Listing A.1 Creating PyTorch tensors

```
import torch

tensor0d = torch.tensor(1)

tensor1d = torch.tensor([1, 2, 3])

tensor2d = torch.tensor([[1, 2],
                         [3, 4]])

tensor3d = torch.tensor([[[1, 2], [3, 4]],
                         [[5, 6], [7, 8]]])
```

Creates a zero-dimensional tensor (scalar) from a Python integer

Creates a one-dimensional tensor (vector) from a Python list

Creates a two-dimensional tensor from a nested Python list

Creates a three-dimensional tensor from a nested Python list

A.2.2 Tensor data types

PyTorch adopts the default 64-bit integer data type from Python. We can access the data type of a tensor via the `.dtype` attribute of a tensor:

```
tensor1d = torch.tensor([1, 2, 3])
print(tensor1d.dtype)
```

This prints

```
torch.int64
```

If we create tensors from Python floats, PyTorch creates tensors with a 32-bit precision by default:

```
floatvec = torch.tensor([1.0, 2.0, 3.0])
print(floatvec.dtype)
```

The output is

```
torch.float32
```

This choice is primarily due to the balance between precision and computational efficiency. A 32-bit floating-point number offers sufficient precision for most deep learning tasks while consuming less memory and computational resources than a 64-bit floating-point number. Moreover, GPU architectures are optimized for 32-bit computations, and using this data type can significantly speed up model training and inference.

Moreover, it is possible to change the precision using a tensor's `.to` method. The following code demonstrates this by changing a 64-bit integer tensor into a 32-bit float tensor:

```
floatvec = tensor1d.to(torch.float32)
print(floatvec.dtype)
```

This returns

```
torch.float32
```

For more information about different tensor data types available in PyTorch, check the official documentation at https://pytorch.org/docs/stable/tensors.html.

A.2.3 Common PyTorch tensor operations

Comprehensive coverage of all the different PyTorch tensor operations and commands is outside the scope of this book. However, I will briefly describe relevant operations as we introduce them throughout the book.

We have already introduced the `torch.tensor()` function to create new tensors:

```
tensor2d = torch.tensor([[1, 2, 3],
                         [4, 5, 6]])
print(tensor2d)
```

This prints

```
tensor([[1, 2, 3],
        [4, 5, 6]])
```

In addition, the `.shape` attribute allows us to access the shape of a tensor:

```
print(tensor2d.shape)
```

The output is

```
torch.Size([2, 3])
```

As you can see, `.shape` returns `[2, 3]`, meaning the tensor has two rows and three columns. To reshape the tensor into a 3×2 tensor, we can use the `.reshape` method:

```
print(tensor2d.reshape(3, 2))
```

This prints

```
tensor([[1, 2],
        [3, 4],
        [5, 6]])
```

However, note that the more common command for reshaping tensors in PyTorch is `.view()`:

```
print(tensor2d.view(3, 2))
```

The output is

```
tensor([[1, 2],
        [3, 4],
        [5, 6]])
```

Similar to `.reshape` and `.view`, in several cases, PyTorch offers multiple syntax options for executing the same computation. PyTorch initially followed the original Lua

Torch syntax convention but then, by popular request, added syntax to make it similar to NumPy. (The subtle difference between `.view()` and `.reshape()` in PyTorch lies in their handling of memory layout: `.view()` requires the original data to be contiguous and will fail if it isn't, whereas `.reshape()` will work regardless, copying the data if necessary to ensure the desired shape.)

Next, we can use `.T` to transpose a tensor, which means flipping it across its diagonal. Note that this is not the same to reshaping a tensor, as you can see based on the following result:

```
print(tensor2d.T)
```

The output is

```
tensor([[1, 4],
        [2, 5],
        [3, 6]])
```

Lastly, the common way to multiply two matrices in PyTorch is the `.matmul` method:

```
print(tensor2d.matmul(tensor2d.T))
```

The output is

```
tensor([[14, 32],
        [32, 77]])
```

However, we can also adopt the `@` operator, which accomplishes the same thing more compactly:

```
print(tensor2d @ tensor2d.T)
```

This prints

```
tensor([[14, 32],
        [32, 77]])
```

As mentioned earlier, I introduce additional operations when needed. For readers who'd like to browse through all the different tensor operations available in PyTorch (we won't need most of these), I recommend checking out the official documentation at https://pytorch.org/docs/stable/tensors.html.

A.3 Seeing models as computation graphs

Now let's look at PyTorch's automatic differentiation engine, also known as autograd. PyTorch's autograd system provides functions to compute gradients in dynamic computational graphs automatically.

A computational graph is a directed graph that allows us to express and visualize mathematical expressions. In the context of deep learning, a computation graph lays