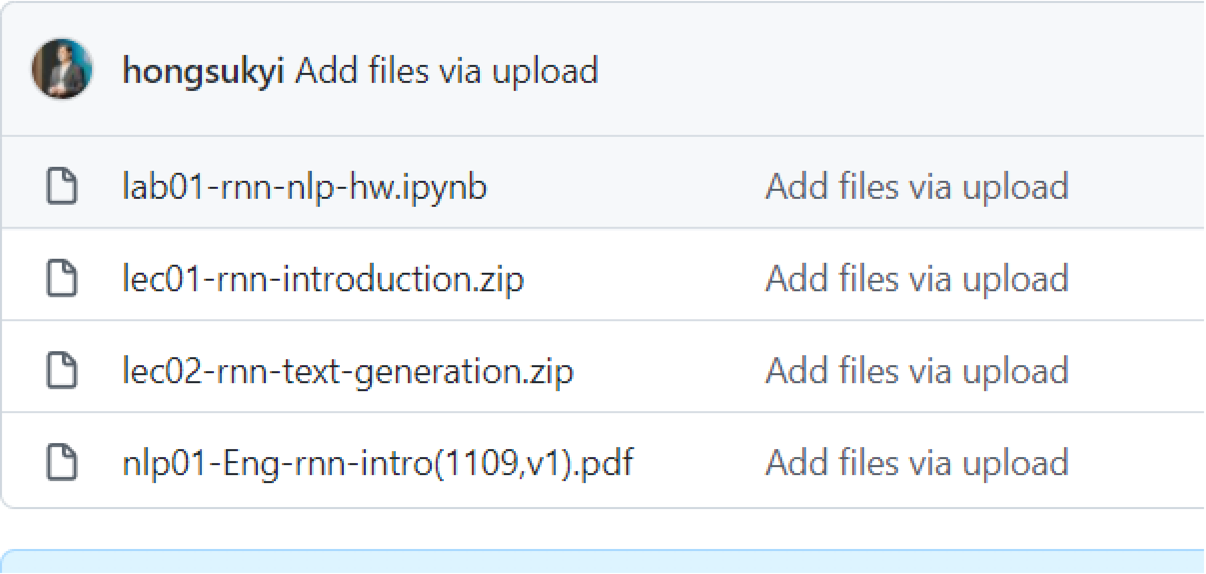
RNN for NLP

RNN, LSTM, GRU

- Hongsuk Yi (KISTI)
- Download material and codes, 강의 자료를 다운로드 받으세요.

https://github.com/hongsukyi/rnn-nlp-lectures



Contents

- Recurrent Neural Network
  - ✓ Practice on RNN and LSTM
- Text generation with RNN
  - ✓ Practice on Char-RNN Language Model
- Text classification with RNN
  - ✓ Practice on IMDB Dataset using RNN
- Text generation with RNN
  - ✓ Practice on Text Generation model with RNN

A simple Example

"Modeling word probabilities is really difficult"

Modeling p(x)

Simplest model:
Assume independence of words

$$p(\mathbf{x}) = \prod_{t=1}^{T} p(x_t)$$

p("modeling") × p("word") × p("probabilities") × p("is") × p("really") × p("difficult")

Word	$p(x_i)$
the	0.049
be	0.028
...	...
really	0.0005
...	...

Modeling p(x)

More realistic model:

Assume conditional dependence of words

$$p(x_T) = p(x_T | x_1, \ldots, x_{T-1})$$

Modeling word probabilities is really ?

Context — Target

	p(x|context)
difficult	0.01
hard	0.009
fun	0.005
...	...
easy	0.00001

Modeling p(x)

The chain rule

Computing the joint p(**x**) from conditionals

$$p(\mathbf{x}) = \prod_{t=1}^{T} p(x_t | x_1, \ldots, x_{t-1})$$

Modeling $p(x_1)$

Modeling **word** $p(x_2 | x_1)$

Modeling word **probabilities** $p(x_3 | x_2, x_1)$

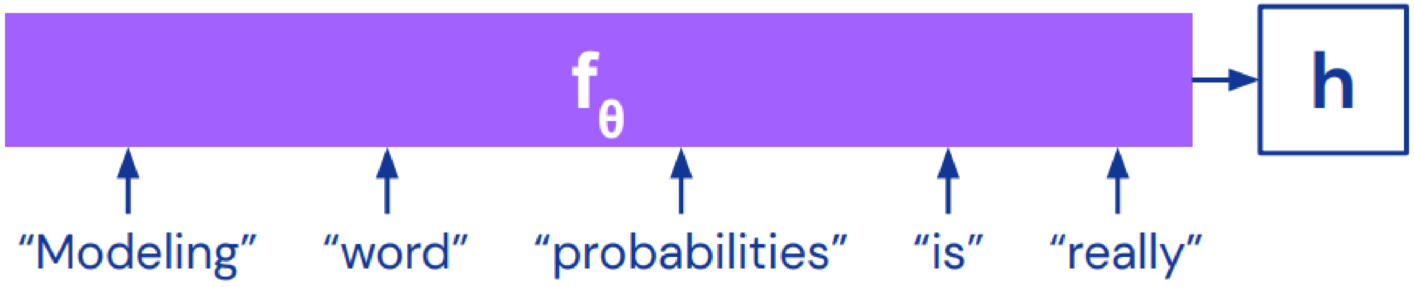
Modeling word probabilities **is** $p(x_4 | x_3, x_2, x_1)$

Modeling word probabilities is **really** $p(x_5 | x_4, x_3, x_2, x_1)$

Modeling word probabilities is really **difficult** $p(x_6 | x_5, x_4, x_3, x_2, x_1)$

Recurrent Neural Networks (RNNs)

- **Learning to model word probabilities**
  - ✓ Vectorising the context



f_θ summarises the context in $\boxed{h}$ such that:

$$p(x_t | x_1, \ldots, x_{t-1}) \approx p(x_t | h)$$

Desirable properties for f_θ:

- Order matters
- Variable length
- Learnable (differentiable)

Recurrent Neural Networks (RNNs)

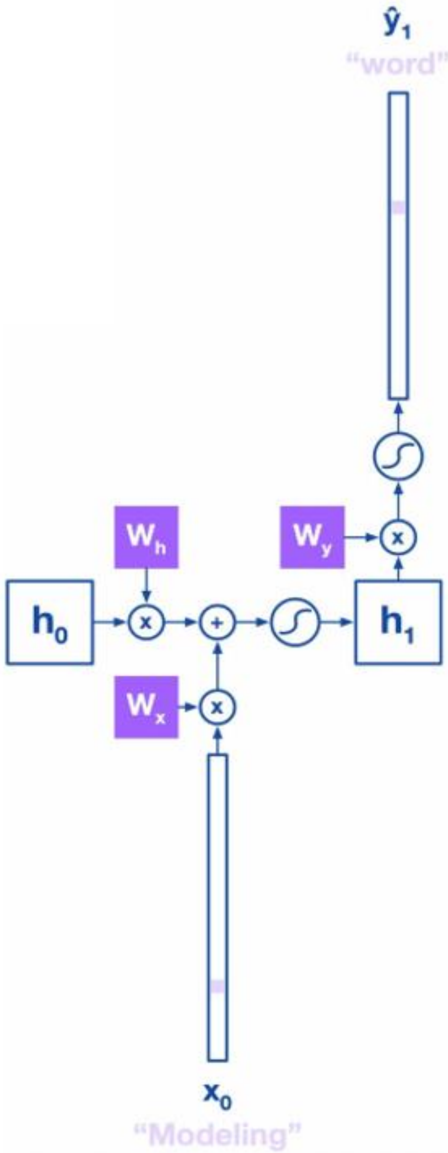
- Persistent state variable h stores information from the context observed so far.

$$\mathbf{h}_t = \tanh(\mathbf{W}_h \mathbf{h}_{t-1} + \mathbf{W}_x \mathbf{x}_t)$$

RNNs predict the target **y** (the next word) from the state **h.**

$$p(\mathbf{y_{t+1}}) = softmax(\mathbf{W}_y \mathbf{h}_t)$$

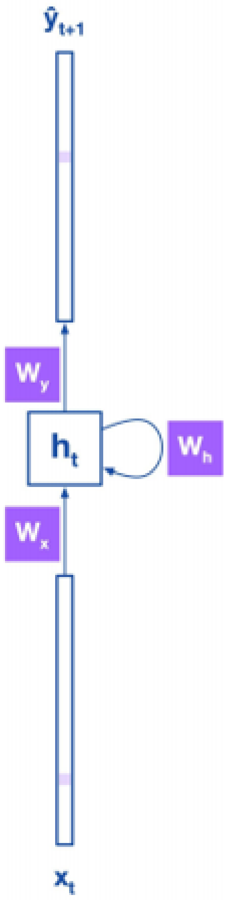
Softmax ensures we obtain a distribution over all possible words.



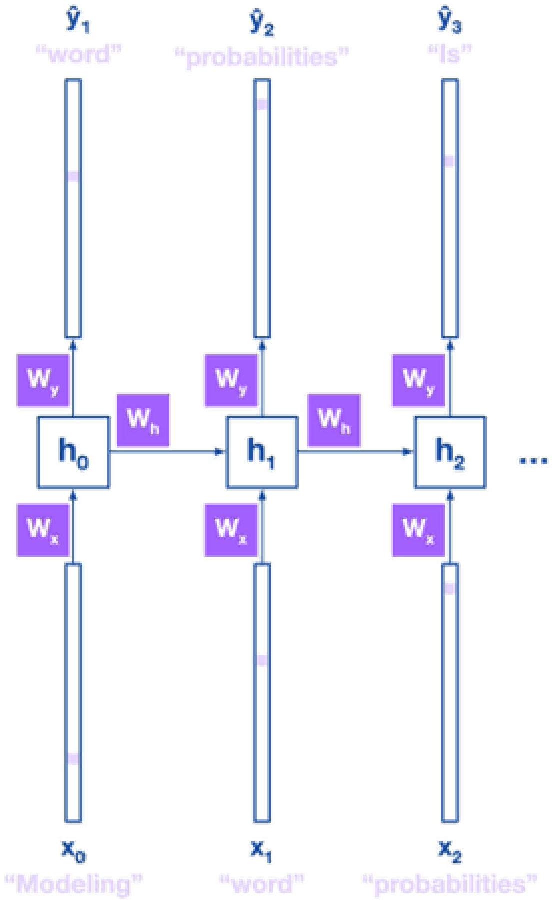
Recurrent Neural Networks (RNNs)

Weights are shared
over time steps

Input next word in sentence x_1



RNN



RNN rolled out over time

Loss: Cross Entropy

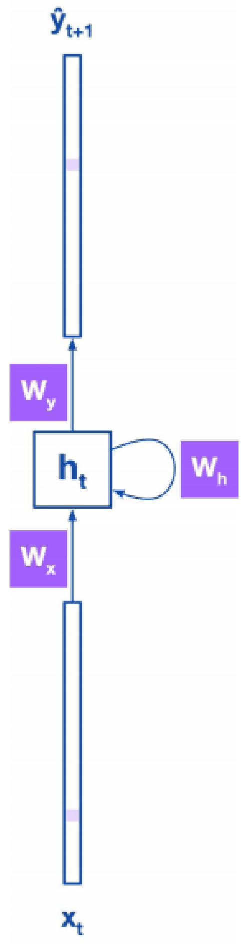
Next word prediction is essentially a classification task where the number of classes is the size of the vocabulary.

As such we use the cross-entropy loss:

For one word: $$\mathcal{L}_\theta(\mathbf{y}, \hat{\mathbf{y}})_t = -\mathbf{y}_t \log \hat{\mathbf{y}}_t$$

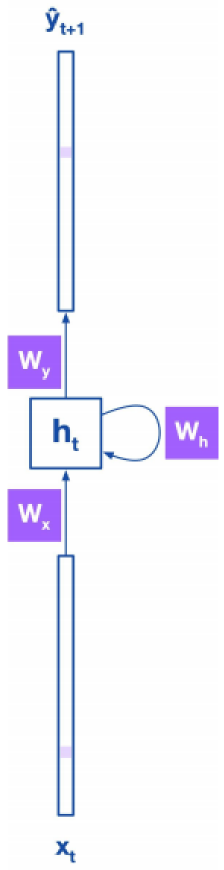
For the sentence: $$\mathcal{L}_\theta(\mathbf{y}, \hat{\mathbf{y}}) = -\sum_{t=1}^{T} \mathbf{y}_t \log \hat{\mathbf{y}}_t$$

With parameters $\theta = \{\mathbf{W}_y, \mathbf{W}_x, \mathbf{W}_h\}$



Differentiating weights (w_y, w_x, w_h) from each other

$$
\begin{aligned}
\mathbf{h}_t &= \tanh(\mathbf{W}_h \mathbf{h}_{t-1} + \mathbf{W}_x \mathbf{x}_t) \\
p(\mathbf{x}_{t+1}) &= softmax(\mathbf{W}_y \mathbf{h}_t) \\
\mathcal{L}_\theta(\mathbf{y}, \hat{\mathbf{y}})_t &= -\mathbf{y}_t \log \hat{\mathbf{y}}_t
\end{aligned}
$$



$$\frac{\partial \mathbf{L}}{\partial W} = \sum_{i=0}^{T} \frac{\partial \mathcal{L}_i}{\partial W} \propto \sum_{i=0}^{T} \left(\prod_{i=k+1}^{y} \frac{\partial h_i}{\partial h_{i-1}} \right) \frac{\partial h_k}{\partial W}$$

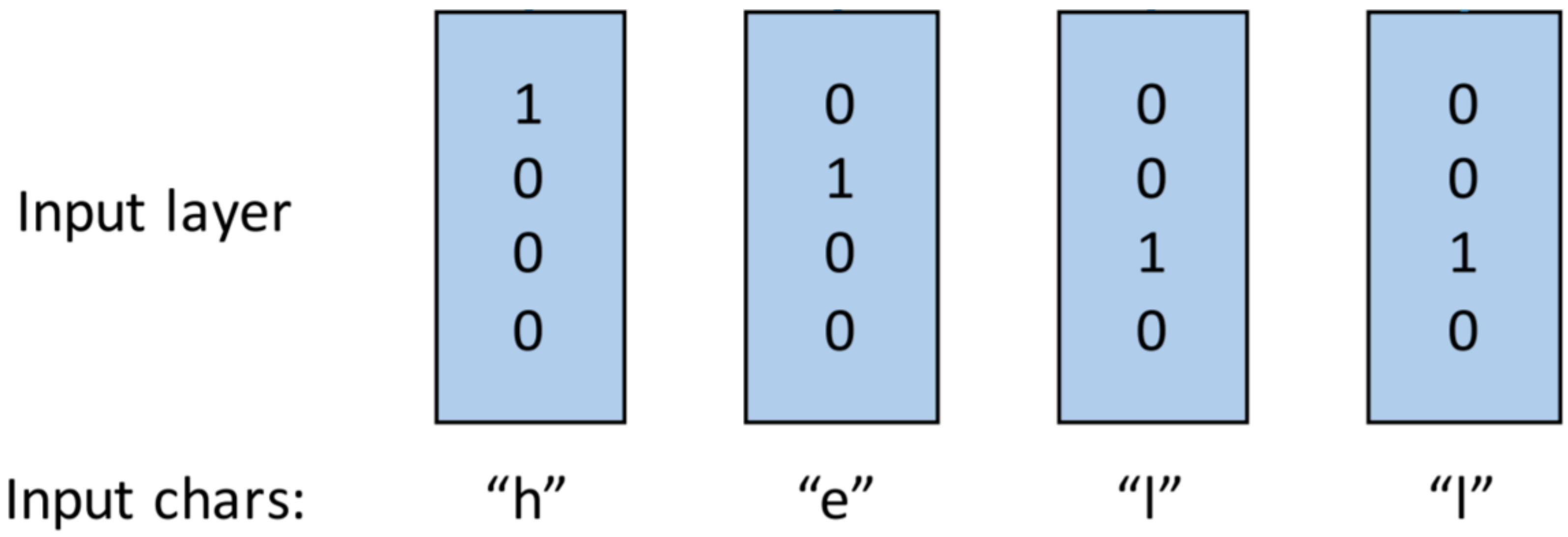
Character-Level Language Models

- We'll give the RNN a huge chunk of text and ask it to model the probability distribution of the next character in the sequence given a sequence of previous characters.
  - ✓ This will then allow us to generate new text one character at a time.

Character-level language model

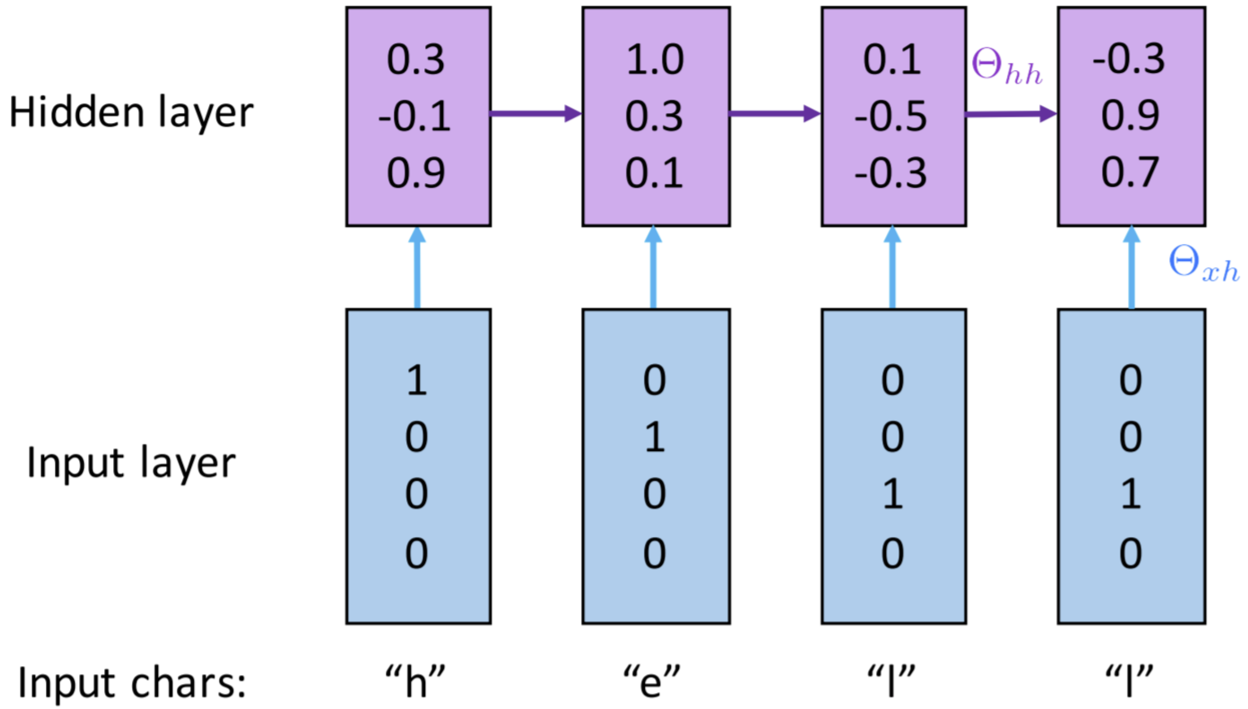
Example training sequence : “hello”

- Character-level language model
  - ✓ Vocabulary : [h,e,l,o]
  - ✓ Encoding into a vector using 1-of-k encoding and feed them into the RNN one at a time.

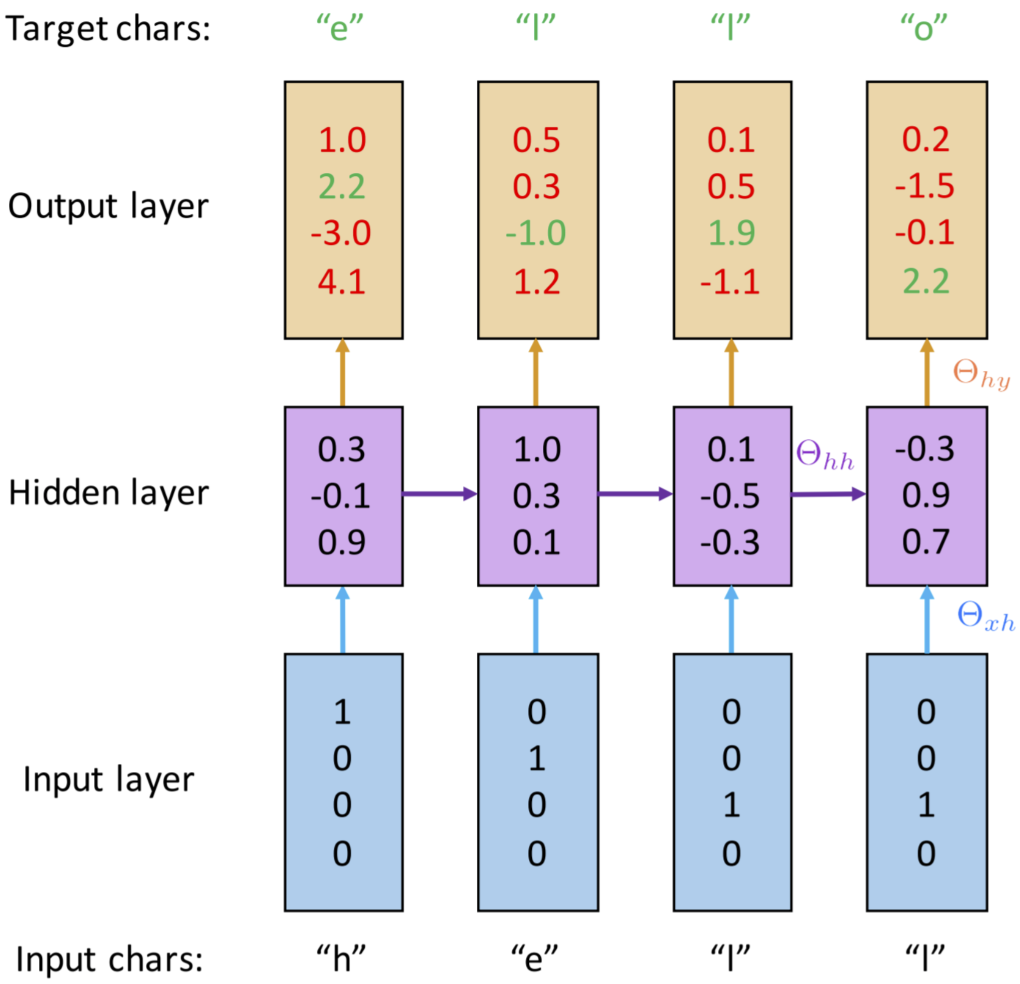


Character-level language model

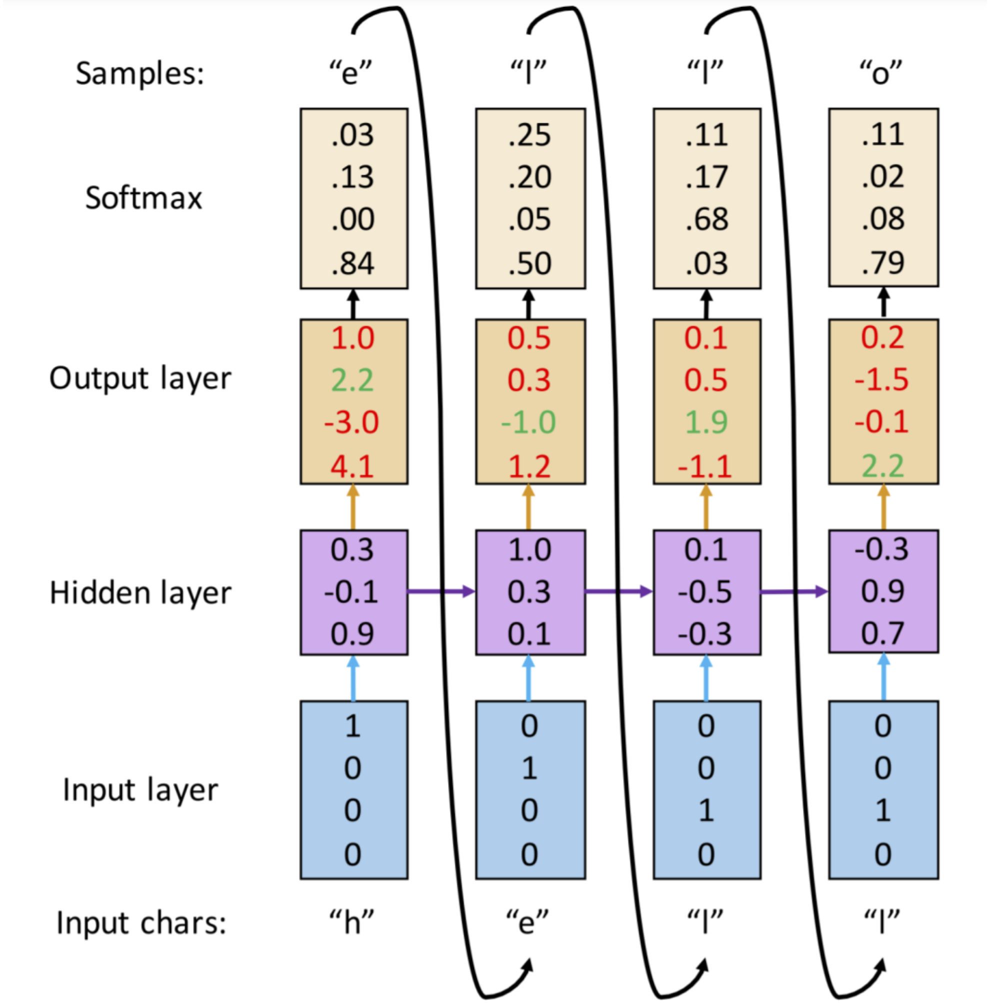
$$\mathbf{h}_t = \tanh(\Theta_{hh}\mathbf{h}_{t-1} + \Theta_{xh}\mathbf{x}_t)$$



For example, we see that in the first time step



a sequence of 4-dimensional output vectors



Training Sequence modelling

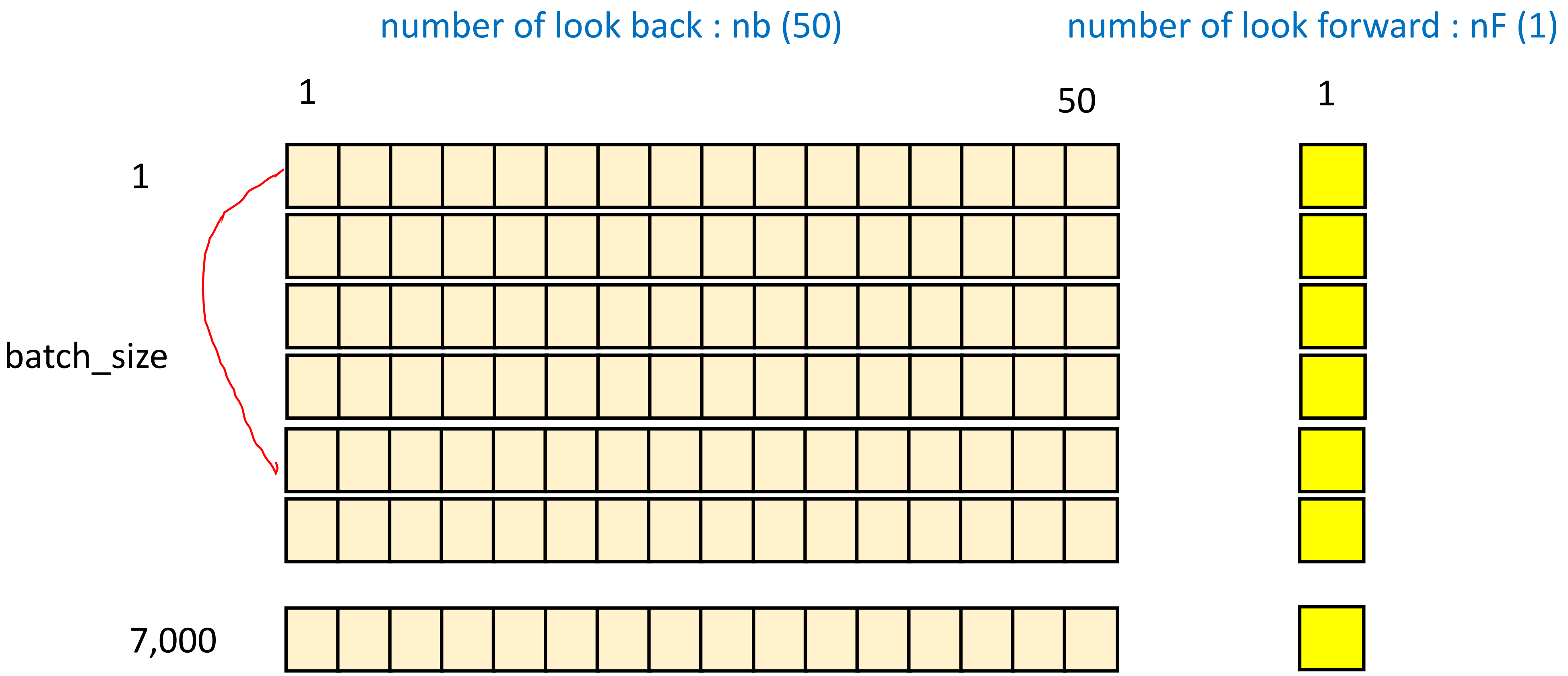
	Supervised learning	Sequence modelling
Data	$\{x, y\}_i$	$\{x\}_i$
Model	$y \approx f_\theta(x)$	$p(x) \approx f_\theta(x)$
Loss	$\mathcal{L}(\theta) = \sum_{i=1}^{N} l(f_\theta(x_i), y_i)$	$\mathcal{L}(\theta) = \sum_{i=1}^{N} \log p(f_\theta(x_i))$
Optimisation	$\theta^* = \arg\min_\theta \mathcal{L}(\theta)$	$\theta^* = \arg\max_\theta \mathcal{L}(\theta)$

LAB01 : RNN-Basics

RNN, LSTM, GRU

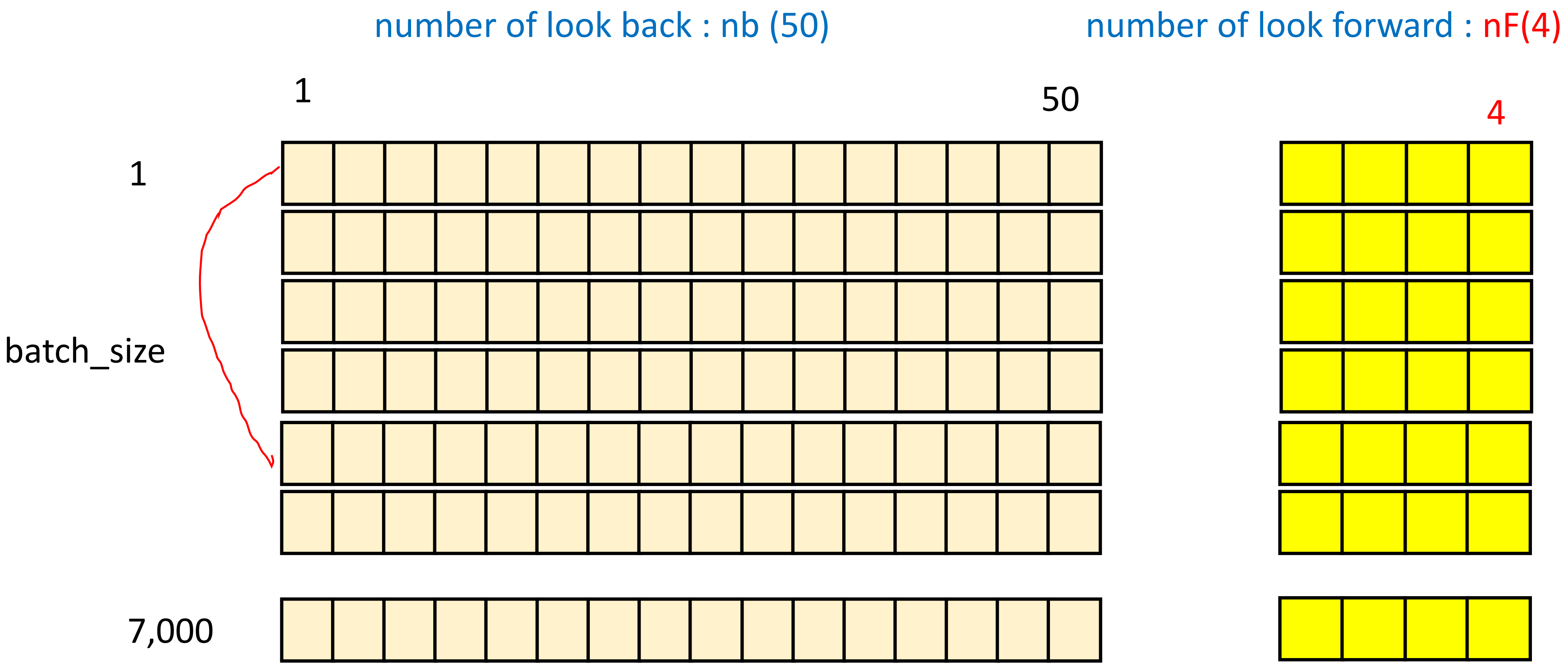
Many-to-One RNN Data Structure

X_train[7000,50,1]   y_train[7000,1,1]

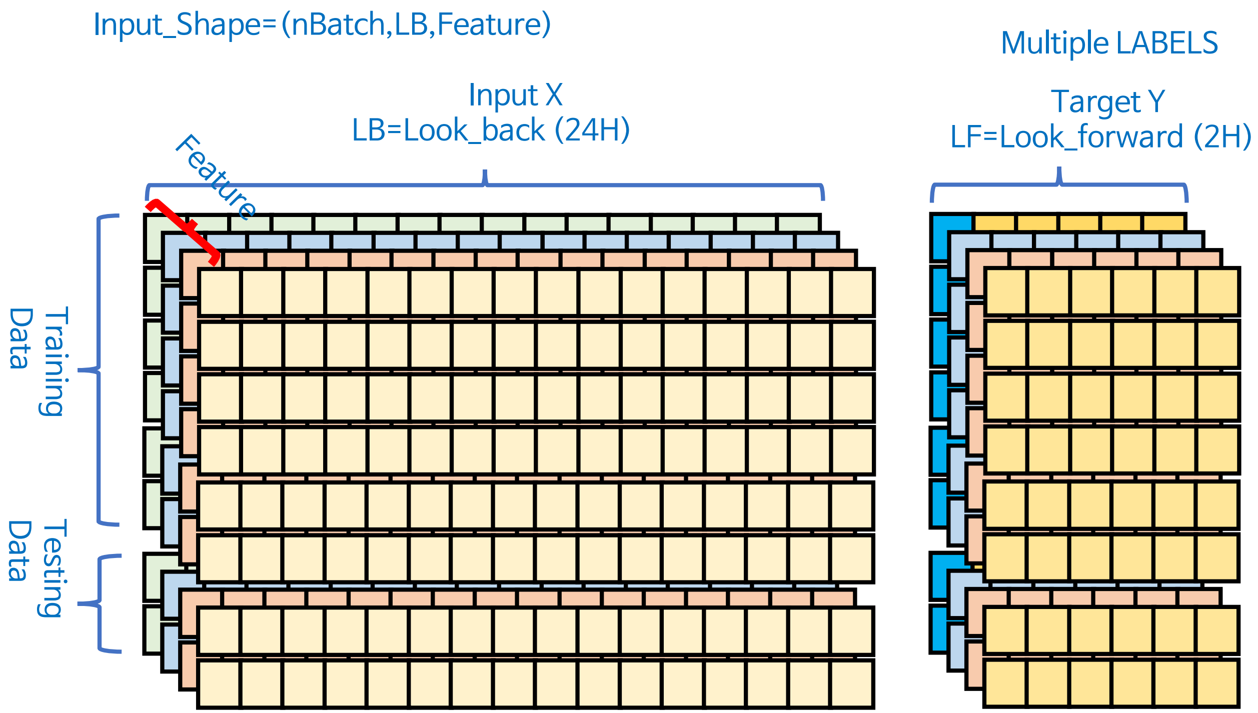


Many-to-Many RNN Data Structure

X_train[7000,50,1]   y_train[7000,nF,1]



RNN Input-Output Data Structure



VDS, RSE Data Preprocessing for LSTM

Forecasting a Time Series

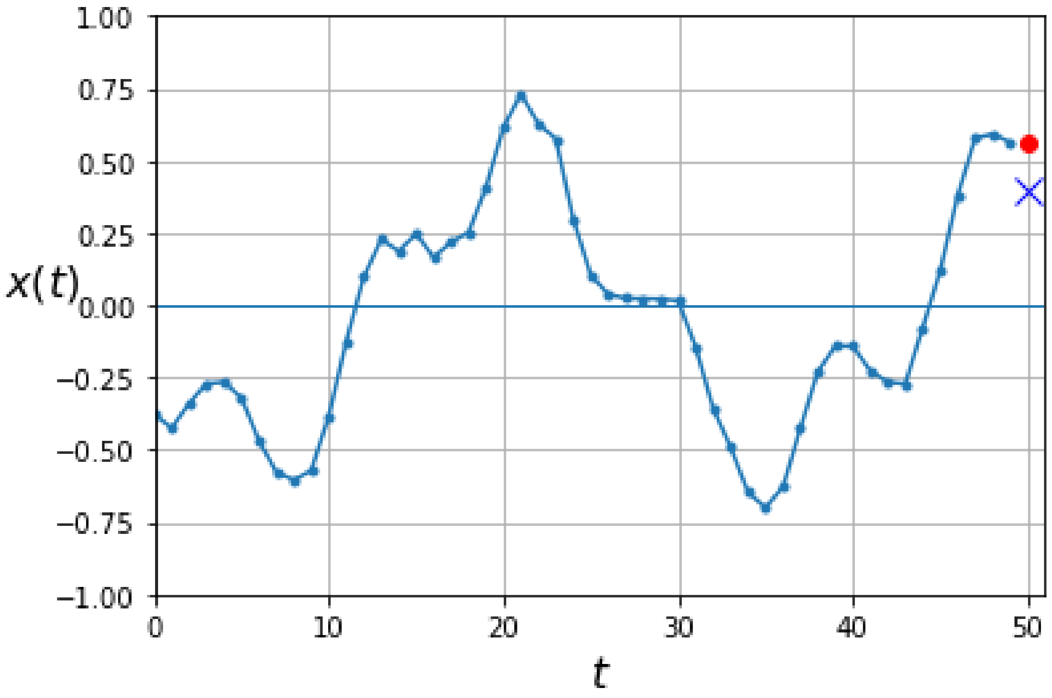
- There is a single value per time step : *univariate time series*
  - ✓ A typical task is to predict future values, which is called *forecasting*.
- For example, figures shows 3 univariate time series
  - ✓ each of them 50 time steps long, and the goal here is to forecast the value at the next time step (represented by the X) for each of them.

Generate the Dataset ¶

In [3]:
```
def generate_time_series(batch_size, n_steps):
    freq1, freq2, offsets1, offsets2 = np.random.rand(4, batch_size, 1)
    time = np.linspace(0, 1, n_steps)
    series = 0.5 * np.sin((time - offsets1) * (freq1 * 10 + 10))  #   wave 1
    series += 0.2 * np.sin((time - offsets2) * (freq2 * 20 + 20)) # + wave 2
    series += 0.1 * (np.random.rand(batch_size, n_steps) - 0.5)   # + noise
    return series[..., np.newaxis].astype(np.float32)
```

Univariate time series

- The function returns a NumPy array of shape : [*batch size*, *time steps*, 1]
  - ✓ where each series is the sum of two sine waves of fixed amplitudes but random frequencies and phases, plus a bit of noise.



bx : for y_values at 51

ro : for y_prediction at 51

plot series

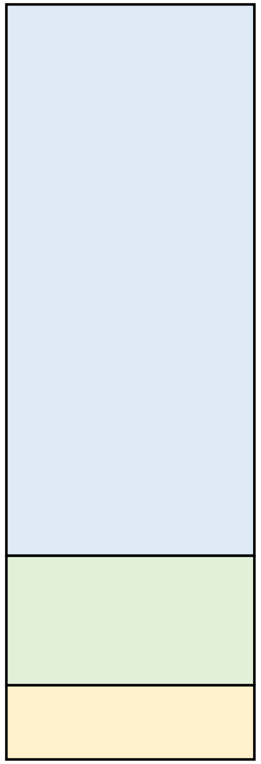
```
def plot_series(series, y=None, y_pred=None, x_label="$t$", y_label="$x(t)$"):
    plt.plot(series, ".-")
    if y is not None:
        plt.plot(n_steps, y, "rx", markersize=10)
    if y_pred is not None:
        plt.plot(n_steps, y_pred, "ro")
    plt.grid(True)
    if x_label:
        plt.xlabel(x_label, fontsize=16)
    if y_label:
        plt.ylabel(y_label, fontsize=16, rotation=0)
    plt.hlines(0, 0, 100, linewidth=1)
    plt.axis([0, n_steps + 1, -1, 1])

fig, axes = plt.subplots(nrows=1, ncols=3, sharey=True, figsize=(12, 4))
for col in range(3):
    plt.sca(axes[col])
    plot_series(X_valid[col, :, 0], y_valid[col, 0],
                y_label=("$x(t)$" if col==0 else None))

plt.show()
```

Now let's create a training set, a validation set, and a test set

X_train: 0 ~ 6999

X_valid: 7000~8999

X_test: 9000~9999

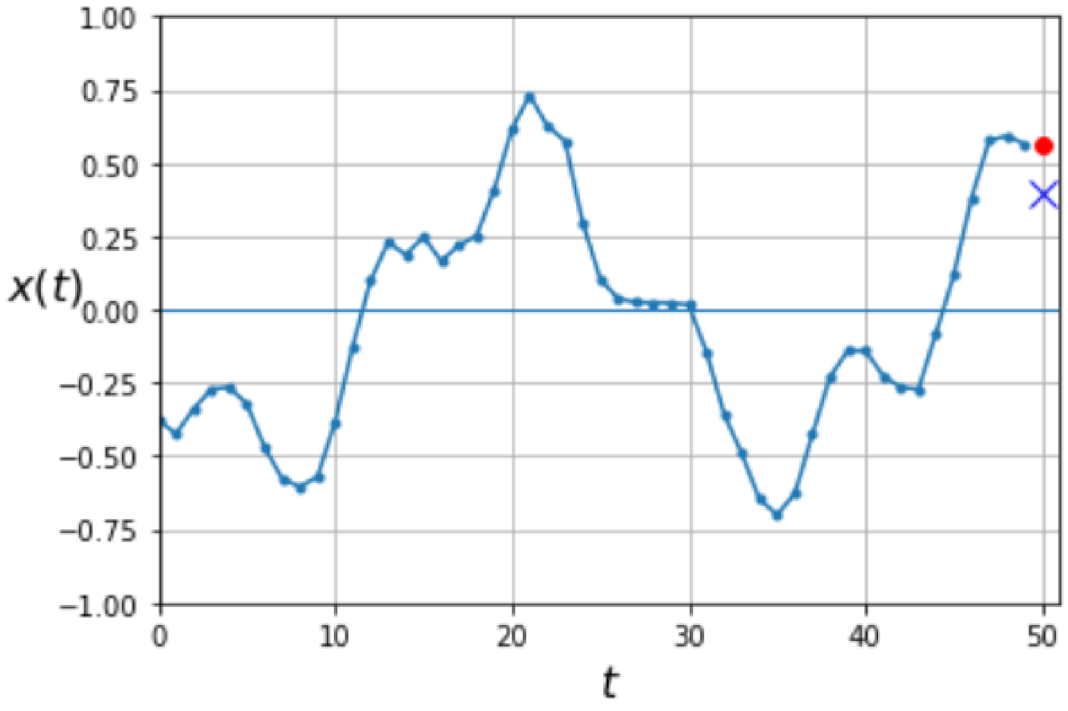


```
np.random.seed(42)

n_steps = 50

series = generate_time_series(10000, n_steps + 1)


X_train, y_train = series[:7000, :n_steps], series[:7000, -1]

X_valid, y_valid = series[7000:9000, :n_steps], series[7000:9000, -1]

X_test, y_test = series[9000:, :n_steps], series[9000:, -1]


X_train.shape, y_train.shape, X_valid.shape
```

```
((7000, 50, 1), (7000, 1), (2000, 50, 1))
```

model1: Computing Some Baselines

- Naive predictions (just predict the last observed value):
  - ✓ to predict the last value in each series
- In this case, it gives us a mean squared error of about 0.020211:




```
y_pred = X_valid[:, -1]
np.mean(keras.losses.mean_squared_error(y_valid, y_pred))
```

model 2: Linear Predictions

- Another simple approach is to use a fully connected network.
  - ✓ Since it expects a flat list of features for each input, we need to add a Flattern layer.

```
m2 = keras.models.Sequential([
    keras.layers.Flatten(input_shape=[50, 1]),
    keras.layers.Dense(1)
])
```

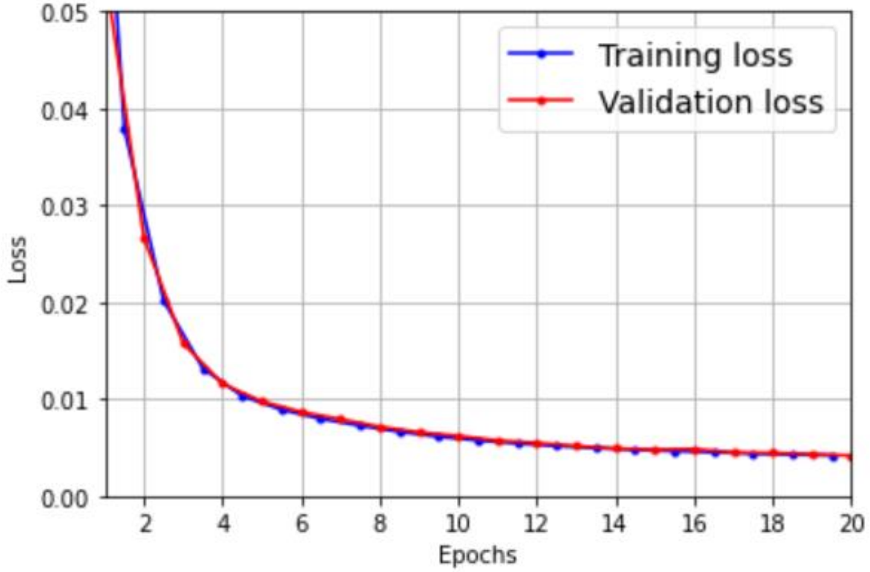
```
m2.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
flatten_1 (Flatten)          (None, 50)                0
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 51
_________________________________________________________________
```

02. Fully connected network : Flatten

- Another simple approach is to use a fully connected network.
  - ✓ Since it expects a flat list of features for each input, we need to add a Flattern layer.
  - ✓ Let's just use a simple Linear Regression model so that each prediction will be a linear combination of the values in the time series:

```
m2 = keras.models.Sequential([
    keras.layers.Flatten(input_shape=[50, 1]),
    keras.layers.Dense(1)
])

m2.compile(loss="mse", optimizer="adam")
history = m_lin.fit(X_train, y_train, epochs=20,
                    validation_data=(X_valid, y_valid))
m2.evaluate(X_valid, y_valid)
```



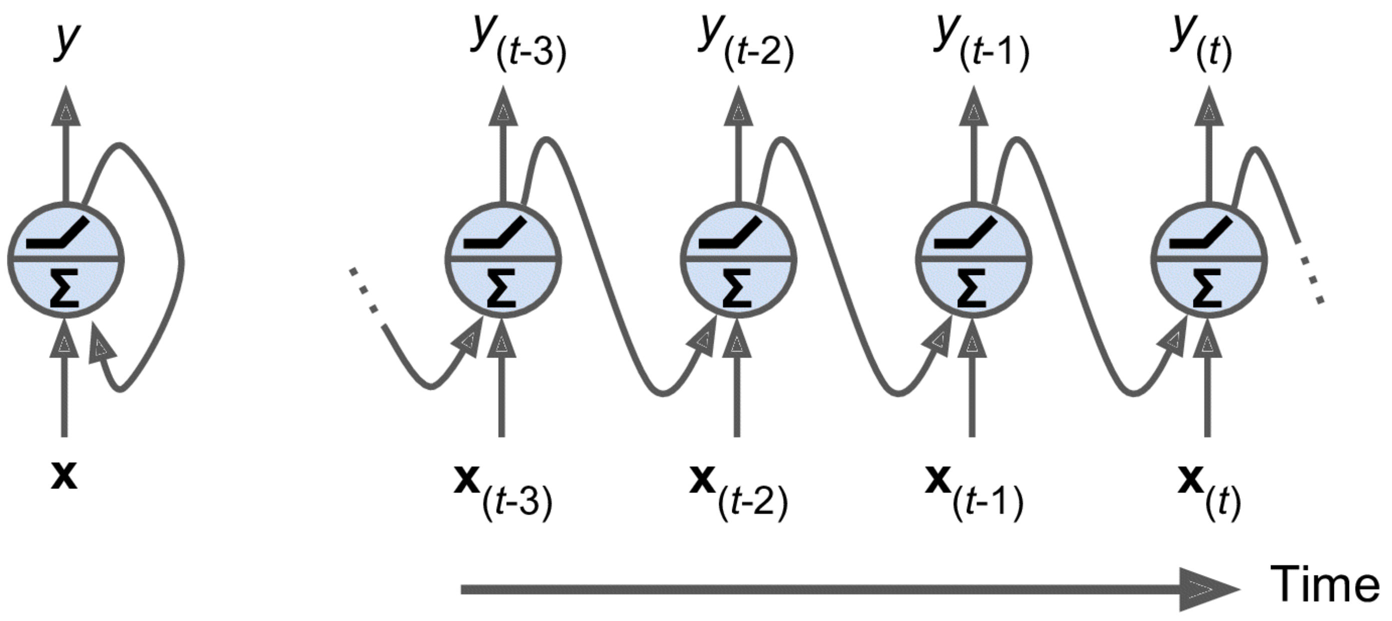

```
Out[9]:  0.004168087150901556
```

Learning Curves function and plot

```
def plot_learning_curves(loss, val_loss):
    plt.plot(np.arange(len(loss)) + 0.5, loss, "b.-", label="Training loss")
    plt.plot(np.arange(len(val_loss)) + 1, val_loss, "r.-", label="Validation loss")
    plt.gca().xaxis.set_major_locator(mpl.ticker.MaxNLocator(integer=True))
    plt.axis([1, 20, 0, 0.05])
    plt.legend(fontsize=14)
    plt.xlabel("Epochs")
    plt.ylabel("Loss")
    plt.grid(True)

plot_learning_curves(history.history["loss"], history.history["val_loss"])
plt.show()
```

03. Implementing a Simple RNN

- Simple RNN : don't need to specify the length of the RNN input sequence
  - ✓ The Simple RNN layer uses the hyperbolic tangent activity function. (-1 ~ 1)
  - ✓ It is set to the initial state h_(init)=0 and transmitted to the circulating neuron together with x(t=0), and then y(0) is output through the activation function.
  - ✓ This new h(0) becomes, and is transferred to the next input x(1) and input.
  - ✓ The last layer will be y (49).



03. Simple RNN

```
m3 = keras.models.Sequential([
    keras.layers.SimpleRNN(1, input_shape=[None, 1])
])

optimizer = keras.optimizers.Adam(lr=0.005)
m3.compile(loss="mse", optimizer=optimizer)
history = m3.fit(X_train, y_train, epochs=20,
                 validation_data=(X_valid, y_valid))
```

We do not need to specify the length of the input sequences (unlike in the previous model), since a recurrent neural network can process any number of time steps

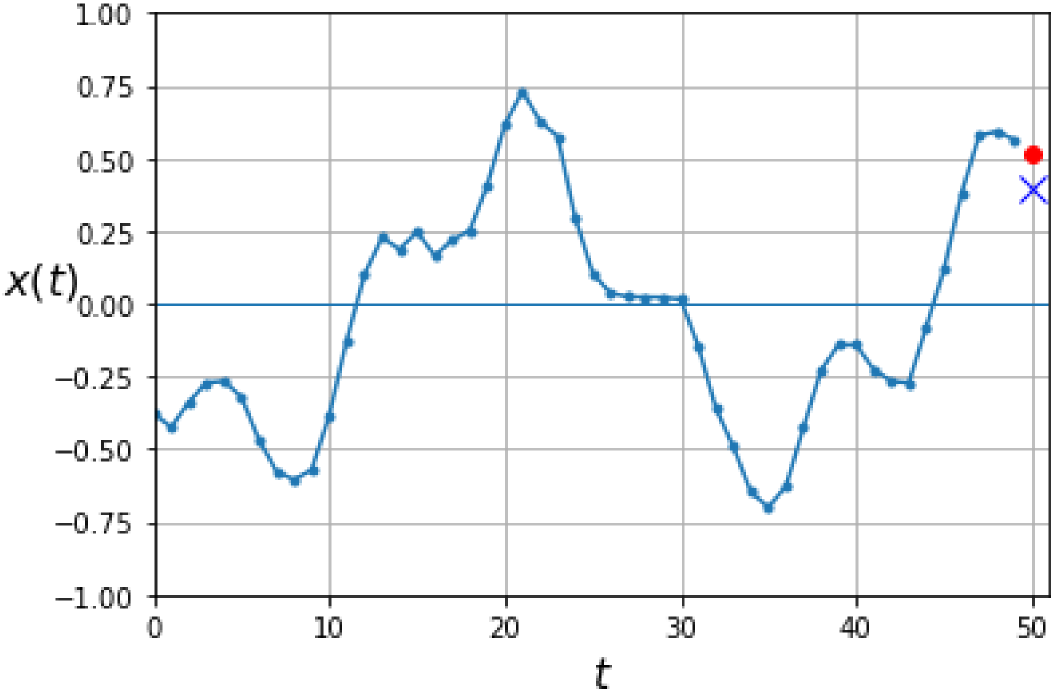
```
m3.summary()
```

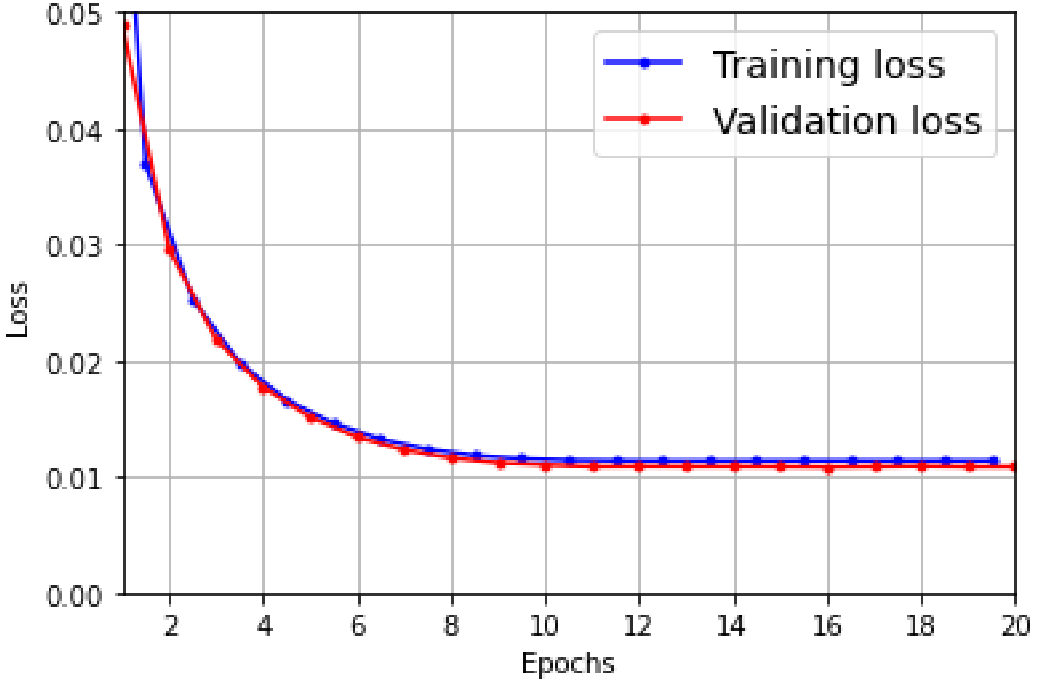
```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
simple_rnn (SimpleRNN)       (None, 1)                 3
=================================================================
Total params: 3
Trainable params: 3
Non-trainable params: 0
_________________________________________________________________
```

SimpleRNN layer uses the hyperbolic tangent activation function

```
Out[31]: 0.010881561785936356
```

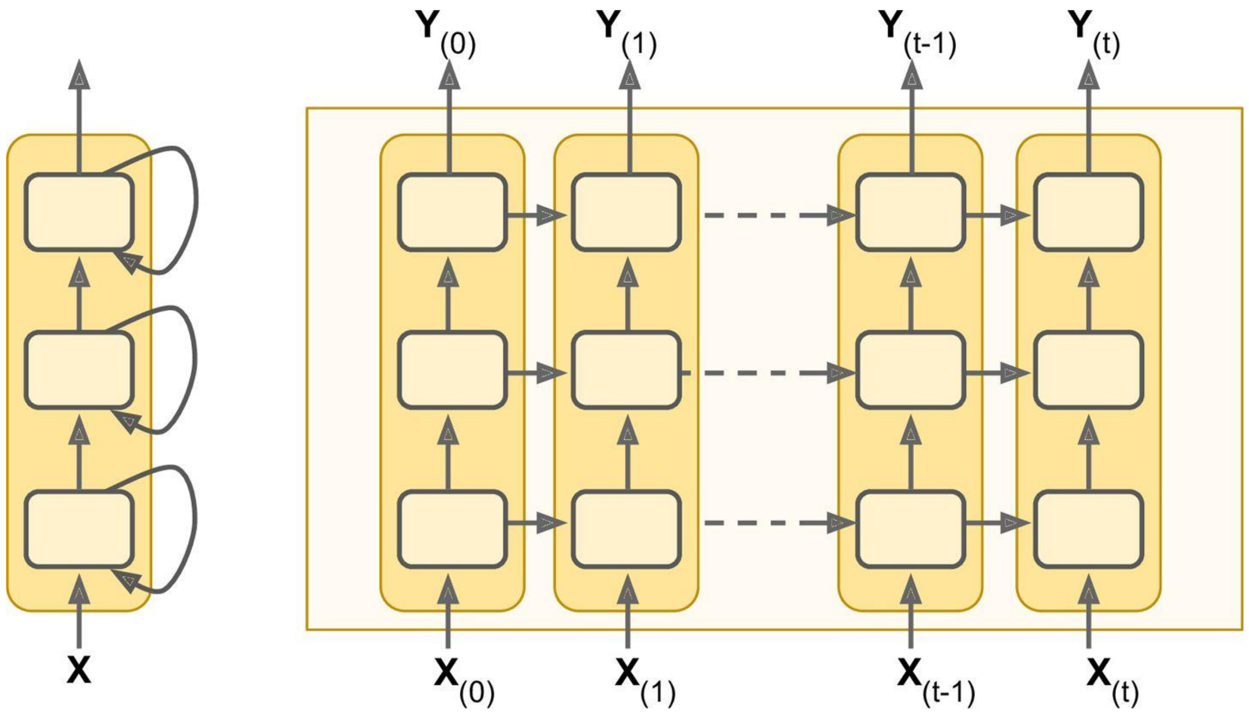
03. Simple RNN





04. Deep RNN (A)

- In Keras, the circulation layer outputs only the final output.
  - ✓ To return the output for each time step, Set setrun_sequences=True



Make sure return_sequence=True for all recurrent layers (except the last one, if you only care about the last output). If you don't, they will output a 2D array (containing only the output of the last time step) instead of a 3D array (containing outputs for all time steps), and the next recurrent layer will complain that you are not feeding it sequences in the expected 3D format.

04. Deep RNN (A)

```
m4 = keras.models.Sequential([
    keras.layers.SimpleRNN(20, return_sequences=True, input_shape=[None, 1]),
    keras.layers.SimpleRNN(20, return_sequences=True),
    keras.layers.SimpleRNN(1)
])
```

```
Model: "sequential_6"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
simple_rnn_2 (SimpleRNN)     (None, None, 20)          440
_________________________________________________________________
simple_rnn_3 (SimpleRNN)     (None, None, 20)          820
_________________________________________________________________
simple_rnn_4 (SimpleRNN)     (None, 1)                 22
=================================================================
Total params: 1,282
Trainable params: 1,282
Non-trainable params: 0
_________________________________________________________________
```

04. Deep RNN (A)

```
m4.evaluate(X_valid, y_valid)
```

```
63/63 [==============================] - 1s 15ms/step - loss: 0.0029

0.0029105639550834894
```

```
m4 = keras.models.Sequential([
    keras.layers.SimpleRNN(20, return_sequences=True, input_shape=[None, 1]),
    keras.layers.SimpleRNN(20, return_sequences=True),
    keras.layers.SimpleRNN(1)
])
```

05. Deep RNN with only single output (unit)

- remove return_sequences = True
  - ✓ it must have a single unit because we want to forecast a univariate time series, and this means we must have a single output value per time step.
  - ✓ However, having a single unit means that the hidden state is just a single number.
  - ✓ That’s really not much, and it’s probably not that useful; presumably, the RNN will mostly use the hidden states of the other recurrent layers to carry over all the information it needs from time step to time step, and it will not use the final layer’s hidden state very much
- Use Dense layer
  - ✓ Simple RNN use tanh(x) activation function (from -1 to 1)
  - ✓ it might be preferable to replace the output layer with a Dense layer

05. Deep RNN with only single output (unit)

```
m5 = keras.models.Sequential([
    keras.layers.SimpleRNN(20, return_sequences=True, input_shape=[None, 1]),
    keras.layers.SimpleRNN(20),
    keras.layers.Dense(1)
])
```

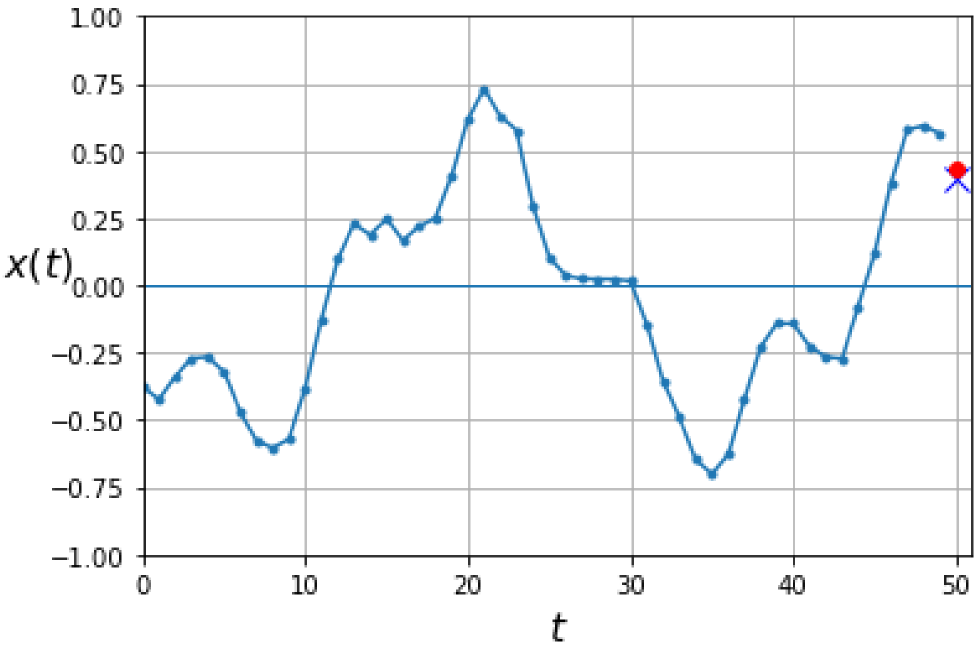
```
m5.summary()
```

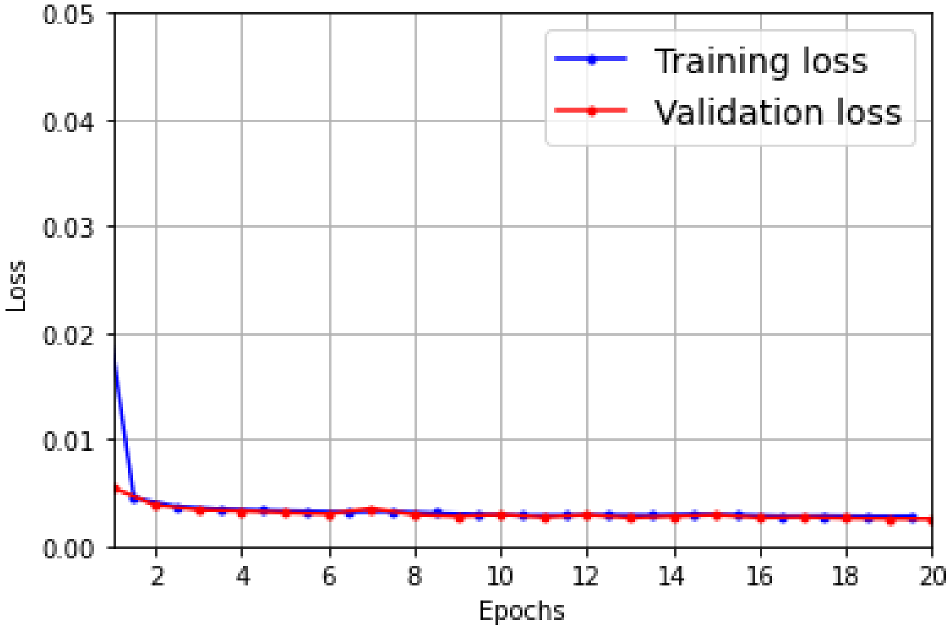
```
Model: "sequential_8"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
simple_rnn_7 (SimpleRNN)     (None, None, 20)          440
_________________________________________________________________
simple_rnn_8 (SimpleRNN)     (None, 20)                820
_________________________________________________________________
dense_5 (Dense)              (None, 1)                 21
=================================================================
Total params: 1,281
Trainable params: 1,281
Non-trainable params: 0
_________________________________________________________________
```

05. Deep RNN with only single output (unit)

- If you train this model, you will see that it converges faster and performs just as well. Plus, you could change the output activation function if you wanted.

Out[45]: 0.002527124481275677





Results Summary of many-to-one

Results Summary of many-to-one ¶

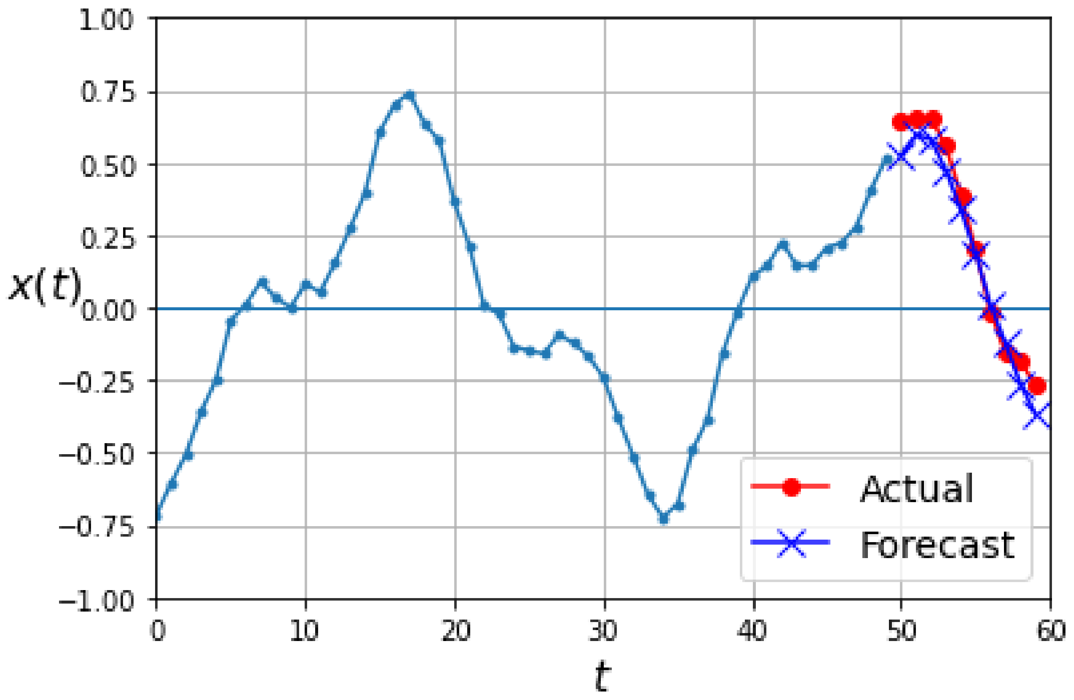
In [47]:

```
models = pd.DataFrame({
    'Model': ['Flatten',  'SimpleRNN','DeepRNN','DeepRNNDense'],
    'Score': [a1, a2, a3, a4]})
models.sort_values(by='Score', ascending=True)
```

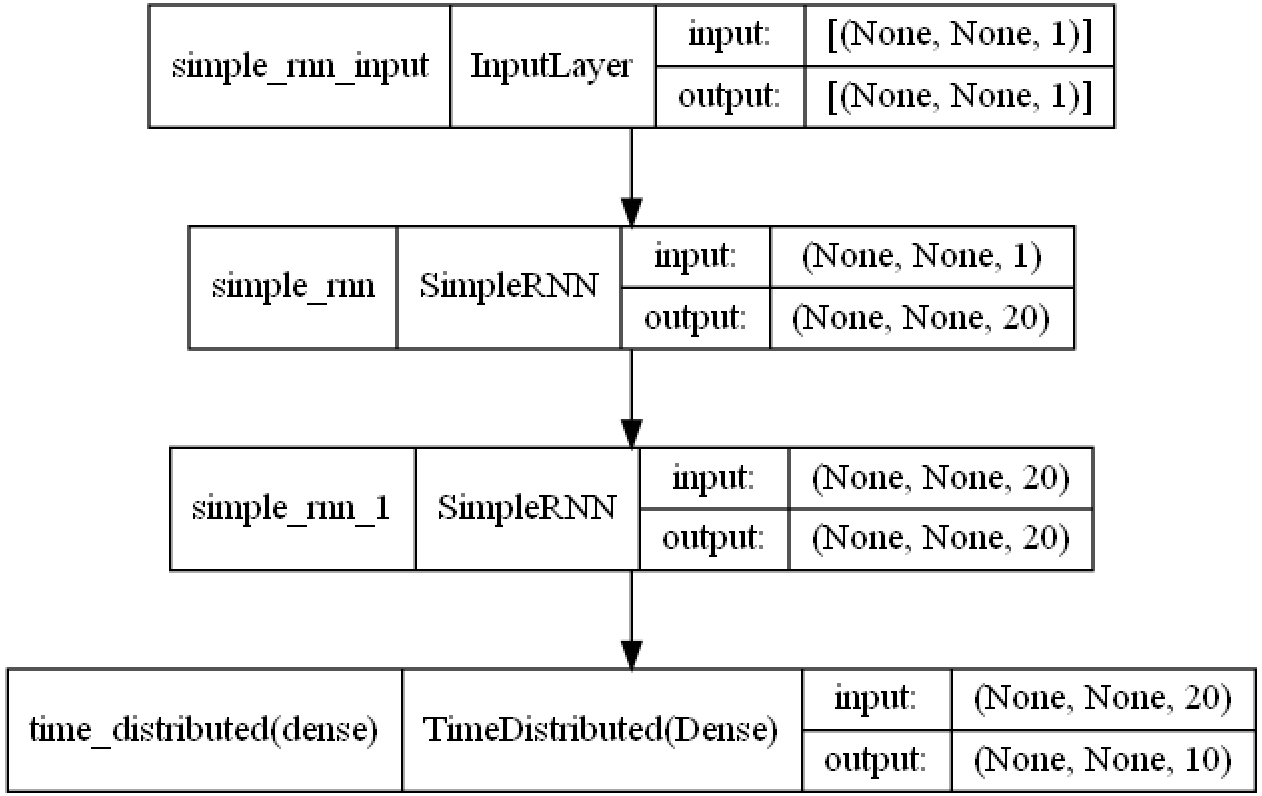
Out[47]:

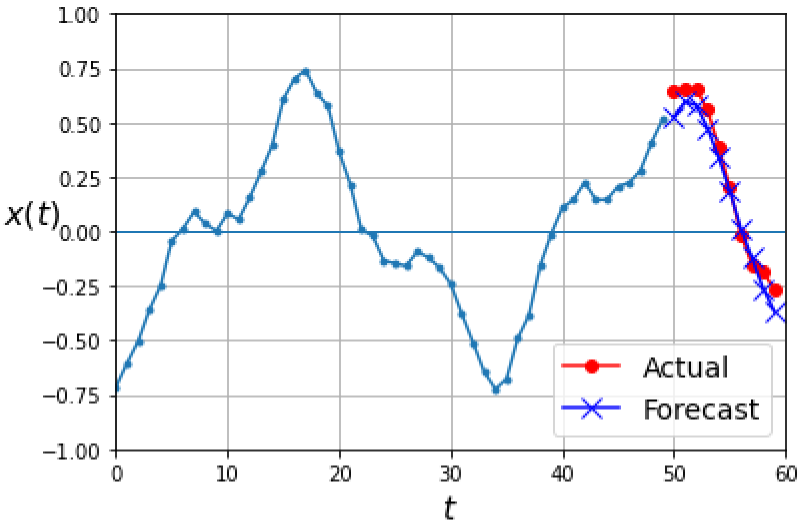
	Model	Score
3	DeepRNNDense	0.003076
2	DeepRNN	0.003980
0	Flatten	0.010993
1	SimpleRNN	0.018042

PART B: Many-to-Many

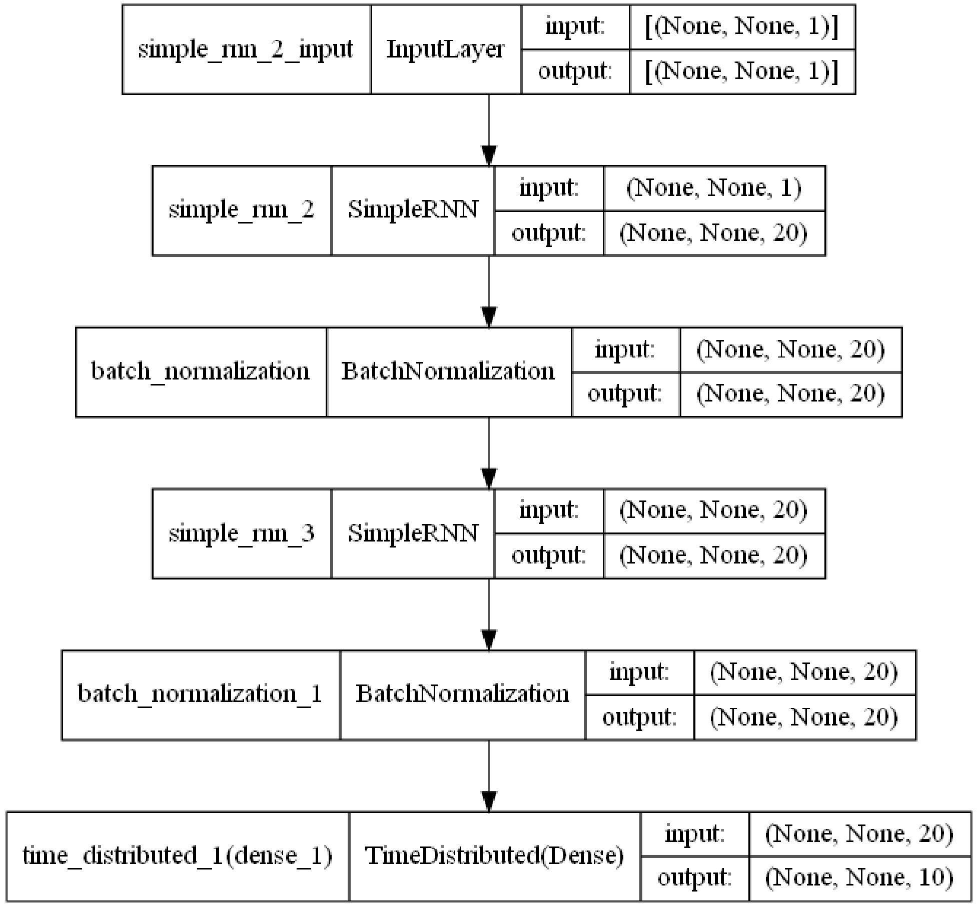


B1. Simple RNN

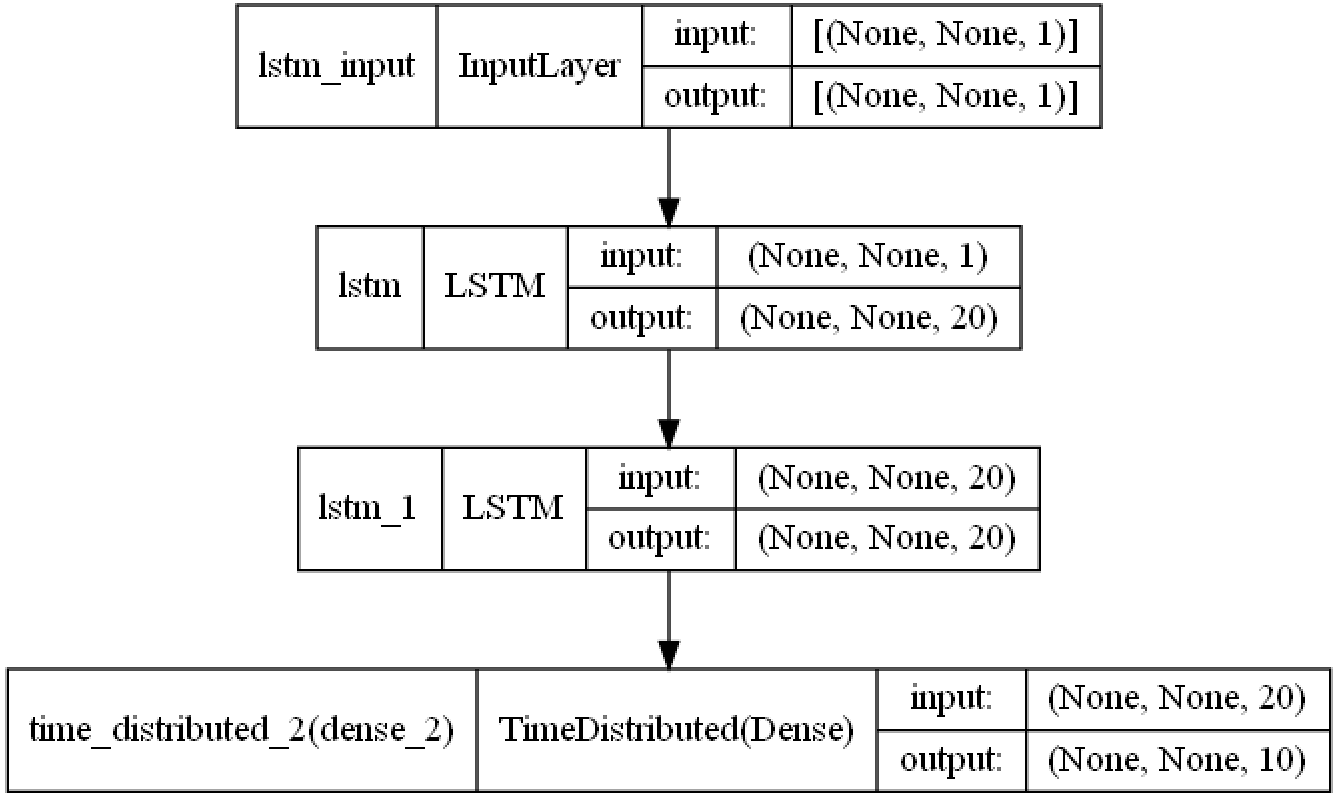




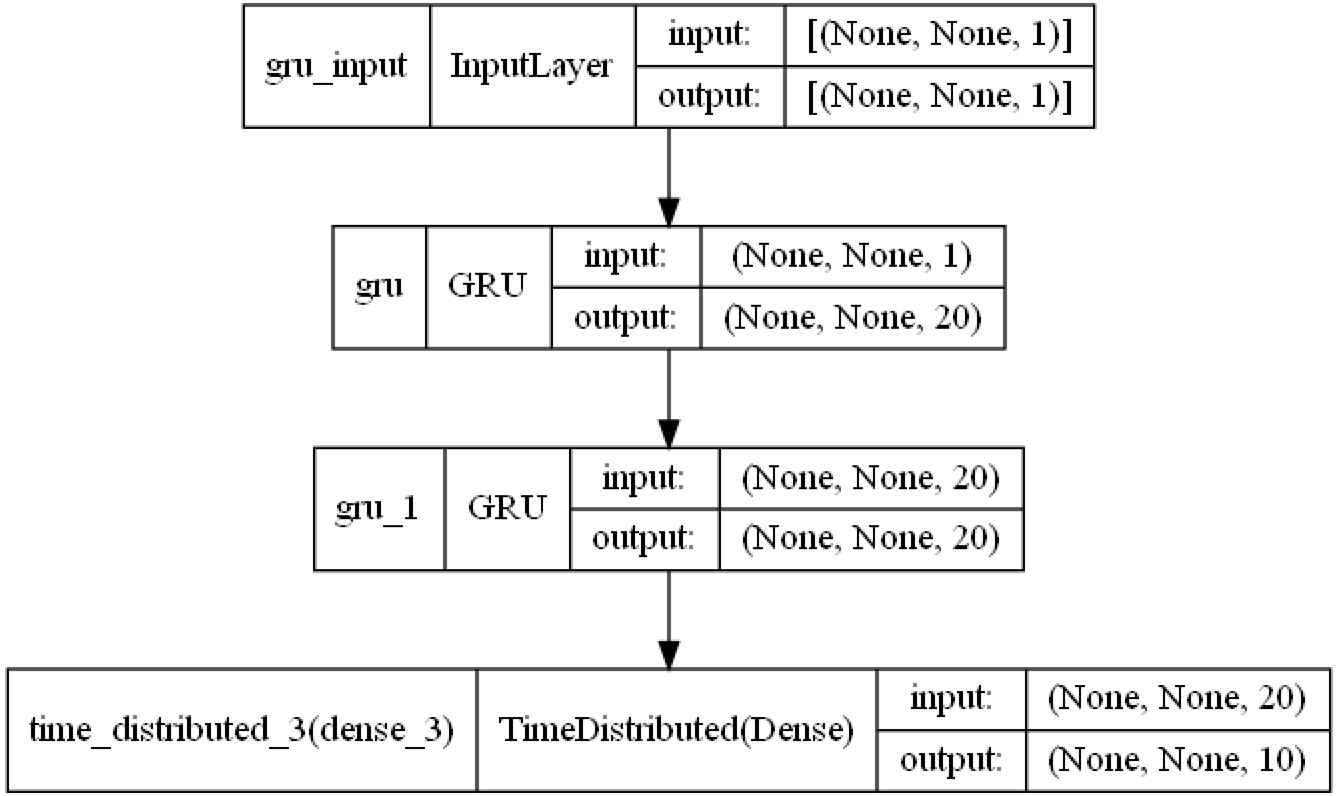
B2. Deep RNN with Batch Norm



B3. LSTM


lstm_input
InputLayer
input:
[(None, None, 1)]
output:
[(None, None, 1)]
lstm
LSTM
input:
(None, None, 1)
output:
(None, None, 20)
lstm_1
LSTM
input:
(None, None, 20)
output:
(None, None, 20)
time_distributed_2(dense_2)
TimeDistributed(Dense)
input:
(None, None, 20)
output:
(None, None, 10)

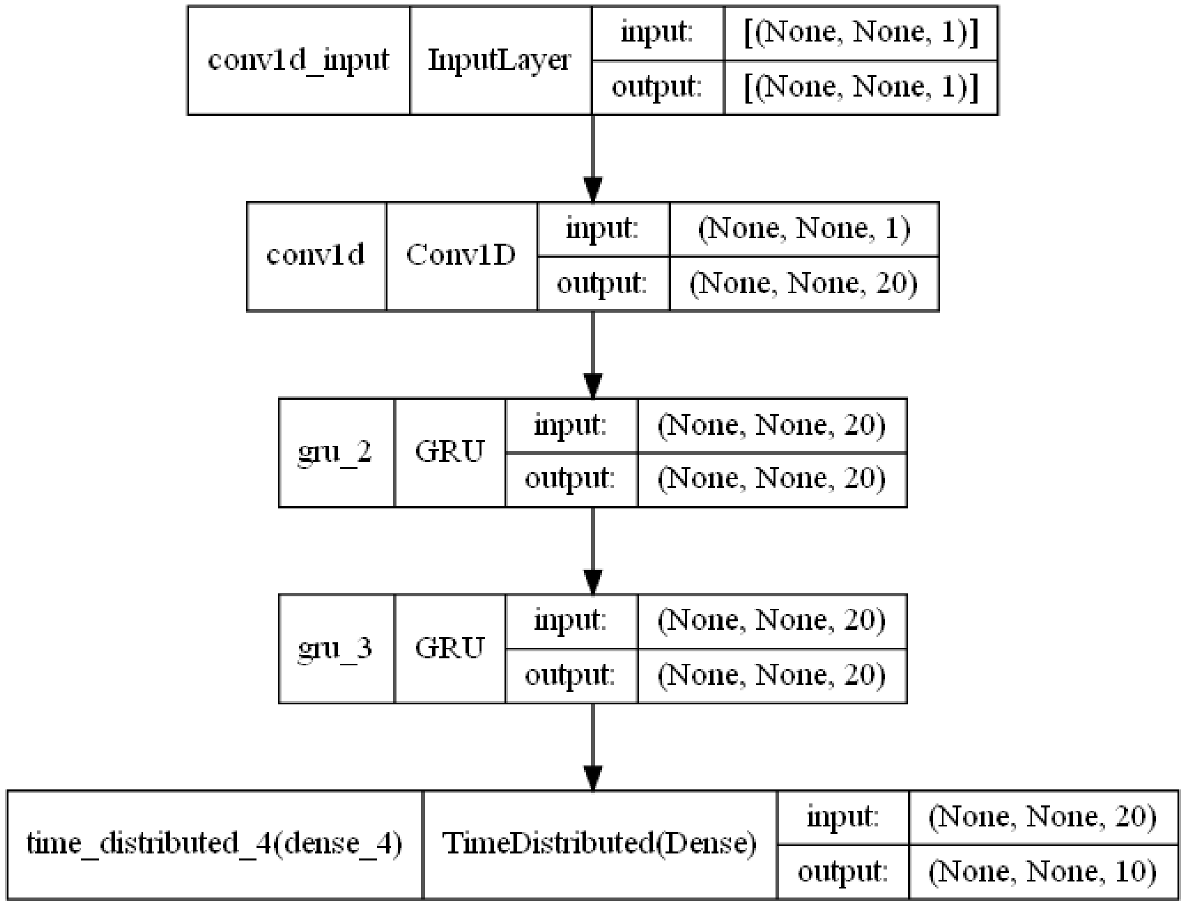
B4. GRU


gru_input
InputLayer
input:
[(None, None, 1)]
output:
[(None, None, 1)]
gru
GRU
input:
(None, None, 1)
output:
(None, None, 20)
gru_1
GRU
input:
(None, None, 20)
output:
(None, None, 20)
time_distributed_3(dense_3)
TimeDistributed(Dense)
input:
(None, None, 20)
output:
(None, None, 10)

B5. 1D-CNN

```
1D conv layer with kernel size 4, stride 2, VALID padding:

               |-----2-----|     |-----5---...------|     |-----23----|
         |-----1-----|     |-----4-----|   ...       |-----22----|
   |-----0----|      |-----3-----|     |---...|-----21----|
X: 0   1   2   3   4   5   6   7   8   9   10 11 12 ... 42 43 44 45 46 47 48 49
Y: 1   2   3   4   5   6   7   8   9   10 11 12 13 ... 43 44 45 46 47 48 49 50
  /10 11  12  13  14  15  16  17  18  19  20 21 22 ... 52 53 54 55 56 57 58 59

Output:

X:      0/3   2/5   4/7   6/9   8/11 10/13 .../43 42/45 44/47 46/49
Y:      4/13  6/15  8/17 10/19 12/21 14/23 .../53 46/55 48/57 50/59
```

B5. 1D-CNN

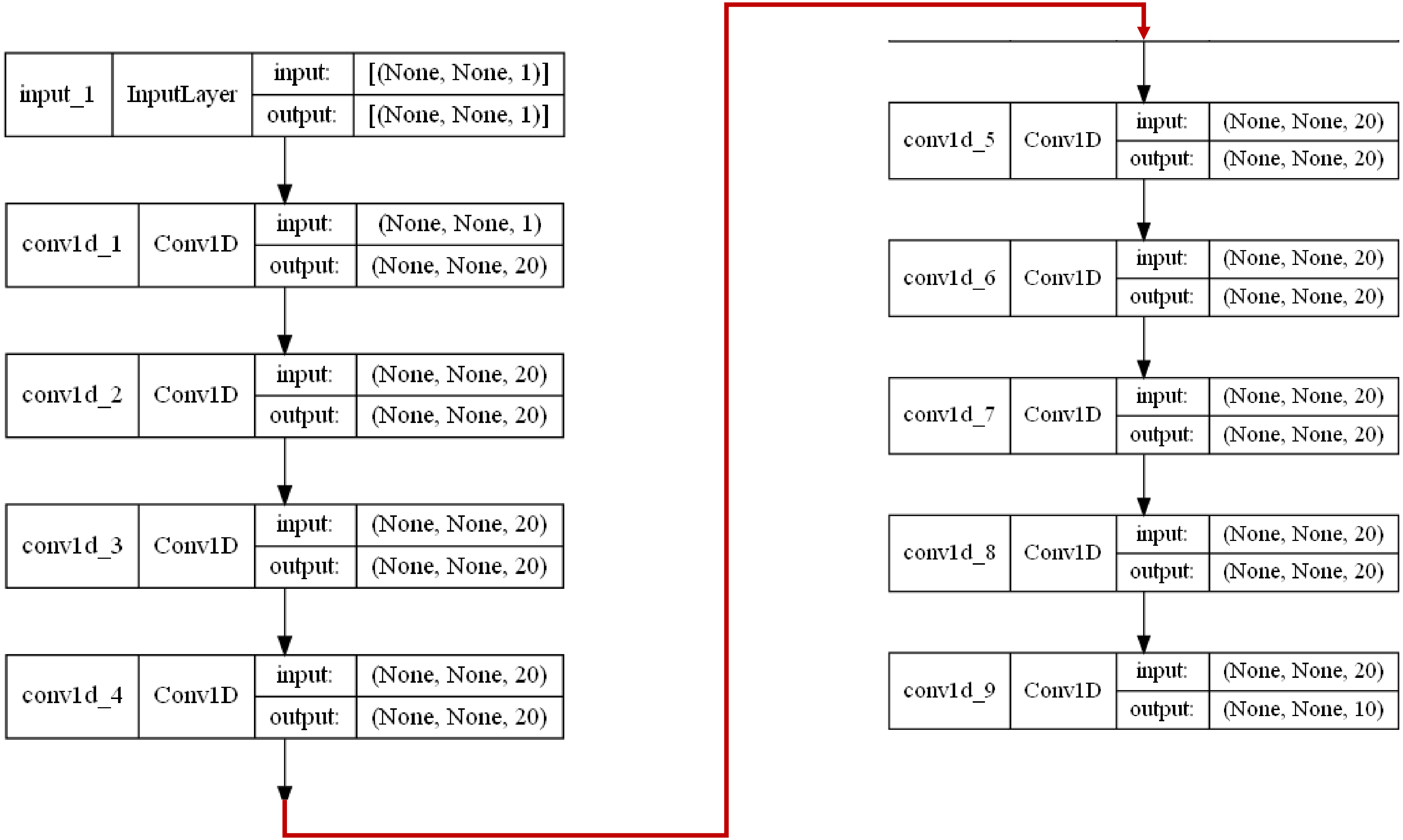


conv1d_input
InputLayer
input:
[(None, None, 1)]
output:
[(None, None, 1)]
conv1d
Conv1D
input:
(None, None, 1)
output:
(None, None, 20)
gru_2
GRU
input:
(None, None, 20)
output:
(None, None, 20)
gru_3
GRU
input:
(None, None, 20)
output:
(None, None, 20)
time_distributed_4(dense_4)
TimeDistributed(Dense)
input:
(None, None, 20)
output:
(None, None, 10)

B6. WaveNet

```
C2   /₩ /₩ /₩ /₩ /₩ /₩ /₩ /₩ /₩ /₩ /₩ /₩ /₩.../₩ /₩ /₩ /₩ /₩ /₩
      ₩  /  ₩  /  ₩  /  ₩  /  ₩  /  ₩  /  ₩       /  ₩  /  ₩  /  ₩
        /    ₩       /    ₩       /    ₩                /    ₩
C1   /₩ /₩ /₩ /₩ /₩ /₩ /₩ /₩ /₩ /₩ /₩  /₩ /.../₩ /₩ /₩ /₩ /₩ /₩ /₩
X:  0  1  2  3  4  5  6  7  8  9  10 11 12 ... 43 44 45 46 47 48 49
Y:  1  2  3  4  5  6  7  8  9  10 11 12 13 ... 44 45 46 47 48 49 50
   /10 11 12 13 14 15 16 17 18 19 20 21 22 ... 53 54 55 56 57 58 59
```

B6. WaveNet



input_1
InputLayer
input:
[(None, None, 1)]
output:
[(None, None, 1)]
conv1d_1
Conv1D
input:
(None, None, 1)
output:
(None, None, 20)
conv1d_2
Conv1D
input:
(None, None, 20)
output:
(None, None, 20)
conv1d_3
Conv1D
input:
(None, None, 20)
output:
(None, None, 20)
conv1d_4
Conv1D
input:
(None, None, 20)
output:
(None, None, 20)
conv1d_5
Conv1D
input:
(None, None, 20)
output:
(None, None, 20)
conv1d_6
Conv1D
input:
(None, None, 20)
output:
(None, None, 20)
conv1d_7
Conv1D
input:
(None, None, 20)
output:
(None, None, 20)
conv1d_8
Conv1D
input:
(None, None, 20)
output:
(None, None, 20)
conv1d_9
Conv1D
input:
(None, None, 20)
output:
(None, None, 10)

Results Summary of Many-to-Many : PART B

In [50]:

```python
models = pd.DataFrame({
    'Model': ['SimpleRNN', 'DeepRNN',  'LSTM', 'GRU', '1D-CNN', 'WaveNet'],
    'Score': [b1, b2, b3, b4, b5, b6]})
models.sort_values(by='Score', ascending=True)
```

Out [50]:

	Model	Score
4	1D-CNN	0.026147
5	WaveNet	0.026312
0	SimpleRNN	0.027985
2	LSTM	0.033550
3	GRU	0.036676
1	DeepRNN	0.042562