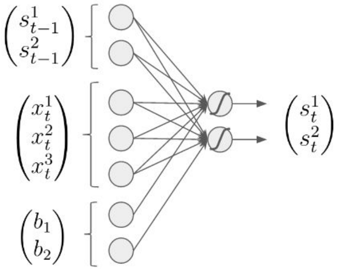
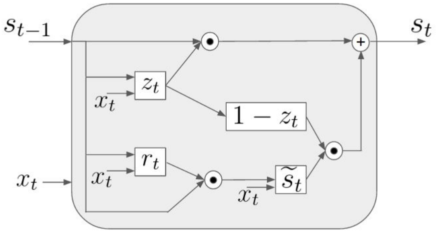
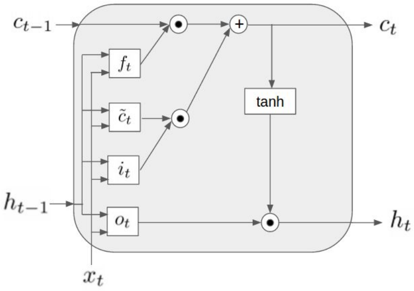
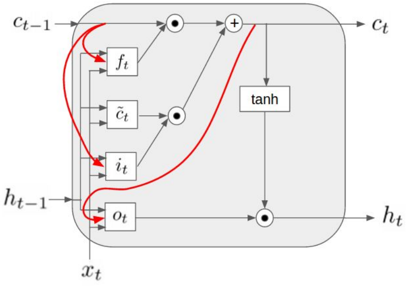
Review from {} deepsystems.ai

Evolution:
from vanilla RNN to GRU & LSTMs



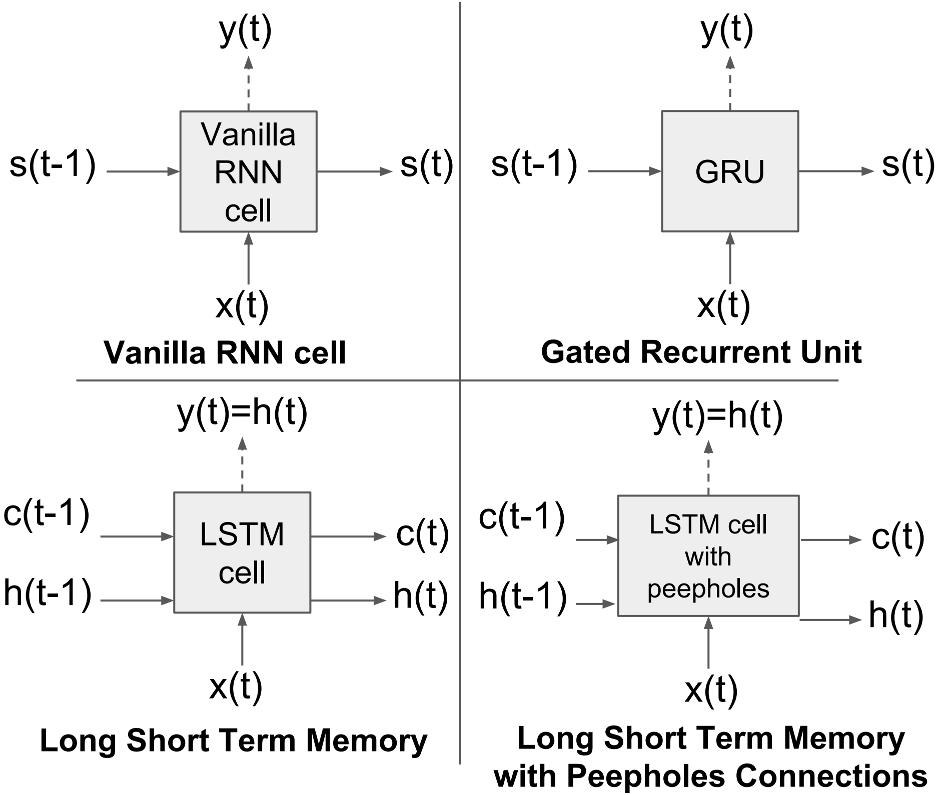






By the end of the talk you will learn

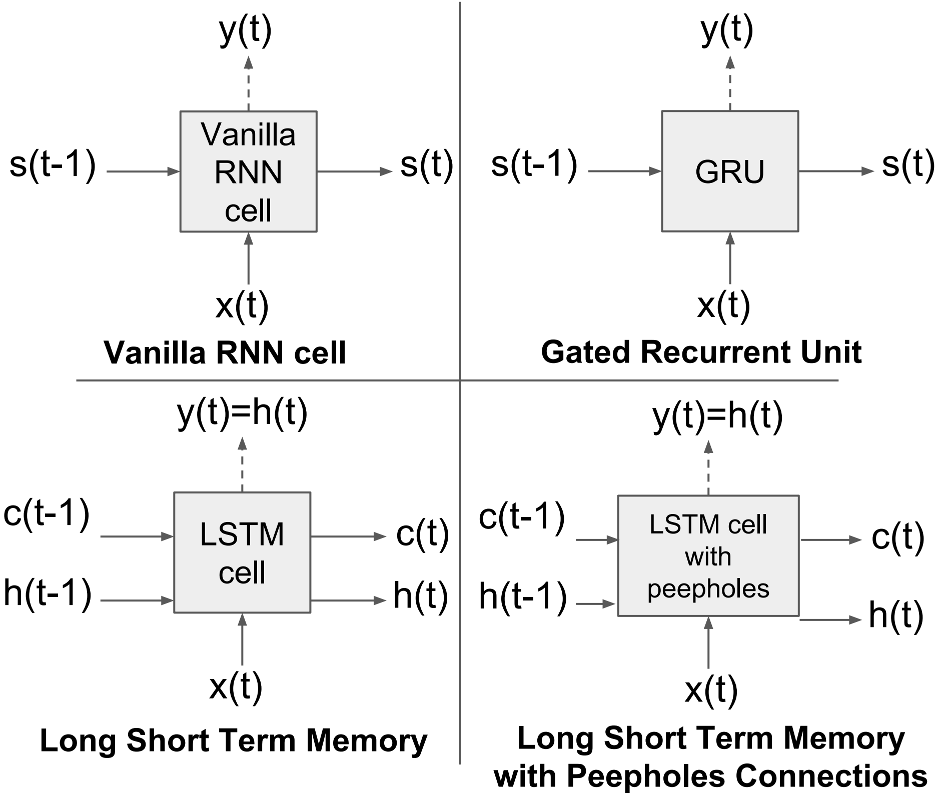
For the most common RNN Cells:



By the end of the talk you will learn

For the most common RNN Cells:

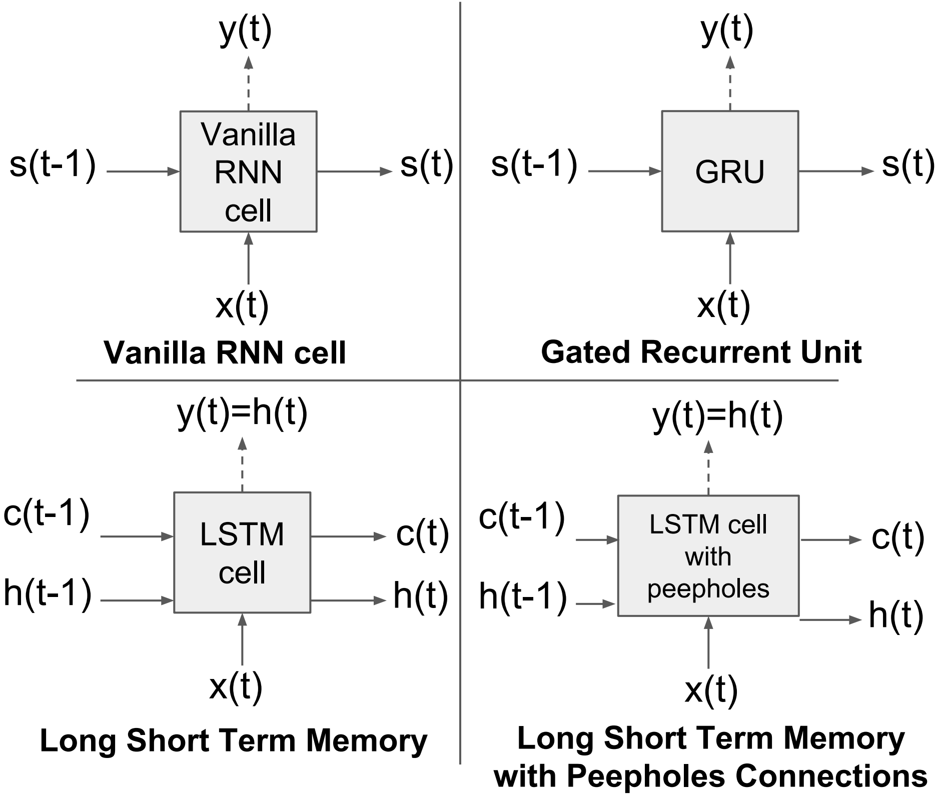
- What's inside & how it works



By the end of the talk you will learn

For the most common RNN Cells:

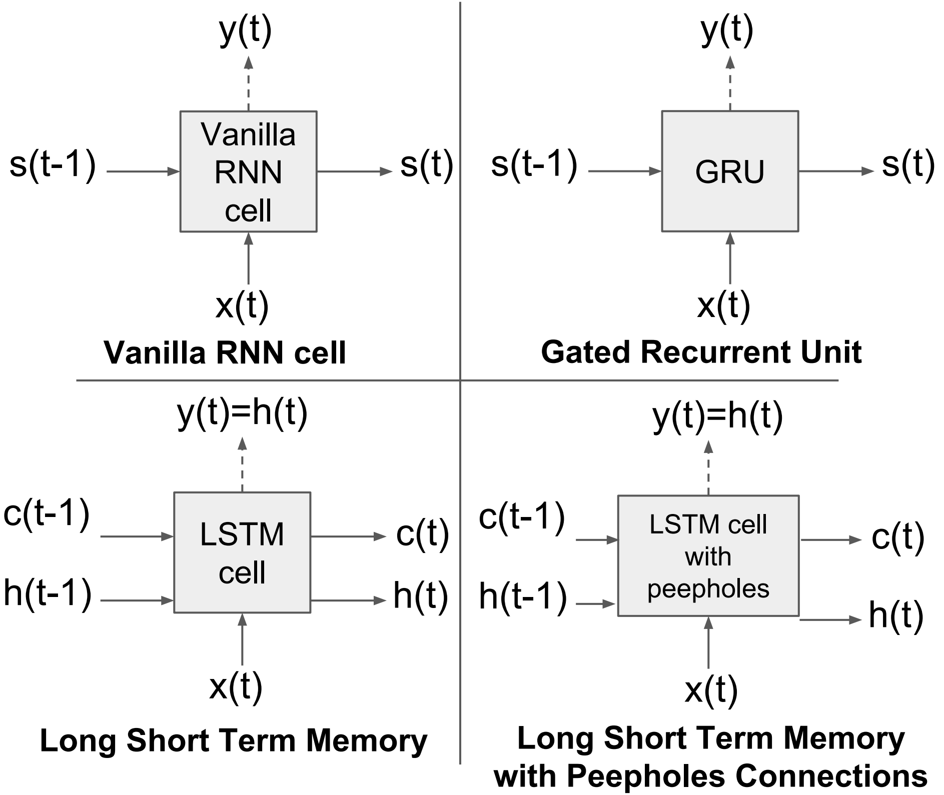
- What's inside & how it works
- Intuition behind



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



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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

Talk outline

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

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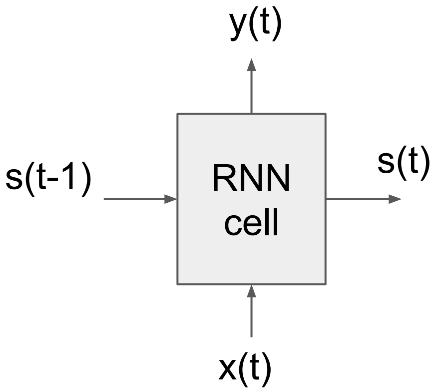
RNN Cell

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

Hidden state at t-1
(previous state)



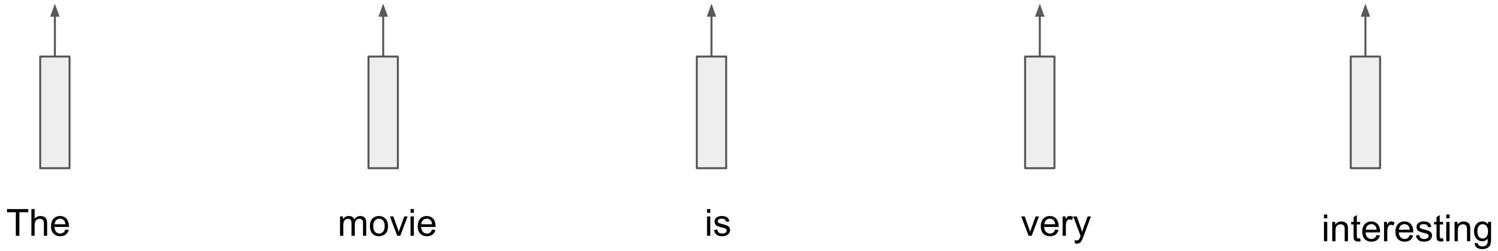
Hidden state at time t
(current state)

Input vector
(optional)

RNN example 1: Sentiment analysis

The movie is very interesting

RNN example 1: Sentiment analysis



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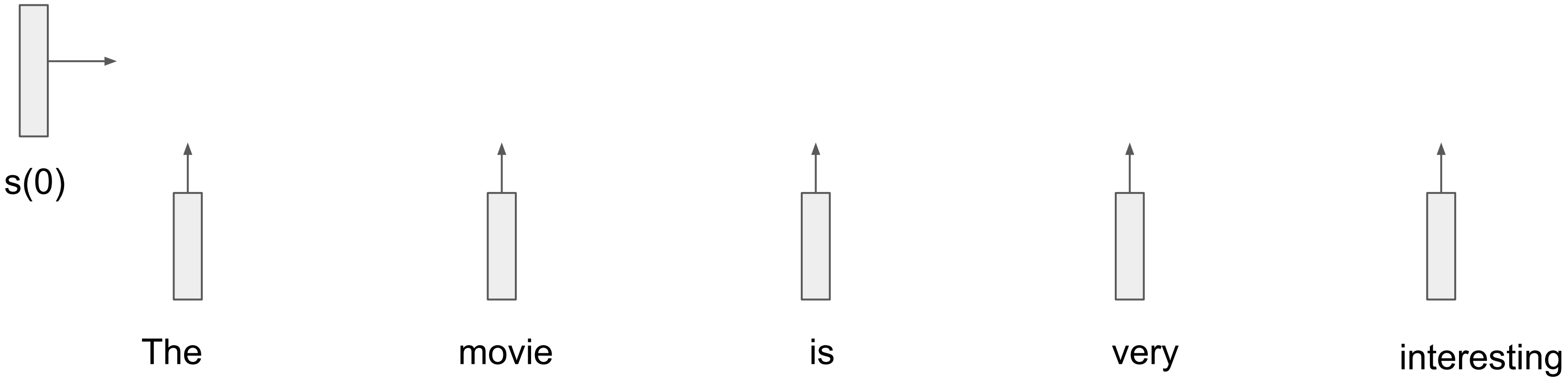
RNN example 1: Sentiment analysis



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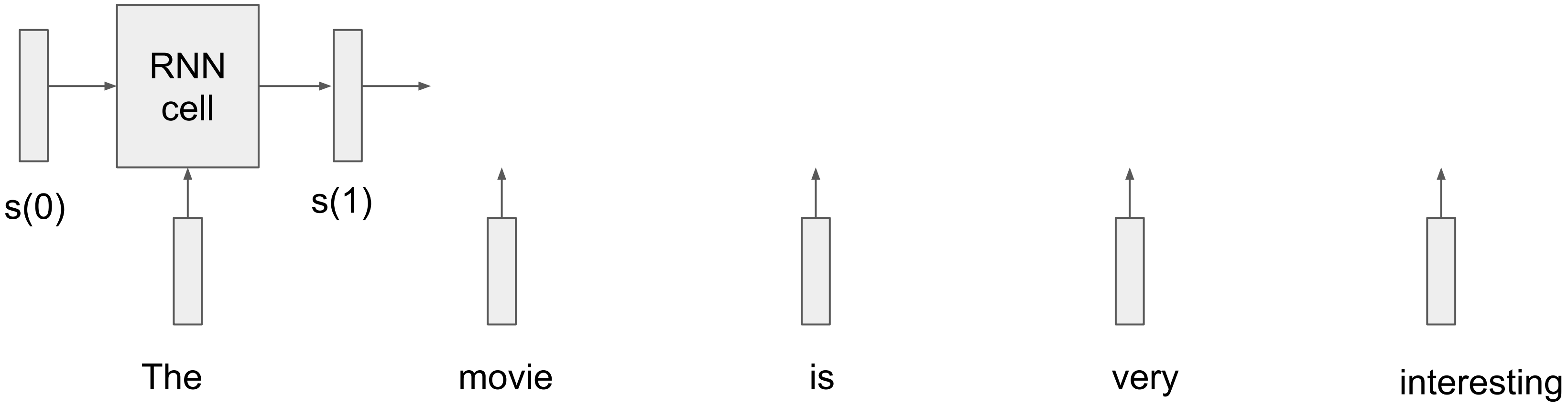
RNN example 1: Sentiment analysis



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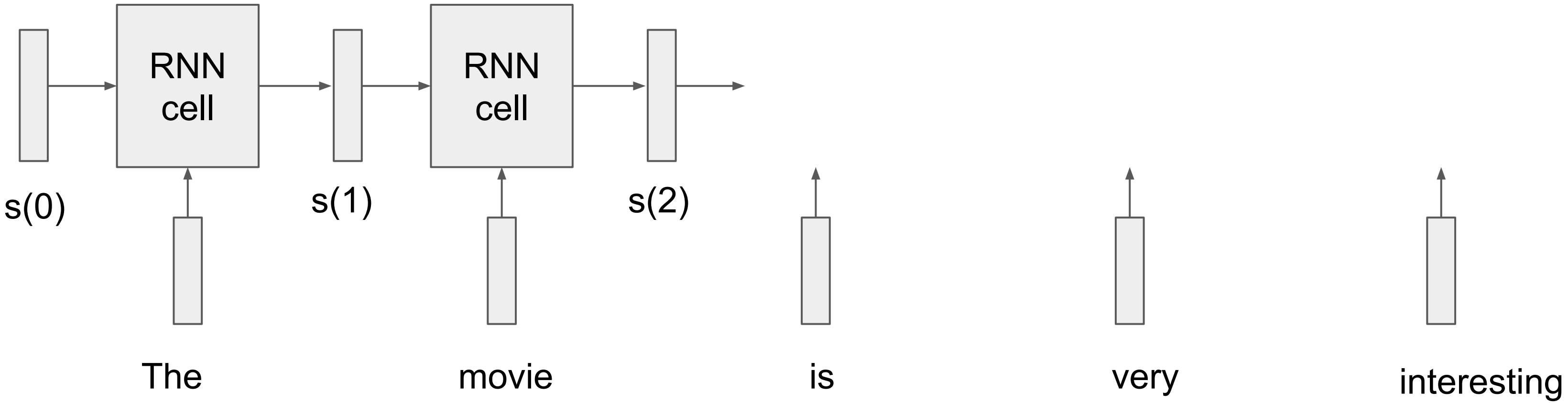
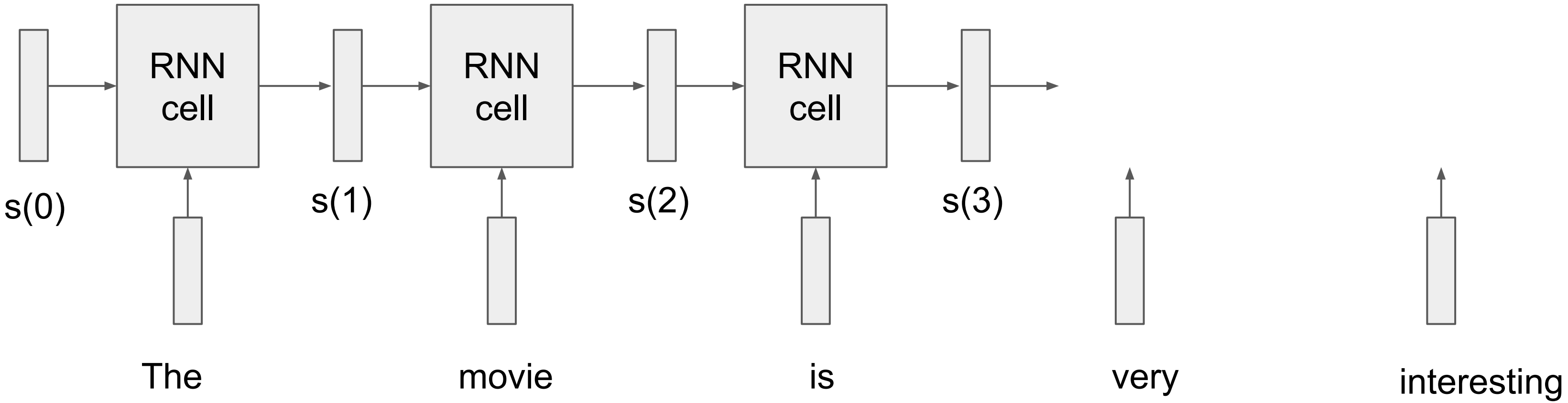
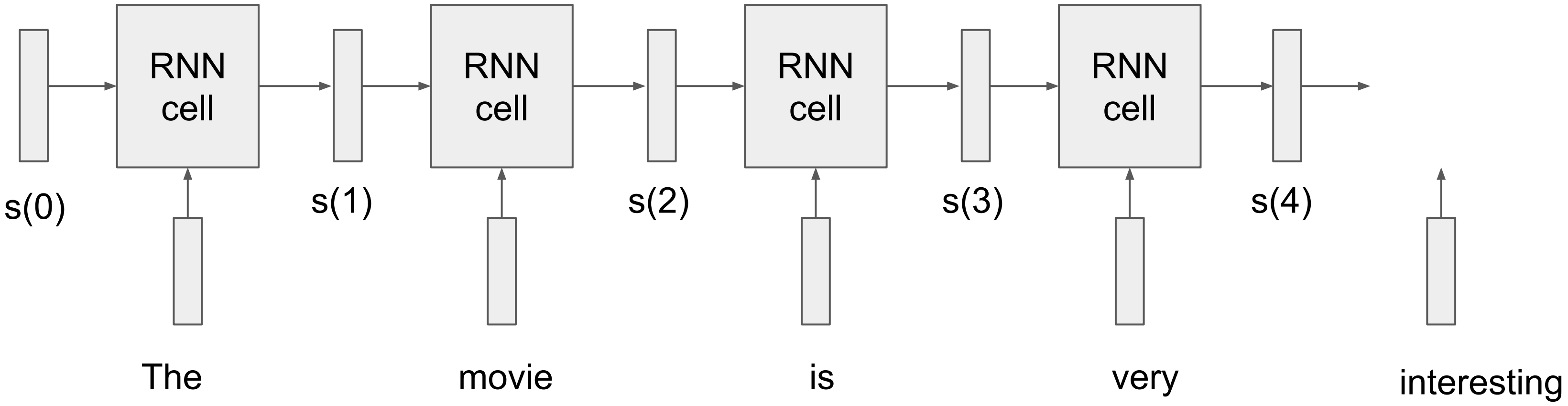
RNN example 1: Sentiment analysis



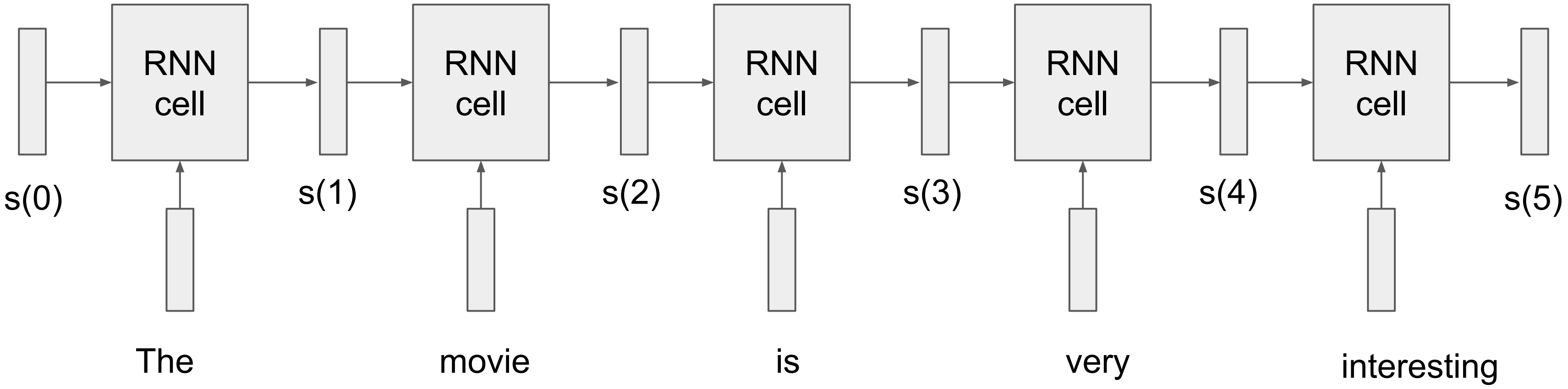
RNN example 1: Sentiment analysis



RNN example 1: Sentiment analysis



RNN example 1: Sentiment analysis



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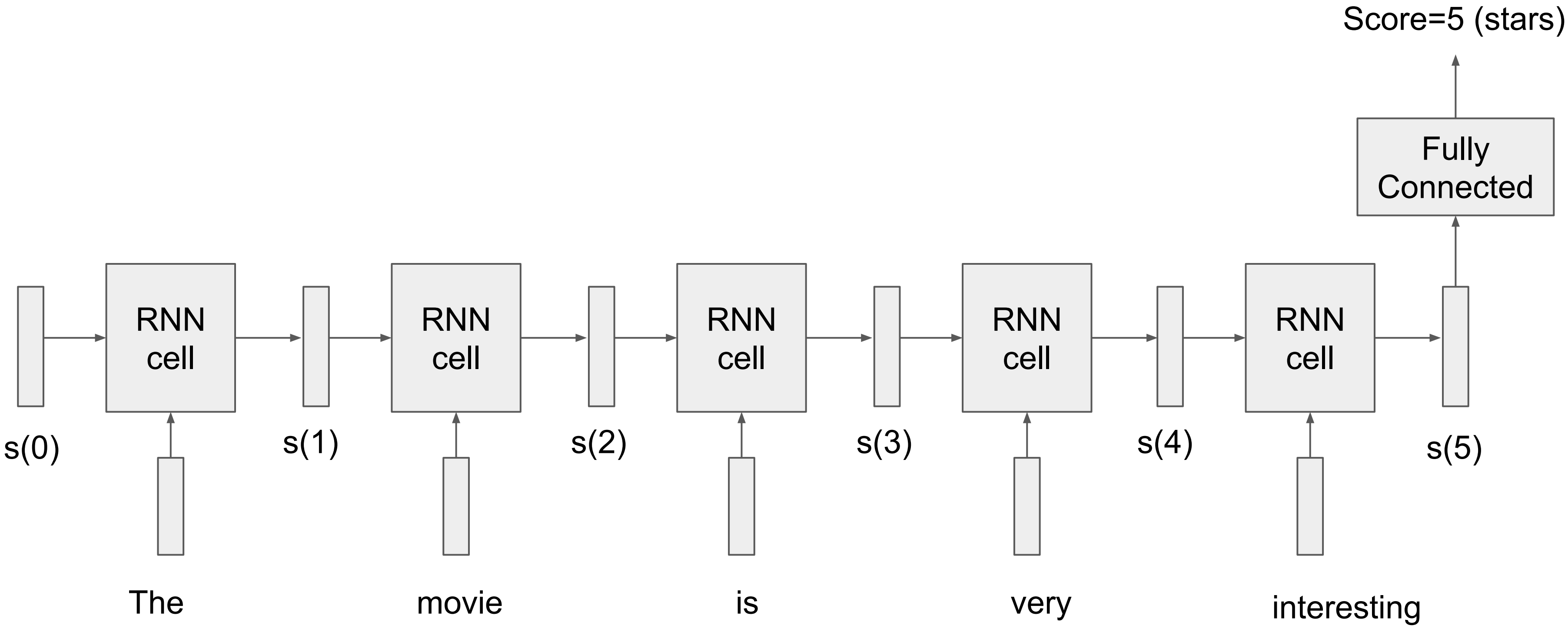
RNN example 1: Sentiment analysis



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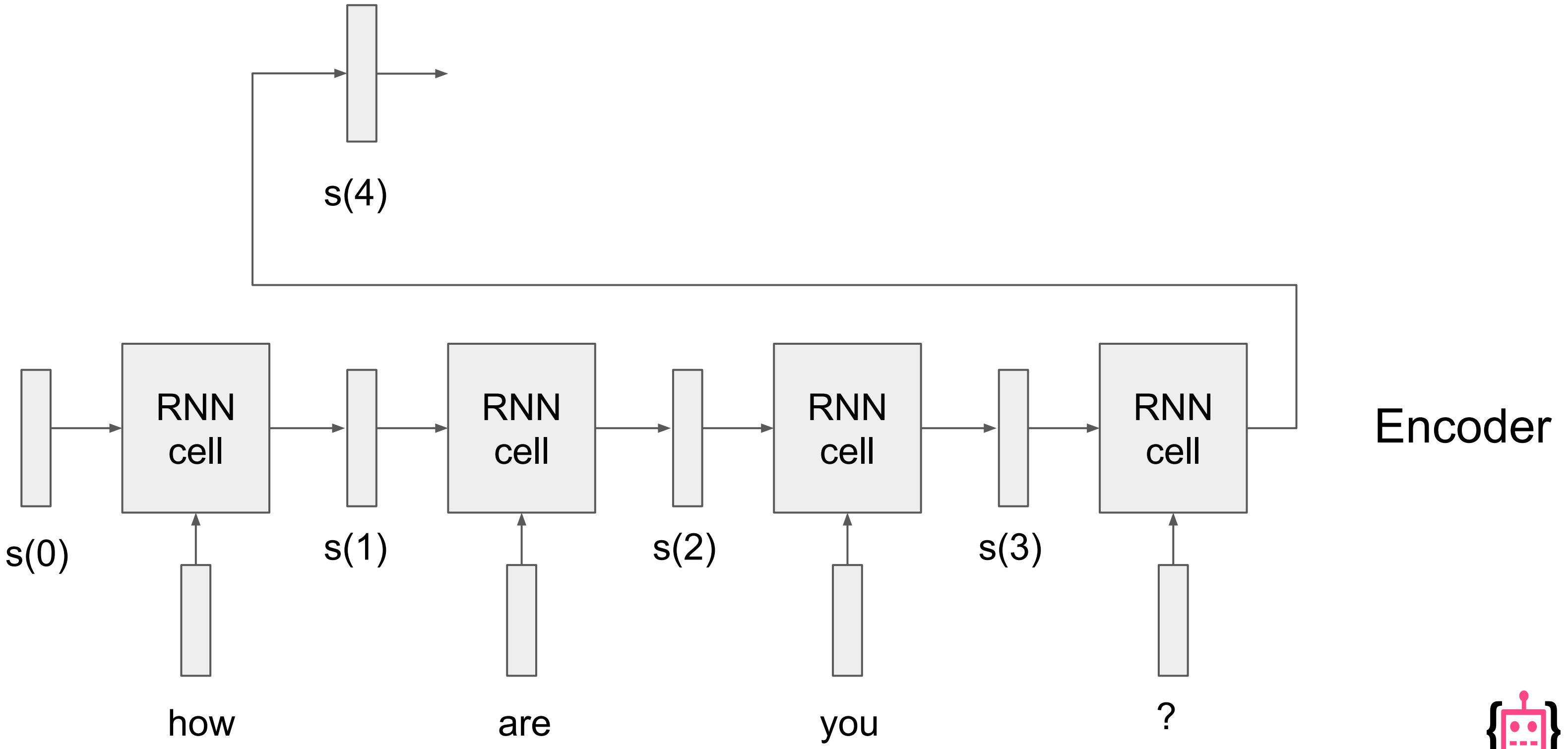
RNN example 2: English to slang English

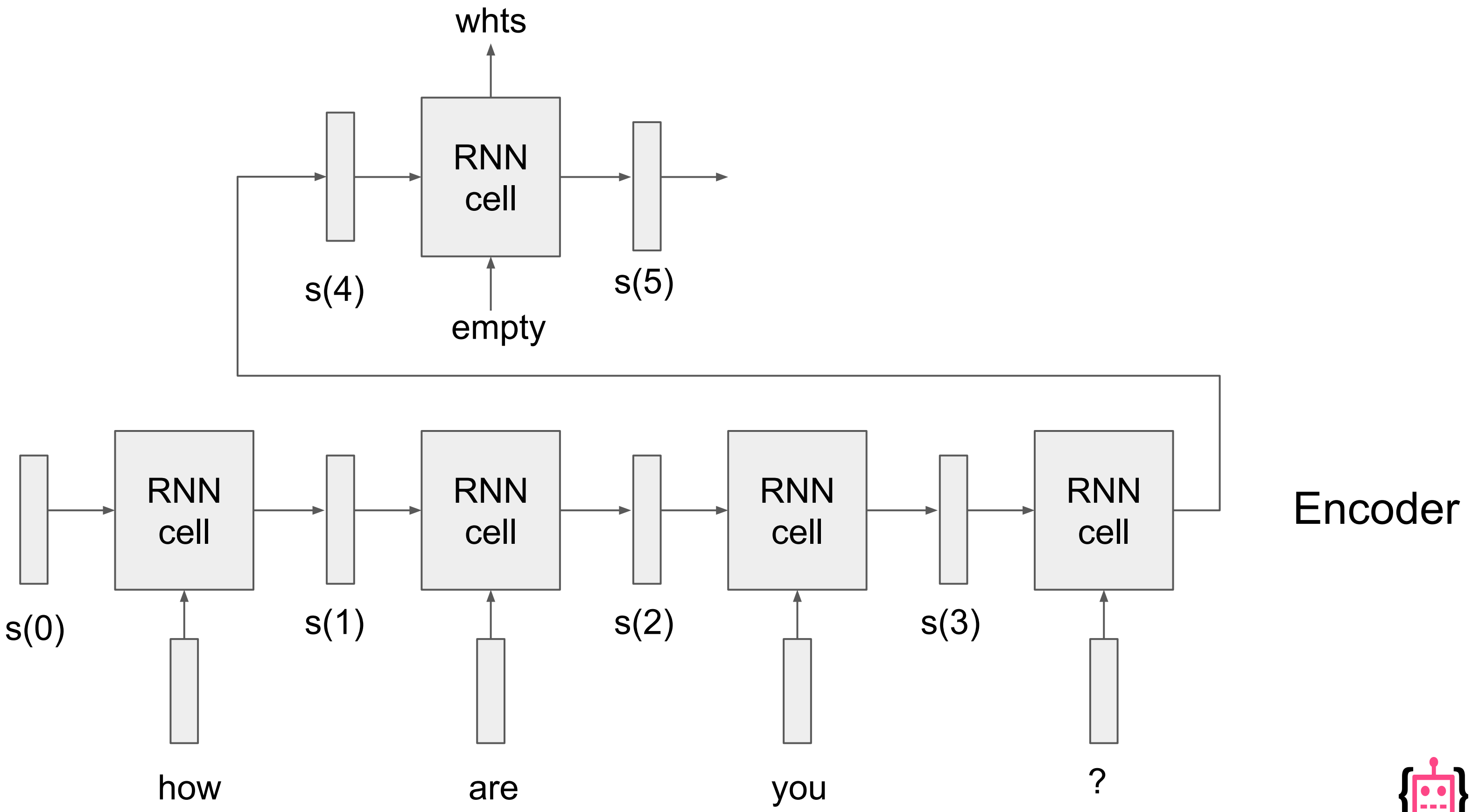
RNN example 2: English to slang English

how are you ?

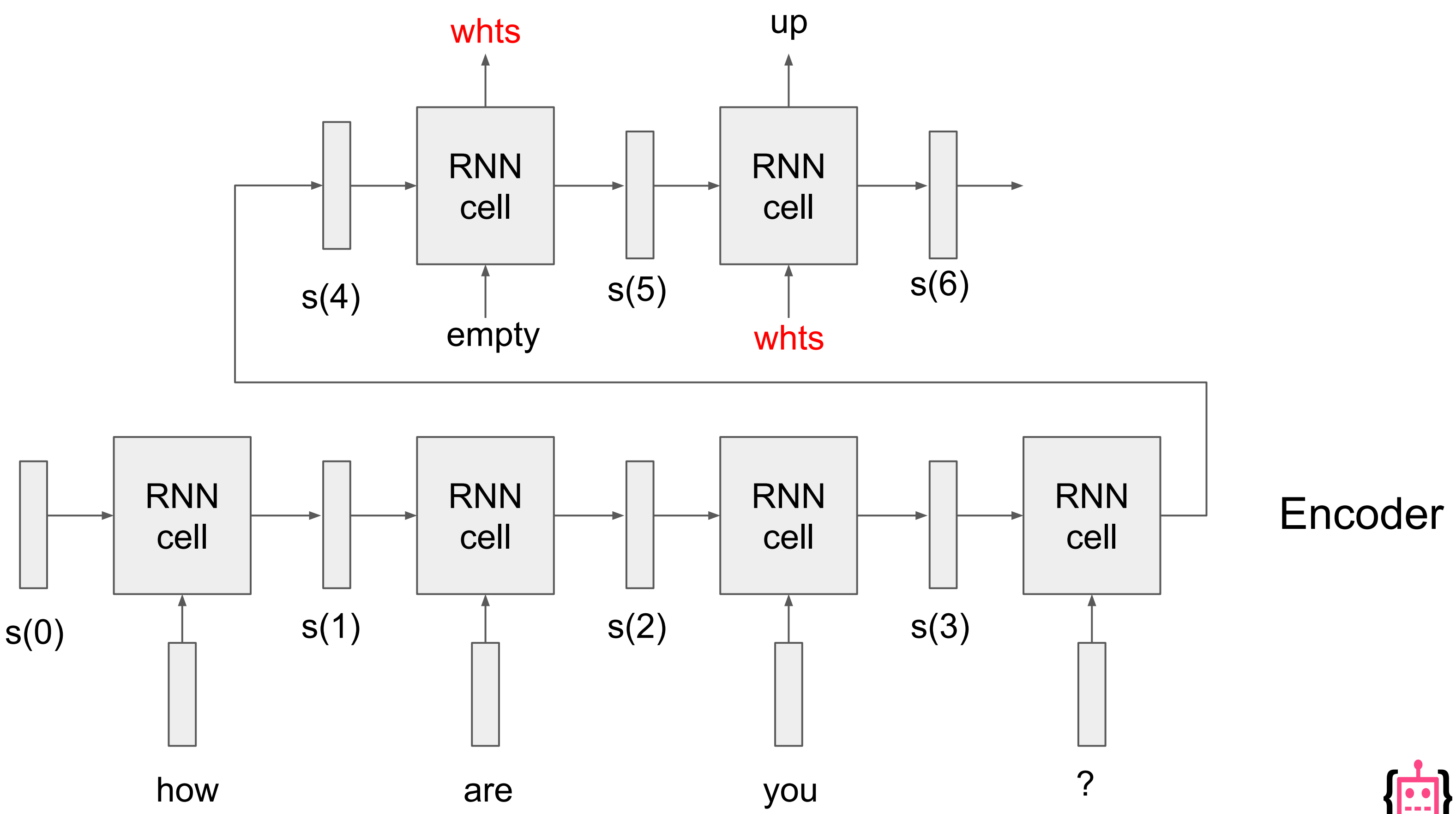
RNN example 2: English to slang English



RNN example 2: English to slang English



RNN example 2: English to slang English



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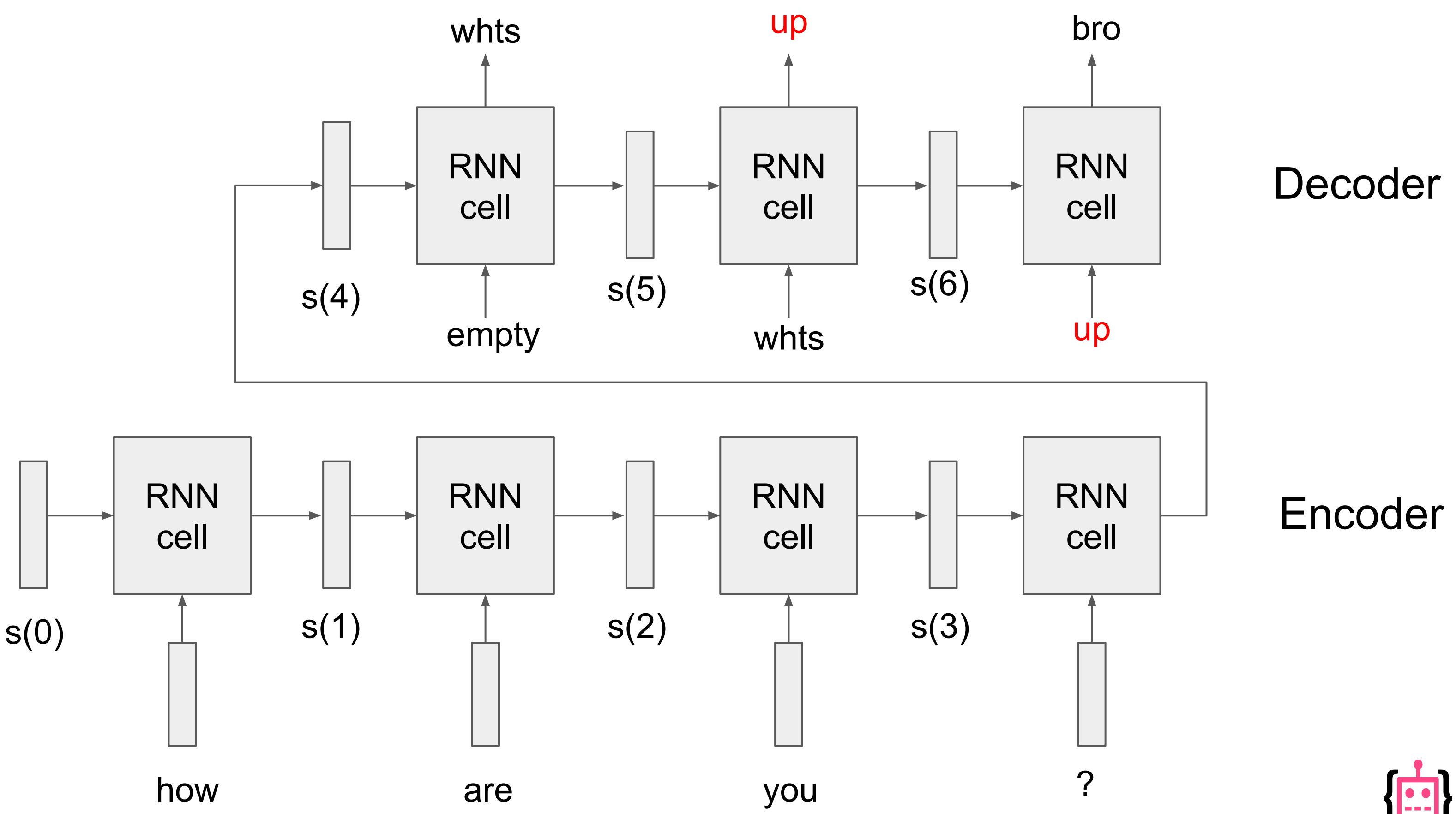

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RNNs: Key Aspects (or ways to state of the art)

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 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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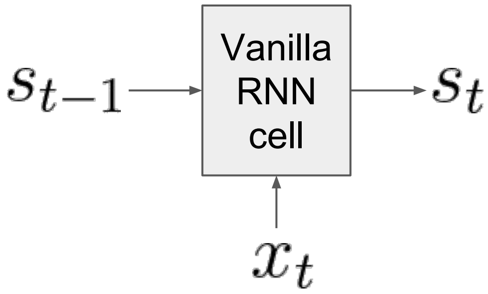
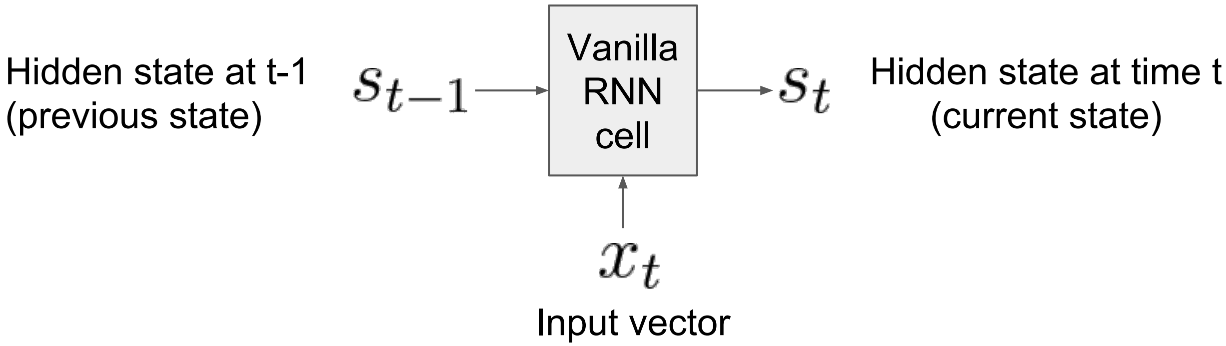
Vanilla RNN



Vanilla RNN



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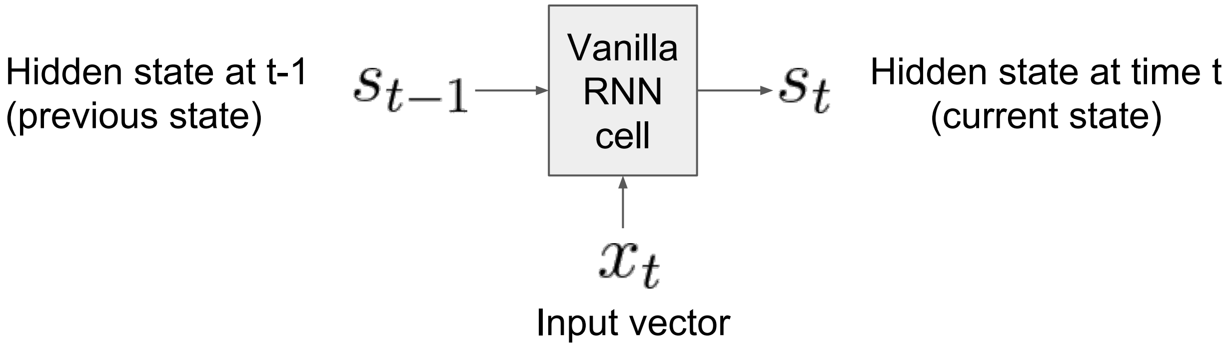
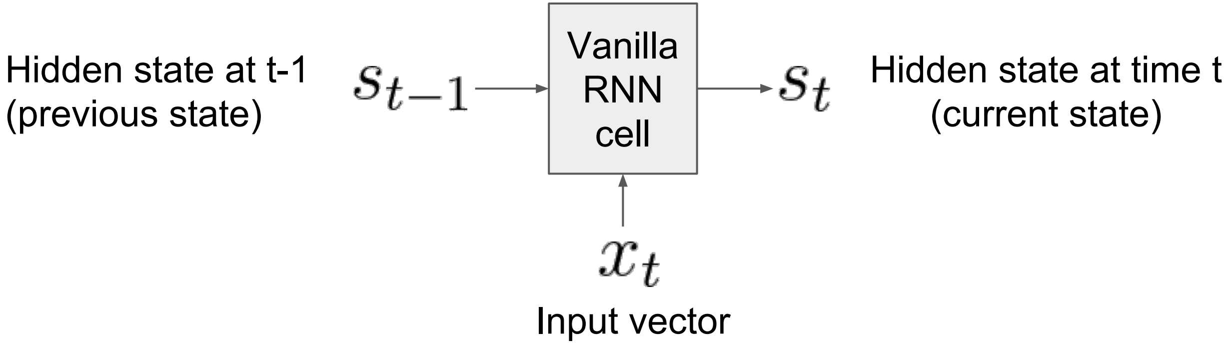
Vanilla RNN

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



Vanilla RNN

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



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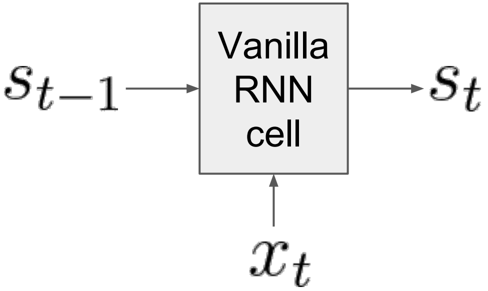
Hidden state at t-1
(previous state)



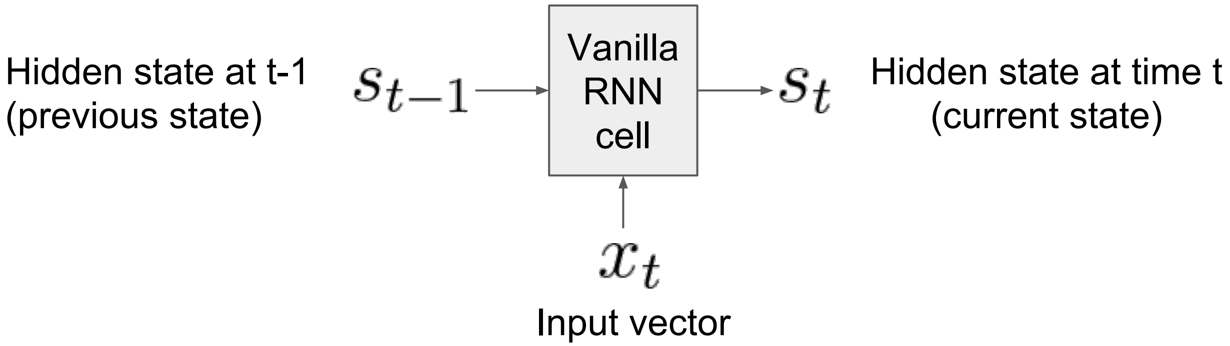
Hidden state at time t
(current state)

Input vector

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

Vanilla RNN

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



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

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

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

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

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)

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

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

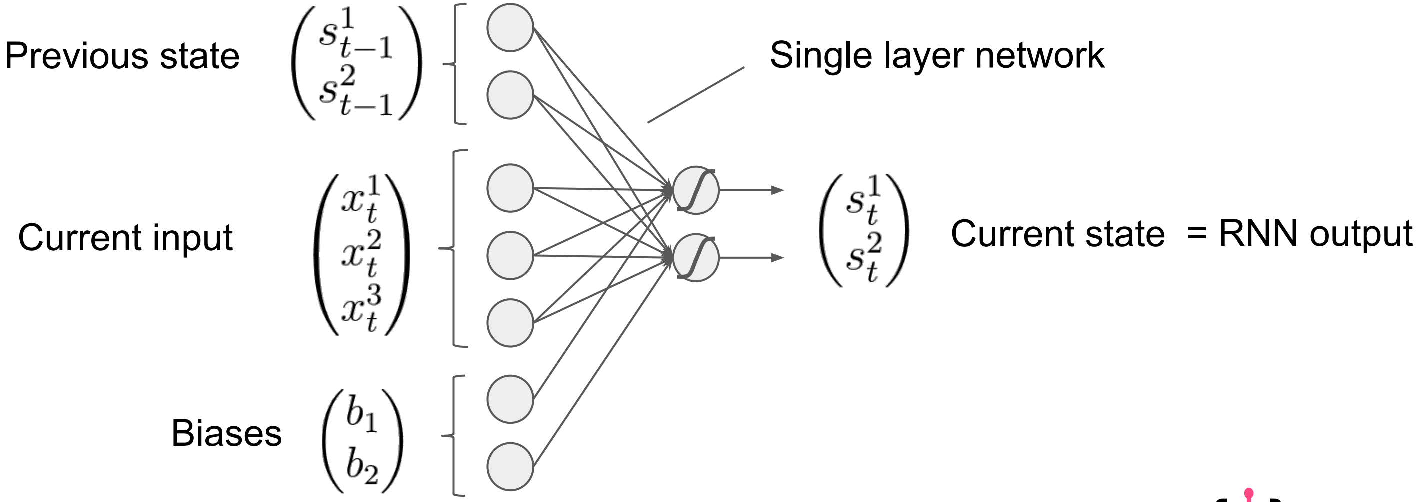
$$= \varphi(\begin{pmatrix} w_{11}s_{t-1}^1 + w_{12}s_{t-1}^2 \\ w_{21}s_{t-1}^1 + w_{22}s_{t-1}^2 \end{pmatrix} + \begin{pmatrix} u_{11}x_t^1 + u_{12}x_t^2 + u_{13}x_t^3 \\ u_{21}x_t^1 + u_{22}x_t^2 + u_{23}x_t^3 \end{pmatrix} + \begin{pmatrix} b_1 \\ b_2 \end{pmatrix})$$

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

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

Vanilla RNN

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



Vanilla RNN

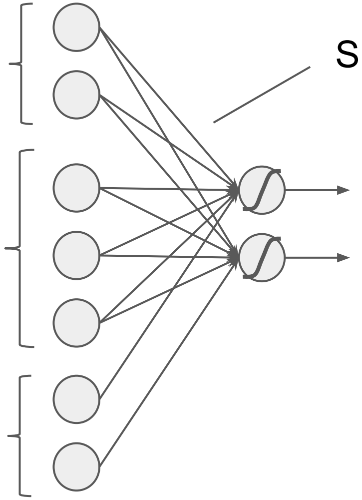
$$s_t = \varphi(W_c[s_{t-1}, x_t] + b)$$

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

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

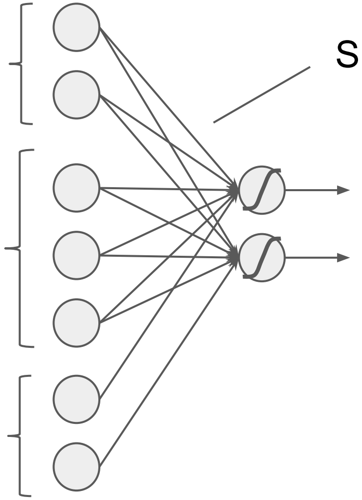
Vanilla RNN

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

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

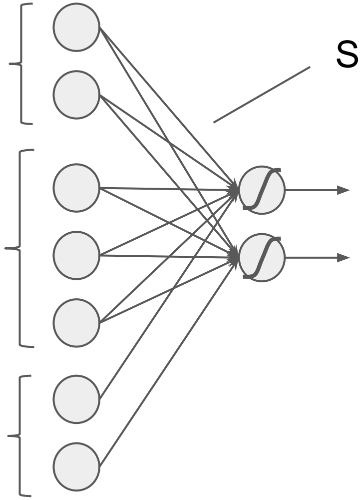
$$s_t = \varphi(W_b[s_{t-1}, x_t, 1])$$

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

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

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

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

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

But often “1” is omitted

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

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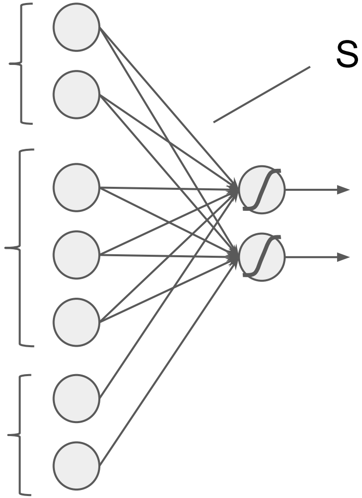

Single layer network

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

Vanilla RNN. Notations

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

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
7. LSTM with peephole connections
8. Conclusions

What’s wrong with Vanilla RNNs?

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↓

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

Main problems:

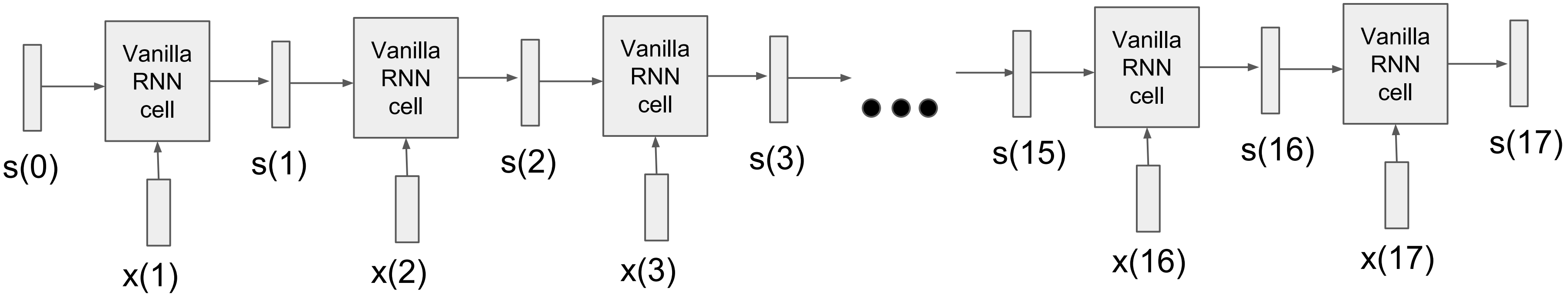
Information morphing (fundamental) ⇨ Inability to keep the memory content for more than a few time steps

⇩

Gradient vanishing (technical)

Information morphing

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



Information morphing

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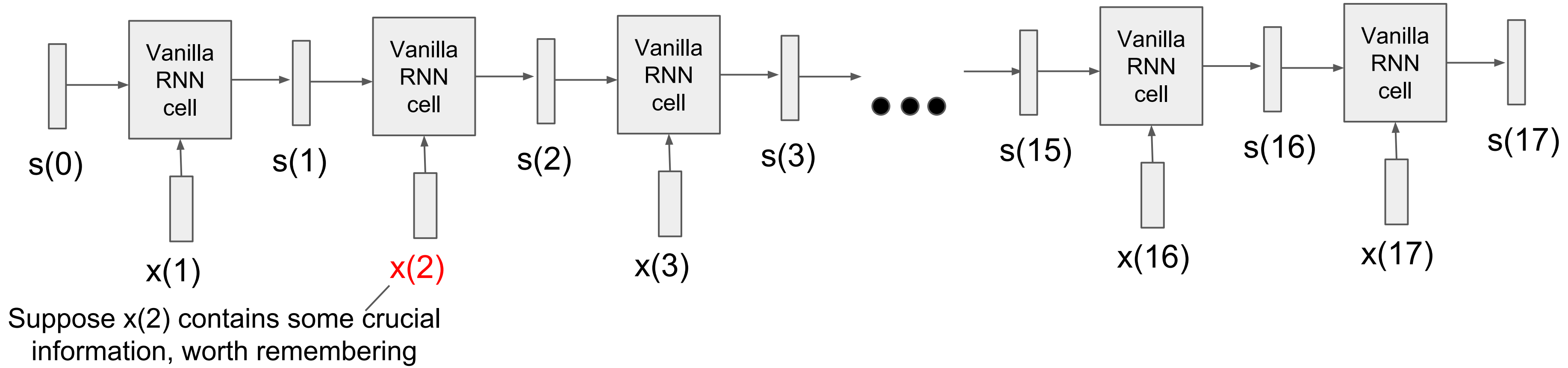

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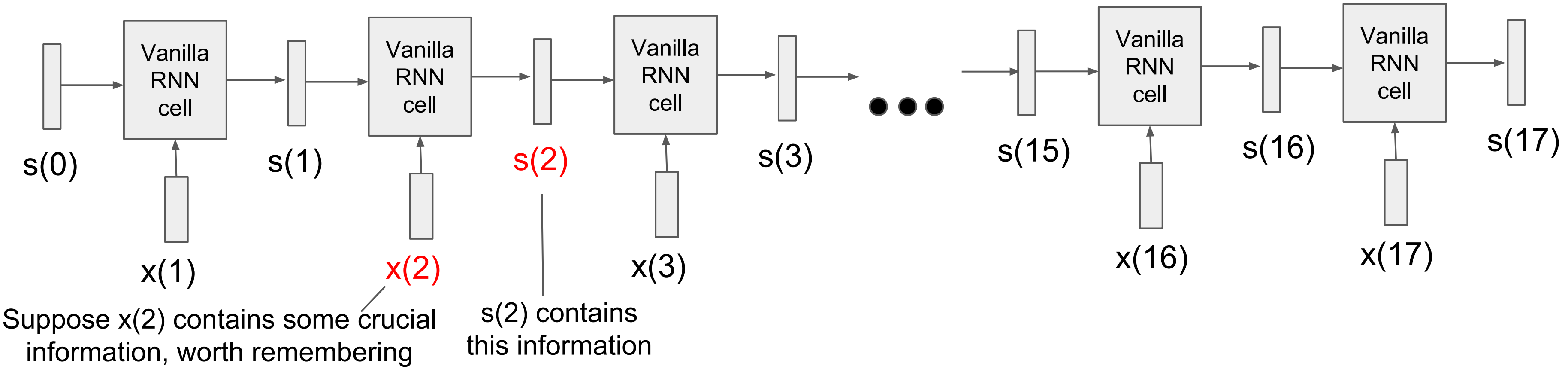

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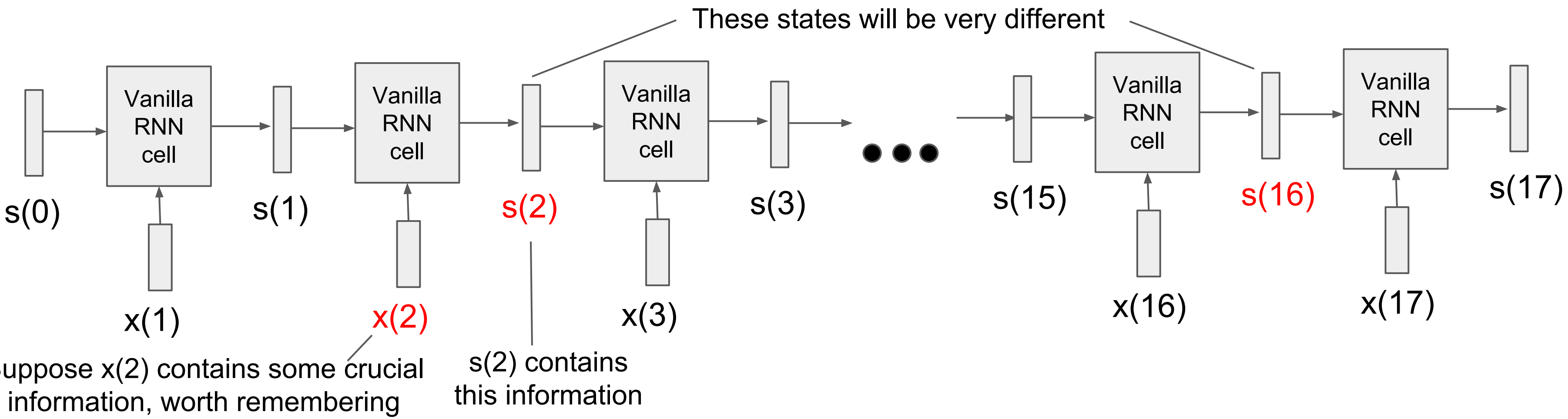

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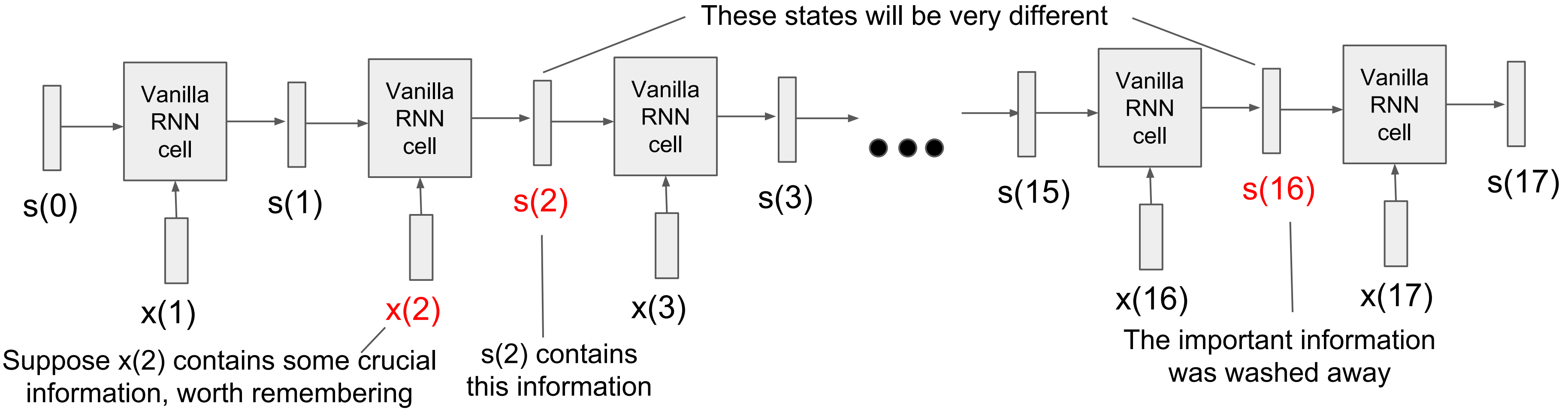

Information morphing

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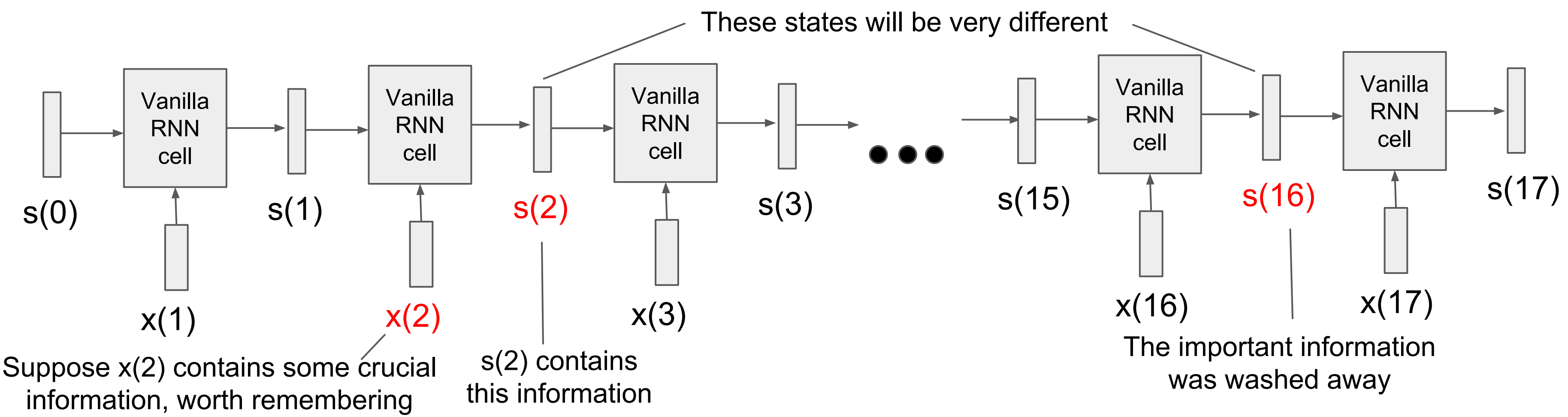
Why this happens?



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Information morphing

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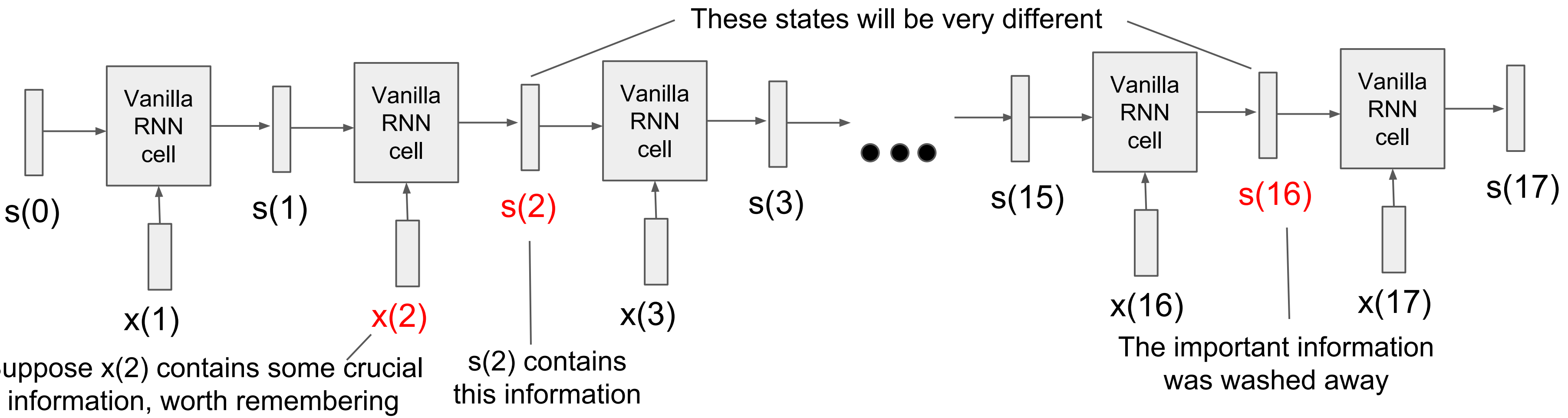
The rnn memory (state) should be protected: use only + or - operations to write to the memory



Information morphing

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Nonlinearity is bad for long term memory

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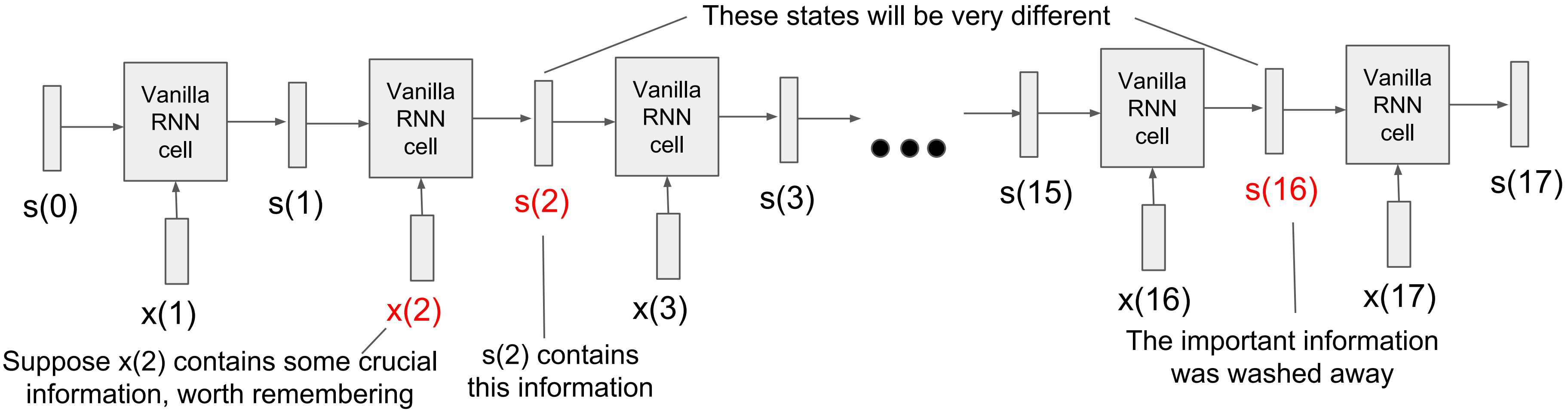

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Nonlinearity is bad for long term memory

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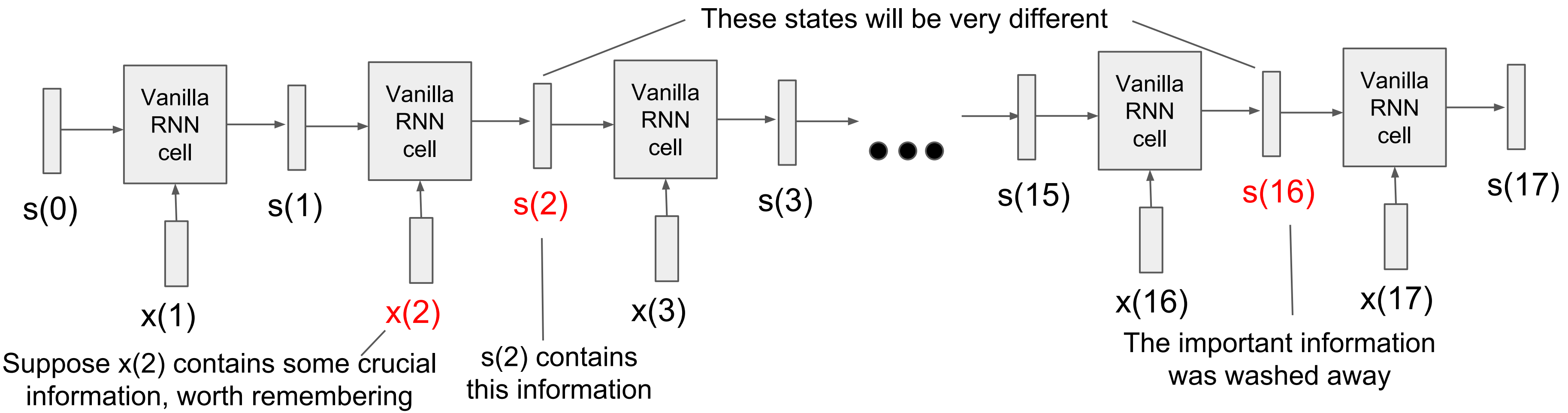
Be selective: choose what to read, write and forget



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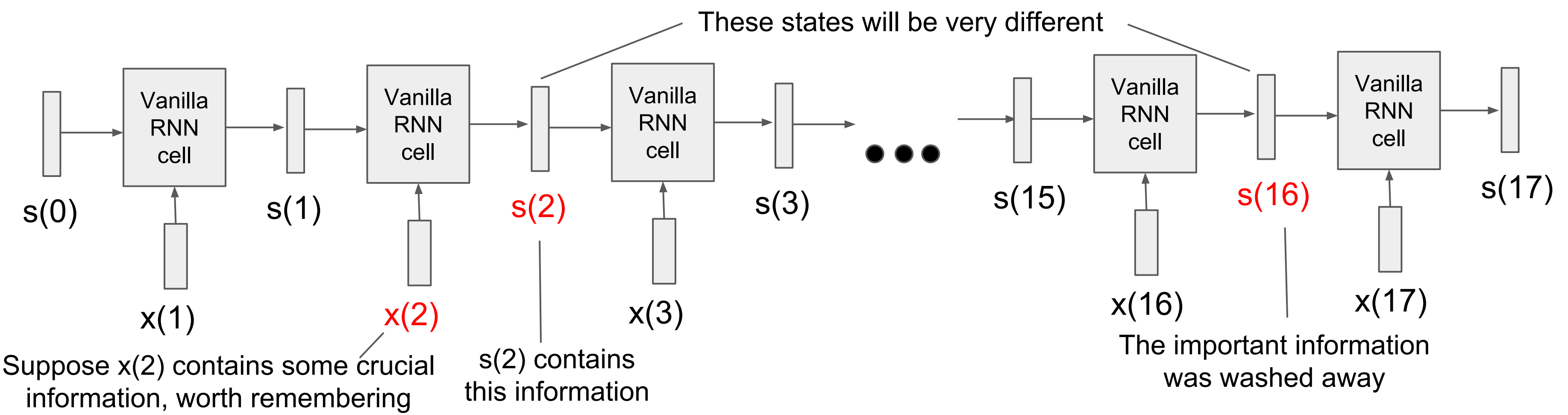

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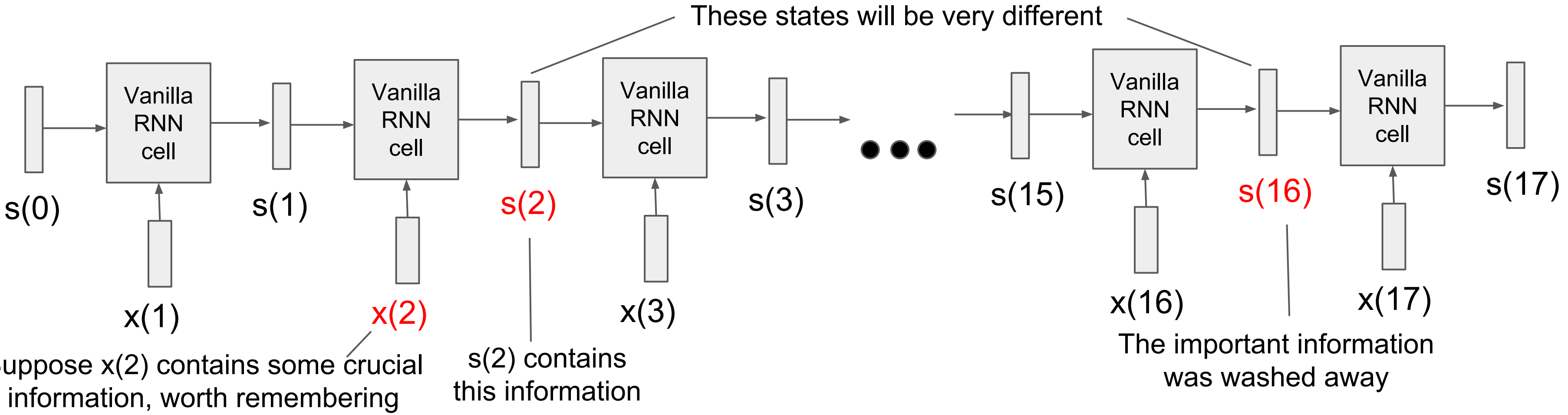

Protecting the state & selectivity through gates

$$\begin{pmatrix}\text{Current}\\\text{state}\end{pmatrix} = \begin{pmatrix}\text{Previous}\\\text{state}\end{pmatrix} + \begin{pmatrix}\text{New}\\\text{state}\\\text{candidate}\end{pmatrix}$$

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

Current state = Previous state + New state candidate

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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)

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

Very important pattern - protecting the state

Protecting the state & selectivity through gates

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

(Current state) = (Forget gate vector) ○ (Previous state) + ○ (New state candidate)

Protecting the state & selectivity through gates

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

$$\text{Current state} = \text{Forget gate vector} \circ \text{Previous state} + \text{Write gate vector} \circ \text{New state candidate}$$

Protecting the state & selectivity through gates

$$\left(\begin{matrix}\text{New}\\\text{state}\\\text{candidate}\end{matrix}\right) = \text{FUNC}\left[\left(\begin{matrix}\text{Read}\\\text{gate}\\\text{vector}\end{matrix}\right) \circ \left(\begin{matrix}\text{Previous}\\\text{state}\end{matrix}\right), \left(\begin{matrix}\text{Current}\\\text{input}\end{matrix}\right)\right]$$

$$\left(\begin{matrix}\text{Current}\\\text{state}\end{matrix}\right) = \left(\begin{matrix}\text{Forget}\\\text{gate}\\\text{vector}\end{matrix}\right) \circ \left(\begin{matrix}\text{Previous}\\\text{state}\end{matrix}\right) + \left(\begin{matrix}\text{Write}\\\text{gate}\\\text{vector}\end{matrix}\right) \circ \left(\begin{matrix}\text{New}\\\text{state}\\\text{candidate}\end{matrix}\right)$$

Protecting the state & selectivity through gates

$$\begin{pmatrix}\text{Forget}\\ \text{gate}\\ \text{vector}\end{pmatrix} = G\_F\left[\begin{pmatrix}\text{Previous}\\ \text{state}\end{pmatrix}, \begin{pmatrix}\text{Current}\\ \text{input}\end{pmatrix}\right]$$

$$\begin{pmatrix}\text{New}\\ \text{state}\\ \text{candidate}\end{pmatrix} = \text{FUNC}\left[\begin{pmatrix}\text{Read}\\ \text{gate}\\ \text{vector}\end{pmatrix} \circ \begin{pmatrix}\text{Previous}\\ \text{state}\end{pmatrix}, \begin{pmatrix}\text{Current}\\ \text{input}\end{pmatrix}\right]$$

$$\begin{pmatrix}\text{Current}\\ \text{state}\end{pmatrix} = \begin{pmatrix}\text{Forget}\\ \text{gate}\\ \text{vector}\end{pmatrix} \circ \begin{pmatrix}\text{Previous}\\ \text{state}\end{pmatrix} + \begin{pmatrix}\text{Write}\\ \text{gate}\\ \text{vector}\end{pmatrix} \circ \begin{pmatrix}\text{New}\\ \text{state}\\ \text{candidate}\end{pmatrix}$$

Protecting the state & selectivity through gates

$$\text{Write gate vector} = G\_W\left[\text{Previous state}, \text{Current input}\right]$$

$$\text{Forget gate vector} = G\_F\left[\text{Previous state}, \text{Current input}\right]$$

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

$$\text{Current state} = \text{Forget gate vector} \circ \text{Previous state} + \text{Write gate vector} \circ \text{New state candidate}$$

Protecting the state & selectivity through gates

$$\text{Read gate vector} = G\_R\left[\text{Previous state}, \text{Current input}\right]$$

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Protecting the state & selectivity through gates

(Read gate vector) = G_R [(Previous state), (Current input)]

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Single layer network

(New state candidate) = FUNC [(Read gate vector) ○ (Previous state), (Current input)]

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Protecting the state & selectivity through gates

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Single layer network

What kind of activation function are used?

(New state candidate) = FUNC [(Read gate vector) ○ (Previous state), (Current input)]

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Protecting the state & selectivity through gates

Read gate vector = G_R [Previous state , Current input]

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sigmoid

sigmoid

sigmoid

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sigmoid

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sigmoid

Single layer network

What kind of activation function are used?

tanh

New state candidate = FUNC [Read gate vector ∘ Previous state, Current input]

Current state = Forget gate vector ∘ Previous state + Write gate vector ∘ New state candidate

Protecting the state & selectivity through gates

$$\begin{pmatrix}\text{Read}\\ \text{gate}\\ \text{vector}\end{pmatrix} = G\_R\left[\begin{pmatrix}\text{Previous}\\ \text{state}\end{pmatrix}, \begin{pmatrix}\text{Current}\\ \text{input}\end{pmatrix}\right] \qquad \begin{pmatrix}\text{Write}\\ \text{gate}\\ \text{vector}\end{pmatrix} = G\_W\left[\begin{pmatrix}\text{Previous}\\ \text{state}\end{pmatrix}, \begin{pmatrix}\text{Current}\\ \text{input}\end{pmatrix}\right] \qquad \begin{pmatrix}\text{Forget}\\ \text{gate}\\ \text{vector}\end{pmatrix} = G\_F\left[\begin{pmatrix}\text{Previous}\\ \text{state}\end{pmatrix}, \begin{pmatrix}\text{Current}\\ \text{input}\end{pmatrix}\right]$$

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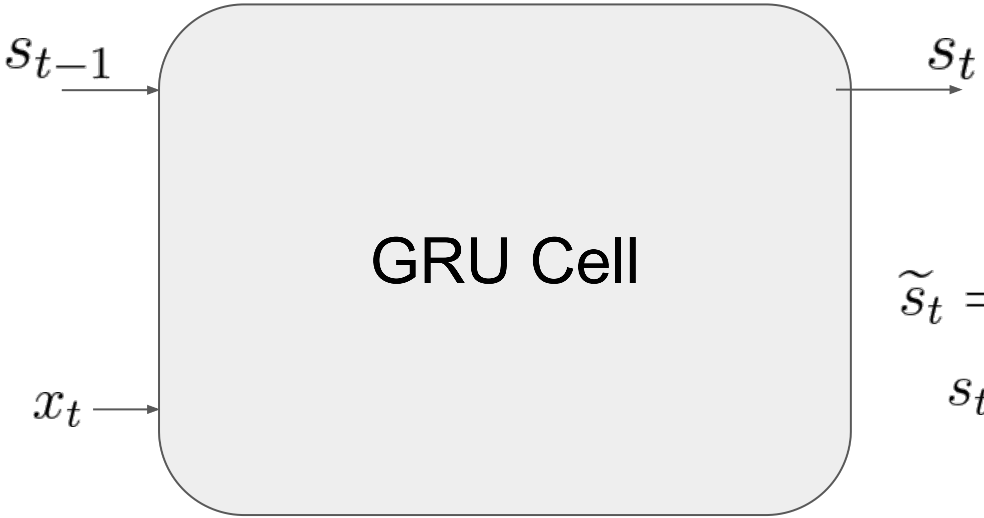
GRU Cell step by step



GRU equations

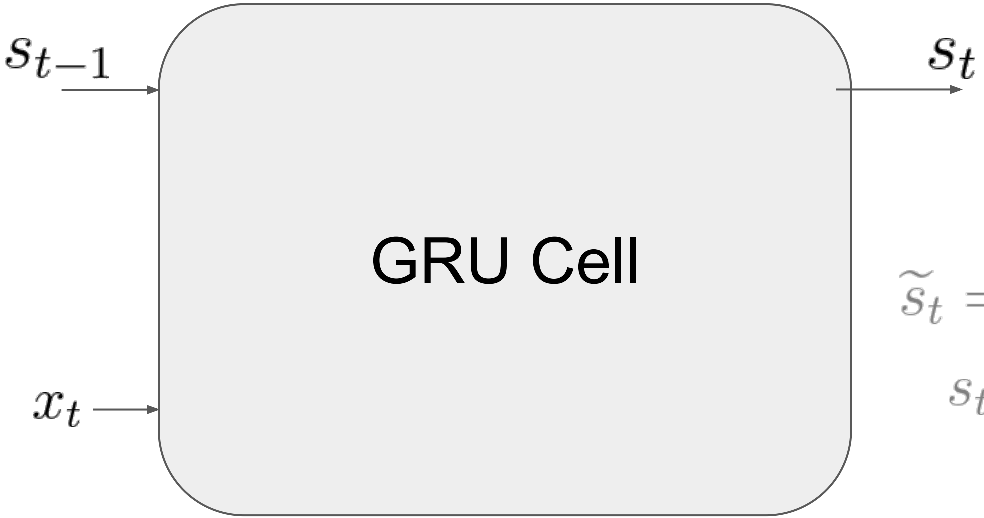
$$r_t = \sigma(W_r s_{t-1} + U_r x_t + b_r) \quad \text{Read gate}$$

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

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

$$s_t = z_t \circ s_{t-1} + \underbrace{(1 - z_t)}_{\text{Write gate}} \circ \widetilde{s}_t \quad \text{Current State}$$

GRU Cell step by step



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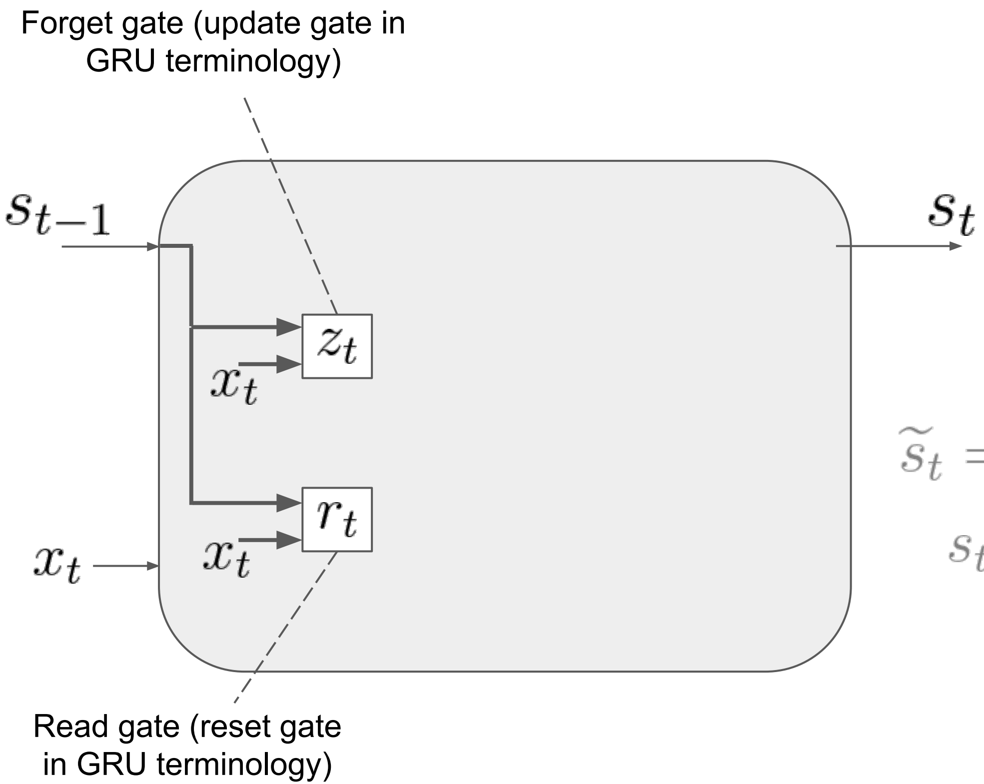

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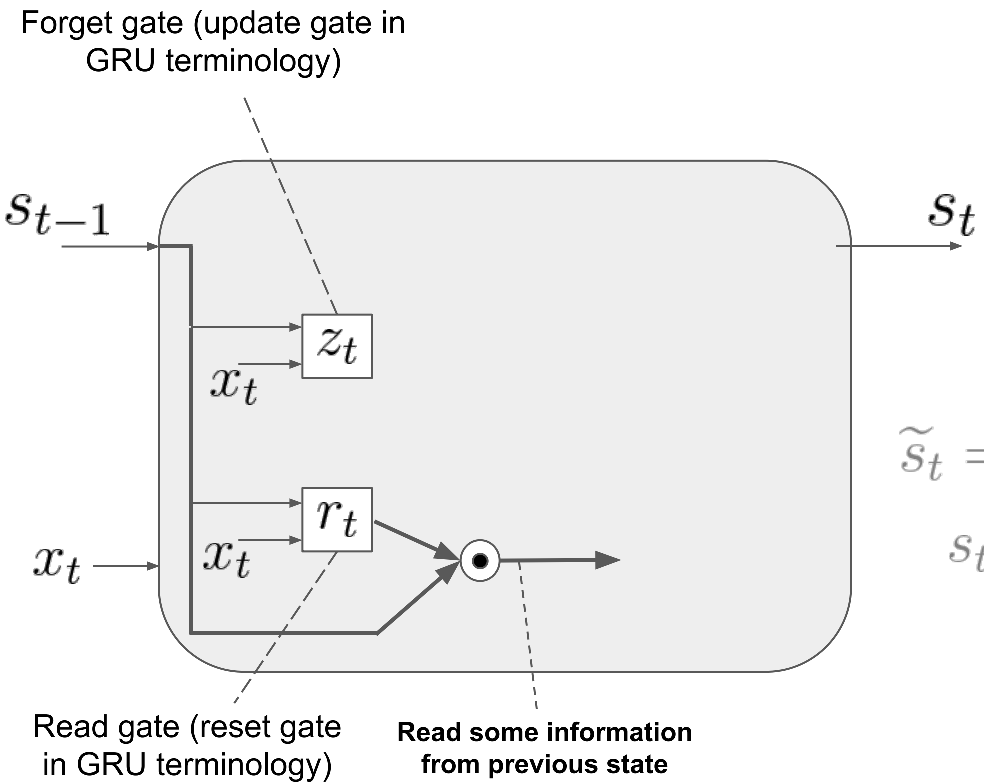

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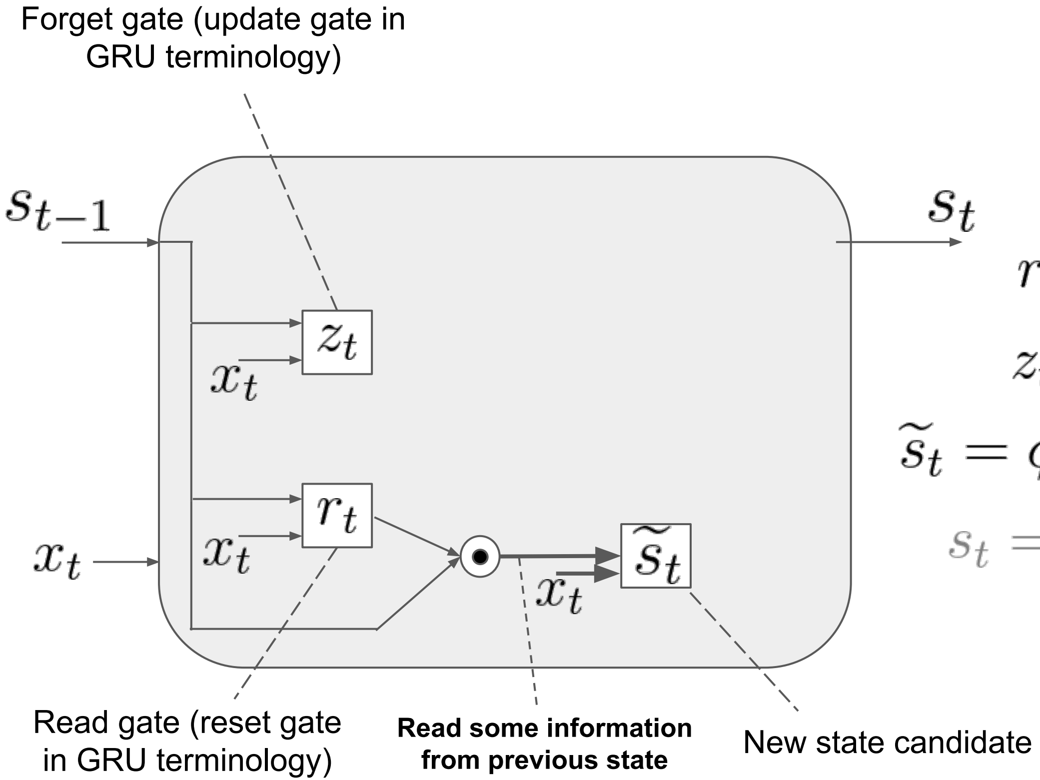

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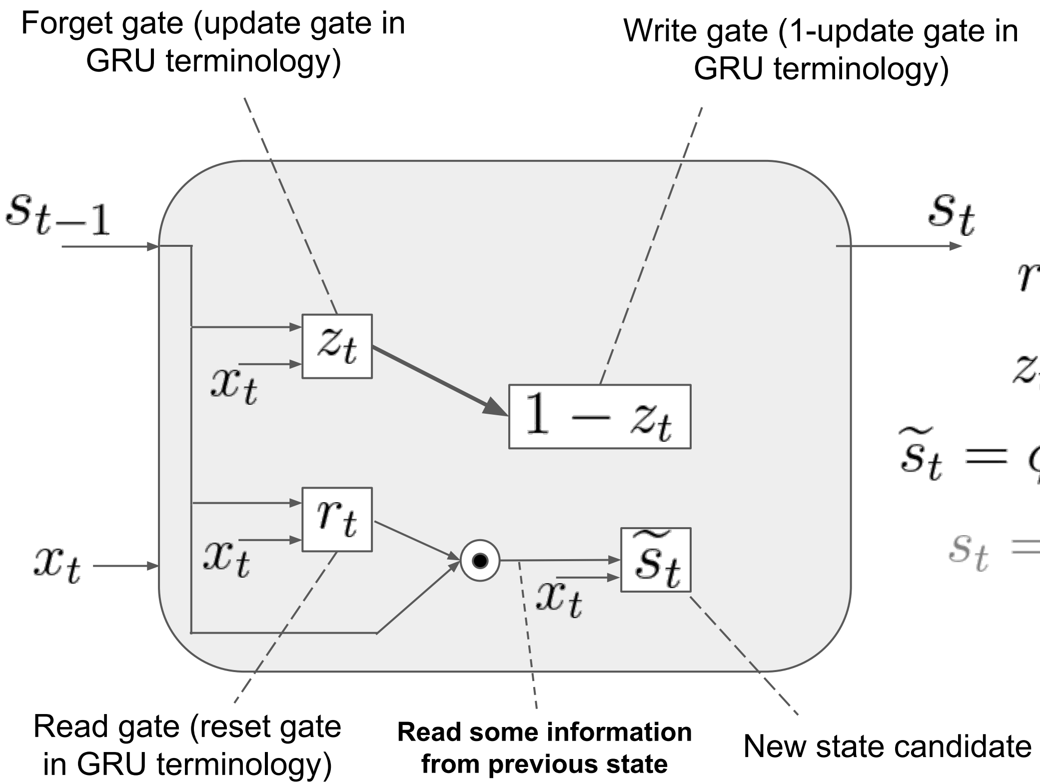

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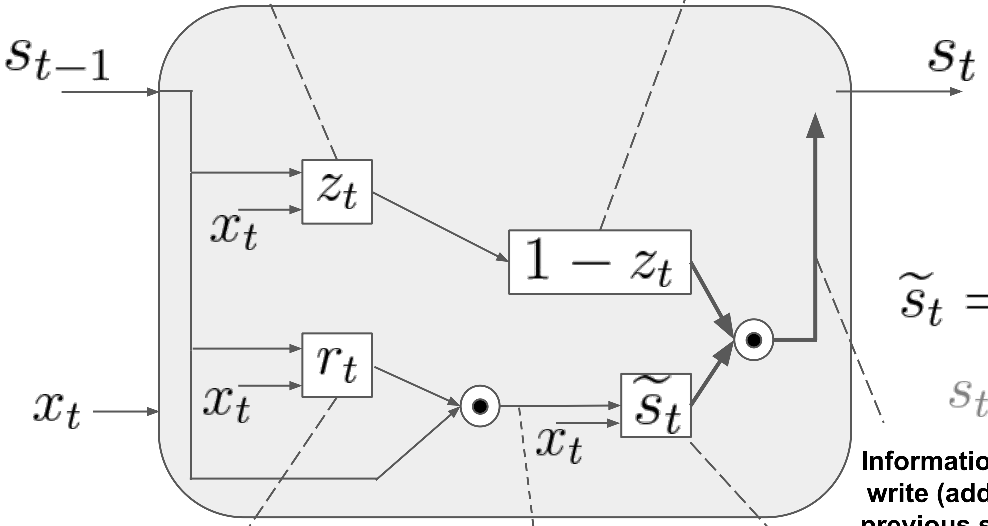
$$s_t = z_t \circ s_{t-1} + \underbrace{(1 - z_t)}_{\text{Write gate}} \circ \tilde{s}_t$$ Current State

GRU Cell step by step



GRU equations

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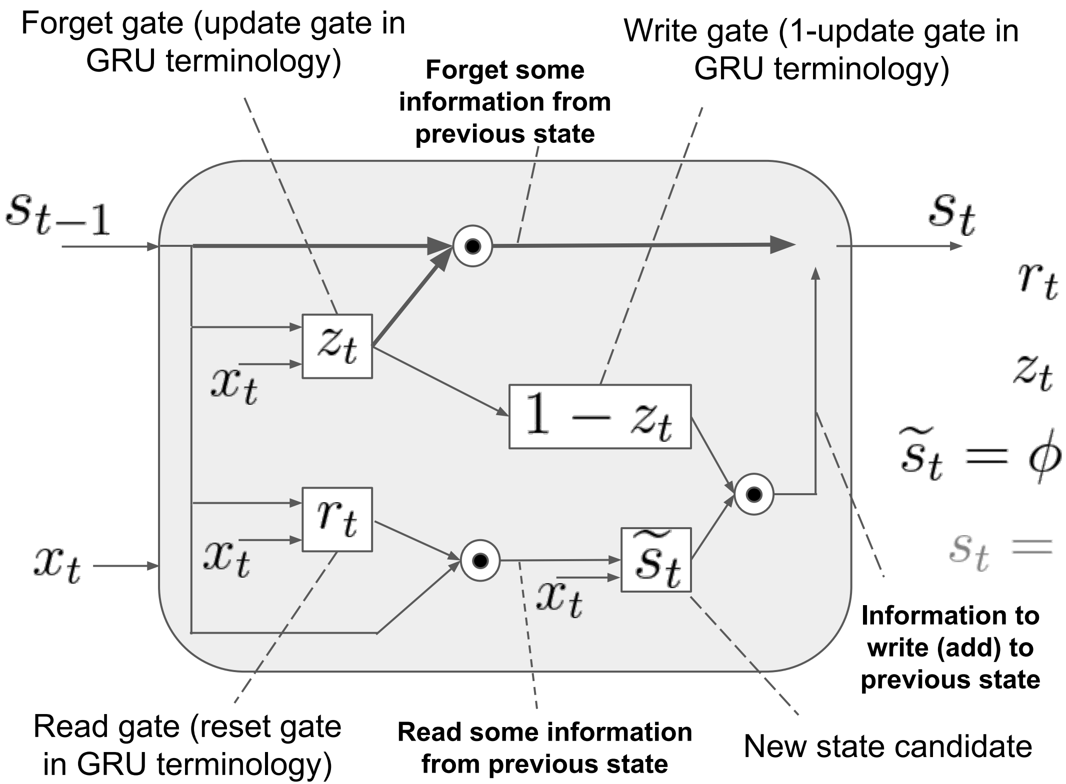
GRU Cell step by step



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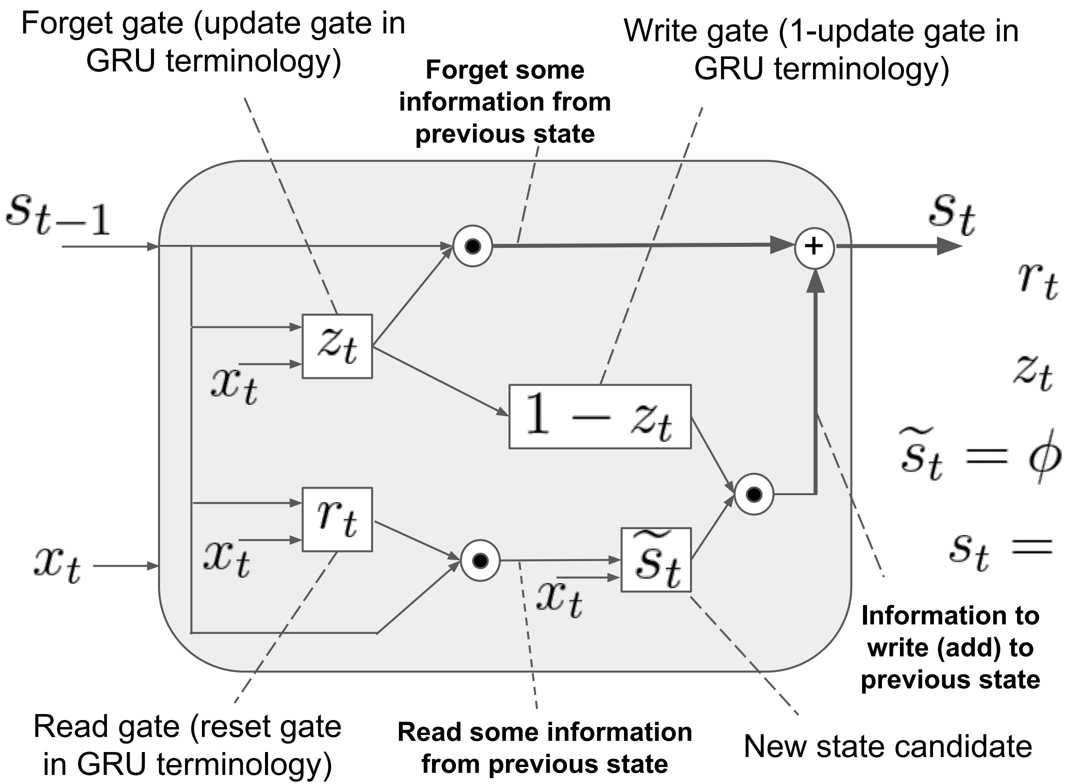

GRU equations

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

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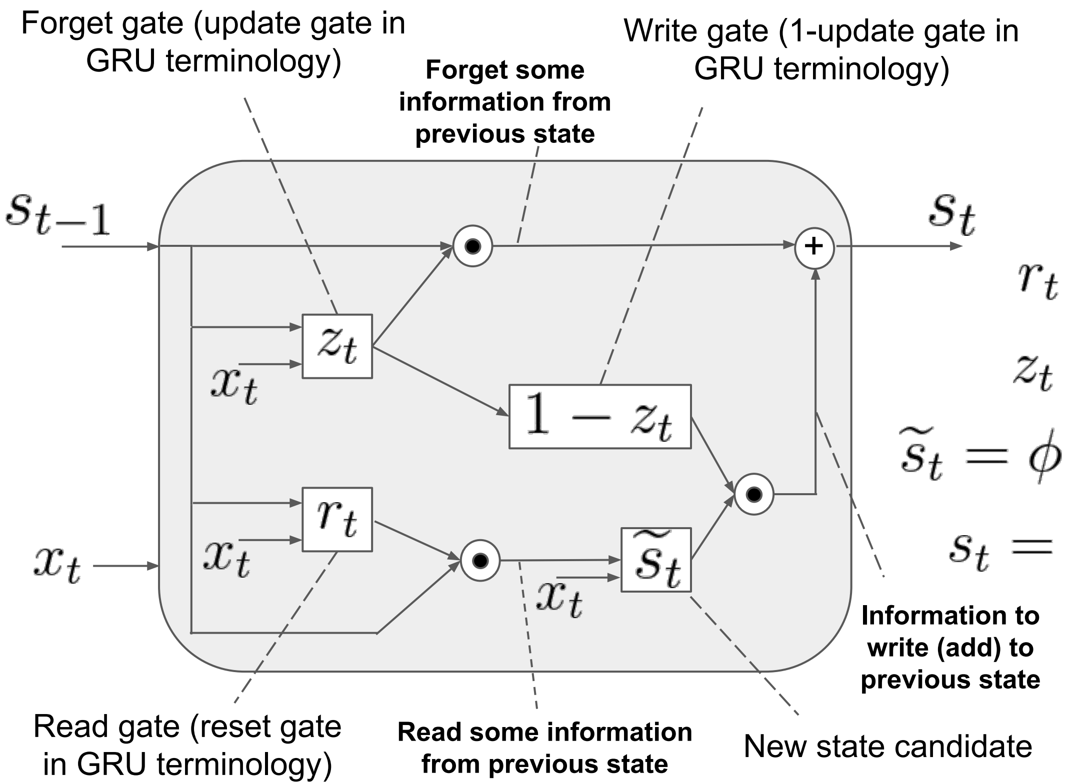
GRU Cell step by step



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

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

GRU Cell step by step

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

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

GRU Cell step by step

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

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GRU Cell step by step

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

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

Update gate = vector of zeros

GRU Cell step by step

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

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

Update gate = vector of zeros

GRU Cell step by step

GRU equations | In GRU terminology

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

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GRU Cell step by step

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

GRU Cell step by step

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

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

Update gate = vector of ones

GRU Cell step by step

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$r_t = \sigma(W_r s_{t-1} + U_r x_t + b_r)$	Reset gate
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$$\begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} \circ \begin{pmatrix} s_{t-1}^1 \\ s_{t-1}^2 \\ s_{t-1}^3 \end{pmatrix} + \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix} \circ \begin{pmatrix} \widetilde{s}_t^1 \\ \widetilde{s}_t^2 \\ \widetilde{s}_t^3 \end{pmatrix}$$

Update gate = vector of ones

GRU Cell step by step

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Update gate = vector of ones

GRU Cell step by step

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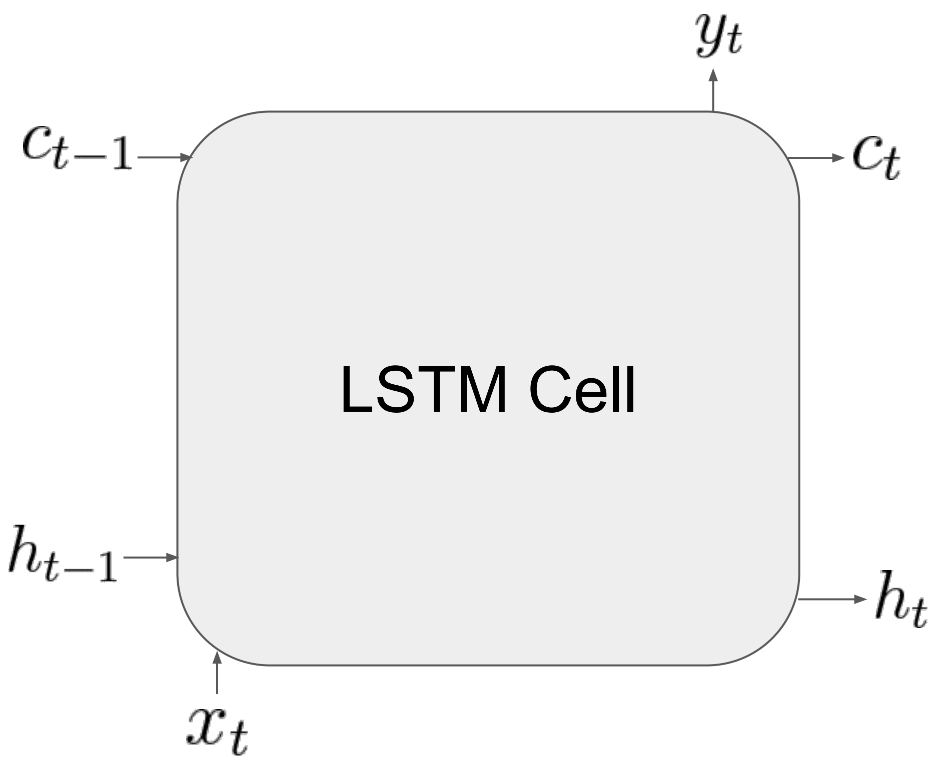
Completely ignore current input and state candidate

Update gate = vector of ones ⇨ **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

LSTM Cell

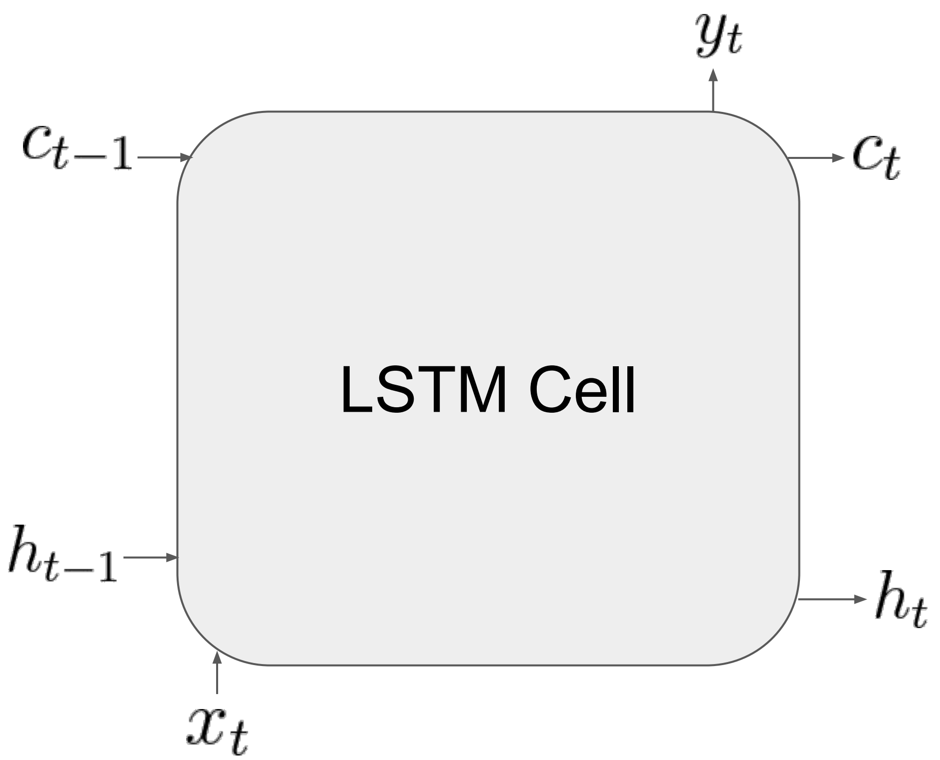


LSTM Cell

The state is a pair of vectors:

c_t — Memory Cell

h_t — Shadow State (gated version of memory cell)



LSTM Cell

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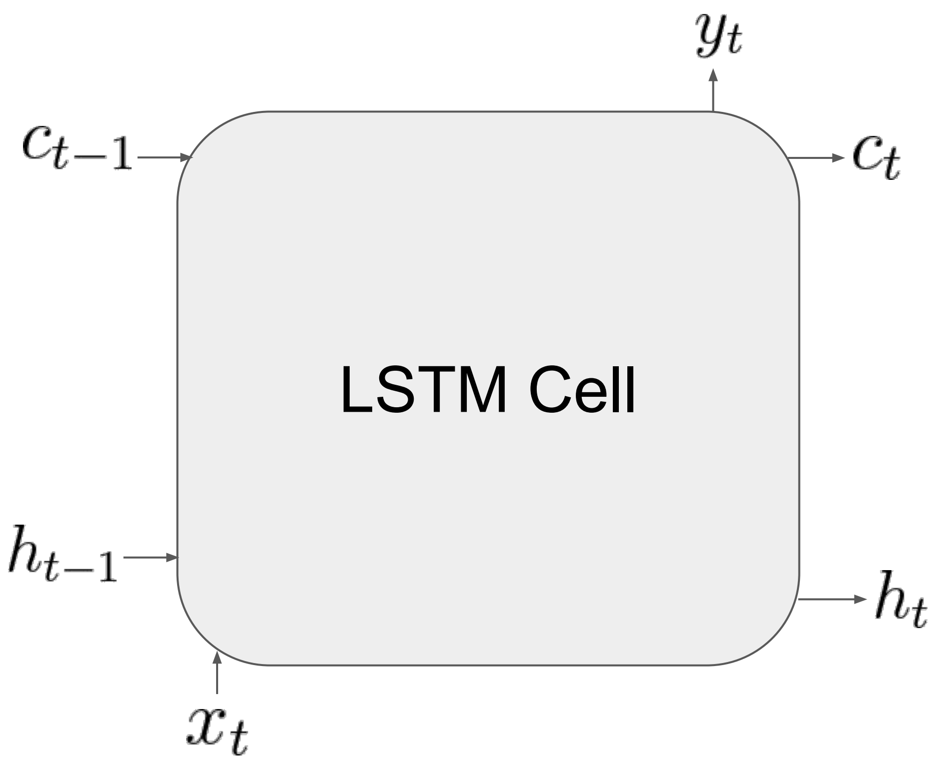
The output is a part of the state:

$y_t = h_t$ — Cell output



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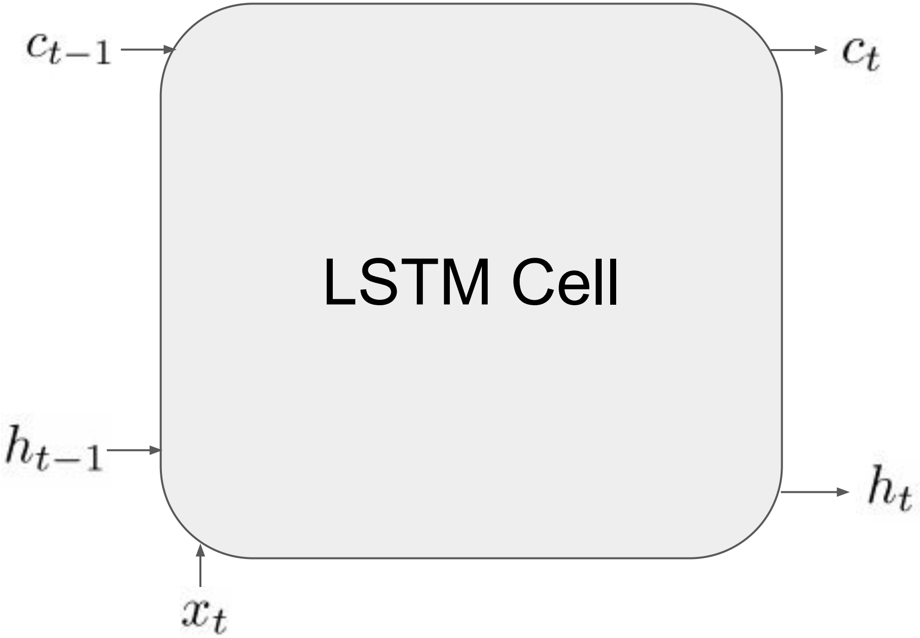

LSTM equations

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

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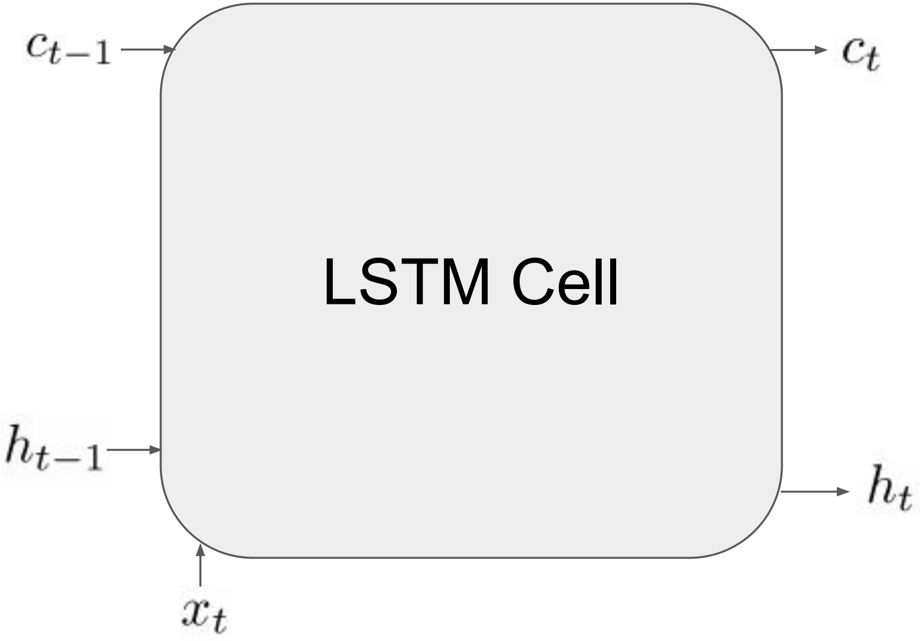
LSTM Cell



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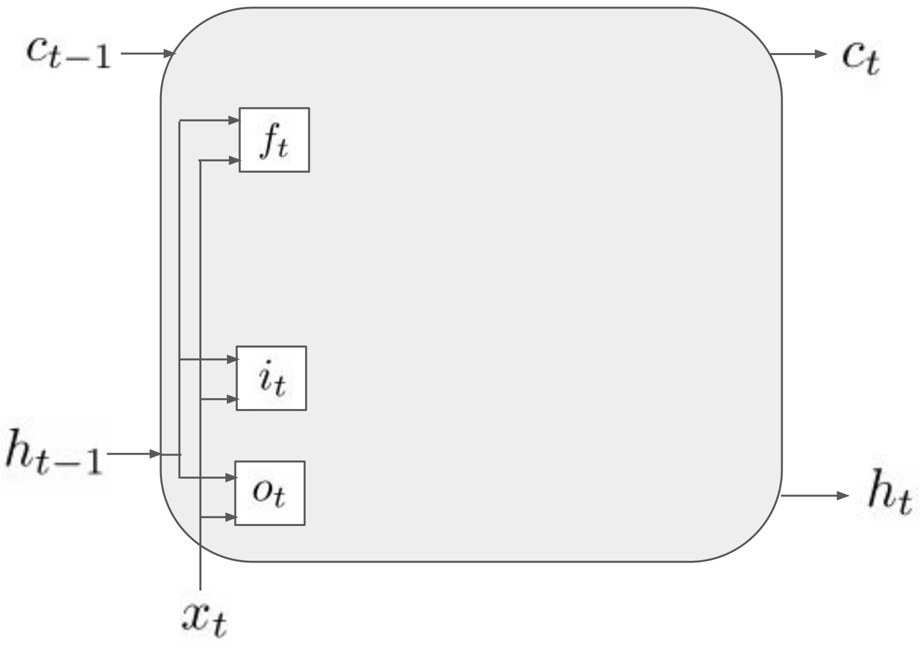

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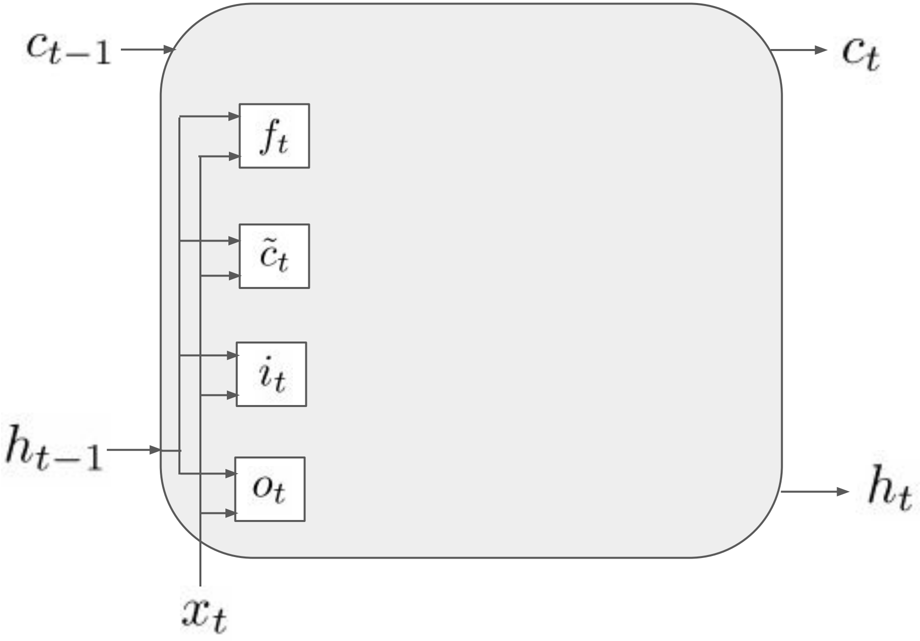

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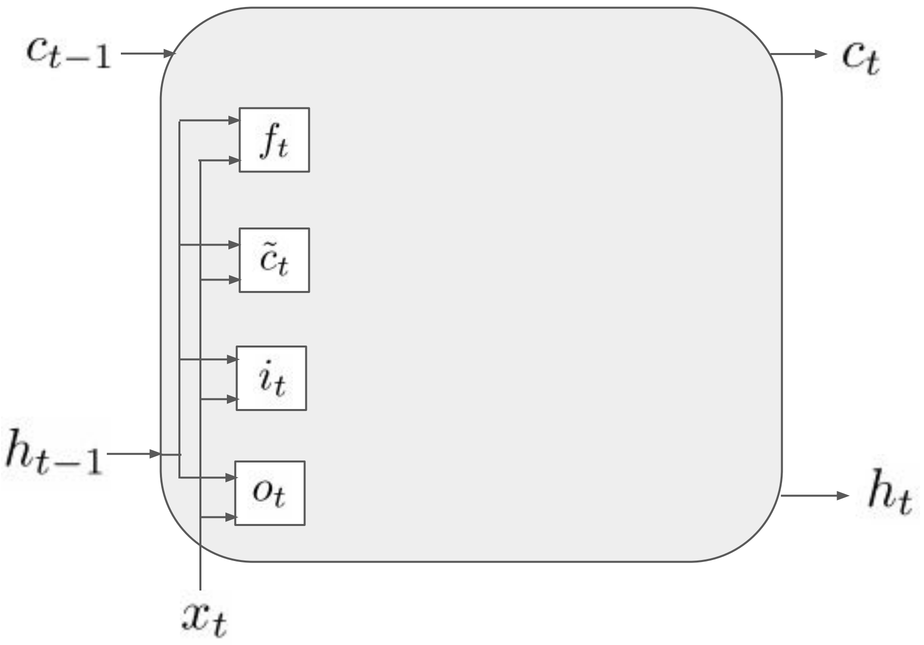
LSTM Cell

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



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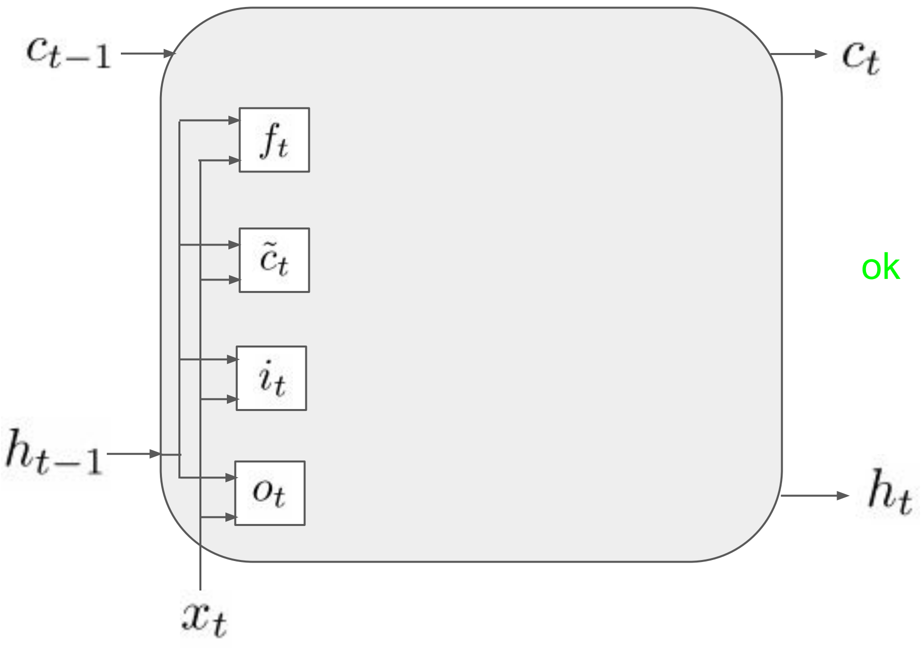

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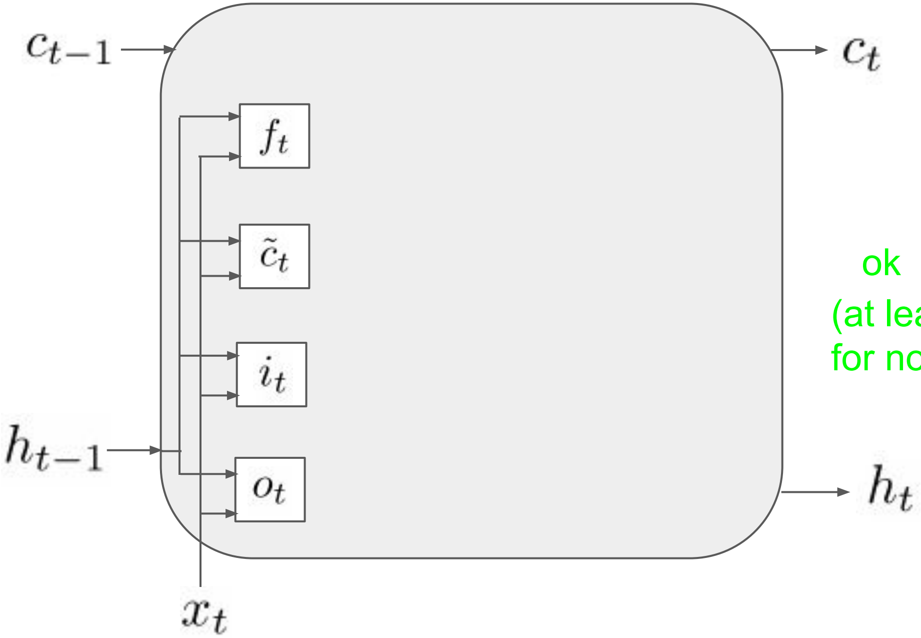

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LSTM Cell

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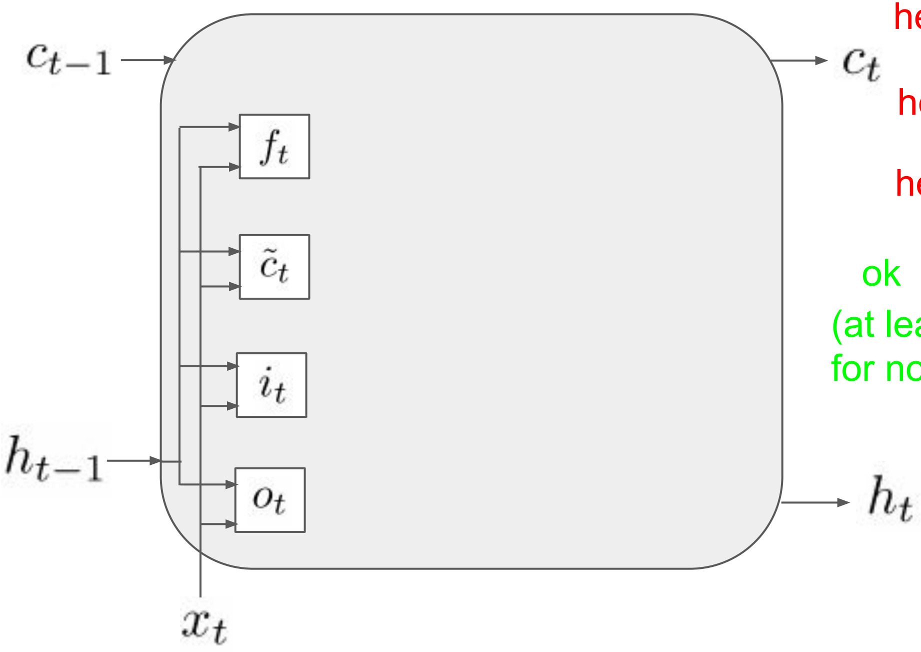

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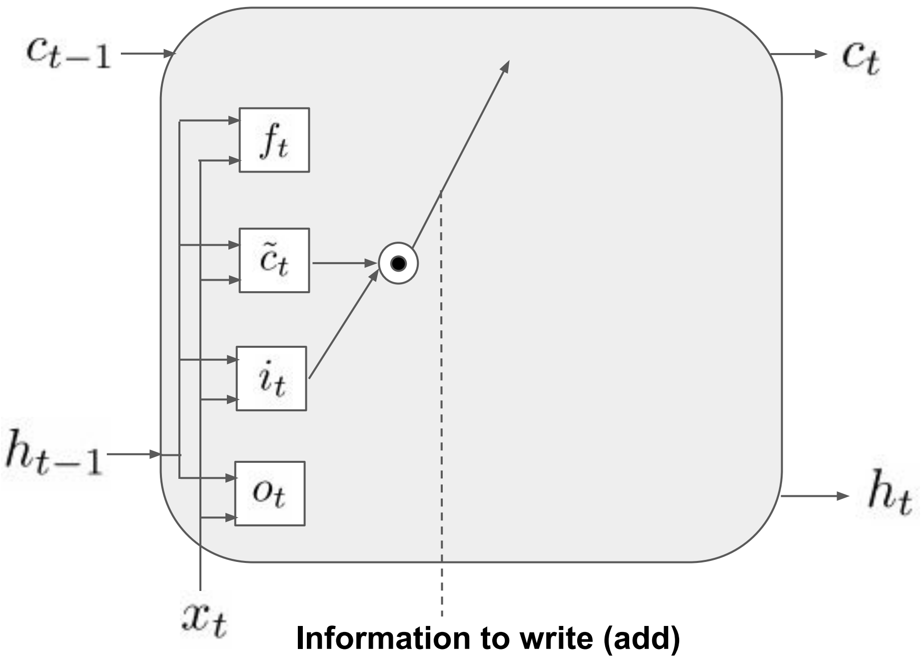
LSTM Cell



Information to write (add) to previous state

LSTM equations

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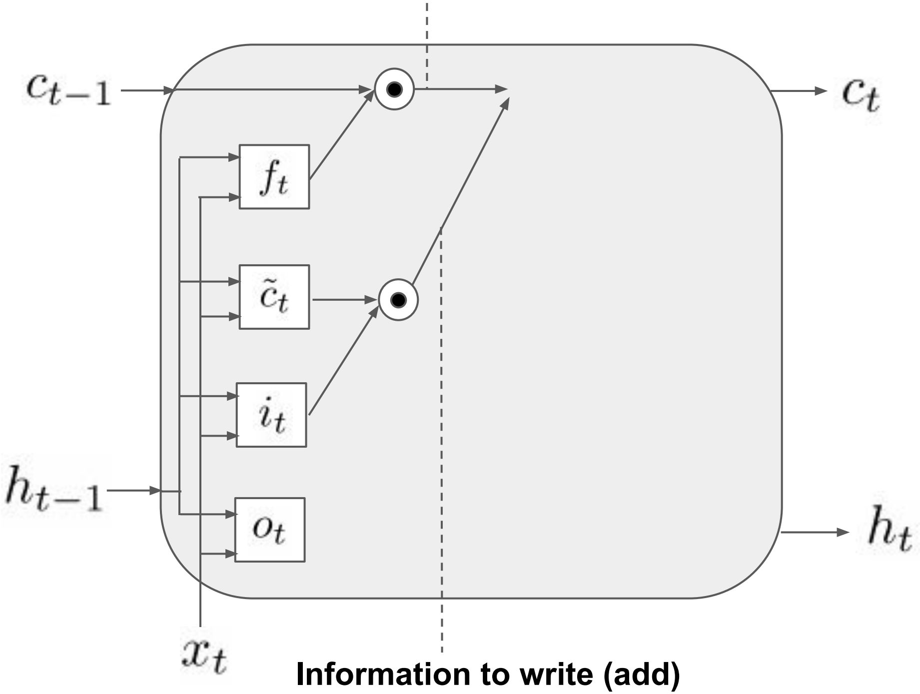
$$y_t = h_t$$ Cell Output

LSTM Cell

Forget some information from previous state



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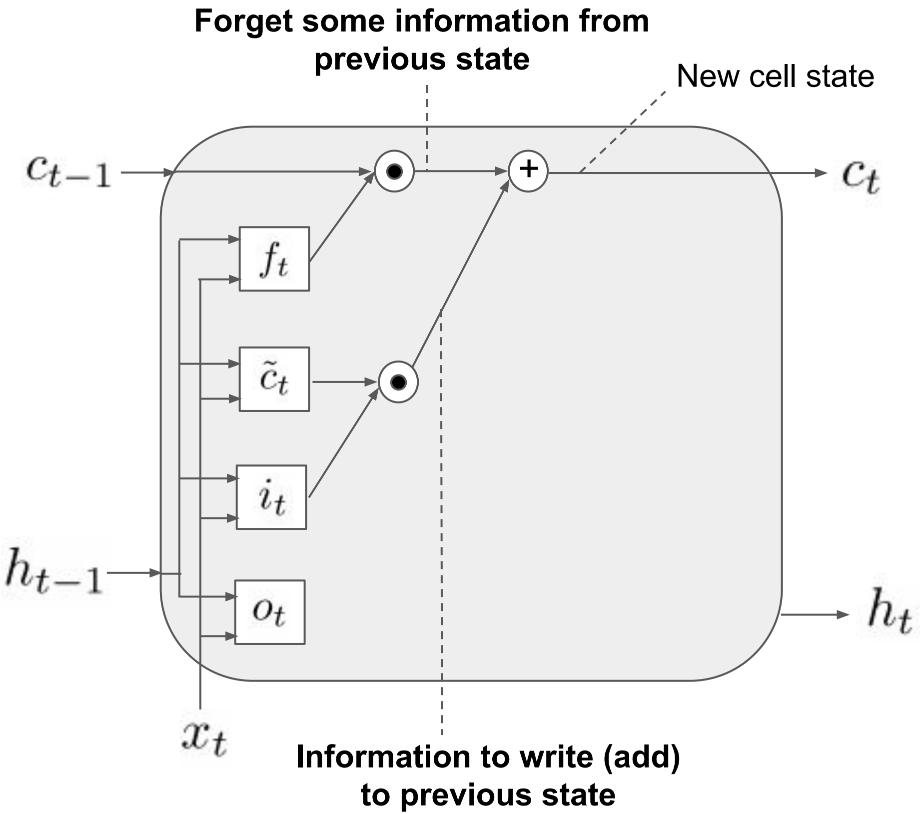
LSTM Cell



LSTM equations

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

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

$$y_t = h_t$$ Cell Output

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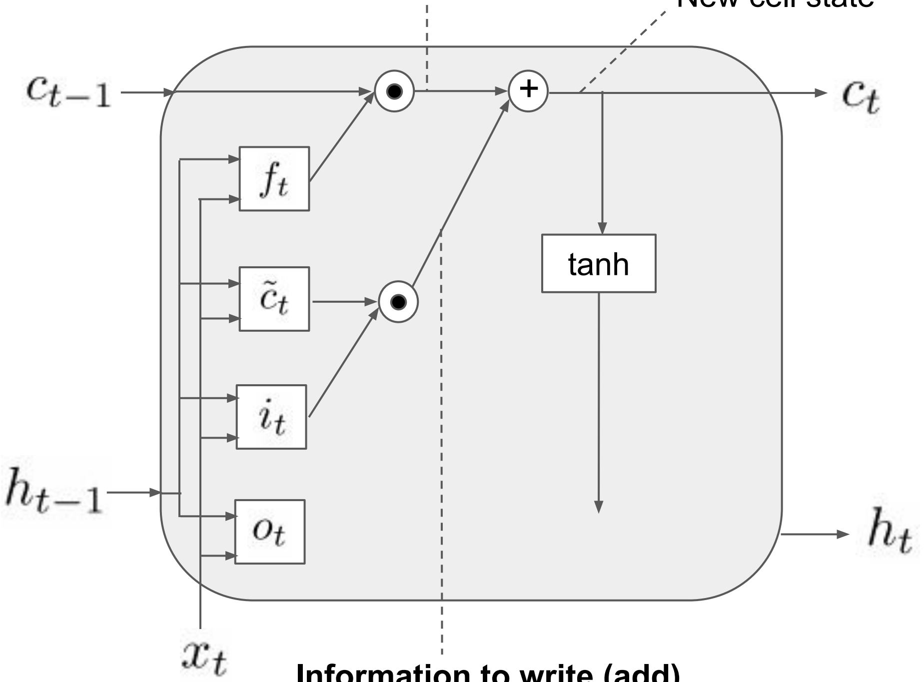
LSTM Cell



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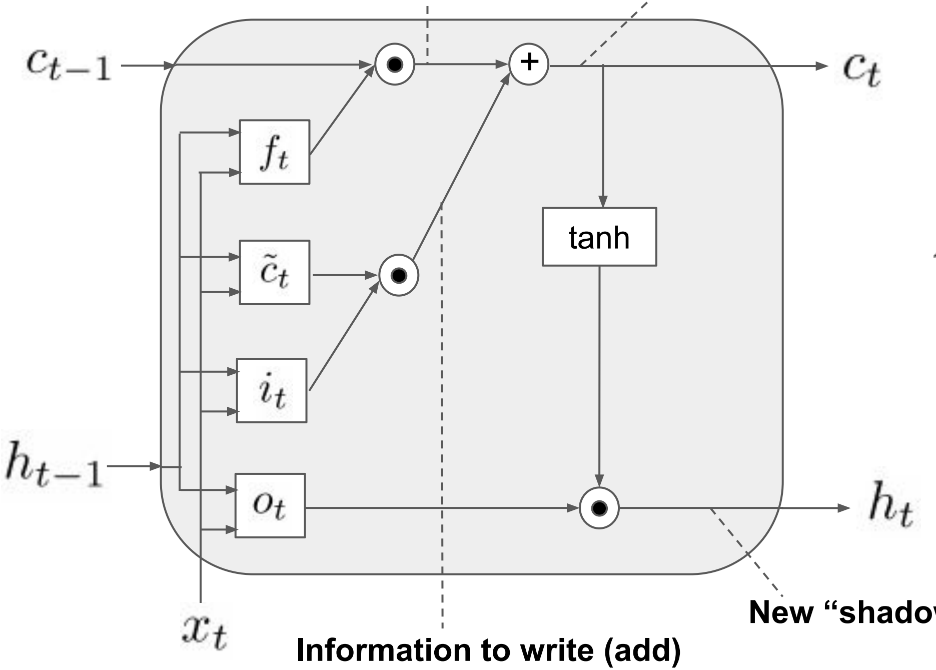

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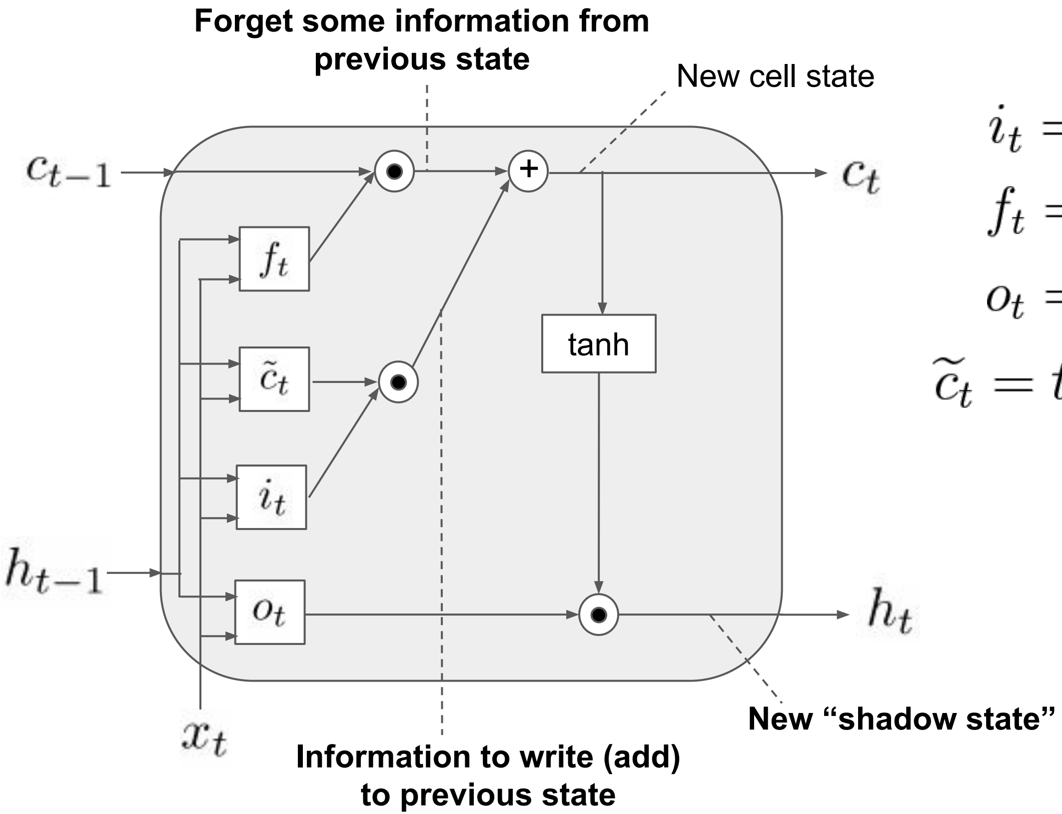

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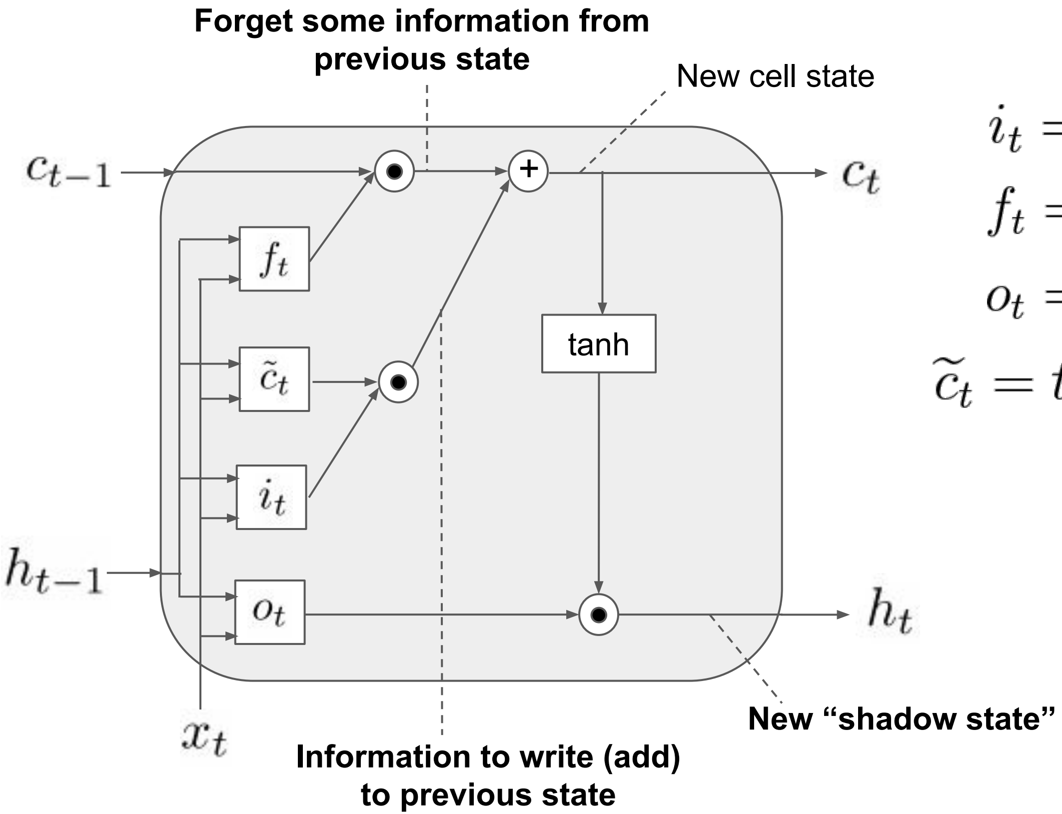

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Where are Read/Write gates?

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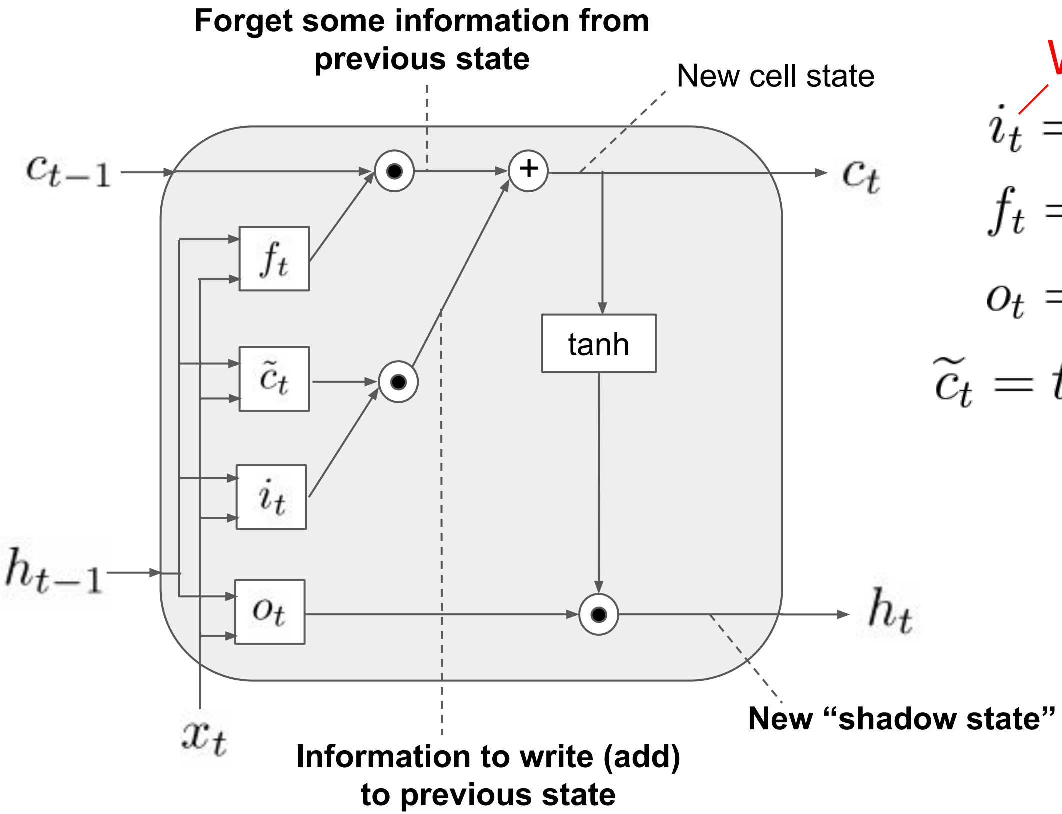
LSTM Cell



LSTM equations

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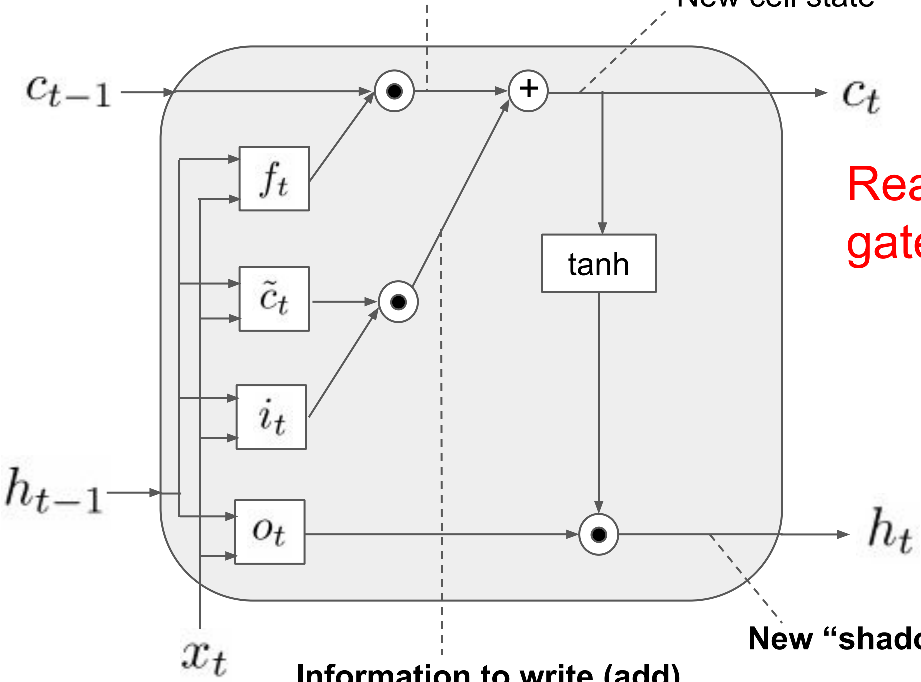

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Write gate

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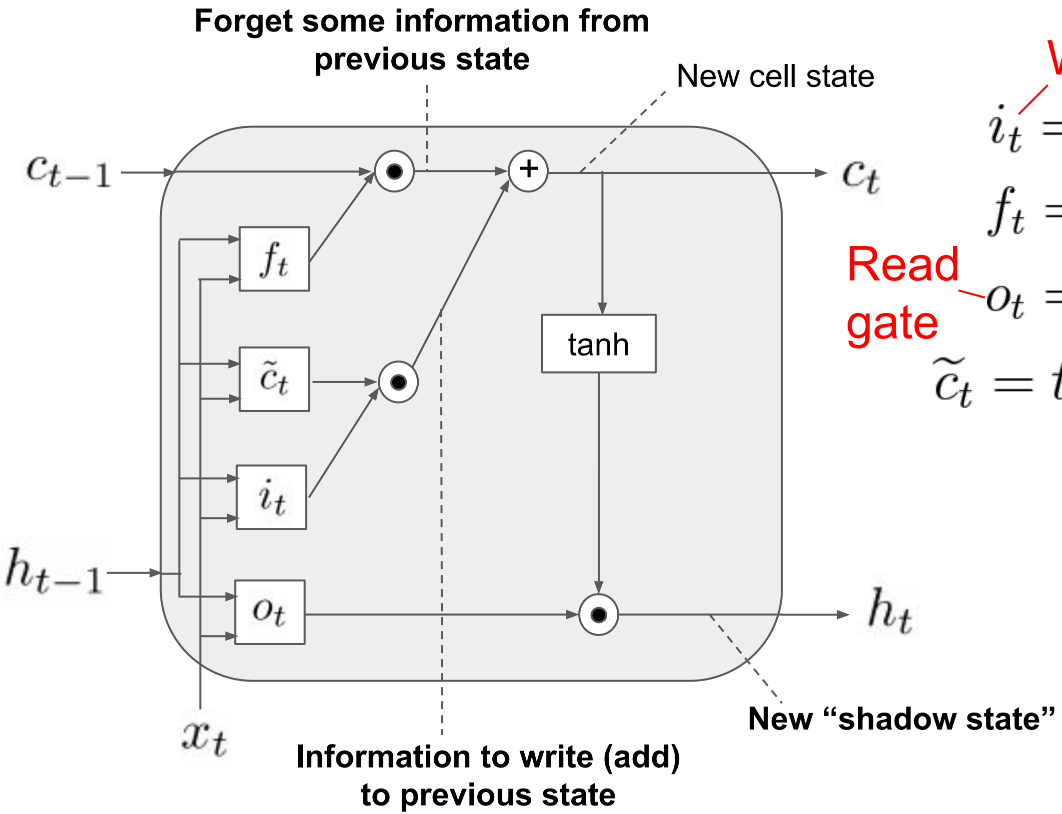

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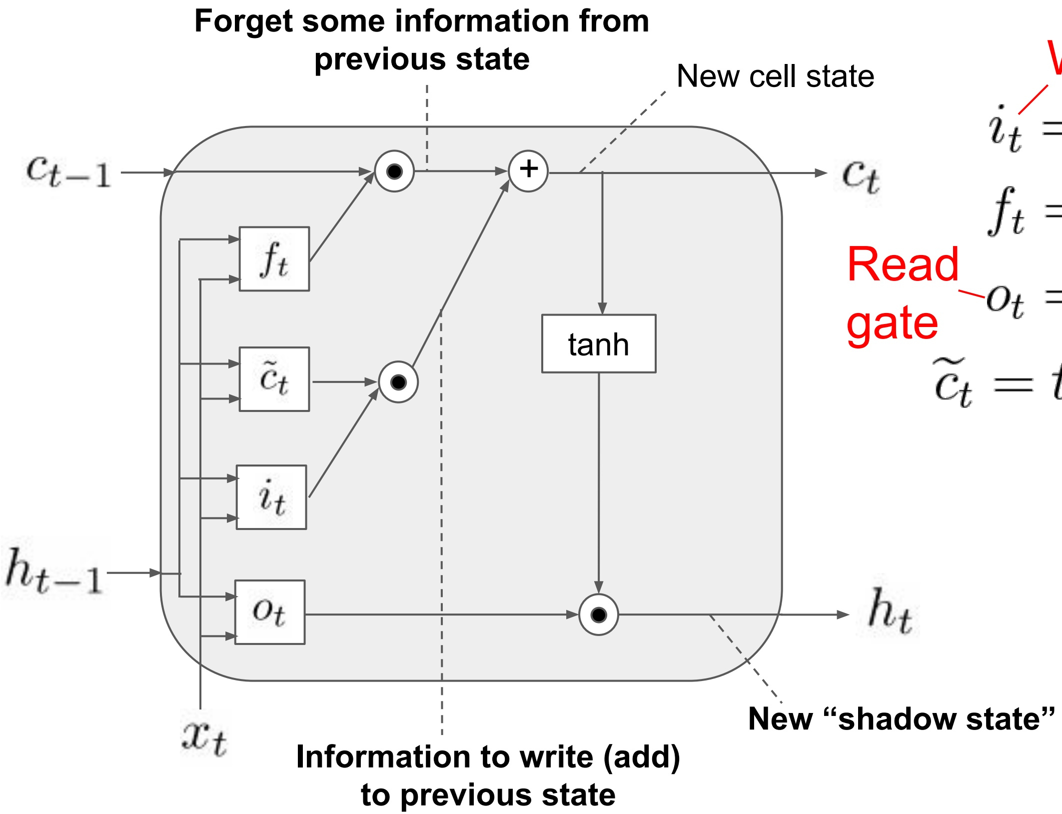
Reading occurs after writing

LSTM Cell



We use shadow state to calculate gates

LSTM equations

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Reading occurs after writing

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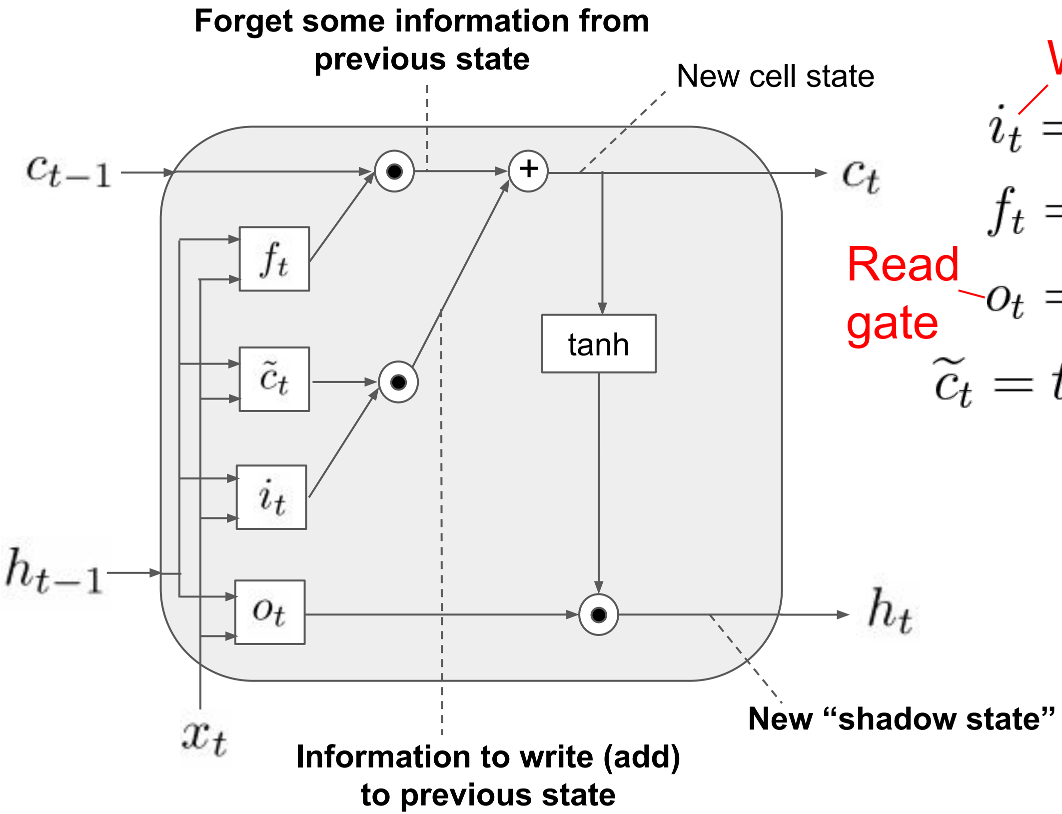
LSTM Cell



Conceptually, we lose information

We use shadow state to calculate gates

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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

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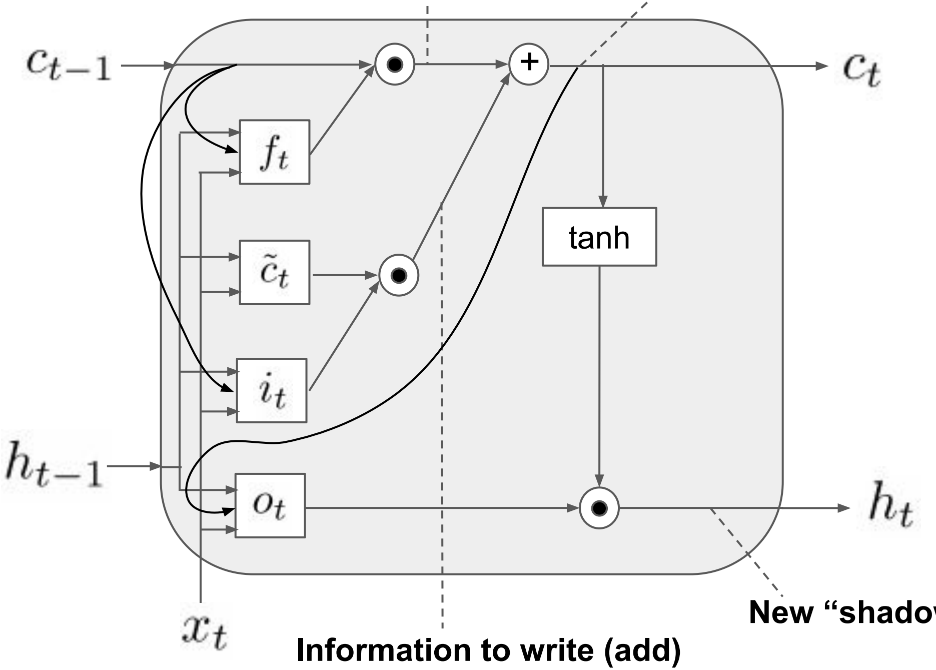
LSTM Cell with Peephole connections



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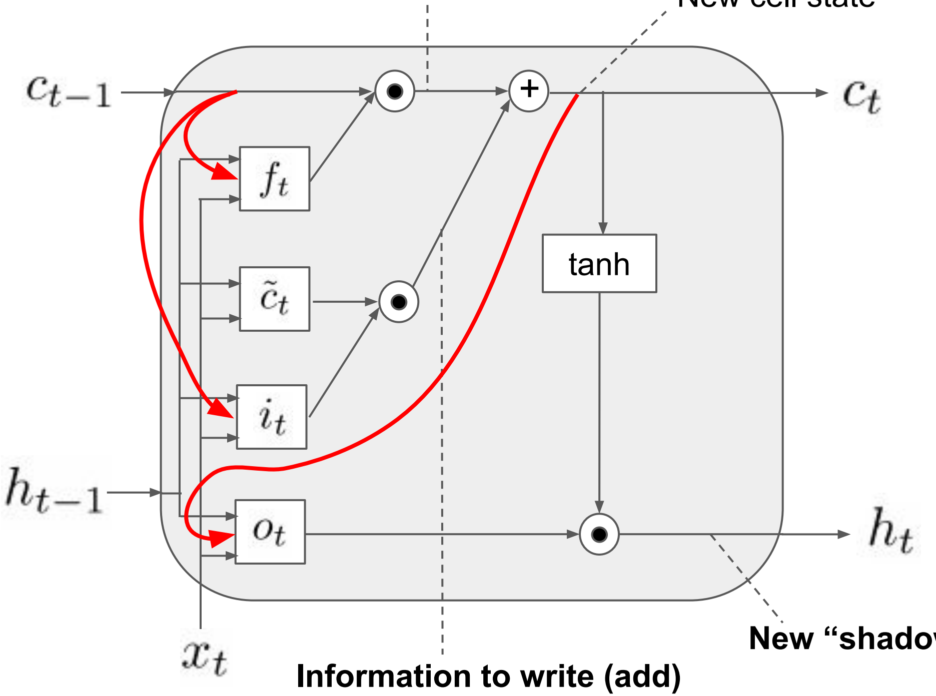

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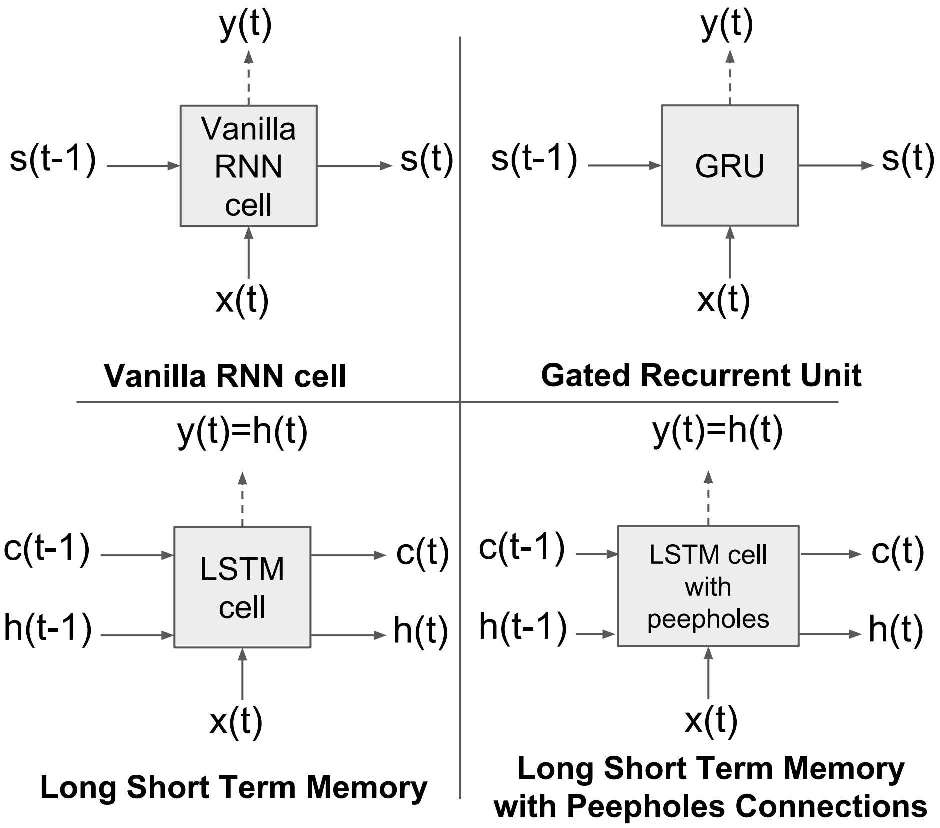
Talk outline

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

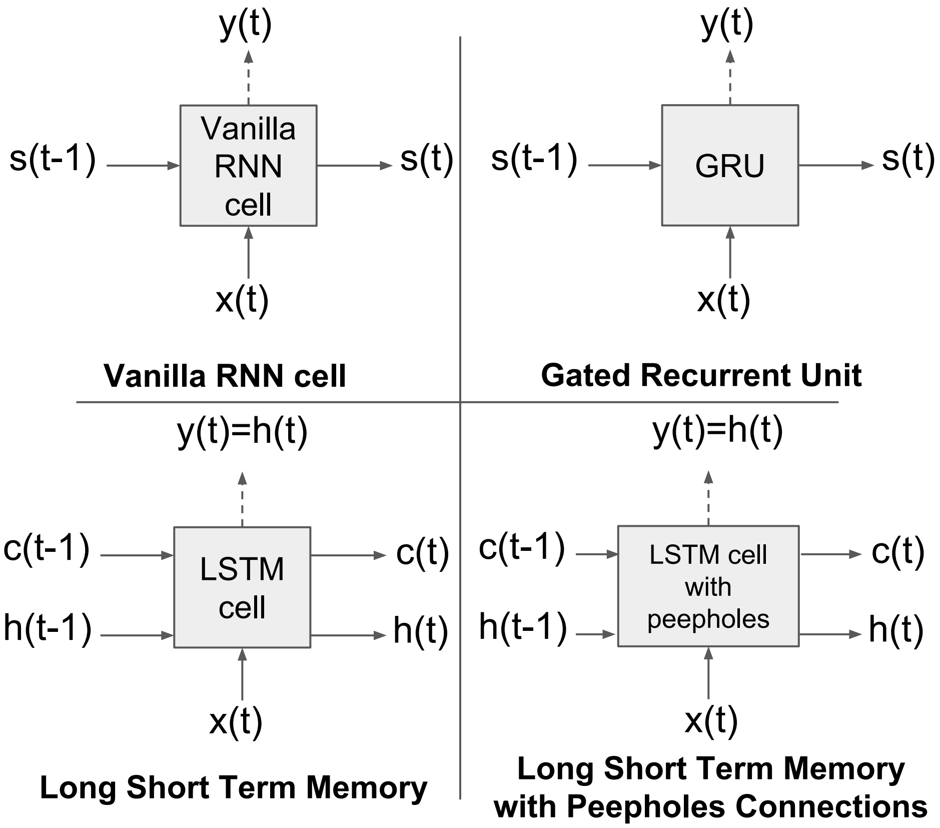
Let's conclude



Let’s conclude

Vanilla RNN

Late 1980s - backpropagation through time to train Vanilla RNN



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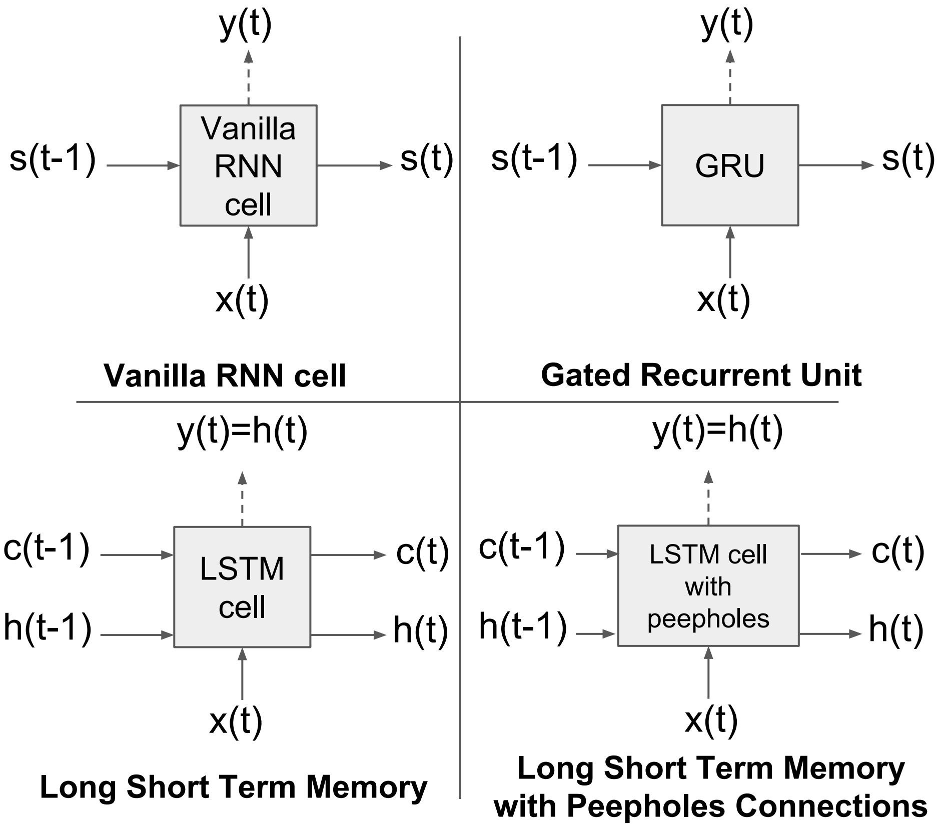

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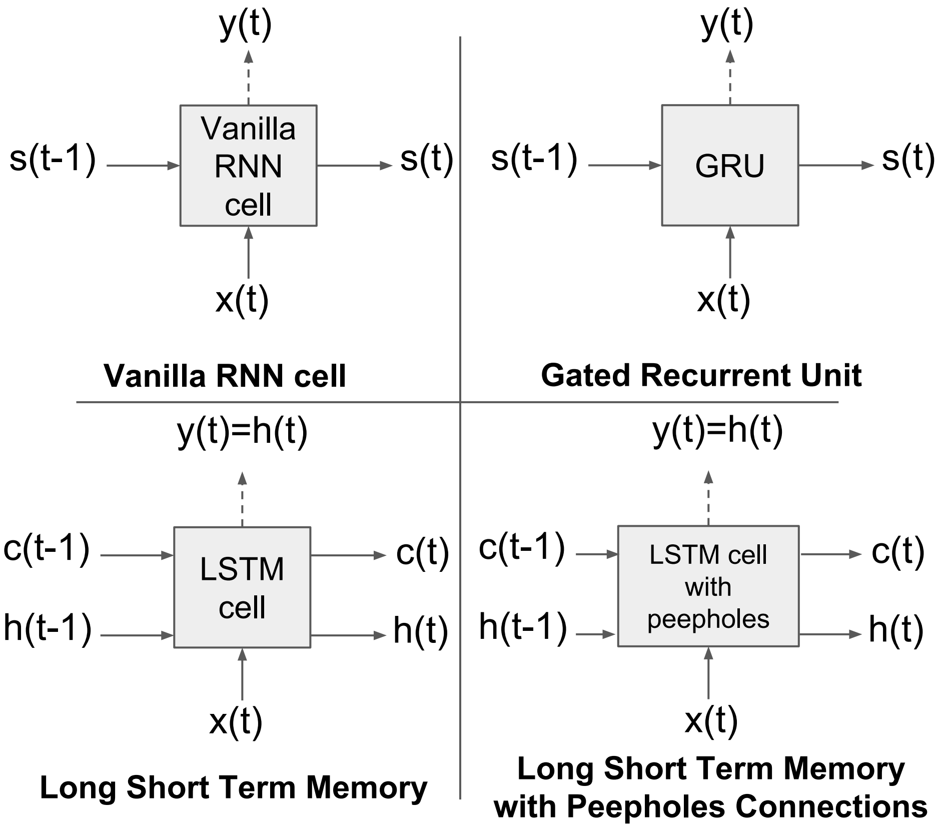
LSTM with Peepholes

2000 - Recurrent nets that time and count (F.A. Gers ; J. Schmidhuber)



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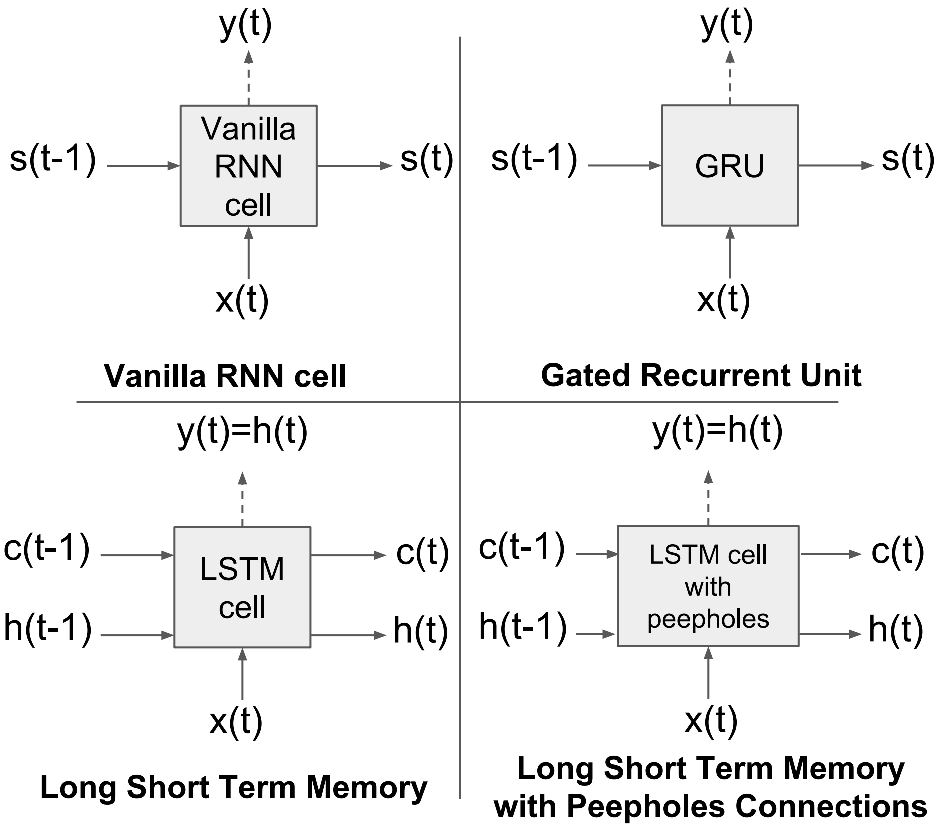
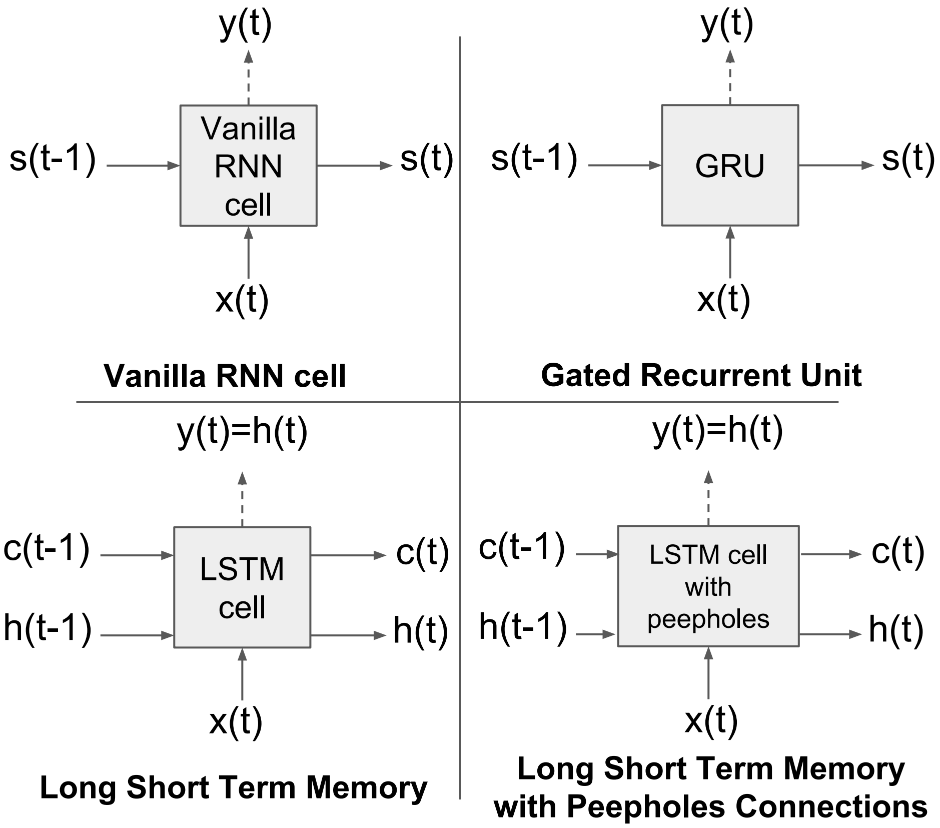
GRU

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



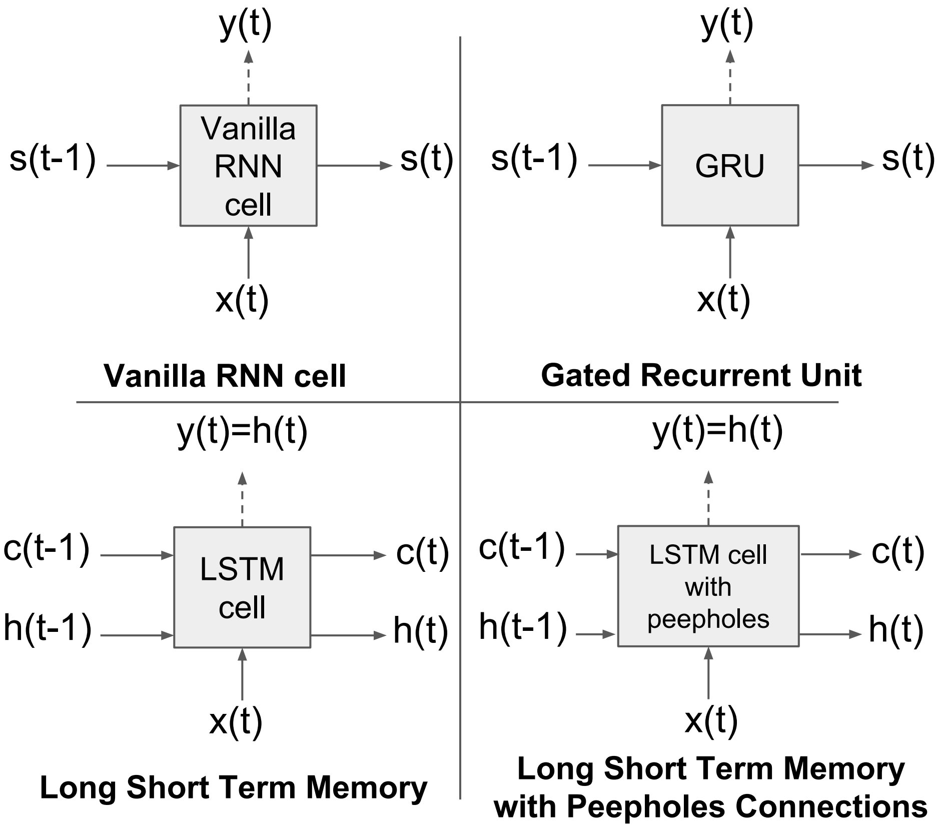
Let's conclude

- 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

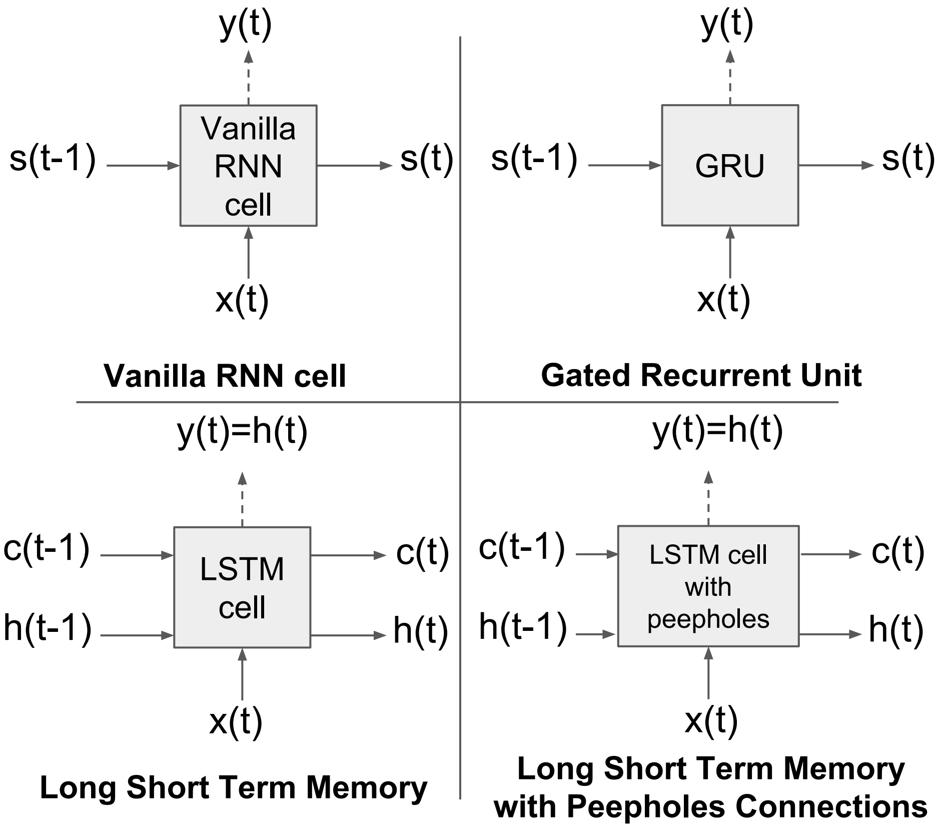


Let’s conclude

- 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 Peephole connections was designed to attack potential loss of information of Basic LSTM cell



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Resources

Great Analysis, Tons of intuition

Written Memories: Understanding, Deriving and Extending the LSTM by R2RT

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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