序列建模:循环和递归网络

Sequence Modeling: Recurrent and Recursive Nets

序列建模：循环和递归网络

主要内容

01 循环神经网络

02 深度循环神经网络

03 双向循环神经网络

04 LSTM及其变种

05 递归神经网络

06 基于编码-解码的序列到序列架构

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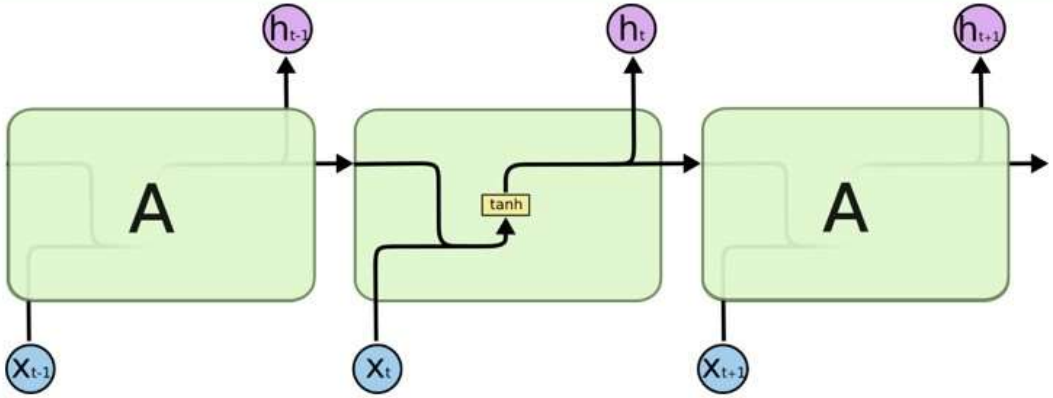
PART FOUR

LSTM及其变种

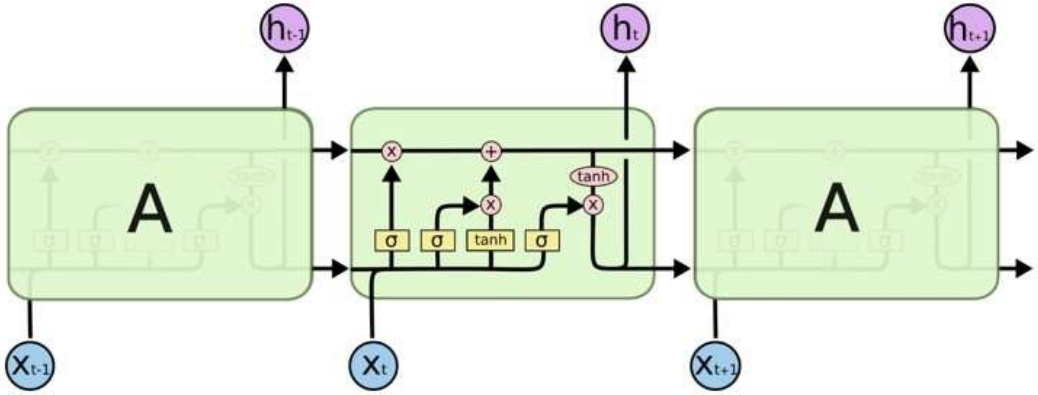
二、长短时记忆网络

RNN



LSTM

Long Short-Term Memory



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填空题 3分

长短时记忆网络 LSTM 有三个门控单元，
分别是
[填空1] [填空2] [填空3]

单选题 1.5分

下列关于长短时记忆网络 LSTM 和循环神经网络 RNN 的关系描述正确的是（ ）

A LSTM 是简化版的 RNN

B LSTM 是双向的 RNN

C LSTM 是多层的 RNN

D LSTM 是 RNN 的扩展，其通过特殊的结构设计来避免长期依赖问题

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单选题 1分

给定一个长度为 n 的不完整单词序列，希望预测下一个字母是什么。
比如输入是“softwar”（7 个字母组成），希望预测第 8 个字母是什么。
下面哪种神经网络结构适用于解决这个任务？（）

A 变分自编码网络

B 循环神经网络

C 卷积神经网络

D 深度信念网络

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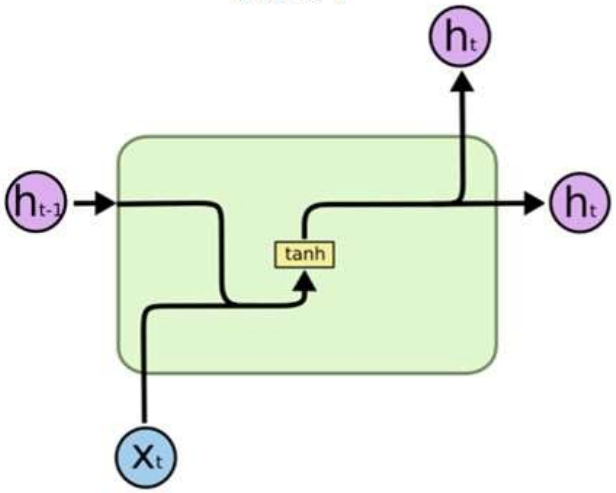
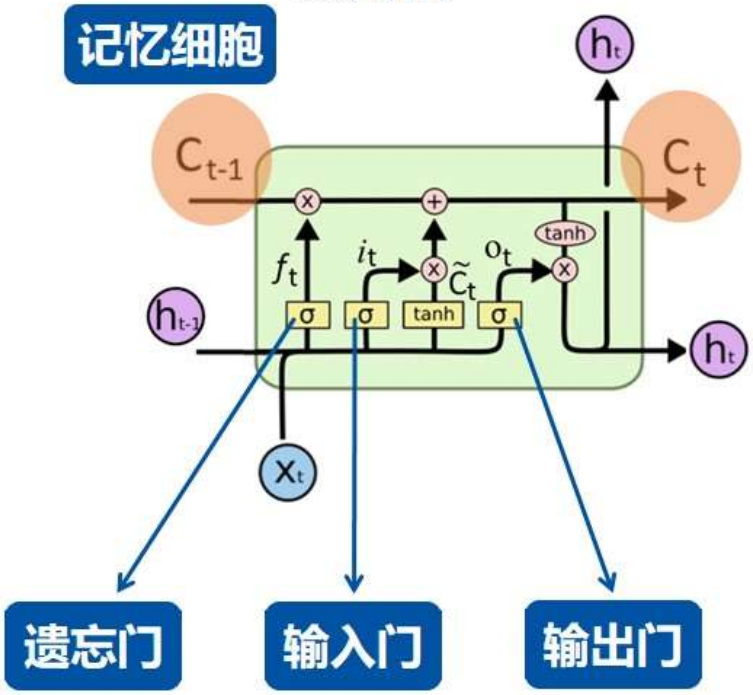
二、长短时记忆网络

好记性不如烂笔头

RNN



LSTM



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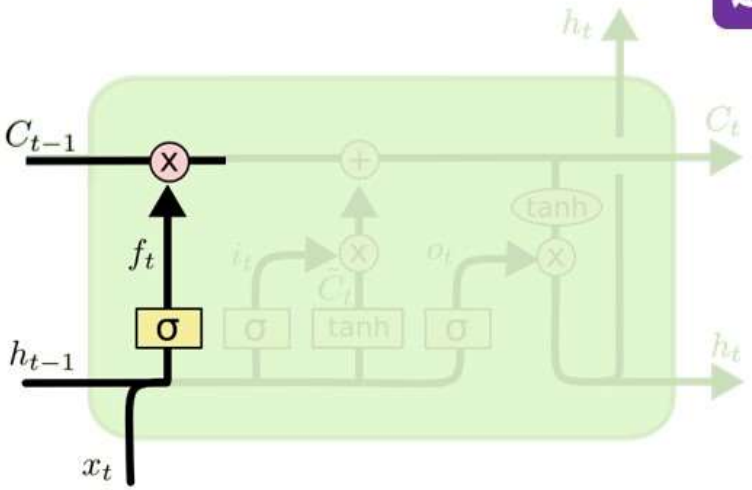
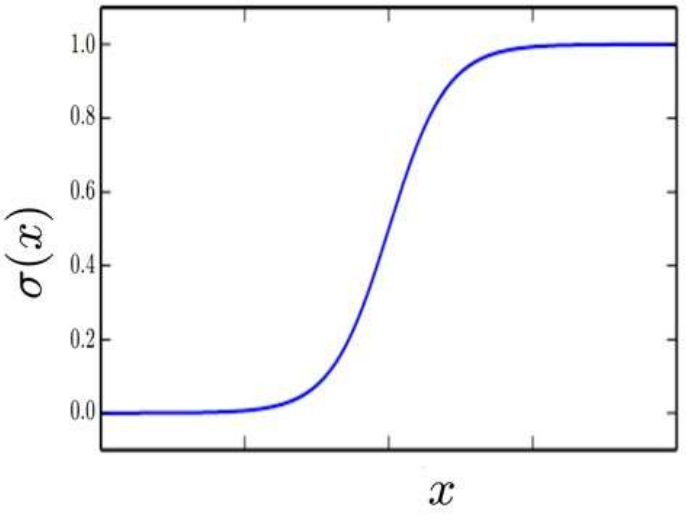
二、长短时记忆网络

遗忘门





$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \; + \; b_f\right)$$

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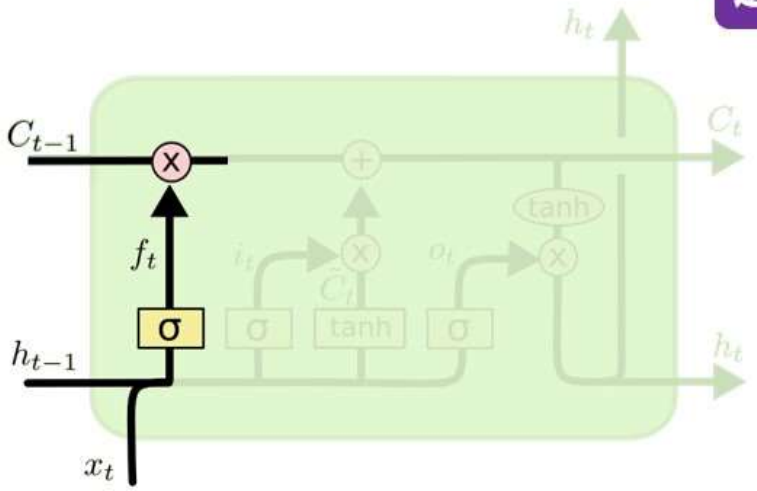
二、长短时记忆网络

遗忘门

决定本子上记的东西中，哪一部分要擦除，以腾出空间记新的事



$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \; + \; b_f\right)$$

$$\begin{bmatrix} 5 & 9 & 3 & 20 \end{bmatrix} \; C_{t-1}$$

$$\begin{bmatrix} 0 & 1 & 0 & 0.2 \end{bmatrix} \; f_t$$

↓

$$\begin{bmatrix} 0 & 9 & 0 & 4 \end{bmatrix} \; f_t * C_{t-1}$$

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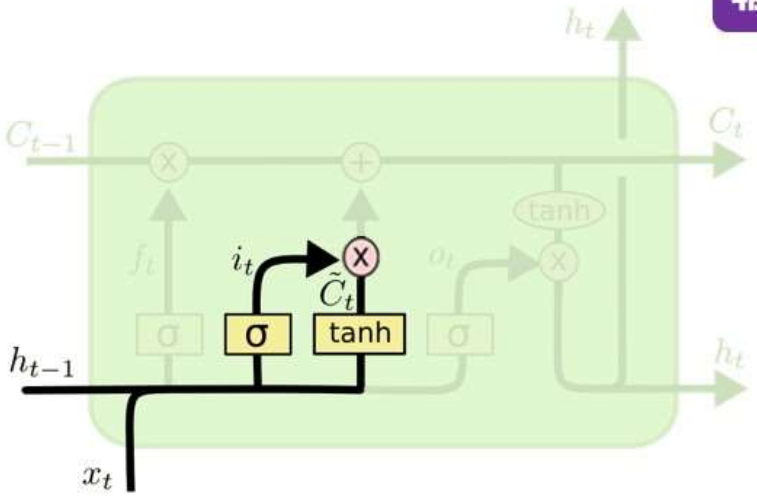
二、长短时记忆网络



输入门

决定当前信息的哪一部分应该记到本子上

$$\begin{bmatrix} 15 & 12 & 20 & 6 \end{bmatrix} \tilde{C}_t$$

$$\begin{bmatrix} 0 & 1 & 0 & 0.5 \end{bmatrix} i_t$$

↓

$$\begin{bmatrix} 0 & 12 & 0 & 3 \end{bmatrix} i_t * \tilde{C}_t$$

$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] + b_i\right)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

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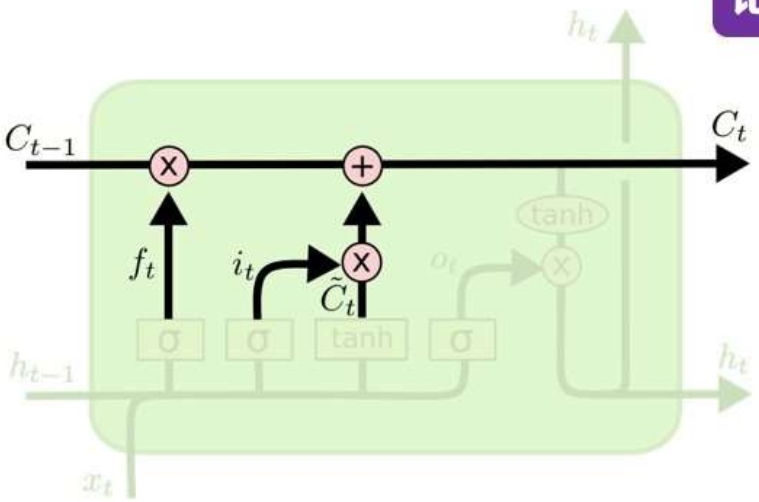
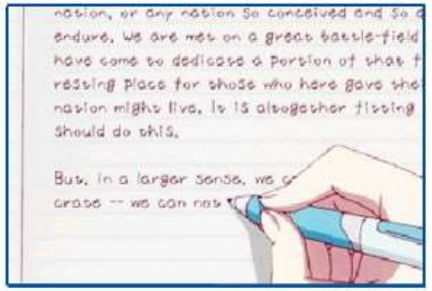
二、长短时记忆网络



$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

记忆更新

新的内容被记录到小本子上



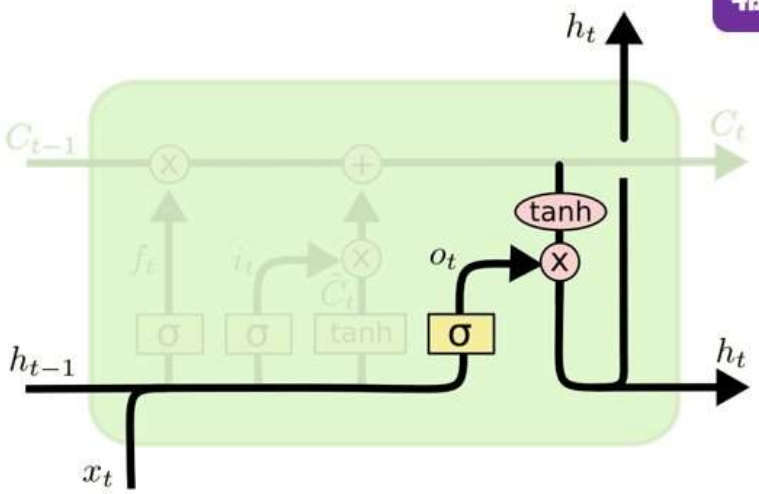
$$\begin{bmatrix} 0 & 9 & 0 & 4 \end{bmatrix} f_t * C_{t-1}$$

$$\begin{bmatrix} 0 & 12 & 0 & 3 \end{bmatrix} i_t * \tilde{C}_t$$

$$\downarrow$$

$$\begin{bmatrix} 0 & 21 & 0 & 7 \end{bmatrix} C_t$$

二、长短时记忆网络



输出门

决定小本子上的哪一部分内容
格外重要，需要牢记在心。
复习之，并记到脑子里。

$$\begin{bmatrix} 0 & 21 & 0 & 7 \end{bmatrix} \tanh(C_t)$$

$$\begin{bmatrix} 0 & 1 & 0 & 0.5 \end{bmatrix} o_t$$

↓

$$\begin{bmatrix} 0 & 21 & 0 & 3.5 \end{bmatrix} h_t$$

$$o_t = \sigma\left(W_o \left[h_{t-1}, x_t\right] + b_o\right)$$

$$h_t = o_t * \tanh\left(C_t\right)$$

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二、长短时记忆网络

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

计算：

$$\delta_{t-1} = \frac{\partial C_T}{\partial C_{t-1}} = \frac{\partial C_T}{\partial C_t}\frac{\partial C_t}{\partial C_{t-1}} = \delta_t \frac{\partial C_t}{\partial C_{t-1}} = \delta_t(f_t + \cdots)$$

当 f_t=1 时，即使其余项很小，梯度仍然可以很好传到上一个时刻，此时即使层数较深也不会发生梯度消失的问题；

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LSTM

LSTM的总结

1. **新记忆产生：**使用输入词x_t和过去隐层状态h_{t-1}来产生新的记忆$\tilde{C}_t$。

2. **输入门：**在产生新记忆之前，我们需要判定一下我们当前看到的新词到底重不重要，这就是输入门的作用。输入门根据输入词和过去隐层状态共同判定输入值是否值得保留，从而判定它以何种程度参与生成新的记忆(或者说对新的记忆做一个约束)。因此，它可以作为输入信息更新的一个指标。

3. **遗忘门：**这个门和输入门很类似。但是它不能决定输入词有效，它能对过去记忆单元是否对当前记忆单元的计算有用做出评估。

4. **最终记忆产生：**这个阶段会根据遗忘门的作用结果，合理地忘记部分过去的记忆C_{t-1}。再根据输入门i_t的作用结果，产生新记忆$\tilde{C}_t$。它将这两个结果相加融合起来产生了最终的记忆C_t。

5. **输出门：**它的目的是从隐层状态分离最终的记忆。最终记忆C_t包含了大量不必需要保存在隐层状态的信息，这个门限能够评估关于记忆C_t哪部分需要显示在隐层状态h_t中。用于评估这部分信息的中间信号叫做o_t，它和$tanh(C_t)$的点乘组成最后的h_t。

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LSTM变体

LSTM变体

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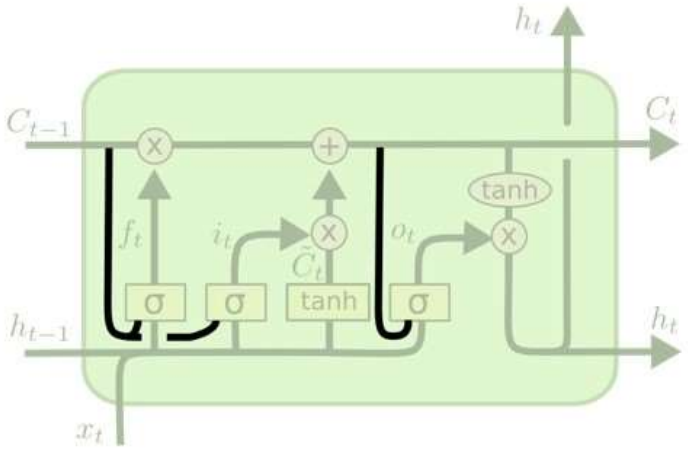
LSTM

变体

变体1

① 增加“peephole connection”。

② 让“门层”也接受细胞状态的输入。



$$f_t = \sigma\left(W_f \cdot [\boldsymbol{C_{t-1}}, h_{t-1}, x_t] + b_f\right)$$
$$i_t = \sigma\left(W_i \cdot [\boldsymbol{C_{t-1}}, h_{t-1}, x_t] + b_i\right)$$
$$o_t = \sigma\left(W_o \cdot [\boldsymbol{C_t}, h_{t-1}, x_t] + b_o\right)$$

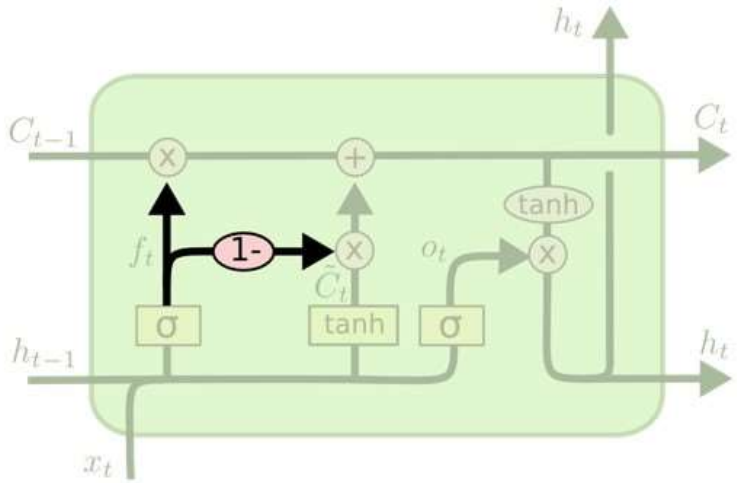
LSTM

变体

变体2

① 通过使用coupled忘记和输入门。

② 不同于之前是分开确定需要忘记和添加的信息，这里是一同做出决定。



$$C_t = f_t * C_{t-1} + (1 - \boldsymbol{f_t}) * \tilde{C}_t$$

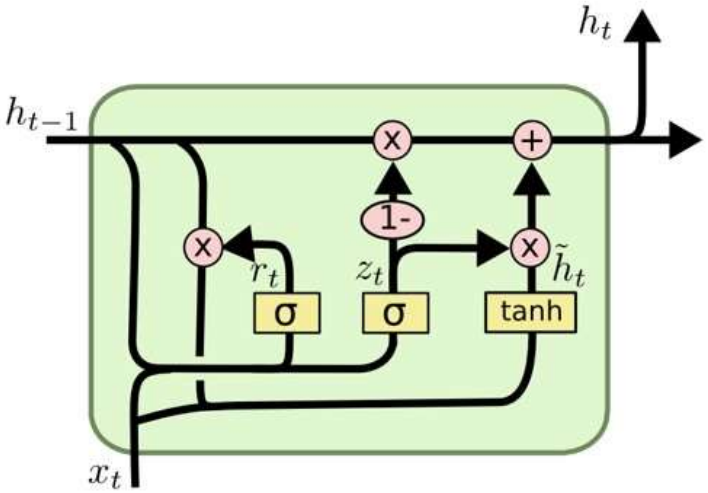
LSTM

变体

- 变体3 -- Gated Recurrent Unit (GRU)

① 将忘记门和输入门合成了一个单一的**更新门**。

② 混合了细胞状态和隐藏状态，和其他一些改动。最终的模型比标准的 LSTM 模型要简单，是非常流行的变体。



$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

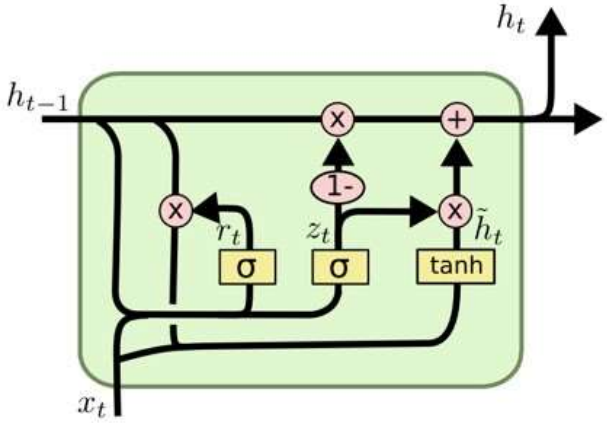
$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

LSTM

变体

GRU的再次理解

- **GRU**模型如下，它只有两个门了，分别为**更新门**和**重置门**，即图中的z_t和r_t。**更新门**用于控制前一时刻的状态信息被带入到当前状态中的程度，更新门的值越小说明前一时刻的状态信息带入越多。**重置门**用于控制忽略前一时刻的状态信息的程度，重置门的值越小说明忽略得越多。



$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

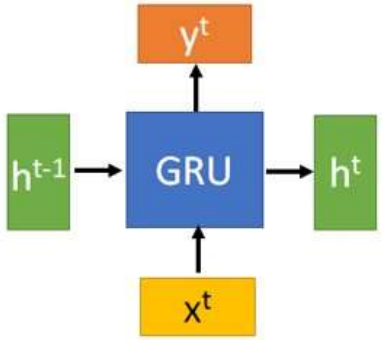
$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

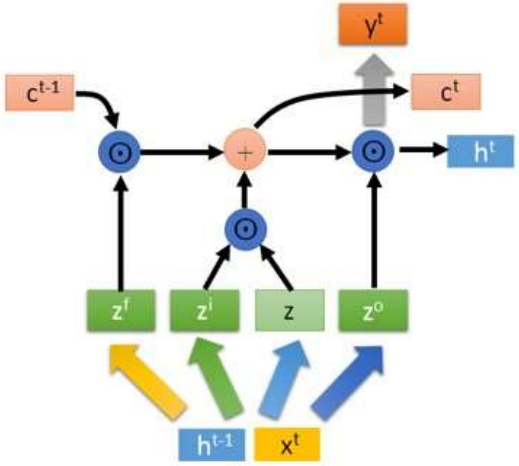
$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

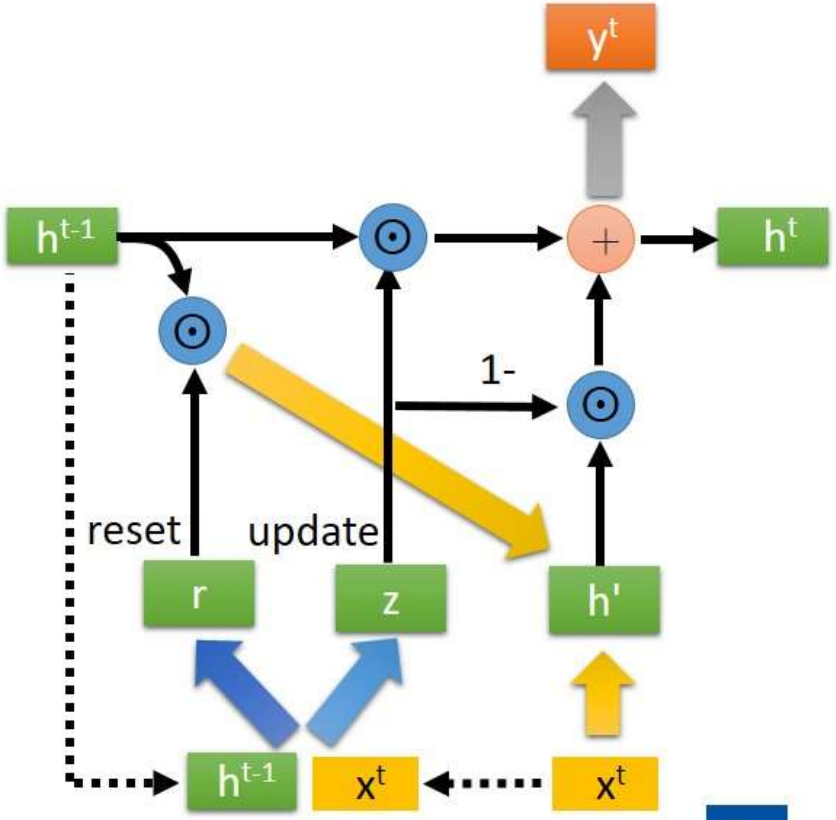
LSTM

变体GRU

$$h^t = z \odot h^{t-1} + (1-z) \odot h'$$







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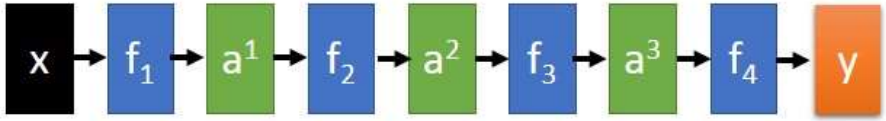
Highway Network

Highway Network
和
Residual Network
(ResNet)

一、循环神经网络的原理

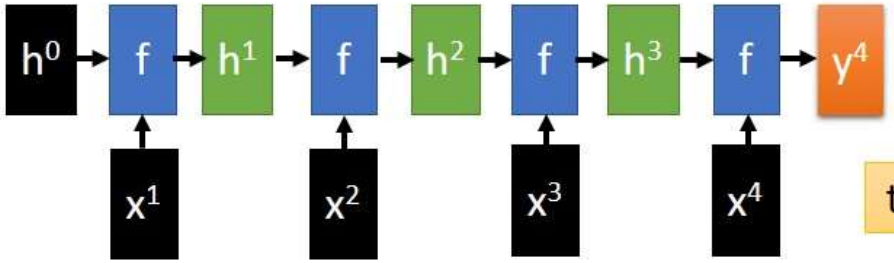
1. Feedforward network does not have input at each step
2. Feedforward network has different parameters for each layer



$$a^t = f_l(a^{t-1}) = \sigma(W^t a^{t-1} + b^t)$$

t is layer

Feedforward v.s. Recurrent



t is time step

$$h^t = f(h^{t-1}, x^t) = \sigma\left(W^h h^{t-1} + W^i x^t + b^i\right)$$

Slide credit: Hung-yi Lee

Applying gated structure in feedforward network

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GRU → Highway Network

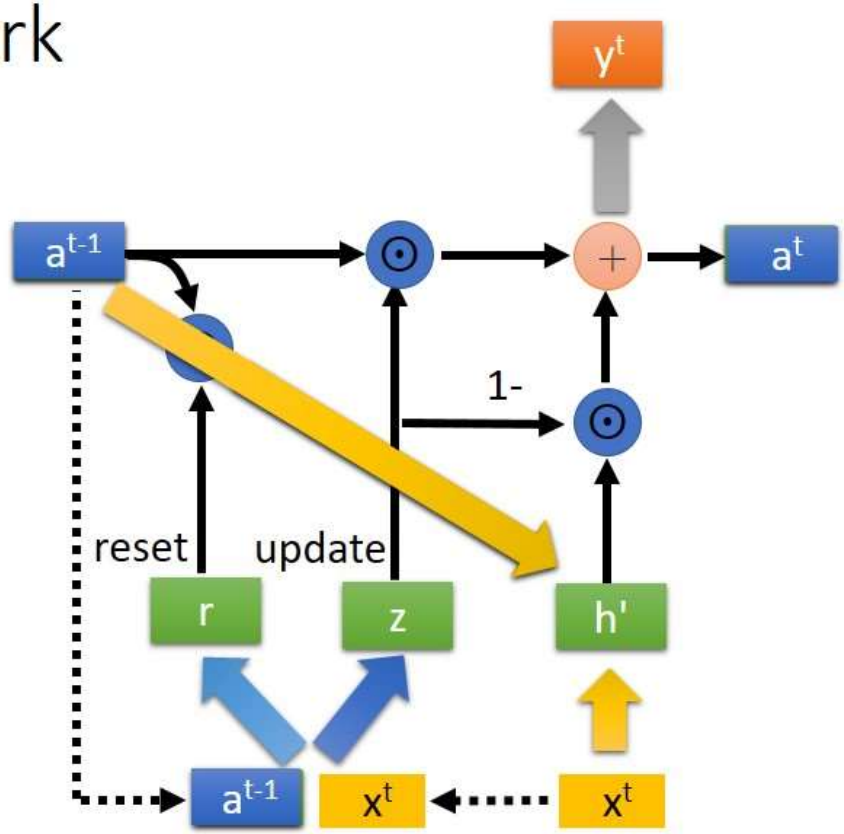
No input x^t at each step

No output y^t at each step

a^{t-1} is the output of the (t-1)-th layer

a^t is the output of the t-th layer

No reset gate



Slide credit: Hung-yi Lee

用 H 来表示一个非线性转换，参数为 W_H ，当输入为 x 时，输出为

$$y = H(x, W_H)$$

上面的公式就是最普通的一层神经网络的表示。而Highway Network则定义了两个非线性变换 $T(x, W_T)$ 和 $C(x, W_C)$ ，这两个作为系数，网络输出为

$$y = H(x, W_H) * T(x, W_T) + x * C(x, W_C)$$

文中将 T 作为 transform gate，表示有多少转换后的信息通过， C 为carry gate，表示有多少原始信息通过，为了简单，设置 $C = 1 - T$ ，那么有

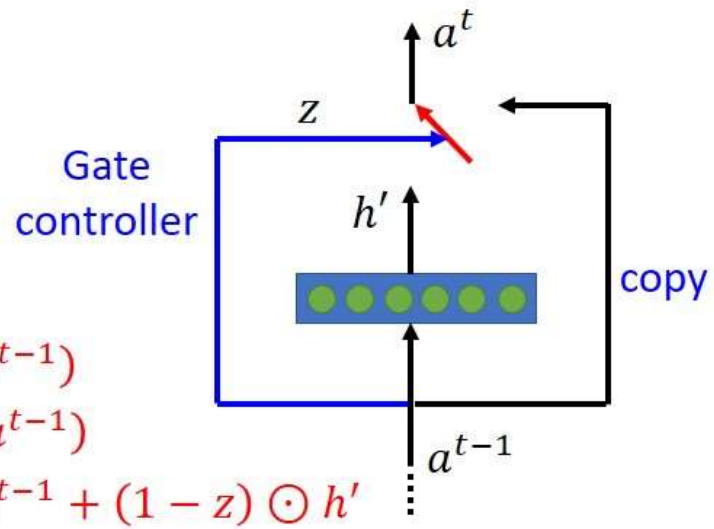
$$y = H(x, W_H) * T(x, W_T) + x * (1 - T(x, W_T))$$

可以看出Highway Network和ResNet是比较相似的，都有两个分支进行合并。论文里 T 的具体定义为 $T(x) = \sigma(W_T^{\mathbf{T}} x + b_T)$ ，σ 是sigmoid函数。

Highway Network

$$a^t = a^{t-1} + h'$$

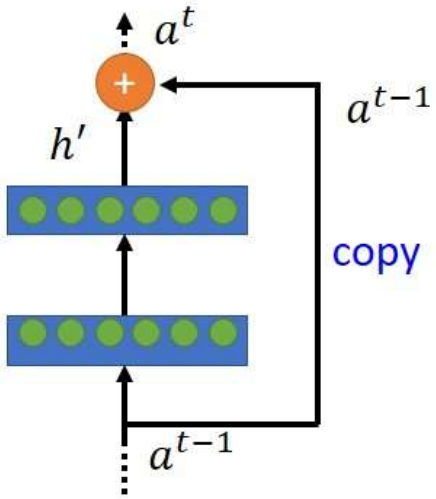
• Highway Network



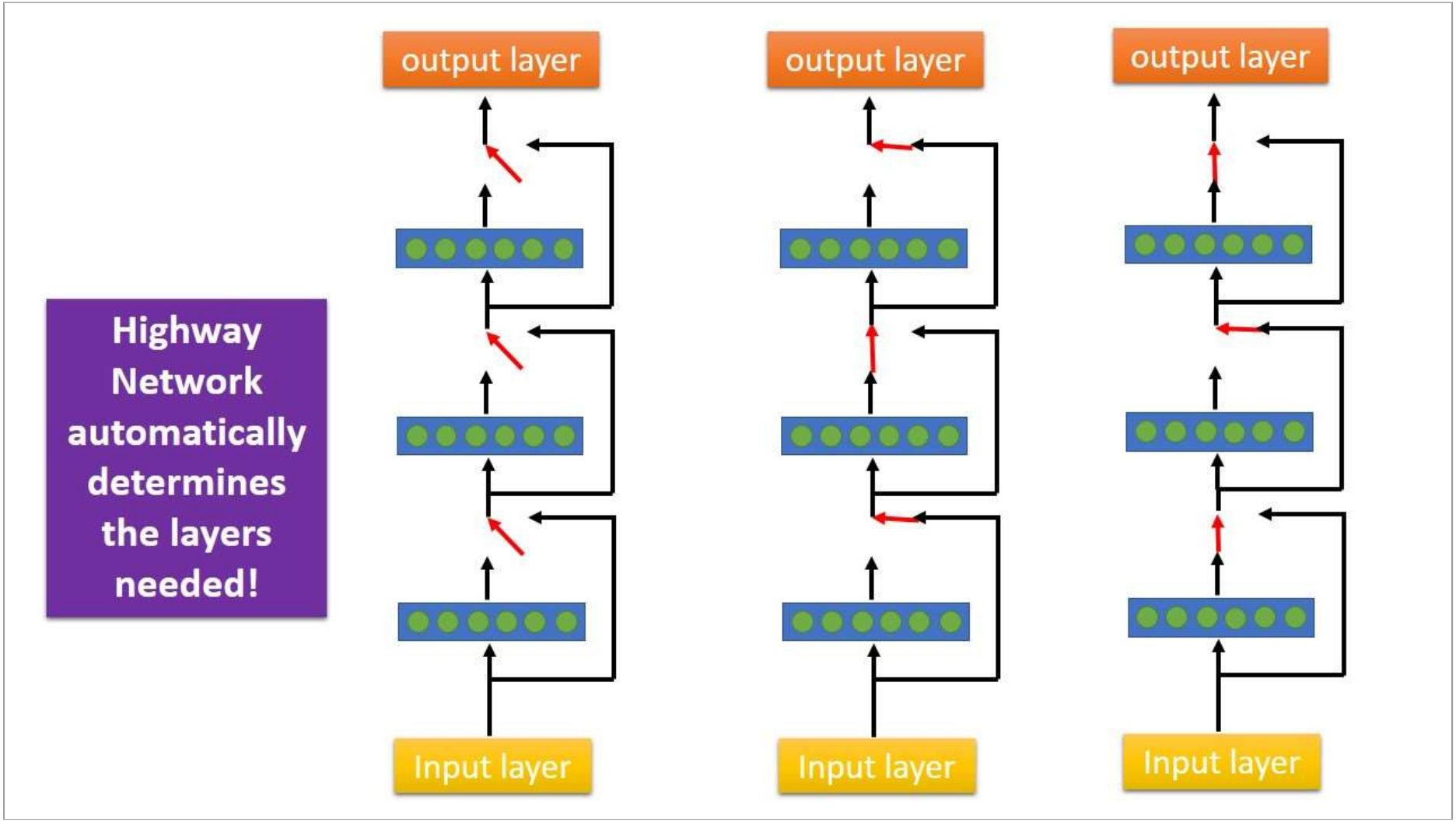
$$h' = \sigma(W a^{t-1})$$
$$z = \sigma(W' a^{t-1})$$
$$a^t = z \odot a^{t-1} + (1 - z) \odot h'$$

Training Very Deep Networks
https://arxiv.org/pdf/1507.06228v2.pdf

• Residual Network

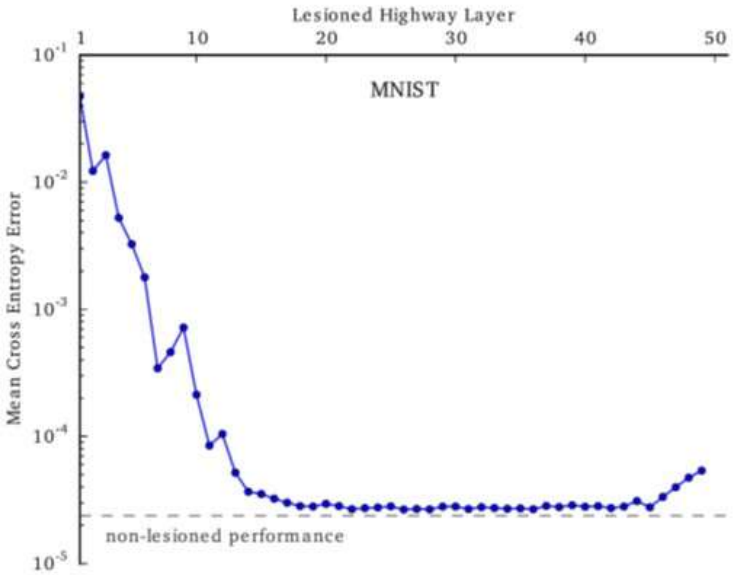


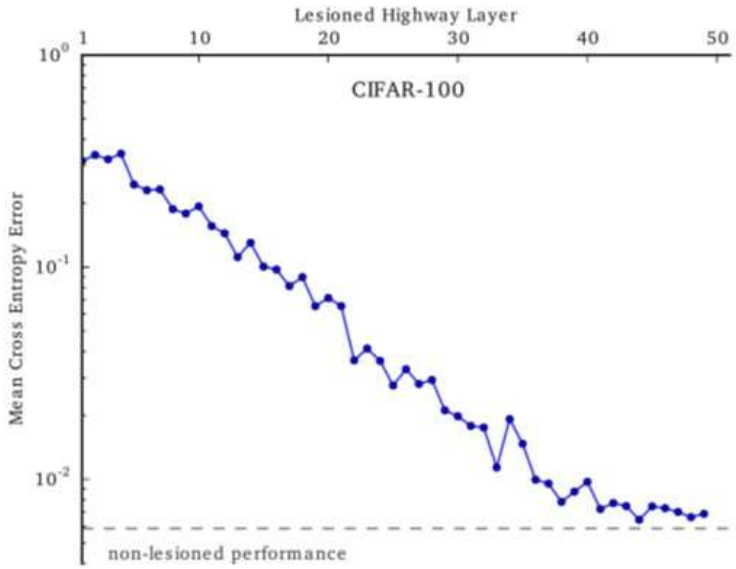
Deep Residual Learning for Image Recognition
http://arxiv.org/abs/1512.03385


Highway Network automatically determines the layers needed!
output layer
output layer
output layer
Input layer
Input layer
Input layer

Highway Network

Highway Network





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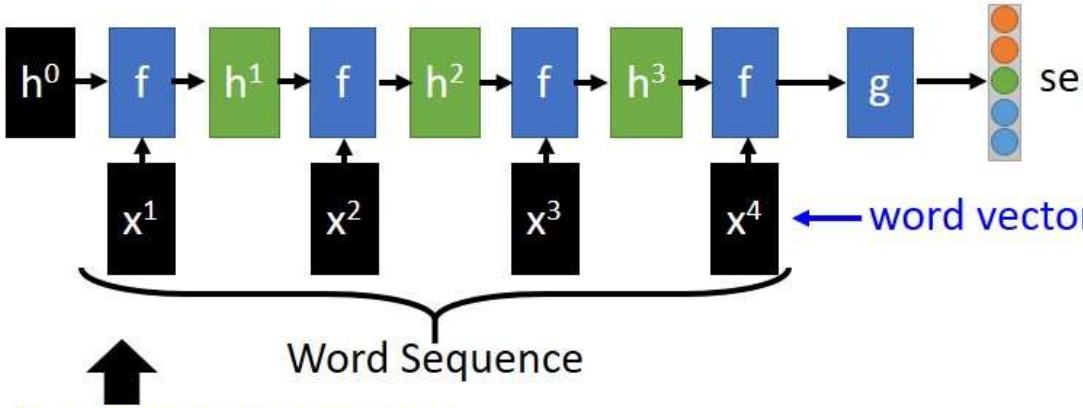
PART FIVE

递归神经网络
Recursive Structure

Application: Sentiment Analysis

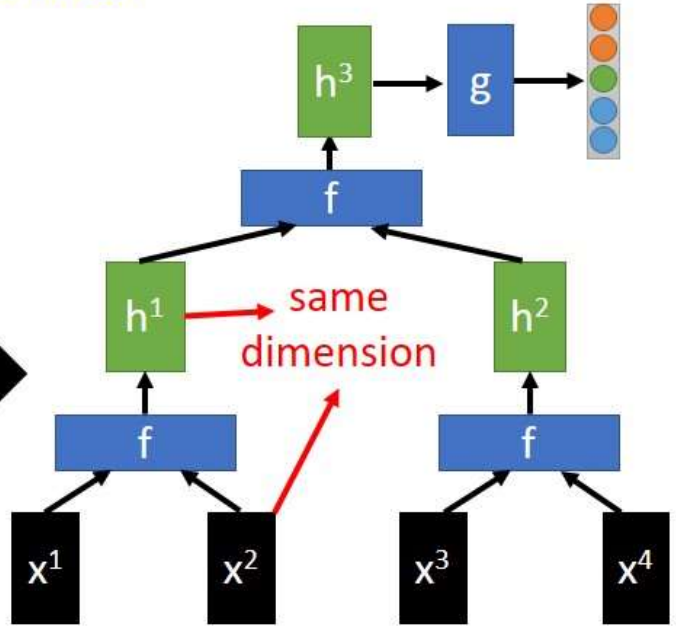


Recurrent Structure

Special case of recursive structure

Recursive Structure

How to stack function f is already determined



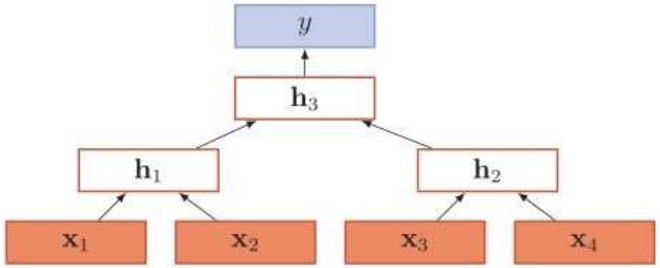
递归神经网络

- 递归神经网络实在一个有向图无循环图上共享一个组合函数
- Recursive Neural Network

$$\mathbf{h}_1 = f(W \begin{bmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \end{bmatrix} + \mathbf{b}),$$

$$\mathbf{h}_2 = f(W \begin{bmatrix} \mathbf{x}_3 \\ \mathbf{x}_4 \end{bmatrix} + \mathbf{b}),$$

$$\mathbf{h}_3 = f(W \begin{bmatrix} \mathbf{h}_1 \\ \mathbf{h}_2 \end{bmatrix} + \mathbf{b}),$$



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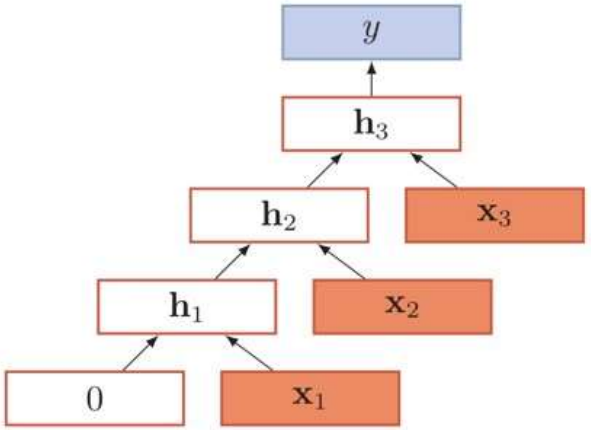
$$\mathbf{h}_t = f(\mathbf{h}_{t-1}, \mathbf{x}_t),$$



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THANK YOU
Q&A