Deep Learning in NLP

Many slides adapted from Richard Socher, Tom Mitchell

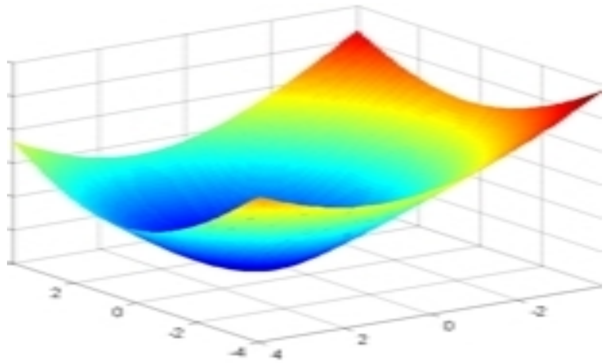
What's Deep Learning (DL)?

- Deep learning is a subfield of machine learning

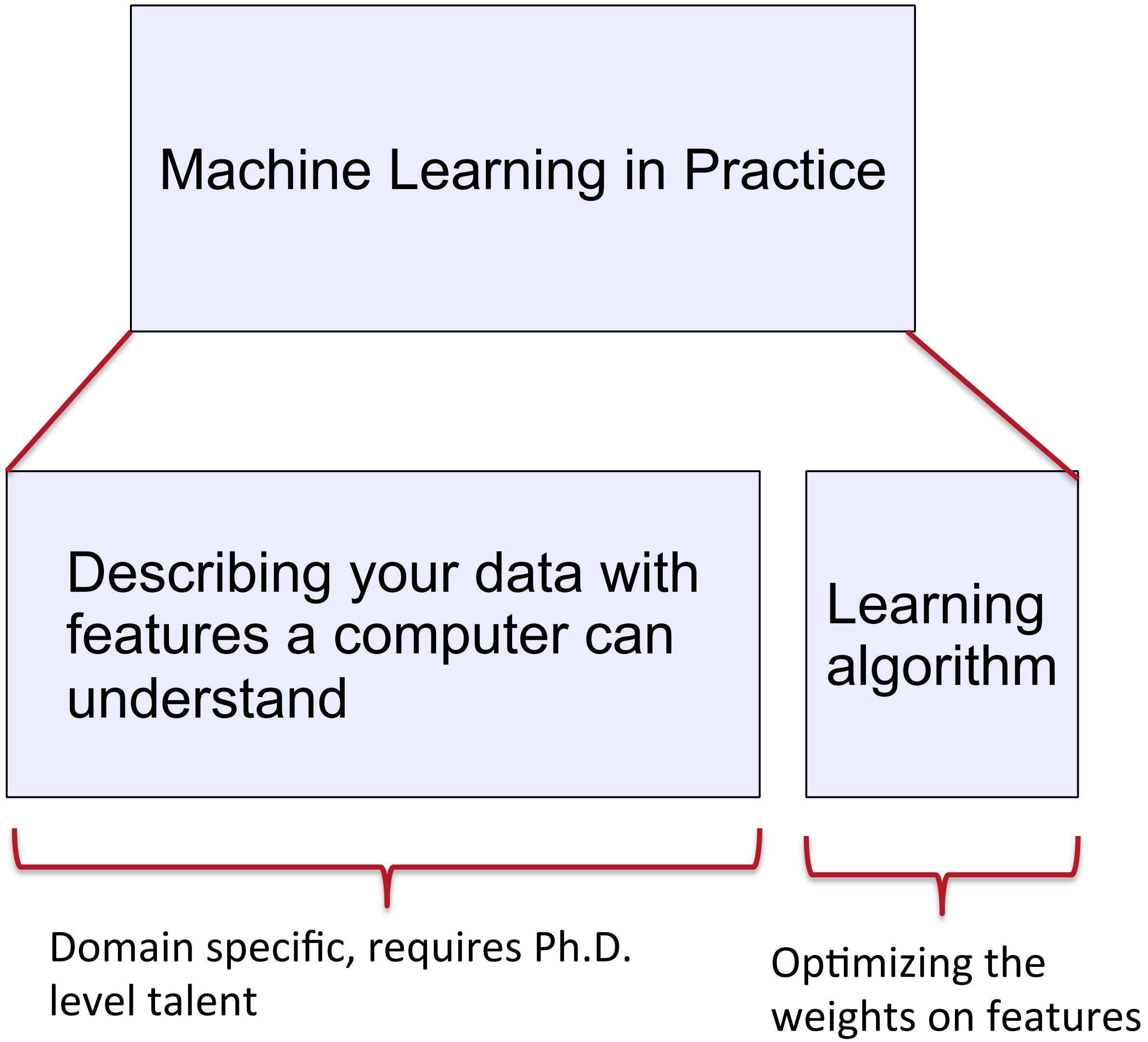
- Most machine learning methods work well because of human-designed representations and input features
  - For example: features for finding named entities like locations or organization names (Finkel, 2010):

Feature	**NER**
Current Word	✓
Previous Word	✓
Next Word	✓
Current Word Character n-gram	all
Current POS Tag	✓
Surrounding POS Tag Sequence	✓
Current Word Shape	✓
Surrounding Word Shape Sequence	✓
Presence of Word in Left Window	size 4
Presence of Word in Right Window	size 4

- Machine learning becomes just optimizing weights to best make a final prediction



Machine Learning vs Deep Learning

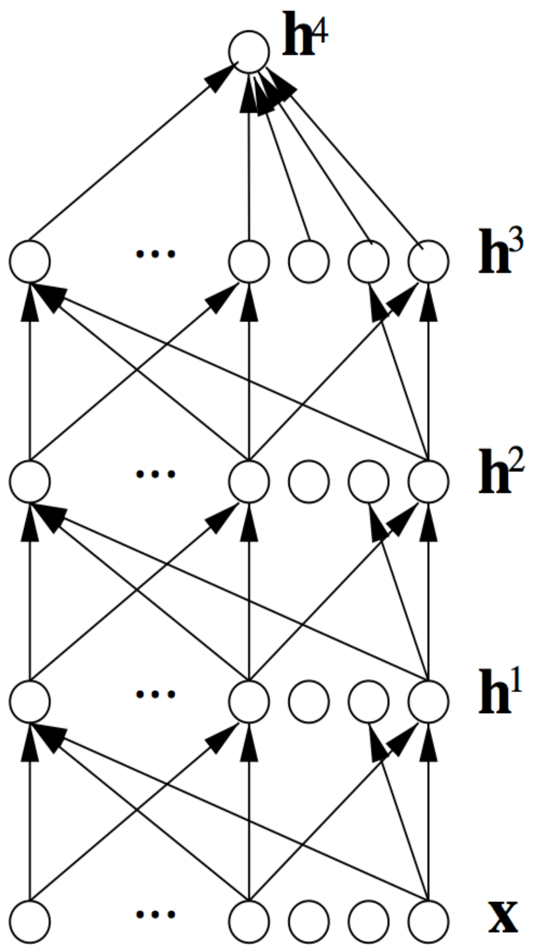


What's Deep Learning (DL)?

- Representation learning attempts to automatically learn good features or representations

- Deep learning algorithms attempt to learn (multiple levels of) representation and an output

- From "raw" inputs **x** (e.g. words)



On the history and term of "Deep Learning"

- We will focus on different kinds of **neural networks**
- The dominant model family inside deep learning

- Only clever terminology for stacked logistic regression units?
  - Somewhat, but interesting modeling principles and actual connections to neuroscience in some cases

Reasons for Exploring Deep Learning

- Manually designed features are often over-specified, incomplete and take a long time to design and validate
- **Learned Features** are easy to adapt, fast to learn

- Deep learning provides a very flexible, (almost?) universal, learnable framework for **representing** world, visual and linguistic information.

- Deep learning can learn **unsupervised** (from raw text) and **supervised** (with specific labels like positive/negative)

Reasons for Exploring Deep Learning

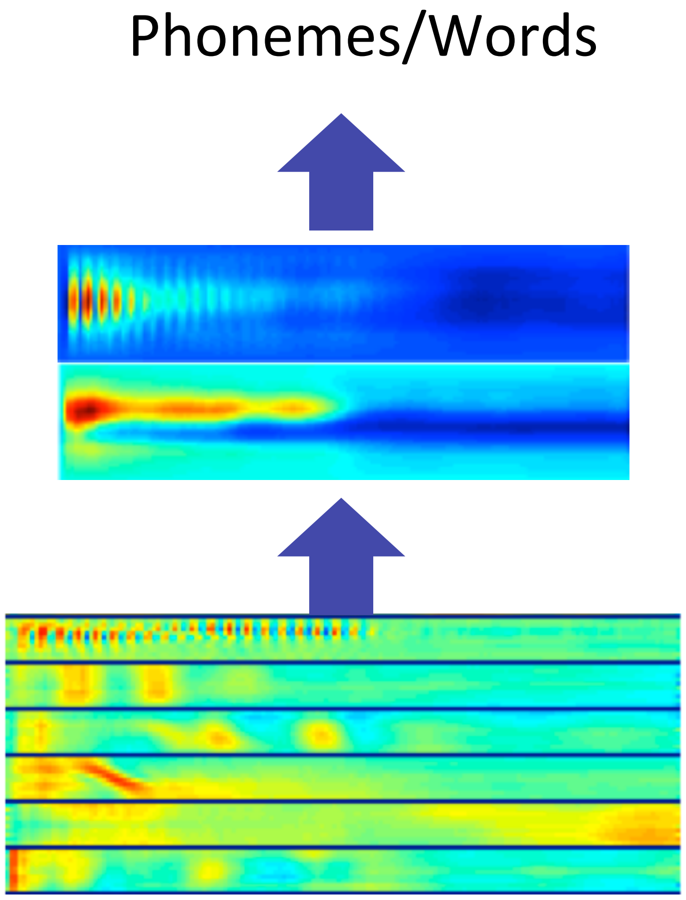
- In 2006 **deep** learning techniques started outperforming other machine learning techniques. Why now?

- DL techniques benefit more from a lot of data
- Faster machines and multicore CPU/GPU help DL
- New models, algorithms, ideas

→ **Improved performance** (first in speech and vision, then NLP)

Deep Learning for Speech

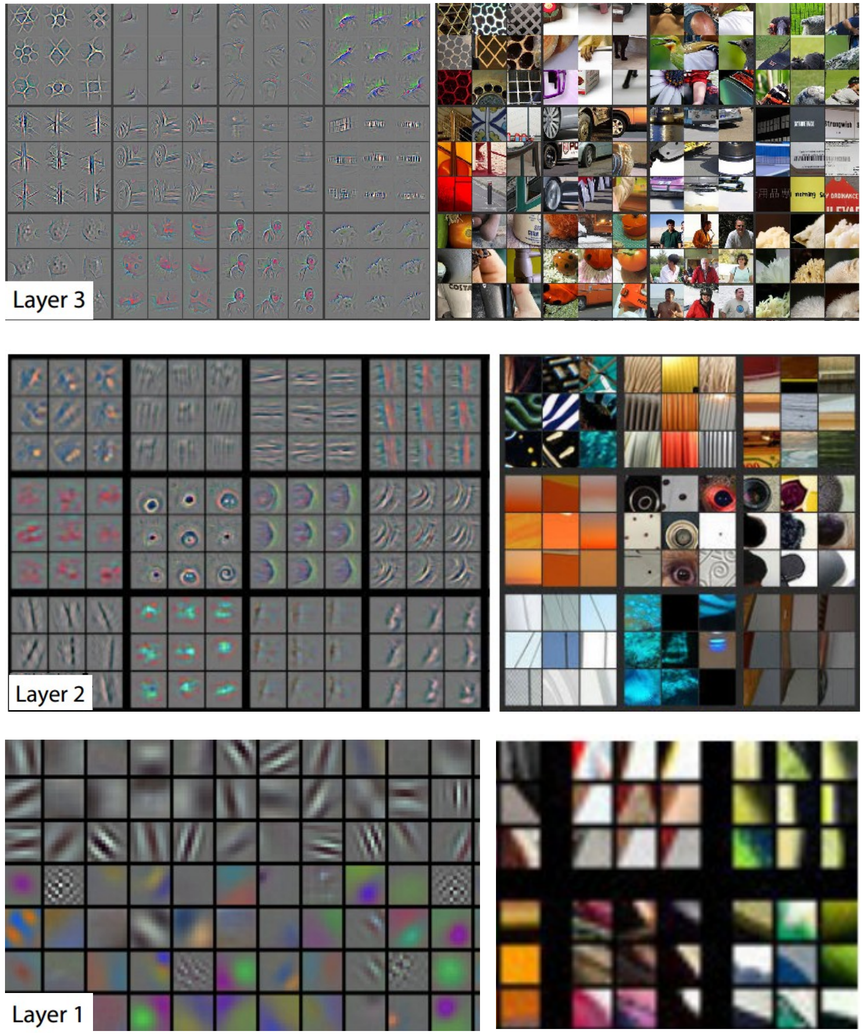
- The first breakthrough results of "deep learning" on large datasets happened in speech recognition
- Context-Dependent Pre-trained Deep Neural Networks for Large Vocabulary Speech Recognition Dahl et al. (2010)



Acoustic model	**Recog \ WER**	**RT03S FSH**	**Hub5 SWB**
Traditional features	1-pass −adapt	**27.4**	**23.6**
Deep Learning	1-pass −adapt	**18.5** (−33%)	**16.1** (−32%)

Deep Learning for Computer Vision

- Most deep learning groups have (until recently) largely focused on computer vision
- Break through paper: ImageNet Classification with Deep Convolutional Neural Networks by Krizhevsky et al. 2012

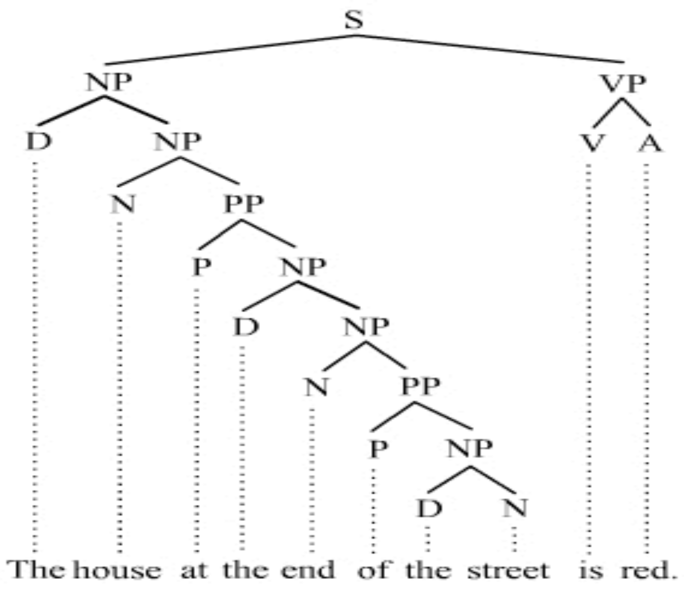


Zeiler and Fergus (2013)

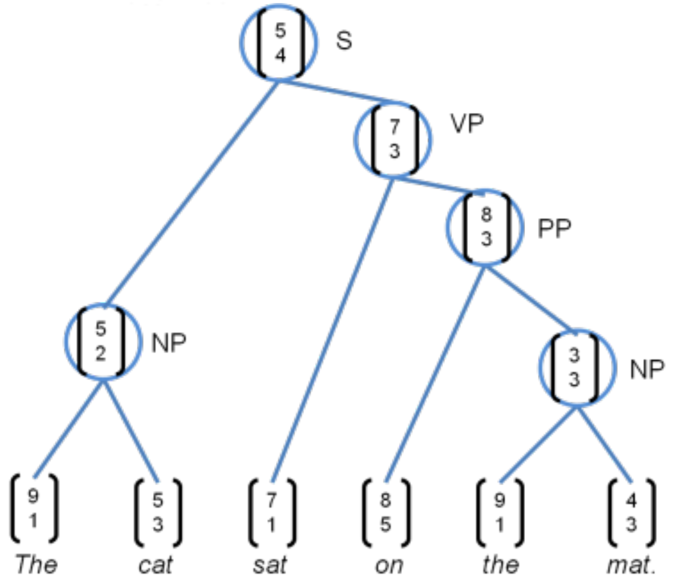
Neural word vectors - visualization

Representations at NLP Levels: Syntax

- Traditional: Phrases
  Discrete categories like NP, VP



- DL:
  - Every word and every phrase is a vector
  - a neural network combines two vectors into one vector
  - Socher et al. 2011



Machine Translation

- Many levels of translation have been tried in the past:

- Traditional MT systems are very large complex systems

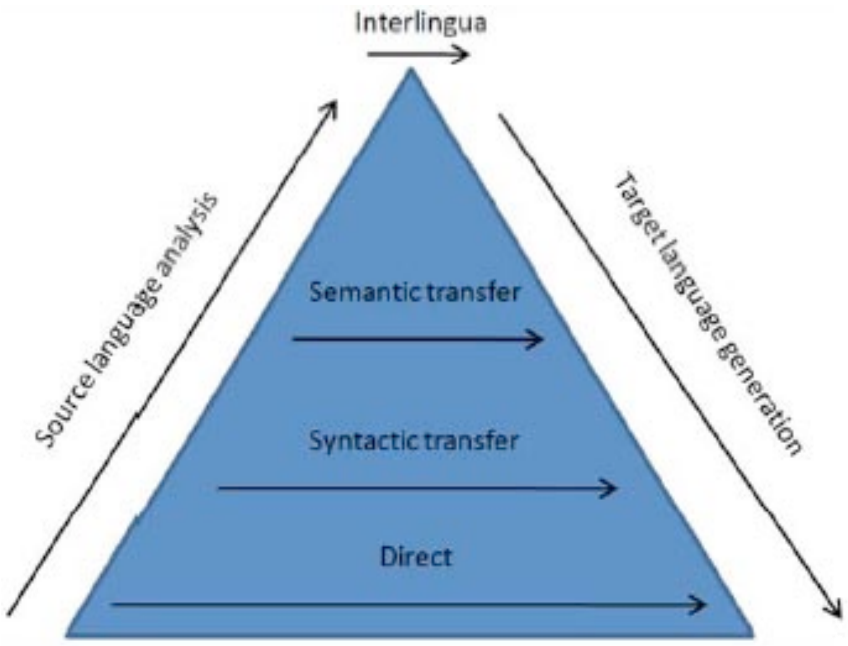
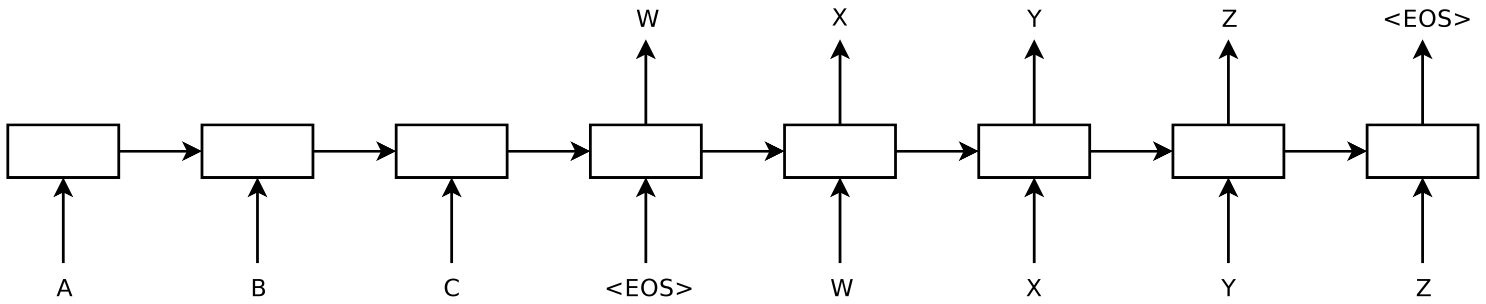


Figure 1: The Vauquois triangle

- What do you think is the interlingua for the DL approach to translation?

Machine Translation

- Source sentence mapped to vector, then output sentence generated.



- Sequence to Sequence Learning with Neural Networks by Sutskever et al. 2014

- Very new but could replace very complex architectures!

Neural Networks

Connectionist Models

Consider humans:

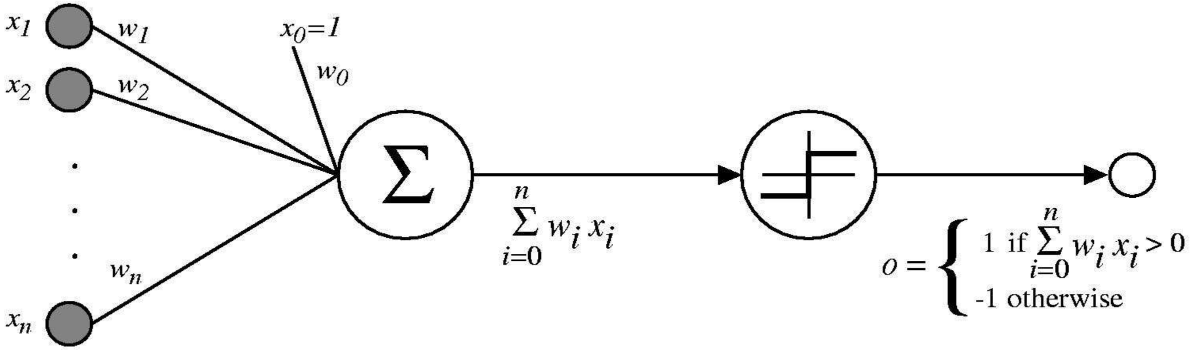
- Neuron switching time $\sim .001$ second
- Number of neurons $\sim 10^{10}$
- Connections per neuron $\sim 10^{4-5}$
- Scene recognition time $\sim .1$ second
- 100 inference steps doesn't seem like enough

$\Rightarrow$ Much parallel computation

Properties of neural nets:

- Many neuron-like threshold switching units
- Many weighted interconnections among units
- Highly parallel, distributed process
- Emphasis on tuning weights automatically

Perceptron

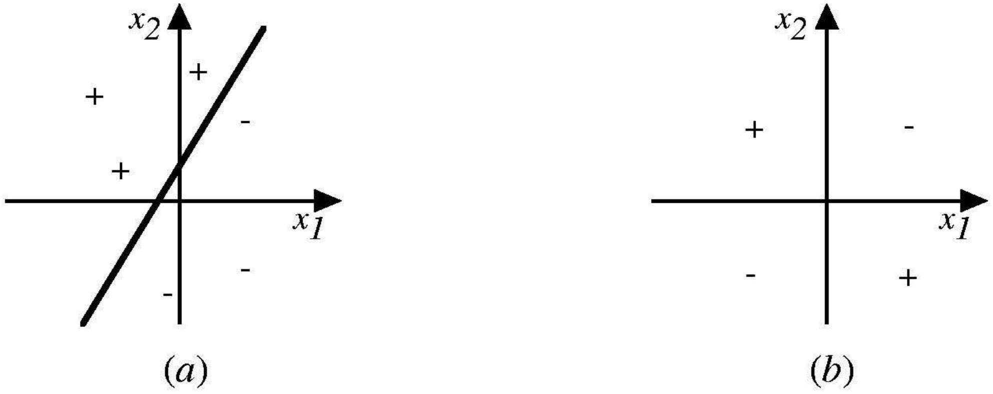


$$o(x_1, \ldots, x_n) = \begin{cases} 1 & \text{if } w_0 + w_1 x_1 + \cdots + w_n x_n > 0 \\ -1 & \text{otherwise.} \end{cases}$$

Sometimes we'll use simpler vector notation:

$$o(\vec{x}) = \begin{cases} 1 & \text{if } \vec{w} \cdot \vec{x} > 0 \\ -1 & \text{otherwise.} \end{cases}$$

Decision Surface of a Perceptron



Represents some useful functions

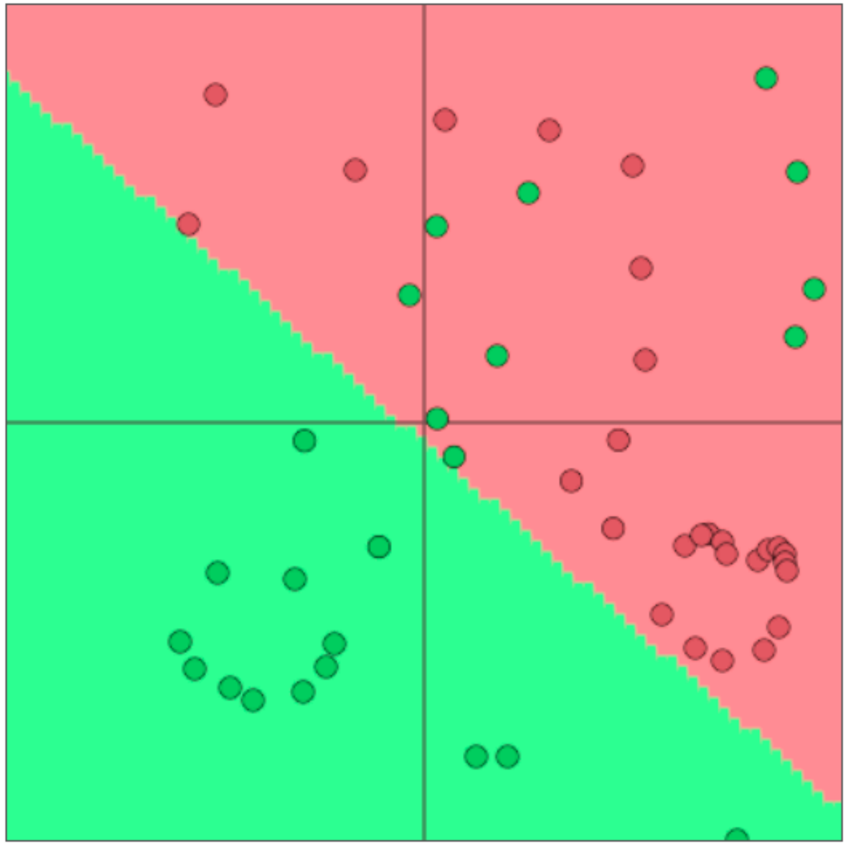
- What weights represent $g(x_1, x_2) = AND(x_1, x_2)$?

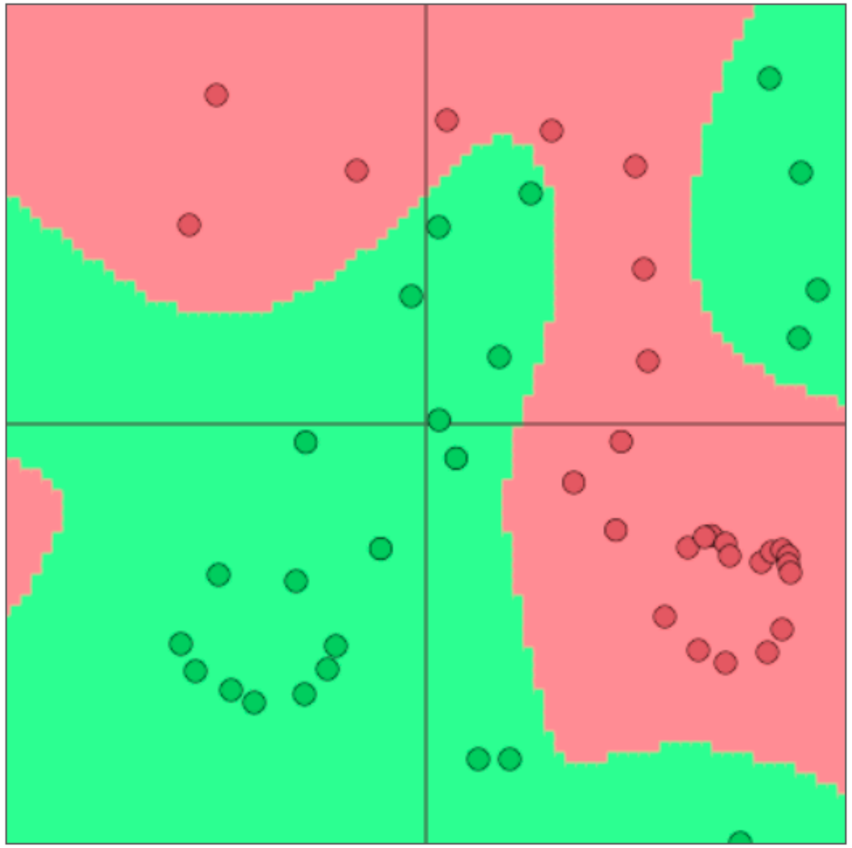
But some functions not representable

- All not linearly separable
- Therefore, we'll want networks of these...

Neural Nets for the Win!

- Neural networks can learn much more complex functions and nonlinear decision boundaries!





Perceptron Training Rule

$$w_i \leftarrow w_i + \Delta w_i$$

where

$$\Delta w_i = \eta(t - o)x_i$$

Where:

- $t = c(\vec{x})$ is target value
- o is perceptron output
- η is small constant (e.g., 0.1) called *learning rate*

Perceptron Training Rule

Can prove it will converge if

- Training data is linearly separable
- η sufficiently small

Gradient Descent

To understand, consider simpler *linear unit*, where

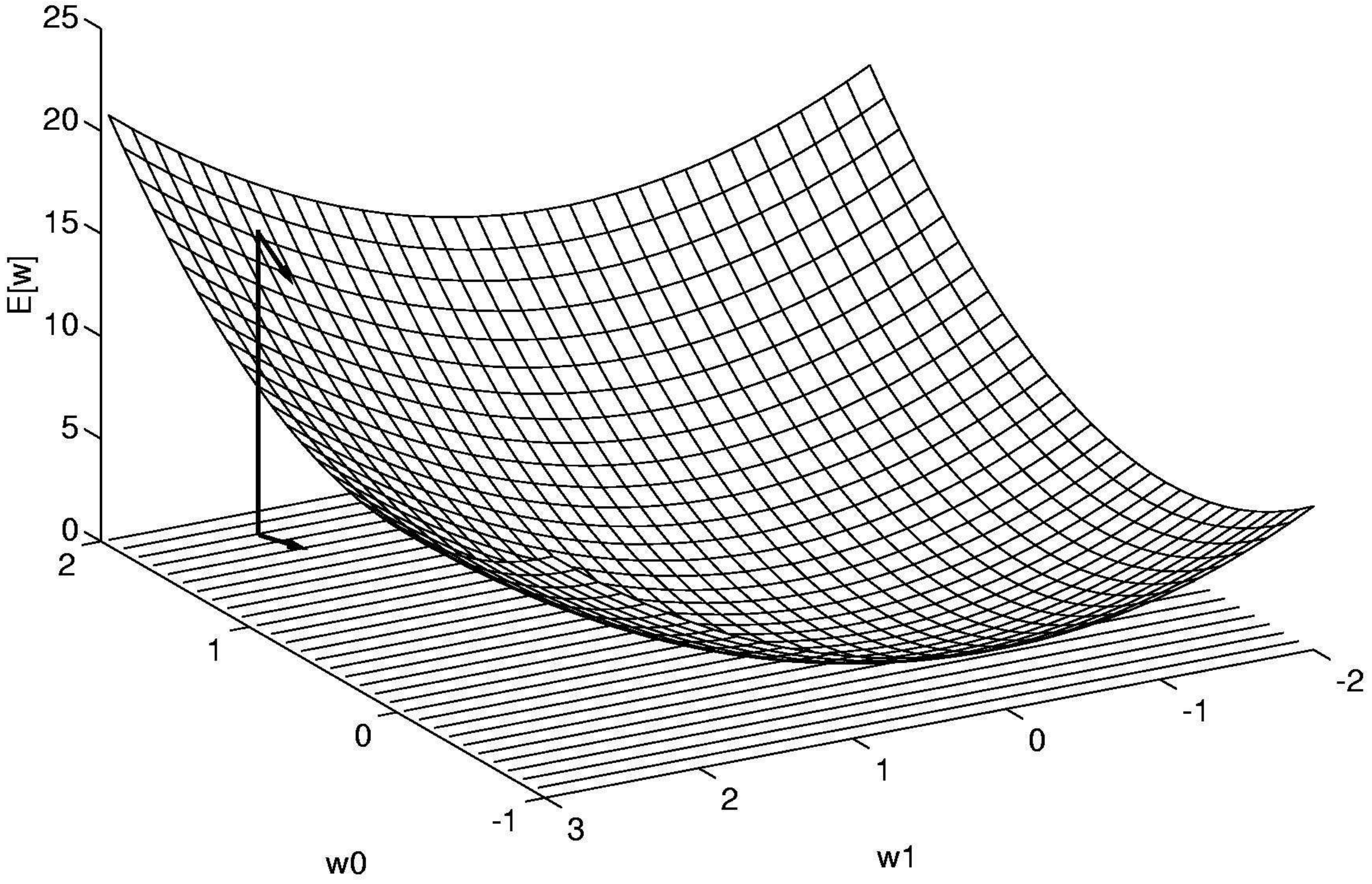
$$o = w_0 + w_1 x_1 + \cdots + w_n x_n$$

Let's learn w_i's that minimize the squared error

$$E[\vec{w}] \equiv \frac{1}{2} \sum_{d \in D} (t_d - o_d)^2$$

Where D is set of training examples

Gradient Descent



Gradient:

$$\nabla E[\vec{w}] \equiv \left[\frac{\partial E}{\partial w_0}, \frac{\partial E}{\partial w_1}, \cdots \frac{\partial E}{\partial w_n}\right]$$

Training rule:

$$\Delta \vec{w} = -\eta \nabla E[\vec{w}]$$

I.e.:

$$\Delta w_i = -\eta \frac{\partial E}{\partial w_i}$$

Gradient Descent

$$
\begin{aligned}
\frac{\partial E}{\partial w_i} &= \frac{\partial}{\partial w_i} \frac{1}{2} \sum_d (t_d - o_d)^2 \\
&= \frac{1}{2} \sum_d \frac{\partial}{\partial w_i} (t_d - o_d)^2 \\
&= \frac{1}{2} \sum_d 2(t_d - o_d) \frac{\partial}{\partial w_i} (t_d - o_d) \\
&= \sum_d (t_d - o_d) \frac{\partial}{\partial w_i} (t_d - \vec{w} \cdot \vec{x_d}) \\
\frac{\partial E}{\partial w_i} &= \sum_d (t_d - o_d)(-x_{i,d})
\end{aligned}
$$

Gradient Descent

GRADIENT-DESCENT($training\_examples, \eta$)

Initialize each w_i to some small random value

Until the termination condition is met, Do

- Initialize each Δw_i to zero.
- For each $\langle \vec{x}, t \rangle$ in $training\_examples$, Do
  - Input instance $\vec{x}$ to unit and compute output o
  - For each linear unit weight w_i, Do

$$\Delta w_i \leftarrow \Delta w_i + \eta(t - o)x_i$$

- For each linear unit weight w_i, Do

$$w_i \leftarrow w_i + \Delta w_i$$

Summary

Perceptron training rule guaranteed to succeed if

- Training examples are linearly separable
- Sufficiently small learning rate η

Linear unit training rule uses gradient descent

- Guaranteed to converge to hypothesis with minimum squared error
- Given sufficiently small learning rate η
- Even when training data contains noise
- Even when training data not separable by H

Batch vs. Incremental Gradient Descent

Batch Mode Gradient Descent:

Do until convergence

1. Compute the gradient $\nabla E_D[\vec{w}]$
2. $\vec{w} \leftarrow \vec{w} - \eta \nabla E_D[\vec{w}]$

Incremental Mode Gradient Descent:

Do until convergence

For each training example d in D

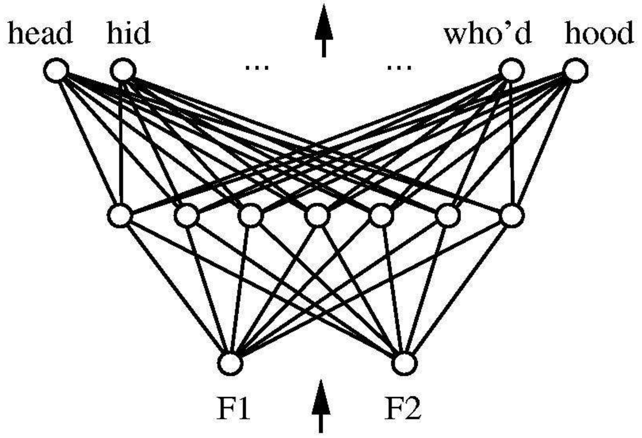
1. Compute the gradient $\nabla E_d[\vec{w}]$
2. $\vec{w} \leftarrow \vec{w} - \eta \nabla E_d[\vec{w}]$

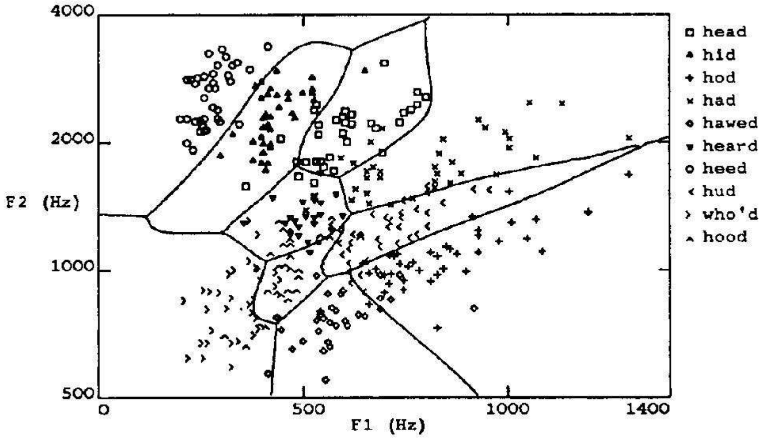
$$E_D[\vec{w}] \equiv \frac{1}{2} \sum_{d \in D} (t_d - o_d)^2$$

$$E_d[\vec{w}] \equiv \frac{1}{2} (t_d - o_d)^2$$

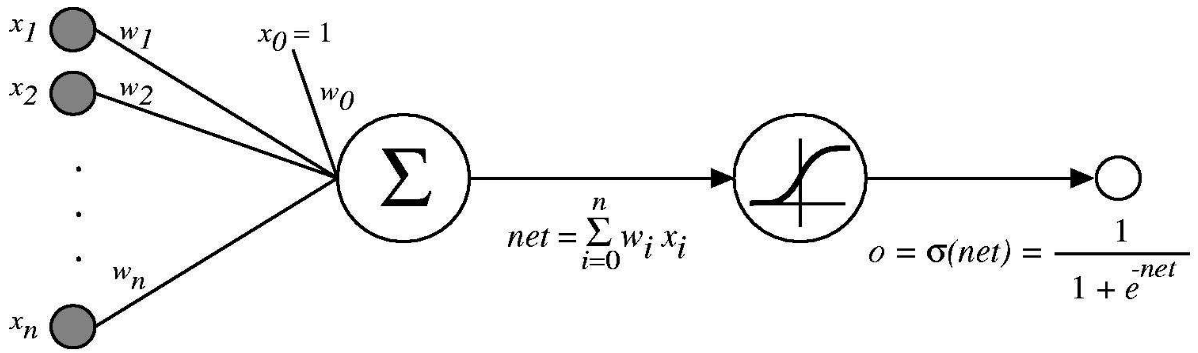
Incremental Gradient Descent can approximate *Batch Gradient Descent* arbitrarily closely if η made small enough

Multilayer Networks of Sigmoid Units





Sigmoid Unit



$\sigma(x)$ is the sigmoid function

$$\frac{1}{1+e^{-x}}$$

Nice property: $\frac{d\sigma(x)}{dx} = \sigma(x)(1-\sigma(x))$

We can derive gradient descent rules to train

- One sigmoid unit
- *Multilayer networks* of sigmoid units $\rightarrow$ Backpropagation

Error Gradient for a Sigmoid Unit

$$
\begin{aligned}
\frac{\partial E}{\partial w_i} &= \frac{\partial}{\partial w_i} \frac{1}{2} \sum_{d \in D} (t_d - o_d)^2 \\
&= \frac{1}{2} \sum_d \frac{\partial}{\partial w_i} (t_d - o_d)^2 \\
&= \frac{1}{2} \sum_d 2(t_d - o_d) \ \frac{\partial}{\partial w_i} (t_d - o_d) \\
&= \sum_d (t_d - o_d) \left(- \frac{\partial o_d}{\partial w_i} \right) \\
&= - \sum_d (t_d - o_d) \ \frac{\partial o_d}{\partial net_d} \ \frac{\partial net_d}{\partial w_i}
\end{aligned}
$$

But we know:

$$\frac{\partial o_d}{\partial net_d} = \frac{\partial \sigma(net_d)}{\partial net_d} = o_d(1 - o_d)$$

$$\frac{\partial net_d}{\partial w_i} = \frac{\partial (\vec{w} \cdot \vec{x}_d)}{\partial w_i} = x_{i,d}$$

So:

$$\frac{\partial E}{\partial w_i} \quad = \quad -\sum_{d \in D} (t_d - o_d) o_d (1 - o_d) x_{i,d}$$

Let: $\delta_k = -\frac{\partial E}{\partial net_k}$

$$
\begin{aligned}
\frac{\partial E}{\partial net_j} &= \sum_{k \in Outs(j)} \frac{\partial E}{\partial net_k} \frac{\partial net_k}{\partial net_j} \\
&= \sum_{k \in Outs(j)} -\delta_k \, \frac{\partial net_k}{\partial net_j} \\
&= \sum_{k \in Outs(j)} -\delta_k \, \frac{\partial net_k}{\partial o_j} \frac{\partial o_j}{\partial net_j} \\
&= \sum_{k \in Outs(j)} -\delta_k \, w_{kj} \, \frac{\partial o_k}{\partial net_j} \\
&= \sum_{k \in Outs(j)} -\delta_k \, w_{kj} \, o_j(1 - o_j) \\
\delta_j &= -\frac{\partial E}{\partial net_j} = o_j(1 - o_j) \sum_{k \in Outs(j)} \delta_k \, w_{kj}
\end{aligned}
$$

Backpropagation Algorithm

Initialize all weights to small random numbers

Until convergence, Do

For each training example, Do

1. Input it to network and compute network outputs
2. For each output unit k

$$\delta_k \leftarrow o_k(1 - o_k)(t_k - o_k)$$

3. For each hidden unit h

$$\delta_h \leftarrow o_h(1 - o_h) \sum_{k \in outputs} w_{h,k}\delta_k$$

4. Update each network weight $w_{i,j}$

$$w_{i,j} \leftarrow w_{i,j} + \Delta w_{i,j}$$

where $\Delta w_{i,j} = \eta \delta_j x_{i,j}$

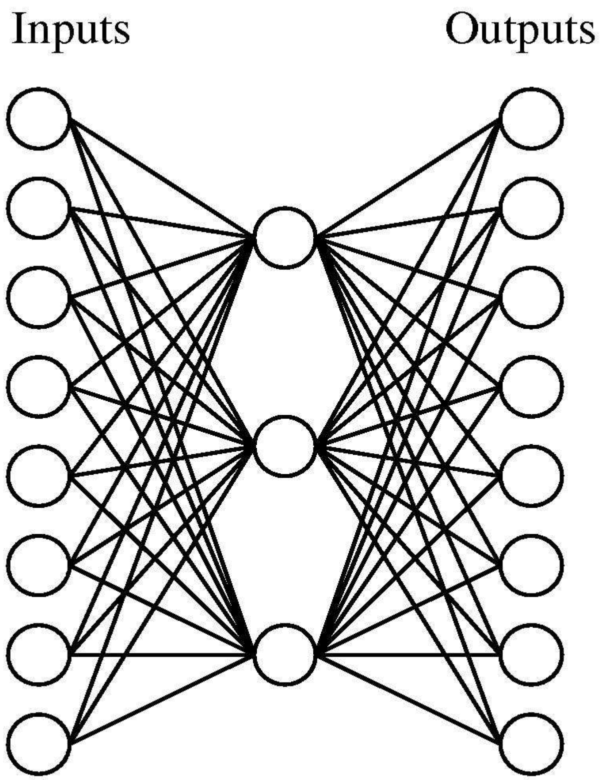
More on Backpropagation

- Gradient descent over entire *network* weight vector
- Easily generalized to arbitrary directed graphs
- Will find a local, not necessarily global error minimum
  - In practice, often works well
    (can run multiple times)
- Often include weight *momentum* α

$$\Delta w_{i,j}(n) = \eta \delta_j x_{i,j} + \alpha \Delta w_{i,j}(n-1)$$

- Minimizes error over *training* examples
  - Will it generalize well to subsequent examples?
- Training can take thousands of iterations $\rightarrow$ slow!
- Using network after training is very fast

Learning Hidden Layer Representations



A target function:

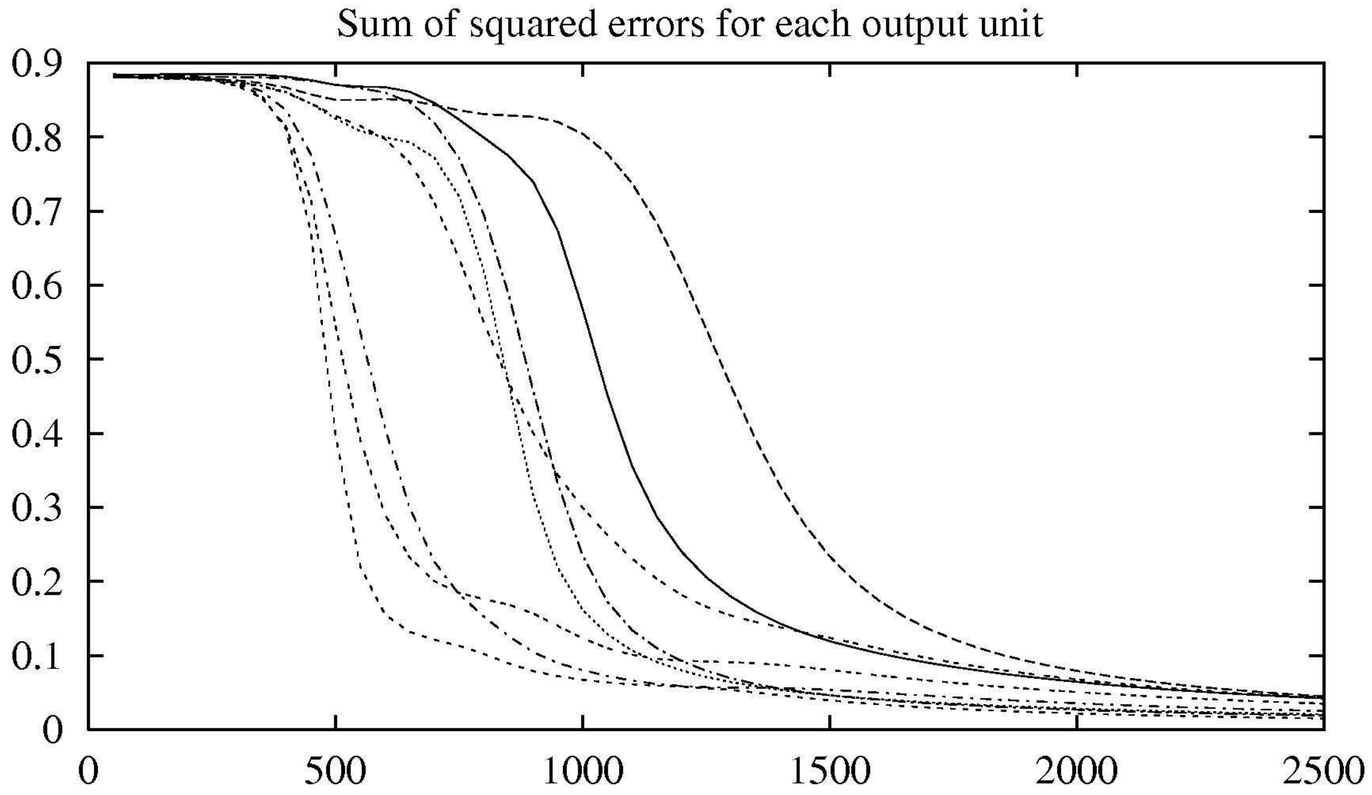
Input		Output
10000000	$\rightarrow$	10000000
01000000	$\rightarrow$	01000000
00100000	$\rightarrow$	00100000
00010000	$\rightarrow$	00010000
00001000	$\rightarrow$	00001000
00000100	$\rightarrow$	00000100
00000010	$\rightarrow$	00000010
00000001	$\rightarrow$	00000001

Can this be learned?

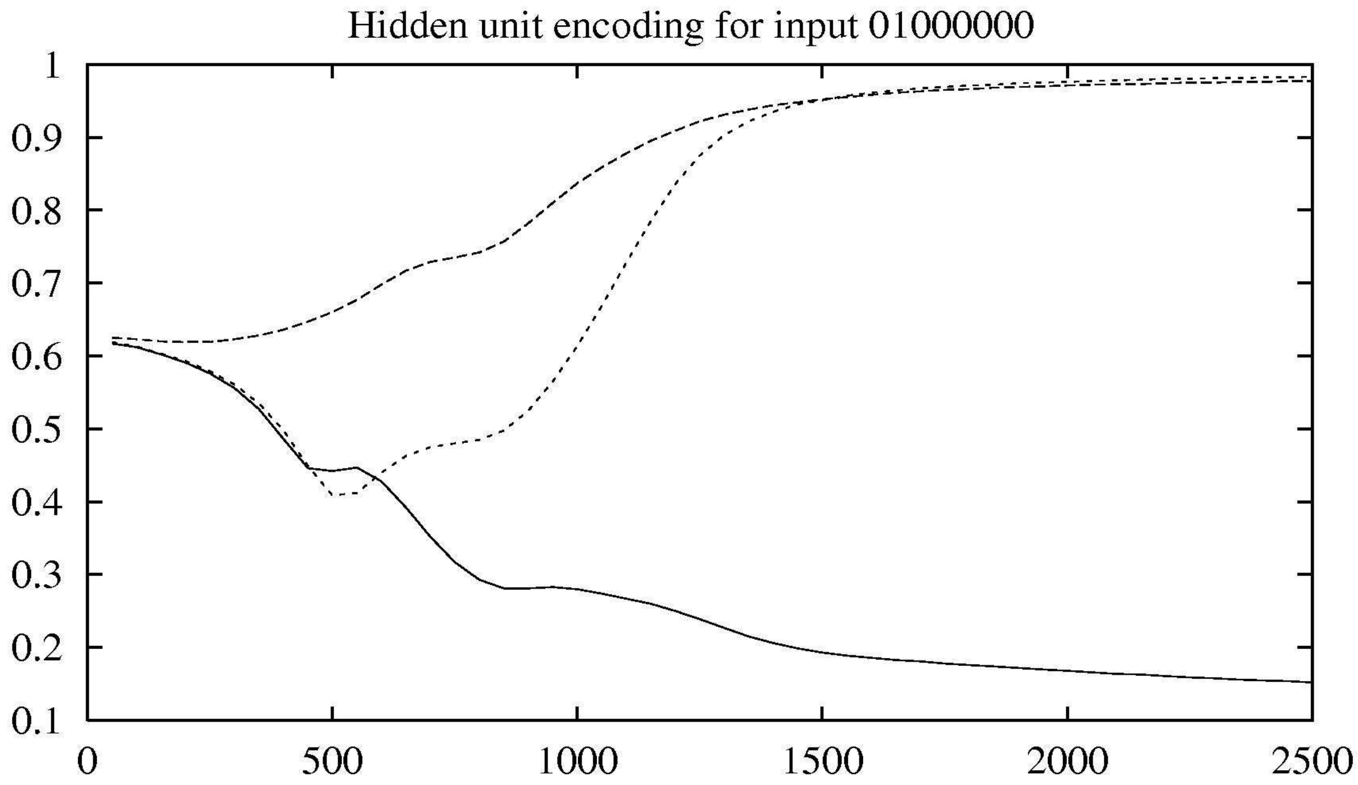
Learned hidden layer representation:

Input		Hidden Values				Output
10000000	→	.89	.04	.08	→	10000000
01000000	→	.01	.11	.88	→	01000000
00100000	→	.01	.97	.27	→	00100000
00010000	→	.99	.97	.71	→	00010000
00001000	→	.03	.05	.02	→	00001000
00000100	→	.22	.99	.99	→	00000100
00000010	→	.80	.01	.98	→	00000010
00000001	→	.60	.94	.01	→	00000001

Training

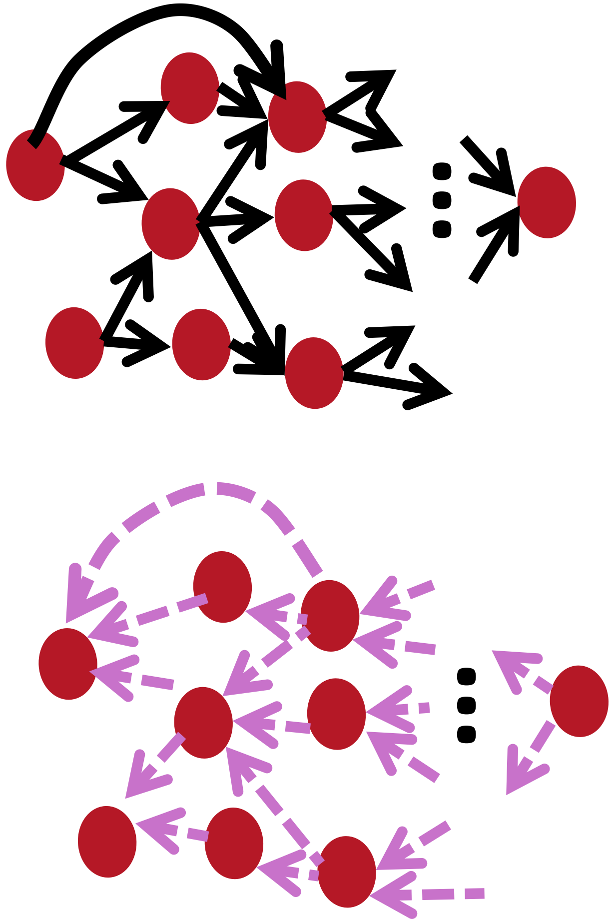

Sum of squared errors for each output unit
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0
500
1000
1500
2000
2500

Training



Hidden unit encoding for input 01000000
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
500
1000
1500
2000
2500

Automatic Differentiation



- The gradient computation can be **automatically inferred** from the symbolic expression of the fprop.
- Each node type needs to know how to compute its output and how to compute the gradient wrt its inputs given the gradient wrt its output.
- Easy and fast prototyping

Recurrent Neural Network Language Models

Language Modeling

- x is a "history" $w_1, w_2, \ldots w_{i-1}$, e.g.,
  Third, the notion "grammatical in English" cannot be identified in any way with the notion "high order of statistical approximation to English". It is fair to assume that neither sentence (1) nor (2) (nor indeed any part of these sentences) has ever occurred in an English discourse. Hence, in any statistical
- y is an "outcome" w_i
- Example features:

$$f_1(x, y) = \begin{cases} 1 & \text{if } y = \texttt{model} \\ 0 & \text{otherwise} \end{cases}$$

$$f_2(x, y) = \begin{cases} 1 & \text{if } y = \texttt{model} \text{ and } w_{i-1} = \texttt{statistical} \\ 0 & \text{otherwise} \end{cases}$$

$$f_3(x, y) = \begin{cases} 1 & \text{if } y = \texttt{model},\ w_{i-2} = \texttt{any},\ w_{i-1} = \texttt{statistical} \\ 0 & \text{otherwise} \end{cases}$$

$$f_4(x,y) = \begin{cases} 1 & \text{if } y = \texttt{model},\ w_{i-2} = \text{any} \\ 0 & \text{otherwise} \end{cases}$$

$$f_5(x,y) = \begin{cases} 1 & \text{if } y = \texttt{model},\ w_{i-1} \text{ is an adjective} \\ 0 & \text{otherwise} \end{cases}$$

$$f_6(x,y) = \begin{cases} 1 & \text{if } y = \texttt{model},\ w_{i-1} \text{ ends in ``ical''} \\ 0 & \text{otherwise} \end{cases}$$

$$f_7(x,y) = \begin{cases} 1 & \text{if } y = \texttt{model},\ \text{author} = \text{Chomsky} \\ 0 & \text{otherwise} \end{cases}$$

$$f_8(x,y) = \begin{cases} 1 & \text{if } y = \texttt{model},\ \text{``model'' is not in } w_1, \ldots w_{i-1} \\ 0 & \text{otherwise} \end{cases}$$

$$f_9(x,y) = \begin{cases} 1 & \text{if } y = \texttt{model},\ \text{``grammatical'' is in } w_1, \ldots w_{i-1} \\ 0 & \text{otherwise} \end{cases}$$

Defining Features in Practice

- We had the following "trigram" feature:

$$f_3(x, y) = \begin{cases} 1 & \text{if } y = \texttt{model},\ w_{i-2} = \texttt{any},\ w_{i-1} = \texttt{statistical} \\ 0 & \text{otherwise} \end{cases}$$

- In practice, we would probably introduce one trigram feature for every trigram seen in the training data: i.e., for all trigrams (u, v, w) seen in training data, create a feature

$$f_{N(u,v,w)}(x, y) = \begin{cases} 1 & \text{if } y = w,\ w_{i-2} = u,\ w_{i-1} = v \\ 0 & \text{otherwise} \end{cases}$$

  where $N(u, v, w)$ is a function that maps each (u, v, w) trigram to a different integer

Language Modeling

- x is a "history" $w_1, w_2, \ldots w_{i-1}$, e.g.,
  Third, the notion "grammatical in English" cannot be identified in any way with the notion "high order of statistical approximation to English". It is fair to assume that neither sentence (1) nor (2) (nor indeed any part of these sentences) has ever occurred in an English discourse. Hence, in any statistical
- Each possible y gets a different score:

$$\begin{aligned} v \cdot f(x, model) &= 5.6 \qquad & v \cdot f(x, the) &= -3.2 \\ v \cdot f(x, is) &= 1.5 \qquad & v \cdot f(x, of) &= 1.3 \\ v \cdot f(x, models) &= 4.5 \qquad & &\ldots \end{aligned}$$

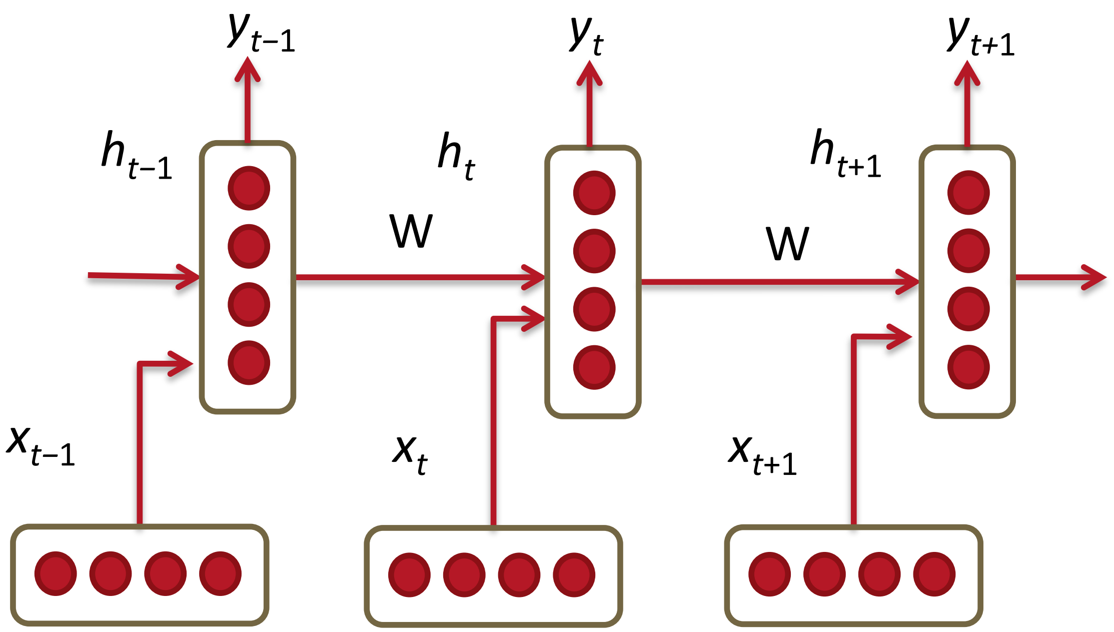
Log-Linear Models

- We have some input domain $\mathcal{X}$, and a finite label set $\mathcal{Y}$. Aim is to provide a conditional probability $p(y \mid x)$ for any $x \in \mathcal{X}$ and $y \in \mathcal{Y}$.
- A feature is a function $f : \mathcal{X} \times \mathcal{Y} \rightarrow \mathbb{R}$
  (Often binary features or indicator functions $f_k : \mathcal{X} \times \mathcal{Y} \rightarrow \{0, 1\}$).
- Say we have m features f_k for $k = 1 \ldots m$
  $\Rightarrow$ A feature vector $f(x, y) \in \mathbb{R}^m$ for any $x \in \mathcal{X}$ and $y \in \mathcal{Y}$.
- We also have a **parameter vector** $v \in \mathbb{R}^m$
- We define

$$p(y \mid x; v) = \frac{e^{v \cdot f(x,y)}}{\sum_{y' \in \mathcal{Y}} e^{v \cdot f(x,y')}}$$

Recurrent Neural Networks!

- RNNs tie the weights at each time step
- Condition the neural network on all previous words
- RAM requirement only scales with number of words



Recurrent Neural Network language model

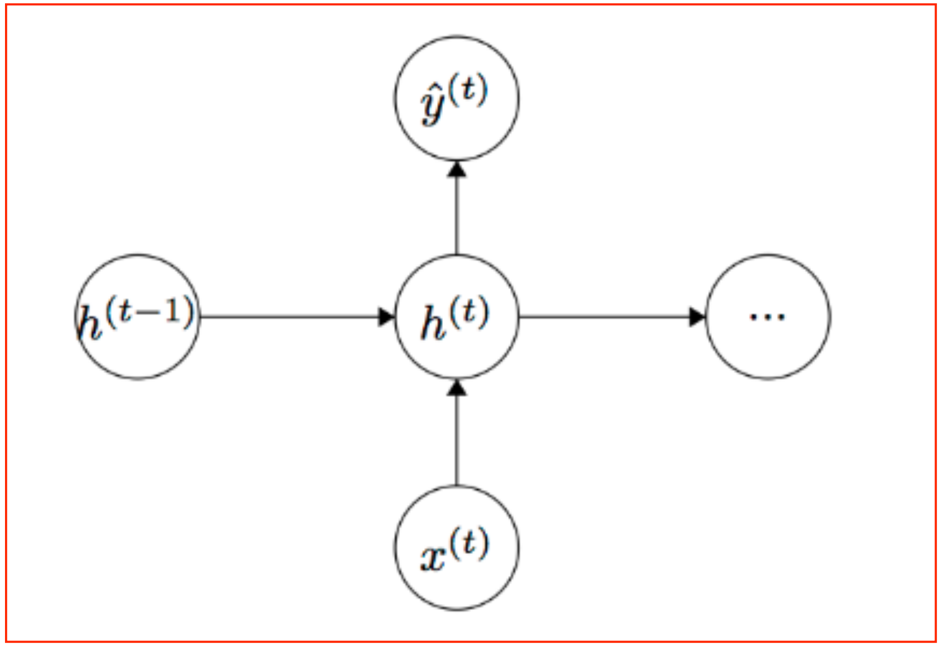
Given list of word **vectors**: $x_1, \ldots, x_{t-1}, x_t, x_{t+1}, \ldots, x_T$

At a single time step:

$$h_t = \sigma\left(W^{(hh)}h_{t-1} + W^{(hx)}x_{[t]}\right)$$

$$\hat{y}_t = \text{softmax}\left(W^{(S)}h_t\right)$$

$$\hat{P}(x_{t+1} = v_j \mid x_t, \ldots, x_1) = \hat{y}_{t,j}$$



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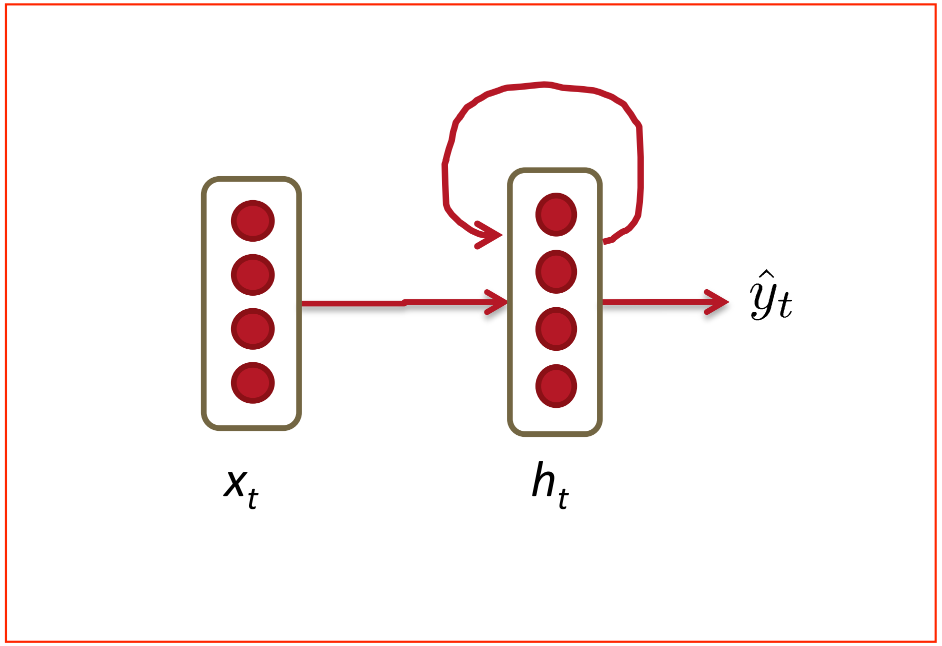


Recurrent Neural Network language model

Main idea: we use the same set of W weights at all time steps!

Everything else is the same:

$$
\begin{aligned}
h_t &= \sigma\left(W^{(hh)} h_{t-1} + W^{(hx)} x_{[t]}\right) \\
\hat{y}_t &= \mathrm{softmax}\left(W^{(S)} h_t\right) \\
\hat{P}(x_{t+1} = v_j \mid x_t, \ldots, x_1) &= \hat{y}_{t,j}
\end{aligned}
$$

$h_0 \in \mathbb{R}^{D_h}$ is some initialization vector for the hidden layer at time step 0

$x_{[t]}$ is the column vector of L at index [t] at time step t

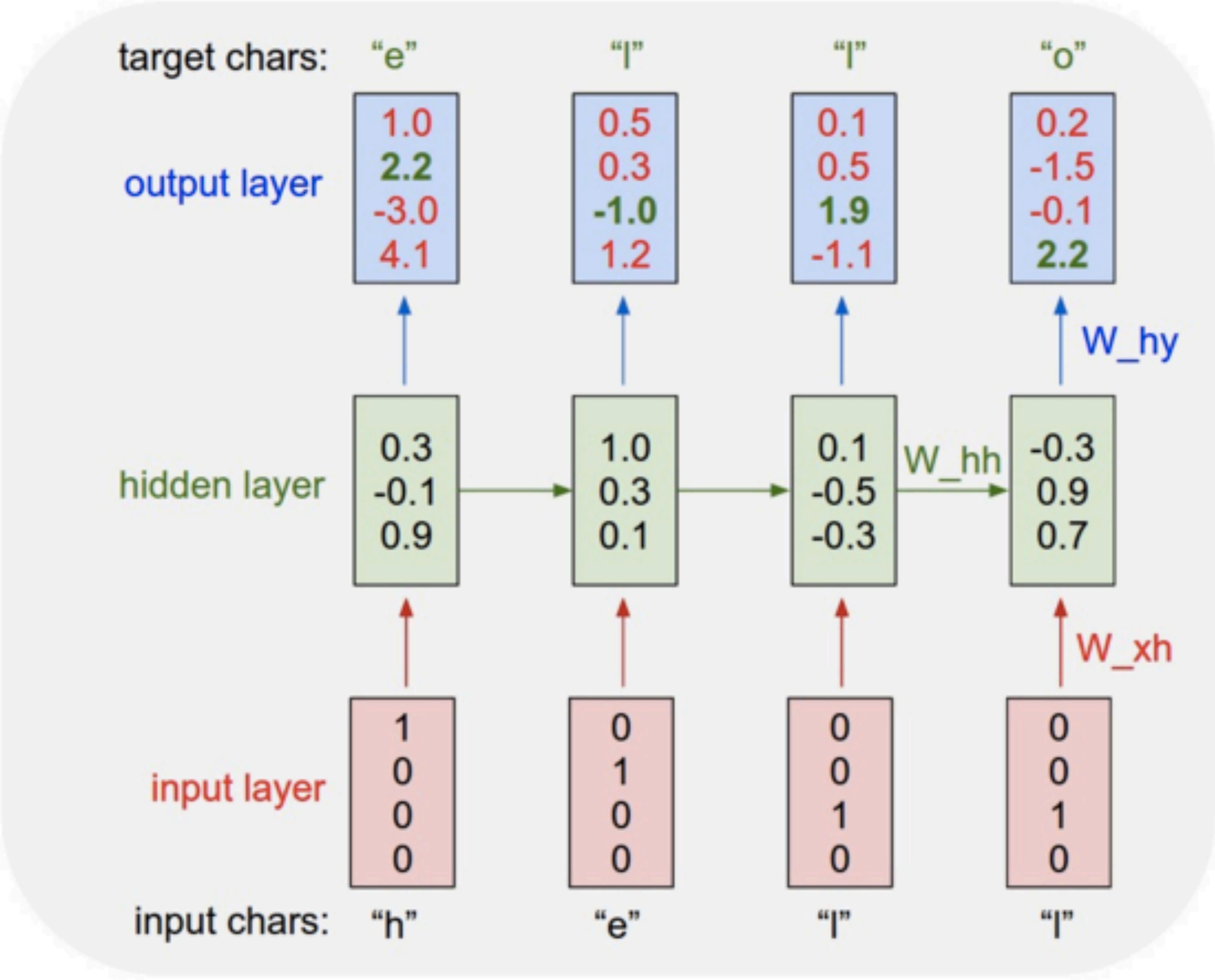
$W^{(hh)} \in \mathbb{R}^{D_h \times D_h}$ $\quad W^{(hx)} \in \mathbb{R}^{D_h \times d}$ $\quad W^{(S)} \in \mathbb{R}^{|V| \times D_h}$

Recurrent Neural Network language model

$\hat{y} \in \mathbb{R}^{|V|}$ is a probability distribution over the vocabulary

Same cross entropy loss function but predicting words instead of classes

$$J^{(t)}(\theta) = -\sum_{j=1}^{|V|} y_{t,j} \log \hat{y}_{t,j}$$


target chars: "e" "l" "l" "o"
output layer
1.0 2.2 -3.0 4.1
0.5 0.3 -1.0 1.2
0.1 0.5 1.9 -1.1
0.2 -1.5 -0.1 2.2
W_hy
hidden layer
0.3 -0.1 0.9
1.0 0.3 0.1
0.1 -0.5 -0.3
-0.3 0.9 0.7
W_hh
W_xh
input layer
1 0 0 0
0 1 0 0
0 0 1 0
0 0 1 0
input chars: "h" "e" "l" "l"

Summary

- Deep learning is a popular area in machine learning recently
    - Very successful in speech recognition and computer vision
- Becoming very popular in NLP these days
- Main motivation:
    - Learn feature representations from data
    - Alternative to hand-engineered features
- Neural networks:
    - Primary deep learning approach
    - Layers of logistic regressions – can directly calculate gradients from outputs
    - Nonlinear decision boundaries