ML Week

0x07b Artificial Neural Networks

Jeff Abrahamson

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Roughly, wtf is Deep Learning?

- Machine learning
- Model high-level abstraction by using multiple non-linear transformations.

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- Machine learning
- Model high-level abstraction by using multiple non-linear transformations.
- Example: Image:

pixels $\Rightarrow$ edges $\Rightarrow$ shapes $\Rightarrow$ faces.

Review

Broadly, ML comes in three flavors:

- Supervised learning: Predict output given input
- Reinforcement learning: Select action to maximize payoff
- Unsupervised learning: Discover a good internal representation of input

Review

Supervised learning comes in two flavors:

- Regression: real-valued output
- Classification: labeled output

Review

The idea behind supervised learning is often written thus:

$$y = f(x, W)$$

Review

The idea behind supervised learning is often written thus:

$$y = f(x, W)$$

where

$$y = \text{predicted output}$$

$$x = \text{input}$$

$$W = \text{parameters}$$

and our goal is to adjust parameters to minimize loss (error)

Labels are expensive

Review

Unsupervised learning

- Historically, it's clustering
- Now we can do more

Review

Unsupervised learning

- Historically, it's clustering
- Now we can do more
- Create an internal representation of the input that is useful for later supervised or reinforcement learning
- Find a compact, low-dimensional representation of the input

Some architectures

- Deep neural networks
- Convolutional deep neural networks
- Deep belief networks

Some successful applications

- Computer vision (CV)
- Speech recognition (ASR)
- Natural language processing (NLP)
- Music and audio recognition

Some famous data sets

- TIMIT (ASR)
- MNIST (image classification)
- ImageNet

Some successful hardware

- GPU's
- Data centers

Luiz André Barroso and Urs Hölzle, The Datacenter as a Computer: An Introduction to the Design of Warehouse-Scale Machines, 2009.

GPU's

http://petewarden.com/2014/06/09/deep-learning-on-the-raspberry-pi/

What is Hello World for GPU's?

Some things to look at. (Disclaimer: I haven't.)

- CUDA (but only nvidia)
  `www.nvidia.com/object/cuda_home_new.html`
- OpenCL (originally Apple)
  `https://en.wikipedia.org/wiki/OpenCL`
- GPU++ / GPGPU `http://gpgpu.org/`
- libSh `http://libsh.org/`
- OpenACC `http://www.openacc-standard.org/`

Data Centers

https://www.google.com/about/datacenters/

Why ML at all?

- We don't know how *we* do it
- Write programs to write programs

Brains (yum!)

- Neurons, synapses, chemistry
- Special kind of parallelism
- Power (but we're not there yet)

A brief tour of some neurons

Linear neuron

$$y = b + \sum_i x_i w_i$$

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$$\begin{aligned} y &= \text{output} \\ b &= \text{bias} \\ x_i &= i^{\text{th}} \text{ input} \\ w_i &= \text{weight on } i^{\text{th}} \text{ input} \end{aligned}$$

Linear neuron

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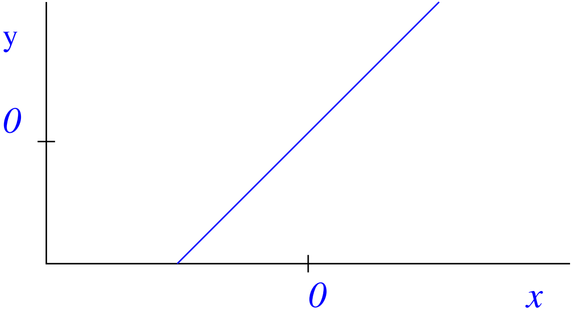

Binary threshold neuron

$$z = \sum_i x_i w_i$$

$$y = \begin{cases} 1 \text{ if } z \geqslant 0 \\ 0 \text{ otherwise} \end{cases}$$

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W. McCulloch and W. Pitts, A logical calculus of the ideas immanent in nervous activity. Bulletin of Mathematical Biophysics, 7:115–133, 1943.

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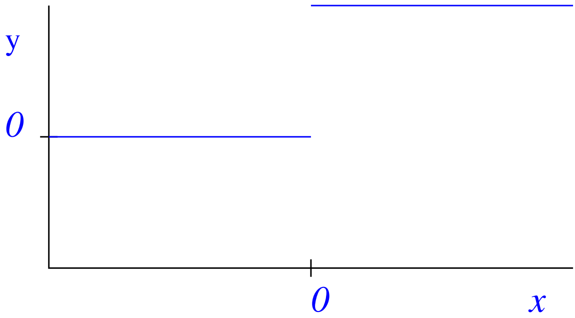

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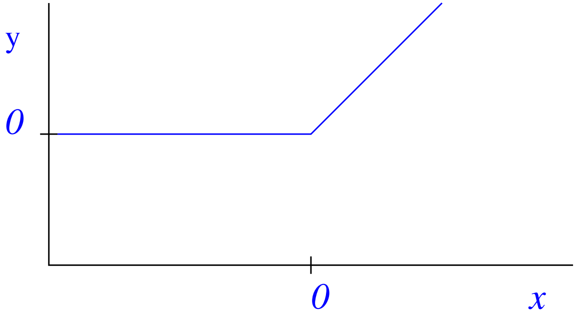

Sigmoid neuron

$$z = b + \sum_i x_i w_i$$

$$y = \frac{1}{1 + e^{-z}}$$

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(It's differentiable!)

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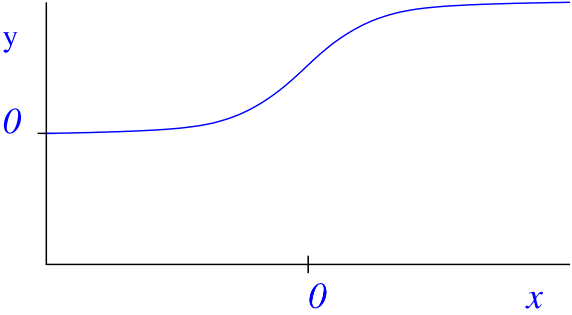

Stochastic binary neuron

$$z = b + \sum_i x_i w_i$$

$$p = \frac{1}{1 + e^{-z}}$$

$$y = \begin{cases} 1 \text{ with probability } p \\ 0 \text{ with probability } 1 - p \end{cases}$$

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(a probability distribution)

Stochastic binary neuron

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Can also do something similar with rectified linear neurons, produce spikes with probability p with a Poisson distribution.

A (too) quick example

Example: handwriting recognition of digits

- Input neurons: pixels
- Output neurons: classes (digits)
- Connect them all! *(bipartite)*

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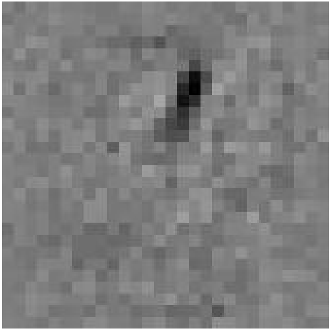

Example: handwriting recognition of digits

To train this ANN:

- Increment weights from active pixels going to correct class
- Decrement weights from active pixels going to predicted class

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When it's right, nothing happens. This is good.

Some notes on architectures

Architectures

It’s about how we connect the neurons.

Feedforward neural networks

- Input comes into input neurons
- Flow is unidirectional
- No loops
- Output at output neurons

Recurrent neural networks

- Cycles
- Memory
- Oscillations
- More powerful
- Hard to train (research interest)
- More biologically realistic

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Deep RNN is just a special case of a general recurrent NN with some hidden links missing.

Backpropagation

- Backward propagation of errors
- To calculate loss function, need a known, desired output for each input
- Gradient descent
- Calculate gradient of loss function w.r.t. all weights and minimize loss function

Layers

- Each layer computes a representation of its input
- Can change similarity

Layers

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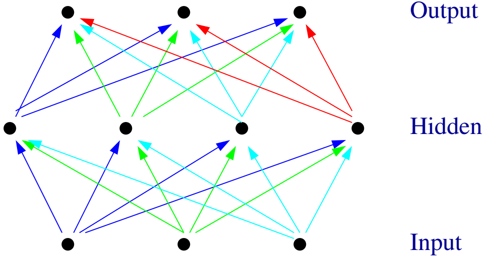
- Can change similarity
- Example:
  - (different speakers, same word) should become more similar
  - (same speaker, different words) should become more dissimilar

Layers

- If more than two hidden layers, then we call it deep
- Neuron activity at each layer must be a non-linear function of previous layer



Some inspirations

- Biology: David H. Hubel and Torsten Wiesel (1959) found two types of cells in the visual primary cortex: simple and complex.
- Cascading models

M Riesenhuber, T Poggio. Hierarchical models of object recognition in cortex. Nature neuroscience, 1999(11) 1019–1025.

History

- ANN's exist pre-1980. Backpropagation since 1974.

P. Werbos., "Beyond Regression: New Tools for Prediction and Analysis in the Behavioral Sciences," PhD thesis, Harvard University, 1974.

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- Neocognitron (Kunihiko Fukushima, 1980), partially unsupervised

K. Fukushima., "Neocognitron: A self-organizing neural network model for a mechanism of pattern recognition unaffected by shift in position," Biol. Cybern., 36, 193–202, 1980.

History

- ANN's exist pre-1980. Backpropagation since 1974.
- Neocognitron (Kunihiko Fukushima, 1980), partially unsupervised
- Yann LeCun et al. recognize handwritten postal codes (backpropagation)

LeCun et al., "Backpropagation Applied to Handwritten Zip Code Recognition," Neural Computation, 1, pp. 541–551, 1989.

History

Aside: statistical pattern recognition looks like this:

1. Convert raw input vector into a vector of feature activations (hand-written)
2. Learn weights on feature activation to get single scalar quantity
3. If scalar quantity exceeds some threshold, then decide that input vector is an example of the target

Perceptron

- Perceptron is an example of SPR for image recognition
- Initially very promising

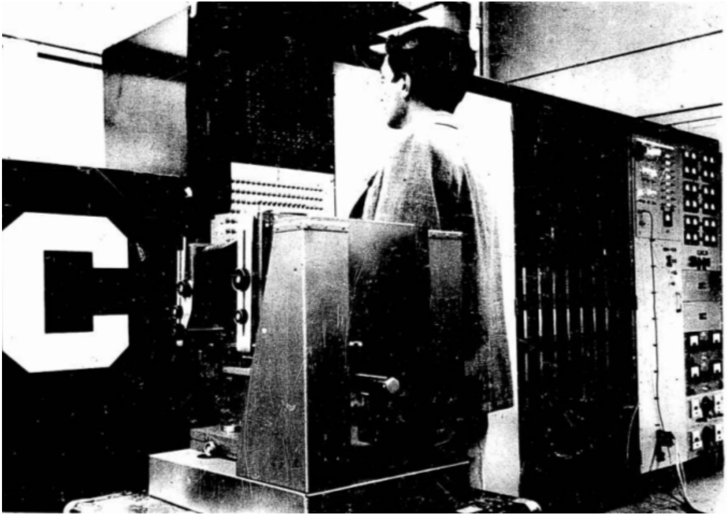
Frank Rosenblatt, The Perceptron: A Probabilistic Model for Information Storage and Organization in the Brain, Cornell Aeronautical Laboratory, Psychological Review, v65, No. 6, pp. 386—408, 1958. doi:10.1037/h0042519

Perceptron

- Perceptron is an example of SPR for image recognition
- Initially very promising
- IBM 704 (software implementation of algorithm)
- Mark 1 Perceptron at the Smithsonian Institution
- 400 photocells randomly connected to neurons.
- Weights encoded in potentiometers, updated during learning by electric motors

Frank Rosenblatt, The Perceptron: A Probabilistic Model for Information Storage and Organization in the Brain, Cornell Aeronautical Laboratory, Psychological Review, v65, No. 6, pp. 386—408, 1958. doi:10.1037/h0042519

Mark 1 Perceptron



Frank Rosenblatt, Principles of Neurodynamics: Perceptrons and the Theory of Brain Mechanisms, Report No. 1196-G-8, 15 March 1961, Cornell Aeronautical Laboratory

Perceptron

- Minksy and Papert showed perceptrons are incapable of recognizing certain classes of images
- AI community mistakenly over-generalized to all NN's
- So NN research stagnated for some time

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- Single layer perceptrons only recognize linearly separable input
- Hidden layers overcome this problem

M. L. Minsky and S. A. Papert, Perceptrons. Cambridge, MA: MIT Press. 1969.

Paradise glimpsed, paradise lost

- ANN's were slow.
- Vanishing gradient problem (Sepp Hochreiter)
- Support vector machines (SVN) were faster

S. Hochreiter., "Untersuchungen zu dynamischen neuronalen Netzen," Diploma thesis. Institut f. Informatik, Technische Univ. Munich. Advisor: J. Schmidhuber, 1991.

S. Hochreiter et al., "Gradient flow in recurrent nets: the difficulty of learning long-term dependencies," In S. C. Kremer and J. F. Kolen, editors, A Field Guide to Dynamical Recurrent Neural Networks. IEEE Press, 2001.

Some progress

Multi-level hierarchy of networks (pre-train by level, unsupervised, backpropagation) (1992)

J. Schmidhuber., "Learning complex, extended sequences using the principle of history compression," Neural Computation, 4, pp. 234–242, 1992.

Some progress

Long short term memory network (LSTM) (1997)

Hochreiter, Sepp; and Schmidhuber, Jürgen; Long Short-Term Memory, Neural Computation, 9(8):1735–1780, 1997.

Some progress

Deep multidimensional LSTM networks win three ICDAR competitions in handwriting recognition without prior language knowledge (2009)

Graves, Alex; and Schmidhuber, Jürgen; Offline Handwriting Recognition with Multidimensional Recurrent Neural Networks, in Bengio, Yoshua; Schuurmans, Dale; Lafferty, John; Williams, Chris K. I.; and Culotta, Aron (eds.), Advances in Neural Information Processing Systems 22 (NIPS'22), December 7th–10th, 2009, Vancouver, BC, Neural Information Processing Systems (NIPS) Foundation, 2009, pp. 545–552.

A. Graves, M. Liwicki, S. Fernandez, R. Bertolami, H. Bunke, J. Schmidhuber. A Novel Connectionist System for Improved Unconstrained Handwriting Recognition. IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 31, no. 5, 2009.

Some progress

Use sign of gradient (Rprop) for image reconstruction and face localization (2003)

Sven Behnke (2003). Hierarchical Neural Networks for Image Interpretation.. Lecture Notes in Computer Science 2766. Springer.

And then there was Hinton

- Geoffrey Hinton and Ruslan Salakhutdinov
- Train many-layered feedforward NN's one layer at a time
- Treat layers as unsupervised restricted Boltzmann machines (Smolensky, 1986)
- Use supervised backprogagation for label classification
- Also: Schmidhuber and recurrent NN's

And then there was Hinton (bibliography)

G. E. Hinton., "Learning multiple layers of representation," Trends in Cognitive Sciences, 11, pp. 428–434, 2007.

J. Schmidhuber., "Learning complex, extended sequences using the principle of history compression," Neural Computation, 4, pp. 234–242, 1992.

J. Schmidhuber., "My First Deep Learning System of 1991 + Deep Learning Timeline 1962–2013."

Smolensky, P. (1986). "Information processing in dynamical systems: Foundations of harmony theory.". In D. E. Rumelhart, J. L. McClelland, and the PDP Research Group, Parallel Distributed Processing: Explorations in the Microstructure of Cognition. 1. pp. 194–281.

And then there was Hinton (bibliography)

Hinton, G. E.; Osindero, S.; Teh, Y. (2006). "A fast learning algorithm for deep belief nets". Neural Computation 18 (7): 1527–1554. doi:10.1162/neco.2006.18.7.1527. PMID 16764513.

Hinton, G. (2009). "Deep belief networks". Scholarpedia 4 (5): 5947. doi:10.4249/scholarpedia.5947. edit

Yet more progress

Google Brain project (Andrew Ng, Jeff Dean) recognized cats in youtube videos.

Ng, Andrew; Dean, Jeff (2012). “Building High-level Features Using Large Scale Unsupervised Learning”.

John Markoff (25 June 2012). “How Many Computers to Identify a Cat? 16,000.”, New York Times.

More progress

Brute force!

Dan Ciresan et al. (IDSIA, 2010) use lots of GPU's to bulldoze the vanishing gradient problem and outperform LeCun (and everyone else) on MNIST.

D. C. Ciresan et al., "Deep Big Simple Neural Nets for Handwritten Digit Recognition," Neural Computation, 22, pp. 3207–3220, 2010.

State of the art, 2011

Deep learning feedforward networks

- Convolutional layers
- Max-pooling layers
- Plus pure classification layers

D. C. Ciresan, U. Meier, J. Masci, L. M. Gambardella, J. Schmidhuber. Flexible, High Performance Convolutional Neural Networks for Image Classification. International Joint Conference on Artificial Intelligence (IJCAI-2011, Barcelona), 2011.

Martines, H., Bengio, Y., and Yannakakis, G. N. (2013). Learning Deep Physiological Models of Affect. I EEE Computational Intelligence, 8(2), 20.

State of the art, post-2011

Lots of GPU's. Sometimes human-competitive performance!

- IJCNN 2011 Traffic Sign Recognition Competition
- ISBI 2012 Segmentation of neuronal structiosn in EM stacks challenge
- and more

State of the art, post-2011

D. C. Ciresan, U. Meier, J. Masci, L. M. Gambardella, J. Schmidhuber. Flexible, High Performance Convolutional Neural Networks for Image Classification. International Joint Conference on Artificial Intelligence (IJCAI-2011, Barcelona), 2011

D. C. Ciresan, U. Meier, J. Masci, J. Schmidhuber. Multi-Column Deep Neural Network for Traffic Sign Classification. Neural Networks, 2012.

D. Ciresan, A. Giusti, L. Gambardella, J. Schmidhuber. Deep Neural Networks Segment Neuronal Membranes in Electron Microscopy Images. In Advances in Neural Information Processing Systems (NIPS 2012), Lake Tahoe, 2012.

D. C. Ciresan, U. Meier, J. Schmidhuber. Multi-column Deep Neural Networks for Image Classification. IEEE Conf. on Computer Vision and Pattern Recognition CVPR 2012.

Basic ideas

- Distributed representations: observed data is organized at multiple levels of abstraction or composition
- Higher level concepts learned from lower level concepts (hierarchical explanatory factors)
- Often can frame problems as unsupervised. (Labeling is expensive.)

Y. Bengio, A. Courville, and P. Vincent., "Representation Learning: A Review and New Perspectives," IEEE Trans. PAMI, special issue Learning Deep Architectures, 2013.

Basic ideas

- Unsupervised $\Rightarrow$ unlabeled data is ok
- Often greedy between layers

Basic ideas

- Science advances in fits and starts
- Sometimes dead-ends just take time
- We still can't recognize cats at 100W powered by bananas

Questions?

`purple.com/talk-feedback`