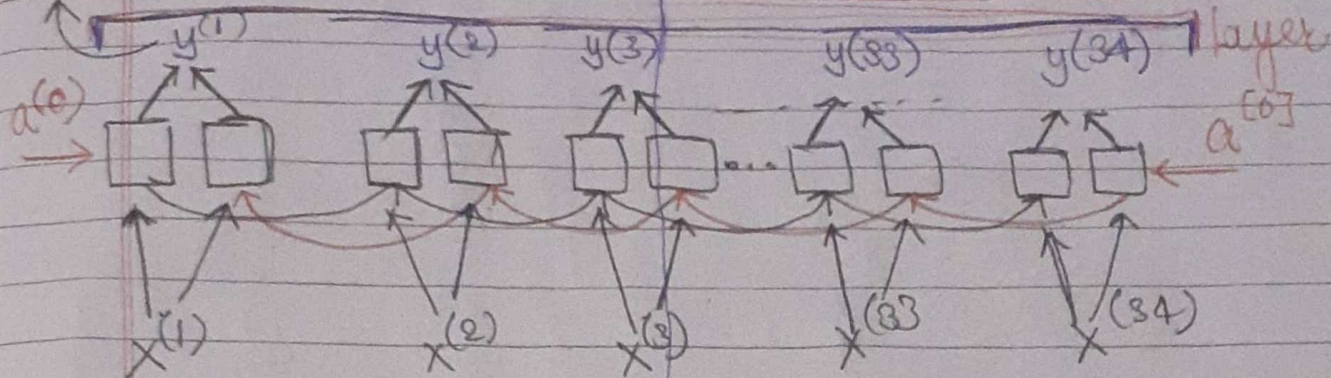


Project Work

hidden state

34 LSTM (Core Bidirectional LSTM layer)



Word embedding (300 dimensional)

few sentences are padded so that length of all sentences goes upto 34 i.e. length of longest sentence

ch $A = \text{BidirectionalLSTM}(n_a, \text{return_seq}=\text{True})$ (X)

This A will be the hidden state from function each of Bidirectional LSTM Cell

of Numbers of training examples (m) $A = m \times 34 \times (n_a)$

$m \times 34 \times (n_a)$ dimensions of each hidden state ($y^{(i)}$)

Number of training examples

Number of hidden state required for each training examples

Note Size of each $y^{(i)}$ is n_a ($n_a = 32$)

Context Vector is Calculated as:

$$C^{[i]} = \sum_{j=1}^{32} \alpha^{(i, t_j)} y^{(t_j)}$$

This is input to first ~~time~~ Timestep of Post attention LSTM.

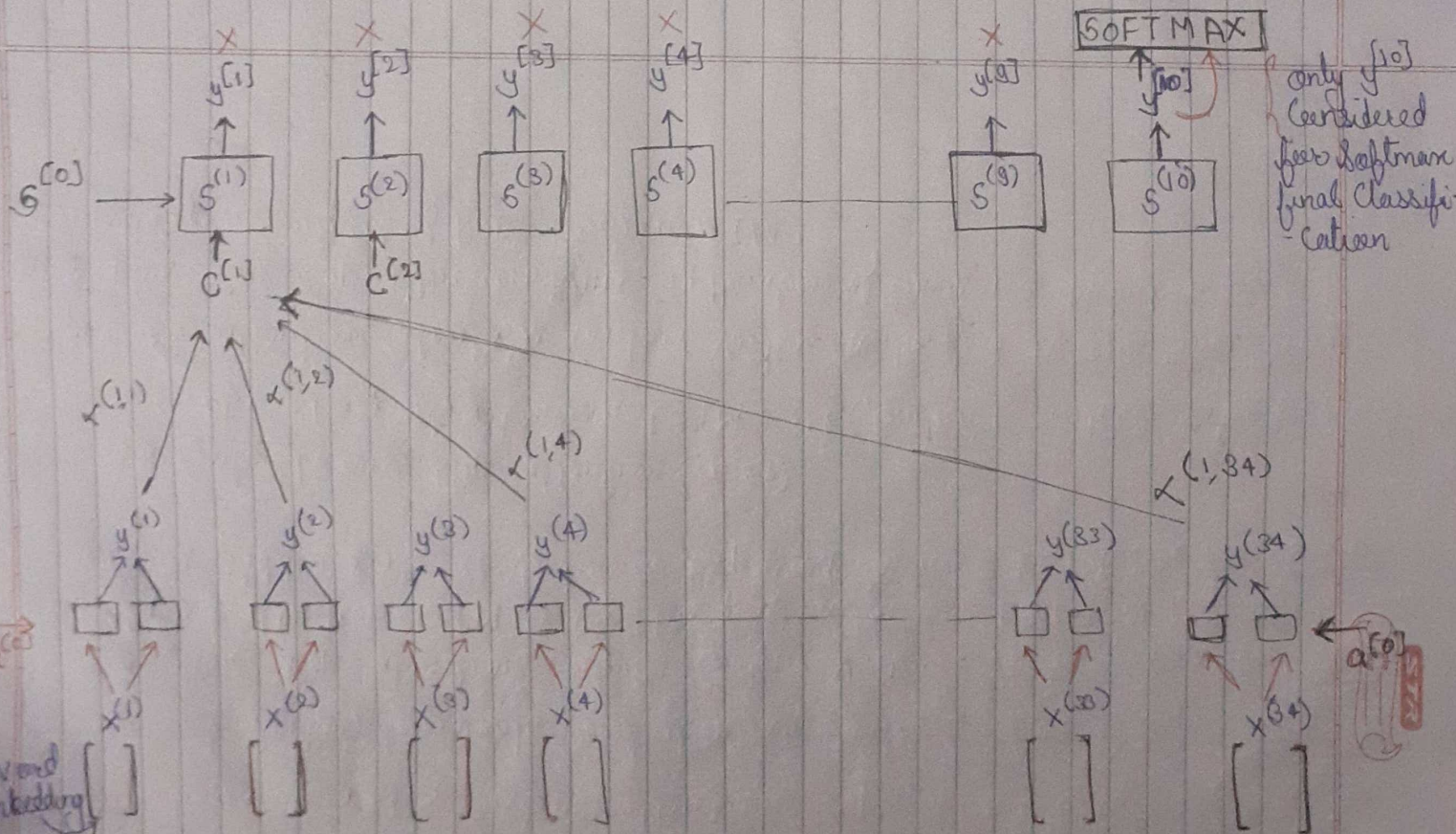
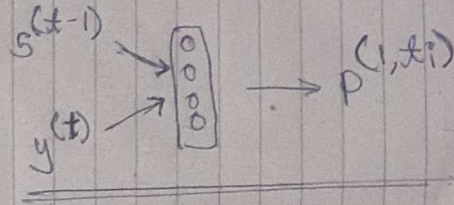
$C^{[i]}$ will have Same dimension as That of $y^{(t_i)}$

$\alpha^{(i, t_i)}$ is a Simple Number.

Amount of attention $y^{(t_i)}$ should give ~~to~~ While ~~reading~~ reading 1st Word.

$$\alpha^{(i, t_i)} = \frac{e^{p^{(i, t_i)}}}{\sum_{j=1}^{32} e^{p^{(i, t_j)}}}$$

Now this $p^{(i, t_i)}$ is Calculated using a Small NN



we have created a Custom attention layer, which calculates Context Vector for each Post attention (2nd Layer LSTM) input Timestamp

One-step-attention outputs Context Vector, to be feed as input to 1 timestamp ~~the~~ post-attention-LSTM-Cell. This post-attention-LSTM Cell further outputs hidden state & Vector to be passed to next LSTM-Cell timestamp

Context 1 = one-step-attention(a, s_i)

s_{i+1}, c_i = post attention-LSTM-Cell(Context 1, initial state $\in [s_i, c_i]$)

one-step-attention calculates Context Vector to be feed to one timestamp, and This One-step-attention runs T_i Number of times i.e. Number of timestamp in output of Post attention LSTM.