2022

Deep Learning based Text Processing

Lec 10: Introduction to Long-Short Term Memory

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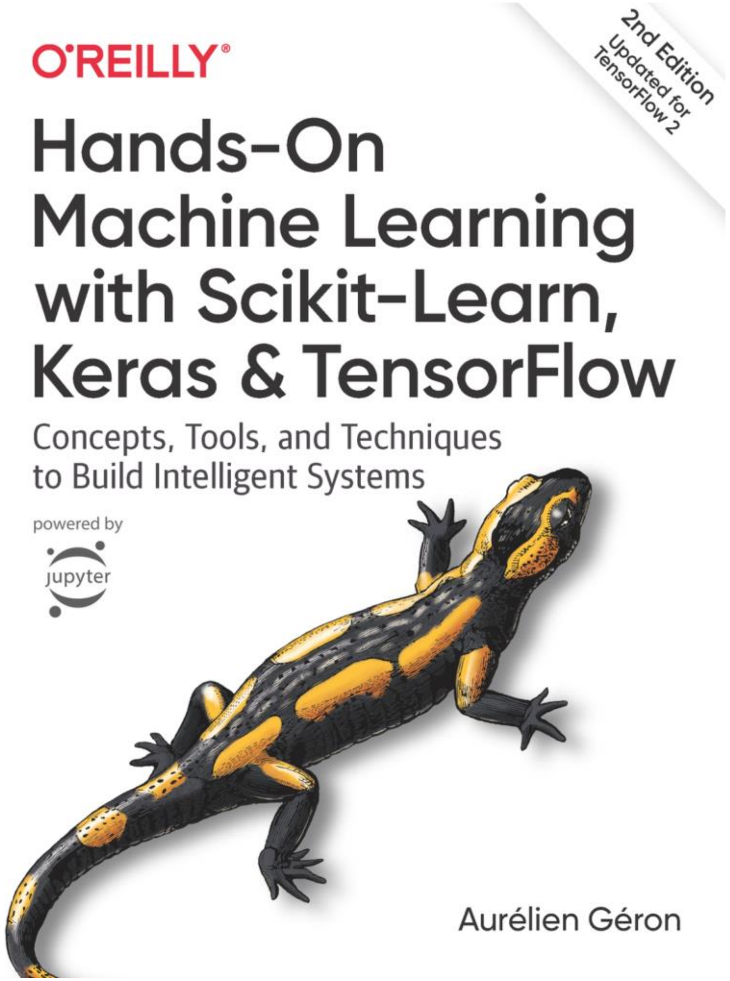
Overview of Course

- 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 Learning model with RNN
  - ✓ Introduction to Seq2Seq and Attention model
  - ✓ Code: Character-Level Neural Machine Translation



딥 러닝을 이용한 자연어 처리 입문

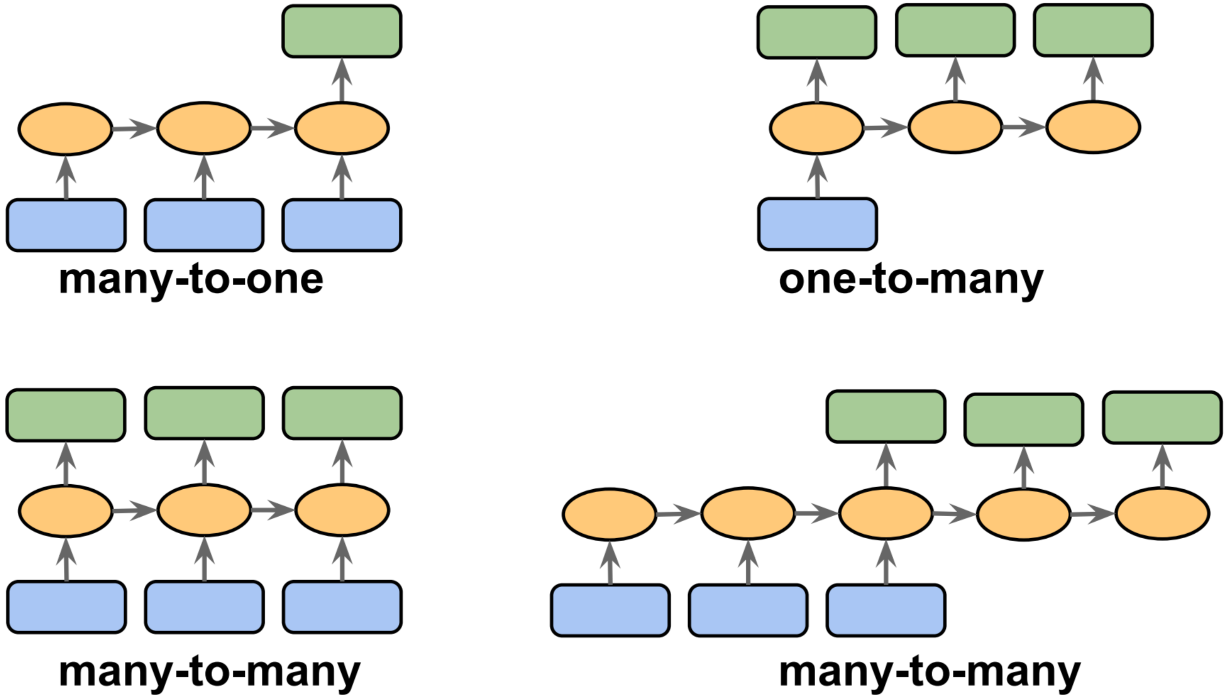
https://wikidocs.net/book/2155

Reviewing the last class: RNN

Recurrent NN for processing sequences

- RNN can handle interactions more flexibly
- they are applied in a step-by-step fashion to a sequential input
  - ✓ a sequence of words, characters, or something else
- RNNs use a state representing what has happened previously
  - ✓ after each step, a new state is computed

Different Types of Sequence Modeling Tasks



RNN example

https://chalmers.instructure.com/courses/16100

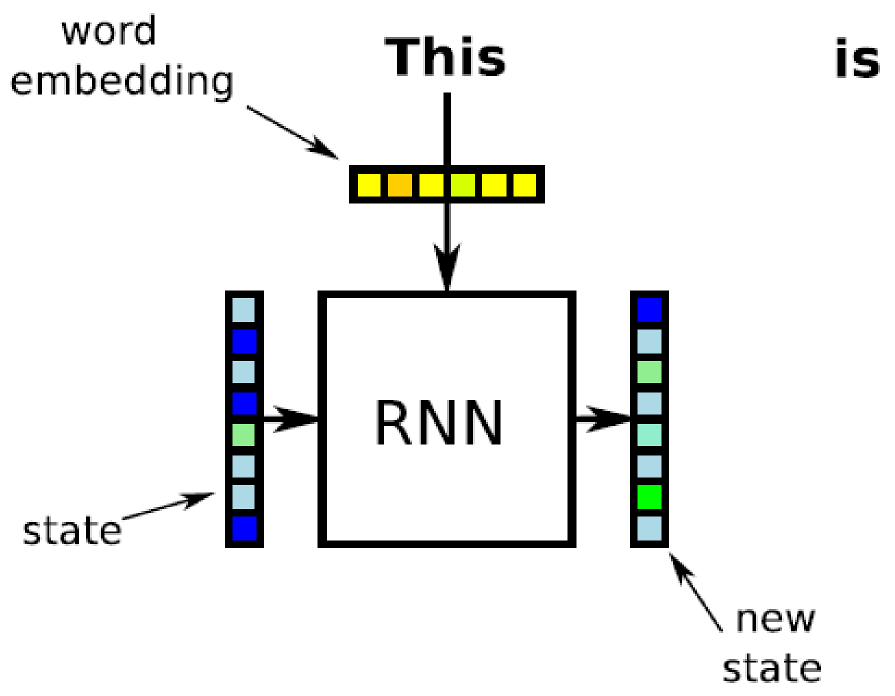


image borrowed from Richard Johansson (*Chalmers Technical University and University of Gothenburg)*

training RNNs: backpropagation through time

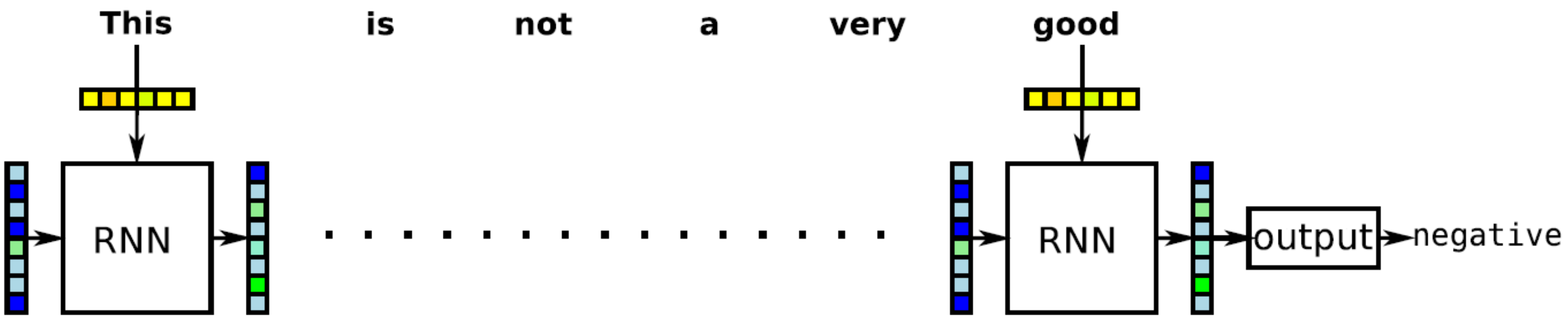


image borrowed from Richard Johansson (*Chalmers Technical University and University of Gothenburg)*

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- the simple RNN looks similar to a feedforward NN
  - ✓ the next state is computed like a hidden layer in a feedforward NN
  - ✓ the output is identical to the state representation:

$$y_t = \boxed{s_t}$$

$$\boxed{s_t} = \boxed{g}(\boldsymbol{W} \cdot (s_{t-1} \oplus x_t) + \boldsymbol{b})$$

actication is typically tanh

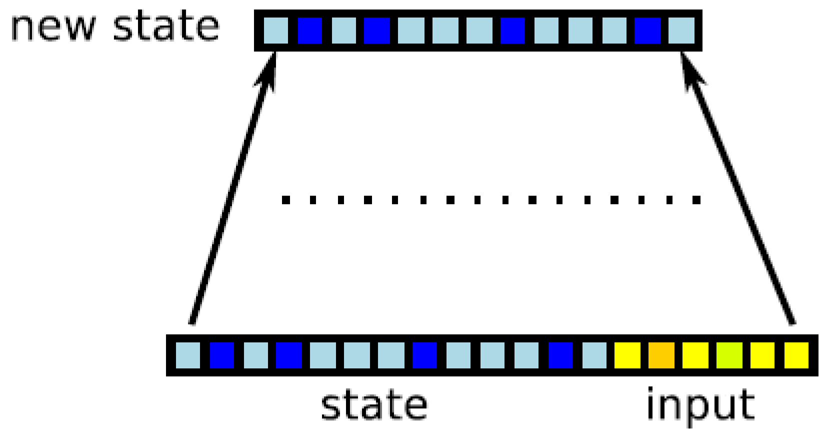
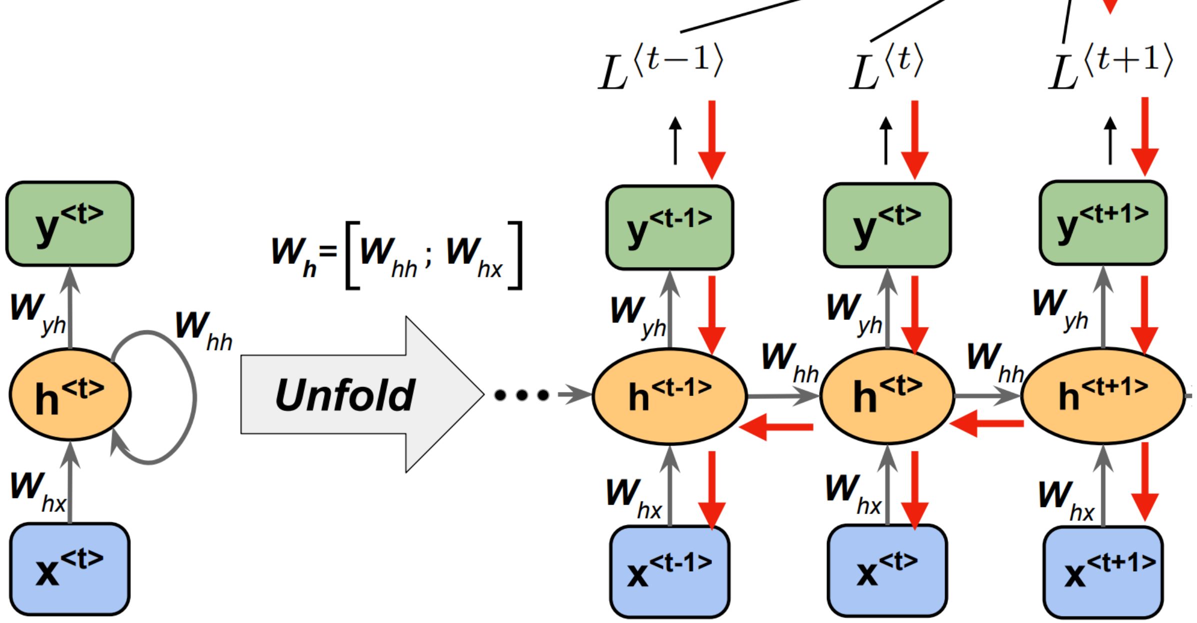


image borrowed from Richard Johansson (*Chalmers Technical University and University of Gothenburg)*

✓ To train an RNN the trick is to unroll it through time and then simply use regular backpropagation.

Backpropagation through time (BPTT)

$$L = \sum_{t=1}^{T} L^{\langle t \rangle}$$



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

computed as a multiplication of adjacent time steps:

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

- RNNs suffer from the problem of vanishing gradients (Hochreiter, 1998)

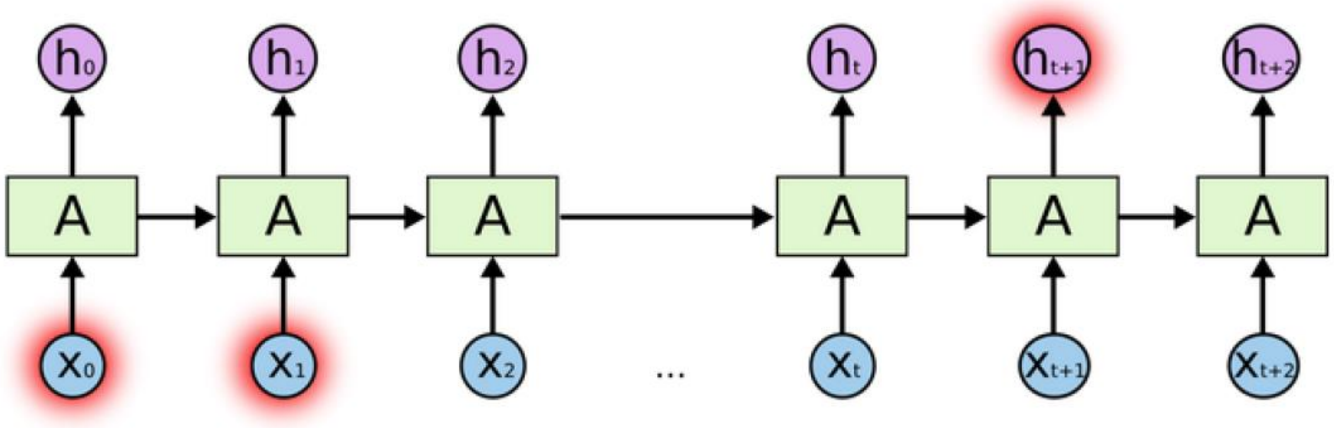


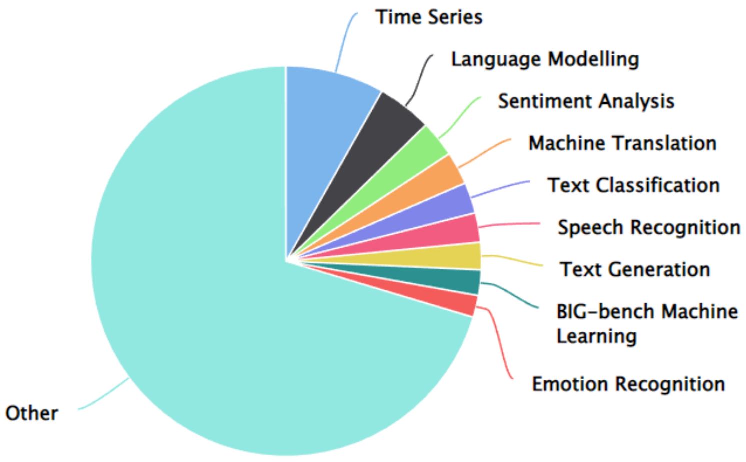
image borrowed from Richard Johansson (*Chalmers Technical University and University of Gothenburg)*

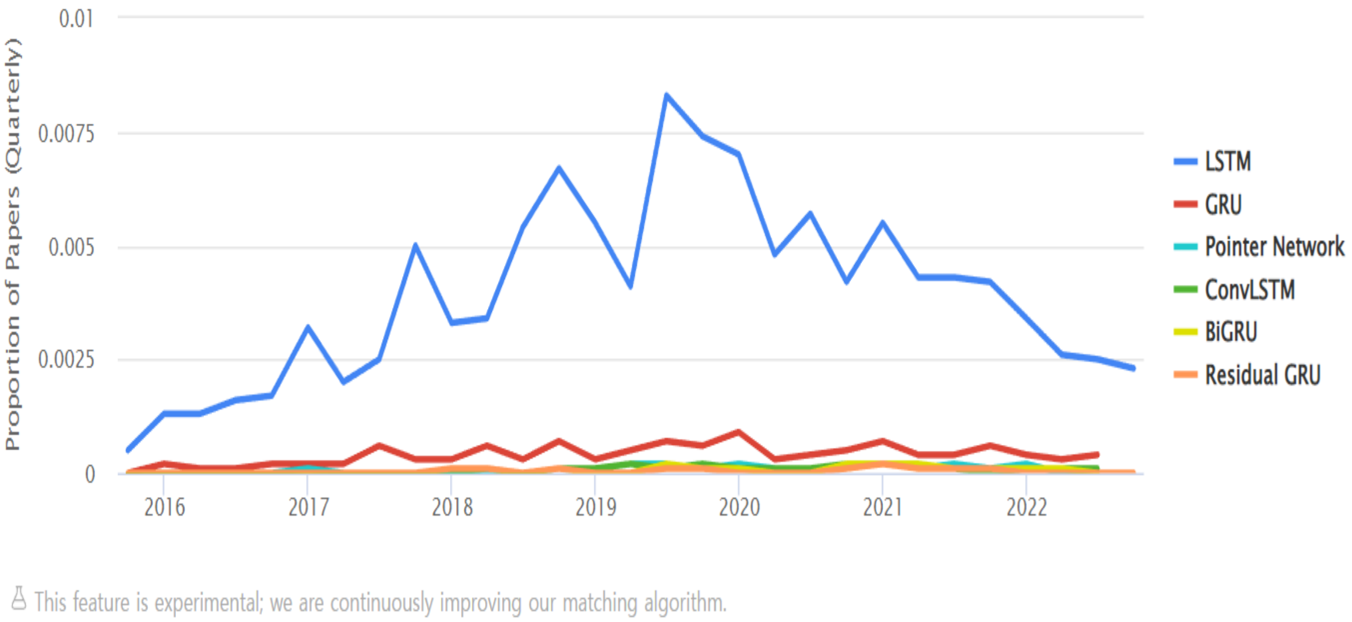
Solutions to the vanishing/exploding gradient problems

- ## Truncated backpropagation through time (TBPTT)
  - ✓ simply limits the number of time steps the signal can backpropagate after each forward pass.
    - E.g., even if the sequence has 100 elements/steps, we may only backpropagate through 20 or so
- ## Long short-term memory (LSTM)
  - ✓ uses a memory cell for modeling long-range dependencies and avoid vanishing gradient problems
- ## Gradient Clipping
  - ✓ set a max value for gradients if they grow to large
    - solves only exploding gradient problem)

Long-Short Term Memory
(장단기 메모리)

LSTM Tasks and Usage Over Time : 2022





<source> https://paperswithcode.com/method/lstm

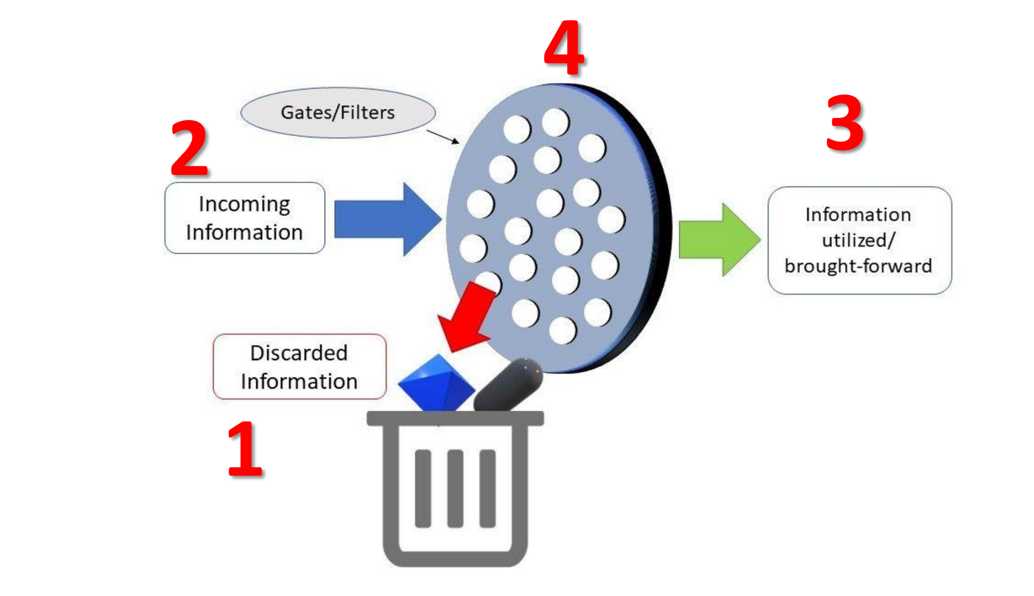
Cell states and Gates

❖ Long-short term memory (LSTM) : Cell state

- ✓Gates control the flow of information to/from the memory
- ✓Forget Gate
- ✓Input Gate
- ✓New information: Memory Upgate
- ✓Output Gate

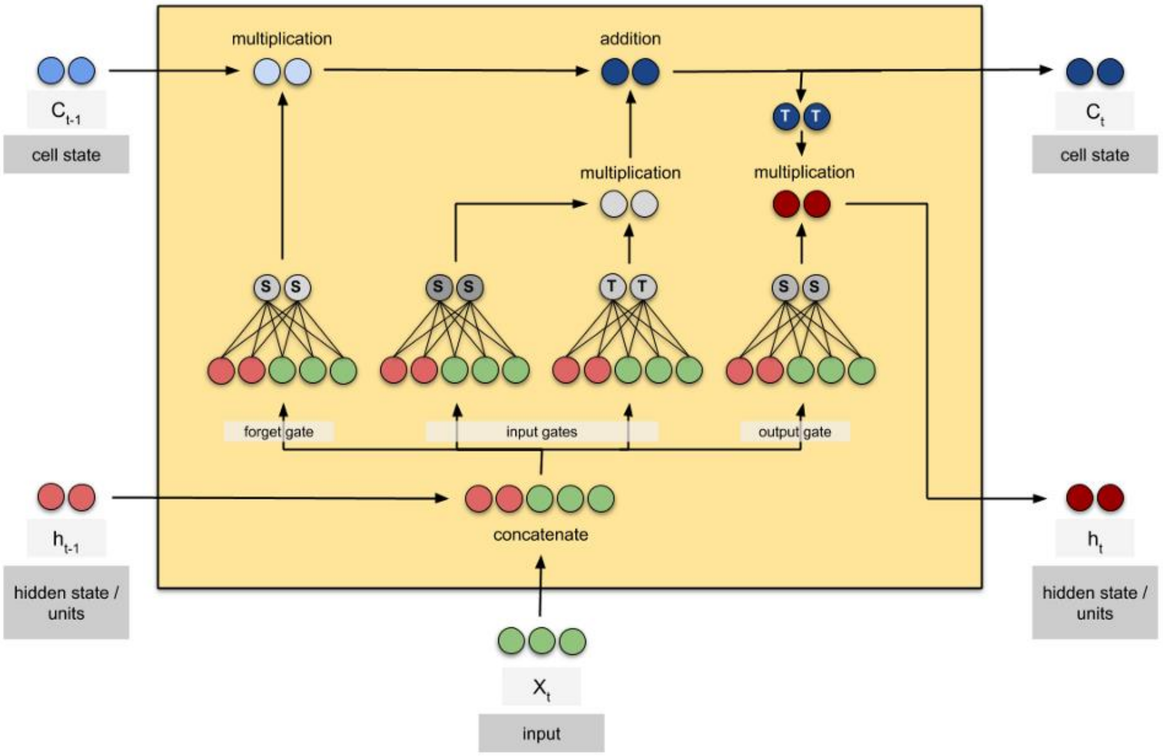
$$y_t = s_t \quad s_t = g(\boldsymbol{W} \cdot (s_{t-1} \oplus x_t) + \boldsymbol{b})$$

$$\underbrace{\begin{bmatrix} 8 \\ 11 \\ 3 \\ 7 \\ 5 \\ 15 \end{bmatrix}}_{\mathbf{s}'} \leftarrow \underbrace{\begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}}_{\mathbf{g}} \odot \underbrace{\begin{bmatrix} 10 \\ 11 \\ 12 \\ 13 \\ 14 \\ 15 \end{bmatrix}}_{\mathbf{x}} + \underbrace{\begin{bmatrix} 1 \\ 0 \\ 1 \\ 1 \\ 1 \\ 0 \end{bmatrix}}_{(\mathbf{1}-\mathbf{g})} \odot \underbrace{\begin{bmatrix} 8 \\ 9 \\ 3 \\ 7 \\ 5 \\ 8 \end{bmatrix}}_{\mathbf{s}}$$



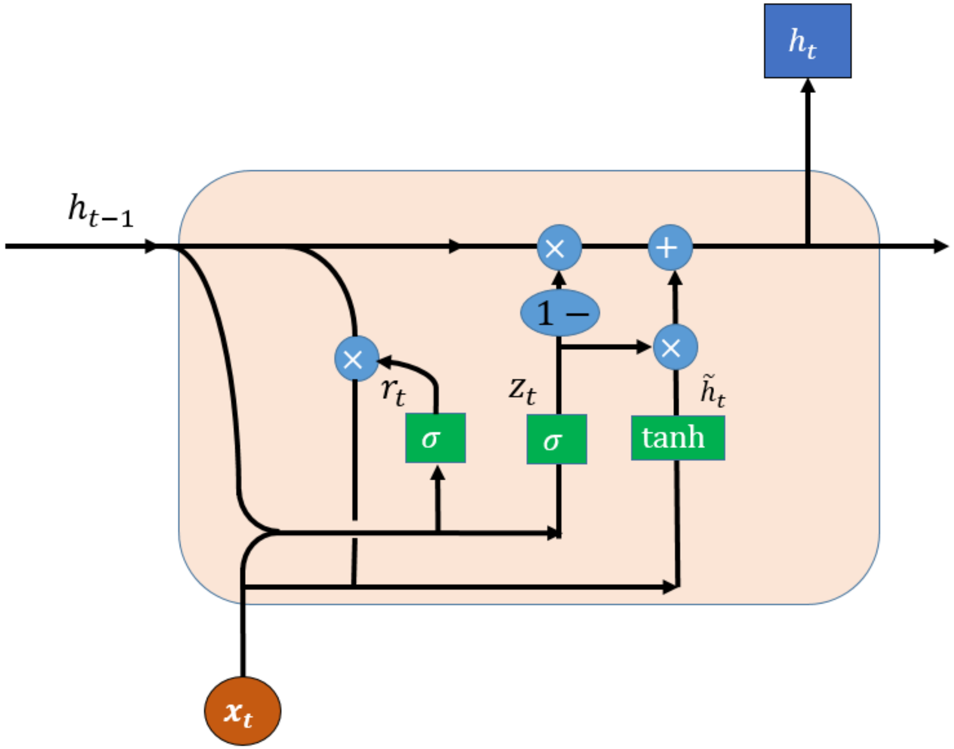
LSTM : Cell state and hidden state

- Gates are controlled by a concatenation of the output from the previous time step and the current input and optionally the cell state vector.



❖ Just like LSTM, GRU uses gates to control the flow of information

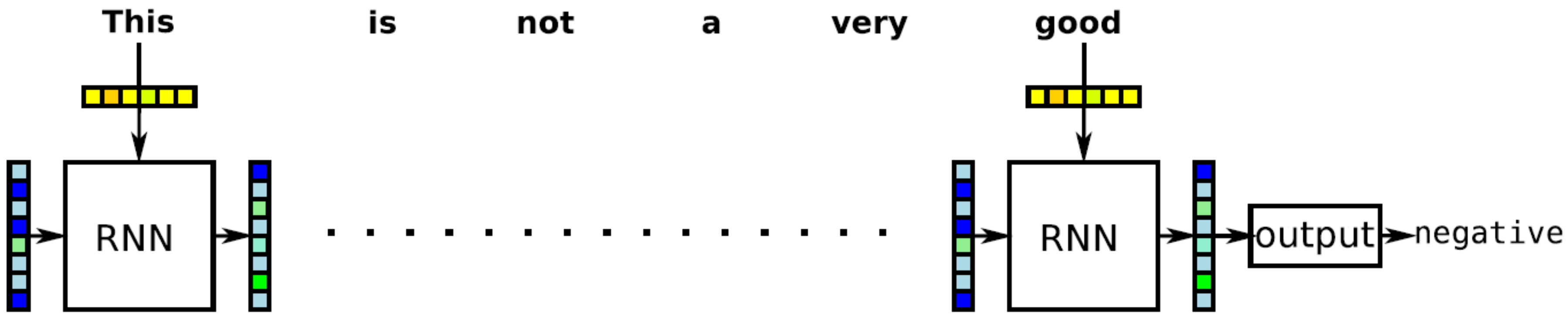
$$r_t = \sigma(W_{xr}x_t + W_{hr}h_{t-1} + b_r)$$
$$z_t = \sigma(W_{xz}x_t + W_{hz}h_{t-1} + b_z)$$
$$g_t = tanh(W_{hg}(r_t \circ h_{t-1}) + W_{xg}x_t + b_g)$$
$$h_t = (1 - z_t) \circ g_t + z_t \circ h_{t-1}$$



source: https://www.researchgate.net/figure/Structure-of-a-GRU-cell_fig1_334385520

limitations of RNNs

- Even with gated RNNs, it can be hard to cram the useful information into the last state

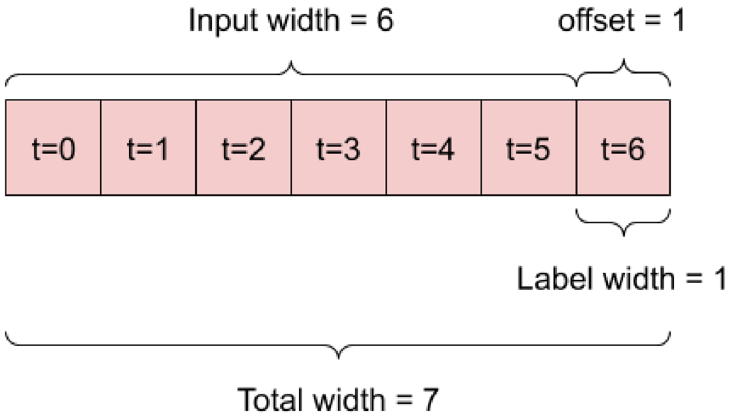


RNN
Memory and Prediction

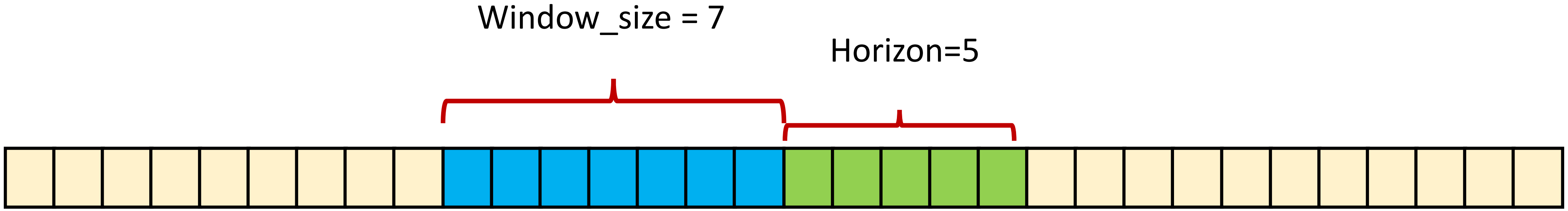
RNN sliding window size and horizon

❖ A Many-to-One RNN model:

✓ (e.g., prediction one hour into the future, given six hours of history)



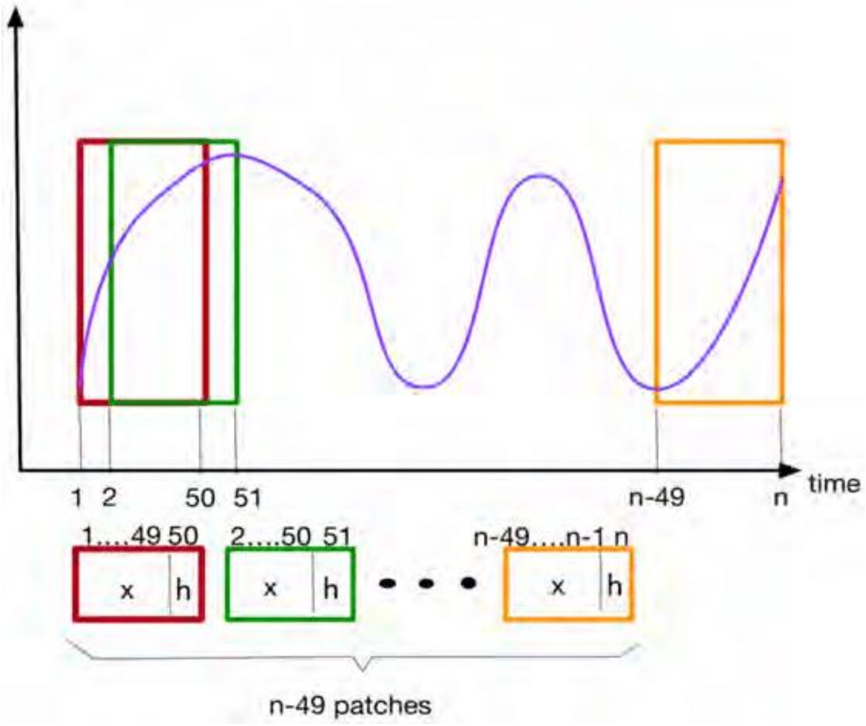
❖ A Many-to-One RNN model:



An example : RNN sliding window size and horizon

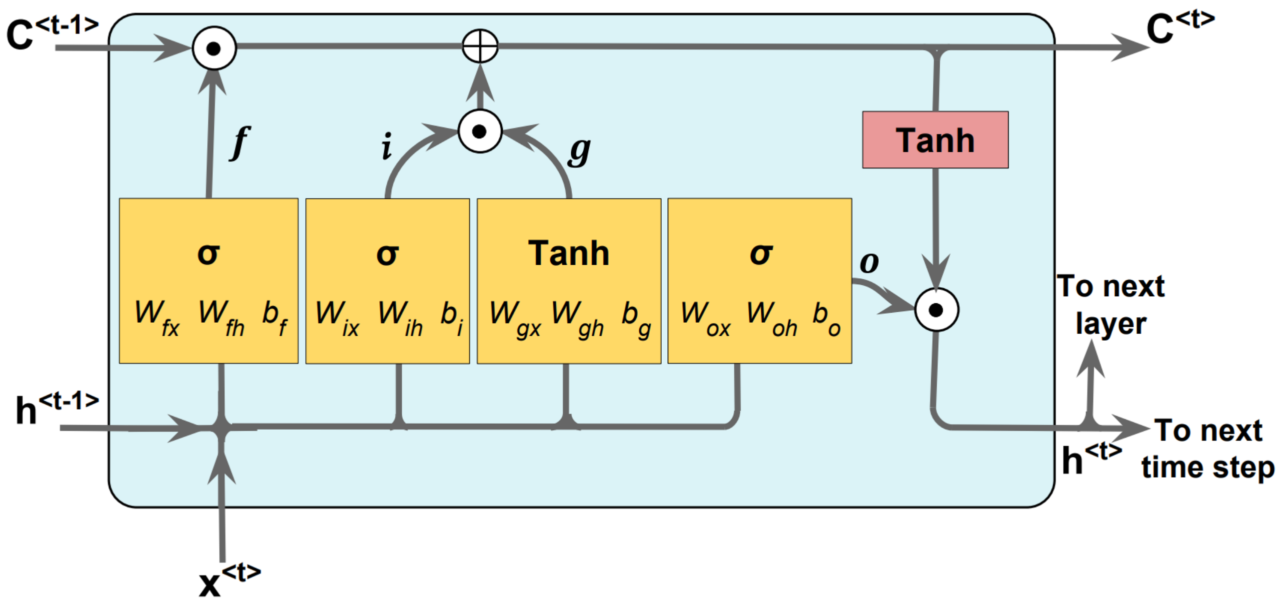
❖ Sine function

- ✓ window size (기억의 길이) = 49
- ✓ horizon (예측 개수) = 1



❖ LSTM has 3 important parameters

- ✓ **neurons** : dimensionality of the output space
- ✓ **return_sequences**: whether to return the last output. (hidden state, memory cell,h)
  - Default: False.
- ✓ **return_state**: whether to return the last state in addition to the output. (cell state, c)
  - Default: False.

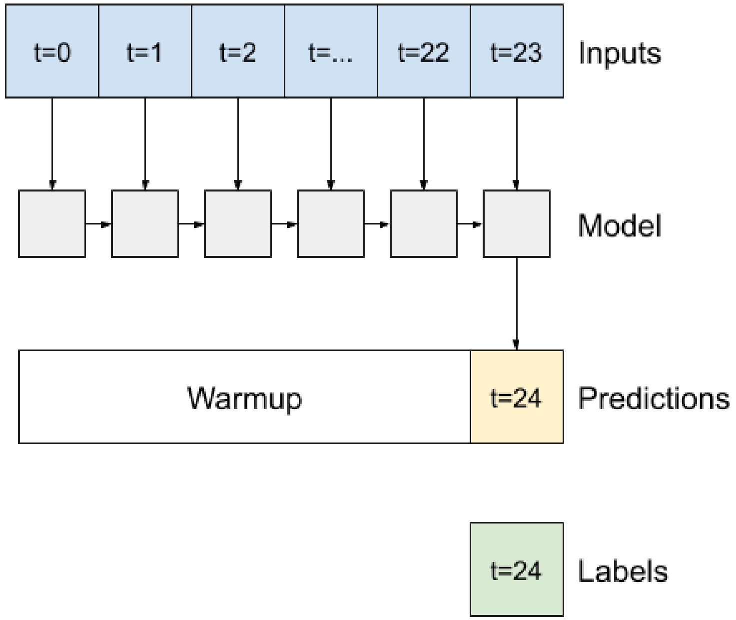


❖ Return_sequences=False

✓ the default

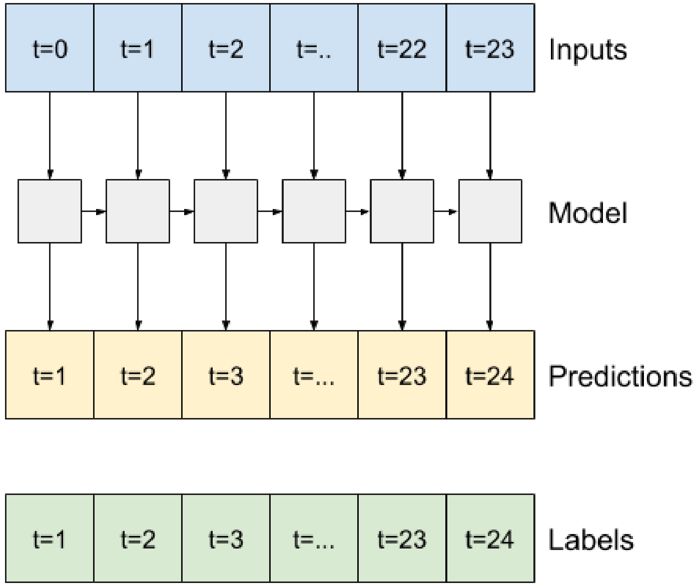
✓ the layer only returns the output of the final time step

✓ giving the model time to warm up its internal state



❖ Return_sequences=False

✓ the layer returns an output for each input



A Visual Guide to Recurrent Layers in Keras

source: https://amitness.com/2020/04/recurrent-layers-keras/

❖ Let's take a simple example of encoding

For simplicity, let's assume we used some word embedding to convert each word into 2 numbers.

I am groot

Credits: Marvel Studios

Word	E1	E2
I	0.5	0.4
am	0.3	0.1
groot	0.7	0.5

We could either use one-hot encoding, pretrained word vectors, or learn word embeddings from scratch

https://amitness.com/2020/04/recurrent-layers-keras/

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❖ SimpleRNN with a Dense layer

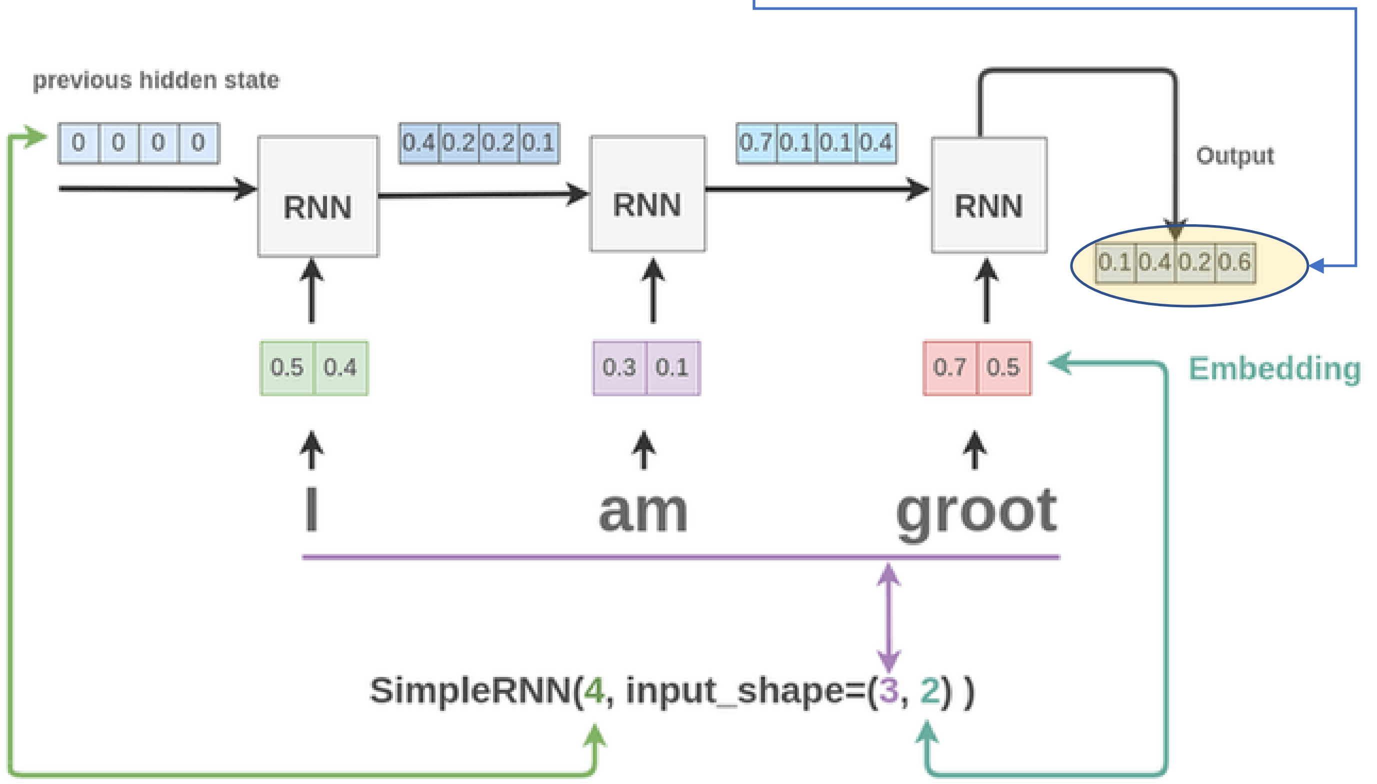
✓ to build an architecture for something like sentiment analysis or text classification.

```
import tensorflow as tf
from tensorflow.keras.layers import SimpleRNN   #Dense, LSTM
# from tensorflow.keras.models import Sequential

x = tf.random.normal((1, 3, 2))

layer = SimpleRNN(4, input_shape=(3, 2))
output = layer(x)

print(output.shape)
print(x)
```

```
(1, 4)
tf.Tensor(
[[[ 0.6887584   1.3883604 ]
  [ 0.01564607 -1.4314882 ]
  [-0.05214449 -0.65099174]]], shape=(1, 3, 2), dtype=float32)
```

- we treat each word as a time-step and the embedding as features.

```
model.add(layers.SimpleRNN(4, input_shape=(3,2)))
```



SimpleRNN (3) : return_sequences=True

```
# multiple output
layer = SimpleRNN(4, input_shape=(3, 2), return_sequences=True )
output = layer(x)
print(output.shape)
print(output)
```

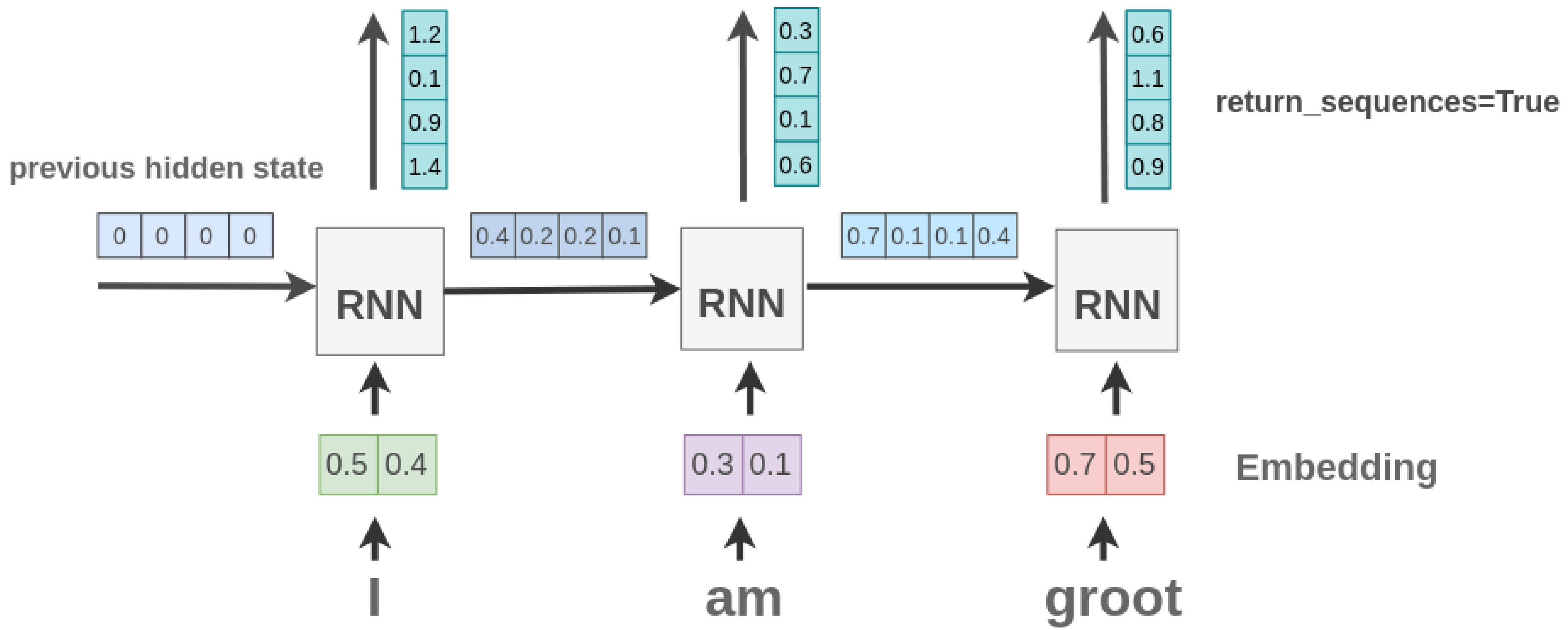
```
(1, 3, 4)
tf.Tensor(
[[[-0.6854385   0.08265962  0.30888444 -0.30752325]
  [ 0.4584542  -0.1935767  -0.91095936 -0.2416075 ]
  [ 0.7241105  -0.49960855 -0.5059616   0.7261468 ]]], shape=(1, 3, 4), dtype=float32)
```

RNN with return_sequences : Many-to-Many

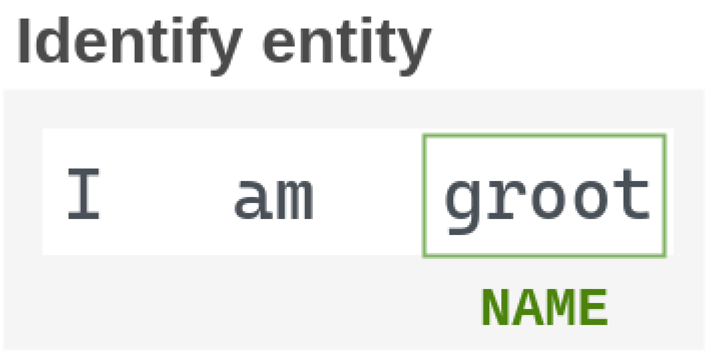
❖ return_sequences = True

✓True : the output from each unfolded RNN cell is returned instead of only the last cell.

```
model.add(SimpleRNN(4, input_shape=(3, 2), return_sequences=True))
```

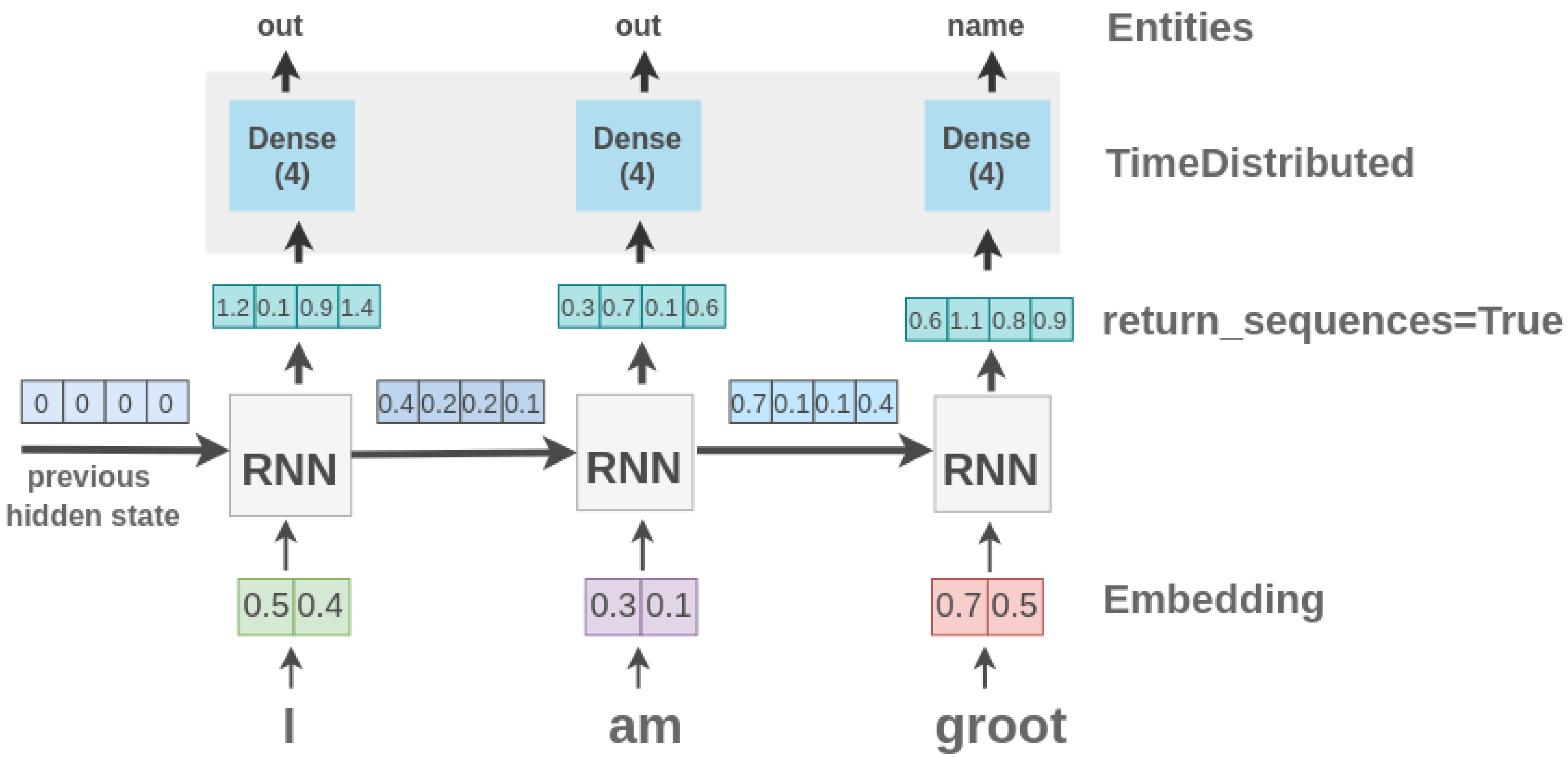


- Suppose we want to recognize entities in a text.
  - ✓ For example, in our text “I am Groot”, we want to identify “Groot” as a name.



(3) RNN: TimeDistributed Layer

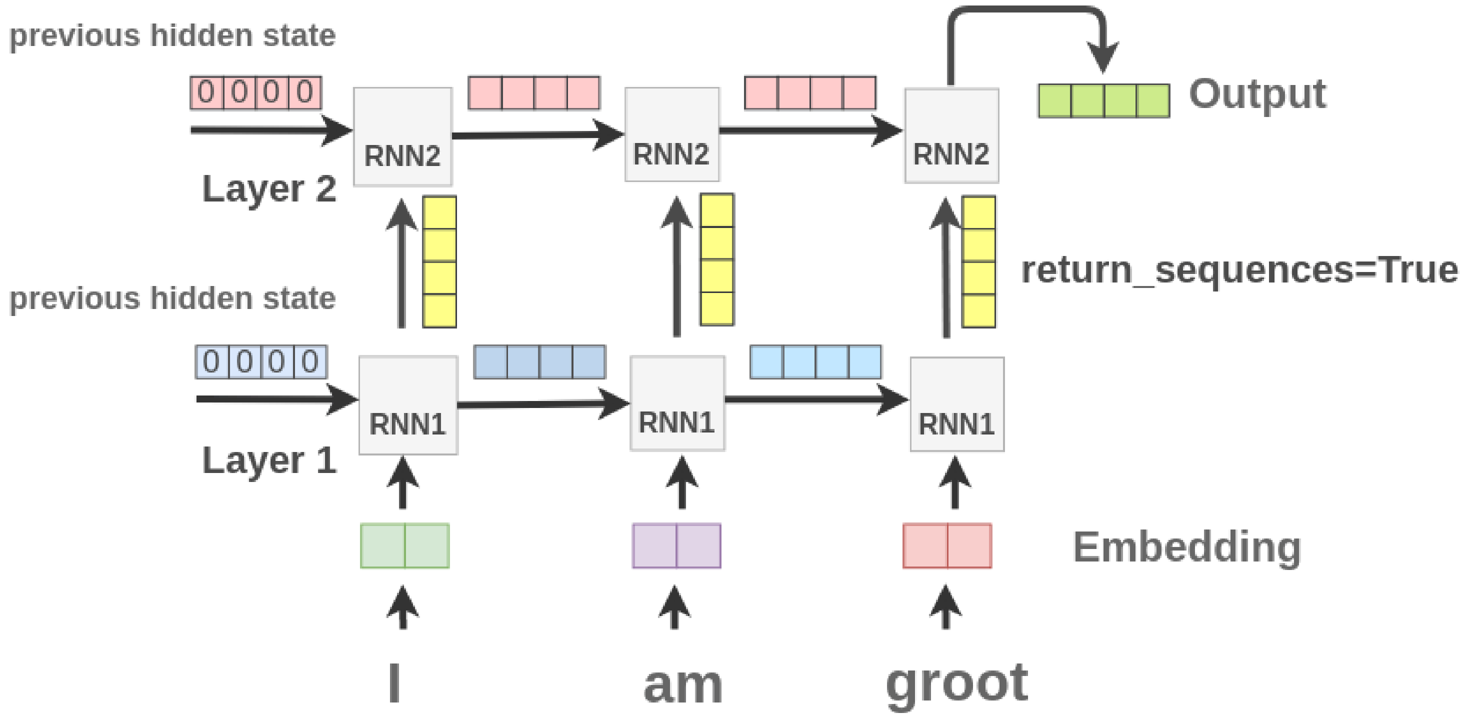
```
model.add(SimpleRNN(4, input_shape=(3, 2), return_sequences=True))
model.add(TimeDistributed(Dense(4, activation='softmax')))
```



RNN Stacking Layer : Deep but Many-to-One

❖ We can also stack multiple recurrent layers one after another in Keras

```
model.add(SimpleRNN(4, input_shape=(3, 2), return_sequences=True))
model.add(SimpleRNN(4))
```



Let’s Code : LSTM

LSTM Parameters

- 이미지가 입력되고 이미지 라벨이 출력됨.
- Input Data (Image)
  - ✓ image pixel(28x28)
  - ✓ windows =7
  - ✓ horizon = 10
  - ✓ X_train(buffer, windows_size, images)
  - ✓ X_train(batch, 64, 28x28)
- LSTM parameters
  - ✓ Neurons = 128
  - ✓ Two LSTM layer
  - ✓ Retrun_Sequence=True

LSTM Example

batch_size=64
input_size=28
hidden_size=128
layer_size =2
output_size=10

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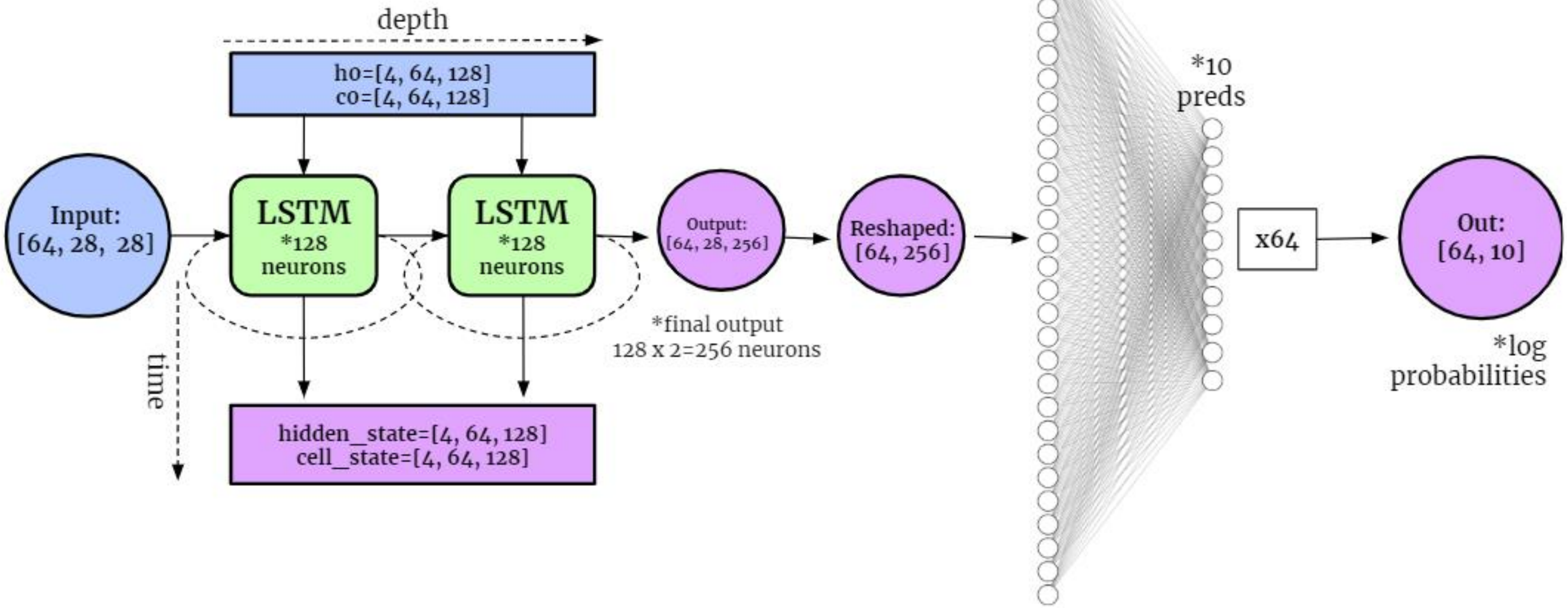
LSTM Example

batch_size=64
input_size=28
hidden_size=128
layer_size =2
output_size=10



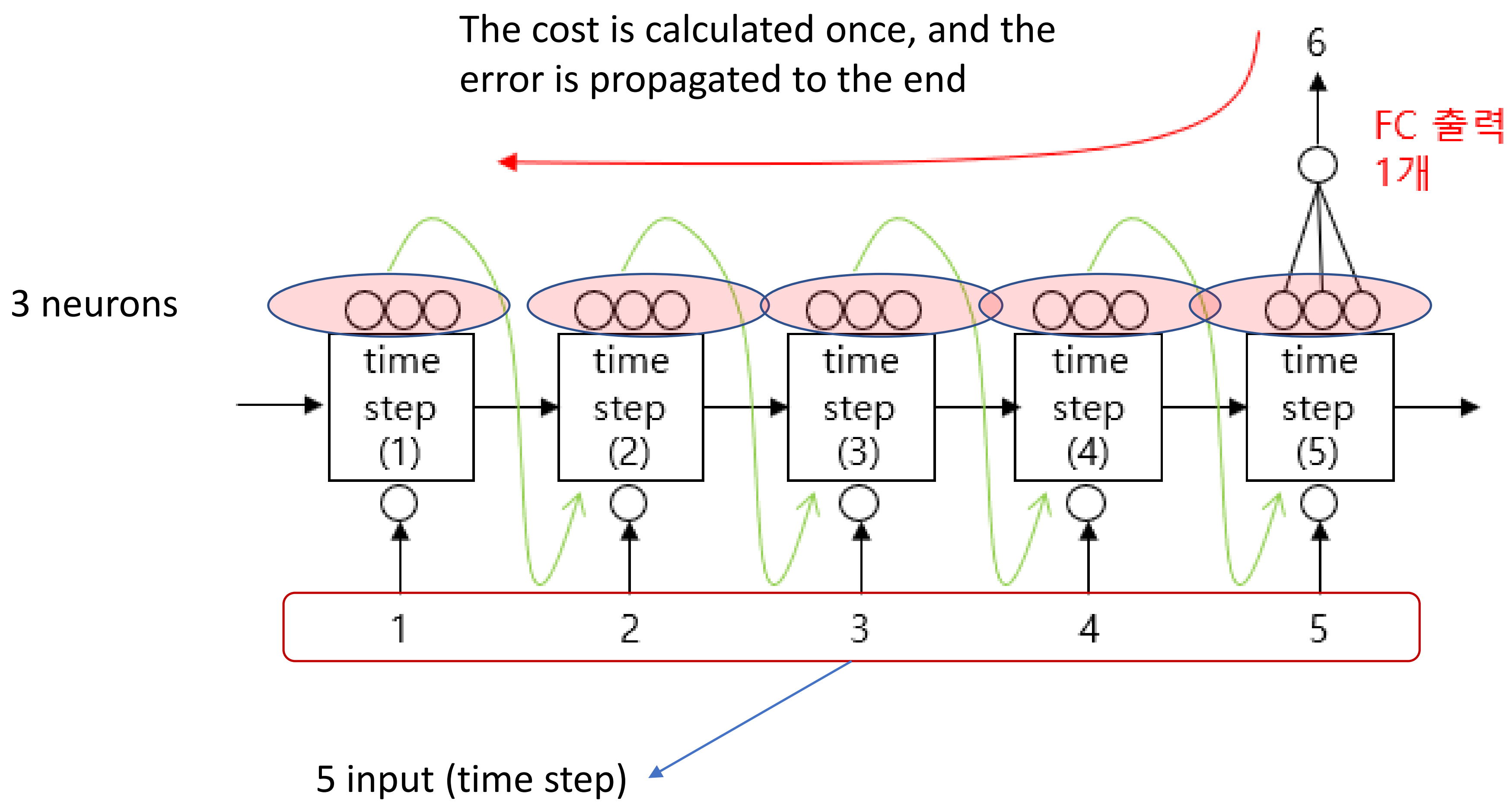
LSTM Example : many-to-one

```
from keras.models import Model
from keras.layers import Input, Dense, LSTM
import numpy as np

x = np.array([[[1.], [2.], [3.], [4.], [5.]]])
y = np.array([[6.]])

xInput = Input(batch_shape=(None, 5, 1))
xLstm = LSTM(3)(xInput)
xOutput = Dense(1)(xLstm)

model = Model(xInput, xOutput)
model.compile(loss='mean_squared_error', optimizer='adam')
print(model.summary())

model.fit(x, y, epochs=50, batch_size=1, verbose=0)
model.predict(x, batch_size=1)
```

```
Model: "model_4"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_5 (InputLayer)         [(None, 5, 1)]            0

lstm_6 (LSTM)                (None, 3)                 60

dense_6 (Dense)              (None, 1)                 4

=================================================================
Total params: 64
Trainable params: 64
Non-trainable params: 0
```

Unfolded LSTM : Many to One

return_sequences=False



LSTM many-to-many with TimeDistributed Layer

```python
import tensorflow as tf
from tensorflow import keras
import numpy as np
x = np.array([[[1.], [2.], [3.], [4.], [5.]]])
y = np.array([[[2.], [3.], [4.], [5.], [6.]]])
```

```python
model2 = keras.models.Sequential([
    keras.layers.LSTM(3, return_sequences=True, input_shape=[5, 1]),
    keras.layers.TimeDistributed(keras.layers.Dense(1) )                ])
model2.compile(loss='mean_squared_error', optimizer='adam')
model2.summary()
```

```
Model: "sequential_7"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_18 (LSTM)              (None, 5, 3)              60

 time_distributed_8 (TimeDis  (None, 5, 1)              4
 tributed)

=================================================================
Total params: 64
Trainable params: 64
Non-trainable params: 0
_________________________________________________________________
```

LSTM Output is 5x3(neurons)

Final Output is 5x1

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