Prof. Alexander Huth 3.31.2020

COURSE ADMIN / ZOOM

- * Welcome to the new zoom era
- * If you're watching this, you've found the lecture links posted on Canvas
- * This (and future) lectures will be **recorded** and shared with the class via Canvas
 - * If you don't want your face recorded, please disable your video!
 - * Please don't share the recordings outside of class!
- * And please don't share the zoom link outside of class!

COURSE ADMIN / ZOOM

- * Current plan for zoom etiquette:
 - * Please keep yourselves muted except when you are actively speaking
 - * If you want to ask a question, use the "Raise hand" button and I'll call on you
 - * If I miss your raised hand (apologies in advance), toggle it a few times, or just un-mute yourself and ask
 - * I probably won't be able to keep track of chat messages while lecturing & screen-sharing, so please avoid using the chat feature

COURSE ADMIN / ZOOM

- * Office hours will also happen on zoom, Tuesdays & Wednesdays, 10:30am-12:00pm
- * I'll start a zoom meeting & post the link on canvas around when my office hours start

COURSE ADMIN / HW

- * Homework 1 is not graded yet, but will hopefully be returned to you in ~1 week
- * Homework 2 covers linearized model comparison and variance partitioning. It is posted today & will be due in 2 weeks (April 14)

- * Goal is to apply or explore something / anything we've talked about in this class
 - * could be using real data (e.g. fit some kind of model to a neural dataset)
 - * could be theory/methods (e.g. find a better way to do something)

- * Since there are so many people in this class, I will require you to work on your projects in groups of 2-4
- * If you can't find a group, please contact me or come to office hours to discuss

- * Proposal due next Thursday (April 9):
 - * ~1-2 paragraphs describing what you plan to do & who is in your group. Email to huth@cs.utexas.edu before class
- * Writeup (3-4 pages explaining background & what you did) due May 5
- * In-class presentations (5-10 minutes)
 May 5 & 7

- * Presentations should be live (zoom) and include slides describing the background, your method/approach, and results
- * It is essential that every person in your group participates in both the project work and the presentation

- * Sources of neural data (among many more):
 - * CRCNS: https://crcns.org/data-sets
 - * Allen Inst.: http://www.brain-map.org
 - * Study Forrest: http://studyforrest.org/

COURSE ADMIN / ?

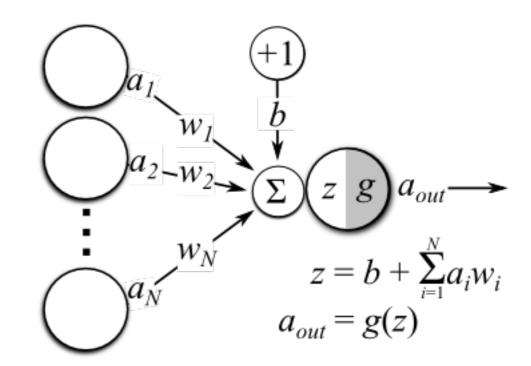
* Any further questions about any of these administrative things?

RECAP: NONLINEAR METHODS

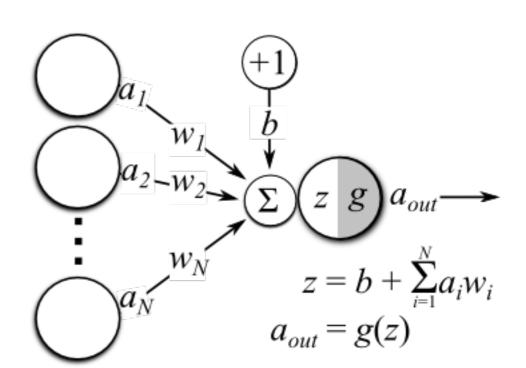
- * Volterra series
- * Kernel regression (samples, not features!)
- * Artificial neural network (1 hidden layer)

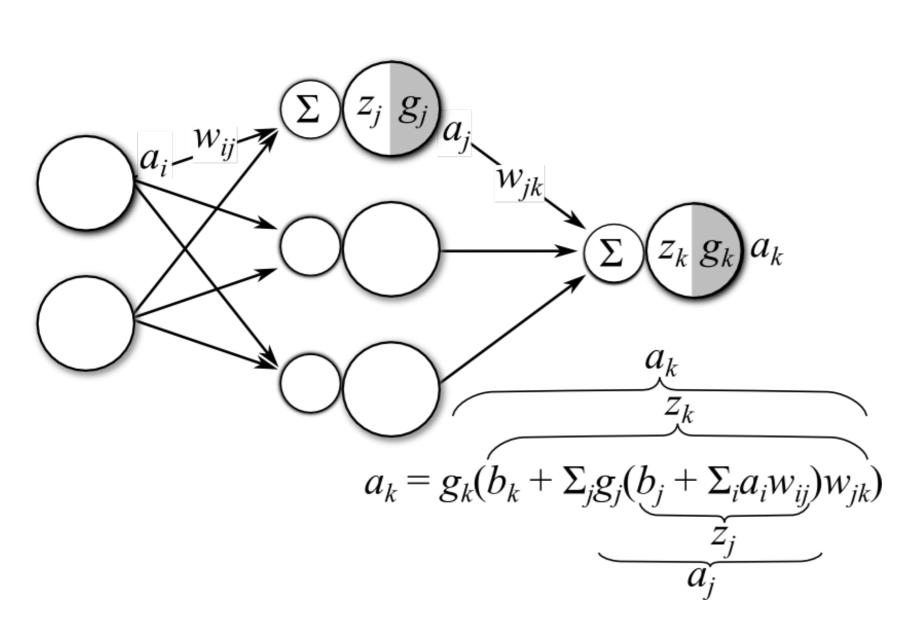
- * We previously talked about Perceptrons, simple 1-layer networks with a stepfunction output nonlinearity
- * We looked at the Perceptron learning rule, which can be used to iteratively learn weights

- * Generic 1-layer neural "network"
- * g(z) is the output nonlinearity
- * Update rule? Just
 differentiate the loss
 function! (As long as
 g(z) is differentiable)



- * Problem: this network is not much more "expressive" than the Perceptron
 - * It still can't XOR
- * Solution: stack it! add a "hidden layer"





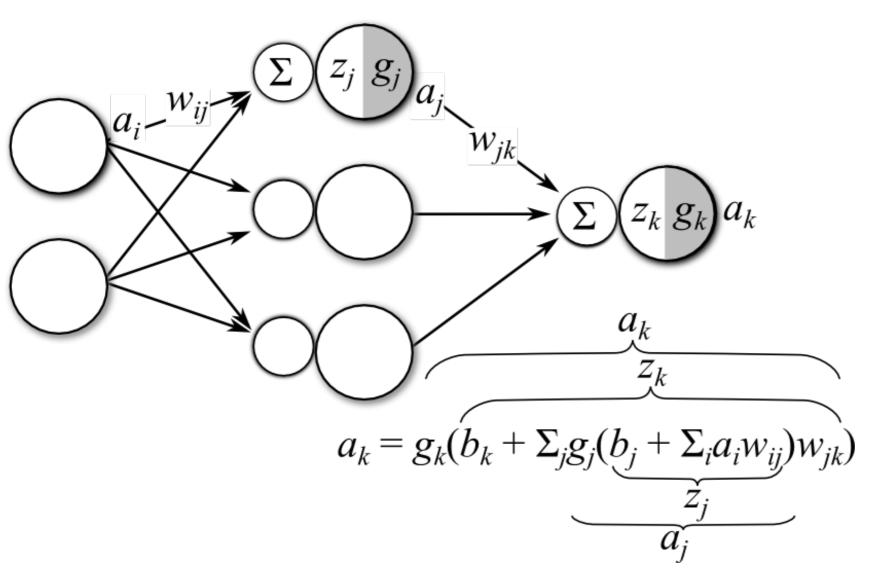
w = weights

a = activations

z = total input

g = activ. fxn

b = bias

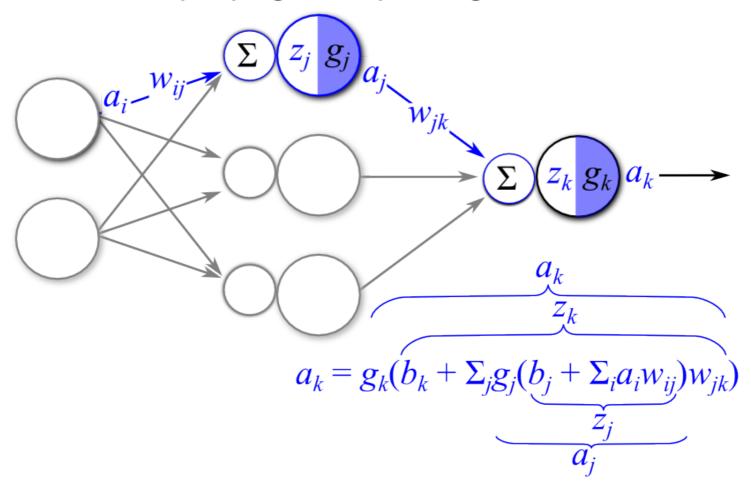


* How do we
 train this
 beast?

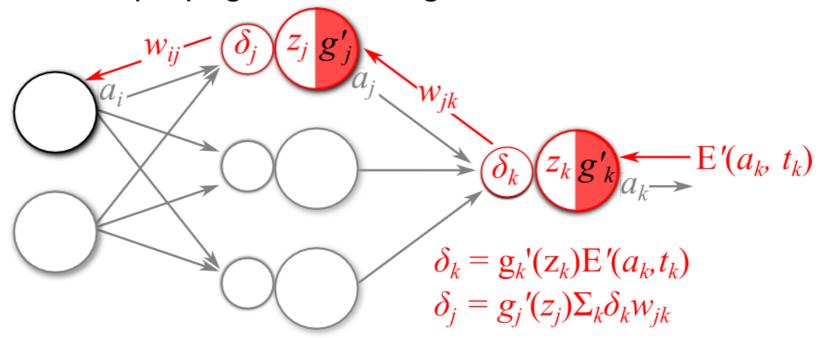
* Differentiate the loss function, same as ever!

* (Derivation of backpropagation)

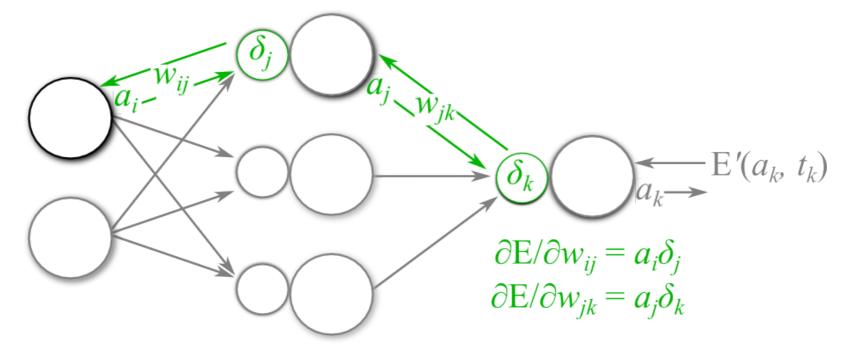
I. Forward-propagate Input Signal



II. Back-propagate Error Signals



III. Calculate Parameter Gradients



IV. Update Parameters

$$w_{ij} = w_{ij} - \eta(\partial E/\partial w_{ij})$$

 $w_{jk} = w_{jk} - \eta(\partial E/\partial w_{jk})$
for learning rate η

- * Backprop enables **efficient** computation of gradients in networks of **arbitrary depth** by caching intermediate values δ
- * It has probably been discovered in some form a few times in different fields
- * In this field we often credit Rumelhart, Hinton, & Williams (1986)

- * What can networks with hidden layers do?
- * Universal approximation theorem: These networks can do *literally anything* (as long as there is a non-polynomial output nonlinearity)
 - * See Cybenko (1989) paper attached to this lecture for proof

- * But: it is not necessarily true that every function is *learnable* using backprop
- * Different network architectures (e.g. different numbers of hidden layers & units per layer) are good at learning different functions

NEXT TIME

* Artificial neural networks for solving vision problems (e.g. categorization)