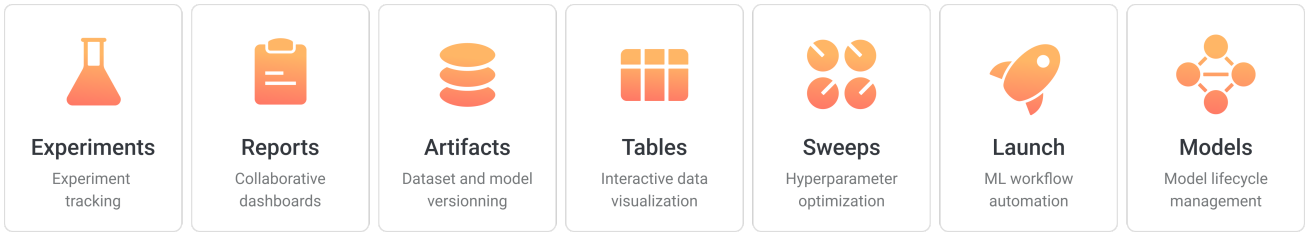
PyTorch

Use Weights & Biases for machine learning experiment tracking, dataset versioning, and project collaboration.

Try in a Colab Notebook here →



What this notebook covers:

We show you how to integrate Weights & Biases with your PyTorch code to add experiment tracking to your pipeline.

The resulting interactive W&B dashboard will look like:

In pseudocode, what we'll do is:

```
# import the library
import wandb

# start a new experiment
wandb.init(project="new-sota-model")

# capture a dictionary of hyperparameters with config
wandb.config = {"learning_rate": 0.001, "epochs": 100, "batch_size": 128}

# set up model and data
model, dataloader = get_model(), get_data()

# optional: track gradients
wandb.watch(model)

for batch in dataloader:
  metrics = model.training_step()
  # log metrics inside your training loop to visualize model performance
```

```
  wandb.log(metrics)

# optional: save model at the end
model.to_onnx()
wandb.save("model.onnx")
```

Follow along with a video tutorial!

Note: Sections starting with *Step* are all you need to integrate W&B in an existing pipeline. The rest just loads data and defines a model.

🚀 Install, Import, and Log In

```
import os
import random

import numpy as np
import torch
import torch.nn as nn
import torchvision
import torchvision.transforms as transforms
from tqdm.auto import tqdm

# Ensure deterministic behavior
torch.backends.cudnn.deterministic = True
random.seed(hash("setting random seeds") % 2**32 - 1)
np.random.seed(hash("improves reproducibility") % 2**32 - 1)
torch.manual_seed(hash("by removing stochasticity") % 2**32 - 1)
torch.cuda.manual_seed_all(hash("so runs are repeatable") % 2**32 - 1)

# Device configuration
device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")

# remove slow mirror from list of MNIST mirrors
torchvision.datasets.MNIST.mirrors = [mirror for mirror in
torchvision.datasets.MNIST.mirrors
                                      if not mirror.startswith("http://yann.lecun.com")]
```

0️⃣ Step 0: Install W&B

To get started, we'll need to get the library. `wandb` is easily installed using `pip`.

```
!pip install wandb onnx -Uq
```

1️⃣ Step 1: Import W&B and Login

In order to log data to our web service, you'll need to log in.

If this is your first time using W&B, you'll need to sign up for a free account at the link that appears.

```
import wandb

wandb.login()
```

👩‍🔬 Define the Experiment and Pipeline

2️⃣ Step 2: Track metadata and hyperparameters with `wandb.init`

Programmatically, the first thing we do is define our experiment: what are the hyperparameters? what metadata is associated with this run?

It's a pretty common workflow to store this information in a `config` dictionary (or similar object) and then access it as needed.

For this example, we're only letting a few hyperparameters vary and hand-coding the rest. But any part of your model can be part of the `config`!

We also include some metadata: we're using the MNIST dataset and a convolutional architecture. If we later work with, say, fully-connected architectures on CIFAR in the same project, this will help us separate our runs.

```
config = dict(
    epochs=5,
    classes=10,
    kernels=[16, 32],
    batch_size=128,
    learning_rate=0.005,
    dataset="MNIST",
    architecture="CNN")
```

Now, let's define the overall pipeline, which is pretty typical for model-training:

1. we first `make` a model, plus associated data and optimizer, then
2. we `train` the model accordingly and finally
3. `test` it to see how training went.

We'll implement these functions below.

```
def model_pipeline(hyperparameters):

    # tell wandb to get started
    with wandb.init(project="pytorch-demo", config=hyperparameters):
      # access all HPs through wandb.config, so logging matches execution!
      config = wandb.config
```

```
        # make the model, data, and optimization problem
        model, train_loader, test_loader, criterion, optimizer = make(config)
        print(model)

        # and use them to train the model
        train(model, train_loader, criterion, optimizer, config)

        # and test its final performance
        test(model, test_loader)

    return model
```

The only difference here from a standard pipeline is that it all occurs inside the context of `wandb.init`. Calling this function sets up a line of communication between your code and our servers.

Passing the `config` dictionary to `wandb.init` immediately logs all that information to us, so you'll always know what hyperparameter values you set your experiment to use.

To ensure the values you chose and logged are always the ones that get used in your model, we recommend using the `wandb.config` copy of your object. Check the definition of `make` below to see some examples.

> *Side Note*: We take care to run our code in separate processes, so that any issues on our end (e.g. a giant sea monster attacks our data centers) don't crash your code. Once the issue is resolved (e.g. the Kraken returns to the deep) you can log the data with `wandb sync`.

```
def make(config):
    # Make the data
    train, test = get_data(train=True), get_data(train=False)
    train_loader = make_loader(train, batch_size=config.batch_size)
    test_loader = make_loader(test, batch_size=config.batch_size)

    # Make the model
    model = ConvNet(config.kernels, config.classes).to(device)

    # Make the loss and optimizer
    criterion = nn.CrossEntropyLoss()
    optimizer = torch.optim.Adam(
        model.parameters(), lr=config.learning_rate)

    return model, train_loader, test_loader, criterion, optimizer
```

📡 Define the Data Loading and Model

Now, we need to specify how the data is loaded and what the model looks like.

This part is very important, but it's no different from what it would be without `wandb`, so we won't dwell on it.

```
def get_data(slice=5, train=True):
    full_dataset = torchvision.datasets.MNIST(root=".",
                                              train=train,
                                              transform=transforms.ToTensor(),
                                              download=True)
    #  equiv to slicing with [::slice]
    sub_dataset = torch.utils.data.Subset(
      full_dataset, indices=range(0, len(full_dataset), slice))

    return sub_dataset


def make_loader(dataset, batch_size):
    loader = torch.utils.data.DataLoader(dataset=dataset,
                                         batch_size=batch_size,
                                         shuffle=True,
                                         pin_memory=True, num_workers=2)
    return loader
```

Defining the model is normally the fun part!

But nothing changes with `wandb`, so we're gonna stick with a standard ConvNet architecture.

Don't be afraid to mess around with this and try some experiments -- all your results will be logged on wandb.ai!

```
# Conventional and convolutional neural network

class ConvNet(nn.Module):
    def __init__(self, kernels, classes=10):
        super(ConvNet, self).__init__()

        self.layer1 = nn.Sequential(
            nn.Conv2d(1, kernels[0], kernel_size=5, stride=1, padding=2),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2))
        self.layer2 = nn.Sequential(
            nn.Conv2d(16, kernels[1], kernel_size=5, stride=1, padding=2),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2))
        self.fc = nn.Linear(7 * 7 * kernels[-1], classes)

    def forward(self, x):
        out = self.layer1(x)
        out = self.layer2(out)
        out = out.reshape(out.size(0), -1)
```

```
        out = self.fc(out)
        return out
```

👟 Define Training Logic

Moving on in our `model_pipeline`, it's time to specify how we `train`.

Two `wandb` functions come into play here: `watch` and `log`.

3️⃣ Step 3. Track gradients with `wandb.watch` and everything else with `wandb.log`

`wandb.watch` will log the gradients and the parameters of your model, every `log_freq` steps of training.

All you need to do is call it before you start training.

The rest of the training code remains the same: we iterate over epochs and batches, running forward and backward passes and applying our `optimizer`.

```
def train(model, loader, criterion, optimizer, config):
    # Tell wandb to watch what the model gets up to: gradients, weights, and more!
    wandb.watch(model, criterion, log="all", log_freq=10)

    # Run training and track with wandb
    total_batches = len(loader) * config.epochs
    example_ct = 0  # number of examples seen
    batch_ct = 0
    for epoch in tqdm(range(config.epochs)):
        for _, (images, labels) in enumerate(loader):

            loss = train_batch(images, labels, model, optimizer, criterion)
            example_ct +=  len(images)
            batch_ct += 1

            # Report metrics every 25th batch
            if ((batch_ct + 1) % 25) == 0:
                train_log(loss, example_ct, epoch)


def train_batch(images, labels, model, optimizer, criterion):
    images, labels = images.to(device), labels.to(device)

    # Forward pass ➡
    outputs = model(images)
    loss = criterion(outputs, labels)

    # Backward pass ⬅
    optimizer.zero_grad()
    loss.backward()

    # Step with optimizer
```

```
    optimizer.step()

    return loss
```

The only difference is in the logging code: where previously you might have reported metrics by printing to the terminal, now you pass the same information to `wandb.log`.

`wandb.log` expects a dictionary with strings as keys. These strings identify the objects being logged, which make up the values. You can also optionally log which `step` of training you're on.

> *Side Note*: I like to use the number of examples the model has seen, since this makes for easier comparison across batch sizes, but you can use raw steps or batch count. For longer training runs, it can also make sense to log by `epoch`.

```
def train_log(loss, example_ct, epoch):
    # Where the magic happens
    wandb.log({"epoch": epoch, "loss": loss}, step=example_ct)
    print(f"Loss after {str(example_ct).zfill(5)} examples: {loss:.3f}")
```

🧪 Define Testing Logic

Once the model is done training, we want to test it: run it against some fresh data from production, perhaps, or apply it to some hand-curated "hard examples".

4️⃣ Optional Step 4: Call `wandb.save`

This is also a great time to save the model's architecture and final parameters to disk. For maximum compatibility, we'll `export` our model in the Open Neural Network eXchange (ONNX) format.

Passing that filename to `wandb.save` ensures that the model parameters are saved to W&B's servers: no more losing track of which `.h5` or `.pb` corresponds to which training runs!

For more advanced `wandb` features for storing, versioning, and distributing models, check out our Artifacts tools.

```
def test(model, test_loader):
    model.eval()

    # Run the model on some test examples
    with torch.no_grad():
        correct, total = 0, 0
        for images, labels in test_loader:
            images, labels = images.to(device), labels.to(device)
            outputs = model(images)
            _, predicted = torch.max(outputs.data, 1)
            total += labels.size(0)
            correct += (predicted == labels).sum().item()
```

```
        print(f"Accuracy of the model on the {total} " +
              f"test images: {correct / total:%}")

        wandb.log({"test_accuracy": correct / total})

    # Save the model in the exchangeable ONNX format
    torch.onnx.export(model, images, "model.onnx")
    wandb.save("model.onnx")
```

🏃 Run training and watch your metrics live on wandb.ai!

Now that we've defined the whole pipeline and slipped in those few lines of W&B code, we're ready to run our fully-tracked experiment.

We'll report a few links to you: our documentation, the Project page, which organizes all the runs in a project, and the Run page, where this run's results will be stored.

Navigate to the Run page and check out these tabs:

1. **Charts**, where the model gradients, parameter values, and loss are logged throughout training
2. **System**, which contains a variety of system metrics, including Disk I/O utilization, CPU and GPU metrics (watch that temperature soar 🔥), and more
3. **Logs**, which has a copy of anything pushed to standard out during training
4. **Files**, where, once training is complete, you can click on the `model.onnx` to view our network with the Netron model viewer.

Once the run in finished (i.e. the `with wandb.init` block is exited), we'll also print a summary of the results in the cell output.

```
# Build, train and analyze the model with the pipeline
model = model_pipeline(config)
```

🧹 Test Hyperparameters with Sweeps

We only looked at a single set of hyperparameters in this example. But an important part of most ML workflows is iterating over a number of hyperparameters.

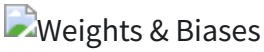
You can use Weights & Biases Sweeps to automate hyperparameter testing and explore the space of possible models and optimization strategies.

Check out Hyperparameter Optimization in PyTorch using W&B Sweeps $\rightarrow$

Running a hyperparameter sweep with Weights & Biases is very easy. There are just 3 simple steps:

1. **Define the sweep:** We do this by creating a dictionary or a YAML file that specifies the parameters to search through, the search strategy, the optimization metric et all.
2. **Initialize the sweep:** `sweep_id = wandb.sweep(sweep_config)`
3. **Run the sweep agent:** `wandb.agent(sweep_id, function=train)`

And voila! That's all there is to running a hyperparameter sweep!



🖼️ Example Gallery

See examples of projects tracked and visualized with W&B in our Gallery →

🤓 Advanced Setup

1. Environment variables: Set API keys in environment variables so you can run training on a managed cluster.
2. Offline mode: Use `dryrun` mode to train offline and sync results later.
3. On-prem: Install W&B in a private cloud or air-gapped servers in your own infrastructure. We have local installations for everyone from academics to enterprise teams.
4. Sweeps: Set up hyperparameter search quickly with our lightweight tool for tuning.