# Sequential Data

22 October 2022 13:09

ANN → tabular data

CNN → images

RNN → Recurrent NN

↳ is type of sequential model to work on sequential data

iq | marks | gender | placement

placement → does not matter

iq, marks, gender → O → No

eg → text → sequential data

Hi my name is Nitish

RNN → NLP → ML

NLP → RNN

CNN → images → computer vision

Time series → sequential

2001 2002 2003

Speech → sequential

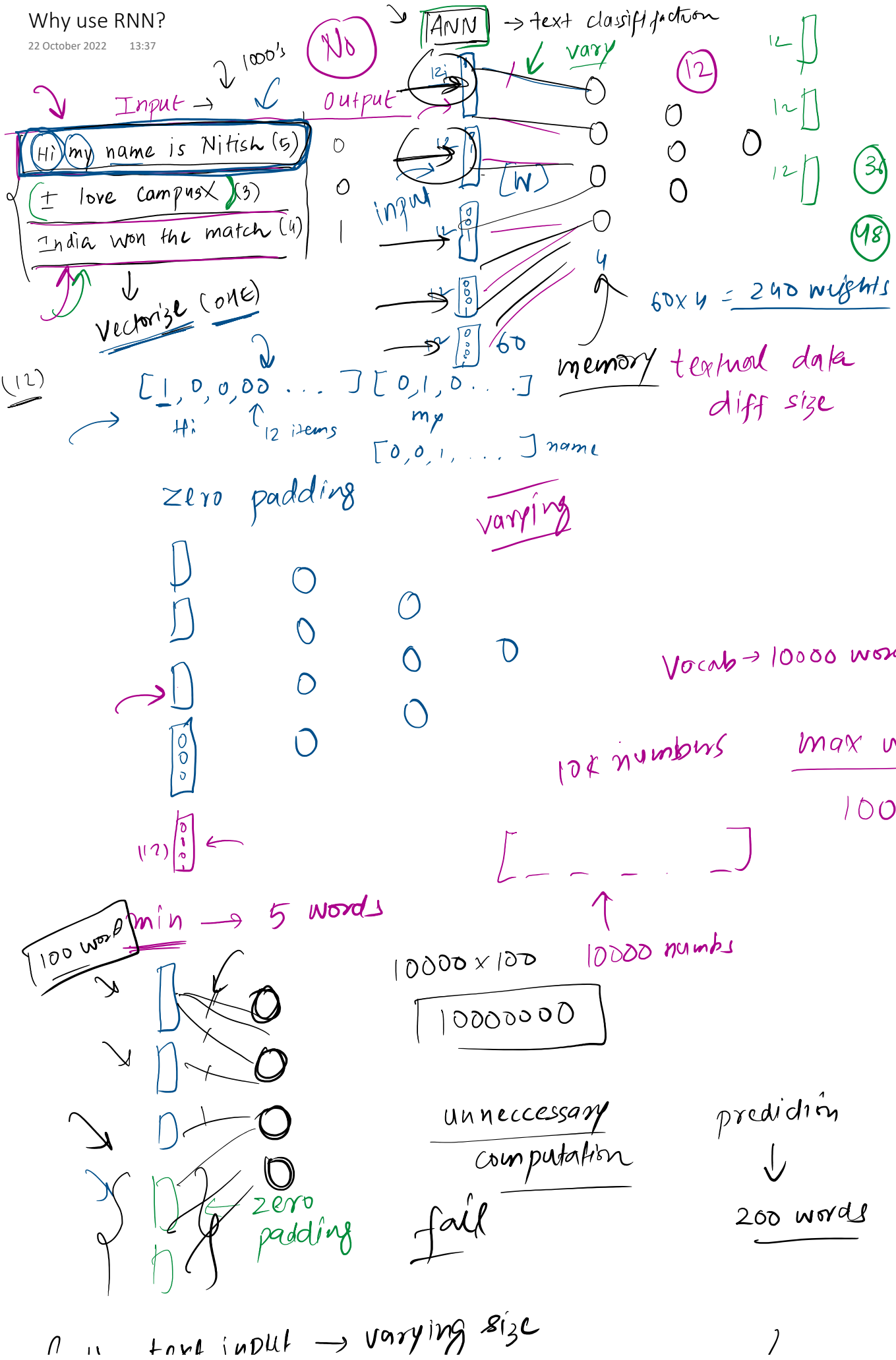
DNA sequence

RNN

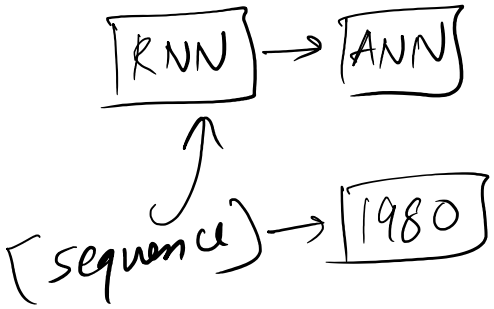
- ANN/CNN
- RNN Why?
- Application → RNN
- Roadmap

# Why use RNN?

22 October 2022 13:37



1) text input → varying size
2) zero padding → unnecessary computation
3) Prediction problem
4) Totally disregarding the sequence info

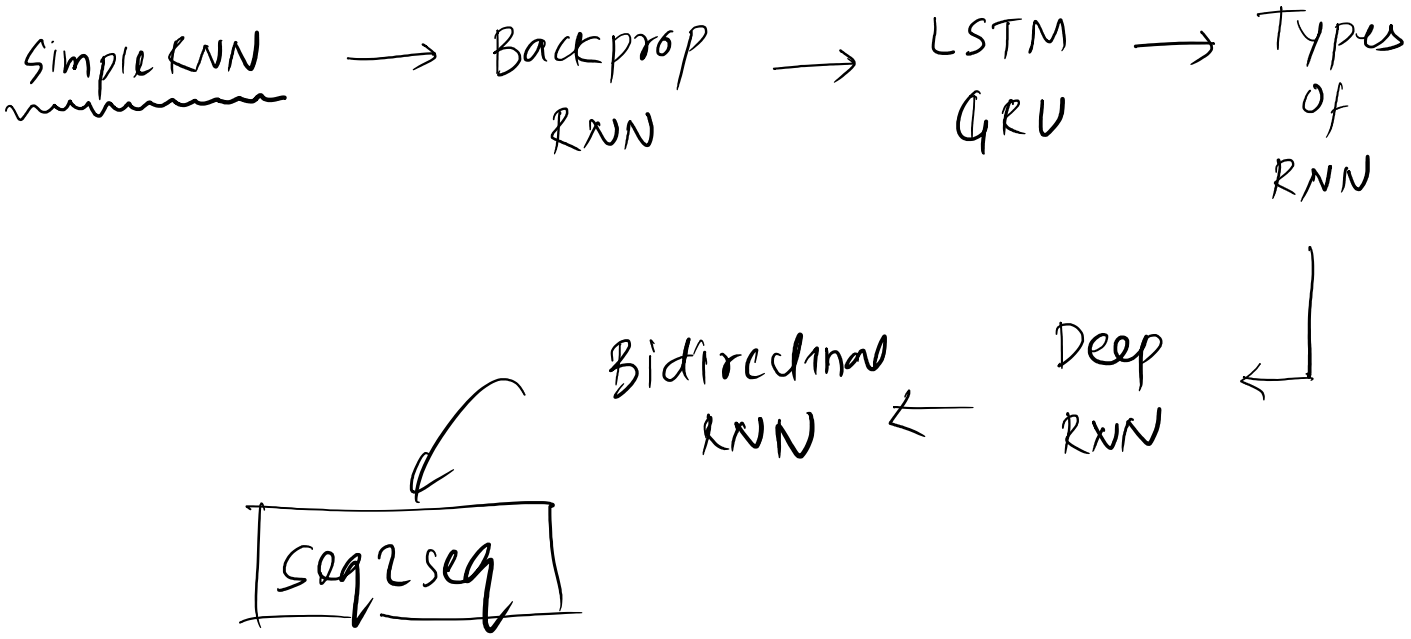


# RNN Applications

22 October 2022 13:37

# Roadmap

22 October 2022 13:37



Why RNNs?

29 October 2022 13:30

zero padding → cost of compu ↑

1) Sequence → any length → ANN → fixed input size

movie reviews

RNNs

NNs

same

2) sequence contains some meaning

ANN → input

memory feature

RNN architecture

RNN forward prop → prediction

↳ input → output

Codes → solidify

# Data for RNN

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[(timesteps, input_features)]

t=1, t=2, t=3

| Review | Sentiment |
|---|---|
| movie was good | 1 |
| movie was bad | 0 |
| movie was not good | 0 |

(4)

review 1

[[10000], [01000], [00100]]

vocab → 5 word

movie was good

[10000] [01000] [00100]

[00010] [00001]

bad not

(3,5) → (# of features, no of timesteps)

(3,5) (4,5)

Keras → SimpleRNN → batch size, timesteps, input_features

(3, 4, 5) → 3D tensor → RNN

# RNN Architecture

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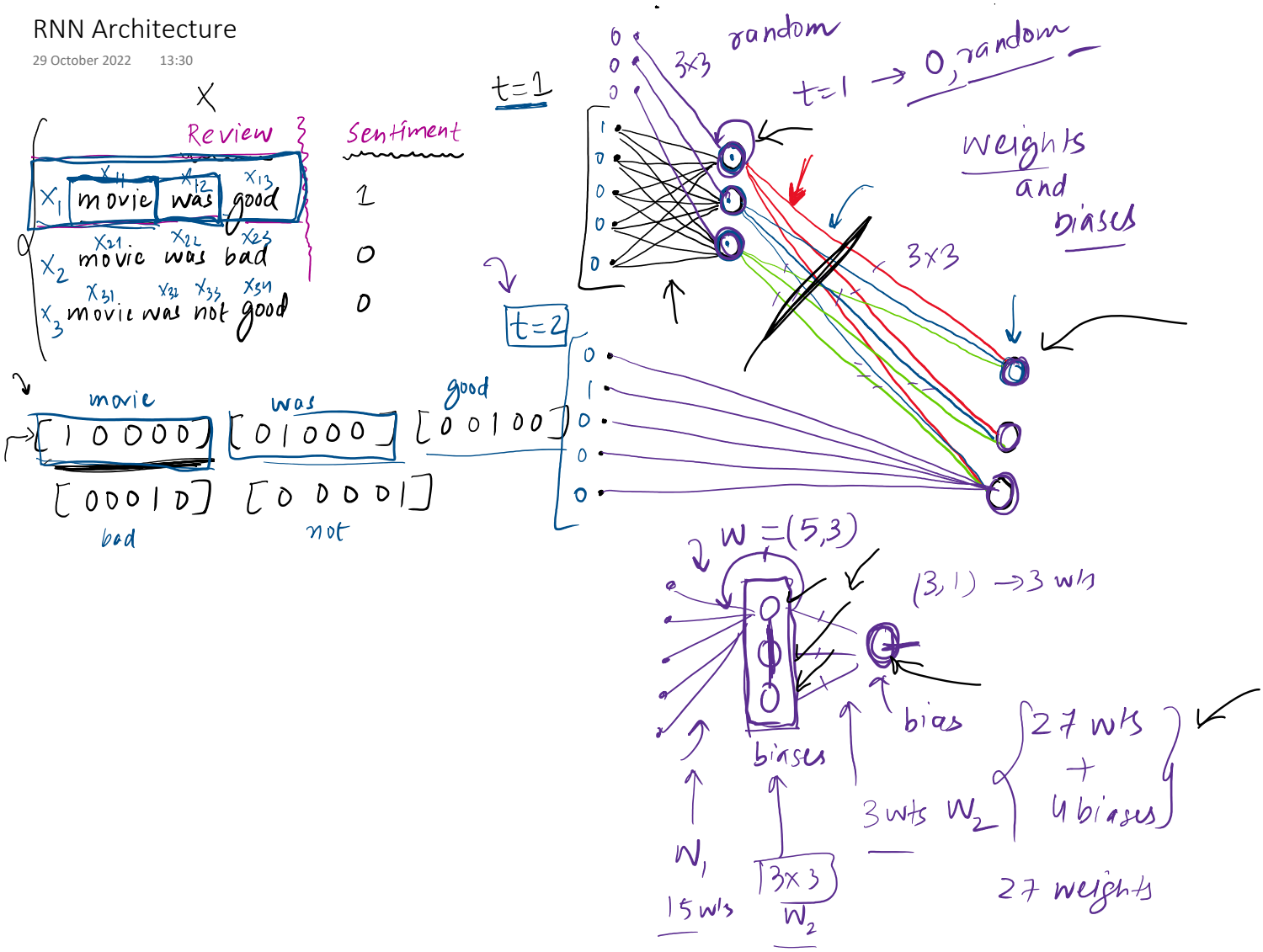
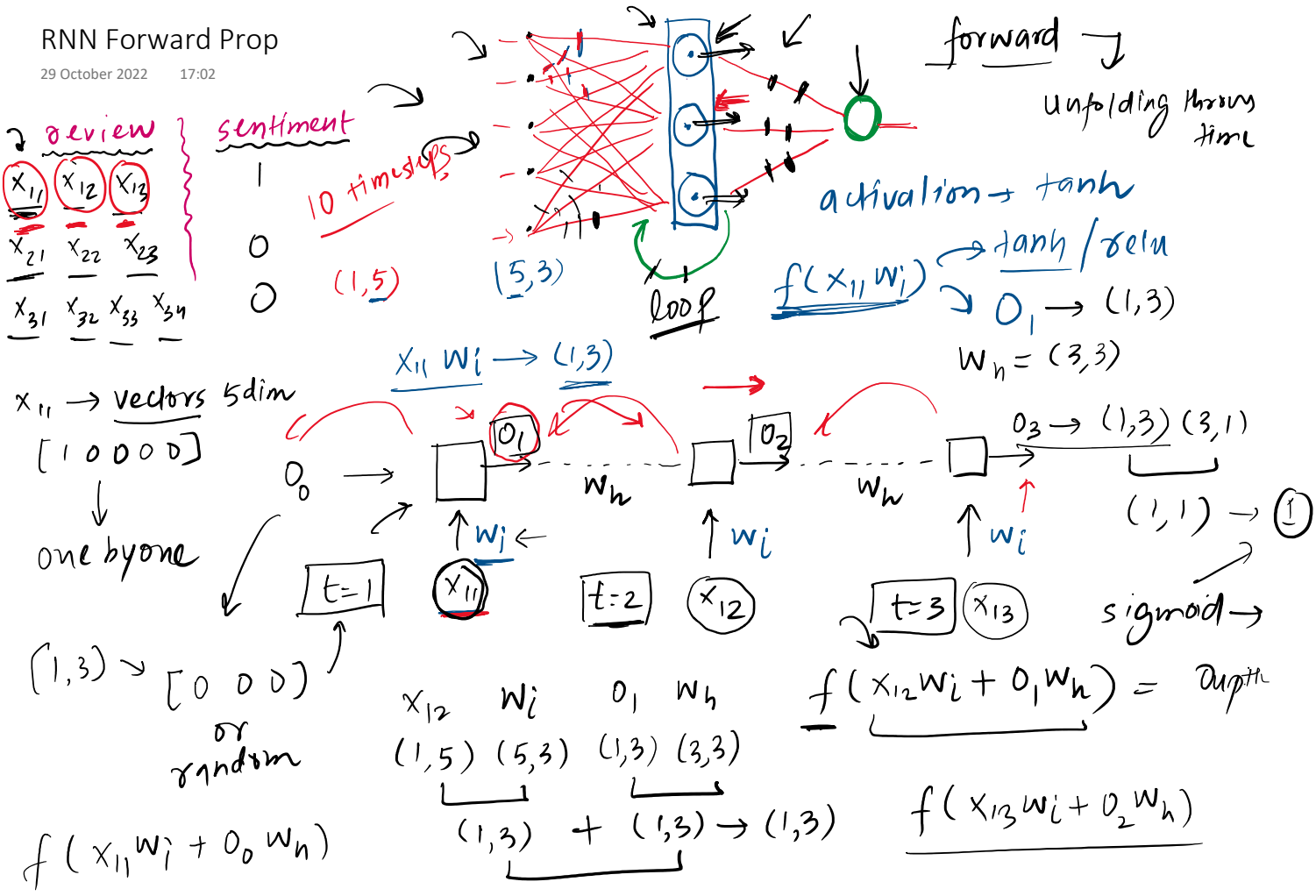


# RNN Forward Prop

29 October 2022 17:02



# Simplified Representation

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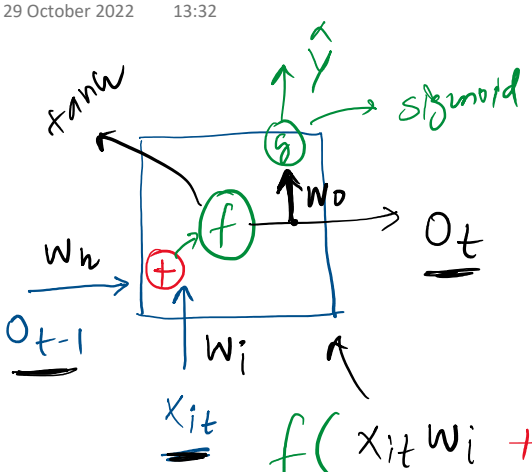
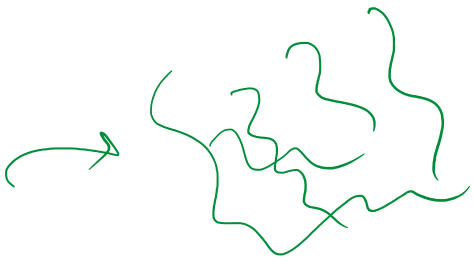


$\hat{y} = g(O_t W_o)$

$f(X_{it} W_i + O_{t-1} W_h) \rightarrow$ vector $\rightarrow O_t$

i = row #

t = time step

$X_{11} \rightarrow$

Hello how are you?

# Code

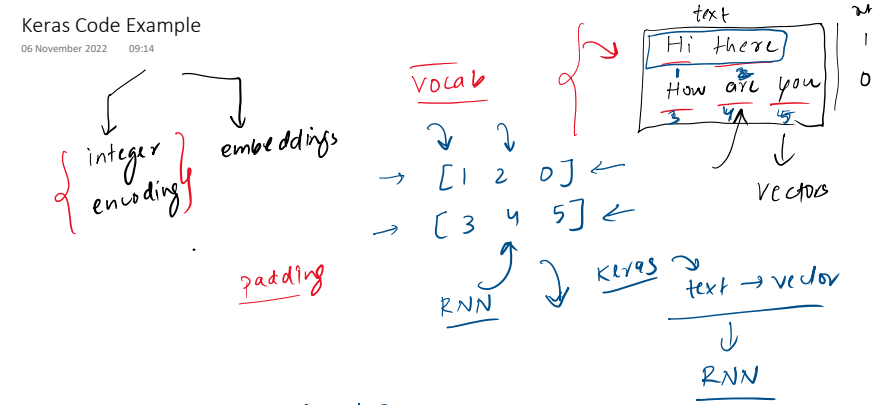
29 October 2022 13:32

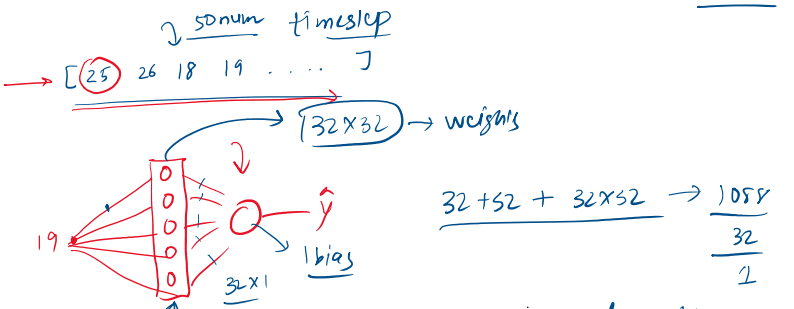
# State and Memory

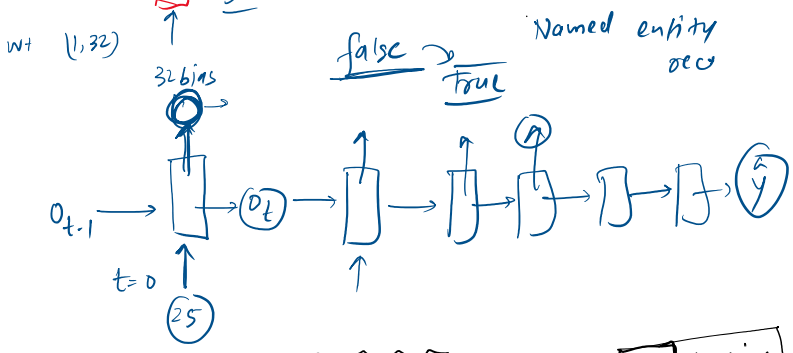
29 October 2022 13:33

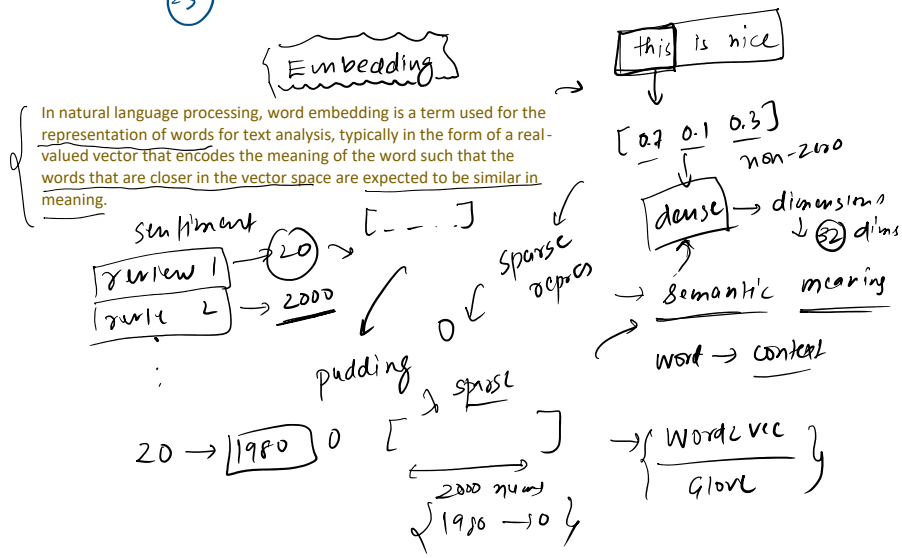
Keras Code Example

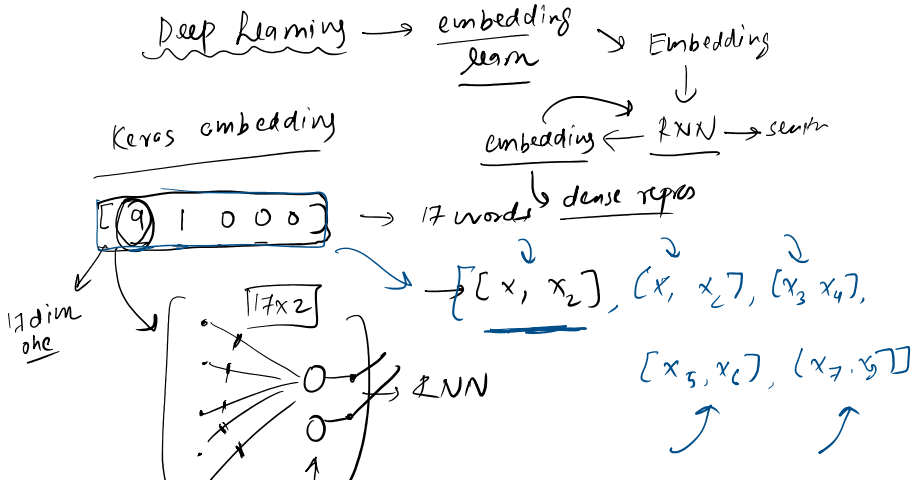
06 November 2022 09:14

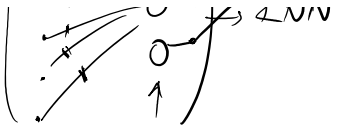


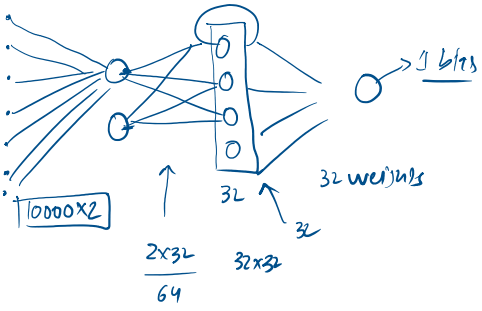





17 nodes




population in 9th year = x

$x + 10\%\text{ of } x = 10000$

$x + 0.1x = 10000$

$1.1x = 10000$

$x = \frac{10000}{1.1}$

$\frac{x-1}{x} + \frac{1}{2}\left(\frac{x-1}{x}\right)^2 + \frac{1}{2}\left(\frac{x-1}{x}\right)^3 + \frac{1}{2}\left(\frac{x-1}{x}\right)^4 + \cdots$

t(n-1)

+ 2 +

+ (n-1)

50 → 500

A

A[35] → t sec

A[35] →

35

1 x 4 x35

x

1 25 50 100

12

O(n)

$O(n^2)$ → nested loops

input → 10 (100x100)

time → $(x)^2$ 4

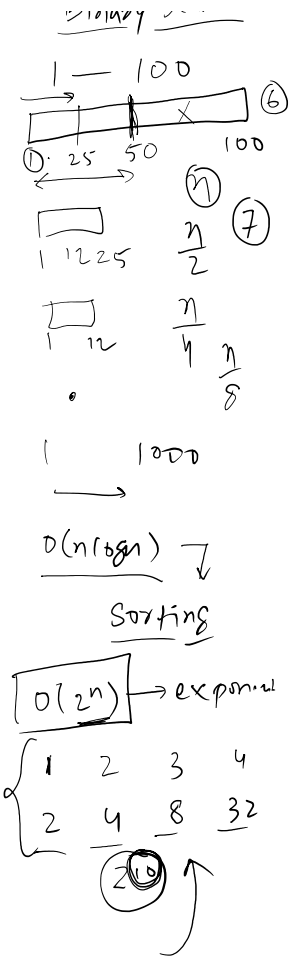
O(log(n))

Binary search

1 — 100

→ (6)

$\sqrt{(x_1}$


Binary
1 — 100
100
25 50
n/2
n/4
n/8
1000
O(nlogn)
Sorting
O(2^n) → exponential
1 2 3 4
2 4 8 32
for i in scan
O(n)
for j in (n^2)
O(n)
O(n+n) →
O(2n)
→ O(n)
O(n+n^2) O(n^2)
for i in arr:
for j in
25 → '25'
str()
n = 345%10
digits[5]
5 + ''
= '5'
345//10 → 34 != 0
34//10 → 3

34 // 10 → 4

4 + '5' →
45

34 // 10 → 3

3 != 0

3 // 10 => 3

digits[3]

3 + '45'
= '345'

---

Loop n → 10 times

345 = n ⇒ 345 0

3 → 4

inp → 10
time → 1 → log

---

O(n) → O(n+n)
O(n) O(2n) → O(n)

O(n) → O(n*n)
O(n) O(n²)

O(n)
O(n)
O(10000000)

$n^2$ 10000000
×
$O(n^2)$

log(2)/2
1 → $\frac{n}{2}$

4 $\frac{n}{2}$ 2n

O(n) n=100

50, 100 $\frac{n}{2}$

2 → 100=n $\frac{n}{2}$

j=1 → 2
j=2 → 4 2-100
j=3 → 8
j=4 → 32

$\frac{n}{2} \times \log n$

n log n

O(1) → constant

n = 345

3+4+5 → 12

5

3 4 4

3 3

0

3450 → 4

log

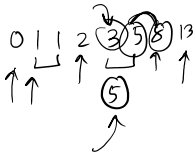
inp → 10 100

out → 1 2 3

fibonacci

↳ function

↳ recursion




n=1 n=0 → 1

fib(n)

↓

function calls

input → n → 10

#fcalls →

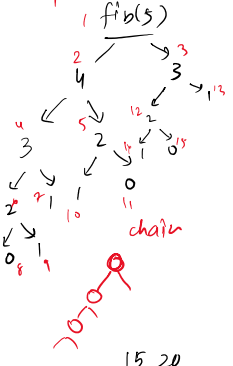
fib(3) n=3 1

fib(2) 2 fib(1) 3 → 1

fib(1) fib(0)

1 1

exponential → bad




O(2^n) 15 20 50

input 1 2 3 4

1 2 4 8 16

$O(2^n)$ (50)

input 1 2 3 4

t1 2 4 8 16

$n = 50, 100, 500$

↑ weeks

exponential

↳ days/weeks

subset → O(?)

power set

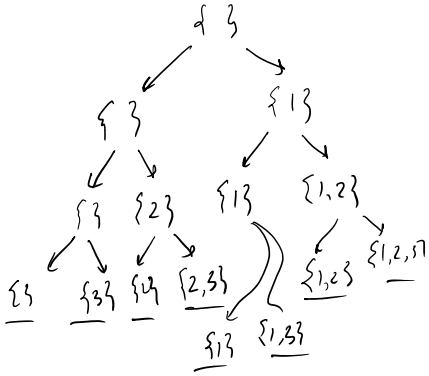
{1,2} → {{},{1},{2},{1,2}}

{1,2,3} →

{},{1},{2},{3},{1,2},{2,3}

{3,1} {1,2,3}

{1,2,3}




reduce → divide → log

Increase → multi → exp

→ exponential

{1,2} → 4 $2^2 = 4$

{1,2,3} → 8 $2^3 = 8$

$2^4 = 16$

$O(2^n)$

O(?)

$$T(n) = \begin{cases} 3T(n-1) & \text{if } n>0 \\ 1, & \text{otherwise} \end{cases}$$

$n > 0$

$T(n) = 3T(n-1)$

$= 3[3T(n-2)]$

$= 3^2 T(n-2)$

$= 3^2[3T(n-3)]$

$= 3^3 T(n-3)$

$= 3^n T(n-n)$

$= 3^n T(0)$

$T(n) = \boxed{3^n} \rightarrow O(3^n)$

$$T(n) = \begin{cases} 2T(n-1)-1 & \text{if } n>0 \\ 1, & \text{otherwise} \rightarrow \text{constant} \end{cases}$$

$=$

$T(n) = 2T(n-1)-1$

$= 2[2T(n-2)-1]-1$

$= 2^2 T(n-2) - 2 - 1$

$= 2^2[2T(n-3)-1] - 2 - 1$

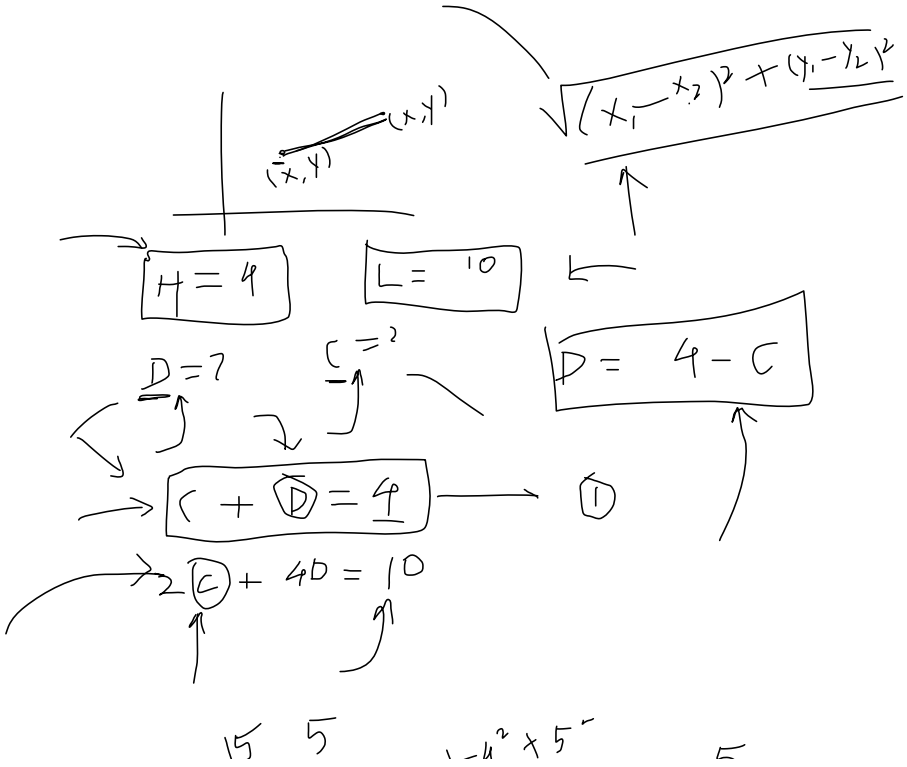
$= 2^3 T(n-3) - 2^2 - 2^1 - 2^0$

$= 2^n T(n-n) - 2^{n-1} - 2^{n-2} \ldots - 2^1 - 2^0$

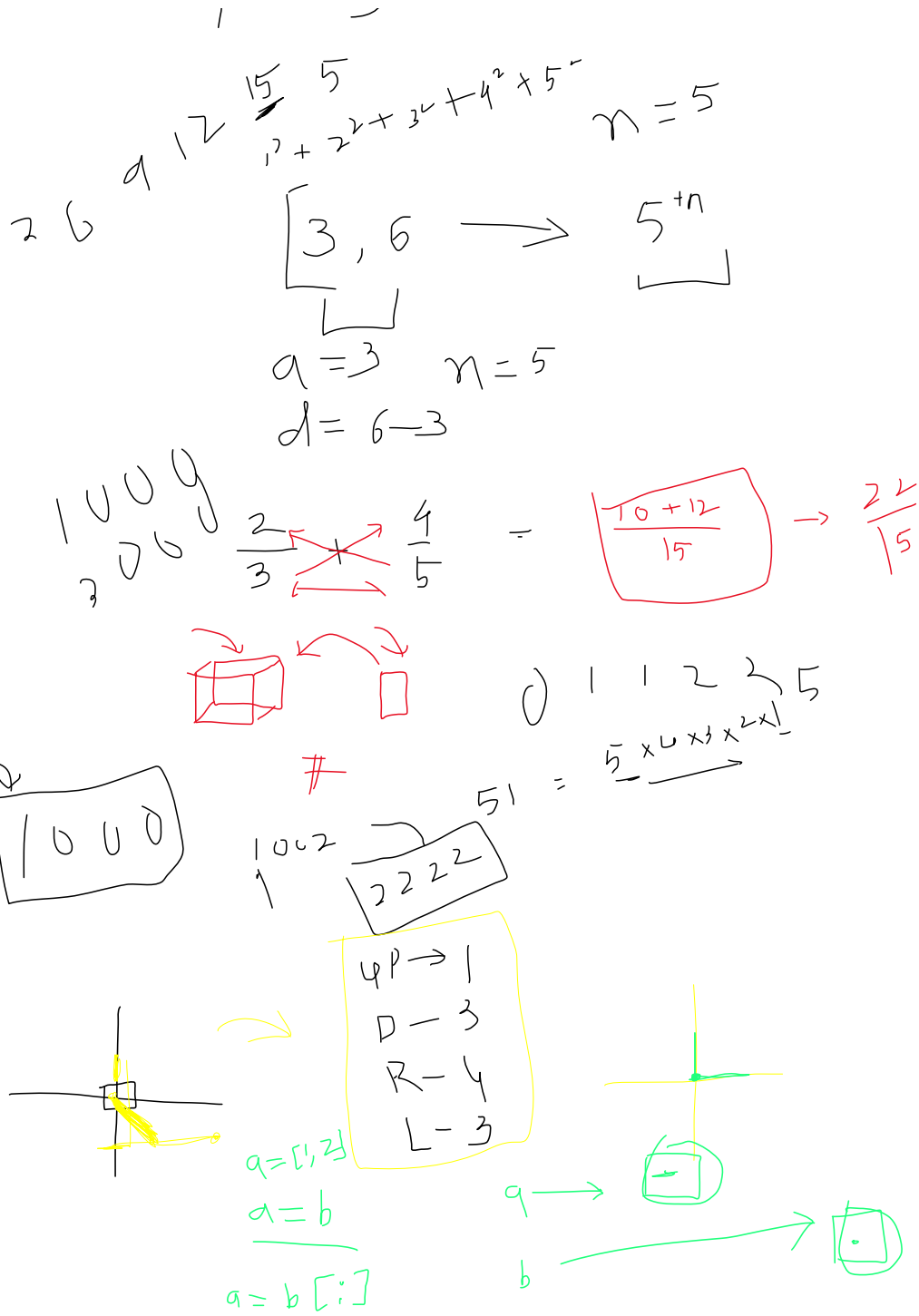
$= 2^n - [2^{n-1} + 2^{n-2} + \ldots + 2^1 + 2^0]$

$= 2^n - [2^n - 1] = 2^n - 2^n + 1$

$O(1) \rightarrow$ constant

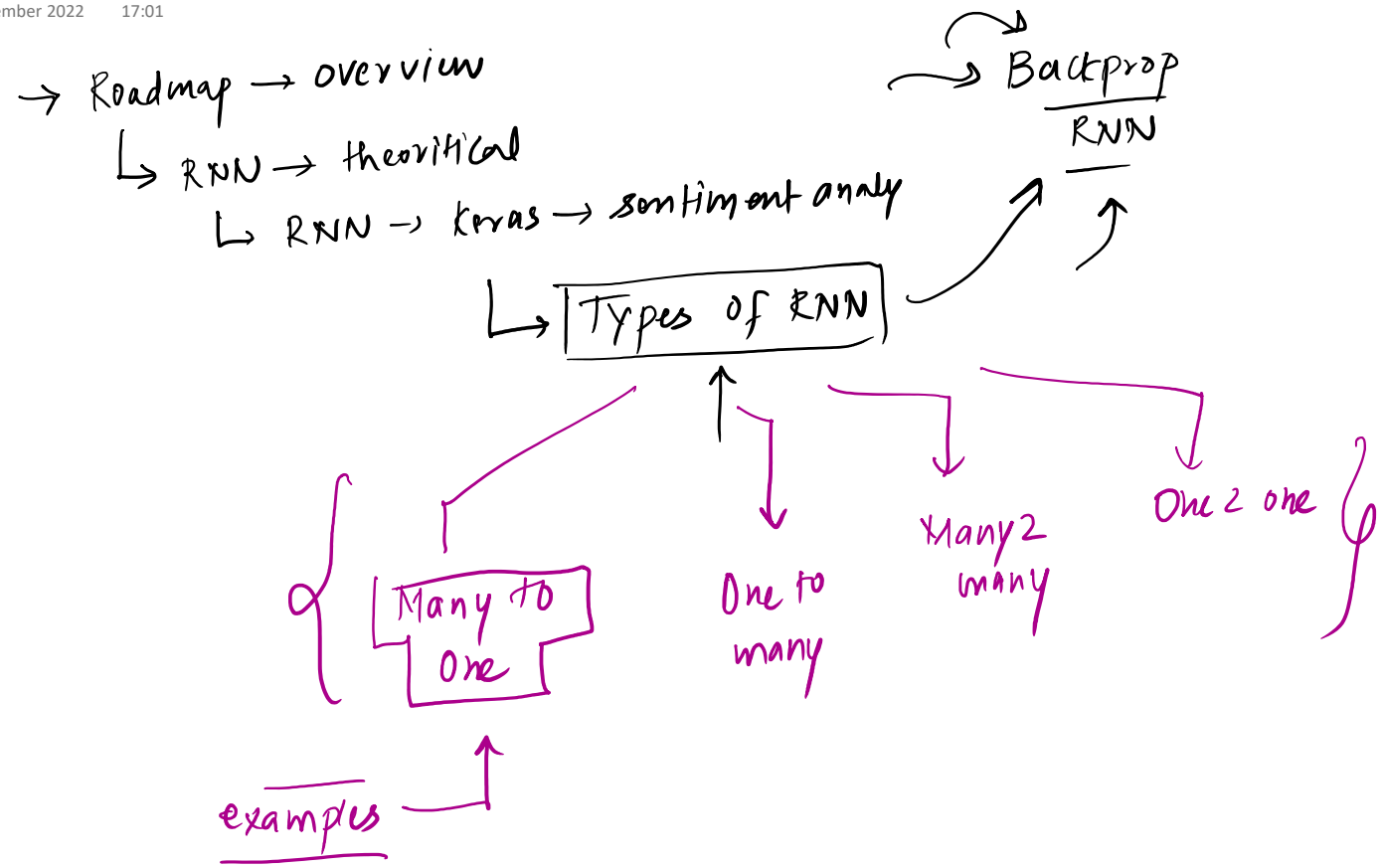



15 5 $\quad -4^2 \times 5^{-}$ $\quad -$


n = 5
[3, 6 → 5^n
q = 3 n = 5
d = 6 − 3
10 + 12 / 15 → 22/5
0 1 1 2 3 5
5 x 4 x 3 x 2 x 1
1000
1002
2222
51 =
up → 1
D − 3
R − 4
L − 3
q = [1, 2]
a = b
a = b [:]
q
b

# Till Now

17 November 2022 17:01



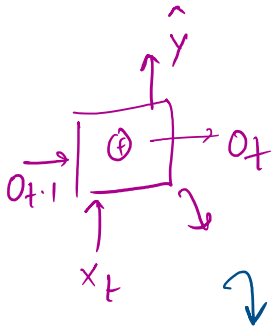
# Many to One

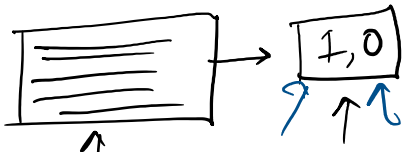
17 November 2022 17:02

input → sequence → sent, chars, time series

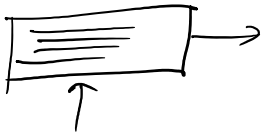
out → non-sequ → int/num → scalars → (1,0)

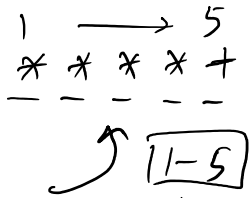
↳ sentiment → ∀any



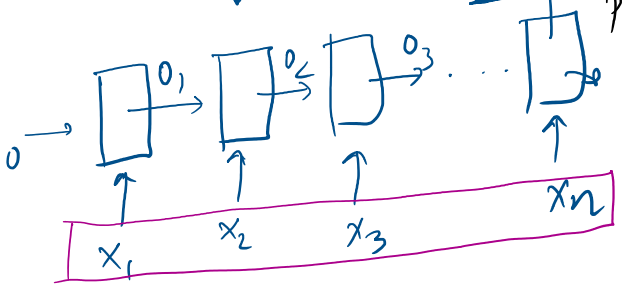

sequence






multiclass classifi


Rating prediction



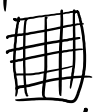

recurrent → simple RNN

many to one

# One to Many

17 November 2022 17:02

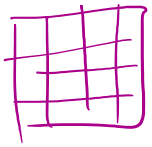
→ normal non sequential

↳ 

→ Output → sequences




image captioning

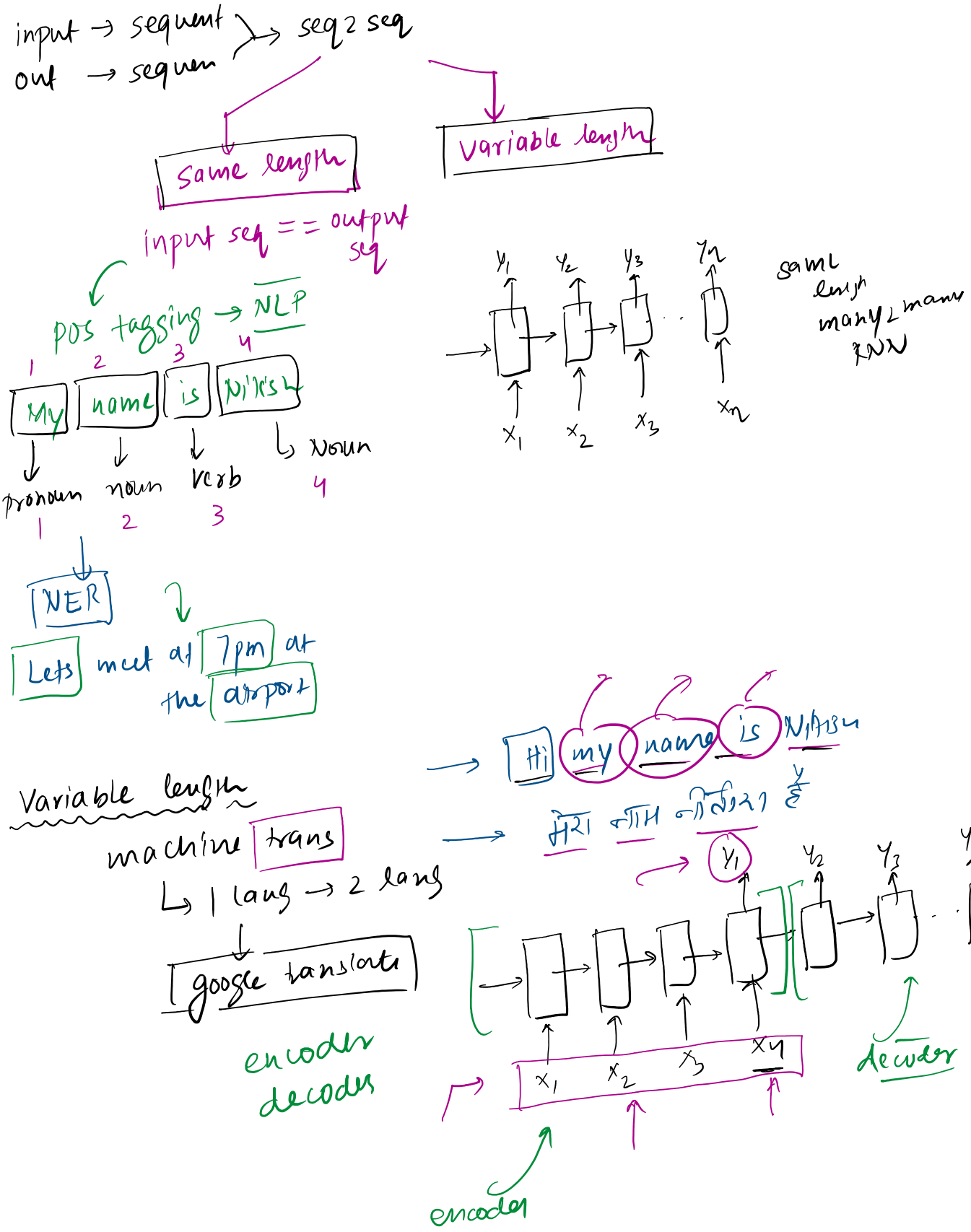
 → textual repres

 → NN → A man is playing cricket

→ music generation

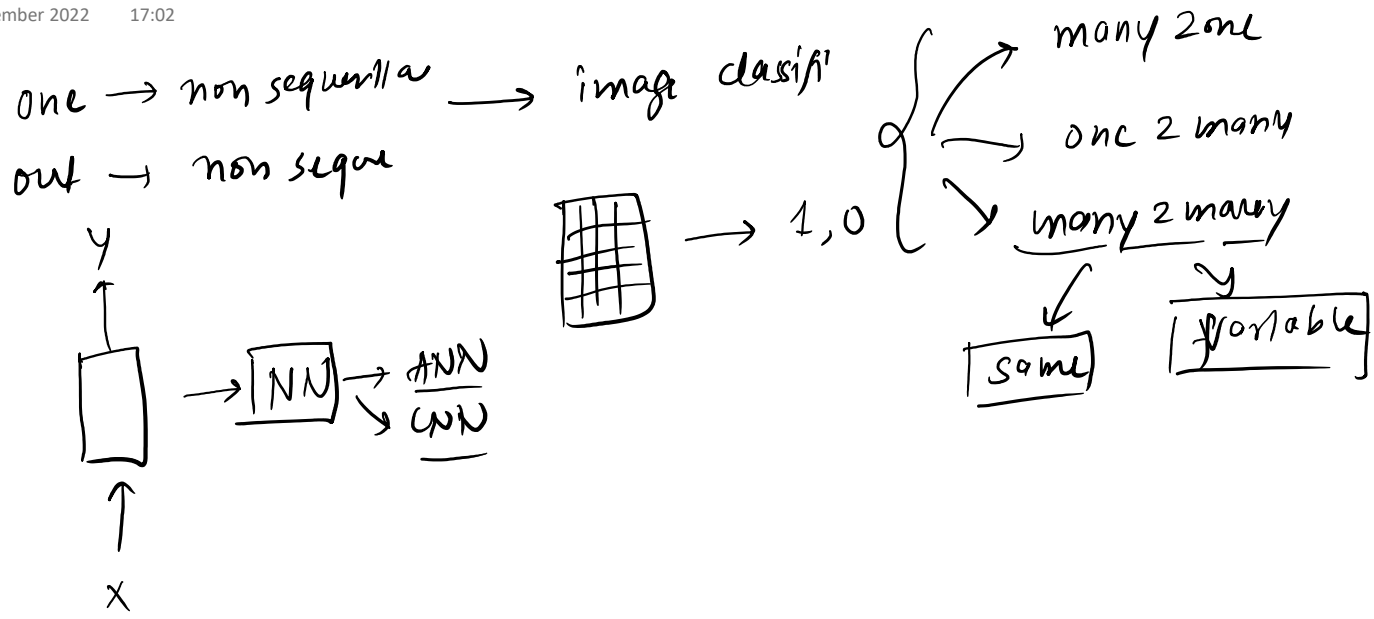
# Many to Many

17 November 2022 17:02



# One to One

17 November 2022 17:02



# Backpropagation in RNN

01 December 2022 16:43

RNN intro → RNN → practical

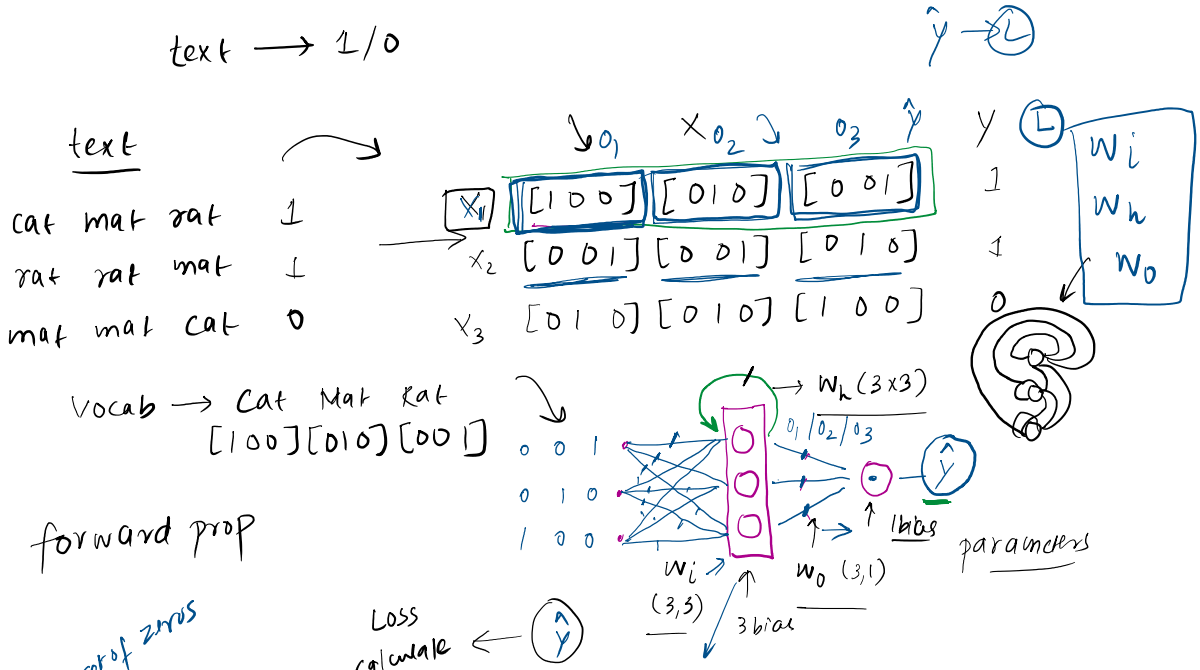
types of RNN

→ RNN → Backprop → BPTT

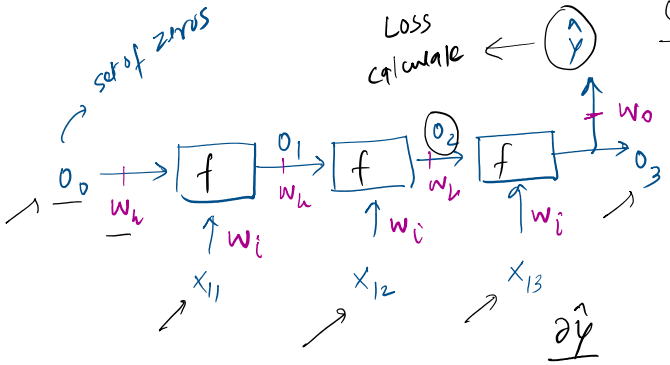
Many to One RNN

Sentiment Analysis

text → 1/0




forward prop




$O_1 = f(X_{11} W_i + O_0 W_h)$

$O_2 = f(X_{12} W_i + O_1 W_h)$

$O_3 = f(X_{13} W_i + O_2 W_h)$

$\hat{y} = \sigma(O_3 W_0)$

$L = -y_i \log \hat{y}_i - (1-y_i) \log(1-\hat{y}_i)$

loss calculate → minimize

L min gradient descent

$W_i$ $W_h$ $W_0$

$\frac{\partial \hat{y}}{\partial W_0}$ $\frac{\partial L}{\partial \hat{y}}$

$W_i = W_i - \eta \frac{\partial L}{\partial W_i}$

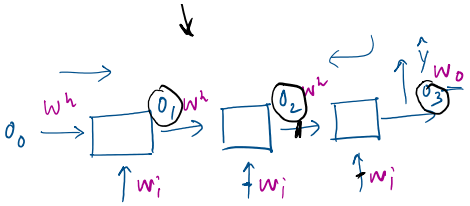
$W_h = W_h - \eta \frac{\partial L}{\partial W_h}$

$W_0 = W_0 - \eta \frac{\partial L}{\partial W_0}$

Backprop

unfold → 3 times

$\frac{\partial L}{\partial W_0}$ $L \rightarrow \hat{y} \rightarrow O_3 \rightarrow W_0$



$\frac{\partial L}{\partial w_0}, \frac{\partial L}{\partial w_i}, \frac{\partial L}{\partial w_h}$

$o_1 = f(x_{i1} w_i + o_0 w_h)$

$o_2 = f(x_{i2} w_i + o_1 w_h)$

$o_3 = f(x_{i3} w_i + o_2 w_h)$

$\hat{y} = \sigma(o_3 w_0)$

$\frac{\partial L}{\partial w_0} = \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial w_0}$

$\frac{\partial L}{\partial w_i} = \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial o_3} \frac{\partial o_3}{\partial w_i} + \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial o_3} \frac{\partial o_3}{\partial o_2} \frac{\partial o_2}{\partial w_i} + \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial o_3} \frac{\partial o_3}{\partial o_2} \frac{\partial o_2}{\partial o_1} \frac{\partial o_1}{\partial w_i}$

3 terms

$\frac{\partial \hat{y}}{\partial o_1} = \frac{\partial \hat{y}}{\partial o_3} \frac{\partial o_3}{\partial o_2} \frac{\partial o_2}{\partial o_1}$

10 words → 10 terms

$t = 1$

$\frac{\partial L}{\partial w_i} = \sum_{j=1}^{3} \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial o_j} \frac{\partial o_j}{\partial w_i}$

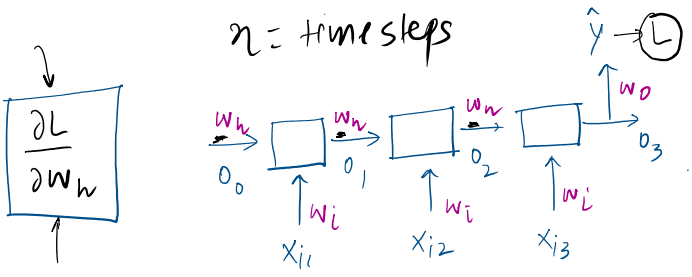
$\frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial o_3} \frac{\partial o_3}{\partial w_i}$

$= \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial o_1} \frac{\partial o_1}{\partial w_i} = \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial o_3} \frac{\partial o_3}{\partial o_2} \frac{\partial o_2}{\partial o_1} \frac{\partial o_1}{\partial w_i}$

$\frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial o_2} \frac{\partial o_2}{\partial w_i} = \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial o_3} \frac{\partial o_3}{\partial o_2} \frac{\partial o_2}{\partial w_i}$

$\frac{\partial L}{\partial w_i} = \sum_{j=1}^{n} \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial o_j} \frac{\partial o_j}{\partial w_i}$

$n$ = timesteps



$\frac{\partial L}{\partial w_h}$

$\frac{\partial L}{\partial w_h} = \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial o_3} \frac{\partial o_3}{\partial w_h} +$

$\frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial o_3} \frac{\partial o_3}{\partial o_2} \frac{\partial o_2}{\partial} +$

$\partial w_h$ $\partial y$ $\partial o_3$ ...

$$\frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial o_3} \frac{\partial o_3}{\partial o_2} \frac{\partial o_2}{\partial w_h} +$$

$$\frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial o_3} \frac{\partial o_3}{\partial o_2} \frac{\partial o_2}{\partial o_1} \frac{\partial o_1}{\partial w_h}$$

$$\frac{\partial L}{\partial w_h} = \sum_{j=1}^{n} \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial o_j} \frac{\partial o_j}{\partial w_h}$$

$n$ = timesteps

for $j=3$

$$\frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial o_3} \frac{\partial o_3}{\partial w_h} \rightarrow \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial o_3} \frac{\partial o_3}{\partial o_1} \frac{\partial o_1}{\partial w_h}$$

for $j=10$

$$\frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial o_{10}} \frac{\partial o_{10}}{\partial o_1} \frac{\partial o_1}{\partial w_h}$$

$$\prod_{t=2}^{j} \frac{\partial o_t}{\partial o_{t-1}}$$

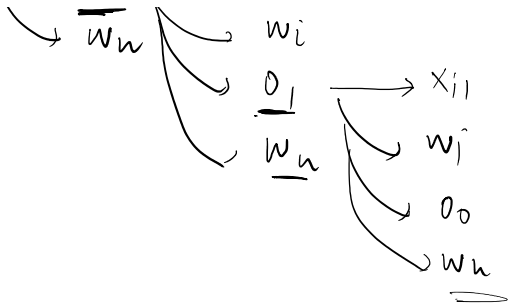
$$t=3 \quad \frac{\partial o_t}{\partial o_{t-1}} = \frac{\partial o_2}{\partial o_1} \frac{\partial o_3}{\partial o_2}$$

$t=2$

$$o_t = f(x_{it} w_{inp} + o_{t-1} w_h)$$

$$\frac{\partial o_t}{\partial o_{t-1}} = \prod_{t=2}^{j} f'(x_{it} w_{inp} + o_{t-1} w_h) w_h$$

$[0-1]$



# Problem with RNN

19 December 2022 16:33

RNNs → sequential data → textual, time series

suffer (2) major problems → LTSMs (Why)

RNN

→ Problem of long term dependency
→ Unstable gradients stagnated training → Unstable gradients

Applications next word predictor

→ RNN

# timesteps

Marathi is spoken in Maha

short

Maha is a beautiful place I went there last year, but I could not enjoyed properly bcz I don't understand marathi

long term

RNN

keypad

RNN

{ vanishing gradient prob }

{ Exploding gradient problem } → RNN

possible solⁿ

↳ remove

## Problem # 1 → Problem of long term dependency → Vanishing

| inp | out |
|---|---|
| 1 0 1 | 1 |
| 0 0 1 | 0 |
| 0 0 0 | 0 |
| 1 1 1 | 1 |

0-1

inp hidden out 1 0 1 $W_h$ $W_{in}$ $W_{out}$

L → min

$W_h$, $W_{in}$, $W_{out}$

↓

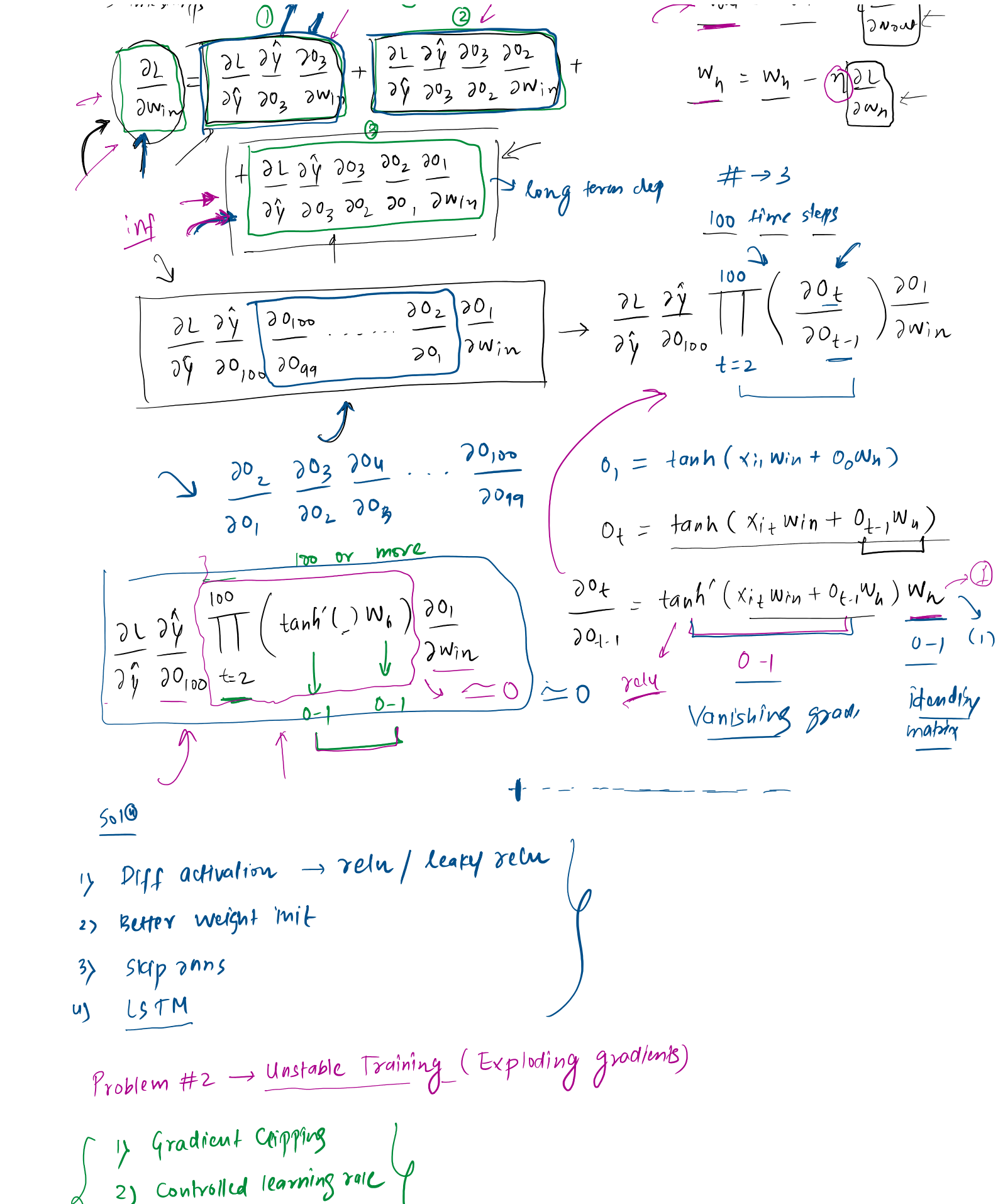
gradient des

$W_{in} = W_{in} - \eta \frac{\partial L}{\partial W_{in}}$

$W_{out} = W_{out} - \eta \frac{\partial L}{\partial W_{out}}$

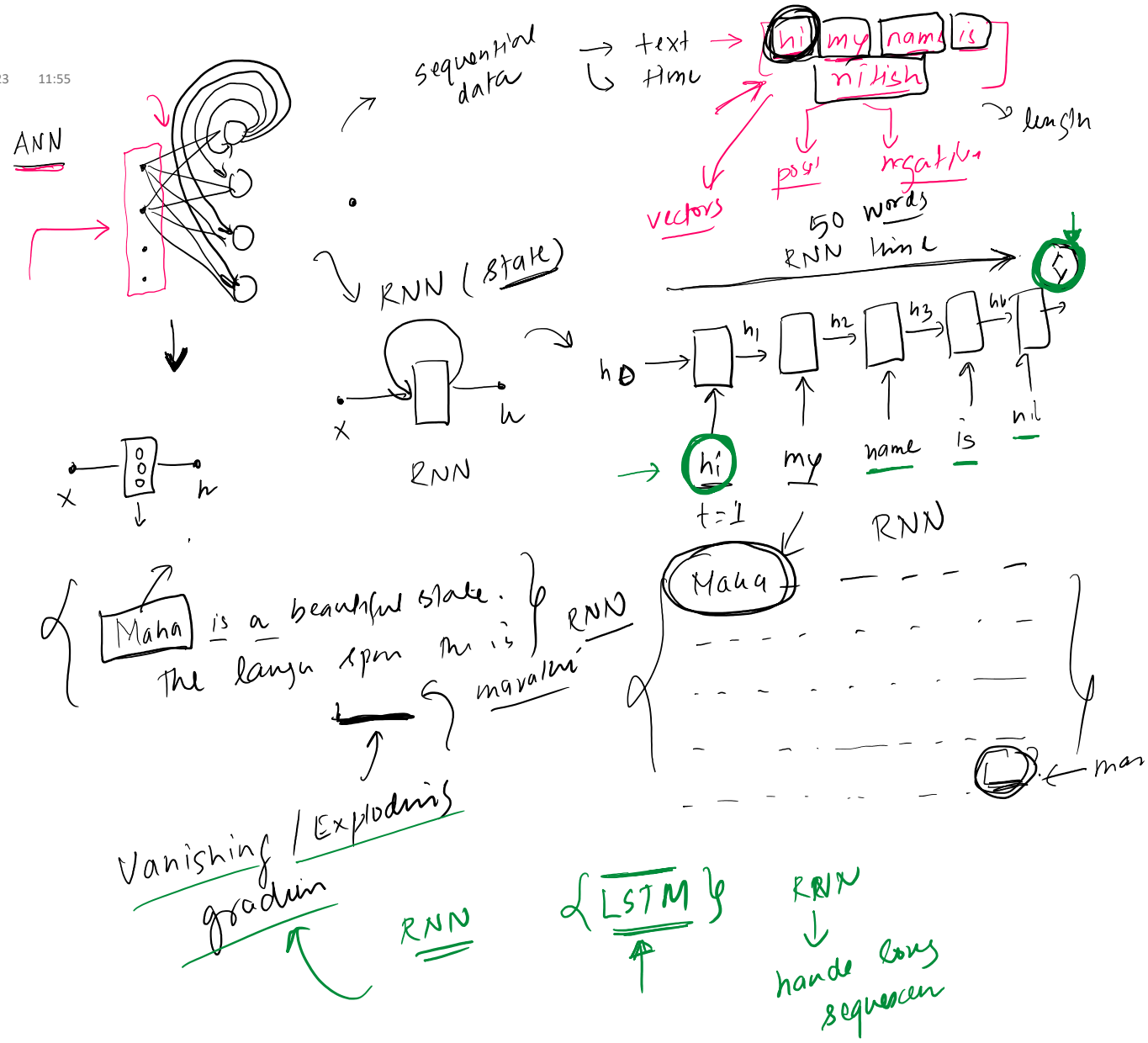
short term dep

3 time stamps


Long term dep
100 time steps
100 or more
Vanishing grad
identity matrix
Sol(n)
1) Diff activation → relu / leaky relu
2) Better weight init
3) Skip anns
4) LSTM
Problem #2 → Unstable Training (Exploding gradients)
1) Gradient Clipping
2) Controlled learning rate
3) LSTM

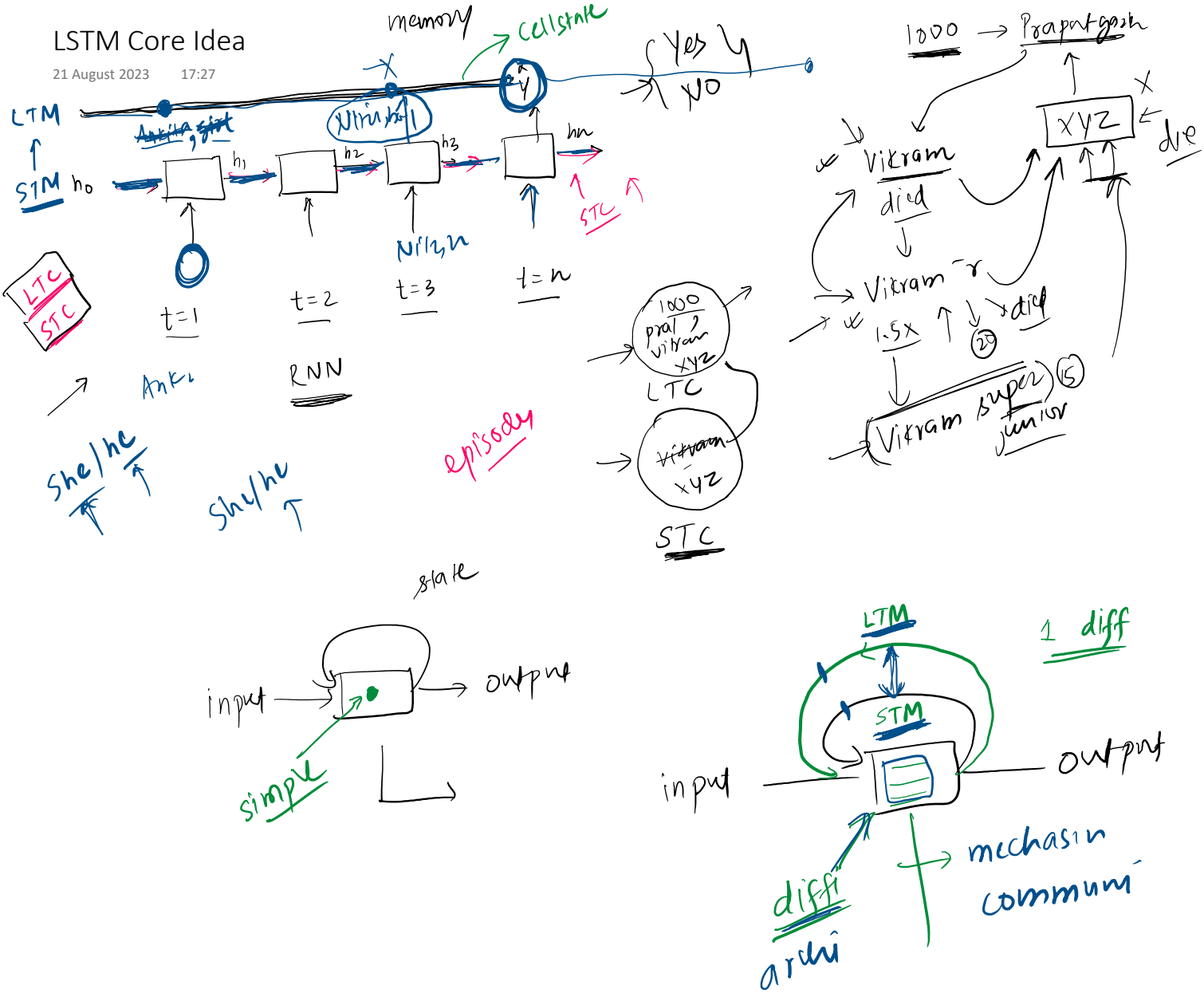
# Recap

21 August 2023 11:55



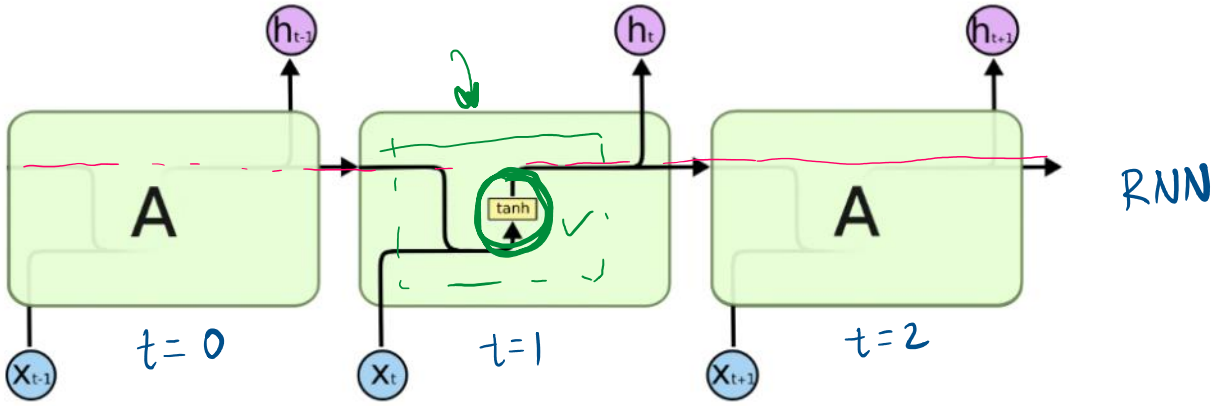
# LSTM Core Idea

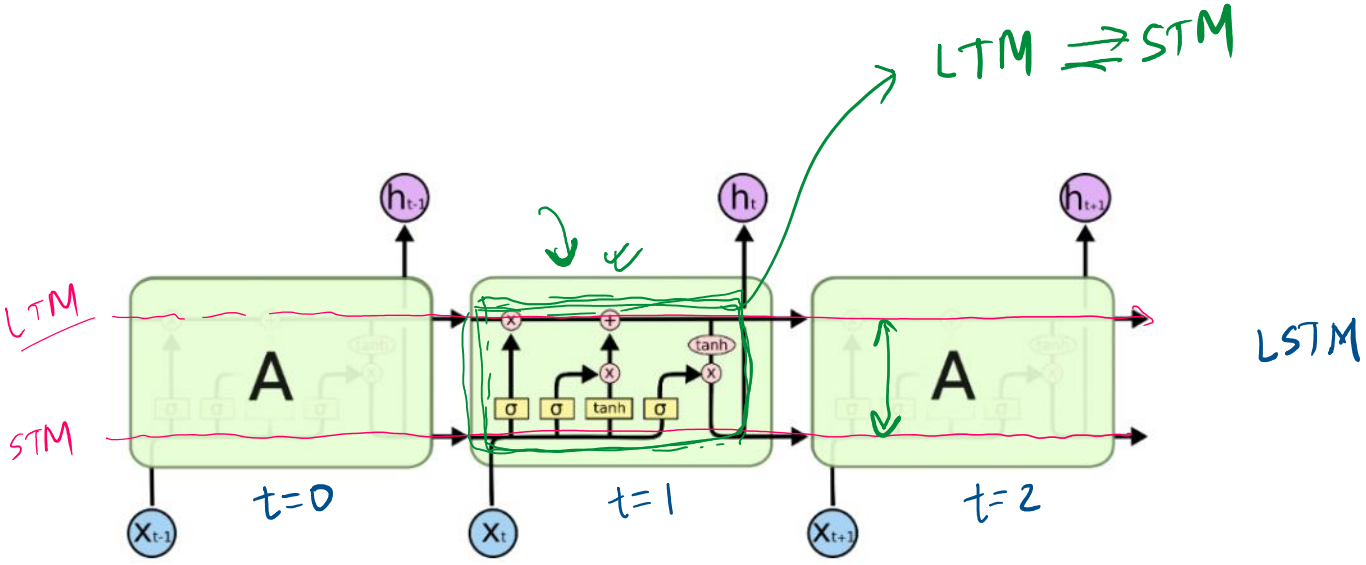
21 August 2023 17:27

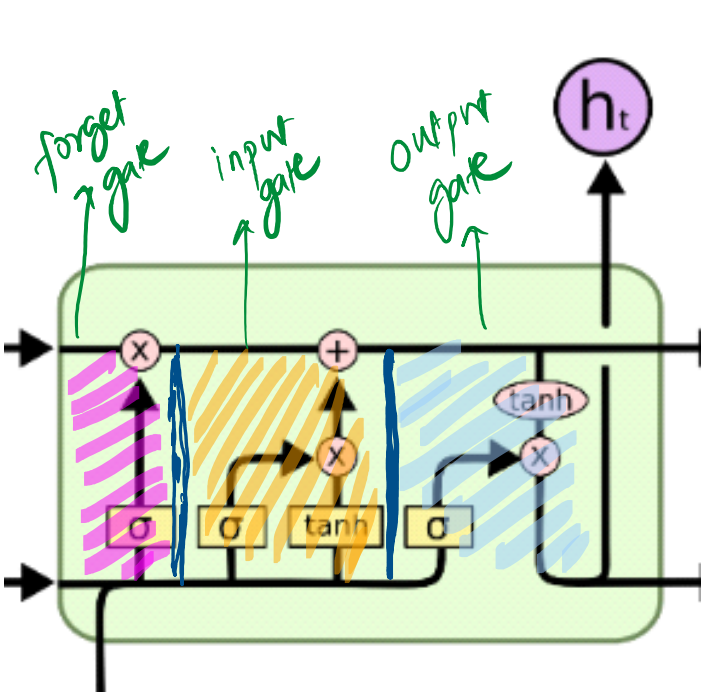


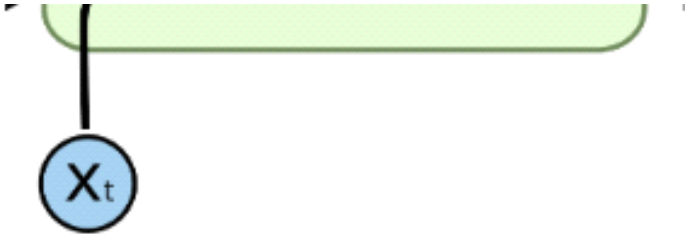
# LSTM Architecture

21 August 2023 18:41



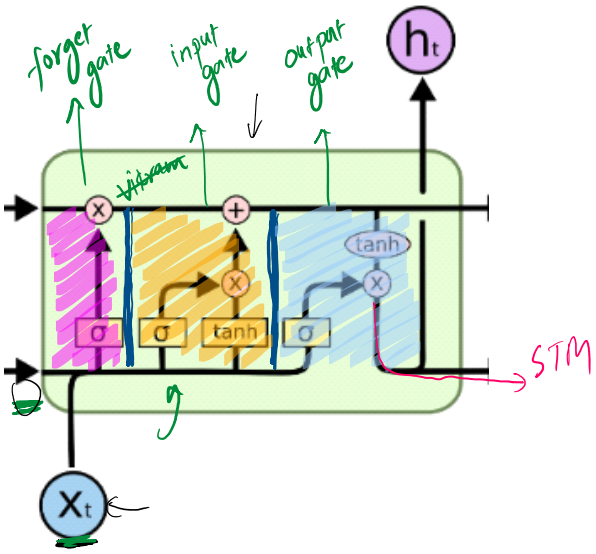




$X_t$

# LSTM Gates

21 August 2023 19:06

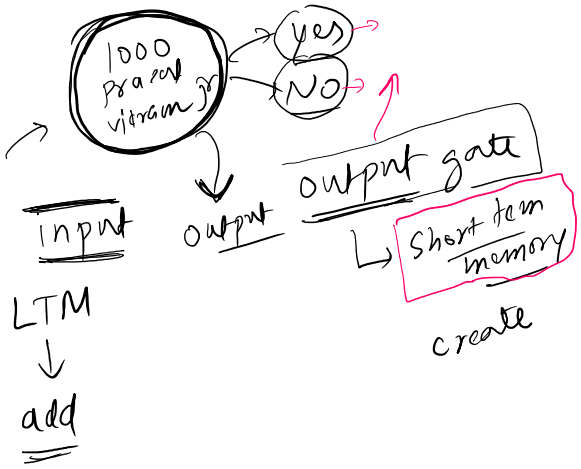



forget

input

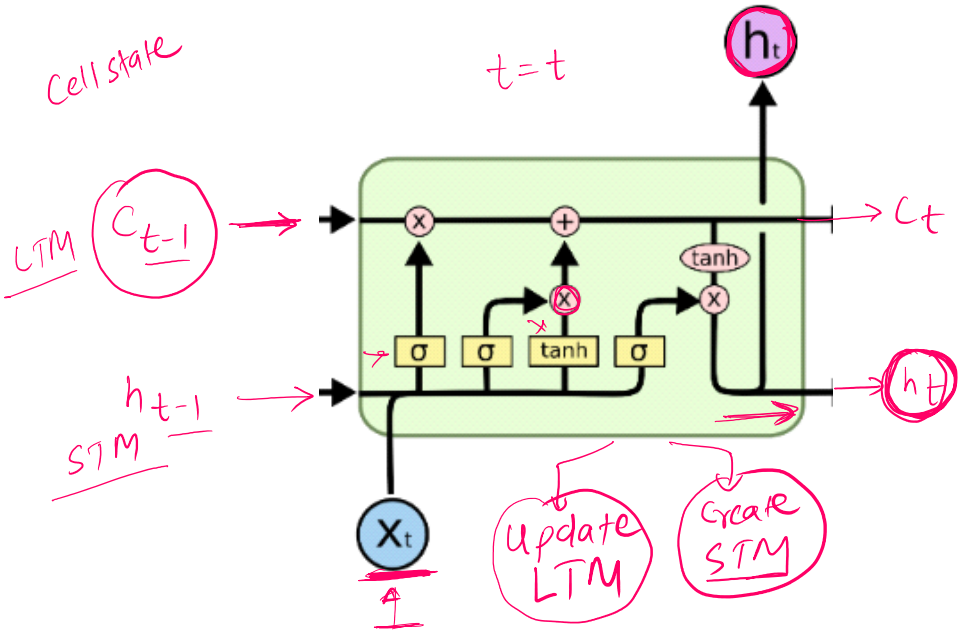
LTM

remove



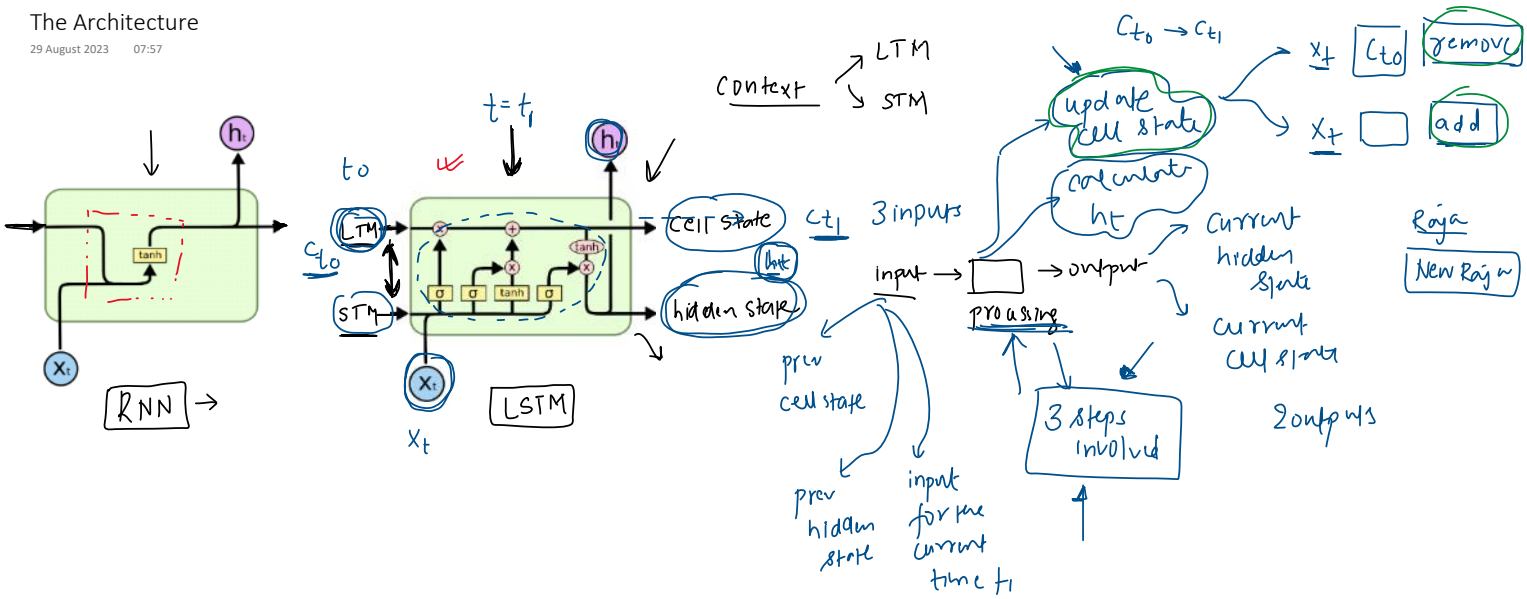
# Summary

21 August 2023 19:29



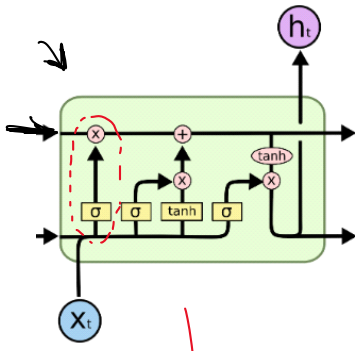
# The Architecture

29 August 2023 07:57

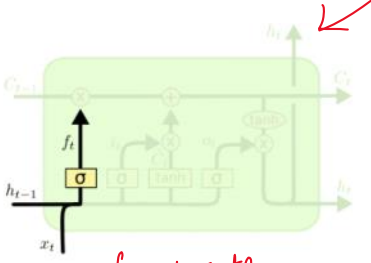


The Gates

29 August 2023 08:09




3 gates

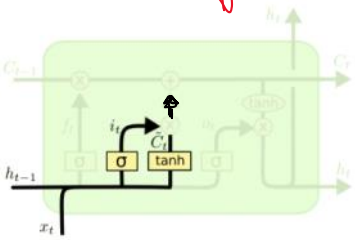



forget gate

to remove something from $C_t$

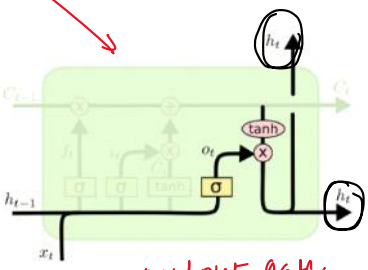
update $C_t$

+




input gate

to add something to the $C_t$

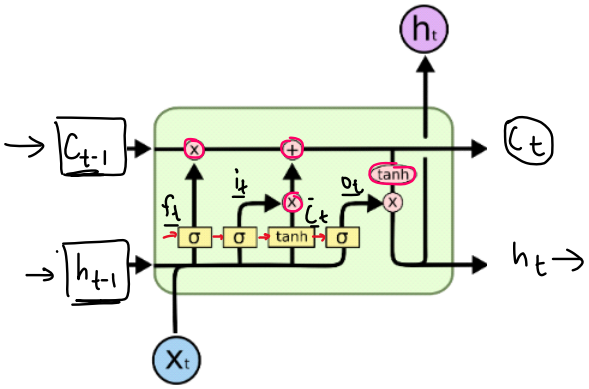



output gate

calculat hidden state $h_t$

# What are $C_t$ and $h_t$

29 August 2023 08:08




$h_t$ $C_t$ → [0.1 0.3 0.9]

vectors

3d vector

$h_t$ $C_t$ dim equal

same

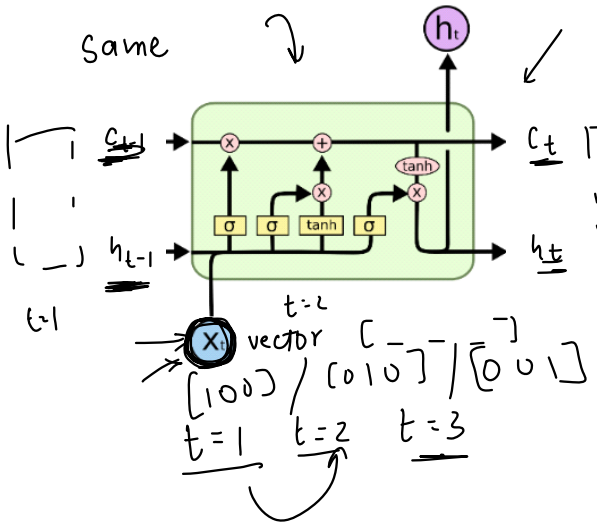
$h_t$ [0.1 0.45 0.6]

$C_t$ [0.55 0.6 0.0]

# What is $X_t$

29 August 2023 17:40

RNN




sentiment

vectorization

| | |
|---|---|
| cat mat rat | 0 ← |
| cat rat rat | 0 |
| mat mat cat | 1 |

[100] [010] [001]

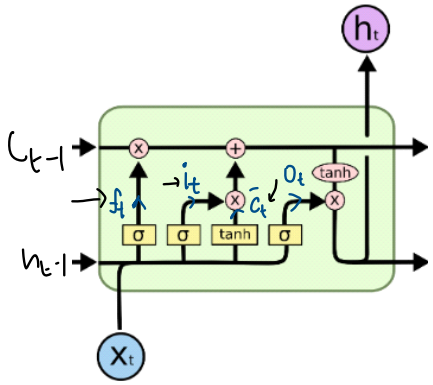
word vector

OHE

| Cat | mat | rat |
|---|---|---|
| 1 | 0 | 0 |
| 0 | 1 | 0 |
| 0 | 0 | 1 |

What are $f_t$, $i_t$, $o_t$ and $\bar{C}t$

29 August 2023 08:09




$f_t$ $i_t$ $\bar{C}_t$ → candidate cell state $o_t$

forget gate — input gate — output gate

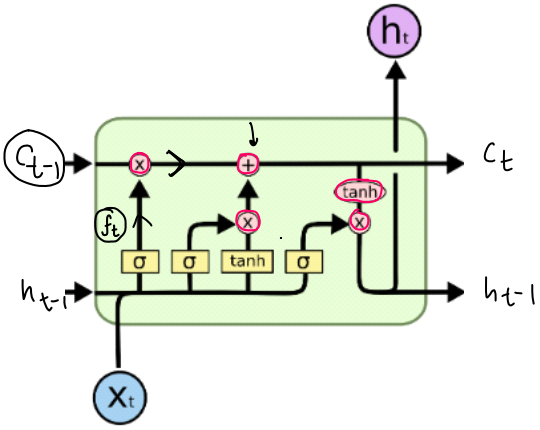
vectors → $C_t$ $h_t$

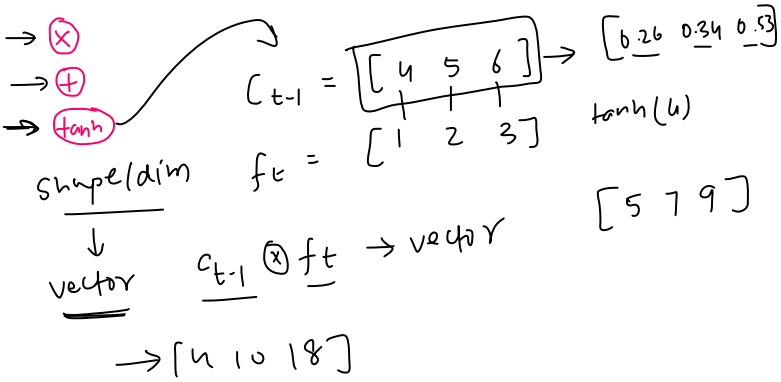
$f_t$ $i_t$ $\bar{C}_t$ $o_t$

[ x y z ]
[ ]

# Pointwise Operations

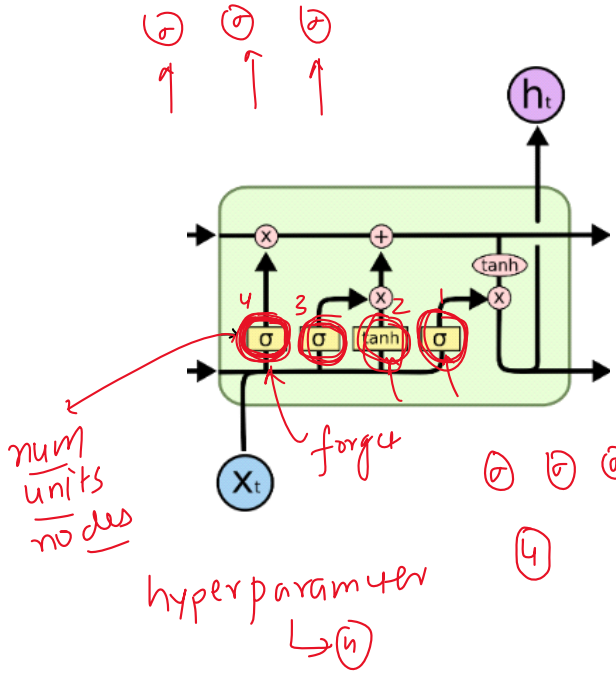
29 August 2023 18:26

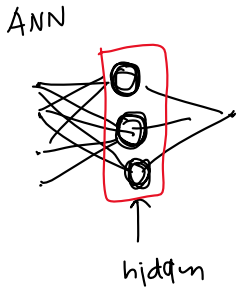


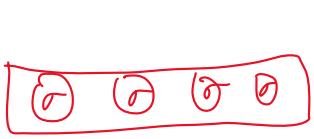



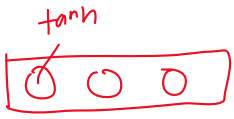
→Neural Network Layers

29 August 2023 18:34



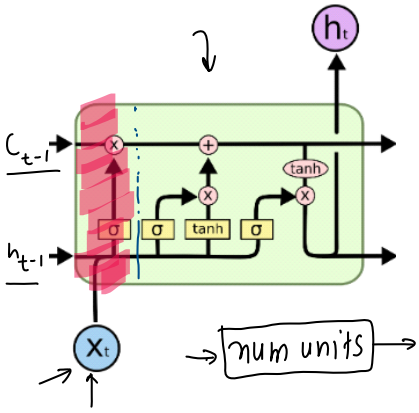





# The Forget Gate

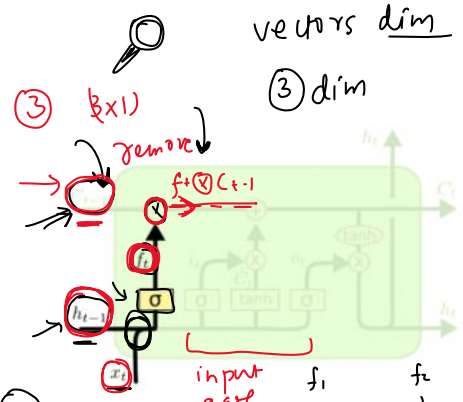
29 August 2023 19:58




→ num units → 3

4 dim vector

$[x_{i1}\ x_{i2}\ x_{i3}\ x_{in}]$




input
output → Cell state → remove

(3x1) ⊗ (3x1)

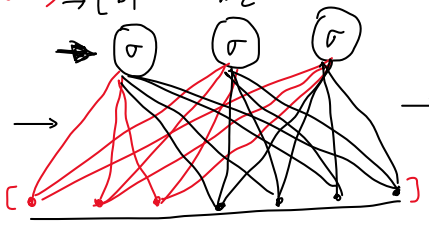
→ 1) Calculate $f_t$
2) $C_{t-1} \otimes f_t$

σ σ σ

$f_1$ $f_2$ $f_3$ → $[f_1\ f_2\ f_3]$ → $f_t(3)$

$b_1$ $b_2$ $b_3]$ (3x1) (3x7) (7x1)

→ (3x1) + (3x1) = (3x1)




→ $W_{3x7}$ (21 weights) 21 wts
biases 4 biases

→ 7x1

forget gate ← 0%
50%
100%

remove

$[h_{t-1}, x_t]$

long term

$f_t$

$[4\ 5\ 6]$

$C_{t-1}$ $f_t$ $[0\ 0\ 0]$ $[\frac{1}{2}\ \frac{1}{2}\ \frac{1}{2}]$ ⊗

$[1\ 1\ 1]$

$[2\ 2.5\ 3]$

$[4\ 5\ 6]$

$[0\ 0\ 0]$ → 100% remove

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

(3x1) (3x7) (7x1) (3x1) + (3x1) → (3x1) (3x1)

removal

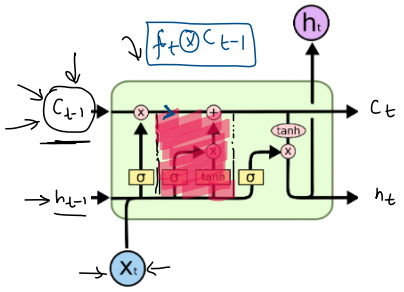
$f_t \otimes C_{t-1}$ → (3x1)

$(C_{t-1})$ → remove

# The Input Gate

30 August 2023 04:38

add some new imp info to ml $C_t$



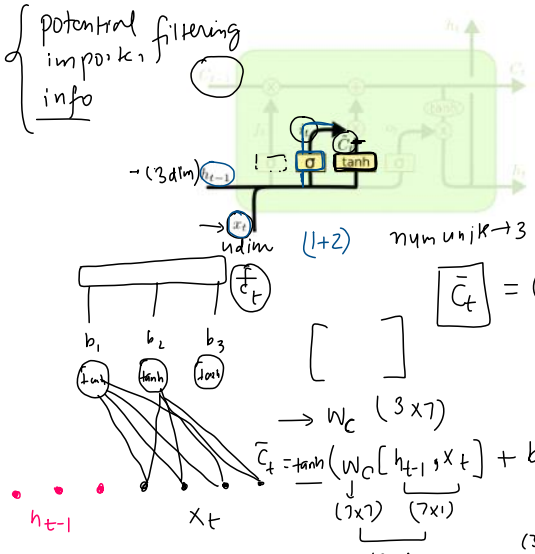

stages

1> $\bar{C}_t$ candidate cell state

2> $i_t$

3> $C_t$ → current cell state

potential filtering important info



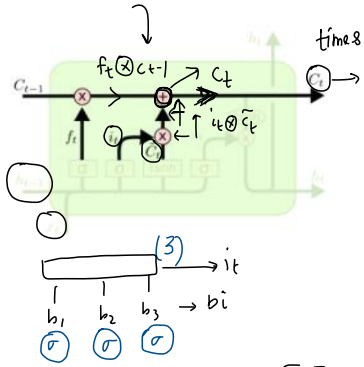

$\bar{C}_t$ = (3x1)

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

$W_C$ (3x7)

(3x7) (7x1) (3x1)

(3x1) → (3x1)




pointwise $i_t \otimes \bar{C}_t \rightarrow \bar{C}_t^*$ (filtered candidate cell state)

(3x1) (3x1)

[0.5 0.5 0.5] [4 5 6]

1 1 1 ↓ 50% 0% 100%

[2, 2.5 3]

$C_t = f_t \otimes C_{t-1} \oplus i_t \otimes \bar{C}_t$

→ [ ] $W_i$

$h_{t-1}$ $X_t$

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

(3x7) (7x1) (3x1)

(3x1) → (3x1)

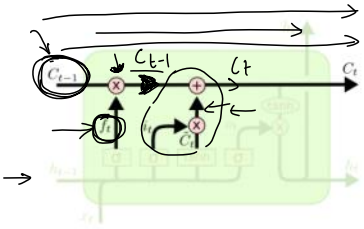
$i_t$ - filter

$\bar{C}_t \rightarrow C_t$

10%

[4 5 6] → [4 5 6]

t=t-1 t=t



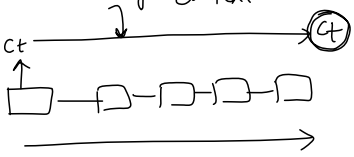

$f_t = [1\ 1\ 1]$

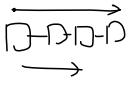
$i_t \otimes \bar{C}_t = [0\ 0\ 0]$

[4 5 6] [0 0 0]

$C_t = [4\ 5\ 6]$

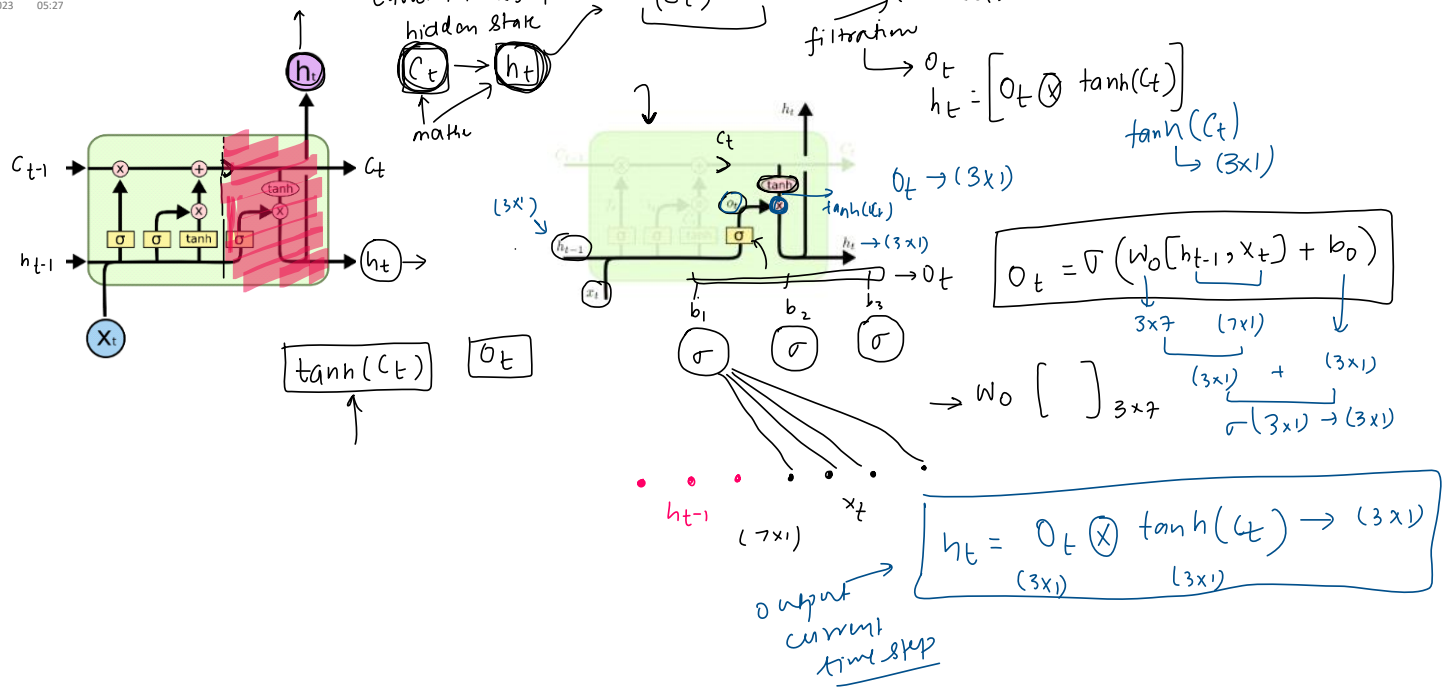
long term context



# The Output Gate

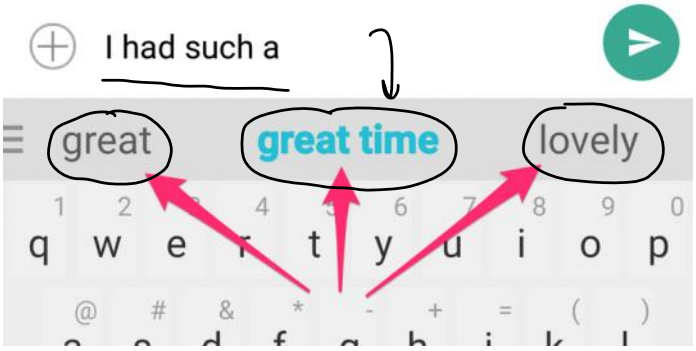
30 August 2023 05:27

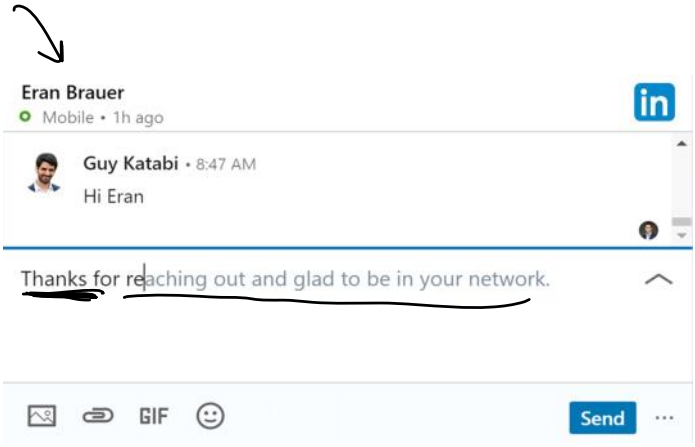


# What is a Next Word Predictor

08 September 2023 08:50

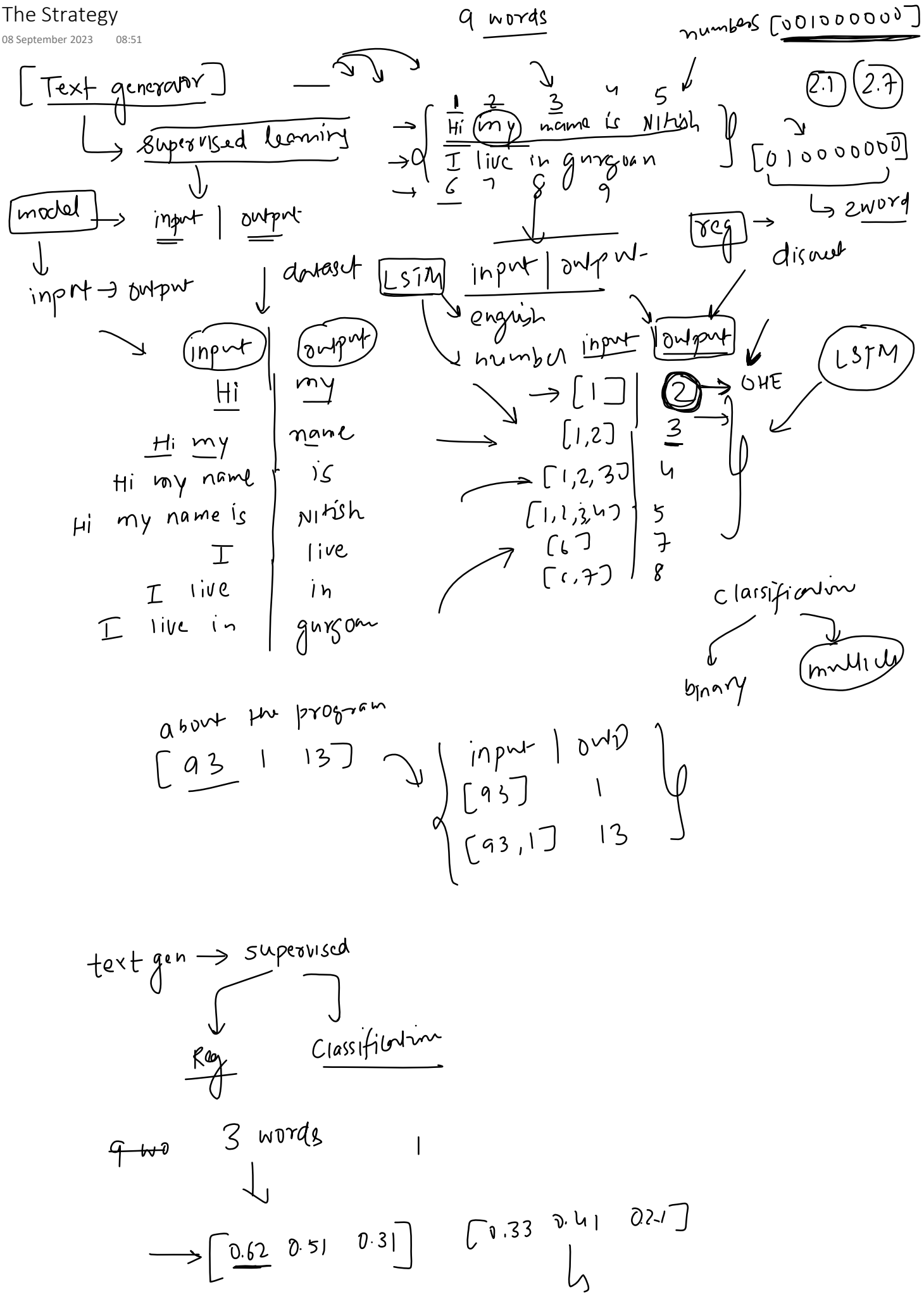
code

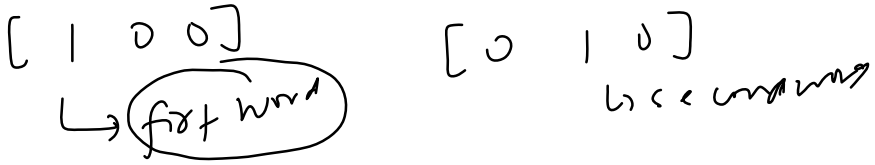


# The Strategy

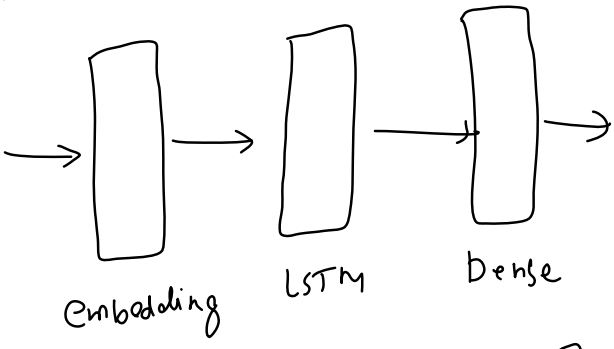
08 September 2023 08:51

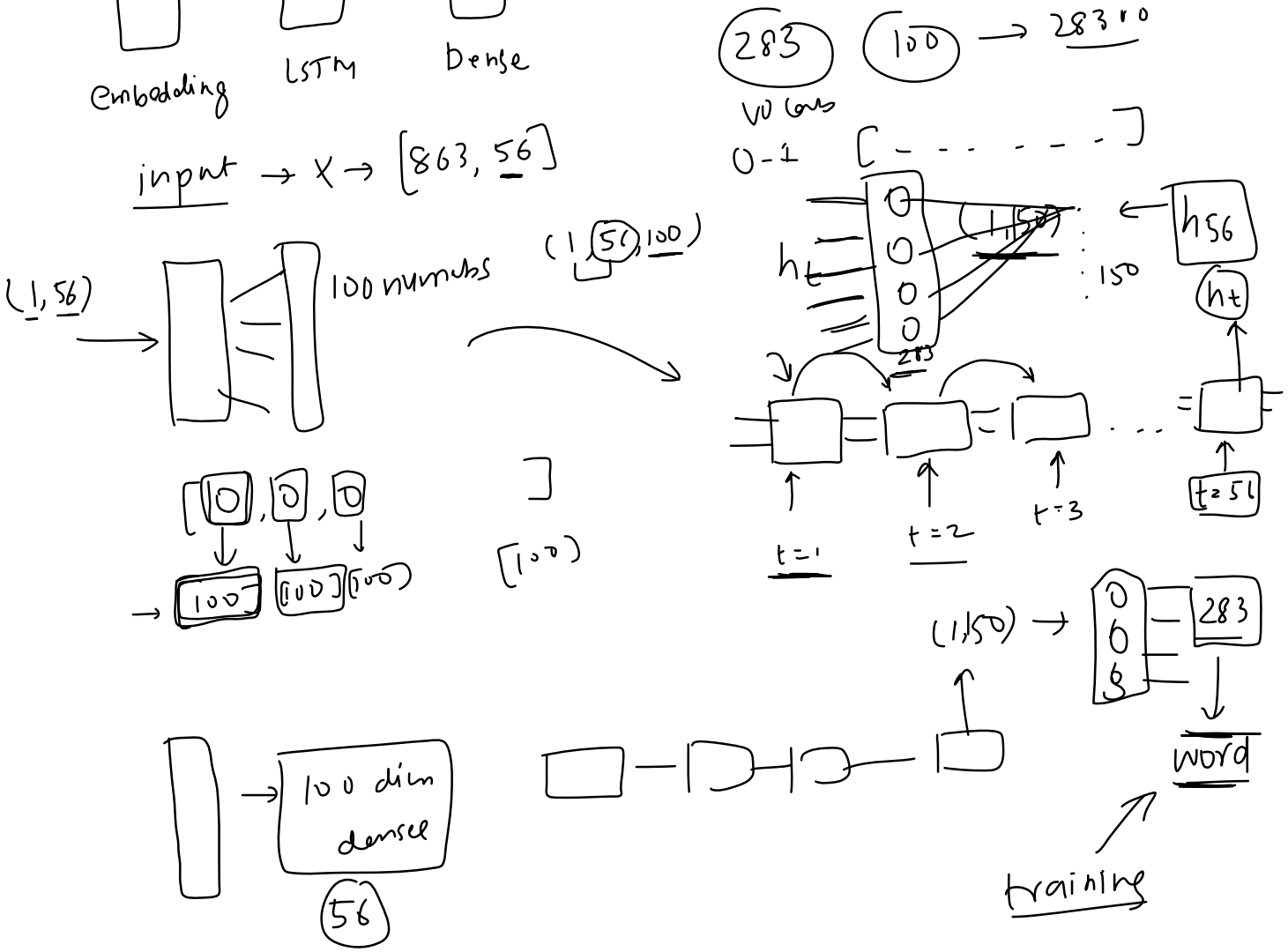



[ 1 0 0 ]
first word
[ 0 1 0 ]

# The Architecture

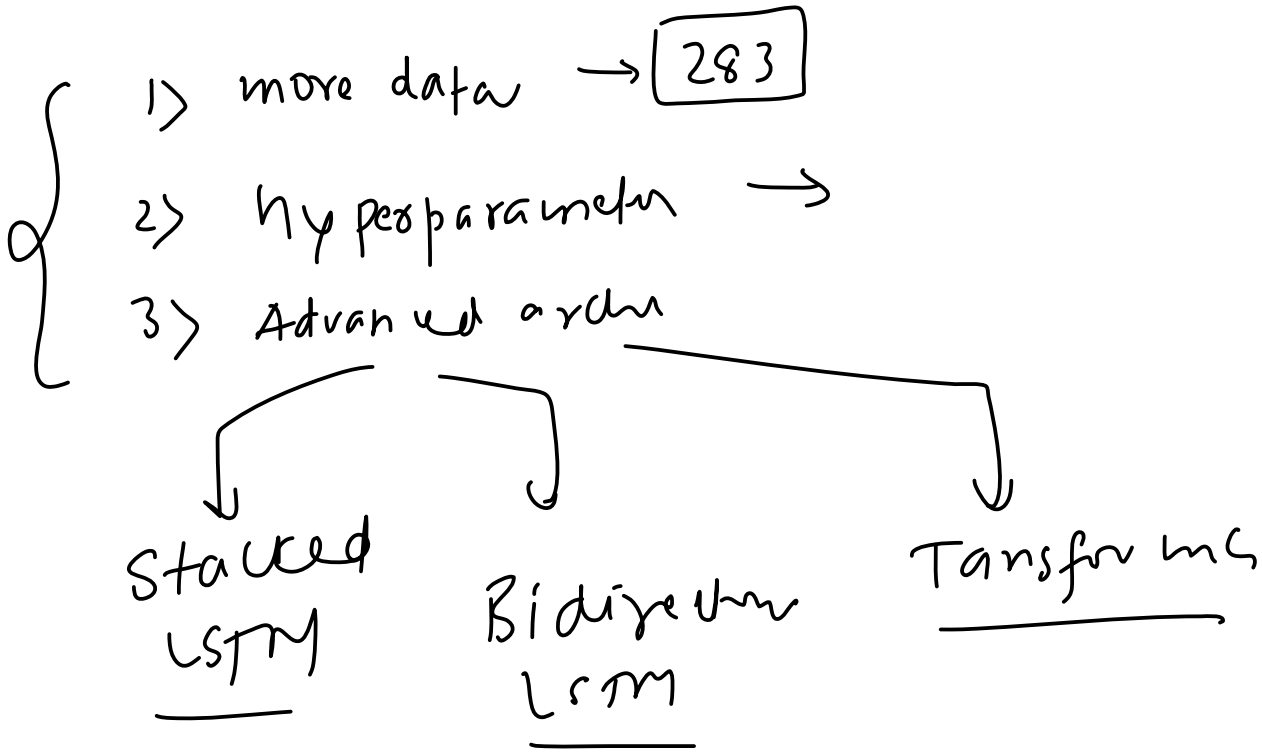
08 September 2023 08:55



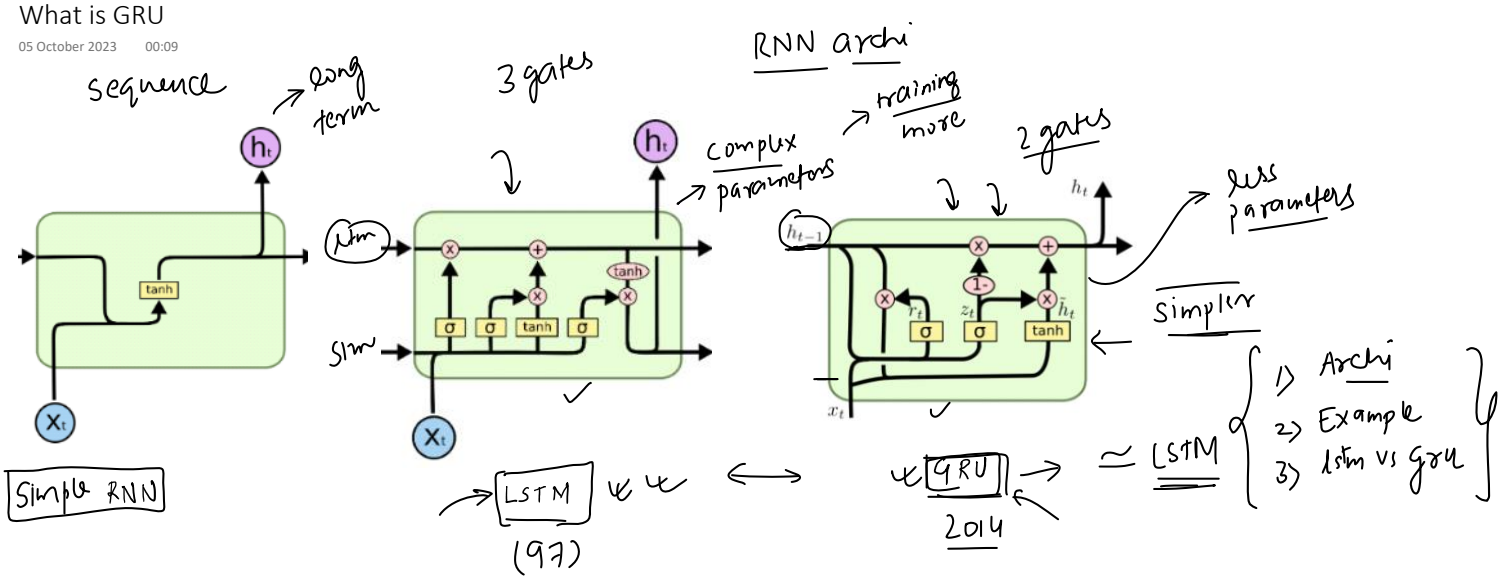
# How to improve performance?

08 September 2023 08:51



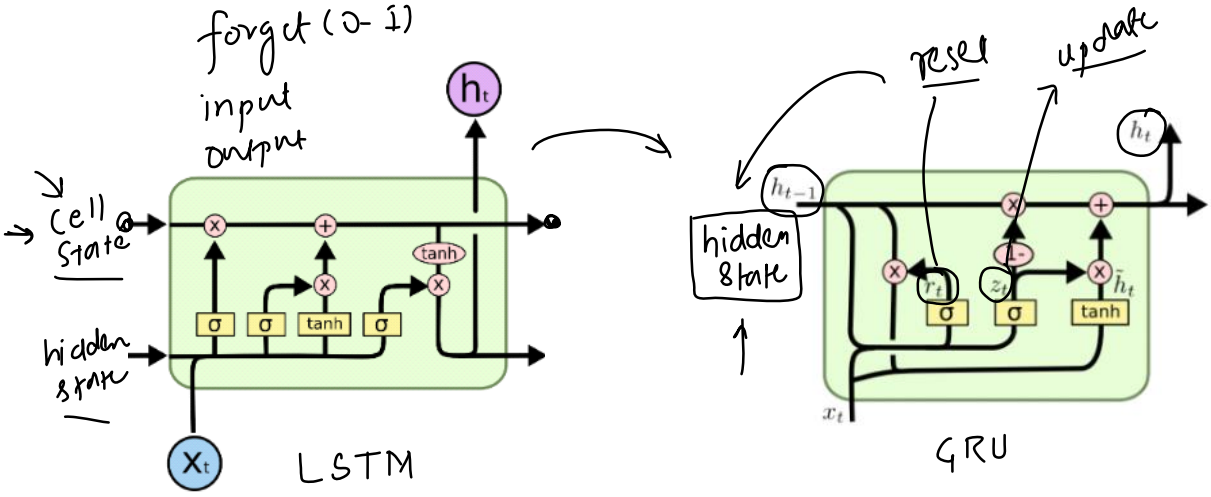
# What is GRU

05 October 2023 00:09



# The Big Idea Behind GRU

05 October 2023 00:47

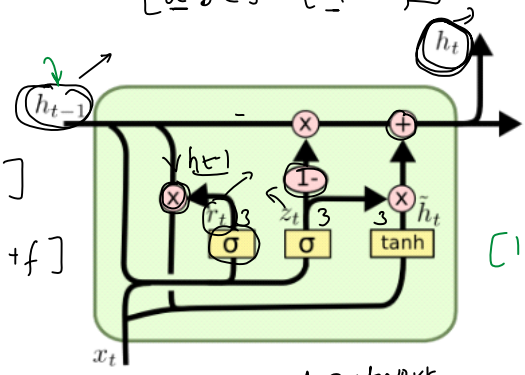


# The Setup

05 October 2023 01:07

→ Advise → LSTM / GRU → confusing

goal → t




[a b c] [d e f]

[ad be cf]

[a+d b+e c+f]

neural network layers (FC layers)

prev hidden state — curr hidden state — input

$h_{t-1}$, $x_t$ → $h_t$

vectors

$h_{t-1}$, $h_t$, $x_t$, $r_t$, $z_t$, $\tilde{h}_t$ ? → candidate hidden state

σ, tanh ?

reset gate, update gate

[1 2 3 4]

x + 1- ?

[1 2 3 4] dim same

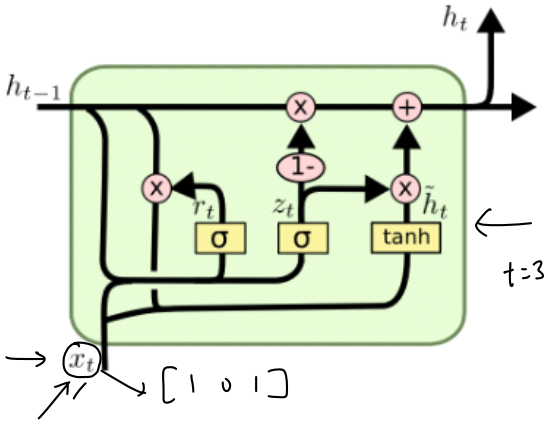
number of = 5 6

10

σ → σ σ σ σ σ

# The Input Xt

05 October 2023 01:52




OHE / BOW / Word2Vec

Sentiment

| text | review |
|---|---|
| cat mat rat | 1 |
| cat rat rat | 0 |
| → mat rat mat | 1 |

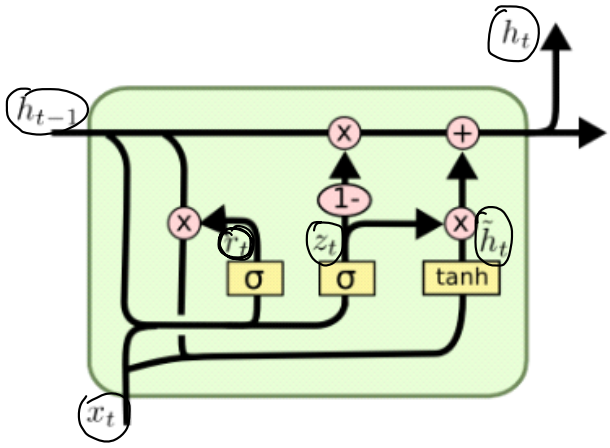
S1 [1 0 0] [0 1 0] [0 0 1]

S2 [1 0 0] [0 0 1] [0 0 1]

S3 [0 1 0] [0 0 1] [0 1 0]

# Architecture

05 October 2023 02:10



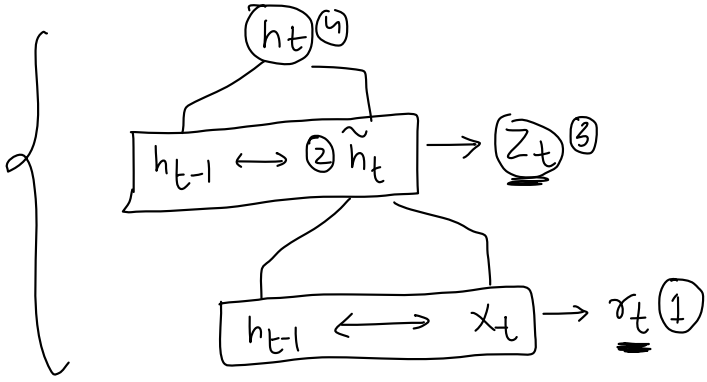

$h_{t-1}$ , $x_t$ ⟶ $h_t$

→ 1) Calculate $r_t$ (reset gate)

→ 2) Calculate $\tilde{h}_t$ (candidate hidden state)

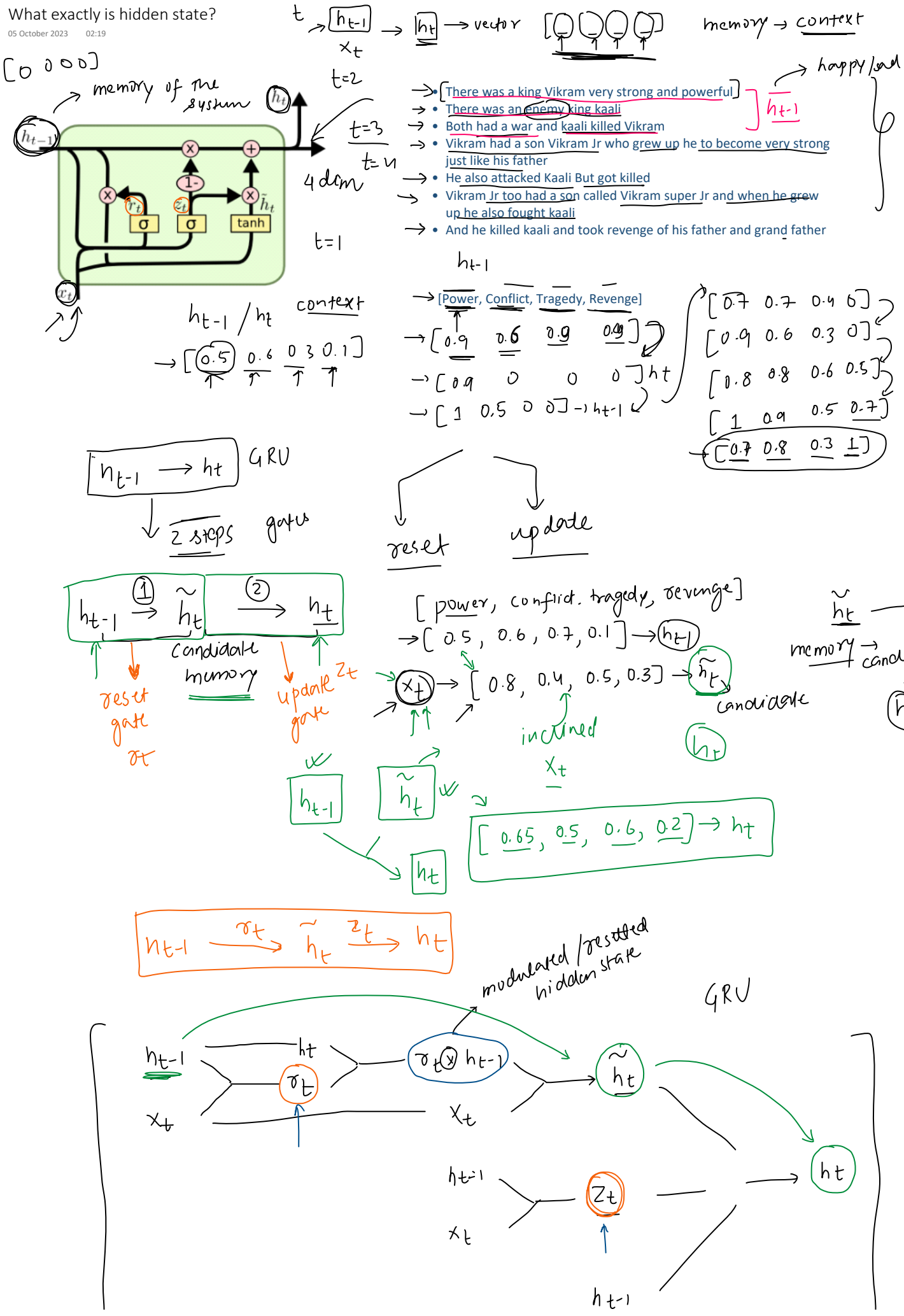
→ 3) Calculate $z_t$ (update gate)

→ 4) Calculate $h_t$ (current hidden state)



What exactly is hidden state?

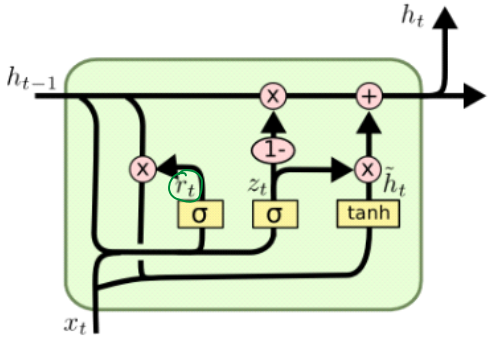
05 October 2023 02:19




$h_{t-1}$

Calculating the reset gate

05 October 2023 14:24




reset

$r_t$ → vector → $h_{t-1}$

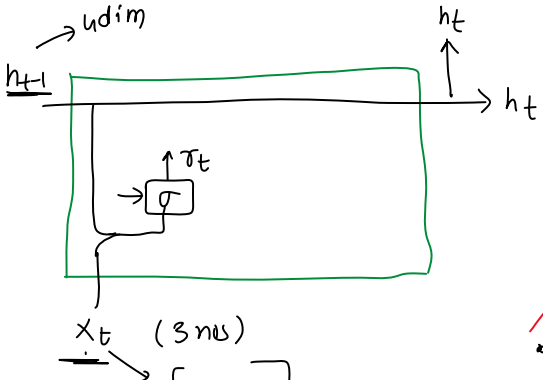
↳ gate

$h_{t-1} = [0.6, 0.6, 0.7, 0.1]$ (lower lower higher)

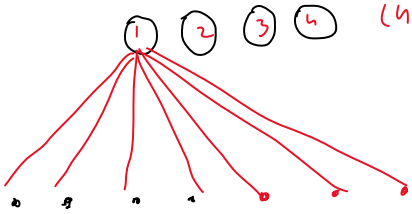
$r_t = [0.8, 0.2, 0.1, 0.9]$

gate

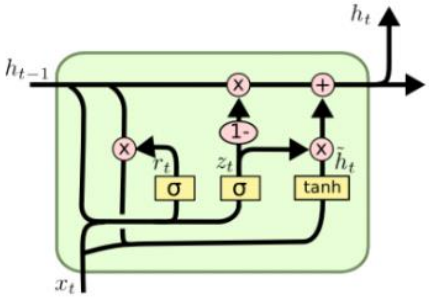
80% percent 20% 90%




$r_t = \sigma(W_r[h_{t-1}, x_t] + b_r)$




← (7x4) = 28 + 4




$h_{t-1}$ modulated reseted

$h_{t-1}$ → $h_{t-1}$, $r_t$, $x_t$ → $r_t \otimes h_{t-1}$ → $\tilde{h}_t$

(1x7) (7x4)

(1x4) + (1x4) → ((1x4))

(1x4) → $r_t$

$h_t$

$h_{t-1} = [0.6, 0.6, 0.7, 0.1]$

$r_t = [0.8, 0.2, 0.1, 0.9]$

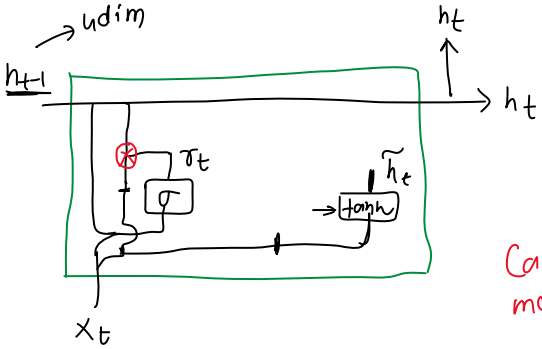
90%

power conflict tragedy revenge

$\tilde{h}_t = [0.7\ 0.2\ 0.1\ 0.2]$

$x_t$

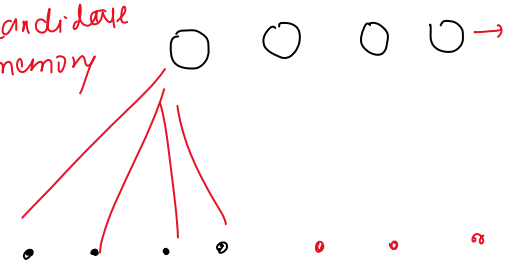
$h_{t-1} \otimes r_t = [0.48, 0.12, 0.07, 0.09]$ → $x_t$

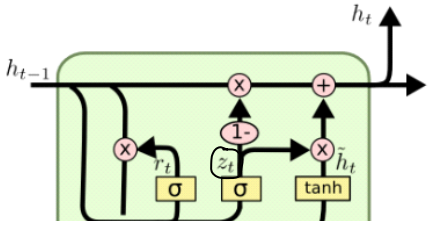



$h_{t-1}$ / $\tilde{h}_t$ → $z_t$

$\tilde{h}_t = \tanh(W_c[h_{t-1} \otimes r_t, x_t] + b_c)$

Candidate memory



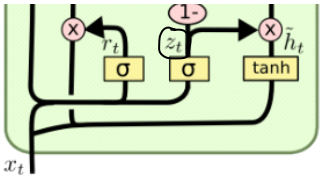




$h_{t-1}$ → $h_{t-1}$, $r_t$, $x_t$ → $r_t \otimes h_{t-1}$ → $\tilde{h}_t$

$\tilde{h}_t = [0.7\ 0.2\ 0.1\ 0.2]$

$h_{t-1} = [0.6\ 0.6\ 0.7\ 0.1]$

$h_{t-1}$ → $z_t$




$h_{t-1}$ $x_t$ → $z_t$

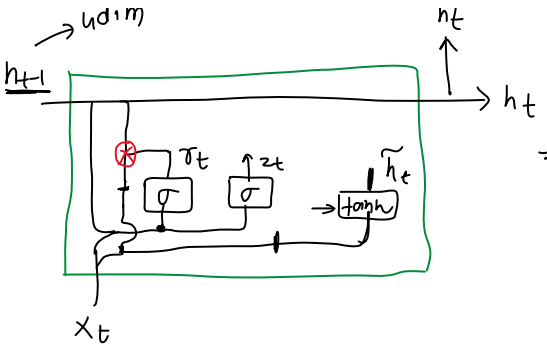
$[[ - - - - ]]$ (0-1)

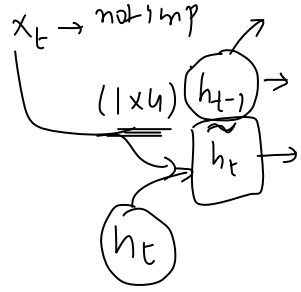
gate $z_t = \sigma(W_z[h_{t-1}, x_t] + b_z)$

$h_{t-1}$ and $\tilde{h}_t$ ($h_t$)

$x_t$ → important

$x_t$ → not imp

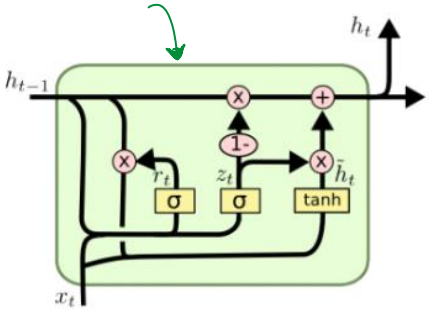



→ bias(4)

→ (7x4)

$h_{t-1}$




$\tilde{h}_t = [0.7\ 0.2\ 0.1\ 0.2]$

$h_{t-1} = [0.6\ 0.6\ 0.7\ 0.1]$

$z_t = [0.1\ 0.7\ 0.8\ 0.2]$

$h_t$ [0.07 0.14 0.08 0.04]

0.1 0.1

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

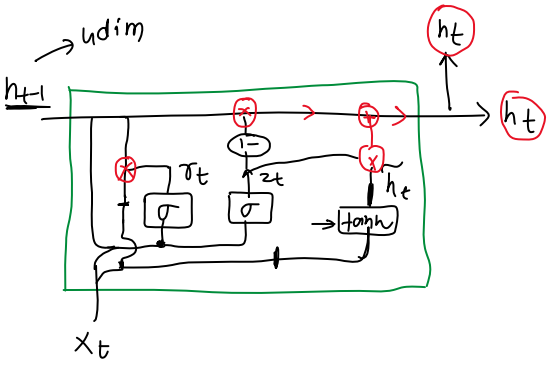
$(1-z_t)$ → 0.9

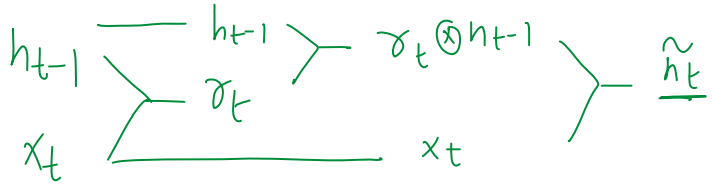
$(1-z_t)$ [0.9 0.3 0.2 0.8] [0.6 0.6 0.7 0.1]

[0.54 0.18 0.14 0.08]

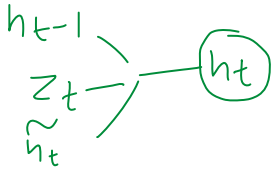
$h_t$ [0.61 0.32 0.22 0.12]

power conflict tragedy revenge







# LSTM vs GRU

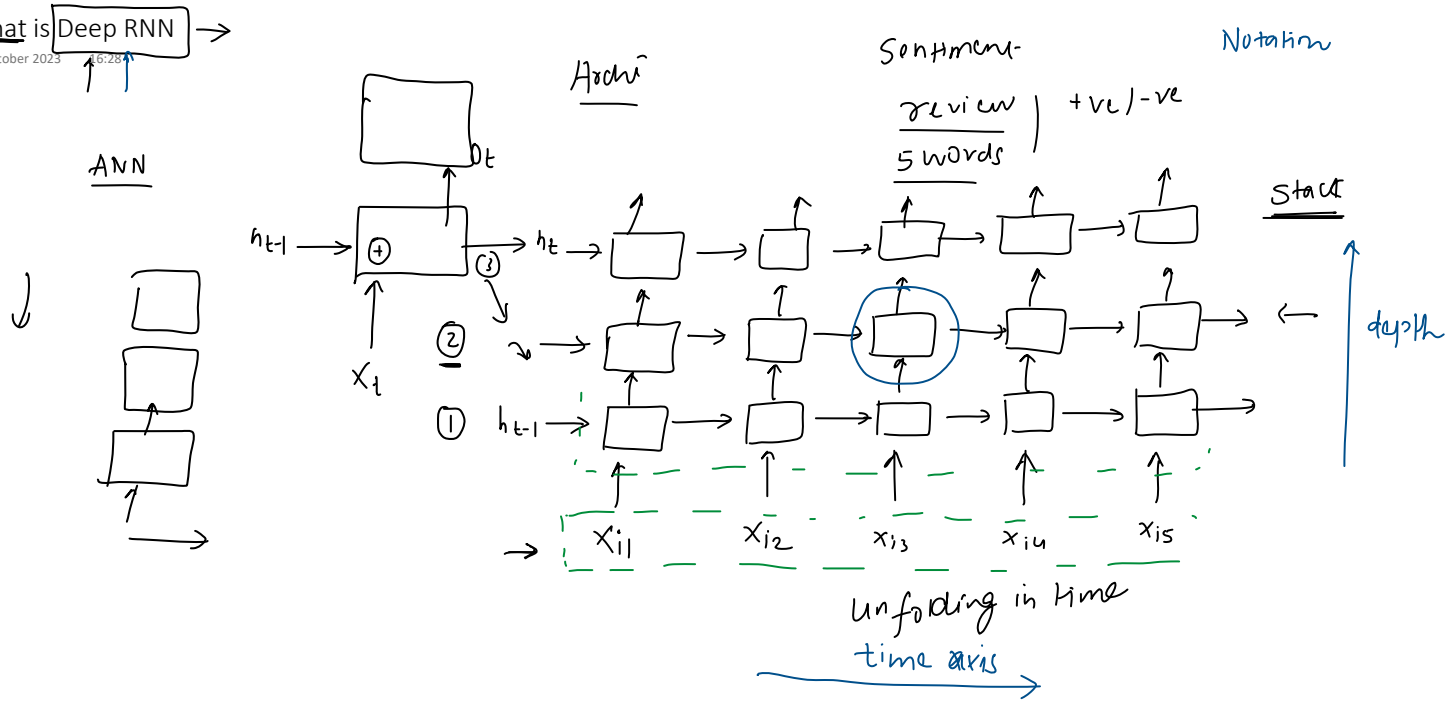
05 October 2023 16:45

Here are the main differences between LSTM and GRU:

1. Number of Gates:
   - LSTM: Has three gates — input (or update) gate, forget gate, and output gate.
   - GRU: Has two gates — reset gate and update gate.
2. Memory Units:
   - LSTM: Uses two separate states - the cell state (ct) and the hidden state (ht). The cell state acts as an "internal memory" and is crucial for carrying long-term dependencies.
   - GRU: Simplifies this by using a single hidden state (ht) to both capture and output the memory.
3. Parameter Count:
   - LSTM: Generally has more parameters than a GRU because of its additional gate and separate cell state. For an input size of d and a hidden size of h, the LSTM has 4 ×((d×$h$)+($h$×$h$)+$h$)4×((d×h)+(h×h)+h)parameters.
   - GRU: Has fewer parameters. For the same sizes, the GRU has 3×((d×$h$)+($h$×$h$)+$h$)3 ×((d×h)+(h×h)+h)parameters.
4. Computational Complexity:
   - LSTM: Due to the extra gate and cell state, LSTMs are typically more computationally intensive than GRUs.
   - GRU: Is simpler and can be faster to compute, especially on smaller datasets or when computational resources are limited.
5. Empirical Performance:
   - LSTM: In many tasks, especially more complex ones, LSTMs have been observed to perform slightly better than GRUs.
   - GRU: Can perform comparably to LSTMs on certain tasks, especially when data is limited or tasks are simpler. They can also train faster due to fewer parameters.
6. Choice in Practice:
   - The choice between LSTM and GRU often comes down to empirical testing. Depending on the dataset and task, one might outperform the other. However, GRUs, due to their simplicity, are often the first choice when starting out.

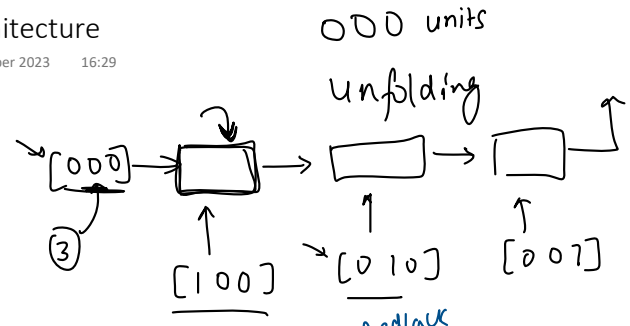
What is Deep RNN →

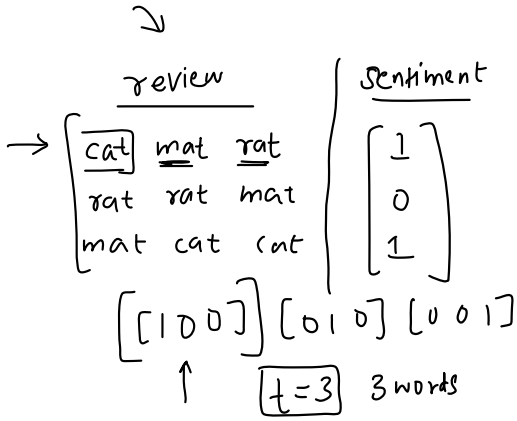
17 October 2023 16:28

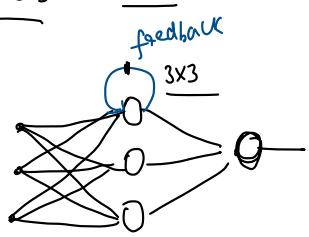


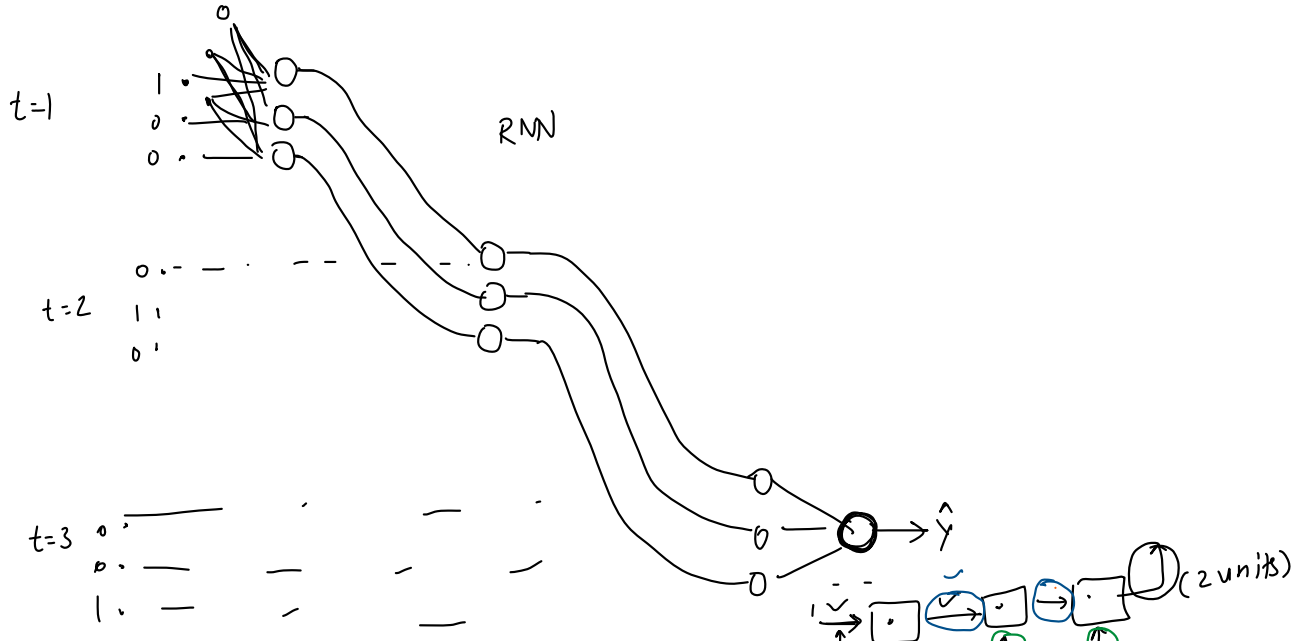
Architecture

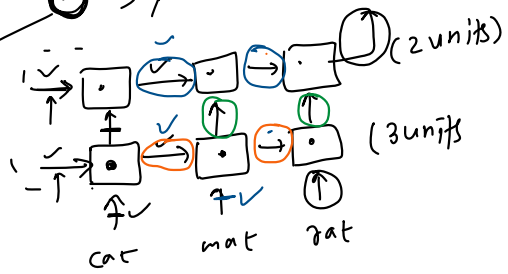
17 October 2023 16:29

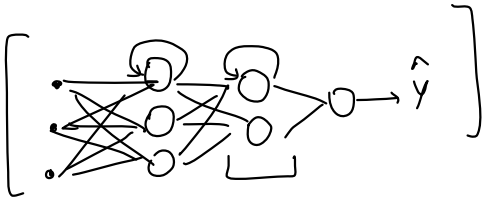


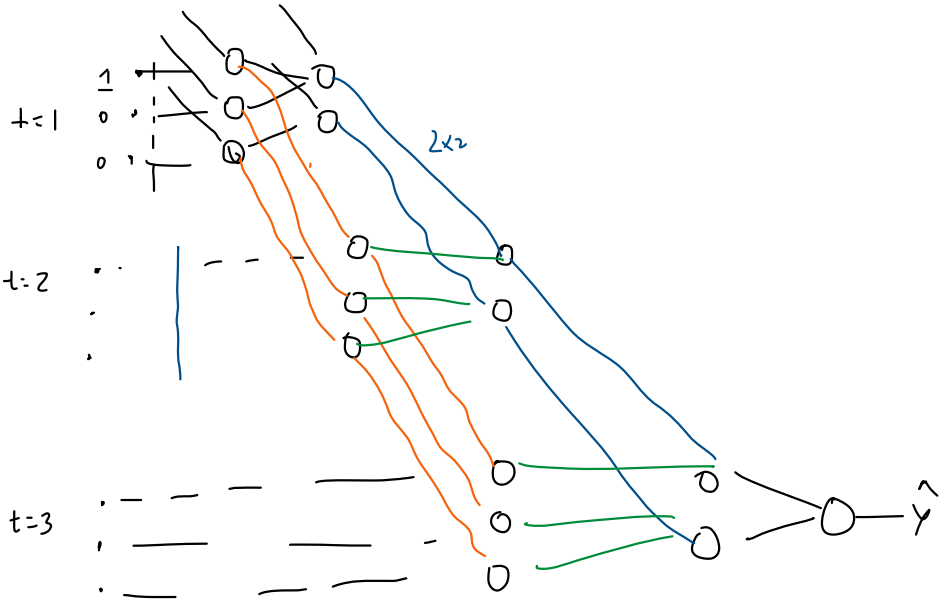



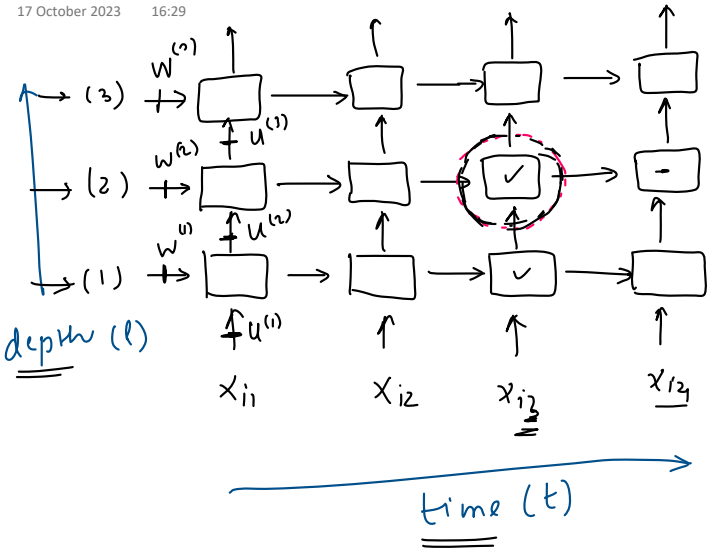



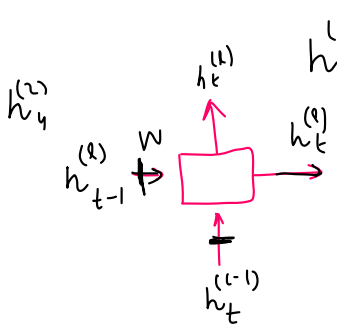




t=3

# Notation

17 October 2023 16:29



$$h_t^{(l)} = \tanh\left( W^{(l)} h_{t-1}^{(l)} + U^{(l)} h_t^{(l-1)} + b^{(l)} \right)$$

Why and When to use?

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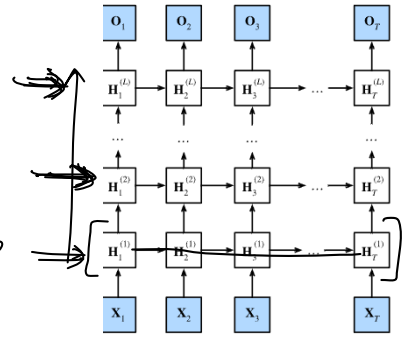
deep RNN

Stack

product

sentence

1. Hierarchical Representation ✓
2. Customization for Advanced Tasks




encoder-decoder

machine

deep RNNs

love hate amazing terrible

deep RNN

Audio is bad

Display is great

Overall I am happy

→ sentiment

When to use Deep RNNs?

Complex tasks

Speech recog

Machine translation

Large datasets

Overfitting

Computational

Simpler Models

Deep RNN

# Code Example

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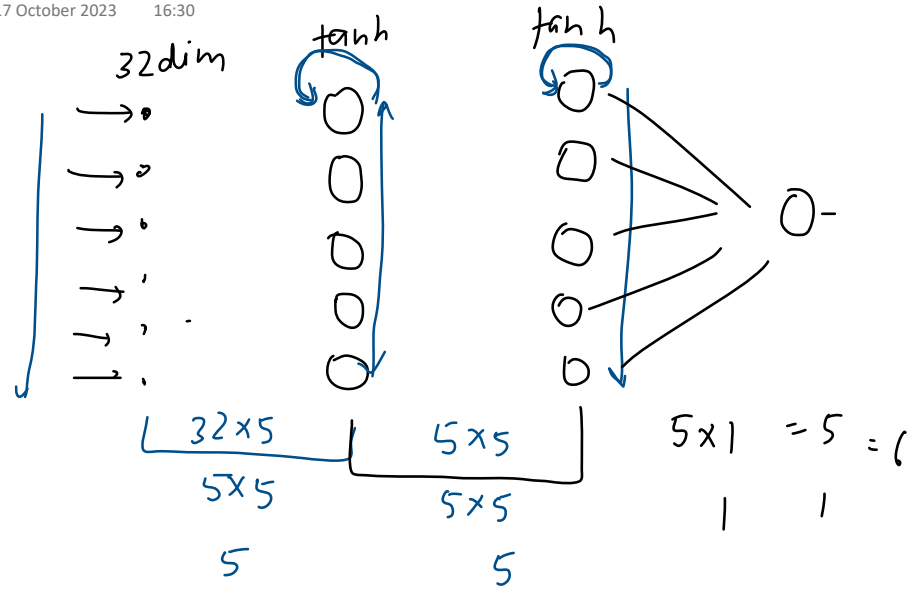



→ embedded

10000 x 32 = 3,20,000

simple RNN 1

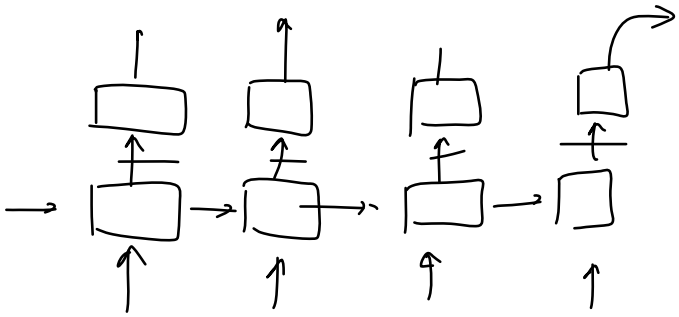
190

simple RNN 2

55

Dense

6



# Variants

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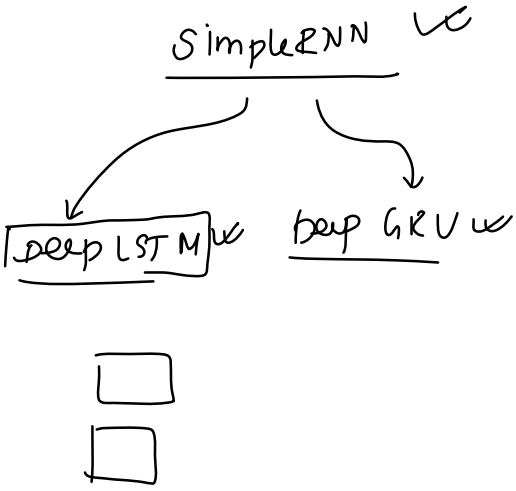


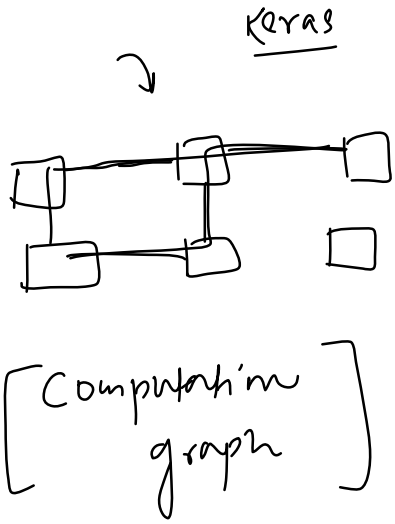

# Disadvantages

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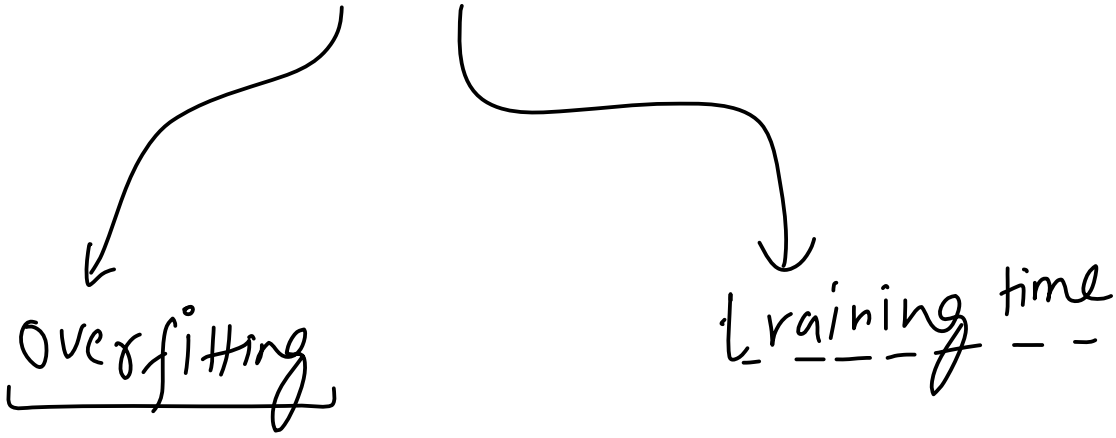

The Why?
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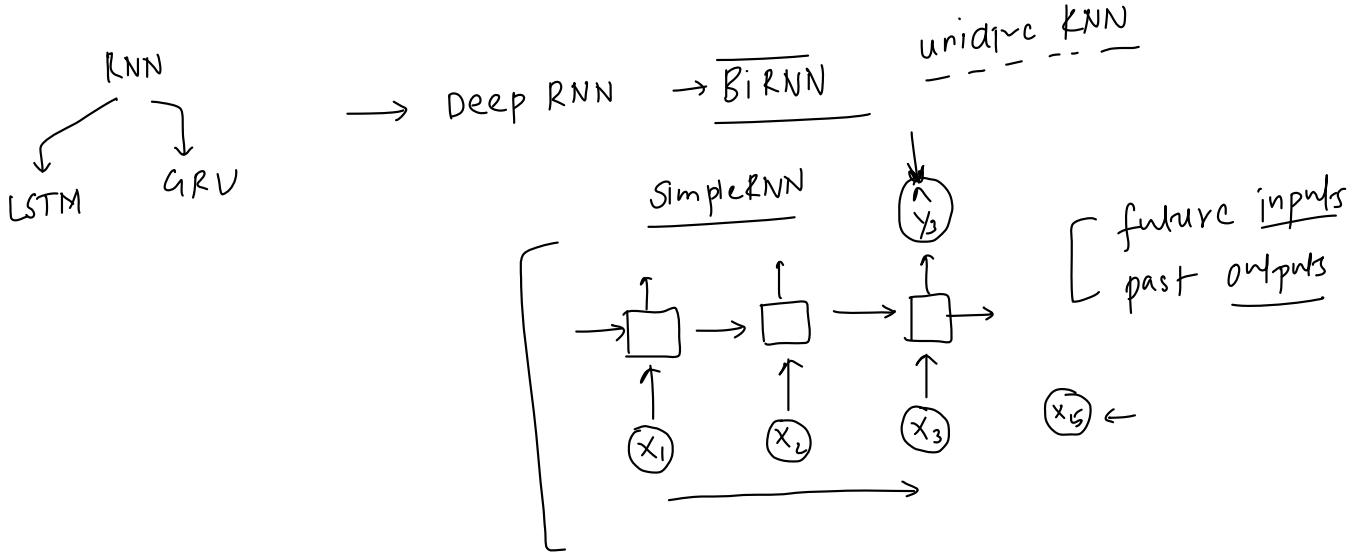
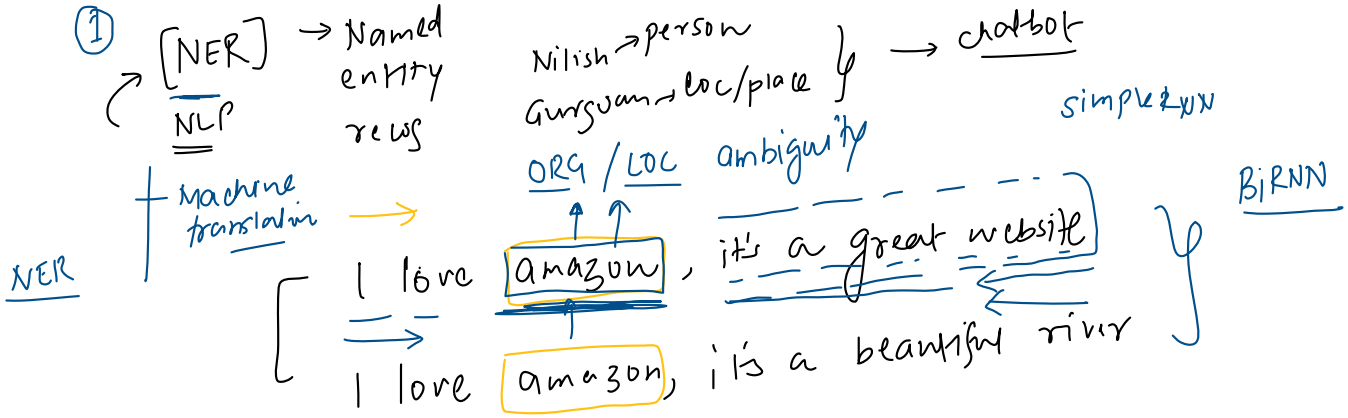
# BiRNN



# Bidirectional RNN Architecture

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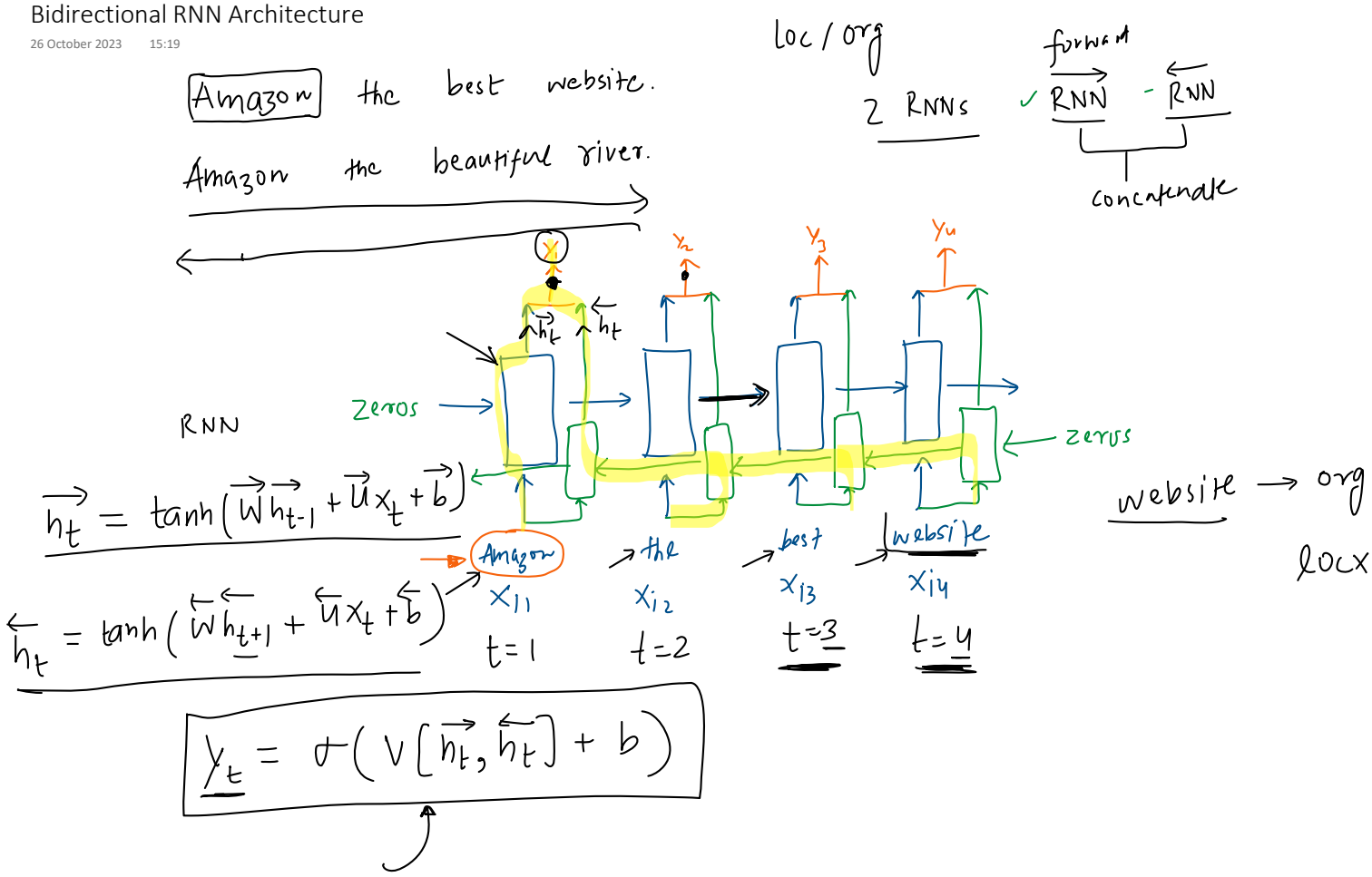
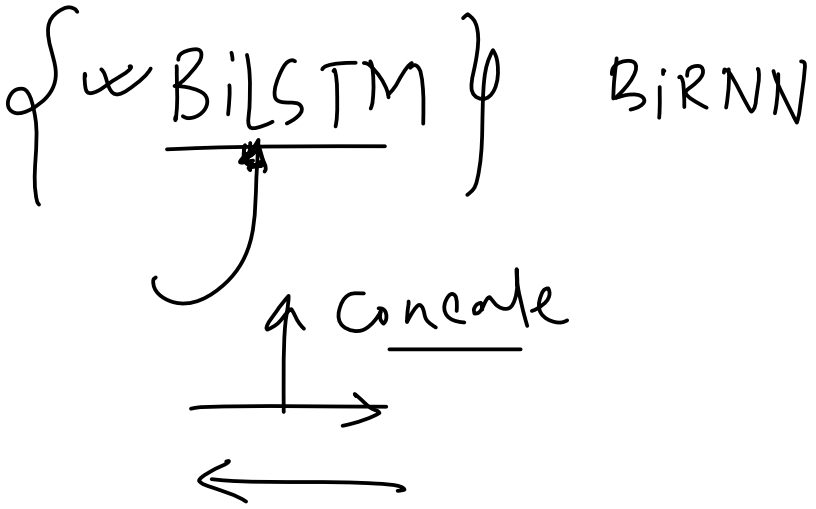


# Code

26 October 2023 15:21



# Applications and Drawbacks

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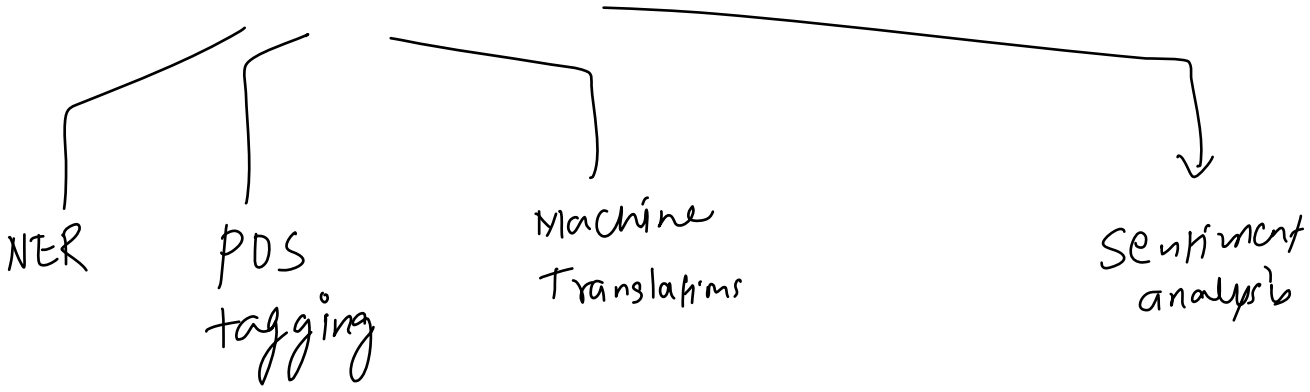


[Time series forecasting]

→ ←

→ Complexity → 190 → 380 → training → overfitting
double

→ → ← [Speech recog] → bi rnn
↳ latency → slow