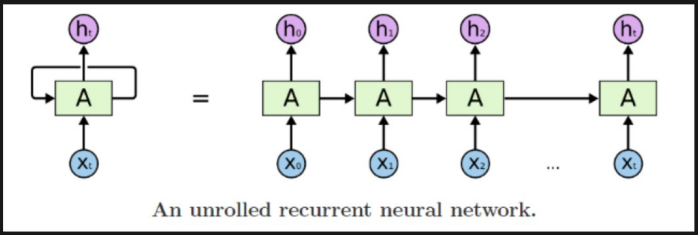
LSTM RNN [Long Short Term Memory RNN]

RNN ⟶ Long Term Dependencies ⟶ Vanishing Gradient Problem

1. RNN ⟶ Problem ? ✓
2. Why LSTM RNN ? ✓ Basic Representation.
3. How LSTM RNN Works
   - Long Term Memory ✓
   - Short Term Memory ✓
4. LSTM Architecture
5. Working of LSTM RNN

Problems With RNN → Long Term Dependency



An unrolled recurrent neural network.

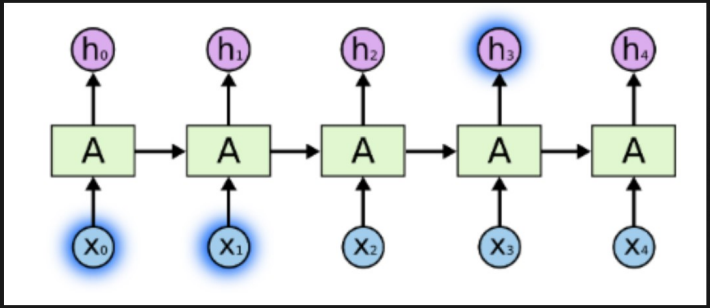
Vanishing Gradient Problem

Task:

Next Word In a Sentence

The color of the sky is blue

further context



Gap is less

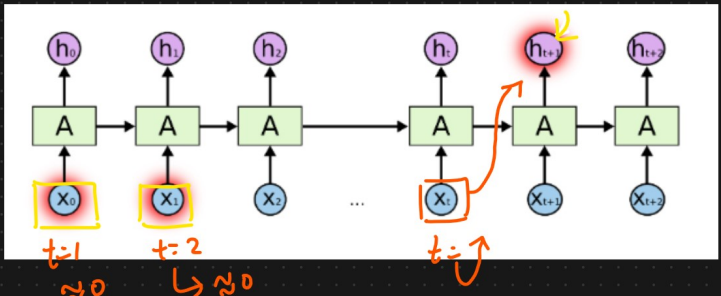
Huge gap O/p ← Context

I grew up in India .... I speak fluent

Context

Name of language

further Context



0-0.25

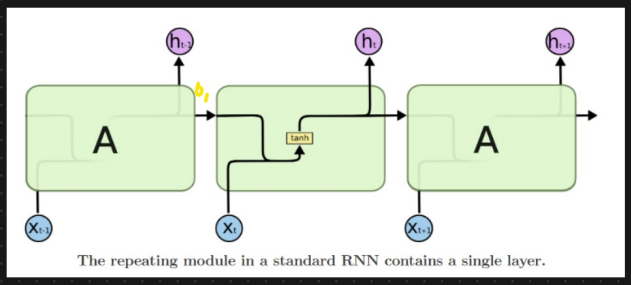
0-1

Huge Gap → Long Term Dependency

RNN → Long Term Dependency → Vanishing Gradient Problem

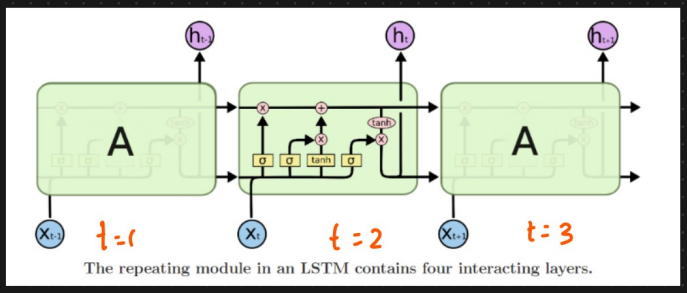
Chain Rule → ≈0.

Basic Representation of RNN And LSTM RNN

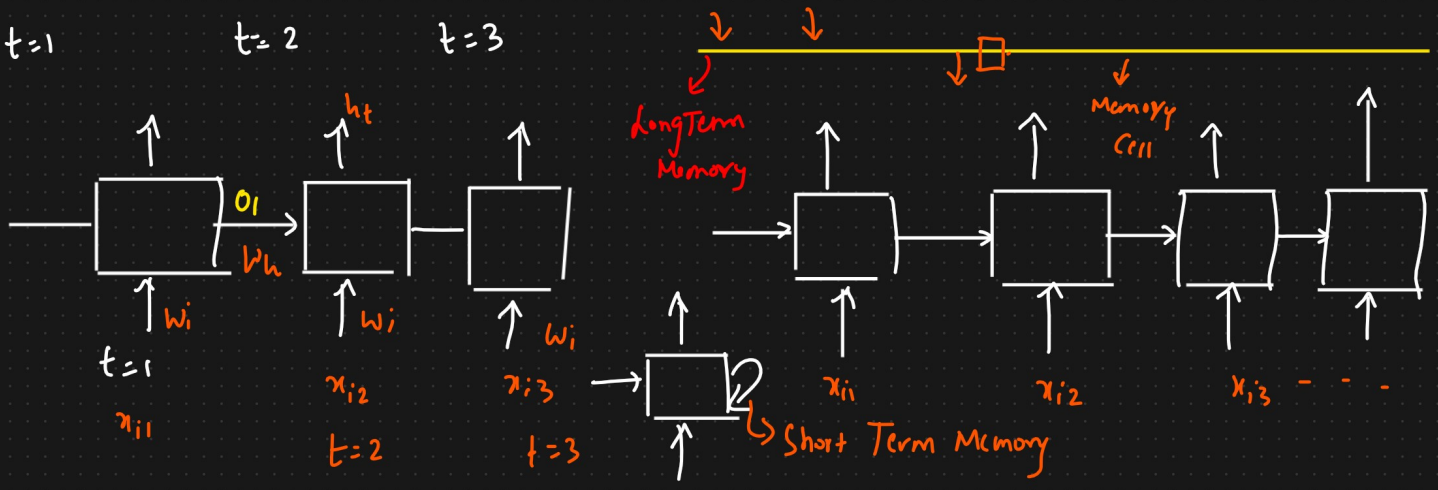


The repeating module in a standard RNN contains a single layer.

LSTM RNN



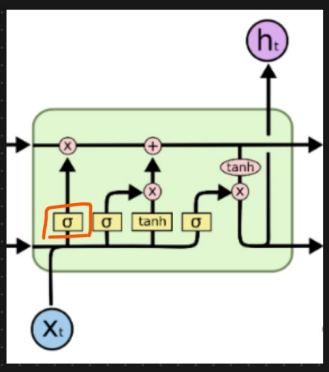
The repeating module in an LSTM contains four interacting layers.



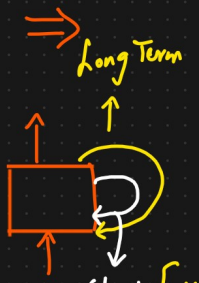
LSTM RNN → Long Term Memory
LSTM RNN → Short Term Memory

Conveyance But : Luggages

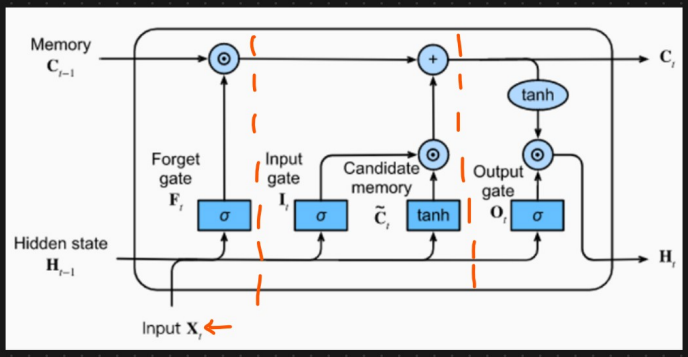
LSTM Architecture



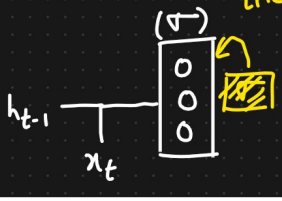
Basic Architecture

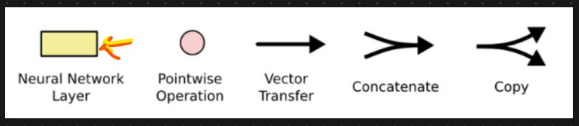


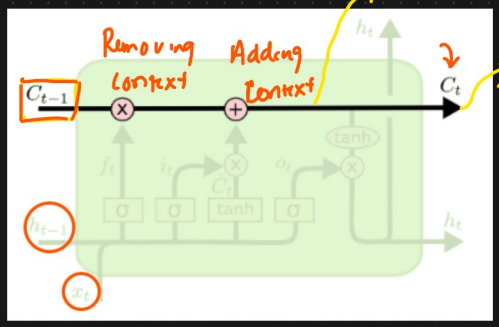
LSTM RNN



{Neural Nw Layer}





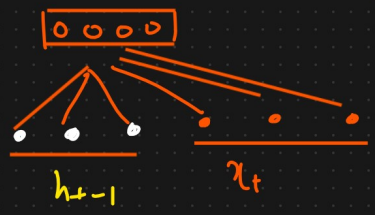


Long Term Memory ⊗ ⊕ tanh

Combining 2 vectors

$h_{t-1} = [1 \quad 2 \quad 3]$

$x_t = [2 \quad 3 \quad 4]$



Duplicate copy

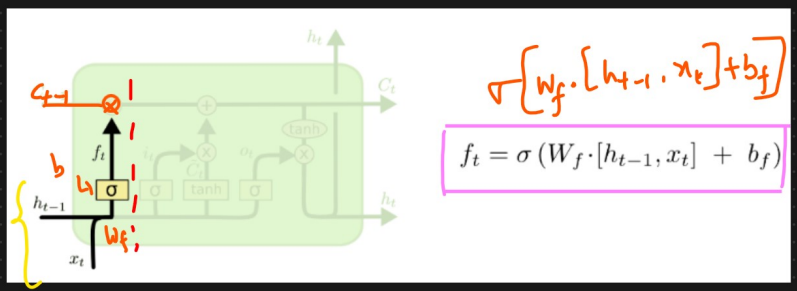
V1 $[1 \quad 2 \quad 3]$ ← tanh

V2 $[4 \quad 5 \quad 6]$

⊗ ⇒ [4 10 18]

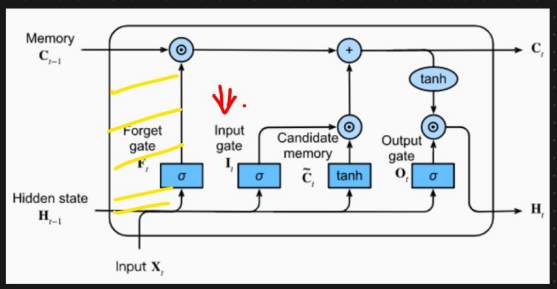
⊕ ⇒ [5 7 9]

tanh ⇒ [tanh(1) tanh(2) tanh(3)]



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

$\sigma\left[W_f \cdot [h_{t-1}, x_t] + b_f\right]$



Forget Gate

h_{t-1} = Hidden state of previous time stamp

x_t = Word passed as i/p in the current time stamp

Text — Next Word

$x_{11} \quad x_{12} \quad x_{13} \quad x_{14}$ — y_{15}

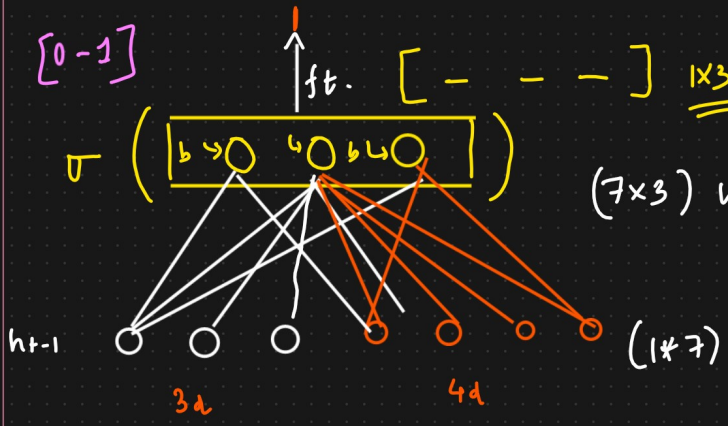
$[0 \quad 2 \quad 4 \quad 1]$ $[4 \quad 5 \quad 12]$ - - - - -

x_t x_{t+1}

Memory Cell

h_{t-1} $[1 \quad 2 \quad 4]$ 3d

C_{t-1} $[4 \quad 2 \quad 1]$ 3d ⇐



$$f_t = [0 \quad 0 \quad 0]$$ ← Complete Sentence

Context changed

① $C_{t-1} = [6 \quad 8 \quad 9]$ ⊗ $[0 \quad 0 \quad 0]$

$= [0 \quad 0 \quad 0]$ ← Removing all the previous Context

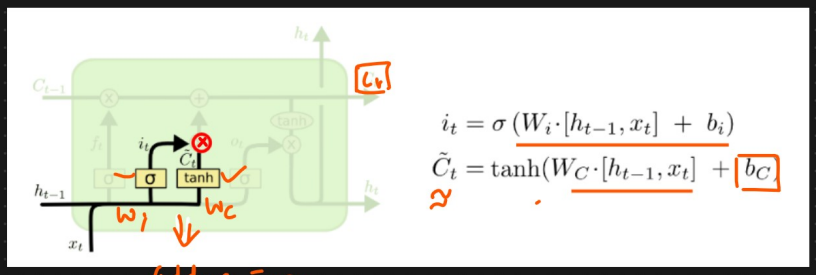
$f_t = [1 \quad 1 \quad 1]$

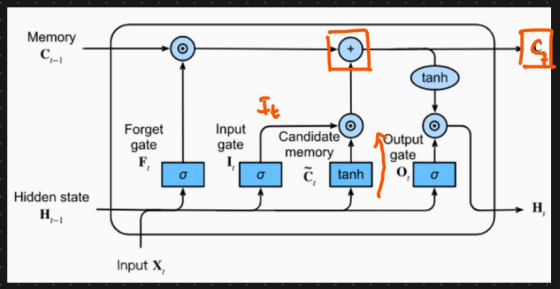
② $C_{t-1} = [6 \quad 8 \quad 9]$ ⊗ $[1 \quad 1 \quad 1] = [6 \quad 8 \quad 9]$

③ $C_{t-1} = [6 \quad 8 \quad 9]$ ⊗ $[0.5, 1, 0.5] = [3 \quad 8 \quad 4.5]$

Conclusion : Based on the context → Forget gate will let go some information or will not let go some Info {Forgetting}.

② Input Gate And Candidate Memory

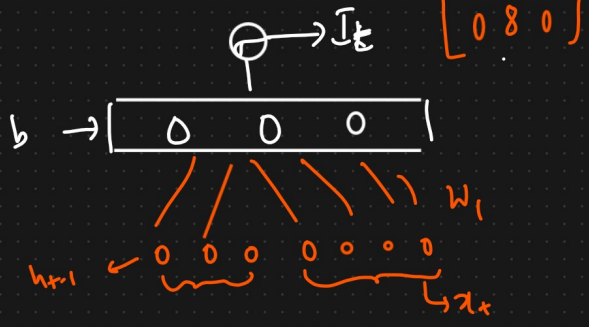


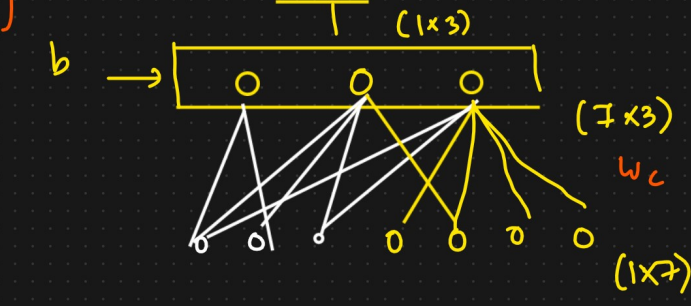


Adding Info

$I_t = [\,2\ \boxed{4}\ 6\,]$ —— ⊛ —— C_t $[\,0\ 2\ 0\,]$ ⇒ I/p Gate

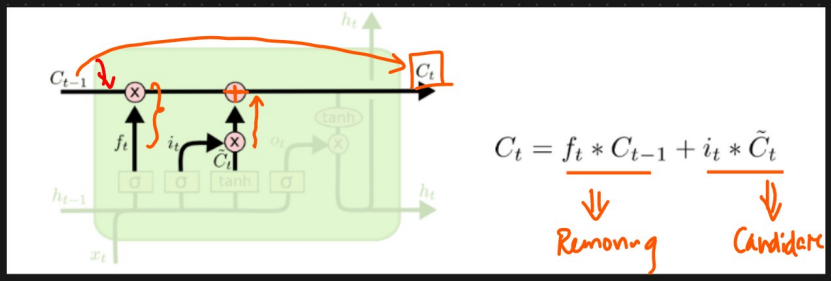
$[\,0\ 8\ 0\,]$





Context = If any information needed to be added it the memory

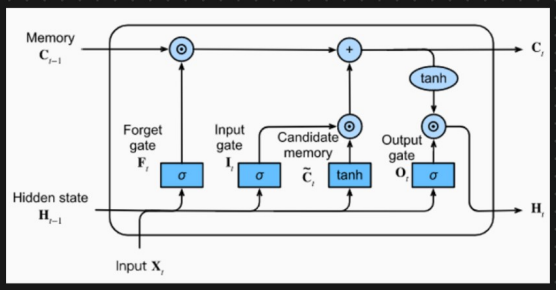
C_{t-1} ⟶ The information will be added



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

f_t ⇓ Removing

$i_t * \tilde{C}_t$ ⇓ Candidate



I stay in India . . . . . and I speak → English → Hindi

Or Forgetting Some info

Memory.

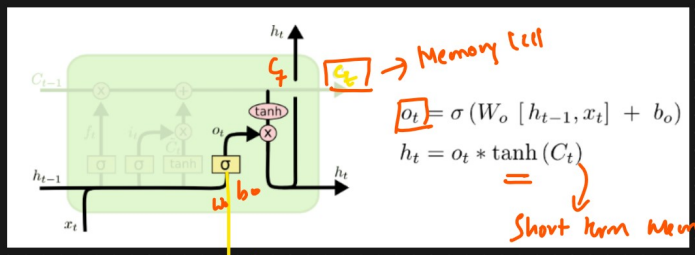
Forget Gate

I/p Gate (*) Candidate memory

+

Ct-1 => Cf.

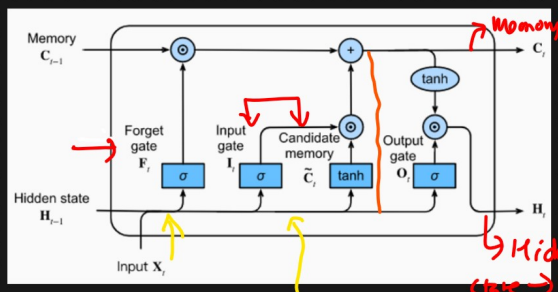
Output gate LSTM RNN



→ Memory Cell

→ Short term Memory.

→ Neural Network

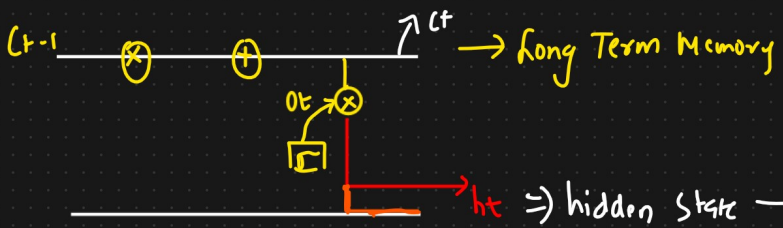


Memory

→ Hidden state → ST Memory.

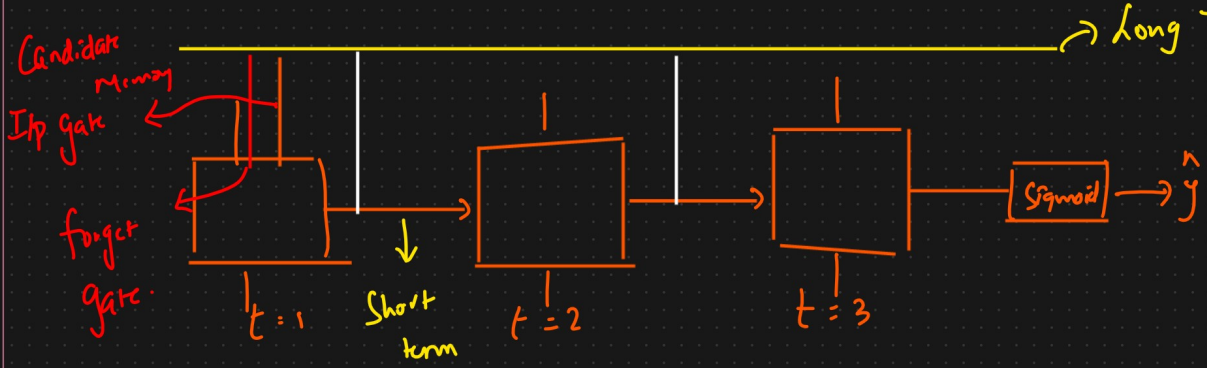
Forget → Some Info → context → Memory Cell

Add Info → Context



→ Long Term Memory

ht ⇒ hidden state → Short term Memory



→ Long Term

loss ↓↓.

[Wi, Wc, Wo] → Updating ← Back Propogation

GRU RNN ⇒ LSTM Variant

Training Data With LSTM RNN

{Training} Text Paragraph

I Went to Restaurant and order burger

The burger looked tasty and crispy

But burger is not good for health

It has lot of fats, cholestrol

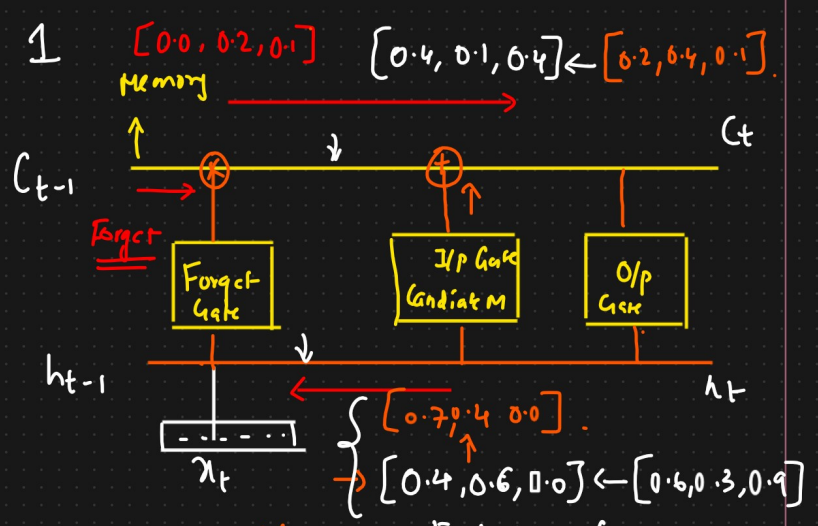
But this burger was made with whey protein and only vegetables were used, so it was good.

O/p [good/bad]

Forget gate

I/p gate

O/p gate



Word → Vectors → Embedding Layer

Word2Vec [3 dimension-vector]

→ [[Good] [Bad] [Healthy]] ← Black Box

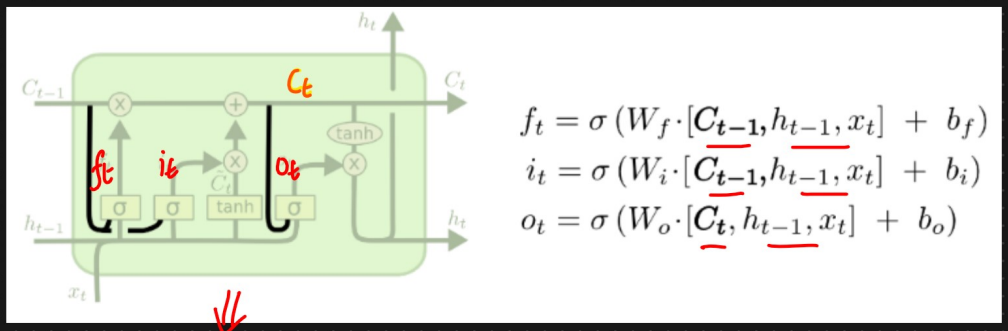
Tasty [0.9 0.0 0.1] ← 3 d.

Variants of LSTM RNN

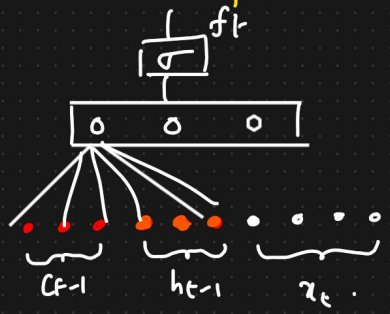
LSTM Variants Introduced By Gers & Schmidhuber [2000]

↳ Research paper

LSTM RNN [1970-80]



$$f_t = \sigma\left(W_f \cdot [C_{t-1}, h_{t-1}, x_t] + b_f\right)$$
$$i_t = \sigma\left(W_i \cdot [C_{t-1}, h_{t-1}, x_t] + b_i\right)$$
$$o_t = \sigma\left(W_o \cdot [C_t, h_{t-1}, x_t] + b_o\right)$$

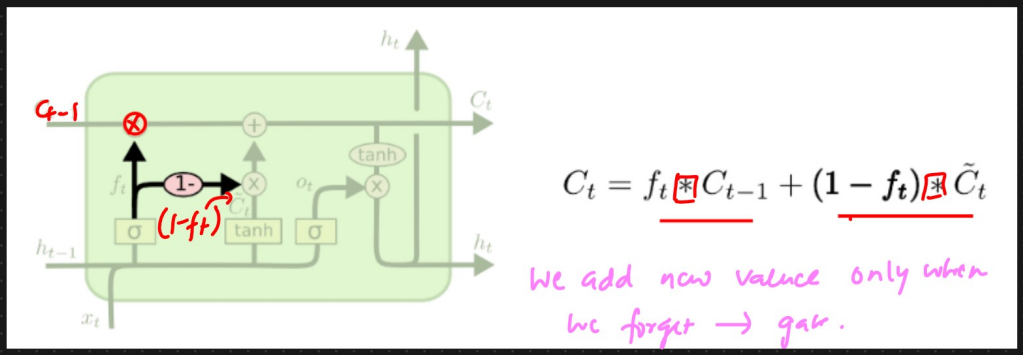


focus

Connections → From Memory cell to forget gate, i/p gate, O/p gate ⇒ Peephole Connections

Peephole Connections : We let the gate layers look at the cell state

Another variation → Coupling Forget And I/p Gates



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

We add new value only when we forget → gate.

Goal : We only forget when we're going to i/p something in its place.

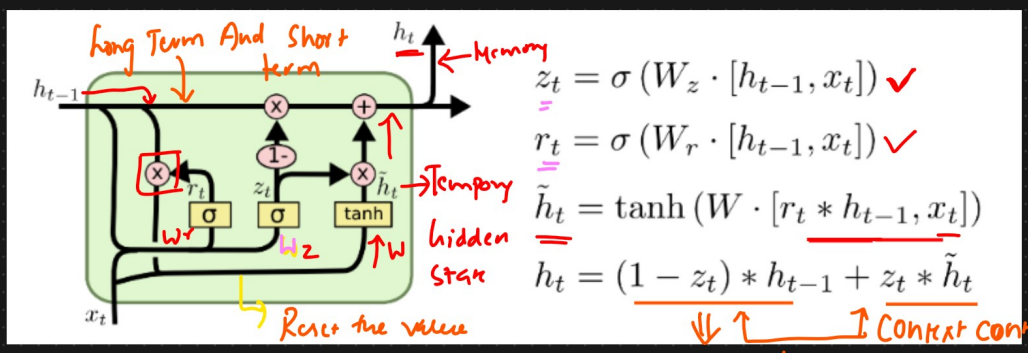
⇓

We only i/p new values to the state when we forget something older.

Instead of seperately deciding what to forget and what we should add new Info, we make this decision together.

GRU → Gated Recurrent Unit [Cho, et al [2014]]

1980 → LSTM
2000 - Variants
2014 → GRU



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

Context context

⇓ Coupled.

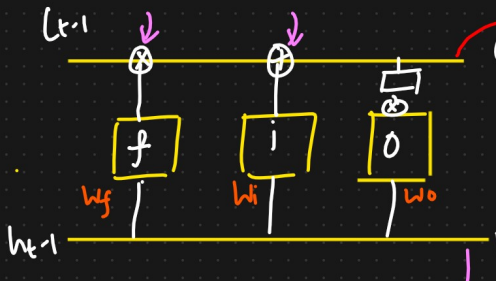
z_t ⇒ Update Gate ←

r_t ⇒ Reset Gate ←

$\tilde{h}_t$ ⇒ Temporary hidden state.

Trainable parameters

bias → $[W_f, W_i, W_o]$

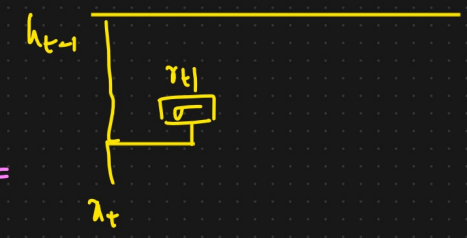


LSTM : Complex Architecture → forget, i/p + Candidate memory, O/p

Training Time ↑↑

z_t ,

Reset gate = r_t =

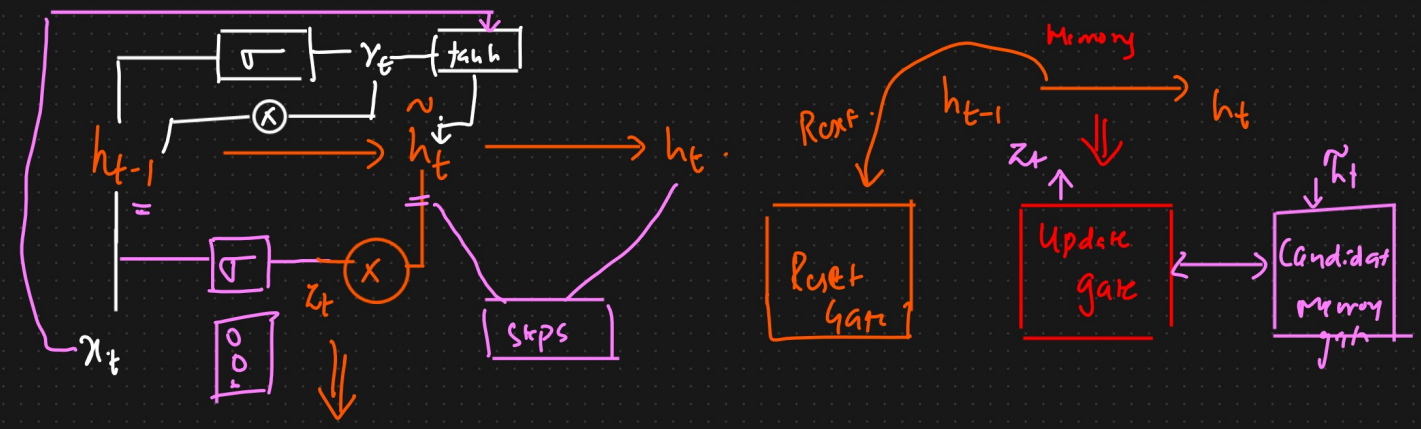


→ Reseting some info from h_{t-1} ⇒ Memory → LTM + STM

h_{t-1} [0.6 0.5 0.3 0.9]

$\otimes \leftarrow r_t$ [0.2 0.4 0.8 0.2]

$x_t \rightarrow$ [0.12 0.20 0.24 0.18] ← Resetting → Context



What context Info needs to be Added

⇓

Candidate hidden state · [current Context]

⇓

Imp → Add Info

$z_t \Rightarrow$ Imp Info