A few elements about environmental impacts of AI for environment

Aurélie Bugeau
joint work with Anne-Laure Ligozat (LISN), Julien Lefèvre (AMU), Jacques Combaz (Verimag)

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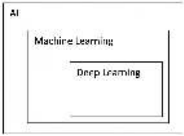
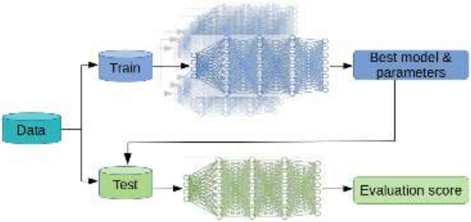
Enlight-Rise workshop

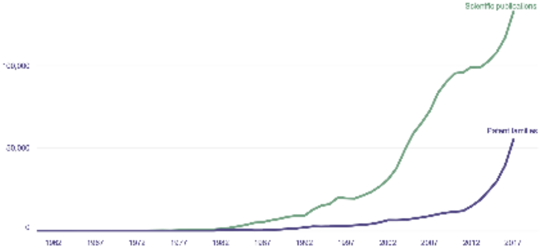
AI

Abuse of language





AI growth



[WIPO Technology Trends 2019]

AI and environment

2 communities

- AI for green: AI as a tool for sustainable development
- green AI: measure and reduce AI impacts

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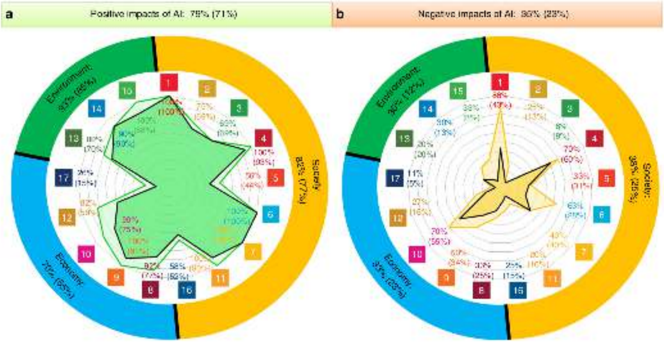
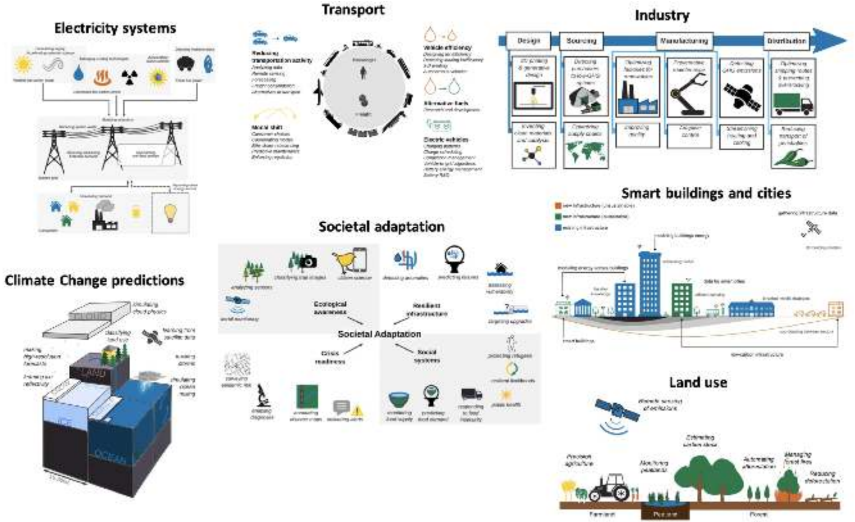
AI for achieving the Sustainable Development Goals

[Vinuesa et al., 2020] : 444 references for 169 goals



Tackling climate change with machine learning

[Rolnick et al., 2019]: 826 references in 13 domains



Tackling climate change with machine learning

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	Causal inference	Computer vision	Interpretable models	NLP	RL & Control	Time-series analysis	Transfer learning	Uncertainty quantification	Unsupervised learning
1 Electricity systems									
Enabling low-carbon electricity		•	•		•	•		•	•
Reducing current-system impacts		•				•		•	•
Ensuring global impact		•					•		•
2 Transportation									
Reducing transport activity		•				•		•	•
Improving vehicle efficiency		•			•				
Alternative fuels & electrification					•				•
Modal shift	•	•				•		•	
3 Buildings and cities									
Optimizing buildings	•				•	•	•		
Urban planning		•				•	•		•
The future of cities				•			•	•	•
4 Industry									
Optimizing supply chains		•			•	•			
Improving materials									•
Production & energy		•	•		•				
5 Farms & forests									
Remote sensing of emissions		•							
Precision agriculture		•			•	•			
Monitoring peatlands		•							
Managing forests		•			•	•			
6 Carbon dioxide removal									

Tackling climate change with machine learning

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Techno-optimist perspective.

But **uncertain impacts** and Jevon's paradox are mentioned:

- Transportation: *"autonomous vehicles could cause people to drive far more"*
- Industry: *"it is worth noting that greater efficiency may increase the production of goods" and thus GHG emissions"*
- Farms and forests: *"making forestry more efficient can have a negative effect by increasing the amount of wood harvested"*

Tackling climate change with machine learning

[Rolnick et al., 2019]: 826 references in 13 domains

Recommendations are proposed:

"In all these cases, projects should be pursued with great care so as not to impede or prolong the transition to a low-carbon electricity system; ideally, projects should be ***preceded by system impact analyses*** *to ensure that they will indeed decrease GHG emissions."* p10

"When designing and promoting new mobility services, it is important that industry and public policy prioritize lowering GHG emissions. Misaligned incentives in the early stages of technological development could result in the ***lock-in to a service with high GHG emissions****"* p15

AI and environment

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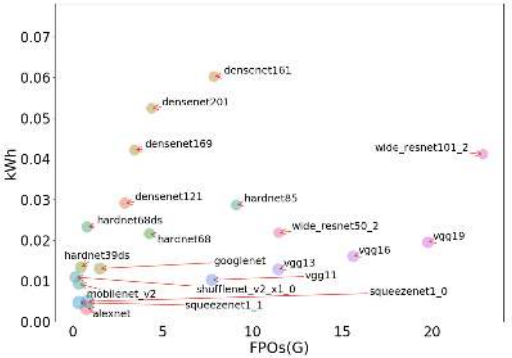
- **green AI: measure and reduce AI impacts**

Measuring impacts **while training** (green AI)

Method 1 : count the number of basic operations

- Reflects the amount of calculations
- Partially correlated with execution time, hardware independent
- Not completely correlated to energy consumption



[Henderson et al., 2020]

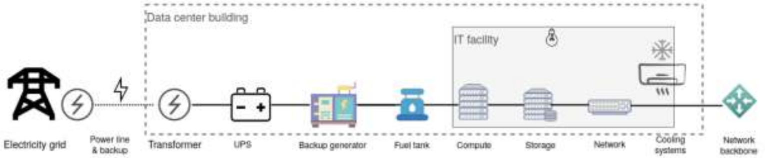
Measuring impacts while training (green AI)

Method 2 : Measuring energy use

$$E_{total} = PUE\,(E_{dram} + E_{cpu} + E_{gpu})$$

where

$$PUE = \frac{\text{Total facility power}}{\text{IT equipment power}}$$



source : B. Davy via B. Petit

Some existing tools

http://www.green-algorithms.org/

codecarbon (mlco2)

```
from codecarbon import EmissionsTracker

tracker = EmissionsTracker()
tracker.start()
# GPU Intensive code goes here
tracker.stop()
```

Some results

- 4 NLP models (natural language processing) [Strubell et al., 2019]
- Estimated energy consumption while training

Model	Hardware	Power (W)	Hours	kWh·PUE	CO_2e	Cloud compute cost
$\text{Transformer}_{base}$	P100x8	1415.78	12	27	26	\$41–\$140
Transformer_{big}	P100x8	1515.43	84	201	192	\$289–\$981
ELMo	P100x3	517.66	336	275	262	\$433–\$1472
BERT_{base}	V100x64	12,041.51	79	1507	1438	\$3751–\$12,571
BERT_{base}	TPUv2x16	—	96	—	—	\$2074–\$6912
NAS	P100x8	1515.43	274,120	656,347	626,155	\$942,973–\$3,201,722
NAS	TPUv2x1	—	32,623	—	—	\$44,055–\$146,848
GPT-2	TPUv3x32	—	168	—	—	\$12,902–\$43,008

lbs

Most widley used model at the time
652 kg C02e
~1 round-trip Paris Hong Kong by plane
or ~2 500km en voiture

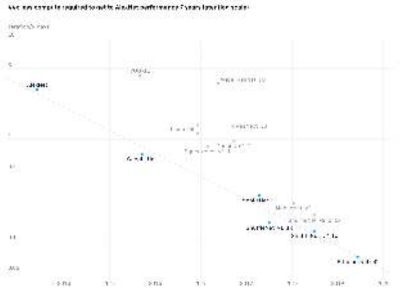
PUE = 1.58 (Ascierto, 2018)
FE = 0.954

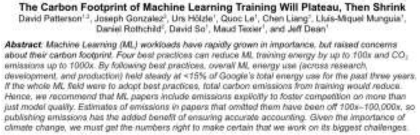
Conclusions from authors

- Need for cost-resource/accuracy analysis
- Public and shared computing resources for academics (price)
- Development of less consuming hardware and algorithms

Limits of existing works

- Limits of existing measuring tools:
  - Mono-criterion (CO2e)
  - Perimeter: electricity consumption during training only
- AI community not well aware of existing works on impacts
- And at the same time: promises





The Carbon Footprint of Machine Learning Training Will Plateau, Then Shrink

David Patterson[1,2], Joseph Gonzalez[2], Urs Hölzle[1], Quoc Le[1], Chen Liang[1], Lluís-Miquel Munguía[1], Daniel Rothchild[2], David So[1], Maud Texier[1], and Jeff Dean[1]

***Abstract**: Machine Learning (ML) workloads have rapidly grown in importance, but raised concerns about their carbon footprint. Four best practices can reduce ML training energy by up to 100x and CO_2 emissions up to 1000x. By following best practices, overall ML energy use (across research, development, and production) held steady at <15% of Google's total energy use for the past three years. If the whole ML field were to adopt best practices, total carbon emissions from training would reduce. Hence, we recommend that ML papers include emissions explicitly to foster competition on more than just model quality. Estimates of emissions in papers that omitted them have been off 100x–100,000x, so publishing emissions has the added benefit of ensuring accurate accounting. Given the importance of climate change, we must get the numbers right to make certain that we work on its biggest challenges.*

Limits of existing works

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$\rightarrow$ How to completely evaluate AI services dedicated to environment?

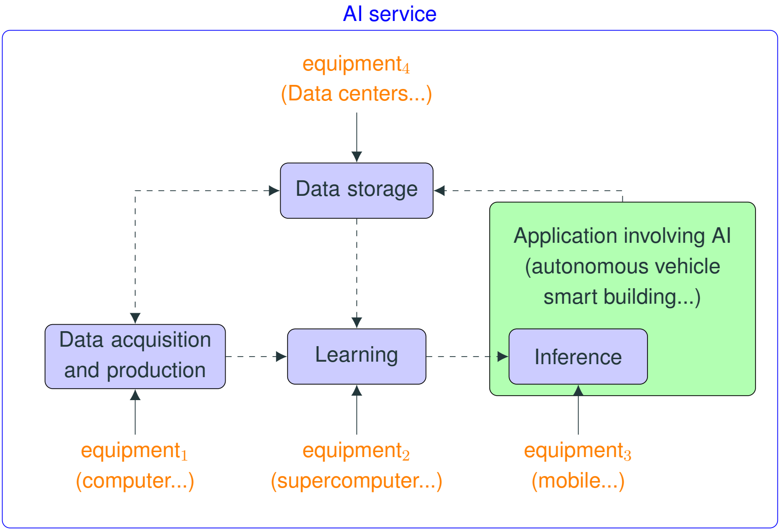
Limits of existing works

- Limits of existing measuring tools:
  - Mono-criterion (CO_2e)
  - Perimeter: electricity consumption during training only

→ How to completely evaluate AI services dedicated to environment? [Ligozat et al., 2021]

→ **Life cycle assessment (LCA)**: internationally standardised methodology for assessing environmental impacts associated with all the stages of the life cycle of product, or a service.

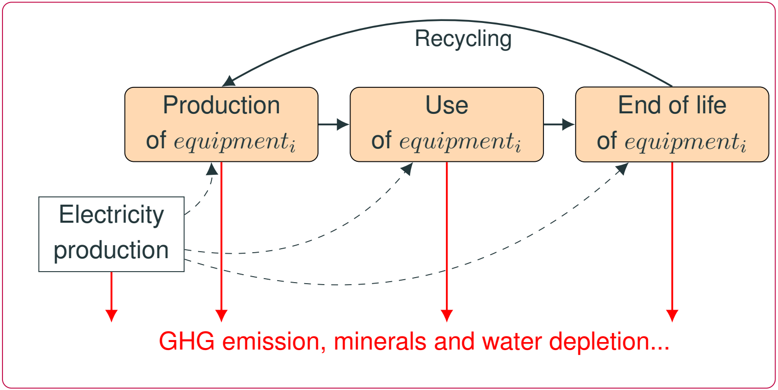
Life cycle of an AI service



Environmental impacts of a service

The life cycle assessment (LCA) of a service relies on:

- LCAs of the equipments/devices involved in the service



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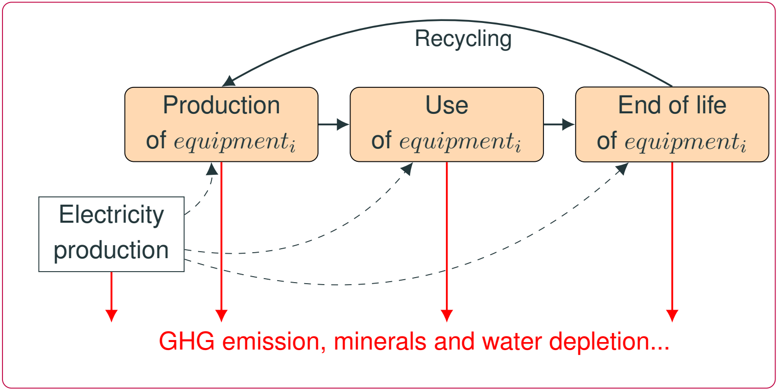

- allocation procedures (keys) to determine the fraction of the impacts attributed to the service.

Measuring environmental benefits of an AI solution

- What should be done:
  The (potential) benefits of an AI solution M_2 which is a substitute for a reference solution M_1 (typically without AI) can be deduced from a comparative LCA:

$$\Delta(M_2|M_1) = LCA(M_2) - LCA(M_1) \in \mathbb{R}^d$$

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- Common pitfalls in such evaluations:
  - focusing on a single environmental criterion (burden shift)
  - restricted perimeter
  - generalization of contextual solutions/benefits
  - third-order effects (e.g. rebound effects) are overlooked.

Is AI for green aware of its own impact ?

If yes, how is it measured ?

Do the authors are able to say that a new solution is better than an old one ?

		Causal inference	Computer vision	Interpretable models	NLP	RL & Control	Time series analysis	Transfer learning	Uncertainty quantification	Unsupervised learning
Mitigation	**Electricity systems**									
	Enabling low-carbon electricity		•	•		•	•		•	•
	Reducing current-system impacts		•				•		•	•
	Ensuring global impact		•					•		•
	Transportation									
	Reducing transport activity		•				•		•	•
	Improving vehicle efficiency		•			•				
	Alternative fuels & electrification					•				•
	Modal shift	•	•				•		•	
	Buildings and cities									
	Optimizing buildings	•				•	•	•		
	Urban planning		•				•	•		•
	The future of cities				•			•	•	•
	Industry									
	Optimizing supply chains		•			•	•			
	Improving materials									•
	Production & energy		•	•		•				
	Farms & forests									
	Remote sensing of emissions		•							
	Precision agriculture		•			•	•			
	Monitoring peatlands		•							
	Managing forests		•			•	•			
	Carbon dioxide removal									
	Direct air capture									•
	Sequestering CO_2		•						•	•
Adaptation	**Climate prediction**									
	Uniting data, ML & climate science		•	•			•		•	
	Forecasting extreme events		•	•			•		•	
	Societal impacts									
	Ecology		•					•		
	Infrastructure					•	•		•	
	Social systems		•				•			•
	Crisis		•		•					
	Solar geoengineering									
	Understanding & improving aerosols						•		•	
	Engineering a control system					•			•	
	Modeling impacts						•		•	
Tools for Action	**Individual action**									
	Understanding personal footprint	•			•	•	•			
	Facilitating behavior change				•					•
	Collective decisions									
	Modeling social interactions			•		•				
	Informing policy	•	•		•				•	•
	Designing markets					•	•			•
	Education				•	•				
	Finance				•		•		•	

[Rolnick et al., 2019]

Case studies

Analysis of several domains in [Rolnick et al., 2019] identified with "high leverage" (Modelling demand/freight, Electric vehicle, Low carbon, Smart buildings).

57 articles have an environmental evaluation following the categories:

a No mention of the environmental gain.
b General mention of the environmental gain.
c No quantitative evaluation or only indirect estimation.
d Evaluation of the energy gain without the AI program.
e Evaluation of the energy gain taking the use phase of the AI service into account.
f Comprehensive evaluation of the environmental gain (comparison of LCAs).

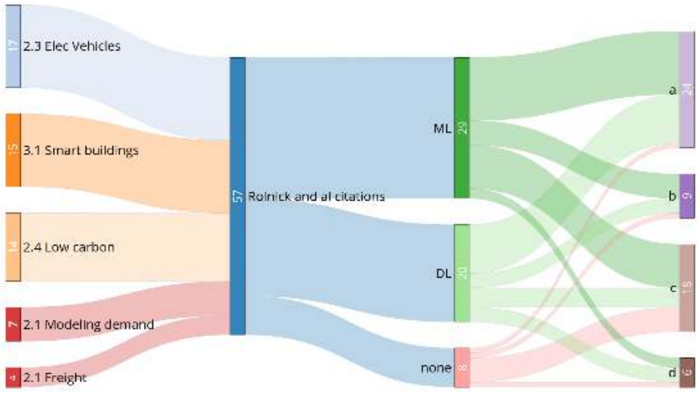
Main result

We found no studies that follow the categories:

e Evaluation of the energy gain taking the use phase of the AI service into account.

f Comprehensive evaluation of the environmental gain (comparison of LCAs).

Main results



a No mention of the environmental gain.

b General mention of the environmental gain.

c No quantitative evaluation or only indirect estimation.

d Evaluation of the energy gain without the AI program.

Example: a smart-building

Commonly overlooked aspects:

- life cycle impacts of devices (sensors, DC, networks, ...)
- impacts of the training phase
- what are the impacts of the smart solution(s) on the design of the building?
  is the solution(s) applicable to old buildings?
- are claimed energy gains reliable in the operational context?
- human interactions: rebound effects, counteracting behaviors.

Discussions

- Current environmental evaluation of AI services is under estimated (mostly energy/GHG)
  => LCA, multi-criteria

- Many unknowns in the LCA (e.g. production of GPU)
  => lobby the companies to open a part of their data

- Large structural changes are difficult to take into account
  => Consequential LCA instead of attributional LCA

- The promises suggested by AI for green must be more evaluated and debated

Thank you !

Questions ?

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