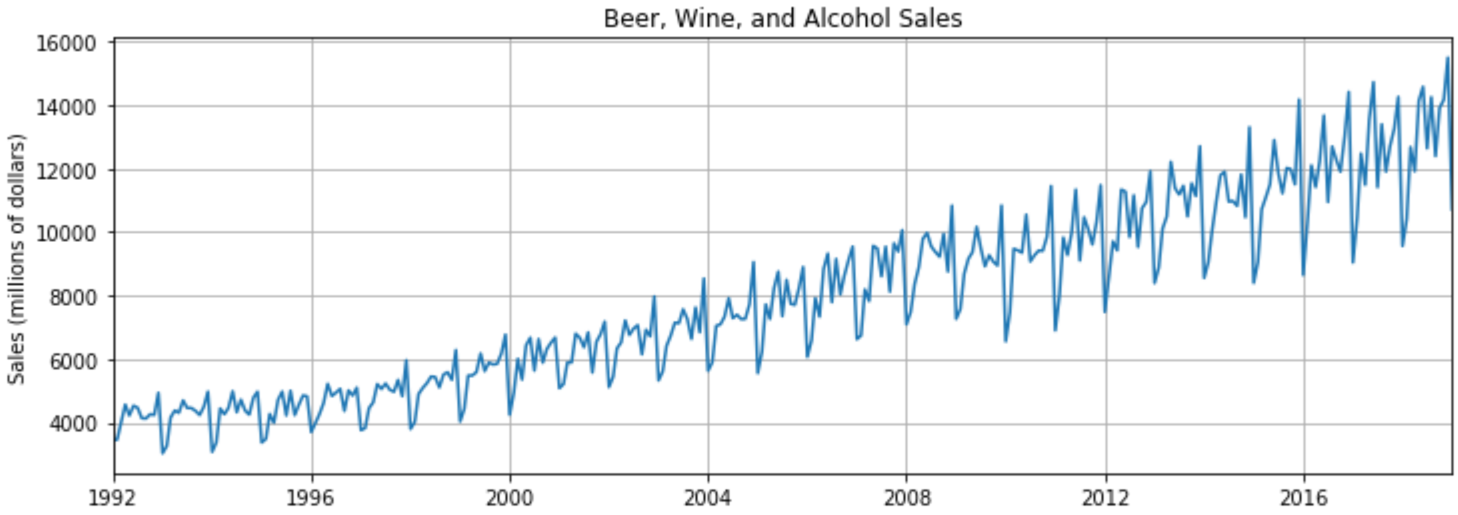
Recurrent
Neural Networks

- We’ve used Neural Networks to solve Classification and Regression problems, but we still haven’t seen how Neural Networks can deal with sequence information.

- Just as CNNs were more effective for use with 2D image data, RNNs are more effective for sequence data (e.g. time-stamped sales data, sequence of text, heart beat data, etc…)

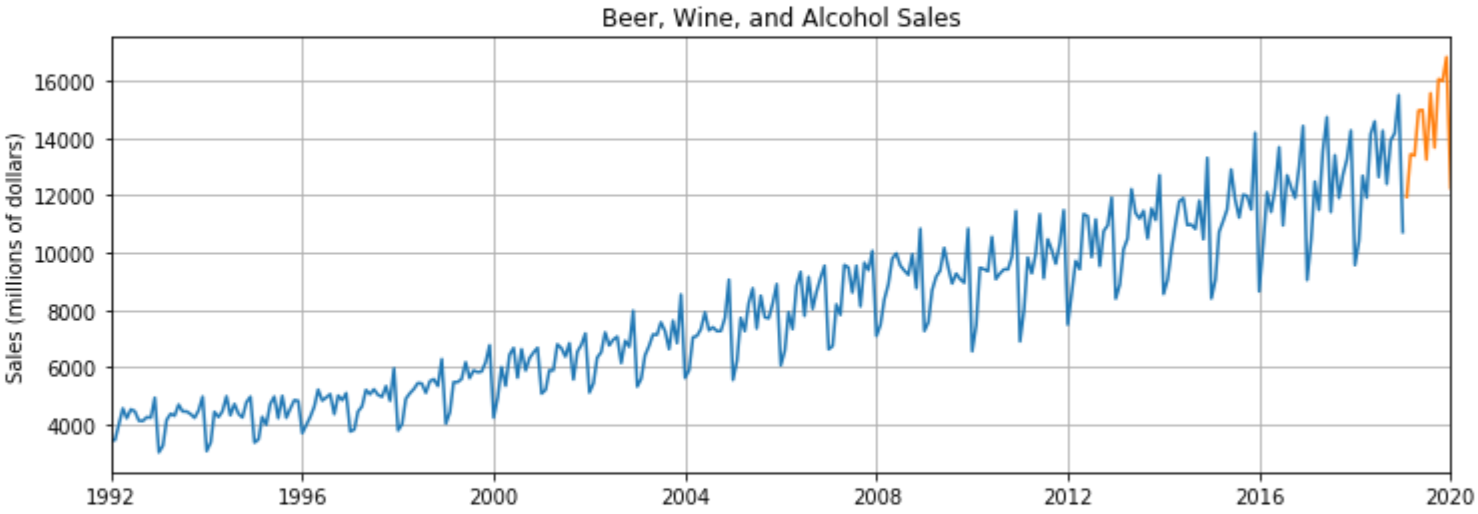
Deep Learning

- Time Series

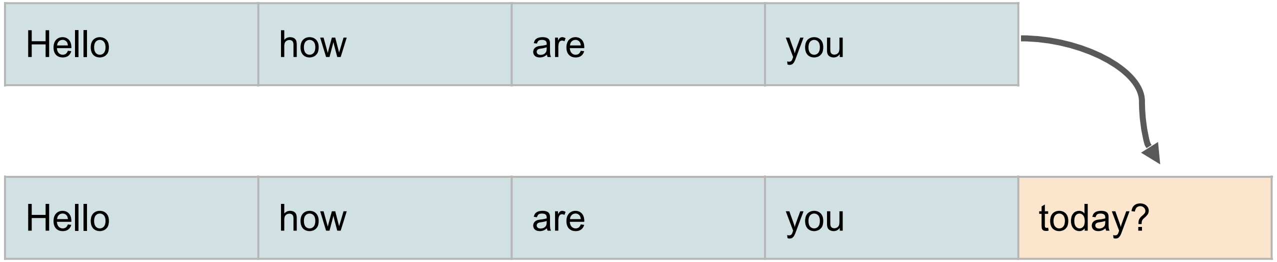


Deep Learning

- Time Series



- Sequences



Deep Learning

- Section Overview
  - RNN Theory
  - LSTMs and GRU Theory
  - Basic Implementation of RNN
  - Time Series with an RNN
  - Exercise and Solution

Let’s get started!

Recurrent Neural Networks Theory

Deep Learning

- Examples of Sequences
  - Time Series Data (Sales)
  - Sentences
  - Audio
  - Car Trajectories
  - Music

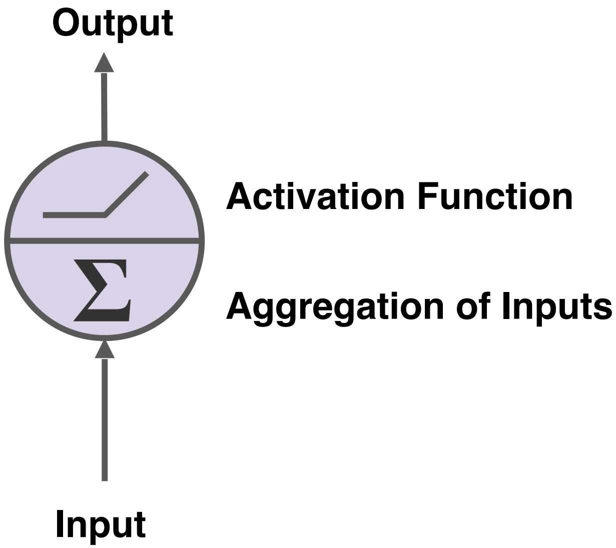
- Let's imagine a sequence:
  - [1,2,3,4,5,6]
- Would you be able to predict a similar sequence shifted one time step into the future?
  - [2,3,4,5,6,7]

Deep Learning

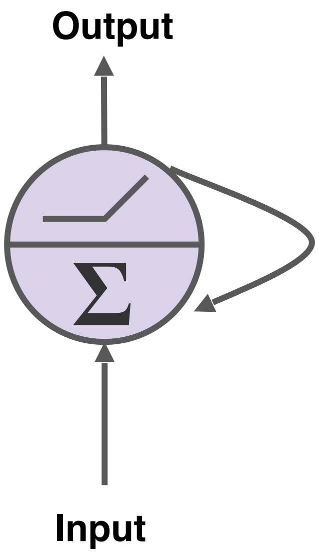
- To do this properly, we need to somehow let the neuron “know” about its previous history of outputs.
- One easy way to do this is to simply feed its output back into itself as an input!

Deep Learning

- Normal Neuron in Feed Forward Network

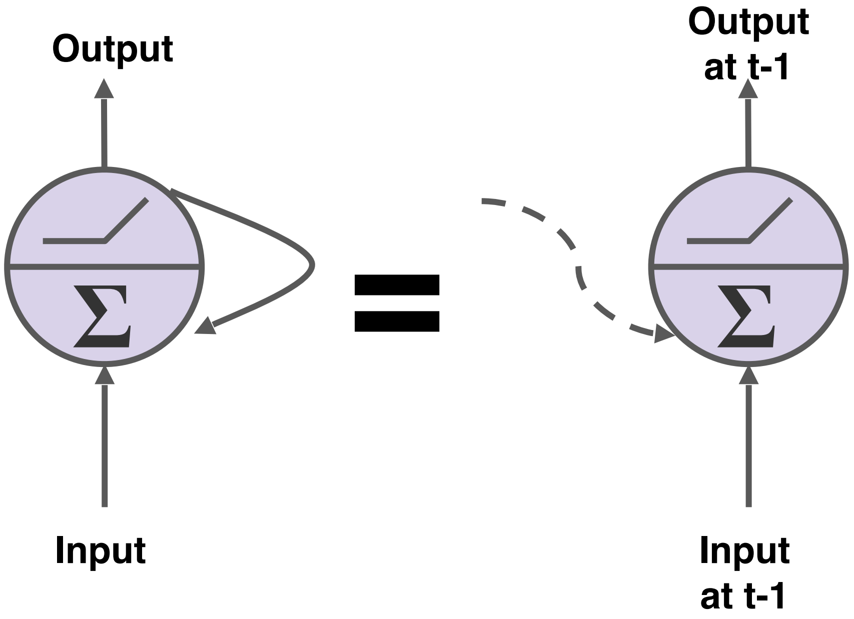


- Recurrent Neuron

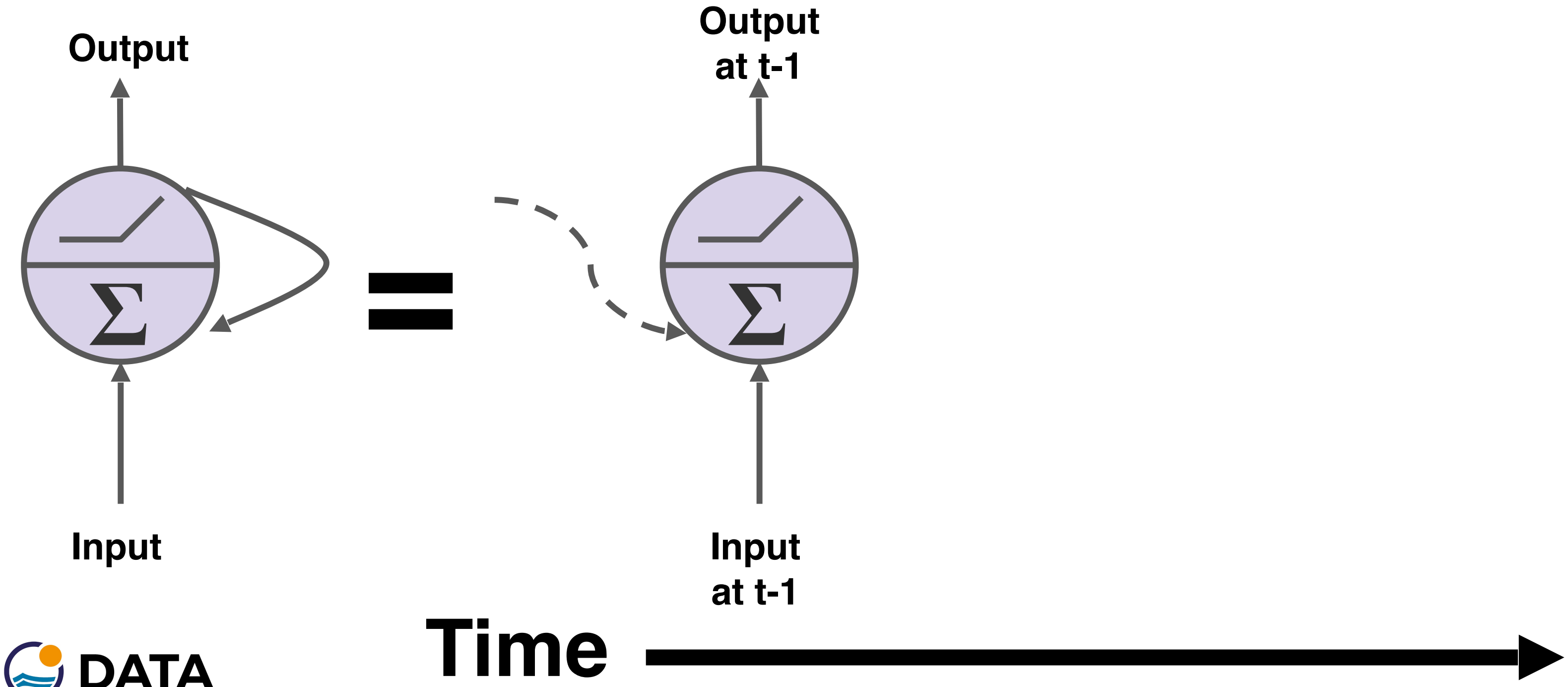


- Sends output back to itself!
- Let's see what this looks like over time!

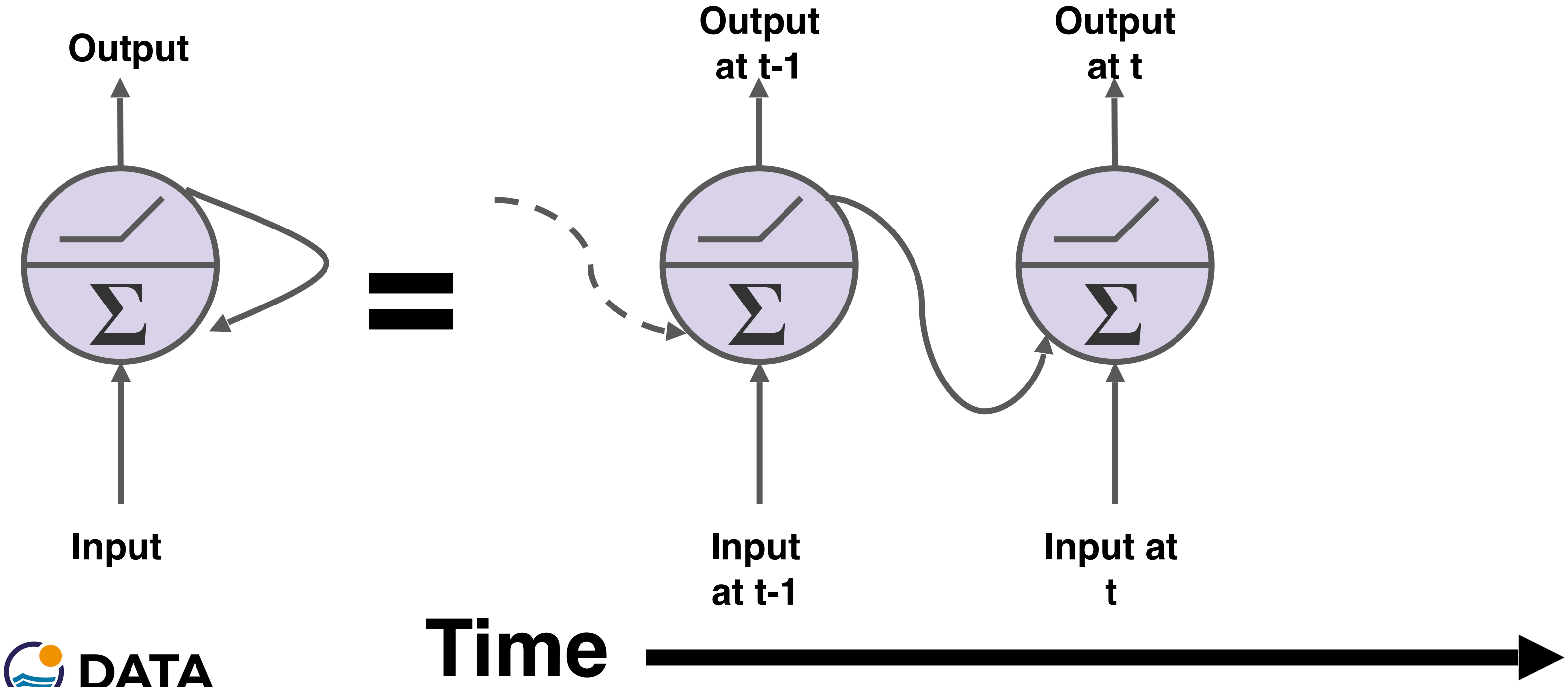
- Recurrent Neuron



- Recurrent Neuron

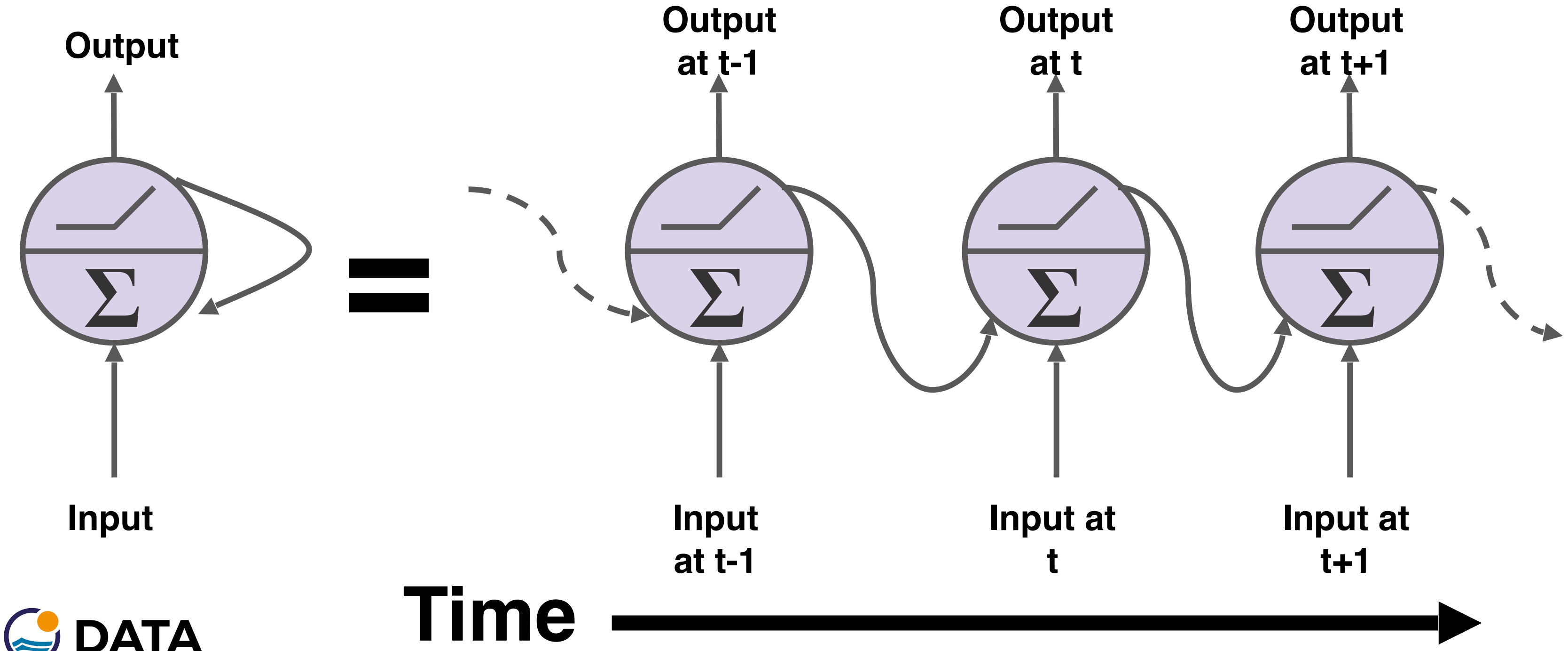


- Recurrent Neuron



Deep Learning

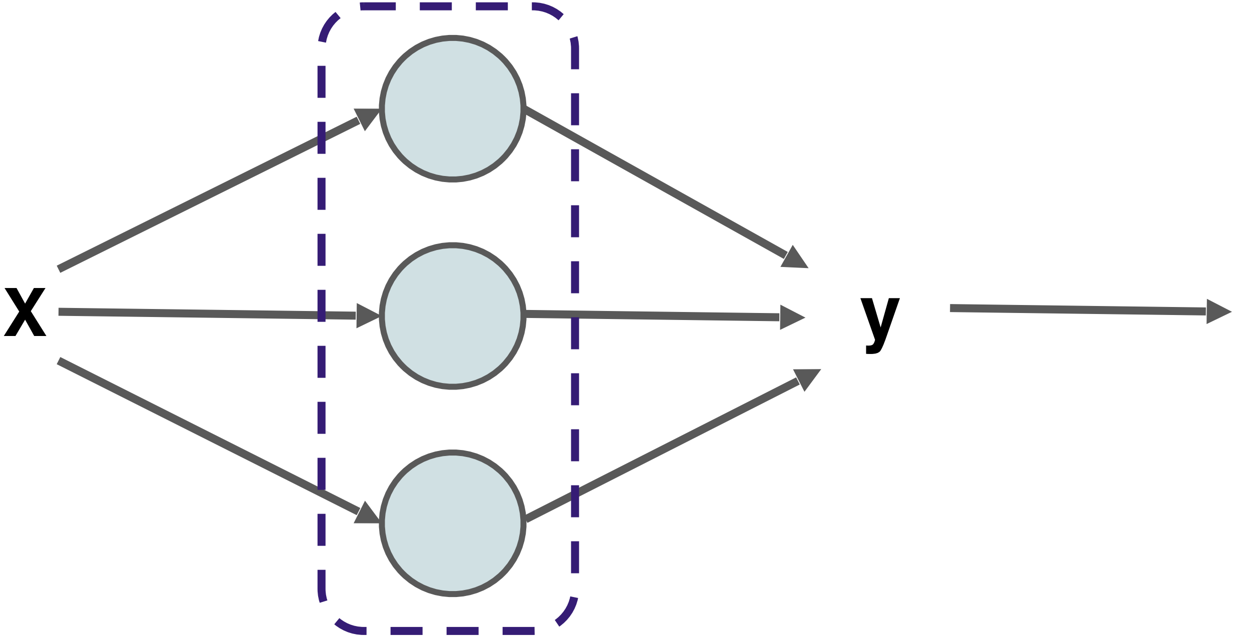
- Recurrent Neuron



- Cells that are a function of inputs from previous time steps are also known as *memory cells.*
- RNN are also flexible in their inputs and outputs, for both sequences and single vector values.

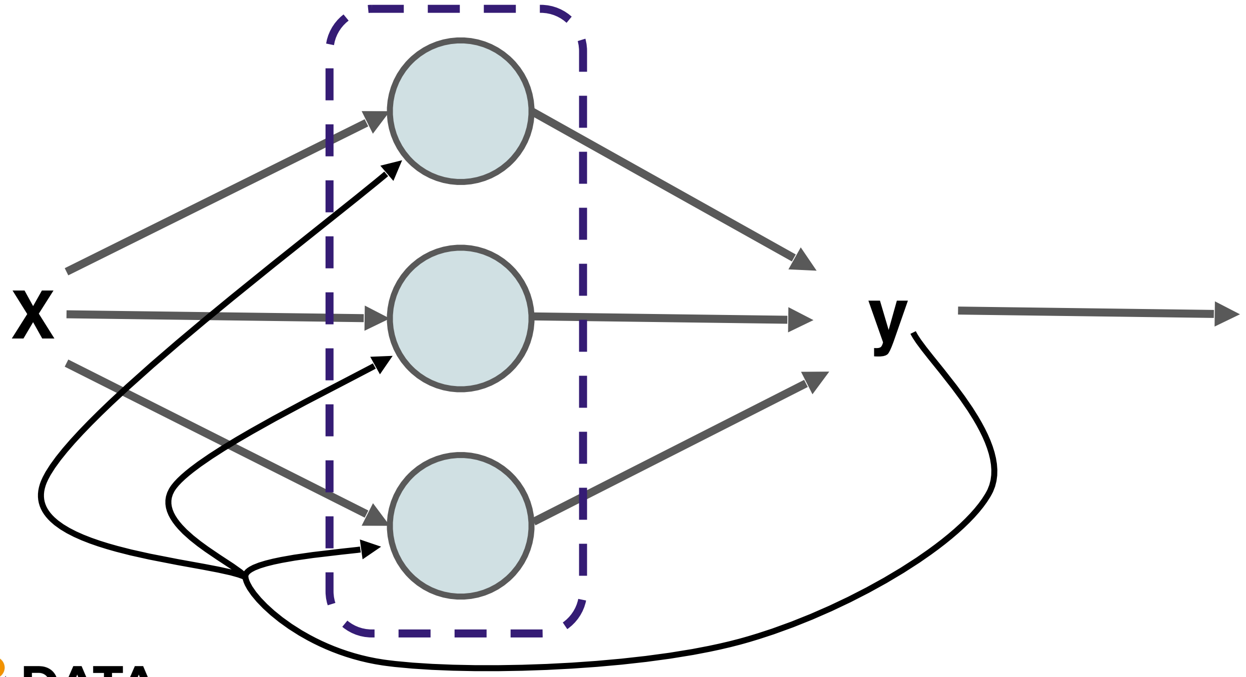
- We can also create entire layers of Recurrent Neurons...

- ANN Layer with 3 Neurons:

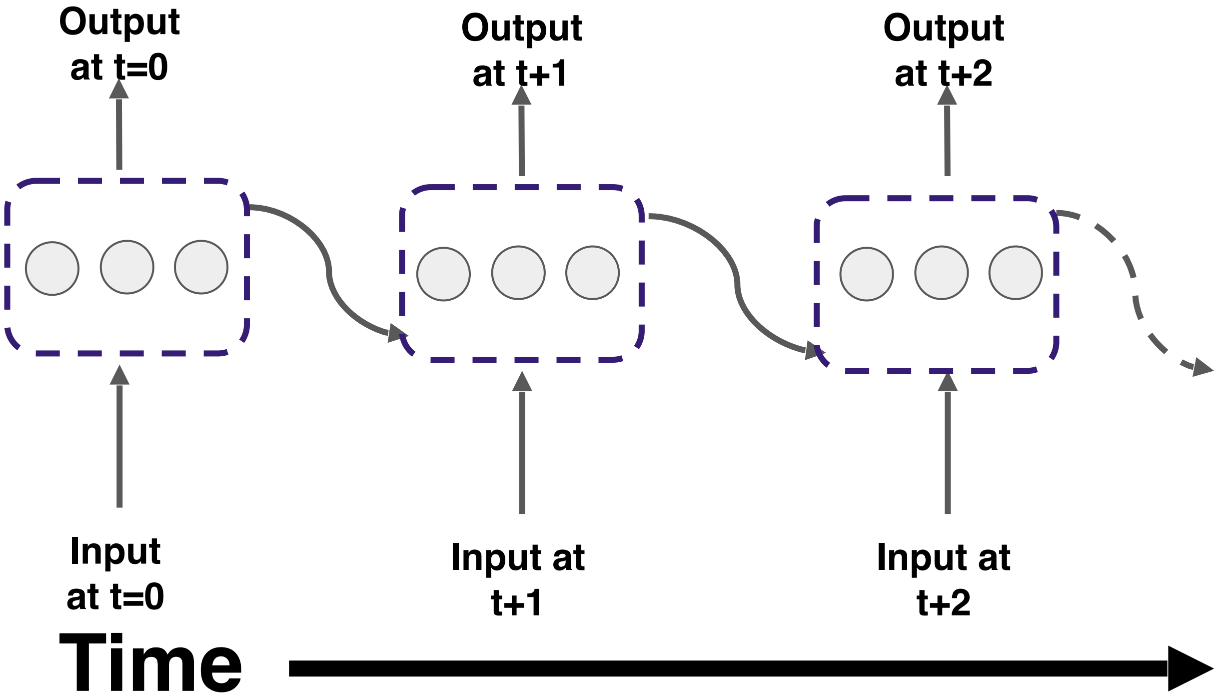


Deep Learning

- RNN Layer with 3 Neurons:

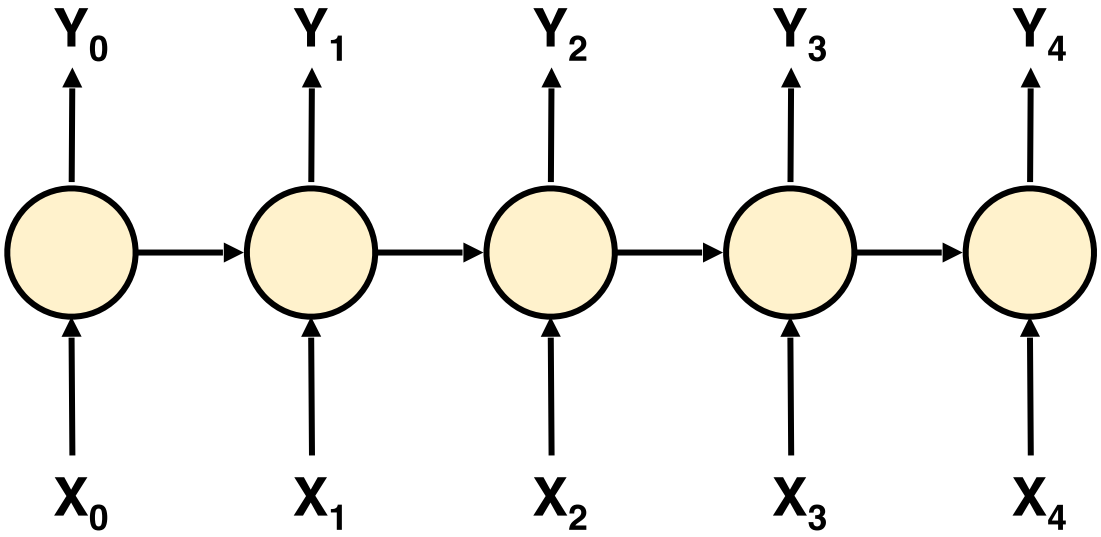


- “Unrolled” layer.

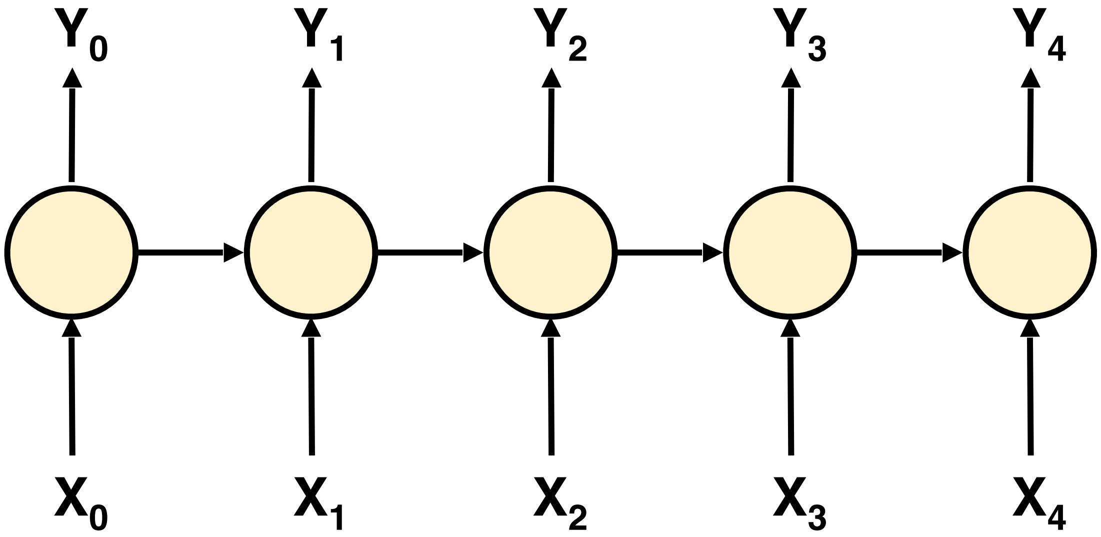


- RNN are also very flexible in their inputs and outputs.
- Let’s see a few examples.

- Sequence to Sequence (Many to Many)

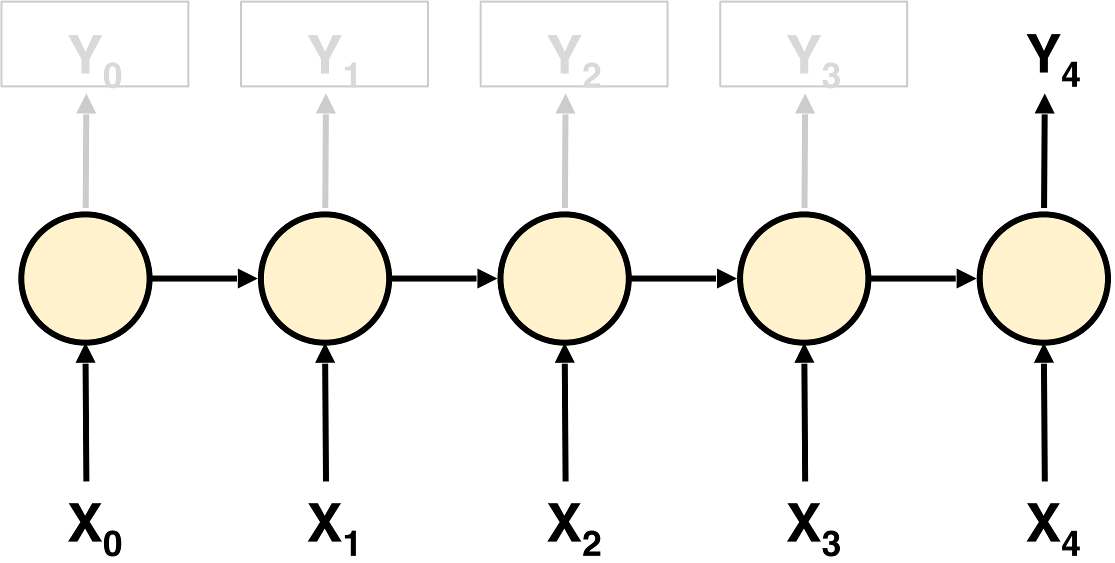


- Given 5 previous words, predict the next 5

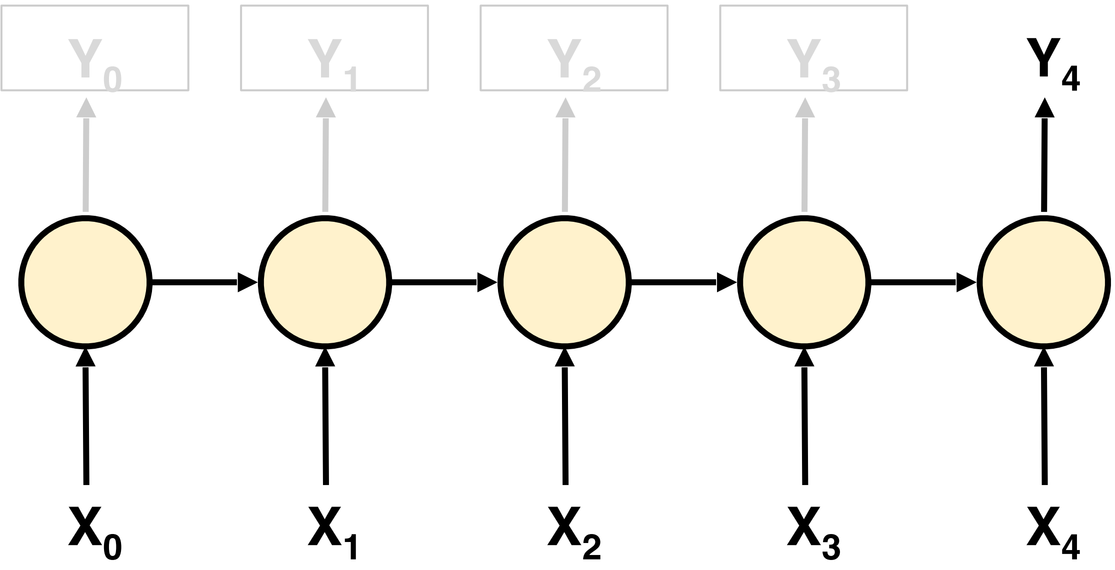


Deep Learning

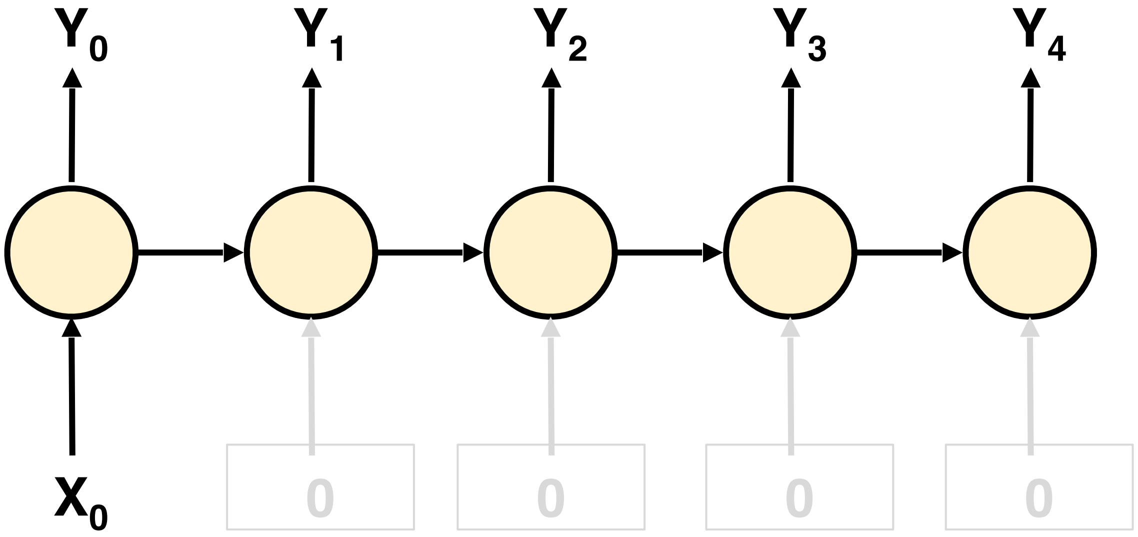
- Sequence to Vector (Many to One)



- Given 5 previous words, predict next word

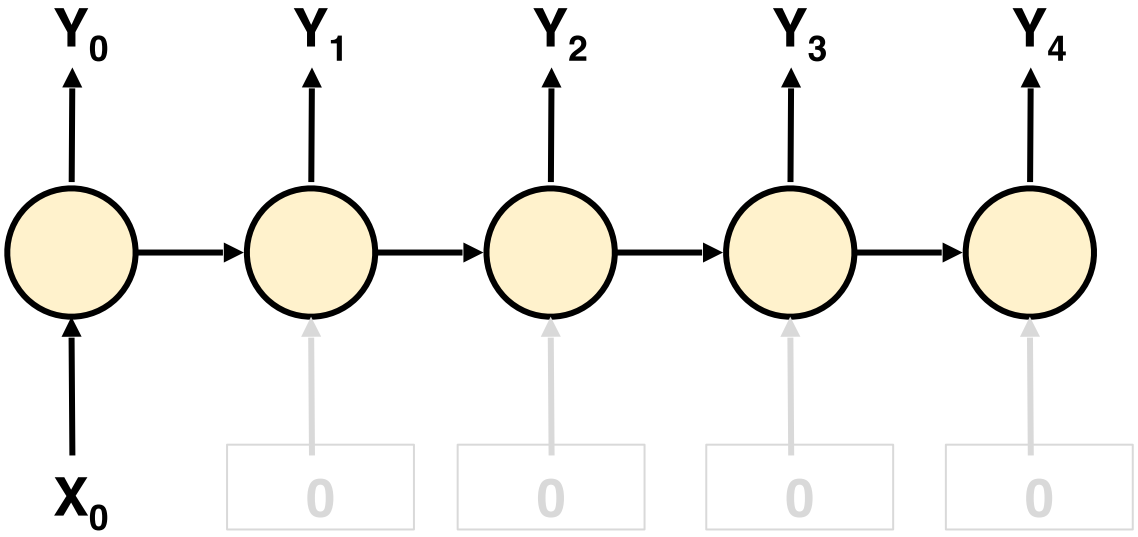


- Vector to Sequence (One to Many)



Deep Learning

- Given 1 word predict the next 5 words



- A basic RNN has a major disadvantage, we only really “remember” the previous output.
- It would be great it we could keep track of longer history, not just short term history.

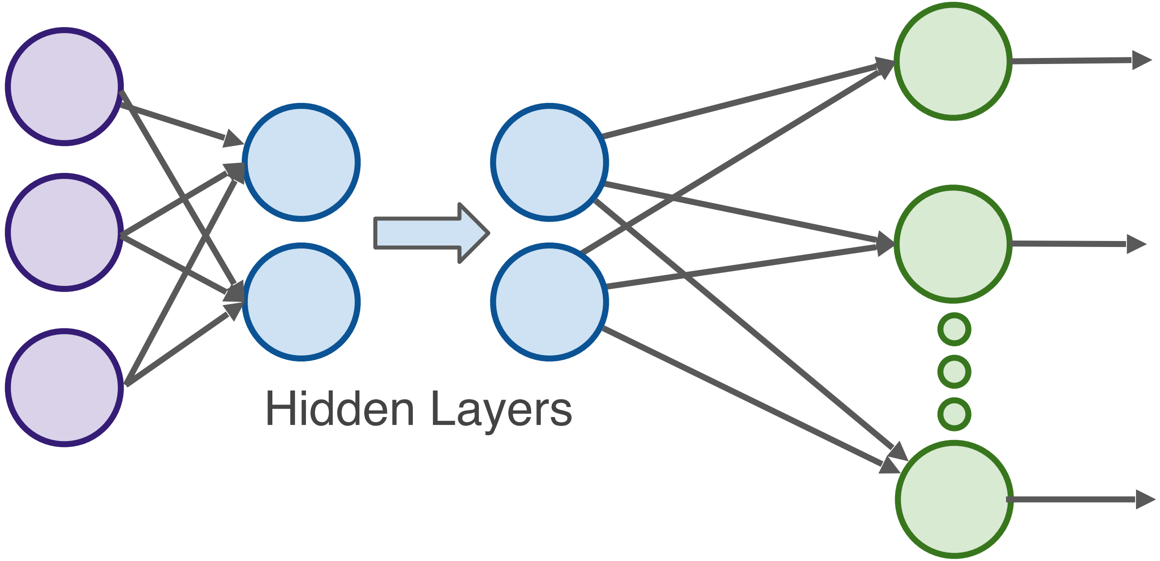
- Another issue that arises during training is the “vanishing gradient”.
- Let’s explore vanishing gradients in more detail before moving on to discussing LSTM (Long Short Term Memory Units).

Exploding and Vanishing Gradients

- As our networks grow deeper and more complex, we have 2 issues arise:
  - Exploding Gradients
  - Vanishing Gradients
- Recall that the gradient is used in our calculation to adjust weights and biases in our network.

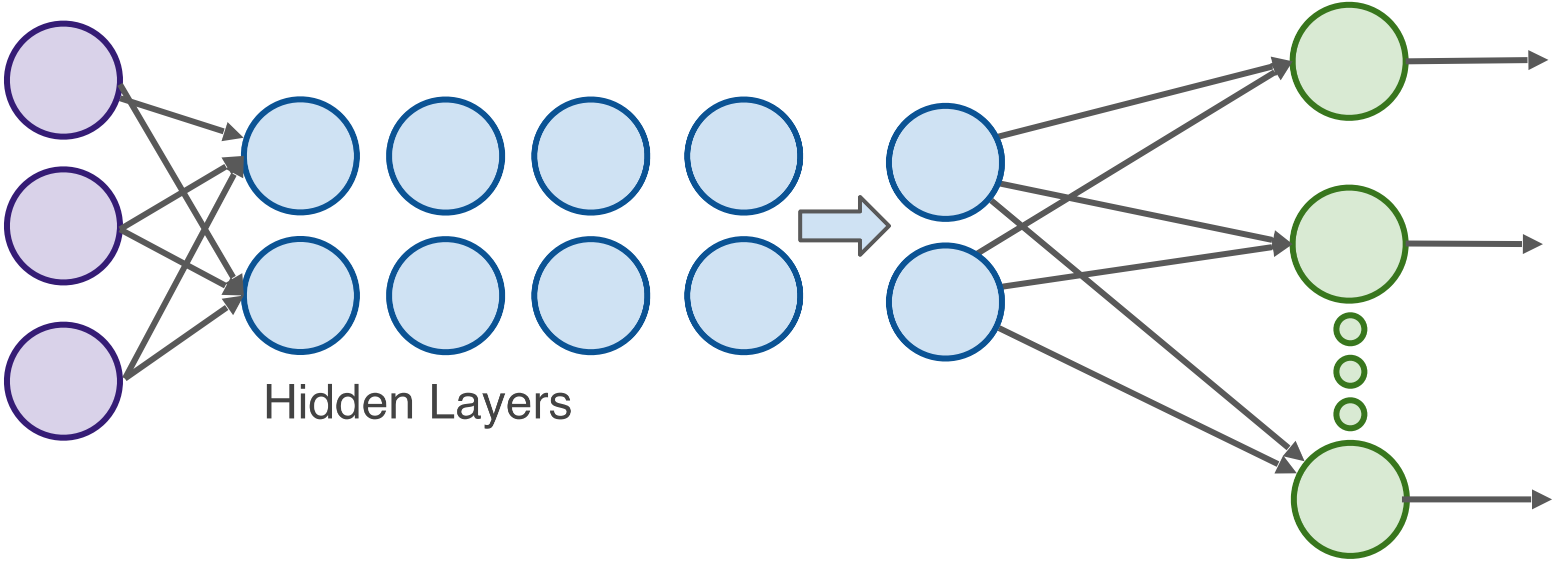
Deep Learning

- Let’s think about a network.



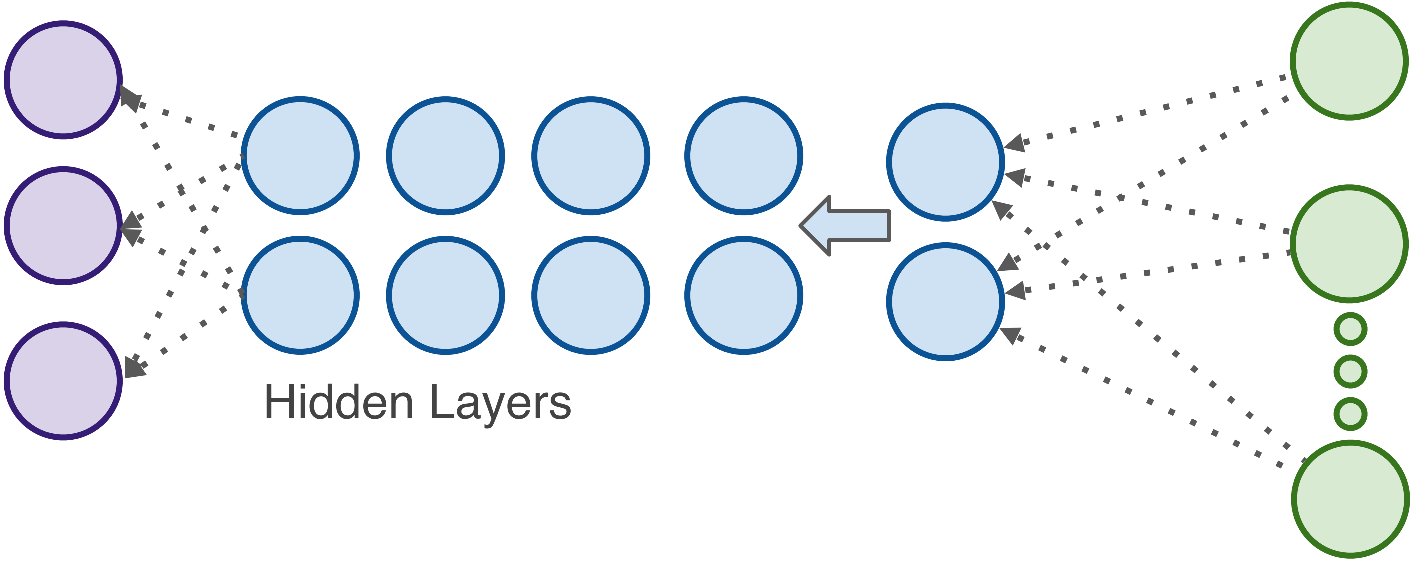
Deep Learning

- For complex data we need deep networks



Deep Learning

- Issues can arise during backpropagation

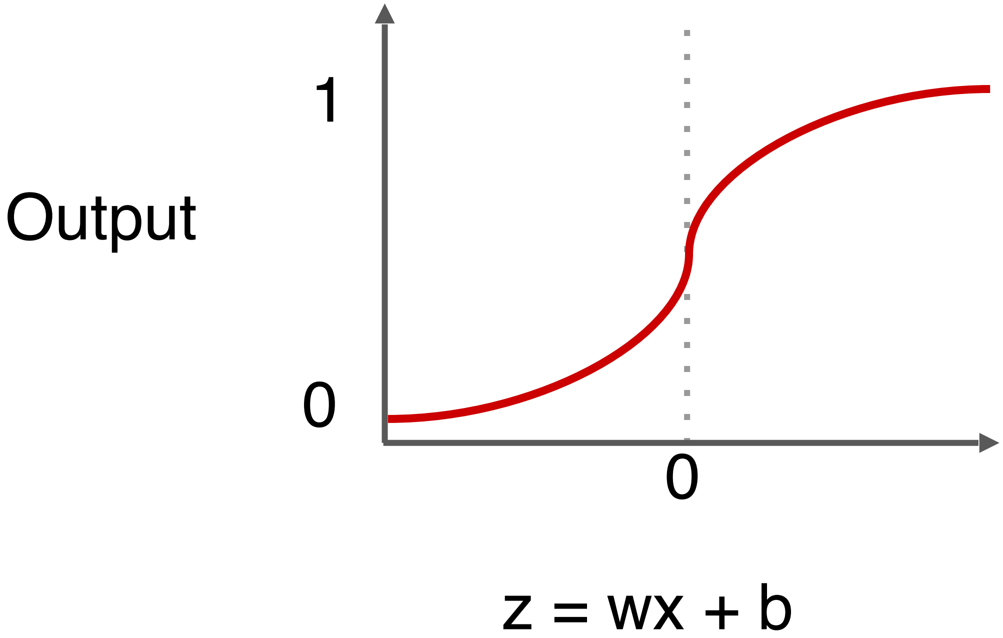


- Backpropagation goes backwards from the output to the input layer, propagating the error gradient.
- For deeper networks issues can arise from backpropagation, vanishing and exploding gradients!

- As you go back to the “lower” layers, gradients often get smaller, eventually causing weights to never change at lower levels.
- The opposite can also occur, gradients explode on the way back, causing issues.

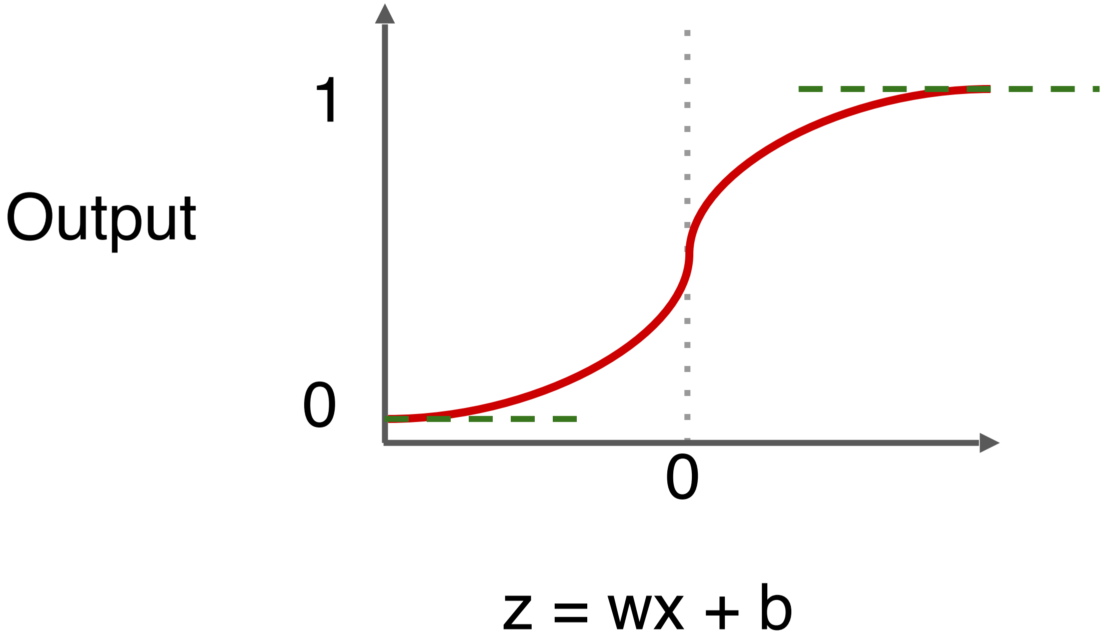
- Let’s discuss why this might occur and how we can fix it.
- Then in the next lecture we’ll discuss how these issues specifically affect RNN and how to use LSTM and GRU to fix them.

- Why does this happen?



$$f(x) = \frac{1}{1 + e^{-(x)}}$$

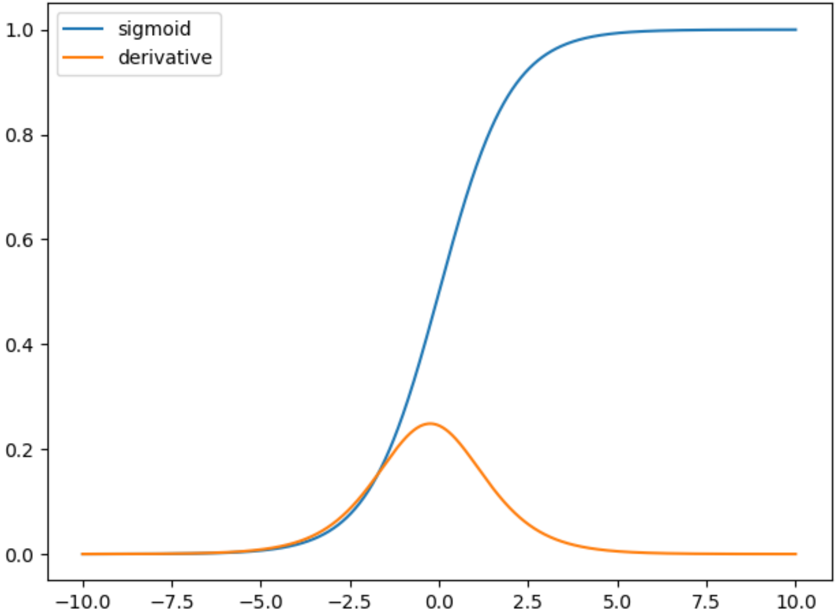
- Why does this happen?



$$f(x) = \frac{1}{1+e^{-(x)}}$$

Deep Learning

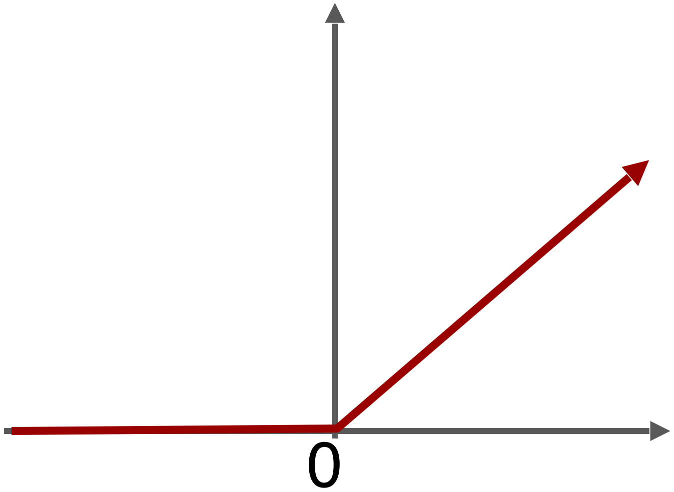
- The derivative can be much smaller!



* When **n** hidden layers use an activation like the sigmoid function, **n** small derivatives are multiplied together.
* The gradient could decrease exponentially as we propagate down to the initial layers.

- Using Different Activation Functions

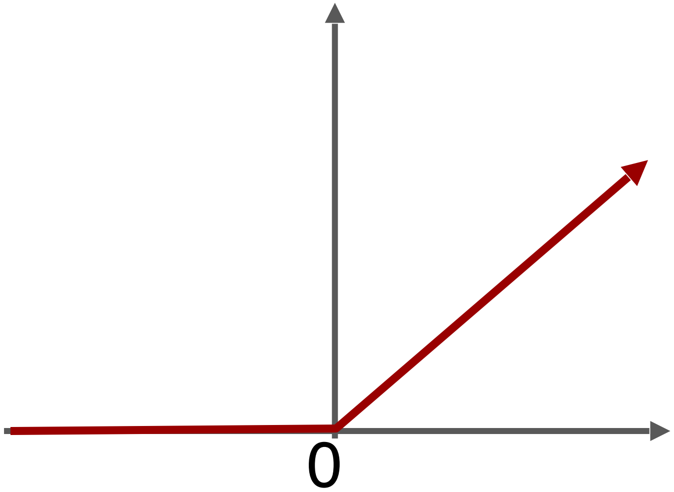
Output



$z = wx + b$

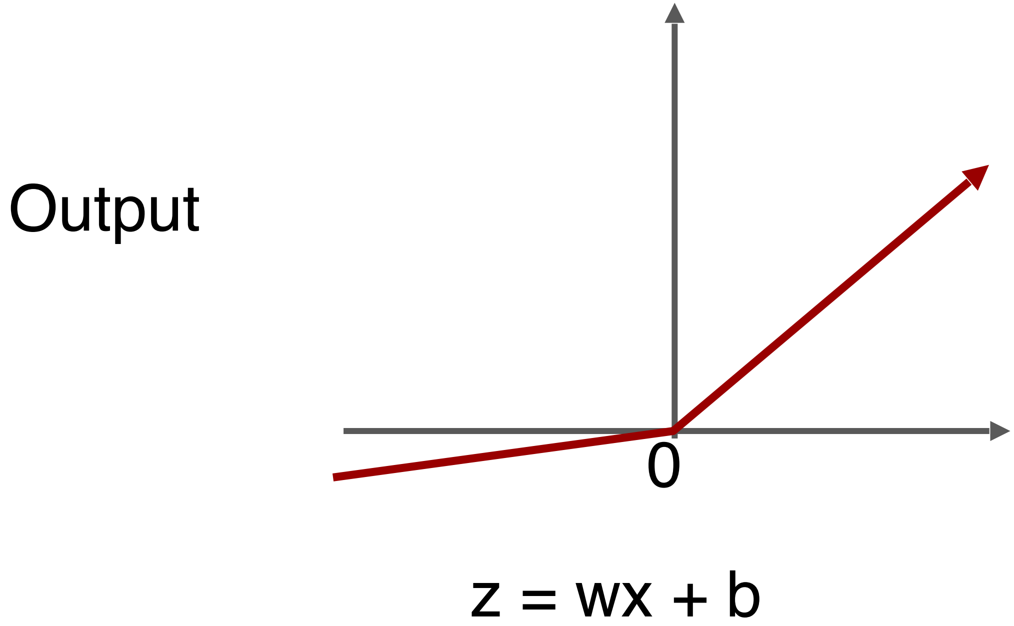
- The ReLu doesn't saturate positive values.

Output



z = wx + b

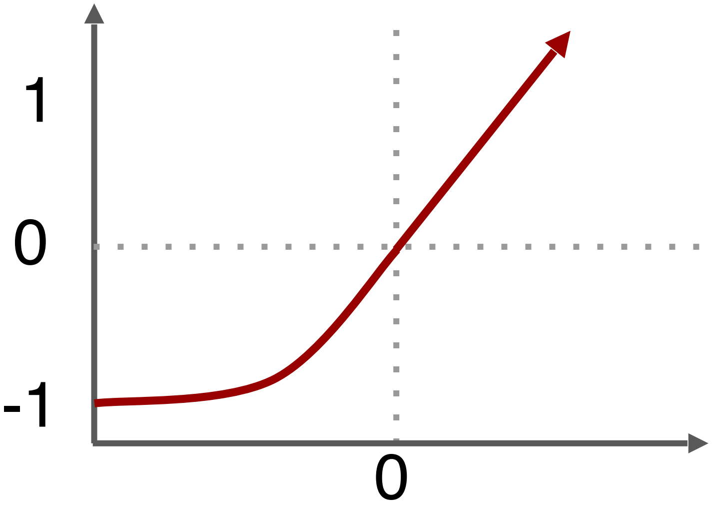
- "Leaky" ReLU



Deep Learning

- Exponential Linear Unit (ELU)

Output



$z = wx + b$

* Another solution is to perform batch normalization, where your model will normalize each batch using the batch mean and standard deviation.

- Choosing different initialization of weights can also help alleviate these issues (Xavier Initialization).

- Apart from batch normalization, researchers have also used “gradient clipping”, where gradients are cut off before reaching a predetermined limit (e.g. cut off gradients to be between -1 and 1)

- RNN for Time Series present their own gradient challenges, let’s explore special LSTM (Long Short Term Memory) neuron units that help fix these issues!

LSTM and GRU Units

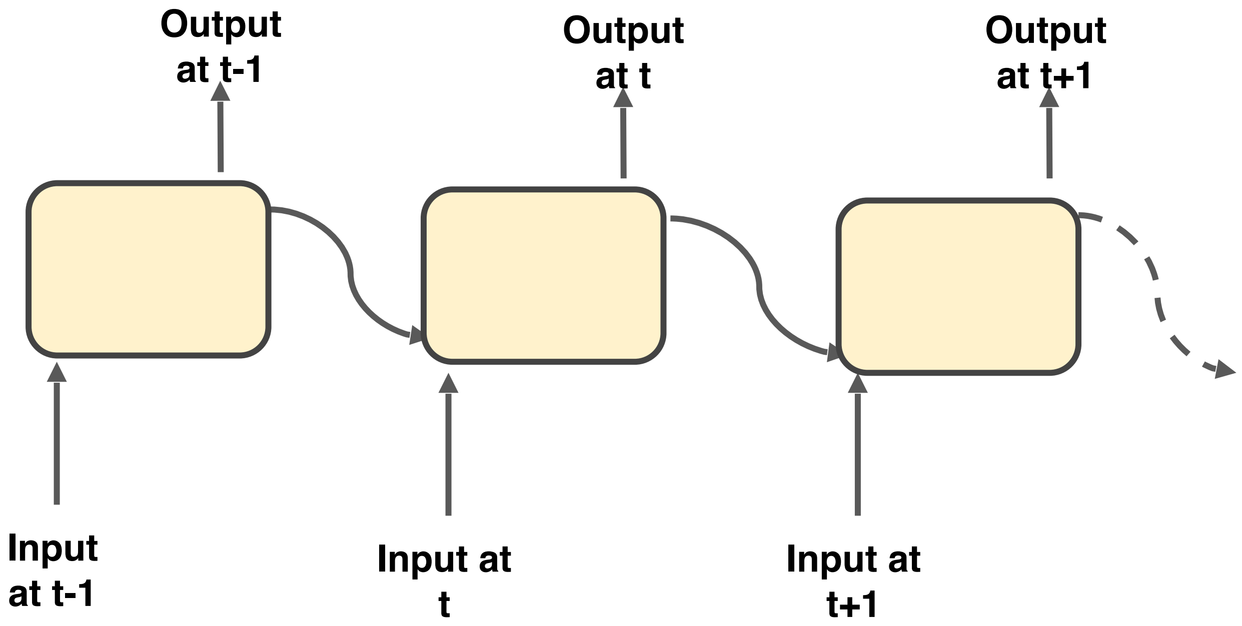
- Many of the solutions previously presented for vanishing gradients can also apply to RNN: different activation functions, batch normalizations, etc…
- However because of the length of time series input, these could slow down training

- A possible solution would be to just shorten the time steps used for prediction, but this makes the model worse at predicting longer trends.

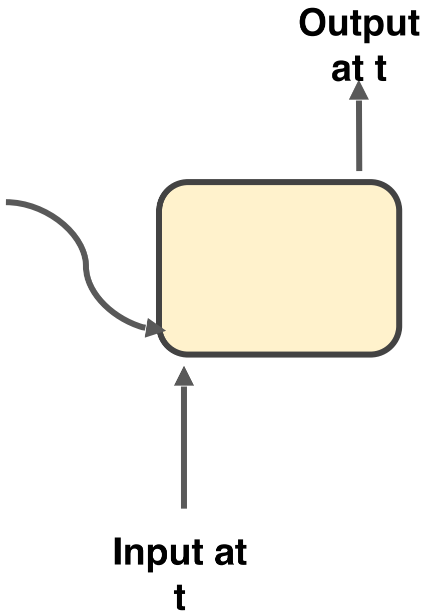
* Another issue RNN face is that after awhile the network will begin to “forget” the first inputs, as information is lost at each step going through the RNN.
* We need some sort of “long-term memory” for our networks.

- The LSTM (Long Short-Term Memory) cell was created to help address these RNN issues.
- Let’s go through how an LSTM cell works!

- A typical RNN

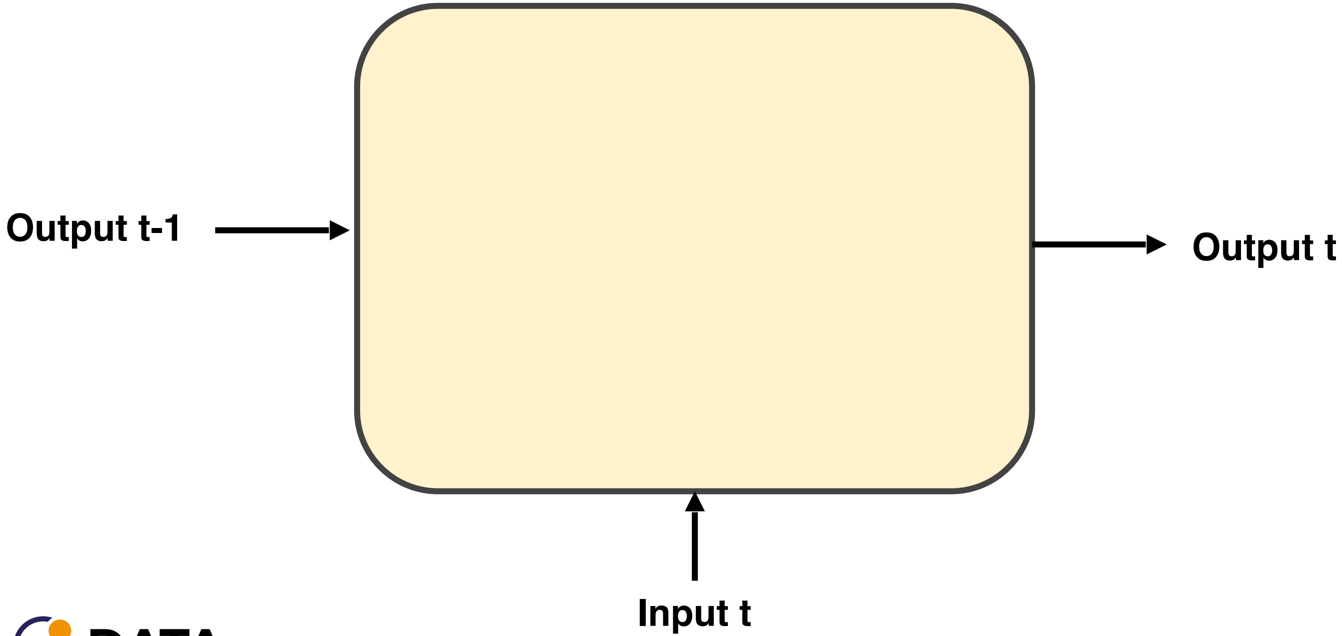


- RNN



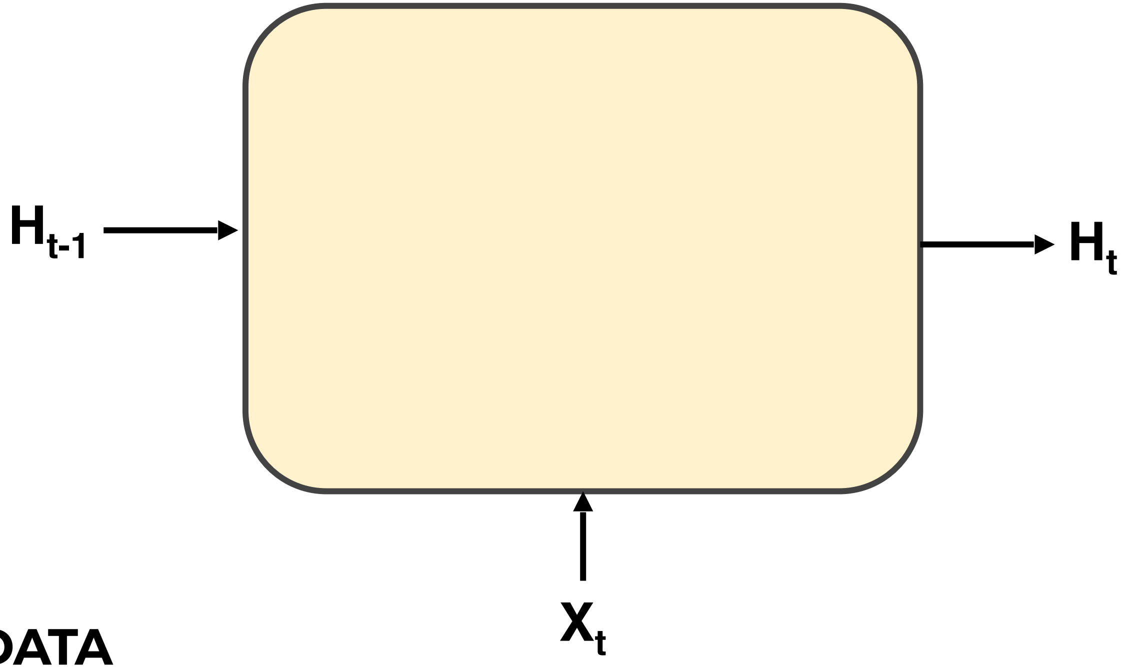
Deep Learning

- RNN

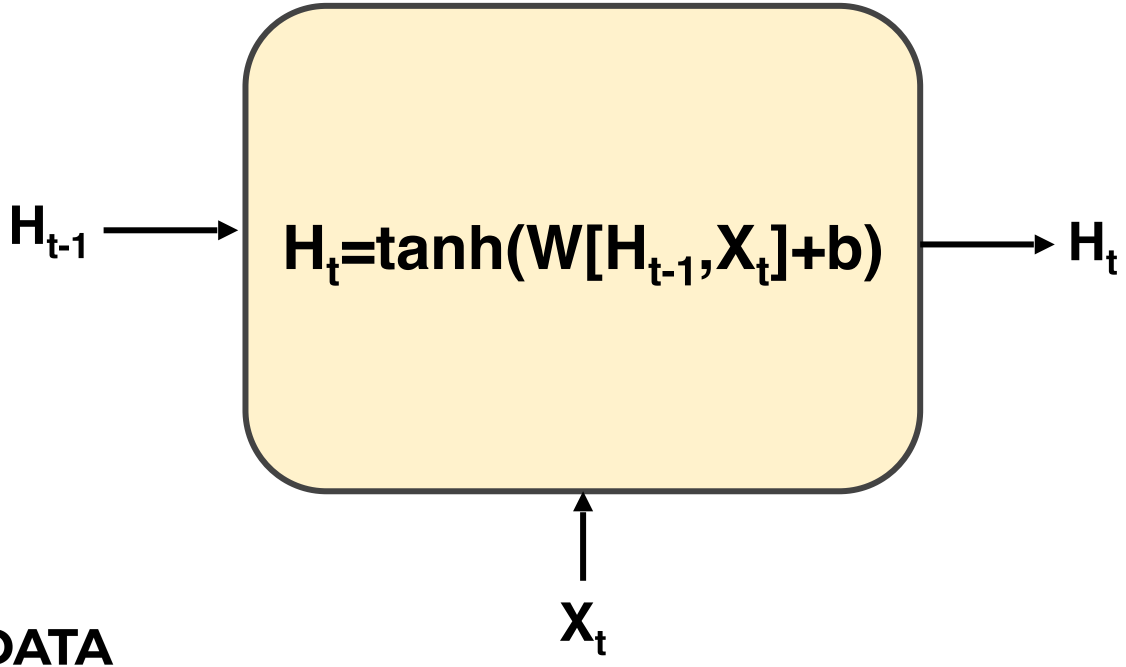


Deep Learning

- RNN

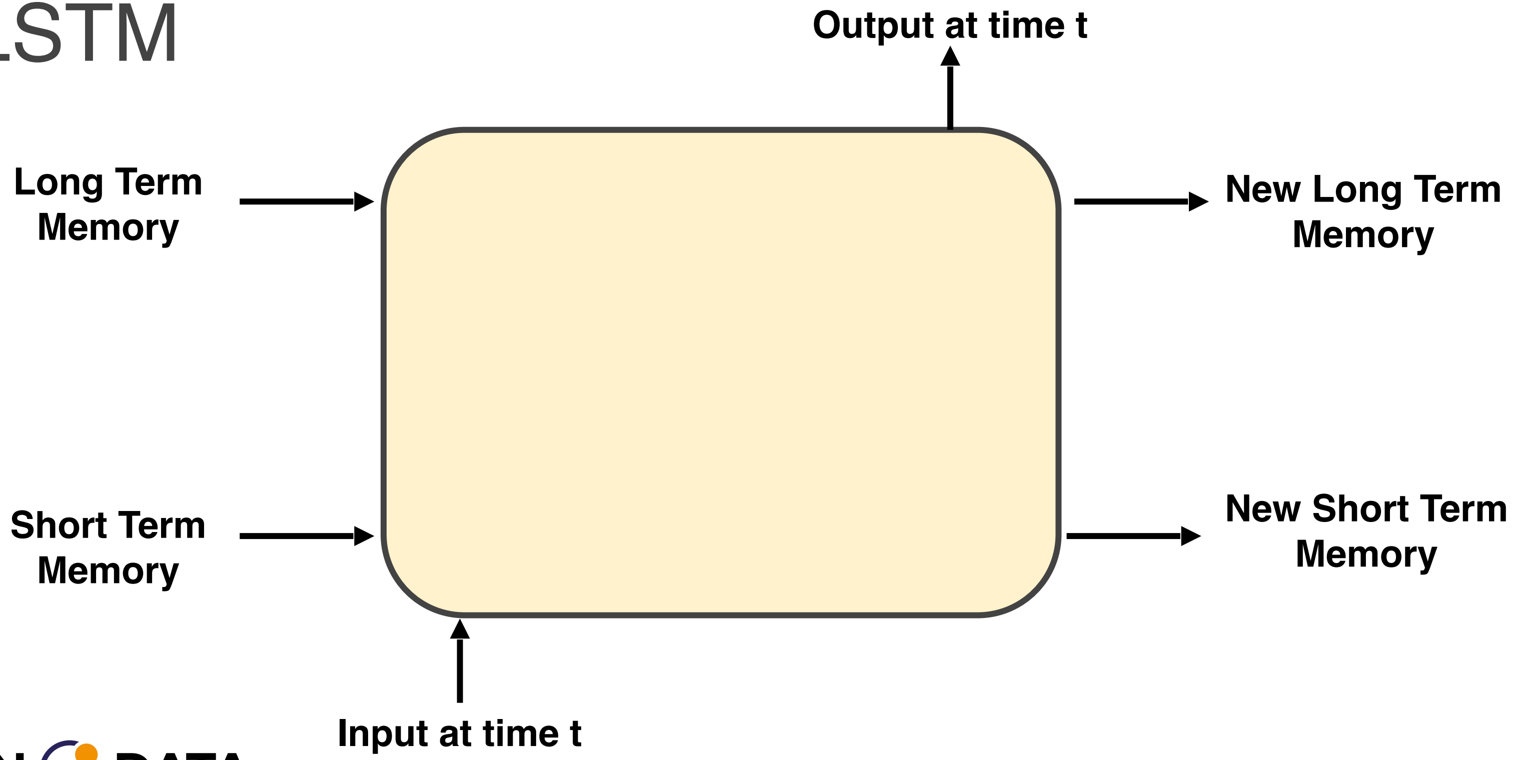


- RNN



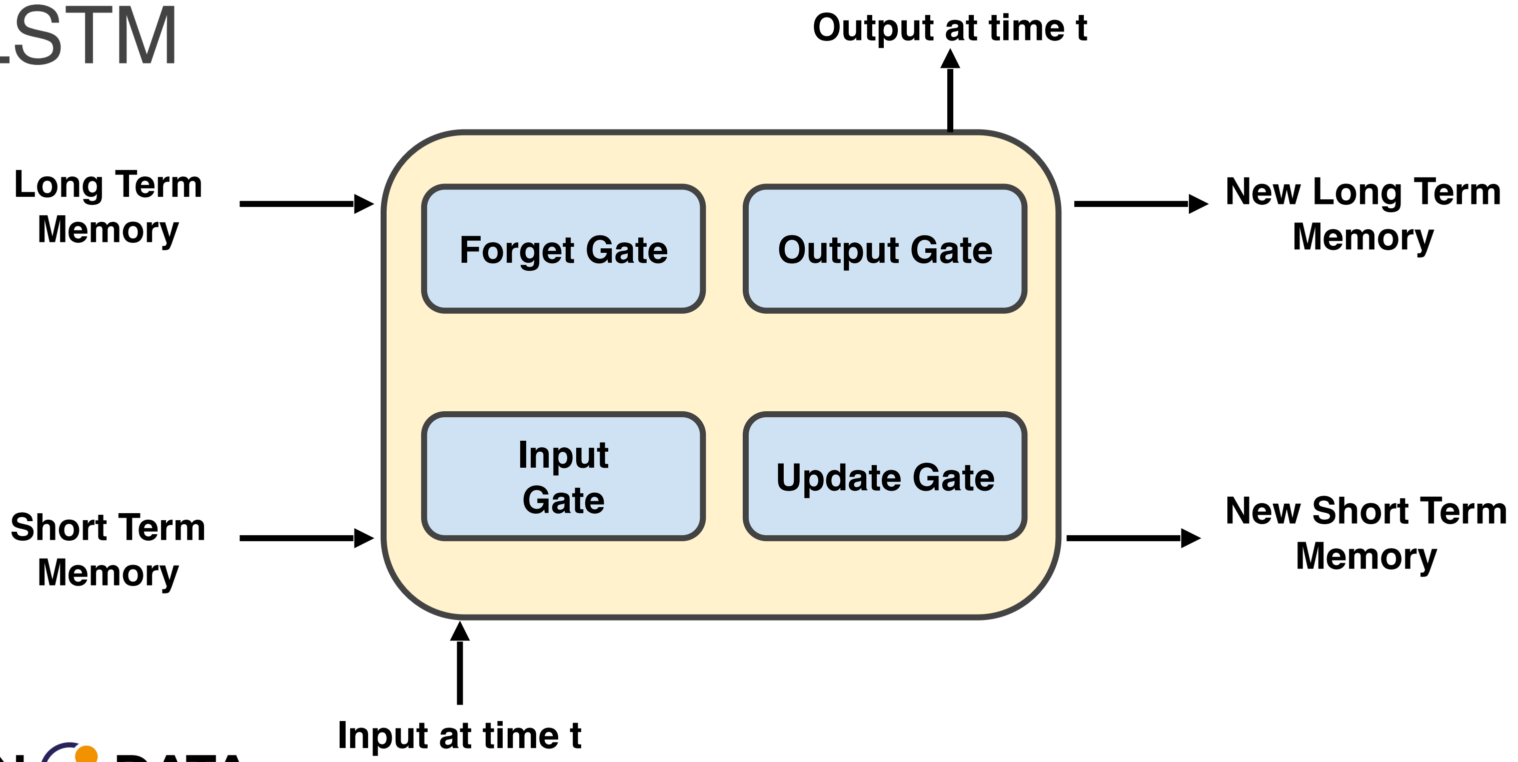
- LSTM

- LSTM

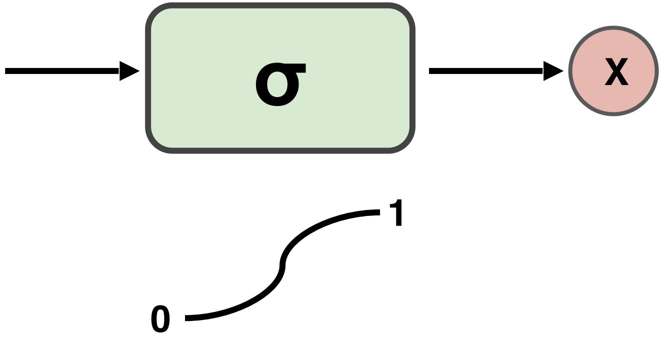

Output at time t
Long Term Memory
New Long Term Memory
Short Term Memory
New Short Term Memory
Input at time t

Deep Learning

- LSTM

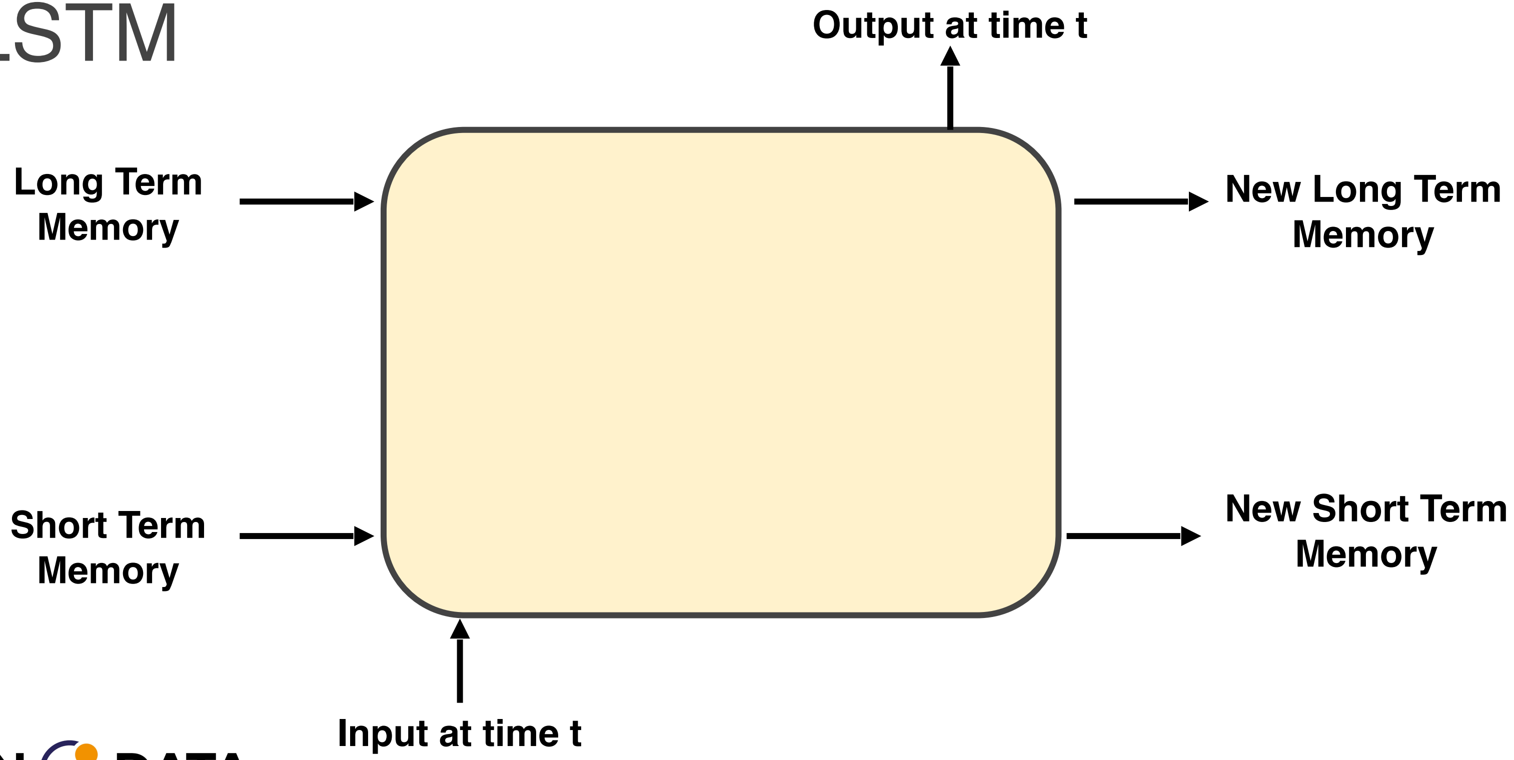


- Gates optionally let information through

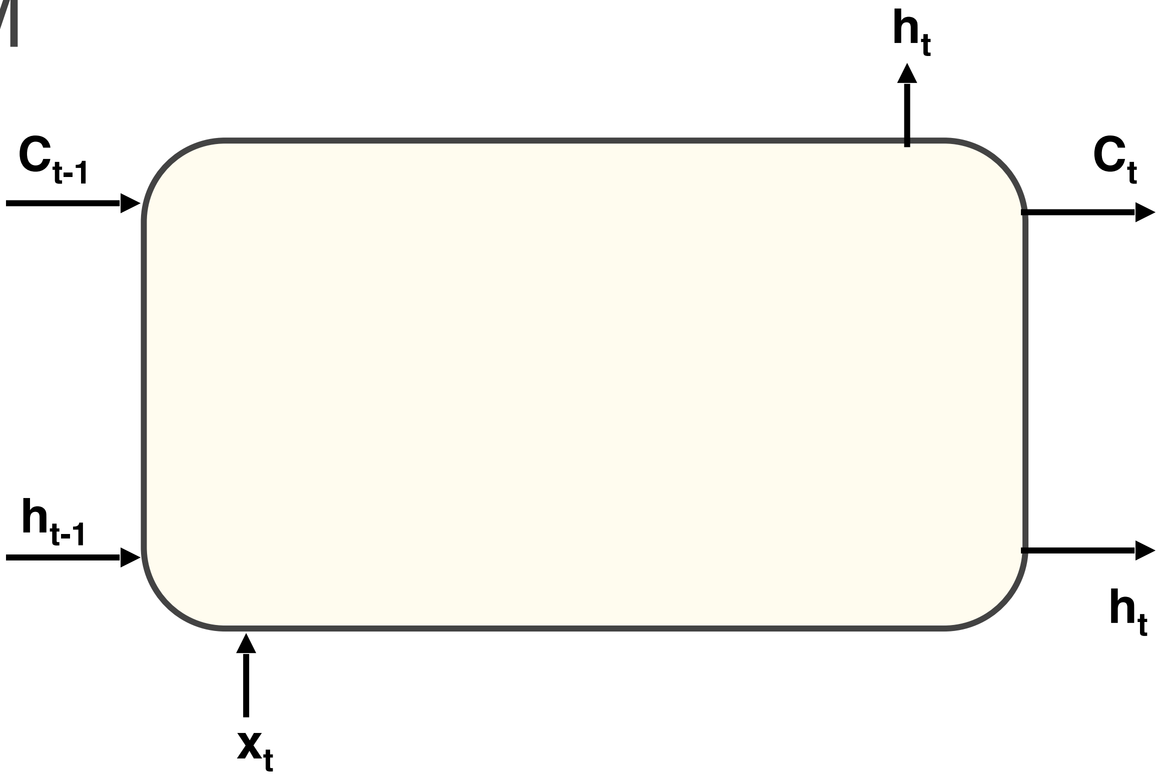


Deep Learning

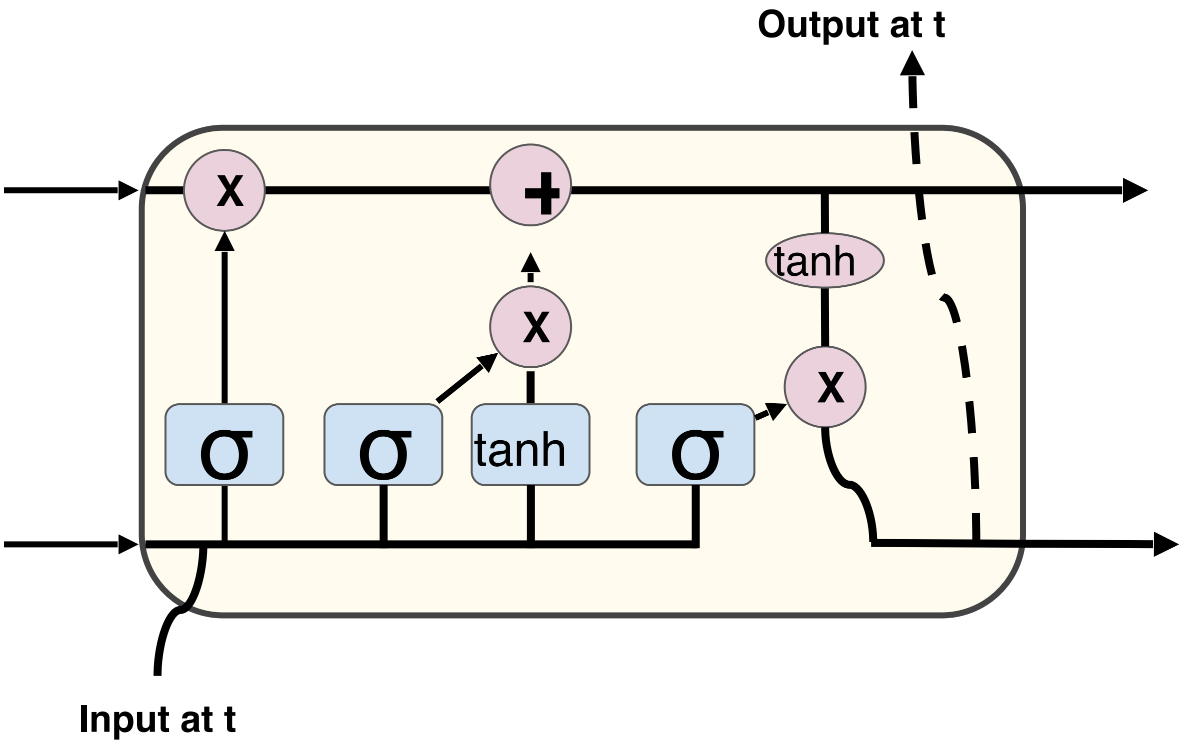
- LSTM



- LSTM



An LSTM Cell

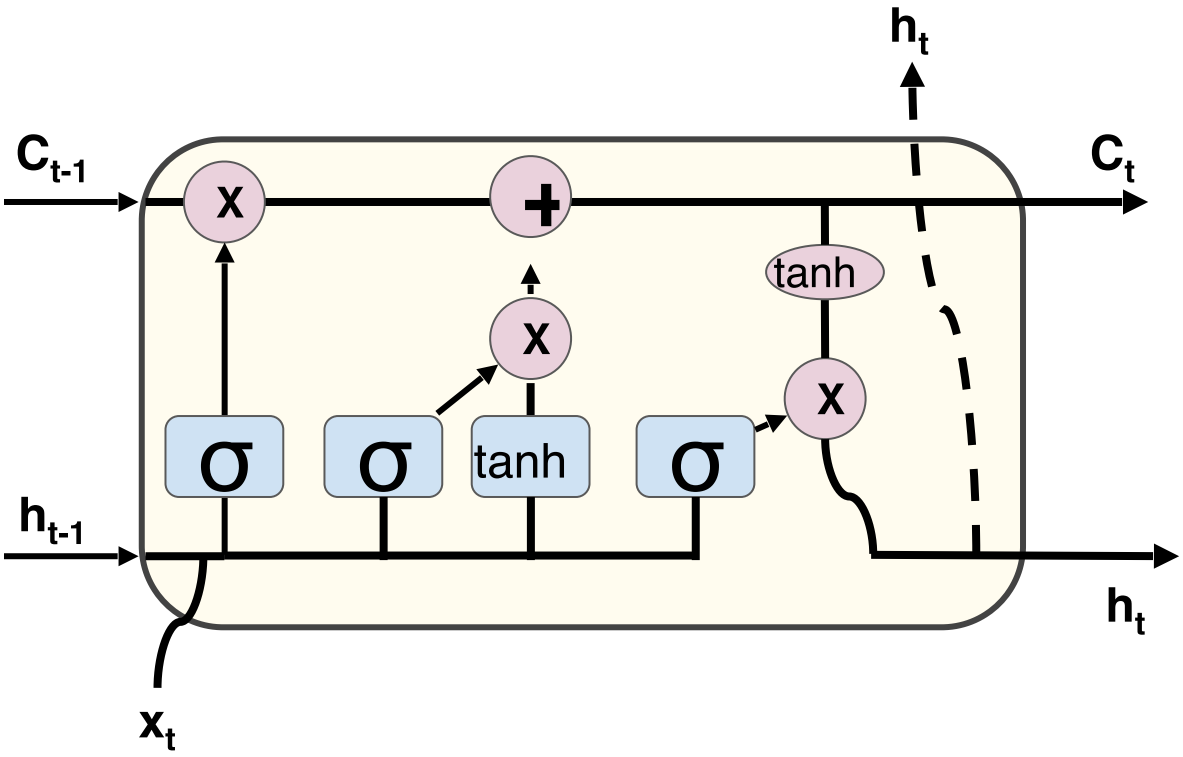


Here we can see the entire LSTM cell.

Let's go through the process!

http://colah.github.io/posts/2015-08-Understanding-LSTMs/

An LSTM Cell



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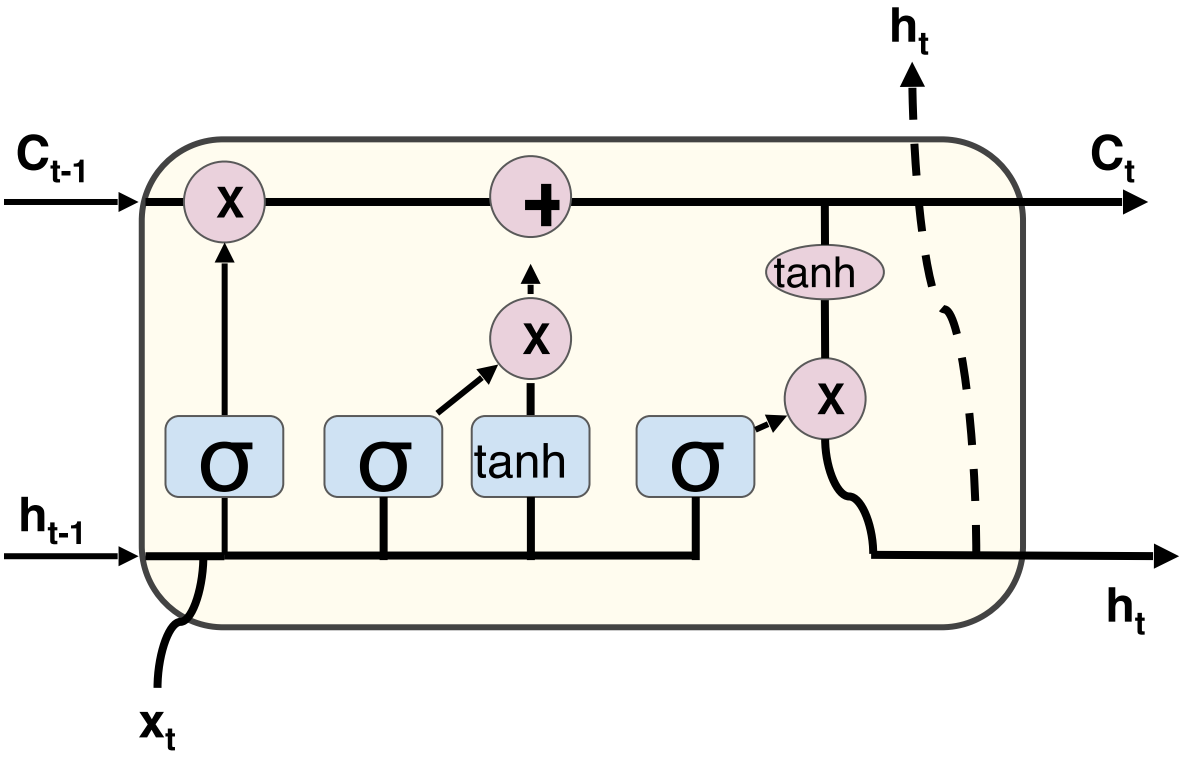
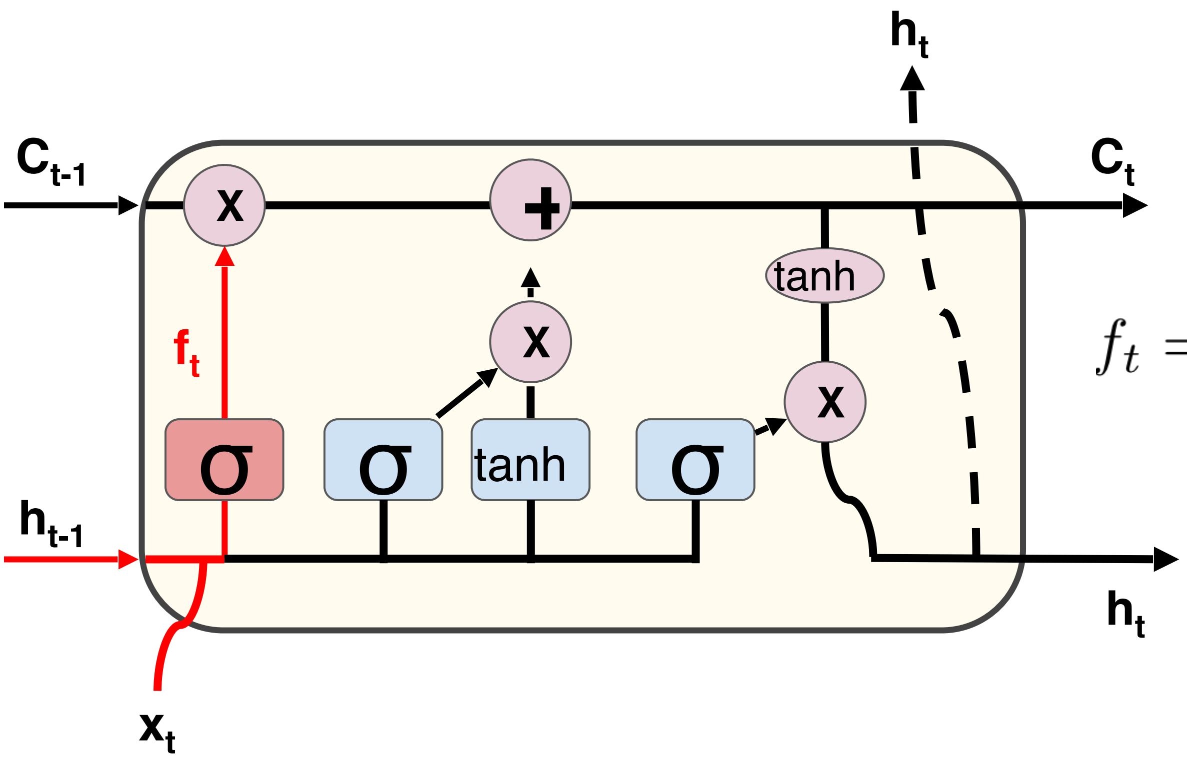
Let's go through the process!

An LSTM Cell

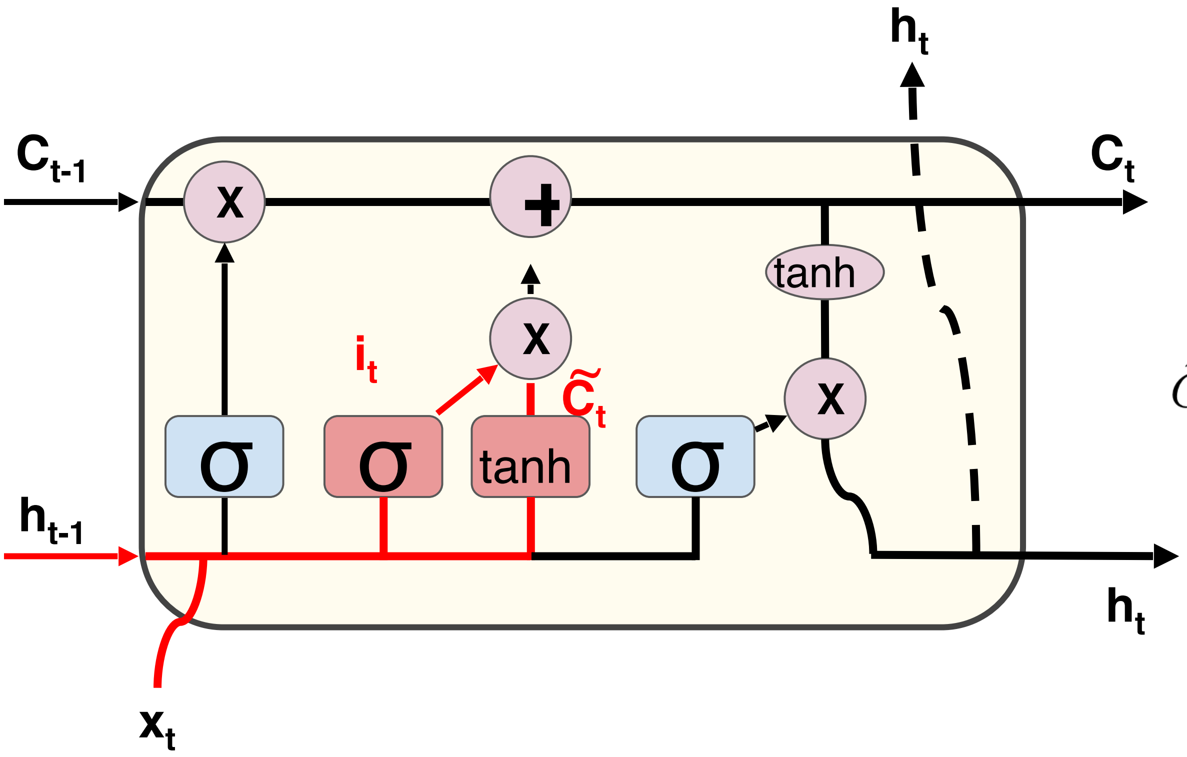


An LSTM Cell



$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \; + \; b_f\right)$$

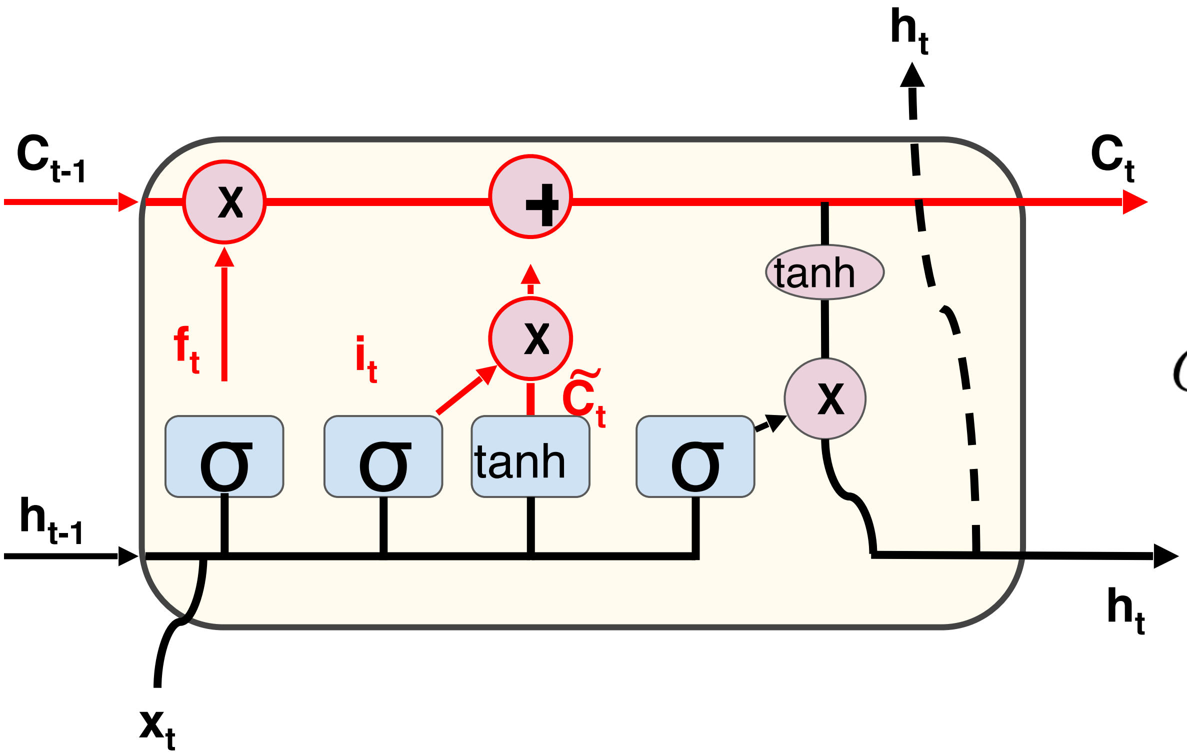
An LSTM Cell



$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \; + \; b_i\right)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \; + \; b_C)$$

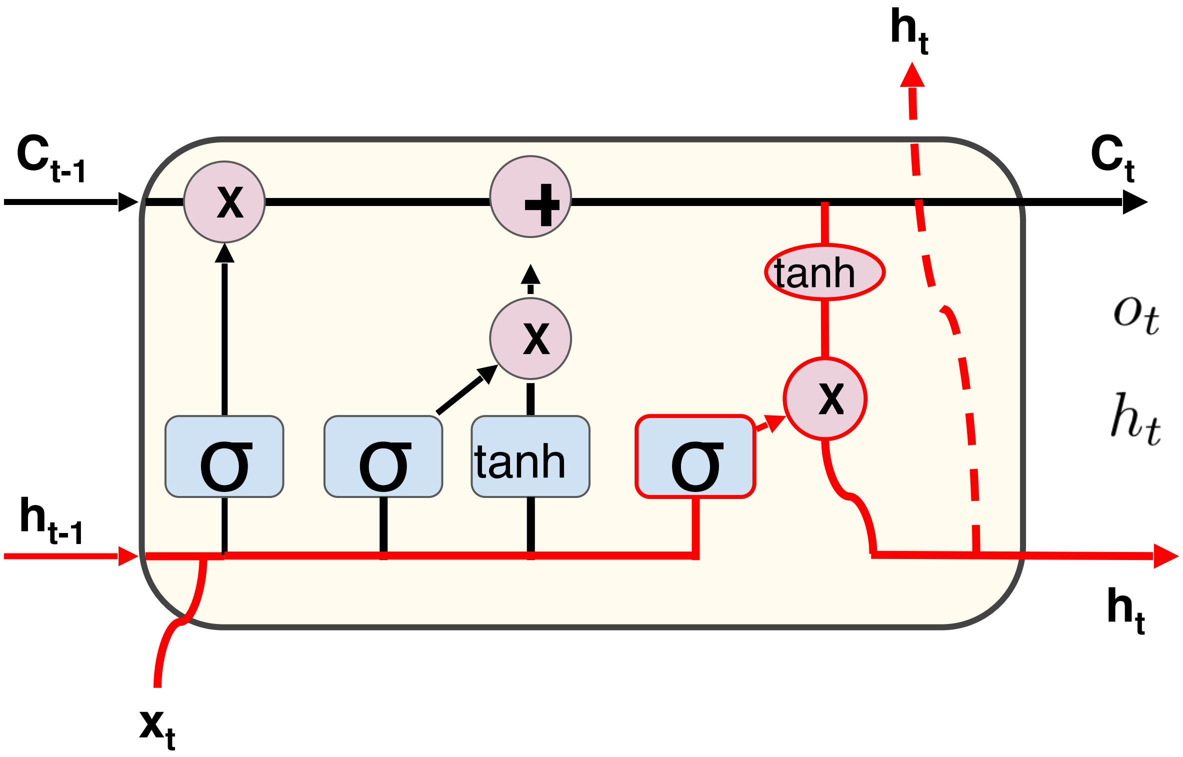
An LSTM Cell



$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

PIERIAN DATA

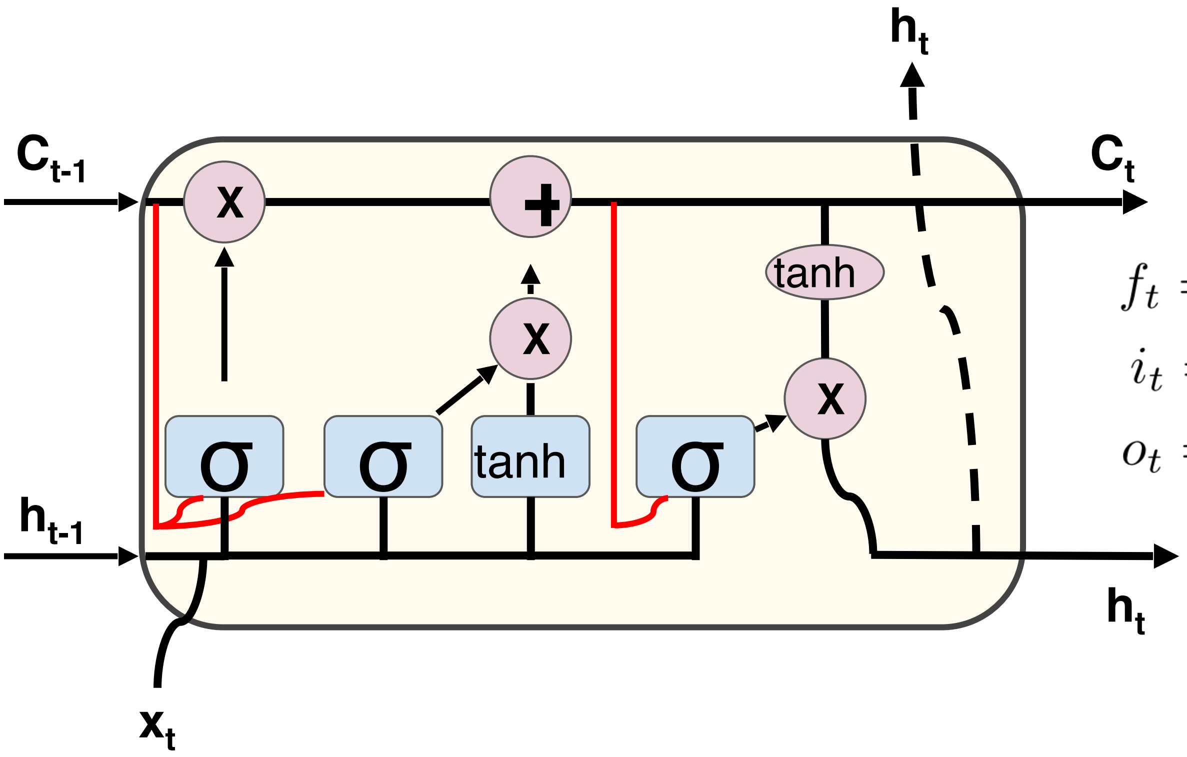
An LSTM Cell



$$o_t = \sigma\left(W_o \left[h_{t-1}, x_t\right] + b_o\right)$$

$$h_t = o_t * \tanh\left(C_t\right)$$

An LSTM Cell with “peepholes”



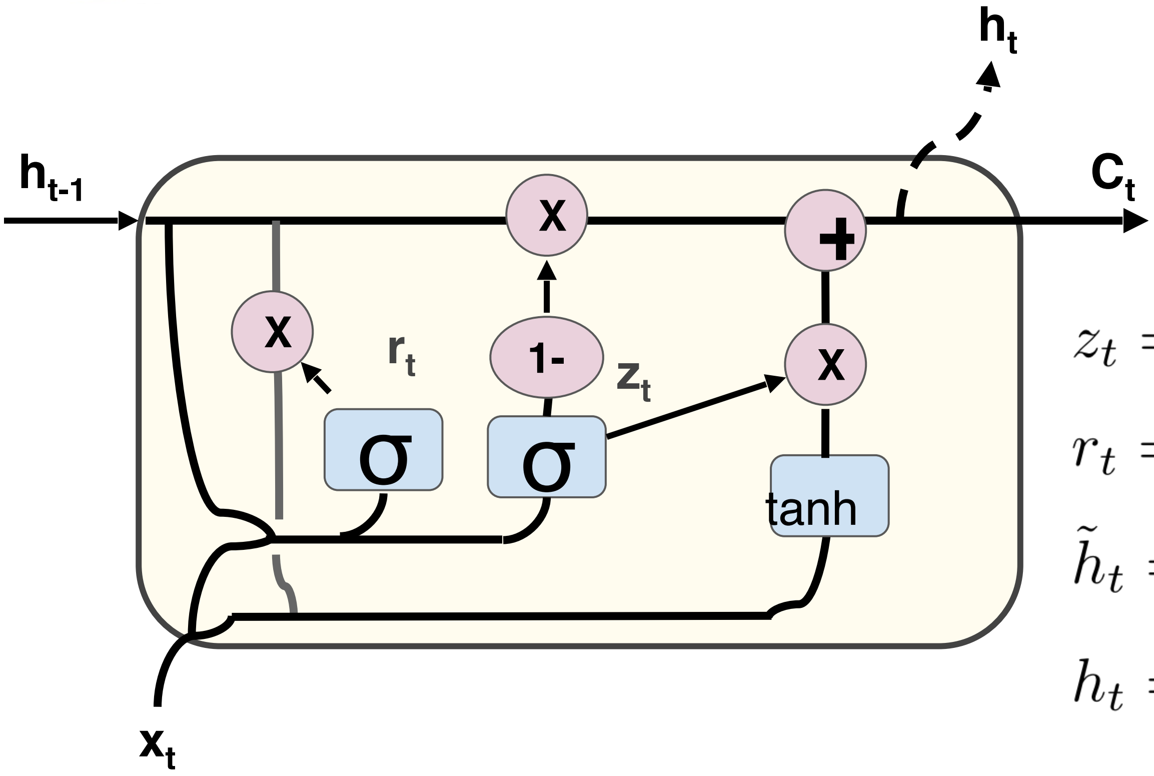
$$f_t = \sigma\left(W_f \cdot [\boldsymbol{C_{t-1}}, h_{t-1}, x_t] \; + \; b_f\right)$$

$$i_t = \sigma\left(W_i \cdot [\boldsymbol{C_{t-1}}, h_{t-1}, x_t] \; + \; b_i\right)$$

$$o_t = \sigma\left(W_o \cdot [\boldsymbol{C_t}, h_{t-1}, x_t] \; + \; b_o\right)$$

PIERIAN DATA

Gated Recurrent Unit (GRU)



$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

Deep Learning

- Fortunately with our deep learning python library , we simply need to call the import for RNN or LSTM instead of needing to code all of this ourselves!
- Let’s explore how to use LSTMs with Python code!

Basic RNN

Deep Learning

- Let's now explore how to use RNN on a basic time series, such as a sine wave.
- Before we jump to the notebook, let's quickly discuss what RNN sequence batches look like.

- Let’s imagine a simple time series:
    - **[0,1,2,3,4,5,6,7,8,9]**
- We separate this into 2 parts:
    - **[0,1,2,3,4,5,6,7,8] ⇨ [9]**
- Given **training sequence**, predict the **next sequence value**.

- Keep in mind we can usually decide how long the training sequence and predicted label should be:
    - [0,1,2,3,4] ⇨ [5,6,7,8,9]

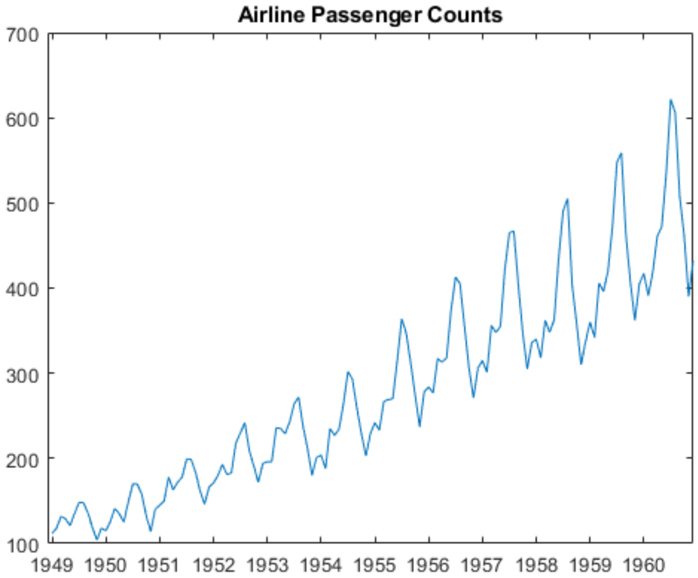
- We can also edit the size of the training point, as well as how many sequences to feed per batch:
  - [0,1,2,3] [4]
  - [1,2,3,4] → [5]
  - [2,3,4,5] →[6]

→

- So how do we decide how long the training sequence should be?
  - There is no definitive answer, but it should be at least long enough to capture any useful trend information.

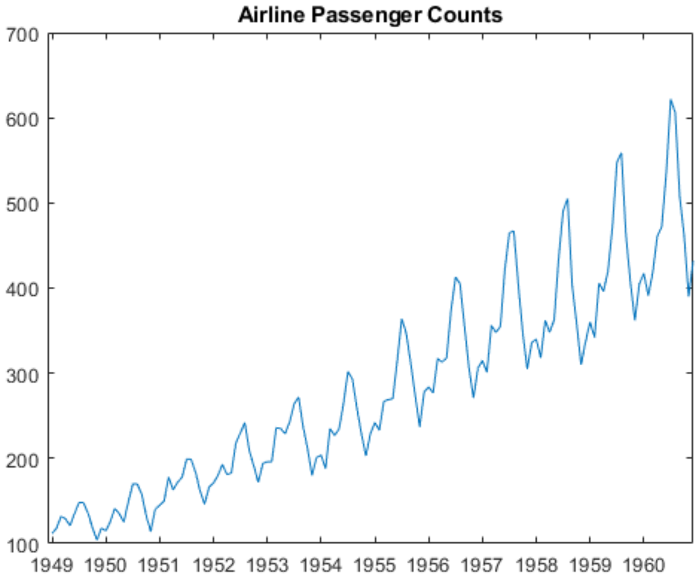
Deep Learning

- For example, if dealing with seasonal data:



Deep Learning

- If this is monthly, we should include at least 12 months in the training sequence



- This often takes domain knowledge and experience, as well as simply experimenting and using RMSE to measure error of forecasted predictions.
- Typically a good starting choice for the label is just one data point into the future.

Deep Learning

- How do we forecast with RNNs?
- Let’s imagine all our data is:
    - **[0,1,2,3,4,5,6,7,8,9]**
- And we trained on sequences such as:
    - **[0,1,2,3]** **[4]**
    - **[1,2,3,4]** **[5]**
    - **[2,3,4,5]** **[6]**

- Then our forecasting technique is to predict a time step ahead, and then incorporate our prediction into the next sequence we predict off of.
- Let’s walk through a quick example!

Deep Learning

- How do we forecast with RNNs?
- Let's imagine all our data is:
  - **[0,1,2,3,4,5,6,7,8,9]**
- And we trained on sequences such as:
  - **[0,1,2,3] → [4]**
  - **[1,2,3,4] → [5]**
  - **[2,3,4,5] → [6]**

Deep Learning

- [6,7,8,9] ⇨[10] Forecast prediction!

- [6,7,8,9] ⇨[10] Forecast prediction!
- Then to keep predicting further:

- [6,7,8,9] ⇨[10] Forecast prediction!
- Then to keep predicting further:
  - [7,8,9,10] ⇨[11.2]

Deep Learning

- [6,7,8,9] ⇨ [10] Forecast prediction!
- Then to keep predicting further:
    - [7,8,9,10] ⇨ [11.2]
    - [8,9,10,11.2] ⇨ [12.4]

Deep Learning

- [6,7,8,9] ⇨[10] Forecast prediction!
- Then to keep predicting further:
  - [7,8,9,10] ⇨[11.2]
  - [8,9,10,11.2] ⇨ [12.4]
  - [9,10,11.2,12.4] ⇨ [14]

Deep Learning

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  - [8,9,10,11.2]⇨ [12.4]
  - [9,10,11.2,12.4]⇨ [14]
  - [10,11.2,12.4,14]⇨ Completed Forecast

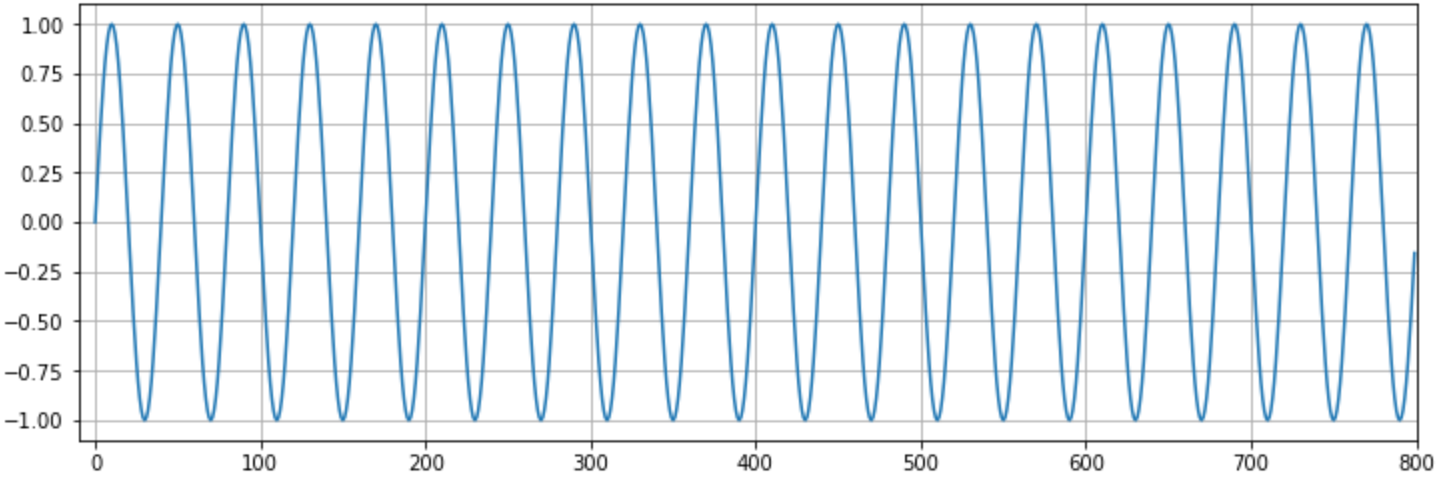
Deep Learning

- Let’s explore this further with Python!

Basic RNN on a Sine Wave

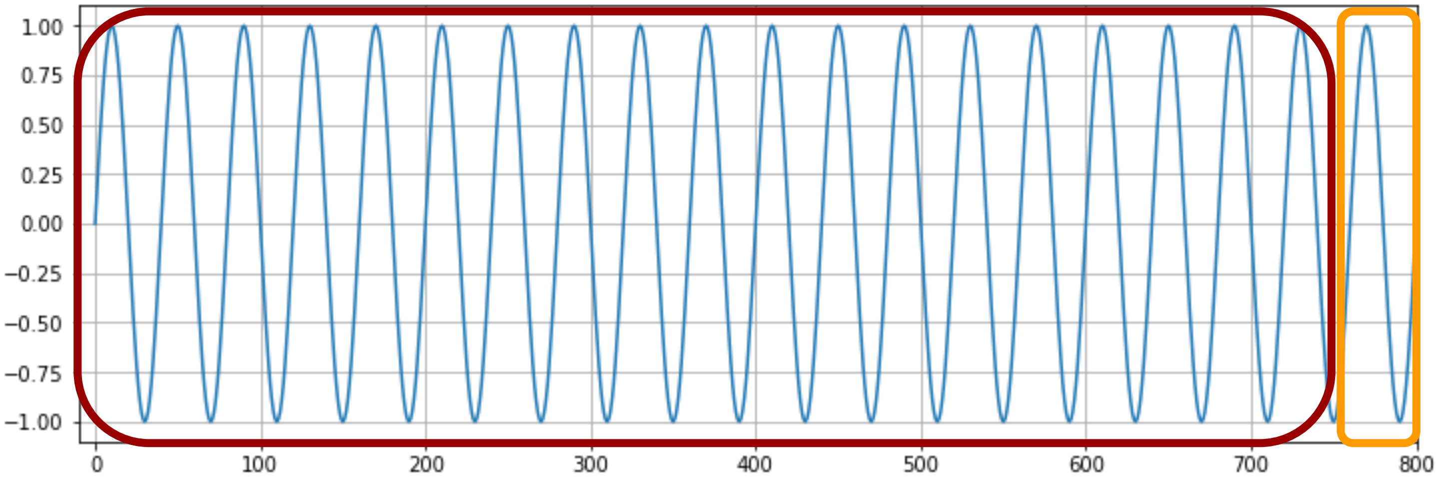
Deep Learning

- Let's now train and evaluate our RNN
- Recall our original data:

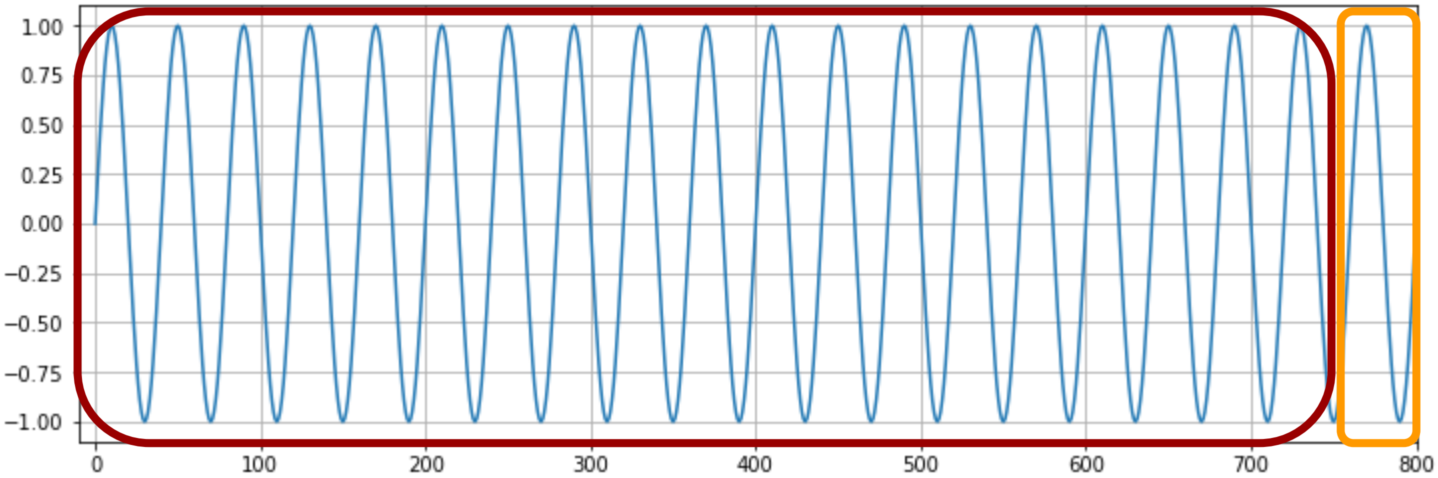


Deep Learning

- We split this into **train_set** and **test_set**:

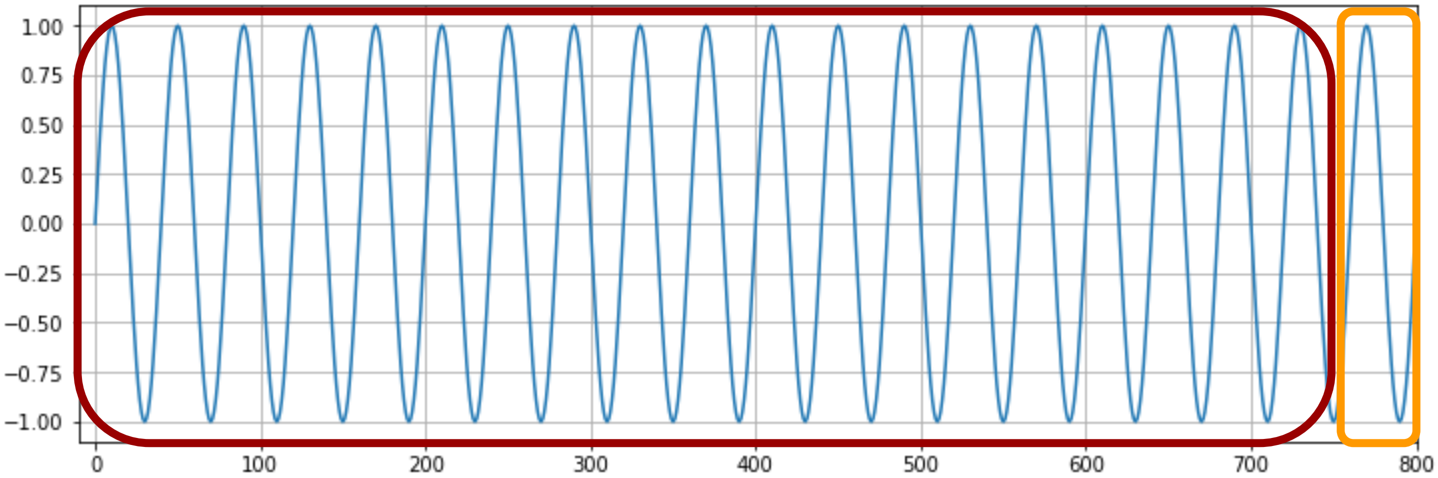


- During training, we could evaluate performance on the test data.

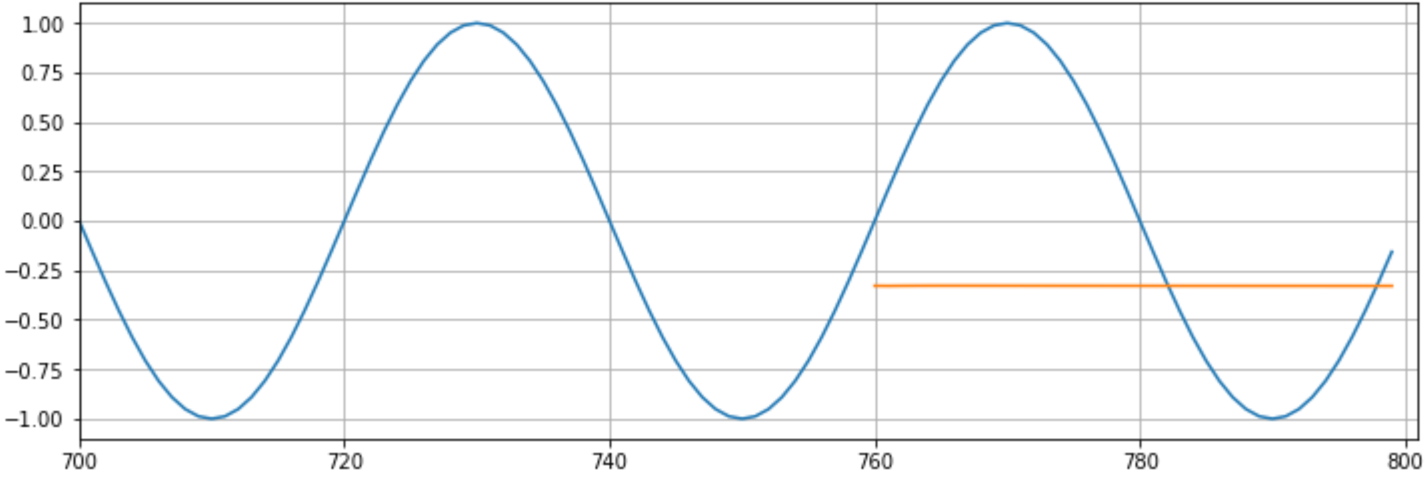


Deep Learning

* Let's zoom in on that range!



- As we train, we will forecast on this range to visually see the training.



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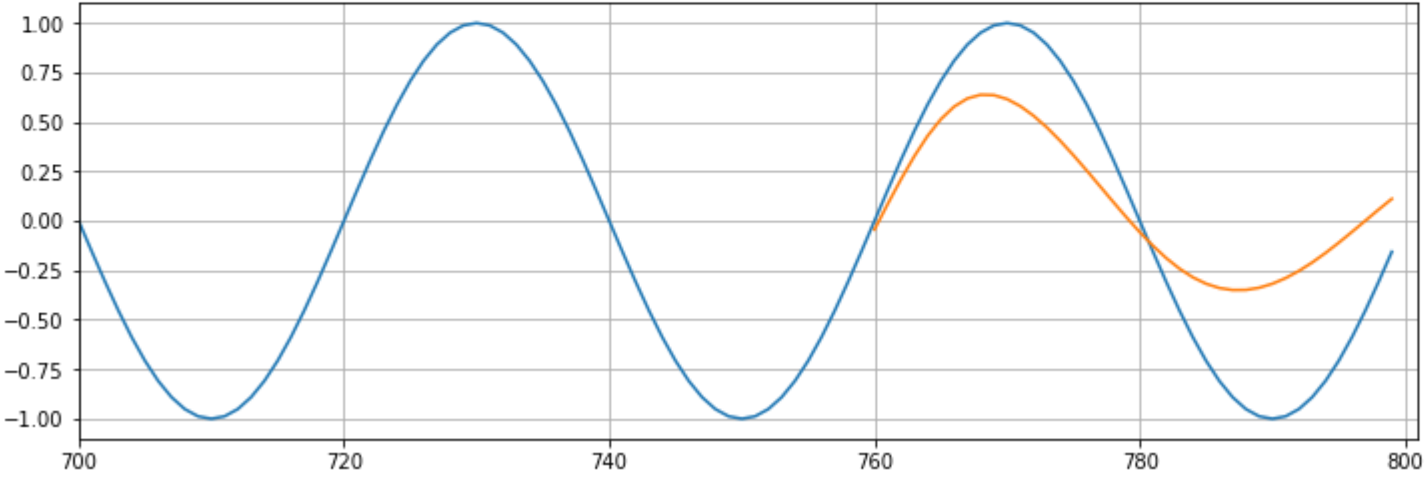

Deep Learning

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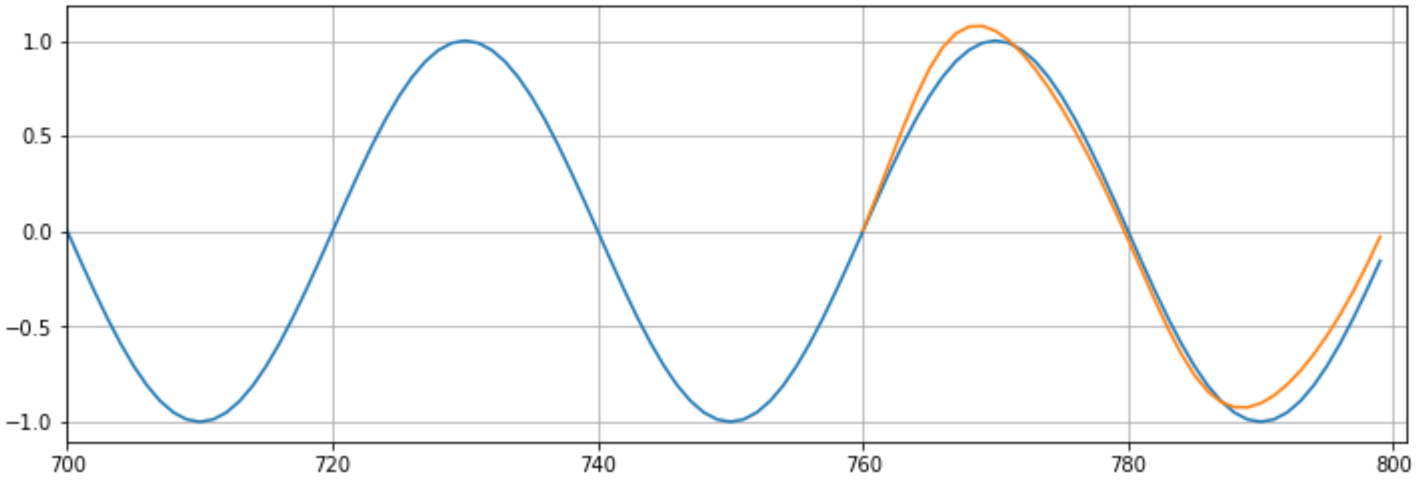
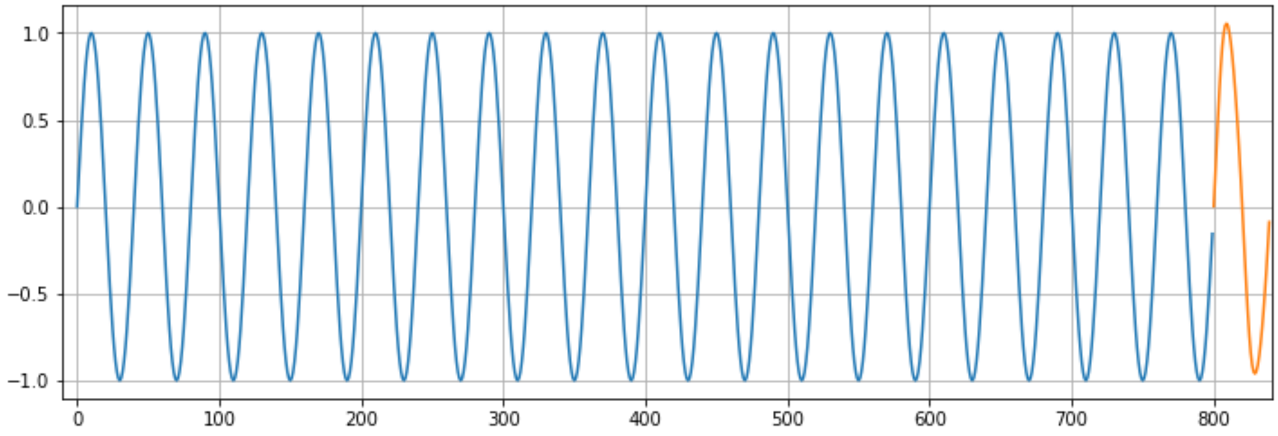


- Eventually once we are satisfied with the results on the test portion, it will be time to forecast into the unknown future.
- This means **retraining** on **all** available data (both train and test) and forecasting beyond the scope of the original data.

Deep Learning

- Keep in mind, for real data, we would no longer have values to compare these predictions to!



RNN on a

RNN Exercises

RNN Exercises Solutions

Multivariate Time Series with LSTM RNNs

* As a quick bonus, we'll discuss how to use LSTMs and RNNs to predict multivariate time series.
* Keep in mind, there are a few cons to using LSTMs for this approach!

Deep Learning

- As with all neural networks, the model is essentially a black box, difficult to interpret.
- Also there are many well-studied alternatives that are simpler, such as SARIMAX and VARMAX models.

- We highly recommend you try those more conventional approaches before settling on LSTMs or RNNs for multivariate time series data.
- Fortunately, setting up for multivariate data only requires 2 main changes.

Deep Learning

- Multivariate Time Series:
    - Change input shape in LSTM layer to reflect 2-D structure
    - Final dense layer should have a neuron per feature/variable.
- Let's explore these changes!