# Deep Learning for NLP

## (without Magic)


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*with a big thank you to Yoshua Bengio, with whom we participated in the previous ACL 2012 version of this tutorial

Part 1.2: The Basics

# From logistic regression to neural nets

# Demystifying neural networks

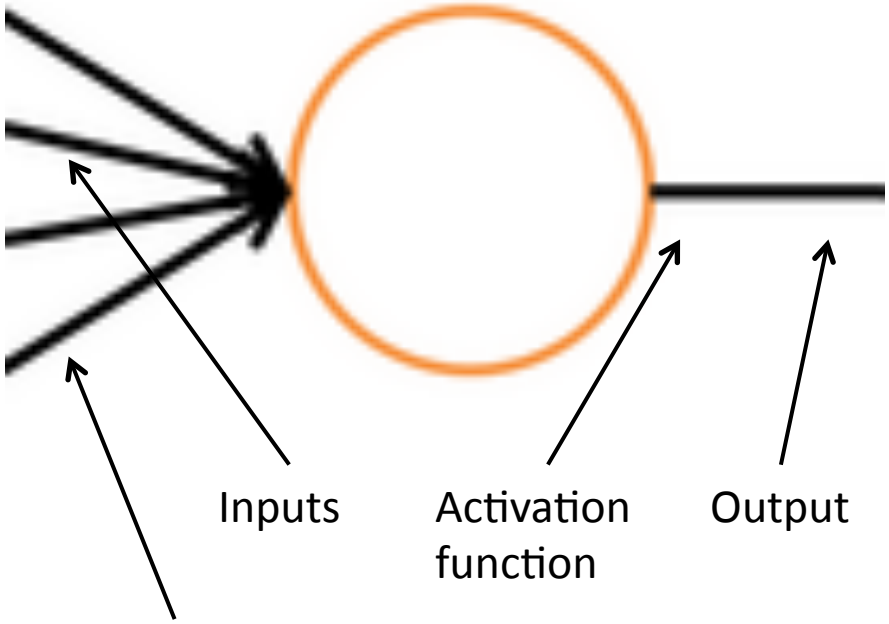
Neural networks come with their own terminological baggage

… just like SVMs

But if you understand how logistic regression or maxent models work

Then **you already understand** the operation of a basic neural network neuron!

**A single neuron**
A computational unit with *n* (3) inputs and 1 output and parameters *W, b*

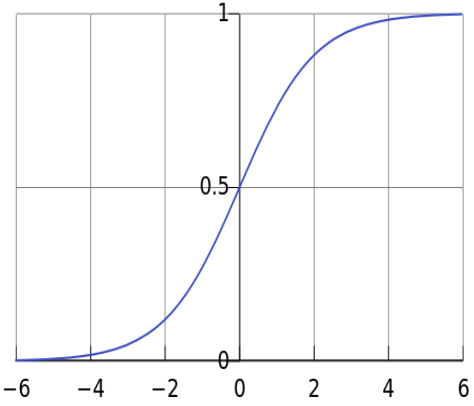


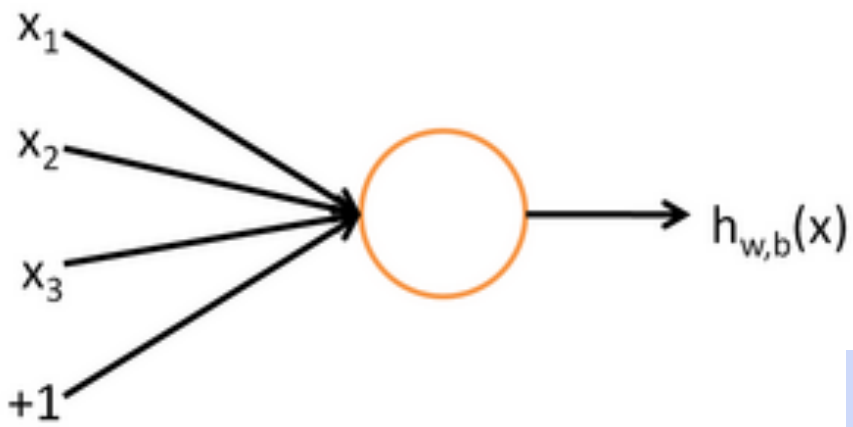
# This is exactly what a neuron computes

$$h_{w,b}(x) = f(w^{\mathsf{T}}x + b)$$

$$f(z) = \frac{1}{1+e^{-z}}$$

*b:* We can have an "always on" feature, which gives a class prior, or separate it out, as a bias term

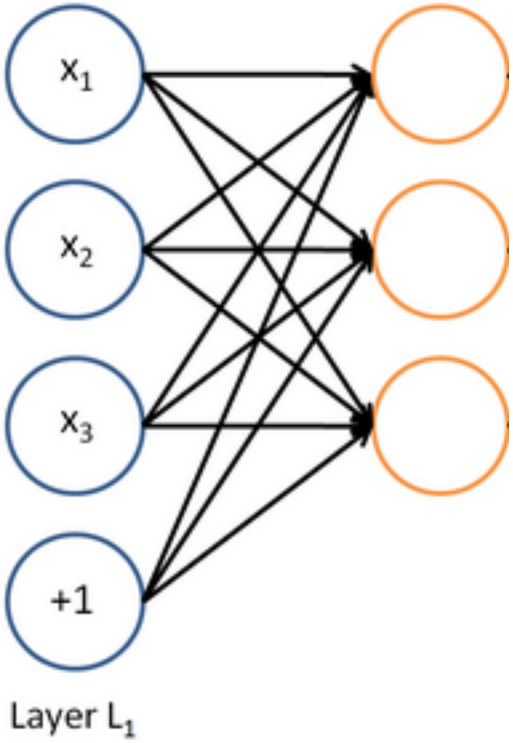



*w*, *b* are the parameters of this neuron i.e., this logistic regression model

# A neural network = running several logistic regressions at the same time

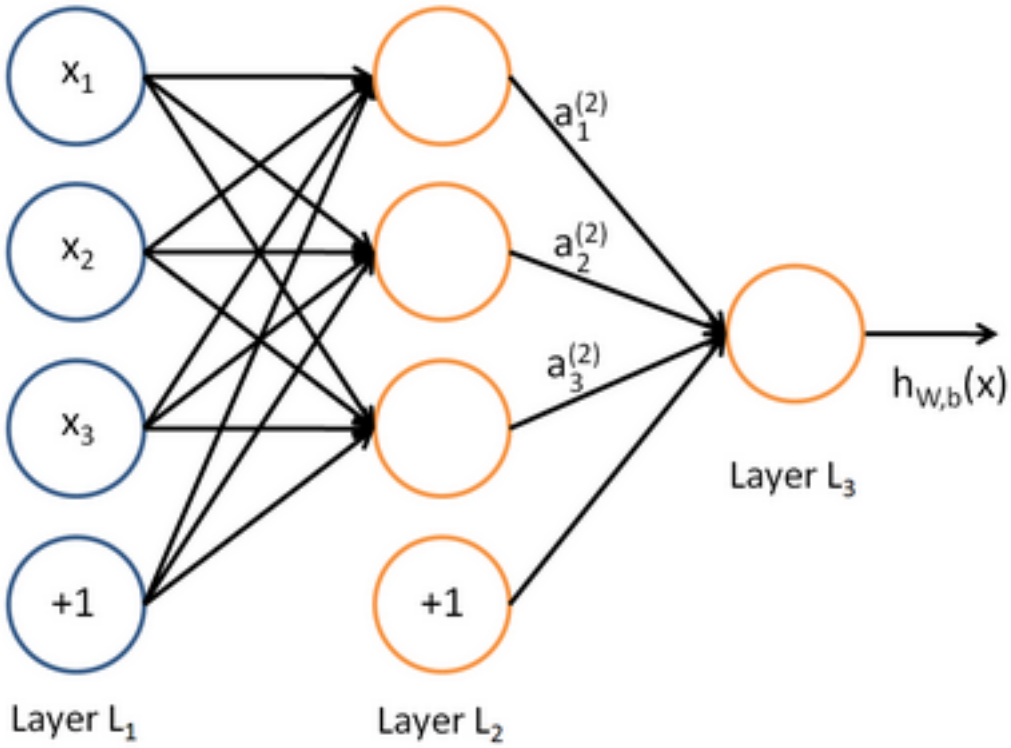
If we feed a vector of inputs through a bunch of logistic regression functions, then we get a vector of outputs …




*But we don't have to decide ahead of time what variables these logistic regressions are trying to predict!*

# A neural network = running several logistic regressions at the same time

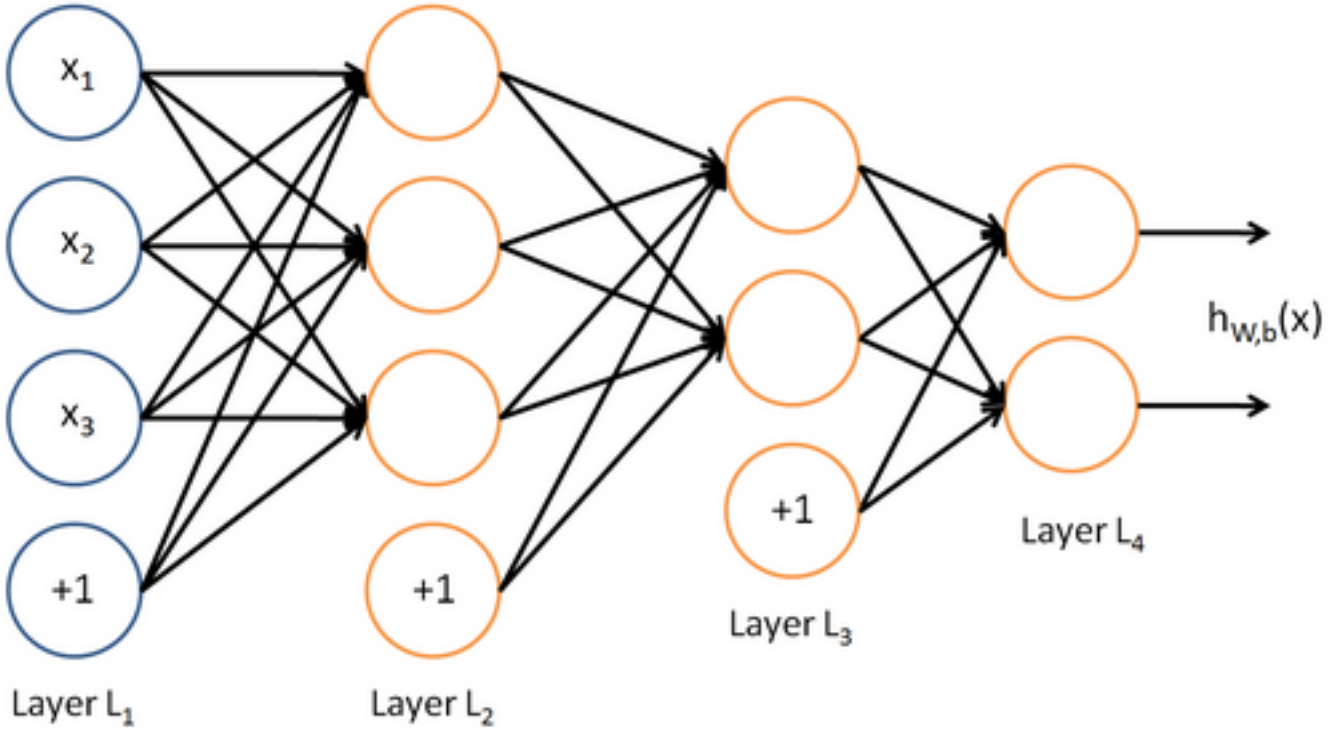
… which we can feed into another logistic regression function




*It is the training criterion that will direct what the intermediate hidden variables should be, so as to do a good job at predicting the targets for the next layer, etc.*

# A neural network = running several logistic regressions at the same time

Before we know it, we have a multilayer neural network….



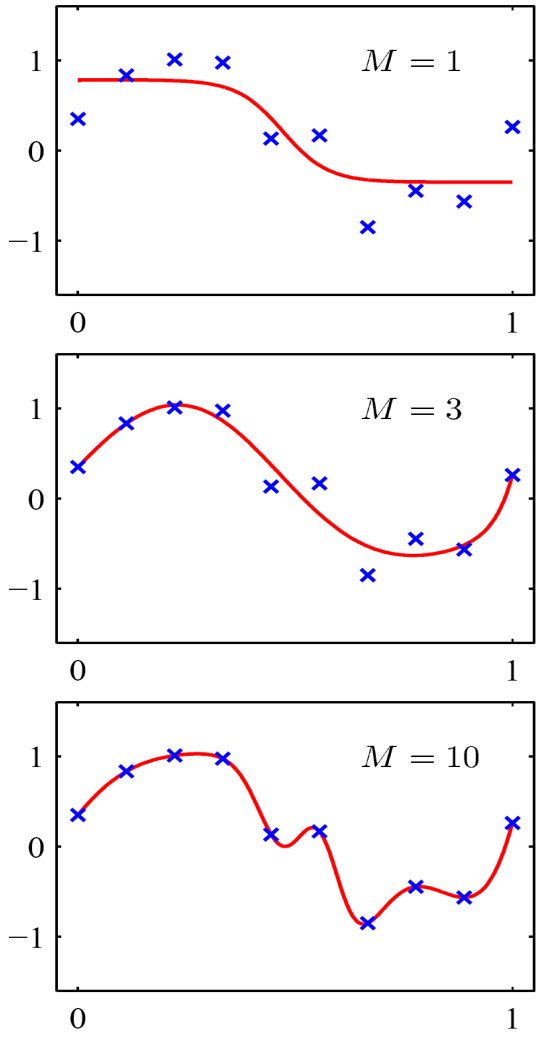
# How do we train the weights W?

- For a single supervised layer, we train just like a maxent model – we calculate and use error derivatives (gradients) to improve
  - Online learning: Stochastic gradient descent (SGD)
    - Or improved versions like AdaGrad (Duchi, Hazan, & Singer 2010)
  - Batch learning: Conjugate gradient or L-BFGS

- A multilayer net could be more complex because the internal ("hidden") logistic units make the function non-convex … just as for hidden CRFs [Quattoni et al. 2005, Gunawardana et al. 2005]
  - But we can use the same ideas and techniques
    - Just without guarantees …
  - We "backpropagate" error derivatives through the model

# Non-Linearities: Why they're needed

- For logistic regression: map to probabilities
- Here: function approximation,
  e.g., regression or classification
  - Without non-linearities, deep neural networks can't do anything more than a linear transform
    - Extra layers could just be compiled down into a single linear transform
  - Probabilistic interpretation unnecessary except in the Boltzmann machine/graphical models
    - People often use other non-linearities, such as **tanh**, as we'll discuss in part 3



# Summary
# Knowing the meaning of words!

You now understand the basics and the relation to other models

- Neuron = logistic regression or similar function
- Input layer = input training/test vector
- Bias unit = intercept term/always on feature
- Activation = response
- Activation function is a logistic (or similar "sigmoid" nonlinearity)
- Backpropagation = running stochastic gradient descent backward layer-by-layer in a multilayer network
- Weight decay = regularization / Bayesian prior