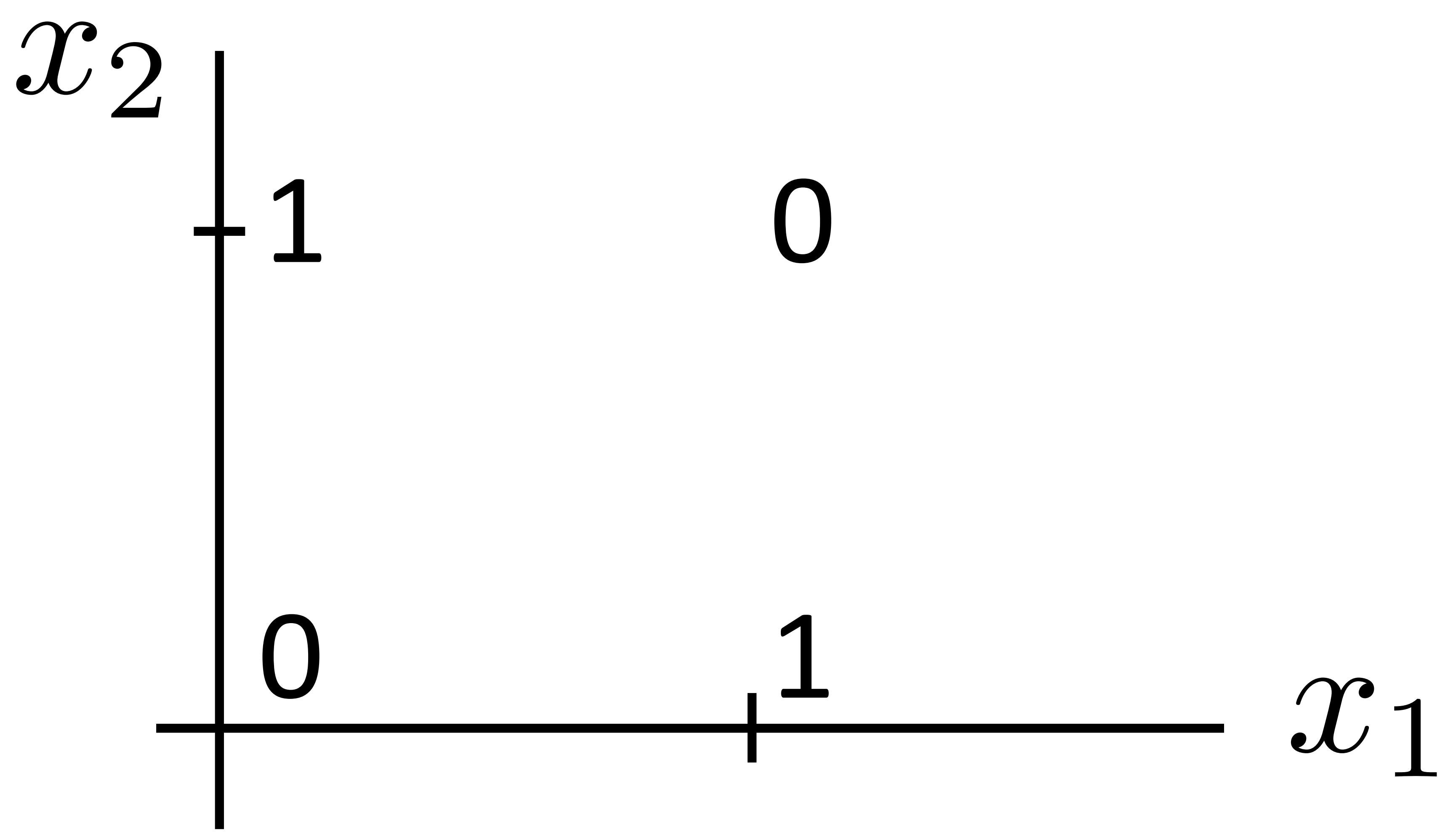
I[contains *not*], I[contains *good*]

Neural Networks: XOR

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

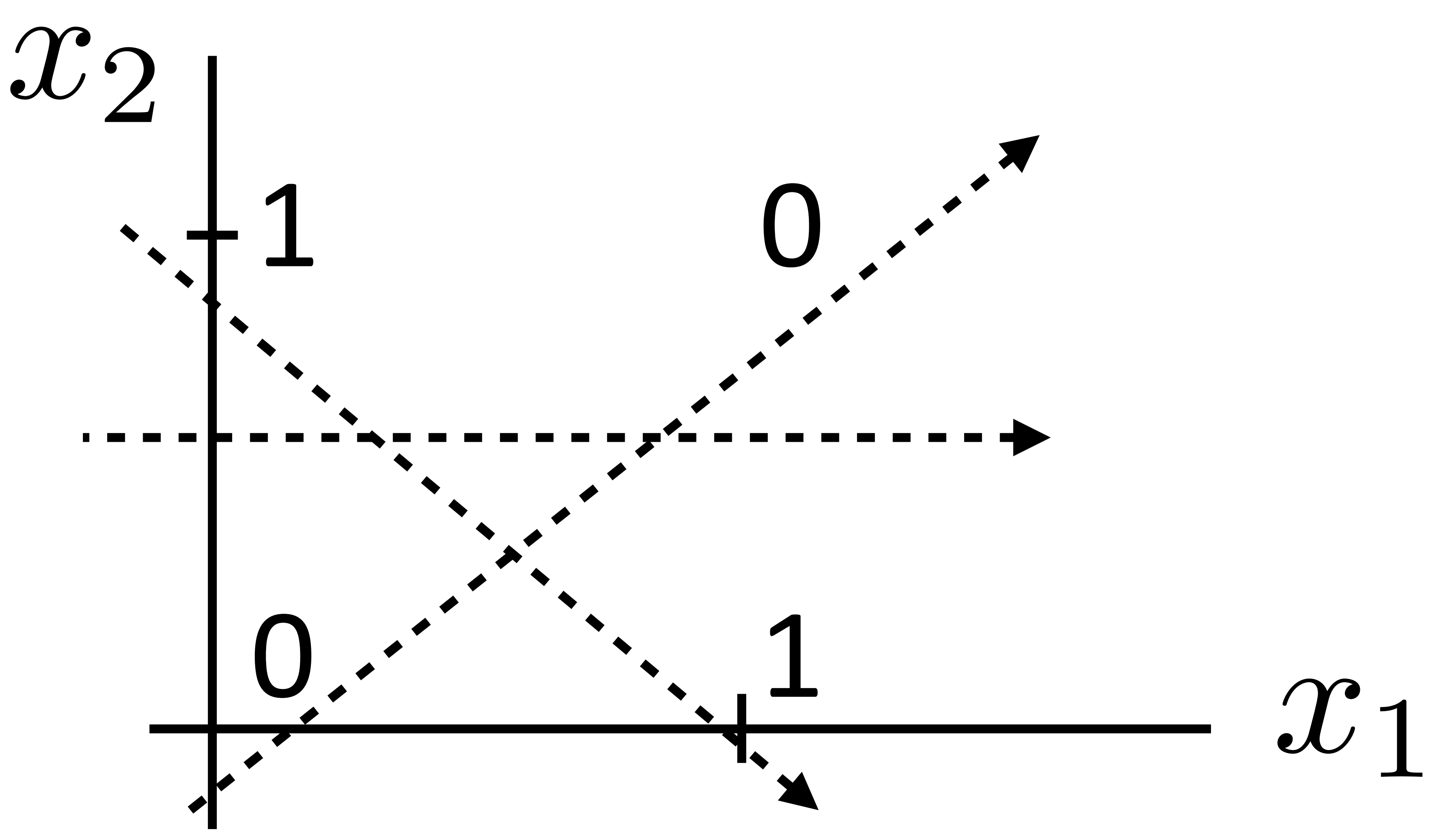
  $(\text{generally } \mathbf{x} = (x_1, \ldots, x_m))$
- Output y

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



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



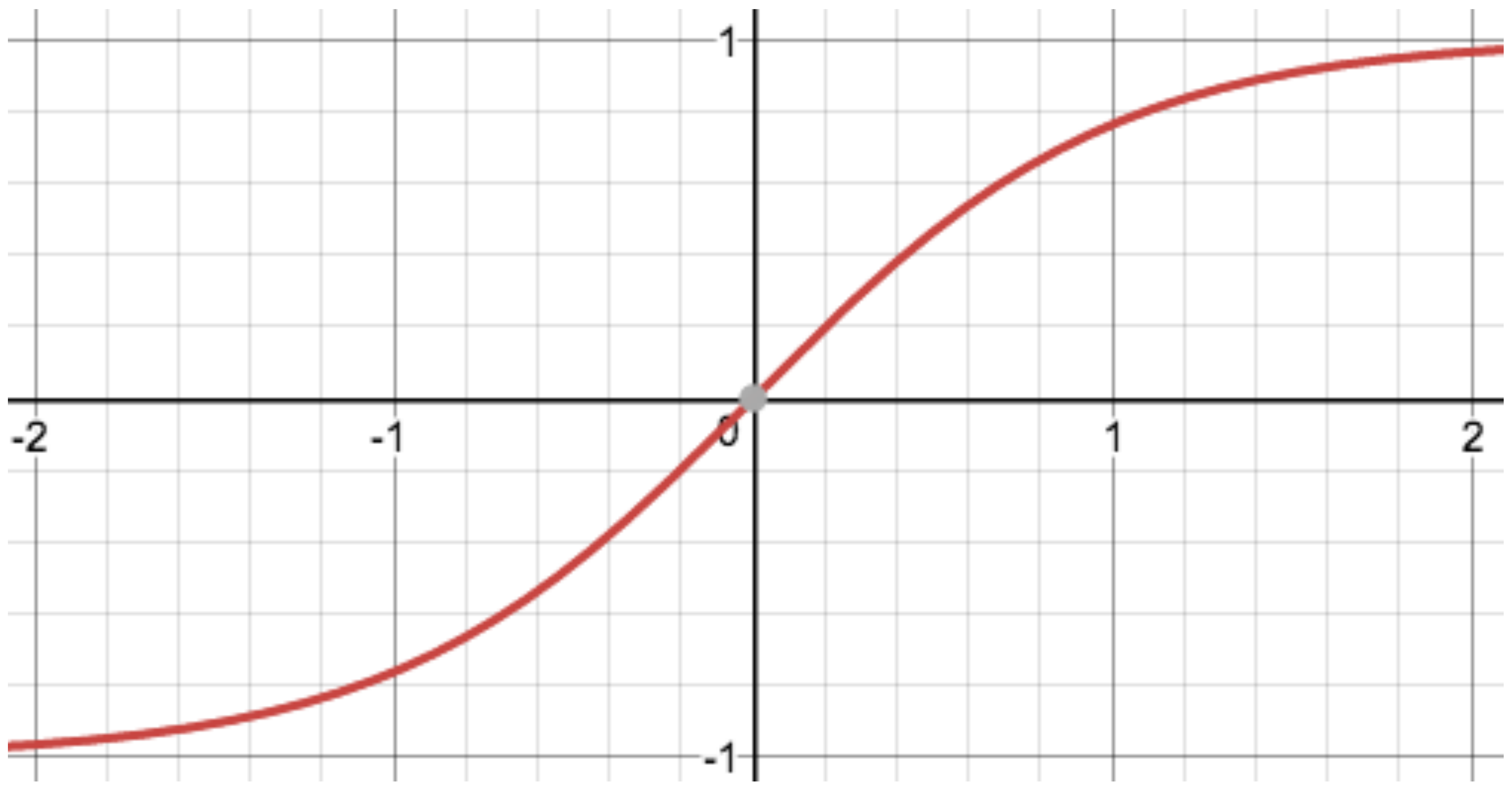
$$y = a_1 x_1 + a_2 x_2$$ X

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

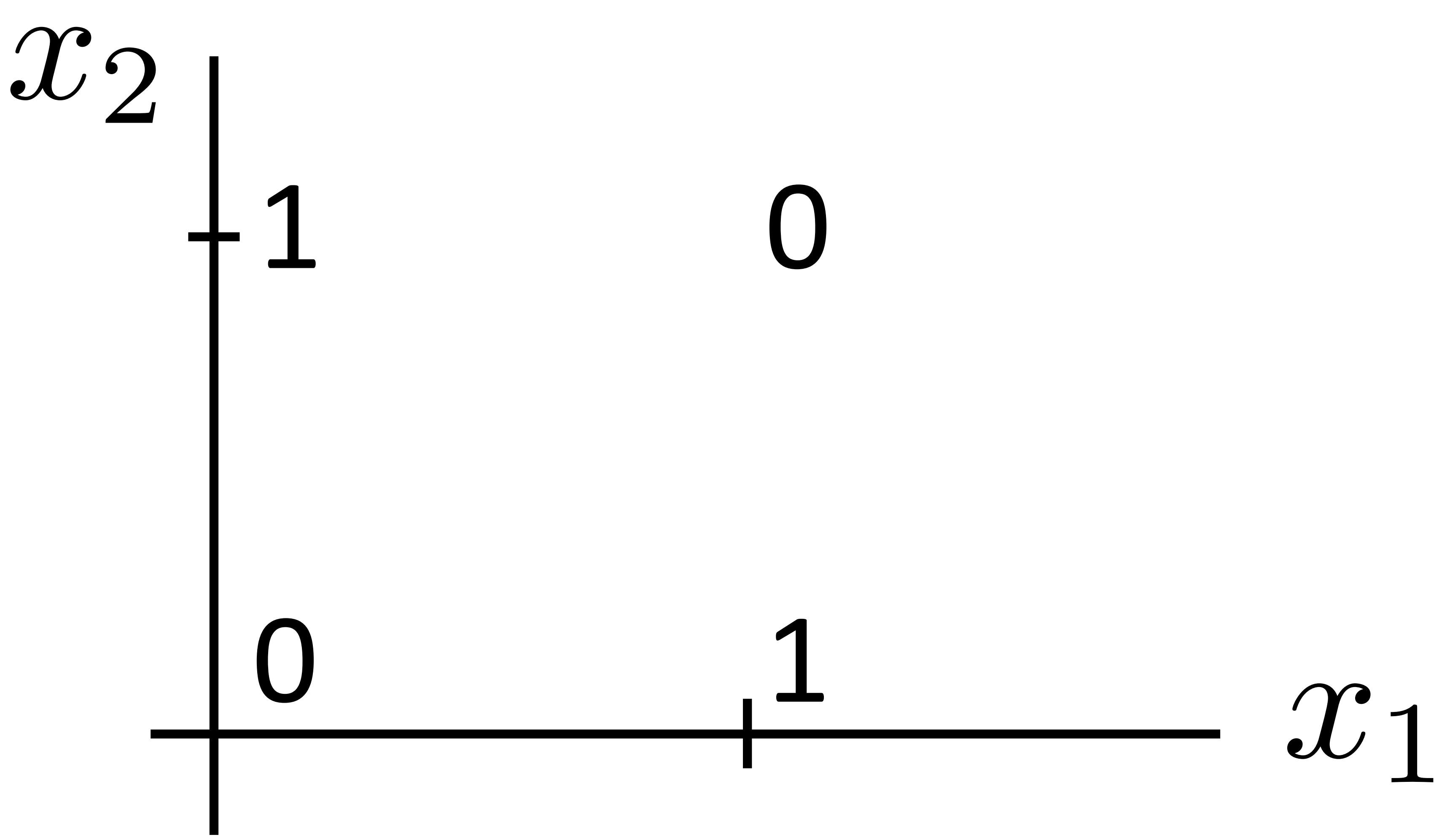
"or"

(looks like action potential in neuron)

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



Neural Networks: XOR



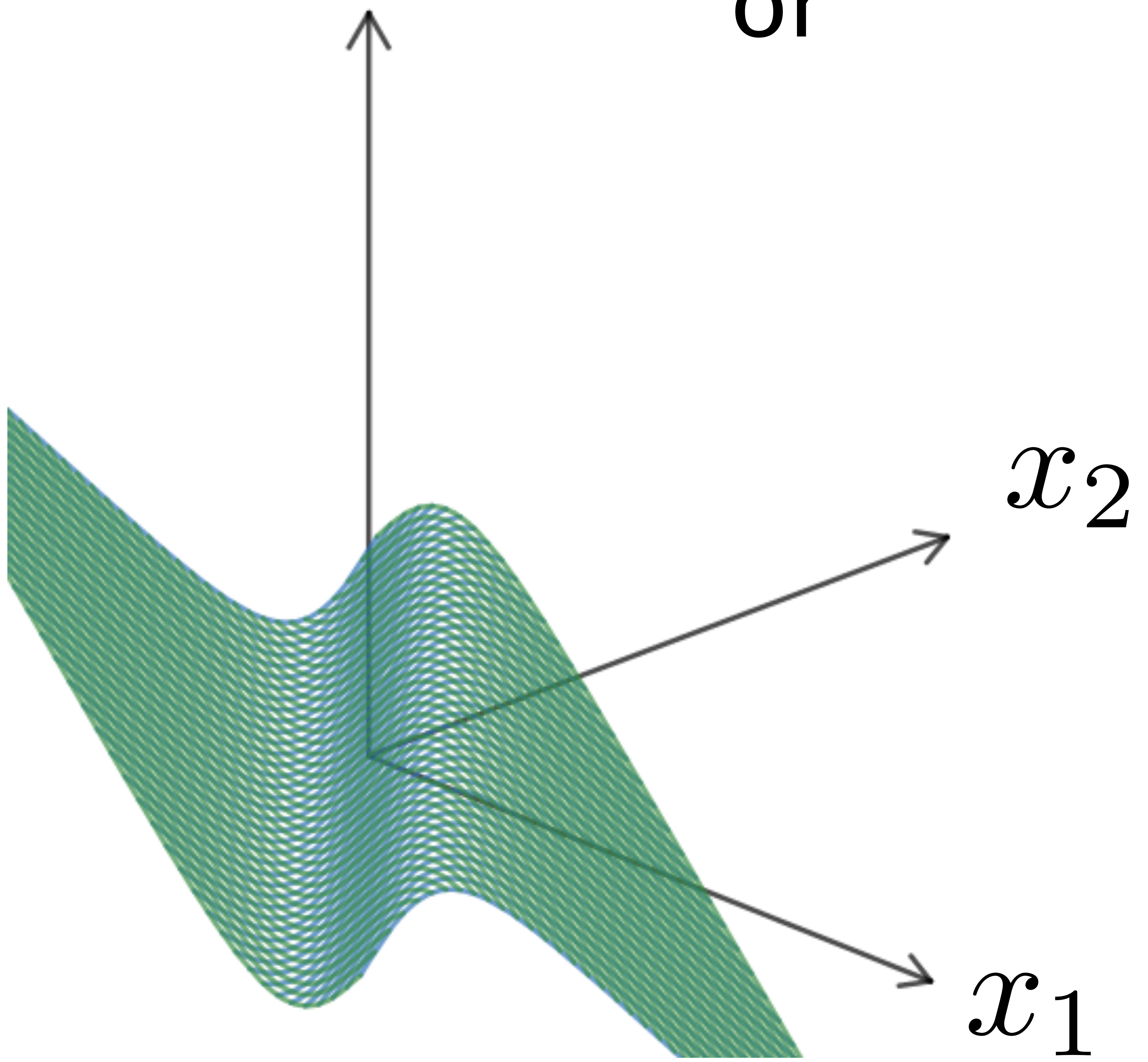
x_1	x_2	x_1 XOR x_2
0	0	0
0	1	1
1	0	1
1	1	0

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

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

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

"or"



Neural Networks

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

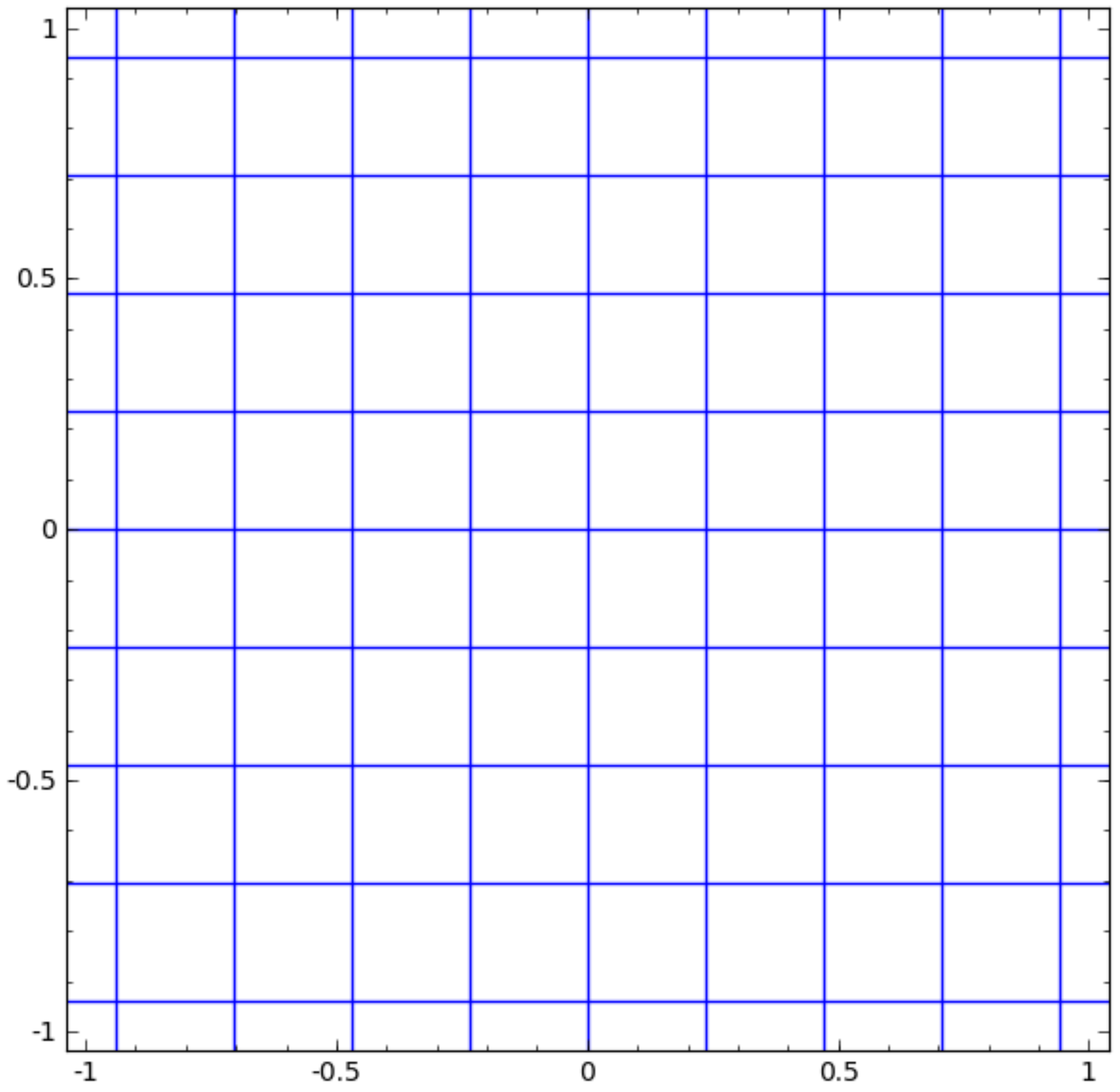
$$y = g(\mathbf{w} \cdot \mathbf{x} + b)$$

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

Nonlinear transformation

Warp space

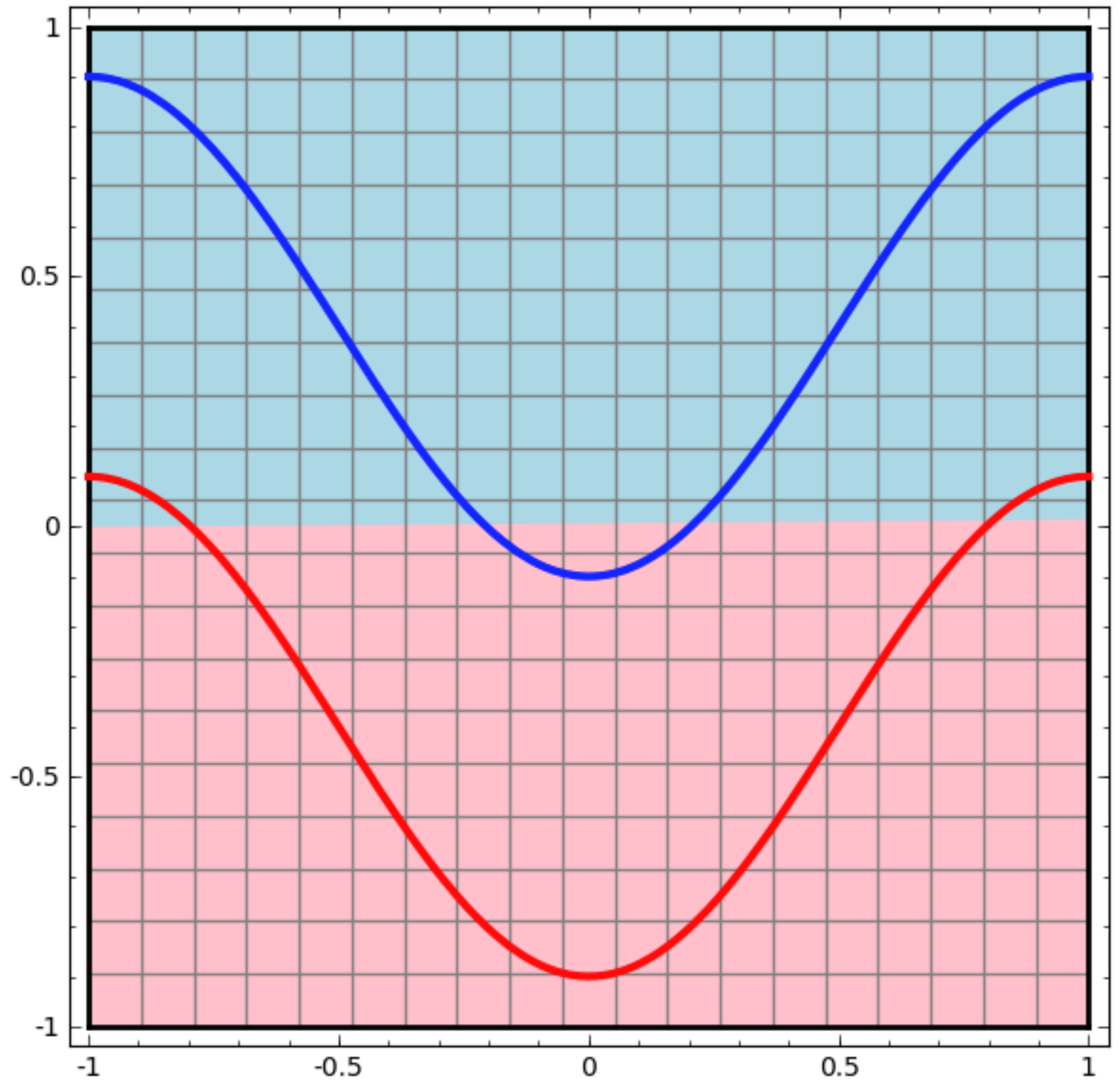
Shift



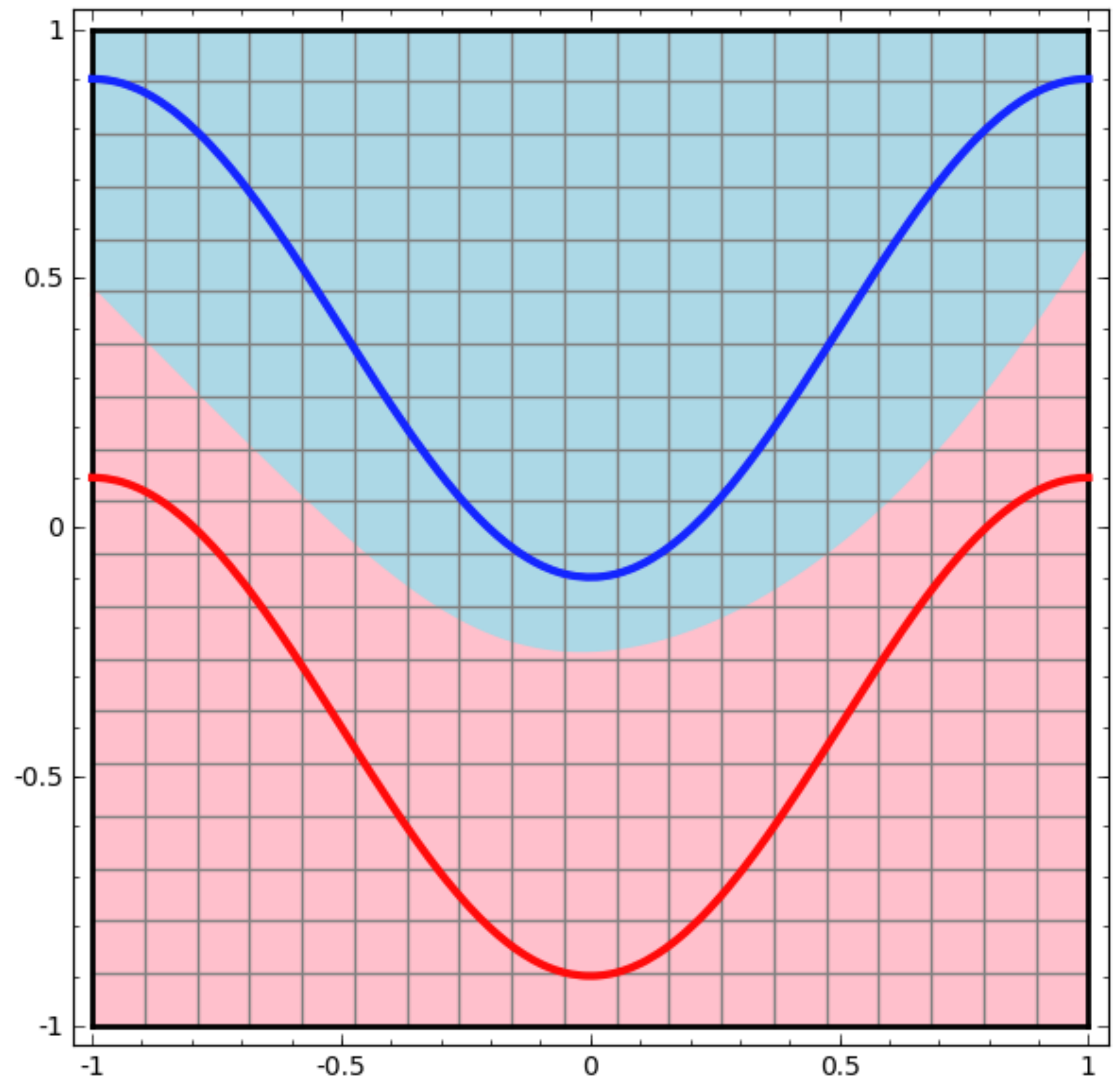
Taken from http://colah.github.io/posts/2014-03-NN-Manifolds-Topology/

Neural Networks

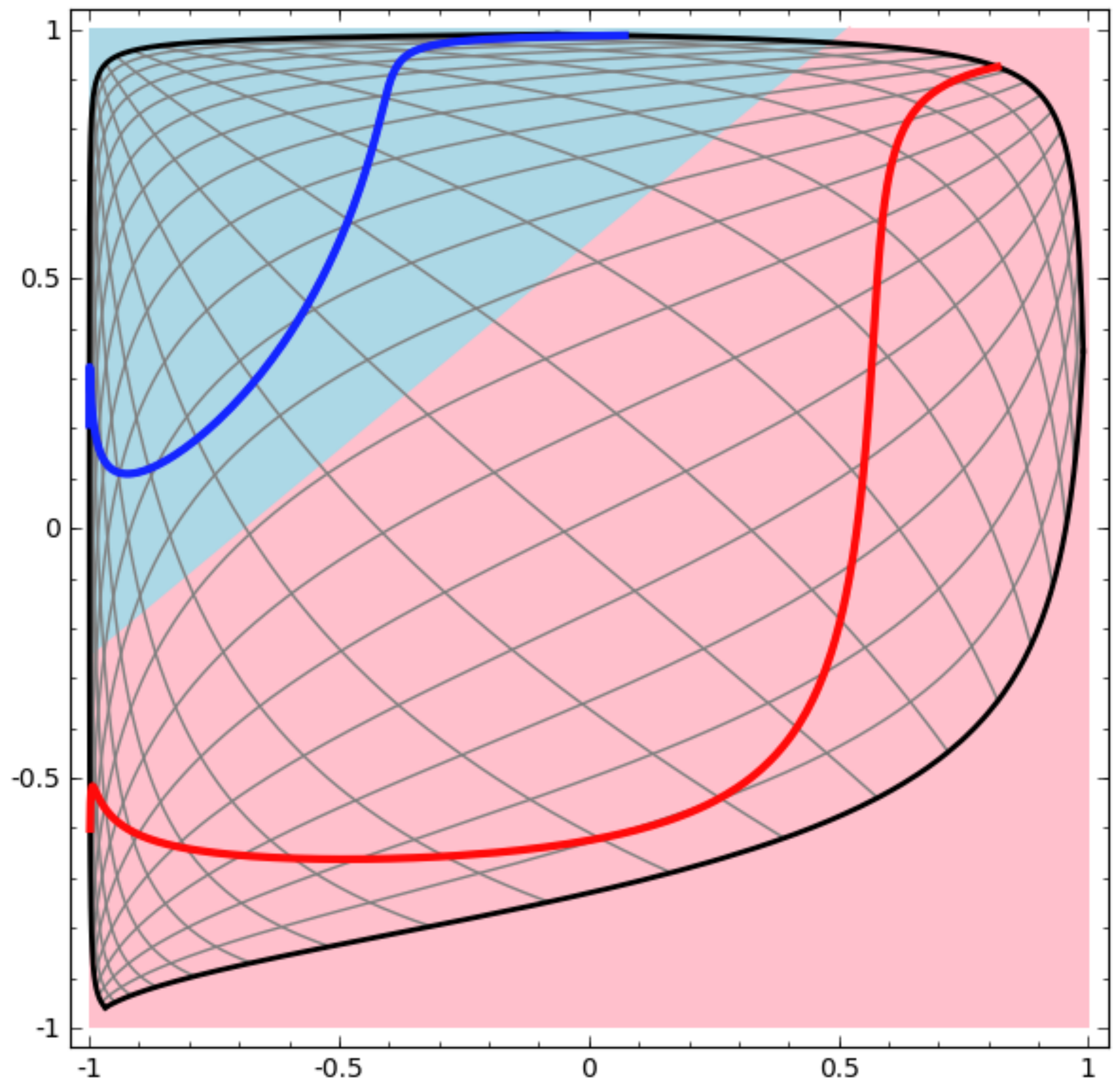
Linear classifier



Neural network



…possible because we transformed the space!



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

Deep Neural Networks

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

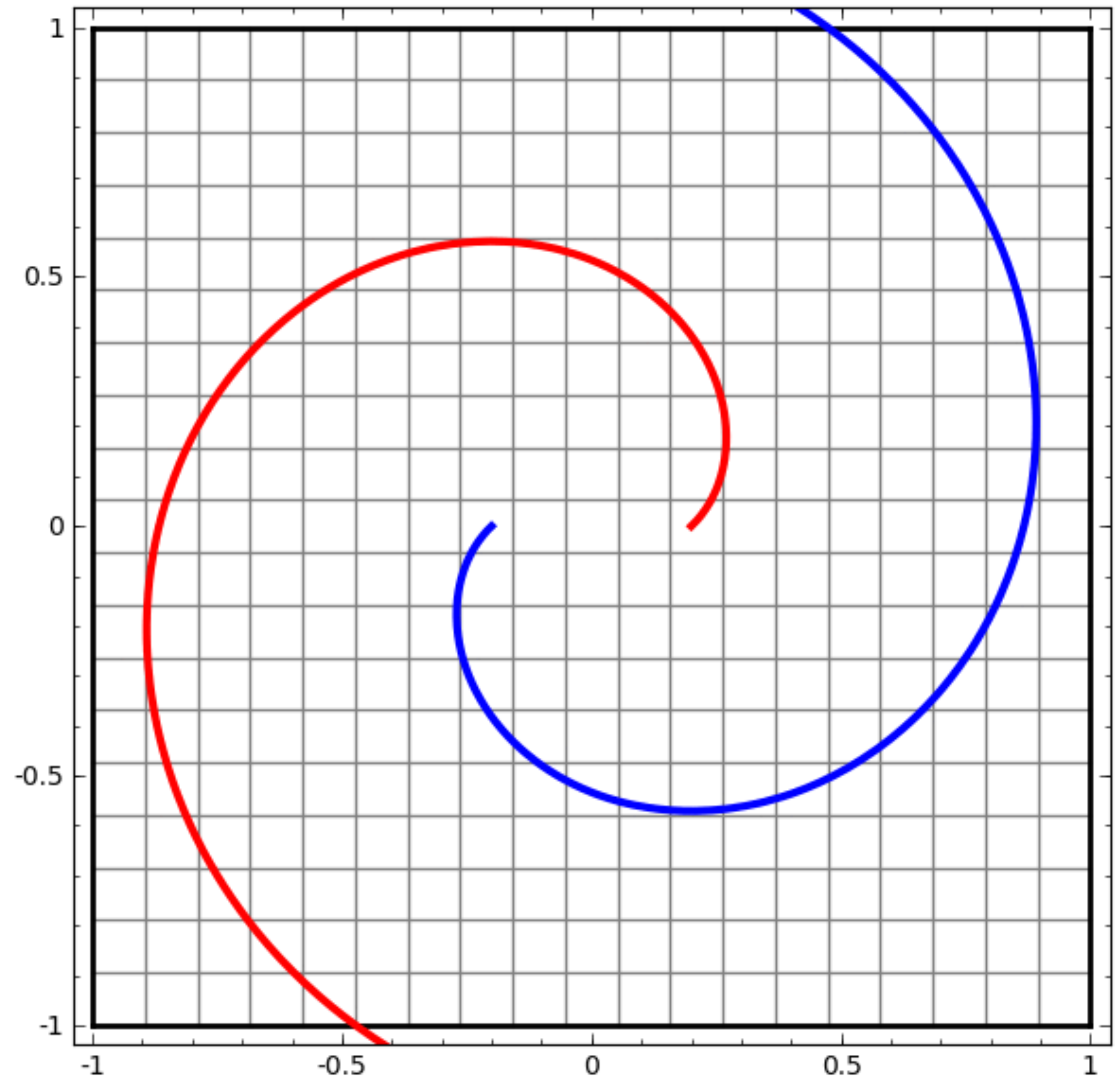
$$\mathbf{z} = g(\mathbf{V}\mathbf{y} + \mathbf{c})$$

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

Check: what happens if no nonlinearity?

More powerful than basic linear models?

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



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

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

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

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

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

- softmax: exps and normalizes a given vector

$$P(\mathbf{y}|\mathbf{x}) = \mathrm{softmax}(W f(\mathbf{x}))$$

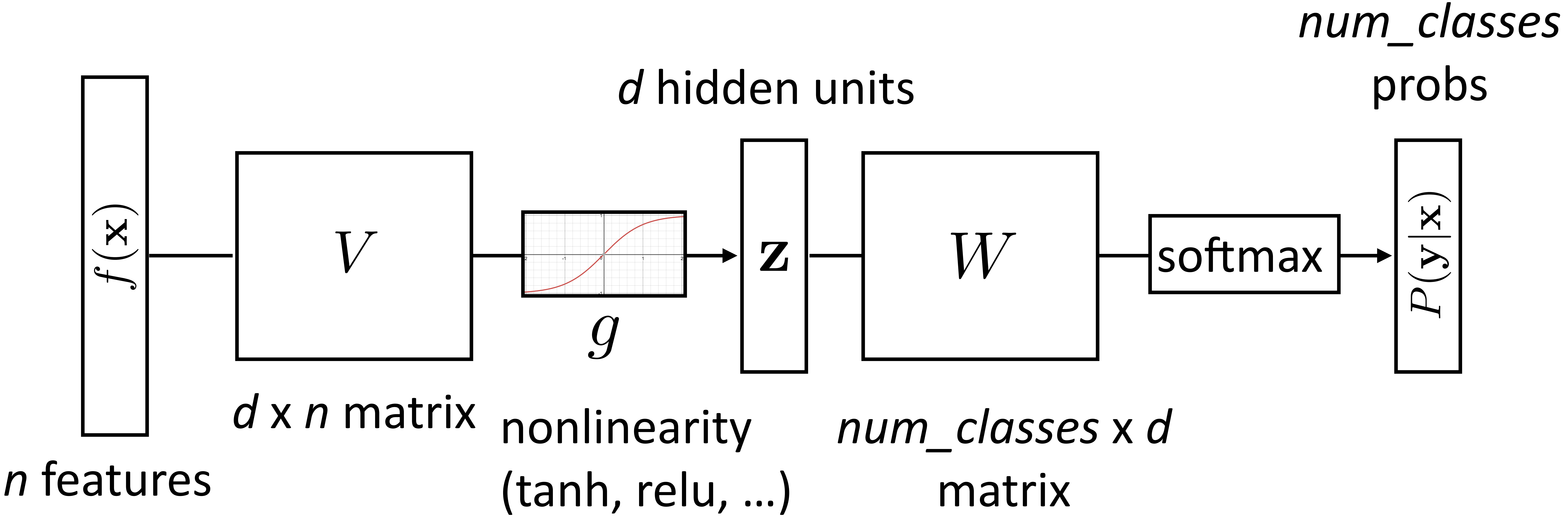
- Weight vector per class;
  W is [num classes x num feats]

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

- Now one hidden layer

Neural Networks for Classification

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



Training Neural Networks

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

- Maximize log likelihood of training data

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

- *i**: index of the gold label

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

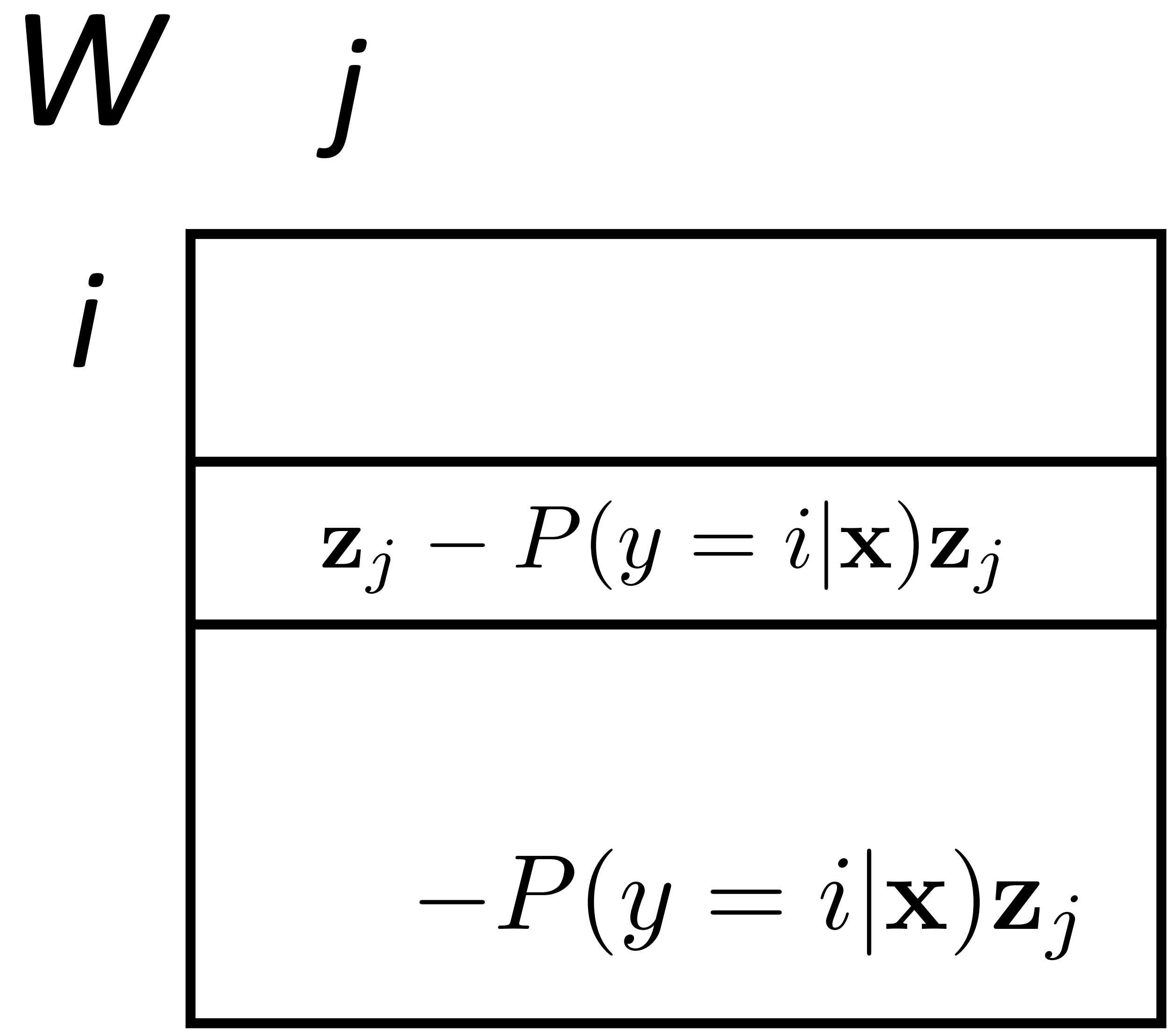
$$\mathcal{L}(\mathbf{x}, i^*) = W\mathbf{z} \cdot e_{i^*} - \log \sum_j \exp(W\mathbf{z}) \cdot e_j$$

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*

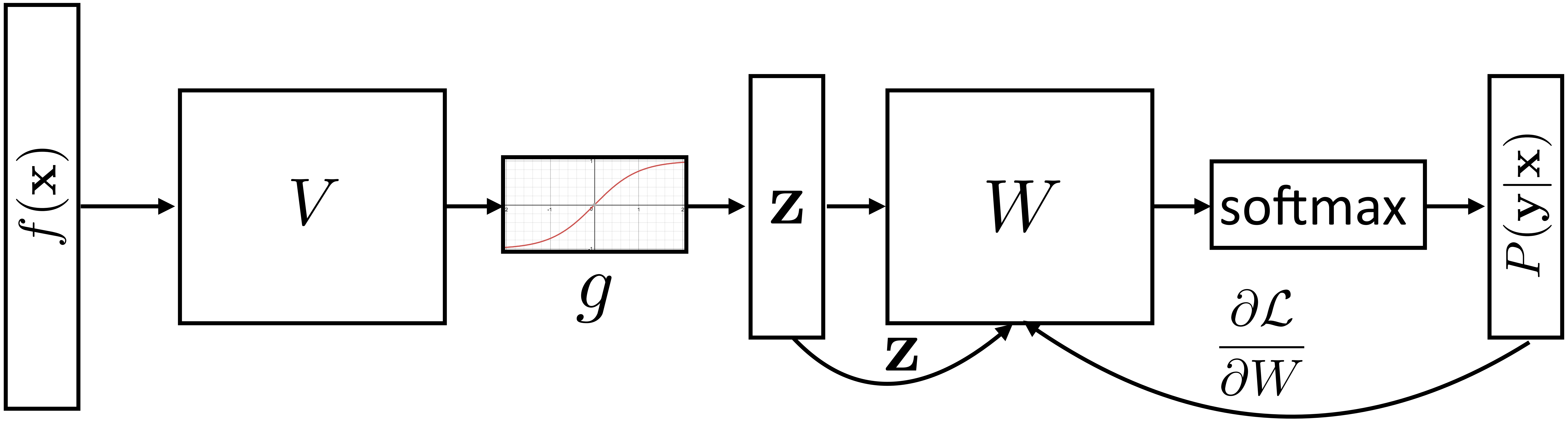
$$\frac{\partial}{\partial W_{ij}} \mathcal{L}(\mathbf{x}, i^*) = \begin{cases} \mathbf{z}_j - P(y = i|\mathbf{x})\mathbf{z}_j & \text{if } i = i^* \\ -P(y = i|\mathbf{x})\mathbf{z}_j & \text{otherwise} \end{cases}$$



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

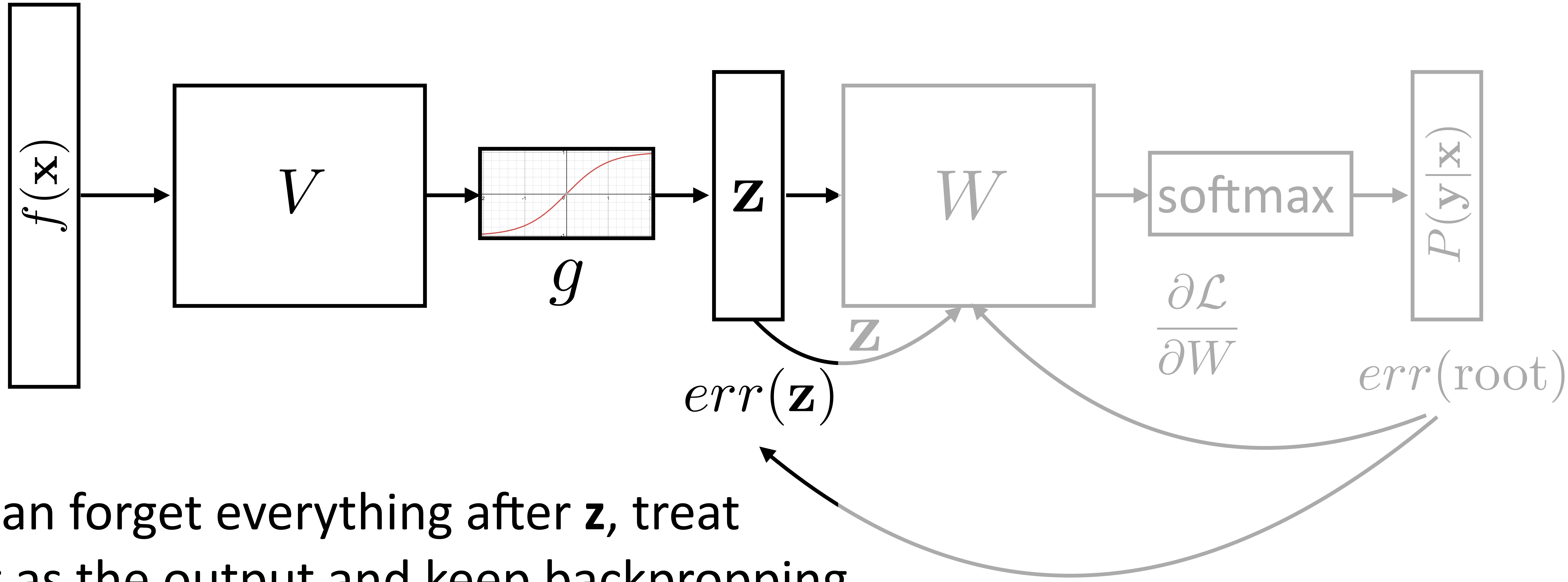
Neural Networks for Classification

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



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 ***z*** as feature vector
- Can compute derivative of loss with respect to ***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

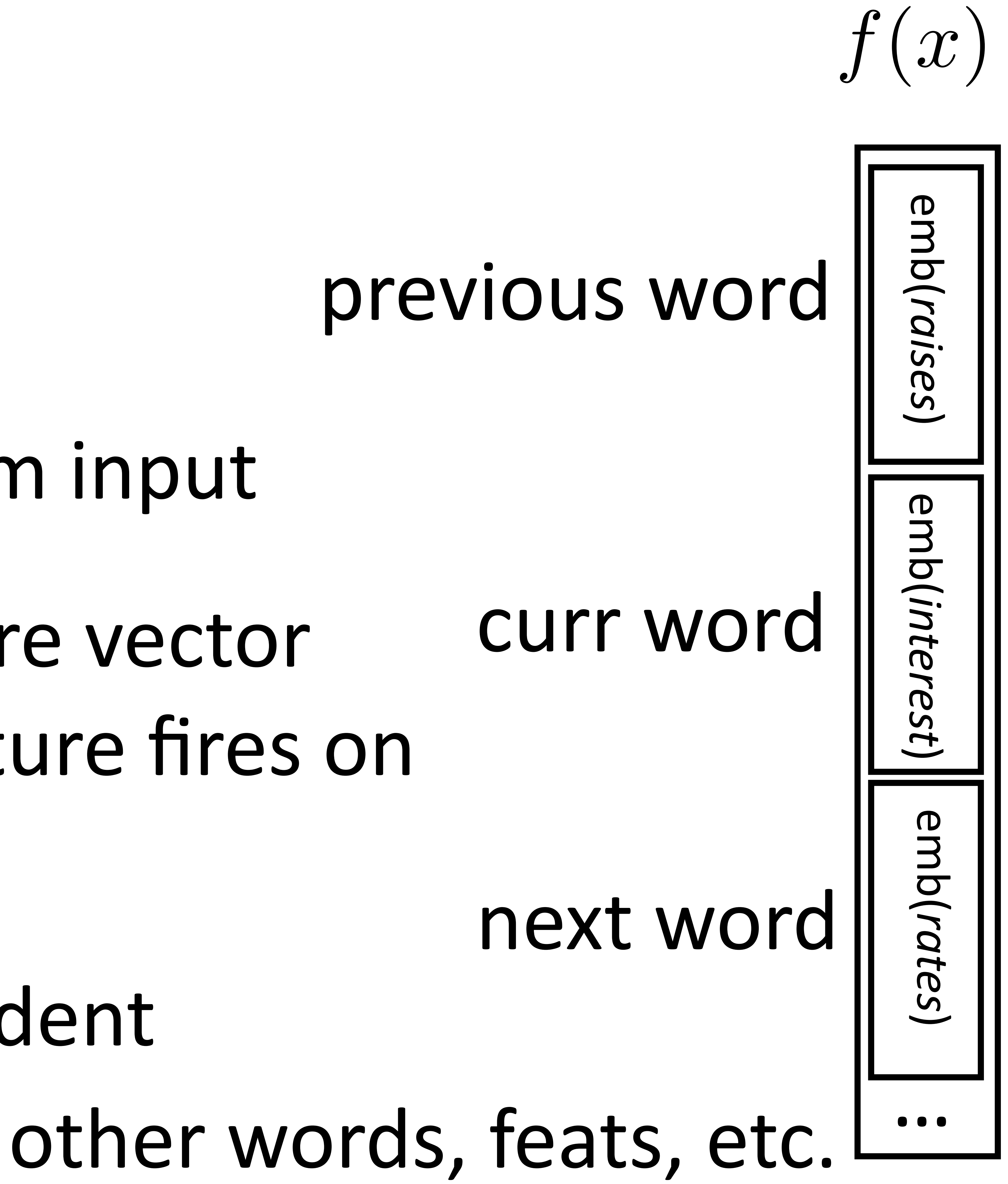
Applications

NLP with Feedforward Networks

- Part-of-speech tagging with FFNNs

??

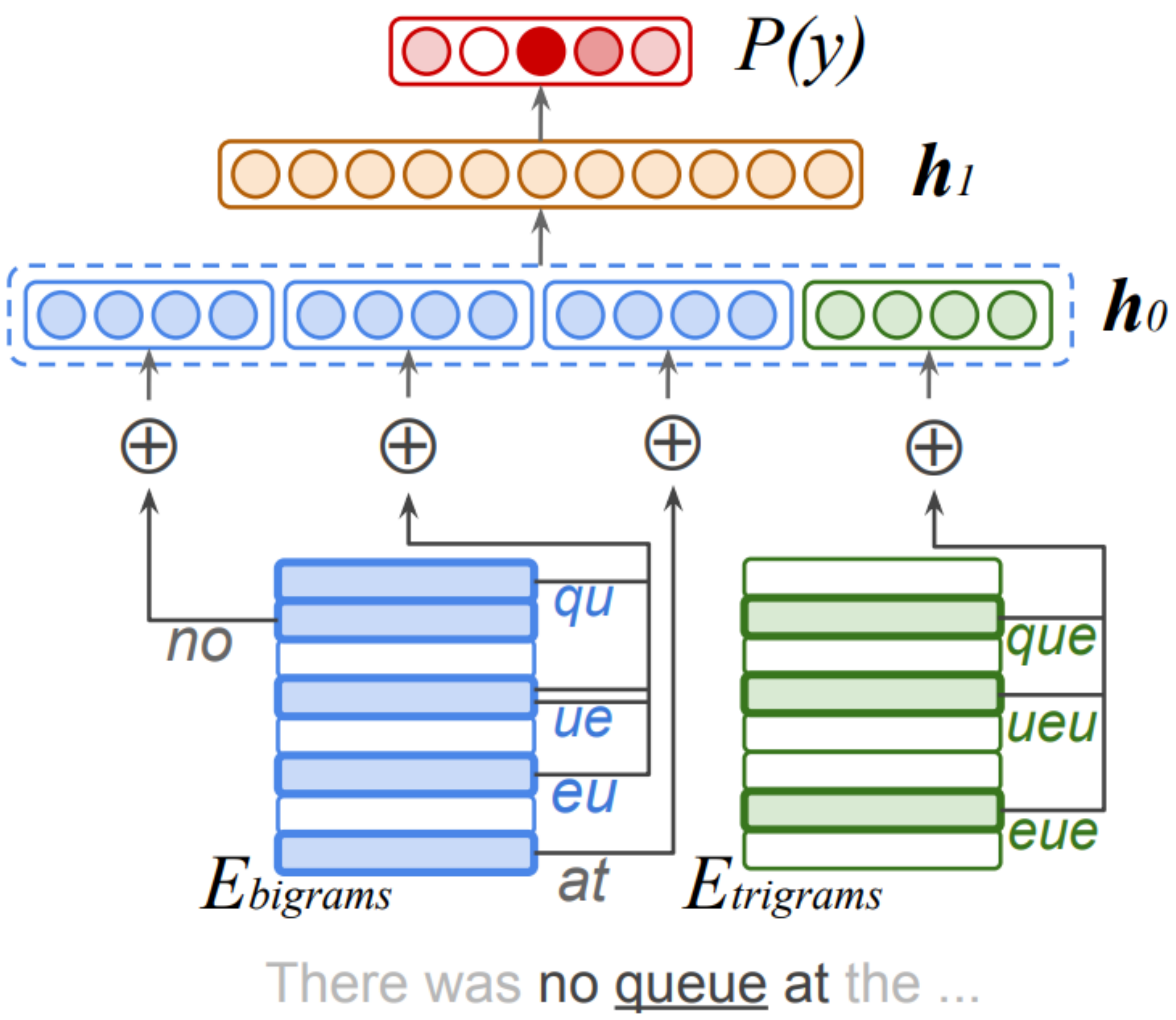
Fed raises ***interest*** *rates in order to …*



- 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:

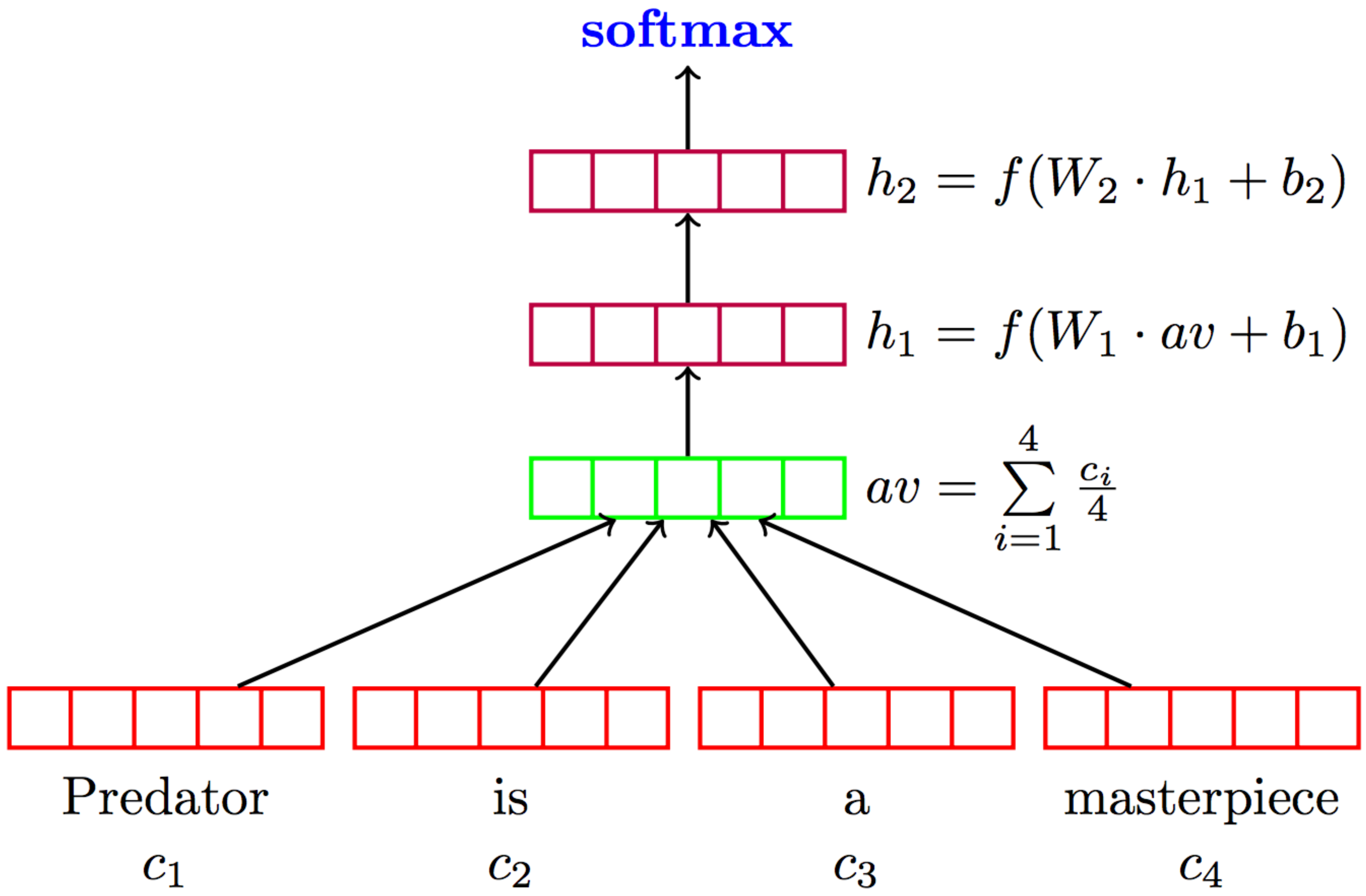
Model	Acc.	Wts.	MB	Ops.
Gillick et al. (2016)	95.06	900k	-	6.63m
Small FF	94.76	241k	0.6	0.27m
+Clusters	95.56	261k	1.0	0.31m
$\frac{1}{2}$ Dim.	95.39	143k	0.7	0.18m

- 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)

Implementation Details

Computation Graphs

- Computing gradients is hard! Computation graph abstraction allows us to define a computation symbolically and will do this for us

- Automatic differentiation: keep track of derivatives / be able to backpropagate through each function:

```
y = x * x      --codegen-->      (y,dy) = (x * x, 2 * x * dx)
```

- Use a library like Pytorch or Tensorflow. This class: Pytorch

Computation Graphs in Pytorch

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

```
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

Take step with optimizer

Decode test set

Next Time

- Training neural networks
- Word representations / word vectors
- word2vec, GloVe