jupyter hw4_colab (autosaved)

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HW4: Autoencoders & RNNs

The homework is broken up as follows:

1. Question 1: Masked Autoencoder, Revisited (three points total)
2. Question 2: A Simple Sequence Task (three points total)
3. Question 3: Sequence-to-Sequence Translation (three points total)
4. Question 4: Short Response (two points total)

How to Submit This Homework

This homework has been provided to you as an `.ipynb` file. I expect you to complete the notebook and submit the following on Canvas:

1. The completed notebook itself with your answers filled in (including any source code used to answer the question)
2. A `.pdf` file of the notebook that shows all your answers. This will make grading easier and I will appreciate that.

If you submit only one of these, you will lose points. No late homework will be graded. No submissions via email or other media will be graded.

Finally, each question specifies exactly what should be provided in your answer -- for example, if no code is requested, do not provide it. Your submitted notebook (and PDF) should not contain any additional content or cells beyond what is requested.

Setup

If you do not have access to a CUDA-compatible NVIDIA GPU, it is recommended that you run this notebook in Google Colab. There, you will have the option to enable GPU acceleration with `Runtime` >> `Change runtime type` >> `Hardware accelerator` >> `GPU` >> `Save`. Note that you may have to re-connect or restart the notebook after changing runtime types.

In [ ]:
```
# helper code from the course repository
!git clone https://github.com/interactiveaudiolab/course-deep-learning.git
# install common pacakges used for deep learning
!cd course-deep-learning/ && pip install -r requirements.txt
```

```
Cloning into 'course-deep-learning'...
remote: Enumerating objects: 398, done.
remote: Counting objects: 100% (19/19), done.
remote: Compressing objects: 100% (16/16), done.
remote: Total 398 (delta 7), reused 10 (delta 3), pack-reused 379
Receiving objects: 100% (398/398), 138.22 MiB | 27.40 MiB/s, done.
Resolving deltas: 100% (186/186), done.
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: torch in /usr/local/lib/python3.7/dist-packages (from -r requirements.txt (line
1)) (1.11.0+cu113)
Requirement already satisfied: torchvision in /usr/local/lib/python3.7/dist-packages (from -r requirements.txt (l
ine 2)) (0.12.0+cu113)
Requirement already satisfied: gdown>=4.4.0 in /usr/local/lib/python3.7/dist-packages (from -r requirements.txt
(line 3)) (4.4.0)
Requirement already satisfied: torchaudio in /usr/local/lib/python3.7/dist-packages (from -r requirements.txt (li
ne 4)) (0.11.0+cu113)
Requirement already satisfied: librosa in /usr/local/lib/python3.7/dist-packages (from -r requirements.txt (line
5)) (0.8.1)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.7/dist-packages (from -r requirements.txt (li
```

In [ ]:
```
%matplotlib inline
%cd course-deep-learning/

import datetime
import math
import torch
import matplotlib.pyplot as plt
import numpy as np
import IPython.display as ipd
from matplotlib.animation import FuncAnimation
from pathlib import Path
from torch.utils.tensorboard import SummaryWriter
from torchsummary import summary
from tqdm import tqdm
import torchvision
from IPython.display import display, Image
from torch import nn

from utils.gan import *
```

```
[Errno 2] No such file or directory: 'course-deep-learning/'
/content/course-deep-learning
```

Question 1: Masked Autoencoder, Revisited (three points total)

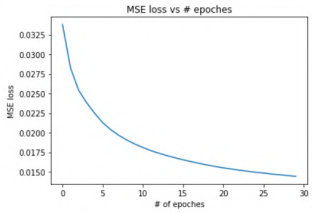
1.1 A Bigger Mask (one point)

Train the MLP-based inpainting autoencoder from notebook 7 but this time, re-write `apply_mask()` (and your training code) to **deterministically zero-out the *left half* of every input image. Train for 30 epochs, and place a plot of your reconstruction loss vs. epochs below.**

Hint: make sure that you apply the mask to a copy of each input rather than destructively editing the input itself, as the original input still has to serve as a target!

(YOUR LOSS PLOT HERE)

In [ ]:
```
display(Image.open("/home/alen/Downloads/hw4q1.1.png"))
```



In [ ]:
```
class MLPEncoder(torch.nn.Module):

    def __init__(self,
                 number_of_hidden_layers: int,
                 input_size: int,
                 hidden_size: int,
                 latent_size: int,
                 activation: torch.nn.Module):
        """Construct a simple MLP encoder"""

        super().__init__()

        assert number_of_hidden_layers >= 0, "Encoder number_of_hidden_layers must be at least 0"

        dims_in = [input_size] + [hidden_size] * number_of_hidden_layers
        dims_out = [hidden_size] * number_of_hidden_layers + [latent_size]  # final output should be latent siz
        layers = []
        for i in range(number_of_hidden_layers + 1):
            layers.append(torch.nn.Linear(dims_in[i], dims_out[i]))

            if i < number_of_hidden_layers:
                layers.append(activation)

        self.net = torch.nn.Sequential(*layers)

    def forward(self, x: torch.Tensor):
        return self.net(x)
```

```python
        return self.net(x)


class MLPDecoder(torch.nn.Module):

    def __init__(self,
                 number_of_hidden_layers: int,
                 latent_size: int,
                 hidden_size: int,
                 input_size: int,
                 activation: torch.nn.Module):
        """Construct a simple MLP decoder"""

        super().__init__()

        assert number_of_hidden_layers >= 0, "Decoder number_of_hidden_layers must be at least 0"

        dims_in = [latent_size] + [hidden_size] * number_of_hidden_layers
        dims_out = [hidden_size] * number_of_hidden_layers + [input_size]  # final output is an image

        layers = []
        for i in range(number_of_hidden_layers + 1):
            layers.append(torch.nn.Linear(dims_in[i], dims_out[i]))

            if i < number_of_hidden_layers:
                layers.append(activation)

        # apply Tanh after final layer to bound pixels to range [-1, 1]
        layers.append(torch.nn.Sigmoid())

        self.net = torch.nn.Sequential(*layers)

    def forward(self, x: torch.Tensor):
        return self.net(x)


class MLPAutoencoder(torch.nn.Module):

    def __init__(self,
                 number_of_hidden_layers: int,
                 input_size: int,
                 hidden_size: int,
                 latent_size: int,
                 activation_encoder: torch.nn.Module = torch.nn.ReLU(),
                 activation_decoder: torch.nn.Module = torch.nn.LeakyReLU(0.2)
                ):
        """Construct a simple MLP autoencoder

        number_of_hidden_layers: An int. Must be >=0. Defines the number of
                hidden layers for both the encoder E and decoder D
        latent_size:  An int. Defines the size of the latent representation produced by
                      the encoder.
        hidden_size: An int. The size of each hidden layer for the encoder E and
                     the decoder D.
        input_size: An int. Determines the size of the input and output images
        activation_encoder: A torch.nn.Module defining the activation function in every
                            hidden layer of the encoder.
        activation_decoder: A torch.nn.Module defining the activation function in every
                            hidden layer of the decoder.
        """
        super().__init__()

        self.encoder = MLPEncoder(
            number_of_hidden_layers=number_of_hidden_layers,
            input_size=input_size,
            hidden_size=hidden_size,
            latent_size=latent_size,
            activation=activation_encoder
        )

        self.decoder = MLPDecoder(
            number_of_hidden_layers=number_of_hidden_layers,
            input_size=input_size,
            hidden_size=hidden_size,
            latent_size=latent_size,
            activation=activation_decoder
        )

    def encode(self, x: torch.Tensor):
        return self.encoder(x)

    def decode(self, x: torch.Tensor):
        return self.decoder(x)

    def forward(self, x: torch.Tensor):
        return(self.decode(self.encode(x)))

```

In [ ]:

```python
# def apply_mask(x: torch.Tensor, image_size: int, mask_size: int):
def apply_mask(x: torch.Tensor):
    """Apply random masks to each input in batch"""
#     if len(x.shape) == 3:
#         x = x.unsqueeze(0)

    n_batch = x.shape[0]
    if x.shape[-1] != x.shape[-2]:
        Exception(f"Not square image")
    image_size= x.shape[-1]
    # mask placement can be defined by location of upper-left corner
#     valid_idx = image_size - mask_size - 1
#     batch_corners = torch.randint(low=0, high=valid_idx, size=(n_batch, 2))

    x_masked = x.clone()

    # apply masks to each image in batch
    for i in range(n_batch):
        x_masked[
                 i,
                 :,
                 :,
                 : image_size // 2: ,
                 ] = 0
    return x_masked
```

In [ ]:

```python
# autoencoder training hyperparameters
image_size = 28
batch_size = 64
latent_size = 64
hidden_size = 256
number_of_hidden_layers = 2
lr = 0.0002
epochs = 30

# fix random seed
torch.manual_seed(0)

# select device
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print(device)
# load MNIST dataset
mnist = load_mnist(batch_size=batch_size)

# initialize the model
model = MLPAutoencoder(
    number_of_hidden_layers=number_of_hidden_layers,
    latent_size=latent_size,
    hidden_size=hidden_size,
    input_size=image_size*image_size,
).to(device)

# use an optimizer to handle parameter updates
opt = torch.optim.Adam(model.parameters(), lr=lr)

# loss function: mean-squared error between original and reconstructed images
loss = torch.nn.MSELoss()
```

```
cuda
Downloading http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz
Downloading http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz to ./data/MNIST/raw/train-images-idx3-ubyte.gz

  0%|          | 0/9912422 [00:00<?, ?it/s]
```

```
Extracting ./data/MNIST/raw/train-images-idx3-ubyte.gz to ./data/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/train-labels-idx1-ubyte.gz
Downloading http://yann.lecun.com/exdb/mnist/train-labels-idx1-ubyte.gz to ./data/MNIST/raw/train-labels-idx1-ubyt
e.gz

  0%|          | 0/28881 [00:00<?, ?it/s]

Extracting ./data/MNIST/raw/train-labels-idx1-ubyte.gz to ./data/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/t10k-images-idx3-ubyte.gz
Downloading http://yann.lecun.com/exdb/mnist/t10k-images-idx3-ubyte.gz to ./data/MNIST/raw/t10k-images-idx3-ubyte.
gz

  0%|          | 0/1648877 [00:00<?, ?it/s]

Extracting ./data/MNIST/raw/t10k-images-idx3-ubyte.gz to ./data/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz
Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz to ./data/MNIST/raw/t10k-labels-idx1-ubyte.
gz

  0%|          | 0/4542 [00:00<?, ?it/s]

Extracting ./data/MNIST/raw/t10k-labels-idx1-ubyte.gz to ./data/MNIST/raw
```

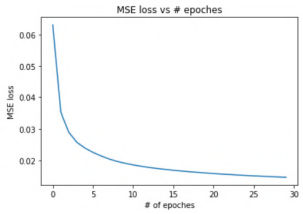
In [ ]:

```python

def training_loop():
        # we'll start with small 10x10 masks
    mask_size = 10
    ans = []

    for epoch in range(epochs):

        # weight batch losses/scores proportional to batch size
        iter_count = 0
        loss_epoch = 0

        for batch_idx, batch_data in enumerate(mnist):

            # we only care about inputs, not labels
            x_real, _ = batch_data

            # obtain batch of inputs and move to device
            x_real = x_real.to(device)
            n_batch = x_real.shape[0]

            # apply random masks
            x_masked = apply_mask(x_real)
#             plt.imshow(x_masked[0].squeeze().cpu(), cmap='gray')
#             plt.show()
            x_masked = x_masked.reshape(n_batch, -1)

            # flatten input images
            x_real = x_real.reshape(n_batch, -1)

            model.zero_grad()

            # train on a batch of inputs
            x_reconstructed = model(x_masked)
            loss_batch = loss(x_real, x_reconstructed)
            loss_batch.backward()
            opt.step()

            # log loss
            loss_epoch += loss_batch.detach().item() * n_batch
            iter_count += n_batch

        # plot loss
        loss_epoch /= iter_count
        ans.append(loss_epoch)

        if not epoch % 10:
            print(f"Epoch: {epoch + 1}\tMSE Loss: {loss_epoch :0.4f}")

    return ans
```

In [ ]:

```python
res = training_loop()
plt.plot(res)
plt.title("MSE loss vs # epoches")
plt.xlabel("# of epoches")
plt.ylabel("MSE loss")
plt.show()
```

```
Epoch: 1        MSE Loss: 0.0632
Epoch: 11       MSE Loss: 0.0185
Epoch: 21       MSE Loss: 0.0157
```

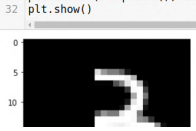


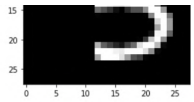
1.2 Reconstruction (one point)

The code below provides a hard-coded example image of a "3." **Pass this image through your new inpainting autoencoder and include the reconstructed image below. Does your autoencoder faithfully reconstruct the input (i.e. produce a similar-looking image of the same class)? If not, briefly explain why you think the reconstruction looks the way it does.**

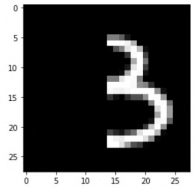
In [ ]:

```python
x = torch.as_tensor(
    [[[0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
      [0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
      [0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
      [0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
      [0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
      [0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.8667,
      [0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.9961,
      [0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0157,
      [0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
      [0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
      [0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
      [0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.3216,
      [0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.9961,
      [0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.9961,
      [0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.4314,
      [0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0157,
      [0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
      [0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
      [0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0039,
      [0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.6980,
      [0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.9961,
      [0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.6471,
      [0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
      [0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
      [0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
      [0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,

plt.imshow(x.squeeze(), cmap='gray')
plt.show()
```



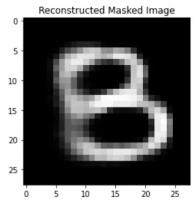


In [ ]:
```
xx = torch.unsqueeze(x, 0)
masked_x = apply_mask(xx).to(device)
plt.imshow(masked_x.squeeze().cpu(), cmap='gray')
plt.show()

```



In [ ]:
```
# print(device)
masked_x = torch.squeeze(xx, 0).to(device)
# print(model)
print(masked_x.shape)
reconstructed_image = reconstructed_image = model(masked_x.flatten().unsqueeze(0).to(device)).reshape(1, 28,28)
print(res.shape)

plt.imshow(reconstructed_image.squeeze(), cmap='gray')
plt.title("Reconstructed Masked Image")
plt.show()
```

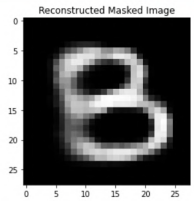
```
torch.Size([1, 28, 28])
torch.Size([1, 28, 28])
```



In [ ]:
```

```

(YOUR RECONSTRUCTED IMAGE HERE)

In [ ]:
```
display(Image.open("/home/alen/Downloads/hw4q1.2.png"))
```



(YOUR EXPLANATION HERE)

No, reconstructed image does NOT look like original class, digit 3; the possible reason is that left half masked 3 image is almost analogous to left half masked 8, corrupted 3 and 8 share too many same features. Even human cannot distinguish if it is 3 or 8.

1.3 Augmentation (one point)

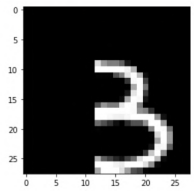
In notebook 4, we learned how to apply random augmentations to image data. **Create a `RandomAffine` transform that applies:**

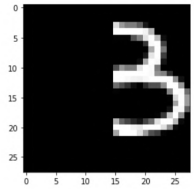
- **Rotations between -10 and 10 degrees**
- **Horizontal and vertical translations of at most 0.2**
- **Shear between -5 and 5 degrees**

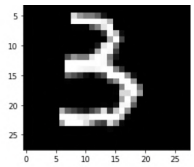
Using this randomized transform, create three augmented versions of the hard-coded image above. For each augmented version obtain a reconstruction by passing it to your inpainting autoencoder. Include the three augmented images and three corresponding reconstructions below.

Finally, answer the following question: does your autoencoder reconstruct the augmented images correctly and consistently? If not, explain why you think this may be the case.

In [ ]:
```
affine_aug = torchvision.transforms.RandomAffine(degrees=(-10, 10), translate=(0.2, 0.2), shear=(-5, 5))
augmented1 = affine_aug(x)
augmented2 = affine_aug(x)
augmented3 = affine_aug(x)

plt.imshow(augmented1.squeeze(), cmap='gray')
plt.show()
plt.imshow(augmented2.squeeze(), cmap='gray')
plt.show()
plt.imshow(augmented3.squeeze(), cmap='gray')
plt.show()
```

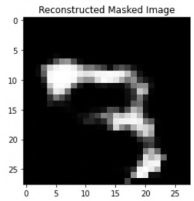


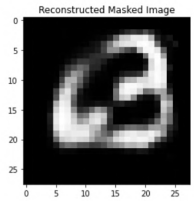


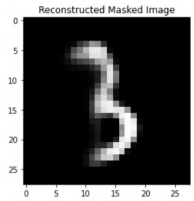


In [ ]:

```python
# according to TA from campuswire, we dont need to apply left half masking
maskaug1 = torch.unsqueeze(augmented1, 0).to(device)
# maskaug1 = apply_mask(maskaug1).to(device)
reconstruct1 = model(maskaug1.flatten().unsqueeze(0).to(device)).reshape(1, 28,28).detach().cpu()

maskaug2 = torch.unsqueeze(augmented2, 0).to(device)
# maskaug2 = apply_mask(maskaug2).to(device)
reconstruct2 = model(maskaug2.flatten().unsqueeze(0).to(device)).reshape(1, 28,28).detach().cpu()

maskaug3 = torch.unsqueeze(augmented3, 0).to(device)
# maskaug3 = apply_mask(maskaug3).to(device)
reconstruct3 = model(maskaug3.flatten().unsqueeze(0).to(device)).reshape(1, 28,28).detach().cpu()

plt.imshow(reconstruct1.squeeze().cpu(), cmap='gray')
plt.title("Reconstructed Masked Image")
plt.show()

plt.imshow(reconstruct2.squeeze().cpu(), cmap='gray')
plt.title("Reconstructed Masked Image")
plt.show()

plt.imshow(reconstruct3.squeeze().cpu(), cmap='gray')
plt.title("Reconstructed Masked Image")
plt.show()
```



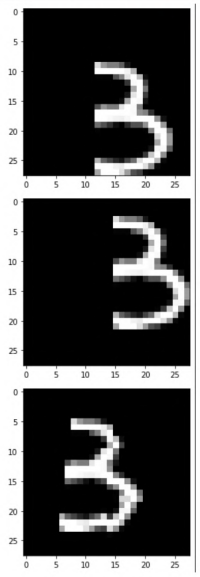




(YOUR AUGMENTED IMAGES HERE)

In [ ]:

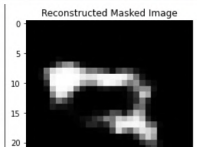
```python
display(Image.open("/content/plots/p111.png"))
```

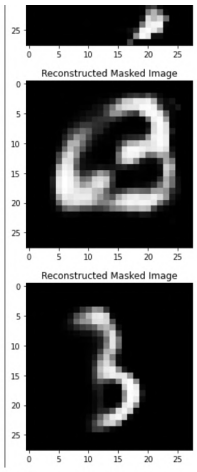


(YOUR RECONSTRUCTED IMAGES HERE)

In [ ]:

```python
display(Image.open("/content/plots/p1111.png"))
```





(YOUR EXPLANATION HERE)

No, most of the time (~90%) the model cannot reconstruct the transformed images correctly, I assume the reasons are that our model's training objective is to reconstruct left-half masked images, and here we want to reconstruct transformed images to correct version, they are different tasks so the model cannot generalize well. Also previous part shows model tends to reconstruct 3 to 8, our transformed images has a skew 3 thus cookie shape are generated. Impaiting model relies on corrupted images features and transformed data removes these features, which can also be an explanation of bad outputs.

Question 2: A Simple Sequence Task (three points total)

In this question, we'll explore the differences between standard recurrent neural networks (RNNs) and long short-term memory networks (LSTMs) using a simple addition task akin to the one used in the original LSTM paper.

2.1 Theoretical Comparison (0.5 points)

Explain the argument for why we would expect an LSTM to outperform a standard RNN on problems that involve processing long sequences.

(YOUR ANSWER HERE)

LSTM has memory cell to record extra information. It allows LSTM to be able to learn when to remember or forget inputs in hidden state, namely LSTM can know which part of sequence to focus at current time step.

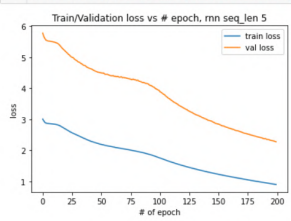
2.2 Empirical Comparison (1.5 points)

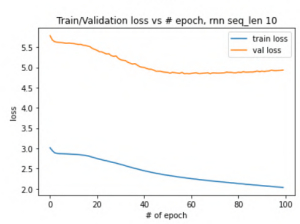
Use the code provided below to compare the performance of a standard RNN to an LSTM on the task defined by the `Add2DigitsDataset`. Do this for three different lengths of sequence (5, 10, and 30). For all experiments, use a hidden size of 128 and 2 layers. Keep your network architecture the same, except for the substitution of the LSTM for an RNN. Provide the following graphs for each sequence length:

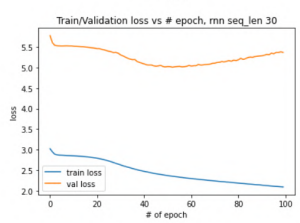
1. **Loss as a function of the number of training steps**
2. **Training accuracy & validation accuracy as a function of the number of training steps.**

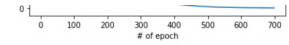
(YOUR LOSS PLOTS HERE)

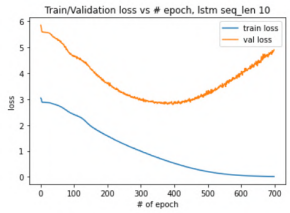
In [ ]:
```
from IPython.display import display, Image
display(Image("/content/plot/rnnloss5.png"))
display(Image("/content/plot/rnnloss10.png"))
display(Image("/content/plot/rnnloss30.png"))

display(Image("/content/plot/lstmloss5.png"))
display(Image("/content/plot/lstmloss10.png"))
display(Image("/content/plot/lstmloss30.png"))
```

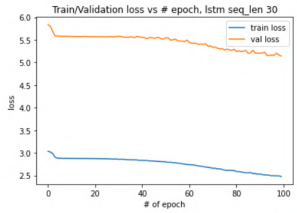








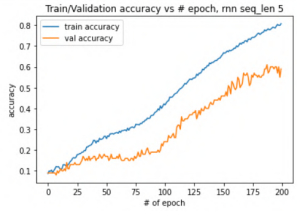


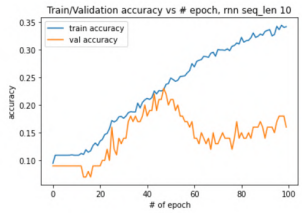


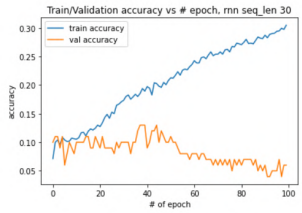
(YOUR ACCURACY PLOTS HERE)

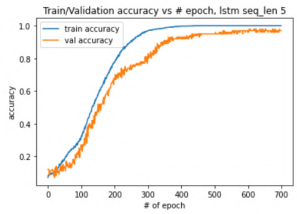
In [ ]:

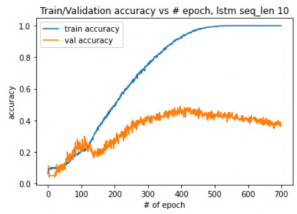
```
display(Image("/content/plot/rnnacc5.png"))
display(Image("/content/plot/rnnacc10.png"))
display(Image("/content/plot/rnnacc30.png"))

display(Image("/content/plot/lstmacc5.png"))
display(Image("/content/plot/lstmacc10.png"))
display(Image("/content/plot/lstmacc30.png"))
```

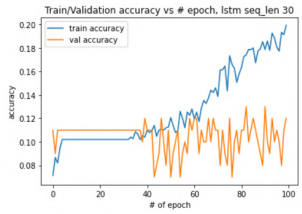












The following utility code is provided to help with the question. Note that the addition task is formulated as a *classification* rather than *regression* problem: because the operands are digits, their sum must be a positive integer in [0, 18], allowing us to output a vector of "class scores" over these potential values.

In [ ]:

```python
def MakeItHot(data, num_tokens):
    """ Make the one hot encoding of the input."""
    i_size, j_size = data.shape
    one_hot_data = torch.zeros(i_size, j_size, num_tokens)
    for i in range(0,i_size):
        for j in range(0,j_size):
            one_hot_data[i,j,data[i,j]] = 1
    return one_hot_data

def KeepItCool(data):
    """Just use the data as-is...but with a new dimension added"""
    return torch.unsqueeze(data,2)


class Add2DigitsDataset(torch.utils.data.Dataset):
    """Add2DigitsDataset"""

    def __init__(self, num_examples=3, seq_length=10):
        """Create a set of examples, where each example is a sequence of single
        positive digits (0 through 9) interspersed with 1 instance of a negative
        one. The game is to sum the final digit in the sequence with the
        digit after the -1. The correct label y for the sequence x is the sum of
        these two digits. Here are 3 examples.

        x = [1, -1, 3, 7, 8, 9] y = 12
        x = [9, 1, 2, 4, -1, 7, 2, 3, 1, 0] y = 7
        x = [9, -1, 9, 2 , 1, 3, 0, 5, 6, 4, 7, 8, 5, 1] y = 10


        PARAMETERS
        ----------
        num_examples    A non-negative integer determining how much data we'll generate
        seq_length      A non-negative integer saying how long the sequences all are.

        EXAMPLE USE
        -----------
        dataset = Add2DigitsDataset(num_examples = 100, seq_length = 9)
        data, one_hot_data, labels  = dataset[:]
        print(f'Train instances: one_hot_data (shape {one_hot_data.shape}), labels (shape {labels.shape})')
        loader =  torch.utils.data.DataLoader(dataset, batch_size=10, shuffle=True)
        """

        assert seq_length >=3, "Seq_length must be a minimum of 3"
        self.seq_length = seq_length
        self.num_tokens = 11

        # make random sequences of integers of the right length
        data = torch.randint(10, (num_examples, seq_length))
        # the labels will go here...
        label = torch.ones(num_examples,1)

        # Now insert our special tokens
        for x in range(0, num_examples):
          # figure out where to place our special token
            a_idx = torch.randint(0, seq_length-2, (1,1)).squeeze()
          # insert the special_tokens
            data[x,[a_idx]] = -1
          # create the label by summing the digit after the special -1 token
          # with the final digit in the sequence
            label[x] = data[x,a_idx+1]+data[x,-1]

        # OK. Store data for later.
        self.data = KeepItCool(data)
        self.one_hot_data = MakeItHot(data, num_tokens=self.num_tokens)
        self.label = label.squeeze().long()
        self.lengths = self.seq_length * torch.ones_like(self.label)
        self.lengths = self.lengths.squeeze().long().tolist()

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

    def __getitem__(self, idx):
        return self.data[idx], self.one_hot_data[idx], self.label[idx] #, self.lengths[idx]



# Make sure our dataset looks correct by looking at a few examples...
dataset = Add2DigitsDataset(num_examples=100,seq_length=5)
data, one_hot_data, labels = dataset[:3]
# inputs have shape (B, MAX_L, V) where MAX_L is largest length in batch
print(f'data.shape: {data.shape}, one_hot_data.shape: {one_hot_data.shape}, labels.shape: {labels.shape}')
print(f'data: {data}, one_hot_data: {one_hot_data}, labels: {labels}')
```

```
data.shape: torch.Size([3, 5, 1]), one_hot_data.shape: torch.Size([3, 5, 11]), labels.shape: torch.Size([3])
data: tensor([[[ 5],
        [-1],
        [ 4],
        [ 8],
        [ 9]],

       [[ 7],
        [-1],
        [ 9],
        [ 2],
        [ 3]],

       [[ 9],
        [ 2],
        [-1],
        [ 2],
        [ 9]]]), one_hot_data: tensor([[[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., 1., 0., 0., 0., 0., 0., 0.],
        [0., 0., 0., 0., 0., 0., 0., 0., 1., 0., 0.],
        [0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 0.]],

       [[0., 0., 0., 0., 0., 0., 0., 1., 0., 0., 0.],
        [0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 1.],
        [0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 0.],
        [0., 0., 1., 0., 0., 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., 0., 1., 0.],
        [0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0.],
        [0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 1.],
        [0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0.],
        [0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 0.]]]), labels: tensor([13, 12, 11])
```

In [ ]:

```python
class MyRNN(nn.Module):
    """ A simple RNN that that lets you select architectural features when creating
    a new instance """

    def __init__(self,
                 input_size: int,
                 hidden_size: int,
                 output_size: int,
                 num_layers: int = 1,
                 use_LSTM: bool = True):

        super().__init__()

        if use_LSTM:
            self.rnn = nn.LSTM(
                            input_size=input_size,
                            hidden_size=hidden_size,
                            num_layers=num_layers,
                            batch_first=True)
        else:
            self.rnn = nn.RNN(
                            input_size=input_size,
                            hidden_size=hidden_size,
                            num_layers=num_layers,
                        batch_first=True)

        self.out_proj = nn.Linear(hidden_size, output_size)


    def forward(self, x: torch.Tensor):

        # require batched inputs: (B, MAX_L, V)
        # Here b = the batch size, l = sequence length , v = input token size (i.e.
        # the number of positiions in a one-hot-encoding array)
```

```python
        assert x.ndim == 3
        b, l, v = x.shape

        # built-in PyTorch layer handles loop along sequence dimension,
        # including passing hidden state back each time step. It also
        # handles creating a new initial state for each batch!
        output, hidden = self.rnn(x)

        # for each item in batch, take final output state
        output = output[:,-1,:]

        # apply final linear layer to get predictions
        output = self.out_proj(output)

        return output


# declare the model and try out th untrained model on a sequence
model = MyRNN(
    input_size=11,
    hidden_size= 128,
    output_size=19, # allow outputs in range [0, 18]
    num_layers=2,
    use_LSTM=False)

# you should use `num_token` = 11: ten tokens for the digits, plus the special -1 token
input =  MakeItHot(torch.tensor([[1,2,3,1,5,6,-1,9,3,4,5,0]]), num_tokens=11)
prediction = model(input)
print('My prediction is ', torch.argmax(prediction))
```

```
My prediction is  tensor(8)
```

In [ ]:

```python
#Your experiment code goes here
def train_recurrent(model, sl=5, num_epoch=10):
    train_ds = Add2DigitsDataset(num_examples=1500, seq_length=sl)
    val_ds = Add2DigitsDataset(num_examples=100, seq_length=sl)

    # initialize data loader for random batching
    train_loader = torch.utils.data.DataLoader(
        train_ds,
        batch_size=50,
        shuffle=True
    )
    val_loader = torch.utils.data.DataLoader(
        val_ds,
        batch_size=50,
        shuffle=True
    )
    optimizer = torch.optim.Adam(model.parameters(), lr=1e-4)
    criterion = nn.CrossEntropyLoss()

    # train!
    epochs = num_epoch
    trainls,trainacc = [], []
    valls, valacc = [], []


    for epoch in range(epochs):
        model.train()
        correct = 0
        n = 0

        pbar = tqdm(enumerate(train_loader), total=len(train_loader))
        sum_loss =0
        for j, batch in pbar:

            optimizer.zero_grad()

            x, ohx,y = batch
#             print(batch)
#             print(x.shape)
            predictions = model(ohx)

            loss = criterion(predictions, y)

            loss.backward()
            optimizer.step()

            pbar.set_description(f'Loss: {loss.item() :0.4f}')
            sum_loss += loss.item()

            # track training accuracy per epoch
            correct += ((predictions.argmax(dim=-1) == y) > 0).sum().item()
            n += len(y)

#         print(f'Epoch {epoch + 1} training accuracy: {correct/n :0.4f}')
        sum_loss /= j
        trainls.append(sum_loss)
        trainacc.append(correct/n)

        model.eval()
        val_sum_loss= 0
        n_val = 0
        val_correct = 0
        for k, val_batch in enumerate(val_loader):
            x, ohx, y = val_batch
            n_val += len(y)
            pred = model(ohx)

            val_ls = criterion(pred, y)
            val_sum_loss+=val_ls.item()

            val_correct += ((pred.argmax(dim=-1) == y) > 0).sum().item()

        val_acc = val_correct / n_val
        val_avg_ls = val_sum_loss/k
        valls.append(val_avg_ls)
        valacc.append(val_acc)
#         print(f'Epoch {epoch + 1} validation accuracy: {val_acc :0.4f}')

    return trainls,trainacc, valls, valacc

```

In [ ]:

```python
def plot_fig(train_dt, val_dt, typ="acc", title_=""):
    plt.clf()
    if typ == "acc":
        ptyp = "accuracy"
    elif typ == 'loss':
        ptyp = "loss"
    plt.plot(train_dt, label=f"train {ptyp}")
    plt.plot(val_dt, label=f"val {ptyp}")
    plt.ylabel(ptyp)
    plt.xlabel("# of epoch")
    plt.title(f"Train/Validation {ptyp} vs # epoch, {title_}")
    plt.legend()

    plt.show()
```

In [ ]:

```python
model1 = MyRNN(
    input_size=11,
    hidden_size= 128,
    output_size=19, # allow outputs in range [0, 18]
    num_layers=2,
    use_LSTM=False)
trls1, tracc1, vlls1, vlacc1 = train_recurrent(model1, 5, 200)
plot_fig(trls1, vlls1, 'loss', "rnn seq_len 5")
plot_fig(tracc1, vlacc1, 'acc', "rnn seq_len 5")
print('============================================================')

model2 = MyRNN(
    input_size=11,
    hidden_size= 128,
    output_size=19,
    num_layers=2,
    use_LSTM=False)
trls2, tracc2, vlls2, vlacc2 = train_recurrent(model2, 10, 100)
plot_fig(trls2, vlls2, 'loss', "rnn seq_len 10")
plot_fig(tracc2, vlacc2, 'acc', "rnn seq_len 10")
print('============================================================')
model3 = MyRNN(
    input_size=11,
    hidden_size= 128,
```

```
    output_size=19,
    num_layers=2,
    use_LSTM=False)
trls3, tracc3, vlls3, vlacc3 = train_recurrent(model3, 30, 100)
plot_fig(trls3, vlls3, 'loss', "rnn seq_len 30")
plot_fig(tracc3, vlacc3, 'acc', "rnn seq_len 30")
print('============================================================')
model4 =MyRNN(
    input_size=11,
    hidden_size= 128,
    output_size=19,
    num_layers=2,
    use_LSTM=True)

trls4, tracc4, vlls4, vlacc4= train_recurrent(model4, 5, 700)
plot_fig(trls4, vlls4, 'loss', "lstm seq_len 5")
plot_fig(tracc4, vlacc4, 'acc', "lstm seq_len 5")
print('============================================================')
model5 = MyRNN(
    input_size=11,
    hidden_size= 128,
    output_size=19,
    num_layers=2,
    use_LSTM=True)

trls5, tracc5, vlls5, vlacc5= train_recurrent(model5, 10, 700)
plot_fig(trls5, vlls5, "loss", "lstm seq_len 10")
plot_fig(tracc5, vlacc5, 'acc', "lstm seq_len 10")
print('============================================================')
model6 = MyRNN(
    input_size=11,
    hidden_size= 128,
    output_size=19,
    num_layers=2,
    use_LSTM=True)

trls6, tracc6, vlls6, vlacc6= train_recurrent(model6, 30, 100)
plot_fig(trls6, vlls6, 'loss', "lstm seq_len 30")
plot_fig(tracc6, vlacc6, 'acc', "lstm seq_len 30")
print('============================================================')
```

In [ ]:

```
temp = MakeItHot(torch.tensor([[1,2,3,1,5,6,-1,9,3,4,5,0]]), num_tokens=11)
prediction = model5(temp)
print('My prediction is ', torch.argmax(prediction))
```

```
My prediction is  tensor(6)
```

2.3 Analysis (one point)

Provide your analysis of the above experiment. Was the hypothesis from question 2.1 supported by your data? Why or why not? What might be the limitations of your experiment?

(YOUR ANALYSIS HERE)

Yes the 2.2 results resonate with 2.1 conclusion. For same seq_len, LSTM outperform plain RNN in both loss and accuracy, LSTM almost double RNN accuracy with same seq_len, especially when seq_len=5, LSTM can even reach ~100% accuracy on validation set. Both RNN and LSTM performances downgrade as seq_len increases, both models have poor performance on seq_len=30; I think this is a limitation of experiment because index after -1 is too specific, we cannot expect neural net model produce highly accurate results, similarly we don't want neural nets to do arithmatics with precision, HW2 conclusions. Another limitation might be all information between two target indices are not used, for long seq_len, the model is hard to train, resulting poor performances.

Question 3: Sequence-to-Sequence Translation (three points total)

Sequence-to-sequence tasks such as language translation require a model capable of converting variable-length inputs to variable-length outputs, with no guarantee that each position in the input will map directly to a position in the output. This can be thought of as a "many-to-many" task, as illustrated by the second figure from the right in Andrej Karpathy's diagram:

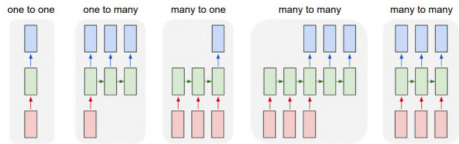


Image source: "The Unreasonable Effectiveness of Recurrent Neural Networks" (Karpathy)

For example, consider the following English-to-Spanish translation:

`I like chocolate` --> `Me gusta el chocolate`

The input sequence contains three words, while the output sequence contains four. Moreover, the individual words and grammatical structure of the sentences do not cleanly correspond, as `chocolate` is preceded by the definite article `el` and the subject switches from the speaker to the chocolate. It's easy to see why sequence-to-sequence translation can be a challenging task!

To overcome these difficulties, Sutskever et al. proposed to use recurrent **encoder** and **decoder** networks. First, special **start and stop tokens** are added to the ends of all sentences. Then, the encoder RNN loops over an input sequence, and its final hidden state is taken as a representation of the entire input "context." This context is passed to the decoder RNN, which generates one word at a time **autoregressively** (taking its own past predictions as inputs) until it produces a stop token. This allows for arbitrary input and output lengths, as (a) the only representation of the input that the decoder sees is a single context vector, and (b) the decoder is free to generate for as long as it wants to before emitting a stop token.

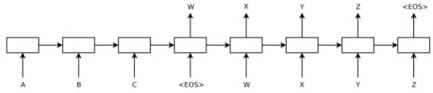


Image source: "Sequence to Sequence Learning with Neural Networks" (Sutskever et al. 2014). "EOS" is the end-of-sentence stop token.

In this question, we'll explore how to use the encoder-decoder architecture to perform German-to-English translation. This will require a bit of setup, which is documented in the next section. To simplify the process and avoid messing with your local Python environment, it's recommended that you use Google Colab.

As a final note, elements of this question are adapted from Ben Trevett's tutorials on sequence modeling in PyTorch. You are welcome to look at these tutorials for additional information.

3.1 Installation & Data Preparation (zero points)

Run these cells to prepare your environment and load data. You may be prompted to approve the installation by typing `y`, as well as to restart your notebook environment once the installation is complete.

In [ ]:

```
# the torchtext library provides a number of utilites for handling text data
# !pip uninstall torchtext
!pip install torchtext==0.9.0 --no-cache-dir
!pip install torch==1.8.1+cu111 torchvision==0.9.1+cu111 torchaudio==0.8.1 -f https://download.pytorch.org/whl/
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: torchtext==0.9.0 in /usr/local/lib/python3.7/dist-packages (0.9.0)
Requirement already satisfied: numpy in /usr/local/lib/python3.7/dist-packages (from torchtext==0.9.0) (1.21.6)
Requirement already satisfied: requests in /usr/local/lib/python3.7/dist-packages (from torchtext==0.9.0) (2.23.0)
Requirement already satisfied: tqdm in /usr/local/lib/python3.7/dist-packages (from torchtext==0.9.0) (4.64.0)
Requirement already satisfied: torch==1.8.0 in /usr/local/lib/python3.7/dist-packages (from torchtext==0.9.0) (1.
8.0)
Requirement already satisfied: typing-extensions in /usr/local/lib/python3.7/dist-packages (from torch==1.8.0->tor
chtext==0.9.0) (4.2.0)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.7/dist-packages (from requests->torcht
ext==0.9.0) (2022.5.18.1)
Requirement already satisfied: chardet<4,>=3.0.2 in /usr/local/lib/python3.7/dist-packages (from requests->torchte
xt==0.9.0) (3.0.4)
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in /usr/local/lib/python3.7/dist-packages
(from requests->torchtext==0.9.0) (1.24.3)
```

```
Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.7/dist-packages (from requests->torchtext==
0.9.0) (2.10)
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Looking in links: https://download.pytorch.org/whl/torch_stable.html
Collecting torch==1.8.1+cu111
  Downloading https://download.pytorch.org/whl/cu111/torch-1.8.1%2Bcu111-cp37-cp37m-linux_x86_64.whl (1982.2 MB)
     |                                | 834.1 MB 1.2 MB/s eta 0:15:48tcmalloc: large alloc 1147494400 bytes == 0x3
a9a2000 @  0x7f4282152615 0x592b76 0x4df71e 0x59afff 0x515655 0x549576 0x593fce 0x548ae9 0x51566f 0x549576 0x593fc
e 0x548ae9 0x5127f1 0x598e3b 0x511f68 0x598e3b 0x511f68 0x598e3b 0x511f68 0x4bc98a 0x532e76 0x594b72 0x515600 0x54
9576 0x593fce 0x548ae9 0x5127f1 0x549576 0x593fce 0x5118f8 0x593dd7
     |                                | 1055.7 MB 1.2 MB/s eta 0:13:13tcmalloc: large alloc 1434370048 bytes == 0x
7eff8000 @  0x7f4282152615 0x592b76 0x4df71e 0x59afff 0x515655 0x549576 0x593fce 0x548ae9 0x51566f 0x549576 0x593f
ce 0x548ae9 0x5127f1 0x598e3b 0x511f68 0x598e3b 0x511f68 0x598e3b 0x511f68 0x4bc98a 0x532e76 0x594b72 0x515600 0x5
49576 0x593fce 0x548ae9 0x5127f1 0x549576 0x593fce 0x5118f8 0x593dd7
     |                                | 1336.2 MB 1.2 MB/s eta 0:08:45tcmalloc: large alloc 1792966656 bytes == 0x
3e2a000 @  0x7f4282152615 0x592b76 0x4df71e 0x59afff 0x515655 0x549576 0x593fce 0x548ae9 0x51566f 0x549576 0x593fc
e 0x548ae9 0x5127f1 0x598e3b 0x511f68 0x598e3b 0x511f68 0x598e3b 0x511f68 0x4bc98a 0x532e76 0x594b72 0x515600 0x54
9576 0x593fce 0x548ae9 0x5127f1 0x549576 0x593fce 0x5118f8 0x593dd7
     |                                | 1691.1 MB 1.1 MB/s eta 0:04:21tcmalloc: large alloc 2241208320 bytes == 0x
6ec12000 @  0x7f4282152615 0x592b76 0x4df71e 0x59afff 0x515655 0x549576 0x593fce 0x548ae9 0x51566f 0x549576 0x593f
ce 0x548ae9 0x5127f1 0x598e3b 0x511f68 0x598e3b 0x511f68 0x598e3b 0x511f68 0x4bc98a 0x532e76 0x594b72 0x515600 0x5
49576 0x593fce 0x548ae9 0x5127f1 0x549576 0x593fce 0x5118f8 0x593dd7
     |                                | 1982.2 MB 117.4 MB/s eta 0:00:01tcmalloc: large alloc 1982177280 bytes ==
0xf4574000 @  0x7f42821511e7 0x4a3940 0x4a39cc 0x592b76 0x4df71e 0x59afff 0x515655 0x549576 0x593fce 0x511e2c 0x54
9576 0x593fce 0x511e2c 0x549576 0x593fce 0x511e2c 0x549576 0x593fce 0x511e2c 0x549576 0x593fce 0x511e2c 0x593dd7 0
x511e2c 0x549576 0x593fce 0x548ae9 0x5127f1 0x549576 0x593fce 0x548ae9
tcmalloc: large alloc 2477727744 bytes == 0x16a7ce000 @  0x7f4282152615 0x592b76 0x4df71e 0x59afff 0x515655 0x5495
76 0x593fce 0x511e2c 0x549576 0x593fce 0x511e2c 0x549576 0x593fce 0x511e2c 0x549576 0x593fce 0x511e2c 0x549576 0x5
93fce 0x511e2c 0x593dd7 0x511e2c 0x549576 0x593fce 0x548ae9 0x5127f1 0x549576 0x593fce 0x548ae9 0x5127f1 0x549576
     |                                | 1982.2 MB 2.7 kB/s
Collecting torchvision==0.9.1+cu111
  Downloading https://download.pytorch.org/whl/cu111/torchvision-0.9.1%2Bcu111-cp37-cp37m-linux_x86_64.whl (17.6 M
B)
     |                                | 17.6 MB 222 kB/s
Collecting torchaudio==0.8.1
  Downloading torchaudio-0.8.1-cp37-cp37m-manylinux1_x86_64.whl (1.9 MB)
     |                                | 1.9 MB 4.2 MB/s
Requirement already satisfied: typing-extensions in /usr/local/lib/python3.7/dist-packages (from torch==1.8.1+cu11
1) (4.2.0)
Requirement already satisfied: numpy in /usr/local/lib/python3.7/dist-packages (from torch==1.8.1+cu111) (1.21.6)
Requirement already satisfied: pillow>=4.1.1 in /usr/local/lib/python3.7/dist-packages (from torchvision==0.9.1+cu
111) (7.1.2)
Installing collected packages: torch, torchvision, torchaudio
  Attempting uninstall: torch
    Found existing installation: torch 1.8.0
    Uninstalling torch-1.8.0:
      Successfully uninstalled torch-1.8.0
  Attempting uninstall: torchvision
    Found existing installation: torchvision 0.12.0+cu113
    Uninstalling torchvision-0.12.0+cu113:
      Successfully uninstalled torchvision-0.12.0+cu113
  Attempting uninstall: torchaudio
    Found existing installation: torchaudio 0.11.0+cu113
    Uninstalling torchaudio-0.11.0+cu113:
      Successfully uninstalled torchaudio-0.11.0+cu113
ERROR: pip's dependency resolver does not currently take into account all the packages that are installed. This be
haviour is the source of the following dependency conflicts.
torchtext 0.9.0 requires torch==1.8.0, but you have torch 1.8.1+cu111 which is incompatible.
Successfully installed torch-1.8.1+cu111 torchaudio-0.8.1 torchvision-0.9.1+cu111
```

We'll use the `spaCy` library to "tokenize" our input sentences (break them up into word units), but the library is also widely used for a variety of natural language processing tasks -- feel free to take a look if that's of interest.

In [ ]:

```python
# the spacy library will allow us to "tokenize" text datasets into individual word units
!python -m spacy download en_core_web_sm
!python -m spacy download de_core_news_sm
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Collecting en_core_web_sm==2.2.5
  Downloading https://github.com/explosion/spacy-models/releases/download/en_core_web_sm-2.2.5/en_core_web_sm-2.
2.5.tar.gz (12.0 MB)
     |                                | 12.0 MB 4.2 MB/s
Requirement already satisfied: spacy>=2.2.2 in /usr/local/lib/python3.7/dist-packages (from en_core_web_sm==2.2.
5) (2.2.4)
Requirement already satisfied: preshed<3.1.0,>=3.0.2 in /usr/local/lib/python3.7/dist-packages (from spacy>=2.2.2
->en_core_web_sm==2.2.5) (3.0.6)
Requirement already satisfied: murmurhash<1.1.0,>=0.28.0 in /usr/local/lib/python3.7/dist-packages (from spacy>=
2.2.2->en_core_web_sm==2.2.5) (1.0.7)
Requirement already satisfied: thinc==7.4.0 in /usr/local/lib/python3.7/dist-packages (from spacy>=2.2.2->en_core
_web_sm==2.2.5) (7.4.0)
Requirement already satisfied: tqdm<5.0.0,>=4.38.0 in /usr/local/lib/python3.7/dist-packages (from spacy>=2.2.2->
en_core_web_sm==2.2.5) (4.64.0)
Requirement already satisfied: catalogue<1.1.0,>=0.0.7 in /usr/local/lib/python3.7/dist-packages (from spacy>=2.
2.2->en_core_web_sm==2.2.5) (1.0.0)
Requirement already satisfied: plac<1.2.0,>=0.9.6 in /usr/local/lib/python3.7/dist-packages (from spacy>=2.2.2->e
n_core_web_sm==2.2.5) (1.1.3)
```

In [ ]:

```python
import torch
import torch.nn as nn
import torch.optim as optim
from torchtext.legacy.datasets import Multi30k
from torchtext.legacy.data import Field, BucketIterator
import spacy
import numpy as np
import random
import math
import time
import en_core_web_sm
import de_core_news_sm
from typing import Union

# set device (default to GPU if available)
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
```

We'll start by loading German and English text datasets. Then, we'll preprocess and reformat our string data so that we can pass it to PyTorch neural network models.

In [ ]:

```python
# load spacy tokenizers for English and German text
spacy_de = de_core_news_sm.load()
spacy_en = en_core_web_sm.load()

def tokenize_de(text): return [tok.text for tok in spacy_de.tokenizer(text)]
def tokenize_de_reverse(text): return [tok.text for tok in spacy_de.tokenizer(text)][::-1]
def tokenize_en(text): return [tok.text for tok in spacy_en.tokenizer(text)]

# boilerplate for torchtext dataset formatting
source_field = Field(tokenize = tokenize_de_reverse, init_token = '<sos>', eos_token = '<eos>', lower = True)
target_field = Field(tokenize = tokenize_en, init_token = '<sos>', eos_token = '<eos>', lower = True)

# create datasets; by torchtext convention, instances are stored under the `examples` attribute
train_data, valid_data, test_data = Multi30k.splits(exts = ('.de', '.en'), fields = (source_field, target_field

print(f"Dataset size (train/val/test): {len(train_data.examples)} / {len(valid_data.examples)} / {len(test_data
```

```
Dataset size (train/val/test): 29000 / 1014 / 1000
```

We can see that for each instance, our dataset stores the input sentence (`src`) and output sentence (`trg`):

In [ ]:

```python
vars(train_data.examples[0])
```

Out[3]:

```
{'src': ['.',
  'büsche',
  'vieler',
  'nähe',
  'der',
  'in',
  'freien',
  'im',
  'sind',
  'männer',
  'weiße',
  'junge',
  'zwei'],
 'trg': ['two',
  'young',
  ',',
  'white',
  'males',
  'are',
```

```
 'outside',
 'near',
 'many',
 'bushes',
 '.']}
```

Rather than one-hot-encode individual characters, we'll encode words. We'll associate each word with an index in the **vocabulary** of all words present in the data. To limit the size of this vocabulary (and thus our model's inputs), we'll associate all words that show up at most once with a single "unknown" index. Note that we only consider words present in the training data -- we can't expect our model to predict words it has never seen!

In [ ]:

```python
# min_freq = 2 --> all words appearing only once are mapped to "unknown"
source_field.build_vocab(train_data, min_freq = 2)
target_field.build_vocab(train_data, min_freq = 2)

print(f"Unique tokens in source (de) vocabulary: {len(source_field.vocab)}")
print(f"Unique tokens in target (en) vocabulary: {len(target_field.vocab)}")

# rather than deal with DataLoader objects and collation, we'll simply
# use Python iterators to walk through our datasets
train_iterator, valid_iterator, test_iterator = BucketIterator.splits(
    (train_data, valid_data, test_data),
    batch_size = 128,
    device = device)
```

```
Unique tokens in source (de) vocabulary: 7855
Unique tokens in target (en) vocabulary: 5893
```

Our data preparation is now complete. When training, we can fetch one input/output pair at a time from our iterator, encode the input, and pass it to our model to make predictions and compute losses.

In [ ]:

```python
# demonstration of how data loading will work in training
for i, batch in enumerate(train_iterator):

  # note that each batch is already padded to the maximum sequence length!
  x = batch.src
  y = batch.trg

  print(f"`x` is a {type(x)} of shape {x.shape} (in_seq_len, batch_size) \n`y` is a {type(y)} of shape {y.shape
  break
```

```
`x` is a <class 'torch.Tensor'> of shape torch.Size([36, 128]) (in_seq_len, batch_size)
`y` is a <class 'torch.Tensor'> of shape torch.Size([31, 128]) (out_seq_len, batch_size)
```

3.2 RNN Translation (one point)

Finally, we can train an encoder-decoder model to perform sequence-to-sequence translation. We'll operate the encoder similar to the "layer" format we discussed in notebook 8, while the decoder will predict for one step at a time -- more akin to the "cell" format.

Modify the definitions in the cell below as instructed by the accompanying comments. Then, run the following cell to train and evaluate your encoder-decoder network for German-to-English translation. Finally, include a plot of your training and validation lossses by epoch where instructed below.

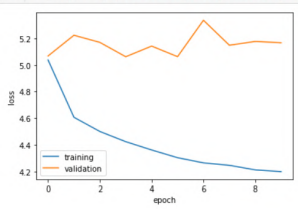
If your implementation is "correct," you should not see loss values far above `5.0` as your model trains. You can also check your implementation by running the example translation provided after the training code. Don't worry if your model isn't perfrect -- as long as a few predicted words roughly correspond to the actual translation, it indicates that your implementation is mostly correct:

Actual Translation	Predicted Translation
a dog walked by the park	a a animal a walked EOS EOS

(YOUR LOSS PLOT HERE)

In [ ]:

```python
display(Image("/content/plot/q3rnnloss.png"))
```



DO modify the following cell as instructed.

In [ ]:

```python
class RNNEncoder(nn.Module):

    def __init__(self,
                 input_size: int,
                 embedding_size: int,
                 hidden_size: int,
                 num_layers: int):

# !python -m spacy download de_core_news_sm
        super().__init__()

        self.hidden_size = hidden_size
        self.num_layers = num_layers

        # embedding layer: similar to one-hot encoding, we will map
        # integer indices to vectors
        self.embedding = nn.Embedding(input_size, embedding_size)

        ##########################################################
        # YOUR CODE STARTS HERE (1/5)
        ##########################################################

        # define the RNN
        self.rnn = nn.RNN(
            input_size=embedding_size,
            hidden_size=self.hidden_size,
            num_layers= self.num_layers,
            dropout=0.5)

        ##########################################################
        # YOUR CODE ENDS HERE (1/5)
        ##########################################################

        # a droupout layer can improve generalization
        self.dropout = nn.Dropout(0.5)

    def forward(self, x: torch.Tensor):

        assert x.ndim == 2
        seq_len, batch_size = x.shape

        # convert integer indices to vector representations
        embedded = self.dropout(self.embedding(x))  # (seq_len, batch_size, embedding_size)

        ##########################################################
        # YOUR CODE STARTS HERE (2/5)
        ##########################################################

        # pass the embedded input to the RNN and obtain the hidden state
        # for the final time step; dimension of hidden state should be
        # (num_layers, batch_size, hidden_size)
        rnn_out, rnn_hs = self.rnn(embedded)

        # return only the final hidden state
        return rnn_hs

        ##########################################################
        # YOUR CODE ENDS HERE (2/5)
        ##########################################################


class RNNDecoder(nn.Module):

    def __init__(self,
```

```python
                 output_size: int,
                 embedding_size: int,
                 hidden_size: int,
                 num_layers: int):

        super().__init__()

        self.hidden_size = hidden_size
        self.num_layers = num_layers
        self.output_size = output_size

        # embedding layer: similar to one-hot encoding, we will map
        # integer indices to vectors
        self.embedding = nn.Embedding(output_size, embedding_size)

        ############################################################
        # YOUR CODE STARTS HERE (3/5)
        ############################################################

        # define the RNN
        self.rnn = nn.RNN(
            input_size=embedding_size,
            hidden_size=self.hidden_size,
            num_layers=self.num_layers,
            dropout=0.5)

        # define a fully-connected layer that maps vectors of dimension
        # `hidden_size` to vectors of dimension `output_size`
        self.out_proj = nn.Linear(self.hidden_size, self.output_size)

        ############################################################
        # YOUR CODE ENDS HERE (3/5)
        ############################################################

        # a droupout layer can improve generalization
        self.dropout = nn.Dropout(0.5)

    def forward(self, x: torch.Tensor, hidden: torch.Tensor):

        # take a single time-step of input and a single hidden state
        assert x.ndim == 1
        x = x.unsqueeze(0)
        _, batch_size = x.shape

        # convert integer indices to vector representations
        embedded = self.dropout(self.embedding(x))  # (1, batch_size, embedding_size)

        ############################################################
        # YOUR CODE STARTS HERE (4/5)
        ############################################################

        # call the RNN on our single-step input and prior hidden state
        # to obtain the output and hidden state; the dimension of the
        # output should be (1, batch_size, hidden_size), and the
        # dimension of the hidden state should be
        # (num_layers, batch_size, hidden_size)
        rnn_out, rnn_hs = self.rnn(embedded, hidden)

        # apply fully-connected layer to map output dimension to (1, batch_size, output_size)
        prediction = self.out_proj(rnn_out)

        # squeeze output to remove first (sequence) dimension
        prediction = prediction.squeeze(0)  # (batch_size, output_size)

        # return final output and hidden state
        return prediction, rnn_hs

        ############################################################
        # YOUR CODE ENDS HERE (4/5)
        ############################################################


class RNNTranslator(nn.Module):

    def __init__(self,
                 encoder: nn.Module,
                 decoder: nn.Module,
                 device: Union[str, torch.device]):

        super().__init__()

        self.encoder = encoder
        self.decoder = decoder
        self.device = device

        assert encoder.hidden_size == decoder.hidden_size, \
        f"Mismatch: `encoder.hidden_size` = {encoder.hidden_size}, `decoder.hidden_size` = {decoder.hidden_size

        assert encoder.num_layers == decoder.num_layers, \
        f"Mismatch: `encoder.num_layers` = {encoder.num_layers}, `decoder.num_layers` = {decoder.num_layers}"

    def forward(self, x: torch.Tensor, y: torch.Tensor, teacher_forcing_ratio: float = 0.5):

        # inputs should have shape (in_seq_len, batch_size)
        assert x.ndim == 2
        in_seq_len, batch_size = x.shape

        # targets should have shape (out_seq_len, batch size)
        assert y.ndim == 2
        out_seq_len, _ = y.shape
        out_vocab_size = self.decoder.output_size

        # prepare to store decoder outputs. We only need to allocate
        # the "true" number of time steps during training, but for inference
        # we can simply pass in an empty `y` of any length; this will serve as
        # a maximum length constraint on the output translation (which may end
        # sooner if an <EOS> token is predicted).
        outputs = torch.zeros(out_seq_len, batch_size, out_vocab_size).to(self.device)

        ############################################################
        # YOUR CODE STARTS HERE (5/5)
        ############################################################

        # pass inputs to encoder to obtain final hidden state
        hidden = self.encoder.forward(x)

        ############################################################
        # YOUR CODE ENDS HERE (5/5)
        ############################################################

        # first input to the decoder is the <SOS> start token
        input = y[0,:]

        for t in range(1, out_seq_len):

            # given input for current time step (either previous decoder
            # prediction or <SOS> token) and previous hidden state, compute
            # new output and hidden states
            output, hidden = self.decoder(input, hidden)

            # write predicted word probabilities to output buffer
            outputs[t] = output

            # during training, we may randomly decide whether to use
            # the decoder's previous predictions or the ground-truth
            # tokens for the previous time step. When we do the latter,
            # it is called "teacher-forcing." We will randomly apply
            # teacher-forcing during training only.
            teacher_force = random.random() < teacher_forcing_ratio

            # take highest-scoring token from decoder's previous prediction
            top1 = output.argmax(1)

            # optionally apply teacher-forcing
            input = y[t] if teacher_force else top1

        return outputs
```

DO NOT modify the following cell.

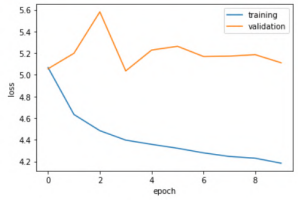
In [ ]:

```python
# training hyperparameters
INPUT_DIM = len(source_field.vocab)
```

```python
OUTPUT_DIM = len(target_field.vocab)
ENC_EMB_DIM = 256
DEC_EMB_DIM = 256
HID_DIM = 512
N_LAYERS = 2
ENC_DROPOUT = 0.5
DEC_DROPOUT = 0.5
TRG_PAD_IDX = target_field.vocab.stoi[target_field.pad_token]
N_EPOCHS = 10
CLIP = 1

# initialize encoder-decoder model
enc = RNNEncoder(INPUT_DIM, ENC_EMB_DIM, HID_DIM, N_LAYERS)
dec = RNNDecoder(OUTPUT_DIM, DEC_EMB_DIM, HID_DIM, N_LAYERS)
model = RNNTranslator(enc, dec, device).to(device)

# initialize model weights
def init_weights(m):
    for name, param in m.named_parameters():
        nn.init.uniform_(param.data, -0.08, 0.08)
model.apply(init_weights)

# parameter count
def count_parameters(model):
    return sum(p.numel() for p in model.parameters() if p.requires_grad)
print(f'The model has {count_parameters(model):,} trainable parameters')

# optimizer and loss function
optimizer = optim.Adam(model.parameters())
criterion = nn.CrossEntropyLoss(ignore_index = TRG_PAD_IDX)

# track training and validation losses
training_loss = []
validation_loss = []

def train(model, iterator, optimizer, criterion, clip):

    model.train()
    epoch_loss = 0

    for i, batch in enumerate(iterator):

        src = batch.src
        trg = batch.trg

        optimizer.zero_grad()
        output = model(src, trg)

        output_dim = output.shape[-1]
        output = output[1:].view(-1, output_dim)
        trg = trg[1:].view(-1)

        loss = criterion(output, trg)
        loss.backward()

        torch.nn.utils.clip_grad_norm_(model.parameters(), clip)
        optimizer.step()

        epoch_loss += loss.item()

    return epoch_loss / len(iterator)

def evaluate(model, iterator, criterion):

    model.eval()
    epoch_loss = 0

    with torch.no_grad():

        for i, batch in enumerate(iterator):

            src = batch.src
            trg = batch.trg

            output = model(src, trg, 0) #turn off teacher forcing
            output_dim = output.shape[-1]

            output = output[1:].view(-1, output_dim)
            trg = trg[1:].view(-1)

            loss = criterion(output, trg)
            epoch_loss += loss.item()

    return epoch_loss / len(iterator)

def epoch_time(start_time, end_time):
    elapsed_time = end_time - start_time
    elapsed_mins = int(elapsed_time / 60)
    elapsed_secs = int(elapsed_time - (elapsed_mins * 60))
    return elapsed_mins, elapsed_secs

best_valid_loss = float('inf')

for epoch in range(N_EPOCHS):

    start_time = time.time()

    train_loss = train(model, train_iterator, optimizer, criterion, CLIP)
    valid_loss = evaluate(model, valid_iterator, criterion)

    training_loss.append(train_loss)
    validation_loss.append(valid_loss)

    end_time = time.time()
    epoch_mins, epoch_secs = epoch_time(start_time, end_time)

    if valid_loss < best_valid_loss:
        best_valid_loss = valid_loss
        torch.save(model.state_dict(), 'rnn-model.pt')

    print(f'Epoch: {epoch+1:02} | Time: {epoch_mins}m {epoch_secs}s')
    print(f'\tTrain Loss: {train_loss:.3f}')
    print(f'\t Val. Loss: {valid_loss:.3f}')

model.load_state_dict(torch.load('rnn-model.pt'))
test_loss = evaluate(model, test_iterator, criterion)

print(f'| Test Loss: {test_loss:.3f}')

# generate loss plot
import matplotlib.pyplot as plt
plt.plot(training_loss, label="training")
plt.plot(validation_loss, label="validation")
plt.legend()
plt.xlabel("epoch")
plt.ylabel("loss")
plt.show()
```

```
The model has 8,381,701 trainable parameters
Epoch: 01 | Time: 0m 26s
        Train Loss: 5.067
         Val. Loss: 5.056
Epoch: 02 | Time: 0m 26s
        Train Loss: 4.633
         Val. Loss: 5.199
Epoch: 03 | Time: 0m 26s
        Train Loss: 4.484
         Val. Loss: 5.581
Epoch: 04 | Time: 0m 26s
        Train Loss: 4.397
         Val. Loss: 5.036
Epoch: 05 | Time: 0m 26s
        Train Loss: 4.358
         Val. Loss: 5.228
Epoch: 06 | Time: 0m 26s
        Train Loss: 4.322
         Val. Loss: 5.263
Epoch: 07 | Time: 0m 26s
        Train Loss: 4.279
         Val. Loss: 5.169
Epoch: 08 | Time: 0m 26s
        Train Loss: 4.246
         Val. Loss: 5.172
Epoch: 09 | Time: 0m 26s
```

```
        Train Loss: 4.230
         Val. Loss: 5.185
Epoch: 10 | Time: 0m 26s
        Train Loss: 4.183
         Val. Loss: 5.111
| Test Loss: 5.046
```



We can examine the model's translations over it's training data to get a sense of how well it is performing (you don't have to turn anything in for this part).

In [ ]:
```python
def str_to_tensor(s: str, tokenize_fn, field):
  """Convert string to tensor of shape (seq_len, 1)"""

  s_tokenized = tokenize_fn(s)
  s_encoded = []

  for word in s_tokenized:

    if word in field.vocab.stoi:
      s_encoded.append(field.vocab.stoi[word])
    else:
      s_encoded.append(field.vocab.unk_index)

  return torch.as_tensor(s_encoded).reshape(-1, 1)

def tensor_to_str(t: torch.Tensor, field):
  """Convert tensor of shape (seq_len, 1) to string)"""

  s_encoded = t.flatten().tolist()
  s_tokenized = []

  for idx in s_encoded:
    s_tokenized.append(field.vocab.itos[idx])  # ignore "unknown" tokens

  return " ".join(s_tokenized)

# select a random training translation
german_phrase = " ".join(train_data.examples[0].src)
english_phrase = " ".join(train_data.examples[0].trg)
german_phrase_encoded = str_to_tensor(german_phrase, tokenize_de, source_field).to(model.device)

german_phrase, english_phrase
```

Out[8]:
```
('. büsche vieler nähe der in freien im sind männer weiße junge zwei',
 'two young , white males are outside near many bushes .')
```

In [ ]:
```python
model.eval()

with torch.no_grad():

    output = model(german_phrase_encoded, torch.zeros_like(german_phrase_encoded), 0) #turn off teacher forcing
    output_dim = output.shape[-1]
    output = output[1:].view(-1, output_dim).argmax(dim=-1)

tensor_to_str(output, target_field)
```

Out[9]:
```
'a man in a a a a a a a . <eos>'
```

3.3 LSTM Translation (one point)

Next, we'll substitute `nn.RNN` for `nn.LSTM` in our encoder and decoder networks. This means we'll also have to deal with both hidden *and* cell states, as covered in notebook 8.

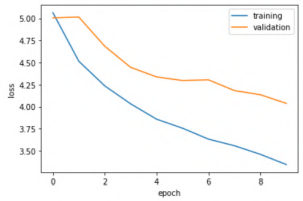
Modify the definitions in the cell below as instructed by the accompanying comments. Then, run the following cell to train and evaluate your encoder-decoder network for German-to-English translation. Finally, include a plot of your training and validation lossses by epoch where instructed below.

If your implementation is "correct," you should not see loss values far above `5.0` as your model trains. You can also check your implementation by running the example translation provided after the training code. Don't worry if your model isn't perfrect -- as long as a few predicted words roughly correspond to the actual translation, it indicates that your implementation is mostly correct:

Actual Translation	Predicted Translation
a dog walked by the park	a a animal a walked EOS EOS

(YOUR LOSS PLOT HERE)

In [ ]:
```python
display(Image("/content/plot/q3lstmloss.png"))
```



DO modify the following cell as instructed.

In [ ]:
```python
class LSTMEncoder(nn.Module):

    def __init__(self,
                 input_size: int,
                 embedding_size: int,
                 hidden_size: int,
                 num_layers: int):

        super().__init__()

        self.hidden_size = hidden_size
        self.num_layers = num_layers

        # embedding layer: similar to one-hot encoding, we will map
        # integer indices to vectors
        self.embedding = nn.Embedding(input_size, embedding_size)

        ##########################################################
        # YOUR CODE STARTS HERE (1/5)
        ##########################################################

        # define the LSTM
        self.rnn = nn.LSTM(
            input_size=embedding_size,
            hidden_size=self.hidden_size,
            num_layers=self.num_layers,
            dropout=0.5)

        ##########################################################
        # YOUR CODE ENDS HERE (1/5)
        ##########################################################

        # a droupout layer can improve generalization
        self.dropout = nn.Dropout(0.5)

    def forward(self, x: torch.Tensor):
```

```python
        assert x.ndim == 2
        seq_len, batch_size = x.shape

        # convert integer indices to vector representations
        embedded = self.dropout(self.embedding(x))  # (seq_len, batch_size, embedding_size)

        ##########################################################
        # YOUR CODE STARTS HERE (2/5)
        ##########################################################

        # pass the embedded input to the LSTM and obtain both the
        # hidden state and cell state for the final time step; the
        # dimension of both should be (num_layers, batch_size, hidden_size)
        lstm_out, (lstm_hn, lstm_cn) = self.rnn(embedded)

        # return only the final hidden state and cell state
        return lstm_hn, lstm_cn

        ##########################################################
        # YOUR CODE ENDS HERE (2/5)
        ##########################################################


class LSTMDecoder(nn.Module):

    def __init__(self,
                 output_size: int,
                 embedding_size: int,
                 hidden_size: int,
                 num_layers: int):

        super().__init__()

        self.hidden_size = hidden_size
        self.num_layers = num_layers
        self.output_size = output_size

        # embedding layer: similar to one-hot encoding, we will map
        # integer indices to vectors
        self.embedding = nn.Embedding(output_size, embedding_size)

        ##########################################################
        # YOUR CODE STARTS HERE (3/5)
        ##########################################################

        # define the LSTM
        self.rnn = nn.LSTM(
            input_size=embedding_size,
            hidden_size=self.hidden_size,
            num_layers=self.num_layers,
            dropout=0.5)

        # define a fully-connected layer that maps vectors of dimension
        # `hidden_size` to vectors of dimension `output_size`
        self.out_proj = nn.Linear(self.hidden_size, self.output_size)

        ##########################################################
        # YOUR CODE ENDS HERE (3/5)
        ##########################################################

        # a droupout layer can improve generalization
        self.dropout = nn.Dropout(0.5)

    def forward(self, x: torch.Tensor, hidden: torch.Tensor, cell: torch.Tensor):

        # take a single time-step of input, a single hidden state, and a single cell state
        assert x.ndim == 1
        x = x.unsqueeze(0)
        _, batch_size = x.shape

        # convert integer indices to vector representations
        embedded = self.dropout(self.embedding(x))  # (1, batch_size, embedding_size)

        ##########################################################
        # YOUR CODE STARTS HERE (4/5)
        ##########################################################

        # call the LSTM on our single-step input and a tuple containing
        # the hidden and cell states. This should return an output state,
        # a final hidden state, and a final cell state. The dimension of
        # the output should be (1, batch_size, hidden_size), and the
        # dimension of the updated hidden and cell states should be
        # (num_layers, batch_size, hidden_size)
        lstm_out, (lstm_hn, lstm_cn) =  self.rnn(embedded,(hidden, cell))

        # apply fully-connected layer to map output dimension to (1, batch_size, output_size)
        prediction = self.out_proj(lstm_out)

        # squeeze output to remove first (sequence) dimension
        prediction = prediction.squeeze(0)  # (batch_size, output_size)

        # return final output, hidden state, and cell state
        return prediction, lstm_hn, lstm_cn

        ##########################################################
        # YOUR CODE ENDS HERE (4/5)
        ##########################################################


class LSTMTranslator(nn.Module):

    def __init__(self,
                 encoder: nn.Module,
                 decoder: nn.Module,
                 device: Union[str, torch.device]):

        super().__init__()

        self.encoder = encoder
        self.decoder = decoder
        self.device = device

        assert encoder.hidden_size == decoder.hidden_size, \
        f"Mismatch: `encoder.hidden_size` = {encoder.hidden_size}, `decoder.hidden_size` = {decoder.hidden_size

        assert encoder.num_layers == decoder.num_layers, \
        f"Mismatch: `encoder.num_layers` = {encoder.num_layers}, `decoder.num_layers` = {decoder.num_layers}"

    def forward(self, x: torch.Tensor, y: torch.Tensor, teacher_forcing_ratio: float = 0.5):

        # inputs should have shape (in_seq_len, batch_size)
        assert x.ndim == 2
        in_seq_len, batch_size = x.shape

        # targets should have shape (out_seq_len, batch size)
        assert y.ndim == 2
        out_seq_len, _ = y.shape
        out_vocab_size = self.decoder.output_size

        # prepare to store decoder outputs. We only need to allocate
        # the "true" number of time steps during training, but for inference
        # we can simply pass in an empty `y` of any length; this will serve as
        # a maximum length constraint on the output translation (which may end
        # sooner if an <EOS> token is predicted).
        outputs = torch.zeros(out_seq_len, batch_size, out_vocab_size).to(self.device)

        ##########################################################
        # YOUR CODE STARTS HERE (5/5)
        ##########################################################

        # pass inputs to encoder to obtain final hidden state and
        # cell state
        hidden, cell = self.encoder(x)
        # print(type(hidden))
        # print(type(cell))
        ##########################################################
        # YOUR CODE ENDS HERE (5/5)
        ##########################################################

        # first input to the decoder is the <SOS> start token
        input = y[0,:]

        for t in range(1, out_seq_len):
```

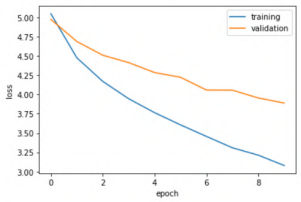
```python

            # given input for current time step (either previous decoder
            # prediction or <SOS> token) and previous hidden state and
            # cell state, compute new output, hidden, and cell states
            output, hidden, cell = self.decoder(input, hidden, cell)

            # write predicted word probabilities to output buffer
            outputs[t] = output

            # during training, we may randomly decide whether to use
            # the decoder's previous predictions or the ground-truth
            # tokens for the previous time step. When we do the latter,
            # it is called "teacher-forcing." We will randomly apply
            # teacher-forcing during training only.
            teacher_force = random.random() < teacher_forcing_ratio

            # take highest-scoring token from decoder's previous prediction
            top1 = output.argmax(1)

            # optionally apply teacher-forcing
            input = y[t] if teacher_force else top1

        return outputs
```

DO NOT modify the following cell.

In [ ]:

```python
# initialize encoder-decoder model
enc_lstm = LSTMEncoder(INPUT_DIM, ENC_EMB_DIM, HID_DIM, N_LAYERS)
dec_lstm = LSTMDecoder(OUTPUT_DIM, DEC_EMB_DIM, HID_DIM, N_LAYERS)
model_lstm = LSTMTranslator(enc_lstm, dec_lstm, device).to(device)

# initialize model weights
def init_weights(m):
    for name, param in m.named_parameters():
        nn.init.uniform_(param.data, -0.08, 0.08)
model_lstm.apply(init_weights)

# parameter count
def count_parameters(model):
    return sum(p.numel() for p in model.parameters() if p.requires_grad)
print(f'The model has {count_parameters(model_lstm):,} trainable parameters')

# optimizer and loss function
optimizer = optim.Adam(model_lstm.parameters())
criterion = nn.CrossEntropyLoss(ignore_index = TRG_PAD_IDX)

# track training and validation losses
training_loss = []
validation_loss = []

best_valid_loss = float('inf')

for epoch in range(N_EPOCHS):

    start_time = time.time()

    train_loss = train(model_lstm, train_iterator, optimizer, criterion, CLIP)
    valid_loss = evaluate(model_lstm, valid_iterator, criterion)

    training_loss.append(train_loss)
    validation_loss.append(valid_loss)

    end_time = time.time()
    epoch_mins, epoch_secs = epoch_time(start_time, end_time)

    if valid_loss < best_valid_loss:
        best_valid_loss = valid_loss
        torch.save(model_lstm.state_dict(), 'lstm-model.pt')

    print(f'Epoch: {epoch+1:02} | Time: {epoch_mins}m {epoch_secs}s')
    print(f'\tTrain Loss: {train_loss:.3f}')
    print(f'\t Val. Loss: {valid_loss:.3f}')

model_lstm.load_state_dict(torch.load('lstm-model.pt'))
test_loss = evaluate(model_lstm, test_iterator, criterion)

print(f'| Test Loss: {test_loss:.3f}')

# generate loss plot
import matplotlib.pyplot as plt
plt.plot(training_loss, label="training")
plt.plot(validation_loss, label="validation")
plt.legend()
plt.xlabel("epoch")
plt.ylabel("loss")
plt.show()
```

```
The model has 13,899,013 trainable parameters
Epoch: 01 | Time: 0m 34s
        Train Loss: 5.047
         Val. Loss: 4.974
Epoch: 02 | Time: 0m 34s
        Train Loss: 4.476
         Val. Loss: 4.687
Epoch: 03 | Time: 0m 34s
        Train Loss: 4.170
         Val. Loss: 4.509
Epoch: 04 | Time: 0m 34s
        Train Loss: 3.944
         Val. Loss: 4.413
Epoch: 05 | Time: 0m 34s
        Train Loss: 3.763
         Val. Loss: 4.284
Epoch: 06 | Time: 0m 34s
        Train Loss: 3.605
         Val. Loss: 4.223
Epoch: 07 | Time: 0m 34s
        Train Loss: 3.455
         Val. Loss: 4.057
Epoch: 08 | Time: 0m 34s
        Train Loss: 3.308
         Val. Loss: 4.056
Epoch: 09 | Time: 0m 34s
        Train Loss: 3.212
         Val. Loss: 3.954
Epoch: 10 | Time: 0m 34s
        Train Loss: 3.077
         Val. Loss: 3.888
| Test Loss: 3.872
```



In [ ]:

```python
# select a random training translation
german_phrase = " ".join(train_data.examples[0].src)
english_phrase = " ".join(train_data.examples[0].trg)
german_phrase_encoded = str_to_tensor(german_phrase, tokenize_de_reverse, source_field).to(model.device)

model_lstm.eval()

with torch.no_grad():

    output = model_lstm(german_phrase_encoded, torch.zeros_like(german_phrase_encoded), 0) #turn off teacher fo
    output_dim = output.shape[-1]
    output = output[1:].view(-1, output_dim).argmax(dim=-1)

tensor_to_str(output, target_field)
```

Out[17]: 'five people in in in the , and and in . <eos>'

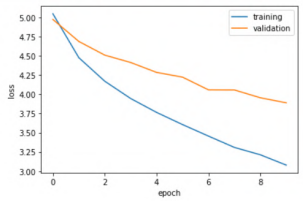
3.4 Reversing Sequences (one point)

Sutskever et al. also performed experiments in which the source sequence was reversed before being passed to the encoder network. We

Modify the data-loading code above so that all references to `tokenize_de` are replaced with `tokenize_de_reverse`. Re-generate the data and re-train your LSTM model from question 3.3. Include a plot of your training and validation lossses by epoch where instructed below. Finally, give a brief explanation of how (if at all) your network's performance changed, and why (if a change occurs).

(YOUR LOSS PLOT HERE)

In [ ]:
```
from IPython.display import display, Image
display(Image("/content/plot/q3.4.png"))
```



(YOUR EXPLANATION HERE)

I don't see a big differnece, and translated sentences are in similar quality. Possible reasons are that encoder output entire input sequence information and decoder model can choose what piece of source sequence to use to generate current target word. For translation tasks, encoder outputs represents source sequence meaning, the order does not matter; for example, if first word in source corresponding to first words in target, after reversing, new model learns to map last word in source to first word in target, LSTM allows us to output based on necessary information.

Question 4: Short Response (two points total)

4.1 State Initialization (one point)

Assume we are given the task from notebook 8, in which we must predict the language from which a given name originates. Assume we are training an RNN in "cell" configuration, meaning we must manually handle the propagation of states, and that we pass our network one training example at a time. Finally, recall that in notebook 8, we demonstrate how to re-initialize the RNN cell's hidden state with a zero vector.

What kind of information does the RNN cell's hidden state hold *after* processing a full name input (but before re-initializing)?

(YOUR ANSWER HERE)

RNN cells hidden state holds encoded information of the all previous letters, namely entire sequence.

Assume that we do not re-initialize the RNN cell's hidden state after processing a name input. What does this mean for the hidden state when we start processing the next name input?

(YOUR ANSWER HERE)

it will contain information of previous traning example, RNN will have information that does not belong to current name string; names / training examples are not independent.

Based on your answers above, when does it make most sense to re-initialize the hidden state for our task?

1. **Only once, at the beginning of training**
2. **After processing each individual name input**
3. **After processing each epoch (i.e. after iterating over all names once)**

Include a brief explanation supporting your answer.

(YOUR ANSWER HERE)

I will choose 2. After processing each individual name input.

This way every traning example will be independent, inside each name we want latter letters have information regarding previous letters in the same name but not from another name of a training example.

4.2 Network Size (one point)

Assume we are given a simplified version of our task from notebook 8, in which we must predict the language from which a given name originates. In this simplified task, names are at most 10 characters long, and characters are drawn only from the standard english alphabet (26 possibilities). Names are drawn from the same 18 languages. Assume all inputs are one-hot encoded.

We consider two different network architectures:

- Network A pads all inputs to the maximum sequence length, flattens them, and passes them through two fully connected layers with sizes 256 and 18, respectively.
- Network B is a recurrent neural network identical to `RNNCell` in notebook 8, with hidden size 256 and output size 18.

How many parameters does each network contain? Explain your reasoning.

(YOUR ANSWER HERE)

Input seq_len 10, H_in 26 since one hot encoding, flatten 26*10 = 260

Number of parameters in model A, $260 * 256 + 256 + 256 * 18 + 18 = 71442$

Number of parameters in model B, i2h $(26 + 256) * 256 + 256 = 72448$, i2o $(26 + 256) * 18 + 18 = 5094$, total $72448 + 5094 = 77542$

What if the maximum input length is 20 characters? What does your answer say about the sizes of fully-connected and recurrent networks as the sequence length grows?

(YOUR ANSWER HERE)

RNN is insensible to sequence length. Only fully connected model will have more trainable parameters as seq_len increases. Model A parameters after flatten, $26 * 20 = 520$.

Number of parameters in model A, $520 * 256 + 256 + 256 * 18 + 18 = 138002$

Number of parameters in model B remains same, i2h $(26 + 256) * 256 + 256 = 72448$, i2o $(26 + 256) * 18 + 18 = 5094$, total $72448 + 5094 = 77542$

In this case RNN has much less number of trainable parameters.