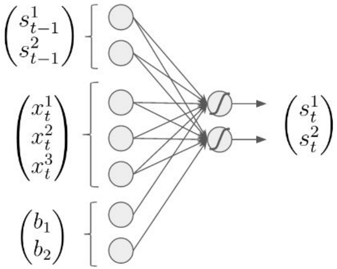
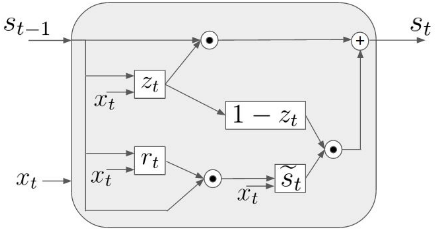
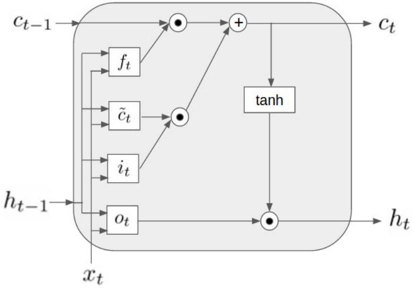
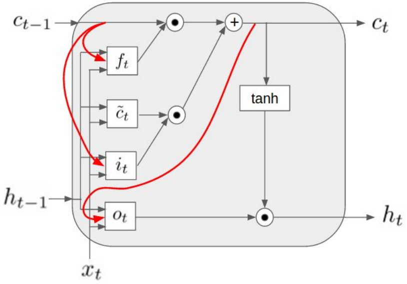
Review from deepsystems.ai

Evolution:
from vanilla RNN to GRU & LSTMs



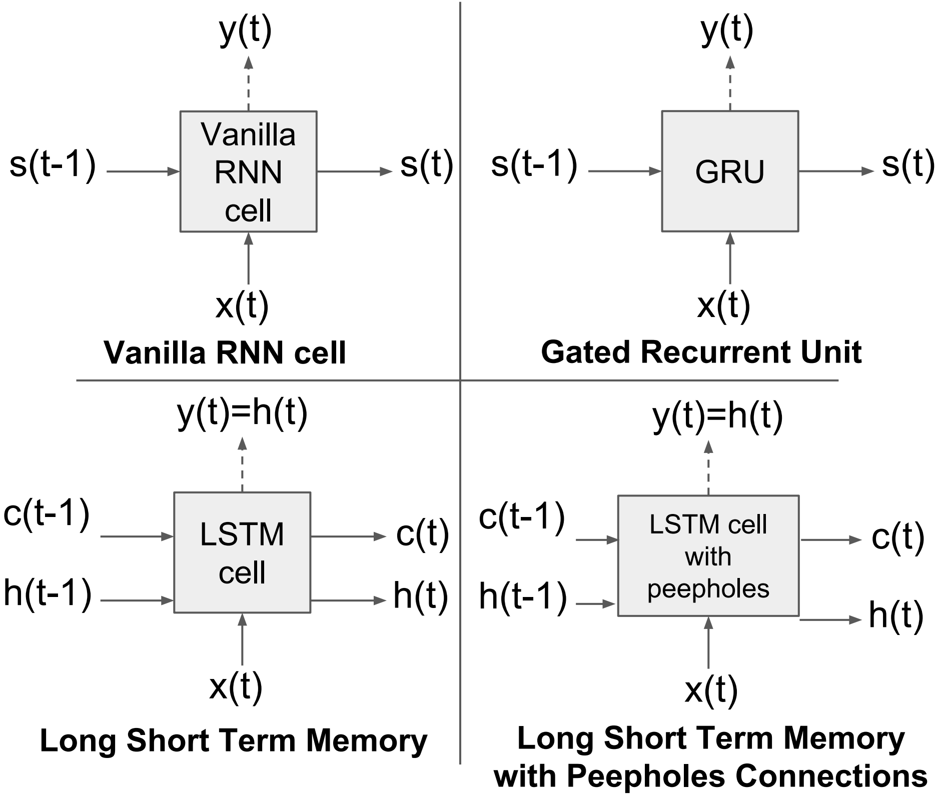






By the end of the talk you will learn

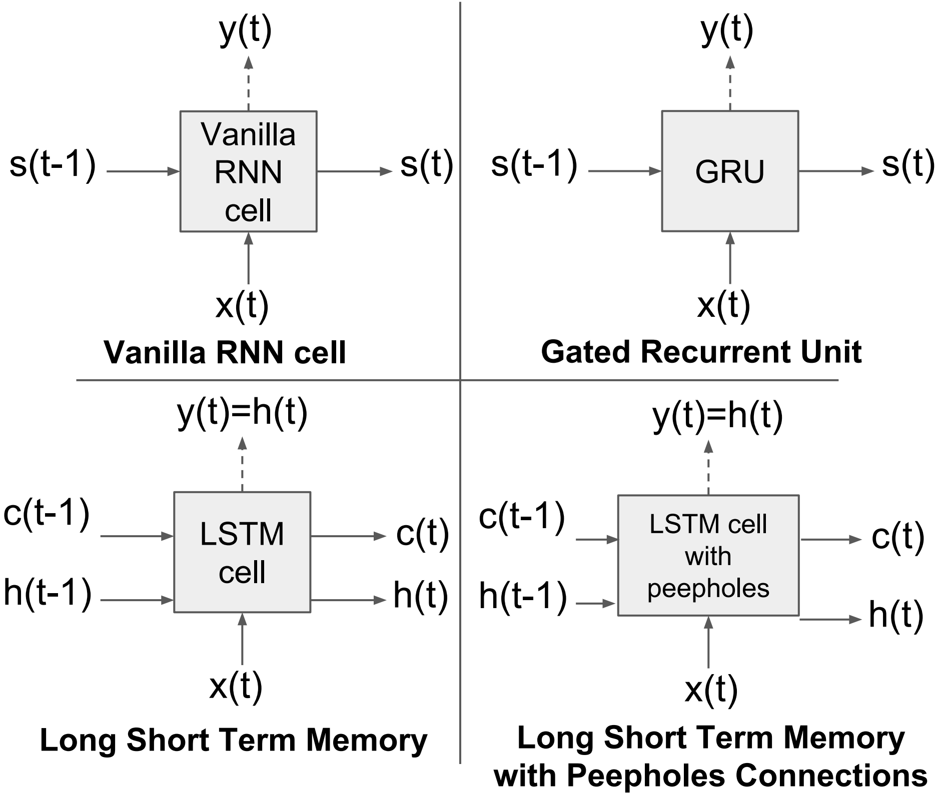
For the most common RNN Cells:



By the end of the talk you will learn

For the most common RNN Cells:

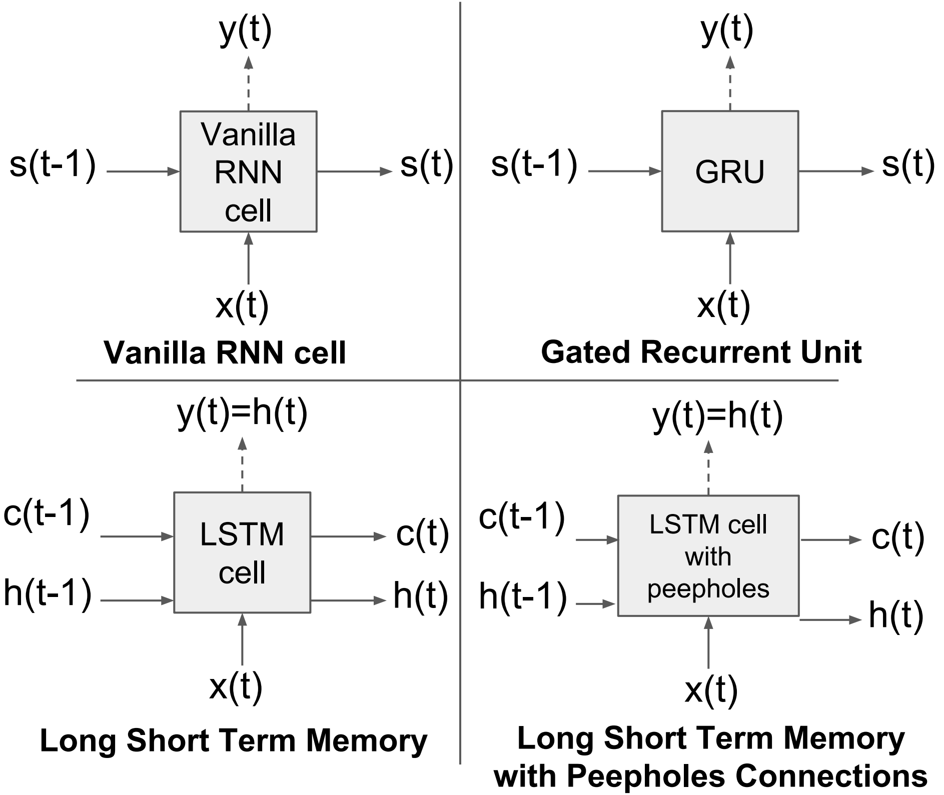
- What’s inside & how it works



By the end of the talk you will learn

For the most common RNN Cells:

- What's inside & how it works
- Intuition behind



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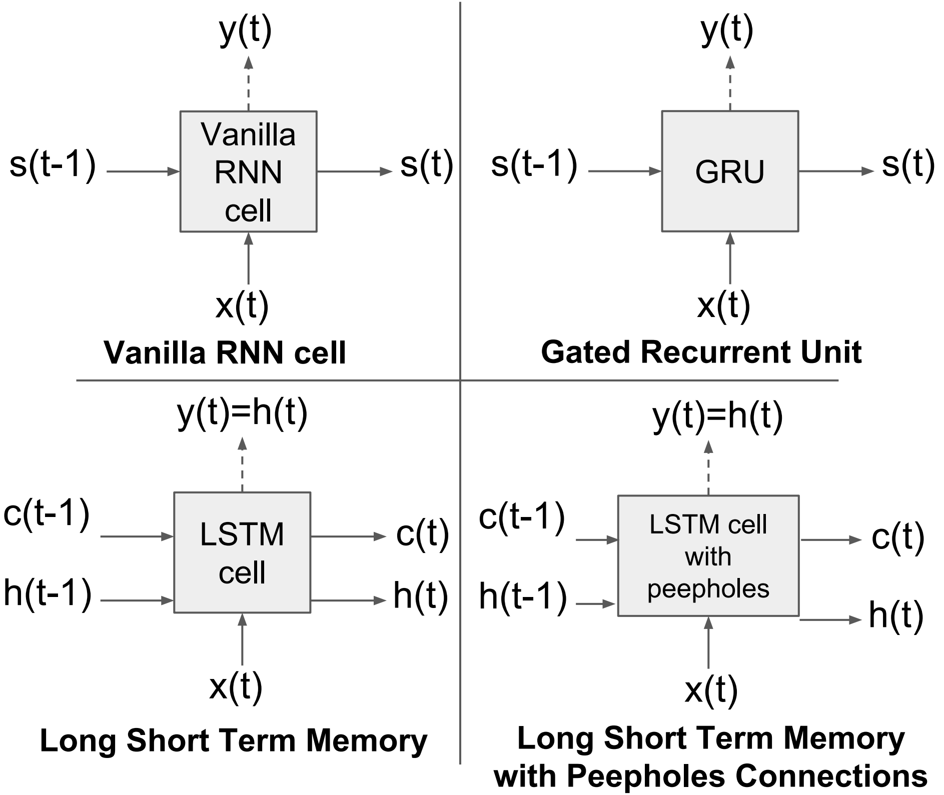
By the end of the talk you will learn

For the most common RNN Cells:

- What's inside & how it works
- Intuition behind
- Advantages and potential problems



Talk outline

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1. RNN: the cell & simple examples

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2. Key aspects (or ways to state of the art)

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4. Problems with Vanilla RNN and motivation for the more powerful cells

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1. RNN: the cell & simple examples
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5. GRU: step by step

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1. RNN: the cell & simple examples
2. Key aspects (or ways to state of the art)
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5. GRU: step by step
6. LSTM: step by step

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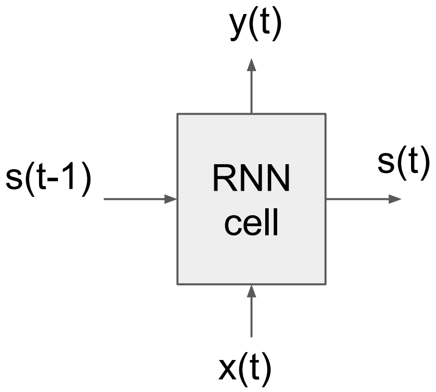
RNN Cell

rnn cell output (optional, in most cases y(t)=s(t))

Hidden state at t-1
(previous state)



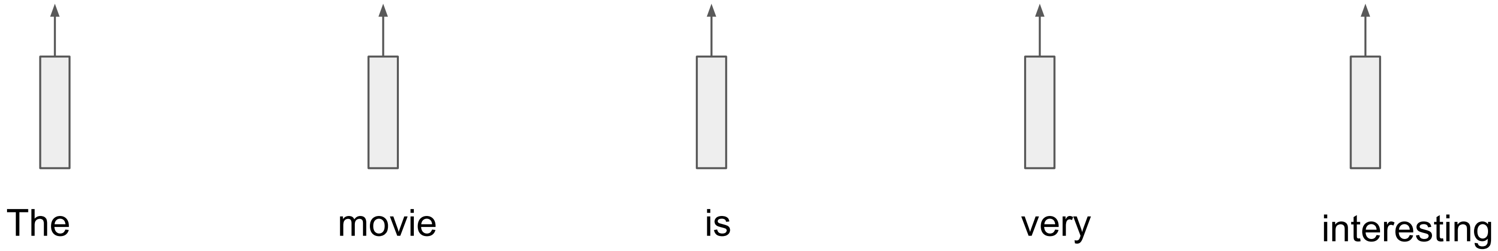
Hidden state at time t
(current state)

Input vector
(optional)

RNN example 1: Sentiment analysis

The movie is very interesting

RNN example 1: Sentiment analysis



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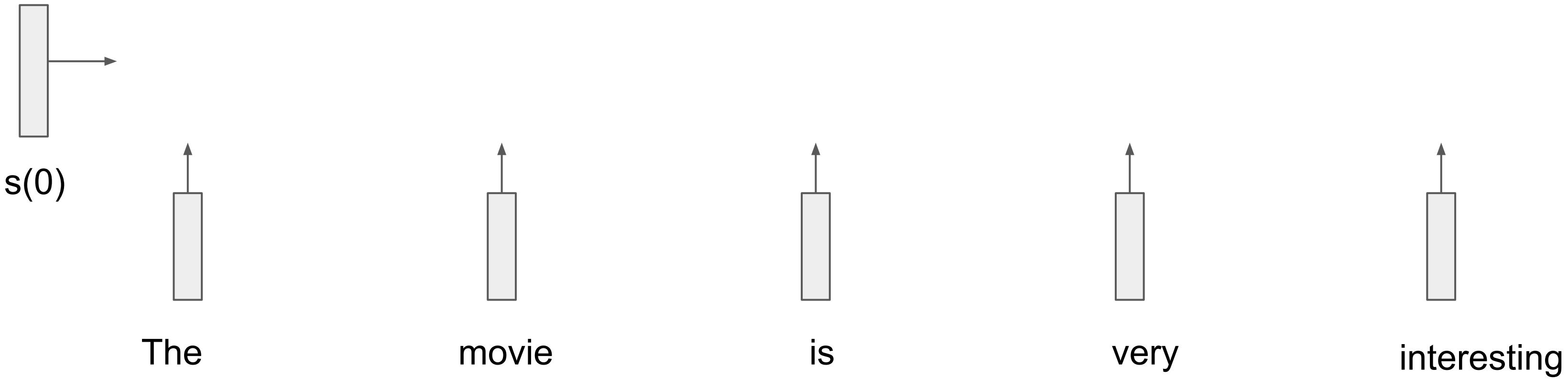
RNN example 1: Sentiment analysis



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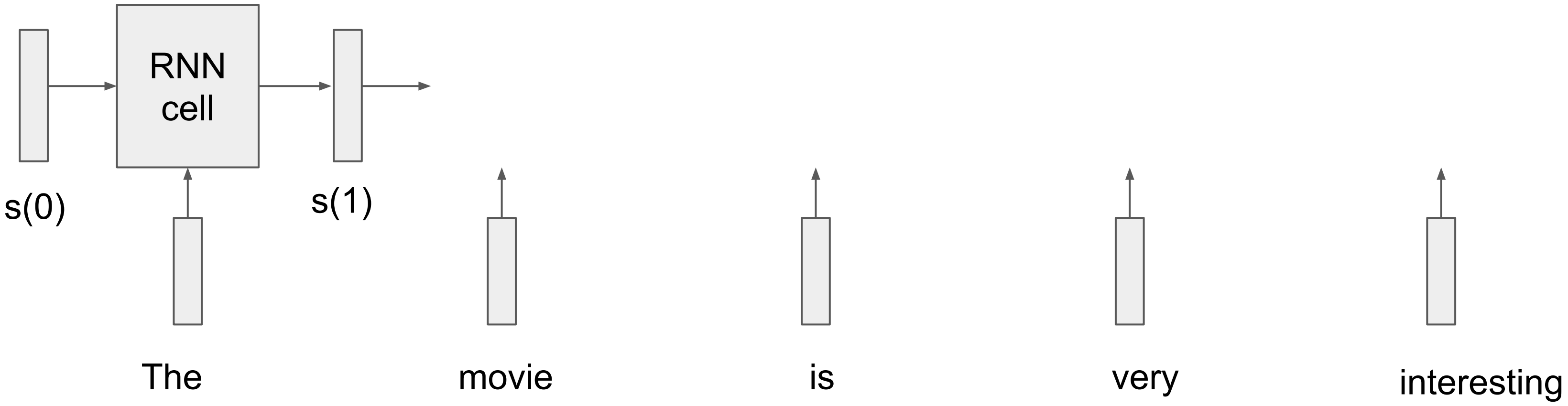
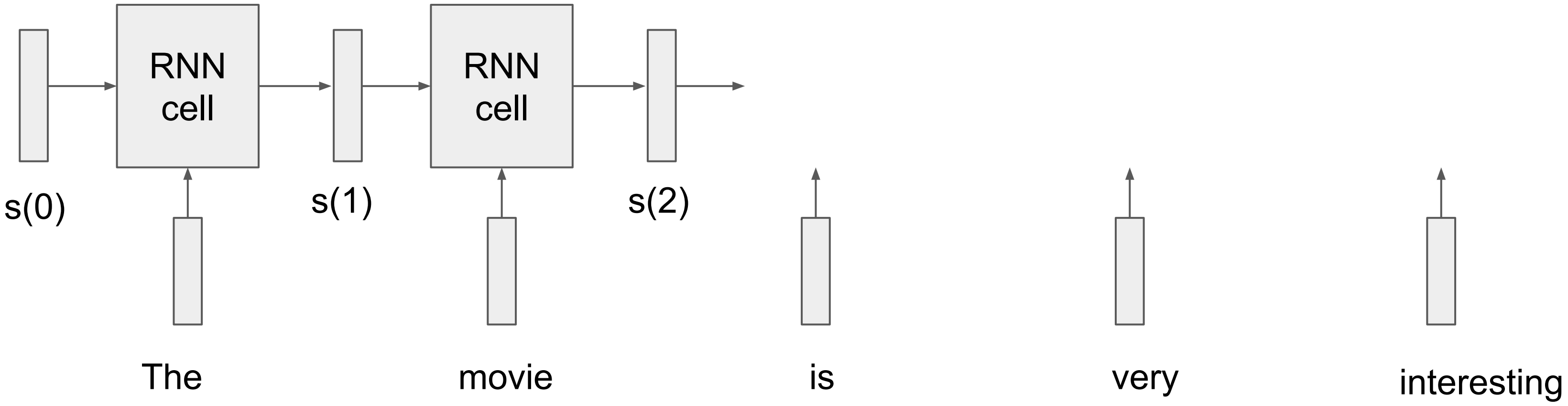
RNN example 1: Sentiment analysis



RNN example 1: Sentiment analysis



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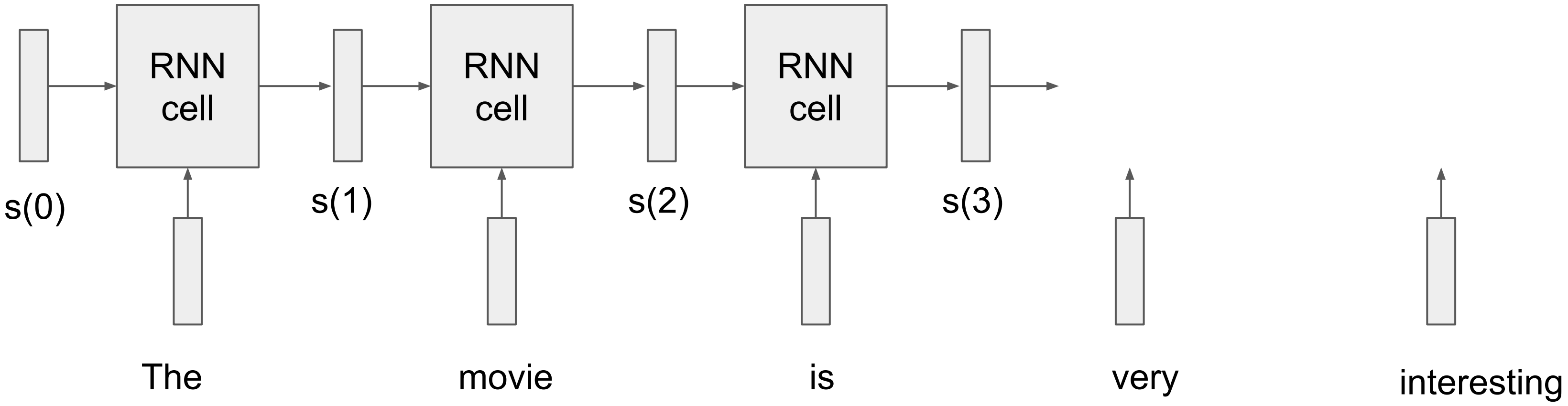
RNN example 1: Sentiment analysis



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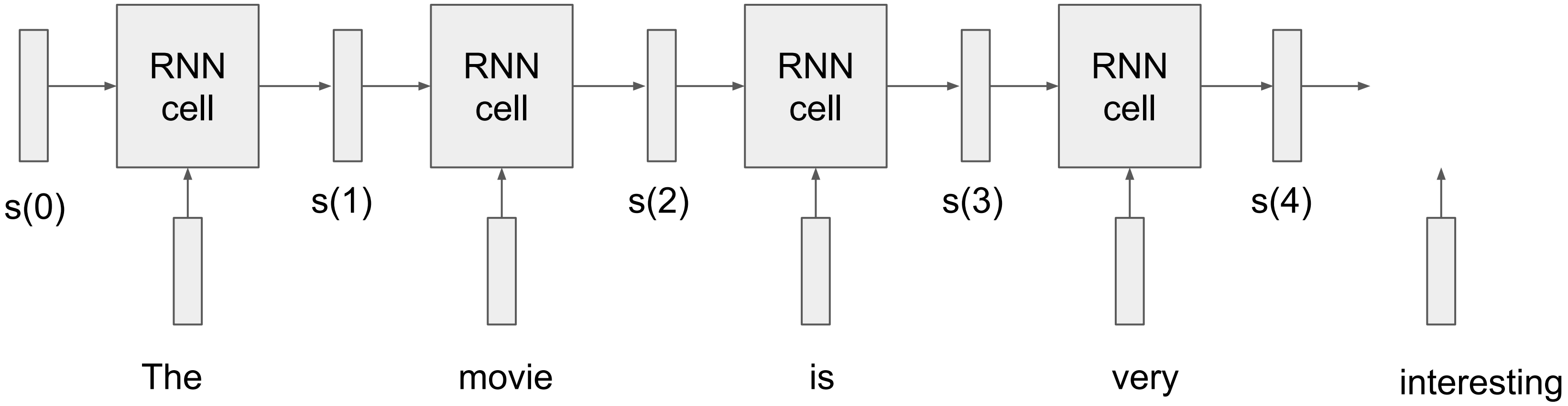
RNN example 1: Sentiment analysis



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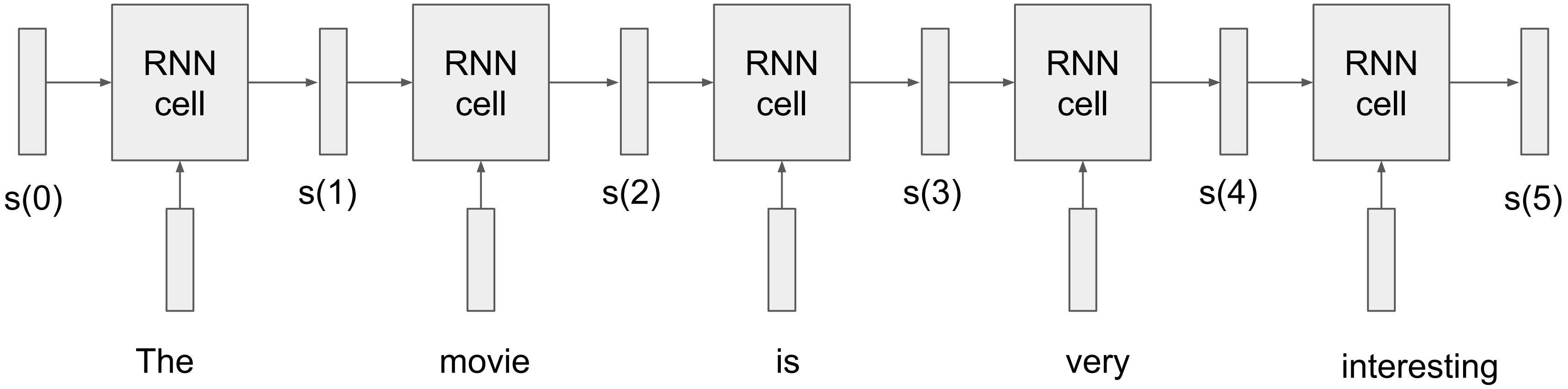
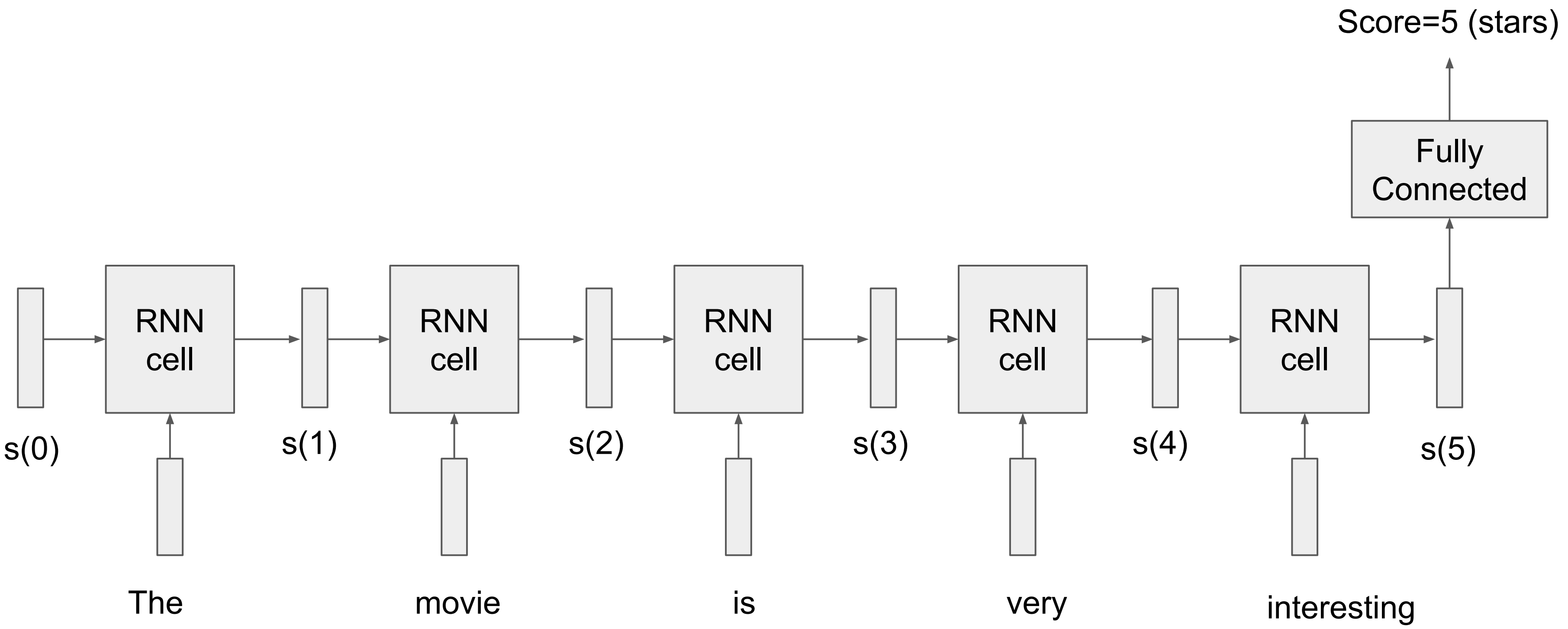
RNN example 1: Sentiment analysis



RNN example 1: Sentiment analysis



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RNN example 2: English to slang English

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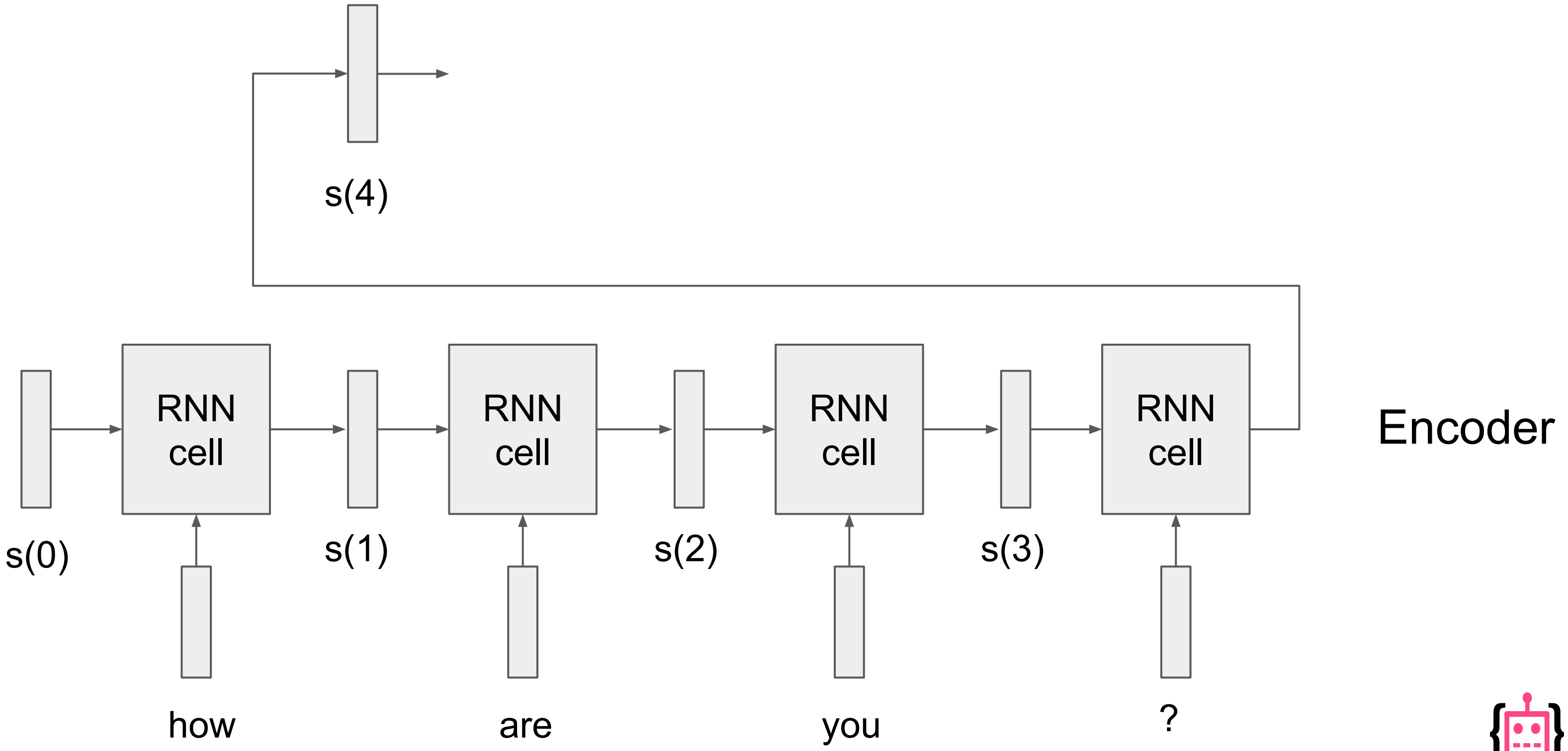
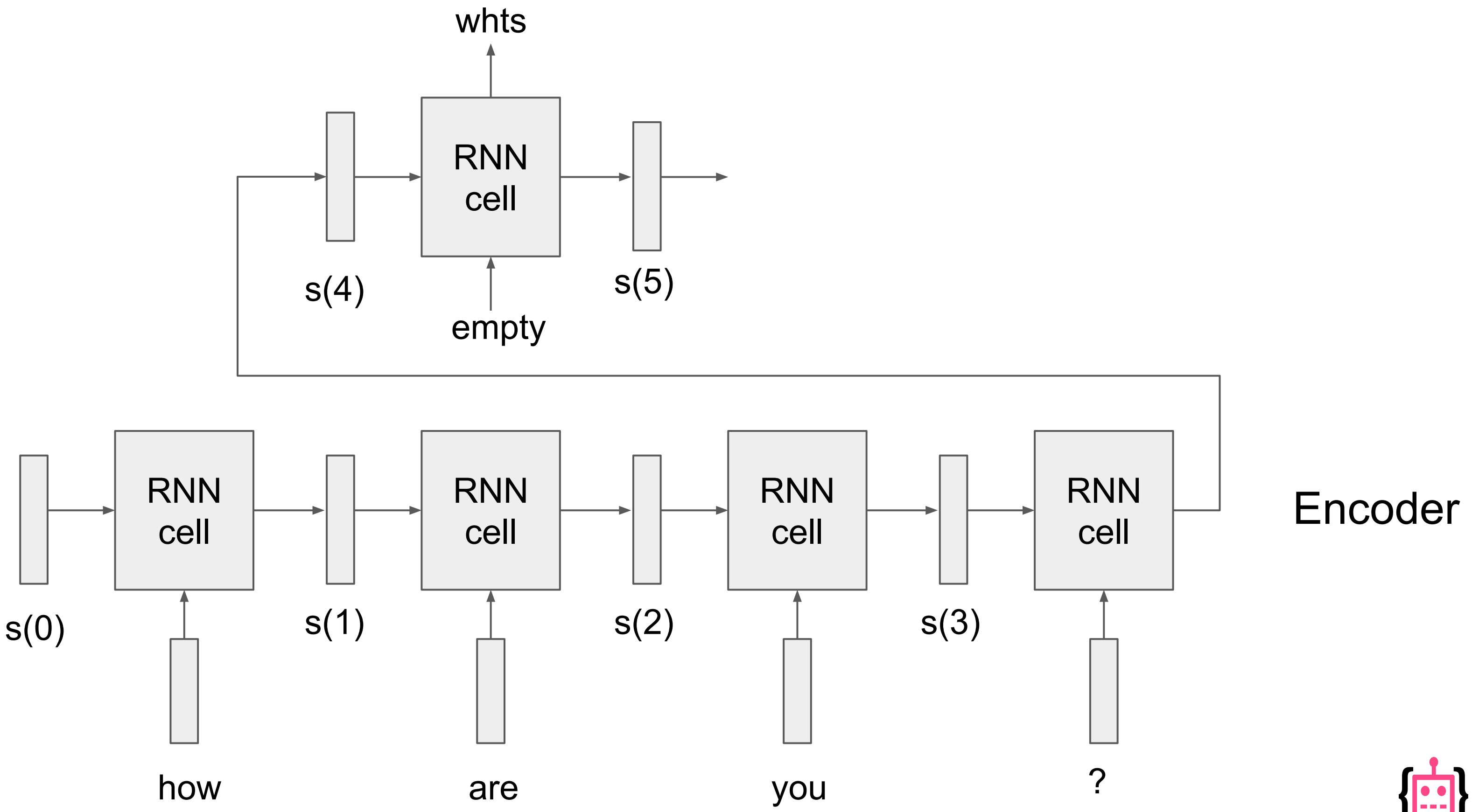
how are you ?

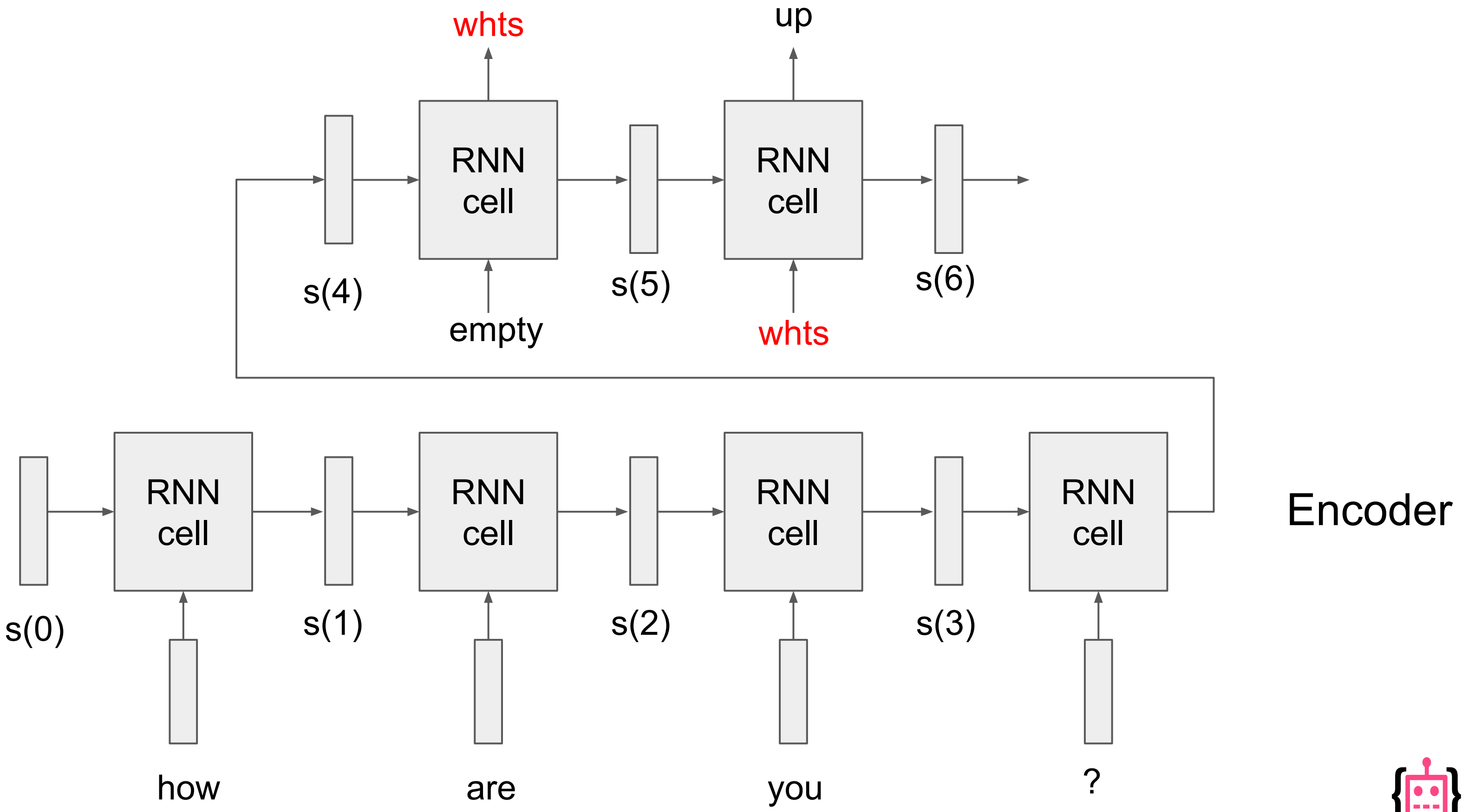
RNN example 2: English to slang English



RNN example 2: English to slang English



RNN example 2: English to slang English



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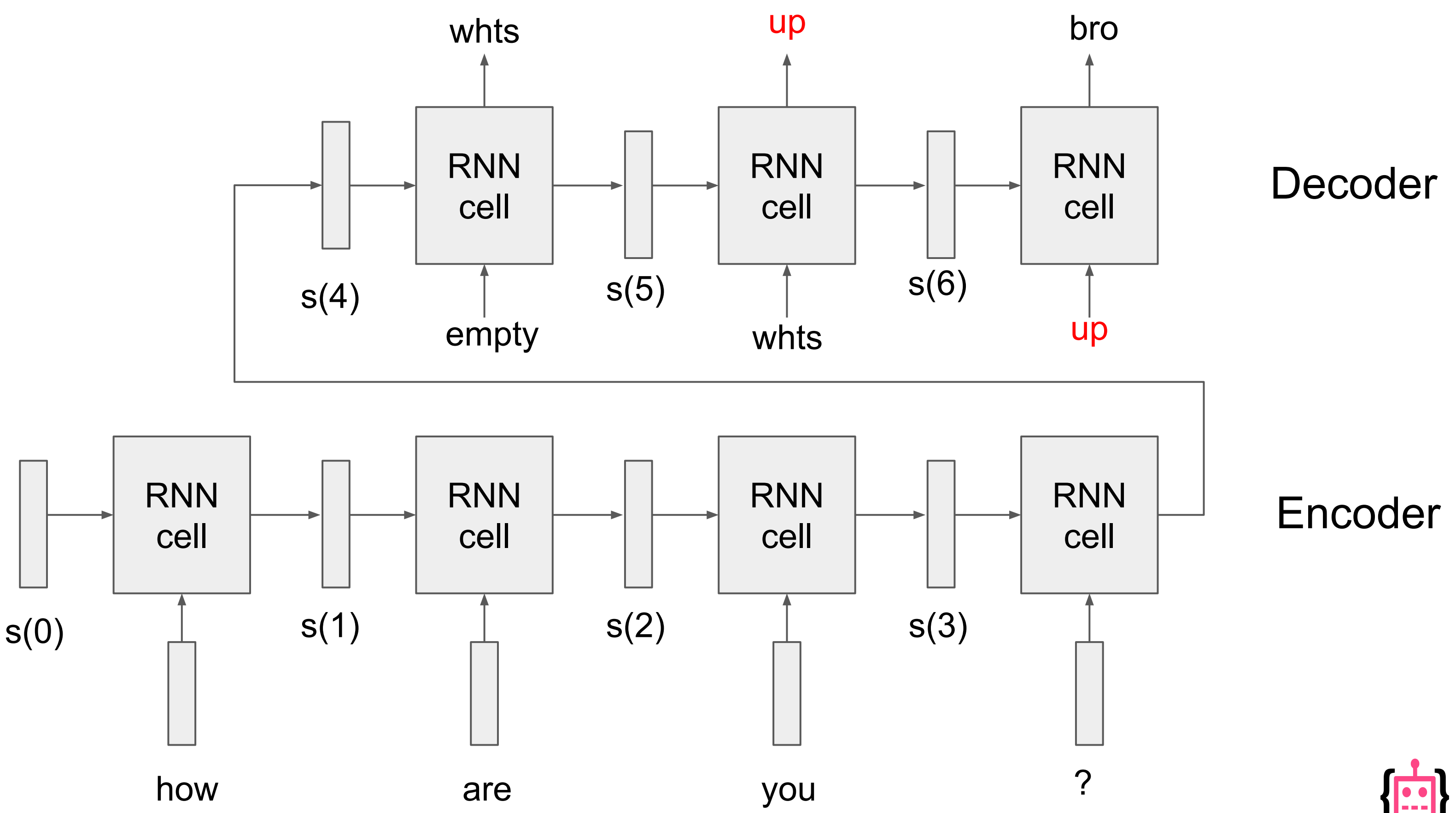

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RNNs: Key Aspects (or ways to state of the art)

RNN Cell structure
(What's inside the cell)

- Legacy
  - Vanilla rnn cell
- Widely used
  - GRU
  - LSTM
- Other alternatives
  - LSTM with peepholes connections
  - MI-LSTM

RNN Cells Topology
(How the cells interconnected)

- Single/Multilayer
- Encoder/Decoder
- Bidirectional
- Grid LSTM
- Tree LSTM

Additional components
(How to make it work)

- Attention
- Regularization
- Normalization
- Share something
- Unshare something (hyper lstm)
- CTC loss

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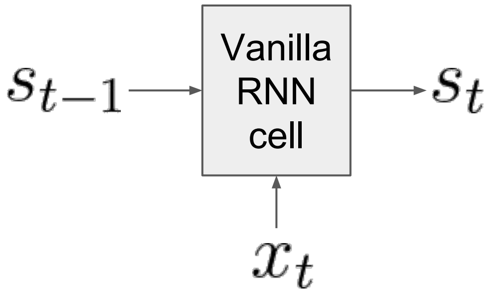
Vanilla RNN



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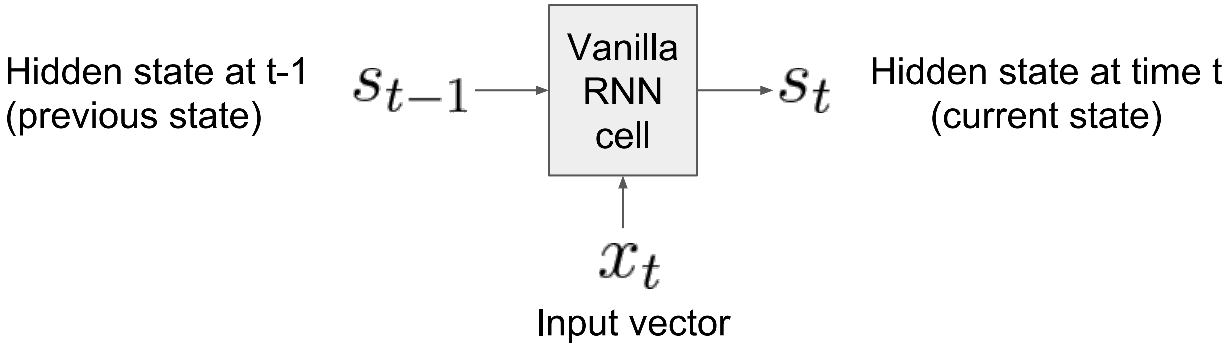
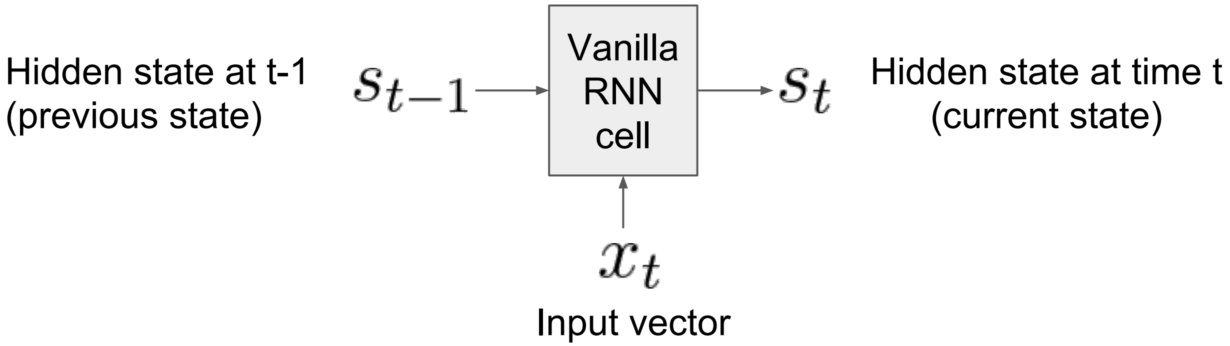
Vanilla RNN



Hidden state at t-1
(previous state)
s_{t-1}
Vanilla
RNN
cell
s_t
Hidden state at time t
(current state)
x_t
Input vector

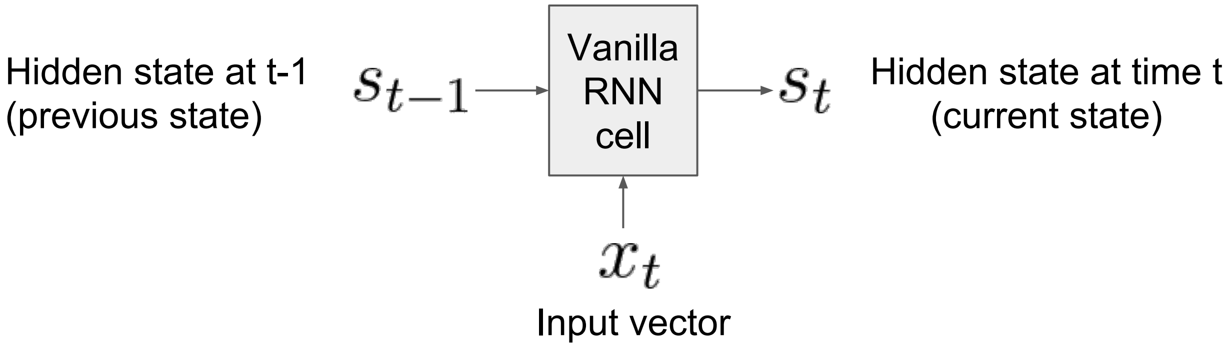
Vanilla RNN

$$s_t = \varphi(W s_{t-1} + U x_t + b)$$



Vanilla RNN

$$\overset{(n\times 1)}{s_t} = \varphi\big(\overset{(n\times n)}{W}\,\overset{(n\times 1)}{s_{t-1}} + \overset{(n\times m)}{U}\,\overset{(m\times 1)}{x_t} + \overset{(n\times 1)}{b}\big)$$



Vanilla RNN

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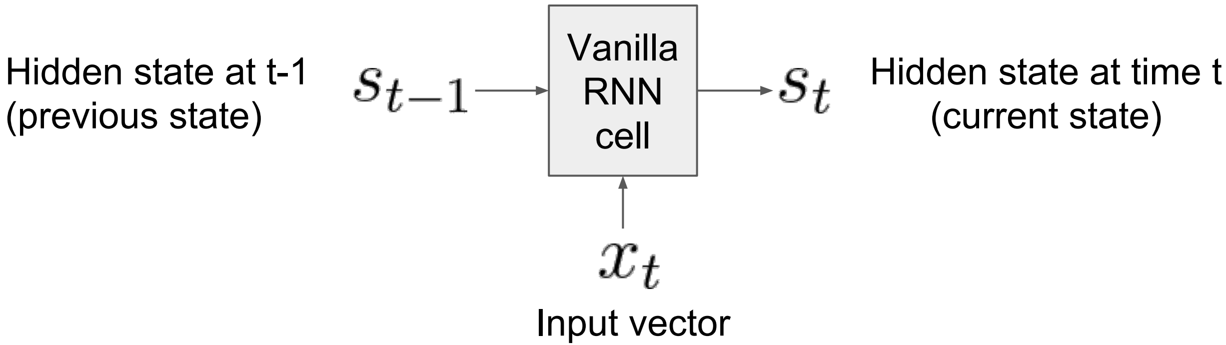
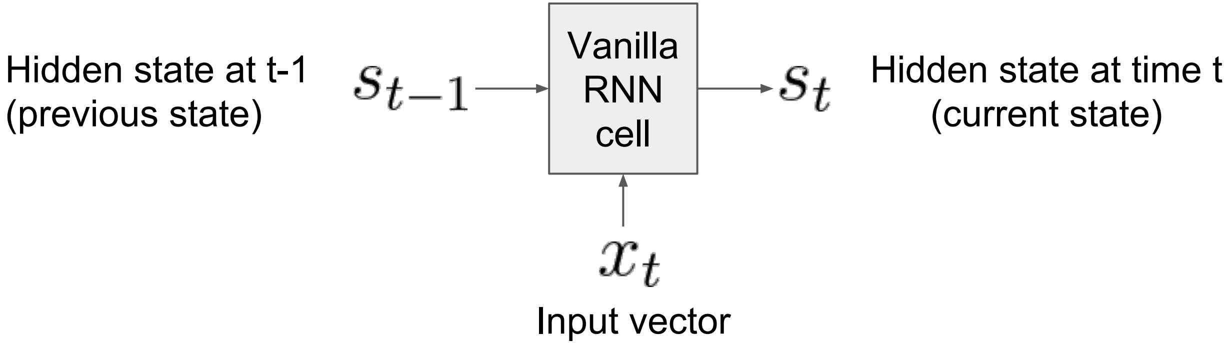


Let’s show that Vanilla RNN is just Single Layer Network (with feedback)

Vanilla RNN

$$\overset{(n \times 1)}{s_t} = \varphi(\overset{(n \times n)(n \times 1)}{W s_{t-1}} + \overset{(n \times m)(m \times 1)}{U x_t} + \overset{(n \times 1)}{b})$$



Let’s show that Vanilla RNN is just Single Layer Network (with feedback)

Let $n = 2, m = 3$

Vanilla RNN

$$s_t = \varphi(W s_{t-1} + U x_t + b)$$

$n = 2$ (state size),
$m = 3$ (input size)

Vanilla RNN

$n = 2$ (state size),
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$$s_t = \varphi(W s_{t-1} + U x_t + b)$$

$$\begin{pmatrix} s_t^1 \\ s_t^2 \end{pmatrix} = \varphi(\begin{pmatrix} w_{11} & w_{12} \\ w_{21} & w_{22} \end{pmatrix} \begin{pmatrix} s_{t-1}^1 \\ s_{t-1}^2 \end{pmatrix} + \begin{pmatrix} u_{11} & u_{12} & u_{13} \\ u_{21} & u_{22} & u_{23} \end{pmatrix} \begin{pmatrix} x_t^1 \\ x_t^2 \\ x_t^3 \end{pmatrix} + \begin{pmatrix} b_1 \\ b_2 \end{pmatrix})$$

Vanilla RNN

$n = 2$ (state size),
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$$s_t = \varphi(W s_{t-1} + U x_t + b)$$

$$\begin{pmatrix} s_t^1 \\ s_t^2 \end{pmatrix} = \varphi(\begin{pmatrix} w_{11} & w_{12} \\ w_{21} & w_{22} \end{pmatrix} \begin{pmatrix} s_{t-1}^1 \\ s_{t-1}^2 \end{pmatrix} + \begin{pmatrix} u_{11} & u_{12} & u_{13} \\ u_{21} & u_{22} & u_{23} \end{pmatrix} \begin{pmatrix} x_t^1 \\ x_t^2 \\ x_t^3 \end{pmatrix} + \begin{pmatrix} b_1 \\ b_2 \end{pmatrix})$$

$$= \varphi(\begin{pmatrix} w_{11}s_{t-1}^1 + w_{12}s_{t-1}^2 \\ w_{21}s_{t-1}^1 + w_{22}s_{t-1}^2 \end{pmatrix} + \begin{pmatrix} u_{11}x_t^1 + u_{12}x_t^2 + u_{13}x_t^3 \\ u_{21}x_t^1 + u_{22}x_t^2 + u_{23}x_t^3 \end{pmatrix} + \begin{pmatrix} b_1 \\ b_2 \end{pmatrix})$$

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$$\begin{pmatrix} s_t^1 \\ s_t^2 \end{pmatrix} = \varphi(\begin{pmatrix} w_{11} & w_{12} \\ w_{21} & w_{22} \end{pmatrix} \begin{pmatrix} s_{t-1}^1 \\ s_{t-1}^2 \end{pmatrix} + \begin{pmatrix} u_{11} & u_{12} & u_{13} \\ u_{21} & u_{22} & u_{23} \end{pmatrix} \begin{pmatrix} x_t^1 \\ x_t^2 \\ x_t^3 \end{pmatrix} + \begin{pmatrix} b_1 \\ b_2 \end{pmatrix})$$

$$= \varphi(\begin{pmatrix} w_{11} s_{t-1}^1 + w_{12} s_{t-1}^2 \\ w_{21} s_{t-1}^1 + w_{22} s_{t-1}^2 \end{pmatrix} + \begin{pmatrix} u_{11} x_t^1 + u_{12} x_t^2 + u_{13} x_t^3 \\ u_{21} x_t^1 + u_{22} x_t^2 + u_{23} x_t^3 \end{pmatrix} + \begin{pmatrix} b_1 \\ b_2 \end{pmatrix})$$

$$= \varphi(\begin{pmatrix} w_{11} s_{t-1}^1 + w_{12} s_{t-1}^2 + u_{11} x_t^1 + u_{12} x_t^2 + u_{13} x_t^3 \\ w_{21} s_{t-1}^1 + w_{22} s_{t-1}^2 + u_{21} x_t^1 + u_{22} x_t^2 + u_{23} x_t^3 \end{pmatrix} + \begin{pmatrix} b_1 \\ b_2 \end{pmatrix})$$

Vanilla RNN

$n = 2$ (state size),
$m = 3$ (input size)

$$s_t = \varphi(W s_{t-1} + U x_t + b)$$

$$\begin{pmatrix} s_t^1 \\ s_t^2 \end{pmatrix} = \varphi(\begin{pmatrix} w_{11} & w_{12} \\ w_{21} & w_{22} \end{pmatrix} \begin{pmatrix} s_{t-1}^1 \\ s_{t-1}^2 \end{pmatrix} + \begin{pmatrix} u_{11} & u_{12} & u_{13} \\ u_{21} & u_{22} & u_{23} \end{pmatrix} \begin{pmatrix} x_t^1 \\ x_t^2 \\ x_t^3 \end{pmatrix} + \begin{pmatrix} b_1 \\ b_2 \end{pmatrix})$$

$$= \varphi(\begin{pmatrix} w_{11} s_{t-1}^1 + w_{12} s_{t-1}^2 \\ w_{21} s_{t-1}^1 + w_{22} s_{t-1}^2 \end{pmatrix} + \begin{pmatrix} u_{11} x_t^1 + u_{12} x_t^2 + u_{13} x_t^3 \\ u_{21} x_t^1 + u_{22} x_t^2 + u_{23} x_t^3 \end{pmatrix} + \begin{pmatrix} b_1 \\ b_2 \end{pmatrix})$$

$$= \varphi(\begin{pmatrix} w_{11} s_{t-1}^1 + w_{12} s_{t-1}^2 + u_{11} x_t^1 + u_{12} x_t^2 + u_{13} x_t^3 \\ w_{21} s_{t-1}^1 + w_{22} s_{t-1}^2 + u_{21} x_t^1 + u_{22} x_t^2 + u_{23} x_t^3 \end{pmatrix} + \begin{pmatrix} b_1 \\ b_2 \end{pmatrix})$$

$$= \varphi(\begin{pmatrix} w_{11} & w_{12} & u_{11} & u_{12} & u_{13} \\ w_{21} & w_{22} & u_{21} & u_{22} & u_{23} \end{pmatrix} \begin{pmatrix} s_{t-1}^1 \\ s_{t-1}^2 \\ x_t^1 \\ x_t^2 \\ x_t^3 \end{pmatrix} + \begin{pmatrix} b_1 \\ b_2 \end{pmatrix})$$

Vanilla RNN

$n = 2$ (state size),
$m = 3$ (input size)

$$s_t = \varphi(W s_{t-1} + U x_t + b)$$

$$\begin{pmatrix} s_t^1 \\ s_t^2 \end{pmatrix} = \varphi(\begin{pmatrix} w_{11} & w_{12} \\ w_{21} & w_{22} \end{pmatrix} \begin{pmatrix} s_{t-1}^1 \\ s_{t-1}^2 \end{pmatrix} + \begin{pmatrix} u_{11} & u_{12} & u_{13} \\ u_{21} & u_{22} & u_{23} \end{pmatrix} \begin{pmatrix} x_t^1 \\ x_t^2 \\ x_t^3 \end{pmatrix} + \begin{pmatrix} b_1 \\ b_2 \end{pmatrix})$$

$$= \varphi(\begin{pmatrix} w_{11}s_{t-1}^1 + w_{12}s_{t-1}^2 \\ w_{21}s_{t-1}^1 + w_{22}s_{t-1}^2 \end{pmatrix} + \begin{pmatrix} u_{11}x_t^1 + u_{12}x_t^2 + u_{13}x_t^3 \\ u_{21}x_t^1 + u_{22}x_t^2 + u_{23}x_t^3 \end{pmatrix} + \begin{pmatrix} b_1 \\ b_2 \end{pmatrix})$$

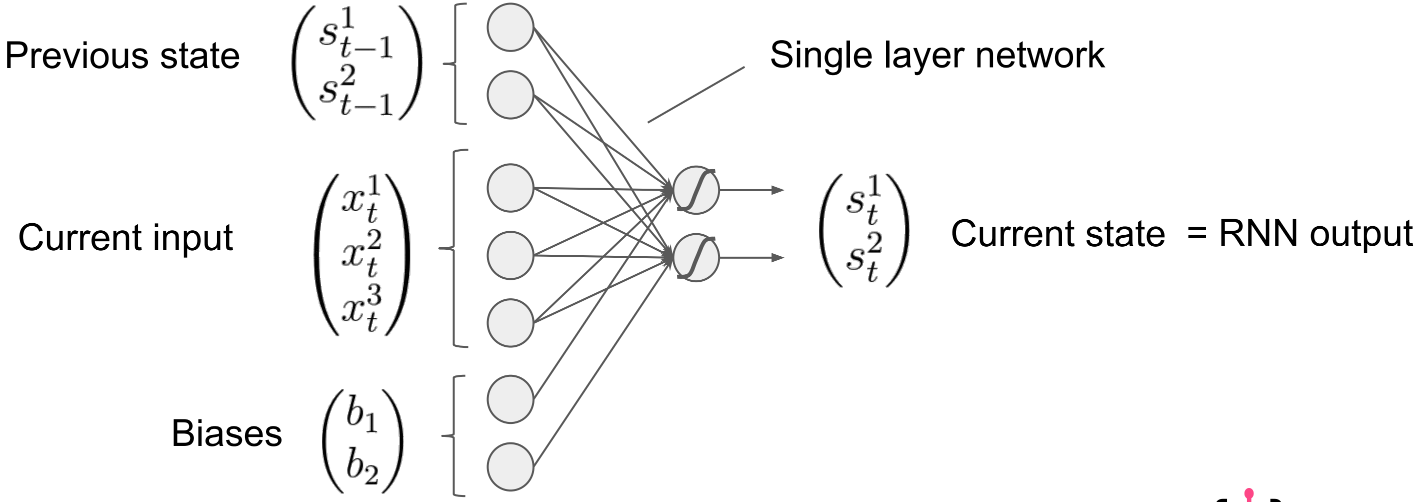
$$= \varphi(\begin{pmatrix} w_{11}s_{t-1}^1 + w_{12}s_{t-1}^2 + u_{11}x_t^1 + u_{12}x_t^2 + u_{13}x_t^3 \\ w_{21}s_{t-1}^1 + w_{22}s_{t-1}^2 + u_{21}x_t^1 + u_{22}x_t^2 + u_{23}x_t^3 \end{pmatrix} + \begin{pmatrix} b_1 \\ b_2 \end{pmatrix})$$

$$= \varphi(\begin{pmatrix} w_{11} & w_{12} & u_{11} & u_{12} & u_{13} \\ w_{21} & w_{22} & u_{21} & u_{22} & u_{23} \end{pmatrix} \begin{pmatrix} s_{t-1}^1 \\ s_{t-1}^2 \\ x_t^1 \\ x_t^2 \\ x_t^3 \end{pmatrix} + \begin{pmatrix} b_1 \\ b_2 \end{pmatrix})$$

\- single layer network

Vanilla RNN

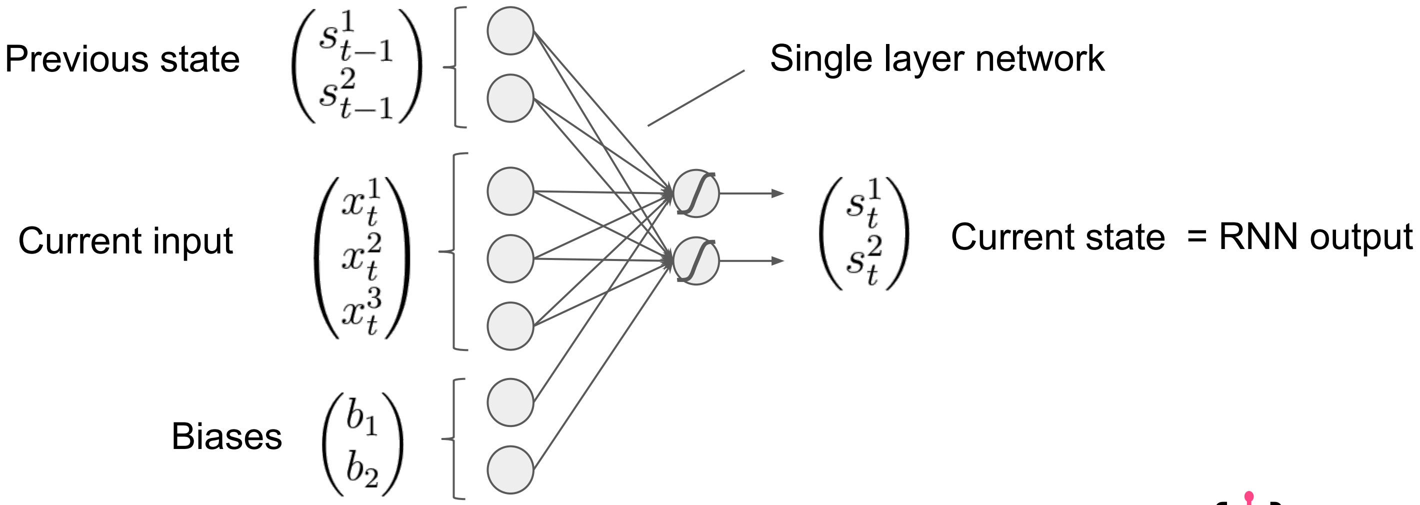
$$\begin{pmatrix} s_t^1 \\ s_t^2 \end{pmatrix} = \varphi\left(\begin{pmatrix} w_{11} & w_{12} & u_{11} & u_{12} & u_{13} \\ w_{21} & w_{22} & u_{21} & u_{22} & u_{23} \end{pmatrix} \begin{pmatrix} s_{t-1}^1 \\ s_{t-1}^2 \\ x_t^1 \\ x_t^2 \\ x_t^3 \end{pmatrix} + \begin{pmatrix} b_1 \\ b_2 \end{pmatrix} \right)$$



Vanilla RNN

$$s_t = \varphi(W_c[s_{t-1}, x_t] + b)$$

$$\begin{pmatrix} s_t^1 \\ s_t^2 \end{pmatrix} = \varphi\left(\begin{pmatrix} w_{11} & w_{12} & u_{11} & u_{12} & u_{13} \\ w_{21} & w_{22} & u_{21} & u_{22} & u_{23} \end{pmatrix} \begin{pmatrix} s_{t-1}^1 \\ s_{t-1}^2 \\ x_t^1 \\ x_t^2 \\ x_t^3 \end{pmatrix} + \begin{pmatrix} b_1 \\ b_2 \end{pmatrix}\right)$$



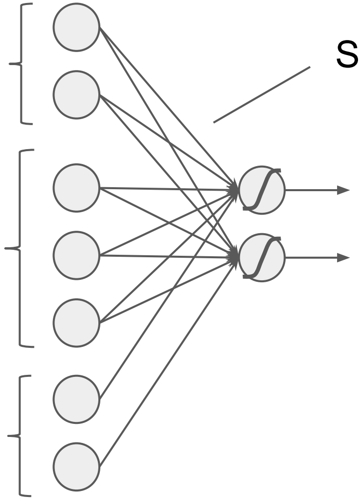
Vanilla RNN

$$\begin{pmatrix} s_t^1 \\ s_t^2 \end{pmatrix} = \varphi\left(\begin{pmatrix} w_{11} & w_{12} & u_{11} & u_{12} & u_{13} & b_1 \\ w_{21} & w_{22} & u_{21} & u_{22} & u_{23} & b_2 \end{pmatrix} \begin{pmatrix} s_{t-1}^1 \\ s_{t-1}^2 \\ x_t^1 \\ x_t^2 \\ x_t^3 \\ 1 \end{pmatrix}\right)$$

Previous state $\begin{pmatrix} s_{t-1}^1 \\ s_{t-1}^2 \end{pmatrix}$

Current input $\begin{pmatrix} x_t^1 \\ x_t^2 \\ x_t^3 \end{pmatrix}$

Biases $\begin{pmatrix} b_1 \\ b_2 \end{pmatrix}$



Single layer network

$\begin{pmatrix} s_t^1 \\ s_t^2 \end{pmatrix}$ Current state = RNN output

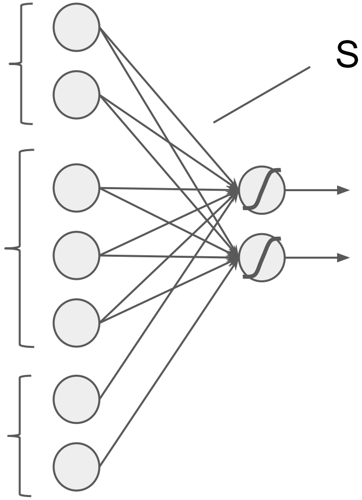
Vanilla RNN

$$s_t = \varphi(W_b[s_{t-1}, x_t, 1])$$

$$\begin{pmatrix} s_t^1 \\ s_t^2 \end{pmatrix} = \varphi(\begin{pmatrix} w_{11} & w_{12} & u_{11} & u_{12} & u_{13} & b_1 \\ w_{21} & w_{22} & u_{21} & u_{22} & u_{23} & b_2 \end{pmatrix} \begin{pmatrix} s_{t-1}^1 \\ s_{t-1}^2 \\ x_t^1 \\ x_t^2 \\ x_t^3 \\ 1 \end{pmatrix})$$

Previous state $\begin{pmatrix} s_{t-1}^1 \\ s_{t-1}^2 \end{pmatrix}$

Single layer network



Current input $\begin{pmatrix} x_t^1 \\ x_t^2 \\ x_t^3 \end{pmatrix}$

$\begin{pmatrix} s_t^1 \\ s_t^2 \end{pmatrix}$ Current state = RNN output

Biases $\begin{pmatrix} b_1 \\ b_2 \end{pmatrix}$

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Vanilla RNN

$$s_t = \varphi(W_b[s_{t-1}, x_t, 1])$$

$$s_t = \varphi(W_b[s_{t-1}, x_t])$$

But often “1” is omitted

$$\begin{pmatrix} s_t^1 \\ s_t^2 \end{pmatrix} = \varphi\left(\begin{pmatrix} w_{11} & w_{12} & u_{11} & u_{12} & u_{13} & b_1 \\ w_{21} & w_{22} & u_{21} & u_{22} & u_{23} & b_2 \end{pmatrix} \begin{pmatrix} s_{t-1}^1 \\ s_{t-1}^2 \\ x_t^1 \\ x_t^2 \\ x_t^3 \\ 1 \end{pmatrix}\right)$$

Previous state $\begin{pmatrix} s_{t-1}^1 \\ s_{t-1}^2 \end{pmatrix}$

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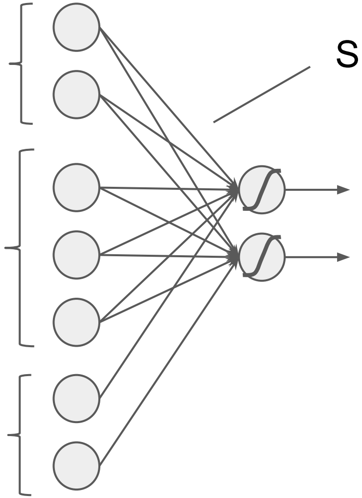
Biases $\begin{pmatrix} b_1 \\ b_2 \end{pmatrix}$



Single layer network

$\begin{pmatrix} s_t^1 \\ s_t^2 \end{pmatrix}$ Current state = RNN output

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Vanilla RNN. Notations

$$s_t = \varphi(Ws_{t-1} + Ux_t + b)$$

sometimes written as

$$s_t = \varphi(W_c[s_{t-1}, x_t] + b)$$

sometimes as

$$s_t = \varphi(W_b[s_{t-1}, x_t])$$

Talk outline

1. RNN: the cell & simple examples
2. Key aspects (or ways to state of the art)
3. Vanilla RNN
4. Problems with Vanilla RNN and motivation for the more powerful cells
5. GRU: step by step
6. LSTM: step by step
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What’s wrong with Vanilla RNNs?

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$\Downarrow$

Gradient vanishing (technical)

What’s wrong with Vanilla RNNs?

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They fail to solve complex tasks (the ones that have practical applications)

Main problems:

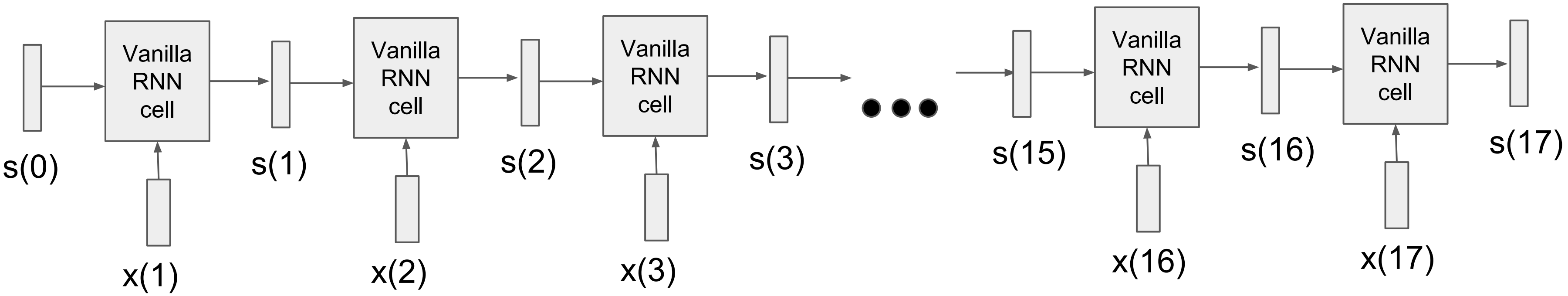
Information morphing (fundamental) ⇨ Inability to keep the memory content for more than a few time steps

⇩

Gradient vanishing (technical)

Information morphing

$$s_t = \varphi(W s_{t-1} + U x_t + b)$$



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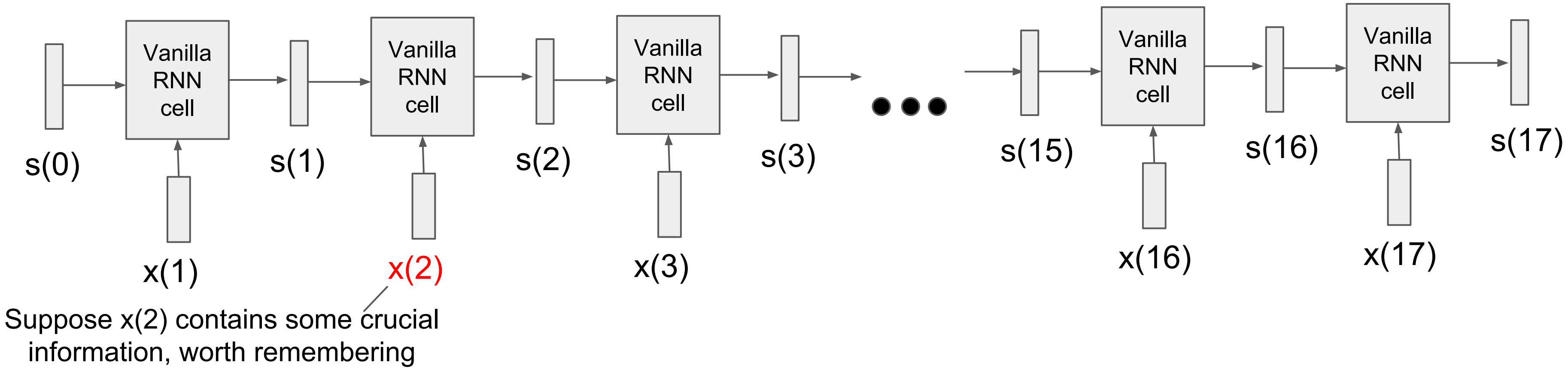

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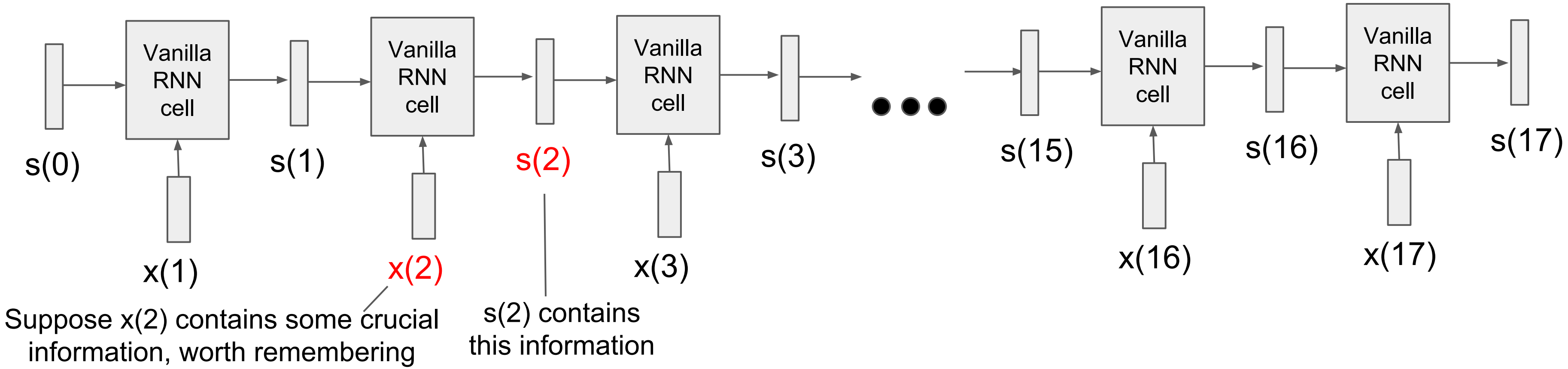

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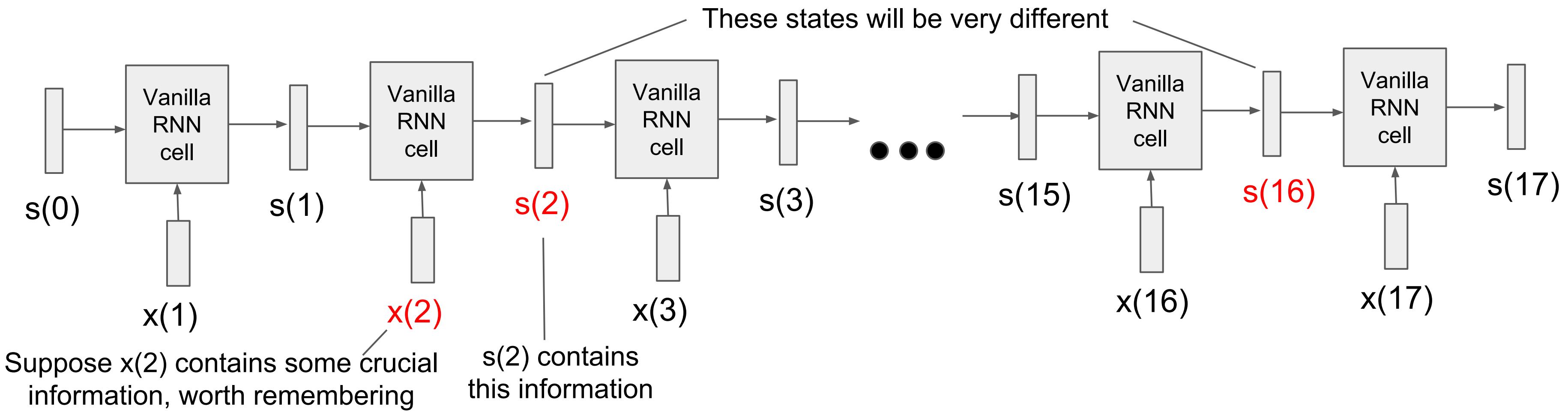

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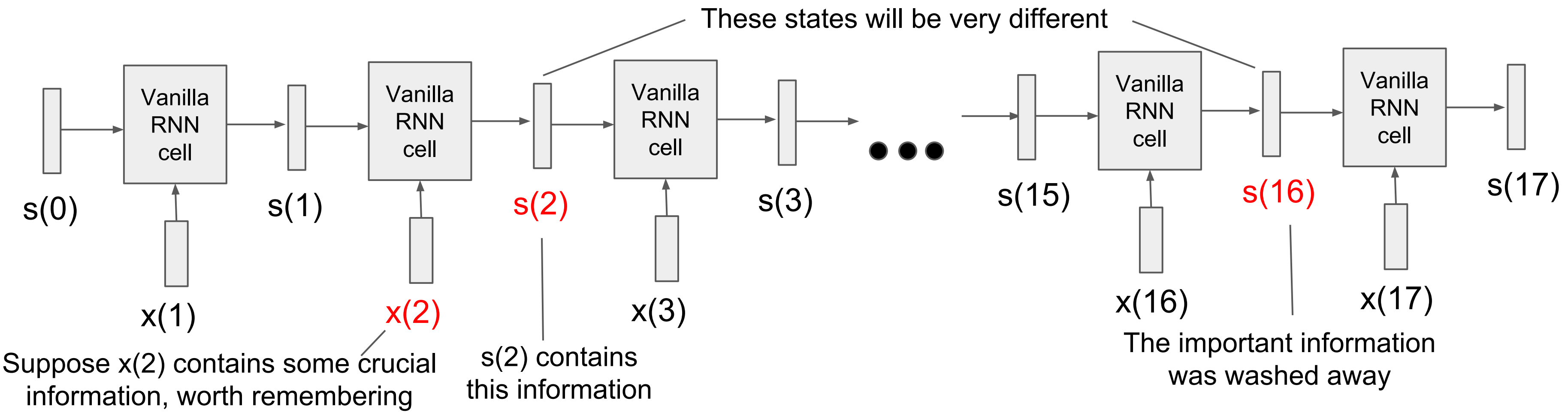

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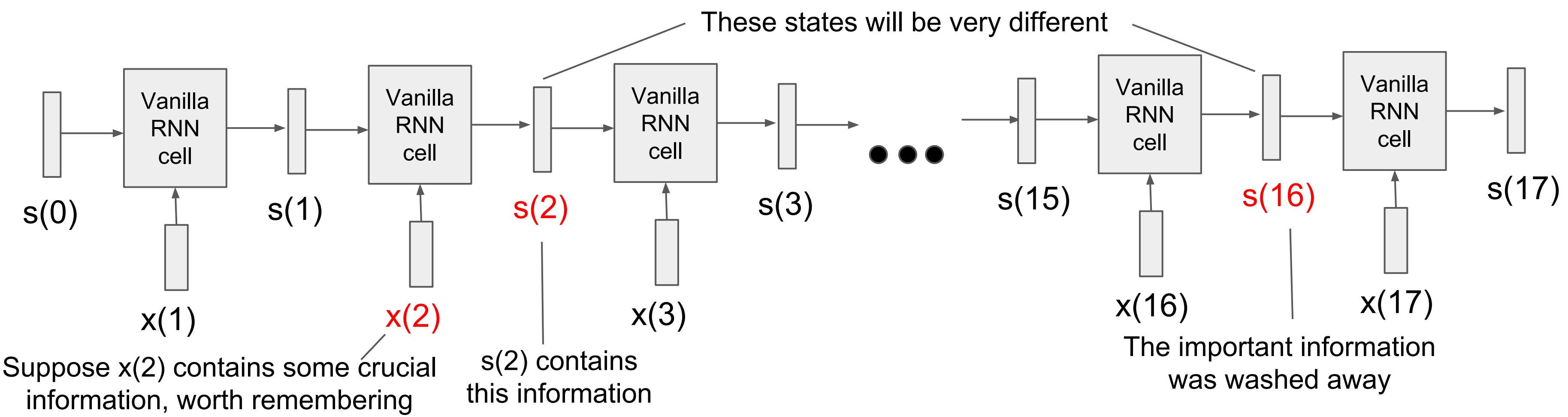

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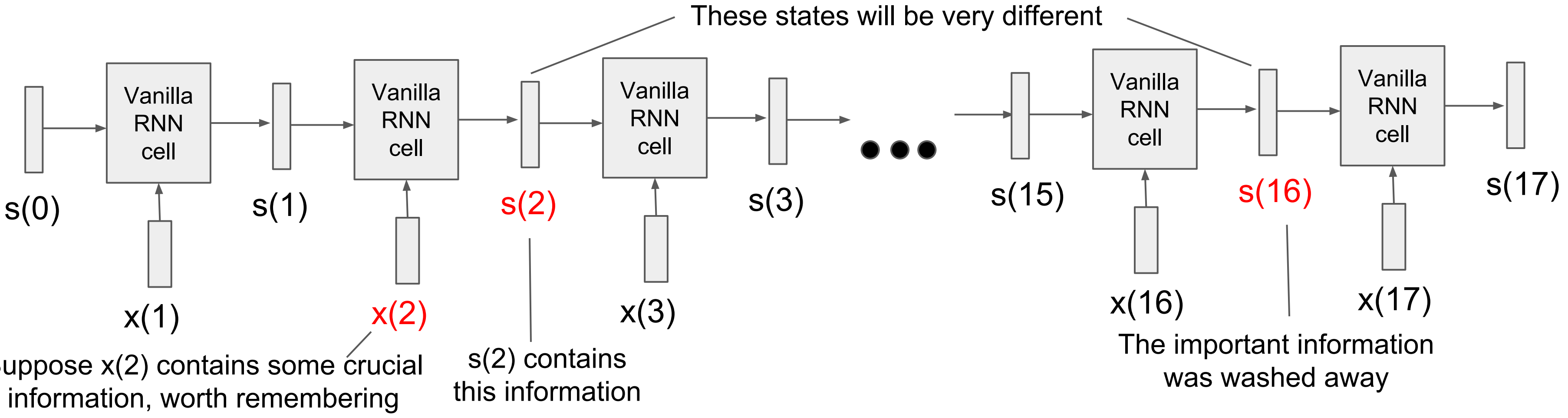
Why this happens?

The rnn memory (state) should be protected: use only + or - operations to write to the memory



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Information morphing

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Nonlinearity is bad for long term memory

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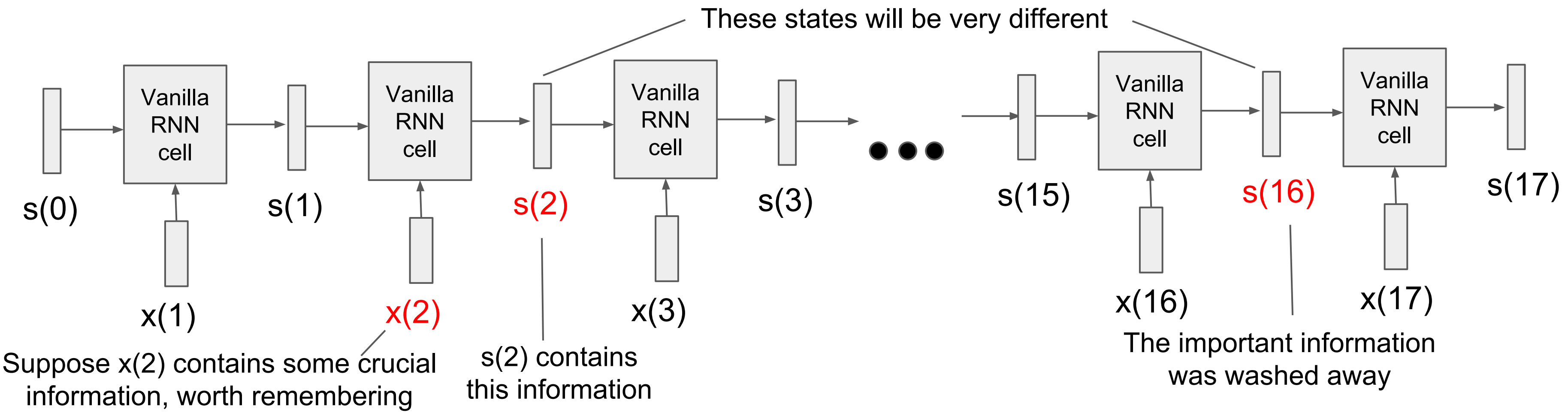

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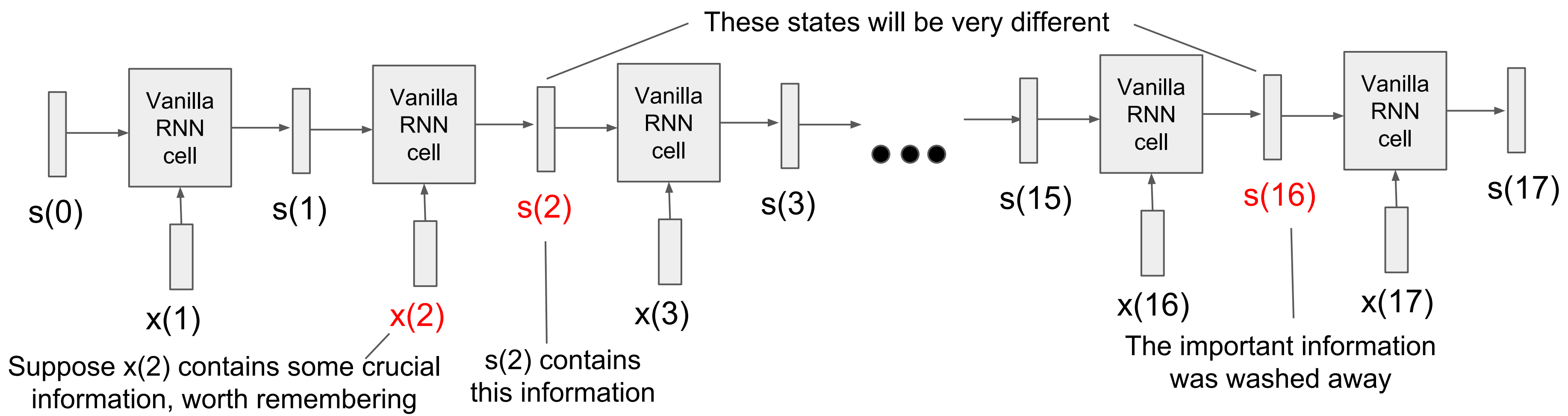
Be selective: choose what to read, write and forget



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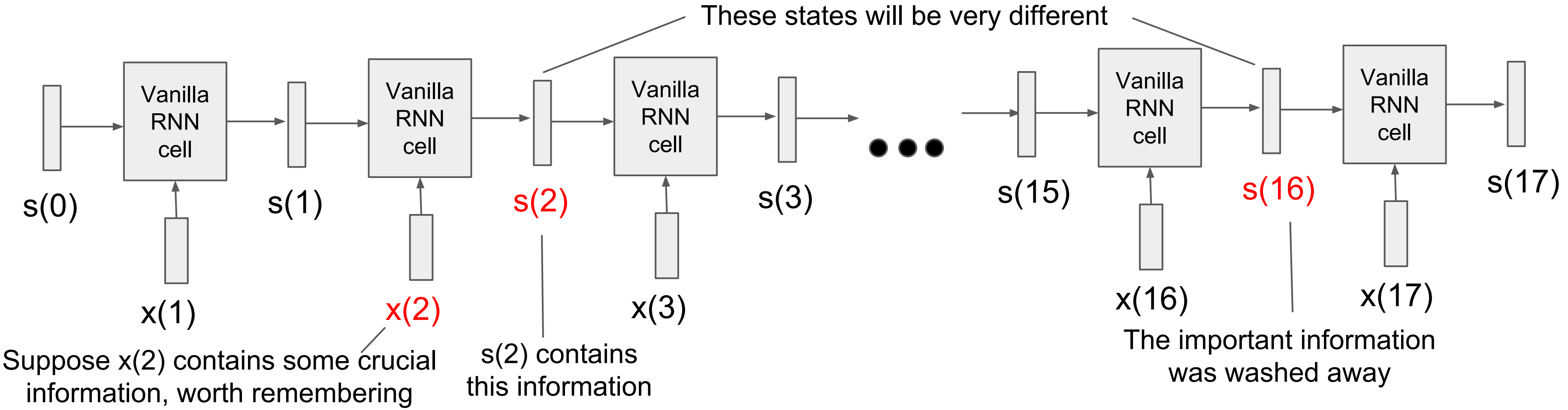

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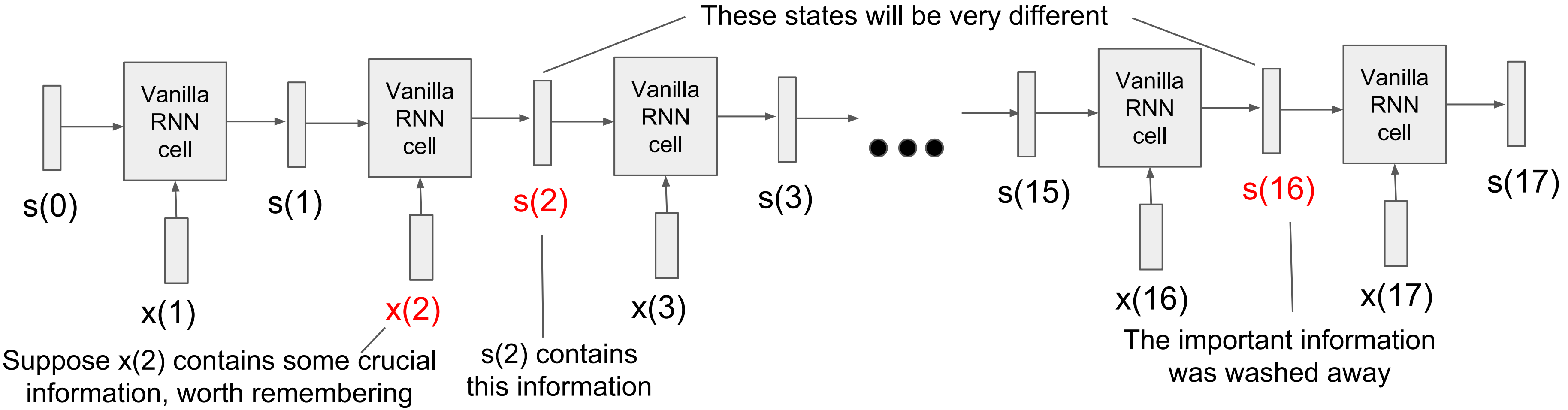

Protecting the state & selectivity through gates

Current state = Previous state + New state candidate

Protecting the state & selectivity through gates

“New state candidate” is a vector of **positive** numbers

Current state = Previous state + New state candidate

Protecting the state & selectivity through gates

“New state candidate” is a vector of **positive** numbers

“New state candidate” is a vector of **negative** numbers

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Protecting the state & selectivity through gates

“New state candidate” is a vector of **positive** numbers

“New state candidate” is a vector of **negative** numbers

We don’t corrupt the whole memory, just add or subtract something

Current state = Previous state + New state candidate

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Protecting the state & selectivity through gates

Current state = Previous state + New state candidate

Protecting the state & selectivity through gates

New state candidate = FUNC [Previous state , Current input]

Current state = Previous state + New state candidate

Protecting the state & selectivity through gates

(New state candidate) = FUNC [(Previous state) , (Current input)]

(Current state) = (Previous state) + (New state candidate)

Vanilla RNN with “New State candidate”

Protecting the state & selectivity through gates

$$\text{New state candidate} = \text{FUNC}\left[\text{Previous state}, \text{Current input}\right]$$

$$\text{Current state} = \text{What to forget} \circ \text{Previous state} + \text{New state candidate}$$

Protecting the state & selectivity through gates

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Protecting the state & selectivity through gates

$$\text{What to forget} = G\_F\left[\text{Previous state}, \text{Current input}\right]$$

$$\text{New state candidate} = \mathrm{FUNC}\left[\text{What to read} \circ \text{Previous state}, \text{Current input}\right]$$

$$\text{Current state} = \text{What to forget} \circ \text{Previous state} + \text{What to write} \circ \text{New state candidate}$$

Protecting the state & selectivity through gates

$$\begin{pmatrix}\text{What}\\\text{to}\\\text{write}\end{pmatrix} = G\_W\left[\begin{pmatrix}\text{Previous}\\\text{state}\end{pmatrix}, \begin{pmatrix}\text{Current}\\\text{input}\end{pmatrix}\right] \qquad \begin{pmatrix}\text{What}\\\text{to}\\\text{forget}\end{pmatrix} = G\_F\left[\begin{pmatrix}\text{Previous}\\\text{state}\end{pmatrix}, \begin{pmatrix}\text{Current}\\\text{input}\end{pmatrix}\right]$$

$$\begin{pmatrix}\text{New}\\\text{state}\\\text{candidate}\end{pmatrix} = \text{FUNC}\left[\begin{pmatrix}\text{What}\\\text{to}\\\text{read}\end{pmatrix} \circ \begin{pmatrix}\text{Previous}\\\text{state}\end{pmatrix}, \begin{pmatrix}\text{Current}\\\text{input}\end{pmatrix}\right]$$

$$\begin{pmatrix}\text{Current}\\\text{state}\end{pmatrix} = \begin{pmatrix}\text{What}\\\text{to}\\\text{forget}\end{pmatrix} \circ \begin{pmatrix}\text{Previous}\\\text{state}\end{pmatrix} + \begin{pmatrix}\text{What}\\\text{to}\\\text{write}\end{pmatrix} \circ \begin{pmatrix}\text{New}\\\text{state}\\\text{candidate}\end{pmatrix}$$

Protecting the state & selectivity through gates

$$\text{What to read} = G\_R\left[\text{Previous state}, \text{Current input}\right]$$

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$$\text{New state candidate} = \text{FUNC}\left[\text{What to read} \circ \text{Previous state}, \text{Current input}\right]$$

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Protecting the state & selectivity through gates

Read gate

(What to read) = G_R [(Previous state) , (Current input)]

Write gate

(What to write) = G_W [(Previous state) , (Current input)]

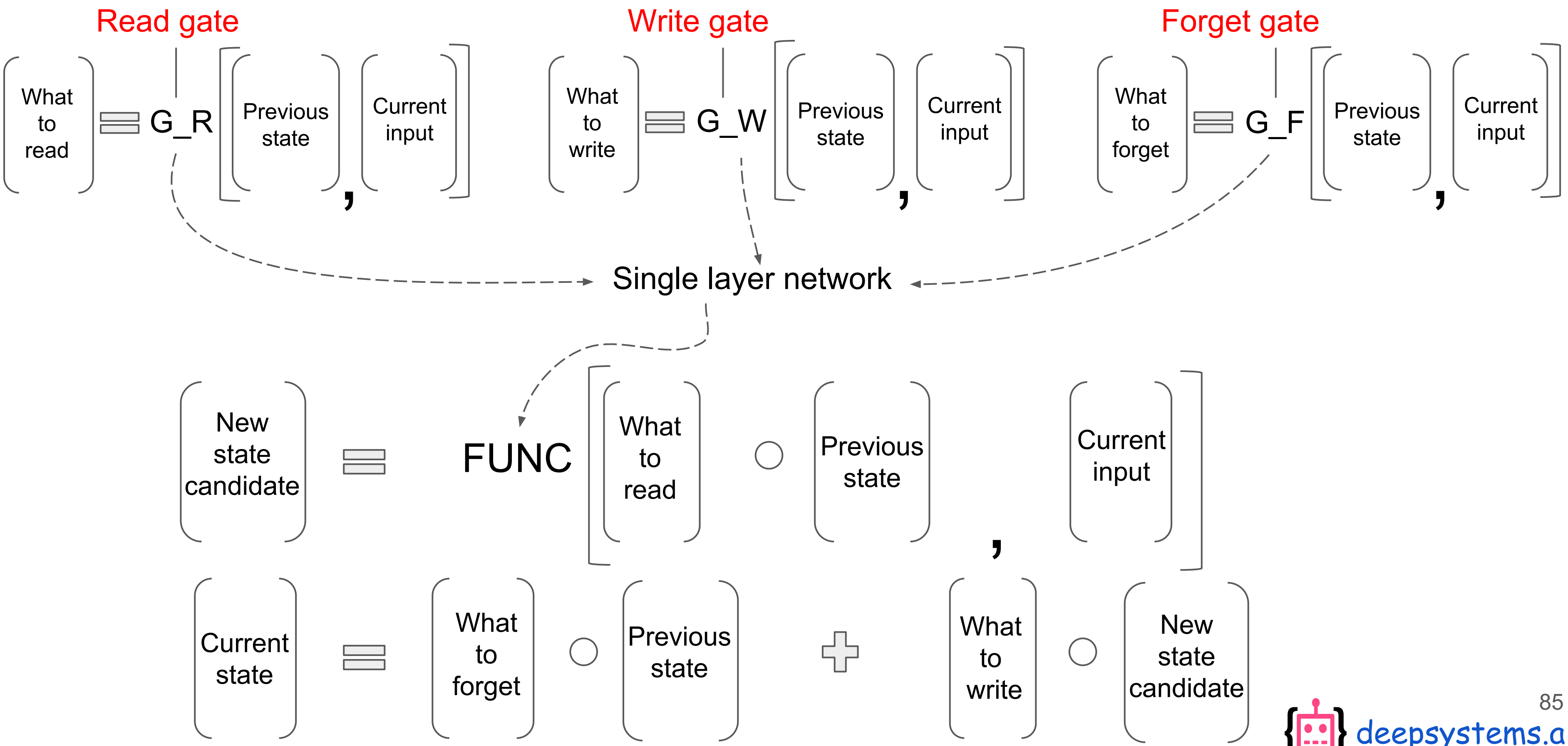
Forget gate

(What to forget) = G_F [(Previous state) , (Current input)]

(New state candidate) = FUNC [(What to read) ○ (Previous state) , (Current input)]

(Current state) = (What to forget) ○ (Previous state) + (What to write) ○ (New state candidate)

Protecting the state & selectivity through gates



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Single layer network

What kind of activation function are used?

(New state candidate) = FUNC [(What to read) ○ (Previous state), (Current input)]

(Current state) = (What to forget) ○ (Previous state) + (What to write) ○ (New state candidate)

Protecting the state & selectivity through gates

Read gate

$$\text{What to read} = G\_R\left[\text{Previous state}, \text{Current input}\right]$$

sigmoid

Write gate

$$\text{What to write} = G\_W\left[\text{Previous state}, \text{Current input}\right]$$

sigmoid

Forget gate

$$\text{What to forget} = G\_F\left[\text{Previous state}, \text{Current input}\right]$$

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Single layer network

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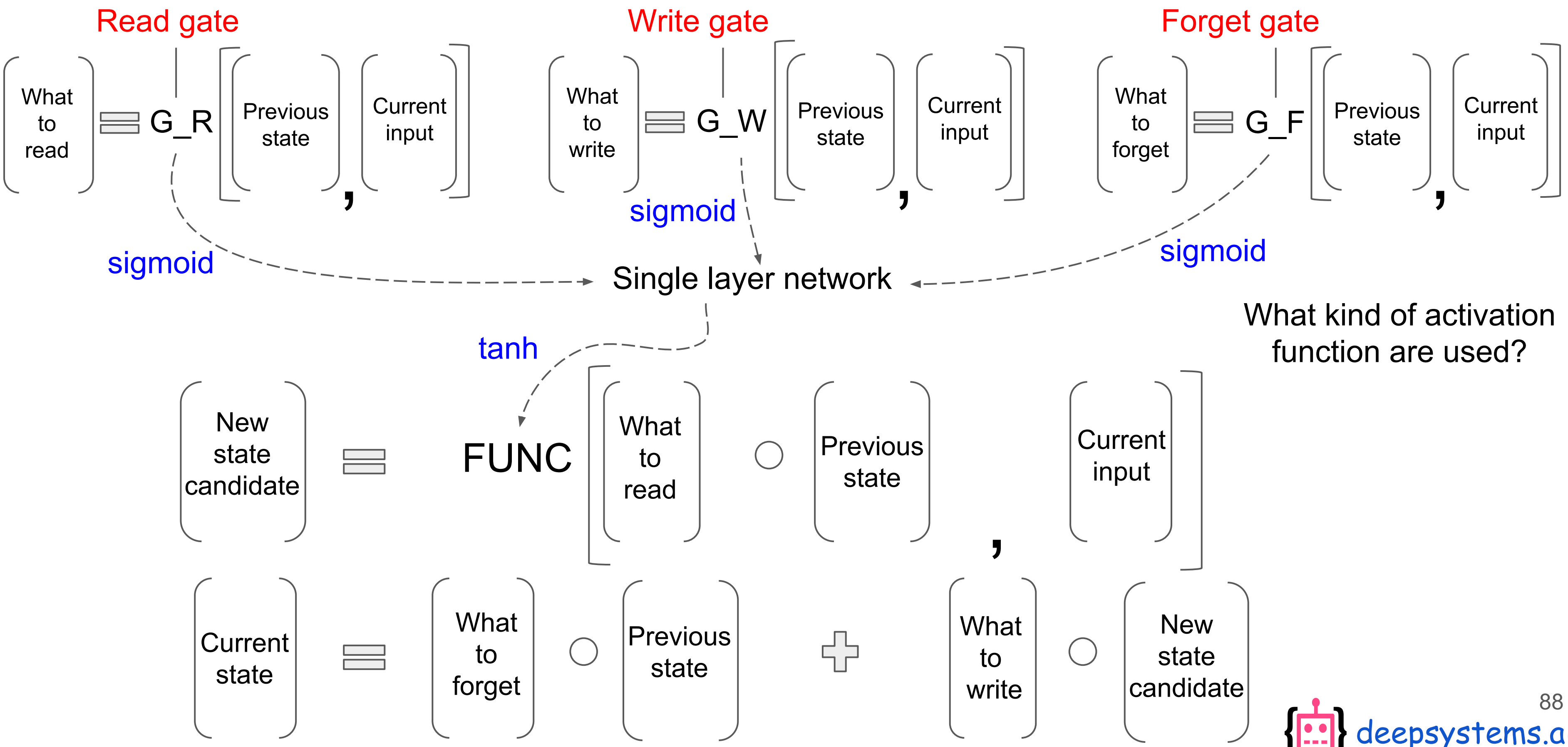

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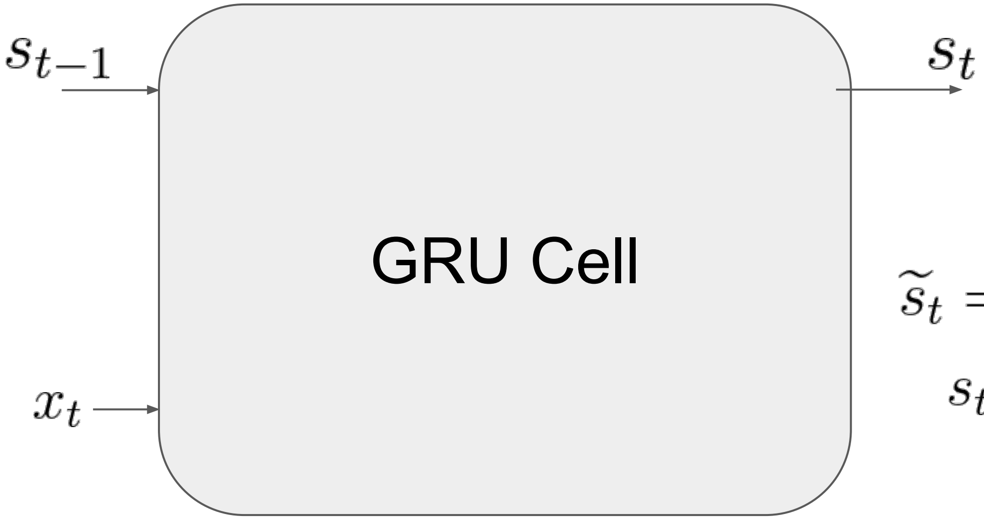
GRU Cell step by step



GRU equations

$$r_t = \sigma(W_r s_{t-1} + U_r x_t + b_r) \quad \text{Read gate}$$

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$$\widetilde{s}_t = \phi(W\ (r_t \circ s_{t-1}) + U x_t + b) \quad \text{State candidate}$$

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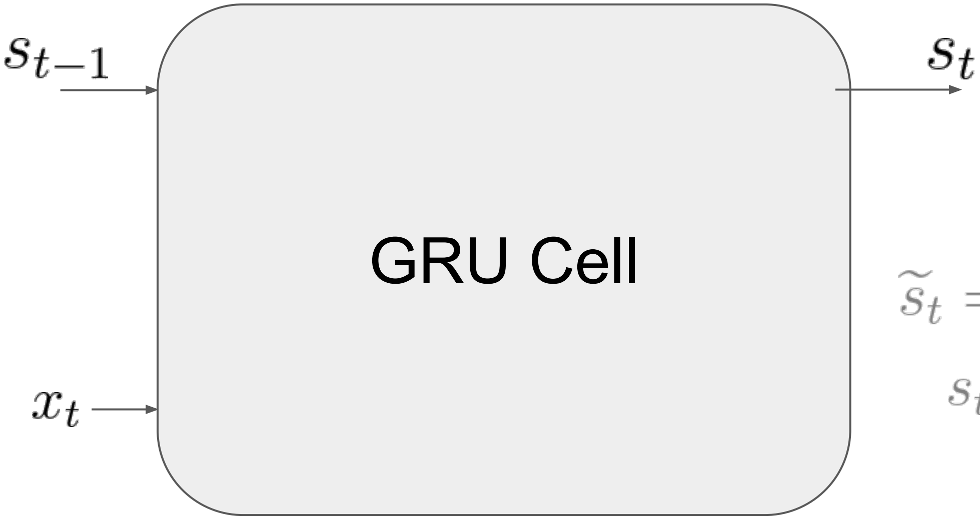

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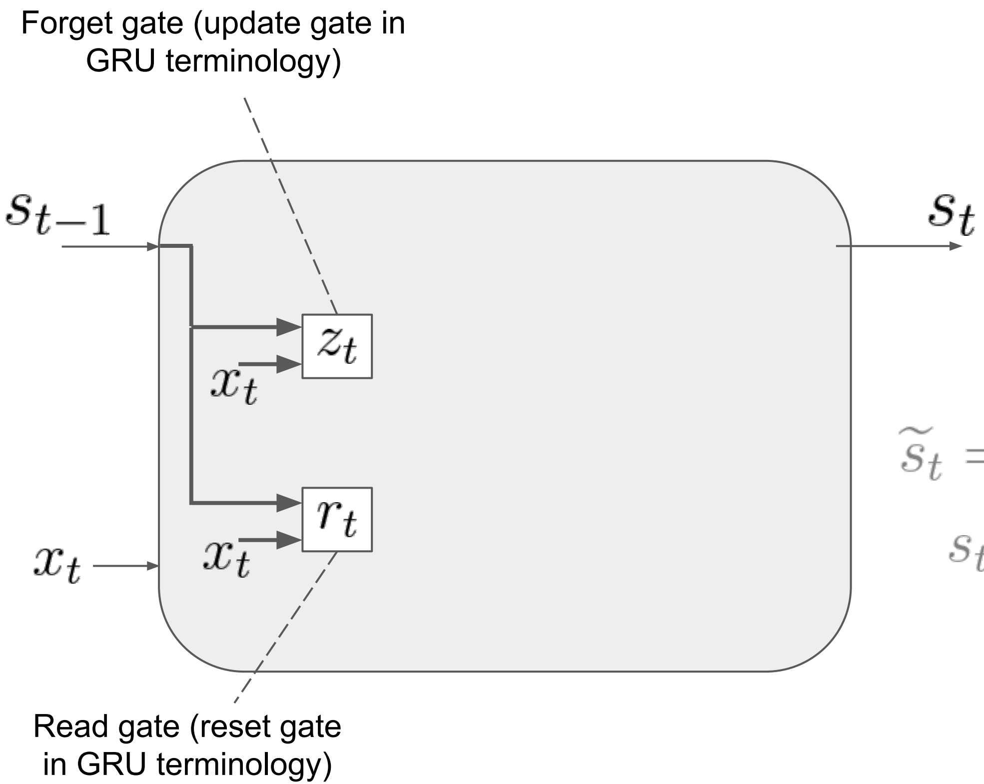

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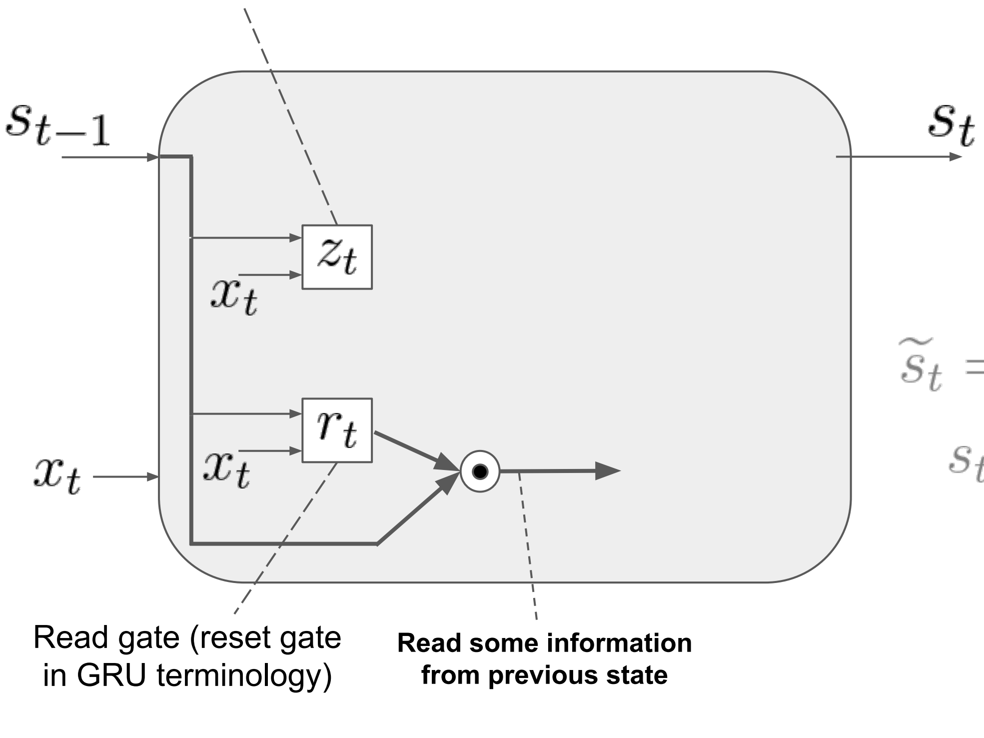

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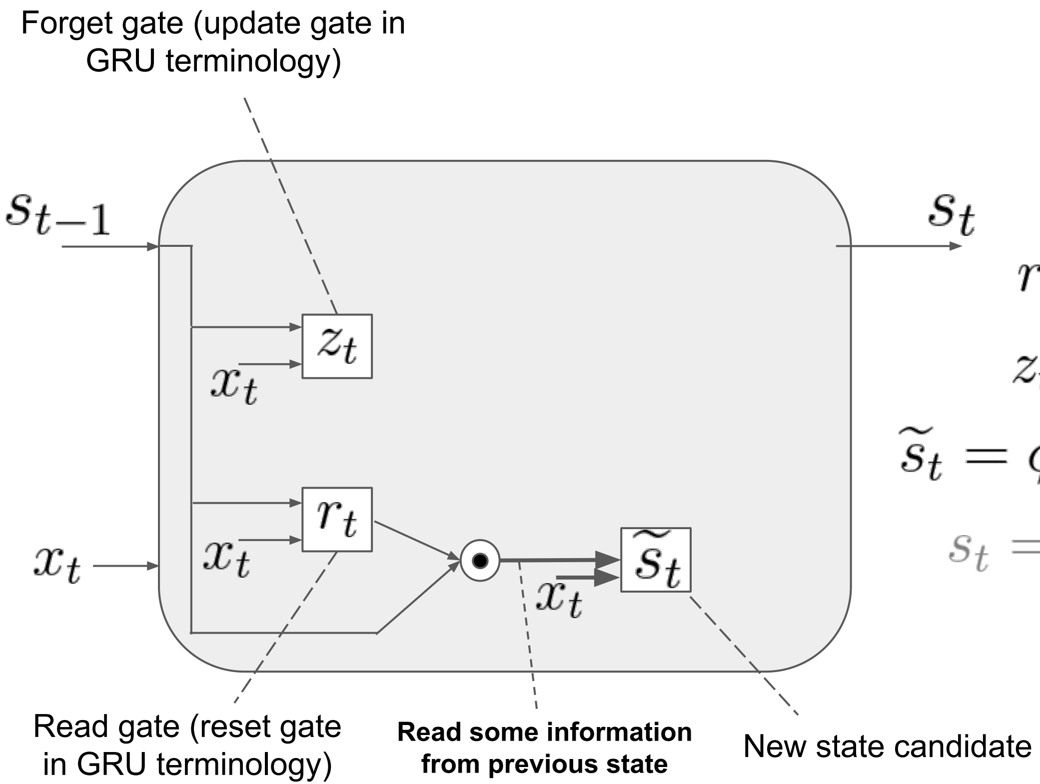

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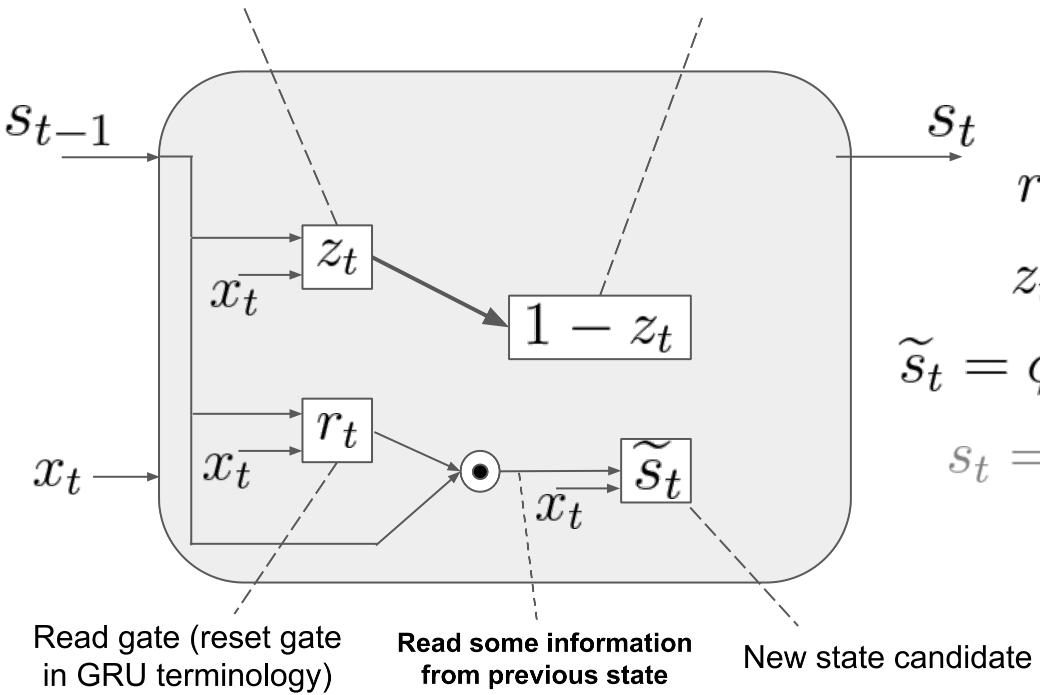

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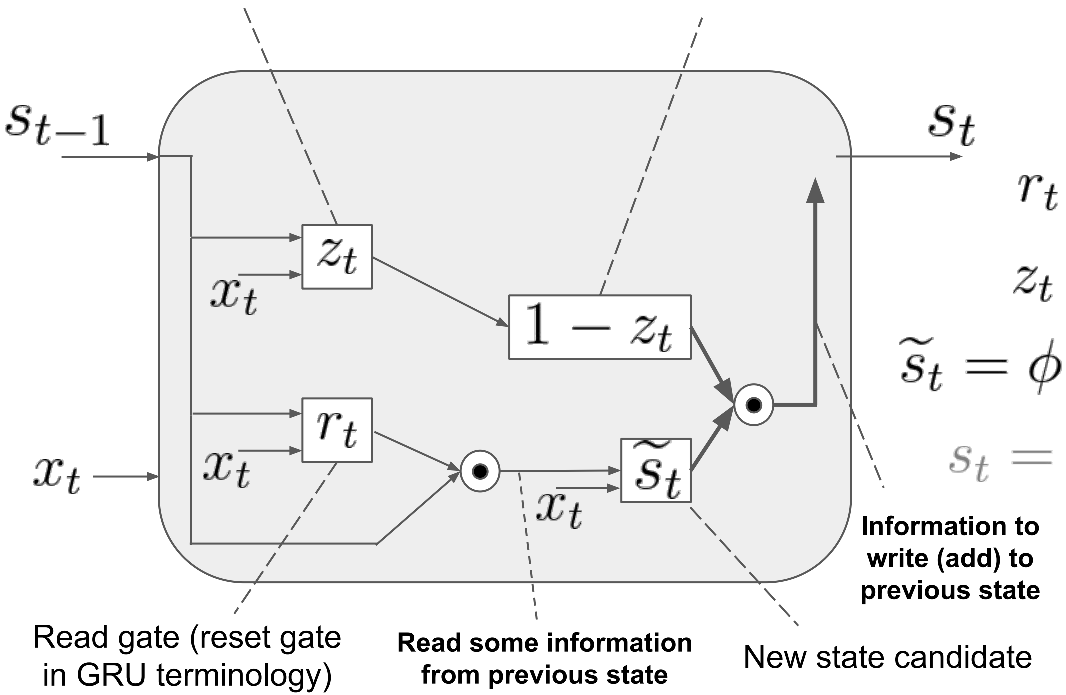

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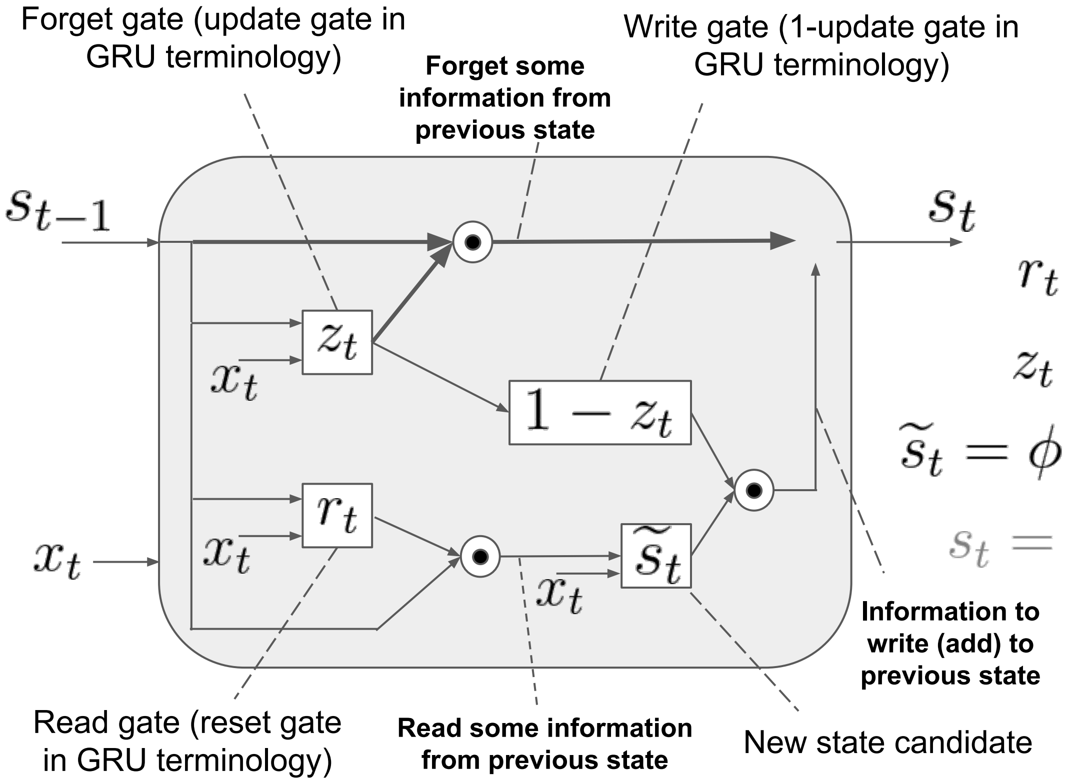

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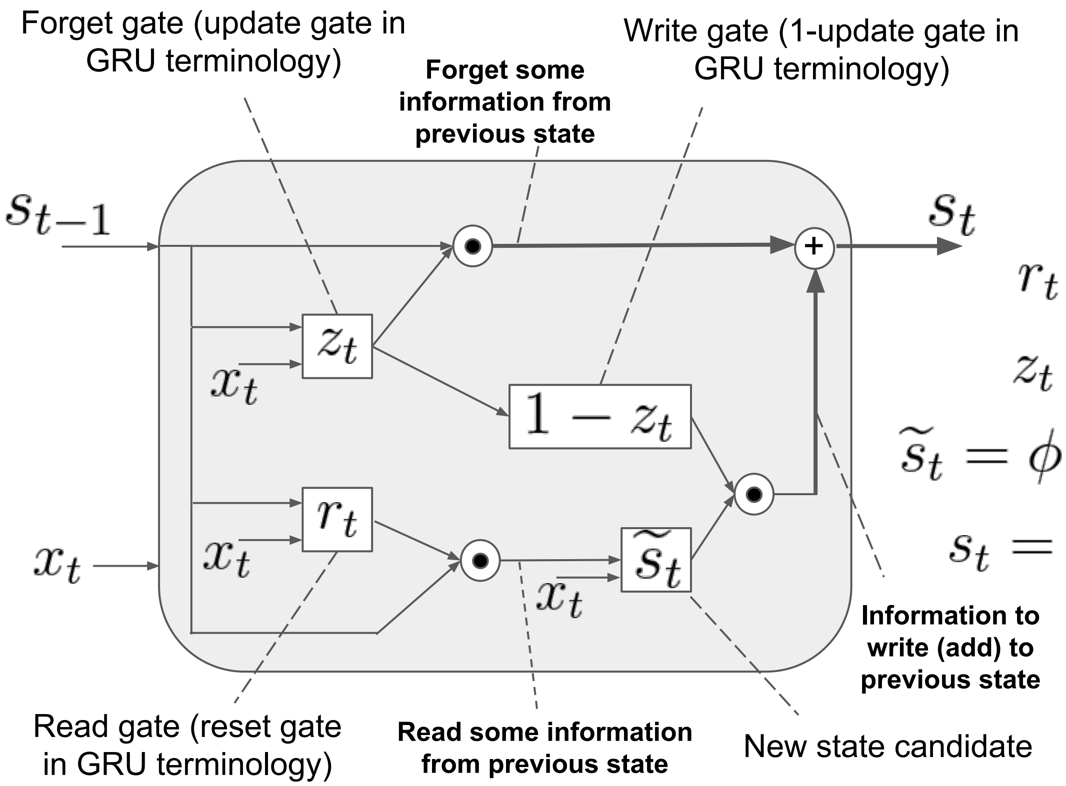

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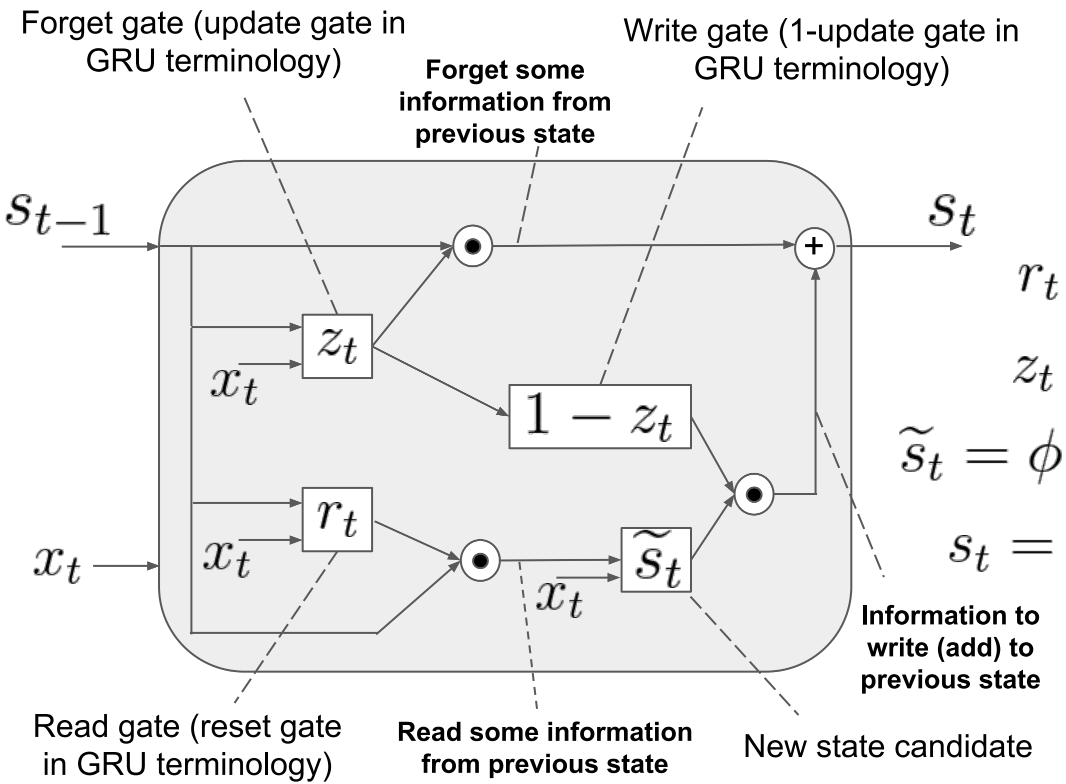

GRU equations	In GRU terminology
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$\widetilde{s}_t = \phi(W\ (r_t \circ s_{t-1}) + U x_t + b)$	State candidate
$s_t = z_t \circ s_{t-1} + (1 - z_t) \circ \widetilde{s}_t$	Current State

Let's take a closer look at the way the gates operate

GRU Cell step by step

GRU equations	In GRU terminology
$r_t = \sigma(W_r s_{t-1} + U_r x_t + b_r)$	Reset gate
$z_t = \sigma(W_z s_{t-1} + U_z x_t + b_z)$	Update gate
$\widetilde{s}_t = \phi(W\ (r_t \circ s_{t-1}) + U x_t + b)$	State candidate
$s_t = z_t \circ s_{t-1} + (1 - z_t) \circ \widetilde{s}_t$	Current State

$$\begin{pmatrix} s_{t-1}^1 \\ s_{t-1}^2 \\ s_{t-1}^3 \end{pmatrix}$$

GRU Cell step by step

GRU equations	In GRU terminology
$r_t = \sigma(W_r s_{t-1} + U_r x_t + b_r)$	Reset gate
$z_t = \sigma(W_z s_{t-1} + U_z x_t + b_z)$	Update gate
$\widetilde{s}_t = \phi(W\ (r_t \circ s_{t-1}) + U x_t + b)$	State candidate
$s_t = z_t \circ s_{t-1} + (1 - z_t) \circ \widetilde{s}_t$	Current State

$$\begin{pmatrix} s^1_{t-1} \\ s^2_{t-1} \\ s^3_{t-1} \end{pmatrix} \qquad \begin{pmatrix} \widetilde{s}^1_{t-1} \\ \widetilde{s}^2_{t-1} \\ \widetilde{s}^3_{t-1} \end{pmatrix}$$

GRU Cell step by step

GRU equations	In GRU terminology
$r_t = \sigma(W_r s_{t-1} + U_r x_t + b_r)$	Reset gate
$z_t = \sigma(W_z s_{t-1} + U_z x_t + b_z)$	Update gate
$\widetilde{s}_t = \phi(W\ (r_t \circ s_{t-1}) + U x_t + b)$	State candidate
$s_t = z_t \circ s_{t-1} + (1 - z_t) \circ \widetilde{s}_t$	Current State

$$\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix} \circ \begin{pmatrix} s_{t-1}^1 \\ s_{t-1}^2 \\ s_{t-1}^3 \end{pmatrix} \qquad \begin{pmatrix} \widetilde{s}_{t-1}^1 \\ \widetilde{s}_{t-1}^2 \\ \widetilde{s}_{t-1}^3 \end{pmatrix}$$

Update gate = vector of zeros

GRU Cell step by step

GRU equations | In GRU terminology

$$r_t = \sigma(W_r s_{t-1} + U_r x_t + b_r)$$ Reset gate

$$z_t = \sigma(W_z s_{t-1} + U_z x_t + b_z)$$ Update gate

$$\widetilde{s}_t = \phi(W\ (r_t \circ s_{t-1}) + U x_t + b)$$ State candidate

$$s_t = z_t \circ s_{t-1} + (1 - z_t) \circ \widetilde{s}_t$$ Current State

$$\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix} \circ \begin{pmatrix} s_{t-1}^1 \\ s_{t-1}^2 \\ s_{t-1}^3 \end{pmatrix} + \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} \circ \begin{pmatrix} \widetilde{s}_{t-1}^1 \\ \widetilde{s}_{t-1}^2 \\ \widetilde{s}_{t-1}^3 \end{pmatrix}$$

Update gate = vector of zeros

GRU Cell step by step

GRU equations	In GRU terminology
$r_t = \sigma(W_r s_{t-1} + U_r x_t + b_r)$	Reset gate
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$s_t = z_t \circ s_{t-1} + (1 - z_t) \circ \widetilde{s}_t$	Current State

$$\begin{pmatrix} \widetilde{s}^1_{t-1} \\ \widetilde{s}^2_{t-1} \\ \widetilde{s}^3_{t-1} \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix} \circ \begin{pmatrix} s^1_{t-1} \\ s^2_{t-1} \\ s^3_{t-1} \end{pmatrix} + \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} \circ \begin{pmatrix} \widetilde{s}^1_{t-1} \\ \widetilde{s}^2_{t-1} \\ \widetilde{s}^3_{t-1} \end{pmatrix}$$

Update gate = vector of zeros

GRU Cell step by step

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$$\begin{pmatrix} \widetilde{s}^1_{t-1} \\ \widetilde{s}^2_{t-1} \\ \widetilde{s}^3_{t-1} \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix} \circ \begin{pmatrix} s^1_{t-1} \\ s^2_{t-1} \\ s^3_{t-1} \end{pmatrix} + \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} \circ \begin{pmatrix} \widetilde{s}^1_{t-1} \\ \widetilde{s}^2_{t-1} \\ \widetilde{s}^3_{t-1} \end{pmatrix}$$

Update gate = vector of zeros ⇨ **Replace all memory content with the State Candidate**

GRU Cell step by step

GRU equations	In GRU terminology
$r_t = \sigma(W_r s_{t-1} + U_r x_t + b_r)$	Reset gate
$z_t = \sigma(W_z s_{t-1} + U_z x_t + b_z)$	Update gate
$\widetilde{s}_t = \phi(W\ (r_t \circ s_{t-1}) + U x_t + b)$	State candidate
$s_t = z_t \circ s_{t-1} + (1 - z_t) \circ \widetilde{s}_t$	Current State

$$\begin{pmatrix}1\\1\\1\end{pmatrix} \circ \begin{pmatrix}s_{t-1}^1\\s_{t-1}^2\\s_{t-1}^3\end{pmatrix} \qquad \circ \begin{pmatrix}\widetilde{s}_{t-1}^1\\\widetilde{s}_{t-1}^2\\\widetilde{s}_{t-1}^3\end{pmatrix}$$

Update gate = vector of ones

GRU Cell step by step

GRU equations | In GRU terminology

$$r_t = \sigma(W_r s_{t-1} + U_r x_t + b_r)$$ Reset gate

$$z_t = \sigma(W_z s_{t-1} + U_z x_t + b_z)$$ Update gate

$$\widetilde{s}_t = \phi(W\ (r_t \circ s_{t-1}) + U x_t + b)$$ State candidate

$$s_t = z_t \circ s_{t-1} + (1 - z_t) \circ \widetilde{s}_t$$ Current State

$$\begin{pmatrix}1\\1\\1\end{pmatrix} \circ \begin{pmatrix}s_{t-1}^1\\s_{t-1}^2\\s_{t-1}^3\end{pmatrix} + \begin{pmatrix}0\\0\\0\end{pmatrix} \circ \begin{pmatrix}\widetilde{s}_{t-1}^1\\\widetilde{s}_{t-1}^2\\\widetilde{s}_{t-1}^3\end{pmatrix}$$

Update gate = vector of ones

GRU Cell step by step

GRU equations	In GRU terminology
$r_t = \sigma(W_r s_{t-1} + U_r x_t + b_r)$	Reset gate
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$\widetilde{s}_t = \phi(W\ (r_t \circ s_{t-1}) + U x_t + b)$	State candidate
$s_t = z_t \circ s_{t-1} + (1 - z_t) \circ \widetilde{s}_t$	Current State

$$\begin{pmatrix} s_{t-1}^1 \\ s_{t-1}^2 \\ s_{t-1}^3 \end{pmatrix} = \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} \circ \begin{pmatrix} s_{t-1}^1 \\ s_{t-1}^2 \\ s_{t-1}^3 \end{pmatrix} + \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix} \circ \begin{pmatrix} \widetilde{s}_{t-1}^1 \\ \widetilde{s}_{t-1}^2 \\ \widetilde{s}_{t-1}^3 \end{pmatrix}$$

Update gate = vector of ones

GRU Cell step by step

GRU equations | In GRU terminology

$$r_t = \sigma(W_r s_{t-1} + U_r x_t + b_r)$$ Reset gate

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$$\begin{pmatrix} s_{t-1}^1 \\ s_{t-1}^2 \\ s_{t-1}^3 \end{pmatrix} = \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} \circ \begin{pmatrix} s_{t-1}^1 \\ s_{t-1}^2 \\ s_{t-1}^3 \end{pmatrix} + \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix} \circ \begin{pmatrix} \widetilde{s}_{t-1}^1 \\ \widetilde{s}_{t-1}^2 \\ \widetilde{s}_{t-1}^3 \end{pmatrix}$$

Update gate = vector of ones ⇒

Completely ignore current input and state candidate

The current state equals the previous state

Talk outline

1. RNN: the cell & simple examples
2. Key aspects (or ways to state of the art)
3. Vanilla RNN
4. Problems with Vanilla RNN and motivation for the more powerful cells
5. GRU: step by step
6. LSTM: step by step
7. LSTM with peephole connections
8. Conclusions

Protecting the state & selectivity through gates

$$\left(\text{What to read}\right) = \underbrace{G\_R}_{\text{Read gate}}\left[\left(\text{Previous state}\right), \left(\text{Current input}\right)\right]$$

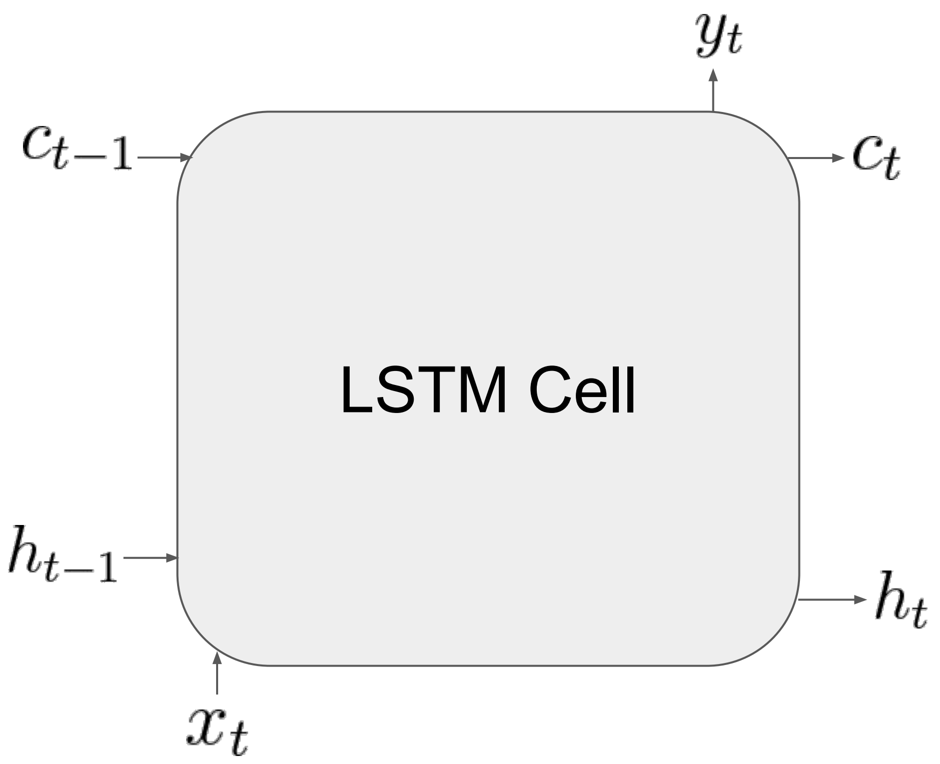
$$\left(\text{What to write}\right) = \underbrace{G\_W}_{\text{Write gate}}\left[\left(\text{Previous state}\right), \left(\text{Current input}\right)\right]$$

$$\left(\text{What to forget}\right) = \underbrace{G\_F}_{\text{Forget gate}}\left[\left(\text{Previous state}\right), \left(\text{Current input}\right)\right]$$

$$\left(\text{New state candidate}\right) = \overbrace{\text{FUNC}}^{\text{State Candidate}}\left[\left(\text{What to read}\right) \circ \left(\text{Previous state}\right), \left(\text{Current input}\right)\right]$$

$$\left(\text{Current state}\right) = \left(\text{What to forget}\right) \circ \left(\text{Previous state}\right) + \left(\text{What to write}\right) \circ \left(\text{New state candidate}\right)$$

LSTM Cell

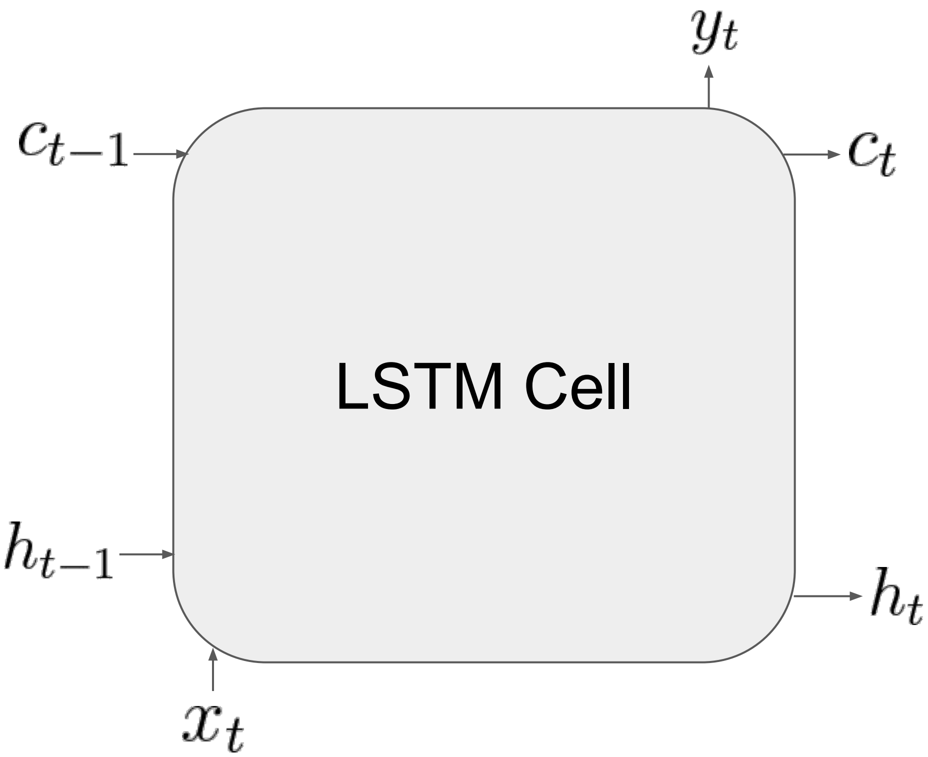


LSTM Cell

The state is a pair of vectors:

c_t — Memory Cell

h_t — Shadow State (gated version of memory cell)



LSTM Cell

The state is a pair of vectors:

c_t — Memory Cell

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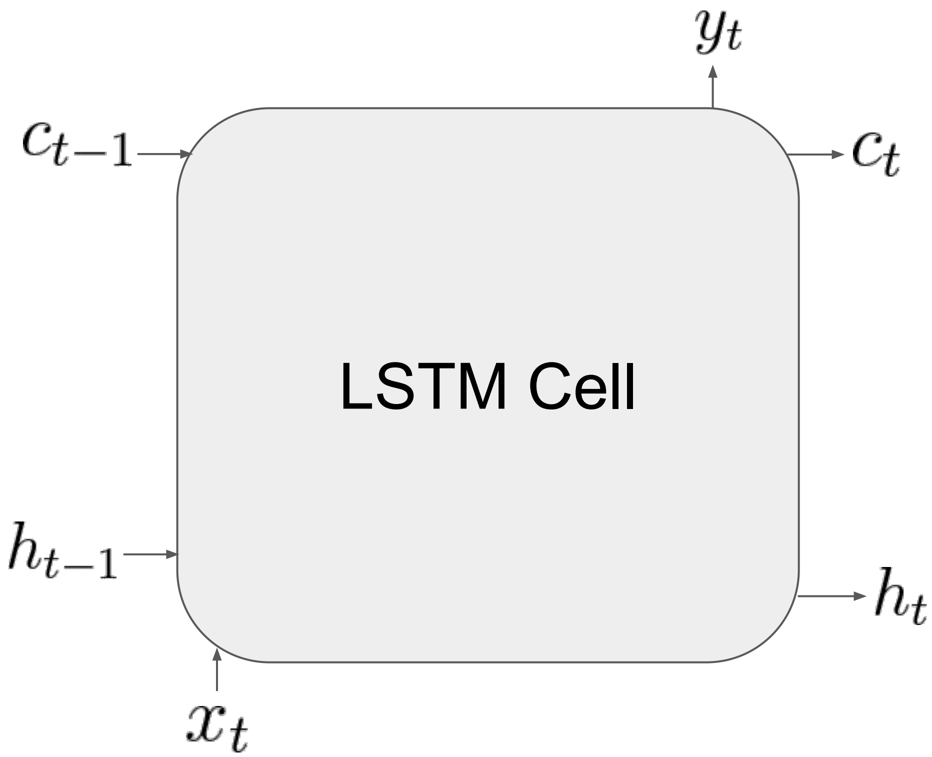
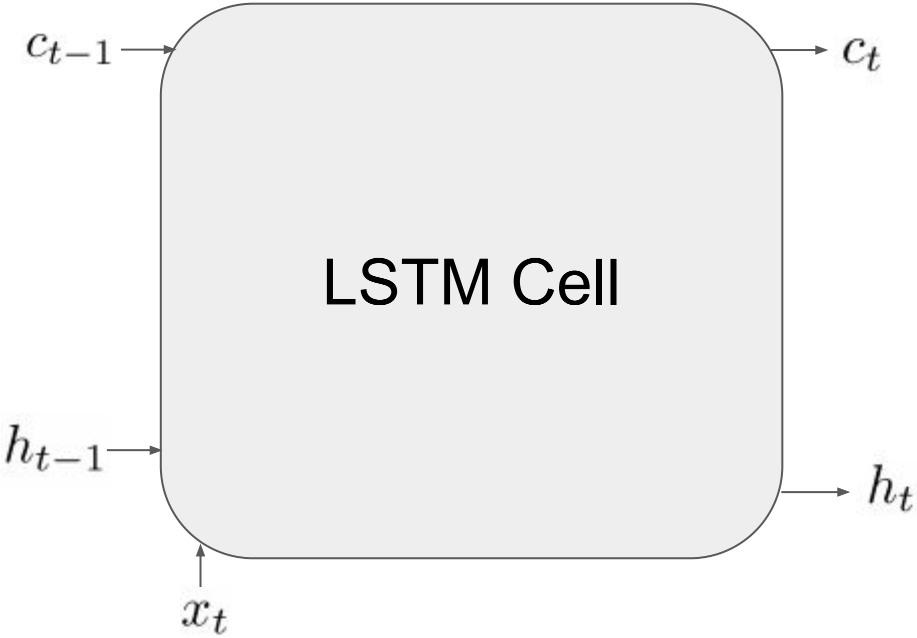
The output is a part of the state:

$y_t = h_t$ — Cell output



LSTM Cell



LSTM equations

$$i_t = \sigma(W_i h_{t-1} + U_i x_t + b_i)$$ Input gate

$$f_t = \sigma(W_f h_{t-1} + U_f x_t + b_f)$$ Forget gate

$$o_t = \sigma(W_o h_{t-1} + U_o x_t + b_o)$$ Output gate

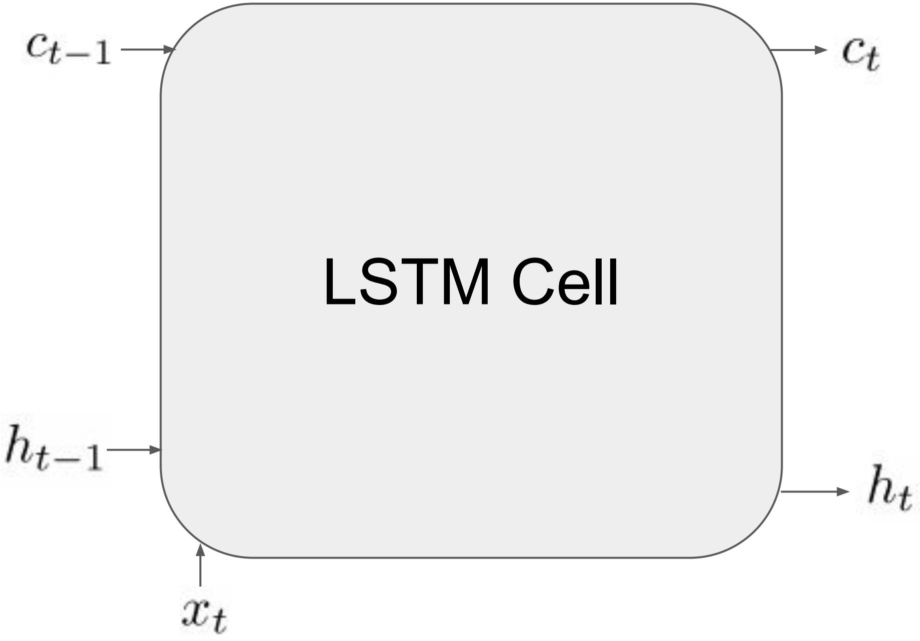
$$\widetilde{c}_t = tanh(W h_{t-1} + U x_t + b)$$ Memory cell candidate

$$c_t = f_t \circ c_{t-1} + i_t \circ \widetilde{c}_t$$ Memory cell

$$h_t = o_t \circ tanh(c_t)$$ Shadow state

$$y_t = h_t$$ Cell Output

LSTM Cell



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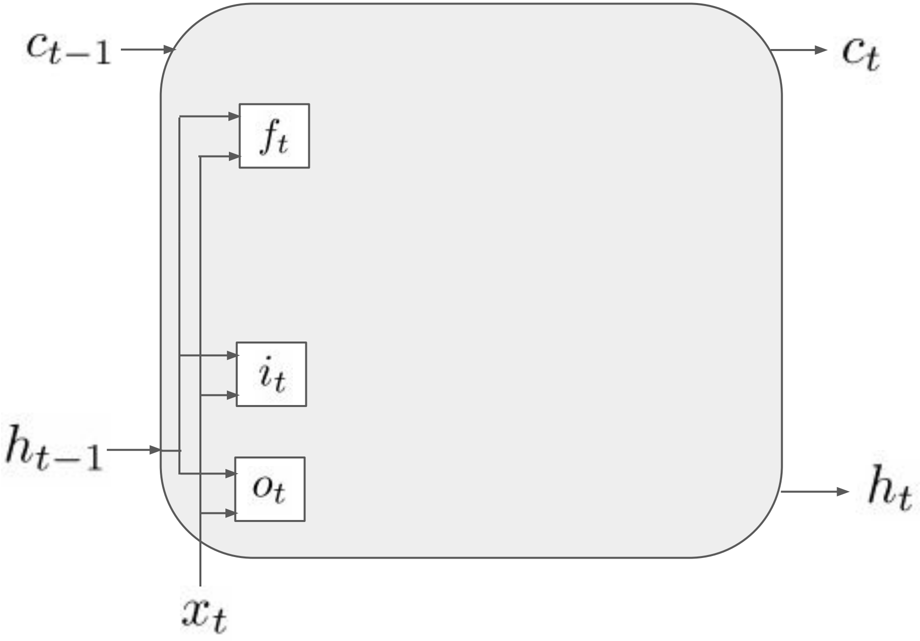
LSTM Cell



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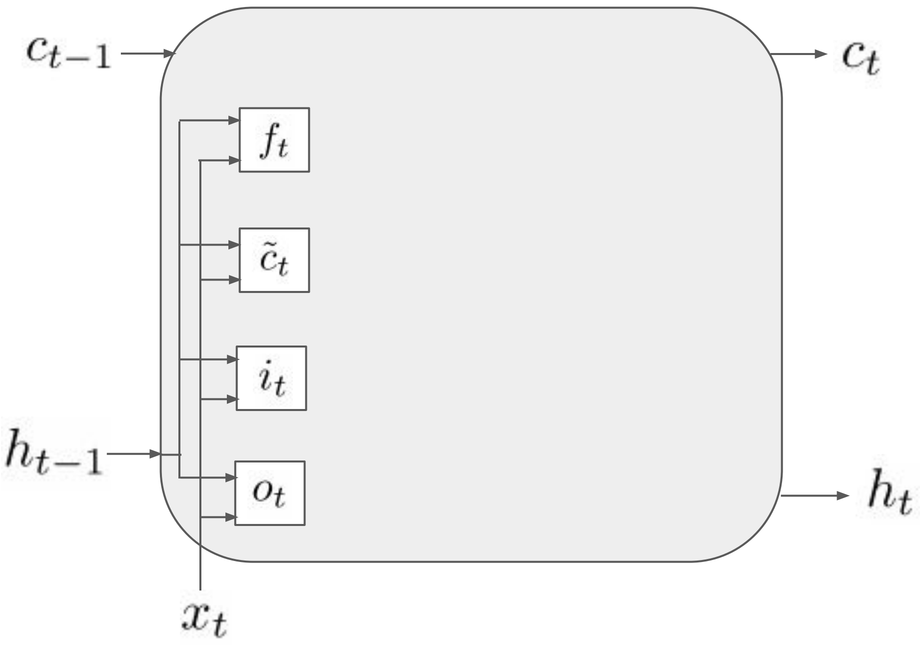
LSTM Cell



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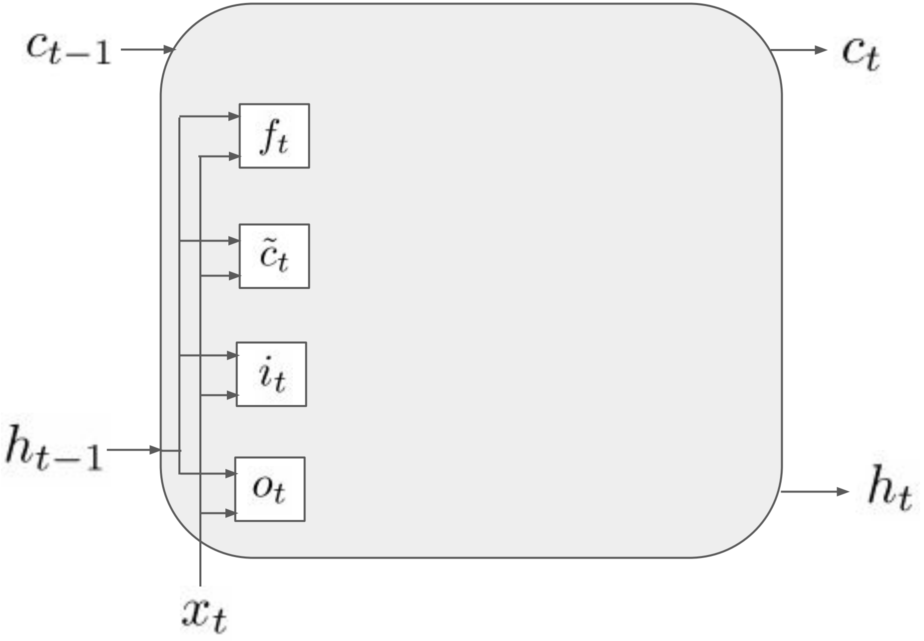
LSTM Cell

If h_{t-1} is a gated version of a memory content, where is a potential problem?



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LSTM Cell

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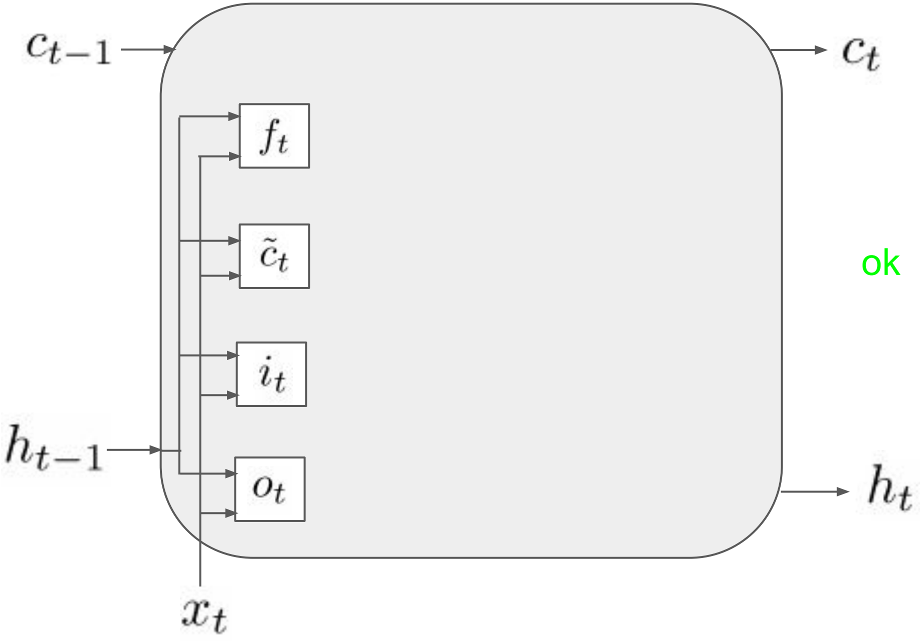

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LSTM Cell

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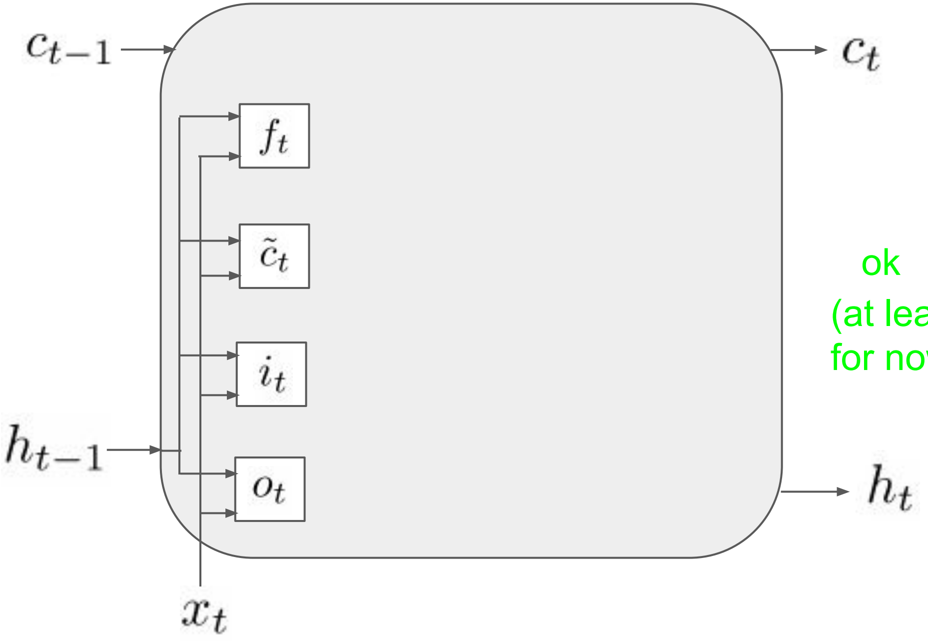

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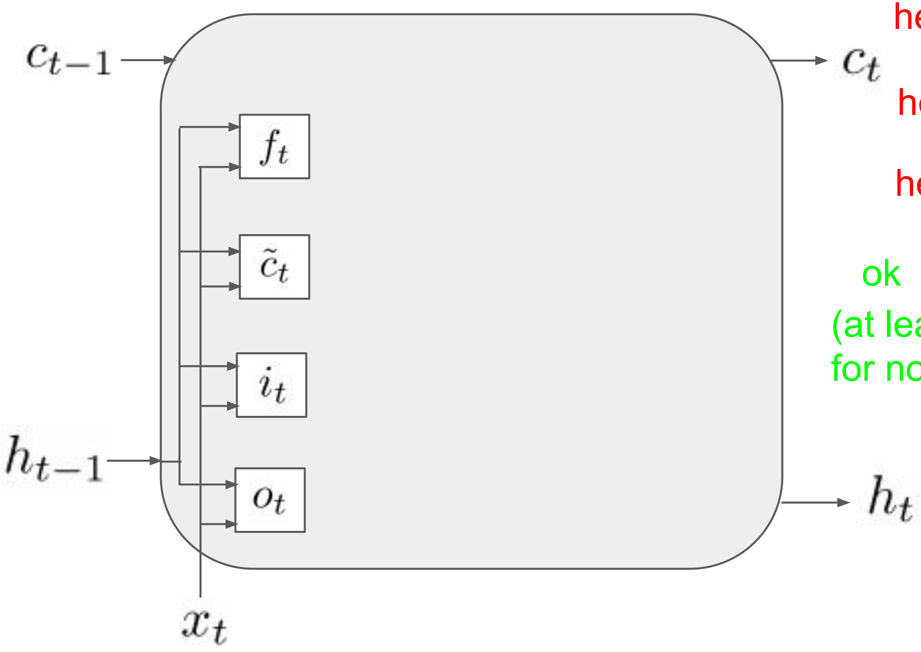
LSTM Cell

If h_{t-1} is a gated version of a memory content, where is a potential problem?



LSTM equations

here $i_t = \sigma(W_i h_{t-1} + U_i x_t + b_i)$ Input gate

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$y_t = h_t$ Cell Output

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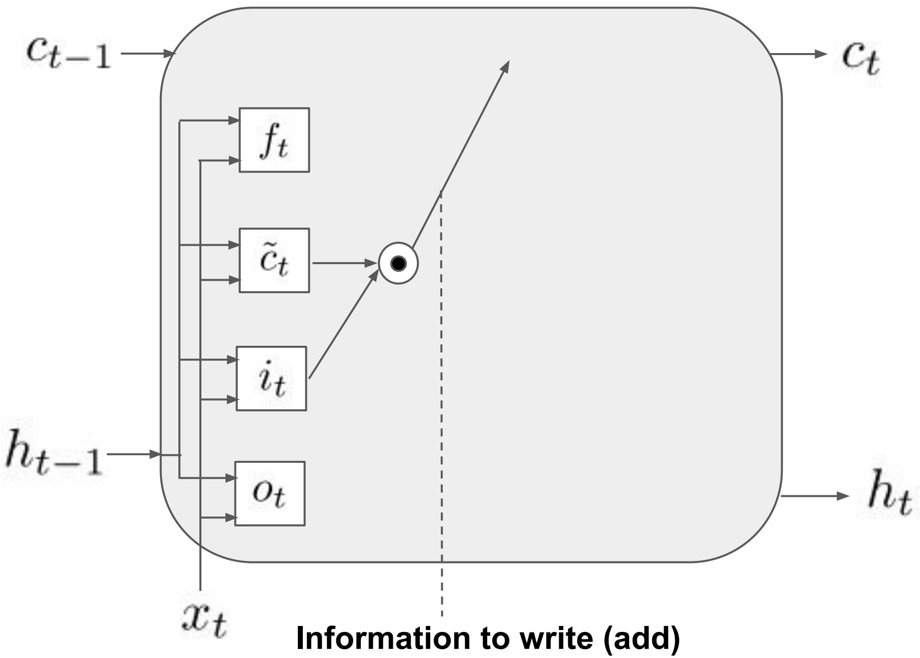
LSTM Cell



Information to write (add) to previous state

LSTM equations

$$i_t = \sigma(W_i h_{t-1} + U_i x_t + b_i)$$ Input gate

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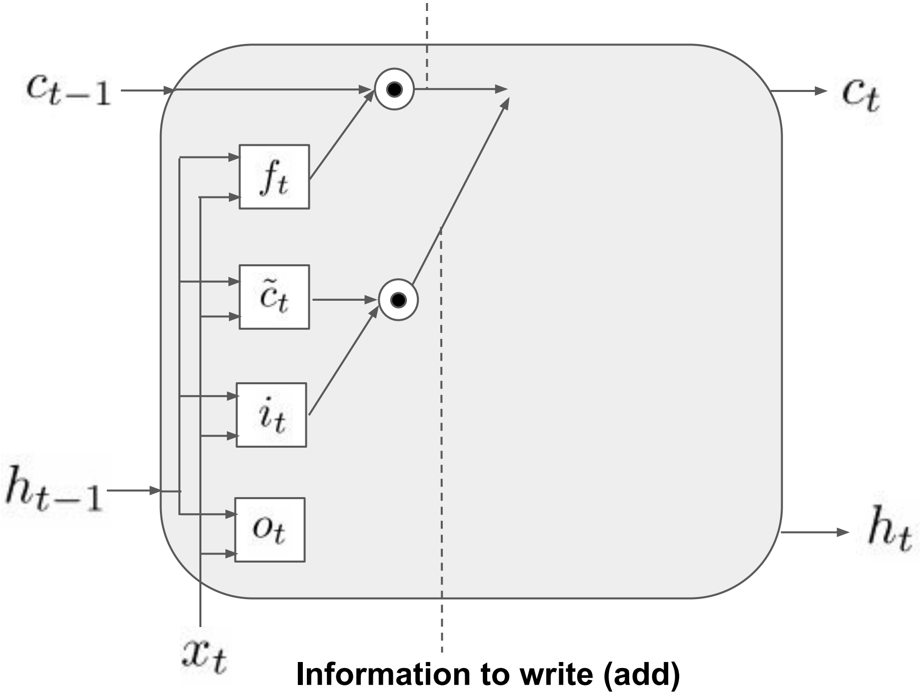
LSTM Cell



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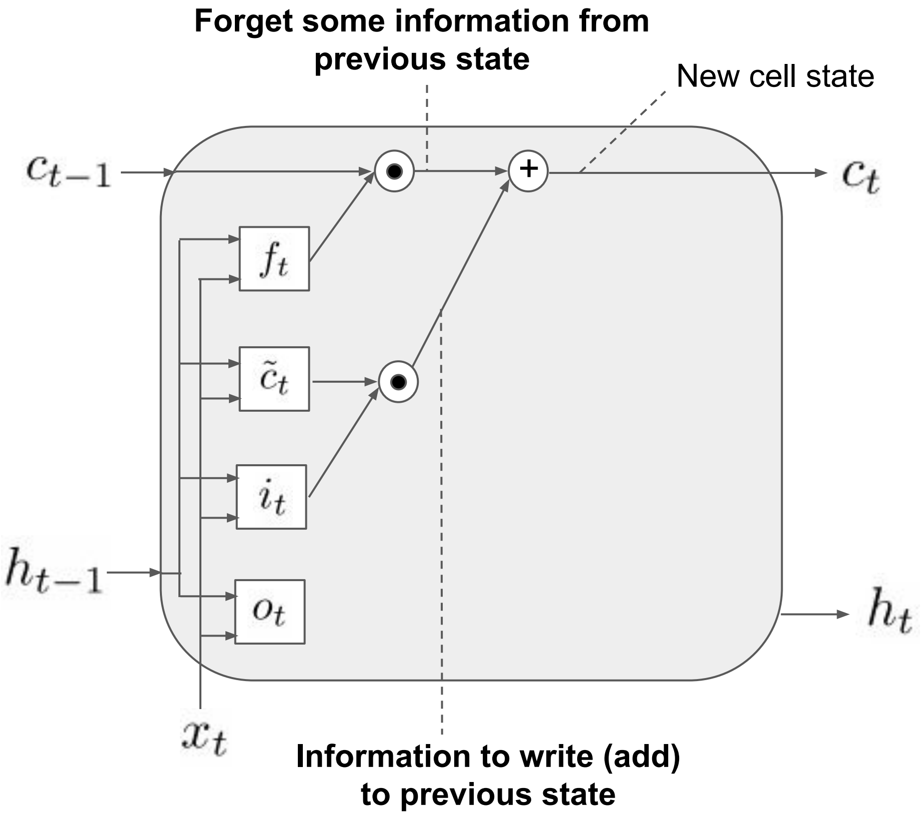
LSTM Cell



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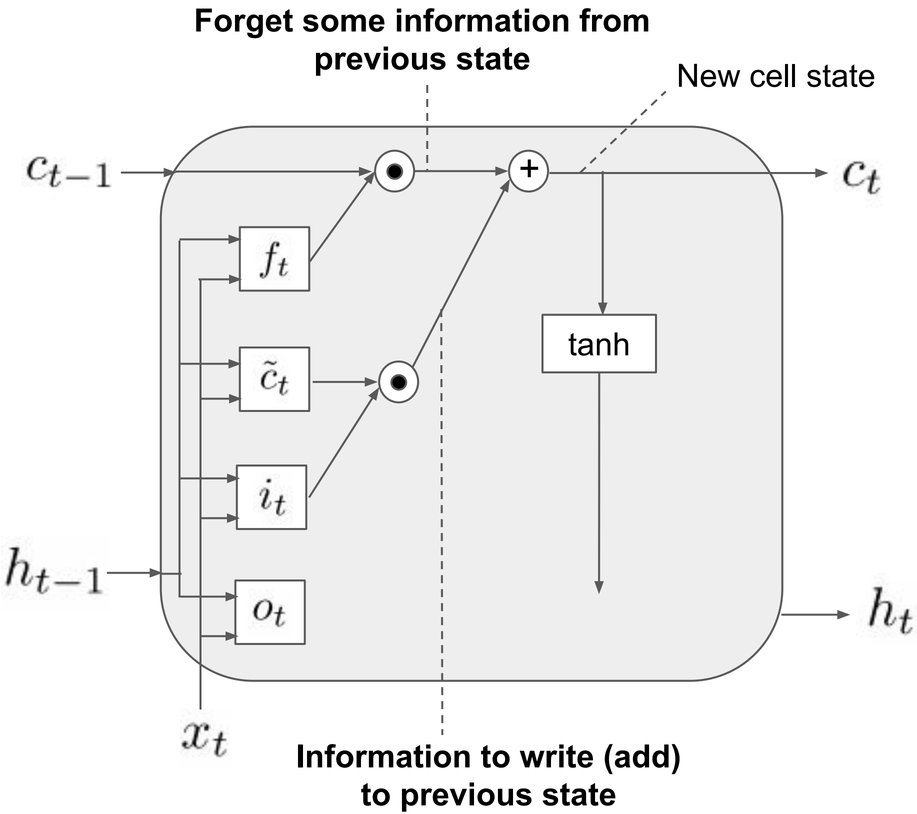
LSTM Cell



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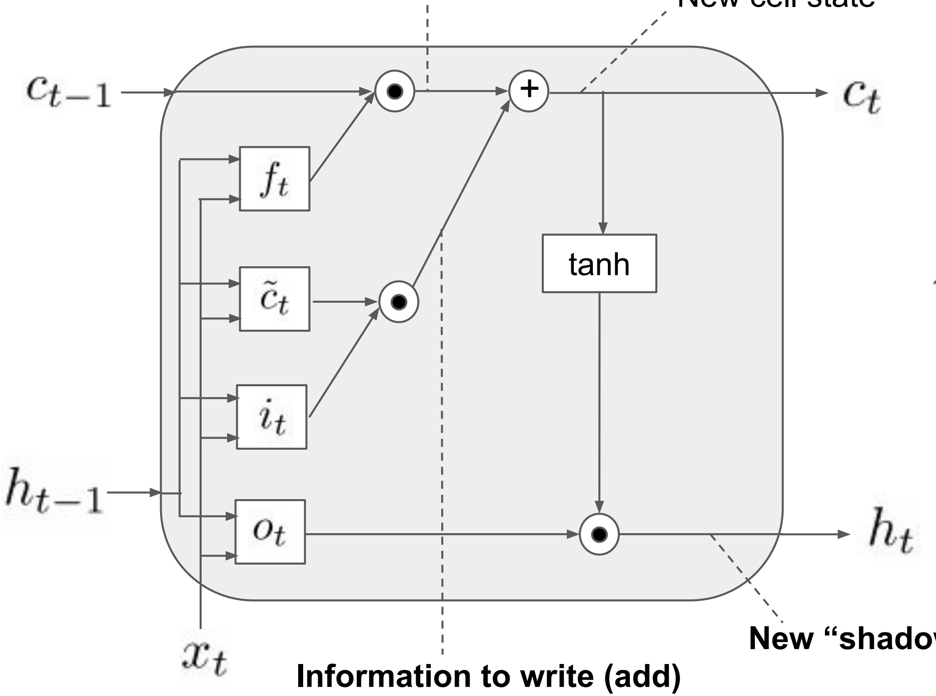
LSTM Cell



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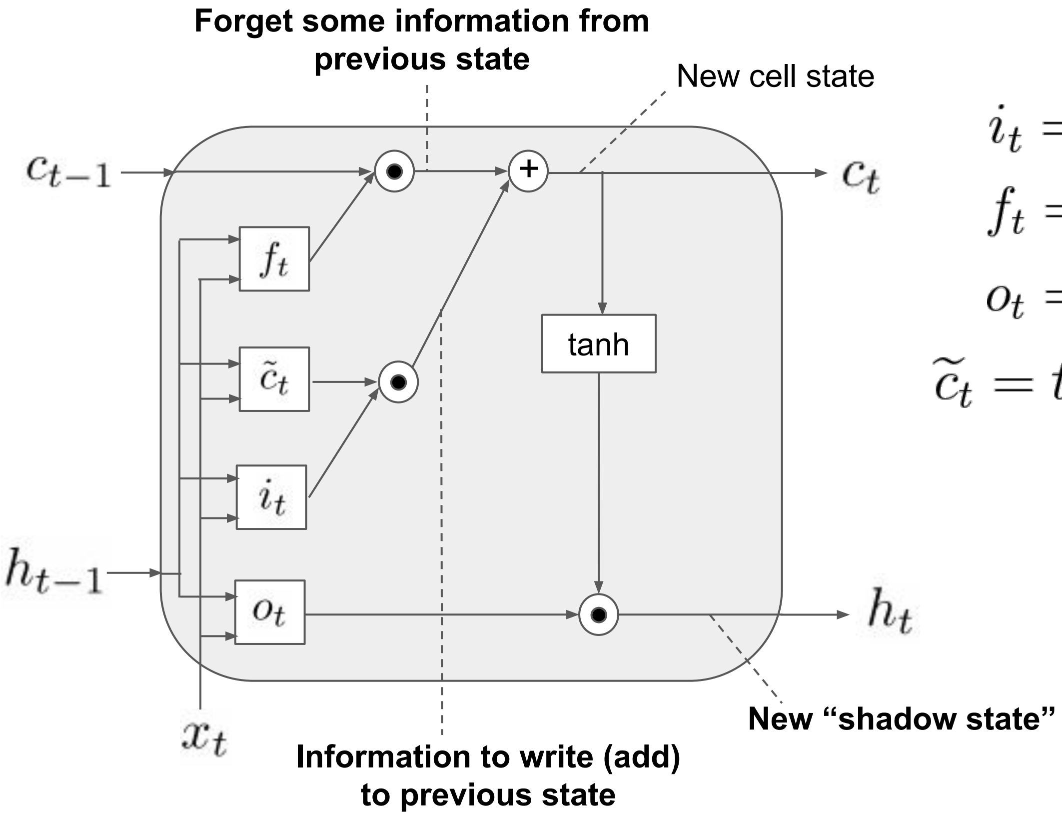
LSTM Cell



LSTM equations

$$i_t = \sigma(W_i h_{t-1} + U_i x_t + b_i)$$ Input gate

$$f_t = \sigma(W_f h_{t-1} + U_f x_t + b_f)$$ Forget gate

$$o_t = \sigma(W_o h_{t-1} + U_o x_t + b_o)$$ Output gate

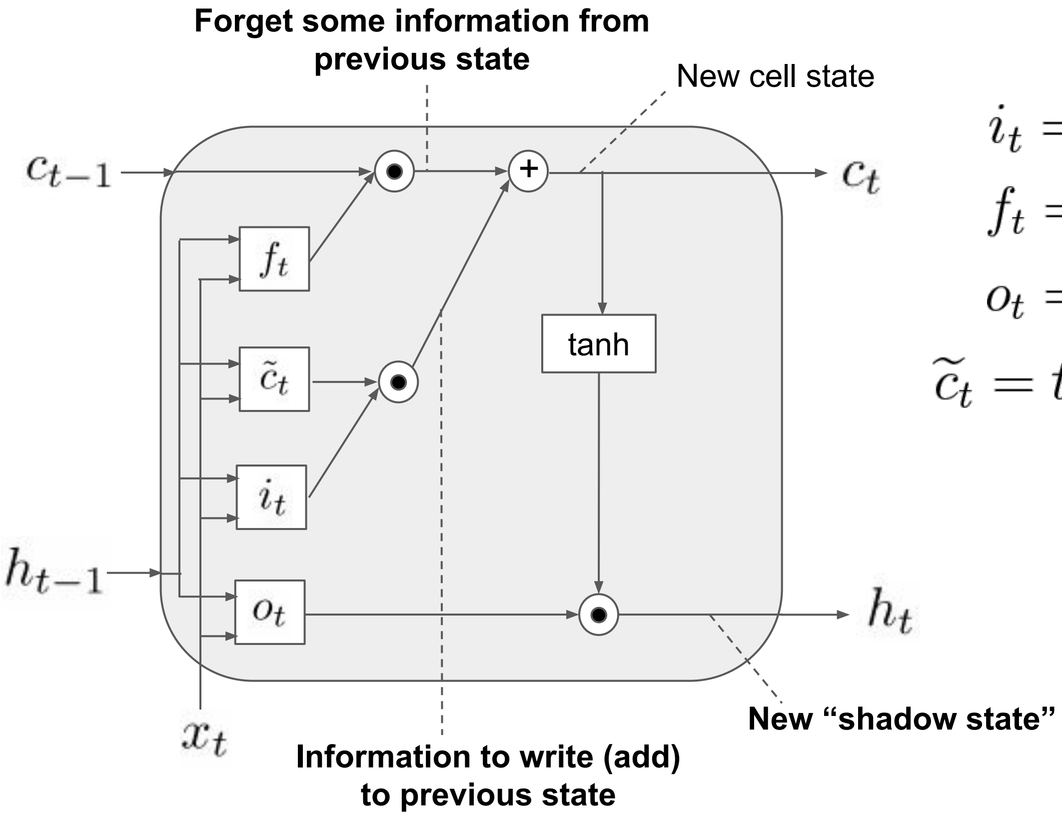
$$\widetilde{c}_t = tanh(W h_{t-1} + U x_t + b)$$ Memory cell candidate

$$c_t = f_t \circ c_{t-1} + i_t \circ \widetilde{c}_t$$ Memory cell

$$h_t = o_t \circ tanh(c_t)$$ Shadow state

$$y_t = h_t$$ Cell Output

LSTM Cell



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Where is Read/Write gates?

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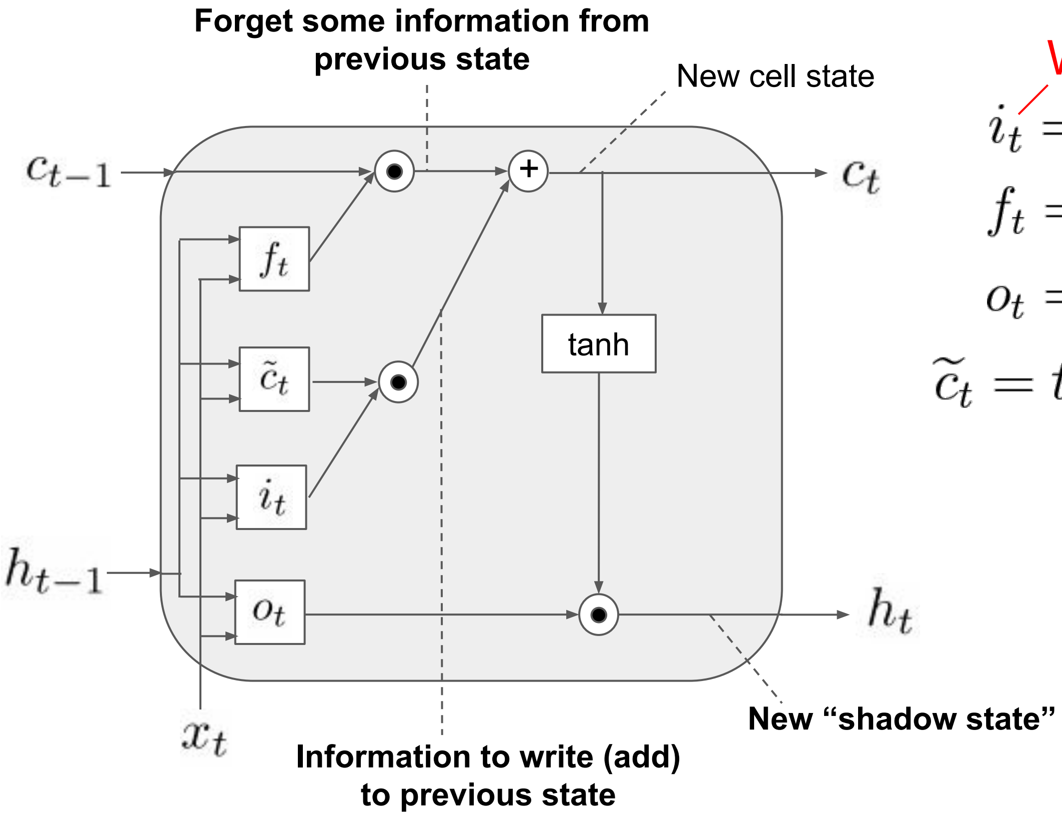
LSTM Cell



LSTM equations

Write gate

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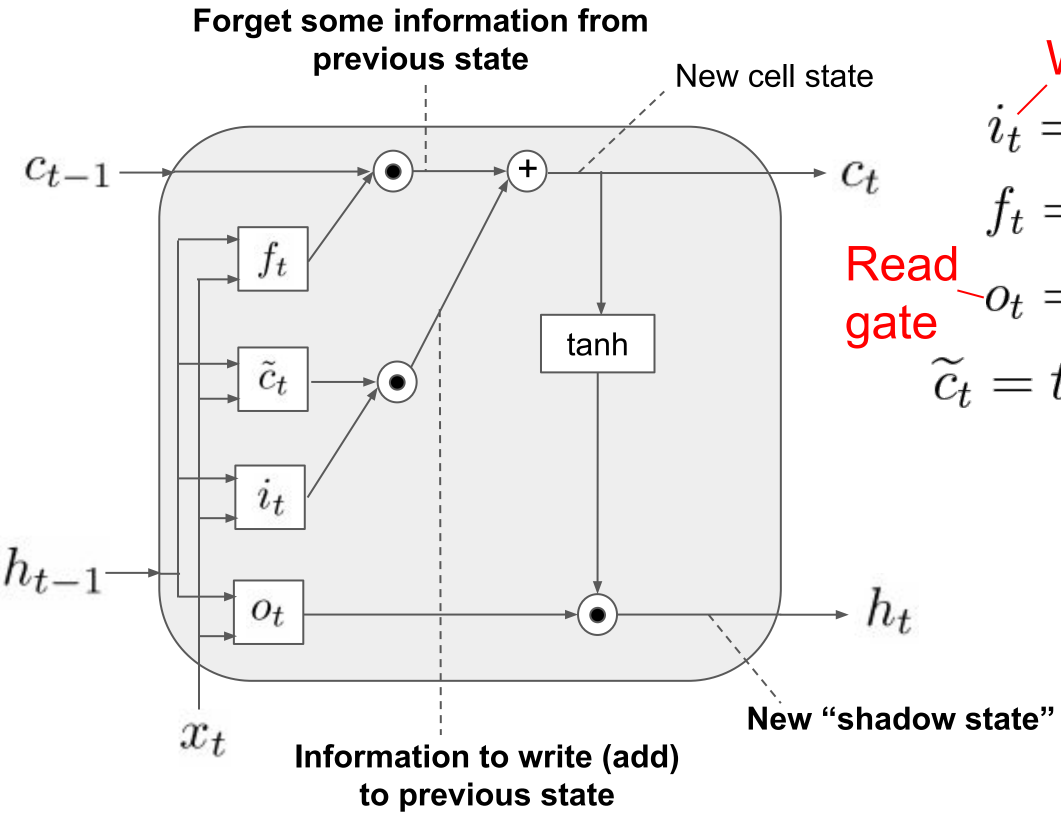

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Where is Read/Write gates?

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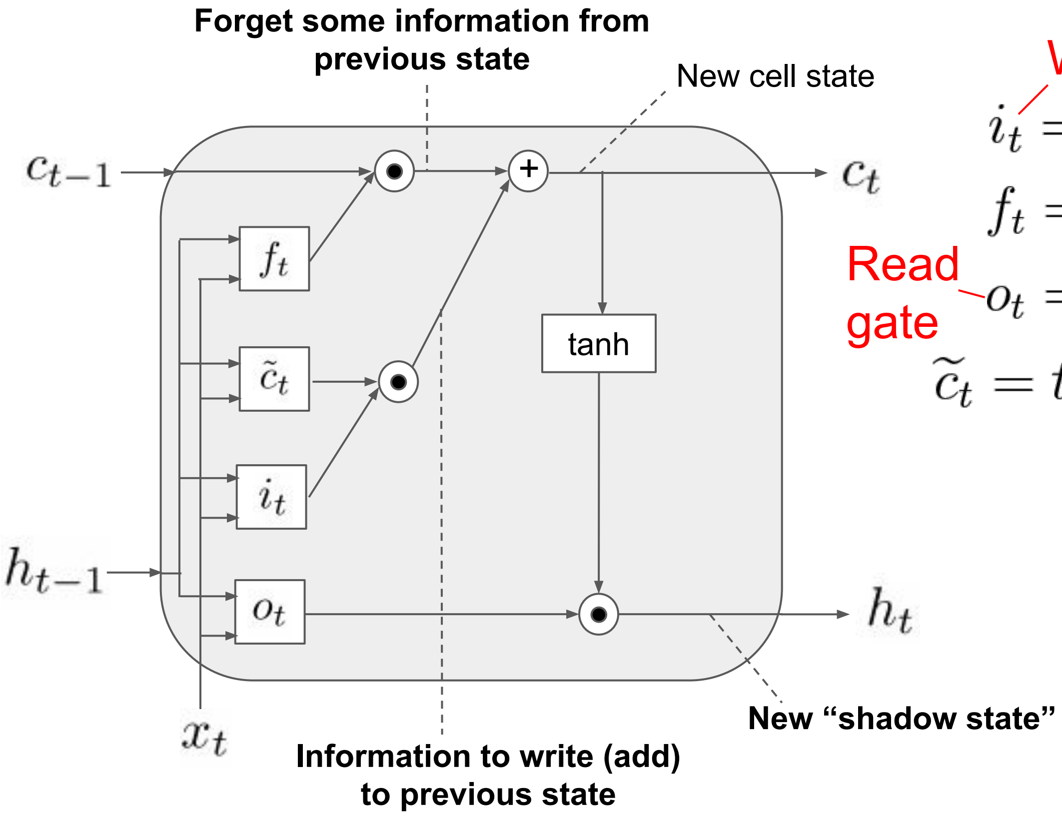

LSTM equations

Write gate

$$i_t = \sigma(W_i h_{t-1} + U_i x_t + b_i) \quad \text{Input gate}$$

$$f_t = \sigma(W_f h_{t-1} + U_f x_t + b_f) \quad \text{Forget gate}$$

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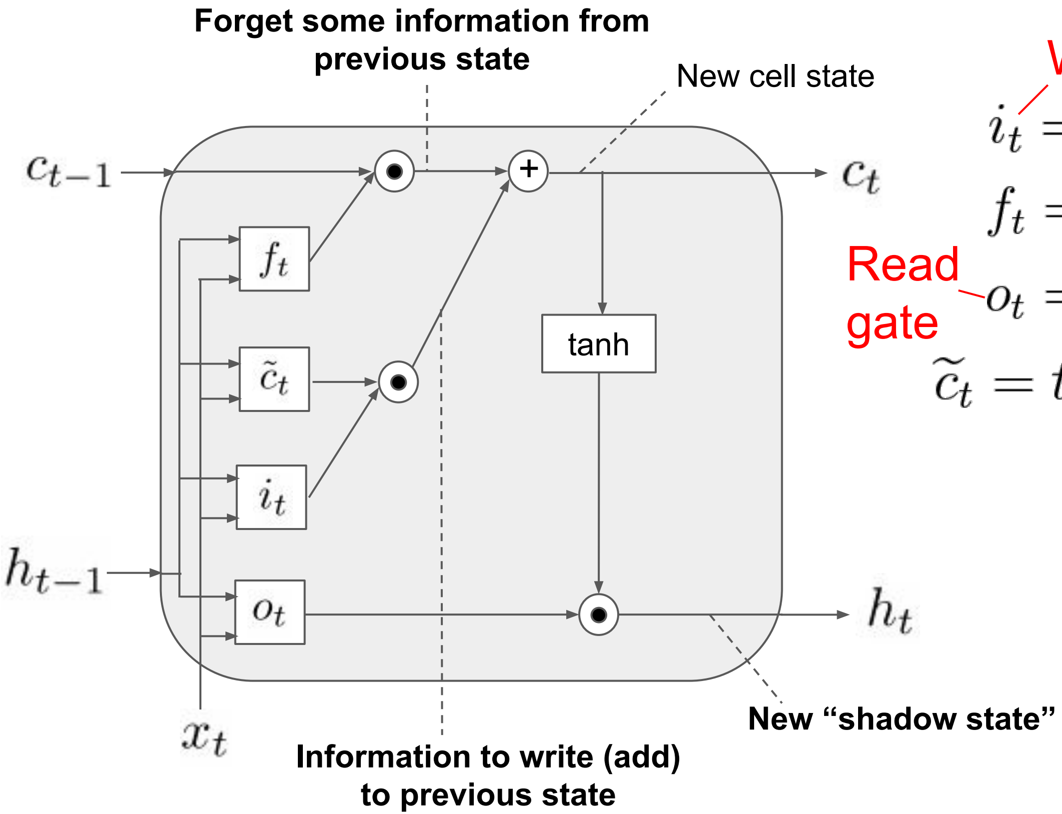
$$y_t = h_t \quad \text{Cell Output}$$

Read occurs after writing

LSTM Cell



LSTM equations

We use shadow state to calculate gates

Write gate

$$i_t = \sigma(W_i h_{t-1} + U_i x_t + b_i)$$ Input gate

$$f_t = \sigma(W_f h_{t-1} + U_f x_t + b_f)$$ Forget gate

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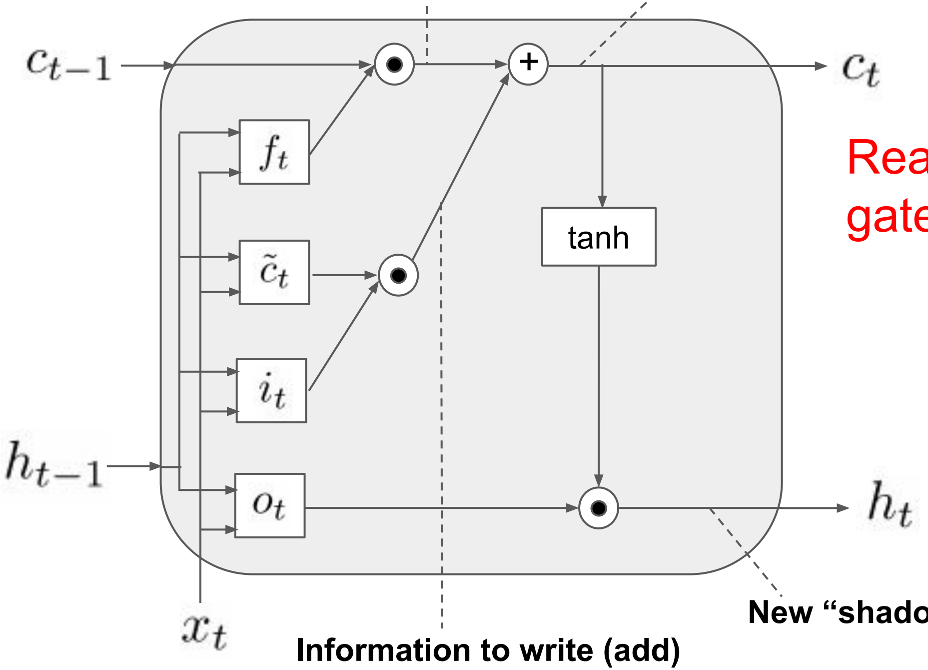
LSTM Cell



Conceptually, we loose information

LSTM equations

We use shadow state to calculate gates

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Read occurs after writing

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LSTM Cell with Peephole connections

LSTM equations

$$i_t = \sigma(W_i h_{t-1} + U_i x_t + b_i)$$

$$f_t = \sigma(W_f h_{t-1} + U_f x_t + b_f)$$

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$$y_t = h_t$$

LSTM with peephole connections

$$i_t = \sigma(W_i h_{t-1} + U_i x_t + P_i c_{t-1} + b_i)$$

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LSTM Cell with Peephole connections

LSTM equations

$$i_t = \sigma(W_i h_{t-1} + U_i x_t + b_i)$$
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LSTM with peephole connections

$$i_t = \sigma(W_i h_{t-1} + U_i x_t + \underline{P_i c_{t-1}} + b_i)$$
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LSTM Cell with Peephole connections

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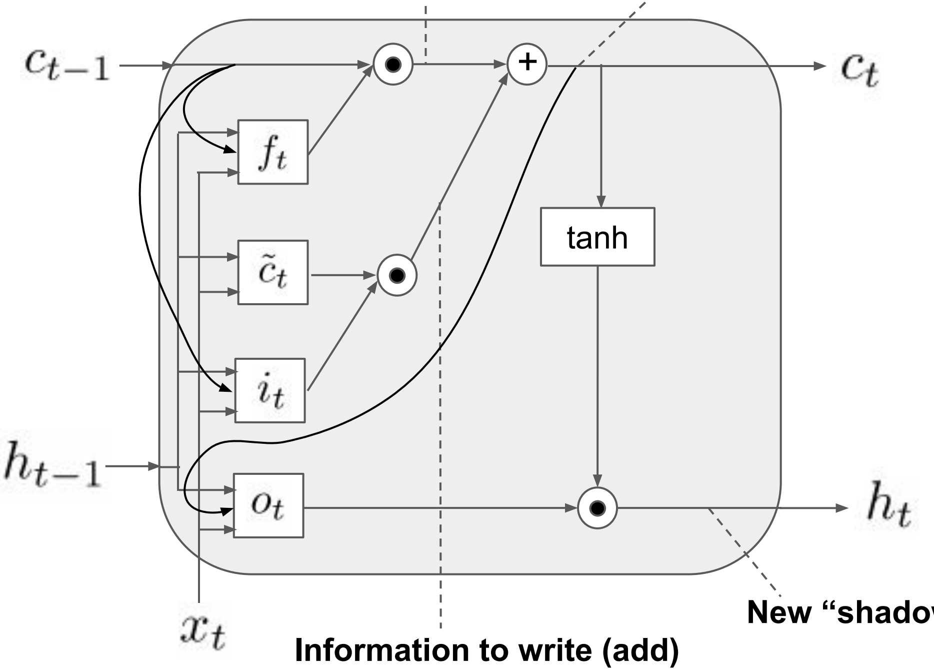
LSTM Cell



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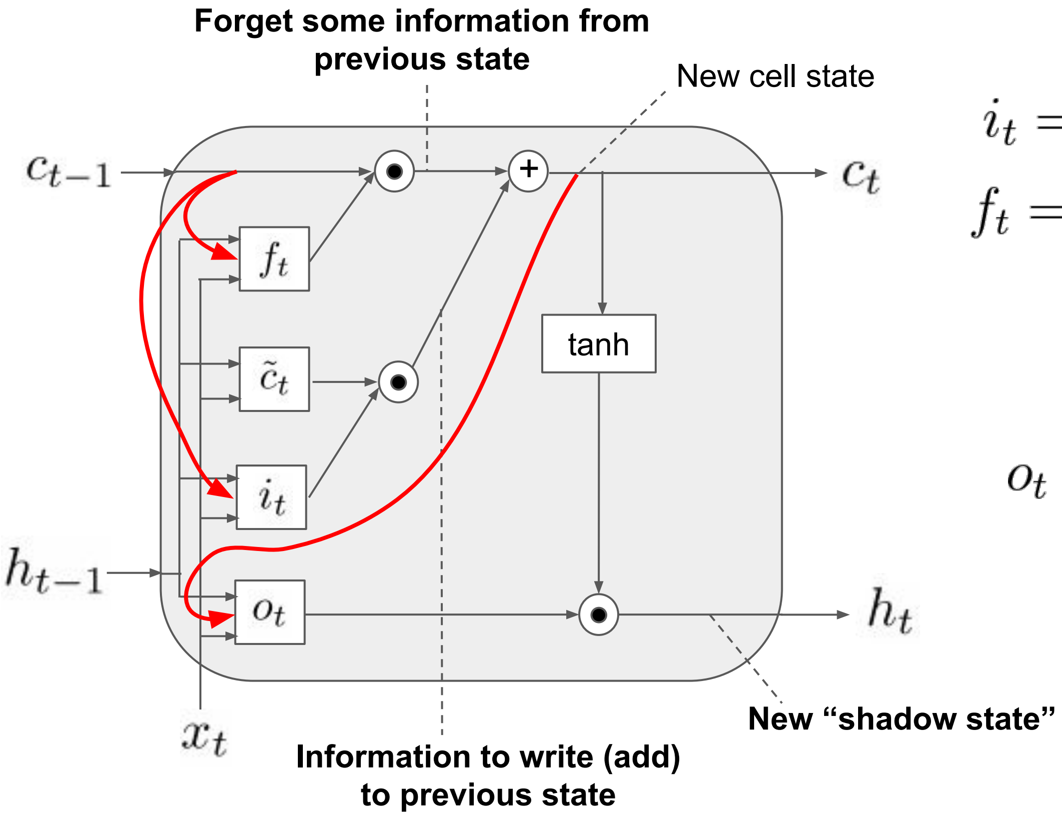

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$$\tilde{c}_t = tanh(W h_{t-1} + U x_t + b)$$

$$c_t = f_t \circ c_{t-1} + i_t \circ \tilde{c}_t$$

$$o_t = \sigma(W_o h_{t-1} + U_o x_t + \underline{P_o c_t} + b_o)$$

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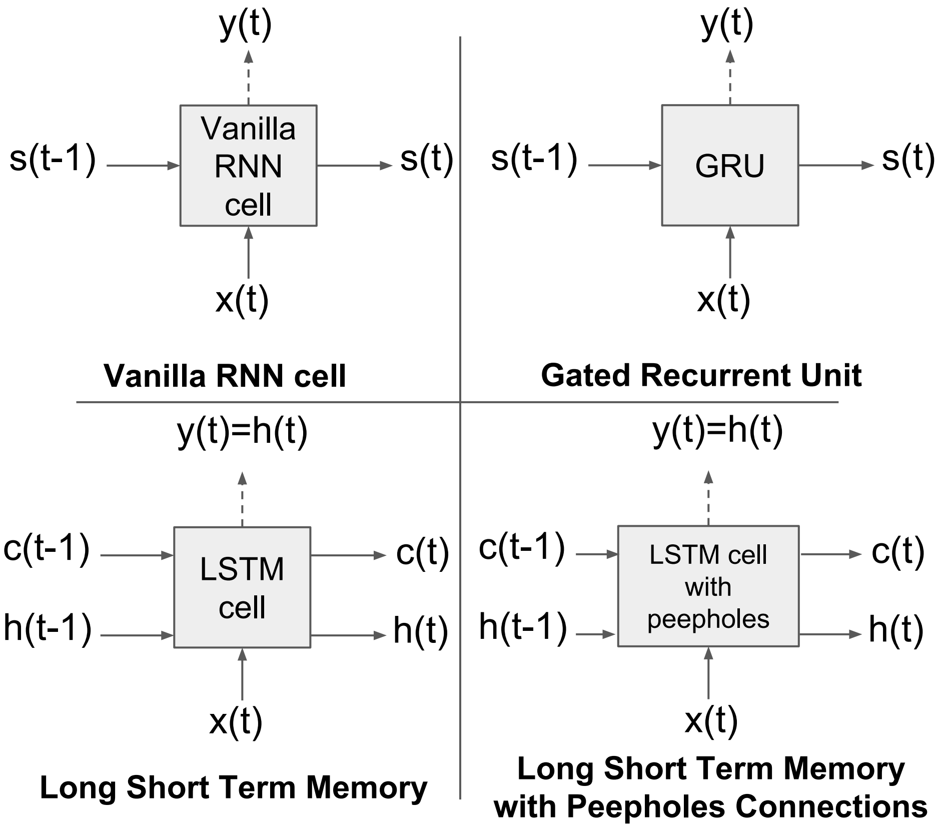
Talk outline

1. RNN: the cell & simple examples
2. Key aspects (or ways to state of the art)
3. Vanilla RNN
4. Problems with Vanilla RNN and motivation for the more powerful cells
5. GRU: step by step
6. LSTM: step by step
7. LSTM with peephole connections
8. Conclusions

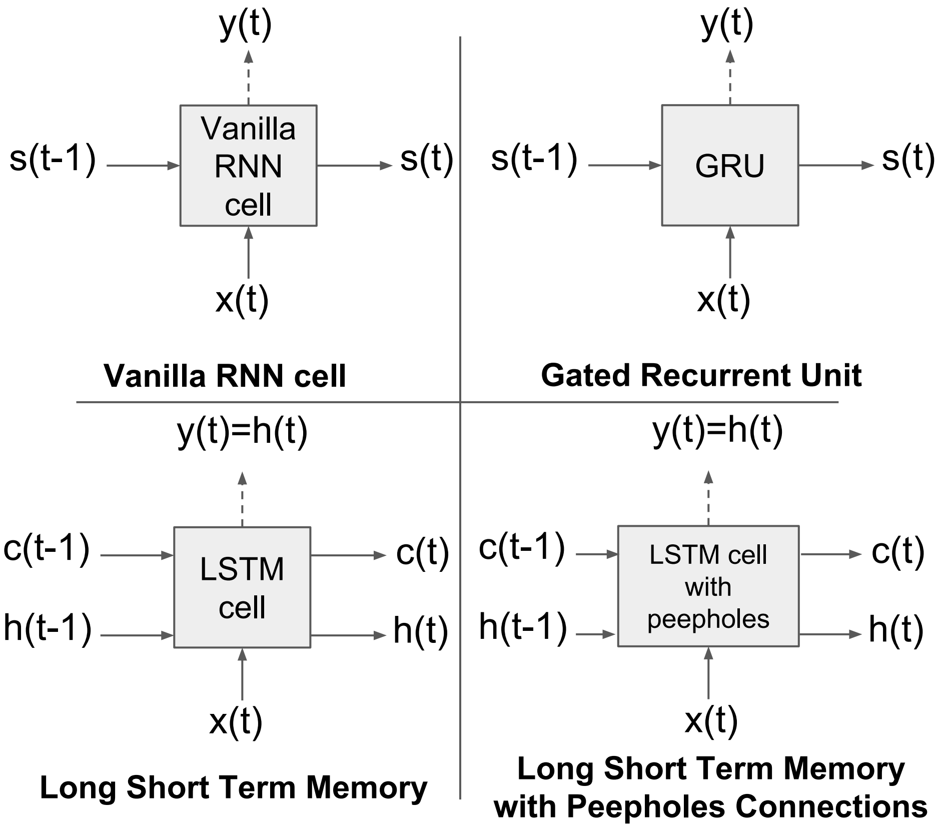
Let’s conclude



Let’s conclude

Vanilla RNN

Late 1980s - backpropagation through time to train Vanilla RNN



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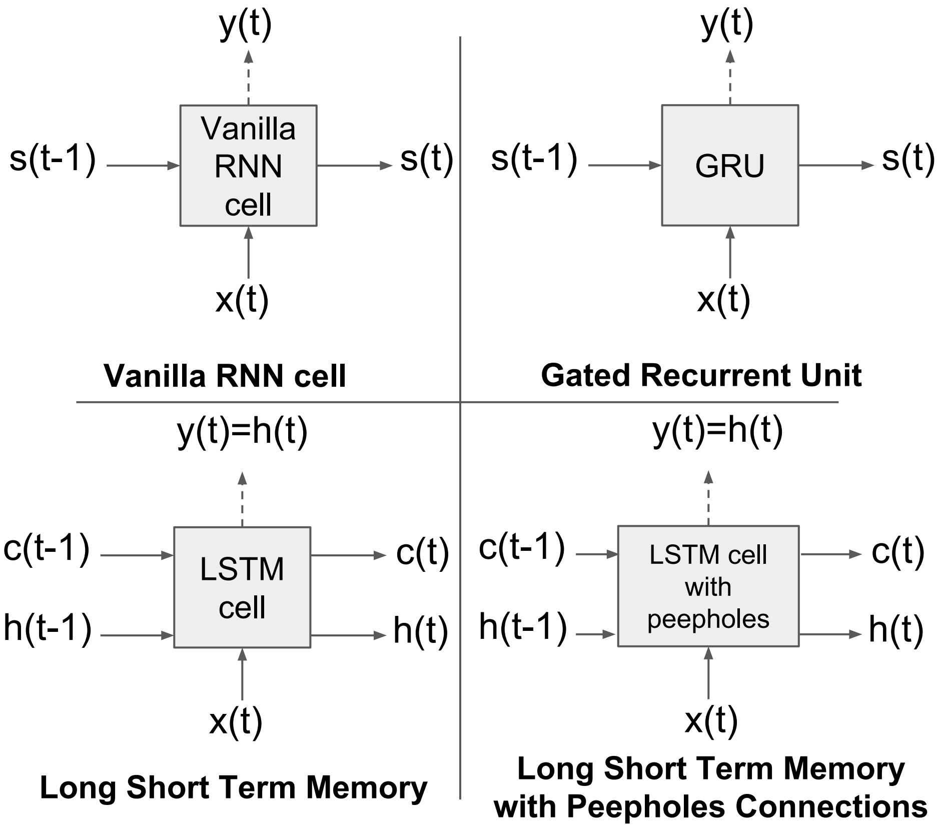

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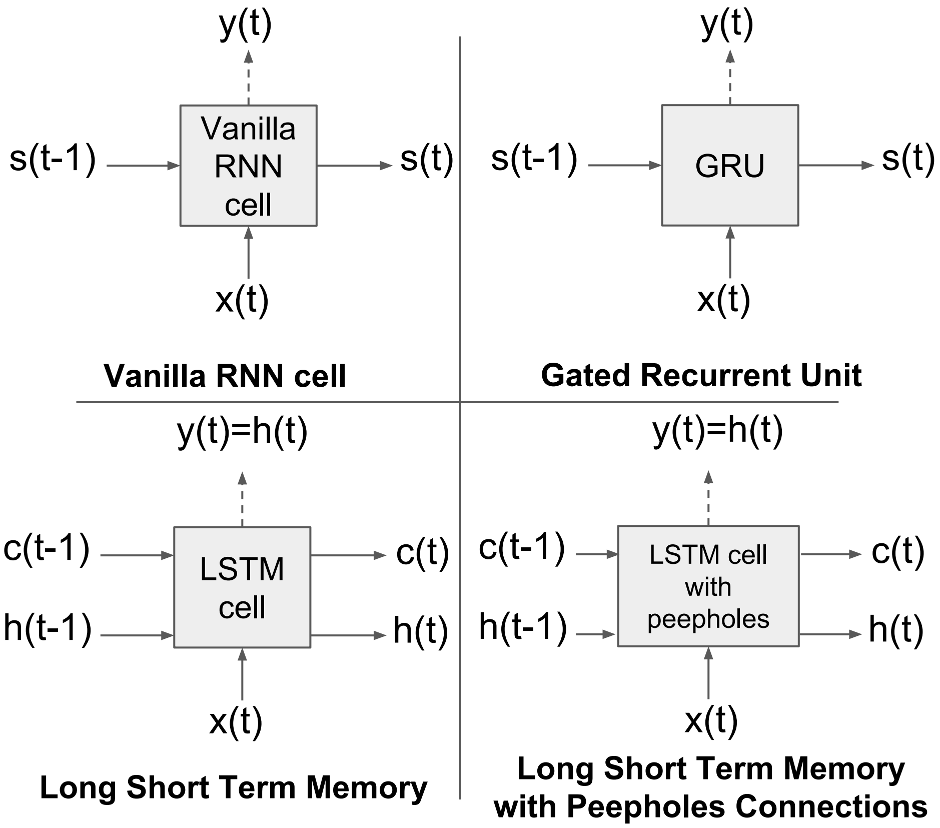

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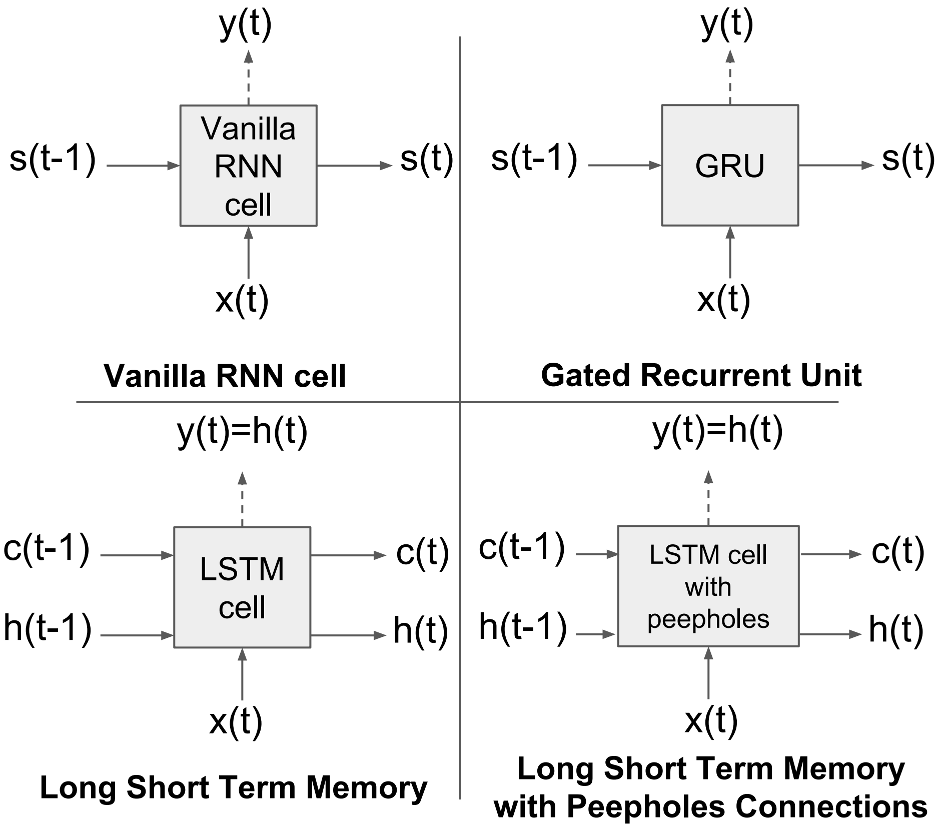
GRU

2014 - Learning Phrase Representations using RNN Encoder–Decoder for Statistical Machine Translation (Kyunghyun Cho, Yoshua Bengio, and others)



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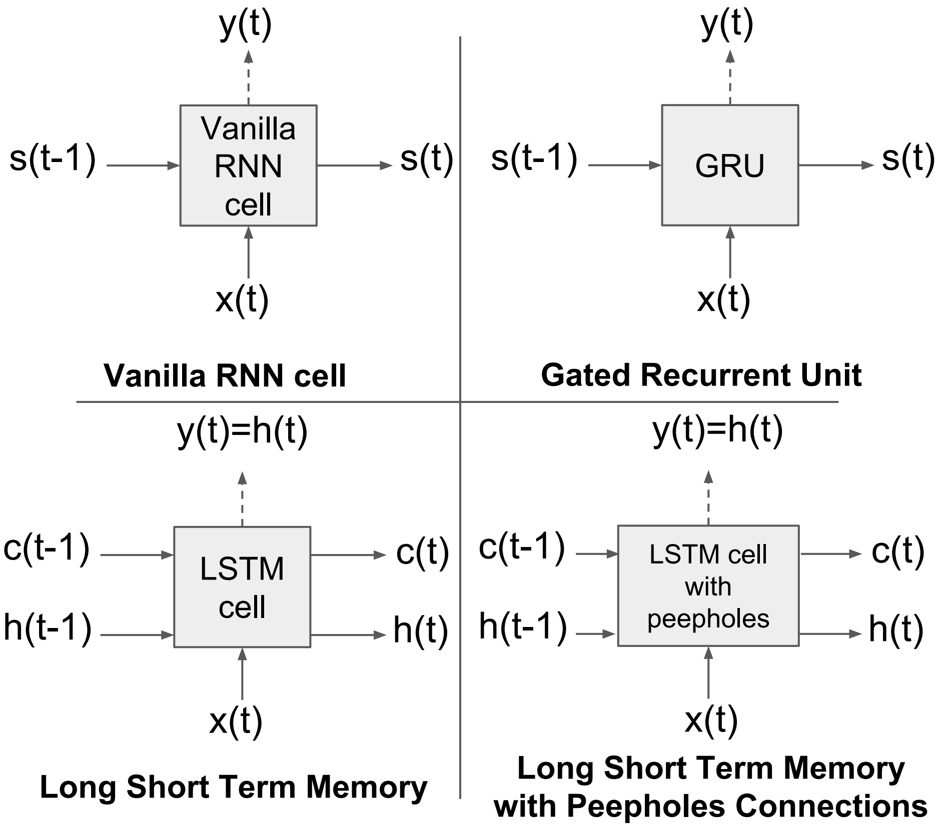
Let’s conclude

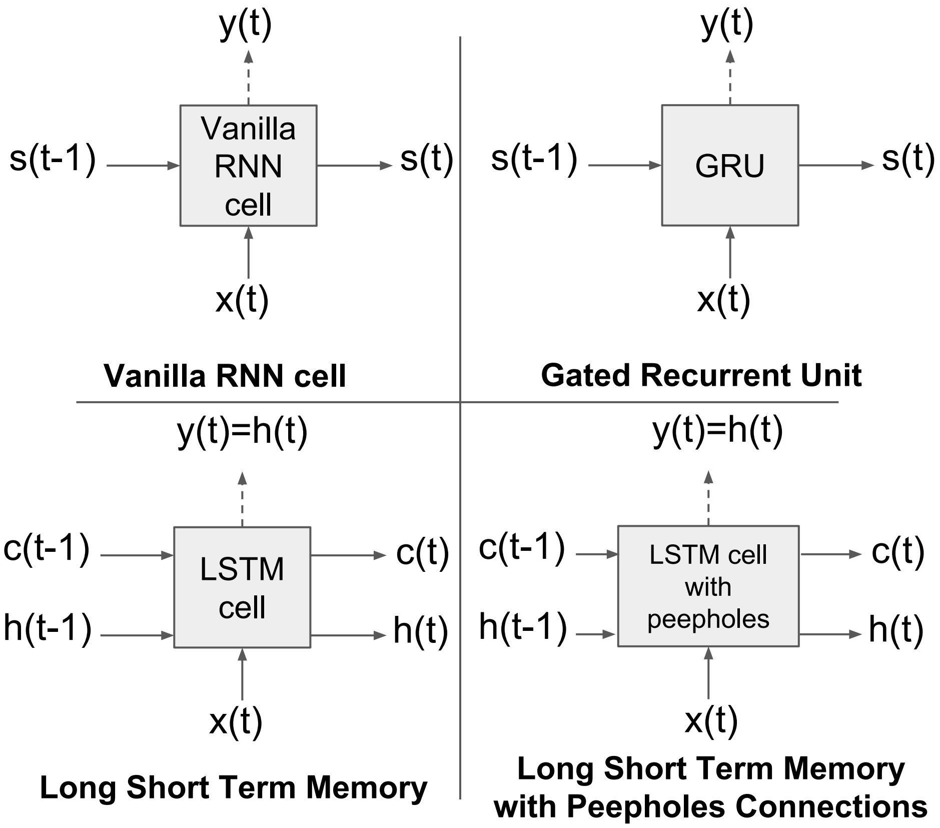
- LSTM and GRU are the most widely used cells in production systems and to achieve state of the art



Let’s conclude

- LSTM and GRU are the most widely used cells in production systems and to achieve state of the art

- GRU cell, perhaps, is the most intuitive one



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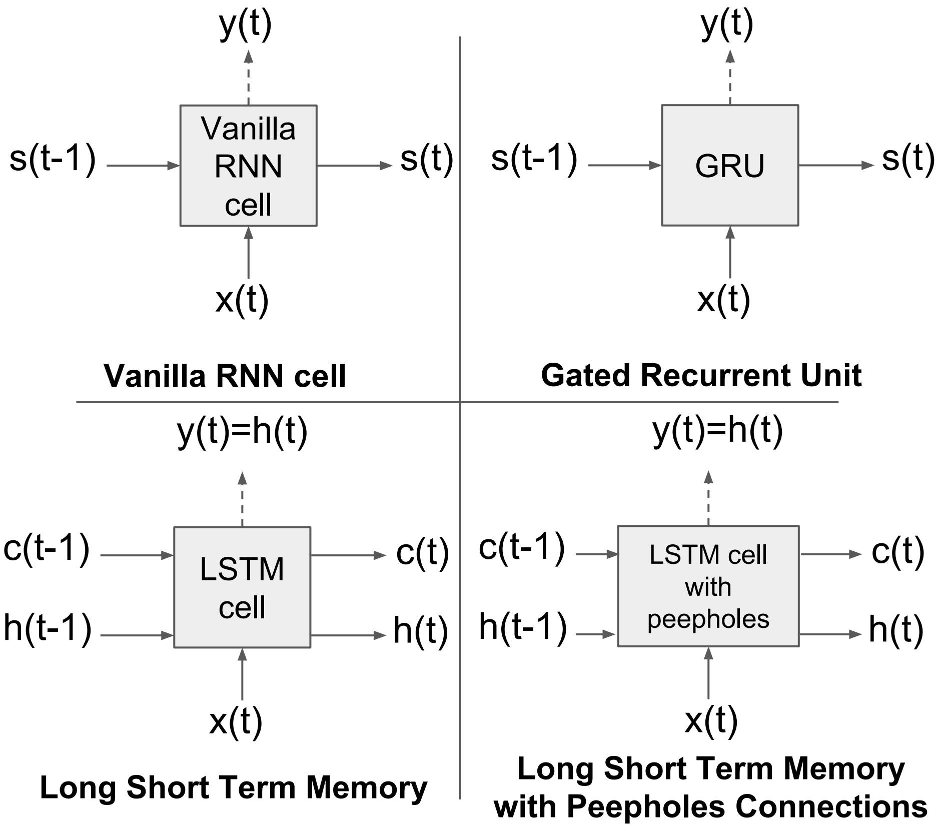
Let’s conclude

- LSTM and GRU are the most widely used cells in production systems and to achieve state of the art
- GRU cell, perhaps, is the most intuitive one
- LSTM with Peepholes connection was designed to attack potential loss of information of Basic LSTM cell



Resources

Great Analysis, Tons of intuition

Written Memories: Understanding, Deriving and Extending the LSTM

LSTM: original paper

Long Short-Term Memory (S.Hochreiter, J.Schmidhuber)

LSTM with Peephole connections

Recurrent nets that time and count (F.A. Gers ; J. Schmidhuber)

GRU

Learning Phrase Representations using RNN Encoder–Decoder for Statistical Machine Translation (K.Cho, Y.Bengio, and others)

Empirical Evaluation of Gated Recurrent Neural Networks on Sequence Modeling (J.Chung, C.Gulcehre, K.Cho, Y.Bengio)

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