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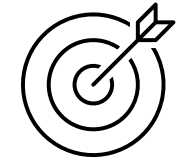
## DEEP LEARNING

### 23AD2205A

Topic:  
**LSTM**

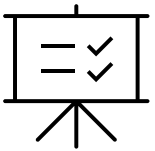
Session - 23

## AIM OF THE SESSION



To familiarize students with the sequence prediction problems

## INSTRUCTIONAL OBJECTIVES



This Session is designed to:

1. Discuss the Contractive Autoencoders and Variational autoencoder
2. Demonstrate the concept of Contractive Autoencoders and Variational autoencoder  
Discussion on Contractive Autoencoders and Variational autoencoder

## LEARNING OUTCOMES



At the end of this session, you should be able to: concepts for real time applications

1. To build Contractive Autoencoders and Variational autoencoder
2. To apply different types of Contractive Autoencoders and Variational autoencoder

# Long Short Term Memory Networks (LSTMs)

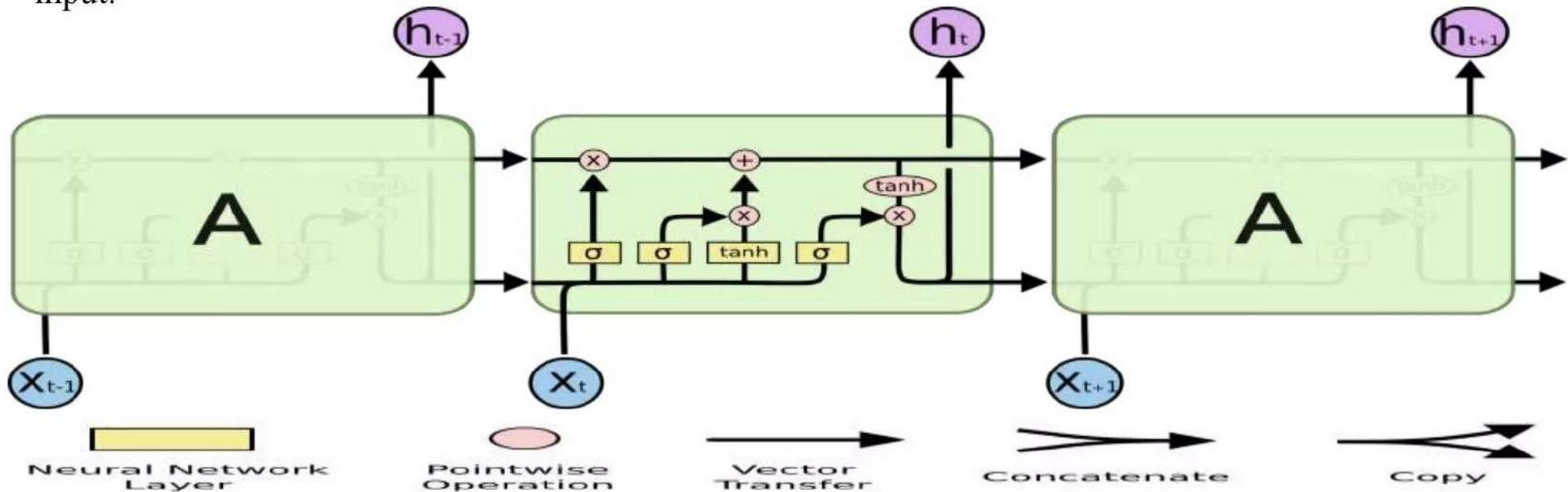
- LSTMs are a type of recurrent neural network (RNN) that can learn and memorize **long-term dependencies**.
- LSTMs retain past information for long period of time. Hence, It is very useful in time-series prediction.
- LSTMs have a chain-like structure where four (memory cell, forget, input, output) interacting layers communicate in a unique way.
- LSTM has three gates (forget, input, output) to protect and control the cell state.

## LSTMs Working principle:

- First, they forget irrelevant information of the previous state or keep the relevant information of the previous state.
- Next, they selectively update the memory cell-state values.
- The memory cell state carry relevant information from the earlier time steps to later time steps throughout the processing of the sequence that reducing the effects of short-term memory.
- As the cell state goes on its journey, information get's **added** or **removed** to the cell state via gates.
- The gates are different neural networks that decide which **information is allowed** on the cell state. The gates can learn what information is relevant to keep or forget during training.
- Finally, provides the output of certain parts of the cell state.

# Long Term Short Memory(LSTM):

Long short-term memory is a type of RNN model designed to prevent the output of a neural network from either exploding or decaying (long-term dependency) as it passes through the feedback loops for a given input.



# Gates of LSTM

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- An LSTM has three of these gates, to protect and control the cell state:

– Forget gate layer		Keep gate
– Input gate layer		Write gate
– Output gate layer		Read gate



# Cont...

## Forget gate

- This gate decides what information should be thrown away or kept.
- Information from the previous hidden state and information from the current input is passed through the sigmoid function.
- Values come out between 0 and 1. The closer to 0 means to forget, and the closer to 1 means to keep.

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

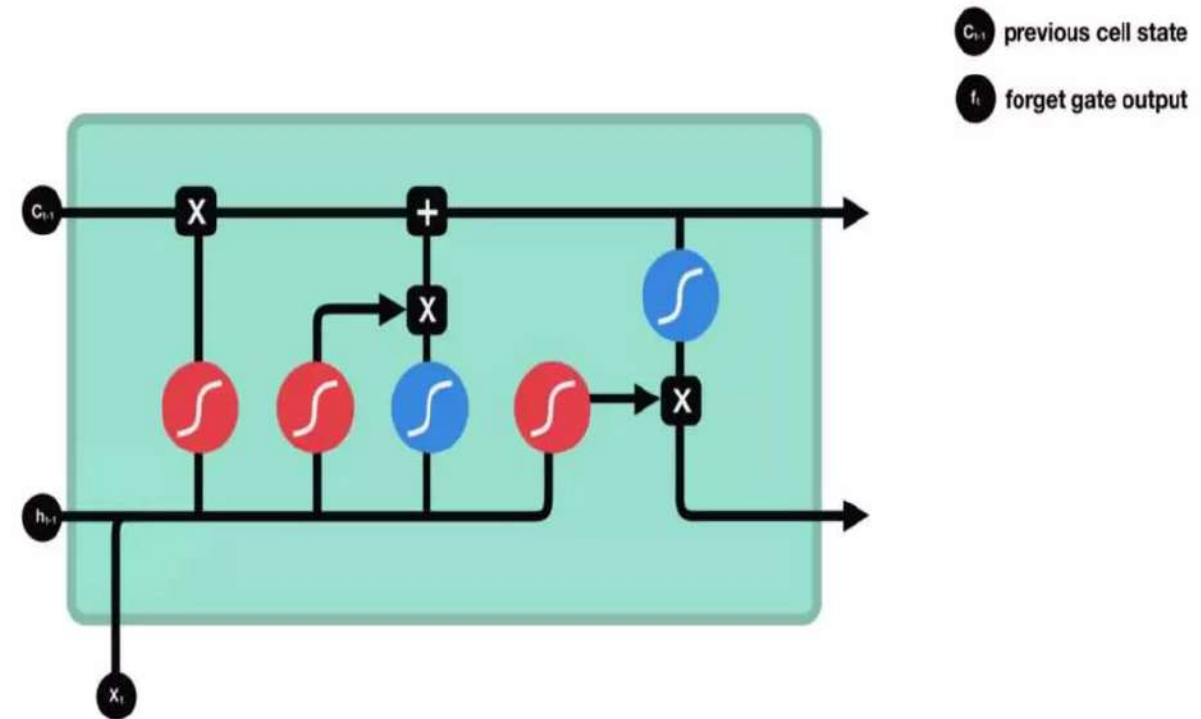


Figure: Forget Gate.

# Cont...

## Input Gate

- The goal of this gate is to determine what new information should be added to the networks long-term memory (cell state), given the previous hidden state and new input data.
- The input gate is a sigmoid activated network which acts as a filter, identifying which components of the 'new memory vector' are worth retaining. This network will output a vector of values in  $[0,1]$ .
- It is also passed the hidden state and current input into the tanh function to squish values between -1 and 1 to help regulate the network.

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

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

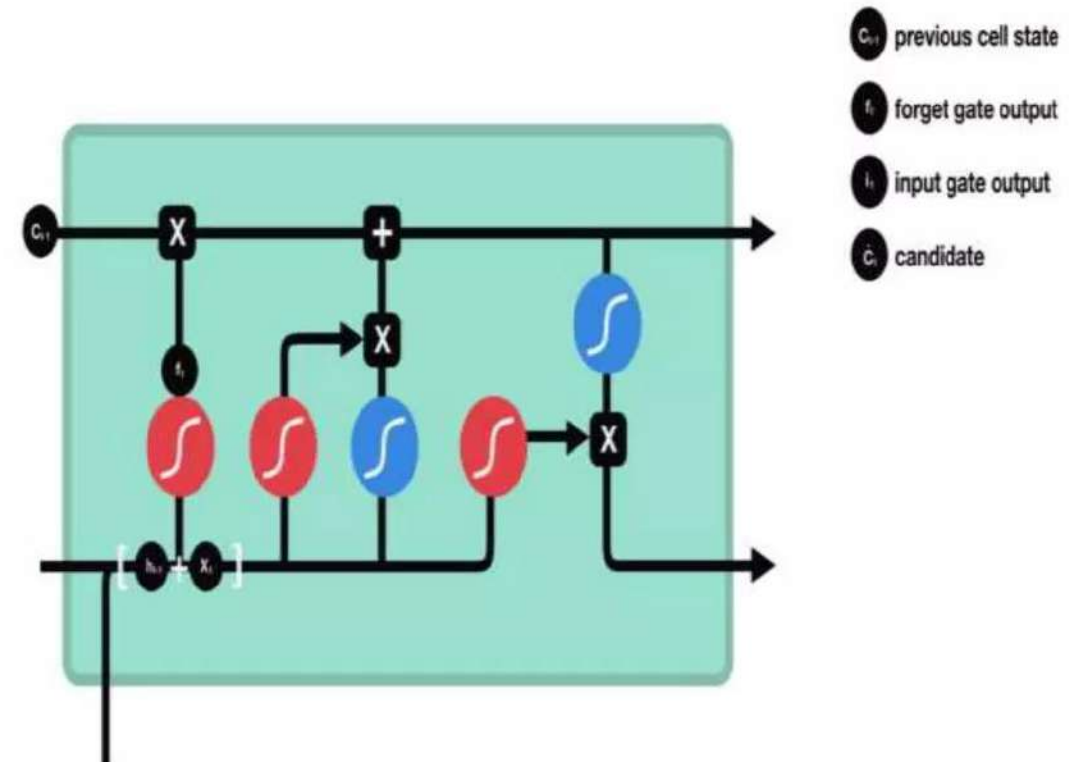


Figure: Input Gate.



# Cont...

## Cell State

- The next step is to decide and store the information from the new state in the cell state.
- The previous cell state  $C(t-1)$  gets multiplied with forget vector  $f(t)$ . If the outcome is 0, then values will get dropped in the cell state.
- Next, the network takes the output value of the input vector  $i(t)$  and performs point-by-point addition, which updates the cell state giving the network a *new cell state*  $C(t)$ .

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

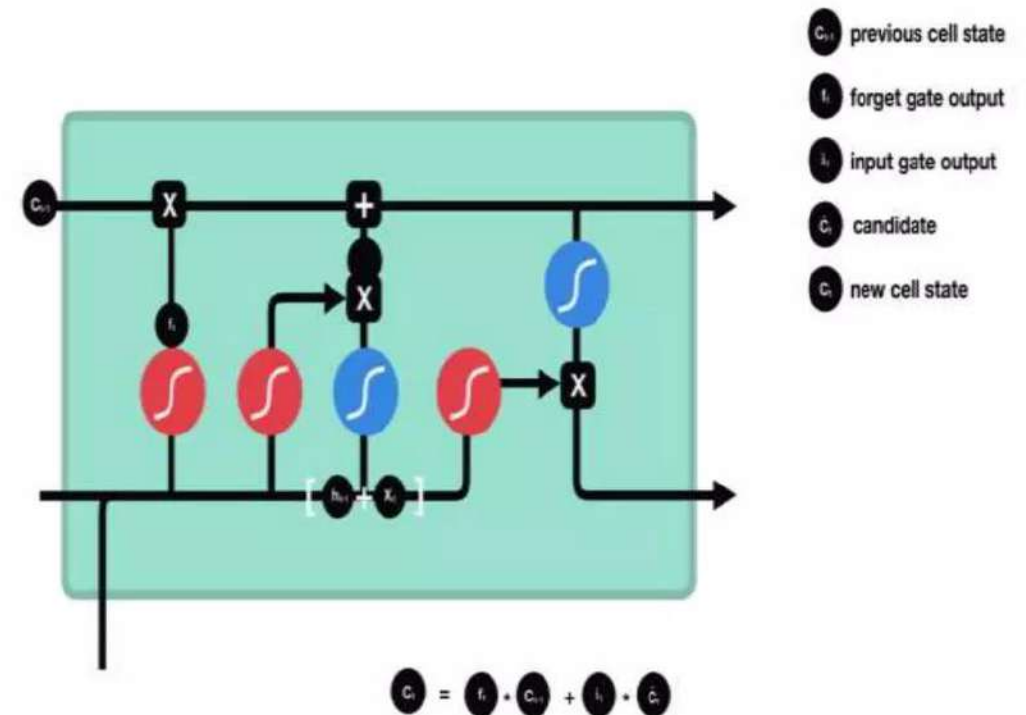


Figure: Cell State.

# Cont...

## Output Gate

- The output gate decides what the next hidden state should be. The hidden state contains information on previous inputs. The hidden state is also used for predictions.

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

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

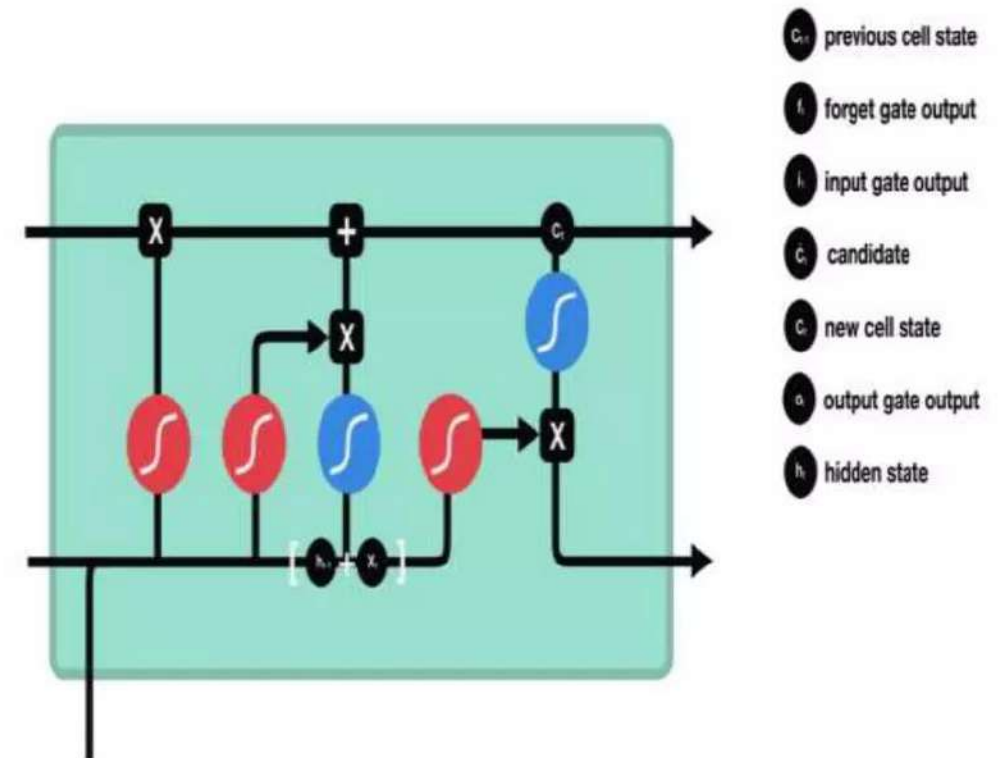
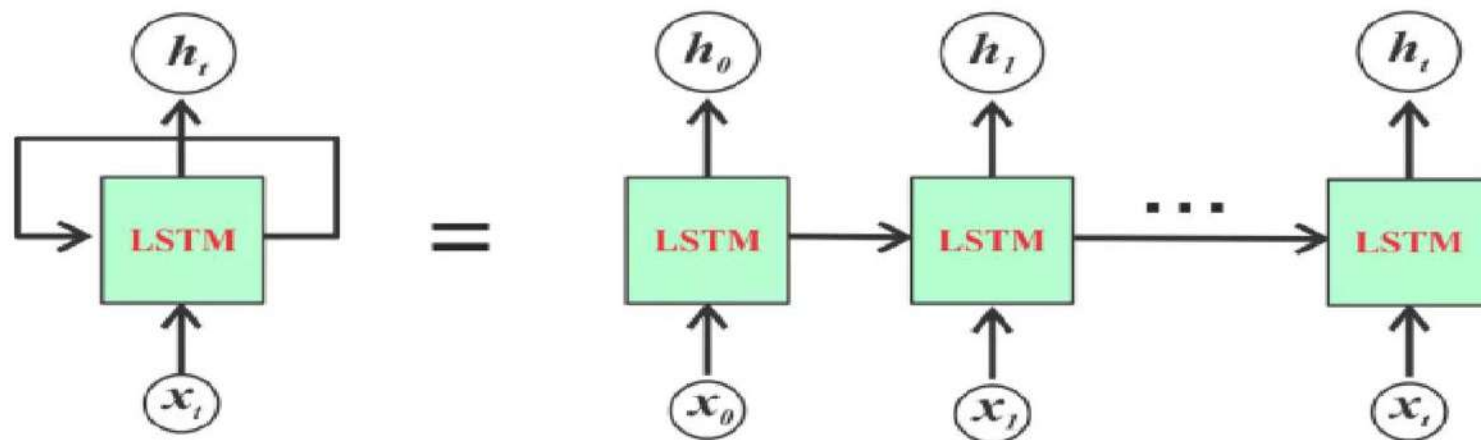


Figure: Output Gate.

# LSTM Architecture



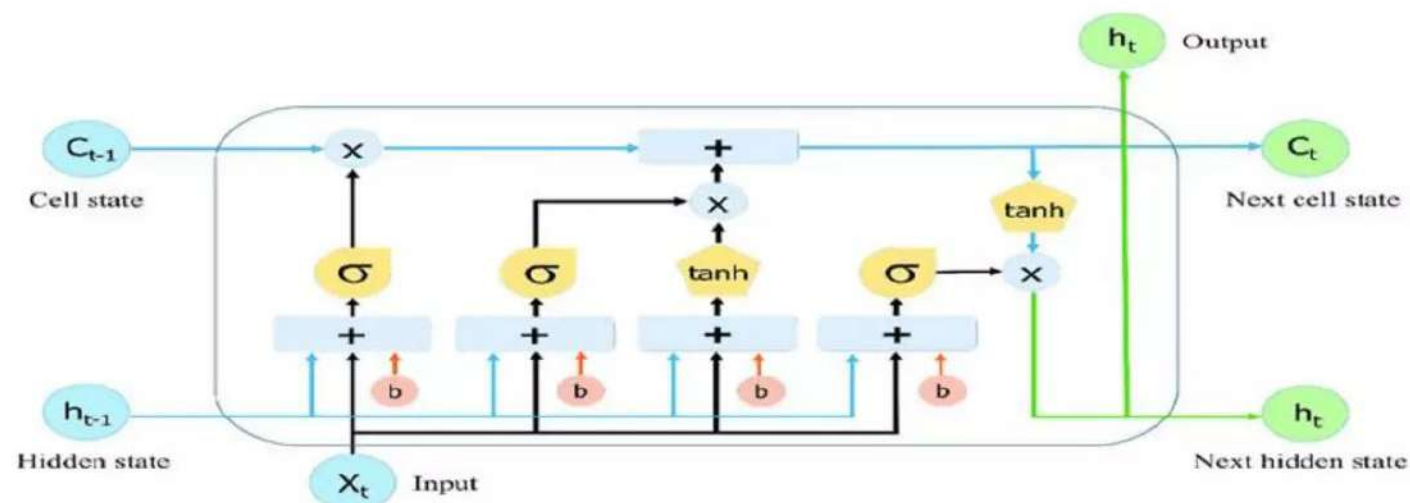
- **Forward Propagation:** Processes the data passing on information. The differences are the operations within the LSTM's cells.
- These operations are used to allow the LSTM to **keep** or **forget** information.

## Backward Propagation

- Update the parameters to reduce the error.

## Components in LSTM:

- *Three gates:* forget gate, input gate and output gate.
- Memory cell state



### Inputs:

- $x_t$  Current input
- $c_{t-1}$  Memory from last LSTM unit
- $h_{t-1}$  Output of last LSTM unit

### Outputs:

- $c_t$  New updated memory
- $h_t$  Current output

### Nonlinearities:

- $\sigma$  Sigmoid layer
- $\tanh$  Tanh layer
- $b$  Bias

### Vector operations:

- $\times$  Scaling of information
- $+$  Adding information

## LSTM Unit Structure



# LSTM layers working principle

- Gates are composed with a sigmoid neural net layer and a pointwise multiplication operation.
- The sigmoid layer output range is between zero and one that describe how much of each component pass/remove information. A value of zero means “no information allows,” while a value of one means “pass everything”.

## Forget gate layer:

- Decides what information going to throw away from the memory cell state.
- 1 represents “completely keep this” while a 0 represents “completely reject this.”

## Input gate layer:

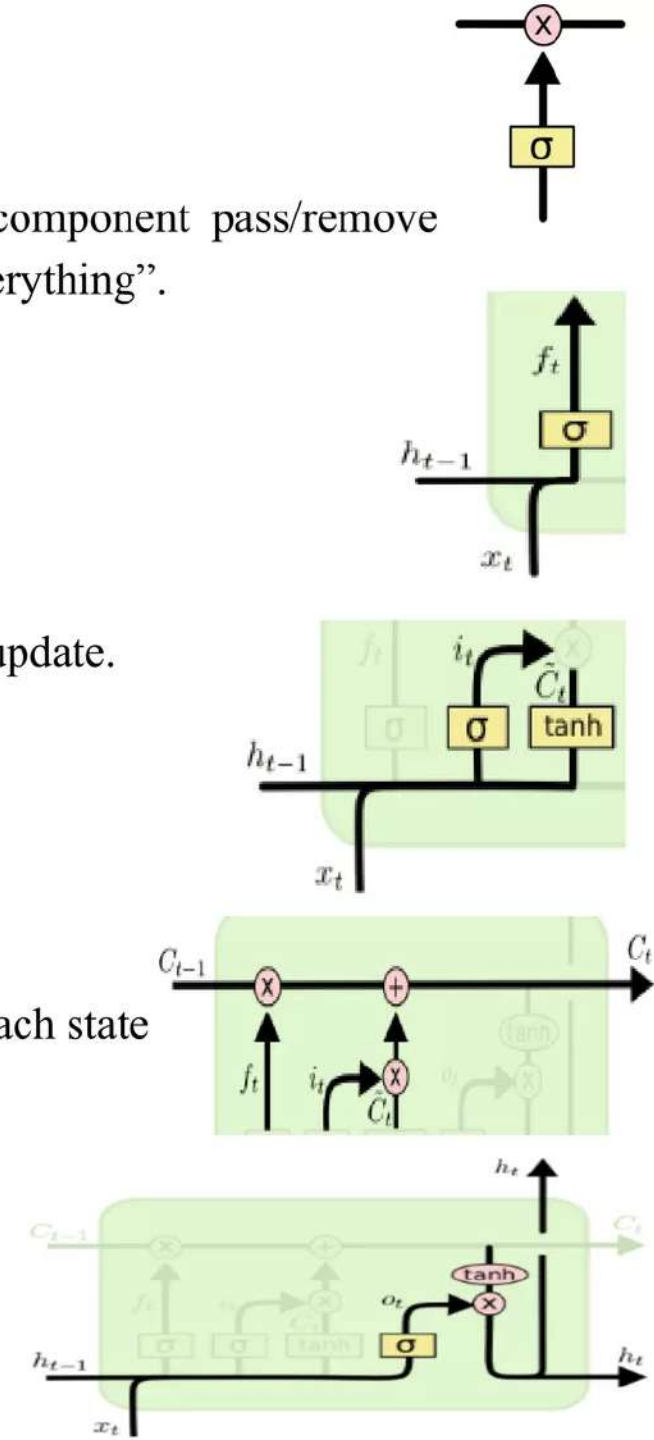
- The next step is to decide what new information we’re going to store in the cell state.
- This has two parts. First, a sigmoid layer called the “input gate layer” decides which values we’ll update.
- Next, a tanh layer creates a vector of new candidate values,  $\tilde{C}_t$ , that could be added to the state.
- In the next step, we’ll combine these two to create an update to the state.

## Memory Cell State:

- Update the old cell state,  $C_{t-1}$ , into the new cell state  $C_t$ .
- Multiply the old state by  $f_t$ , forgetting the things we decided to forget earlier.
- Then we add  $i_t * C_t$ . This is the new candidate values, scaled by how much we decided to update each state

## Output gate layer:

- Decides output based on cell state, but will be a filtered version.
- First, run a sigmoid layer which decides what parts of the cell state to be output.
- Then, we put the cell state through  $\tanh$  (to push the values to be between  $-1$  and  $1$ ) and multiply it by the output of the sigmoid gate, so that we only output the parts we decided to.



## Types of LSTM models based on input and output

- **One input to One output** - eg : Giving labels to image
- **One input to many outputs**- eg : Giving description/caption to image  
(description will have sequence of words - many output)
- **Many inputs to one output** - eg : Predicting the next word in given incomplete statement
- **Many inputs to Many outputs**- eg : Stock market prediction for following days based on past data





## **Applications of LSTM**

1. Speech Recognition (Input is audio and output is text) - Google Assistant, Microsoft Cortana, Apple Siri
2. Machine Translation (Input is text and output is also text) - Google Translate
3. Image Captioning (Input is image and output is text)
4. Sentiment Analysis (Input is text and output is rating)
5. Music Generation/Synthesis ( input music notes and output is music)
6. Video Activity Recognition (input is video and output is type of activity)