Using the PyTorch C++ Frontend

The PyTorch C++ frontend is a pure C++ interface to the PyTorch machine learning framework. While the primary interface to PyTorch naturally is Python, this Python API sits atop a substantial C++ codebase providing foundational data structures and functionality such as tensors and automatic differentiation. The C++ frontend exposes a pure C++11 API that extends this underlying C++ codebase with tools required for machine learning training and inference. This includes a built-in collection of common components for neural network modeling; an API to extend this collection with custom modules; a library of popular optimization algorithms such as stochastic gradient descent; a parallel data loader with an API to define and load datasets; serialization routines and more.

This tutorial will walk you through an end-to-end example of training a model with the C++ frontend. Concretely, we will be training a DCGAN – a kind of generative model – to generate images of MNIST digits. While conceptually a simple example, it should be enough to give you a whirlwind overview of the PyTorch C++ frontend and wet your appetite for training more complex models. We will begin with some motivating words for why you would want to use the C++ frontend to begin with, and then dive straight into defining and training our model.

Tip

Watch this lightning talk from CppCon 2018 for a quick (and humorous) presentation on the C++ frontend.

Tip

This note provides a sweeping overview of the C++ frontend's components and design philosophy.

Tip

Documentation for the PyTorch C++ ecosystem is available at https://pytorch.org/cppdocs. There you can find high level descriptions as well as API-level documentation.

Motivation

Before we embark on our exciting journey of GANs and MNIST digits, let's take a step back and discuss why you would want to use the C++ frontend instead of the Python one to begin with. We (the PyTorch team) created the C++ frontend to enable research in environments in which Python cannot be used, or is simply not the right tool for the job. Examples for such environments include:

- **Low Latency Systems**: You may want to do reinforcement learning research in a pure C++ game engine with high frames-per-second and low latency requirements. Using a pure C++ library is a much better fit to such an environment than a Python library. Python may not be tractable at all because of the slowness of the Python interpreter.

- **Highly Multithreaded Environments**: Due to the Global Interpreter Lock (GIL), Python cannot run more than one system thread at a time. Multiprocessing is an alternative, but not as scalable and has significant shortcomings. C++ has no such constraints and threads are easy to use and create. Models requiring heavy parallelization, like those used in Deep Neuroevolution, can benefit from this.

- **Existing C++ Codebases**: You may be the owner of an existing C++ application doing anything from serving web pages in a backend server to rendering 3D graphics in photo editing software, and wish to integrate machine learning methods into your system. The C++ frontend allows you to remain in C++ and spare yourself the hassle of binding back and forth between Python and C++, while retaining much of the flexibility and intuitiveness of the traditional PyTorch (Python) experience.

The C++ frontend is not intended to compete with the Python frontend. It is meant to complement it. We know researchers and engineers alike love PyTorch for its simplicity, flexibility and intuitive API. Our goal is to make sure you can take advantage of these core design principles in every possible environment, including the ones described above. If one of these scenarios describes your use case well, or if you are simply interested or curious, follow along as we explore the C++ frontend in detail in the following paragraphs.

Tip

The C++ frontend tries to provide an API as close as possible to that of the Python frontend. If you are experienced with the Python frontend and ever ask yourself “how do I do X with the C++ frontend?”, write your code the way you would in Python, and more often than not the same functions and methods will be available in C++ as in Python (just remember to replace dots with double colons).

Writing a Basic Application

Let’s begin by writing a minimal C++ application to verify that we’re on the same page regarding our setup and build environment. First, you will need to grab a copy of the *LibTorch* distribution – our ready-built zip archive that packages all relevant headers, libraries and CMake build files required to use the C++ frontend. The LibTorch distribution is available for download on the PyTorch website for Linux, MacOS and Windows. The rest of this tutorial will assume a basic Ubuntu Linux environment, however you are free to follow along on MacOS or Windows too.

Tip

The note on Installing C++ Distributions of PyTorch describes the following steps in more detail.

Tip

On Windows, debug and release builds are not ABI-compatible. If you plan to build your project in debug mode, please try the debug version of LibTorch. Also, make sure you specify the correct configuration in the `cmake --build .` line below.

The first step is to download the LibTorch distribution locally, via the link retrieved from the PyTorch website. For a vanilla Ubuntu Linux environment, this means running:

```
# If you need e.g. CUDA 9.0 support, please replace "cpu" wi
wget https://download.pytorch.org/libtorch/nightly/cpu/libto
unzip libtorch-shared-with-deps-latest.zip
```

Next, let’s write a tiny C++ file called `dcgan.cpp` that includes `torch/torch.h` and for now simply prints out a three by three identity matrix:

```
#include <torch/torch.h>
#include <iostream>

int main() {
  torch::Tensor tensor = torch::eye(3);
  std::cout << tensor << std::endl;
}
```

To build this tiny application as well as our full-fledged training script later on we’ll use this `CMakeLists.txt` file:

```
cmake_minimum_required(VERSION 3.0 FATAL_ERROR)
project(dcgan)

find_package(Torch REQUIRED)

add_executable(dcgan dcgan.cpp)
target_link_libraries(dcgan "${TORCH_LIBRARIES}")
set_property(TARGET dcgan PROPERTY CXX_STANDARD 14)
```

Note

While CMake is the recommended build system for LibTorch, it is not a hard requirement. You can also use Visual Studio project files, QMake, plain Makefiles or any other build environment you feel comfortable with. However, we do not provide out-of-the-box support for this.

Make note of line 4 in the above CMake file: `find_package(Torch REQUIRED)`. This instructs CMake to find the build configuration for the LibTorch library. In order for CMake to know *where* to find these files, we must set the `CMAKE_PREFIX_PATH` when invoking `cmake`. Before we do this, let's agree on the following directory structure for our `dcgan` application:

```
dcgan/
  CMakeLists.txt
  dcgan.cpp
```

Further, I will refer to the path to the unzipped LibTorch distribution as `/path/to/libtorch`. Note that this **must be an absolute path**. In particular, setting `CMAKE_PREFIX_PATH` to something like `../../libtorch` will break in unexpected ways. Instead, write `$PWD/../../libtorch` to get the corresponding absolute path. Now, we are ready to build our application:

```
root@fa350df05ecf:/home# mkdir build
root@fa350df05ecf:/home# cd build
root@fa350df05ecf:/home/build# cmake -DCMAKE_PREFIX_PATH=/pa
-- The C compiler identification is GNU 5.4.0
-- The CXX compiler identification is GNU 5.4.0
-- Check for working C compiler: /usr/bin/cc
-- Check for working C compiler: /usr/bin/cc -- works
-- Detecting C compiler ABI info
-- Detecting C compiler ABI info - done
-- Detecting C compile features
-- Detecting C compile features - done
-- Check for working CXX compiler: /usr/bin/c++
-- Check for working CXX compiler: /usr/bin/c++ -- works
-- Detecting CXX compiler ABI info
-- Detecting CXX compiler ABI info - done
-- Detecting CXX compile features
-- Detecting CXX compile features - done
-- Looking for pthread.h
-- Looking for pthread.h - found
-- Looking for pthread_create
-- Looking for pthread_create - not found
-- Looking for pthread_create in pthreads
-- Looking for pthread_create in pthreads - not found
-- Looking for pthread_create in pthread
-- Looking for pthread_create in pthread - found
-- Found Threads: TRUE
-- Found torch: /path/to/libtorch/lib/libtorch.so
-- Configuring done
-- Generating done
-- Build files have been written to: /home/build
root@fa350df05ecf:/home/build# cmake --build . --config Rele
Scanning dependencies of target dcgan
[ 50%] Building CXX object CMakeFiles/dcgan.dir/dcgan.cpp.o
[100%] Linking CXX executable dcgan
[100%] Built target dcgan
```

Above, we first created a `build` folder inside of our `dcgan` directory, entered this folder, ran the `cmake` command to generate the necessary build (Make) files and finally compiled the project successfully by running `cmake --build . --config Release`. We are now all set to execute our minimal binary and complete this section on basic project configuration:

```
root@fa350df05ecf:/home/build# ./dcgan
1  0  0
0  1  0
0  0  1
[ Variable[CPUFloatType]{3,3} ]
```

Looks like an identity matrix to me!

Defining the Neural Network Models

Now that we have our basic environment configured, we can dive into the much more interesting parts of this tutorial. First, we will discuss how to define and interact with modules in the C++ frontend. We'll begin with basic, small-scale example modules and then implement a full-fledged GAN using the extensive library of built-in modules provided by the C++ frontend.

Module API Basics

In line with the Python interface, neural networks based on the C++ frontend are composed of reusable building blocks called *modules*. There is a base module class from which all other modules are derived. In Python, this class is `torch.nn.Module` and in C++ it is `torch::nn::Module`. Besides a `forward()` method that implements the algorithm the module encapsulates, a module usually contains any of three kinds of sub-objects: parameters, buffers and submodules.

Parameters and buffers store state in form of tensors. Parameters record gradients, while buffers do not. Parameters are usually the trainable weights of your neural network. Examples of buffers include means and variances for batch normalization. In order to re-use particular blocks of logic and state, the PyTorch API allows modules to be nested. A nested module is termed a *submodule*.

Parameters, buffers and submodules must be explicitly registered. Once registered, methods like `parameters()` or `buffers()` can be used to retrieve a container of all parameters in the entire (nested) module hierarchy. Similarly, methods like `to(...)`, where e.g. `to(torch::kCUDA)` moves all parameters and buffers from CPU to CUDA memory, work on the entire module hierarchy.

Defining a Module and Registering Parameters

To put these words into code, let's consider this simple module written in the Python interface:

```
import torch

class Net(torch.nn.Module):
  def __init__(self, N, M):
    super(Net, self).__init__()
    self.W = torch.nn.Parameter(torch.randn(N, M))
    self.b = torch.nn.Parameter(torch.randn(M))

  def forward(self, input):
    return torch.addmm(self.b, input, self.W)
```

In C++, it would look like this:

```
#include <torch/torch.h>

struct Net : torch::nn::Module {
  Net(int64_t N, int64_t M) {
    W = register_parameter("W", torch::randn({N, M}));
    b = register_parameter("b", torch::randn(M));
  }
  torch::Tensor forward(torch::Tensor input) {
    return torch::addmm(b, input, W);
  }
  torch::Tensor W, b;
};
```

Just like in Python, we define a class called `Net` (for simplicity here a `struct` instead of a `class`) and derive it from the module base class. Inside the constructor, we create tensors using `torch::randn` just like we use `torch.randn` in Python. One interesting difference is how we register the parameters. In Python, we wrap the tensors with the `torch.nn.Parameter` class, while in C++ we have to pass the tensor through the `register_parameter` method instead. The reason for this is that the Python API can detect that an attribute is of type `torch.nn.Parameter` and automatically registers such tensors. In C++, reflection is very limited, so a more traditional (and less magical) approach is provided.

Registering Submodules and Traversing the Module Hierarchy

In the same way we can register parameters, we can also register submodules. In Python, submodules are automatically detected and registered when they are assigned as an attribute of a module:

```
class Net(torch.nn.Module):
  def __init__(self, N, M):
      super(Net, self).__init__()
      # Registered as a submodule behind the scenes
      self.linear = torch.nn.Linear(N, M)
      self.another_bias = torch.nn.Parameter(torch.rand(M))

  def forward(self, input):
    return self.linear(input) + self.another_bias
```

This allows, for example, to use the `parameters()` method to recursively access all parameters in our module hierarchy:

```
>>> net = Net(4, 5)
>>> print(list(net.parameters()))
[Parameter containing:
tensor([0.0808, 0.8613, 0.2017, 0.5206, 0.5353], requires_gr
tensor([[-0.3740, -0.0976, -0.4786, -0.4928],
        [-0.1434,  0.4713,  0.1735, -0.3293],
        [-0.3467, -0.3858,  0.1980,  0.1986],
        [-0.1975,  0.4278, -0.1831, -0.2709],
        [ 0.3730,  0.4307,  0.3236, -0.0629]], requires_grad
tensor([ 0.2038,  0.4638, -0.2023,  0.1230, -0.0516], requir
```

To register submodules in C++, use the aptly named `register_module()` method to register a module like `torch::nn::Linear`:

```
struct Net : torch::nn::Module {
  Net(int64_t N, int64_t M)
      : linear(register_module("linear", torch::nn::Linear(N
    another_bias = register_parameter("b", torch::randn(M));
  }
  torch::Tensor forward(torch::Tensor input) {
    return linear(input) + another_bias;
  }
  torch::nn::Linear linear;
  torch::Tensor another_bias;
};
```

⧉

Tip

You can find the full list of available built-in modules like `torch::nn::Linear`, `torch::nn::Dropout` or `torch::nn::Conv2d` in the documentation of the `torch::nn` namespace here.

One subtlety about the above code is why the submodule was created in the constructor's initializer list, while the parameter was created inside the constructor body. There is a good reason for this, which we'll touch upon this in the section on the C++ frontend's *ownership model* further below. The end result, however, is that we can recursively access our module tree's parameters just like in Python. Calling `parameters()` returns a `std::vector<torch::Tensor>`, which we can iterate over:

```
int main() {
  Net net(4, 5);
  for (const auto& p : net.parameters()) {
    std::cout << p << std::endl;
  }
}
```

⧉

which prints:

```
root@fa350df05ecf:/home/build# ./dcgan
0.0345
1.4456
-0.6313
-0.3585
-0.4008
[ Variable[CPUFloatType]{5} ]
-0.1647  0.2891  0.0527 -0.0354
0.3084  0.2025  0.0343  0.1824
-0.4630 -0.2862  0.2500 -0.0420
0.3679 -0.1482 -0.0460  0.1967
0.2132 -0.1992  0.4257  0.0739
[ Variable[CPUFloatType]{5,4} ]
0.01 *
3.6861
-10.1166
-45.0333
7.9983
-20.0705
[ Variable[CPUFloatType]{5} ]
```

with three parameters just like in Python. To also see the names of these parameters, the C++ API provides a `named_parameters()` method which returns an `OrderedDict` just like in Python:

```
Net net(4, 5);
for (const auto& pair : net.named_parameters()) {
  std::cout << pair.key() << ": " << pair.value() << std::en
}
```

which we can execute again to see the output:

```
root@fa350df05ecf:/home/build# make && ./dcgan
Scanning dependencies of target dcgan
[ 50%] Building CXX object CMakeFiles/dcgan.dir/dcgan.cpp.o
```

```
[100%] Linking CXX executable dcgan
[100%] Built target dcgan
b: -0.1863
-0.8611
-0.1228
1.3269
0.9858
[ Variable[CPUFloatType]{5} ]
linear.weight:  0.0339  0.2484  0.2035 -0.2103
-0.0715 -0.2975 -0.4350 -0.1878
-0.3616  0.1050 -0.4982  0.0335
-0.1605  0.4963  0.4099 -0.2883
0.1818 -0.3447 -0.1501 -0.0215
[ Variable[CPUFloatType]{5,4} ]
linear.bias: -0.0250
0.0408
0.3756
-0.2149
-0.3636
[ Variable[CPUFloatType]{5} ]
```

Note

The documentation for `torch::nn::Module` contains the full list of methods that operate on the module hierarchy.

Running the Network in Forward Mode

To execute the network in C++, we simply call the `forward()` method we defined ourselves:

```
int main() {
  Net net(4, 5);
  std::cout << net.forward(torch::ones({2, 4})) << std::endl
}
```

which prints something like:

```
root@fa350df05ecf:/home/build# ./dcgan
0.8559  1.1572  2.1069 -0.1247  0.8060
0.8559  1.1572  2.1069 -0.1247  0.8060
[ Variable[CPUFloatType]{2,5} ]
```

Module Ownership

At this point, we know how to define a module in C++, register parameters, register submodules, traverse the module hierarchy via methods like `parameters()` and finally run the module's `forward()` method. While there are many more methods, classes and topics to devour in the C++ API, I will refer you to docs for the full menu. We'll also touch upon some more concepts as we implement the DCGAN model and end-to-end training pipeline in just a second. Before we do so, let me briefly touch upon the *ownership model* the C++ frontend provides for subclasses of `torch::nn::Module`.

For this discussion, the ownership model refers to the way modules are stored and passed around – which determines who or what *owns* a particular module instance. In Python, objects are always allocated dynamically (on the heap) and have reference semantics. This is very easy to work with and straightforward to understand. In fact, in Python, you can largely forget about where objects live and how they get referenced, and focus on getting things done.

C++, being a lower level language, provides more options in this realm. This increases complexity and heavily influences the design and ergonomics of the C++ frontend. In particular, for modules in the C++ frontend, we have the option of using *either* value semantics *or* reference semantics. The first case is the simplest and was shown in the examples thus far: module objects are allocated on the stack and when passed to a function, can be either copied, moved (with `std::move`) or taken by reference or by pointer:

```
struct Net : torch::nn::Module { };

void a(Net net) { }
void b(Net& net) { }
void c(Net* net) { }

int main() {
  Net net;
  a(net);
  a(std::move(net));
  b(net);
  c(&net);
}
```

For the second case – reference semantics – we can use `std::shared_ptr`. The advantage of reference semantics is that, like in Python, it reduces the cognitive overhead of thinking about how modules must be passed to functions and how arguments must be declared (assuming you use `shared_ptr` everywhere).

```
struct Net : torch::nn::Module {};

void a(std::shared_ptr<Net> net) { }

int main() {
  auto net = std::make_shared<Net>();
  a(net);
}
```

In our experience, researchers coming from dynamic languages greatly prefer reference semantics over value semantics, even though the latter is more “native” to C++. It is also important to note that `torch::nn::Module`’s design, in order to stay close to the ergonomics of the Python API, relies on shared ownership. For example, take our earlier (here shortened) definition of `Net`:

```
struct Net : torch::nn::Module {
  Net(int64_t N, int64_t M)
    : linear(register_module("linear", torch::nn::Linear(N,
  { }
  torch::nn::Linear linear;
};
```

In order to use the `linear` submodule, we want to store it directly in our class. However, we also want the module base class to know about and have access to this submodule. For this, it must store a reference to this submodule. At this point, we have already arrived at the need for shared ownership. Both the `torch::nn::Module` class and concrete `Net` class require a reference to the submodule. For this reason, the base class stores modules as `shared_ptr`s, and therefore the concrete class must too.

But wait! I don’t see any mention of `shared_ptr` in the above code! Why is that? Well, because `std::shared_ptr<MyModule>` is a hell of a lot to type. To keep our researchers productive, we came up with an elaborate scheme to hide the mention of `shared_ptr` – a benefit usually reserved for value semantics – while retaining reference semantics. To understand how this works, we can take a look at a simplified definition of the `torch::nn::Linear` module in the core library (the full definition is here):

```
struct LinearImpl : torch::nn::Module {
  LinearImpl(int64_t in, int64_t out);

  Tensor forward(const Tensor& input);

  Tensor weight, bias;
};

TORCH_MODULE(Linear);
```

In brief: the module is not called `Linear`, but `LinearImpl`. A macro, `TORCH_MODULE` then defines the actual `Linear` class. This “generated” class is effectively a wrapper over a `std::shared_ptr<LinearImpl>`. It is a wrapper instead of a simple typedef so that, among other things, constructors still work as expected, i.e. you can still write `torch::nn::Linear(3, 4)` instead of `std::make_shared<LinearImpl>(3, 4)`. We call the class created by the macro the module *holder*. Like with (shared) pointers, you access the underlying object using the arrow operator (like `model->forward(...)`). The end result is an ownership model that resembles that of the Python API quite closely. Reference semantics become the default, but without the extra typing of `std::shared_ptr` or `std::make_shared`. For our `Net`, using the module holder API looks like this:

```
struct NetImpl : torch::nn::Module {};
TORCH_MODULE(Net);

void a(Net net) { }

int main() {
  Net net;
  a(net);
}
```

There is one subtle issue that deserves mention here. A default constructed `std::shared_ptr` is “empty”, i.e. contains a null pointer. What is a default constructed `Linear` or `Net`? Well, it’s a tricky choice. We could say it should be an empty (null) `std::shared_ptr<LinearImpl>`. However, recall that `Linear(3, 4)` is the same as `std::make_shared<LinearImpl>(3, 4)`. This means that if we had decided that `Linear linear;` should be a null pointer, then there would be no way to construct a module that does not take any constructor arguments, or defaults all of them. For this reason, in the current API, a default constructed module holder (like `Linear()`) invokes the default constructor of the underlying module (`LinearImpl()`). If the underlying module does not have a default constructor, you get a compiler error. To instead construct the empty holder, you can pass `nullptr` to the constructor of the holder.

In practice, this means you can use submodules either like shown earlier, where the module is registered and constructed in the *initializer list*:

```
struct Net : torch::nn::Module {
  Net(int64_t N, int64_t M)
    : linear(register_module("linear", torch::nn::Linear(N,
  { }
  torch::nn::Linear linear;
};
```

or you can first construct the holder with a null pointer and then assign to it in the constructor (more familiar for Pythonistas):

```
struct Net : torch::nn::Module {
  Net(int64_t N, int64_t M) {
    linear = register_module("linear", torch::nn::Linear(N,
  }
  torch::nn::Linear linear{nullptr}; // construct an empty h
};
```

In conclusion: Which ownership model – which semantics – should you use? The C++ frontend’s API best supports the ownership model provided by module holders. The only disadvantage of this mechanism is one extra line of boilerplate below the module declaration. That said, the simplest model is still the value semantics model shown in the introduction to C++ modules. For small, simple scripts, you may get away with it too. But you’ll find sooner or later that, for technical reasons, it is not always supported. For example, the serialization API (`torch::save` and `torch::load`) only supports module holders (or plain `shared_ptr`). As such, the module holder API is the recommended way of defining modules with the C++ frontend, and we will use this API in this tutorial henceforth.

Defining the DCGAN Modules

We now have the necessary background and introduction to define the modules for the machine learning task we want to solve in this post. To recap: our task is to generate images of digits from the MNIST dataset. We want to use a generative adversarial network (GAN) to solve this task. In particular, we'll use a DCGAN architecture – one of the first and simplest of its kind, but entirely sufficient for this task.

Tip

You can find the full source code presented in this tutorial in this repository.

What was a GAN aGAN?

A GAN consists of two distinct neural network models: a *generator* and a *discriminator*. The generator receives samples from a noise distribution, and its aim is to transform each noise sample into an image that resembles those of a target distribution – in our case the MNIST dataset. The discriminator in turn receives either *real* images from the MNIST dataset, or *fake* images from the generator. It is asked to emit a probability judging how real (closer to `1`) or fake (closer to `0`) a particular image is. Feedback from the discriminator on how real the images produced by the generator are is used to train the generator. Feedback on how good of an eye for authenticity the discriminator has is used to optimize the discriminator. In theory, a delicate balance between the generator and discriminator makes them improve in tandem, leading to the generator producing images indistinguishable from the target distribution, fooling the discriminator's (by then) excellent eye into emitting a probability of `0.5` for both real and fake images. For us, the end result is a machine that receives noise as input and generates realistic images of digits as its output.

The Generator Module

We begin by defining the generator module, which consists of a series of transposed 2D convolutions, batch normalizations and ReLU activation units. We explicitly pass inputs (in a functional way) between modules in the `forward()` method of a module we define ourselves:

```
struct DCGANGeneratorImpl : nn::Module {
  DCGANGeneratorImpl(int kNoiseSize)
      : conv1(nn::ConvTranspose2dOptions(kNoiseSize, 256, 4)
                  .bias(false)),
        batch_norm1(256),
        conv2(nn::ConvTranspose2dOptions(256, 128, 3)
                  .stride(2)
                  .padding(1)
                  .bias(false)),
        batch_norm2(128),
        conv3(nn::ConvTranspose2dOptions(128, 64, 4)
                  .stride(2)
                  .padding(1)
                  .bias(false)),
        batch_norm3(64),
        conv4(nn::ConvTranspose2dOptions(64, 1, 4)
                  .stride(2)
                  .padding(1)
                  .bias(false))
 {
   // register_module() is needed if we want to use the para
   register_module("conv1", conv1);
   register_module("conv2", conv2);
   register_module("conv3", conv3);
   register_module("conv4", conv4);
   register_module("batch_norm1", batch_norm1);
   register_module("batch_norm2", batch_norm2);
   register_module("batch_norm3", batch_norm3);
 }

 torch::Tensor forward(torch::Tensor x) {
   x = torch::relu(batch_norm1(conv1(x)));
   x = torch::relu(batch_norm2(conv2(x)));
   x = torch::relu(batch_norm3(conv3(x)));
   x = torch::tanh(conv4(x));
   return x;
 }

 nn::ConvTranspose2d conv1, conv2, conv3, conv4;
 nn::BatchNorm2d batch_norm1, batch_norm2, batch_norm3;
};
```

```
TORCH_MODULE(DCGANGenerator);

DCGANGenerator generator(kNoiseSize);
```

⧉

We can now invoke `forward()` on the `DCGANGenerator` to map a noise sample to an image.

The particular modules chosen, like `nn::ConvTranspose2d` and `nn::BatchNorm2d`, follows the structure outlined earlier. The `kNoiseSize` constant determines the size of the input noise vector and is set to `100`. Hyperparameters were, of course, found via grad student descent.

Attention

No grad students were harmed in the discovery of hyperparameters. They were fed Soylent regularly.

Note

A brief word on the way options are passed to built-in modules like `Conv2d` in the C++ frontend: Every module has some required options, like the number of features for `BatchNorm2d`. If you only need to configure the required options, you can pass them directly to the module’s constructor, like `BatchNorm2d(128)` or `Dropout(0.5)` or `Conv2d(8, 4, 2)` (for input channel count, output channel count, and kernel size). If, however, you need to modify other options, which are normally defaulted, such as `bias` for `Conv2d`, you need to construct and pass an *options* object. Every module in the C++ frontend has an associated options struct, called `ModuleOptions` where `Module` is the name of the module, like `LinearOptions` for `Linear`. This is what we do for the `Conv2d` modules above.

The Discriminator Module

The discriminator is similarly a sequence of convolutions, batch normalizations and activations. However, the convolutions are now regular ones instead of transposed, and we use a leaky ReLU with an alpha value of 0.2 instead of a vanilla ReLU. Also, the final activation becomes a Sigmoid, which squashes values into a range between 0 and 1. We can then interpret these squashed values as the probabilities the discriminator assigns to images being real.

To build the discriminator, we will try something different: a *Sequential* module. Like in Python, PyTorch here provides two APIs for model definition: a functional one where inputs are passed through successive functions (e.g. the generator module example), and a more object-oriented one where we build a *Sequential* module containing the entire model as submodules. Using *Sequential*, the discriminator would look like:

```
nn::Sequential discriminator(
  // Layer 1
  nn::Conv2d(
      nn::Conv2dOptions(1, 64, 4).stride(2).padding(1).bias(
  nn::LeakyReLU(nn::LeakyReLUOptions().negative_slope(0.2)),
  // Layer 2
  nn::Conv2d(
      nn::Conv2dOptions(64, 128, 4).stride(2).padding(1).bia
  nn::BatchNorm2d(128),
  nn::LeakyReLU(nn::LeakyReLUOptions().negative_slope(0.2)),
  // Layer 3
  nn::Conv2d(
      nn::Conv2dOptions(128, 256, 4).stride(2).padding(1).bi
  nn::BatchNorm2d(256),
  nn::LeakyReLU(nn::LeakyReLUOptions().negative_slope(0.2)),
  // Layer 4
  nn::Conv2d(
      nn::Conv2dOptions(256, 1, 3).stride(1).padding(0).bias
  nn::Sigmoid());
```

⧉

Tip

A `Sequential` module simply performs function composition. The output of the first submodule becomes the input of the second, the output of the third becomes the input of the fourth and so on.

Loading Data

Now that we have defined the generator and discriminator model, we need some data we can train these models with. The C++ frontend, like the Python one, comes with a powerful parallel data loader. This data loader can read batches of data from a dataset (which you can define yourself) and provides many configuration knobs.

Note

While the Python data loader uses multi-processing, the C++ data loader is truly multi-threaded and does not launch any new processes.

The data loader is part of the C++ frontend's `data` api, contained in the `torch::data::` namespace. This API consists of a few different components:

- The data loader class,
- An API for defining datasets,
- An API for defining *transforms*, which can be applied to datasets,
- An API for defining *samplers*, which produce the indices with which datasets are indexed,
- A library of existing datasets, transforms and samplers.

For this tutorial, we can use the `MNIST` dataset that comes with the C++ frontend. Let's instantiate a `torch::data::datasets::MNIST` for this, and apply two transformations: First, we normalize the images so that they are in the range of `-1` to `+1` (from an original range of `0` to `1`). Second, we apply the `Stack` *collation*, which takes a batch of tensors and stacks them into a single tensor along the first dimension:

```
auto dataset = torch::data::datasets::MNIST("./mnist")
    .map(torch::data::transforms::Normalize<>(0.5, 0.5))
    .map(torch::data::transforms::Stack<>());
```

Note that the MNIST dataset should be located in the `./mnist` directory relative to wherever you execute the training binary from. You can use this script to download the MNIST dataset.

Next, we create a data loader and pass it this dataset. To make a new data loader, we use `torch::data::make_data_loader`, which returns a `std::unique_ptr` of the correct type (which depends on the type of the dataset, the type of the sampler and some other implementation details):

```
auto data_loader = torch::data::make_data_loader(std::move(d
```

The data loader does come with a lot of options. You can inspect the full set here. For example, to speed up the data loading, we can increase the number of workers. The default number is zero, which means the main thread will be used. If we set `workers` to `2`, two threads will be spawned that load data concurrently. We should also increase the batch size from its default of `1` to something more reasonable, like `64` (the value of `kBatchSize`). So let's create a `DataLoaderOptions` object and set the appropriate properties:

```
auto data_loader = torch::data::make_data_loader(
    std::move(dataset),
    torch::data::DataLoaderOptions().batch_size(kBatchSize).
```

We can now write a loop to load batches of data, which we'll only print to the console for now:

```
for (torch::data::Example<>& batch : *data_loader) {
  std::cout << "Batch size: " << batch.data.size(0) << " | L
  for (int64_t i = 0; i < batch.data.size(0); ++i) {
    std::cout << batch.target[i].item<int64_t>() << " ";
  }
  std::cout << std::endl;
}
```

The type returned by the data loader in this case is a `torch::data::Example`. This type is a simple struct with a `data` field for the data and a `target` field for the label. Because we applied the `Stack` collation earlier, the data loader returns only a single such example. If we had not applied the collation, the data loader would yield `std::vector<torch::data::Example<>>` instead, with one element per example in the batch.

If you rebuild and run this code, you should see something like this:

```
root@fa350df05ecf:/home/build# make
Scanning dependencies of target dcgan
[ 50%] Building CXX object CMakeFiles/dcgan.dir/dcgan.cpp.o
[100%] Linking CXX executable dcgan
[100%] Built target dcgan
root@fa350df05ecf:/home/build# make
[100%] Built target dcgan
root@fa350df05ecf:/home/build# ./dcgan
Batch size: 64 | Labels: 5 2 6 7 2 1 6 7 0 1 6 2 3 6 9 1 8 4
Batch size: 64 | Labels: 2 2 4 7 1 2 8 8 6 9 0 2 2 9 3 6 1 3
Batch size: 64 | Labels: 4 5 4 2 1 4 8 3 8 3 6 1 5 4 3 6 2 2
Batch size: 64 | Labels: 3 3 7 1 4 1 6 1 0 3 6 4 0 2 5 4 0 4
Batch size: 64 | Labels: 3 0 5 5 9 8 3 9 8 9 5 9 5 0 4 1 2 7
Batch size: 64 | Labels: 9 6 7 5 3 5 9 0 8 6 6 7 8 2 1 9 8 8
Batch size: 64 | Labels: 9 3 0 3 6 5 1 8 6 0 1 9 9 1 6 1 7 7
Batch size: 64 | Labels: 9 1 9 2 7 2 6 0 8 6 8 7 7 4 8 6 1 1
Batch size: 64 | Labels: 8 8 3 1 8 6 4 2 9 5 8 0 2 8 6 6 7 0
Batch size: 64 | Labels: 9 2 7 0 8 4 4 2 7 5 0 0 6 2 0 5 9 5
Batch size: 64 | Labels: 7 6 5 7 7 5 2 2 4 9 9 4 8 7 4 8 9 4
...
```

Which means we are successfully able to load data from the MNIST dataset.

Writing the Training Loop

Let’s now finish the algorithmic part of our example and implement the delicate dance between the generator and discriminator. First, we’ll create two optimizers, one for the generator and one for the discriminator. The optimizers we use implement the Adam algorithm:

```
torch::optim::Adam generator_optimizer(
    generator->parameters(), torch::optim::AdamOptions(2e-4)
torch::optim::Adam discriminator_optimizer(
    discriminator->parameters(), torch::optim::AdamOptions(5
```

Note

As of this writing, the C++ frontend provides optimizers implementing Adagrad, Adam, LBFGS, RMSprop and SGD. The docs have the up-to-date list.

Next, we need to update our training loop. We’ll add an outer loop to exhaust the data loader every epoch and then write the GAN training code:

```
for (int64_t epoch = 1; epoch <= kNumberOfEpochs; ++epoch) {
  int64_t batch_index = 0;
  for (torch::data::Example<>& batch : *data_loader) {
    // Train discriminator with real images.
    discriminator->zero_grad();
    torch::Tensor real_images = batch.data;
    torch::Tensor real_labels = torch::empty(batch.data.size
    torch::Tensor real_output = discriminator->forward(real_
    torch::Tensor d_loss_real = torch::binary_cross_entropy(
    d_loss_real.backward();

    // Train discriminator with fake images.
    torch::Tensor noise = torch::randn({batch.data.size(0),
    torch::Tensor fake_images = generator->forward(noise);
    torch::Tensor fake_labels = torch::zeros(batch.data.size
    torch::Tensor fake_output = discriminator->forward(fake_
    torch::Tensor d_loss_fake = torch::binary_cross_entropy(
    d_loss_fake.backward();

    torch::Tensor d_loss = d_loss_real + d_loss_fake;
    discriminator_optimizer.step();

    // Train generator.
    generator->zero_grad();
    fake_labels.fill_(1);
    fake_output = discriminator->forward(fake_images);
    torch::Tensor g_loss = torch::binary_cross_entropy(fake_
    g_loss.backward();
    generator_optimizer.step();

    std::printf(
        "\r[%2ld/%2ld][%3ld/%3ld] D_loss: %.4f | G_loss: %.4
        epoch,
        kNumberOfEpochs,
        ++batch_index,
        batches_per_epoch,
        d_loss.item<float>(),
        g_loss.item<float>());
  }
}
```

Above, we first evaluate the discriminator on real images, for which it should assign a high probability. For this, we use `torch::empty(batch.data.size(0)).uniform_(0.8, 1.0)` as the target probabilities.

Note

We pick random values uniformly distributed between 0.8 and 1.0 instead of 1.0 everywhere in order to make the discriminator training more robust. This trick is called *label smoothing*.

Before evaluating the discriminator, we zero out the gradients of its parameters. After computing the loss, we back-propagate it through the network by calling `d_loss.backward()` to compute new gradients. We repeat this spiel for the fake images. Instead of using images from the dataset, we let the generator create fake images for this by feeding it a batch of random noise. We then forward those fake images to the discriminator. This time, we want the discriminator to emit low probabilities, ideally all zeros. Once we have computed the discriminator loss for both the batch of real and the batch of fake images, we can progress the discriminator's optimizer by one step in order to update its parameters.

To train the generator, we again first zero its gradients, and then re-evaluate the discriminator on the fake images. However, this time we want the discriminator to assign probabilities very close to one, which would indicate that the generator can produce images that fool the discriminator into thinking they are actually real (from the dataset). For this, we fill the `fake_labels` tensor with all ones. We finally step the generator's optimizer to also update its parameters.

We should now be ready to train our model on the CPU. We don't have any code yet to capture state or sample outputs, but we'll add this in just a moment. For now, let's just observe that our model is doing *something* – we'll later verify based on the generated images whether this something is meaningful. Re-building and running should print something like:

```
root@3c0711f20896:/home/build# make && ./dcgan
Scanning dependencies of target dcgan
[ 50%] Building CXX object CMakeFiles/dcgan.dir/dcgan.cpp.o
[100%] Linking CXX executable dcgan
[100%] Built target dcga
[ 1/10][100/938] D_loss: 0.6876 | G_loss: 4.1304
[ 1/10][200/938] D_loss: 0.3776 | G_loss: 4.3101
[ 1/10][300/938] D_loss: 0.3652 | G_loss: 4.6626
[ 1/10][400/938] D_loss: 0.8057 | G_loss: 2.2795
[ 1/10][500/938] D_loss: 0.3531 | G_loss: 4.4452
[ 1/10][600/938] D_loss: 0.3501 | G_loss: 5.0811
[ 1/10][700/938] D_loss: 0.3581 | G_loss: 4.5623
[ 1/10][800/938] D_loss: 0.6423 | G_loss: 1.7385
[ 1/10][900/938] D_loss: 0.3592 | G_loss: 4.7333
[ 2/10][100/938] D_loss: 0.4660 | G_loss: 2.5242
[ 2/10][200/938] D_loss: 0.6364 | G_loss: 2.0886
[ 2/10][300/938] D_loss: 0.3717 | G_loss: 3.8103
[ 2/10][400/938] D_loss: 1.0201 | G_loss: 1.3544
[ 2/10][500/938] D_loss: 0.4522 | G_loss: 2.6545
...
```

Moving to the GPU

While our current script can run just fine on the CPU, we all know convolutions are a lot faster on GPU. Let's quickly discuss how we can move our training onto the GPU. We'll need to do two things for this: pass a GPU device specification to tensors we allocate ourselves, and explicitly copy any other tensors onto the GPU via the `to()` method all tensors and modules in the C++ frontend have. The simplest way to achieve both is to create an instance of `torch::Device` at the top level of our training script, and then pass that device to tensor factory functions like `torch::zeros` as well as the `to()` method. We can start by doing this with a CPU device:

```
// Place this somewhere at the top of your training script.
torch::Device device(torch::kCPU);
```

New tensor allocations like

```
torch::Tensor fake_labels = torch::zeros(batch.data.size(0))
```

should be updated to take the `device` as the last argument:

```
torch::Tensor fake_labels = torch::zeros(batch.data.size(0),
```

For tensors whose creation is not in our hands, like those coming from the MNIST dataset, we must insert explicit `to()` calls. This means

```
torch::Tensor real_images = batch.data;
```

becomes

```
torch::Tensor real_images = batch.data.to(device);
```

and also our model parameters should be moved to the correct device:

```
generator->to(device);
discriminator->to(device);
```

Note

If a tensor already lives on the device supplied to `to()`, the call is a no-op. No extra copy is made.

At this point, we’ve just made our previous CPU-residing code more explicit. However, it is now also very easy to change the device to a CUDA device:

```
torch::Device device(torch::kCUDA)
```

And now all tensors will live on the GPU, calling into fast CUDA kernels for all operations, without us having to change any downstream code. If we wanted to specify a particular device index, it could be passed as the second argument to the `Device` constructor. If we wanted different tensors to live on different devices, we could pass separate device instances (for example one on CUDA device 0 and the other on CUDA device 1). We can even do this configuration dynamically, which is often useful to make our training scripts more portable:

```
torch::Device device = torch::kCPU;
if (torch::cuda::is_available()) {
  std::cout << "CUDA is available! Training on GPU." << std:
  device = torch::kCUDA;
}
```

or even

```
torch::Device device(torch::cuda::is_available() ? torch::kC
```

Checkpointing and Recovering the Training State

The last augmentation we should make to our training script is to periodically save the state of our model parameters, the state of our optimizers as well as a few generated image samples. If our computer were to crash in the middle of the training procedure, the first two will allow us to restore the training state. For long-lasting training sessions, this is absolutely essential. Fortunately, the C++ frontend provides an API to serialize and deserialize both model and optimizer state, as well as individual tensors.

The core API for this is `torch::save(thing,filename)` and `torch::load(thing,filename)`, where `thing` could be a `torch::nn::Module` subclass or an optimizer instance like the `Adam` object we have in our training script. Let’s update our training loop to checkpoint the model and optimizer state at a certain interval:

```
if (batch_index % kCheckpointEvery == 0) {
  // Checkpoint the model and optimizer state.
  torch::save(generator, "generator-checkpoint.pt");
  torch::save(generator_optimizer, "generator-optimizer-chec
  torch::save(discriminator, "discriminator-checkpoint.pt");
  torch::save(discriminator_optimizer, "discriminator-optimi
  // Sample the generator and save the images.
  torch::Tensor samples = generator->forward(torch::randn({8
  torch::save((samples + 1.0) / 2.0, torch::str("dcgan-sampl
  std::cout << "\n-> checkpoint " << ++checkpoint_counter <<
}
```

where `kCheckpointEvery` is an integer set to something like `100` to checkpoint every `100` batches, and `checkpoint_counter` is a counter bumped every time we make a checkpoint.

To restore the training state, you can add lines like these after all models and optimizers are created, but before the training loop:

```
torch::optim::Adam generator_optimizer(
    generator->parameters(), torch::optim::AdamOptions(2e-4)
torch::optim::Adam discriminator_optimizer(
    discriminator->parameters(), torch::optim::AdamOptions(2

if (kRestoreFromCheckpoint) {
  torch::load(generator, "generator-checkpoint.pt");
  torch::load(generator_optimizer, "generator-optimizer-chec
  torch::load(discriminator, "discriminator-checkpoint.pt");
  torch::load(
      discriminator_optimizer, "discriminator-optimizer-chec
}

int64_t checkpoint_counter = 0;
for (int64_t epoch = 1; epoch <= kNumberOfEpochs; ++epoch) {
  int64_t batch_index = 0;
  for (torch::data::Example<>& batch : *data_loader) {
```

Inspecting Generated Images

Our training script is now complete. We are ready to train our GAN, whether on CPU or GPU. To inspect the intermediary output of our training procedure, for which we added code to periodically save image samples to the `"dcgan-sample-xxx.pt"` file, we can write a tiny Python script to load the tensors and display them with matplotlib:

```
import argparse

import matplotlib.pyplot as plt
import torch


parser = argparse.ArgumentParser()
parser.add_argument("-i", "--sample-file", required=True)
parser.add_argument("-o", "--out-file", default="out.png")
parser.add_argument("-d", "--dimension", type=int, default=3
options = parser.parse_args()

module = torch.jit.load(options.sample_file)
images = list(module.parameters())[0]

for index in range(options.dimension * options.dimension):
  image = images[index].detach().cpu().reshape(28, 28).mul(2
  array = image.numpy()
  axis = plt.subplot(options.dimension, options.dimension, 1
  plt.imshow(array, cmap="gray")
  axis.get_xaxis().set_visible(False)
  axis.get_yaxis().set_visible(False)
```

```
plt.savefig(options.out_file)
print("Saved ", options.out_file)
```

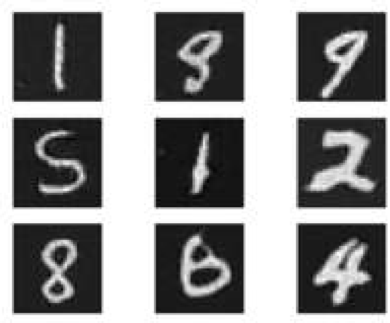
Let’s now train our model for around 30 epochs:

```
root@3c0711f20896:/home/build# make && ./dcgan
Scanning dependencies of target dcgan
[ 50%] Building CXX object CMakeFiles/dcgan.dir/dcgan.cpp.o
[100%] Linking CXX executable dcgan
[100%] Built target dcgan
CUDA is available! Training on GPU.
[ 1/30][200/938] D_loss: 0.4953 | G_loss: 4.0195
-> checkpoint 1
[ 1/30][400/938] D_loss: 0.3610 | G_loss: 4.8148
-> checkpoint 2
[ 1/30][600/938] D_loss: 0.4072 | G_loss: 4.36760
-> checkpoint 3
[ 1/30][800/938] D_loss: 0.4444 | G_loss: 4.0250
-> checkpoint 4
[ 2/30][200/938] D_loss: 0.3761 | G_loss: 3.8790
-> checkpoint 5
[ 2/30][400/938] D_loss: 0.3977 | G_loss: 3.3315
...
-> checkpoint 120
[30/30][938/938] D_loss: 0.3610 | G_loss: 3.8084
```

And display the images in a plot:

```
root@3c0711f20896:/home/build# python display.py -i dcgan-sa
Saved out.png
```

Which should look something like this:



Digits! Hooray! Now the ball is in your court: can you improve the model to make the digits look even better?

Conclusion

This tutorial has hopefully given you a digestible digest of the PyTorch C++ frontend. A machine learning library like PyTorch by necessity has a very broad and extensive API. As such, there are many concepts we did not have time or space to discuss here. However, I encourage you to try out the API, and consult our documentation and in particular the Library API section when you get stuck. Also, remember that you can expect the C++ frontend to follow the design and semantics of the Python frontend whenever we could make this possible, so you can leverage this fact to increase your learning rate.

Tip

You can find the full source code presented in this tutorial in this repository.

As always, if you run into any problems or have questions, you can use our forum or GitHub issues to get in touch.