Natural Language Processing (CS-472) Spring-2023

Muhammad Naseer Bajwa

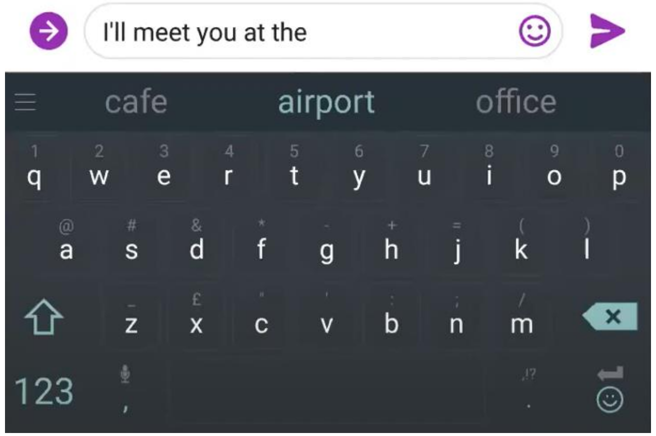
Assistant Professor,
Department of Computing, SEECS
Co-Principal Investigator,
Deep Learning Lab, NCAI
NUST, Islamabad
naseer.bajwa@seecs.edu.pk

Overview of this week's lecture

Language Models

- n-gram Language Models
- Neural Language Models
- Recurrent Neural Networks
- GRUs and LSTMs

Language Modelling is the task of predicting next word in a sequence

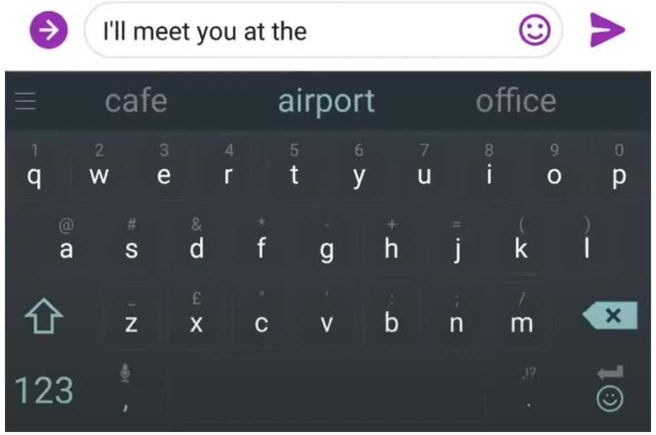


Language Modelling is the task of predicting next word in a sequence

- A language model predicts the probability distribution of the word $x^{<t+1>}$, given a sequence of words $x^{<1>}, x^{<2>}, \ldots, x^{<t>}$.

$$P(x^{<t+1>} | x^{<1>}, x^{<2>}, \ldots, x^{<t>})$$

where $x^{<t+1>}$ can be any word in the vocabulary $V = \{w_1, w_2, \ldots, w_V\}$



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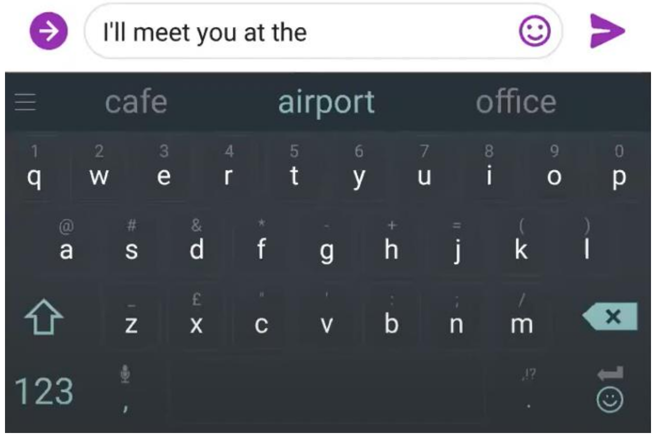

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where $x^{<t+1>}$ can be any word in the vocabulary $V = \{w_1, w_2, \ldots, w_V\}$

- In other words, a language model is a system that assigns probability to a piece of text.

$$P(x^{<1>}, x^{<2>}, \ldots, x^{<T>}) = P(x^{<1>}) \times P(x^{<2>} | x^{<1>}) \times \cdots \times P(x^{<T>} | x^{<T>}, \ldots, x^{<1>})$$
$$= \prod_{t=1}^{T} P(x^{<t+1>} | x^{<t>}, \ldots, x^{<1>})$$

How to learn a language model?

- n-gram language models were used before the advent of deep learning.
  - n-gram is a sequence of n consecutive words.
    - unigrams: the, students, opened, their
    - bigrams: the students, students opened, opened their
    - trigrams: the students opened, students opened their
    - 4-grams: the students opened their

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    - 4-grams: the students opened their
- They use statistical data to calculate how frequent different n-grams are in a given corpus and use those statistics to predict the next word.
  - Make a **Markov assumption**: The next word depends only on $n-1$ preceding words.

$$P(x^{<t+1>}|x^{<t>}, \dots, x^{<1>}) = P(x^{<t+1>}|x^{<t>}, \dots, x^{<t-n+2>})$$

$$= \frac{P(x^{<t+1>}, x^{<t>}, \dots, x^{<t-n+2>})}{P(x^{<t>}, \dots, x^{<t-n+2>})}$$

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Probability of n-gram

Probability of $n - 1$-gram

Let's take an example of n-gram language model

- Suppose we are learning a 4-gram Language Model.

~~as the proctor started the clock, the~~ students opened their ________

$$P(w|students\ opened\ their) = \frac{count(students\ opened\ their\ w)}{count(students\ opened\ their)}$$

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- If in the corpus we find,
    - students opened their ($\times$ 1000).
    - students opened their books ($\times$ 400). $\rightarrow$ $P(books|students\ open\ their) = 0.4$
    - students opened their exams ($\times$ 100). $\rightarrow$ $P(exams|students\ open\ their) = 0.1$

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- Should we have discarded the 'proctor' context?

n-gram language models have sparsity problem

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  - Apply **Smoothing**: Add a small δ to the count for every $w \in V$.

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- Increasing n makes sparsity problems worse. Typically $n \leq 5$ is used.

n-gram language models have storage problem also

$$P(w|students\ opened\ their) = \frac{count(students\ opened\ their\ w)}{count(students\ opened\ their)}$$

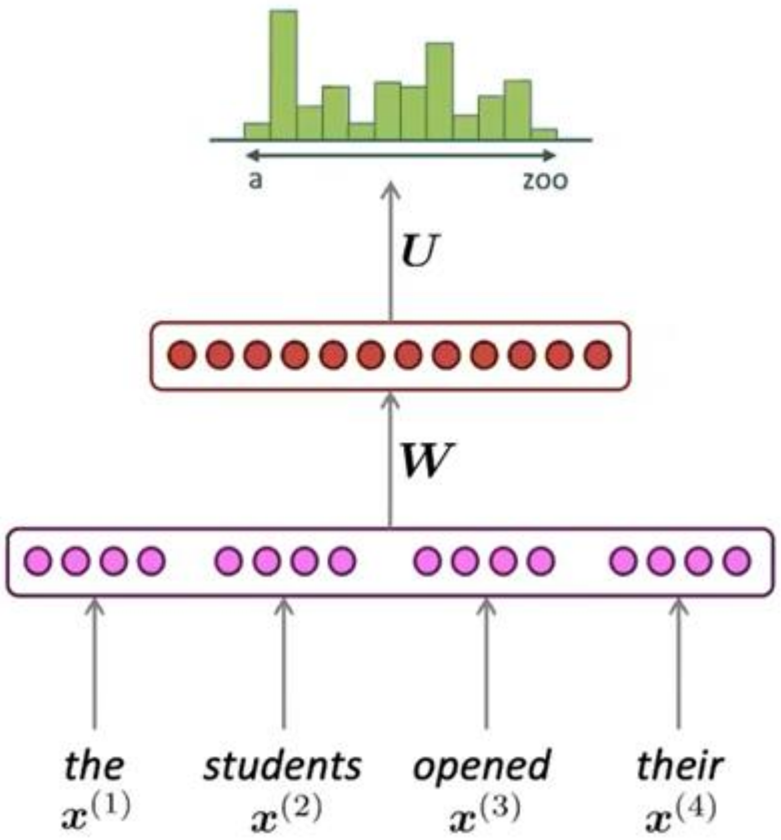
- We need to store count for **all** n-grams in the corpus.

- Increasing n or corpus size increases model size exponentially.

How to build a neural language model?

Words

$x^{<1>}, x^{<2>}, x^{<3>}, x^{<4>}$



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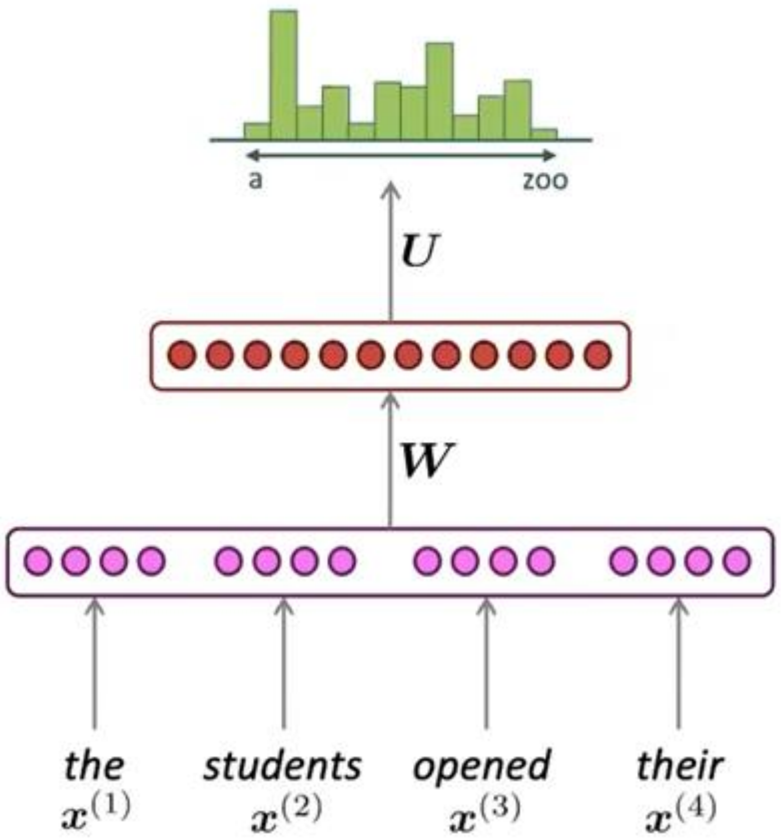

Concatenated word embeddings

$$\boldsymbol{e} = [\boldsymbol{e}^{<1>}, \boldsymbol{e}^{<2>}, \boldsymbol{e}^{<3>}, \boldsymbol{e}^{<4>}]$$

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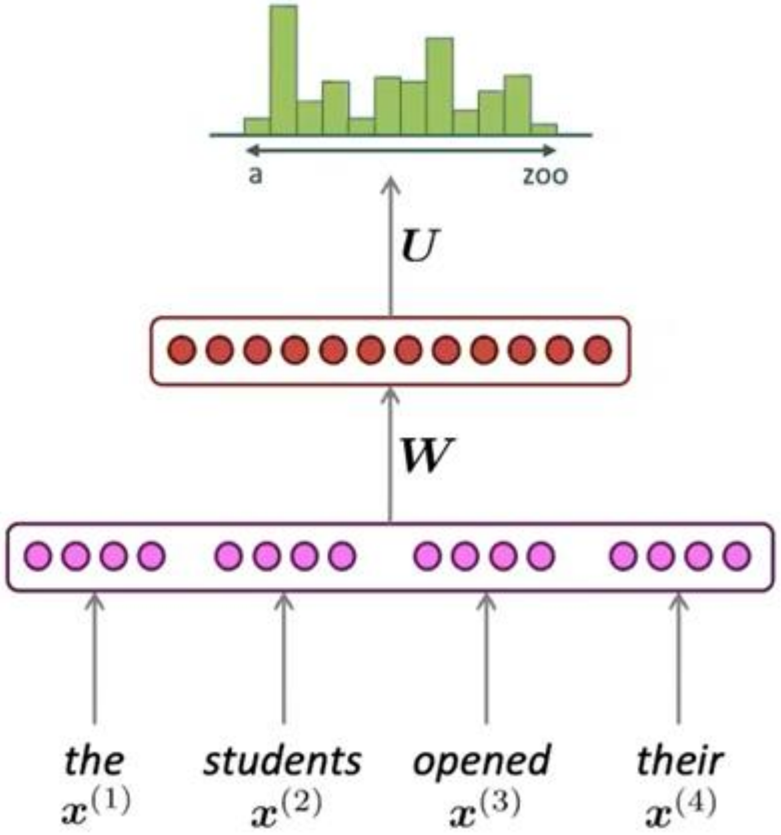

Hidden layer

$$a = g(W.e + b_a)$$

Concatenated word embeddings

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$x^{(1)}$ $x^{(2)}$ $x^{(3)}$ $x^{(4)}$

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Output distribution

$$\hat{\boldsymbol{y}} = \boldsymbol{softmax}(\boldsymbol{U}.\boldsymbol{a} + \boldsymbol{b_y}) \in \mathbb{R}^V$$

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$$\boldsymbol{a} = \boldsymbol{g}(\boldsymbol{W}.\boldsymbol{e} + \boldsymbol{b_2})$$

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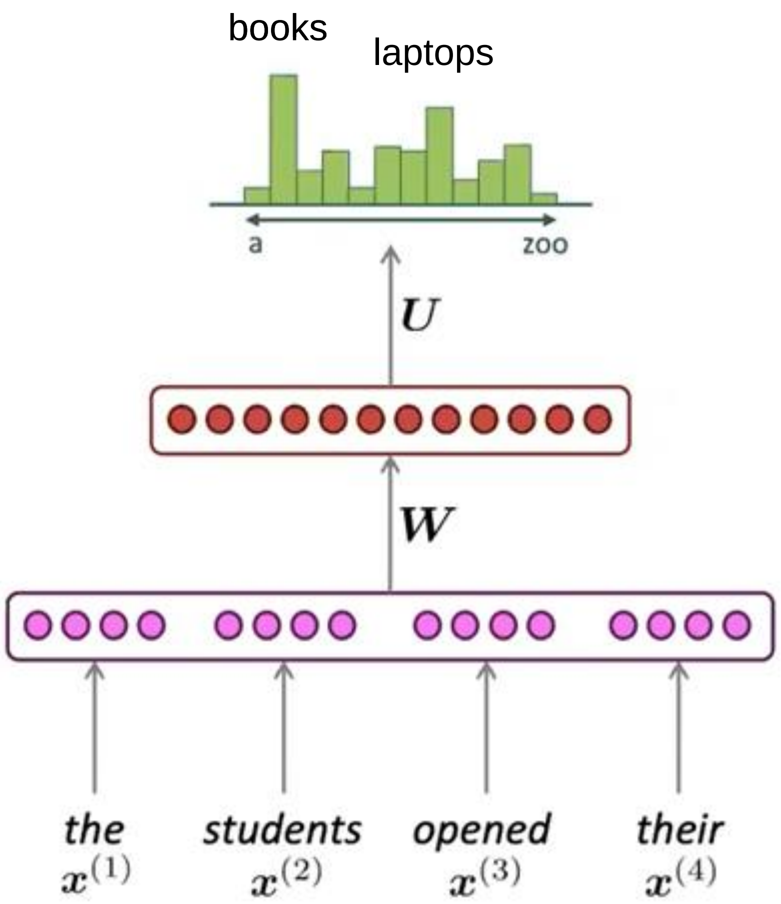

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- Improvements over n-grams LMs:
  - No Sparsity, low storage.
  - Use of distributional semantics

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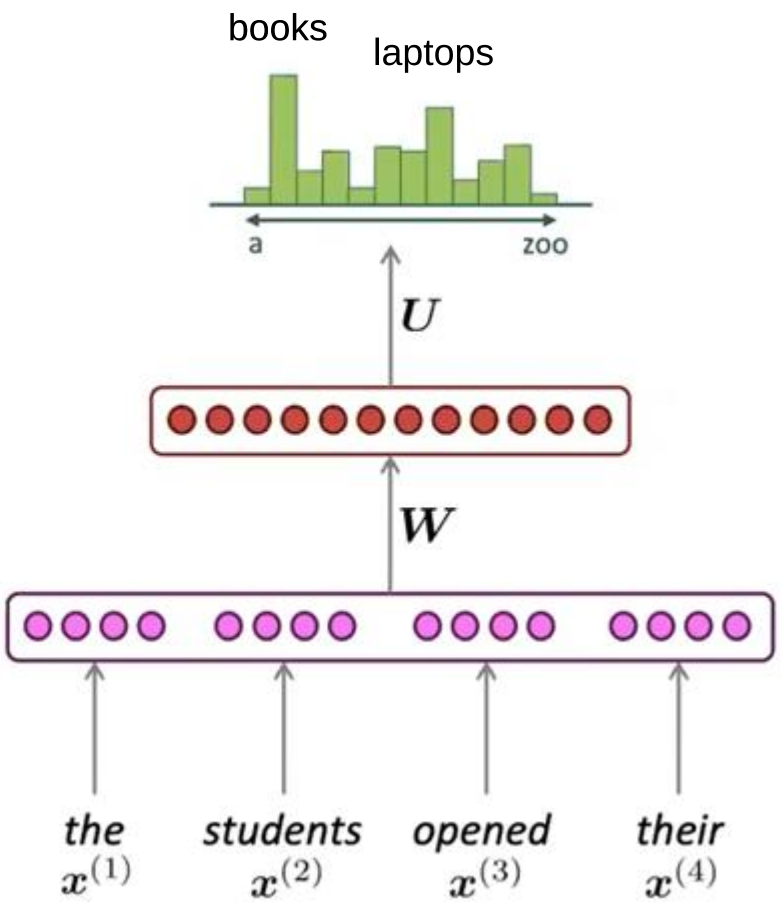

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How to build a neural language model?

- Improvements over n-grams LMs:
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- Remaining Problems:
  - Fixed window is too small.
  - Enlarging window enlarges W.
  - Window can never be large enough.
  - Consecutive words are multiplied by different weights.

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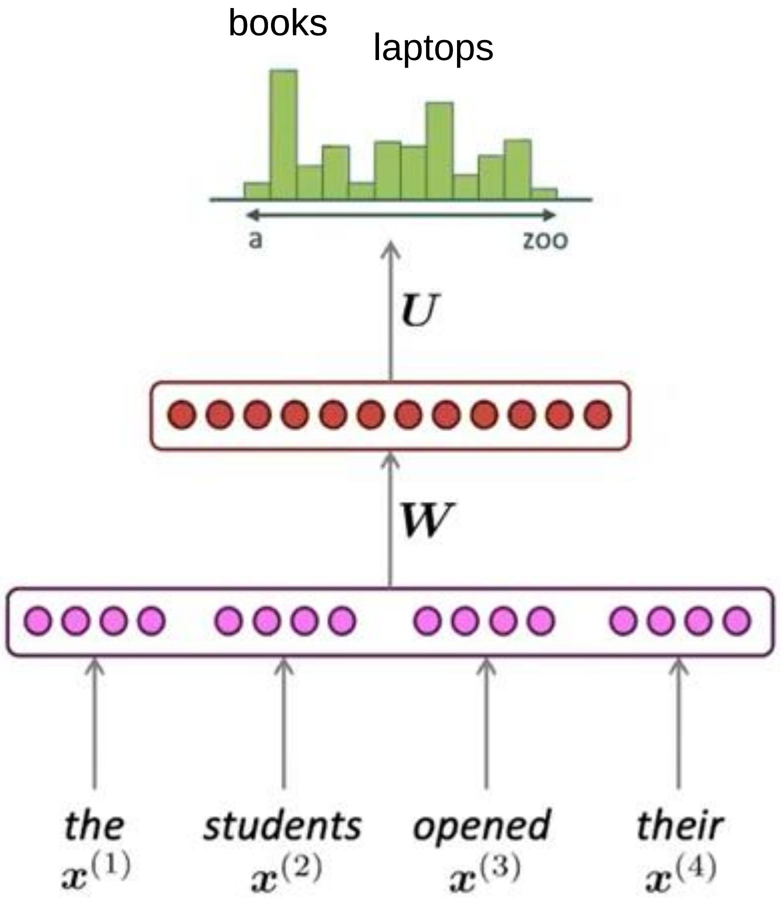

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- Solution?
  - A neural architecture that can share weights and process variable-length input.

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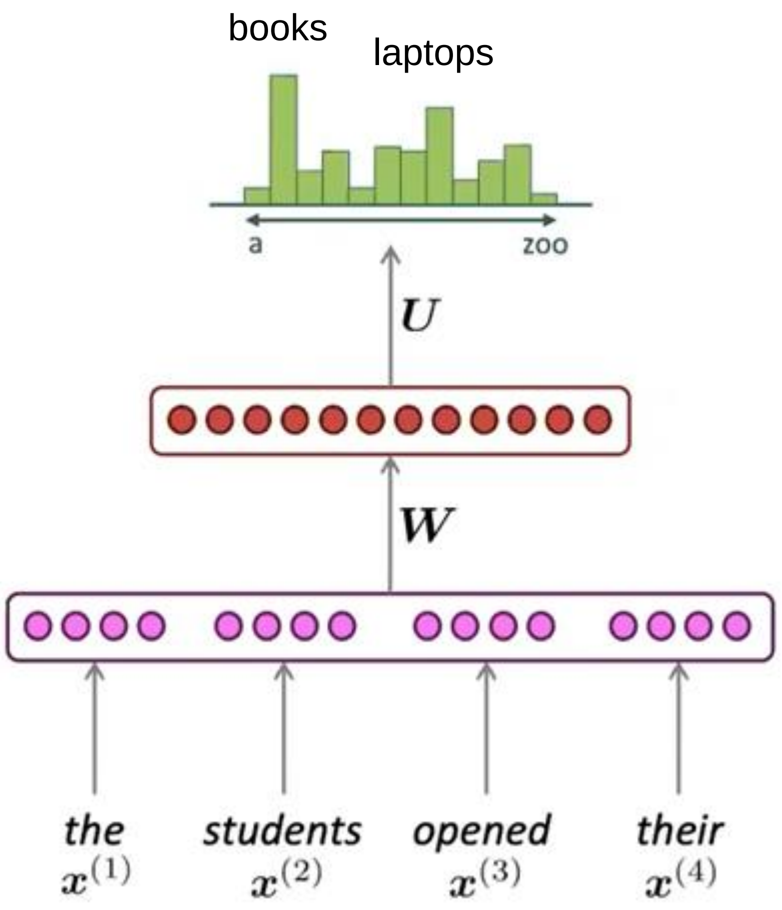

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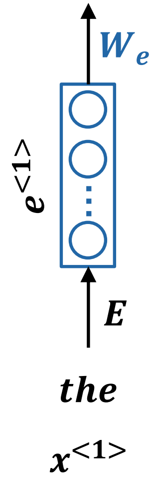
Recurrent Neural Networks are better suited for sequence modelling



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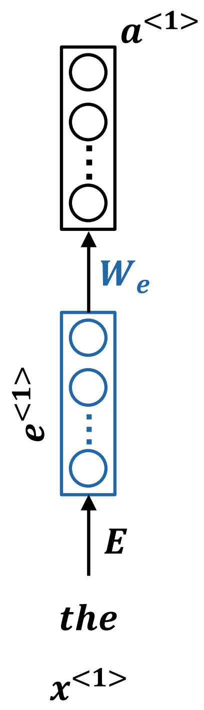

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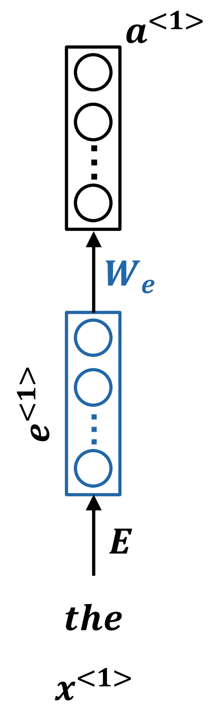

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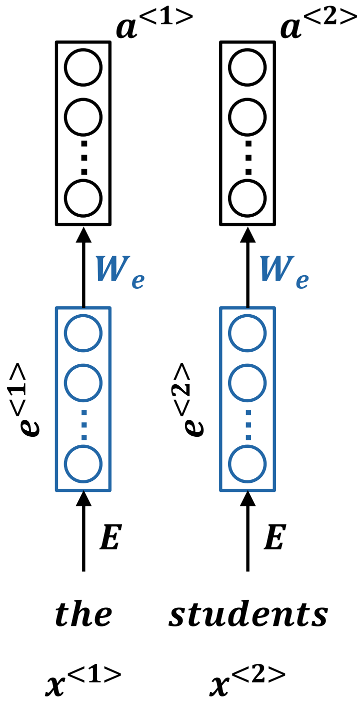

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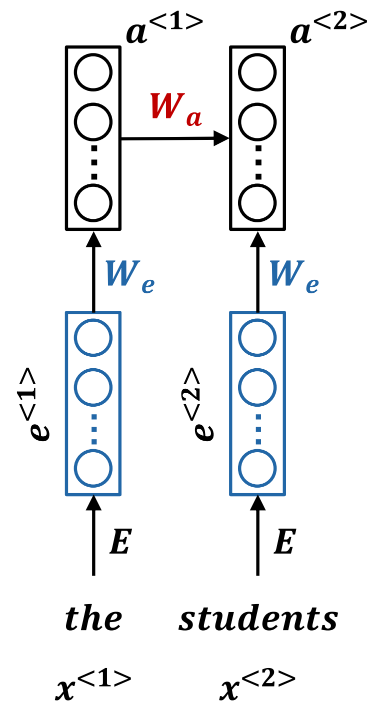

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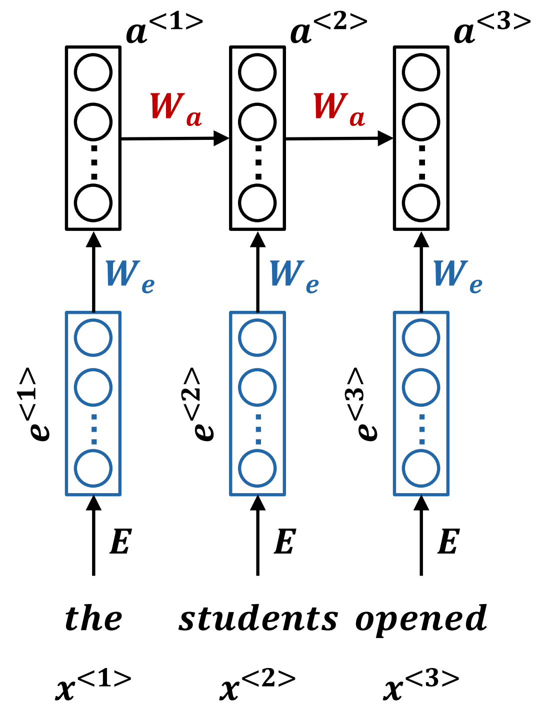

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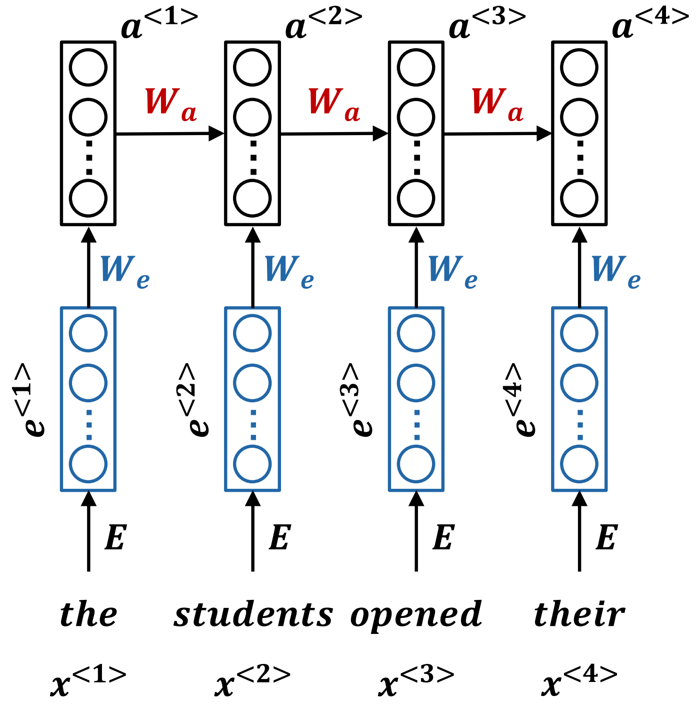

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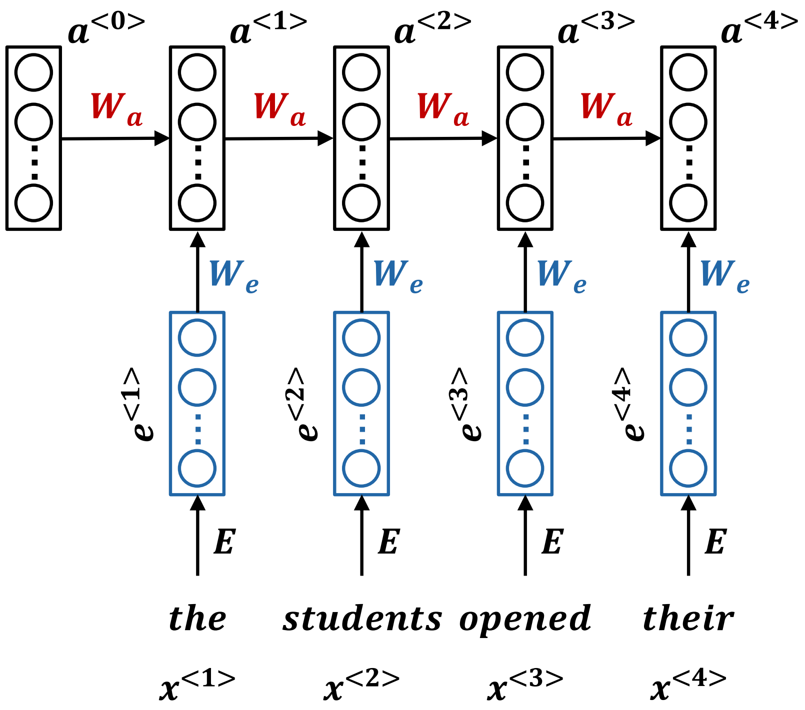

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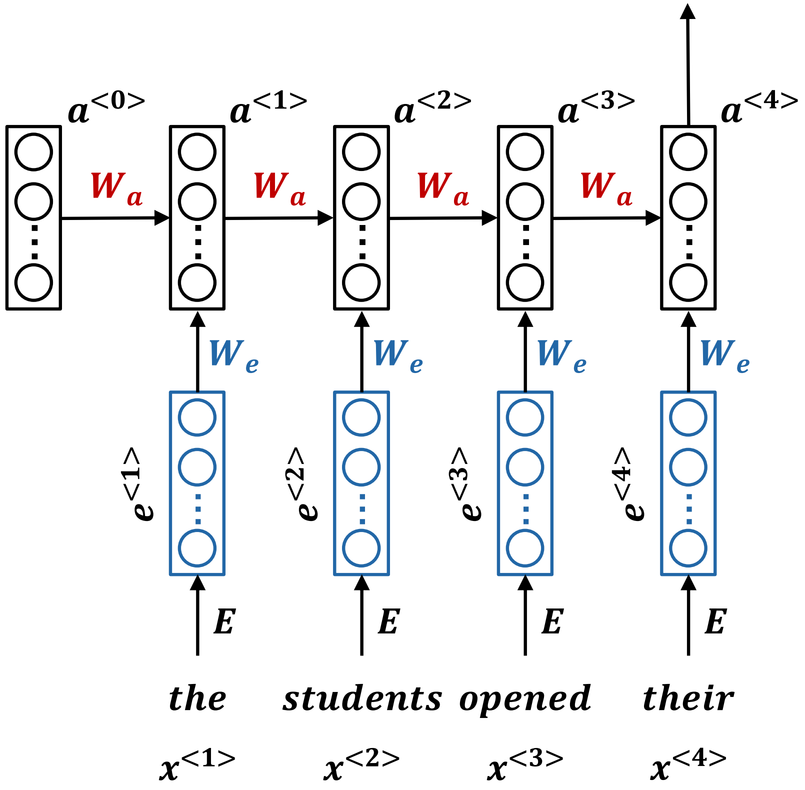

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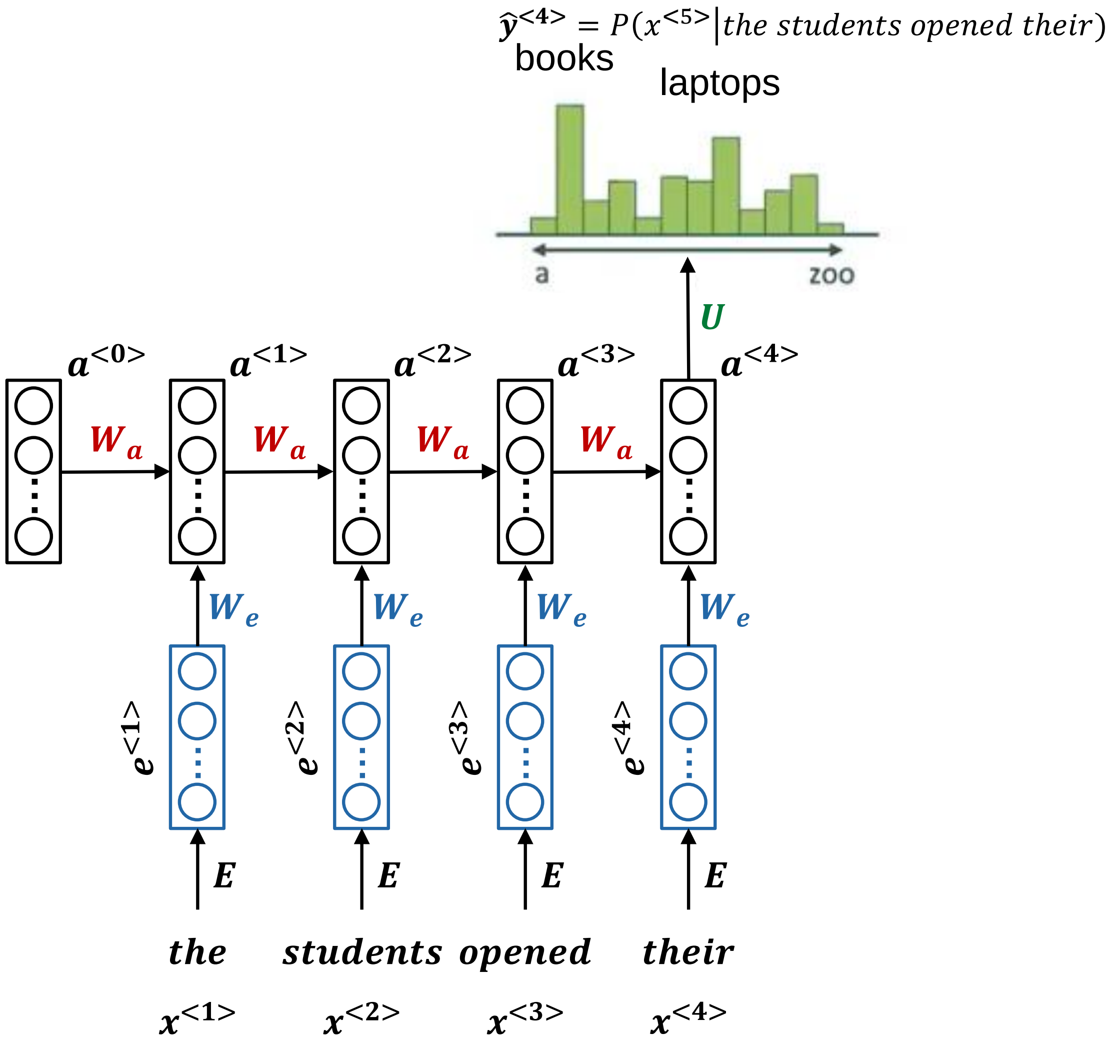


Recurrent Neural Networks are better suited for sequence modelling

Output distribution

$$\hat{y} = softmax(Ua^{<t>} + b_y) \in \mathbb{R}^V$$

Hidden states

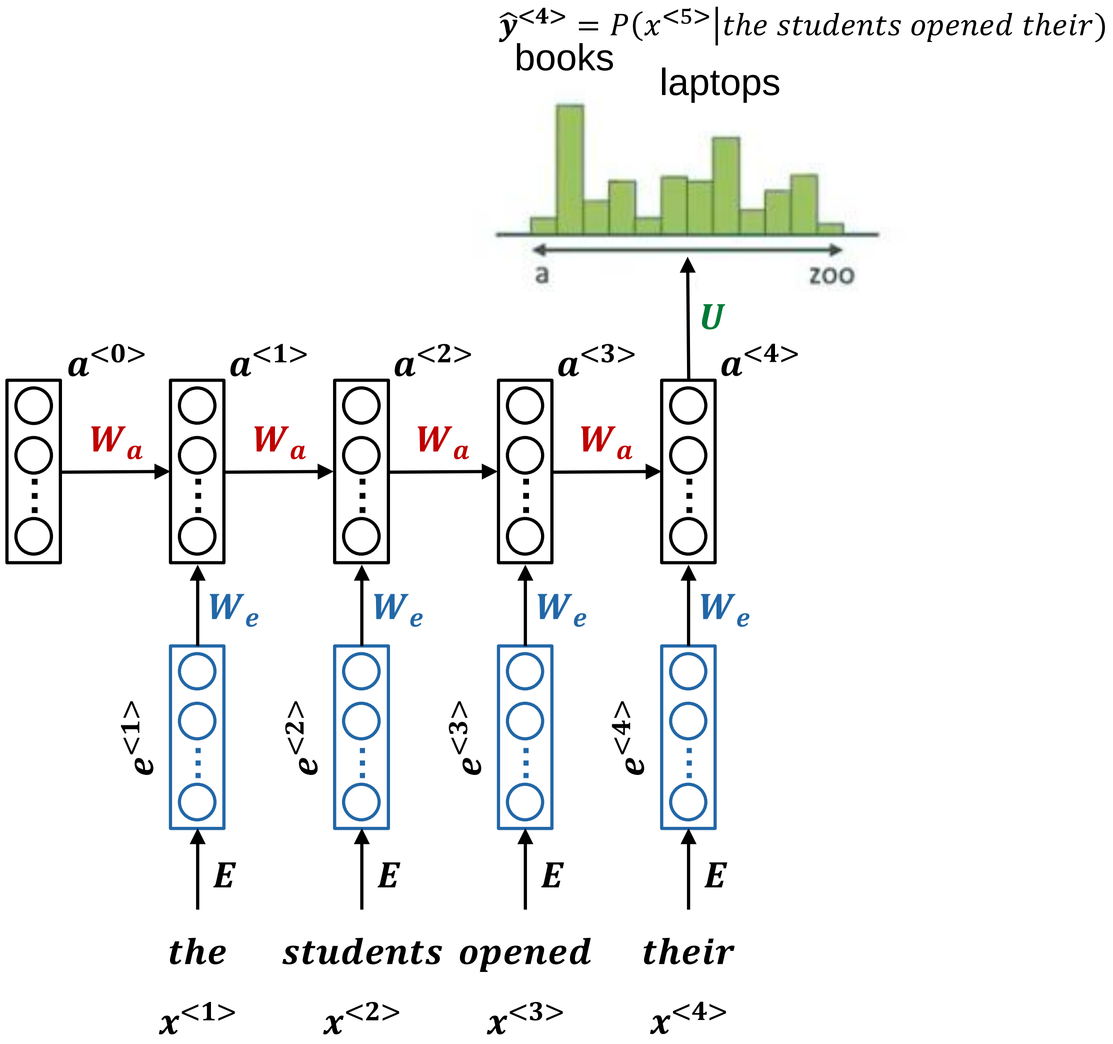
$$a^{<t>} = tanh(W_a a^{<t-1>} + W_e e^{<t>} + b_a)$$

Word embeddings

$$e^{<t>} = Ex^{<t>}$$

Words/one-hot vectors

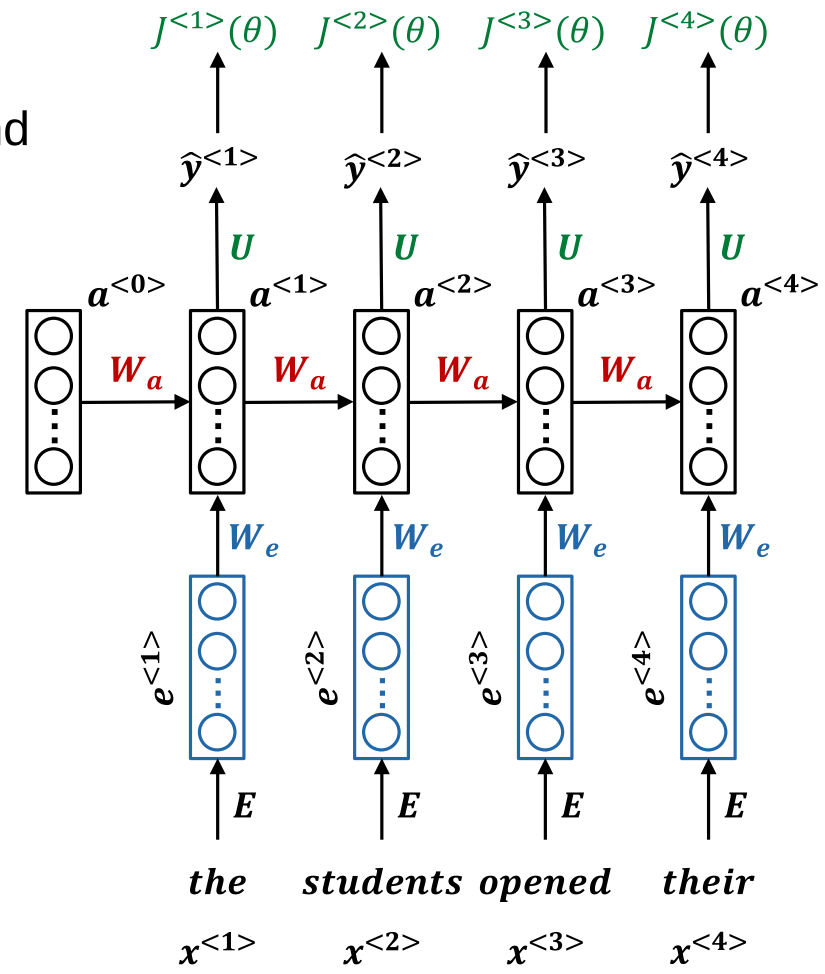
$$x^{<t>} \in \mathbb{R}^V$$



How to train an RNN-based Language Model?

- Get a large corpus of text.

- Feed the sequence of word into RNN model one by one and calculated $\hat{y}^{<t>}$ for every time step t.



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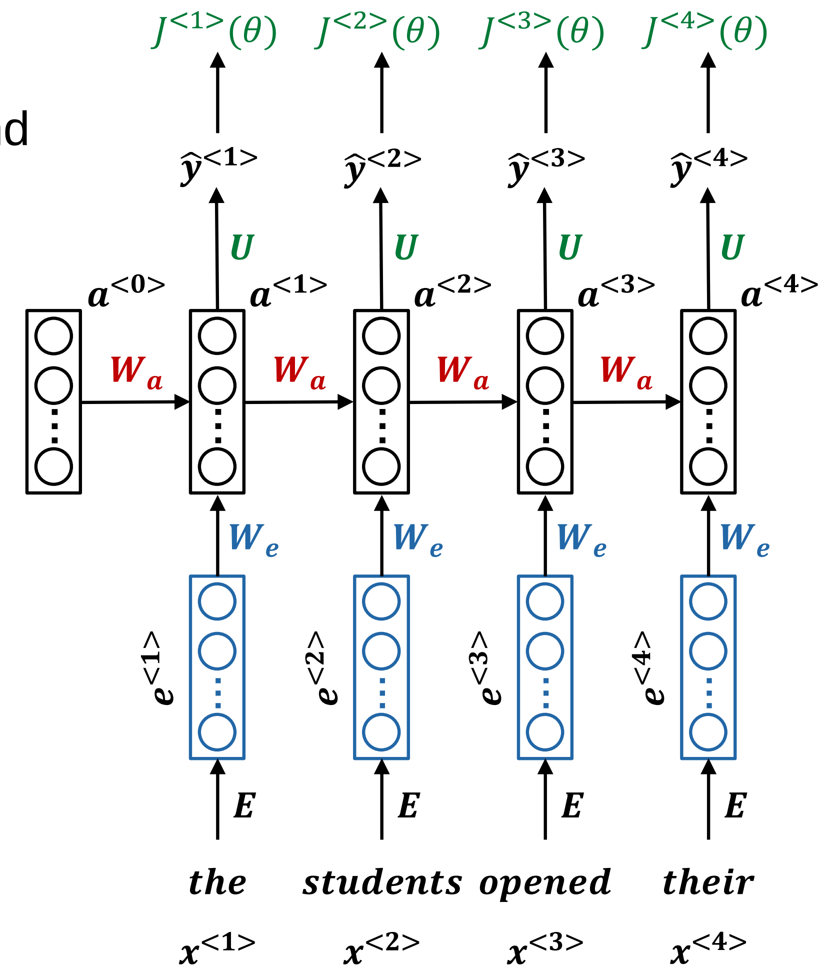
- Average the loss values to get cost for the entire training set.

$$J\,(\theta) = \frac{1}{T}\sum_{t=1}^{T} J^{<t>}(\theta) = \frac{1}{T}\sum_{t=1}^{T} -\log \hat{y}^{<t>}_{x_{t+1}}$$



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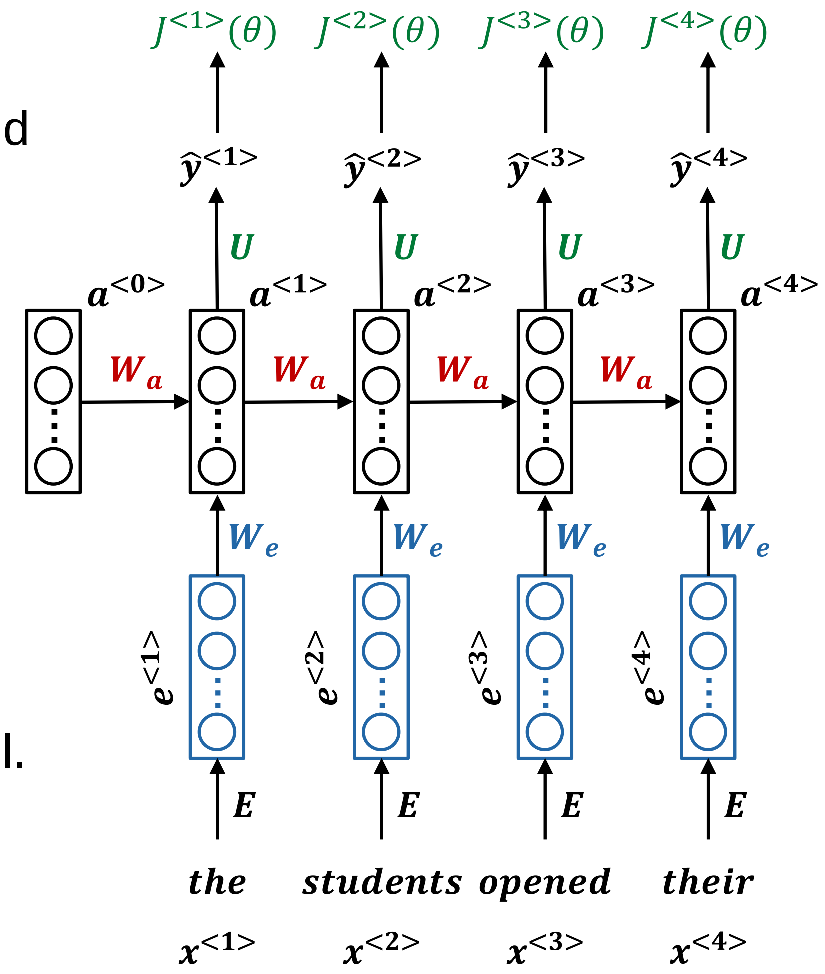
- **Teacher Forcing** is used during training of language model.



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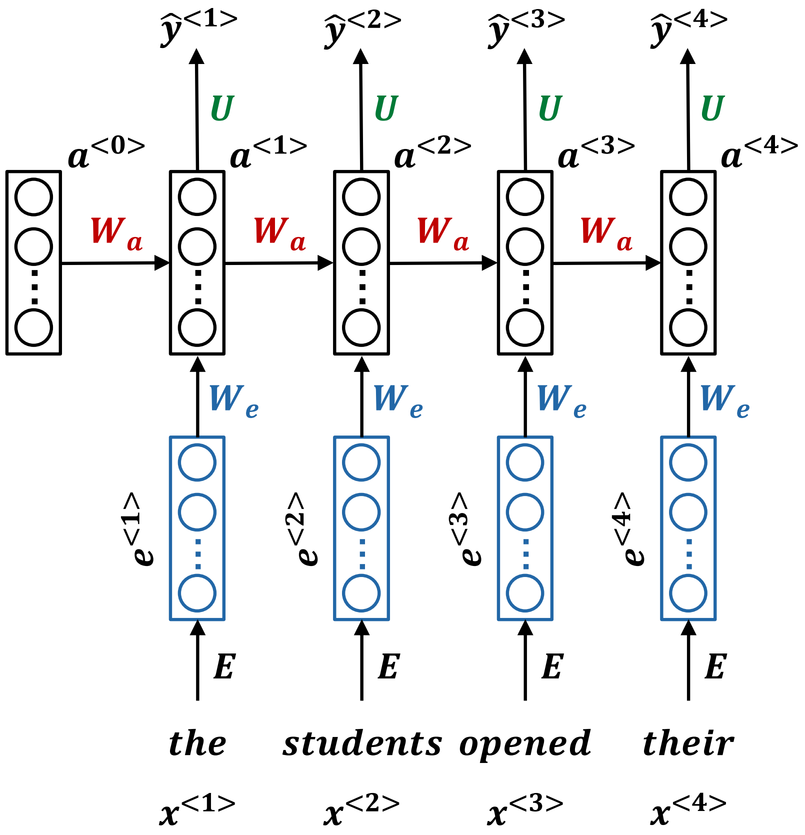
RNN-based models make recurrent use of the same unit



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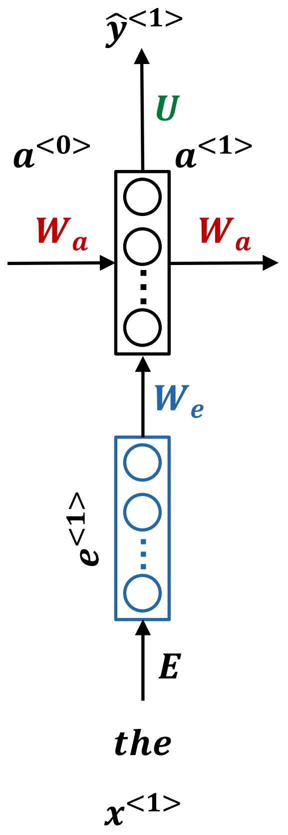

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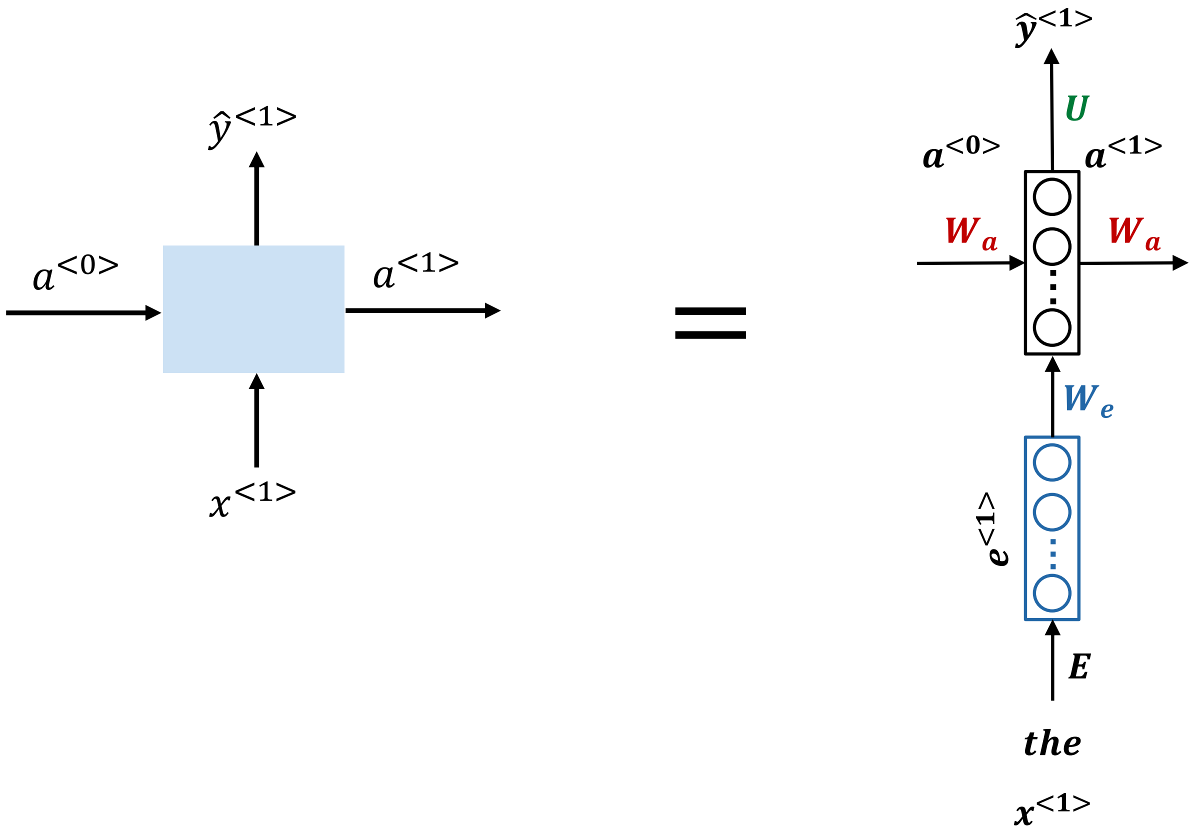

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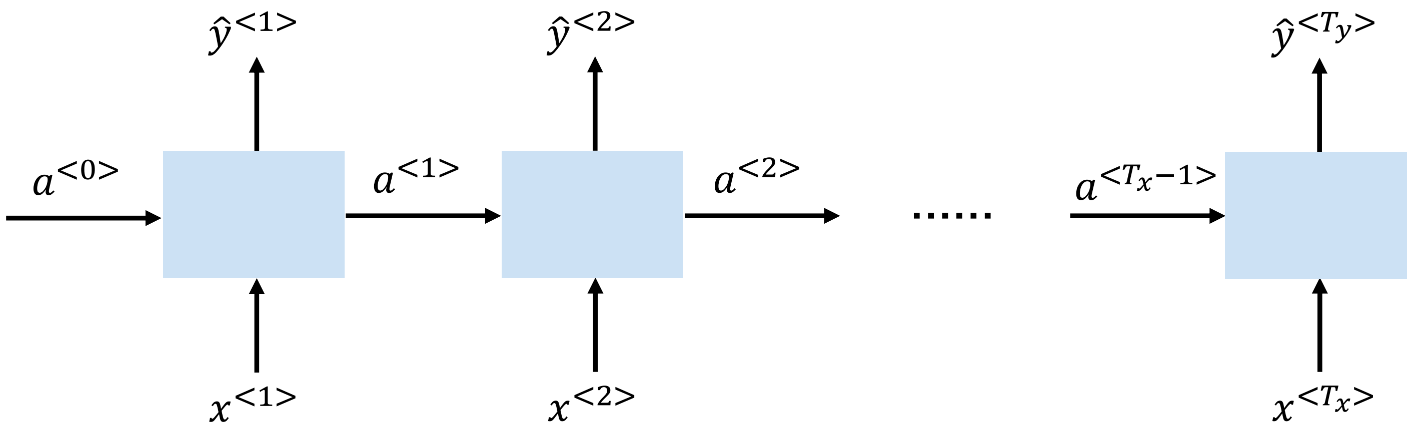
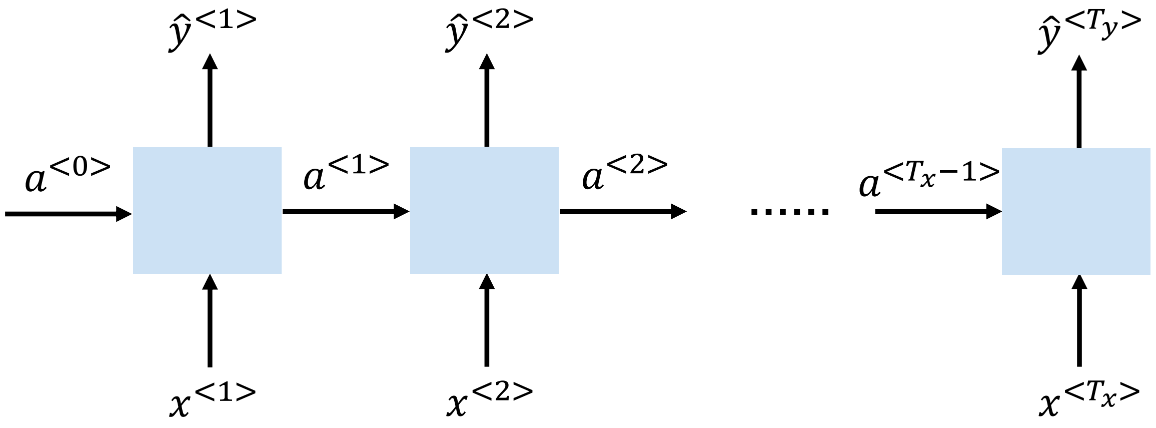
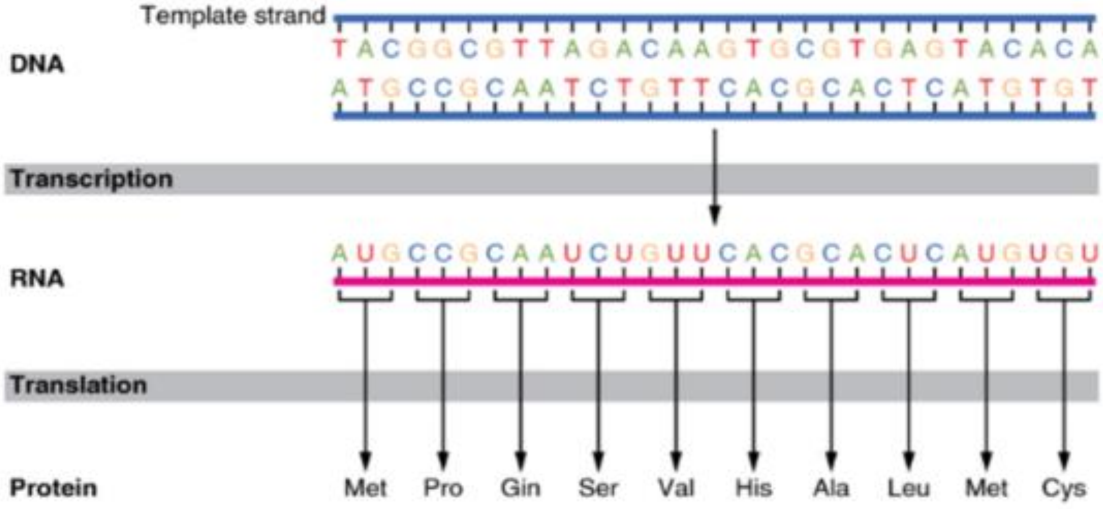


Architecture of RNN will change depending on input/output relationships



Many-to-Many



DNA Sequencing

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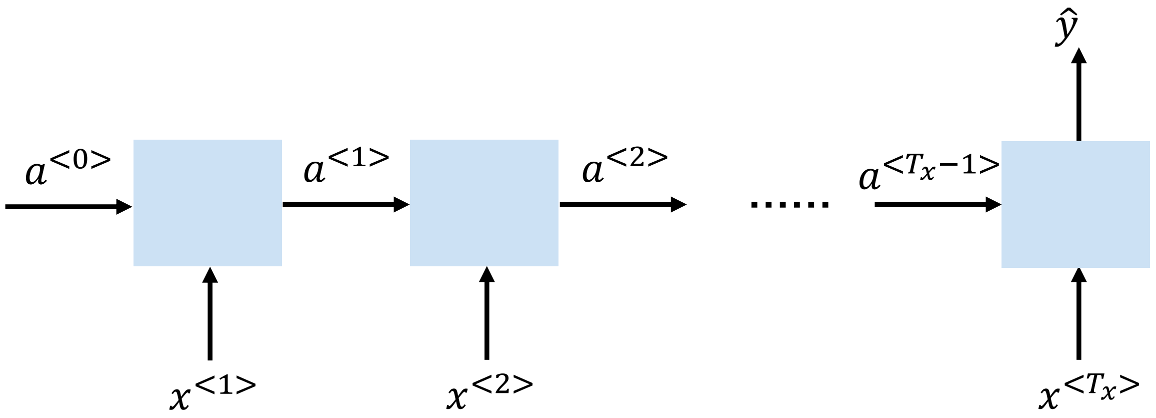


Many-to-One

I paid 100 Euros for a really flavourless food and not so delightful ambience.

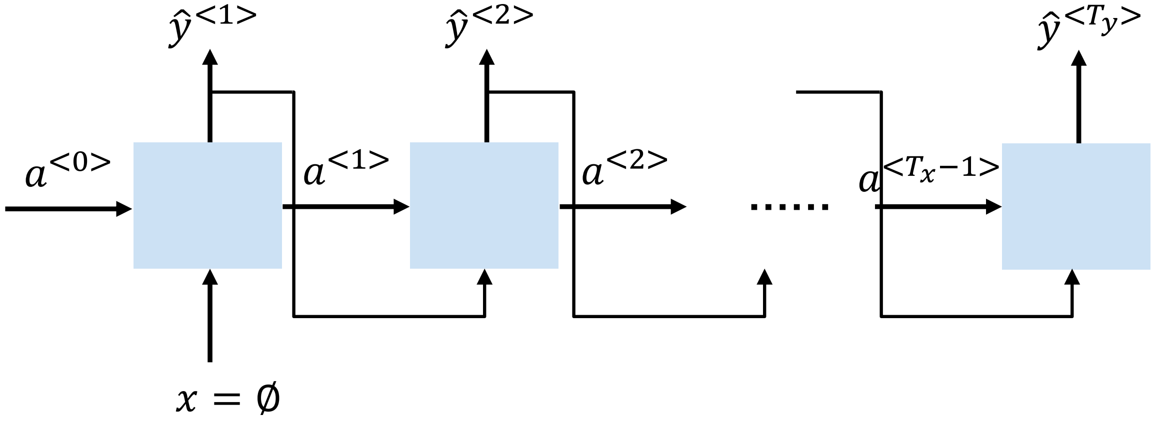
Food was fine and I wouldn't say it was the best place I have ever tried.

We loved the food. Menu is perfect in here, something for everyone. Visiting this one again.

Sentiment Analysis

Architecture of RNN will change depending on input/output relationships

Music Generation



One-to-Many

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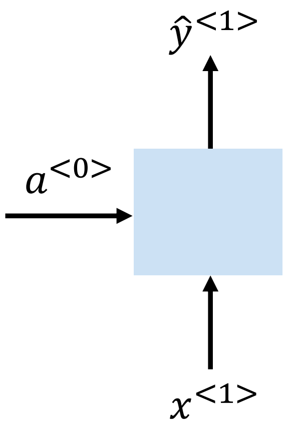
- There’s no NLP task that requires a one-to-one model architecture.



One-to-One

Encoder-Decoder model is a special case of many-to-many architecture

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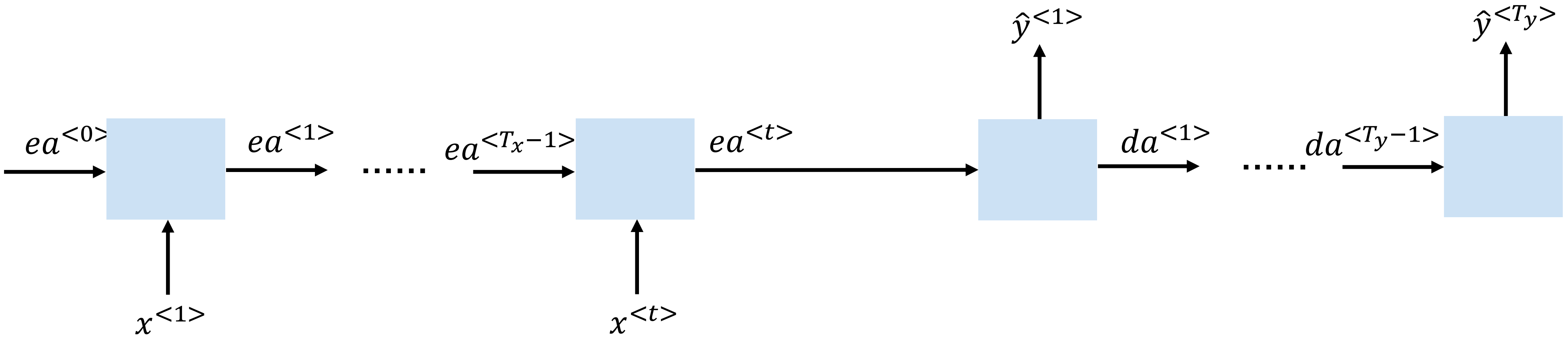

Many-to-Many V2

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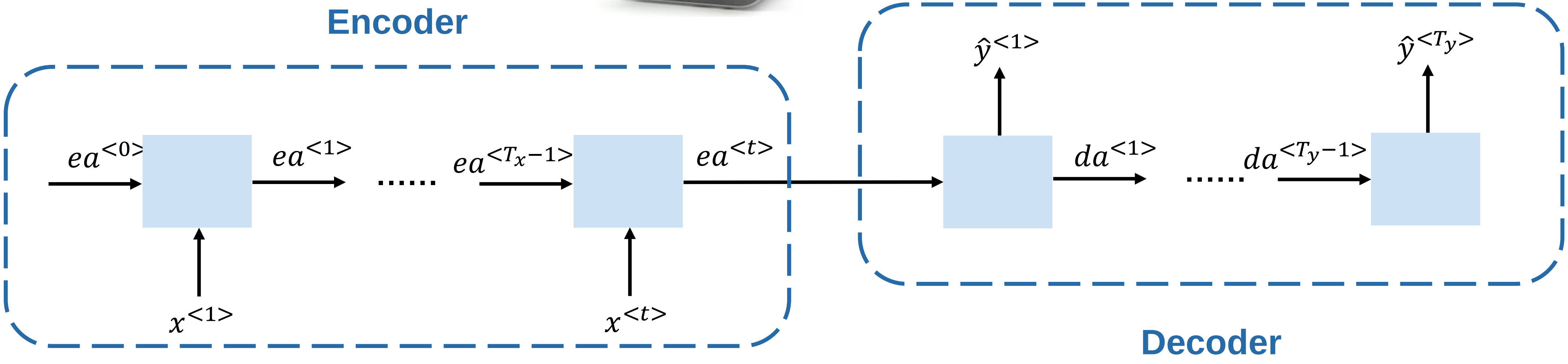

Many-to-Many V2

Let's simplify RNN equations and schematics

$$a^{<t>} = g\left(W[a^{<t-1>},\ x^{<t>}] + b_y\right)$$

$$\hat{y}^{<t>} = g(Ua^{<t>} + b_a)$$

$[W_a \,\vdots\, W_e] = W$ (Think of it as a vector of matrices)

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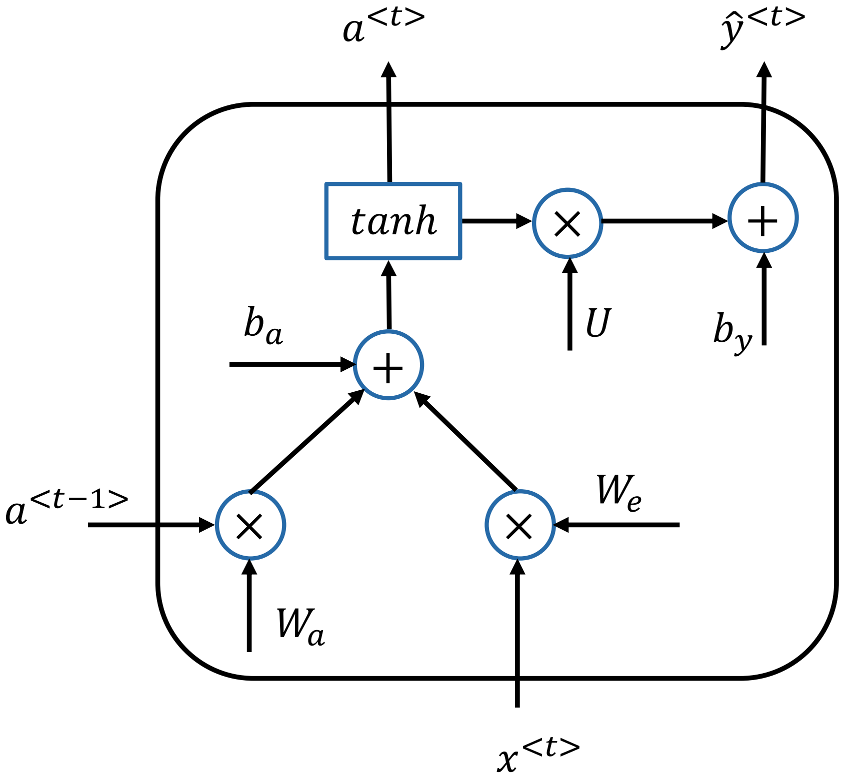

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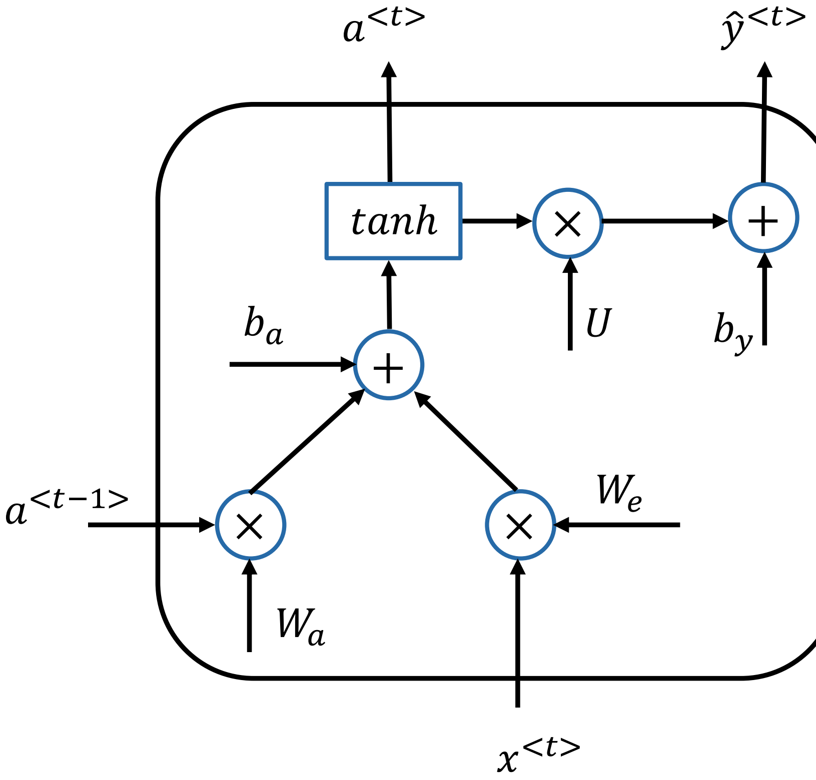

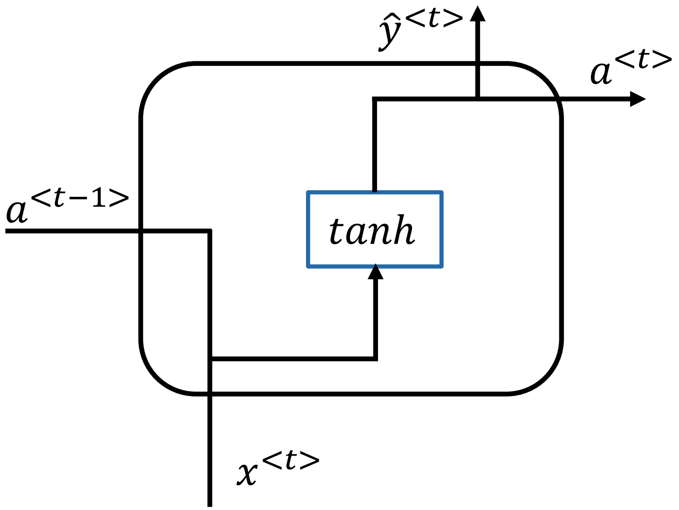

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- Advantages of RNNs:
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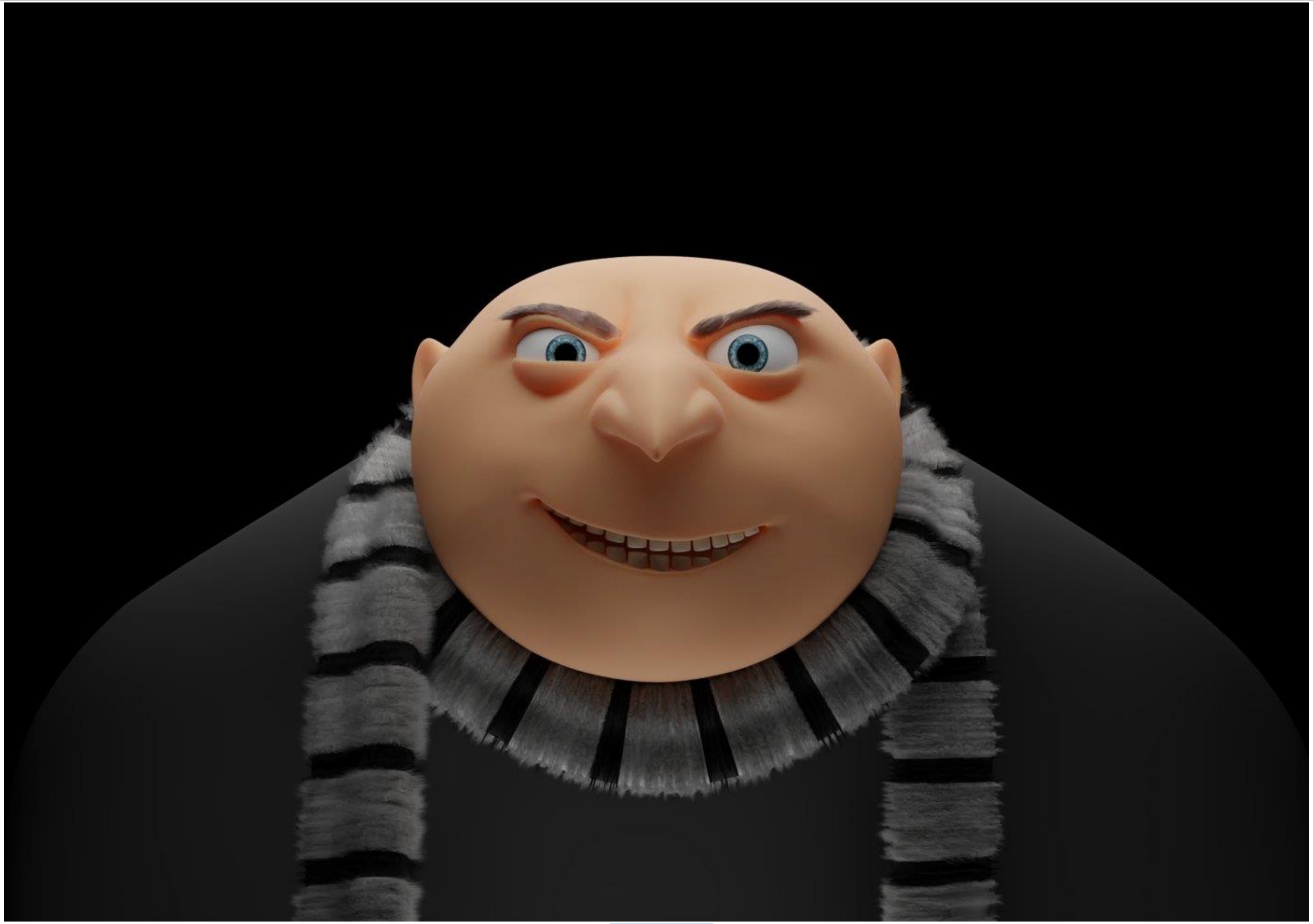
  - Computations are sequential.
  - Difficult to access information from many steps back.
- Solution?



Gated Recurrent Unit (GRU) stores previous information for future use

- Let c is a Memory **C**ell.

- For now, let $c^{<t>} = a^{<t>}$.

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- So the update equation for c becomes,

$$c^{<t>} = \Gamma_u * \tilde{c}^{<t>} + (1 - \Gamma_u) * c^{<t-1>}$$

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Simplified model of GRU has only one gate

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- What if Γ is in between 0 and 1?

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- More expensive than standard RNN but more powerful and robust as well.

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Long Short Term Memory (LSTM) Cell is older yet more powerful than GRU

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Which of the two is better?

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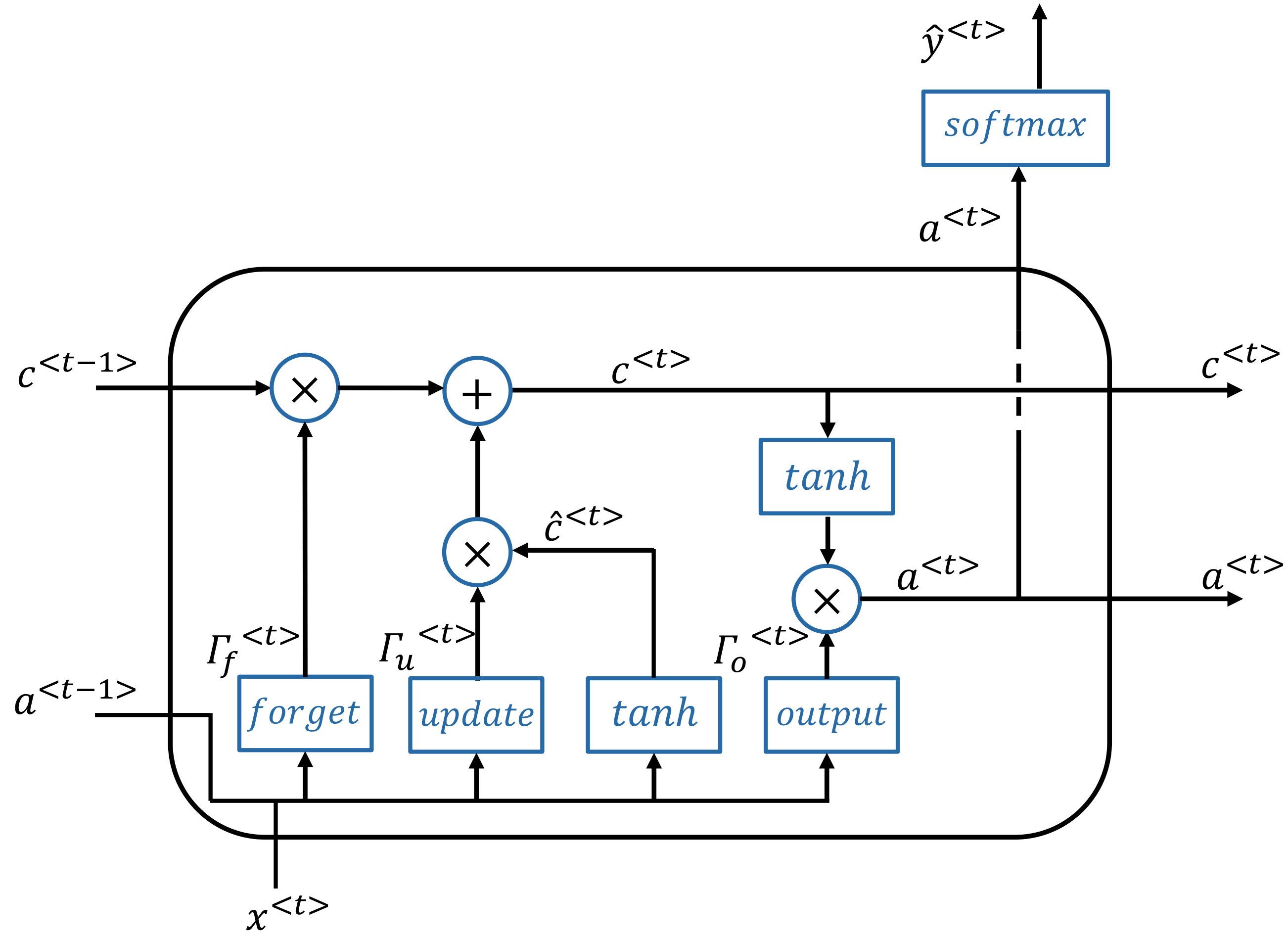
Schematic Diagram of LSTM



Bidirectional RNNs use past and future information at the same time

In Pakistan, cricket is a

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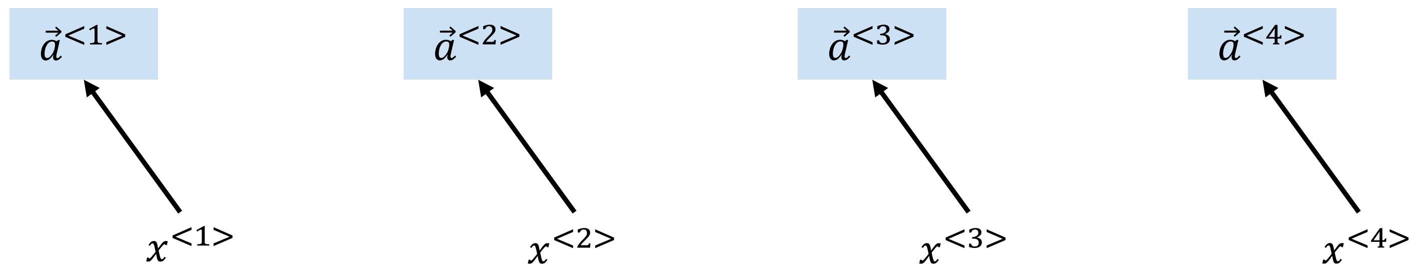

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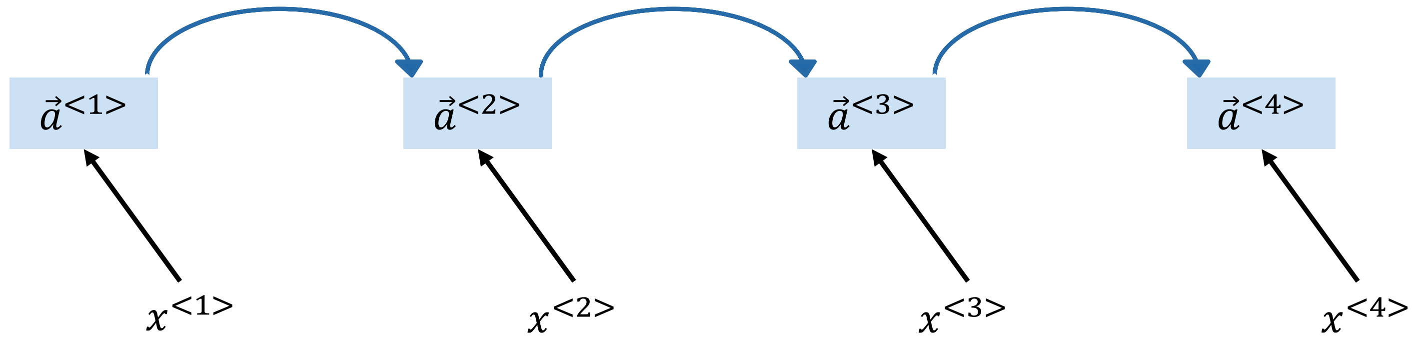

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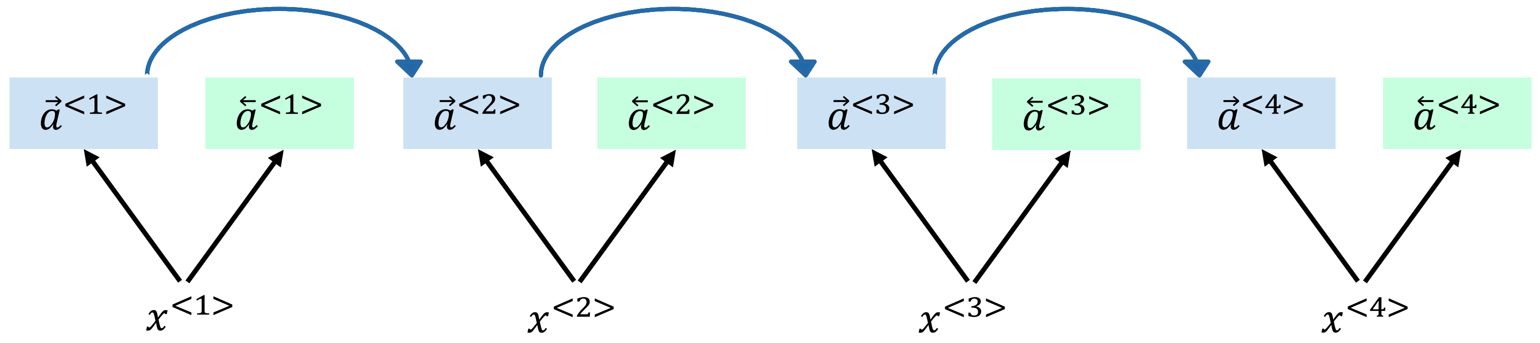

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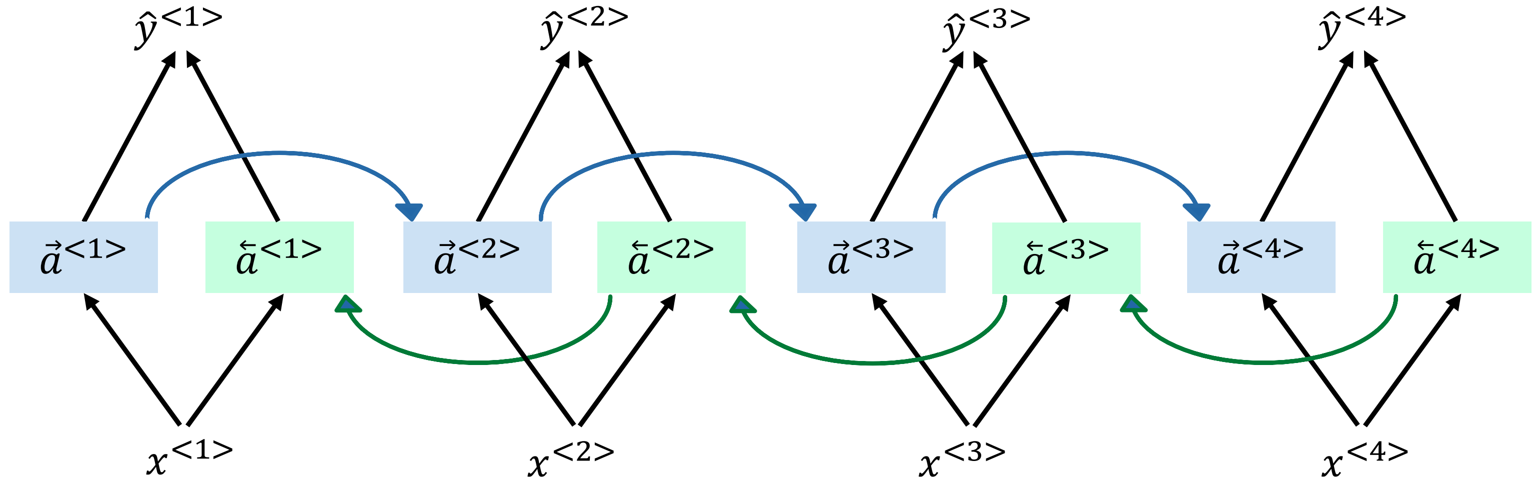
In Pakistan, cricket is a popular sport.



https://www.youtube.com/watch?v=bTXGpATdKRY

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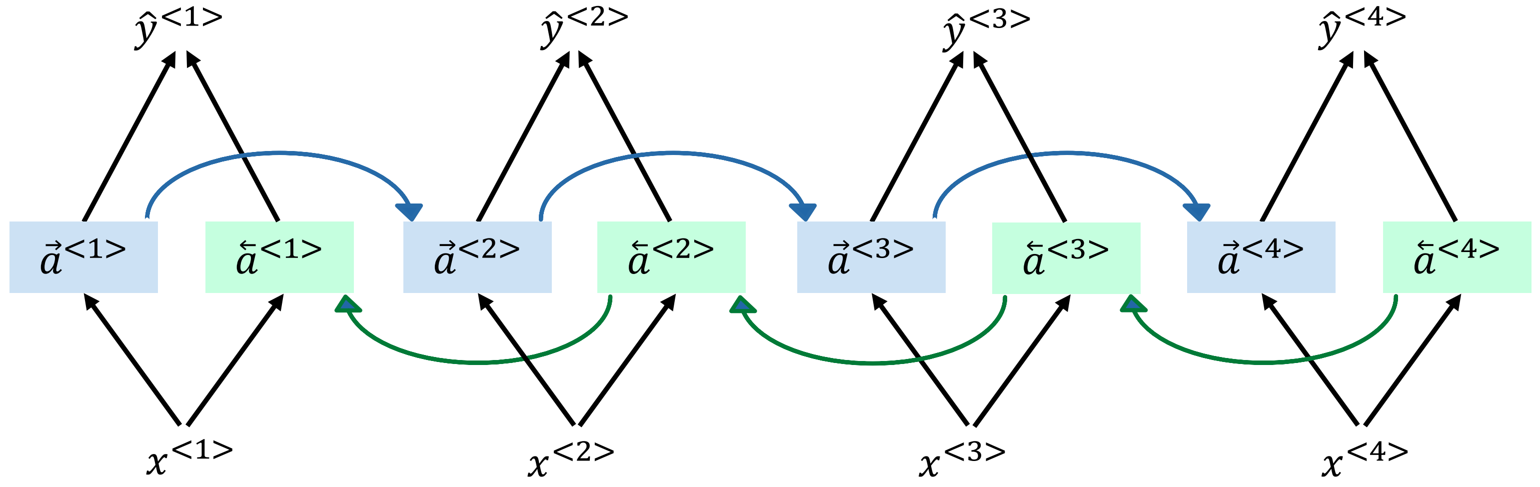

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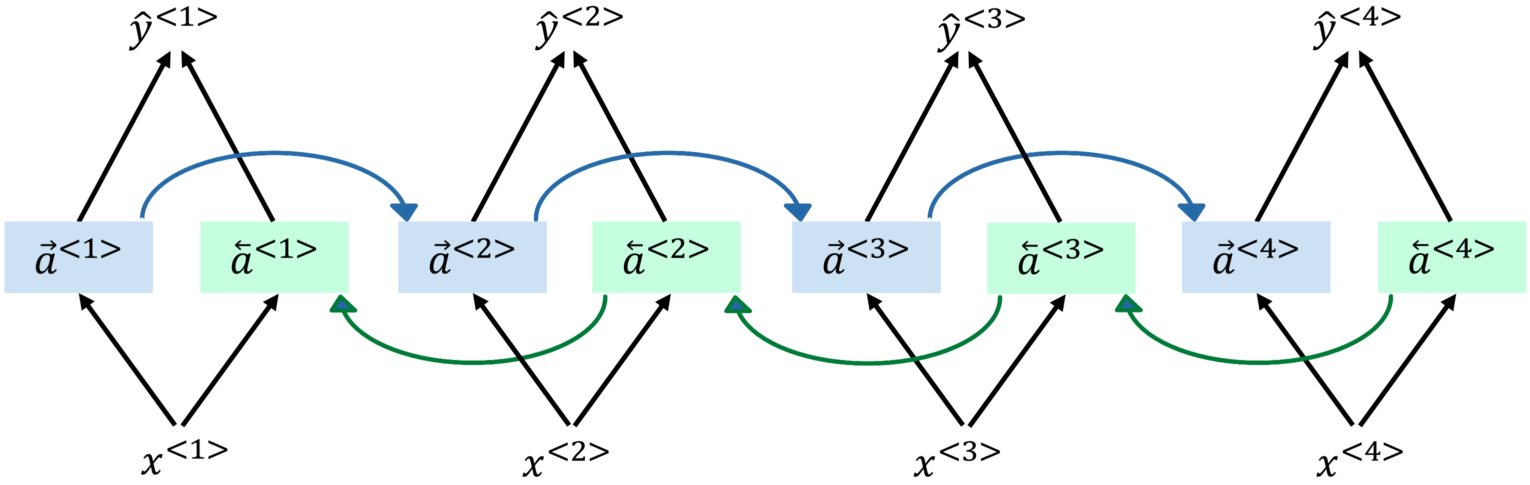

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$$\hat{y}^{<t>} = g\left(W_y[\vec{a}^{<1>}, \overleftarrow{a}^{<1>}] + b_y\right)$$

- Forward pass consists of going from left to right and coming back from right to left.

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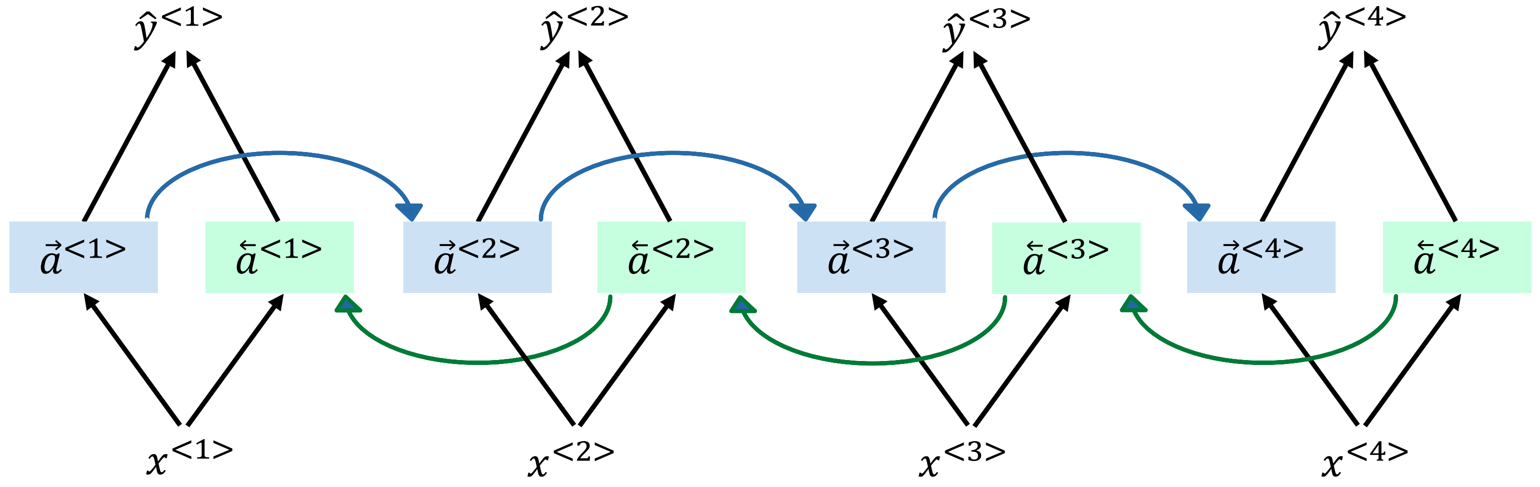

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Can we use BRNN for real-time language translation?

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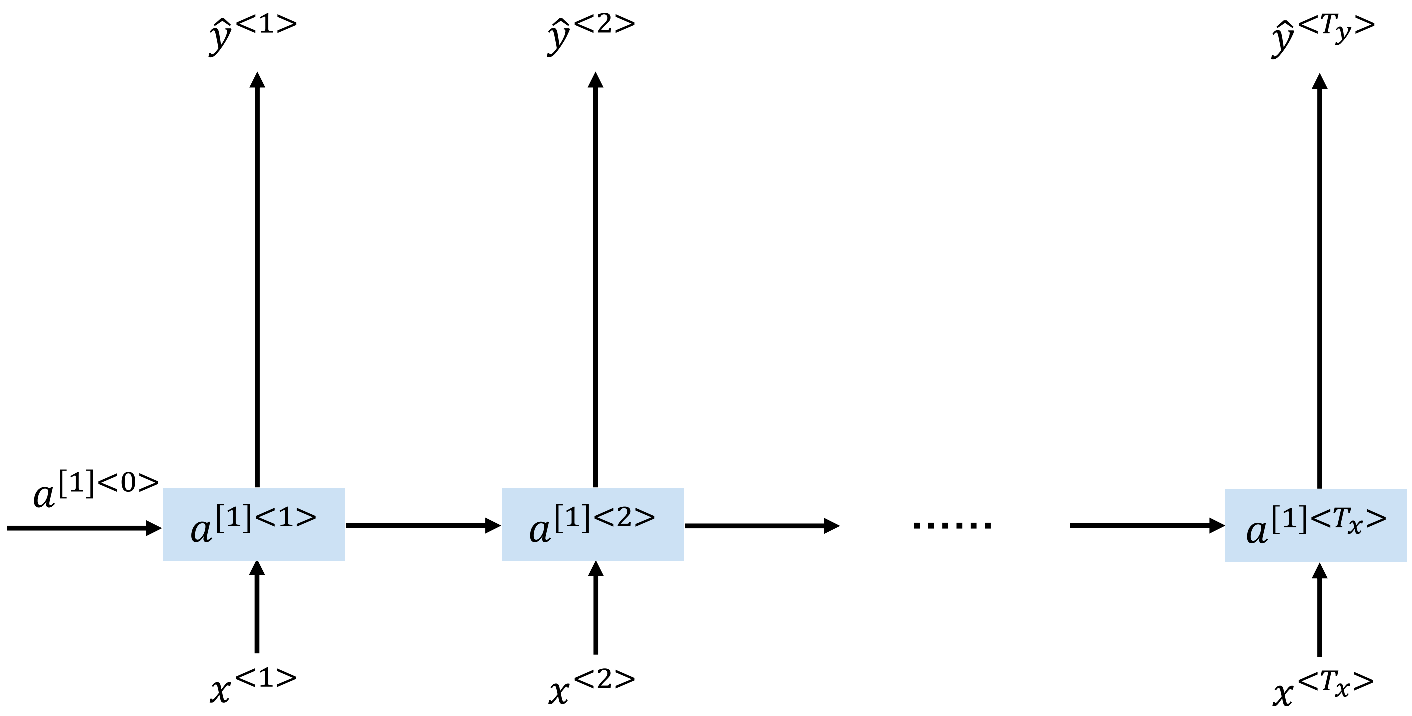
Deep RNNs are too computationally expensive



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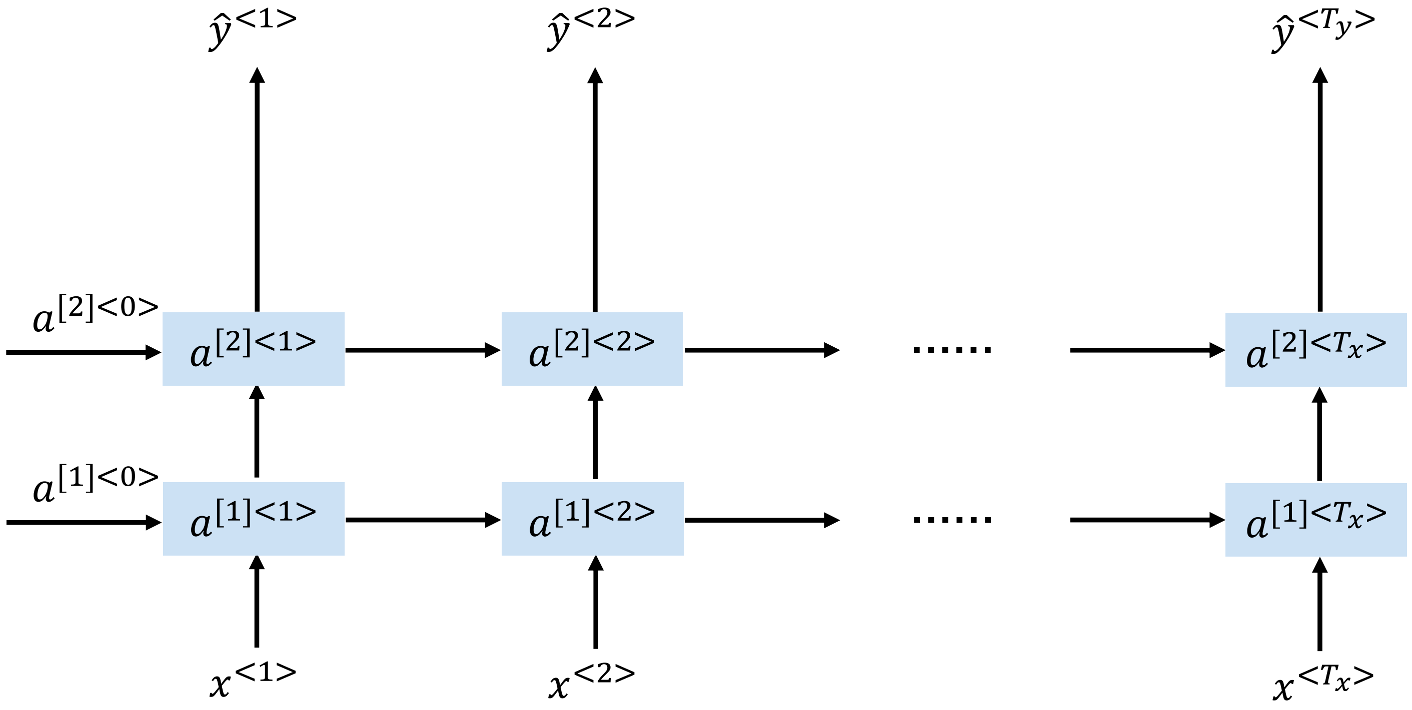

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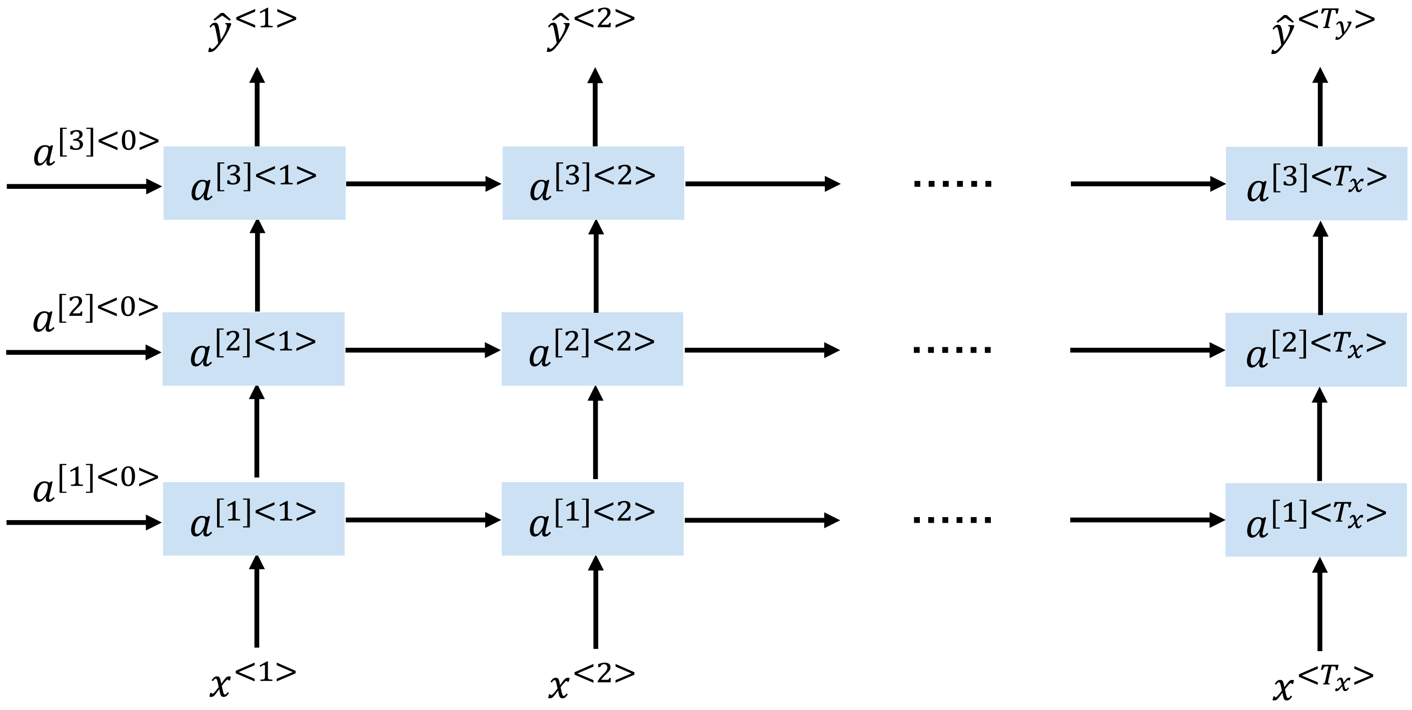

$$a^{[l]<t>} = g\left(W_a^l \, [a^{[l]<t-1>}, a^{[l-1]<t>}] + b_a^l\right)$$

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Do you have any problem?

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