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Recurrent Neural Networks

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Why sequence models?

Examples of sequence data

	x		y
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.	→	Yesterday, Harry Potter met Hermione Granger.

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Notation

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Motivating example

NLP

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

$\rightarrow \underline{x^{<1>}} \quad x^{<2>} \quad x^{<3>} \quad \dots \quad x^{<t>} \quad \dots \quad x^{<9>}$

$T_x = 9$

$\rightarrow$ y: 1 1 0 1 1 0 0 0 0

$y^{<1>} \quad y^{<2>} \quad y^{<3>} \quad \dots \quad y^{<9>}$

$T_y = 9$

$X^{(i)<t>}$ $\qquad T_x^{(i)} = 9 \qquad 15$

$y^{(i)<t>}$ $\qquad T_y^{(i)}$

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Representing words

$x^{<t>}$ (x, y)

$x \rightarrow y$

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

$x^{<1>}$ $x^{<2>}$ $x^{<3>}$ … $x^{<7>}$ $x^{<9>}$

Vocabulary

$$\begin{bmatrix} \text{a} \\ \text{aaron} \\ \vdots \\ \text{and} \\ \vdots \\ \text{harry} \\ \vdots \\ \text{potter} \\ \vdots \\ \text{zulu} \end{bmatrix} \begin{array}{l} 1 \\ 2 \\ \vdots \\ 367 \\ \vdots \\ \underline{4075} \\ \vdots \\ 6830 \\ \vdots \\ 10{,}000 \end{array}$$

<UNK> 10,000

$$x^{<1>} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \leftarrow 4075 \qquad x^{<2>} = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ 1 \\ \vdots \\ 0 \end{bmatrix} \leftarrow 6830 \qquad x^{<3>} = \begin{bmatrix} 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \end{bmatrix} \leftarrow 367 \qquad 10{,}000 \qquad x^{<7>} = \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

One-hot

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Representing words

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

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

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

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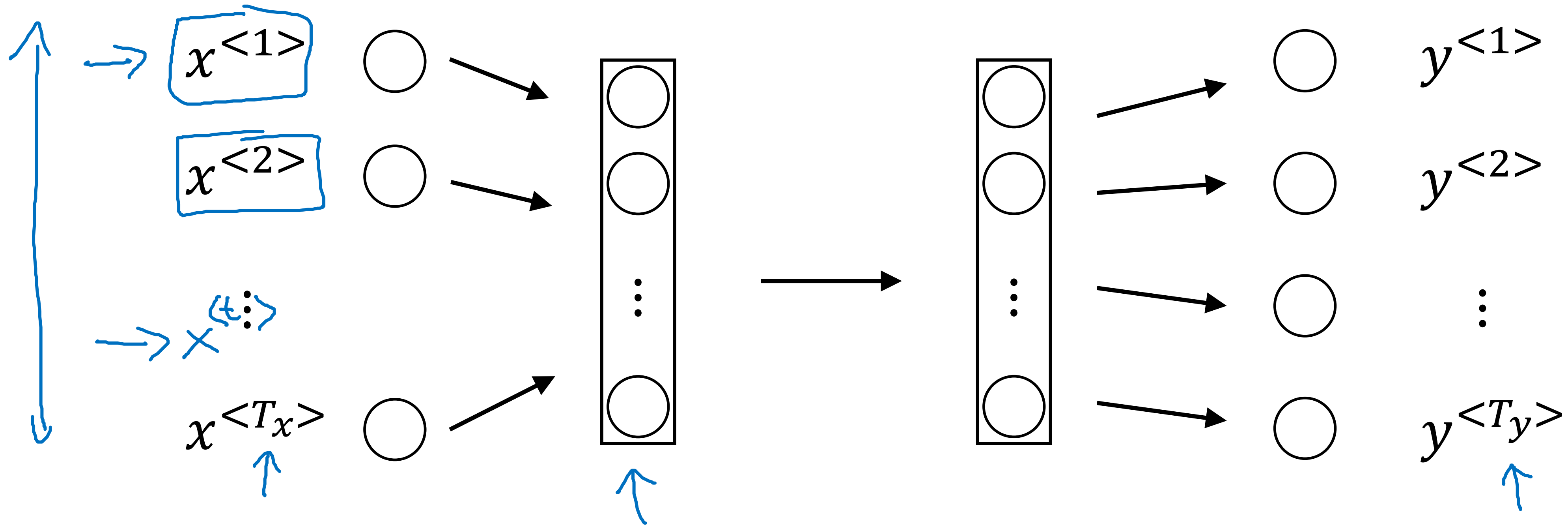
Recurrent Neural Network Model

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.

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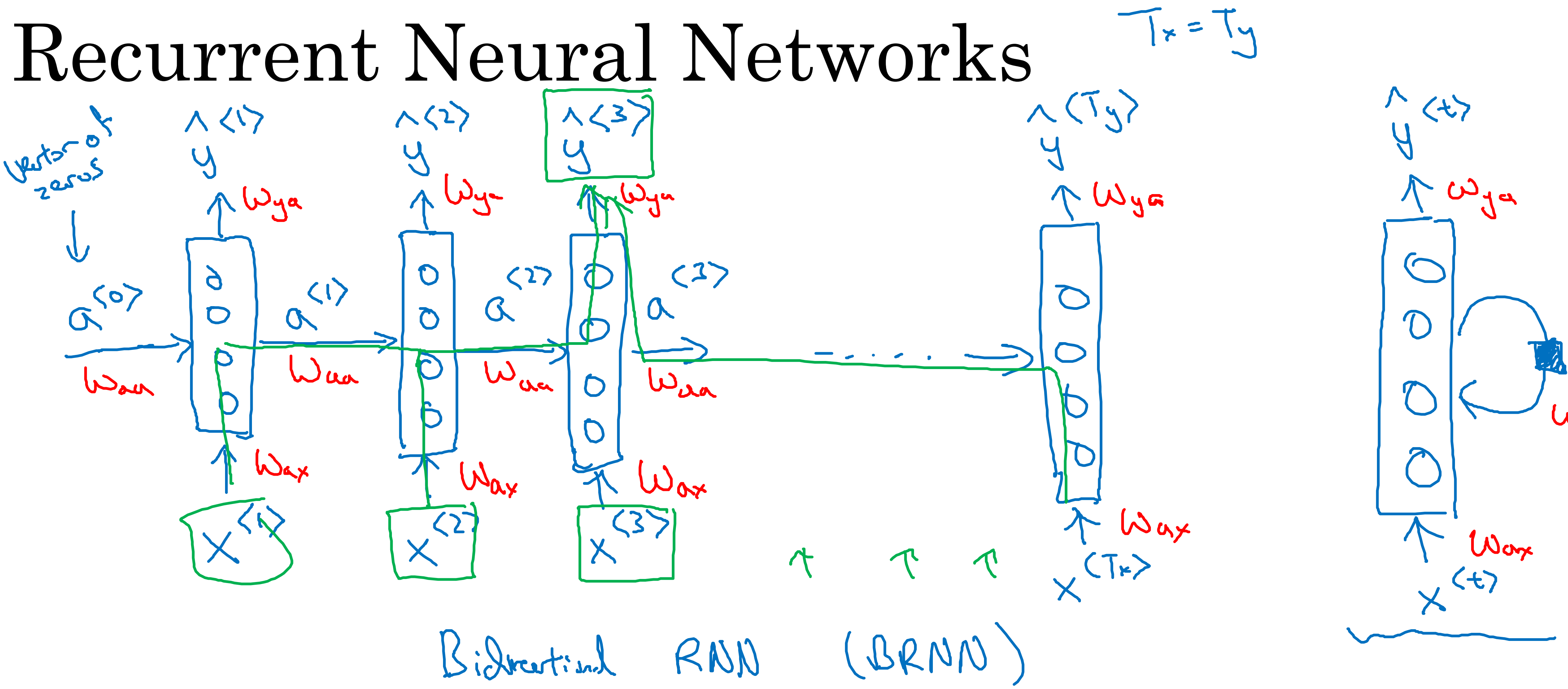

He said, “Teddy Roosevelt was a great President.”

He said, “Teddy bears are on sale!”

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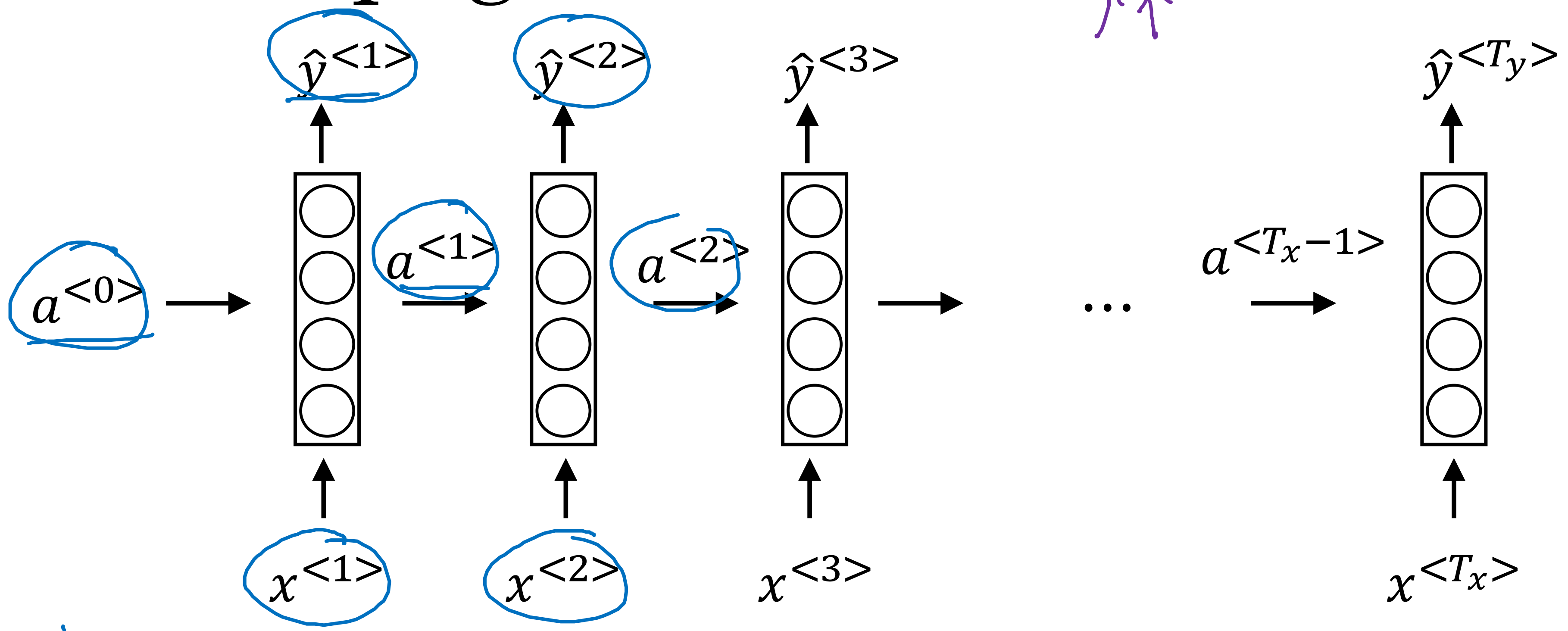
Forward Propagation

$a \leftarrow W_{ax} x^{<1>}$



$a^{<0>} = \vec{0}.$

$$a^{<1>} = g_1(W_{aa} a^{<0>} + W_{ax} x^{<1>} + b_a) \leftarrow \text{tanh / ReLU}$$

$$\hat{y}^{<1>} = g_2(W_{ya} a^{<1>} + b_y) \leftarrow \text{sigmoid}$$

$$\boxed{\begin{aligned} a^{<t>} &= g(W_{aa} a^{<t-1>} + W_{ax} x^{<t>} + b_a) \\ \hat{y}^{<t>} &= g(W_{ya} a^{<t>} + b_y) \end{aligned}}$$

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Simplified RNN notation

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

(100,100) 100 (100,10,000) 10,000

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

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

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

$$\left[W_{aa} \,\vdots\, W_{ax} \right] = W_a$$

100; 100; 10 000; (100, 10100)

$$[a^{<t-1>}, x^{<t>}] = \begin{bmatrix} a^{<t-1>} \\ x^{<t>} \end{bmatrix}$$

100; 10000; 10100

$$\left[W_{aa} \,\vdots\, W_{ax} \right] \begin{bmatrix} a^{<t-1>} \\ x^{<t>} \end{bmatrix} = W_{aa}a^{<t-1>} + W_{ax}x^{<t>}$$

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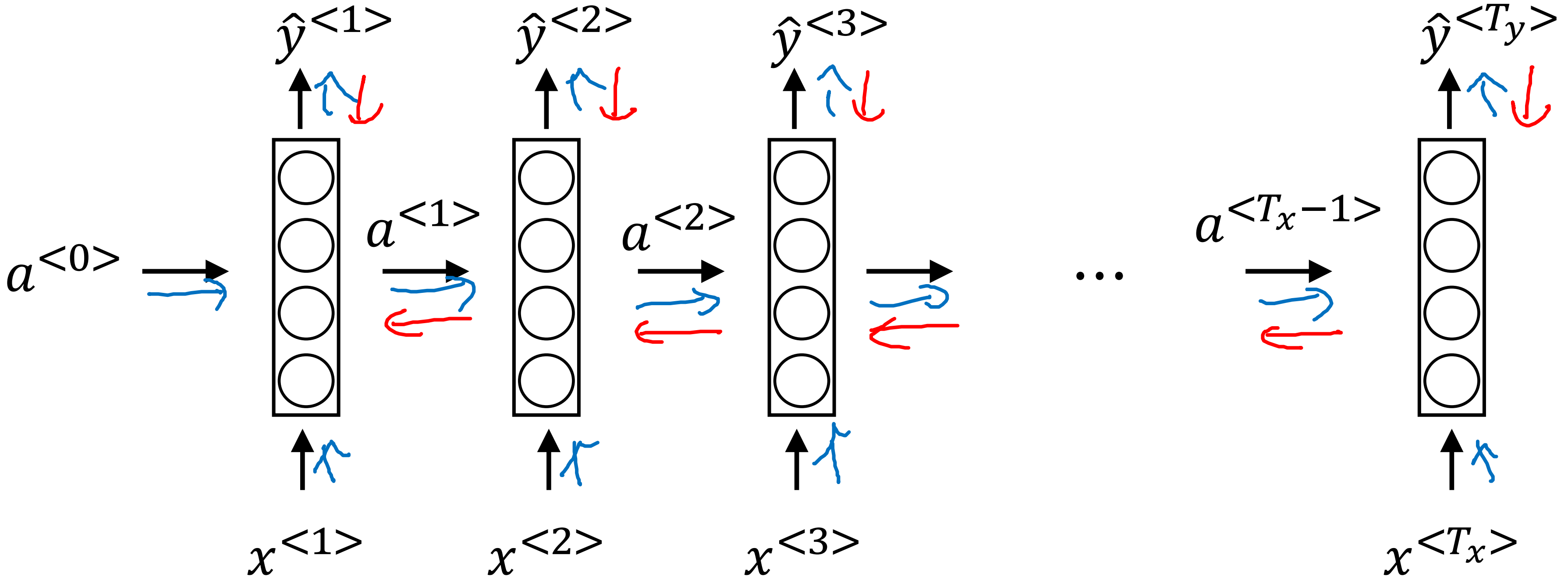
Recurrent Neural Networks

Backpropagation through time

Forward propagation and backpropagation



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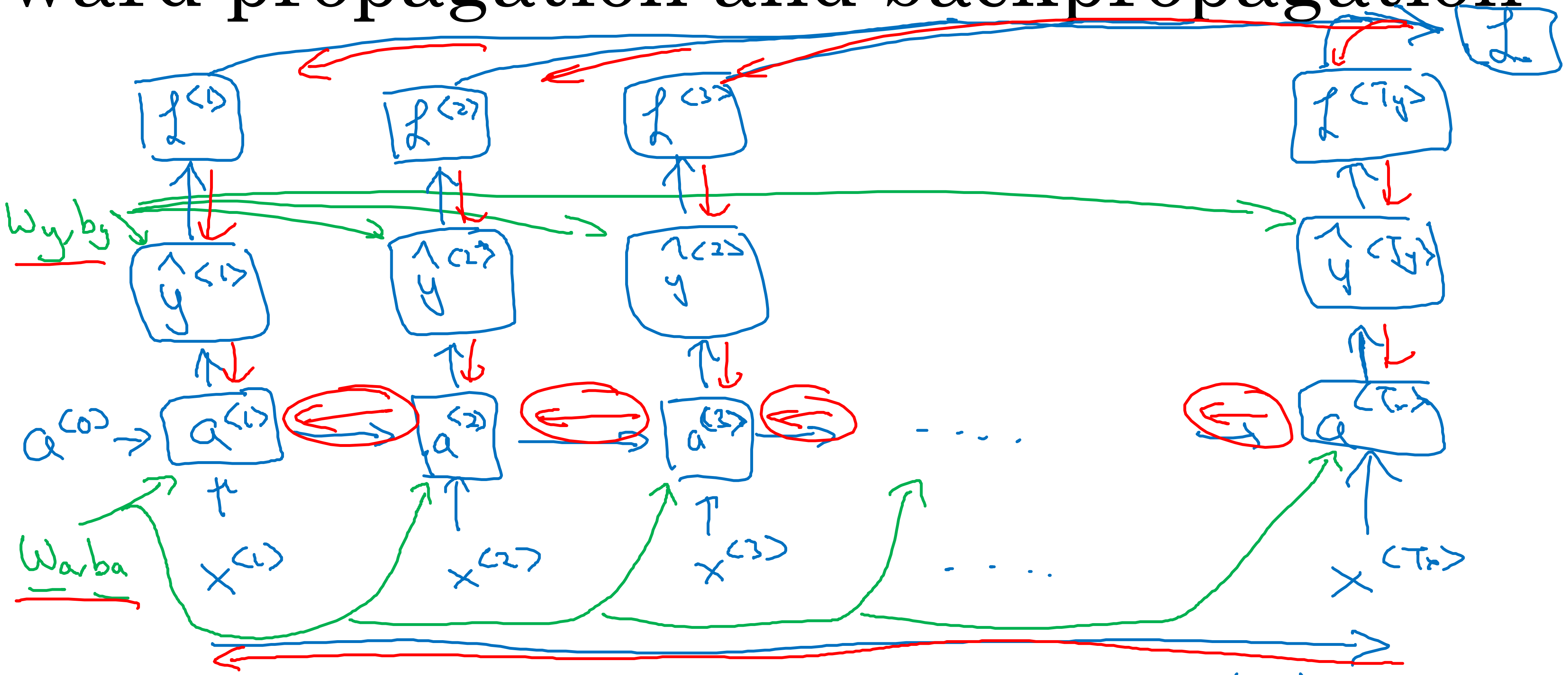
Forward propagation and backpropagation



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

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

Backpropagation through time

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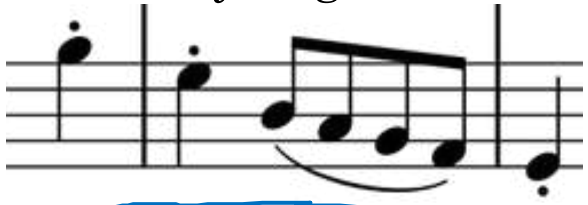
Different types of RNNs

Examples of sequence data

T_x $\quad$ T_y

	x		y
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.	→	Yesterday, Harry Potter met Hermione Granger.

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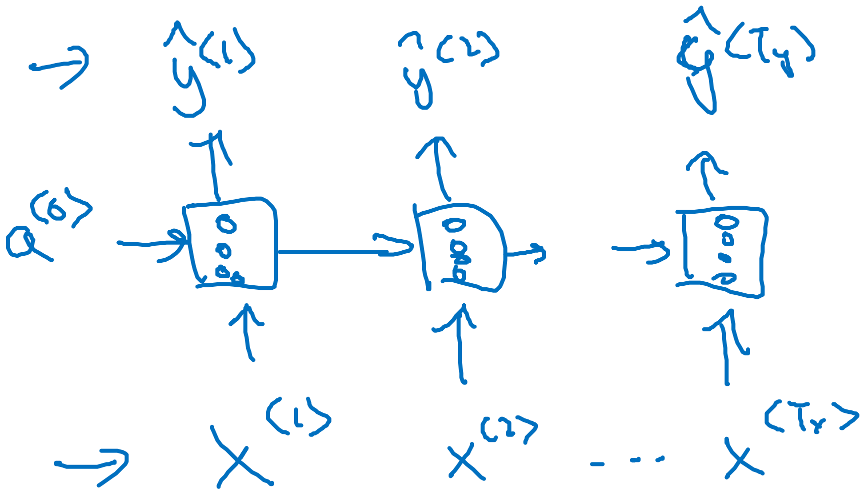
Examples of RNN architectures

$T_x = T_y$

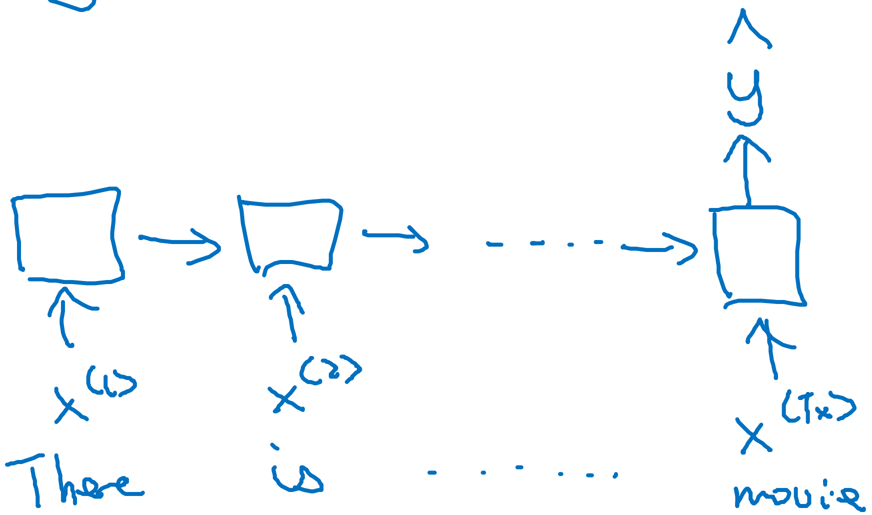


Many-to-many

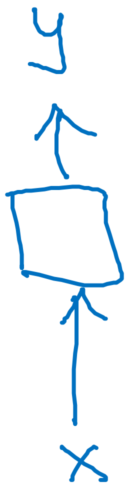
Sentiment classification

x = text

$y = 0/1 \qquad 1 \ldots 5$



Many-to-one



one-to-one

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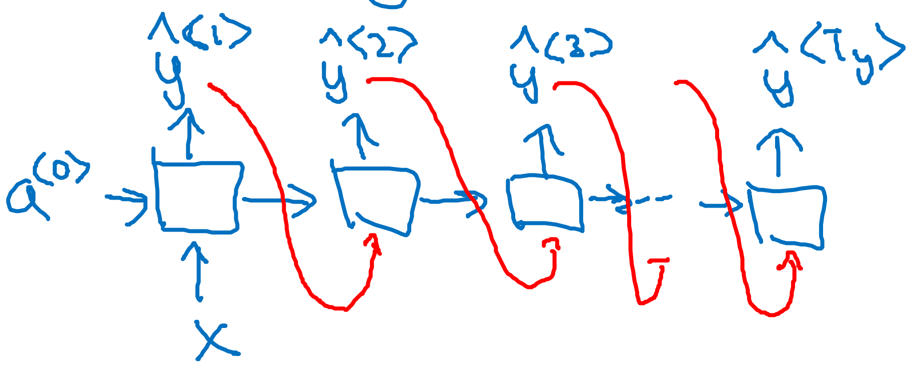
Examples of RNN architectures

Music generation

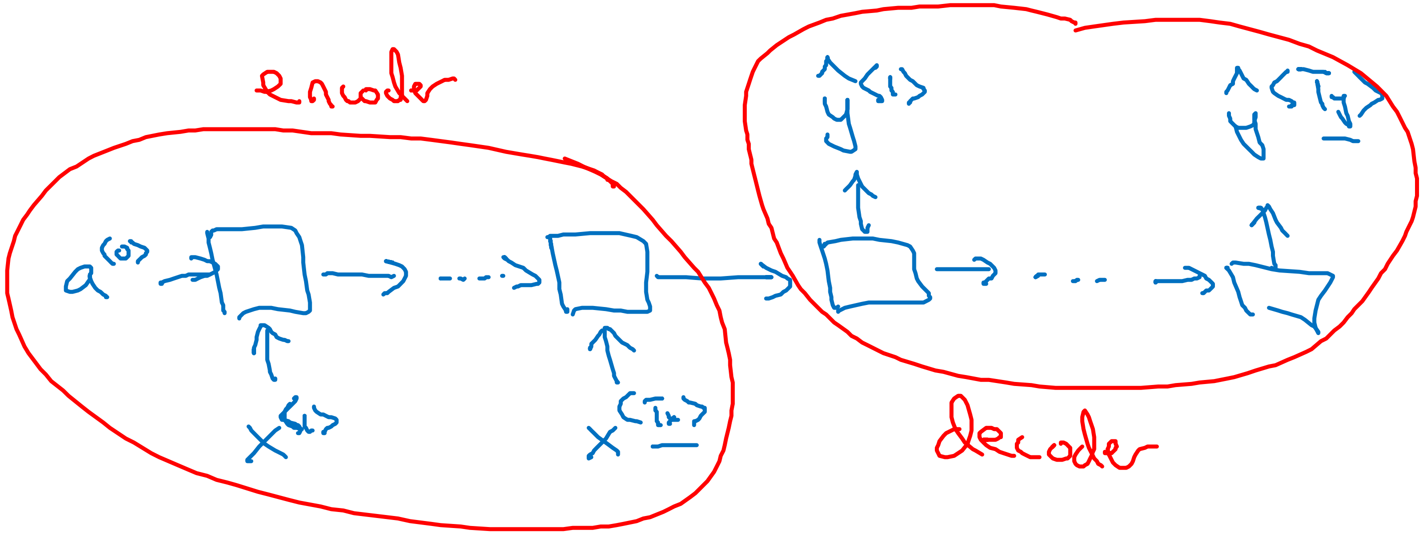
$x \rightarrow y^{<1>} y^{<2>} \dots y^{<T_y>}$



One-to-many

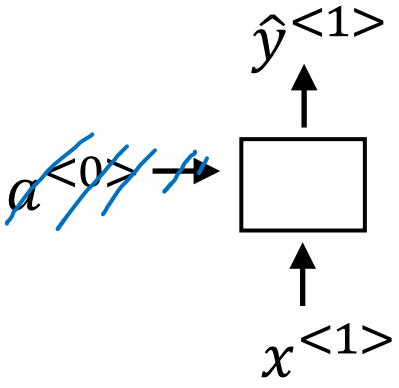
$x = \emptyset$

Machine translation

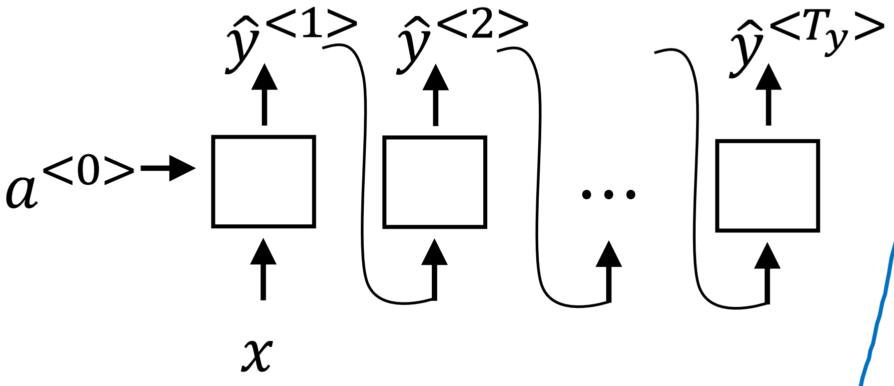


Many-to-many

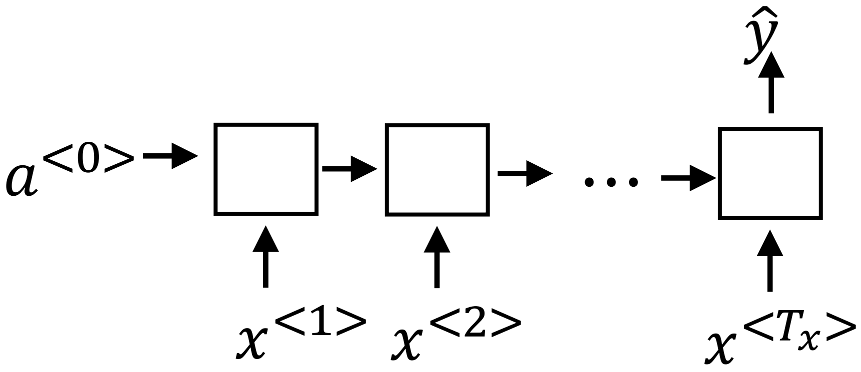
Summary of RNN types



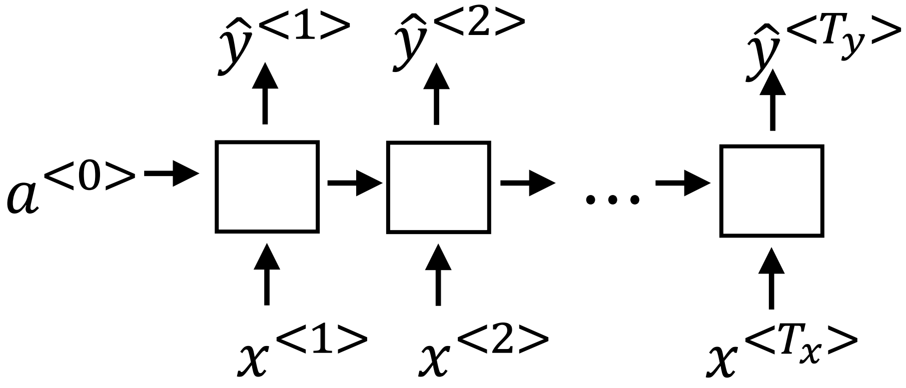
One to one



One to many

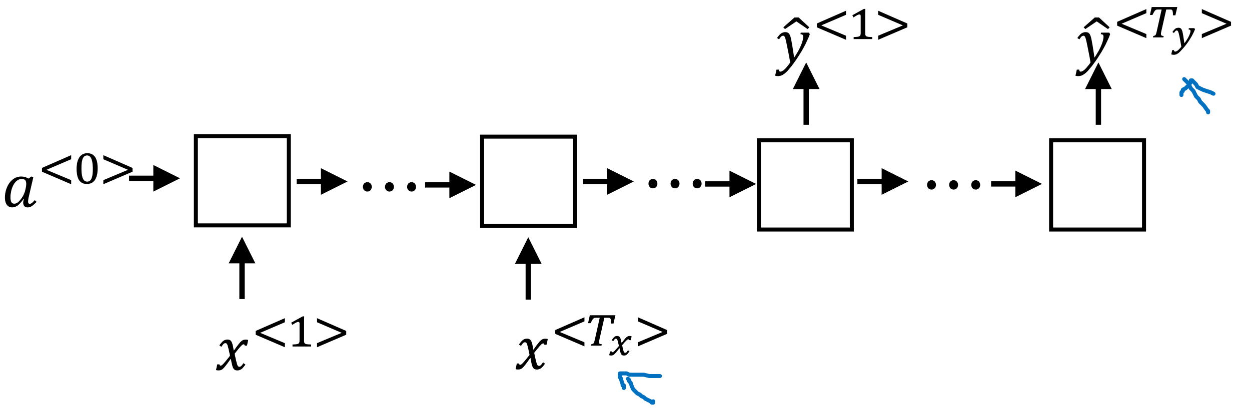


Many to one



Many to many

$T_x = T_y$



Many to many

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Language model and sequence generation

What is language modelling?

Speech recognition

The apple and pair salad.

The apple and pear salad.

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

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

$P(\text{sentence}) = ?$

$P(y^{<1>}, y^{<2>}, \ldots, y^{<T_y>})$

Language modelling with an RNN

Training set: large corpus of english text.

Tokenize

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

$y^{<1>}$ $y^{<2>}$ $y^{<3>}$ . . . $y^{<8>}$ $y^{<9>}$

$x^{<t>} = y^{<t-1>}$

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

<UNK>

10,000

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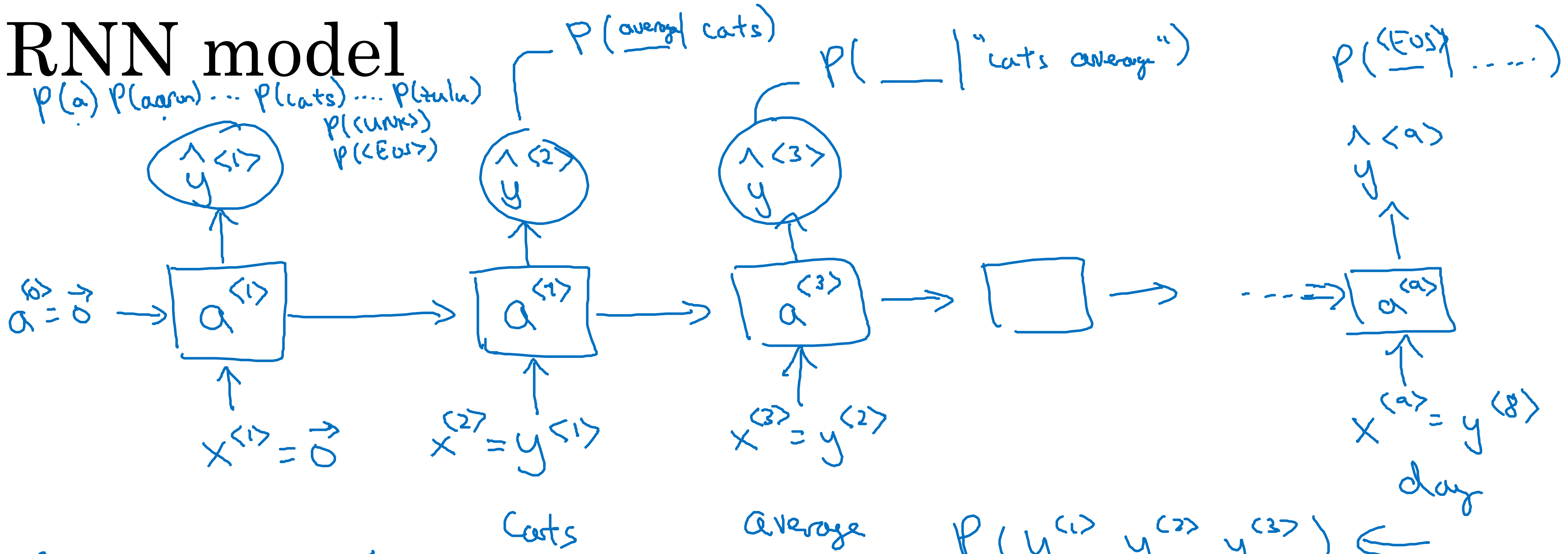
RNN model



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

$$P(y^{<1>}, y^{<2>}, y^{<3>}) = P(y^{<1>})\,P(y^{<2>} \mid y^{<1>})\,P(y^{<3>} \mid y^{<1>}, y^{<2>})$$

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

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

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Recurrent Neural Networks

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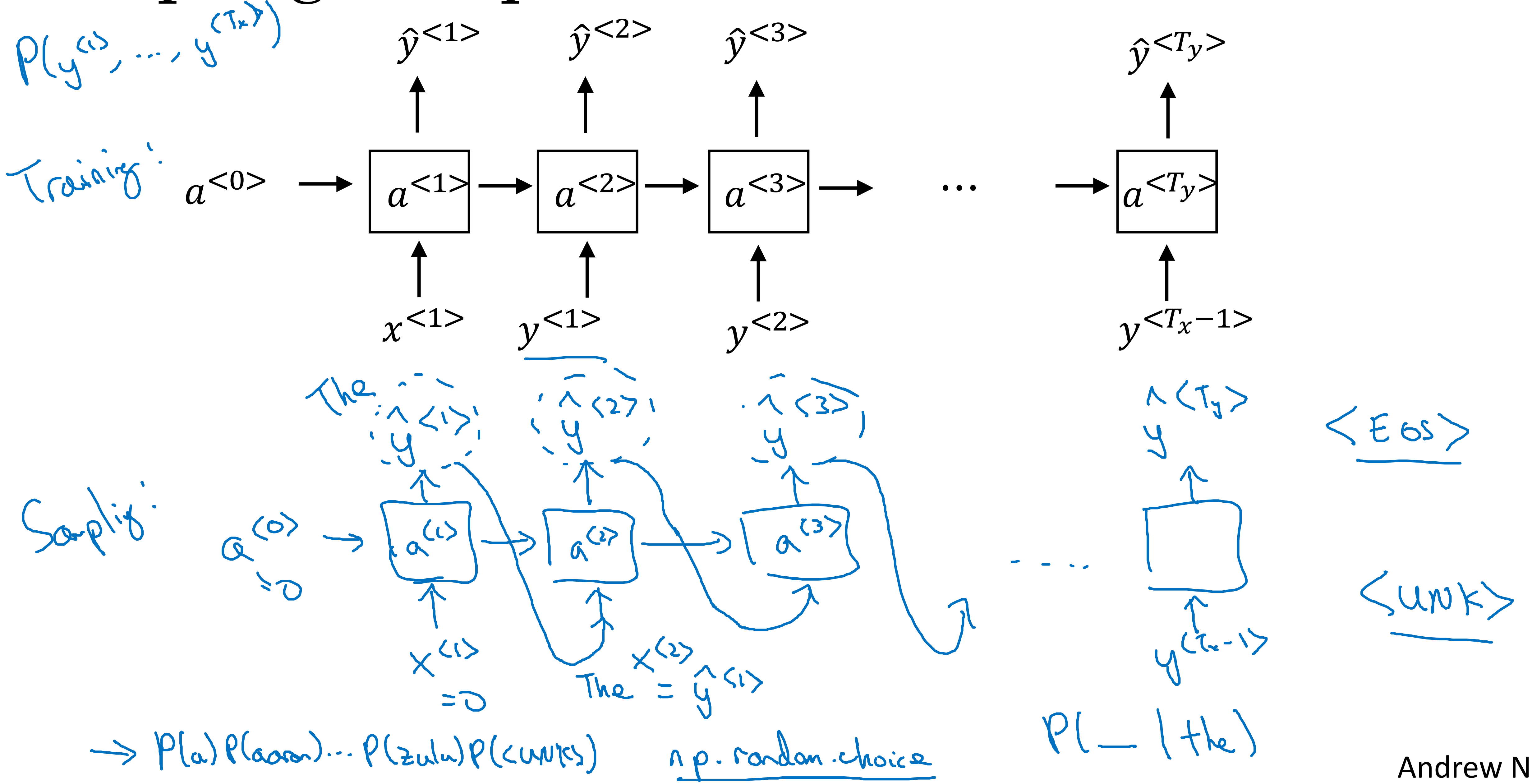
Sampling novel sequences

Sampling a sequence from a trained RNN



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Character-level language model

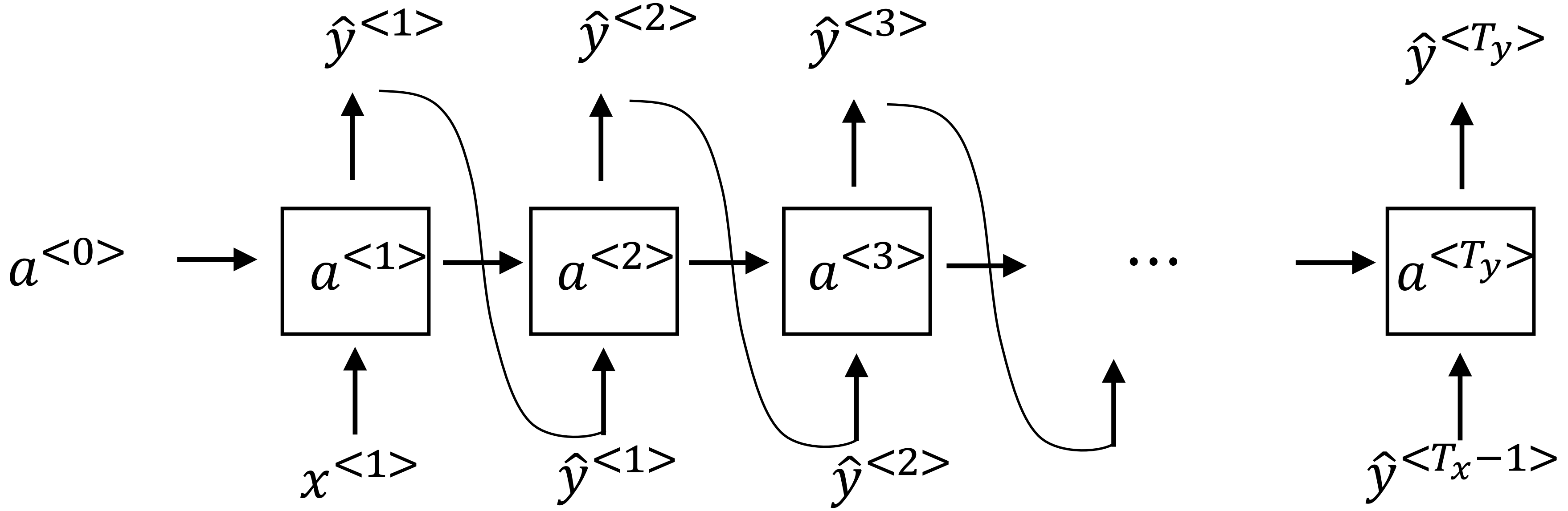
- Vocabulary = [a, aaron, …, zulu, <UNK>]

- Vocabulary = [a, b, c, …, z, ␣, ., ,, ;, 0, …, 9, A, …, Z]

$y^{<1>}$ $y^{<2>}$ $y^{<3>}$ $y^{<4>}$

Cat average …

Man



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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.

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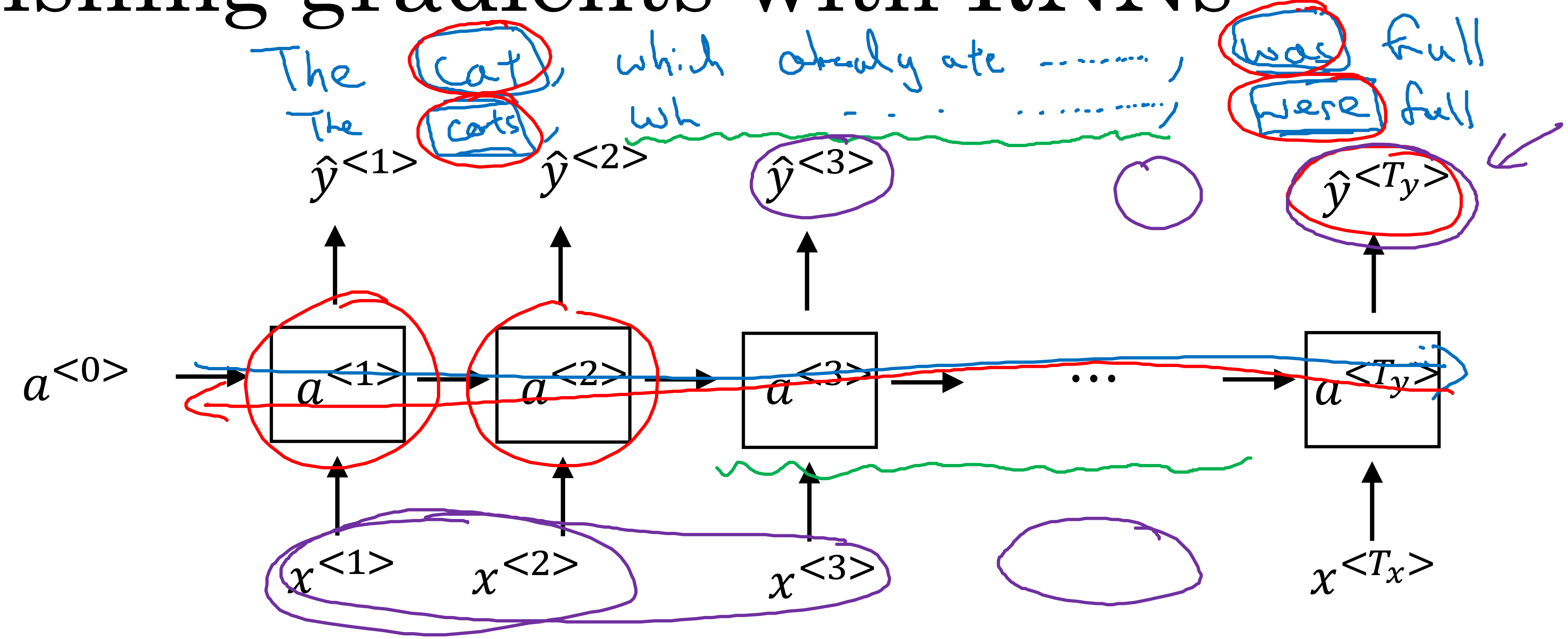
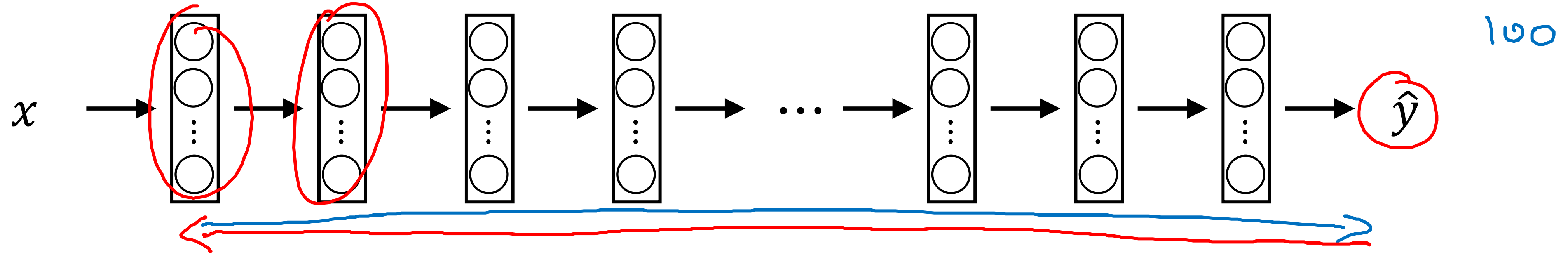
Vanishing gradients with RNNs

Vanishing gradients with RNNs





Exploding gradients.

NaN

Gradient clipping

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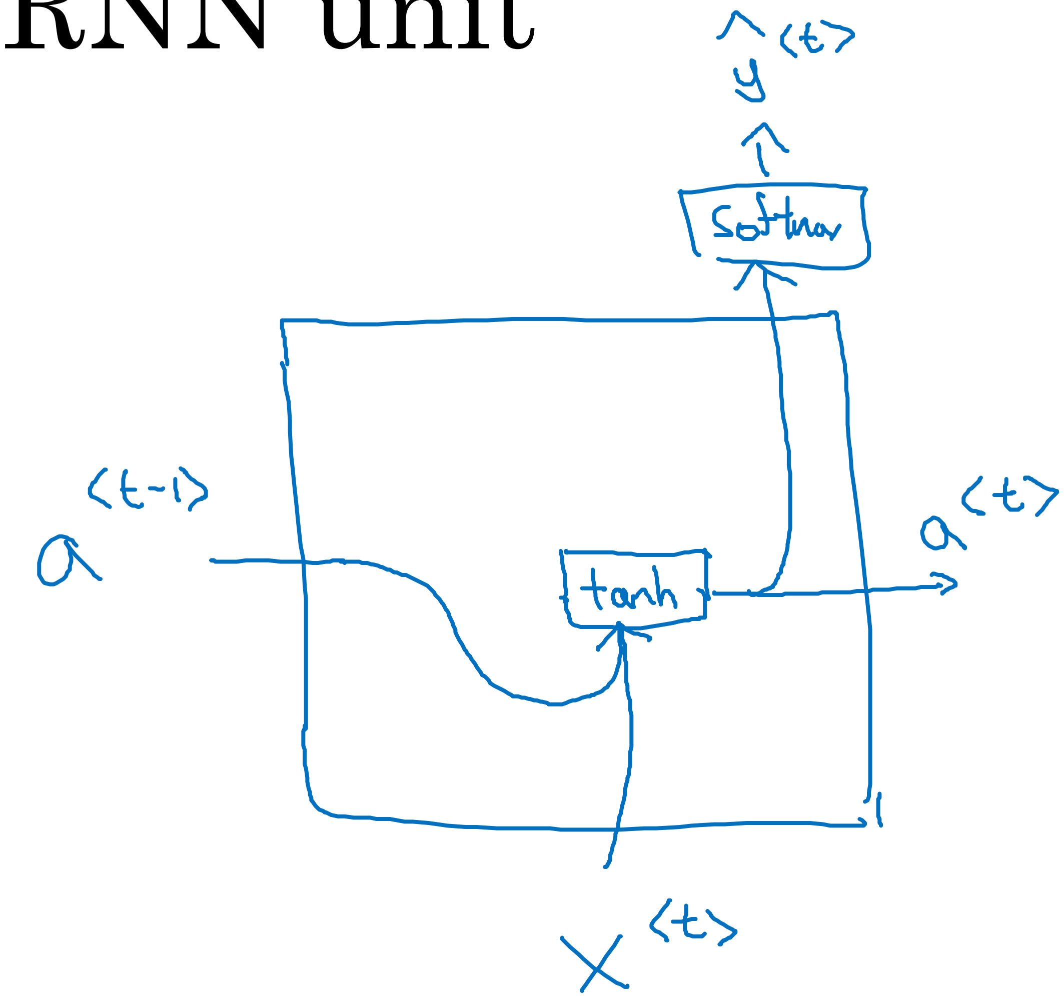
Recurrent Neural Networks

Gated Recurrent Unit (GRU)

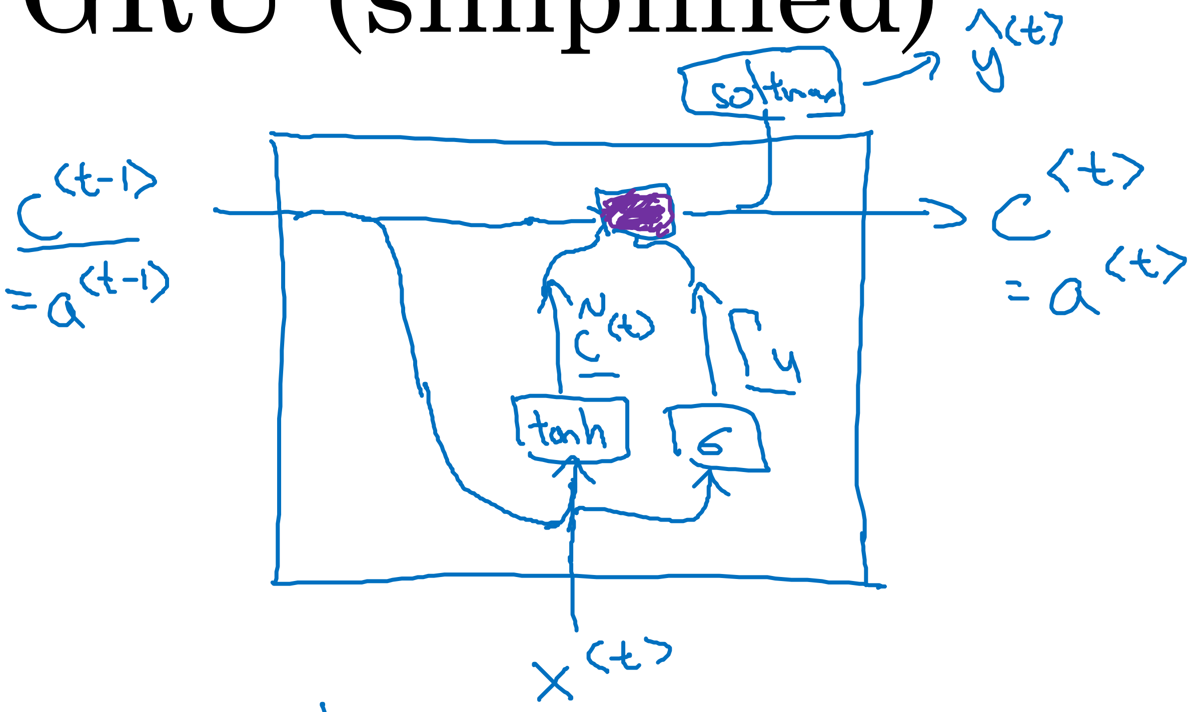
RNN unit

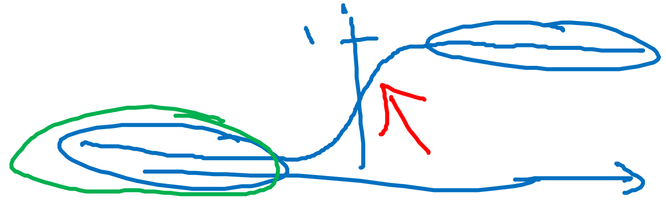


tanh

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

GRU (simplified)





c = memory cell

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

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

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

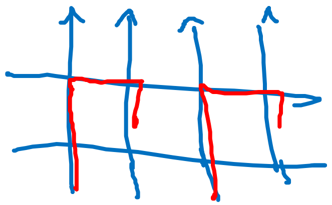
"update"

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

$\Gamma_u = 1$

element-wise

$\Gamma_u = 0.000001$



Gate

$\Gamma_u = 1$ $\Gamma_u = 0$ $\Gamma_u = 0$ $\Gamma_u = 0$ .....

$c^{<t>} = 1$ .... $= 1$

The cat, which already ate …, was full.

[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

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

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

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

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

LSTM

The cat, which ate already, was full.

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LSTM (long short term memory) unit

LSTMs have three important gates:
the update gate, the forget gate, and the output gate.
These gates help the LSTM decide what information to keep, what to forget,
and what to output at each step of the sequence.
This makes LSTMs really good at capturing long-term dependencies in the data.

GRU and LSTM

GRU

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

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

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

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

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

LSTM

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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LSTM in pictures

GRU is simpler and faster
LSTM is more complicated and powerful
there is no clear winner
but conventionally, use LSTM

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

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

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

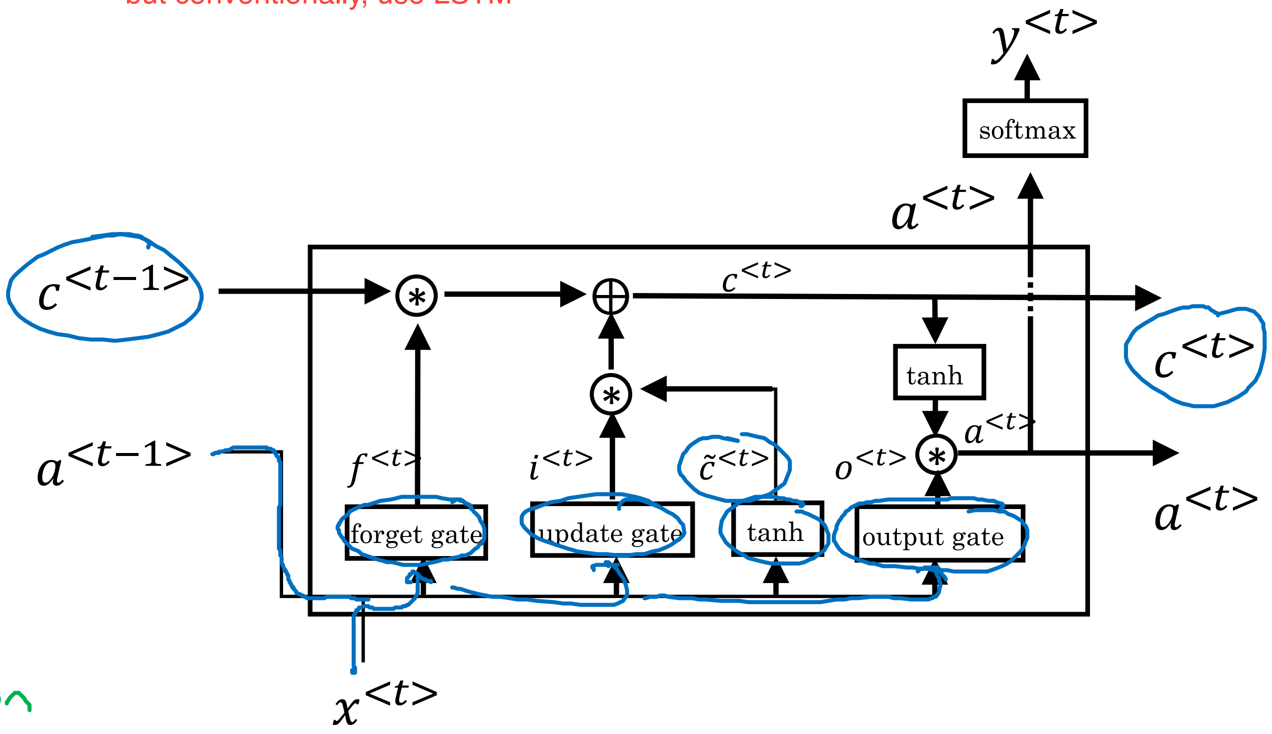
$$\Gamma_o = \sigma(W_o[a^{<t-1>}, x^{<t>}] + b_o)$$

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

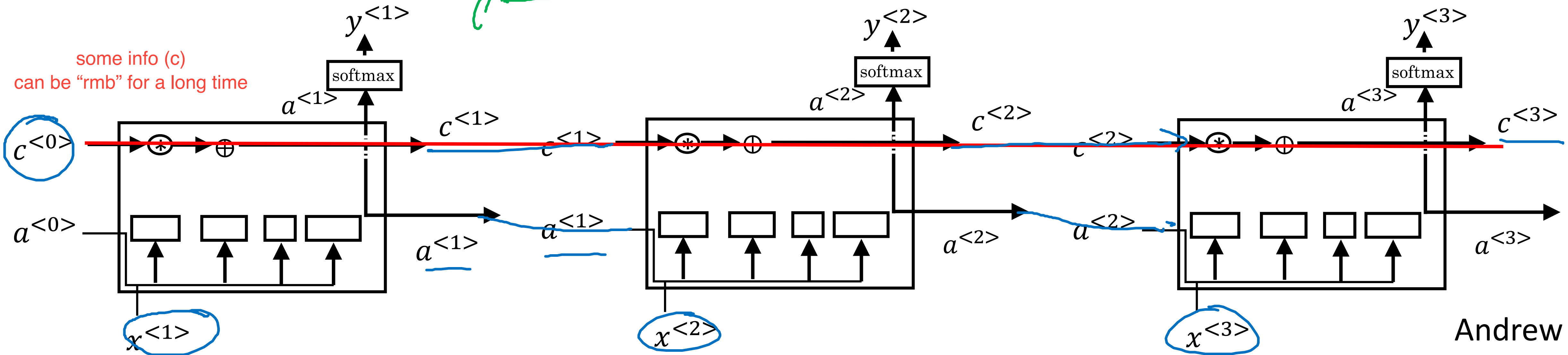
$$a^{<t>} = \Gamma_o * c^{<t>}$$

$\boxed{c^{<t-1>}}$

peephole connection



some info (c)
can be "rmb" for a long time



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Bidirectional RNN

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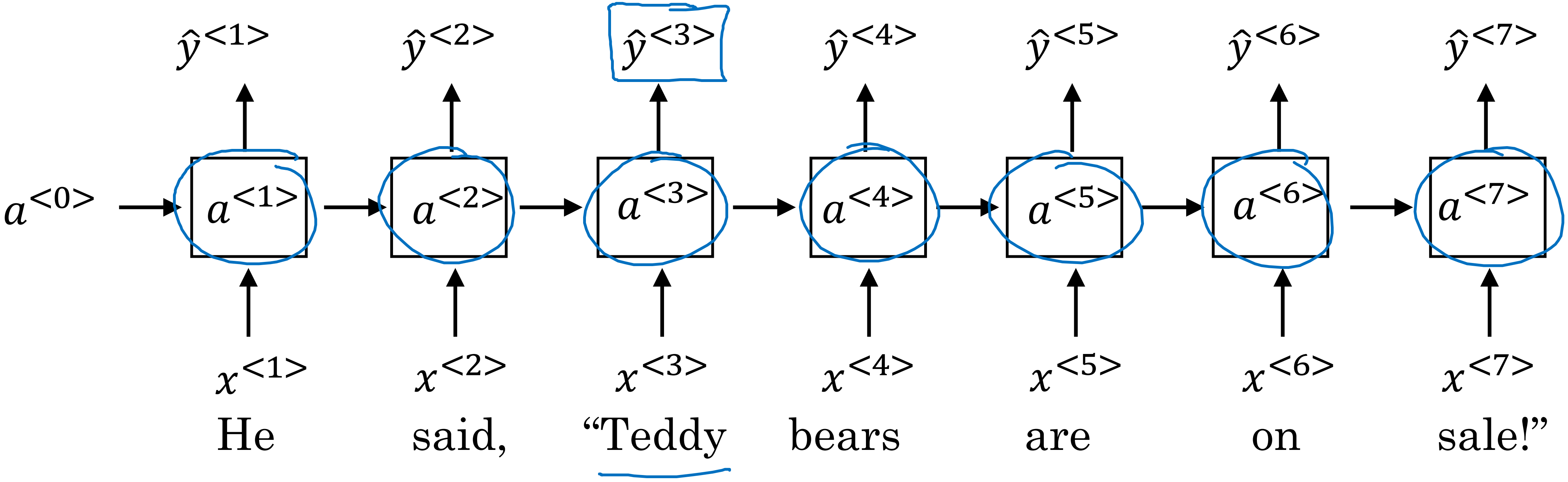
Getting information from the future

He said, “Teddy bears are on sale!”

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

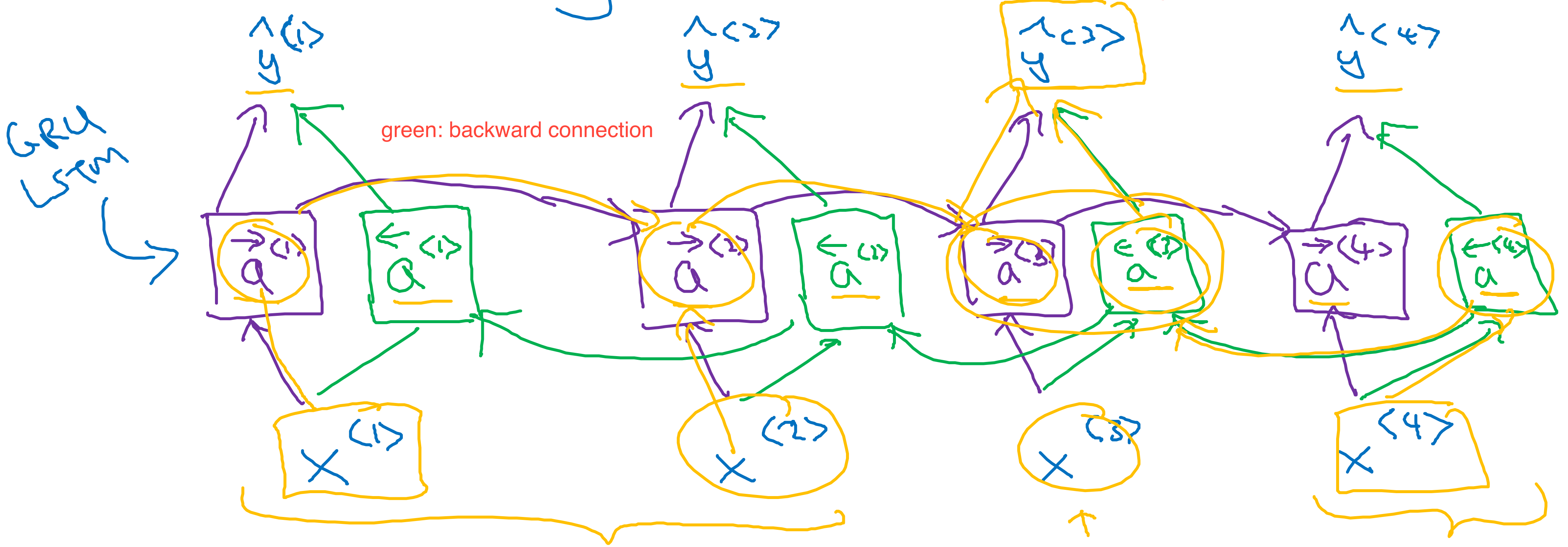


RNN
GRU
LSTM

Bidirectional RNN (BRNN)

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

y3 get info from the past and what come after



Acyclic graph

He said "Teddy Roosevelt ...."

BRNN w/ LSTM

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Recurrent Neural Networks

Deep RNNs

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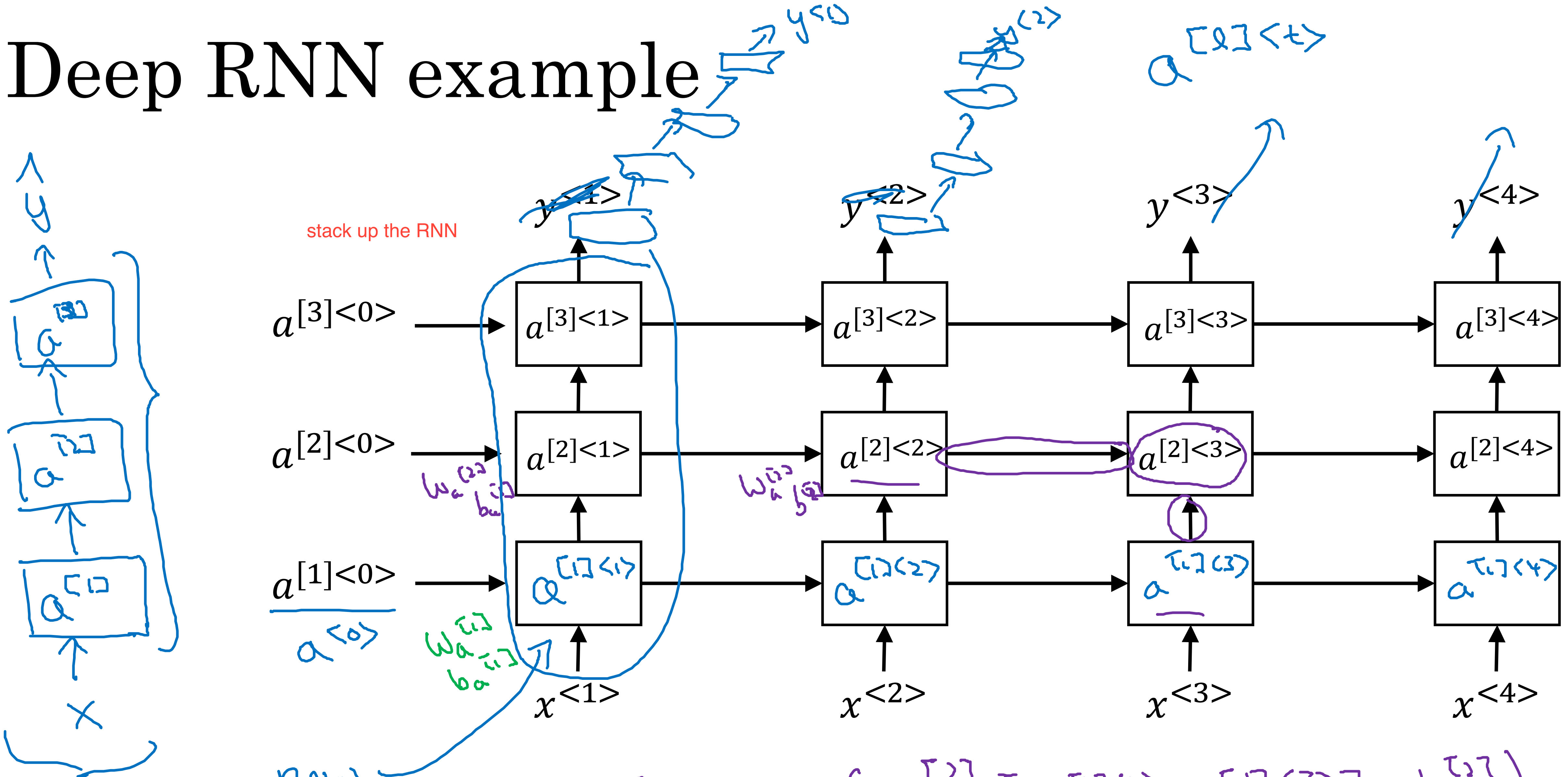
Deep RNN example



RNN
GRU
LSTM

BRNN

$$a^{[2]<3>} = g\left(W_a^{[2]}\left[a^{[2]<2>}, a^{[1]<3>}\right] + b_a^{[2]}\right)$$

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