Neural_Language_Model

June 20, 2024

```
<h1>Natural Language Processing</h1>
Assignment 05
<h3>General Information:</h3>
<p>Please do not add or delete any cells. Answers belong into the corresponding cells (below t
<p>Code cells where you are supposed to give your answer often include the line  ```raise NotI
<h3>Submission:</h3>
<p>Please submit your notebook via the web interface (in the main view -> Assignments -> Submi
<h3>Group Work:</h3>
<p>You are allowed to work in groups of up to three people. Please enter the UID (your usernam
<h3>Questions about the Assignment:</h3>
<p>If you have questions about the assignment please post them in the LEA forum before the dea
```

[41]:
```python
'''
Group Work:
Enter the username of each team member into the variables.
If you work alone please leave the other variables empty.
'''
member1 = 'mfarra2s'
member2 = 'rhusai2s'
member3 = ''
```

1 Neural Language Model

In this task we want to implement the neural language model given in chapter 7 of the book (p. 16) using PyTorch.

1.1 Helper Functions

You are given some helper functions to make this assignment easier.

First a tokenizer that turns strings into lists of token ids.

[42]:
```python
from tokenizers import Tokenizer
from tokenizers.models import WordLevel
from tokenizers.trainers import WordLevelTrainer
from tokenizers.pre_tokenizers import Whitespace
from typing import List
```

```python
def tokenizer_from_strings(strings: List[str], vocab_size: int = None) ->␣
↪Tokenizer:
    """
    Create and train a WordLevel Tokenizer for tokenizing text from the given␣
↪strings.

    Args:
        strings (List[str]): A list of strings containing the text data for␣
↪training.
        vocab_size (int, optional): The maximum vocabulary size to limit the␣
↪number of tokens
                                    in the tokenizer. If None, the vocabulary␣
↪size is determined automatically.
                                    Defaults to None.

    Returns:
        Tokenizer: A trained WordLevel Tokenizer capable of tokenizing text␣
↪data.
    """
    tokenizer = Tokenizer(WordLevel(unk_token="[UNK]"))

    # We can also pass a vocab_size to the trainer to only keep the most␣
↪frequent words
    # Special tokens are tokens that we want to use but are not part of the␣
↪text we train on
    trainer = WordLevelTrainer(
        special_tokens=["[UNK]", "<s>", "</s>"],
    )
    if vocab_size is not None:
        trainer.vocab_size = vocab_size
    tokenizer.pre_tokenizer = Whitespace()
    tokenizer.train_from_iterator(strings, trainer=trainer)
    return tokenizer
```

[43]:
```python
# Example texts for our tokenizer. This can be a list of one our more documents
my_text = [
    "<s> I like NLP. </s>",
    "It is very interesting",
    "But it is also hard"
]

tokenizer = tokenizer_from_strings(my_text)

# Let us look at our trained vocabulary
print("The vocabulary")
```

```python
print(tokenizer.get_vocab())

# Size of the vocabulary
print("\nThe size of the vocabulary")
print(tokenizer.get_vocab_size())

# Now lets turn a sentence into a list of token indices
encoded_input = tokenizer.encode("NLP is hard")

# This is how it splits it into tokens
print("\nThe tokens from our input string")
print(encoded_input.tokens)
# This is how we get the ids
print("\nThe ids for the tokens")
print(encoded_input.ids)

# Let us look what happens if we put in unknown words
encoded_input = tokenizer.encode("NLP is a tough subject")
print("\nThe tokens from our input string. Notice how everything unknown is␣
↪represented as [UNK]")
print(encoded_input.tokens)
print("\nThe ids for the tokens")
print(encoded_input.ids)

# Finally we can also turn back ids into strings
tokenizer.decode([6, 13, 8])
```

```
The vocabulary
{'is': 4, '</': 8, 'also': 13, 's': 5, '</s>': 2, 'But': 9, 'NLP': 12, 'It': 11,
'very': 18, 'it': 16, 'like': 17, 'I': 10, 'interesting': 15, '[UNK]': 0, '<s>':
1, '<': 7, '.': 6, 'hard': 14, '>': 3}

The size of the vocabulary
19

The tokens from our input string
['NLP', 'is', 'hard']

The ids for the tokens
[12, 4, 14]

The tokens from our input string. Notice how everything unknown is represented
as [UNK]
['NLP', 'is', '[UNK]', '[UNK]', '[UNK]']

The ids for the tokens
[12, 4, 0, 0, 0]
```

[43]: '. also </'

1.2 Neural Language Model A)

1.2.1 One Hot Encoder

First we create a one-hot encoder that produces tensors. We will use the built-in function `torch.nn.functional.one_hot` to create our embeddings.

First look at the example in the following cell.

Then complete the class `OneHotEncoder` below. You need to implement the method `encode`, which encodes a single index into a one-hot embedding and the method `encode_sequence`, which will take a list of indices and should return a list of one-hot embeddings.

[44]:
```python
from torch import tensor
from torch.nn.functional import one_hot

index = 5
vocab_size = 20

my_one_hot_embedding = one_hot(
    tensor(index),
    num_classes=vocab_size
).float()

print(my_one_hot_embedding)          # The embedding
print(my_one_hot_embedding.shape)    # The size of the embedding
print(my_one_hot_embedding.argmax()) # The index of the 1
```

```
tensor([0., 0., 0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
        0., 0.])
torch.Size([20])
tensor(5)
```

[45]:
```python
from torch.nn.functional import one_hot
from torch import tensor, float32
from typing import List

class OneHotEncoder:

    def __init__(self, vocab_size: int):
        """
        OneHotEncoder class for converting token IDs to one-hot encoded tensors.

        Args:
            vocab_size (int): The size of the vocabulary, i.e., the number of␣
↪unique tokens.
        """
```

```python
        self.vocab_size = vocab_size

    def encode(self, token_id: int) -> tensor:
        """
        Encode a single token ID as a one-hot encoded tensor.

        Args:
            token_id (int): The token ID to be encoded.

        Returns:
            tensor: The one-hot encoded tensor representing the input token ID.
        """
        return one_hot(tensor(token_id), num_classes= self.vocab_size).float()

    def encode_sequence(self, token_ids: List[int]) -> List[tensor]:
        """
        Encode a sequence of token IDs as a list of one-hot encoded tensors.

        Args:
            token_ids (List[int]): A list of token IDs to be encoded.

        Returns:
            List[tensor]: A list of one-hot encoded tensors representing the␣
↪input token IDs.
        """
        embedings = []
        for ind in token_ids:
            embedings.append(one_hot(tensor(ind), num_classes= self.vocab_size).
↪float())

        return embedings
```

[46]:
```python
# This is for you to test if your implementation is working

vocabulary_size = 50

encoder = OneHotEncoder(vocabulary_size)

# Test with a single index
embedding = encoder.encode(5)

assert embedding.shape[0] == vocabulary_size, "All embeddings should have the␣
↪size of the vocabulary"
assert embedding.argmax() == 5, "The single one should be at index 5"

# Test with a list of indices
```

```
indices = [5, 3, 7]
embeddings = encoder.encode_sequence(indices)

assert len(embeddings) == 3, "We put in three indices so we want three␣
 ↪embeddings"
assert isinstance(embeddings, list), "We want to return a list"

for idx, embedding in zip(indices, embeddings):
    assert embedding.shape[0] == vocabulary_size, "All embeddings should have␣
 ↪the size of the vocabulary"
    assert embedding.argmax() == idx, "The single one should be at index 5"
```

1.3 Neural Language Model B)

1.3.1 The model

Complete the model class below.

Hint: To get from three tensors of size d to a tensor of size $3d$ we need to concatenate. See the next cell for an example

[47]:
```
import torch

# Create our encoder and encode three indices
encoder = OneHotEncoder(12)
indices = [5, 3, 7]
embedding1, embedding2, embedding3 = encoder.encode_sequence(indices)

# Concatenate them into a single embedding of size 3*vocab_size
concatenated_embeddings = torch.concatenate((embedding1, embedding2,␣
 ↪embedding3))

print(concatenated_embeddings.shape) # This is three times our vocabulary size
print(concatenated_embeddings)
```

```
torch.Size([36])
tensor([0., 0., 0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 0., 0.,
        0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 0., 0., 0., 0.])
```

[48]:
```
import torch.nn as nn
from torch import TensorType

class NeuralLanguageModel(nn.Module):
    """
    A neural language model that predicts a word from two input words
    """

    def __init__(self, vocab_size: int, embedding_size: int, hidden_size: int):
```

```
        """
        Initializes the NeuralLanguageModel.

        Args:
            vocab_size (int): The size of the vocabulary.
            embedding_size (int): The size of word embeddings.
            hidden_size (int): The size of the hidden layer
        """
        super().__init__()
        self.vocab_size = vocab_size
        self.embedding_size = embedding_size
        self.hidden_size = hidden_size

        # Create your layers here. All layers are linear
        # We want an embedding layer
        self.embedding = nn.Linear(self.vocab_size, self.embedding_size)
        # Then a hidden layer
        self.hidden = nn.Linear(3*self.embedding_size, self.hidden_size)
        # Then an output layer
        self.output = nn.Linear(self.hidden_size,self.vocab_size)
        # Then we define our activation functions and the softmax
        self.activation = nn.ReLU()
        self.softmax = nn.Softmax()


    def forward(
        self,
        word1: TensorType,
        word2: TensorType,
        word3: TensorType,
        inference: bool=False
    ) -> TensorType:
        """
        Forward pass of the neural language model.

        Args:
            word1 (torch.TensorType): Tensor representing the first word␣
↪(one-hot).
            word2 (torch.TensorType): Tensor representing the second word␣
↪(one-hot).
            word3 (torch.TensorType): Tensor representing the third word␣
↪(one-hot).
            inference (bool, optional): Flag representing if we are doing␣
↪inference or not.
                                        This is needed since during training␣
↪PyTorch does not work well with
                                        the softmax.
```

```
        Returns:
            torch.TensorType: Output tensor representing the probability␣
 ↪distribution over the vocabulary.
        """
        # This will be our output
        x1 = self.embedding(word1)
        x2 = self.embedding(word2)
        x3 = self.embedding(word3)
        y = torch.cat((x1, x2, x3), dim=-1)

#         x = torch.concatenate((word1, word2, word3))
#         print(word1.shape)
#         print(x.shape)
#         y = self.embedding(x)
        y = self.hidden(y)
        y = self.activation(y)
        y = self.output(y)

        # The loss we will use later does not play well with softmax.
        # So we only apply it for inferencing
        if inference:
            y = self.softmax(y)
        return y
```

[49]:
```
# This is to test your implementation

# First create the model
vocab_size = 50
model = NeuralLanguageModel(
    vocab_size=vocab_size,
    embedding_size=16,
    hidden_size=10
)

# Next create some inputs for our model
encoder = OneHotEncoder(vocab_size)

word1, word2, word3 = encoder.encode_sequence([3, 7, 2])

# Now we feed it to our model
output = model(word1, word2, word3)

print(output)
assert output.shape[0] == vocab_size, "Our output should have the size of the␣
 ↪vocabulary"
```

```python
# Next we do the same for inference (we check if the softmax is applied then)
output = model(word1, word2, word3, inference=True)
print(output)

assert abs(output.sum().item() - 1) < 10e-6, "The outputs should sum up to 1"
```

```
tensor([ 0.0740,  0.0229,  0.1719,  0.0541, -0.0604,  0.1465, -0.3477, -0.1297,
         0.2599, -0.2497,  0.2973, -0.1395, -0.1857,  0.2469,  0.0942, -0.1472,
         0.1477, -0.2054, -0.2845, -0.3283,  0.0500, -0.2007,  0.1455, -0.2583,
         0.0714,  0.0671, -0.2971, -0.1860,  0.2659,  0.0637,  0.1151,  0.1627,
        -0.2914, -0.0198, -0.3259, -0.2389, -0.2950, -0.0595,  0.0064,  0.2538,
         0.1873,  0.0719,  0.2822, -0.2693, -0.2765,  0.1144, -0.2607, -0.0305,
         0.0829, -0.2906], grad_fn=<ViewBackward0>)
tensor([0.0219, 0.0209, 0.0242, 0.0215, 0.0192, 0.0236, 0.0144, 0.0179, 0.0264,
        0.0159, 0.0274, 0.0177, 0.0169, 0.0261, 0.0224, 0.0176, 0.0236, 0.0166,
        0.0153, 0.0147, 0.0214, 0.0167, 0.0236, 0.0157, 0.0219, 0.0218, 0.0151,
        0.0169, 0.0266, 0.0217, 0.0229, 0.0240, 0.0152, 0.0200, 0.0147, 0.0160,
        0.0152, 0.0192, 0.0205, 0.0263, 0.0246, 0.0219, 0.0270, 0.0156, 0.0155,
        0.0229, 0.0157, 0.0198, 0.0221, 0.0152], grad_fn=<SoftmaxBackward0>)
```

```
/opt/conda/lib/python3.11/site-packages/torch/nn/modules/module.py:1511:
UserWarning: Implicit dimension choice for softmax has been deprecated. Change
the call to include dim=X as an argument.
  return self._call_impl(*args, **kwargs)
```

1.4 The Dataset

The dataset class was already implemented for you. Look at it and understand what it does.

[50]:
```python
from torch.utils.data import Dataset, DataLoader
from typing import List, Any, Tuple

def sliding_window(sequence: List[Any], window_size: int) -> List[Any]:
    """
    Generate a sliding window over a sequence (list).

    Args:
        sequence (list): The input sequence.
        window_size (int): The size of the sliding window.

    Yields:
        list: A window of elements from the input sequence.
    """
    for i in range(len(sequence) - window_size + 1):
        yield sequence[i:i + window_size]


class NGramTextDataset(Dataset):
```

```
    """
    A PyTorch Dataset class for generating trigram-based text datasets.

    Args:
        sentences (List[str]): A list of input sentences.
        vocab_size (int, optional): The size of the vocabulary to use for
tokenization.
                                    Defaults to None.

    Methods:
        __len__(self) -> int: Returns the total number of examples in the
dataset.

        __getitem__(self, index: int) -> Tuple[List[int], int]:
            Returns a tuple containing the input trigram and its corresponding
label for the specified index.

    Example:
        sentences = ["This is a sample sentence.", "Another example sentence."]
        dataset = TrigramTextDataset(sentences, vocab_size=10000)
        dataloader = DataLoader(dataset, batch_size=64, shuffle=True)
    """

    def __init__(self, sentences: List[str], vocab_size: int=None):
        """
        Initializes the TrigramTextDataset with input sentences and vocabulary
size.

        Args:
            sentences (List[str]): A list of input sentences.
            vocab_size (int, optional): The size of the vocabulary to use for
tokenization.
                                        Defaults to None.
        """
        # First augment the sentences with a start and end symbol
        # We add three of each since we look at four grams
        sentences = [
            '<s> <s> <s>' + sentence + ' </s> </s> </s>'
            for sentence in sentences
        ]
        # Next we train our tokenizer
        self.tokenizer = tokenizer_from_strings(sentences, vocab_size)
        self.encoder = OneHotEncoder(self.tokenizer.get_vocab_size())

        # Prepare our examples
        self.inputs = []
        self.labels = []
```

```
        for sentence in sentences:
            # Go over each trigram of the encoded sentence
            for trigram in sliding_window(self.tokenizer.encode(sentence).ids,␣
↪4):
                # Take the first two tokens as input
                self.inputs.append(trigram[:-1])
                # Take the last token as the label
                self.labels.append(trigram[-1])

    def __len__(self) -> int:
        """
        Returns the total number of examples in the dataset.

        Returns:
            int: The number of examples in the dataset.
        """
        return len(self.labels)

    def __getitem__(self, index: int) -> Tuple[List[torch.tensor], torch.
↪tensor]:
        """
        Returns a tuple containing the input trigram and its corresponding␣
↪label for the specified index.

        Args:
            index (int): The index of the example to retrieve.

        Returns:
            Tuple[List[int], int]: A tuple containing the input trigram (a list␣
↪of integers) and
            its corresponding label (an integer).
        """
        return self.encoder.encode_sequence(self.inputs[index]), self.encoder.
↪encode(self.labels[index])
```

[51]:
```
# Open our training data
# This file has one sentence per line
with open('/srv/shares/NLP/datasets/marvel/spider_man_homecoming.txt', 'r') as␣
↪f:
    text = f.read()

# Create the dataset
dataset = NGramTextDataset(text.split("\n"))

# Look at one example
inputs, label = dataset[4]
```

```
print(inputs)
print(label)

# We can also turn this back into strings using the tokenizer
word1, word2, word3 = inputs

# Turn the one-hot vectors back to indices
indices = [
    word1.argmax().item(),
    word2.argmax().item(),
    word3.argmax().item()
]

label_index = label.argmax().item()

# Turn these indices back to strings
dataset.tokenizer.decode(indices), dataset.tokenizer.decode([label_index])
```

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

[51]: ('Adrian Toomes and', 'his')

[52]:
```
print(word1)
```

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

1.5 Neural Language Model C)

1.5.1 The training loop and optimizer

Please implement the training loop below. This method receives a model, an optimizer, a loss function and a dataloader.

[53]:
```
from typing import List
from torch.optim import Optimizer
from torch.nn.modules.loss import _Loss
import numpy as np

def train_one_epoch(
    model: nn.Module,
    optimizer: Optimizer,
    loss_fn: _Loss,
    dataloader: DataLoader) -> float:
    """
    Trains a neural network model for one epoch using the specified data.
```

```
    Parameters:
        model (nn.Module): The neural network model to be trained.
        optimizer (Optimizer): The optimizer used for updating model weights.
        loss_fn (_Loss): The loss function used to compute the training loss.
        dataloader (DataLoader): The data loader providing batches of training␣
↪data.

    Returns:
        float: The mean training loss for the entire epoch.
    """
    batch_losses = []

    for batch_id, data in enumerate(dataloader):
#         print("b",batch_id)
#         print("d",data)

        inputs, labels = data
        word1, word2, word3 = inputs
        print(word1)
#         print("w",word1[0])
#         outputs = model(word1[0], word2[0], word3[0])

        # We need to zero our gradients for every batch!
        optimizer.zero_grad()

        # Calculate loss
        loss = loss_fn(outputs, labels[0])

        # Calculate gradient from loss
        loss.backward()

        # Update weights
        optimizer.step()

        # Record the loss
        batch_losses.append(loss.item())

        return np.mean(batch_losses)
```

1.6 Neural Language Model D)

1.6.1 Creating the optimizer, loss, model and dataloader

Use a batch size of 256 for your data loader.

Initialize your model with an embedding size of 8 and a hidden size of 12.

Use AdamW as your optimizer with a learning rate of 0.01.

Use the CrossEntropyLoss as the loss function

```
[54]: from torch.nn import CrossEntropyLoss
from torch.optim import AdamW

vocab_size = dataset.tokenizer.get_vocab_size()

model = NeuralLanguageModel(vocab_size= vocab_size, embedding_size=8,␣
↪hidden_size=12)
dataloader = DataLoader(dataset, batch_size=256, shuffle=True)
loss_fn = CrossEntropyLoss()
optimizer = AdamW(model.parameters(), lr=0.01)
```

1.7 Neural Language Model E)

1.7.1 Train the model

Train the model for at least 10 epochs (this should take about 3 minutes).

Hint: If you want a progress bar for your loops you can use the following code:

```
[55]: from tqdm.notebook import tqdm_notebook

epoch_losses = []

for i in tqdm_notebook(range(10), desc="Processing"):



#     epoch_losses.append( train_one_epoch( model,
#                       optimizer,
#                       loss_fn,
#                       dataloader))

    batch_losses = []

    for batch_id, data in enumerate(dataloader):
#         print("b",batch_id)
#         print("d",data)

        inputs, labels = data
        word1, word2, word3 = inputs
#         print(word1)
#         print("w",word1[0])
        outputs = model(word1, word2, word3)

        # We need to zero our gradients for every batch!
        optimizer.zero_grad()
```

```
        # Calculate loss
        loss = loss_fn(outputs, labels)

        # Calculate gradient from loss
        loss.backward()

        # Update weights
        optimizer.step()

        # Record the loss
        batch_losses.append(loss.item())

    epoch_losses.append(np.mean(batch_losses))

epoch_losses
```

```
Processing:   0%|          | 0/10 [00:00<?, ?it/s]
```

[55]:
```
[5.05574184773015,
 4.002994163363588,
 3.6176302877126956,
 3.3918839435951385,
 3.2453005570991365,
 3.1354138862852956,
 3.047662863544389,
 2.9745425605306437,
 2.9141877655889474,
 2.8609562714894614]
```

1.8 Neural Language Model F)

1.8.1 Plot the losses

Create a plot with the batch losses. Your x axis is the epoch, your y axis is the loss.

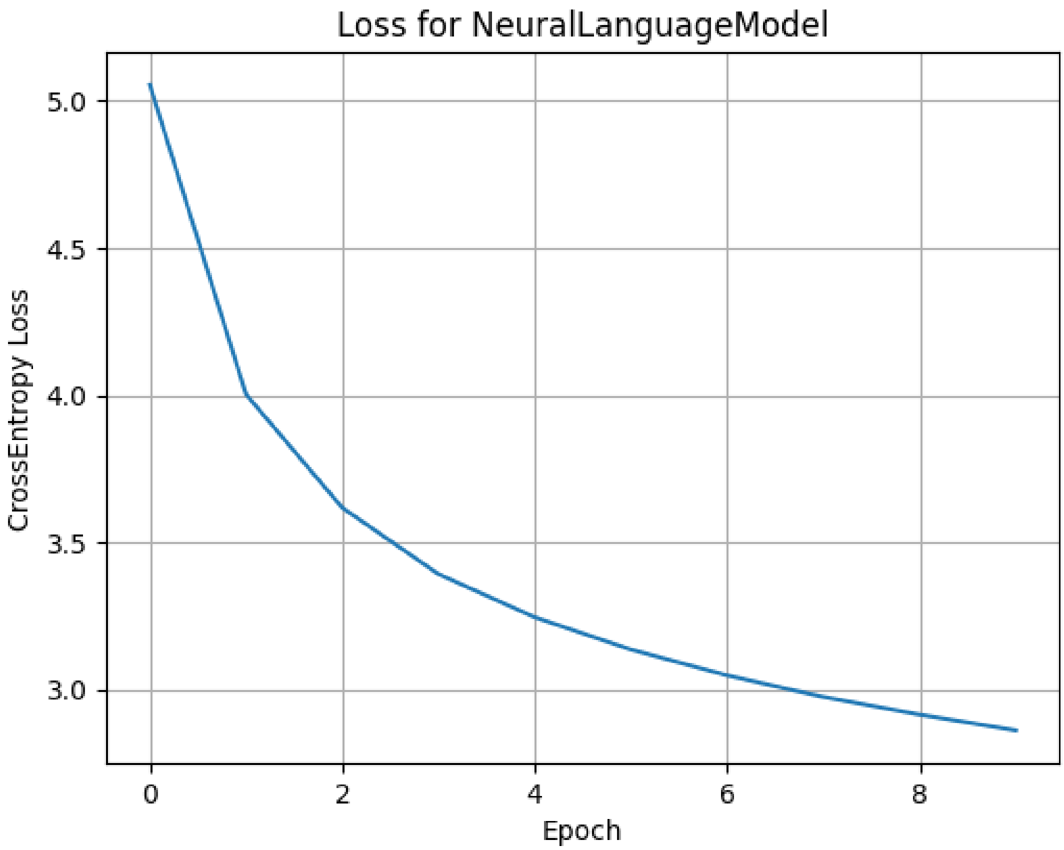
Don't forget labels, a title and a grid

[56]:
```
import matplotlib.pyplot as plt

plt.plot(epoch_losses)

plt.grid()
plt.xlabel("Epoch")
plt.ylabel("CrossEntropy Loss")
plt.title("Loss for NeuralLanguageModel")

plt.show()
```



[57]:
```
# Here we can do inference
sentence = "<s> <s> I'm a little station on the ground"

tokenized = dataset.tokenizer.encode(sentence)
token_ids = tokenized.ids

onehots = dataset.encoder.encode_sequence(token_ids)[-3:]

predicted_index = model(*onehots, inference=True).argmax().item()

dataset.tokenizer.decode([predicted_index])

def generate_random_sentence(model, dataset, input_sequence):
    sentence_end = False
    while not sentence_end:
        tokenized = dataset.tokenizer.encode(input_sequence)
        token_ids = tokenized.ids

        onehots = dataset.encoder.encode_sequence(token_ids)[-3:]
```

```
        probabilities = model(*onehots, inference=True).detach().numpy()



        next_index = np.random.choice(model.vocab_size, p=probabilities)

        # We specified <s> and </s> as special tokens. To have them be part of␣
 ↪the output
        # we need to set the flag skip_special_tokens=False
        next_word = dataset.tokenizer.decode([next_index],␣
 ↪skip_special_tokens=False)
        sentence_end = next_word == "</s>"
        input_sequence += f" {next_word}"
    return input_sequence

generate_random_sentence(model, dataset, "<s> <s> <s> No")
```

[57]:
```
'<s> <s> <s> No , no , no , no . </s>'
```

[ ]:
```

```