LAB 5: ADVANCED RECURRENT NERUAL NETWORKS

University of Washington, Seattle

Spring 2025

OUTLINE

Part 1: Encoder-Decoder RNNs

- Many-to-many RNN Recap
- Encoder-Decoder Architecture
- Training Encoder-Deocder RNNs

Part 2: RNN Extensions

- Deep RNN
- Bidirectional RNN

Part 3: Training tips for RNNs

- Mini-batch Gradient in RNNs

Part 4: Additional RNN examples

- Signal Denoising (Many-to-many)
- Signal Prediction (Encoder-decoder)

Part 6: Lab Assignment

- Stock Prediction

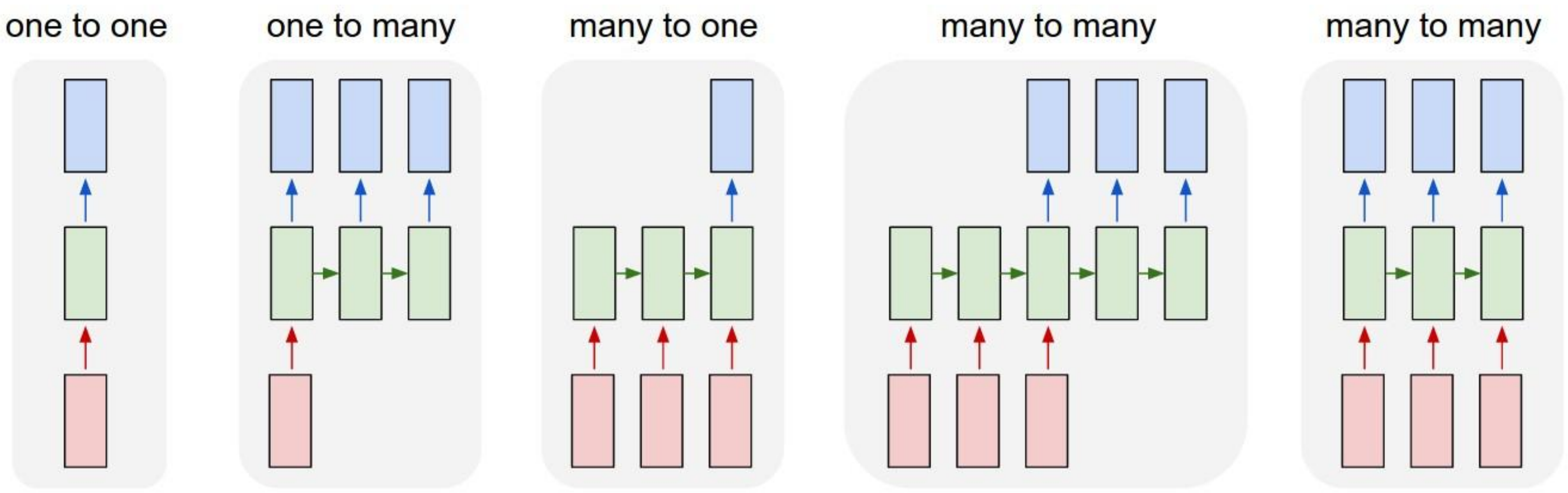
ENCODER-DECODER RNNs

Many-to-Many RNN Recap

Encoder-Decoder Architecture

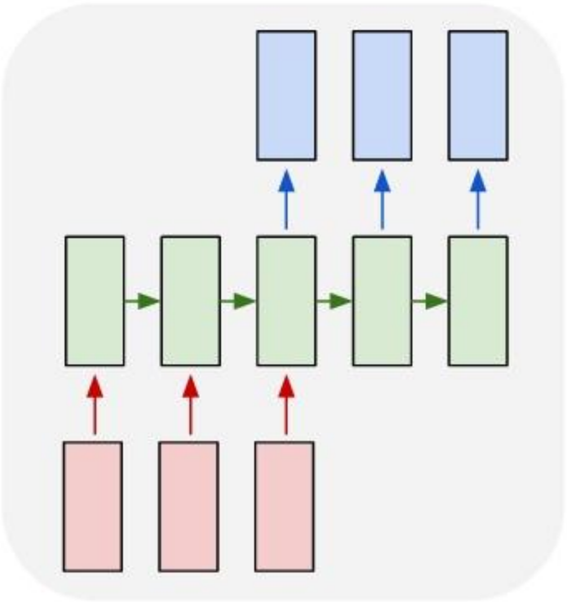
Training Encoder-Decoder RNNs

RNN Configurations

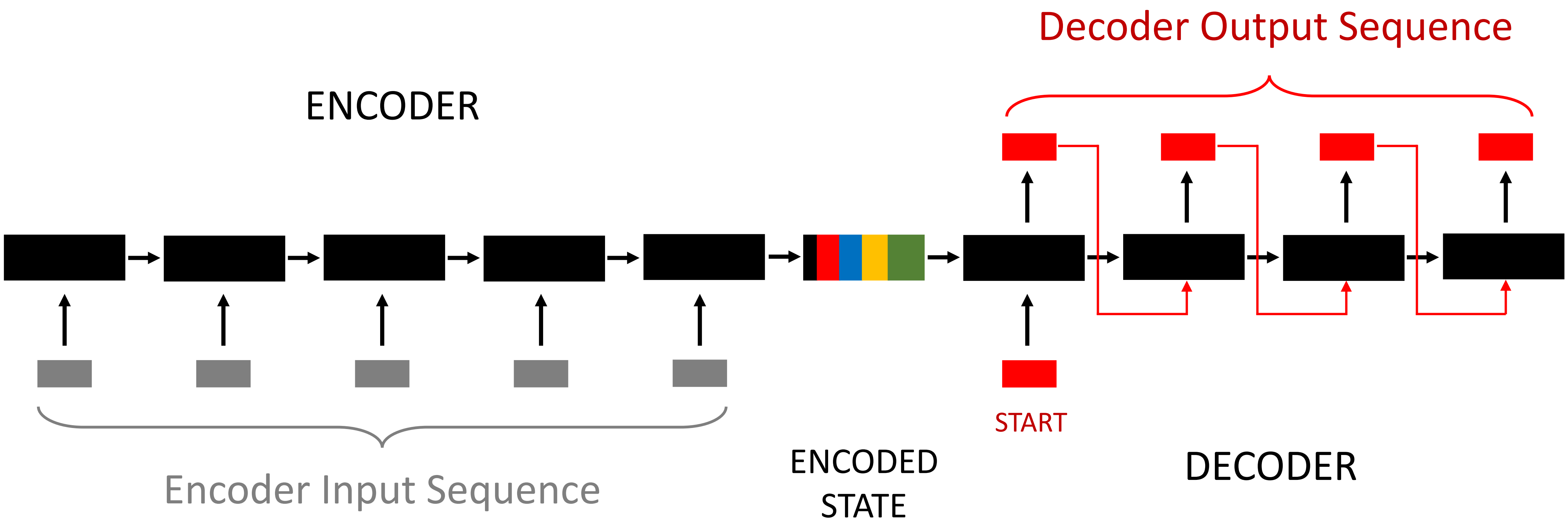


Many-to-Many

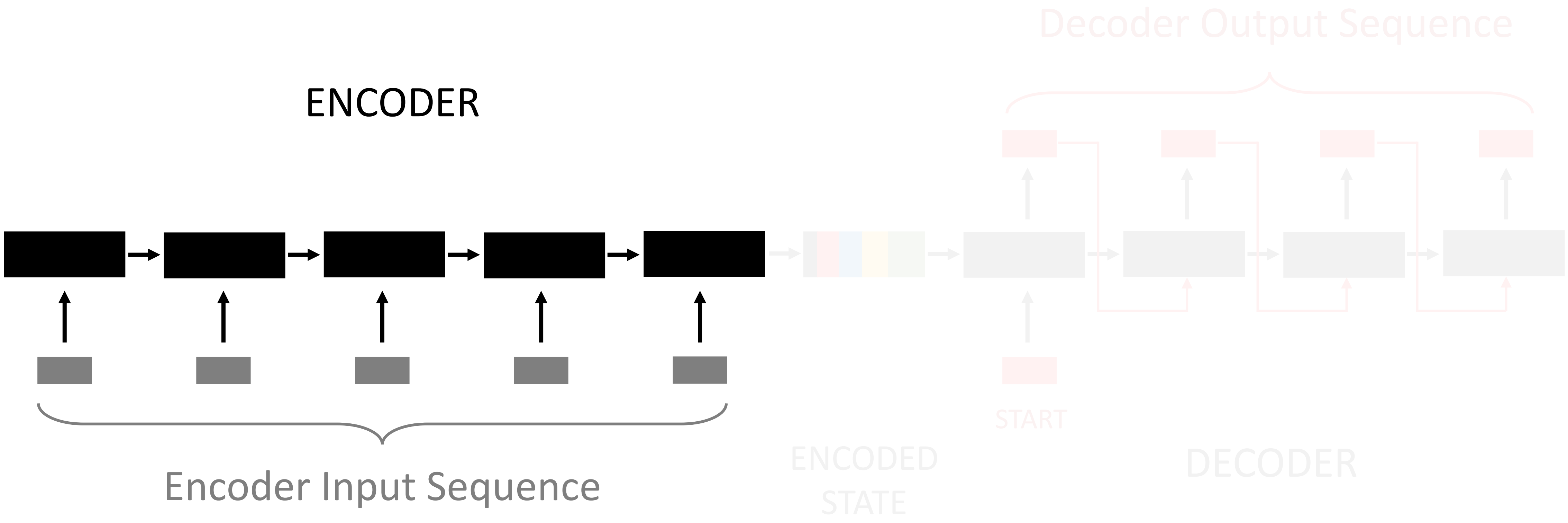
many to many



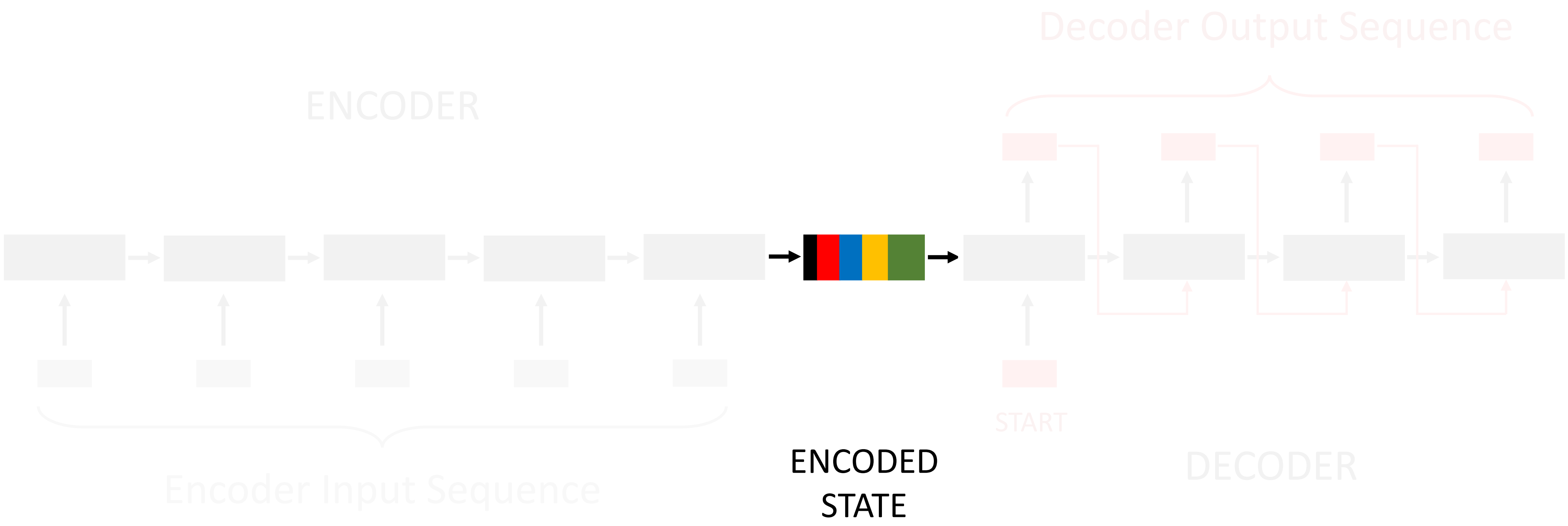
Encoder-Decoder Architecture



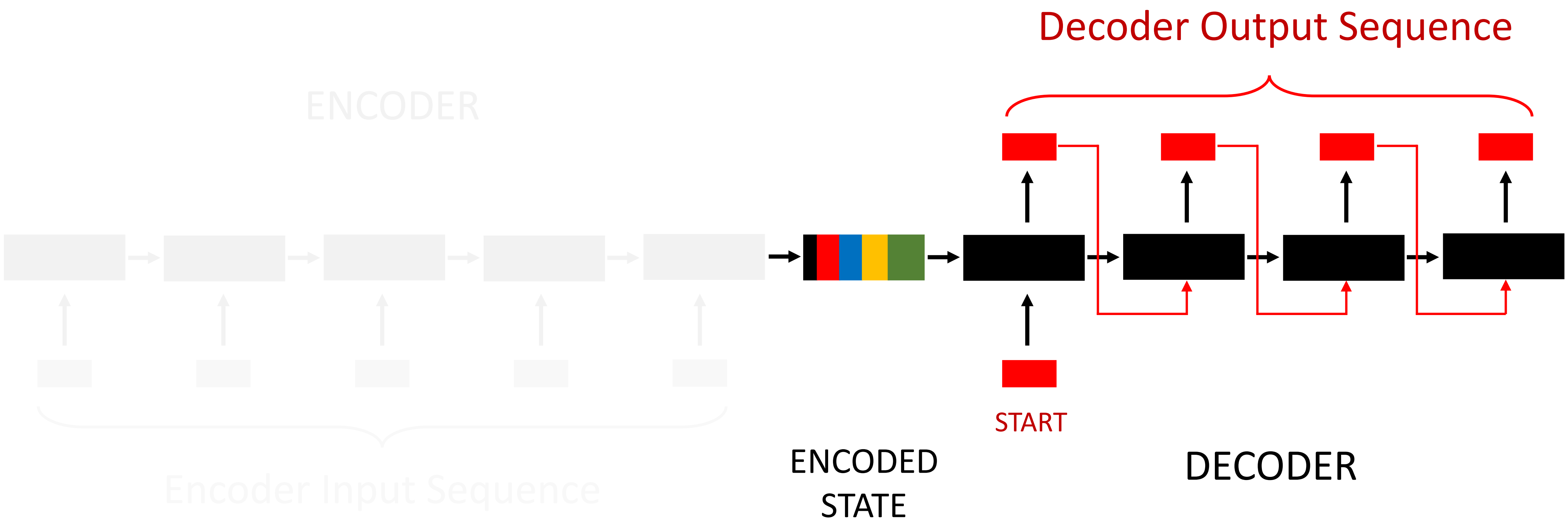
Encoder


Decoder Output Sequence
ENCODER
START
ENCODED STATE
DECODER
Encoder Input Sequence

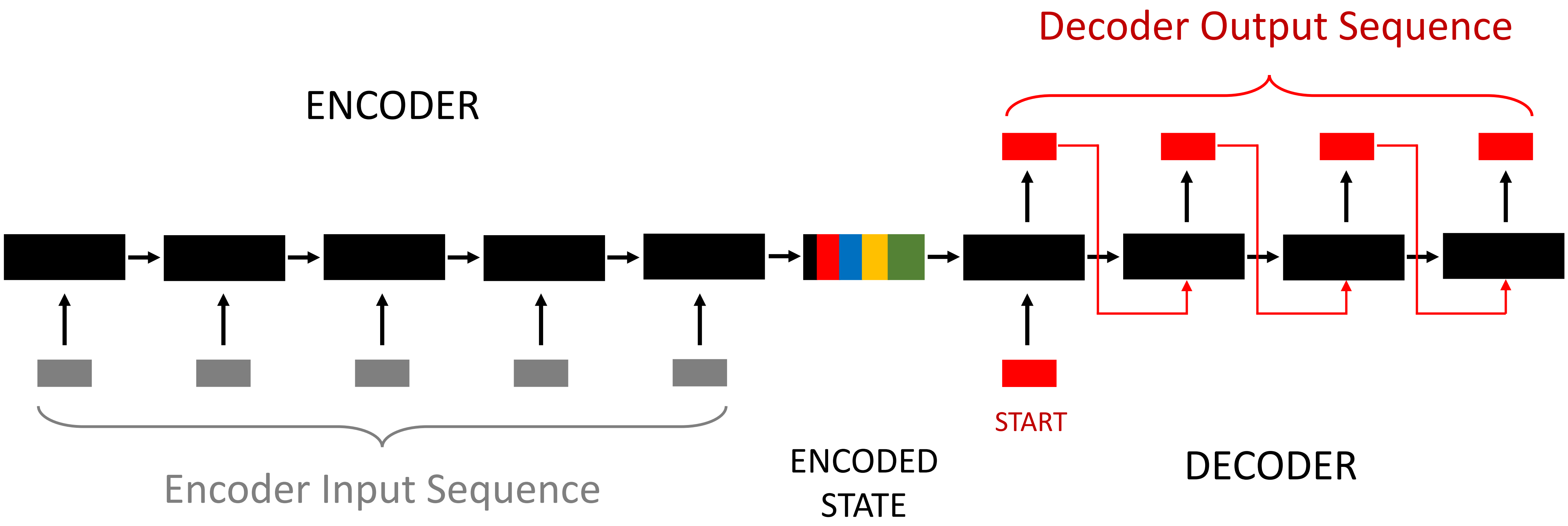
Encoded State



Decoder

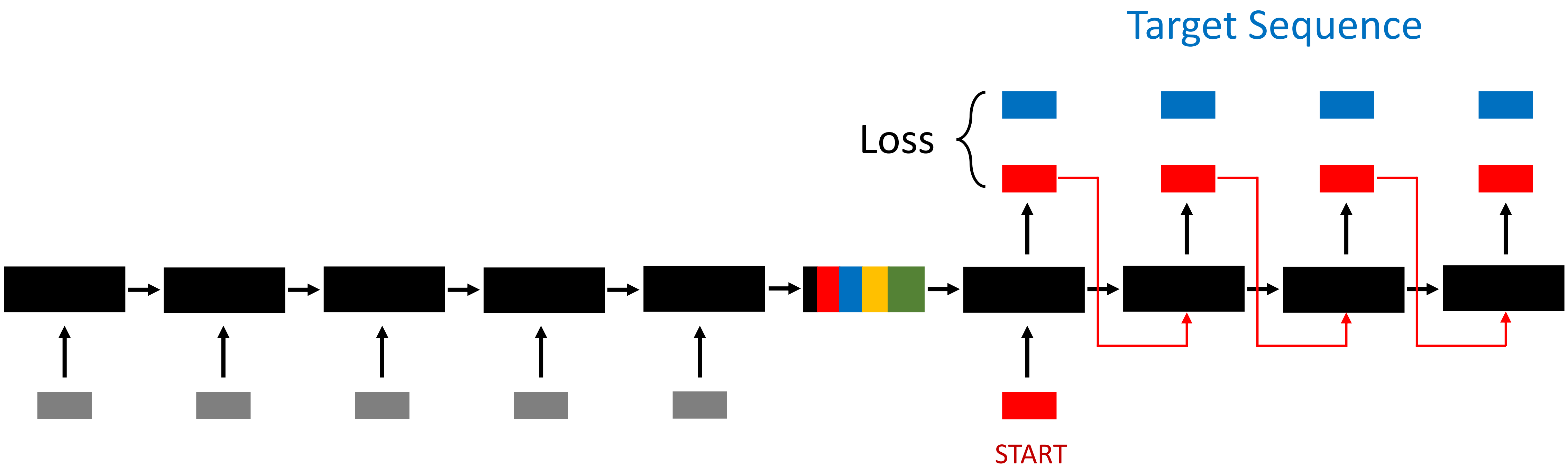

Decoder Output Sequence
ENCODER
START
ENCODED
STATE
DECODER
Encoder Input Sequence

Encoder-Decoder Architecture

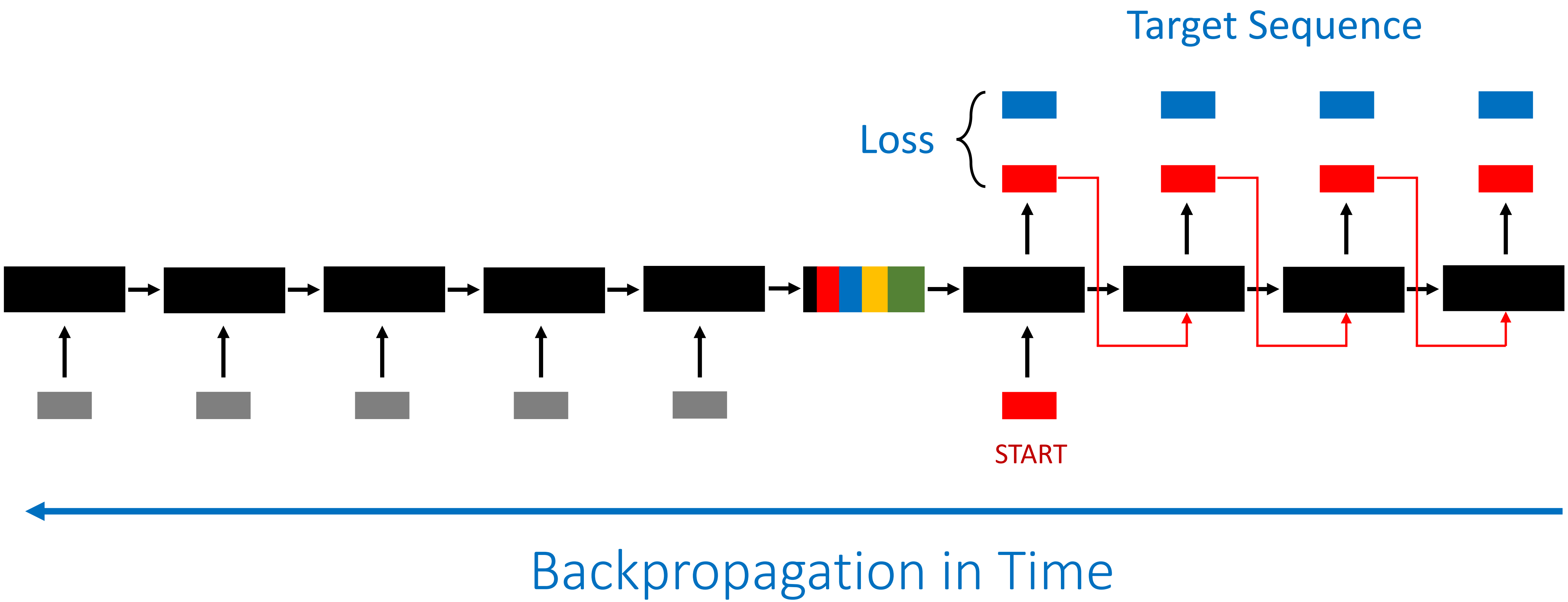


Input sequence length to Encoder (Tx) can be different from the output sequence length of Decoder (Ty)

Training Encoder-Decoder



Training Encoder-Decoder

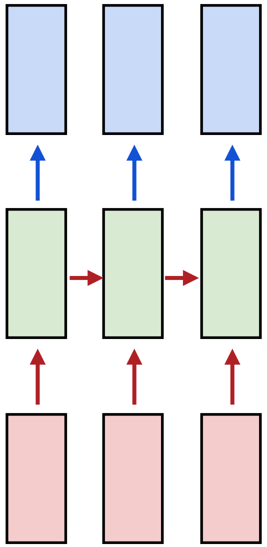


RNN Extensions

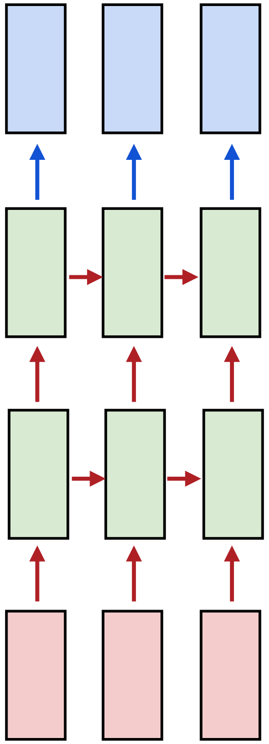
Deep RNNs

Bidirectional RNNs

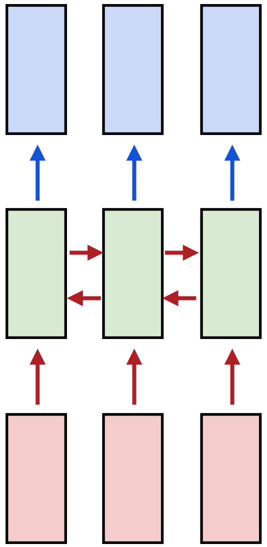
RNN Extensions



Regular RNN

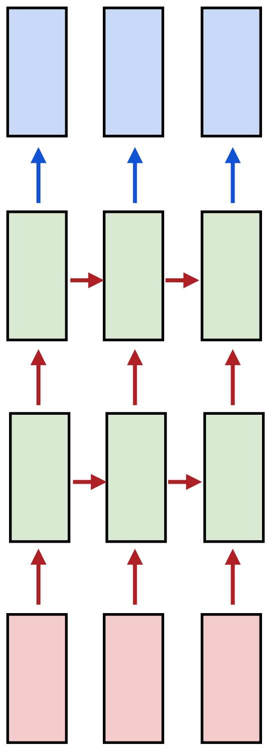


Deep RNN



Bi-directional RNN

Deep RNN



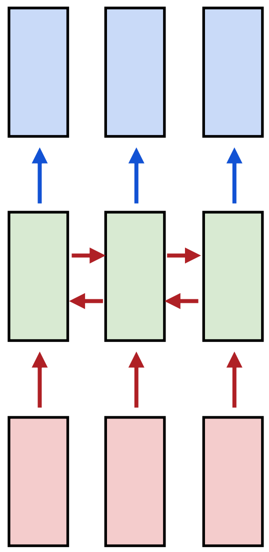
Deep RNN

(+)
Can provide better performance
Often used for complex problems

(-)
Potential for overfitting
Longer training time

Implemented as ‘num_layers’ parameters in torch.nn.RNN()

Bi-directional RNNs



Bi-directional RNN

(+)

Higher performance in Natural Language Processing tasks

Suitable when both left and right contexts are used

(-)

Harder to train than Uni-directional RNN

Not suitable for real-time processing

Implemented as 'bidirectional' parameter in torch.nn.RNN()

RNN Extensions in LSTM/GRU

```python
class example_LSTM(torch.nn.Module):

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

        super(example_LSTM, self).__init__()

        self.lstm = torch.nn.LSTM(input_size=input_size, hidden_size=hidden_size,
                                  num_layers = num_layers,
                                  batch_first = True,
                                  bidirectional = False,
                                  dropout = 0.1)

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

    def forward(self, input_seq, hidden_state):

        pred, hidden = self.lstm(input_seq, hidden_state)

        pred = self.decoder(pred)

        return pred
```

Set to hidden_size * 2 if bidirectional = True

num_layers:
LSTM layers to be stacked

batch_first:
Tells PyTorch we are using (batchsize, seq_len, feature #)

bidirectional:
Whether to configure bidirectional LSTM

dropout:
introduces dropout layer on the outputs of each LSTM layer except for last layer (use when num_layers > 1)

RNN Extensions in LSTM/GRU

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

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

        super(example_GRU, self).__init__()

        self.gru = torch.nn.GRU(input_size=input_size, hidden_size=hidden_size,
                                num_layers = num_layers,
                                batch_first = True,
                                bidirectional = False,
                                dropout = 0.1)

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

    def forward(self, input_seq, hidden_state):

        pred, hidden = self.gru(input_seq, hidden_state)

        pred = self.decoder(pred)

        return pred
```

Set to hidden_size * 2 if bidirectional = True

num_layers:
GRU layers to be stacked

batch_first:
Tells PyTorch we are using (batchsize, seq_len, feature #)

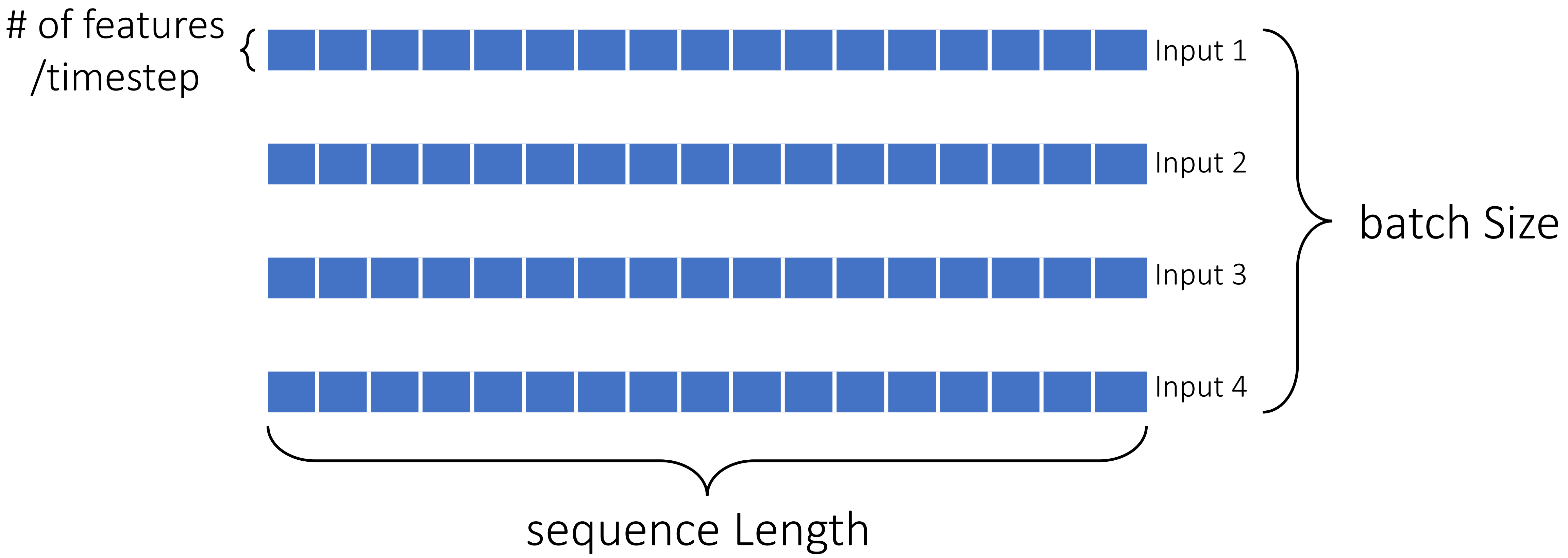
bidirectional:
Whether to configure bidirectional GRU

dropout:
introduces dropout layer on the outputs of each GRU layer except for last layer
(use when num_layers > 1)

TRAINING Tips for RNNs

Mini-batch Gradient in RNNs

Mini-batch Gradient in RNNs



RNN input format in PyTorch = (batch size, sequence length, # of features)
Example above = (4, 17, 1)

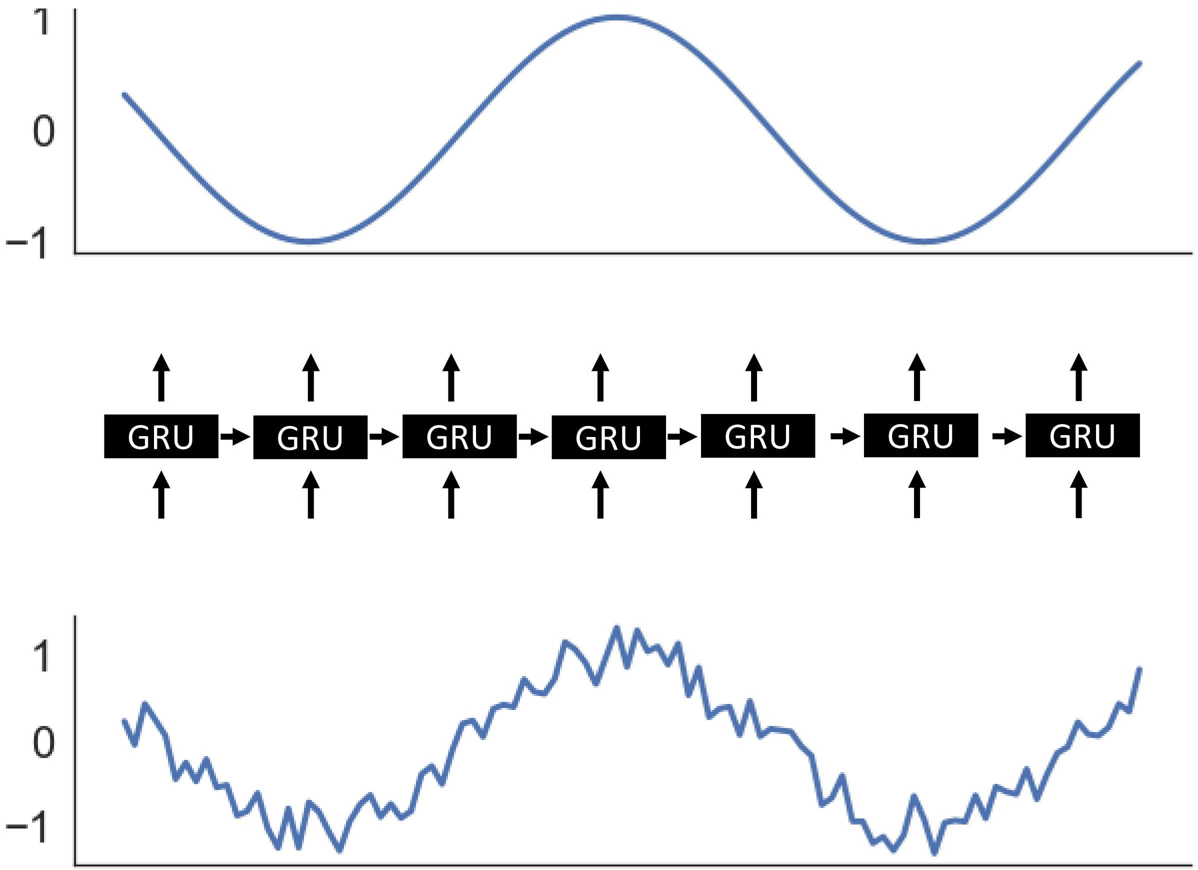
with batch_first = True

IMPLEMENTATION OF GATED RNNs in PYTORCH

Signal Denoising

Signal Denoising

Output Sequence



Input Sequence

Prepare Data

```python
def sinusoidal_generator(X, signal_freq=60.):

    return np.sin(2 * np.pi * (X) / signal_freq)

def add_noise(Y, noise_range=(-0.35, 0.35)):

    noise = np.random.uniform(noise_range[0], noise_range[1], size=Y.shape)

    return Y + noise

def sample_seq(sequence_length):

    random_offset = random.randint(0, sequence_length)
    X = np.arange(sequence_length)

    denoised_output_seq = sinusoidal_generator(X + random_offset)
    noisy_input_seq = add_noise(denoised_output_seq)

    return noisy_input_seq, denoised_output_seq
```

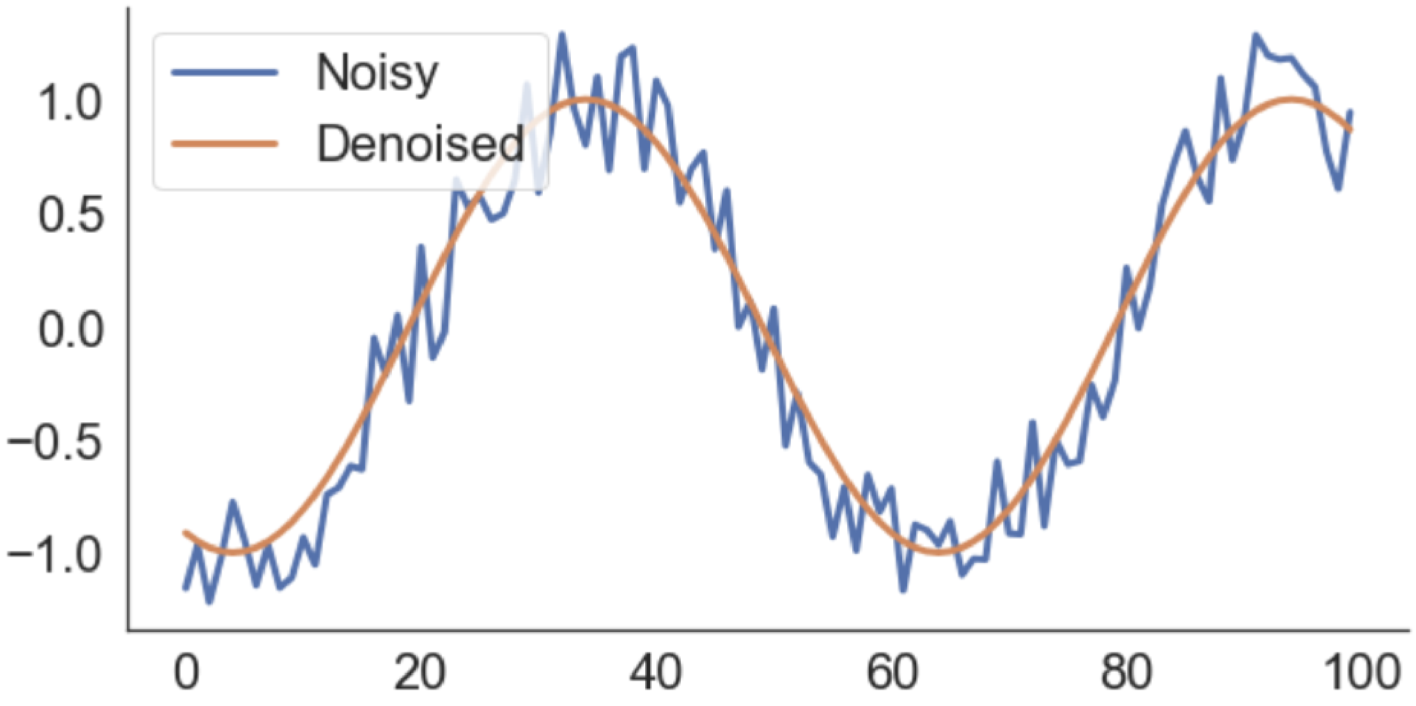
Sinusoidal wave generator

Add noise function

Generate sample ground truth/noisy sinusoidal waves

Prepare Data

```python
noisy_input_seq, denoised_output_seq = sample_seq(sequence_length = 100)

plt.figure(figsize = (10, 5))

plt.plot(noisy_input_seq, label ='Noisy', linewidth = 3)
plt.plot(denoised_output_seq, label ='Denoised', linewidth = 3)
plt.legend()
sns.despine()
```



Example sample ground truth & noisy sinusoidal wave with sequence length = 100

Prepare Data

```python
def create_synthetic_dataset(n_samples, sequence_length):

    noisy_seq_inputs = np.zeros((n_samples, sequence_length))
    denoised_seq_outputs = np.zeros((n_samples, sequence_length))

    for i in range(n_samples):

        noisy_inp, denoised_out = sample_seq(sequence_length)

        noisy_seq_inputs[i, :] = noisy_inp
        denoised_seq_outputs[i, :] = denoised_out

    return noisy_seq_inputs, denoised_seq_outputs
```

Using the sample_seq() function to generate synthetic ground truth/noisy dataset of n-samples

```python
noisy_seq_inputs, denoised_seq_outputs = create_synthetic_dataset(n_samples = 12000,
                                                                   sequence_length = 100)

train_input_seqs, train_output_seqs = noisy_seq_inputs[:8000], denoised_seq_outputs[:8000]
test_input_seqs, test_output_seqs = noisy_seq_inputs[8000:], denoised_seq_outputs[8000:]
```

Take first 8000 as training dataset and 4000 as testing dataset

```python
train_input_seqs = train_input_seqs.reshape((train_input_seqs.shape[0], -1, 1))
train_output_seqs = train_output_seqs.reshape((train_output_seqs.shape[0], -1, 1))

test_input_seqs = test_input_seqs.reshape((test_input_seqs.shape[0], -1, 1))
test_output_seqs = test_output_seqs.reshape((test_output_seqs.shape[0], -1, 1))
```

Reshape training and testing dataset to conform to (# of samples, seq_len, feature #) format

Define Model

```python
class Denoiser_GRU(torch.nn.Module):

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

        super(Denoiser_GRU, self).__init__()

        self.gru = torch.nn.GRU(input_size=input_size, hidden_size=hidden_size,
                                num_layers = num_layers,
                                batch_first = True,
                                bidirectional = False)

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

        self.output_activation = torch.nn.Tanh()

    def forward(self, input_seq, hidden_state):

        pred, hidden = self.gru(input_seq, hidden_state)

        pred = self.output_activation(self.decoder(pred))

        return pred
```

Using GRU with batch_first = True

Decoder layer to convert hidden states to final output

Using **Tanh** on decoder output layer to squeeze output value between -1 and 1

Input_sequence, hidden_states → GRU → output_sequence, hidden_states → Decoder Layer → Tanh activation

Define Hyperparameters

```
denoiser_GRU = Denoiser_GRU(input_size = 1, hidden_size = 30,
                            num_layers = 1, output_size = 1)

learning_rate = 0.0003
epochs = 100

batchsize = 300

loss_func = torch.nn.L1Loss()
optimizer = torch.optim.Adam(denoiser_GRU.parameters(), lr=learning_rate)

denoiser_GRU
```

Input dim to GRU = 1
Hidden state size = 30
GRU layers to be stacked = 1
Output dim of decoder layer = 1

Define learning rate, epochs and batch size

Using L1Loss (Least Absolute Deviations) and Adam optimizer

Identify Tracked Values

```
train_loss_list = []
```

Empty Python list to keep track of training loss

Train Model

```
train_input_seqs = torch.from_numpy(train_input_seqs).float()
train_output_seqs = torch.from_numpy(train_output_seqs).float()

test_input_seqs = torch.from_numpy(test_input_seqs).float()
test_output_seqs = torch.from_numpy(test_output_seqs).float()

train_batches_features = torch.split(train_input_seqs, batchsize)
train_batches_targets = torch.split(train_output_seqs, batchsize)

batch_split_num = len(train_batches_features)

for epoch in range(epochs):

    for k in range(batch_split_num):

        hidden_state = None

        pred = denoiser_GRU(train_batches_features[k], hidden_state)

        optimizer.zero_grad()

        loss = loss_func(pred, train_batches_targets[k])
        train_loss_list.append(loss.item())

        loss.backward()

        optimizer.step()

    print("Averaged Training Loss for Epoch ", epoch,": ", np.mean(train_loss_list[-batch_split_num:]))
```

Convert training and testing data to Tensors

Split training data into mini-batches

Training loop with mini-batch gradient

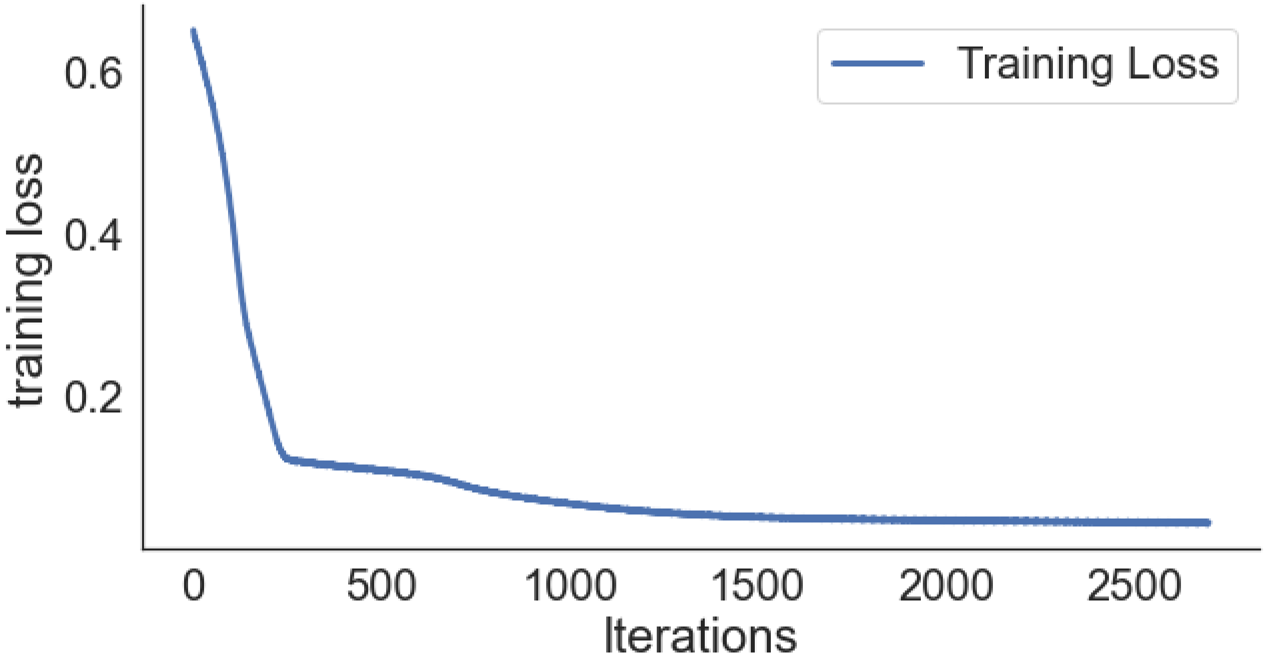
Print averaged loss throughout the epoch

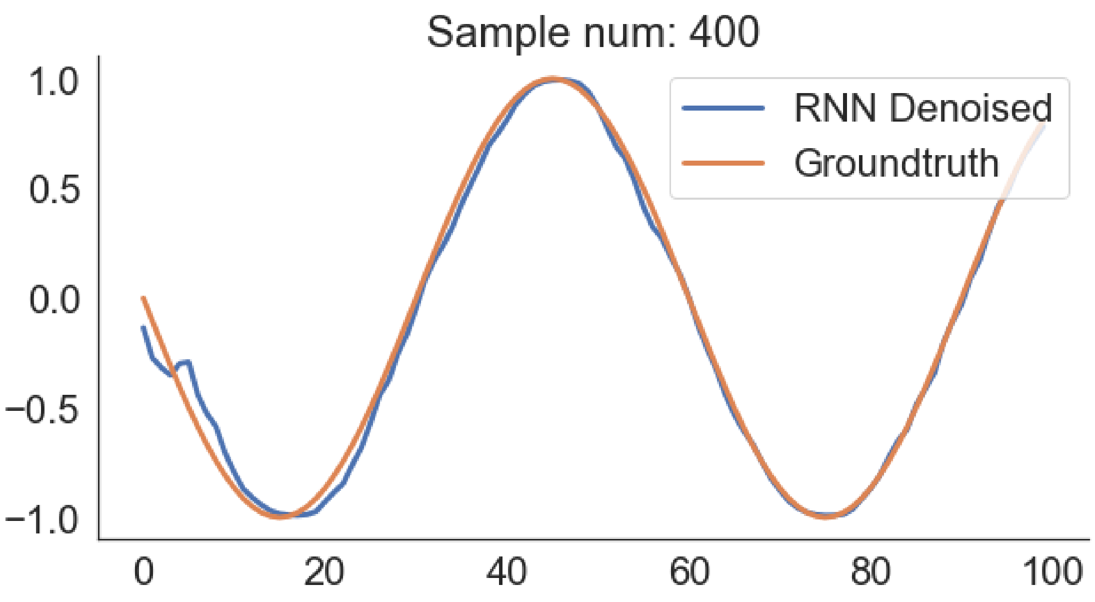
Visualize & Evaluate Model

```
plt.figure(figsize = (10, 5))

plt.plot(train_loss_list, linewidth = 3, label = 'Training Loss')
plt.ylabel("training loss")
plt.xlabel("Iterations")
plt.legend()
sns.despine()
```

```
with torch.no_grad():

    test_prediction = denoiser_GRU(test_input_seqs, None)
    print("Testing Loss (Least Absolute Deviations): ",
          loss_func(test_prediction, test_output_seqs).item())
```

```
Testing Loss (Least Absolute Deviations):  0.04158925637602806
```

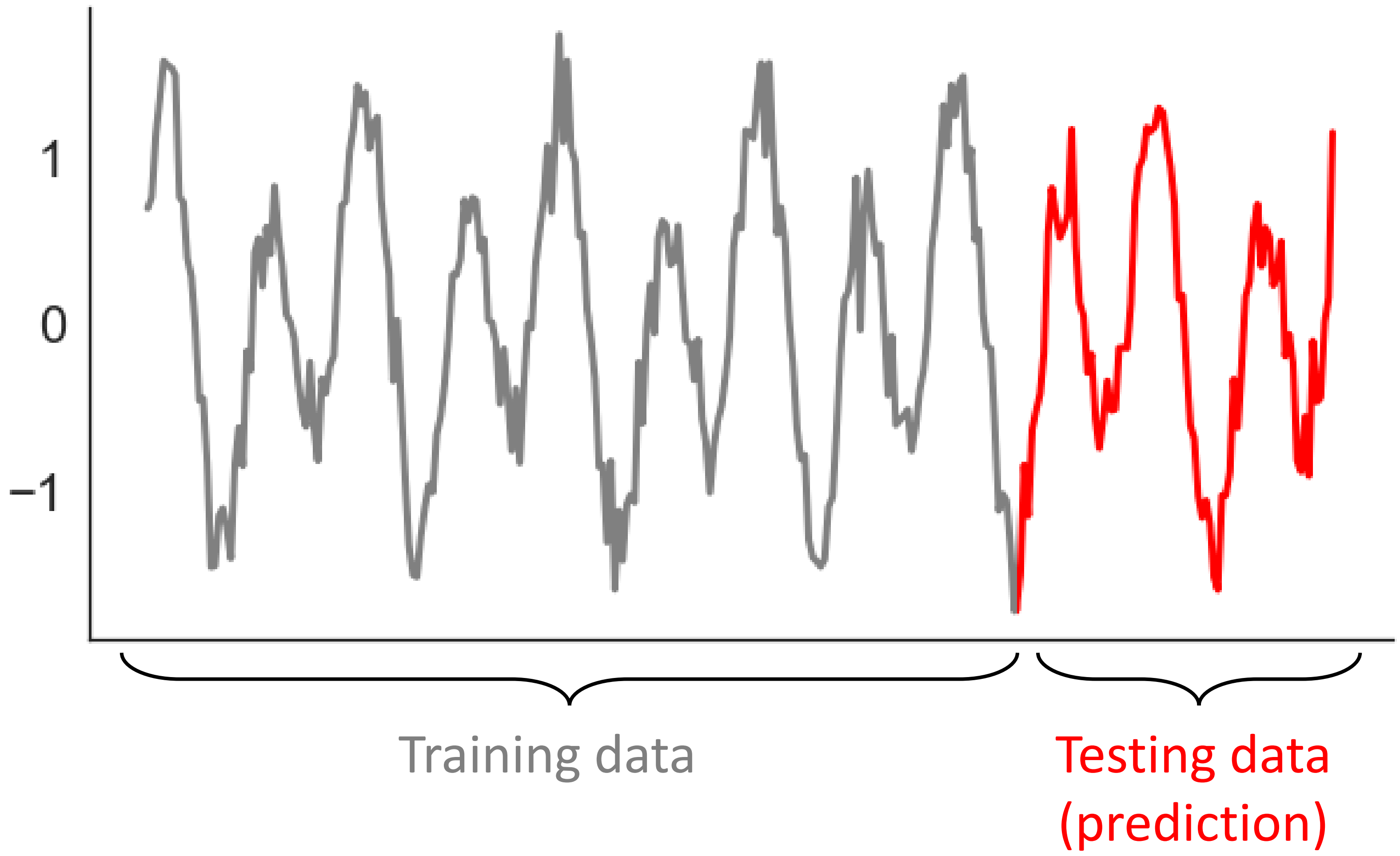




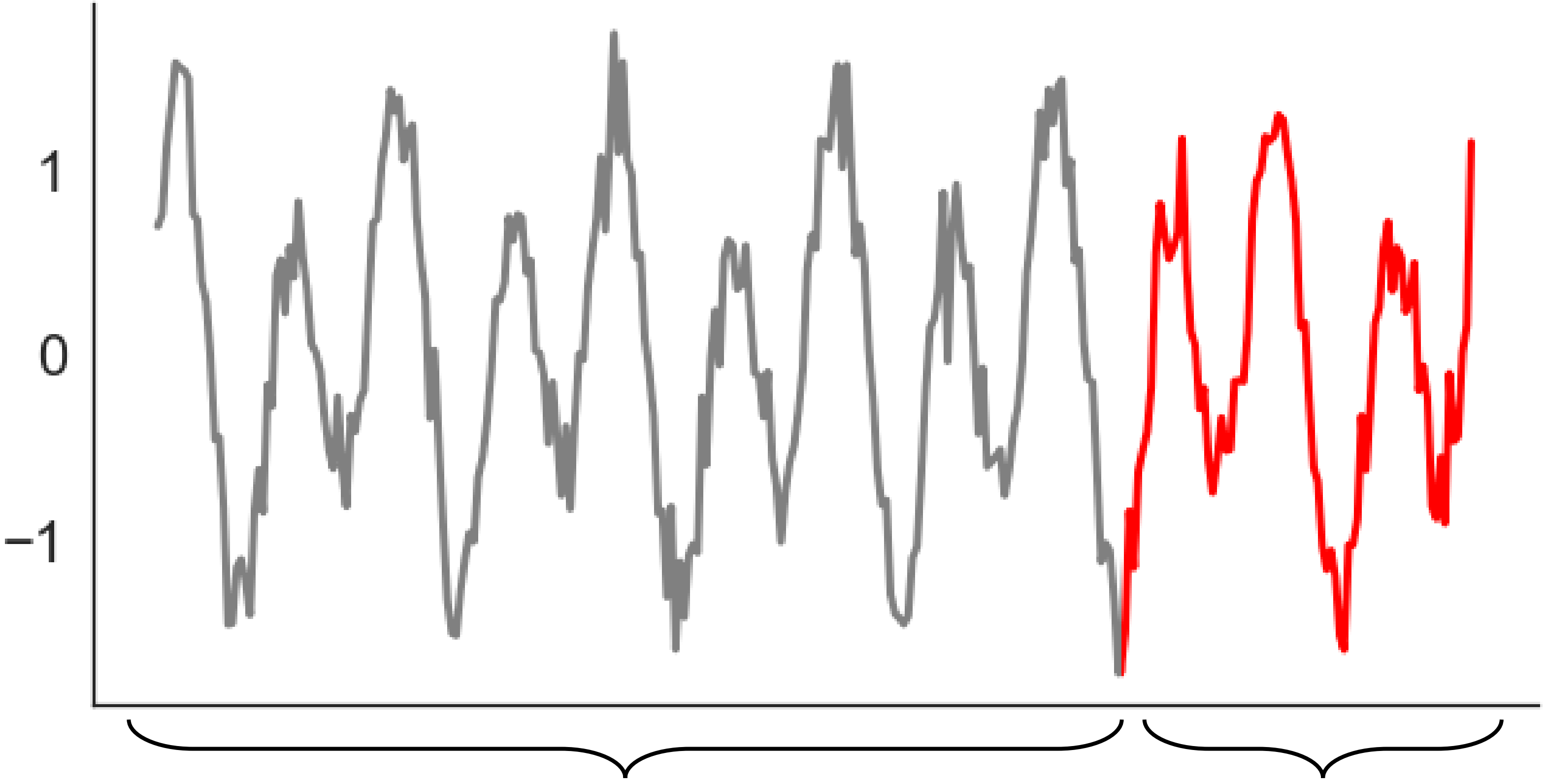
ENCODER-DECODER APPLICATION IN PYTORCH

Signal Prediction

Example Task Description

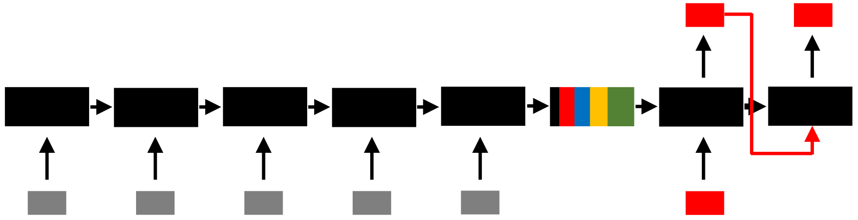


Example Task Description



Training data

Testing data (prediction)



Encoder input sequence length = 5

Decoder output sequence length = 2 (prediction)

Prepare Data

```python
def generate_noisy_signal(datapoints_num, tf):

    t = np.linspace(0., tf, datapoints_num)
    y = np.sin(2. * t) + 0.5 * np.cos(t) + np.random.normal(0., 0.2, datapoints_num)

    return y.reshape(-1, 1)
```

Function for generating a noisy signal (sin + cos + noise)

```python
def generate_input_output_seqs(y, encoder_inputseq_len, decoder_outputseq_len, stride = 1, num_features = 1):

    L = y.shape[0]
    num_samples = (L - encoder_inputseq_len - decoder_outputseq_len) // stride + 1

    train_input_seqs = np.zeros([num_samples, encoder_inputseq_len, num_features])
    train_output_seqs = np.zeros([num_samples, decoder_outputseq_len, num_features])

    for ff in np.arange(num_features):

        for ii in np.arange(num_samples):

            start_x = stride * ii
            end_x = start_x + encoder_inputseq_len
            train_input_seqs[ii, :, ff] = y[start_x:end_x, ff]

            start_y = stride * ii + encoder_inputseq_len
            end_y = start_y + decoder_outputseq_len
            train_output_seqs[ii, :, ff] = y[start_y:end_y, ff]

    return train_input_seqs, train_output_seqs
```

Function for generating

- input sequences to encoder
- output target sequences for decoder

e.g., y = [1,2,3,4,5,6,7,8]

Encoder inputseq len = 3

Decoder outputseq len = 2

train_input_seqs = [[1,2,3],[2,3,4],[3,4,5],[4,5,6]]

train_output_seqs = [[4,5],[5,6],[6,7],[7,8]]

Prepare Data

```python
encoder_inputseq_len = 5
decoder_outputseq_len = 2
testing_sequence_len = 50

y = generate_noisy_signal(datapoints_num = 2000, tf = 80 * np.pi)
y_train = y[:-testing_sequence_len]
```

- Encoder input sequence length = 5
- Decoder output sequence length = 2
- Testing sequence length = 50

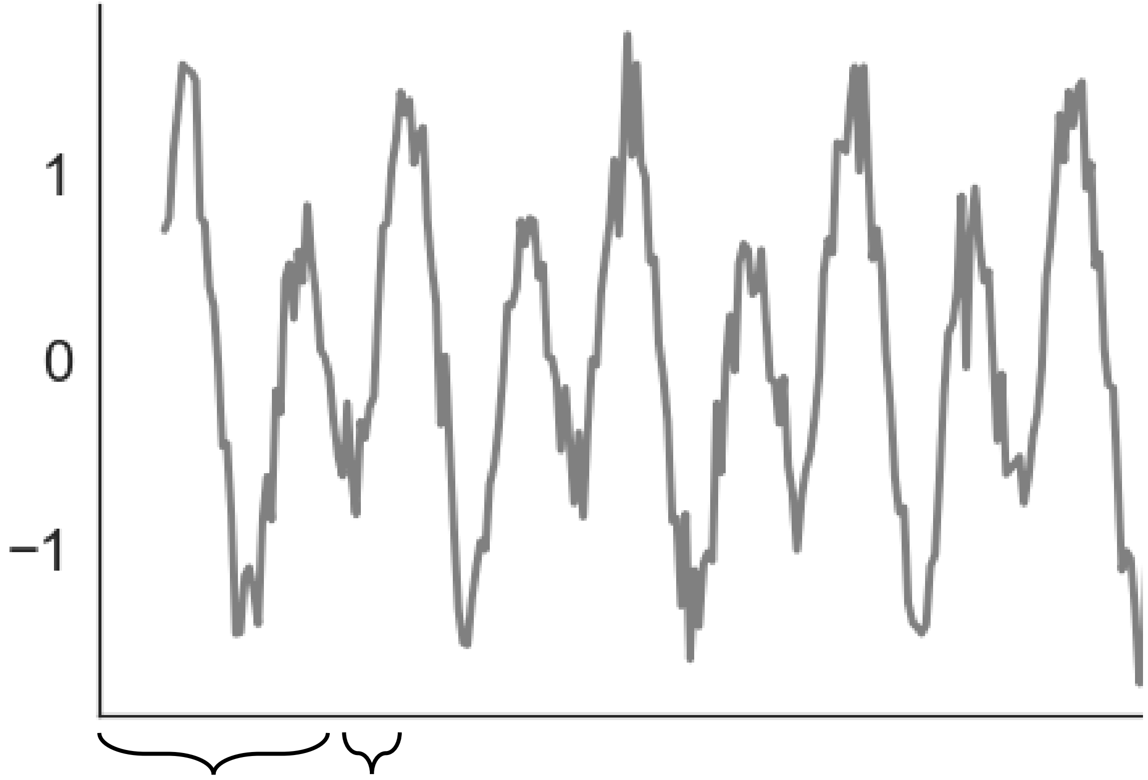
```python
train_input_seqs, train_output_seqs = generate_input_output_seqs(y = y_train,
                                                                 encoder_inputseq_len = encoder_inputseq_len,
                                                                 decoder_outputseq_len = decoder_outputseq_len,
                                                                 stride = 1,
                                                                 num_features = 1)
```

```python
print("Encoder Training Inputs Shape: ", train_input_seqs.shape)
print("Decoder Training Outputs Shape: ", train_output_seqs.shape)
```

```
Encoder Training Inputs Shape:  (1944, 5, 1)
Decoder Training Outputs Shape:  (1944, 2, 1)
```

(sample size, sequence length, feature/timestep)

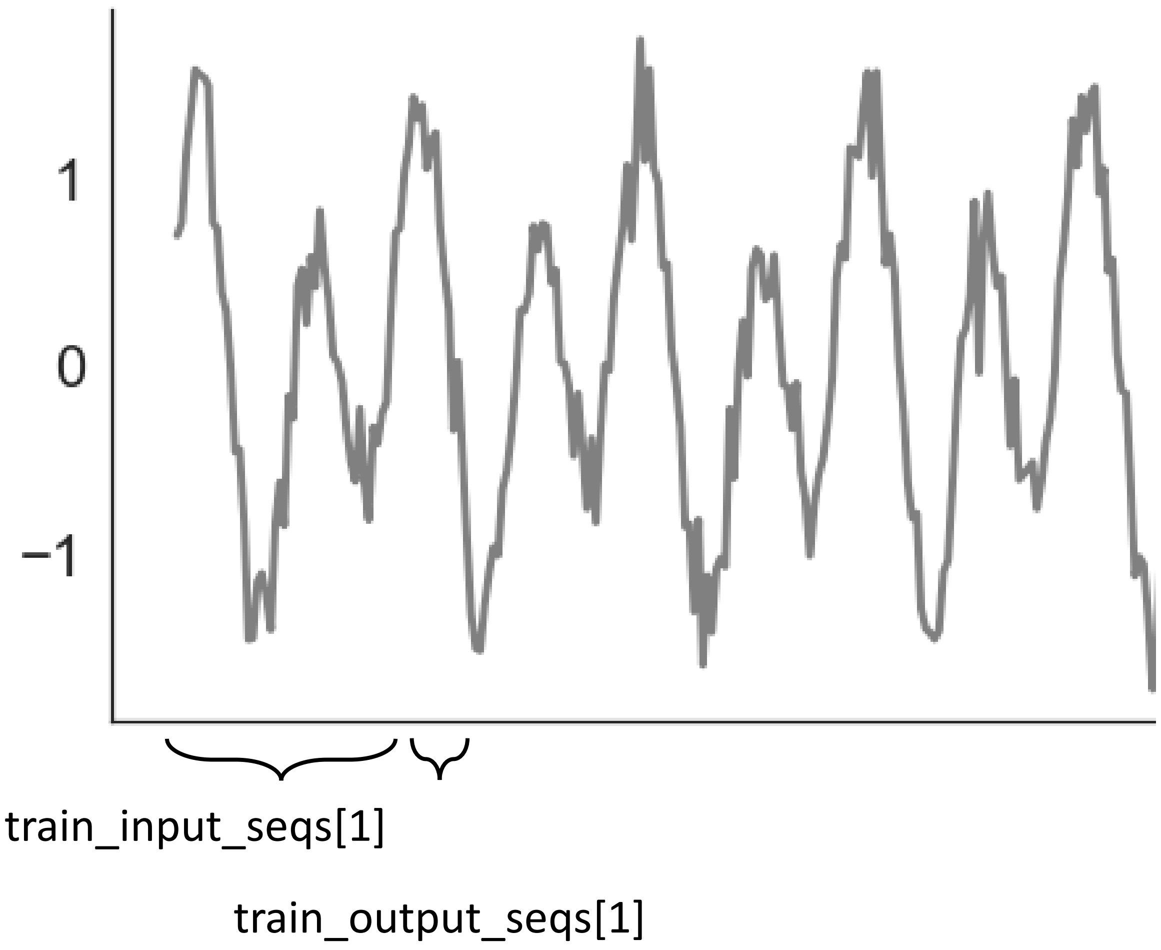
Prepare Data



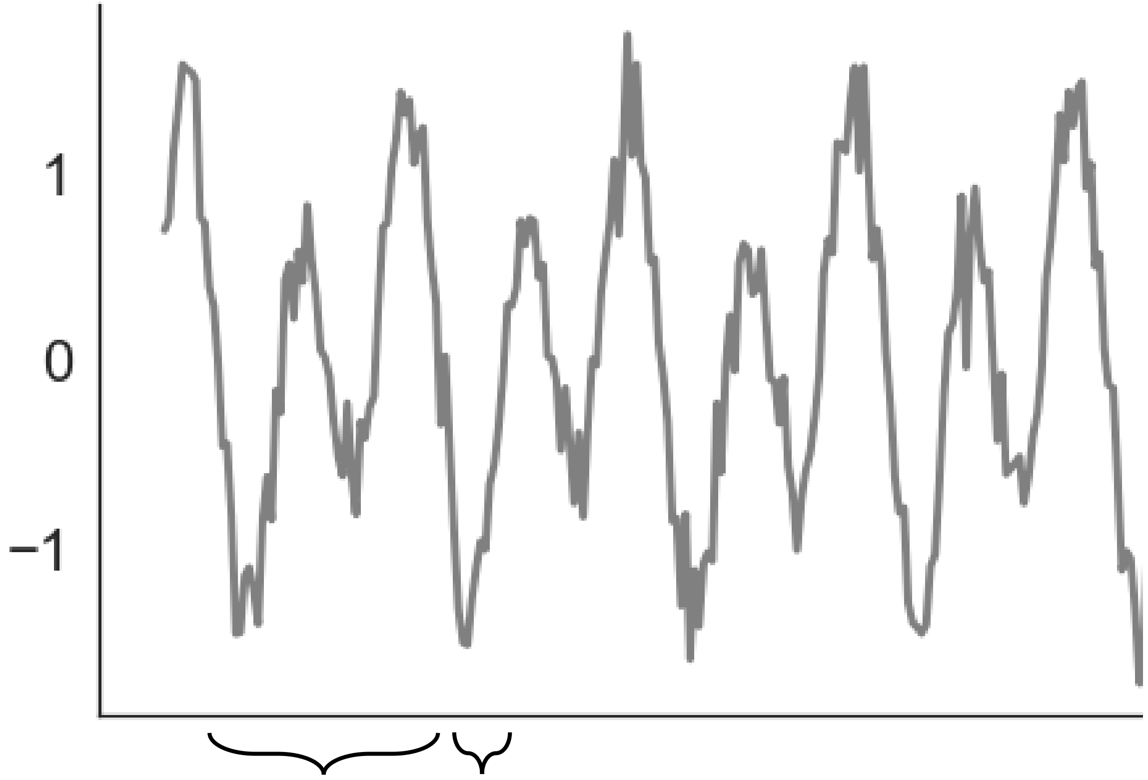
train_input_seqs[0]
(input to encoder)

train_output_seqs[0]
(output target by decoder)

Prepare Data



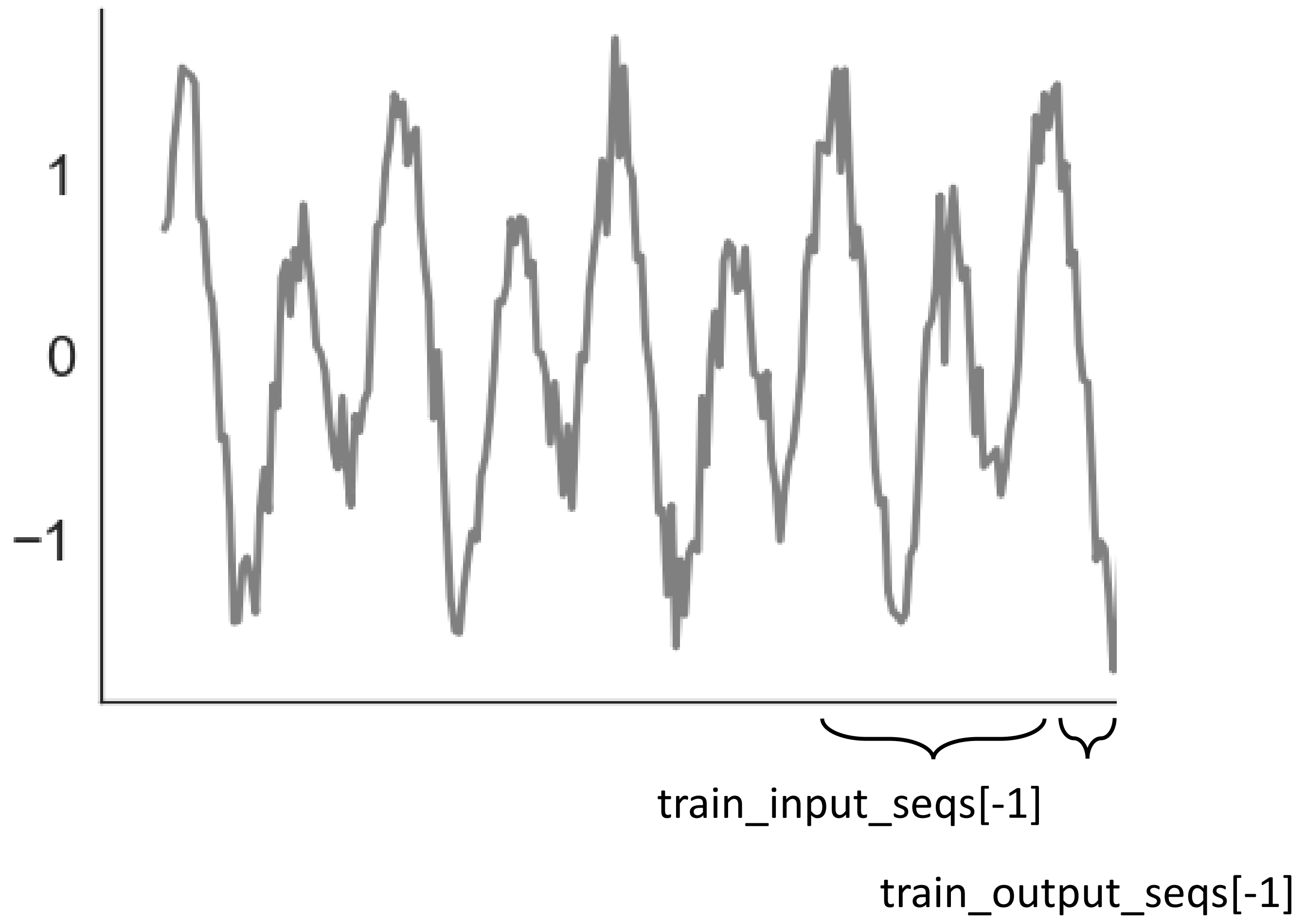
Prepare Data



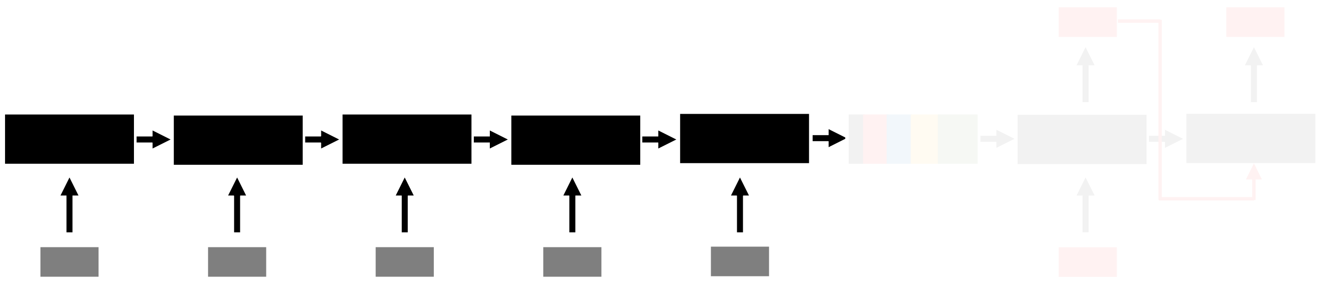
train_input_seqs[2]

train_output_seqs[2]

Prepare Data



Define Model

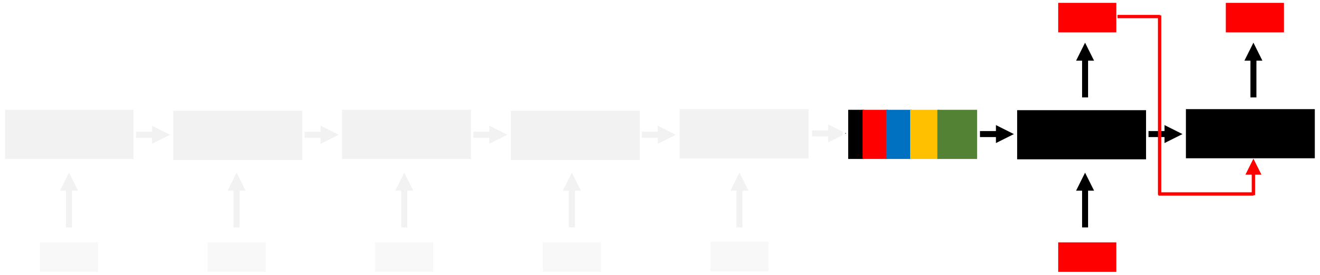


Using LSTM for Encoder

No need for FC layer since encoder only passes hidden states to Decoder

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

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

        super(Encoder, self).__init__()

        self.lstm = torch.nn.LSTM(input_size = input_size, hidden_size = hidden_size,
                                  num_layers = num_layers,
                                  batch_first = True)

    def forward(self, input_seq, hidden_state):

        lstm_out, hidden = self.lstm(input_seq, hidden_state)

        return lstm_out, hidden
```

Define Model

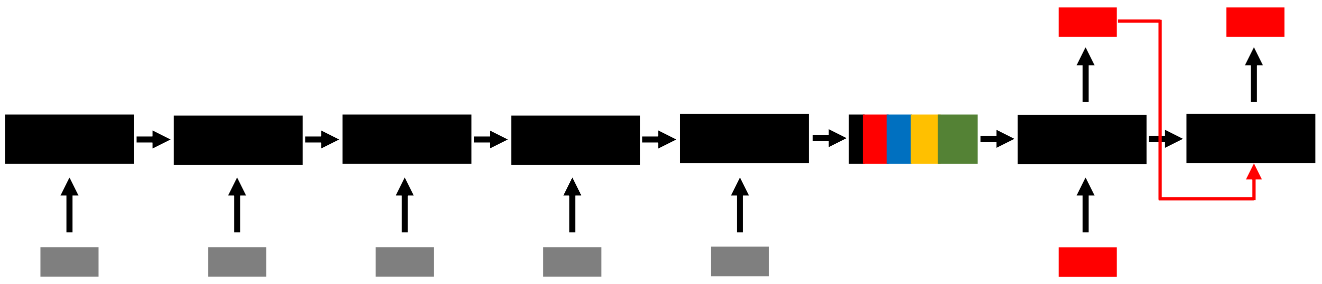


Using LSTM for Decoder

FC layer for converting hidden states to a single number (prediction)

```python
class Decoder(torch.nn.Module):

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

        super(Decoder, self).__init__()

        self.lstm = torch.nn.LSTM(input_size = input_size, hidden_size = hidden_size,
                                  num_layers = num_layers,
                                  batch_first = True)

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

    def forward(self, input_seq, encoder_hidden_states):

        lstm_out, hidden = self.lstm(input_seq, encoder_hidden_states)
        output = self.fc_decoder(lstm_out)

        return output, hidden
```

Define Model



Combine Encoder and Decoder classes into a single class (Encoder_Decoder)

```python
class Encoder_Decoder(torch.nn.Module):

    def __init__(self, input_size, hidden_size, decoder_output_size, num_layers):

        super(Encoder_Decoder, self).__init__()

        self.Encoder = Encoder(input_size = input_size, hidden_size = hidden_size,
                               num_layers = num_layers)

        self.Decoder = Decoder(input_size = input_size, hidden_size = hidden_size,
                               output_size = decoder_output_size, num_layers = num_layers)
```

Define Hyperparameters

```
Encoder_Decoder_RNN = Encoder_Decoder(input_size = 1, hidden_size = 15,
                                      decoder_output_size = 1, num_layers = 1)

learning_rate = 0.01
epochs = 50

batchsize = 5
num_features = train_output_seqs.shape[2]

loss_func = torch.nn.MSELoss()
optimizer = torch.optim.Adam(Encoder_Decoder_RNN.parameters(), lr=learning_rate)

Encoder_Decoder_RNN
```

Define Encoder Decoder Specifics

Define Learning rate, epochs, batchsize and num_features/timestep

Define loss function and optimizer

Identify Tracked Values

```python
train_loss_list = []
```

Empty Python list for keeping track of loss values

Train Model

```
train_input_seqs = torch.from_numpy(train_input_seqs).float()
train_output_seqs = torch.from_numpy(train_output_seqs).float()

train_batches_features = torch.split(train_input_seqs, batchsize)[:-1]
train_batches_targets = torch.split(train_output_seqs, batchsize)[:-1]

batch_split_num = len(train_batches_features)
```

Convert numpy arrays to torch tensors

Split training data into mini-batches (skip last mini-batch since it can have smaller batch size)

Compute total number of mini-batches

Train Model

```python
for epoch in range(epochs): # For each epoch

    for k in range(batch_split_num):

        hidden_state = None

        decoder_output_seq = torch.zeros(batchsize, decoder_outputseq_len, num_features)

        optimizer.zero_grad()

        encoder_output, encoder_hidden = Encoder_Decoder_RNN.Encoder(train_batches_features[k], hidden_state)
        decoder_hidden = encoder_hidden

        decoder_input = train_batches_features[k][:, -1, :]
        decoder_input = torch.unsqueeze(decoder_input, 2)

        for t in range(decoder_outputseq_len):

            decoder_output, decoder_hidden = Encoder_Decoder_RNN.Decoder(decoder_input, decoder_hidden)

            decoder_output_seq[:, t, :] = torch.squeeze(decoder_output, 2)

            decoder_input = train_batches_targets[k][:, t, :]
            decoder_input = torch.unsqueeze(decoder_input, 2)

        loss = loss_func(torch.squeeze(decoder_output_seq), torch.squeeze(train_batches_targets[k]))

        train_loss_list.append(loss.item())

        loss.backward()

        optimizer.step()

    print("Averaged Training Loss for Epoch ", epoch,": ", np.mean(train_loss_list[-batch_split_num:]))
```

Define initial hidden states and empty tensor for decoder outputs

Pass training input sequence + hidden states to encoder

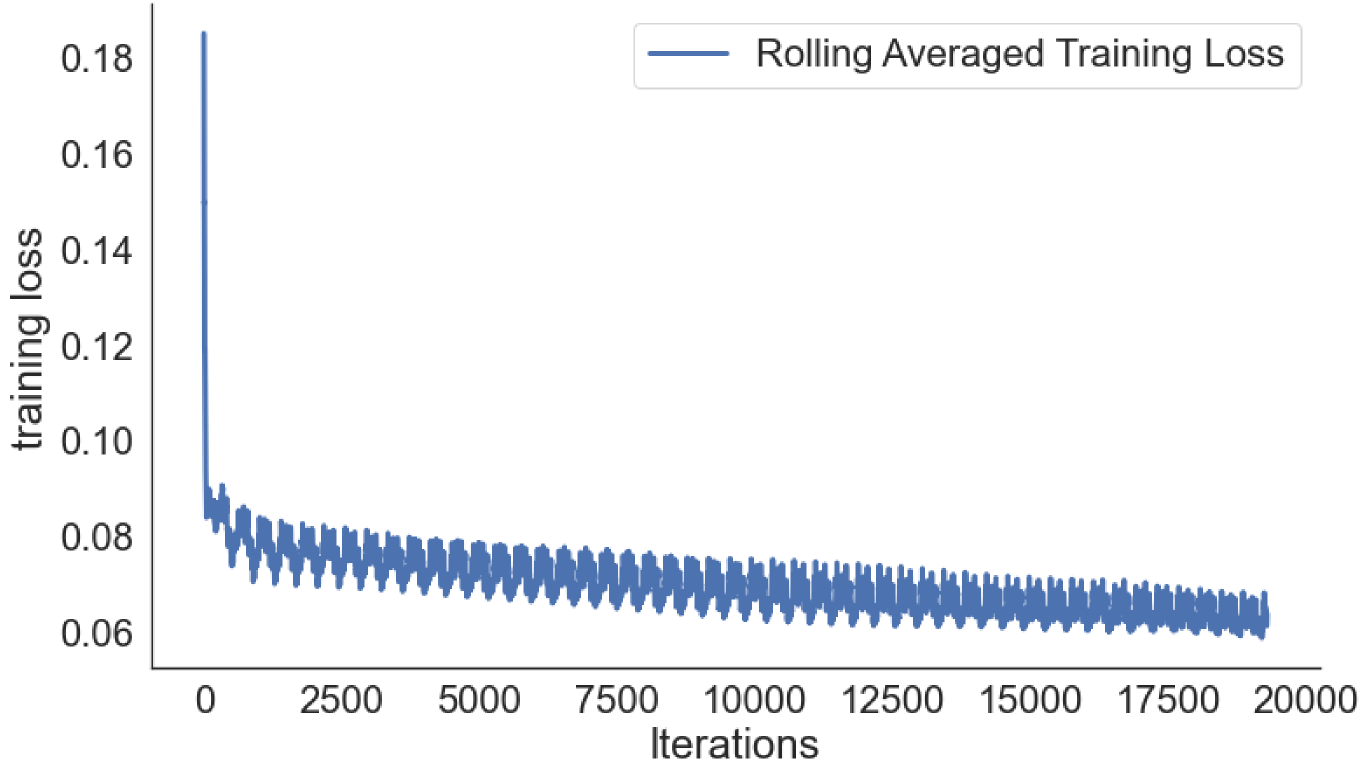
Initial input to decoder = last value of the input sequence

Fill in decoder output tensor by using teacher forcing method
(provide ground truth inputs)

Compute and append Loss
Back-propagation
Update network

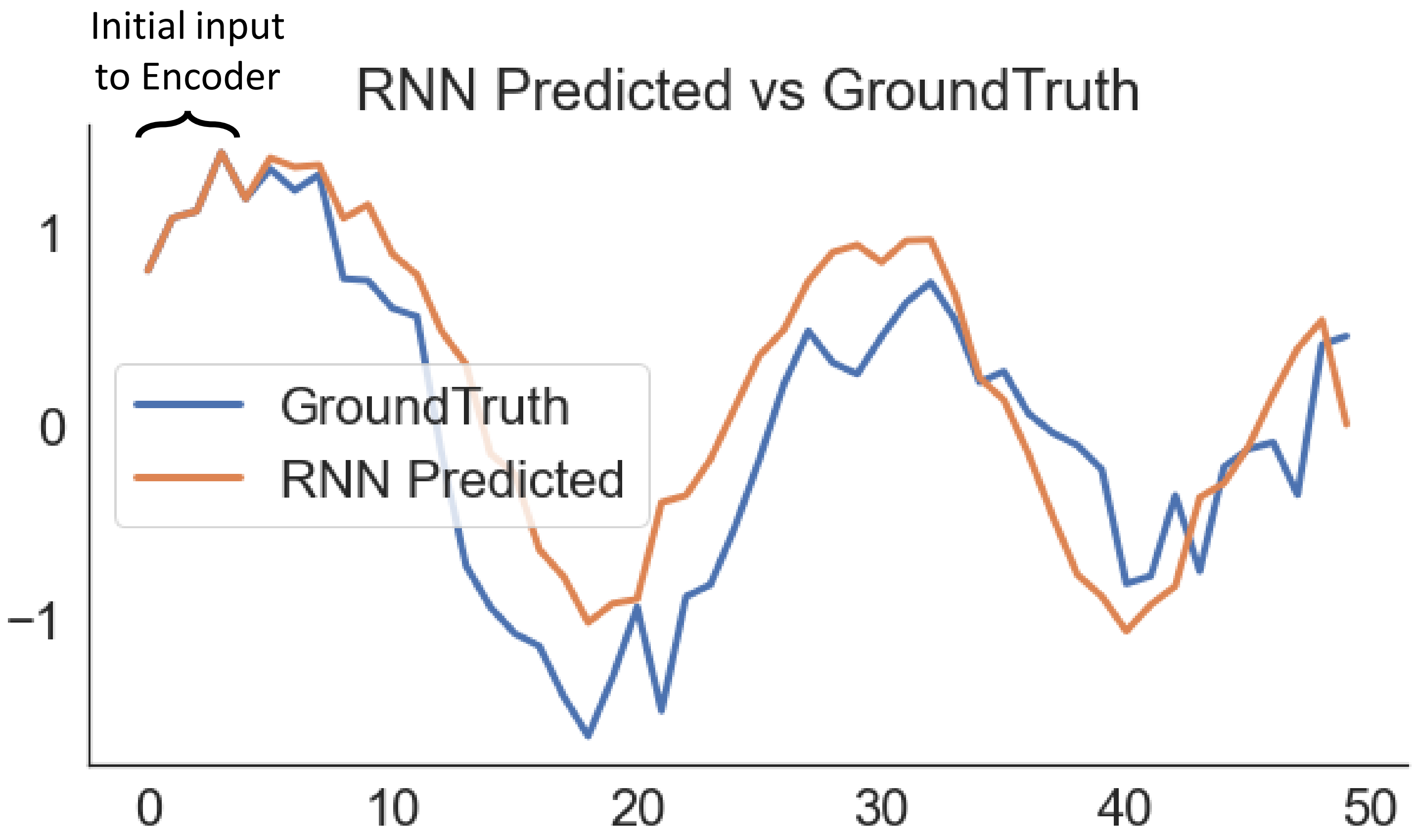
Visualize & Evaluate Model

```python
plt.figure(figsize = (12, 7))

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 moving average training loss

Visualize & Evaluate Model



See example notebook for detailed code implementation

LAB 5 ASSIGNMENT:

Stock Prediction AI with Encoder-Decoder RNN

Stock Dataset

	Date	Open	High	Low	Close	Adj Close	Volume
0	2010-06-29	19.000000	25.00	17.540001	23.889999	23.889999	18766300
1	2010-06-30	25.790001	30.42	23.299999	23.830000	23.830000	17187100
2	2010-07-01	25.000000	25.92	20.270000	21.959999	21.959999	8218800
3	2010-07-02	23.000000	23.10	18.709999	19.200001	19.200001	5139800
4	2010-07-06	20.000000	20.00	15.830000	16.110001	16.110001	6866900

- TSLA.csv
- 2227 days
- 7 attributes

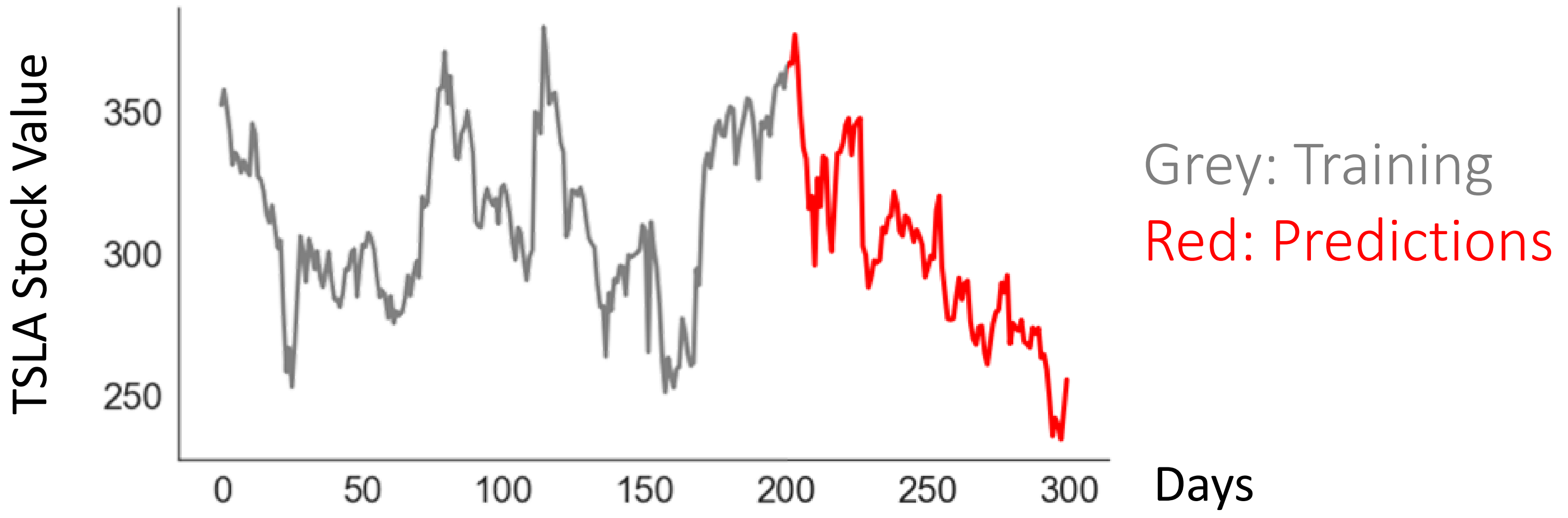
	Date	Open	High	Low	Close	Adj Close	Volume
0	2004-08-19	50.050049	52.082081	48.028027	50.220219	50.220219	44659000
1	2004-08-20	50.555557	54.594593	50.300301	54.209209	54.209209	22834300
2	2004-08-23	55.430431	56.796795	54.579578	54.754753	54.754753	18256100
3	2004-08-24	55.675674	55.855854	51.836838	52.487488	52.487488	15247300
4	2004-08-25	52.532532	54.054054	51.991993	53.053055	53.053055	9188600

- GOOGL.csv
- 3702 days
- 7 attributes

	Date	Open	High	Low	Close	Adj Close	Volume
0	1985-01-29	1277.719971	1295.489990	1266.890015	1292.619995	1292.619995	13560000
1	1985-01-30	1297.369995	1305.099976	1278.930054	1287.880005	1287.880005	16820000
2	1985-01-31	1283.239990	1293.400024	1272.640015	1286.770020	1286.770020	14070000
3	1985-02-01	1276.939941	1286.109985	1269.770020	1277.719971	1277.719971	10980000
4	1985-02-04	1272.079956	1294.939941	1268.989990	1290.079956	1290.079956	11630000

- DJI.csv
- 8636 days
- 7 attributes

Stock Prediction AI with Encoder-Decoder RNN



In this exercise, you will use Encoder-Decoder RNN architecture to predict the **last 100 days'** stock values.

You are given **3 stock datasets (TSLA, GOOGL, DJI)** for training and testing your model. Use **closing stock value (i.e., "Close" column)** for both training and testing data.

Feel free to pick **encoder/decoder sequence sizes** of your choice**, LSTM or GRU** for your RNN cell as well as **RNN extensions** such as Deep RNN or Bi-directional RNN.

Before training, **normalize the data** and create **train_input_seqs** and **train_output_seqs** like the example task.

After training, plot your **RNN predicted stock value** against the **ground truth test values** and calculate its **MSE error for all 3 datasets.** Use **Teacher forcing method** for predicting test outputs (i.e., next day prediction given ground-truth inputs).

Your predicted stock values should match very closely to ground truth with a little delay.