Deep learning

4.6. Writing a PyTorch module

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```
>>> from torchvision.datasets import MNIST
>>> mnist = MNIST('./data/mnist/', train = True, download = True)
>>> d = mnist.train_data
>>> d.size()
torch.Size([60000, 28, 28])
>>> x = d.view(d.size(0), 1, d.size(1), d.size(2))
>>> x.size()
torch.Size([60000, 1, 28, 28])
>>> x = x.view(x.size(0), -1)
>>> x.size()
torch.Size([60000, 784])
```

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Total 105,506 parameters and 1,333,200 products for the forward pass.

Creating a module

PyTorch offers a sequential container module `torch.nn.Sequential` to build simple architectures.

For instance a MLP with a 10 dimension input, 2 dimension output, ReLU activation and two hidden layers of dimensions 100 and 50 can be written as:

```
model = nn.Sequential(
    nn.Linear(10, 100), nn.ReLU(),
    nn.Linear(100, 50), nn.ReLU(),
    nn.Linear(50, 2)
)
```

However for any model of reasonable complexity, the best is to write a sub-class of `torch.nn.Module`.

To create a `Module`, one has to inherit from the base class and implement the constructor `__init__(self, ...)` and the forward pass `forward(self, x)`.

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```
class Net(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(1, 32, kernel_size=5)
        self.conv2 = nn.Conv2d(32, 64, kernel_size=5)
        self.fc1 = nn.Linear(256, 200)
        self.fc2 = nn.Linear(200, 10)

    def forward(self, x):
        x = F.relu(F.max_pool2d(self.conv1(x), kernel_size=3, stride=3))
        x = F.relu(F.max_pool2d(self.conv2(x), kernel_size=2, stride=2))
        x = x.view(-1, 256)
        x = F.relu(self.fc1(x))
        x = self.fc2(x)
        return x
```

Inheriting from `torch.nn.Module` provides many mechanisms implemented in the superclass.

First, the `(...)` operator is redefined to call the `forward(...)` method and run additional operations. The forward pass should be executed through this operator and not by calling `forward` explicitly.

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Using the class `Net` we just defined

```
model = Net()
input = torch.empty(12, 1, 28, 28).normal_()
output = model(input)
print(output.size())
```

prints

```
torch.Size([12, 10])
```

Also, the `Parameter`s added as class attributes, or from modules added as class attributes, are seen by `Module.parameters()`.

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class Net(nn.Module):
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model = Net()

for k in model.parameters():
    print(k.size())
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```

prints

```
torch.Size([32, 1, 5, 5])
torch.Size([32])
torch.Size([64, 32, 5, 5])
torch.Size([64])
torch.Size([200, 256])
torch.Size([200])
torch.Size([10, 200])
torch.Size([10])
```

⚠ Parameters added in dictionaries or arrays are not seen.

```
class Buggy(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv = nn.Conv2d(1, 32, kernel_size=5)
        self.param = Parameter(torch.zeros(123, 456))
        self.other_stuff = [ nn.Linear(543, 21) ]

model = Buggy()

for k in model.parameters():
    print(k.size())
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model = Buggy()

for k in model.parameters():
    print(k.size())
```

prints

```
torch.Size([123, 456])
torch.Size([32, 1, 5, 5])
torch.Size([32])
```

A simple option is to add modules in a `torch.nn.ModuleList`, which is a list of modules properly dealt with by PyTorch's machinery.

```
class NotBuggy(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv = nn.Conv2d(1, 32, kernel_size=5)
        self.param = Parameter(torch.zeros(123, 456))
        self.other_stuff = nn.ModuleList()
        self.other_stuff.append(nn.Linear(543, 21))

model = NotBuggy()

for k in model.parameters():
    print(k.size())
```

prints

```
torch.Size([123, 456])
torch.Size([32, 1, 5, 5])
torch.Size([32])
torch.Size([21, 543])
torch.Size([21])
```

As long as you use autograd-compliant operations, the backward pass is implemented automatically.

This is crucial to allow the optimization of the `Parameter`s with gradient descent.

The end