Deep Learning for Computer Vision

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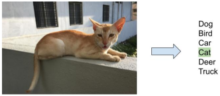
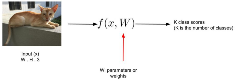
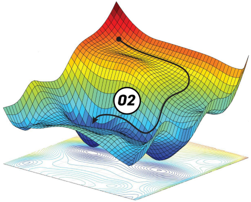
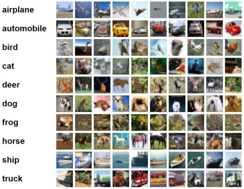
So far in the course...

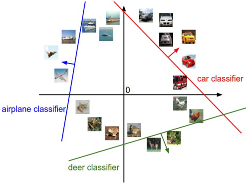
- Image classification: elementary task in CV
- Linear classifier: scoring and loss functions
- Optimization: Gradient descent

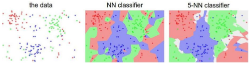












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- “Crude” attempt to imitate the human brain in learning

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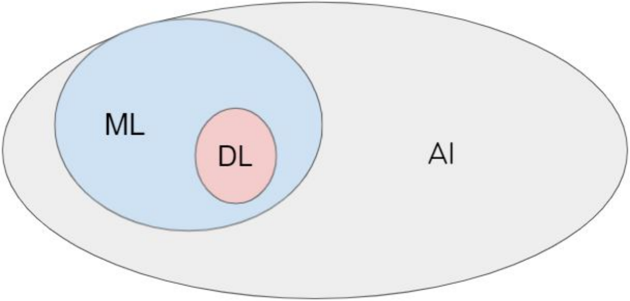

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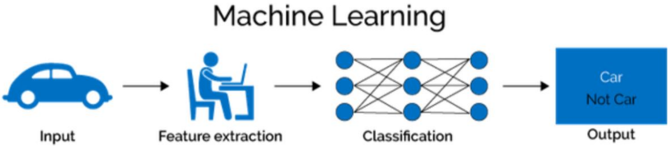

Figure credits: Jay Shaw & Quora

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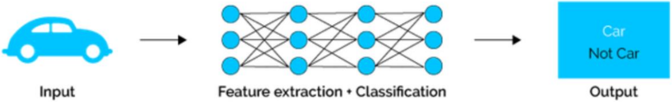

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Classical ML vs. DL

- 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

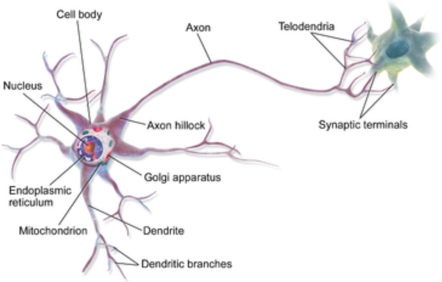

Figure credits: Wikipedia

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

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Deep Learning

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

ILSVRC Error

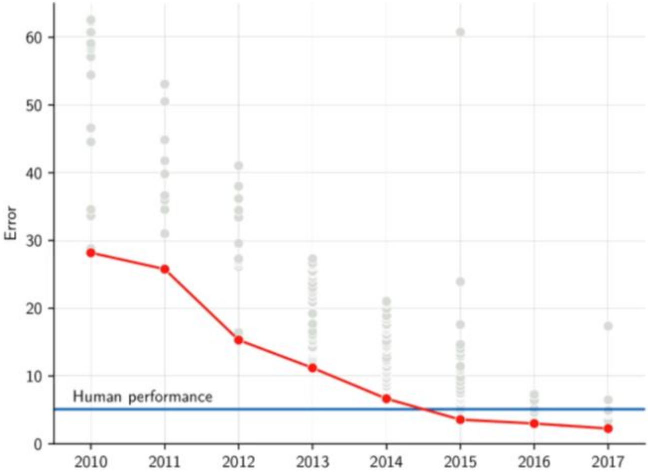

Figure credits: Gershgorn, 2017

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- Huge research and progress in ML
- Hardware developments - CPUs/GPUs/Storage technologies
- Piles of data over the Internet
- Collaborative development (open source tools and forums for sharing/discussions, etc)
- Collective efforts from large institutions/corporations
- . . .

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

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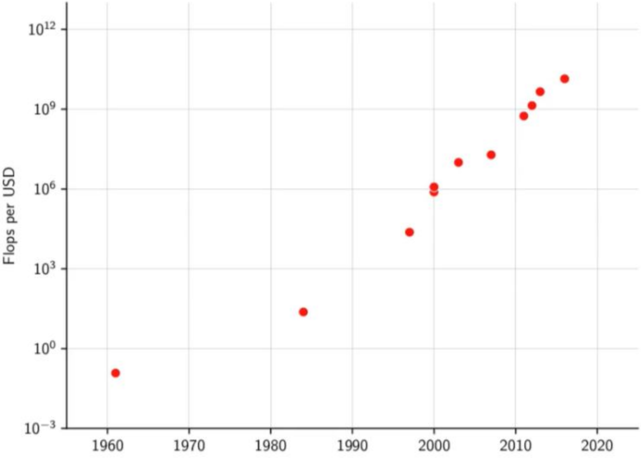
- Leverages modern hardware
- Doesn't seem to plateau with more data
- Makes the trained models a commodity

Compute getting cheaper



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Storage getting cheaper

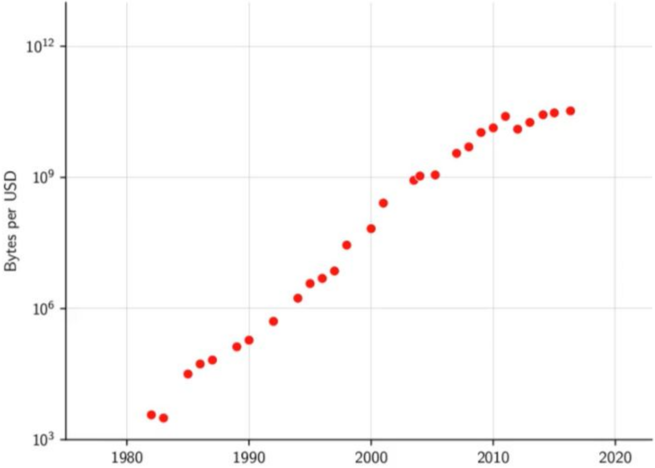

Figure Credits: John C Mccallum

AlexNet to AlphaGo: 300000X increase in compute

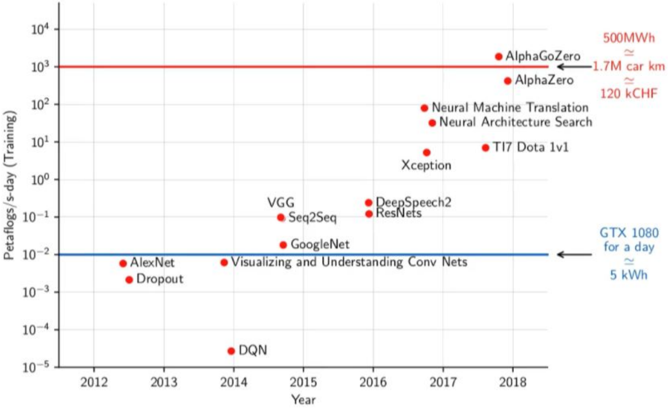

Figure Credits: Radford, 2018. 1 petaflop/s-day ≈ 100 GTX 1080 GPUs for a day, ≈ 500kwh

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 PyTroch for this course

PyTorch

http://pytorch.org

Threshold Logic Unit

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- Boolean inputs and output

$$f(x) = \mathbb{1}(w \sum_i x_i + b \geq 0) \tag{1}$$

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- What one unit does? - Learn linear separation
- No learning; heuristics approach

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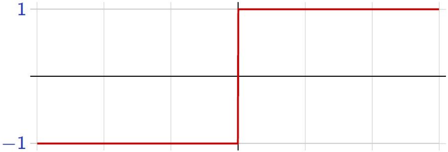
$$f(x) = \begin{cases} 1 & \text{when } \sum_i w_i x_i + b \geq 0 \\ 0 & \text{else} \end{cases}$$

Perceptron

- For simplicity we consider +1 and -1 responses

$$\sigma(x) = \begin{cases} 1 & \text{when } x \geq 0 \\ -1 & \text{else} \end{cases}$$



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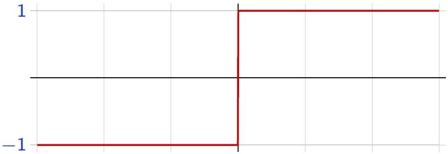

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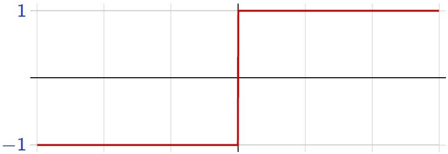

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- Inputs can be real
- Weights are different on the input components
- Mechanism for learning weights!

Weights and Bias

- Why are the weights important?

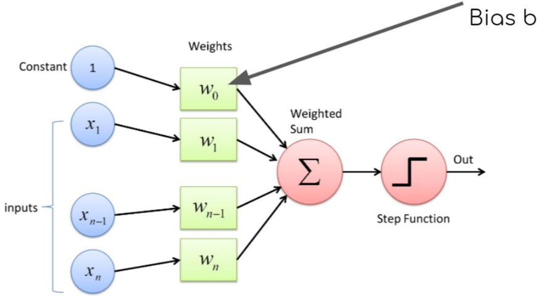
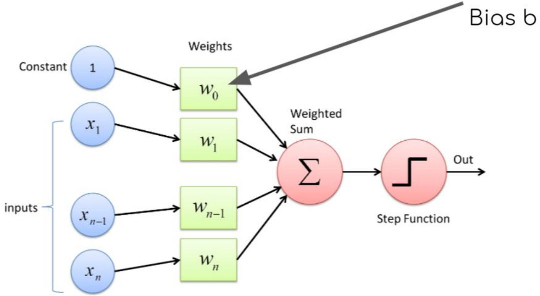


Figure credits: DeepAI

Weights and Bias

- Why are the weights important?
- Why is it called ‘bias’? What does it capture?



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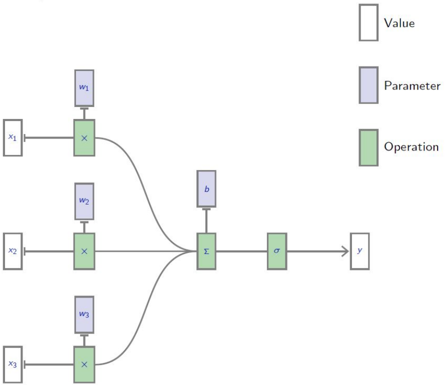

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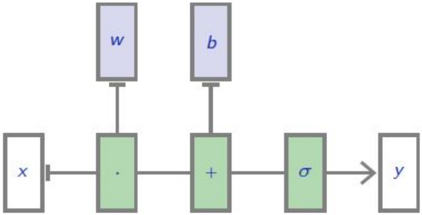

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- Note that the bias b is absorbed as a component of $\mathbf{w}$ and $\mathbf{x}$ is appended with 1 suitably

Perceptron Learning Algorithm

▸ Colab Notebook: Perceptron

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- Other algorithms maximize the margin from boundary to the samples

Next lecture..

- More on NNs: MLP, . . .