COMP 691 Assignment 2

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Note: The Jupyter notebook is attached at the end. There are some hyperlinks that you can click to jump to that specific page. Like this: Jump to Jupyter

1 Problem 1

Exercise 1. *Find the receptive field (with respect to the input) at the center position of layer 1.*

Solution. The receptive field on each layer is based on the input it receives from the previous layer. And it can be described by its center location and size. Essentially, it is the region in the input space that a particular CNN's feature is affected by. It would normally increase along with the depth of the layer.

According to the convolution arithmetic guide for deep learning by Dumoulin and Visin [1], we have the following equations to calculate the receptive field:

- k: kernel size
- p: padding size
- s: stride size
- $start$: center coordinate
- n: feature map size $n \times n$
- r: receptive field size $r \times r$
- j: distance between consecutive features

$$n_{out} = \lfloor \frac{n_{in} + 2p - k}{s} \rfloor + 1$$

$$j_{out} = j_{in} * s$$

$$r_{out} = r_{in} + (k - 1) * j_{in}$$

So each layer has four variables:$n, j, r, start$ (center), and each layer uses the information of the previous layer (e.g. n_{in}) to calculate these values.

We can calculate using the above equations. For the image, we have 227 features and the receptive field is 1*1 with jump 1, start at (114,114) - center of the 227*227 input. The initial stride s is 4 and filter size k is 11 , p is 0.

Therefore for Layer 1 we have

$$n_{out} = \lfloor \frac{227 + 2 * 0 - 11}{4} \rfloor + 1 = 54 + 1 = 55$$

$$j_{out} = 1 * 4 = 4$$

$$r_{out} = 1 + (11 - 1) * 1 = 11$$

So for layer 1 we have receptive size $= 11 * 11$ and its center at $(6, 6)$, we can then get the point at the bottom left corner and upper right corner:

Layer 1

$$Height_1, Width_1 = (114 - \frac{11-1}{2}, 114 - \frac{11-1}{2}) = (109, 109)$$

$$Height_2, Width_2 = (114 + \frac{11-1}{2}, 114 + \frac{11-1}{2}) = (119, 119)$$

So for **Layer 1**:

- Receptive field : $11 * 11$
- Center: $(114, 114)$
- $Height_1, Width_1$: $109, 109$
- $Height_2, Width_2$: $119, 119$

Use the values we calculate from Layer 1 to infer the values of Layer 2:

$$n_{out} = \lfloor \frac{55 + 2 * 0 - 3}{2} \rfloor + 1 = 26 + 1 = 27$$

$$j_{out} = 2 * 4 = 8$$

$$r_{out} = 11 + (3 - 1) * 4 = 19$$

$$Height_1, Width_1 = (114 - \frac{19-1}{2}, 114 - \frac{19-1}{2}) = (105, 105)$$

$$Height_2, Width_2 = (114 + \frac{19-1}{2}, 114 + \frac{19-1}{2}) = (123, 123)$$

So for **Layer 2**:

- Receptive field : $19 * 19$
- Center: $(114, 114)$
- $Height_1, Width_1$: $105, 105$
- $Height_2, Width_2$: $123, 123$

Use the values we calculate from Layer 2 to infer the values of Layer 3:

$$n_{out} = \lfloor \frac{27 + 2 * 2 - 5}{1} \rfloor + 1 = 26 + 1 = 27$$

$$j_{out} = 1 * 8 = 8$$

$$r_{out} = 19 + (5 - 1) * 8 = 51$$

$$Height_1, Width_1 = (114 - \frac{51 - 1}{2}, 10 - \frac{51 - 1}{2}) = (89, 89)$$

$$Height_2, Width_2 = (114 + \frac{51 - 1}{2}, 10 + \frac{51 - 1}{2}) = (139, 139)$$

So for **Layer 3**:

- Receptive field : $51 * 51$
- Center: $(114, 114)$
- $Height_1, Width_1$: $89, 89$
- $Height_2, Width_2$: $139, 139$

Exercise 2. *Implement Alexnet in PyTorch*

Solution. See the Jupyter notebook.Jump to Jupyter

Exercise 3. *Create an adversarial example for each of 2 randomly selected images*

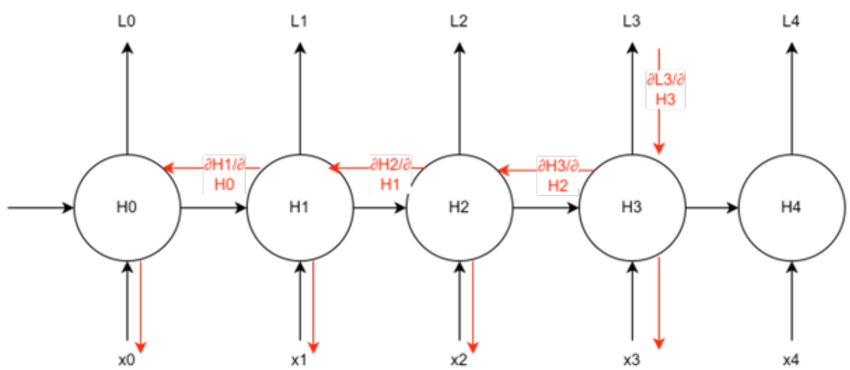
Solution. See the Jupyter notebook.Jump to Jupyter

2 Problem 2

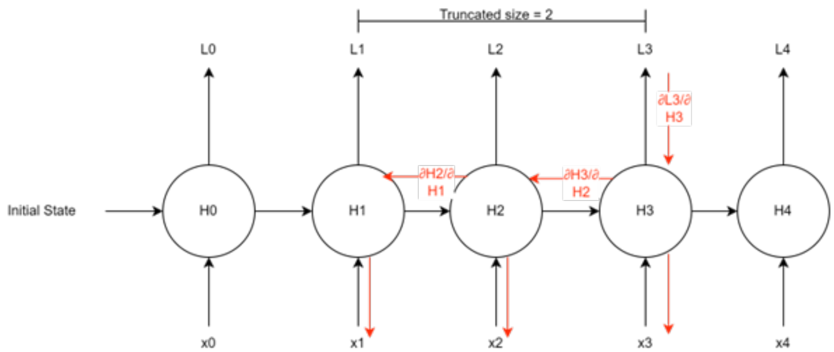
Exercise 4. *Q2.1 Detaching or not? (10 points)*

Solution. The implementation uses the single-layer RNN with LSTM, while the detach function detaches the hidden states from the nodes. In the for loop for training, the step size is the same as the seq_length, so the sum is truncated after $\tau = seq\_length$ steps. During backpropagation, this allows the sum to end at $\frac{\partial h_{t-\tau}}{\partial w_h}$ instead of the full sum. Compare this to not using truncated backpropagation through time, it will lead to the approximation of the exact gradient and make the model focus on the short-term (i.e truncated) influence instead of long influence, which could be beneficial for simpler and stable models. With the full computation, however, the gradient is exact but due to the amount of computation to be performed being much higher, the speed is a lot slower, and alternation in the initial condition will affect the outcome by a large margin leading to a less robust model. [2]

An example computational graph could be drawn as follows, assuming input have 5 tokens: [3]



Here, H stands for hidden state and L stands for loss, while x_0 to x_4 are input tokens. At time step 3, in order to calculate the gradient to update our weight W, we need to calculate $\frac{\partial L_3}{\partial H_3}\frac{\partial H_3}{\partial W}$. But this value is depending o the value of H_2, which depends on W and s_1, and for RNN, W is used for every step, then the equation essentially becomes $\sum_{k=0}^{3} \frac{\partial L_3}{\partial H_3}\frac{\partial H_3}{\partial H_k}\frac{\partial H_k}{\partial W}$. However when we use the detach function, we are truncating it so it doesn't go all the way back to 0, and instead, we have $\sum_{k=3-\tau}^{3} \frac{\partial L_3}{\partial H_3} \frac{\partial H_3}{\partial H_k} \frac{\partial H_k}{\partial W}$. A computation graph for $\tau = 2$ will be like this :



As a result, for truncated backpropagation, we limit the depth that we can go into the computational graph. The gradients are computed and stored only for a limited number of steps. This reduces the memory requirements for storing variables and intermediates, which leads to lower GPU consumption in general.

Exercise 5. *Q2.2 Sampling strategy*

Solution. See the Jupyter notebook.Jump to Jupyter

Exercise 6. *Q2.3 Embedding Distance (8 points)*

Solution. See the Jupyter notebook. Jump to Jupyter

Exercise 7. *Q2.4 Teacher Forcing (Extra Credit 2 points) Compare the performance of this model, to original model, what can you conclude? (compare perplexity and convergence rate)*

Solution. When we do not use teacher forcing, we can see that the training time is much longer (around $5x$ times) and the perplexity is higher with an overall slower convergence. The reason for that is because the teacher forcing provides the model with the correct word at each time step during training, even if the prediction from the previous time step is wrong. This ensures the model learn the relationships between words in the context more effectively, which reaches the optimal performance sooner and hence faster convergence.

Also, teacher forcing helps the model focus on learning the correct predictions during the training, which results in a better ability to generalize and predict the next data. This eventually leads to a lower perplexity.

Generally, the model with teacher forcing will have a better performance and our result has proved that.

Exercise 8. *Q2.5 Distance Comparison (+1 point) Repeat the work you did for ‘ Q2.3 Embedding Distance‘ for the model in ‘ Q2.4 Teacher Forcing‘ and compare the distances produced by these two models (i.e. with and without the teacher forcing), what can you conclude?*

Solution. The cosine distance between two words has a slight change but it's not significant. Teacher forcing is a training strategy to help models learn more efficiently and generate meaningful sentences, but it should not have a significant impact on the word embedding between two individual words.

In conclusion, the effect of using teacher forcing or not for the cosine distance between two words is minimal.

3 Problem 3

Exercise 9. *Consider the self-attention operation S(X) defined as follows. Show that for any permutation matrix P , $PS(X) = S(PX)$*

Solution. First, we can rewrite the expression using PX,

$$\begin{aligned} S(PX)_t &= softmax(\frac{1}{\alpha}PXW_qW_k^T(PX)^T)PXW_v \\ &= softmax(\frac{1}{\alpha}PXW_qW_k^TX^TP^T)PXW_v \end{aligned} \tag{1}$$

Next, we are going to prove that

$$softmax(PAP^T) = Psoftmax(A)P^T \tag{2}$$

where A is a $R^{N\times N}$ matrix. [4]

$$(P \cdot softmax(A) \cdot P^T)_{p(i)p(j)} = softmax(A)_{ij}$$
$$= \frac{e^{A_{ij}}}{\sum_{n=1}^{N} e^{A_{ij}}}$$
$$= \frac{e^{PAP^T_{p(i)p(j)}}}{\sum_{n=1}^{N} e^{PAP^T_{p(i)p(j)}}}$$
$$= softmax(P \cdot A \cdot P^T)_{p(i)p(j)}$$

Now in equation(1) we have :

$$XW_qW_k^TX^T$$

We can write its shape $T \times D_{in} \times D_{in} \times D_k \times ... \times T$, so its shape is $R^{T\times T}$.

We can rewrite (1) using (2):

$$softmax(\frac{1}{\alpha}PXW_qW_k^TX^TP^T)PXW_v$$

$$= Psoftmax(\frac{1}{\alpha}XW_qW_k^TX^T)P^TPXW_v$$

$$= Psoftmax(\frac{1}{\alpha}XW_qW_k^TX^T)(P^TP)XW_v$$

$$= Psoftmax(\frac{1}{\alpha}XW_qW_k^TX^T)XW_v$$

$$= PS(X)$$

Therefore we have proven that $PS(X) = S(PX)$

Exercise 10. *We would like to use S(X) and a linear operation to construct a permutation invariant function G(X) that outputs the same feature representation for any ordering of the input sequence*

Solution. To make it permutation invariant, we can simply construct a vector w to add each column of the $S(X)$ matrix, essentially a sum operation over each column.

So an example vector could simply be:

$$w = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}$$

Let's assume the result of our softmax :

$$S(X) = \begin{bmatrix} 1 & 2 & 3 & 4 \\ 5 & 6 & 7 & 8 \\ 2 & 1 & 4 & 3 \\ 9 & 8 & 7 & 6 \end{bmatrix}$$

Then no matter the permutation we apply, the result would always be

$$w^T S(X) = \begin{bmatrix} 17 & 17 & 21 & 21 \end{bmatrix}$$

Exercise 11. *Implement a nn.module or python function using functionalize that takes Z and applies a "Position wise feedforward network" layer.*

Solution. See the Jupyter notebook. Jump to Jupyter

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March 31, 2023

1 Question 1

1.0.1 Exercise 1.(b)

[ ]:
```python
import torch
import torchvision.transforms as transforms
from torchvision import models
import matplotlib.pyplot as plt

# Load the pretrained model from pytorch
alexnet = models.alexnet(weights= models.AlexNet_Weights.DEFAULT)
alexnet.eval()
```

[ ]:
```
AlexNet(
  (features): Sequential(
    (0): Conv2d(3, 64, kernel_size=(11, 11), stride=(4, 4), padding=(2, 2))
    (1): ReLU(inplace=True)
    (2): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1,
ceil_mode=False)
    (3): Conv2d(64, 192, kernel_size=(5, 5), stride=(1, 1), padding=(2, 2))
    (4): ReLU(inplace=True)
    (5): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1,
ceil_mode=False)
    (6): Conv2d(192, 384, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (7): ReLU(inplace=True)
    (8): Conv2d(384, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (9): ReLU(inplace=True)
    (10): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (11): ReLU(inplace=True)
    (12): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1,
ceil_mode=False)
  )
  (avgpool): AdaptiveAvgPool2d(output_size=(6, 6))
  (classifier): Sequential(
    (0): Dropout(p=0.5, inplace=False)
    (1): Linear(in_features=9216, out_features=4096, bias=True)
    (2): ReLU(inplace=True)
    (3): Dropout(p=0.5, inplace=False)
```

```
    (4): Linear(in_features=4096, out_features=4096, bias=True)
    (5): ReLU(inplace=True)
    (6): Linear(in_features=4096, out_features=1000, bias=True)
  )
)
```

[ ]:
```python
import requests
import ast
from PIL import Image
from io import BytesIO

device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")

alexnet.to(device)


# Load labels
class_labels_url = "https://gist.githubusercontent.com/yrevar/
 ↪942d3a0ac09ec9e5eb3a/raw/238f720ff059c1f82f368259d1ca4ffa5dd8f9f5/
 ↪imagenet1000_clsidx_to_labels.txt"
response = requests.get(class_labels_url)
class_label_dict = ast.literal_eval(response.text)

transform = transforms.Compose([
    transforms.Resize(224),
    transforms.ToTensor(),
    transforms.Normalize(
        mean=[0.485, 0.456, 0.406],
        std=[0.229, 0.224, 0.225]
    )
])

# prediction function , get the top predicted class
def predict(imgurl, model):
    response = requests.get(imgurl)
    img = Image.open(BytesIO(response.content))
    img_t = transform(img)
    batch_t = torch.unsqueeze(img_t, 0)
    model.eval()
    with torch.no_grad():
        out = model(batch_t.to(device))
    _, top_pred = torch.topk(out, 1)
    top_pred = top_pred.item()
    label = class_label_dict[top_pred]
    plt.imshow(img)
    plt.axis('off')
    plt.title(label)
```

```
    plt.show()

# Load the image
list_of_images = ["https://raw.githubusercontent.com/ajschumacher/imagen/master/
↪imagen/n02129165_19260_lion.jpg",
                  "https://raw.githubusercontent.com/ajschumacher/imagen/master/
↪imagen/n01495701_1216_ray.jpg",
                    "https://raw.githubusercontent.com/ajschumacher/imagen/
↪master/imagen/n01662784_3789_turtle.jpg",
                    "https://raw.githubusercontent.com/ajschumacher/imagen/
↪master/imagen/n01944390_7816_snail.jpg",
                    "https://raw.githubusercontent.com/ajschumacher/imagen/
↪master/imagen/n02084071_19639_dog.jpg"



                  ]

for img in list_of_images:
    predict(img, alexnet)
```

lion, king of beasts, Panthera leo

stingray

terrapin

snail

Sussex spaniel

1.0.2 Exercise 1.(c)

```
[ ]: import random
import torch.optim as optim


def preprocess_image(img):
    img_t = transform(img)
    batch_t = torch.unsqueeze(img_t, 0).to(device)
    return batch_t

def deprocess_image(img):
    inv_normalize = transforms.Normalize(
        mean=[-0.485/0.229, -0.456/0.224, -0.406/0.225],
        std=[1/0.229, 1/0.224, 1/0.225]
    )
    img = inv_normalize(img)
    img = img.clamp(0, 1)
    img = transforms.ToPILImage()(img.cpu().squeeze(0))
    return img


# Create adversarial examples
def create_adversarial_example(img, target_class, model, alpha, learning_rate,␣
 ↪max_iter = 1000):
    img_var = img.clone().detach().requires_grad_(True)
    optimizer = optim.Adam([img_var], lr=learning_rate)
    target_class_var = torch.tensor([target_class], dtype=torch.long).to(device)
    for i in range(max_iter):
        optimizer.zero_grad()
        out = model(img_var)
        loss = alpha * torch.norm(img_var-img , p =1)+ torch.nn.
 ↪CrossEntropyLoss()(out, target_class_var)
        loss.backward()
        optimizer.step()
        _, top_pred = torch.topk(out, 1)
        if top_pred.item() == target_class:
            print("Target class reached. Iteration: {}, Loss: {}".format(i,␣
 ↪loss.item()))
            break
    return img_var.detach()

random_sample_image = ["https://raw.githubusercontent.com/ajschumacher/imagen/
 ↪master/imagen/n02219486_21998_ant.jpg",
```

```
                        "https://raw.githubusercontent.com/ajschumacher/imagen/
↪master/imagen/n02324045_13467_rabbit.jpg"]

alpha = 0.001
learning_rate = 0.01
max_iter = 100

for img_url in random_sample_image:
    response = requests.get(img_url)
    img = Image.open(BytesIO(response.content))
    img_t= preprocess_image(img)
    with torch.no_grad():
        true_class = torch.argmax(alexnet(img_t)).item()
    target_classes = random.sample([i for i in range(1000) if i != true_class],␣
↪3)
    print ("Original image: ")
    predict(img_url, alexnet)
    adversarial_list = []
    for target_class in target_classes:
        adversial_example = create_adversarial_example(img_t, target_class,␣
↪alexnet, alpha, learning_rate, max_iter)
        adversial_example_img = deprocess_image(adversial_example)
        adversarial_list.append(adversial_example_img)
        print (f"Adversarial example for target class␣
↪{class_label_dict[target_class]}")
    fig, axs = plt.subplots(1, 3, figsize=(15, 5))
    for i, adv_example_img in enumerate(adversarial_list):
        axs[i].imshow(adv_example_img)
        axs[i].set_title(class_label_dict[torch.
↪argmax(alexnet(preprocess_image(adv_example_img))).item()])
        axs[i].axis('off')
    plt.show()
```

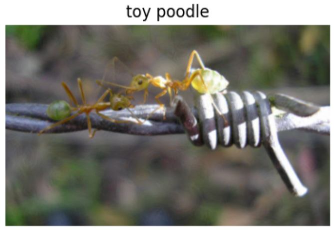
```
Original image:
```

grasshopper, hopper

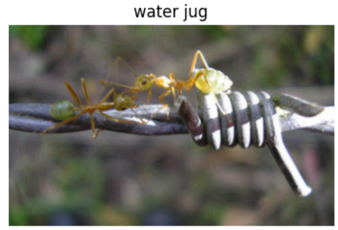
```
Target class reached. Iteration: 8, Loss: 7.674493312835693
Adversarial example for target class Kerry blue terrier
Target class reached. Iteration: 6, Loss: 7.784191131591797
Adversarial example for target class toy poodle
Target class reached. Iteration: 4, Loss: 6.469971179962158
Adversarial example for target class water jug
```

Kerry blue terrier

toy poodle



water jug

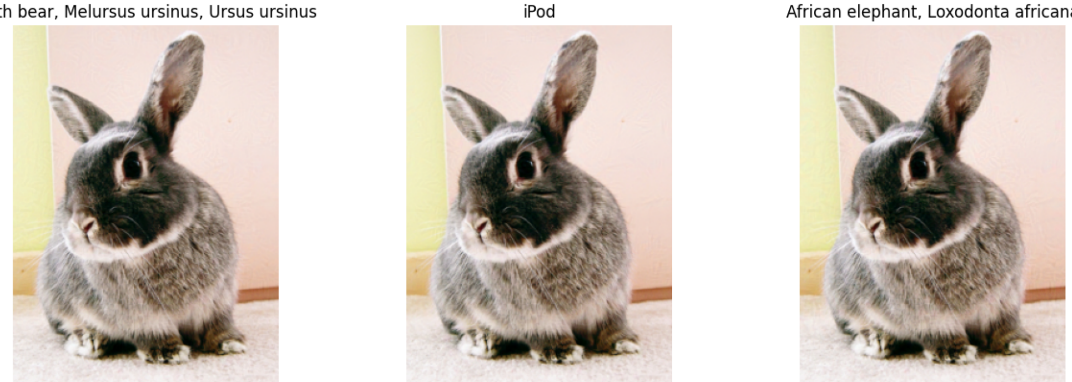


```
Original image:
```

wood rabbit, cottontail, cottontail rabbit

```
Target class reached. Iteration: 4, Loss: 5.4907050132751465
Adversarial example for target class sloth bear, Melursus ursinus, Ursus ursinus
Target class reached. Iteration: 7, Loss: 6.2488932609558105
Adversarial example for target class iPod
Target class reached. Iteration: 7, Loss: 7.710564136505127
Adversarial example for target class African elephant, Loxodonta africana
```

sloth bear, Melursus ursinus, Ursus ursinus | iPod | African elephant, Loxodonta africana



2 Question 3

2.0.1 Exercise 3.(c)

[ ]:
```
import torch
import torch.nn as nn
import torch.nn.functional as F

#Using nn.Linear
class PositionwiseFeedForwardLinear(nn.Module):
    def __init__(self, d_model):
        super(PositionwiseFeedForwardLinear, self).__init__()
        self.w_1 = nn.Linear(d_model, d_model)

    def forward(self, x):
        return (F.relu(self.w_1(x)))

#Using nn.Conv1d
class PositionwiseFeedForwardConv(nn.Module):
    def __init__(self, d_model):
        super(PositionwiseFeedForwardConv, self).__init__()
        self.w_1 = nn.Conv1d(d_model, d_model, kernel_size=1)

    def forward(self, x):
        x = x.permute(0, 2, 1)
        x = F.relu(self.w_1(x))
        return x.permute(0, 2, 1)

B,T,D = 16,32,64
Z = torch.randn(B,T,D)

linear_ffn = PositionwiseFeedForwardLinear(D)
conv_ffn = PositionwiseFeedForwardConv(D)

with torch.no_grad():
    linear_ffn.w_1.weight.copy_(conv_ffn.w_1.weight.squeeze())
    linear_ffn.w_1.bias.copy_(conv_ffn.w_1.bias)

linear_output = linear_ffn(Z)
conv1d_output = conv_ffn(Z)



assert torch.allclose(linear_output, conv1d_output, atol=1e-5), "Outputs do not␣
 ↪match"

print("Success!")
```

```
```

```
Success!
```

assignment2_starter_code

March 31, 2023

1 NN-Based Language Model

In this excercise we will run a basic RNN based language model and answer some questions about the code. It is advised to use GPU to run the code. First run the code then answer the questions below that require modifying it.

[ ]:
```
#@title   Imports & Hyperparameter Setup
#@markdown Feel free to experiment with the following hyperparameters at your
#@markdown leasure. For the purpose of this assignment, leave the default values
#@markdown and run the code with these suggested values.
# Some part of the code was referenced from below.
# https://github.com/pytorch/examples/tree/master/word_language_model
# https://github.com/yunjey/pytorch-tutorial/tree/master/tutorials/
 ↪02-intermediate/language_model

! git clone https://github.com/yunjey/pytorch-tutorial/
%cd pytorch-tutorial/tutorials/02-intermediate/language_model/

import torch
import torch.nn as nn
import numpy as np
from torch.nn.utils import clip_grad_norm_

# Device configuration
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')

# Hyper-parameters
embed_size = 128 #@param {type:"number"}
hidden_size = 1024 #@param {type:"number"}
num_layers = 1 #@param {type:"number"}
num_epochs = 5 #@param {type:"slider", min:1, max:10, step:1}
batch_size = 20 #@param {type:"number"}
seq_length = 30 #@param {type:"number"}
learning_rate = 0.002 #@param {type:"number"}
#@markdown Number of words to be sampled
num_samples = 50 #@param {type:"number"}

print(f"--> Device selected: {device}")
```

```
c:\Users\x_zhu202\Documents\GitHub\COMP691_LABS\pytorch-
tutorial\tutorials\02-intermediate\language_model
--> Device selected: cuda
```

```
fatal: destination path 'pytorch-tutorial' already exists and is not an empty
directory.
```

[ ]:
```
from data_utils import Dictionary, Corpus

# Load "Penn Treebank" dataset
corpus = Corpus()
ids = corpus.get_data('data/train.txt', batch_size)
vocab_size = len(corpus.dictionary)
num_batches = ids.size(1) // seq_length

print(f"Vcoabulary size: {vocab_size}")
print(f"Number of batches: {num_batches}")
```

```
Vcoabulary size: 10000
Number of batches: 1549
```

1.1 Model Definition

As you can see below, this model stacks `num_layers` many LSTM units vertically to construct our basic RNN-based language model. The diagram below shows a pictorial representation of the model in its simplest form (i.e `num_layers`=1).

[ ]:
```
# RNN based language model
class RNNLM(nn.Module):
    def __init__(self, vocab_size, embed_size, hidden_size, num_layers):
        super(RNNLM, self).__init__()
        self.embed = nn.Embedding(vocab_size, embed_size)
        self.lstm = nn.LSTM(embed_size, hidden_size, num_layers,␣
↪batch_first=True)
        self.linear = nn.Linear(hidden_size, vocab_size)

    def forward(self, x, h):
        # Embed word ids to vectors
        x = self.embed(x)

        # Forward propagate LSTM
        out, (h, c) = self.lstm(x, h)

        # Reshape output to (batch_size*sequence_length, hidden_size)
        out = out.reshape(out.size(0)*out.size(1), out.size(2))

        # Decode hidden states of all time steps
        out = self.linear(out)
        return out, (h, c)
```

1.2 Training

In this section we will train our model, this should take a couple of minutes! Be patient

[ ]:
```
model = RNNLM(vocab_size, embed_size, hidden_size, num_layers).to(device)

# Loss and optimizer
criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(model.parameters(), lr=learning_rate)

# Truncated backpropagation
def detach(states):
    return [state.detach() for state in states]


# Train the model
for epoch in range(num_epochs):
    # Set initial hidden and cell states
    states = (torch.zeros(num_layers, batch_size, hidden_size).to(device),
              torch.zeros(num_layers, batch_size, hidden_size).to(device))

    for i in range(0, ids.size(1) - seq_length, seq_length):
        # Get mini-batch inputs and targets
        inputs = ids[:, i:i+seq_length].to(device)
        targets = ids[:, (i+1):(i+1)+seq_length].to(device)

        # Forward pass
        states = detach(states)
        outputs, states = model(inputs, states)
        loss = criterion(outputs, targets.reshape(-1))

        # Backward and optimize
        optimizer.zero_grad()
        loss.backward()
        clip_grad_norm_(model.parameters(), 0.5)
        optimizer.step()

        step = (i+1) // seq_length
        if step % 100 == 0:
            print ('Epoch [{}/{}], Step[{}/{}], Loss: {:.4f}, Perplexity: {:5.
↪2f}'
                   .format(epoch+1, num_epochs, step, num_batches, loss.item(),␣
↪np.exp(loss.item())))
```

```
Epoch [1/5], Step[0/1549], Loss: 9.2069, Perplexity: 9965.54
Epoch [1/5], Step[100/1549], Loss: 6.0190, Perplexity: 411.16
Epoch [1/5], Step[200/1549], Loss: 5.9211, Perplexity: 372.81
Epoch [1/5], Step[300/1549], Loss: 5.7155, Perplexity: 303.54
```

```
Epoch [1/5], Step[400/1549], Loss: 5.6774, Perplexity: 292.19
Epoch [1/5], Step[500/1549], Loss: 5.1143, Perplexity: 166.39
Epoch [1/5], Step[600/1549], Loss: 5.2022, Perplexity: 181.68
Epoch [1/5], Step[700/1549], Loss: 5.3083, Perplexity: 202.01
Epoch [1/5], Step[800/1549], Loss: 5.2033, Perplexity: 181.86
Epoch [1/5], Step[900/1549], Loss: 5.0703, Perplexity: 159.23
Epoch [1/5], Step[1000/1549], Loss: 5.1053, Perplexity: 164.90
Epoch [1/5], Step[1100/1549], Loss: 5.3635, Perplexity: 213.47
Epoch [1/5], Step[1200/1549], Loss: 5.1588, Perplexity: 173.95
Epoch [1/5], Step[1300/1549], Loss: 5.1094, Perplexity: 165.56
Epoch [1/5], Step[1400/1549], Loss: 4.8076, Perplexity: 122.44
Epoch [1/5], Step[1500/1549], Loss: 5.1488, Perplexity: 172.23
Epoch [2/5], Step[0/1549], Loss: 5.4710, Perplexity: 237.69
Epoch [2/5], Step[100/1549], Loss: 4.5282, Perplexity: 92.60
Epoch [2/5], Step[200/1549], Loss: 4.7244, Perplexity: 112.66
Epoch [2/5], Step[300/1549], Loss: 4.7133, Perplexity: 111.41
Epoch [2/5], Step[400/1549], Loss: 4.5950, Perplexity: 98.98
Epoch [2/5], Step[500/1549], Loss: 4.0911, Perplexity: 59.81
Epoch [2/5], Step[600/1549], Loss: 4.4466, Perplexity: 85.33
Epoch [2/5], Step[700/1549], Loss: 4.3328, Perplexity: 76.16
Epoch [2/5], Step[800/1549], Loss: 4.4553, Perplexity: 86.08
Epoch [2/5], Step[900/1549], Loss: 4.2215, Perplexity: 68.13
Epoch [2/5], Step[1000/1549], Loss: 4.3278, Perplexity: 75.78
Epoch [2/5], Step[1100/1549], Loss: 4.5604, Perplexity: 95.62
Epoch [2/5], Step[1200/1549], Loss: 4.4022, Perplexity: 81.63
Epoch [2/5], Step[1300/1549], Loss: 4.2522, Perplexity: 70.26
Epoch [2/5], Step[1400/1549], Loss: 3.9612, Perplexity: 52.52
Epoch [2/5], Step[1500/1549], Loss: 4.3102, Perplexity: 74.45
Epoch [3/5], Step[0/1549], Loss: 4.4508, Perplexity: 85.69
Epoch [3/5], Step[100/1549], Loss: 3.8243, Perplexity: 45.80
Epoch [3/5], Step[200/1549], Loss: 4.0313, Perplexity: 56.34
Epoch [3/5], Step[300/1549], Loss: 4.0065, Perplexity: 54.95
Epoch [3/5], Step[400/1549], Loss: 3.8685, Perplexity: 47.87
Epoch [3/5], Step[500/1549], Loss: 3.4581, Perplexity: 31.76
Epoch [3/5], Step[600/1549], Loss: 3.7979, Perplexity: 44.61
Epoch [3/5], Step[700/1549], Loss: 3.6312, Perplexity: 37.76
Epoch [3/5], Step[800/1549], Loss: 3.7922, Perplexity: 44.35
Epoch [3/5], Step[900/1549], Loss: 3.5325, Perplexity: 34.21
Epoch [3/5], Step[1000/1549], Loss: 3.6896, Perplexity: 40.03
Epoch [3/5], Step[1100/1549], Loss: 3.7728, Perplexity: 43.50
Epoch [3/5], Step[1200/1549], Loss: 3.7255, Perplexity: 41.49
Epoch [3/5], Step[1300/1549], Loss: 3.4818, Perplexity: 32.52
Epoch [3/5], Step[1400/1549], Loss: 3.2329, Perplexity: 25.35
Epoch [3/5], Step[1500/1549], Loss: 3.6102, Perplexity: 36.97
Epoch [4/5], Step[0/1549], Loss: 3.6704, Perplexity: 39.27
Epoch [4/5], Step[100/1549], Loss: 3.2356, Perplexity: 25.42
Epoch [4/5], Step[200/1549], Loss: 3.4683, Perplexity: 32.08
Epoch [4/5], Step[300/1549], Loss: 3.4890, Perplexity: 32.75
```

```
Epoch [4/5], Step[400/1549], Loss: 3.4009, Perplexity: 29.99
Epoch [4/5], Step[500/1549], Loss: 2.9435, Perplexity: 18.98
Epoch [4/5], Step[600/1549], Loss: 3.3262, Perplexity: 27.83
Epoch [4/5], Step[700/1549], Loss: 3.1705, Perplexity: 23.82
Epoch [4/5], Step[800/1549], Loss: 3.3215, Perplexity: 27.70
Epoch [4/5], Step[900/1549], Loss: 3.0867, Perplexity: 21.90
Epoch [4/5], Step[1000/1549], Loss: 3.2723, Perplexity: 26.37
Epoch [4/5], Step[1100/1549], Loss: 3.2085, Perplexity: 24.74
Epoch [4/5], Step[1200/1549], Loss: 3.1873, Perplexity: 24.22
Epoch [4/5], Step[1300/1549], Loss: 3.0351, Perplexity: 20.80
Epoch [4/5], Step[1400/1549], Loss: 2.6961, Perplexity: 14.82
Epoch [4/5], Step[1500/1549], Loss: 3.1527, Perplexity: 23.40
Epoch [5/5], Step[0/1549], Loss: 3.2509, Perplexity: 25.81
Epoch [5/5], Step[100/1549], Loss: 2.8687, Perplexity: 17.61
Epoch [5/5], Step[200/1549], Loss: 3.0505, Perplexity: 21.13
Epoch [5/5], Step[300/1549], Loss: 3.1495, Perplexity: 23.32
Epoch [5/5], Step[400/1549], Loss: 3.0962, Perplexity: 22.11
Epoch [5/5], Step[500/1549], Loss: 2.6367, Perplexity: 13.97
Epoch [5/5], Step[600/1549], Loss: 2.9966, Perplexity: 20.02
Epoch [5/5], Step[700/1549], Loss: 2.8827, Perplexity: 17.86
Epoch [5/5], Step[800/1549], Loss: 2.9748, Perplexity: 19.59
Epoch [5/5], Step[900/1549], Loss: 2.7764, Perplexity: 16.06
Epoch [5/5], Step[1000/1549], Loss: 2.8969, Perplexity: 18.12
Epoch [5/5], Step[1100/1549], Loss: 2.9826, Perplexity: 19.74
Epoch [5/5], Step[1200/1549], Loss: 2.8895, Perplexity: 17.98
Epoch [5/5], Step[1300/1549], Loss: 2.6705, Perplexity: 14.45
Epoch [5/5], Step[1400/1549], Loss: 2.3726, Perplexity: 10.73
Epoch [5/5], Step[1500/1549], Loss: 2.9207, Perplexity: 18.55
```

2 Questions

2.1 1 Q2.1 Detaching or not? (10 points)

The above code implements a version of truncated backpropagation through time. The implementation only requires the `detach()` function (lines 7-9 of the cell) defined above the loop and used once inside the training loop. * Explain the implementation (compared to not using truncated backprop through time). * What does the `detach()` call here achieve? Draw a computational graph. You may choose to answer this question outside the notebook. * When using using line 7-9 we will typically observe less GPU memory being used during training, explain why in your answer.

[ ]:
```
print ("Answered in the above PDF. Outside of the notebook.")
```

```
Answered in the above PDF. Outside of the notebook.
```

2.2 Model Prediction

Below we will use our model to generate text sequence!

[ ]:
```python
# Sample from the model
with torch.no_grad():
    with open('sample.txt', 'w') as f:
        # Set intial hidden ane cell states
        state = (torch.zeros(num_layers, 1, hidden_size).to(device),
                 torch.zeros(num_layers, 1, hidden_size).to(device))

        # Select one word id randomly
        prob = torch.ones(vocab_size)
        input = torch.multinomial(prob, num_samples=1).unsqueeze(1).to(device)

        for i in range(num_samples):
            # Forward propagate RNN
            output, state = model(input, state)

            # Sample a word id
            prob = output.exp()
            word_id = torch.multinomial(prob, num_samples=1).item()

            # Fill input with sampled word id for the next time step
            input.fill_(word_id)

            # File write
            word = corpus.dictionary.idx2word[word_id]
            word = '\n' if word == '<eos>' else word + ' '
            f.write(word)

            if (i+1) % 100 == 0:
                print('Sampled [{}/{}] words and save to {}'.format(i+1,␣
 ↪num_samples, 'sample.txt'))
! type sample.txt
```

```
had little more than N years
but the report 's current account seems to be this is likely to <unk> because it
tends to enter out office of the cars from the u.s.
cancer patients clearly shortages giving the studio mr. reitman 's
it is n't starting
```

2.3 2 Q2.2 Sampling strategy (7 points)

Consider the sampling procedure above. The current code samples a word:

`word_id = torch.multinomial(prob, num_samples=1).item()`

in order to feed the model at each output step and feeding those to the next timestep. Copy below the above cell and modify this sampling startegy to use a greedy sampling which selects the highest probability word at each time step to feed as the next input.

```
[ ]: # Sample greedily from the model
     # Sample from the model using greedy sampling
     with torch.no_grad():
         with open('sample_greedy.txt', 'w') as f:
             # Set initial hidden and cell states
             state = (torch.zeros(num_layers, 1, hidden_size).to(device),
                      torch.zeros(num_layers, 1, hidden_size).to(device))

             # Select one word id randomly
             prob = torch.ones(vocab_size)
             input = torch.multinomial(prob, num_samples=1).unsqueeze(1).to(device)

             for i in range(num_samples):
                 # Forward propagate RNN
                 output, state = model(input, state)

                 # Sample a word id using greedy approach
                 prob = output.exp()
                 word_id = torch.argmax(prob, dim=-1).item()

                 # Fill input with sampled word id for the next time step
                 input.fill_(word_id)

                 # File write
                 word = corpus.dictionary.idx2word[word_id]
                 word = '\n' if word == '<eos>' else word + ' '
                 f.write(word)

                 if (i+1) % 100 == 0:
                     print('Sampled [{}/{}] words and save to {}'.format(i+1,␣
      ↪num_samples, 'sample_greedy.txt'))
     ! type sample_greedy.txt
```

```
's unexpected strengthening on the economy and the economy
the index which uses the dollar began at N down N
the index was N N
the index registered N in august compared with N in july and N
the index registered N in august with the
```

2.4 3 Q2.3 Embedding Distance (8 points)

Our model has learned a specific set of word embeddings. * Write a function that takes in 2 words and prints the cosine distance between their embeddings using the word embeddings from the above models. * Use it to print the cosine distance of the word "army" and the word "taxpayer".

Refer to the sampling code for how to output the words corresponding to each index. To get the index you can use the function ***`corpus.dictionary.word2idx`***.

[ ]:
```python
# Embedding distance
import torch.nn.functional as F

def get_cosine_distance(a, b,model):
    idx1 = corpus.dictionary.word2idx[a]
    idx2 = corpus.dictionary.word2idx[b]

    embed1 = model.embed.weight[idx1]
    embed2 = model.embed.weight[idx2]

    similarity = F.cosine_similarity(embed1.unsqueeze(0), embed2.unsqueeze(0))

    distance = 1 - similarity.item()

    return distance

word1 = 'army'
word2 = 'taxpayer'
distance = get_cosine_distance(word1, word2, model)
print(f"The cosine distance between '{word1}' and '{word2}' is {distance:.4f}")
```

```
The cosine distance between 'army' and 'taxpayer' is 1.1022
```

2.5 4 Q2.4 Teacher Forcing (Extra Credit 2 points)

What is teacher forcing? > Teacher forcing works by using the actual or expected output from the training dataset at the current time step $y(t)$ as input in the next time step $X(t+1)$, rather than the output generated by the network.

In the `Training` code this is achieved, implicitly, when we pass the entire input sequence (`inputs = ids[:, i:i+seq_length].to(device)`) to the model at once.

Copy below the `Training` code and modify it to disable teacher forcing training. Compare the performance of this model, to original model, what can you conclude? (compare perplexity and convergence rate)

[ ]:
```python
# Training code without Teacher Forcing

model = RNNLM(vocab_size, embed_size, hidden_size, num_layers).to(device)
optimizer = torch.optim.Adam(model.parameters(), lr=learning_rate)

for epoch in range(num_epochs):
    # Set initial hidden and cell states
    states = (torch.zeros(num_layers, batch_size, hidden_size).to(device),
              torch.zeros(num_layers, batch_size, hidden_size).to(device))

    for i in range(0, ids.size(1) - seq_length, seq_length):
        # Get mini-batch inputs and targets
        inputs = ids[:, i:i+seq_length].to(device)
```

```
        targets = ids[:, (i+1):(i+1)+seq_length].to(device)

        loss = 0

        # Forward pass
        for time_step in range(seq_length):
            states = detach(states)
            outputs, states = model(inputs, states)
            reshaped_outputs = outputs.view(batch_size, -1, vocab_size)[:, -1, :
↪]
            current_loss = criterion(reshaped_outputs, targets[:, time_step].
↪view(-1))
            loss += current_loss

            inputs = torch.argmax(reshaped_outputs, dim=-1).detach().
↪unsqueeze(1)

        loss /= seq_length

        # Backward and optimize
        optimizer.zero_grad()
        loss.backward()
        clip_grad_norm_(model.parameters(), 0.5)
        optimizer.step()

        step = (i+1) // seq_length
        if step % 100 == 0:
            print ('Epoch [{}/{}], Step[{}/{}], Loss: {:.4f}, Perplexity: {:5.
↪2f}'
                   .format(epoch+1, num_epochs, step, num_batches, loss.item(),␣
↪np.exp(loss.item())))
```

```
Epoch [1/5], Step[0/1549], Loss: 9.2097, Perplexity: 9993.40
Epoch [1/5], Step[100/1549], Loss: 6.5312, Perplexity: 686.22
Epoch [1/5], Step[200/1549], Loss: 6.6389, Perplexity: 764.24
Epoch [1/5], Step[300/1549], Loss: 6.6714, Perplexity: 789.52
Epoch [1/5], Step[400/1549], Loss: 6.5736, Perplexity: 715.95
Epoch [1/5], Step[500/1549], Loss: 6.5178, Perplexity: 677.10
Epoch [1/5], Step[600/1549], Loss: 6.4526, Perplexity: 634.37
Epoch [1/5], Step[700/1549], Loss: 6.6863, Perplexity: 801.36
Epoch [1/5], Step[800/1549], Loss: 6.4238, Perplexity: 616.33
Epoch [1/5], Step[900/1549], Loss: 6.5778, Perplexity: 718.94
Epoch [1/5], Step[1000/1549], Loss: 6.5673, Perplexity: 711.42
Epoch [1/5], Step[1100/1549], Loss: 6.7199, Perplexity: 828.71
Epoch [1/5], Step[1200/1549], Loss: 6.5152, Perplexity: 675.32
Epoch [1/5], Step[1300/1549], Loss: 6.7478, Perplexity: 852.22
Epoch [1/5], Step[1400/1549], Loss: 6.5587, Perplexity: 705.35
```

```
Epoch [1/5], Step[1500/1549], Loss: 6.6037, Perplexity: 737.79
Epoch [2/5], Step[0/1549], Loss: 8.1542, Perplexity: 3478.01
Epoch [2/5], Step[100/1549], Loss: 6.3141, Perplexity: 552.29
Epoch [2/5], Step[200/1549], Loss: 6.3861, Perplexity: 593.51
Epoch [2/5], Step[300/1549], Loss: 6.5283, Perplexity: 684.22
Epoch [2/5], Step[400/1549], Loss: 6.4733, Perplexity: 647.60
Epoch [2/5], Step[500/1549], Loss: 6.2380, Perplexity: 511.85
Epoch [2/5], Step[600/1549], Loss: 6.2412, Perplexity: 513.46
Epoch [2/5], Step[700/1549], Loss: 6.4999, Perplexity: 665.05
Epoch [2/5], Step[800/1549], Loss: 6.3046, Perplexity: 547.09
Epoch [2/5], Step[900/1549], Loss: 6.4421, Perplexity: 627.74
Epoch [2/5], Step[1000/1549], Loss: 6.4385, Perplexity: 625.46
Epoch [2/5], Step[1100/1549], Loss: 6.5548, Perplexity: 702.58
Epoch [2/5], Step[1200/1549], Loss: 6.4065, Perplexity: 605.79
Epoch [2/5], Step[1300/1549], Loss: 6.5075, Perplexity: 670.12
Epoch [2/5], Step[1400/1549], Loss: 6.4204, Perplexity: 614.22
Epoch [2/5], Step[1500/1549], Loss: 6.4570, Perplexity: 637.18
Epoch [3/5], Step[0/1549], Loss: 6.7246, Perplexity: 832.63
Epoch [3/5], Step[100/1549], Loss: 6.2055, Perplexity: 495.49
Epoch [3/5], Step[200/1549], Loss: 6.2376, Perplexity: 511.61
Epoch [3/5], Step[300/1549], Loss: 6.4465, Perplexity: 630.50
Epoch [3/5], Step[400/1549], Loss: 6.4238, Perplexity: 616.37
Epoch [3/5], Step[500/1549], Loss: 6.1189, Perplexity: 454.37
Epoch [3/5], Step[600/1549], Loss: 6.2208, Perplexity: 503.12
Epoch [3/5], Step[700/1549], Loss: 6.4263, Perplexity: 617.90
Epoch [3/5], Step[800/1549], Loss: 6.2033, Perplexity: 494.39
Epoch [3/5], Step[900/1549], Loss: 6.3113, Perplexity: 550.74
Epoch [3/5], Step[1000/1549], Loss: 6.3096, Perplexity: 549.85
Epoch [3/5], Step[1100/1549], Loss: 6.3997, Perplexity: 601.69
Epoch [3/5], Step[1200/1549], Loss: 6.2745, Perplexity: 530.87
Epoch [3/5], Step[1300/1549], Loss: 6.3819, Perplexity: 591.05
Epoch [3/5], Step[1400/1549], Loss: 6.3023, Perplexity: 545.81
Epoch [3/5], Step[1500/1549], Loss: 6.2675, Perplexity: 527.17
Epoch [4/5], Step[0/1549], Loss: 6.5475, Perplexity: 697.48
Epoch [4/5], Step[100/1549], Loss: 6.1811, Perplexity: 483.54
Epoch [4/5], Step[200/1549], Loss: 6.2515, Perplexity: 518.80
Epoch [4/5], Step[300/1549], Loss: 6.3563, Perplexity: 576.14
Epoch [4/5], Step[400/1549], Loss: 6.2971, Perplexity: 543.01
Epoch [4/5], Step[500/1549], Loss: 6.0442, Perplexity: 421.66
Epoch [4/5], Step[600/1549], Loss: 6.1266, Perplexity: 457.86
Epoch [4/5], Step[700/1549], Loss: 6.3525, Perplexity: 573.91
Epoch [4/5], Step[800/1549], Loss: 6.1367, Perplexity: 462.51
Epoch [4/5], Step[900/1549], Loss: 6.2070, Perplexity: 496.20
Epoch [4/5], Step[1000/1549], Loss: 6.2381, Perplexity: 511.89
Epoch [4/5], Step[1100/1549], Loss: 6.3913, Perplexity: 596.66
Epoch [4/5], Step[1200/1549], Loss: 6.2039, Perplexity: 494.66
Epoch [4/5], Step[1300/1549], Loss: 6.3092, Perplexity: 549.63
Epoch [4/5], Step[1400/1549], Loss: 6.1635, Perplexity: 475.06
```

```
Epoch [4/5], Step[1500/1549], Loss: 6.1648, Perplexity: 475.70
Epoch [5/5], Step[0/1549], Loss: 6.3928, Perplexity: 597.53
Epoch [5/5], Step[100/1549], Loss: 6.1331, Perplexity: 460.84
Epoch [5/5], Step[200/1549], Loss: 6.1405, Perplexity: 464.29
Epoch [5/5], Step[300/1549], Loss: 6.3862, Perplexity: 593.62
Epoch [5/5], Step[400/1549], Loss: 6.2252, Perplexity: 505.33
Epoch [5/5], Step[500/1549], Loss: 5.8803, Perplexity: 357.91
Epoch [5/5], Step[600/1549], Loss: 6.0875, Perplexity: 440.34
Epoch [5/5], Step[700/1549], Loss: 6.2520, Perplexity: 519.07
Epoch [5/5], Step[800/1549], Loss: 6.0414, Perplexity: 420.50
Epoch [5/5], Step[900/1549], Loss: 6.3427, Perplexity: 568.33
Epoch [5/5], Step[1000/1549], Loss: 6.1992, Perplexity: 492.36
Epoch [5/5], Step[1100/1549], Loss: 6.3112, Perplexity: 550.68
Epoch [5/5], Step[1200/1549], Loss: 6.1178, Perplexity: 453.89
Epoch [5/5], Step[1300/1549], Loss: 6.2769, Perplexity: 532.12
Epoch [5/5], Step[1400/1549], Loss: 6.1248, Perplexity: 457.07
Epoch [5/5], Step[1500/1549], Loss: 6.0773, Perplexity: 435.85
```

2.6 5 Q2.5 Distance Comparison (+1 point)

Repeat the work you did for `3 Q2.3 Embedding Distance` for the model in `4 Q2.4 Teacher Forcing` and compare the distances produced by these two models (i.e. with and without the teacher forcing), what can you conclude?

[ ]:
```
distance_without_teacher_forcing = get_cosine_distance(word1, word2, model)
print(f"The cosine distance between '{word1}' and '{word2}' is␣
↪{distance_without_teacher_forcing:.4f}")
```

```
The cosine distance between 'army' and 'taxpayer' is 0.9217
```

References

[1] Vincent Dumoulin and Francesco Visin. "A guide to convolution arithmetic for deep learning". In: *arXiv preprint arXiv:1603.07285* (2018).

[2] *Backpropagation Through Time*. `https://d2l.ai/chapter_recurrent-neural-networks/bptt.html`. Accessed: 2023-03-29. 2021.

[3] Denny Britz. *Recurrent Neural Networks Tutorial, Part 3 - Backpropagation Through Time and Vanishing Gradients*. Accessed: 2023-03-30. 2015. URL: `https://dennybritz.com/posts/wildml/recurrent-neural-networks-tutorial-part-3/`.

[4] Jiancheng Yang et al. *Modeling Point Clouds with Self-Attention and Gumbel Subset Sampling*. 2019. arXiv: `1904.03375 [cs.CV]`.