LAB 4: RECURRENT NEURAL NETWORKS (RNNs)

University of Washington, Seattle

Fall 2025

OUTLINE

Part 1: Introduction to RNNs

- Why do we need RNNs?
- RNN in PyTorch
- Embedding and Decoder

Part 2: RNN Implementation in PyTorch

- Character Level Generation Shakespeare Dataset

Lab Assignment

- Create Arthur Conan Doyle AI

INTRODUCTION TO RNNs

Why do we need RNNs?

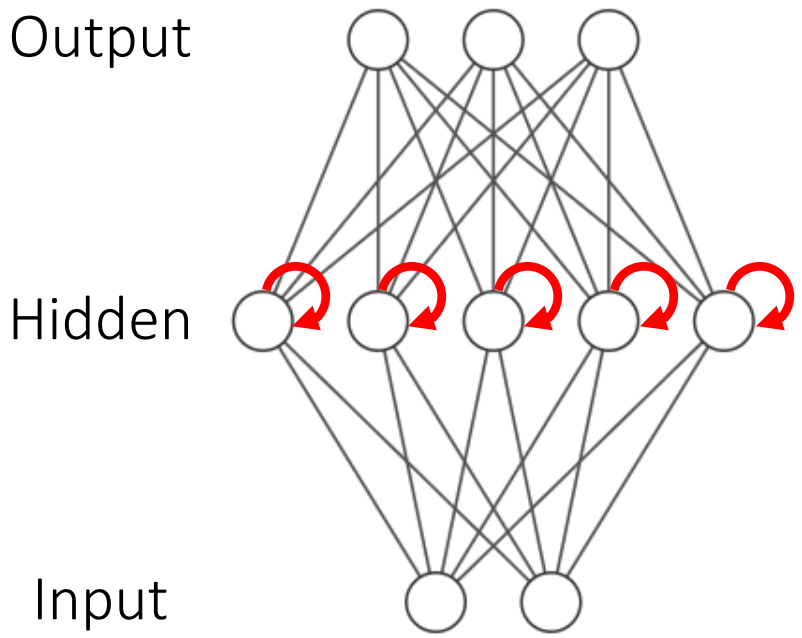
RNN in PyTorch

Embedding and Decoder

Why Do We Need RNNs?

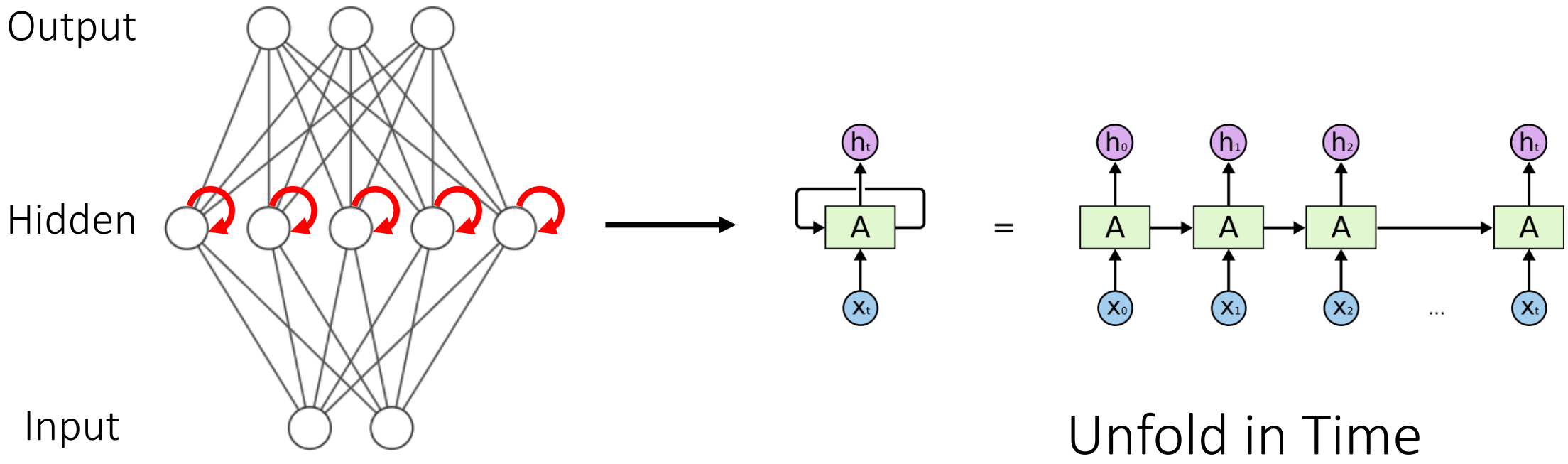
We need a neural network architecture that can handle:

- Data order
- Temporal dependencies
- Variable input sizes

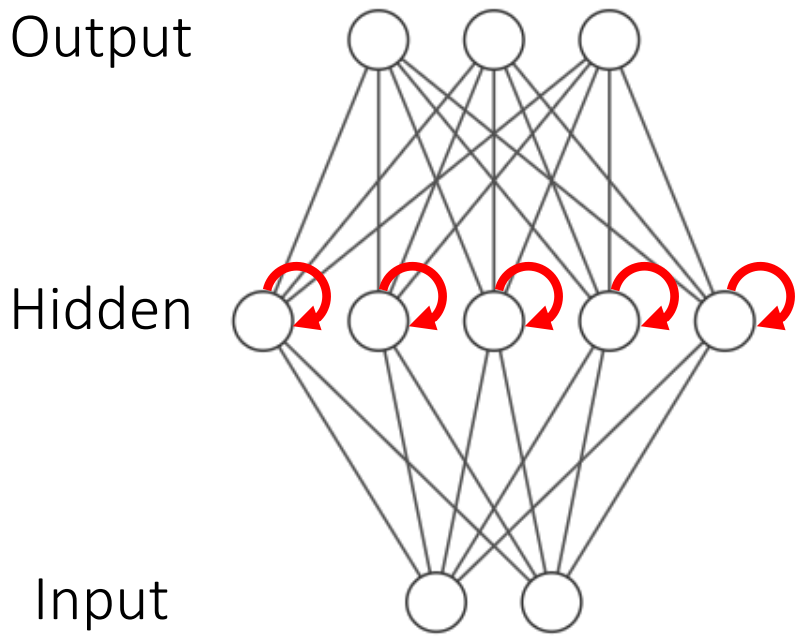


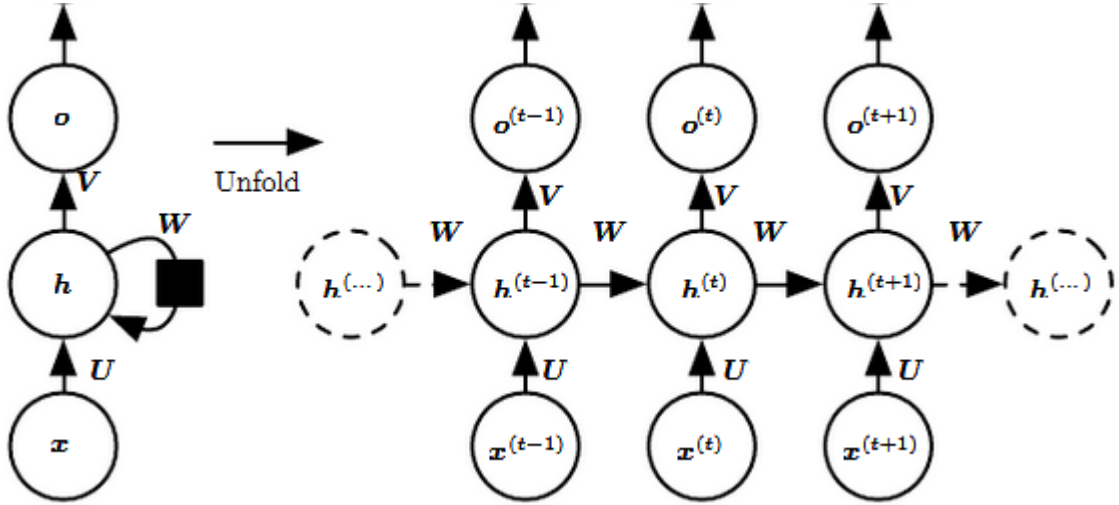
Recurrent Neural Network

RNN Architecture



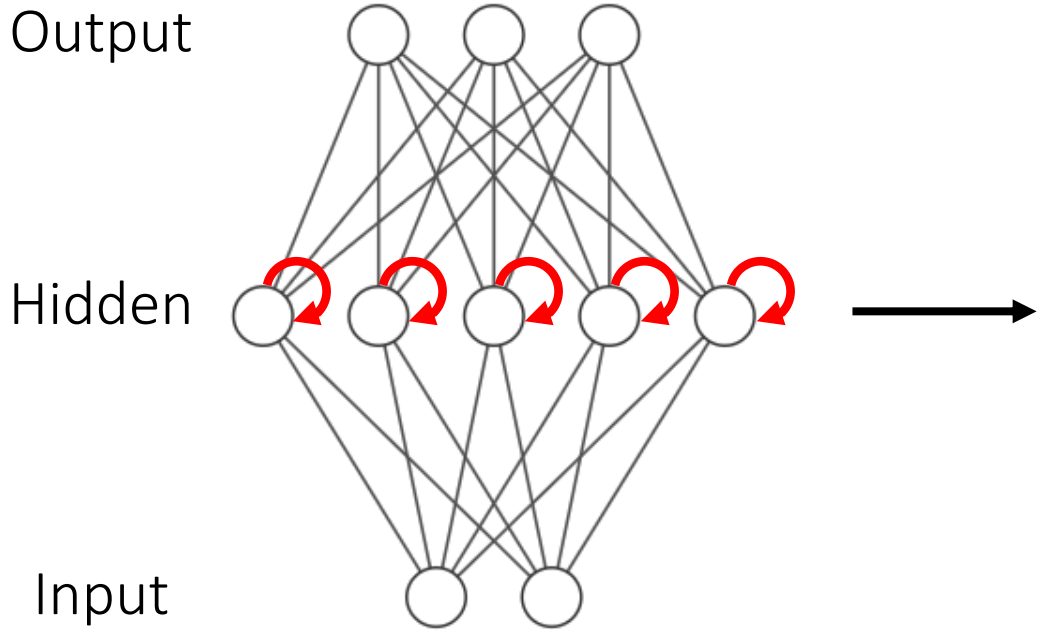
RNN Architecture

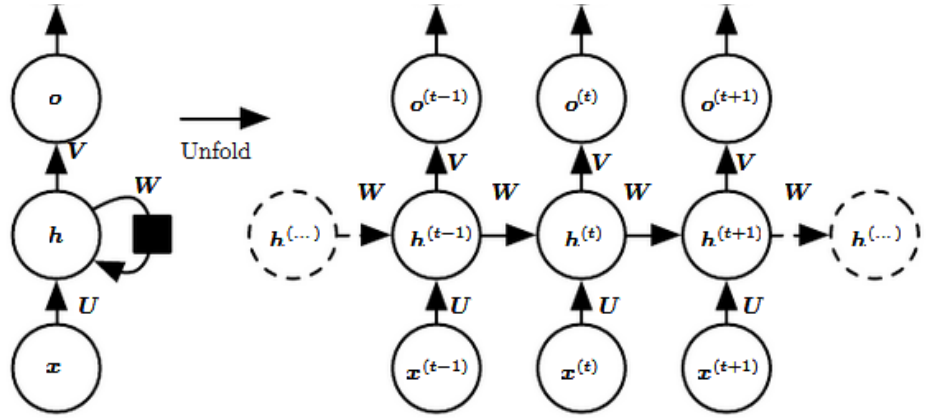




Unfold in Time

RNN Architecture

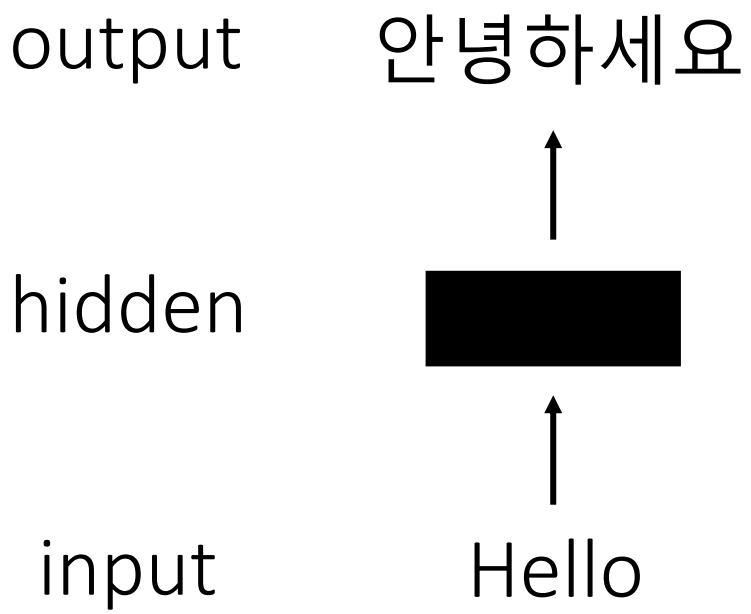




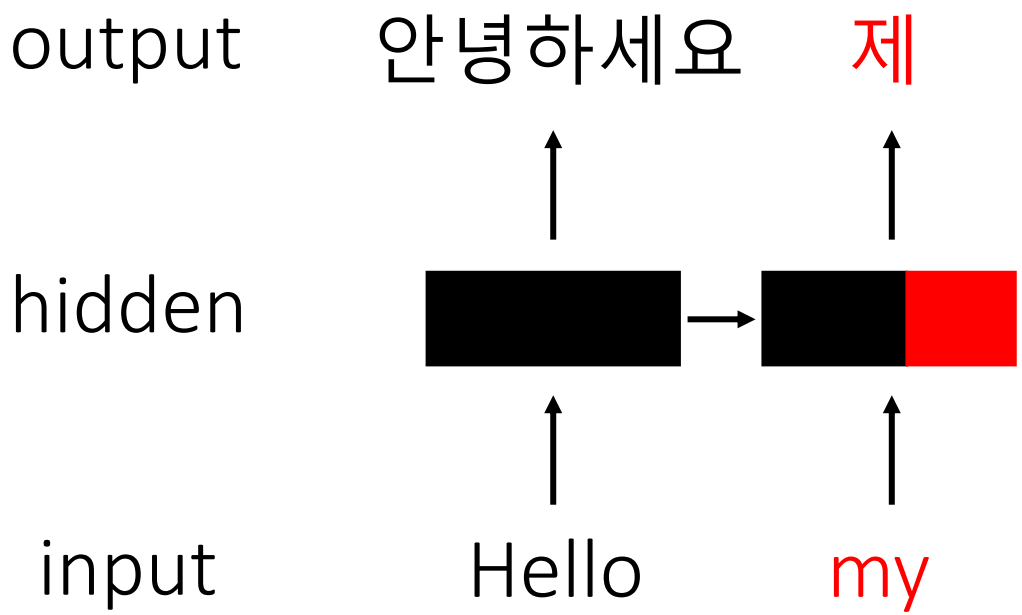
Unfold in Time

$$
\begin{aligned}
\boldsymbol{a}^{(t)} &= \boldsymbol{b} + \boldsymbol{W}\boldsymbol{h}^{(t-1)} + \boldsymbol{U}\boldsymbol{x}^{(t)} \\
\boldsymbol{h}^{(t)} &= \tanh(\boldsymbol{a}^{(t)}) \\
\boldsymbol{o}^{(t)} &= \boldsymbol{c} + \boldsymbol{V}\boldsymbol{h}^{(t)} \\
\hat{\boldsymbol{y}}^{(t)} &= \operatorname{softmax}(\boldsymbol{o}^{(t)})
\end{aligned}
$$

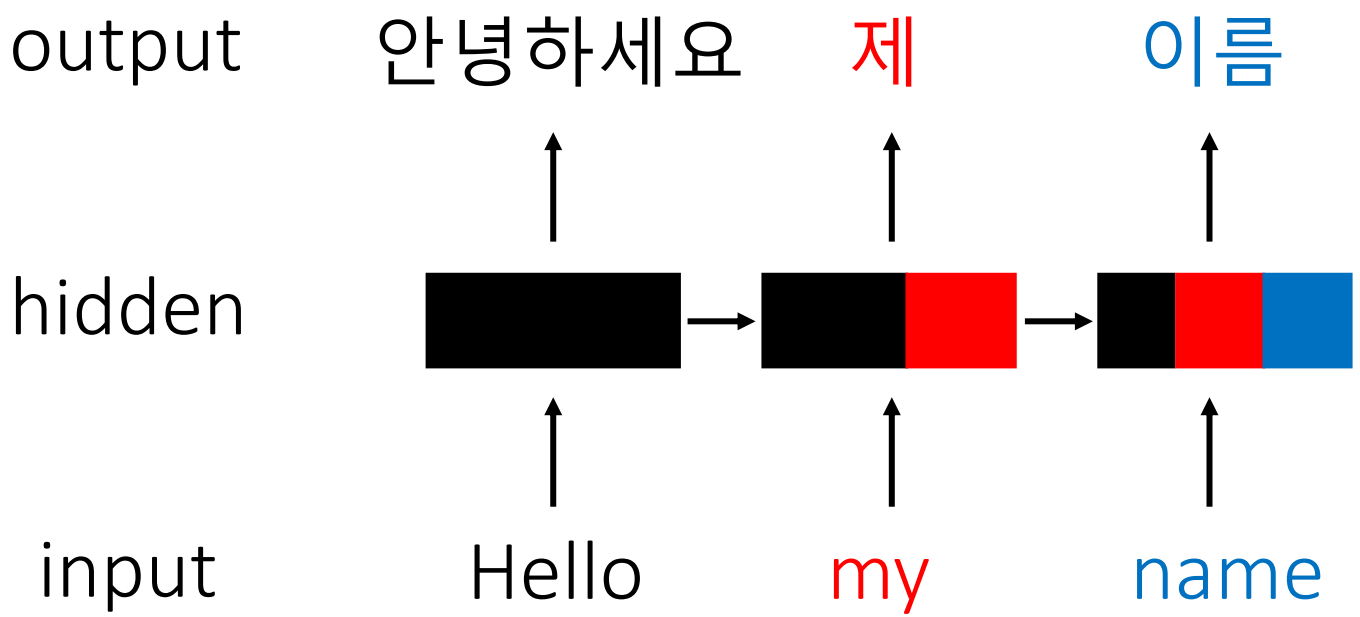
RNN Architecture



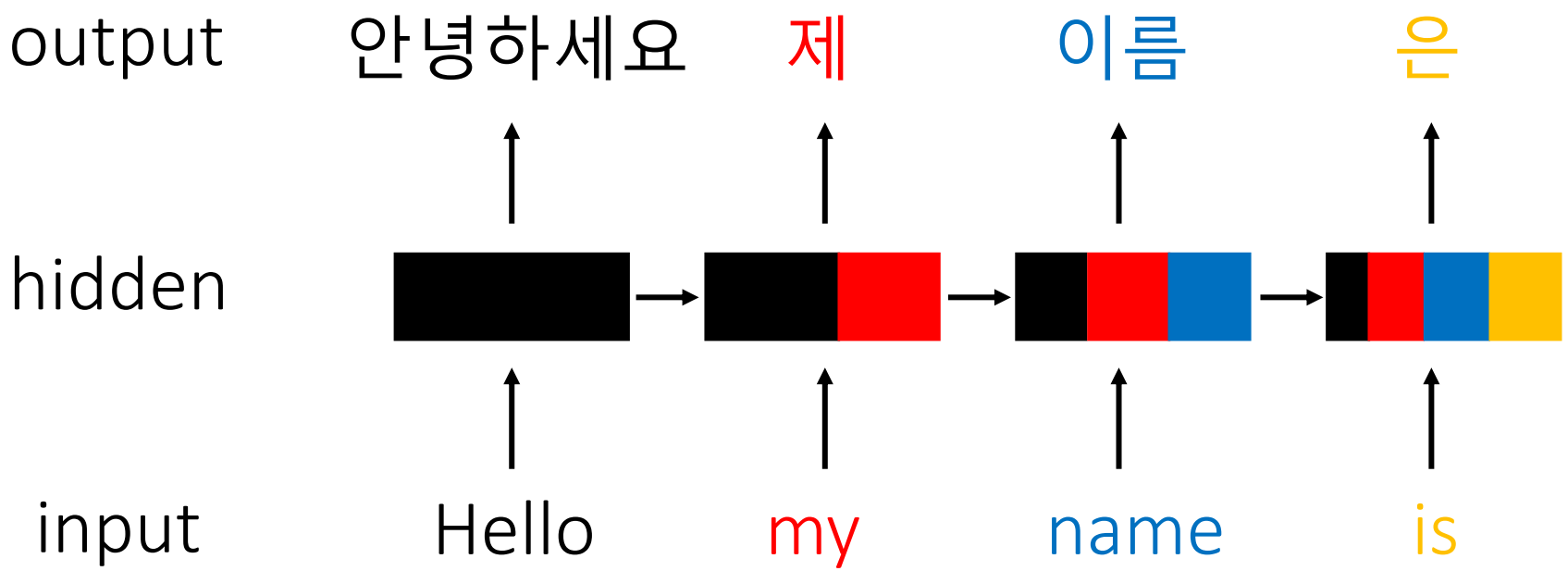
RNN Architecture



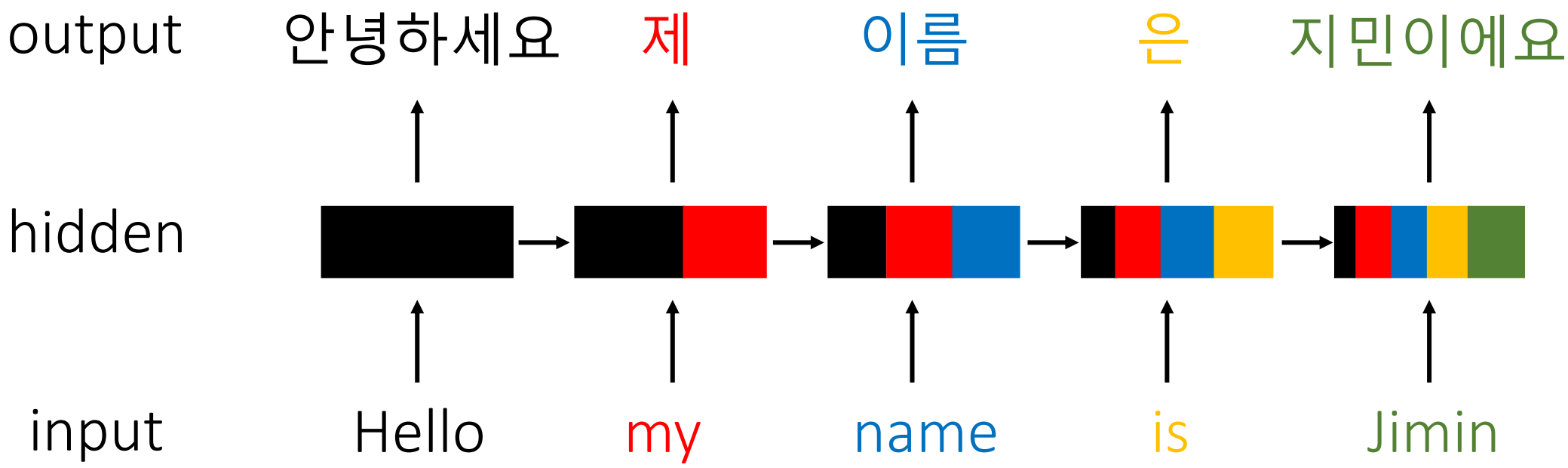
RNN Architecture



RNN Architecture



RNN Architecture



RNN in PyTorch

torch.nn.RNN(	Parameter description	Data type
- input_size	# of expected features in the input	int
- hidden_size	# of features in the hidden state	int
- num_layers	# of recurrent layers	Default = 1
- Nonlinearity	Non-linearity to use	int or tuple (default = ‘tanh’)

)

Official documentation: https://pytorch.org/docs/stable/generated/torch.nn.RNN.html

RNN in PyTorch

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Input dimensions: (sequence length, batch size, input size)

RNN in PyTorch

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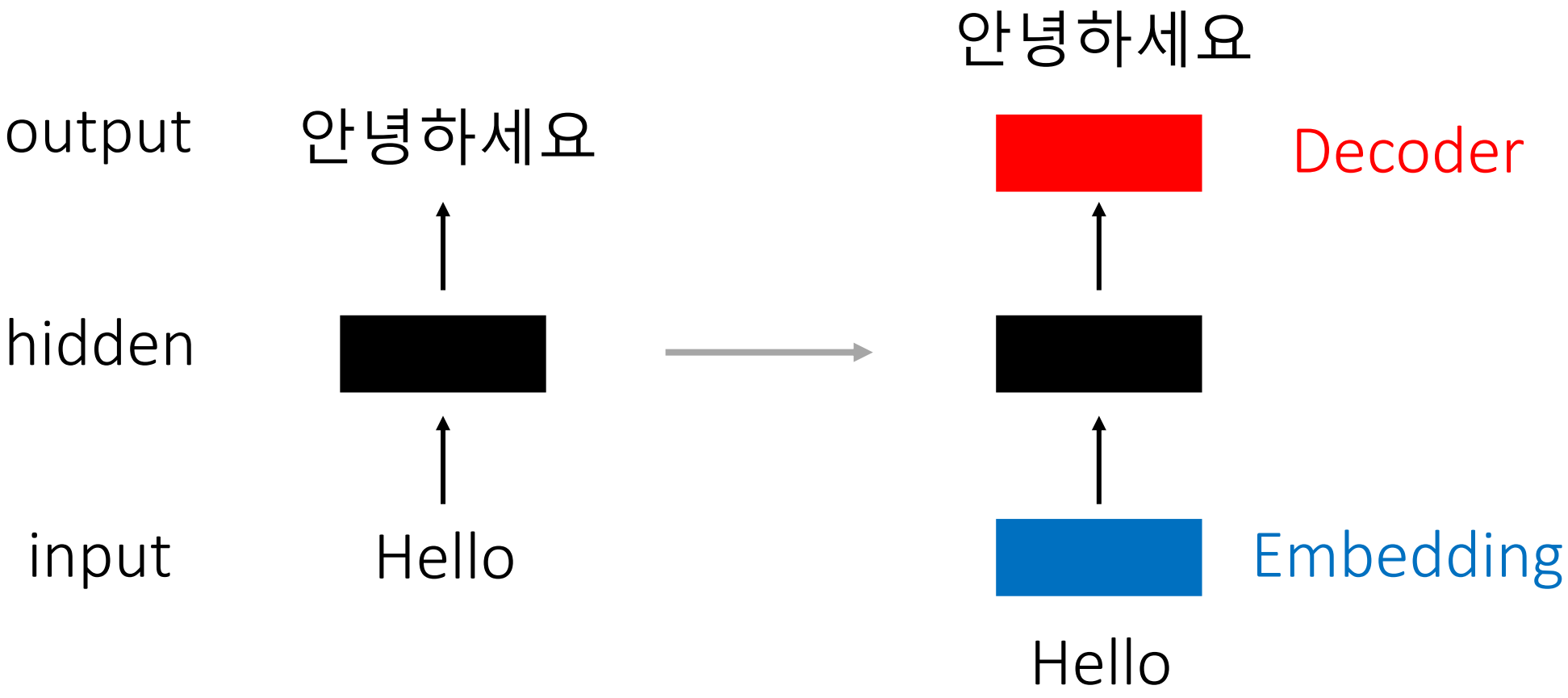
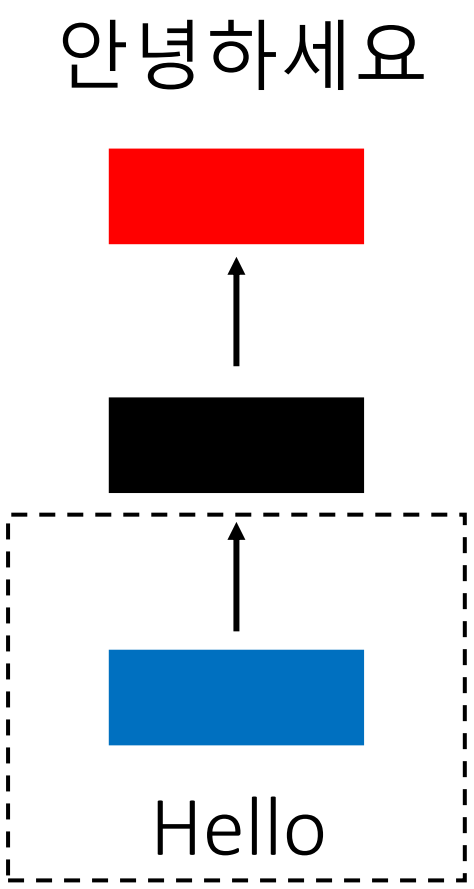
)

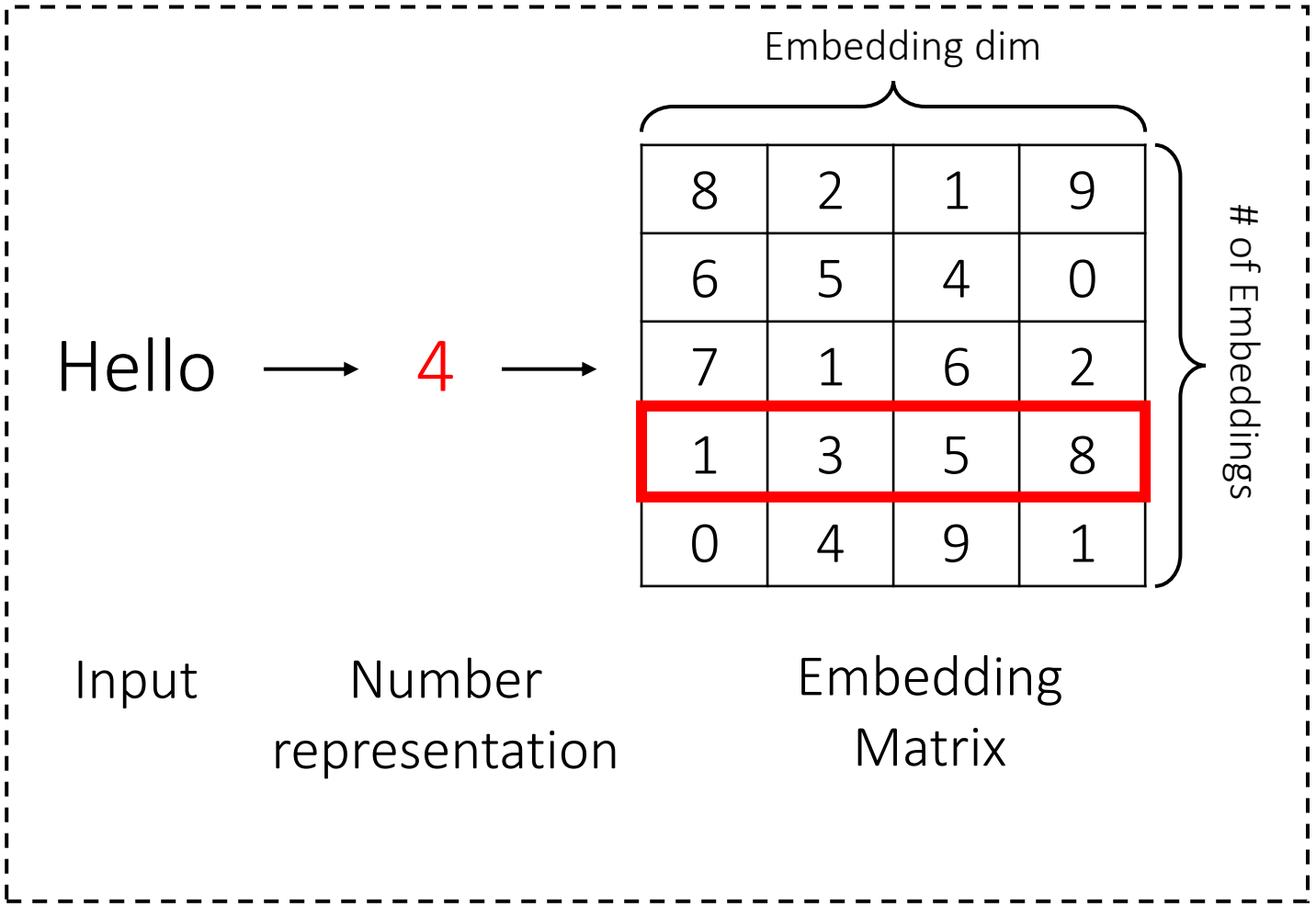
Input dimensions (batch_first = True): (batch size, sequence length, input size)

Embedding and Decoder

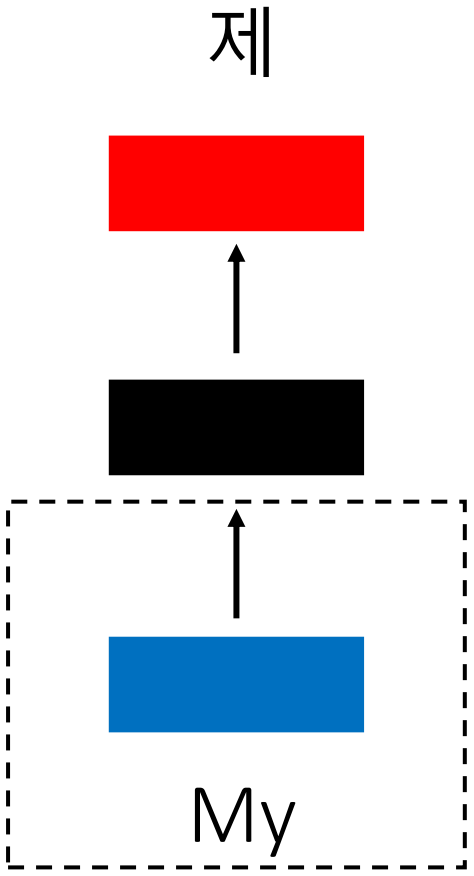


Embedding


안녕하세요
Hello


Embedding dim
Hello
4
8 2 1 9
6 5 4 0
7 1 6 2
1 3 5 8
0 4 9 1
# of Embeddings
Input
Number representation
Embedding Matrix

Embedding



My → 2 →

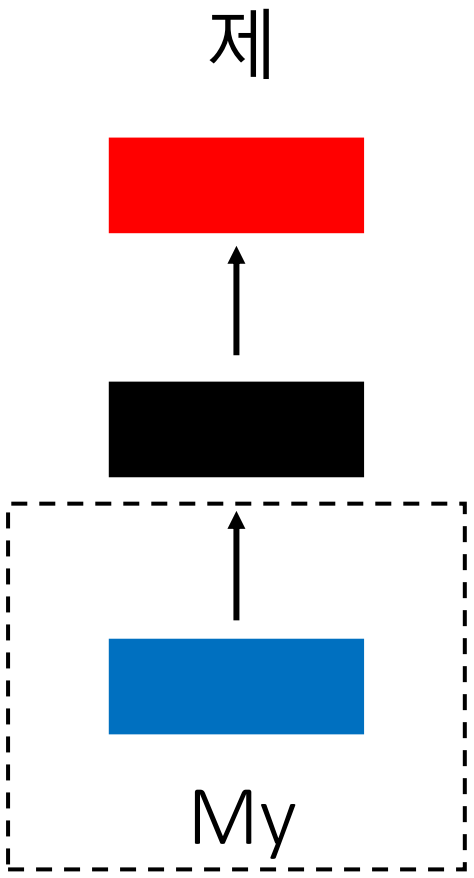
8	2	1	9
6	5	4	0
7	1	6	2
1	3	5	8
0	4	9	1

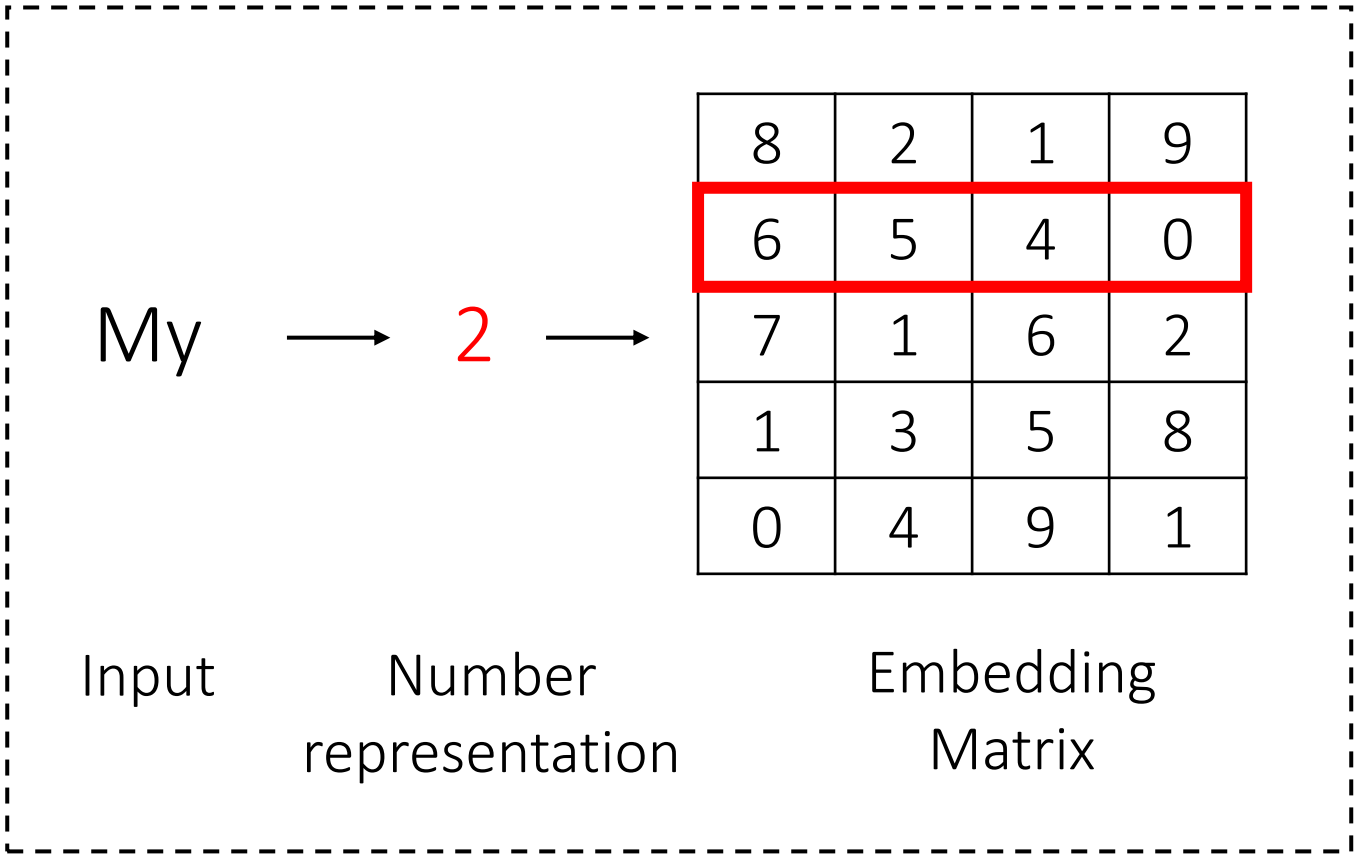
Input

Number representation

Embedding Matrix

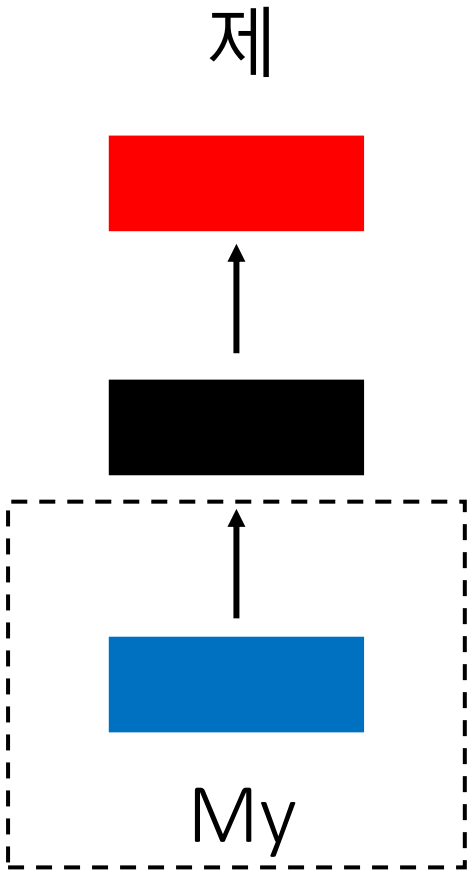
Embedding

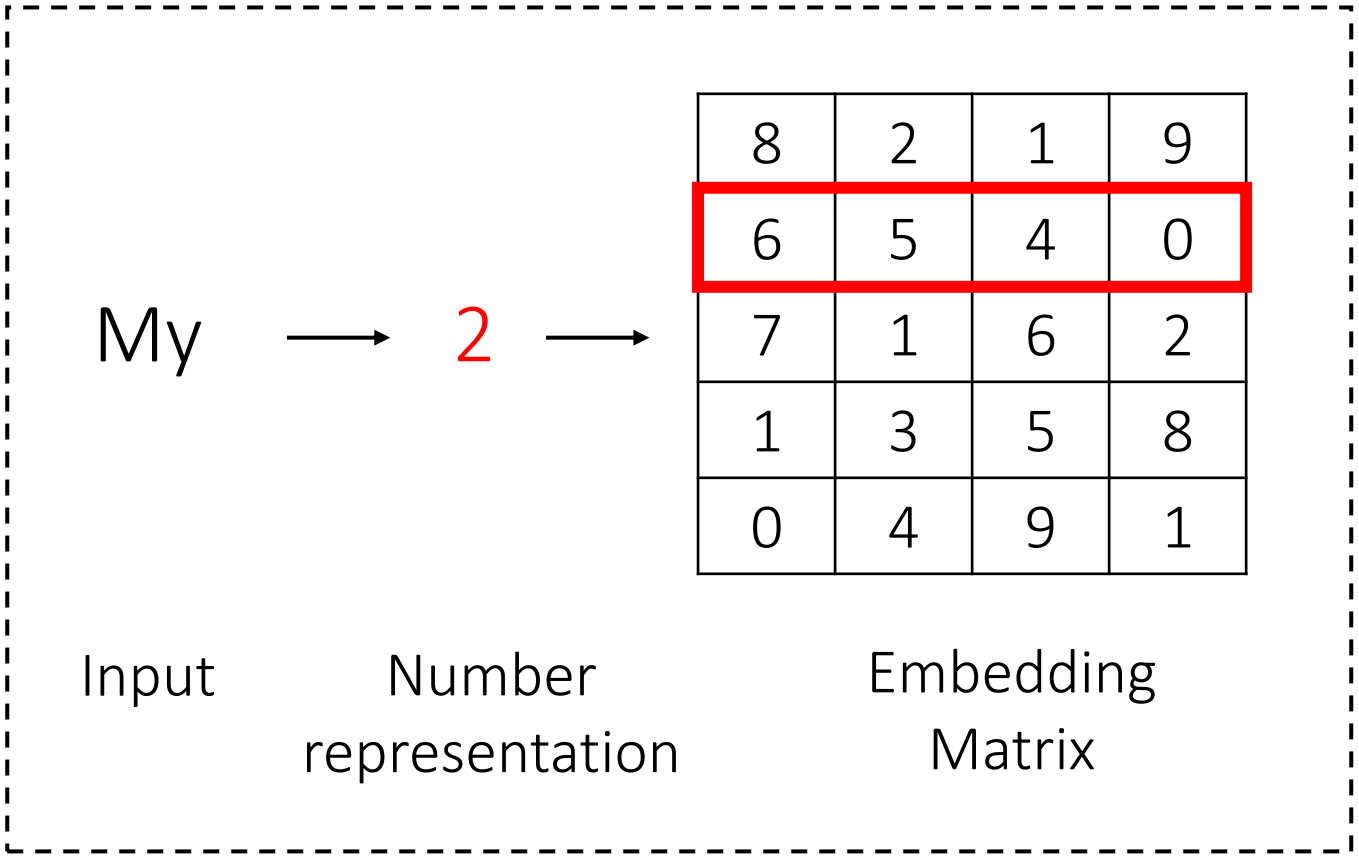




Embedding matrix is trainable

Embedding

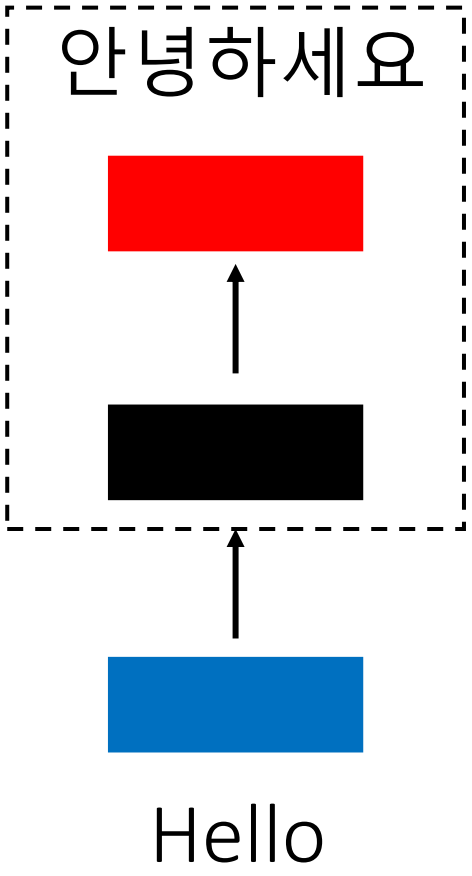


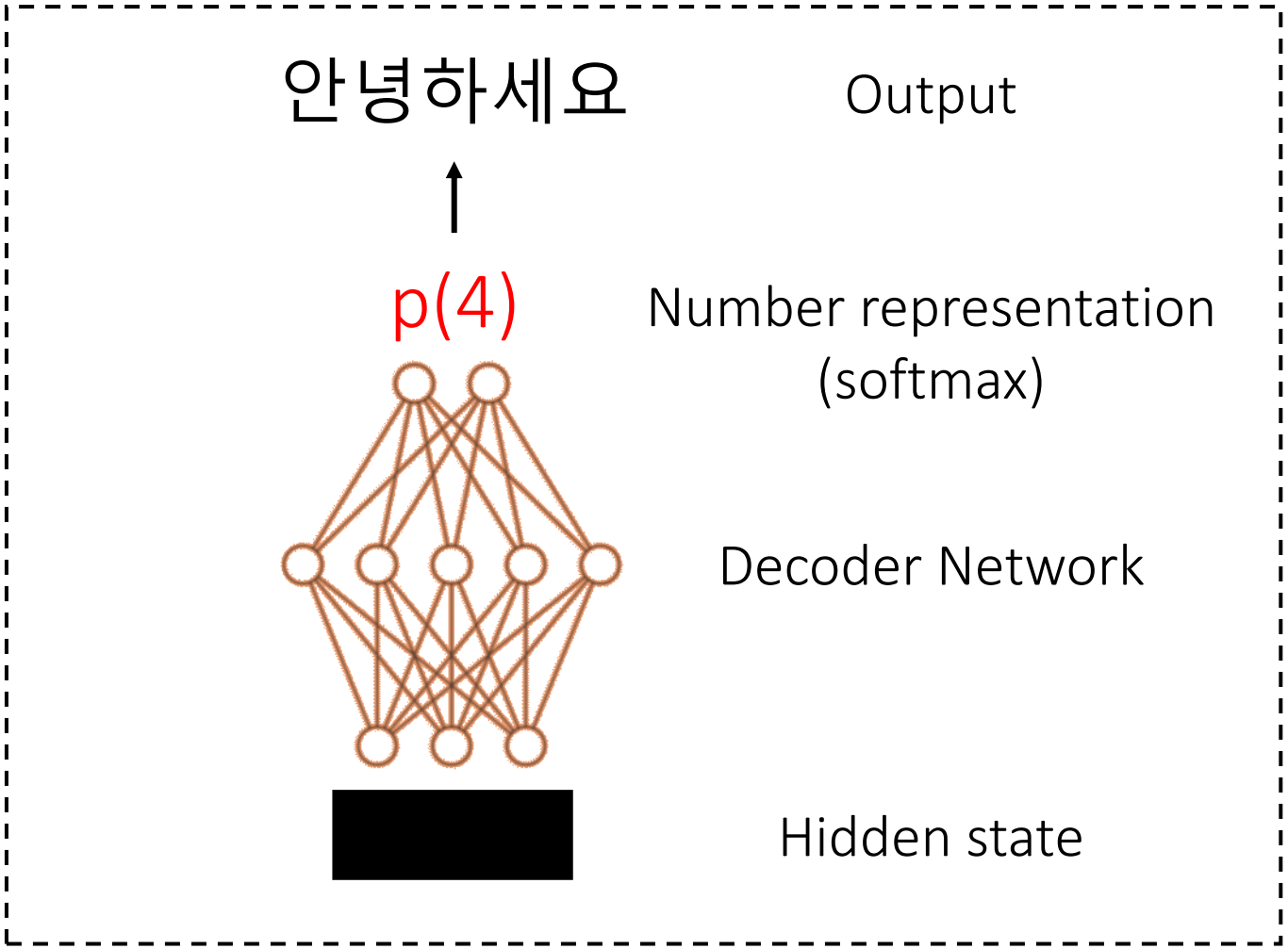


torch.nn.embedding(num_embeddings, embedding dim)

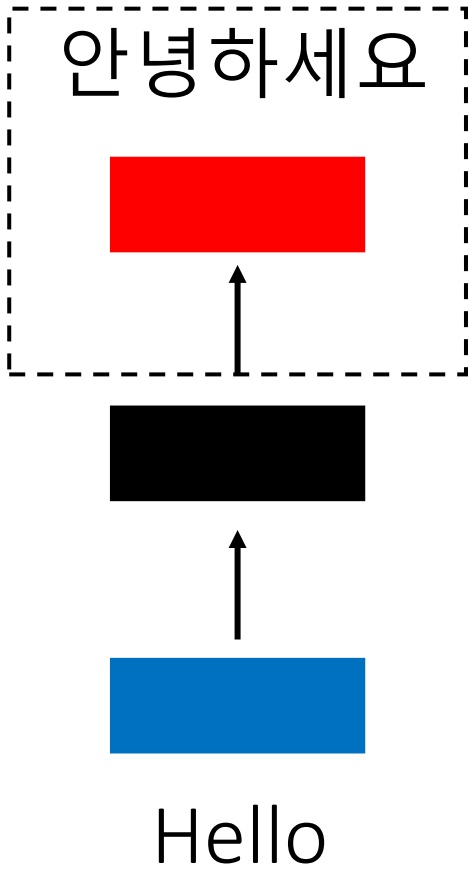
https://pytorch.org/docs/stable/generated/torch.nn.Embedding.html

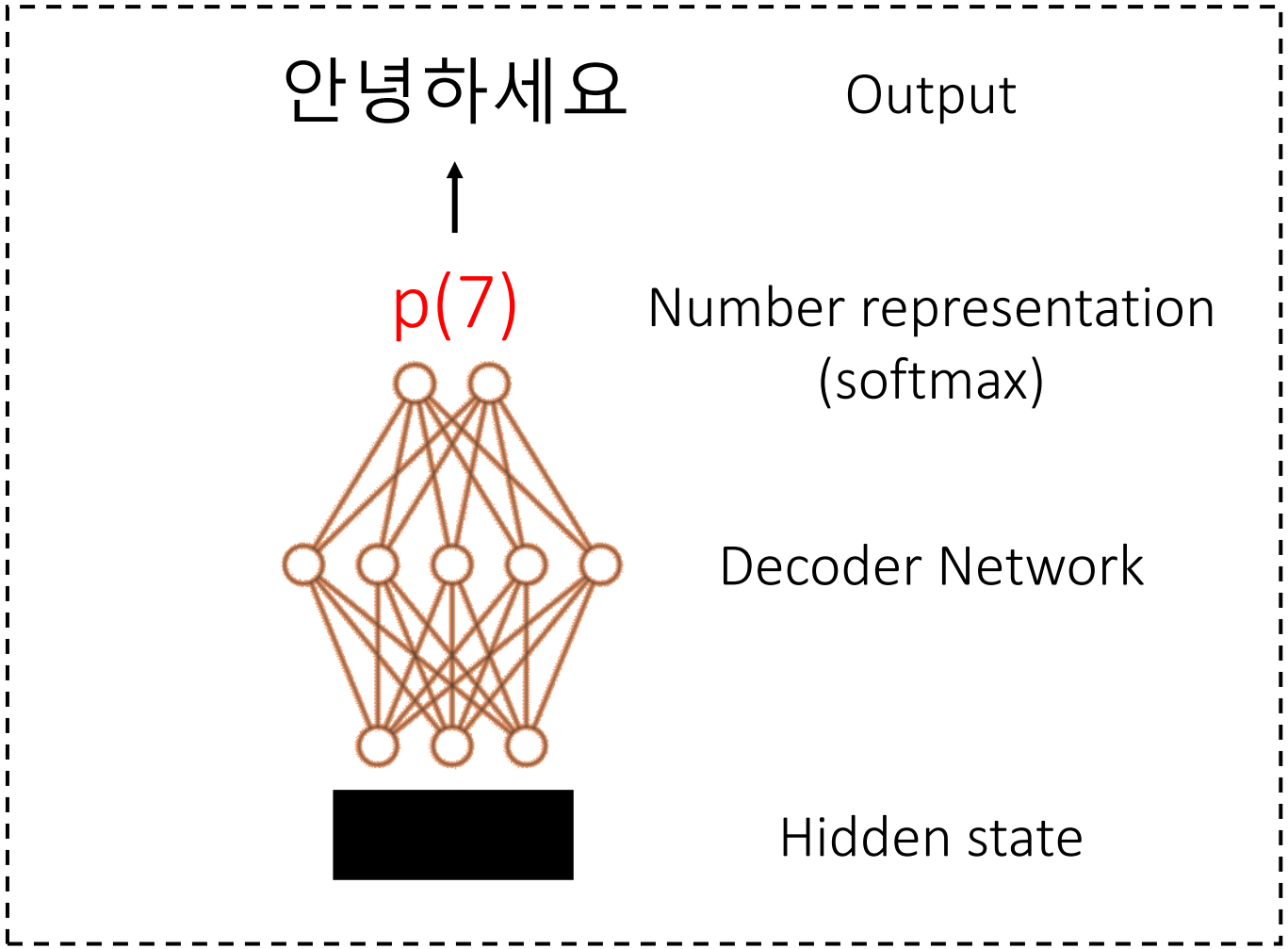
Decoder


안녕하세요
Hello


안녕하세요
Output
p(4)
Number representation
(softmax)
Decoder Network
Hidden state

Decoder





torch.nn.Linear(hidden_size, output_size)

RNN IMPLEMENTATION IN PYTORCH

Character Level Text Generation using

Shakespeare Dataset

Shakespeare Dataset

```
First Citizen:
Before we proceed any further, hear me speak.

All:
Speak, speak.

First Citizen:
You are all resolved rather to die than to famish?

All:
Resolved. resolved.

First Citizen:
First, you know Caius Marcius is chief enemy to the people.

All:
We know't, we know't.

First Citizen:
Let us kill him, and we'll have corn at our own price.
Is't a verdict?

All:
No more talking on't; let it be done: away, away!

Second Citizen:
One word, good citizens.

First Citizen:
We are accounted poor citizens, the patricians good.
What authority surfeits on would relieve us: if they
would yield us but the superfluity, while it were
wholesome, we might guess they relieved us humanely;
```

Full script of “**Tragedy of Coriolanus**” in .txt format

3801089 characters (including space)

66 unique characters

Prepare Data

```
1  data_size_to_train = 10000
2
3  data = open('shakespeare.txt', 'r').read()[:data_size_to_train]
4  characters = sorted(list(set(data)))
5  data_size, vocab_size = len(data), len(characters)
6
7  print("Data has {} characters, {} unique".format(data_size, vocab_size))
```

Define length of training data to be used for training

Load .txt file and sort unique characters using set()

Print # of total and unique characters

```
Data has 10000 characters, 57 unique
```

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

Create dictionaries that map each character to numbers and vice versa

```
1  print(character_to_num)
```

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

Prepare Data

```
1  data = list(data)
2
3  for i, ch in enumerate(data):
4      data[i] = character_to_num[ch]
```

Convert data into Python list

Map each character in the data to a number

```
1  print(data[:10])
```

```
[17, 48, 57, 58, 59, 1, 14, 48, 59, 48]
```

First 10 characters of the data

Define Model

```
class CharRNN(torch.nn.Module):

    def __init__(self, num_embeddings, embedding_dim, input_size, hidden_size, num_layers, output_size):

        super(CharRNN, self).__init__()

        self.embedding = torch.nn.Embedding(num_embeddings, embedding_dim)

        self.rnn = torch.nn.RNN(input_size=input_size, hidden_size=hidden_size,
                                num_layers=num_layers,
                                nonlinearity = 'relu')

        self.decoder = torch.nn.Linear(hidden_size, output_size)

    def forward(self, input_seq, hidden_state):

        embedding = self.embedding(input_seq)

        output, hidden_state = self.rnn(embedding, hidden_state)

        output = self.decoder(output)

        return output, hidden_state.detach()
```

Define embedding layer

Define RNN cell

Define decoder layer

Input_seq -> embedding layer

Embedding, hidden_state -> RNN cell

RNN output -> decoder layer -> output

Return both **output** & **hidden state**

Select Hyperparameters

```
1  torch.manual_seed(25)
2
3  rnn = CharRNN(num_embeddings = vocab_size, embedding_dim = 100,
4                input_size = 100, hidden_size = 512, num_layers = 3,
5                output_size = vocab_size)
6
7  lr = 0.001
8  epochs = 50
9  training_sequence_len = 50
10 validation_sequence_len = 200
11
12 loss_fn = torch.nn.CrossEntropyLoss()
13 optimizer = torch.optim.Adam(rnn.parameters(), lr=lr)
14
15 rnn
```

Define RNN specifics

- # of Embedding = vocab size
- Embedding dim = 100
- Input_size = 100
- Hidden_size = 512
- Num_layers = 3
- Output_size = vocab size

Define learning rate, epochs, length of training/validation text sequence

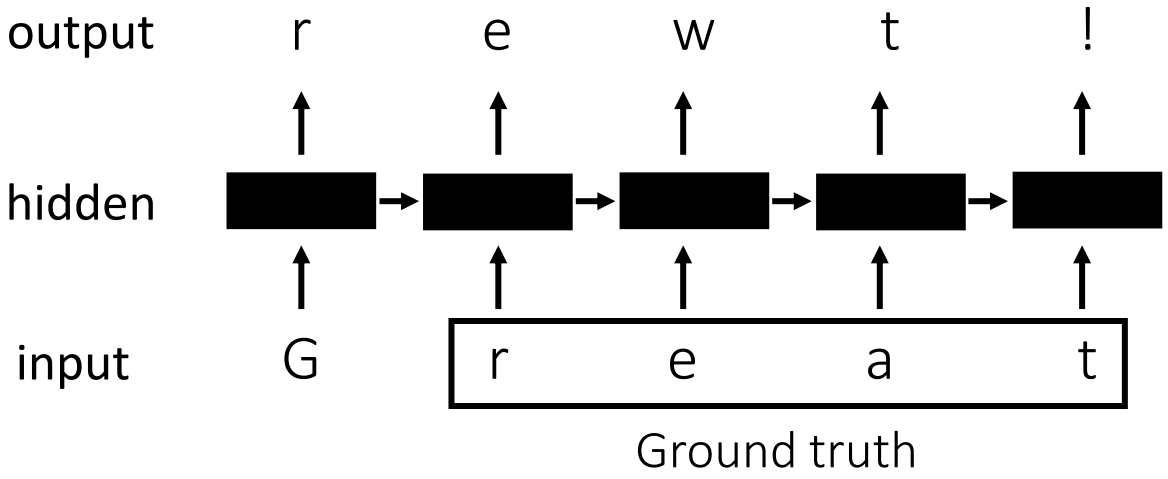
Define loss function and optimizer

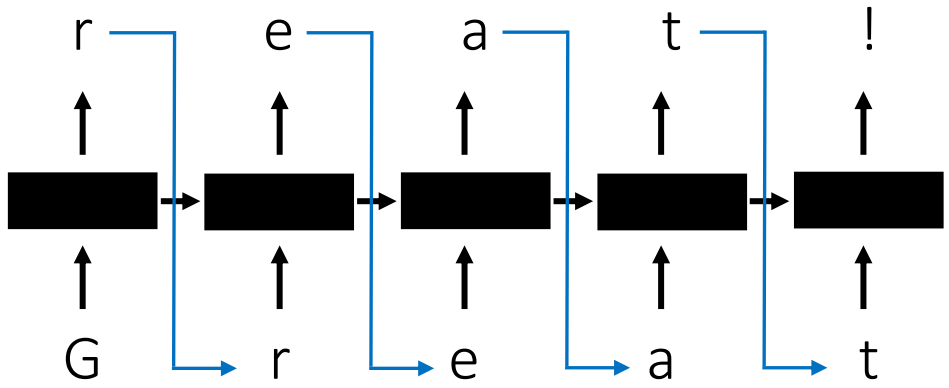
Identify Tracked Values

```
1 train_loss_list = []
```

Python list to track training loss

Train Model





During Training
(Ground truth **sequence** is given as inputs using **Teacher Forcing**)

During Validation
(Individual **RNN character output** is used as next input)

Train Model

```
1  data = torch.unsqueeze(torch.tensor(data), dim = 1)
2
3  # Training Loop ------------------------------------------------------------------------
4
5  for epoch in range(epochs):
6
7      character_loc = np.random.randint(100)
8      iteration = 0
9      hidden_state = None
10
11     while character_loc + training_sequence_len + 1 < data_size:
12
13         input_seq = data[character_loc : character_loc + training_sequence_len]
14         target_seq = data[character_loc + 1 : character_loc + training_sequence_len + 1]
15
16         output, hidden_state = rnn(input_seq, hidden_state)
17
18         loss = loss_fn(torch.squeeze(output), torch.squeeze(target_seq))
19
20         train_loss_list.append(loss.item())
21
22         optimizer.zero_grad()
23         loss.backward()
24         optimizer.step()
25
26         character_loc += training_sequence_len
27
28         iteration += 1
29
30     print("Averaged Training Loss for Epoch ", epoch,": ", np.mean(train_loss_list[-iteration:]))
31
```

Convert data into torch tensor in vertical orientation (data_length, 1)

For each epoch, randomly select a starting character from first 100 characters

input_seq =
character location -> training sequence size
target_seq =
character location + 1 -> training sequence size + 1

Retrieve output & hidden state from RNN cell and compute loss using **Teacher Forcing method**

Save training loss

Backpropagation in time & update network

Update the character location

Update the iteration count

Print the averaged training loss throughout an epoch

Train Model

```
32      # Sample and generate a text sequence after every epoch ------------------
33
34      character_loc = 0
35      hidden_state = None
36
37      rand_index = np.random.randint(data_size-1)
38      input_seq = data[rand_index : rand_index+1]
39
40      print("----------------------------------------")
41      with torch.no_grad():
42
43          while character_loc < validation_sequence_len:
44
45              output, hidden_state = rnn(input_seq, hidden_state)
46
47              output = torch.nn.functional.softmax(torch.squeeze(output), dim=0)
48              character_distribution = torch.distributions.Categorical(output)
49              character_num = character_distribution.sample()
50
51              print(num_to_character[character_num.item()], end='')
52
53              input_seq[0][0] = character_num.item()
54
55              character_loc += 1
56
57      print("\n----------------------------------------")
```

Initialize character location and hidden state for validation

Pick a random **character** from the dataset as an initial input to RNN

Generate new output by using the previous RNN output as an input

Convert the output into character number via sampling from the decoder layer output (probability distribution of characters)

Print the actual character from the number

New input_seq is the output character we just generated

Update the character location

Train Model

```
Averaged Training Loss for Epoch  0 :  2.7497982840345365
---------------------------------------
cous zend yous leaogkal.

MENUNUNENNNNNENNENEUNNENNNNUENNNNNNUNNUNUNNNNENENENNNRNSESNNUNENNUNENN
NNNANN
Suwirs touy to
Ther'krn;

MNENUNUNN
NNNNNNINNNNNENYNNS:
NENUSNSNThat balt,
Theoud cogvrifing of
```

Generated text sequence after 1 epoch

```
Averaged Training Loss for Epoch  49 :  0.26021135710741405
---------------------------------------
the Capitol; who's fide our trumpetersvile in awe, which else
Would feed on one another? What's their abundance; our
seike.
it takes, cracking ten thus--
For, look o' the moon,
Shouting their emulatio
---------------------------------------
```

Generated text sequence after 50 epoch

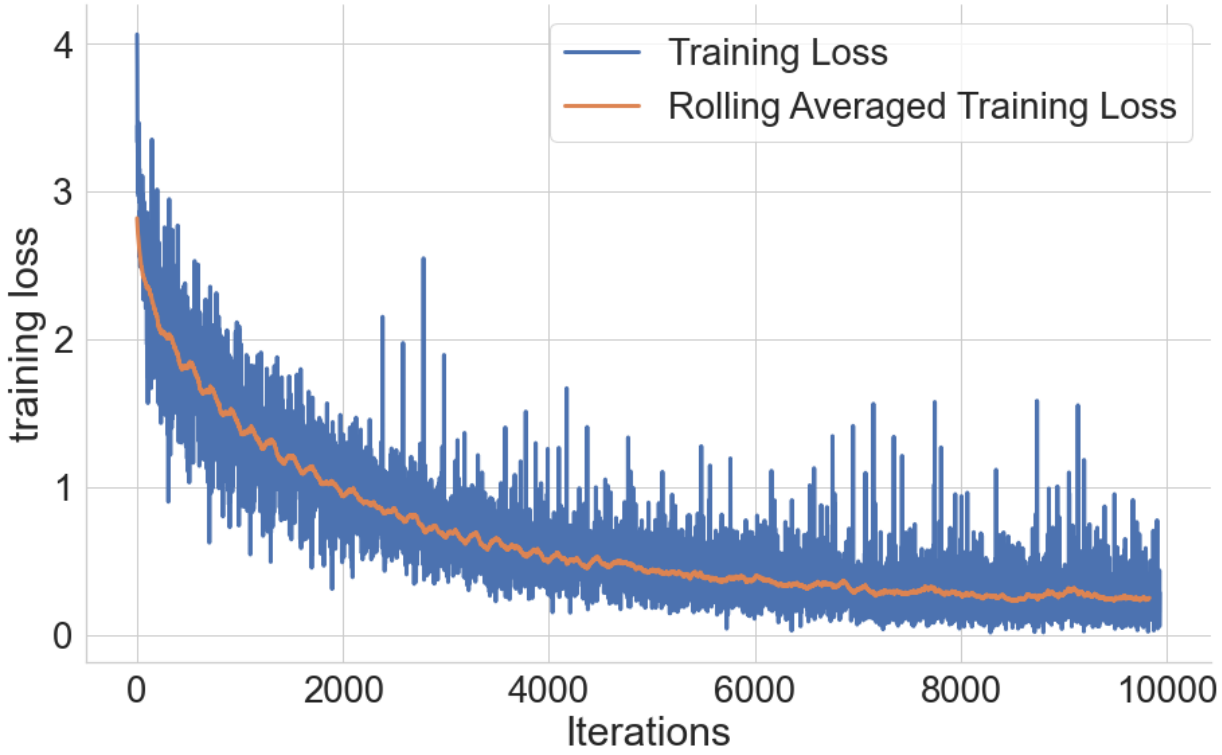
Validate & Evaluate Model

```
import seaborn as sns

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

```
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()
```



Plot the training loss + rolling average training loss after training

LAB 4 ASSIGNMENT:

Create Arthur Conan Doyle AI with RNNs

Sherlock Holmes Dataset

PART I

(Being a reprint from the reminiscences of
John H. Watson, M.D.,
late of the Army Medical Department.)

CHAPTER I
Mr. Sherlock Holmes

In the year 1878 I took my degree of Doctor of Medicine of the University of London, and proceeded to Netley to go through the course prescribed for surgeons in the army. Having completed my studies there, I was duly attached to the Fifth Northumberland Fusiliers as Assistant Surgeon. The regiment was stationed in India at the time, and before I could join it, the second Afghan war had broken out. On landing at Bombay, I learned that my corps had advanced through the passes, and was already deep in the enemy's country. I followed, however, with many other officers who were in the same situation as myself, and succeeded in reaching Candahar in safety, where I found my regiment, and at once entered upon my new duties.

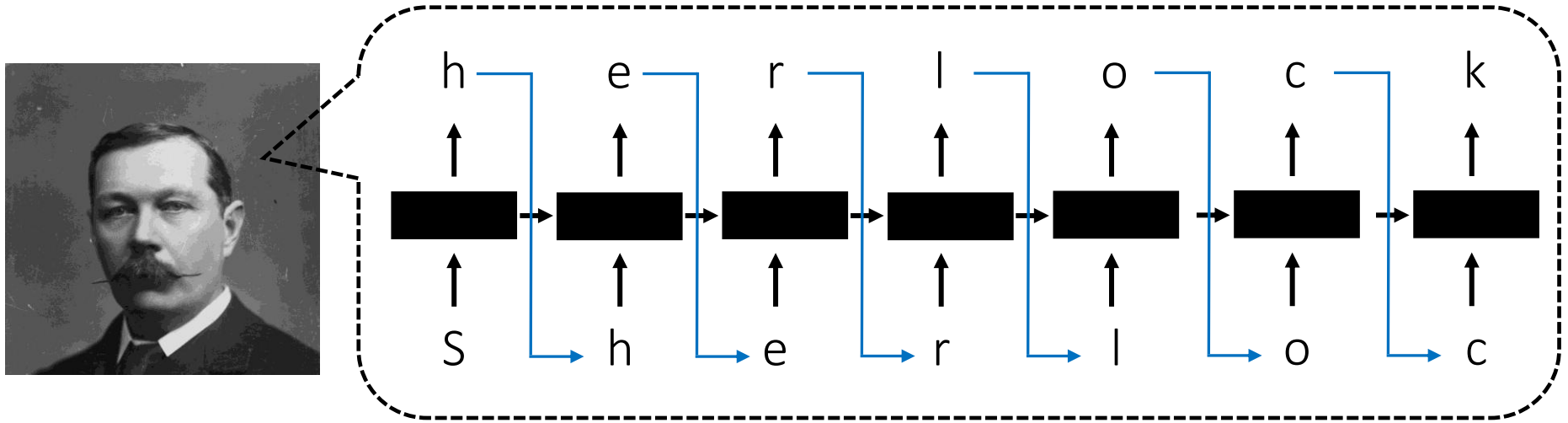
The campaign brought honours and promotion to many, but for me it had nothing but misfortune and disaster. I was removed from my brigade and attached to the Berkshires, with whom I served at the fatal battle of Maiwand. There I was struck on the shoulder by a Jezail bullet, which shattered the bone and grazed the subclavian artery. I should have fallen into the hands of the murderous Ghazis had it not been for the devotion and courage shown by Murray, my orderly, who threw me across a pack-horse, and succeeded in bringing me safely to the British lines.

Full collection of **Sherlock Holmes series**

3011055 total characters (including space)

102 unique characters

Create Arthur Conan Doyle AI using RNN



In this exercise, you will implement **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, and training sequence size etc.

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

Describe how the quality of validation text depends on the choice of hyperparameters you experimented during training. Which hyperparameter affects the quality the most?

Tips for Training Your RNN

First things to decide

- Training data size (# of characters)
- Embedding dimension & RNN input
- RNN hidden size
- (Vanilla RNN) Activation function (ReLU, Tanh)
- Decoder output size
- Learning rate
- Optimizer
- Number of training epochs
- Training input sequence length

Additional tips

- If you get ‘nan’ errors while training -> your training is unstable -> decrease lr or training input sequence length
- With ReLU you might be able to process longer sequence
- Choose your training data size according to your machine spec
- Higher ‘num_layers’ might give you better performance but longer training.