KiSTi 한국과학기술정보연구원 Korea Institute of Science and Technology Information

2022

Deep Learning based Text Processing

Lec 09: Introduction to Recurrent Neural Network

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Lecturer

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- affiliation
  - ✓Principal Researcher, Dept. of Data-centric Problem Solving Research, KISTI
  - ✓Professor, Dept. of Applied AI, UST
- Research details
  - ✓Traffic congestion prediction in urban areas based on deep learning (2018-2021)
  - ✓Research on Intelligent Infrastructure Technology (2018~2019)
  - ✓Study on the Transformer Model for Traffic Prediction in Urban Areas (2022-2025)
- Computing technology
  - ✓GPU-based accelerated computing technology: CUDA, OpenCL
  - ✓Supercomputing Parallel Processing Technology: MPI, OpenMP, ManyCore Computing
  - ✓Deep Learning Technology: Tensorflow, PyTorch, Keras, Theano

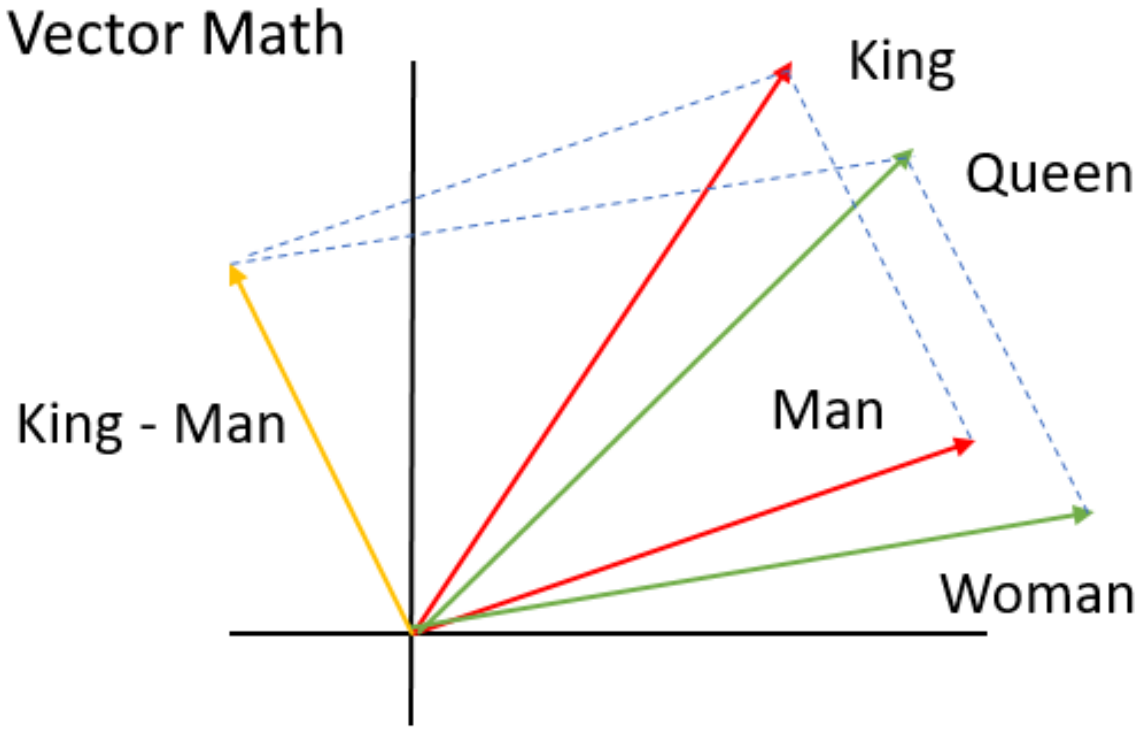
A personal website: sites.google.com/view/deepai/home

Course Materials : github.com/hongsuk.yi
Information : sites.google.com/view/deepai/home
publication :https://www.researchgate.net/profile/Hongsuk-Yi/publications

Reviewing the last time!

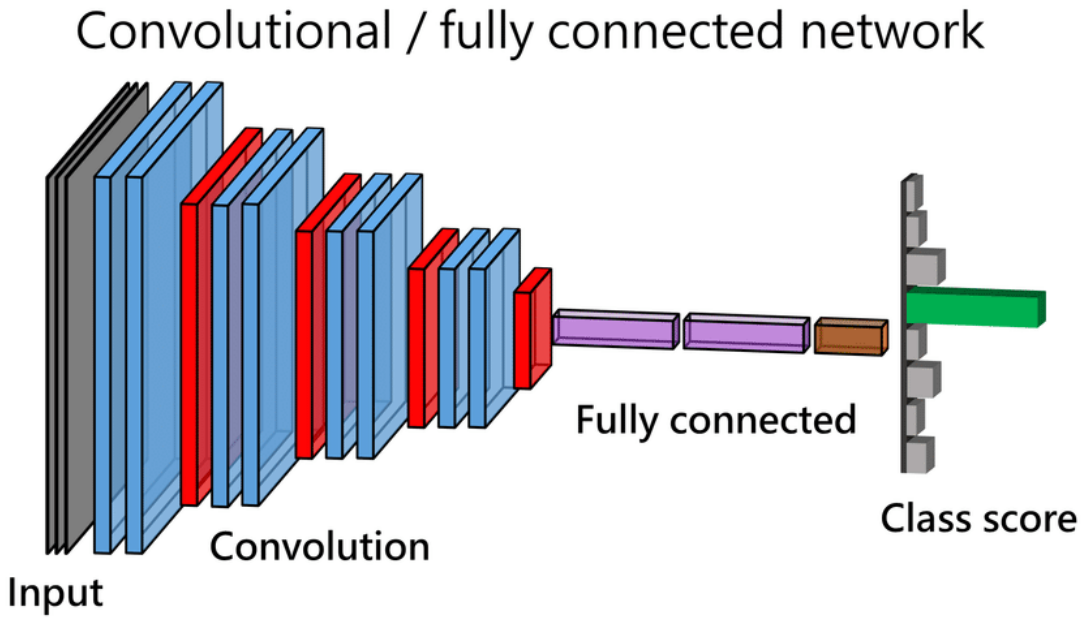
❖ Basic knowledge of NLP

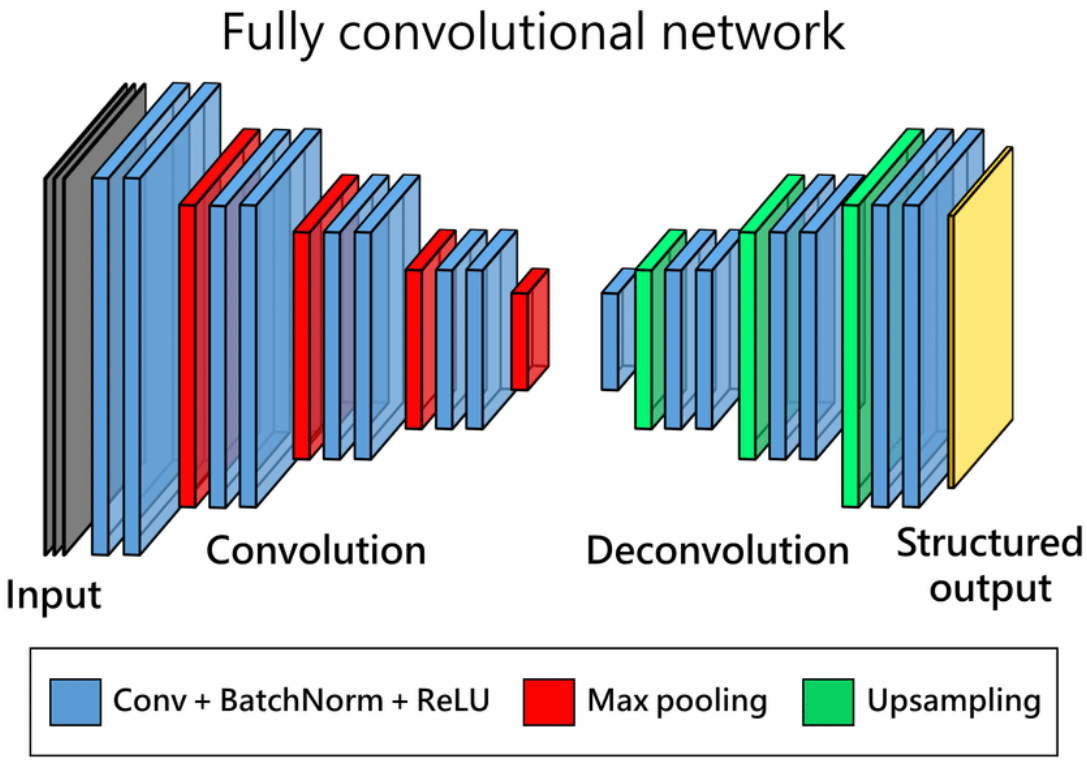
✓ **Word Embedding Theory :** Word2Vec



❖ Text Analysis Practice with FCN

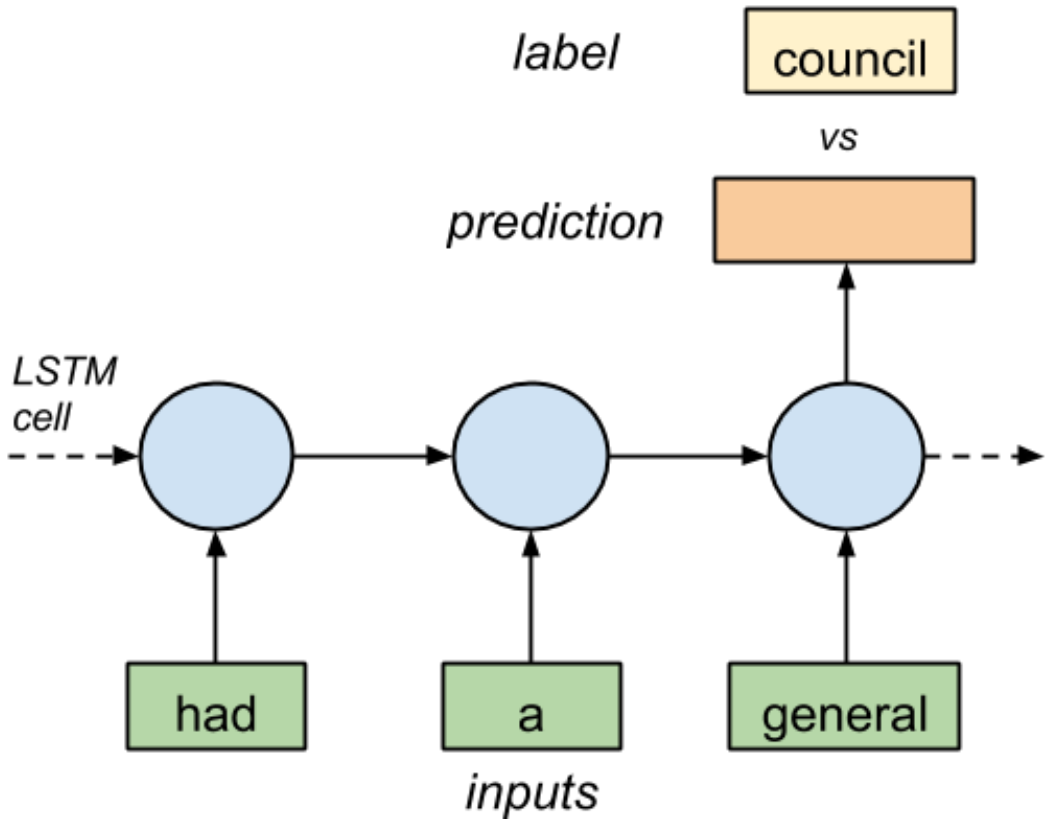
✓The concept of machine learning and deep learning





Sequence Modeling: Design Criteria

- Design criteria to model sequences, we need:
  - ✓RNN meet these sequence modeling design critiera

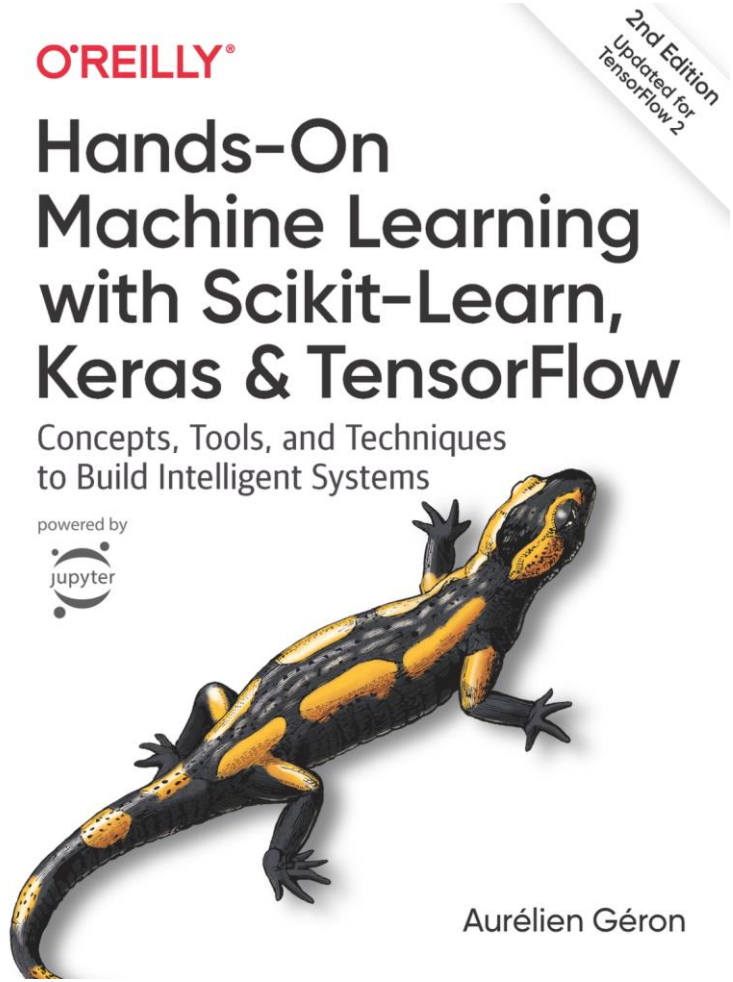


Overview of Course (III)

- **Introduction to Recurrent Neural Network**
  - ✓Simple RNN, BPTT, Memory Cell
  - ✓Code: Implementing an RNN with Keras
- **Introduction to Long-Short Term Memroy**
  - ✓Cell state, LSTM, and GRU, and Applications
  - ✓A Visual Guide to Recurrent Layers in Keras
  - ✓Code: A simple LSTM layers
- **Text generation with RNN**
  - ✓Tokenizer, Character-Level Language model
  - ✓Code: Alice's Adventures in Wonderland
- **Sequence to Sequence model with RNN**
  - ✓Introduction to Seq2Seq and Attention model
  - ✓Code: Character-Level Neural Machine Translation

Introduction to Recurrent Neural Network

Reference Materials

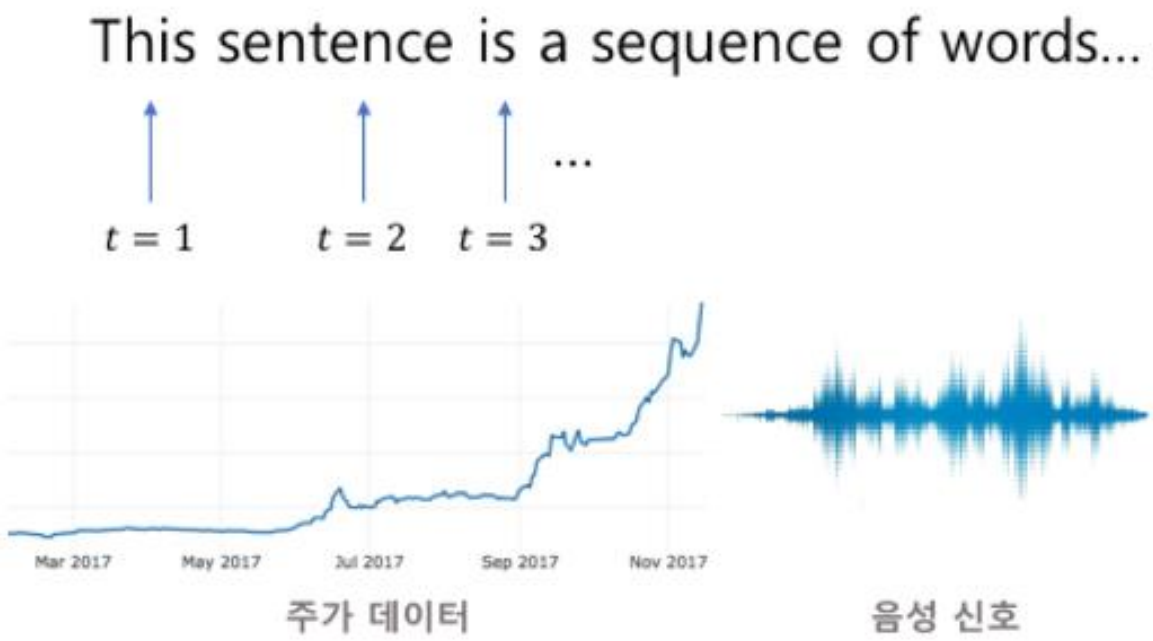


딥 러닝을 이용한 자연어 처리 입문

https://wikidocs.net/book/2155

What is a time series problem?

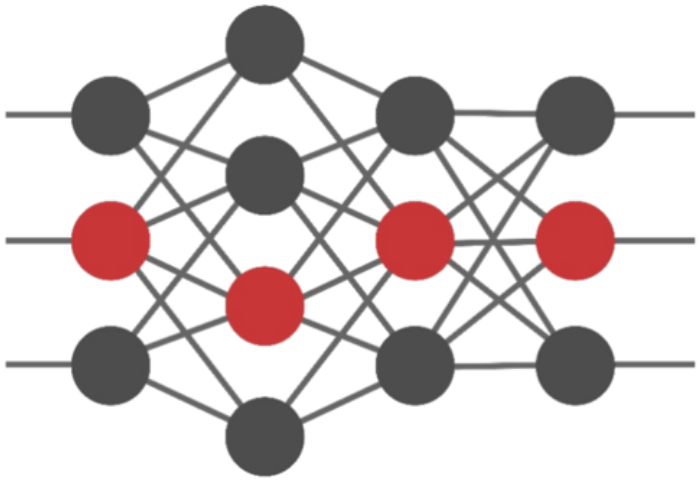
- Time series deals with data over time: Predicting
  - ✓weather (short term forecasts), climate (long term forecasts)

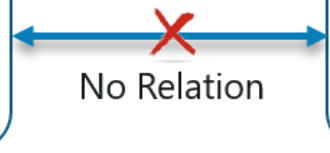


Why Not Feedforward Networks

In the existing FeedForWared Networks,

Input at t-1





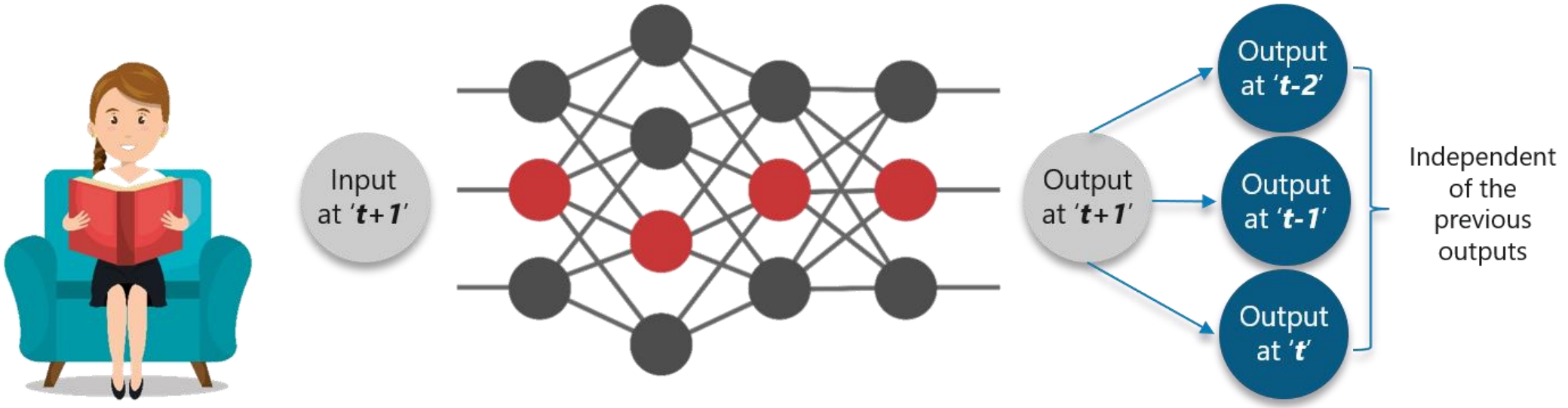
No Relation

Output at 't'

Output at 't-1'

Why Not Feedforward Networks

- If you are reading a book, you should be well aware of the previous page.

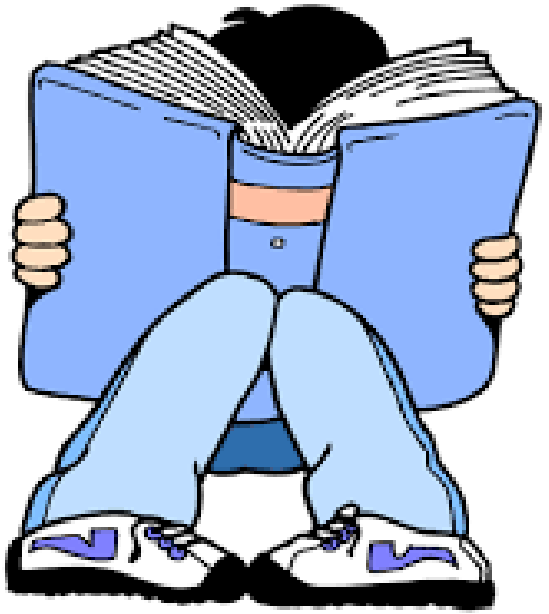


No order when reading a book

- a 10 page picture book

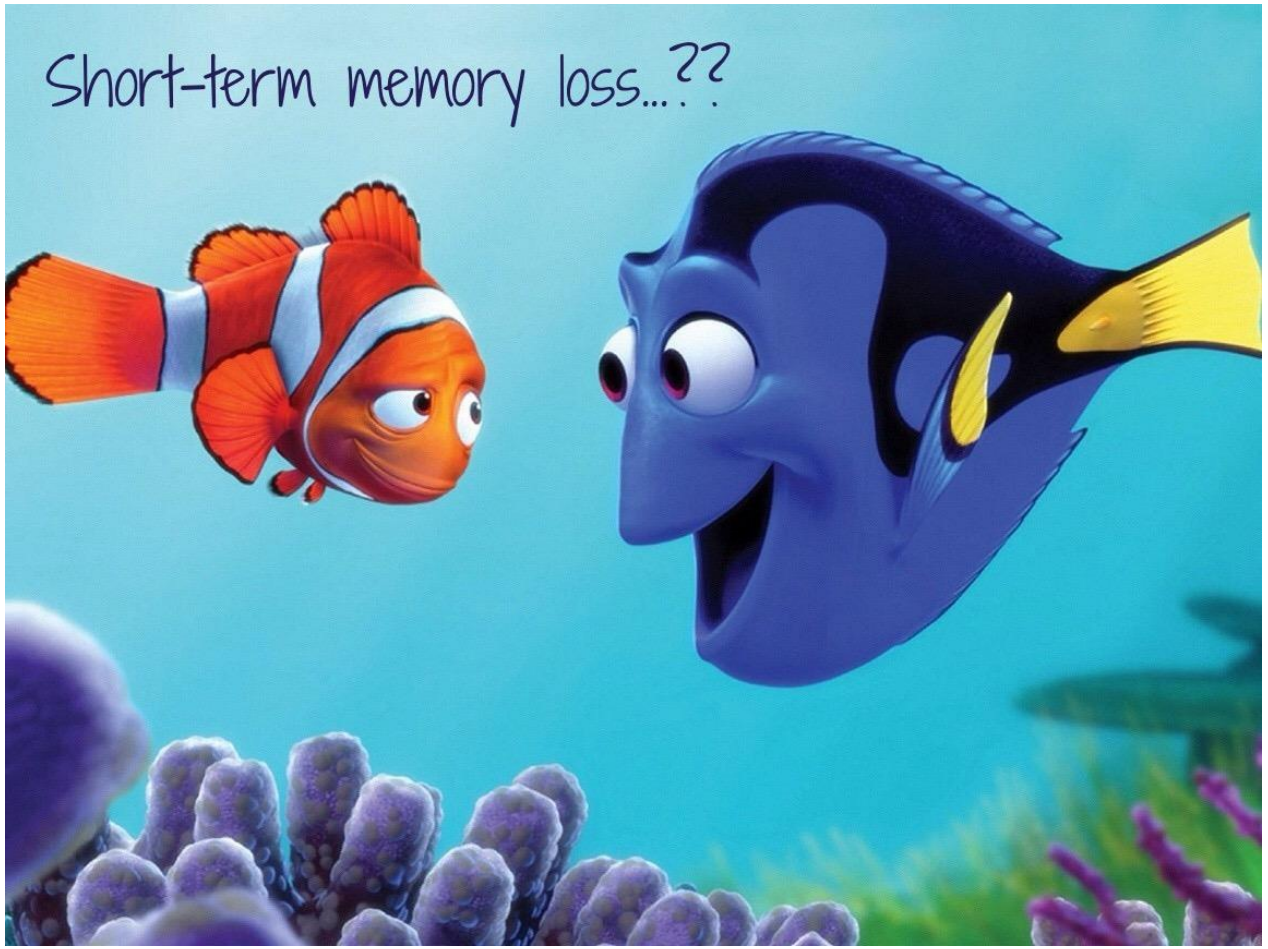
What is Memory

- How much content do you remember?
  - ✓A sime example: History Book
- What is the memory when reading a book
  - ✓Sequence Data Pattern?
  - ✓Memory Cell



When reading a full-length novel

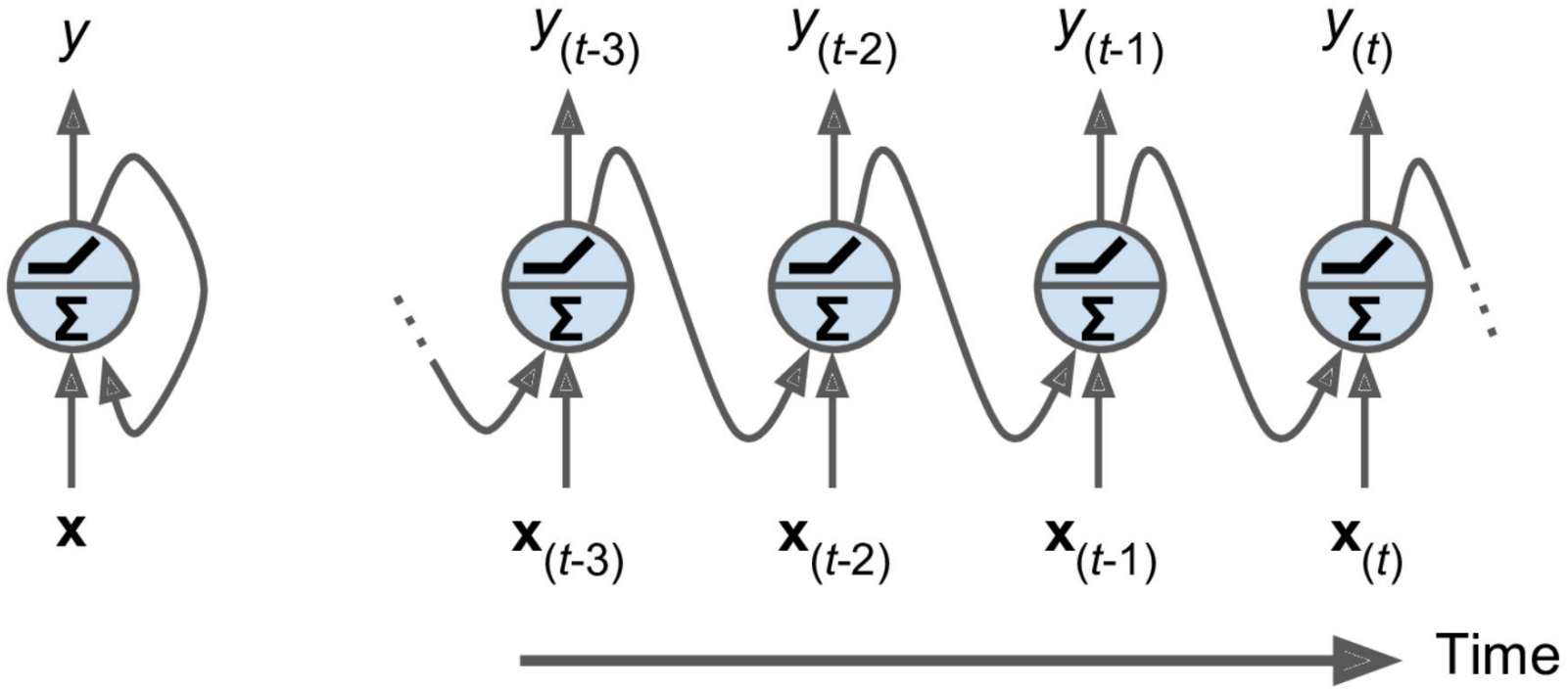
❖ Short-term and Long Term Memory Loss



❖ Attention : No order?

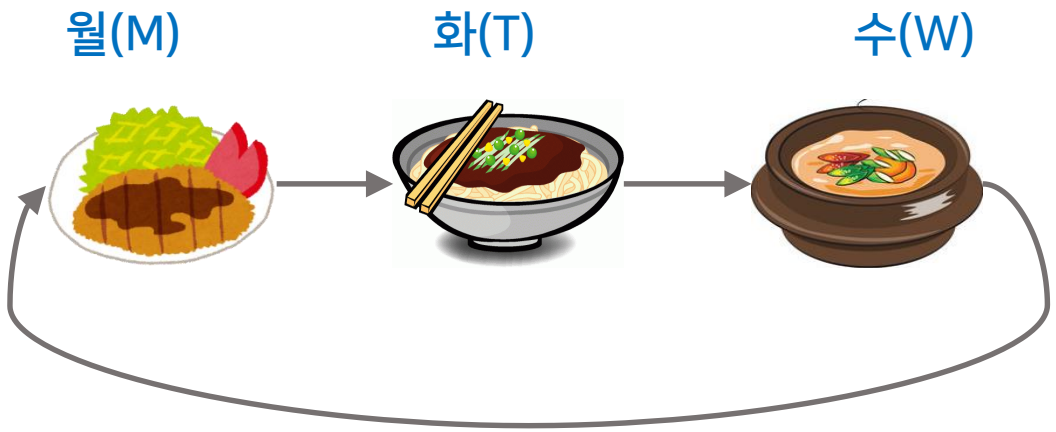
❖ Memory Cells ~ a form of memory

✓ A RNN looks like a feedforward NN, except it also has connections pointing backward.



A simple of RNN (1/3)

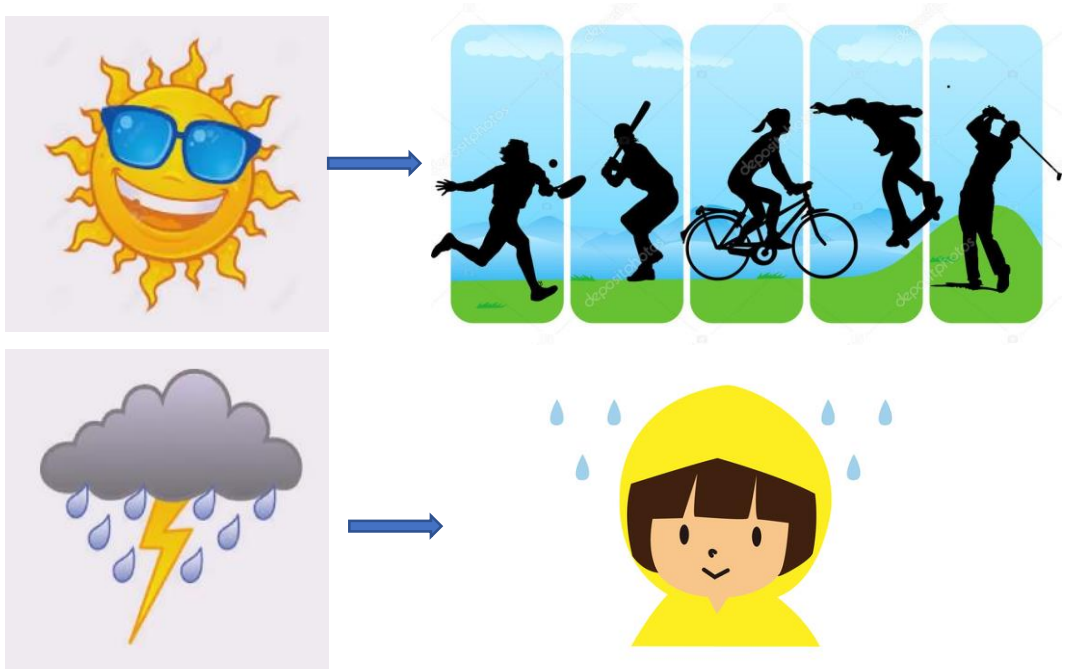
- There is a pattern in dinner.
  - ✓Only three types of meals are available.



RNN = Recurrent Neural Network

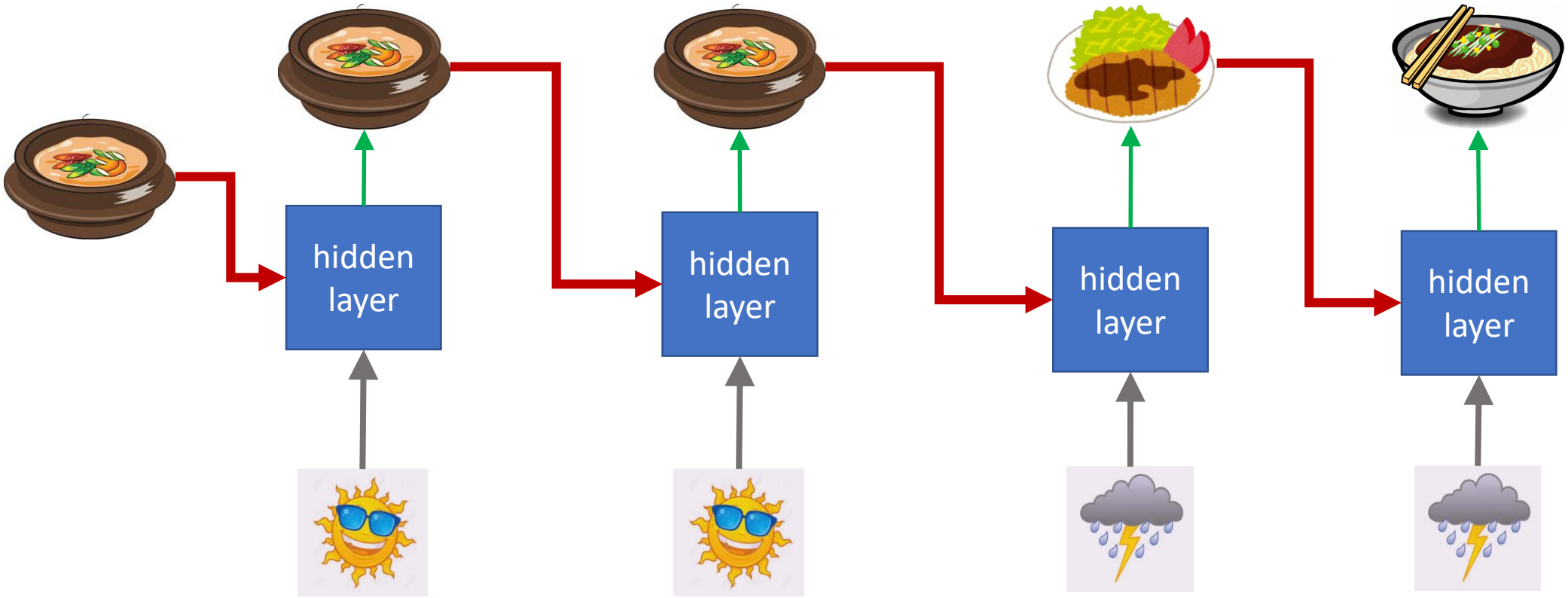
A simple of RNN (2/3)

- The menu varies depending on the weather
  - ✓If the weather is nice, I eat food the day before.
  - ✓When it rains, I eat food according to the pattern



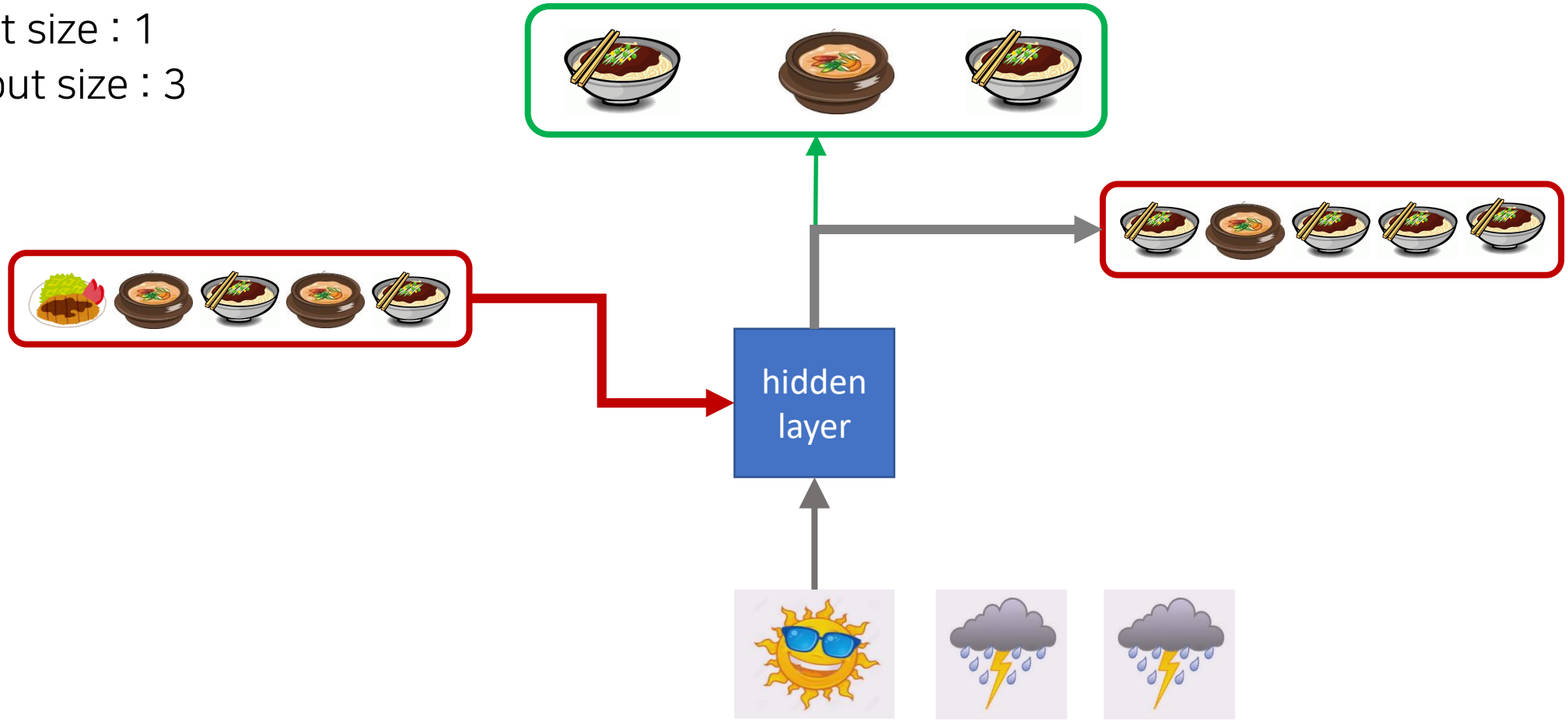
A simple of RNN (3/3)

- You can predict food depending on the weather



❖ A example of Length of memory

- ✓memory size: 5
- ✓input size : 1
- ✓output size : 3



Neurons in RNN

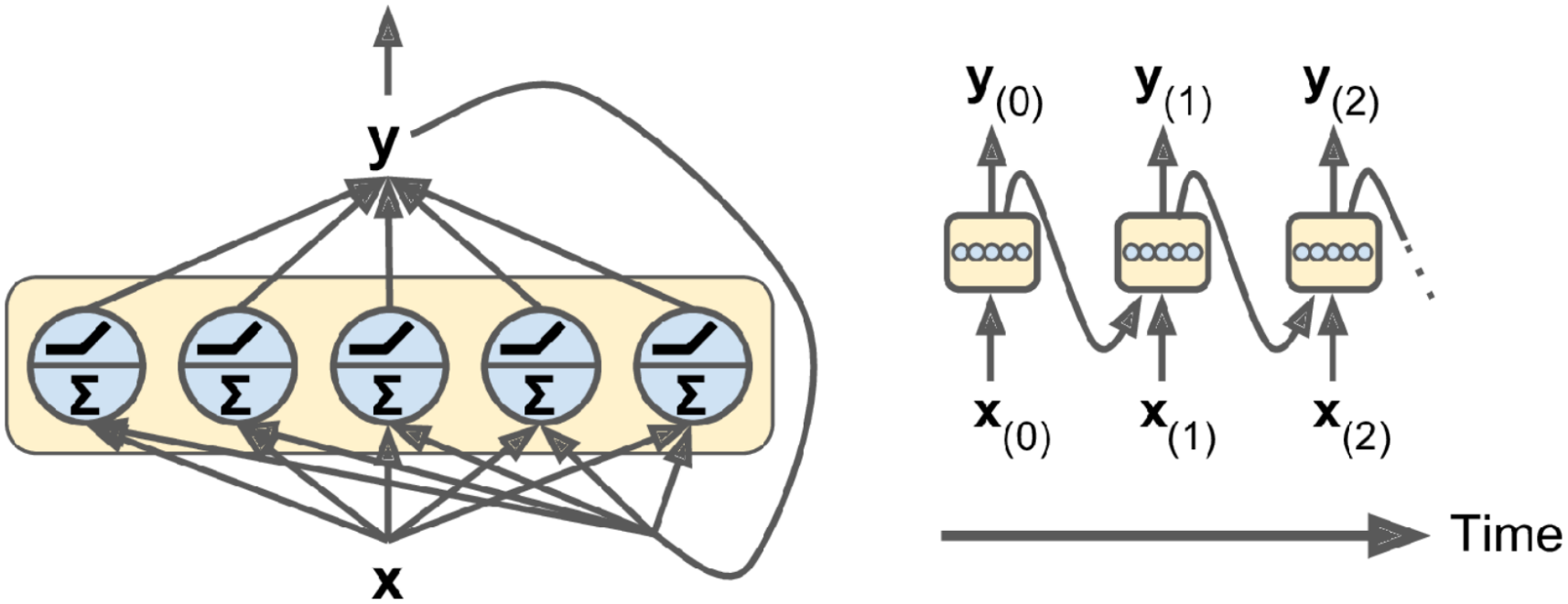
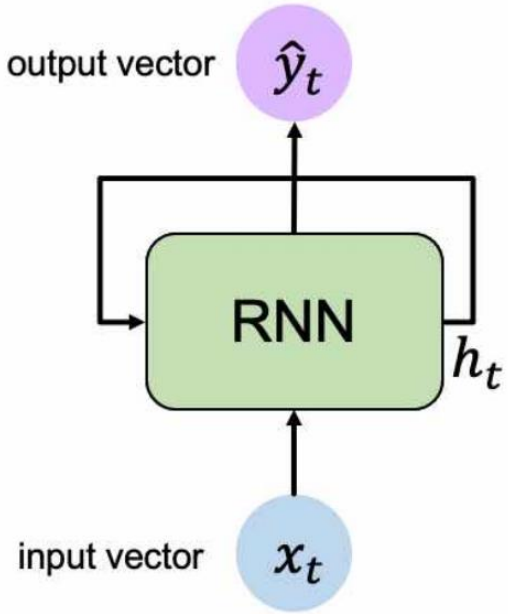


Figure 15-2. A layer of recurrent neurons (left) unrolled through time (right)

$$\mathbf{y}_{(t)} = \phi\left(\mathbf{W}_x{}^{\intercal}\mathbf{x}_{(t)} + \mathbf{W}_y{}^{\intercal}\mathbf{y}_{(t-1)} + \mathbf{b}\right)$$

How to train RNN?

RNN State Update and Output



Output Vector

$$\hat{y}_t = \boldsymbol{W}_{hy}^{T} h_t$$

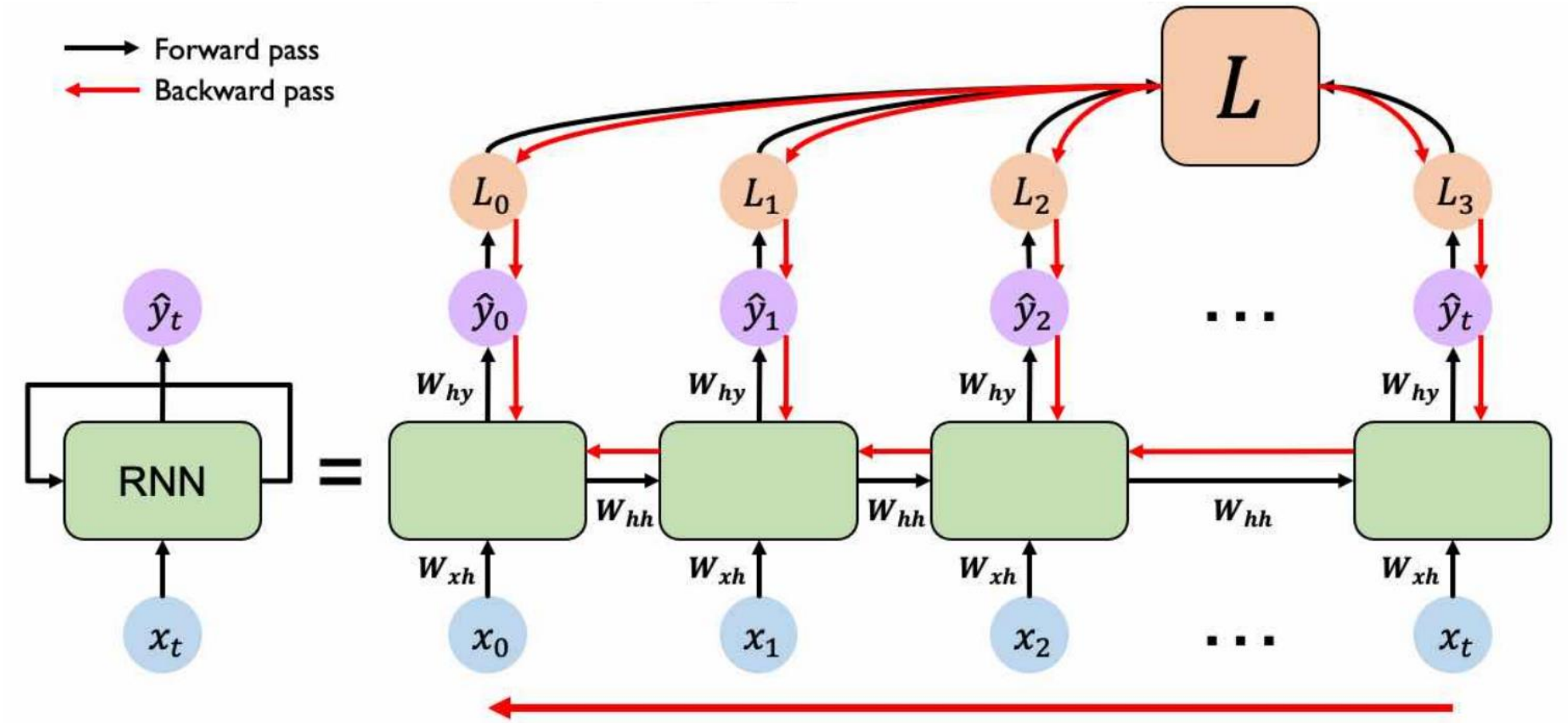
Update Hidden State

$$h_t = \tanh(\boldsymbol{W}_{hh}^{T} h_{t-1} + \boldsymbol{W}_{xh}^{T} x_t)$$

Input Vector

$$x_t$$

BPTT: Backpropagation Through Time



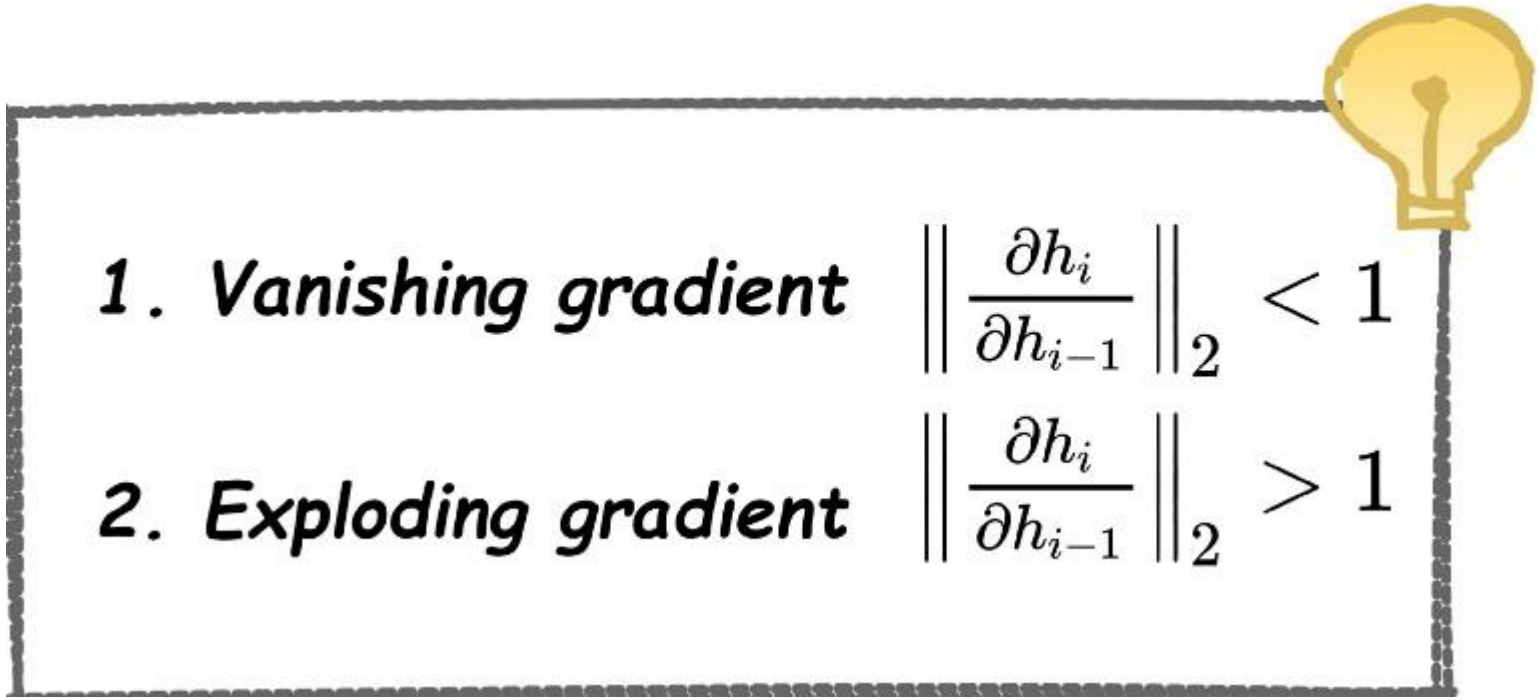
Standard RNN Gradient Flow

$$\frac{\partial L^{(t)}}{\partial \mathbf{W}_{hh}} = \frac{\partial L^{(t)}}{\partial y^{(t)}} \cdot \frac{\partial y^{(t)}}{\partial \mathbf{h}^{(t)}} \cdot \left(\sum_{k=1}^{t} \frac{\partial \mathbf{h}^{(t)}}{\partial \mathbf{h}^{(k)}} \cdot \frac{\partial \mathbf{h}^{(k)}}{\partial \mathbf{W}_{hh}} \right)$$

computed as a multiplication of adjacent time steps:

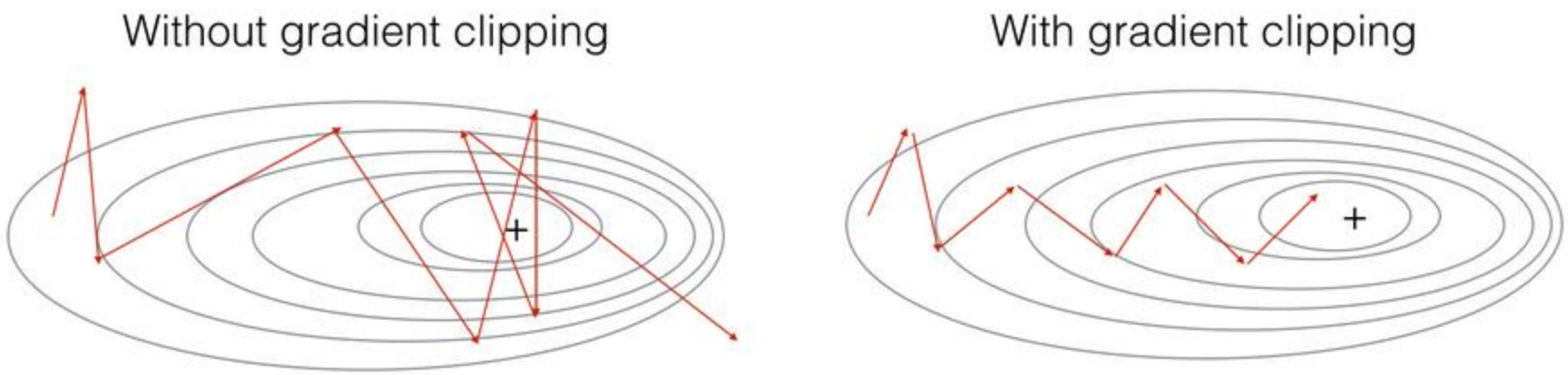
$$\frac{\partial \mathbf{h}^{(t)}}{\partial \mathbf{h}^{(k)}} = \prod_{i=k+1}^{t} \frac{\partial \mathbf{h}^{(i)}}{\partial \mathbf{h}^{(i-1)}}$$

RNN suffer from the problem of VGP and EGP



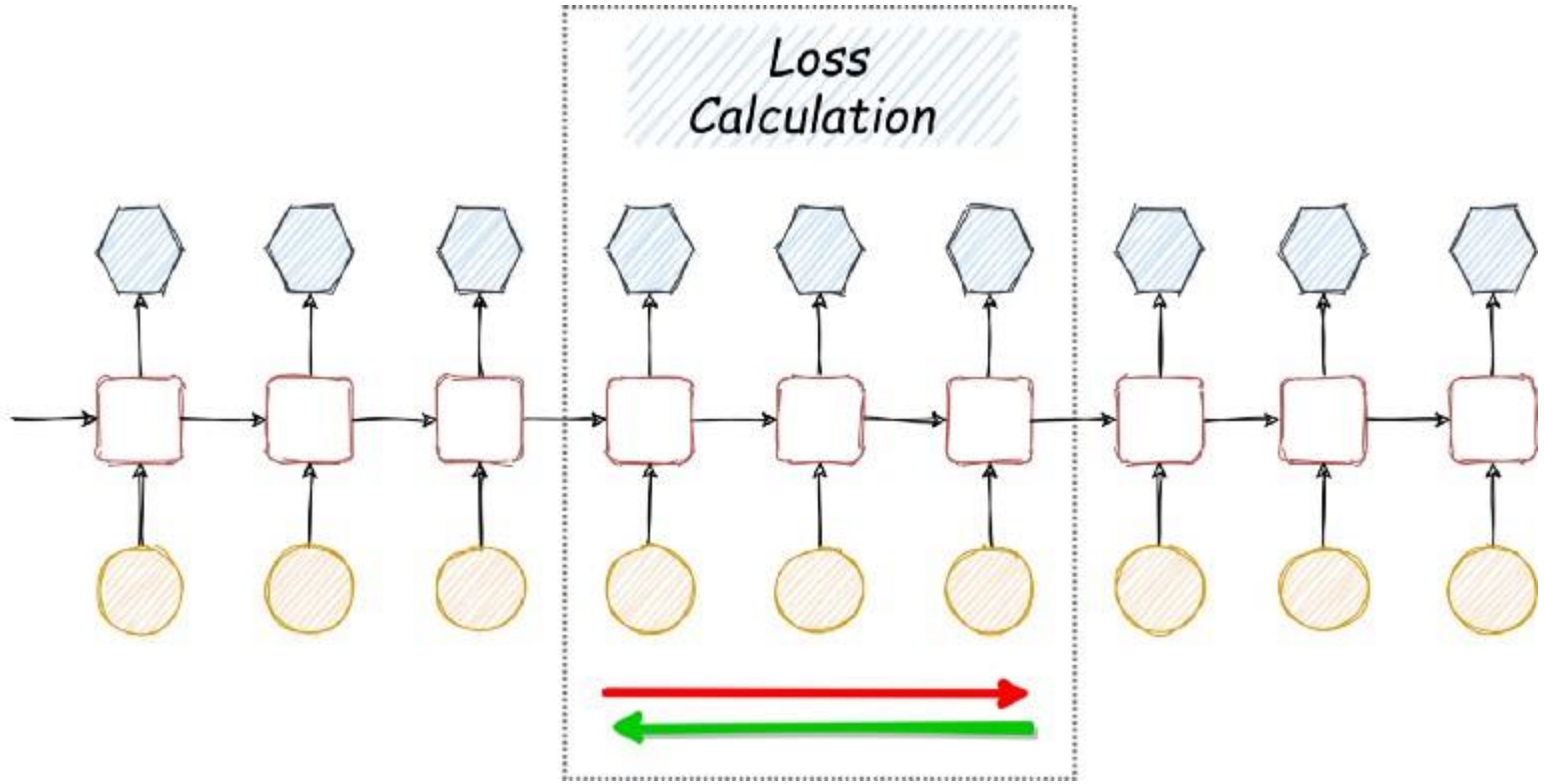
Solutions

- Truncated backpropagation through time (TBPTT)
- Long short-term memory (LSTM)
- Gradient Clipping



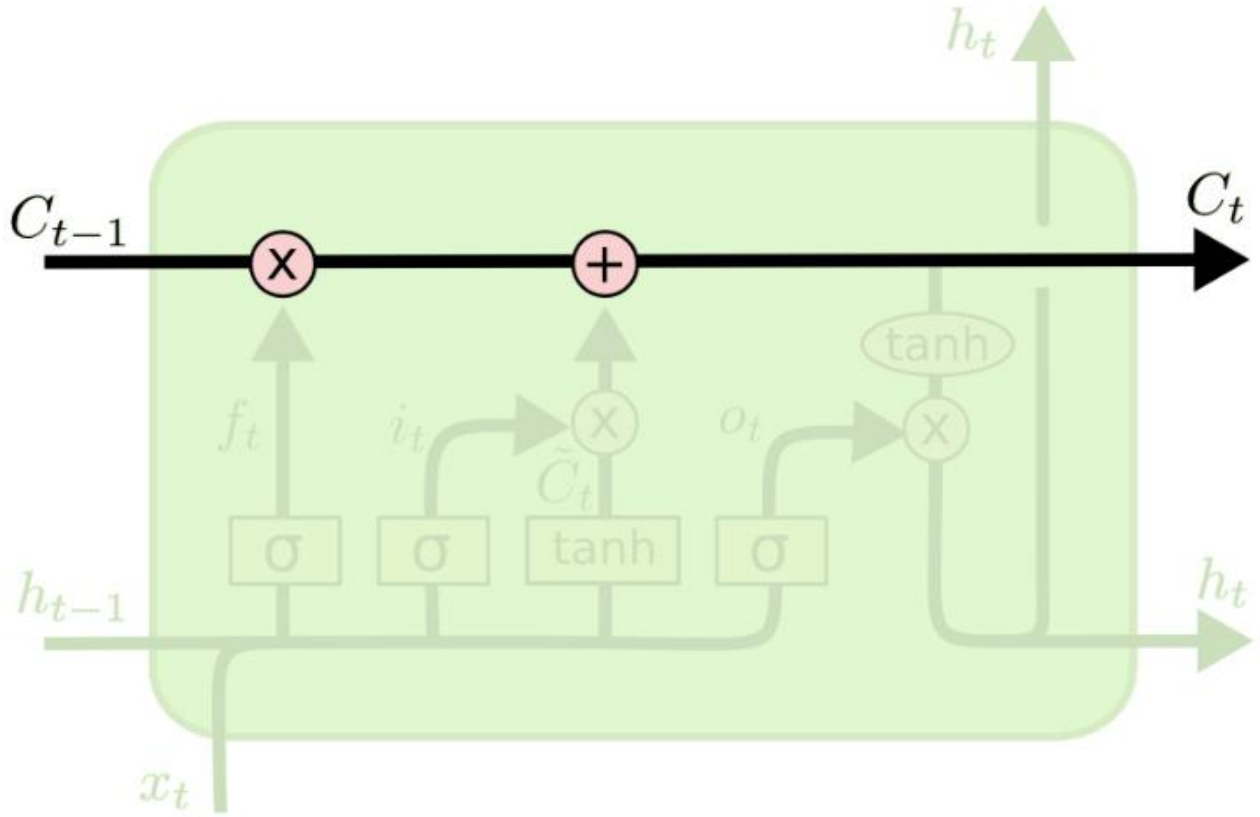
Truncated Backpropagation Through Time

- TBPTT: Truncated BPTT trick by considering a moving window through the training process

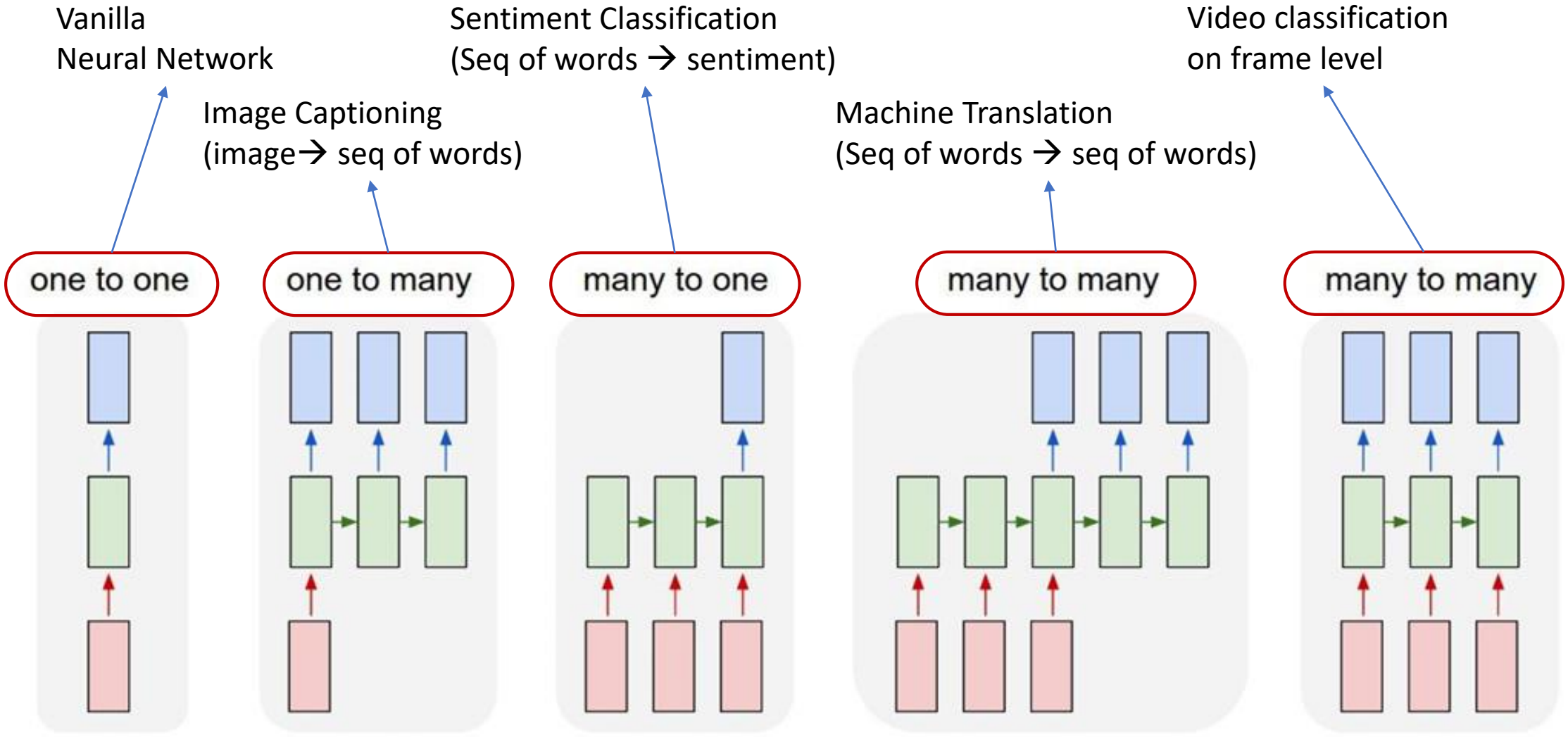


LSTMs

- Capable of learning long-term dependencies by remembering information
- Cell state



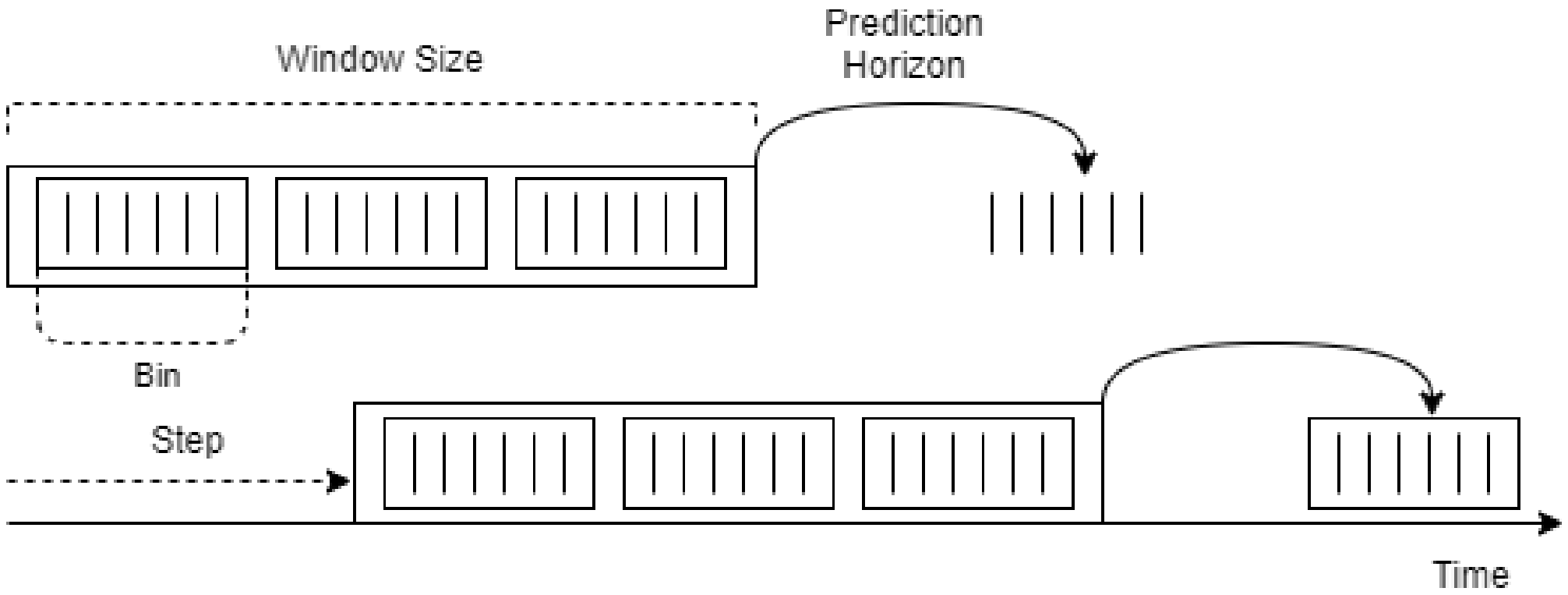
Recurrent Neural Networks: Process Sequences



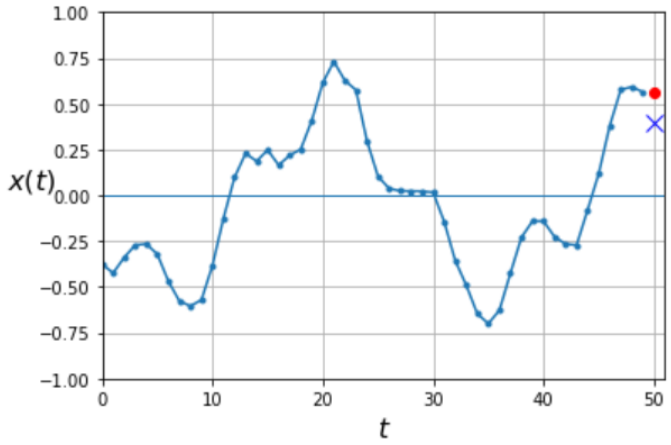
RNN Hyperparameters

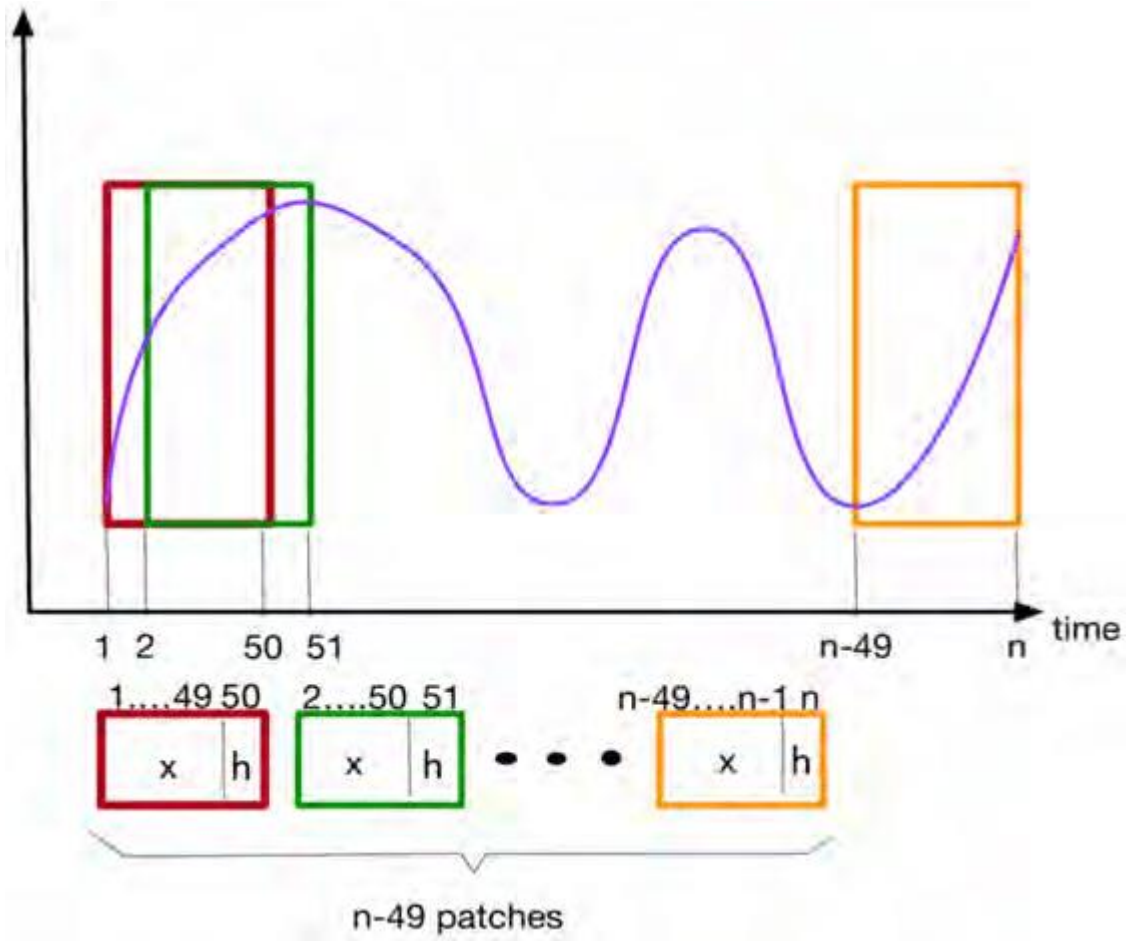
Modelling Experiments

- Two terms are really important in the type of forecasting model :
  - ✓**Window Size** :The number of timesteps we take to predict into the future
  - ✓**Horizon** : The number of timesteps ahead into the future we predict.

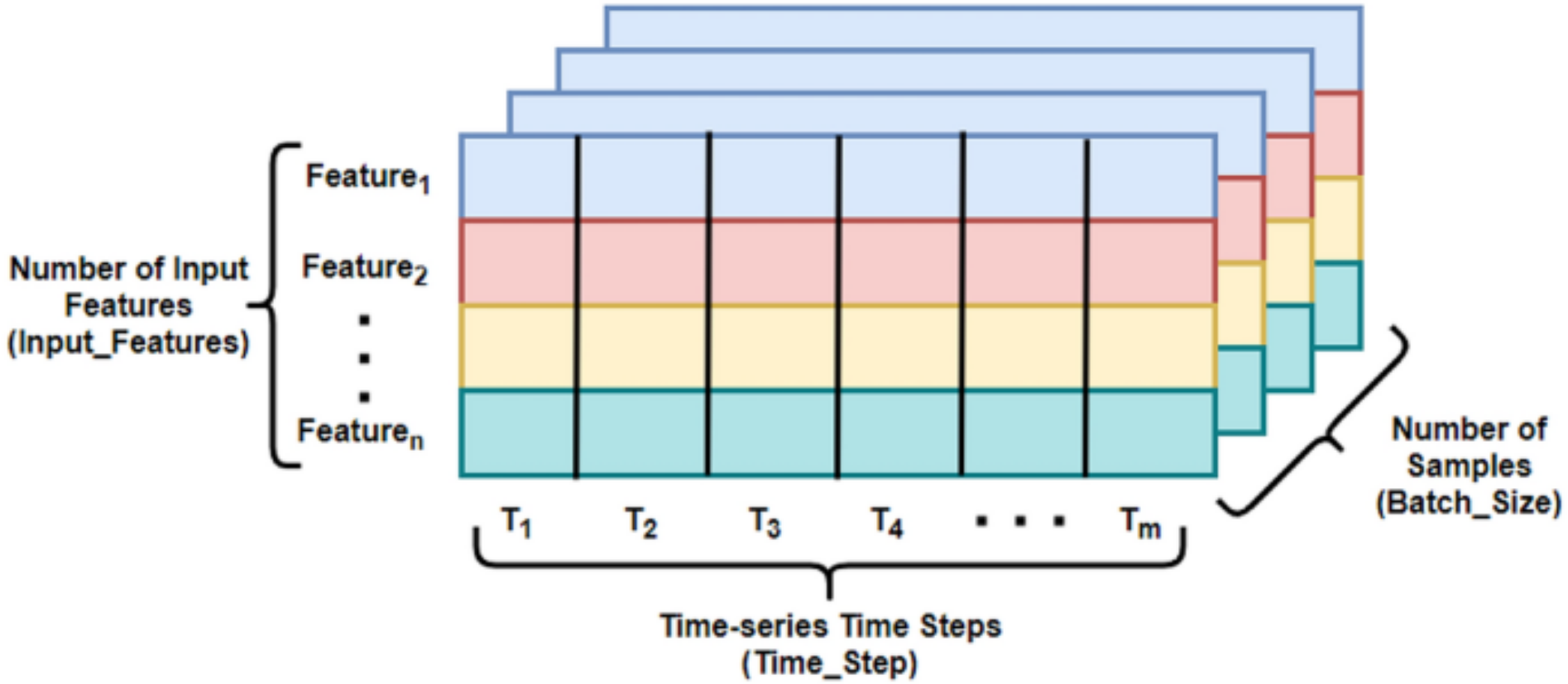


RNN Sliding window size and horizon



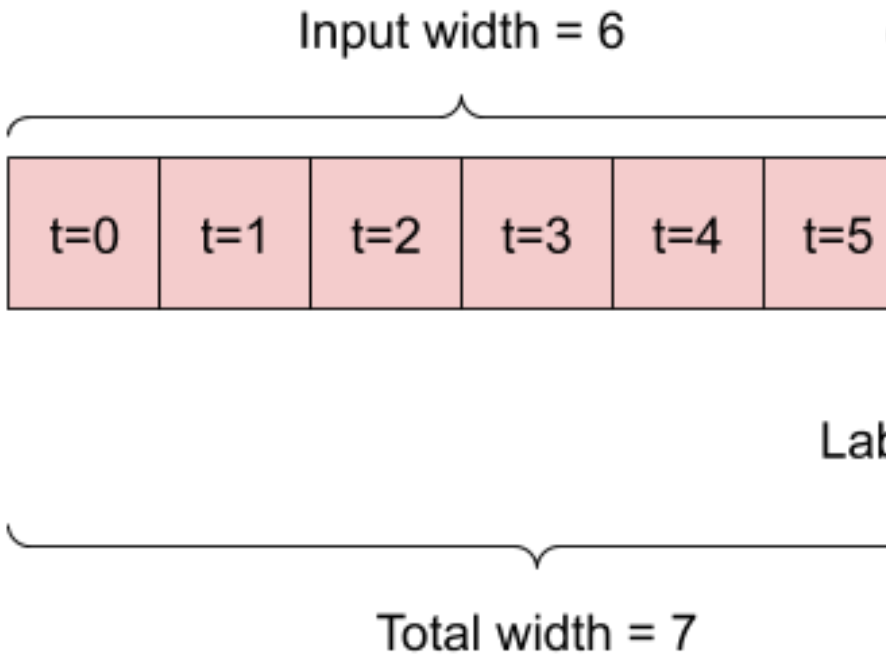


❖ RNN Input Data



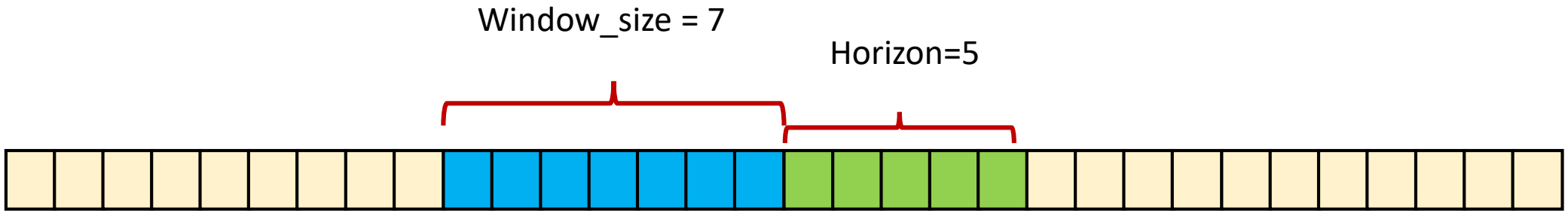
Data windowing

- A model : prediction one hour into the future, given six hours of history

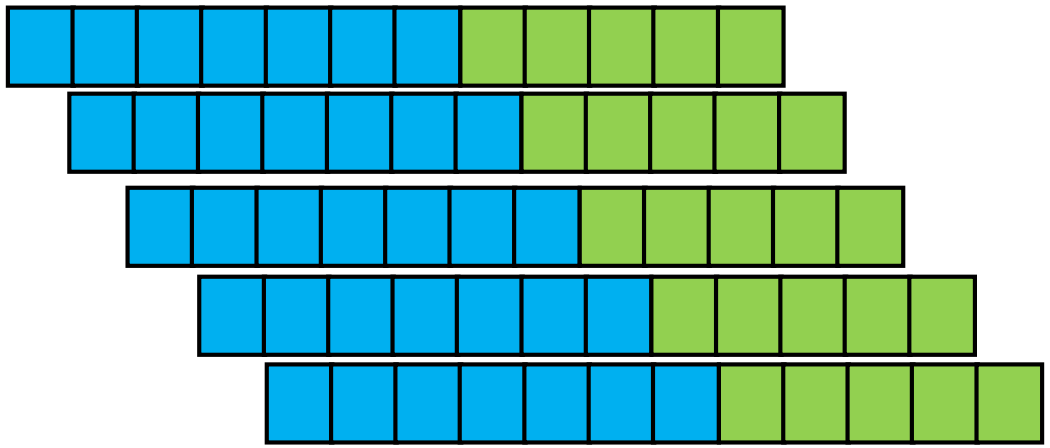


Many-to-One RNN Data Structure

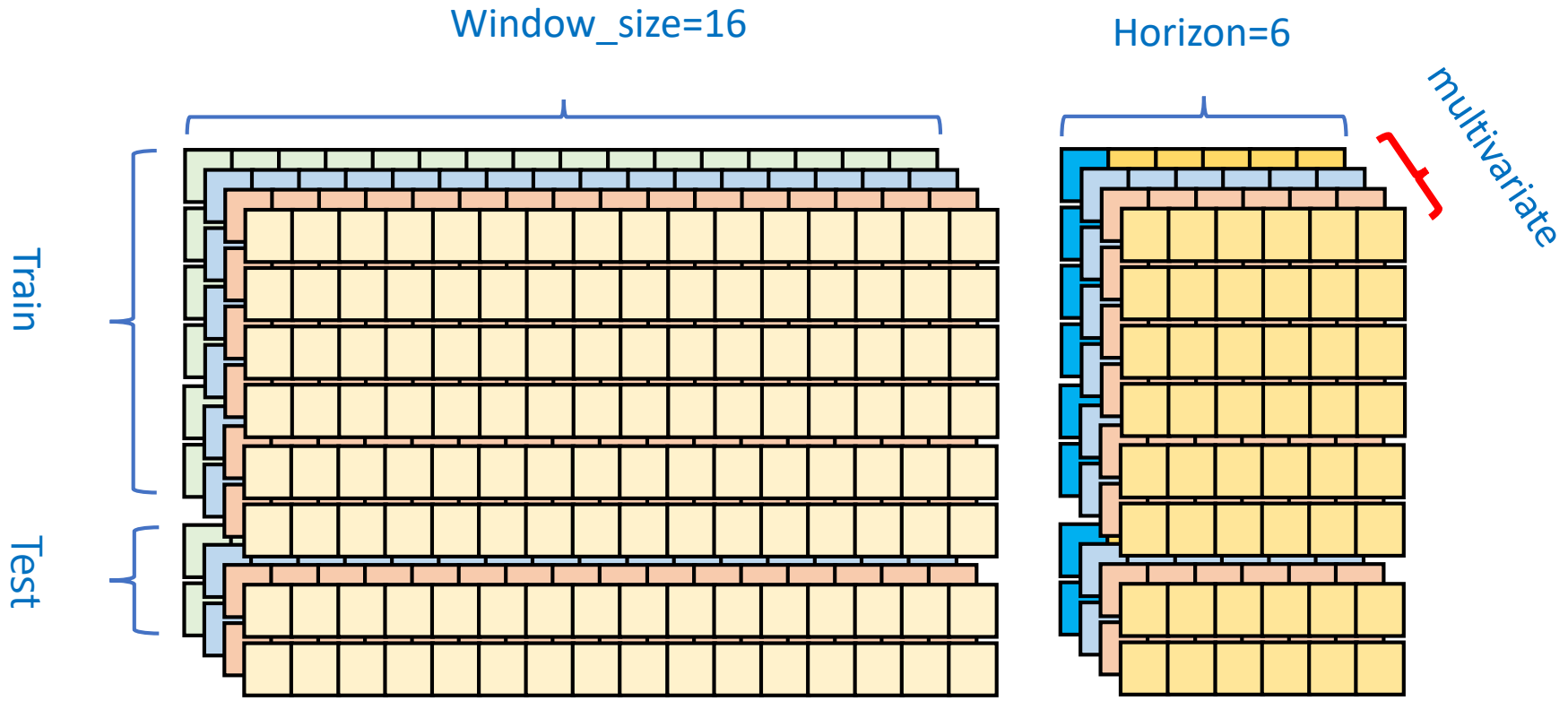
Step1: set the number of window_size, horizon



Step2: set the number of window_size, horizon

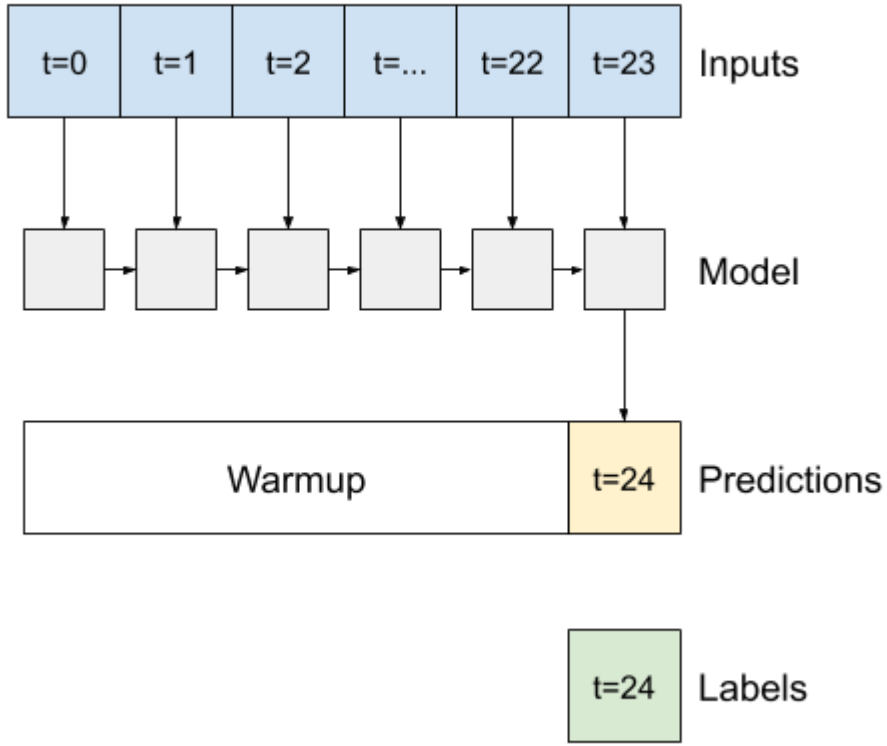


RNN Input-Output Data Structure



(Examples) return_sequences=False (the default)

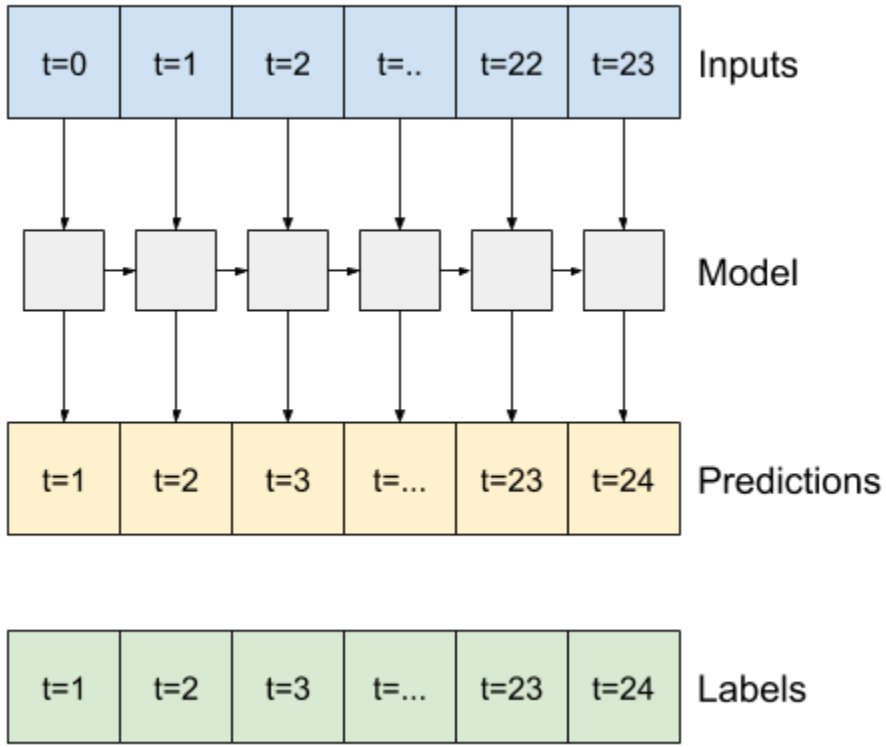
- the layer only returns the output of the final time step, giving the model time to warm up its internal state before making a single prediction:



(Examples) RNN: return_sequences=True

❖ Return_sequences=True

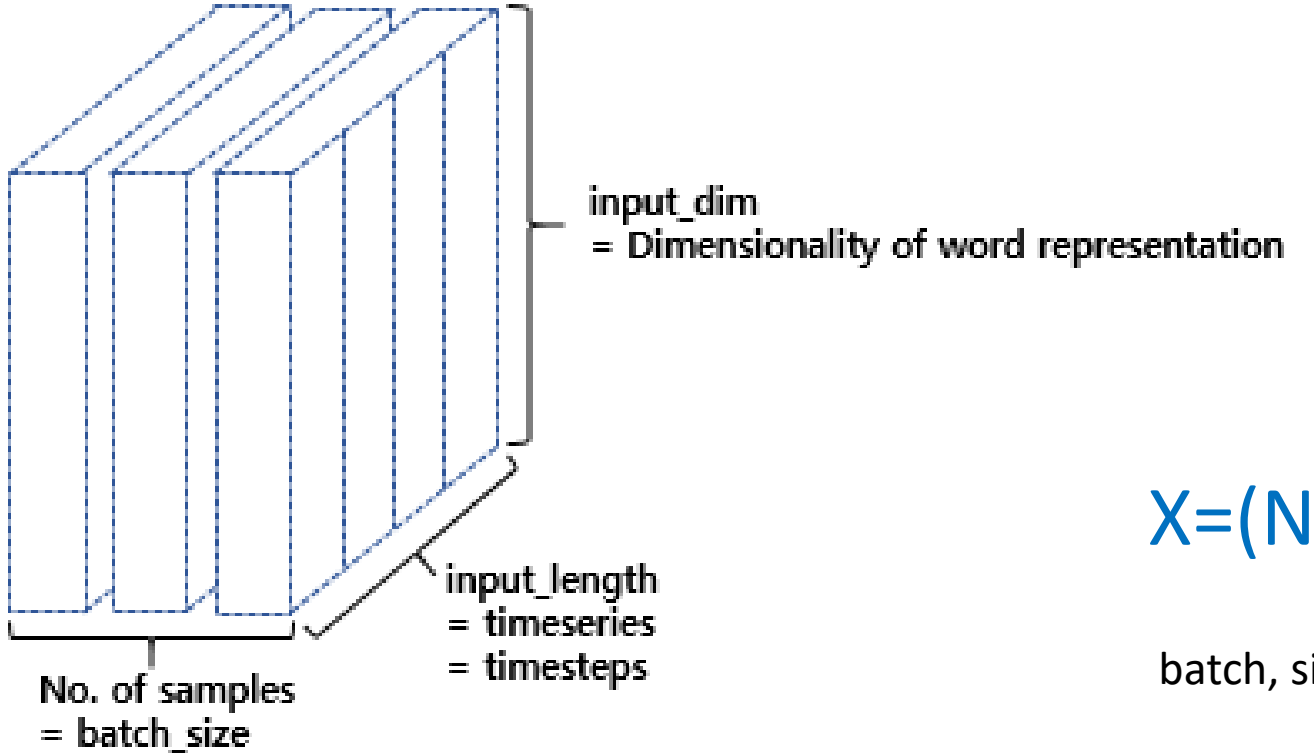
- ✓ the layer returns an output for each input. This is useful for:Stacking RNN layers.
- ✓ Training a model on multiple time steps simultaneously



Implementing an RNN with Keras

RNN Input : X Dimension

- The RNN layer receives a 3D tensor of size as input
  - ✓batch_size, timesteps, and input_dim



X=(None, 2, 10)

batch, size of memory, input_dim)

SimpleRNN without Batch

```
model.add(SimpleRNN(3, input_shape=(2,10)))
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
simple_rnn (SimpleRNN)       (None, 3)                 42
=================================================================
Total params: 42
Trainable params: 42
Non-trainable params: 0
```

X=(None, 2, 10)

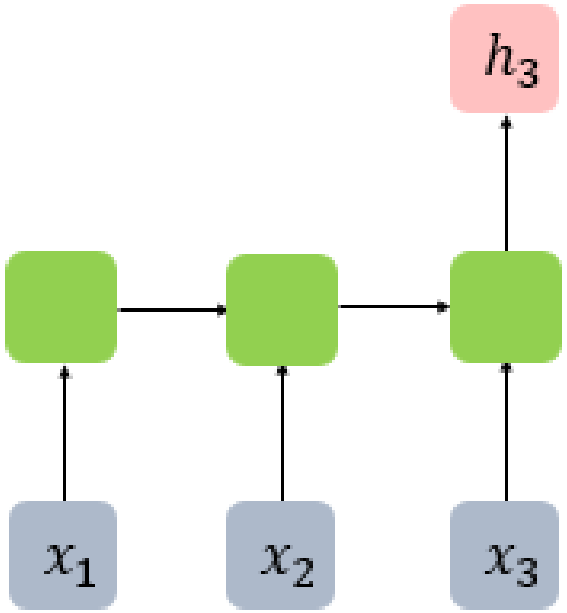
batch size

```
# with Batch size = 8
model.add(SimpleRNN(3, batch_input_shape=(8,2,10)))
```

Layer (type)	Output Shape	Param #
simple_rnn_1 (SimpleRNN)	(8, 3)	42

❖ Setting the return_sequences of the RNN layer

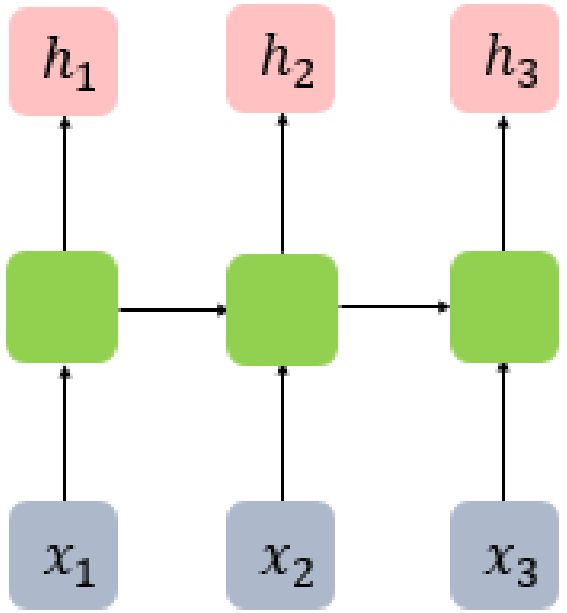
return_sequences=False



다음층으로 마지막 은닉 상태만 전달

many-to-one task

return_sequences=True



다음층으로 모든 은닉 상태 전달

many-to-many task

[HW] Let's Code!
Simple RNN

Input Data and Train Data Shape

```
1 import numpy as np
2 import tensorflow as tf
3 from tensorflow.keras.layers import SimpleRNN, GRU, LSTM, Bidirectional
4 train_X = [[0.1, 4.2, 1.5, 1.1, 2.8], [1.0, 3.1, 2.5, 0.7, 1.1], [0.3, 2.1, 1.5, 2.1, 0.1], [2.2, 1.4, 0.5, 0.9, 1.1]]
5 print(np.shape(train_X))
```

```
1 train_X=np.reshape(train_X, (-1,4,5))
2 print(train_X.shape)
```

```
(4, 5)
(1, 4, 5)
```

SimpleRNN and Hidden states

```
1 rnn = SimpleRNN(3)
2 # rnn = SimpleRNN(3, return_sequences=False, return_state=False)와 동일.
3 hidden_state = rnn(train_X)
4
5 print('hidden state : {}, shape: {}'.format(hidden_state, hidden_state.shape))
```

```
hidden state : [[ 0.9206875  -0.9963834  -0.99492633]], shape: (1, 3)
```

```
1 rnn = SimpleRNN(3, return_sequences=True)
2 hidden_states = rnn(train_X)
3
4 print('hidden states : {}, shape: {}'.format(hidden_states, hidden_states.shape))
```

```
hidden states : [[[-0.91097903 -0.99876505 -0.95570076]
  [ 0.9831649  -0.52204293 -0.94400156]
  [-0.7801549   0.03199867 -0.44760188]
  [ 0.8878632  -0.20588721  0.7986243 ]]], shape: (1, 4, 3)
```

SimpleRNN and Return Sequence

```
1 rnn = SimpleRNN(3, return_sequences=True, return_state=True)
2 hidden_states, last_state = rnn(train_X)
3
4 print('hidden states : {}, shape: {}'.format(hidden_states, hidden_states.shape))
5 print('last hidden state : {}, shape: {}'.format(last_state, last_state.shape))
```

```
hidden states : [[[0.99741    0.5095164  0.9999336 ]
  [0.97162277 0.32083237 0.99995947]
  [0.95783615 0.86253214 0.99940664]
  [0.99748254 0.7658603  0.9743646 ]]], shape: (1, 4, 3)
last hidden state : [[0.99748254 0.7658603  0.9743646 ]], shape: (1, 3)
```

Simple RNN and Return_Sequence

```
1 rnn = SimpleRNN(3, return_sequences=False, return_state=True)
2 hidden_state, last_state = rnn(train_X)
3
4 print('hidden state : {}, shape: {}'.format(hidden_state, hidden_state.shape))
5 print('last hidden state : {}, shape: {}'.format(last_state, last_state.shape))
```

```
hidden state : [[0.9096651 0.9990103 0.7855833]], shape: (1, 3)
last hidden state : [[0.9096651 0.9990103 0.7855833]], shape: (1, 3)
```

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