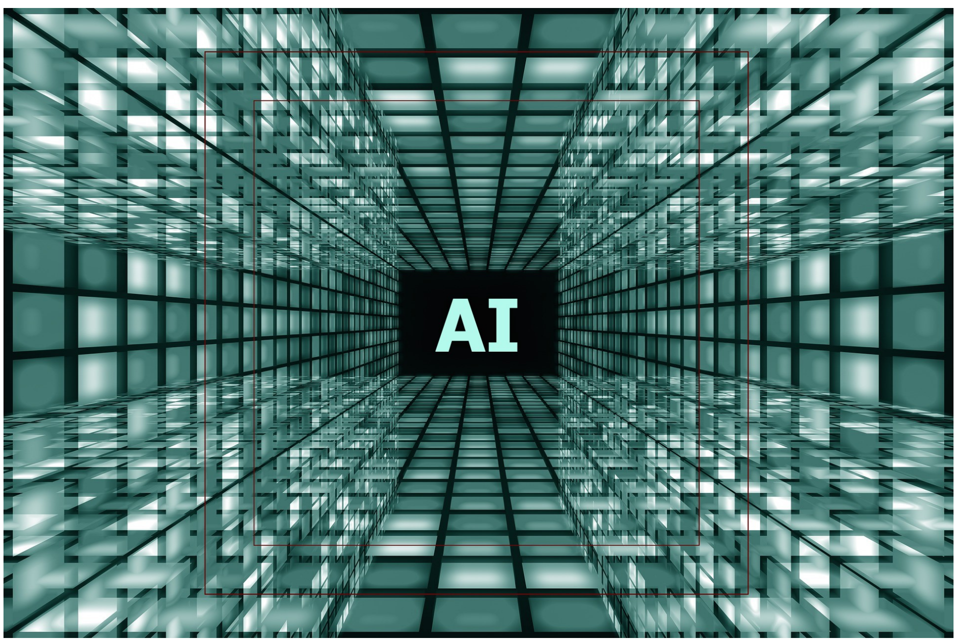
Artificial Intelligence

Conclusion



Outline

I - Deep Learning

II - Robotics: Invited Speaker

III - Review and Conclusion

Neural Networks

- Algorithms that try to mimic how the brain functions.
- Worked extremely well to recognize:
  1. Handwritten characters (LeCun et a. 1989),
  2. spoken words (Lang et al. 1990),
  3. faces (Cottrel 1990)
- Extensively studied in the 1990's with a moderate success.
- Now back with lots of success with deep learning thanks to the algorithmic and computational progress.
- The first algorithm used was the Perceptron (Resenblatt 1959).

History

- 1950-60s: Neural networks (Rosenblatt, etc.)
- 1970's: Slow progress
- 1986: Backpropagation
- 1990s: Convolutional neural networks (LeCun)
- 1990s: Recurrent neural networks (Schmidhuber)
- 2006: NN, le retour. Breakthrough: Deep belief networks (Hinton et al., 2006) and Autoencoders (Bengio et al., 2007).
- 2013: Huge industrial interest. Why now?

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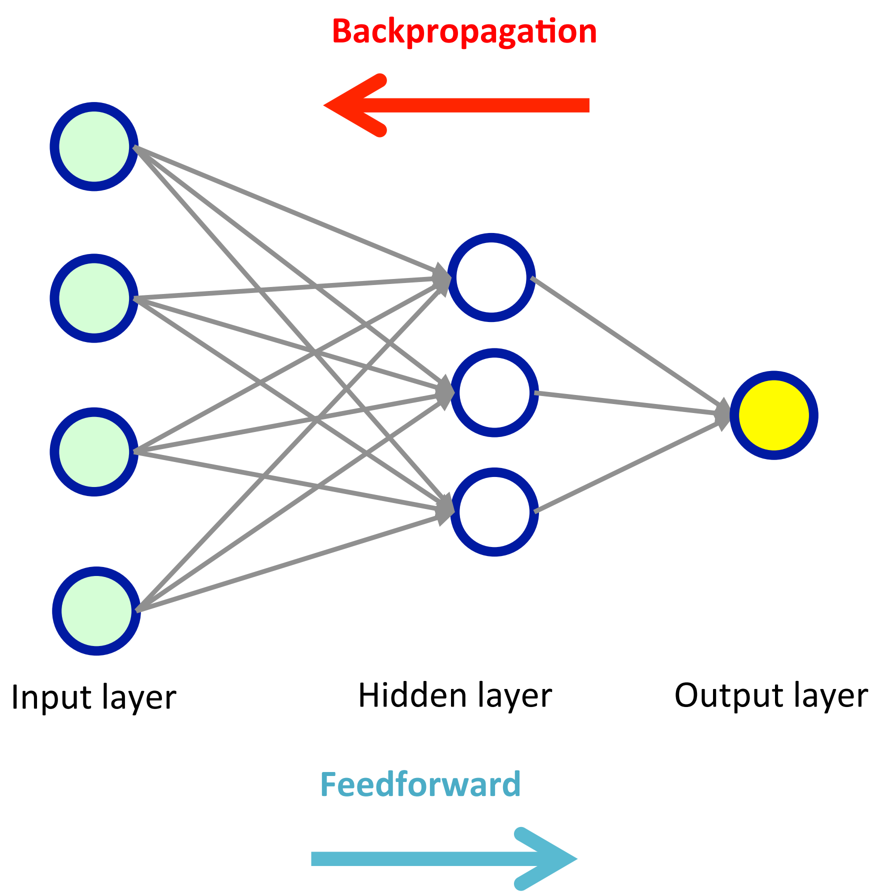
- 2013: Huge industrial interest. Why now?

Lots of data and more computational power!

Work well, breakthrough results (vision and speech)

Feedforward-Backpropagation



Backpropagation algorithm

- Feedforward NN (as opposed to recurrent networks) have no connections that loop.
- Backpropagation stands for "backward propagation of errors".
- Learn the weights for a multilayer network.
- Given a network with a fixed architecture (units and interconnections).
- Use Gradient descent to minimize the squared error between the network output value o and the ground truth y.
- We suppose multiple output k.
- Challenge: Search in all possible weight values for all units in the network.
- Backpropagation does not scale well.

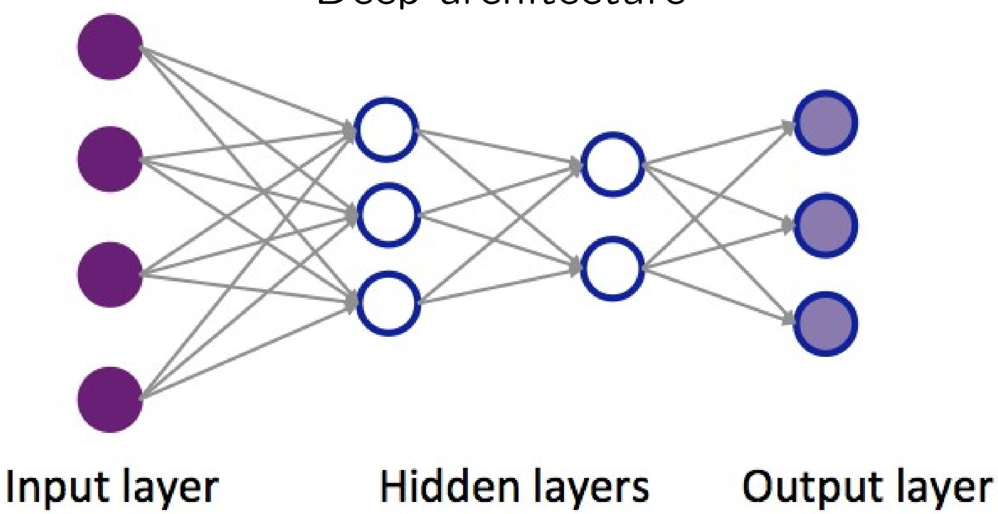
How many layers?

Theorem (Cybenko 1989):
No more than 2 hidden layers can represent any arbitrary region (assuming sufficient number of neurons or units).

The number of neurons in each hidden layer are found by cross validation.

What is Deep Learning?

Deep architecture



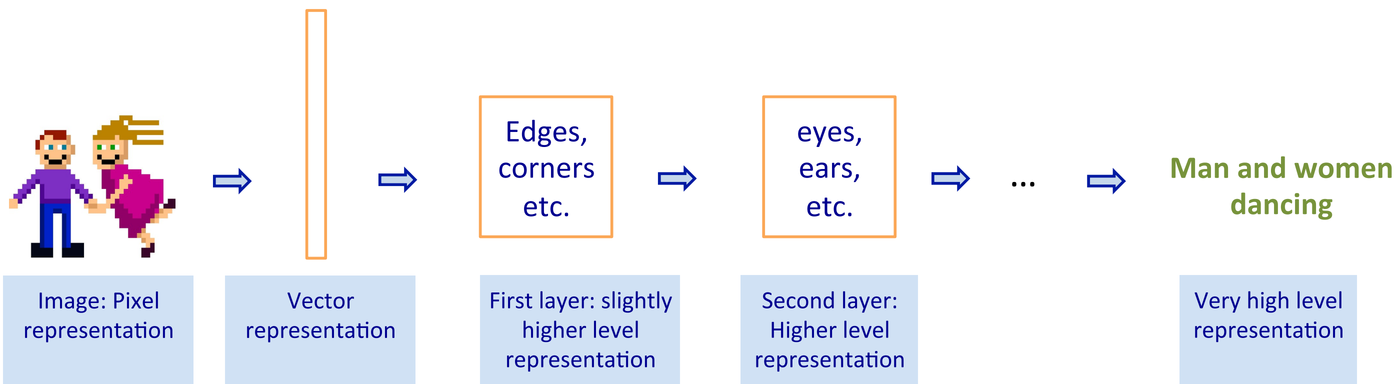
Deep learning: means using a neural network with a series of hidden layers of non-linear operations between input and output.

Shallow architectures

Most ML algorithms have a shallow architecture with 1 to 3 levels.
Examples: perceptron, SVMs, kNN, etc.

$$f(x) = sign(\sum_{i=0}^{d} w_i x_i)$$

Why a deep architecture?



Deep architecture: The series of layers between input and output learn feature hierarchies/feature identification at different levels.

Hidden layers: Act as feature detectors, will leads to an *automatic abstraction of data*.

Successive layers: Learn high level features.

Inspiration

T. Serre, et al., "A quantitative theory of immediate visual recognition," Progress in Brain Research, Computational Neuroscience: Theoretical Insights into Brain Function, vol. 165, pp. 3356, 2007.

Inspiration: The Mammalian Visual Cortex is Hierarchical with 5-10 levels just for the visual system.

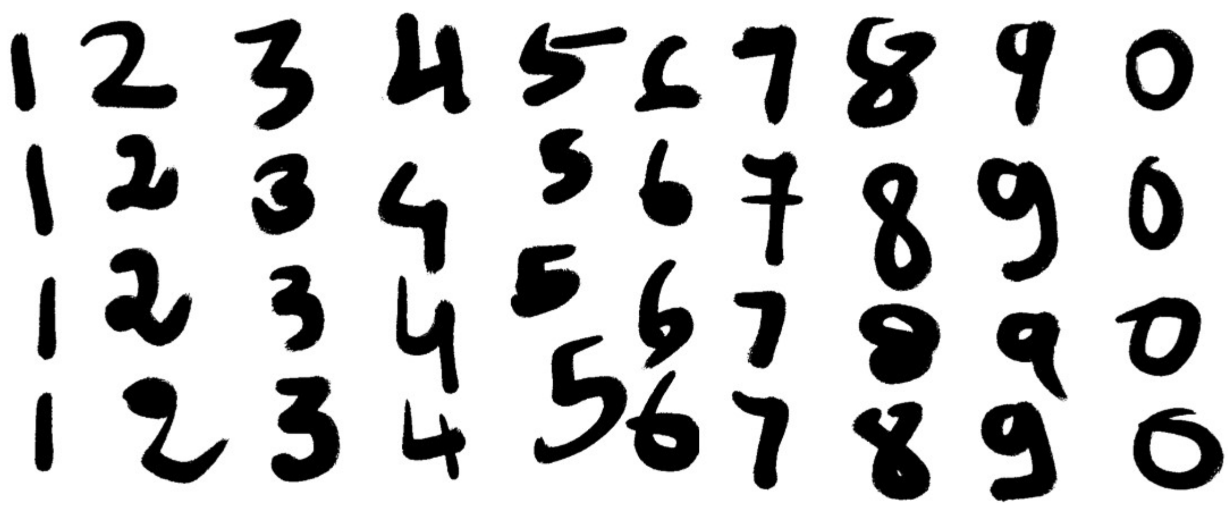
Learning the weights

Question: Multilayer Neural networks are around for few decades. Why is Deep Learning revolutionary?

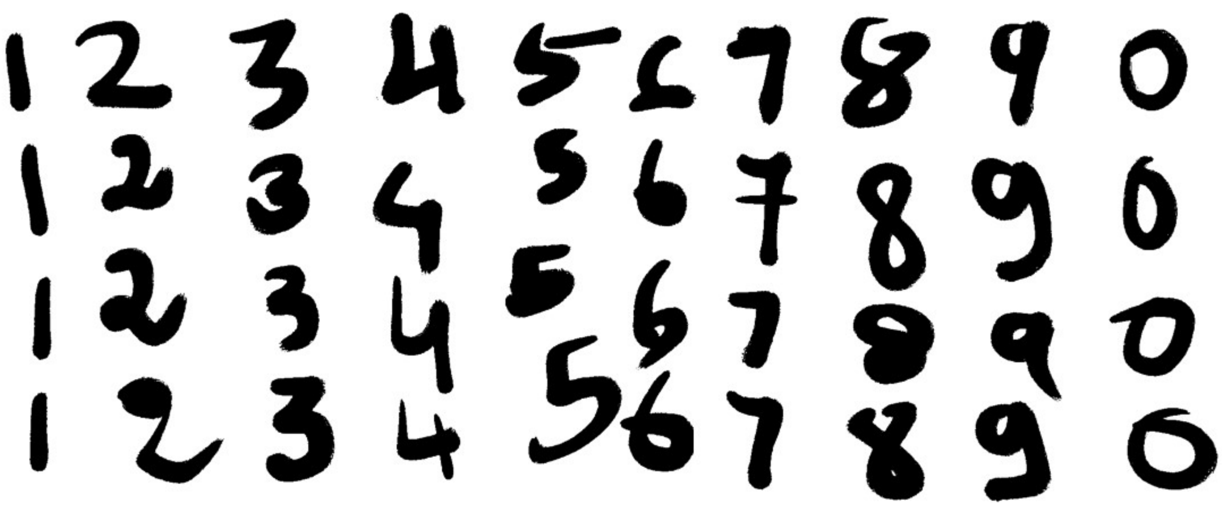
Answer: We know how to learn the weights with ONE hidden layers, with more layers it is more difficult.

Novelty: New algorithms for learning the weights for deep NN.

Multilayers make sense

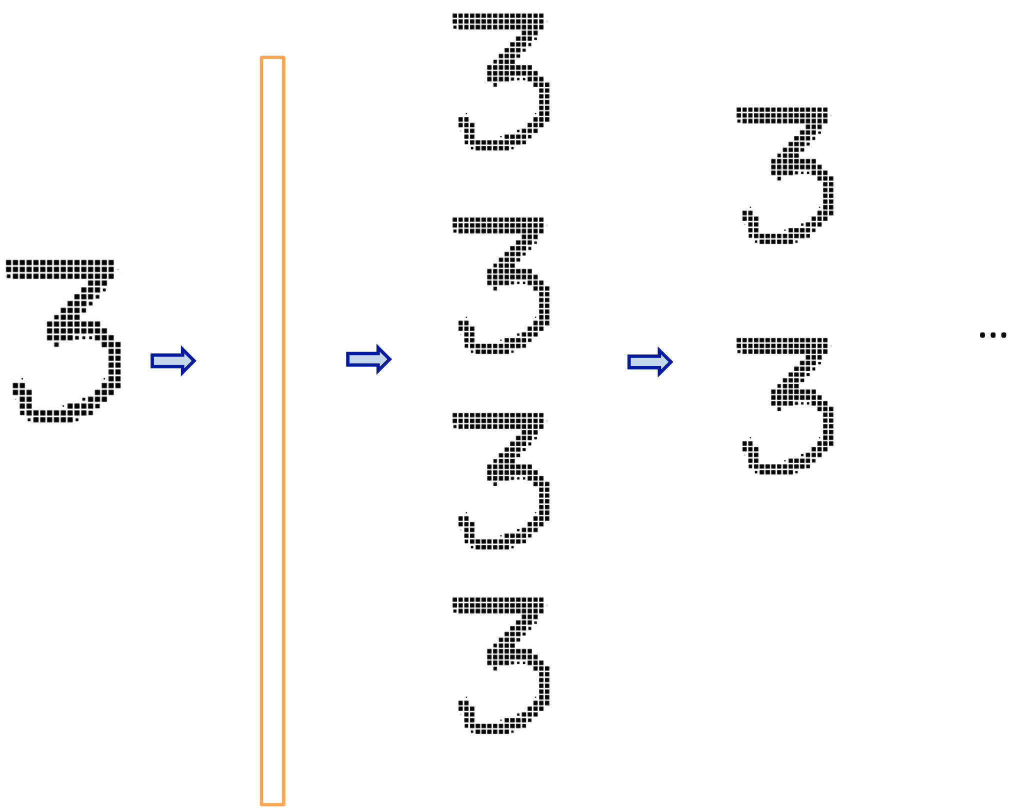


Multilayers make sense



Features that make sense?

Multilayers make sense



Convolutional Networks

- Deep NN are very hard to train. Why?
- Too much connections requires long training time and lots of data.
- We need to relax the connection
- One variant: Convolutional Neural Networks (CNN) with fewer connections and parameters.
- Inspired by visual architecture with 5-7 layers (hard to train with DNN).
- Easier to train, interesting even if the performance is slightly worse.

LeNet-5, LeCun 1998

Y. LeCun, L. Bottou, Y. Bengio and P. Haffner: Gradient-Based Learning Applied to Document Recognition, Proceedings of the IEEE, 86(11):2278-2324, November 1998.

http://yann.lecun.com/exdb/lenet/index.html

Deep Learning software

1. Torch: Scripting with LUA
2. Theano: Python
3. Caffe: Suited for vision
4. TensorFlow: Python, very popular

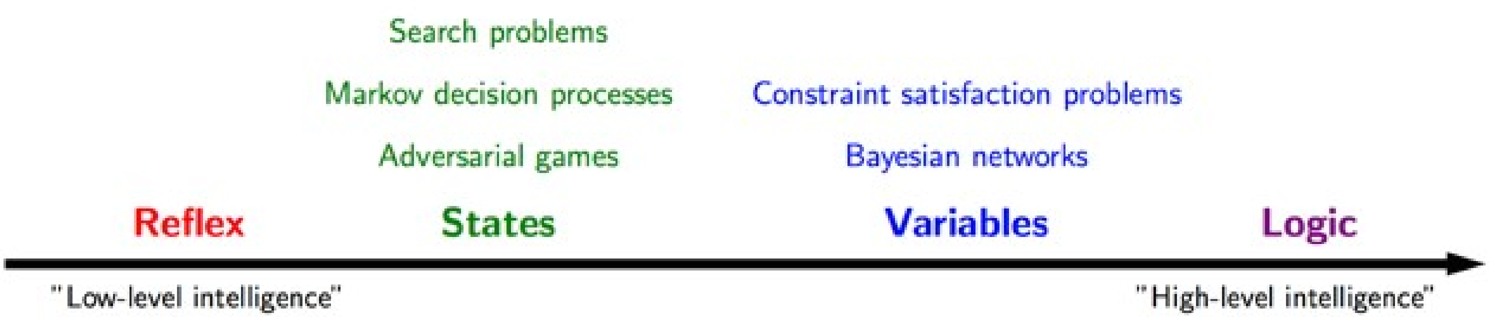
http://deeplearning.net/tutorial/

Robotics: Invited Speaker

Peter Allen

Peter K. Allen is a professor of computer science at Columbia Engineering. His current research interests include robotic grasping, 3-D vision and modeling, and medical robotics. In recognition of his work, Allen has been named a Presidential Young Investigator by the National Science Foundation. He received an A.B. degree from Brown University in mathematics and economics, an M.S. in computer science from the University of Oregon, and a Ph.D. in computer science from the University of Pennsylvania, where he was the recipient of the CBS Foundation Fellowship, Army Research Office fellowship, and the Rubinoff Award for innovative uses of computers.

Course summary



Credit: Courtesy Percy Liang

Course summary

- AI is a hard (computational complexity, language, vision, etc), and a broad field with high impact on humanity and society.

- What can AI do for us is already amazing!

- AI systems do not have to model human/nature but can act like or be inspired by human/nature.

Summary

- Since the Darmouth meeting, ups and downs, AI has made huge progress.
- AI is a flourishing and exciting field: everyone can contribute
- AI may be perceived as a threat to our humankind
- Deep learning is a very promising direction
- Theoretical research, and more applications of deep learning
- Next topics: machine learning, natural language processing, computer vision, robotics, statistical learning theory, probabilistic graphical models.

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- Shu-Yi Hsu
- Leander Keizer

Thanks & congratulations!

Credit

- ImageNet Classification with Deep Convolutional Neural Networks. Krizhevsky, Sutskever, and Hinton. NIPS 2012.
- Hinton, G. E, Osindero, S., and Teh, Y. W. (2006). A fast learning algorithm for deep belief nets. Neural Computation, 18:1527-1554. Autoencoders
- Bengio, Y., Lamblin, P., Popovici, P., Larochelle, H. (2007). Greedy Layer-Wise Training of Deep Networks, Advances in Neural Information Processing Systems 19
- Professor Percy Liang's lecture notes.