

# Recurrent Neural Networks

COMP-550

Oct 5, 2017

# Outline

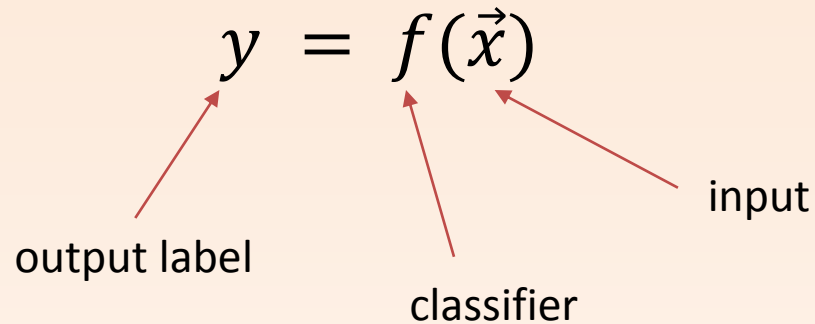
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Introduction to neural networks and deep learning

Feedforward neural networks

Recurrent neural networks

# Classification Review



Represent input  $\vec{x}$  as a list of features

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$x_1$   $x_2$   $x_3$   $x_4$   $x_5$   $x_6$   $x_7$   $x_8$  ...  
1.0, 0.0, 1.0, 1.0, 0.0, 0.0, 0.0, 1.0 ...

# Logistic Regression

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Linear regression:

$$y = a_1x_1 + a_2x_2 + \dots + a_nx_n + b$$

**Intuition:** Linear regression gives as continuous values in  $[-\infty, \infty]$  —let's squish the values to be in  $[0, 1]$ !

Function that does this: logit function

$$P(y|\vec{x}) = \frac{1}{Z} e^{a_1x_1 + a_2x_2 + \dots + a_nx_n + b}$$

 This  $Z$  is a normalizing constant to ensure this is a probability distribution.

(a.k.a., maximum entropy or MaxEnt classifier)

N.B.: Don't be confused by name—this method is most often used to solve classification problems.

# Linear Model

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Logistic regression, support vector machines, etc. are examples of **linear models**.

$$P(y|\vec{x}) = \frac{1}{Z} e^{\underbrace{a_1x_1 + a_2x_2 + \dots + a_nx_n + b}_{\text{Linear combination of feature weights and values}}}$$

Linear combination of feature weights and values

Cannot learn complex, non-linear functions from input features to output labels (without adding features)

e.g., Starts with a capital AND not at beginning of sentence -> proper noun

# (Artificial) Neural Networks

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A kind of learning model which automatically learns non-linear functions from input to output

Biologically inspired metaphor:

- Network of computational units called neurons
- Each neuron takes scalar inputs, and produces a scalar output, very much like a logistic regression model

$$\text{Neuron}(\vec{x}) = g(a_1x_1 + a_2x_2 + \dots + a_nx_n + b)$$

As a whole, the network can theoretically compute any computable function, given enough neurons. (These notions can be formalized.)

# Responsible For:

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AlphaGo (Google) (2015)

- Beat Go champion Lee Sedol in a series of 5 matches, 4-1

Atari game-playing bot (Google) (2015)

Above results use NNs in conjunction with **reinforcement learning**

State of the art in:

- Speech recognition
- Machine translation
- Object detection
- Other NLP tasks

# Feedforward Neural Networks

All connections flow forward (no loops); each layer of hidden units is fully connected to the next.

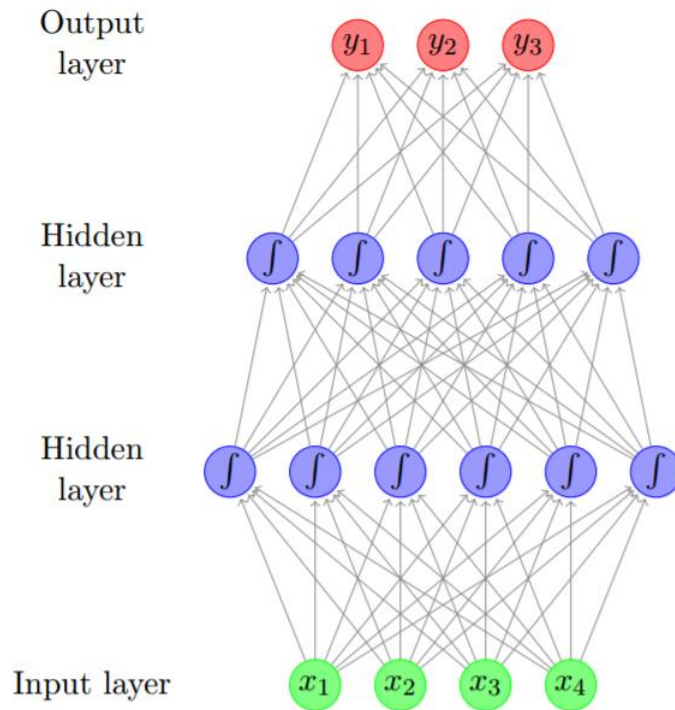


Figure 2: Feed-forward neural network with two hidden layers.

Figure from Goldberg (2015)



# Inference in a FF Neural Network

Perform computations forwards through the graph:

$$\mathbf{h}^1 = g^1(\mathbf{x}\mathbf{W}^1 + \mathbf{b}^1)$$

$$\mathbf{h}^2 = g^2(\mathbf{h}^1\mathbf{W}^2 + \mathbf{b}^2)$$

$$\mathbf{y} = \mathbf{h}^2\mathbf{W}^3$$

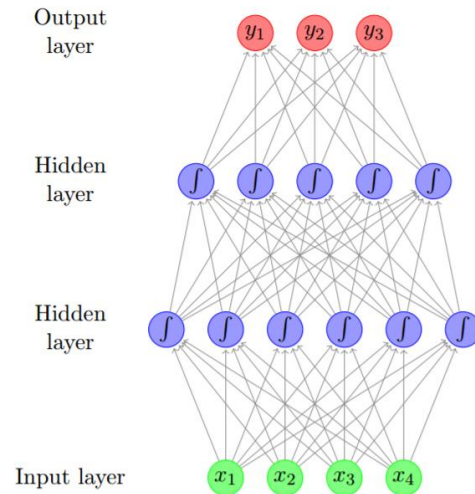


Figure 2: Feed-forward neural network with two hidden layers.


Note that we are now representing each layer as a vector; combining all of the weights in a layer across the units into a weight matrix

# Activation Function

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In one unit:

Linear combination of inputs and weight values → non-linearity

$$\mathbf{h}^1 = g^1(\mathbf{x}\mathbf{W}^1 + \mathbf{b}^1)$$


Popular choices:

Sigmoid function (just like logistic regression!)

tanh function

Rectifier/ramp function:  $g(x) = \max(0, x)$

Why do we need the non-linearity?

# Softmax Layer

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In NLP, we often care about discrete outcomes

- e.g., words, POS tags, topic label

Output layer can be constructed such that the output values sum to one:

$$\text{Let } \mathbf{x} = x_1 \dots x_k$$
$$\text{softmax}(x_i) = \frac{\exp(x_i)}{\sum_j^k \exp(x_j)}$$

**Interpretation:** unit  $x_i$  represents probability that outcome is  $i$ .

Essentially, the last layer is like a multinomial logistic regression

# Loss Function

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A neural network is optimized with respect to a **loss function**, which measures how much error it is making on predictions:

$\mathbf{y}$ : correct, gold-standard distribution over class labels

$\hat{\mathbf{y}}$ : system predicted distribution over class labels

$L(\mathbf{y}, \hat{\mathbf{y}})$ : loss function between the two

Popular choice for classification (usually with a softmax output layer) – **cross entropy**:

$$L_{ce}(\mathbf{y}, \hat{\mathbf{y}}) = - \sum_i y_i \log(\hat{y}_i)$$

# Training Neural Networks

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Typically done by **stochastic gradient descent**

- For one training example, find gradient of loss function wrt parameters of the network (i.e., the weights of each layer); “travel along in that direction”.

Network has very many parameters!

Efficient algorithm to compute the gradient with respect to all parameters: **backpropagation** (Rumelhart et al., 1986)

- Boils down to an efficient way to use the chain rule of derivatives to propagate the error signal from the loss function backwards through the network back to the inputs

# SGD Overview

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## Inputs:

- Function computed by neural network,  $f(\mathbf{x}; \theta)$
- Training samples  $\{\mathbf{x}^k, \mathbf{y}^k\}$
- Loss function  $L$

## Repeat for a while:

Sample a training case,  $\mathbf{x}^k, \mathbf{y}^k$

Compute loss  $L(f(\mathbf{x}^k; \theta), \mathbf{y}^k)$

Forward pass

Compute gradient  $\nabla L(\mathbf{x}^k)$  wrt the parameters  $\theta$

Update  $\theta \leftarrow \theta - \eta \nabla L(\mathbf{x}^k)$

By backpropagation

Return  $\theta$

# Example: Forward Pass

$$\mathbf{h}^1 = g^1(\mathbf{x}\mathbf{W}^1 + \mathbf{b}^1)$$

$$\mathbf{h}^2 = g^2(\mathbf{h}^1\mathbf{W}^2 + \mathbf{b}^2)$$

$$f(\mathbf{x}) = \mathbf{y} = g^3(\mathbf{h}^2) = \mathbf{h}^2\mathbf{W}^3$$

Loss function:  $L(\mathbf{y}, \mathbf{y}^{gold})$

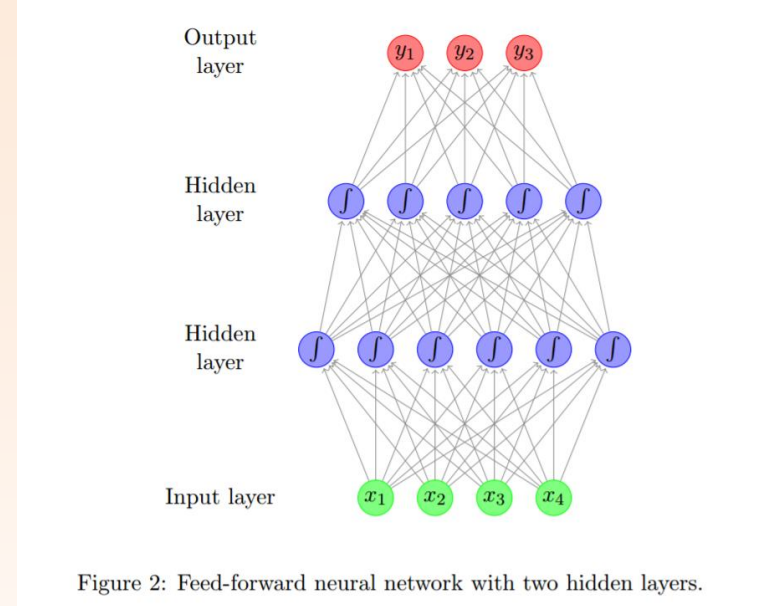


Figure 2: Feed-forward neural network with two hidden layers.

Save the values for  $\mathbf{h}^1, \mathbf{h}^2, \mathbf{y}$  too!

# Example Cont'd: Backpropagation

$$f(\mathbf{x}) = g^3(g^2(g^1(\mathbf{x})))$$

Need to compute:  $\frac{\partial L}{\partial \mathbf{W}^3}$ ,  $\frac{\partial L}{\partial \mathbf{W}^2}$ ,  $\frac{\partial L}{\partial \mathbf{W}^1}$

By calculus and chain rule:

- $\frac{\partial L}{\partial \mathbf{W}^3} = \frac{\partial L}{\partial g^3} \frac{\partial g^3}{\partial \mathbf{W}^3}$
- $\frac{\partial L}{\partial \mathbf{W}^2} = \frac{\partial L}{\partial g^3} \frac{\partial g^3}{\partial g^2} \frac{\partial g^2}{\partial \mathbf{W}^2}$
- $\frac{\partial L}{\partial \mathbf{W}^1} = \frac{\partial L}{\partial g^3} \frac{\partial g^3}{\partial g^2} \frac{\partial g^2}{\partial g^1} \frac{\partial g^1}{\partial \mathbf{W}^1}$

Notice the overlapping computations? Be sure to do this in a smart order to avoid redundant computations!



# Example: Time Delay Neural Network

Let's draw a neural network architecture for POS tagging using a feedforward neural network.

We'll construct a context window around each word, and predict the POS tag of that word as the output.

Limitations of this approach?

# Recurrent Neural Networks

A neural network **sequence model**:

$$RNN(\mathbf{s}_0, \mathbf{x}_{1:n}) = \mathbf{s}_{1:n}, \mathbf{y}_{1:n}$$

$$\mathbf{s}_i = R(\mathbf{s}_{i-1}, \mathbf{x}_i) \quad \# \mathbf{s}_i : \text{state vector}$$

$$\mathbf{y}_i = O(\mathbf{s}_i) \quad \# \mathbf{y}_i : \text{output vector}$$

$R$  and  $O$  are parts of the neural network that compute the next state vector and the output vector

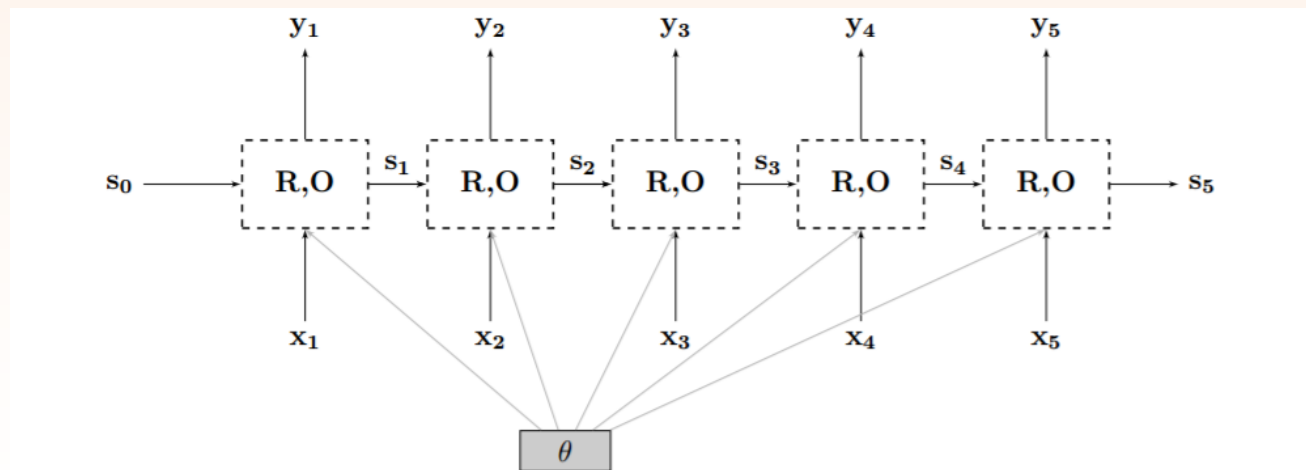


Figure 6: Graphical representation of an RNN (unrolled).

# Long-Term Dependencies in Language

There can be dependencies between words that are *arbitrarily* far apart.

- *I will look the word that you have described that doesn't make sense to her up.*
- Can you think of some other examples in English of long-range dependencies?

Cannot easily model with HMMs or even LC-CRFs, but can with RNNs

# Vanishing and Exploding Gradients

If  $R$  and  $O$  are simple fully connected layers, we have a problem. In the unrolled network, the gradient signal can get lost on its way back to the words far in the past:

- Suppose it is  $\mathbf{W}^1$  that we want to modify, and there are  $N$  layers between that and the loss function.

$$\frac{\partial L}{\partial \mathbf{W}^1} = \frac{\partial L}{\partial g^N} \frac{\partial g^N}{\partial g^{N-1}} \cdots \frac{\partial g^2}{\partial g^1} \frac{\partial g^1}{\partial \mathbf{W}^1}$$

- If the gradient norms are small ( $<1$ ), the gradient will vanish to near-zero (or explode to near-infinity if  $>1$ )
- This happens especially because we have repeated applications of the same weight matrices in the recurrence

# Long Short-Term Memory Networks

Currently one of the most popular RNN architectures for NLP (Hochreiter and Schmidhuber, 1997)

- Explicitly models a “memory” cell (i.e., a hidden-layer vector), and how it is updated as a response to the current input and the previous state of the memory cell.

Visual step-by-step explanation:

<http://colah.github.io/posts/2015-08-Understanding-LSTMs/>



# Hardware for NNs

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Common operations in inference and learning:

- Matrix multiplication
- Component-wise operations (e.g., activation functions)

This operation is **highly parallelizable!**

**Graphical processing units (GPUs)** are specifically designed to perform this type of computation efficiently



# Packages for Implementing NNs

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TensorFlow <https://www.tensorflow.org/>

PyTorch <http://pytorch.org/>

Caffe <http://caffe.berkeleyvision.org/>

Theano <http://deeplearning.net/software/theano/>

- These packages support GPU and CPU computations
- Write interface code in high-level programming language, like Python



# Summary: Advantages of NNs

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Learn relationships between inputs and outputs:

- Complex features and dependencies between inputs and states over long ranges with no fixed horizon assumption (i.e., **non-Markovian**)
- Reduces need for feature engineering
- More efficient use of input data via weight sharing

Highly flexible, generic architecture

- **Multi-task learning:** jointly train model that solves multiple tasks simultaneously
- **Transfer learning:** Take part of a neural network used for an initial task, use that as an initialization for a second, related task

# Summary: Challenges of NNs

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Complex models may need a lot of training data

Many fiddly hyperparameters to tune, little guidance on how to do so, except empirically or through experience:

- Learning rate, number of hidden units, number of hidden layers, how to connect units, non-linearity, loss function, how to sample data, training procedure, etc.

Can be difficult to interpret the output of a system

- *Why* did the model predict a certain label? Have to examine weights in the network.
- Important to convince people to act on the outputs of the model!

# NNs for NLP

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Neural networks have “taken over” mainstream NLP since 2014; most empirical work at recent conferences use them in some way

Lots of interesting open research questions:

- How to use linguistic structure (e.g., word senses, parses, other resources) with NNs, either as input or output?
- When is linguistic feature engineering a good idea, rather than just throwing more data with a simple representation for the NN to learn the features?
- Multitask and transfer learning for NLP
- Defining and solving new, challenging NLP tasks