

# NLP

Week-3

# Examples of sequence data

Speech recognition



“The quick brown fox jumped  
over the lazy dog.”

Music generation

∅



Sentiment classification

“There is nothing to like  
in this movie.”



DNA sequence analysis

AGCCCCTGTGAGGAACTA  
G



AG**CCCCTGTGAGGAACTA**  
G

Machine translation

Voulez-vous chanter avec  
moi?



Do you want to sing with  
me?

Video activity recognition



Running

Name entity recognition

Yesterday, Harry Potter  
met Hermione Granger.



Yesterday, **Harry Potter**  
met **Hermione Granger**.

## Motivating example

x:        Harry Potter and Hermione Granger invented a new spell.

Named Entity Recognition  
Find out input and output.

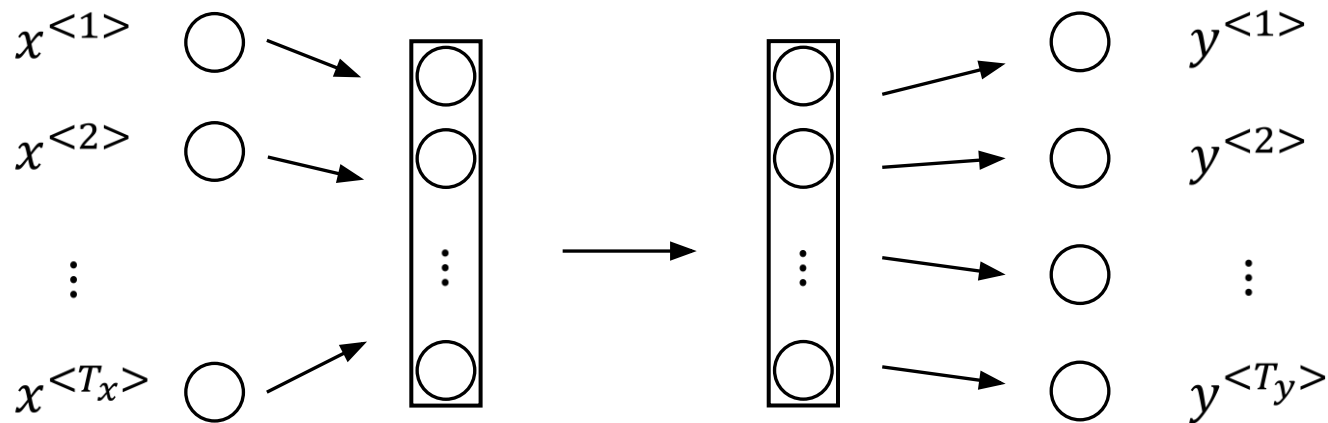
# Representing words

Use Dictionary for the feature  
representation of words

x: Harry Potter and Hermione Granger invented a new spell.

$x^{<1>}$   $x^{<2>}$   $x^{<3>}$  ...  $x^{<9>}$

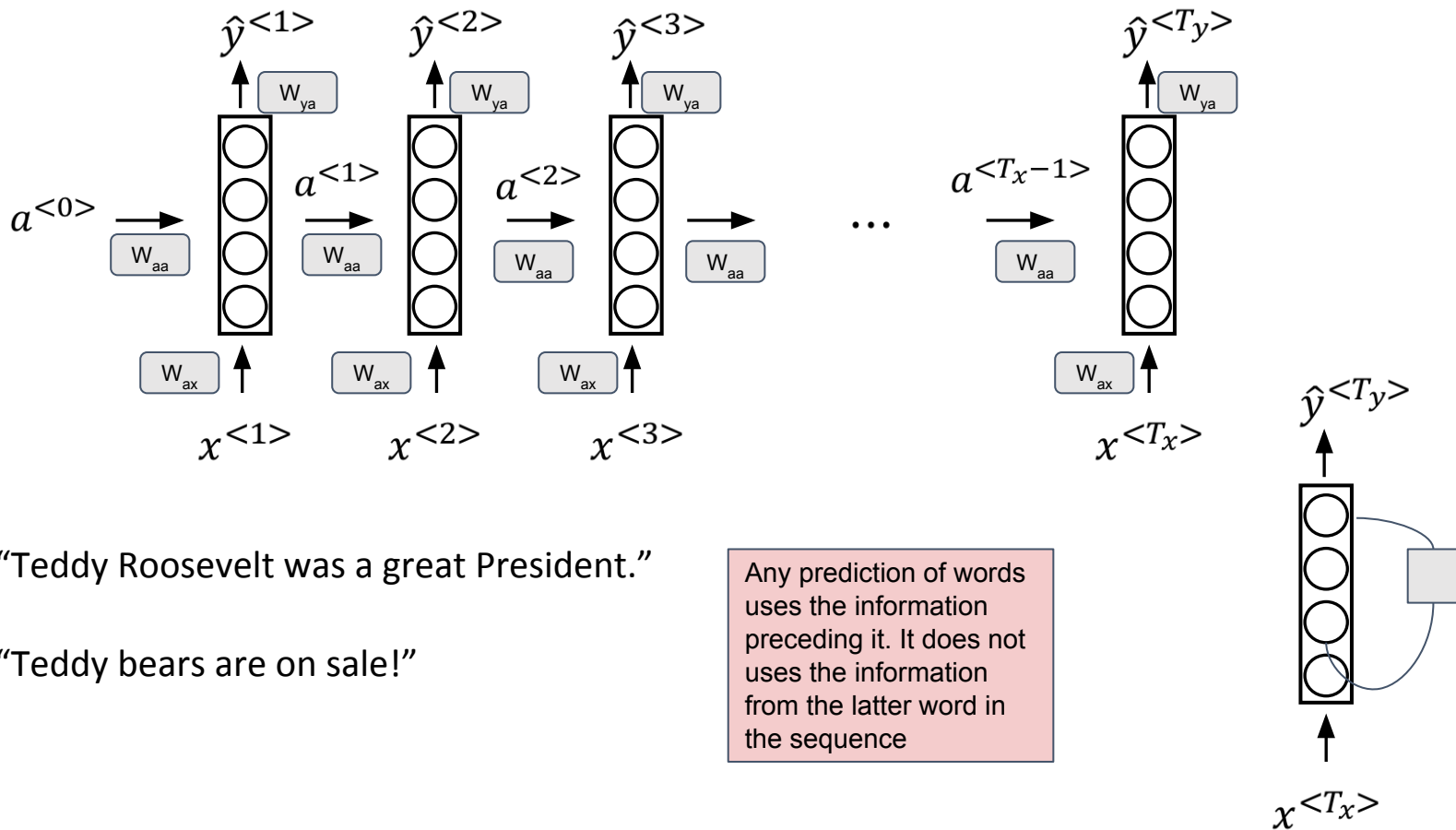
# Why not a standard network?



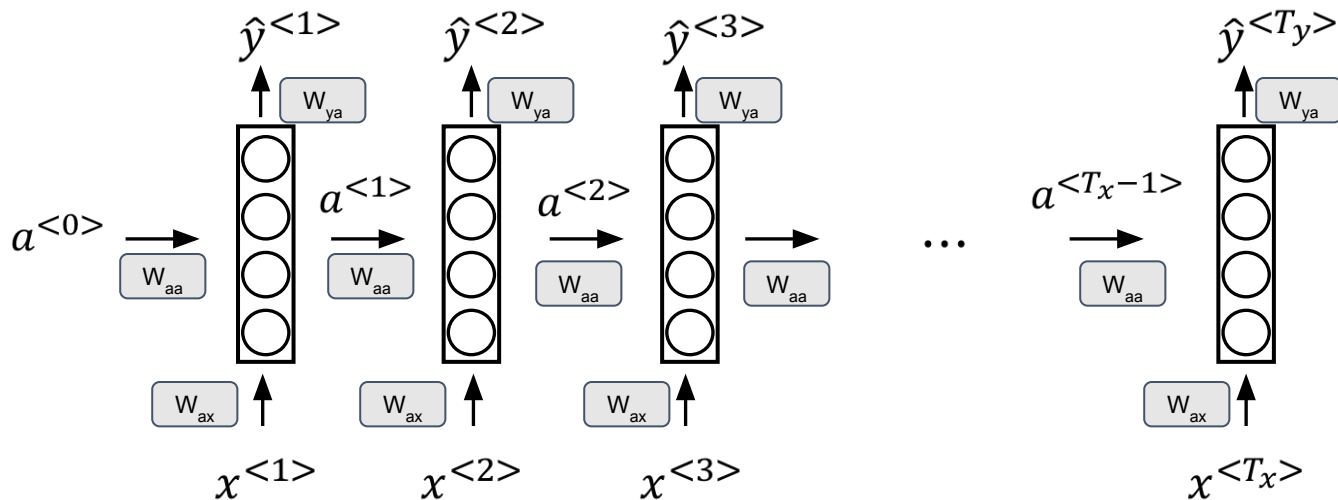
## Problems:

- Inputs, outputs can be different lengths in different examples.
- Doesn't share features learned across different positions of text.

# Recurrent Neural Networks



# Forward Propagation

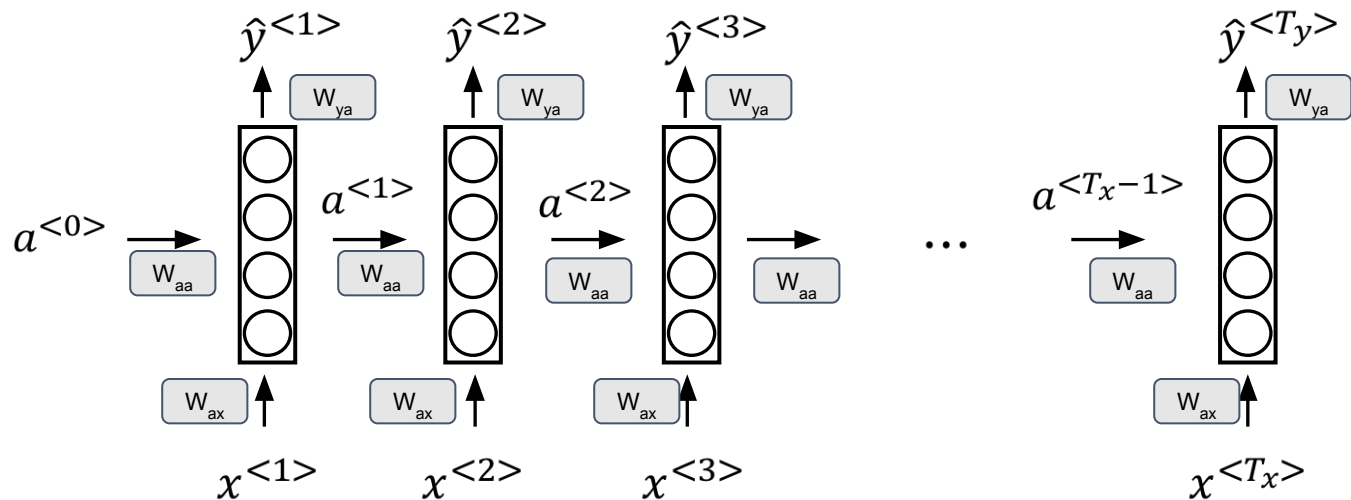


$$a^{<t>} = g(W_{aa}a^{<t-1>} + W_{ax}x^{<t>} + b_a)$$

$$\hat{y}^{<t>} = g(W_{ya}a^{<t>} + b_y)$$

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

# Forward propagation and backpropagation



$$\mathcal{L}^{<t>}(\hat{y}^{<t>}, y^{<t>}) = -y^{<t>} \log \hat{y}^{<t>} - (1 - y^{<t>}) \log(1 - \hat{y}^{<t>})$$



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$\Theta$



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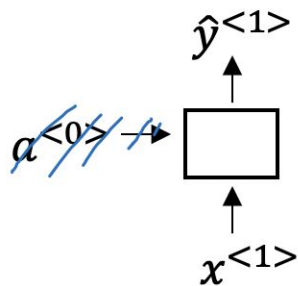
Name entity recognition

Yesterday, Harry Potter  
met Hermione Granger.

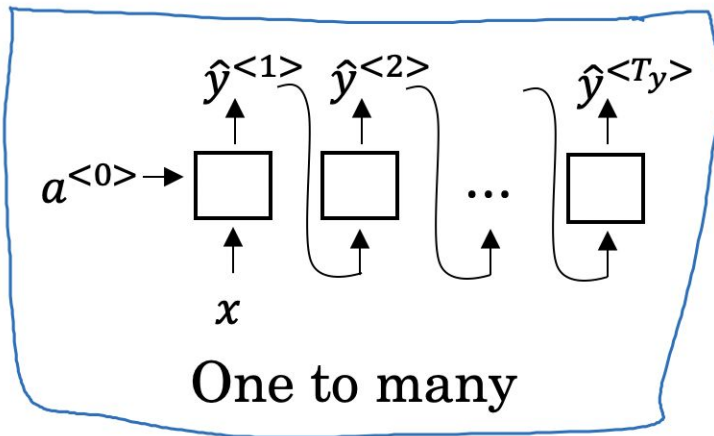


Yesterday, **Harry Potter**  
met **Hermione Granger**.

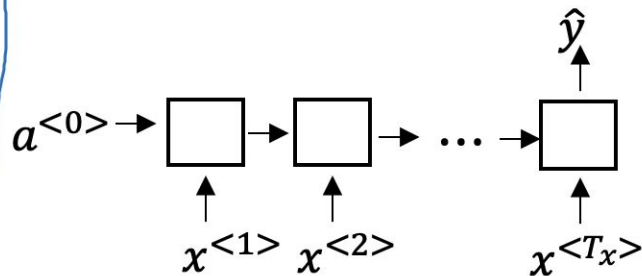
# Examples of RNN types



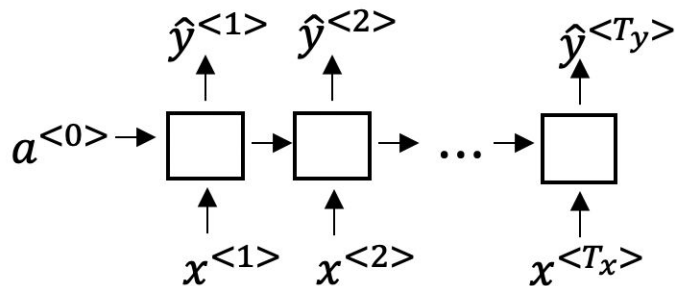
One to one



One to many

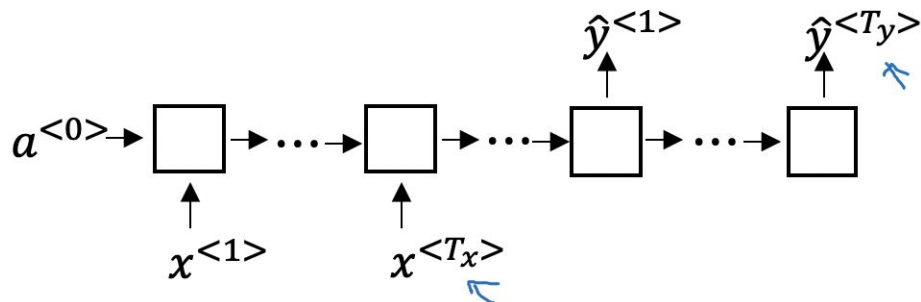


Many to one



Many to many

$T_x = T_y$



Many to many

# What is language modelling?

## Speech recognition

The apple and pair salad.

The apple and pear salad.

$P(\text{The apple and pair salad}) =$

$P(\text{The apple and pear salad}) =$

Language model tells what is the probability of the sentence being correct. It estimates the probability of the given sequence of words

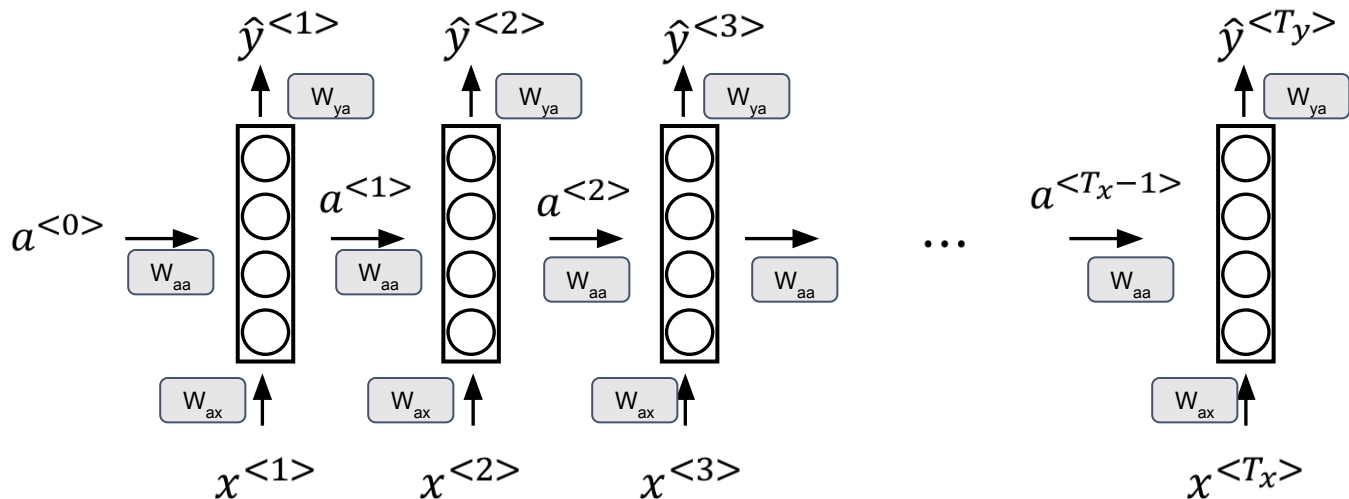
# Language modelling with an RNN

Training set: large corpus of english text.

Cats average 15 hours of sleep a day.

The Egyptian Mau is a breed of cat. <EOS>

# RNN model



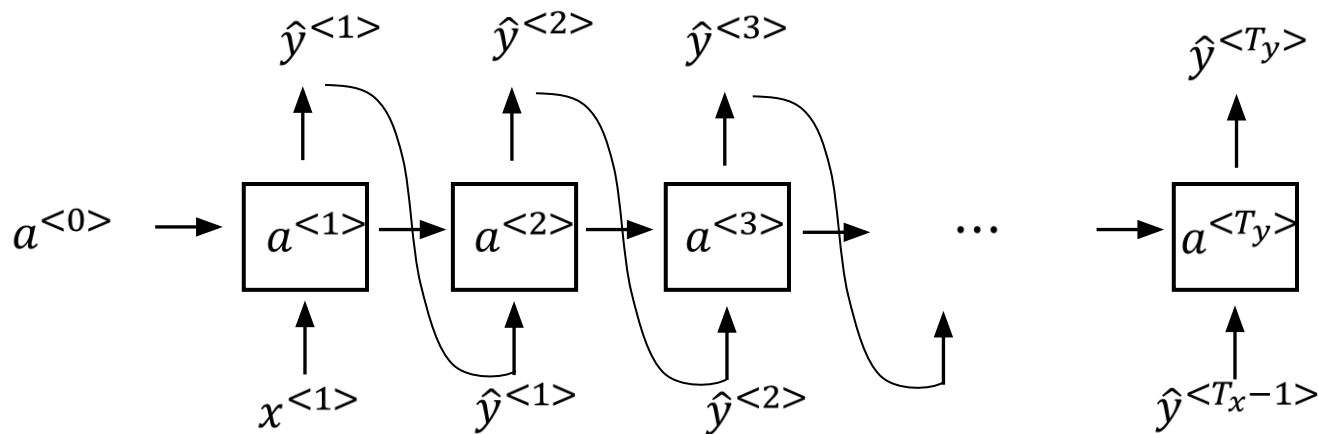
Cats average 15 hours of sleep a day. <EOS>

$$\mathcal{L} = \sum_t \mathcal{L}^{<t>}(\hat{y}^{<t>}, y^{<t>})$$

At every step of RNN, we look at some set of preceding words.

# Character-level language model

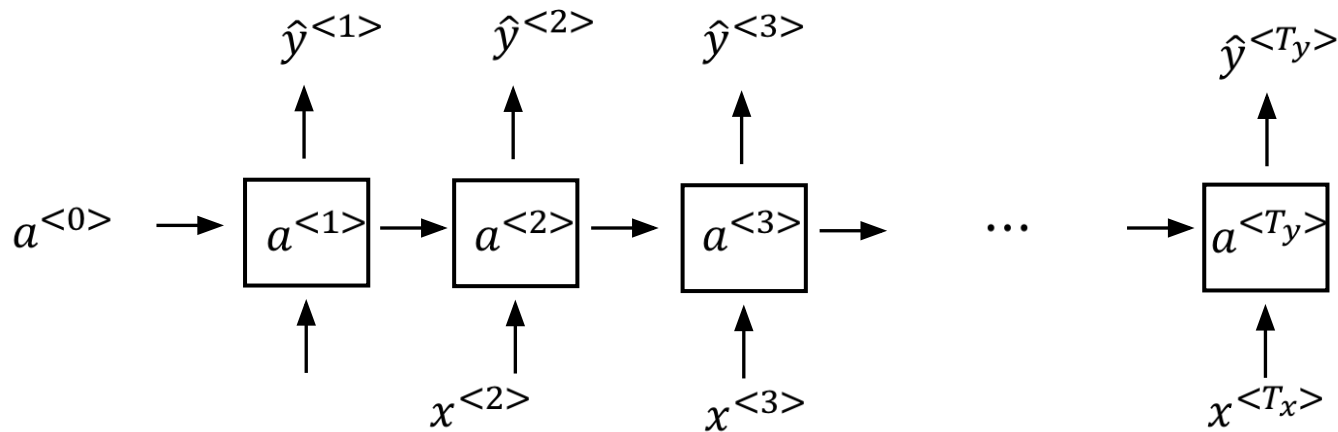
Vocabulary = [a, aaron, ..., zulu, <UNK>]



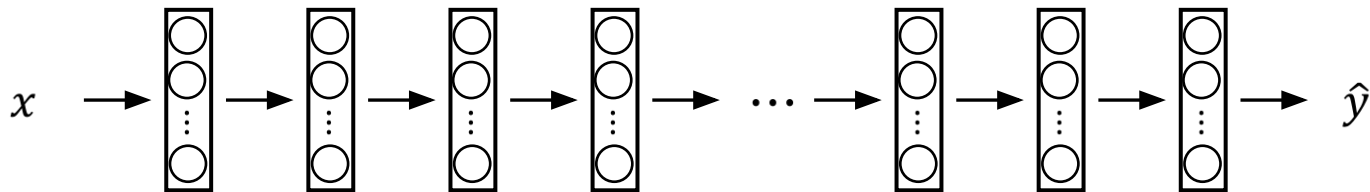
No need to worry about  
<UNK> word token

Ends up in much longer  
sequences  
Computationally Expensive

# Vanishing gradients with RNNs



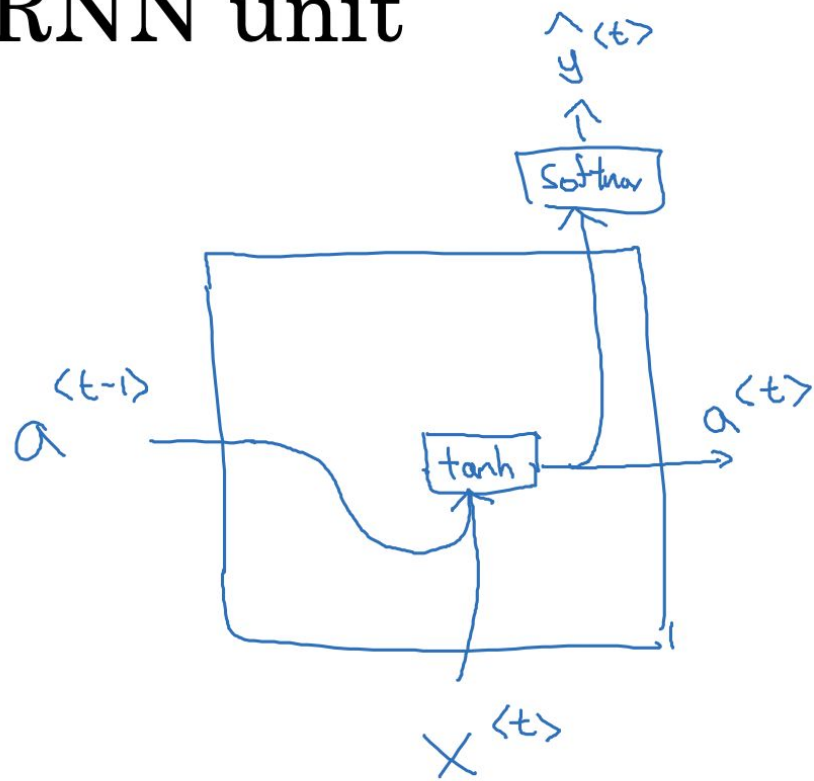
Earlier words determines what word comes later.  
Output is influenced by the input which is very early in the sequence.  
This makes RNN unable to catch long range dependencies.



Gradient clipping - Solution for exploding gradient.  
If Gradient is beyond certain threshold then rescales the values to avoid NaNs.

Exploding gradients.

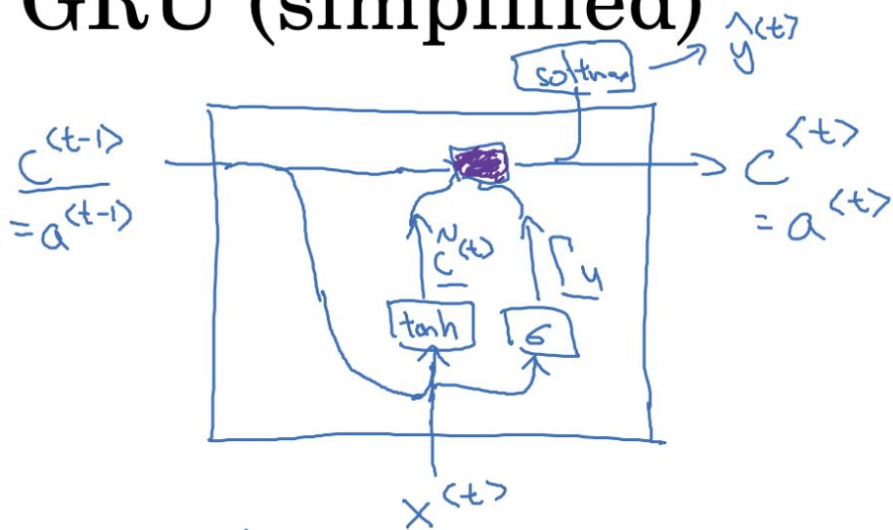
# RNN unit



$$\underline{a^{<t>}} = \underline{g}(\overset{\tanh}{\downarrow} \underline{W_a[a^{<t-1>}, x^{<t>}]} + \underline{b_a})$$



# GRU (simplified)



$$\tilde{c}^{<t>} = \tanh(W_c[\Gamma_r * c^{<t-1>}, x^{<t>}] + b_c)$$

$$\Gamma_u = \sigma(W_u[c^{<t-1>}, x^{<t>}] + b_u)$$

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

$$a^{<t>} = c^{<t>}$$

The cat, which already ate ..., was full.

# LSTM units

## GRU

$$\tilde{c}^{<t>} = \tanh(W_c[\Gamma_r * c^{<t-1>}, x^{<t>}] + b_c)$$

$$\Gamma_u = \sigma(W_u[ c^{<t-1>}, x^{<t>}] + b_u)$$

$$\Gamma_r = \sigma(W_r[ c^{<t-1>}, x^{<t>}] + b_r)$$

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

$$a^{<t>} = c^{<t>}$$

## LSTM

$$\tilde{c}^{<t>} = \tanh(W_c[a^{<t-1>}, x^{<t>}] + b_c)$$

$$\Gamma_u = \sigma(W_u[ a^{<t-1>}, x^{<t>}] + b_u)$$

$$\Gamma_f = \sigma(W_f[ a^{<t-1>}, x^{<t>}] + b_f)$$

$$\Gamma_o = \sigma(W_o[ a^{<t-1>}, x^{<t>}] + b_o)$$

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

$$a^{<t>} = \Gamma_o * c^{<t>}$$

# LSTM in pictures

$$\tilde{c}^{<t>} = \tanh(W_c[a^{<t-1>}, x^{<t>}] + b_c)$$

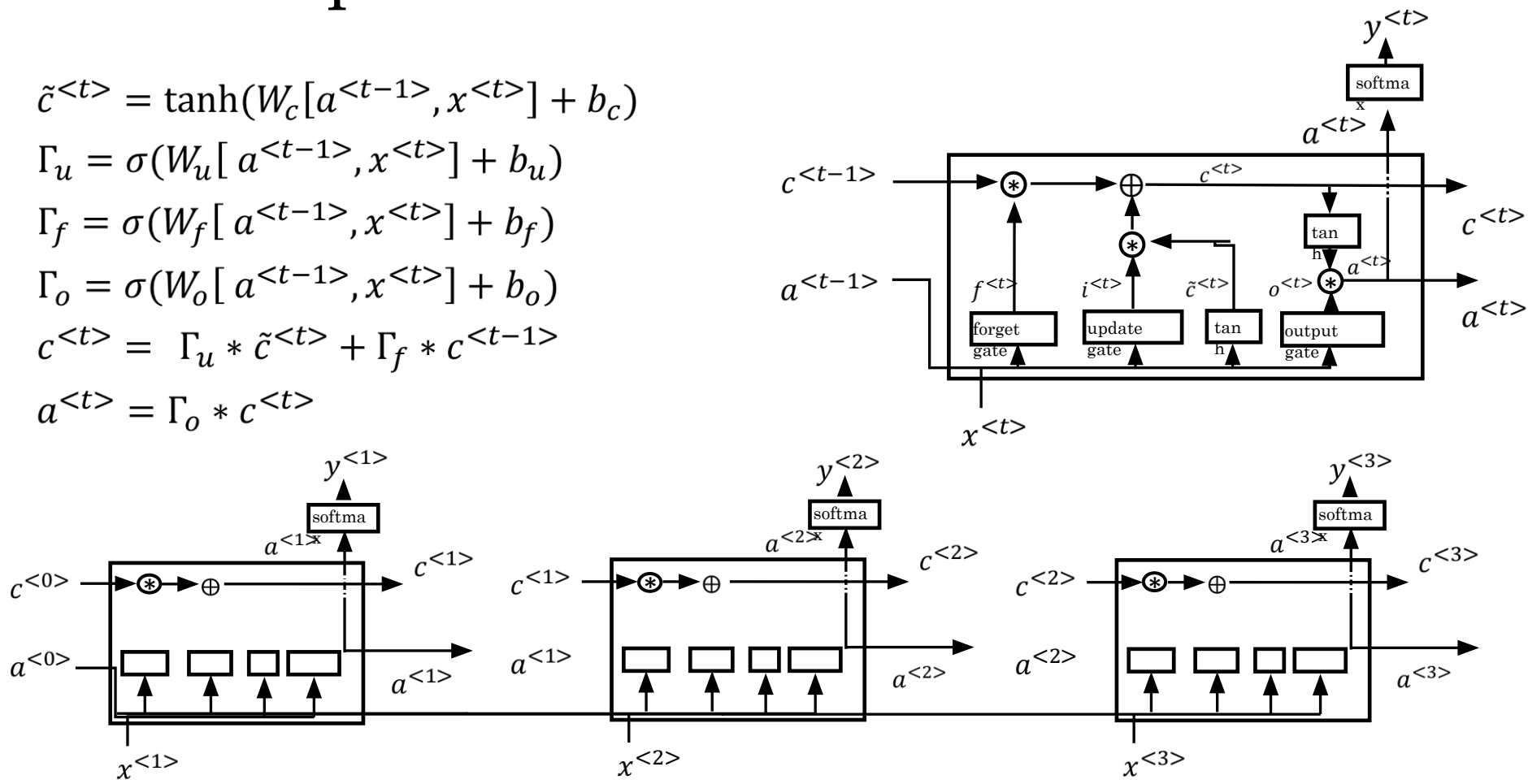
$$\Gamma_u = \sigma(W_u[a^{<t-1>}, x^{<t>}] + b_u)$$

$$\Gamma_f = \sigma(W_f[a^{<t-1>}, x^{<t>}] + b_f)$$

$$\Gamma_o = \sigma(W_o[a^{<t-1>}, x^{<t>}] + b_o)$$

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

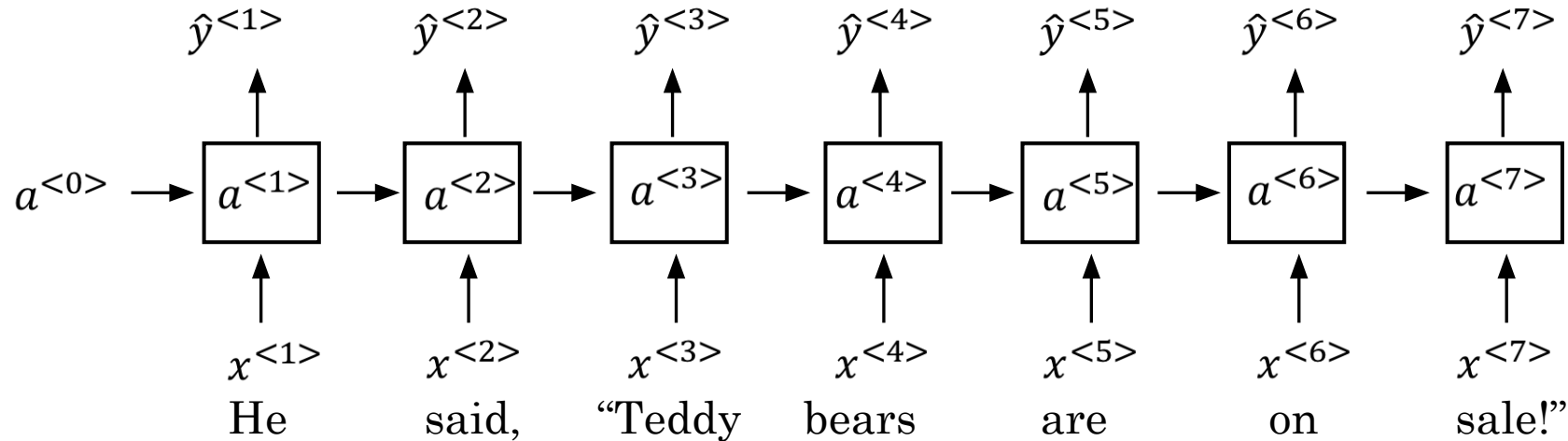
$$a^{<t>} = \Gamma_o * c^{<t>}$$



# BRNN - Getting information from the future

He said, “Teddy bears are on sale!”

He said, “Teddy Roosevelt was a great President!”



# Deep RNN example

