Track models and datasets

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In this notebook, we'll show you how to track your ML experiment pipelines using W&B Artifacts.

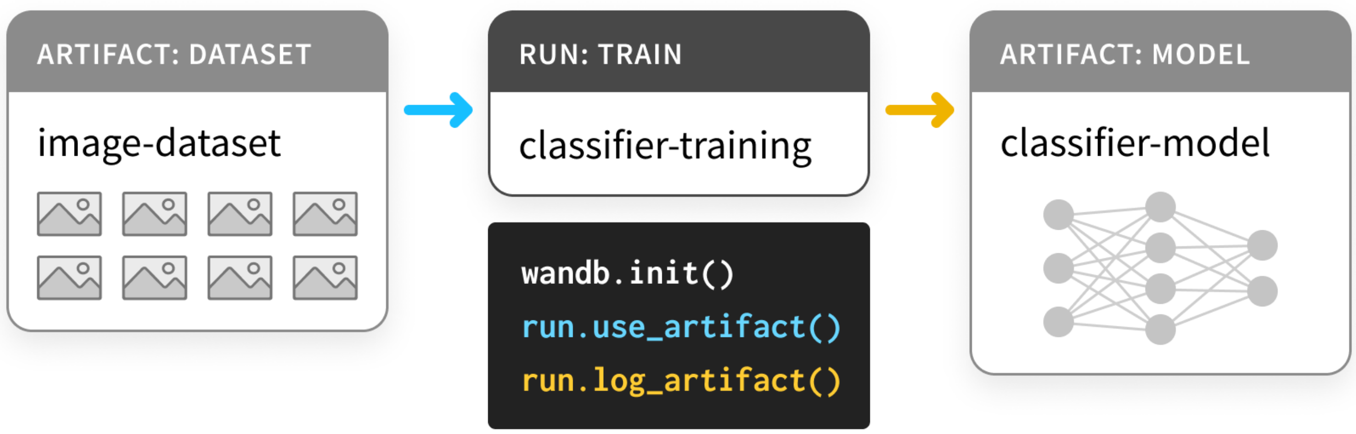
Follow along with a video tutorial!

🤔 What are Artifacts and Why Should I Care?

An "artifact", like a Greek amphora 🏺, is a produced object -- the output of a process. In ML, the most important artifacts are *datasets* and *models*.

And, like the Cross of Coronado, these important artifacts belong in a museum! That is, they should be cataloged and organized so that you, your team, and the ML community at large can learn from them. After all, those who don't track training are doomed to repeat it.

Using our Artifacts API, you can log `Artifact`s as outputs of W&B `Run`s or use `Artifact`s as input to `Run`s, as in this diagram, where a training run takes in a dataset and produces a model.



Since one run can use another's output as an input, Artifacts and Runs together form a directed graph -- actually, a bipartite DAG! -- with nodes for `Artifact`s and `Run`s and arrows connecting `Run`s to the `Artifact`s they consume or produce.

0️⃣ Install and Import

Artifacts are part of our Python library, starting with version `0.9.2`.

Like most parts of the ML Python stack, it's available via `pip`.

```
# Compatible with wandb version 0.9.2+
!pip install wandb -qqq
```

```
!apt install tree
```

```
import os
import wandb
```

1 Log a Dataset

First, let's define some Artifacts.

This example is based off of this PyTorch "Basic MNIST Example", but could just as easily have been done in TensorFlow, in any other framework, or in pure Python.

We start with the `Dataset`s:

- a `train`ing set, for choosing the parameters,
- a `validation` set, for choosing the hyperparameters,
- a `test`ing set, for evaluating the final model

The first cell below defines these three datasets.

```
import random

import torch
import torchvision
from torch.utils.data import TensorDataset
from tqdm.auto import tqdm

# Ensure deterministic behavior
torch.backends.cudnn.deterministic = True
random.seed(0)
torch.manual_seed(0)
torch.cuda.manual_seed_all(0)

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

# Data parameters
num_classes = 10
input_shape = (1, 28, 28)

# drop 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")]

def load(train_size=50_000):
    """
    # Load the data
```

```
    """

    # the data, split between train and test sets
    train = torchvision.datasets.MNIST("./", train=True, download=True)
    test = torchvision.datasets.MNIST("./", train=False, download=True)
    (x_train, y_train), (x_test, y_test) = (train.data, train.targets), (test.data,
test.targets)

    # split off a validation set for hyperparameter tuning
    x_train, x_val = x_train[:train_size], x_train[train_size:]
    y_train, y_val = y_train[:train_size], y_train[train_size:]

    training_set = TensorDataset(x_train, y_train)
    validation_set = TensorDataset(x_val, y_val)
    test_set = TensorDataset(x_test, y_test)

    datasets = [training_set, validation_set, test_set]

    return datasets
```

This sets up a pattern we'll see repeated in this example: the code to log the data as an Artifact is wrapped around the code for producing that data. In this case, the code for `load`ing the data is separated out from the code for `load_and_log`ging the data.

This is good practice!

In order to log these datasets as Artifacts, we just need to

1. create a `Run` with `wandb.init`, (L4)
2. create an `Artifact` for the dataset (L10), and
3. save and log the associated `file`s (L20, L23).

Check out the example the code cell below and then expand the sections afterwards for more details.

```
def load_and_log():

    # 🚀 start a run, with a type to label it and a project it can call home
    with wandb.init(project="artifacts-example", job_type="load-data") as run:

        datasets = load()  # separate code for loading the datasets
        names = ["training", "validation", "test"]

        # 🏺 create our Artifact
        raw_data = wandb.Artifact(
            "mnist-raw", type="dataset",
            description="Raw MNIST dataset, split into train/val/test",
            metadata={"source": "torchvision.datasets.MNIST",
                      "sizes": [len(dataset) for dataset in datasets]})

        for name, data in zip(names, datasets):
```

```python
        # 🐣 Store a new file in the artifact, and write something into its
contents.
        with raw_data.new_file(name + ".pt", mode="wb") as file:
            x, y = data.tensors
            torch.save((x, y), file)

    # ✍️ Save the artifact to W&B.
    run.log_artifact(raw_data)

load_and_log()
```

🚀 `wandb.init`

When we make the `Run` that's going to produce the `Artifact`s, we need to state which `project` it belongs to.

Depending on your workflow, a project might be as big as `car-that-drives-itself` or as small as `iterative-architecture-experiment-117`.

> **Rule of 👍**: if you can, keep all of the `Run`s that share `Artifact`s inside a single project. This keeps things simple, but don't worry -- `Artifact`s are portable across projects!

To help keep track of all the different kinds of jobs you might run, it's useful to provide a `job_type` when making `Runs`. This keeps the graph of your Artifacts nice and tidy.

> **Rule of 👍**: the `job_type` should be descriptive and correspond to a single step of your pipeline. Here, we separate out `load`ing data from `preprocess`ing data.

🏺 `wandb.Artifact`

To log something as an `Artifact`, we have to first make an `Artifact` object.

Every `Artifact` has a `name` -- that's what the first argument sets.

> **Rule of 👍**: the `name` should be descriptive, but easy to remember and type -- we like to use names that are hyphen-separated and correspond to variable names in the code.

It also has a `type`. Just like `job_type`s for `Run`s, this is used for organizing the graph of `Run`s and `Artifact`s.

> **Rule of 👍**: the `type` should be simple: more like `dataset` or `model` than `mnist-data-YYYYMMDD`.

You can also attach a `description` and some `metadata`, as a dictionary. The `metadata` just needs to be serializable to JSON.

> **Rule of 👍**: the `metadata` should be as descriptive as possible.

🐣 `artifact.new_file` and ✍️ `run.log_artifact`

Once we've made an `Artifact` object, we need to add files to it.

You read that right: *files* with an *s*. `Artifact`s are structured like directories, with files and sub-directories.

> **Rule of 👍**: whenever it makes sense to do so, split the contents of an `Artifact` up into multiple files. This will help if it comes time to scale!

We use the `new_file` method to simultaneously write the file and attach it to the `Artifact`. Below, we'll use the `add_file` method, which separates those two steps.

Once we've added all of our files, we need to `log_artifact` to wandb.ai.

You'll notice some URLs appeared in the output, including one for the Run page. That's where you can view the results of the `Run`, including any `Artifact`s that got logged.

We'll see some examples that make better use of the other components of the Run page below.

2️⃣ Use a Logged Dataset Artifact

`Artifact`s in W&B, unlike artifacts in museums, are designed to be *used*, not just stored.

Let's see what that looks like.

The cell below defines a pipeline step that takes in a raw dataset and uses it to produce a `preprocess`ed dataset: `normalize`d and shaped correctly.

Notice again that we split out the meat of the code, `preprocess`, from the code that interfaces with `wandb`.

```
def preprocess(dataset, normalize=True, expand_dims=True):
    """
    ## Prepare the data
    """
    x, y = dataset.tensors

    if normalize:
        # Scale images to the [0, 1] range
        x = x.type(torch.float32) / 255

    if expand_dims:
        # Make sure images have shape (1, 28, 28)
        x = torch.unsqueeze(x, 1)

    return TensorDataset(x, y)
```

Now for the code that instruments this `preprocess` step with `wandb.Artifact` logging.

Note that the example below both `use`s an `Artifact`, which is new, and `log`s it, which is the same as the last step. `Artifact`s are both the inputs and the outputs of `Run`s!

We use a new `job_type`, `preprocess-data`, to make it clear that this is a different kind of job from the previous one.

```
def preprocess_and_log(steps):

    with wandb.init(project="artifacts-example", job_type="preprocess-data") as run:

        processed_data = wandb.Artifact(
            "mnist-preprocess", type="dataset",
            description="Preprocessed MNIST dataset",
            metadata=steps)

        # ✔️ declare which artifact we'll be using
        raw_data_artifact = run.use_artifact('mnist-raw:latest')

        # 📥 if need be, download the artifact
        raw_dataset = raw_data_artifact.download()

        for split in ["training", "validation", "test"]:
            raw_split = read(raw_dataset, split)
            processed_dataset = preprocess(raw_split, **steps)

            with processed_data.new_file(split + ".pt", mode="wb") as file:
                x, y = processed_dataset.tensors
                torch.save((x, y), file)

        run.log_artifact(processed_data)


def read(data_dir, split):
    filename = split + ".pt"
    x, y = torch.load(os.path.join(data_dir, filename))

    return TensorDataset(x, y)
```

One thing to notice here is that the `steps` of the preprocessing are saved with the `preprocessed_data` as `metadata`.

If you're trying to make your experiments reproducible, capturing lots of metadata is a good idea!

Also, even though our dataset is a "`large artifact`", the `download` step is done in much less than a second.

Expand the markdown cell below for details.

```
steps = {"normalize": True,
         "expand_dims": True}

preprocess_and_log(steps)
```

✔️ `run.use_artifact`

These steps are simpler. The consumer just needs to know the `name` of the `Artifact`, plus a bit more.

That "bit more" is the `alias` of the particular version of the `Artifact` you want.

By default, the last version to be uploaded is tagged `latest`. Otherwise, you can pick older versions with `v0`/`v1`, etc., or you can provide your own aliases, like `best` or `jit-script`. Just like Docker Hub tags, aliases are separated from names with `:`, so the `Artifact` we want is `mnist-raw:latest`.

> **Rule of 👍**: Keep aliases short and sweet. Use custom `alias`es like `latest` or `best` when you want an `Artifact` that satisifies some property

📥 `artifact.download`

Now, you may be worrying about the `download` call. If we download another copy, won't that double the burden on memory?

Don't worry friend. Before we actually download anything, we check to see if the right version is available locally. This uses the same technology that underlies torrenting and version control with `git`: hashing.

As `Artifact`s are created and logged, a folder called `artifacts` in the working directory will start to fill with sub-directories, one for each `Artifact`. Check out its contents with `!tree artifacts`:

```
!tree artifacts
```

🌐 The Artifacts page on wandb.ai

Now that we've logged and used an `Artifact`, let's check out the Artifacts tab on the Run page.

Navigate to the Run page URL from the `wandb` output and select the "Artifacts" tab from the left sidebar (it's the one with the database icon, which looks like three hockey pucks stacked on top of one another).

Click a row in either the "Input Artifacts" table or in the "Output Artifacts" table, then check out the tabs ("Overview", "Metadata") to see everything logged about the `Artifact`.

We particularly like the "Graph View". By default, it shows a graph with the `type`s of `Artifact`s and the `job_type`s of `Run` as the two types of nodes, with arrows to represent consumption and production.

3️⃣ Log a Model

That's enough to see how the API for `Artifact`s works, but let's follow this example through to the end of the pipeline so we can see how `Artifact`s can improve your ML workflow.

This first cell here builds a DNN `model` in PyTorch -- a really simple ConvNet.

We'll start by just initializing the `model`, not training it. That way, we can repeat the training while keeping everything else constant.

```
from math import floor

import torch.nn as nn

class ConvNet(nn.Module):
    def __init__(self, hidden_layer_sizes=[32, 64],
                  kernel_sizes=[3],
                  activation="ReLU",
                  pool_sizes=[2],
                  dropout=0.5,
                  num_classes=num_classes,
                  input_shape=input_shape):

        super(ConvNet, self).__init__()

        self.layer1 = nn.Sequential(
              nn.Conv2d(in_channels=input_shape[0], out_channels=hidden_layer_sizes[0],
kernel_size=kernel_sizes[0]),
              getattr(nn, activation)(),
              nn.MaxPool2d(kernel_size=pool_sizes[0])
        )
        self.layer2 = nn.Sequential(
              nn.Conv2d(in_channels=hidden_layer_sizes[0],
out_channels=hidden_layer_sizes[-1], kernel_size=kernel_sizes[-1]),
              getattr(nn, activation)(),
              nn.MaxPool2d(kernel_size=pool_sizes[-1])
        )
        self.layer3 = nn.Sequential(
              nn.Flatten(),
              nn.Dropout(dropout)
        )

        fc_input_dims = floor((input_shape[1] - kernel_sizes[0] + 1) / pool_sizes[0]) #
layer 1 output size
        fc_input_dims = floor((fc_input_dims - kernel_sizes[-1] + 1) / pool_sizes[-1]) #
layer 2 output size
        fc_input_dims = fc_input_dims*fc_input_dims*hidden_layer_sizes[-1] # layer 3
output size

        self.fc = nn.Linear(fc_input_dims, num_classes)

    def forward(self, x):
        x = self.layer1(x)
```

```
        x = self.layer2(x)
        x = self.layer3(x)
        x = self.fc(x)
        return x
```

Here, we're using W&B to track the run, and so using the `wandb.config` object to store all of the hyperparameters.

The `dict`ionary version of that `config` object is a really useful piece of `metadata`, so make sure to include it!

```
def build_model_and_log(config):
    with wandb.init(project="artifacts-example", job_type="initialize", config=config) as run:
        config = wandb.config

        model = ConvNet(**config)

        model_artifact = wandb.Artifact(
            "convnet", type="model",
            description="Simple AlexNet style CNN",
            metadata=dict(config))

        torch.save(model.state_dict(), "initialized_model.pth")
        # ➕ another way to add a file to an Artifact
        model_artifact.add_file("initialized_model.pth")

        wandb.save("initialized_model.pth")

        run.log_artifact(model_artifact)

model_config = {"hidden_layer_sizes": [32, 64],
                "kernel_sizes": [3],
                "activation": "ReLU",
                "pool_sizes": [2],
                "dropout": 0.5,
                "num_classes": 10}

build_model_and_log(model_config)
```

➕ `artifact.add_file`

Instead of simultaneously writing a `new_file` and adding it to the `Artifact`, as in the dataset logging examples, we can also write files in one step (here, `torch.save`) and then `add` them to the `Artifact` in another.

> **Rule of** 👍: use `new_file` when you can, to prevent duplication.

4️⃣ Use a Logged Model Artifact

Just like we could call `use_artifact` on a `dataset`, we can call it on our `initialized_model` to use it in another `Run`.

This time, let's `train` the `model`.

For more details, check out our Colab on instrumenting W&B with PyTorch.

```
import torch.nn.functional as F

def train(model, train_loader, valid_loader, config):
    optimizer = getattr(torch.optim, config.optimizer)(model.parameters())
    model.train()
    example_ct = 0
    for epoch in range(config.epochs):
        for batch_idx, (data, target) in enumerate(train_loader):
            data, target = data.to(device), target.to(device)
            optimizer.zero_grad()
            output = model(data)
            loss = F.cross_entropy(output, target)
            loss.backward()
            optimizer.step()

            example_ct += len(data)

            if batch_idx % config.batch_log_interval == 0:
                print('Train Epoch: {} [{}/{} ({:.0%})]\tLoss: {:.6f}'.format(
                    epoch, batch_idx * len(data), len(train_loader.dataset),
                    batch_idx / len(train_loader), loss.item()))

                train_log(loss, example_ct, epoch)

        # evaluate the model on the validation set at each epoch
        loss, accuracy = test(model, valid_loader)
        test_log(loss, accuracy, example_ct, epoch)


def test(model, test_loader):
    model.eval()
    test_loss = 0
    correct = 0
    with torch.no_grad():
        for data, target in test_loader:
            data, target = data.to(device), target.to(device)
            output = model(data)
            test_loss += F.cross_entropy(output, target, reduction='sum')  # sum up
batch loss
            pred = output.argmax(dim=1, keepdim=True)  # get the index of the max log-
probability
            correct += pred.eq(target.view_as(pred)).sum()

    test_loss /= len(test_loader.dataset)
```

```
    accuracy = 100. * correct / len(test_loader.dataset)

    return test_loss, accuracy


def train_log(loss, example_ct, epoch):
    loss = float(loss)

    # where the magic happens
    wandb.log({"epoch": epoch, "train/loss": loss}, step=example_ct)
    print(f"Loss after " + str(example_ct).zfill(5) + f" examples: {loss:.3f}")


def test_log(loss, accuracy, example_ct, epoch):
    loss = float(loss)
    accuracy = float(accuracy)

    # where the magic happens
    wandb.log({"epoch": epoch, "validation/loss": loss, "validation/accuracy":
accuracy}, step=example_ct)
    print(f"Loss/accuracy after " + str(example_ct).zfill(5) + f" examples:
{loss:.3f}/{accuracy:.3f}")
```

We'll run two separate `Artifact`-producing `Run`s this time.

Once the first finishes `train`ing the `model`, the `second` will consume the `trained-model` `Artifact` by `evaluate`ing its performance on the `test_dataset`.

Also, we'll pull out the 32 examples on which the network gets the most confused -- on which the `categorical_crossentropy` is highest.

This is a good way to diagnose issues with your dataset and your model!

```
def evaluate(model, test_loader):
    """
    ## Evaluate the trained model
    """

    loss, accuracy = test(model, test_loader)
    highest_losses, hardest_examples, true_labels, predictions =
get_hardest_k_examples(model, test_loader.dataset)

    return loss, accuracy, highest_losses, hardest_examples, true_labels, predictions

def get_hardest_k_examples(model, testing_set, k=32):
    model.eval()

    loader = DataLoader(testing_set, 1, shuffle=False)

    # get the losses and predictions for each item in the dataset
    losses = None
```

```
    predictions = None
    with torch.no_grad():
        for data, target in loader:
            data, target = data.to(device), target.to(device)
            output = model(data)
            loss = F.cross_entropy(output, target)
            pred = output.argmax(dim=1, keepdim=True)

            if losses is None:
                losses = loss.view((1, 1))
                predictions = pred
            else:
                losses = torch.cat((losses, loss.view((1, 1))), 0)
                predictions = torch.cat((predictions, pred), 0)

    argsort_loss = torch.argsort(losses, dim=0)

    highest_k_losses = losses[argsort_loss[-k:]]
    hardest_k_examples = testing_set[argsort_loss[-k:]][0]
    true_labels = testing_set[argsort_loss[-k:]][1]
    predicted_labels = predictions[argsort_loss[-k:]]

    return highest_k_losses, hardest_k_examples, true_labels, predicted_labels
```

These logging functions don't add any new `Artifact` features, so we won't comment on them: we're just `use`ing, `download`ing, and `log`ging `Artifact`s.

```
from torch.utils.data import DataLoader

def train_and_log(config):

    with wandb.init(project="artifacts-example", job_type="train", config=config) as 
run:
        config = wandb.config

        data = run.use_artifact('mnist-preprocess:latest')
        data_dir = data.download()

        training_dataset =  read(data_dir, "training")
        validation_dataset = read(data_dir, "validation")

        train_loader = DataLoader(training_dataset, batch_size=config.batch_size)
        validation_loader = DataLoader(validation_dataset, batch_size=config.batch_size)

        model_artifact = run.use_artifact("convnet:latest")
        model_dir = model_artifact.download()
        model_path = os.path.join(model_dir, "initialized_model.pth")
        model_config = model_artifact.metadata
        config.update(model_config)

        model = ConvNet(**model_config)
```

```
        model.load_state_dict(torch.load(model_path))
        model = model.to(device)

        train(model, train_loader, validation_loader, config)

        model_artifact = wandb.Artifact(
            "trained-model", type="model",
            description="Trained NN model",
            metadata=dict(model_config))

        torch.save(model.state_dict(), "trained_model.pth")
        model_artifact.add_file("trained_model.pth")
        wandb.save("trained_model.pth")

        run.log_artifact(model_artifact)

    return model


def evaluate_and_log(config=None):

    with wandb.init(project="artifacts-example", job_type="report", config=config) as
run:
        data = run.use_artifact('mnist-preprocess:latest')
        data_dir = data.download()
        testing_set = read(data_dir, "test")

        test_loader = torch.utils.data.DataLoader(testing_set, batch_size=128,
shuffle=False)

        model_artifact = run.use_artifact("trained-model:latest")
        model_dir = model_artifact.download()
        model_path = os.path.join(model_dir, "trained_model.pth")
        model_config = model_artifact.metadata

        model = ConvNet(**model_config)
        model.load_state_dict(torch.load(model_path))
        model.to(device)

        loss, accuracy, highest_losses, hardest_examples, true_labels, preds =
evaluate(model, test_loader)

        run.summary.update({"loss": loss, "accuracy": accuracy})

        wandb.log({"high-loss-examples":
            [wandb.Image(hard_example, caption=str(int(pred)) + "," +  str(int(label)))
             for hard_example, pred, label in zip(hardest_examples, preds,
true_labels)]})
```

```
train_config = {"batch_size": 128,
                "epochs": 5,
```

```
                "batch_log_interval": 25,
                "optimizer": "Adam"}

model = train_and_log(train_config)
evaluate_and_log()
```

🔁 The Graph View

Notice that we changed the `type` of the `Artifact`: these `Run`s used a `model`, rather than `dataset`. `Run`s that produce `model`s will be separated from those that produce `dataset`s in the graph view on the Artifacts page.

Go check it out! As before, you'll want to head to the Run page, select the "Artifacts" tab from the left sidebar, pick an `Artifact`, and then click the "Graph View" tab.

💣 Exploded Graphs

You may have noticed a button labeled "Explode". Don't click that, as it will set off a small bomb underneath your humble author's desk in the W&B HQ!

Just kidding. It "explodes" the graph in a much gentler way: `Artifact`s and `Run`s become separated at the level of a single instance, rather than a `type`: the nodes are not `dataset` and `load-data`, but `dataset:mnist-raw:v1` and `load-data:sunny-smoke-1`, and so on.

This provides total insight into your pipeline, with logged metrics, metadata, and more all at your fingertips -- you're only limited by what you choose to log with us.

What's next?

The next tutorial, you will learn how to communicate changes to your models and manage the model development lifecycle with W&B Models:

👉 Track Model Development Lifecycle