Subsymbolic learning. Neural nets

Deep Learning Revolution

- Recent machine learning methods for training "deep" neural networks (NNs) have demonstrated remarkable progress on many challenging AI problems (e.g. speech recognition, visual object recognition, machine translation, game playing).
- However, their capabilities are prone to "hype."
- Deep learning has not "solved" AI and current methods have clear limitations.

Very Brief History of Machine Learning

- Single-layer neural networks (1957-1969)
- Symbolic AI & knowledge engineering (1970-1985)
- Multi-layer NNs and symbolic learning (1985-1995)
- Statistical (Bayesian) learning and kernel methods (1995-2010)
- Deep learning (CNNs and RNNs) (2010-?)

Single-Layer Neural Network (Linear Threshold Unit)

• Mathematical model of an individual neuron.



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Inputs

Perceptron

- Rosenblatt (1957) developed an iterative, hill-climbing algorithm for learning the weights of single-layer NN to try to fit a set of training examples.
- Unable to learn or represent many classification functions (e.g. XOR), only the "linearly separable" ones are learnable.

Perceptron Learning Rule

• Update weights by:

 $w_i = w_i + \eta (t - o) x_i$

where η is the "learning rate," *t* is the teacher output, and *o* is the network output.

- Equivalent to rules:
 - If output is correct do nothing.
 - If output is high, lower weights on active inputs
 - If output is low, increase weights on active inputs

Perceptron Learning Algorithm

• Iteratively update weights until convergence.

Initialize weights to random values Until outputs of all training examples are correct For each training pair, E, do: Compute current output o for E given its inputs Compare current output to target value, $t_{,}$ for EUpdate weights using learning rule

Perceptron Demise

- *Perceptons* (1969) by Minsky and Papert illuminated the limitations of the perceptron.
- Work on neural-networks dissipated during the 70's and early 80's.

Neural Net Resurgence (1986)

- Interest in NNs revived in the mid 1980's due to the rise of "connectionism."
- Backpropagation algorithm popularized for training three-layer NN's.
- Generalized the iterative "hill climbing" method to approximate fitting two layers of synaptic connections, but no convergence guarantees.

3-Layer NN Backpropagation



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Second NN Demise (1995-2010)

- Generic backpropagation did not generalize that well to training deeper networks.
- Little theoretical justification for underlying methods.
- Machine learning research moved to graphical models and kernel methods.

Deep Learning Revolution (2010...)

- Improved methods developed for training deep neural works.
- Particular successes with:
 - Convolutional neural nets (CNNs) for vision.
 - Recurrent neural nets (RNNs) for machine translation and speech recognition.
 - Deep reinforcement learning for game playing.

Massive Data and Specialized Hardware

- Large collections of supervised (crowdsourced) training data has been critical.
- Efficient processing of this big data using specialized hardware (Graphics Processing Units, GPUs) has been critical.

CNNs

- Convolutional layers learn to extract local features from image regions (receptive fields) analogous to human vision (LeCun, et al., 1998).
- Deeper layers extract higher-level features.
- Pool activity of multiple neurons into one at the next layer using max or mean.
- Nonlinear processing with Rectified Linear Units (ReLUs)
- Decision made using final fully connected layers.

CNNs



ImageNet Large Scale Visual Recognition Challenge (ILSVRC)

 Recognize 1,000 categories of objects in 150K test images (given 1.2M training images).

Mongoose

Canoé

Missile

Trombone









ImageNet Performance Over Time



CNN for text



Convolutional networks in NLP

Collobert, Weston et al. (2011) semantic-role labeling

Kalchbrenner et al (2014) sentiment classification

Kim (Kim, 2014) question-type classification