

## EE-559 – Deep learning

### 1.1. From artificial neural networks to deep learning

François Fleuret

<https://fleuret.org/ee559/>

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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)

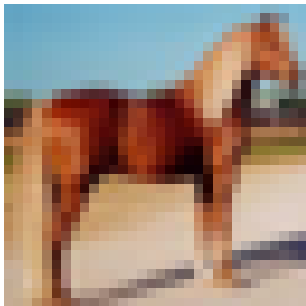
Our brain is so good at interpreting visual information that the “semantic gap” is hard to assess intuitively.

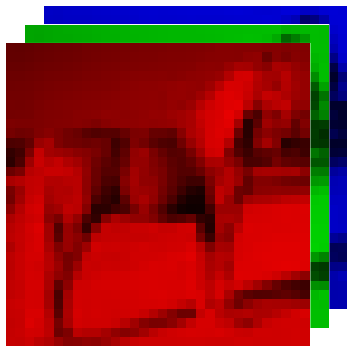
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This:



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],
          [ 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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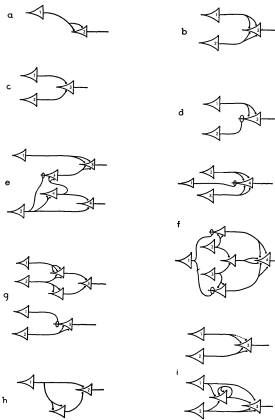
Classical ML methods combine a “learnable” model from statistics (e.g. “linear regression”) with prior knowledge in pre-processing.

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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)



1949 – Donald Hebb proposes the Hebbian Learning principle.

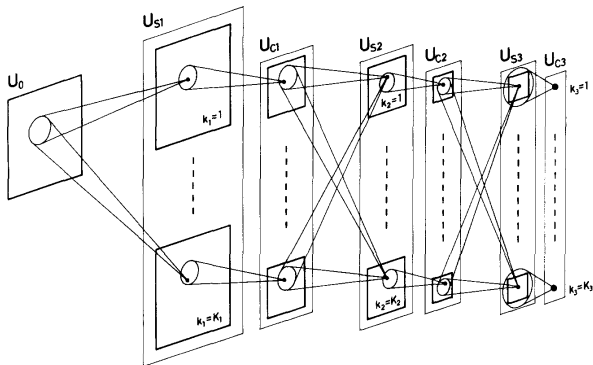
1951 – Marvin Minsky creates the first ANN (Hebbian learning, 40 neurons).

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- 1959 – David H. Hubel and Torsten Wiesel demonstrate orientation selectivity and columnar organization in the cat's visual cortex.
- 1982 – Paul Werbos proposes back-propagation for ANNs.

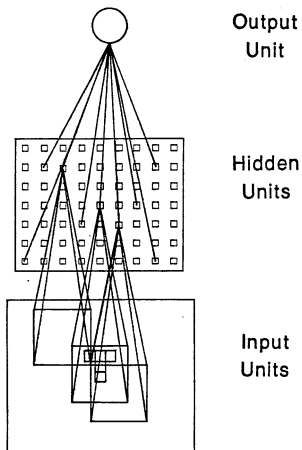
## Neocognitron



Follows Hubel and Wiesel's results.

(Fukushima, 1980)

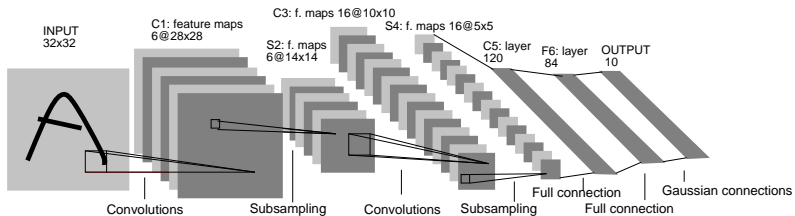
## Network for the T-C problem



Trained with back-prop.

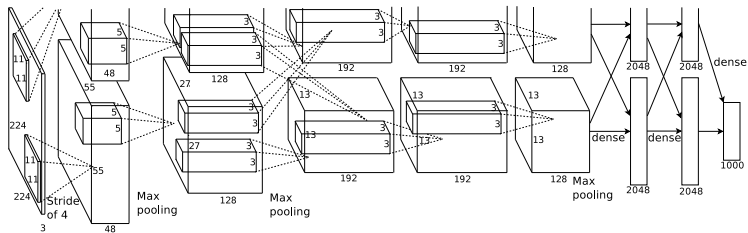
(Rumelhart et al., 1988)

## LeNet-5



(leCun et al., 1998)

## AlexNet



(Krizhevsky et al., 2012)

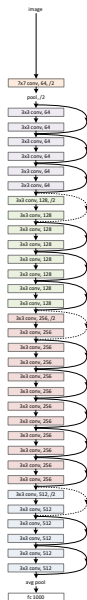


## GoogLeNet



(Szegedy et al., 2015)

# Resnet



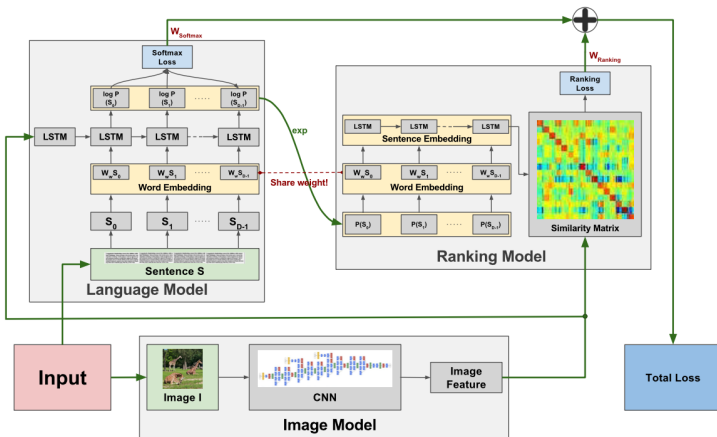
(He et al., 2015)

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 descent,
- convolutions,
- parallel operations on GPUs.

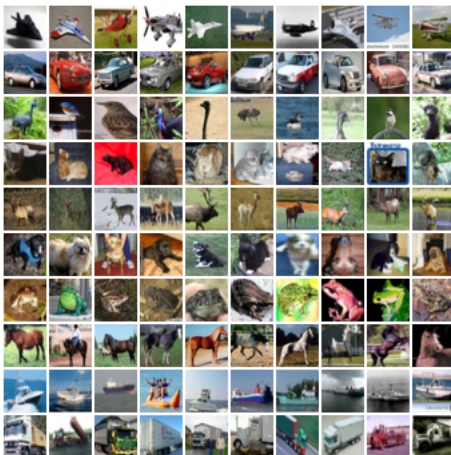
This does not differ much from networks from the 90s

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)

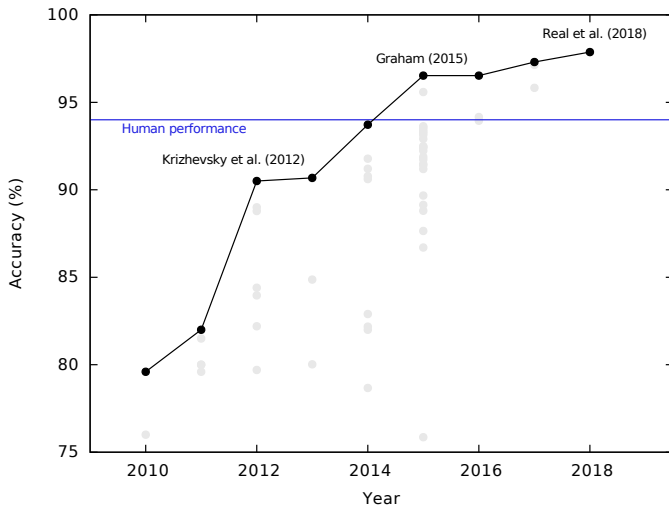
## CIFAR10



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

(Krizhevsky, 2009, chap. 3)

## Performance on CIFAR10



# ImageNet Large Scale Visual Recognition Challenge.

1000 categories, > 1M images

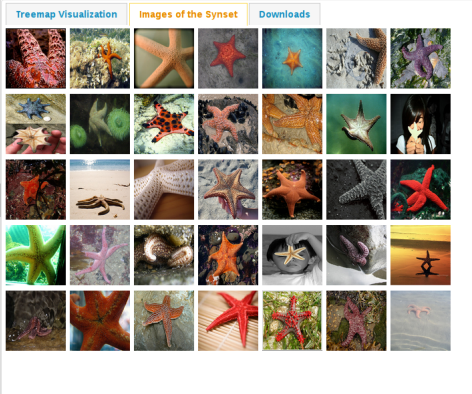
## Starfish, sea star

Echinoderms characterized by five arms extending from a central disk

1396  
pictures

Numbers in brackets: (the number of synsets in the subtree)

- ImageNet 2011 Fall Release (32)
- plant, flora, plant life (4486)
- geological formation, formation
- natural object (1112)
- sport, athletics (176)
- artifact, artefact (10504)
- fungus (308)
- person, individual, someone, s
- animal, animate being, beast,
- invertebrate (766)
  - arthropod (579)
  - zoophyte (0)
  - sponge, poriferan, paraz
  - coelenterate, cnidarian (
  - ctenophore, comb jelly (
  - worm (38)
  - woodborer, borer (0)
  - rotifer (0)
  - mollusk, mollusc, shellfis
  - phoronid (0)
  - bryozoan, polyzoan, sea
  - ectoproct (0)
  - entoproct (0)
  - Symbion pandora (0)
  - brachiopod, lamp shell, l



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

# ImageNet Large Scale Visual Recognition Challenge.

1000 categories, > 1M images

## Angora, Angora rabbit

Domestic breed of rabbit with long white silky hair

1103  
pictures

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ImageNet 2011 Fall Release (32)

plant, flora, plant life (4486)

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fungus (308)

person, individual, someone, s

animal, animate being, beast,

invertebrate (766)

homeotherm, homoiotherm

work animal (4)

darter (0)

survivor (0)

range animal (0)

creepy-crawly (0)

domestic animal, domestica

molt, moult (0)

varmint, varment (0)

mutant (0)

critter (0)

game (47)

young, offspring (45)

poikilotherm, ectotherm (0)

herbivore (0)

TreeMap Visualization

Images of the Synset

Downloads



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



# ImageNet Large Scale Visual Recognition Challenge.

1000 categories, > 1M images

## Hatchet

A small ax with a short handle used with one hand (usually to chop wood)

849  
pictures

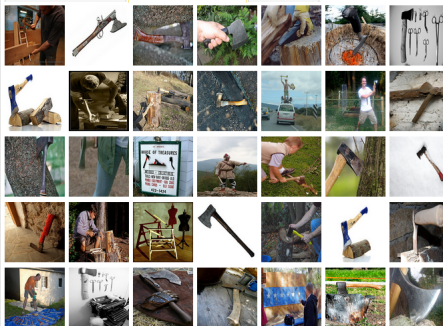
Numbers in brackets: (the number of synsets in the subtree)

- ImageNet 2011 Fall Release (32)
- plant, flora, plant life (4486)
- geological formation, formation
- natural object (1112)
- sport, athletics (176)
- artifact, artefact (10504)
- instrumentality, instrumenta
- device (2760)
- implement (726)
- tool (347)
- abrader, abradant
- bender (0)
- clincher (0)
- comb (1)
- cutting implement (
- bit (12)
- blade (2)
- cutter, cutlery, c
- bolt cutter (0
- cigar cutter (
- die (0)
- edge tool (9
- adz, adze
- ax, axe (1
- broad

### Treemap Visualization

### Images of the Synset

### Downloads



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

method	top-1 err.	top-5 err.
VGG [41] (ILSVRC'14)	-	8.43 <sup>†</sup>
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	<b>19.38</b>	<b>4.49</b>

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

method	top-5 err. ( <b>test</b> )
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
<b>ResNet (ILSVRC'15)</b>	<b>3.57</b>

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

## References

- K. Fukushima. Neocognitron: A self-organizing neural network model for a mechanism of pattern recognition unaffected by shift in position. *Biological Cybernetics*, 36(4): 193–202, April 1980.
- K. He, X. Zhang, S. Ren, and J. Sun. Deep residual learning for image recognition. *CoRR*, abs/1512.03385, 2015.
- A. Krizhevsky. Learning multiple layers of features from tiny images. Master’s thesis, Department of Computer Science, University of Toronto, 2009.
- A. Krizhevsky, I. Sutskever, and G. Hinton. Imagenet classification with deep convolutional neural networks. In *Neural Information Processing Systems (NIPS)*, 2012.
- Y. leCun, L. Bottou, Y. Bengio, and P. Haffner. Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11):2278–2324, 1998.
- W. S. McCulloch and W. Pitts. A logical calculus of the ideas immanent in nervous activity. *The bulletin of mathematical biophysics*, 5(4):115–133, 1943.
- D. E. Rumelhart, G. E. Hinton, and R. J. Williams. *Neurocomputing: Foundations of Research*, chapter Learning Representations by Back-propagating Errors, pages 696–699. MIT Press, 1988.
- C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich. Going deeper with convolutions. In *Conference on Computer Vision and Pattern Recognition (CVPR)*, 2015.
- S. Yeung, O. Russakovsky, G. Mori, and L. Fei-Fei. End-to-end learning of action detection from frame glimpses in videos. *CoRR*, abs/1511.06984, 2015.