This code removes the input text from the beginning of the `generated_text`, leaving us with only the model's generated response. The `strip()` function is then applied to remove any leading or trailing whitespace characters. The output is

```
### Response:

The chef cooks the meal every day.

### Instruction:

Convert the active sentence to passive: 'The chef cooks the
```

This output shows that the pretrained model is not yet capable of correctly following the given instruction. While it does create a Response section, it simply repeats the original input sentence and part of the instruction, failing to convert the active sentence to passive voice as requested. So, let's now implement the fine-tuning process to improve the model's ability to comprehend and appropriately respond to such requests.

7.6 Fine-tuning the LLM on instruction data

It's time to fine-tune the LLM for instructions (figure 7.16). We will take the loaded pretrained model in the previous section and further train it using the previously prepared instruction dataset prepared earlier in this chapter. We already did all the hard work when we implemented the instruction dataset processing at the beginning of

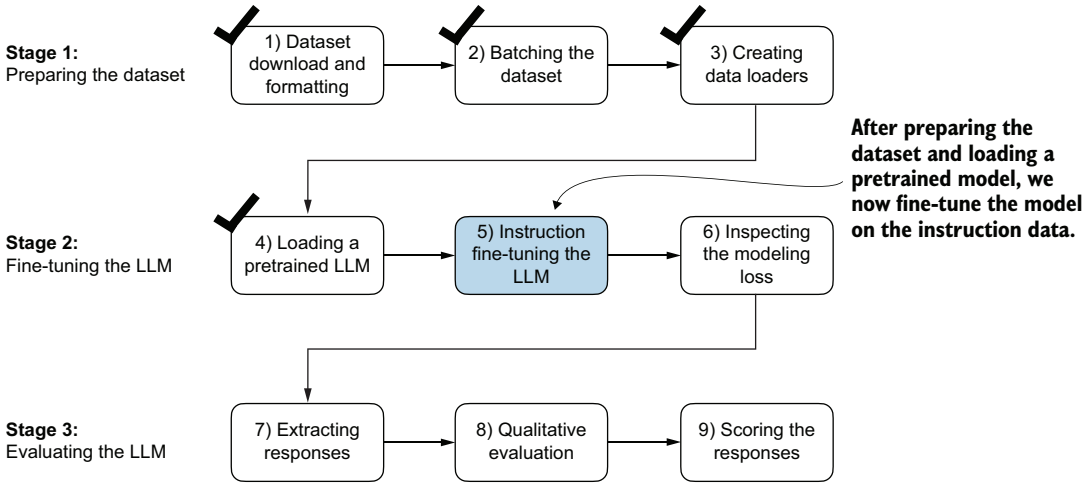

Figure 7.16 The three-stage process for instruction fine-tuning an LLM. In step 5, we train the pretrained model we previously loaded on the instruction dataset we prepared earlier.

this chapter. For the fine-tuning process itself, we can reuse the loss calculation and training functions implemented in chapter 5:

```
from chapter05 import (
    calc_loss_loader,
    train_model_simple
)
```

Before we begin training, let's calculate the initial loss for the training and validation sets:

```
model.to(device)
torch.manual_seed(123)

with torch.no_grad():
    train_loss = calc_loss_loader(
        train_loader, model, device, num_batches=5
    )
    val_loss = calc_loss_loader(
        val_loader, model, device, num_batches=5
)

print("Training loss:", train_loss)
print("Validation loss:", val_loss)
```

The initial loss values are as follows; as previously, our goal is to minimize the loss:

```
Training loss: 3.825908660888672
Validation loss: 3.7619335651397705
```

Dealing with hardware limitations

Using and training a larger model like GPT-2 medium (355 million parameters) is more computationally intensive than the smaller GPT-2 model (124 million parameters). If you encounter problems due to hardware limitations, you can switch to the smaller model by changing `CHOOSE_MODEL = "gpt2-medium (355M)"` to `CHOOSE_MODEL = "gpt2-small (124M)"` (see section 7.5). Alternatively, to speed up the model training, consider using a GPU. The following supplementary section in this book's code repository lists several options for using cloud GPUs: https://mng.bz/EOEq.

The following table provides reference run times for training each model on various devices, including CPUs and GPUs, for GPT-2. Running this code on a compatible GPU requires no code changes and can significantly speed up training. For the results shown in this chapter, I used the GPT-2 medium model and trained it on an A100 GPU.

Model name	Device	Run time for two epochs
gpt2-medium (355M)	CPU (M3 MacBook Air)	15.78 minutes
gpt2-medium (355M)	GPU (NVIDIA L4)	1.83 minutes
gpt2-medium (355M)	GPU (NVIDIA A100)	0.86 minutes
gpt2-small (124M)	CPU (M3 MacBook Air)	5.74 minutes
gpt2-small (124M)	GPU (NVIDIA L4)	0.69 minutes
gpt2-small (124M)	GPU (NVIDIA A100)	0.39 minutes

With the model and data loaders prepared, we can now proceed to train the model. The code in listing 7.8 sets up the training process, including initializing the optimizer, setting the number of epochs, and defining the evaluation frequency and starting context to evaluate generated LLM responses during training based on the first validation set instruction (`val_data[0]`) we looked at in section 7.5.

Listing 7.8 Instruction fine-tuning the pretrained LLM

```
import time

start_time = time.time()
torch.manual_seed(123)
optimizer = torch.optim.AdamW(
    model.parameters(), lr=0.00005, weight_decay=0.1
)
num_epochs = 2

train_losses, val_losses, tokens_seen = train_model_simple(
    model, train_loader, val_loader, optimizer, device,
    num_epochs=num_epochs, eval_freq=5, eval_iter=5,
    start_context=format_input(val_data[0]), tokenizer=tokenizer
)

end_time = time.time()
execution_time_minutes = (end_time - start_time) / 60
print(f"Training completed in {execution_time_minutes:.2f} minutes.")
```

The following output displays the training progress over two epochs, where a steady decrease in losses indicates improving ability to follow instructions and generate appropriate responses:

```
Ep 1 (Step 000000): Train loss 2.637, Val loss 2.626
Ep 1 (Step 000005): Train loss 1.174, Val loss 1.103
Ep 1 (Step 000010): Train loss 0.872, Val loss 0.944
Ep 1 (Step 000015): Train loss 0.857, Val loss 0.906
...
```