Lecture 1 - Energy Consumption in Machine Learning

Efficacy and efficiency evaluation of machine learning models
Ph.D. Course

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Outline

1. The Increase of Power Demand in ML

2. Estimating the Energy Consumption of ML Algorithms
   - 2.1 Empirical tools to estimate the effective hardware usage
   - 2.2 Theoretical Models of Energy Consumption
   - 2.3 ML estimators of energy consumption

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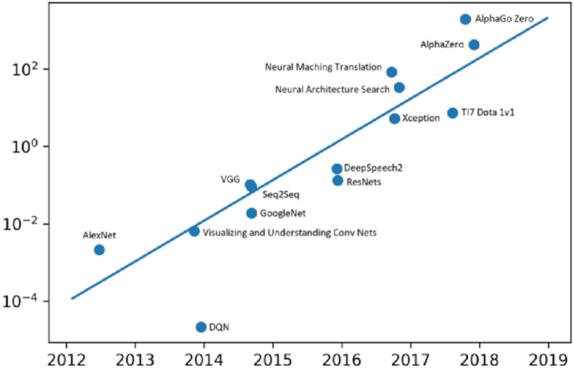

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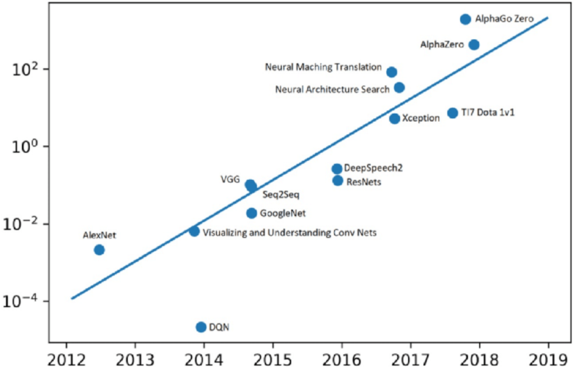

Amodei, D. and Hernandez, D. Ai and compute. https://openai.com/index/ai-and-compute/ 2018.

- To train *AlphaGO Zero* it took 4 TPUs, 64 GPUs and 19 CPUs for days!! Around 3 millions of $!!!

Growth in Required Compute

Bruckner, T., et *al*. Energy systems. In Climate Change 2014: Mitigation of Climate Change.

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- If this exponential trend continue, ML and mainly Deep Learning (DL) compute may become a significant contributor to climate change
- This can be mitigated by exploring how to improve energy efficiency in ML

Need to Change of the Assessment Paradigm

Strubell, E., Ganesh, A., and McCallum, A. Energy and Policy Considerations for Deep Learning in NLP. pp. 3645–3650, 2019. doi: 10.18653/v1/p19-1355.

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- Hot subject for scientific meetings and conferences, which ask to include results about ML energy consumption estimate
  - E.g. Workshop on Simplification, Compression, Efficiency and Frugality for Artificial intelligence (ECML PKDD 2023)

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  - E.g. Workshop on Simplification, Compression, Efficiency and Frugality for Artificial intelligence (ECML PKDD 2023)
- **PROBLEM**: lack of tools to appropriately compute the energy consumption
  - Accounting for all involved factor is almost impossible, and several assumptions are needed

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Estimating the Energy Consumption of ML Algorithms

Three main approaches:

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3. ML estimators of energy ML algorithms consumption (what?!?)

For a survey:
García-Martín, E. et *al*. Estimation of energy consumption in machine learning, Journal of Parallel and Distributed Computing, 134, 2019,pp 75-88.

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Empirical tools to estimate the effective hardware usage

- Some tools to estimate code carbon footprint:
  - *Machine Learning Emissions Calculator*. The tool can estimate the carbon footprint of GPU compute by specifying hardware type, hours used, cloud provider, and region [Lacoste 2019].
    - Available as web tool (`https://mlco2.github.io/impact/`)
  - *Experiment-impact-tracker* [Henderson 2020]
  - *CarbonTracker* [Anthony et *al.*]
  - *Tracarbon* [`https://github.com/fvaleye/tracarbon`]
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- They need to know the cloud resource provider (Google Cloud Provider, Amazon Web Services, etc.) and the country
  - Different providers and different countries produce electricity by using different sources, with different emissions

– Lacoste, A.et *al*. Quantifying the Carbon Emissions of Machine – Learning. Technical report, 2019.

– Henderson, P., et *al.* Towards the Systematic Reporting of the Energy and Carbon Footprints of Machine Learning. http://arxiv.org/abs/2002.05651. 2020

– Anthony LFW. et *al*. Carbontracker: Tracking and Predicting the Carbon Footprint of Training Deep Learning Models, ICML Workshop on Challenges in Deploying and monitoring Machine Learning Systems, 2020

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- Easy to integrate in your Python code
- It estimates the amount of carbon dioxide (CO_2) produced by the cloud or personal computing resources used to execute the code
- Effective visualization of outputs in an integrated dashboard

CodeCarbon: Carbon Dioxide Emissions Estimation

Carbon dioxide (CO_2) emissions are estimated as the product of two main factors:

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2. Energy Consumed by the computational infrastructure, quantified as kilowatt-hours

CodeCarbon: Carbon Intensity (CI)

- Like most tools of this type, CodeCarbon computes the carbon intensity of electricity per cloud provider and per country
  - based on public data of each country about the energy source composition (and their relative CO_2 emissions): e.g. *biofuel*, *coal*, *fossil*, *gas*, *hydroelectricity*, *nuclear*, *solar*, *wind*

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- The mix varies by country (there are tables available)
- When carbon intensity is not available, but the energy mix yes, it is assumed to be following average:

Energy Source	**Carbon Intensity (kg/kWh)**
Coal	995
Petroleum	816
Natural Gas	743
Geothermal	38
Hydroelectricity	26
Nuclear	29
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Source: Codecarbon https://mlco2.github.io/codecarbon/methodology.html

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Then, for example, if the energy mix of a grid electricity is 25% Coal, 35% Petroleum, 26% Natural Gas and 14% Nuclear, but no carbon intensity in known for that region, we get
Net Carbon Intensity =

$$0.25 \cdot 995 + 0.35 \cdot 816 + 0.26 \cdot 743 + 0.14 \cdot 29 = 731.59\ gCO_2/kWh$$

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- If neither the global carbon intensity of a country nor its electricity mix is available, they apply a world average carbon intensity per kilowatt/hour of 475 gCO_2

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  3. *CPU*, here the processors energy consumption is differentiated between Intel, Apple Silicon Chips (M1, M2) and AMD processor (see docs for details)
- Let's move to the notebook

References: https://arxiv.org/pdf/1911.08354

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- Then, the energy of one run is the sum of the energy costs of all layers involved from input to output
- More suitable to estimate the energy cost of one inference than than of training (it needs to be adapted)

See for instance:

– Brooks, D. et *al.*. Wattch: a framework for architectural-level power analysis and optimizations. SIGARCH Comput. Archit. 28:2 2000, 83–94.

– W. Ye,et *al.*. The design and use of simplepower: a cycle-accurate energy estimation tool. DAC '00, pp. 340–345.

Theoretical Models of Energy Consumption: An Example

Wiedemann, S. Müller, K.R. and Samek, W. Compact and computationally efficient representation of deep neural networks. IEEE Transactions on Neural Networks and Learning Systems, 31(3):772–785, 2020.

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  mul, the binary multiplication operator,
  sum, the binary addition operator,
  read, which reads a value from memory, and
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- Then, each elementary operation is associated with an energy cost, estimated from hardware

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In the paper above the y provide the following estimate of elementary operations energy cost for a 45-nm CMOS processor:

Table: Energy is in pJ (Picojoule). MB and KB denotes megabytes and kilobytes, respectively.

Operation	**8 bits**	**16 bits**	**32 bits**
float add	0.2	0.4	0.9
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R/W (<8KB)	1.25	2.5	5.0
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- But to compare algorithms for the same task that's not a problem

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ML to estimate Energy Consumption of ML Algorithm

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  - Pipeline to estimate the energy consumption of a model

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  - A data set of energy consumption of various models and layer types
  - A collection of predictors for different layer types, forming an energy-prediction baseline to more complex Deep Learning architectures

Getzner, J. Charpentier, B. and Günnemann, S.. (2023). Accuracy is not the only Metric that matters: Estimating the Energy Consumption of Deep Learning Models. arXiv:2304.00897.

Accuracy is not the only Metric that matters: Estimating the Energy Consumption of Deep Learning Models

- Different parameters considered for each layer (when present): *batch-size*, *image-size*, *kernel-size*, *in-channels/size*, *out-channels/size*, *stride*, *padding*

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- Use Codecarbon to measure the CPU energy of the randomly configured models obtained

– Krizhevsky, A. Sutskever, I. and Hinton, G.E. Imagenet classification with deep convolutional neural networks. Communications of the ACM, 60(6):84–90, 2017.

Accuracy is not the only Metric that matters: Estimating the Energy Consumption of Deep Learning Models

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- They use Linear/Polynomial Regression models to predict the CPU energy consumption of each layer Different layer types: *Conv2d, MaxPool2D, Linear*
  - They did not expect any higher-order dependencies or strong non-linear relationships omong features
  - Used models have superior transparency and interpretablity

Accuracy is not the only Metric that matters: Estimating the Energy Consumption of Deep Learning Models

- They use Linear/Polynomial Regression models to predict the CPU energy consumption of each layer Different layer types: *Conv2d, MaxPool2D, Linear*
  - They did not expect any higher-order dependencies or strong non-linear relationships omong features
  - Used models have superior transparency and interpretablity
- For linear (FC) and convolutional layers, the multiply accumulate count (MAC) as the only feature and achieved an R^2 test score > 0.999!!

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- A few of them would largely impact on the energy consumption
- Main limitation: only CPU estimates are available