

Deep Learning



Neural networks → Deep learning?

Neural networks

- Perceptron
- Multilayer perceptron
- Radial basis function network
- **Autoencoder**
- Hopfield network
- **Boltzmann machine**
- **Restricted Boltzmann machine**
- Recurrent neural network
- LSTM
- **Self-organizing map**

Deep learning

- Deep multilayer perceptron
- Deep belief networks
- Deep Boltzmann machines
- (Deep) Convolutional neural networks
- Deep Recurrent neural networks
- Stacked Auto-Encoders
- ...

One has to mention the MNIST database results

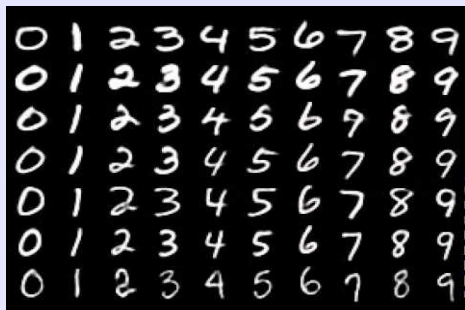


Each digit is a 28x28 “grayscale” image.

60 000 images in the training set.

10 000 image in the test set.

Best result so far are based on (deep) convolutional neural networks or deep neural networks with an error rate of **0.23%** (23 misclassified images)

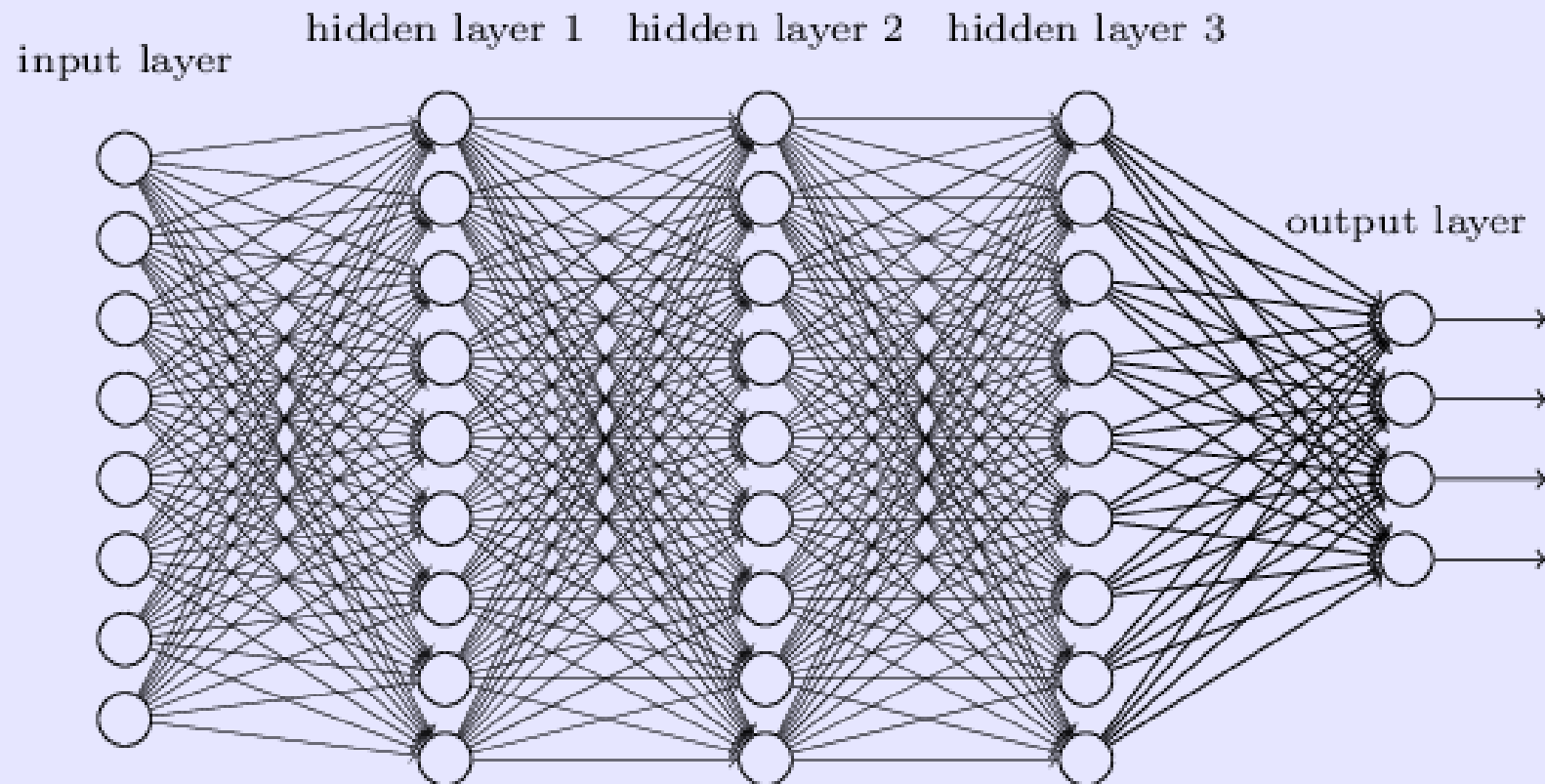


Summary of results (Wikipedia)

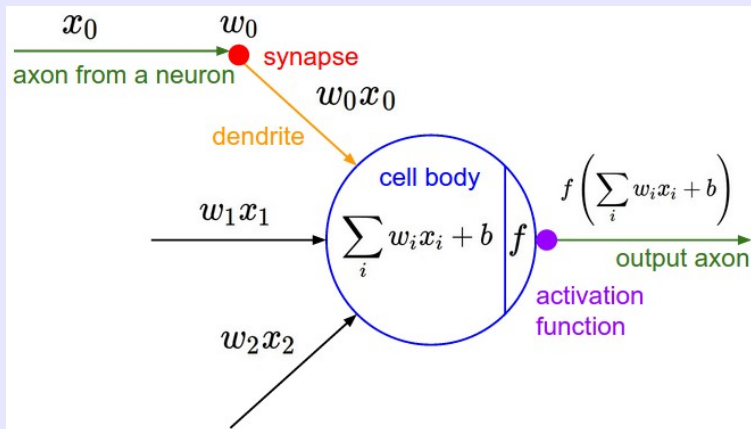
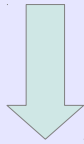
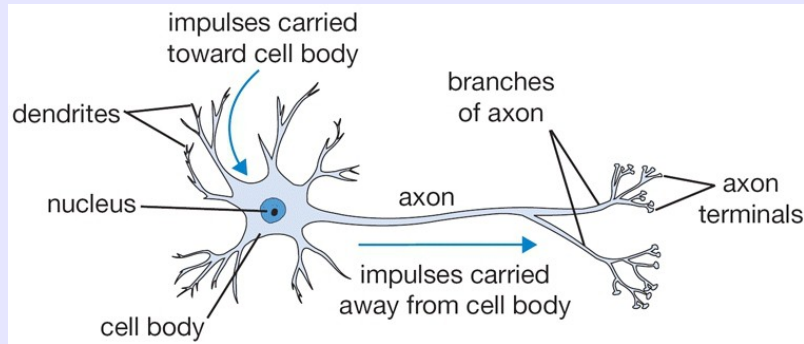
Type	Classifier	Distortion	Preprocessing	Error rate (%)
Linear classifier	Pairwise linear classifier	None	Deskewing	7.6 ^[9]
K-Nearest Neighbors	K-NN with non-linear deformation (P2DHMDM)	None	Shiftable edges	0.52 ^[17]
Boosted Stumps	Product of stumps on Haar features	None	Haar features	0.87 ^[18]
Non-linear classifier	40 PCA + quadratic classifier	None	None	3.3 ^[9]
Support vector machine	Virtual SVM, deg-9 poly, 2-pixel jittered	None	Deskewing	0.56 ^[19]
Neural network	2-layer 784-800-10	None	None	1.6 ^[20]
Neural network	2-layer 784-800-10	elastic distortions	None	0.7 ^[20]
Deep neural network	6-layer 784-2500-2000-1500-1000-500-10	elastic distortions	None	0.35 ^[21]
Convolutional neural network	6-layer 784-40-80-500-1000-2000-10	None	Expansion of the training data	0.31 ^[14]
Convolutional neural network	6-layer 784-50-100-500-1000-10-10	None	Expansion of the training data	0.27 ^[15]
Convolutional neural network	Committee of 35 CNNs, 1-20-P-40-P-150-10	elastic distortions	Width normalizations	0.23 ^[8]
Convolutional neural network	Committee of 5 CNNs, 6-layer 784-50-100-500-1000-10-10	None	Expansion of the training data	0.21 ^[16]

They represent deep networks!

So what makes deep networks so special?



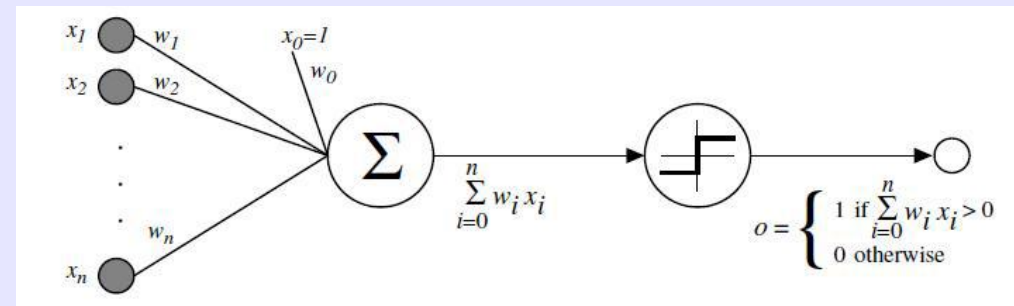
But first a bit of neural networks history



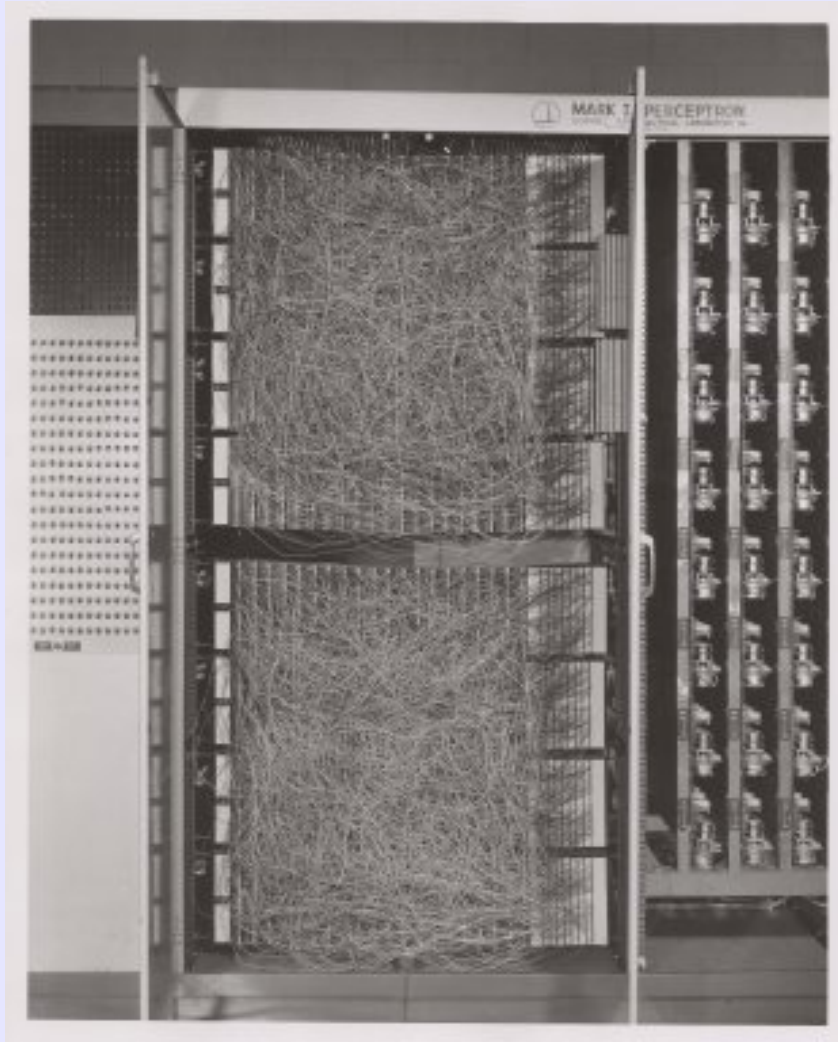
1943 McCulloch-Pitts model

1949 Hebb's rule. Learning occurs by formation and changing of synapses (weights).

1957 Roseblatt's perceptron learning algorithm.



The Mark I Perceptron (1957-58)



- 20x20 photocells
- weights were encoded in potentiometers
- weight updates during learning were performed by electric motors

The first winter!

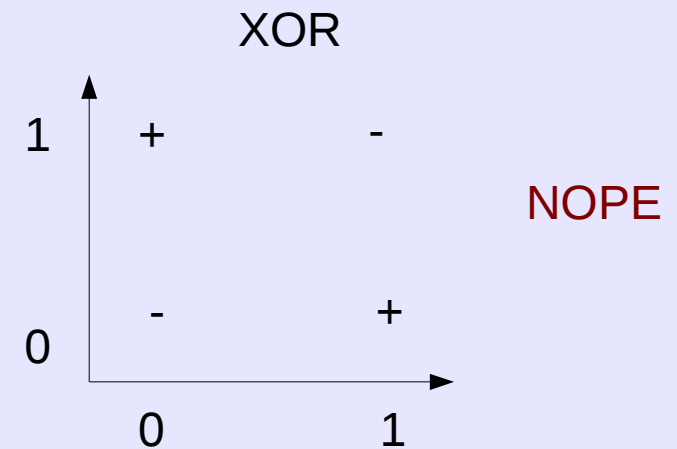
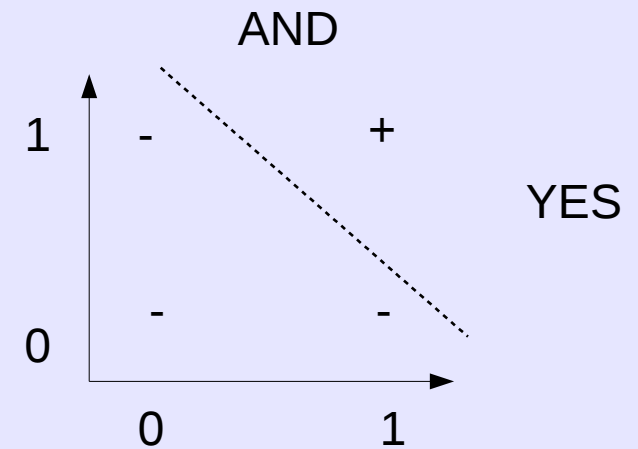
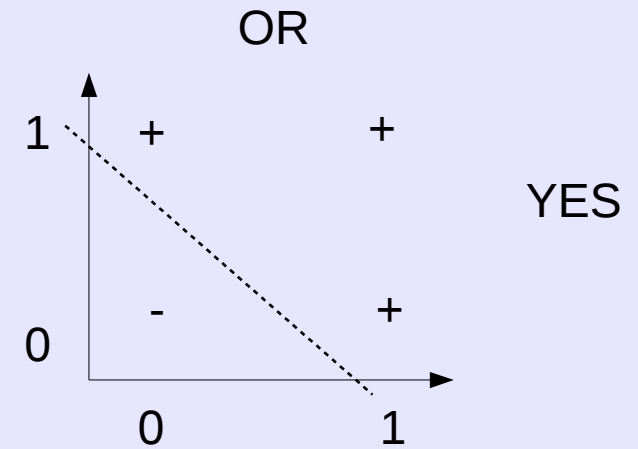
1969: Perceptrons by Minsky and Papert showed limitations of the perceptron

$$y = f\left(\sum_i x_i w_i + b\right)$$

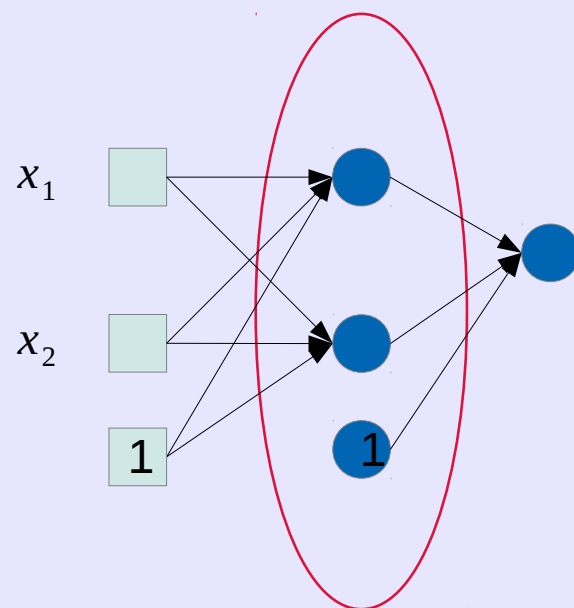
y changes class when

$$\sum_i x_i w_i + b = 0$$

→ decision boundary is a hyperplane



The solution to the XOR problem



The first return of neural networks

1982: Hopfield. “Hopfield model”

1985: Hinton: Learning in Boltzmann machines

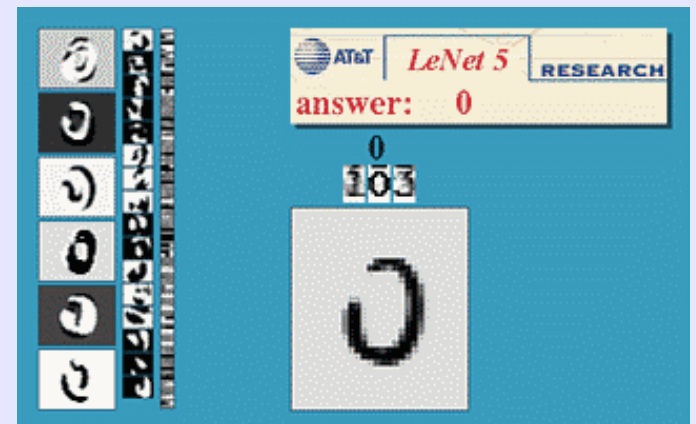
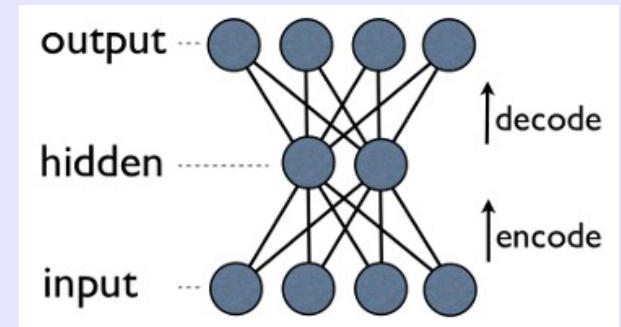
1986: Rumelhart, Hinton, Williams, backpropagation to train networks with several layers.
(Already 1974 by Werbos)

1986: Unsupervised, The autoencoder

1989: Hornik & White: Neural networks are universal approximators

1989: Lecun et al.: LeNet, the first convolutional neural network. Example of classifying handwritten digits.

: Recurrent networks, Backpropagation through time.



The second winter, mid 90's!

- Backpropagation does not work well for networks with many layers. E.g. recurrent networks were difficult to train.
- They were seen as a hassle to work with
- Not fast enough computers
- Some bad papers ...
- New algorithms that in some comparisons worked better. Support vector machines, random forest etc.
- Machine learning community “abandoned” neural networks.

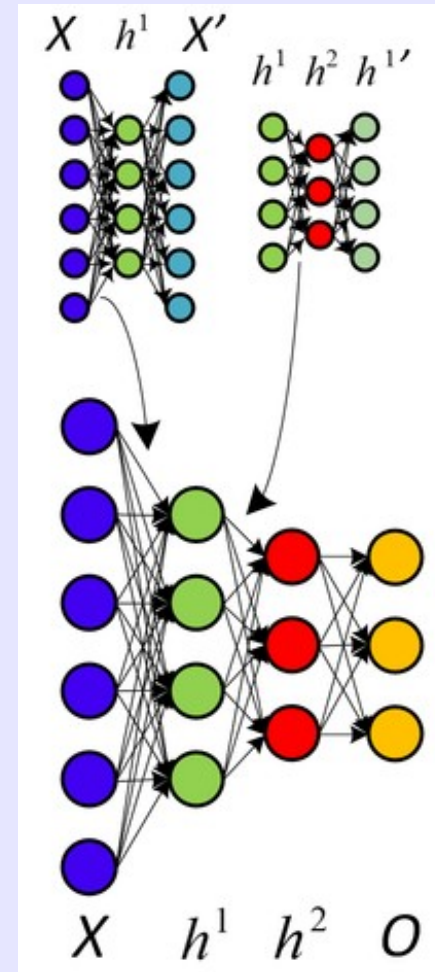
→ Schmidhuber, 1997, LSTM = “Long short term memory”.

Very popular today!!

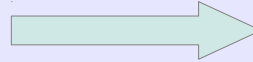
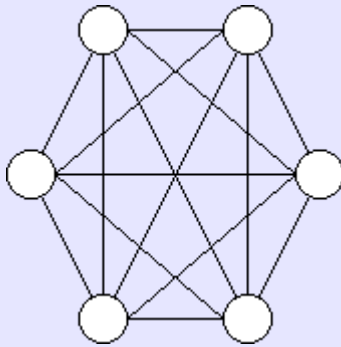
The second return of neural networks (with a new name, “deep learning”)

2006: Hinton et al., “A fast learning algorithm for deep belief nets”.

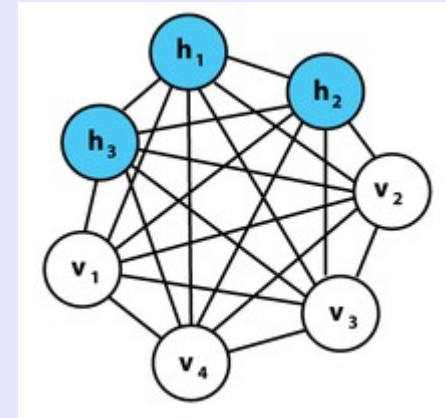
2007: Bengio et al. “Greedy layer-wise training of deep networks”



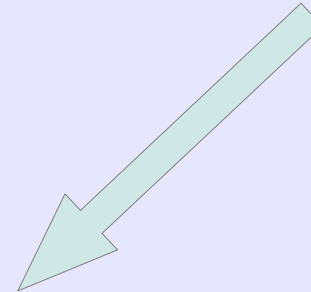
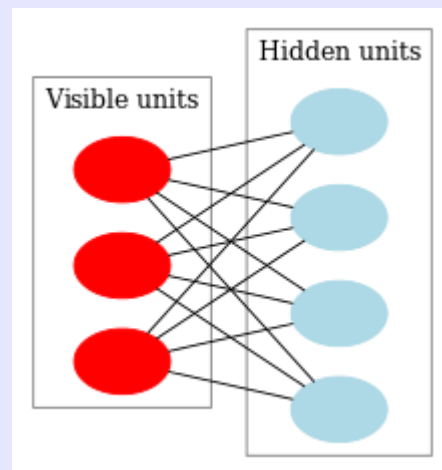
Hopfield model

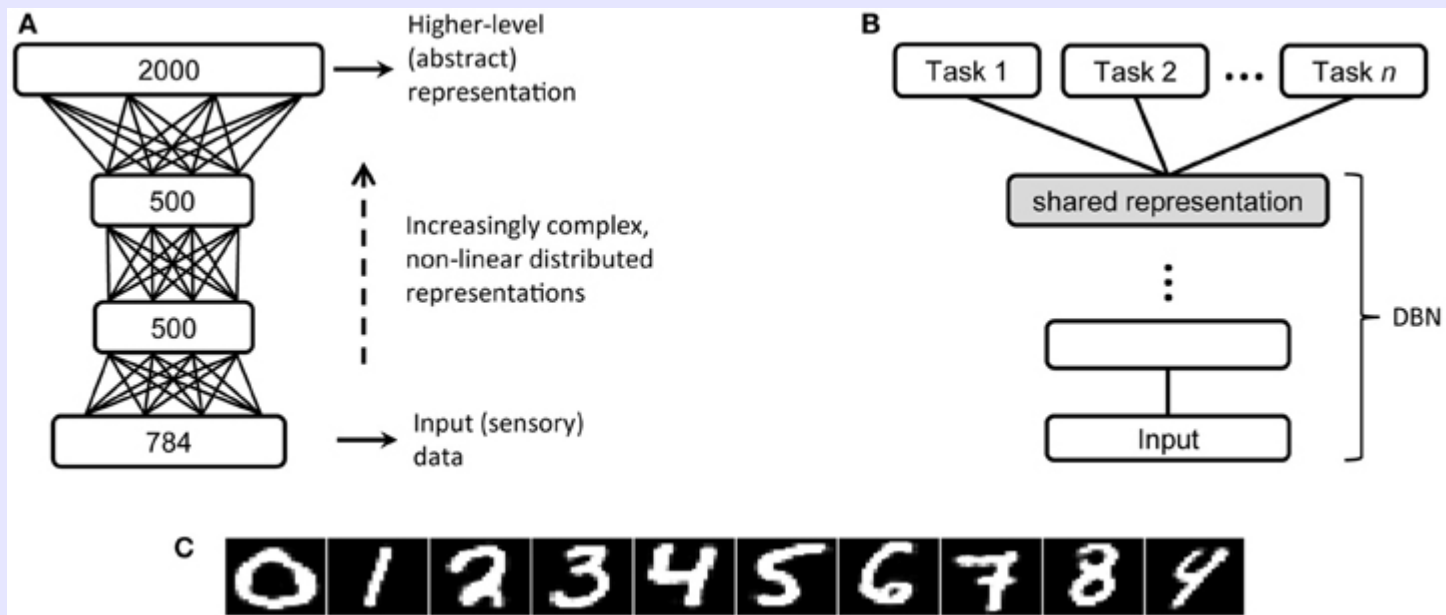
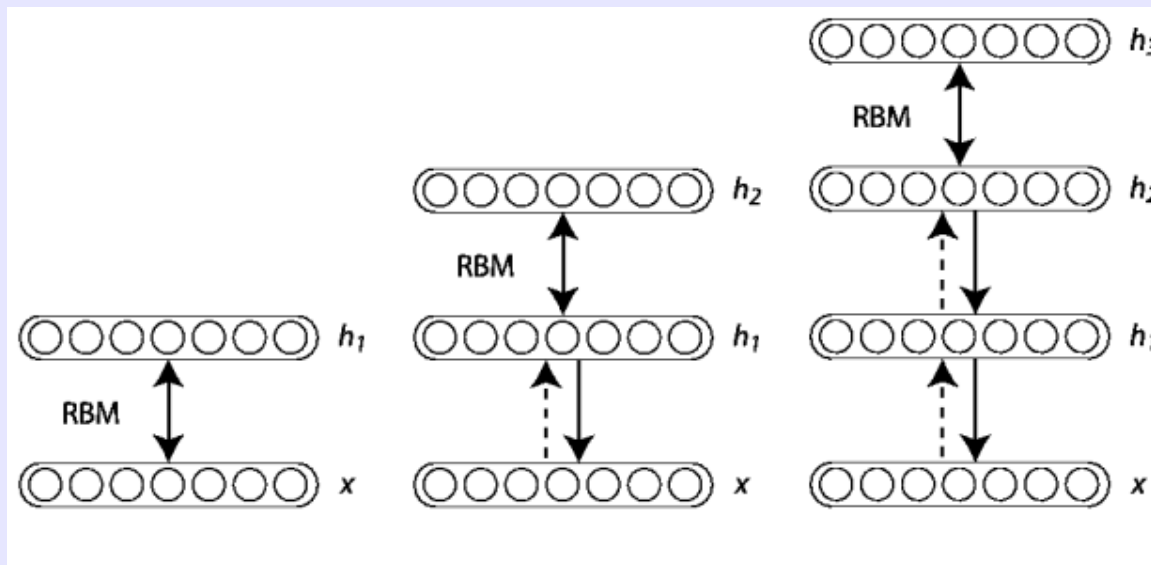


Boltzmann machine



Restricted Boltzmann machine





Very large momentum right now!

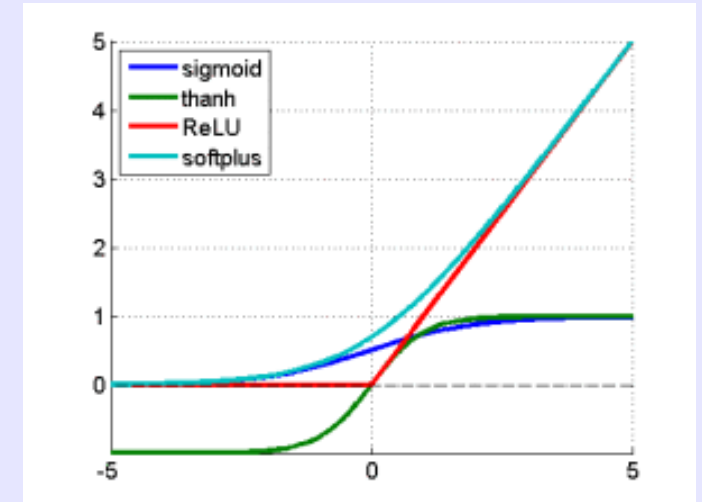
Technical developments

GPU's

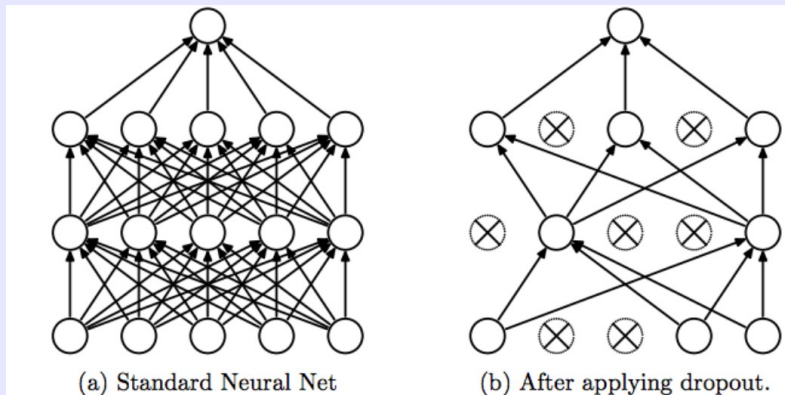


A lot of data!

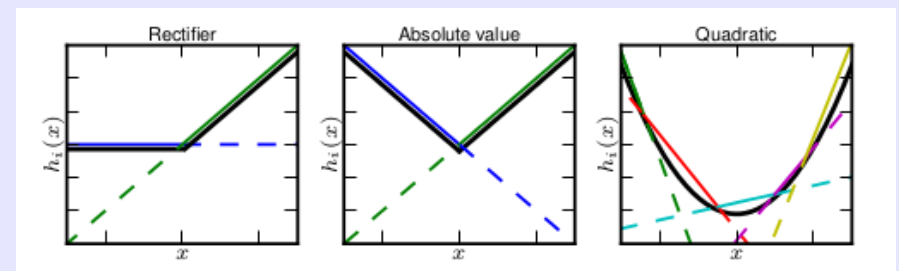
2010: Hinton et al. Rectifier activation functions



2012: Hinton et al. "Dropout"

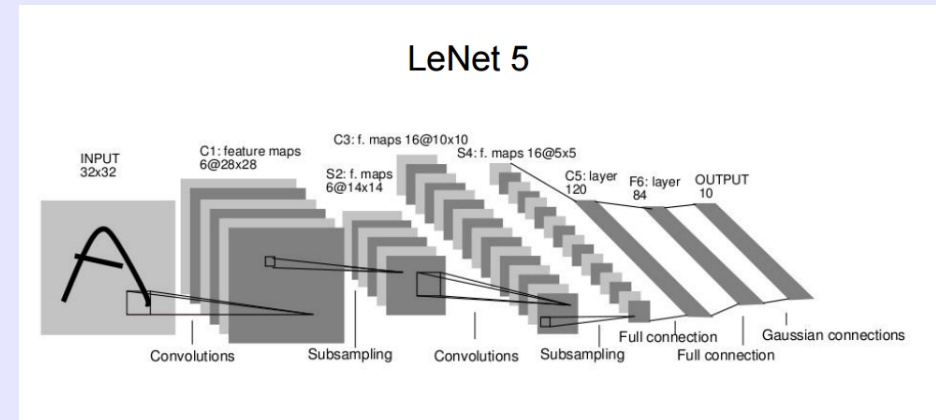
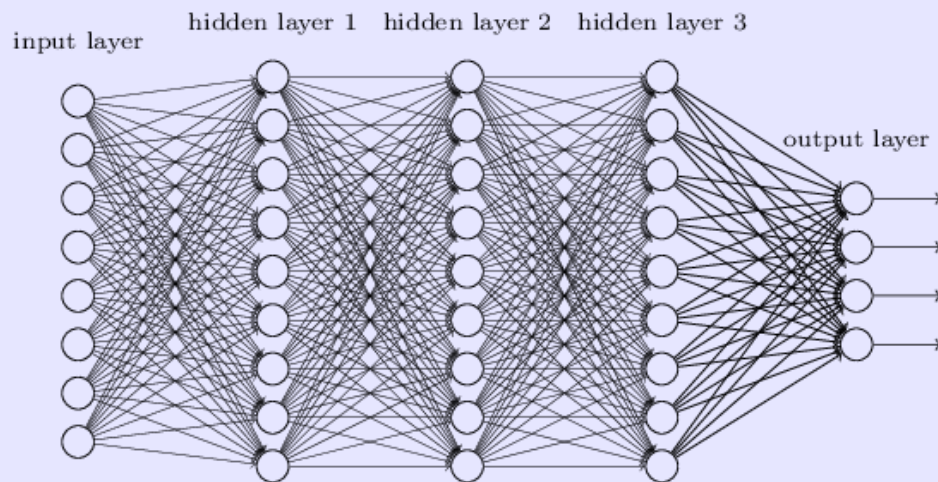


"Learnable" activation function!



So what about deep learning?

To make it simple: Deep learning = the ability to learn in deep neural networks

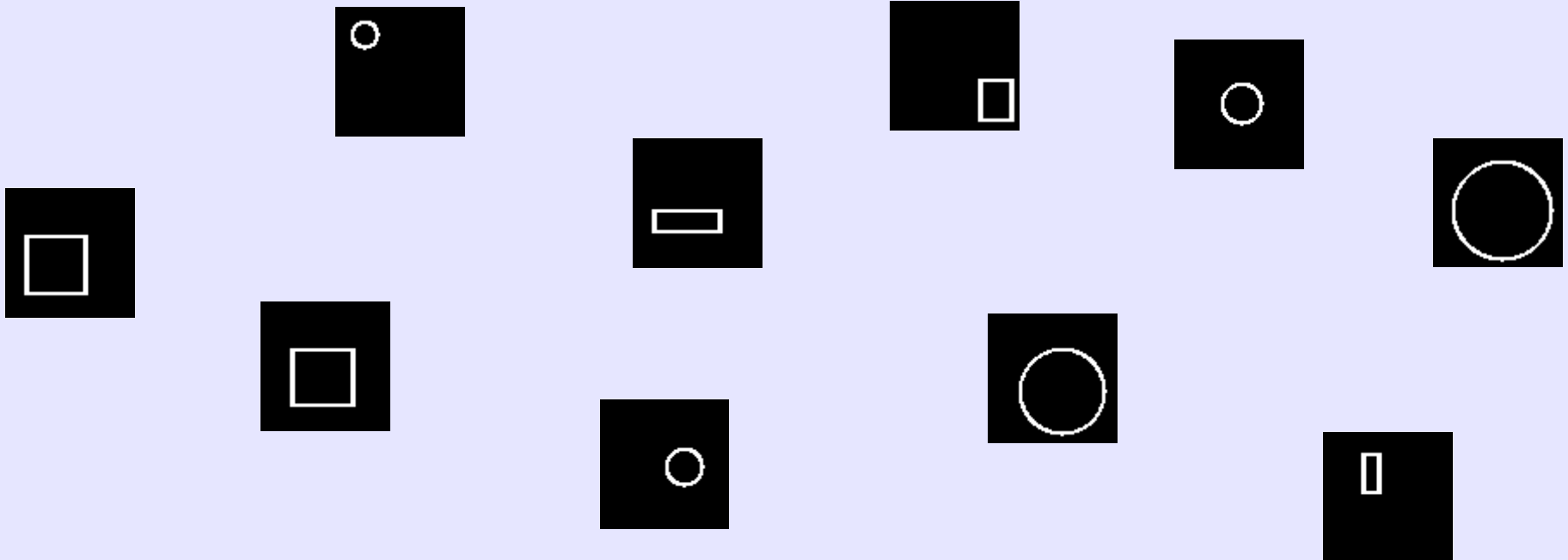


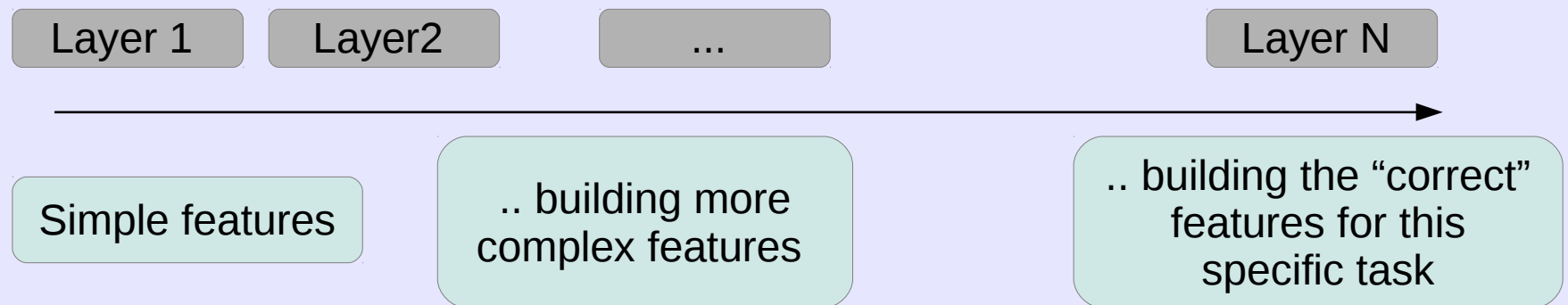
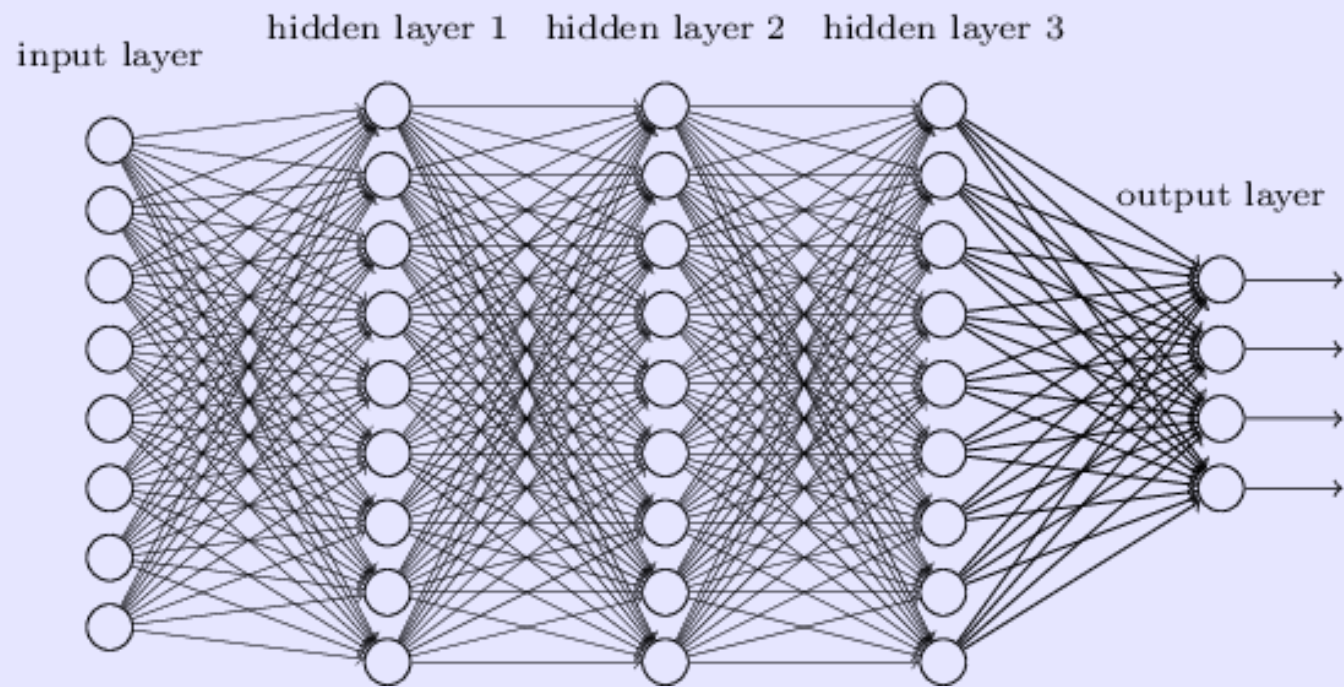
Better!: Deep learning = Representation learning

Rectangle or circle?

Divide into two groups based on area.

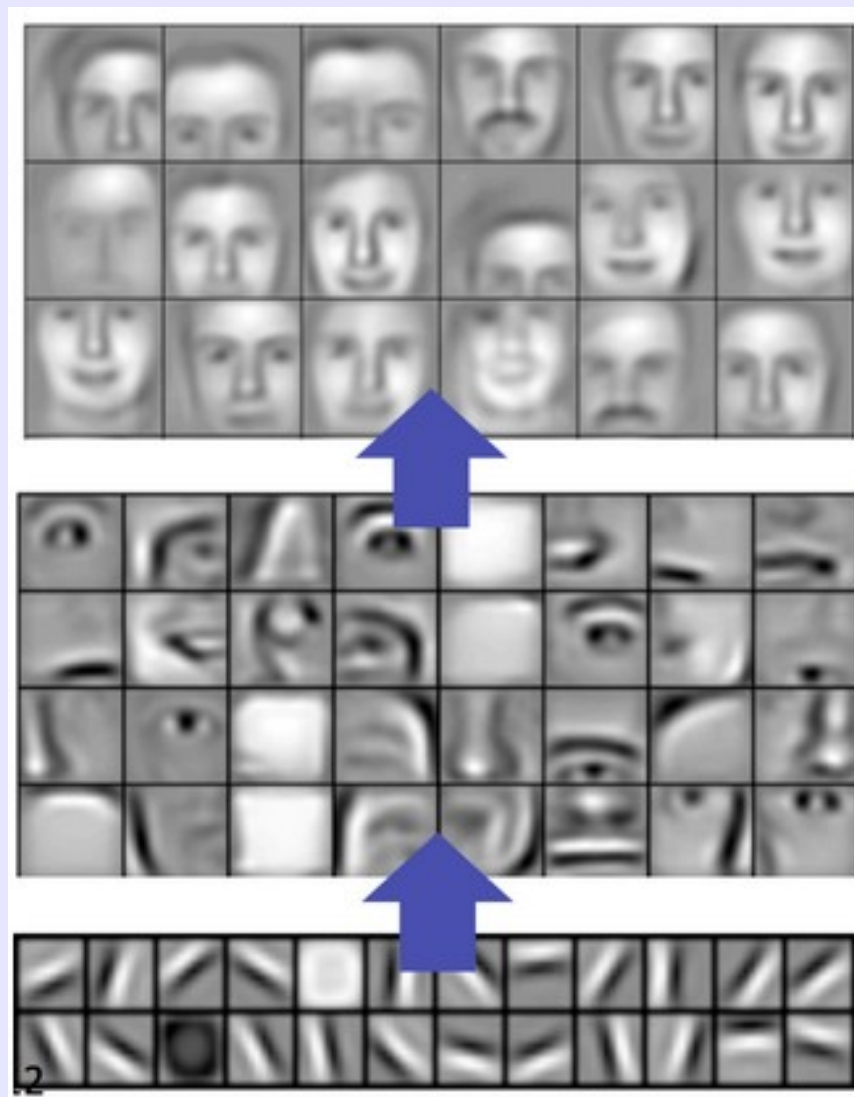
Which representation to use?



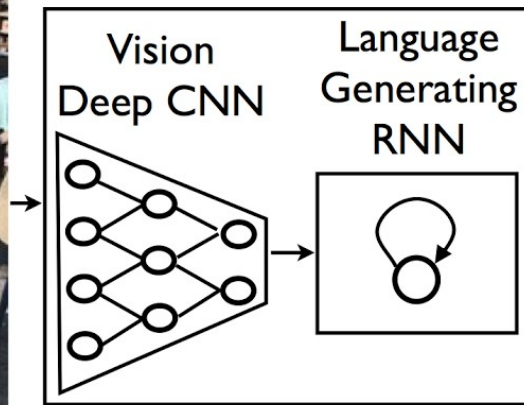


Feature learning

Feature learning



Some examples!



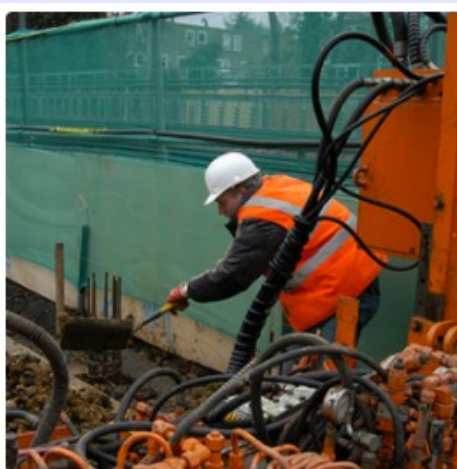
A group of people shopping at an outdoor market.

There are many vegetables at the fruit stand.

<https://gigaom.com/2014/11/18/google-stanford-build-hybrid-neural-networks-that-can-explain-photos/>



"man in black shirt is playing guitar."



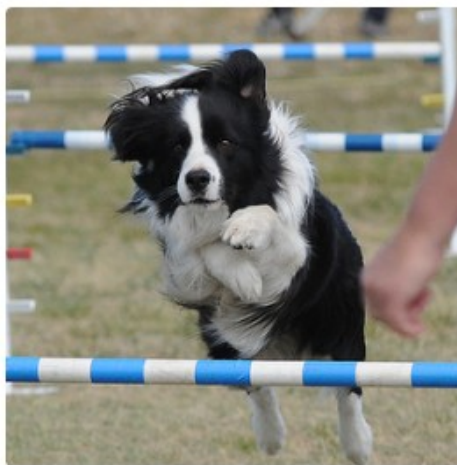
"construction worker in orange safety vest is working on road."



"two young girls are playing with lego toy."



"girl in pink dress is jumping in air."

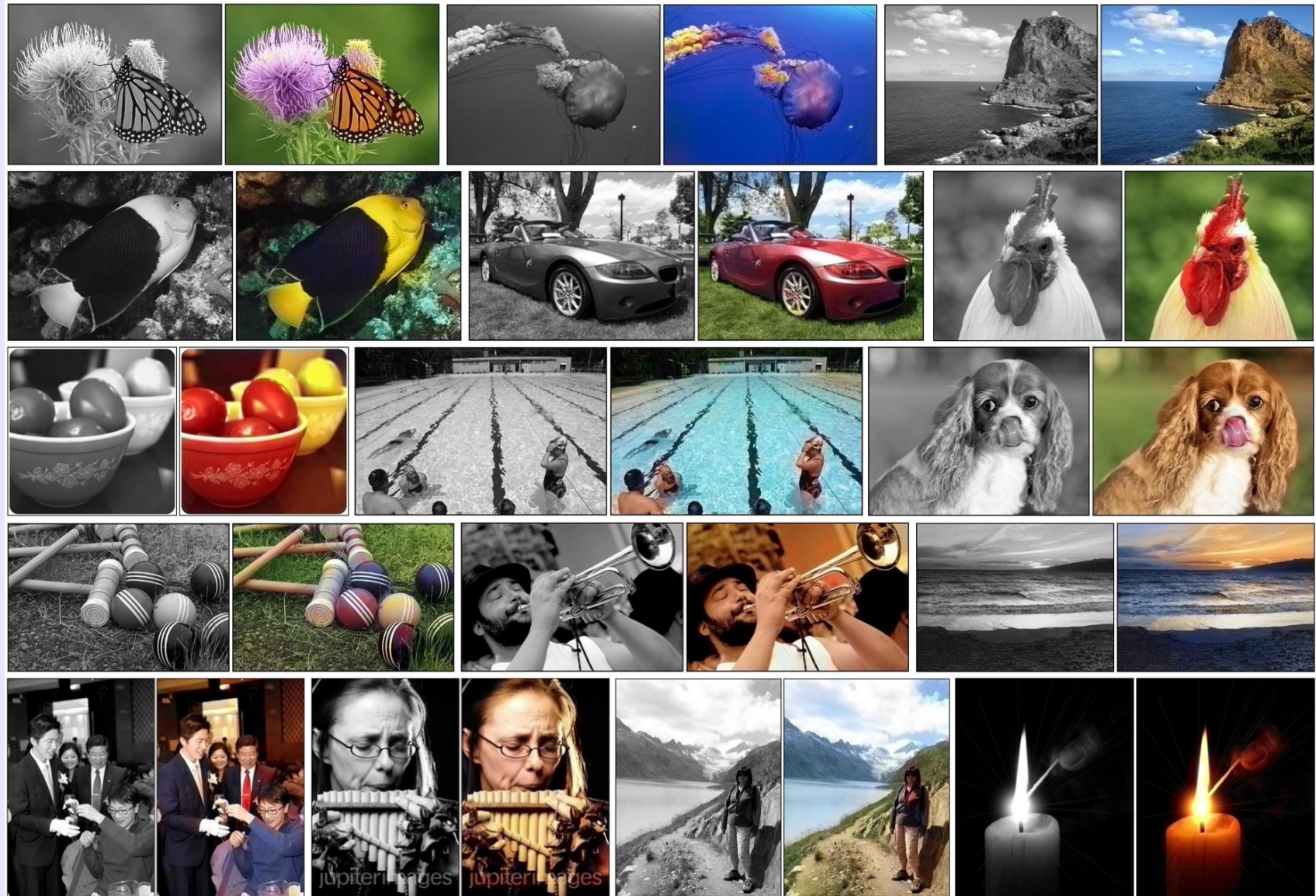


"black and white dog jumps over bar."





"young girl in pink shirt is swinging on swing."

Colorizing black-white images





Google translate

Svenska ▾

Automatisk översättning av text till andra språk använder idag "deep learning" tekniker.

På ängen finns det många får.

Vi får mycket sol på oss när vi är på ängen.

Engelska ▾

Automatic translation of text into other languages today uses "deep learning" techniques.

In the meadow there are many sheep.

We get a lot of sun on us when we are in the meadow.

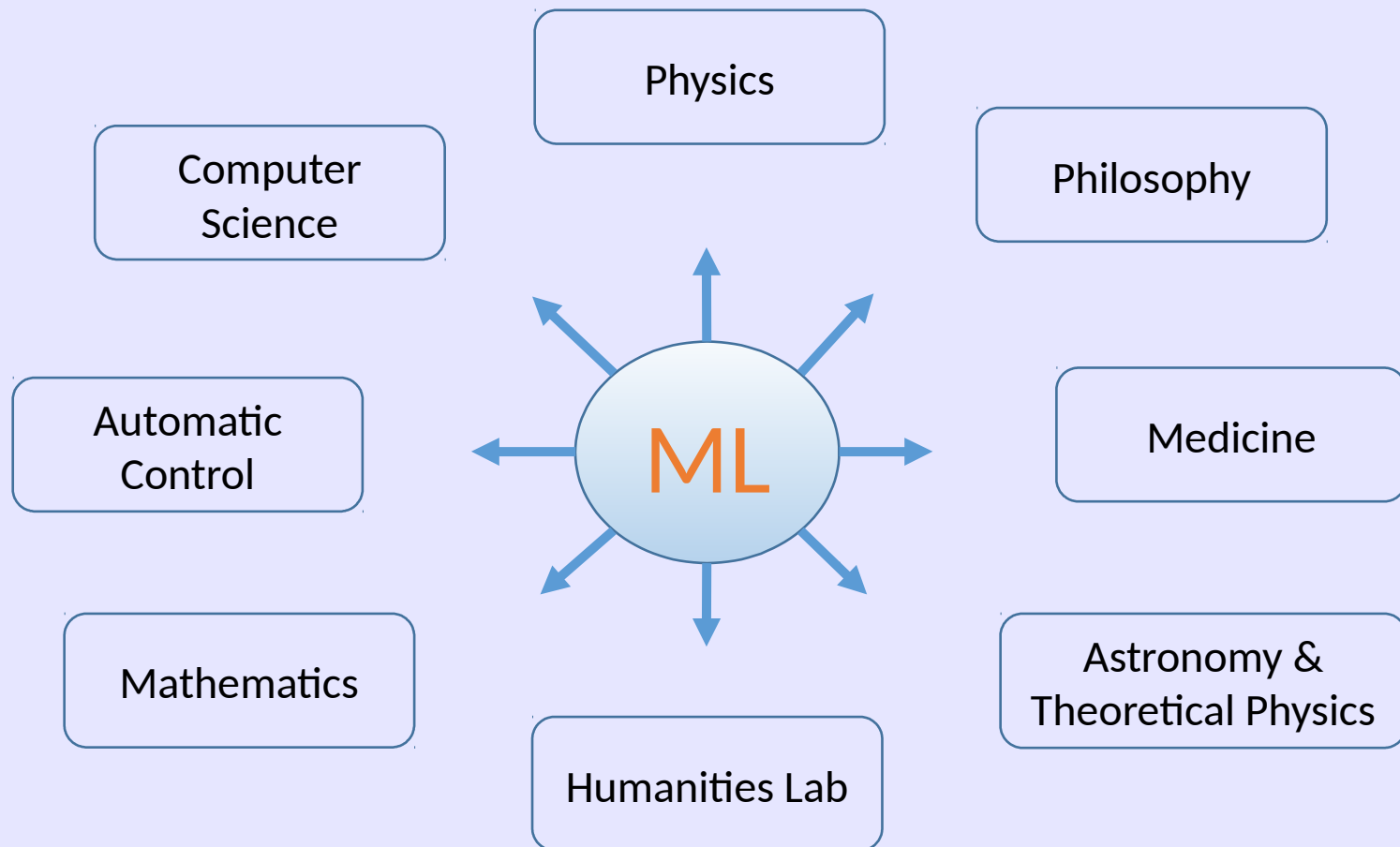
Öppna i Google Översätt

Feedback

Semantic segmentation



Machine Learning research and applications in Lund



Computational Biology & Biological Physics, Lund

Mattias Ohlsson, Patrik Edén, Carsten Peterson, Najmeh Abiri,
Björn Linse

