Electrical and Computer Engineering Department
Tarbiat Modares University

Introduction

Foad Ghaderi, PhD

Artificial intelligence (AI) is a thriving field with many practical applications and active research topics.
Intelligent software:

- Automate routine labor,
- Understand speech or images,
- Make diagnoses in medicine and
- Support basic scientific research.

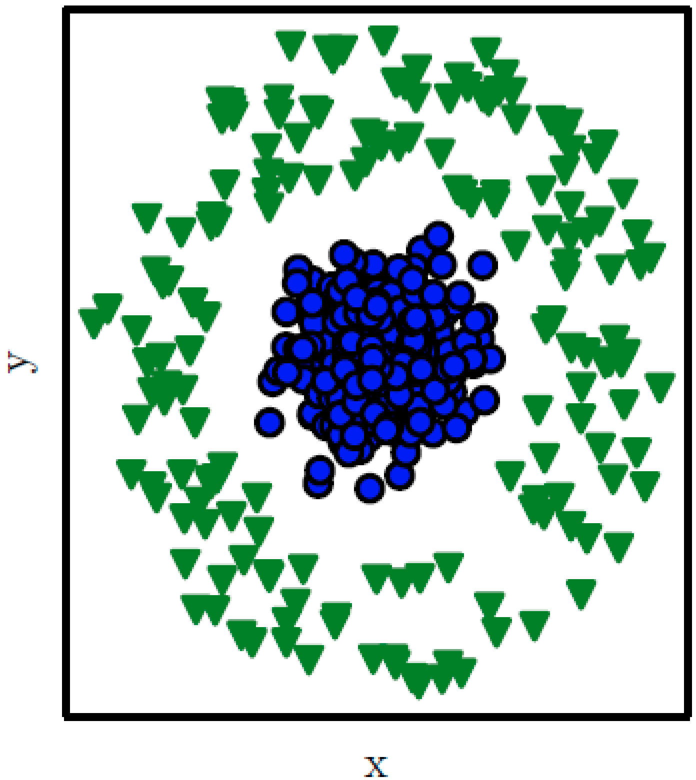
- Problems that are intellectually difficult for human beings but relatively straightforward for computers (problems that can be described by a list of formal, mathematical rules).
- The true challenge to artificial intelligence proved to be solving the tasks that are easy for people to perform but hard for people to describe formally

Learn from experience and understand the world in terms of a hierarchy of concepts

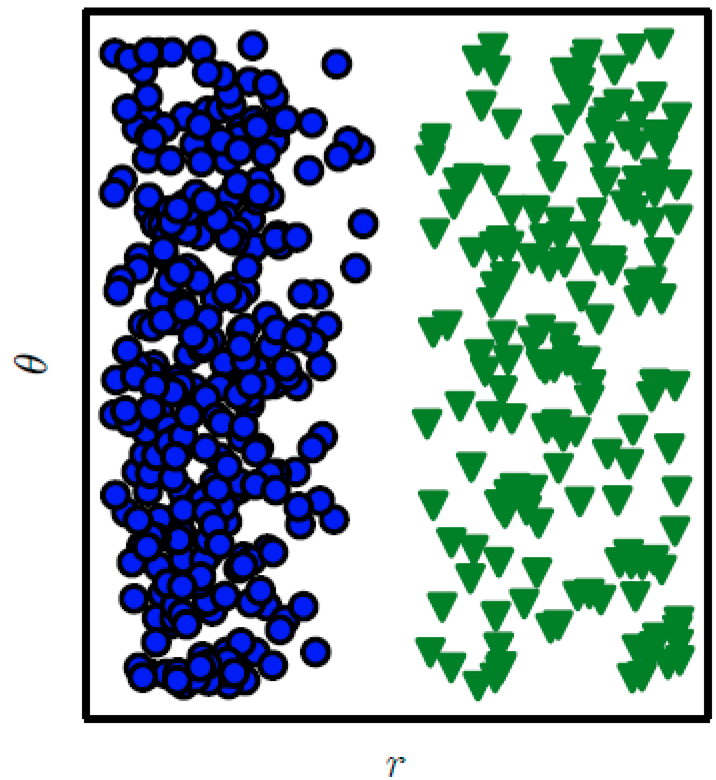
Representations Matter

It is not surprising that the choice of representation has an enormous effect on the performance of machine learning algorithms.

Cartesian coordinates



Polar coordinates



Representations Matter

Many artificial intelligence tasks can be solved by designing the right set of features to extract for that task, then providing these features to a simple machine learning algorithm.

For many tasks, it is difficult to know what features should be extracted.

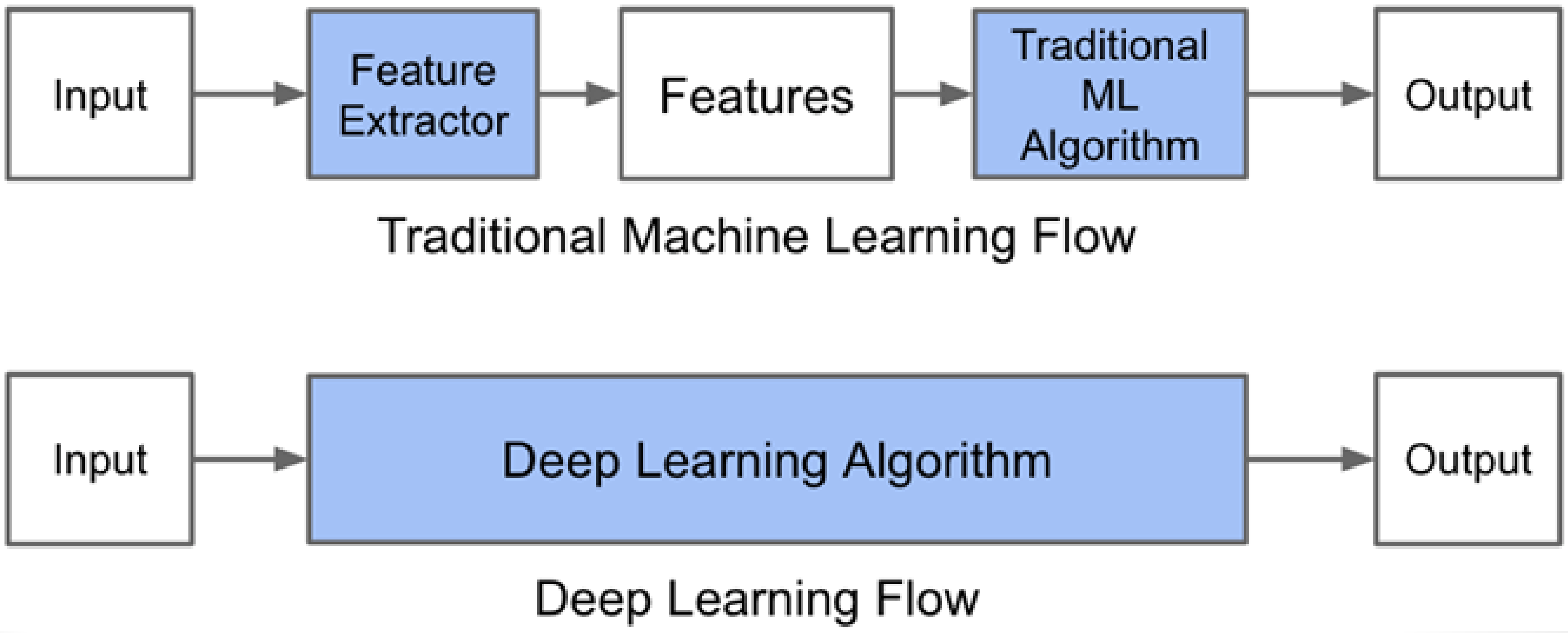
- We would like to write a program to detect cars in photographs.

Representation learning

One solution to this problem is to use machine learning to discover not only the mapping from representation to output but also the representation itself, e.g. Autoencoders.

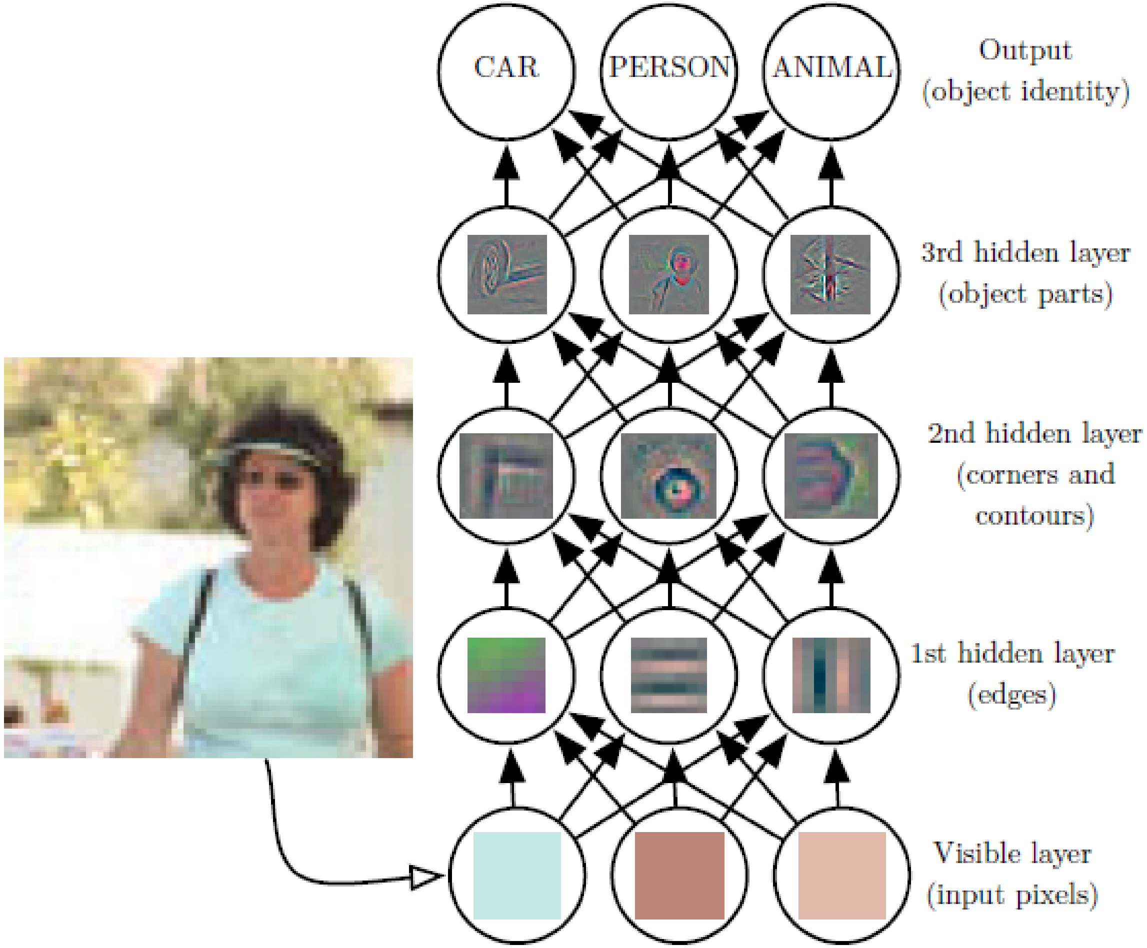
It can be very difficult to extract such high-level, abstract features from raw data.

Machine Learning vs Deep Learning



Depth: Repeated Composition

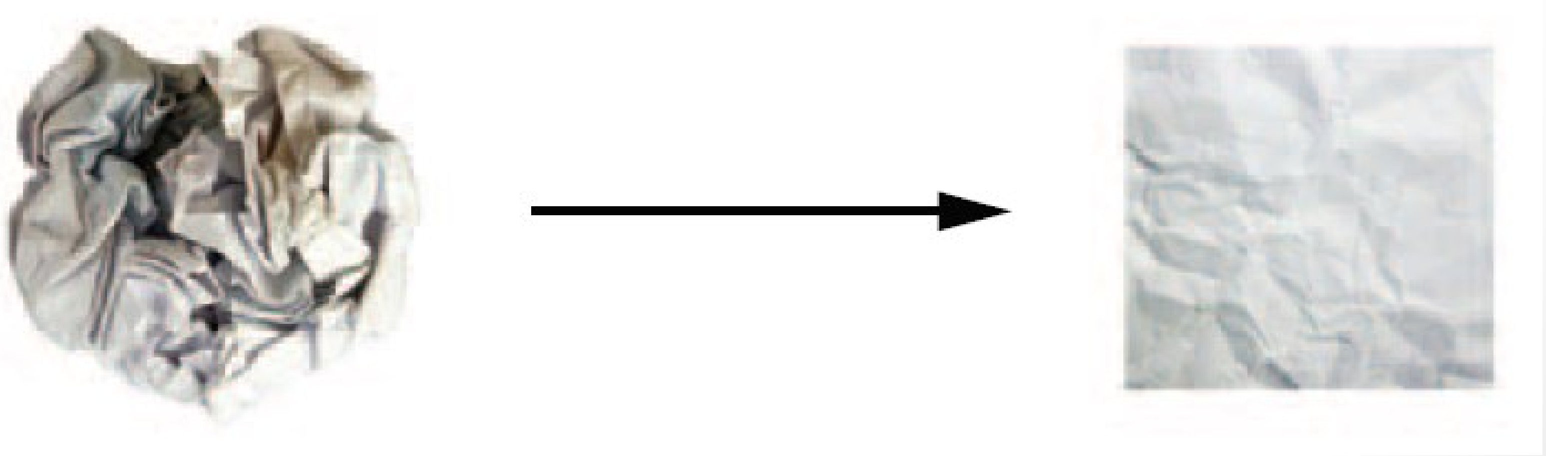
- ✓ Deep learning allows the computer to build complex concepts out of simpler concepts.
- ✓ Another perspective on deep learning is that depth allows the computer to learn a multi-step computer program.



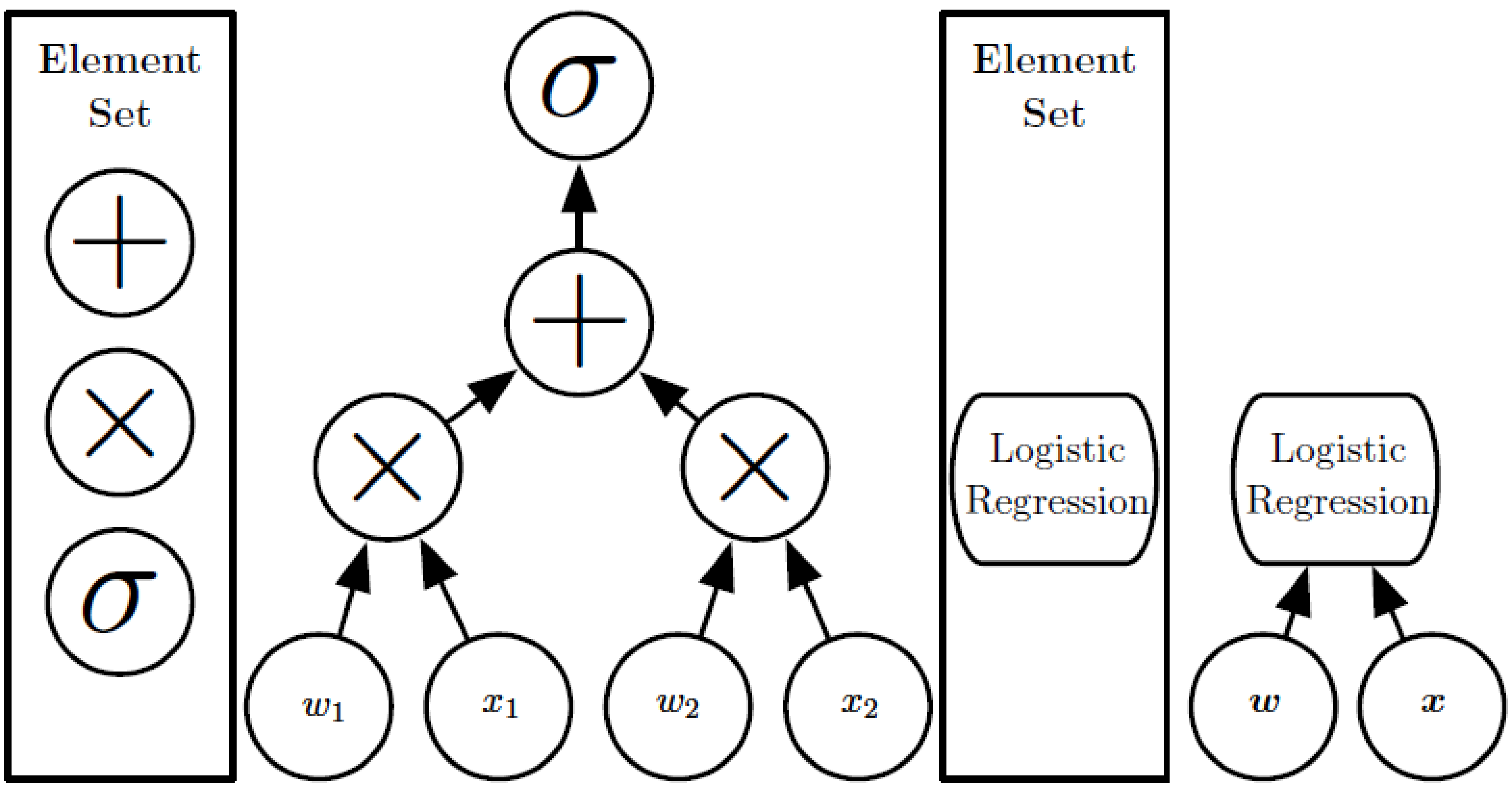
A geometric interpretation of deep learning

Neural networks consist entirely of chains of tensor operations and that all of these tensor operations are just geometric transformations of the input data.

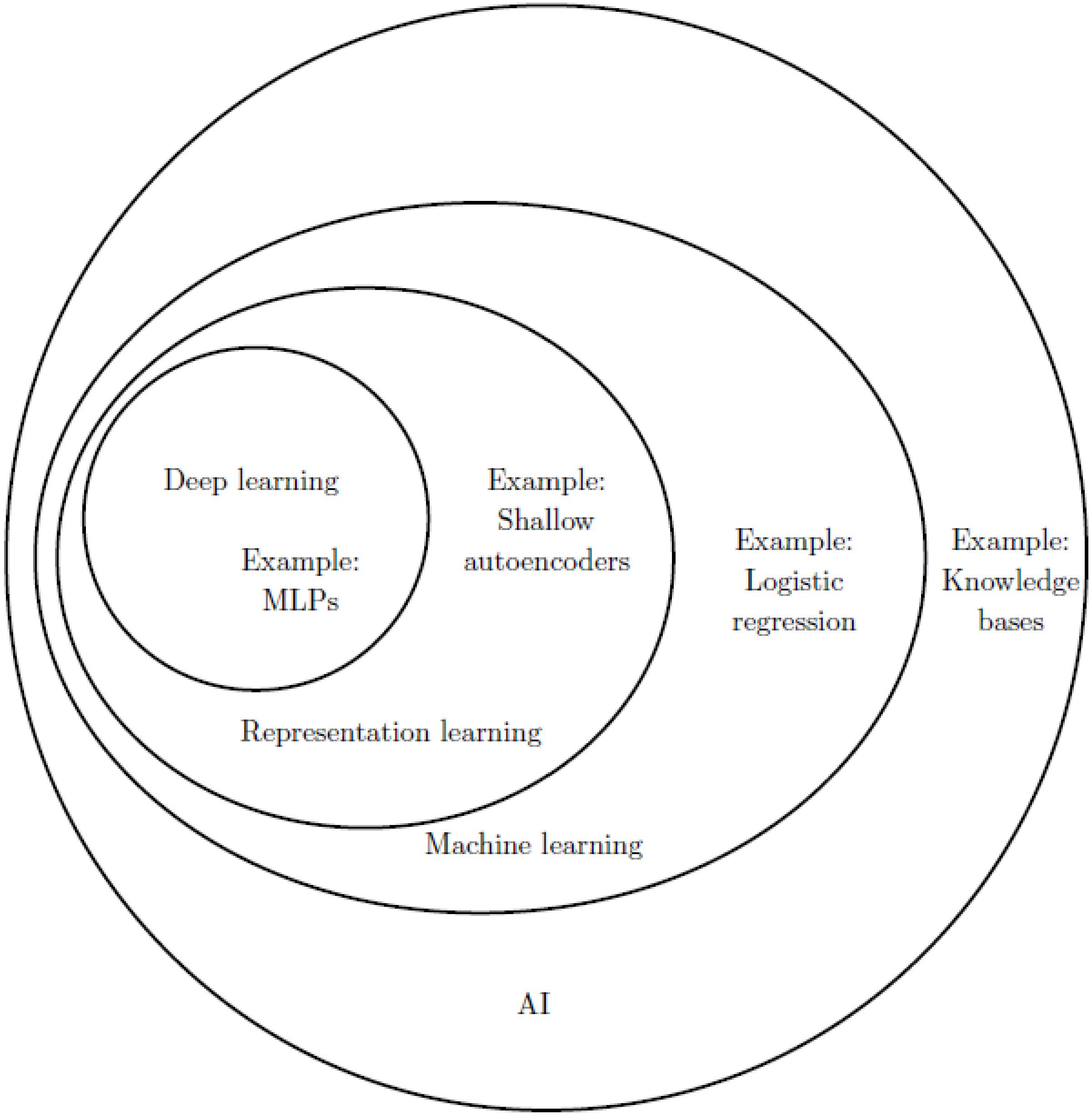
You can interpret a neural network as a very complex geometric transformation in a high-dimensional space.



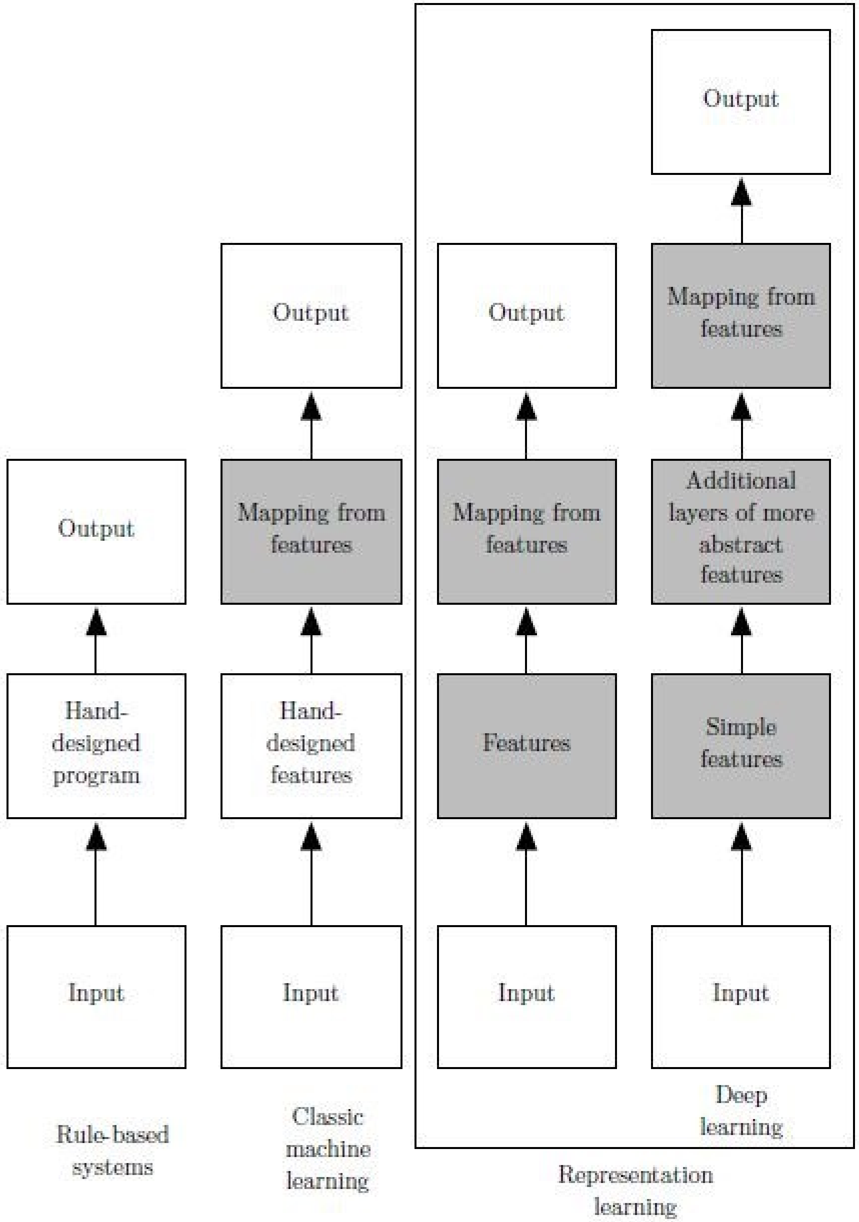
Computational Graphs



Machine Learning and AI



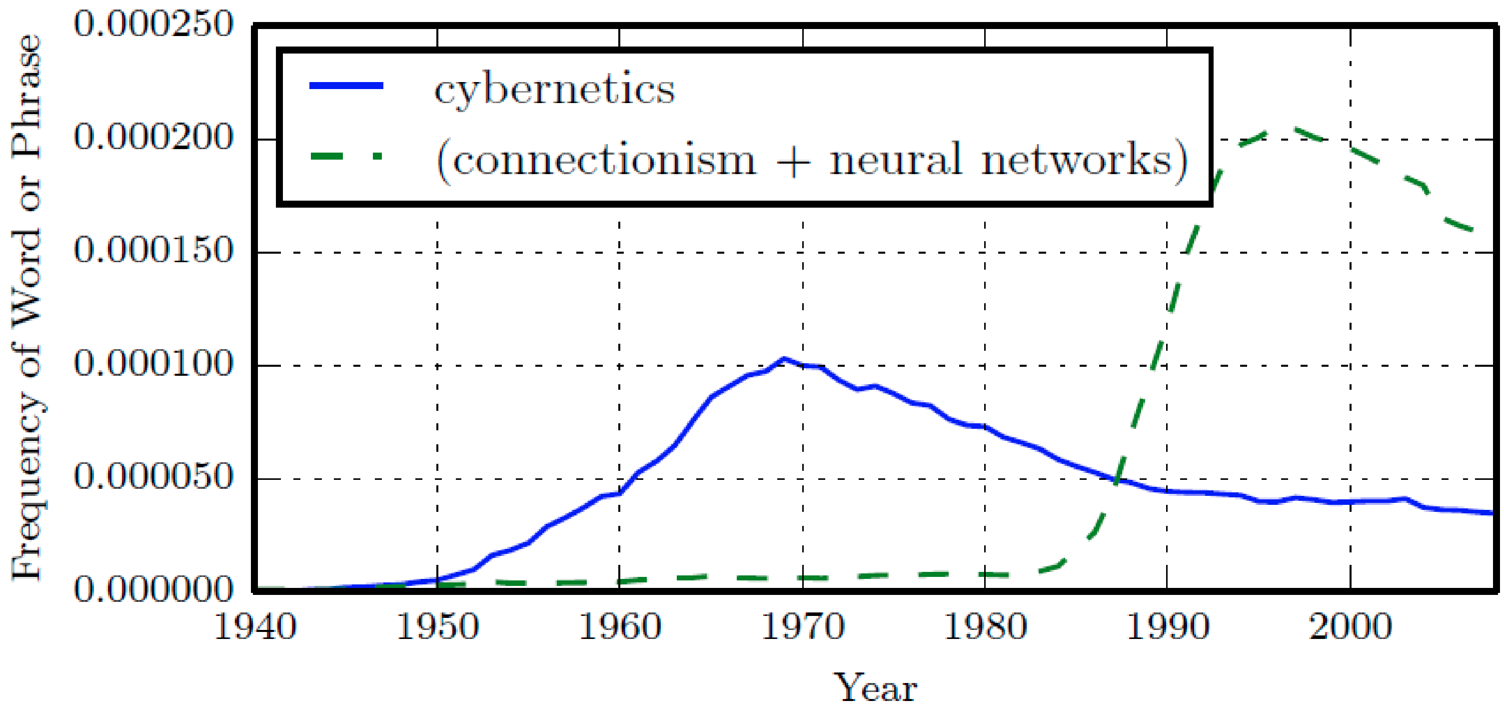
Learning Multiple Components



Historical Waves

The neural perspective on deep learning is motivated by two main ideas:

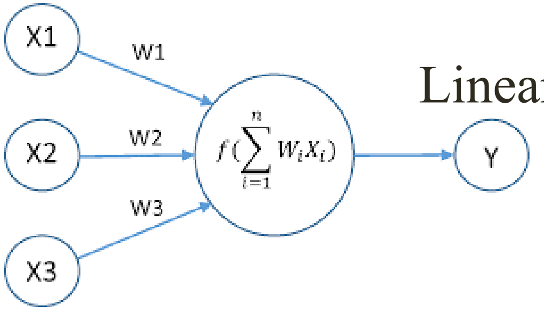
- ✓ The brain provides a proof by example that intelligent behavior is possible,
- ✓ Another perspective is that it would be deeply interesting to understand the brain and the principles that underlie human intelligence.



Historical Waves

The modern term "deep learning" goes beyond the neuroscientific perspective.

✓ learning *multiple levels of composition*



Linear models have many limitations, e.g. XOR

Neuroscience is regarded as an important source of inspiration for deep learning researchers, but it is no longer the predominant guide for the field.

- we simply do not have enough information about the brain to use it as a guide.

Modern deep learning draws inspiration from many fields, especially

✓ Linear algebra,

✓ Probability,

✓ Information theory, and

✓ Numerical optimization.

Historical Waves

In the 1980s, the second wave of neural network research emerged in great part via a movement called *connectionism or parallel distributed processing.*

D*istributed representation*

Suppose we have a vision system that can recognize cars, trucks, and birds and these objects can each be red, green, or blue.

- ✓ separate neuron or hidden unit that activates for each of the nine possible combinations
- ✓ Three neurons describing the color and three neurons describing the object identity.

Deep networks were too computationally costly to allow much experimentation with the hardware available at the time.

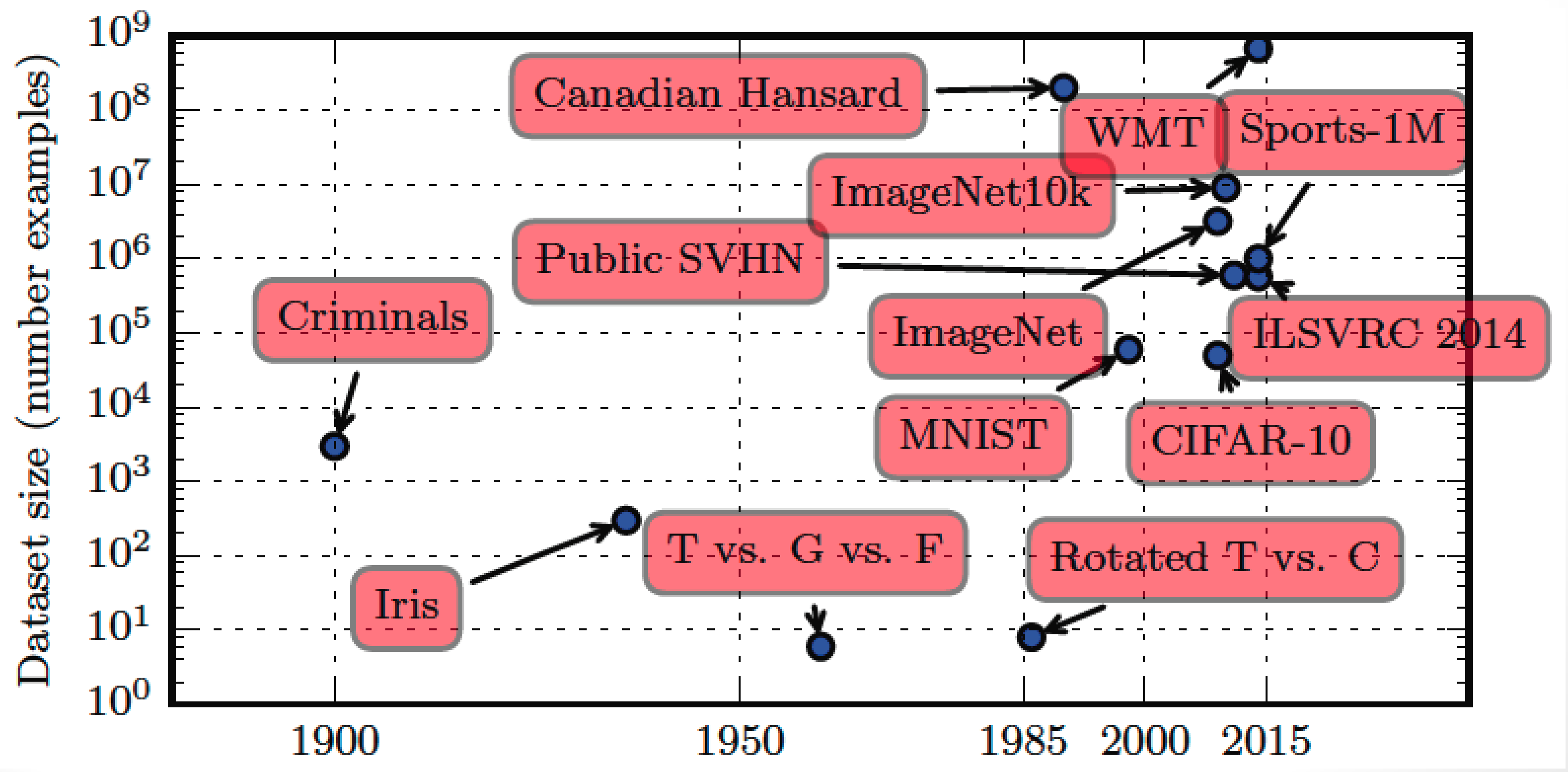
Historical Waves

The third wave of neural networks research began in 2006. Geoffrey Hinton showed that a kind of neural network called a deep belief network could be efficiently trained using a strategy called greedy layer-wise pre-training.

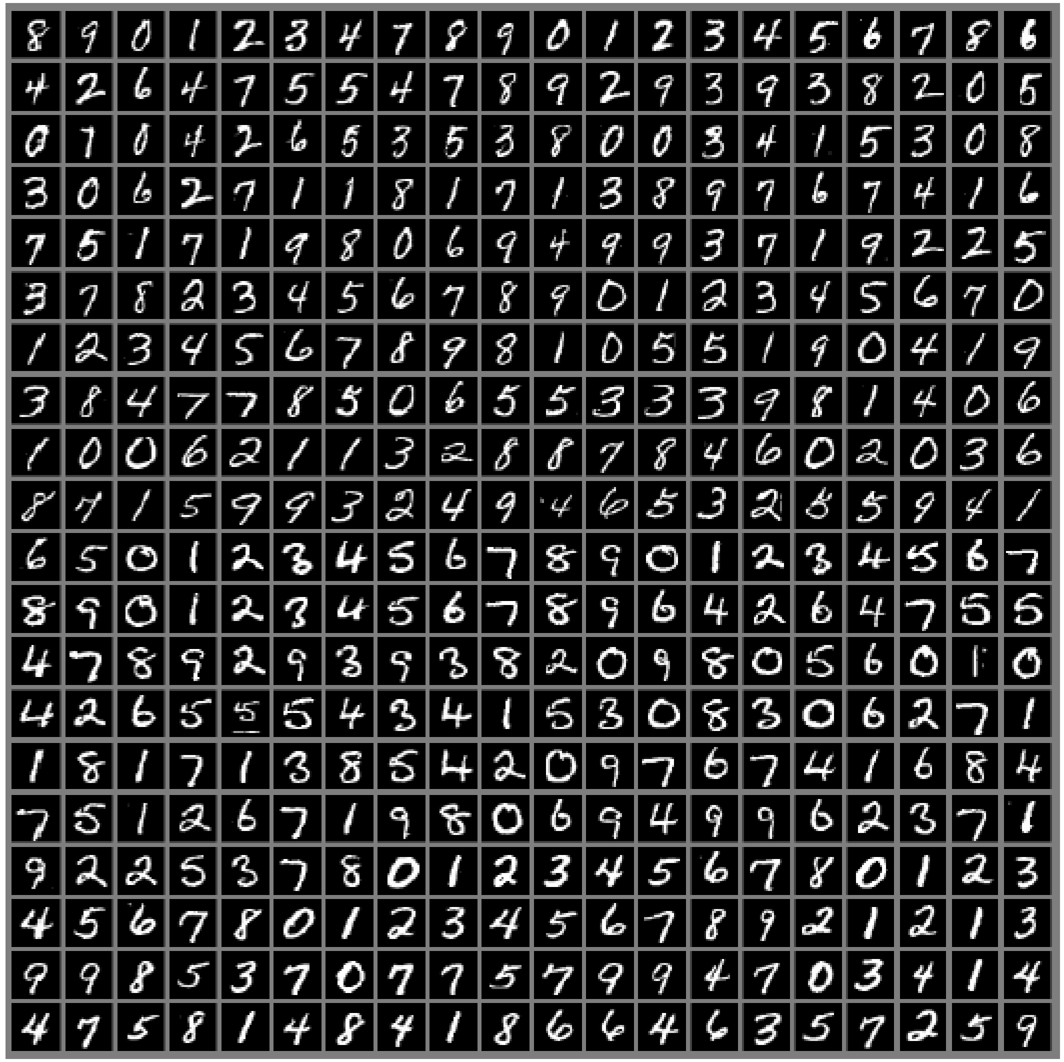
It was also showed that the same strategy could be used to train many other kinds of deep networks and systematically helped to improve generalization on test examples.

Historical Trends: Growing Datasets

Some skill is required to get good performance from a deep learning algorithm.
Fortunately, the amount of skill required reduces as the amount of training data increases.

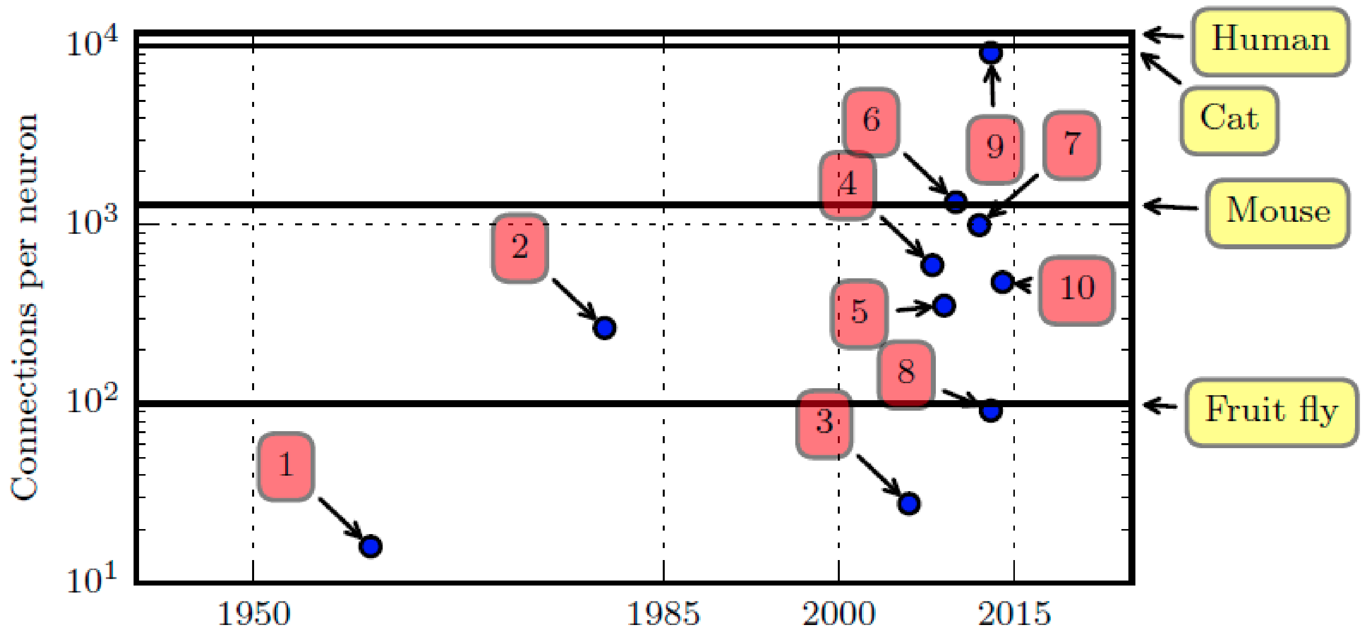


Historical Trends: Growing Datasets



The “NIST” stands for National Institute of Standards and Technology, the agency that originally collected this data. The “M” stands for “modified,” since the data has been preprocessed for easier use with machine learning algorithms.

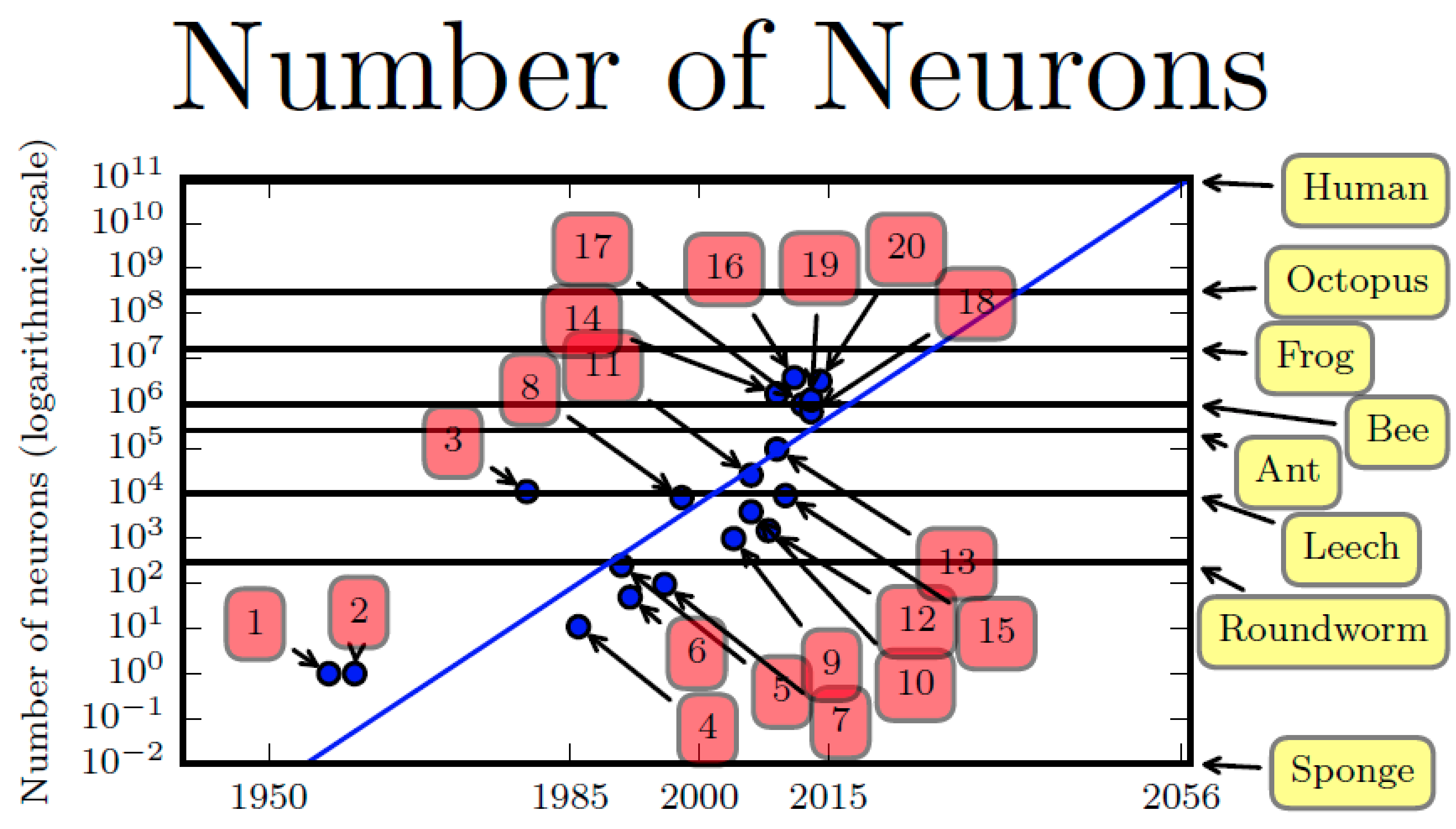
Increasing Model Sizes



1. Adaptive linear element (Widrow and Hoff, 1960)
2. Neocognitron (Fukushima, 1980)
3. GPU-accelerated convolutional network (Chellapilla *et al.*, 2006)
4. Deep Boltzmann machine (Salakhutdinov and Hinton, 2009a)
5. Unsupervised convolutional network (Jarrett *et al.*, 2009)
6. GPU-accelerated multilayer perceptron (Ciresan *et al.*, 2010)
7. Distributed autoencoder (Le *et al.*, 2012)
8. Multi-GPU convolutional network (Krizhevsky *et al.*, 2012)
9. COTS HPC unsupervised convolutional network (Coates *et al.*, 2013)
10. GoogLeNet (Szegedy *et al.*, 2014a)

Increasing Model Sizes

In terms of the total number of neurons, neural networks have been astonishingly small until quite recently



Increasing Model Sizes

The increase in model size over time, due to

- ✓ the availability of faster CPUs,
- ✓ the advent of general purpose GPUs, TPU, IPU, …,
- ✓ faster network connectivity and
- ✓ better software infrastructure for distributed computing,

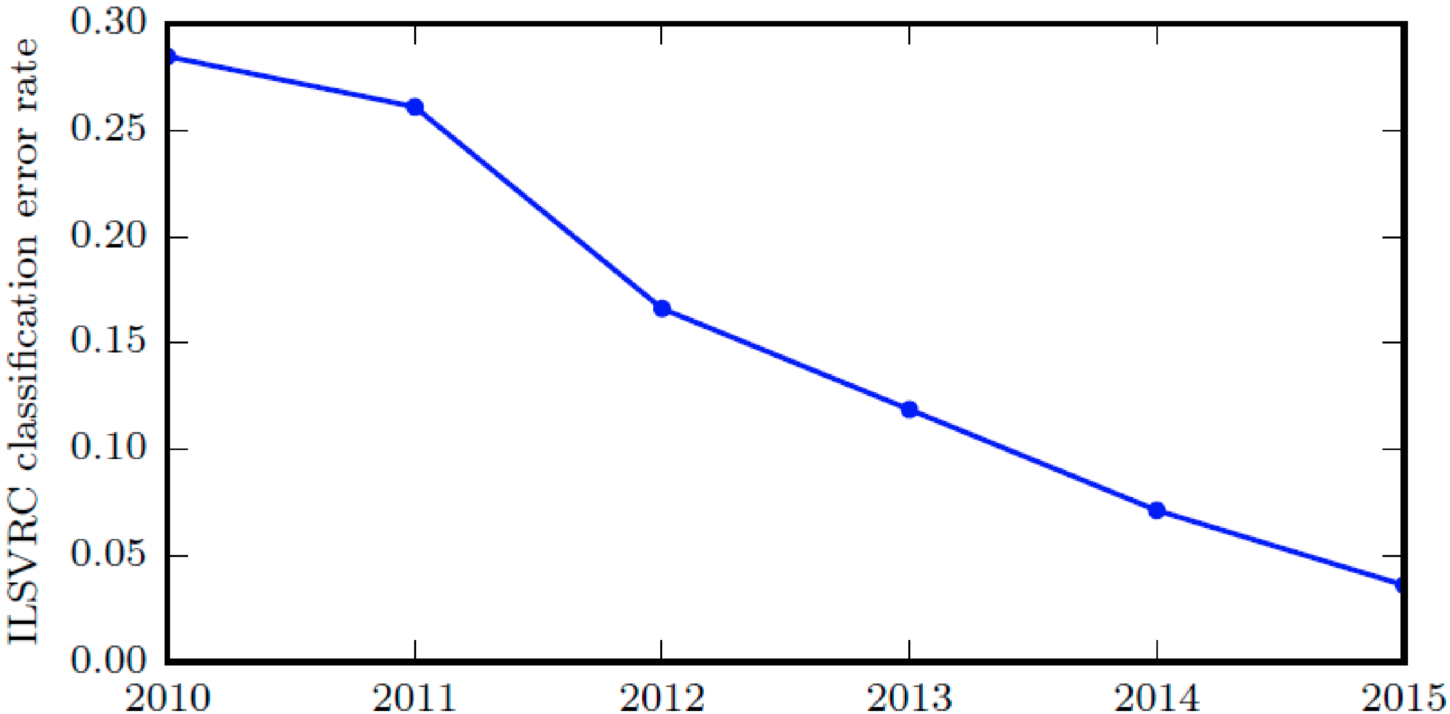
is one of the most important trends in the history of deep learning.

This trend is generally expected to continue well into the future.

Increasing Accuracy, Complexity and Real-World Impact

The earliest deep models were used to
- recognize individual objects,
- tightly cropped,
- extremely small images,
- only two kinds of objects.

Modern object recognition networks
- ✓ rich high-resolution photographs,
- ✓ do not need the photo be cropped,
- ✓ recognize 1,000 different categories of objects.

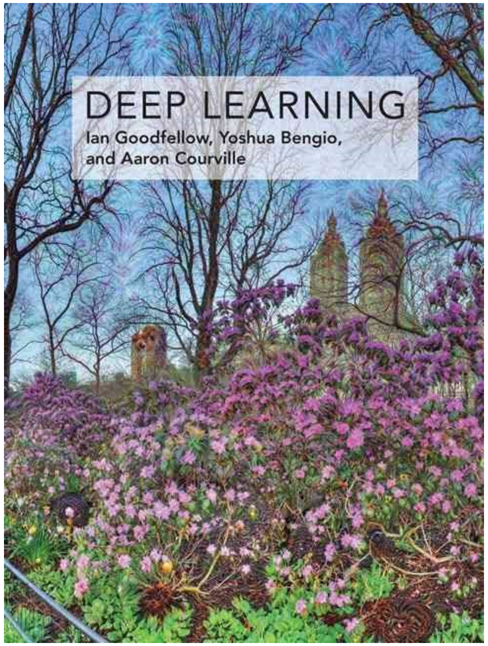


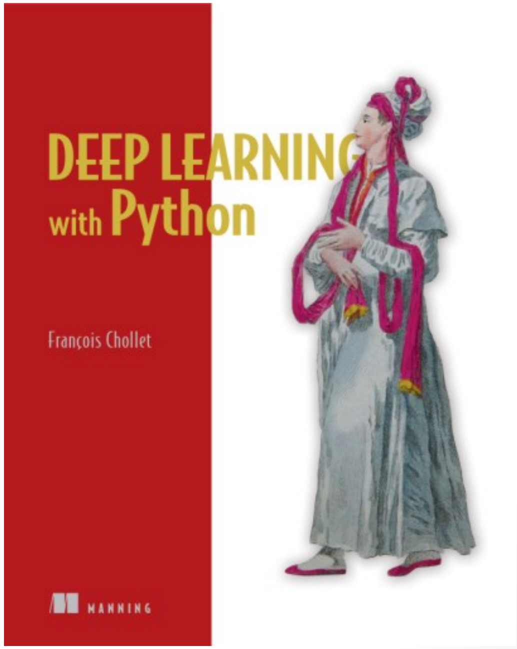
ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) outcome

Resources

Goodfellow, Ian, Yoshua Bengio, and Aaron Courville. "Deep learning. Book in preparation for MIT Press." *URL: http://www.deeplearningbook.org* (2016).

Francois, Chollet. "Deep learning with Python." (2017).





Grading policy

Homeworks:	10%
Project:	20%
Seminar:	10%
Midterm:	25%
Final exam:	35%

Seminar topics

Dropout

Srivastava, Nitish, et al. "Dropout: A simple way to prevent neural networks from overfitting." *The Journal of Machine Learning Research* 15.1 (2014): 1929-1958.

Generative adversarial nets

Goodfellow, Ian, et al. "Generative adversarial nets." *Advances in neural information processing systems*. 2014.

A survey on feature selection methods

Chandrashekar, Girish, and Ferat Sahin. "A survey on feature selection methods." *Computers & Electrical Engineering* 40.1 (2014): 16-28.

Seminar topics

Batch normalization

Ioffe, Sergey, and Christian Szegedy. "Batch normalization: Accelerating deep network training by reducing internal covariate shift." In *International conference on machine learning*, pp. 448-456. 2015.

Deep residual learning

He, Kaiming, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. "Deep residual learning for image recognition." In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 770-778. 2016.

Image-to-image translation

Isola, Phillip, Jun-Yan Zhu, Tinghui Zhou, and Alexei A. Efros. "Image-to-image translation with conditional adversarial networks." *arXiv preprint* (2017).

Seminar topics

<u>**Deep reinforcement learning**</u>

Mnih, Volodymyr, Koray Kavukcuoglu, David Silver, Andrei A. Rusu, Joel Veness, Marc G. Bellemare, Alex Graves et al. "Human-level control through deep reinforcement learning." *Nature* 518, no. 7540 (2015): 529

<u>**Capsule learning**</u>

Sabour, Sara, Nicholas Frosst, and Geoffrey E. Hinton. "Dynamic routing between capsules." In *Advances in Neural Information Processing Systems*, pp. 3859-3869. 2017.

<u>**Fast R-CNN**</u>

Girshick, Ross. "Fast R-CNN." In *Computer Vision (ICCV), 2015 IEEE International Conference on*, pp. 1440-1448. IEEE, 2015.

Seminar topics

<u>**U-Net**</u>

Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. "U-net: Convolutional networks for biomedical image segmentation." *International Conference on Medical image computing and computer-assisted intervention*. Springer, Cham, 2015.

<u>**Mobilenets**</u>

Howard, Andrew G., et al. "Mobilenets: Efficient convolutional neural networks for mobile vision applications." *arXiv preprint arXiv:1704.04861* (2017).

<u>**Federated learning**</u>

McMahan, H. Brendan, et al. "Communication-efficient learning of deep networks from decentralized data." *arXiv preprint arXiv:1602.05629* (2016).