FAKULTÄT FÜR !NFORMATIK
Faculty of Informatics

AI/ML in the Era of Climate Change

Lecture 2: Large-Scale AI Models and Sustainability Aspects + Assignment 1 Specs

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Credits for most of the material used in this presentation go to Dr. Shashikant Ilager.

What Is A Large-Scale AI Model?

AI models are built upon a wide range of algorithms and techniques, e.g., regression models, ensemble models, (deep) neural networks.

A **large-scale AI model** is a model that:

- it is trained on very large datasets
- it has a huge size
- it is composed by complex architectures with billions of parameters
- it is trained high-powered computational resources

<u>However</u>, no single & accepted definition of when it can be classified as "large-scale"

Here, we focus on their impact on sustainability, in particular:

1. **energy consumption** and **carbon footprint** during both training and inference
2. **mitigation strategies**

Examples of Large-Scale Models

- Multi-modal (e.g., Dall-E, Chamaleon, Qwen2-VL)
- Large Language Models (LLMs) (e.g., GPT, PaLM, Llama, Grok)
- ...the next one they will release tomorrow :-)

“a teddy bear on a skateboard in times square”

“a painting of a fox sitting in a field at sunrise in the style of Claude Monet”

Source: OpenAI.com

The recent breakthroughs in AI are achieved by sheer scale rather than new algorithmic techniques!

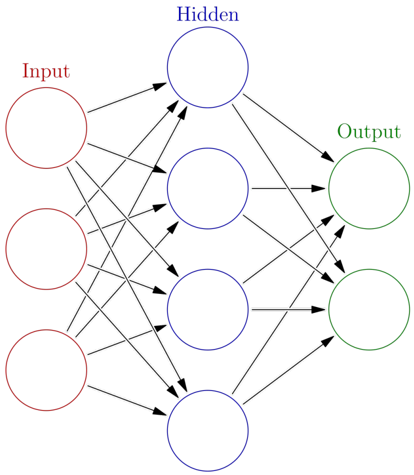
Why Is It More the Scale?

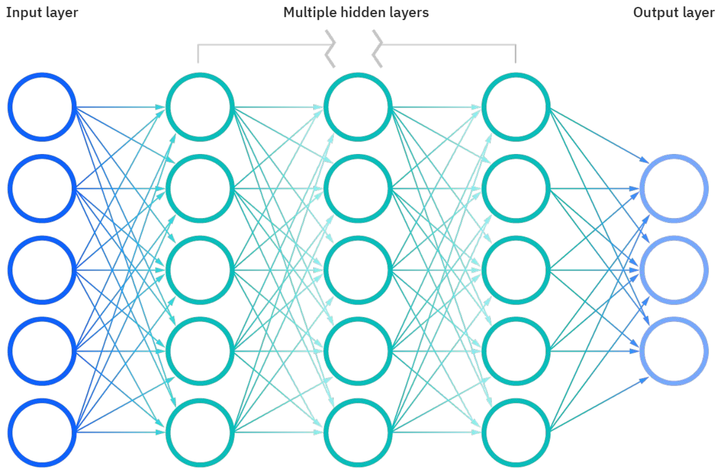
- Most of the algorithms are there since a while…
  - Transformer-based models (e.g., GPT) is deep learning technique published in 2017
  - Recurrent Neural Networks (RNNs) have been revamped in the 80-90s, but they are even older!
  - Neural Networks (NNs) have been in general started be the practical applied in the 2000s

It is in the possibility to train on a ***massive amount of data****, using data centers composed of GPUs and other* ***accelerators****, disposable* ***cloud resources****, and* ***industry attention*** *that made possible the current "AI boom"!*

From Artificial (Shallow) NNs to Deep NNs

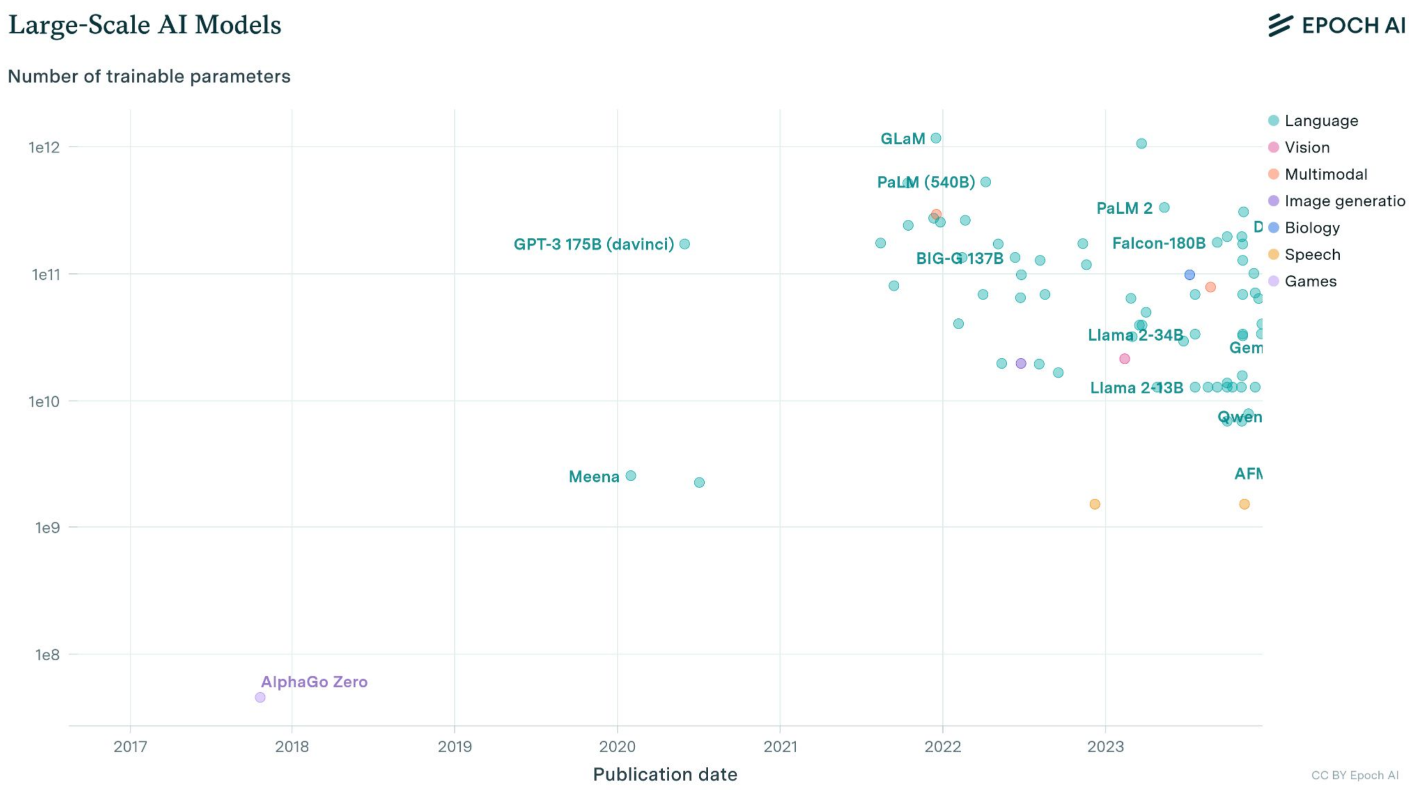
Most of these large-scale models are fundamentally based on Deep Neural Networks (DNNs)





Sources:
- https://commons.wikimedia.org/wiki/File:Colored_neural_network.svg
- https://www.analyticsvidhya.com/blog/2022/11/analyzing-and-comparing-deep-learning-models/

How Large Are the Models?



How Large Are the (Language) Models?

System	Domain	Publication date	Parameters	Training compute (FLOP)	Training dataset size (...	Training time (hours)	Training hardware	Hardware quantity	Training compute cost ...
GLaM	Language	2021-12-13	1200000000000.00	3.74e+23	600000000000	1366.0	Google TPU v4	1024	$541,437.42
PanGu-Σ	Language	2023-03-20	1085000000000.00	4.669999999999999e+23	246750000000	2400.0	Huawei Ascend 910	512	
PaLM (540B)	Language	2022-04-04	540350000000.00	2.5272e+24	585000000000	1536.0	Google TPU v4	6144	$2,945,949.76
Megatron-Turing NLG 530B	Language	2021-10-11	530000000000.00	1.17e+24	270000000000	770.0	NVIDIA A100 SXM4 80 GB	4480	$3,704,291.31
MegaScale (530B)	Language	2024-02-23	530000000000.00	9.6910000000001e+23	300000000000	117.9	NVIDIA A100	11200	
MegaScale (Production)	Language	2024-02-23	530000000000.00	1.2e+25		504.0	NVIDIA A100	12288	
Llama 3.1-405B	Language	2024-07-23	405000000000.00	3.8e+25	15600000000000	2142.0	NVIDIA H100 SXM5 80GB	16000	
PaLM 2	Language	2023-05-10	340000000000.00	7.34e+24	2700000000000		Google TPU v4		$4,865,570.06
Nemotron-4 340B	Language	2024-06-14	340000000000.00	1.8000000000000003e+25	6750000000000	2200.0	NVIDIA H100 SXM5 80GB		
Grok-1	Language	2023-11-04	314000000000.00	2.90000000001e+24	6200000000000				
Gopher (280B)	Language	2021-12-08	280000000000.00	6.31e+23	300000000000	920.0	Google TPU v3	4096	$616,611.14
ST-MoE	Language	2022-02-17	269000000000.00	2.9000000000000005e+23	1500000000000				
ERNIE 3.0 Titan	Language	2021-12-23	260000000000.00	1.0421e+24	668000000000		Huawei Ascend 910 NVIDI	1920	
Yuan 1.0	Language	2021-10-12	245730000000.00	3.5380000000001e+23	1000000000000			2128	
DeepSeek-Coder-V2 236B	Language	2024-06-17	236000000000.00	1.2852e+24	3191000000000				
DeepSeek-V2	Language	2024-05-07	236000000000.00	1.02e+24	8100000000000		NVIDIA H800		
DeepSeek-V2.5	Language	2024-09-06	236000000000.00	1.7892000000000004e+24					
HyperCLOVA 204B	Language	2021-09-10	204000000000.00				NVIDIA A100		
Mi:dm 200B	Language	2023-10-31	200000000000.00	1.2e+24	1000000000000				
Falcon-180B	Language	2023-09-06	180000000000.00	3.76e+24	2625000000000	4320.0	NVIDIA A100 SXM4 40 GB	4096	$10,340,911.71

Source: https://epochai.org/data/large-scale-ai-models?view=table

Computational Requirements

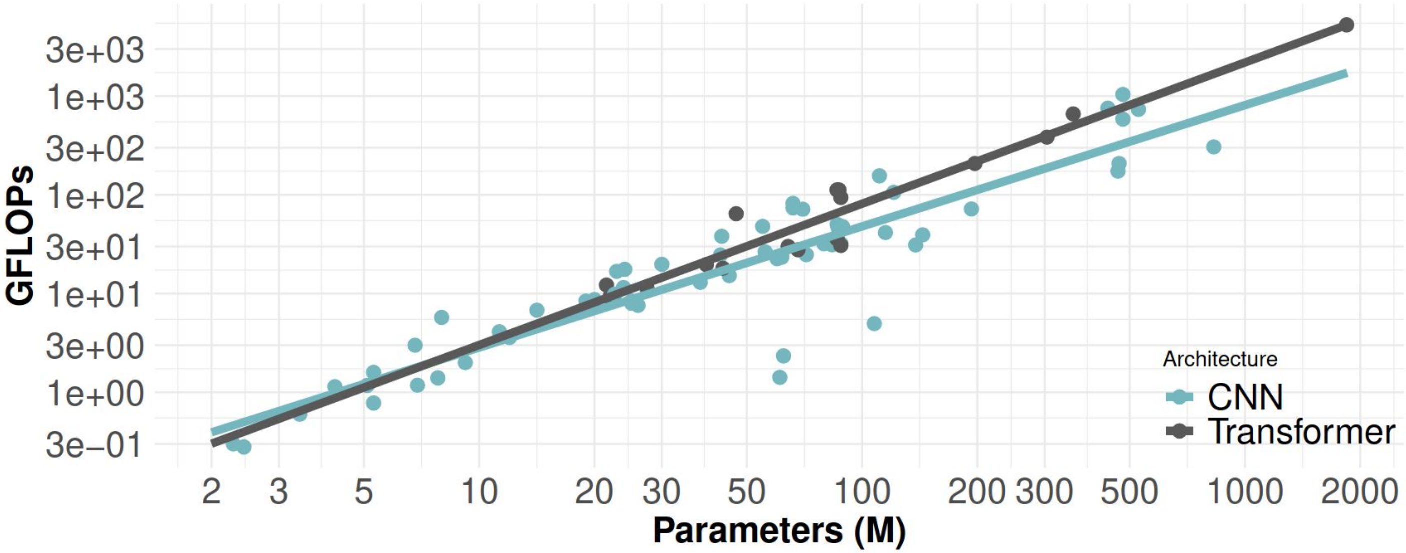


Figure 1: Relation between the number of parameters and FLOPs (both axes are logarithmic).

Source: Desislavov, R., Martínez-Plumed, F., & Hernández-Orallo, J. (2021). Compute and energy consumption trends in deep learning inference. arXiv preprint arXiv:2109.05472.

Environmental Cost of Large-Scale Models

- We have to collect, store, and use a large amount of data…all come with a cost!
- We need powerful data centers and supercomputers
- Using energy creates CO_2, the primary greenhouse gas emitted by humans
- The majority of cloud computing providers’ energy is not sourced from renewable sources or still uses brown energy to introduce reliability
- Renewable energy sources are still costly to the environment

Some Facts & Numbers

- Microsoft pumped 11.5 million gallons of water to its cluster of Iowa data centers (DCs), before the OpenAI chatgpt release, creating a water shortage in the district

- Total 1.7 billion gallons of water, across all Microsoft DCs in 2022

- ChatGPT gulps up 500 milliliters of water (close to what's in a 16-ounce water bottle) every time you ask questions with 5 to 50 prompts

- Data centers alone are estimated to consume 1/5th of global electricity generated (more than the airline industry!)

Most people are not aware of the resource usage underlying models like GPT, if we are not aware of the resource usage, then there's no way that we can help conserve the resources!

Sources:

- https://fortune.com/2023/09/09/ai-chatgpt-usage-fuels-spike-in-microsoft-water-consumption/
- Li, P., Yang, J., Islam, M. A., & Ren, S. (2023). Making ai less" thirsty": Uncovering and addressing the secret water footprint of ai models. *arXiv preprint arXiv:2304.03271*.
- https://www.weforum.org/agenda/2024/02/harnessing-waste-energy-data-centres/
- https://www.iea.org/energy-system/buildings/data-centres-and-data-transmission-networks

How Do We Move Towards Greener AI?

We need 3 key ingredients:

1. **Measurements:** e.g., standard metrics
2. **Methods:** e.g., algorithm optimization, efficient hardware
3. **Tools:** e.g., off-the-shelf tools to apply methods

Metrics for Measuring ML Impact

CO_2-equivalent emissions (CO_2e): CO_2 and all the other greenhouse gasses (e.g., methane, nitrous oxide, and so on)

Measure of CO_2: metric tons (tCO_2e), representing 1,000 kg (2,205 lb)

Measure of energy: 1 MWh, representing 1 million W of electricity used continuously for 1 h

Data center efficiency: Power usage effectiveness (PUE), the ratio between total energy use (including all overheads, such as cooling) divided by the computing equipment's energy

Carbon intensity: tCO2e/MWh (metric tons per megawatt hour), measures of the cleanliness of a data center's energy

Source: Patterson, D., Gonzalez, J., Hölzle, U., Le, Q., Liang, C., Munguia, L. M., ... & Dean, J. (2022). The carbon footprint of machine learning training will plateau, then shrink. Computer, 55(7), 18-28.

Example for Model Training

MWh = hours to train × number of processors × average power per processor

...Let's refine it including data center efficiency (PUE)

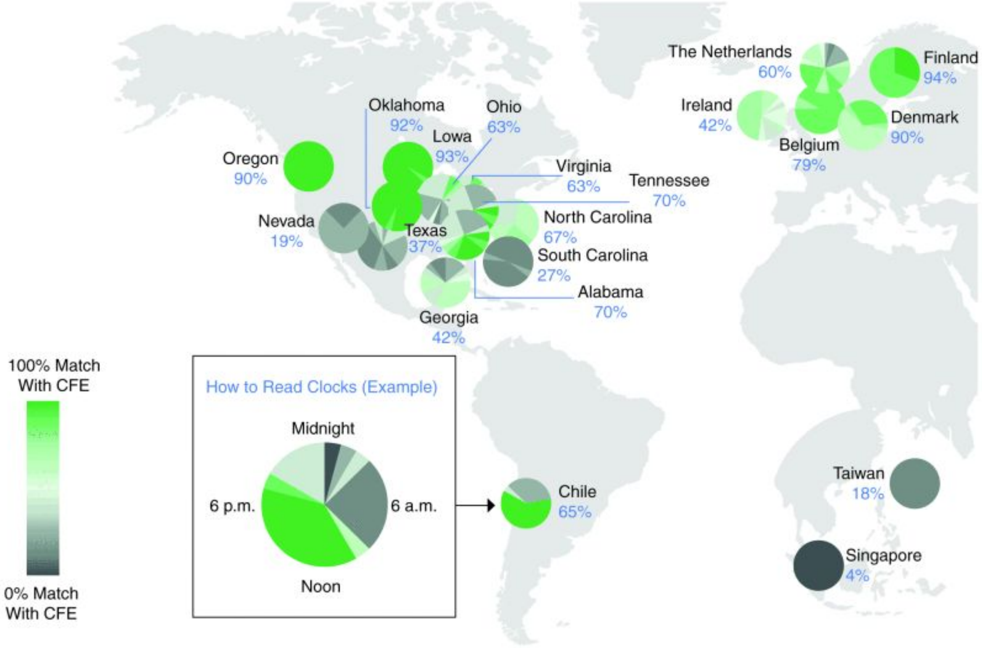
MWh = (hours to train × number of processors × average power per processor) × PUE

...We turn energy into carbon by multiplying it with the carbon intensity of the energy supply

tCO_2e = MWh x tCO_2e per MWh.

Source: Patterson, D., Gonzalez, J., Hölzle, U., Le, Q., Liang, C., Munguia, L. M., ... & Dean, J. (2022). The carbon footprint of machine learning training will plateau, then shrink. Computer, 55(7), 18-28.

How Green is The DCs Energy?



- The percentage of CFE by Google Cloud location in 2020
- The map shows the percentage and how it changes by time of day
- Chile has a high CFE percentage from 6 a.m. to 8 p.m. but not at night
- The U.S. examples range from 19% CFE in Nevada to 93% in Iowa, which has strong prevailing winds during the night and day

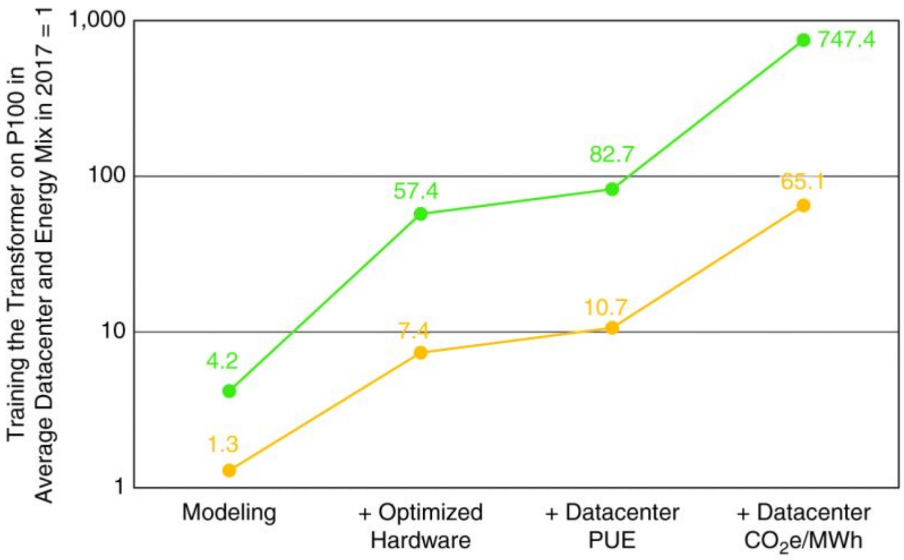
Source: Patterson, D., Gonzalez, J., Hölzle, U., Le, Q., Liang, C., Munguia, L. M., ... & Dean, J. (2022). The carbon footprint of machine learning training will plateau, then shrink. Computer, 55(7), 18-28.

The 4M Practices

1. **Model**: Selecting efficient ML model architectures, such as sparse models versus dense modes
   a. can reduce computation by factors of about 5–10x
2. **Machine**: Using processors optimized for ML training, such as tensor processing units (TPUs) and recent GPUs VS general-purpose processors
   a. can improve performance/watt by factors of 2–5.
3. **Mechanization**: Computing in the cloud rather than on-premise
   a. reducing energy costs by a factor of 1.4–2, the cloud DCs are usually more optimized than your premises
4. **Map**: Select the location with the cleanest energy
   a. reducing the gross carbon footprint by factors of 5–10.

Source: Patterson, D., Gonzalez, J., Hölzle, U., Le, Q., Liang, C., Munguia, L. M., ... & Dean, J. (2022). The carbon footprint of machine learning training will plateau, then shrink. Computer, 55(7), 18-28.

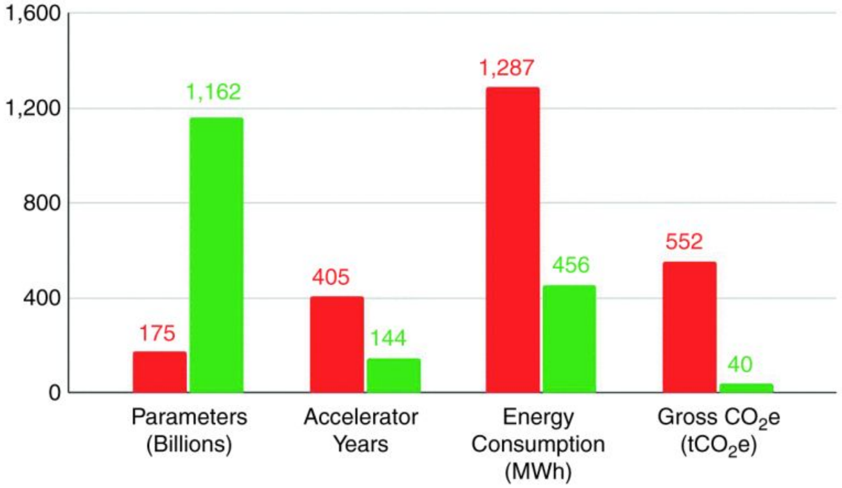
Case Study 1: Transformer vs Evolved Transformer vs Primer



- The reduction in gross carbon dioxide (CO_2) emissions since 2017 by applying the 4M best practices
- The gross CO_2 emissions here exclude Google's carbon-neutral and 100% renewable energy credits and reflect its 24/7 carbon-free energy methodology
- The yellow line is for the Evolved Transformer7 on TPU v2s in 2019, and the green line is for the Primer8 on TPU v4s in 2021
- Both types run in Google data centers

Source: Patterson, D., Gonzalez, J., Hölzle, U., Le, Q., Liang, C., Munguia, L. M., ... & Dean, J. (2022). The carbon footprint of machine learning training will plateau, then shrink. Computer, 55(7), 18-28.

Case Study 2: GPT-3 vs GLaM



The parameters, accelerator years of computation, energy consumption, and gross CO2e for GPT-3 (V100 in 2020, in red) and GLaM (TPU v4 in 2021, in green).

Source: Patterson, D., Gonzalez, J., Hölzle, U., Le, Q., Liang, C., Munguia, L. M., ... & Dean, J. (2022). The carbon footprint of machine learning training will plateau, then shrink. Computer, 55(7), 18-28.

Some Modeling Methods...

- Model pruning: dense VS sparse models
- Model **quantization**: reduces memory space by sacrificing some accuracy
- Learning approach: zero-shot vs few-shot learning
- Model cascading

What About Inference?

- Although doesn't consume much energy compared to training, *the sheer number of invocation creates energy bottlenecks*

- Smaller energy footprint, *but billions of invocation*

- Different inference location:
    - Data centers:
        - Enterprise applications
        - Ads serving platforms
        - recommender systems
    - At the Edge:
        - Time-critical applications
        - Smart assistants
        - Connected vehicles
        - Object detection

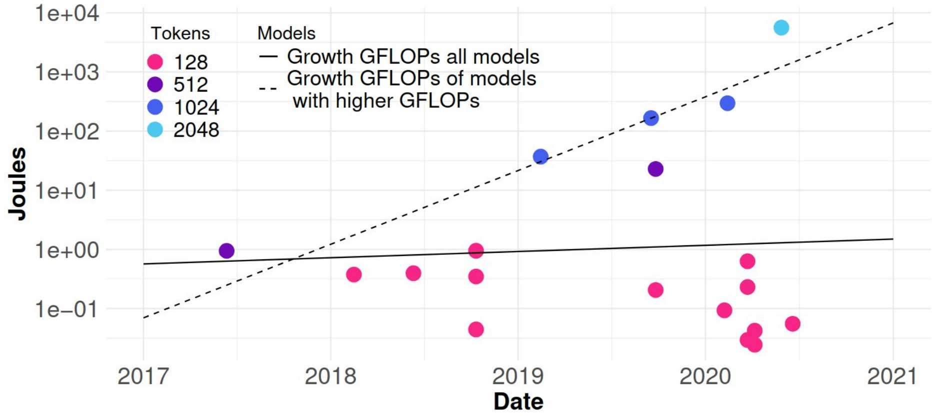
Inference at Edge

- Main challenges:
    - Heterogeneous deployment devices and architectures
    - Limited resources
    - Battery-based or limited power supply
    - Unreliable environments (e.g., network links)
- Optimization methods:
    - Pruning
    - Quantization
    - Cascading
    - context-aware model selection

Estimating Inference Energy Consumption

$$\text{Efficiency} = \frac{\text{HW Perf.}}{\text{Power}} \text{ in units: } \frac{FLOPS}{Watt} = \frac{FLOPs/s}{Joules/s} = \frac{FLOPs}{Joule}$$

$$\text{Energy} = \frac{\text{Fwd. Pass}}{\text{Efficiency}} \text{ in units: } \frac{FLOPs}{FLOPs/Joule} = Joule$$



Estimated Joules of a forward pass (NLP)

Source: Desislavov, R., Martínez-Plumed, F., & Hernández-Orallo, J. (2021). Compute and energy consumption trends in deep learning inference. arXiv preprint arXiv:2109.05472.

Model Quantization

It is about approximating the data by introducing limits on the precision (e.g., rounding errors) and range of a value

- Commonly used method for transforming models for different architectures and reducing computational overhead (e.g., to run inference at the Edge)
- In the context of neural networks, quantization reduces the bits needed to store tensors (i.e., weights, activations, etc.),

Example: mapping 32-bit floating-point numbers (default) to 8-bit integers.

Quantization: The Good & The Bad

Benefits:

- Size reduction
- Reduces computational cost
- Latency reduction
- Better power efficiency

Drawbacks:

- Lower precision/accuracy
- Difficult to predict accuracy ahead of time

Quantization Methods

Pre-training quantization

Induce the expected errors from reduced precision so the network learns the effect of quantization during training

Post-training quantization:

- Weights
- Weights and activations

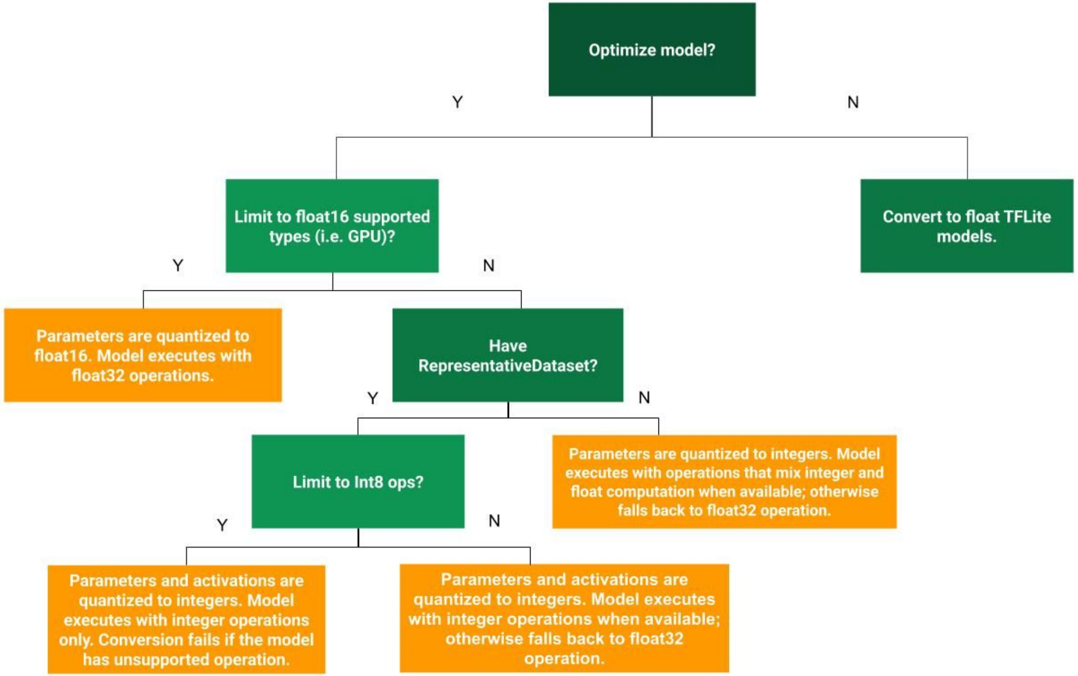
Some Details on Post-Training Quantization

Technique	Benefits	Hardware
Dynamic range quantization	4x smaller, 2x-3x speedup	CPU
Full integer quantization	4x smaller, 3x+ speedup	CPU, Edge TPU, Microcontrollers
Float16 quantization	2x smaller, GPU acceleration	CPU, GPU

Please note: these are information for TensorFlow, but absolute numbers can be different with other frameworks

Source: https://ai.google.dev/edge/litert/models/post_training_quantization

A Decision Tree to Determine the Method



Please note: this is a decision tree valid for TensorFlow post-quantization methods

Source: https://ai.google.dev/edge/litert/models/post_training_quantization

Assignment 1: Specifications

Assignment 1: Quantization of ML Models

Aim: tackle energy efficiency by applying post-quantization methods

Subprojects: One sub-project is the domain of object-detection, the other one is in the domain of LLMs

Tasks:

- quantizing the pre-trained models
- measuring the accuracy and computational cost
- writing the report
- presentation

Resources:

- Your own machine (e.g., your laptop)
- Google Collab provides a Jupyter notebook with a free T4 GPU
- Any other platform you like (e.g., HuggingFace)

Assignment 1.1: Quantization of OD Models

- **Model**: A pre-trained object-detection model that you like that is compatible with TensorFlow
  - Model Zoo
  - Find Pre-trained Models | Kaggle
  - https://github.com/tensorflow/models/tree/master/official
  - Models - Hugging Face
- **Dataset**: COCO dataset 2017 (https://cocodataset.org/#download)
- **Tasks**:
  - Get the model and use LiteRT (formerly TensorFlow Lite) to quantize the model
  - Choose the following three configurations (weights only):
    - float32
    - float 16
    - int8
- **Evaluation**:
  - Accuracy: average precision (see: https://cocodataset.org/#detection-eval) or pick up another one (...with a motivation!)
  - Inference time: seconds
  - Memory: model size (MB)
- **Note**:
  - You should perform the inference from at least thousand images (randomly selection) from the COCO test dataset
  - Average results can be reported for all the input dataset

What is LiteRT?

- LiteRT (short for Lite Runtime), formerly known as TensorFlow Lite, is Google's high-performance runtime for on-device AI

- You can convert and run TensorFlow, PyTorch, and JAX models to the TFLite format using the AI Edge conversion and optimization tools

Source: https://ai.google.dev/edge/litert

Assignment 1.2: Quantization of LLMs

- **Model**: A pre-trained LLMs model that you like (e.g., GPT, LLaMA, OPT)
    - Model Zoo
    - Find Pre-trained Models | Kaggle
    - Models - Hugging Face
- **Dataset**: LAMBADA (https://paperswithcode.com/dataset/lambada)
- **Tasks**:
    - Get the model and use AutoGPTQ to quantize the model (...feel free to pick up another tool if you like!)
    - Choose the following three configurations (weights only):
        - int8
        - int4
        - int2
- **Evaluation**:
    - Accuracy: Top-k Accuracy
    - Speed: Tokens/s
    - Memory: model size (MB)

Assignment 1: Report

- **Introduction**: Brief about Object detection models (ODMs), LLMs, and their applications
- **Background**: The need for quantization, challenges in deploying ODMS and LLMs, and an overview of quantization techniques
- **Experiments**: Explained setup and goals of the experiments
- **Results**: Detailed results from the quantization, including the benefits and any trade-offs. It should include at least 3 plots:
  - Results 1.1:
    - Model Size (MB) vs Type of ODM (type and quantization)
    - Accuracy metric vs Type of ODM (type and quantization)
    - Inference time vs Type of ODM (type and quantization)
  - Results 1.2:
    - Model Size (MB) vs Type of LLM (type and quantization)
    - Accuracy vs. Type of LLM (type and quantization)
    - Tokens/s vs. Type of LLM (type and quantization)
- **Conclusions**: Insights gained from the project, potential implications, and future recommendations

Assignment 1: Info & Deadlines

- Submission
  - Report (PDF file)
  - Presentation file (PDF file)
  - Source code and artifacts created during the assignment (compressed in a ZIP archive)
- Dates and Timeline
  - Group formation deadline: 23.10.2024
  - Submission deadline: 15.11.2024
  - Presentation: 20.11.2024 (probably only online, further info will be posted)
  - Presentation duration: 10 minutes per group

Please use the forum for assignment-related questions!