Deep learning

1.2. Current applications and success

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https://fleuret.org/dlc/







Object detection and segmentation



(Pinheiro et al., 2016)

Reinforcement learning



Self-trained, plays 49 games at human level.

(Mnih et al., 2015)

Strategy games



March 2016, 4-1 against a 9-dan professional without handicap.

(Silver et al., 2016)

Translation

"The reason Boeing are doing this is to cram more seats in to make their plane more competitive with our products," said Kevin Keniston, head of passenger comfort at Europe's Airbus.

"La raison pour laquelle Boeing fait cela est de créer plus de sièges pour rendre son avion plus compétitif avec nos produits", a déclaré Kevin Keniston, chef du confort des passagers chez Airbus.

When asked about this, an official of the American administration replied: "The United States is not conducting electronic surveillance aimed at offices of the World Bank and IMF in Washington."

Interrogé à ce sujet, un fonctionnaire de l'administration américaine a répondu:

→ "Les États-Unis n'effectuent pas de surveillance électronique à l'intention des bureaux de la Banque mondiale et du FMI à Washington"

(Wu et al., 2016)

Question answering

```
I: Jane went to the hallway.
I: Mary walked to the bathroom.
I: Sandra went to the garden.
I: Daniel went back to the garden.
I: Sandra took the milk there.
Q: Where is the milk?
A: garden
I: It started boring, but then it got interesting.
Q: What's the sentiment?
A: positive
```

(Kumar et al., 2015)

Auto-captioning

A person riding a motorcycle on a dirt road.



A group of young people playing a game of frisbee.

A herd of elephants walking across a dry grass field.



Two dogs play in the grass.



Two hockey players are fighting over the puck.





(Vinyals et al., 2015)

Image generation



(Brock et al., 2018)

Text generation

System Prompt (human-written)

In a shocking finding, scientist discovered a herd of unicorns living in a remote, previously unexplored valley, in the Andes Mountains. Even more surprising to the researchers was the fact that the unicorns spoke perfect English.

Model Completion (machine-written, 10 tries)

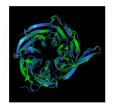
The scientist named the population, after their distinctive horn, Ovid's Unicorn. These four-horned, silver-white unicorns were previously unknown to science.

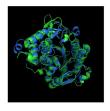
Now, after almost two centuries, the mystery of what sparked this odd phenomenon is finally solved.

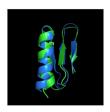
Dr. Jorge Pérez, an evolutionary biologist from the University of La Paz, and several companions, were exploring the Andes Mountains when they found a small valley, with no other animals or humans. Pérez noticed that the valley had what appeared to be a natural fountain, surrounded by two peaks of rock and silver snow.

(Radford et al., 2019)

Protein folding prediction







(Jumper et al., 2021)

Plasma confinement



(Degrave et al., 2022)

Why does it work now?

The success of deep learning is multi-factorial:

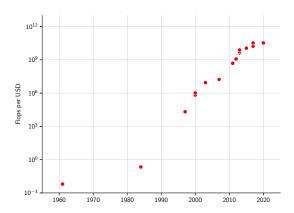
- Five decades of research in machine learning,
- CPUs/GPUs/storage developed for other purposes,
- lots of data from "the internet",
- tools and culture of collaborative and reproducible science,
- resources and efforts from large corporations.

Five decades of research in ML provided

- a taxonomy of ML concepts (classification, generative models, clustering, kernels, linear embeddings, etc.),
- a sound statistical formalization (Bayesian estimation, PAC),
- a clear picture of fundamental issues (bias/variance dilemma, VC dimension, generalization bounds, etc.),
- a good understanding of optimization issues,
- · efficient large-scale algorithms.

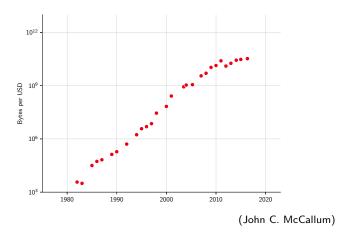
From a practical perspective, deep learning

- · lessens the need for a deep mathematical grasp,
- makes the design of large learning architectures a system/software development task,
- allows to leverage modern hardware (clusters of GPUs),
- · does not plateau when using more data,
- makes large trained networks a commodity.



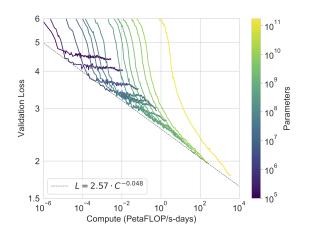
(Wikipedia "FLOPS")

	TFlops (10 ¹²)	Price	GFlops per \$
Intel Core i7-6700K	0.2	\$275	0.7
Intel Core i9-7980XE	0.9	\$1'999	0.5
AMD Ryzen 7 PRO 4750G	1.1	\$640	1.7
NVIDIA GTX 2080 Ti	14.2	\$999	14.2
NVIDIA GTX 3090	35.5	\$1'500	23.7
AMD Radeon RX 6900 XT	23.0	\$ 999	23.0

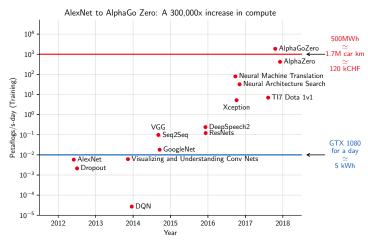


The typical cost of a 4Tb hard disk is <\$100 (Jan 2020).

Validation loss for language models vs. training compute.



(Brown et al., 2020)



(Radford, 2018)

1 petaflop/s-day \simeq 100 GPUs for a day, \simeq 500kwh, \simeq 100CHF of electricity

Computer vision

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

Natural Language Processing

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

The biggest lesson that can be read from 70 years of AI research is that general methods that leverage computation are ultimately the most effective, and by a large margin.

(Richard Sutton, 2019)

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Quantity has a Quality All Its Own.

(Thomas A. Callaghan Jr., 1979)

Implementing a deep network, PyTorch

Deep-learning development is usually done in a framework:

	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

A fast, low-level, compiled backend to access computation devices, combined with a slow, high-level, interpreted language. Python has an incredible ecosystem and is used across fields.

We will use the PyTorch framework for our experiments (Paszke et al., 2019).



http://pytorch.org

"PyTorch is a python package that provides two high-level features:

- Tensor computation (like NumPy) with strong GPU acceleration
- Deep Neural Networks built on a tape-based autograd system"

MNIST data-set

```
1/836/03/00/12730465
26471899307102035465
86375809103122336475
06279859211445641253
93905965741340480436
87609757211689415229
03967203543658954742
13489192879187413110
23949216841744925724
42197287692238165110
409/1243273869056076
264583 (5192744481589
56799370906623901548
09412801261030118203
94050617781920512273
54971839603/12635768
29585741131755525870
9775090089248/6/6518
34055836239211521328
73724697742811384065
```

 28×28 grayscale images, 60K train samples, 10K test samples.

(LeCun et al., 1998)

```
model = nn.Sequential(
    nn.Conv2d(1, 32, 5), nn.MaxPool2d(3), nn.ReLU(),
    nn.Conv2d(32, 64, 5), nn.MaxPool2d(2), nn.ReLU(),
    nn.Flatten().
    nn.Linear(256, 200), nn.ReLU(),
    nn.Linear(200, 10)
nb_epochs, batch_size = 10, 100
criterion = nn.CrossEntropvLoss()
optimizer = torch.optim.SGD(model.parameters(), lr = 0.1)
model.to(device)
criterion.to(device)
train_input, train_targets = train_input.to(device), train_targets.to(device)
mu, std = train_input.mean(), train_input.std()
train input.sub (mu).div (std)
for e in range(nb_epochs):
    for input, targets in zip(train_input.split(batch_size),
                              train targets.split(batch size)):
        output = model(input)
        loss = criterion(output, targets)
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
```

 \simeq 8s on a GTX1080, \simeq 1% test error



(He, 2019)



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