

Why sequence models?

Examples of sequence data

Speech recognition

*→* ,



**→** 

"The quick brown fox jumped over the lazy dog."

Music generation







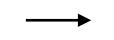
Sentiment classification

"There is nothing to like in this movie."





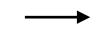
DNA sequence analysis -> AGCCCCTGTGAGGAACTAG



AGCCCCTGTGAGGAACTAG

Machine translation

Voulez-vous chanter avec moi?



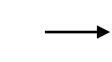
Do you want to sing with me?

Video activity recognition



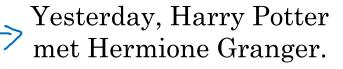






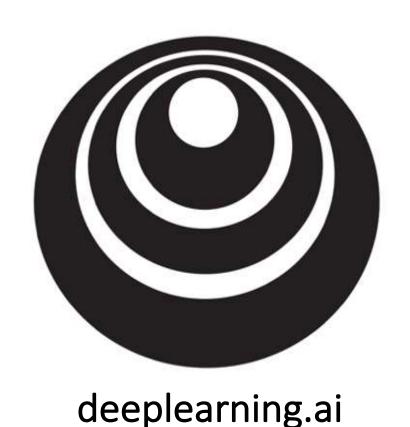
Running

Name entity recognition



Yesterday, Harry Potter met Hermione Granger.

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#### Notation

#### Motivating example

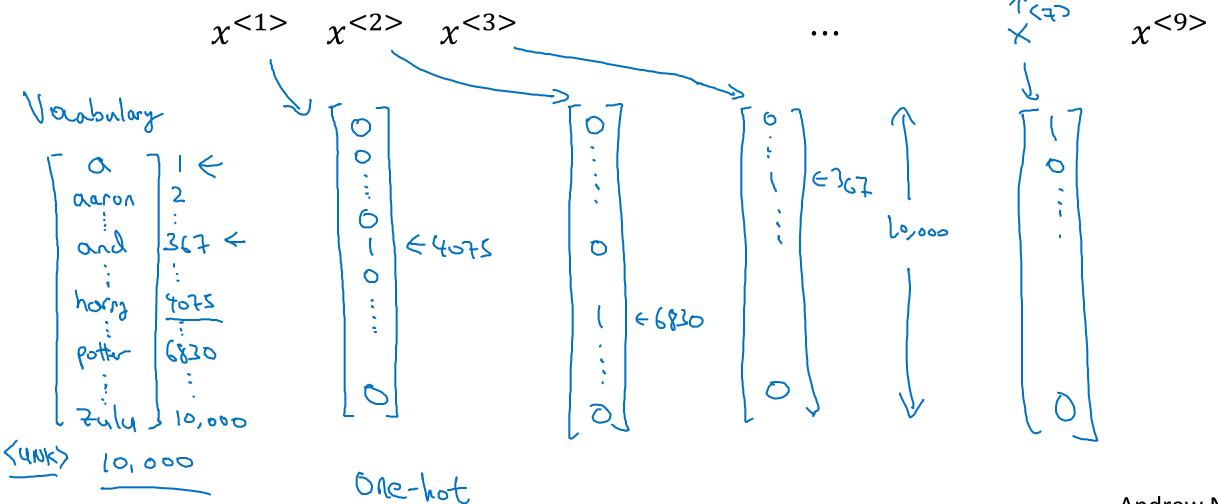
NLP

Harry Potter and Hermione Granger invented a new spell.  $\rightarrow$   $\times$   $\langle 1 \rangle$   $\times$   $\langle 2 \rangle$   $\langle 3 \rangle$ Tx = 9 1 (2) (2) (3)  $\rightarrow$  4.  $\times$  (i)<t>  $T_{X}^{(i)} = 9$ 

#### Representing words



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



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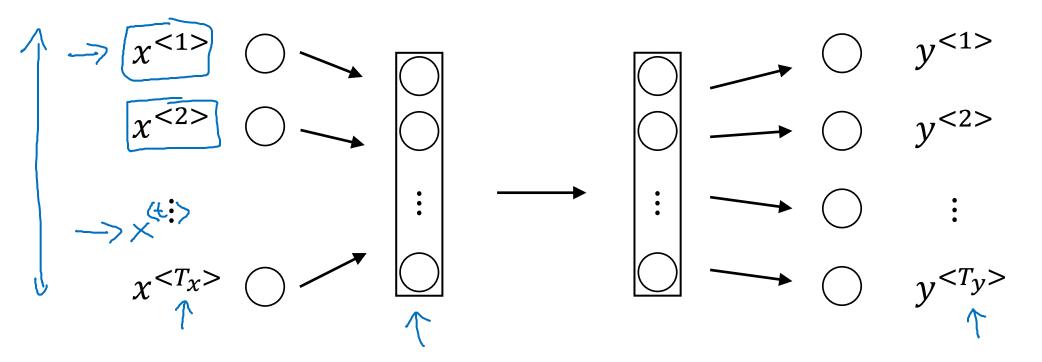
$$\chi$$
<1>  $\chi$ <2>  $\chi$ <3> ...  $\chi$ <9>

And = 367 Invented = 4700 A = 1 New = 5976 Spell = 8376 Harry = 4075 Potter = 6830 Hermione = 4200 Gran... = 4000



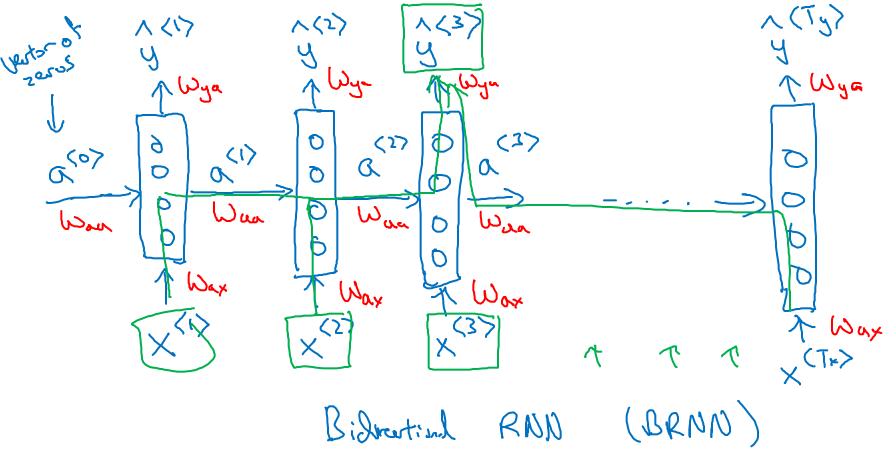
# Recurrent Neural Network Model

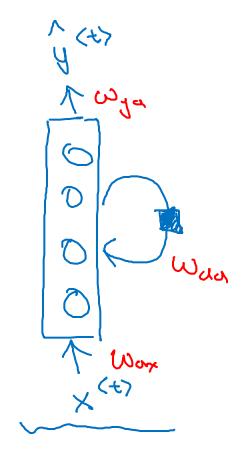
#### Why not a standard network?



#### Problems:

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





He said, "Teddy Roosevelt was a great President."

He said, "Teddy bears are on sale!"

Forward Propagation a - Wax x  $a^{<T_{\chi}-1>}$  $a^{(0)} = \vec{o}$ .  $a^{(1)} = g_1(W_{aa} a^{(0)} + W_{ax} x^{(1)} + b_a) \in tanh | Rely$   $a^{(1)} = g_2(W_{aa} a^{(1)} + b_y) \in Signoid$ act = g(Waa act-1) + Wax x + ba)

g(t) = g(Wya act) + by)

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Simplified RNN notation

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

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

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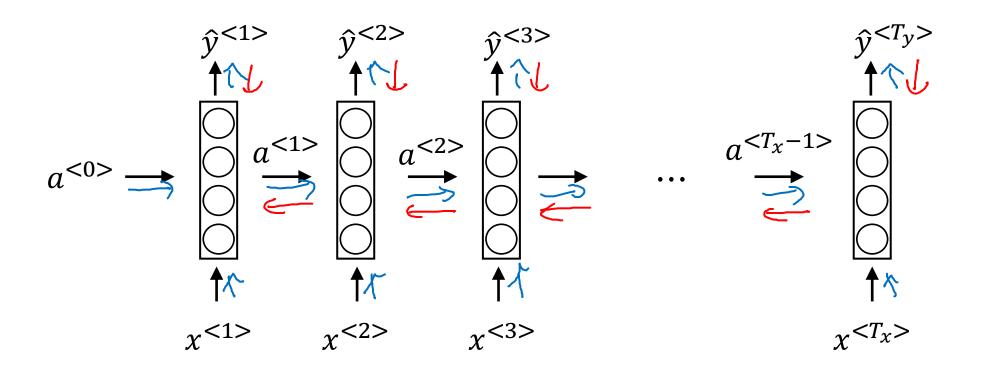
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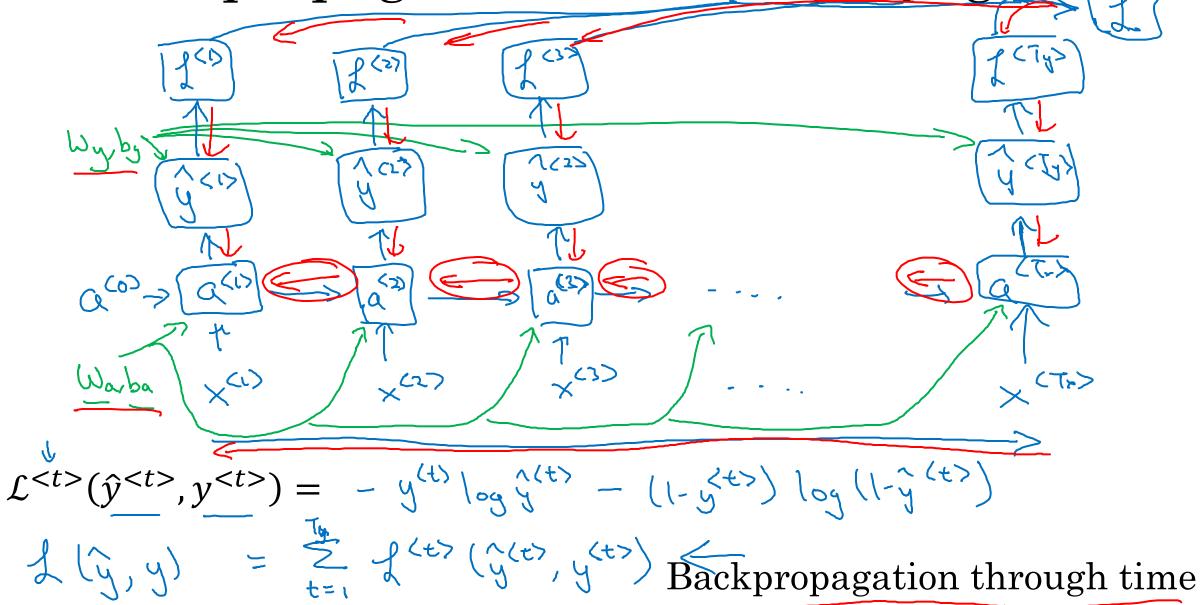


# Backpropagation through time

#### Forward propagation and backpropagation



Forward propagation and backpropagation





# Different types of RNNs

#### Examples of sequence data

Speech recognition

Music generation

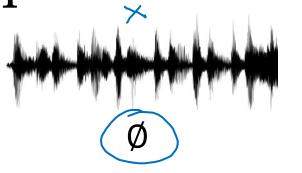
Sentiment classification

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"There is nothing to like in this movie."

AGCCCCTGTGAGGAACTAG

Voulez-vous chanter avec moi?



Yesterday, Harry Potter met Hermione Granger. "The quick brown fox jumped over the lazy dog."



AGCCCCTGTGAGGAACTAG

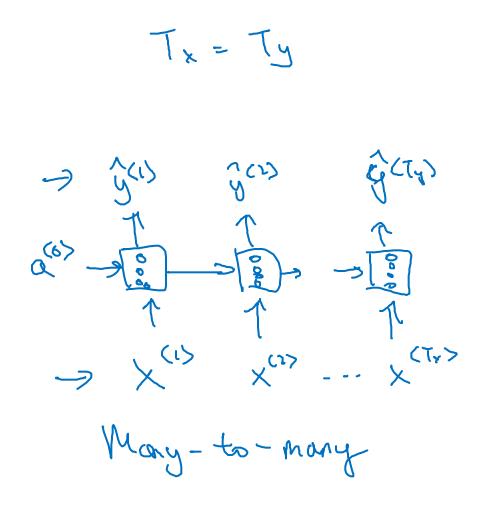
Do you want to sing with me?

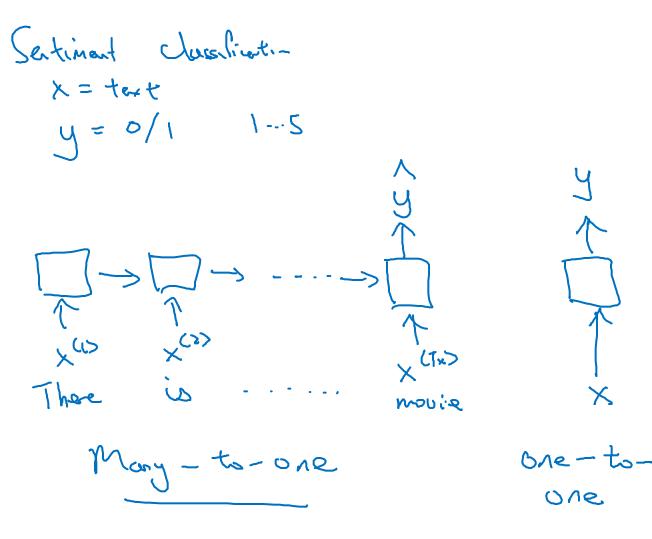
Running

Yesterday, Harry Potter met Hermione Granger.

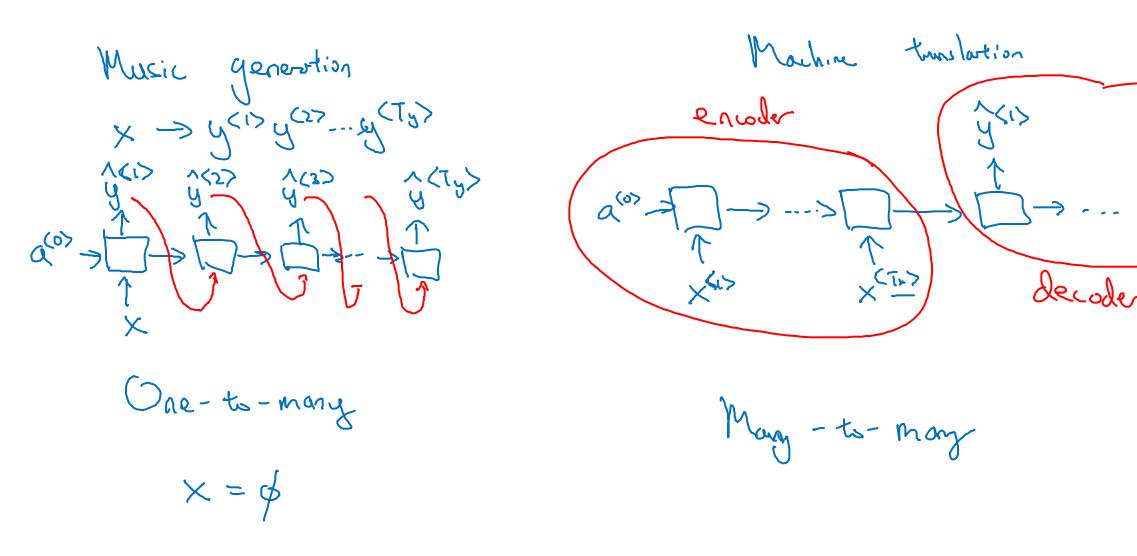
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#### Examples of RNN architectures

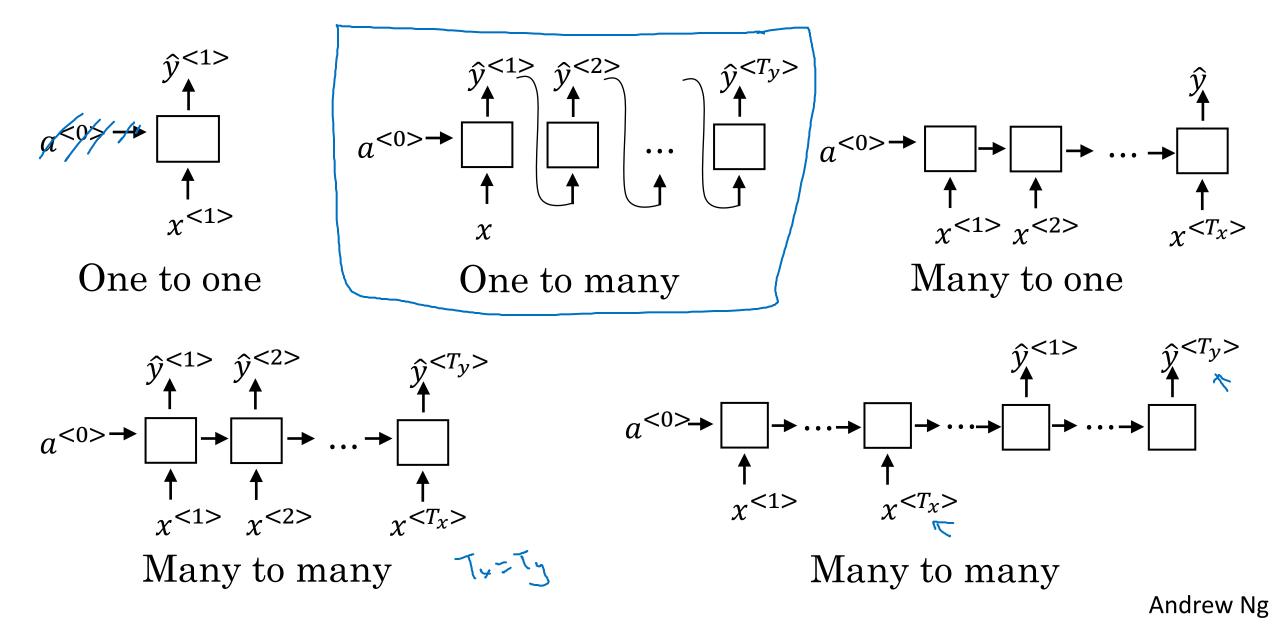




#### Examples of RNN architectures



#### Summary of RNN types





Language model and sequence generation

#### What is language modelling?

Speech recognition

The apple and pair salad.

The apple and pear salad.

$$P(\text{The apple and pair salad}) = 3.2 \times 10^{-13}$$

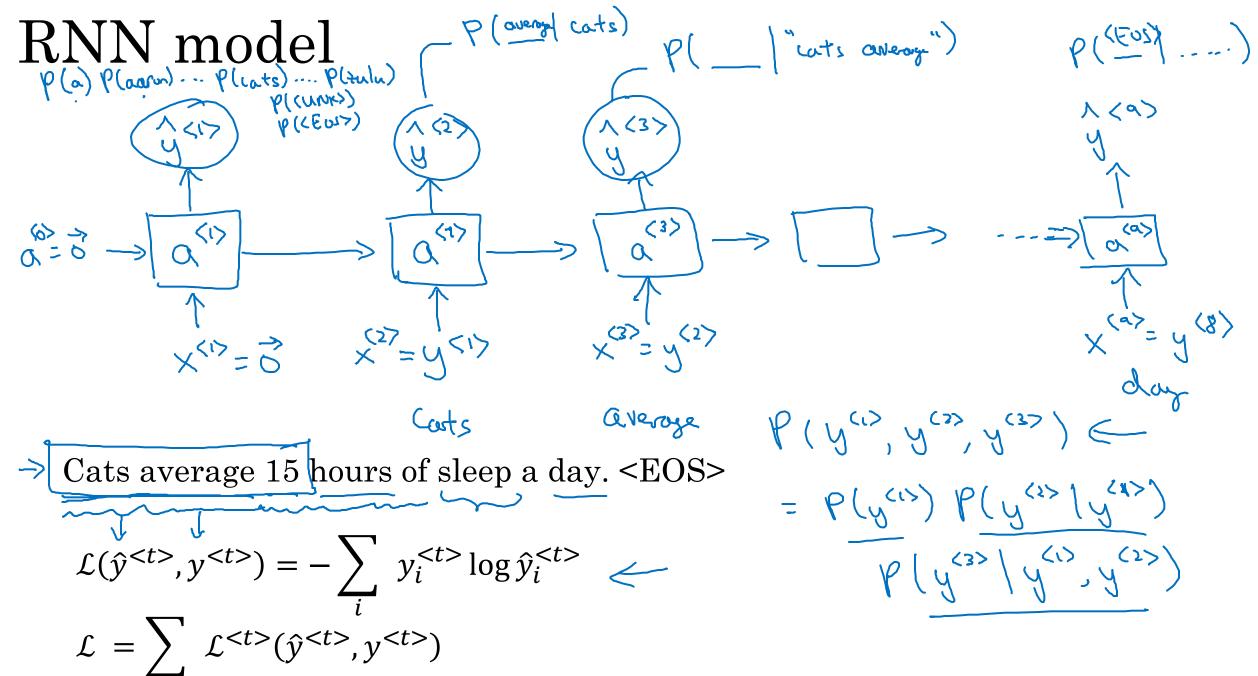
$$P(\text{The apple and pear salad}) = 5.7 \times 10^{-10}$$

#### Language modelling with an RNN

Training set: large corpus of english text.

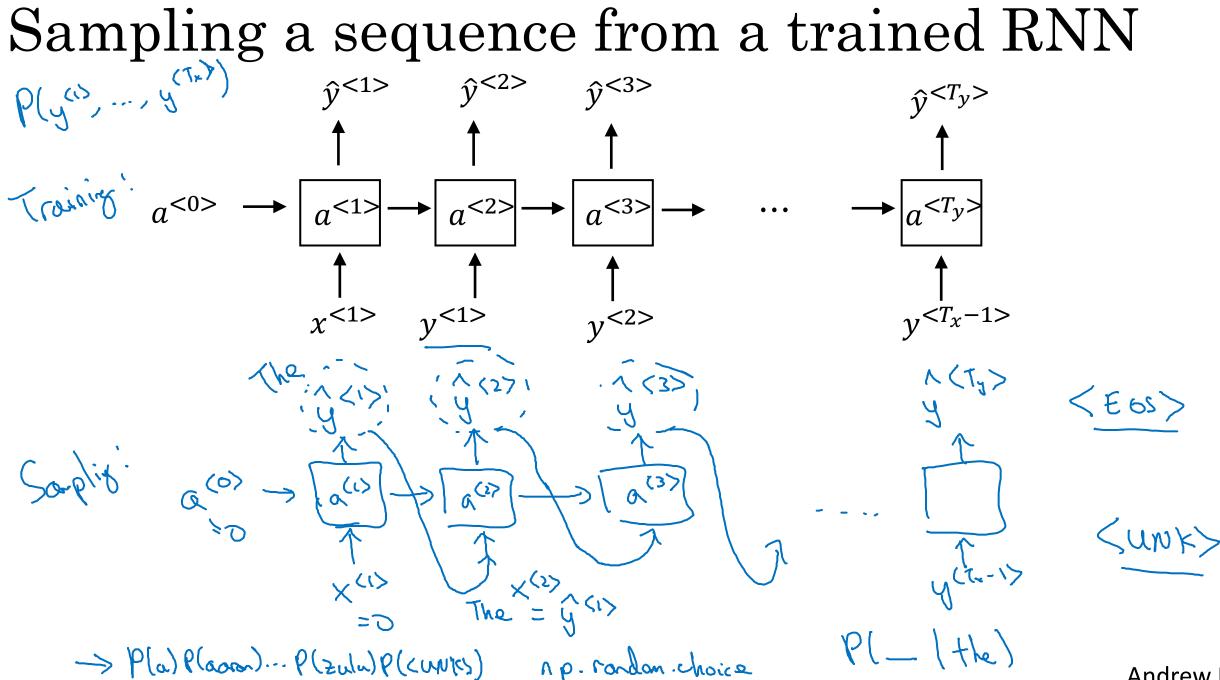
The Egyptian Mau is a bread of cat. <EOS>







# Sampling novel sequences



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#### Character-level language model

> Vocabulary = [a, aaron, ..., zulu, <UNK>] > Vocabulag = [a,b,c,...,2, u,o,i,o,...,9, A,...,2] y(1) y (2) y (2) (a) Cat overage  $\hat{v}^{<1>}$   $\hat{v}^{<2>}$   $\hat{v}^{<3>}$  $a^{<2>|}$  $a^{<1>|}$ 

#### Sequence generation

#### News

President enrique peña nieto, announced sench's sulk former coming football langston paring.

"I was not at all surprised," said hich langston.

"Concussion epidemic", to be examined.

The gray football the told some and this has on the uefa icon, should money as.

#### Shakespeare

The mortal moon hath her eclipse in love.

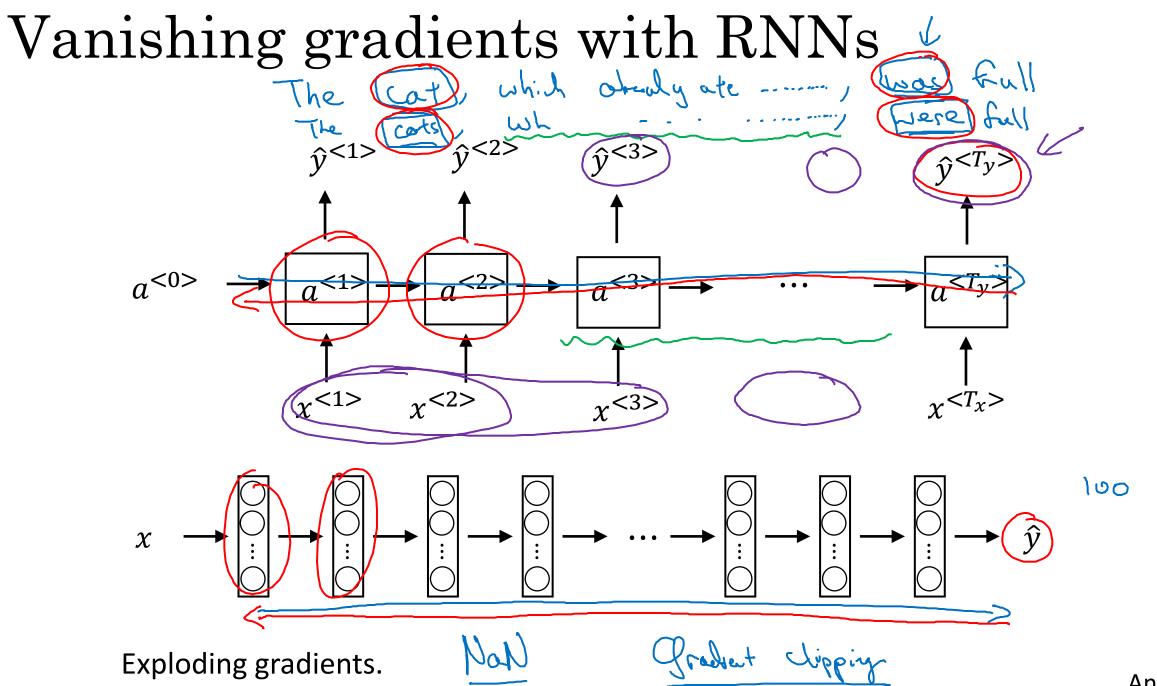
And subject of this thou art another this fold.

When besser be my love to me see sabl's.

For whose are ruse of mine eyes heaves.



# Vanishing gradients with RNNs

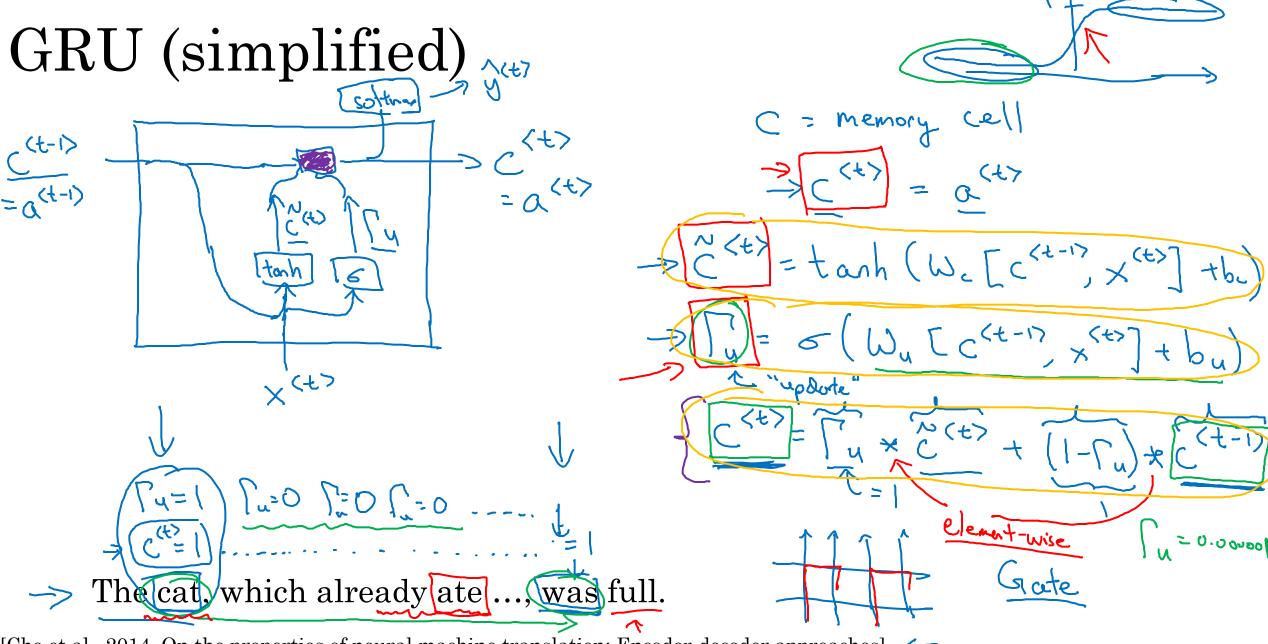




# Gated Recurrent Unit (GRU)

# RNN unit 9 (F) < E-1> (t) tanh

$$a^{} = g(W_a[a^{}, x^{}] + b_a)$$



[Cho et al., 2014. On the properties of neural machine translation: Encoder-decoder approaches] (Chung et al., 2014. Empirical Evaluation of Gated Recurrent Neural Networks on Sequence Modeling)

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#### Full GRU

$$\tilde{c}^{} = \tanh(W_c[\tilde{c}^{}, x^{}] + b_c)$$

$$W = \sigma(W_u[c^{}, x^{}] + b_u)$$

$$C = \sigma(W_v[c^{}, x^{}] + b_c)$$

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$$C = \sigma(W_v[c^{}, x^{}] + b_c)$$

The cat, which ate already, was full.



LSTM (long short term memory) unit

#### GRU and LSTM

#### GRU

#### LSTM

$$\underbrace{\tilde{c}^{< t>}}_{c} = \tanh(W_{c}[\Gamma_{r} * \underline{c^{< t-1>}}, x^{< t>}] + b_{c})$$

$$\underline{\Gamma}_{u} = \sigma(W_{u}[c^{< t-1>}, x^{< t>}] + b_{u})$$

$$\underline{\Gamma}_{v} = \sigma(W_{v}[c^{< t-1>}, x^{< t>}] + b_{u})$$

$$\underline{\Gamma}_{r} = \sigma(W_{r}[c^{< t-1>}, x^{< t>}] + b_{r})$$

$$\underline{C}^{< t>}_{v} = \sigma(W_{v}[c^{< t-1>}, x^{< t>}] + b_{r})$$

$$\underline{C}^{< t>}_{v} = \sigma(W_{v}[c^{< t-1>}, x^{< t>}] + b_{r})$$

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$$\underline{C}^{< t} = \sigma(W_{v}[c^{< t-1>}, x^{< t}] + b_{v}$$

$$\underline{C}^{< t} = \sigma(W_{v$$



#### LSTM units

#### **GRU**

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

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

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

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

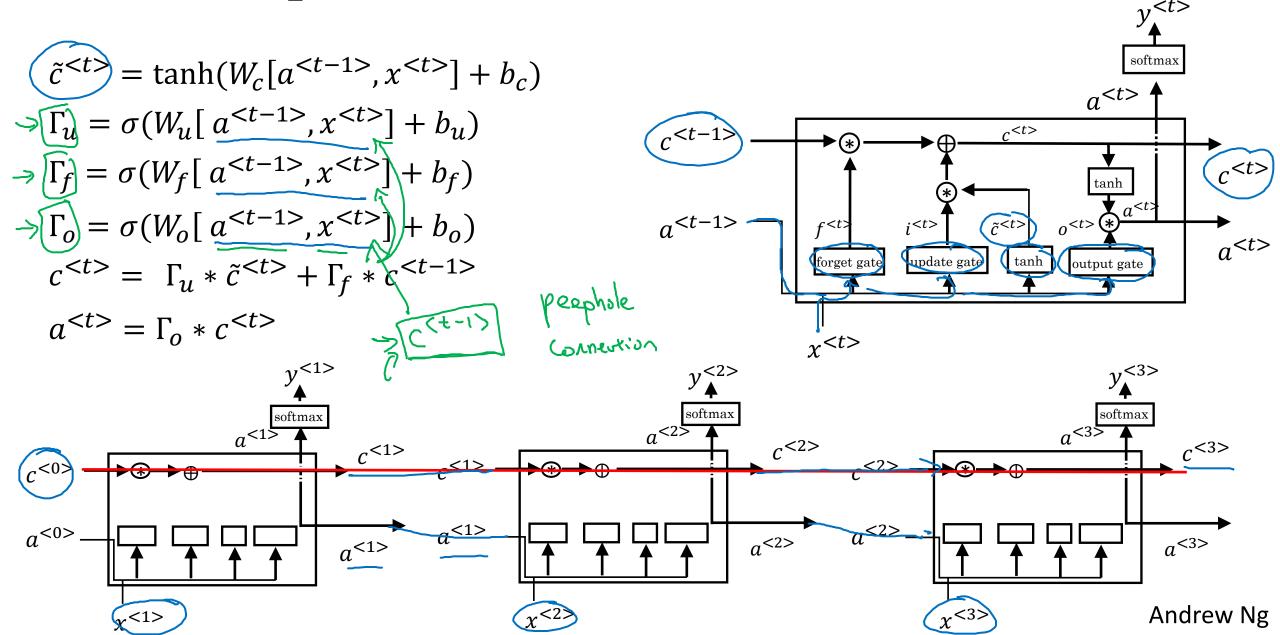
$$c^{< t>} = \Gamma_u * \tilde{c}^{< t>} + \Gamma_f * c^{< t-1>}$$

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

[Hochreiter & Schmidhuber 1997. Long short-term memory]

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#### LSTM in pictures



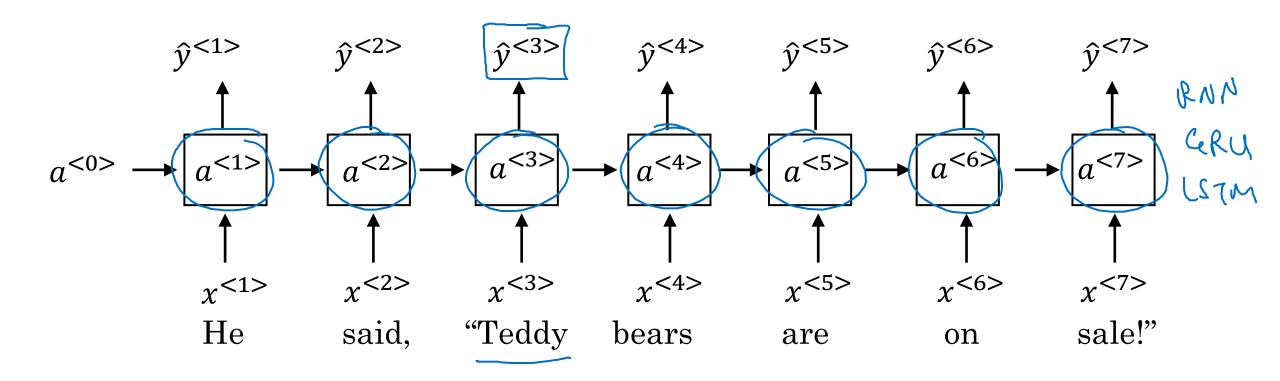


### **Bidirectional RNN**

#### Getting information from the future

He said, "Teddy bears are on sale!"

He said, "Teddy Roosevelt was a great President!"



Bidirectional RNN (BRNN) 1 4 4 14 <1> 3CB ₹(4s (2> (1) Acydic graph Telly

WILSTM

BRNN



# Deep RNNs

