Deep Learning Optimized - Jean Zay

Introduction – Jean Zay – GPU

cnrs
INSTITUT DU DÉVELOPPEMENT ET DES RESSOURCES EN INFORMATIQUE SCIENTIFIQUE

DLO-JZ presentation

IDRIS ◂

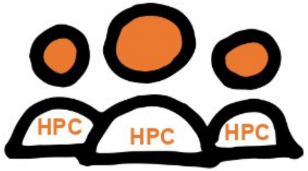
Agenda ◂

Presentation of the participants ◂

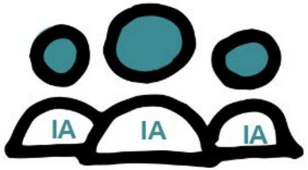
IDRIS

System

User Assistance



11 ingénieur·e·s

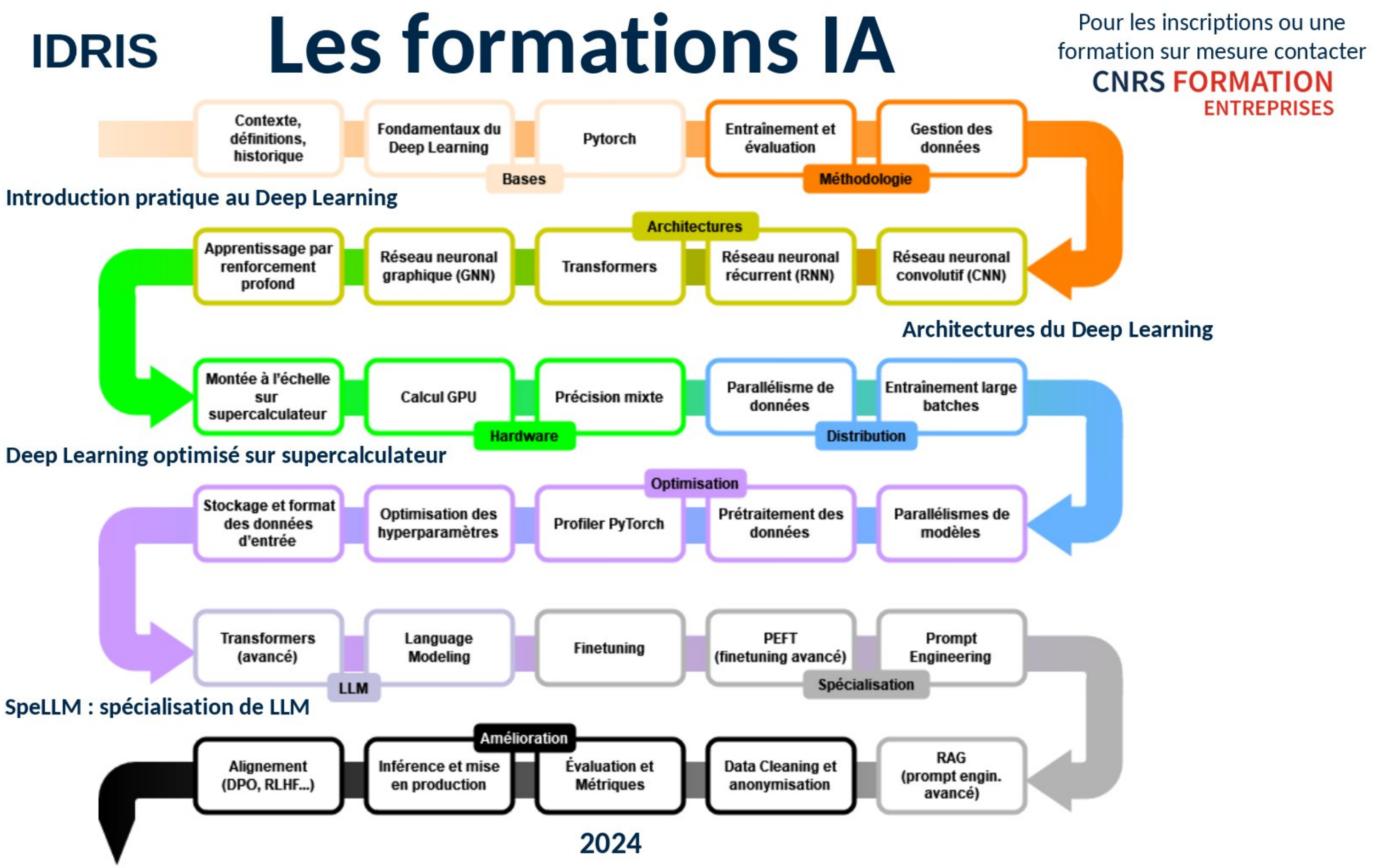


12 ingénieur·e·s

BLOOM on Jean Zay

Pre-training :
117 days (2022)
384 x 80GB A100 GPUs

Train modulaire de formations IDRIS



Spécialisation des LLM

DLO-JZ & SpeLLM

Being able to specialize an LLM to meet your specific needs.

Learn to make a prototype in 3 days → The training is hands-on centered

1st day
Transformers theory
Classic Fine-Tuning
Use case presentation
System improvement environment
Metrics and Evaluations (1st part)

2nd day
Data Cleaning
Prompt Engineering
Retrieval Augmentation Generation
Parameter Efficient Fine-Tuning
Hyper Parameter Optimization

3rd day
Metrics and Evaluations (2nd part)
Alignment
Inference
Discussions

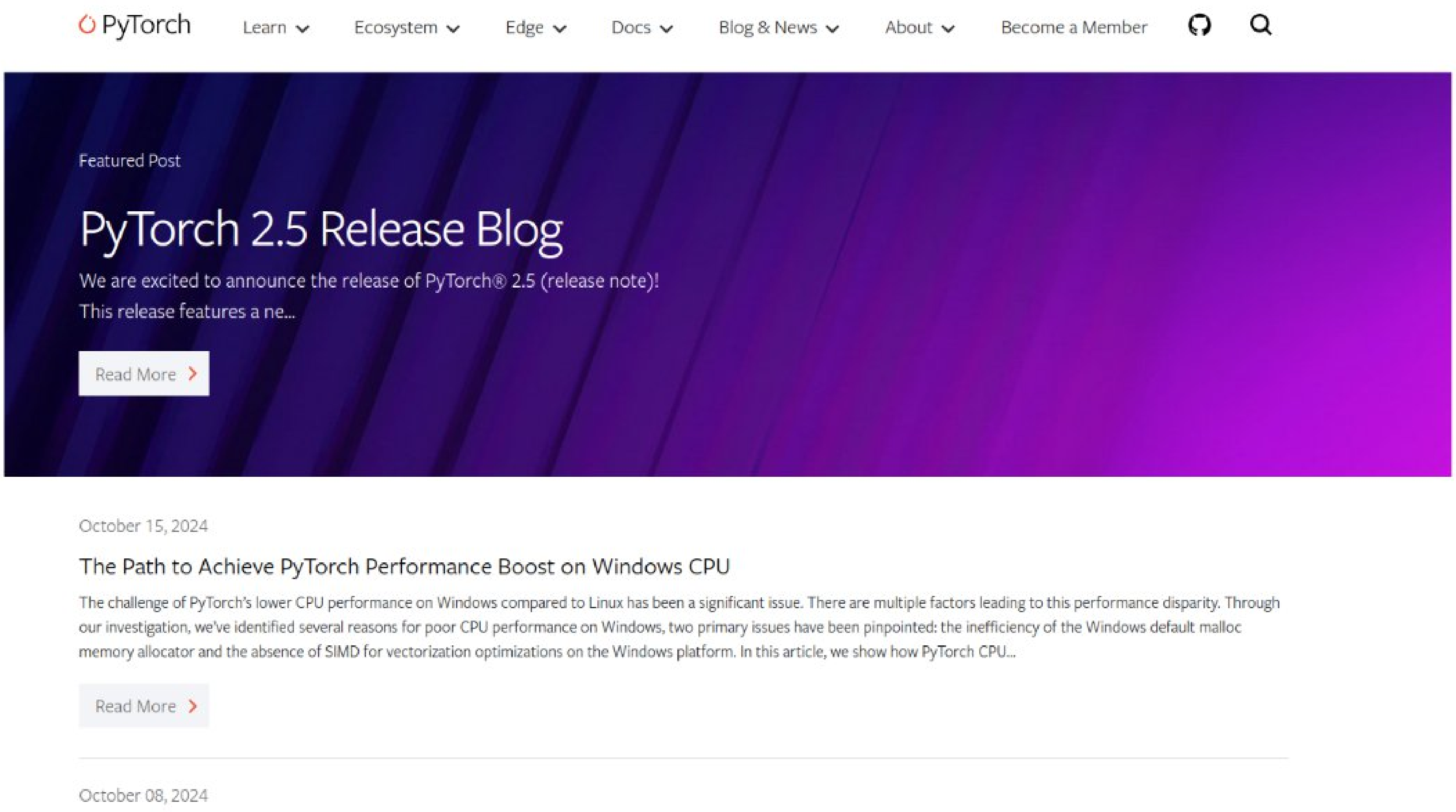
DLO-JZ

Super Computing 21 Event

SC21

St. Louis, MO | science & beyond.

Pytorch



PyTorch Learn Ecosystem Edge Docs Blog & News About Become a Member

Featured Post

PyTorch 2.5 Release Blog

We are excited to announce the release of PyTorch® 2.5 (release note)!
This release features a ne...

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October 15, 2024

The Path to Achieve PyTorch Performance Boost on Windows CPU

The challenge of PyTorch's lower CPU performance on Windows compared to Linux has been a significant issue. There are multiple factors leading to this performance disparity. Through our investigation, we've identified several reasons for poor CPU performance on Windows, two primary issues have been pinpointed: the inefficiency of the Windows default malloc memory allocator and the absence of SIMD for vectorization optimizations on the Windows platform. In this article, we show how PyTorch CPU...

Read More

October 08, 2024

Nvidia

Core Concepts

Before we discuss the details of the graph and legacy APIs, this section introduces the key concepts that are common to both.

cuDNN Handle

The cuDNN library exposes a host API but assumes that for operations using the GPU, the necessary data is directly accessible from the device.

An application using cuDNN must initialize a handle to the library context by calling cudnnCreate(). This handle is explicitly passed to every subsequent library function that operates on GPU data. Once the application finishes using cuDNN, it can release the resources associated with the library handle using cudnnDestroy(). This approach allows the user to explicitly control the library's functioning when using multiple host threads, GPUs, and CUDA streams.

For example, an application can use cudaSetDevice (prior to creating a cuDNN handle) to associate different devices with different host threads, and in each of those host threads, create a unique cuDNN handle that directs the subsequent library calls to the device associated with it. In this case, the cuDNN library calls made with different handles would automatically run on different devices.

The device associated with a particular cuDNN context is assumed to remain unchanged between the corresponding cudnnCreate() and cudnnDestroy() calls. In order for the cuDNN library to use a different device within the same host thread, the application must set the new device to be used by calling `cudaSetDevice` and then create another cuDNN context, which will be associated with the new device, by calling cudnnCreate().

Tensors and Layouts

Whether using the graph API or the legacy API, cuDNN operations take tensors as input and produce tensors as output.

Tensor Descriptor

The cuDNN library describes data with a generic n-D tensor descriptor defined with the following parameters:

- a number of dimensions from 3 to 8
- a data type (32-bit floating-point, 64 bit-floating point, 16-bit floating-point...)
- an integer array defining the size of each dimension
- an integer array defining the stride of each dimension (for example, the number of elements to add to reach the next element from the same dimension)

This tensor definition allows, for example, to have some dimensions overlapping each other within the same tensor by having the stride of one

Hugging Face

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Efficient Training on Multiple GPUs

If training a model on a single GPU is too slow or if the model's weights do not fit in a single GPU's memory, transitioning to a multi-GPU setup may be a viable option. Prior to making this transition, thoroughly explore all the strategies covered in the Methods and tools for efficient training on a single GPU as they are universally applicable to model training on any number of GPUs. Once you have employed those strategies and found them insufficient for your case on a single GPU, consider moving to multiple GPUs.

Transitioning from a single GPU to multiple GPUs requires the introduction of some form of parallelism, as the workload must be distributed across the resources. Multiple techniques can be employed to achieve parallelism, such as data parallelism, tensor parallelism, and pipeline parallelism. It's important to note that there isn't a one-size-fits-all solution, and the optimal settings depend on the specific hardware configuration you are using.

This guide offers an in-depth overview of individual types of parallelism, as well as guidance on ways to combine techniques and choosing an appropriate approach. For step-by-step tutorials on distributed training, please refer to the 🤗 Accelerate documentation.

> While the main concepts discussed in this guide are likely applicable across frameworks, here we focus on PyTorch-based implementations.

Before diving deeper into the specifics of each technique, let's go over the rough decision process when training large models on a large infrastructure.

Scalability strategy

Begin by estimating how much vRAM is required to train your model. For models hosted on the 🤗 Hub, use our Model Memory

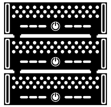
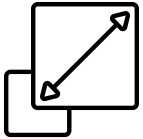
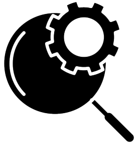
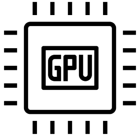
Agenda – Covered topics

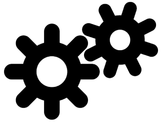
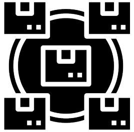
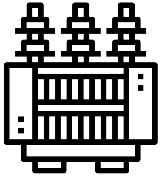
Day 1
- Jean Zay
- Code review
- The challenges of scaling up
- **GPU computing**
- **Tensor Cores**
- Pytorch Profiler

Day 2
- **DataLoader optimizations**
- **Distribution - Data Parallelism** ❤
- Data storage and formats

Day 3
- JIT
- **Training and large batches**
- HyperParameter Optimization

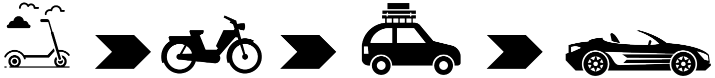
Day4
- Visualization tools
- **Model parallelisms**
- Model parallelisms API
- Good practices

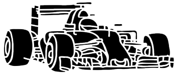






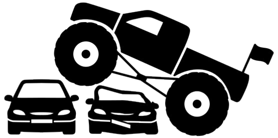
Practical Workshop

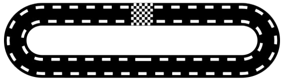
- Day 1, 2, 3, 4 :
  - System Optimization : GPU, Mixed Precision, Data Parallelism
  - Profiler
  - DataLoader
  - *Optimizer*s & LR scheduler
  - *Hyper-Parameters Optimization (HPO)*
  - *FSDP (New)*



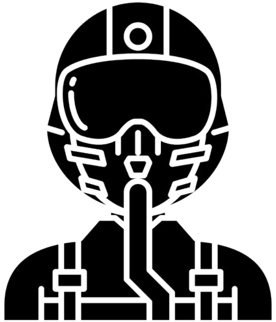


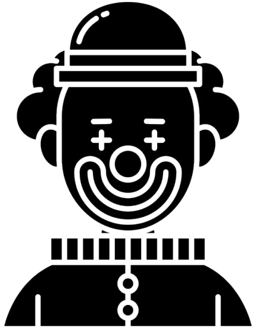
- Day 4 (à la carte) :
  - *Model parallelism* with Huge Model
  - *Advanced HPO*
  - *Tensor parallelism* & *2D parallelism* from scratch
  - Data Augmentation
  - torch.compile & torchscript

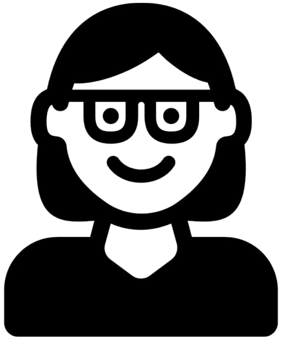




Présentation des participant·e·s







Jean Zay

Supercomputer ◂

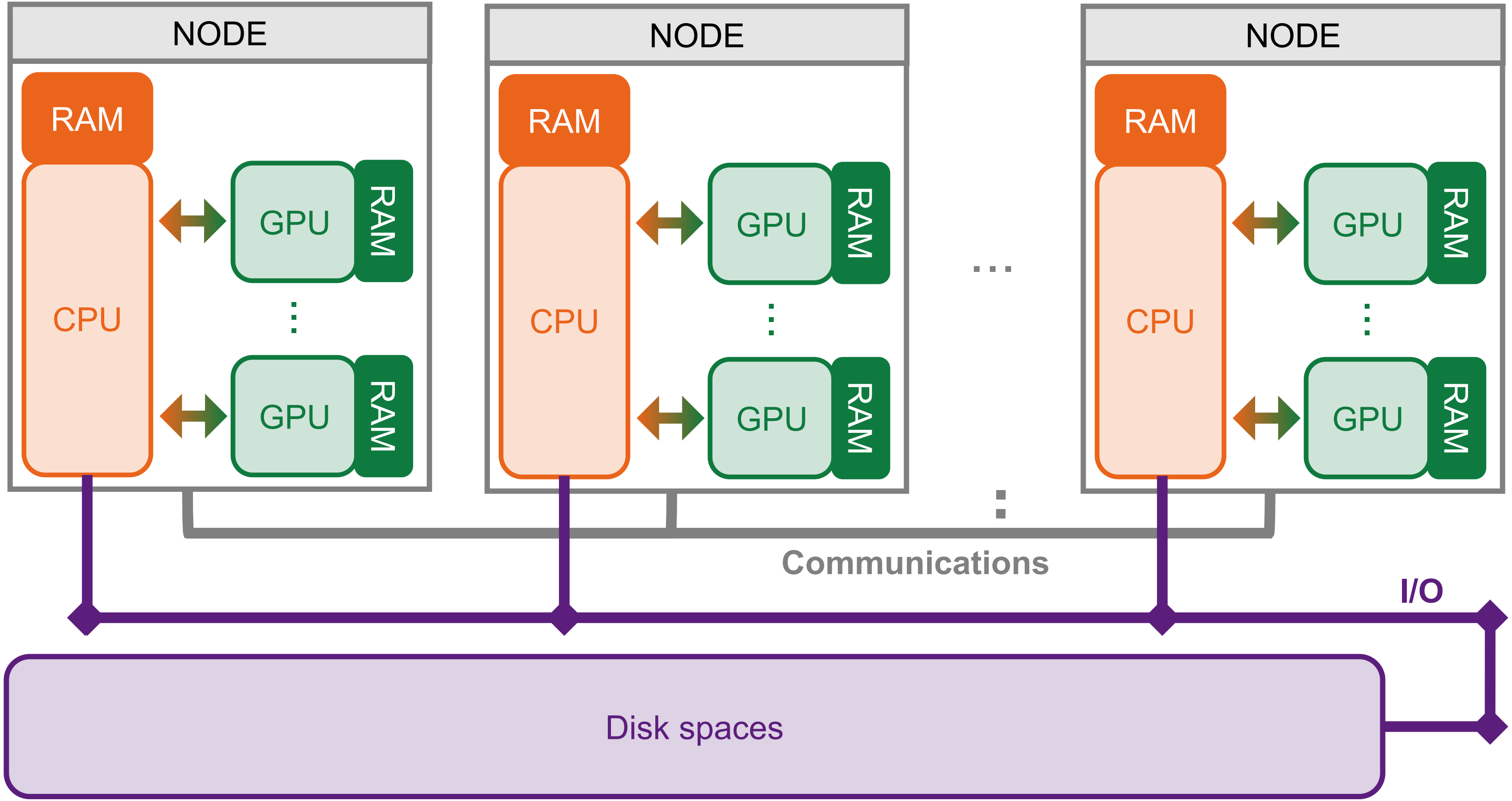
Jean Zay ◂

Job submission with Slurm ◂

JupyterHub on Jean Zay ◂

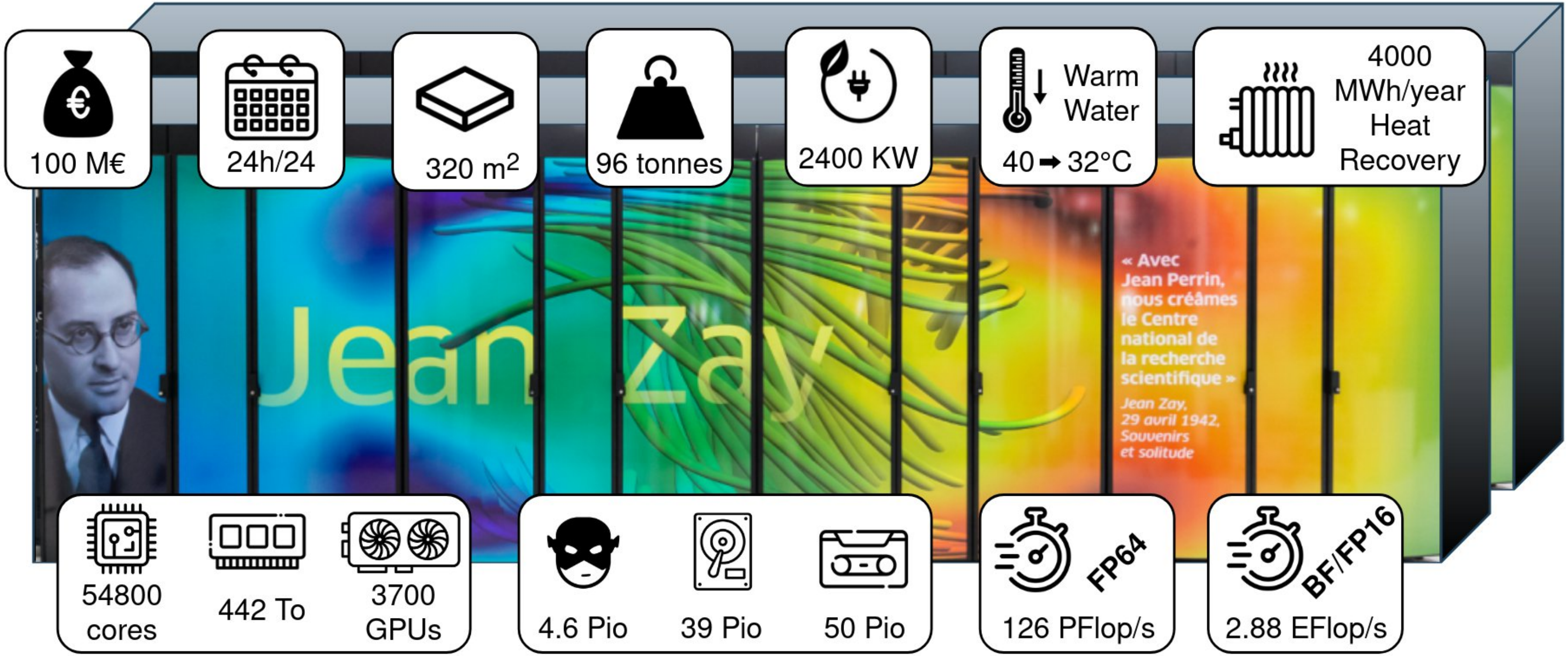
Slurm tools for python notebooks ◂

What's a supercomputer?

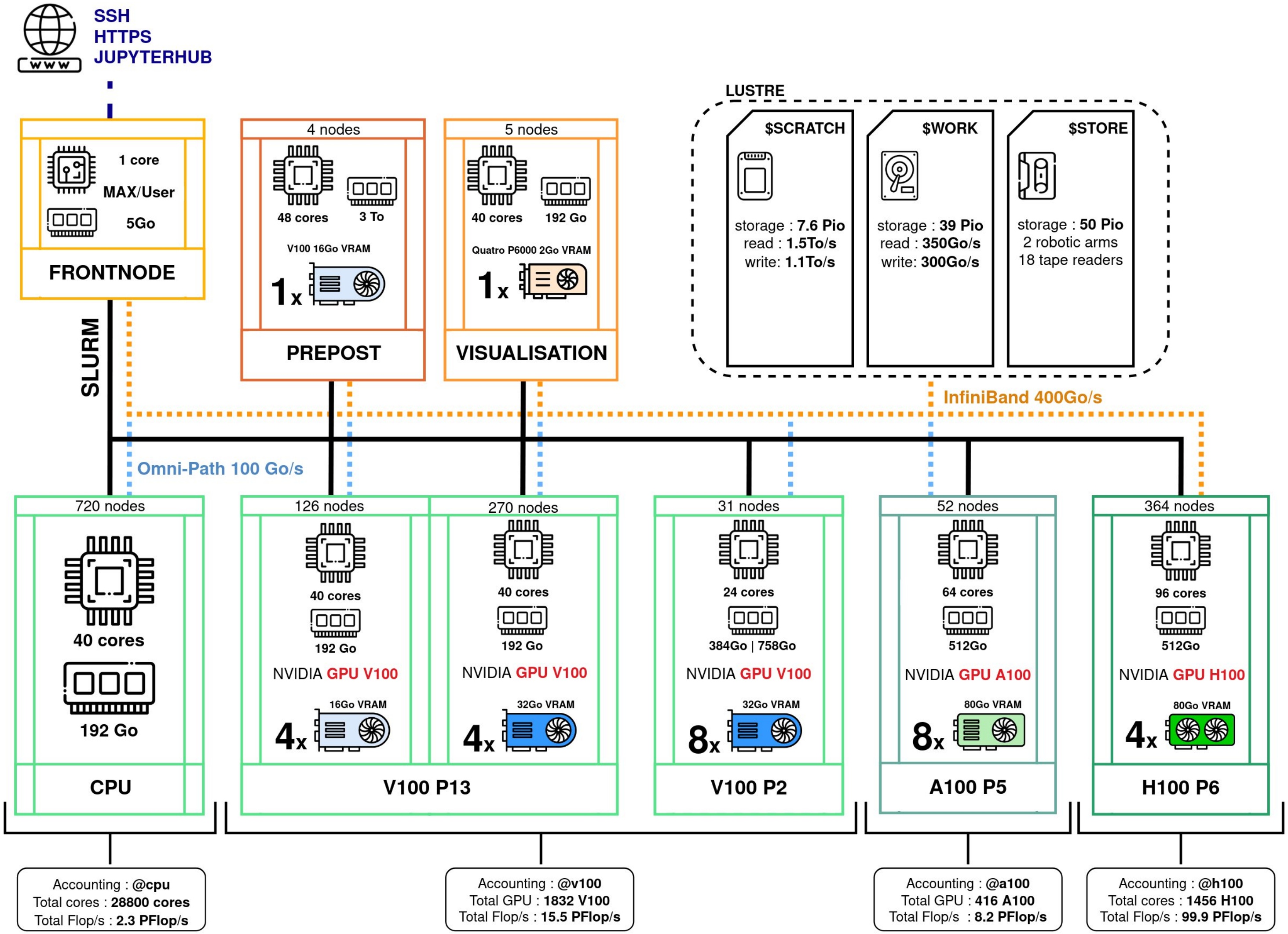


Jean Zay

First national converged supercomputer dedicated to Artificial Intelligence (AI) and High Performance Computing (HPC)



Jean Zay



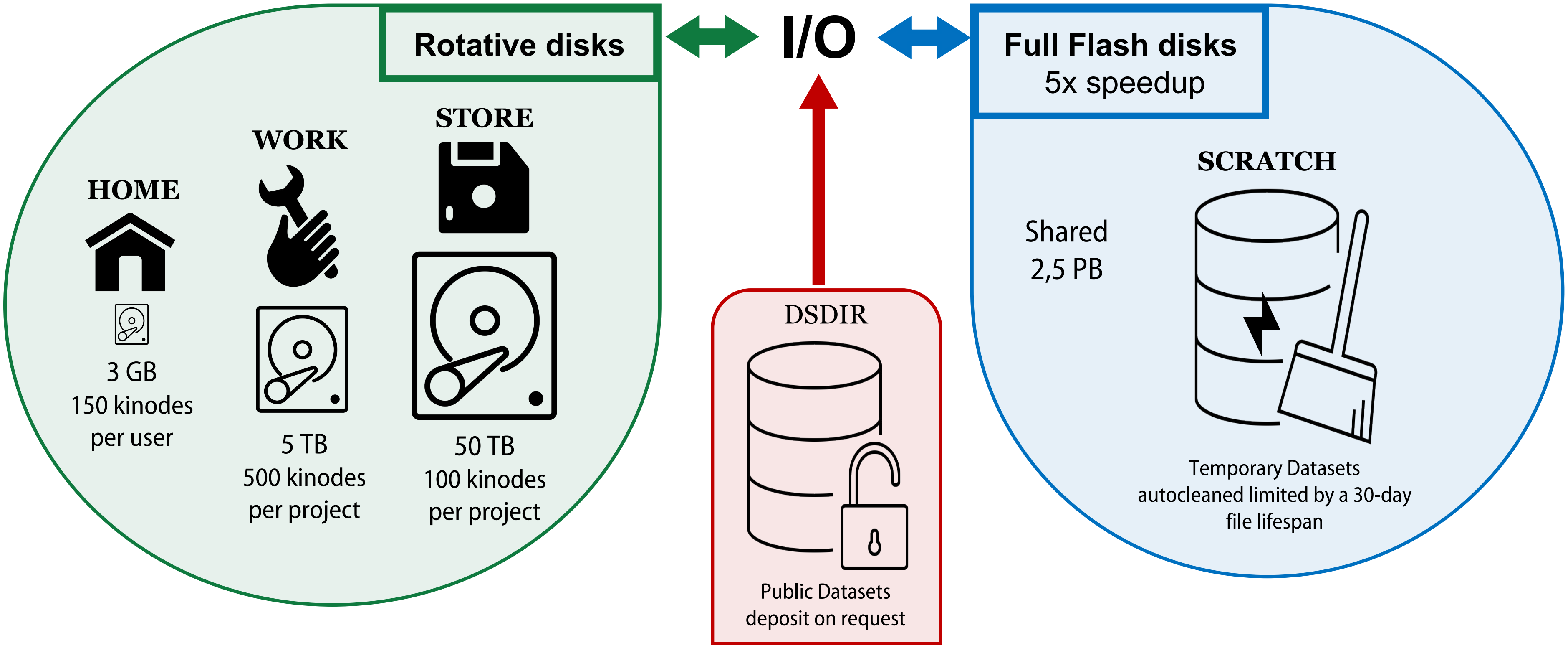
SSH
HTTPS
JUPYTERHUB
1 core
MAX/User
5Go
FRONTNODE
SLURM
4 nodes
48 cores
3 To
V100 16Go VRAM
1x
PREPOST
5 nodes
40 cores
192 Go
Quatro P6000 2Go VRAM
1x
VISUALISATION
LUSTRE
$SCRATCH
storage : 7.6 Pio
read : 1.5To/s
write: 1.1To/s
$WORK
storage : 39 Pio
read : 350Go/s
write: 300Go/s
$STORE
storage : 50 Pio
2 robotic arms
18 tape readers
InfiniBand 400Go/s
Omni-Path 100 Go/s
720 nodes
40 cores
192 Go
CPU
126 nodes
40 cores
192 Go
NVIDIA GPU V100
16Go VRAM
4x
270 nodes
40 cores
192 Go
NVIDIA GPU V100
32Go VRAM
4x
V100 P13
31 nodes
24 cores
384Go | 758Go
NVIDIA GPU V100
32Go VRAM
8x
V100 P2
52 nodes
64 cores
512Go
NVIDIA GPU A100
80Go VRAM
8x
A100 P5
364 nodes
96 cores
512Go
NVIDIA GPU H100
80Go VRAM
4x
H100 P6
Accounting : @cpu
Total cores : 28800 cores
Total Flop/s : 2.3 PFlop/s
Accounting : @v100
Total GPU : 1832 V100
Total Flop/s : 15.5 PFlop/s
Accounting : @a100
Total GPU : 416 A100
Total Flop/s : 8.2 PFlop/s
Accounting : @h100
Total cores : 1456 H100
Total Flop/s : 99.9 PFlop/s

Jean Zay: Available resources

New on Jean Zay...

- Resources: **+ 1456 NVIDIA H100 80GB GPUs**
- New interconnection network: OmniPath **+ InfiniBand**
- New parallel file system: from IBM Spectrum Scale to **Lustre**

Jean Zay: Storage spaces



Jean Zay: Work environment

ENVIRONMENT MODULES

Catalogue of shared modules (conda environments)

- Installed by IDRIS
- Completed on request

```
login@jean-zay3:~$ module load pytorch-gpu/py3/1.11.0
  Loading requirement: ...
(pytorch-gpu-1.11.0+py3.9.12) login@jean-zay3:~$
```

- Customizable

```
~$ pip install --user --no-cache-dir <paquet>
```

Conflicts between versions
Storage spaces saturation

Personal conda environments

```
login@jean-zay3:~$ module load anaconda-py3/2023.03
(base) login@jean-zay3:~$ conda create -n myenv
```

Storage spaces saturation ++

Singularity containers

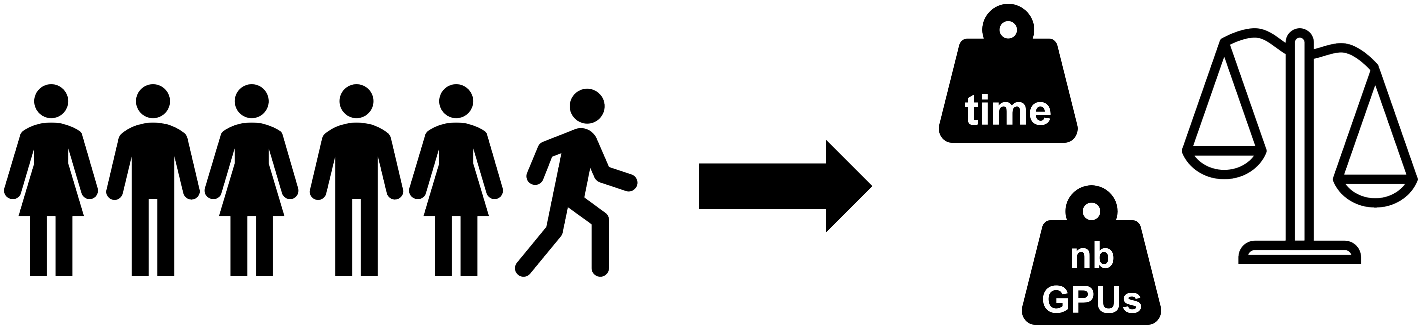
```
login@jean-zay3:~$ module load singularity
```

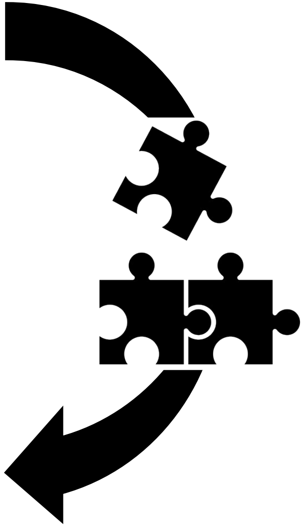
Import SIF images on Jean Zay

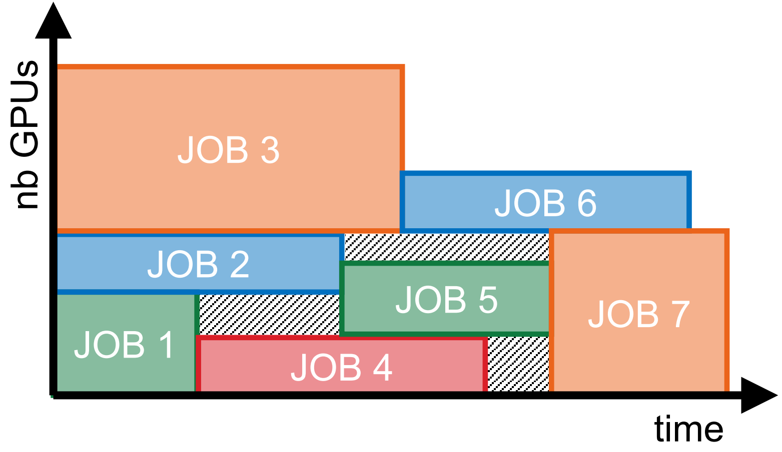
- From your PC
- From public deposits
- Possible conversion from docker

docker

Job submission with Slurm

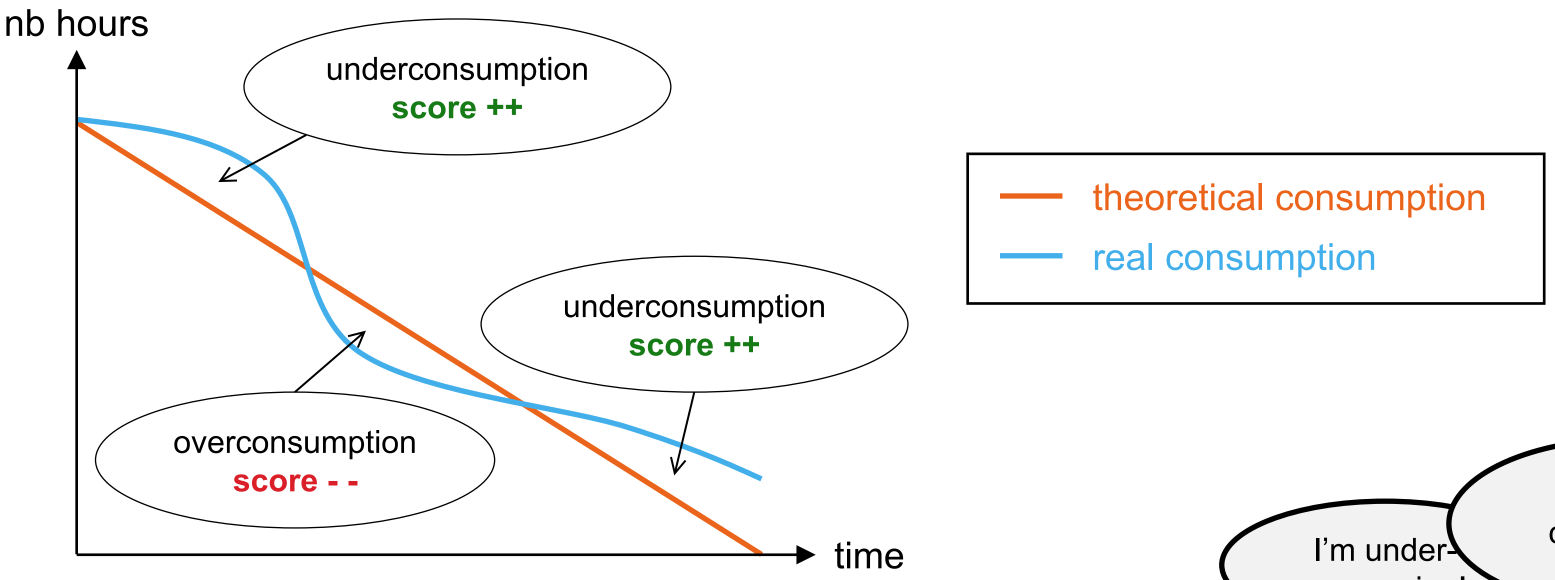


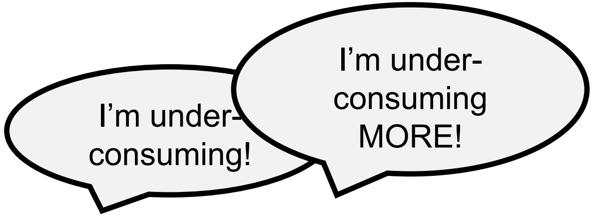




Job submission with Slurm

Slurm gives your job a **priority score** depending on your consumption.





Slurm compares all users' scores to define job position in the queue.

Job submission with Slurm

Adjust the **QoS (Quality of Service)** to improve the priority score of your job!

QoS	Max elapsed time	Resource limits			
		Per job	Per user	Per project	Per QoS
qos_gpu-dev	2h	32 GPUs	32 GPUs (10 jobs max at the same time)	32 GPUs	512 GPUs
qos_gpu-t3 (default)	20h	512 GPUs	512 GPUs	512 GPUs	
qos_gpu-t4 (V100)	100h	16 GPUs	96 GPUs	96 GPUs	256 GPUs

+ priority -

dev

prod

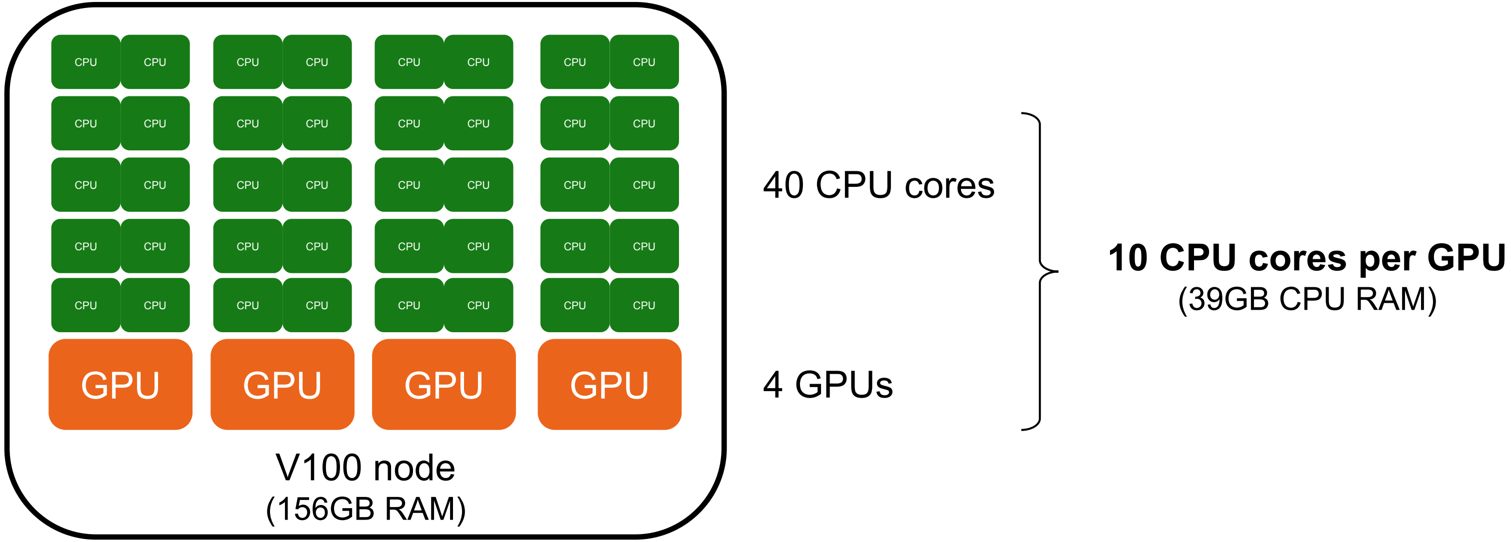
And keep your job in the queue, its priority score will increase with time.

Job submission with Slurm

How to configure my job?

- How many GPUs?
- How many time?
- How many CPUs per GPU?

→ **1 CPU core = 3.9GB RAM** (on V100 nodes)
→ interesting to have **several CPU cores to feed a GPU** (cf “DataLoader optimizations” part of this course)

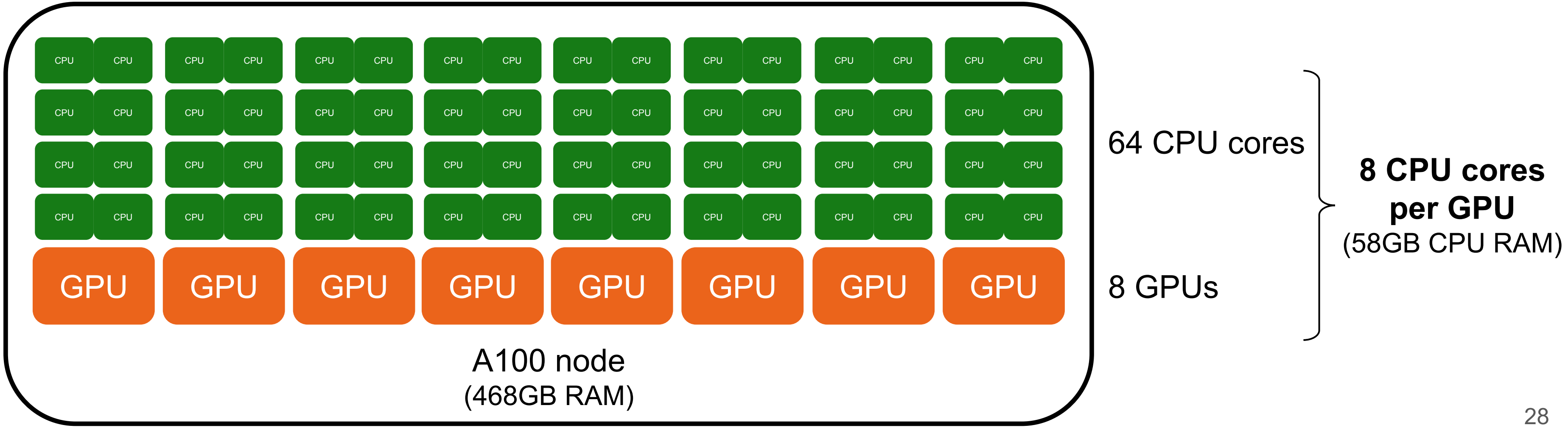


Job submission with Slurm

How to configure my job?

- How many GPUs?
- How many time?
- How many CPUs per GPU?

→ **1 CPU core = 7.3GB RAM** (on A100 nodes)
→ interesting to have **several CPU cores to feed a GPU**
(cf “DataLoader optimizations” part of this course)



Job submission with Slurm

slurm
workload manager

Example: reservation of 2 x 4 V100 GPUs

script.slurm

```
#!/bin/bash

#SBATCH --job-name="dlojz"              # name of the job
#SBATCH --output="dlojz%j.out"          # output file
#SBATCH --error="dlojz%j.err"           # error file
#SBATCH --nodes=2                       # nb of nodes
#SBATCH --gres=gpu:4                    # nb of GPUs/node
#SBATCH --ntasks-per-node=4             # nb of tasks/node
#SBATCH --cpus-per-task=10              # nb of CPU cores/task
#SBATCH --hint=nomultithread            # no hyperthreading
#SBATCH --time=01:00:00                 # max execution time
#SBATCH --qos=qos_gpu-dev               # adjust QoS

module load pytorch-gpu/py3/2.2.0       # environment

srun python script.py                   # run script
```

Job submission with Slurm

script.slurm

```
#!/bin/bash

#SBATCH --job-name="dlojz"
#SBATCH --output="dlojz%j.out"
#SBATCH --error="dlojz%j.err"
#SBATCH --nodes=2
#SBATCH --gres=gpu:4
#SBATCH --ntasks-per-node=4
#SBATCH --cpus-per-task=10
#SBATCH --hint=nomultithread
#SBATCH --time=01:00:00
#SBATCH --qos=qos_gpu-dev

module load pytorch-gpu/py3/2.2.0

srun python script.py
```

```
login@jean-zay3:~$ sbatch script.slurm
```

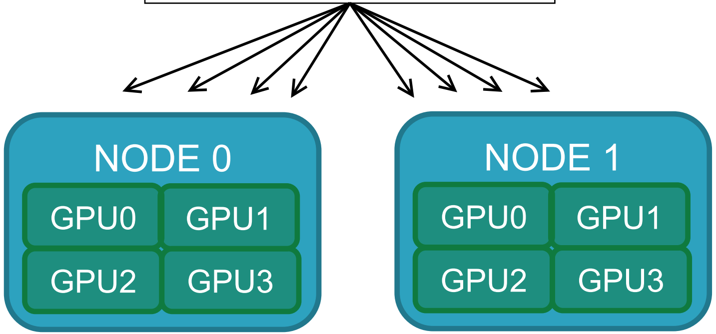
Job submission

Waiting in queue

```
login@jean-zay3:~$ squeue --me
  JOBID PARTITION     NAME     USER ST       TIME  NODES NODELIST(REASON)
 223225   gpu_p13    dlojz           PD       0:00      2 (Priority)
```

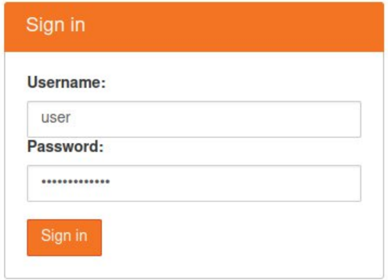
Lauching job

srun python script.py



JupyterHub on Jean Zay

1. Authentication on https://jupyterhub.idris.fr

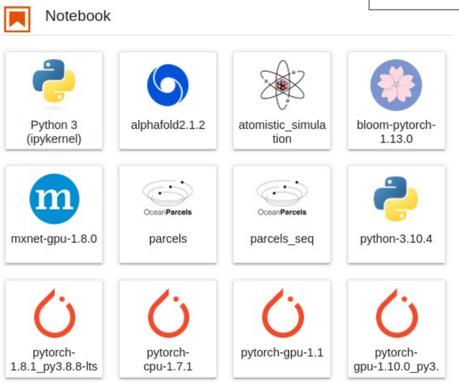


2. Choose and configure an instance

Run on a connection node

Run on a compute node

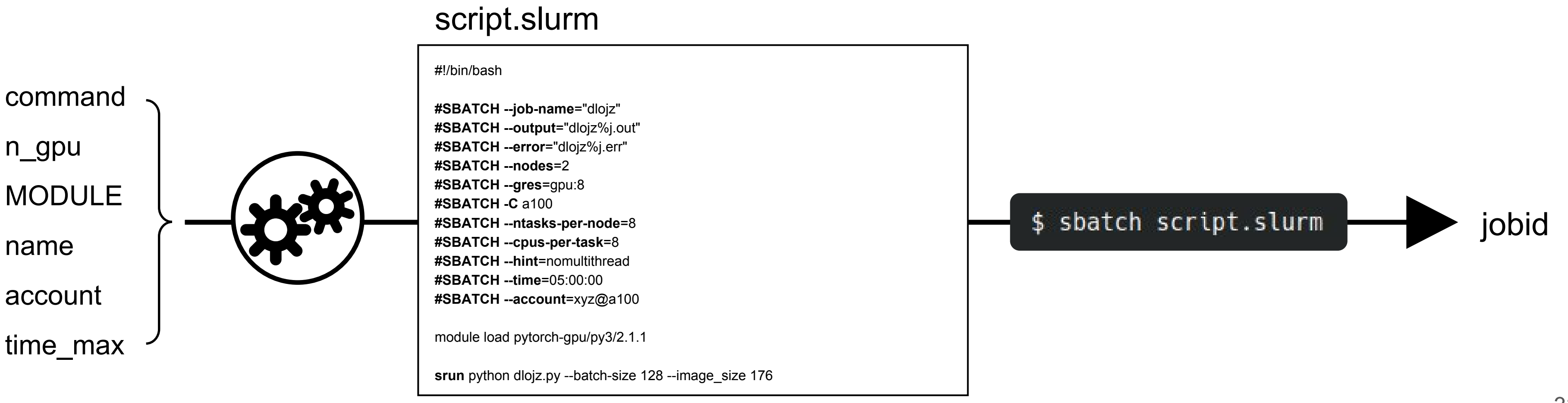
3. Choose a kernel (pytorch-gpu-2.2.0)



Slurm tools for python notebooks

```python
from idr_pytools import gpu_jobs_submitter
```

```python
command = ‘dlojz.py --batch-size 128 --image_size 176’
n_gpu = 8
MODULE = ‘pytorch-gpu/py3/2.2.0’
name = ‘dlojz’

jobid = gpu_jobs_submitter(command, n_gpu, MODULE, name=name, account='xyz@a100', time_max='05:00:00')
```



Slurm tools for python notebooks

```
from idr_pytools import display_slurm_queue
```

```
name = 'dlojz'
display_slurm_queue(name)
```

```
$ squeue --me -n <name>
```

```
from idr_pytools import search_log
```

```
jobid = ['12345']

search_log(contains=jobid)[0]

search_log(contains=jobid, with_err=True)[0]
```

output filename

error filename

The Challenges of Scaling

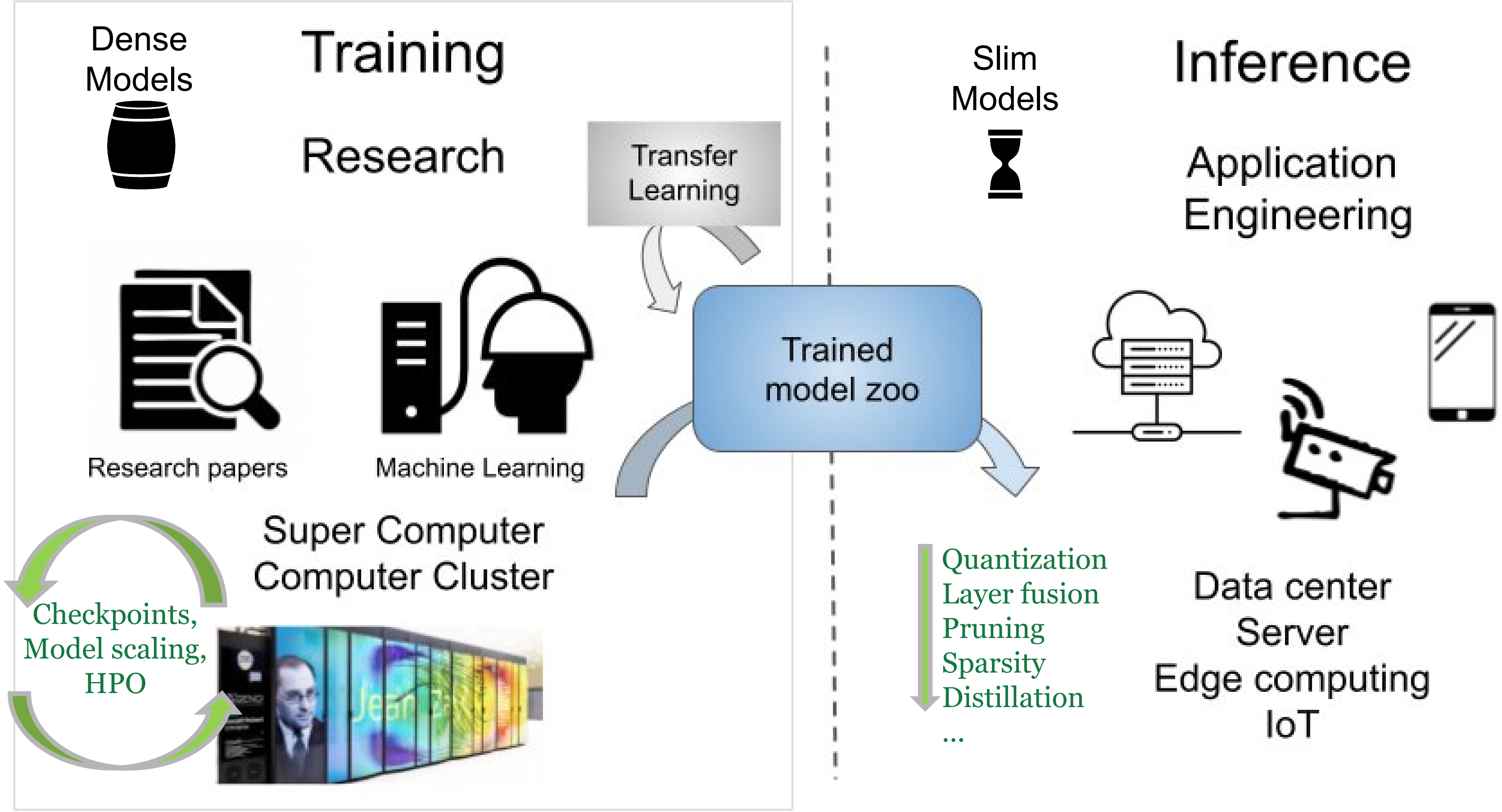
Training Time ◀

Memory Footprint ◀

Solutions ◀

Energy saving ◀

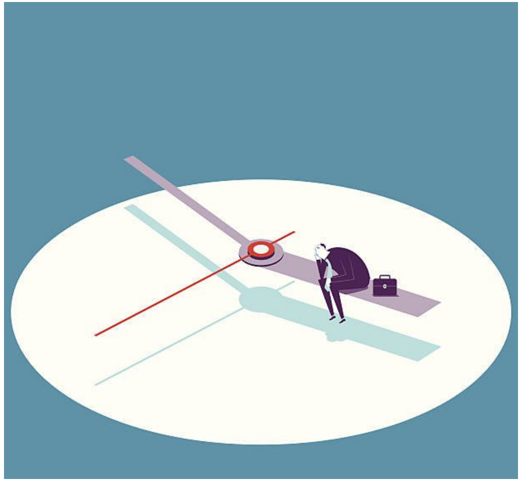
Training / Inference



Constraints of Deep Learning

2 problems to deal with:

Training Time



Memory Overconsumption (OOM)

Training Time

Training Resnet-50 on Imagenet

Goal:

Classification (1000 classes)

Model :

25 M parameters

Dataset:

1,2 M labeled images

14 Days

1 NVIDIA M40 GPU

Training Time

Training Resnet-50 on Imagenet

Facebook Caffe2	UC Berkeley, TACC, UC Davis Tensorflow	Preferred Network ChainerMN	Tencent TensorFlow	Sony Neural Network Library (NNL)	Fujitsu MXNet
1 hour	31 mins	15 mins	6.6 mins	2.0 mins	1.2 mins
Tesla P100 x 256	1,600 CPUs	Tesla P100 x 1,024	Tesla P40 x 2,048	Tesla V100 x 3,456	Tesla V100 x 2,048
Apr	Sept	Nov	July	Nov	Apr
2017				2018	2019

Fast.ai tips and engineering

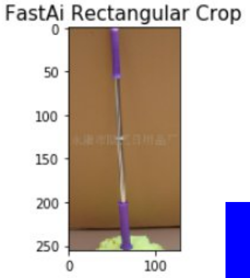
2018

« Now anyone can train Imagenet in 18 minutes »

Our approach uses **128** processing units and costs around **$40** to run.

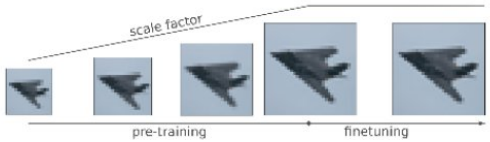
OneCycle lr scheduler + lr finder → Popularizes the works of [Leslie N. Smith]

Thanks to Global Average Pooling



Test Rectangular Validation Technique

Progressive image resizing



Dynamic batch size

Training Time

2022

a BigScience initiative

BLOOM

176B params · 59 languages · Open-access

Goal:

Text Generation Fundation Model (LLM)

Model :

176 B parameters

Dataset:

366 B tokens

117 Days

384 A100 GPUs

Training Time

2024

Llama 3
From Meta

Goal:

Text Generation Fundation Model (LLM)

Model :

405 B parameters

Dataset:

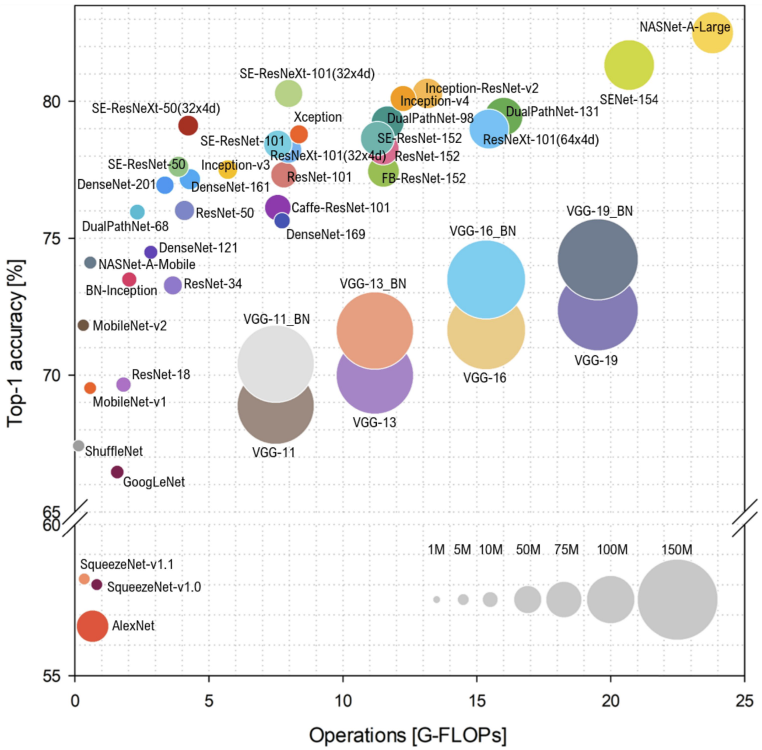
15 T tokens

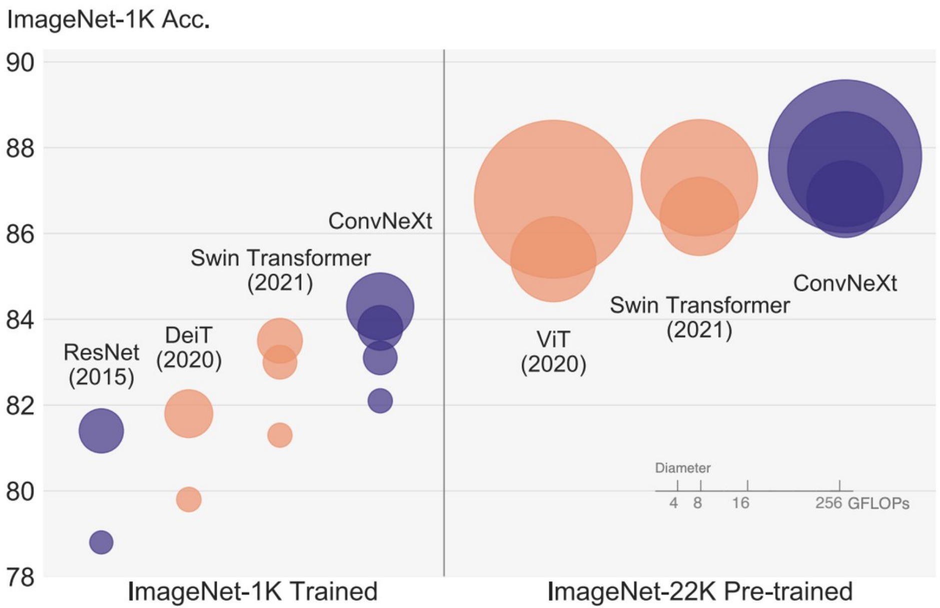
54 Days

16 384 H100 GPUs

Large Model

Vision Neural Network

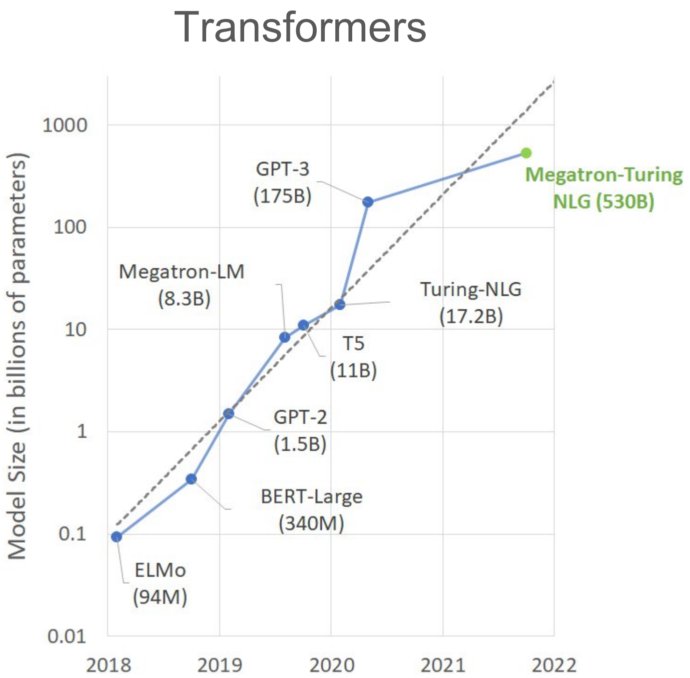


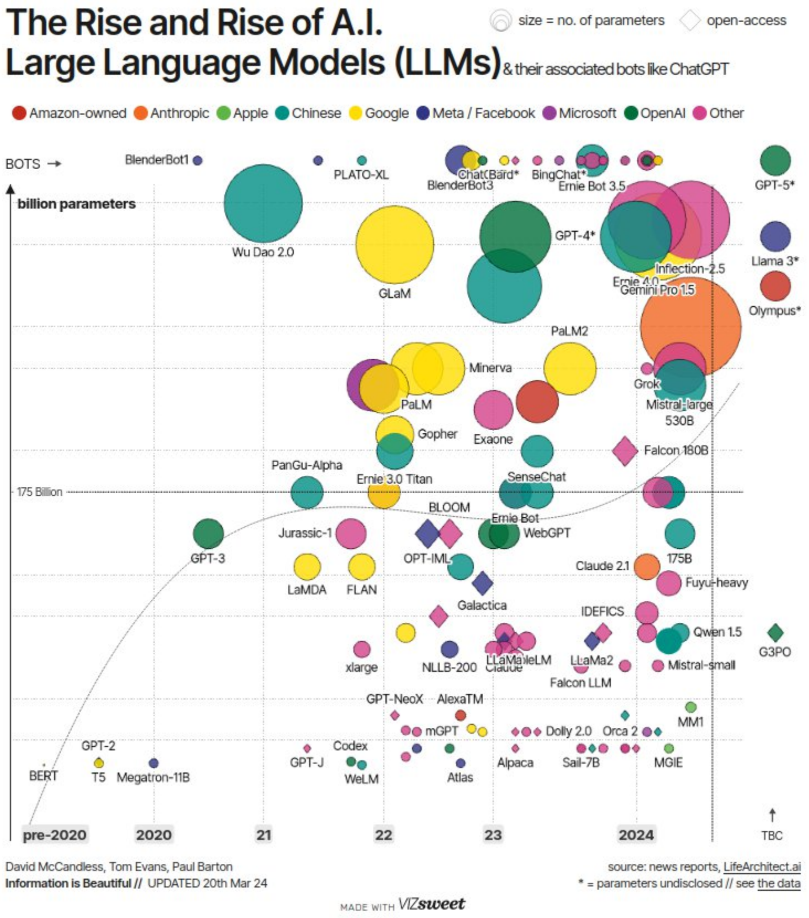


Large and deep models provide better accuracy metrics.

Large Model

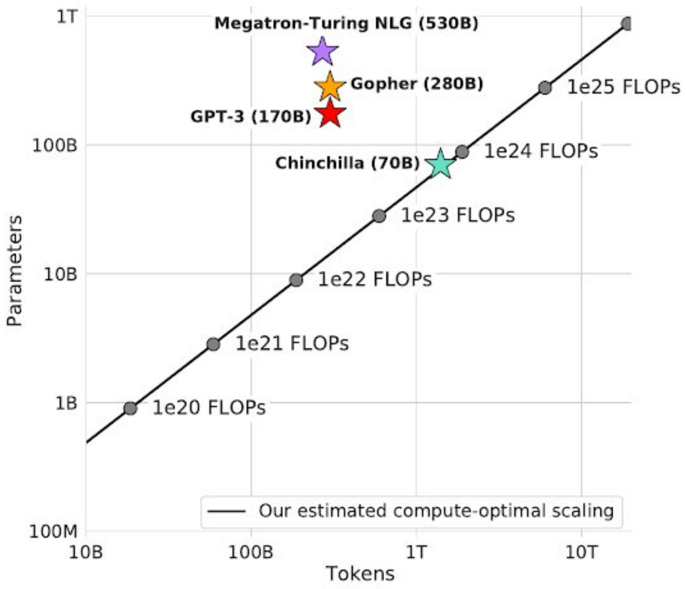
Huge models cause very expensive compute work times and large memory footprints (4 GB for a model with 1 billion parameters).

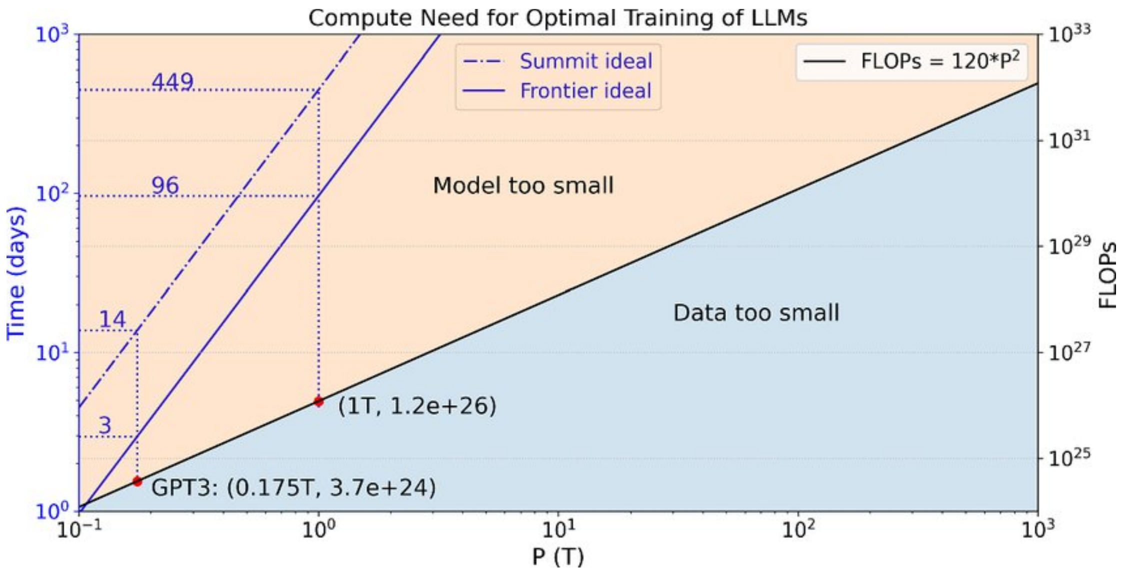




Large Model

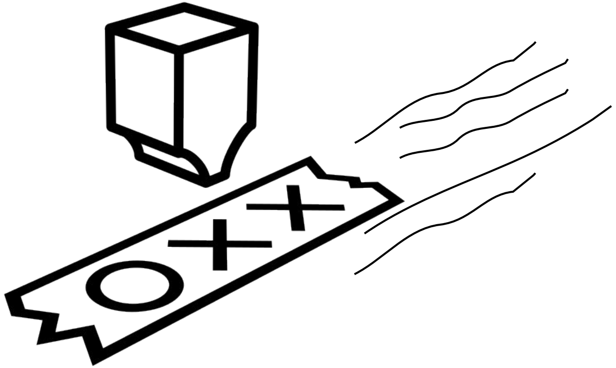
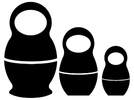
Chinchilla Law Impact



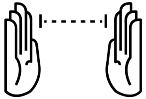
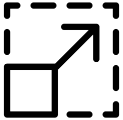
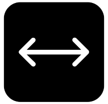
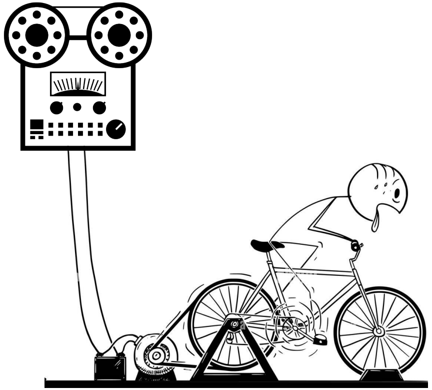


Compute Work Times

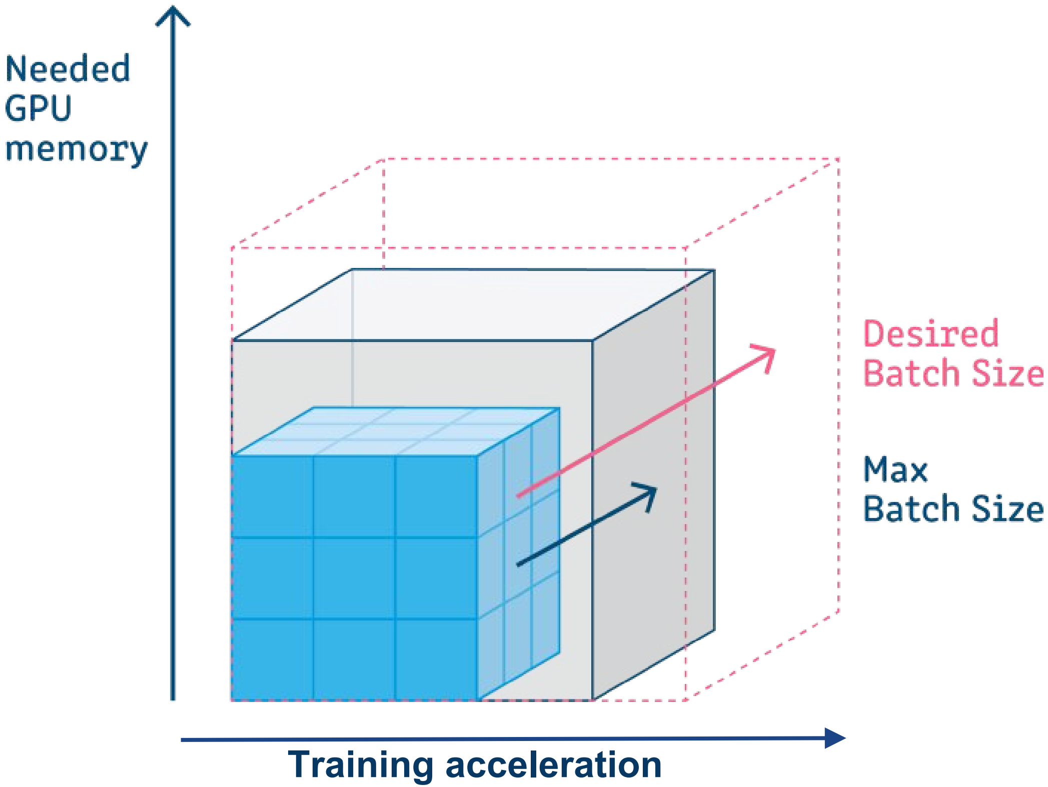
The compute time increases with the **number of FLOPs** required, depending on:

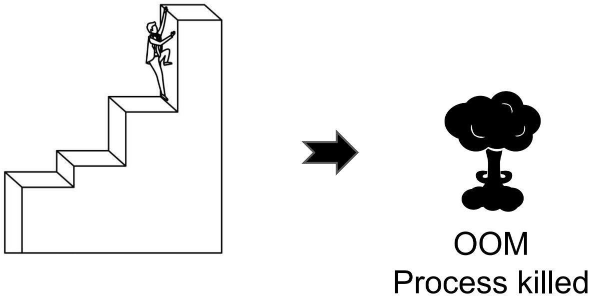
- The size of the model
- The depth of the model
- The size of the input data (image resolution, length of the sequence, etc.)
- The size of the dataset
- Number of epochs required

Batch Size & Memory Usage



Increasing the batch size and thus increasing the iteration step speeds up learning.

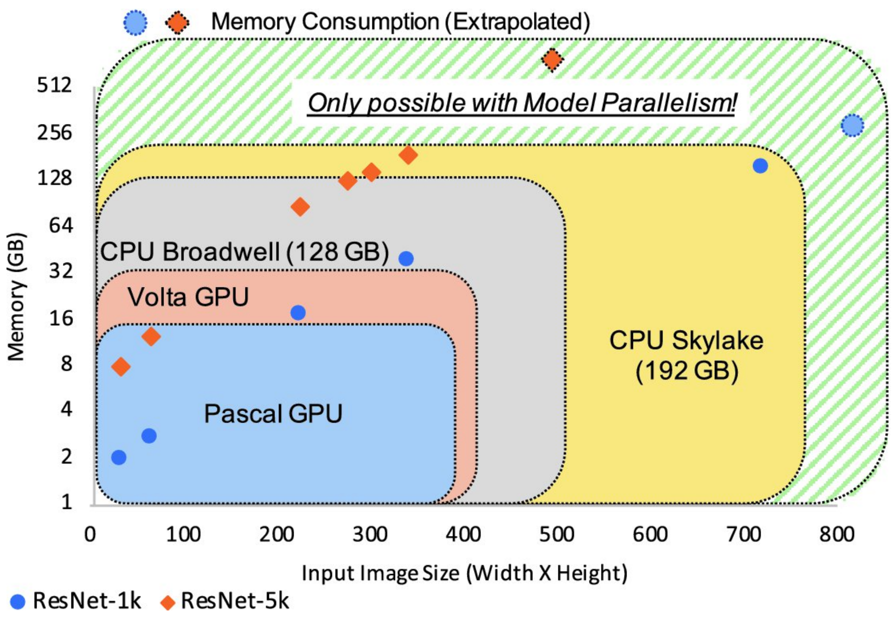


However, this increases the memory footprint and risks reaching the system limit.

Large size Input Data

Large input data causes **serious memory occupancy problems** during training, **accentuated by the depth of the model**.

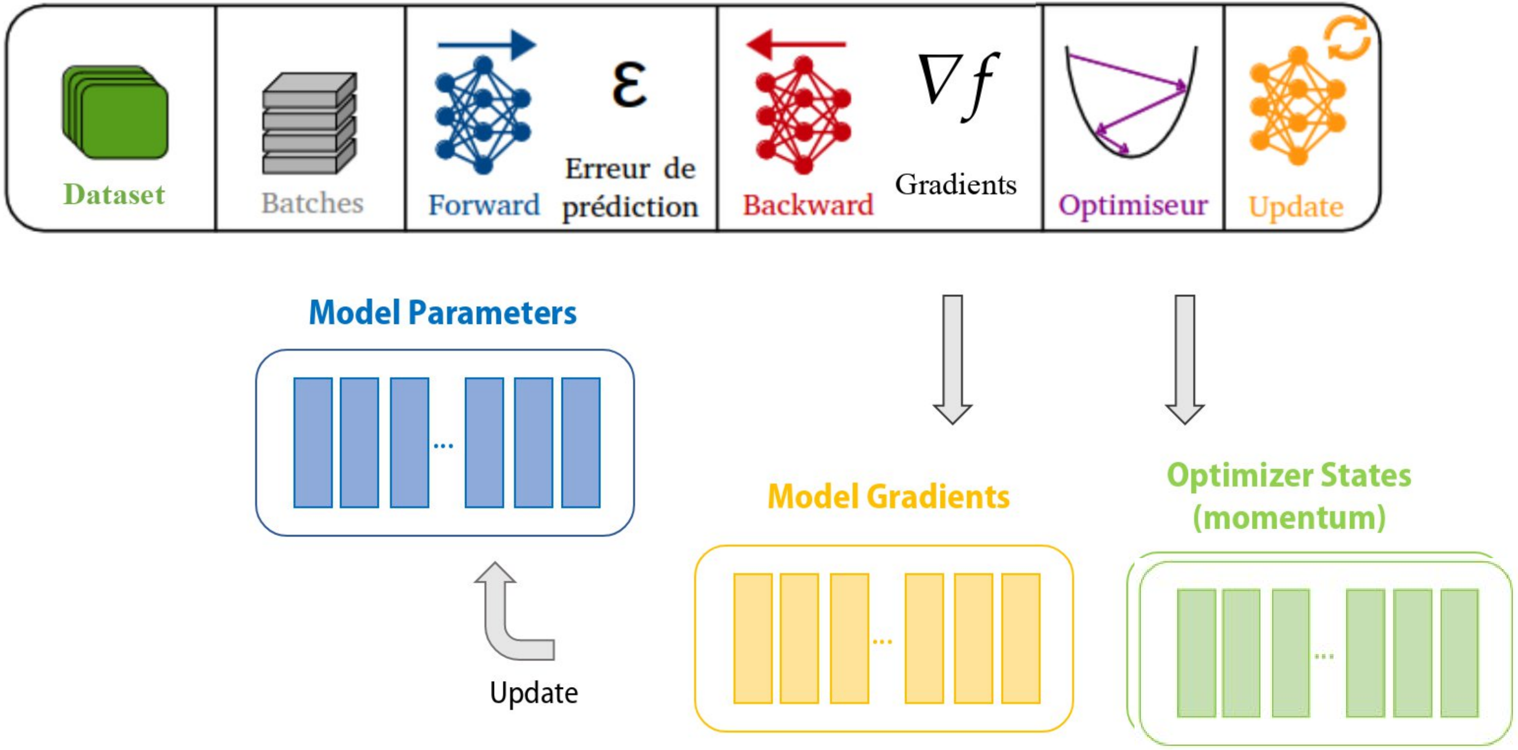
- ➔ Text (N, 100, 500) ***~x1***
- ➔ Image 2D (N, 226, 226, 3) ***~x3***
- ➔ Image 3D (N, 226, 226, 100, 3) ***~x300***
- ➔ Video (N, 100, 226, 226, 3) ***~x300***



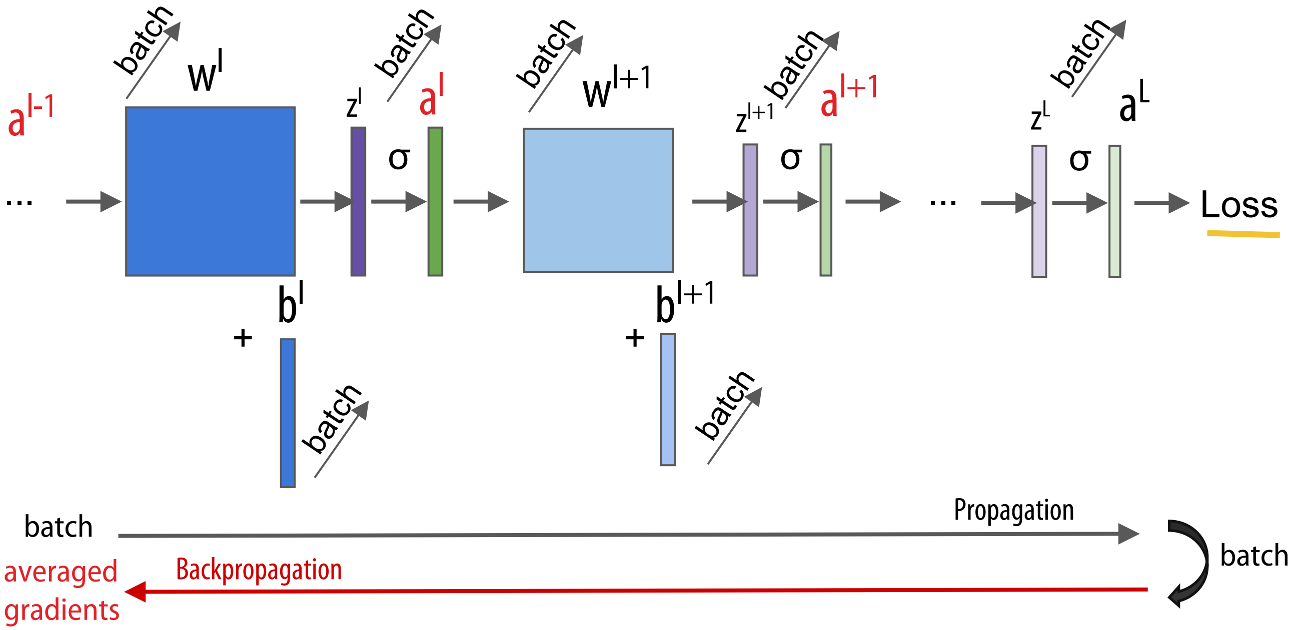
(GNN : Graph from tiny to huge !!)

Source : HyPar-Flow

Forward / Backward – Model Memory Occupancy



Forward / Backward – Activations Memory Occupancy



Propagation

$$a^l = \sigma(w^l a^{l-1} + b^l) = \sigma z^l$$

Backpropagation

$$\delta^l = \frac{\partial C}{\partial z^l}$$

$$w^l \rightarrow w^l - \frac{\eta}{m} \cdot \frac{\partial C}{\partial w^l}$$

$$b^l \rightarrow b^l - \frac{\eta}{m} \cdot \frac{\partial C}{\partial b^l}$$

$$\delta^L = \nabla_a C \odot \sigma'(z^L)$$

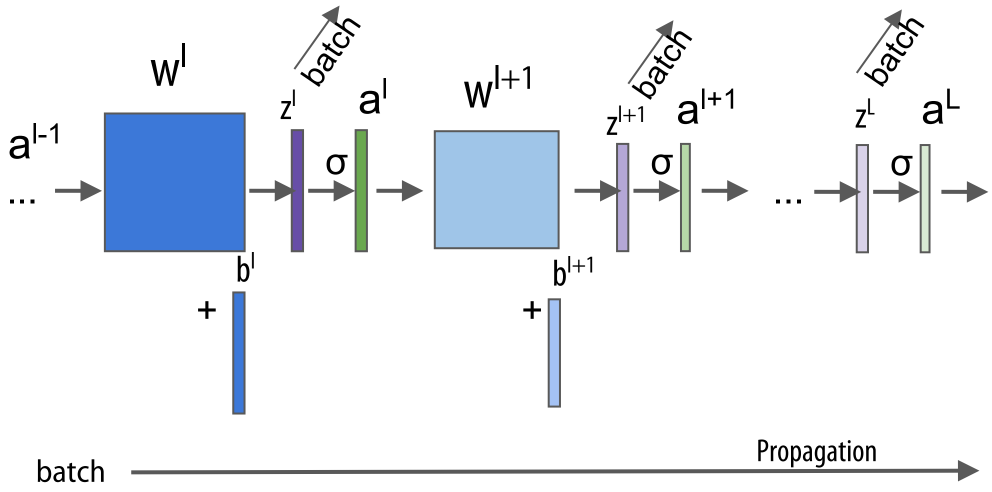
$$\delta^l = ((w^{l+1})^T \delta^{l+1}) \odot \sigma'(z^l)$$

$$\frac{\partial C}{\partial w^l} = \delta^l (a^{l-1})^T$$

$$\frac{\partial C}{\partial b^l} = \delta^l$$

Note: For backpropagation, it is necessary to save intermediate activations.

Inference & evaluation

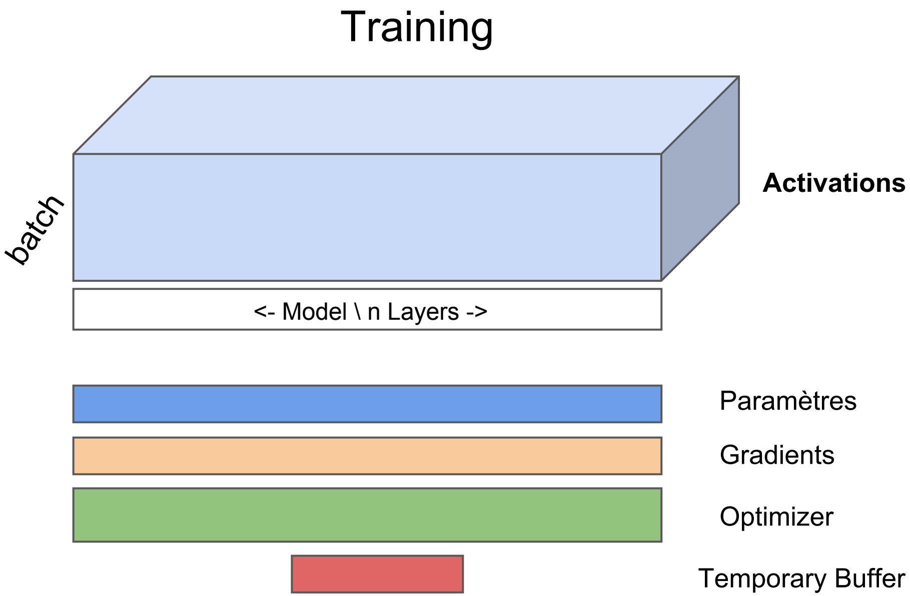


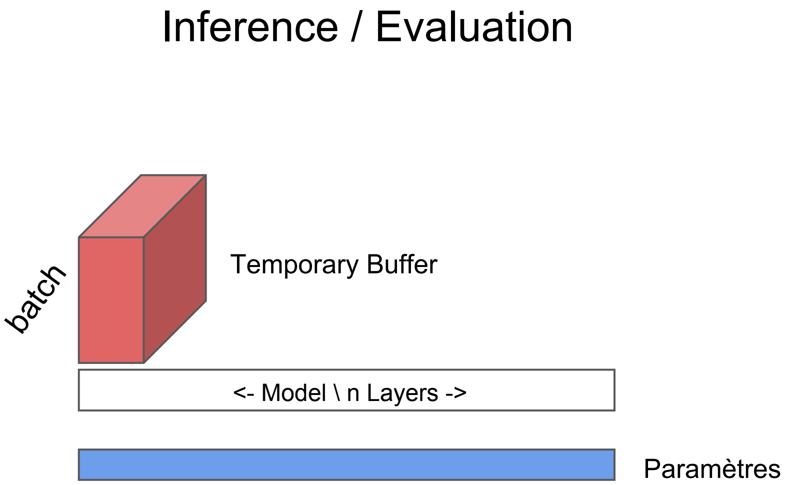

```
...
with torch.no_grad():
    val_outputs = model(val_images)
    loss = criterion(val_outputs, val_labels)
...
```

Propagation

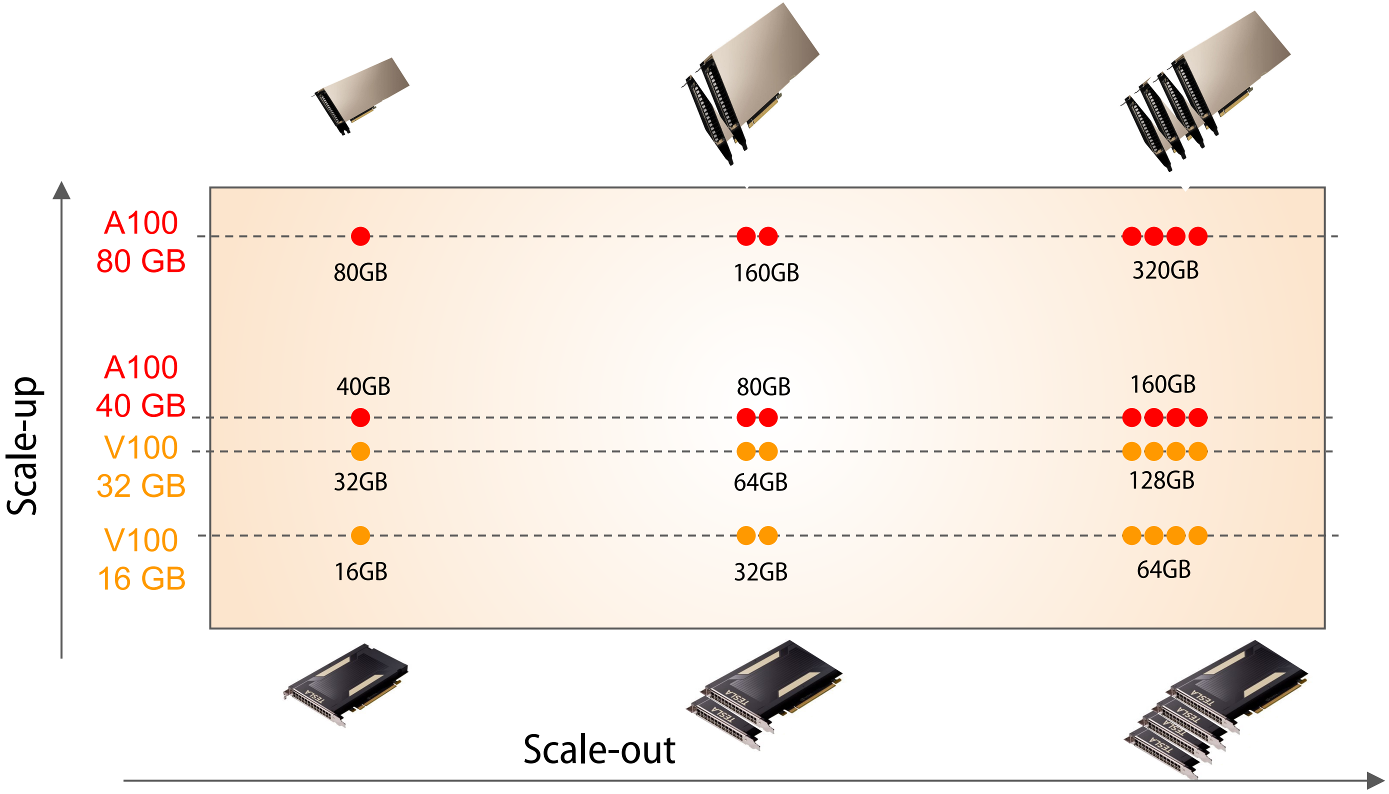
$$a^l = \sigma(w^l a^{l-1} + b^l) = \sigma z^l$$

Memory Footprint



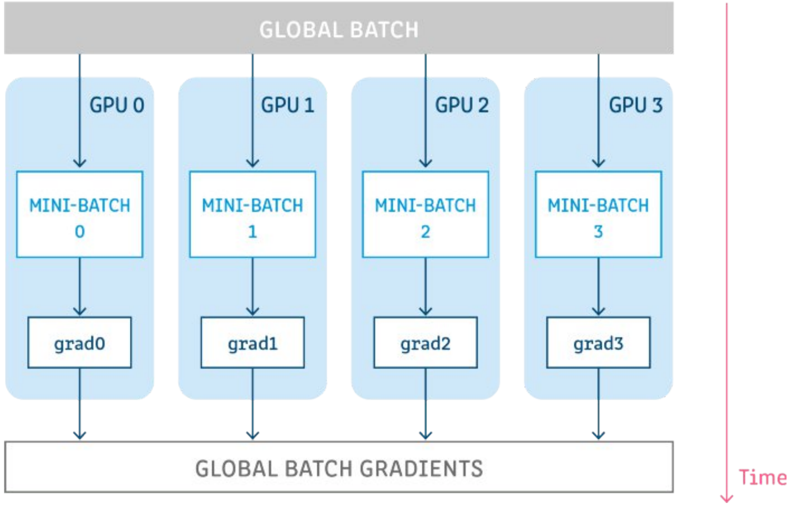


System Solutions

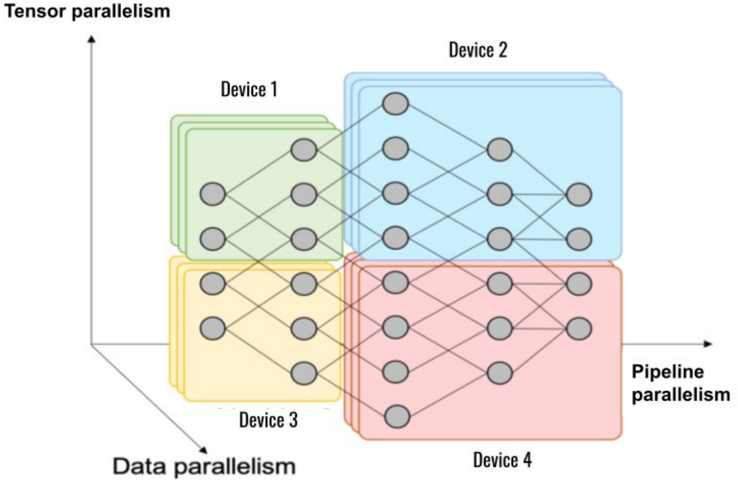


Solutions: Distribution – Scale-out

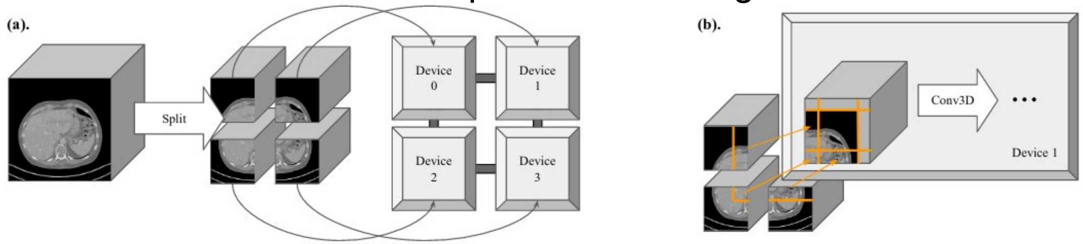
Data Parallelism



Model Parallelism

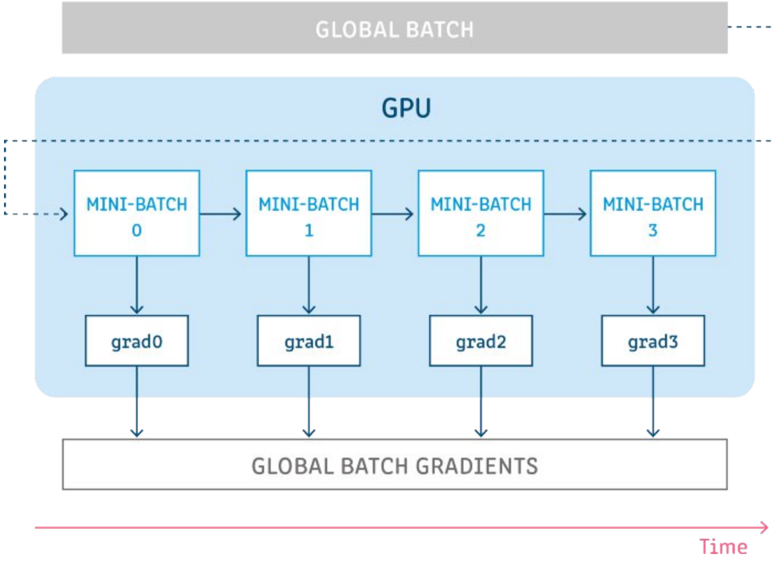


Spatial Partitioning

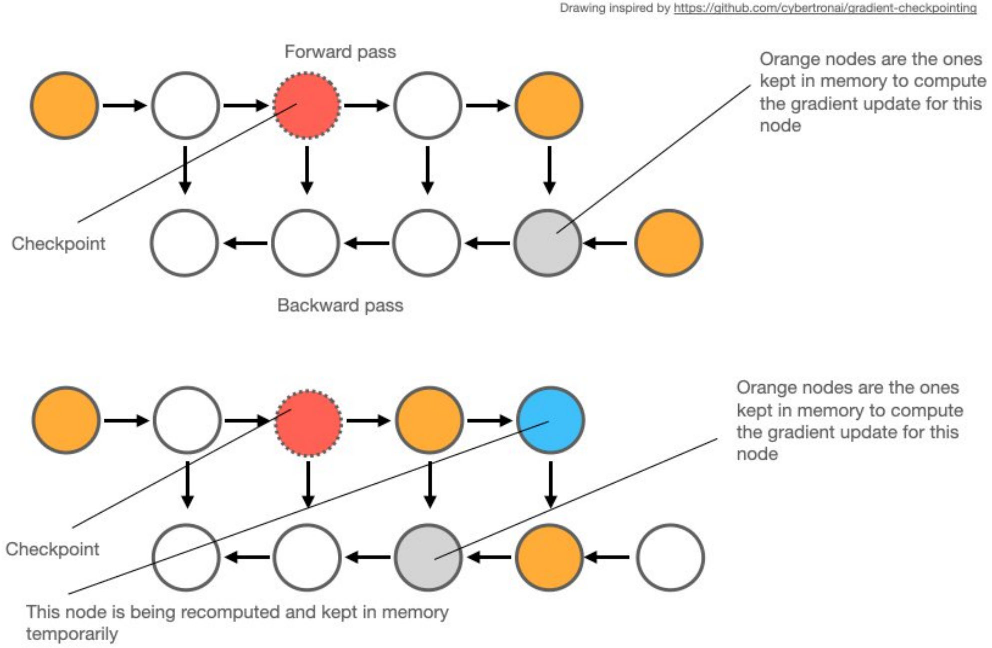


Workaround Solutions

Gradient aggregation



Gradient/activation checkpointing

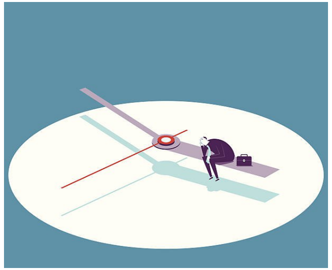


A 3rd problem to deal with ...

Power Consumption !!

2 problems to deal with:

Training Time



Memory Overconsumption (OOM)

Power Consumption

	A100 PCIe	A100 SXM2	V100 PCIe	V100 SXM2
Max Power	250W	400W	250W	300W
Idle Power	~30W	~60W	~40W	~45W
Performance	90%	100%	45%	50%

For a node: The CPU (often 2 processors) consumes what approximately 1 GPU consumes.

Power consumption varies depending on partial or overall GPU usage.

However, the power efficiency ratio is in favor of full use of the GPU.

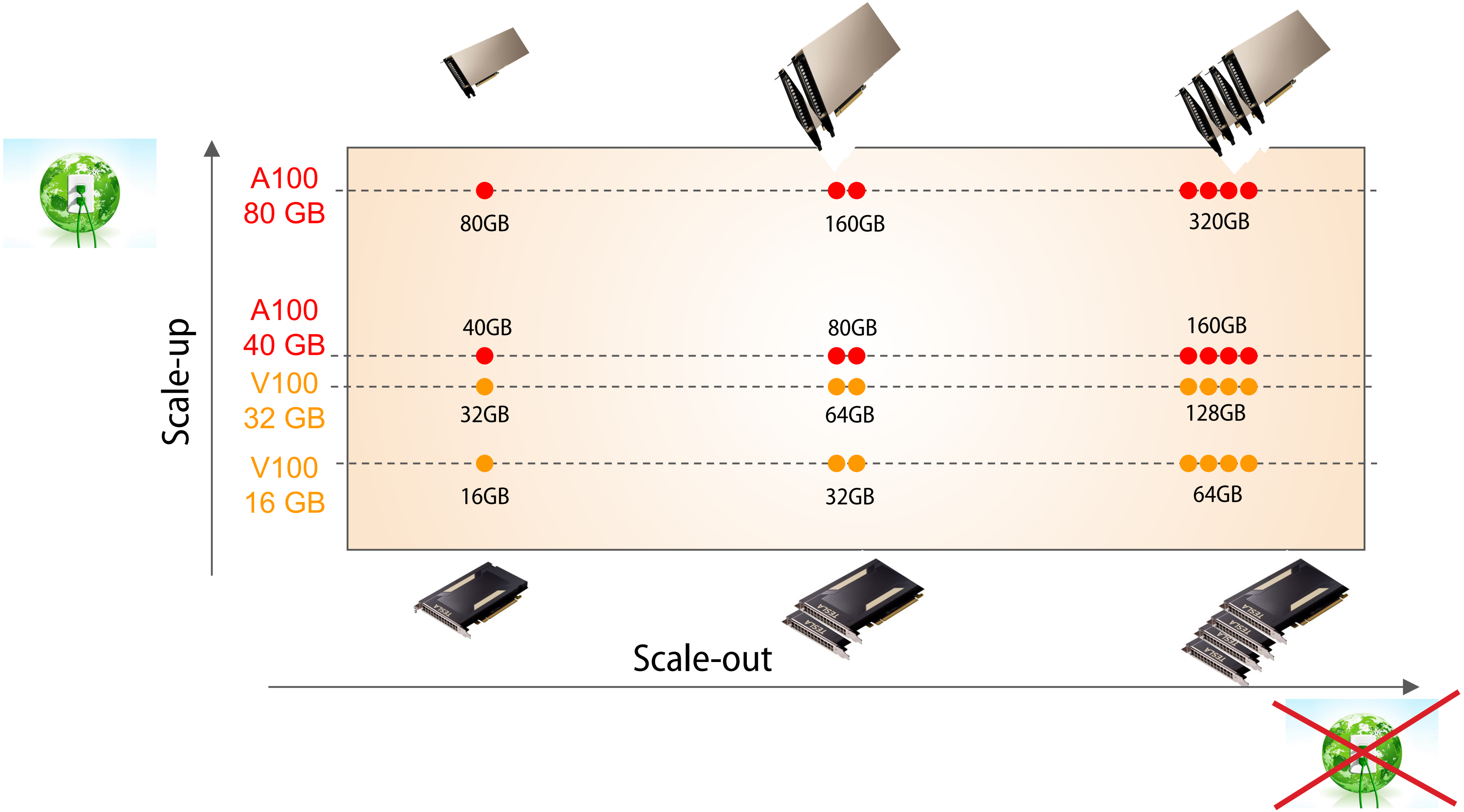
Energy Consumption / GPU Hours

Energy Saving
≅
GPU Hours Saving

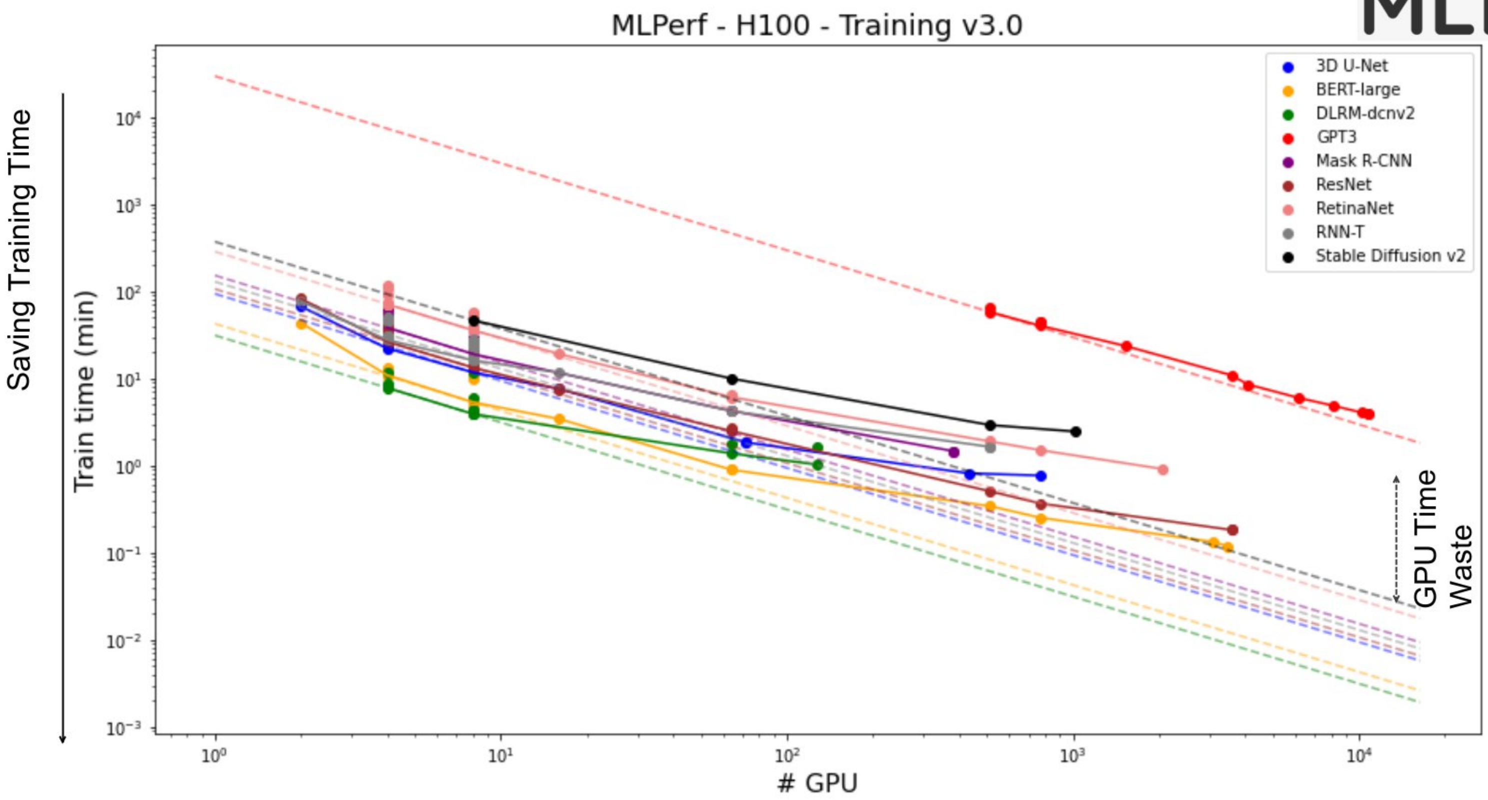
System optimization (DLO-JZ)

- Find the most important throughput
- Optimize data loading to eliminate GPU idle times
- Parallelize training to the right scale: neither too much nor too little

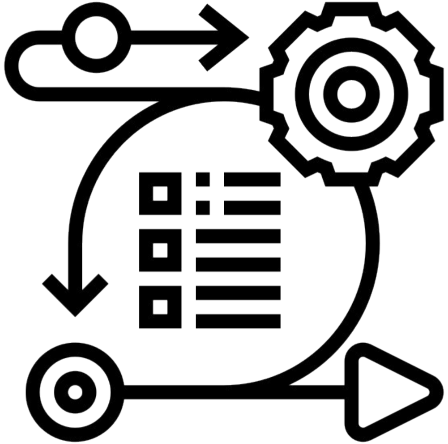
Energy Consumption / GPU Hours

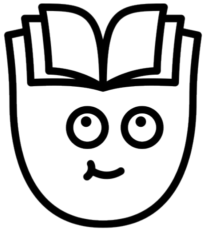


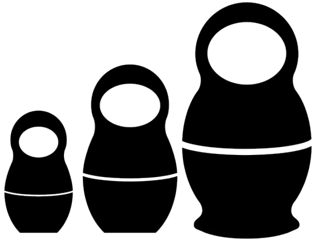
ML Perf Result - Scaling



Energy Consumption / GPU Hours







Methodology (saving research, not repeating learning unnecessarily)

- Search for hyperparameters in publications and reproduce the state-of-the-art
- Find the right hyper parameters on smaller models, then apply them at scale
- *Hyper-Parameter Optimization* (HPO) techniques

Code review

General overview ◂

Detailed overview ◂

Data - Imagenet

Goal:

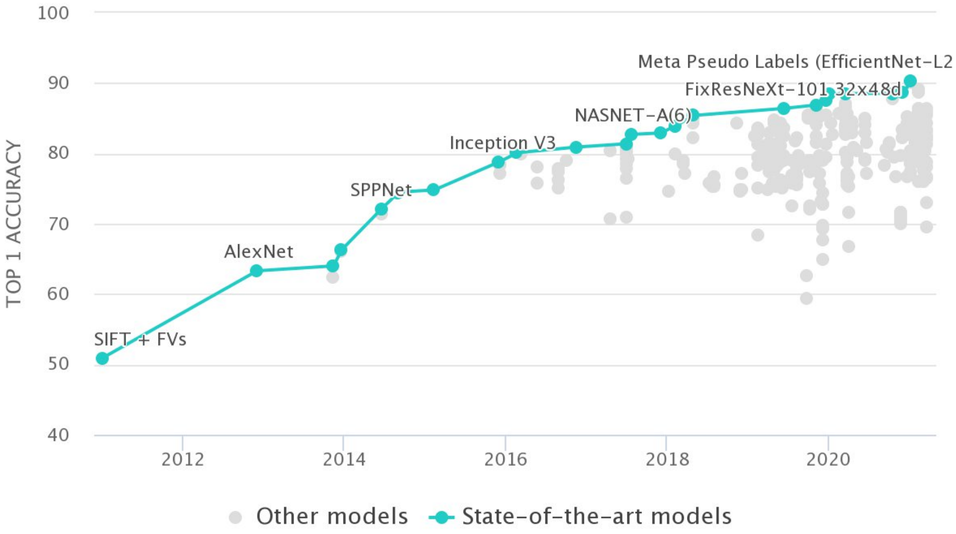
Classification (1000 classes)

Dataset:

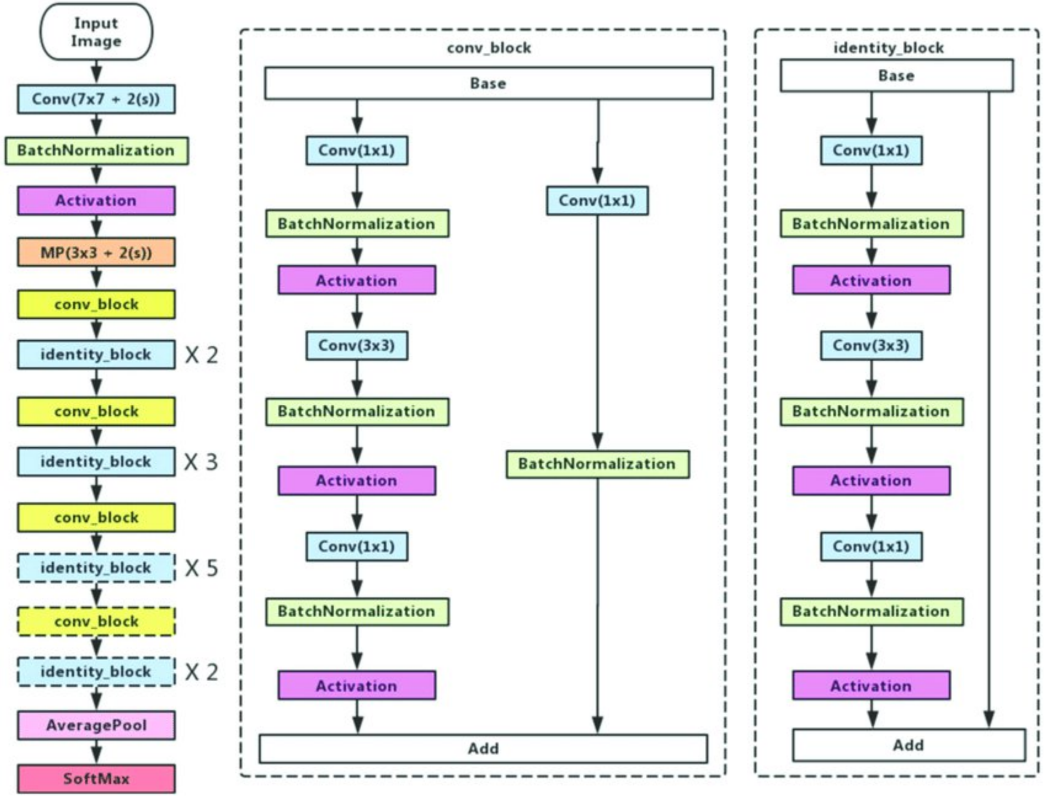
Train dataset: **1,2 M** labeled images

Validation dataset: **50 000** labeled images

http://www.image-net.org/



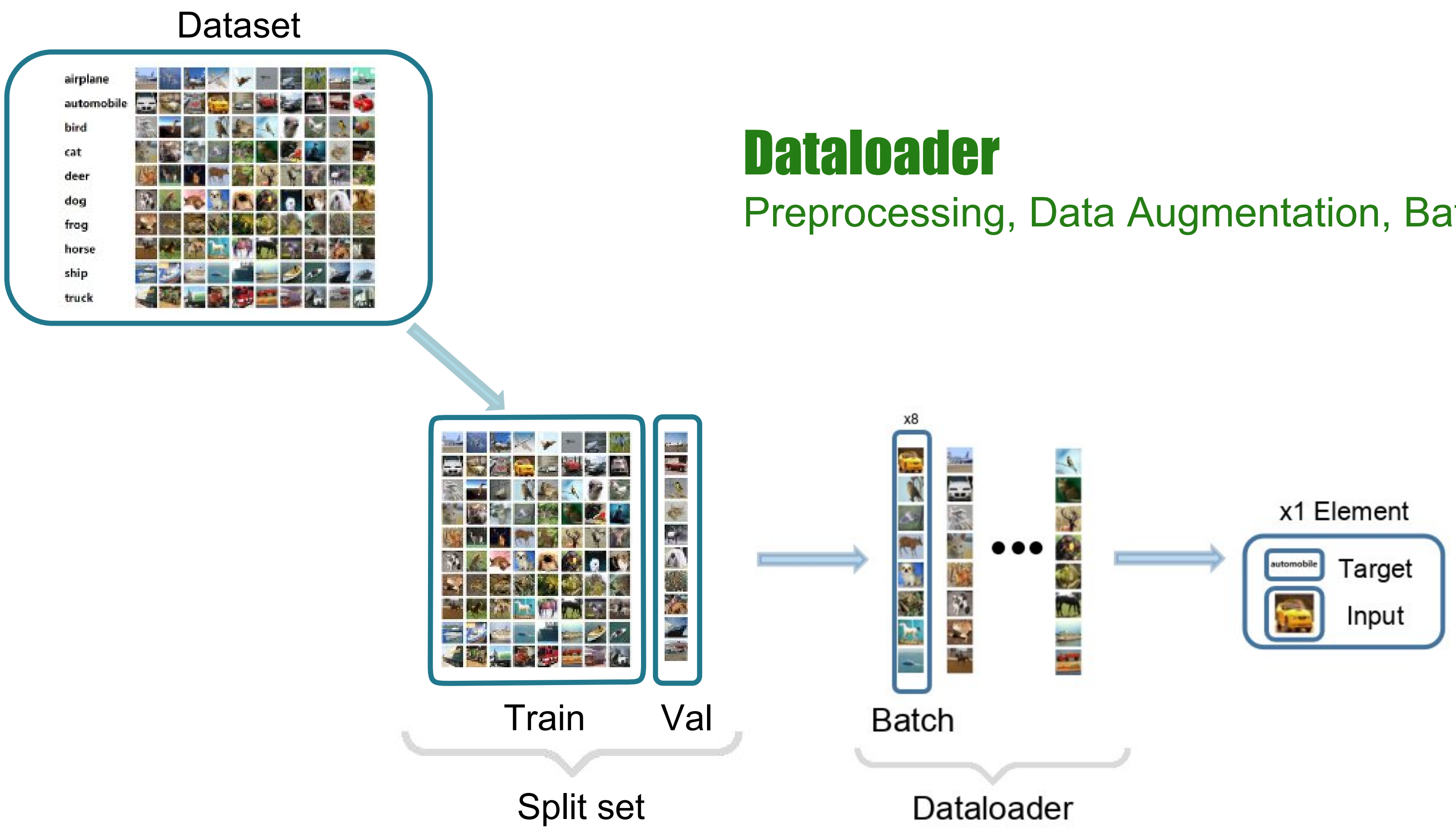
Imagenet - Resnet



Resnet :

- Residual Learning
- BatchNorm layer
  - Instead of Bias layers with conv.
- Average Pooling
  - Makes the model independent of the size of the input images

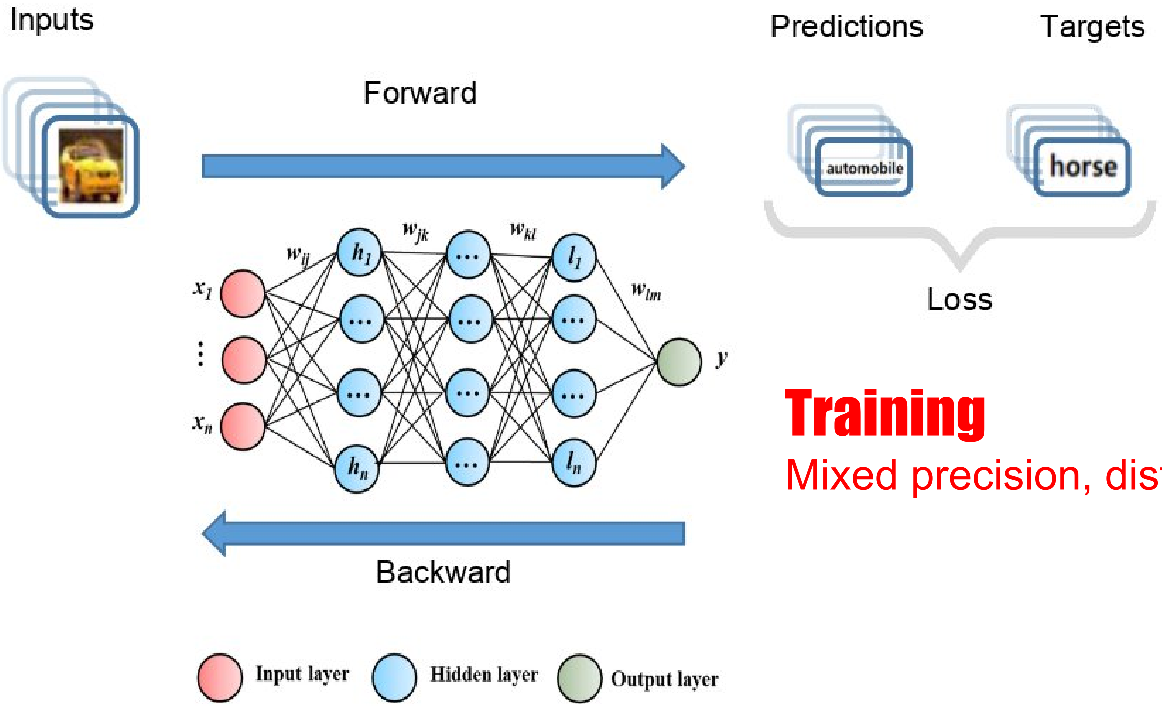
Training Loop – DataLoader



Dataloader

Preprocessing, Data Augmentation, Batching ...

Training Loop – Forward/Backward

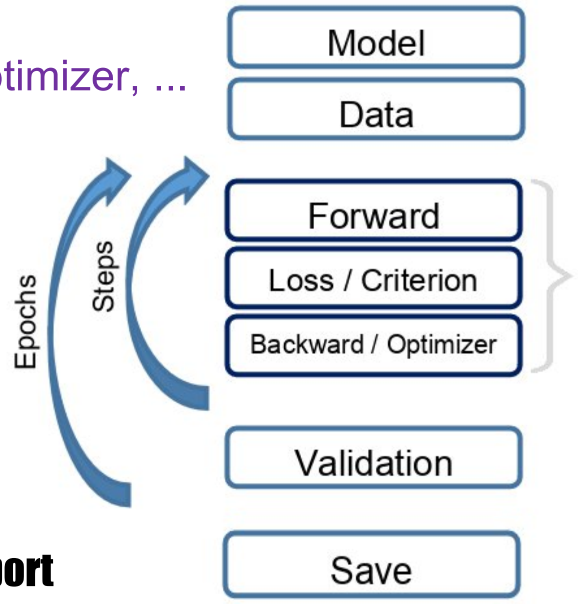


Training

Mixed precision, distribution, ...

Training Loop

Instanciation
Model, distribution, optimizer, ...



Checkpoint & report

Dataloader
Preprocessing, Data Augmentation, Batching ...

Training
Mixed precision, distribution, ...

Validation
Mixed precision, distribution, ...

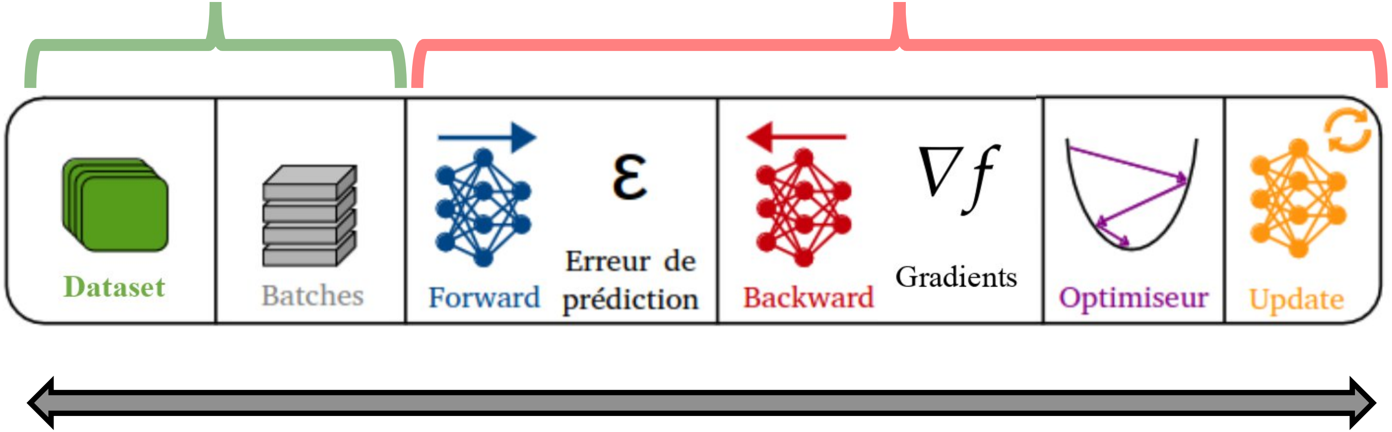
Training step

Dataloader

Preprocessing, Batching , ...

Training

Mixed precision, distribution, ...

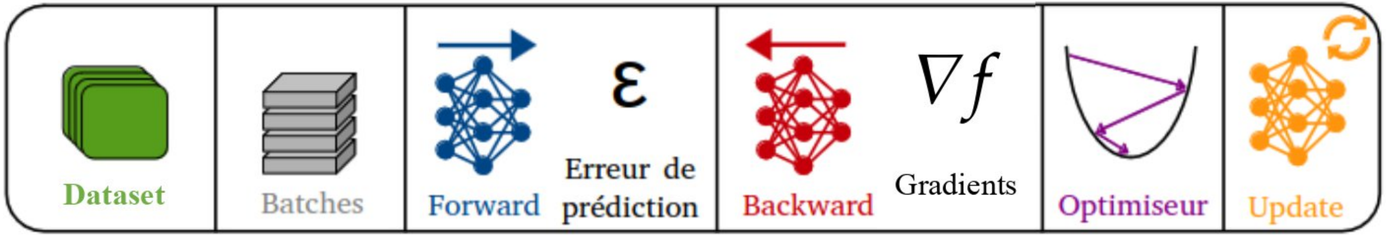


on CPU

Training step – GPU Acceleration

Dataloader
Preprocessing, Batching , ...

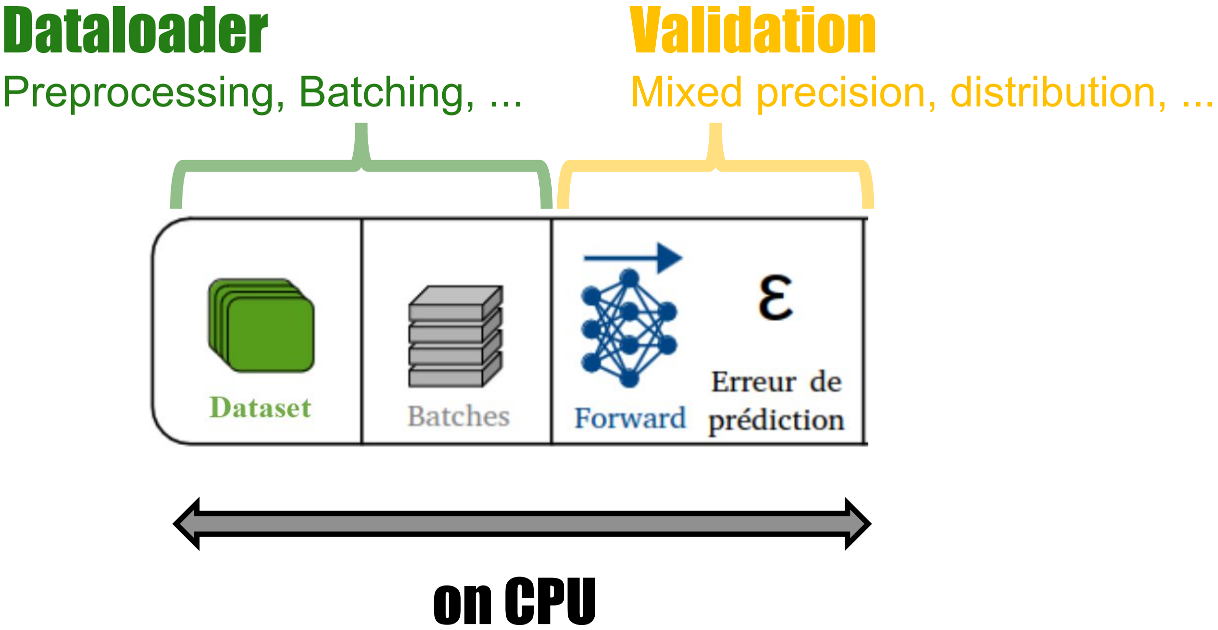
Training
Mixed precision, distribution, ...



on CPU

to GPU

Validation step



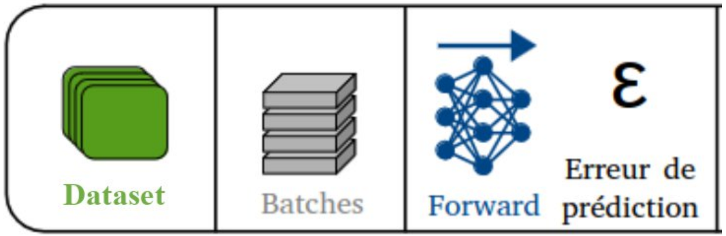
Validation step – GPU Acceleration

Dataloader

Preprocessing, Batching, ...

Validation

Mixed precision, distribution, ...



on CPU

to GPU

Code dlojz.py Review

Import

argparse : arguments

Instanciation

Model, distribution, optimizer, ...

Dataloader

Preprocessing, Batching, ...

Instanciation

Training

Mixed precision, distribution, ...

Validation

Mixed precision, distribution, ...

Checkpoint & report

Runner

dlojz.py – Import & run

```python
import os
import contextlib
import argparse
import torchvision
import torchvision.transforms as transforms
import torchvision.models as models
from torch.utils.checkpoint import checkpoint_sequential
import torch
import numpy as np
import apex

import idr_torch
from dlojz_chrono import Chronometer
from dlojz_torch import distributed_accuracy

import random
random.seed(123)
np.random.seed(123)
torch.manual_seed(123)
```

reproductibility

Import libraries

os

contextlib

argparse

PyTorch

NumPy

torchvision

NVIDIA - APEX

Chronometer (DLO-JZ)

time log & home profiler

idr_torch (JZ users)

distribution utils for Jean Zay

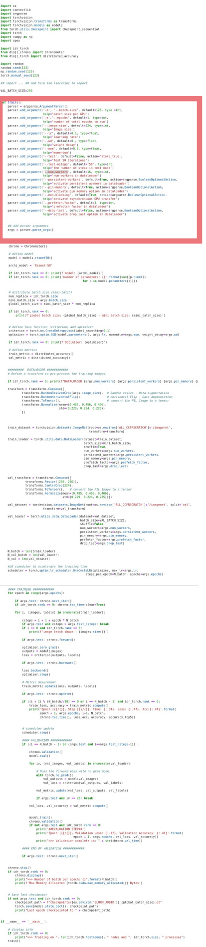
distributed_accuracy (DLO-JZ)

home metric utils (torchmetric-like)

```python
if __name__ == '__main__':

    # display info
    if idr_torch.rank == 0:
        print(">>> Training on ", len(idr_torch.hostnames), " nodes and ", idr_torch.size, " processes")
    train()
```

```python
#*******************************************
def train():
    parser = argparse.ArgumentParser()
    parser.add_argument('-b', '--batch-s
```

dlojz.py - arguments parser



```python
## import ... ## Add here the libraries to import

VAL_BATCH_SIZE=256

#*************************************************************************
def train():
    parser = argparse.ArgumentParser()
    parser.add_argument('-b', '--batch-size', default=128, type =int,
                        help='batch size per GPU')
    parser.add_argument('-e','--epochs', default=1, type=int,
                        help='number of total epochs to run')
    parser.add_argument('--image-size', default=224, type=int,
                        help='Image size')
    parser.add_argument('--lr', default=0.1, type=float,
                        help='learning rate')
    parser.add_argument('--wd', default=0., type=float,
                        help='weight decay')
    parser.add_argument('--mom', default=0.9, type=float,
                        help='momentum')
    parser.add_argument('--test', default=False, action='store_true',      ##    DON'T MODIFY    ########
                        help='Test 50 iterations')
    parser.add_argument('--test-nsteps', default='50', type=int,
                        help='the number of steps in test mode')
    parser.add_argument('--num-workers', default=10, type=int,
                        help='num workers in dataloader')
    parser.add_argument('--persistent-workers', default=True, action=argparse.BooleanOptionalAction,
                        help='activate persistent workers in dataloader')
    parser.add_argument('--pin-memory', default=True, action=argparse.BooleanOptionalAction,
                        help='activate pin memory option in dataloader')
    parser.add_argument('--non-blocking', default=True, action=argparse.BooleanOptionalAction,
                        help='activate asynchronuous GPU transfer')
    parser.add_argument('--prefetch-factor', default=3, type=int,
                        help='prefectch factor in dataloader')
    parser.add_argument('--drop-last', default=False, action=argparse.BooleanOptionalAction,
                        help='activate drop_last option in dataloader')
#*************************************************************************

    ## Add parser arguments

    args = parser.parse_args()
```

Configurable Arguments :

`--batch-size` : batch size per GPU
`--epochs` : number of epochs
`--image-size` : image size

Optimizer :

`--lr` : learning rate
`--wd` : weight decay
`--mom` : momentum

Modes spéciaux :

`--test` : test mode
`--test-nsteps` : n steps for test mode

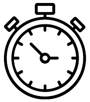
Optimisation du DataLoader :

`--num-workers`
`--persistent-workers`
`--pin-memory`
`--non-blocking`
`--prefetch-factor`
`--drop-last`

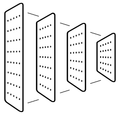
dlojz.py - instantiation

```python
## chronometer initialisation
chrono = Chronometer()

# define model
model = models.resnet50()

archi_model = 'Resnet-50'

if idr_torch.rank == 0: print(f'model: {archi_model}')
if idr_torch.rank == 0: print('number of parameters: {}'.format(sum([p.numel()
                                          for p in model.parameters()])))


# distribute batch size (mini-batch)
num_replica = idr_torch.size
mini_batch_size = args.batch_size
global_batch_size = mini_batch_size * num_replica

if idr_torch.rank == 0:
    print(f'global batch size: {global_batch_size} - mini batch size: {mini_batch_size}')


# define loss function (criterion) and optimizer
criterion = torch.nn.CrossEntropyLoss(label_smoothing=0.1)
optimizer = torch.optim.SGD(model.parameters(), args.lr, momentum=args.mom, weight_decay=args.wd)

if idr_torch.rank == 0: print(f'Optimizer: {optimizer}')

# define metrics
train_metric = distributed_accuracy()
val_metric = distributed_accuracy()
```

```python
#LR scheduler to accelerate the training time
scheduler = torch.optim.lr_scheduler.OneCycleLR(optimizer, max_lr=args.lr,
                                          steps_per_epoch=N_batch, epochs=args.epochs)
```



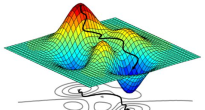
Chronometer



model : Resnet-152

mini batch size ⟺ global batch size

ℰ CrossEntropyLoss

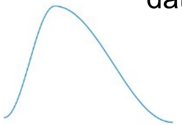


SGD Optimizer

Metric

?

need *N_batch*, given by dataloader



LR scheduler

dlojz.py - Dataloader

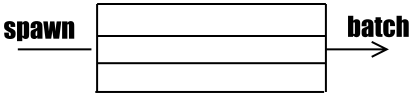
```python
######### DATALOADER ############
# Define a transform to pre-process the training images.

if idr_torch.rank == 0: print(f"DATALOADER {args.num_workers} {args.persistent_workers} {args.pin_memory}

transform = transforms.Compose([
        transforms.RandomResizedCrop(args.image_size),  # Random resize - Data Augmentation
        transforms.RandomHorizontalFlip(),               # Horizontal Flip - Data Augmentation
        transforms.ToTensor(),                           # convert the PIL Image to a tensor
        transforms.Normalize(mean=(0.485, 0.456, 0.406),
                             std=(0.229, 0.224, 0.225))
        ])


train_dataset = torchvision.datasets.ImageNet(root=os.environ['ALL_CCFRSCRATCH']+'/imagenet',
                                              transform=transform)

train_loader = torch.utils.data.DataLoader(dataset=train_dataset,
                                           batch_size=mini_batch_size,
                                           shuffle=True,
                                           num_workers=args.num_workers,
                                           persistent_workers=args.persistent_workers,
                                           pin_memory=args.pin_memory,
                                           prefetch_factor=args.prefetch_factor,
                                           drop_last=args.drop_last)


val_transform = transforms.Compose([
          transforms.Resize((256, 256)),
          transforms.CenterCrop(224),
          transforms.ToTensor(),   # convert the PIL Image to a tensor
          transforms.Normalize(mean=(0.485, 0.456, 0.406),
                               std=(0.229, 0.224, 0.225))])

val_dataset = torchvision.datasets.ImageNet(root=os.environ['ALL_CCFRSCRATCH']+'/imagenet', split='val',
                                            transform=val_transform)

val_loader = torch.utils.data.DataLoader(dataset=val_dataset,
                                         batch_size=VAL_BATCH_SIZE,
                                         shuffle=False,
                                         num_workers=args.num_workers,
                                         persistent_workers=args.persistent_workers,
                                         pin_memory=args.pin_memory,
                                         prefetch_factor=args.prefetch_factor,
                                         drop_last=args.drop_last)

N_batch = len(train_loader)
N_val_batch = len(val_loader)
N_val = len(val_dataset)
```

<u>train dataset :</u>

RandomResizedCrop
RandomHorizontalFlip
+ Normalize

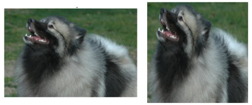
Shuffling

DataLoader optimization



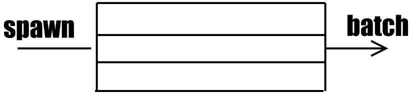
<u>validation dataset :</u>

Resize
CenterCrop
+ Normalize



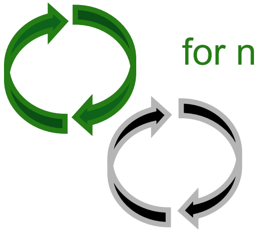
no shuffling

DataLoader optimization



dlojz.py - Training

```python
chrono.start()

#### TRAINING ############
for epoch in range(args.epochs):

    if args.test: chrono.next_iter()
    if idr_torch.rank == 0: chrono.tac_time(clear=True)

    for i, (images, labels) in enumerate(train_loader):

        csteps = i + 1 + epoch * N_batch
        if args.test and csteps > args.test_nsteps: break
        if i == 0 and idr_torch.rank == 0:
            print(f'image batch shape : {images.size()}')

        if args.test: chrono.forward()

        optimizer.zero_grad()
        outputs = model(images)
        loss = criterion(outputs, labels)

        if args.test: chrono.backward()

        loss.backward()
        optimizer.step()

        # Metric mesurement
        train_metric.update(loss, outputs, labels)

        if args.test: chrono.update()

        if ((i + 1) % (N_batch//10) == 0 or i == N_batch - 1) and idr_torch.rank == 0:
            train_loss, accuracy = train_metric.compute()
            print('Epoch [{}/{}], Step [{}/{}], Time: {:.3f}, Loss: {:.4f}, Acc:{:.4f}'.format(
                epoch + 1, args.epochs, i+1, N_batch,
                chrono.tac_time(), loss_acc, accuracy, accuracy_top5))


    # scheduler update
    scheduler.step()
```



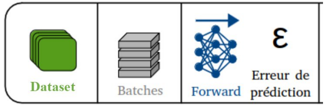
for n epochs

for each *batch*

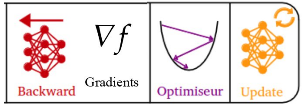
test mode : 50 steps

CPU compute by default !!


```python
optimizer.zero_grad()
outputs = model(images)
loss = criterion(outputs, labels)
```

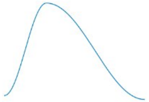




```python
loss.backward()
optimizer.step()
```

Aggregate the metrics (loss, accuracy)
10x per epoch, compute and print the metrics

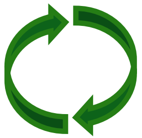
Log 10x per epoch



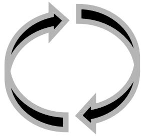
Step up LR scheduler

dlojz.py - Validation

```python
#### VALIDATION ############
if ((i == N_batch - 1) or (args.test and i==args.test_nsteps-1)) :

    chrono.validation()
    model.eval()

    for iv, (val_images, val_labels) in enumerate(val_loader):

        # Runs the forward pass with no grad mode.
        with torch.no_grad():
            val_outputs = model(val_images)
            val_loss = criterion(val_outputs, val_labels)

        val_metric.update(val_loss, val_outputs, val_labels)

        if args.test and iv >= 20: break

    val_loss, val_accuracy = val_metric.compute()


    model.train()
    chrono.validation()
    if not args.test and idr_torch.rank == 0:
        print('##EVALUATION STEP##')
        print('Epoch [{}/{}], Validation Loss: {:.4f}, Validation Accuracy: {:.4f}'.format(
                        epoch + 1, args.epochs, val_loss, val_accuracy))
        print(">>> Validation complete in: " + str(chrono.val_time))

#### END OF VALIDATION ############
```



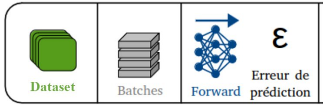
after each epoch
(or at the end of test mode)



for each *batch of validation*

(test mode : 20 steps)

```python
# Runs the forward pass with no grad mode.
with torch.no_grad():
    val_outputs = model(val_images)
    loss = criterion(val_outputs, val_labels)
```



Aggregate the metrics (loss, accuracy)

when it is over:

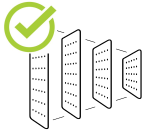
compute & **Log**

dlojz.py – Checkpoint & Report

```python
chrono.stop()
if idr_torch.rank == 0:
    chrono.display()
    print(">>> Number of batch per epoch: {}".format(N_batch))
    print(f'Max Memory Allocated {torch.cuda.max_memory_allocated()} Bytes')


# Save last checkpoint
if not args.test and idr_torch.rank == 0:
    checkpoint_path = f"checkpoints/{os.environ['SLURM_JOBID']}_{global_batch_size}.pt"
    torch.save(model.state_dict(), checkpoint_path)
    print("Last epoch checkpointed to " + checkpoint_path)
```

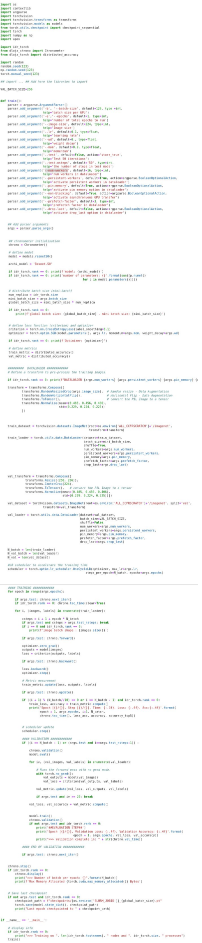
Log + Chronometer Display

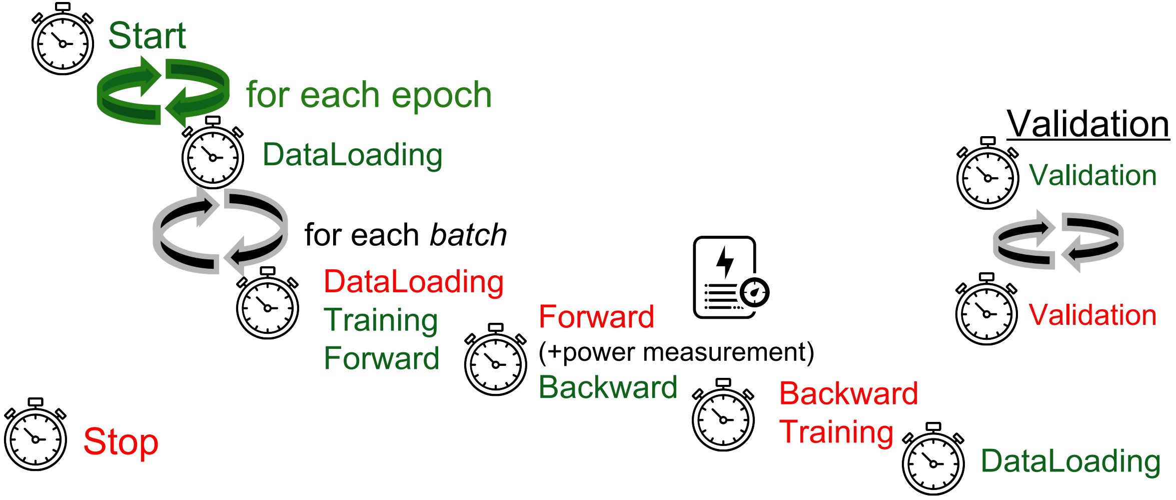
Checkpoint at the end of training (=> not in test mode)



pre-trained model

dlojz.py - Chronometer

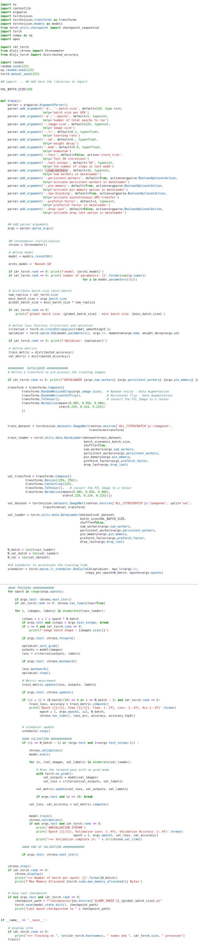




Display

```
def display(self, val_steps):
    if self.rank == 0:
        print(">>> Training complete in: " + str(datetime.now() - self.start_proc))
        if self.test:
            print(">>> Training performance time: min {} avg {} seconds (+/- {})".format(np.min(self.time_perf_train[1:]), np.median(self.time_perf_train[1:]),
np.std(self.time_perf_train[1:])))
            print(">>> Loading performance time: min {} avg {} seconds (+/- {})".format(np.min(self.time_perf_load[1:]), np.mean(self.time_perf_load[1:]),
np.std(self.time_perf_load[1:])))
            print(">>> Forward performance time: {} seconds (+/- {})".format(np.mean(self.time_perf_forward[1:]), np.std(self.time_perf_forward[1:])))
            print(">>> Backward performance time: {} seconds (+/- {})".format(np.mean(self.time_perf_backward[1:]), np.std(self.time_perf_backward[1:])))
            if len(self.power)>0: print(">>> Peak Power during training: {} W)".format(np.max(self.power)))
            print(">>> Validation time estimation: {}".format(self.val_time/20 * val_steps))
            print(">>> Sortie trace #####################################" )
            print(">>>JSON", json.dumps({'GPU process - Forward/Backward':self.time_perf_train, 'CPU process - Dataloader':self.time_perf_load}))
```

dlojz.py – Distributed_accuracy



```python
class distributed_accuracy():
    def __init__(self):
        self.dist = dist.is_initialized()
        self.correct = torch.tensor(0)
        self.total = torch.tensor(0)
        self.loss = torch.tensor(0, dtype=torch.float)

    def update(self, losses, outputs, labels):
        _, predicted = torch.max(outputs.data, 1)
        ## for mixed data augmentation
        if len(labels.size()) > 1: labels = torch.argmax(labels, dim=1)
        self.correct += (predicted == labels).sum().item()
        self.total += labels.size(0)
        self.loss += losses.sum().item()

    def clear(self):
        self.correct = torch.tensor(0)
        self.total = torch.tensor(0)
        self.loss = torch.tensor(0, dtype=torch.float)

    def compute(self):
        if self.dist and idr_torch.size > 1:
            self.correct = self.correct.to('cuda')
            self.total = self.total.to('cuda')
            self.loss = self.loss.to('cuda')
            dist.all_reduce(self.correct, op=dist.ReduceOp.SUM)
            dist.all_reduce(self.total, op=dist.ReduceOp.SUM)
            dist.all_reduce(self.loss, op=dist.ReduceOp.SUM)
        accuracy = (self.correct / self.total).item()
        loss = (self.loss / self.total).item()
        self.clear()
        return loss, accuracy
```

dlojz.py – Distributed_accuracy

```python
class distributed_accuracy():
    def __init__(self):
        self.dist = dist.is_initialized()
        self.correct = torch.tensor(0)
        self.total = torch.tensor(0)
```

Equivalent to Torchmetric !!!

https://lightning.ai/docs/torchmetrics/stable/pages/overview.html

```python
from torchmetrics.classification import MulticlassAccuracy
```

The **metrics API** provides `update()`, `compute()`, `reset()` functions to the user.
These metrics **work with DDP** in PyTorch and PyTorch Lightning by default. When `.compute()` is called in distributed mode, the internal state of each metric is synced and reduced across each process, so that the logic present in `.compute()` is applied to state information from all processes.

```python
        accuracy = (self.correct / self.total).item()
        loss = (self.loss / self.total).item()
        self.clear()
        return loss, accuracy
```

TP0 : Préparation de l'environnement

- Lancer un terminal et faire les copies nécéssaires

```
local:~$ ssh jean-zay

jz:~$ cd $WORK
jz:~$ git clone https://github.com/IDRIS-CNRS/DLO-JZ.git
```

- Lancer firefox
- Accéder à jupyterhub.idris.fr

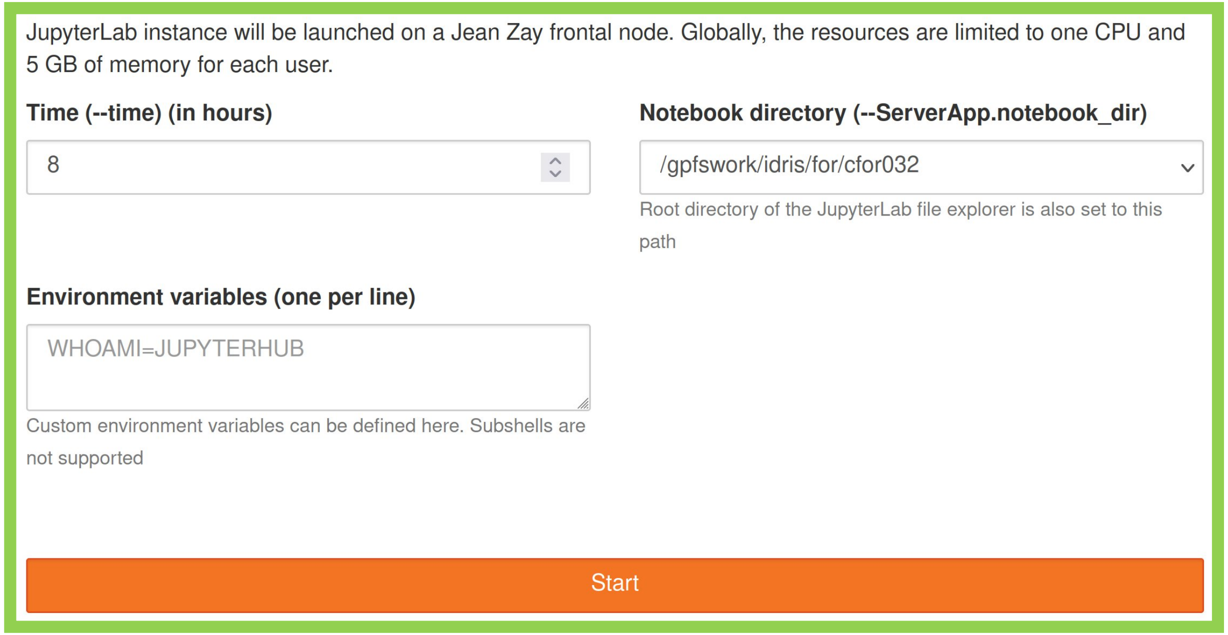
TP0 : Accès et prise en main de JupyterHub

- Se connecter avec vos identifiants de formation

- Lancer une instance

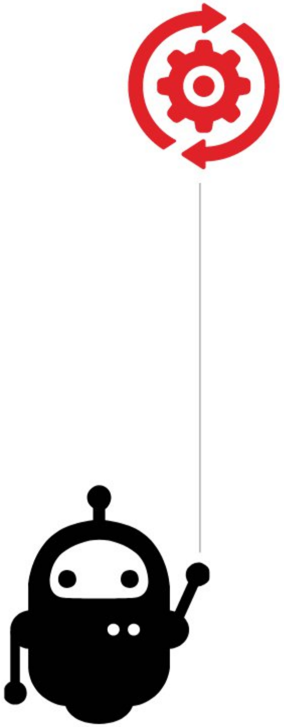
- Sélectionner le spawner 'Interactive'

- Remplir la configuration



- Start

TP0 : Accès et prise en main du notebook



- Ouvrir le notebook DLO-JZ_Jour1.ipynb
- Choisir le kernel pytorch-gpu/py3/2.1.1 (en haut à droite) s’il n’est pas détecté automatiquement
- Choisir un pseudonyme
- Lancer un job
- Prendre en main le script de référence et les différentes fonctionnalités

GPU computing

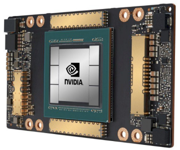
V100, A100 ◀

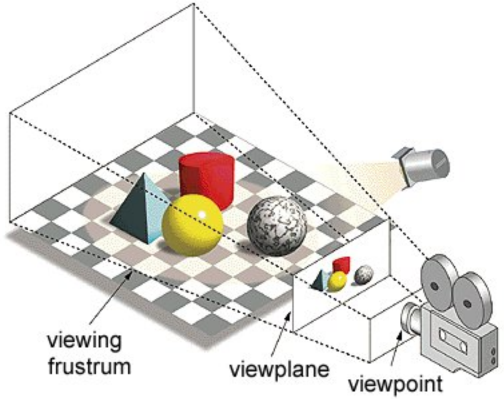
CUDA ◀

CuDNN ◀

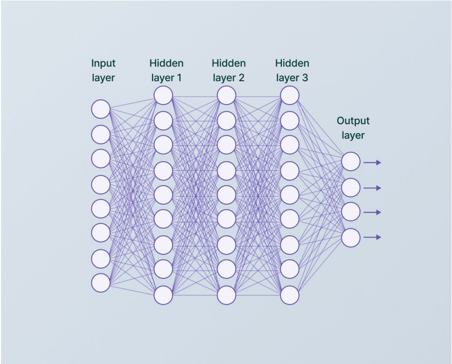
AMP ◀

GPU computing

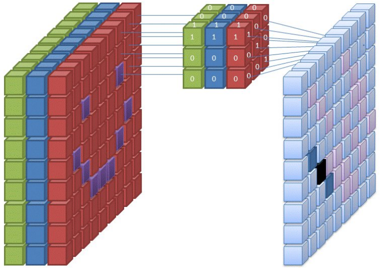




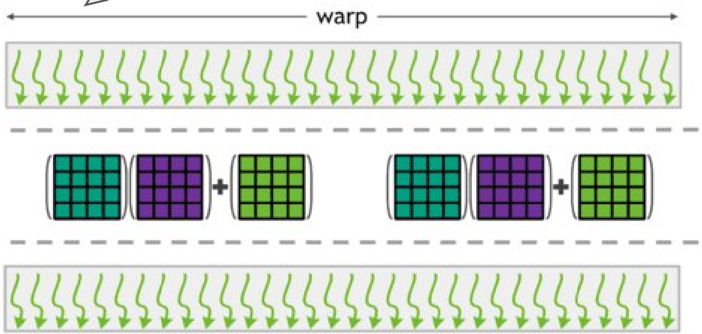
GPU Rendering & Game Graphics Pipeline



NN

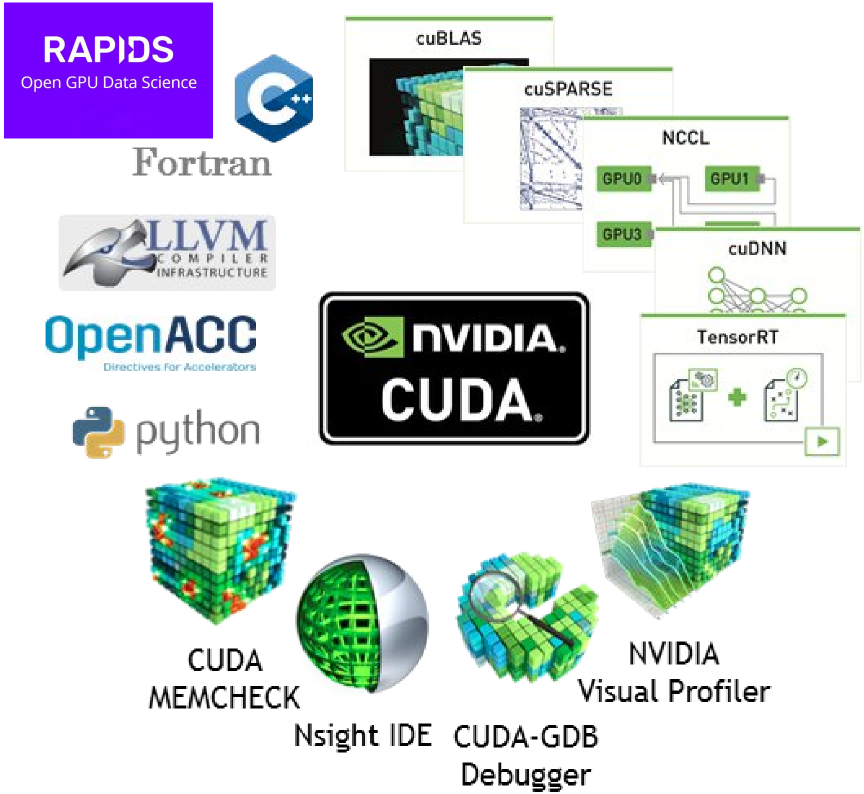


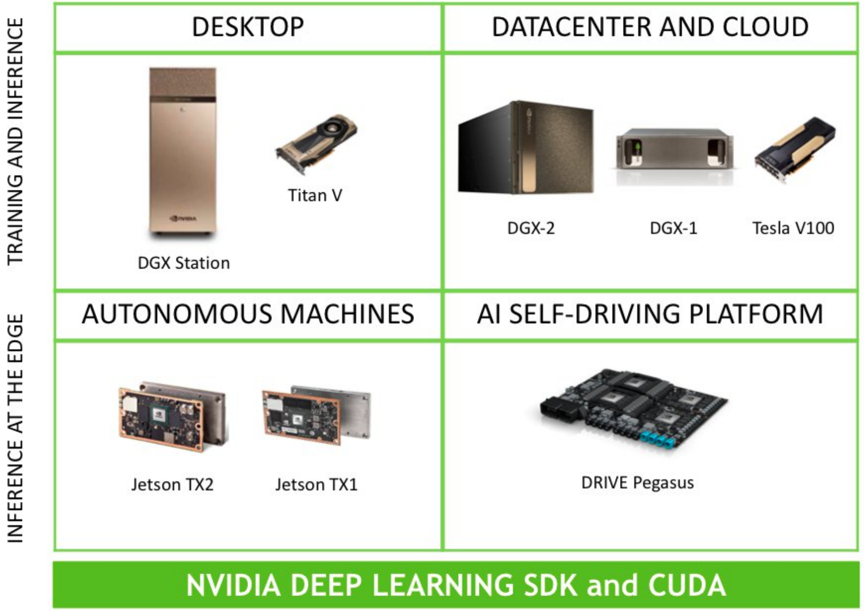
CNN



Matrix Multiply-accumulate operations

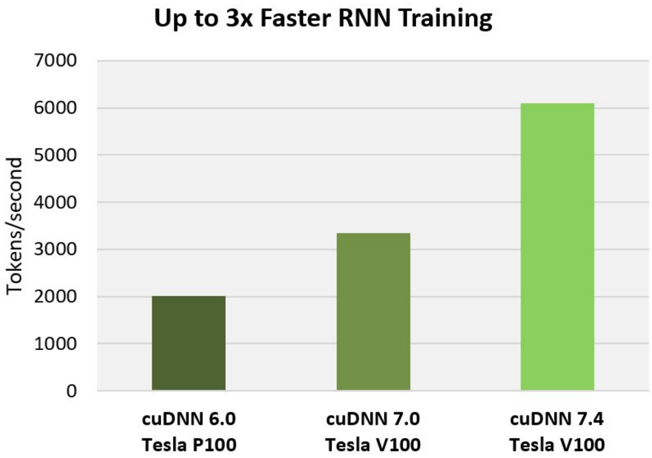
NVIDIA Galaxy





Source : NVidia

CuDNN

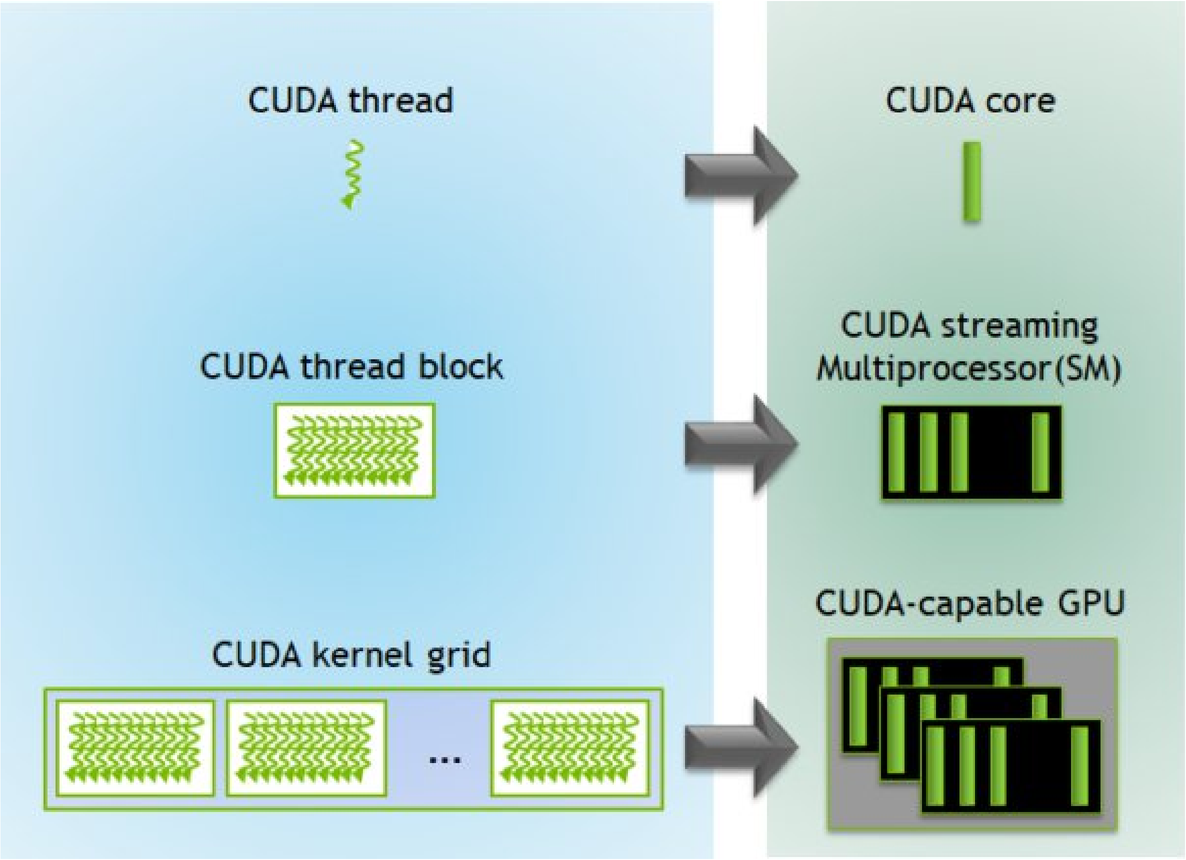


TensorFlow performance (tokens/sec), Tesla P100 + cuDNN 6 (FP32) on 17.12 NGC container, Tesla V100 + cuDNN 7.0 (Mixed) on 18.02 NGC container, Telsa V100 + cuDNN 7.4 (Mixed) on 18.10 NGC container, OpenSeq2Seq (GNMT), Batch Size: 64

CUDA engineering for deep learning on GPU is handled by cuDNN.
Thanks cuDNN!!

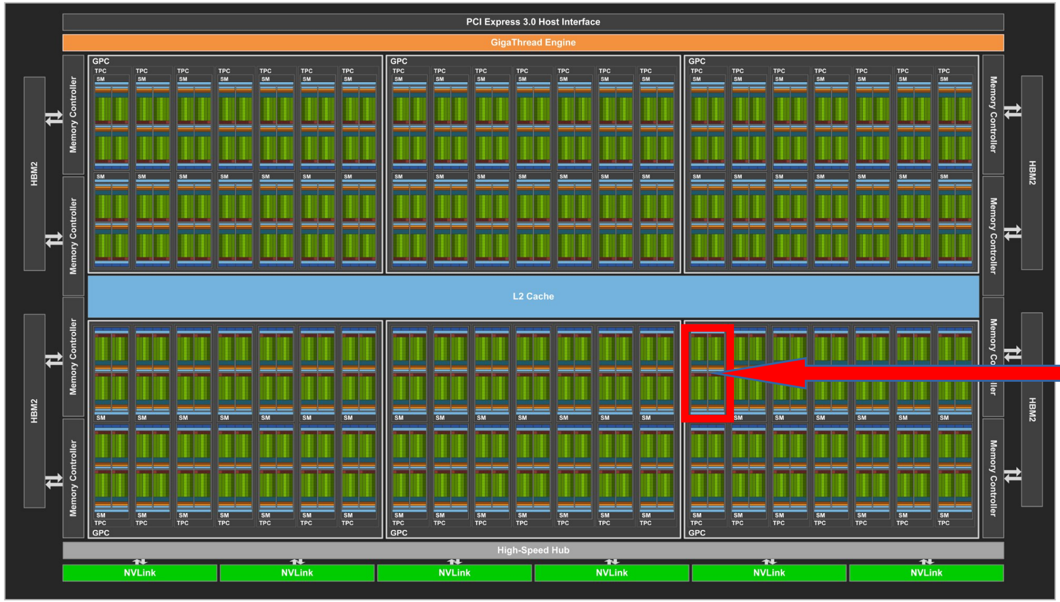
Recommendation: to optimize the use of Tensor Cores and Cuda Cores: Use tensors with dimensions (batch size, sample size, channel, layer dimension, etc.) **multiples of 8**!!

GPU computing : CUDA



Source : NVidia

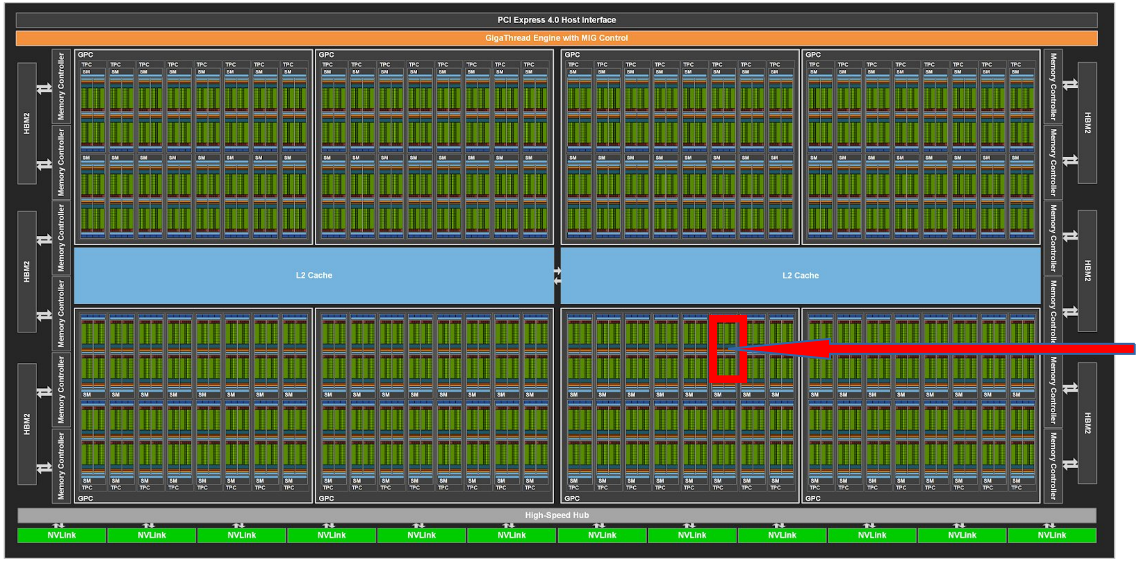
V100 Architecture



- 6 GPC
- **84** Streaming Multiprocessors (SMs)
- 5376 CUDA Cores
- **672 2eGen** Tensor Cores per full GPU

Source : NVidia

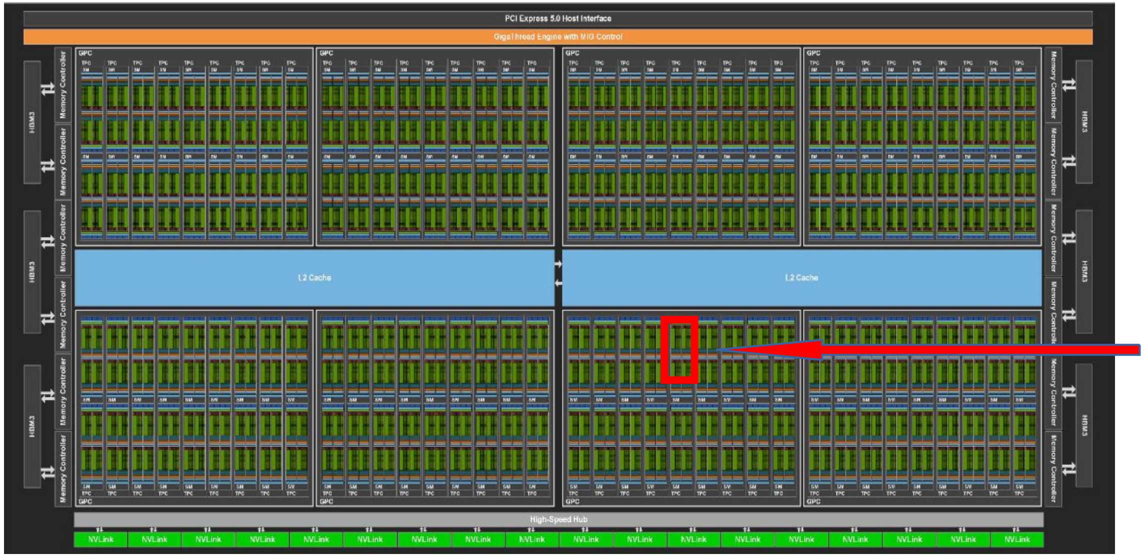
A100 Architecture



- 8 GPC
- **128** Streaming Multiprocessors (SMs)
- 8192 CUDA Cores
- **512 3eGen** Tensor Cores per full GPU

Source : NVidia

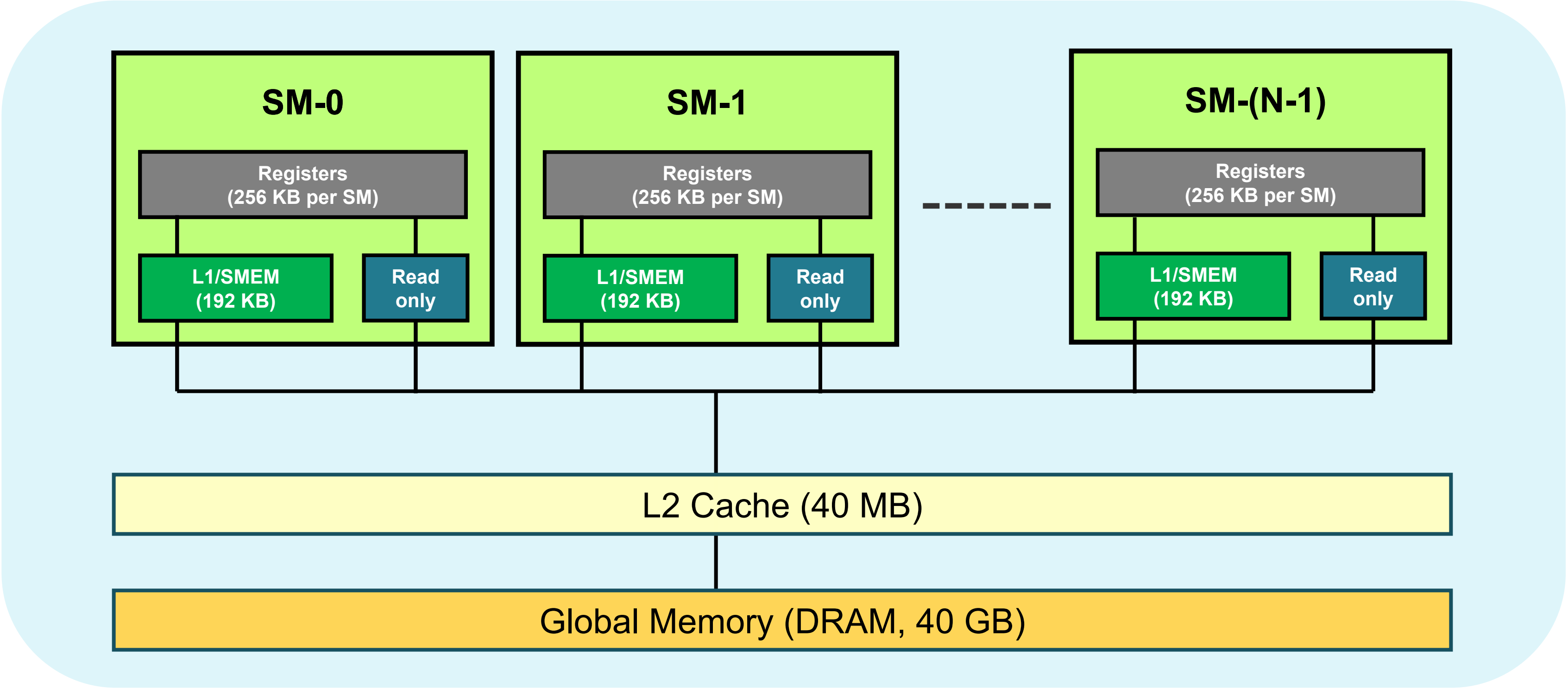
H100 Architecture



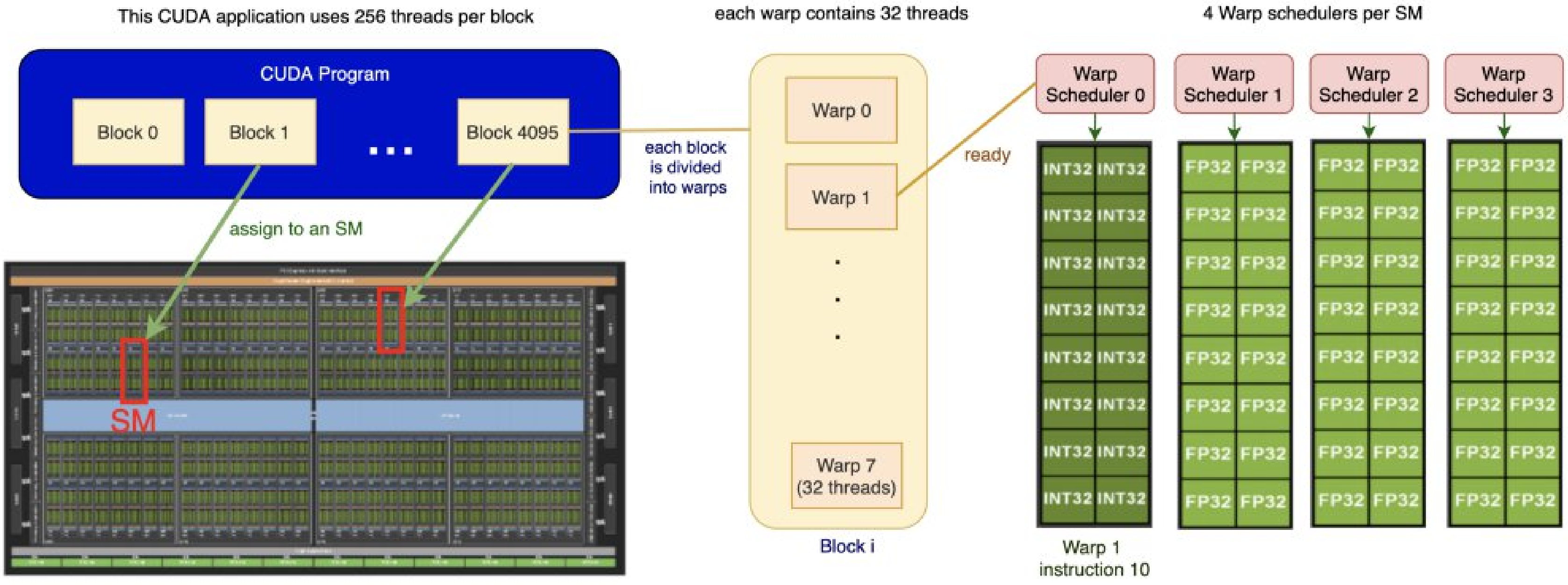
- 8 GPC
- **132** Streaming Multiprocessors (SMs)
- 16896 CUDA Cores
- **528 4eGen** Tensor Cores per full GPU

Source : NVidia

Optimized memory management



CUDA Engineering



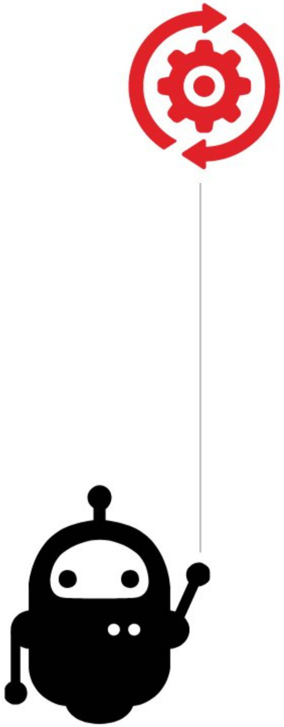
Optimzation :

- Block occupancy
- Streaming dispersion

Advanced Optimization :

- Kernel Fusion to override initialization times

TP1 : Accélération GPU



- Envoyer le calcul sur le GPU
- Test Mémoire

Tensor Cores

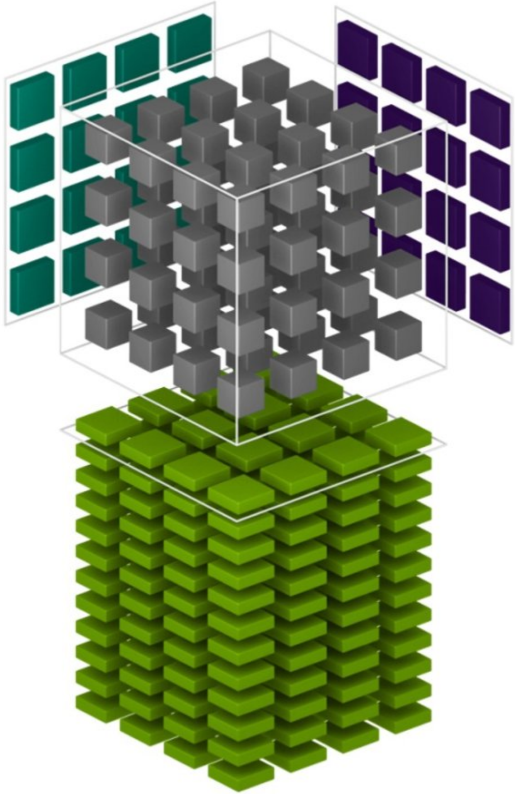
Tensor Cores ◄

Precisions ◄

AMP ◄

Channel last memory format ◄

Tensor Cores



CUDA Core are specialized for **vector computing**.

Tensor Cores are specialized for **matrix calculation**.

$$D = \begin{pmatrix} A_{0,0} & A_{0,1} & A_{0,2} & A_{0,3} \\ A_{1,0} & A_{1,1} & A_{1,2} & A_{1,3} \\ A_{2,0} & A_{2,1} & A_{2,2} & A_{2,3} \\ A_{3,0} & A_{3,1} & A_{3,2} & A_{3,3} \end{pmatrix} \begin{pmatrix} B_{0,0} & B_{0,1} & B_{0,2} & B_{0,3} \\ B_{1,0} & B_{1,1} & B_{1,2} & B_{1,3} \\ B_{2,0} & B_{2,1} & B_{2,2} & B_{2,3} \\ B_{3,0} & B_{3,1} & B_{3,2} & B_{3,3} \end{pmatrix} + \begin{pmatrix} C_{0,0} & C_{0,1} & C_{0,2} & C_{0,3} \\ C_{1,0} & C_{1,1} & C_{1,2} & C_{1,3} \\ C_{2,0} & C_{2,1} & C_{2,2} & C_{2,3} \\ C_{3,0} & C_{3,1} & C_{3,2} & C_{3,3} \end{pmatrix}$$

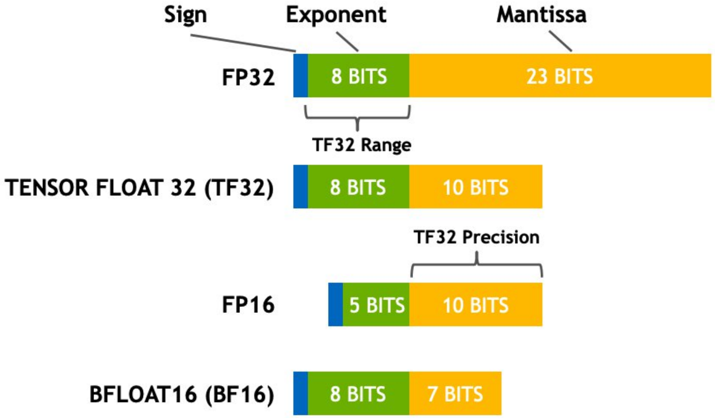
FP16 or FP32 FP16 FP16 FP16 or FP32

Each Tensor Core is capable of processing 64 operations in 1 clock time.

Source : NVidia

Precisions & Tensor Cores

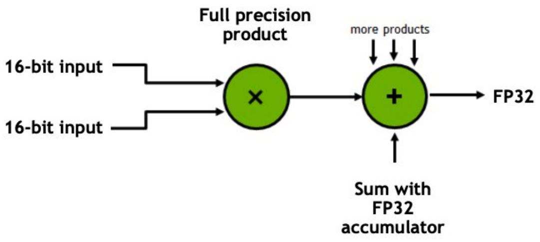
	NVIDIA H100	NVIDIA A100	NVIDIA Volta
Supported Tensor Core Precisions	**FP8**, FP64, TF32, bfloat16, FP16, ...	FP64, TF32, bfloat16, FP16, INT8, INT4, INT1	FP16
Supported CUDA® Core Precisions	FP64, FP32, FP16, bfloat16, INT8	FP64, FP32, FP16, bfloat16, INT8	FP64, FP32, FP16, INT8

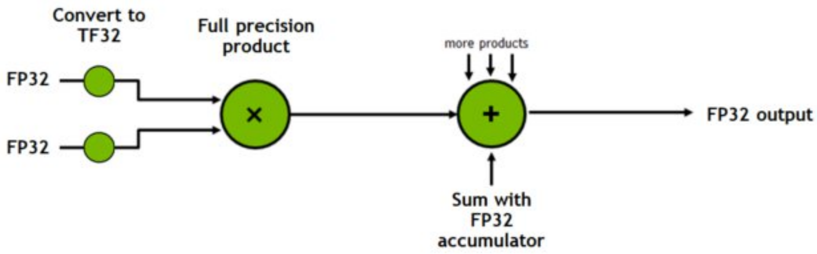


Source : NVidia

Precisions & Tensor Cores

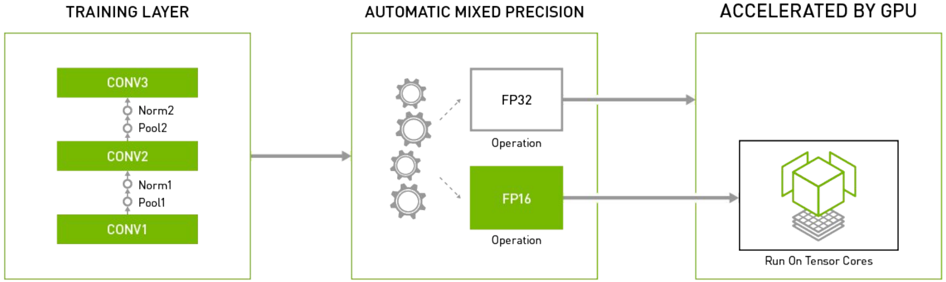
	INPUT OPERANDS	ACCUMULATOR	TOPS	X-factor vs. FFMA	SPARSE TOPS	SPARSE X-factor vs. FFMA
V100	FP32	FP32	15.7	1x	-	-
	FP16	FP32	125	8x	-	-
A100	FP32	FP32	19.5	1x	-	-
	TF32	FP32	156	8x	312	16x
	FP16	FP32	312	16x	624	32x
	BF16	FP32	312	16x	624	32x
	FP16	FP16	312	16x	624	32x
	INT8	INT32	624	32x	1248	64x
	INT4	INT32	1248	64x	2496	128x
	BINARY	INT32	4992	256x	-	-
	IEEE FP64		19.5	1x	-	-

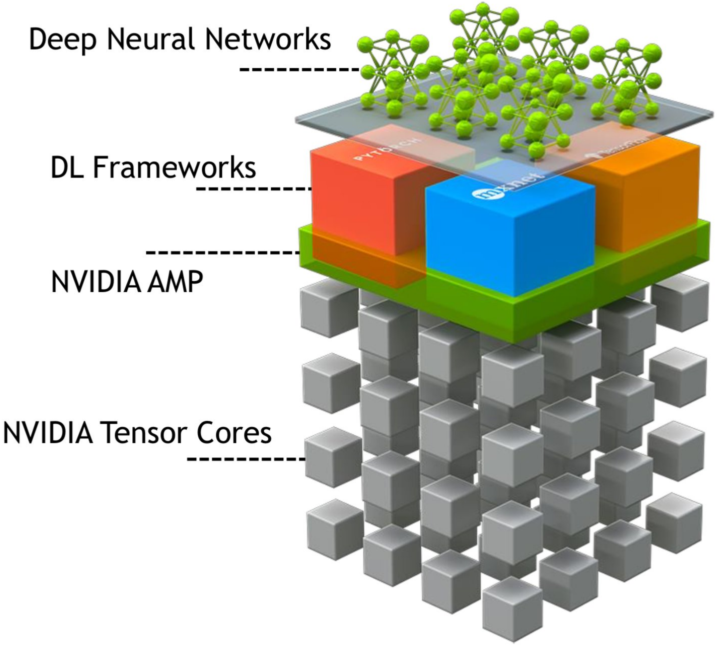




Automatic Mixed Precision

- Automatic Mixed Precision :
  - Necessary with V100 to use Tensor Core
  - The A100s use Tensor Cores with or without MP

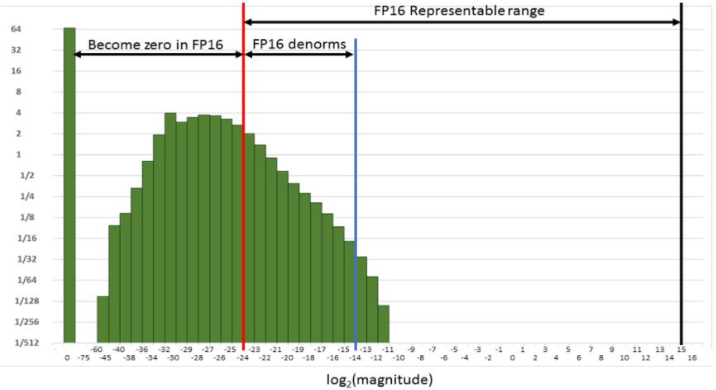




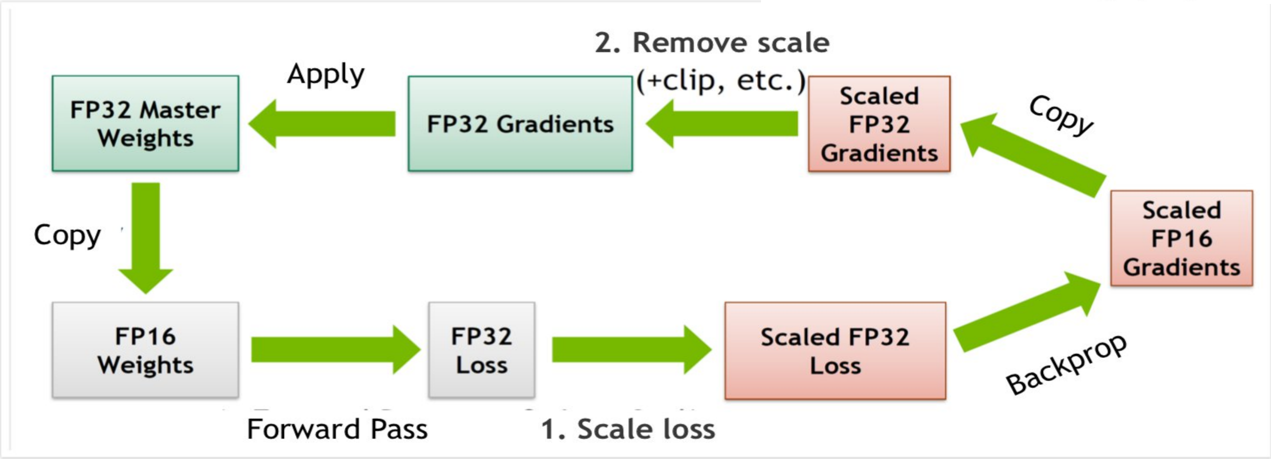
- Pros:
  - **Insignificant** loss of precision for model training (gradient, loss, accuracy)
  - **Reduces memory** footprint
  - **Speeds up** calculations
- 2 steps to code :
  - Transforms eligible layers into FP16
  - Uses scaling to calculate gradients

AMP Scaler

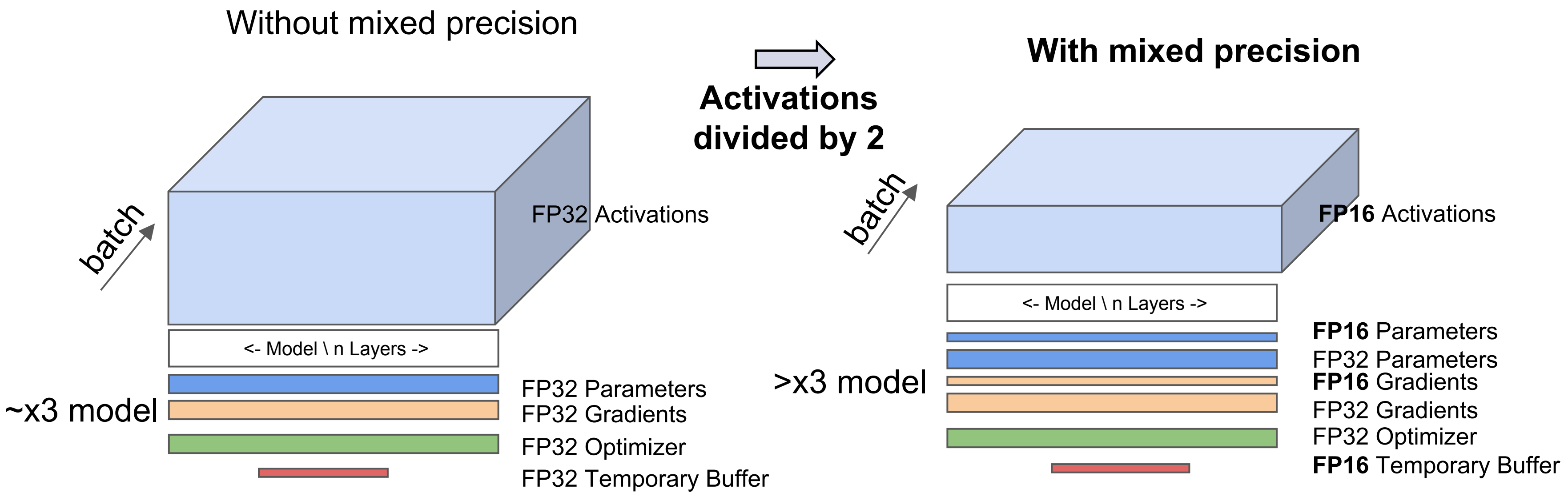
Gradients Distribution



In FP16, values lower than 2^{-24} ($5.96e^{-8}$) are considered 0.



Memory Footprint with Mixed Precision



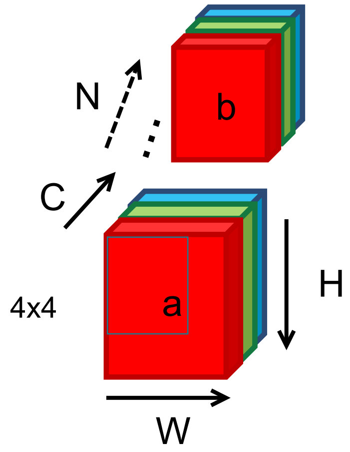
Channel last memory format

batch channel height width

NCHW

.shape()

memory contiguity by default



classic (contiguous) memory storage of NCHW tensor :

.stride()

b 0x: 0 1 2 3 4 5 6 7 8 9 a b c d e f 0 1 2 3 4 5 6 7 8 9 a b c d e f 0 1 2 3 4 5 6 7 8 9 a b c d e f

a 0x: 0 1 2 3 4 5 6 7 8 9 a b c d e f 0 1 2 3 4 5 6 7 8 9 a b c d e f 0 1 2 3 4 5 6 7 8 9 a b c d e f

Channels last memory format orders data differently:

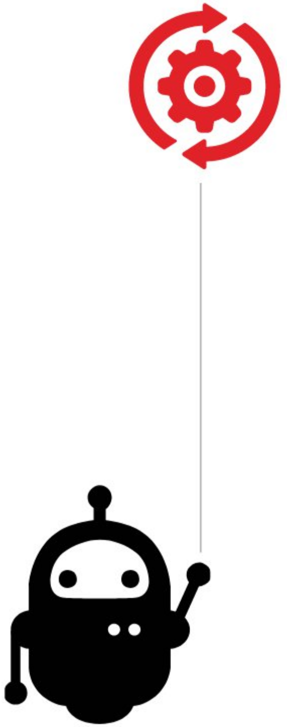
.stride()

b 0x: 0 0 0 1 1 1 2 2 2 3 3 3 4 4 4 5 5 5 6 6 6 7 7 7 8 8 8 9 9 9 a a a b b b c c c d d d e e e f f f

a 0x: 0 0 0 1 1 1 2 2 2 3 3 3 4 4 4 5 5 5 6 6 6 7 7 7 8 8 8 9 9 9 a a a b b b c c c d d d e e e f f f

3x3 Convolution filter

TP2&3 : Automatic Mixed Precision



- Activer l’Automatic Mixed Precision
- Test Mémoire
- Activer le channel last memory format