Lecture_11_introduction_to_pytorch

October 5, 2024

Introduction to PyTorch

1 1. Setting Up PyTorch

[1]:
```
import torch  # now import the pytorch module
from torch import nn
import numpy as np
print(torch.__version__)  # check the version
```

```
1.10.2
```

1.1 2. Linear regression with PyTorch

Suppose we are given input and output pairs $(x_1, y_1), ..., (x_n, y_n)$, where each $x_i \in \mathbb{R}^d$ is a d dimensional feature vector and y_i is the output. We consider the following linear regression model

$$y = w^T x + b$$

where w, b are the model parameters. The loss function is the squared loss

$$\ell(w, b) = \frac{1}{n} \sum_{i=1}^{n} (y_i - w^T x_i)^2$$

The training process is to minimize the the loss function via gradient descent.

1.1.1 Key steps in pytorch machine learning programming

- Step 1: Build the model: The model is a subclass of nn.Module. It stores the model parameters, and also specifies how to calculate the model output given the model input
- Step 2: Prepare the training and testing data
- Step 3: Conduct training loops

1.2 2.1 Build Linear Regression Model

[2]:
```
from torch import nn

class MyLinearRegressionModel(nn.Module):
    def __init__(self,d): # d is the dimension of the input
        super(MyLinearRegressionModel,self).__init__()   # call the init␣
 ↪function of super class
        # we usually create variables for all our model parameters (w and b in␣
 ↪our case) in __init__ and give them initial values.
        # need to create them as nn.Parameter so that the model knows it is an␣
 ↪parameter that needs to be trained
        self.w = nn.Parameter(torch.zeros(1,d, dtype=torch.float))
        self.b = nn.Parameter(torch.zeros(1,dtype=torch.float))
    def forward(self,x):
        # The main purpose of the forward function is to specify given input x,␣
 ↪how the output is calculated.
        return torch.inner(x,self.w) + self.b

# Let's check out our model

mymodel = MyLinearRegressionModel(1) # creating a model instance with input␣
 ↪dimension 1
print(mymodel.w)
print(mymodel.b)
```

```
Parameter containing:
tensor([[0.]], requires_grad=True)
Parameter containing:
tensor([0.], requires_grad=True)
```

[3]:
```
x = torch.tensor(2)
print(mymodel(x)) # we should expect this to be w*x+b = 0*2+0 = 0 (recall that␣
 ↪w is initialized to be 0, and b is 0)
```

```
tensor([[0.]], grad_fn=<AddBackward0>)
```

1.3 2.2 Prepare Training Data

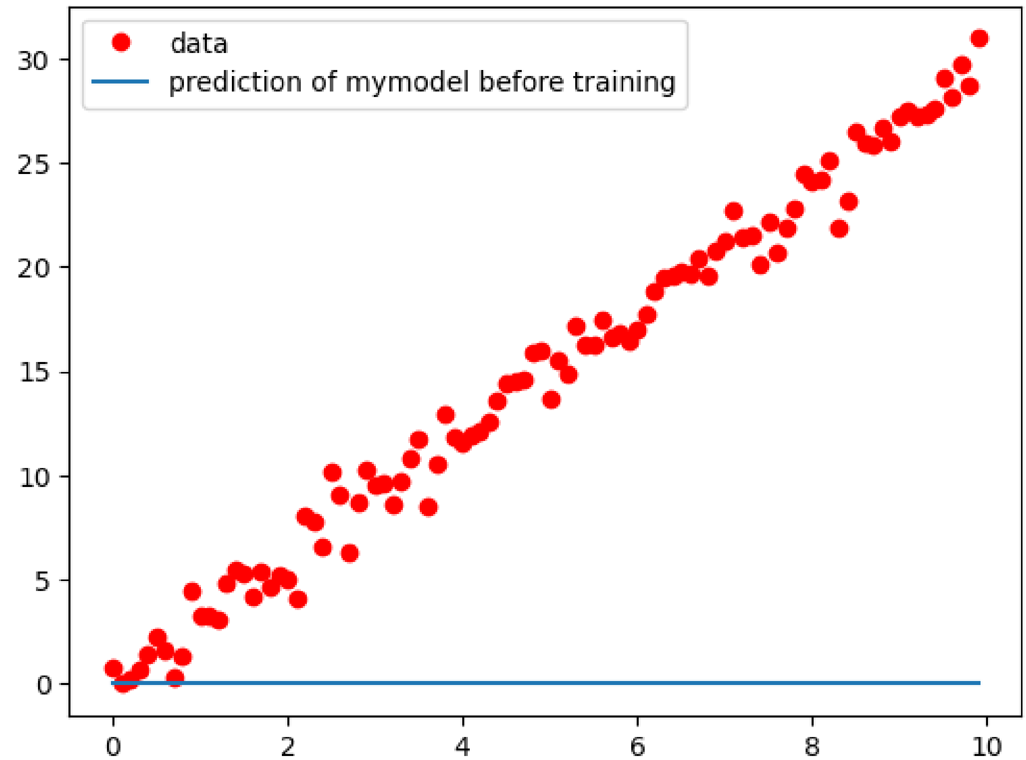
[4]:
```
# Now let's create some simple synthetic data

import matplotlib.pyplot as plt

x = torch.arange(0,10,.1,dtype=torch.float)
x = x[:,None]
y = x*3+torch.randn(x.shape)
```

```
prediction = mymodel(x).detach().numpy()
plt.plot(x,y,'ro')
plt.plot(x,prediction)
plt.legend(['data','prediction of mymodel before training'])
```

[4]: <matplotlib.legend.Legend at 0x7fd3191e2610>



1.4 2.3 Performing Gradient Descent

1.4.1 Forward Pass

The first step to calculate gradient is to do a "fowrad pass", which means compute the loss from the current parameters and the training data.

[5]:
```
# Let's try to calculate the gradient

prediction = mymodel(x)

loss = torch.mean((prediction - y)**2)

print(loss)
```

```
tensor(292.7288, grad_fn=<MeanBackward0>)
```

1.4.2 Backward

Before we talk about backward, let's see what the gradients are now. They are stored in `.grad` attributes in the two model parameters. They should be `None` as we haven't computed it yet.

[6]:
```
print(mymodel.w.grad,mymodel.b.grad)
```

```
None None
```

The backward function computes the gradient, and you can check the gradient values.

[7]:
```
loss.backward()
print(mymodel.w.grad,mymodel.b.grad)
```

```
tensor([[-195.7584]]) tensor([-29.5983])
```

1.4.3 Training loop

Let's now write a training loop for gradient descent! The training procedure is a loop of multiple gradient steps. In each training step in the training loop,

- First the prediction is computed based on the input variable of the training data set.
- Then, the prediction, together with the training output, is used to compute the loss.
- Then, we run the optimizer.zero_grad(), which clears the gradient computed from the previous loop.
- Then, we run loss.backward() which calculates the gradient of the loss w.r.t. the parameters
- Finally, optimizer.step() conducts a gradient step

[8]:
```
# Now let's do the training!

maxIter = 100

mymodel = MyLinearRegressionModel(1)

# this creates a optimizer, and we tell optimizer we are optimizing the␣
↪parameters in mymodel
optimizer = torch.optim.SGD(mymodel.parameters(), lr = 1e-3)

for _ in range(maxIter):

    # pass input data to get the prediction outputs by the current model
    prediction = mymodel(x)

    # compare prediction and the actual output and compute the loss
    loss = torch.mean((prediction - y)**2)

    # compute the gradient
    optimizer.zero_grad()
    loss.backward()
```

```
    # update parameters
    optimizer.step()


# let
```

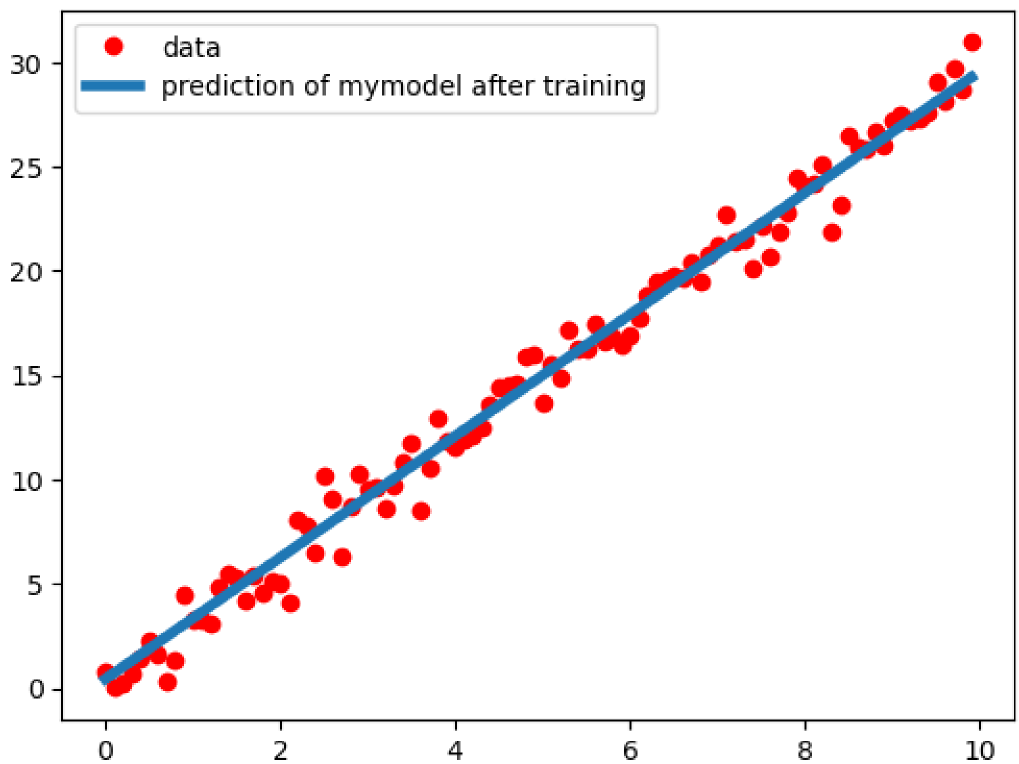
[9]:
```
# let's see how the model looks like!

print(mymodel.w,mymodel.b)

prediction = mymodel(x).detach().numpy()
plt.plot(x,y,'ro')
plt.plot(x,prediction,linewidth = 4)
plt.legend(['data','prediction of mymodel after training'])
```

```
Parameter containing:
tensor([[2.9131]], requires_grad=True) Parameter containing:
tensor([0.4291], requires_grad=True)
```

[9]: <matplotlib.legend.Legend at 0x7fd2f8eaf8e0>



1.5 2.4 Visualizing Gradient Descent

[10]:

```
import io
import imageio
from matplotlib.backends.backend_agg import FigureCanvasAgg as FigureCanvas
from matplotlib.figure import Figure

mymodel = MyLinearRegressionModel(1) # creating a model instance with input␣
 ↪dimension 1
lr = 3e-2
optimizer = torch.optim.SGD(mymodel.parameters(), lr = lr) # this line creates␣
 ↪a optimizer, and we tell optimizer we are optimizing the parameters in␣
 ↪mymodel


frames = []

losses = []

maxIter = 100

for i in range(maxIter):

    # pass input data to get the prediction outputs by the current model
    prediction = mymodel(x)

    # compare prediction and the actual output and compute the loss
    loss = torch.mean((prediction - y)**2)

    # compute the gradient
    optimizer.zero_grad()
    loss.backward()

    # update parameters
    optimizer.step()
    fig, ax = plt.subplots(nrows = 1, ncols = 2)
    canvas = FigureCanvas(fig)
    ax[0].plot(x,y,'ro')
    ax[0].plot(x,prediction.detach(),linewidth = 2)
    ax[0].legend(['data','prediction of mymodel'],loc = 'upper left')
    ax[0].set_title(f"Learning rate = {lr}, Iteration {i}")
    ax[0].set_xlim((0,10))
    ax[0].set_ylim((0,30))

    losses.append(loss.detach().numpy())
    ax[1].plot(np.arange(i+1),np.array(losses).squeeze(),linewidth=2 )
    ax[1].set_xlim((0,maxIter))
```

```python
    ax[1].set_ylim((0,300))
    ax[1].set_title("Training loss")
    canvas.draw()       # draw the canvas, cache the renderer

    image = np.frombuffer(canvas.tostring_rgb(), dtype='uint8')

    image = image.reshape(fig.canvas.get_width_height()[::-1] + (3,))

    frames.append(image)
    plt.close(fig)


print("Saving GIF file")
with imageio.get_writer("GD.gif", mode="I") as writer:
    for frame in frames:
        writer.append_data(frame)
```

```
Saving GIF file
```