RNN: simple RNN

Why RNN

Why RNN?

There are two 2 radar points obtained at (t-1) and (t), we want to predict the radar point at (t+1)

Training	x(t-1)			
		x(t)		
			у	

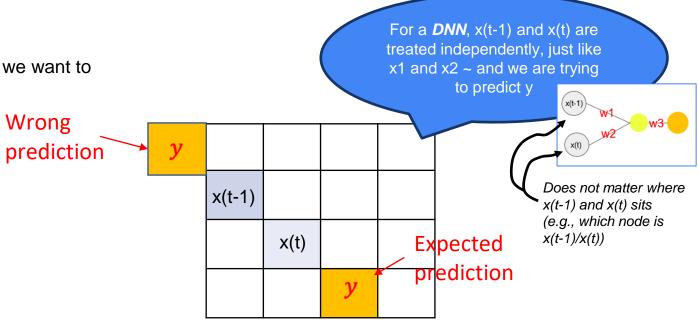
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- y: the truth in the training data at (t+1)

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If we use a neural network such as Densely connected NN, we are not able to tell the sequential information for "x", therefore, the prediction might end up the wrong direction

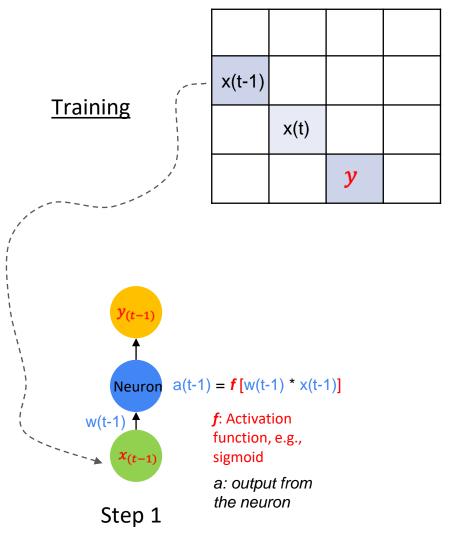
How RNN works: concept

In order to make such a prediction right, we need a sequential of training dataset and model, e.g.,

Training

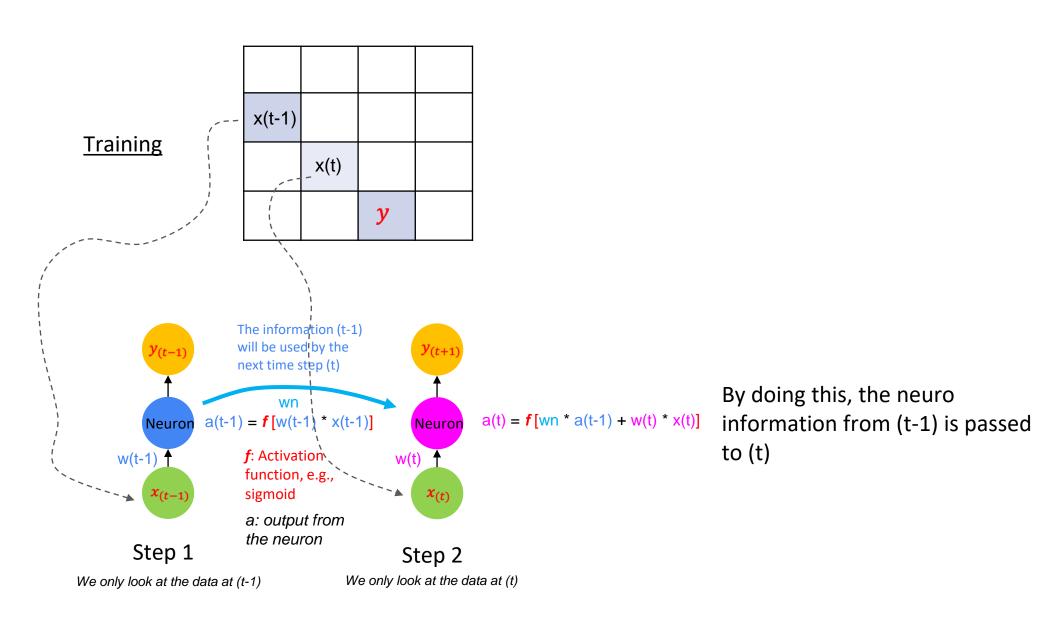
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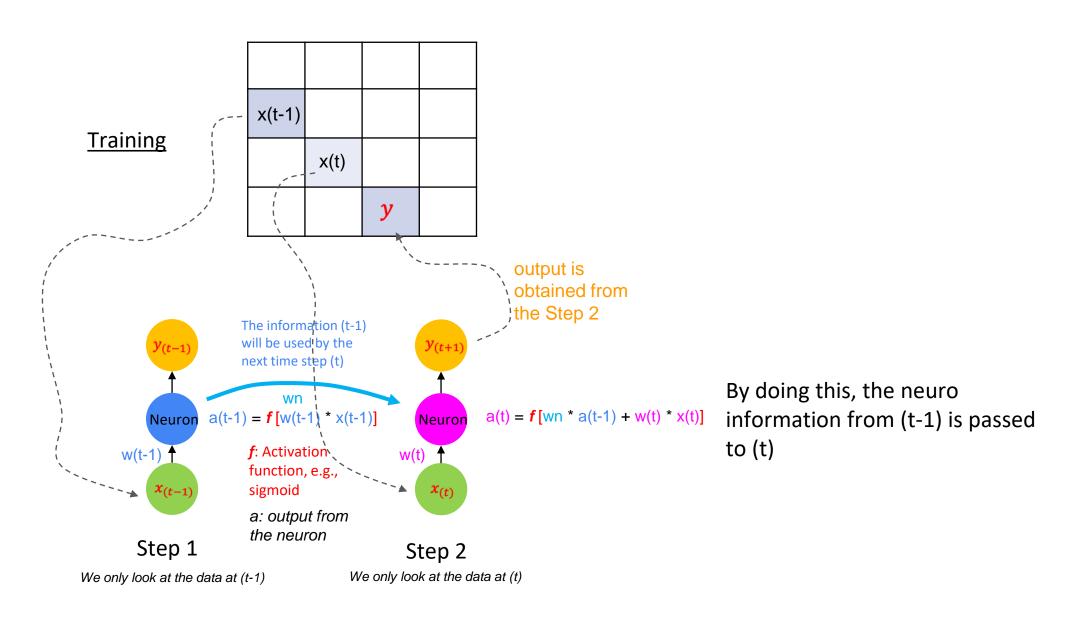


We only look at the data at (t-1)

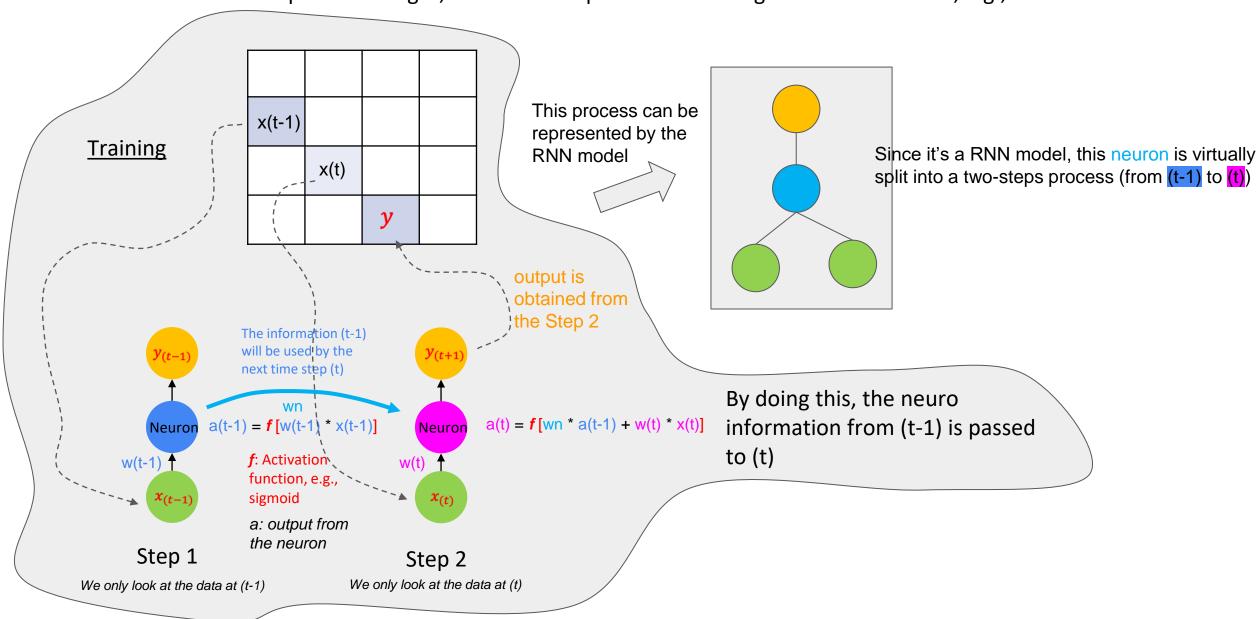
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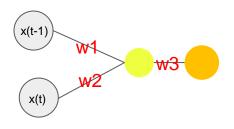


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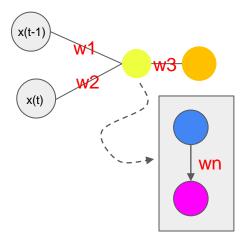


Compared to an ANN model, RNN requires more parameters to be trained. To make it simpler, let's we only have 1 neuron here:

x(t-1)			
	x(t)		
		у	



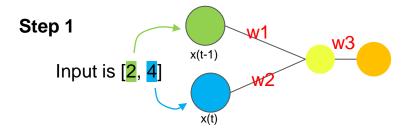
If it is an ANN model, we will have to train 3 parameters (w1, w2, and w3)



If it is a RNN model, in addition to the 3 parameters (w1, w2, and w3), there is an additional parameter to be trained (wn) to represent the information passing from (t-1) to (t)

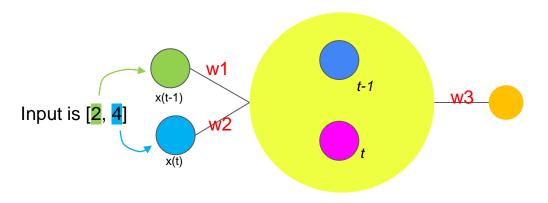
How RNN works: a simple example

Let's look at a real example, to make it simple, let's say we only have one neuron



Step 2

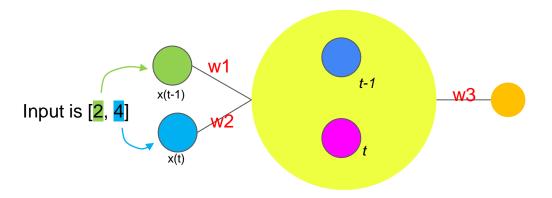
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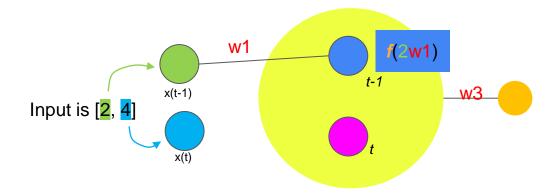
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Step 3

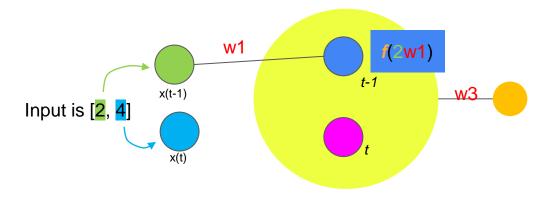
The neuron output for (t-1) is (w1), where f is the activation function



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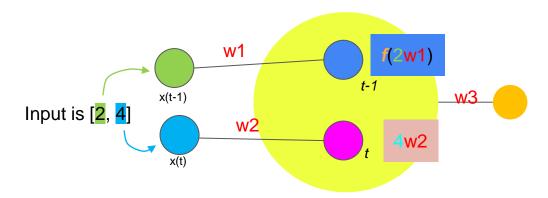
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Step 4

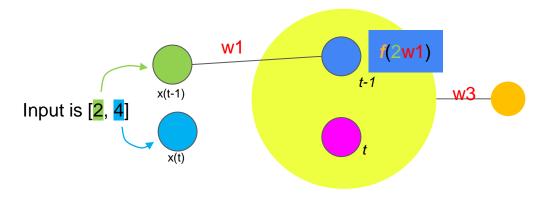
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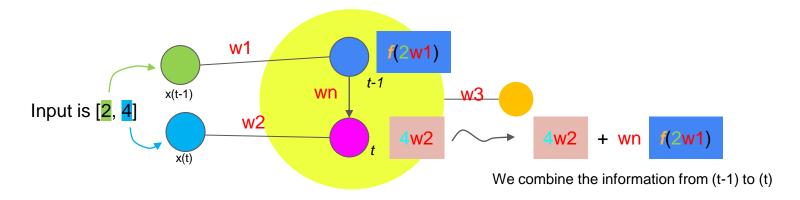
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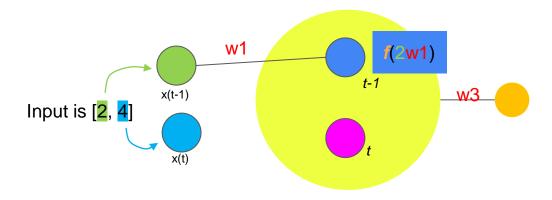
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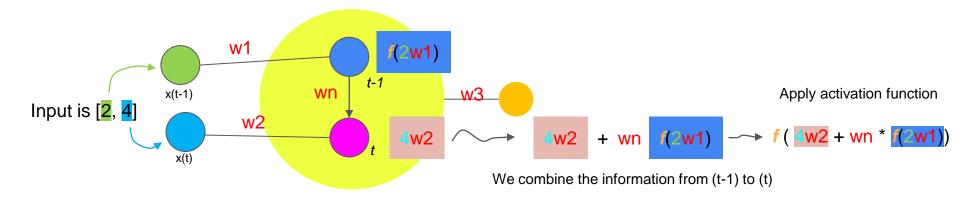
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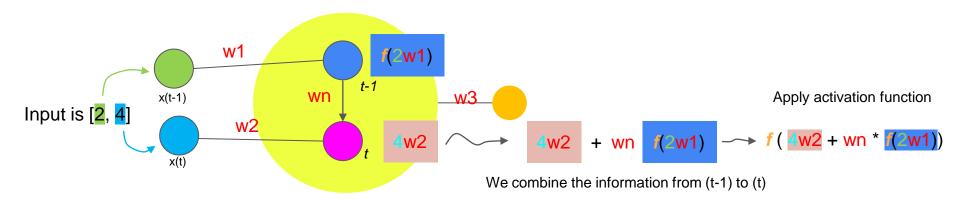
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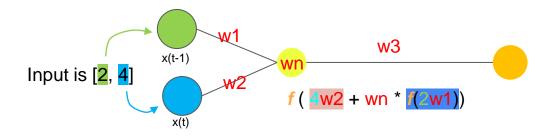
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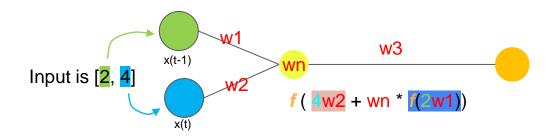
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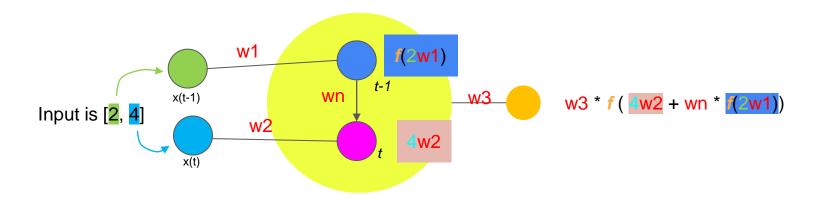
So the final output can be calculated as: w3 * f (w2 + wn * w1)

Note: All the weights, w1, w2, w3 and wn are to be trained by the model

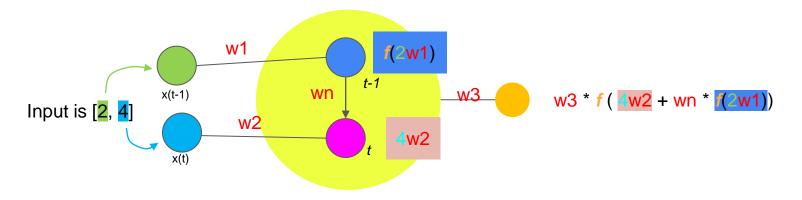


Issues in RNN

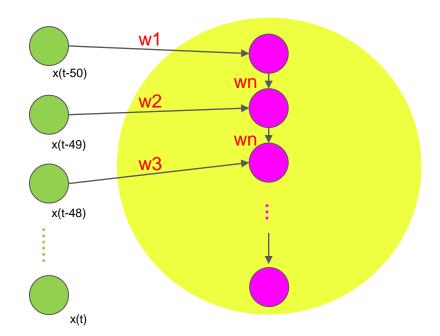
In the above example, we have two inputs (t-1) and (t)



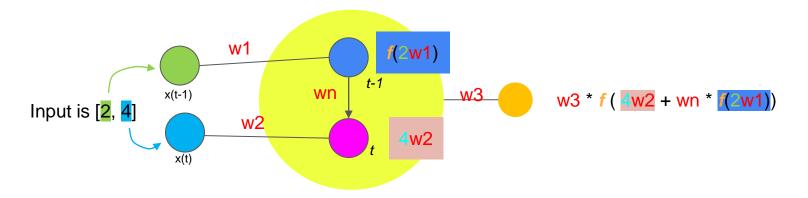
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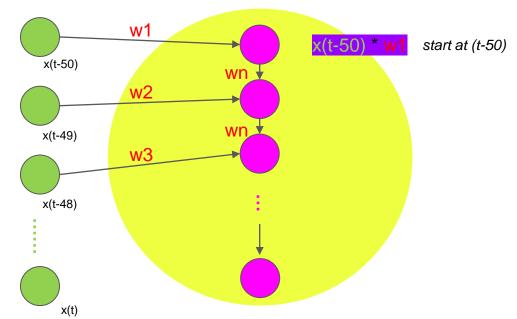
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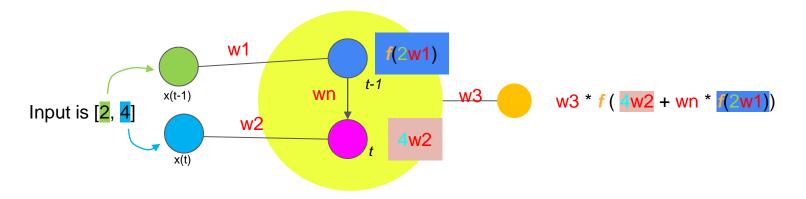
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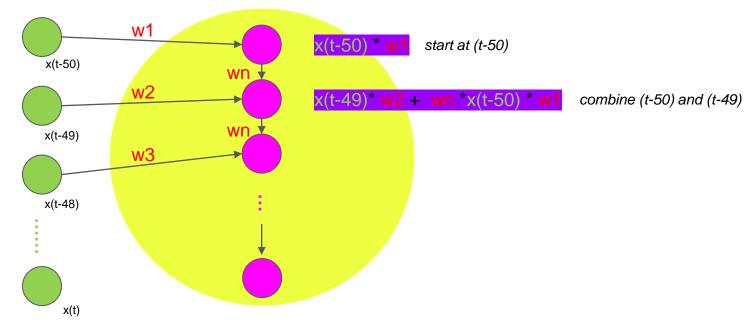
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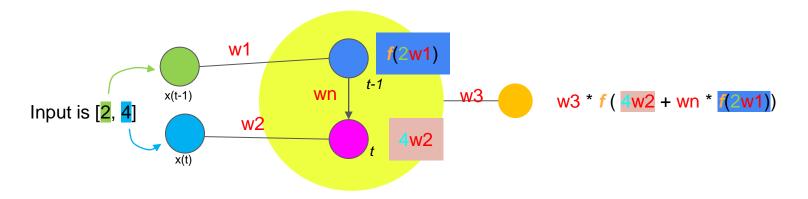
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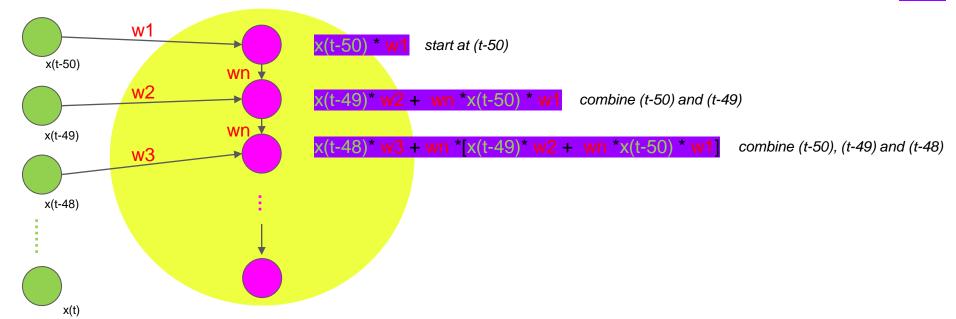
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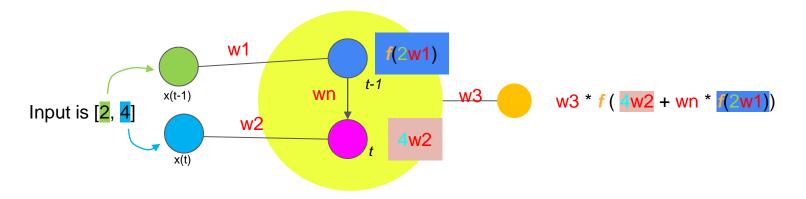
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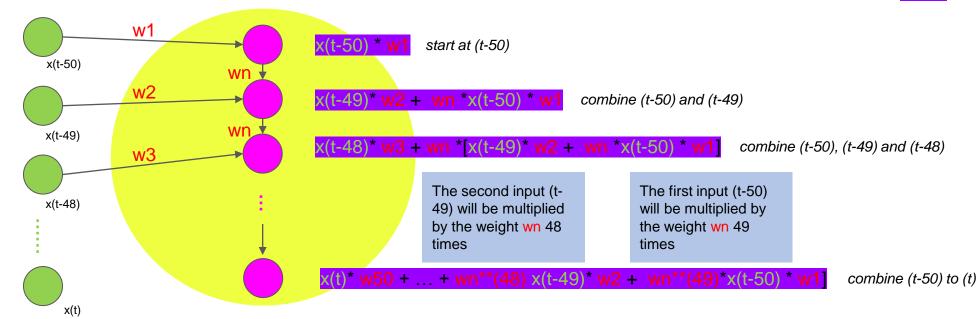
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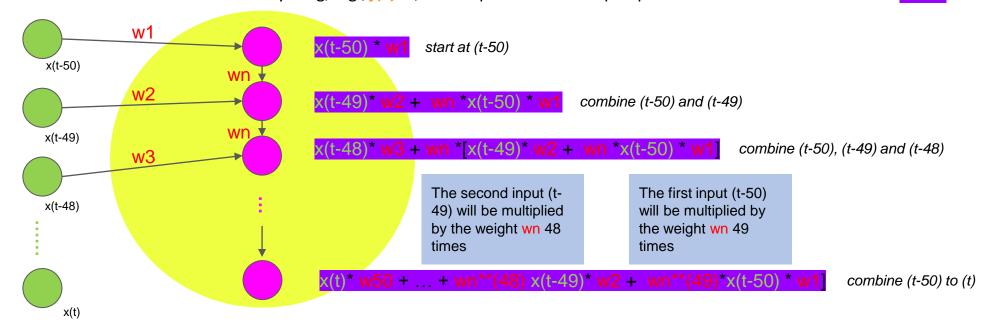


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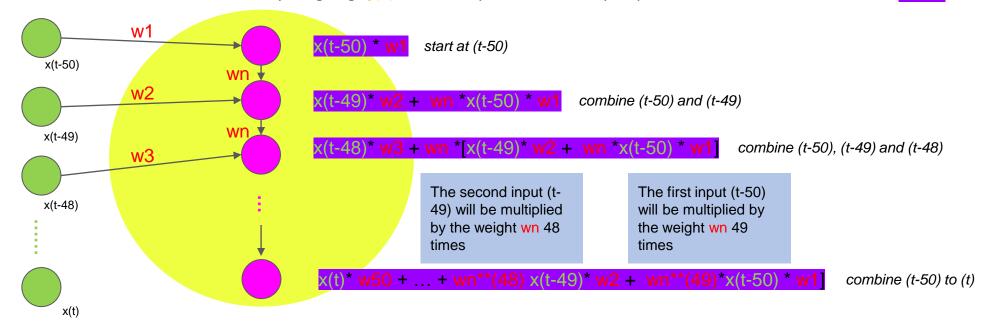
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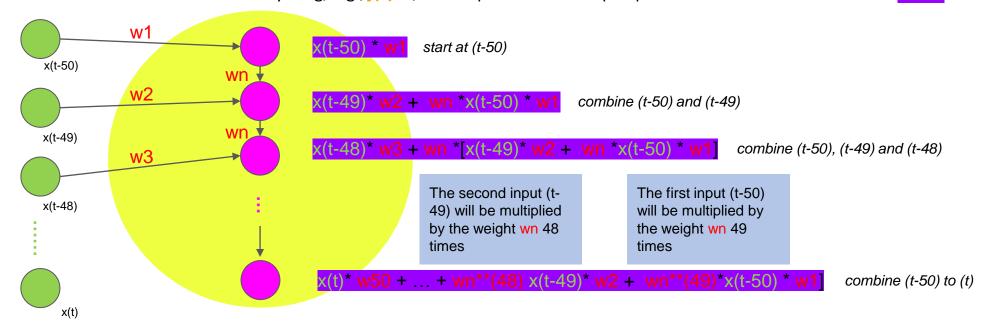


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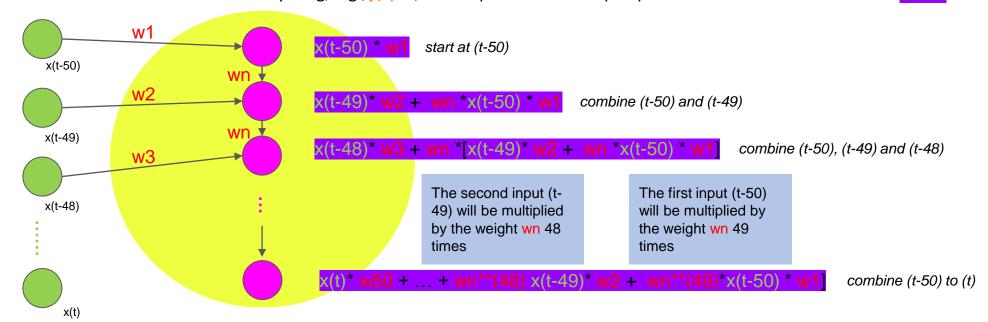
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