

# CS 4063 – Natural Language Processing

Lecture Notes – week 7 Lec 1+2

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# Today's Lecture

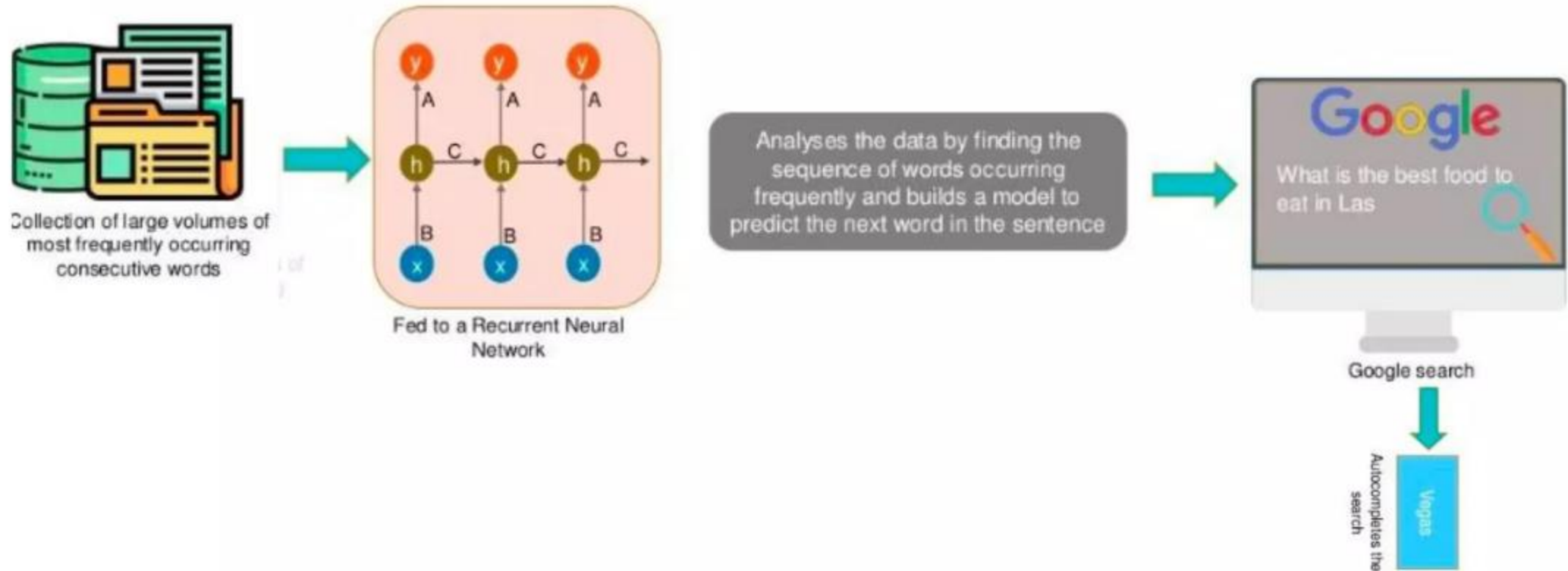
- Revision of RNN
- LSTM

# RNN

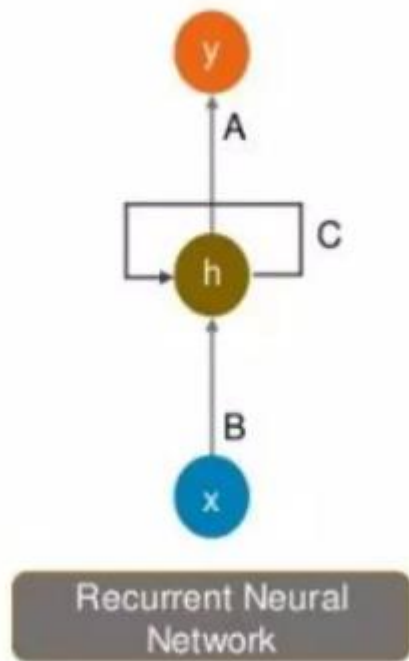
- Handle sequential data
- Each word in a sentence (or token in text) is fed into the network one at a time.
- Maintain a hidden state that captures information from previous steps, allowing them to learn patterns in sequences, such as the relationship between words.

# RNN

Do you know how Google's autocomplete feature predicts the rest of the words a user is typing?

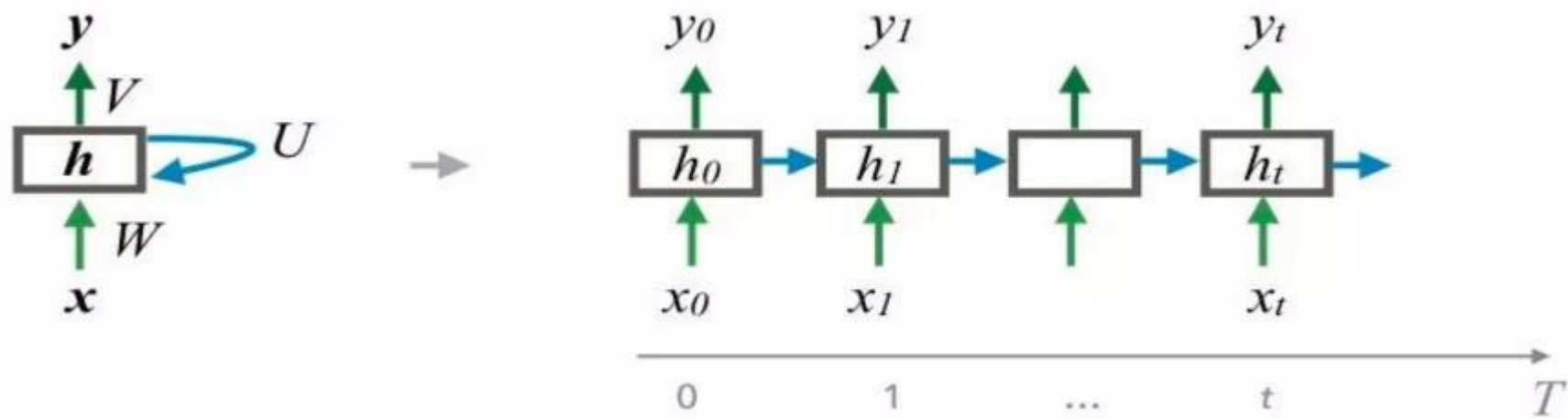


# RNN

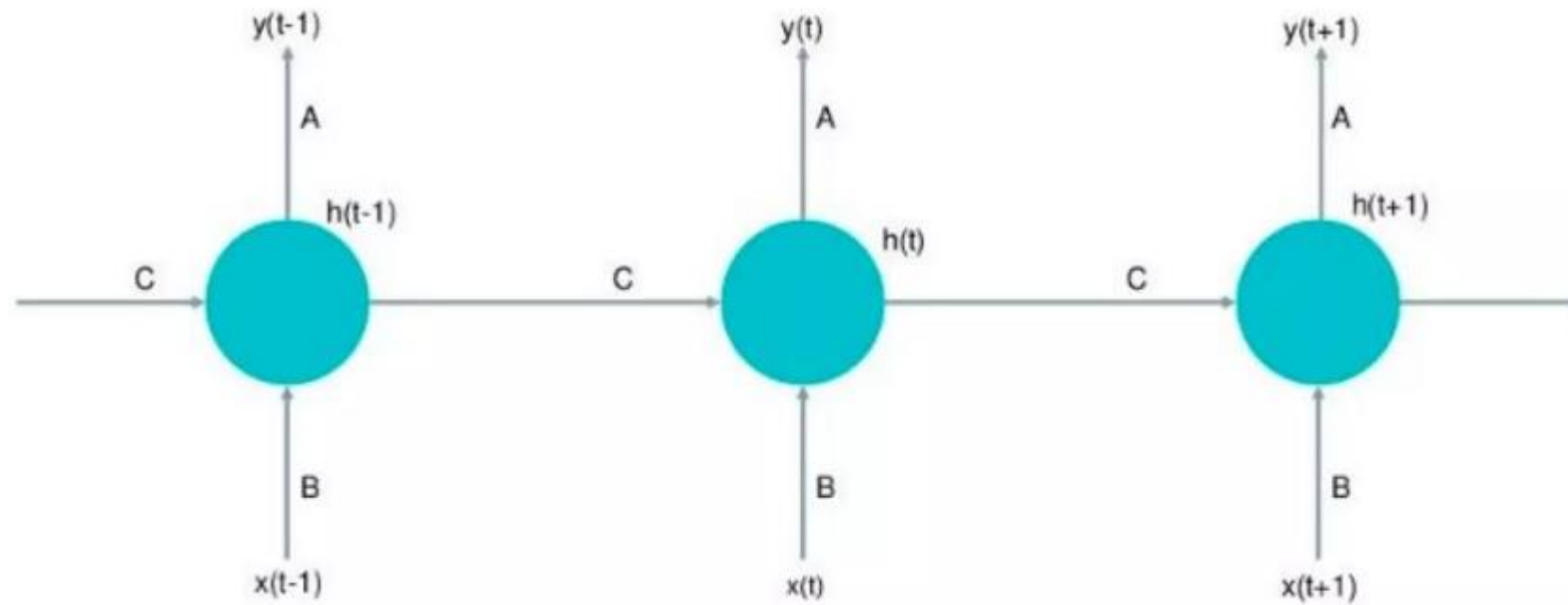


- 01 can handle sequential data
- 02 considers the current input and also the previously received inputs
- 03 can memorize previous inputs due to its internal memory

# RNN



# RNN



$$h(t) = f_c(h(t-1), x(t))$$

$h(t)$  = new state  
 $f_c$  = function with parameter  $c$   
 $h(t-1)$  = old state  
 $x(t)$  = input vector at time step  $t$

# Limitation

- **Vanishing Gradient Problem:** When training RNNs, the gradients used in backpropagation can become too small (vanish), making it difficult to capture long-term dependencies.
- **Long-Term Dependencies:** Basic RNNs struggle to remember information over long sequences, which is why advanced variations like LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Units) are often used.



# Limitation-Exploding Gradient Problem



...and this **HUGE NUMBER**  
would cause the gradient,  
which we need for **Gradient  
Descent**...

$$= \text{Input}_1 \times 2^{50}$$

$$= \text{Input}_1 \times \text{A HUGE NUMBER}$$



# Limitation-Vanishing Gradient Problem



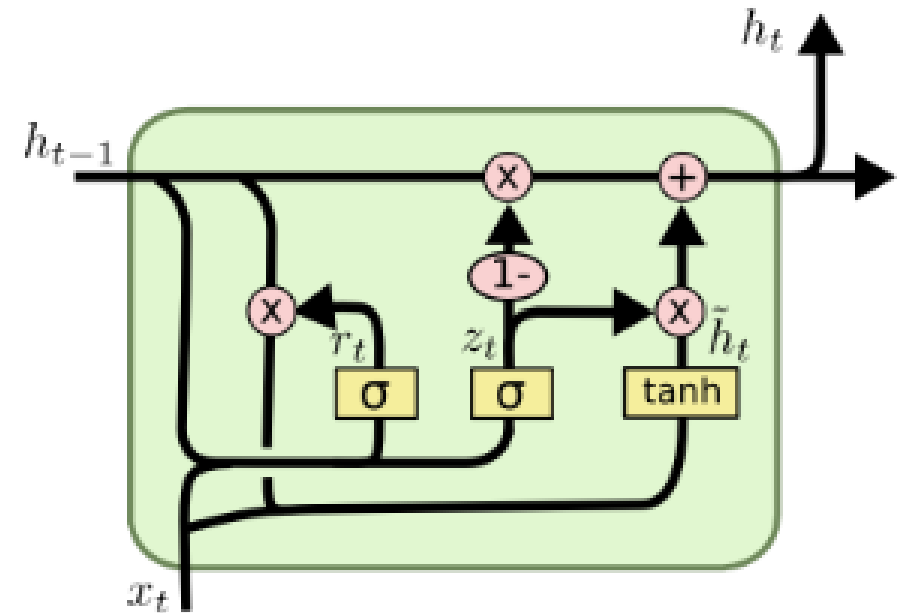
Alternatively, we saw that if the **Weight** on the feedback loop was less than **1**, and now we have it set to **0.5...**

$$= \text{Input}_1 \times 0.5^{50}$$



# LSTM

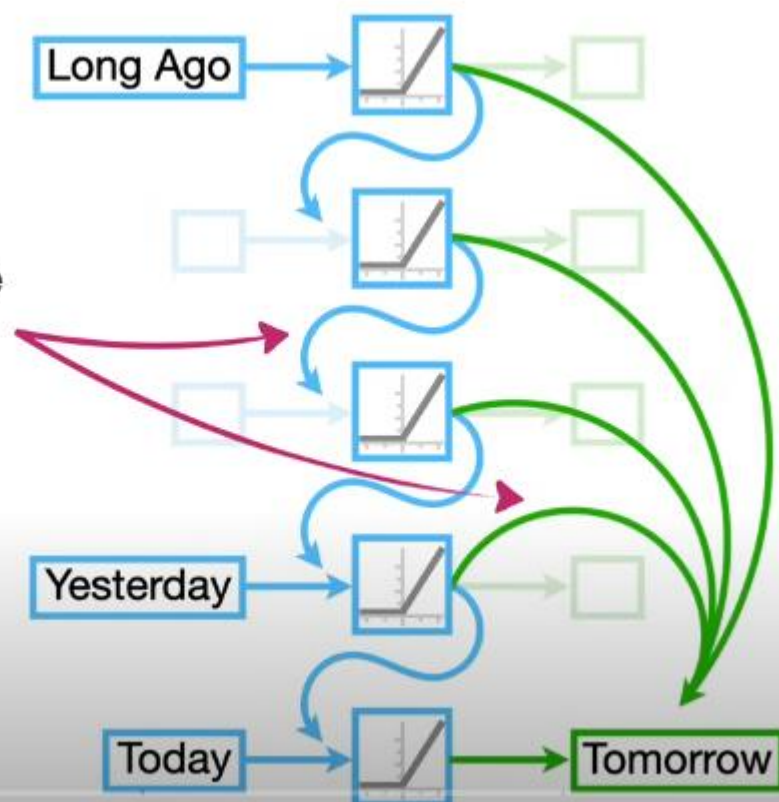
- The LSTM architecture involves the memory cell which is controlled by three gates: the input gate, the forget gate, and the output gate.
- These gates decide what information to add to, remove from, and output from the memory cell.



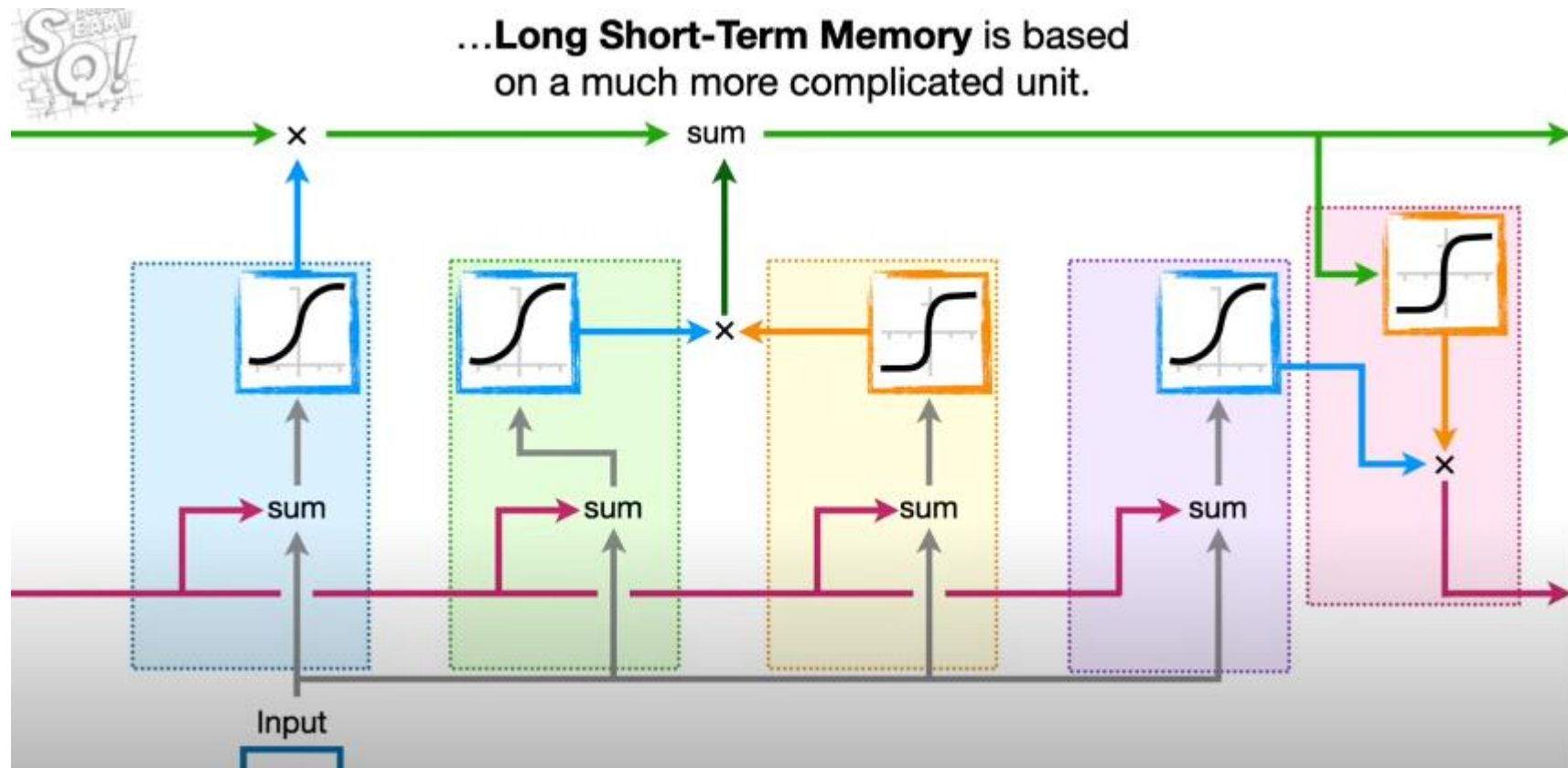
# LSTM



...**Long Short-Term Memory** uses two separate paths to make predictions about tomorrow.

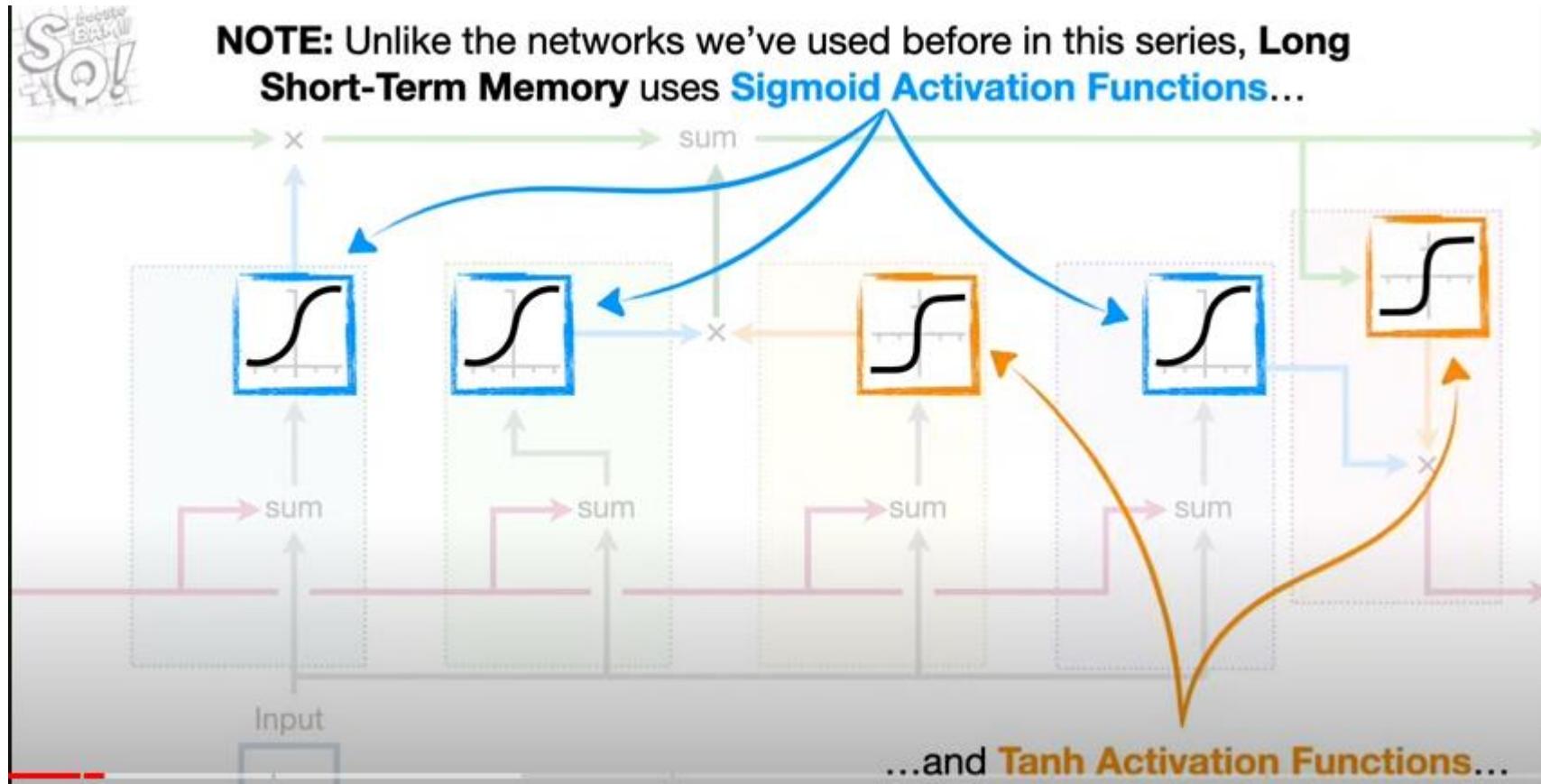


# LSTM



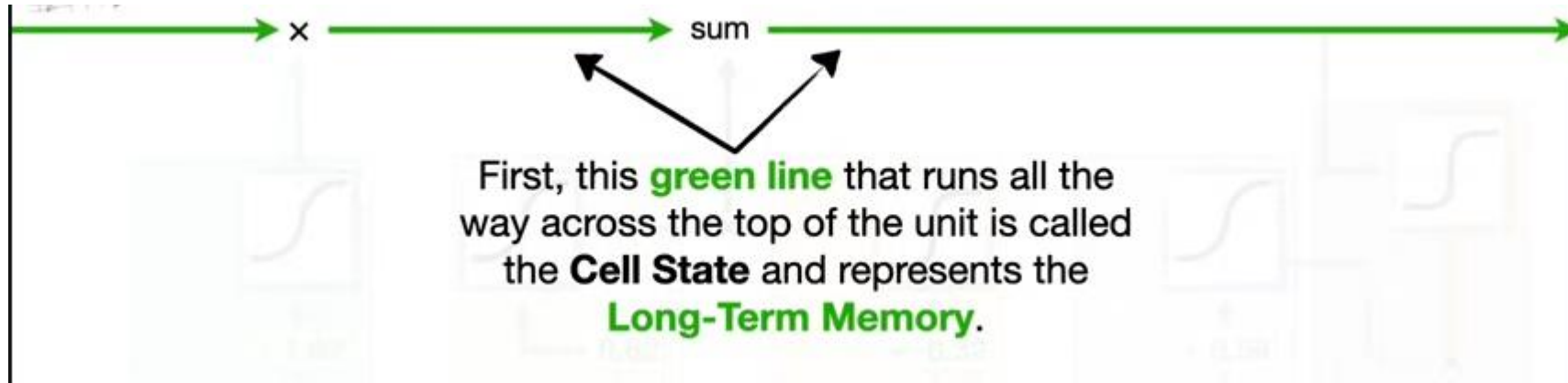
# LSTM

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

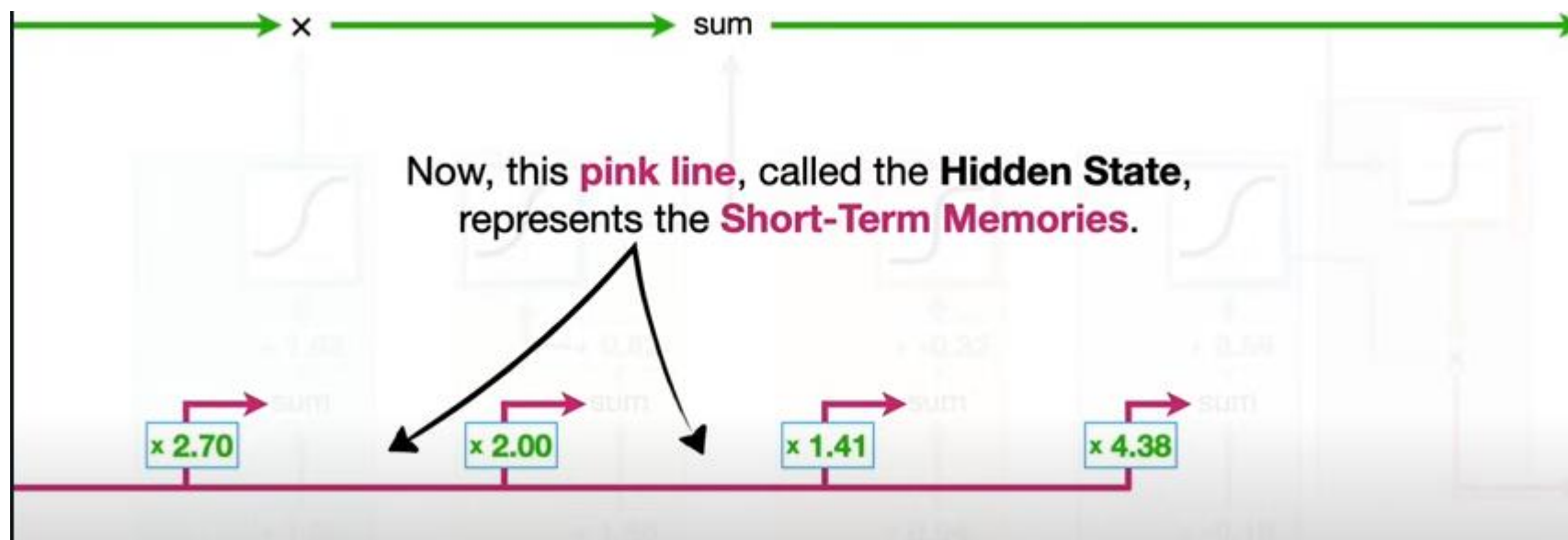


$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

# LSTM

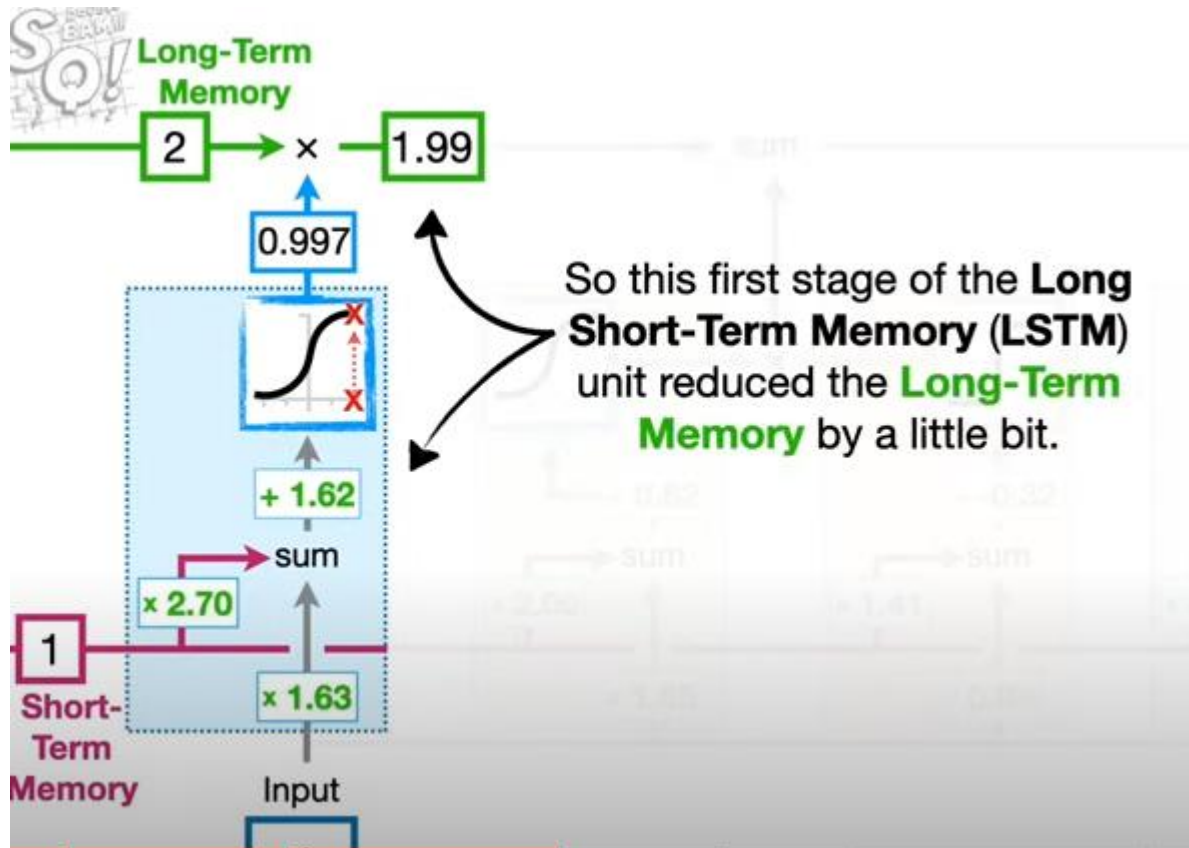


# LSTM





# LSTM- Forget gate

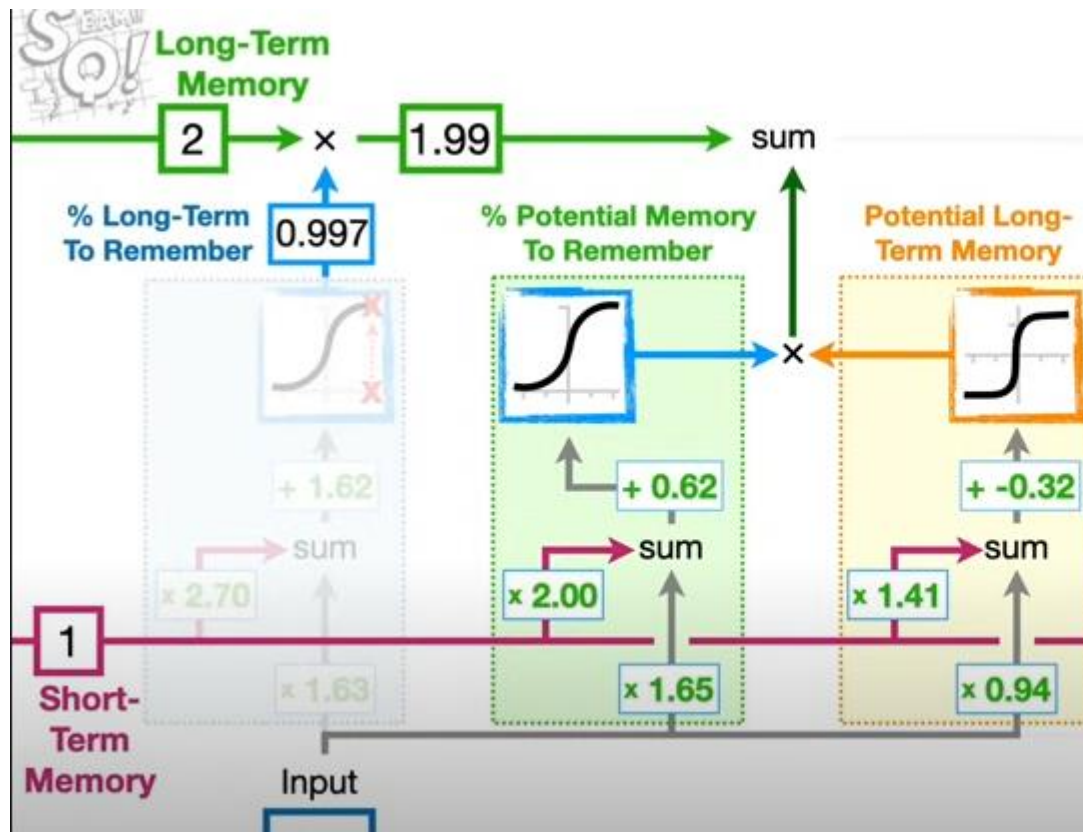


## TERMINOLOGY ALERT!!!

Even though this part of the **Long Short-Term Memory** unit determines what percentage of the **Long-Term Memory** will be remembered...

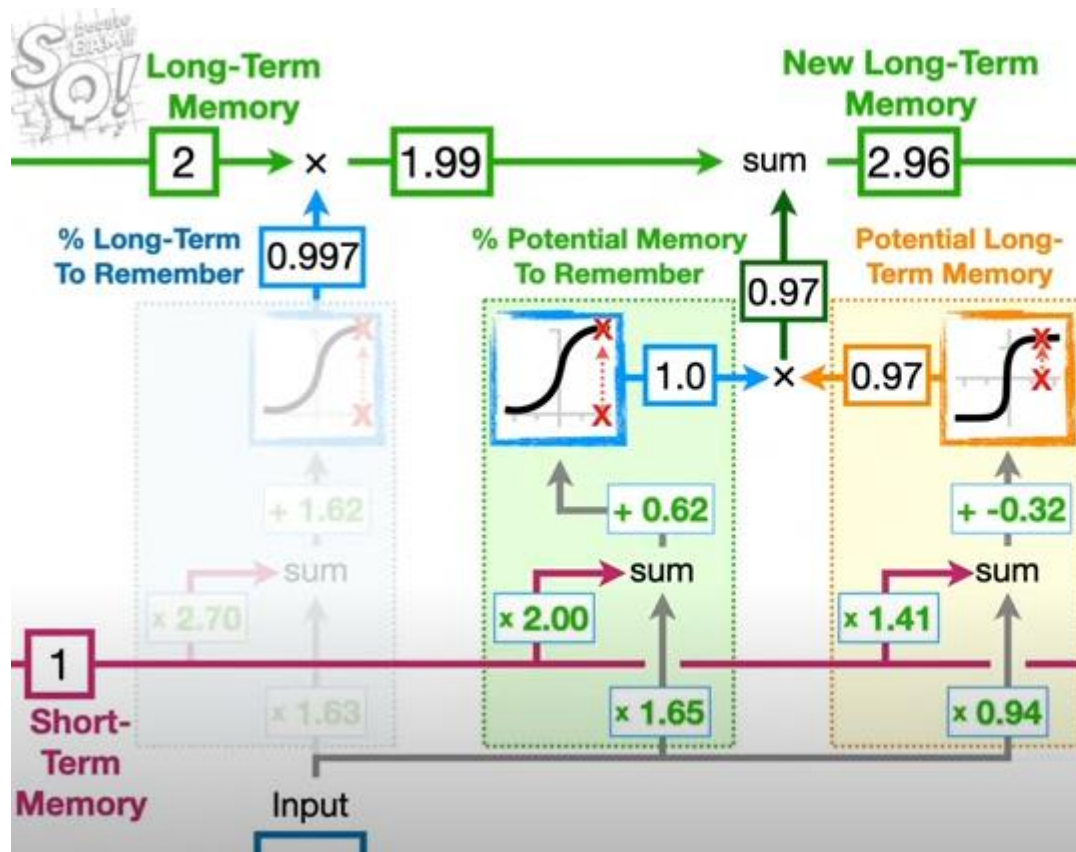
...it is usually called the **Forget Gate**.

# LSTM- Input gate



So let's plug the numbers in and do the math to see how a **Potential Memory** is created and how much of it is added to the **Long-Term Memory**.

# LSTM- Input gate

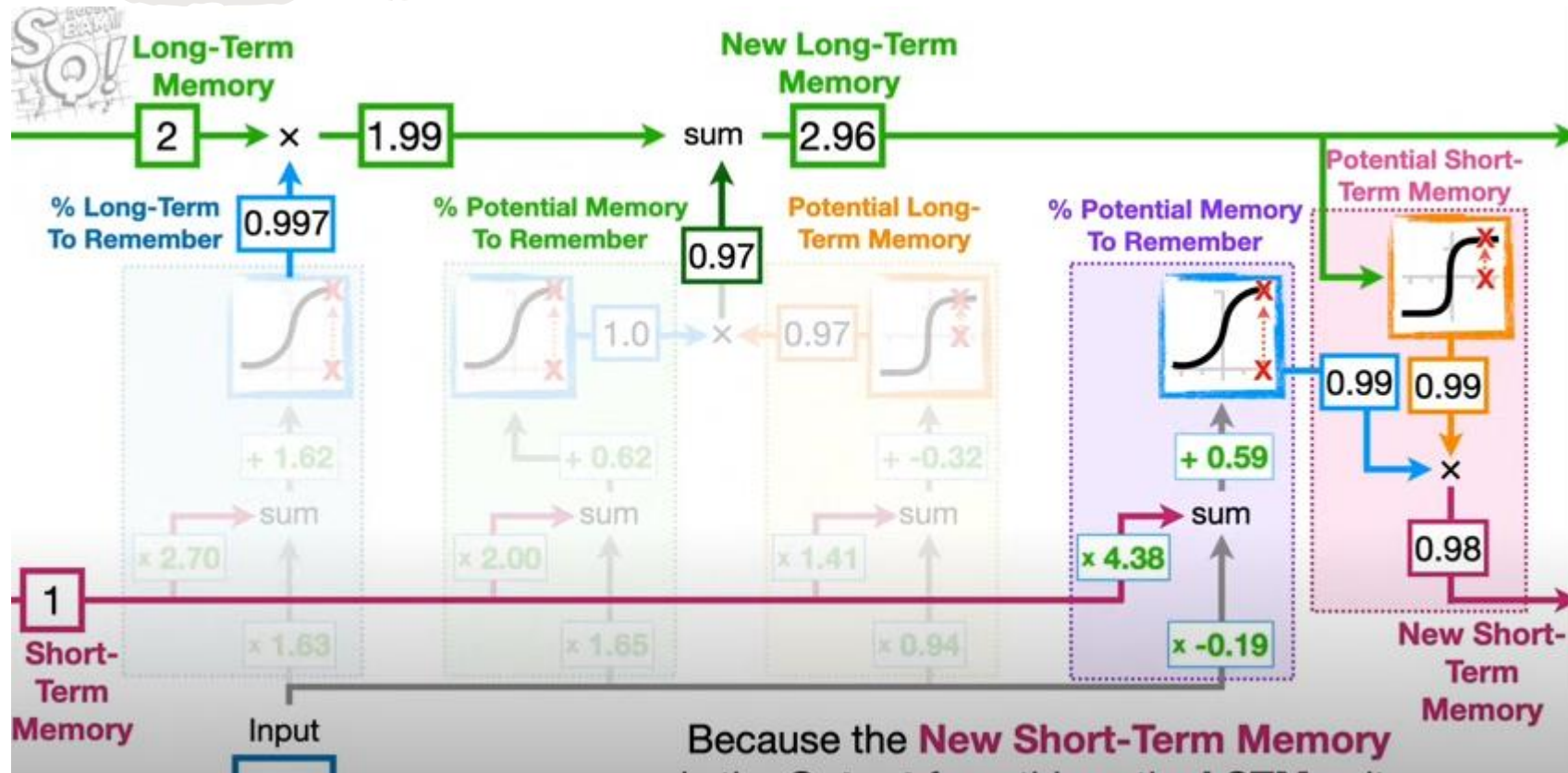


## TERMINOLOGY ALERT!!!

Even though this part of the **Long Short-Term Memory** unit determines how we should update the **Long-Term Memory**...

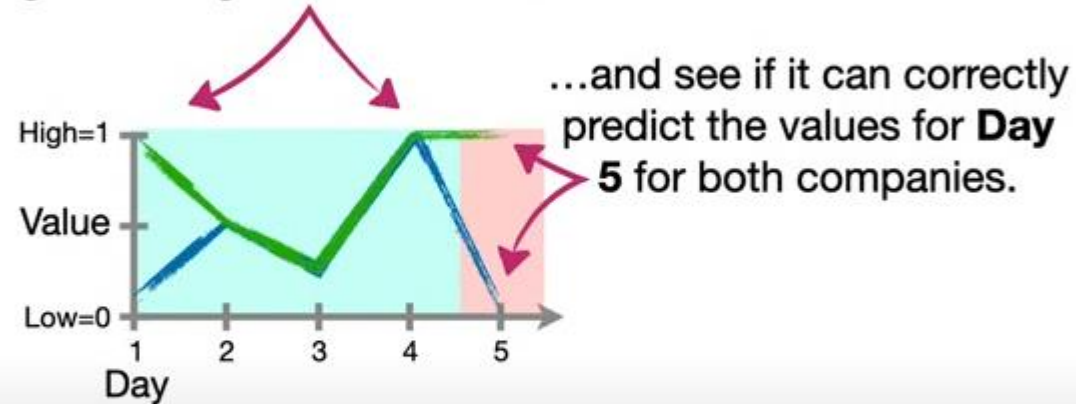
...it is usually called the **Input Gate**.



# LSTM- Output gate



# LSTM- Example

In other words, we're going to sequentially run the data from **Days 1** through **4** through an unrolled **LSTM**...



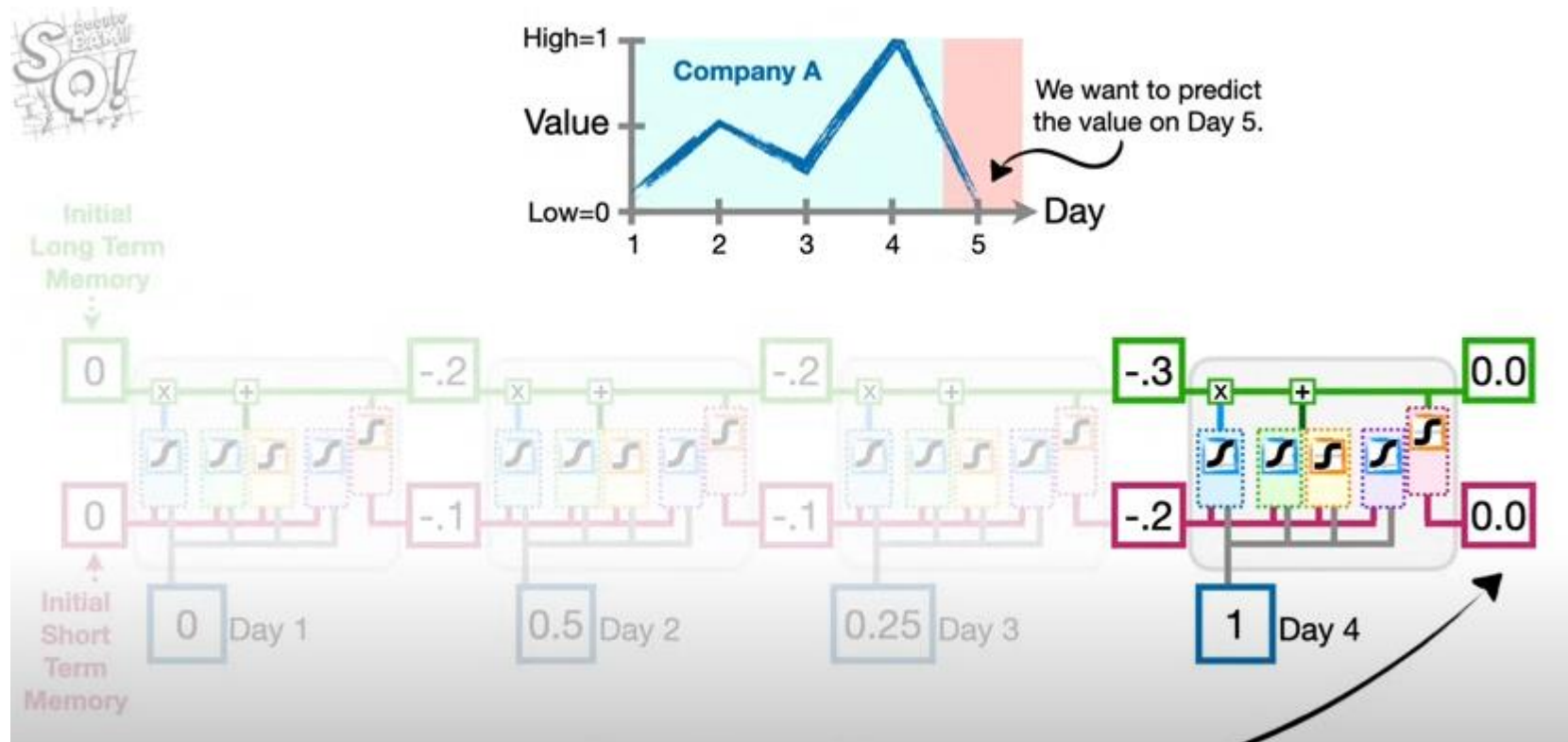
Company A =   
Company B = 



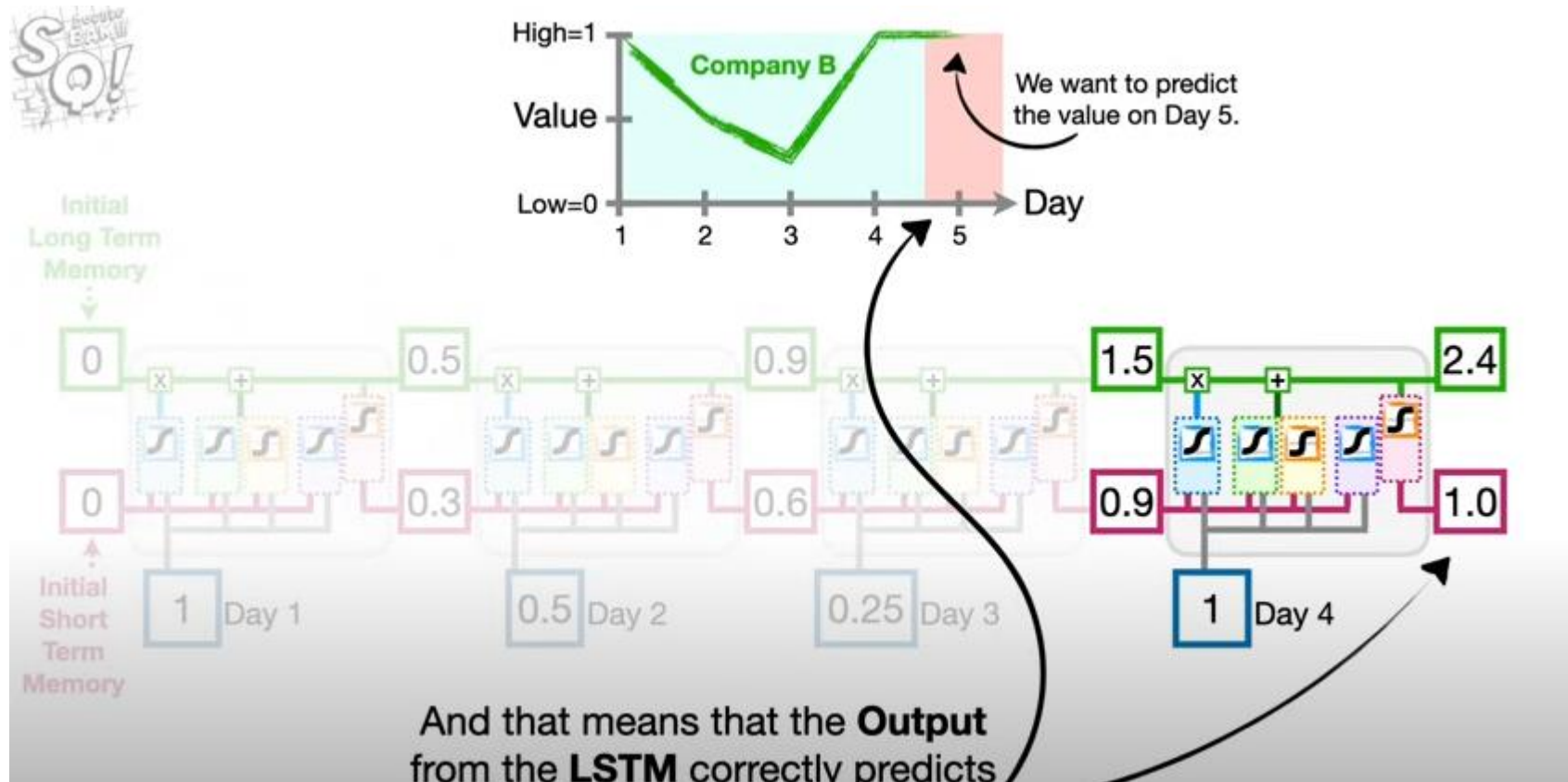
# LSTM- Example



# LSTM- Example(Company A)



# LSTM- Example(Company B)





# LSTM- Example 2

Dhaval eats samosa almost everyday, it shouldn't be hard to guess that his favorite cuisine is Indian



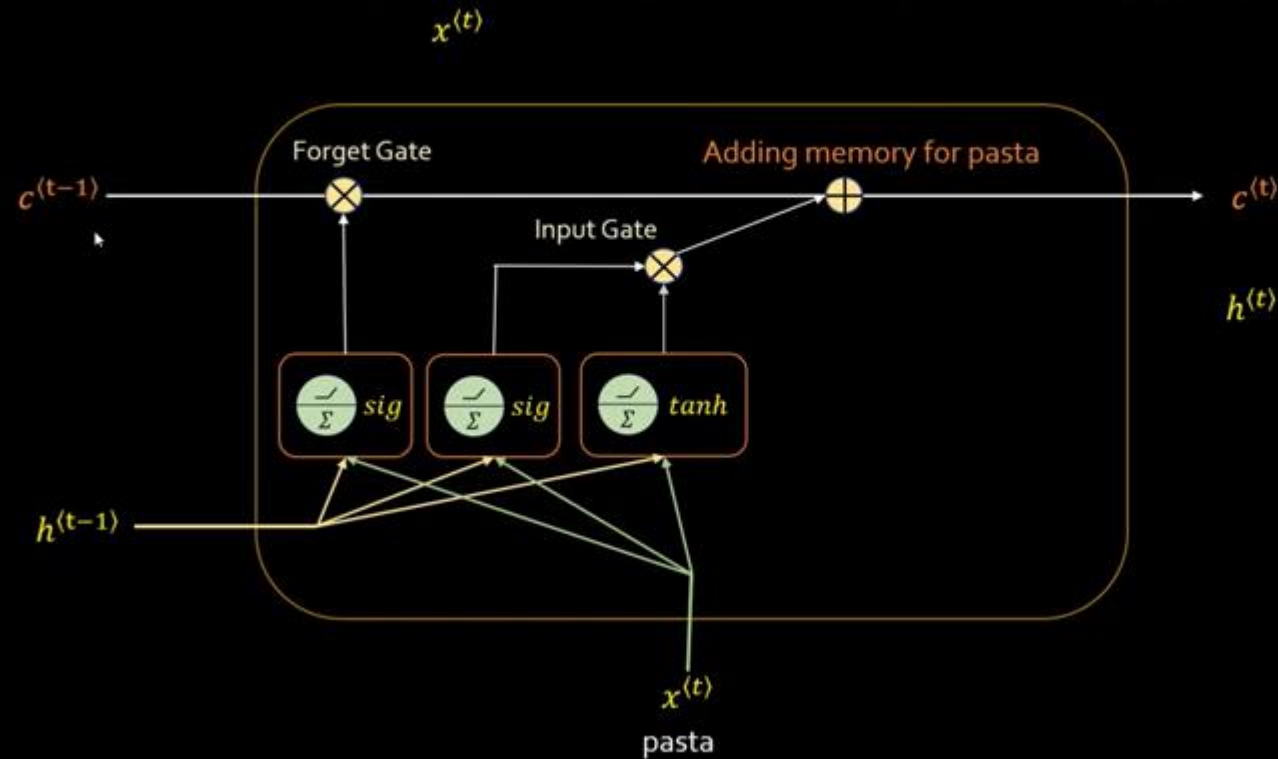
# LSTM- Example 2

Dhaval eats samosa almost everyday, it shouldn't be hard to guess that his favorite cuisine is Indian. His brother Bhavin however is a lover of pasta and cheese that means Bhavin's favorite cuisine is Italian



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Dhaval eats samosa almost everyday, it shouldn't be hard to guess that his favorite cuisine is Indian. His brother Bhavin however is a lover of pasta and cheese that means Bhavin's favorite cuisine is Italian



# Reference

- <https://colah.github.io/posts/2015-08-Understanding-LSTMs/>
- <https://www.youtube.com/watch?v=LfnrRPFhkuY>
- <https://www.youtube.com/watch?v=YCzL96nL7j0&t=5s>