

# Advanced School in Artificial Intelligence

## Introduction to Recurrent Neural Networks

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**Università  
degli Studi  
di Ferrara**

## Outline

- Introduction to Python
- Introduction to Neural Networks
- Convolutional NN
- Recurrent NN
- Autoencoders and self supervised learning

## Outline

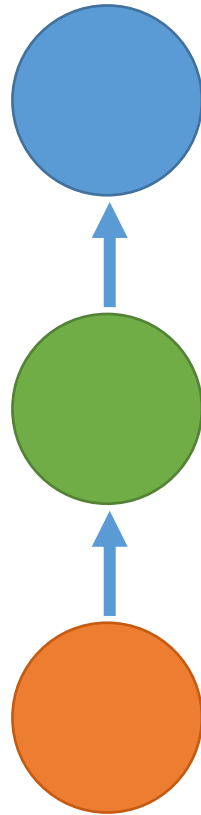
- Introduction to Python
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## Recurrent Neural Network

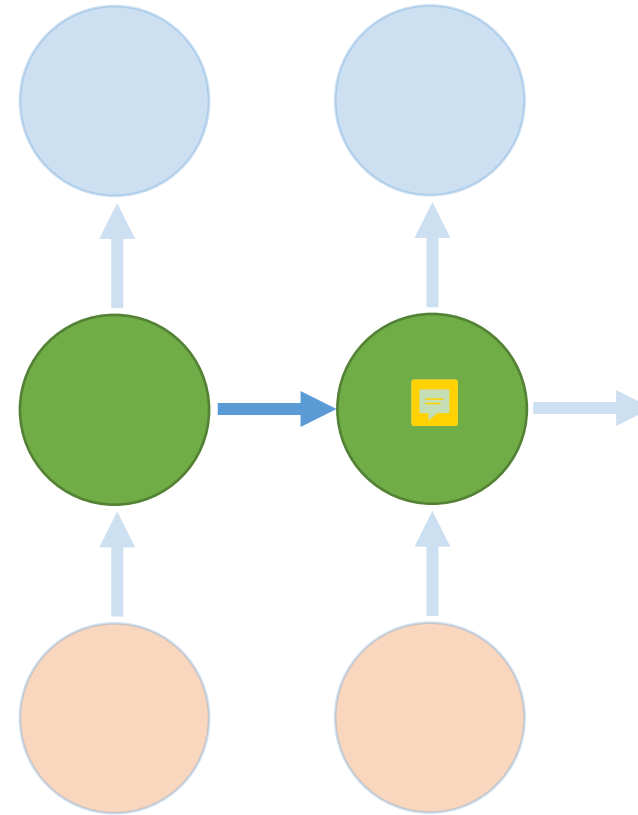
- **Recurrent neural networks** or RNNs are a family of neural networks for processing sequential data  $x^{(1)}, \dots, x^{(\tau)}$ .
- They are developed in order to be able to scale to very long sequences, that would be impractical to be managed without sequence-based specialization.
- We could say that, as much CNNs are thought for managing grid of values, as much RNNs are designed for sequences.

## NN vs RNN

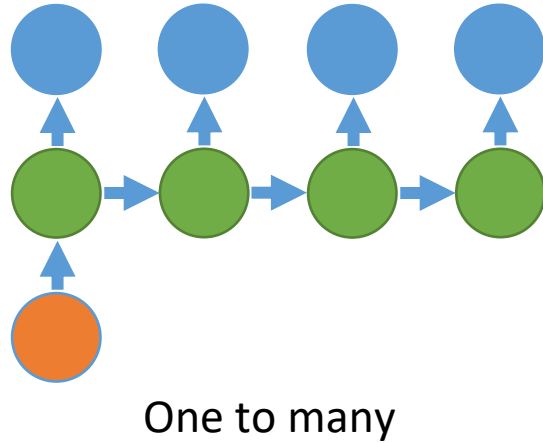
*Vanilla NN*



*Vanilla RNN*

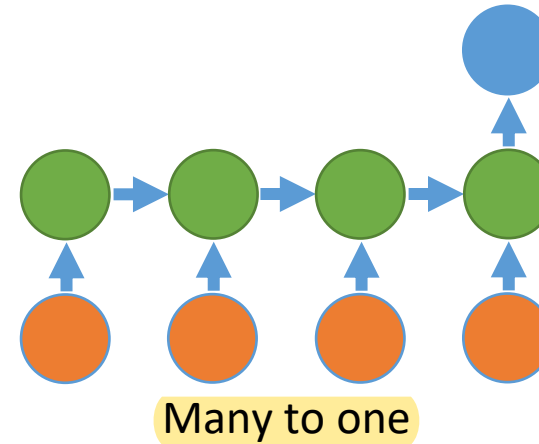
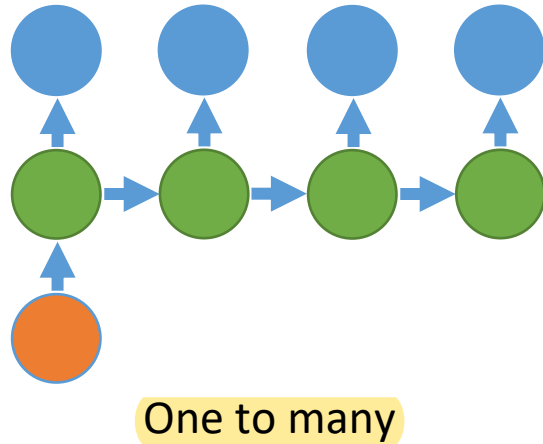


## Many different types of RNNs

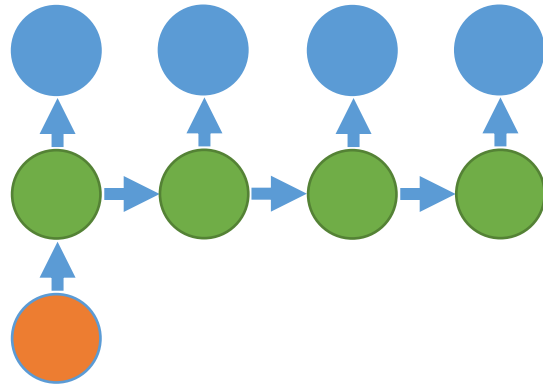




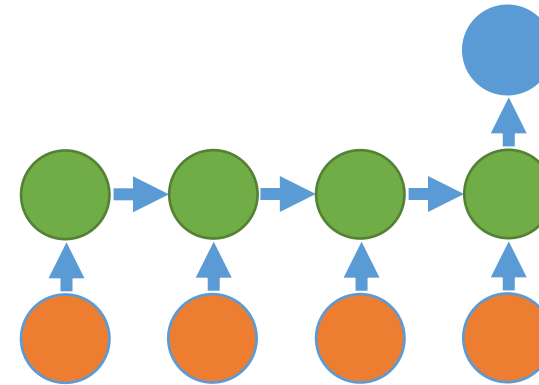
## Many different types of RNNs



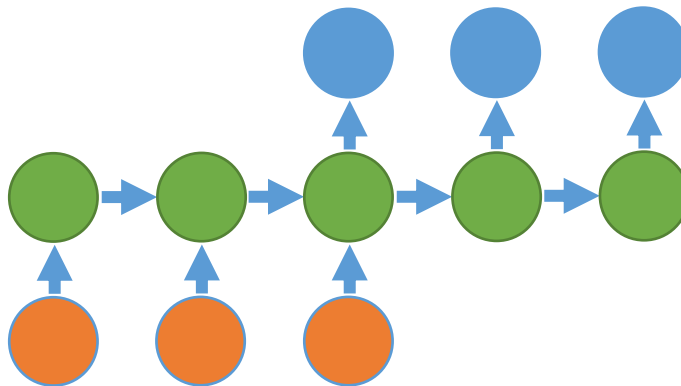
## Many different types of RNNs



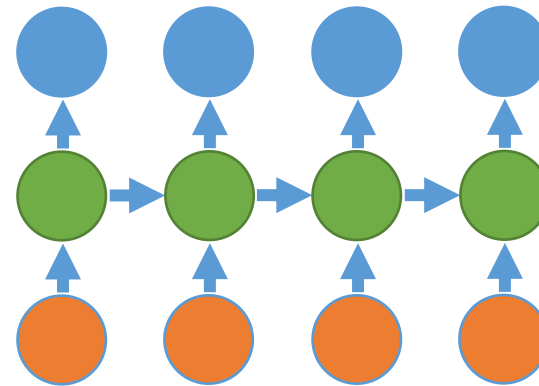
One to many



Many to one



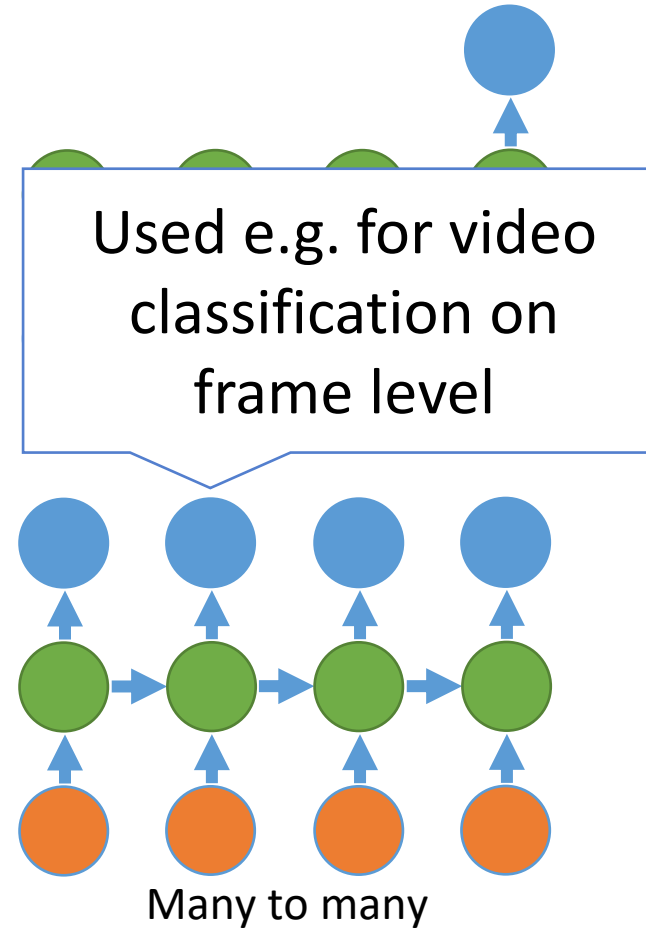
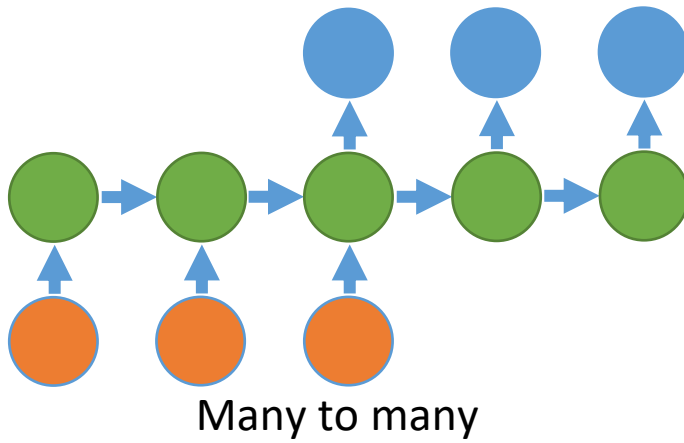
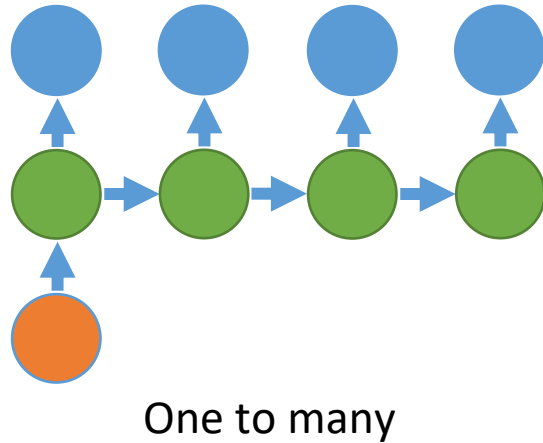
Many to many



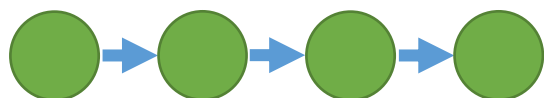
Many to many



## Many different types of RNNs

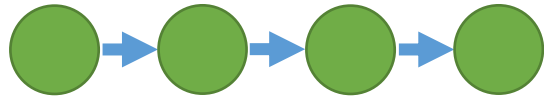


## Many different types of RNNs



- **Sharing parameters across different parts of a model.** Parameter sharing makes it possible to extend and apply the model to examples of different forms (different lengths, here) and generalize across them.
- If we had separate parameters for each value of the time index, we could not generalize to sequence lengths not seen during training, nor share statistical strength across different sequence lengths and across different positions in time.
- Such sharing is particularly important when a specific piece of information can occur at multiple positions within the sequence.

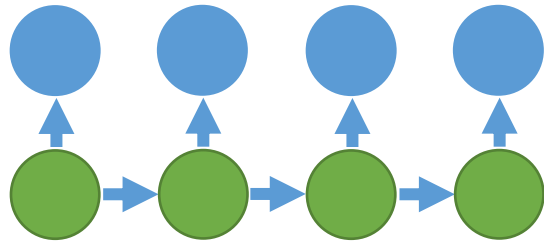
## Many different types of RNNs



Classify images by  
taking a series of lines

- Sharing parameters across different parts of a model. Parameter sharing makes it possible to extend and apply the model to examples of different forms (different lengths, here) and generalize across them.
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## Many different types of RNNs



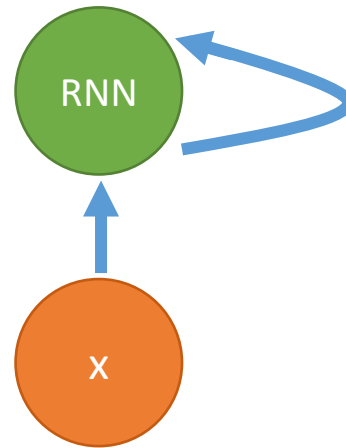
A recurrent neural network shares the same weights across several time steps.

Each member of the output is a function of the previous members of the output.

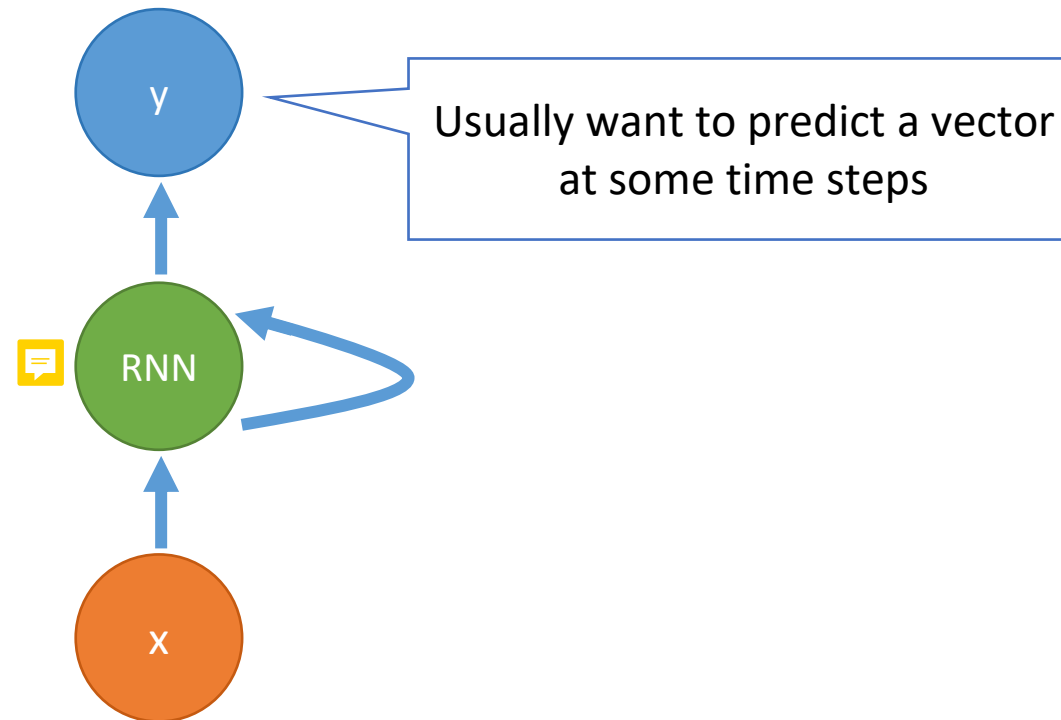
Each member of the output is produced using the same update rule applied to the previous outputs.

This recurrent formulation results in the sharing of parameters through a very deep computational graph.

## Recurrent NN

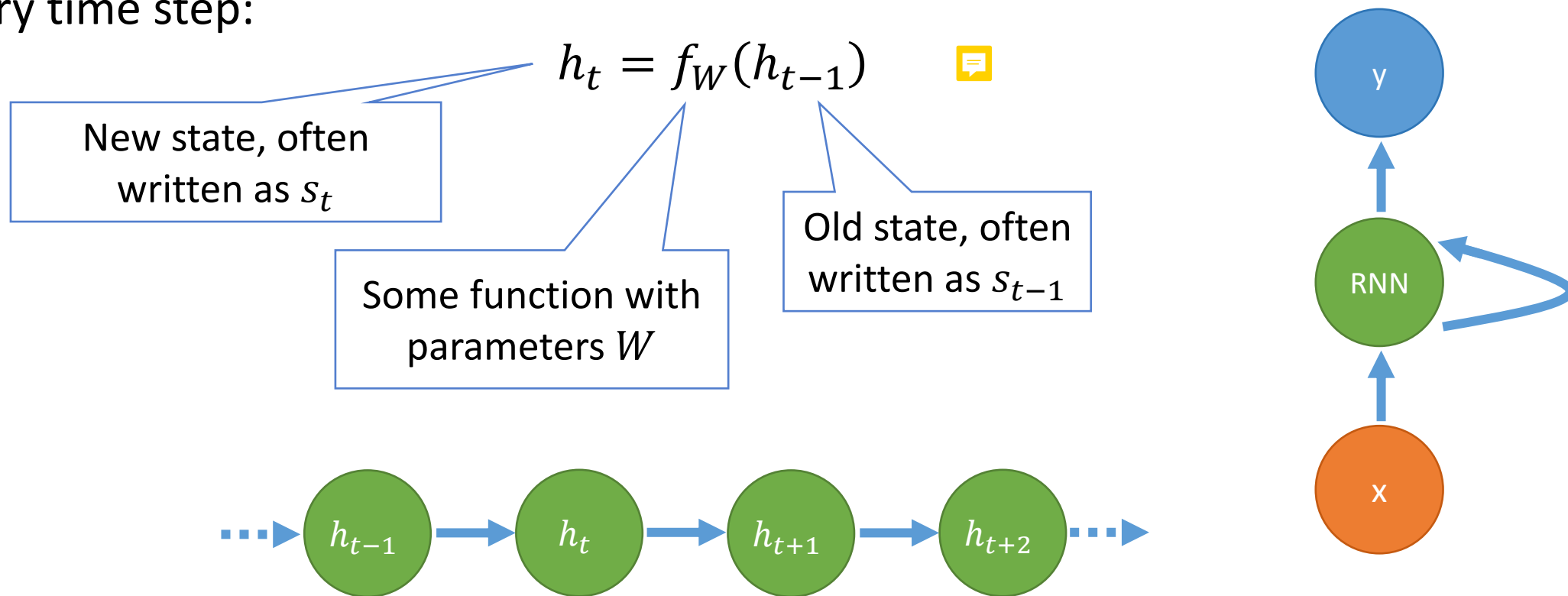


## Recurrent NN



## Unfolding Recurrent NN

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



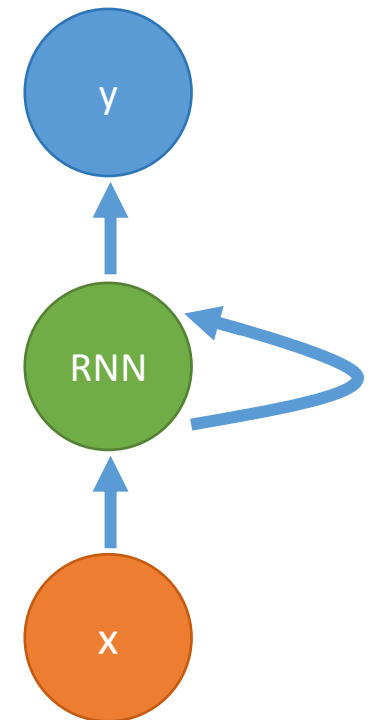
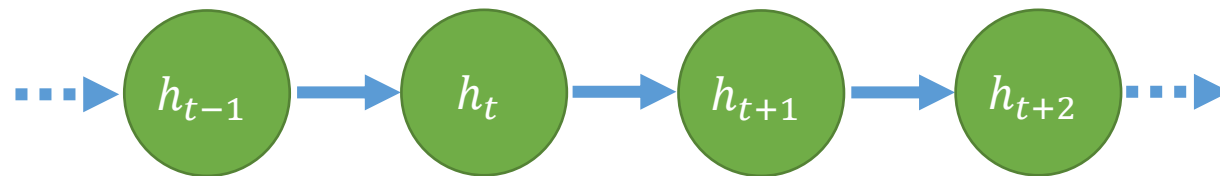


## Unfolding Recurrent NN

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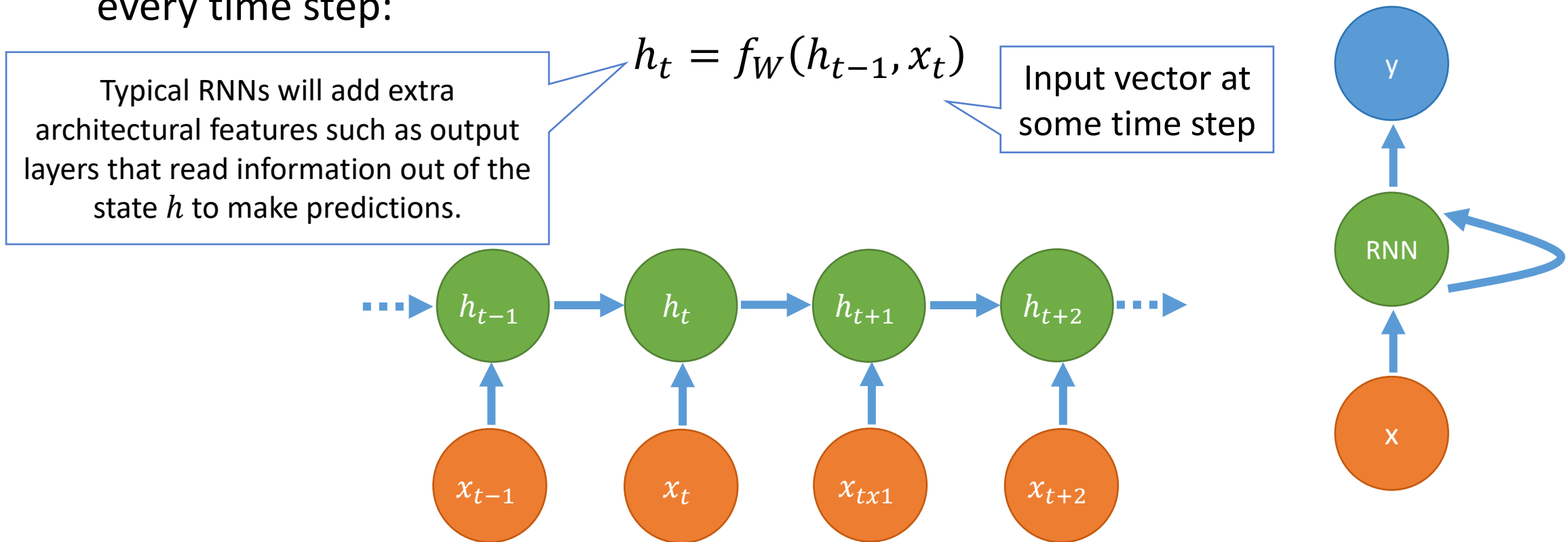
$$h_t = f_W(h_{t-1})$$

The resulting expression is  
$$h_t = f_W(h_{t-1}) = f_W(f_W(h_{t-2}))$$



## Unfolding Recurrent NN

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



## Unfolding Recurrent NN

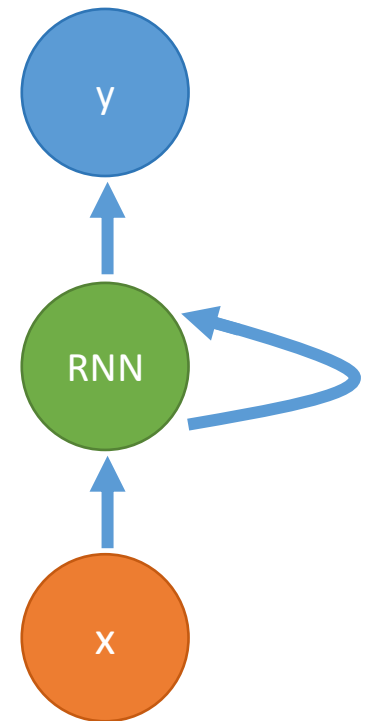
- We can process a sequence of vectors  $x$  by applying a **recurrence formula** at every time step:

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

The resulting expression is

$$\begin{aligned} h_t &= f_W(h_{t-1}, x_t) = f_W(f_W(h_{t-2}, x_{t-1}), x_t) \\ &= g_t(x_t, x_{t-1}, x_{t-2}, \dots, x_2, x_1) \end{aligned}$$

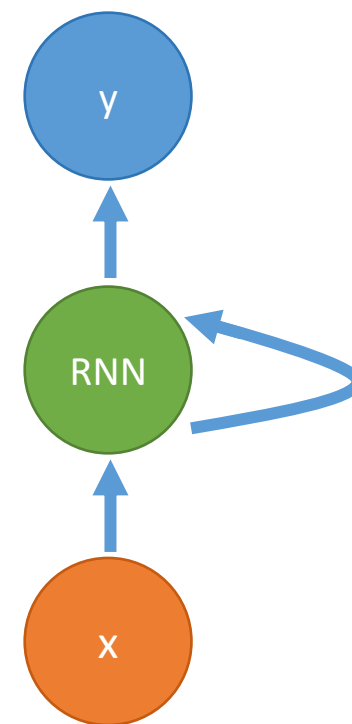
Here  $g_t$  is a function taking the whole past sequence as input and produces the current state



## Unfolding Recurrent NN

- Note that in both scenarios the same function and the same set of parameters are used at every time step!

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



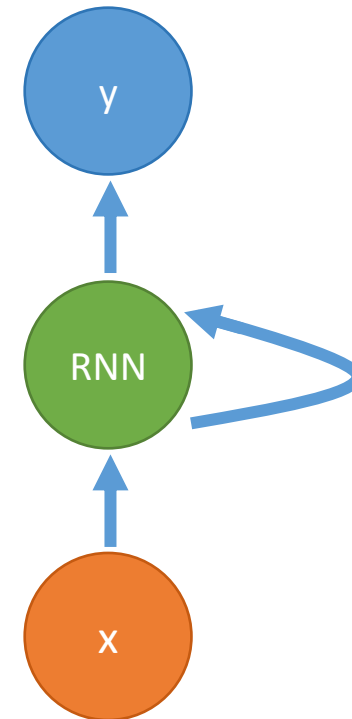
## Vanilla Recurrent NN

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

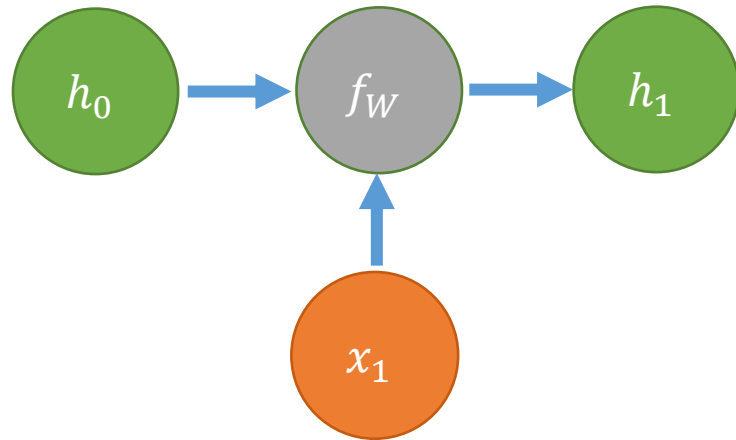
🗨️ 
$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t)$$

The state consists of  
a single “hidden”  
vector  $h$

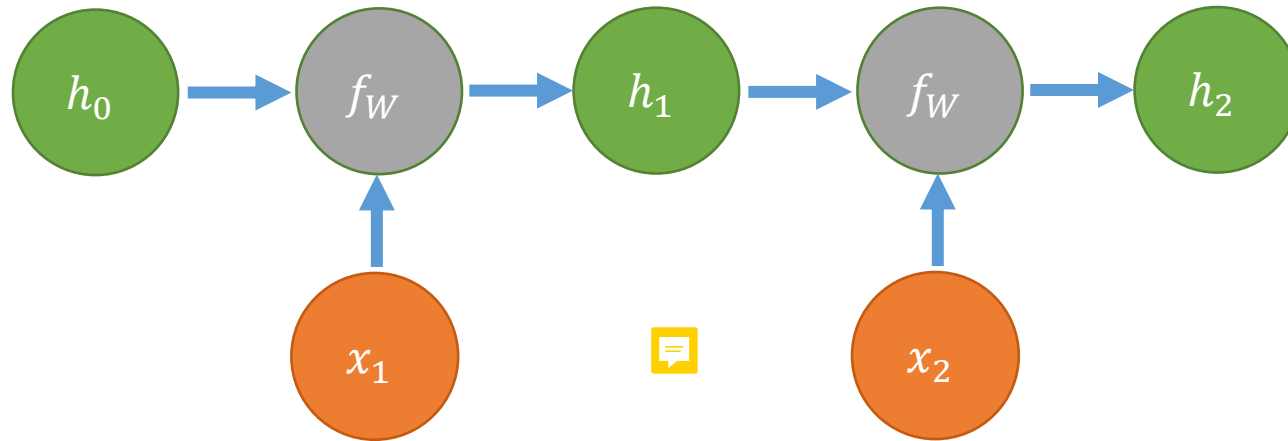
$$y_t = W_{hy}h_t$$



## RNN: Computational Graph

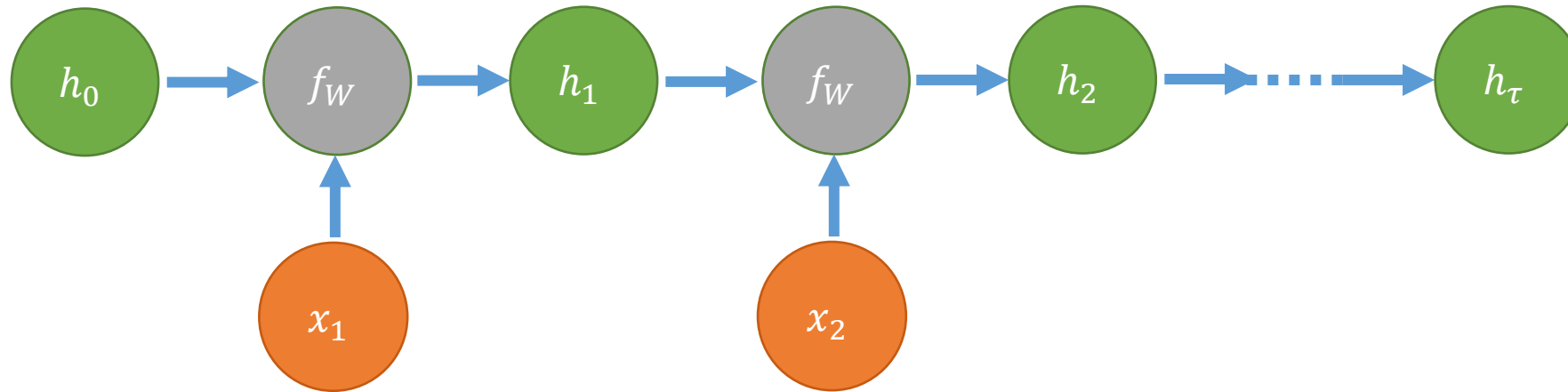


## RNN: Computational Graph

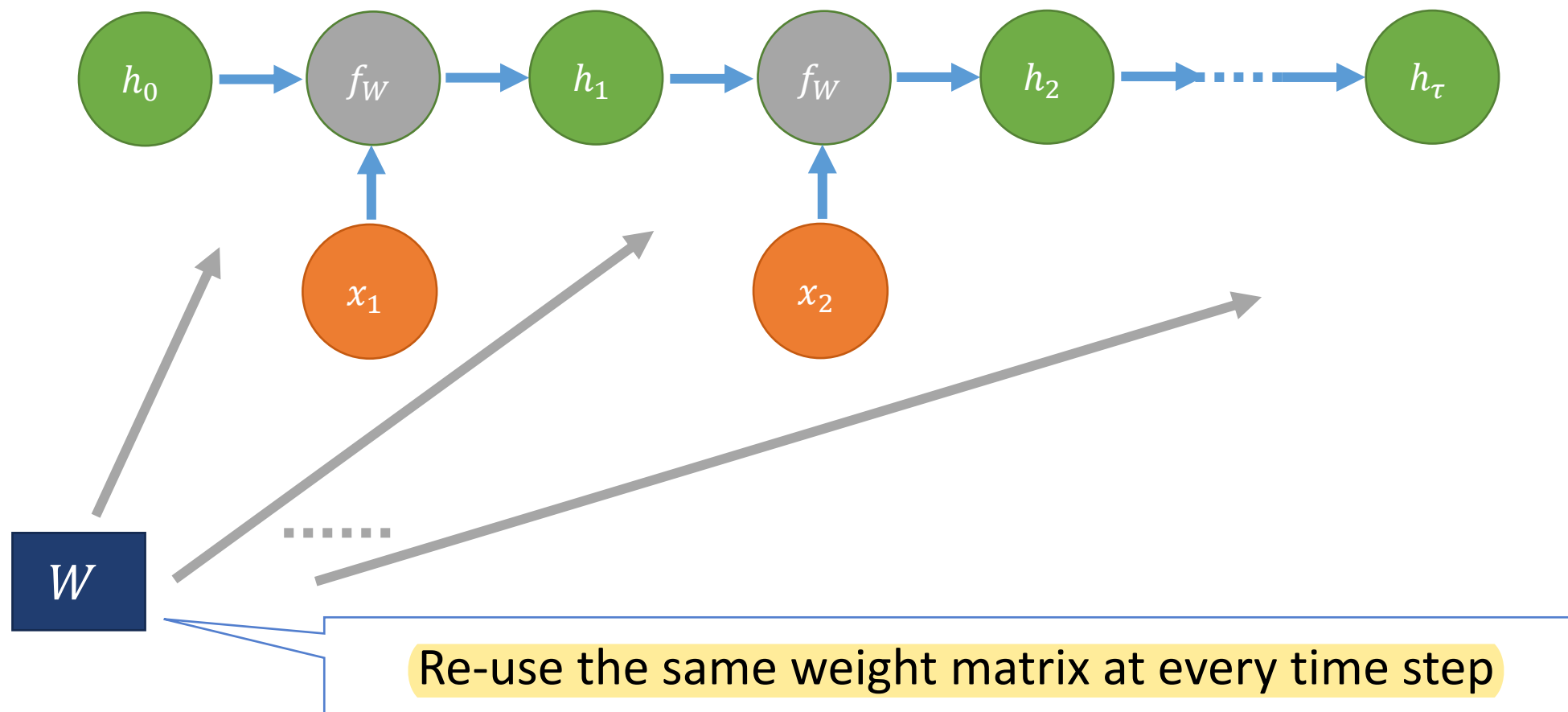




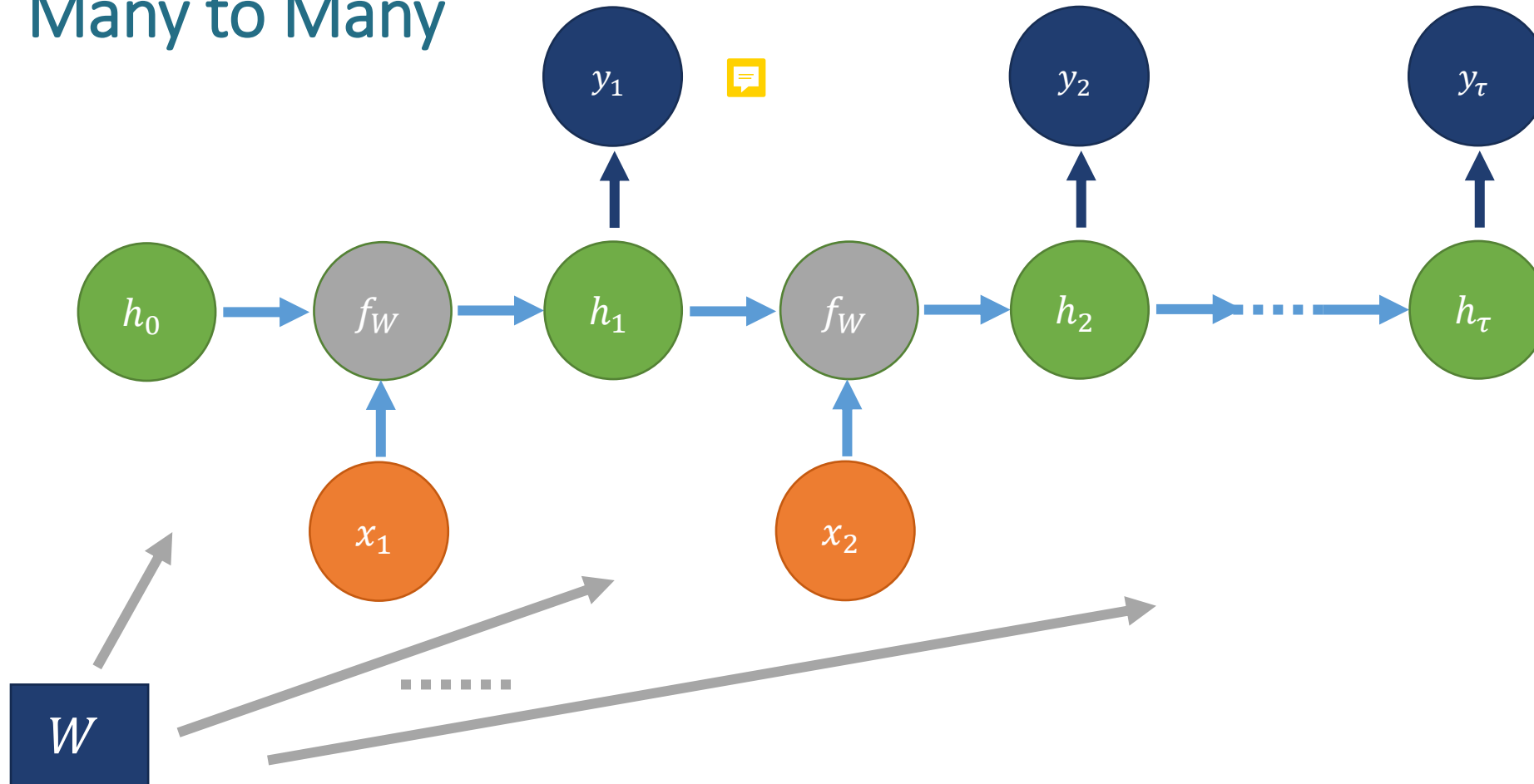
## RNN: Computational Graph



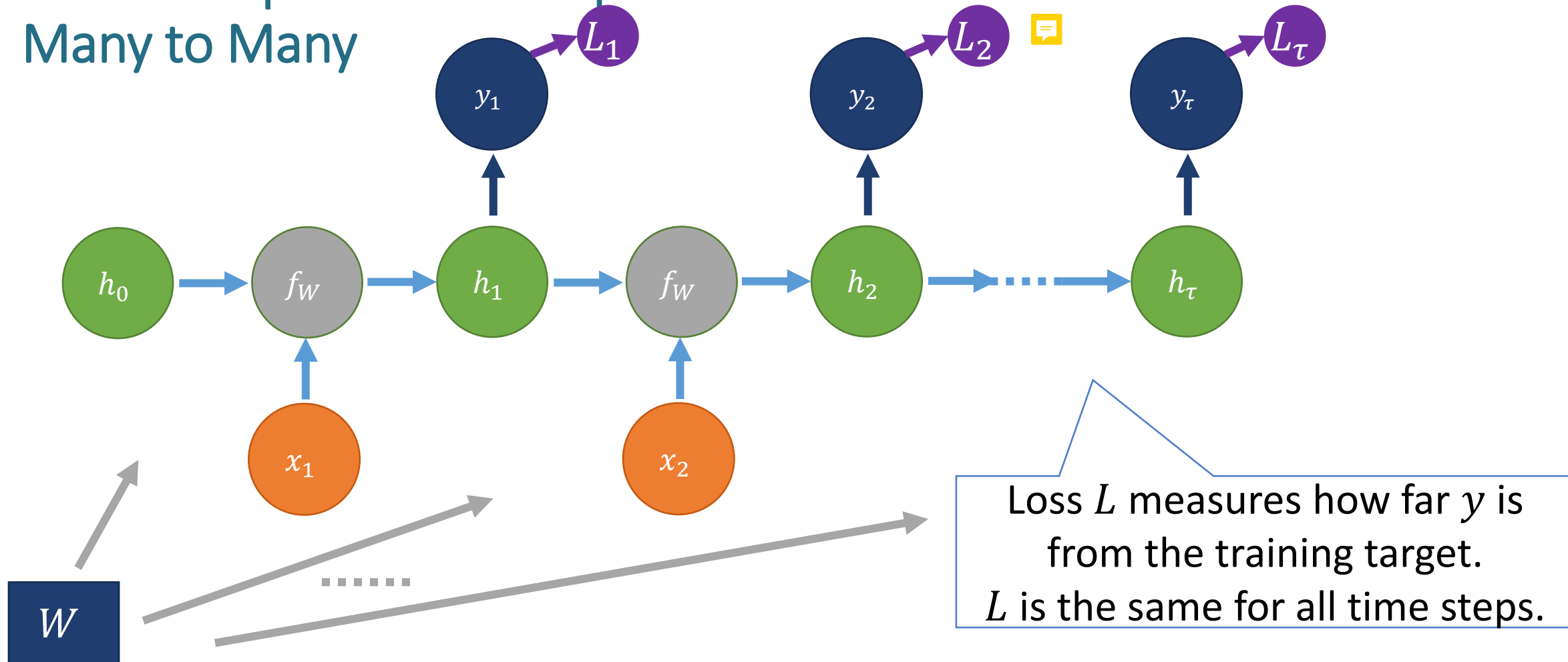
## RNN: Computational Graph



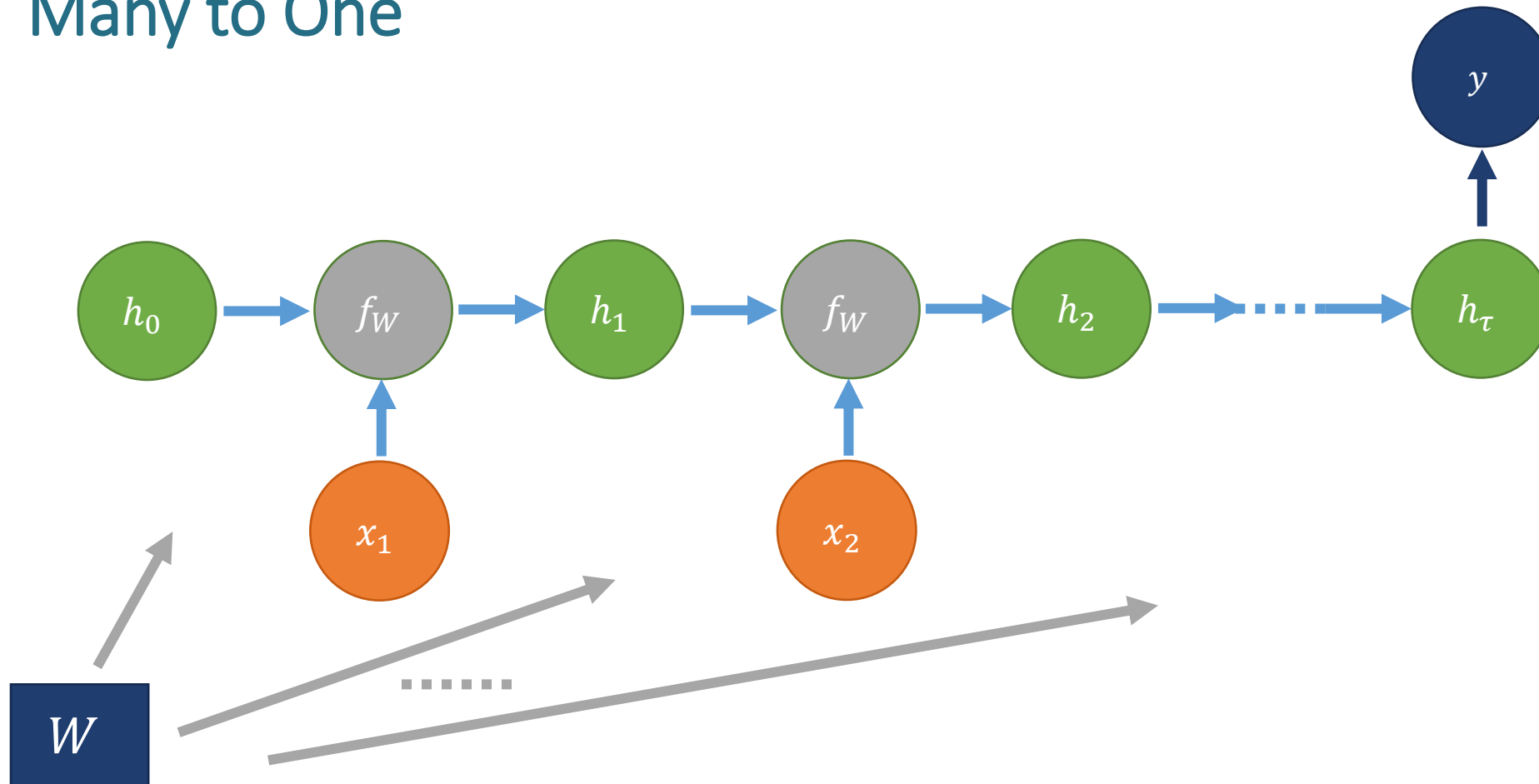
## RNN: Computational Graph Many to Many



## RNN: Computational Graph Many to Many



## RNN: Computational Graph Many to One



## RNN: Computational Graph One to Many

