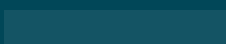
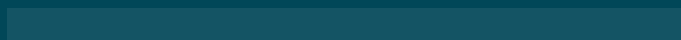




**AI for Good**

# Code Carbon

*Track your code's CO2 emissions*





## AMINE SABONI



MLOps Engineer, Pruna AI  
Maintainer at CodeCarbon



# Today's agenda

**1.**

**Environmental  
impact of AI**

**2.**

**CodeCarbon**

**3.**

**Mitigation**

# 1. Environmental impact of AI





~2%

Estimated share of Data Centers in global emissions

IEA : <https://8billiontrees.com/carbon-offsets-credits/carbon-ecological-footprint-calculators/carbon-footprint-of-data-centers/>

# Not only CO2



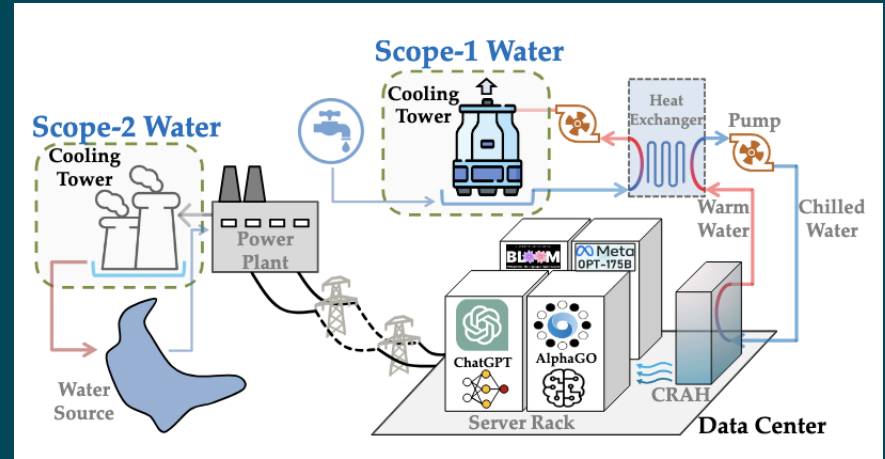
# Water usage

Complex water consumption model,  
with multiple leaking points :

- Scope 1 : datacenter cooling
- Scope 2 : electricity production
- Scope 3 : chips manufacture

→ 1 to 9L of water evaporated for  
each kWh of electricity.

→ 4.2 to 6 billion m<sup>3</sup> each year (half  
of UK's consumption)

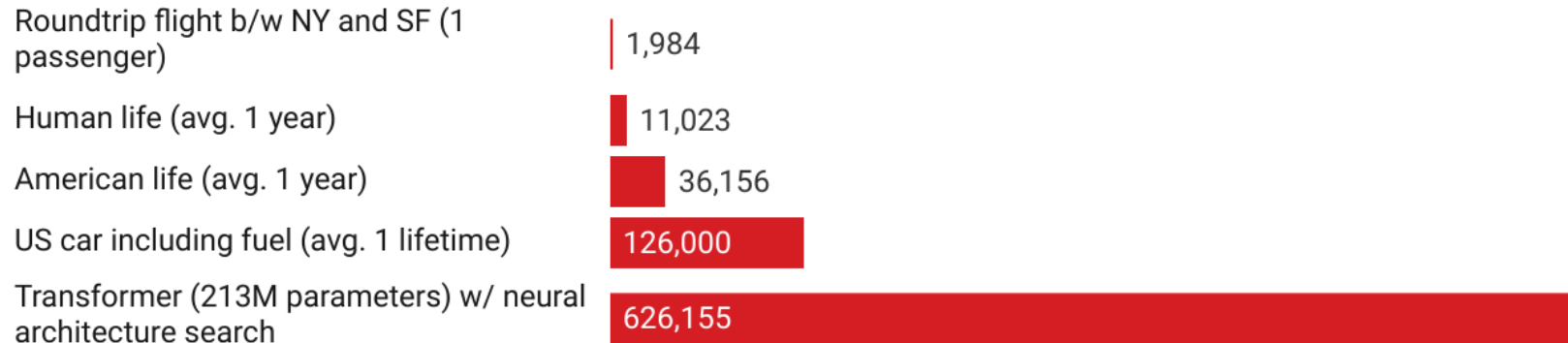


[Making AI Less "Thirsty": Uncovering and Addressing the Secret Water Footprint of AI Models](#), Li & al, March 25

# Training a single AI model can emit as much carbon as five cars in their lifetimes

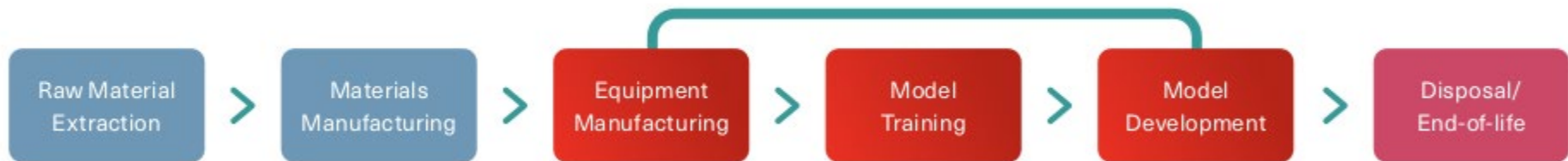
## Common carbon footprint benchmarks

in lbs of CO2 equivalent





# Above and beyond training

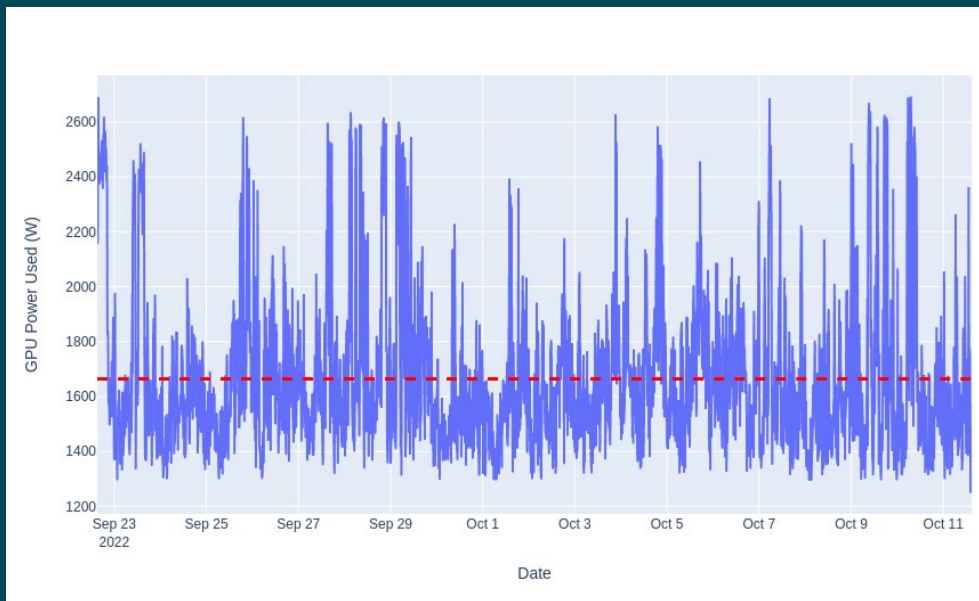
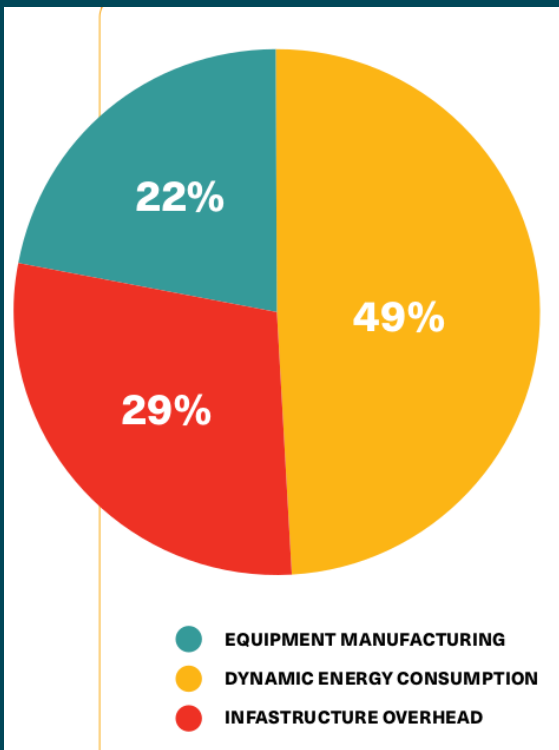


a BigScience initiative

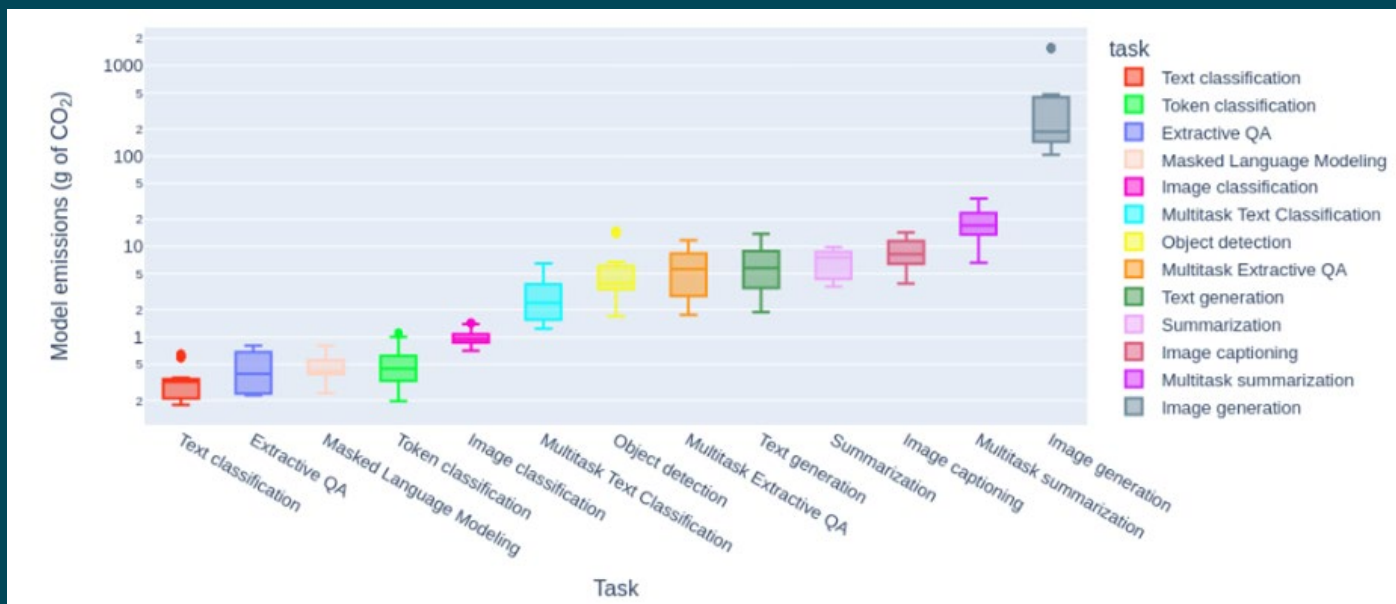
**BLM**

**176B params · 59 languages · Open-access**

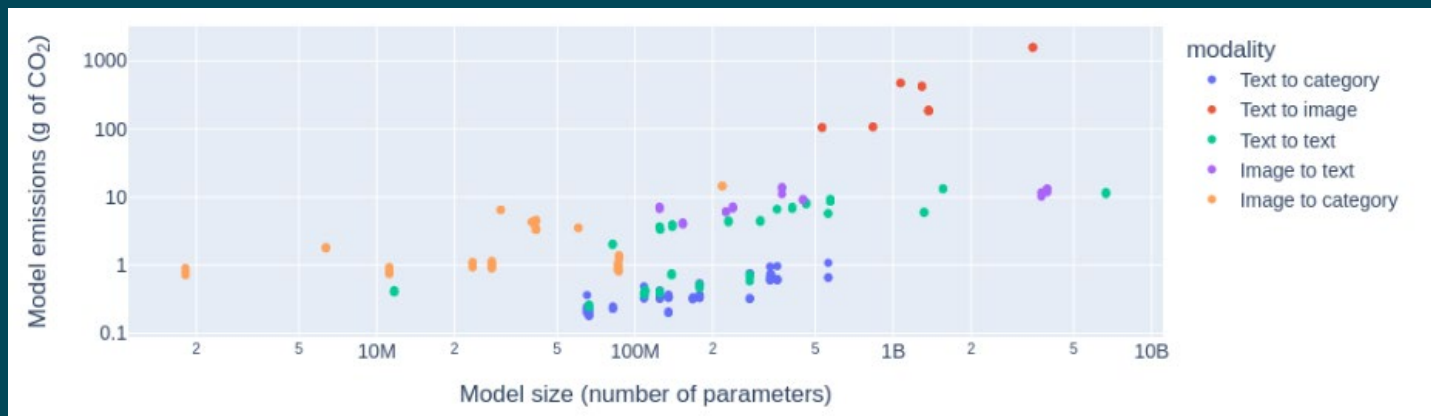
# Above and beyond training



# All tasks are not equivalent



# Key findings



Modality matters

	BLOOMz-7B	BLOOMz-3B	BLOOMz-1B	BLOOMz-560M
<b>Training energy (kWh)</b>	51,686	25,634	17,052	10,505
<b>Finetuning energy (kWh)</b>	7,571	3,242	1,081	543
<b>Inference energy (kWh)</b>	$1.0 \times 10^{-4}$	$7.3 \times 10^{-5}$	$6.2 \times 10^{-5}$	$5.4 \times 10^{-5}$
<b>Cost parity (# inferences)</b>	592,570,000	395,602,740	292,467,741	204,592,592

Inference adds up

Table 5. The BLOOMz models from our study with their training energy cost (from [31]), finetuning energy cost (from [34]), inference cost (from the present study), and cost parity, as the number of inferences required to sum to the training cost.

## 2. CodeCarbon



# A bit of History

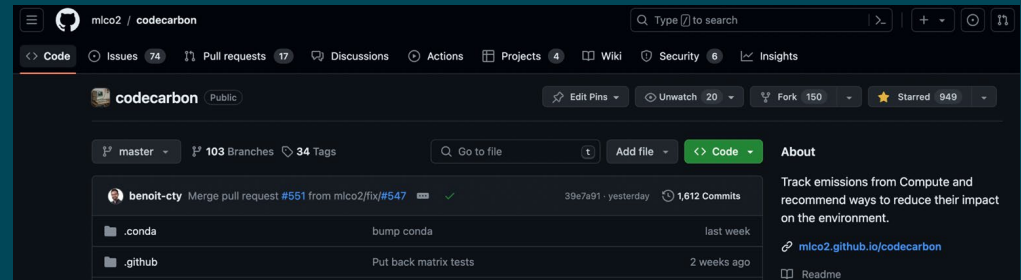


**2019** : MLC02, online tool to quantify ML emissions by researchers from MILA Research Institute

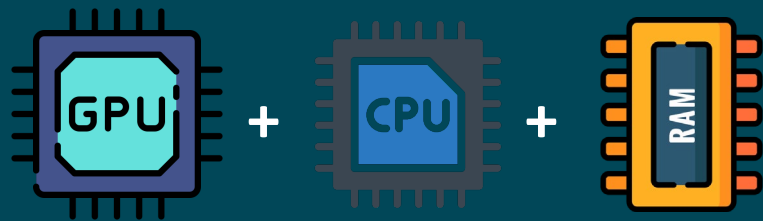
**2020** : CodeCarbon launch, open source python package to measure any code (not just ML) emissions

**2021** : Development of the CodeCarbon API and Dashboard with Data For Good

**2023** : Creation of a non-profit in France to support the project



# Hardware energy consumption

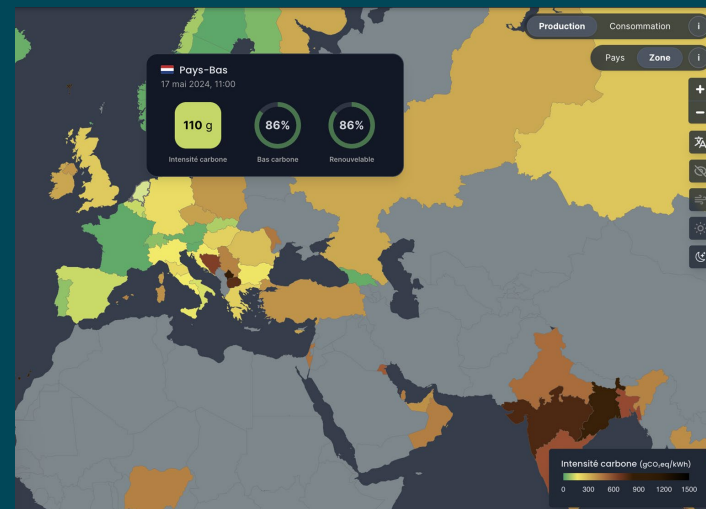


nvidia-smi  
RocM (AMD)

RAPL  
psutils

RAPL  
psutils

# Electrical mix of workload data center



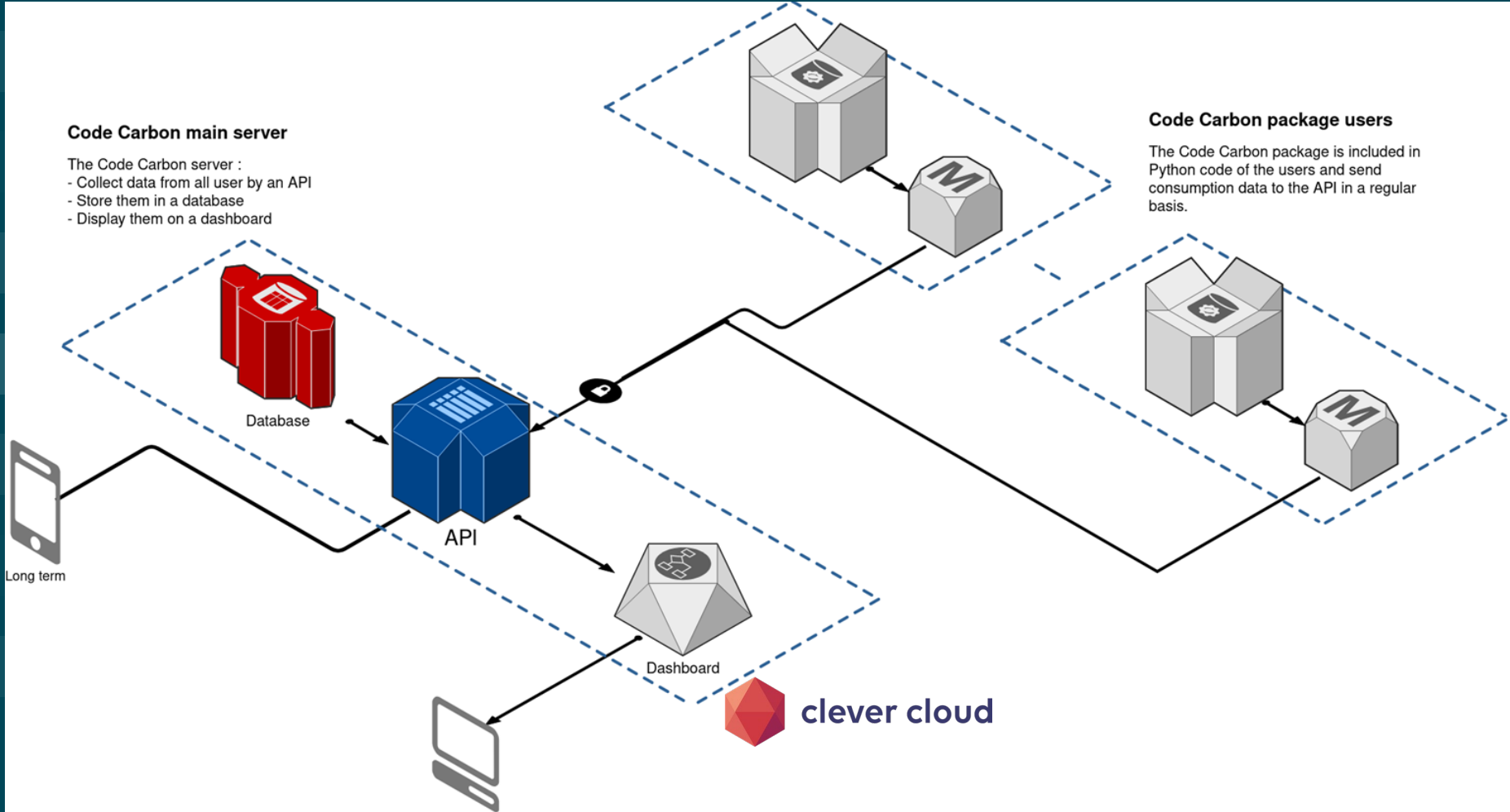
## Code Carbon main server

The Code Carbon server :

- Collect data from all user by an API
- Store them in a database
- Display them on a dashboard

## Code Carbon package users

The Code Carbon package is included in Python code of the users and send consumption data to the API in a regular basis.



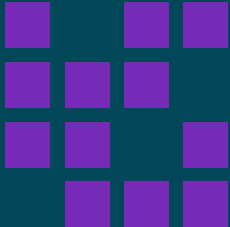


# 3. Mitigation

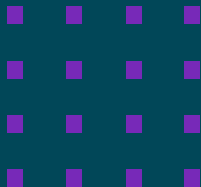


# Model compression & optimization

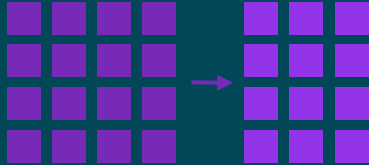
Pruning



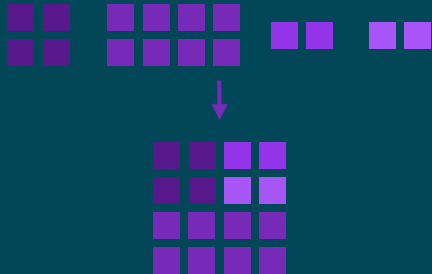
Quantization



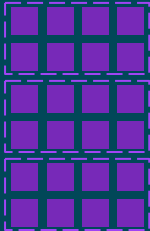
Distillation



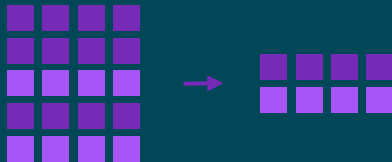
Compilation



Batching



Caching





# Reducing Code's emissions

## As a developer

Build lighter websites  
Pause Copilot when not needed  
Keep hardware longer

## As a user

Use AI systems responsibly

- Smallest model for your need

Keep you hardware longer

## As a data scientist

Use fine-tuned models  
Location and time of trainings  
Use optimization tools  
like [Zeus](#) or [Pruna](#)  
Keep hardware longer

## In IT Operations

Pick hosting location according to  
carbon intensity  
Keep hardware longer

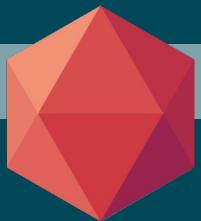


# Thanks !

See you on <https://github.com/mlco2/codecarbon> !



Data For Good



clever cloud

**moz://a**  
Mozilla Tech Fund 2024