

Climate Change

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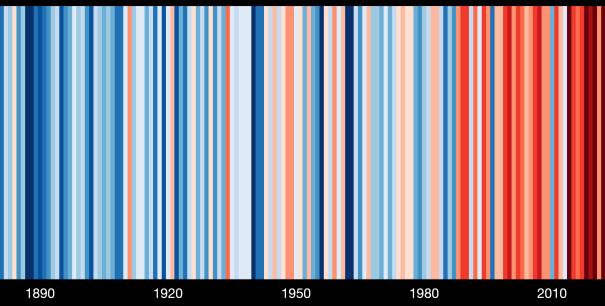
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Climate Change

- Caused by emission of greenhouse gases
- Gather in the atmosphere, reflect heat emissions from earth back to earth
- Consequences
 - Increase in average temperature worldwide
 - Change of weather patterns, ocean currents
 - More extreme weather conditions for a longer period of time
 - Rise of the ocean level due to melting ice in Greenland / Antarctica

Temperature change in Nordrhein-Westfalen since 1881



Why is that a topic for us?

Greenhouse gas emissions by sector, World

Our World in Data

Greenhouse gas emissions¹ are measured in tonnes of carbon dioxide-equivalents² over a 100-year timescale.

Electricity and heat 14 billion t 12 billion t 10 billion t 8 billion Transport Manufacturing and construction 6 billion t Agriculture 4 billion t **Fugitive emissions** Industry Buildings 2 hillion Waste Land-use change and forestry Aviation and shipping Other fuel combustion 1990 1995 2000 2005 2010 2015 2020 Data source: Climate Watch (2023) OurWorldInData.org/co2-and-greenhouse-gas-emissions | CC BY

Because electricity production is among the top polluters:

Climate Change

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Three Areas of Discussion

- 1. Using machine learning to fight climate change
- 2. Energy consumption by machine learning
- 3. Computing in the Future

Nicolas Kayser-Bril (2021) Luccioni et al. (2023); Strubell et al. (2019) Mathew Duggan (2022)

Section 1

Using Machine Learning to Fight Climate Change

Using machine learning to fight climate change

Nicolas Kayser-Bril (2021). "Falsche Versprechen". In: *netzpolitik.org*. URL: https://netzpolitik.org/2021/ki-und-klimawandel-falsche-versprechen/

Section 2

Energy Consumption by Machine Learning

Introduction

- ► Large language models (BERT, GPT, etc.) are becoming the dominant form of ML
- Using them requires a lot of computation, which consume power
- Estimating carbon footprint of such models is difficult
 - Ultimately depends on the primary energy source
- Use cases
 - Ignored: Hardware production, delivery, deployment, computing centre maintenance...
 - Training
 - Application (often called inference)

Training

▶ Generally: The more parameters, the more computation

Model	Hardware	Power (W)	Hours	kWh·PUE	CO_2e	Cloud compute cost
$T2T_{base}$	P100x8	1415.78	12	27	26	\$41-\$140
$T2T_{big}$	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

Table: CO₂ emission estimates by Strubell et al. (2019). Comparison: NY–SF by plane: 1984 CO₂e

Energy Consumption by Machine Learning

Inference

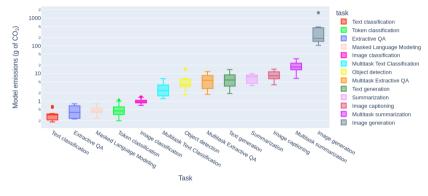


Figure: Per-task analysis by Luccioni et al. (2023)

Energy Consumption by Machine Learning

Training vs. Inference

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

Table: Model training, fine-tuning and inference costs for variants of BLOOMz (Luccioni et al., 2023). Washing machine: ca. 1kWh.

Key Take-Aways from Luccioni et al. (2023)

- Generative tasks are more energy- and carbon-intensive compared to discriminative tasks.
- Tasks involving images are more energy- and carbon-intensive compared to those involving text alone.
- Decoder-only models are slightly more energy- and carbon- intensive than sequence-to-sequence models for models of a similar size and applied to the same tasks.
- > Training remains orders of magnitude more energy- and carbon- intensive than inference.
- Using multi-purpose models for discriminative tasks is more energy-intensive compared to task-specific models for these same tasks.

Section 3

Computing in the Future

Computing in the Future

Introduction

- ► This is (reasonable) speculation
- Based on: Mathew Duggan (2022). Programming in the Apocalypse. URL: https://matduggan.com/programming-in-the/

Computing in the Future

Introduction

- This is (reasonable) speculation
- Based on: Mathew Duggan (2022). Programming in the Apocalypse. URL: https://matduggan.com/programming-in-the/
- Scenario: It's 2050
 - Some consequences of climate change have happened
 - How does that impact information technology?

Computing Infrastructure

- Operating a datacentre is hard
- Requires constant delivery
 - of parts
 - ▶ For computers, but also cooling, cables, power supply, ...
 - of electricity
- Many sea ports become unusable due to rising sea levels

Computing Infrastructure

- Operating a datacentre is hard
- Requires constant delivery
 - of parts

[...] raising 221 of the world's most active seaports by 2 meters (6.5 feet) would require 436 million cubic meters of construction materials, an amount large enough to create global shortages of some commodities. The estimated amount of cement – 49 million metric tons – alone would cost \$60 billion in 2022 dollars. (Jacques Leslie, 2022)

Computing Infrastructure

- Operating a datacentre is hard
- Requires constant delivery
 - of parts
 - For computers, but also cooling, cables, power supply, ...
 - of electricity
- Many sea ports become unusable due to rising sea levels
- Disturbance of supply chains
- ➔ Consequences
 - More frequent server downtimes
 - 99.999% availability are a thing of the past
 - Distributed service engines will be more popular, because cloud provider knows which computing center is currently operational

Power Infrastructure

- Power grids are old, even in 2024
- More load for heating and cooling due to changed weather
- Power grid suffers from supply chain issues as well
- ➔ Consequences
 - Regular power downtimes
 - Prioritization of who gets the remaining power

Programming

Difficult to maintain

- Programming environments that rely heavily on cloud services
 - E.g., dependency management by Node/NPM
- Containers that consume a lot of bandwidth
 - E.g., docker
- Open source projects, because
 - many projects are developed in the spare time of individuals
 - and they will be under increased economic pressure

Programming

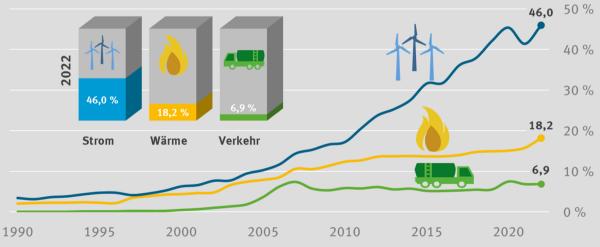
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- Open source projects, because
 - many projects are developed in the spare time of individuals
 - and they will be under increased economic pressure
- More important
 - Energy-efficient programming
 - Robustness due to tests and test coverage

But there is also some good news

Erneuerbare Energien:

Anteile in den Sektoren Strom, Wärme und Verkehr bis 2022



Quelle: Umweltbundesamt auf Basis Arbeitsgruppe Erneuerbare Energien-Statistik (AGEE-Stat) Datenstand: 10/2023

References I

- Jacques Leslie (2022). "How Climate Change Is Disrupting the Global Supply Chain". In: Yale Environment 360. URL: https://e360.yale.edu/features/how-climatechange-is-disrupting-the-global-supply-chain.
- Luccioni, Alexandra Sasha/Yacine Jernite/Emma Strubell (2023). Power Hungry Processing: Watts Driving the Cost of AI Deployment?
- Mathew Duggan (2022). Programming in the Apocalypse. URL: https://matduggan.com/programming-in-the/.
- Nicolas Kayser-Bril (2021). "Falsche Versprechen". In: netzpolitik.org. URL: https://netzpolitik.org/2021/ki-und-klimawandel-falsche-versprechen/.
- Strubell, Emma/Ananya Ganesh/Andrew McCallum (2019). "Energy and Policy Considerations for Deep Learning in NLP". In: Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics. Florence, Italy: Association for Computational Linguistics, S. 3645–3650. DOI: 10.18653/v1/P19-1355. URL: https://www.aclweb.org/anthology/P19-1355.pdf.

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