```
Ep 1 (Step 000115): Train loss 0.520, Val loss 0.665
Below is an instruction that describes a task. Write a response that
appropriately completes the request.  ### Instruction: Convert the
active sentence to passive: 'The chef cooks the meal every day.'
### Response: The meal is prepared every day by the chef.<|endoftext|>
The following is an instruction that describes a task.
Write a response that appropriately completes the request.
### Instruction: Convert the active sentence to passive:
Ep 2 (Step 000120): Train loss 0.438, Val loss 0.670
Ep 2 (Step 000125): Train loss 0.453, Val loss 0.685
Ep 2 (Step 000130): Train loss 0.448, Val loss 0.681
Ep 2 (Step 000135): Train loss 0.408, Val loss 0.677
...
Ep 2 (Step 000230): Train loss 0.300, Val loss 0.657
Below is an instruction that describes a task. Write a response
that appropriately completes the request.  ### Instruction:
Convert the active sentence to passive: 'The chef cooks the meal
every day.'  ### Response: The meal is cooked every day by the
chef.<|endoftext|>The following is an instruction that describes
a task. Write a response that appropriately completes the request.
### Instruction: What is the capital of the United Kingdom
Training completed in 0.87 minutes.
```

The training output shows that the model is learning effectively, as we can tell based on the consistently decreasing training and validation loss values over the two epochs. This result suggests that the model is gradually improving its ability to understand and follow the provided instructions. (Since the model demonstrated effective learning within these two epochs, extending the training to a third epoch or more is not essential and may even be counterproductive as it could lead to increased overfitting.)

Moreover, the generated responses at the end of each epoch let us inspect the model's progress in correctly executing the given task in the validation set example. In this case, the model successfully converts the active sentence `"The chef cooks the meal every day."` into its passive voice counterpart: `"The meal is cooked every day by the chef."`

We will revisit and evaluate the response quality of the model in more detail later. For now, let's examine the training and validation loss curves to gain additional insights into the model's learning process. For this, we use the same `plot_losses` function we used for pretraining:

```
from chapter05 import plot_losses
epochs_tensor = torch.linspace(0, num_epochs, len(train_losses))
plot_losses(epochs_tensor, tokens_seen, train_losses, val_losses)
```

From the loss plot shown in figure 7.17, we can see that the model's performance on both the training and validation sets improves substantially over the course of training. The rapid decrease in losses during the initial phase indicates that the model quickly learns meaningful patterns and representations from the data. Then, as training progresses to the second epoch, the losses continue to decrease but at a slower

rate, suggesting that the model is fine-tuning its learned representations and converging to a stable solution.

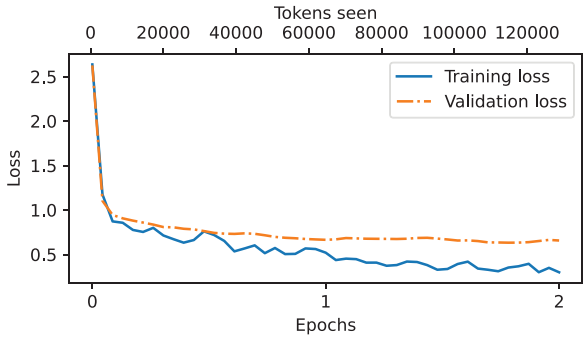

Figure 7.17 The training and validation loss trends over two epochs. The solid line represents the training loss, showing a sharp decrease before stabilizing, while the dotted line represents the validation loss, which follows a similar pattern.

While the loss plot in figure 7.17 indicates that the model is training effectively, the most crucial aspect is its performance in terms of response quality and correctness. So, next, let's extract the responses and store them in a format that allows us to evaluate and quantify the response quality.

Exercise 7.3 Fine-tuning on the original Alpaca dataset

The Alpaca dataset, by researchers at Stanford, is one of the earliest and most popular openly shared instruction datasets, consisting of 52,002 entries. As an alternative to the `instruction-data.json` file we use here, consider fine-tuning an LLM on this dataset. The dataset is available at https://mng.bz/NBnE.

This dataset contains 52,002 entries, which is approximately 50 times more than those we used here, and most entries are longer. Thus, I highly recommend using a GPU to conduct the training, which will accelerate the fine-tuning process. If you encounter out-of-memory errors, consider reducing the `batch_size` from 8 to 4, 2, or even 1. Lowering the `allowed_max_length` from 1,024 to 512 or 256 can also help manage memory problems.

7.7 Extracting and saving responses

Having fine-tuned the LLM on the training portion of the instruction dataset, we are now ready to evaluate its performance on the held-out test set. First, we extract the model-generated responses for each input in the test dataset and collect them for manual analysis, and then we evaluate the LLM to quantify the quality of the responses, as highlighted in figure 7.18.

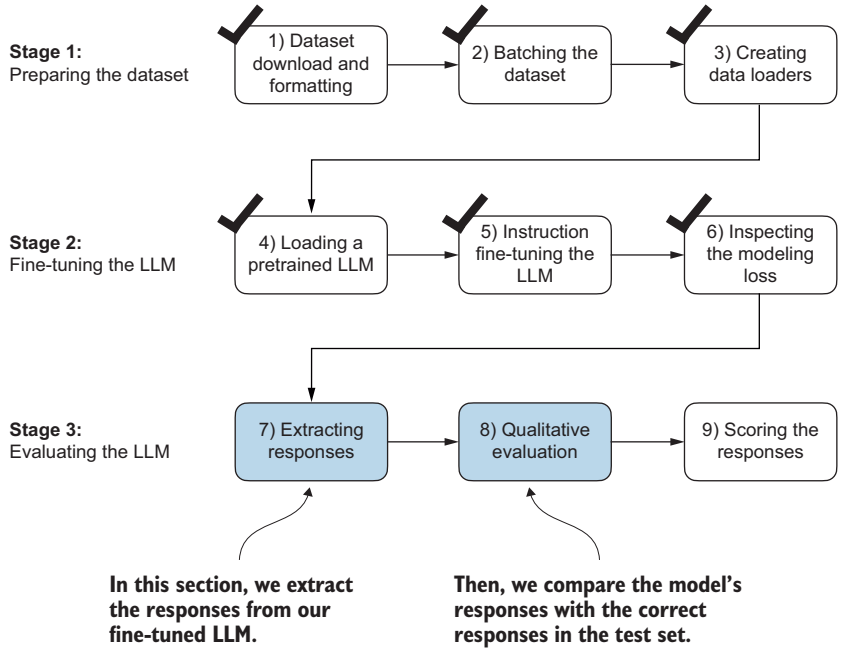

Figure 7.18 The three-stage process for instruction fine-tuning the LLM. In the first two steps of stage 3, we extract and collect the model responses on the held-out test dataset for further analysis and then evaluate the model to quantify the performance of the instruction-fine-tuned LLM.

To complete the response instruction step, we use the `generate` function. We then print the model responses alongside the expected test set answers for the first three test set entries, presenting them side by side for comparison:

```
torch.manual_seed(123)

for entry in test_data[:3]:
    input_text = format_input(entry)
    token_ids = generate(
        model=model,
        idx=text_to_token_ids(input_text, tokenizer).to(device),
        max_new_tokens=256,
        context_size=BASE_CONFIG["context_length"],
        eos_id=50256
    )
    generated_text = token_ids_to_text(token_ids, tokenizer)

    response_text = (
        generated_text[len(input_text):]
        .replace("### Response:", "")
        .strip()
    )
```

Iterates over the first three test set samples

Uses the generate function imported in section 7.5