GATES, LSTM

Deep Neural Networks

Session 20

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Agenda

- LSTM
- LSTM vs GRU
- Bidirectional RNN
- Putting all together – Deep RNN
- Attention Model

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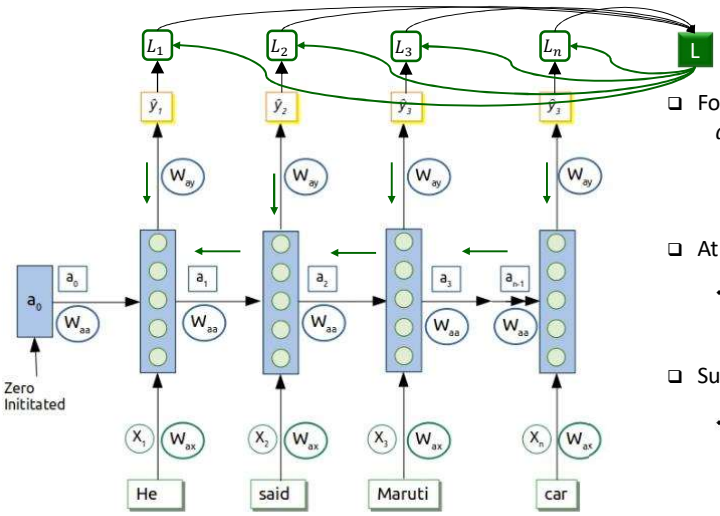
Back Propagation



Recurrent Neural Network

- Forword propagation:

$$a_t = g_1([a_{t-1}, x_t] \,.\, W_a + b_a)$$
$$\hat{y}_t = g_2(a_t . W_y + b_y)$$

- At time step 't'; Loss Function for single prediction
  - $L_t(\hat{y}_t, y) = - y_t \,.\, \log(\hat{y}_t) - (1 - y_t) \,.\, \log(1 - \hat{y}_t)$
- Sum of losses at all time steps:
  - $L(\hat{y}, y) = \sum_{t=1}^{T_y} L_t(\hat{y}_t, y)$

Back Propagation through Time.

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Long Short Term Memory network – LSTM

- A special kind of RNN, capable of learning long-term dependencies
- Introduced by Hochreiter & Schmidhuber (1997)
- Were refined and popularized by many people in following work
- LSTM were on a kind of back burner till 2013
- Original paper is quite mathematical and little overwhelming to follow
  - It goes into depths of Exploding and Vanishing Gradients
  - AI Community could not appreciate its value at that time

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Long Short Term Memory network – LSTM

- LSTM work tremendously well on a large variety of problems, and are now widely used.
  - Speech recognition, Language modeling, Translation, Image captioning…
- LSTMs are explicitly designed to avoid the long-term dependency problem
- Designed to remember information for multiple time steps
- The key to LSTMs is the cell state
  - We have seen similar cell in GRU
- The cell state carry information through either unchanged or with updates

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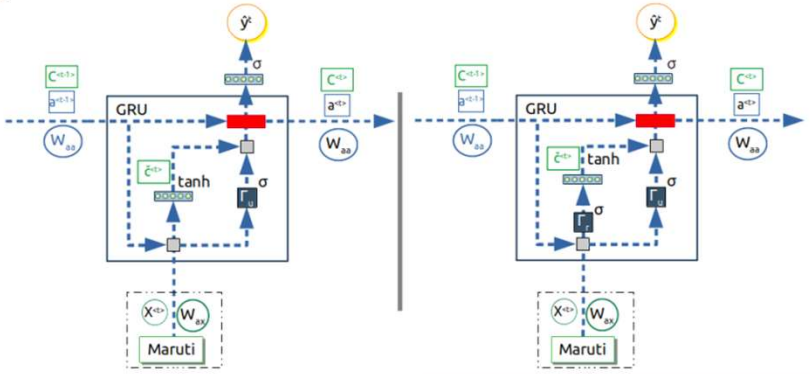
GRU Cell



$a_t = g^1(a_{t-1} \cdot W_{aa} + X_t \cdot W_{ax} + b_a)$

[100,100] [100, 100] [100,10000] [10000, 100]

$\hat{y}_t = g^2(a_t \cdot W_{ya} + b_y)$

$a_t = g^1([a_{t-1} : X_t] \cdot W_a + b_a)$

$\hat{y}_t = g^2(a_t \cdot W_y + b_y)$

$[a_{t-1} : X_t] = [a_{t-1} : X_t]$ [100] [100 x 10100] [100] [10000]

$W_a = \begin{pmatrix} W_{aa} \\ W_{ax} \end{pmatrix}$ [100] [10000]

Simple GRU:

$\check{C}^{<t>} = \tanh([C^{<t-1>} : X^{<t>}] \cdot W_c + b_c)$

$\Gamma_u = \sigma([C^{<t-1>} : X^{<t>}] \cdot W_u + b_u)$

$C^{<t>} = \Gamma_u \cdot \check{C}^{<t>} + (1 - \Gamma_u) \cdot C^{<t-1>}$

If $\Gamma_u = 1$ then $C^{<t>}$ will be equal to $\check{C}^{<t>}$,
If $\Gamma_u = 0$ then $C^{<t>}$ will be equal to $C^{<t-1>}$.

GRU:

$\check{C}^{<t>} = \tanh([\Gamma_r * C^{<t-1>} : X^{<t>}] \cdot W_c + b_c)$

$\Gamma_u = \sigma([C^{<t-1>} : X^{<t>}] \cdot W_u + b_u)$

$\Gamma_r = \sigma([C^{<t-1>} : X^{<t>}] \cdot W_r + b_r)$

$C^{<t>} = \Gamma_u \cdot \check{C}^{<t>} + (1 - \Gamma_u) \cdot C^{<t-1>}$

If $\Gamma_r = 1$ then consider $C^{<t-1>}$ in $\check{C}^{<t>}$ calculations,
If $\Gamma_r = 0$ then do not consider $C^{<t-1>}$ in $\check{C}^{<t>}$ calculations.

If $\Gamma_u = 1$ then $C^{<t>}$ will be equal to $\check{C}^{<t>}$,
If $\Gamma_u = 0$ then $C^{<t>}$ will be equal to $C^{<t-1>}$.

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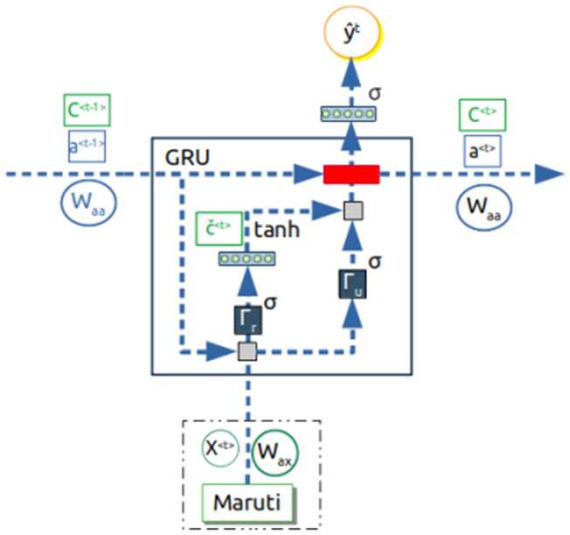
7 GRU Cell



- Recall our discussions on GRU

Extended GRU:

$\check{c}_t = \tanh([\Gamma_r * c_{t-1} : x_t] . W_c + b_c)$
$\Gamma_u = \sigma([c_{t-1} : x_t] . W_u + b_u)$
$\Gamma_r = \sigma([c_{t-1} : x_t] . W_r + b_r)$
$c_t = \Gamma_u . \check{c}_t + (1 - \Gamma_u) . c_{t-1}$

If $\Gamma_u = 1$ then c_t will be equal to $\check{c}_t$,
If $\Gamma_u = 0$ then c_t will be equal to c_{t-1}

And as usual $a_t = c_t$

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8 Long Short Term Memory network – LSTM

- Information can be removed or added to the cell state
- The structure regulating the information is called gates
- Gates are a way to optionally let information through or otherwise.
- Gates have sigmoid activation resulting in almost 0, 1 (all or nothing) kind of behavior

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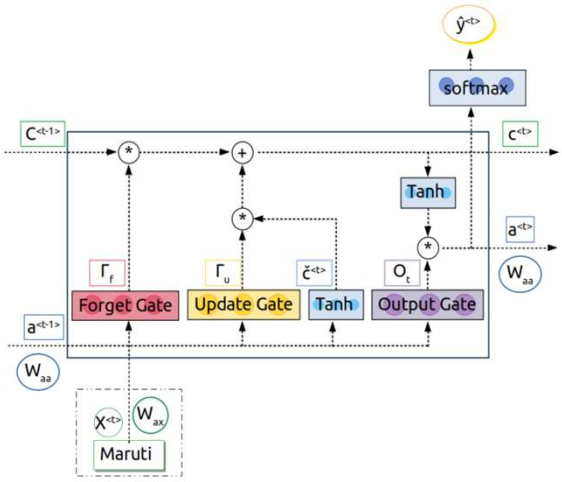
Overall



- Lets make a few changes in GRU Cell

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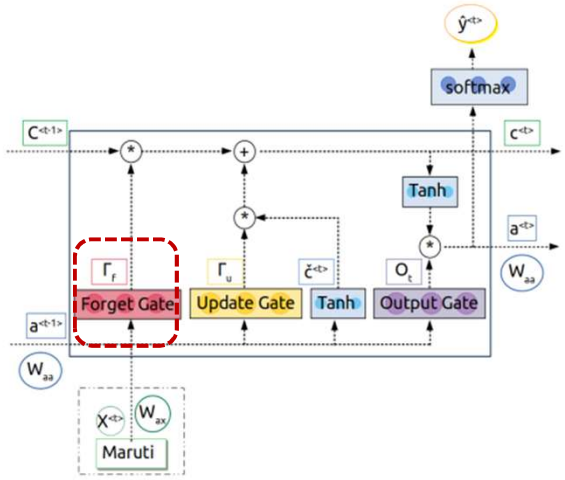
Forget Gate



- Lets make a few changes in GRU Cell
  - Equation $c_t = \Gamma_u * \hat{c}_t + (1- \Gamma_u) * c_{t-1}$ is modified to
  - Equation $c_t = \Gamma_u * \hat{c}_t + \Gamma_f * c_{t-1}$
- Forget gate decides what information to throw away from the cell state
  - $\Gamma_f = \sigma ([a_{t-1} : X_t] . W_f + b_f)$
- Forget gate value is between 0 and 1 depending upon a_{t-1} and X_t.
  - 1 represents “completely keep this”
  - 0 represents “completely get rid of this”
  - Or something “in-between”…

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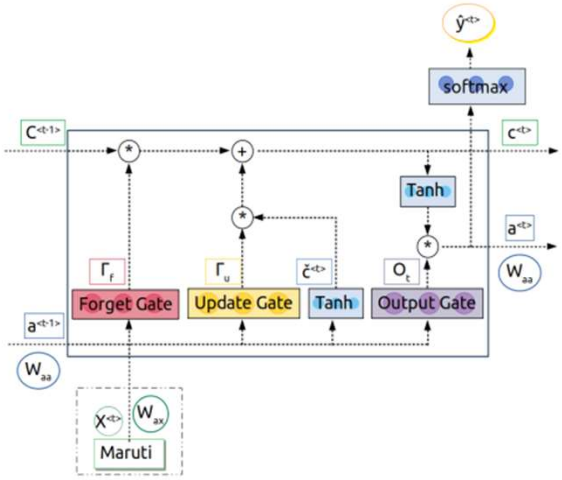
11 Forget Gate



I **felt happy** because I saw the others **were happy**

Keep

Keep

and because I knew I should **feel happy**, but I

Forget

wasn't really happy.

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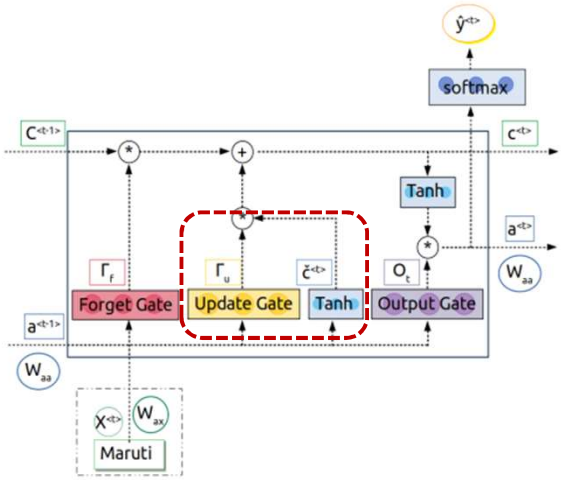
12 Update Gate



- What new information we're going to store in the cell state.
- Two step Process
  - First, a sigmoid layer called the "Update Gate" decides which values we'll update
  - $\Gamma_u = \sigma([a_{t-1} : X_t] \cdot W_u + b_u)$
- Next, a tanh layer creates a vector of new candidate values, $\hat{c}_t$
  - $\hat{c}_t = \tanh([a_{t-1} : X_t] \cdot W_c + b_c)$
- Next step, combine these two to create an update to the state.
  - $c_t = \Gamma_u * \hat{c}_t + \Gamma_f * c_{t-1}$

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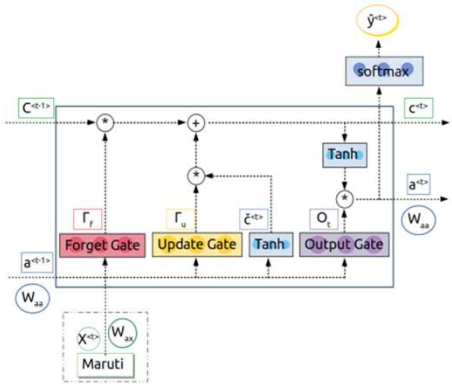
13 Update Gate



New, update

Keep

I **felt happy** because I saw the others **were happy**

Keep

and because I knew I should **feel happy**, but I

forget, update

wasn't really happy.

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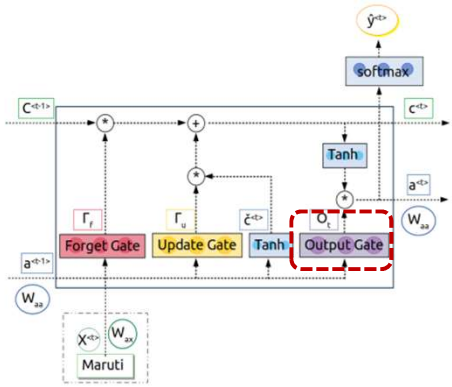
14 Output Gate



- What's output.
- Two step Process
  - First, we run a sigmoid layer which decides what parts of the cell state we're going to output.

  $\Gamma_o = \sigma ([a_{t-1} : X_t] . W_o + b_o)$
  - Next, a process c_t through tanh activation and multiply by Γ_o
  - $a_t = \Gamma_o$ * tanh (c_t)
- We can also use a_t to calculate $\hat{y}_t$

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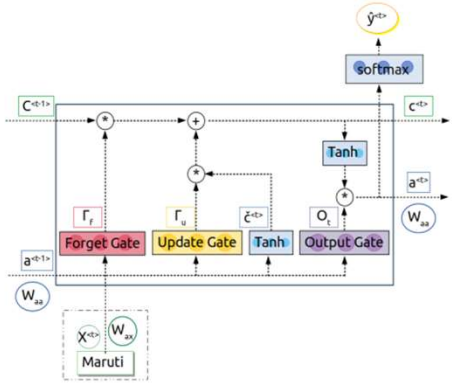
Output Gate



Positive

Positive

I **felt happy** because I saw the others **were happy**

Positive

and because I knew I should **feel happy**, but I

Negative Review

wasn't really happy.

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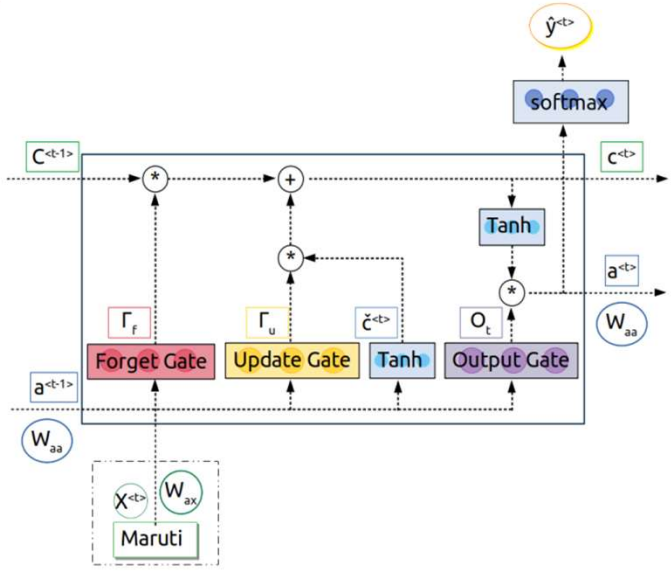
Overall



$\hat{c}_t = \tanh ([a_{t-1} : X_t] . W_c + b_c)$

$\Gamma_u = \sigma ([a_{t-1} : X_t] . W_u + b_u)$

$\Gamma_f = \sigma ([a_{t-1} : X_t] . W_f + b_f)$

$\Gamma_o = \sigma ([a_{t-1} : X_t] . W_o + b_o)$

$c_t = \Gamma_u * \hat{c}_t + \Gamma_f * c_{t-1}$

$a_t = \Gamma_o * \tanh (c_t)$

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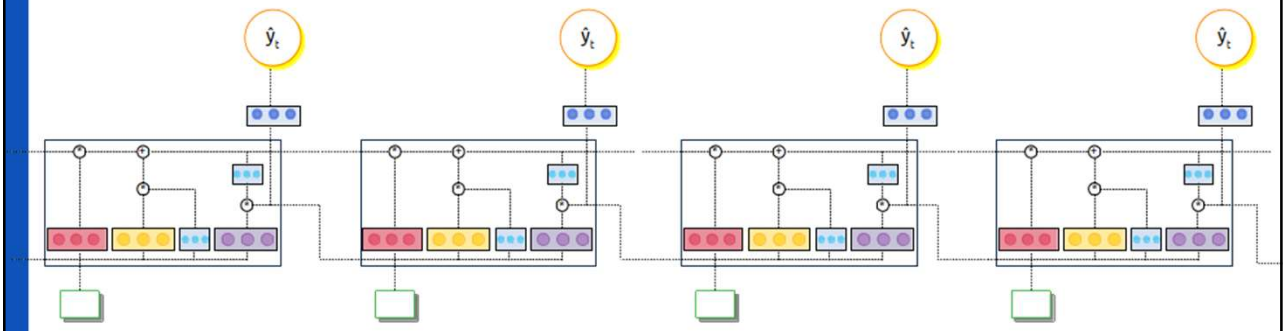
Chain of LSTM cell…



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Variants of LSTM

- Almost every other paper comes out with some variant of LSTM
- LSTM variant, introduced by Gers & Schmidhuber (2000),
  - Adding "peephole connections."
  - Let the gate layers look at the cell state.

$\hat{c}_t = \tanh ([a_{t-1} : X_t : c_{t-1}] . W_c + b_c)$

$\Gamma u = \sigma ([a_{t-1} : X_t : c_{t-1}] . W_u + b_u)$

$\Gamma f = \sigma ([a_{t-1} : X_t : c_{t-1}] . W_f + b_f)$

$\Gamma o = \sigma ([a_{t-1} : X_t : c_{t-1}] . W_o + b_o)$

$c_t = \Gamma_u * \hat{c}_t + \Gamma_f * c_{t-1}$

$a_t = \Gamma_o * \tanh (c_t)$

$\hat{c}_t = \tanh ([a_{t-1} : X_t] . W_c + b_c)$

$\Gamma_u = \sigma ([a_{t-1} : X_t] . W_u + b_u)$

$\Gamma_f = \sigma ([a_{t-1} : X_t] . W_f + b_f)$

$\Gamma_o = \sigma ([a_{t-1} : X_t] . W_o + b_o)$

$c_t = \Gamma_u * \hat{c}_t + \Gamma_f * c_{t-1}$

$a_t = \Gamma_o * \tanh (c_t)$

- You have already seen other most popular variant GRU

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LSTM vs GRU

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LSTM vs GRU

- Different Problems, different algorithms work
- NO clear choices
- In general, GRU is faster
- Try both and see which one produces better results.

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Bidirectional RNN

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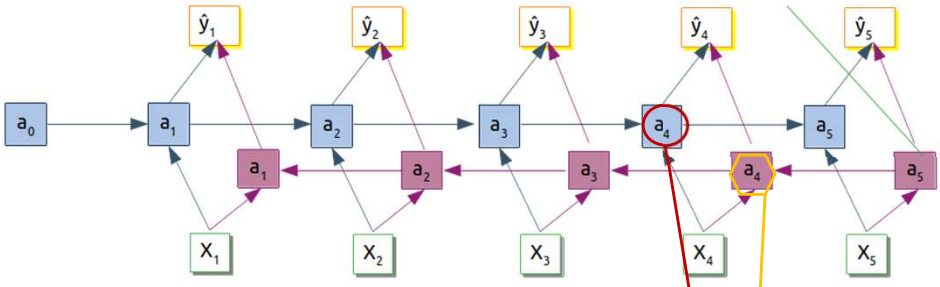
Bidirectional RNN

Bidirectional RNN (BRNN)

They can be RNN or GRU or LSTM blocks
More often these are LSTM blocks in the BRNN



- "**He said Maruti is** most fuel efficient"
- "**He said Maruti is** most expensive shop"
- "**He said Maruti is** strongest"

- $\hat{y}_l = g([a_l : a_l] . W_y + b_y)$
- One limitation: you need complete sentences before any predictions. May not work for voice translation as we need the dialog to finish which can be way out…

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Putting all together – Deep RNN

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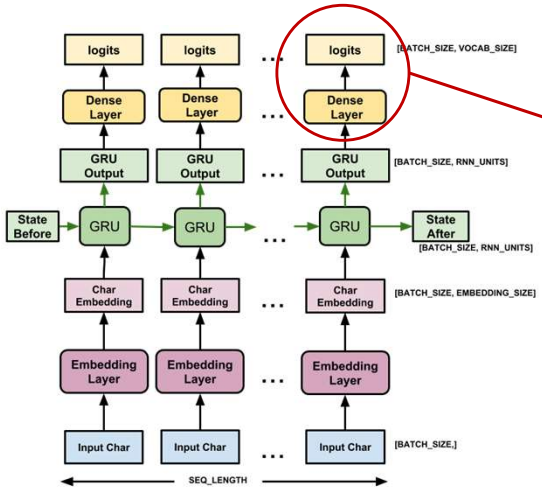
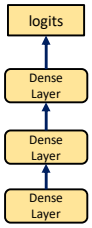
Putting it together…





- You may see multiple dense layers without horizontal connection
- Its rare to see more than 3 GRU or LSTM units stacked up vertically… Network is already too big!

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Attention Model

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Given a very long sentence

- “As he crossed toward the pharmacy at the corner he involuntarily turned his head because of a burst of light that had ricocheted from his temple, and saw, with that quick smile with which we greet a rainbow or a rose, a blindingly white parallelogram of sky being unloaded from the van—a dresser with mirrors across which, as across a cinema screen, passed a flawlessly clear reflection of boughs sliding and swaying not arboreally, but with a human vacillation, produced by the nature of those who were carrying this sky, these boughs, this gliding façade.”

How would a human being would translate???????

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Attention Model

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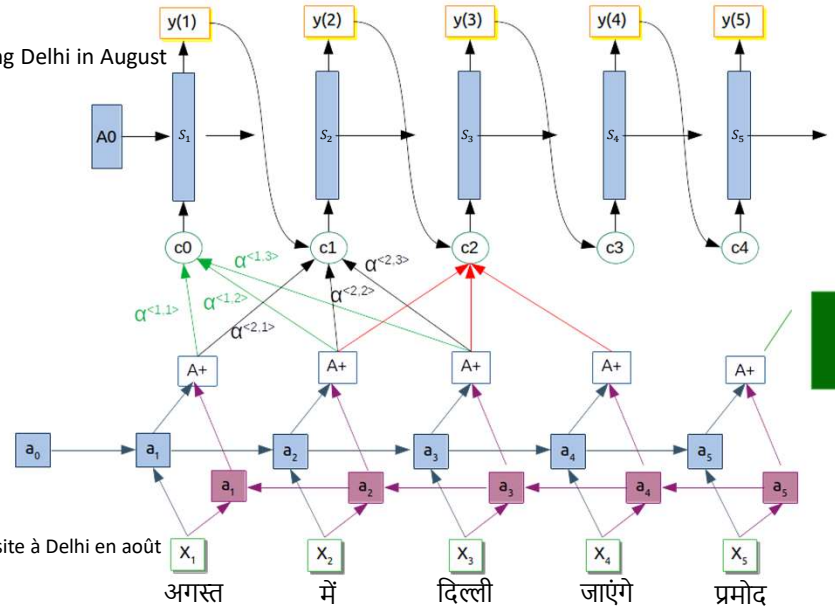
Attention Model

Pramod is visiting Delhi in August



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