AI for Nature & Environment: Electricity generation/grids – and – Cost-benefit & critiques

Dan Stowell

Dept of Cognitive Science & AI, Tilburg University
- and -
Evolutionary Ecology Research Group, Naturalis Biodiversity Centre

Today

1. Electricity grids and generation
2. Cost-benefit analysis of interventions
3. Carbon footprint of AI

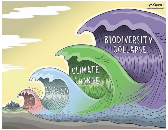
"Tackling Climate Change with Machine Learning"

Rolnick et al (2019)

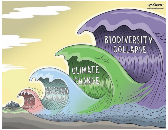
DOI 10.1145/3485128

	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									
Direct air capture									•
Sequestering CO_2		•						•	•
7 Climate prediction									
Uniting data, ML & climate science		•	•			•		•	
Forecasting extreme events		•	•			•		•	
8 Societal impacts									
Ecology		•					•		
Infrastructure					•	•		•	
Social systems		•				•			•
Crisis		•		•					
9 Solar geoengineering									
Understanding & improving aerosols						•		•	
Engineering a planetary control system					•			•	
Modeling impacts						•		•	
10 Individual action									
Understanding personal footprint	•			•	•	•			
Facilitating behavior change				•					•
11 Collective decisions									
Modeling social interactions			•		•				
Informing policy	•	•		•				•	•
Designing markets					•	•			•
12 Education				•	•				
13 Finance				•		•		•	

Table 1: Climate change solution domains, corresponding to sections of this paper, matched with selec
areas of ML that are relevant to each.



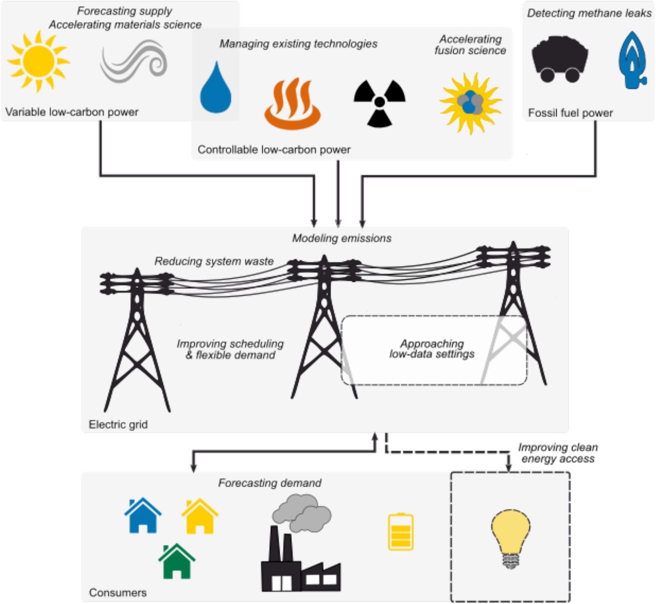
AI is not the solution...



AI is not the solution...

...but AI can help implement/monitor/control the solutions

Electricity systems



(*Rolnick et al 2019*)

Renewable energy

Massive growth in *distributed* power sources

POLITICO

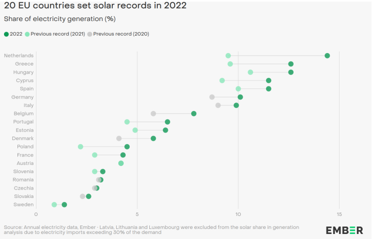
EU blindsided by 'spectacular' solar rollout

Large majority of EU countries will hit 2030 solar targets ahead of schedule, according to new data.

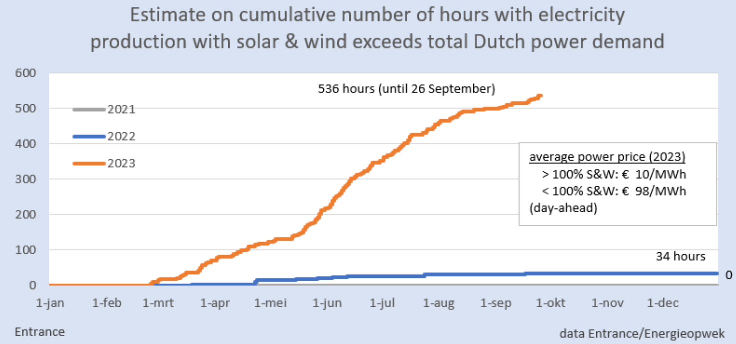
Oscar Del Pozo/AFP via Getty Images

BY VICTOR JACK

AUGUST 12, 2023 | 1:22 PM CET | 4 MINUTES READ



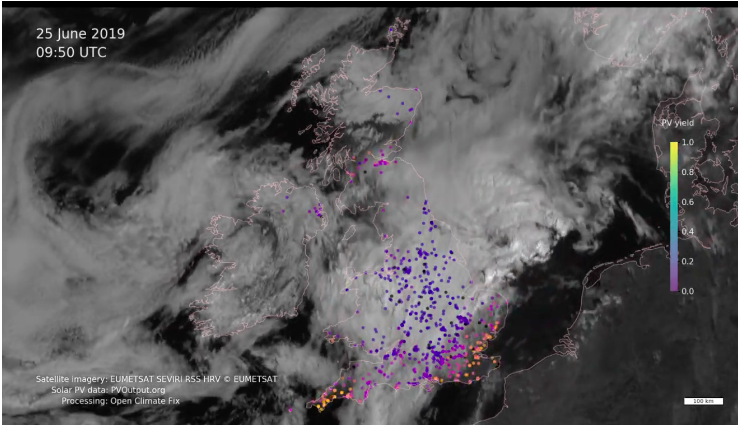
Renewable energy in NL 2023



- 7% of hours in the year-to-date with solar & wind producing >100% of national electricity demand
  - 536 h, inc 109 h from solar PV alone

(Source: @BM_Visser@mastodon.energy)

Renewable sources are **variable** and **distributed**

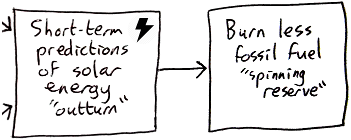


youtube.com/watch?v=IOp-tj-IJpk

The grid was not built for this

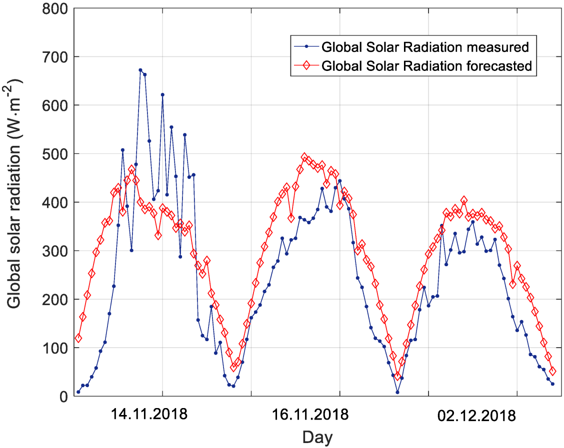
Electricity 1: solar power forecasting

"Nowcasting" (short-term forecasting)



Electricity 1: solar power forecasting

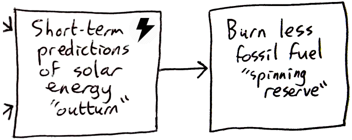
Short-term prediction of local solar power (e.g. 2 hours)



Yang et al (2019)

But HOW to forecast solar power?

Inputs to the prediction:



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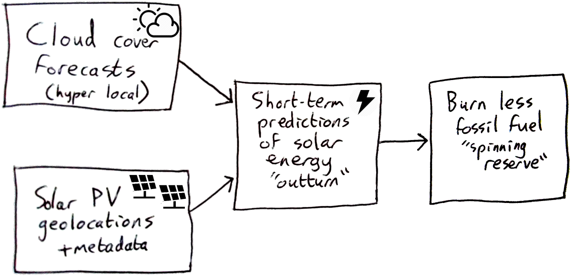


Electricity 2: solar power assets — where are they?

Geolocations: Use crowdsourcing and/or computer vision to detect solar panels

Solar farms

Small-scale PV

Electricity 2: solar power assets — where are they?

Geolocations: Use crowdsourcing and/or computer vision to detect solar panels

Solar farms

UK: 8 GW

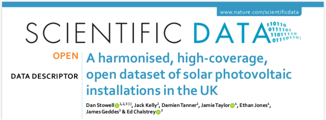
Small-scale PV

UK: 4 GW

Solar PV (photovoltaic) data

Solar panels / solar farms around the world ...global database?

UK : Stowell et al 2020


www.nature.com/scientificdata

SCIENTIFIC DATA

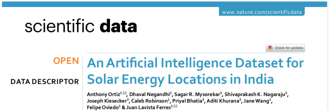
OPEN

DATA DESCRIPTOR

A harmonised, high-coverage, open dataset of solar photovoltaic installations in the UK

Dan Stowell[1,2,3], Jack Kelly[2], Damien Tanner[2], Jamie Taylor[4], Ethan Jones[4], James Geddes[3] & Ed Chalstrey[3]

India : Ortiz et al 2022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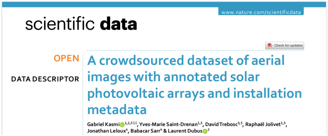
DATA DESCRIPTOR

An Artificial Intelligence Dataset for Solar Energy Locations in India

Anthony Ortiz[1], Dhaval Negandhi[2], Sagar R. Mysorekar[3], Shivaprakash K. Nagaraju[3], Joseph Kiesecker[3], Caleb Robinson[1], Priyal Bhatia[3], Aditi Khurana[3], Jane Wang[1], Felipe Oviedo[1] & Juan Lavista Ferres[1]

France : Kasmi et al 2023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DATA DESCRIPTOR

A crowdsourced dataset of aerial images with annotated solar photovoltaic arrays and installation metadata

Gabriel Kasmi[1,2,5], Yves-Marie Saint-Drenan[1,5], David Trebosc[3,5], Raphaël Jolivet[1,5], Jonathan Leloux[4], Babacar Sarr[4] & Laurent Dubus[2]

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Germany : Clark et al 2023

www.nature.com/scientificdata

scientific **data**

OPEN

DATA DESCRIPTOR

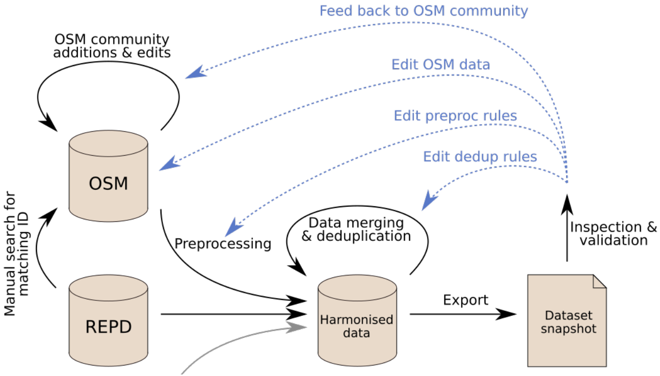
A solar panel dataset of very high resolution satellite imagery to support the Sustainable Development Goals

Cecilia N. Clark & Fabio Pacifici

Software engineering challenge: dataset preprocessing

Building a good **dataset** needs to be automated

- Frequent changes (new PV installations, new data releases)
- Merge data sources: official, crowdsourced, AI



...OK, *now* can we train an ML algorithm?

Software engineering challenge: dataset size

"we need to load about 2.5 GB (about the same amount of data as one hour of a high-definition movie) per second off disk"

Satellite/aerial images are very large, e.g. one px = 25cm x 25cm
Netherlands (PDOK): entire country, how many pixels?

www.pdok.nl/-/nieuw-luchtfoto-2020-nu-beschikbaar-bij-pdok

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Netherlands (PDOK): entire country, how many pixels? 669 billion
www.pdok.nl/-/nieuw-luchtfoto-2020-nu-beschikbaar-bij-pdok

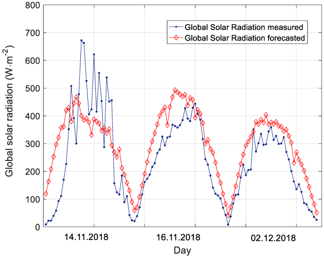
Computer vision for solar PV detection

See lecture 3 “Remote sensing” – e.g. segmentation methods

- SolarMapper (Hu et al 2019)
- DeepSolar (Yu et al 2018)
- ...

1. ML to detect new solar PV
   - Computer vision

2. ML to predict local solar power generation
   - Time-series forecasting



Predicting local solar power generation

Inputs: NWP (numerical weather prediction) & solar geolocations
youtube.com/watch?v=nTY3vNzAdp4

Electricity 3: wind turbines and bats

Bat/bird collisions with wind turbines can happen

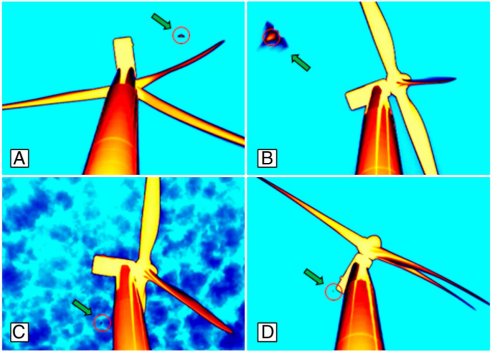
(Image: OekoFor)

How to reduce?

Electricity 3: wind turbines and bats

Bat/bird collisions with wind turbines can happen

(Image: Cryan et al)



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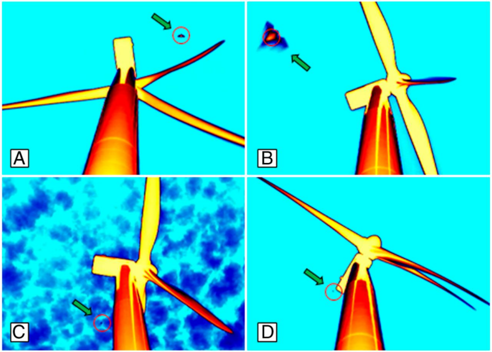
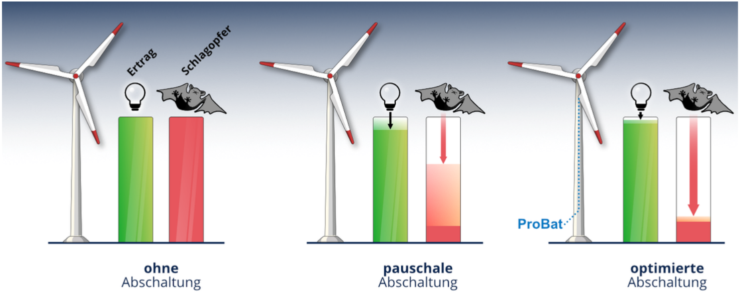


How to reduce?

Electricity 3: wind turbines and bats

Pausing turbines:

None | Fixed schedule | Auto



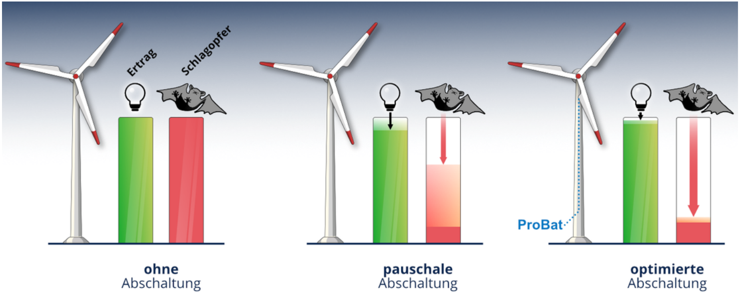
(Image: Ulrike Eberius; ProBat by OekoFor)

Sense animals and avoid: Image? Radar? Sonar? Audio?

Electricity 3: wind turbines and bats

Pausing turbines:

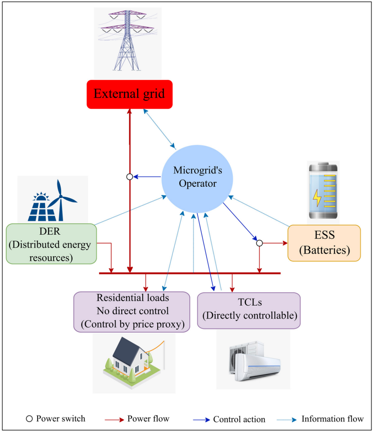
None | Fixed schedule | Auto



(Image: Ulrike Eberius; ProBat by OekoFor)

Sense animals and avoid: Image? Radar? Sonar? Audio?

Electricity 4: Smart microgrids



Local minute-by-minute decisions:

- charge/discharge
- buy/sell
- consume/wait

Reinforcement learning method (Nakabi 2021)

STRATEGY EXERCISE

Based on "Tackling Climate Change with Machine Learning"
Rolnick et al (2019)
arxiv.org/abs/1906.05433

In your group:

- Take 4 ideas per group (see handouts)
- **Rank** them in priority, from the perspective of an **AI Software Engineering funder/planner**
- Criterion:
  applied AI likely to make a big impact on global heating

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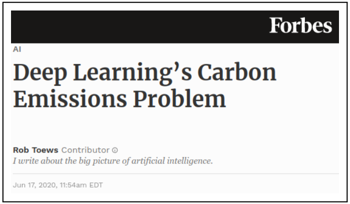
Strategy exercise: now we allocate our money

https://sli.do/ Event code XXX XXXX

Source: https://admin.sli.do/event/6ijcSv5sCma6xgrCadVZxJ/polls

What about AI's own carbon footprint?

What about AI's own carbon footprint?


Forbes

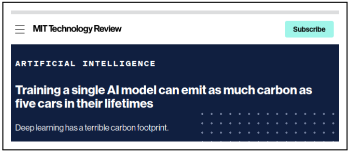
AI

Deep Learning's Carbon Emissions Problem

Rob Toews Contributor

I write about the big picture of artificial intelligence.

Jun 17, 2020, 11:54am EDT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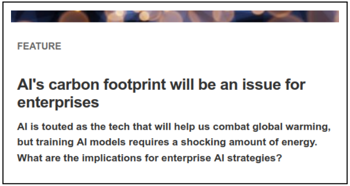
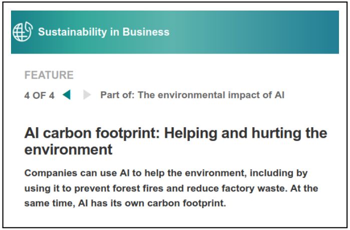
Training a single AI model can emit as much carbon as five cars in their lifetimes

Deep learning has a terrible carbon footprint.


FEATURE

AI's carbon footprint will be an issue for enterprises

AI is touted as the tech that will help us combat global warming, but training AI models requires a shocking amount of energy. What are the implications for enterprise AI strategies?


Sustainability in Business

FEATURE

4 OF 4 Part of: The environmental impact of AI

AI carbon footprint: Helping and hurting the environment

Companies can use AI to help the environment, including by using it to prevent forest fires and reduce factory waste. At the same time, AI has its own carbon footprint.

A related example: Ethereum

Note: Ethereum/Bitcoin are not AI! (Blockchain)

How Bitcoin's vast energy use could burst its bubble

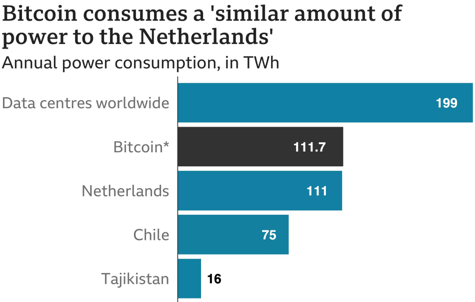
27 February 2021

Crypto mining could hinder U.S. ability to battle climate change, White House says

CNBC · 6 days ago

- Industry incentives create greener crypto mining | Cornell Chronicle
  Cornell Chronicle · 1 hour ago

View Full Coverage



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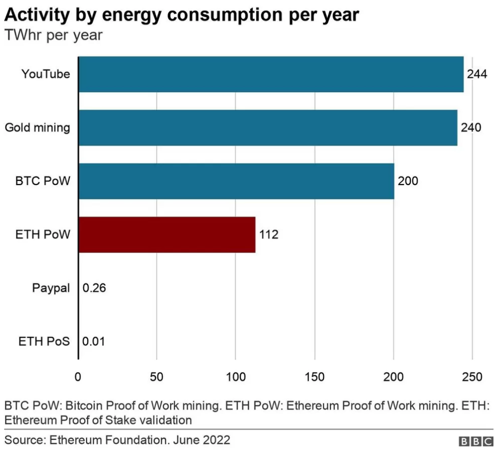

How to measure emissions?

1. From the inside: “Process lifecycle analysis”
   - List and quantify all the processes used (energy, hardware manufacture, transport, etc)
2. From the outside: “Input-output analysis”
   - Measure the overall consumption e.g. with electricity metering

Exact numbers?
estimates are often needed for some numbers;
numbers often fluctuate.

Carbon-intensity of AI

Let's itemise the CO_{2eq}used in:

(a) Developing a model
(training, evaluating)

(b) Deploying a model
(running, monitoring)
-|-

Q: How **often** does each of these run?

Carbon-intensity of AI

Let's itemise the CO_{2eq} used in:

(a) Developing a model (training, evaluating)

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-|-

- Electricity for GPU servers
- Electricity for data servers
- Cooling the servers
- Embedded CO_{2eq} of hardware manufacture
- Cost of transmitting information

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Calculating the CO_{2eq} impact

Power usage (MWh) =

Training time (hours)
x Number of processors
x Power per processor (MW)

Calculating the CO_{2eq} impact

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x PUE

Calculating the CO_{2eq}impact

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PUE = factor to include other data centre power e.g. cooling

Calculating the CO_{2eq}impact

Power usage (MWh) =
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x Power per processor (MW)
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CO_{2eq}impact =
Power usage (MWh)
x Carbon intensity (CO_{2eq}emitted per MWh)

Calculating the CO_{2eq}impact

Power usage (MWh) =

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x Number of processors
x Power per processor (MW)
x PUE (1.58)

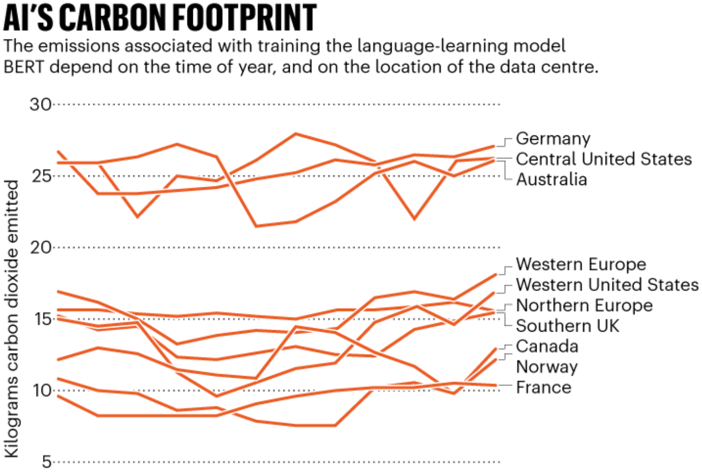
PUE = factor to include other data centre power e.g. cooling

CO_{2eq}impact =

Power usage (MWh) *(→Data centre)*
x Carbon intensity (CO_{2eq}emitted per MWh)
(→Energy provider)

CO_{2eq} footprint of 1 kWh electricity

– varies with: country, time of day, time of year



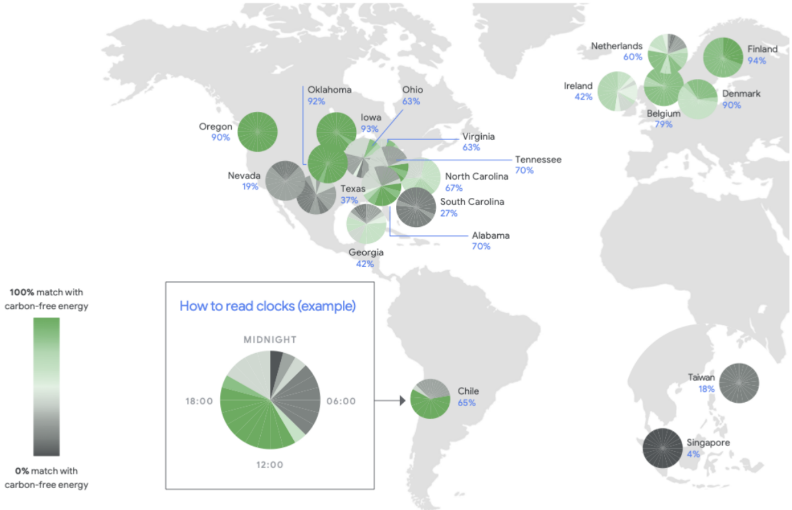


Figure 2. Percent Carbon Free Energy by Google Cloud Location in 2020. The map shows the %CFE and how the percentage changes by time of day. Chile has a high %CFE from 6AM to 8PM, but not at night. The US examples on this map range from 19% CFE in Nevada to 93% in Iowa, which has strong prevailing winds both night and day. (sustainability.google/progress/energy/)

Case study: Strubell et al 2019

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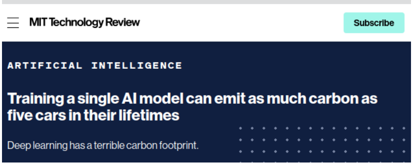
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Energy and Policy Considerations for Deep Learning in NLP

Emma Strubell **Ananya Ganesh** **Andrew McCallum**
College of Information and Computer Sciences
University of Massachusetts Amherst
{strubell, aganesh, mccallum}@cs.umass.edu

Abstract

Recent progress in hardware and methodology for training neural networks has ushered in a new generation of large networks trained on abundant data. These models have obtained notable gains in accuracy across many NLP tasks. However, these accuracy improvements depend on the availability of exception-

Consumption	CO_2e (lbs)
Air travel, 1 passenger, NY↔SF	1984
Human life, avg, 1 year	11,023
American life, avg, 1 year	36,156
Car, avg incl. fuel, 1 lifetime	126,000
Training one model (GPU)	
NLP pipeline (parsing, SRL)	39

Improvements since 2019

Google reported on their own carbon intensity (Patterson 2022):

1. Improved **model**: 4.2x faster
2. Improved **machine** (TPUv4): 13.7x lower energy
3. Improved **datacentre**: PUE 1.60 $\rightarrow$1.10
4. Improved **electricity source**: CO_{2eq}-per-MWh 0.43 $\rightarrow$0.09

Overall: 747x lower footprint

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4. Improved **electricity source**: CO_{2eq}-per-MWh 0.43 $\rightarrow$0.09

Overall: 747x lower footprint

Log your carbon

Henderson et al (2020) provide a Python library to:

- Log the estimated power (kWh) and CO_{2eq} of your whole **experiment**
- Output a 'Carbon Impact Statement'

Carbon Impact Statement
This work contributed 8.021 kg of CO_{2eq} to the atmosphere and used 24.344 kWh of electricity, having a USA-specific social cost of carbon of $0.38 ($0.00, $0.95).

github.com/Breakend/experiment-impact-tracker

NB: whole-experiment cost, not just training-time or inference-time

Log your carbon

Henderson et al (2020) provide a Python library to:

- Log the estimated power (kWh) and CO_{2eq} of your whole **experiment**
- Output a 'Carbon Impact Statement'

Carbon Impact Statement
This work contributed 8.021 kg of CO_{2eq} to the atmosphere and used 24.344 kWh of electricity, having a USA-specific social cost of carbon of \$0.38 (\$0.00, \$0.95).

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Reducing the CO_{2eq}footprint of an AI

Assume you plan to train and deploy an AI algorithm (e.g. a CNN) for a small business.

Q: What can you do to reduce the footprint?

-|-

Reducing the CO_{2eq} footprint of an AI

- Efficient CNN layers (e.g. depthwise-separable):
  "can reduce computation by factors of 5–10"
- Efficient hardware: GPU choice, or TPU
  "can improve performance/Watt by factors of 2–5"
- Select cloud/local computers using green energy:
  "[cloud] reducing energy costs by a factor of 1.4–2"
  "[location] reducing the gross carbon footprint by 5–10"
- Use pre-trained model(s)
- Smaller CNN (fewer layers, fewer channels)
- Single CNN, not an ensemble
- Use optimised software libraries (e.g. TFlite)
- Schedule your algorithms, to run during low elec demand / low-carbon elec
- Cache results (don't re-calculate)
- Don't produce outputs you won't use (e.g. lazy evaluation)

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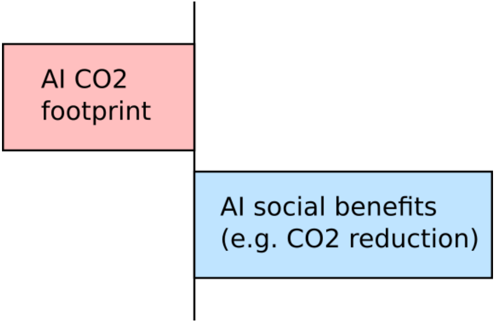
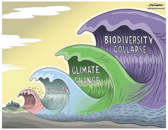
-

Cost-benefit





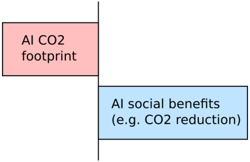
AI is not the solution...

...but AI can help implement/monitor/control the solutions

Putting it all together

- Electricity sector
  - ML for renewable energy
  - ML for managing microgrids
- Carbon footprint of AI (mostly: electricity)
  - Quantifying it
  - Reducing it

→Cost-benefit analysis
Estimating positive & negative impacts



Next steps

- Lab this afternoon: Animal movement data

Next time:

- Hardware devices
- With guest lecturer!