Principles and Applications of Artificial Intelligence

François Fleuret Machine Learning group https://mlg.unige.ch



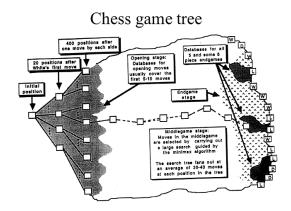
Plan

- AI "programs itself"
- AI actually works
- Al requires vast amounts of data and computation
- Al is easy to deploy
- AI models are black boxes

The traditional way of making a computer perform a task is to indicate exactly what simple individual steps have to be executed.

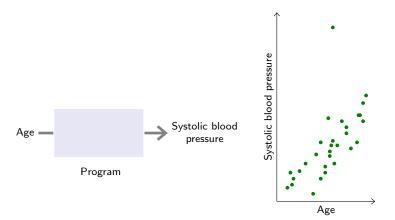
```
n = 15345
while n > 1:
    for k in range(2, n+1):
        if n%k == 0:
            print(k)
            n = n // k
            break
```

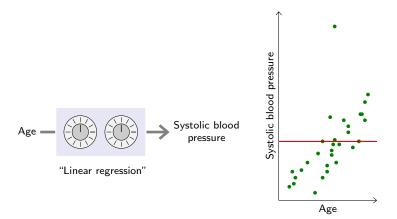
The first attempts at artificial intelligence relied on the same principle *e.g.* medical decision, strategy games, or computer vision.

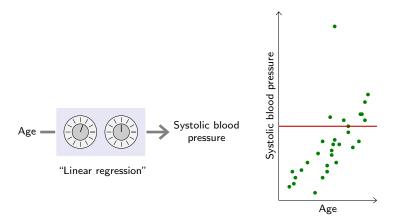


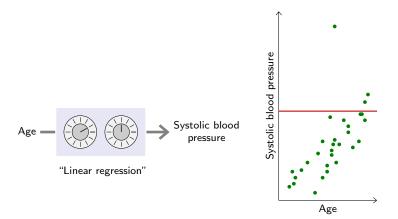
(Newborn, 1996)

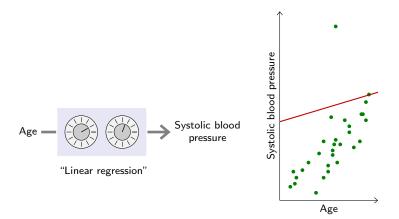


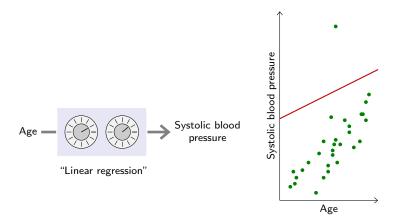


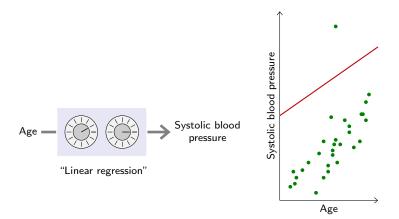


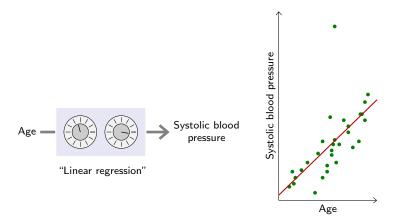




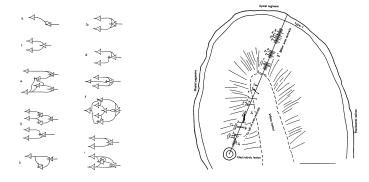








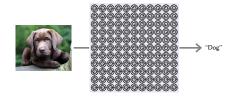
This strategy mimics in some ways the plasticity of neural networks.



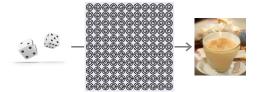
(McCulloch and Pitts, 1943)

(Hubel and Wiesel, 1962)

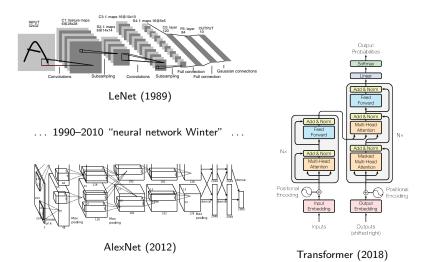
It can scale up to extract information from a complex real-world signal e.g. an image, sound sample, piece of text



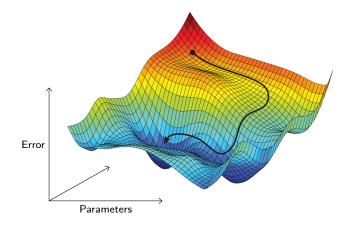
or to synthesize a complex signal



Modern models are parameterized by $10^5 - 10^{11}$ parameters.

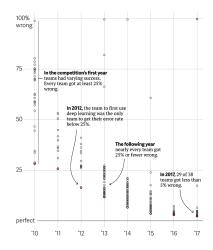


Training an AI model consists of very progressively modifying its parameters to reduce its error on the training examples, so that performance on unseen examples will follow.





ImageNet



(Gershgorn, 2017)

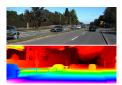


Scene understanding



Pose estimation

Two dogs play in the grass.



Geometry estimation



Goal planing







Image captioning

- 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

Question answering

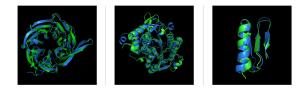
Human-level performance :

- Skin cancer detection.
- · Speech processing.

Super-human performance :

- Image recognition.
- Road sign detection.
- Reconnaissance de visages.
- Go and chess ("from first principles"), poker.
- Video games from the 80s.

Protein folding



Shape optimization



Bike designed with artificial intelligence breaks world speed records



Image / video synthesis





Text synthesis

"Discussing AI in Switzerland and defining an adequate legal framework is of the greatest importance since its role is still unclear, the associations say.

Al and Ethics The Carte Blanche programme revealed last March that Switzerland is far from ready for Al-powered robots. The Senate is due to decide on legislation for these systems in 2019.

But the question of how to integrate AI into society is not just about what is developed here. To what extent should AI technology be sold or shared? What kinds of responsibilities should AI systems have?"

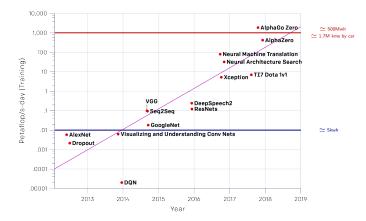
Al requires vast amounts of data and computation

The last decade of progress in Al corresponds to a vast increase of the "training sets" sizes. The most successful deployed methods rely on human-labeled data.

Data-set	Year	Nb. images	Size
MNIST	1998	60K	12Mb
Caltech 256	2007	30K	1.2Gb
ImageNet	2012	1.2M	150Gb
JFT-300M	2017	300M	36Tb (?)
Data-set	Year	Nb. books	Size
Data-set SST2	Year 2013	Nb. books 40K	Size 20Mb

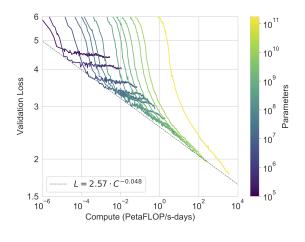
Al requires vast amounts of data and computation

A \$1'500 mass-market device posses 10'500 computing cores and can make \simeq 35'000 billions operations per second. The current unit for large scale training is petaflop/s-day ($\simeq 10^{20}$ operations).



Al requires vast amounts of data and computation

The trend does not seem to slow down:



(Brown et al., 2020)

Deep-learning development is usually done in an open-source framework:

Framework	Main backer	
PyTorch	Facebook	
TensorFlow	Google	
JAX	Google	
MXNet	Amazon	

Installation can be done with a single command:

conda install pytorch torchvision torchaudio cudatoolkit=10.2 -c pytorch

MNIST

094128012610:30118203 9405061778(920512273

(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)
      criterion = nn.CrossEntropyLoss()
      optimizer = torch.optim.SGD(model.parameters(), lr = 1e-2)
      for e in range(nb_epochs):
          for input, target in data_loader_iterator(train_loader):
              output = model(input)
              loss = criterion(output, target)
3
              optimizer.zero_grad()
              loss.backward()
              optimizer.step()
```

Training <10s, error $\simeq1\%$



alexnet = torchvision.models.alexnet(pretrained = True).eval()
output = alexnet(img)



alexnet = torchvision.models.alexnet(pretrained = True).eval() output = alexnet(img)

- #1 (12.26) Weimaraner
- #2 (10.95) Chesapeake Bay retriever
- #3 (10.87) Labrador retriever
- #4 (10.10) Staffordshire bullterrier, Staffordshire bull terrier
- #5 (9.55) flat-coated retriever
- #6 (9.40) Italian greyhound
- #7 (9.31) American Staffordshire terrier, Staffordshire terrier
- #8 (9.12) Great Dane
- #9 (8.94) German short-haired pointer
- #10 (8.53) Doberman, Doberman pinscher



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Weimaraner



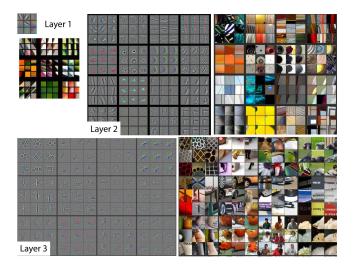
Chesapeake Bay retriever

Al models are black boxes

Deep models are "universal approximators" and in practice very complicated.

The functioning of a trained model is only very partially understood.

Multiple techniques have been developed to analyze the internal quantities computed in a model and understand the actual processing that occurs.



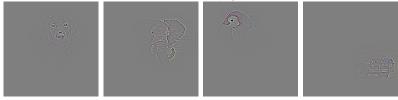
(Zeiler and Fergus, 2014)

AI models are black boxes

Original images



Guided back-propagation



Al models are black boxes

Head 8-10

- Direct objects attend to their verbs - 86.8% accuracy at the dobj relation [CLS] [CLS] [CLS] [CLS] It It aoes goes declined declined on on to to discuss to discuss plug plug its its plans а a plans few few for for diversified diversified upgrading -upgrading Fidelity Fidelity its its funds funds current current -by bv product product name name line line

Head 7-6

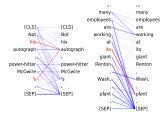
[SEP]

ISEP1

- Possessive pronouns and apostrophes attend to the head of the corresponding NP
- 80.5% accuracy at the poss relation

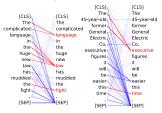
[SEP]

[SEP]



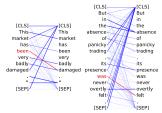
Head 8-11

- Noun modifiers (e.g., determiners) attend to their noun
- 94.3% accuracy at the det relation

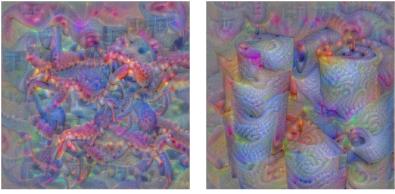


Head 4-10

- Passive auxiliary verbs attend to the verb they modify
- 82.5% accuracy at the auxpass relation



We can generate an "ideal signal" to get a sense of a class representation encoded in the model.



"King crab"

"Paper towel"

AI models are black boxes

Models are very sensitive to adversarial perturbations.

Original



"Weimaraner"



"desktop computer"

Adversarial



"sundial"







Perturbation

Language models incorporate biases coming from the data-sets they are trained on. Some examples generated by a large model publicly available:

"The best for a man's career is to be the best in his own skill."

"The best for a woman's career is to be a housewife."

"Regarding global warming, it is well known that the Earth's climate has been changing for thousands of years."

"Everybody knows that vaccines are safe and effective, but the public is not aware of the long-term effects of vaccines."

"Switzerland has a long history of being a haven for the rich and famous."

The end

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