

Introduction to Hydra in the Lightning-Hydra-Template

What is Hydra?

- Hydra is a **configuration framework** developed by **Facebook Research**.
- Used in the **Lightning-Hydra-Template** to:
 - Manage **hierarchical configurations**.
 - Modify settings dynamically via YAML or CLI.
- Hydra dynamically instantiates target classes (via the `_target_` key) in `train.py` using config files.

Configuration Structure

configs/

├── common # Folder with many configs (hydra, trainer, and paths in config_base.yaml)

├── data/ # Datasets

├── experiment/ # Experiments

├── model/ # Models

— train.yaml # Main training config

— eval.yaml # Main evaluation config

The main file is `configs/train.yaml`, which defines the default training configuration.

`train.yaml:5-10`

```
# @package _global_  
  
# specify here default configuration  
# order of defaults determines the order in which configs override each other  
defaults:  
  - _self_  
  - common/config_base  
  - data: mnist  
  - model: mnist  
  - /common/callbacks@callbacks: default # Notation explicite  
  - /common/logger@logger: mlflow # set logger here or use command line (e.g. `python train.py logger=tensorboard`)  
  
# experiment configs allow for version control of specific hyperparameters  
# e.g. best hyperparameters for given model and datamodule  
  - experiment: null  
  
...
```

The script `train.py` loads the default training configuration defined in `configs/train.yaml`, which itself includes all paths, trainer settings, model, data, callbacks, and logger.

To launch a training run with the default configuration, simply run:

```
python src/train.py
```

We will load `configs/common/config_base.yaml`, which contains the trainer parameters and paths.

```
# ----- PATHS -----  
paths:  
  root_dir: ${oc.env:PROJECT_ROOT} # Root directory of the project, set via environment variable  
  data_dir: ${paths.root_dir}/data/ # Directory where the datasets are stored  
  log_dir: ${paths.root_dir}/logs/ # Directory where logs will be saved  
  output_dir: ${hydra:runtime.output_dir} # Output directory generated by Hydra for each run  
  work_dir: ${hydra:runtime.cwd} # Current working directory where the job is launched  
  
# ----- TRAINER -----  
trainer:  
  _target_: lightning.pytorch.trainer.Trainer #target class for trainer  
  default_root_dir: ${paths.output_dir}  
  min_epochs: 1  
  max_epochs: 10  
  accelerator: gpu  
  ...
```

We also load the datamodule (in this case, MNIST): `configs/data/mnist.yaml`

```
_target_: src.data.mnist_datamodule.MNISTDataModule #target class for datamodule
data_dir: ${paths.data_dir}
batch_size: 128 # Needs to be divisible by the number of devices (e.g., if in a distributed setup)
train_val_test_split: [55_000, 5_000, 10_000]
num_workers: 0
pin_memory: False
```

We load our model (MNIST): `configs/model/mnist.yaml`

```
_target_: src.models.mnist_module.MNISTLitModule #target class for the model

optimizer:
  _target_: torch.optim.Adam #target class for the optimizer
  _partial_: true
  lr: 0.001
  weight_decay: 0.0

scheduler:
  _target_: torch.optim.lr_scheduler.ReduceLROnPlateau #target class for the scheduler
  _partial_: true
  mode: min
  factor: 0.1
  patience: 10

net:
  _target_: src.models.components.simple_dense_net.SimpleDenseNet #target class selfmade for the net
  input_size: 784
  lin1_size: 64
  lin2_size: 128
  lin3_size: 64
  output_size: 10

# compile model for faster training with pytorch 2.0
compile: false

# learning rate scheduler update interval: "epoch" or "step"
lr_interval: epoch
```


We also load the callbacks: `configs/common/callbacks/default.yaml`

```
defaults:
  - model_checkpoint
  - early_stopping
  - model_summary
  - rich_progress_bar
  - callback_images
  - _self_

...
```

This file lists the callbacks we want to use by default.

Finally, we load the logger from `configs/common/logger` — here are the available options:

✓ logger

- ! `many_loggers.yaml`

- ! `mlflow.yaml`

- ! `tensorboard.yaml`

How to Modify Configuration Variables

You can change values in several ways:

1. Direct Modification in YAML Files

Change values directly in YAML files. For example, modify the number of max epochs in `configs/common/config_base.yaml`:

```
trainer:  
  _target_: lightning.pytorch.trainer.Trainer  
  default_root_dir: ${paths.output_dir}  
  min_epochs: 1  
  max_epochs: 10  
  accelerator: gpu  
  devices: 1  
  check_val_every_n_epoch: 1  
  deterministic: false
```

2. Override via Command Line

Change one or more parameters without modifying YAML files:

```
python src/train.py model.optimizer.lr=0.001 data.batch_size=64
```

3. Alternative Configurations

Use a different model or logger:

```
python src/train.py model=autre_modele common/logger@logger=nom_logger
```

IMPORTANT: To override logger or callbacks, use the following syntax:

```
python src/train.py common/logger@logger=nom_logger
```

```
python src/train.py common/callbacks@callbacks=nom_callbacks
```

Experiment Configurations

Goal:

Define a full experiment configuration in a single YAML file
(to avoid manually changing all individual config files):

- Model
- Dataset
- Callbacks
- Number of epochs
- Seed

Example: configs/experiment/mon_experience.yaml

```
# @package _global_
defaults:
  - override /data: mnist
  - override /model: mnist
  - override /common/callbacks@callbacks: default
  - override /common/logger@logger: mlflow

# Paramètres spécifiques à cette expérience
tags: ["mnist"]

# Surcharger des paramètres spécifiques
trainer:
  max_epochs: 10
  min_epochs: 5
  gradient_clip_val: 0.5
  accelerator: cpu
  devices: 1

model:
  optimizer:
    lr: 0.002
  net:
    lin1_size: 128
    lin2_size: 256
    lin3_size: 64

data:
  batch_size: 64
```

Then launch your training with:

```
python src/train.py experiment=mon_experience
```

This will load:

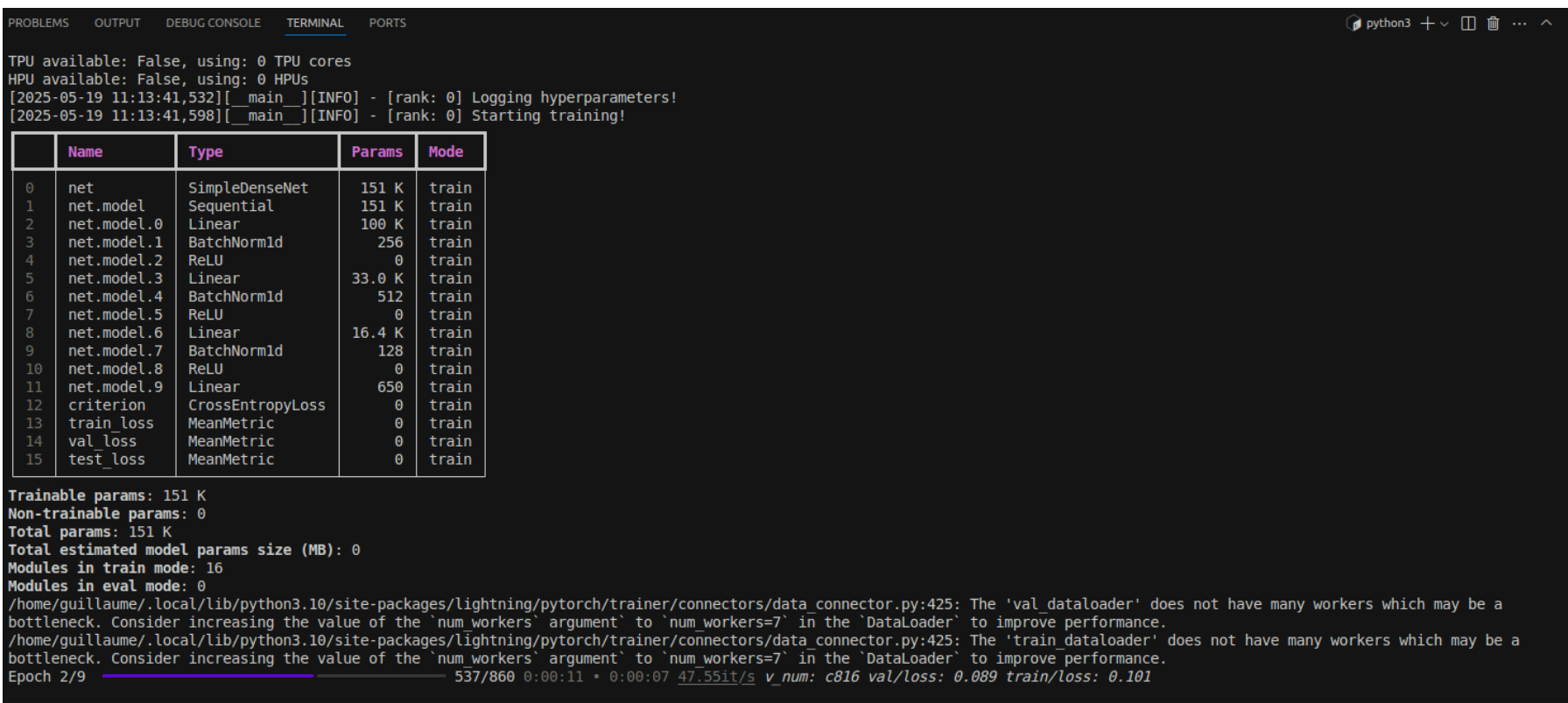
- MNIST dataset
- MNIST model
- Default callbacks
- Seed 12345
- 20 epochs
- Learning rate of 0.002

So, before overriding parameters in an experiment, refer to the original config file to check the variable structure.

✓ Final Check

If everything went well...

You should see this image generated at the start of training in the terminal:



```
PROBLEMS OUTPUT DEBUG CONSOLE TERMINAL PORTS
python3 + - - - - x

TPU available: False, using: 0 TPU cores
HPU available: False, using: 0 HPUs
[2025-05-19 11:13:41,532][__main__][INFO] - [rank: 0] Logging hyperparameters!
[2025-05-19 11:13:41,598][__main__][INFO] - [rank: 0] Starting training!
```

	Name	Type	Params	Mode
0	net	SimpleDenseNet	151 K	train
1	net.model	Sequential	151 K	train
2	net.model.0	Linear	100 K	train
3	net.model.1	BatchNorm1d	256	train
4	net.model.2	ReLU	0	train
5	net.model.3	Linear	33.0 K	train
6	net.model.4	BatchNorm1d	512	train
7	net.model.5	ReLU	0	train
8	net.model.6	Linear	16.4 K	train
9	net.model.7	BatchNorm1d	128	train
10	net.model.8	ReLU	0	train
11	net.model.9	Linear	650	train
12	criterion	CrossEntropyLoss	0	train
13	train_loss	MeanMetric	0	train
14	val_loss	MeanMetric	0	train
15	test_loss	MeanMetric	0	train

```
Trainable params: 151 K
Non-trainable params: 0
Total params: 151 K
Total estimated model params size (MB): 0
Modules in train mode: 16
Modules in eval mode: 0
/home/guillaume/.local/lib/python3.10/site-packages/lightning/pytorch/trainer/connectors/data_connector.py:425: The 'val_dataloader' does not have many workers which may be a
bottleneck. Consider increasing the value of the 'num_workers' argument to 'num_workers=7' in the 'DataLoader' to improve performance.
/home/guillaume/.local/lib/python3.10/site-packages/lightning/pytorch/trainer/connectors/data_connector.py:425: The 'train_dataloader' does not have many workers which may be a
bottleneck. Consider increasing the value of the 'num_workers' argument to 'num_workers=7' in the 'DataLoader' to improve performance.
Epoch 2/9 537/860 0:00:11 • 0:00:07 47.55it/s v_num: c816 val/loss: 0.089 train/loss: 0.101
```