RNN for NLP

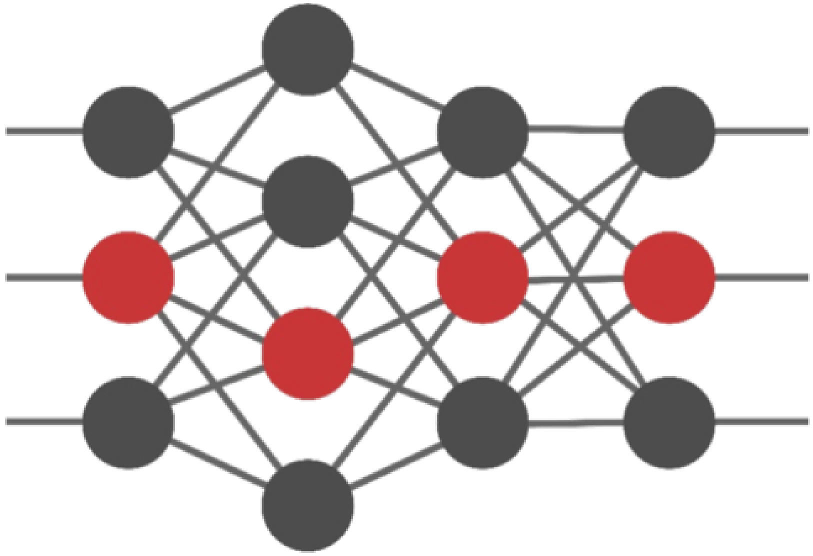
RNN, LSTM, GRU

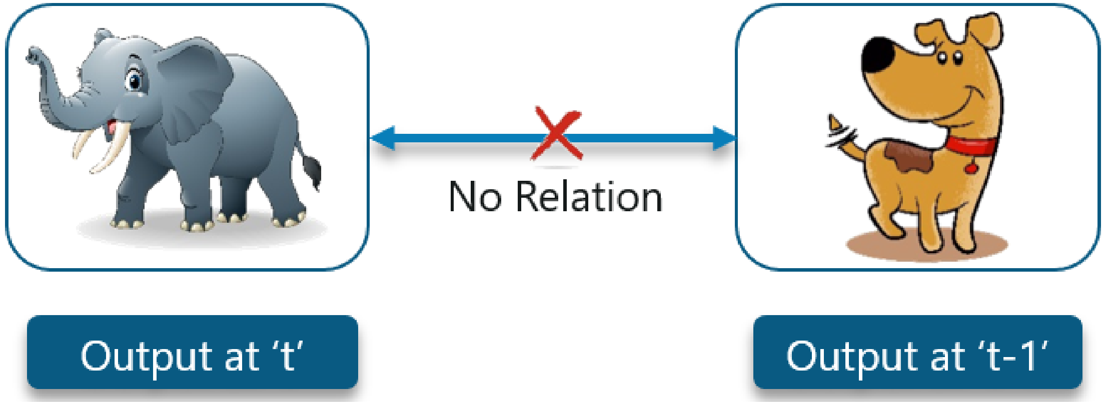
Contents

- 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

Why Not Feedforward Networks

- In the existing FeedForWared Networks,
  - ✓ The input is a dog image, and a well-learned neural network outputs a dog label.
  - ✓ The next elephant image is input to output an elephant (label).
  - ✓ However, elephants and dogs are not related to each other and are independent.

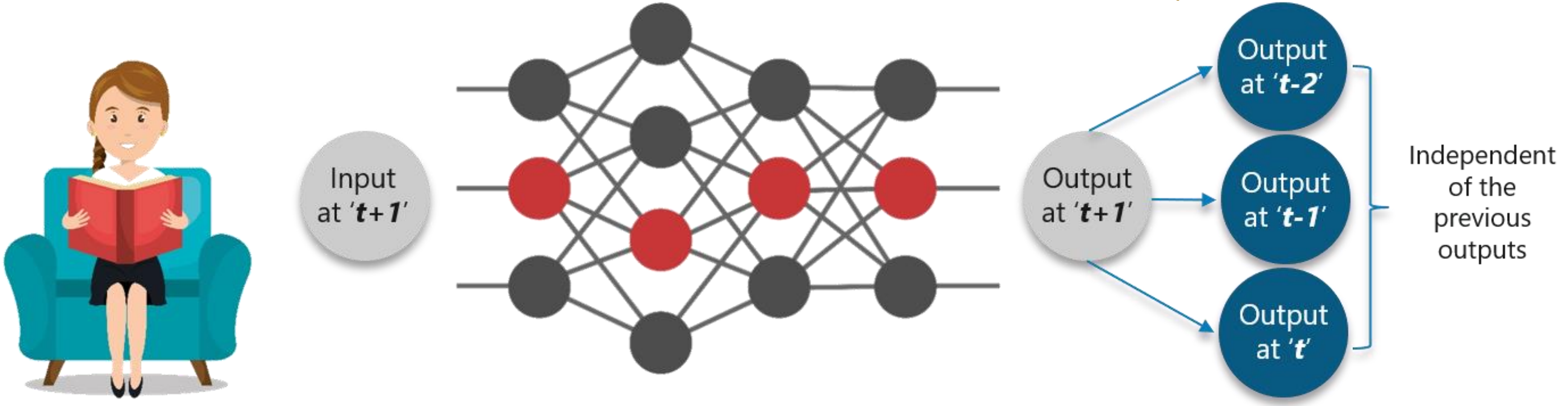




ref: https://www.edureka.co/blog/recurrent-neural-networks/

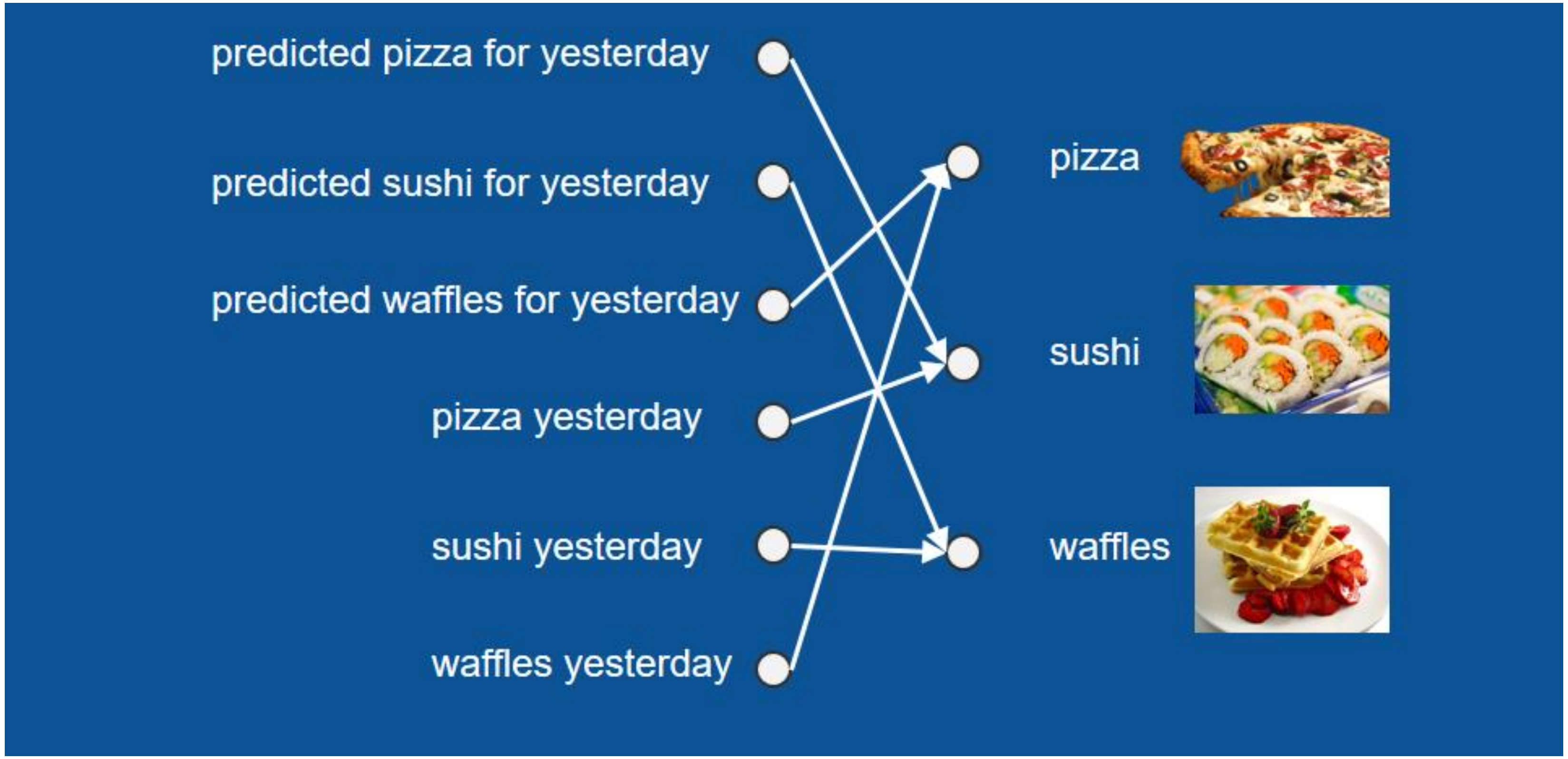
Why Not Feedforward Networks

- If you are reading a book, you should be well aware of the previous page.
  - ✓ In order to understand the context of the book, you must remember the previous contents.
  - ✓ Feeforward network cannot predict the relationship between the following words with previous words.
  - ✓ In other words, there is a need for a network that can remember the previous content (word).



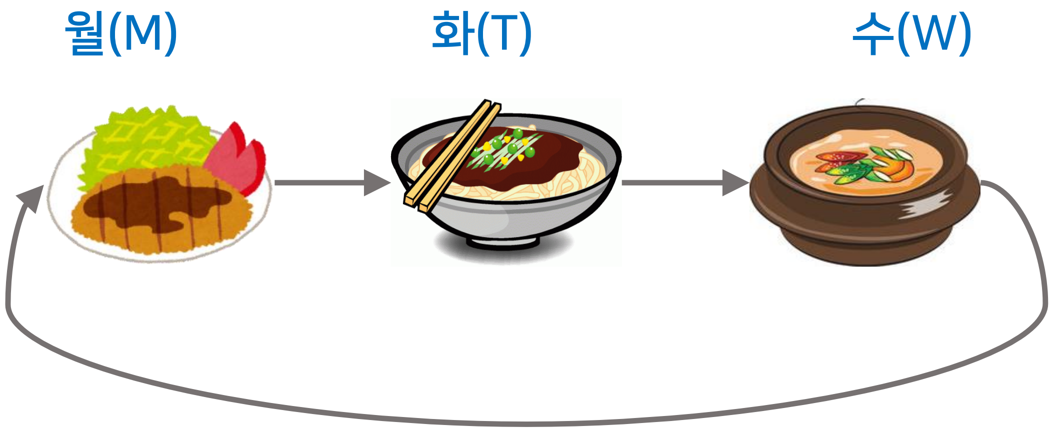
What Are Recurrent Neural Networks?

- Previous memories are also important when eating food
  - ✓ RNNs are a **type** of **artificial neural network** designed to **recognize patterns** in sequences of data



Recurrent Neural Networks : a simple example

- One friend who lives with him cooks only three kinds.
  - ✓ It repeats three foods sequentially: pork cutlet on Mondays, black bean noodles on Tuesdays, and stew on Wednesdays.
  - ✓ The pattern that the roommate remembers is simple.



RNN = Recurrent Neural Network

Recurrent Neural Networks : a simple example

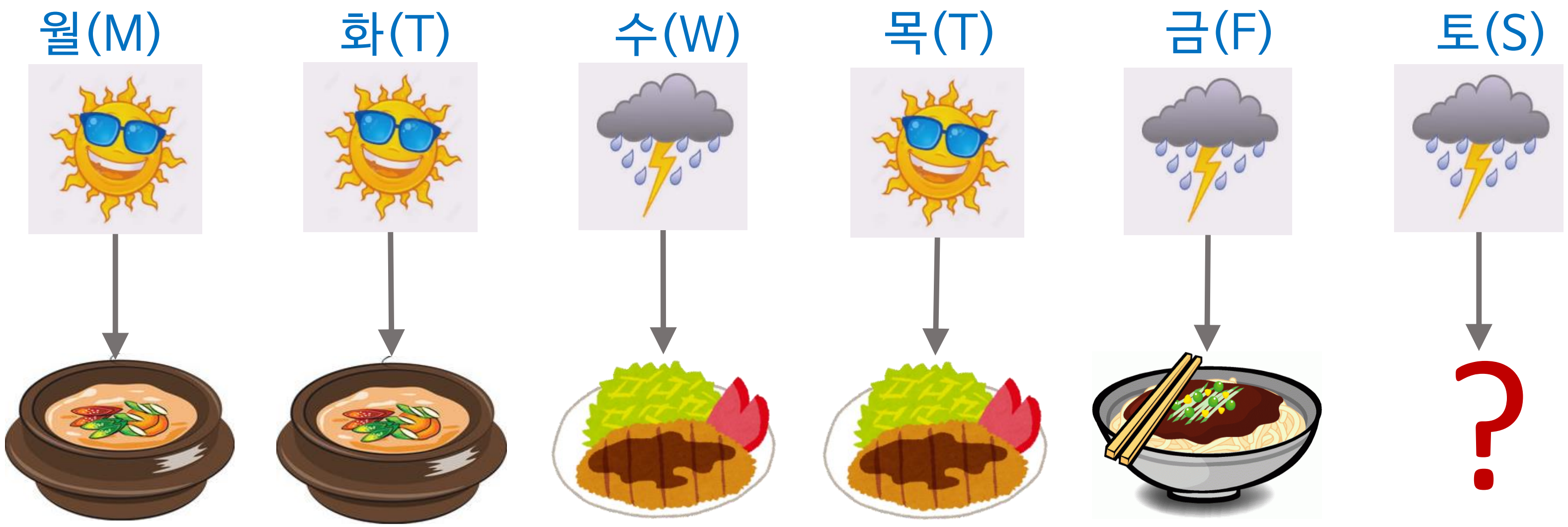
- In fact, roommates have rules on their meal menus depending on the weather.
  - ✓ On a fine day, he goes home late because he is outdoors, so I eat the food I ate the previous day again
  - ✓ However, on rainy days, he return home early and make food according to his patterns.

The food I ate yesterday

The original RNN pattern.

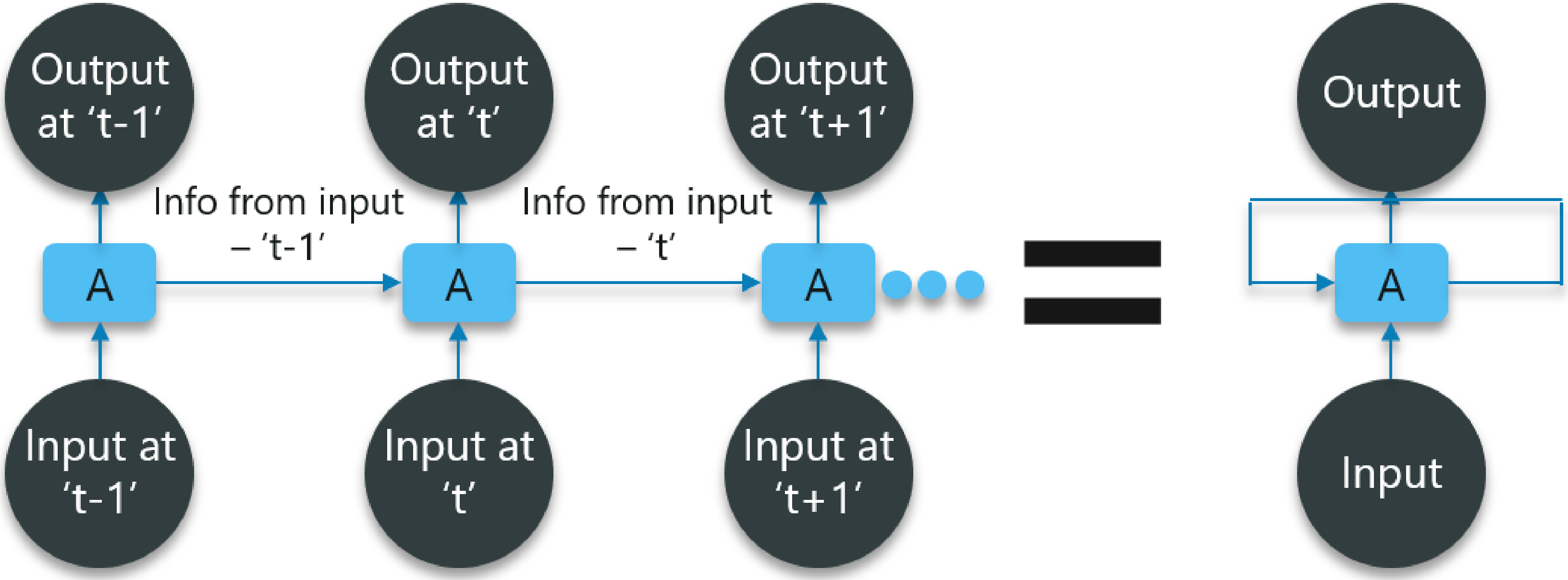
Recurrent Neural Network depending on the weather

- I can predict what to eat in the evening depending on the weather this morning.
  - ✓ On Monday, I ate stew in the evening, and the weather was nice on Tuesday morning, so I ate stew in the evening.
  - ✓ On Friday, it rained, so I ate jajangmyeon, the original pattern.
  - ✓ It rained on Saturday, what was the dinner menu?



RNN diagram

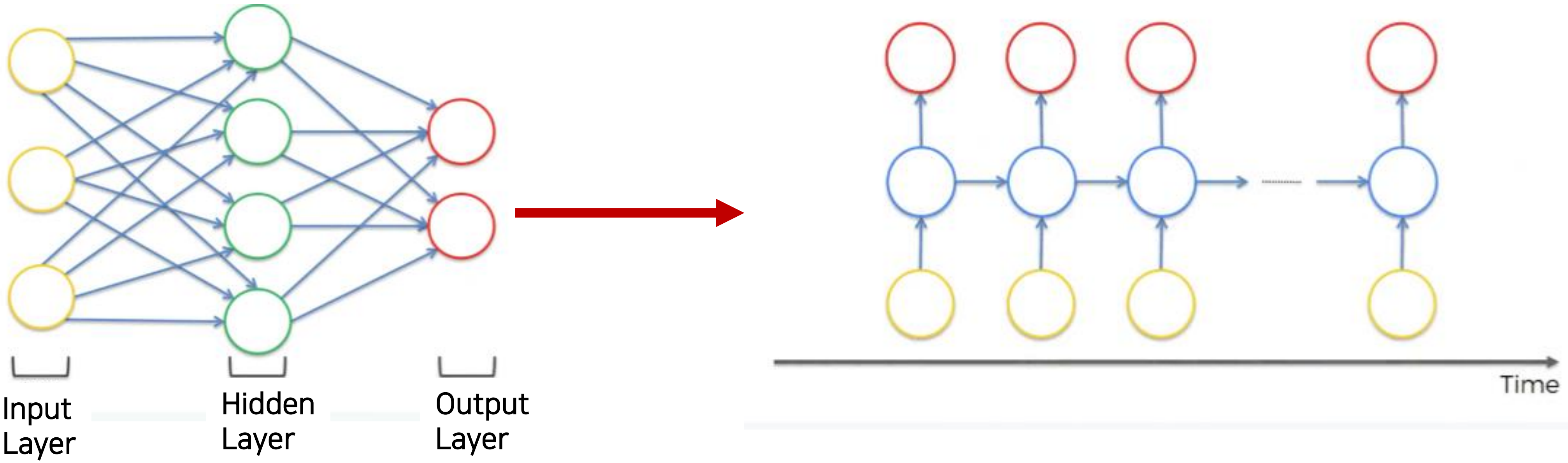
- Let's draw current neural networks (RNNs).
  - ✓ The information (memory pattern) obtained as an input of the previous time t-1 is used as an input at the next time t.
  - ✓ The input of the current time t and the memory of the previous time t-1 are input to output the current time t.



Overview of the feed-forward neural network and RNN structures

- Regarding the difference between the existing ANN and RNN,
  - ✓ Now each circle represents not only one neuron, but a whole layer of neurons.
  - ✓ Hidden layer, the number of neurons, and the number of weights are model parameters.

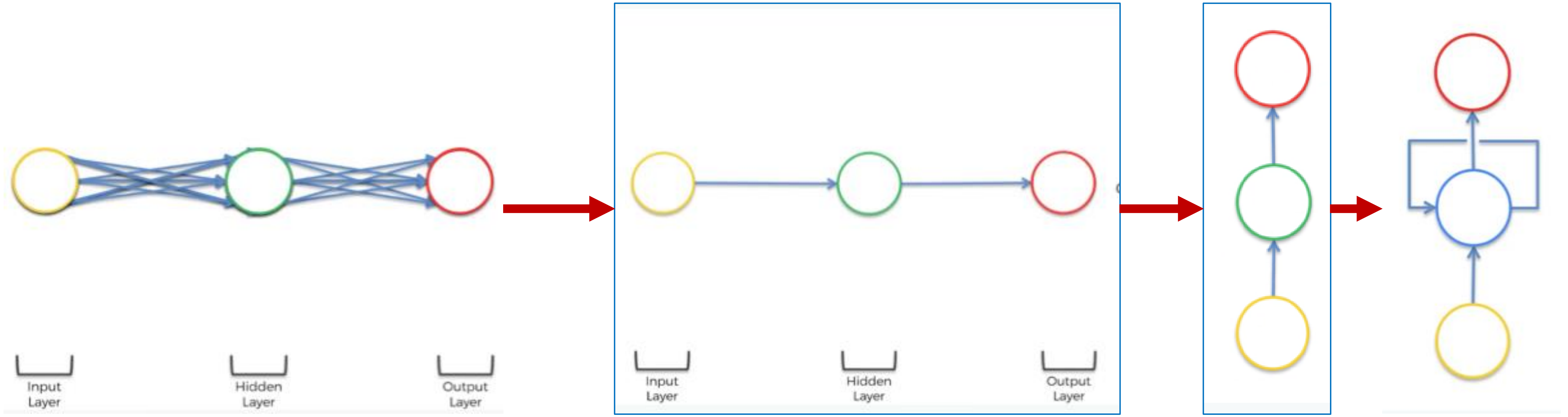
Unrolling the temporal loop and representing RNNs in a new way.



1 Hidden Layer (4 neurons)

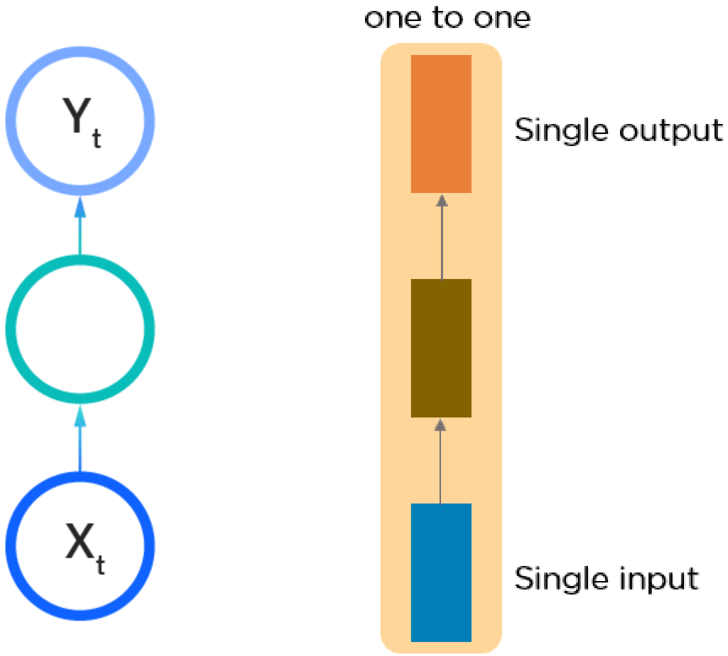
Transformation of a simple ANN into RNN

- Squashing the network.
- Changing the multiple arrows into two.
- Twisting it to make it vertical because that's the standard representation.
- Adding a line, which represents a temporal loop.



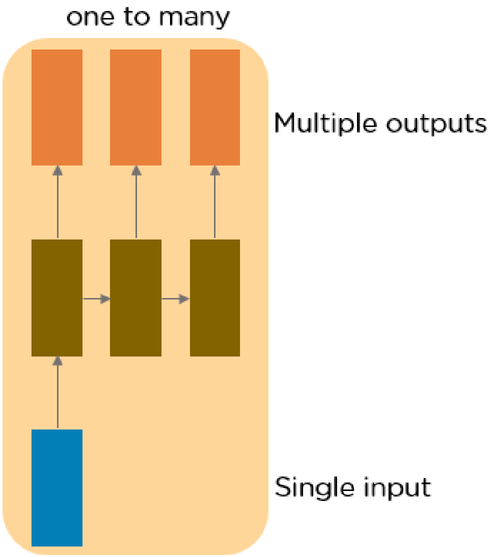
Examples of RNN Application

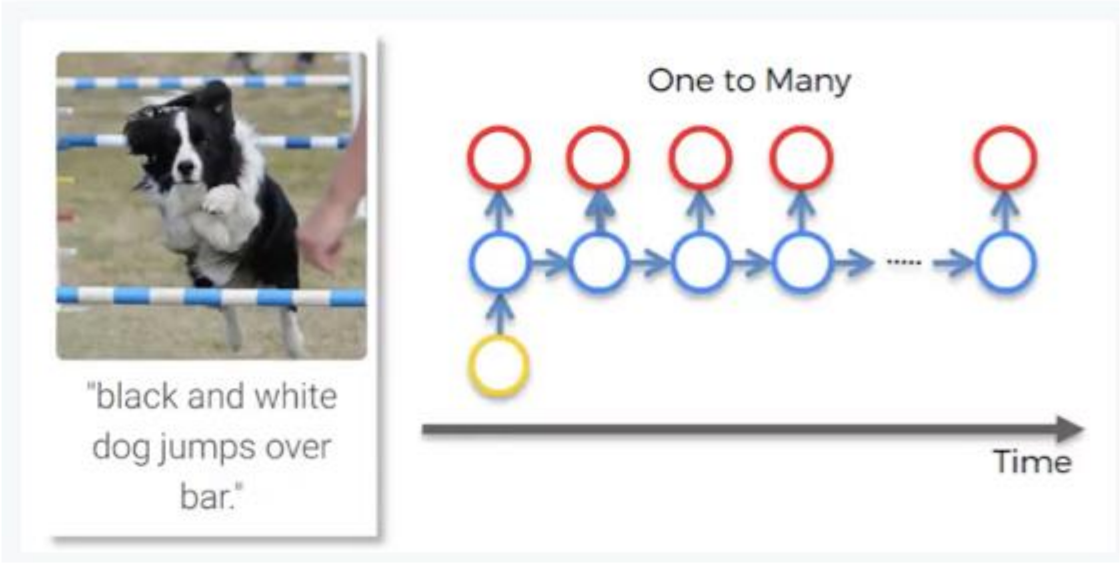
- One to One
  - ✓ This type of neural network is known as the Vanilla Neural Network.
  - ✓ It's used for general machine learning problems, which has a single input and a single output.



Examples of RNN Application

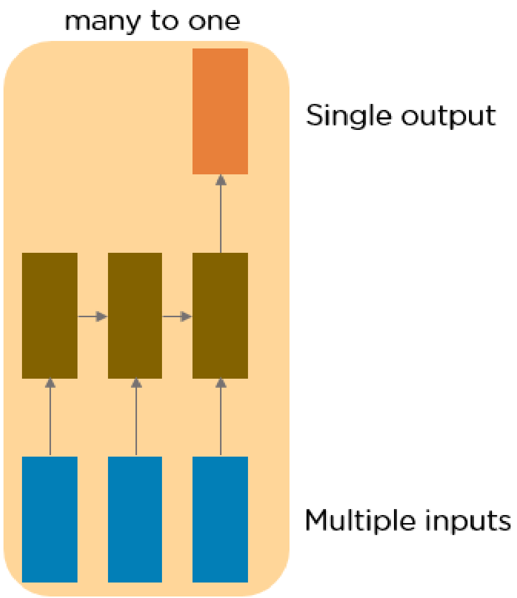
- One to many : This is a network with one input and multiple outputs
  - ✓ it could be an image (input), which is described by a computer with words (outputs).
    - This picture of the dog first went through CNN and then was fed into RNN. The network describes the given picture as “black and white dog jumps over bar”. This is pretty accurate, isn’t it?

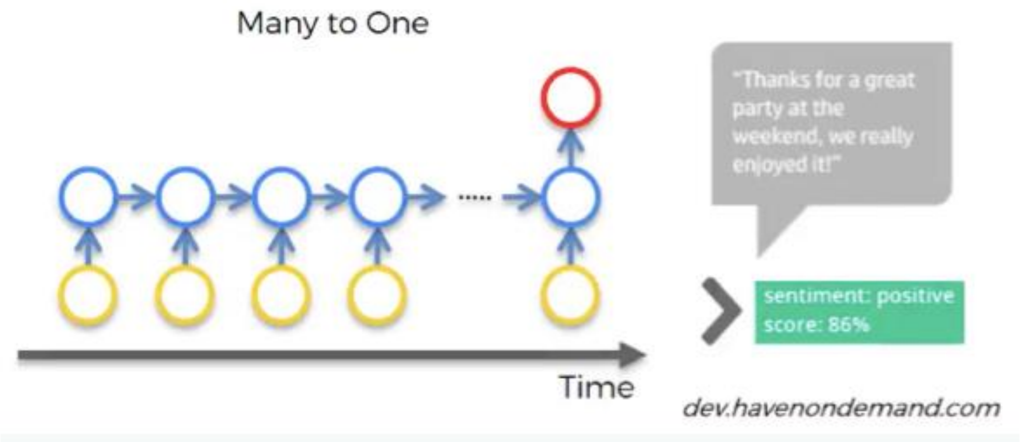




Examples of RNN Application

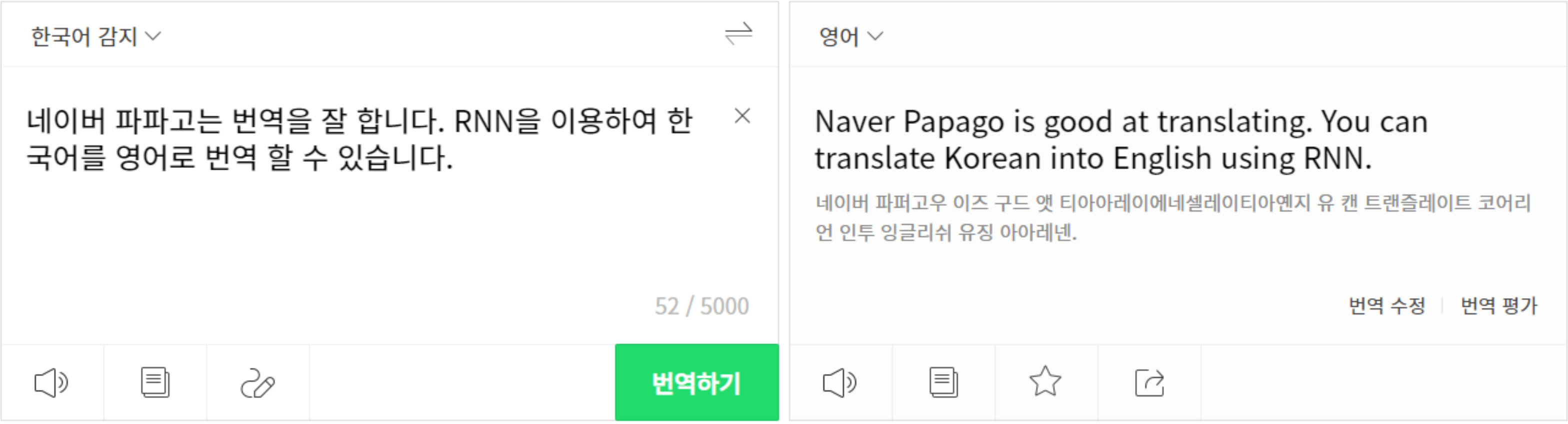
- Many to one : RNN takes a sequence of inputs and generates a single output.
  - ✓ Sentiment analysis is a good example of this kind of network where a given sentence can be classified as expressing positive or negative sentiments.

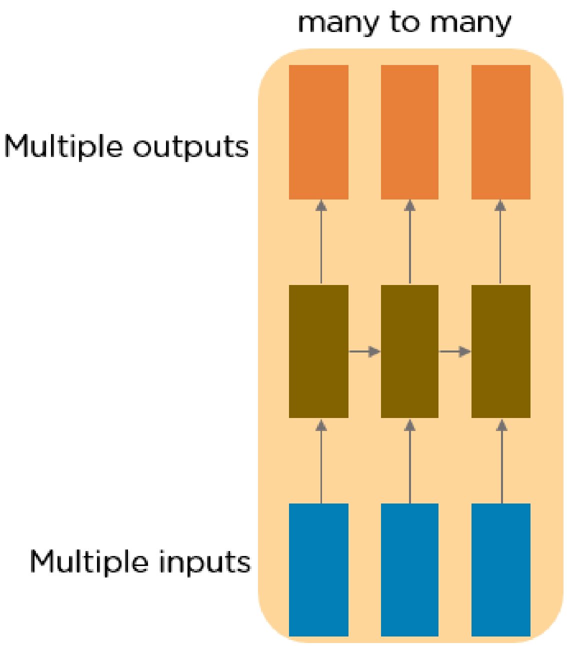




Examples of RNN Application

- Many to many :
  - ✓ RNN takes a sequence of inputs and generates a sequence of outputs.
  - ✓ Machine translation is one of the examples.





How to train RNN?

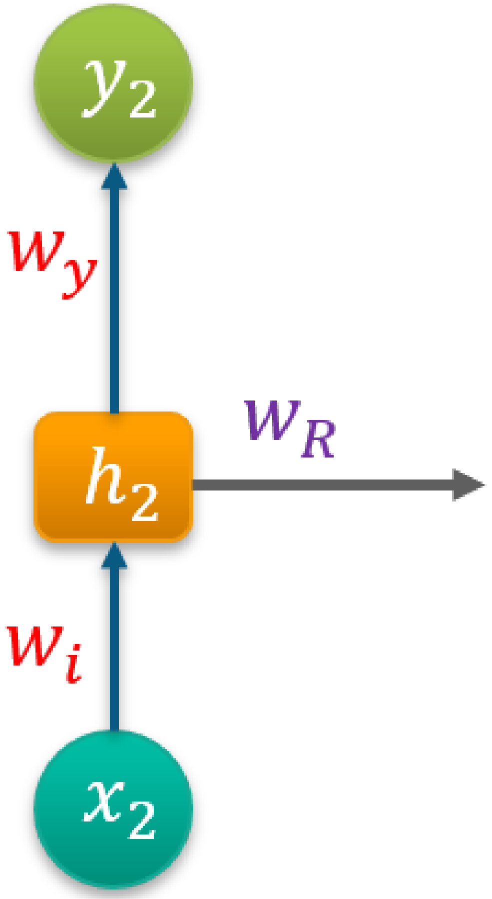
Backpropagation Through Time (BPTT)

Recurrent Neural Network

- Recurrent Neural Network
  - ✓ Output : usually want to predict a vector at some time steps
  - ✓ 3 weights(input, output, hidden)
  - ✓ 2 bias

$$h^{(t)} = g_h\left(w_i x^{(t)} + w_R h^{(t-1)} + b_h\right)$$

$$y^{(t)} = g_y\left(w_y h^{(t)} + b_y\right)$$



Recurrent Neural Network

- The same function and the same set of paramenters are used at the every time setp
  - ✓ input vectors : x and memory information : h

We can process a sequence of vectors **x** by applying a **recurrence formula** at every time step:

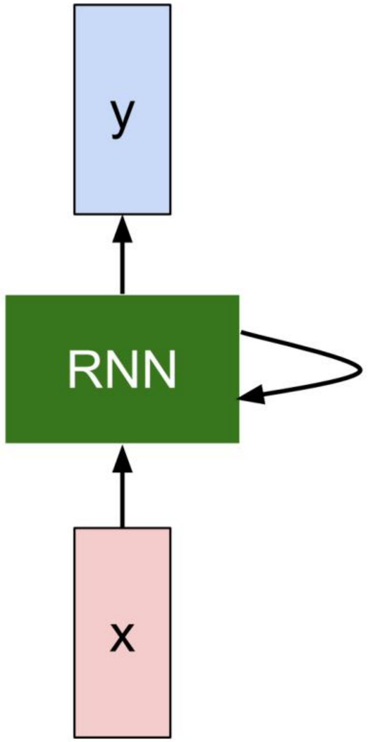
$$\boxed{h_t} = \boxed{f_W}(\boxed{h_{t-1}}, \boxed{x_t})$$

new state

some function with parameters W

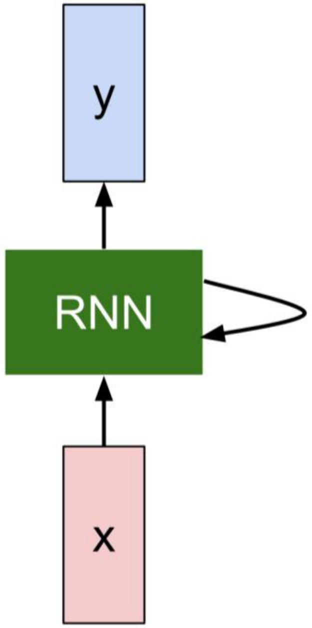
old state

input vector at some time step



(Vanilla) Recurrent Neural Network

- Vanilla RNN: One-to--One RNN
  - ✓ A neural network with one hidden vector.
  - ✓ The state consists of a single "hidden" vector h: tanh()

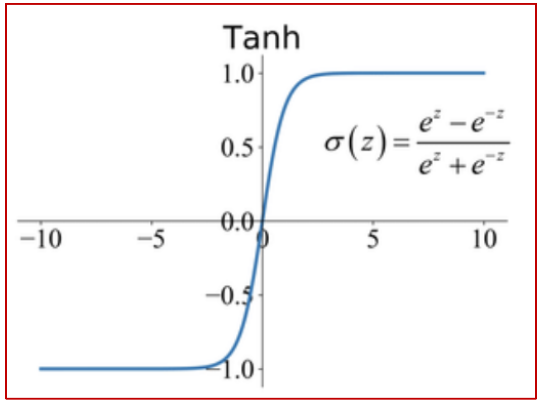


$$h_t = f_W(h_{t-1}, x_t)$$

$$\downarrow$$

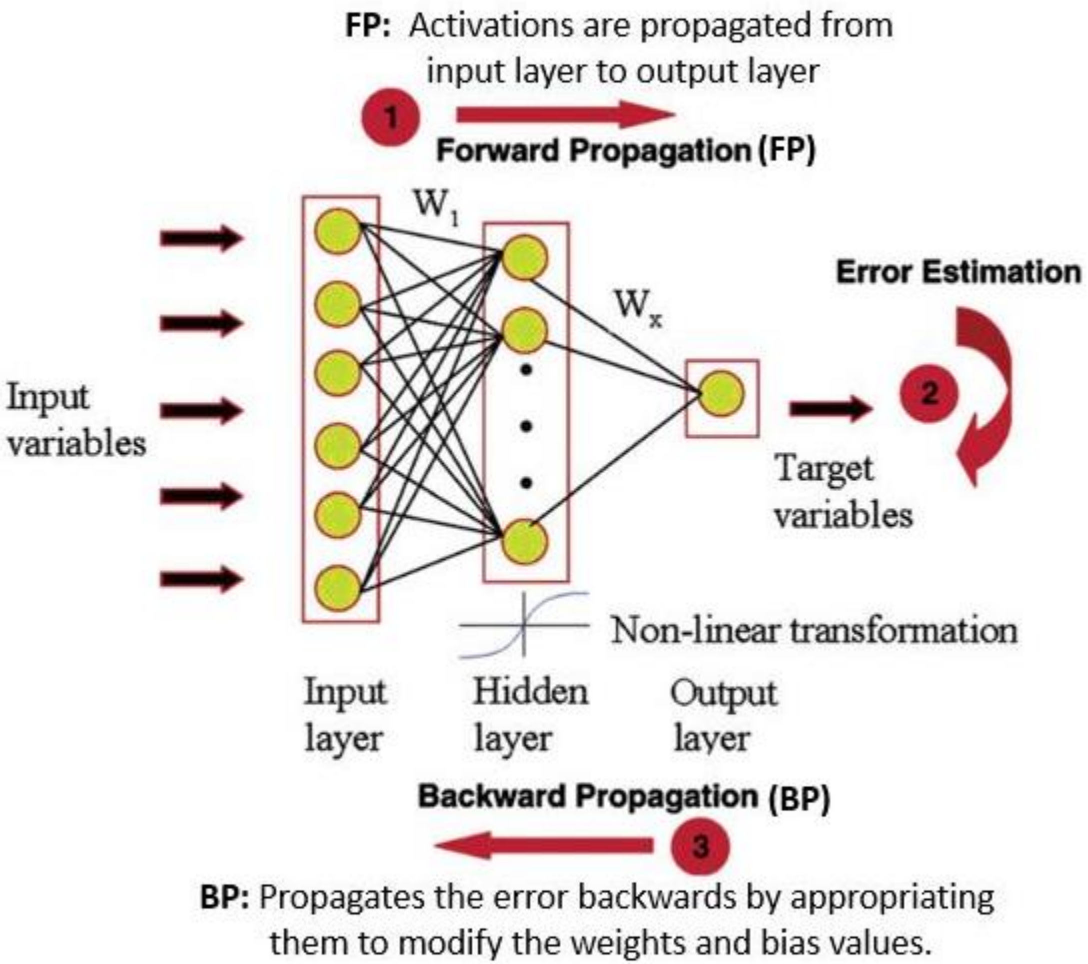
$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t)$$

$$y_t = W_{hy}h_t$$



Training MLP(ANN) models

MLP uses forward propagation followed by a supervised learning technique called *backpropagation* for training

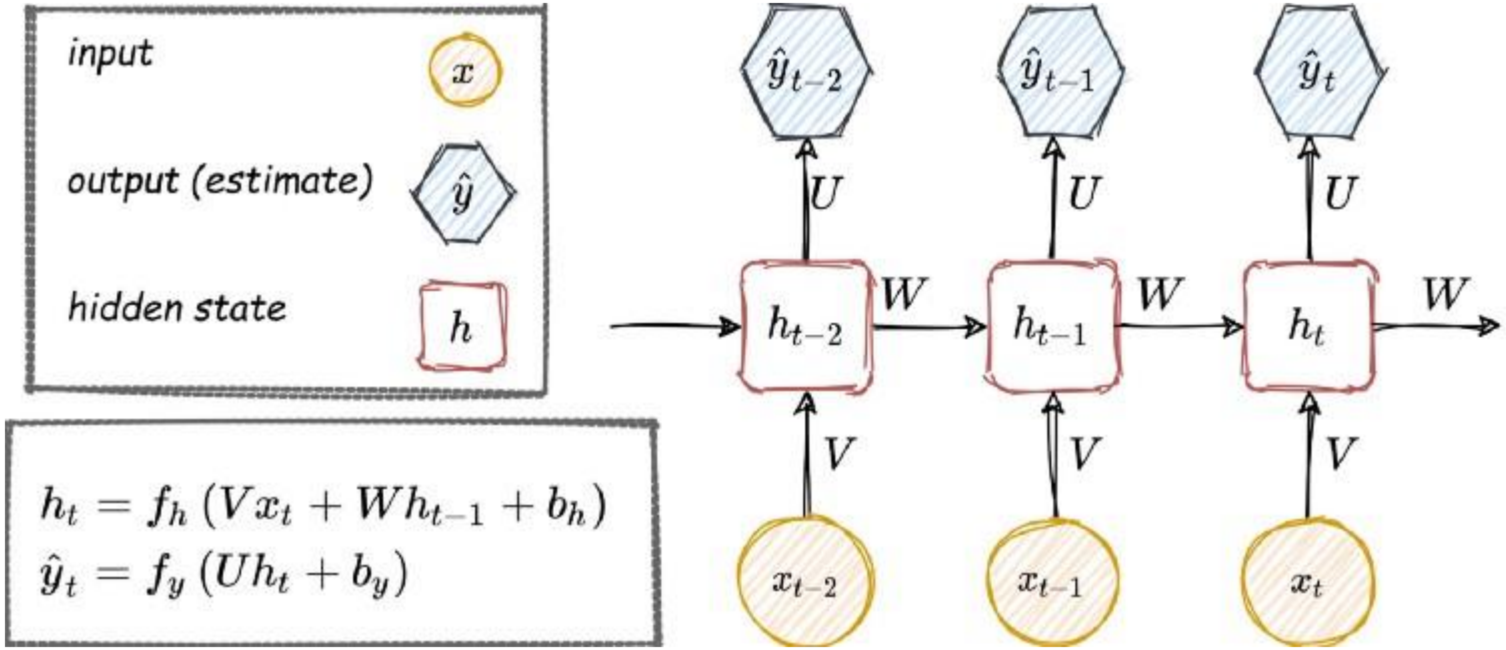


Supervised learning

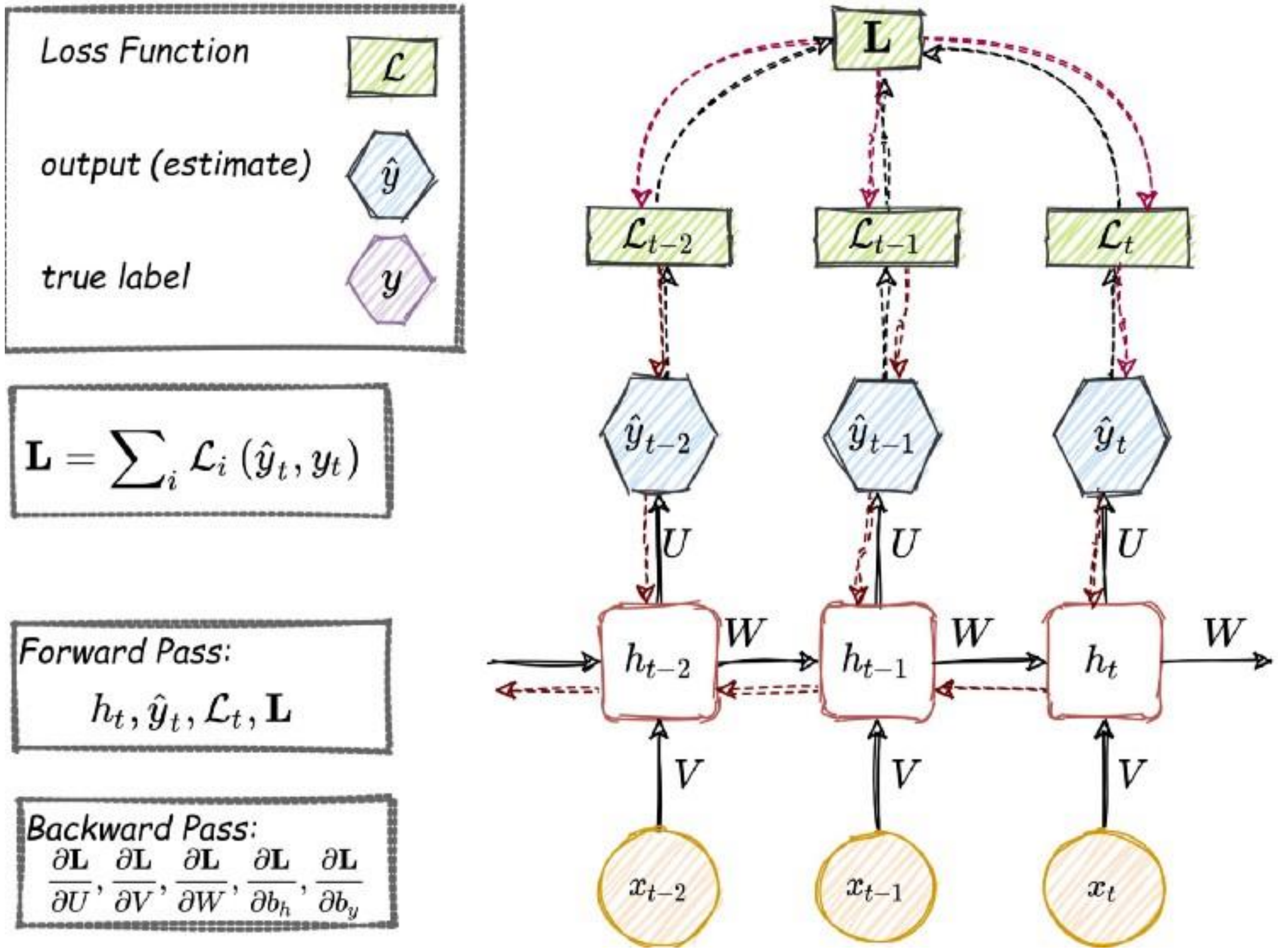
Data	$\{x, y\}_i$
Model	$y \approx f_\theta(x)$
Loss	$\mathcal{L}(\theta) = \sum_{i=1}^{N} l(f_\theta(x_i), y_i)$
Optimisation	$\theta^* = \arg\min_\theta \mathcal{L}(\theta)$

Training for Recurrent Neural Networks

- A simple RNN architecture is shown below, where V, W, and U are the weights matrices, and b is the bias vector.



Backpropagation Through Time (BPTT)



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	$\theta^* = \arg\min_\theta \mathcal{L}(\theta)$	$\theta^* = \arg\max_\theta \mathcal{L}(\theta)$

Modeling p(x)

"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

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

Modeling p(x)

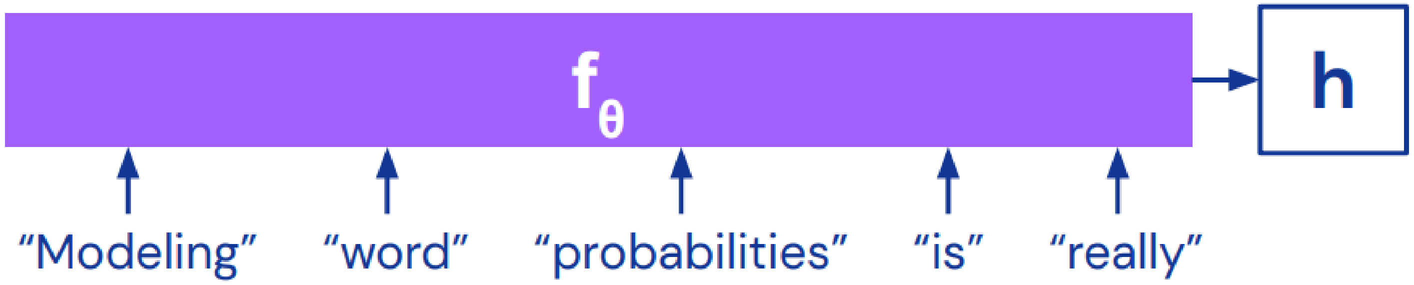
The chain rule
Computing the joint p($\mathbf{x}$) from conditionals

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

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)

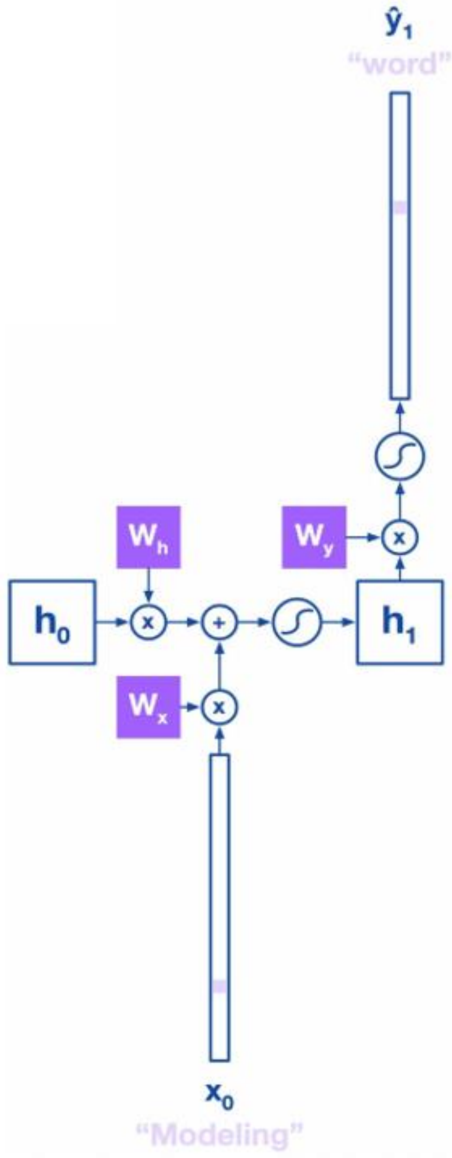
- Persistent state variable h stores information from the context observed so far.

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

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

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

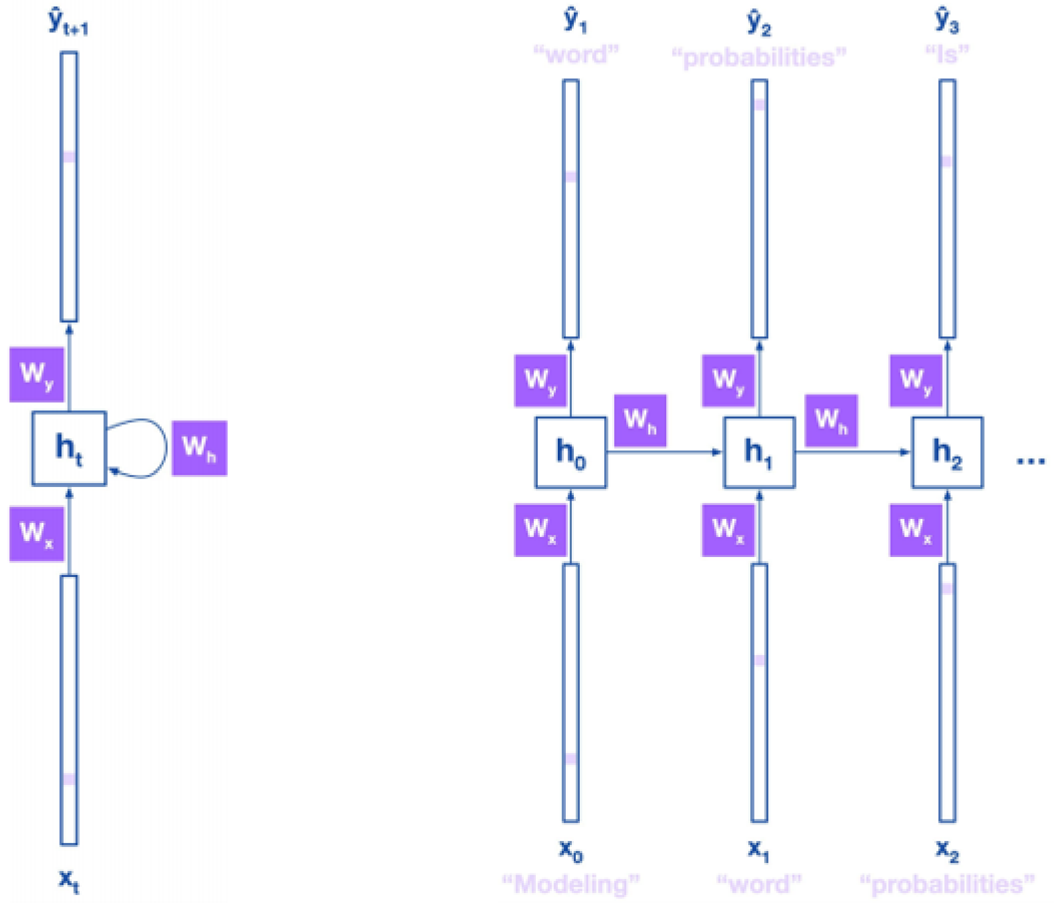
Softmax ensures we obtain a distribution over all possible words.



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

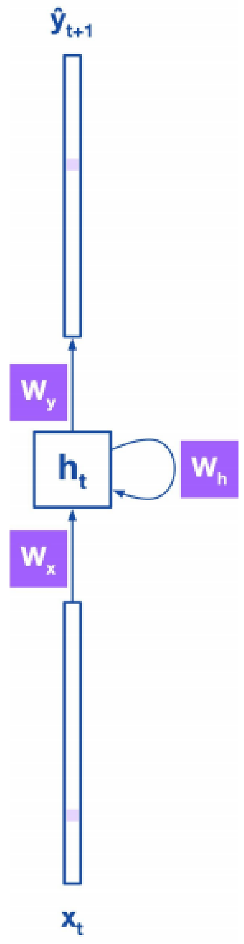
Next word prediction is essentially a classification task where the number of classes is the size of the vocabulary.

As such we use the cross-entropy loss:

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

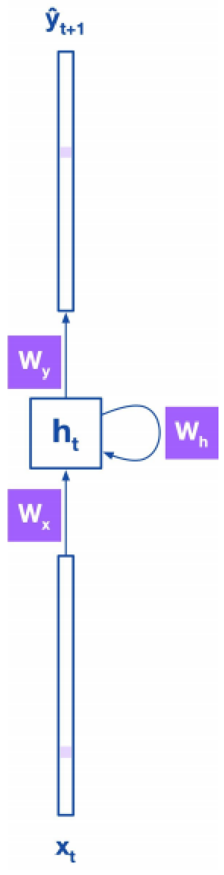
For the sentence: $$\mathcal{L}_\theta(\mathbf{y}, \hat{\mathbf{y}}) = -\sum_{t=1}^{T} \mathbf{y}_t \log \hat{\mathbf{y}}_t$$

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



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

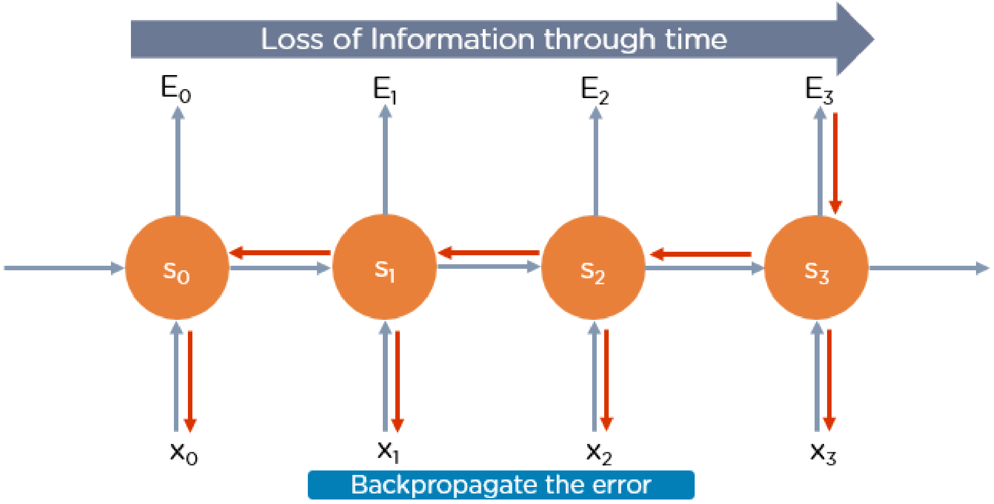
$$\begin{aligned}
\mathbf{h}_t &= \tanh(\mathbf{W}_h \mathbf{h}_{t-1} + \mathbf{W}_x \mathbf{x}_t) \\
p(\mathbf{x}_{t+1}) &= softmax(\mathbf{W}_y \mathbf{h}_t) \\
\mathcal{L}_\theta(\mathbf{y}, \hat{\mathbf{y}})_t &= -\mathbf{y}_t \log \hat{\mathbf{y}}_t
\end{aligned}$$



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

Backpropagation Through Time (BPTT)

- The training of RNN is not trivial, as we backpropagate gradients through layers and also through time
- In this equation, the contribution of a state at time step k to the gradient of the entire loss function L, at time step t=T is calculated.
- The challenge during the training is in the ratio of the hidden state



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

Vanishing Gradient Problem

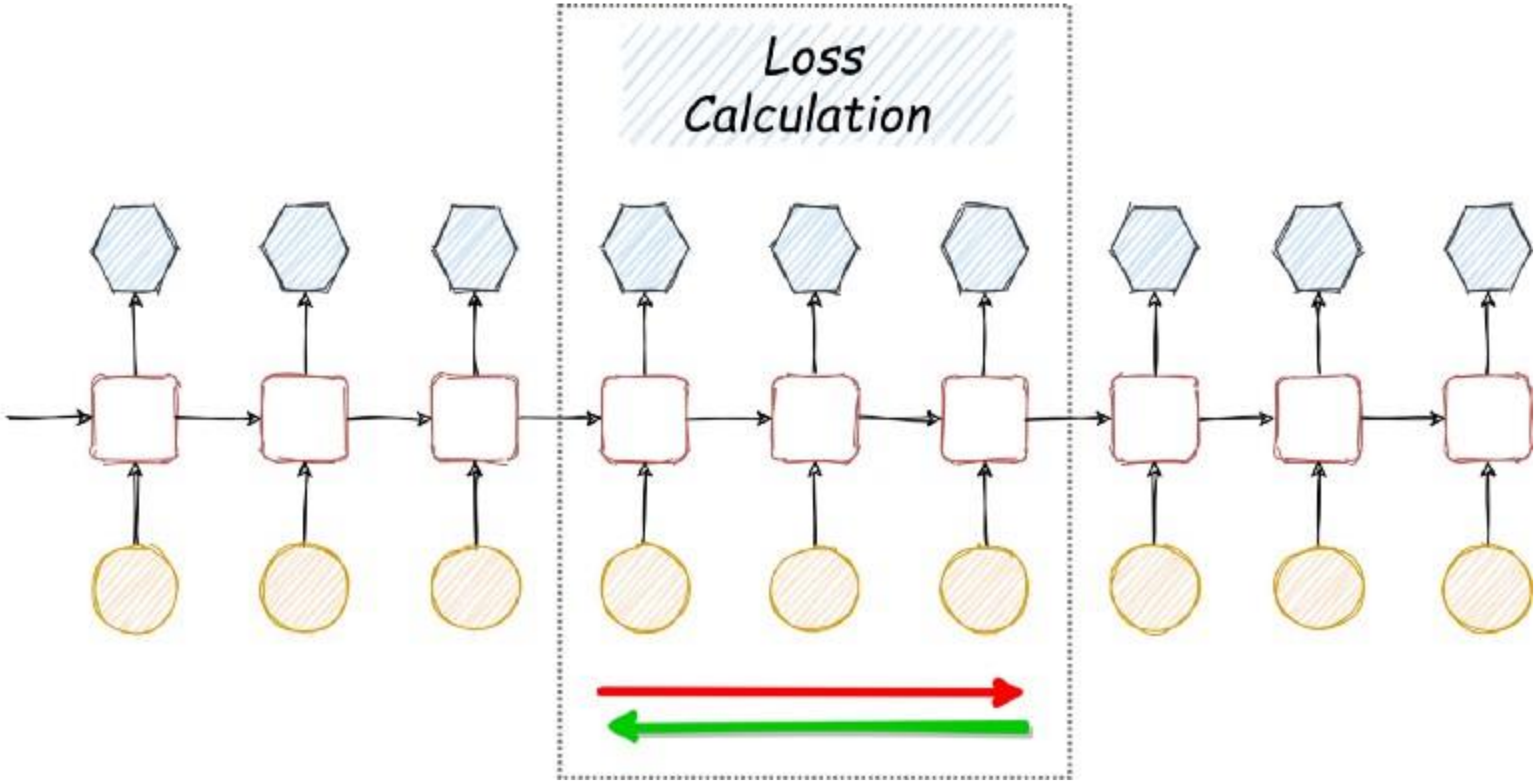
- RNNs suffer from the problem of vanishing gradients.
  - ✓ The gradients carry information used in the RNN, and when the gradient becomes too small, the parameter updates become insignificant.
    - This makes the learning of long data sequences difficult.
- Exploding Gradient Problem
  - ✓ While training a neural network, if the slope tends to grow exponentially instead of decaying
  - ✓ This problem arises when large error gradients accumulate, resulting in very large updates to the neural network model weights during the training process.
    - Long training time, poor performance, and bad accuracy are the major issues in gradient problems.

1. Vanishing gradient $\left\| \frac{\partial h_i}{\partial h_{i-1}} \right\|_2 < 1$

2. Exploding gradient $\left\| \frac{\partial h_i}{\partial h_{i-1}} \right\|_2 > 1$

Truncated Backpropagation Through Time (Truncated BPTT)

- Truncated BPTT trick tries to overcome the VGP
  - ✓ by considering a moving window through the training process

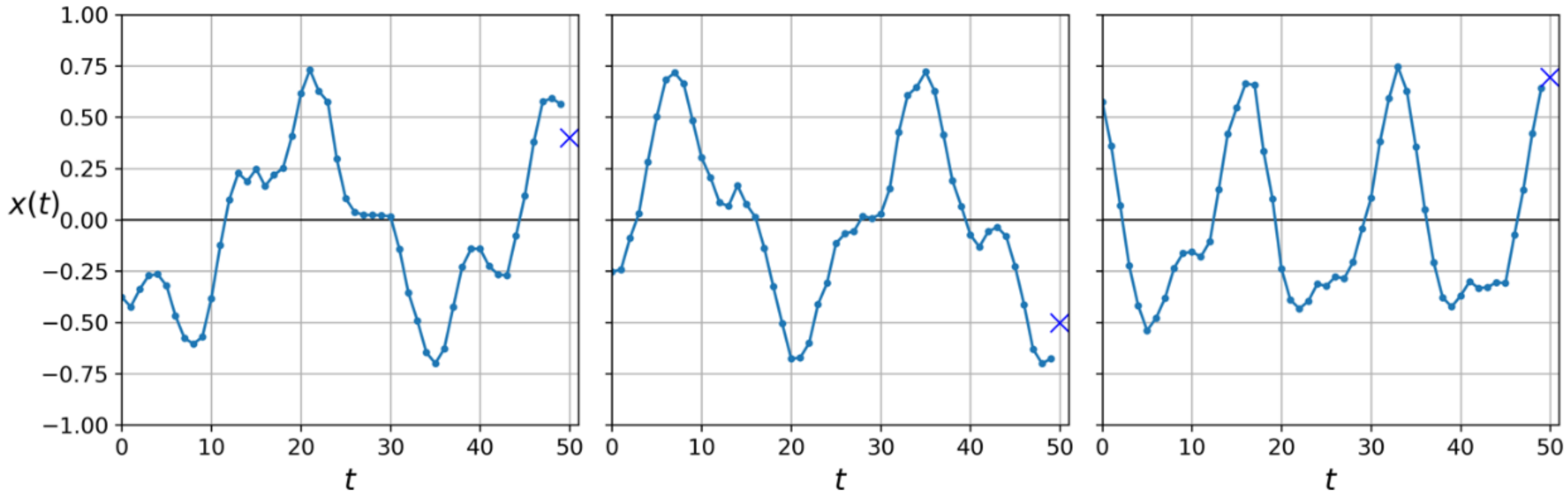


LAB01 : RNN-Basics

RNN, LSTM, GRU

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.



For simplicity, we are using a time series generated by the function

Generate the Dataset ¶

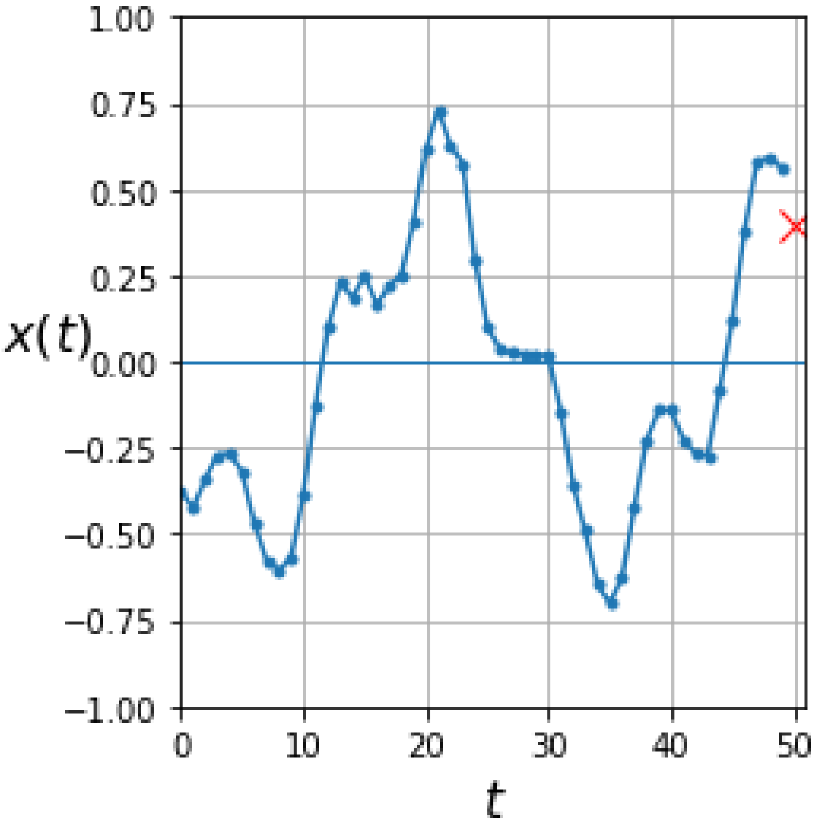
In [3]:
```
def generate_time_series(batch_size, n_steps):
    freq1, freq2, offsets1, offsets2 = np.random.rand(4, batch_size, 1)
    time = np.linspace(0, 1, n_steps)
    series = 0.5 * np.sin((time - offsets1) * (freq1 * 10 + 10))  #   wave 1
    series += 0.2 * np.sin((time - offsets2) * (freq2 *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

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.

단변량 시계열 데이터 생성

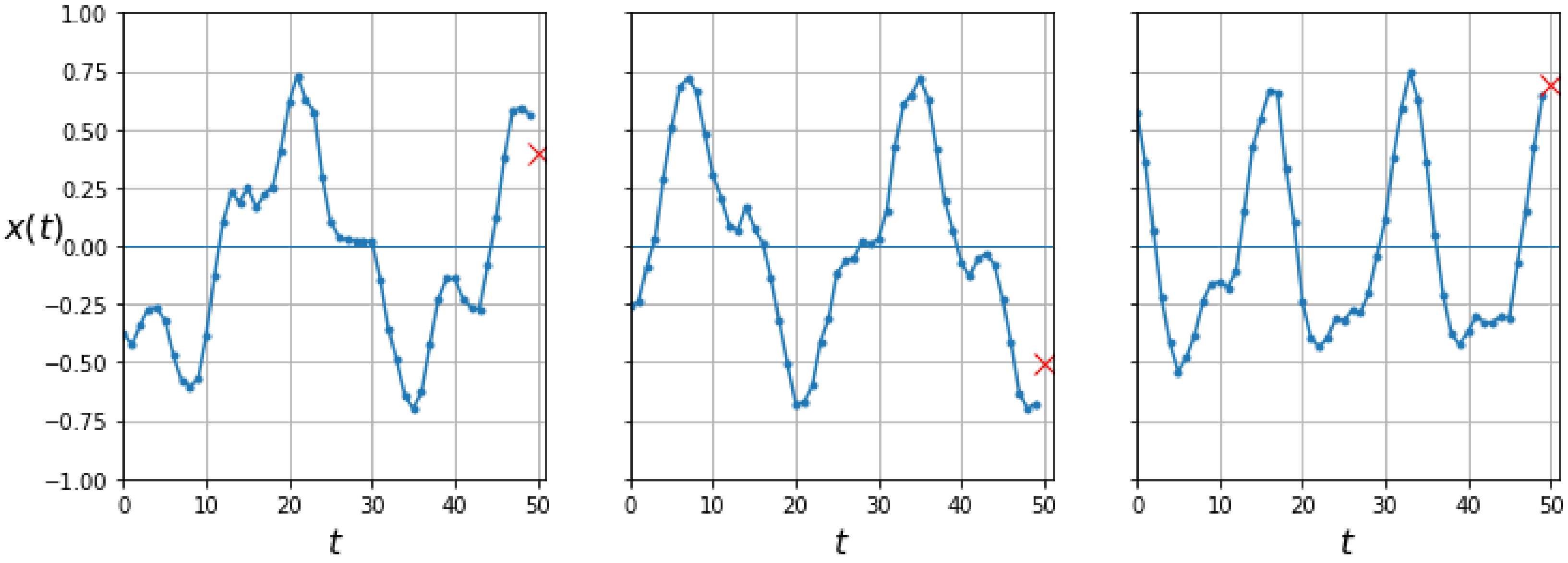
- sin() 함수 2개를 변형하여 합하고 일부 노이즈를 넣은 데이터
  - ✓ 배치사이즈: 10,000
  - ✓ 타임 스텝 : 50
  - ✓ 차원(값) : 1개



단별량 시계열 데이터 생성

- 시계열 데이터 생성하는 일반적인 방법은 3D 배열로

데이터 A = [배치크기, 타입 스텝 수, 차원수]

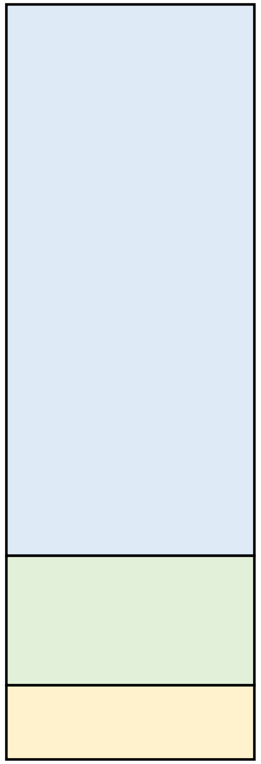


Now let's create a training set, a validation set, and a test set

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))
```

plot series

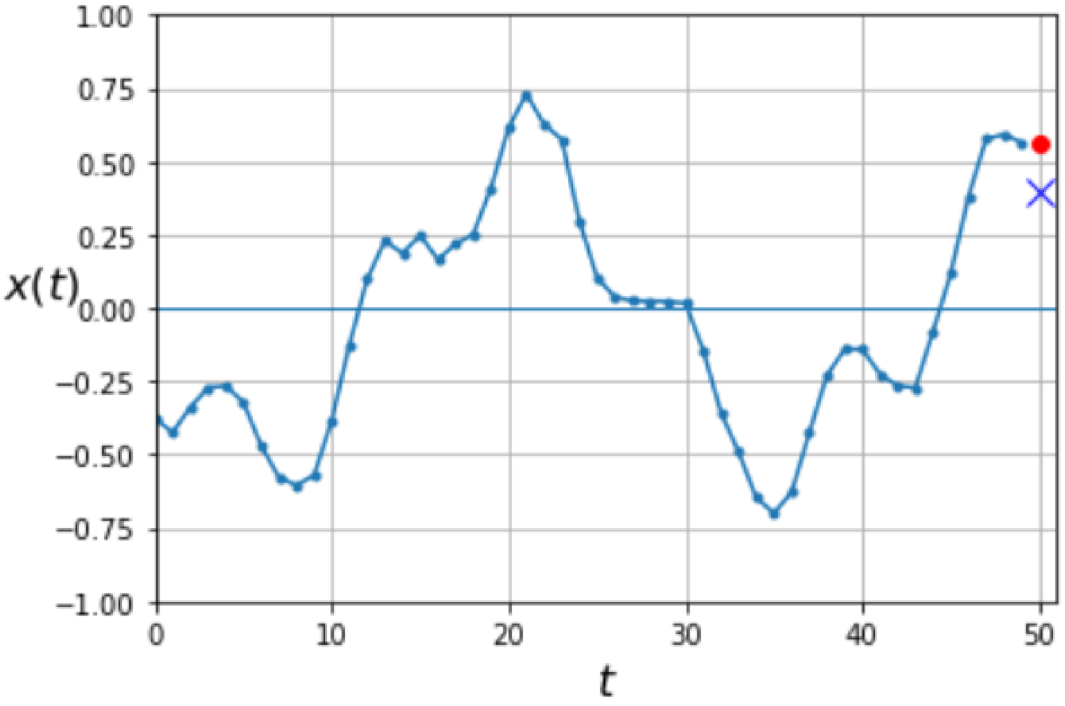
```
def plot_series(series, y=None, y_pred=None, x_label="$t$", y_label="$x(t)$"):
    plt.plot(series, ".-")
    if y is not None:
        plt.plot(n_steps, y, "rx", markersize=10)
    if y_pred is not None:
        plt.plot(n_steps, y_pred, "ro")
    plt.grid(True)
    if x_label:
        plt.xlabel(x_label, 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()
```

Computing Some Baselines

- Naive predictions (just predict the last observed value):
  - ✓ it is often a good idea to have a few baseline metrics,
  - ✓ For example, the simplest approach is to predict the last value in each series
  - ✓ This is called *naive forecasting*, and it is sometimes surprisingly difficult to outperform. 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))
```

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.

```
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
=================================================================
Total params: 51
Trainable params: 51
Non-trainable params: 0
```

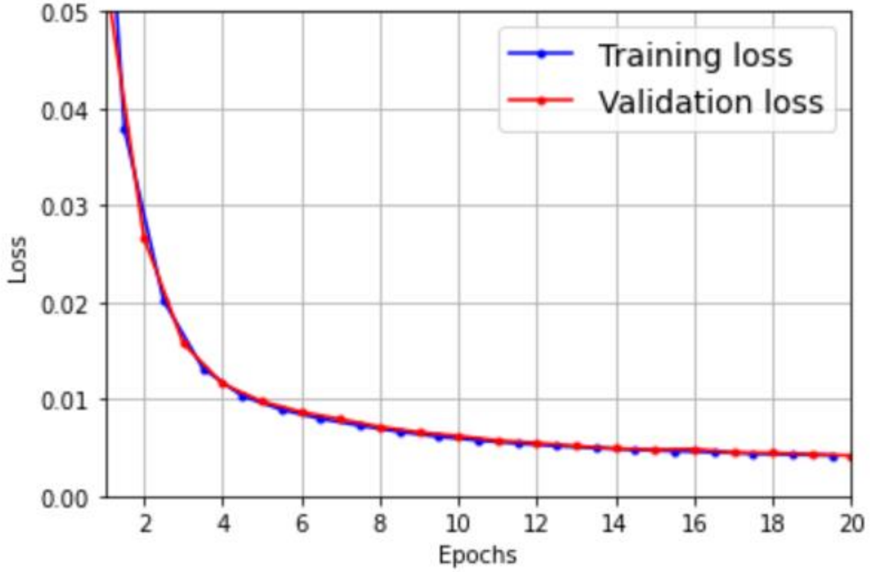
02. Fully connected network : Flatten

- 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
```



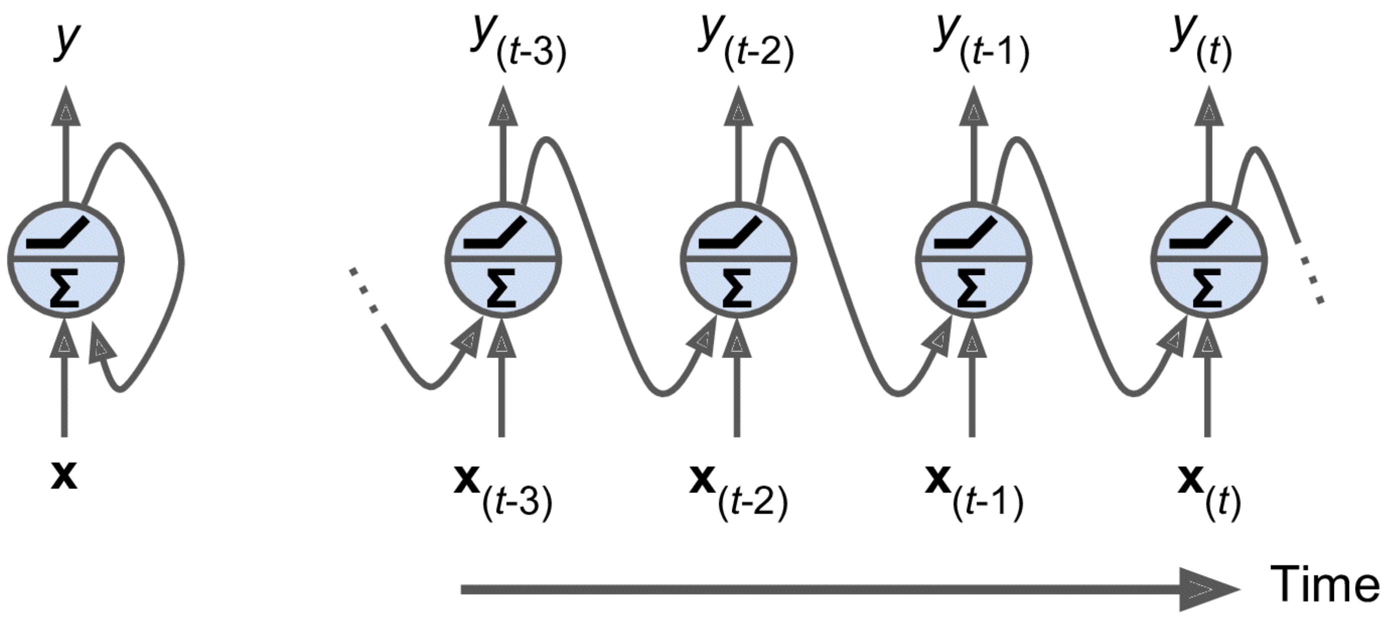
Learning Curves function and plot

```
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

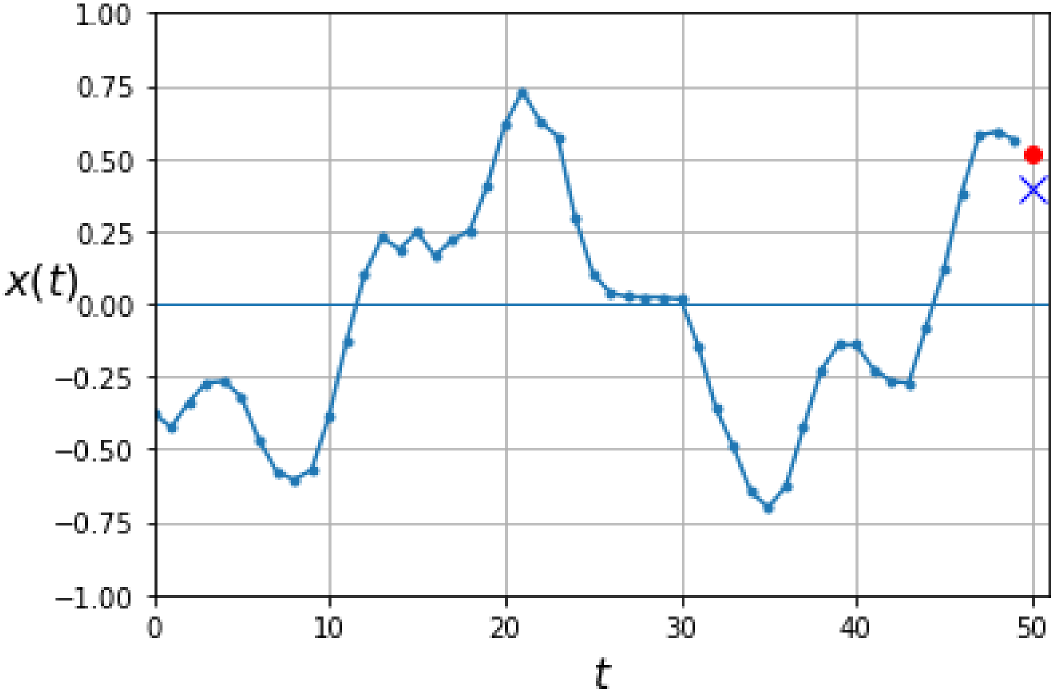
```
m3.summary()
```

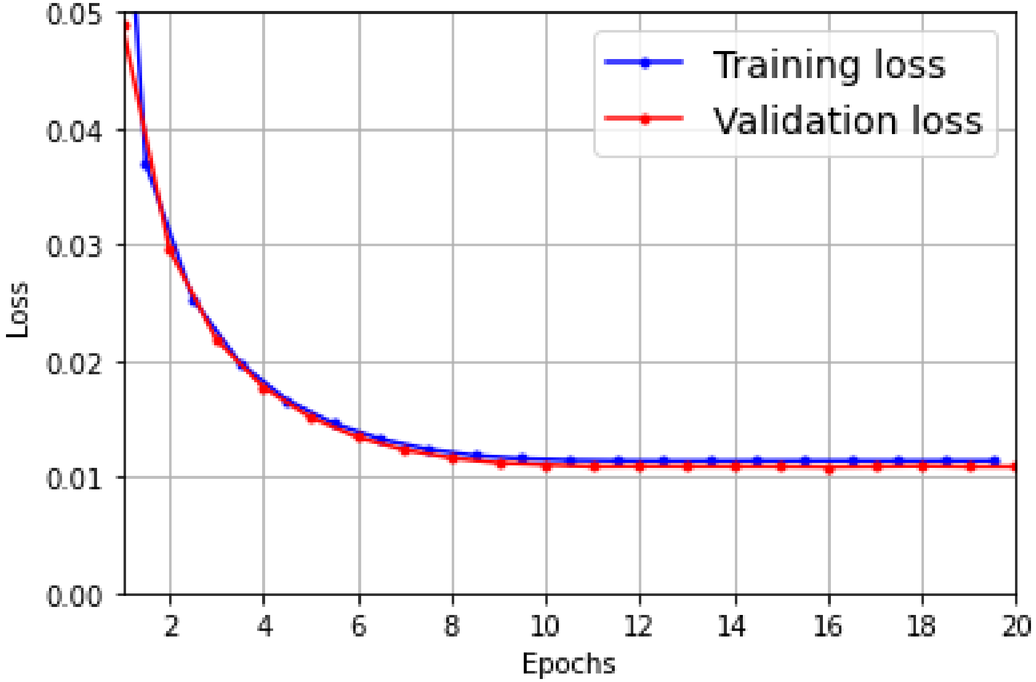
```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
simple_rnn (SimpleRNN)       (None, 1)                 3
=================================================================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

SimpleRNN layer uses the hyperbolic tangent activation function

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

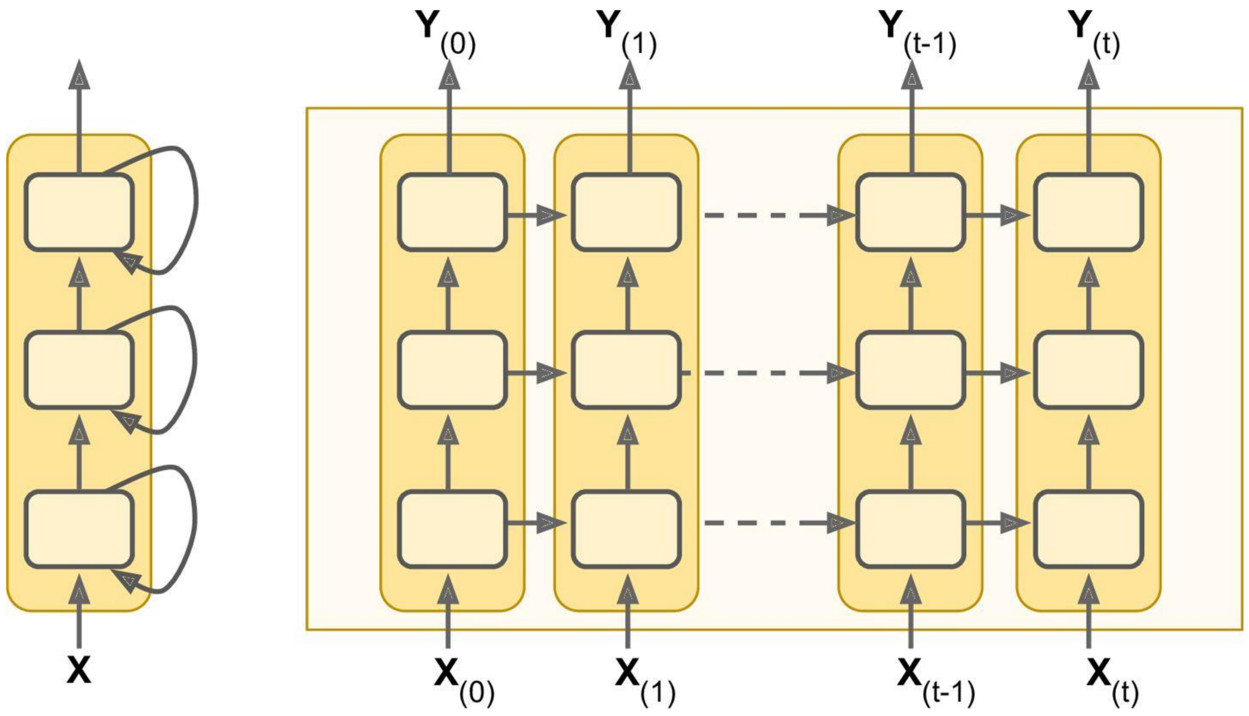
03. Simple RNN





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]: 0.0025271244812756777
```