Deep learning

1.1. From neural networks to deep learning

François Fleuret

https://fleuret.org/dlc/

UNIVERSITÉ DE GENÈVE

Many applications require the automatic extraction of "refined" information from raw signal (e.g. image recognition, automatic speech processing, natural language processing, robotic control, geometry reconstruction).

(ImageNet)

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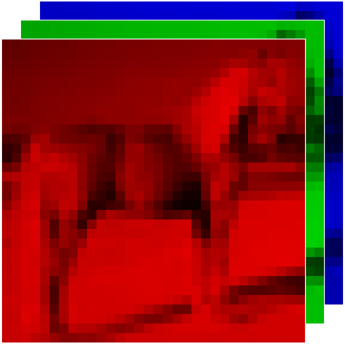
This:  is a horse



```
>>> from torchvision.datasets import CIFAR10
>>> cifar = CIFAR10('./data/cifar10/', train=True, download=True)
Files already downloaded and verified
>>> x = torch.from_numpy(cifar.data)[43].permute(2, 0, 1)
>>> x[:, :4, :8]
tensor([[[ 99,  98, 100, 103, 105, 107, 108, 110],
         [100, 100, 102, 105, 107, 109, 110, 112],
         [104, 104, 106, 109, 111, 112, 114, 116],
         [109, 109, 111, 113, 116, 117, 118, 120]],

        [[166, 165, 167, 169, 171, 172, 173, 175],
         [166, 164, 167, 169, 169, 171, 172, 174],
         [169, 167, 170, 171, 171, 173, 174, 176],
         [170, 169, 172, 173, 175, 176, 177, 178]],

        [[198, 196, 199, 200, 200, 202, 203, 204],
         [195, 194, 197, 197, 197, 199, 200, 201],
         [197, 195, 198, 198, 198, 199, 201, 202],
         [197, 196, 199, 198, 198, 199, 200, 201]]], dtype=torch.uint8)
```

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Deep learning encompasses software technologies to scale-up to billions of model parameters and as many training examples.

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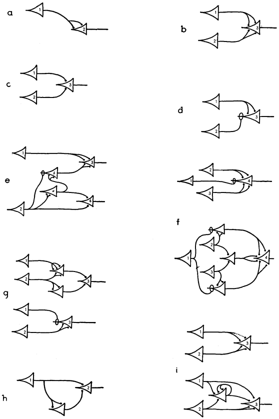
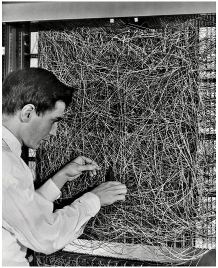
"Artificial neural networks" pre-dated these approaches, and do not follow this dichotomy. They consist of "deep" stacks of parametrized processing.

From artificial neural networks to "Deep Learning"

Networks of "Threshold Logic Unit"



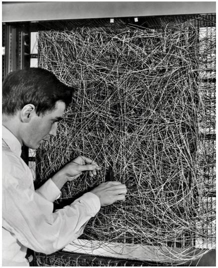
(McCulloch and Pitts, 1943)



Frank Rosenblatt working on the Mark I perceptron (1956)

1949 – Donald Hebb proposes the Hebbian Learning principle (Hebb, 1949).

1951 – Marvin Minsky creates the first ANN (Hebbian learning, 40 neurons).



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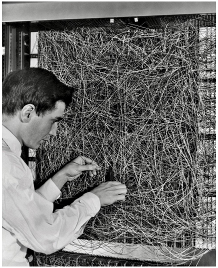

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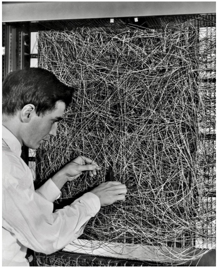

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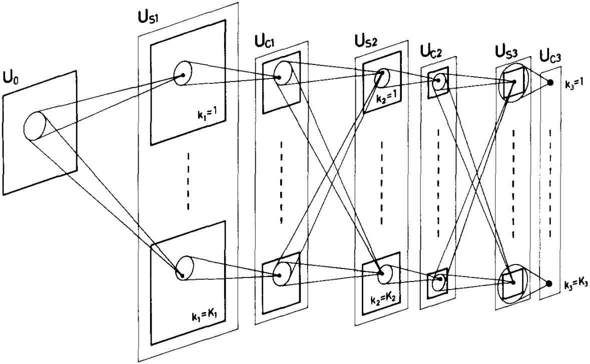
1982 – Paul Werbos proposes back-propagation for ANNs (Werbos, 1981).

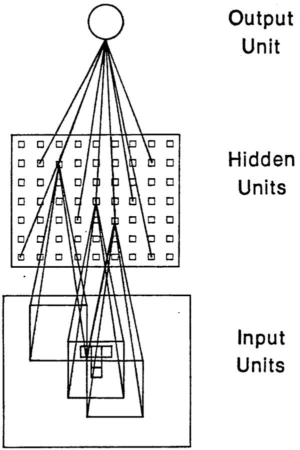
Neocognitron



(Fukushima, 1980)

This model follows Hubel and Wiesel's results.

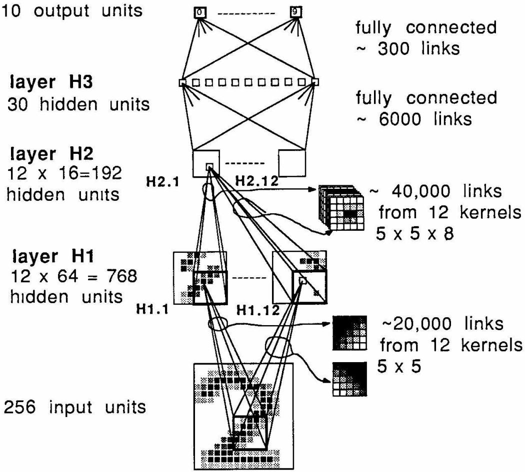
Network for the T-C problem



Trained with back-prop.

(Rumelhart et al., 1988)

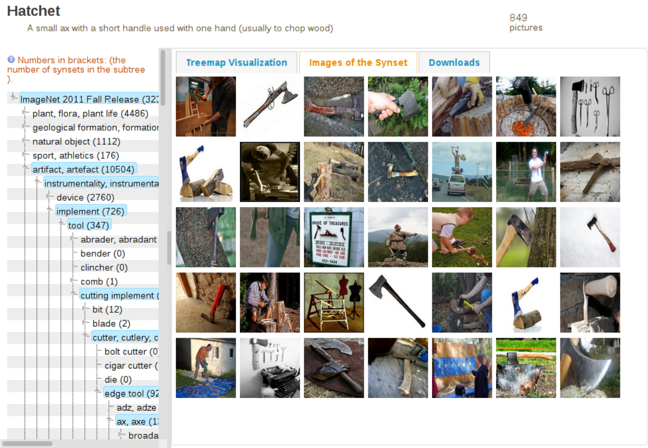
LeNet family



(LeCun et al., 1989)

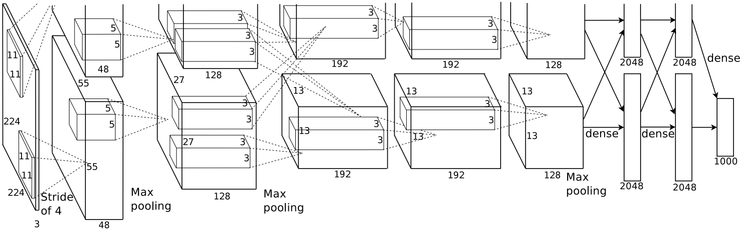
ImageNet Large Scale Visual Recognition Challenge.

Started 2010, 1 million images, 1000 categories



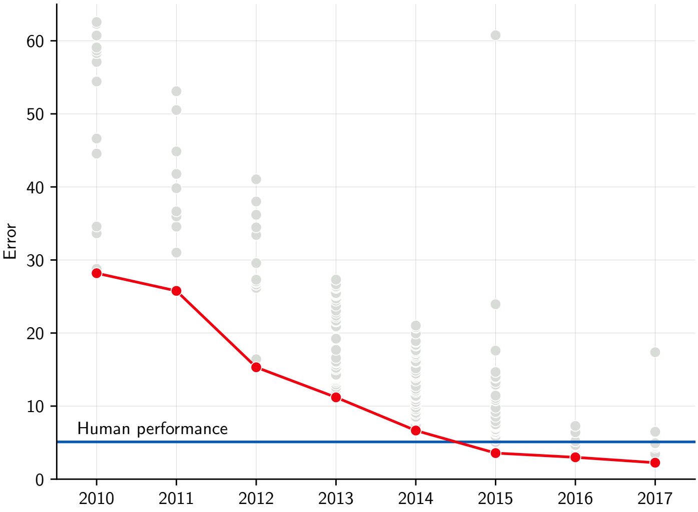
(http://image-net.org/challenges/LSVRC/2014/browse-synsets)

AlexNet

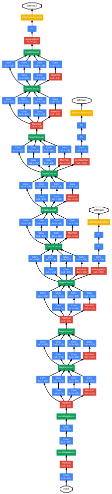


(Krizhevsky et al., 2012)

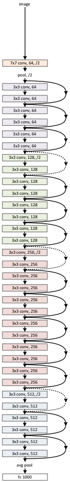
Top-5 error rate on ImageNet



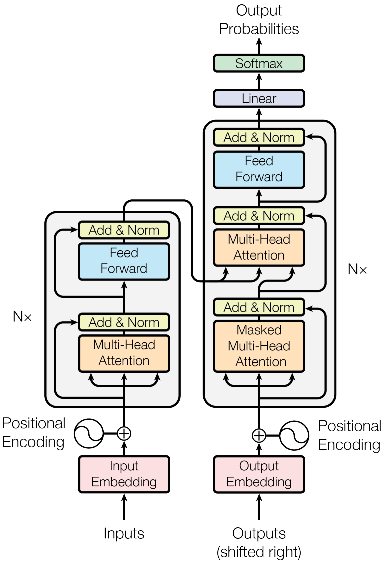
(Gershgorn, 2017)



GoogleNet (Szegedy et al., 2015)



ResNet (He et al., 2015)



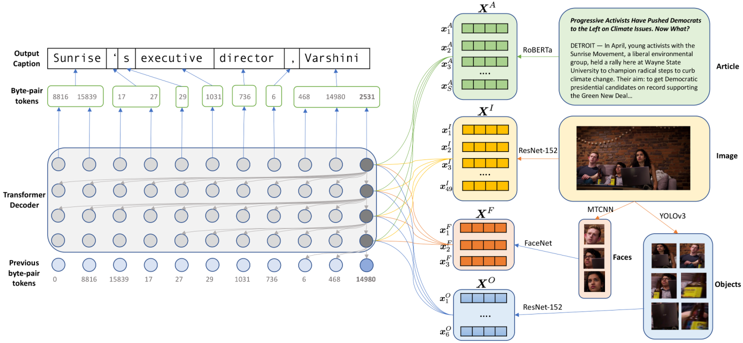
(Vaswani et al., 2017)

Deep learning is built on a natural generalization of a neural network: **a graph of tensor operators**, taking advantage of

- the chain rule (aka "back-propagation"),
- stochastic gradient decent,
- convolutions,
- parallel operations on GPUs.

This does not differ much from networks from the 90s.

This generalization allows to design complex networks of operators dealing with images, sound, text, sequences, etc. and to train them end-to-end.



(Tran et al., 2020)

The end

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