## TUTORIAL - 2

### NEXT WORD PREDICTION

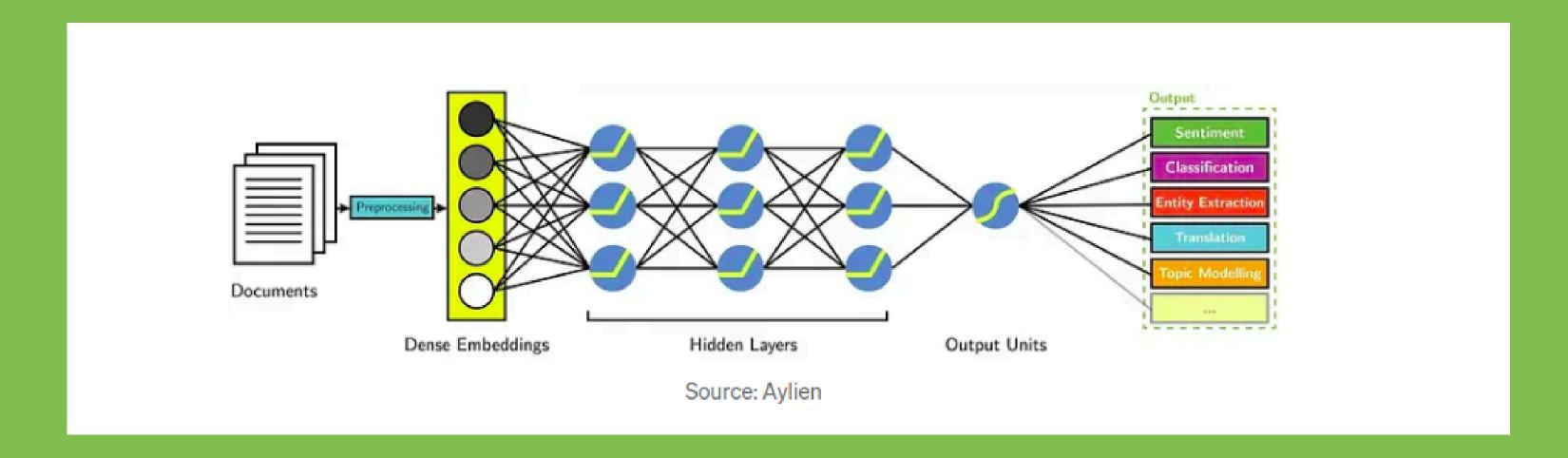
• For example, if we have some text  $x^{(1)}, \dots, x^{(T)}$ , then the probability of this text (according to the Language Model) is:

$$P(\mathbf{x}^{(1)}, \dots, \mathbf{x}^{(T)}) = P(\mathbf{x}^{(1)}) \times P(\mathbf{x}^{(2)} | \mathbf{x}^{(1)}) \times \dots \times P(\mathbf{x}^{(T)} | \mathbf{x}^{(T-1)}, \dots, \mathbf{x}^{(1)})$$

$$= \prod_{t=1}^{T} P(\mathbf{x}^{(t)} | \mathbf{x}^{(t-1)}, \dots, \mathbf{x}^{(1)})$$

This is what our LM provides

### 



Input data: We need a Mathematical representation of the textual data for computational purposes.

Simple Idea????

Simple Idea: One hot encoding.

Can we do better? Can we learn the embeddings of the words as we train our model. We can use pytorch for embeddings

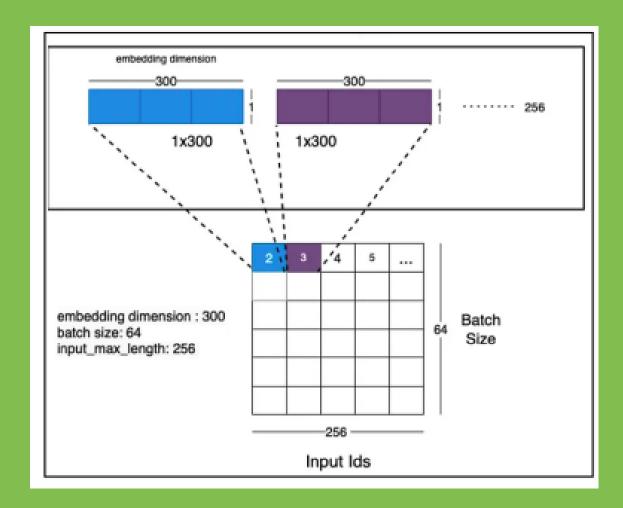
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Embedding layer is also a Matrix, and what is the Matrix dimension? PyTorch provides a Module for Embedding layer, which we can initialize with appropriate dimensions



$$h_t = \sigma(\mathbf{W}_1 \mathbf{x}_t + \mathbf{b}_1)$$

$$\hat{y}_t = \text{softmax}(\mathbf{W}_2 \mathbf{h}_t + \mathbf{b}_2)$$

 $W_1$  and  $b_1$  are the weight matrix and bias vector for the hidden layer, respectively. They are learned during the training process during back propagation

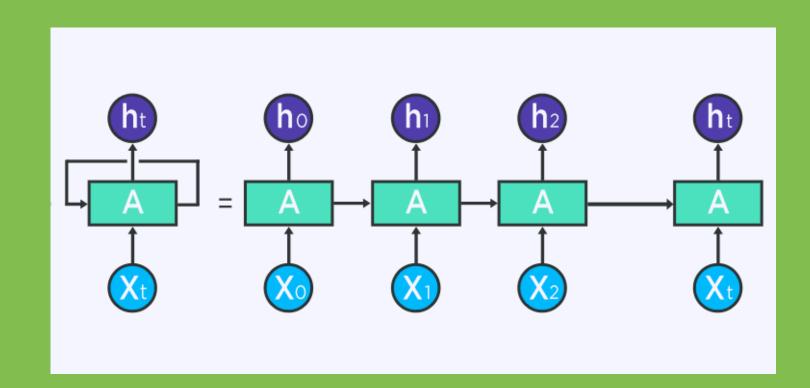
Cross-Entropy Loss: 
$$ext{Loss} = -\sum_{i=1}^N y_i \cdot \log(\hat{y}_i)$$

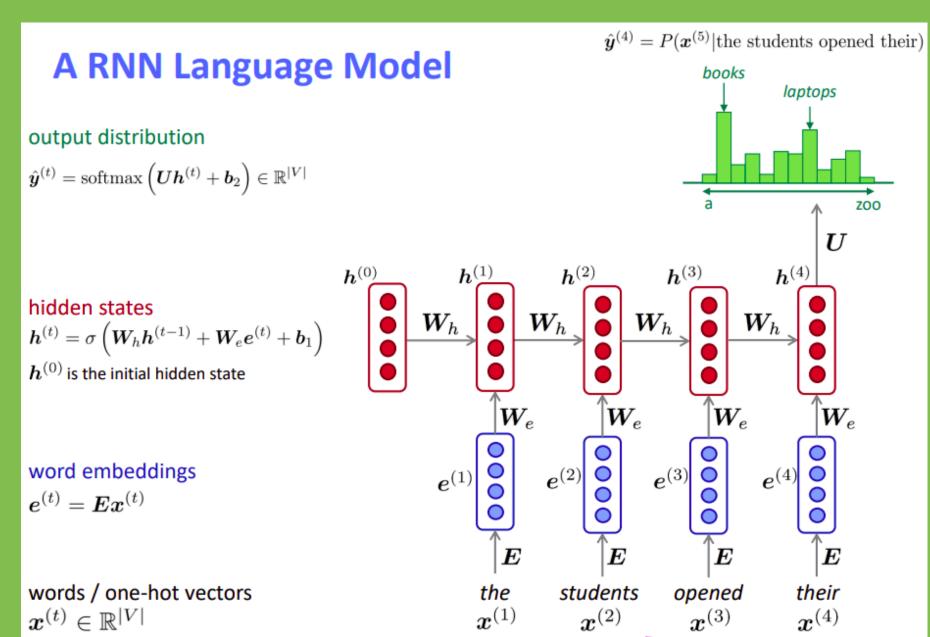
CE Loss and Adam optimizer can be used for back propogating the loss

 $\hat{y}_t$  is the predicted probability distribution over all the possible output words at time step t.

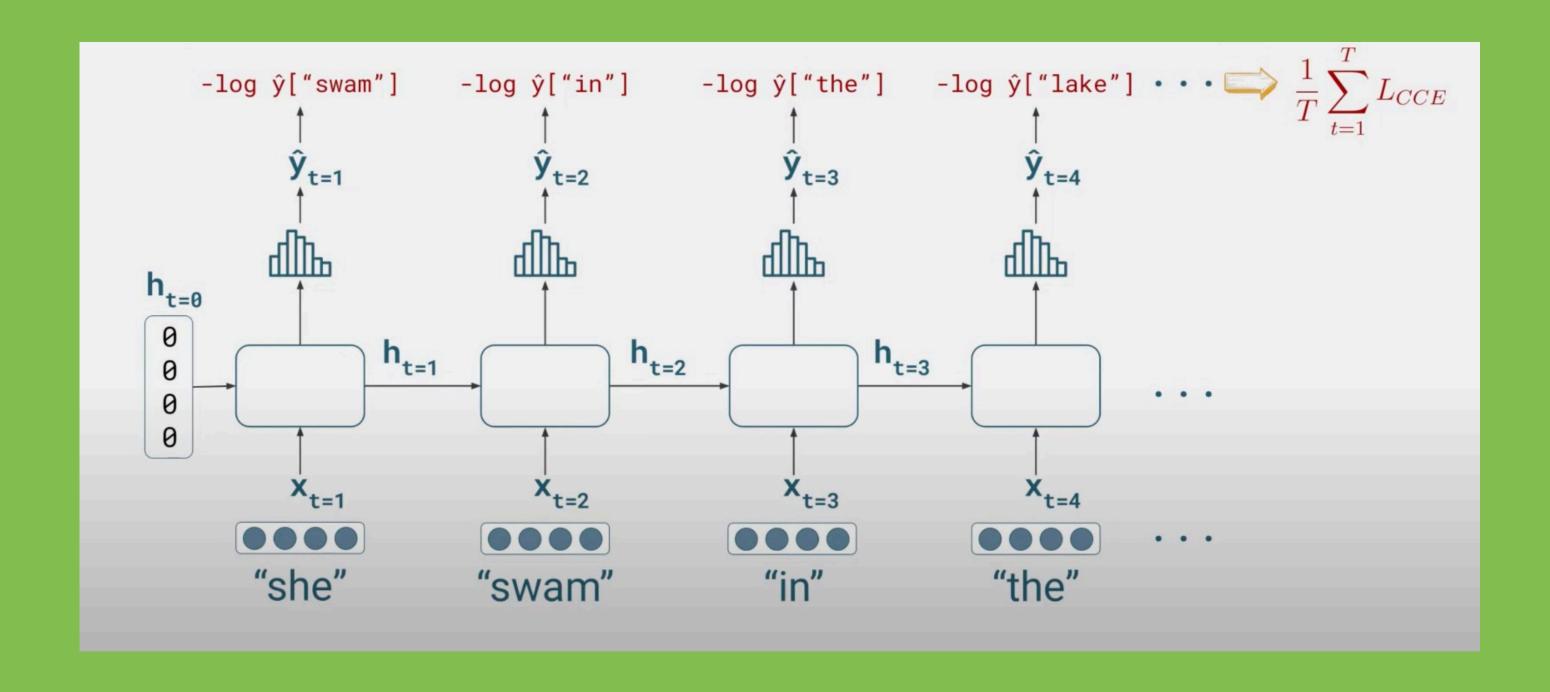
## RAN

concept of memory - introduces a hidden state that carries information from previous inputs.

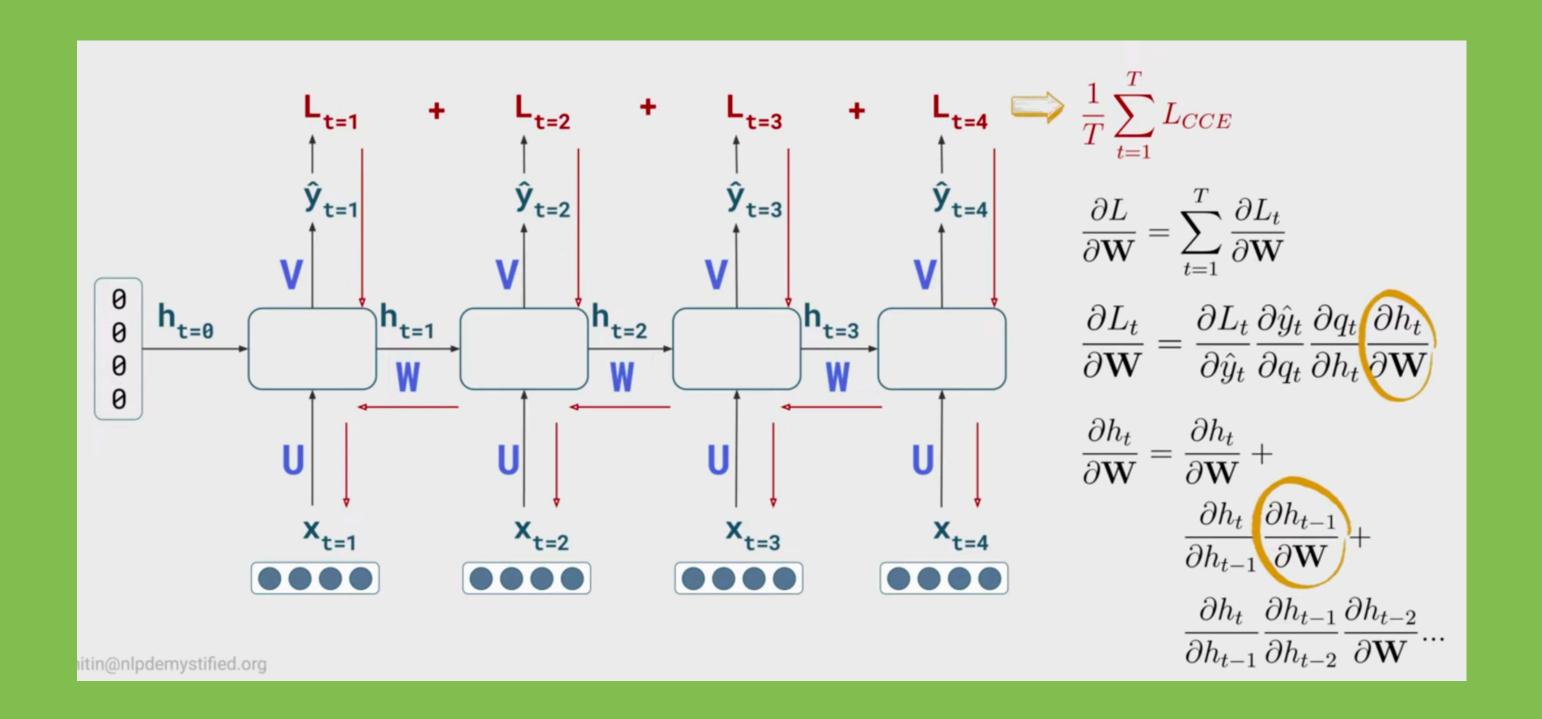




## TRAINING RNN



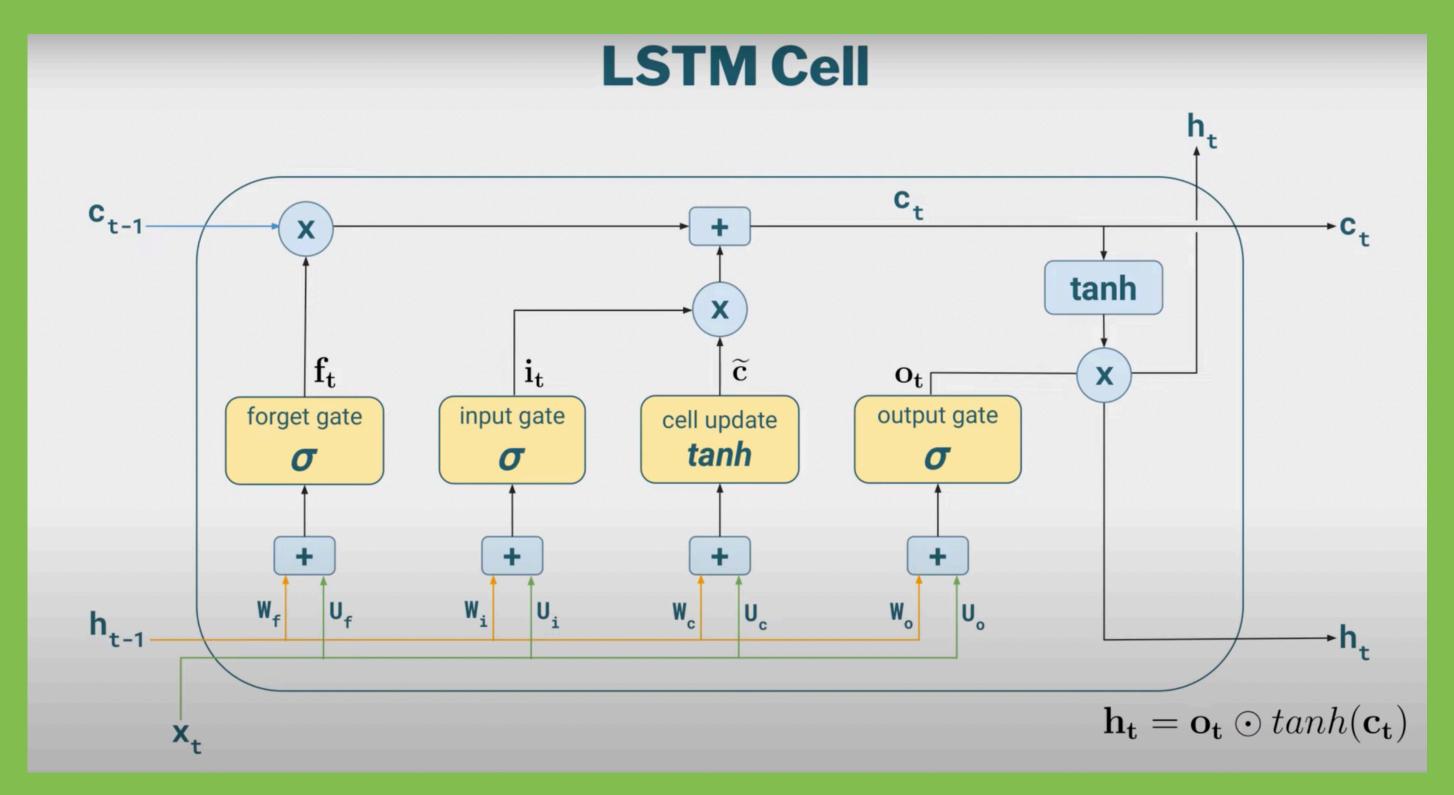
### BACKPROPOGATION



## DISADVANTAGE



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