This local implementation can significantly decrease latency and reduce server-related costs. Furthermore, custom LLMs grant developers complete autonomy, allowing them to control updates and modifications to the model as needed.

The general process of creating an LLM includes pretraining and fine-tuning. The "pre" in "pretraining" refers to the initial phase where a model like an LLM is trained on a large, diverse dataset to develop a broad understanding of language. This pretrained model then serves as a foundational resource that can be further refined through fine-tuning, a process where the model is specifically trained on a narrower dataset that is more specific to particular tasks or domains. This two-stage training approach consisting of pretraining and fine-tuning is depicted in figure 1.3.

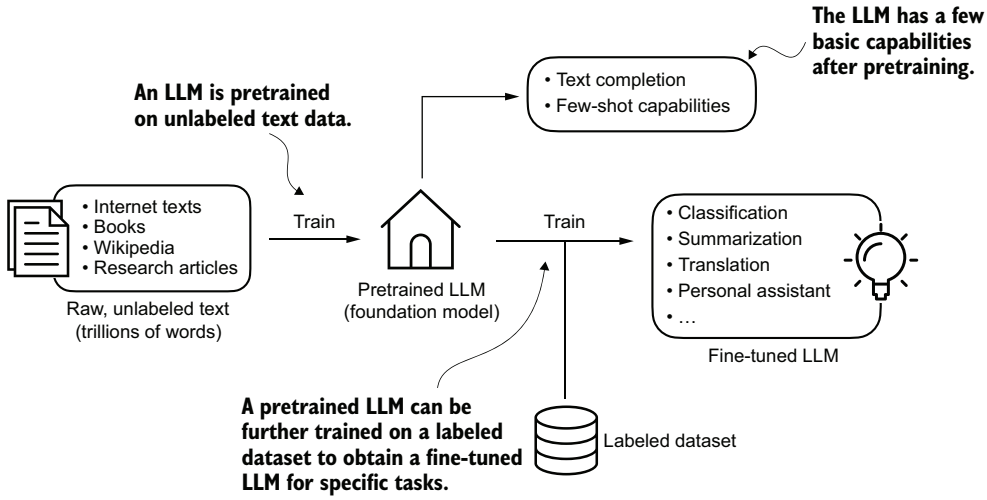

Figure 1.3 Pretraining an LLM involves next-word prediction on large text datasets. A pretrained LLM can then be fine-tuned using a smaller labeled dataset.

The first step in creating an LLM is to train it on a large corpus of text data, sometimes referred to as *raw* text. Here, "raw" refers to the fact that this data is just regular text without any labeling information. (Filtering may be applied, such as removing formatting characters or documents in unknown languages.)

> **NOTE** Readers with a background in machine learning may note that labeling information is typically required for traditional machine learning models and deep neural networks trained via the conventional supervised learning paradigm. This is not the case for the pretraining stage of LLMs. In this phase, LLMs use self-supervised learning, where the model generates its own labels from the input data.

This first training stage of an LLM is also known as *pretraining*, creating an initial pretrained LLM, often called a *base* or *foundation model*. A typical example of such a model is the GPT-3 model (the precursor of the original model offered in ChatGPT). This model is capable of text completion—that is, finishing a half-written sentence provided by a user. It also has limited few-shot capabilities, which means it can learn to perform new tasks based on only a few examples instead of needing extensive training data.

After obtaining a pretrained LLM by training on large text datasets, where the LLM is trained to predict the next word in the text, we can further train the LLM on labeled data, also known as *fine-tuning*.

The two most popular categories of fine-tuning LLMs are *instruction fine-tuning* and *classification fine-tuning*. In instruction fine-tuning, the labeled dataset consists of instruction and answer pairs, such as a query to translate a text accompanied by the correctly translated text. In classification fine-tuning, the labeled dataset consists of texts and associated class labels—for example, emails associated with "spam" and "not spam" labels.

We will cover code implementations for pretraining and fine-tuning an LLM, and we will delve deeper into the specifics of both instruction and classification fine-tuning after pretraining a base LLM.

1.4 Introducing the transformer architecture

Most modern LLMs rely on the *transformer* architecture, which is a deep neural network architecture introduced in the 2017 paper "Attention Is All You Need" (https://arxiv.org/abs/1706.03762). To understand LLMs, we must understand the original transformer, which was developed for machine translation, translating English texts to German and French. A simplified version of the transformer architecture is depicted in figure 1.4.

The transformer architecture consists of two submodules: an encoder and a decoder. The encoder module processes the input text and encodes it into a series of numerical representations or vectors that capture the contextual information of the input. Then, the decoder module takes these encoded vectors and generates the output text. In a translation task, for example, the encoder would encode the text from the source language into vectors, and the decoder would decode these vectors to generate text in the target language. Both the encoder and decoder consist of many layers connected by a so-called self-attention mechanism. You may have many questions regarding how the inputs are preprocessed and encoded. These will be addressed in a step-by-step implementation in subsequent chapters.

A key component of transformers and LLMs is the self-attention mechanism (not shown), which allows the model to weigh the importance of different words or tokens in a sequence relative to each other. This mechanism enables the model to capture long-range dependencies and contextual relationships within the input data, enhancing its ability to generate coherent and contextually relevant output. However, due to

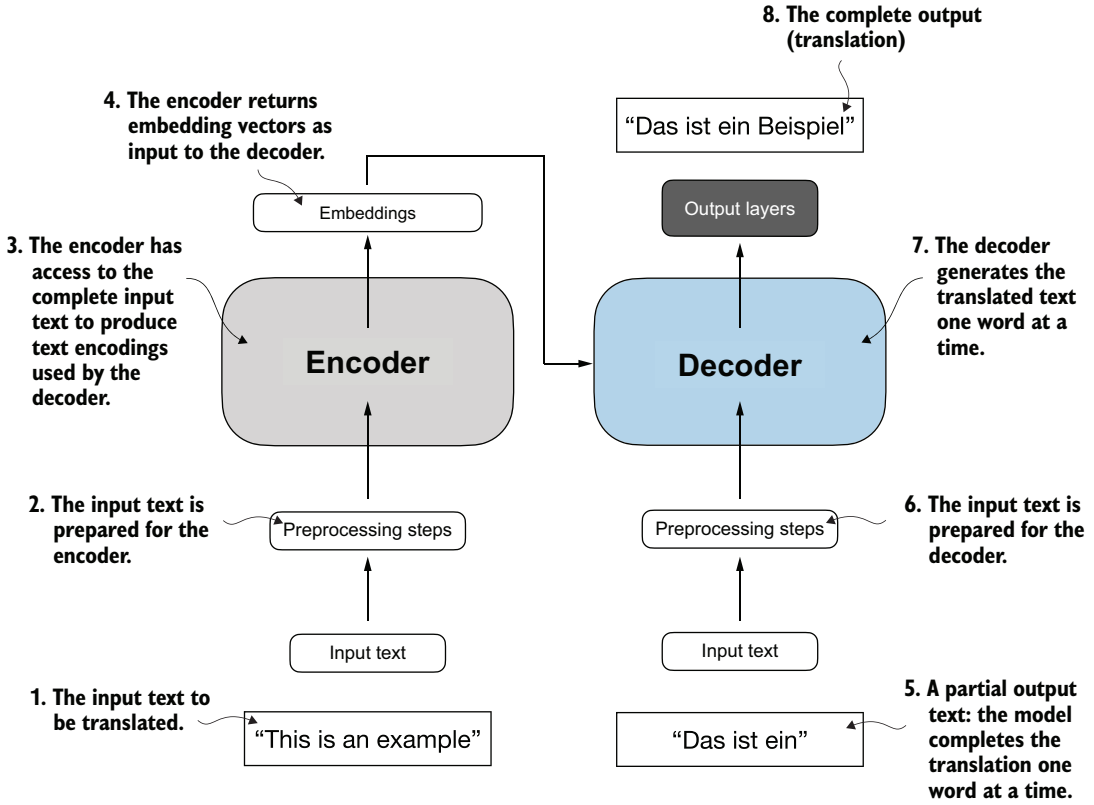

Figure 1.4 A simplified depiction of the original transformer architecture, which is a deep learning model for language translation. The transformer consists of two parts: (a) an encoder that processes the input text and produces an embedding representation (a numerical representation that captures many different factors in different dimensions) of the text that the (b) decoder can use to generate the translated text one word at a time. This figure shows the final stage of the translation process where the decoder has to generate only the final word ("Beispiel"), given the original input text ("This is an example") and a partially translated sentence ("Das ist ein"), to complete the translation.

its complexity, we will defer further explanation to chapter 3, where we will discuss and implement it step by step.

Later variants of the transformer architecture, such as BERT (short for *bidirectional encoder representations from transformers*) and the various GPT models (short for *generative pretrained transformers*), built on this concept to adapt this architecture for different tasks. If interested, refer to appendix B for further reading suggestions.

BERT, which is built upon the original transformer's encoder submodule, differs in its training approach from GPT. While GPT is designed for generative tasks, BERT and its variants specialize in masked word prediction, where the model predicts masked