Reading in a short story as text sample into Python.

Step 1: Creating Tokens

The print command prints the total number of characters followed by the first 100 characters of this file for illustration purposes.

In [3]:

```
with open("the-verdict.txt", "r", encoding="utf-8") as f:
    raw_text = f.read()

print("Total number of character:", len(raw_text))
print(raw_text[:99])
```

```
Total number of character: 20479
I HAD always thought Jack Gisburn rather a cheap genius--though a good fellow enough--so
it was no
```

Our goal is to tokenize this 20,479-character short story into individual words and special characters that we can then turn into embeddings for LLM training

Note that it's common to process millions of articles and hundreds of thousands of books -- many gigabytes of text -- when working with LLMs. However, for educational purposes, it's sufficient to work with smaller text samples like a single book to illustrate the main ideas behind the text processing steps and to make it possible to run it in reasonable time on consumer hardware.

How can we best split this text to obtain a list of tokens? For this, we go on a small excursion and use Python's regular expression library re for illustration purposes. (Note that you don't have to learn or memorize any regular expression syntax since we will transition to a pre-built tokenizer later in this chapter.)

Using some simple example text, we can use the re.split command with the following syntax to split a text on whitespace characters:

In [4]:

```
import re

text = "Hello, world. This, is a test."
result = re.split(r'(\s)', text)

print(result)
```

```
['Hello,', ' ', 'world.', ' ', 'This,', ' ', 'is', ' ', 'a', ' ', 'test.']
```

The result is a list of individual words, whitespaces, and punctuation characters:

Let's modify the regular expression splits on whitespaces (\s) and commas, and periods ([,.]):

In [5]:

```
result = re.split(r'([,.]|\s)', text)

print(result)
```

```
['Hello', ',', '', ' ', 'world', '.', '', ' ', 'This', ',', '', ' ', 'is', ' ', 'a', ' ',
'test', '.', '']
```

We can see that the words and punctuation characters are now separate list entries just as we wanted

A small remaining issue is that the list still includes whitespace characters. Optionally, we can remove these redundant characters safely as follows:

In [6]:

```
result = [item for item in result if item.strip()]
print(result)
```

```
['Hello', ',', 'world', '.', 'This', ',', 'is', 'a', 'test', '.']
```

REMOVING WHITESPACES OR NOT When developing a simple tokenizer, whether we should encode whitespaces as separate characters or just remove them depends on our application and its requirements. Removing whitespaces reduces the memory and computing requirements. However, keeping whitespaces can be useful if we train models that are sensitive to the exact structure of the text (for example, Python code, which is sensitive to indentation and spacing). Here, we remove whitespaces for simplicity and brevity of the tokenized outputs. Later, we will switch to a tokenization scheme that includes whitespaces.

The tokenization scheme we devised above works well on the simple sample text. Let's modify it a bit further so that it can also handle other types of punctuation, such as question marks, quotation marks, and the double-dashes we have seen earlier in the first 100 characters of Edith Wharton's short story, along with additional special characters:

In [7]:

```
text = "Hello, world. Is this-- a test?"
result = re.split(r'([,.:;?_!"()\']|--|\s)', text)
result = [item.strip() for item in result if item.strip()]
print(result)
```

```
['Hello', ',', 'world', '.', 'Is', 'this', '--', 'a', 'test', '?']
```

In [8]:

```
# Strip whitespace from each item and then filter out any empty strings.
result = [item for item in result if item.strip()]
print(result)
```

```
['Hello', ',', 'world', '.', 'Is', 'this', '--', 'a', 'test', '?']
```

In [9]:

```
text = "Hello, world. Is this-- a test?"

result = re.split(r'([,.:;?_!"()\']|--|\s)', text)
result = [item.strip() for item in result if item.strip()]
```

```
print(result)
```

```
['Hello', ',', 'world', '.', 'Is', 'this', '--', 'a', 'test', '?']
```

Now that we got a basic tokenizer working, let's apply it to Edith Wharton's entire short story:

In [10]:

```
preprocessed = re.split(r'([,.:;?_!"()\']|--|\s)', raw_text)
preprocessed = [item.strip() for item in preprocessed if item.strip()]
print(preprocessed[:30])
```

```
['I', 'HAD', 'always', 'thought', 'Jack', 'Gisburn', 'rather', 'a', 'cheap', 'genius', '-
-', 'though', 'a', 'good', 'fellow', 'enough', '--', 'so', 'it', 'was', 'no', 'great', 's
urprise', 'to', 'me', 'to', 'hear', 'that', ',', 'in']
```

In [11]:

```
print(len(preprocessed))
```

```
4690
```

Step 2: Creating Token IDs

In the previous section, we tokenized Edith Wharton's short story and assigned it to a Python variable called preprocessed. Let's now create a list of all unique tokens and sort them alphabetically to determine the vocabulary size:

In [12]:

```
all_words = sorted(set(preprocessed))
vocab_size = len(all_words)

print(vocab_size)
```

```
1130
```

After determining that the vocabulary size is 1,130 via the above code, we create the vocabulary and print its first 51 entries for illustration purposes:

In [13]:

```
vocab = {token:integer for integer,token in enumerate(all_words)}
```

In [14]:

```
for i, item in enumerate(vocab.items()):
    print(item)
    if i >= 50:
        break
```

```
('!', 0)
('"', 1)
("'", 2)
('(', 3)
(')', 4)
(',', 5)
('--', 6)
('.', 7)
(':', 8)
(';', 9)
('?', 10)
```

```
('A', 11)
('Ah', 12)
('Among', 13)
('And', 14)
('Are', 15)
('Arrt', 16)
('As', 17)
('At', 18)
('Be', 19)
('Begin', 20)
('Burlington', 21)
('But', 22)
('By', 23)
('Carlo', 24)
('Chicago', 25)
('Claude', 26)
('Come', 27)
('Croft', 28)
('Destroyed', 29)
('Devonshire', 30)
('Don', 31)
('Dubarry', 32)
('Emperors', 33)
('Florence', 34)
('For', 35)
('Gallery', 36)
('Gideon', 37)
('Gisburn', 38)
('Gisburns', 39)
('Grafton', 40)
('Greek', 41)
('Grindle', 42)
('Grindles', 43)
('HAD', 44)
('Had', 45)
('Hang', 46)
('Has', 47)
('He', 48)
('Her', 49)
('Hermia', 50)
```

As we can see, based on the output above, the dictionary contains individual tokens associated with unique integer labels.

Later in this book, when we want to convert the outputs of an LLM from numbers back into text, we also need a way to turn token IDs into text. For this, we can create an inverse version of the vocabulary that maps token IDs back to corresponding text tokens.

Let's implement a complete tokenizer class in Python. The class will have an encode method that splits text into tokens and carries out the string-to-integer mapping to produce token IDs via the vocabulary. In addition, we implement a decode method that carries out the reverse integer-to-string mapping to convert the token IDs back into text.

Step 1: Store the vocabulary as a class attribute for access in the encode and decode methods Step 2: Create an inverse vocabulary that maps token IDs back to the original text tokens Step 3: Process input text into token IDs Step 4: Convert token IDs back into text Step 5: Replace spaces before the specified punctuation

In [15]:

```
class SimpleTokenizerV1:
    def __init__(self, vocab):
        self.str_to_int = vocab
        self.int_to_str = {i:s for s,i in vocab.items()}

    def encode(self, text):
        preprocessed = re.split(r'([,.:;?_!"()\']|--|\s)', text)

        preprocessed = [
            item.strip() for item in preprocessed if item.strip()
        ]
        ids = [self.str_to_int[s] for s in preprocessed]
        return ids

    def decode(self, ids):
        text = " ".join([self.int_to_str[i] for i in ids])
        # Replace spaces before the specified punctuations
        text = re.sub(r'\s+([,.?!"()\'])', r'\1', text)
        return text
```

Let's instantiate a new tokenizer object from the SimpleTokenizerV1 class and tokenize a passage from Edith Wharton's short story to try it out in practice:

In [16]:

```
tokenizer = SimpleTokenizerV1(vocab)

text = """"It's the last he painted, you know,"
           Mrs. Gisburn said with pardonable pride."""
ids = tokenizer.encode(text)
print(ids)
```

```
[1, 56, 2, 850, 988, 602, 533, 746, 5, 1126, 596, 5, 1, 67, 7, 38, 851, 1108, 754, 793, 7
]
```

The code above prints the following token IDs: Next, let's see if we can turn these token IDs back into text using the decode method:

In [17]:

```
tokenizer.decode(ids)
```

Out[17]:

```
'" It\' s the last he painted, you know," Mrs. Gisburn said with pardonable pride.'
```

Based on the output above, we can see that the decode method successfully converted the token IDs back into the original text.

So far, so good. We implemented a tokenizer capable of tokenizing and de-tokenizing text based on a snippet from the training set. Let's now apply it to a new text sample that is not contained in the training set:

In [18]:

```
text = "Hello, do you like tea?"
print(tokenizer.encode(text))
```

```
---------------------------------------------------------------------------
KeyError                                  Traceback (most recent call last)
Cell In[18], line 2
```

```
      1 text = "Hello, do you like tea?"
----> 2 print(tokenizer.encode(text))

Cell In[15], line 12, in SimpleTokenizerV1.encode(self, text)
      7 preprocessed = re.split(r'([,.:;?_!"()\']|--|\s)', text)
      9 preprocessed = [
     10     item.strip() for item in preprocessed if item.strip()
     11 ]
---> 12 ids = [self.str_to_int[s] for s in preprocessed]
     13 return ids

KeyError: 'Hello'
```

The problem is that the word "Hello" was not used in the The Verdict short story. Hence, it is not contained in the vocabulary. This highlights the need to consider large and diverse training sets to extend the vocabulary when working on LLMs.

ADDING SPECIAL CONTEXT TOKENS

In the previous section, we implemented a simple tokenizer and applied it to a passage from the training set.

In this section, we will modify this tokenizer to handle unknown words.

In particular, we will modify the vocabulary and tokenizer we implemented in the previous section, SimpleTokenizerV2, to support two new tokens, <|unk|> and <|endoftext|>

We can modify the tokenizer to use an <|unk|> token if it encounters a word that is not part of the vocabulary. Furthermore, we add a token between unrelated texts. For example, when training GPT-like LLMs on multiple independent documents or books, it is common to insert a token before each document or book that follows a previous text source

Let's now modify the vocabulary to include these two special tokens, and <|endoftext|>, by adding these to the list of all unique words that we created in the previous section:

In [19]:

```
all_tokens = sorted(list(set(preprocessed)))
all_tokens.extend(["<|endoftext|>", "<|unk|>"])

vocab = {token:integer for integer,token in enumerate(all_tokens)}
```

In [20]:

```
len(vocab.items())
```

Out[20]:

```
1132
```

Based on the output of the print statement above, the new vocabulary size is 1132 (the vocabulary size in the previous section was 1130).

As an additional quick check, let's print the last 5 entries of the updated vocabulary:

In [21]:

```
for i, item in enumerate(list(vocab.items())[-5:]):
    print(item)
```

```
('younger', 1127)
('your', 1128)
('yourself', 1129)
('<|endoftext|>', 1130)
('<|unk|>', 1131)
```

A simple text tokenizer that handles unknown words

Step 1: Replace unknown words by <|unk|> tokens Step 2: Replace spaces before the specified punctuations

In [22]:

```
class SimpleTokenizerV2:
    def __init__(self, vocab):
        self.str_to_int = vocab
        self.int_to_str = { i:s for s,i in vocab.items()}

    def encode(self, text):
        preprocessed = re.split(r'([,.:;?_!"()\']|--|\s)', text)
        preprocessed = [item.strip() for item in preprocessed if item.strip()]
        preprocessed = [
            item if item in self.str_to_int
            else "<|unk|>" for item in preprocessed
        ]

        ids = [self.str_to_int[s] for s in preprocessed]
        return ids

    def decode(self, ids):
        text = " ".join([self.int_to_str[i] for i in ids])
        # Replace spaces before the specified punctuations
        text = re.sub(r'\s+([,.:;?!"()\'])', r'\1', text)
        return text
```

In [23]:

```
tokenizer = SimpleTokenizerV2(vocab)

text1 = "Hello, do you like tea?"
text2 = "In the sunlit terraces of the palace."

text = " <|endoftext|> ".join((text1, text2))

print(text)
```

```
Hello, do you like tea? <|endoftext|> In the sunlit terraces of the palace.
```

In [24]:

```
tokenizer.encode(text)
```

Out[24]:

```
[1131, 5, 355, 1126, 628, 975, 10, 1130, 55, 988, 956, 984, 722, 988, 1131, 7]
```

In [25]:

```
tokenizer.decode(tokenizer.encode(text))
```

Out[25]:

```
'<|unk|>, do you like tea? <|endoftext|> In the sunlit terraces of the <|unk|>.'
```

Based on comparing the de-tokenized text above with the original input text, we know that the training dataset, Edith Wharton's short story The Verdict, did not contain the words "Hello" and "palace."

So far, we have discussed tokenization as an essential step in processing text as input to LLMs. Depending on the LLM, some researchers also consider additional special tokens such as the following: [BOS] (beginning of sequence): This token marks the start of a text. It signifies to the LLM where a piece of content begins. [EOS] (end of sequence): This token is positioned at the end of a text, and is especially useful when concatenating multiple unrelated texts, similar to <|endoftext|>. For instance, when combining two different Wikipedia articles or books, the [EOS] token indicates where one article ends and the next one begins. [PAD] (padding): When training LLMs with batch sizes larger than one, the batch might contain texts of varying lengths. To ensure all texts have the same length, the shorter texts are extended or "padded" using the [PAD] token, up to the length of the longest text in the batch.

Note that the tokenizer used for GPT models does not need any of these tokens mentioned above but only uses an <|endoftext|> token for simplicity

the tokenizer used for GPT models also doesn't use an <|unk|> token for outof-vocabulary words. Instead, GPT models use a byte pair encoding tokenizer, which breaks down words into subword units

BYTE PAIR ENCODING (BPE)

We implemented a simple tokenization scheme in the previous sections for illustration purposes. This section covers a more sophisticated tokenization scheme based on a concept called byte pair encoding (BPE). The BPE tokenizer covered in this section was used to train LLMs such as GPT-2, GPT-3, and the original model used in ChatGPT.

Since implementing BPE can be relatively complicated, we will use an existing Python open-source library called tiktoken (https://github.com/openai/tiktoken). This library implements the BPE algorithm very efficiently based on source code in Rust.

In [26]:

```
! pip3 install tiktoken
```

```
Requirement already satisfied: tiktoken in /Library/Frameworks/Python.framework/Versions/
3.12/lib/python3.12/site-packages (0.6.0)
Requirement already satisfied: regex>=2022.1.18 in /Library/Frameworks/Python.framework/V
ersions/3.12/lib/python3.12/site-packages (from tiktoken) (2024.4.28)
Requirement already satisfied: requests>=2.26.0 in /Library/Frameworks/Python.framework/V
ersions/3.12/lib/python3.12/site-packages (from tiktoken) (2.31.0)
Requirement already satisfied: charset-normalizer<4,>=2 in /Library/Frameworks/Python.fra
mework/Versions/3.12/lib/python3.12/site-packages (from requests>=2.26.0->tiktoken) (3.3.
2)
Requirement already satisfied: idna<4,>=2.5 in /Library/Frameworks/Python.framework/Versi
ons/3.12/lib/python3.12/site-packages (from requests>=2.26.0->tiktoken) (3.6)
Requirement already satisfied: urllib3<3,>=1.21.1 in /Library/Frameworks/Python.framework
/Versions/3.12/lib/python3.12/site-packages (from requests>=2.26.0->tiktoken) (2.2.1)
Requirement already satisfied: certifi>=2017.4.17 in /Library/Frameworks/Python.framework
/Versions/3.12/lib/python3.12/site-packages (from requests>=2.26.0->tiktoken) (2024.2.2)

[notice] A new release of pip is available: 24.0 -> 24.2
[notice] To update, run: pip3 install --upgrade pip
```

In [27]:

```
import importlib
import tiktoken

print("tiktoken version:", importlib.metadata.version("tiktoken"))
```

```
tiktoken version: 0.6.0
```

Once installed, we can instantiate the BPE tokenizer from tiktoken as follows:

In [28]:

```
tokenizer = tiktoken.get_encoding("gpt2")
```

The usage of this tokenizer is similar to SimpleTokenizerV2 we implemented previously via an encode method:

In [29]:

```
text = (
    "Hello, do you like tea? <|endoftext|> In the sunlit terraces"
     "of someunknownPlace."
)

integers = tokenizer.encode(text, allowed_special={"<|endoftext|>"})

print(integers)
```

```
[15496, 11, 466, 345, 588, 8887, 30, 220, 50256, 554, 262, 4252, 18250, 8812, 2114, 1659,
617, 34680, 27271, 13]
```

The code above prints the following token IDs:

We can then convert the token IDs back into text using the decode method, similar to our SimpleTokenizerV2 earlier:

In [30]:

```
strings = tokenizer.decode(integers)

print(strings)
```

```
Hello, do you like tea? <|endoftext|> In the sunlit terracesof someunknownPlace.
```

We can make two noteworthy observations based on the token IDs and decoded text above. First, the <|endoftext|> token is assigned a relatively large token ID, namely, 50256. In fact, the BPE tokenizer, which was used to train models such as GPT-2, GPT-3, and the original model used in ChatGPT, has a total vocabulary size of 50,257, with <|endoftext|> being assigned the largest token ID.

Second, the BPE tokenizer above encodes and decodes unknown words, such as "someunknownPlace" correctly. The BPE tokenizer can handle any unknown word. How does it achieve this without using <|unk|> tokens?

The algorithm underlying BPE breaks down words that aren't in its predefined vocabulary into smaller subword units or even individual characters. The enables it to handle out-ofvocabulary words. So, thanks to the BPE algorithm, if the tokenizer encounters an unfamiliar word during tokenization, it can represent it as a sequence of subword tokens or characters

Let us take another simple example to illustrate how the BPE tokenizer deals with unknown tokens

In [31]:

```
integers = tokenizer.encode("Akwirw ier")
print(integers)

strings = tokenizer.decode(integers)
print(strings)
```

```
[33901, 86, 343, 86, 220, 959]
Akwirw ier
```

In [32]:

```
import tiktoken

# Initialize the encodings for GPT-2, GPT-3, and GPT-4
encodings = {
    "gpt2": tiktoken.get_encoding("gpt2"),
    "gpt3": tiktoken.get_encoding("p50k_base"),  # Commonly associated with GPT-3 models
    "gpt4": tiktoken.get_encoding("cl100k_base")  # Used for GPT-4 and later versions
}

# Get the vocabulary size for each encoding
vocab_sizes = {model: encoding.n_vocab for model, encoding in encodings.items()}

# Print the vocabulary sizes
for model, size in vocab_sizes.items():
    print(f"The vocabulary size for {model.upper()} is: {size}")
```

```
The vocabulary size for GPT2 is: 50257
The vocabulary size for GPT3 is: 50281
The vocabulary size for GPT4 is: 100277
```

CREATING INPUT-TARGET PAIRS

In this section we implement a data loader that fetches the input-target pairs using a sliding window approach.

To get started, we will first tokenize the whole The Verdict short story we worked with earlier using the BPE tokenizer introduced in the previous section:

In [33]:

```
with open("the-verdict.txt", "r", encoding="utf-8") as f:
    raw_text = f.read()

enc_text = tokenizer.encode(raw_text)
print(len(enc_text))
```

```
5145
```

Executing the code above will return 5145, the total number of tokens in the training set, after applying the BPE tokenizer.

Next, we remove the first 50 tokens from the dataset for demonstration purposes as it results in a slightly more interesting text passage in the next steps:

In [34]:

```
enc_sample = enc_text[50:]
```

One of the easiest and most intuitive ways to create the input-target pairs for the nextword prediction task is to create two variables, x and y, where x contains the input tokens and y contains the targets, which are the inputs shifted by 1:

The context size determines how many tokens are included in the input

In [35]:

```
context_size = 4 #length of the input
#The context_size of 4 means that the model is trained to look at a sequence of 4 words (
or tokens)
#to predict the next word in the sequence.
#The input x is the first 4 tokens [1, 2, 3, 4], and the target y is the next 4 tokens [2
, 3, 4, 5]

x = enc_sample[:context_size]
y = enc_sample[1:context_size+1]

print(f"x: {x}")
print(f"y:      {y}")
```

```
x: [290, 4920, 2241, 287]
y:      [4920, 2241, 287, 257]
```

Processing the inputs along with the targets, which are the inputs shifted by one position, we can then create the next-word prediction tasks as follows:

In [36]:

```
for i in range(1, context_size+1):
    context = enc_sample[:i]
    desired = enc_sample[i]

    print(context, "---->", desired)
```

```
[290] ----> 4920
[290, 4920] ----> 2241
[290, 4920, 2241] ----> 287
[290, 4920, 2241, 287] ----> 257
```

Everything left of the arrow (---->) refers to the input an LLM would receive, and the token ID on the right side of the arrow represents the target token ID that the LLM is supposed to predict.

For illustration purposes, let's repeat the previous code but convert the token IDs into text:

In [37]:

```
for i in range(1, context_size+1):
```

```
for i in range(1, context_size+1):
    context = enc_sample[:i]
    desired = enc_sample[i]

    print(tokenizer.decode(context), "---->", tokenizer.decode([desired]))
```

```
and ---->  established
and established ---->  himself
and established himself ---->  in
and established himself in ---->  a
```

We've now created the input-target pairs that we can turn into use for the LLM training in upcoming chapters.

There's only one more task before we can turn the tokens into embeddings:implementing an efficient data loader that iterates over the input dataset and returns the inputs and targets as PyTorch tensors, which can be thought of as multidimensional arrays.

In particular, we are interested in returning two tensors: an input tensor containing the text that the LLM sees and a target tensor that includes the targets for the LLM to predict,

IMPLEMENTING A DATA LOADER

For the efficient data loader implementation, we will use PyTorch's built-in Dataset and DataLoader classes.

Step 1: Tokenize the entire text Step 2: Use a sliding window to chunk the book into overlapping sequences of max_length Step 3: Return the total number of rows in the dataset Step 4: Return a single row from the dataset

In [38]:

```python
from torch.utils.data import Dataset, DataLoader


class GPTDatasetV1(Dataset):
    def __init__(self, txt, tokenizer, max_length, stride):
        self.input_ids = []
        self.target_ids = []

        # Tokenize the entire text
        token_ids = tokenizer.encode(txt, allowed_special={"<|endoftext|>"})

        # Use a sliding window to chunk the book into overlapping sequences of max_length
        for i in range(0, len(token_ids) - max_length, stride):
            input_chunk = token_ids[i:i + max_length]
            target_chunk = token_ids[i + 1: i + max_length + 1]
            self.input_ids.append(torch.tensor(input_chunk))
            self.target_ids.append(torch.tensor(target_chunk))

    def __len__(self):
        return len(self.input_ids)

    def __getitem__(self, idx):
        return self.input_ids[idx], self.target_ids[idx]
```

The GPTDatasetV1 class in listing 2.5 is based on the PyTorch Dataset class. It defines how individual rows are fetched from the dataset. Each row consists of a number of token IDs (based on a max_length) assigned to an input_chunk tensor. The target_chunk tensor contains the corresponding targets. I recommend reading on to see how the data returned from this dataset looks like when we combine the dataset with a PyTorch DataLoader -- this will bring additional intuition and clarity.

The following code will use the GPTDatasetV1 to load the inputs in batches via a PyTorch DataLoader:

Step 1: Initialize the tokenizer Step 2: Create dataset Step 3: drop_last=True drops the last batch if it is shorter than the specified batch_size to prevent loss spikes during training Step 4: The number of CPU processes to use for preprocessing

In [39]:

```python
def create_dataloader_v1(txt, batch_size=4, max_length=256,
                         stride=128, shuffle=True, drop_last=True,
                         num_workers=0):

    # Initialize the tokenizer
    tokenizer = tiktoken.get_encoding("gpt2")

    # Create dataset
    dataset = GPTDatasetV1(txt, tokenizer, max_length, stride)

    # Create dataloader
    dataloader = DataLoader(
        dataset,
        batch_size=batch_size,
        shuffle=shuffle,
        drop_last=drop_last,
        num_workers=num_workers
    )

    return dataloader
```

Let's test the dataloader with a batch size of 1 for an LLM with a context size of 4, This will develop an intuition of how the GPTDatasetV1 class and the create_dataloader_v1 function work together:

In [40]:

```python
with open("the-verdict.txt", "r", encoding="utf-8") as f:
    raw_text = f.read()
```

Convert dataloader into a Python iterator to fetch the next entry via Python's built-in next() function

In [41]:

```python
import torch
print("PyTorch version:", torch.__version__)
dataloader = create_dataloader_v1(
    raw_text, batch_size=1, max_length=4, stride=1, shuffle=False
)

data_iter = iter(dataloader)
first_batch = next(data_iter)
print(first_batch)
```

```
PyTorch version: 2.3.0
[tensor([[   40,   367,  2885,  1464]]), tensor([[  367,  2885,  1464,  1807]])]
```

```
[tensor([[  40,   367,  2885,  1464]]), tensor([[ 367,  2885,  1464,  1807]])]
```

The first_batch variable contains two tensors: the first tensor stores the input token IDs, and the second tensor stores the target token IDs. Since the max_length is set to 4, each of the two tensors contains 4 token IDs. Note that an input size of 4 is relatively small and only chosen for illustration purposes. It is common to train LLMs with input sizes of at least 256.

To illustrate the meaning of stride=1, let's fetch another batch from this dataset:

In [42]:

```python
second_batch = next(data_iter)
print(second_batch)
```

```
[tensor([[ 367, 2885, 1464, 1807]]), tensor([[2885, 1464, 1807, 3619]])]
```

If we compare the first with the second batch, we can see that the second batch's token IDs are shifted by one position compared to the first batch. For example, the second ID in the first batch's input is 367, which is the first ID of the second batch's input. The stride setting dictates the number of positions the inputs shift across batches, emulating a sliding window approach

Batch sizes of 1, such as we have sampled from the data loader so far, are useful for illustration purposes. If you have previous experience with deep learning, you may know that small batch sizes require less memory during training but lead to more noisy model updates. Just like in regular deep learning, the batch size is a trade-off and hyperparameter to experiment with when training LLMs.

Before we move on to the two final sections of this chapter that are focused on creating the embedding vectors from the token IDs, let's have a brief look at how we can use the data loader to sample with a batch size greater than 1:

In [43]:

```python
dataloader = create_dataloader_v1(raw_text, batch_size=8, max_length=4, stride=4, shuffl
e=False)

data_iter = iter(dataloader)
inputs, targets = next(data_iter)
print("Inputs:\n", inputs)
print("\nTargets:\n", targets)
```

```
Inputs:
 tensor([[   40,   367,  2885,  1464],
        [ 1807,  3619,   402,   271],
        [10899,  2138,   257,  7026],
        [15632,   438,  2016,   257],
        [  922,  5891,  1576,   438],
        [  568,   340,   373,   645],
        [ 1049,  5975,   284,   502],
        [  284,  3285,   326,    11]])

Targets:
 tensor([[  367,  2885,  1464,  1807],
        [ 3619,   402,   271, 10899],
        [ 2138,   257,  7026, 15632],
        [  438,  2016,   257,   922],
        [ 5891,  1576,   438,   568],
        [  340,   373,   645,  1049],
        [ 5975,   284,   502,   284],
        [ 3285,   326,    11,   287]])
```

Note that we increase the stride to 4. This is to utilize the data set fully (we don't skip a single word) but also avoid any overlap between the batches, since more overlap could lead to increased overfitting.

CREATING TOKEN EMBEDDINGS

Let's illustrate how the token ID to embedding vector conversion works with a hands-on example. Suppose we have the following four input tokens with IDs 2, 3, 5, and 1:

In [44]:

```
input_ids = torch.tensor([2, 3, 5, 1])
```

For the sake of simplicity and illustration purposes, suppose we have a small vocabulary of only 6 words (instead of the 50,257 words in the BPE tokenizer vocabulary), and we want to create embeddings of size 3 (in GPT-3, the embedding size is 12,288 dimensions):

Using the vocab_size and output_dim, we can instantiate an embedding layer in PyTorch, setting the random seed to 123 for reproducibility purposes:

In [45]:

```
vocab_size = 6
output_dim = 3

torch.manual_seed(123)
embedding_layer = torch.nn.Embedding(vocab_size, output_dim)
```

The print statement in the code prints the embedding layer's underlying weight matrix:

In [46]:

```
print(embedding_layer.weight)
```

```
Parameter containing:
tensor([[ 0.3374, -0.1778, -0.1690],
        [ 0.9178,  1.5810,  1.3010],
        [ 1.2753, -0.2010, -0.1606],
        [-0.4015,  0.9666, -1.1481],
        [-1.1589,  0.3255, -0.6315],
        [-2.8400, -0.7849, -1.4096]], requires_grad=True)
```

We can see that the weight matrix of the embedding layer contains small, random values. These values are optimized during LLM training as part of the LLM optimization itself, as we will see in upcoming chapters. Moreover, we can see that the weight matrix has six rows and three columns. There is one row for each of the six possible tokens in the vocabulary. And there is one column for each of the three embedding dimensions.

After we instantiated the embedding layer, let's now apply it to a token ID to obtain the embedding vector:

In [47]:

```
print(embedding_layer(torch.tensor([3])))
```

```
tensor([[-0.4015,  0.9666, -1.1481]], grad_fn=<EmbeddingBackward0>)
```

If we compare the embedding vector for token ID 3 to the previous embedding matrix, we see that it is identical to the 4th row (Python starts with a zero index, so it's the row corresponding to index 3). In other words, the embedding layer is essentially a look-up operation that retrieves rows from the embedding layer's weight matrix via a token ID.

Previously, we have seen how to convert a single token ID into a three-dimensional embedding vector. Let's now apply that to all four input IDs we defined earlier (torch.tensor([2, 3, 5, 1])):

In [48]:

```
print(embedding_layer(input_ids))
```

```
tensor([[ 1.2753, -0.2010, -0.1606],
        [-0.4015,  0.9666, -1.1481],
        [-2.8400, -0.7849, -1.4096],
        [ 0.9178,  1.5810,  1.3010]], grad_fn=<EmbeddingBackward0>)
```

Each row in this output matrix is obtained via a lookup operation from the embedding weight matrix

POSITIONAL EMBEDDINGS (ENCODING WORD POSITIONS)

Previously, we focused on very small embedding sizes in this chapter for illustration purposes. We now consider more realistic and useful embedding sizes and encode the input tokens into a 256-dimensional vector representation. This is smaller than what the original GPT-3 model used (in GPT-3, the embedding size is 12,288 dimensions) but still reasonable for experimentation. Furthermore, we assume that the token IDs were created by the BPE tokenizer that we implemented earlier, which has a vocabulary size of 50,257:

In [49]:

```
vocab_size = 50257
output_dim = 256

token_embedding_layer = torch.nn.Embedding(vocab_size, output_dim)
```

Using the token_embedding_layer above, if we sample data from the data loader, we embed each token in each batch into a 256-dimensional vector. If we have a batch size of 8 with four tokens each, the result will be an 8 x 4 x 256 tensor.

Let's instantiate the data loader (Data sampling with a sliding window), first:

In [50]:

```
max_length = 4
dataloader = create_dataloader_v1(
    raw_text, batch_size=8, max_length=max_length,
    stride=max_length, shuffle=False
)
data_iter = iter(dataloader)
inputs, targets = next(data_iter)
```

In [51]:

```
print("Token IDs:\n", inputs)
print("\nInputs shape:\n", inputs.shape)
```

```
Token IDs:
 tensor([[   40,   367,  2885,  1464],
        [ 1807,  3619,   402,   271],
        [10899,  2138,   257,  7026],
        [15632,   438,  2016,   257],
        [  922,  5891,  1576,   438],
        [  568,   340,   373,   645],
        [ 1049,  5975,   284,   502],
        [  284,  3285,   326,    11]])

Inputs shape:
 torch.Size([8, 4])
```

As we can see, the token ID tensor is 8x4-dimensional, meaning that the data batch consists of 8 text samples with 4 tokens each.

Let's now use the embedding layer to embed these token IDs into 256-dimensional vectors:

In [52]:

```
token_embeddings = token_embedding_layer(inputs)
print(token_embeddings.shape)
```

```
torch.Size([8, 4, 256])
```

As we can tell based on the 8x4x256-dimensional tensor output, each token ID is now embedded as a 256-dimensional vector.

For a GPT model's absolute embedding approach, we just need to create another embedding layer that has the same dimension as the token_embedding_layer:

In [53]:

```
context_length = max_length
pos_embedding_layer = torch.nn.Embedding(context_length, output_dim)
```

In [54]:

```
pos_embeddings = pos_embedding_layer(torch.arange(max_length))
print(pos_embeddings.shape)
```

```
torch.Size([4, 256])
```

As shown in the preceding code example, the input to the pos_embeddings is usually a placeholder vector torch.arange(context_length), which contains a sequence of numbers 0, 1, ..., up to the maximum input length – 1. The context_length is a variable that represents the supported input size of the LLM. Here, we choose it similar to the maximum length of the input text. In practice, input text can be longer than the supported context length, in which case we have to truncate the text.

As we can see, the positional embedding tensor consists of four 256-dimensional vectors. We can now add these directly to the token embeddings, where PyTorch will add the 4x256- dimensional pos_embeddings tensor to each 4x256-dimensional token embedding tensor in each of the 8 batches:

In [55]:

```
input_embeddings = token_embeddings + pos_embeddings
print(input_embeddings.shape)
```

```
torch.Size([8, 4, 256])
```

The input_embeddings we created are the embedded input examples that can now be processed by the main LLM modules

IMPLEMENTING A SIMPLIFIED ATTENTION MECHANISM

Consider the following input sentence, which has already been embedded into 3- dimensional vectors. We choose a small embedding dimension for illustration purposes to ensure it fits on the page without line breaks:

In [56]:

```
import torch

inputs = torch.tensor(
  [[0.43, 0.15, 0.89], # Your     (x^1)
   [0.55, 0.87, 0.66], # journey  (x^2)
   [0.57, 0.85, 0.64], # starts   (x^3)
   [0.22, 0.58, 0.33], # with     (x^4)
   [0.77, 0.25, 0.10], # one      (x^5)
   [0.05, 0.80, 0.55]] # step     (x^6)
)
```

In [57]:

```
# Create 3D plot with vectors from origin to each point, using different colors
fig = plt.figure()
ax = fig.add_subplot(111, projection='3d')

# Define a list of colors for the vectors
colors = ['r', 'g', 'b', 'c', 'm', 'y']

# Plot each vector with a different color and annotate with the corresponding word
for (x, y, z, word, color) in zip(x_coords, y_coords, z_coords, words, colors):
    # Draw vector from origin to the point (x, y, z) with specified color and smaller arr
ow length ratio
    ax.quiver(0, 0, 0, x, y, z, color=color, arrow_length_ratio=0.05)
    ax.text(x, y, z, word, fontsize=10, color=color)

# Set labels for axes
ax.set_xlabel('X')
ax.set_ylabel('Y')
ax.set_zlabel('Z')

# Set plot limits to keep arrows within the plot boundaries
ax.set_xlim([0, 1])
ax.set_ylim([0, 1])
ax.set_zlim([0, 1])

plt.title('3D Plot of Word Embeddings with Colored Vectors')
plt.show()
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Cell In[57], line 2
      1 # Create 3D plot with vectors from origin to each point, using different colors
----> 2 fig = plt.figure()
      3 ax = fig.add_subplot(111, projection='3d')
      5 # Define a list of colors for the vectors

NameError: name 'plt' is not defined
```

Each row represents a word, and each column represents an embedding dimension

The second input token serves as the query

In [58]:

```
query = inputs[1]  # 2nd input token is the query

attn_scores_2 = torch.empty(inputs.shape[0])
for i, x_i in enumerate(inputs):
    attn_scores_2[i] = torch.dot(x_i, query) # dot product (transpose not necessary here
since they are 1-dim vectors)

print(attn_scores_2)
```

```
tensor([0.9544, 1.4950, 1.4754, 0.8434, 0.7070, 1.0865])
```

In the next step, we normalize each of the attention scores that we computed previously.

The main goal behind the normalization is to obtain attention weights that sum up to 1. This normalization is a convention that is useful for interpretation and for maintaining training stability in an LLM. Here's a straightforward method for achieving this normalization step:

In [59]:

```
attn_weights_2_tmp = attn_scores_2 / attn_scores_2.sum()

print("Attention weights:", attn_weights_2_tmp)
print("Sum:", attn_weights_2_tmp.sum())
```

```
Attention weights: tensor([0.1455, 0.2278, 0.2249, 0.1285, 0.1077, 0.1656])
Sum: tensor(1.0000)
```

In practice, it's more common and advisable to use the softmax function for normalization. This approach is better at managing extreme values and offers more favorable gradient properties during training. Below is a basic implementation of the softmax function for normalizing the attention scores:

In [60]:

```
def softmax_naive(x):
    return torch.exp(x) / torch.exp(x).sum(dim=0)

attn_weights_2_naive = softmax_naive(attn_scores_2)

print("Attention weights:", attn_weights_2_naive)
print("Sum:", attn_weights_2_naive.sum())
```

```
Attention weights: tensor([0.1385, 0.2379, 0.2333, 0.1240, 0.1082, 0.1581])
```

```
Sum: tensor(1.)
```

As the output shows, the softmax function also meets the objective and normalizes the attention weights such that they sum to 1:

In addition, the softmax function ensures that the attention weights are always positive. This makes the output interpretable as probabilities or relative importance, where higher weights indicate greater importance.

Note that this naive softmax implementation (softmax_naive) may encounter numerical instability problems, such as overflow and underflow, when dealing with large or small input values. Therefore, in practice, it's advisable to use the PyTorch implementation of softmax, which has been extensively optimized for performance:

In [61]:

```
attn_weights_2 = torch.softmax(attn_scores_2, dim=0)
print("Attention weights:", attn_weights_2)
print("Sum:", attn_weights_2.sum())
```

```
Attention weights: tensor([0.1385, 0.2379, 0.2333, 0.1240, 0.1082, 0.1581])
Sum: tensor(1.)
```

In this case, we can see that it yields the same results as our previous softmax_naive function:

The context vector z(2)is calculated as a weighted sum of all input vectors. This involves multiplying each input vector by its corresponding attention weight:

In [62]:

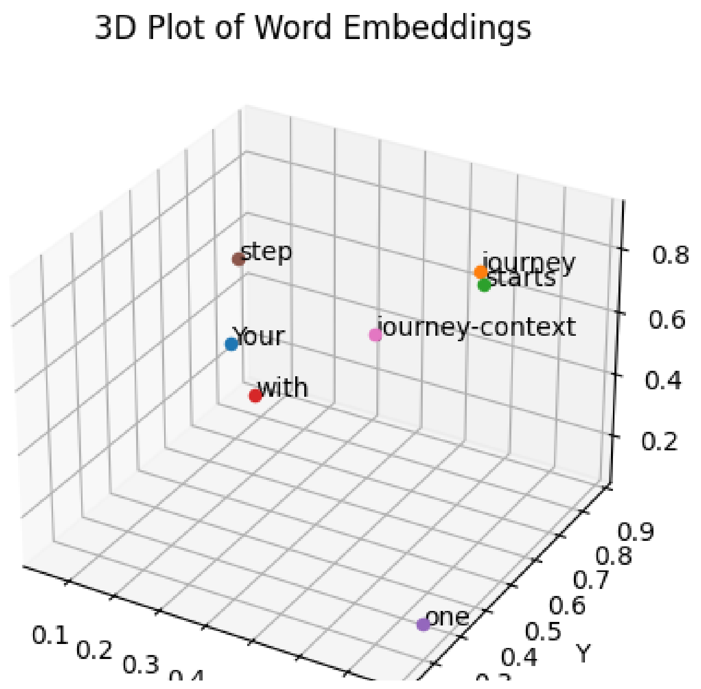
```
query = inputs[1] # 2nd input token is the query

context_vec_2 = torch.zeros(query.shape)
for i,x_i in enumerate(inputs):
    context_vec_2 += attn_weights_2[i]*x_i

print(context_vec_2)
```

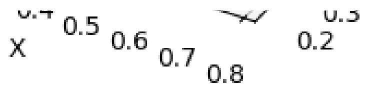
```
tensor([0.4419, 0.6515, 0.5683])
```

In [63]:

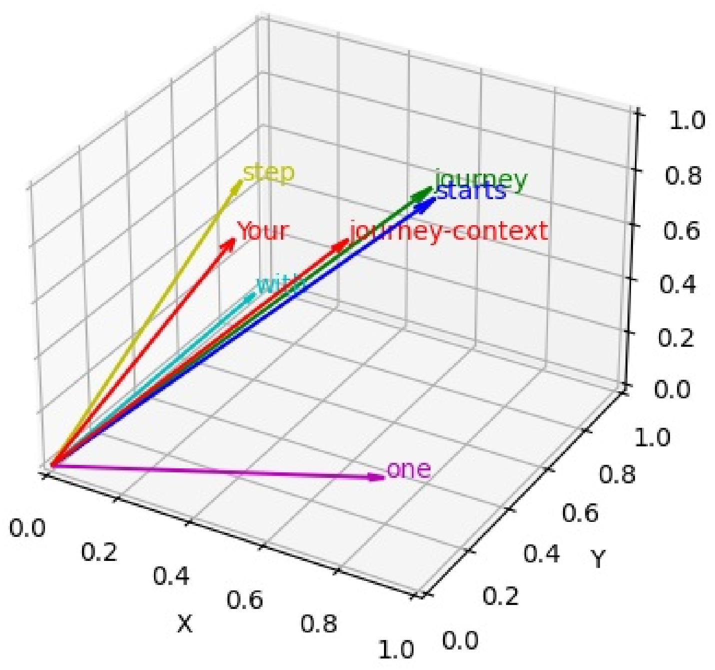
```
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D

inputs2 = torch.tensor(
  [[0.43, 0.15, 0.89], # Your     (x^1)
   [0.55, 0.87, 0.66], # journey  (x^2)
   [0.57, 0.85, 0.64], # starts   (x^3)
   [0.22, 0.58, 0.33], # with     (x^4)
   [0.77, 0.25, 0.10], # one      (x^5)
   [0.05, 0.80, 0.55], # step     (x^6)
   [0.4419, 0.6515, 0.5683]]
)

# Corresponding words
words2 = ['Your', 'journey', 'starts', 'with', 'one', 'step', 'journey-context']
```

```python
# Extract x, y, z coordinates
x_coords = inputs2[:, 0].numpy()
y_coords = inputs2[:, 1].numpy()
z_coords = inputs2[:, 2].numpy()

# Create 3D plot
fig = plt.figure()
ax = fig.add_subplot(111, projection='3d')

# Plot each point and annotate with corresponding word
for x, y, z, word in zip(x_coords, y_coords, z_coords, words2):
    ax.scatter(x, y, z)
    ax.text(x, y, z, word, fontsize=10)

# Set labels for axes
ax.set_xlabel('X')
ax.set_ylabel('Y')
ax.set_zlabel('Z')

plt.title('3D Plot of Word Embeddings')
plt.show()

# Create 3D plot with vectors from origin to each point, using different colors
fig = plt.figure()
ax = fig.add_subplot(111, projection='3d')

# Define a list of colors for the vectors
colors = ['r', 'g', 'b', 'c', 'm', 'y', 'r']

# Plot each vector with a different color and annotate with the corresponding word
for (x, y, z, word, color) in zip(x_coords, y_coords, z_coords, words2, colors):
    # Draw vector from origin to the point (x, y, z) with specified color and smaller arr
ow length ratio
    ax.quiver(0, 0, 0, x, y, z, color=color, arrow_length_ratio=0.05)
    ax.text(x, y, z, word, fontsize=10, color=color)

# Set labels for axes
ax.set_xlabel('X')
ax.set_ylabel('Y')
ax.set_zlabel('Z')

# Set plot limits to keep arrows within the plot boundaries
ax.set_xlim([0, 1])
ax.set_ylim([0, 1])
ax.set_zlim([0, 1])

plt.title('3D Plot of Word Embeddings with Colored Vectors')
plt.show()
```





3D Plot of Word Embeddings with Colored Vectors



Now, we can extend this computation to calculate attention weights and context vectors for all inputs.

First, we add an additional for-loop to compute the dot products for all pairs of inputs.

In [64]:

```
attn_scores = torch.empty(6, 6)

for i, x_i in enumerate(inputs):
    for j, x_j in enumerate(inputs):
        attn_scores[i, j] = torch.dot(x_i, x_j)

print(attn_scores)
```

```
tensor([[0.9995, 0.9544, 0.9422, 0.4753, 0.4576, 0.6310],
        [0.9544, 1.4950, 1.4754, 0.8434, 0.7070, 1.0865],
        [0.9422, 1.4754, 1.4570, 0.8296, 0.7154, 1.0605],
        [0.4753, 0.8434, 0.8296, 0.4937, 0.3474, 0.6565],
        [0.4576, 0.7070, 0.7154, 0.3474, 0.6654, 0.2935],
        [0.6310, 1.0865, 1.0605, 0.6565, 0.2935, 0.9450]])
```

Each element in the preceding tensor represents an attention score between each pair of inputs.

When computing the preceding attention score tensor, we used for-loops in Python. However, for-loops are generally slow, and we can achieve the same results using matrix multiplication:

In [65]:

```
attn_scores = inputs @ inputs.T
print(attn_scores)
```

```
tensor([[0.9995, 0.9544, 0.9422, 0.4753, 0.4576, 0.6310],
tensor([[0.9995, 0.9544, 0.9422, 0.4753, 0.4576, 0.6310],
        [0.9544, 1.4950, 1.4754, 0.8434, 0.7070, 1.0865],
        [0.9422, 1.4754, 1.4570, 0.8296, 0.7154, 1.0605],
        [0.4753, 0.8434, 0.8296, 0.4937, 0.3474, 0.6565],
        [0.4576, 0.7070, 0.7154, 0.3474, 0.6654, 0.2935],
        [0.6310, 1.0865, 1.0605, 0.6565, 0.2935, 0.9450]])
```

We now normalize each row so that the values in each row sum to 1:

In [66]:

```
attn_weights = torch.softmax(attn_scores, dim=-1)
print(attn_weights)
```

```
tensor([[0.2098, 0.2006, 0.1981, 0.1242, 0.1220, 0.1452],
        [0.1385, 0.2379, 0.2333, 0.1240, 0.1082, 0.1581],
        [0.1390, 0.2369, 0.2326, 0.1242, 0.1108, 0.1565],
        [0.1435, 0.2074, 0.2046, 0.1462, 0.1263, 0.1720],
        [0.1526, 0.1958, 0.1975, 0.1367, 0.1879, 0.1295],
        [0.1385, 0.2184, 0.2128, 0.1420, 0.0988, 0.1896]])
```

In the context of using PyTorch, the dim parameter in functions like torch.softmax specifies the dimension of the input tensor along which the function will be computed. By setting dim=-1, we are instructing the softmax function to apply the normalization along the last dimension of the attn_scores tensor. If attn_scores is a 2D tensor (for example, with a shape of [rows, columns]), dim=-1 will normalize across the columns so that the values in each row (summing over the column dimension) sum up to 1.

Let's briefly verify that the rows indeed all sum to 1:

In [67]:

```
row_2_sum = sum([0.1385, 0.2379, 0.2333, 0.1240, 0.1082, 0.1581])
print("Row 2 sum:", row_2_sum)
print("All row sums:", attn_weights.sum(dim=-1))
```

```
Row 2 sum: 1.0
All row sums: tensor([1.0000, 1.0000, 1.0000, 1.0000, 1.0000, 1.0000])
```

In the third and last step, we now use these attention weights to compute all context vectors via matrix multiplication:

In [68]:

```
all_context_vecs = attn_weights @ inputs
print(all_context_vecs)
```

```
tensor([[0.4421, 0.5931, 0.5790],
        [0.4419, 0.6515, 0.5683],
        [0.4431, 0.6496, 0.5671],
        [0.4304, 0.6298, 0.5510],
        [0.4671, 0.5910, 0.5266],
        [0.4177, 0.6503, 0.5645]])
```

We can double-check that the code is correct by comparing the 2nd row with the context vector z(2) calculated previously

In [69]:

```
print("Previous 2nd context vector:", context_vec_2)
print("Previous 2nd context vector:", context_vec_2)
```

```
Previous 2nd context vector: tensor([0.4419, 0.6515, 0.5683])
```

Based on the result, we can see that the previously calculated context_vec_2 matches the second row in the previous tensor exactly

This concludes the code walkthrough of a simple self-attention mechanism.

IMPLEMENTING SELF ATTENTION WITH TRAINABLE WEIGHTS

In [70]:

```
import torch

inputs = torch.tensor(
  [[0.43, 0.15, 0.89], # Your     (x^1)
   [0.55, 0.87, 0.66], # journey  (x^2)
   [0.57, 0.85, 0.64], # starts   (x^3)
   [0.22, 0.58, 0.33], # with     (x^4)
   [0.77, 0.25, 0.10], # one      (x^5)
   [0.05, 0.80, 0.55]] # step     (x^6)
)
```

Let's begin by defining a few variables:

#A The second input element #B The input embedding size, d=3 #C The output embedding size, d_out=2

In [71]:

```
x_2 = inputs[1] #A
d_in = inputs.shape[1] #B
d_out = 2 #C
```

Note that in GPT-like models, the input and output dimensions are usually the same. But for illustration purposes, to better follow the computation, we choose different input (d_in=3) and output (d_out=2) dimensions here.

Next, we initialize the three weight matrices Wq, Wk and Wv

In [72]:

```
torch.manual_seed(123)
W_query = torch.nn.Parameter(torch.rand(d_in, d_out), requires_grad=False)
W_key = torch.nn.Parameter(torch.rand(d_in, d_out), requires_grad=False)
W_value = torch.nn.Parameter(torch.rand(d_in, d_out), requires_grad=False)
```

In [73]:

```
print(W_query)
```

```
Parameter containing:
tensor([[0.2961, 0.5166],
        [0.2517, 0.6886],
        [0.0740, 0.8665]])
```

In [74]:

```
print(W_key)
```

```
Parameter containing:
tensor([[0.1366, 0.1025],
        [0.1841, 0.7264],
        [0.3153, 0.6871]])
```

In [75]:

```
print(W_value)
```

```
Parameter containing:
tensor([[0.0756, 0.1966],
        [0.3164, 0.4017],
        [0.1186, 0.8274]])
```

Note that we are setting requires_grad=False to reduce clutter in the outputs for illustration purposes. If we were to use the weight matrices for model training, we would set requires_grad=True to update these matrices during model training.

Next, we compute the query, key, and value vectors as shown earlier

In [76]:

```
query_2 = x_2 @ W_query
key_2 = x_2 @ W_key
value_2 = x_2 @ W_value
print(query_2)
```

```
tensor([0.4306, 1.4551])
```

As we can see based on the output for the query, this results in a 2-dimensional vector. This is because: we set the number of columns of the corresponding weight matrix, via d_out, to 2:

Even though our temporary goal is to only compute the one context vector z(2), we still require the key and value vectors for all input elements. This is because they are involved in computing the attention weights with respect to the query q(2)

We can obtain all keys and values via matrix multiplication:

In [77]:

```
keys = inputs @ W_key
values = inputs @ W_value
queries = inputs @ W_query
print("keys.shape:", keys.shape)

print("values.shape:", values.shape)

print("queries.shape:", queries.shape)
```

```
keys.shape: torch.Size([6, 2])
values.shape: torch.Size([6, 2])
queries.shape: torch.Size([6, 2])
```

As we can tell from the outputs, we successfully projected the 6 input tokens from a 3D onto a 2D embedding space:

First, let's compute the attention score ω22

In [78]:

```
keys_2 = keys[1] #A
attn_score_22 = query_2.dot(keys_2)
print(attn_score_22)
```

```
tensor(1.8524)
```

Again, we can generalize this computation to all attention scores via matrix multiplication:

In [79]:

```
attn_scores_2 = query_2 @ keys.T # All attention scores for given query
print(attn_scores_2)
```

```
tensor([1.2705, 1.8524, 1.8111, 1.0795, 0.5577, 1.5440])
```

In [80]:

```
attn_scores = queries @ keys.T # omega
print(attn_scores)
```

```
tensor([[0.9231, 1.3545, 1.3241, 0.7910, 0.4032, 1.1330],
        [1.2705, 1.8524, 1.8111, 1.0795, 0.5577, 1.5440],
        [1.2544, 1.8284, 1.7877, 1.0654, 0.5508, 1.5238],
        [0.6973, 1.0167, 0.9941, 0.5925, 0.3061, 0.8475],
        [0.6114, 0.8819, 0.8626, 0.5121, 0.2707, 0.7307],
        [0.8995, 1.3165, 1.2871, 0.7682, 0.3937, 1.0996]])
```

We compute the attention weights by scaling the attention scores and using the softmax function we used earlier. The difference to earlier is that we now scale the attention scores by dividing them by the square root of the embedding dimension of the keys. Note that taking the square root is mathematically the same as exponentiating by 0.5:

In [81]:

```
d_k = keys.shape[-1]
attn_weights_2 = torch.softmax(attn_scores_2 / d_k**0.5, dim=-1)
print(attn_weights_2)
print(d_k)
```

```
tensor([0.1500, 0.2264, 0.2199, 0.1311, 0.0906, 0.1820])
2
```

WHY DIVIDE BY SQRT (DIMENSION)

Reason 1: For stability in learning The softmax function is sensitive to the magnitudes of its inputs. When the inputs are large, the differences between the exponential values of each input become much more pronounced. This causes the softmax output to become "peaky," where the highest value receives almost all the probability mass, and the rest receive very little. In attention mechanisms, particularly in transformers, if the dot products between query and key vectors become too large (like multiplying by 8 in this example), the attention scores can become very large. This results in a very sharp softmax distribution,

making the model overly confident in one particular "key." Such sharp distributions can make learning unstable,

In [82]:

```
import torch

# Define the tensor
tensor = torch.tensor([0.1, -0.2, 0.3, -0.2, 0.5])

# Apply softmax without scaling
softmax_result = torch.softmax(tensor, dim=-1)
print("Softmax without scaling:", softmax_result)

# Multiply the tensor by 8 and then apply softmax
scaled_tensor = tensor * 8
softmax_scaled_result = torch.softmax(scaled_tensor, dim=-1)
print("Softmax after scaling (tensor * 8):", softmax_scaled_result)
```

```
Softmax without scaling: tensor([0.1925, 0.1426, 0.2351, 0.1426, 0.2872])
Softmax after scaling (tensor * 8): tensor([0.0326, 0.0030, 0.1615, 0.0030, 0.8000])
```

BUT WHY SQRT?

Reason 2: To make the variance of the dot product stable The dot product of Q and K increases the variance because multiplying two random numbers increases the variance. The increase in variance grows with the dimension. Dividing by sqrt (dimension) keeps the variance close to 1

In [83]:

```
import numpy as np

# Function to compute variance before and after scaling
def compute_variance(dim, num_trials=1000):
    dot_products = []
    scaled_dot_products = []

    # Generate multiple random vectors and compute dot products
    for _ in range(num_trials):
        q = np.random.randn(dim)
        k = np.random.randn(dim)

        # Compute dot product
        dot_product = np.dot(q, k)
        dot_products.append(dot_product)

        # Scale the dot product by sqrt(dim)
        scaled_dot_product = dot_product / np.sqrt(dim)
        scaled_dot_products.append(scaled_dot_product)

    # Calculate variance of the dot products
    variance_before_scaling = np.var(dot_products)
    variance_after_scaling = np.var(scaled_dot_products)

    return variance_before_scaling, variance_after_scaling

# For dimension 5
variance_before_5, variance_after_5 = compute_variance(5)
print(f"Variance before scaling (dim=5): {variance_before_5}")
print(f"Variance after scaling (dim=5): {variance_after_5}")

# For dimension 20
variance_before_100, variance_after_100 = compute_variance(100)
print(f"Variance before scaling (dim=100): {variance_before_100}")
print(f"Variance after scaling (dim=100): {variance_after_100}")
```

```
Variance before scaling (dim=5): 5.283825250832946
Variance after scaling (dim=5): 1.056765050166589
Variance before scaling (dim=100): 93.85173621515662
Variance after scaling (dim=100): 0.9385173621515661
```

We now compute the context vector as a weighted sum over the value vectors. Here, the attention weights serve as a weighting factor that weighs the respective importance of each value vector. We can use matrix multiplication to obtain the output in one step:

In [84]:

```python
context_vec_2 = attn_weights_2 @ values
print(context_vec_2)
```

```
tensor([0.3061, 0.8210])
```

So far, we only computed a single context vector, z(2). In the next section, we will generalize the code to compute all context vectors in the input sequence, z(1)to z (T)

IMPLEMENTING A COMPACT SELF ATTENTION PYTHON CLASS

In the previous sections, we have gone through a lot of steps to compute the self-attention outputs. This was mainly done for illustration purposes so we could go through one step at a time. In practice, with the LLM implementation in the next chapter in mind, it is helpful to organize this code into a Python class as follows:

In [85]:

```python
import torch.nn as nn

class SelfAttention_v1(nn.Module):

    def __init__(self, d_in, d_out):
        super().__init__()
        self.W_query = nn.Parameter(torch.rand(d_in, d_out))
        self.W_key   = nn.Parameter(torch.rand(d_in, d_out))
        self.W_value = nn.Parameter(torch.rand(d_in, d_out))

    def forward(self, x):
        keys = x @ self.W_key
        queries = x @ self.W_query
        values = x @ self.W_value

        attn_scores = queries @ keys.T # omega
        attn_weights = torch.softmax(
            attn_scores / keys.shape[-1]**0.5, dim=-1
        )

        context_vec = attn_weights @ values
        return context_vec
```

In this PyTorch code, SelfAttention_v1 is a class derived from nn.Module, which is a fundamental building block of PyTorch models, which provides necessary functionalities for model layer creation and management.

The __init__ method initializes trainable weight matrices (W_query, W_key, and W_value) for queries, keys, and values, each transforming the input dimension d_in to an output dimension d_out.

During the forward pass, using the forward method, we compute the attention scores (attn_scores) by multiplying queries and keys, normalizing these scores using softmax.

Finally, we create a context vector by weighting the values with these normalized attention scores.

In [86]:

```
torch.manual_seed(123)
sa_v1 = SelfAttention_v1(d_in, d_out)
print(sa_v1(inputs))
```

```
tensor([[0.2996, 0.8053],
        [0.3061, 0.8210],
        [0.3058, 0.8203],
        [0.2948, 0.7939],
        [0.2927, 0.7891],
        [0.2990, 0.8040]], grad_fn=<MmBackward0>)
```

Since inputs contains six embedding vectors, we get a matrix storing the six context vectors, as shown in the above result.

As a quick check, notice how the second row ([0.3061, 0.8210]) matches the contents of context_vec_2 in the previous section.

We can improve the SelfAttention_v1 implementation further by utilizing PyTorch's nn.Linear layers, which effectively perform matrix multiplication when the bias units are disabled.

Additionally, a significant advantage of using nn.Linear instead of manually implementing nn.Parameter(torch.rand(...)) is that nn.Linear has an optimized weight initialization scheme, contributing to more stable and effective model training.

In [87]:

```
class SelfAttention_v2(nn.Module):

    def __init__(self, d_in, d_out, qkv_bias=False):
        super().__init__()
        self.W_query = nn.Linear(d_in, d_out, bias=qkv_bias)
        self.W_key   = nn.Linear(d_in, d_out, bias=qkv_bias)
        self.W_value = nn.Linear(d_in, d_out, bias=qkv_bias)

    def forward(self, x):
        keys = self.W_key(x)
        queries = self.W_query(x)
        values = self.W_value(x)

        attn_scores = queries @ keys.T
        attn_weights = torch.softmax(attn_scores / keys.shape[-1]**0.5, dim=-1)

        context_vec = attn_weights @ values
        return context_vec
```

You can use the SelfAttention_v2 similar to SelfAttention_v1:

In [88]:

```
torch.manual_seed(789)
sa_v2 = SelfAttention_v2(d_in, d_out)
print(sa_v2(inputs))
```

```
tensor([[-0.0739,  0.0713],
        [-0.0748,  0.0703],
        [-0.0749,  0.0702],
        [-0.0760,  0.0685],
        [-0.0763,  0.0679],
        [-0.0754,  0.0693]], grad_fn=<MmBackward0>)
```

Note that SelfAttention_v1 and SelfAttention_v2 give different outputs because they use different initial weights for the weight matrices since nn.Linear uses a more sophisticated weight initialization scheme.

HIDING FUTURE WORDS WITH CAUSAL ATTENTION

Let's work with the attention scores and weights from the previous section to code the causal attention mechanism.

In the first step illustrated in Figure 3.20, we compute the attention weights using the softmax function as we have done in previous sections:

Reuse the query and key weight matrices of the SelfAttention_v2 object from the previous section for convenience

In [89]:

```
inputs = torch.tensor(
  [[0.43, 0.15, 0.89], # Your     (x^1)
   [0.55, 0.87, 0.66], # journey  (x^2)
   [0.57, 0.85, 0.64], # starts   (x^3)
   [0.22, 0.58, 0.33], # with     (x^4)
   [0.77, 0.25, 0.10], # one      (x^5)
   [0.05, 0.80, 0.55]] # step     (x^6)
)
```

In [90]:

```
queries = sa_v2.W_query(inputs)  #A
keys = sa_v2.W_key(inputs)
attn_scores = queries @ keys.T
attn_weights = torch.softmax(attn_scores / keys.shape[-1]**0.5, dim=1)
print(attn_weights)
```

```
tensor([[0.1921, 0.1646, 0.1652, 0.1550, 0.1721, 0.1510],
        [0.2041, 0.1659, 0.1662, 0.1496, 0.1665, 0.1477],
        [0.2036, 0.1659, 0.1662, 0.1498, 0.1664, 0.1480],
        [0.1869, 0.1667, 0.1668, 0.1571, 0.1661, 0.1564],
        [0.1830, 0.1669, 0.1670, 0.1588, 0.1658, 0.1585],
        [0.1935, 0.1663, 0.1666, 0.1542, 0.1666, 0.1529]],
       grad_fn=<SoftmaxBackward0>)
```

We can now use PyTorch's tril function to create a mask where the values above the diagonal are zero:

We can now use PyTorch's tril function to create a mask where the values above the diagonal are zero:

In [91]:

```
torch.ones(context_length, context_length)
```

Out[91]:

```
tensor([[1., 1., 1., 1.],
        [1., 1., 1., 1.],
        [1., 1., 1., 1.],
        [1., 1., 1., 1.]])
```

In [92]:

```
context_length = attn_scores.shape[0]
mask_simple = torch.tril(torch.ones(context_length, context_length))
print(mask_simple)
```

```
tensor([[1., 0., 0., 0., 0., 0.],
        [1., 1., 0., 0., 0., 0.],
        [1., 1., 1., 0., 0., 0.],
        [1., 1., 1., 1., 0., 0.],
        [1., 1., 1., 1., 1., 0.],
        [1., 1., 1., 1., 1., 1.]])
```

Now, we can multiply this mask with the attention weights to zero out the values above the diagonal:

In [93]:

```
masked_simple = attn_weights*mask_simple
print(masked_simple)
```

```
tensor([[0.1921, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000],
        [0.2041, 0.1659, 0.0000, 0.0000, 0.0000, 0.0000],
        [0.2036, 0.1659, 0.1662, 0.0000, 0.0000, 0.0000],
        [0.1869, 0.1667, 0.1668, 0.1571, 0.0000, 0.0000],
        [0.1830, 0.1669, 0.1670, 0.1588, 0.1658, 0.0000],
        [0.1935, 0.1663, 0.1666, 0.1542, 0.1666, 0.1529]],
       grad_fn=<MulBackward0>)
```

As we can see, the elements above the diagonal are successfully zeroed out

The third step is to renormalize the attention weights to sum up to 1 again in each row. We can achieve this by dividing each element in each row by the sum in each row:

In [94]:

```
row_sums = masked_simple.sum(dim=1, keepdim=True)
masked_simple_norm = masked_simple / row_sums
print(masked_simple_norm)
```

```
tensor([[1.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000],
        [0.5517, 0.4483, 0.0000, 0.0000, 0.0000, 0.0000],
        [0.3800, 0.3097, 0.3103, 0.0000, 0.0000, 0.0000],
        [0.2758, 0.2460, 0.2462, 0.2319, 0.0000, 0.0000],
        [0.2175, 0.1983, 0.1984, 0.1888, 0.1971, 0.0000],
        [0.1935, 0.1663, 0.1666, 0.1542, 0.1666, 0.1529]],
       grad_fn=<DivBackward0>)
```

The result is an attention weight matrix where the attention weights above the diagonal are zeroed out and where the rows sum to 1.

While we could be technically done with implementing causal attention at this point, we can take advantage of a mathematical property of the softmax function. We can implement the computation of the masked attention weights more efficiently in fewer steps.

The softmax function converts its inputs into a probability distribution. When negative infinity values (-∞) are present in a row, the softmax function treats them as zero probability. (Mathematically, this is because e -∞ approaches 0.) We can implement this more efficient masking "trick" by creating a mask with 1's above the diagonal and then replacing these 1's with negative infinity (-inf) values:

In [95]:

```
print(attn_scores)
```

```
tensor([[ 0.2899,  0.0716,  0.0760, -0.0138,  0.1344, -0.0511],
        [ 0.4656,  0.1723,  0.1751,  0.0259,  0.1771,  0.0085],
        [ 0.4594,  0.1703,  0.1731,  0.0259,  0.1745,  0.0090],
        [ 0.2642,  0.1024,  0.1036,  0.0186,  0.0973,  0.0122],
        [ 0.2183,  0.0874,  0.0882,  0.0177,  0.0786,  0.0144],
        [ 0.3408,  0.1270,  0.1290,  0.0198,  0.1290,  0.0078]],
       grad_fn=<MmBackward0>)
```

In [96]:

```
torch.triu(torch.ones(context_length, context_length))
```

Out[96]:

```
tensor([[1., 1., 1., 1., 1., 1.],
        [0., 1., 1., 1., 1., 1.],
        [0., 0., 1., 1., 1., 1.],
        [0., 0., 0., 1., 1., 1.],
        [0., 0., 0., 0., 1., 1.],
        [0., 0., 0., 0., 0., 1.]])
```

In [97]:

```
mask = torch.triu(torch.ones(context_length, context_length), diagonal=1)
print(mask)
```

```
tensor([[0., 1., 1., 1., 1., 1.],
        [0., 0., 1., 1., 1., 1.],
        [0., 0., 0., 1., 1., 1.],
        [0., 0., 0., 0., 1., 1.],
        [0., 0., 0., 0., 0., 1.],
        [0., 0., 0., 0., 0., 0.]])
```

In [98]:

```
mask = torch.triu(torch.ones(context_length, context_length), diagonal=1)
masked = attn_scores.masked_fill(mask.bool(), -torch.inf)
print(masked)
```

```
tensor([[0.2899,   -inf,   -inf,   -inf,   -inf,   -inf],
        [0.4656, 0.1723,   -inf,   -inf,   -inf,   -inf],
        [0.4594, 0.1703, 0.1731,   -inf,   -inf,   -inf],
        [0.2642, 0.1024, 0.1036, 0.0186,   -inf,   -inf],
        [0.2183, 0.0874, 0.0882, 0.0177, 0.0786,   -inf],
        [0.3408, 0.1270, 0.1290, 0.0198, 0.1290, 0.0078]],
       grad_fn=<MaskedFillBackward0>)
```

Now, all we need to do is apply the softmax function to these masked results, and we are done.

In [99]:

```
attn_weights = torch.softmax(masked / keys.shape[-1]**0.5, dim=1)
print(attn_weights)
```

```
tensor([[1.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000],
        [0.5517, 0.4483, 0.0000, 0.0000, 0.0000, 0.0000],
        [0.3800, 0.3097, 0.3103, 0.0000, 0.0000, 0.0000],
        [0.2758, 0.2460, 0.2462, 0.2319, 0.0000, 0.0000],
        [0.2175, 0.1983, 0.1984, 0.1888, 0.1971, 0.0000],
        [0.1935, 0.1663, 0.1666, 0.1542, 0.1666, 0.1529]],
       grad_fn=<SoftmaxBackward0>)
```

As we can see based on the output, the values in each row sum to 1, and no further normalization is necessary.

Masking in Transformers sets scores for future tokens to a large negative value, making their influence in the softmax calculation effectively zero. The softmax function then recalculates attention weights only among the unmasked tokens. This process ensures no information leakage from masked tokens, focusing the model solely on the intended data.

We could now use the modified attention weights to compute the context vectors via context_vec = attn_weights @ values. However, in the next section, we first cover another minor tweak to the causal attention mechanism that is useful for reducing overfitting when training LLMs.

MASKING ADDITIONAL ATTENTION WEIGHTS WITH DROPOUT

In the following code example, we use a dropout rate of 50%, which means masking out half of the attention weights. When we train the GPT model in later chapters, we will use a lower dropout rate, such as 0.1 or 0.2.

In the following code, we apply PyTorch's dropout implementation first to a 6×6 tensor consisting of ones for illustration purposes:

In [100]:

```
example = torch.ones(6, 6) #B
print(example)
```

```
tensor([[1., 1., 1., 1., 1., 1.],
        [1., 1., 1., 1., 1., 1.],
        [1., 1., 1., 1., 1., 1.],
        [1., 1., 1., 1., 1., 1.],
        [1., 1., 1., 1., 1., 1.],
        [1., 1., 1., 1., 1., 1.]])
```

In [101]:

```
torch.manual_seed(123)
dropout = torch.nn.Dropout(0.5) #A
example = torch.ones(6, 6) #B
print(dropout(example))
```

```
tensor([[2., 2., 0., 2., 2., 0.],
        [0., 0., 0., 2., 0., 2.],
        [2., 2., 2., 2., 0., 2.],
        [0., 2., 2., 0., 0., 2.],
        [0., 2., 0., 2., 0., 2.],
        [0., 2., 2., 2., 2., 0.]])
```

When applying dropout to an attention weight matrix with a rate of 50%, half of the elements in the matrix are randomly set to zero. To compensate for the reduction in active elements, the values of the remaining elements in the matrix are scaled up by a factor of 1/0.5 =2. This scaling is crucial to maintain the overall balance of the attention weights, ensuring that the average influence of the attention mechanism remains consistent during both the training and inference phases.

Now, let's apply dropout to the attention weight matrix itself:

In [102]:

```
torch.manual_seed(123)
print(dropout(attn_weights))
```

```
tensor([[2.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000],
        [0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000],
        [0.7599, 0.6194, 0.6206, 0.0000, 0.0000, 0.0000],
        [0.0000, 0.4921, 0.4925, 0.0000, 0.0000, 0.0000],
        [0.0000, 0.3966, 0.0000, 0.3775, 0.0000, 0.0000],
        [0.0000, 0.3327, 0.3331, 0.3084, 0.3331, 0.0000]],
       grad_fn=<MulBackward0>)
```

As we can see above, the resulting attention weight matrix now has additional elements zeroed out and the remaining ones rescaled.

Having gained an understanding of causal attention and dropout masking, we will develop a concise Python class in the following section. This class is designed to facilitate the efficient application of these two techniques.

IMPLEMENTING A COMPACT CAUSAL ATTENTION CLASS

In this section, we will now incorporate the causal attention and dropout modifications into the SelfAttention Python class we developed in section 3.4. This class will then serve as a template for developing multi-head attention in the upcoming section.

Before we begin, one more thing is to ensure that the code can handle batches consisting of more than one input. This will ensure that the CausalAttention class supports the batch outputs produced by the data loader we implemented earlier.

For simplicity, to simulate such batch inputs, we duplicate the input text example:

2 inputs with 6 tokens each, and each token has embedding dimension 3

In [103]:

```
inputs = torch.tensor(
  [[0.43, 0.15, 0.89], # Your     (x^1)
   [0.55, 0.87, 0.66], # journey  (x^2)
   [0.57, 0.85, 0.64], # starts   (x^3)
   [0.22, 0.58, 0.33], # with     (x^4)
   [0.77, 0.25, 0.10], # one      (x^5)
   [0.05, 0.80, 0.55]] # step     (x^6)
)
batch = torch.stack((inputs, inputs), dim=0)
print(batch.shape)
```

```
torch.Size([2, 6, 3])
```

This results in a 3D tensor consisting of 2 input texts with 6 tokens each, where each token is a 3-dimensional embedding vector.

The following CausalAttention class is similar to the SelfAttention class we implemented earlier, except that we now added the dropout and causal mask components as highlighted in the following code.

Step 1: Compared to the previous SelfAttention_v1 class, we added a dropout layer. Step 2: The register_buffer call is also a new addition (more information is provided in the following text). Step 3: We transpose dimensions 1 and 2, keeping the batch dimension at the first position (0). Step 4: In PyTorch, operations with a trailing underscore are performed in-place, avoiding unnecessary memory copies

In [104]:

```
class CausalAttention(nn.Module):

    def __init__(self, d_in, d_out, context_length,
                 dropout, qkv_bias=False):
        super().__init__()
        self.d_out = d_out
        self.W_query = nn.Linear(d_in, d_out, bias=qkv_bias)
        self.W_key   = nn.Linear(d_in, d_out, bias=qkv_bias)
        self.W_value = nn.Linear(d_in, d_out, bias=qkv_bias)
        self.dropout = nn.Dropout(dropout) # New
        self.register_buffer('mask', torch.triu(torch.ones(context_length, context_lengt
h), diagonal=1)) # New

    def forward(self, x):
        b, num_tokens, d_in = x.shape # New batch dimension b
        keys = self.W_key(x)
        queries = self.W_query(x)
        values = self.W_value(x)

        attn_scores = queries @ keys.transpose(1, 2) # Changed transpose
        attn_scores.masked_fill_(  # New, _ ops are in-place
            self.mask.bool()[:num_tokens, :num_tokens], -torch.inf)  # `:num_tokens` to
account for cases where the number of tokens in the batch is smaller than the supported c
ontext_size
        attn_weights = torch.softmax(
            attn_scores / keys.shape[-1]**0.5, dim=-1
        )
        attn_weights = self.dropout(attn_weights) # New

        context_vec = attn_weights @ values
        return context_vec
```

The use of register_buffer in PyTorch is not strictly necessary for all use cases but offers several advantages here. For instance, when we use the CausalAttention class in our LLM, buffers are automatically moved to the appropriate device (CPU or GPU) along with our model, which will be relevant when training the LLM in future chapters. This means we don't need to manually ensure these tensors are

on the same device as your model parameters, avoiding device mismatch errors.

We can use the CausalAttention class as follows, similar to SelfAttention previously:

In [105]:

```
print(d_in)
```

```
3
```

In [106]:

```
print(d_out)
```

```
2
```

In [107]:

```
torch.manual_seed(123)
context_length = batch.shape[1]
ca = CausalAttention(d_in, d_out, context_length, 0.0)
context_vecs = ca(batch)
print("context_vecs.shape:", context_vecs.shape)
```

```
context_vecs.shape: torch.Size([2, 6, 2])
```

In [108]:

```
print(context_vecs)
```

```
tensor([[[-0.4519,  0.2216],
         [-0.5874,  0.0058],
         [-0.6300, -0.0632],
         [-0.5675, -0.0843],
         [-0.5526, -0.0981],
         [-0.5299, -0.1081]],

        [[-0.4519,  0.2216],
         [-0.5874,  0.0058],
         [-0.6300, -0.0632],
         [-0.5675, -0.0843],
         [-0.5526, -0.0981],
         [-0.5299, -0.1081]]], grad_fn=<UnsafeViewBackward0>)
```

As we can see, the resulting context vector is a 3D tensor where each token is now represented by a 2D embedding:

In the next section, we will expand on this concept and implement a multi-head attention module, that implements several of such causal attention mechanisms in parallel.

EXTENDING SINGLE HEAD ATTENTION TO MULTI-HEAD ATTENTION

In practical terms, implementing multi-head attention involves creating multiple instances of the self-attention mechanism, each with its own weights, and then combining their outputs

In code, we can achieve this by implementing a simple MultiHeadAttentionWrapper class that stacks

multiple instances of our previously implemented CausalAttention module:

In [109]:

```
class MultiHeadAttentionWrapper(nn.Module):

    def __init__(self, d_in, d_out, context_length, dropout, num_heads, qkv_bias=False):
        super().__init__()
        self.heads = nn.ModuleList(
            [CausalAttention(d_in, d_out, context_length, dropout, qkv_bias)
             for _ in range(num_heads)]
        )

    def forward(self, x):
        return torch.cat([head(x) for head in self.heads], dim=-1)
```

For example, if we use this MultiHeadAttentionWrapper class with two attention heads (via num_heads=2) and CausalAttention output dimension d_out=2, this results in a 4- dimensional context vectors (d_out*num_heads=4)

To illustrate further with a concrete example, we can use the MultiHeadAttentionWrapper class similar to the CausalAttention class before:

In [110]:

```
inputs = torch.tensor(
  [[0.43, 0.15, 0.89], # Your     (x^1)
   [0.55, 0.87, 0.66], # journey  (x^2)
   [0.57, 0.85, 0.64], # starts   (x^3)
   [0.22, 0.58, 0.33], # with     (x^4)
   [0.77, 0.25, 0.10], # one      (x^5)
   [0.05, 0.80, 0.55]] # step     (x^6)
)
batch = torch.stack((inputs, inputs), dim=0)
print(batch.shape)
```

```
torch.Size([2, 6, 3])
```

In [111]:

```
torch.manual_seed(123)
context_length = batch.shape[1] # This is the number of tokens = 6
d_in, d_out = 3, 2
mha = MultiHeadAttentionWrapper(d_in, d_out, context_length, 0.0, num_heads=2)
context_vecs = mha(batch)
print(context_vecs)
print("context_vecs.shape:", context_vecs.shape)
```

```
tensor([[[-0.4519,  0.2216,  0.4772,  0.1063],
         [-0.5874,  0.0058,  0.5891,  0.3257],
         [-0.6300, -0.0632,  0.6202,  0.3860],
         [-0.5675, -0.0843,  0.5478,  0.3589],
         [-0.5526, -0.0981,  0.5321,  0.3428],
         [-0.5299, -0.1081,  0.5077,  0.3493]],

        [[-0.4519,  0.2216,  0.4772,  0.1063],
         [-0.5874,  0.0058,  0.5891,  0.3257],
         [-0.6300, -0.0632,  0.6202,  0.3860],
         [-0.5675, -0.0843,  0.5478,  0.3589],
         [-0.5526, -0.0981,  0.5321,  0.3428],
         [-0.5299, -0.1081,  0.5077,  0.3493]]], grad_fn=<CatBackward0>)
context_vecs.shape: torch.Size([2, 6, 4])
```

The first dimension of the resulting context_vecs tensor is 2 since we have two input texts (the input texts are duplicated, which is why the context vectors are exactly the same for those). The second dimension refers to the 6 tokens in each input. The third dimension refers to the 4-dimensional embedding of each token.

In this section, we implemented a MultiHeadAttentionWrapper that combined multiple single-head attention modules. However, note that these are processed sequentially via [head(x) for head in self.heads] in the forward method. We can improve this implementation by processing the heads in parallel. One way to achieve this is by computing the outputs for all attention heads simultaneously via matrix multiplication, as we will explore in the next section.

IMPLEMENTING MULTI-HEAD ATTENTION WITH WEIGHT SPLITS

Instead of maintaining two separate classes, MultiHeadAttentionWrapper and CausalAttention, we can combine both of these concepts into a single MultiHeadAttention class. Also, in addition to just merging the MultiHeadAttentionWrapper with the CausalAttention code, we will make some other modifications to implement multi-head attention more efficiently.

In the MultiHeadAttentionWrapper, multiple heads are implemented by creating a list of CausalAttention objects (self.heads), each representing a separate attention head. The CausalAttention class independently performs the attention mechanism, and the results from each head are concatenated. In contrast, the following MultiHeadAttention class integrates the multi-head functionality within a single class. It splits the input into multiple heads by reshaping the projected query, key, and value tensors and then combines the results from these heads after computing attention.

Let's take a look at the MultiHeadAttention class before we discuss it further:

In [112]:

```
class MultiHeadAttention(nn.Module):
    def __init__(self, d_in, d_out, context_length, dropout, num_heads, qkv_bias=False):
        super().__init__()
        assert (d_out % num_heads == 0), \
            "d_out must be divisible by num_heads"

        self.d_out = d_out
        self.num_heads = num_heads
        self.head_dim = d_out // num_heads # Reduce the projection dim to match desired 
output dim

        self.W_query = nn.Linear(d_in, d_out, bias=qkv_bias)
        self.W_key = nn.Linear(d_in, d_out, bias=qkv_bias)
        self.W_value = nn.Linear(d_in, d_out, bias=qkv_bias)
        self.out_proj = nn.Linear(d_out, d_out)  # Linear layer to combine head outputs
        self.dropout = nn.Dropout(dropout)
        self.register_buffer(
            "mask",
            torch.triu(torch.ones(context_length, context_length),
                       diagonal=1)
        )

    def forward(self, x):
        b, num_tokens, d_in = x.shape

        keys = self.W_key(x) # Shape: (b, num_tokens, d_out)
        queries = self.W_query(x)
        values = self.W_value(x)

        # We implicitly split the matrix by adding a `num_heads` dimension
        # Unroll last dim: (b, num_tokens, d_out) -> (b, num_tokens, num_heads, head_dim
)
        keys = keys.view(b, num_tokens, self.num_heads, self.head_dim)
        values = values.view(b, num_tokens, self.num_heads, self.head_dim)
        queries = queries.view(b, num_tokens, self.num_heads, self.head_dim)

        # Transpose: (b, num_tokens, num_heads, head_dim) -> (b, num_heads, num_tokens,
head_dim)
        keys = keys.transpose(1, 2)
        queries = queries.transpose(1, 2)
        values = values.transpose(1, 2)

        # Compute scaled dot-product attention (aka self-attention) with a causal mask
        attn_scores = queries @ keys.transpose(2, 3)  # Dot product for each head

        # Original mask truncated to the number of tokens and converted to boolean
        mask_bool = self.mask.bool()[:num_tokens, :num_tokens]

        # Use the mask to fill attention scores
        attn_scores.masked_fill_(mask_bool, -torch.inf)

        attn_weights = torch.softmax(attn_scores / keys.shape[-1]**0.5, dim=-1)
        attn_weights = self.dropout(attn_weights)

        # Shape: (b, num_tokens, num_heads, head_dim)
        context_vec = (attn_weights @ values).transpose(1, 2)

        # Combine heads, where self.d_out = self.num_heads * self.head_dim
        context_vec = context_vec.contiguous().view(b, num_tokens, self.d_out)
        context_vec = self.out_proj(context_vec) # optional projection

        return context_vec
```

Step 1: Reduce the projection dim to match desired output dim Step 2: Use a Linear layer to combine head outputs Step 3: Tensor shape: (b, num_tokens, d_out) Step 4: We implicitly split the matrix by adding a `num_heads` dimension. Then we unroll last dim: (b, num_tokens, d_out) -> (b, num_tokens, num_heads, head_dim) Step 5: Transpose from shape (b, num_tokens, num_heads, head_dim) to (b, num_heads, num_tokens, head_dim) Step 6: Compute dot product for each head Step 7: Mask truncated to the number of tokens Step 8: Use the mask to fill attention scores Step 9: Tensor shape: (b, num_tokens, n_heads, head_dim) Step 10: Combine heads, where self.d_out = self.num_heads * self.head_dim Step 11: Add an optional linear projection

Even though the reshaping (.view) and transposing (.transpose) of tensors inside the MultiHeadAttention class looks very complicated, mathematically, the MultiHeadAttention class implements the same concept as the MultiHeadAttentionWrapper earlier.

On a big-picture level, in the previous MultiHeadAttentionWrapper, we stacked multiple single-head attention layers that we combined into a multi-head attention layer. The MultiHeadAttention class takes an integrated approach. It starts with a multi-head layer and then internally splits this layer into individual attention heads

DETAILED EXPLANATION OF THE MULTI-HEAD ATTENTION CLASS

The splitting of the query, key, and value tensors, is achieved through tensor reshaping and transposing operations using PyTorch's .view and .transpose methods. The input is first transformed (via linear layers for queries, keys, and values) and then reshaped to represent multiple heads.

The key operation is to split the d_out dimension into num_heads and head_dim, where head_dim = d_out / num_heads. This splitting is then achieved using the .view method: a tensor of dimensions (b, num_tokens, d_out) is reshaped to dimension (b, num_tokens, num_heads, head_dim).

The tensors are then transposed to bring the num_heads dimension before the num_tokens dimension, resulting in a shape of (b, num_heads, num_tokens, head_dim). This transposition is crucial for correctly aligning the queries, keys, and values across the different heads and performing batched matrix multiplications efficiently.

To illustrate this batched matrix multiplication, suppose we have the following example tensor:

Continuing with MultiHeadAttention, after computing the attention weights and context vectors, the context vectors from all heads are transposed back to the shape (b, num_tokens, num_heads, head_dim). These vectors are then reshaped (flattened) into the shape (b, num_tokens, d_out), effectively combining the outputs from all heads

Additionally, we added a so-called output projection layer (self.out_proj) to MultiHeadAttention after combining the heads, which is not present in the CausalAttention class. This output projection layer is not strictly necessary, but it is commonly used in many LLM architectures, which is why we added it here for completeness.

Even though the MultiHeadAttention class looks more complicated than the MultiHeadAttentionWrapper due to the additional reshaping and transposition of tensors, it is more efficient. The reason is that we only need one matrix multiplication to compute the keys, for instance, keys = self.W_key(x) (the same is true for the queries and values). In the MultiHeadAttentionWrapper, we needed to repeat this matrix multiplication, which is computationally one of the most expensive steps, for each attention head.

The MultiHeadAttention class can be used similar to the SelfAttention and CausalAttention classes we implemented earlier:

In [113]:

```
torch.manual_seed(123)

# Define the tensor with 3 rows and 6 columns
inputs = torch.tensor(
    [[0.43, 0.15, 0.89, 0.55, 0.87, 0.66],  # Row 1
     [0.57, 0.85, 0.64, 0.22, 0.58, 0.33],  # Row 2
     [0.77, 0.25, 0.10, 0.05, 0.80, 0.55]]  # Row 3
)

batch = torch.stack((inputs, inputs), dim=0)
print(batch.shape)

batch_size, context_length, d_in = batch.shape
d_out = 6
mha = MultiHeadAttention(d_in, d_out, context_length, 0.0, num_heads=2)
context_vecs = mha(batch)
```

```python
print(context_vecs)
print("context_vecs.shape:", context_vecs.shape)
```

```
torch.Size([2, 3, 6])
tensor([[[ 0.1569, -0.0873,  0.0210,  0.0215, -0.3243, -0.2518],
         [ 0.1117, -0.0547,  0.0406, -0.0213, -0.3251, -0.2993],
         [ 0.1196, -0.0491,  0.0318, -0.0635, -0.2788, -0.2578]],

        [[ 0.1569, -0.0873,  0.0210,  0.0215, -0.3243, -0.2518],
         [ 0.1117, -0.0547,  0.0406, -0.0213, -0.3251, -0.2993],
         [ 0.1196, -0.0491,  0.0318, -0.0635, -0.2788, -0.2578]]],
       grad_fn=<ViewBackward0>)
context_vecs.shape: torch.Size([2, 3, 6])
```

As we can see based on the results, the output dimension is directly controlled by the d_out argument:

In this section, we implemented the MultiHeadAttention class that we will use in the upcoming sections when implementing and training the LLM itself. Note that while the code is fully functional, we used relatively small embedding sizes and numbers of attention heads to keep the outputs readable.

For comparison, the smallest GPT-2 model (117 million parameters) has 12 attention heads and a context vector embedding size of 768. The largest GPT-2 model (1.5 billion parameters) has 25 attention heads and a context vector embedding size of 1600. Note that the embedding sizes of the token inputs and context embeddings are the same in GPT models (d_in = d_out).

IMPLEMENTING A GPT MODEL FROM SCRATCH TO GENERATE TEXT

In [114]:

```python
GPT_CONFIG_124M = {
    "vocab_size": 50257,     # Vocabulary size
    "context_length": 1024, # Context length
    "emb_dim": 768,          # Embedding dimension
    "n_heads": 12,           # Number of attention heads
    "n_layers": 12,          # Number of layers
    "drop_rate": 0.1,        # Dropout rate
    "qkv_bias": False        # Query-Key-Value bias
}
```

GPT ARCHITECTURE PART 1: DUMMY GPT MODEL CLASS

Step 1: Use a placeholder for TransformerBlock Step 2: Use a placeholder for LayerNorm

In [115]:

```python
import torch
import torch.nn as nn


class DummyGPTModel(nn.Module):
    def __init__(self, cfg):
        super().__init__()
        self.tok_emb = nn.Embedding(cfg["vocab_size"], cfg["emb_dim"])
        self.pos_emb = nn.Embedding(cfg["context_length"], cfg["emb_dim"])
        self.drop_emb = nn.Dropout(cfg["drop_rate"])
        # Use a placeholder for TransformerBlock
        self.trf_blocks = nn.Sequential(
            *[DummyTransformerBlock(cfg) for _ in range(cfg["n_layers"])])

        # Use a placeholder for LayerNorm
        self.final_norm = DummyLayerNorm(cfg["emb_dim"])
        self.out_head = nn.Linear(
            cfg["emb_dim"], cfg["vocab_size"], bias=False
        )

    def forward(self, in_idx):
        batch_size, seq_len = in_idx.shape
        tok_embeds = self.tok_emb(in_idx)
        pos_embeds = self.pos_emb(torch.arange(seq_len, device=in_idx.device))
        x = tok_embeds + pos_embeds
        x = self.drop_emb(x)
        x = self.trf_blocks(x)
        x = self.final_norm(x)
        logits = self.out_head(x)
        return logits


class DummyTransformerBlock(nn.Module):
    def __init__(self, cfg):
        super().__init__()
        # A simple placeholder

    def forward(self, x):
        # This block does nothing and just returns its input.
        return x


class DummyLayerNorm(nn.Module):
    def __init__(self, normalized_shape, eps=1e-5):
        super().__init__()
        # The parameters here are just to mimic the LayerNorm interface.

    def forward(self, x):
        # This layer does nothing and just returns its input.
        return x
```

The DummyGPTModel class in this code defines a simplified version of a GPT-like model using PyTorch's neural network module (nn.Module). The model architecture in the DummyGPTModel class consists of token and positional embeddings, dropout, a series of transformer blocks (DummyTransformerBlock), a final layer normalization (DummyLayerNorm), and a linear output layer (out_head). The configuration is passed in via a Python dictionary, for instance, the GPT_CONFIG_124M dictionary we created earlier.

The forward method describes the data flow through the model: it computes token and positional embeddings for the input indices, applies dropout, processes the data through the transformer blocks, applies normalization, and finally produces logits with the linear output layer.

The code above is already functional, as we will see later in this section after we prepare the input data. However, for now, note in the code above that we have used placeholders (DummyLayerNorm and DummyTransformerBlock) for the transformer block and layer normalization, which we will develop in later sections

Next, we will prepare the input data and initialize a new GPT model to illustrate its usage.

STEP 1: TOKENIZATION

In [116]:

```
import tiktoken
tokenizer = tiktoken.get_encoding("gpt2")
batch = []
txt1 = "Every effort moves you"
txt2 = "Every day holds a"
batch.append(torch.tensor(tokenizer.encode(txt1)))
batch.append(torch.tensor(tokenizer.encode(txt2)))
batch = torch.stack(batch, dim=0)
print(batch)
```

```
tensor([[6109, 3626, 6100,  345],
        [6109, 1110, 6622,  257]])
```

STEP 2: CREATE AN INSTANCE OF DUMMYGPTMODEL

In [117]:

```
torch.manual_seed(123)
model = DummyGPTModel(GPT_CONFIG_124M)
logits = model(batch)
print("Output shape:", logits.shape)
print(logits)
```

```
Output shape: torch.Size([2, 4, 50257])
tensor([[[-1.2034,  0.3201, -0.7130,  ..., -1.5548, -0.2390, -0.4667],
         [-0.1192,  0.4539, -0.4432,  ...,  0.2392,  1.3469,  1.2430],
         [ 0.5307,  1.6720, -0.4695,  ...,  1.1966,  0.0111,  0.5835],
         [ 0.0139,  1.6754, -0.3388,  ...,  1.1586, -0.0435, -1.0400]],

        [[-1.0908,  0.1798, -0.9484,  ..., -1.6047,  0.2439, -0.4530],
         [-0.7860,  0.5581, -0.0610,  ...,  0.4835, -0.0077,  1.6621],
         [ 0.3567,  1.2698, -0.6398,  ..., -0.0162, -0.1296,  0.3717],
         [-0.2407, -0.7349, -0.5102,  ...,  2.0057, -0.3694,  0.1814]]],
       grad_fn=<UnsafeViewBackward0>)
```

The output tensor has two rows corresponding to the two text samples. Each text sample consists of 4 tokens; each token is a 50,257-dimensional vector, which matches the size of the tokenizer's vocabulary. The embedding has 50,257 dimensions because each of these dimensions refers to a unique token in the vocabulary. At the end of this chapter, when we implement the postprocessing code, we will convert these 50,257-dimensional vectors back into token IDs, which we can then decode into words.

Now that we have taken a top-down look at the GPT architecture and its in- and outputs, we will code the individual placeholders in the upcoming sections, starting with the real layer normalization class that will replace the DummyLayerNorm in the previous code.

GPT ARCHITECTURE PART 2: LAYER NORMALIZATION

Explanation with a simple example

In [118]:

```
torch.manual_seed(123)
batch_example = torch.randn(2, 5) #A
layer = nn.Sequential(nn.Linear(5, 6), nn.ReLU())
out = layer(batch_example)
print(out)
```

```
tensor([[0.2260, 0.3470, 0.0000, 0.2216, 0.0000, 0.0000],
        [0.2133, 0.2394, 0.0000, 0.5198, 0.3297, 0.0000]],
       grad_fn=<ReluBackward0>)
```

The neural network layer we have coded consists of a Linear layer followed by a non-linear activation function, ReLU (short for Rectified Linear Unit), which is a standard activation function in neural networks. If you are unfamiliar with ReLU, it simply thresholds negative inputs to 0, ensuring that a layer outputs only positive values, which explains why the resulting layer output does not contain any negative values. (Note that we will use another, more sophisticated activation function in GPT, which we will introduce in the next section).

Before we apply layer normalization to these outputs, let's examine the mean and variance:

In [119]:

```python
mean = out.mean(dim=-1, keepdim=True)
var = out.var(dim=-1, keepdim=True)
print("Mean:\n", mean)
print("Variance:\n", var)
```

```
Mean:
 tensor([[0.1324],
        [0.2170]], grad_fn=<MeanBackward1>)
Variance:
 tensor([[0.0231],
        [0.0398]], grad_fn=<VarBackward0>)
```

The first row in the mean tensor above contains the mean value for the first input row, and the second output row contains the mean for the second input row.

Using keepdim=True in operations like mean or variance calculation ensures that the output tensor retains the same number of dimensions as the input tensor, even though the operation reduces the tensor along the dimension specified via dim. For instance, without keepdim=True, the returned mean tensor would be a 2-dimensional vector [0.1324, 0.2170] instead of a 2×1-dimensional matrix [[0.1324], [0.2170]].

For a 2D tensor (like a matrix), using dim=-1 for operations such as mean or variance calculation is the same as using dim=1. This is because -1 refers to the tensor's last dimension, which corresponds to the columns in a 2D tensor. Later, when adding layer normalization to the GPT model, which produces 3D tensors with shape [batch_size, num_tokens, embedding_size], we can still use dim=-1 for normalization across the last dimension, avoiding a change from dim=1 to dim=2.

Next, let us apply layer normalization to the layer outputs we obtained earlier. The operation consists of subtracting the mean and dividing by the square root of the variance (also known as standard deviation):

In [120]:

```python
out_norm = (out - mean) / torch.sqrt(var)
mean = out_norm.mean(dim=-1, keepdim=True)
var = out_norm.var(dim=-1, keepdim=True)
print("Normalized layer outputs:\n", out_norm)
print("Mean:\n", mean)
print("Variance:\n", var)
```

```
Normalized layer outputs:
 tensor([[ 0.6159,  1.4126, -0.8719,  0.5872, -0.8719, -0.8719],
        [-0.0189,  0.1121, -1.0876,  1.5173,  0.5647, -1.0876]],
        [-0.0189,  0.1121, -1.0876,  1.5173,  0.5647, -1.0876]],
       grad_fn=<DivBackward0>)
Mean:
 tensor([[-5.9605e-08],
        [ 1.9868e-08]], grad_fn=<MeanBackward1>)
Variance:
 tensor([[1.0000],
        [1.0000]], grad_fn=<VarBackward0>)
```

Note that the value 2.9802e-08 in the output tensor is the scientific notation for 2.9802 × 10-8, which is 0.0000000298 in decimal form. This value is very close to 0, but it is not exactly 0 due to small numerical errors that can accumulate because of the finite precision with which computers represent numbers.

To improve readability, we can also turn off the scientific notation when printing tensor values by setting sci_mode to False:

In [121]:

```python
torch.set_printoptions(sci_mode=False)
print("Mean:\n", mean)
print("Variance:\n", var)
```

```
Mean:
 tensor([[    -0.0000],
        [     0.0000]], grad_fn=<MeanBackward1>)
Variance:
 tensor([[1.0000],
        [1.0000]], grad_fn=<VarBackward0>)
```

Let's now encapsulate this process in a PyTorch module that we can use in the GPT model later:

In [122]:

```python
class LayerNorm(nn.Module):
    def __init__(self, emb_dim):
        super().__init__()
        self.eps = 1e-5
        self.scale = nn.Parameter(torch.ones(emb_dim))
        self.shift = nn.Parameter(torch.zeros(emb_dim))

    def forward(self, x):
        mean = x.mean(dim=-1, keepdim=True)
        var = x.var(dim=-1, keepdim=True, unbiased=False)
        norm_x = (x - mean) / torch.sqrt(var + self.eps)
        return self.scale * norm_x + self.shift
```

This specific implementation of layer Normalization operates on the last dimension of the input tensor x, which represents the embedding dimension (emb_dim). The variable eps is a small constant (epsilon) added to the variance to prevent division by zero during normalization. The scale and shift are two trainable parameters (of the same dimension as the input) that the LLM automatically adjusts during training if it is determined that doing so would improve the model's performance on its training task. This allows the model to learn appropriate scaling and shifting that best suit the data it is processing.

A small note on biased variance

In our variance calculation method, we have opted for an implementation detail by setting unbiased=False. For those curious about what this means, in the variance calculation, we divide by the number of inputs n in the variance formula. This approach does not apply Bessel's correction, which typically uses n-1 instead of

n in the denominator to adjust for bias in sample variance estimation. This decision results in a so-called biased estimate of the variance. For large-scale language models (LLMs), where the embedding dimension n is significantly large, the difference between using n and n-1 is practically negligible. We chose this approach to ensure compatibility with the GPT-2 model's normalization layers and because it reflects TensorFlow's default behavior, which was used to implement the original GPT2 model.

Let's now try the LayerNorm module in practice and apply it to the batch input:

In [123]:

```
print(batch_example)
```

```
tensor([[-0.1115,  0.1204, -0.3696, -0.2404, -1.1969],
        [ 0.2093, -0.9724, -0.7550,  0.3239, -0.1085]])
```

In [124]:

```
ln = LayerNorm(emb_dim=5)
out_ln = ln(batch_example)
mean = out_ln.mean(dim=-1, keepdim=True)
var = out_ln.var(dim=-1, unbiased=False, keepdim=True)
print("Mean:\n", mean)
print("Variance:\n", var)
```

```
Mean:
 tensor([[    -0.0000],
        [     0.0000]], grad_fn=<MeanBackward1>)
Variance:
 tensor([[1.0000],
        [1.0000]], grad_fn=<VarBackward0>)
```

As we can see based on the results, the layer normalization code works as expected and normalizes the values of each of the two inputs such that they have a mean of 0 and a variance of 1:

GPT ARCHITECTURE PART 3: FEEDFORWARD NEURAL NETWORK WITH GELU ACTIVATION

Let's implement the GELU activation function approximation used by GPT-2:

In [125]:

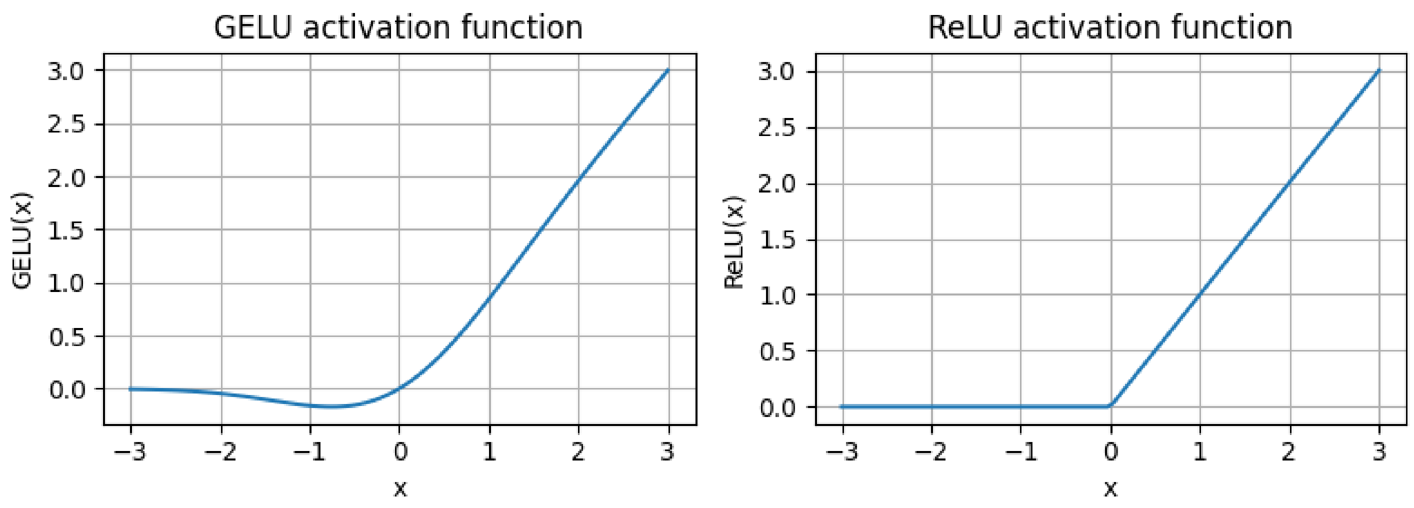
```
class GELU(nn.Module):
    def __init__(self):
        super().__init__()

    def forward(self, x):
        return 0.5 * x * (1 + torch.tanh(
            torch.sqrt(torch.tensor(2.0 / torch.pi)) *
            (x + 0.044715 * torch.pow(x, 3))
        ))
```

To get an idea of what this GELU function looks like and how it compares to the ReLU function, let's plot these functions side by side:

In [126]:

```
import matplotlib.pyplot as plt
```

```
gelu, relu = GELU(), nn.ReLU()

# Some sample data
x = torch.linspace(-3, 3, 100)
y_gelu, y_relu = gelu(x), relu(x)

plt.figure(figsize=(8, 3))
for i, (y, label) in enumerate(zip([y_gelu, y_relu], ["GELU", "ReLU"]), 1):
    plt.subplot(1, 2, i)
    plt.plot(x, y)
    plt.title(f"{label} activation function")
    plt.xlabel("x")
    plt.ylabel(f"{label}(x)")
    plt.grid(True)

plt.tight_layout()
plt.show()
```



As we can see in the resulting plot, ReLU is a piecewise linear function that outputs the input directly if it is positive; otherwise, it outputs zero. GELU is a smooth, nonlinear function that approximates ReLU but with a non-zero gradient for negative values.

The smoothness of GELU, as shown in the above figure, can lead to better optimization properties during training, as it allows for more nuanced adjustments to the model's parameters. In contrast, ReLU has a sharp corner at zero, which can sometimes make optimization harder, especially in networks that are very deep or have complex architectures. Moreover, unlike RELU, which outputs zero for any negative input, GELU allows for a small, non-zero output for negative values. This characteristic means that during the training process, neurons that receive negative input can still contribute to the learning process, albeit to a lesser extent than positive inputs.

Next, let's use the GELU function to implement the small neural network module, FeedForward, that we will be using in the LLM's transformer block later:

In [127]:

```
GPT_CONFIG_124M = {
    "vocab_size": 50257,    # Vocabulary size
    "context_length": 1024, # Context length
    "emb_dim": 768,         # Embedding dimension
    "n_heads": 12,          # Number of attention heads
    "n_layers": 12,         # Number of layers
    "drop_rate": 0.1,       # Dropout rate
    "qkv_bias": False       # Query-Key-Value bias
}
```

In [128]:

```
class FeedForward(nn.Module):
    def __init__(self, cfg):
        super().__init__()
        self.layers = nn.Sequential(
            nn.Linear(cfg["emb_dim"], 4 * cfg["emb_dim"]), ## Expansion
            GELU(), ## Activation
            nn.Linear(4 * cfg["emb_dim"], cfg["emb_dim"]), ## Contraction
        )

    def forward(self, x):
        return self.layers(x)
```

In [129]:

```
print(GPT_CONFIG_124M["emb_dim"])
```

```
768
```

As we can see in the preceding code, the FeedForward module is a small neural network consisting of two Linear layers and a GELU activation function. In the 124 million parameter GPT model, it receives the input batches with tokens that have an embedding size of 768 each via the GPT_CONFIG_124M dictionary where GPT_CONFIG_124M["emb_dim"] = 768.

Let's use the GELU function to implement the small neural network module, FeedForward, that we will be using in the LLM's transformer block later:

In [130]:

```
ffn = FeedForward(GPT_CONFIG_124M)
x = torch.rand(2, 3, 768) #A
out = ffn(x)
print(out.shape)
```

```
torch.Size([2, 3, 768])
```

The FeedForward module we implemented in this section plays a crucial role in enhancing the model's ability to learn from and generalize the data. Although the input and output dimensions of this module are the same, it internally expands the embedding dimension into a higher-dimensional space through the first linear layer. This expansion is followed by a non-linear GELU activation, and then a contraction back to the original dimension with the second linear transformation. Such a design allows for the exploration of a richer representation space.

Moreover, the uniformity in input and output dimensions simplifies the architecture by enabling the stacking of multiple layers, as we will do later, without the need to adjust dimensions between them, thus making the model more scalable.

GPT ARCHITECTURE PART 4: SHORTCUT CONNECTIONS

Let us see how we can add shortcut connections to the forward method:

In [131]:

```
class ExampleDeepNeuralNetwork(nn.Module):
    def __init__(self, layer_sizes, use_shortcut):
        super().__init__()
        self.use_shortcut = use_shortcut
        self.layers = nn.ModuleList([
            nn.Sequential(nn.Linear(layer_sizes[0], layer_sizes[1]), GELU()),
            nn.Sequential(nn.Linear(layer_sizes[1], layer_sizes[2]), GELU()),
            nn.Sequential(nn.Linear(layer_sizes[2], layer_sizes[3]), GELU()),
            nn.Sequential(nn.Linear(layer_sizes[3], layer_sizes[4]), GELU()),
            nn.Sequential(nn.Linear(layer_sizes[4], layer_sizes[5]), GELU())
        ])

    def forward(self, x):
        for layer in self.layers:
            # Compute the output of the current layer
            layer_output = layer(x)
            # Check if shortcut can be applied
            if self.use_shortcut and x.shape == layer_output.shape:
                x = x + layer_output
            else:
                x = layer_output
        return x
```

The code implements a deep neural network with 5 layers, each consisting of a Linear layer and a GELU activation function. In the forward pass, we iteratively pass the input through the layers and optionally add the shortcut connections if the self.use_shortcut attribute is set to True.

Let's use this code to first initialize a neural network without shortcut connections. Here, each layer will be initialized such that it accepts an example with 3 input values and returns 3 output values. The last layer returns a single output value:

In [132]:

```
layer_sizes = [3, 3, 3, 3, 3, 1]
sample_input = torch.tensor([[1., 0., -1.]])
torch.manual_seed(123) # specify random seed for the initial weights for reproducibility
model_without_shortcut = ExampleDeepNeuralNetwork(
layer_sizes, use_shortcut=False
)
```

Next, we implement a function that computes the gradients in the the model's backward pass:

In [133]:

```
def print_gradients(model, x):
    # Forward pass
    output = model(x)
    target = torch.tensor([[0.]])

    # Calculate loss based on how close the target
    # and output are
    loss = nn.MSELoss()
    loss = loss(output, target)

    # Backward pass to calculate the gradients
    loss.backward()

    for name, param in model.named_parameters():
        if 'weight' in name:
            # Print the mean absolute gradient of the weights
            print(f"{name} has gradient mean of {param.grad.abs().mean().item()}")
```

In the preceding code, we specify a loss function that computes how close the model output and a user-specified target (here, for simplicity, the value 0) are. Then, when calling loss.backward(), PyTorch computes the loss gradient for each layer in the model. We can iterate through the weight parameters via model.named_parameters(). Suppose we have a 3×3 weight parameter matrix for a given layer. In that case, this layer will have 3×3 gradient values, and we print the mean absolute gradient of these 3×3 gradient values to obtain a single gradient value per layer to compare the gradients between layers more easily.

In short, the .backward() method is a convenient method in PyTorch that computes loss gradients, which are required during model training, without implementing the math for the gradient calculation ourselves, thereby making working with deep neural networks much more accessible.

Let's now use the print_gradients function and apply it to the model without skip connections:

In [134]:

```
print_gradients(model_without_shortcut, sample_input)
```

```
layers.0.0.weight has gradient mean of 0.00020173587836325169
layers.1.0.weight has gradient mean of 0.00012011159560643137
layers.2.0.weight has gradient mean of 0.0007152039906941354
layers.3.0.weight has gradient mean of 0.0013988736318424344
layers.4.0.weight has gradient mean of 0.005049645435065031
```

As we can see based on the output of the print_gradients function, the gradients become smaller as we progress from the last layer (layers.4) to the first layer (layers.0), which is a phenomenon called the vanishing gradient problem.

Let's now instantiate a model with skip connections and see how it compares:

In [135]:

```
torch.manual_seed(123)
model_with_shortcut = ExampleDeepNeuralNetwork(
layer_sizes, use_shortcut=True
)
print_gradients(model_with_shortcut, sample_input)
```

```
layers.0.0.weight has gradient mean of 0.22169792652130127
layers.1.0.weight has gradient mean of 0.20694106817245483
layers.2.0.weight has gradient mean of 0.32896995544433594
layers.3.0.weight has gradient mean of 0.2665732204914093
layers.4.0.weight has gradient mean of 1.3258540630340576
```

As we can see, based on the output, the last layer (layers.4) still has a larger gradient than the other layers. However, the gradient value stabilizes as we progress towards the first layer (layers.0) and doesn't shrink to a vanishingly small value.

In conclusion, shortcut connections are important for overcoming the limitations posed by the vanishing gradient problem in deep neural networks. Shortcut connections are a core building block of very large models such as LLMs, and they will help facilitate more effective training by ensuring consistent gradient flow across layers when we train the GPT model

GPT ARCHITECTURE PART 5: CODING ATTENTION AND LINEAR LAYERS IN A TRANSFORMER BLOCK

In [136]:

```
GPT_CONFIG_124M = {
    "vocab_size": 50257,     # Vocabulary size
    "context_length": 1024, # Context length
    "emb_dim": 768,          # Embedding dimension
    "n_heads": 12,           # Number of attention heads
    "n_layers": 12,          # Number of layers
    "drop_rate": 0.1,        # Dropout rate
    "qkv_bias": False        # Query-Key-Value bias
}
```

THE BUILDING BLOCKS: LAYER NORMALIZATION, GELU AND FEED-FORWARD NEURAL NETWORK

In [137]:

```
class LayerNorm(nn.Module):
    def __init__(self, emb_dim):
        super().__init__()
        self.eps = 1e-5
        self.scale = nn.Parameter(torch.ones(emb_dim))
        self.shift = nn.Parameter(torch.zeros(emb_dim))

    def forward(self, x):
        mean = x.mean(dim=-1, keepdim=True)
        var = x.var(dim=-1, keepdim=True, unbiased=False)
        norm_x = (x - mean) / torch.sqrt(var + self.eps)
        return self.scale * norm_x + self.shift

class GELU(nn.Module):
    def __init__(self):
        super().__init__()

    def forward(self, x):
        return 0.5 * x * (1 + torch.tanh(
            torch.sqrt(torch.tensor(2.0 / torch.pi)) *
            (x + 0.044715 * torch.pow(x, 3))
        ))


class FeedForward(nn.Module):
    def __init__(self, cfg):
        super().__init__()
        self.layers = nn.Sequential(
            nn.Linear(cfg["emb_dim"], 4 * cfg["emb_dim"]), ## Expansion
            GELU(), ## Activation
            nn.Linear(4 * cfg["emb_dim"], cfg["emb_dim"]), ## Contraction
        )

    def forward(self, x):
        return self.layers(x)
```

Let us code a transformer block as follows:

Step 1: Shortcut connection for attention block Step 2: Shortcut connection for feed forward block Step 3: Add the original input back

In [138]:

```
class TransformerBlock(nn.Module):
    def __init__(self, cfg):
        super().__init__()
        self.att = MultiHeadAttention(
            d_in=cfg["emb_dim"],
            d_out=cfg["emb_dim"],
            context_length=cfg["context_length"],
            num_heads=cfg["n_heads"],
            dropout=cfg["drop_rate"],
            qkv_bias=cfg["qkv_bias"])
        self.ff = FeedForward(cfg)
        self.norm1 = LayerNorm(cfg["emb_dim"])
        self.norm2 = LayerNorm(cfg["emb_dim"])
        self.drop_shortcut = nn.Dropout(cfg["drop_rate"])

    def forward(self, x):
        # Shortcut connection for attention block
        shortcut = x
        x = self.norm1(x)
        x = self.att(x)   # Shape [batch_size, num_tokens, emb_size]
        x = self.drop_shortcut(x)
        x = x + shortcut  # Add the original input back

        # Shortcut connection for feed forward block
        shortcut = x
        x = self.norm2(x)
        x = self.ff(x)
        # 2*4*768
        x = self.drop_shortcut(x)
        x = x + shortcut  # Add the original input back

        return x
        # 2*4*768
```

The given code defines a TransformerBlock class in PyTorch that includes a multi-head attention mechanism (MultiHeadAttention) and a feed forward network (FeedForward), both configured based on a provided configuration dictionary (cfg), such as GPT_CONFIG_124M

Layer normalization (LayerNorm) is applied before each of these two components, and dropout is applied after them to regularize the model and prevent overfitting. This is also known as Pre-LayerNorm. Older architectures, such as the original transformer model, applied layer normalization after the self-attention and feed-forward networks instead, known as Post-LayerNorm, which often leads to worse training dynamics.

The class also implements the forward pass, where each component is followed by a shortcut connection that adds the input of the block to its output. This critical feature helps gradients flow through the network during training and improves the learning of deep models

Using the GPT_CONFIG_124M dictionary we defined earlier, let's instantiate a transformer block and feed it some sample data

Create sample input of shape [batch_size, num_tokens, emb_dim]

In [139]:

```
torch.manual_seed(123)
```

```
x = torch.rand(2, 4, 768) #A
block = TransformerBlock(GPT_CONFIG_124M)
output = block(x)
print("Input shape:", x.shape)
print("Output shape:", output.shape)
```

```
Input shape: torch.Size([2, 4, 768])
Output shape: torch.Size([2, 4, 768])
```

As we can see from the code output, the transformer block maintains the input dimensions in its output, indicating that the transformer architecture processes sequences of data without altering their shape throughout the network.

The preservation of shape throughout the transformer block architecture is not incidental but a crucial aspect of its design. This design enables its effective application across a wide range of sequence-to-sequence tasks, where each output vector directly corresponds to an input vector, maintaining a one-to-one relationship.

However, the output is a context vector that encapsulates information from the entire input sequence. This means that while the physical dimensions of the sequence (length and feature size) remain unchanged as it passes through the transformer block, the content of each output vector is re-encoded to integrate contextual information from across the entire input sequence.

GPT ARCHITECTURE PART 6: ENTIRE GPT MODEL ARCHITECTURE IMPLEMENTATION

In [140]:

```
GPT_CONFIG_124M = {
    "vocab_size": 50257,     # Vocabulary size
    "context_length": 1024, # Context length
    "emb_dim": 768,          # Embedding dimension
    "n_heads": 12,           # Number of attention heads
    "n_layers": 12,          # Number of layers
    "drop_rate": 0.1,        # Dropout rate
    "qkv_bias": False        # Query-Key-Value bias
}
```

We started with this: A dummy GPT model class

In [141]:

```
import torch
import torch.nn as nn


class DummyGPTModel(nn.Module):
    def __init__(self, cfg):
        super().__init__()
        self.tok_emb = nn.Embedding(cfg["vocab_size"], cfg["emb_dim"])
        self.pos_emb = nn.Embedding(cfg["context_length"], cfg["emb_dim"])
        self.drop_emb = nn.Dropout(cfg["drop_rate"])

        # Use a placeholder for TransformerBlock
        self.trf_blocks = nn.Sequential(
            *[DummyTransformerBlock(cfg) for _ in range(cfg["n_layers"])])

        # Use a placeholder for LayerNorm
        self.final_norm = DummyLayerNorm(cfg["emb_dim"])
        self.out_head = nn.Linear(
            cfg["emb_dim"], cfg["vocab_size"], bias=False
        )

    def forward(self, in_idx):
        batch_size, seq_len = in_idx.shape
        tok_embeds = self.tok_emb(in_idx)
        pos_embeds = self.pos_emb(torch.arange(seq_len, device=in_idx.device))
        x = tok_embeds + pos_embeds
        x = self.drop_emb(x)
        x = self.trf_blocks(x)
        x = self.final_norm(x)
        logits = self.out_head(x)
        return logits


class DummyTransformerBlock(nn.Module):
    def __init__(self, cfg):
        super().__init__()
        # A simple placeholder

    def forward(self, x):
        # This block does nothing and just returns its input.
        return x


class DummyLayerNorm(nn.Module):
    def __init__(self, normalized_shape, eps=1e-5):
        super().__init__()
        # The parameters here are just to mimic the LayerNorm interface.

    def forward(self, x):
        # This layer does nothing and just returns its input.
        return x
```

Then, we coded the Layer Normalization class, Feedforward Neural Network class and also the Transformer class

LAYER NORMALIZATION AND FEEDFORWARD NEURAL NETWORK CLASS

In [142]:

```
class LayerNorm(nn.Module):
    def __init__(self, emb_dim):
        super().__init__()
        self.eps = 1e-5
        self.scale = nn.Parameter(torch.ones(emb_dim))
        self.shift = nn.Parameter(torch.zeros(emb_dim))

    def forward(self, x):
        mean = x.mean(dim=-1, keepdim=True)
        var = x.var(dim=-1, keepdim=True, unbiased=False)
        norm_x = (x - mean) / torch.sqrt(var + self.eps)
        return self.scale * norm_x + self.shift

class GELU(nn.Module):
    def __init__(self):
        super().__init__()

    def forward(self, x):
        return 0.5 * x * (1 + torch.tanh(
            torch.sqrt(torch.tensor(2.0 / torch.pi)) *
            (x + 0.044715 * torch.pow(x, 3))
        ))
```

```
class FeedForward(nn.Module):
    def __init__(self, cfg):
        super().__init__()
        self.layers = nn.Sequential(
            nn.Linear(cfg["emb_dim"], 4 * cfg["emb_dim"]), ## Expansion
            GELU(), ## Activation
            nn.Linear(4 * cfg["emb_dim"], cfg["emb_dim"]), ## Contraction
        )

    def forward(self, x):
        return self.layers(x)
```

TRANSFORMER CLASS

In [143]:

```
class TransformerBlock(nn.Module):
    def __init__(self, cfg):
        super().__init__()
        self.att = MultiHeadAttention(
            d_in=cfg["emb_dim"],
            d_out=cfg["emb_dim"],
            context_length=cfg["context_length"],
            num_heads=cfg["n_heads"],
            dropout=cfg["drop_rate"],
            qkv_bias=cfg["qkv_bias"])
        self.ff = FeedForward(cfg)
        self.norm1 = LayerNorm(cfg["emb_dim"])
        self.norm2 = LayerNorm(cfg["emb_dim"])
        self.drop_shortcut = nn.Dropout(cfg["drop_rate"])

    def forward(self, x):
        # Shortcut connection for attention block
        shortcut = x
        x = self.norm1(x)
        x = self.att(x)  # Shape [batch_size, num_tokens, emb_size]
        x = self.drop_shortcut(x)
        x = x + shortcut  # Add the original input back

        # Shortcut connection for feed forward block
        shortcut = x
        x = self.norm2(x)
        x = self.ff(x)
        # 2*4*768
        x = self.drop_shortcut(x)
        x = x + shortcut  # Add the original input back

        return x
        # 2*4*768
```

Now, let us use all this knowledge and code the entire GPT architecture

In [144]:

```
class GPTModel(nn.Module):
    def __init__(self, cfg):
        super().__init__()
        self.tok_emb = nn.Embedding(cfg["vocab_size"], cfg["emb_dim"])
        self.pos_emb = nn.Embedding(cfg["context_length"], cfg["emb_dim"])
        self.drop_emb = nn.Dropout(cfg["drop_rate"])

        self.trf_blocks = nn.Sequential(
            *[TransformerBlock(cfg) for _ in range(cfg["n_layers"])])

        self.final_norm = LayerNorm(cfg["emb_dim"])
        self.out_head = nn.Linear(
            cfg["emb_dim"], cfg["vocab_size"], bias=False
        )

    def forward(self, in_idx):
        batch_size, seq_len = in_idx.shape
        tok_embeds = self.tok_emb(in_idx)
        pos_embeds = self.pos_emb(torch.arange(seq_len, device=in_idx.device))
        x = tok_embeds + pos_embeds  # Shape [batch_size, num_tokens, emb_size]
        x = self.drop_emb(x)
        x = self.trf_blocks(x)
        x = self.final_norm(x)
        logits = self.out_head(x)
        return logits
```

The __init__ constructor of this GPTModel class initializes the token and positional embedding layers using the configurations passed in via a Python dictionary, cfg. These embedding layers are responsible for converting input token indices into dense vectors and adding positional information.

Next, the __init__ method creates a sequential stack of TransformerBlock modules equal to the number of layers specified in cfg. Following the transformer blocks, a LayerNorm layer is applied, standardizing the outputs from the transformer blocks to stabilize the learning process. Finally, a linear output head without bias is defined, which projects the transformer's output into the vocabulary space of the tokenizer to generate logits for each token in the vocabulary.

The forward method takes a batch of input token indices, computes their embeddings, applies the positional embeddings, passes the sequence through the transformer blocks, normalizes the final output, and then computes the logits, representing the next token's unnormalized probabilities. We will convert these logits into tokens and text outputs in the next section.

Let's now initialize the 124 million parameter GPT model using the GPT_CONFIG_124M dictionary we pass into the cfg parameter and feed it with the batch text input we created at the beginning of this chapter:

In [145]:

```
torch.manual_seed(123)
model = GPTModel(GPT_CONFIG_124M)
out = model(batch)
print("Input batch:\n", batch)
print("\nOutput shape:", out.shape)
print(out)
```

```
Input batch:
 tensor([[6109, 3626, 6100,  345],
        [6109, 1110, 6622,  257]])

Output shape: torch.Size([2, 4, 50257])
tensor([[[ 0.3613,  0.4222, -0.0711,  ...,  0.3483,  0.4661, -0.2838],
         [-0.1792, -0.5660, -0.9485,  ...,  0.0477,  0.5181, -0.3168],
         [ 0.7120,  0.0332,  0.1085,  ...,  0.1018, -0.4327, -0.2553],
         [-1.0076,  0.3418, -0.1190,  ...,  0.7195,  0.4023,  0.0532]],

        [[-0.2564,  0.0900,  0.0335,  ...,  0.2659,  0.4454, -0.6806],
         [ 0.1230,  0.3653, -0.2074,  ...,  0.7705,  0.2710,  0.2246],
         [ 1.0558,  1.0318, -0.2800,  ...,  0.6936,  0.3205, -0.3178],
         [-0.1565,  0.3926,  0.3288,  ...,  1.2630, -0.1858,  0.0388]]],
       grad_fn=<UnsafeViewBackward0>)
```

As we can see, the output tensor has the shape [2, 4, 50257], since we passed in 2 input texts with 4 tokens each. The last dimension, 50,257, corresponds to the vocabulary size of the tokenizer. In the next section, we will see how to convert each of these 50,257- dimensional output vectors back into tokens.

Using the numel() method, short for "number of elements," we can collect the total number of parameters in the model's parameter tensors:

In [146]:

```
total_params = sum(p.numel() for p in model.parameters())
print(f"Total number of parameters: {total_params:,}")
```

```
Total number of parameters: 163,009,536
```

Earlier, we spoke of initializing a 124 million parameter GPT model, so why is the actual number of parameters 163 million, as shown in the preceding code output?

The reason is a concept called weight tying that is used in the original GPT-2 architecture, which means that the original GPT-2 architecture is reusing the weights from the token embedding layer in its output layer. To understand what this means, let's take a look at the shapes of the token embedding layer and linear output layer that we initialized on the model via the GPTModel earlier:

In [147]:

```
print("Token embedding layer shape:", model.tok_emb.weight.shape)
print("Output layer shape:", model.out_head.weight.shape)
```

```
Token embedding layer shape: torch.Size([50257, 768])
Output layer shape: torch.Size([50257, 768])
```

As we can see based on the print outputs, the weight tensors for both these layers have the same shape:

The token embedding and output layers are very large due to the number of rows for the 50,257 in the tokenizer's vocabulary. Let's remove the output layer parameter count from the total GPT-2 model count according to the weight tying:

In [148]:

```
total_params_gpt2 = total_params - sum(p.numel() for p in model.out_head.parameters())
print(f"Number of trainable parameters considering weight tying: {total_params_gpt2:,}")
```

```
Number of trainable parameters considering weight tying: 124,412,160
```

As we can see, the model is now only 124 million parameters large, matching the original size of the GPT-2 model.

Weight tying reduces the overall memory footprint and computational complexity of the model. However, in my experience, using separate token embedding and output layers results in better training and model performance; hence, we are using separate layers in our GPTModel implementation. The same is true for modern LLMs.

Lastly, let us compute the memory requirements of the 163 million parameters in our GPTModel object:

In [149]:

```
total_size_bytes = total_params * 4 #A
total_size_mb = total_size_bytes / (1024 * 1024) #B
print(f"Total size of the model: {total_size_mb:.2f} MB")
```

```
Total size of the model: 621.83 MB
```

In conclusion, by calculating the memory requirements for the 163 million parameters in our GPTModel object and assuming each parameter is a 32-bit float taking up 4 bytes, we find that the total size of the model amounts to 621.83 MB, illustrating the relatively large storage capacity required to accommodate even relatively small LLMs.

In this section, we implemented the GPTModel architecture and saw that it outputs numeric tensors of shape [batch_size, num_tokens, vocab_size]. In the next section, we will write the code to convert these output tensors into text.

GPT ARCHITECTURE PART 7: GENERATING TEXT FROM OUTPUT TOKENS

Let us implement the token-generation process as follows:

Step 1: idx is a (batch, n_tokens) array of indices in the current context Step 2: Crop current context if it exceeds the supported context size E.g., if LLM supports only 5 tokens, and the context size is 10 then only the last 5 tokens are used as context Step 3: Focus only on the last time step, so that (batch, n_token, vocab_size) becomes (batch, vocab_size) Step 4: probas has shape (batch, vocab_size) Step 5: idx_next has shape (batch, 1) Step 6: Append sampled index to the running sequence, where idx has shape (batch, n_tokens+1)

In [150]:

```
def generate_text_simple(model, idx, max_new_tokens, context_size):
    # idx is (batch, n_tokens) array of indices in the current context

    ###Input batch:
 ###tensor([[6109, 3626, 6100,  345],
        ##[6109, 1110, 6622,  257]])

    for _ in range(max_new_tokens):

        # Crop current context if it exceeds the supported context size
        # E.g., if LLM supports only 5 tokens, and the context size is 10
        # then only the last 5 tokens are used as context
        idx_cond = idx[:, -context_size:]

        # Get the predictions
        with torch.no_grad():
            logits = model(idx_cond) ### batch, n_tokens, vocab_size

        # Focus only on the last time step
        # (batch, n_tokens, vocab_size) becomes (batch, vocab_size)
        logits = logits[:, -1, :]
        # Apply softmax to get probabilities
        probas = torch.softmax(logits, dim=-1)  # (batch, vocab_size)

        # Get the idx of the vocab entry with the highest probability value
        idx_next = torch.argmax(probas, dim=-1, keepdim=True)  # (batch, 1)

        # Append sampled index to the running sequence
        idx = torch.cat((idx, idx_next), dim=1)  # (batch, n_tokens+1)

    return idx
```

In the preceeding code, the generate_text_simple function, we use a softmax function to convert the logits into a probability distribution from which we identify the position with the highest value via torch.argmax. The softmax function is monotonic, meaning it preserves the order of its inputs when transformed into outputs. So, in practice, the softmax step is redundant since the position with the highest score in the softmax output tensor is the same position in the logit tensor. In other words, we could apply the torch.argmax function to the logits tensor directly and get identical results. However, we coded the conversion to illustrate the full process of transforming logits to probabilities, which can add additional intuition, such as that the model generates the most likely next token, which is known as greedy decoding.

In the next chapter, when we will implement the GPT training code, we will also introduce additional sampling techniques where we modify the softmax outputs such that the model doesn't always select the most likely token, which introduces variability and creativity in the generated text.

Let's now try out the generate_text_simple function with the "Hello, I am" context as model input

First, we encode the input context into token IDs:

In [151]:

```
start_context = "Hello, I am"
encoded = tokenizer.encode(start_context)
print("encoded:", encoded)
encoded_tensor = torch.tensor(encoded).unsqueeze(0) #A
print("encoded_tensor.shape:", encoded_tensor.shape)
```

```
encoded: [15496, 11, 314, 716]
encoded_tensor.shape: torch.Size([1, 4])
```

Next, we put the model into .eval() mode, which disables random components like dropout, which are only used during training, and use the generate_text_simple function on the encoded input tensor:

We disable dropout since we are not training the model

In [152]:

```
model.eval() #A
#model = GPTModel(GPT_CONFIG_124M)
out = generate_text_simple(
model=model,
idx=encoded_tensor,
max_new_tokens=6,
context_size=GPT_CONFIG_124M["context_length"]
)
```

```
print("Output:", out)
print("Output length:", len(out[0]))
```

```
Output: tensor([[15496,    11,   314,   716, 27018, 24086, 47843, 30961, 42348,  7267]])
Output length: 10
```

Using the .decode method of the tokenizer, we can convert the IDs back into text:

In [153]:

```
decoded_text = tokenizer.decode(out.squeeze(0).tolist())
print(decoded_text)
```

```
Hello, I am Featureiman Byeswickattribute argue
```

As we can see, based on the preceding output, the model generated gibberish, which is not at all coherent text. What happened? The reason why the model is unable to produce coherent text is that we haven't trained it yet. So far, we just implemented the GPT architecture and initialized a GPT model instance with initial random weights.

EVALUATING GENERATIVE TEXT MODELS

GPT Model class we coded earlier

In [154]:

```
class GPTModel(nn.Module):
    def __init__(self, cfg):
        super().__init__()
        self.tok_emb = nn.Embedding(cfg["vocab_size"], cfg["emb_dim"])
        self.pos_emb = nn.Embedding(cfg["context_length"], cfg["emb_dim"])
        self.drop_emb = nn.Dropout(cfg["drop_rate"])

        self.trf_blocks = nn.Sequential(
            *[TransformerBlock(cfg) for _ in range(cfg["n_layers"])])

        self.final_norm = LayerNorm(cfg["emb_dim"])
        self.out_head = nn.Linear(
            cfg["emb_dim"], cfg["vocab_size"], bias=False
        )

    def forward(self, in_idx):
        batch_size, seq_len = in_idx.shape
        tok_embeds = self.tok_emb(in_idx)
        pos_embeds = self.pos_emb(torch.arange(seq_len, device=in_idx.device))
        x = tok_embeds + pos_embeds  # Shape [batch_size, num_tokens, emb_size]
        x = self.drop_emb(x)
        x = self.trf_blocks(x)
        x = self.final_norm(x)
        logits = self.out_head(x)
        return logits
```

Using GPT to generate text

We initialize a GPT model using the code from the previous chapter

In [155]:

```
import torch
```

```
GPT_CONFIG_124M = {
    "vocab_size": 50257,   # Vocabulary size
    "context_length": 256, # Shortened context length (orig: 1024)
    "emb_dim": 768,        # Embedding dimension
    "n_heads": 12,         # Number of attention heads
    "n_layers": 12,        # Number of layers
    "drop_rate": 0.1,      # Dropout rate
    "qkv_bias": False      # Query-key-value bias
}

torch.manual_seed(123)
model = GPTModel(GPT_CONFIG_124M)
model.eval();  # Disable dropout during inference
```

We reduce the context length (context_length) of only 256 tokens to reduce the computational resource requirements for training the model, whereas the original 124 million parameter GPT-2 model used 1024 tokens This is so that more readers will be able to follow and execute the code examples on their laptop computer

Next, we use the generate_text_simple function from the previous chapter to generate text. In addition, we define two convenience functions, text_to_token_ids and token_ids_to_text, for converting between token and text representations that we use throughout this chapter

In [156]:

```
import tiktoken

def text_to_token_ids(text, tokenizer):
    encoded = tokenizer.encode(text, allowed_special={'<|endoftext|>'})
    encoded_tensor = torch.tensor(encoded).unsqueeze(0) # add batch dimension
    return encoded_tensor

def token_ids_to_text(token_ids, tokenizer):
    flat = token_ids.squeeze(0) # remove batch dimension
    return tokenizer.decode(flat.tolist())

start_context = "Every effort moves you"



token_ids = generate_text_simple(
    model=model,
    idx=text_to_token_ids(start_context, tokenizer),
    max_new_tokens=10,
    context_size=GPT_CONFIG_124M["context_length"]
)

print("Output text:\n", token_ids_to_text(token_ids, tokenizer))
```

```
Output text:
 Every effort moves you rentingetic wasnم refres RexMeCHicular stren
```

As we can see above, the model does not produce good text because it has not been trained yet How do we measure or capture what "good text" is, in a numeric form, to track it during training? The next subsection introduces metrics to calculate a loss metric for the generated outputs that we can use to measure the training progress The next chapters on finetuning LLMs will also introduce additional ways to measure model quality

Calculating the text generation loss: cross-entropy and perplexity

Suppose we have an inputs tensor containing the token IDs for 2 training examples (rows) Corresponding to the inputs, the targets contain the desired token IDs that we want the model to generate Notice that the targets are the inputs shifted by 1 position, as explained in chapter 2 when we implemented the data loader

In [157]:

```
inputs = torch.tensor([[16833, 3626, 6100],   # ["every effort moves",
                       [40,    1107, 588]])   #  "I really like"]

targets = torch.tensor([[3626, 6100, 345  ],  # [" effort moves you",
                        [1107,  588, 11311]]) #  " really like chocolate"]
```

Feeding the inputs to the model, we obtain the logits vector for the 2 input examples that consist of 3 tokens each Each of the tokens is a 50,257-dimensional vector corresponding to the size of the vocabulary Applying the softmax function, we can turn the logits tensor into a tensor of the same dimension containing probability scores

In [158]:

```
with torch.no_grad():
    logits = model(inputs)

probas = torch.softmax(logits, dim=-1) # Probability of each token in vocabulary
print(probas.shape) # Shape: (batch_size, num_tokens, vocab_size)
```

```
torch.Size([2, 3, 50257])
```

As discussed in the previous chapter, we can apply the argmax function to convert the probability scores into predicted token IDs. The softmax function above produced a 50,257-dimensional vector for each token; the argmax function returns the position of the highest probability score in this vector, which is the predicted token ID for the given token. Since we have 2 input batches with 3 tokens each, we obtain 2 by 3 predicted token IDs:

In [159]:

```
token_ids = torch.argmax(probas, dim=-1, keepdim=True)
print("Token IDs:\n", token_ids)
```

```
Token IDs:
 tensor([[[16657],
         [  339],
         [42826]],

        [[49906],
         [29669],
         [41751]]])
```

If we decode these tokens, we find that these are quite different from the tokens we want the model to predict, namely the target tokens. That's because the model wasn't trained yet. To train the model, we need to know how far it is away from the correct predictions (targets)

In [160]:

```
print(f"Targets batch 1: {token_ids_to_text(targets[0], tokenizer)}")
print(f"Outputs batch 1: {token_ids_to_text(token_ids[0].flatten(), tokenizer)}")
```

```
Targets batch 1:  effort moves you
Outputs batch 1:  Armed heNetflix
```

Cross-entropy loss

The token probabilities corresponding to the target indices are as follows:

In [161]:

```
text_idx = 0
target_probas_1 = probas[text_idx, [0, 1, 2], targets[text_idx]]
print("Text 1:", target_probas_1)

text_idx = 1
target_probas_2 = probas[text_idx, [0, 1, 2], targets[text_idx]]
print("Text 2:", target_probas_2)
```

```
Text 1: tensor([    0.0001,     0.0000,     0.0000])
Text 2: tensor([    0.0000,     0.0001,     0.0000])
```

We want to maximize all these values, bringing them close to a probability of 1. In mathematical optimization, it is easier to maximize the logarithm of the probability score than the probability score itself.

In [162]:

```
# Compute logarithm of all token probabilities
log_probas = torch.log(torch.cat((target_probas_1, target_probas_2)))
print(log_probas)
```

```
tensor([ -9.5042, -10.3796, -11.3677, -11.4798,  -9.7764, -12.2561])
```

Next, we compute the average log probability:

In [163]:

```
# Calculate the average probability for each token
avg_log_probas = torch.mean(log_probas)
print(avg_log_probas)
```

```
tensor(-10.7940)
```

The goal is to make this average log probability as large as possible by optimizing the model weights. Due to the log, the largest possible value is 0, and we are currently far away from 0. In deep learning, instead of maximizing the average log-probability, it's a standard convention to minimize the negative average log-probability value; in our case, instead of maximizing -10.7722 so that it approaches 0, in deep learning, we would minimize 10.7722 so that it approaches 0. The value negative of -10.7722, i.e., 10.7722, is also called cross-entropy loss in deep learning.

In [164]:

```
neg_avg_log_probas = avg_log_probas * -1
print(neg_avg_log_probas)
```

```
tensor(10.7940)
```

PyTorch already implements a cross_entropy function that carries out the previous steps Before we apply the cross_entropy function, let's check the shape of the logits and targets

In [165]:

```
# Logits have shape (batch_size, num_tokens, vocab_size)
print("Logits shape:", logits.shape)

# Targets have shape (batch_size, num_tokens)
print("Targets shape:", targets.shape)
```

```
Logits shape: torch.Size([2, 3, 50257])
Targets shape: torch.Size([2, 3])
```

For the cross_entropy function in PyTorch, we want to flatten these tensors by combining them over the batch dimension:

In [166]:

```
logits_flat = logits.flatten(0, 1)
targets_flat = targets.flatten()

print("Flattened logits:", logits_flat.shape)
print("Flattened targets:", targets_flat.shape)
```

```
Flattened logits: torch.Size([6, 50257])
Flattened targets: torch.Size([6])
```

Note that the targets are the token IDs, which also represent the index positions in the logits tensors that we want to maximize. The cross_entropy function in PyTorch will automatically take care of applying the softmax and log-probability computation internally over those token indices in the logits that are to be maximized

In [167]:

```
loss = torch.nn.functional.cross_entropy(logits_flat, targets_flat)
print(loss)
```

```
tensor(10.7940)
```

Perplexity

A concept related to the cross-entropy loss is the perplexity of an LLM. The perplexity is simply the exponential of the cross-entropy loss.

In [168]:

```
perplexity = torch.exp(loss)
print(perplexity)
```

```
tensor(48725.8203)
```

The perplexity is often considered more interpretable because it can be understood as the effective vocabulary size that the model is uncertain about at each step (in the example above, that'd be 48,725 words or tokens). In other words, perplexity provides a measure of how well the probability distribution predicted by the model matches the actual distribution of the words in the dataset. Similar to the loss, a lower perplexity indicates that the model predictions are closer to the actual distribution

Calculating the training and validation set losses

We use a relatively small dataset for training the LLM (in fact, only one short story) The reasons are: You

can run the code examples in a few minutes on a laptop computer without a suitable GPU. The training finishes relatively fast (minutes instead of weeks), which is good for educational purposes. We use a text from the public domain, which can be included in this GitHub repository without violating any usage rights or bloating the repository size. For example, Llama 2 7B required 184,320 GPU hours on A100 GPUs to be trained on 2 trillion tokens At the time of this writing, the hourly cost of an 8xA100 cloud server at AWS is approximately 30 dollars. So, via an off-the-envelope calculation, training this LLM would cost 184,320 / 8 * 30 = 690,000 dollars Below, we use the same dataset we used in chapter 2.

In [169]:

```
import os
import urllib.request

file_path = "the-verdict.txt"
url = "https://raw.githubusercontent.com/rasbt/LLMs-from-scratch/main/ch02/01_main-chapte
r-code/the-verdict.txt"

if not os.path.exists(file_path):
    with urllib.request.urlopen(url) as response:
        text_data = response.read().decode('utf-8')
    with open(file_path, "w", encoding="utf-8") as file:
        file.write(text_data)
else:
    with open(file_path, "r", encoding="utf-8") as file:
        text_data = file.read()
```

A quick check that the text loaded ok by printing the first and last 100 words

In [170]:

```
# First 100 characters
print(text_data[:99])
```

```
I HAD always thought Jack Gisburn rather a cheap genius--though a good fellow enough--so
it was no
```

In [171]:

```
# Last 100 characters
print(text_data[-99:])
```

```
it for me! The Strouds stand alone, and happen once--but there's no exterminating our kin
d of art."
```

In [172]:

```
import tiktoken

tokenizer = tiktoken.get_encoding("gpt2")
```

In [173]:

```
total_characters = len(text_data)
total_tokens = len(tokenizer.encode(text_data))

print("Characters:", total_characters)
print("Tokens:", total_tokens)
```

```
Characters: 20479
Tokens: 5145
```

With 5,145 tokens, the text is very short for training an LLM, but again, it's for educational purposes (we will also load pretrained weights later). Next, we divide the dataset into a training and a validation set and use the data loaders from chapter 2 to prepare the batches for LLM training. Since we train the LLM to predict the next word in the text, the targets look the same as these inputs, except that the targets are shifted by

one position

Implementing the DataLoader:

In [174]:

```
from torch.utils.data import Dataset, DataLoader


class GPTDatasetV1(Dataset):
    def __init__(self, txt, tokenizer, max_length, stride):
        self.input_ids = []
        self.target_ids = []

        # Tokenize the entire text
        token_ids = tokenizer.encode(txt, allowed_special={"<|endoftext|>"})

        # Use a sliding window to chunk the book into overlapping sequences of max_length
        for i in range(0, len(token_ids) - max_length, stride):
            input_chunk = token_ids[i:i + max_length]
            target_chunk = token_ids[i + 1: i + max_length + 1]
            self.input_ids.append(torch.tensor(input_chunk))
            self.target_ids.append(torch.tensor(target_chunk))

    def __len__(self):
        return len(self.input_ids)

    def __getitem__(self, idx):
        return self.input_ids[idx], self.target_ids[idx]


def create_dataloader_v1(txt, batch_size=4, max_length=256,
                         stride=128, shuffle=True, drop_last=True,
                         num_workers=0):

    # Initialize the tokenizer
    tokenizer = tiktoken.get_encoding("gpt2")

    # Create dataset
    dataset = GPTDatasetV1(txt, tokenizer, max_length, stride)

    # Create dataloader
    dataloader = DataLoader(
        dataset,
        batch_size=batch_size,
        shuffle=shuffle,
        drop_last=drop_last,
        num_workers=num_workers
    )

    return dataloader
```

In [175]:

```
GPT_CONFIG_124M = {
    "vocab_size": 50257,    # Vocabulary size
    "context_length": 256, # Shortened context length (orig: 1024)
    "emb_dim": 768,         # Embedding dimension
    "n_heads": 12,          # Number of attention heads
    "n_layers": 12,         # Number of layers
    "drop_rate": 0.1,       # Dropout rate
    "qkv_bias": False       # Query-key-value bias
}
```

In [176]:

```
# Train/validation ratio
train_ratio = 0.90
```

```
split_idx = int(train_ratio * len(text_data))
train_data = text_data[:split_idx]
val_data = text_data[split_idx:]


torch.manual_seed(123)

train_loader = create_dataloader_v1(
    train_data,
    batch_size=2,
    max_length=GPT_CONFIG_124M["context_length"],
    stride=GPT_CONFIG_124M["context_length"],
    drop_last=True,
    shuffle=True,
    num_workers=0
)

val_loader = create_dataloader_v1(
    val_data,
    batch_size=2,
    max_length=GPT_CONFIG_124M["context_length"],
    stride=GPT_CONFIG_124M["context_length"],
    drop_last=False,
    shuffle=False,
    num_workers=0
)
```

In [177]:

```
# Sanity check

if total_tokens * (train_ratio) < GPT_CONFIG_124M["context_length"]:
    print("Not enough tokens for the training loader. "
          "Try to lower the `GPT_CONFIG_124M['context_length']` or "
          "increase the `training_ratio`")

if total_tokens * (1-train_ratio) < GPT_CONFIG_124M["context_length"]:
    print("Not enough tokens for the validation loader. "
          "Try to lower the `GPT_CONFIG_124M['context_length']` or "
          "decrease the `training_ratio`")
```

We use a relatively small batch size to reduce the computational resource demand, and because the dataset is very small to begin with. Llama 2 7B was trained with a batch size of 1024, for example.

An optional check that the data was loaded correctly:

In [178]:

```
print("Train loader:")
for x, y in train_loader:
    print(x.shape, y.shape)

print("\nValidation loader:")
for x, y in val_loader:
    print(x.shape, y.shape)

print(len(train_loader))
print(len(val_loader))
```

```
Train loader:
torch.Size([2, 256]) torch.Size([2, 256])
torch.Size([2, 256]) torch.Size([2, 256])
torch.Size([2, 256]) torch.Size([2, 256])
torch.Size([2, 256]) torch.Size([2, 256])
torch.Size([2, 256]) torch.Size([2, 256])
torch.Size([2, 256]) torch.Size([2, 256])
torch.Size([2, 256]) torch.Size([2, 256])
torch.Size([2, 256]) torch.Size([2, 256])
torch.Size([2, 256]) torch.Size([2, 256])
torch.Size([2, 256]) torch.Size([2, 256])

Validation loader:
torch.Size([2, 256]) torch.Size([2, 256])
9
1
```

An optional check that the data was loaded correctly:

In [179]:

```python
train_tokens = 0
for input_batch, target_batch in train_loader:
    train_tokens += input_batch.numel()

val_tokens = 0
for input_batch, target_batch in val_loader:
    val_tokens += input_batch.numel()

print("Training tokens:", train_tokens)
print("Validation tokens:", val_tokens)
print("All tokens:", train_tokens + val_tokens)
```

```
Training tokens: 4608
Validation tokens: 512
All tokens: 5120
```

Here is the GPT Model class we coded earlier. We will need this

In [180]:

```python
class GPTModel(nn.Module):
    def __init__(self, cfg):
        super().__init__()
        self.tok_emb = nn.Embedding(cfg["vocab_size"], cfg["emb_dim"])
        self.pos_emb = nn.Embedding(cfg["context_length"], cfg["emb_dim"])
        self.drop_emb = nn.Dropout(cfg["drop_rate"])

        self.trf_blocks = nn.Sequential(
            *[TransformerBlock(cfg) for _ in range(cfg["n_layers"])])

        self.final_norm = LayerNorm(cfg["emb_dim"])
        self.out_head = nn.Linear(
            cfg["emb_dim"], cfg["vocab_size"], bias=False
        )

    def forward(self, in_idx):
        batch_size, seq_len = in_idx.shape
        tok_embeds = self.tok_emb(in_idx)
        pos_embeds = self.pos_emb(torch.arange(seq_len, device=in_idx.device))
        x = tok_embeds + pos_embeds  # Shape [batch_size, num_tokens, emb_size]
        x = self.drop_emb(x)
        x = self.trf_blocks(x)
        x = self.final_norm(x)
        logits = self.out_head(x)
        return logits

torch.manual_seed(123)
model = GPTModel(GPT_CONFIG_124M)
model.eval();  # Disable dropout during inference
```

Next, we implement a utility function to calculate the cross-entropy loss of a given batch. In addition, we implement a second utility function to compute the loss for a user-specified number of batches in a data loader.

In [181]:

```
def calc_loss_batch(input_batch, target_batch, model, device):
    input_batch, target_batch = input_batch.to(device), target_batch.to(device)
    logits = model(input_batch)
    loss = torch.nn.functional.cross_entropy(logits.flatten(0, 1), target_batch.flatten(
))
    return loss


def calc_loss_loader(data_loader, model, device, num_batches=None):
    total_loss = 0.
    if len(data_loader) == 0:
        return float("nan")
    elif num_batches is None:
        num_batches = len(data_loader)
    else:
        # Reduce the number of batches to match the total number of batches in the data l
oader
        # if num_batches exceeds the number of batches in the data loader
        num_batches = min(num_batches, len(data_loader))
    for i, (input_batch, target_batch) in enumerate(data_loader):
        if i < num_batches:
            loss = calc_loss_batch(input_batch, target_batch, model, device)
            total_loss += loss.item()
        else:
            break
    return total_loss / num_batches
```

If you have a machine with a CUDA-supported GPU, the LLM will train on the GPU without making any changes to the code. Via the device setting, we ensure that the data is loaded onto the same device as the LLM model.

In [182]:

```
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

# Note:
# Uncommenting the following lines will allow the code to run on Apple Silicon chips, if
applicable,
# which is approximately 2x faster than on an Apple CPU (as measured on an M3 MacBook Air
).
# However, the resulting loss values may be slightly different.

#if torch.cuda.is_available():
#    device = torch.device("cuda")
#elif torch.backends.mps.is_available():
#    device = torch.device("mps")
#else:
#    device = torch.device("cpu")
#
# print(f"Using {device} device.")


model.to(device) # no assignment model = model.to(device) necessary for nn.Module classes


torch.manual_seed(123) # For reproducibility due to the shuffling in the data loader

with torch.no_grad(): # Disable gradient tracking for efficiency because we are not train
ing, yet
    train_loss = calc_loss_loader(train_loader, model, device)
    val_loss = calc_loss_loader(val_loader, model, device)

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

```
Training loss: 10.98758347829183
Training loss: 10.98758347829183
Validation loss: 10.98110580444336
```

TRAINING LOOP FOR THE LLM

In [183]:

```
def train_model_simple(model, train_loader, val_loader, optimizer, device, num_epochs,
                       eval_freq, eval_iter, start_context, tokenizer):
    # Initialize lists to track losses and tokens seen
    train_losses, val_losses, track_tokens_seen = [], [], []
    tokens_seen, global_step = 0, -1

    # Main training loop
    for epoch in range(num_epochs):
        model.train()  # Set model to training mode

        for input_batch, target_batch in train_loader:
            optimizer.zero_grad() # Reset loss gradients from previous batch iteration
            loss = calc_loss_batch(input_batch, target_batch, model, device)
            loss.backward() # Calculate loss gradients
            optimizer.step() # Update model weights using loss gradients
            tokens_seen += input_batch.numel() # Returns the total number of elements (o
r tokens) in the input_batch.
            global_step += 1

            # Optional evaluation step
            if global_step % eval_freq == 0:
                train_loss, val_loss = evaluate_model(
                    model, train_loader, val_loader, device, eval_iter)
                train_losses.append(train_loss)
                val_losses.append(val_loss)
                track_tokens_seen.append(tokens_seen)
                print(f"Ep {epoch+1} (Step {global_step:06d}): "
                      f"Train loss {train_loss:.3f}, Val loss {val_loss:.3f}")

        # Print a sample text after each epoch
        generate_and_print_sample(
            model, tokenizer, device, start_context
        )

    return train_losses, val_losses, track_tokens_seen
```

Step 1: Initialize lists to track losses and tokens seen Step 2: Start the main training loop Step 3: Reset loss gradients from previous batch iteration Step 4: Calculate loss gradients Step 5: Update model weights using loss gradients Step 6: Optional evaluation step Step 7: Print a sample text after each epoch

In [184]:

```
def evaluate_model(model, train_loader, val_loader, device, eval_iter):
    model.eval()
    with torch.no_grad():
        train_loss = calc_loss_loader(train_loader, model, device, num_batches=eval_iter
)
        val_loss = calc_loss_loader(val_loader, model, device, num_batches=eval_iter)
    model.train()
    return train_loss, val_loss
```

The evaluate_model function calculates the loss over the training and validation set while ensuring the model is in evaluation mode with gradient tracking and dropout disabled when calculating the loss over the training and validation sets

In [185]:

```
def generate_and_print_sample(model, tokenizer, device, start_context):
    model.eval()
    context_size = model.pos_emb.weight.shape[0]
    encoded = text_to_token_ids(start_context, tokenizer).to(device)
    with torch.no_grad():
        token_ids = generate_text_simple(
            model=model, idx=encoded,
            max_new_tokens=50, context_size=context_size
        )
    decoded_text = token_ids_to_text(token_ids, tokenizer)
    print(decoded_text.replace("\n", " "))  # Compact print format
    model.train()
```

The generate_and_print_sample function is a convenience function that we use to track whether the model improves during the training. In particular, the generate_and_print_sample function takes a text snippet (start_context) as input, converts it into token IDs, and feeds it to the LLM to generate a text sample using the generate_text_simple function we used earlier

Let's see this all in action by training a GPTModel instance for 10 epochs using an AdamW optimizer and the train_model_simple function we defined earlier.

In [ ]:

```
# Note:
# Uncomment the following code to calculate the execution time
import time
start_time = time.time()

torch.manual_seed(123)
model = GPTModel(GPT_CONFIG_124M)
model.to(device)›
optimizer = torch.optim.AdamW(model.parameters(), lr=0.0004, weight_decay=0.1)

num_epochs = 10
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="Every effort moves you", tokenizer=tokenizer
)

# Note:
# Uncomment the following code to show the execution time
end_time = time.time()
execution_time_minutes = (end_time - start_time) / 60
print(f"Training completed in {execution_time_minutes:.2f} minutes.")
```

As we can see, based on the results printed during the training, the training loss improves drastically, starting with a value of 9.781 and converging to 0.391. The language skills of the model have improved quite a lot. In the beginning, the model is only able to append commas to the start context ("Every effort moves you,,,,,,,,,,,") or repeat the word "and". At the end of the training, it can generate grammatically correct text.

Similar to the training set loss, we can see that the validation loss starts high (9.856) and decreases during the training. However, it never becomes as small as the training set loss and remains at 6.372 after the 10th epoch.

Let's create a simple plot that shows the training and validation set losses side by side

In [188]:

```
import matplotlib.pyplot as plt
from matplotlib.ticker import MaxNLocator


def plot_losses(epochs_seen, tokens_seen, train_losses, val_losses):
    fig, ax1 = plt.subplots(figsize=(5, 3))

    # Plot training and validation loss against epochs
    ax1.plot(epochs_seen, train_losses, label="Training loss")
    ax1.plot(epochs_seen, val_losses, linestyle="-.", label="Validation loss")
    ax1.set_xlabel("Epochs")
    ax1.set_ylabel("Loss")
    ax1.legend(loc="upper right")
    ax1.xaxis.set_major_locator(MaxNLocator(integer=True))  # only show integer labels o
n x-axis

    # Create a second x-axis for tokens seen
    ax2 = ax1.twiny()  # Create a second x-axis that shares the same y-axis
    ax2.plot(tokens_seen, train_losses, alpha=0)  # Invisible plot for aligning ticks
    ax2.set_xlabel("Tokens seen")

    fig.tight_layout()  # Adjust layout to make room
    plt.savefig("loss-plot.pdf")
    plt.show()

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

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Cell In[188], line 25
     22     plt.savefig("loss-plot.pdf")
     23     plt.show()
---> 25 epochs_tensor = torch.linspace(0, num_epochs, len(train_losses))
     26 plot_losses(epochs_tensor, tokens_seen, train_losses, val_losses)

NameError: name 'num_epochs' is not defined
```

Both the training and validation losses start to improve for the first epoch. However, the losses start to diverge past the second epoch. This divergence and the fact that the validation loss is much larger than the training loss indicate that the model is overfitting to the training data. We can confirm that the model memorizes the training data verbatim by searching for the generated text snippets, such as "quite insensible to the irony" in the "The Verdict" text file. This memorization is expected since we are working with a very, very small training dataset and training the model for multiple epochs. Usually, it's common to train a model on a much, much larger dataset for only one epoch.

DECODING STRATEGIES TO CONTROL RANDOMNESS

First, we briefly revisit the generate_text_simple function from the previous chapter that we used inside the generate_and_print_sample earlier in this chapter. Then, we will cover two techniques, temperature scaling, and top-k sampling, to improve this function.

We begin by transferring the model back from the GPU to the CPU since inference with a relatively small model does not require a GPU. Also, after training, we put the model into evaluation model to turn off random components such as dropout:

In [186]:

```
model.to("cpu")
model.eval()
```

Out[186]:

```
GPTModel(
  (tok_emb): Embedding(50257, 768)
  (pos_emb): Embedding(256, 768)
  (drop_emb): Dropout(p=0.1, inplace=False)
  (trf_blocks): Sequential(
    (0): TransformerBlock(
      (att): MultiHeadAttention(
        (W_query): Linear(in_features=768, out_features=768, bias=False)
        (W_key): Linear(in_features=768, out_features=768, bias=False)
        (W_value): Linear(in_features=768, out_features=768, bias=False)
        (out_proj): Linear(in_features=768, out_features=768, bias=True)
        (dropout): Dropout(p=0.1, inplace=False)
      )
      (ff): FeedForward(
        (layers): Sequential(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU()
          (2): Linear(in_features=3072, out_features=768, bias=True)
        )
      )
      (norm1): LayerNorm()
      (norm2): LayerNorm()
      (drop_shortcut): Dropout(p=0.1, inplace=False)
    )
    (1): TransformerBlock(
      (att): MultiHeadAttention(
        (W_query): Linear(in_features=768, out_features=768, bias=False)
        (W_key): Linear(in_features=768, out_features=768, bias=False)
        (W_value): Linear(in_features=768, out_features=768, bias=False)
        (out_proj): Linear(in_features=768, out_features=768, bias=True)
        (dropout): Dropout(p=0.1, inplace=False)
      )
      (ff): FeedForward(
        (layers): Sequential(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU()
          (2): Linear(in_features=3072, out_features=768, bias=True)
        )
      )
      (norm1): LayerNorm()
      (norm2): LayerNorm()
      (drop_shortcut): Dropout(p=0.1, inplace=False)
    )
    (2): TransformerBlock(
      (att): MultiHeadAttention(
        (W_query): Linear(in_features=768, out_features=768, bias=False)
        (W_key): Linear(in_features=768, out_features=768, bias=False)
        (W_value): Linear(in_features=768, out_features=768, bias=False)
        (out_proj): Linear(in_features=768, out_features=768, bias=True)
        (dropout): Dropout(p=0.1, inplace=False)
      )
      (ff): FeedForward(
        (layers): Sequential(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU()
          (2): Linear(in_features=3072, out_features=768, bias=True)
        )
      )
      (norm1): LayerNorm()
      (norm2): LayerNorm()
      (drop_shortcut): Dropout(p=0.1, inplace=False)
    )
    (3): TransformerBlock(
      (att): MultiHeadAttention(
        (W_query): Linear(in_features=768, out_features=768, bias=False)
        (W_key): Linear(in_features=768, out_features=768, bias=False)
        (W_value): Linear(in_features=768, out_features=768, bias=False)
        (out_proj): Linear(in_features=768, out_features=768, bias=True)
        (dropout): Dropout(p=0.1, inplace=False)
        (dropout): Dropout(p=0.1, inplace=False)
      )
      (ff): FeedForward(
        (layers): Sequential(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU()
          (2): Linear(in_features=3072, out_features=768, bias=True)
        )
      )
      (norm1): LayerNorm()
      (norm2): LayerNorm()
      (drop_shortcut): Dropout(p=0.1, inplace=False)
    )
    (4): TransformerBlock(
      (att): MultiHeadAttention(
        (W_query): Linear(in_features=768, out_features=768, bias=False)
        (W_key): Linear(in_features=768, out_features=768, bias=False)
        (W_value): Linear(in_features=768, out_features=768, bias=False)
        (out_proj): Linear(in_features=768, out_features=768, bias=True)
        (dropout): Dropout(p=0.1, inplace=False)
      )
      (ff): FeedForward(
        (layers): Sequential(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU()
          (2): Linear(in_features=3072, out_features=768, bias=True)
        )
      )
      (norm1): LayerNorm()
      (norm2): LayerNorm()
      (drop_shortcut): Dropout(p=0.1, inplace=False)
    )
    (5): TransformerBlock(
      (att): MultiHeadAttention(
        (W_query): Linear(in_features=768, out_features=768, bias=False)
        (W_key): Linear(in_features=768, out_features=768, bias=False)
        (W_value): Linear(in_features=768, out_features=768, bias=False)
        (out_proj): Linear(in_features=768, out_features=768, bias=True)
        (dropout): Dropout(p=0.1, inplace=False)
      )
      (ff): FeedForward(
        (layers): Sequential(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU()
          (2): Linear(in_features=3072, out_features=768, bias=True)
        )
      )
      (norm1): LayerNorm()
      (norm2): LayerNorm()
      (drop_shortcut): Dropout(p=0.1, inplace=False)
    )
    (6): TransformerBlock(
      (att): MultiHeadAttention(
        (W_query): Linear(in_features=768, out_features=768, bias=False)
        (W_key): Linear(in_features=768, out_features=768, bias=False)
        (W_value): Linear(in_features=768, out_features=768, bias=False)
        (out_proj): Linear(in_features=768, out_features=768, bias=True)
        (dropout): Dropout(p=0.1, inplace=False)
      )
      (ff): FeedForward(
        (layers): Sequential(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU()
          (2): Linear(in_features=3072, out_features=768, bias=True)
        )
      )
      (norm1): LayerNorm()
      (norm2): LayerNorm()
      (drop_shortcut): Dropout(p=0.1, inplace=False)
    )
    (7): TransformerBlock(
      (att): MultiHeadAttention(
        (W_query): Linear(in_features=768, out_features=768, bias=False)
        (W_key): Linear(in_features=768, out_features=768, bias=False)
        (W_value): Linear(in_features=768, out_features=768, bias=False)
        (out_proj): Linear(in_features=768, out_features=768, bias=True)
        (dropout): Dropout(p=0.1, inplace=False)
      )
      (ff): FeedForward(
        (layers): Sequential(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU()
          (2): Linear(in_features=3072, out_features=768, bias=True)
        )
      )
      (norm1): LayerNorm()
      (norm2): LayerNorm()
      (drop_shortcut): Dropout(p=0.1, inplace=False)
    )
    (8): TransformerBlock(
      (att): MultiHeadAttention(
        (W_query): Linear(in_features=768, out_features=768, bias=False)
        (W_key): Linear(in_features=768, out_features=768, bias=False)
        (W_value): Linear(in_features=768, out_features=768, bias=False)
        (out_proj): Linear(in_features=768, out_features=768, bias=True)
        (dropout): Dropout(p=0.1, inplace=False)
      )
      (ff): FeedForward(
        (layers): Sequential(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU()
          (2): Linear(in_features=3072, out_features=768, bias=True)
        )
      )
      (norm1): LayerNorm()
      (norm2): LayerNorm()
      (drop_shortcut): Dropout(p=0.1, inplace=False)
    )
    (9): TransformerBlock(
      (att): MultiHeadAttention(
        (W_query): Linear(in_features=768, out_features=768, bias=False)
        (W_key): Linear(in_features=768, out_features=768, bias=False)
        (W_value): Linear(in_features=768, out_features=768, bias=False)
        (out_proj): Linear(in_features=768, out_features=768, bias=True)
        (dropout): Dropout(p=0.1, inplace=False)
      )
      (ff): FeedForward(
        (layers): Sequential(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU()
          (2): Linear(in_features=3072, out_features=768, bias=True)
        )
      )
      (norm1): LayerNorm()
      (norm2): LayerNorm()
      (drop_shortcut): Dropout(p=0.1, inplace=False)
    )
    (10): TransformerBlock(
      (att): MultiHeadAttention(
        (W_query): Linear(in_features=768, out_features=768, bias=False)
        (W_key): Linear(in_features=768, out_features=768, bias=False)
        (W_value): Linear(in_features=768, out_features=768, bias=False)
        (out_proj): Linear(in_features=768, out_features=768, bias=True)
        (dropout): Dropout(p=0.1, inplace=False)
      )
      (ff): FeedForward(
        (layers): Sequential(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU()
          (2): Linear(in_features=3072, out_features=768, bias=True)
        )
      )
      (norm1): LayerNorm()
      (norm2): LayerNorm()
```

```
      (drop_shortcut): Dropout(p=0.1, inplace=False)
    )
    (11): TransformerBlock(
      (att): MultiHeadAttention(
        (W_query): Linear(in_features=768, out_features=768, bias=False)
        (W_key): Linear(in_features=768, out_features=768, bias=False)
        (W_value): Linear(in_features=768, out_features=768, bias=False)
        (out_proj): Linear(in_features=768, out_features=768, bias=True)
        (dropout): Dropout(p=0.1, inplace=False)
      )
      (ff): FeedForward(
        (layers): Sequential(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU()
          (2): Linear(in_features=3072, out_features=768, bias=True)
        )
      )
      (norm1): LayerNorm()
      (norm2): LayerNorm()
      (drop_shortcut): Dropout(p=0.1, inplace=False)
    )
  )
  (final_norm): LayerNorm()
  (out_head): Linear(in_features=768, out_features=50257, bias=False)
)
```

Next, we plug the GPTModel instance (model) into the generate_text_simple function, which uses the LLM to generate one token at a time:

In [187]:

```python
tokenizer = tiktoken.get_encoding("gpt2")

token_ids = generate_text_simple(
    model=model,
    idx=text_to_token_ids("Every effort moves you", tokenizer),
    max_new_tokens=25,
    context_size=GPT_CONFIG_124M["context_length"]
)

print("Output text:\n", token_ids_to_text(token_ids, tokenizer))
```

```
Output text:
 Every effort moves you rentingetic wasnم refres RexMeCHicular stren Mortgage TT remember
gard ACTIONSussedOND Land Engeleddedemate breaths proxies GalaxyForm
```

DECODING STRATEGY 1: TEMPERATURE SCALING

Previously, inside the generate_text_simple function, we always sampled the token with the highest probability as the next token using torch.argmax, also known as greedy decoding. To generate text with more variety, we can replace the argmax with a function that samples from a probability distribution (here, the probability scores the LLM generates for each vocabulary entry at each token generation step).

To illustrate the probabilistic sampling with a concrete example, let's briefly discuss the next-token generation process using a very small vocabulary for illustration purposes:

In [188]:

```python
vocab = {
    "closer": 0,
    "every": 1,
    "effort": 2,
    "forward": 3,
    "inches": 4,
    "moves": 5,
    "pizza": 6,
    "toward": 7,
    "you": 8,
}

inverse_vocab = {v: k for k, v in vocab.items()}
```

Next, assume the LLM is given the start context "every effort moves you" and generates the following next-token logits:

In [189]:

```
next_token_logits = torch.tensor(
[4.51, 0.89, -1.90, 6.75, 1.63, -1.62, -1.89, 6.28, 1.79]
)

next_token_logits2 = next_token_logits/0.1

next_token_logits3 = next_token_logits/5
```

As discussed in the previous chapter, inside the generate_text_simple, we convert the logits into probabilities via the softmax function and obtain the token ID corresponding the generated token via the argmax function, which we can then map back into text via the inverse vocabulary:

In [190]:

```
probas = torch.softmax(next_token_logits2, dim=0)

print(probas)
```

```
tensor([    0.0000,     0.0000,     0.0000,     0.9910,     0.0000,     0.0000,
            0.0000,     0.0090,     0.0000])
```

In [191]:

```
probas = torch.softmax(next_token_logits3, dim=0)

print(probas)
```

```
tensor([0.1546, 0.0750, 0.0429, 0.2421, 0.0869, 0.0454, 0.0430, 0.2203, 0.0898])
```

In [192]:

```
probas = torch.softmax(next_token_logits, dim=0)

print(probas)

next_token_id = torch.argmax(probas).item()

print(next_token_id)

print(inverse_vocab[next_token_id])
```

```
tensor([    0.0609,     0.0016,     0.0001,     0.5721,     0.0034,     0.0001,
            0.0001,     0.3576,     0.0040])
3
forward
```

To implement a probabilistic sampling process, we can now replace the argmax with the multinomial function in PyTorch:

In [193]:

```
torch.manual_seed(123)
next_token_id = torch.multinomial(probas, num_samples=1).item()
print(inverse_vocab[next_token_id])
```

```
forward
```

The printed output is "forward" just like before. What happened? The multinomial function samples the next token proportional to its probability score. In other words, "forward" is still the most likely token and will be selected by multinomial most of the time but not all the time. To illustrate this, let's implement a function that repeats this sampling 1000 times:

In [194]:

```
def print_sampled_tokens(probas):
    torch.manual_seed(123) # Manual seed for reproducibility
    sample = [torch.multinomial(probas, num_samples=1).item() for i in range(1_000)]
    sampled_ids = torch.bincount(torch.tensor(sample))
    for i, freq in enumerate(sampled_ids):
        print(f"{freq} x {inverse_vocab[i]}")

print_sampled_tokens(probas)
```

```
73 x closer
0 x every
0 x effort
582 x forward
2 x inches
0 x moves
0 x pizza
343 x toward
```

As we can see based on the output, the word "forward" is sampled most of the time (582 out of 1000 times), but other tokens such as "closer", "inches", and "toward" will also be sampled some of the time. This means that if we replaced the argmax function with the multinomial function inside the generate_and_print_sample function, the LLM would sometimes generate texts such as "every effort moves you toward", "every effort moves you inches", and "every effort moves you closer" instead of "every effort moves you forward".

We can further control the distribution and selection process via a concept called temperature scaling, where temperature scaling is just a fancy description for dividing the logits by a number greater than 0:

Temperatures greater than 1 result in more uniformly distributed token probabilities, and Temperatures smaller than 1 will result in more confident (sharper or more peaky) distributions. Let's illustrate this by plotting the original probabilities alongside probabilities scaled with different temperature values:

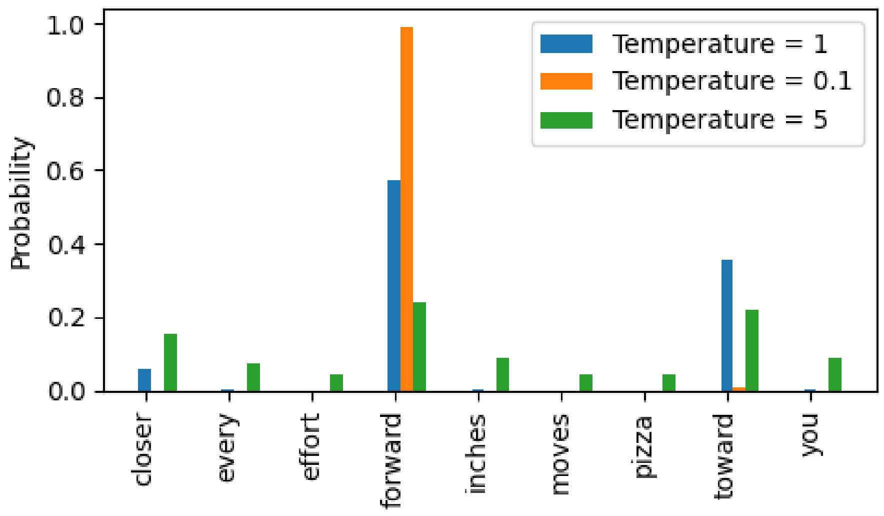
In [195]:

```
def softmax_with_temperature(logits, temperature):
    scaled_logits = logits / temperature
    return torch.softmax(scaled_logits, dim=0)

# Temperature values
temperatures = [1, 0.1, 5]  # Original, higher confidence, and lower confidence

# Calculate scaled probabilities
scaled_probas = [softmax_with_temperature(next_token_logits, T) for T in temperatures]
```

```
##Multinomial
```

In [196]:

```
# Plotting
x = torch.arange(len(vocab))
bar_width = 0.15

fig, ax = plt.subplots(figsize=(5, 3))
for i, T in enumerate(temperatures):
    rects = ax.bar(x + i * bar_width, scaled_probas[i], bar_width, label=f'Temperature = {T}')

ax.set_ylabel('Probability')
ax.set_xticks(x)
ax.set_xticklabels(vocab.keys(), rotation=90)
ax.legend()

plt.tight_layout()
plt.savefig("temperature-plot.pdf")
plt.show()
```



A temperature of 1 divides the logits by 1 before passing them to the softmax function to compute the probability scores. In other words, using a temperature of 1 is the same as not using any temperature scaling. In this case, the tokens are selected with a probability equal to the original softmax probability scores via the multinomial sampling function in PyTorch.

Applying very small temperatures, such as 0.1, will result in sharper distributions such that the behavior of the multinomial function selects the most likely token (here: "forward") almost 100% of the time, approaching the behavior of the argmax function. Vice versa, a temperature of 5 results in a more uniform distribution where other tokens are selected more often. This can add more variety to the generated texts but also more often results in nonsensical text. For example, using the temperature of 5 results in texts such as "every effort moves you pizza" about 4% of the time.

DECODING STRATEGY 2: Top-k sampling

In the previous section, we implemented a probabilistic sampling approach coupled with temperature scaling to increase the diversity of the outputs. We saw that higher temperature values result in more uniformly distributed next-token probabilities, which result in more diverse outputs as it reduces the likelihood of the model repeatedly selecting the most probable token. This method allows for exploring less likely but potentially more interesting and creative paths in the generation process. However, One downside of this approach is that it sometimes leads to grammatically incorrect or completely nonsensical outputs

such as "every effort moves you pizza".

In this section, we introduce another concept called top-k sampling, which, when combined with probabilistic sampling and temperature scaling, can improve the text generation results. In top-k sampling, we can restrict the sampled tokens to the top-k most likely tokens and exclude all other tokens from the selection process by masking their probability scores.

In [197]:

```
next_token_logits = torch.tensor(
[4.51, 0.89, -1.90, 6.75, 1.63, -1.62, -1.89, 6.28, 1.79]
)
```

In [198]:

```
top_k = 3
top_logits, top_pos = torch.topk(next_token_logits, top_k)
print("Top logits:", top_logits)
print("Top positions:", top_pos)
```

```
Top logits: tensor([6.7500, 6.2800, 4.5100])
Top positions: tensor([3, 7, 0])
```

Subsequently, we apply PyTorch's where function to set the logit values of tokens that are below the lowest logit value within our top-3 selection to negative infinity (-inf).

In [199]:

```
new_logits = torch.where(
    condition=next_token_logits < top_logits[-1],
    input=torch.tensor(float("-inf")),
    other=next_token_logits
)

print(new_logits)
```

```
tensor([4.5100,   -inf,   -inf, 6.7500,   -inf,   -inf,   -inf, 6.2800,   -inf])
```

Lastly, let's apply the softmax function to turn these into next-token probabilities:

In [200]:

```
topk_probas = torch.softmax(new_logits, dim=0)
print(topk_probas)
```

```
tensor([0.0615, 0.0000, 0.0000, 0.5775, 0.0000, 0.0000, 0.0000, 0.3610, 0.0000])
```

Merge Temperature Scaling and Top-k sampling

We can now apply the temperature scaling and multinomial function for probabilistic sampling introduced in the previous section to select the next token among these 3 nonzero probability scores to generate the next token. We do this in the next section by modifying the text generation function.

The previous two subsections introduced two concepts to increase the diversity of LLMgenerated text: temperature sampling and top-k sampling. In this section, we combine and add these concepts to modify the generate_simple function we used to generate text via the LLM earlier, creating a new generate

function:

Step 1: For-loop is the same as before: Get logits, and only focus on last time step Step 2: In this new section, we filter logits with top_k sampling Step 3: This is the new section where we apply temperature scaling Step 4: Carry out greedy next-token selection as before when temperature scaling is disabled Step 5: Stop generating early if end-of-sequence token is encountered and eos_id is specified

In [201]:

```
def generate(model, idx, max_new_tokens, context_size, temperature=0.0, top_k=None, eos_i
d=None):

    # For-loop is the same as before: Get logits, and only focus on last time step
    for _ in range(max_new_tokens):
        idx_cond = idx[:, -context_size:]
        with torch.no_grad():
            logits = model(idx_cond)
        logits = logits[:, -1, :]

        # New: Filter logits with top_k sampling
        if top_k is not None:
            # Keep only top_k values
            top_logits, _ = torch.topk(logits, top_k)
            min_val = top_logits[:, -1]
            logits = torch.where(logits < min_val, torch.tensor(float("-inf")).to(logits
.device), logits)

        # New: Apply temperature scaling
        if temperature > 0.0:
            logits = logits / temperature

            # Apply softmax to get probabilities
            probs = torch.softmax(logits, dim=-1)  # (batch_size, context_len)

            # Sample from the distribution
            idx_next = torch.multinomial(probs, num_samples=1)  # (batch_size, 1)

        # Otherwise same as before: get idx of the vocab entry with the highest logits va
lue
        else:
            idx_next = torch.argmax(logits, dim=-1, keepdim=True)  # (batch_size, 1)

        if idx_next == eos_id:  # Stop generating early if end-of-sequence token is enco
untered and eos_id is specified
            break

        # Same as before: append sampled index to the running sequence
        idx = torch.cat((idx, idx_next), dim=1)  # (batch_size, num_tokens+1)

    return idx
```

Let's now see this new generate function in action:

In [202]:

```
torch.manual_seed(123)

token_ids = generate(
    model=model,
    idx=text_to_token_ids("Every effort moves you", tokenizer),
    max_new_tokens=15,
    context_size=GPT_CONFIG_124M["context_length"],
    top_k=25,
    temperature=1.4
)

print("Output text:\n", token_ids_to_text(token_ids, tokenizer))
```

```
Output text:
 Every effort moves youEveryiliaralso stabbed OrleansAllowsean 52anche crime winter unbea
ten quoteembedreportprint earning
```

As we can see, the generated text is very different from the one we previously generated via the generate_simple function earlier ("Every effort moves you know," was one of the axioms he laid...!"), which was a memorized passage from the training set.

LOADING AND SAVING MODEL WEIGHTS IN PYTORCH

Fortunately, saving a PyTorch model is relatively straightforward. The recommended way is to save a model's so-called state_dict, a dictionary mapping each layer to its parameters, using the torch.save function as follows:

In [203]:

```
model = GPTModel(GPT_CONFIG_124M)
torch.save(model.state_dict(), "model.pth")
```

In the preceding code, "model.pth" is the filename where the state_dict is saved. The .pth extension is a convention for PyTorch files, though we could technically use any file extension.

Then, after saving the model weights via the state_dict, we can load the model weights into a new GPTModel model instance as follows:

In [204]:

```
model = GPTModel(GPT_CONFIG_124M)
model.load_state_dict(torch.load("model.pth"))
model.eval()
```

Out[204]:

```
GPTModel(
  (tok_emb): Embedding(50257, 768)
  (pos_emb): Embedding(256, 768)
  (drop_emb): Dropout(p=0.1, inplace=False)
  (trf_blocks): Sequential(
    (0): TransformerBlock(
      (att): MultiHeadAttention(
        (W_query): Linear(in_features=768, out_features=768, bias=False)
        (W_key): Linear(in_features=768, out_features=768, bias=False)
        (W_value): Linear(in_features=768, out_features=768, bias=False)
        (out_proj): Linear(in_features=768, out_features=768, bias=True)
        (dropout): Dropout(p=0.1, inplace=False)
      )
      (ff): FeedForward(
        (layers): Sequential(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU()
          (2): Linear(in_features=3072, out_features=768, bias=True)
        )
      )
      (norm1): LayerNorm()
      (norm2): LayerNorm()
      (drop_shortcut): Dropout(p=0.1, inplace=False)
    )
    (1): TransformerBlock(
      (att): MultiHeadAttention(
        (W_query): Linear(in_features=768, out_features=768, bias=False)
        (W_key): Linear(in_features=768, out_features=768, bias=False)
        (W_value): Linear(in_features=768, out_features=768, bias=False)
        (out_proj): Linear(in_features=768, out_features=768, bias=True)
        (dropout): Dropout(p=0.1, inplace=False)
      )
      (ff): FeedForward(
        (layers): Sequential(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU()
          (2): Linear(in_features=3072, out_features=768, bias=True)
        )
      )
      (norm1): LayerNorm()
      (norm2): LayerNorm()
      (drop_shortcut): Dropout(p=0.1, inplace=False)
    )
    (2): TransformerBlock(
      (att): MultiHeadAttention(
        (W_query): Linear(in_features=768, out_features=768, bias=False)
        (W_key): Linear(in_features=768, out_features=768, bias=False)
        (W_value): Linear(in_features=768, out_features=768, bias=False)
        (out_proj): Linear(in_features=768, out_features=768, bias=True)
        (dropout): Dropout(p=0.1, inplace=False)
      )
      (ff): FeedForward(
        (layers): Sequential(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU()
          (2): Linear(in_features=3072, out_features=768, bias=True)
        )
      )
      (norm1): LayerNorm()
      (norm2): LayerNorm()
      (drop_shortcut): Dropout(p=0.1, inplace=False)
    )
    (3): TransformerBlock(
      (att): MultiHeadAttention(
        (W_query): Linear(in_features=768, out_features=768, bias=False)
        (W_key): Linear(in_features=768, out_features=768, bias=False)
        (W_value): Linear(in_features=768, out_features=768, bias=False)
        (out_proj): Linear(in_features=768, out_features=768, bias=True)
        (dropout): Dropout(p=0.1, inplace=False)
      )
      (ff): FeedForward(
        (layers): Sequential(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU()
          (2): Linear(in_features=3072, out_features=768, bias=True)
        )
      )
      (norm1): LayerNorm()
      (norm2): LayerNorm()
      (drop_shortcut): Dropout(p=0.1, inplace=False)
    )
    (4): TransformerBlock(
      (att): MultiHeadAttention(
        (W_query): Linear(in_features=768, out_features=768, bias=False)
        (W_key): Linear(in_features=768, out_features=768, bias=False)
        (W_value): Linear(in_features=768, out_features=768, bias=False)
        (out_proj): Linear(in_features=768, out_features=768, bias=True)
        (dropout): Dropout(p=0.1, inplace=False)
      )
      (ff): FeedForward(
        (layers): Sequential(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU()
          (2): Linear(in_features=3072, out_features=768, bias=True)
        )
        )
      )
      (norm1): LayerNorm()
      (norm2): LayerNorm()
      (drop_shortcut): Dropout(p=0.1, inplace=False)
    )
    (5): TransformerBlock(
      (att): MultiHeadAttention(
        (W_query): Linear(in_features=768, out_features=768, bias=False)
        (W_key): Linear(in_features=768, out_features=768, bias=False)
        (W_value): Linear(in_features=768, out_features=768, bias=False)
        (out_proj): Linear(in_features=768, out_features=768, bias=True)
        (dropout): Dropout(p=0.1, inplace=False)
      )
      (ff): FeedForward(
        (layers): Sequential(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU()
          (2): Linear(in_features=3072, out_features=768, bias=True)
        )
      )
      (norm1): LayerNorm()
      (norm2): LayerNorm()
      (drop_shortcut): Dropout(p=0.1, inplace=False)
    )
    (6): TransformerBlock(
      (att): MultiHeadAttention(
        (W_query): Linear(in_features=768, out_features=768, bias=False)
        (W_key): Linear(in_features=768, out_features=768, bias=False)
        (W_value): Linear(in_features=768, out_features=768, bias=False)
        (out_proj): Linear(in_features=768, out_features=768, bias=True)
        (dropout): Dropout(p=0.1, inplace=False)
      )
      (ff): FeedForward(
        (layers): Sequential(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU()
          (2): Linear(in_features=3072, out_features=768, bias=True)
        )
      )
      (norm1): LayerNorm()
      (norm2): LayerNorm()
      (drop_shortcut): Dropout(p=0.1, inplace=False)
    )
    (7): TransformerBlock(
      (att): MultiHeadAttention(
        (W_query): Linear(in_features=768, out_features=768, bias=False)
        (W_key): Linear(in_features=768, out_features=768, bias=False)
        (W_value): Linear(in_features=768, out_features=768, bias=False)
        (out_proj): Linear(in_features=768, out_features=768, bias=True)
        (dropout): Dropout(p=0.1, inplace=False)
      )
      (ff): FeedForward(
        (layers): Sequential(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU()
          (2): Linear(in_features=3072, out_features=768, bias=True)
        )
      )
      (norm1): LayerNorm()
      (norm2): LayerNorm()
      (drop_shortcut): Dropout(p=0.1, inplace=False)
    )
    (8): TransformerBlock(
      (att): MultiHeadAttention(
        (W_query): Linear(in_features=768, out_features=768, bias=False)
        (W_key): Linear(in_features=768, out_features=768, bias=False)
        (W_value): Linear(in_features=768, out_features=768, bias=False)
        (out_proj): Linear(in_features=768, out_features=768, bias=True)
        (dropout): Dropout(p=0.1, inplace=False)
      )
      (ff): FeedForward(
        (layers): Sequential(
        (layers): Sequential(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU()
          (2): Linear(in_features=3072, out_features=768, bias=True)
        )
      )
      (norm1): LayerNorm()
      (norm2): LayerNorm()
      (drop_shortcut): Dropout(p=0.1, inplace=False)
    )
    (9): TransformerBlock(
      (att): MultiHeadAttention(
        (W_query): Linear(in_features=768, out_features=768, bias=False)
        (W_key): Linear(in_features=768, out_features=768, bias=False)
        (W_value): Linear(in_features=768, out_features=768, bias=False)
        (out_proj): Linear(in_features=768, out_features=768, bias=True)
        (dropout): Dropout(p=0.1, inplace=False)
      )
      (ff): FeedForward(
        (layers): Sequential(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU()
          (2): Linear(in_features=3072, out_features=768, bias=True)
        )
      )
      (norm1): LayerNorm()
      (norm2): LayerNorm()
      (drop_shortcut): Dropout(p=0.1, inplace=False)
    )
    (10): TransformerBlock(
      (att): MultiHeadAttention(
        (W_query): Linear(in_features=768, out_features=768, bias=False)
        (W_key): Linear(in_features=768, out_features=768, bias=False)
        (W_value): Linear(in_features=768, out_features=768, bias=False)
        (out_proj): Linear(in_features=768, out_features=768, bias=True)
        (dropout): Dropout(p=0.1, inplace=False)
      )
      (ff): FeedForward(
        (layers): Sequential(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU()
          (2): Linear(in_features=3072, out_features=768, bias=True)
        )
      )
      (norm1): LayerNorm()
      (norm2): LayerNorm()
      (drop_shortcut): Dropout(p=0.1, inplace=False)
    )
    (11): TransformerBlock(
      (att): MultiHeadAttention(
        (W_query): Linear(in_features=768, out_features=768, bias=False)
        (W_key): Linear(in_features=768, out_features=768, bias=False)
        (W_value): Linear(in_features=768, out_features=768, bias=False)
        (out_proj): Linear(in_features=768, out_features=768, bias=True)
        (dropout): Dropout(p=0.1, inplace=False)
      )
      (ff): FeedForward(
        (layers): Sequential(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU()
          (2): Linear(in_features=3072, out_features=768, bias=True)
        )
      )
      (norm1): LayerNorm()
      (norm2): LayerNorm()
      (drop_shortcut): Dropout(p=0.1, inplace=False)
    )
  )
  (final_norm): LayerNorm()
  (out_head): Linear(in_features=768, out_features=50257, bias=False)
)
```

If we plan to continue pretraining a model later, for example, using the train_model_simple function we defined earlier in this chapter, saving the optimizer state is also recommended.

Adaptive optimizers such as AdamW store additional parameters for each model weight. AdamW uses historical data to adjust learning rates for each model parameter dynamically. Without it, the optimizer resets, and the model may learn suboptimally or even fail to converge properly, which means that it will lose the ability to generate coherent text. Using torch.save, we can save both the model and optimizer state_dict contents as follows:

In [205]:

```
optimizer = torch.optim.AdamW(model.parameters(), lr=0.0004, weight_decay=0.1)

torch.save({
    "model_state_dict": model.state_dict(),
    "optimizer_state_dict": optimizer.state_dict(),
    },
    "model_and_optimizer.pth"
)
```

Then, we can restore the model and optimizer states as follows by first loading the saved data via torch.load and then using the load_state_dict method:

In [217]:

```
checkpoint = torch.load("model_and_optimizer.pth")
model = GPTModel(GPT_CONFIG_124M)
model.load_state_dict(checkpoint["model_state_dict"])
optimizer = torch.optim.AdamW(model.parameters(), lr=5e-4, weight_decay=0.1)
optimizer.load_state_dict(checkpoint["optimizer_state_dict"])
model.train();
```

LOADING PRETRAINED WEIGHTS FROM OPENAI

Previously, for educational purposes, we trained a small GPT-2 model using a limited dataset comprising a short-story book. This approach allowed us to focus on the fundamentals without the need for extensive time and computational resources. Fortunately, OpenAI openly shared the weights of their GPT-2 models, thus eliminating the need to invest tens to hundreds of thousands of dollars in retraining the model on a large corpus ourselves.

In the remainder of this section, we load these weights into our GPTModel class and use the model for text generation. Here, weights refer to the weight parameters that are stored in the .weight attributes of PyTorch's Linear and Embedding layers, for example. We accessed them earlier via model.parameters() when training the model.

Note that OpenAI originally saved the GPT-2 weights via TensorFlow, which we have to install to load the weights in Python. Moreover, the following code will use a progress bar tool called tqdm to track the download process, which we also have to install.

In [206]:

```
pip install tensorflow>=2.15.0 tqdm>=4.66
```

```
zsh:1: 2.15.0 not found
Note: you may need to restart the kernel to use updated packages.
```

In [207]:

```python
import tensorflow as tf
import tqdm

print("TensorFlow version:", tf.__version__)
print("tqdm version:", tqdm.__version__)
```

```
TensorFlow version: 2.16.1
tqdm version: 4.66.2
```

We download the gpt_download.py Python module directly from this chapter's online repository

We can now import the download_and_load_gpt2 function from the gpt_download.py file as follows, which will load the GPT-2 architecture settings (settings) and weight parameters (params) into our Python session:

In [220]:

```python
from gpt_download3 import download_and_load_gpt2
```

In [221]:

```python
settings, params = download_and_load_gpt2(model_size="124M", models_dir="gpt2")
```

```
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-packages/urllib3/c
onnectionpool.py:1103: InsecureRequestWarning: Unverified HTTPS request is being made to
host 'openaipublic.blob.core.windows.net'. Adding certificate verification is strongly ad
vised. See: https://urllib3.readthedocs.io/en/latest/advanced-usage.html#tls-warnings
  warnings.warn(
```

```
File already exists and is up-to-date: gpt2/124M/checkpoint
```

```
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-packages/urllib3/c
onnectionpool.py:1103: InsecureRequestWarning: Unverified HTTPS request is being made to
host 'openaipublic.blob.core.windows.net'. Adding certificate verification is strongly ad
vised. See: https://urllib3.readthedocs.io/en/latest/advanced-usage.html#tls-warnings
  warnings.warn(
```

```
File already exists and is up-to-date: gpt2/124M/encoder.json
```

```
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-packages/urllib3/c
onnectionpool.py:1103: InsecureRequestWarning: Unverified HTTPS request is being made to
host 'openaipublic.blob.core.windows.net'. Adding certificate verification is strongly ad
vised. See: https://urllib3.readthedocs.io/en/latest/advanced-usage.html#tls-warnings
  warnings.warn(
hparams.json: 100%|████████████████████████| 90.0/90.0 [00:00<00:00, 52.5kiB/s]
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-packages/urllib3/c
onnectionpool.py:1103: InsecureRequestWarning: Unverified HTTPS request is being made to
host 'openaipublic.blob.core.windows.net'. Adding certificate verification is strongly ad
vised. See: https://urllib3.readthedocs.io/en/latest/advanced-usage.html#tls-warnings
  warnings.warn(
```

```
File already exists and is up-to-date: gpt2/124M/model.ckpt.data-00000-of-00001
```

```
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-packages/urllib3/c
onnectionpool.py:1103: InsecureRequestWarning: Unverified HTTPS request is being made to
host 'openaipublic.blob.core.windows.net'. Adding certificate verification is strongly ad
vised. See: https://urllib3.readthedocs.io/en/latest/advanced-usage.html#tls-warnings
  warnings.warn(
```

```
File already exists and is up-to-date: gpt2/124M/model.ckpt.index
```

```
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-packages/urllib3/c
onnectionpool.py:1103: InsecureRequestWarning: Unverified HTTPS request is being made to
```

```
host 'openaipublic.blob.core.windows.net'. Adding certificate verification is strongly ad
vised. See: https://urllib3.readthedocs.io/en/latest/advanced-usage.html#tls-warnings
  warnings.warn(
```

```
File already exists and is up-to-date: gpt2/124M/model.ckpt.meta
```

```
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-packages/urllib3/c
onnectionpool.py:1103: InsecureRequestWarning: Unverified HTTPS request is being made to
host 'openaipublic.blob.core.windows.net'. Adding certificate verification is strongly ad
vised. See: https://urllib3.readthedocs.io/en/latest/advanced-usage.html#tls-warnings
  warnings.warn(
```

```
File already exists and is up-to-date: gpt2/124M/vocab.bpe
```

After the execution of the previous code has been completed, let's inspect the contents of settings and params:

In [222]:

```python
print("Settings:", settings)
print("Parameter dictionary keys:", params.keys())
```

```
Settings: {'n_vocab': 50257, 'n_ctx': 1024, 'n_embd': 768, 'n_head': 12, 'n_layer': 12}
Parameter dictionary keys: dict_keys(['blocks', 'b', 'g', 'wpe', 'wte'])
```

Both settings and params are Python dictionaries. The settings dictionary stores the LLM architecture settings similarly to our manually defined GPT_CONFIG_124M settings. The params dictionary contains the actual weight tensors. Note that we only printed the dictionary keys because printing the weight contents would take up too much screen space

We can inspect these weight tensors by printing the whole dictionary via print(params) or by selecting individual tensors via the respective dictionary keys, for example, the embedding layer weights:

In [223]:

```python
print(params["wte"])
print("Token embedding weight tensor dimensions:", params["wte"].shape)
```

```
[[-0.11010301 -0.03926672  0.03310751 ... -0.1363697   0.01506208
   0.04531523]
 [ 0.04034033 -0.04861503  0.04624869 ...  0.08605453  0.00253983
   0.04318958]
 [-0.12746179  0.04793796  0.18410145 ...  0.08991534 -0.12972379
  -0.08785918]
 ...
 [-0.04453601 -0.05483596  0.01225674 ...  0.10435229  0.09783269
  -0.06952604]
 [ 0.1860082   0.01665728  0.04611587 ... -0.09625227  0.07847701
  -0.02245961]
 [ 0.05135201 -0.02768905  0.0499369  ...  0.00704835  0.15519823
   0.12067825]]
Token embedding weight tensor dimensions: (50257, 768)
```

We downloaded and loaded the weights of the smallest GPT-2 model via the download_and_load_gpt2(model_size="124M", ...) setting. However, note that OpenAI also shares the weights of larger models: "355M", "774M", and "1558M".

Above, we loaded the 124M GPT-2 model weights into Python, however we still need to transfer them into our GPTModel instance. First, we initialize a new GPTModel instance. Note that the original GPT model

initialized the linear layers for the query, key, and value matrices in the multi-head attention module with bias vectors, which is not required or recommended; however, to be able to load the weights correctly, we have to enable these too by setting qkv_bias to True in our implementation, too. We are also using the 1024 token context length that was used by the original GPT-2 model(s)

In [209]:

```
# Define model configurations in a dictionary for compactness
model_configs = {
    "gpt2-small (124M)": {"emb_dim": 768, "n_layers": 12, "n_heads": 12},
    "gpt2-medium (355M)": {"emb_dim": 1024, "n_layers": 24, "n_heads": 16},
    "gpt2-large (774M)": {"emb_dim": 1280, "n_layers": 36, "n_heads": 20},
    "gpt2-xl (1558M)": {"emb_dim": 1600, "n_layers": 48, "n_heads": 25},
}

# Copy the base configuration and update with specific model settings
model_name = "gpt2-small (124M)"  # Example model name
NEW_CONFIG = GPT_CONFIG_124M.copy()
NEW_CONFIG.update(model_configs[model_name])
```

Careful readers may remember that we used a 256-token length earlier, but the original GPT-2 models from OpenAI were trained with a 1,024-token length, so we have to update the NEW_CONFIG accordingly:

Also, OpenAI used bias vectors in the multi-head attention module's linear layers to implement the query, key, and value matrix computations. Bias vectors are not commonly used in LLMs anymore as they don't improve the modeling performance and are thus unnecessary. However, since we are working with pretrained weights, we need to match the settings for consistency and enable these bias vectors:

In [210]:

```
NEW_CONFIG.update({"context_length": 1024, "qkv_bias": True})
gpt = GPTModel(NEW_CONFIG)
gpt.eval();
```

By default, the GPTModel instance is initialized with random weights for pretraining. The last step to using OpenAI's model weights is to override these random weights with the weights we loaded into the params dictionary. For this, we will first define a small assign utility function that checks whether two tensors or arrays (left and right) have the same dimensions or shape and returns the right tensor as trainable PyTorch parameters:

In [208]:

```
def assign(left, right):
    if left.shape != right.shape:
        raise ValueError(f"Shape mismatch. Left: {left.shape}, Right: {right.shape}")
    return torch.nn.Parameter(torch.tensor(right))
```

Next, we define a load_weights_into_gpt function that loads the weights from the params dictionary into a GPTModel instance gpt:

Step 1: Setting the model's positional and token embedding weights to those specified in params. Step 2: Iterate over each transformer block in the model. Step 3: The np.split function is used to divide the attention and bias weights into three equal parts for the query, key, and value components. Step 4: The original GPT-2 model by OpenAI reused the token embedding weights in the output layer to reduce the total number of parameters, which is a concept known as weight tying.

In [209]:

```
import numpy as np

def load_weights_into_gpt(gpt, params):
    gpt.pos_emb.weight = assign(gpt.pos_emb.weight, params['wpe'])
    gpt.tok_emb.weight = assign(gpt.tok_emb.weight, params['wte'])

    for b in range(len(params["blocks"])):
        q_w, k_w, v_w = np.split(
            (params["blocks"][b]["attn"]["c_attn"])["w"], 3, axis=-1)
        gpt.trf_blocks[b].att.W_query.weight = assign(
            gpt.trf_blocks[b].att.W_query.weight, q_w.T)
        gpt.trf_blocks[b].att.W_key.weight = assign(
            gpt.trf_blocks[b].att.W_key.weight, k_w.T)
        gpt.trf_blocks[b].att.W_value.weight = assign(
            gpt.trf_blocks[b].att.W_value.weight, v_w.T)

        q_b, k_b, v_b = np.split(
            (params["blocks"][b]["attn"]["c_attn"])["b"], 3, axis=-1)
        gpt.trf_blocks[b].att.W_query.bias = assign(
            gpt.trf_blocks[b].att.W_query.bias, q_b)
        gpt.trf_blocks[b].att.W_key.bias = assign(
            gpt.trf_blocks[b].att.W_key.bias, k_b)
        gpt.trf_blocks[b].att.W_value.bias = assign(
            gpt.trf_blocks[b].att.W_value.bias, v_b)

        gpt.trf_blocks[b].att.out_proj.weight = assign(
            gpt.trf_blocks[b].att.out_proj.weight,
            params["blocks"][b]["attn"]["c_proj"]["w"].T)
        gpt.trf_blocks[b].att.out_proj.bias = assign(
            gpt.trf_blocks[b].att.out_proj.bias,
            params["blocks"][b]["attn"]["c_proj"]["b"])

        gpt.trf_blocks[b].ff.layers[0].weight = assign(
            gpt.trf_blocks[b].ff.layers[0].weight,
            params["blocks"][b]["mlp"]["c_fc"]["w"].T)
        gpt.trf_blocks[b].ff.layers[0].bias = assign(
            gpt.trf_blocks[b].ff.layers[0].bias,
            params["blocks"][b]["mlp"]["c_fc"]["b"])
        gpt.trf_blocks[b].ff.layers[2].weight = assign(
            gpt.trf_blocks[b].ff.layers[2].weight,
            params["blocks"][b]["mlp"]["c_proj"]["w"].T)
        gpt.trf_blocks[b].ff.layers[2].bias = assign(
            gpt.trf_blocks[b].ff.layers[2].bias,
            params["blocks"][b]["mlp"]["c_proj"]["b"])

        gpt.trf_blocks[b].norm1.scale = assign(
            gpt.trf_blocks[b].norm1.scale,
            params["blocks"][b]["ln_1"]["g"])
        gpt.trf_blocks[b].norm1.shift = assign(
            gpt.trf_blocks[b].norm1.shift,
            params["blocks"][b]["ln_1"]["b"])
        gpt.trf_blocks[b].norm2.scale = assign(
            gpt.trf_blocks[b].norm2.scale,
            params["blocks"][b]["ln_2"]["g"])
        gpt.trf_blocks[b].norm2.shift = assign(
            gpt.trf_blocks[b].norm2.shift,
            params["blocks"][b]["ln_2"]["b"])

    gpt.final_norm.scale = assign(gpt.final_norm.scale, params["g"])
    gpt.final_norm.shift = assign(gpt.final_norm.shift, params["b"])
    gpt.out_head.weight = assign(gpt.out_head.weight, params["wte"])
```

In the load_weights_into_gpt function, we carefully match the weights from OpenAI's implementation with our GPTModel implementation. To pick a specific example, OpenAI stored the weight tensor for the output projection layer for the first transformer block as params["blocks"][0]["attn"]["c_proj"]["w"]. In our implementation, this weight tensor corresponds to gpt.trf_blocks[b].att.out_proj.weight, where gpt is a GPTModel instance.

GPTModel instance.

Developing the load_weights_into_gpt function took a lot of guesswork since OpenAI used a slightly different naming convention from ours. However, the assign function would alert us if we try to match two tensors with different dimensions. Also, if we made a mistake in this function, we would notice this as the resulting GPT model would be unable to produce coherent text.

Let's now try the load_weights_into_gpt out in practice and load the OpenAI model weights into our GPTModel instance gpt:

In [228]:

```
load_weights_into_gpt(gpt, params)
gpt.to(device);
```

If the model is loaded correctly, we can now use it to generate new text using our previous generate function:

In [229]:

```
torch.manual_seed(123)

token_ids = generate(
    model=gpt,
    idx=text_to_token_ids("Every effort moves you", tokenizer).to(device),
    max_new_tokens=25,
    context_size=NEW_CONFIG["context_length"],
    top_k=50,
    temperature=1.4
)

print("Output text:\n", token_ids_to_text(token_ids, tokenizer))
```

```
Output text:
 Every effort moves you toward finding an ideal new way to practice something!

What makes us want to be on this side of the river?
```

We can be confident that we loaded the model weights correctly because the model can produce coherent text. A tiny mistake in this process would cause the model to fail. In the following chapters, we will work further with this pretrained model and fine-tune it to classify text and follow instructions.

FINETUNING FOR CLASSIFICATION

DOWNLOADING DATASET

In [230]:

```
import urllib.request
import ssl
import zipfile
import os
from pathlib import Path

url = "https://archive.ics.uci.edu/static/public/228/sms+spam+collection.zip"
zip_path = "sms_spam_collection.zip"
```

```
extracted_path = "sms_spam_collection"
data_file_path = Path(extracted_path) / "SMSSpamCollection.tsv"

def download_and_unzip_spam_data(url, zip_path, extracted_path, data_file_path):
    if data_file_path.exists():
        print(f"{data_file_path} already exists. Skipping download and extraction.")
        return

    # Create an unverified SSL context
    ssl_context = ssl._create_unverified_context()

    # Downloading the file
    with urllib.request.urlopen(url, context=ssl_context) as response:
        with open(zip_path, "wb") as out_file:
            out_file.write(response.read())

    # Unzipping the file
    with zipfile.ZipFile(zip_path, "r") as zip_ref:
        zip_ref.extractall(extracted_path)

    # Add .tsv file extension
    original_file_path = Path(extracted_path) / "SMSSpamCollection"
    os.rename(original_file_path, data_file_path)
    print(f"File downloaded and saved as {data_file_path}")

download_and_unzip_spam_data(url, zip_path, extracted_path, data_file_path)
```

```
sms_spam_collection/SMSSpamCollection.tsv already exists. Skipping download and extractio
n.
```

After executing the preceding code, the dataset is saved as a tab-separated text file, SMSSpamCollection.tsv, in the sms_spam_collection folder. We can load it into a pandas DataFrame as follows:

In [231]:

```
import pandas as pd

df = pd.read_csv(data_file_path, sep="\t", header=None, names=["Label", "Text"])
df
```

Out[231]:

	Label	Text
0	ham	Go until jurong point, crazy.. Available only ...
1	ham	Ok lar... Joking wif u oni...
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...
3	ham	U dun say so early hor... U c already then say...
4	ham	Nah I don't think he goes to usf, he lives aro...
...	...	...
5567	spam	This is the 2nd time we have tried 2 contact u...
5568	ham	Will ü b going to esplanade fr home?
5569	ham	Pity, * was in mood for that. So...any other s...
5570	ham	The guy did some bitching but I acted like i'd...
5571	ham	Rofl. Its true to its name

5572 rows × 2 columns

When we check the class distribution, we see that the data contains "ham" (i.e., "not spam") much more

frequently than "spam"

In [232]:

```python
print(df["Label"].value_counts())
```

```
Label
ham     4825
spam     747
Name: count, dtype: int64
```

For simplicity, and because we prefer a small dataset for educational purposes anyway (it will make it possible to finetune the LLM faster), we subsample (undersample) the dataset so that it contains 747 instances from each class

In [233]:

```python
def create_balanced_dataset(df):

    # Count the instances of "spam"
    num_spam = df[df["Label"] == "spam"].shape[0]

    # Randomly sample "ham" instances to match the number of "spam" instances
    ham_subset = df[df["Label"] == "ham"].sample(num_spam, random_state=123)

    # Combine ham "subset" with "spam"
    balanced_df = pd.concat([ham_subset, df[df["Label"] == "spam"]])

    return balanced_df

balanced_df = create_balanced_dataset(df)
print(balanced_df["Label"].value_counts())
```

```
Label
ham     747
spam    747
Name: count, dtype: int64
```

After executing the previous code to balance the dataset, we can see that we now have equal amounts of spam and non-spam messages:

Next, we convert the "string" class labels "ham" and "spam" into integer class labels 0 and 1, respectively:

In [234]:

```python
balanced_df["Label"] = balanced_df["Label"].map({"ham": 0, "spam": 1})
```

This process is similar to converting text into token IDs. However, instead of using the GPT vocabulary, which consists of more than 50,000 words, we are dealing with just two token IDs: 0 and 1.

We create a random_split function to split the dataset into three parts: 70% for training, 10% for validation, and 20% for testing. (These ratios are common in machine learning to train, adjust, and evaluate models.)

In [235]:

```python
def random_split(df, train_frac, validation_frac):
    # Shuffle the entire DataFrame
    df = df.sample(frac=1, random_state=123).reset_index(drop=True)

    # Calculate split indices
    train_end = int(len(df) * train_frac)
    validation_end = train_end + int(len(df) * validation_frac)

    # Split the DataFrame
    train_df = df[:train_end]
    validation_df = df[train_end:validation_end]
    test_df = df[validation_end:]

    return train_df, validation_df, test_df

train_df, validation_df, test_df = random_split(balanced_df, 0.7, 0.1)
# Test size is implied to be 0.2 as the remainder
```

In [236]:

```
print(len(train_df))
print(len(validation_df))
print(len(test_df))
```

```
1045
149
300
```

Additionally, we save the dataset as CSV (comma-separated value) files, which we can reuse later:

In [237]:

```
train_df.to_csv("train.csv", index=None)
validation_df.to_csv("validation.csv", index=None)
test_df.to_csv("test.csv", index=None)
```

CREATING DATALOADERS

Previously, we utilized a sliding window technique to generate uniformly sized text chunks, which were then grouped into batches for more efficient model training. Each chunk functioned as an individual training instance In the case of email spam classification, have two primary options: (1) Truncate all messages to the length of the shortest message in the dataset or batch. (2) Pad all messages to the length of the longest message in the dataset or batch.

Option 1 is computationally cheaper, but it may result in significant information loss if shorter messages are much smaller than the average or longest messages, potentially reducing model performance. So, we opt for the second option, which preserves the entire content of all messages. To implement option 2, where all messages are padded to the length of the longest message in the dataset, we add padding tokens to all shorter messages. For this purpose, we use "<|endoftext|>" as a padding token, as discussed in chapter 2. However, instead of appending the string "<|endoftext|>" to each of the text messages directly, we can add the token ID corresponding to "<|endoftext|>" to the encoded text

As we have seen earlier, we first need to implement a PyTorch Dataset, which specifies how the data is loaded and processed, before we can instantiate the data loaders.

For this purpose, we define the SpamDataset class. This SpamDataset class handles several key tasks: it identifies the longest sequence in the training dataset, encodes the text messages, and ensures that all other sequences are padded with a padding token to match the length of the longest sequence.

In [238]:

```python
import torch
from torch.utils.data import Dataset


class SpamDataset(Dataset):
    def __init__(self, csv_file, tokenizer, max_length=None, pad_token_id=50256):
        self.data = pd.read_csv(csv_file)

        # Pre-tokenize texts
        self.encoded_texts = [
            tokenizer.encode(text) for text in self.data["Text"]
        ]

        if max_length is None:
            self.max_length = self._longest_encoded_length()
        else:
            self.max_length = max_length

            # Truncate sequences if they are longer than max_length
            self.encoded_texts = [
                encoded_text[:self.max_length]
                for encoded_text in self.encoded_texts
            ]

        # Pad sequences to the longest sequence
        self.encoded_texts = [
            encoded_text + [pad_token_id] * (self.max_length - len(encoded_text))
            for encoded_text in self.encoded_texts
        ]

    def __getitem__(self, index):
        encoded = self.encoded_texts[index]
        label = self.data.iloc[index]["Label"]
        return (
            torch.tensor(encoded, dtype=torch.long),
            torch.tensor(label, dtype=torch.long)
        )

    def __len__(self):
        return len(self.data)

    def _longest_encoded_length(self):
        max_length = 0
        for encoded_text in self.encoded_texts:
            encoded_length = len(encoded_text)
            if encoded_length > max_length:
                max_length = encoded_length
        return max_length
```

Step 1: Pre-tokenize texts Step 2: Truncate sequences if they are longer than max_length Step 3: Pad sequences to the longest sequence

The SpamDataset class loads data from the CSV files we created earlier, tokenizes the text using the GPT-2 tokenizer from tiktoken and allows us to pad or truncate the sequences to a uniform length determined by either the longest sequence or a predefined maximum length.

This ensures each input tensor is of the same size, which is necessary to create the batches in the training data loader we implement next:

In [239]:

```
train_dataset = SpamDataset(
    csv_file="train.csv",
    max_length=None,
    tokenizer=tokenizer
)

print(train_dataset.max_length)
```

```
120
```

The code outputs 120, showing that the longest sequence contains no more than 120 tokens, a common length for text messages. It's worth noting that the model can handle sequences of up to 1,024 tokens, given its context length limit. If your dataset includes longer texts, you can pass max_length=1024 when creating the training dataset in the preceding code to ensure that the data does not exceed the model's supported input (context) length.

Next, we pad the validation and test sets to match the length of the longest training sequence. It's important to note that any validation and test set samples exceeding the length of the longest training example are truncated using encoded_text[:self.max_length] in the SpamDataset code we defined earlier. This truncation is optional; you could also set max_length=None for both validation and test sets, provided there are no sequences exceeding 1,024 tokens in these sets

In [240]:

```
val_dataset = SpamDataset(
    csv_file="validation.csv",
    max_length=train_dataset.max_length,
    tokenizer=tokenizer
)
test_dataset = SpamDataset(
    csv_file="test.csv",
    max_length=train_dataset.max_length,
    tokenizer=tokenizer
)

print(test_dataset.max_length)
```

```
120
```

Using the datasets as inputs, we can instantiate the data loaders similarly to what we did earlier. However, in this case, the targets represent class labels rather than the next tokens in the text. For instance, choosing a batch size of 8, each batch will consist of 8 training examples of length 120 and the corresponding class label of each example.

In [241]:

```
from torch.utils.data import DataLoader

num_workers = 0
batch_size = 8

torch.manual_seed(123)

train_loader = DataLoader(
    dataset=train_dataset,
    batch_size=batch_size,
    shuffle=True,
    num_workers=num_workers,
    drop_last=True,
)
```

```
val_loader = DataLoader(
    dataset=val_dataset,
    batch_size=batch_size,
    num_workers=num_workers,
    drop_last=False,
)

test_loader = DataLoader(
    dataset=test_dataset,
    batch_size=batch_size,
    num_workers=num_workers,
    drop_last=False,
)
```

To ensure that the data loaders are working and are indeed returning batches of the expected size, we iterate over the training loader and then print the tensor dimensions of the last batch:

In [242]:

```
print("Train loader:")
for input_batch, target_batch in train_loader:
    pass

print("Input batch dimensions:", input_batch.shape)
print("Label batch dimensions", target_batch.shape)
```

```
Train loader:
Input batch dimensions: torch.Size([8, 120])
Label batch dimensions torch.Size([8])
```

As we can see, the input batches consist of 8 training examples with 120 tokens each, as expected. The label tensor stores the class labels corresponding to the 8 training examples.

Lastly, to get an idea of the dataset size, let's print the total number of batches in each dataset:

In [243]:

```
print(f"{len(train_loader)} training batches")
print(f"{len(val_loader)} validation batches")
print(f"{len(test_loader)} test batches")
```

```
130 training batches
19 validation batches
38 test batches
```

This concludes the data preparation. Next, we will prepare the model for finetuning.

INITIALIZING A MODEL WITH PRETRAINED WEIGHTS

In this section, we prepare the model we will use for the classification-finetuning to identify spam messages. We start with initializing the pretrained model we worked with in the previous chapter

In [244]:

```
CHOOSE_MODEL = "gpt2-small (124M)"
```

```python
INPUT_PROMPT = "Every effort moves"

BASE_CONFIG = {
    "vocab_size": 50257,     # Vocabulary size
    "context_length": 1024,  # Context length
    "drop_rate": 0.0,        # Dropout rate
    "qkv_bias": True         # Query-key-value bias
}

model_configs = {
    "gpt2-small (124M)": {"emb_dim": 768, "n_layers": 12, "n_heads": 12},
    "gpt2-medium (355M)": {"emb_dim": 1024, "n_layers": 24, "n_heads": 16},
    "gpt2-large (774M)": {"emb_dim": 1280, "n_layers": 36, "n_heads": 20},
    "gpt2-xl (1558M)": {"emb_dim": 1600, "n_layers": 48, "n_heads": 25},
}

BASE_CONFIG.update(model_configs[CHOOSE_MODEL])

assert train_dataset.max_length <= BASE_CONFIG["context_length"], (
    f"Dataset length {train_dataset.max_length} exceeds model's context "
    f"length {BASE_CONFIG['context_length']}. Reinitialize data sets with "
    f"`max_length={BASE_CONFIG['context_length']}`"
)
```

Next, we import the download_and_load_gpt function from the gpt_download3.py file we downloaded earlier. Furthermore, we also reuse the GPTModel class and load_weights_into_gpt function from chapter 5 to load the downloaded weights into the GPT model:

In [245]:

```python
model_size = CHOOSE_MODEL.split(" ")[-1].lstrip("(").rstrip(")")

from gpt_download3 import download_and_load_gpt2

settings, params = download_and_load_gpt2(model_size=model_size, models_dir="gpt2")

model = GPTModel(BASE_CONFIG)
load_weights_into_gpt(model, params)
model.eval();
```

```
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-packages/urllib3/c
onnectionpool.py:1103: InsecureRequestWarning: Unverified HTTPS request is being made to
host 'openaipublic.blob.core.windows.net'. Adding certificate verification is strongly ad
vised. See: https://urllib3.readthedocs.io/en/latest/advanced-usage.html#tls-warnings
  warnings.warn(
```

```
File already exists and is up-to-date: gpt2/124M/checkpoint
```

```
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-packages/urllib3/c
onnectionpool.py:1103: InsecureRequestWarning: Unverified HTTPS request is being made to
host 'openaipublic.blob.core.windows.net'. Adding certificate verification is strongly ad
vised. See: https://urllib3.readthedocs.io/en/latest/advanced-usage.html#tls-warnings
  warnings.warn(
```

```
File already exists and is up-to-date: gpt2/124M/encoder.json
```

```
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-packages/urllib3/c
onnectionpool.py:1103: InsecureRequestWarning: Unverified HTTPS request is being made to
host 'openaipublic.blob.core.windows.net'. Adding certificate verification is strongly ad
vised. See: https://urllib3.readthedocs.io/en/latest/advanced-usage.html#tls-warnings
  warnings.warn(
```

```
File already exists and is up-to-date: gpt2/124M/hparams.json
```

```
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-packages/urllib3/c
onnectionpool.py:1103: InsecureRequestWarning: Unverified HTTPS request is being made to
host 'openaipublic.blob.core.windows.net'. Adding certificate verification is strongly ad
vised. See: https://urllib3.readthedocs.io/en/latest/advanced-usage.html#tls-warnings
  warnings.warn(
```

```
File already exists and is up-to-date: gpt2/124M/model.ckpt.data-00000-of-00001
File already exists and is up-to-date: gpt2/124M/model.ckpt.data-00000-of-00001
```

```
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-packages/urllib3/c
onnectionpool.py:1103: InsecureRequestWarning: Unverified HTTPS request is being made to
host 'openaipublic.blob.core.windows.net'. Adding certificate verification is strongly ad
vised. See: https://urllib3.readthedocs.io/en/latest/advanced-usage.html#tls-warnings
  warnings.warn(
```

```
File already exists and is up-to-date: gpt2/124M/model.ckpt.index
```

```
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-packages/urllib3/c
onnectionpool.py:1103: InsecureRequestWarning: Unverified HTTPS request is being made to
host 'openaipublic.blob.core.windows.net'. Adding certificate verification is strongly ad
vised. See: https://urllib3.readthedocs.io/en/latest/advanced-usage.html#tls-warnings
  warnings.warn(
```

```
File already exists and is up-to-date: gpt2/124M/model.ckpt.meta
```

```
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-packages/urllib3/c
onnectionpool.py:1103: InsecureRequestWarning: Unverified HTTPS request is being made to
host 'openaipublic.blob.core.windows.net'. Adding certificate verification is strongly ad
vised. See: https://urllib3.readthedocs.io/en/latest/advanced-usage.html#tls-warnings
  warnings.warn(
```

```
File already exists and is up-to-date: gpt2/124M/vocab.bpe
```

To ensure that the model was loaded correctly, let's double-check that it generates coherent text

In [247]:

```
text_1 = "Every effort moves you"

token_ids = generate_text_simple(
    model=model,
    idx=text_to_token_ids(text_1, tokenizer),
    max_new_tokens=15,
    context_size=BASE_CONFIG["context_length"]
)

print(token_ids_to_text(token_ids, tokenizer))
```

```
Every effort moves you forward.

The first step is to understand the importance of your work
```

Now, before we start finetuning the model as a spam classifier, let's see if the model can perhaps already classify spam messages by by prompting it with instructions:

In [248]:

```
text_2 = (
    "Is the following text 'spam'? Answer with 'yes' or 'no':"
    " 'You are a winner you have been specially"
    " selected to receive $1000 cash or a $2000 award.'"
)

token_ids = generate_text_simple(
    model=model,
    idx=text_to_token_ids(text_2, tokenizer),
    max_new_tokens=23,
    context_size=BASE_CONFIG["context_length"]
)

print(token_ids_to_text(token_ids, tokenizer))
```

```
Is the following text 'spam'? Answer with 'yes' or 'no': 'You are a winner you have been
specially selected to receive $1000 cash or a $2000 award.'

The following text 'spam'? Answer with 'yes' or 'no': 'You are a winner
The following text 'spam'? Answer with 'yes' or 'no': 'You are a winner
```

Based on the output, it's apparent that the model struggles with following instructions. This is anticipated, as it has undergone only pretraining and lacks instruction-finetuning, which we will explore in the upcoming chapter The next section prepares the model for classification-finetuning

ADDING A CLASSIFICATION HEAD

In this section, we modify the pretrained large language model to prepare it for classification-finetuning. To do this, we replace the original output layer, which maps the hidden representation to a vocabulary of 50,257, with a smaller output layer that maps to two classes: 0 ("not spam") and 1 ("spam"),

We could technically use a single output node since we are dealing with a binary classification task. However, this would require modifying the loss function. Therefore, we choose a more general approach where the number of output nodes matches the number of classes. For example, for a 3-class problem, such as classifying news articles as "Technology", "Sports", or "Politics", we would use three output nodes, and so forth.

Before we attempt to construct the modified architecture, let's print the model architecture via print(model), which prints the following:

In [249]:

```
print(model)
```

```
GPTModel(
  (tok_emb): Embedding(50257, 768)
  (pos_emb): Embedding(1024, 768)
  (drop_emb): Dropout(p=0.0, inplace=False)
  (trf_blocks): Sequential(
    (0): TransformerBlock(
      (att): MultiHeadAttention(
        (W_query): Linear(in_features=768, out_features=768, bias=True)
        (W_key): Linear(in_features=768, out_features=768, bias=True)
        (W_value): Linear(in_features=768, out_features=768, bias=True)
        (out_proj): Linear(in_features=768, out_features=768, bias=True)
        (dropout): Dropout(p=0.0, inplace=False)
      )
      (ff): FeedForward(
        (layers): Sequential(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU()
          (2): Linear(in_features=3072, out_features=768, bias=True)
        )
      )
      (norm1): LayerNorm()
      (norm2): LayerNorm()
      (drop_shortcut): Dropout(p=0.0, inplace=False)
    )
    (1): TransformerBlock(
      (att): MultiHeadAttention(
        (W_query): Linear(in_features=768, out_features=768, bias=True)
        (W_key): Linear(in_features=768, out_features=768, bias=True)
        (W_value): Linear(in_features=768, out_features=768, bias=True)
        (out_proj): Linear(in_features=768, out_features=768, bias=True)
        (dropout): Dropout(p=0.0, inplace=False)
      )
      (ff): FeedForward(
        (layers): Sequential(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU()
          (2): Linear(in_features=3072, out_features=768, bias=True)
        )
      )
      (norm1): LayerNorm()
      (norm2): LayerNorm()
      (drop_shortcut): Dropout(p=0.0, inplace=False)
    )
    (2): TransformerBlock(
      (att): MultiHeadAttention(
        (W_query): Linear(in_features=768, out_features=768, bias=True)
        (W_key): Linear(in_features=768, out_features=768, bias=True)
        (W_value): Linear(in_features=768, out_features=768, bias=True)
        (out_proj): Linear(in_features=768, out_features=768, bias=True)
        (dropout): Dropout(p=0.0, inplace=False)
      )
      (ff): FeedForward(
        (layers): Sequential(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU()
          (2): Linear(in_features=3072, out_features=768, bias=True)
        )
      )
      (norm1): LayerNorm()
      (norm2): LayerNorm()
      (drop_shortcut): Dropout(p=0.0, inplace=False)
    )
    (3): TransformerBlock(
      (att): MultiHeadAttention(
        (W_query): Linear(in_features=768, out_features=768, bias=True)
        (W_key): Linear(in_features=768, out_features=768, bias=True)
        (W_value): Linear(in_features=768, out_features=768, bias=True)
        (out_proj): Linear(in_features=768, out_features=768, bias=True)
        (dropout): Dropout(p=0.0, inplace=False)
      )
      (ff): FeedForward(
        (layers): Sequential(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU()
          (2): Linear(in_features=3072, out_features=768, bias=True)
        )
      )
      (norm1): LayerNorm()
      (norm2): LayerNorm()
      (drop_shortcut): Dropout(p=0.0, inplace=False)
    )
    (4): TransformerBlock(
      (att): MultiHeadAttention(
        (W_query): Linear(in_features=768, out_features=768, bias=True)
        (W_key): Linear(in_features=768, out_features=768, bias=True)
        (W_value): Linear(in_features=768, out_features=768, bias=True)
        (out_proj): Linear(in_features=768, out_features=768, bias=True)
        (dropout): Dropout(p=0.0, inplace=False)
      )
      (ff): FeedForward(
        (layers): Sequential(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU()
          (2): Linear(in_features=3072, out_features=768, bias=True)
        )
      )
      (norm1): LayerNorm()
      (norm2): LayerNorm()
      (drop_shortcut): Dropout(p=0.0, inplace=False)
    )
    (5): TransformerBlock(
      (att): MultiHeadAttention(
        (W_query): Linear(in_features=768, out_features=768, bias=True)
        (W_key): Linear(in_features=768, out_features=768, bias=True)
        (W_value): Linear(in_features=768, out_features=768, bias=True)
        (out_proj): Linear(in_features=768, out_features=768, bias=True)
        (dropout): Dropout(p=0.0, inplace=False)
      )
      (ff): FeedForward(
        (layers): Sequential(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU()
          (2): Linear(in_features=3072, out_features=768, bias=True)
        )
      )
      (norm1): LayerNorm()
      (norm2): LayerNorm()
      (drop_shortcut): Dropout(p=0.0, inplace=False)
    )
    (6): TransformerBlock(
      (att): MultiHeadAttention(
        (W_query): Linear(in_features=768, out_features=768, bias=True)
        (W_key): Linear(in_features=768, out_features=768, bias=True)
        (W_value): Linear(in_features=768, out_features=768, bias=True)
        (out_proj): Linear(in_features=768, out_features=768, bias=True)
        (dropout): Dropout(p=0.0, inplace=False)
      )
      (ff): FeedForward(
        (layers): Sequential(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU()
          (2): Linear(in_features=3072, out_features=768, bias=True)
        )
      )
      (norm1): LayerNorm()
      (norm2): LayerNorm()
      (drop_shortcut): Dropout(p=0.0, inplace=False)
    )
    (7): TransformerBlock(
      (att): MultiHeadAttention(
        (W_query): Linear(in_features=768, out_features=768, bias=True)
        (W_key): Linear(in_features=768, out_features=768, bias=True)
        (W_value): Linear(in_features=768, out_features=768, bias=True)
        (out_proj): Linear(in_features=768, out_features=768, bias=True)
        (dropout): Dropout(p=0.0, inplace=False)
      )
      (ff): FeedForward(
        (layers): Sequential(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU()
          (2): Linear(in_features=3072, out_features=768, bias=True)
        )
      )
      (norm1): LayerNorm()
      (norm2): LayerNorm()
      (drop_shortcut): Dropout(p=0.0, inplace=False)
    )
    (8): TransformerBlock(
      (att): MultiHeadAttention(
        (W_query): Linear(in_features=768, out_features=768, bias=True)
        (W_key): Linear(in_features=768, out_features=768, bias=True)
        (W_value): Linear(in_features=768, out_features=768, bias=True)
        (out_proj): Linear(in_features=768, out_features=768, bias=True)
        (dropout): Dropout(p=0.0, inplace=False)
      )
      (ff): FeedForward(
        (layers): Sequential(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU()
          (2): Linear(in_features=3072, out_features=768, bias=True)
        )
      )
      (norm1): LayerNorm()
      (norm2): LayerNorm()
      (drop_shortcut): Dropout(p=0.0, inplace=False)
    )
    (9): TransformerBlock(
      (att): MultiHeadAttention(
        (W_query): Linear(in_features=768, out_features=768, bias=True)
        (W_key): Linear(in_features=768, out_features=768, bias=True)
        (W_value): Linear(in_features=768, out_features=768, bias=True)
        (out_proj): Linear(in_features=768, out_features=768, bias=True)
        (dropout): Dropout(p=0.0, inplace=False)
      )
      (ff): FeedForward(
        (layers): Sequential(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU()
          (2): Linear(in_features=3072, out_features=768, bias=True)
        )
      )
      (norm1): LayerNorm()
      (norm2): LayerNorm()
      (drop_shortcut): Dropout(p=0.0, inplace=False)
    )
    (10): TransformerBlock(
      (att): MultiHeadAttention(
        (W_query): Linear(in_features=768, out_features=768, bias=True)
        (W_key): Linear(in_features=768, out_features=768, bias=True)
        (W_value): Linear(in_features=768, out_features=768, bias=True)
        (out_proj): Linear(in_features=768, out_features=768, bias=True)
        (dropout): Dropout(p=0.0, inplace=False)
      )
      (ff): FeedForward(
        (layers): Sequential(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU()
          (2): Linear(in_features=3072, out_features=768, bias=True)
        )
      )
      (norm1): LayerNorm()
      (norm2): LayerNorm()
      (drop_shortcut): Dropout(p=0.0, inplace=False)
    )
    (11): TransformerBlock(
      (att): MultiHeadAttention(
        (W_query): Linear(in_features=768, out_features=768, bias=True)
        (W_key): Linear(in_features=768, out_features=768, bias=True)
        (W_value): Linear(in_features=768, out_features=768, bias=True)
        (out_proj): Linear(in_features=768, out_features=768, bias=True)
        (dropout): Dropout(p=0.0, inplace=False)
      )
      (ff): FeedForward(
        (layers): Sequential(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU()
          (2): Linear(in_features=3072, out_features=768, bias=True)
        )
      )
      (norm1): LayerNorm()
      (norm2): LayerNorm()
      (drop_shortcut): Dropout(p=0.0, inplace=False)
    )
  )
  (final_norm): LayerNorm()
  (out_head): Linear(in_features=768, out_features=50257, bias=False)
)
```

Above, we can see the GPT architecture neatly laid out. As discussed earlier, the GPTModel consists of embedding layers followed by 12 identical transformer blocks (only the last block is shown for brevity), followed by a final LayerNorm and the output layer, out_head.

Next, we replace the out_head with a new output layer, as illustrated in figure 6.9, that we will finetune.

To get the model ready for classification-finetuning, we first freeze the model, meaning that we make all layers non-trainable:

In [250]:

```
for param in model.parameters():
    param.requires_grad = False
```

Then, we replace the output layer (model.out_head), which originally maps the layer inputs to 50,257 dimensions (the size of the vocabulary):

In [251]:

```
torch.manual_seed(123)

num_classes = 2
model.out_head = torch.nn.Linear(in_features=BASE_CONFIG["emb_dim"], out_features=num_cl
asses)
```

Note that in the preceding code, we use BASE_CONFIG["emb_dim"], which is equal to 768 in the "gpt2-small (124M)" model, to keep the code below more general. This means we can also use the same code to work with the larger GPT-2 model variants. This new model.out_head output layer has its requires_grad attribute set to True by default, which means that it's the only layer in the model that will be updated during training.

This new model.out_head output layer has its requires_grad attribute set to True by default, which means that it's the only layer in the model that will be updated during training.

Additionally, we configure the last transformer block and the final LayerNorm module, which connects this block to the output layer, to be trainable

In [253]:

```
for param in model.trf_blocks[-1].parameters():
    param.requires_grad = True

for param in model.final_norm.parameters():
    param.requires_grad = True
```

Even though we added a new output layer and marked certain layers as trainable or nontrainable, we can still use this model in a similar way to previous chapters. For instance, we can feed it an example text identical to how we have done it in earlier chapters. For example, consider the following example text:

In [254]:

```
inputs = tokenizer.encode("Do you have time")
inputs = torch.tensor(inputs).unsqueeze(0)
print("Inputs:", inputs)
print("Inputs dimensions:", inputs.shape) # shape: (batch_size, num_tokens)
```

```
Inputs: tensor([[5211,  345,  423,  640]])
Inputs dimensions: torch.Size([1, 4])
```

Then, we can pass the encoded token IDs to the model as usual:

In [256]:

```
with torch.no_grad():
    outputs = model(inputs)

print("Outputs:\n", outputs)
print("Outputs dimensions:", outputs.shape) # shape: (batch_size, num_tokens, num_classes
)
```

```
Outputs:
 tensor([[[-1.5854,  0.9904],
         [-3.7235,  7.4548],
         [-2.2661,  6.6049],
         [-3.5983,  3.9902]]])
Outputs dimensions: torch.Size([1, 4, 2])
```

In earlier chapters, a similar input would have produced an output tensor of [1, 4, 50257], where 50,257 represents the vocabulary size. As in previous chapters, the number of output rows corresponds to the number of input tokens (in this case, 4). However, each output's embedding dimension (the number of columns) is now reduced to 2 instead of 50,257 since we replaced the output layer of the model.

Remember that we are interested in finetuning this model so that it returns a class label that indicates whether a model input is spam or not spam. To achieve this, we don't need to finetune all 4 output rows but can focus on a single output token. In particular, we will focus on the last row corresponding to the last output token

To extract the last output token, illustrated in figure 6.11, from the output tensor, we use the following code:

In [286]:

```
print("Last output token:", outputs[:, -1, :])
```

```
Last output token: tensor([[-3.5983,  3.9902]])
```

Having modified the model, the next section will detail the process of transforming the last token into class label predictions and calculate the model's initial prediction accuracy. Following this, we will finetune the model for the spam classification task in the subsequent section.

CALCULATING THE CLASSIFICATION LOSS AND ACCURACY

So far in this chapter, we have prepared the dataset, loaded a pretrained model, and modified it for classification-finetuning. Before we proceed with the finetuning itself, only one small part remains: implementing the model evaluation functions used during finetuning,

Before implementing the evaluation utilities, let's briefly discuss how we convert the model outputs into class label predictions.

In the previous chapter, we computed the token ID of the next token generated by the LLM by converting the 50,257 outputs into probabilities via the softmax function and then returning the position of the highest probability via the argmax function. In this chapter, we take the same approach to calculate whether the model outputs a "spam" or "not spam" prediction for a given input, with the only difference being that we work with 2-dimensional instead of 50,257-dimensional outputs.

Let's consider the last token output from the previous section:

In [259]:

```
print("Last output token:", outputs[:, -1, :])
```

```
Last output token: tensor([[-3.5983,  3.9902]])
```

We can obtain the class label via the following code:

In [287]:

```
probas = torch.softmax(outputs[:, -1, :], dim=-1)
print(probas)
label = torch.argmax(probas)
print("Class label:", label.item())
```

```
tensor([[    0.0005,     0.9995]])
Class label: 1
```

In this case, the code returns 1, meaning the model predicts that the input text is "spam." Using the softmax function here is optional because the largest outputs directly correspond to the highest probability scores. Hence, we can simplify the code as follows, without using softmax:

In [264]:

```
logits = outputs[:, -1, :]
label = torch.argmax(logits)
print("Class label:", label.item())
```

```
Class label: 1
```

This concept can be used to compute the so-called classification accuracy, which measures the percentage of correct predictions across a dataset.

To determine the classification accuracy, we apply the argmax-based prediction code to all examples in the dataset and calculate the proportion of correct predictions by defining a calc_accuracy_loader function:

In [265]:

```
def calc_accuracy_loader(data_loader, model, device, num_batches=None):
    model.eval()
    correct_predictions, num_examples = 0, 0

    if num_batches is None:
        num_batches = len(data_loader)
    else:
        num_batches = min(num_batches, len(data_loader))
    for i, (input_batch, target_batch) in enumerate(data_loader):
        if i < num_batches:
            input_batch, target_batch = input_batch.to(device), target_batch.to(device)
            with torch.no_grad():
                logits = model(input_batch)[:, -1, :]  # Logits of last output token
            predicted_labels = torch.argmax(logits, dim=-1)

            num_examples += predicted_labels.shape[0]
            correct_predictions += (predicted_labels == target_batch).sum().item()
        else:
            break
    return correct_predictions / num_examples
```

Let's use the function to determine the classification accuracies across various datasets estimated from 10 batches for efficiency:

In [266]:

```
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

# Note:
# Uncommenting the following lines will allow the code to run on Apple Silicon chips, if
applicable,
# which is approximately 2x faster than on an Apple CPU (as measured on an M3 MacBook Air
).
# As of this writing, in PyTorch 2.4, the results obtained via CPU and MPS were identical
.
# However, in earlier versions of PyTorch, you may observe different results when using M
PS.

#if torch.cuda.is_available():
#    device = torch.device("cuda")
#elif torch.backends.mps.is_available():
#    device = torch.device("mps")
#else:
#    device = torch.device("cpu")
#print(f"Running on {device} device.")

model.to(device) # no assignment model = model.to(device) necessary for nn.Module classes

torch.manual_seed(123) # For reproducibility due to the shuffling in the training data lo
ader

train_accuracy = calc_accuracy_loader(train_loader, model, device, num_batches=10)
val_accuracy = calc_accuracy_loader(val_loader, model, device, num_batches=10)
test_accuracy = calc_accuracy_loader(test_loader, model, device, num_batches=10)

print(f"Training accuracy: {train_accuracy*100:.2f}%")
print(f"Validation accuracy: {val_accuracy*100:.2f}%")
print(f"Test accuracy: {test_accuracy*100:.2f}%")
```

```
Training accuracy: 46.25%
Validation accuracy: 45.00%
Test accuracy: 48.75%
```

As we can see, the prediction accuracies are near a random prediction, which would be 50% in this case. To improve the prediction accuracies, we need to finetune the model.

Classification accuracy is not a differentiable function, so we use cross entropy loss as a proxy to maximize accuracy. This is the same cross entropy loss discussed earlier. Accordingly, the calc_loss_batch function remains the same as in earlier, with one adjustment: we focus on optimizing only the last token, model(input_batch)[:, -1, :], rather than all tokens, model(input_batch):

In [268]:

```
def calc_loss_batch(input_batch, target_batch, model, device):
    input_batch, target_batch = input_batch.to(device), target_batch.to(device)
    logits = model(input_batch)[:, -1, :]  # Logits of last output token
    loss = torch.nn.functional.cross_entropy(logits, target_batch)
    return loss
```

We use the calc_loss_batch function to compute the loss for a single batch obtained from the previously defined data loaders. To calculate the loss for all batches in a data loader, we define the calc_loss_loader function

In [269]:

```
# Same as in chapter 5
def calc_loss_loader(data_loader, model, device, num_batches=None):
    total_loss = 0.
    if len(data_loader) == 0:
        return float("nan")
    elif num_batches is None:
        num_batches = len(data_loader)
    else:
        # Reduce the number of batches to match the total number of batches in the data l
oader
        # if num_batches exceeds the number of batches in the data loader
        num_batches = min(num_batches, len(data_loader))
    for i, (input_batch, target_batch) in enumerate(data_loader):
        if i < num_batches:
            loss = calc_loss_batch(input_batch, target_batch, model, device)
            total_loss += loss.item()
        else:
            break
    return total_loss / num_batches
```

Similar to calculating the training accuracy, we now compute the initial loss for each data set:

In [270]:

```
with torch.no_grad(): # Disable gradient tracking for efficiency because we are not train
ing, yet
    train_loss = calc_loss_loader(train_loader, model, device, num_batches=5)
    val_loss = calc_loss_loader(val_loader, model, device, num_batches=5)
    test_loss = calc_loss_loader(test_loader, model, device, num_batches=5)

print(f"Training loss: {train_loss:.3f}")
print(f"Validation loss: {val_loss:.3f}")
print(f"Test loss: {test_loss:.3f}")
```

```
Training loss: 2.453
Validation loss: 2.583
Test loss: 2.322
```

In the next section, we will implement a training function to finetune the model, which means adjusting the model to minimize the training set loss. Minimizing the training set loss will help increase the classification accuracy, our overall goal

FINETUNING THE MODEL ON SUPERVISED DATA

In this section, we define and use the training function to finetune the pretrained LLM and improve its spam classification accuracy. The training loop is the same overall training loop we used earlier, with the only difference being that we calculate the classification accuracy instead of generating a sample text for evaluating the model.

The training function also closely mirrors the train_model_simple function used for pretraining the model earlier. The only two distinctions are that we now track the number of training examples seen (examples_seen) instead of the number of tokens, and we calculate the accuracy after each epoch instead of printing a sample text:

Step 1: Set model to training mode Step 2: Reset loss gradients from previous batch iteration Step 3: Calculate loss gradients Step 4: Update model weights using loss gradients Step 5: New: track examples instead of tokens Step 6: Optional evaluation step Step 7: Calculate accuracy after each epoch

In [271]:

```
# Overall the same as `train_model_simple` in chapter 5
def train_classifier_simple(model, train_loader, val_loader, optimizer, device, num_epoch
s,
                            eval_freq, eval_iter):
    # Initialize lists to track losses and examples seen
    train_losses, val_losses, train_accs, val_accs = [], [], [], []
    examples_seen, global_step = 0, -1

    # Main training loop
    for epoch in range(num_epochs):
        model.train()  # Set model to training mode

        for input_batch, target_batch in train_loader:
            optimizer.zero_grad() # Reset loss gradients from previous batch iteration
            loss = calc_loss_batch(input_batch, target_batch, model, device)
            loss.backward() # Calculate loss gradients
            optimizer.step() # Update model weights using loss gradients
            examples_seen += input_batch.shape[0] # New: track examples instead of token
s
            global_step += 1

            ## 130 batches: training, eval_Freq = 50 --> after 50 batches are processed
in each epoch, we print train loss and val loss

            # Optional evaluation step
            if global_step % eval_freq == 0:
                train_loss, val_loss = evaluate_model(
                    model, train_loader, val_loader, device, eval_iter)
                train_losses.append(train_loss)
                val_losses.append(val_loss)
                print(f"Ep {epoch+1} (Step {global_step:06d}): "
                      f"Train loss {train_loss:.3f}, Val loss {val_loss:.3f}")

        # Calculate accuracy after each epoch
        train_accuracy = calc_accuracy_loader(train_loader, model, device, num_batches=e
val_iter)
        val_accuracy = calc_accuracy_loader(val_loader, model, device, num_batches=eval_
iter)
        print(f"Training accuracy: {train_accuracy*100:.2f}% | ", end="")
        print(f"Validation accuracy: {val_accuracy*100:.2f}%")
        train_accs.append(train_accuracy)
        val_accs.append(val_accuracy)

    return train_losses, val_losses, train_accs, val_accs, examples_seen
```

The evaluate_model function used in the train_classifier_simple is the same as the one we used earlier.

In [272]:

```
# Same as chapter 5
```

```
def evaluate_model(model, train_loader, val_loader, device, eval_iter):
    model.eval()
    with torch.no_grad():
        train_loss = calc_loss_loader(train_loader, model, device, num_batches=eval_iter
)
        val_loss = calc_loss_loader(val_loader, model, device, num_batches=eval_iter)
    model.train()
    return train_loss, val_loss
```

Next, we initialize the optimizer, set the number of training epochs, and initiate the training using the train_classifier_simple function. We will discuss the choice of the the number of training epochs after we evaluated the results. The training takes about 6 minutes on an M3 MacBook Air laptop computer and less than half a minute on a V100 or A100 GPU:

In [273]:

```
import time

start_time = time.time()

torch.manual_seed(123)

optimizer = torch.optim.AdamW(model.parameters(), lr=5e-5, weight_decay=0.1)

num_epochs = 5
train_losses, val_losses, train_accs, val_accs, examples_seen = train_classifier_simple(
    model, train_loader, val_loader, optimizer, device,
    num_epochs=num_epochs, eval_freq=50, eval_iter=5,
)

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

```
Ep 1 (Step 000000): Train loss 2.153, Val loss 2.392
Ep 1 (Step 000050): Train loss 0.617, Val loss 0.637
Ep 1 (Step 000100): Train loss 0.523, Val loss 0.557
Training accuracy: 70.00% | Validation accuracy: 72.50%
Ep 2 (Step 000150): Train loss 0.561, Val loss 0.489
Ep 2 (Step 000200): Train loss 0.419, Val loss 0.397
Ep 2 (Step 000250): Train loss 0.409, Val loss 0.353
Training accuracy: 82.50% | Validation accuracy: 85.00%
Ep 3 (Step 000300): Train loss 0.333, Val loss 0.320
Ep 3 (Step 000350): Train loss 0.340, Val loss 0.306
Training accuracy: 90.00% | Validation accuracy: 90.00%
Ep 4 (Step 000400): Train loss 0.136, Val loss 0.200
Ep 4 (Step 000450): Train loss 0.153, Val loss 0.132
Ep 4 (Step 000500): Train loss 0.222, Val loss 0.137
Training accuracy: 100.00% | Validation accuracy: 97.50%
Ep 5 (Step 000550): Train loss 0.207, Val loss 0.143
Ep 5 (Step 000600): Train loss 0.083, Val loss 0.074
Training accuracy: 100.00% | Validation accuracy: 97.50%
Training completed in 8.83 minutes.
```

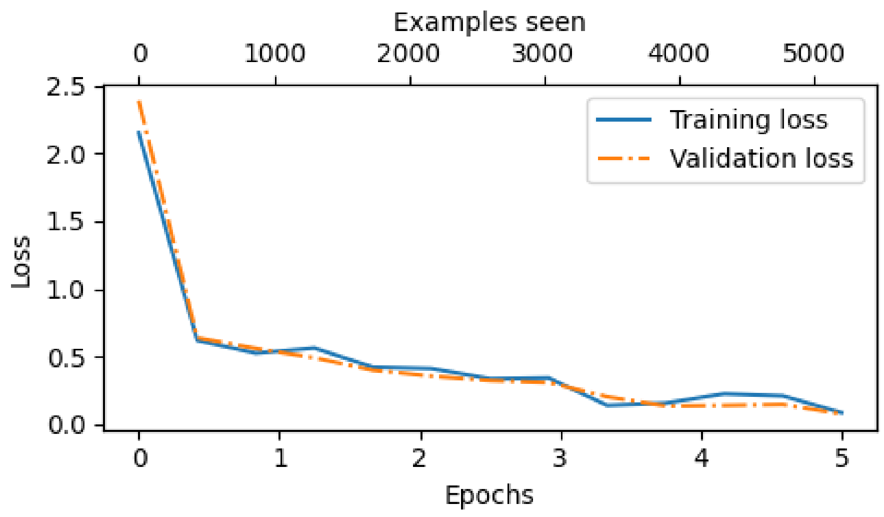
We then use matplotlib to plot the loss function for the training and validation set:

In [276]:

```
import matplotlib.pyplot as plt

def plot_values(epochs_seen, examples_seen, train_values, val_values, label="loss"):
    fig, ax1 = plt.subplots(figsize=(5, 3))

    # Plot training and validation loss against epochs
    ax1.plot(epochs_seen, train_values, label=f"Training {label}")
    ax1.plot(epochs_seen, val_values, linestyle="-.", label=f"Validation {label}")
    ax1.set_xlabel("Epochs")
    ax1.set_ylabel(label.capitalize())
    ax1.legend()

    # Create a second x-axis for examples seen
    ax2 = ax1.twiny()  # Create a second x-axis that shares the same y-axis
    ax2.plot(examples_seen, train_values, alpha=0)  # Invisible plot for aligning ticks
    ax2.set_xlabel("Examples seen")

    fig.tight_layout()  # Adjust layout to make room
    plt.savefig(f"{label}-plot.pdf")
    plt.show()
```

In [277]:

```
epochs_tensor = torch.linspace(0, num_epochs, len(train_losses))
examples_seen_tensor = torch.linspace(0, examples_seen, len(train_losses))

plot_values(epochs_tensor, examples_seen_tensor, train_losses, val_losses)
```

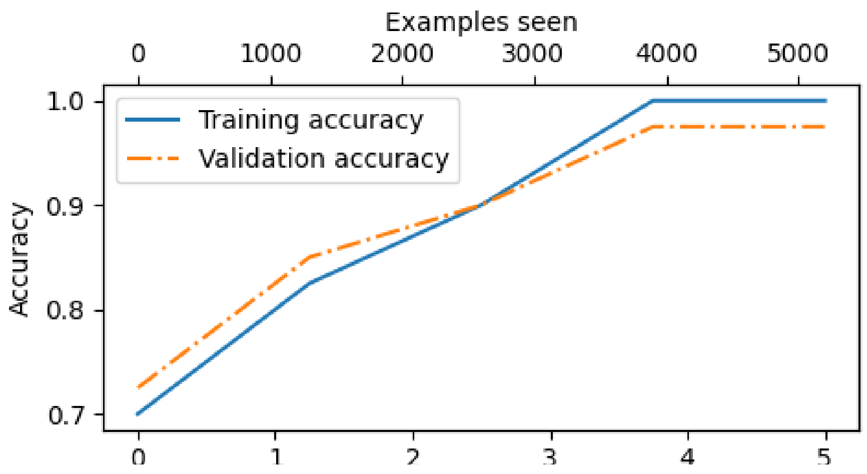


As we can see based on the sharp downward slope, the model is learning well from the training data, and there is little to no indication of overfitting; that is, there is no noticeable gap between the training and validation set losses).

Using the same plot_values function, let's now also plot the classification accuracies:

In [278]:

```
epochs_tensor = torch.linspace(0, num_epochs, len(train_accs))
examples_seen_tensor = torch.linspace(0, examples_seen, len(train_accs))

plot_values(epochs_tensor, examples_seen_tensor, train_accs, val_accs, label="accuracy")
```



Based on the accuracy plot, the model achieves a relatively high training and validation accuracy after epochs 4 and 5. However, it's important to note that we previously set eval_iter=5 when using the train_classifier_simple function, which means our estimations of training and validation performance were based on only 5 batches for efficiency during training. Now, we will calculate the performance metrics for the training, validation, and test sets across the entire dataset by running the following code, this time without defining the eval_iter value:

In [279]:

```
train_accuracy = calc_accuracy_loader(train_loader, model, device)
val_accuracy = calc_accuracy_loader(val_loader, model, device)
test_accuracy = calc_accuracy_loader(test_loader, model, device)

print(f"Training accuracy: {train_accuracy*100:.2f}%")
print(f"Validation accuracy: {val_accuracy*100:.2f}%")
print(f"Test accuracy: {test_accuracy*100:.2f}%")
```

```
Training accuracy: 97.21%
Validation accuracy: 97.32%
Test accuracy: 95.67%
```

The training and test set performances are almost identical. A slight discrepancy between the training and test set accuracies suggests minimal overfitting of the training data. Typically, the validation set accuracy is somewhat higher than the test set accuracy because the model development often involves tuning hyperparameters to perform well on the validation set, which might not generalize as effectively to the test set. This situation is common, but the gap could potentially be minimized by adjusting the model's settings, such as increasing the dropout rate (drop_rate) or the weight_decay parameter in the optimizer configuration.

USING THE LLM AS A SPAM CLASSIFIER

After finetuning and evaluating the model in the previous sections, we are now in the final stage of this chapter: using the model to classify spam messages.

Finally, let's use the finetuned GPT-based spam classification model. The following classify_review function follows data preprocessing steps similar to those we used in the SpamDataset implemented earlier in this chapter. And then, after processing text into token IDs, the function uses the model to predict an integer class label, similar to what we have implemented earlier, and then returns the corresponding class name:

Step 1: Prepare inputs to the model Step 2: Truncate sequences if they too long Step 3: Pad sequences to the longest sequence Step 4: Add batch dimension Step 5: Model inference without gradient tracking Step 6: Logits of the last output token Step 7: Return the classified result

In [281]:

```
def classify_review(text, model, tokenizer, device, max_length=None, pad_token_id=50256)
:
    model.eval()

    # Prepare inputs to the model
    input_ids = tokenizer.encode(text)
    supported_context_length = model.pos_emb.weight.shape[0]
    # Note: In the book, this was originally written as pos_emb.weight.shape[1] by mistak
e
    # It didn't break the code but would have caused unnecessary truncation (to 768 inste
ad of 1024)

    # Truncate sequences if they too long
    input_ids = input_ids[:min(max_length, supported_context_length)]

    # Pad sequences to the longest sequence
    input_ids += [pad_token_id] * (max_length - len(input_ids))
    input_tensor = torch.tensor(input_ids, device=device).unsqueeze(0) # add batch dimen
sion

    # Model inference
    with torch.no_grad():
        logits = model(input_tensor)[:, -1, :]  # Logits of the last output token
    predicted_label = torch.argmax(logits, dim=-1).item()

    # Return the classified result
    return "spam" if predicted_label == 1 else "not spam"
```

Let's try this classify_review function on an example text:

In [282]:

```
text_1 = (
    "You are a winner you have been specially"
    " selected to receive $1000 cash or a $2000 award."
)

print(classify_review(
    text_1, model, tokenizer, device, max_length=train_dataset.max_length
))
```

```
spam
```

The resulting model correctly predicts "spam".

In [283]:

```
text_2 = (
    "Hey, just wanted to check if we're still on"
    " for dinner tonight? Let me know!"
)

print(classify_review(
    text_2, model, tokenizer, device, max_length=train_dataset.max_length
))
```

```
not spam
```

Also, here, the model makes a correct prediction and returns a "not spam" label.

Finally, let's save the model in case we want to reuse the model later without having to train it again using the torch.save method

In [284]:

```
torch.save(model.state_dict(), "review_classifier.pth")
```

Once saved, the model can be loaded as follows:

In [285]:

```
model_state_dict = torch.load("review_classifier.pth")
model.load_state_dict(model_state_dict)
```

Out[285]:

```
<All keys matched successfully>
```

INSTRUCTION FINE-TUNING

STEP 1: PREPARING DATASET

In this section, we download and format the instruction dataset for instruction finetuning a pretrained LLM in this chapter. The dataset consists of 1100 instruction-response pairs. The following code implements and executes a function to download this dataset, which is a relatively small file, only 204 KB in size, in JSON format. JSON, or JavaScript Object Notation, mirrors the structure of Python dictionaries, providing a simple structure for data interchange that is both human-readable and machine-friendly.

In [210]:

```
import json
import os
import urllib
import ssl

def download_and_load_file(file_path, url):
    ssl_context = ssl.create_default_context()
    ssl_context.check_hostname = False
    ssl_context.verify_mode = ssl.CERT_NONE

    if not os.path.exists(file_path):
        with urllib.request.urlopen(url, context=ssl_context) as response:
            text_data = response.read().decode("utf-8")
        with open(file_path, "w", encoding="utf-8") as file:
            file.write(text_data)
    else:
        with open(file_path, "r", encoding="utf-8") as file:
            text_data = file.read()

    with open(file_path, "r", encoding="utf-8") as file:
        data = json.load(file)

    return data


file_path = "instruction-data.json"
url = (
    "https://raw.githubusercontent.com/rasbt/LLMs-from-scratch"
    "/main/ch07/01_main-chapter-code/instruction-data.json"
)

data = download_and_load_file(file_path, url)
print("Number of entries:", len(data))
```

```
Number of entries: 1100
```

The data list , which we loaded from the JSON file contains the 1100 entries of the instruction dataset. Let's print one of the entries to see how each entry is structured:

In [211]:

```
print("Example entry:\n", data[50])
```

```
Example entry:
 {'instruction': 'Identify the correct spelling of the following word.', 'input': 'Ocassi
on', 'output': "The correct spelling is 'Occasion.'"}
```

In [212]:

```
print("Another example entry:\n", data[999])
```

```
Another example entry:
 {'instruction': "What is an antonym of 'complicated'?", 'input': '', 'output': "An anton
ym of 'complicated' is 'simple'."}
```

CONVERTING INSTRUCTIONS INTO ALPACA FORMAT

In [213]:

```
def format_input(entry):
    instruction_text = (
        f"Below is an instruction that describes a task. "
        f"Write a response that appropriately completes the request."
        f"\n\n### Instruction:\n{entry['instruction']}"
    )

    input_text = f"\n\n### Input:\n{entry['input']}" if entry["input"] else ""

    return instruction_text + input_text
```

This format_input function takes a dictionary entry as input and constructs a formatted string.

Let's test it to dataset entry data[50], which to looked at earlier:

In [214]:

```
model_input = format_input(data[50])
desired_response = f"\n\n### Response:\n{data[50]['output']}"

print(model_input + desired_response)
```

```
Below is an instruction that describes a task. Write a response that appropriately comple
tes the request.

### Instruction:
Identify the correct spelling of the following word.

### Input:
Ocassion

### Response:
The correct spelling is 'Occasion.'
```

Note that the format_input skips the optional ### Input: section if the 'input' field is empty, which we can test out by applying the format_input function to entry data[999] that we inspected earlier:

In [215]:

```
model_input = format_input(data[999])
desired_response = f"\n\n### Response:\n{data[999]['output']}"
```

```
print(model_input + desired_response)
```

```
Below is an instruction that describes a task. Write a response that appropriately comple
tes the request.

### Instruction:
What is an antonym of 'complicated'?

### Response:
An antonym of 'complicated' is 'simple'.
```

SPLITTING DATASET INTO TRAIN-TEST-VALIDATION

In [216]:

```
train_portion = int(len(data) * 0.85)  # 85% for training
test_portion = int(len(data) * 0.1)    # 10% for testing
val_portion = len(data) - train_portion - test_portion  # Remaining 5% for validation

train_data = data[:train_portion]
test_data = data[train_portion:train_portion + test_portion]
val_data = data[train_portion + test_portion:]
```

In [217]:

```
print("Training set length:", len(train_data))
print("Validation set length:", len(val_data))
print("Test set length:", len(test_data))
```

```
Training set length: 935
Validation set length: 55
Test set length: 110
```

Having successfully downloaded and partitioned the dataset, and gained a clear understanding of the dataset prompt formatting, we are now ready for the core implementation of the instruction finetuning process.

STEP 2: ORGANIZING DATA INTO TRAINING BATCHES

In the previous chapter, the training batches were created automatically by the PyTorch DataLoader class, which employs a default collate function to combine lists of samples into batches. A collate function is responsible for taking a list of individual data samples and merging them into a single batch that can be processed efficiently by the model during training.

However, the batching process for instruction finetuning in this chapter is a bit more involved and requires us to create our own custom collate function that we will later plug into the DataLoader. We implement this custom collate function to handle the specific requirements and formatting of our instruction finetuning dataset.

First, we code an InstructionDataset class that applies format_input from the previous section and pretokenizes all inputs in the dataset, similar to the SpamDataset in chapter 6.

In [218]:

```
import torch
```

```
from torch.utils.data import Dataset


class InstructionDataset(Dataset):
    def __init__(self, data, tokenizer):
        self.data = data

        # Pre-tokenize texts
        self.encoded_texts = []
        for entry in data:
            instruction_plus_input = format_input(entry)
            response_text = f"\n\n### Response:\n{entry['output']}"
            full_text = instruction_plus_input + response_text
            self.encoded_texts.append(
                tokenizer.encode(full_text)
            )

    def __getitem__(self, index):
        return self.encoded_texts[index]

    def __len__(self):
        return len(self.data)
```

Similar to the approach in chapter 6, we aim to accelerate training by collecting multiple training examples in a batch, which necessitates padding all inputs to a similar length. As with the previous chapter, we use the <|endoftext|> token as a padding token. Instead of appending the <|endoftext|> tokens to the text inputs, we can append its token ID to the pre-tokenized inputs directly. To remind us which token ID we should use, we can use the tokenizer's .encode method on an <|endoftext|> token:

In [219]:

```
import tiktoken
tokenizer = tiktoken.get_encoding("gpt2")

print(tokenizer.encode("<|endoftext|>", allowed_special={"<|endoftext|>"}))
```

```
[50256]
```

In chapter 6, we padded all examples in a dataset to the same length. Moving on, here, we adopt a more sophisticated approach by developing a custom collate function that we can pass to the data loader. This custom collate function pads the training examples in each batch to have the same length, while allowing different batches to have different lengths. This approach minimizes unnecessary padding by only extending sequences to match the longest one in each batch, not the whole dataset.

We can implement the padding process with a custom collate function as follows:

Step 1: Find the longest sequence in the batch Step 2: Pad and prepare inputs Step 3: Remove extra padded token added earlier Step 4: Convert list of inputs to tensor and transfer to target device

In [220]:

```
def custom_collate_draft_1(
    batch,
    pad_token_id=50256,
    device="cpu"
):
    # Find the longest sequence in the batch
    # and increase the max length by +1, which will add one extra
    # padding token below
    batch_max_length = max(len(item)+1 for item in batch)

    # Pad and prepare inputs
    inputs_lst = []

    for item in batch:
        new_item = item.copy()
        # Add an <|endoftext|> token
        new_item += [pad_token_id]
        # Pad sequences to batch_max_length
        padded = (
            new_item + [pad_token_id] *
            (batch_max_length - len(new_item))
        )
        # Via padded[:-1], we remove the extra padded token
        # that has been added via the +1 setting in batch_max_length
        # (the extra padding token will be relevant in later codes)
        inputs = torch.tensor(padded[:-1])
        inputs_lst.append(inputs)

    # Convert list of inputs to tensor and transfer to target device
    inputs_tensor = torch.stack(inputs_lst).to(device)
    return inputs_tensor
```

The custom_collate_draft_1 we implemented is designed to be integrated into a PyTorch DataLoader, but it can also function as a standalone tool. Here, we use it independently to test and verify that it operates as intended.

Let's try it on three different inputs that we want to assemble into a batch, where each example gets padded to the same length:

In [221]:

```
inputs_1 = [0, 1, 2, 3, 4]
inputs_2 = [5, 6]
inputs_3 = [7, 8, 9]

batch = (
    inputs_1,
    inputs_2,
    inputs_3
)

print(custom_collate_draft_1(batch))
```

```
tensor([[    0,     1,     2,     3,     4],
        [    5,     6, 50256, 50256, 50256],
        [    7,     8,     9, 50256, 50256]])
```

As we can see based on the preceding output, all inputs have been padded to the length of the longest input list, inputs_1 containing 5 token IDs.

So far, we have just implemented our first custom collate function to create batches from lists of inputs. However, as you learned in previous lessons, we also need to create batches with the target token IDs, corresponding to the batch of input IDs. These target IDs are crucial because they represent what we want the model to generate and what we need during training to calculate the loss for the weight updates, similar to previous chapters.

CREATING TARGET TOKEN IDS FOR TRAINING

Similar to the process described for pretraining an LLM, the target token IDs match the input token IDs but are shifted one position to the right. This setup allows the LLM to learn how to predict the next token in a sequence.

The following updated collate function generates the target token IDs from the input token IDs:

In [222]:

```
def custom_collate_draft_2(
    batch,
    pad_token_id=50256,
    device="cpu"
):
    # Find the longest sequence in the batch
    batch_max_length = max(len(item)+1 for item in batch)

    # Pad and prepare inputs
    inputs_lst, targets_lst = [], []

    for item in batch:
        new_item = item.copy()
        # Add an <|endoftext|> token
        new_item += [pad_token_id]
        # Pad sequences to max_length
        padded = (
            new_item + [pad_token_id] *
            (batch_max_length - len(new_item))
        )
        inputs = torch.tensor(padded[:-1])  # Truncate the last token for inputs
        targets = torch.tensor(padded[1:])  # Shift +1 to the right for targets
        inputs_lst.append(inputs)
        targets_lst.append(targets)

    # Convert list of inputs to tensor and transfer to target device
    inputs_tensor = torch.stack(inputs_lst).to(device)
    targets_tensor = torch.stack(targets_lst).to(device)
    return inputs_tensor, targets_tensor
```

Step 1: Truncate the last token for inputs Step 2: Shift +1 to the right for targets

In [223]:

```
inputs_1 = [0, 1, 2, 3, 4]
inputs_2 = [5, 6]
inputs_3 = [7, 8, 9]

batch = (
    inputs_1,
    inputs_2,
    inputs_3
)

inputs, targets = custom_collate_draft_2(batch)
print(inputs)
print(targets)
```

```
tensor([[    0,     1,     2,     3,     4],
        [    5,     6, 50256, 50256, 50256],
        [    7,     8,     9, 50256, 50256]])
tensor([[    1,     2,     3,     4, 50256],
        [    6, 50256, 50256, 50256, 50256],
        [    8,     9, 50256, 50256, 50256]])
```

The 1st tensor represents inputs. The 2nd tensor represents the targets

In the next step, we assign a -100 placeholder value to all padding tokens. This special value allows us to exclude these padding tokens from contributing to the training loss calculation, ensuring that only meaningful data influences model learning. In classification fine-tuning, we did not have to worry about this since we only trained the model based on the last output token.)

Note that we retain one end-of-text token, ID 50256, in the target list. This allows the LLM to learn when to generate an end-of-text token in response to instructions, which we use as an indicator that the generated response is complete.

In the following code, we modify our custom collate function to replace tokens with ID 50256 with -100 in the target lists. Additionally, we introduce an allowed_max_length parameter to optionally limit the length of the samples. This adjustment will be useful if you plan to work with your own datasets that exceed the 1024-token context size supported by the GPT-2 model. The code for this updated collate function is as follows:

In [224]:

```
def custom_collate_fn(
    batch,
    pad_token_id=50256,
    ignore_index=-100,
    allowed_max_length=None,
    device="cpu"
):
    # Find the longest sequence in the batch
    batch_max_length = max(len(item)+1 for item in batch)

    # Pad and prepare inputs and targets
    inputs_lst, targets_lst = [], []

    for item in batch:
        new_item = item.copy()
        # Add an <|endoftext|> token
        new_item += [pad_token_id]
        # Pad sequences to max_length
        padded = (
            new_item + [pad_token_id] *
            (batch_max_length - len(new_item))
        )
        inputs = torch.tensor(padded[:-1])  # Truncate the last token for inputs
        targets = torch.tensor(padded[1:])  # Shift +1 to the right for targets

        # New: Replace all but the first padding tokens in targets by ignore_index
        mask = targets == pad_token_id
        indices = torch.nonzero(mask).squeeze()
        if indices.numel() > 1:
            targets[indices[1:]] = ignore_index

        # New: Optionally truncate to maximum sequence length
        if allowed_max_length is not None:
            inputs = inputs[:allowed_max_length]
            targets = targets[:allowed_max_length]

        inputs_lst.append(inputs)
        targets_lst.append(targets)

    # Convert list of inputs and targets to tensors and transfer to target device
    inputs_tensor = torch.stack(inputs_lst).to(device)
    targets_tensor = torch.stack(targets_lst).to(device)
    return inputs_tensor, targets_tensor
```

Step 1: Replace all but the first padding tokens in targets by ignore_index Step 2: Optionally truncate to maximum sequence length

Again, let's try the collate function on the sample batch that we created earlier to check that it works as intended:

In [225]:

```
inputs_1 = [0, 1, 2, 3, 4]
inputs_2 = [5, 6]
inputs_3 = [7, 8, 9]

batch = (
    inputs_1,
    inputs_2,
    inputs_3
)

inputs, targets = custom_collate_fn(batch)
print(inputs)
print(targets)
```

```
tensor([[    0,     1,     2,     3,     4],
        [    5,     6, 50256, 50256, 50256],
        [    7,     8,     9, 50256, 50256]])
tensor([[    1,     2,     3,     4, 50256],
        [    6, 50256,  -100,  -100,  -100],
        [    8,     9, 50256,  -100,  -100]])
```

The modified collate function works as expected, altering the target list by inserting the token ID -100. What is the logic behind this adjustment? Let's explore the underlying purpose of this modification.

For demonstration purposes, consider the following simple and self-contained example where each output logit can correspond to a potential token from the model's vocabulary. Here's how we might calculate the cross entropy loss (introduced in chapter 5) during training when the model predicts a sequence of tokens, similar to what we have done in chapter 5 when pretraining the model, or in chapter 6 when finetuning the model for classification:

In [226]:

```
logits_1 = torch.tensor(
    [[-1.0, 1.0],   # 1st training example
     [-0.5, 1.5]]   # 2nd training example
)
targets_1 = torch.tensor([0, 1])


loss_1 = torch.nn.functional.cross_entropy(logits_1, targets_1)
print(loss_1)
```

```
tensor(1.1269)
```

Adding an additional token ID will, as we would expect, affect the loss calculation.

In [227]:

```
logits_2 = torch.tensor(
    [[-1.0, 1.0],
     [-0.5, 1.5],
     [-0.5, 1.5]]  # New 3rd training example
)
targets_2 = torch.tensor([0, 1, 1])

loss_2 = torch.nn.functional.cross_entropy(logits_2, targets_2)
print(loss_2)
```

```
tensor(0.7936)
```

Now, let's get to the interesting part and see what happens if we replace the third target token ID with -100:

In [228]:

```
logits_2 = torch.tensor(
    [[-1.0, 1.0],
     [-0.5, 1.5],
     [-0.5, 1.5]]  # New 3rd training example
)

targets_3 = torch.tensor([0, 1, -100])

loss_3 = torch.nn.functional.cross_entropy(logits_2, targets_3)
print(loss_3)
print("loss_1 == loss_3:", loss_1 == loss_3)
```

```
tensor(1.1269)
loss_1 == loss_3: tensor(True)
```

Based on this result, we can see that the resulting loss on these 3 training examples is identical to the loss we calculated from the 2 training examples earlier. In other words, the cross entropy loss function ignored the third entry in the targets_3 vector, the token ID corresponding to -100. (Interested readers can try to replace the -100 value with another token IDs that is not 0 or 1, and will see that this results in an error.)

So, what's so special about -100 that it's ignored by the cross entropy loss? The default setting of the cross entropy function in PyTorch is cross_entropy(..., ignore_index=-100). This means that it ignores targets labeled with -100.

In this chapter, we take advantage of this ignore_index to ignore the additional end-oftext (padding) tokens that we used to pad the training examples to have the same length in each batch.

However, we want to keep one 50256 (end-of-text) token ID in the targets because it helps the LLM to learn to generate end-of-text tokens, which we can use as an indicator that a response is complete.

MASKING TARGET TOKEN IDS

In addition to masking out padding tokens, it is also common to mask out the target token IDs that correspond to the instruction

By masking out the target token IDs that correspond to the instruction, the LLM cross entropy loss is only computed for the generated response target IDs. By masking out the instruction tokens, the model is trained to focus on generating accurate responses rather than additionally also memorizing instructions, which can help with reducing overfitting.

Currently, researchers are divided on whether masking the instructions is universally beneficial during instruction finetuning. For instance, a recent paper titled "Instruction Tuning With Loss Over Instructions" demonstrated that not masking the instructions benefits the LLM performance. In this chapter, we do not apply masking and leave it as an optional exercise for the reader.

STEP 3: CREATING DATALOADERS FOR AN INSTRUCTION DATASET

The custom_collate_fn includes code to move the input and target tensors (for example, torch.stack(inputs_lst).to(device)) to a specified device, which can be either "cpu" or "cuda" (for GPUs), or optionally "mps" for Macs with Apple Silicon chips.

In previous chapters, we moved the data onto the target device (for example, the GPU memory when device="cuda") in the main training loop. Having this as part of the collate function offers the advantage of performing this device transfer process as a background process outside the training loop, preventing it from blocking the GPU during model training.

The following code initializes the device variable:

In [229]:

```
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

# Note:
# Uncommenting the following lines will allow the code to run on Apple Silicon chips, if applicable,
# which is much faster than on an Apple CPU (as measured on an M3 MacBook Air).
# However, the resulting loss values may be slightly different.

#if torch.cuda.is_available():
#    device = torch.device("cuda")
#elif torch.backends.mps.is_available():
#    device = torch.device("mps")
#else:
#    device = torch.device("cpu")

print("Device:", device)
```

```
Device: cpu
```

Next, to reuse the chosen device setting in custom_collate_fn when we plug it into the PyTorch DataLoader class later in this section, we use the partial function from Python's functools standard library to create a new version of the function with the device argument pre-filled. Additionally, we set the allowed_max_length to 1024, which truncates the data to the maximum context length supported by the GPT-2 model we finetune later in this chapter:

In [230]:

```
from functools import partial
from functools import partial
customized_collate_fn = partial(custom_collate_fn, device=device, allowed_max_length=102
4)
```

Next, we can set up the data loaders as we did in previous chapters, but this time we will use our custom collate function for the batching process:

In [231]:

```python
from torch.utils.data import DataLoader


num_workers = 0
batch_size = 8

torch.manual_seed(123)

train_dataset = InstructionDataset(train_data, tokenizer)
train_loader = DataLoader(
    train_dataset,
    batch_size=batch_size,
    collate_fn=customized_collate_fn,
    shuffle=True,
    drop_last=True,
    num_workers=num_workers
)

val_dataset = InstructionDataset(val_data, tokenizer)
val_loader = DataLoader(
    val_dataset,
    batch_size=batch_size,
    collate_fn=customized_collate_fn,
    shuffle=False,
    drop_last=False,
    num_workers=num_workers
)

test_dataset = InstructionDataset(test_data, tokenizer)
test_loader = DataLoader(
    test_dataset,
    batch_size=batch_size,
    collate_fn=customized_collate_fn,
    shuffle=False,
    drop_last=False,
    num_workers=num_workers
)
```

Let's examine the dimensions of the input and target batches generated by the training loader:

In [232]:

```python
print("Train loader:")
for inputs, targets in train_loader:
    print(inputs.shape, targets.shape)
```

```
Train loader:
torch.Size([8, 61]) torch.Size([8, 61])
torch.Size([8, 76]) torch.Size([8, 76])
torch.Size([8, 73]) torch.Size([8, 73])
torch.Size([8, 68]) torch.Size([8, 68])
torch.Size([8, 65]) torch.Size([8, 65])
torch.Size([8, 72]) torch.Size([8, 72])
torch.Size([8, 80]) torch.Size([8, 80])
torch.Size([8, 67]) torch.Size([8, 67])
torch.Size([8, 62]) torch.Size([8, 62])
torch.Size([8, 75]) torch.Size([8, 75])
torch.Size([8, 62]) torch.Size([8, 62])
torch.Size([8, 68]) torch.Size([8, 68])
torch.Size([8, 67]) torch.Size([8, 67])
torch.Size([8, 77]) torch.Size([8, 77])
torch.Size([8, 69]) torch.Size([8, 69])
torch.Size([8, 79]) torch.Size([8, 79])
torch.Size([8, 71]) torch.Size([8, 71])
torch.Size([8, 66]) torch.Size([8, 66])
torch.Size([8, 83]) torch.Size([8, 83])
torch.Size([8, 68]) torch.Size([8, 68])
torch.Size([8, 80]) torch.Size([8, 80])
torch.Size([8, 71]) torch.Size([8, 71])
torch.Size([8, 69]) torch.Size([8, 69])
torch.Size([8, 65]) torch.Size([8, 65])
torch.Size([8, 68]) torch.Size([8, 68])
torch.Size([8, 60]) torch.Size([8, 60])
torch.Size([8, 59]) torch.Size([8, 59])
torch.Size([8, 69]) torch.Size([8, 69])
torch.Size([8, 63]) torch.Size([8, 63])
torch.Size([8, 65]) torch.Size([8, 65])
torch.Size([8, 76]) torch.Size([8, 76])
torch.Size([8, 66]) torch.Size([8, 66])
torch.Size([8, 71]) torch.Size([8, 71])
torch.Size([8, 91]) torch.Size([8, 91])
torch.Size([8, 65]) torch.Size([8, 65])
torch.Size([8, 64]) torch.Size([8, 64])
torch.Size([8, 67]) torch.Size([8, 67])
torch.Size([8, 66]) torch.Size([8, 66])
torch.Size([8, 64]) torch.Size([8, 64])
torch.Size([8, 65]) torch.Size([8, 65])
torch.Size([8, 75]) torch.Size([8, 75])
torch.Size([8, 89]) torch.Size([8, 89])
torch.Size([8, 59]) torch.Size([8, 59])
torch.Size([8, 88]) torch.Size([8, 88])
torch.Size([8, 83]) torch.Size([8, 83])
torch.Size([8, 83]) torch.Size([8, 83])
torch.Size([8, 70]) torch.Size([8, 70])
torch.Size([8, 65]) torch.Size([8, 65])
torch.Size([8, 74]) torch.Size([8, 74])
torch.Size([8, 76]) torch.Size([8, 76])
torch.Size([8, 67]) torch.Size([8, 67])
torch.Size([8, 75]) torch.Size([8, 75])
torch.Size([8, 83]) torch.Size([8, 83])
torch.Size([8, 69]) torch.Size([8, 69])
torch.Size([8, 67]) torch.Size([8, 67])
torch.Size([8, 60]) torch.Size([8, 60])
torch.Size([8, 60]) torch.Size([8, 60])
torch.Size([8, 66]) torch.Size([8, 66])
torch.Size([8, 80]) torch.Size([8, 80])
torch.Size([8, 71]) torch.Size([8, 71])
torch.Size([8, 61]) torch.Size([8, 61])
torch.Size([8, 58]) torch.Size([8, 58])
torch.Size([8, 71]) torch.Size([8, 71])
torch.Size([8, 67]) torch.Size([8, 67])
torch.Size([8, 68]) torch.Size([8, 68])
torch.Size([8, 63]) torch.Size([8, 63])
torch.Size([8, 87]) torch.Size([8, 87])
torch.Size([8, 68]) torch.Size([8, 68])
torch.Size([8, 64]) torch.Size([8, 64])
torch.Size([8, 68]) torch.Size([8, 68])
torch.Size([8, 71]) torch.Size([8, 71])
torch.Size([8, 68]) torch.Size([8, 68])
torch.Size([8, 71]) torch.Size([8, 71])
torch.Size([8, 61]) torch.Size([8, 61])
torch.Size([8, 65]) torch.Size([8, 65])
torch.Size([8, 67]) torch.Size([8, 67])
torch.Size([8, 65]) torch.Size([8, 65])
torch.Size([8, 64]) torch.Size([8, 64])
torch.Size([8, 60]) torch.Size([8, 60])
torch.Size([8, 72]) torch.Size([8, 72])
torch.Size([8, 64]) torch.Size([8, 64])
torch.Size([8, 70]) torch.Size([8, 70])
torch.Size([8, 57]) torch.Size([8, 57])
torch.Size([8, 72]) torch.Size([8, 72])
torch.Size([8, 64]) torch.Size([8, 64])
torch.Size([8, 68]) torch.Size([8, 68])
torch.Size([8, 62]) torch.Size([8, 62])
torch.Size([8, 74]) torch.Size([8, 74])
torch.Size([8, 80]) torch.Size([8, 80])
torch.Size([8, 68]) torch.Size([8, 68])
torch.Size([8, 70]) torch.Size([8, 70])
torch.Size([8, 91]) torch.Size([8, 91])
torch.Size([8, 61]) torch.Size([8, 61])
torch.Size([8, 66]) torch.Size([8, 66])
torch.Size([8, 80]) torch.Size([8, 80])
torch.Size([8, 81]) torch.Size([8, 81])
torch.Size([8, 74]) torch.Size([8, 74])
torch.Size([8, 82]) torch.Size([8, 82])
torch.Size([8, 63]) torch.Size([8, 63])
torch.Size([8, 83]) torch.Size([8, 83])
torch.Size([8, 68]) torch.Size([8, 68])
torch.Size([8, 67]) torch.Size([8, 67])
torch.Size([8, 77]) torch.Size([8, 77])
torch.Size([8, 91]) torch.Size([8, 91])
torch.Size([8, 64]) torch.Size([8, 64])
torch.Size([8, 61]) torch.Size([8, 61])
torch.Size([8, 75]) torch.Size([8, 75])
torch.Size([8, 64]) torch.Size([8, 64])
torch.Size([8, 66]) torch.Size([8, 66])
torch.Size([8, 78]) torch.Size([8, 78])
torch.Size([8, 66]) torch.Size([8, 66])
torch.Size([8, 64]) torch.Size([8, 64])
torch.Size([8, 83]) torch.Size([8, 83])
torch.Size([8, 66]) torch.Size([8, 66])
torch.Size([8, 74]) torch.Size([8, 74])
torch.Size([8, 69]) torch.Size([8, 69])
```

In the preceding output, we can see that the first input and target batch have dimensions 8×61, where 8 represents the batch size, and 61 is the number of tokens in each training example in this batch. The second input and target batch have a different number of tokens, for instance, 76. As we saw in the preceding code output, thanks to our custom collate function, the data loader is able to create batches of different lengths. In the next section, we load a pretrained LLM that we can then finetune with this data loader.

STEP 4: LOADING A PRETRAINED LLM

Before beginning instruction finetuning, we first load a pretrained GPT model,

Instead of using the smallest 124 million parameter model as before, we load the medium-sized model with 355 million parameters. The reason for this choice is that the 124 million parameter model is too limited in capacity to achieve qualitatively satisfactory results via instruction finetuning.

This is done using the same code as in section 5.5 of chapter 5 and section 6.4 of the previous chapter, except that we now specify "gpt2-medium (355M)" instead of "gpt2-small (124M)". Please note that executing the code provided below will initiate the download of the medium-sized GPT model, which has a storage requirement of approximately 1.42 gigabytes. This is roughly three times larger than the storage space needed for the small model:

In [233]:

```
from gpt_download3 import download_and_load_gpt2
```

```python
BASE_CONFIG = {
    "vocab_size": 50257,     # Vocabulary size
    "context_length": 1024,  # Context length
    "drop_rate": 0.0,        # Dropout rate
    "qkv_bias": True         # Query-key-value bias
}

model_configs = {
    "gpt2-small (124M)": {"emb_dim": 768, "n_layers": 12, "n_heads": 12},
    "gpt2-medium (355M)": {"emb_dim": 1024, "n_layers": 24, "n_heads": 16},
    "gpt2-large (774M)": {"emb_dim": 1280, "n_layers": 36, "n_heads": 20},
    "gpt2-xl (1558M)": {"emb_dim": 1600, "n_layers": 48, "n_heads": 25},
}

CHOOSE_MODEL = "gpt2-medium (355M)"

BASE_CONFIG.update(model_configs[CHOOSE_MODEL])

model_size = CHOOSE_MODEL.split(" ")[-1].lstrip("(").rstrip(")")
settings, params = download_and_load_gpt2(
    model_size=model_size,
    models_dir="gpt2"
)

model = GPTModel(BASE_CONFIG)
load_weights_into_gpt(model, params)
model.eval();
```

```
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-packages/urllib3/c
onnectionpool.py:1103: InsecureRequestWarning: Unverified HTTPS request is being made to
host 'openaipublic.blob.core.windows.net'. Adding certificate verification is strongly ad
vised. See: https://urllib3.readthedocs.io/en/latest/advanced-usage.html#tls-warnings
  warnings.warn(
```

```
File already exists and is up-to-date: gpt2/355M/checkpoint
```

```
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-packages/urllib3/c
onnectionpool.py:1103: InsecureRequestWarning: Unverified HTTPS request is being made to
host 'openaipublic.blob.core.windows.net'. Adding certificate verification is strongly ad
vised. See: https://urllib3.readthedocs.io/en/latest/advanced-usage.html#tls-warnings
  warnings.warn(
```

```
File already exists and is up-to-date: gpt2/355M/encoder.json
```

```
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-packages/urllib3/c
onnectionpool.py:1103: InsecureRequestWarning: Unverified HTTPS request is being made to
host 'openaipublic.blob.core.windows.net'. Adding certificate verification is strongly ad
vised. See: https://urllib3.readthedocs.io/en/latest/advanced-usage.html#tls-warnings
  warnings.warn(
```

```
File already exists and is up-to-date: gpt2/355M/hparams.json
```

```
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-packages/urllib3/c
onnectionpool.py:1103: InsecureRequestWarning: Unverified HTTPS request is being made to
host 'openaipublic.blob.core.windows.net'. Adding certificate verification is strongly ad
vised. See: https://urllib3.readthedocs.io/en/latest/advanced-usage.html#tls-warnings
  warnings.warn(
```

```
File already exists and is up-to-date: gpt2/355M/model.ckpt.data-00000-of-00001
```

```
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-packages/urllib3/c
onnectionpool.py:1103: InsecureRequestWarning: Unverified HTTPS request is being made to
host 'openaipublic.blob.core.windows.net'. Adding certificate verification is strongly ad
vised. See: https://urllib3.readthedocs.io/en/latest/advanced-usage.html#tls-warnings
  warnings.warn(
```

```
File already exists and is up-to-date: gpt2/355M/model.ckpt.index
```

```
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-packages/urllib3/c
onnectionpool.py:1103: InsecureRequestWarning: Unverified HTTPS request is being made to
host 'openaipublic.blob.core.windows.net'. Adding certificate verification is strongly ad
vised. See: https://urllib3.readthedocs.io/en/latest/advanced-usage.html#tls-warnings
  warnings.warn(
File already exists and is up-to-date: gpt2/355M/model.ckpt.meta
```

```
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-packages/urllib3/c
onnectionpool.py:1103: InsecureRequestWarning: Unverified HTTPS request is being made to
host 'openaipublic.blob.core.windows.net'. Adding certificate verification is strongly ad
vised. See: https://urllib3.readthedocs.io/en/latest/advanced-usage.html#tls-warnings
  warnings.warn(
```

```
File already exists and is up-to-date: gpt2/355M/vocab.bpe
```

Before diving into finetuning the model in the next section, let's take a moment to assess the pretrained LLM's performance on one of the validation tasks by comparing its output to the expected response. This will give us a baseline understanding of how well the model performs on an instruction-following task right out of the box, prior to finetuning, and will help us appreciate the impact of finetuning later on. We use the first example from the validation set for this assessment:

In [234]:

```python
torch.manual_seed(123)
input_text = format_input(val_data[0])
print(input_text)
```

```
Below is an instruction that describes a task. Write a response that appropriately comple
tes the request.

### Instruction:
Convert the active sentence to passive: 'The chef cooks the meal every day.'
```

In [235]:

```python
token_ids = generate(
    model=model,
    idx=text_to_token_ids(input_text, tokenizer),
    max_new_tokens=35,
    context_size=BASE_CONFIG["context_length"],
    eos_id=50256,
)
generated_text = token_ids_to_text(token_ids, tokenizer)
```

It's important to note that the generate function returns the combined input and output text. This behavior was convenient in previous chapters since pretrained LLMs are primarily designed as text-completion models, where the input and output are concatenated to create a coherent and legible text. However, when evaluating the model's performance on a specific task, we often want to focus solely on the model's generated response.

To isolate the model's response text, we need to subtract the length of the input instruction from the start of the generated_text:

In [236]:

```python
response_text = generated_text[len(input_text):].strip()
print(response_text)
```

```
### Response:

The chef cooks the meal every day.

### Instruction:

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

This code snippet 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 as follows:

As we can see from the output, 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. In the upcoming section, we implement the finetuning process to improve the model's ability to comprehend and appropriately respond to such requests.

STEP 5: FINETUNING THE LLM ON INSTRUCTION DATA

We already did all the hard work when we implemented the instruction dataset processing at the beginning of this chapter. For the finetuning process itself, we can reuse the loss calculation and training functions implemented in chapter 5 during the pretraining:

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

PREVIOUSLY DEFINED FUNCTIONS WHICH WE WILL REQUIRE

In [ ]:

```
def calc_loss_batch(input_batch, target_batch, model, device):
    input_batch, target_batch = input_batch.to(device), target_batch.to(device)
    logits = model(input_batch)
    loss = torch.nn.functional.cross_entropy(logits.flatten(0, 1), target_batch.flatten(
))
    return loss


def calc_loss_loader(data_loader, model, device, num_batches=None):
    total_loss = 0.
    if len(data_loader) == 0:
        return float("nan")
    elif num_batches is None:
        num_batches = len(data_loader)
    else:
        # Reduce the number of batches to match the total number of batches in the data l
oader
        # if num_batches exceeds the number of batches in the data loader
        num_batches = min(num_batches, len(data_loader))
    for i, (input_batch, target_batch) in enumerate(data_loader):
        if i < num_batches:
            loss = calc_loss_batch(input_batch, target_batch, model, device)
            total_loss += loss.item()
        else:
            break
    return total_loss / num_batches

def train_model_simple(model, train_loader, val_loader, optimizer, device, num_epochs,
                       eval_freq, eval_iter, start_context, tokenizer):
    # Initialize lists to track losses and tokens seen
    train_losses, val_losses, track_tokens_seen = [], [], []
    tokens_seen, global_step = 0, -1

    # Main training loop
    for epoch in range(num_epochs):
        model.train()  # Set model to training mode
        for input_batch, target_batch in train_loader:
            optimizer.zero_grad() # Reset loss gradients from previous batch iteration
            loss = calc_loss_batch(input_batch, target_batch, model, device)
            loss.backward() # Calculate loss gradients
            optimizer.step() # Update model weights using loss gradients
            tokens_seen += input_batch.numel() # Returns the total number of elements (o
r tokens) in the input_batch.
            global_step += 1

            # Optional evaluation step
            if global_step % eval_freq == 0:
                train_loss, val_loss = evaluate_model(
                    model, train_loader, val_loader, device, eval_iter)
                train_losses.append(train_loss)
                val_losses.append(val_loss)
                track_tokens_seen.append(tokens_seen)
                print(f"Ep {epoch+1} (Step {global_step:06d}): "
                      f"Train loss {train_loss:.3f}, Val loss {val_loss:.3f}")

        # Print a sample text after each epoch
        generate_and_print_sample(
            model, tokenizer, device, start_context
        )

    return train_losses, val_losses, track_tokens_seen
```

In [237]:

```
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)
```

```
Training loss: 3.8258946418762205
Validation loss: 3.7619189739227297
```

With the model and data loaders prepared, we can now proceed to train the model. The following code 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 earlier:

In [238]:

```
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 = 1

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.")
```

```
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 0.945
Ep 1 (Step 000015): Train loss 0.857, Val loss 0.906
Ep 1 (Step 000020): Train loss 0.776, Val loss 0.881
Ep 1 (Step 000025): Train loss 0.754, Val loss 0.859
Ep 1 (Step 000030): Train loss 0.799, Val loss 0.836
Ep 1 (Step 000035): Train loss 0.714, Val loss 0.808
Ep 1 (Step 000040): Train loss 0.672, Val loss 0.806
Ep 1 (Step 000045): Train loss 0.633, Val loss 0.790
Ep 1 (Step 000050): Train loss 0.662, Val loss 0.783
Ep 1 (Step 000055): Train loss 0.760, Val loss 0.764
Ep 1 (Step 000060): Train loss 0.719, Val loss 0.743
Ep 1 (Step 000065): Train loss 0.652, Val loss 0.735
Ep 1 (Step 000070): Train loss 0.532, Val loss 0.729
Ep 1 (Step 000075): Train loss 0.569, Val loss 0.729
Ep 1 (Step 000080): Train loss 0.605, Val loss 0.725
Ep 1 (Step 000085): Train loss 0.509, Val loss 0.709
Ep 1 (Step 000090): Train loss 0.562, Val loss 0.691
Ep 1 (Step 000095): Train loss 0.500, Val loss 0.681
Ep 1 (Step 000100): Train loss 0.502, Val loss 0.677
Ep 1 (Step 000105): Train loss 0.564, Val loss 0.670
Ep 1 (Step 000110): Train loss 0.555, Val loss 0.667
Ep 1 (Step 000115): Train loss 0.508, Val loss 0.664
Below is an instruction that describes a task. Write a response that appropriately comple
tes the request.  ### Instruction: Convert the active sentence to passive: 'The chef cook
s the meal every day.'  ### Response: The meal is prepared every day by the chef.<|endoft
ext|>The following is an instruction that describes a task. Write a response that appropr
iately completes the request.  ### Instruction: Convert the active sentence to passive:
Training completed in 121.19 minutes.
```

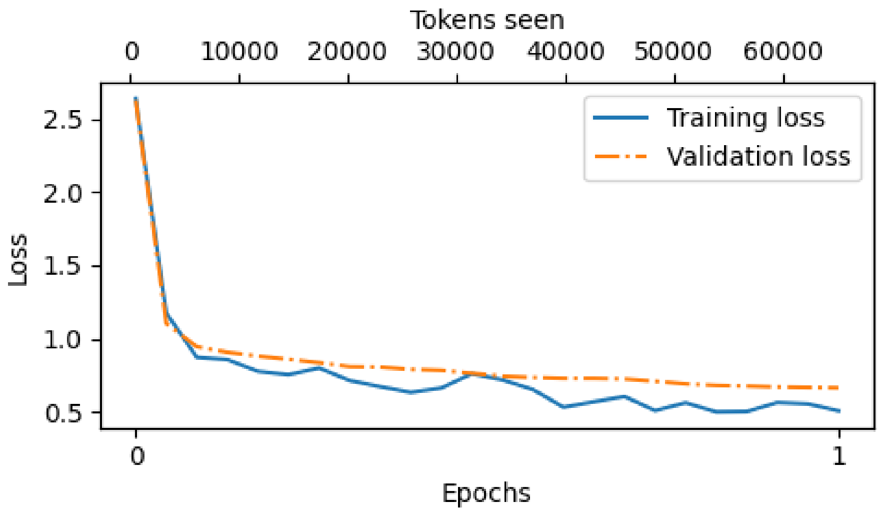
As we can see based on the outputs above, the model trains well, as we can tell based on the decreasing training loss and validation loss values. Furthermore, based on the response text printed after each epoch, we can see that the model almost correctly follows the instruction to convert the input sentence 'The chef cooks the meal every day.' into passive voice 'The meal is prepared every day by the chef.' (We will properly format and evaluate the responses in a later section. To get better results, we need to finetune the model for more epochs. Finally, let's take a look at the training and validation loss curves

In [240]:

```python
import matplotlib.pyplot as plt
from matplotlib.ticker import MaxNLocator


def plot_losses(epochs_seen, tokens_seen, train_losses, val_losses):
    fig, ax1 = plt.subplots(figsize=(5, 3))

    # Plot training and validation loss against epochs
    ax1.plot(epochs_seen, train_losses, label="Training loss")
    ax1.plot(epochs_seen, val_losses, linestyle="-.", label="Validation loss")
    ax1.set_xlabel("Epochs")
    ax1.set_ylabel("Loss")
    ax1.legend(loc="upper right")
    ax1.xaxis.set_major_locator(MaxNLocator(integer=True))  # only show integer labels o
n x-axis

    # Create a second x-axis for tokens seen
    ax2 = ax1.twiny()  # Create a second x-axis that shares the same y-axis
    ax2.plot(tokens_seen, train_losses, alpha=0)  # Invisible plot for aligning ticks
    ax2.set_xlabel("Tokens seen")

    fig.tight_layout()  # Adjust layout to make room
    plt.savefig("loss-plot.pdf")
    plt.show()
```

In [241]:

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



As we can see in the loss plot shown above, 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 is quickly learning 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 finetuning its learned representations and converging to a stable solution. 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. In the remaining sections of this chapter, we will extract the responses and store them in a format that allows us to evaluate and quantify the response quality.

STEP 6: EXTRACTING AND SAVING RESPONSES

After finetuning the LLM on the training portion of the instruction dataset as described in the previous section, we now proceed to evaluate its performance on the held-out test set. To accomplish this, we first extract the model-generated responses for each input in the test dataset and collect them for manual analysis

Step 1: Iterate over the first 3 test set samples Step 2: Use the generate function defined earlier

As mentioned earlier, the generate function returns the combined input and output text, so we use slicing and the .replace() method on the generated_text contents to extract the model's response. The instructions, followed by the given test set response and model response are shown below:

In [242]:

```
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()
)

    print(input_text)
    print(f"\nCorrect response:\n>> {entry['output']}")
    print(f"\nModel response:\n>> {response_text.strip()}")
    print("-------------------------------------")
```

```
Below is an instruction that describes a task. Write a response that appropriately comple
tes the request.

### Instruction:
Rewrite the sentence using a simile.

### Input:
The car is very fast.

Correct response:
>> The car is as fast as lightning.

Model response:
>> The car is as fast as a bullet.
-------------------------------------
Below is an instruction that describes a task. Write a response that appropriately comple
tes the request.

### Instruction:
What type of cloud is typically associated with thunderstorms?

Correct response:
>> The type of cloud typically associated with thunderstorms is cumulonimbus.

Model response:
>> A thunderstorm is a type of cloud that typically forms in the atmosphere over a region
of high pressure. It typically produces a strong wind that blows across the area, creatin
g a dense, dense cloud.
-------------------------------------
Below is an instruction that describes a task. Write a response that appropriately comple
tes the request.

### Instruction:
Name the author of 'Pride and Prejudice'.

Correct response:
>> Jane Austen.

Model response:
>> The author of 'Pride and Prejudice' is George Bernard Shaw.
-------------------------------------
```

As we can see based on the test set instructions, given responses, and the model's responses, the model performs relatively well. The answers to the first instruction is clearly correct, while the second answer and the third answers are not correct. This is because we have done the fine-tuning for only 1 epoch due to hardware limitations. To get better results, we need to increase the epochs to at least 2.

Most importantly, we can see that model evaluation is not as straightforward as in the previous chapter, where we simply calculated the percentage of correct spam/non-spam class labels to obtain the classification accuracy. In practice, instruction-finetuned LLMs such as chatbots are evaluated via multiple approaches: 1. Short-answer and multiple choice benchmarks such as MMLU ("Measuring Massive Multitask Language Understanding," https://arxiv.org/abs/2009. 03300), which test the general knowledge of

a model. 2. Human preference comparison to other LLMs, such as LMSYS chatbot arena (https://arena.lmsys.org). 3. Automated conversational benchmarks, where another LLM like GPT-4 is used to evaluate the responses, such as AlpacaEval (https://tatsulab.github.io/alpaca_eval/). completes the request.

Considering the scale of the task at hand, we will implement an approach similar to method 3, which involves evaluating the responses automatically using another LLM. This will allow us to efficiently assess the quality of the generated responses without the need for extensive human involvement, thereby saving time and resources while still obtaining meaningful performance indicators.

To prepare the responses for this evaluation process, we append the generated model responses to the test_set dictionary and save the updated data as an "instructiondata-with-response.json" file for record keeping. Additionally, by saving this file, we can easily load and analyze the responses in separate Python sessions later on if needed.

The following code uses the generate method in the same manner as before; however, we now iterate over the entire test_set. Also, instead of printing the model responses, we add them to the test_set dictionary:

In [244]:

```python
from tqdm import tqdm

for i, entry in tqdm(enumerate(test_data), total=len(test_data)):

    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(
)

    test_data[i]["model_response"] = response_text


with open("instruction-data-with-response.json", "w") as file:
    json.dump(test_data, file, indent=4)  # "indent" for pretty-printing
```

```
100%|██████████████████████████████████████████████████████████████████████
█████████| 110/110 [18:28<00:00, 10.08s/it]
```

Let's verify that the responses have been correctly added to the test_set dictionary by examining one of the entries:

In [245]:

```python
print(test_data[0])
```

```
{'instruction': 'Rewrite the sentence using a simile.', 'input': 'The car is very fast.',
'output': 'The car is as fast as lightning.', 'model_response': 'The car is as fast as a
bullet.'}
```

Based on the output, we can see that the model_response has been added correctly.

Finally, we save the model as gpt2-medium355M-sft.pth file to be able to reuse it in future projects:

In [246]:

```
import re


file_name = f"{re.sub(r'[ ()]', '', CHOOSE_MODEL) }-sft.pth"
torch.save(model.state_dict(), file_name)
print(f"Model saved as {file_name}")

# Load model via
# model.load_state_dict(torch.load("gpt2-medium355M-sft.pth"))
```

```
Model saved as gpt2-medium355M-sft.pth
```

STEP 7: EVALUATING THE FINE-TUNED LLM

Previously, we judged the performance of an instruction finetuned model by looking at its responses on 3 examples of the test set. While this gives us a rough idea of how well the model performs, this method does not really scale well to larger amounts of responses. So, in this section, we implement a method to automate the response evaluation of the finetuned LLM using another, larger LLM.

To implement the evaluation step which involves evaluating test set responses in an automated fashion, we utilize an existing instruction-finetuned 8 billion parameter Llama 3 model developed by Meta AI. This model can be run locally using the open-source Ollama application (https://ollama.com).

Ollama is an efficient application for running LLMs on a laptop. It serves as a wrapper around the open-source llama.cpp library (https://github.com/ggerganov/llama.cpp), which implements LLMs in pure C/C++ to maximize efficiency. However, note that Ollama is only a tool for generating text using LLMs (inference) and does not support training or finetuning LLMs.

The following code verifies that the Ollama session is running properly before we use Ollama to evaluate the test set responses generated in the previous section:

In [247]:

```
import psutil

def check_if_running(process_name):
    running = False
    for proc in psutil.process_iter(["name"]):
        if process_name in proc.info["name"]:
            running = True
            break
    return running

ollama_running = check_if_running("ollama")

if not ollama_running:
    raise RuntimeError("Ollama not running. Launch ollama before proceeding.")
print("Ollama running:", check_if_running("ollama"))
```

```
Ollama running: True
```

An alternative to the ollama run command for interacting with the model is through its REST API using Python. The following query_model function demonstrates how to use the API:

Step 1: Create the data payload as a dictionary Step 2: Convert the dictionary to a JSON formatted string and encode it to bytes Step 3: Create a request object, setting the method to POST and adding necessary headers Step 4: Send the request and capture the response

In [249]:

```python
import urllib.request

def query_model(
    prompt,
    model="llama3",
    url="http://localhost:11434/api/chat"
):
    # Create the data payload as a dictionary
    data = {
        "model": model,
        "messages": [
            {"role": "user", "content": prompt}
        ],
        "options": {     # Settings below are required for deterministic responses
            "seed": 123,
            "temperature": 0,
            "num_ctx": 2048
        }
    }


    # Convert the dictionary to a JSON formatted string and encode it to bytes
    payload = json.dumps(data).encode("utf-8")

    # Create a request object, setting the method to POST and adding necessary headers
    request = urllib.request.Request(
        url,
        data=payload,
        method="POST"
    )
    request.add_header("Content-Type", "application/json")

    # Send the request and capture the response
    response_data = ""
    with urllib.request.urlopen(request) as response:
        # Read and decode the response
        while True:
            line = response.readline().decode("utf-8")
            if not line:
                break
            response_json = json.loads(line)
            response_data += response_json["message"]["content"]

    return response_data
```

Before running the subsequent code cells in this notebook, ensure that Ollama is still running. The previous code cells should print "Ollama running: True" to confirm that the model is active and ready to receive requests.

Here's an example of how to use the query_llama function we just implemented:

In [251]:

```python
model = "llama3"
result = query_model("What do Llamas eat?", model)
print(result)
```

```
Llamas are herbivores, which means they primarily feed on plant-based foods. Their diet t
ypically consists of:

1. Grasses: Llamas love to graze on various types of grasses, including tall grasses, sho
rt grasses, and even weeds.
2. Hay: High-quality hay, such as alfalfa or timothy hay, is a staple in a llama's diet.
They enjoy the sweet taste and texture of fresh hay.
3. Grains: Llamas may receive grains like oats, barley, or corn as part of their daily ra
tion. However, it's essential to provide these grains in moderation, as they can be high
in calories.
4. Fruits and vegetables: Llamas enjoy a variety of fruits and veggies, such as apples, c
arrots, sweet potatoes, and leafy greens like kale or spinach.
5. Minerals: Llamas require access to mineral supplements, which help maintain their over
all health and well-being.

In the wild, llamas might also eat:

1. Leaves: They'll munch on leaves from trees and shrubs, including plants like willow, a
lder, and birch.
2. Bark: In some cases, llamas may eat the bark of certain trees, like aspen or cottonwoo
d.
3. Mosses and lichens: These non-vascular plants can be a tasty snack for llamas.

In captivity, llama owners typically provide a balanced diet that includes a mix of hay,
grains, and fruits/vegetables. It's essential to consult with a veterinarian or experienc
ed llama breeder to determine the best feeding plan for your llama.
```

Using the query_model function defined earlier, we can evaluate the responses generated by our finetuned model with a prompt that prompts the Llama 3 model to rate our finetuned model's responses on a scale from 0 to 100 based on the given test set response as reference.

First, we apply this approach to the first three examples from the test set that we examined in a previous section:

In [252]:

```python
for entry in test_data[:3]:
    prompt = (
        f"Given the input `{format_input(entry)}` "
        f"and correct output `{entry['output']}`, "
        f"score the model response `{entry['model_response']}`"
        f" on a scale from 0 to 100, where 100 is the best score. "
    )
    print("\nDataset response:")
    print(">>", entry['output'])
    print("\nModel response:")
    print(">>", entry["model_response"])
    print("\nScore:")
    print(">>", query_model(prompt))
    print("\n-------------------------")
```

```
Dataset response:
>> The car is as fast as lightning.

Model response:
>> The car is as fast as a bullet.

Score:
>> I'd rate the model response "The car is as fast as a bullet." an 85 out of 100
>> I'd rate the model response "The car is as fast as a bullet." an 85 out of 100.

Here's why:

* The response uses a simile correctly, comparing the speed of the car to something else
(in this case, a bullet).
* The comparison is relevant and makes sense, as bullets are known for their high velocit
y.
* The phrase "as fast as" is used correctly to introduce the simile.

The only reason I wouldn't give it a perfect score is that some people might find the com
parison slightly less vivid or evocative than others. For example, comparing something to
lightning (as in the original response) can be more dramatic and attention-grabbing. Howe
ver, "as fast as a bullet" is still a strong and effective simile that effectively convey
s the idea of the car's speed.

Overall, I think the model did a great job!

-------------------------

Dataset response:
>> The type of cloud typically associated with thunderstorms is cumulonimbus.

Model response:
>> A thunderstorm is a type of cloud that typically forms in the atmosphere over a region
of high pressure. It typically produces a strong wind that blows across the area, creatin
g a dense, dense cloud.

Score:
>> I'd score this model response as 20 out of 100.

Here's why:

* The response doesn't directly answer the question about what type of cloud is typically
associated with thunderstorms.
* Instead, it provides a general description of thunderstorms, which is not relevant to t
he original question.
* The response also contains some inaccuracies, such as stating that thunderstorms form o
ver high pressure regions (thunderstorms can occur in various weather patterns).

A good model response should directly answer the question, provide accurate and relevant
information, and avoid unnecessary details. In this case, the response fails to meet thes
e criteria, which is why I'd score it relatively low.

-------------------------

Dataset response:
>> Jane Austen.

Model response:
>> The author of 'Pride and Prejudice' is George Bernard Shaw.

Score:
>> I'd rate this model response a 0 out of 100.

Here's why:

* The correct answer is Jane Austen, not George Bernard Shaw.
* George Bernard Shaw was an Irish playwright and author, but he did not write 'Pride and
Prejudice'.
* The response is completely incorrect and does not provide any relevant information abou
t the actual author of the book.

Therefore, I would give this model response a score of 0 out of 100.

-------------------------
```

Based on the generated responses, we can observe that the Llama 3 model provides reasonable evaluations and is capable of assigning partial points when a model's answer is not entirely correct.

The previous prompt returns highly detailed evaluations in addition to the score. We can modify the prompt to just generate integer scores ranging from 0 to 100, where 100 represents the best possible score. This modification allows us to calculate an average score for our model, which serves as a more concise and quantitative assessment of its performance.

The following generate_model_scores function uses a modified the prompt telling the model to "Respond with the integer number only.":

In [255]:

```
for entry in test_data[:2]:
    prompt = (
            f"Given the input `{format_input(entry)}` "
            f"and correct output `{entry['output']}`, "
            f"score the model response `{entry['model_response']}`"
            f" on a scale from 0 to 100, where 100 is the best score. "
            f"Respond with the integer number only."
        )
    score = query_model(prompt, model)
    print("\nDataset response:")
    print(">>", entry['output'])
    print("\nModel response:")
    print(">>", entry["model_response"])
    print("\nScore:")
    print(">>", query_model(prompt, model))
    print("\n-------------------------")
```

```
Dataset response:
>> The car is as fast as lightning.

Model response:
>> The car is as fast as a bullet.

Score:
>> 85

-------------------------

Dataset response:
>> The type of cloud typically associated with thunderstorms is cumulonimbus.

Model response:
>> A thunderstorm is a type of cloud that typically forms in the atmosphere over a region
of high pressure. It typically produces a strong wind that blows across the area, creatin
g a dense, dense cloud.

Score:
>> 20

-------------------------
```

In [253]:

```
def generate_model_scores(json_data, json_key, model="llama3"):
    scores = []
    for entry in tqdm(json_data, desc="Scoring entries"):
        prompt = (
            f"Given the input `{format_input(entry)}` "
            f"and correct output `{entry['output']}`, "
            f"score the model response `{entry[json_key]}`"
            f" on a scale from 0 to 100, where 100 is the best score. "
            f"Respond with the integer number only."
        )
        score = query_model(prompt, model)
        try:
            scores.append(int(score))
        except ValueError:
            print(f"Could not convert score: {score}")
            continue

    return scores
```

I am not running the above function because of hardware limitations. I am using a Macbook Air 2020. It takes about 1 min on a M3 Macbook Air.

When you run the above code, you will see that the evaluation output shows that our finetuned model achieves an average score above 50, which provides a useful benchmark for comparison against other models or for experimenting with different training configurations to improve the model's performance. It's worth noting that Ollama is not entirely deterministic at the time of this writing, which means that the scores you obtain might slightly vary from the ones presented above. To obtain more robust results, you can repeat the evaluation multiple times and average the resulting scores.

To further improve our model's performance, we can explore various strategies, such as: (1) Adjusting the hyperparameters during finetuning, such as the learning rate, batch size, or number of epochs. (2) Increasing the size of the training dataset or diversifying the examples to cover a broader range of topics and styles. (3) Experimenting with different prompts or instruction formats to guide the model's responses more effectively. (4) Considering the use of a larger pretrained model, which may have greater capacity to capture complex patterns and generate more accurate responses. (5) We can also use parameter efficient fine-tuning techniques like LoRA.

In [256]:

```
## CONCLUSIONS
```

In [ ]:

```
```