

From Artificial Neural Networks to Deep Learning

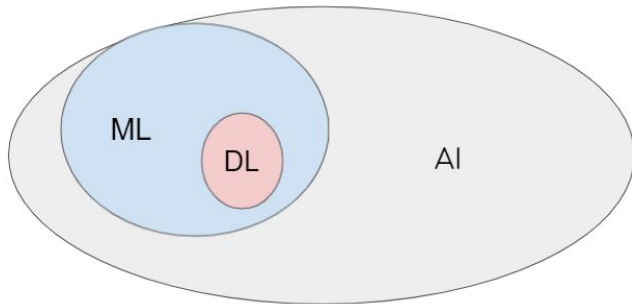
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Aug-Dec 2021

What is DL?

What is DL?

- Subset of ML that is essentially neural networks with more layers
- Crude attempt to imitate the human brain in learning

What is DL?



Classical ML vs. DL

- Classical ML: Handcrafted features + learnable model
- Need strong domain expertise

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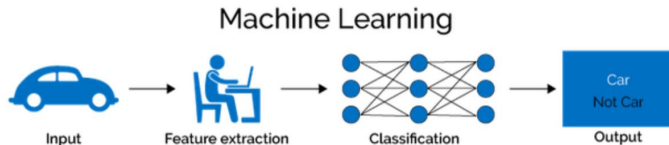


Figure credits: Jay Shaw & Quora

Classical ML vs. DL

- Deep Learning: Deep stack of parameterized processing
- End-to-End learning

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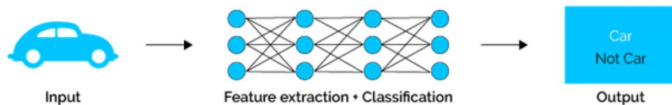


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Classical ML vs. DL

- ANNs predate some of the classical ML techniques
- We are now dealing with a new generation ANNs

Neuron

- About 100 billion neurons in human brain

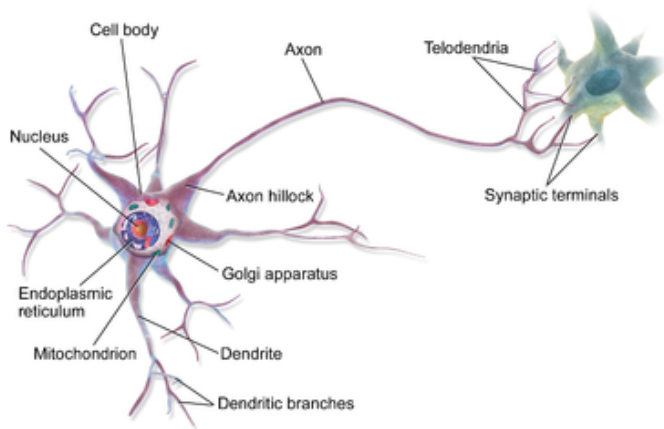


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History of Neural Networks

- ① McCulloch Pitts neuron (1943) - Threshold Logic Unit

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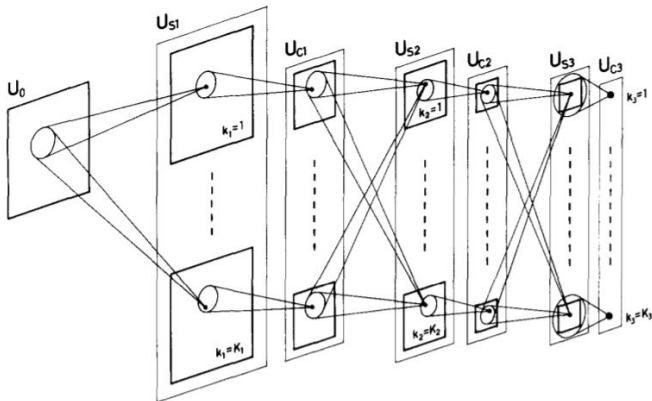
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- ⑤ David H Hubel and Torsten Wiesel (1959) demonstrated orientation selectivity and columnar organization in cat's visual cortex

Backpropagation

- Paul Werbos (1982) proposed back-propagation for ANNs

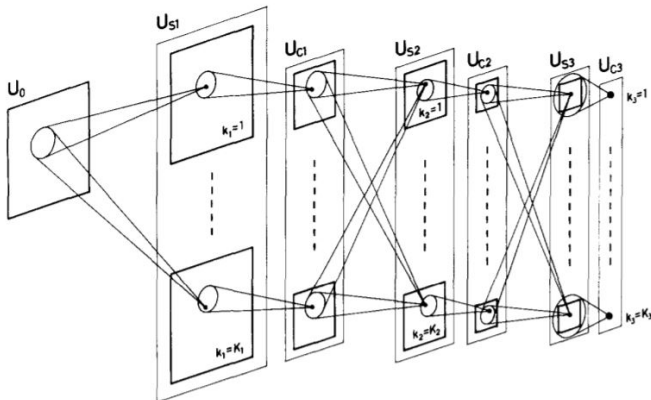
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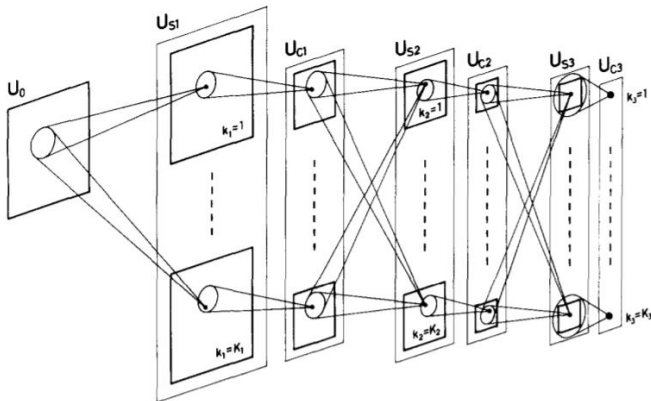
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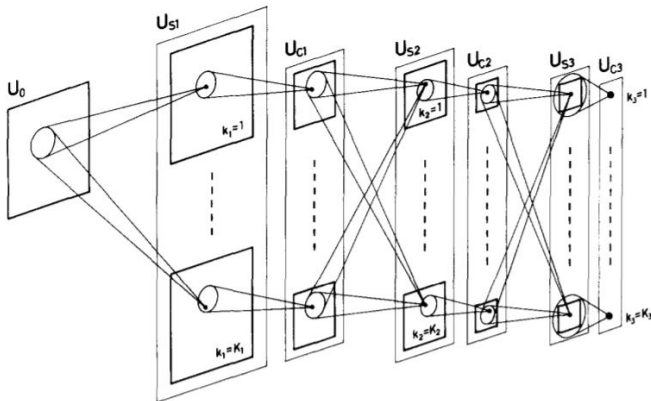
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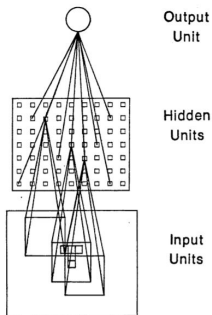
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- ③ Used for hand-written digit recognition
- ④ Viewed as precursor for the modern CNNs



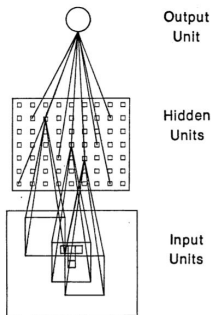
History (contd.)

① Network for TC problem



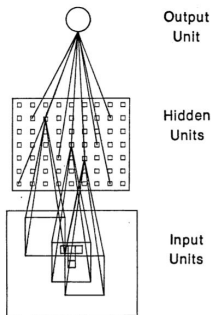
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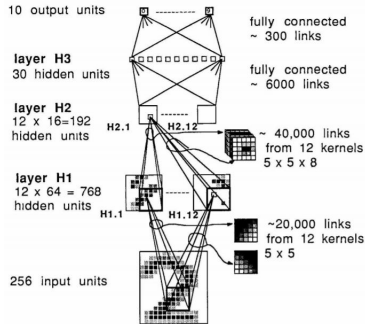
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- ① Network for TC problem
- ② Rumelhart (1988) trained with backprop
- ③ Showed that hidden units learn meaningful representations



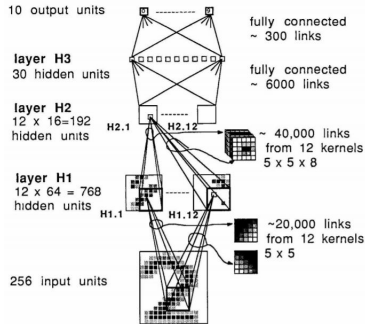
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- 1 LeNet family (Lecun et al. 1989) is a “convent”



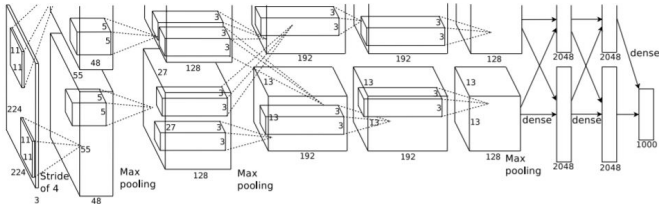
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- ① LeNet family (Lecun et al. 1989) is a “convent”
- ② Very similar to modern architectures



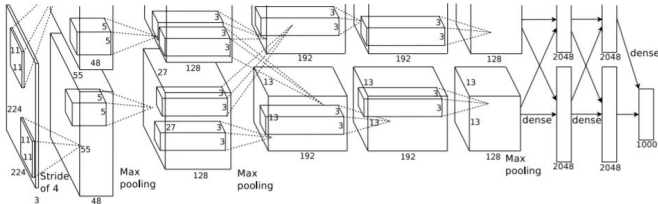
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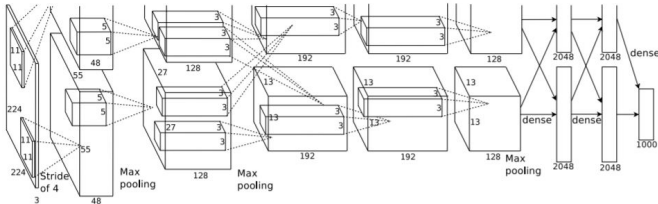
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- ① AlexNet (2012)
- ② Network similar to LeNet5, but of far greater size



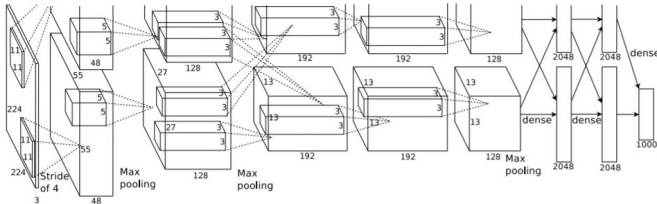
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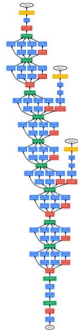
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- ④ Could beat the SoTA image classification methods by a large margin



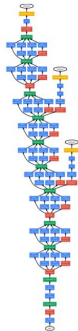
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- 1 AlexNet initiated a trend of more complex and bigger architectures



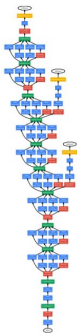
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- ③ ResNet (2015) introduced “skip connections” that facilitate training deeper architectures



History (contd.)

- 1 Transformers (2017) are attention-based architectures

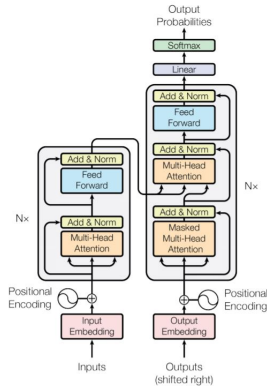


Figure credits: Vaswani et al., 2017

History (contd.)

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- ② Very popular in NLP, and CV

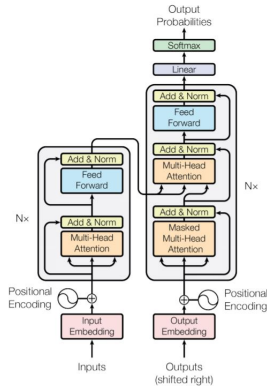


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History (contd.)

- ① Transformers (2017) are attention-based architectures
- ② Very popular in NLP, and CV
- ③ Some of these models are extremely large. GPT-3 has 3 billion parameters (Brown et al. 2020)

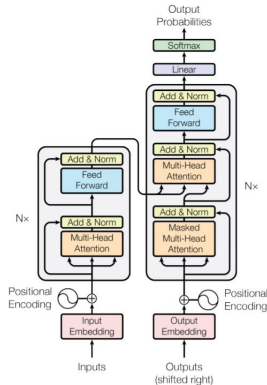


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Deep Learning

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- ② Computational graph of tensor operations that take advantage of
 - Chain rule (back-propagation)
 - SGD
 - GPUs
 - Huge datasets
 - Convolutions, etc.

Deep Learning

- This generalization enables us to build complex networks that work with Images, text, speech and sequences and train end-to-end

ILSVRC Error

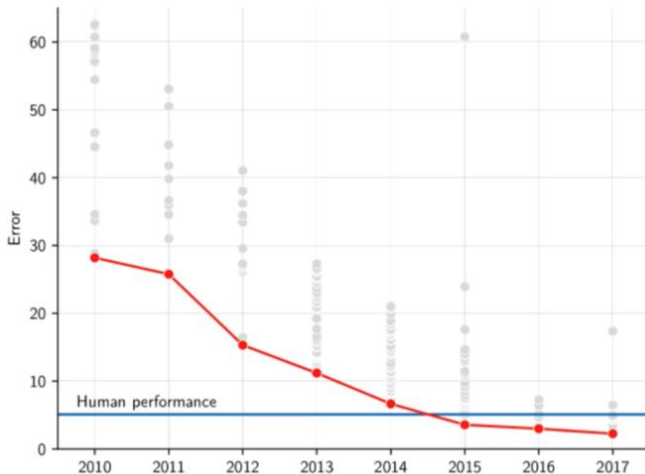


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- ⑥ ...

What makes it work now?

- We have been doing a lot of ML already
 - Taxonomy of ML concepts: Classification, regression, generative models, clustering, etc.
 - Rich statistical formalizations: Bayesian estimation, PAC, etc.
 - Understood fundamentals: Bias-Variance, VC dimension, etc.
 - Good understanding of optimization
 - Efficient large-scale algorithms

Deep Learning - practical perspective

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- ③ Leverages modern hardware
- ④ Doesn't seem to plateau with more data
- ⑤ Makes the trained models a commodity

Compute getting cheaper

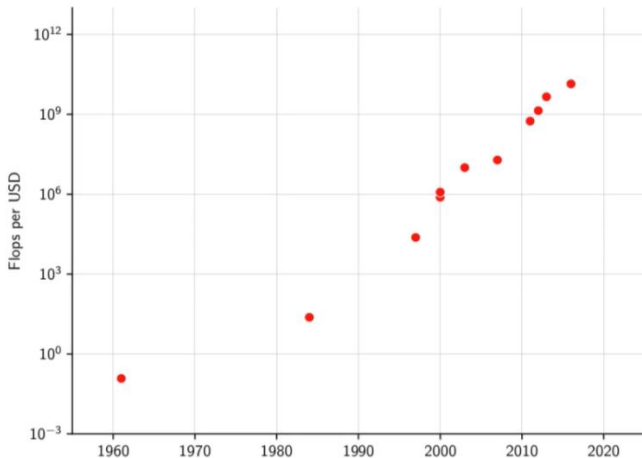


Figure Credits: Wikipedia

Storage getting cheaper

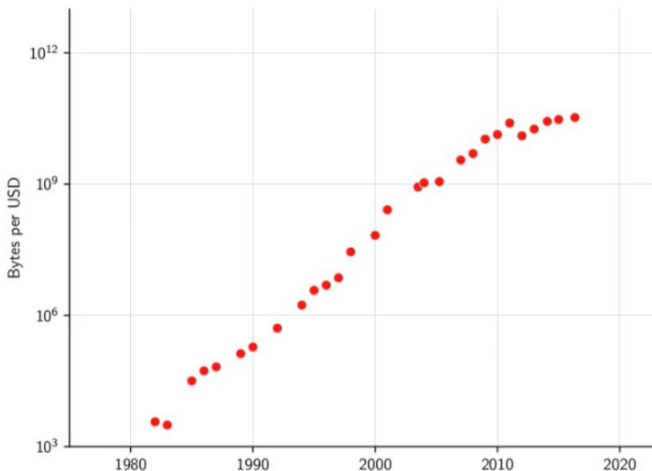


Figure Credits: John C McCallum

AlexNet to AlphaGo: 300000X increase in compute

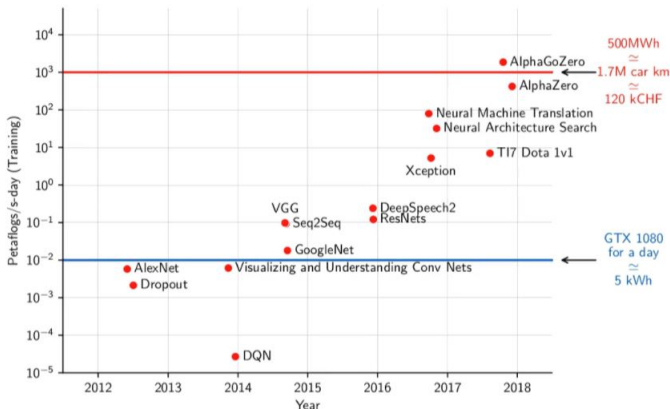


Figure Credits: Radford, 2018. 1 petaflop/s-day ≈ 100 GTX 1080 GPUs for a day, $\approx 500kwh$

Datasets

Data-set		Year	Nb. images	Size
MNIST	(classification)	1998	60K	12Mb
Caltech 101	(classification)	2003	9.1K	130Mb
Caltech 256	(classification)	2007	30K	1.2Gb
CIFAR10	(classification)	2009	60K	160Mb
ImageNet	(classification)	2012	1.2M	150Gb
MS-COCO	(segmentation)	2015	200K	32Gb
Cityscape	(segmentation)	2016	25K	60Gb

Data-set		Year	Size
SST2	(sentiment analysis)	2013	20Mb
WMT-18	(translation)	2018	7Gb
OSCAR	(language model)	2020	6Tb

Figure Credits: François Fleuret

Implementation

	Language(s)	License	Main backer
PyTorch	Python, C++	BSD	Facebook
TensorFlow	Python, C++	Apache	Google
JAX	Python	Apache	Google
MXNet	Python, C++, R, Scala	Apache	Amazon
CNTK	Python, C++	MIT	Microsoft
Torch	Lua	BSD	Facebook
Theano	Python	BSD	U. of Montreal
Caffe	C++	BSD 2 clauses	U. of CA, Berkeley

Figure Credits: François Fleuret

We use PyTorch



<http://pytorch.org>