LLM Part 3 : Data Loader

Reference text

https://www.manning.com/books/build-a-large-language-model-from-scratch

Text Corpus

The text we will tokenize for LLM training is a short story by Edith Wharton called The Verdict, which has been released into the public domain and is thus permitted to be used for LLM training tasks. The text is available on Wikisource at https://en.wikisource.org/wiki/The_Verdict,

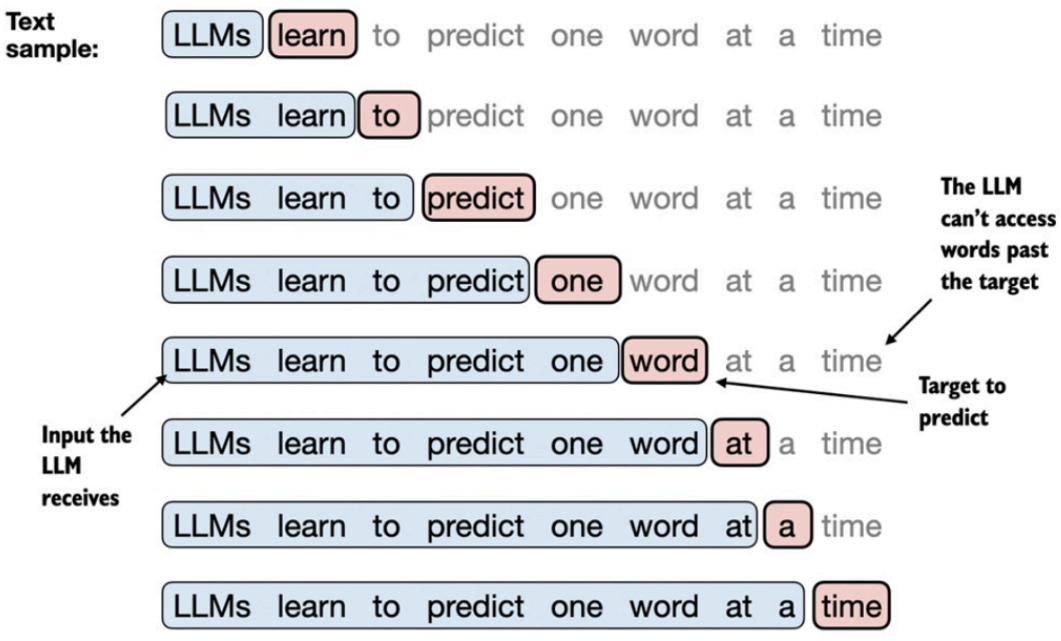
Concept Note Creating the Input - target data pairs

LLMs are pretrained by predicting the next word in a text, as depicted in figure below

Figure Reference : Ch 2 : Build a Large Language Model from Scratch , Sebastian Raschka

Key Notes

- Given a text sample, extract input blocks as subsamples that serve as input to the LLM.
- The LLM's prediction task during training is to predict the next word that follows the input block.
- During training, we mask out all words that are past the target.
- Note that the text shown in this figure would undergo tokenization before the LLM can process it; however, this figure omits the tokenization step for clarity.



STEP 1 : Read Corpus

In [1]:
```
import pandas as pd

file1 = open("the-verdict.txt", "r+", encoding="utf-8")

#print("Output of Read function is ")
corpus = file1.read()
#print(text)

# check count of words
print("word count is -> ", len(corpus))
```

```
word count is ->  20479
```

In [2]:
```
# check input data

import re

# Split corpus into tokens
result = re.split(r'([,.:;?_!"()\']|--|\s)', corpus)

# remove white space
result = [item for item in result if item.strip()]


# display top 100 tokens

top_100 = []
for index, word in enumerate(result):
    if index > 100:
       break
    top_100.append(word)
print(top_100)
```

```
['I', 'HAD', 'always', 'thought', 'Jack', 'Gisburn', 'rather', 'a', 'chea
p', 'genius', '--', 'though', 'a', 'good', 'fellow', 'enough', '--', 'so',
'it', 'was', 'no', 'great', 'surprise', 'to', 'me', 'to', 'hear', 'that',
',', 'in', 'the', 'height', 'of', 'his', 'glory', ',', 'he', 'had', 'droppe
d', 'his', 'painting', ',', 'married', 'a', 'rich', 'widow', ',', 'and', 'e
stablished', 'himself', 'in', 'a', 'villa', 'on', 'the', 'Riviera', '.',
'(', 'Though', 'I', 'rather', 'thought', 'it', 'would', 'have', 'been', 'Ro
me', 'or', 'Florence', '.', ')', '"', 'The', 'height', 'of', 'his', 'glor
y', '"', '--', 'that', 'was', 'what', 'the', 'women', 'called', 'it', '.',
'I', 'can', 'hear', 'Mrs', '.', 'Gideon', 'Thwing', '--', 'his', 'last', 'C
hicago', 'sitter', '--', 'deploring']
```

STEP 2 : Tokenize with BPE

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 notebook

In [3]:
```
import importlib
import tiktoken

# initialize tokenizer
tokenizer = tiktoken.get_encoding("gpt2")

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

```
# check 1st 50  positions
print(enc_text[0:50])

# encode
strings = tokenizer.decode(enc_text)

print(strings[0:50])


# check 1st 100 positions
print(enc_text[0:100])

# encode
strings = tokenizer.decode(enc_text)

print(strings[0:100])
```

```
5145
[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, 287, 262, 6001, 286, 465, 13476, 11, 339, 550, 571
0, 465, 12036, 11, 6405, 257, 5527, 27075, 11]
I HAD always thought Jack Gisburn rather a cheap g
[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, 287, 262, 6001, 286, 465, 13476, 11, 339, 550, 571
0, 465, 12036, 11, 6405, 257, 5527, 27075, 11, 290, 4920, 2241, 287, 257, 4
489, 64, 319, 262, 34686, 41976, 13, 357, 10915, 314, 2138, 1807, 340, 561,
423, 587, 10598, 393, 28537, 2014, 198, 198, 1, 464, 6001, 286, 465, 13476,
1, 438, 5562, 373, 644, 262, 1466, 1444, 340, 13, 314, 460, 3285, 9074, 13,
46606, 536]
I HAD always thought Jack Gisburn rather a cheap genius--though a good fell
ow enough--so it was no g
```

In [4]:
```
##
```

STEP 3: Set Start Point of Corpus

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:

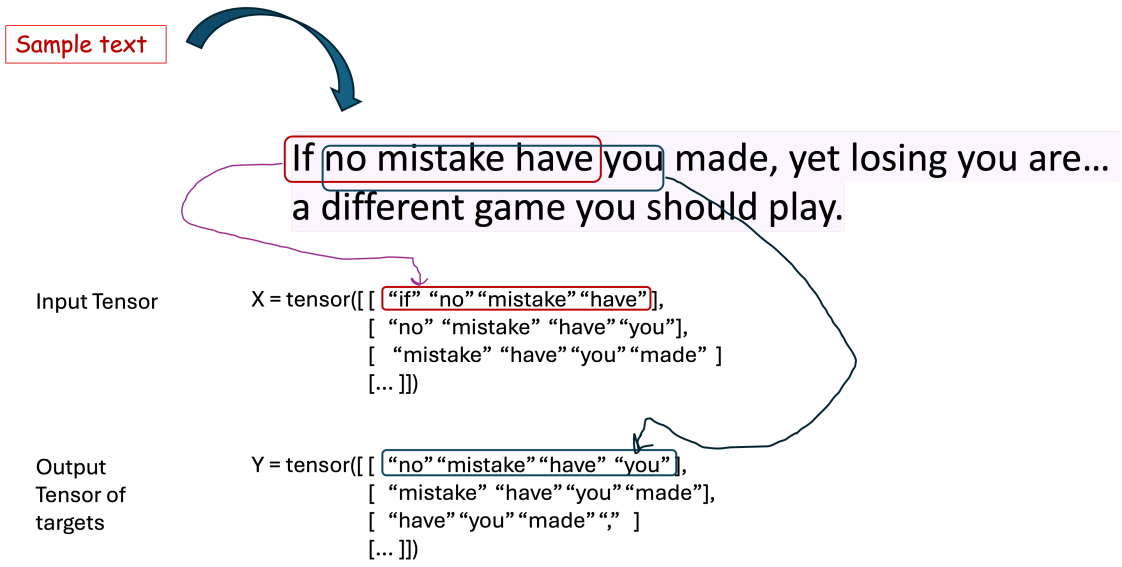
In [5]:
```
enc_sample = enc_text[50:]
```

STEP 4 : Create Input Output Pairs

Note We choose a context size of 4 for this case

- A consecutive set of 4 tokens are selected as x data
- A set of 1 token shifted 4 tokens are the y data

Illustratative example for creation of X, Y Pairs



In [6]:
```
# Set context size
context_size = 4
```

In [7]:
```
# choose x data sample to start from 0 and upto length = context size
x = enc_sample[:context_size]

# choose y ( target) to be 1 token shifted , and of the same length
y = enc_sample[1:context_size+1]

# display and check
print(f"x: {x}")
print(f"y:      {y}")
```

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

Illustrative example on next word prediction

How would the next word predictions look like

The below code snippet output demonstrates how every time a next word is predicted its rolled back as inout context till a max context size is reached

Simulated - next token prediction

In [8]:
```
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
```

Simulated Next Token Prediction Translated to String

In [9]:
```
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
```

Note on Dataset and Data Loader Class from pytorch

- PyTorch provides two data primitives: torch.utils.data.DataLoader and torch.utils.data.Dataset that allow you to use pre-loaded datasets as well as your own data.
- **Dataset** stores the samples and their corresponding labels, and **DataLoader** wraps an iterable around the Dataset to enable easy access to the samples.

REFERENCE https://pytorch.org/tutorials/beginner/basics/data_tutorial.html

Creating a Custom Dataset Class

A custom Dataset class must implement three functions: init, len, and _getitem, The methods are explained below:

init()

The init method is run once when instantiating the Dataset object. It performs the following:

- It instantiates the tokenizer
- The list of tensors for input an doutput token ids are initialized
- The entire corpus is tokenized
- Based on max length (the number of tokens used for one data row to predict the labels), and the stride (shift), X, data and Y data token ids are generated
- The input (X) and output (Y) token id tensors are appended to the list of the input and output token ids

len()

- The len method returns the number of samples in our dataset.

getitem()

- The getitem method loads and returns a sample from the dataset at the given index idx.
- Based on the index, it returns the token ids for the x data and that for the corresponding label

STEP 5 : Define the Custom Data Set Class

In [10]:
```
import torch
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
        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]
```

```
/Users/anishroychowdhury/anaconda3/envs/LLM/lib/python3.10/site-packages/tqdm/auto.py:21: TqdmWarning: IProgress not found. Please update jupyter and ipywidgets. See https://ipywidgets.readthedocs.io/en/stable/user_install.html
  from .autonotebook import tqdm as notebook_tqdm
```

Data Loaders

The Dataset retrieves our dataset's features and labels one sample at a time. While training a model, we typically want to pass samples in "minibatches", reshuffle the data at every epoch to reduce model overfitting, and use Python's multiprocessing to speed up data retrieval.

DataLoader is an iterable that abstracts this complexity for us in an easy API.

STEP 6 : Define the Data Loader Function

Arguments

- txt: The input text data to be processed.
- batch_size (default: 4): Number of samples per batch to load.
- max_length (default: 256): Maximum length of each tokenized sequence.
- stride (default: 128): Stride size for overlapping windows.
- shuffle (default: True): Whether to shuffle the data at every epoch.
- drop_last (default: True): Whether to drop the last incomplete batch if the dataset size is not divisible by the batch size.
- num_workers (default: 0): Number of subprocesses to use for data loading. 0 means data will be loaded in the main process.

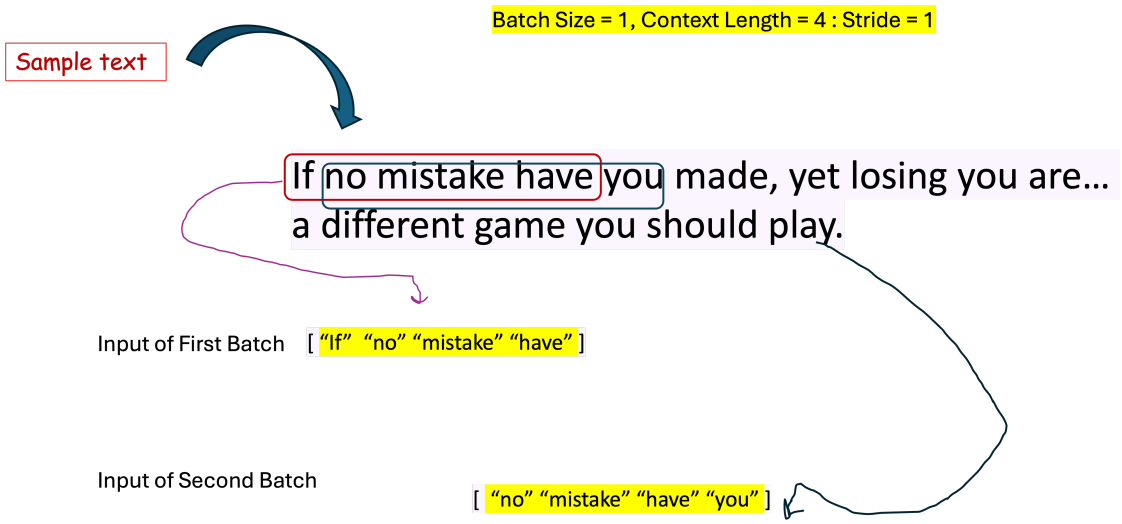
Key Processes

- Tokenizer Initialization: A GPT-2 compatible tokenizer is initialized.
- Dataset Creation: The input text data is processed using the custom GPTDatasetV1 class, which tokenizes the text and prepares sequences based on the provided max_length and stride.
- DataLoader Creation: A DataLoader is created with the specified batch size, shuffling, and other options.
- Return DataLoader: The DataLoader is returned, ready to be used in model training or evaluation.

In [11]:
```
from typing import List
from torch.utils.data import DataLoader

def create_dataloader_v1(txt: List[str], batch_size: int = 4, max_length: in
                         stride: int = 128, shuffle: bool = True, drop_last
                         num_workers: int = 0) -> DataLoader:
    """
    Creates a PyTorch DataLoader for the given text data.

    Args:
        txt (List[str]): The input text data to be processed.
        batch_size (int, optional): Number of samples per batch to load. De
        max_length (int, optional): Maximum length of each tokenized sequen
        stride (int, optional): Stride size for overlapping windows. Default
        shuffle (bool, optional): Whether to shuffle the data at every epoch
        drop_last (bool, optional): Whether to drop the last incomplete batc
                                    is not divisible by the batch size. Defa
        num_workers (int, optional): Number of subprocesses to use for data

    Returns:
        DataLoader: A DataLoader object for the given text data.
    """

    # 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
```

Step 7 a : Example usages for

Case 1: Stride = 1 Batch Size = 1 , Context Size = 4 tokens



Note on Batch Size and tensors

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.

In [12]:
```
# check length of corpus again
print(len(corpus))
```

```
20479
```

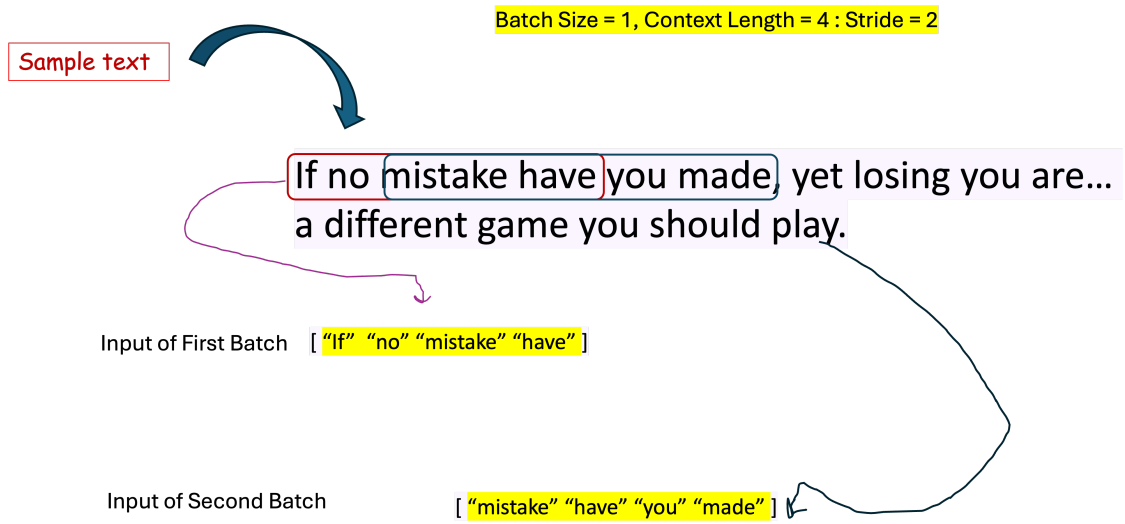
In [13]:
```
# call data loader with

#     batch size = 1
#     stride = 1
#     context length = 4


dataloader = create_dataloader_v1(
    corpus, batch_size=1, max_length=4, stride=1, shuffle=False
)

# Each iter of the data loader fetches a 'batch' size

# initiate iter
data_iter = iter(dataloader)

# First batch Tensor



# get the first batch

first_batch = next(data_iter)
print("first batch tensor  has both input tokens and output tokens ")
print("                                                            ")
print(" display the full tensor from the first batch ")


print(first_batch)
print("                                              ")
```

```
print(" ----------------------    first batch Input tokens ------------------
print(first_batch[0])
print("

print(" ----------------------    first batch  target tokens ----------------
print(first_batch[1])
print("



# get the second batch
print(" ----------------------    second batch input tokens  ----------------
second_batch = next(data_iter)
print(second_batch[0])
print("

print(" ----------------------    second batch  target tokens ----------------
print(second_batch[1])
```

```
first batch tensor  has both input tokens and output tokens

 display the full tensor from the first batch
[tensor([[  40,  367, 2885, 1464]]), tensor([[ 367, 2885, 1464, 1807]])]

 ----------------------    first batch Input tokens ------------------
tensor([[  40,  367, 2885, 1464]])

 ----------------------    first batch  target tokens ----------------
tensor([[ 367, 2885, 1464, 1807]])

 ----------------------    second batch input tokens  ----------------
tensor([[ 367, 2885, 1464, 1807]])

 ----------------------    second batch  target tokens ----------------
tensor([[2885, 1464, 1807, 3619]])
```

Step 7b : Example usages for

Case 2: Stride = 2 Batch Size = 1 , Context Size = 4 tokens

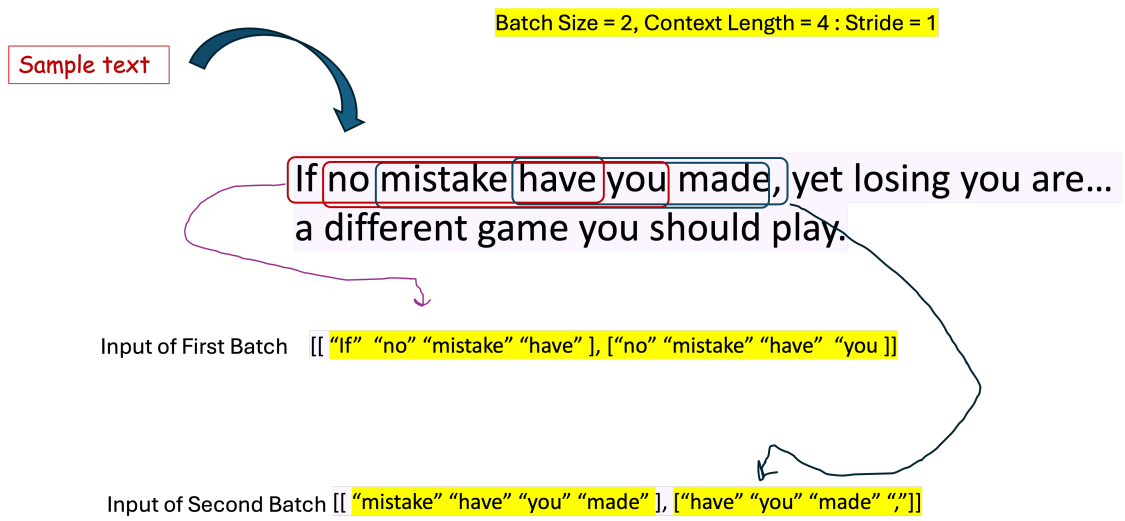


In [14]:
```
# call data loader with

#     batch size = 1
#     stride = 2
#     context length = 4


dataloader = create_dataloader_v1(
    corpus, batch_size=1, max_length=4, stride=2, shuffle=False
)

# Each iter of the data loader fetches a 'batch' size

# initiate iter
data_iter = iter(dataloader)

# get the first batch

first_batch = next(data_iter)


print("first batch tensor  has both input tokens and output tokens ")
print("                                                            ")
print(" display the full tensor from the first batch ")
print(first_batch)

print("                          ")

print(" ---------------------    first batch Input tokens ------------------
print(first_batch[0])
print("

print(" ---------------------    first batch  target tokens ----------------
print(first_batch[1])
print("



# get the second batch
print(" ---------------------    second batch input tokens  ----------------
second_batch = next(data_iter)
print(second_batch[0])
print("

print(" ---------------------    second batch  target tokens ---------------
print(second_batch[1])
```

```
first batch tensor  has both input tokens and output tokens

 display the full tensor from the first batch
[tensor([[  40,  367, 2885, 1464]]), tensor([[ 367, 2885, 1464, 1807]])]

 ---------------------    first batch Input tokens ------------------
tensor([[  40,  367, 2885, 1464]])

 ---------------------    first batch  target tokens ----------------
tensor([[ 367, 2885, 1464, 1807]])

 ---------------------    second batch input tokens  ----------------
tensor([[2885, 1464, 1807, 3619]])

 ---------------------    second batch  target tokens ----------------
tensor([[1464, 1807, 3619,  402]])
```

Step 7c : Example usages for

Case 3: Stride = 1 Batch Size = 2 , Context Size = 4 tokens



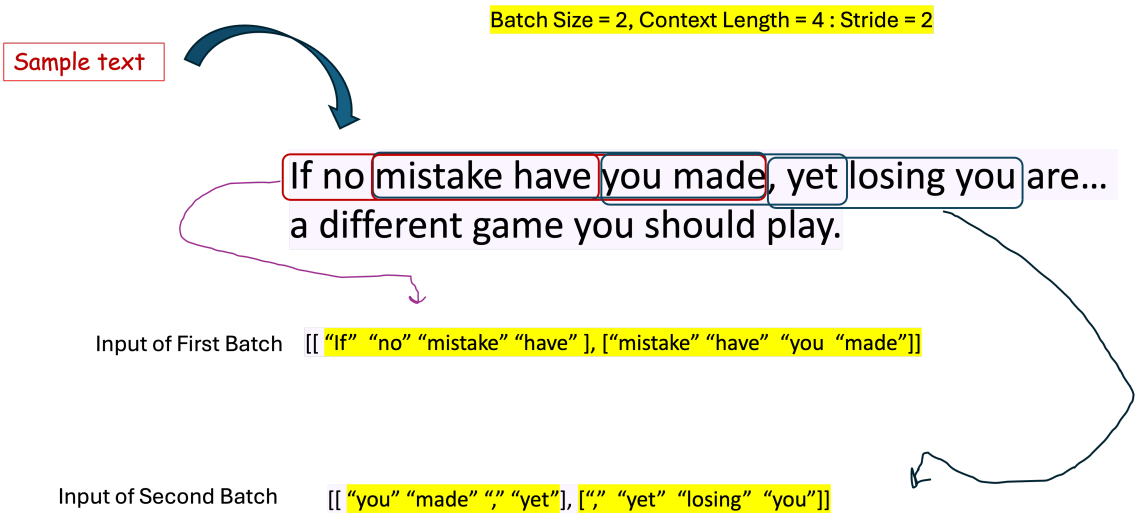
In [15]:
```
# call data loader with

#     batch size = 2
#     stride = 1
#     context length = 4


dataloader = create_dataloader_v1(
    corpus, batch_size=2, max_length=4, stride=1, shuffle=False
)

# Each iter of the data loader fetches a 'batch' size

# initiate iter
data_iter = iter(dataloader)

# get the first batch

first_batch = next(data_iter)
```

```
print("first batch tensor  has both input tokens and output tokens ")
print("                                                            ")
print(" display the full tensor from the first batch ")
print(first_batch)

print("                          ")

print(" ---------------------    first batch Input tokens ------------------
print(first_batch[0])
print("

print(" ---------------------    first batch  target tokens ----------------
print(first_batch[1])
print("



# get the second batch
print(" ---------------------    second batch input tokens  ----------------
second_batch = next(data_iter)
print(second_batch[0])
print("

print(" ---------------------    second batch  target tokens ---------------
print(second_batch[1])
```

```
first batch tensor  has both input tokens and output tokens

 display the full tensor from the first batch
[tensor([[  40,  367, 2885, 1464],
        [ 367, 2885, 1464, 1807]]), tensor([[ 367, 2885, 1464, 1807],
        [2885, 1464, 1807, 3619]])]

 ---------------------    first batch Input tokens ------------------
tensor([[  40,  367, 2885, 1464],
        [ 367, 2885, 1464, 1807]])

 ---------------------    first batch  target tokens ----------------
tensor([[ 367, 2885, 1464, 1807],
        [2885, 1464, 1807, 3619]])

 ---------------------    second batch input tokens  ----------------
tensor([[2885, 1464, 1807, 3619],
        [1464, 1807, 3619,  402]])

 ---------------------    second batch  target tokens ----------------
tensor([[1464, 1807, 3619,  402],
        [1807, 3619,  402,  271]])
```

Step 7d : Example usages for

Case 4: Stride = 2 Batch Size = 2 , Context Size = 4 tokens



In [16]:
```
# call data loader with

#     batch size = 2
#     stride = 2
#     context length = 4


dataloader = create_dataloader_v1(
    corpus, batch_size=2, max_length=4, stride=2, shuffle=False
)

# Each iter of the data loader fetches a 'batch' size

# initiate iter
data_iter = iter(dataloader)

# get the first batch

first_batch = next(data_iter)


print("first batch tensor  has both input tokens and output tokens ")
print("                                                            ")
print(" display the full tensor from the first batch ")
print(first_batch)

print("                          ")

print(" ---------------------    first batch Input tokens ------------------
print(first_batch[0])
print("

print(" ---------------------    first batch  target tokens ----------------
print(first_batch[1])
print("



# get the second batch
print(" ---------------------    second batch input tokens  ----------------
second_batch = next(data_iter)
print(second_batch[0])
print("

print(" ---------------------    second batch  target tokens ---------------
print(second_batch[1])
```

```
first batch tensor  has both input tokens and output tokens

 display the full tensor from the first batch
[tensor([[  40,  367, 2885, 1464],
        [2885, 1464, 1807, 3619]]), tensor([[ 367, 2885, 1464, 1807],
        [1464, 1807, 3619,  402]])]

 ----------------------    first batch Input tokens ------------------
tensor([[  40,  367, 2885, 1464],
        [2885, 1464, 1807, 3619]])

 ----------------------    first batch  target tokens ----------------
tensor([[ 367, 2885, 1464, 1807],
        [1464, 1807, 3619,  402]])

 ----------------------    second batch input tokens  ----------------
tensor([[ 1807,  3619,   402,   271],
        [  402,   271, 10899,  2138]])

 ----------------------    second batch  target tokens -----------------
tensor([[ 3619,   402,   271, 10899],
        [  271, 10899,  2138,   257]])
```

End of notebook

In [ ]: