

Lab 5 Report:

Create Arthur Conan Doyle AI with RNN

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In [23]: `%matplotlib inline`

```
import numpy as np
import matplotlib.pyplot as plt
import torch
from torch.distributions import Categorical
```

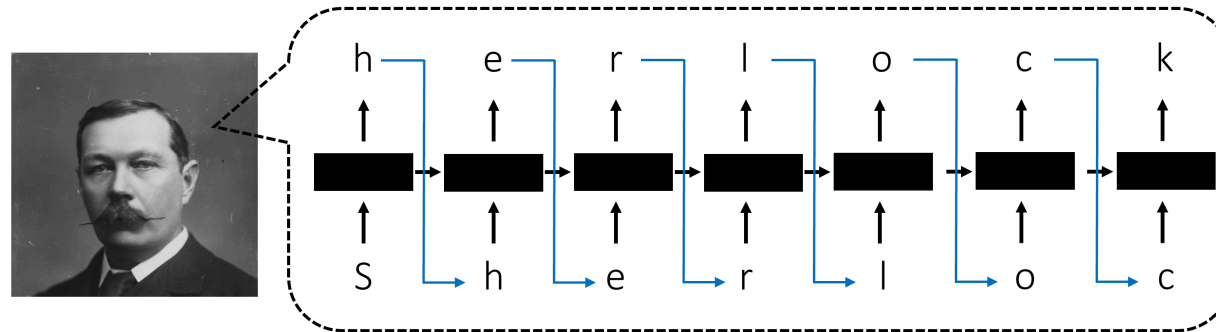
In [24]: `from IPython.display import Image # For displaying images in colab jupyter cell`

In [25]: `Image('lab5_exercise.png', width = 1000)`

Out[25]:



Create Arthur Conan Doyle AI using RNN



In this exercise, you will use RNN to generate **Sherlock Holmes style sequence of texts**.

Prior to training, you can decide the **training size** you want to use for training.
(e.g., first 10k characters, 100k characters, etc)

Design your own RNN architecture with your choice of embedding dimension, hidden state size, number of RNN layers, nonlinearity (tanh or ReLU) and training sequence size.

After training your RNN, **print a validation text sequence** that most closely resembles Sherlock Holmes style in your opinion & plot the training curve to confirm the RNN successfully trained.

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Prepare Data

```
In [ ]: # You will train on the first N characters of the Sherlock Holmes book
# Pick the size of your training data, i.e. N
data_size_to_train = 20000 # made this larger because the training sequence length is also larger than in
# the example

# Load the Sherlock Holmes data up to data_size_to_train

# Skip the table of contents cause its not part of the writing style
start_line = 139
```

```
# Open the file and read from the specified line
with open('sherlock.txt', 'r') as file:
    lines = [line for i, line in enumerate(file) if i >= start_line] # enumerate automatically parses
                                                    # lines, not chars

# Join the lines and truncate to the desired size
data = ''.join(lines)[:data_size_to_train]

# Find the set of unique characters within the training data
characters = sorted(list(set(data)))

# total number of characters in the training data and number of unique characters
data_size, vocab_size = len(data), len(characters)

print("Data has {} characters, {} unique".format(data_size, vocab_size))
```

Data has 20000 characters, 64 unique

```
In [ ]: print("First 100 characters of the training data:\n", data[:100])
        # making sure we skipped the table of contents
```

First 100 characters of the training data:
PART I

(Being a reprint from the reminiscences of

```
In [28]: # Use Python Dictionary to map the characters to numbers and vice versa
```

```
character_to_num = { ch:i for i,ch in enumerate(characters) }
num_to_character = { i:ch for i,ch in enumerate(characters) }
print(character_to_num)
```

```
{'\n': 0, ' ': 1, '!': 2, '"': 3, "'": 4, '(': 5, ')': 6, ',': 7, '-': 8, '.': 9, '1': 10, '2': 11, '7': 12, '8': 13, ';': 14, '?': 15, 'A': 16, 'B': 17, 'C': 18, 'D': 19, 'E': 20, 'F': 21, 'G': 22, 'H': 23, 'I': 24, 'J': 25, 'L': 26, 'M': 27, 'N': 28, 'O': 29, 'P': 30, 'R': 31, 'S': 32, 'T': 33, 'U': 34, 'V': 35, 'W': 36, 'Y': 37, 'a': 38, 'b': 39, 'c': 40, 'd': 41, 'e': 42, 'f': 43, 'g': 44, 'h': 45, 'i': 46, 'j': 47, 'k': 48, 'l': 49, 'm': 50, 'n': 51, 'o': 52, 'p': 53, 'q': 54, 'r': 55, 's': 56, 't': 57, 'u': 58, 'v': 59, 'w': 60, 'x': 61, 'y': 62, 'z': 63}
```

```
In [ ]: # Use the character_to_num dictionary to map each character in the training dataset to a number

data = list(data)
```



```

In [ ]: # Fix random seed
torch.manual_seed(25)

# Define RNN network
# embedding_dim = 100 is relatively small because the high dimensionality capturing
# relationships between words is not needed when dealing only with characters.
# input_size = 100 is the size of the embedding layer, these must match.
# hidden_size = 1024 I expanded the size of the hidden layer to 1024 to allow for more
# complex relationships, especially since we are going character by character
rnn = CharRNN(num_embeddings = vocab_size, embedding_dim = 100,
              input_size = 100, hidden_size = 1024, num_layers = 3,
              output_size = vocab_size)

# Define learning rate and epochs
# chose a slow learning rate so that model could converge towards end of training
learning_rate = 0.0005
epochs = 100 # need a lot of epochs for the loss to converge
loss_target = 0.035 # set a target loss to stop training when reached

# Size of the input sequence to be used during training and validation
training_sequence_len = 200 # this many characters is needed to capture the style specifically.
                             # Any shorter and we would not be able to capture context within a sentence
                             # of standard length.
validation_sequence_len = 200

# Define loss function and optimizer
loss_fn = torch.nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(rnn.parameters(), lr=learning_rate)

# add .cuda() for GPU acceleration
rnn

```

```

Out[ ]: CharRNN(
  (embedding): Embedding(64, 100)
  (rnn): RNN(100, 1024, num_layers=3)
  (decoder): Linear(in_features=1024, out_features=64, bias=True)
)

```

Identify Tracked Values

```
In [32]: # Tracking training loss per each input/target sequence fwd/bwd pass
train_loss_list = []
```

Train Model

```
In [ ]: # Convert training data into torch tensor and make it into vertical orientation (N, 1)
# Attach .cuda() if using GPU
data = torch.unsqueeze(torch.tensor(data), dim = 1)

# Training Loop -----

for epoch in range(epochs):

    # Randomly select a starting character from first 100 characters in training set
    character_loc = np.random.randint(100)

    # iteration number to keep track of until the sequence reaches the end of training data
    iteration = 0

    # initialize initial hidden state as None
    hidden_state = None

    # loop continues until target_seq reaches end of the data
    while character_loc + training_sequence_len + 1 < data_size:

        # Define input/target sequence
        input_seq = data[character_loc : character_loc + training_sequence_len]
        target_seq = data[character_loc + 1 : character_loc + training_sequence_len + 1]
        # using teacher forcing here

        # Pass input sequence and hidden_state to RNN
        output, hidden_state = rnn(input_seq, hidden_state)

        # Compute loss between RNN output sequence vs target sequence
        # torch.squeeze removes the column dimension and make them into horizontal orientation
        loss = loss_fn(torch.squeeze(output), torch.squeeze(target_seq))

        # Append loss
        train_loss_list.append(loss.item())
```

```

    # Empty gradient buffer -> backpropagation -> update network
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()

    # Update starting character for next sequence
    character_loc += training_sequence_len

    # Update iteration number
    iteration += 1

epoch_avg_loss = np.mean(train_loss_list[-iteration:]) # need this later
print("Averaged Training Loss for Epoch ", epoch, ": ", epoch_avg_loss)

# Sample and generate a text sequence after every epoch -----

#Initialize character location and hidden state for validation
character_loc = 0
hidden_state = None

# Pick a random character from the dataset as an initial input to RNN
rand_index = np.random.randint(data_size-1)
input_seq = data[rand_index : rand_index+1]

print("-----")
with torch.no_grad():

    # Loop continues until RNN generated sequence is in desired length
    while character_loc < validation_sequence_len:

        # Pass validation sequence to RNN
        # Note that RNN now uses its previous output character as input
        output, hidden_state = rnn(input_seq, hidden_state)

        # Take the softmax of the decoder output to get the probabilities of predicted characters
        output = torch.nn.functional.softmax(torch.squeeze(output), dim=0)
        # Use the probabilities to sample the output character
        character_distribution = torch.distributions.Categorical(output)
        character_num = character_distribution.sample()

        # Convert the character number selected from sampling to actual character and print

```

```
print(num_to_character[character_num.item()], end='')

# Update the input_seq so that it's using the output of the RNN as new input
input_seq[0][0] = character_num.item()

# Update the character location
character_loc += 1

print("\n-----")

# Break statement to grab best final model state. Once averaged loss is less than the target loss
# stop training, BUT only if the actual loss is not more than the averaged loss
# (makes sure we aren't on a noise spike)
if (train_loss_list[-1] <= epoch_avg_loss) and (epoch_avg_loss < loss_target):
    break
```


Averaged Training Loss for Epoch 0 : 2.9806876616044478

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Averaged Training Loss for Epoch 1 : 2.284456568534928

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Averaged Training Loss for Epoch 2 : 2.053362660937839

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Averaged Training Loss for Epoch 3 : 1.8925096988677979

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Averaged Training Loss for Epoch 4 : 1.7638005752756138

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Wowtt me

 Averaged Training Loss for Epoch 91 : 0.042331864605798866

(Bemade, too," remarked Sherlock Holmes seemed delighted at the idea of sharing his rooms with me. "I things out whe had neither kith nor kin in England, and was therefore as free as

 Averaged Training Loss for Epoch 92 : 0.04150348550856414

ow

could I meet this friend of yours?"

"He is sure to be at the laboratory," returned my companions who was bemoaning himself this cross-examination. "I keep a bull pup," I said, mand I object to

 Averaged Training Loss for Epoch 93 : 0.030371201958394413

ever.

"Woulmory of rows?" he asked, anxiously.

"It depends on the shoulder, and turning round I recognized young Stamford, who had been a dresser and settle everything," hu answered.

"That's

Visualize & Evaluate Model

```
In [ ]: # Print a validation text sequence that most closely resembles Sherlock Holmes style
test_sequence_len = 500
#Initialize character location and hidden state for validation
character_loc = 0
hidden_state = None

# Pick a random character from the dataset as an initial input to RNN
rand_index = np.random.randint(data_size-1)
input_seq = data[rand_index : rand_index+1]
```

```

with torch.no_grad():
    while character_loc < test_sequence_len: # Loop continues until RNN generated sequence desired length

        # Pass validation sequence to RNN
        # Note that RNN now uses its previous output character as input
        output, hidden_state = rnn(input_seq, hidden_state)

        # Take the softmax of the decoder output to get the probabilities of predicted characters
        output = torch.nn.functional.softmax(torch.squeeze(output), dim=0)
        # Use the probabilities to sample the output character
        character_distribution = torch.distributions.Categorical(output)
        character_num = character_distribution.sample()

        # Convert the character number selected from sampling to actual character and print
        print(num_to_character[character_num.item()], end='')

        # Update the input_seq so that it's using the output of the RNN as new input
        input_seq[0][0] = character_num.item()

        # Update the character location
        character_loc += 1

```

Joll was My health forbade me from venturing out unless the weather was exceptionally genial, and I had no friends who would call upon me and break the monotony of my daily existence. Under these circumstances, I eagerly hailed the little mystery which hung around my companion, and spent much of my time in endeavouring to unravel it.

He was not studying medicine. He had himself, in reply to a question, confirmed Stamford's opinion upon that point. Neither did he appear to have purs

```

In [44]: # Import seaborn for prettier plot
import seaborn as sns

sns.set(style = 'whitegrid', font_scale = 2.5)

```

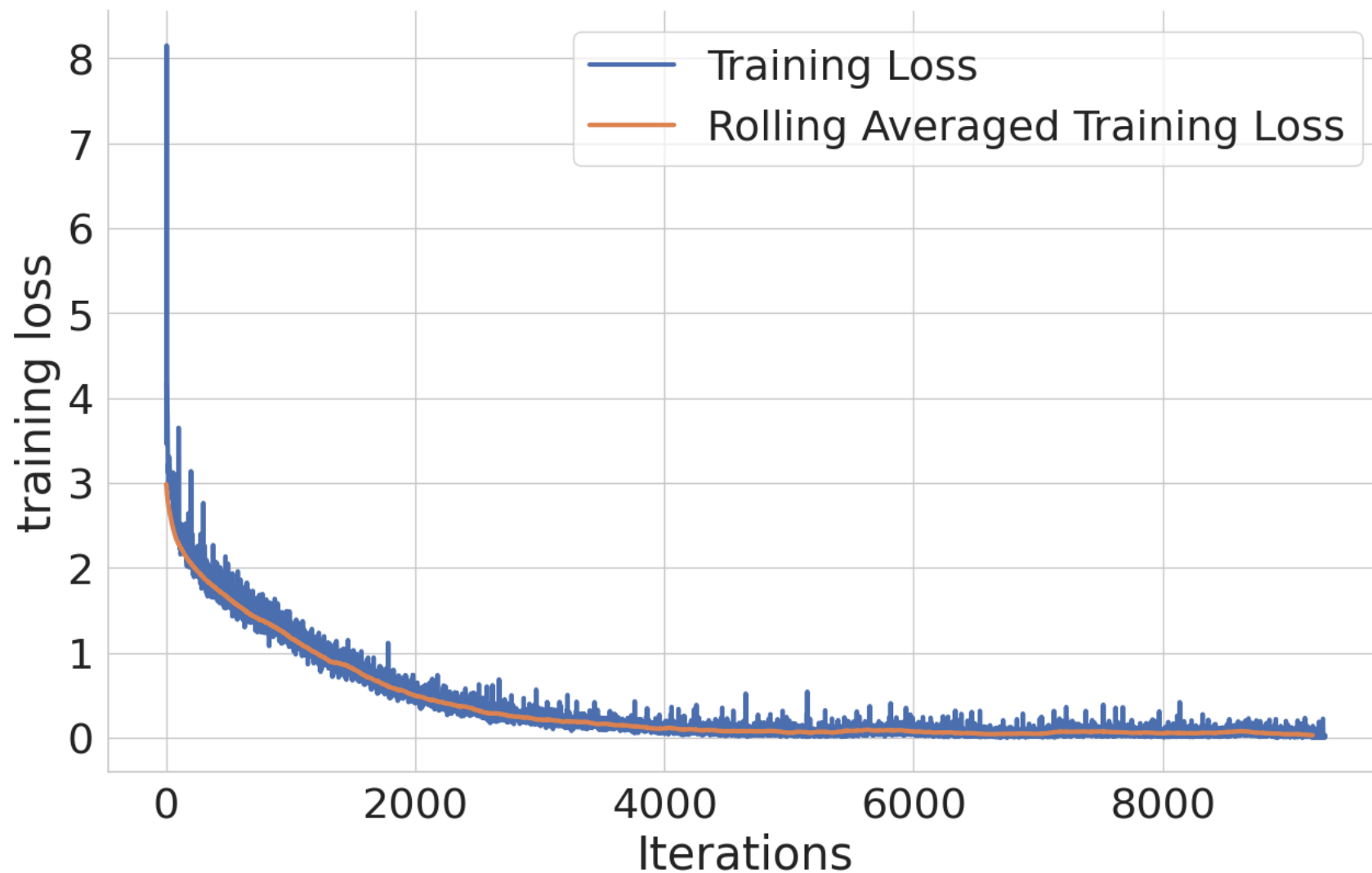
```

In [45]: # Plot the training loss and rolling mean training loss with respect to iterations
# Feel free to change the window size

```

```
plt.figure(figsize = (15, 9))

plt.plot(train_loss_list, linewidth = 3, label = 'Training Loss')
plt.plot(np.convolve(train_loss_list, np.ones(100), 'valid') / 100,
         linewidth = 3, label = 'Rolling Averaged Training Loss')
plt.ylabel("training loss")
plt.xlabel("Iterations")
plt.legend()
sns.despine()
```



In []: