Deep Learning

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Dept. of AI, IIT Hyderabad
Jan-May 2023

Time slot

- B slot

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- B slot
- Monday 10 - 10:55 AM
- Wednesday 9 - 9:55 AM
- Thursday 11 - 11:55 AM

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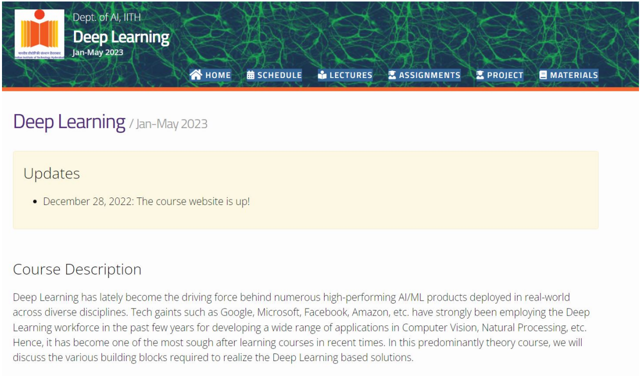
- Monday 10 - 10:55 AM
- Wednesday 9 - 9:55 AM
- Thursday 11 - 11:55 AM
- A-LH-1 (02.01.2023 to 15.01.2023 & 18.02.2023 to 02.05.2023), Auditorium (16.01.2023 to 17.02.2023)

Logistics

भारतीय प्रौद्योगिकी संस्थान हैदराबाद
Indian Institute of Technology Hyderabad

- Course website: `https://krmopuri.github.io/dl/`



Evaluation (Tentative)

- Assignments - 40% (best 4 of 5)
- Course-project - 30%
- End-semester/Viva - 20%
- Tests (unannounced-online?) - 10%

TAs

- Will update soon!

Contents

- Broadly: Building blocks of the Deep Learning based solutions

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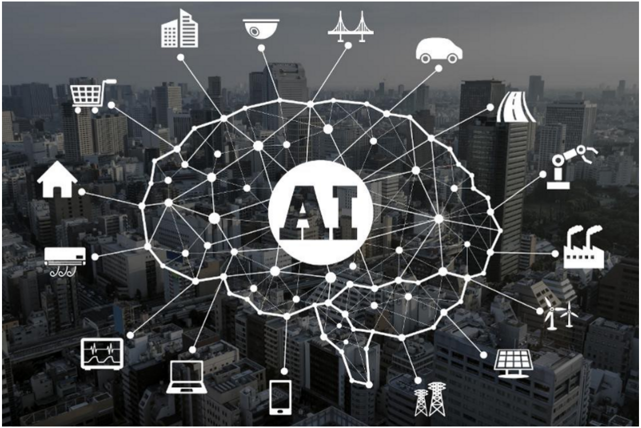
- Specifically: Please visit the website!

Why Deep Learning?



Deep Learning drives the recent AI boom.
Image Source: Artificial Intelligence Magazine

Textbooks and References

- Lot of online resources
  - Deep Learning textbook by Ian Goodfellow *et al.*
  - Deep Learning: Methods and Applications, by D. Li and D. Yu
  - NPTEL course on Deep Learning by Prof. Mitesh Khapra, IITM
  - Michael Nielsen's text book on NN & DL
  - DL course by François Fleuret, Uni. of Geneva
  - PyTorch - https://pytorch.org/
  - Many more that I could not list and am not aware of...

What is DL?

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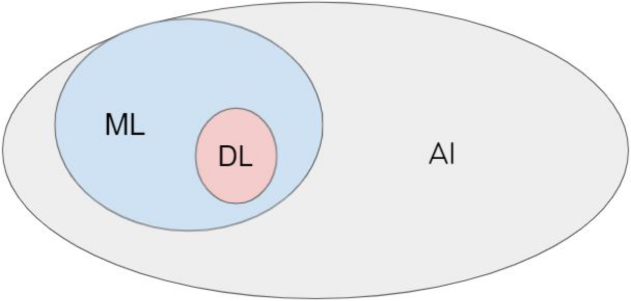

Subset of ML that is essentially Artificial Neural Networks with more layers

What is DL?

- Crude attempt to imitate the human brain in learning

Classical ML vs. DL

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

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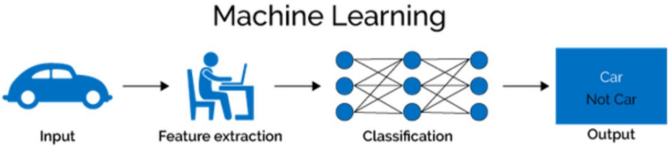

Figure credits: Jay Shaw & Quora

Classical ML vs. DL

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

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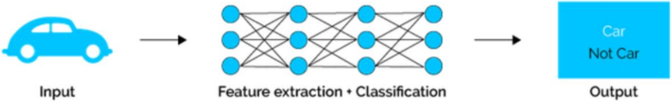

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Classical ML vs. DL

- 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

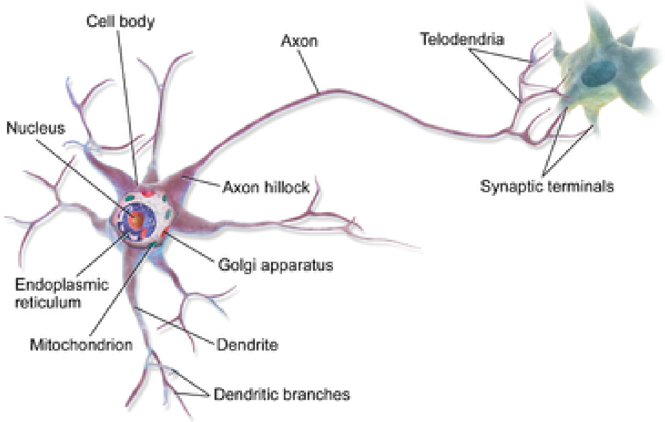

Figure credits: Wikipedia

History of Neural Networks

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

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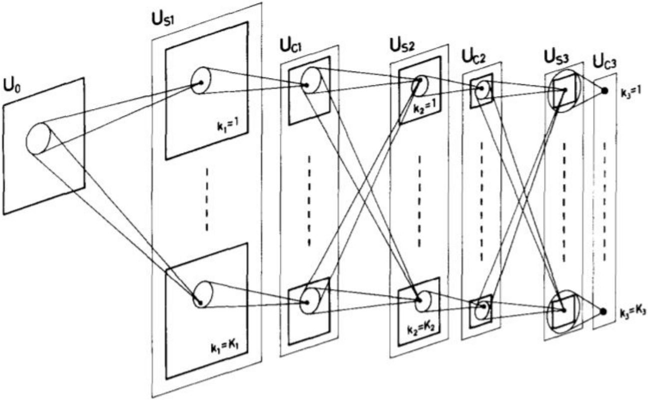
3. Marvin Minsky (1951) - created the first ANN (Hebbian Learning, 40 neurons)
4. Frank Rosenblatt (1958) - created perceptron to classify 20X20 images
5. David H Hubel and Torsten Wiesel (1959) demonstrated orientation selectivity and columnar organization in cat's visual cortex

Backpropagation

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

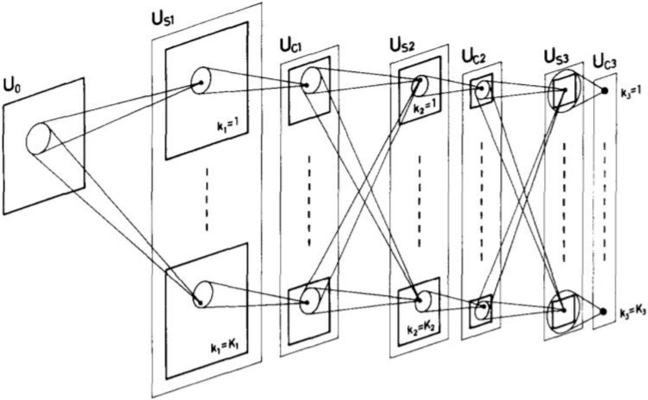
History (contd.)

1. Neocognitron by Fukushima (1980)



History (contd.)

1. Neocognitron by Fukushima (1980)
2. Implements the Hubel and Wiesel's principles



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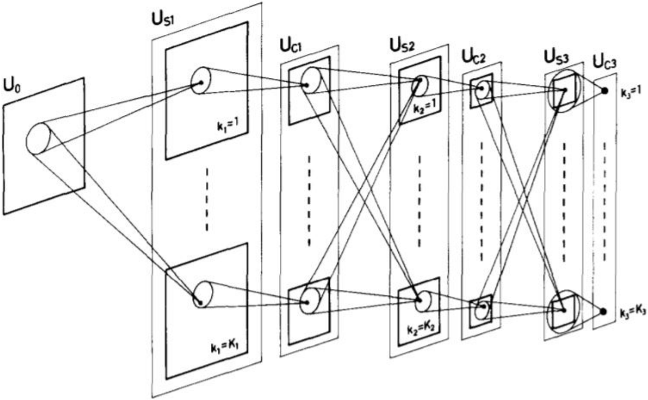
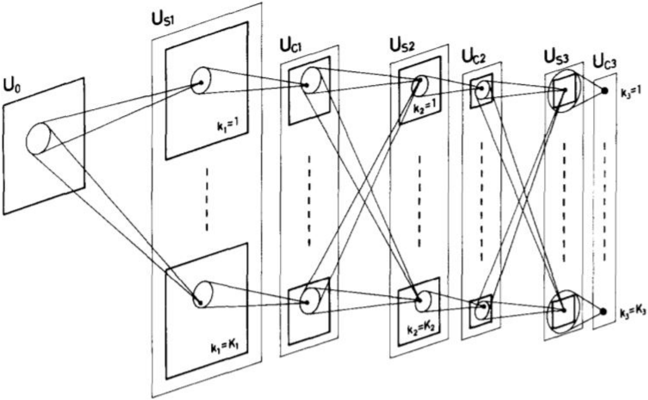


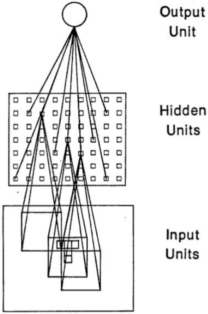
History (contd.)

1. Neocognitron by Fukushima (1980)
2. Implements the Hubel and Wiesel's principles
3. Used for hand-written digit recognition
4. Viewed as precursor for the modern CNNs



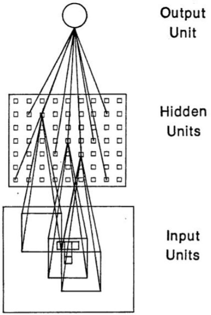
History (contd.)

1. Network for TC problem



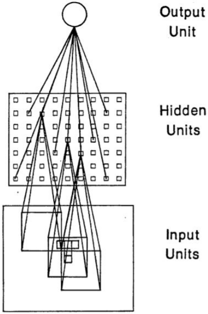
History (contd.)

1. Network for TC problem
2. Rumelhart (1988) trained with backprop



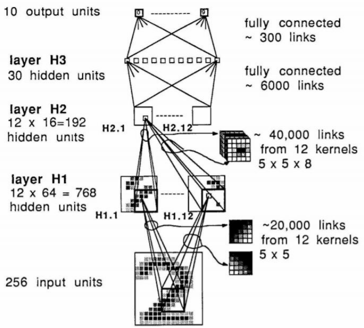
History (contd.)

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



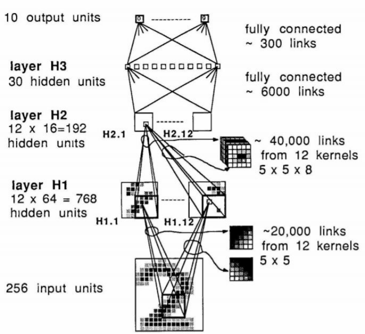
History (contd.)

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



History (contd.)

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



History (contd.)

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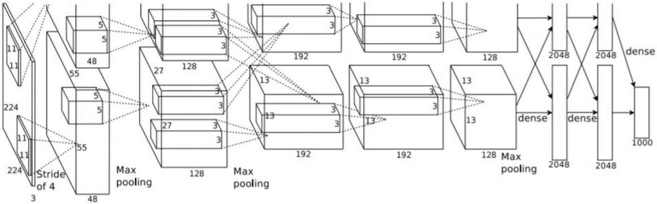
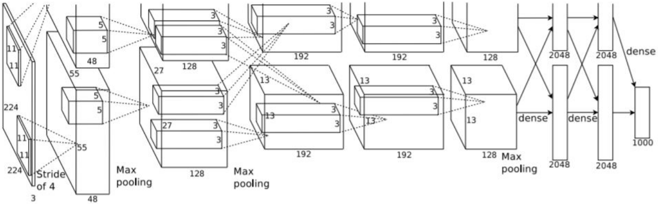


History (contd.)

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



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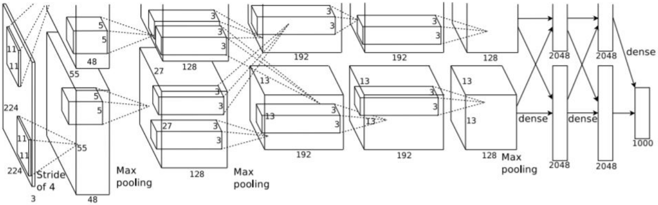
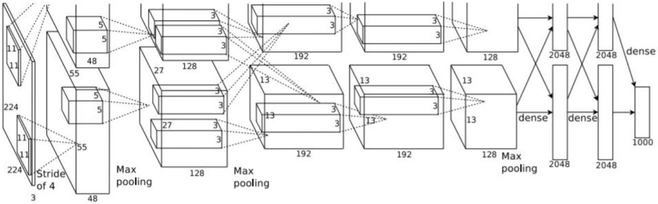


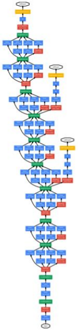
History (contd.)

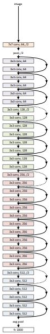
1. AlexNet (2012)
2. Network similar to LeNet5, but of far greater size
3. Implemented using GPUs
4. Could beat the SoTA image classification methods by a large margin



History (contd.)

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





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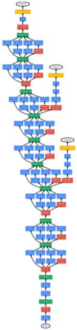
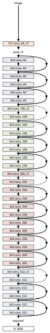
1. AlexNet initiated a trend of more complex and bigger architectures
2. GoogLeNet (2015) contains “inception” modules





History (contd.)

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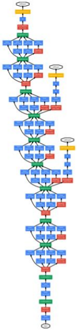
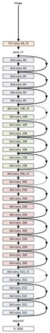
2. GoogLeNet (2015) contains “inception” modules
3. ResNet (2015) introduced “skip connections” that facilitate training deeper architectures





History (contd.)

1. Transformers (2017) are attention-based architectures

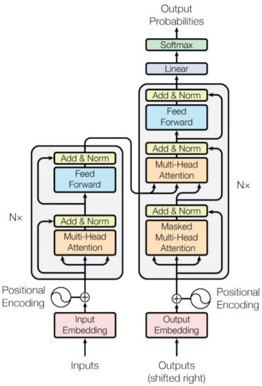
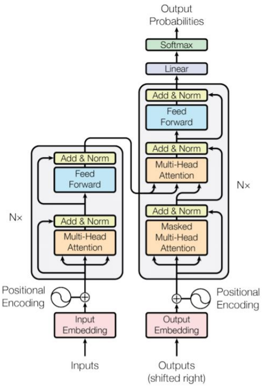


Figure credits: Vaswani et al., 2017

History (contd.)

1. Transformers (2017) are attention-based architectures
2. Very popular in NLP, and CV



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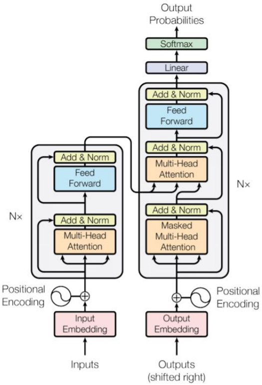
History (contd.)

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

1. Natural generalization to ANNs - Doesn't differ much from the 90s NNs

Deep Learning

1. Natural generalization to ANNs - Doesn't differ much from the 90s NNs
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

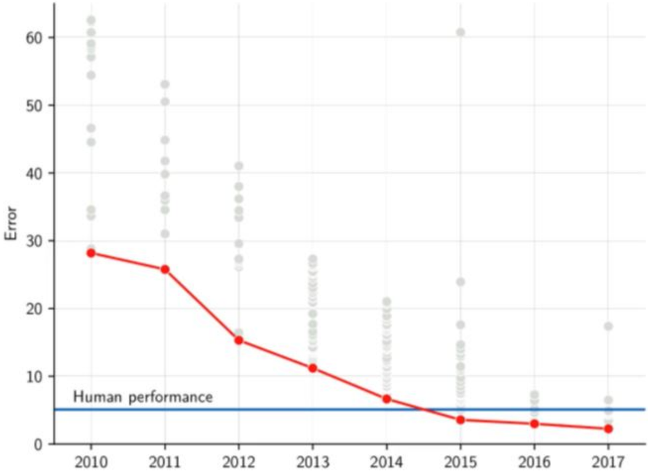

Figure credits: Gershgorn, 2017

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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

1. Doesn't require a deep mathematical grasp

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Deep Learning - practical perspective

1. Doesn't require a deep mathematical grasp
2. Makes the design of large models a system/software development task
3. Leverages modern hardware
4. Doesn't seem to plateau with more data
5. Makes the trained models a commodity

Compute getting cheaper

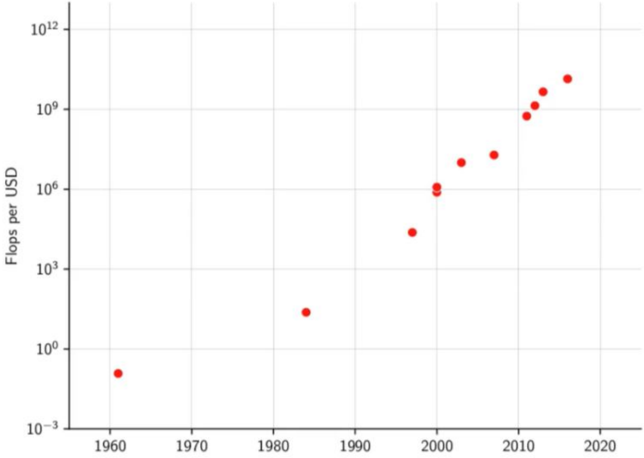

Figure Credits: Wikipedia

Storage getting cheaper

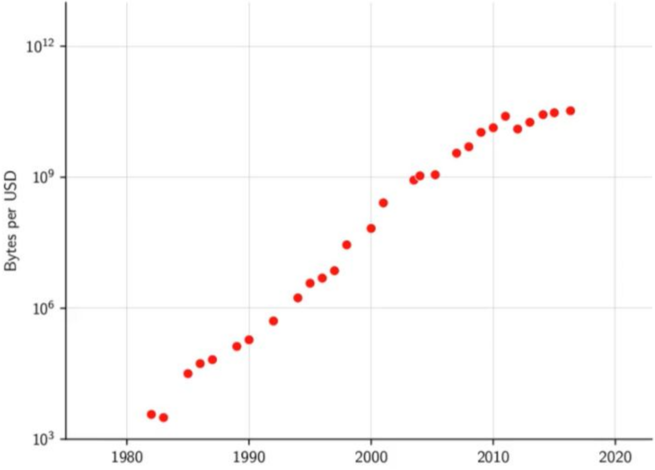

Figure Credits: John C Mccallum

AlexNet to AlphaGo: 300000X increase in compute

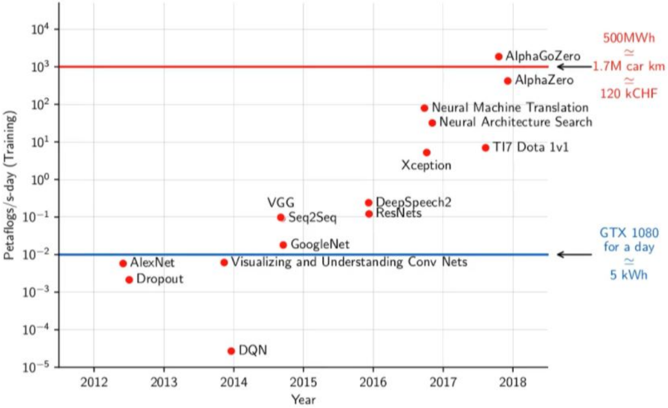

Figure Credits: Radford, 2018. 1 petaflop/s-day ≈ 100 GTX 1080 GPUs for a day, ≈ 500kwh

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