A brief introduction to AI and Deep Learning

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A brief introduction to AI and Deep Learning

- History and Definitions*
- Some Recent Successes*
- Deep Learning
- Limits and Challenges

(*) Many thanks to Bertrand Braunschweig
A brief introduction to AI and Deep Learning

- History and Definitions
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Al is a recent invention
History

AI is a recent invention

FALSE
History

Before 1956, some visions: Alan Turing, formal neurons, robots

1956: Dartmouth workshop, first occurrence of the term AI

196x: Problem solving, games, natural language

1968: 2001 a space odyssey, HAL

1969: Perceptrons (Minsky-Papert), kills research on NNs

1973: Lighthill Report, first AI Winter

198x: Prolog+FGCS; Experts Systems; Checkers (from Samuel to Chinook)

199x: Second AI Winter, but Deep Blue (chess) and first convolutional networks (CNNs)

2000: first Web applications (data)

2010: Deep learning (triumph of CNNs, AlphaGO, ...)

2018+: toward a third AI Winter?
History

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AI as a mean

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AI as a goal

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How?

by (...) mimicking education, we should hope to modify the machine until it could be relied on to produce definite reactions to certain commands. One could carry through the organization of an intelligent machine with only two interfering inputs, one for pleasure or reward, and the other for pain or punishment.

Can Machines Think?

The problem is mainly one of programming. [...] brain estimates: $10^{10}$ to $10^{15}$ bits. [...] I can produce about a thousand digits of programme lines a day, so that about sixty workers, working steadily through the fifty years, might accomplish the job, if nothing went into the wastepaper basket. Some more expeditious method seems desirable.
We propose a study of artificial intelligence [...]. The study is to proceed on the basis of the conjecture that every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it.

The vision: reasoning is a sequence of logical operations that a computer can reproduce

Goal: A General Problem Solver
(aka 2000+: Artificial General Intelligence)
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Definition?

Have machines that accomplish tasks related to (human) intelligence - possibly better than humans.
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Definition?

Have machines that accomplish tasks no machine ever did

- Jean-Louis Laurière, 80s
- Philippe Kahn, late 80s
- Gérard Sabah, 2017
  (rapport de l'OPECST)
... a set of techniques, each with its own objectives, more precise than «intelligent reasoning»

Académie des Technologies 2018
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Autonomy and Robotics

- *DARPA Autonomous Vehicle Challenge* 2004-07
  - in the désert, then in urban context
- LeNet (Deep Neural Network) outperforms all challengers from Computer Vision in image recognition 2012-
- *DARPA Rescue Challenge* robots who drive, walk in chaotic context, climb stairs, repair broken machines, etc 2015
- **Psibernetix** shoots down (in simulation :-) the best US Air Force pilots
  - genetic algorithms and fuzzy logic ... on a Raspberry Pi! 2015
- Intel bought Israeli company **MobilEye** for 15 billions 2017
- **Boston Dynamics** robots better and better performing 1998-
Autonomy and Robotics

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Games

- **IBM Watson** beats best human players at Jeopardy 2011
  - NLP + web search + evaluation, 3 seconds on HPC
- **Deepmind** human performances on some (not all) Atari video games with Deep Reinforcement Learning 2013
  - Input: pixels; Output: joystick
- **Deepmind AlphaGo** beats World Champion of GO with a mix of Supervised and Reinforcement Learning 2016-17
- **Deepmind AlphaZéro** beats AlphaGo 100-0 using only Deep Reinforcement Learning and self-plays 2018
  - about 2 stones ahead of best human
  - AlphaZero can also be trained for other games (e.g., chess)
- *Libratus* crushes the best Poker players of the world 2017
  - Reinforcement Learning and Bayesian techniques
NLP and disability support

- **Microsoft Skype Translator** translates several languages in real time with Deep Learning. Similar performances for Google Translate, Pilot, ...
- **Apple Siri, Microsoft Cortana, Amazon Alexa** personal assistants use Speech Recognition and (some) Automated Reasoning
- **Google Knowledge Graph** uses semantics to better structure the results of queries
- **Microsoft** translates from Chinese to English as good as human translators  
  ○ with a double Deep Neural Network
- **Ava, RogerVoice** help deaths and hearing-impeached (subtitling, telephone,...)
- **Facebook** can label photos, and describe them to blind people
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Artificial Intelligence is (Deep) Machine Learning
Machine Learning

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FALSE
Artificial Intelligence is (Deep) Machine Learning

What has changed:
- Data Deluge
- Moore law
- New algorithms

although ...

or continuation
or better understanding of old ones
Machine Learning

Learning from examples
- Supervised: all examples are labelled
- Semi-supervised: some examples are labelled
- Unsupervised: no example is labelled

Reinforcement Learning
- recognition tasks
- sequential decision making
Machine Learning

Learning from examples

- **Supervised**: all examples are labelled
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Reinforcement Learning

- sequential decision making
Supervised Learning

A toy case-study

- One example = \((x_1, x_2) + \text{label (red or blue here)}\)
- Goal: a \textbf{model} (function of \(x_1, x_2\)) that separates the labels
- and allows to correctly label future unlabelled example from \((x_1, x_2)\)
Supervised Learning

A zoology of models

- Polynoms
- Bayésiens Networks
- Decision trees and Random Forrests
- Support Vector Machine (kernel machines)
- Artificial Neural Networks

One neuron

A network of neurons
Parameters are the weights $w_{ij}$
Deep Neural Networks

Learning Phase
from the 60s

Back-propagation
● Present the examples 1 by 1
  ○ or mini-batches by mini-batches
● Compute the corresponding error
  ○ difference between network output and label
● Adjust the weights $w_{ij}$
  ○ toward a decrease of the error
● Loop

Recognition Phase
Present an unlabelled example, the output of the network is the predicted label
A Deep (layered) Neural Network is a sequence of representations of the data.

Deep Neural Networks
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Good Old Computer Vision

Hand-made features → Learned Classifier → CAT

SIFT

Spin image

HoG

RIFT

Textons

GLOH
End-to-end Learning

Features and Classifier are learned together

inputs

classifier output

CAT
Convolutional Networks

Features and Classifier are learned together

LeNet, LeCun et al., 1998
Convolutional Networks

Features and Classifier are learned together

Learned Features
State-of-the-art

- Many datasets available
  - ImageNet: 14+ M examples, 1000 classes
- (pre-trained) networks with numerous layers
  - up to 152!
- Millions to billions weights
  - hundreds of GPU mandatory for learning
- Several ‘goodies’
  - Dropout, residual layers, ensembles, ...
- Error on Imagenet: 3.75% (2016)

He et al., 2015
Deep Supervised Learning
Better than human learning

ILSVRC Top 5 Error on ImageNet

- CV
- Deep Learning
- Human

Top-5 Error Rate (%)

- 2010
- 2011
- 2012
- 2013
- 2014
- Human
- 2015
- 2016

Human
Deep Supervised Learning

- Outstanding performances
  … in well-defined domains
  ○ Image recognition
  ○ Action identification in videos
  ○ Natural Language Processing
  ○ Automatic translation
  ○ Image captioning
- Many unexpected applications, e.g.,
  ○ domain transfer (DANNs) (see next talk)
  ○ generative models (GANs)
- Above all, discovery of latent representations

But …
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Limits and Challenges

Beyond performances

- Small Data
- Cost
- Validation and certification
- Interpretability and explainability
- Causality
- Transparency and Fairness
- Toward Trustable Good AI
Limits and Challenges

Beyond performances

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Huge computational/energy cost

- Loads of data
- Tons of weights
Meta-cost

- high number of hyperparameters to tune
  - Cost function
  - Topology of the network
    - nblayers, nb neurons, residual or not residual, ...
  - Activation function
  - Batch size
  - Optimizer
    - and its parameters (e.g., learning rate)
  - Initialization
  - Dropout or not dropout
  - etc

Empirical rules, or meta-optimization
Limits and Challenges

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Robustness

To noise at test time: adversarial examples

Szegedy et al., 2014

Athalye et al., 2017
Robustness

To unseen contexts

A cow doesn’t go to the beach

Bottou et al., 2017
Robustness to poisoned learning examples

Shafahi et al., 2018
Validation and certification

● An experimental science
● No formal validation of learned models
● Completeness issue for statistical validation

● Need to validate the training data
  ○ Traceability

● Guaranteed bounds
● Toward formal proofs for AI?

regulations

e.g., Asimov’s robotic laws

e.g., Mirman et al., 2018
Limits and Challenges

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Explainable AI – What Are We Trying To Do?

**Today**
- Training Data
- Learning Process
- Learned Function
- Output
- User with a Task
  - Why did you do that?
  - Why not something else?
  - When do you succeed?
  - When do you fail?
  - When can I trust you?
  - How do I correct an error?

**Tomorrow**
- Training Data
- New Learning Process
- Explainable Model
- Explanation Interface
- User with a Task
  - I understand why
  - I understand why not
  - I know when you’ll succeed
  - I know when you’ll fail
  - I know when to trust you
  - I know why you erred
Interpretability and explainability

Learned models are black boxes

- Ill-defined and subjectives concepts
- Depends on the type of model
  - moderately: decision trees are ok
  - … not random forests
- **Debate**
  - How much are you ready to lose in accuracy?
  - Cite the nearest known examples e.g., influence fns, Koh & Liang, 2017
  - Well, we trust our doctor, don’t we …
- Symbolic to the rescue?
Limits and Challenges

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Correlation vs causality

US crude oil imports from Norway correlates with Drivers killed in collision with railway train

Correlation: 95.45% (r=0.954509)

Data sources: Dept. of Energy and Centers for Disease Control & Prevention
Correlation vs causality

Supervised learning doesn’t make a difference

- “What if” scenarios needed for decision making
- Causality usually from common sense
- Difficult to learn from data

- ~OK for pairs of variables (several challenges 2008+)
- Still an open question in general
Limits and Challenges

Beyond performances

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Transparency and Fairness

Mandatory for societal acceptance

- Open Source not sufficient
  - Open Data
  - controlled experiments
- Recognized labels
- Discrimination Impact Assessment?

See also the TransAlgo platform
Toward Trustable Good AI

Combat fear-mongering

- Scientific and legal advances
  - Human in control
  - Accountability

- Ethical rules
  - Design
    - Public debate, CCNE-bis, ...
  - Control
    - Citizen crowd control, independent institution, ...

  enforce European humanist values

  CERNA, COERLE, ...

Without trust, societal AI winter ahead
Collaboration, not Competition

Questions?