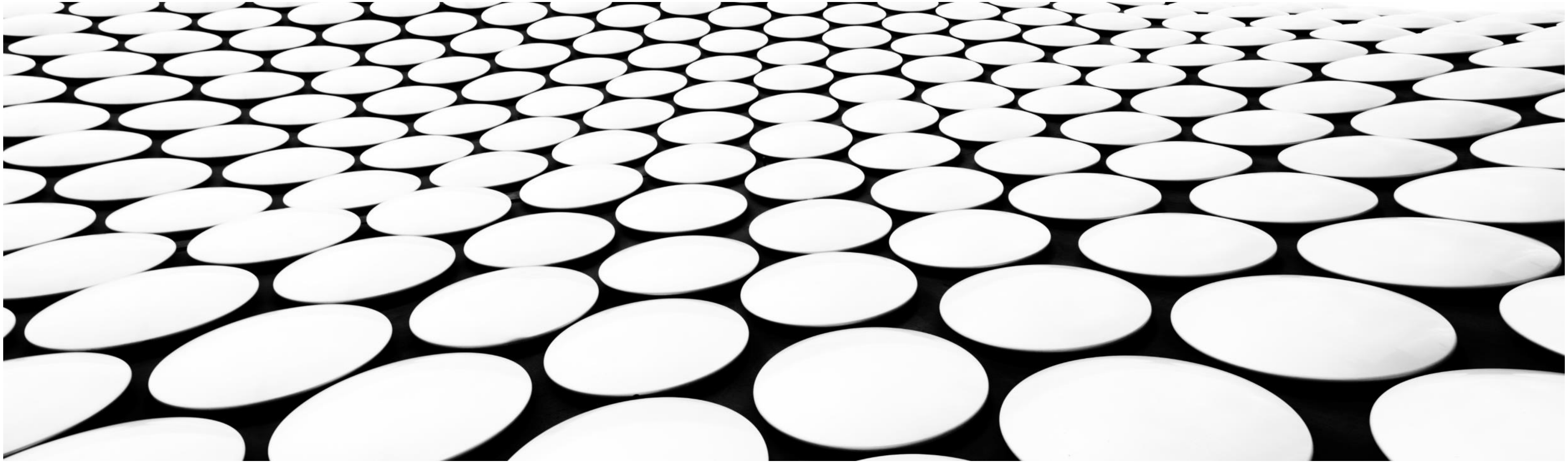
深度学习

邱怡轩



今天的主题

- 循环神经网络（续）

实例演示

性别预测

- 数据来源
- https://github.com/wainshine/Chinese-Names-Corpus
- >114万条已标注性别的人名

```
dict,sex
阿安,男
阿彬,未知
阿斌,男
阿滨,男
阿冰,女
阿冰冰,女
阿兵,男
阿婵,女
阿超,男
阿朝,男
阿琛,女
阿臣,男
阿辰,未知
阿晨,未知
```

```
石晓彦,女
石晓艳,女
石晓燕,女
石晓艺,女
石晓英,女
石晓莹,女
石晓颖,女
石晓影,女
石晓勇,男
石晓宇,男
石晓玉,女
石晓云,女
石晓泽,男
石晓珍,女
石筱,女
```

```
闫志慧,女
闫志坚,男
闫志江,男
闫志杰,男
闫志娟,女
闫志军,男
闫志君,未知
闫志丽,女
闫志利,男
闫志亮,男
闫志林,男
闫志玲,女
闫志龙,男
闫志梅,女
闫志民,男
```

```
佐非,未知
佐江,男
佐军,男
佐丽,女
佐隆,男
佐明,男
佐木,未知
佐娜,女
佐楠,女
佐山,男
佐腾,男
佐威,男
佐为,男
佐樱,女
佐子,男
```

预处理

- 删除未知类别
- 计算每个字出现的频率
- 选取前500个高频字
- 将范围限定在500个常用字中

	char	freq
636	王	50390
926	李	49078
1086	张	47089
1203	陈	41512
1394	刘	39986
...	...	...
2170	墙	1
2171	楼	1
2172	禺	1
2173	据	1
1962	莽	1

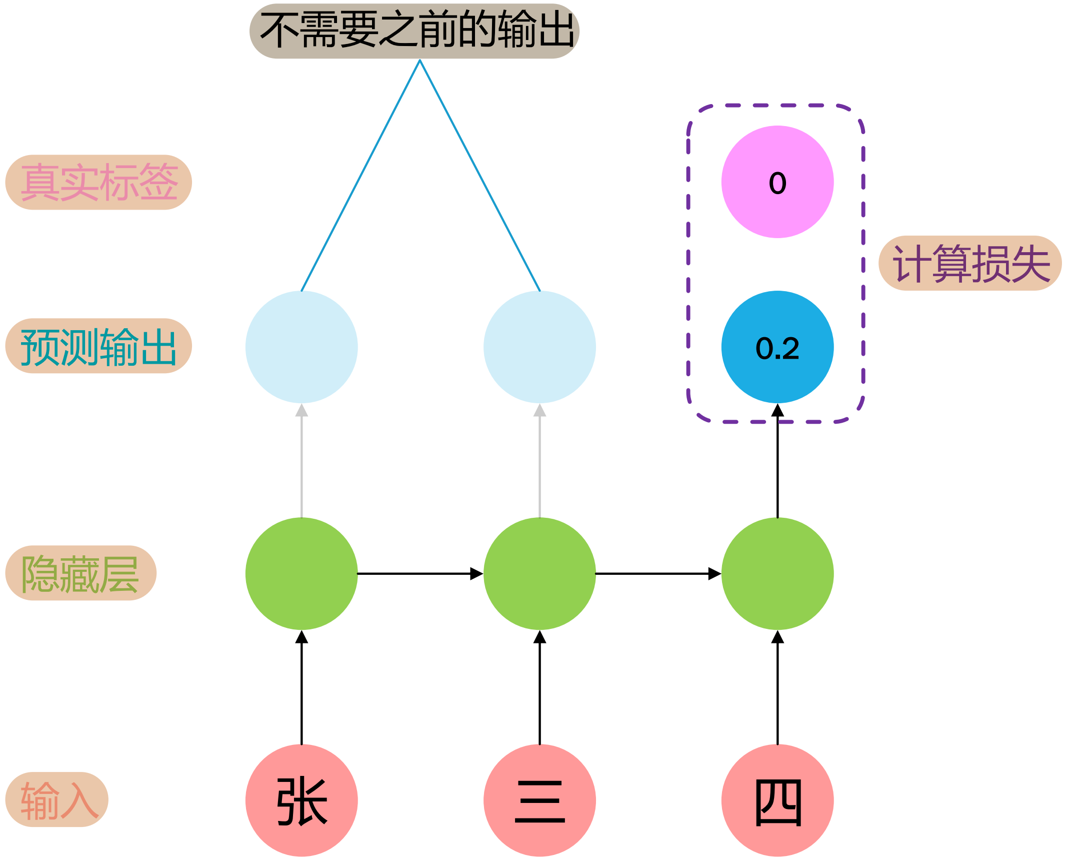
建立字典

- 将500个常用字作为字典

```
array(['王', '李', '张', '陈', '刘', '文', '林', '明', '杨', '华', '黄', '吴', '金',
       '周', '晓', '国', '赵', '玉', '伟', '海', '志', '徐', '丽', '红', '建', '朱',
       '孙', '平', '军', '英', '春', '龙', '胡', '永', '荣', '德', '云', '成', '郭',
       '东', '郑', '高', '芳', '马', '何', '梅', '新', '杰', '辉', '生', '秀', '玲',
       '江', '俊', '洪', '强', '世', '光', '罗', '艳', '燕', '兰', '子', '庆', '峰',
       '忠', '梁', '宇', '凤', '谢', '霞', '美', '宋', '祥', '清', '立', '兴', '萍',
       '许', '叶', '雪', '良', '安', '慧', '娟', '福', '宝', '佳', '方', '家', '唐',
```

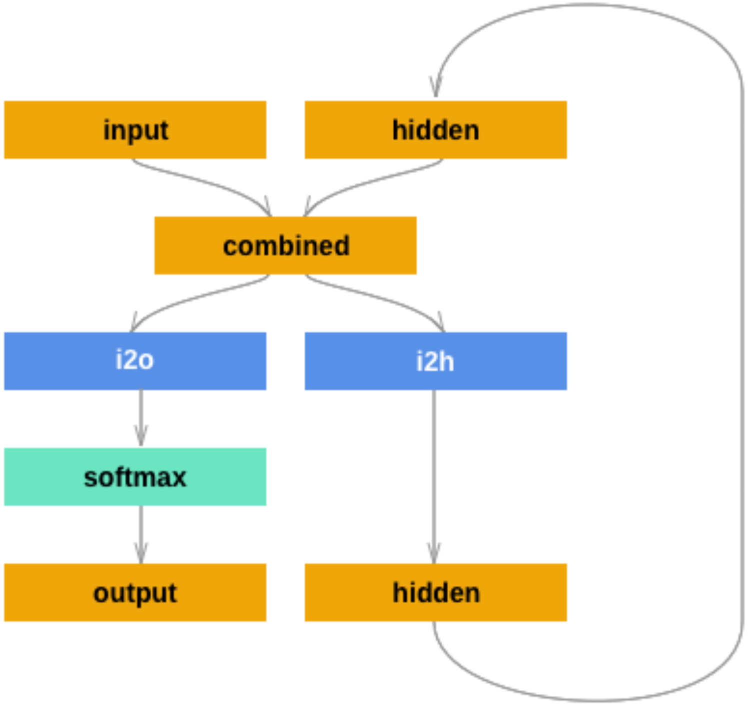
- 将汉字用 one-hot 向量编码
  - 王 = [1,0,0,…]
  - 李 = [0,1,0,…]
  - 张 = [0,0,1,…]
- 每个名字看作是一个序列 $x = (x_1, x_2, \dots)$
  - 每个 x_t 是一个 one-hot 向量

建模原理



建立模型

- 参考：https://pytorch.org/tutorials/intermediate/char_rnn_classification_tutorial.html



测试结果

- 简单构建训练集（1万）和测试集（1千）
- CPU 上训练10秒钟
- 测试集准确率可达 97.9%

代码实现

- 参见 `name_classify.ipynb`

改进 RNN

优缺点

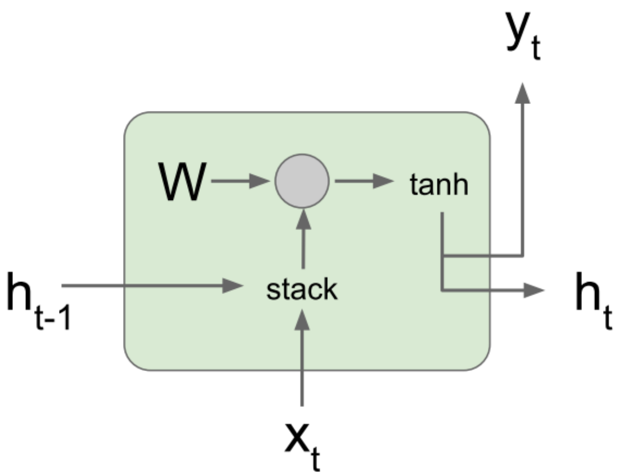
- 相比于前馈神经网络和 CNN，RNN 有其独特的性质
- 优点
  - 处理任意长的序列数据
  - 利用历史信息
  - 参数数量不随序列变长而增加
- 缺点
  - 序列很长时计算量非常大
  - 梯度消失/爆炸问题

反向传播

- 要理解 RNN 的局限，就需要明白它的反向传播原理

Vanilla RNN Gradient Flow

Bengio et al, "Learning long-term dependencies with gradient descent is difficult", IEEE Transactions on Neural Networks, 1994
Pascanu et al, "On the difficulty of training recurrent neural networks", ICML 2013



$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t)$$
$$= \tanh\left(\begin{pmatrix}W_{hh} & W_{hx}\end{pmatrix}\begin{pmatrix}h_{t-1}\\ x_t\end{pmatrix}\right)$$
$$= \tanh\left(W\begin{pmatrix}h_{t-1}\\ x_t\end{pmatrix}\right)$$

资料来自http://cs231n.stanford.edu/

Vanilla RNN Gradient Flow

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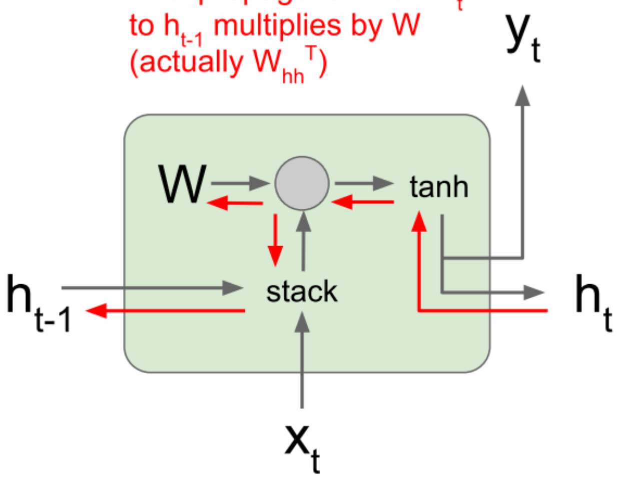

$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t)$$
$$= \tanh\left(\begin{pmatrix} W_{hh} & W_{hx} \end{pmatrix} \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}\right)$$
$$= \tanh\left(W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}\right)$$

Vanilla RNN Gradient Flow

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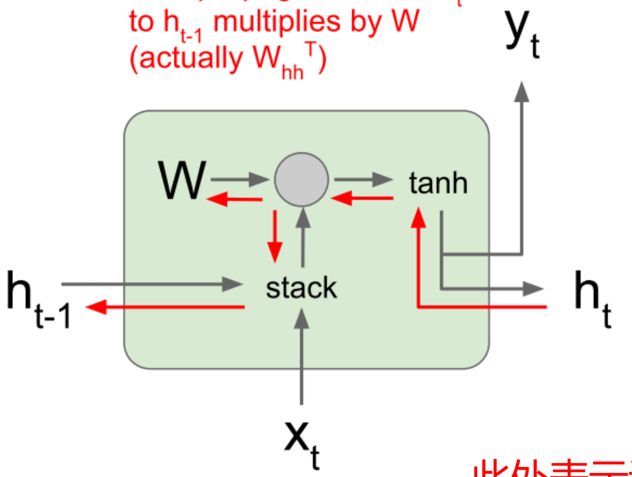
Backpropagation from h_t to h_{t-1} multiplies by W (actually W_{hh}^T)



$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t)$$
$$= \tanh\left(\begin{pmatrix} W_{hh} & W_{hx} \end{pmatrix}\begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}\right)$$
$$= \tanh\left(W\begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}\right)$$

此处表示该向量形成的对角矩阵

$$\frac{\partial h_t}{\partial h_{t-1}} = \boxed{tanh'(W_{hh}h_{t-1} + W_{xh}x_t)}W_{hh}$$

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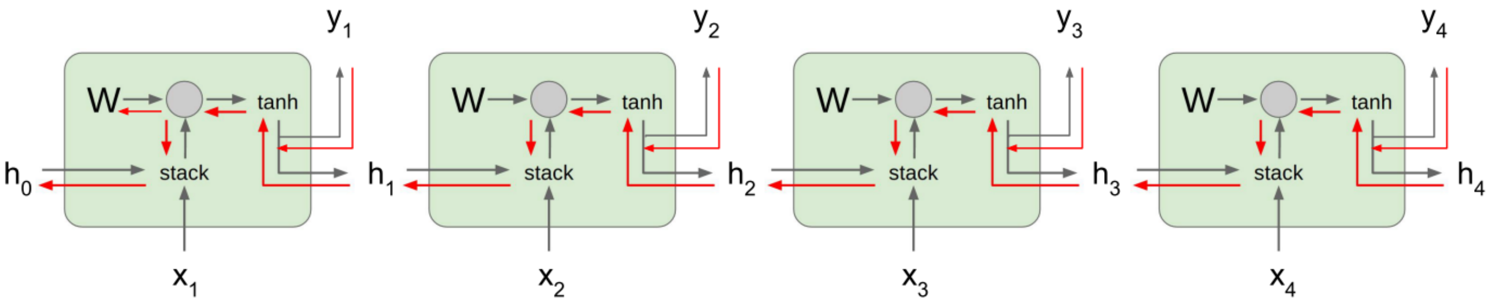

$$\frac{\partial L}{\partial W} = \sum_{t=1}^{T} \frac{\partial L_t}{\partial W}$$

Vanilla RNN Gradient Flow

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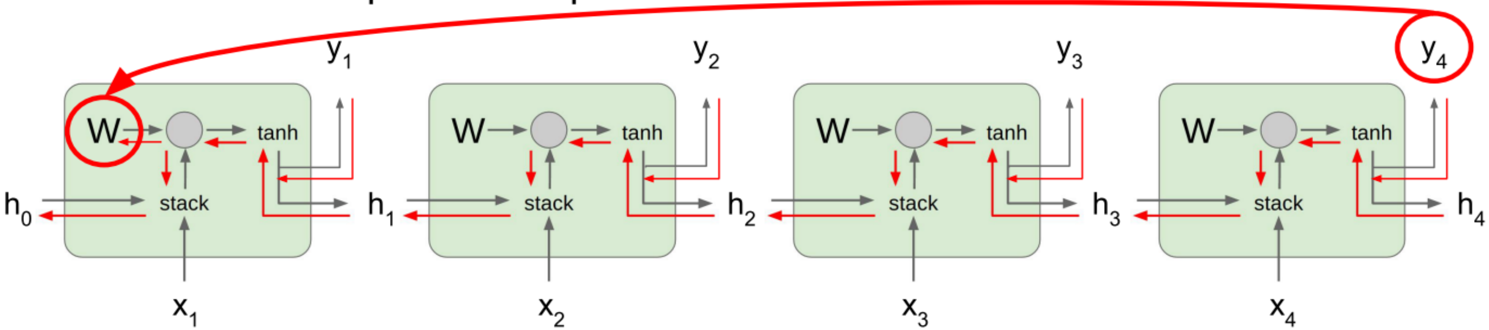
Pascanu et al, "On the difficulty of training recurrent neural networks", ICML 2013

Gradients over multiple time steps:



$$\frac{\partial L}{\partial W} = \sum_{t=1}^{T} \frac{\partial L_t}{\partial W}$$

$$\boxed{\frac{\partial L_T}{\partial W} = \frac{\partial L_T}{\partial h_T} \frac{\partial h_t}{\partial h_{t-1}} \cdots \frac{\partial h_1}{\partial W}}$$

此处并不严谨，实际上等式右边只是导数的其中一项，但这一项能提供一些直观的认识。

Vanilla RNN Gradient Flow

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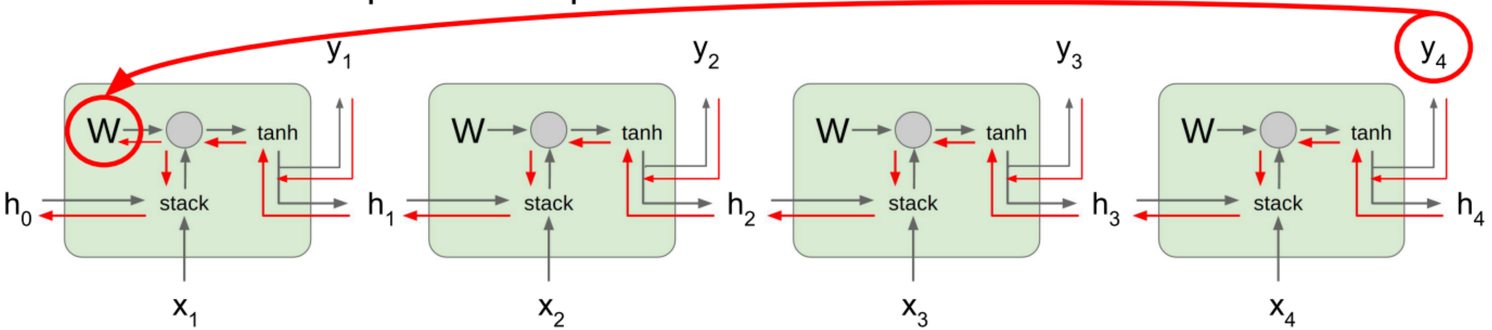
Gradients over multiple time steps:



$$\frac{\partial L}{\partial W} = \sum_{t=1}^{T} \frac{\partial L_t}{\partial W}$$

$$\frac{\partial L_T}{\partial W} = \frac{\partial L_T}{\partial h_T} \frac{\partial h_t}{\partial h_{t-1}} \cdots \frac{\partial h_1}{\partial W} = \frac{\partial L_T}{\partial h_T} \left(\prod_{t=2}^{T} \frac{\partial h_t}{\partial h_{t-1}}\right) \frac{\partial h_1}{\partial W}$$

Vanilla RNN Gradient Flow

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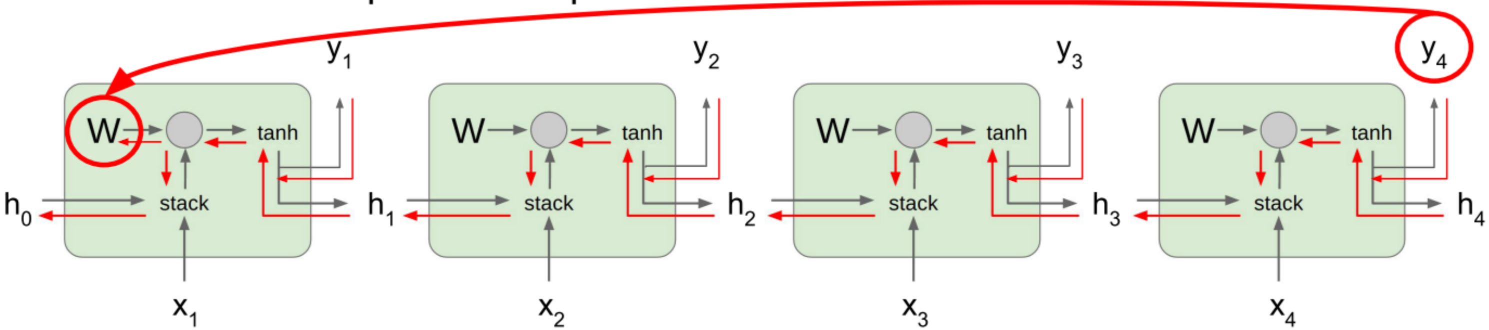
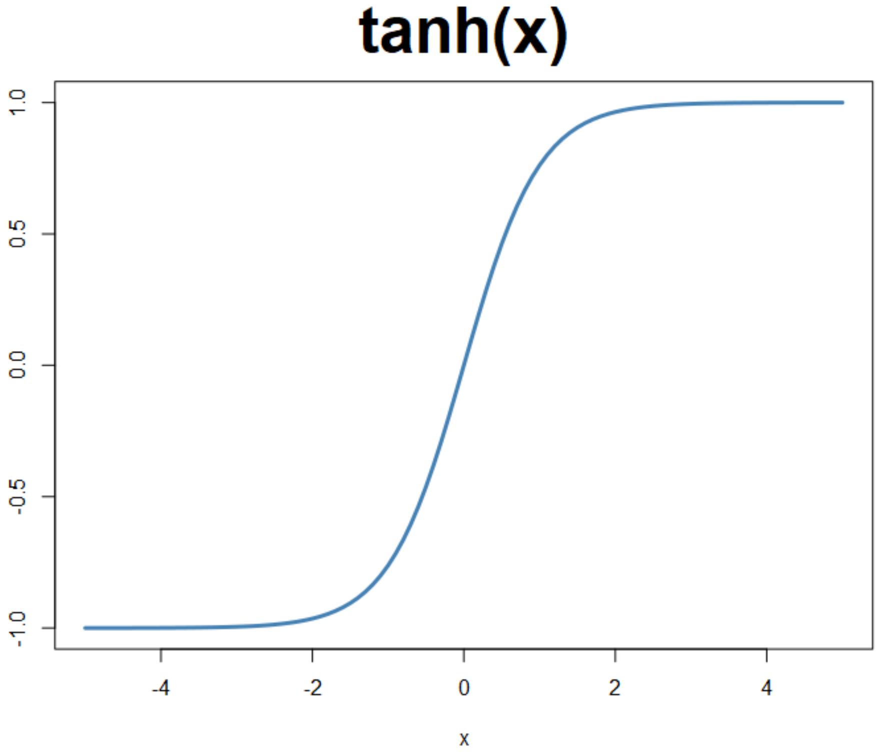
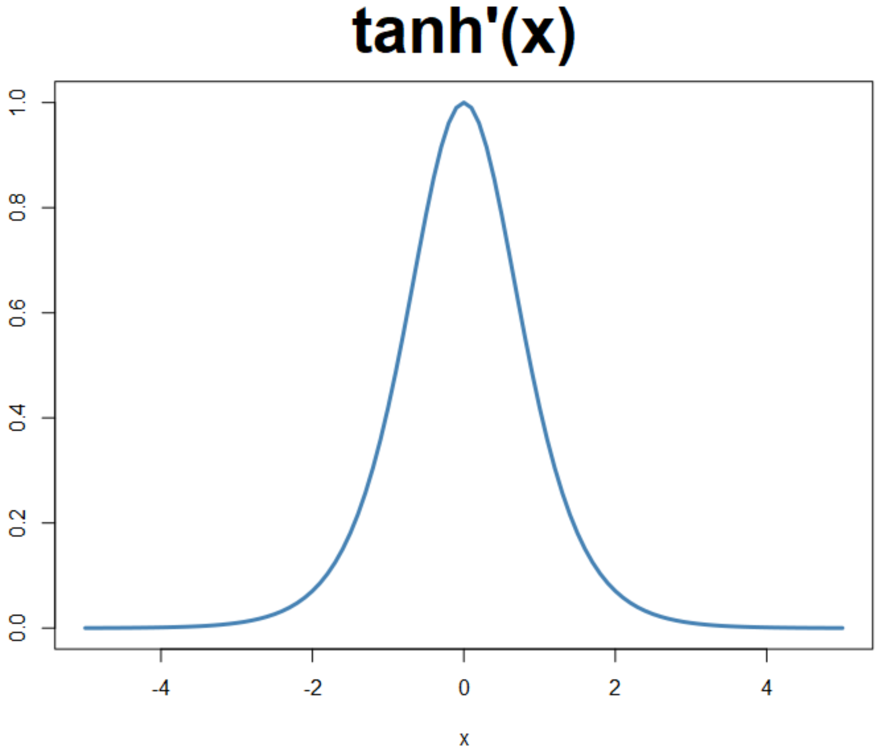
Gradients over multiple time steps:



$$\frac{\partial L}{\partial W} = \sum_{t=1}^{T} \frac{\partial L_t}{\partial W} \qquad \boxed{\frac{\partial h_t}{\partial h_{t-1}} = tanh'(W_{hh}h_{t-1} + W_{xh}x_t)W_{hh}}$$

$$\frac{\partial L_T}{\partial W} = \frac{\partial L_T}{\partial h_T}\frac{\partial h_t}{\partial h_{t-1}} \cdots \frac{\partial h_1}{\partial W} = \frac{\partial L_T}{\partial h_T}\left(\prod_{t=2}^{T} \boxed{\frac{\partial h_t}{\partial h_{t-1}}}\right)\frac{\partial h_1}{\partial W}$$


tanh(x)
1.0
0.5
0.0
-0.5
-1.0
-4
-2
0
2
4
x


tanh'(x)
1.0
0.8
0.6
0.4
0.2
0.0
-4
-2
0
2
4
x

Vanilla RNN Gradient Flow

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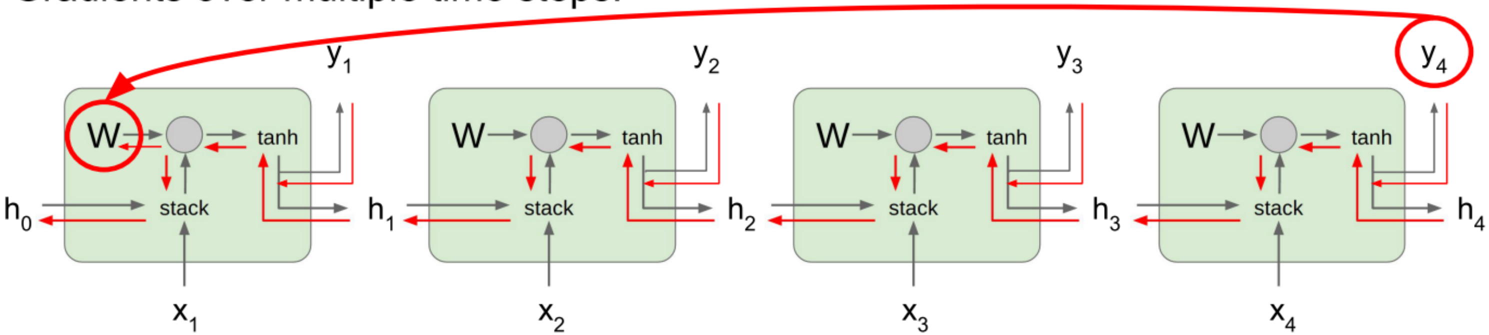
Pascanu et al, "On the difficulty of training recurrent neural networks", ICML 2013

Gradients over multiple time steps:



$$\frac{\partial L}{\partial W} = \sum_{t=1}^{T} \frac{\partial L_t}{\partial W}$$

Almost always < 1

Vanishing gradients

$$\frac{\partial L_T}{\partial W} = \frac{\partial L_T}{\partial h_T}\left(\prod_{t=2}^{T} \boxed{tanh'(W_{hh}h_{t-1} + W_{xh}x_t)}\right) W_{hh}^{T-1} \frac{\partial h_1}{\partial W}$$

Vanilla RNN Gradient Flow

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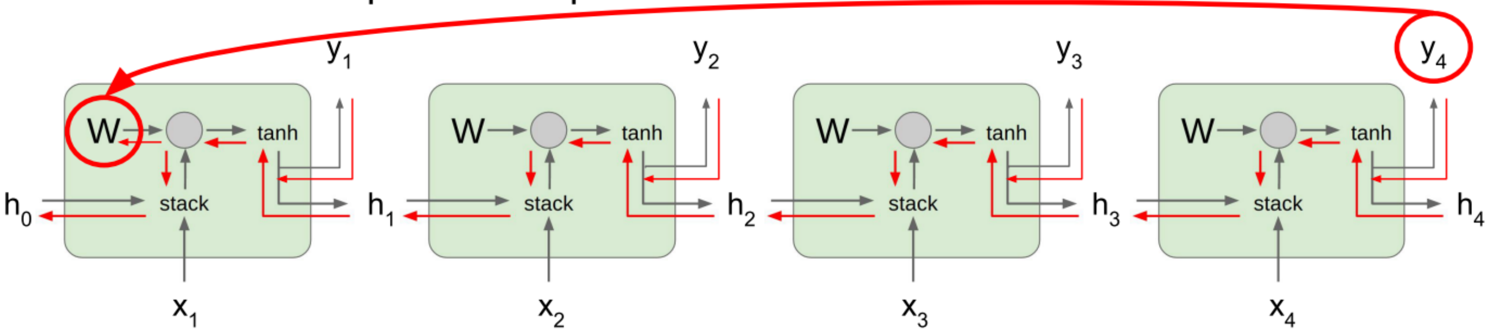
Pascanu et al, "On the difficulty of training recurrent neural networks", ICML 2013

Gradients over multiple time steps:



$$\frac{\partial L}{\partial W} = \sum_{t=1}^{T} \frac{\partial L_t}{\partial W}$$

What if we assumed no non-linearity?

Vanilla RNN Gradient Flow

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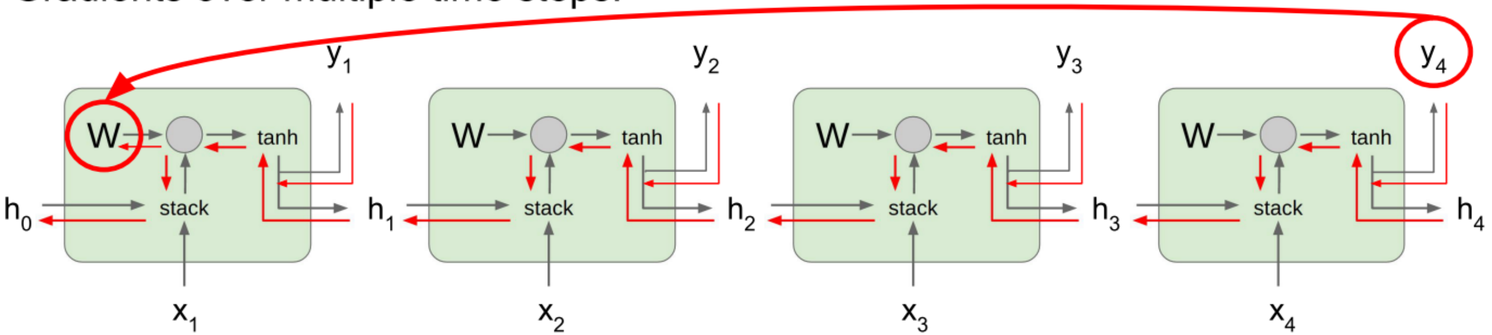
Pascanu et al, "On the difficulty of training recurrent neural networks", ICML 2013

Gradients over multiple time steps:



What if we assumed no non-linearity?

$$\frac{\partial L}{\partial W} = \sum_{t=1}^{T} \frac{\partial L_t}{\partial W}$$

$$\frac{\partial L_T}{\partial W} = \frac{\partial L_T}{\partial h_T} \boxed{W_{in}^{T-1}} \frac{\partial h_1}{\partial W}$$

Largest singular value > 1:
Exploding gradients

Largest singular value < 1:
Vanishing gradients

改进方法

- 梯度爆炸：对梯度的上限进行截断
- 梯度消失：更改 RNN 架构

LSTM

- 长短期记忆神经网络
- Long Short-Term Memory

- Hochreiter and Schmidhuber (1997). Long Short Term Memory, Neural Computation.

LSTM

Vanilla RNN

$$h_t = \tanh\left(W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}\right)$$

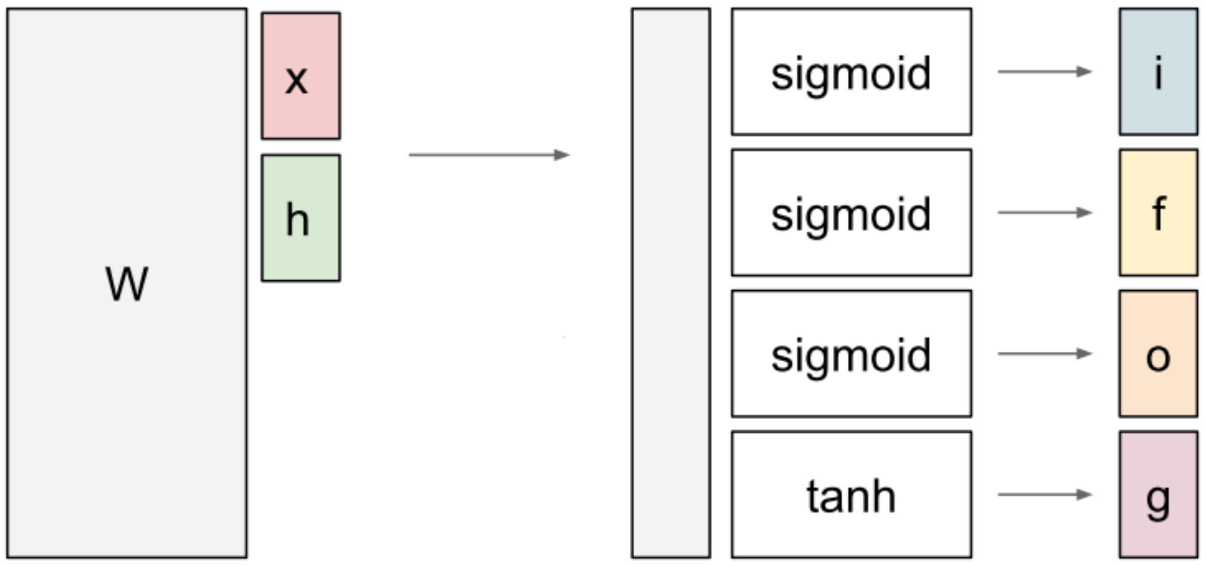
LSTM

$$\begin{pmatrix} i \\ f \\ o \\ g \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}$$

$$c_t = f \odot c_{t-1} + i \odot g$$

$$h_t = o \odot \tanh(c_t)$$

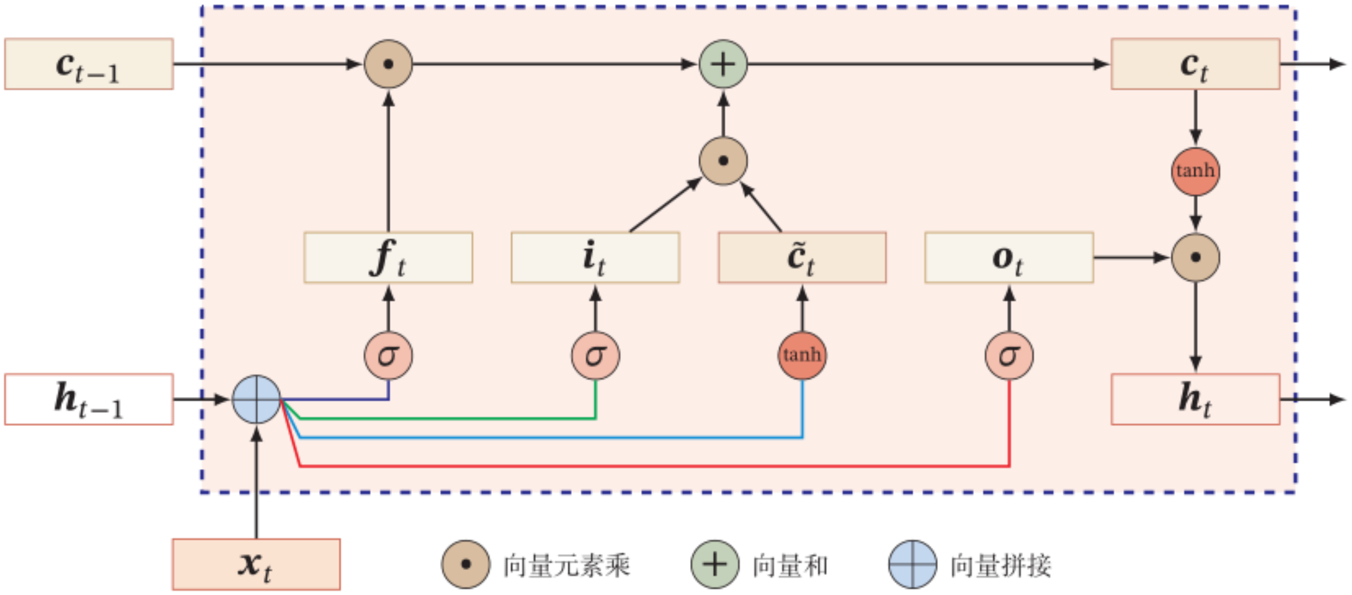
LSTM



$$c_t = f \odot c_{t-1} + i \odot g$$

$$h_t = o \odot \tanh(c_t)$$

LSTM



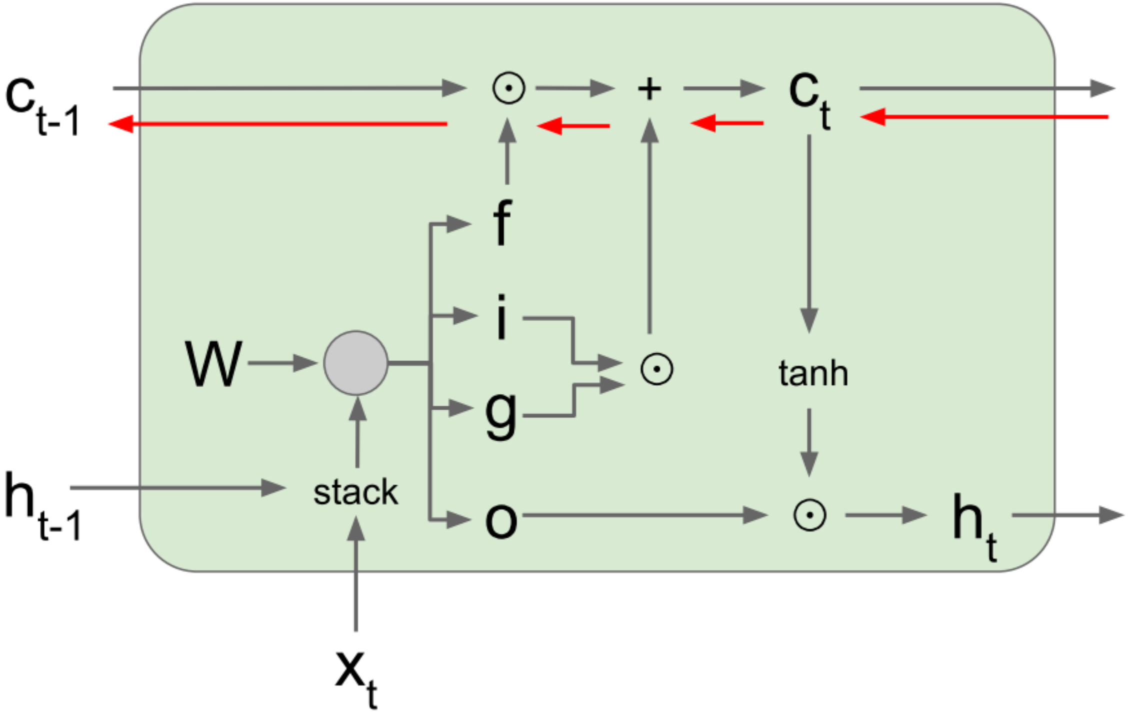
- i：是否写入当前单元
- $g/\tilde{c}$：多大程度上写入当前单元
- f：是否遗忘上一个单元
- o：多大程度上将单元转成隐藏状态

$$c_t = f \odot c_{t-1} + i \odot g$$

$$h_t = o \odot \tanh(c_t)$$

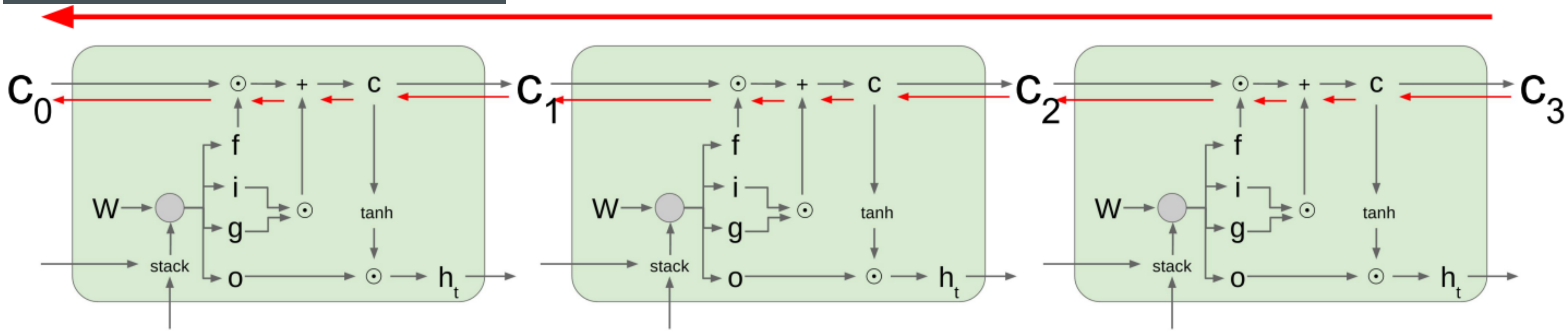
LSTM

- 梯度从 c_t 传向 c_{t-1} 时只牵涉到与 f 的逐元素相乘，没有直接的矩阵乘法



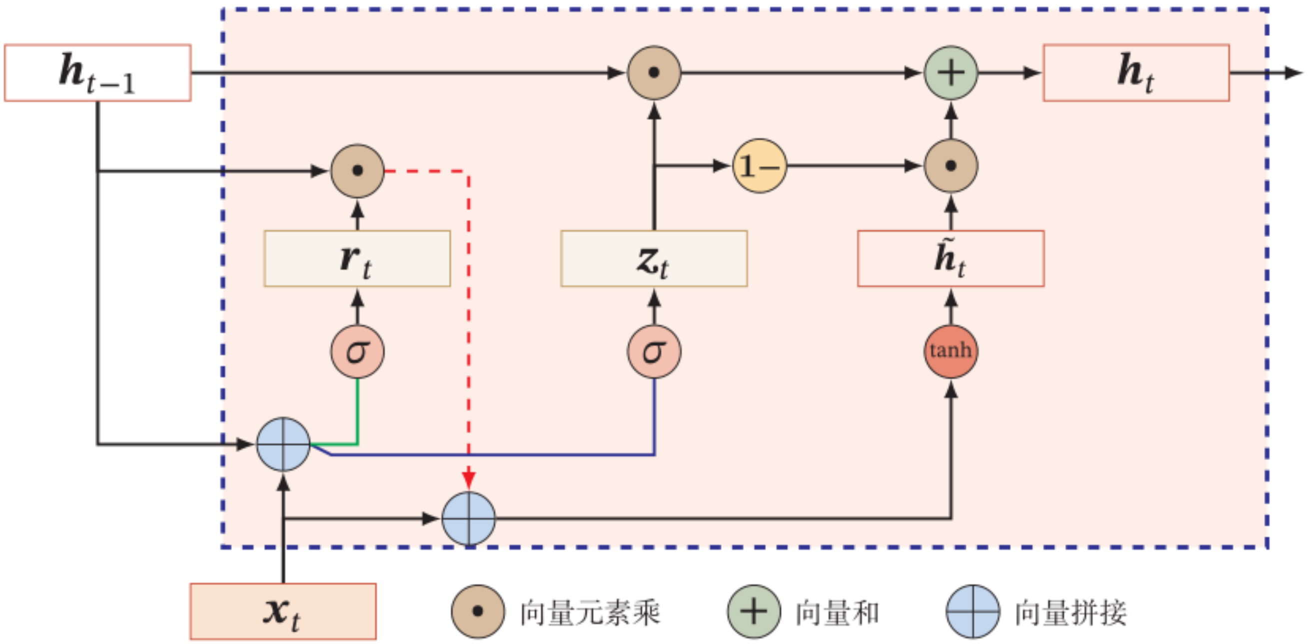
LSTM

- 可以更好地对梯度进行远距离传播
- “没有中间商赚差价”
- 可以类比于残差神经网络



GRU

本页内容取自邱锡鹏
《神经网络与深度学习》



重置门

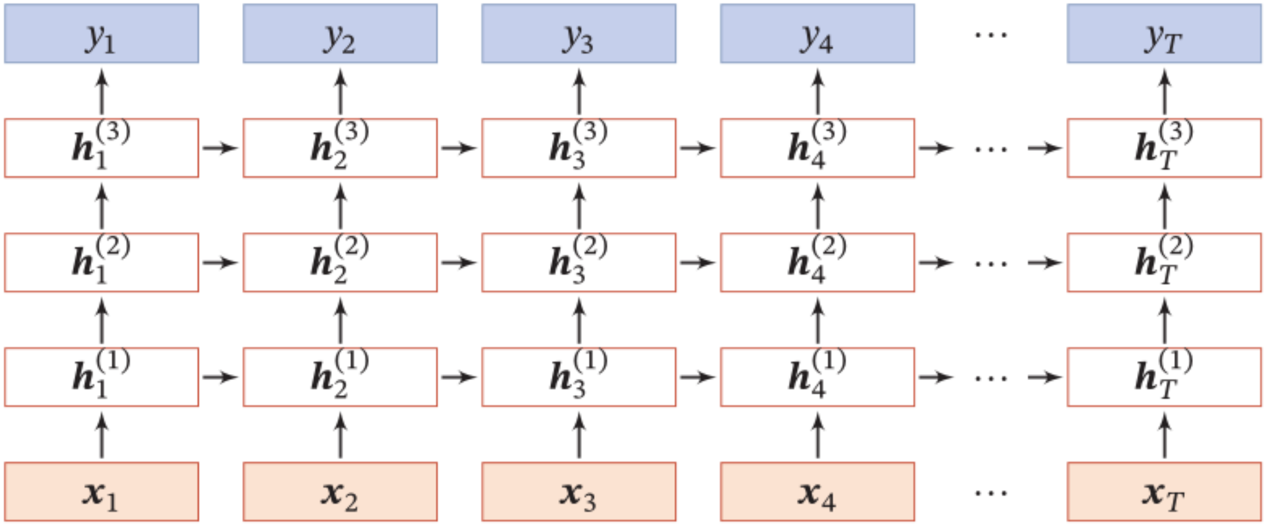
$$\mathbf{r}_t = \sigma(\mathbf{W}_r\mathbf{x}_t + \mathbf{U}_r\mathbf{h}_{t-1} + \mathbf{b}_r), \quad \tilde{\mathbf{h}}_t = \tanh(\mathbf{W}_c\mathbf{x}_t + \mathbf{U}(\mathbf{r}_t \odot \mathbf{h}_{t-1}))$$

$$\mathbf{z}_t = \sigma(\mathbf{W}_z\mathbf{x}_t + \mathbf{U}_z\mathbf{h}_{t-1} + \mathbf{b}_z), \quad \mathbf{h}_t = \mathbf{z}_t \odot \mathbf{h}_{t-1} + (1 - \mathbf{z}_t) \odot \tilde{\mathbf{h}}_t,$$

更新门

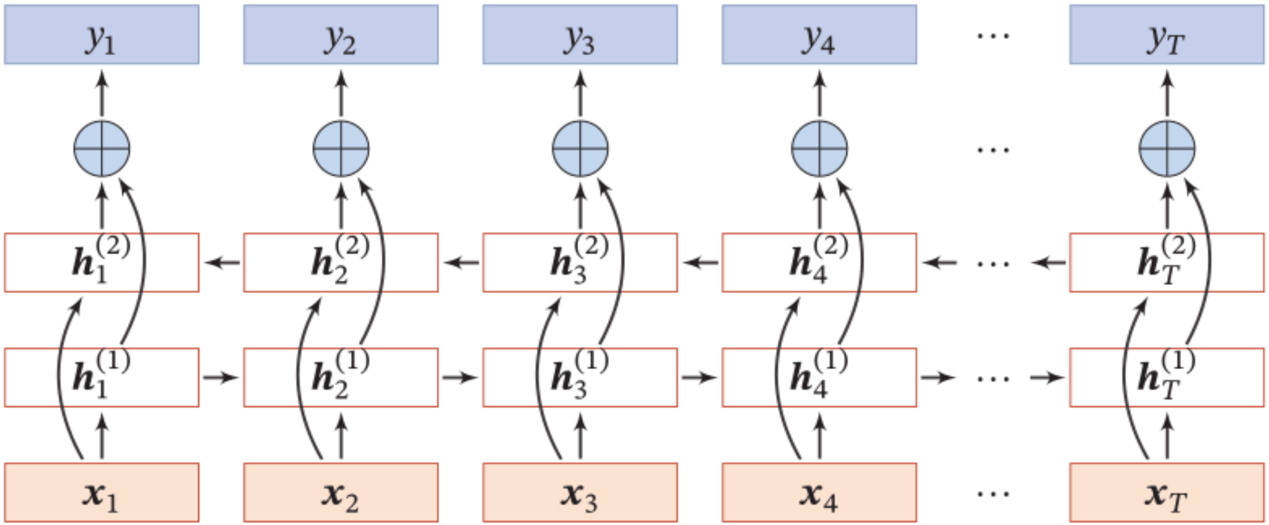
其他架构

- 多层堆叠 RNN



其他架构

- 双向 RNN



y_1
y_2
y_3
y_4
y_T
$h_1^{(2)}$
$h_2^{(2)}$
$h_3^{(2)}$
$h_4^{(2)}$
$h_T^{(2)}$
$h_1^{(1)}$
$h_2^{(1)}$
$h_3^{(1)}$
$h_4^{(1)}$
$h_T^{(1)}$
x_1
x_2
x_3
x_4
x_T