Deep learning

1.2. Current applications and success

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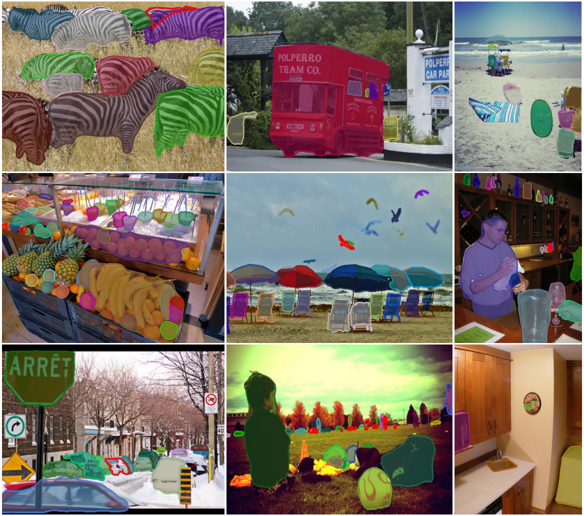
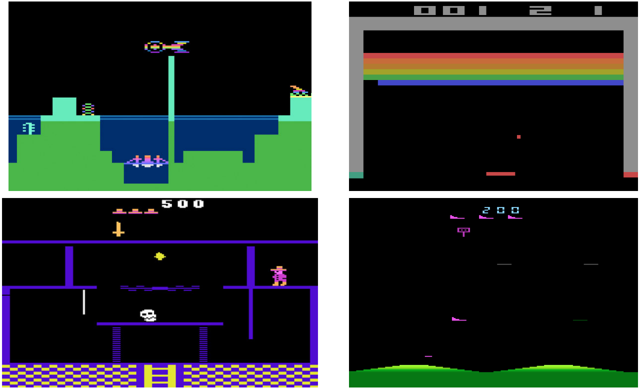
Object detection and segmentation



(Pinheiro et al., 2016)

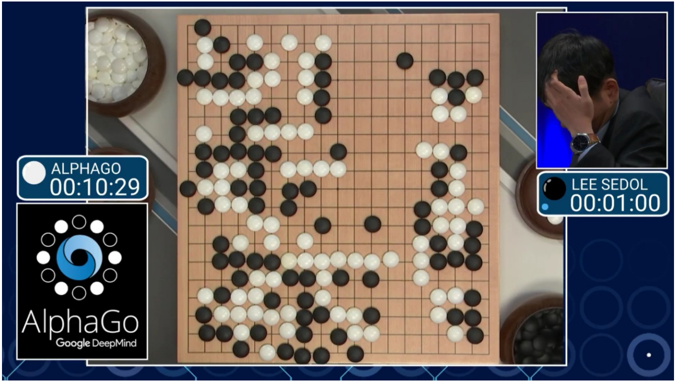
Reinforcement learning



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)

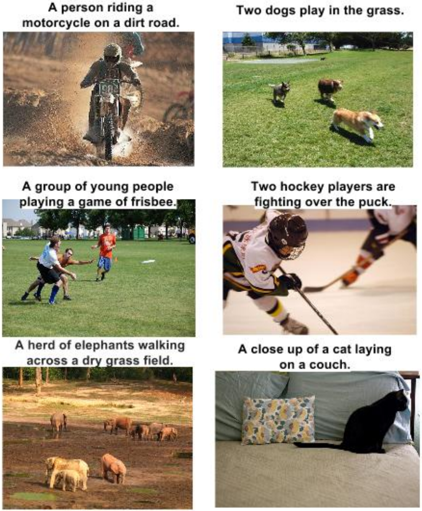
Question answering

```
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



(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)

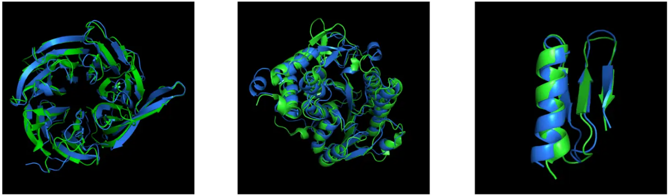
```
The scientist named the population, after their distinctive horn,
Ovid's Unicorn. These four-horned, silver-white unicorns were
previously unknown to science.

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.
```

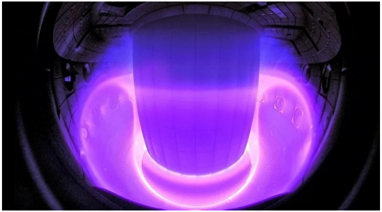
(Radford et al., 2019)

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:

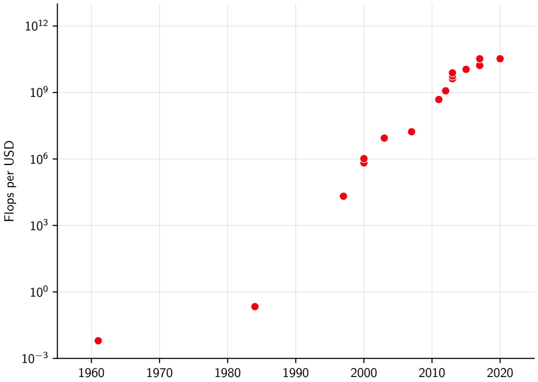
- Five decades of research in machine learning,
- CPUs/GPUs/storage developed for other purposes,
- lots of data from "the internet",
- tools and culture of collaborative and reproducible science,
- resources and efforts from large corporations.

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

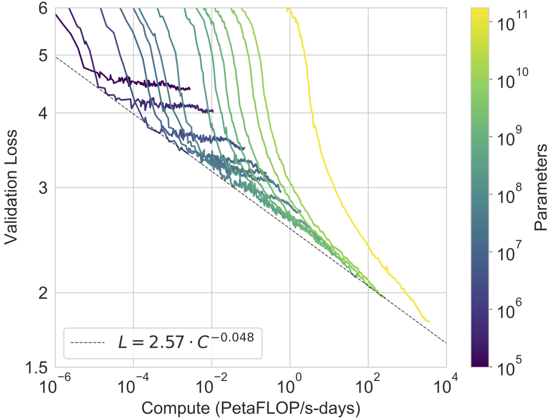
- lessens the need for a deep mathematical grasp,
- makes the design of large learning architectures a system/software development task,
- allows to leverage modern hardware (clusters of GPUs),
- does not plateau when using more data,
- makes large trained networks a commodity.



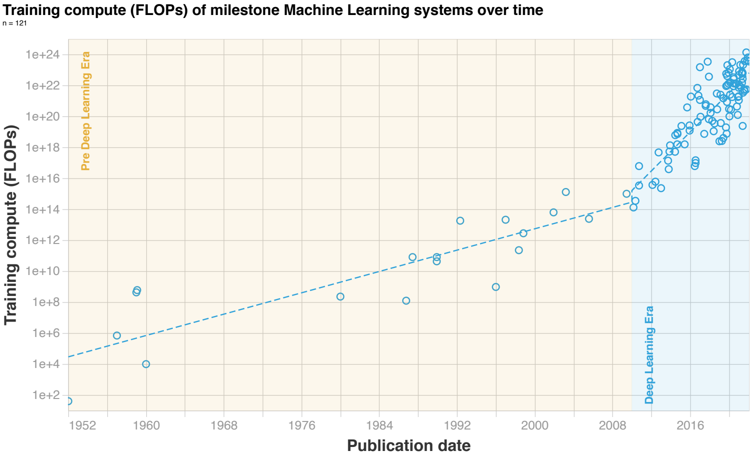
(Wikipedia "FLOPS")

	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

Validation loss for language models vs. training compute.



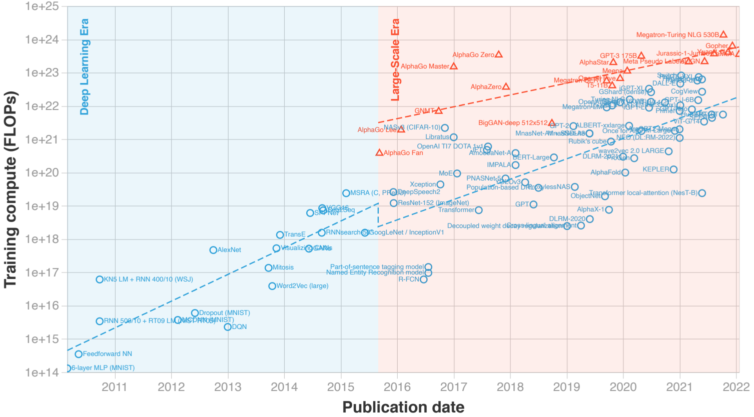
(Brown et al., 2020)



(Sevilla et al., 2022)

Training compute (FLOPs) of milestone Machine Learning systems over time

n = 102



(Sevilla et al., 2022)

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
LAION-5B	(multi-modal)	2022	5.85B	240Tb

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.

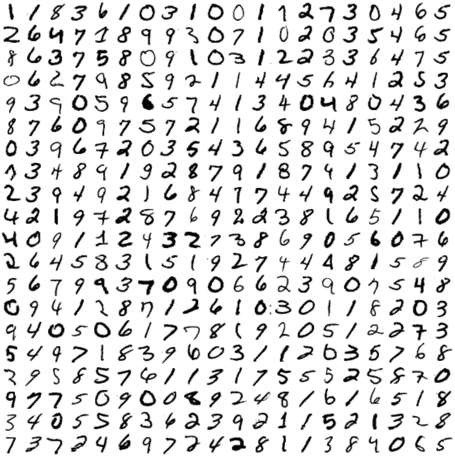
We will use the PyTorch framework for our experiments (Paszke et al., 2019).

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

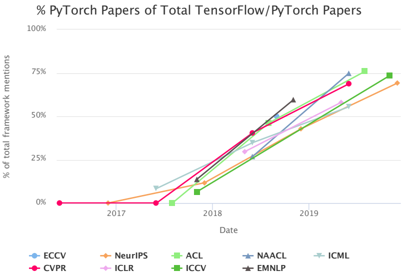


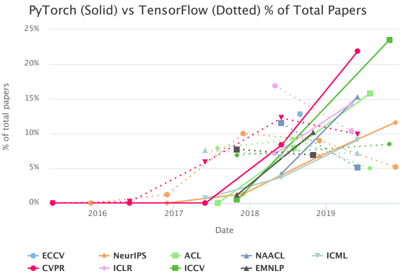
28×28 grayscale images, 60K train samples, 10K test samples.

(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.CrossEntropyLoss()
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


% PyTorch Papers of Total TensorFlow/PyTorch Papers
100%
75%
50%
25%
0%
% of total framework mentions
2017
2018
2019
Date
ECCV
NeurIPS
ACL
NAACL
ICML
CVPR
ICLR
ICCV
EMNLP


PyTorch (Solid) vs TensorFlow (Dotted) % of Total Papers
25%
20%
15%
10%
5%
0%
% of total papers
2016
2017
2018
2019
Date
ECCV
NeurIPS
ACL
NAACL
ICML
CVPR
ICLR
ICCV
EMNLP

(He, 2019)

The End

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