Deep Learning & Knowledge Representation

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CONTEXT & VOCABULARY
What is Artificial intelligence?
How is Artificial intelligence defined?

• The term **Artificial Intelligence**, as a research field, was coined at the conference on the campus of Dartmouth College in the summer of 1956, even though the idea was around since Antiquity: Hephaestus built automatons of metal to work for him or protect others, the Golem in Jewish folklore, etc.

• Closer to the Dartmouth conference but still before, the first manifesto on Artificial Intelligence, an unpublished report **“Intelligent Machinery”**, written by Alan Turing in 1948. He already distinguished two different approaches to AI, which may be termed **“top-down”** and **“bottom-up”** (now more commonly called knowledge-driven AI and data-driven AI respectively).

How is Artificial intelligence defined?

• "top-down" or knowledge-driven AI
  – cognition = high-level phenomenon, independent of low-level details of implementation mechanism

(Figure from: Neurons spike back The invention of inductive machines and the artificial intelligence controversy”, D. Cardon, J.-P. Cointet, A. Mazières, Translated by Elizabeth Libbrecht In Réseaux Volume 211, Issue 5, 2018, pages 173 to 220)
How is Artificial intelligence defined?

• "bottom-up" or data-driven AI
  – opposite approach, start from data to build incrementally and mathematically mechanisms taking decisions

(Figure from: Neurons spike back The invention of inductive machines and the artificial intelligence controversy", D. Cardon, J.-P. Cointet, A. Mazières, Translated by Elizabeth Libbrecht In Réseaux Volume 211, Issue 5, 2018, pages 173 to 220)
Why Artificial Intelligence is so difficult to grasp?

• Frequently, when a technique reaches **mainstream use**, it is no longer considered as artificial intelligence; this phenomenon is described as the **Al effect**: "AI is whatever hasn't been done yet." (Larry Tesler's Theorem)
  -> e.g. Path Finding (GPS), Chess electronic game, Alpha Go...

• Consequently, AI domain is continuously evolving and so very difficult to grasp.
So what is Machine Learning?
Machine Learning

\[(x) \xrightarrow{f(x,\alpha)} y\]

- Face detection
- Scores prediction
- Voice recognition
- Sport bets
Machine Learning

\[(x) \xrightarrow{f(x,\alpha)} y\]

- Logistic Regression
- Random Forest
- Support Vector Machine
- Neural Networks
Machine Learning is not AI

Francis Bach at Frontier Research and Artificial Intelligence Conference (ERC Conference): “Machine Learning is not AI”

Machine Learning

\[
\begin{align*}
\begin{pmatrix}
X \\
\end{pmatrix}
\xrightarrow{f(X,\alpha)}
y
\end{align*}
\]

"Weather Forecasting"

→ Trolley dilemma next slide
Trolley dilemma
(a two-year old kid’s solution)
**ARTIFICIAL INTELLIGENCE**
A program that can sense, reason, act, and adapt

**MACHINE LEARNING**
Algorithms whose performance improve as they are exposed to more data over time

**DEEP LEARNING**
Subset of machine learning in which multilayered neural networks learn from vast amount of data
AI vs Machine Learning vs Deep Learning

**ARTIFICIAL INTELLIGENCE**
A program that can sense, reason, act, and adapt

**MACHINE LEARNING**
Algorithms whose performance improve as they are exposed to more data over time

**DEEP LEARNING**
Subset of machine learning in which multilayered neural networks learn from vast amount of data
A BRIEF OF DEEP LEARNING
At training you want to set the weights, so that your training samples are correctly classified:

At training you want to set the weights:

Source: https://www.3blue1brown.com/neural-networks
Prediction

At testing the weights do not evolve anymore:

Source: https://www.3blue1brown.com/neural-networks
Can we put any structure reducing the space of exploration and providing useful properties (invariance, robustness...)?

Structure the network?
Example with spatial invariance (Scale, Translation,...)
The Mammalian Visual Cortex is structured

- The ventral (recognition) pathway in the visual cortex has multiple stages
- Retina - LGN - V1 - V2 - V4 - PIT - AIT ....
- Lots of intermediate representations

[picture from Simon Thorpe]

[Galvant & Van Essen]
Deep spatial representation
Deep spatial representation

- Deep Networks are as good as humans at recognition, identification...

How much does a deep network understand those tasks?
Fig. 2: EndoNet architecture (best seen in color). The layers shown in the turquoise rectangle are the same as in the AlexNet architecture.
Other domains

• We could have presented similar impressive results for Natural Language Processing (translation, Name Entity Recognition,...), for speech Recognition,...

• These are not limited to signal but have been extended to graph data (among which social networks: pinterest, facebook...)

SO IT IS MAGIC??
Adversarial examples
Amazing but... beware of the adversarial examples (as any other ML algorithms)

Intriguing properties of neural networks
2013
Morphing
Beware of the adversaries
(as any other ML algorithms)
Beware of the adversaries (as any other ML algorithms)
Adversarial Examples

From Thomas Tanay
Beware of the adversaries (as any other ML algorithms)

- ≠ outliers
- regularization: correct one... find another
- high confidence predictions
- Transferability
Beware of the adversaries
(as any other ML algorithms)

Andrej Karpathy blog, http://karpathy.github.io/2015/03/30/breaking-convnets/
Beware of the adversaries
(as any other ML algorithms)

• It “works” for other modalities also:

https://nicholas.carlini.com/code/audio_adversarial_examples/
BIASES
Man is to Computer Programmer as Woman is to Homemaker? Debiasing Word Embeddings

Tolga Bolukbasi\textsuperscript{1}, Kai-Wei Chang\textsuperscript{2}, James Zou\textsuperscript{2}, Venkatesh Saligrama\textsuperscript{1,2}, Adam Kalai\textsuperscript{2}

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From Nello Cristianini, at at Frontier Research and Artificial Intelligence Conference:
https://erc.europa.eu/sites/default/files/events/docs/Nello_Cristianini-ThinkBIG-Patterns-in-Big-Data.pdf
Beware of input bias

From Nello Cristianini, at Frontier Research and Artificial Intelligence Conference:
https://erc.europa.eu/sites/default/files/events/docs/Nello_Cristianini-ThinkBIG-Patterns-in-Big-Data.pdf
Amazon scraps secret AI recruiting tool that showed bias against women

SAN FRANCISCO (Reuters) - Amazon.com Inc’s (AMZN.O) machine-learning specialists uncovered a big problem: their new recruiting engine did not like women.

Google's AI chief isn’t fretting about super-intelligent killer robots. Instead, John Giannandrea is concerned about the danger that may be lurking inside the machine-learning algorithms used to make millions of decisions every minute.

"The real safety question, if you want to call it that, is that if we give these systems biased data, they will be biased," Giannandrea said before a recent Google conference on the relationship between humans and AI systems.

The problem of bias in machine learning is likely to become more significant as the technology spreads to critical areas like medicine and law, and as more people without a deep technical understanding are tasked with deploying it.
Energy Cost...
### Consumption

<table>
<thead>
<tr>
<th>Consumption</th>
<th>CO₂e (lbs)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Air travel, 1 passenger, NY↔SF</td>
<td>1984</td>
</tr>
<tr>
<td>Human life, avg, 1 year</td>
<td>11,023</td>
</tr>
<tr>
<td>American life, avg, 1 year</td>
<td>36,156</td>
</tr>
<tr>
<td>Car, avg incl. fuel, 1 lifetime</td>
<td>126,000</td>
</tr>
</tbody>
</table>

### Training one model (GPU)

<table>
<thead>
<tr>
<th>Training (GPU)</th>
<th>CO₂e (lbs)</th>
</tr>
</thead>
<tbody>
<tr>
<td>NLP pipeline (parsing, SRL)</td>
<td>39</td>
</tr>
<tr>
<td>w/ tuning &amp; experimentation</td>
<td>78,468</td>
</tr>
<tr>
<td>Transformer (big)</td>
<td>192</td>
</tr>
<tr>
<td>w/ neural architecture search</td>
<td>626,155</td>
</tr>
</tbody>
</table>

Table 1: Estimated CO₂ emissions from training common NLP models, compared to familiar consumption.¹

"Energy and Policy Considerations for Deep Learning in NLP"
A POSSIBLE SOLUTION:
BRIDGING SYMBOLIC AND SUBSYMBOLIC
Learning knowledge with neural networks

(work from Prof. Marco Gori and his team, to be continued with Taki-Eddine Mekhalfa)
Bridging symbolic and subsymbolic

17 × 23

Slide from Giuseppe Marra, Universities of Florence and Siena, PhD Defense
In both cases, we carried on a reasoning process:

- In the "angry face" case, it was a fast reasoning process, mostly associative, approximate and effortless.
  - Subsymbolic AI mostly concentrates on these tasks.

- In the "multiplication" case, it was a slow reasoning process, requiring multiple steps and the need to temporary store intermediate results and it was effortful.
  - Symbolic AI mostly concentrates on these tasks.
Many framework already exists:

- Symbolic approaches enhanced by deep learning (e.g. DeepProbLog, NTP, LRNN)
- Subsymbolic approaches enhanced with structure (e.g. CRF, DSL, SBR)
Bridging symbolic and subsymbolic

We consider a logic language $\mathcal{L}$. $\mathcal{C}$ be a set of constants and $\mathcal{R}$ a set of relations of any arity.
For $c_1, c_2, \ldots, c_k \in \mathcal{C}$ and $R \in \mathcal{R}$, we call $R(c_1, c_2, \ldots, c_k)$ a ground atom or fact or triple.
E.g.

$$\mathcal{C} = \{Alice, Bob, Eve\}$$
$$\mathcal{R} = \{smokes, friendOf\}$$

$\textit{smokes}(Alice), \textit{friendOf}(Alice, Bob)$
There exists a feature representation function $g$ defined on a subset of $C$, which provides a feature representation $x$ of some (or all) the constants in $C$.

E.g.

$$x_{Alice} = g(Alice) = \left[ \begin{array}{c} \text{age} \\ 23 \\ \text{height} \\ 165 \\ \text{RGB profile photo} \\ 0.001, 0.22, \cdots, 0.32, \cdots \end{array} \right]$$

$$x = \{ g(c) : c \in C \}$$
Bridging symbolic and subsymbolic

The **Herbrand Base** $HB$ is the set of all possible ground atoms that can be built from $\mathcal{L}$.

E.g.

\[
\mathcal{C} = \{Alice, Bob, Eve\} \\
\mathcal{R} = \{smokes, friendOf\}
\]

\[
HB(\mathcal{L}) = \{smokes(Alice), smokes(Bob), smokes(Eve), \\
friendOf(Alice, Alice), friendOf(Alice, Bob), \\
... \\
friendOf(Eve, Eve)\}
\]
A global example $y$ (also called Herbrand Interpretation or possible world or labels) is an assignment of a truth value to some or all elements of the HB. It is usually defined as a subset of HB composed of only True ground atoms.

E.g.

$$C = \{Alice, Bob, Eve\}$$

$$R = \{smokes, friendOf\}$$

$$y = \{friendOf(Bob, Eve), friendOf(Eve, Bob), smokes(Alice)\}$$
Goal

We want to model the probability distribution $p(y|x)$ in order to:

- reason **under uncertainty**
- about the **truth value**
- of some **symbolic entities** $y$ (ground atoms of the language $\mathcal{L}$; boolean random variables)
- given some **perceptions** $x$ of the constants $C$

We are usually provided with $x$ and (some examples of) $y$
Knowledge Base Completion in the Nations dataset.

- Circles represent constants.
- A grey circle means that the predicate `smokes` is `True`.
- A white circle means that the value of the predicate `smokes` is unknown.
- Links represent the relation `friendOf` (absence of an arrow means that the relation is `False`). The given world is shown on the top (a), while the completed knowledge base is shown on the bottom (b).
- The system learnt the symmetric nature of the friendship relation.
- It learnt that a friend of at least two smokers is also a smoker, and that two smokers, who are friends of the same person, are also friends.
Next Steps

• Learning the world “from scratch” by interacting with it, by perceiving it

• Learning jointly symbolic and subsymbolic models
Deep Learning ↔ Knowledge Representation

(work in collaboration with Fabien Gandon and Anna Bobasheva)
Some existing works

“Learning Structured Inference Neural Networks with Label Relations”

“Deep Multi-Task Learning for Large-Scale Image Classification”
Study Overview

- reason & query on RDF metadata to build balanced, unambiguous, labelled training sets.
- transfer learning & CNN classifiers on targeted categories (topics, techniques, etc.)
- reason & query RDF metadata of results to address silence, noise, and explain

**Joconde database**

- 350,000 images of artworks
- RDF metadata based on external thesauri

**Explain**
Motivation & Challenges

Museum curators have to annotate thousands of artworks acquired over the hundreds of years and now managed as digital collections. This process can be tedious and susceptible to the human errors and omissions.

- Can the existing digital artwork collections be automatically enhanced by combining Machine Learning and Knowledge Representation & Reasoning?

- Can annotation of the new artworks be automated or semi-automated?
Joconde Database

- 350,000 illustrated artwork records from the French museums.
- RDF metadata describing the artwork subject and properties (media, author, museum, etc.).
- The database is searchable on the artwork subjects and other properties but...
- The metadata can be incomplete & noisy.
- The new artworks added continuously.
Enabling Methods

Deep Learning from unstructured data such as images

Semantic Reasoning and querying from semantic metadata
Marrying Methods: Combining Their Strength

- reason to prepare and control training sets & labels
- learn to improve the quality of the existing metadata that is incomplete & noisy
- learn to annotate new artworks with efficiency
- reason to augment and explain results
- learn and reason to improve searchability of the Joconde database
Marrying Methods: Combining Their Strength

MonaLIA 2.0 Data Pipeline

- Joconde RDF KB
- Create new links between categories
- Joconde+ RDF KB
- Query Joconde+ KB to make training set
  - Image set description file (csv)
  - Train CNN image classifier
  - Model Parameters
  - Test classifier, calculate performance statistics
  - Score full dataset, merge scores with JocondeKB
  - Joconde++ RDF KB
  - Query Joconde++
Marrying Methods: Combining Their Strength

• On the road to Mona Lia 3.0
  – Deep Network Layers and Thesaurus Layers (representation level)
  – learning and reasoning techniques (inference level)
  – Induction on RDF data and unstructured data

We want to thank The French Ministry of Culture for the opportunity to work on such an exiting project and for funding it.
“Smart” MLPaaS / “Smart” MLOPS

(work in collaboration with Mireille Blay-Fornarino, Yassine El Amraoui, Julien Muller, and Bora Kizil)
Existing Works

- AutoML
- Auto-Weka
- ...
- Azure Microsoft
- Amazon AWS
- Google Cloud
- ...

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Microsoft Azure Machine Learning Algorithm Cheat Sheet

What do you want to do?

<table>
<thead>
<tr>
<th>Task</th>
<th>Algorithm</th>
<th>Framework</th>
</tr>
</thead>
<tbody>
<tr>
<td>Classification</td>
<td>Logistic Regression</td>
<td>scikit-learn</td>
</tr>
<tr>
<td>Clustering</td>
<td>K-Means</td>
<td>scikit-learn</td>
</tr>
<tr>
<td>Natural Language</td>
<td>Text Classification</td>
<td>NLTK, spaCy</td>
</tr>
<tr>
<td>Dimensionality</td>
<td>PCA, t-SNE</td>
<td>scikit-learn</td>
</tr>
</tbody>
</table>

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Rockflows

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