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Benchmarking tree species classification with synthetic data and deep learning

State of the art and plan for Scalable Computing Systems and Applications in AI, Big Data and HPC

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Why is it important to benchmark the training process of neural networks?

Training speed

Energy efficiency

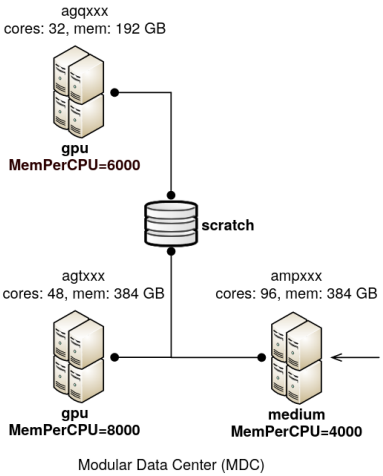
Training speed

- training of neural networks is computationally intensive

↪ workflow needs to be optimized for available hardware

  - How to make good use of clusters with heterogenous hardware?
  - How many GPUs are worth requesting?

⇒ optimization for available accelerators is critical in ML/DL



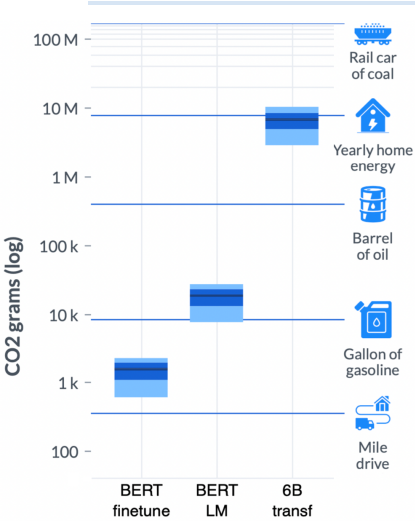
Structure and resources of a part of the Scientific Compute Cluster.

Image source: Adapted from https://www.gwdg.de/web/guest/hpc-on-campus/scc, accessed on: 09.11.2022

Energy efficiency ⚡

- for different neural networks, the required energy ranges from relatively low demands (finetuning) to very high demands (training of a complex network)
- depends on used hardware and energy source

⇒ As deep learning is emerging in several fields, the impact on energy consumption and consequently, our climate is growing



CO_2 Relative Size Comparison

Image source: Adapted from Dodge et al. 2022

Use case

Tree species classification from lidar

- monitoring of tree species is essential for forest restructuring towards more resilient forests in changing environments under climate change condition [a]
- lidar is already in use for forest inventories (White et al. 2016)
- Problem: lack of pre-trained models

Spruce and beech stand close to the national park "Hainich".

Image source: Adapted from Henkel, Hese, and Thiel 2021

[a] https://www.umweltbundesamt.de/angepasster-waldumbau

Outline

Workflow

Pre-training with synthetic data

1. scene generation with Arbaro[a]
2. synthetic lidar data is generated with the lidar operations simulator Helios++ (Esmorís et al. 2022)
3. pre-training of PointNet, which is a very popular architecture for point cloud analysis (Qi et al. 2016)

[a] https://github.com/wdiestel/arbaro

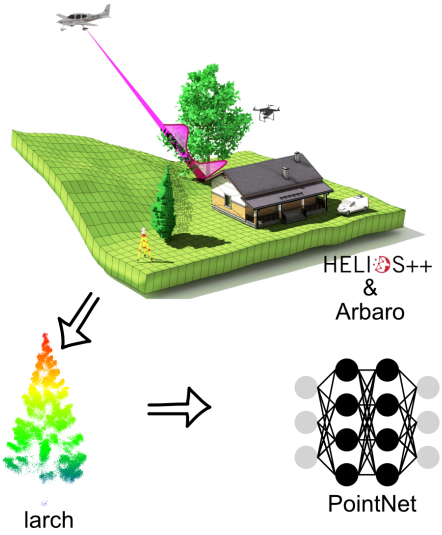


Image source: Adapted from Esmorís et al. 2022

Metrics

metric	purpose
Execution time FLOPS	traditionally
Throughput: $\frac{images}{sec}$	with the advent of GPUs
Time to Accuracy (TTA) Average Time to Multiple Thresholds (ATTMT)	deep learning

Image source: Adapted from https://snehilverma41.github.io/Metrics_ML_FastPath19.pdf

Outline

Tools - Overview

tool	metrics	scope
PyTorch Profiler With TensorBoard	performance metrics (e.g. time, memory)	PyTorch
fvcore	FLOPS	
Vtune	general	Intel-only
likwid	performance metrics	general

⇒ different tools for different use cases

⇒ Vtune and likwid can profile all kind of applications

⇒ here I will focus on profiling tools optimized for PyTorch

PyTorch Profiler With TensorBoard

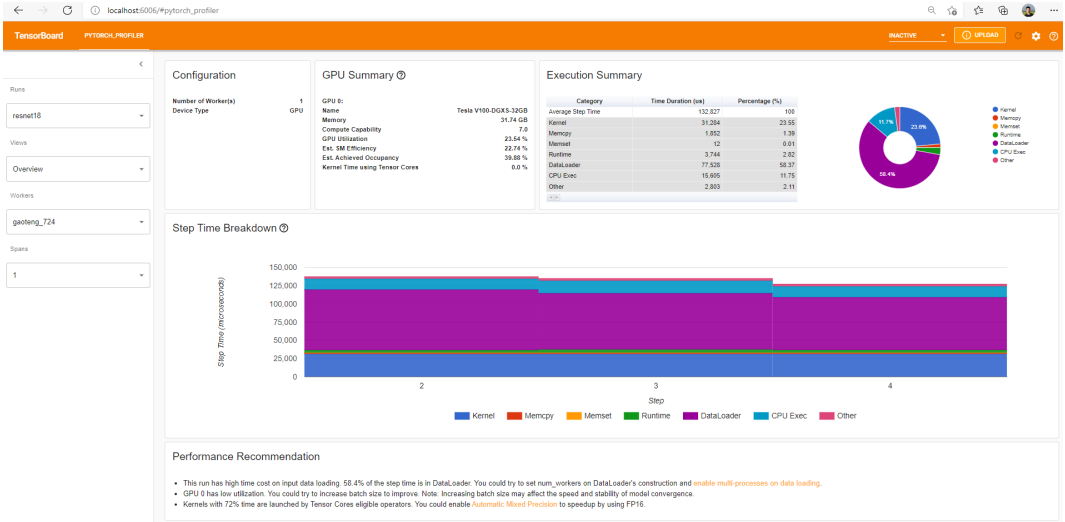
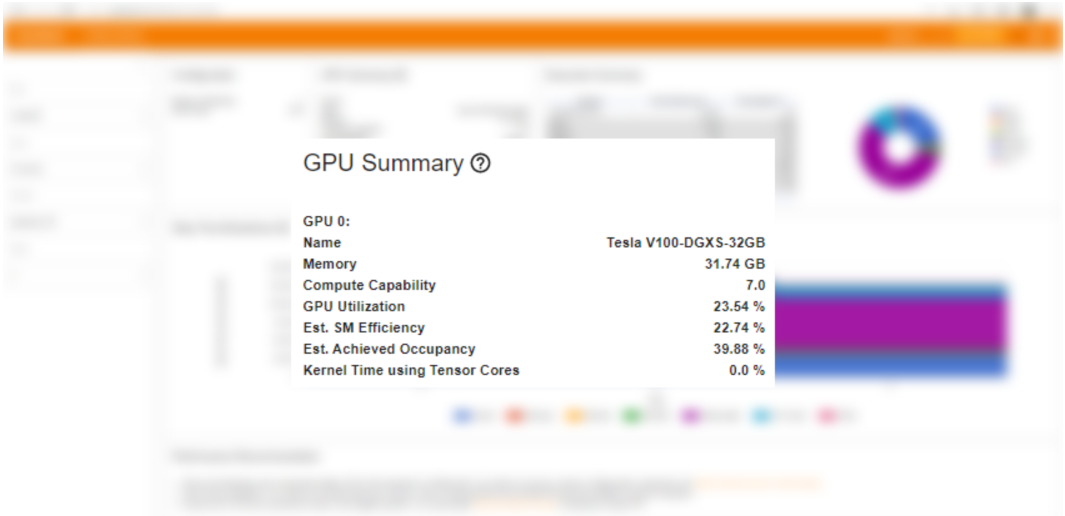


Image source: https://pytorch.org/tutorials/intermediate/tensorboard_profiler_tutorial.html, accessed on: 22.11.2022

PyTorch Profiler With TensorBoard



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PyTorch Profiler With TensorBoard

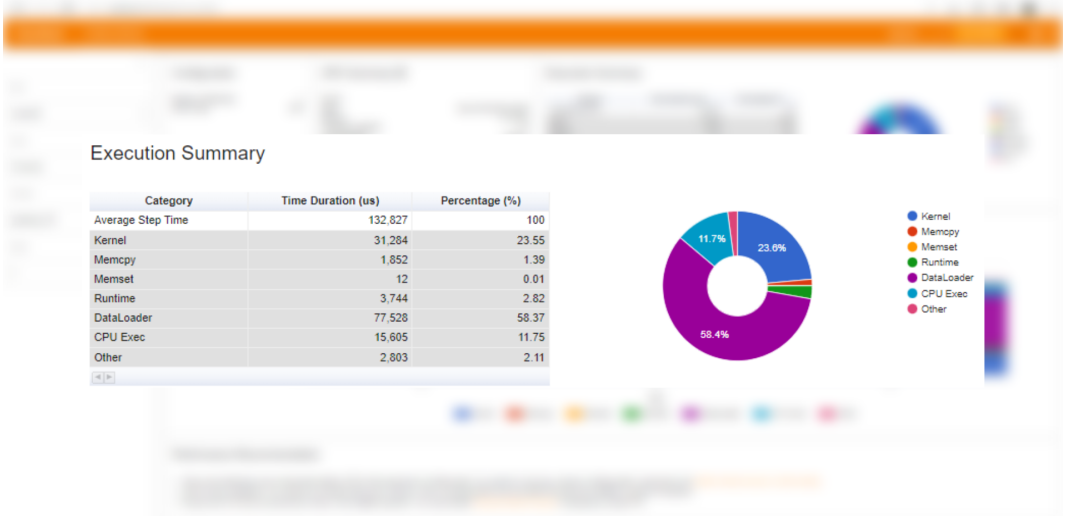
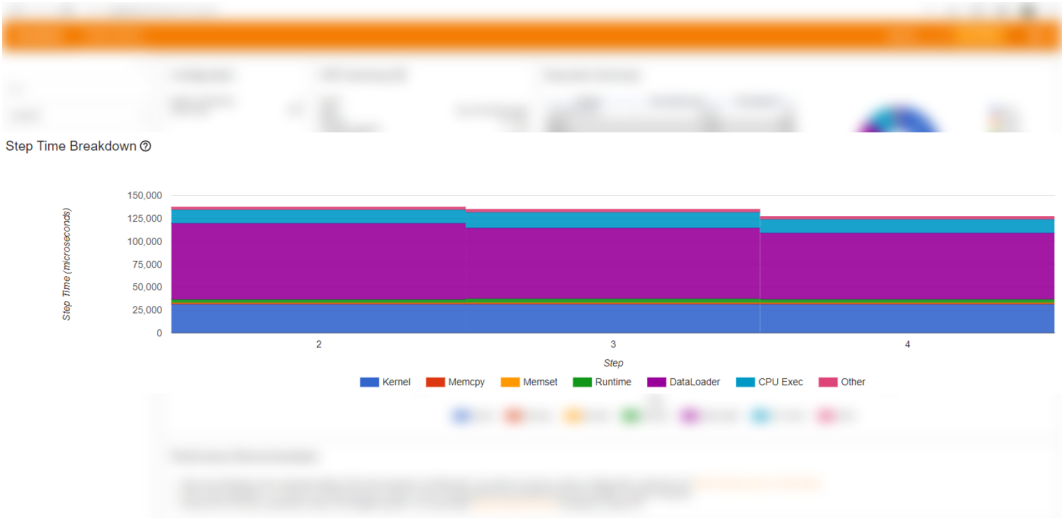


Image source: Adapted from https://pytorch.org/tutorials/intermediate/tensorboard_profiler_tutorial.html, accessed on: 22.11.2022

PyTorch Profiler With TensorBoard



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PyTorch Profiler With TensorBoard

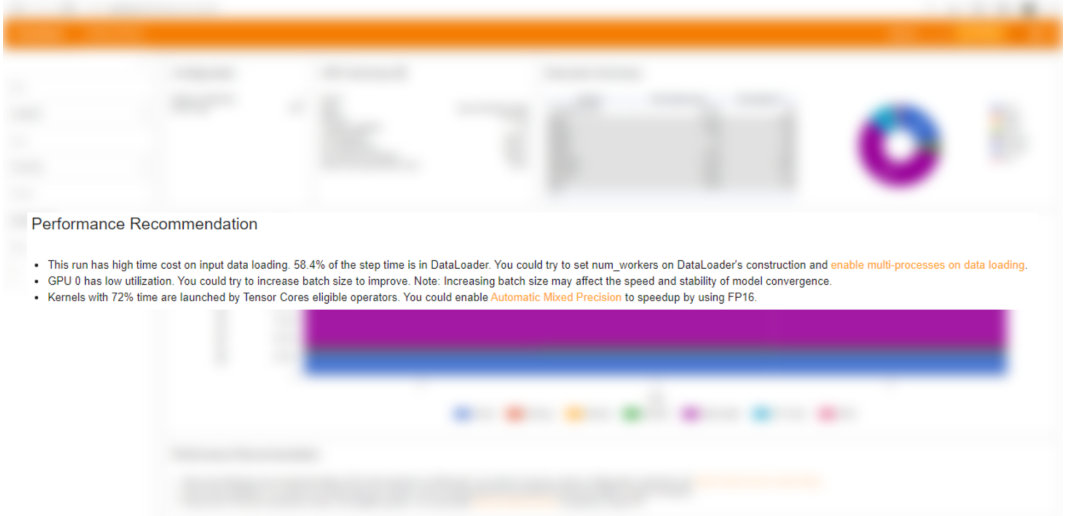

Image source: Adapted from `https://pytorch.org/tutorials/intermediate/tensorboard_profiler_tutorial.html`, accessed on: 22.11.2022

fvcore - Flop Counter for PyTorch Models

```
$ from fvcore.nn import flop_count_table
$ print(flop_count_table(flops))
| module          | #parameters or shape   | #flops   |
|:----------------|:-----------------------|:---------|
| model           | 81.194K                | 0.275M   |
|  conv1          |  60                    |  48.6K   |
|   conv1.weight  |   (6, 1, 3, 3)         |          |
|   conv1.bias    |   (6,)                 |          |
|  conv2          |  0.88K                 |  0.146M  |
|   conv2.weight  |   (16, 6, 3, 3)        |          |
|   conv2.bias    |   (16,)                |          |
|  fc1            |  69.24K                |  69.12K  |
|   fc1.weight    |   (120, 576)           |          |
|   fc1.bias      |   (120,)               |          |
|  fc2            |  10.164K               |  10.08K  |
|   fc2.weight    |   (84, 120)            |          |
|   fc2.bias      |   (84,)                |          |
|  fc3            |  0.85K                 |  0.84K   |
|   fc3.weight    |   (10, 84)             |          |
|   fc3.bias      |   (10,)                |          |
```

```
$ from fvcore.nn import flop_count_str
$ print(flop_count_str(flops))
Net(
  #params: 81.19K, #flops: 0.27M
  (conv1): Conv2d(
    1, 6, kernel_size=(3, 3), stride=(1, 1)
    #params: 60, #flops: 48.6K
  )
  (conv2): Conv2d(
    6, 16, kernel_size=(3, 3), stride=(1, 1)
    #params: 0.88K, #flops: 0.15M
  )
  (fc1): Linear(
    in_features=576, out_features=120, bias=True
    #params: 69.24K, #flops: 69.12K
  )
  (fc2): Linear(
    in_features=120, out_features=84, bias=True
    #params: 10.16K, #flops: 10.08K
  )
  (fc3): Linear(
    in_features=84, out_features=10, bias=True
    #params: 0.85K, #flops: 0.84K
  )
```

Image source: https://github.com/facebookresearch/fvcore/blob/main/docs/flop_count.md, accessed on: 22.11.2022

Research Goals

- Identify **profiling tools** that can help to **optimize an existing PyTorch workflow**.
- As this approach should help scientists, the **usibility is of high importance**. The simplest tool for doing the job is preferred.
- In contrast to training benchmark suites, such as MLPerf, I do not focus on benchmarking hardware but on optimizing an existing PyTorch workflow (viewpoint of a scientist)

Benchmarking is the first step of optimizing

Image generated with stable diffusion:
"Sherlock Holmes locates the best graphical processing unit inside the data center for his deep learning workflow"

- "Stable Diffusion v1 version of the model requires 150,000 A100 GPU Hours for a single training session"[a]

⇒ Optimization of deep learning workflows is of growing importance for energy efficiency.

[a] https://syncedreview.com/2022/11/09/almost-7x-cheaper-colossal-ais-open-source-solution-accelerates-aigc-at-a-low-cost-diffusion-pretraining-and-hardware-fine-tuning-can-be/, accessed on: 10.11.2022

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