EE-559 – Deep learning

1.1. From neural networks to deep learning

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https://fleuret.org/ee559/

Fri Jan 4 17:38:42 UTC 2019

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Why learning

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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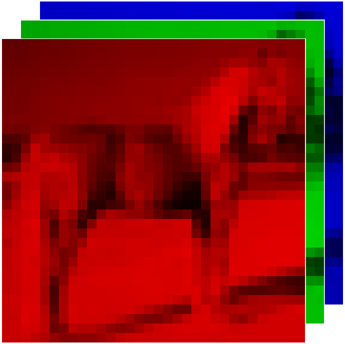
This:  is a horse



```
>>> from torchvision import datasets
>>> cifar = datasets.CIFAR10('./data/cifar10/', train=True, download=True)
Files already downloaded and verified
>>> x = torch.from_numpy(cifar.train_data)[43].transpose(2, 0).transpose(1, 2)
>>> x.size()
torch.Size([3, 32, 32])
>>> 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],
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        [[ 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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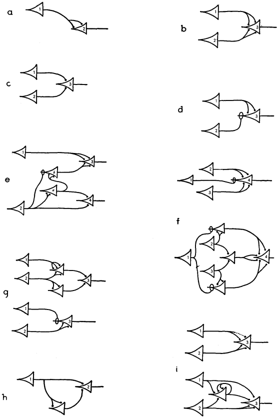
"Artificial neural networks" pre-dated these approaches, and do not follow that dichotomy. They consist of "deep" stacks of parametrized processing.

From artificial neural networks to "Deep Learning"



Networks of "Threshold Logic Unit"

(McCulloch and Pitts, 1943)

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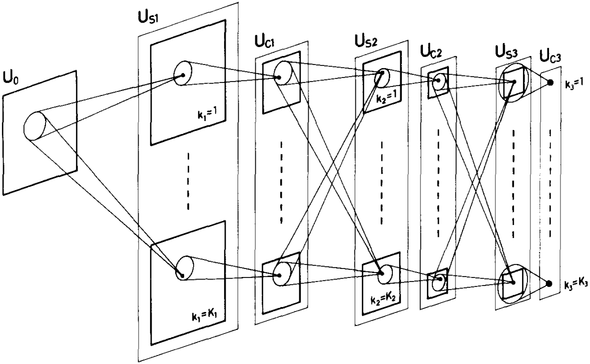
1982 – Paul Werbos proposes back-propagation for ANNs.

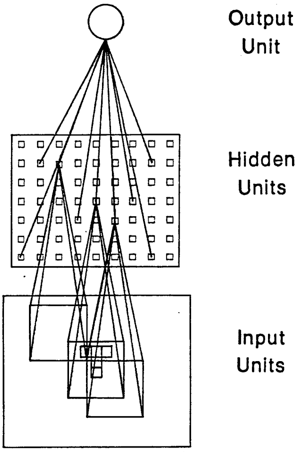
Neocognitron



Follows Hubel and Wiesel's results.

(Fukushima, 1980)

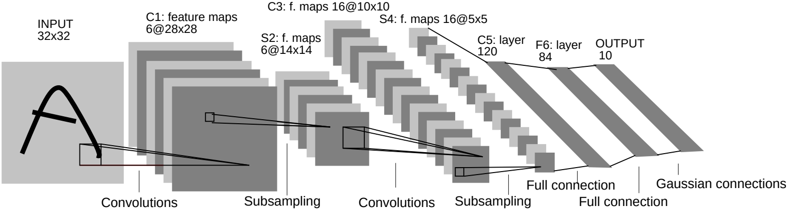
Network for the T-C problem



Trained with back-prop.

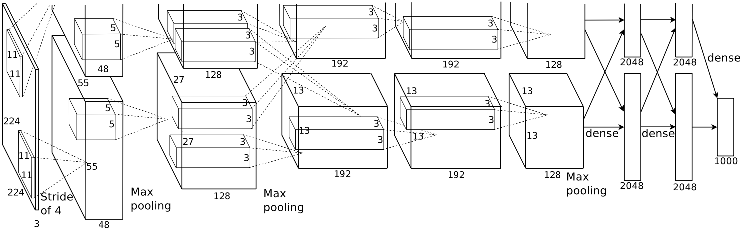
(Rumelhart et al., 1988)

LeNet-5



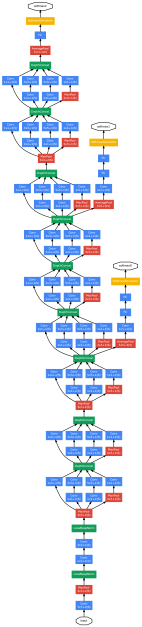
(leCun et al., 1998)

AlexNet



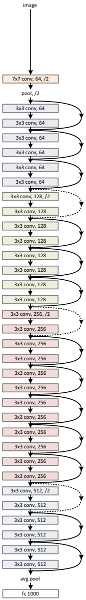
(Krizhevsky et al., 2012)

GoogLeNet



(Szegedy et al., 2015)

Resnet



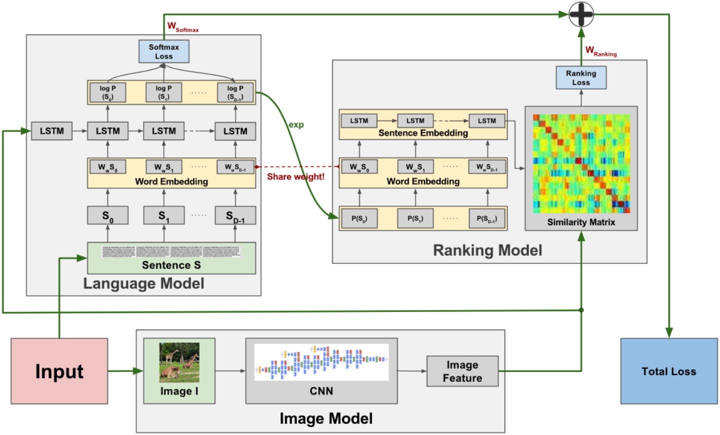
(He et al., 2015)

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.

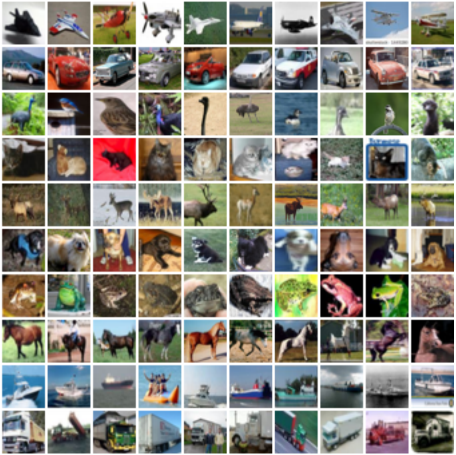
This does not differ much from networks from the 90s

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



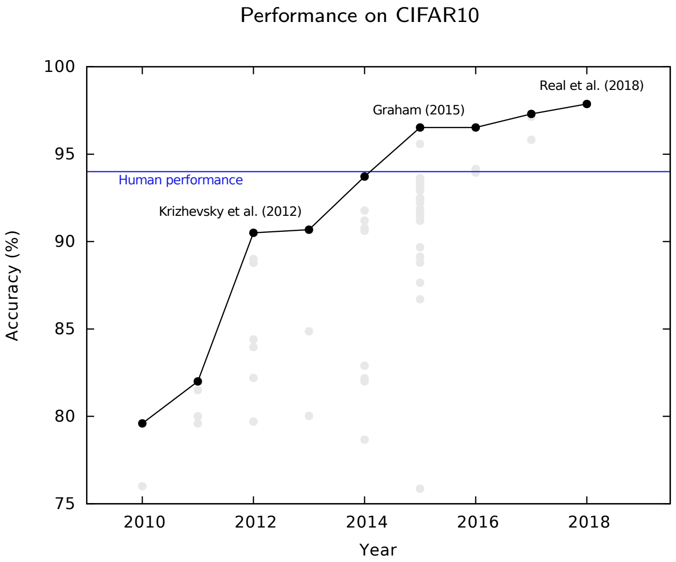
(Yeung et al., 2015)

CIFAR10



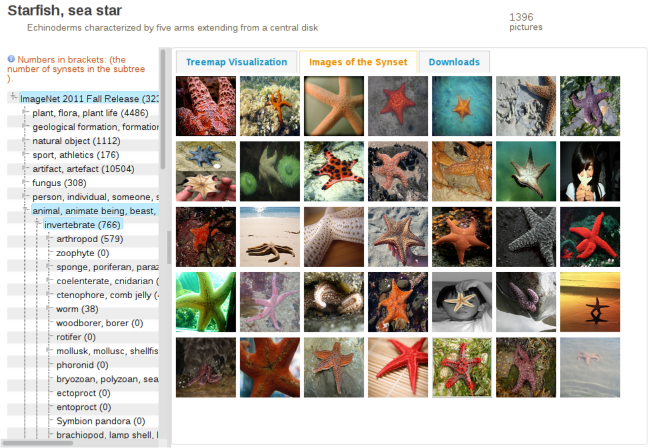
32×32 color images, 50k train samples, 10k test samples.

(Krizhevsky, 2009, chap. 3)


Performance on CIFAR10
100
95
90
85
80
75
2010
2012
2014
2016
2018
Year
Accuracy (%)
Real et al. (2018)
Graham (2015)
Human performance
Krizhevsky et al. (2012)

ImageNet Large Scale Visual Recognition Challenge.

1000 categories, $>$ 1M images



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

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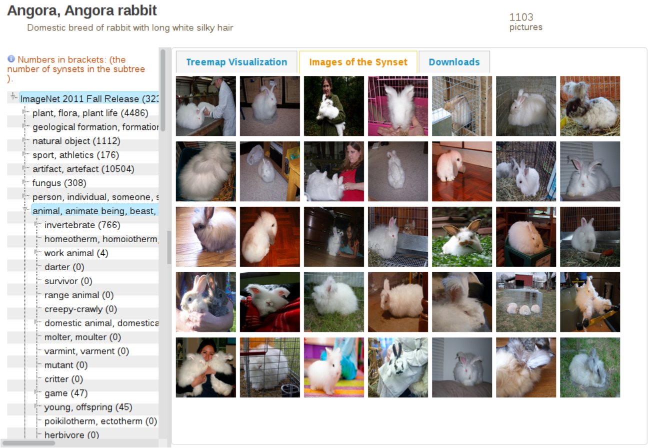

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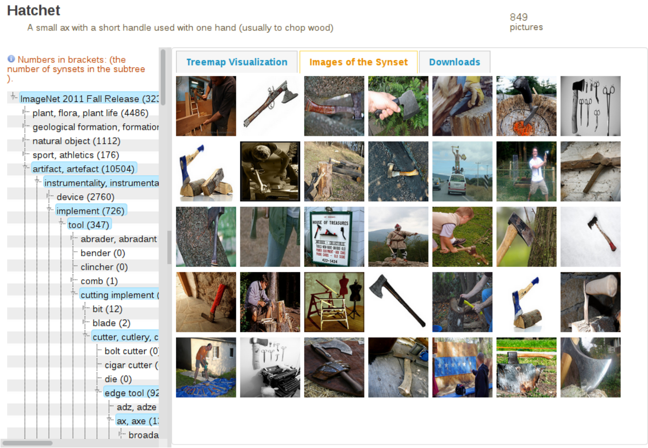

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method	top-1 err.	top-5 err.
VGG [41] (ILSVRC'14)	-	8.43†
GoogLeNet [44] (ILSVRC'14)	-	7.89
VGG [41] (v5)	24.4	7.1
PReLU-net [13]	21.59	5.71
BN-inception [16]	21.99	5.81
ResNet-34 B	21.84	5.71
ResNet-34 C	21.53	5.60
ResNet-50	20.74	5.25
ResNet-101	19.87	4.60
ResNet-152	**19.38**	**4.49**

Table 4. Error rates (%) of **single-model** results on the ImageNet validation set (except † reported on the test set).

method	top-5 err. (**test**)
VGG [41] (ILSVRC'14)	7.32
GoogLeNet [44] (ILSVRC'14)	6.66
VGG [41] (v5)	6.8
PReLU-net [13]	4.94
BN-inception [16]	4.82
ResNet (ILSVRC'15)	**3.57**

Table 5. Error rates (%) of **ensembles**. The top-5 error is on the test set of ImageNet and reported by the test server.

(He et al., 2015)

The end

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