

ECS 189

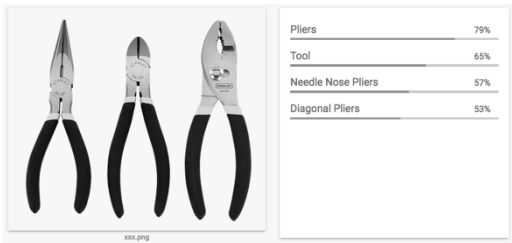
WEB PROGRAMMING

6/5

Exams

- If you are satisfied with your scores on the two midterms, you can skip the final
- As soon as your Photobooth and midterm are graded, I can give you your course grade (so far) so you can decide
- The material in this lecture will not be on the final. It covers the “interesting part” of our project.

Cloud Vision API – the magic

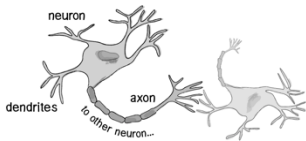


Pliers	79%
Tool	65%
Needle Nose Pliers	57%
Diagonal Pliers	53%

How does it work?

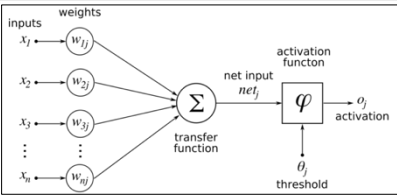
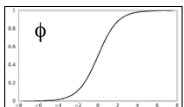
- Sadly, it really is magic...or at least not well understood!
- But we have a word for it...Convolutional Neural Networks!
- References:
 - “Computer eyesight gets a lot more accurate”, NY Times
 - Stanford CS 231n
 - Christopher Olah’s blog
- Take ECS 174!

Neural Networks



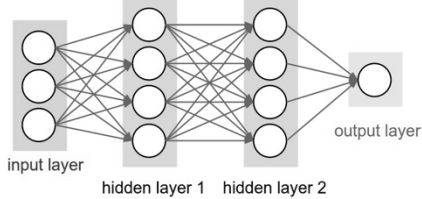
- Program based on metaphor of how brains work
- Highly interconnected collection of neurons
- Input comes in on dendrites
- When input is “enough”, neuron “fires” and sends signal through axon to other neurons

Artificial Neuron

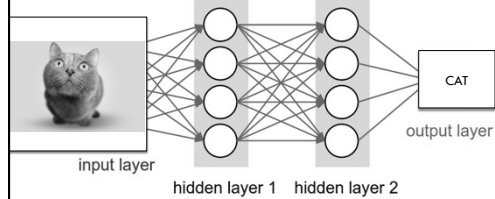
- Possibly many inputs
- Weights
- Continuous ϕ function

Neural Network



- Much bigger; billions of connections
- Different configurations
- "Deep learning" -> many layers

Image Labeling

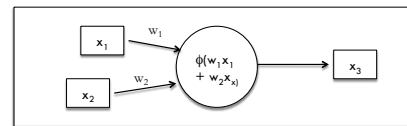


- Input is image pixels
- Output is words

Training

- Large training set of image-label pairs
- Start with random weights
- For each training image:
 - ▣ Adjust weights at every node to move the activation of the training label up and the other labels down
 - ▣ Do this over and over again until cycling through the whole training set does not change the weights any more
 - ▣ This takes a long, long time

Weight adjustment – the chain rule!

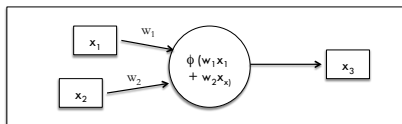


○ = output of whole network

$$dO/dw_1 = dx_3/dw_1 \cdot dO/dx_3$$

$$dO/dx_1 = dx_3/dx_1 \cdot dO/dx_3$$

Weight adjustment – the chain rule!



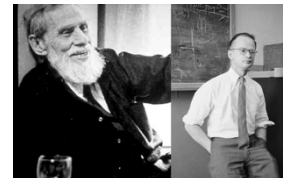
○ = output of whole network

$$dO/dw_1 = dx_3/dw_1 \cdot dO/dx_3$$

$$dO/dx_1 = dx_3/dx_1 \cdot dO/dx_3$$

Start at the output end, work your way back taking derivatives – **back propagation**

Old idea



- McCulloch and Pitts, seminal paper, 1943
- Rosenblatt, weights contain memory, 1958
- Minsky and Pappert, critique, 1969
- Rumelhart, Hinton and Willams, backprop, 1986

So why is it a big thing now?

- Computational power – we can get really big networks to converge
 - Use GPUs
 - Do it at Google in a massive distributed parallel environment (Tensorflow)

So why is it a big thing now?

- Computational power – we can get really big networks to converge
- Big data! We have enough training data to get really big networks to converge

So why is it a big thing now?

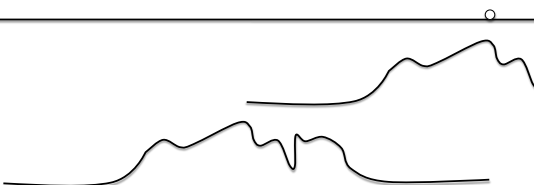
- Computational power – we can get really big networks to converge
- Big data! We have enough training data to get really big networks to converge
- Better organization of networks
 - Convolutional neural network

Convolution



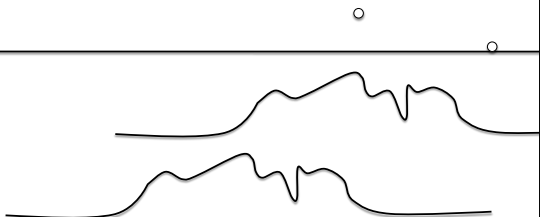
- Convolution is the mathematical operation for pattern matching
- Say we wanted to find a face in a 1D signal

Convolution



- Use a face-shaped pattern. Multiply pattern by face at every point to get a score for pattern position.

Convolution



- Use a face-shaped pattern. Multiply pattern by face at every point to get a score for pattern position.

Convolution

- Best score a position where pattern and signal match the best!

Convolution

- Best score a position where pattern and signal match the best!

Convolution of original image

- Weights get multiplied by input x . So we will get strong signals (o_j) if weights form a pattern that matches part of the image (eg. kitty eyes)

Patterns for images

- Feed all small sub-images to a neuron, and hope we optimize weights so it makes an interesting max.
- Create hundreds or thousands of pattern neurons, optimize each over all possible positions, look for peak outputs

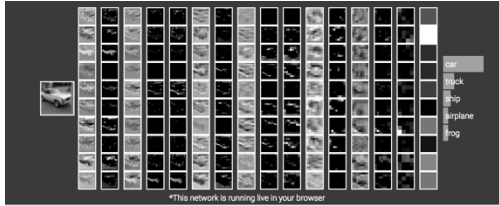
Convolutional Neural Network

- Image as input
- Convolution consider features of small areas
- Pooling layers select the strongest features
- Fully connected layers connect features to outputs

Automatically generated features

- Two sets of convolution features trained on two different GPUs, feeding into the same fully connected layer
- One side looks for dark-to-light, edges, gradients, the other works on color and texture

Recognition in the browser



- Training is slow but recognition is pretty fast (we are seeing seconds, including the round-trip to Google)

Big data for image labeling

- ImageNET training data
- Li Fei-Fei (Stanford) and Kai Li (Princeton)
 - A category for every English noun
 - Over a billion images
 - Massive data collection using Mechanical Turk over several years
 - Key factor that has enabled us to train CNNs for this task

Other big Deep NN applications

- Speech recognition
- Machine translation
 - "The great AI awakening" – NY Times
- Text understanding and question answering (grammar, meaning)