Deep learning and ecology : what practices, what values for the neuroimaging scientific community ?

Nathan Lemmers [1] Marie Jacqué [2,3] Julien Lefèvre [2,4]

[1] INSA Toulouse

[2] Aix-Marseille Université

[3] Laboratoire Population Environnement Développement, CNRS, IRD

[4] Institut de Neurosciences de la Timone, CNRS

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EcoInfo
POUR UNE INFORMATIQUE ÉCO-RESPONSABLE

Atecopol Aix-Marseille

Content

1 - Context

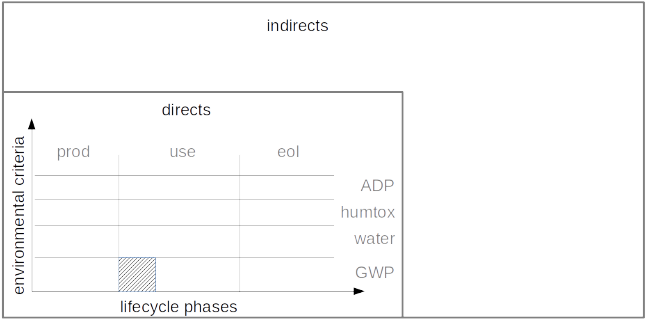
Environmental Impacts of ICT

- GHG emissions of Information and Communication Technology (ICT) are estimated between 2 and 4 % Freitag et al. (2021)
- Uncertainties on how ICT can help to the ecological transition : enablement or jevons paradox Freitag et al. (2021)
- Impacts of ICT suffer from a lot of gaps in knowledge, e.g raw material extraction for direct impacts or indirect impacts in general Roussilhe et al. (2023)

Environmental Impacts of 'AI'

- In the following, 'AI' will refer to *connexionist AI* Cardon et al. (2018) : Machine Learning (ML) and Deep Learning (DL)
- "AI is just 1 % of ICT, so the same for the impacts" (Yann Le Cun, 2021)
- But in the same time, promoters of AI claim it will be everywhere in our everyday life...
- Strong bias in the literature to neglect the environmental footprint of AI, in particular in environmental solutions Ligozat et al. (2021)

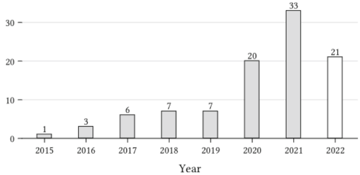
Environmental Impacts of 'AI'



Ligozat et al. (2021) + update for water Li et al. (2023)

Environmental Impacts of 'AI'

- At the moment no global quantification of direct impacts for the (ill-defined) 'AI perimeter'
- Growth of the 'Green AI' topic Verdecchia et al. (2023)



- Big actors self report their impacts :
training for GPT3 = 500T CO2e $\approx$ Training + Inference for Facebook Wu et al. (2022)

What about academic research ?

- Labos1point5l : decrease the carbon footprint of research activity. GES1point5/Ecodiag Mariette et al. (2022)
- Labs are not only consumers of resources or producers of waste/pollution, they use and produce knowledge that circulates between academia, companies, politics...
  => Neutrality in science (see Table ronde at 5 :30pm)
- Several works, **done by computer scientists**, proposed a reflexive point of view :
  Strategies of Big Tobacco and Big Tech Abdalla and Abdalla (2021)
  Values encoded in AI Birhane et al. (2022)

Our Contributions

Inquiry on what is AI in a lab

- We follow the pragmatist program in Monnin (2023)
- 3 months internship of Nathan Lemmers

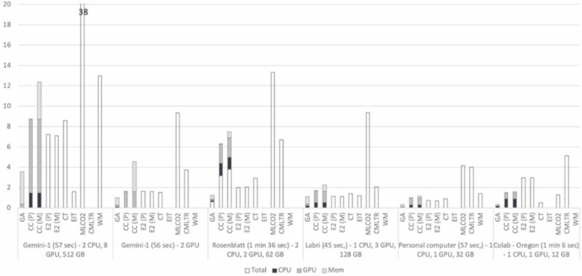
2 perspectives

- Quantify the training phase
- Discover the narratives, the values of AI

2 - Quantitative impacts of ML/DL (in the lab)

State of the art for training phase

- There exist several tools to quantify energy consumption of ML/DL code and CO2e emissions, mostly for training :
  - Embedded packages : CodeCarbon, Eco2AI, CarbonTracker, ...
  - Online : GreenAlgorithm, MLCO2,...
- Several studies have compared those tools, in particular Bouza et al. (2023) : variations can reach 1 order of magnitude



New tool by Nathan Lemmers : GA adapted

- Several drawbacks of existing tools, such as working on servers with no admin rights to manage RAPL files
- Adaptation of http://calculator.green-algorithms.org/
- Several information are required to get :

$$E_{total} = \mathrm{PUE}\left(\mathrm{E_{ram}} + \mathrm{E_{cpu}} + \mathrm{E_{gpu}}\right)$$

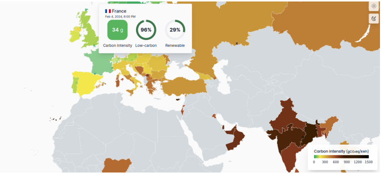
then in CO2e

$$CO2e = EmissionFactor * E_{total}$$

https://github.com/nathanlemmers/EnergyTracker

New tool by Nathan Lemmers : GA adapted

- Power Usage Efficiency : adjustable depending on the server
- $E_{component}$ can be estimated as $Time \times PowerEstimate$ where the second term depends on *usage factor*, *TDP* that can be estimated through python tools
- Static node consumption may be complicated to compute
- *EmissionFactor* can be tracked in real-time with https://app.electricitymaps.com/map



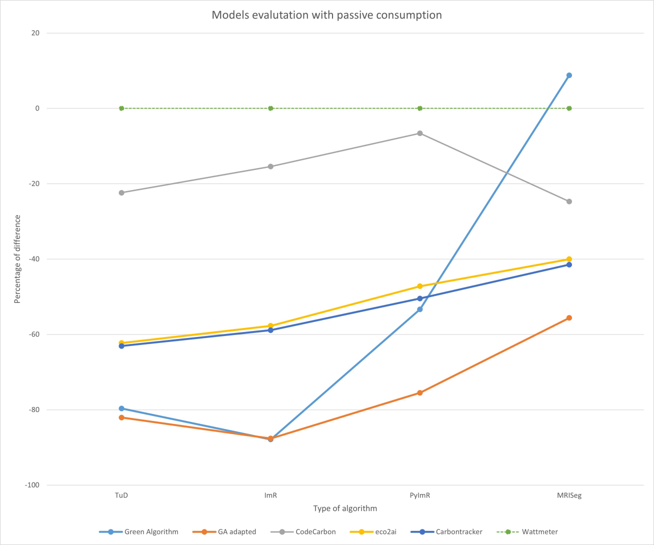
https://github.com/nathanlemmers/EnergyTracker

Experimental conditions

- 4 tools + GA adapted
- 2 different servers (AMU mesocenter and grid5000)
- 4 algorithms

	Execution time (min)		CPU utilization	GPU utilization
	Mesocentre	Grid5000		
Tumor Detection (TuD)	27.46	15.03	yes	no
Image Recognition (ImR)	2.24	1.75	yes	no
Pytorch Image Recognition (PyImR)	1.72	1.44	yes	yes
MRI segmentation (MRISeg)	25.83	24.6	yes	yes

Results


Models evalutation with passive consumption
20
0
-20
-40
-60
-80
-100
Percentage of difference
TuD
ImR
PyImR
MRISeg
Type of algorithm
Green Algorithm
GA adapted
CodeCarbon
eco2ai
Carbontracker
Wattmeter

Yet another quantification of training ?

Yes and no...

- Our results confirm the variability between the tool and w.r.t. ground truth (wattmeters)
- The approach is important in an 'inquiry' perspective to bring answers to colleagues who claim (without proofs) : *"computational tools are nothing in terms of carbon footprint regarding flight travels or purchasing"*
- Possible to obtain an individualized monitoring of computation/DL but is it really useful ? efficient (to change uses) ?

Yet another quantification of training ?

But it is not enough. There could be incomplete conclusion, such as the one given in Abrol et al. (2021) :

"Instead, we compare the computational time complexities of standard implementations of the SML and DL methods to address the reactionary, but inconsistent response that standard implementations of DL methods have a high computational time complexity and take forever to run. In contrast, the high order of computational complexity growth of the standard, CPU-based SML implementations on large training data sets is often over-looked. Indeed, this demonstration is crucial at the current stage in the neuroimaging community, as researchers may be discouraged from undertaking the use of DL methods based on this reactionary, but inaccurate response."

3 - Interviews about DL in the lab

Beyond quantification

- Quantifying the environmental impacts remains largely non trivial and undone
- It may be a very long process, parallel to the massive diffusion of IA in the labs and the society.
- Without moratorium or precautionary principle, another perspective can be to develop *reflexivity* practices in the labs (inspiration : atelier SEnS, S. Quinton, E. Tannier)

Definition (Olmos-Vega et al. (2023))

A set of continuous, collaborative, and multifaceted practices through which researchers self-consciously critique, appraise, and evaluate how their subjectivity and context influence the research processes.

An inspiring article

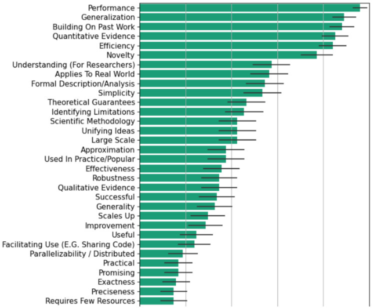
In Birhane et al. (2022) the authors claim :

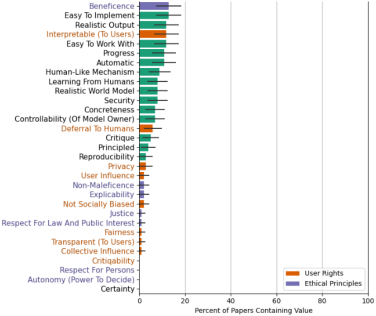
[...] the objectives and values of ML research are influenced by many social forces that shape factors including what research gets done and who benefits. Therefore, it is important to challenge perceptions of neutrality and universal benefit, and document and understand the emergent values of the field.

For this they :

- Identify main *values* from 100 influential ML research papers
- Quantify and analyze the affiliations and funding sources

An inspiring article





An inspiring article

Example for efficiency

"[...] a model is efficient typically indicates the model uses less of some resource, e.g., data efficiency, energy efficiency, label efficiency, memory efficiency, being low cost, fast, or having reduced training time.

***Efficiency is commonly referenced to indicate the ability to scale up, not to save resources**. For example, a more efficient inference method allows you to do inference in much larger models or on larger datasets, using the same amount of resources used previously, or more. This mirrors the classic Jevon's paradox : greater resource efficiency often leads to overall greater utilization of that resource. This is reflected in our value annotations, where 84% of papers mention valuing efficiency, but only 15% of those value requiring few resources."*

Our qualitative analysis

- 8 men (!) of 3 different labs in Neuromarseille, representative of users of AI in the community
- Several statuses (1 DR, 5 engineers, 2 PhD)
- Semi-directed interviews following a grid of themes
- Initially, should help to build a survey for the neuroscience community

Grid of Themes

AI use

- Definition of AI
- Frequency of use, average execution time and used platform

Change of practice

- Previous methods
- How has AI changed your work/profession ?

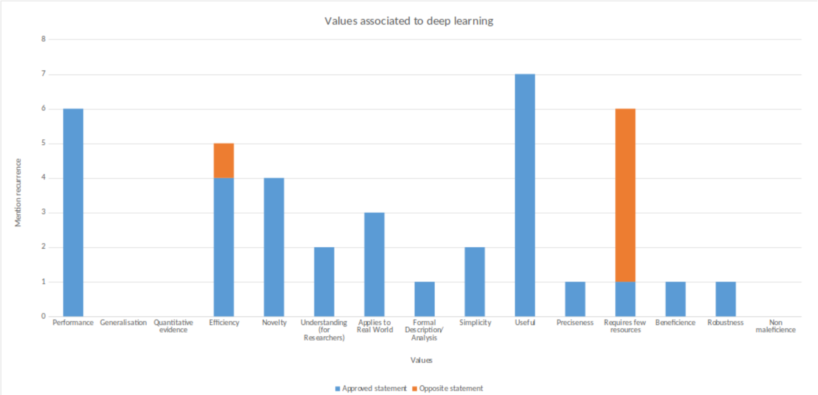
Opinion on AI

- Do you see AI as the future ?
- Is it important to quantify the impact of AI in research ? Do you think efforts are needed ?
- What is your general thinking for the use of AI in your field, and that of medicine ?

Results

- 7 recorded interviews, duration between 20' to 1H40
- Identification of values, following the categories identified in Birhane et al. (2022), by two independent raters
- Identification of "Ideal Types" in the discourse (Max Weber). Can be present for the same person (cognitive dissonance or cognitive variability ?)
  - Technological
  - Ecological
  - Dialectical/Ethical

Results


Values associated to deep learning
Mention recurrence
0
1
2
3
4
5
6
7
8
Performance
Generalisation
Quantitative evidence
Efficiency
Novelty
Understanding (for Researchers)
Applies to Real World
Formal Description/ Analysis
Simplicity
Useful
Preciseness
Requires few resources
Beneficience
Robustness
Non maleficience
Values
Approved statement
Opposite statement

Results

Technological discourse

AI to replace previous tracking systems : *"En économie de temps ça va être monstrueux [...] économie d'argent [...] ces systèmes de tracking vidéos ils coutent une blinde"*

"Pour poser un diagnostic sur une pathologie, c'est tellement compliqué d'analyser des paramètres de la modalité [...] le DL va être indispensable"

"Tout ce qui est segmentation d'images [...] on ne pourra pas y échapper c'est ce qui marche le mieux"

Results

Ecological discourse

"Même si c'est plus pertinent pour la santé, il y a toujours moyen de faire des économies, l'écologie c'est pas 2-3 endroits où on peut polluer à max..."

"Ce que j'espère [...] c'est quand tu fais ta demande de projet [...] on vise un bilan carbone de tant et que ça fasse partie d'un critère de choix des projets"

Results

Dialectic/ethical discourse

"On a plein de contradictions, il faut mettre les données en Open mais il y a la RGPD [...] c'est un bazar incroyable"

"Il faudrait être capable de mettre en place des comités qui quand on veut utiliser une très grosse infrastructure pour faire de l'entrainement évalue [...] si le bénéfice contrecarre le coup pour accepter."

About impact of AI *"... il faut se pencher sur la question [...] j'ai peur que derrière un discours comme ça soit utilisé pour dire 'on sait pas mais on continue'..."*

4 - Conclusion and Perspectives

Our Contributions

Inquiry on what is AI in a lab

- We follow the pragmatist program of Alexandre Monnin
- 3 months internship of Nathan Lemmers

2 perspectives

- Quantify the training phase
- Discover the narratives, the attachments, the values associated to AI

What is new ?

Discussion

What's new or undone ?

- Reflexive research impulsed by members of a scientific community
- Way to introduce reflexivity among colleagues

Several issues

- It can be problematic to use methodologies or concepts outside the field
  => Is there a risk of stealing the jobs of sociologists ?
  => Scientific legitimacy
- Inquiry : identify a problematic situation.
  => Important to solve it later or try to, else it can be only greenwashing !

And next ?

- Use all possible ways to diffuse reflexivity in our communities, e.g. "hacking hackathons" (Brainhack Marseille, 2022, 2023)
- Reflexivity and critical thinking should generate conflictuality, e.g. politicize choices in the lab w.r.t. environmental goals (cf labos1point5)
- Main part of a research project developed in the neuroscience community in Marseille : *UNITAE : What Neuroscience In The Anthropocene Era* https://zenodo.org/records/10122489

More answers to come during the panel session "What sense can we make of computer science research in the Anthropocene ?" ! :-)

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