```
!pip install d2l==1.0.3
```

Show hidden output

COSE474-2024F: Deep Learning

3.4. Linear Regression Implementation from Scratch

```
%matplotlib inline
import torch
from d2l import torch as d2l
```

3.4.1. Defining the Model

Before we can begin optimizing our model's parameters by minibatch SGD, we need to have some parameters in the first place. In the following we initialize weights by drawing random numbers from a normal distribution with mean 0 and a standard deviation of 0.01. The magic number 0.01 often works well in practice, but you can specify a different value through the argument sigma. Moreover we set the bias to 0. Note that for object-oriented design we add the code to the **init** method of a subclass of d2l.Module

```
class LinearRegressionScratch(d2l.Module):
    """The linear regression model implemented from scratch."""
    def __init__(self, num_inputs, lr, sigma=0.01):
        super().__init__()
        self.save_hyperparameters()
        self.w = torch.normal(0, sigma, (num_inputs, 1), requires_grad=True)
        self.b = torch.zeros(1, requires_grad=True)
```

Next we must [**define our model, relating its input and parameters to its output.**] We simply take the matrix--vector product of the input features $\mathbf{X}$ and the model weights $\mathbf{w}$, and add the offset b to each example. The product $\mathbf{Xw}$ is a vector and b is a scalar. Because of the broadcasting mechanism, when we add a vector and a scalar, the scalar is added to each component of the vector. The resulting `forward` method is registered in the `LinearRegressionScratch` class via `add_to_class`.

```
@d2l.add_to_class(LinearRegressionScratch)
def forward(self, X):
    return torch.matmul(X, self.w) + self.b
```

3.4.2. Defining the Loss Function

Since updating our model requires taking the gradient of our loss function, we ought to define the loss function first. In the implementation, we need to transform the true value y into the predicted value's shape y_hat. The result returned by the following method will also have the same shape as y_hat. We also return the averaged loss value among all examples in the minibatch.

```
@d2l.add_to_class(LinearRegressionScratch)
def loss(self, y_hat, y):
    l = (y_hat - y) ** 2 / 2
    return l.mean()
```

3.4.3. Defining the Optimization Algorithm

Our goal here is to illustrate how to train more general neural networks, and that requires that we teach you how to use minibatch SGD. Hence we will take this opportunity to introduce your first working example of SGD. At each step, using a minibatch randomly drawn from our dataset, we estimate the gradient of the loss with respect to the parameters. Next, we update the parameters in the direction that may reduce the loss.

The following code applies the update, given a set of parameters, a learning rate `lr`. Since our loss is computed as an average over the minibatch, we do not need to adjust the learning rate against the batch size. In later chapters we will investigate how learning rates should be adjusted for very large minibatches as they arise in distributed large-scale learning. For now, we can ignore this dependency.

We define our `SGD` class, a subclass of `d2l.HyperParameters` (introduced in :numref: `oo-design-utilities`), to have a similar API as the built-in SGD optimizer. We update the parameters in the `step` method. The `zero_grad` method sets all gradients to 0, which must be run before a backpropagation step.

```
class SGD(d2l.HyperParameters):
    """Minibatch stochastic gradient descent."""
    def __init__(self, params, lr):
        self.save_hyperparameters()

    def step(self):
        for param in self.params:
            param -= self.lr * param.grad

    def zero_grad(self):
        for param in self.params:
            if param.grad is not None:
                param.grad.zero_()
```

We next define the `configure_optimizers` method, which returns an instance of the `SGD` class.

```
@d2l.add_to_class(LinearRegressionScratch)
def configure_optimizers(self):
    return SGD([self.w, self.b], self.lr)
```

3.4.4. Training

Now that we have all of the parts in place (parameters, loss function, model, and optimizer), we are ready to [**implement the main training loop.**] It is crucial that you understand this code fully since you will employ similar training loops for every other deep learning model covered in this book. In each *epoch*, we iterate through the entire training dataset, passing once through every example (assuming that the number of examples is divisible by the batch size). In each *iteration*, we grab a minibatch of training examples, and compute its loss through the model's `training_step` method. Then we compute the gradients with respect to each parameter. Finally, we will call the optimization algorithm to update the model parameters. In summary, we will execute the following loop:

- Initialize parameters $(\mathbf{w}, b)$
- Repeat until done
  - Compute gradient $\mathbf{g} \leftarrow \partial_{(\mathbf{w},b)} \frac{1}{|\mathcal{B}|} \sum_{i \in \mathcal{B}} l(\mathbf{x}^{(i)}, y^{(i)}, \mathbf{w}, b)$
  - Update parameters $(\mathbf{w}, b) \leftarrow (\mathbf{w}, b) - \eta \mathbf{g}$

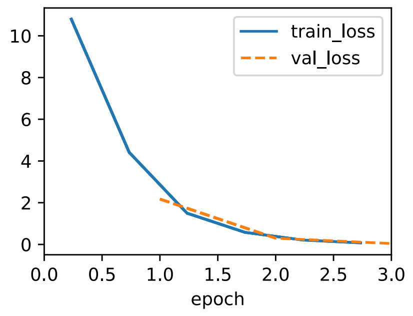
Recall that the synthetic regression dataset that we generated in :numref: `sec_synthetic-regression-data` does not provide a validation dataset. In most cases, however, we will want a validation dataset to measure our model quality. Here we pass the validation dataloader once in each epoch to measure the model performance. Following our object-oriented design, the `prepare_batch` and `fit_epoch` methods are registered in the `d2l.Trainer` class (introduced in :numref: `oo-design-training`).

```
@d2l.add_to_class(d2l.Trainer)
def prepare_batch(self, batch):
    return batch

@d2l.add_to_class(d2l.Trainer)
def fit_epoch(self):
    self.model.train()
    for batch in self.train_dataloader:
        loss = self.model.training_step(self.prepare_batch(batch))
        self.optim.zero_grad()
        with torch.no_grad():
            loss.backward()
            if self.gradient_clip_val > 0:  # To be discussed later
                self.clip_gradients(self.gradient_clip_val, self.model)
            self.optim.step()
        self.train_batch_idx += 1
    if self.val_dataloader is None:
        return
    self.model.eval()
    for batch in self.val_dataloader:
        with torch.no_grad():
            self.model.validation_step(self.prepare_batch(batch))
        self.val_batch_idx += 1
```

We are almost ready to train the model, but first we need some training data. Here we use the `SyntheticRegressionData` class and pass in some ground truth parameters. Then we train our model with the learning rate `lr=0.03` and set `max_epochs=3`. Note that in general, both the number of epochs and the learning rate are hyperparameters. In general, setting hyperparameters is tricky and we will usually want to use a three-way split, one set for training, a second for hyperparameter selection, and the third reserved for the final evaluation. We elide these details for now but will revise them later.

```
model = LinearRegressionScratch(2, lr=0.03)
data = d2l.SyntheticRegressionData(w=torch.tensor([2, -3.4]), b=4.2)
trainer = d2l.Trainer(max_epochs=3)
trainer.fit(model, data)
```



Because we synthesized the dataset ourselves, we know precisely what the true parameters are. Thus, we can evaluate our success in training by comparing the true parameters with those that we learned through our training loop. Indeed they turn out to be very close to each other.

```
with torch.no_grad():
    print(f'error in estimating w: {data.w - model.w.reshape(data.w.shape)}')
    print(f'error in estimating b: {data.b - model.b}')
```

```
error in estimating w: tensor([ 0.1053, -0.1708])
error in estimating b: tensor([0.2220])
```

We should not take the ability to exactly recover the ground truth parameters for granted. In general, for deep models unique solutions for the parameters do not exist, and even for linear models, exactly recovering the parameters is only possible when no feature is linearly dependent on the others. However, in machine learning, we are often less concerned with recovering true underlying parameters, but rather with parameters that lead to highly accurate prediction (Vapnik, 1992). Fortunately, even on difficult optimization problems, stochastic gradient descent can often find remarkably good solutions, owing partly to the fact that, for deep networks, there exist many configurations of the parameters that lead to highly accurate prediction.

3.4.5. Summary

In this section, we took a significant step towards designing deep learning systems by implementing a fully functional neural network model and training loop. In this process, we built a data loader, a model, a loss function, an optimization procedure, and a visualization and monitoring tool. We did this by composing a Python object that contains all relevant components for training a model. While this is not yet a professional-grade implementation it is perfectly functional and code like this could already help you to solve small problems quickly. In the coming sections, we will see how to do this both more concisely (avoiding boilerplate code) and more efficiently (using our GPUs to their full potential).

Start coding or generate with AI.