LSTM RNN 简介

潘睿

- **历史 & 基础知识**
- **简介**
- 优化
- 应用
- 实现细节
- **工具库**
- 展望

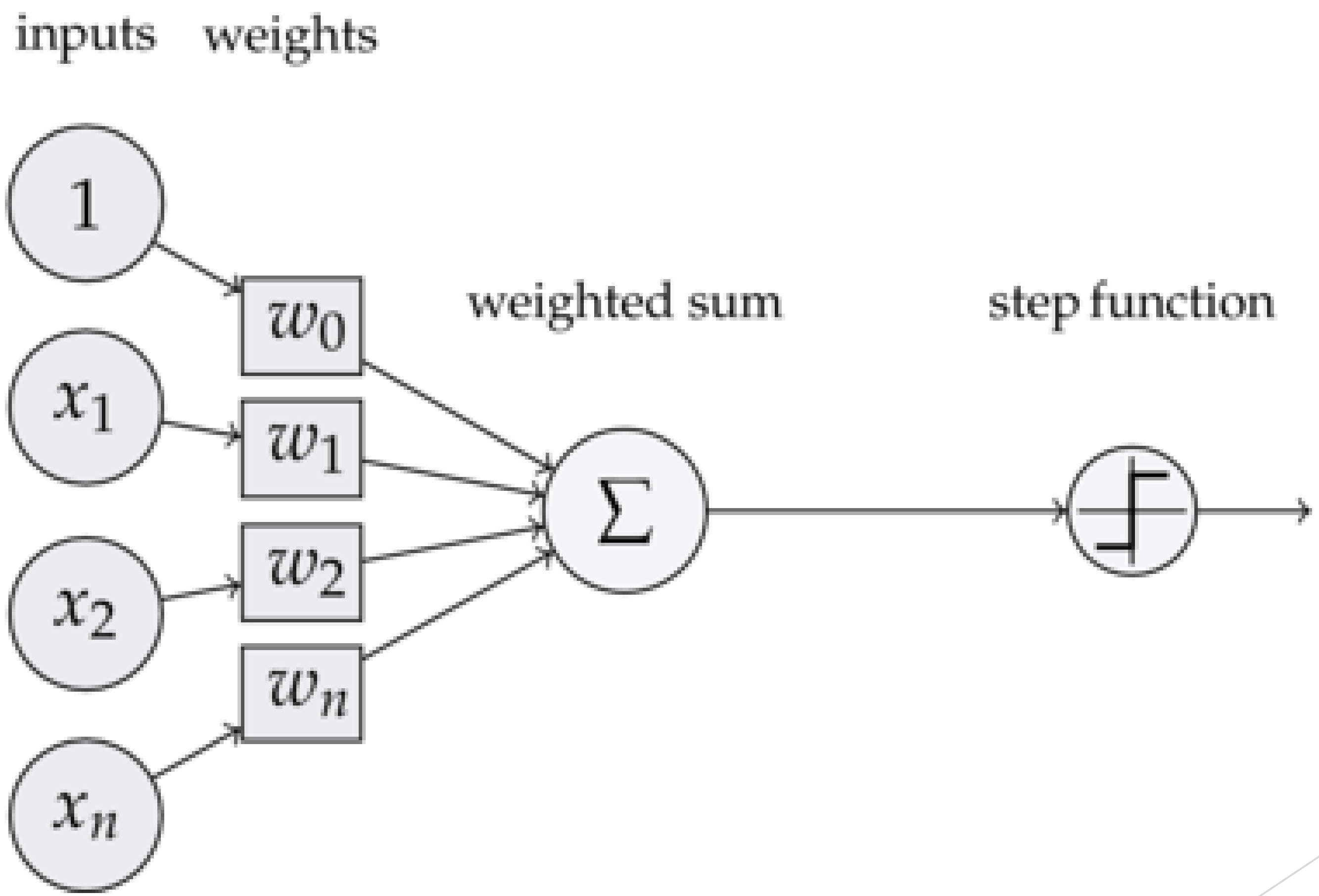
历史& 基础知识

- 1943年MP模型提出
- 标志着神经计算时代的开始

历史& 基础知识

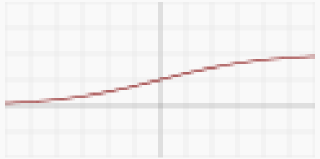
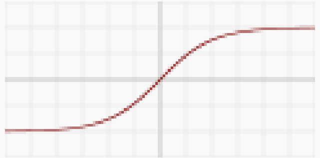
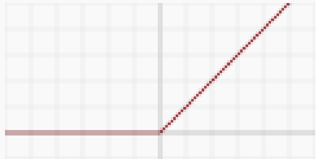
- 1957年提出Perceptron模型（感知器）
- 可以解决分类问题

- 单个神经元

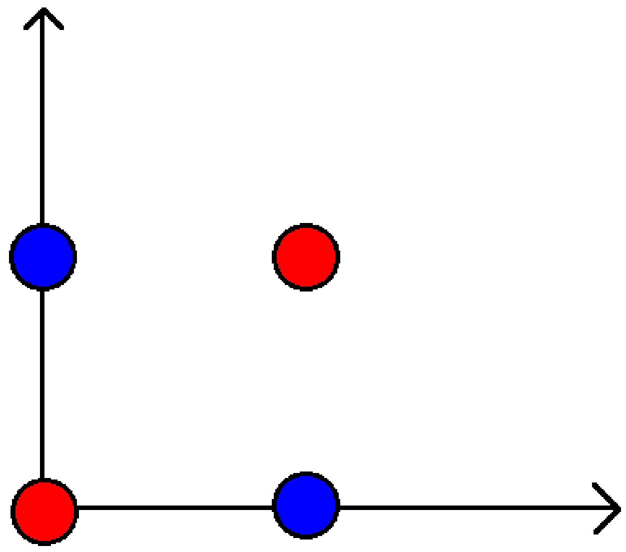

inputs
weights
1
x_1
x_2
x_n
w_0
w_1
w_2
w_n
weighted sum
Σ
step function

历史& 基础知识

- Step function 也叫Activation function
- 比较常用的有

Sigmoid		$f(x)=\frac{1}{1+e^{-x}}$	$f'(x)=f(x)(1-f(x))$
TanH		$f(x)=\tanh(x)=\frac{2}{1+e^{-2x}}-1$	$f'(x)=1-f(x)^2$
Rectified Linear Unit (ReLU)		$f(x)=\begin{cases} 0 & \text{for } x<0 \\ x & \text{for } x\geq 0\end{cases}$	$f'(x)=\begin{cases} 0 & \text{for } x<0 \\ 1 & \text{for } x\geq 0\end{cases}$

- 1969年Perceptron被指出只能做线性划分
- 神经网络进入第一次低潮



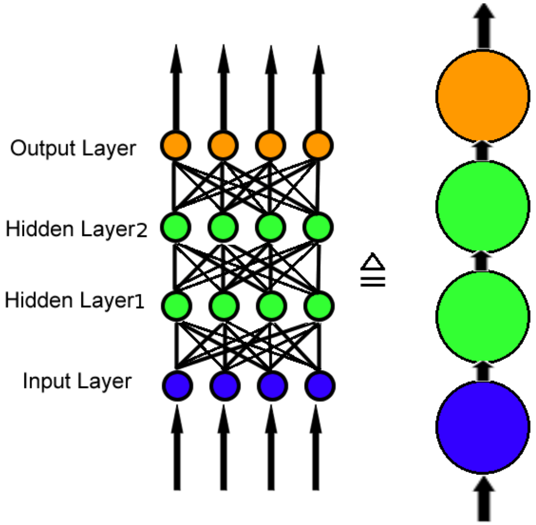
- 1982年John J. Hopfield提出一个具有完整理论基础的神经网络模型
- 神经网络复兴时期开始

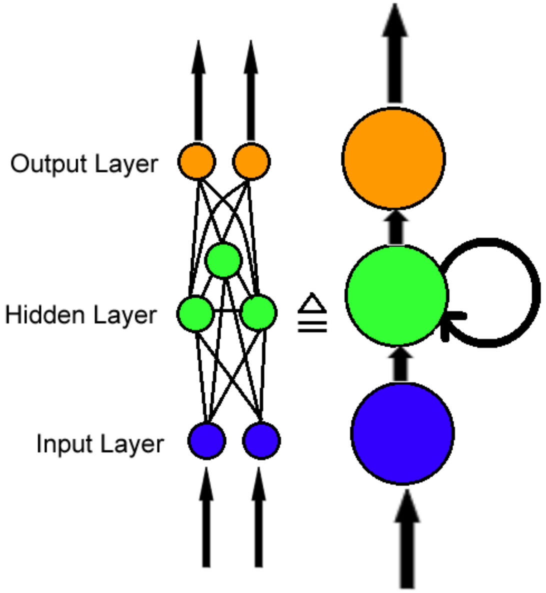
历史& 基础知识

- 1986年提出Back Propagation（BP）反向传播学习算法

- 流行至今

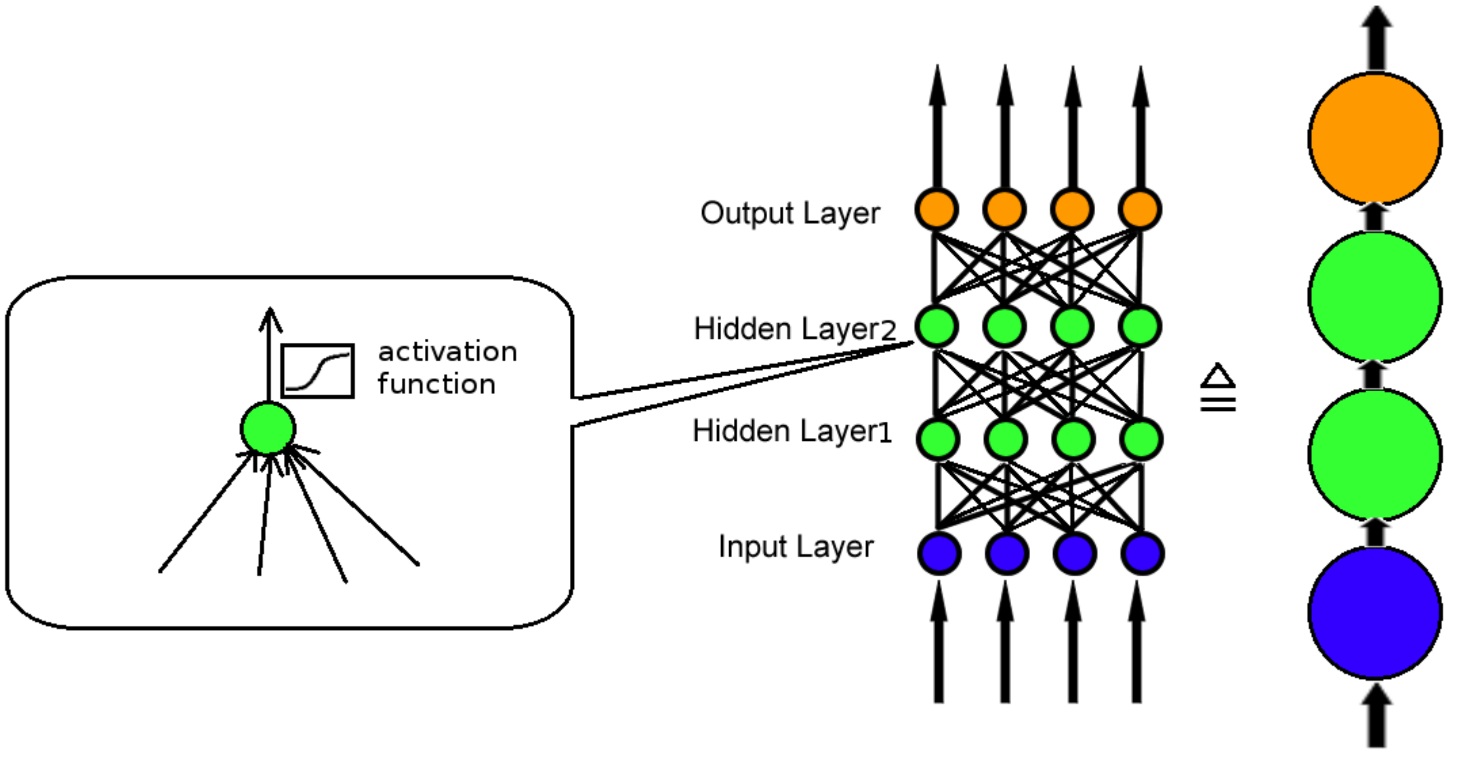
- 同一时期
- Multilayer perceptron（MLP） 多层感知器
- Recurrent Neural Network（RNN） 循环神经网络





- Multilayer perceptron 多层感知器
  - 定义
  - 训练
  - 理论基础

- Multilayer perceptron 多层感知器
- 定义
  - An MLP consists of multiple layers of nodes in a directed graph, with each layer fully connected to the next one.
  - 多层感知器就是多层神经元，每层有一堆神经元，这一层和下一层的每个神经元全连上



- Multilayer perceptron 多层感知器
- 训练
  - Forward Propagation 前向传播
  - Back Propagation 反向传播

- Multilayer perceptron 多层感知器
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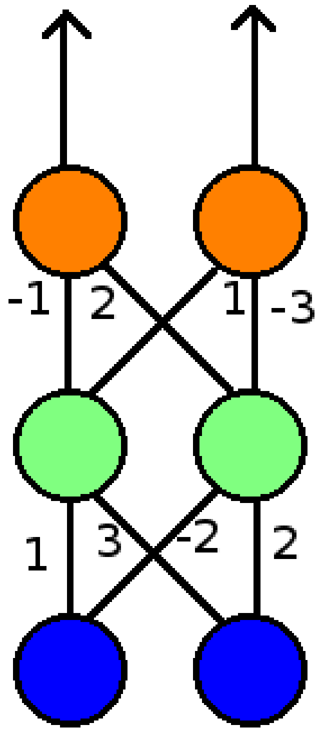
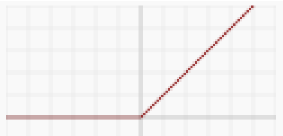


Rectified Linear Unit (ReLU)



$$f(x) = \begin{cases} 0 & \text{for} \quad x < 0 \\ x & \text{for} \quad x \geq 0 \end{cases}$$

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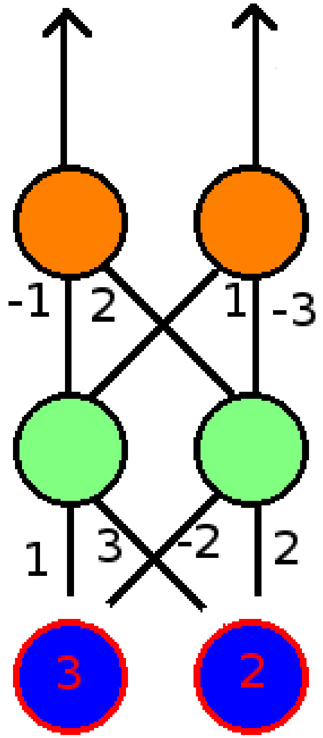

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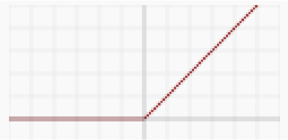

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历史& 基础知识

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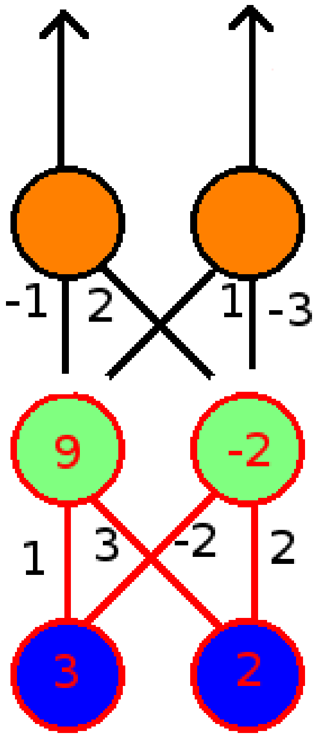
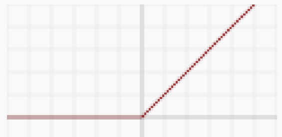


Rectified Linear Unit (ReLU)



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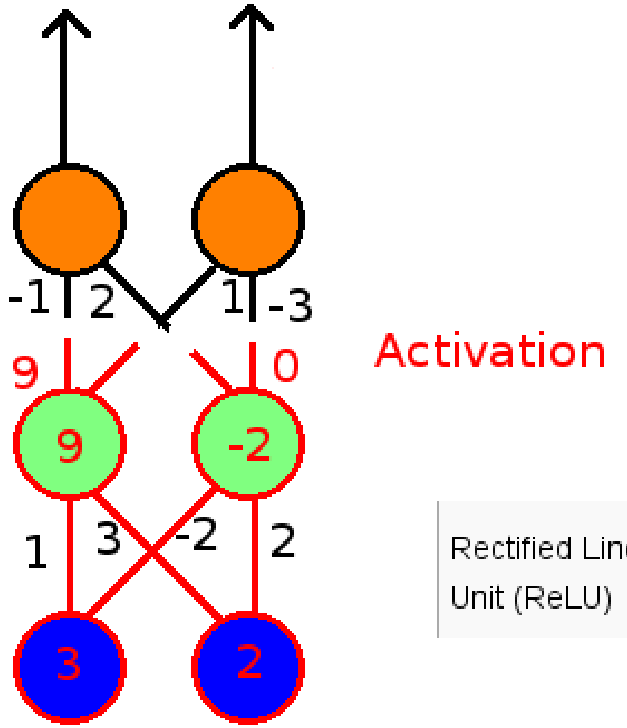

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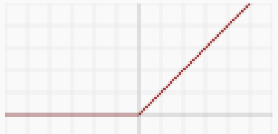

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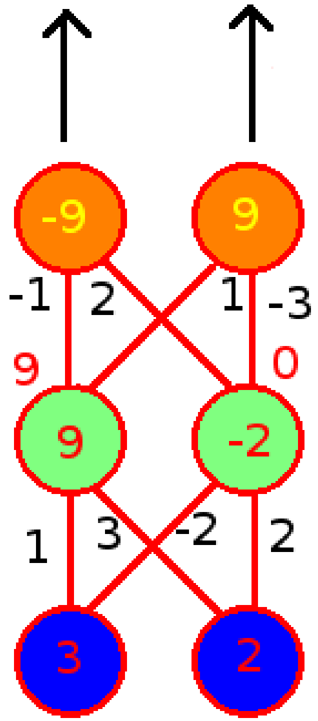

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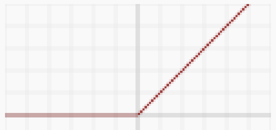

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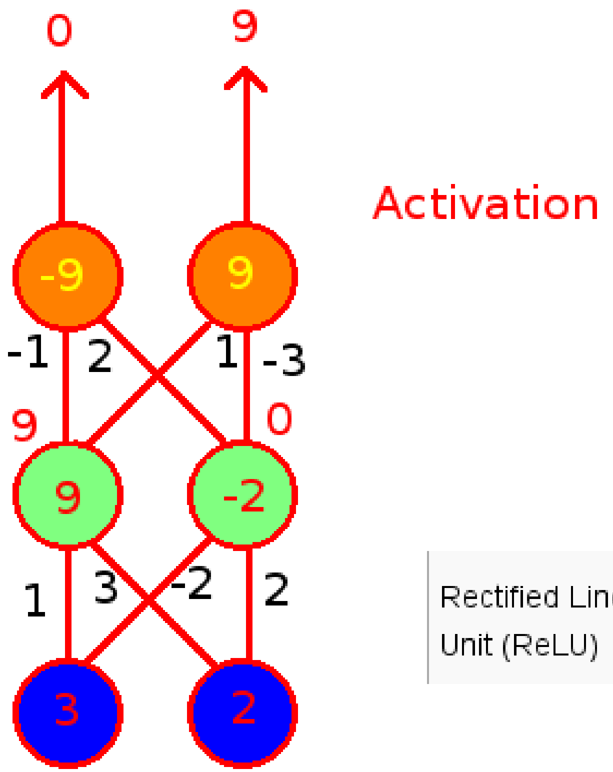

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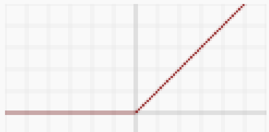

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- Multilayer perceptron 多层感知器
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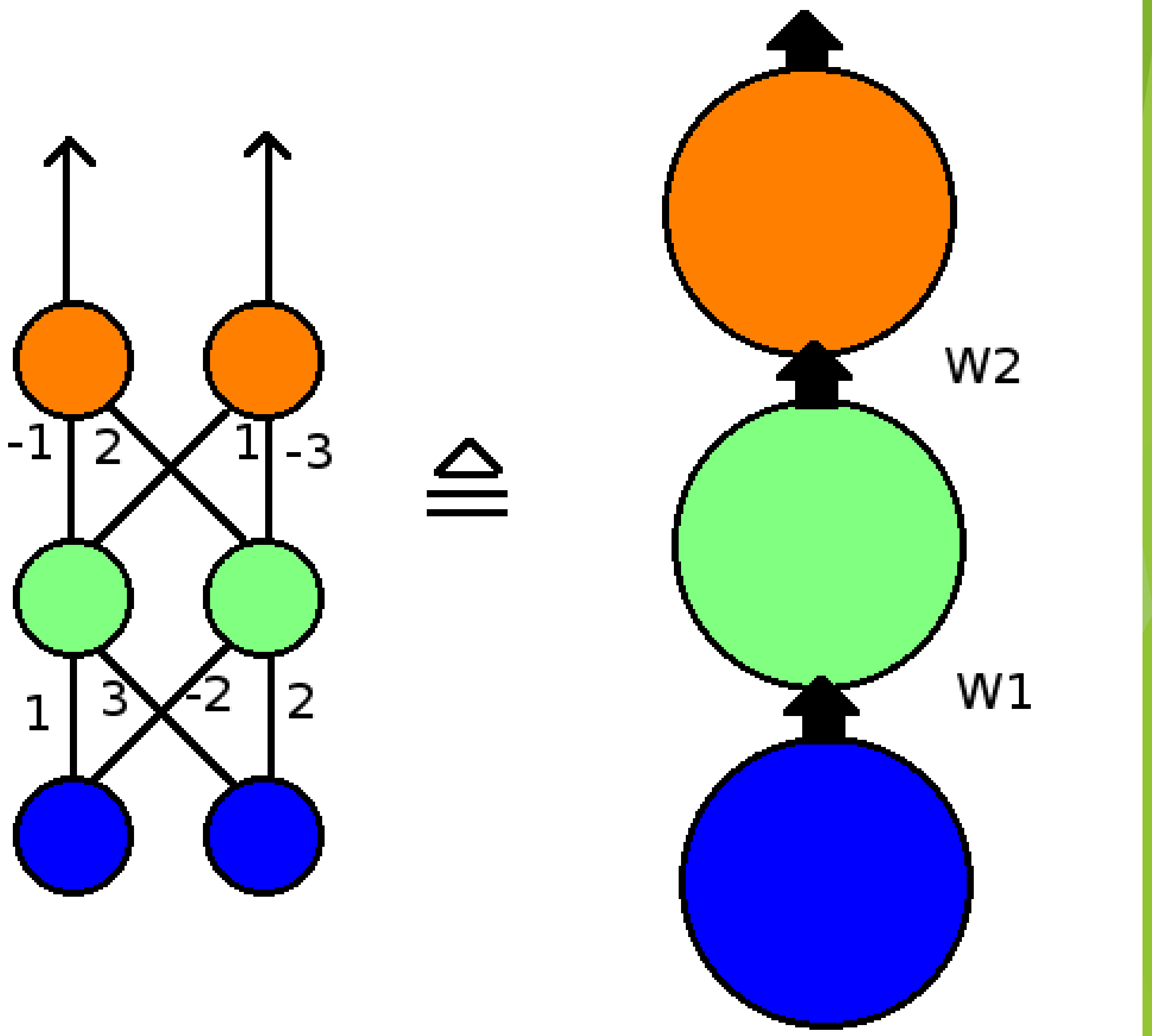
- 矩阵的观点
- W1 =   W2 =
- [1   3]   [-1   2]
- [-2 2]   [1   -3]



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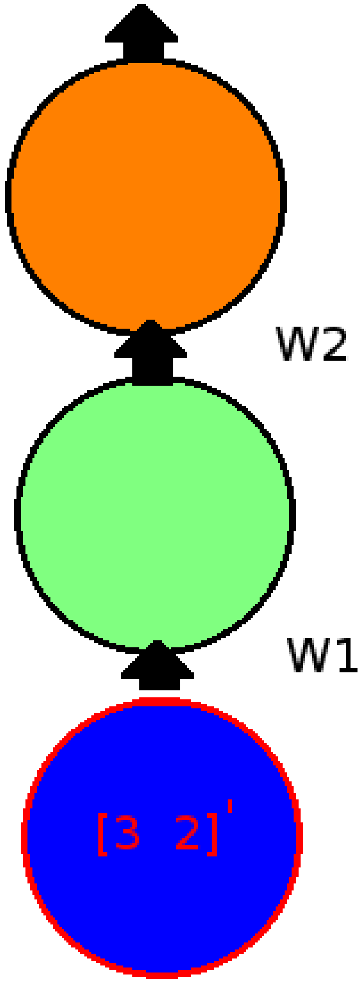

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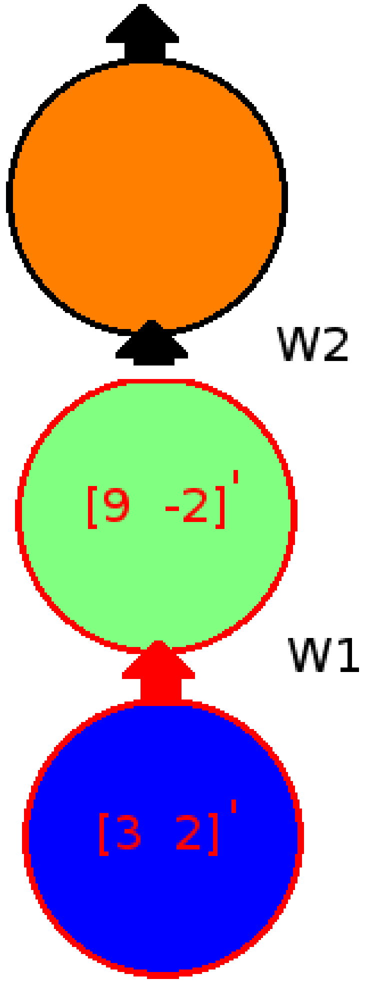

- 矩阵的观点

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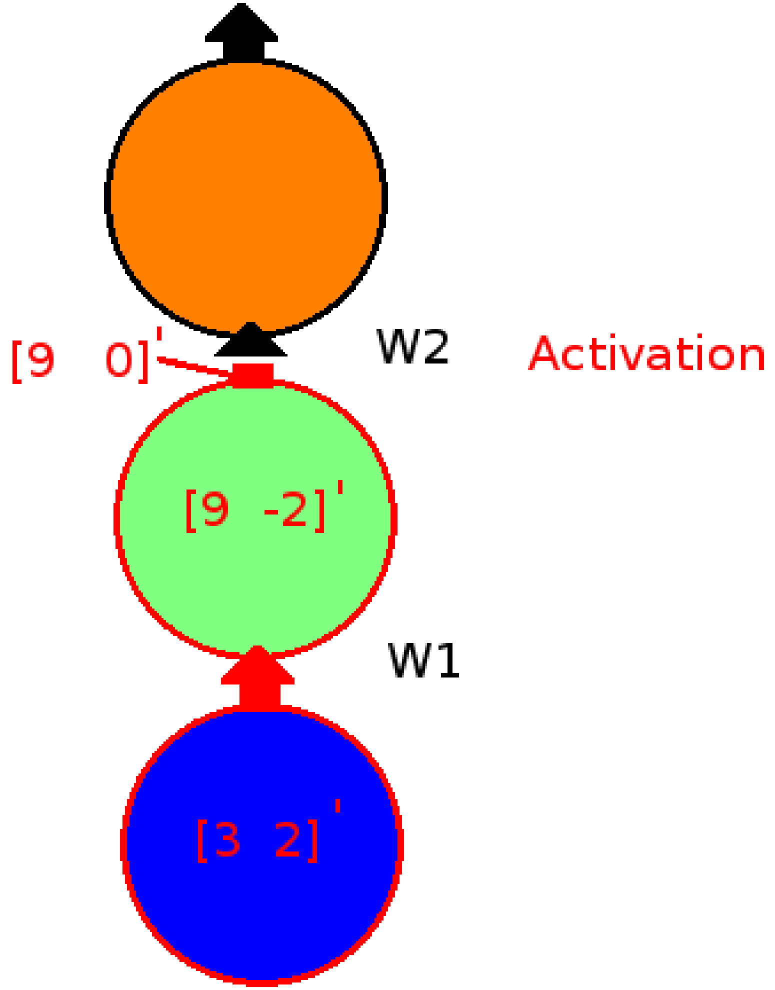

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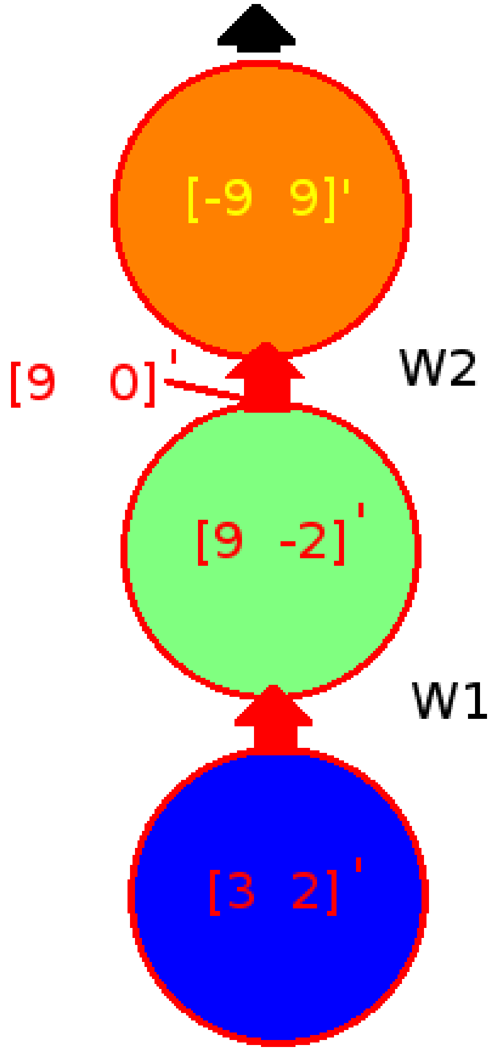

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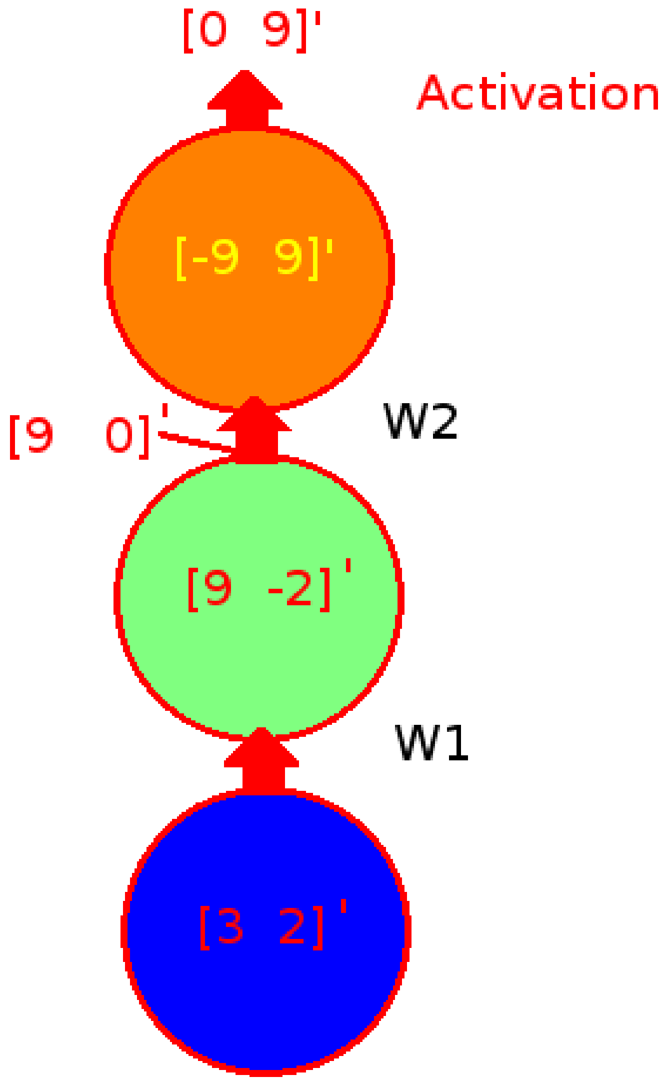

历史& 基础知识

- Multilayer perceptron 多层感知器
- 训练
  - Back Propagation 反向传播

- 高中题目：如何计算f(g(x))的导函数

- Multilayer perceptron 多层感知器
- 训练
  - Back Propagation 反向传播
- 高中题目：如何计算f(g(x))的导函数
- 答： f'(g(x)) * g'(x)

- Multilayer perceptron 多层感知器
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- 大学题目：如何计算f(g(**x**))的导函数

- Multilayer perceptron 多层感知器
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- 大学题目：如何计算f(g(**x**))的导函数

- 答：$D_{\mathbf{a}}(f \circ g) = D_{g(\mathbf{a})} f \circ D_{\mathbf{a}} g,$

$$Df(\mathbf{a}) = \begin{bmatrix} \frac{\partial f_1}{\partial x_1}(\mathbf{a}) & \frac{\partial f_1}{\partial x_2}(\mathbf{a}) & \ldots & \frac{\partial f_1}{\partial x_n}(\mathbf{a}) \\ \frac{\partial f_2}{\partial x_1}(\mathbf{a}) & \frac{\partial f_2}{\partial x_2}(\mathbf{a}) & \ldots & \frac{\partial f_2}{\partial x_n}(\mathbf{a}) \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial f_m}{\partial x_1}(\mathbf{a}) & \frac{\partial f_m}{\partial x_2}(\mathbf{a}) & \ldots & \frac{\partial f_m}{\partial x_n}(\mathbf{a}) \end{bmatrix}.$$

- Multilayer perceptron 多层感知器
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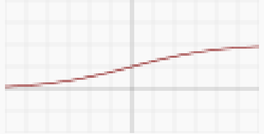
- 一个特例：如何计算σ(**Wx**)的导函数

Sigmoid		$f(x) = \frac{1}{1+e^{-x}}$	$f'(x) = f(x)(1 - f(x))$

$$
Df(\mathbf{a}) = \begin{bmatrix} \frac{\partial f_1}{\partial x_1}(\mathbf{a}) & \frac{\partial f_1}{\partial x_2}(\mathbf{a}) & \ldots & \frac{\partial f_1}{\partial x_n}(\mathbf{a}) \\ \frac{\partial f_2}{\partial x_1}(\mathbf{a}) & \frac{\partial f_2}{\partial x_2}(\mathbf{a}) & \ldots & \frac{\partial f_2}{\partial x_n}(\mathbf{a}) \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial f_m}{\partial x_1}(\mathbf{a}) & \frac{\partial f_m}{\partial x_2}(\mathbf{a}) & \ldots & \frac{\partial f_m}{\partial x_n}(\mathbf{a}) \end{bmatrix}.
$$

- Multilayer perceptron 多层感知器
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- 一个特例：如何计算σ(**Wx**)的导函数

$$\frac{\partial \sigma(\mathbf{x})}{\partial \mathbf{x}} = D_\sigma(\mathbf{x}) = \begin{bmatrix} \sigma(x_1)(1-\sigma(x_1)) & 0 & \cdots & 0 \\ 0 & \sigma(x_2)(1-\sigma(x_2)) & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma(x_m)(1-\sigma(x_m)) \end{bmatrix}$$

$$\frac{\partial \mathbf{Wx}}{\partial \mathbf{x}} = \mathbf{W}$$

- Multilayer perceptron 多层感知器
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- 一个特例：如何计算σ(**Wx**)的导函数

$$\frac{\partial \sigma(\mathbf{Wx})}{\partial \mathbf{x}} = \frac{\partial \sigma(\mathbf{Wx})}{\partial \mathbf{Wx}} * \frac{\partial \mathbf{Wx}}{\partial \mathbf{x}} = D_\sigma(\mathbf{Wx}) * \mathbf{W}$$

- Multilayer perceptron 多层感知器
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- 另一个特例：如何计算sum(σ(**Wx**)) 的导函数

$$\frac{\partial \sum \sigma(\mathbf{Wx})}{\partial \mathbf{x}} = \frac{\partial \sum \sigma(\mathbf{Wx})}{\partial \sigma(\mathbf{Wx})} * \frac{\partial \sigma(\mathbf{Wx})}{\partial \mathbf{Wx}} * \frac{\partial \mathbf{Wx}}{\partial \mathbf{x}} =$$

$$[1, 1, \ldots, 1] * D_\sigma(\mathbf{Wx}) * \mathbf{W} =$$

$$(\sigma(\mathbf{Wx}))^T \odot (1 - \sigma(\mathbf{Wx}))^T * \mathbf{W}$$

- Multilayer perceptron 多层感知器
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- 另一个特例：如何计算sum(σ(**Wx**)) 的导函数

$$(\sigma(\mathbf{Wx}))^T \odot (1 - \sigma(\mathbf{Wx}))^T * \mathbf{W}$$

Hadamard product (逐元素相乘)

全1向量

矩阵乘法

- Multilayer perceptron 多层感知器
- 训练
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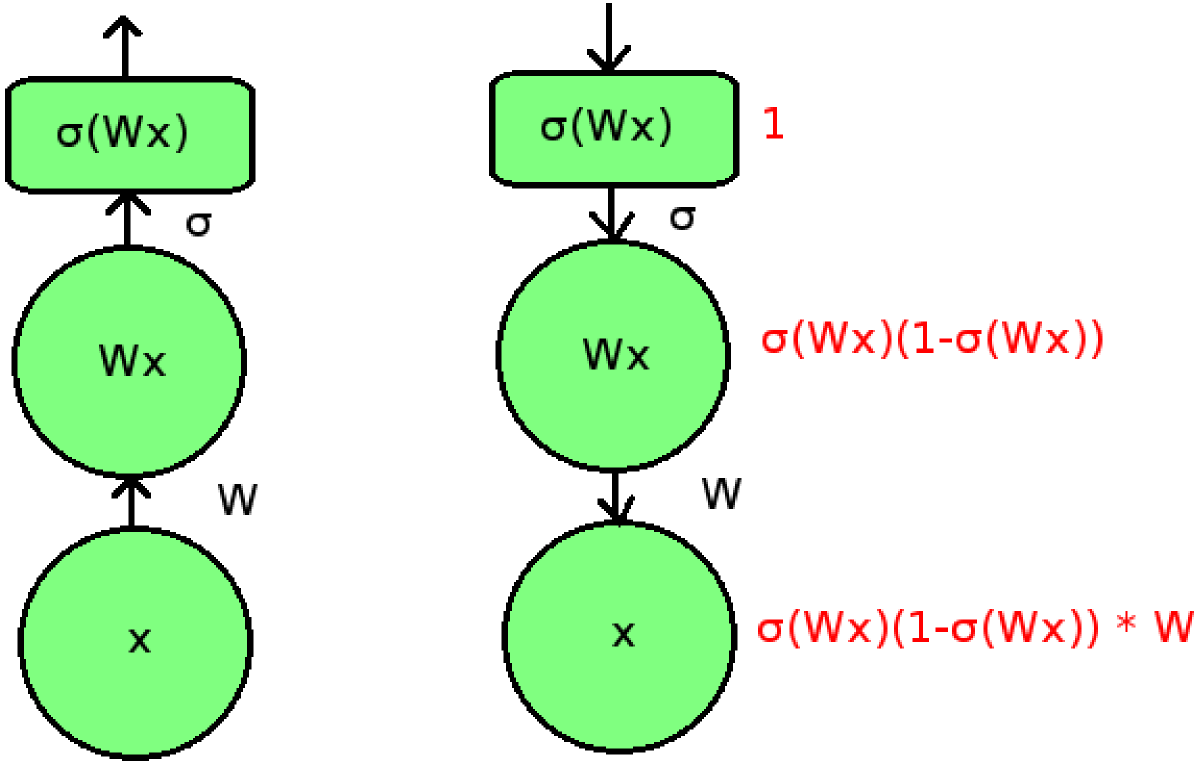

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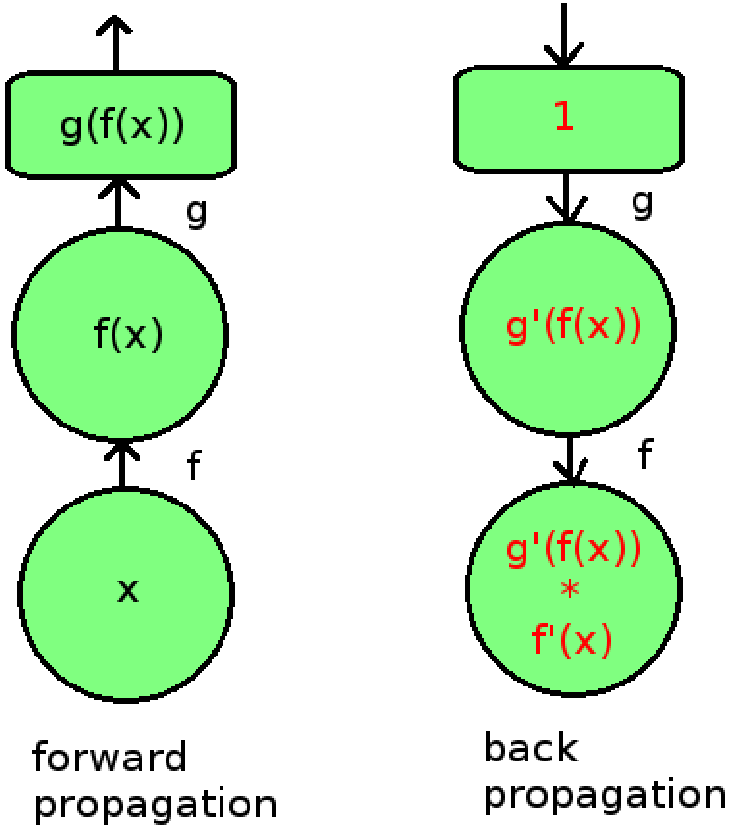

- Multilayer perceptron 多层感知器
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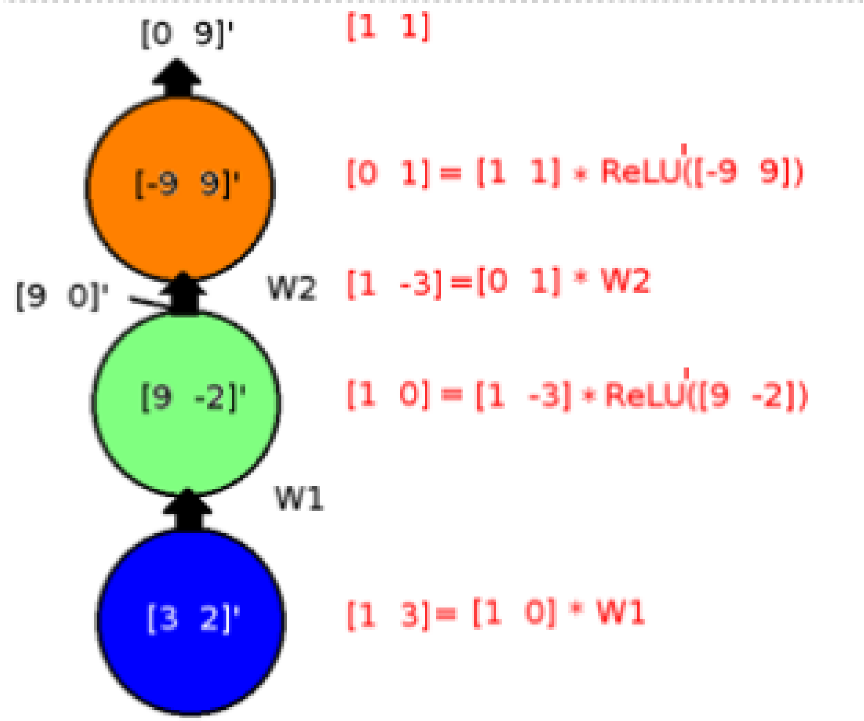
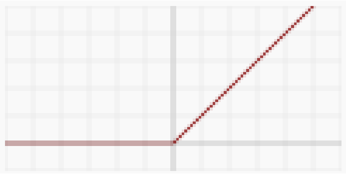
- W1 =
- [1 3]
- [-2 2]

W2 =

[-1 2]

[1 -3]



Rectified Linear Unit (ReLU)		$f(x) = \begin{cases} 0 & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} 0 & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$

- Multilayer perceptron 多层感知器
- 训练
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- W1 = W2 =
- [1 3] [-1 2]
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- W1，W2的导函数？

- Multilayer perceptron 多层感知器
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- W1，W2的导函数？

$$\frac{\partial f(\mathbf{Wx})}{\partial \mathbf{W}} = \frac{\partial f(\mathbf{Wx})}{\partial \mathbf{Wx}} * \frac{\partial \mathbf{Wx}}{\partial \mathbf{W}} = \frac{\partial f(\mathbf{Wx})}{\partial \mathbf{Wx}} * \mathbf{T}_{n*n*m}$$

- Multilayer perceptron 多层感知器
- 训练
  - Back Propagation 反向传播
- W1，W2的导函数？

$$\frac{\partial \mathbf{Wx}}{\partial \mathbf{W}_{i,j}} = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ x_j (ith\ row) \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

$$let\ \mathbf{a}^T\ denote \frac{\partial f(\mathbf{Wx})}{\partial \mathbf{Wx}},$$

$$\frac{\partial f(\mathbf{Wx})}{\partial \mathbf{W}_{i,j}} = a_i x_j$$

$$\frac{\partial f(\mathbf{Wx})}{\partial \mathbf{W}} = \mathbf{ax}^T$$

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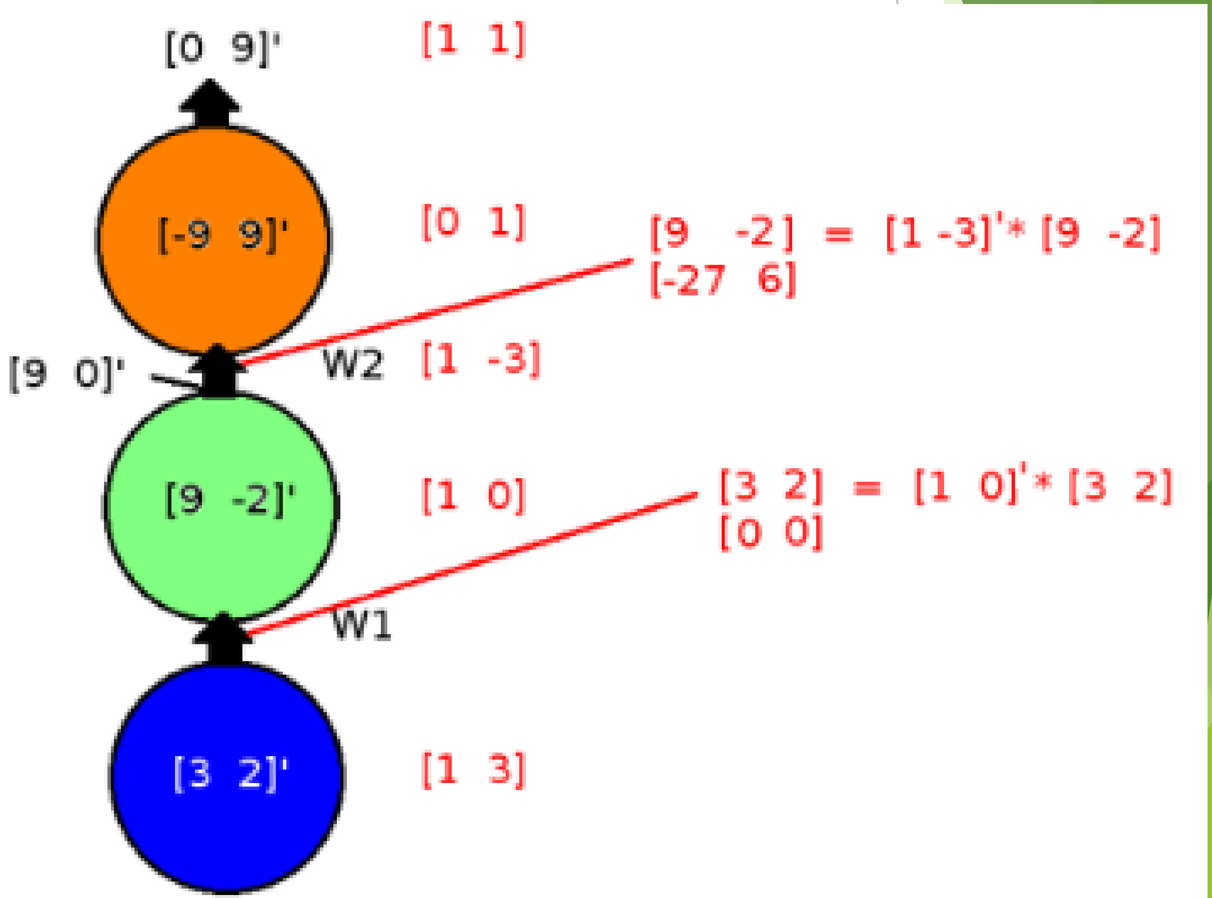


- Multilayer perceptron 多层感知器
- 理论基础
  - Universal approximation theorem 通用近似定理
    - 大意就是三层神经网络只要隐层点够多，就可以近似任何连续函数
    - 视觉直观解释见 http://neuralnetworksanddeeplearning.com/chap4.html

Let $\varphi(\cdot)$ be a nonconstant, bounded, and monotonically-increasing continuous function. Let I_m denote the m-dimensional unit hypercube $[0,1]^m$. The space of continuous functions on I_m is denoted by $C(I_m)$. Then, given any function $f \in C(I_m)$ and $\varepsilon > 0$, there exists an integer N and real constants $v_i, b_i \in \mathbb{R}$, where $i = 1, \cdots, N$ such that we may define:

$$F(x) = \sum_{i=1}^{N} v_i \varphi\left(w_i^T x + b_i\right)$$

as an approximate realization of the function f where f is independent of φ; that is,

$$|F(x) - f(x)| < \varepsilon$$

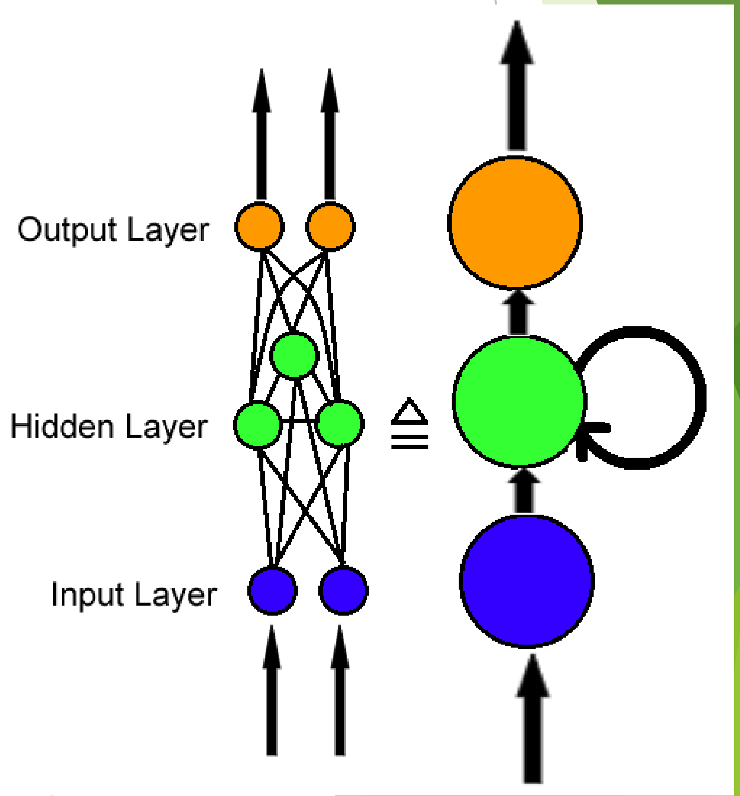
for all $x \in I_m$. In other words, functions of the form $F(x)$ are dense in $C(I_m)$.

- Recurrent Neural Network 循环神经网络
  - 定义
  - 用法
  - 训练
  - 理论基础
  - 优缺点

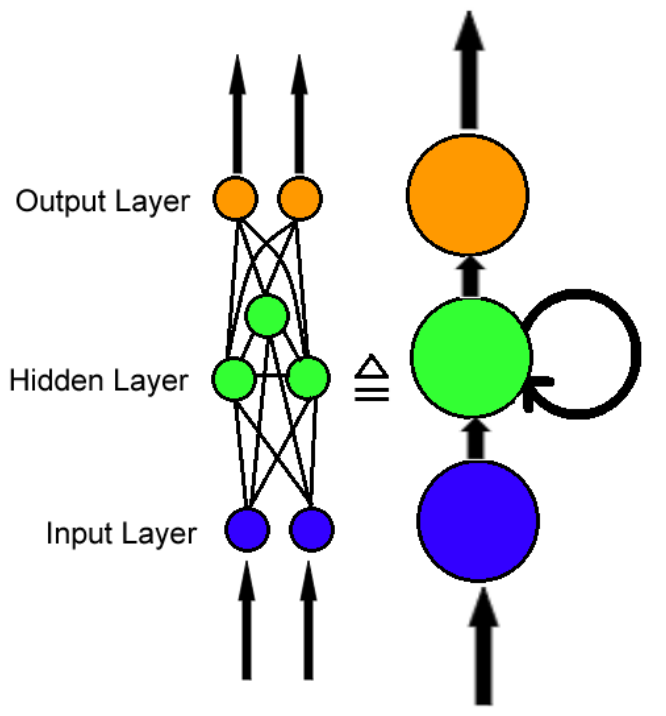
Recurrent Neural Network 循环神经网络

定义

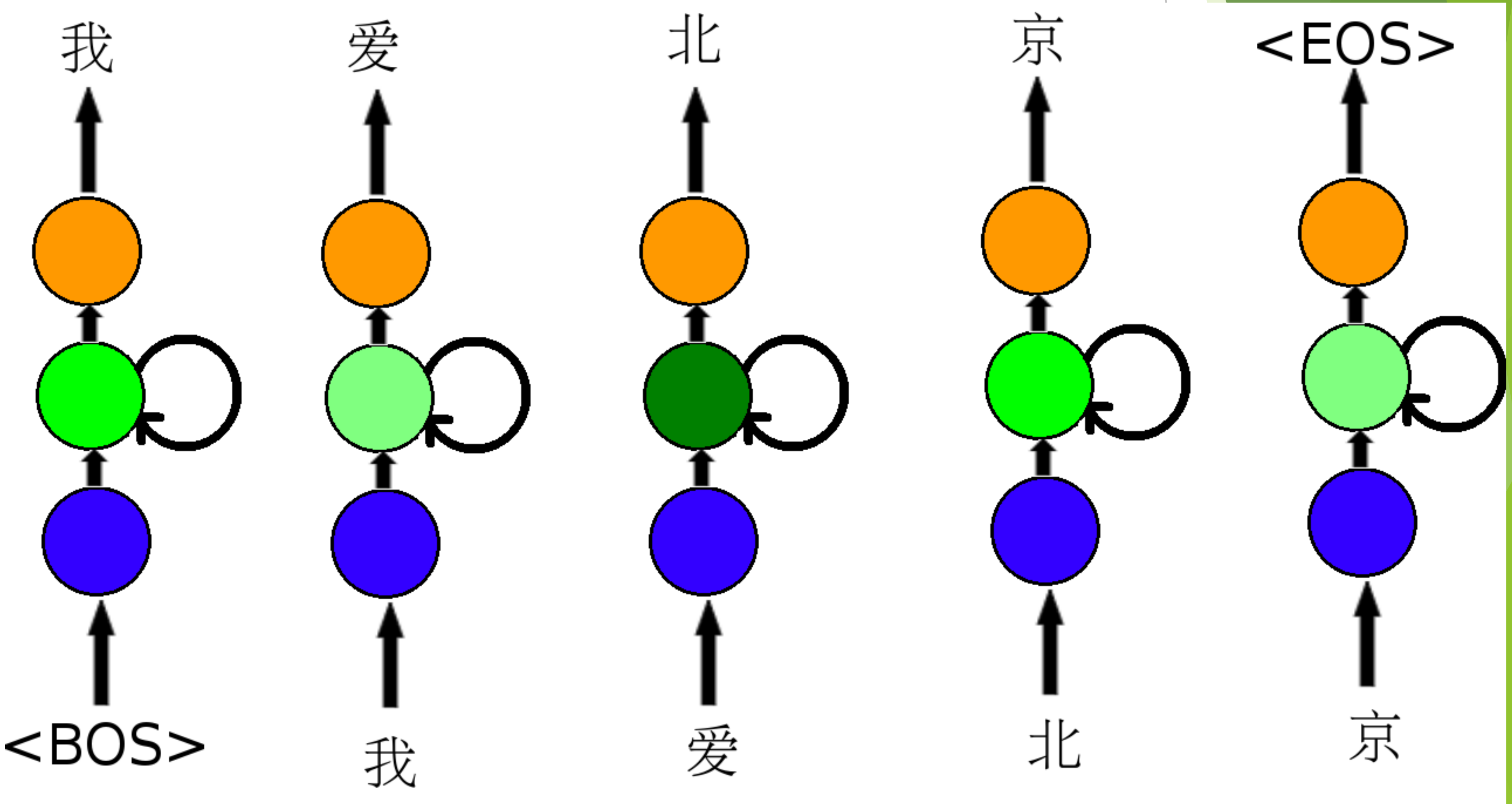
- A recurrent neural network (RNN) is a class of artificial neural network where connections between units form a directed cycle.
- 这个定义更广泛些，下图所示的是当前比较常见的RNN



- Recurrent Neural Network 循环神经网络
- 定义
  - 注意不要与Recursive Neural Network（递归神经网络）弄混
  - Recurrent Neural Network是Recursive Neural Network的一个特例
  - Recursive Neural Network代表了更复杂的结构（树状，图状）
  - Recurrent Neural Network只代表**链状(?)** 时序结构

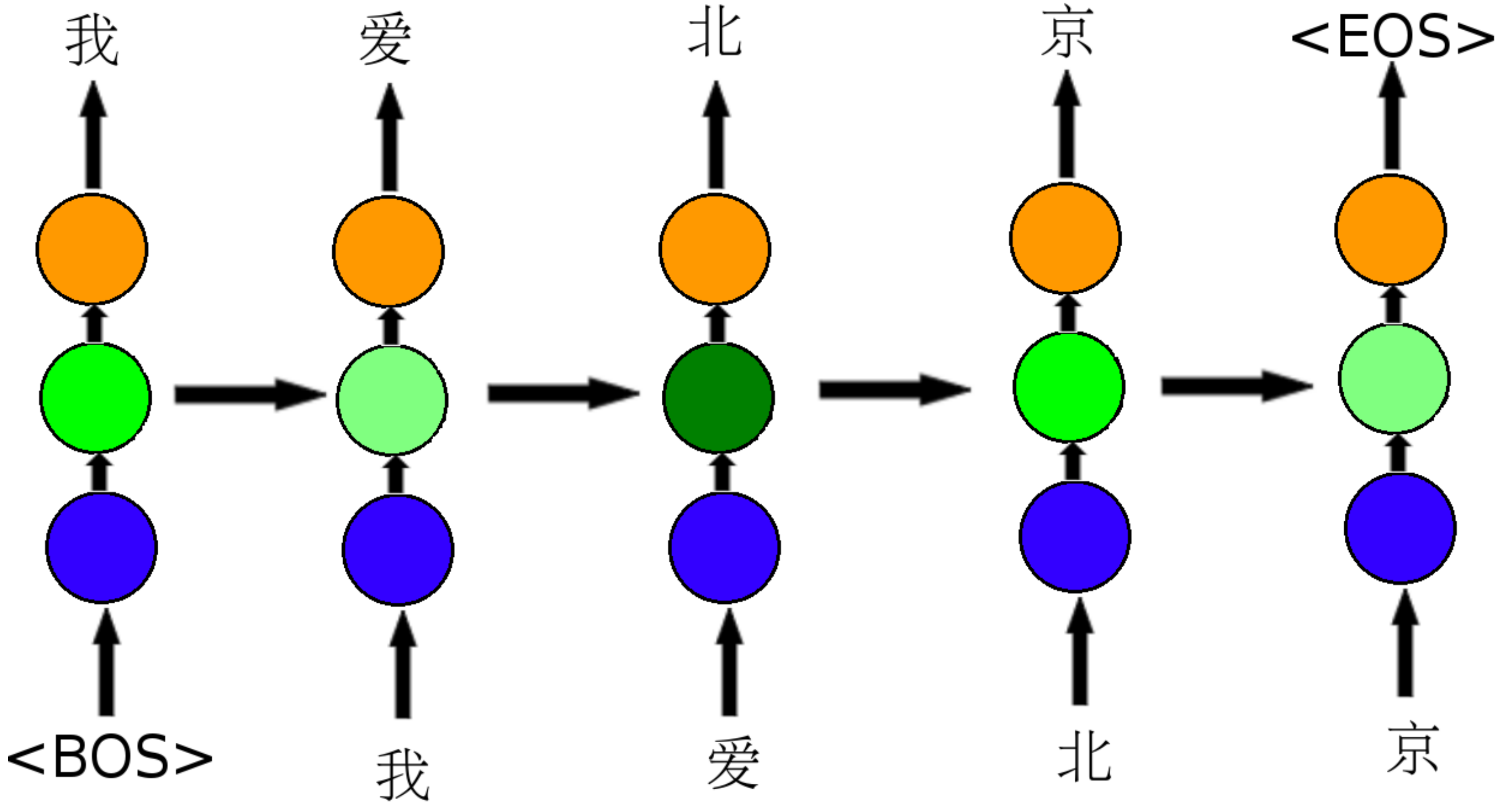


- Recurrent Neural Network 循环神经网络
- 用法
  - 序列映射

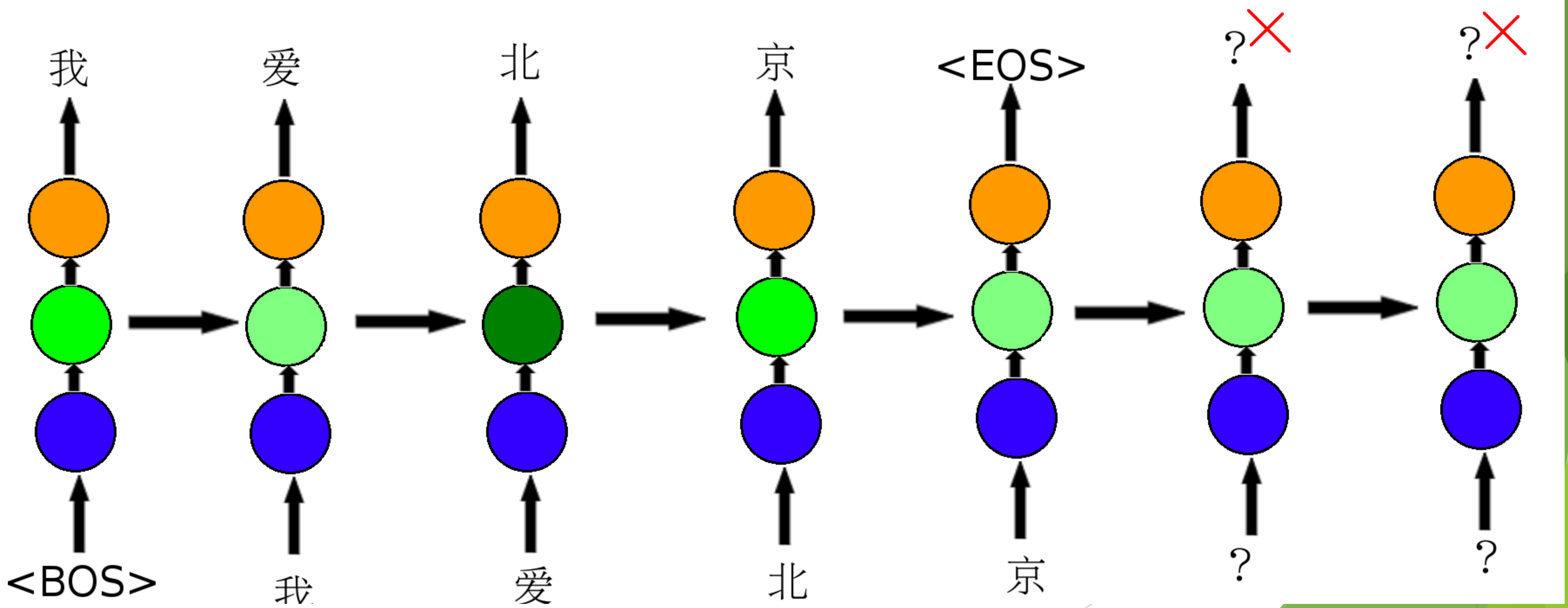


- Recurrent Neural Network循环神经网络
- 训练
  - Back Propagation Through Time (BPTT)沿时间反向传播
  - 1987、1988、1995年由多名研究者分别独立提出
  - BPTT有多种变种，这里只介绍目前最常用的一种

- Recurrent Neural Network循环神经网络
- 训练
  - Back Propagation Through Time (BPTT)沿时间反向传播



- Recurrent Neural Network循环神经网络
- 训练
  - 实际情况中往往展开一个最大的固定长度（下图中为7）



- Recurrent Neural Network循环神经网络
- 训练
  - 对于过长的数据，可以作截断处理
  - 使用上一截的隐层状态初始化（当然梯度仍无法回传至上一截数据）

- Recurrent Neural Network循环神经网络
- 理论基础
  - 输入输出连续的情形下： 如果隐藏层神经元足够多，RNN可以一致逼近任意连续曲线
  - （对于输入输出离散情形也是如此）

Theorem

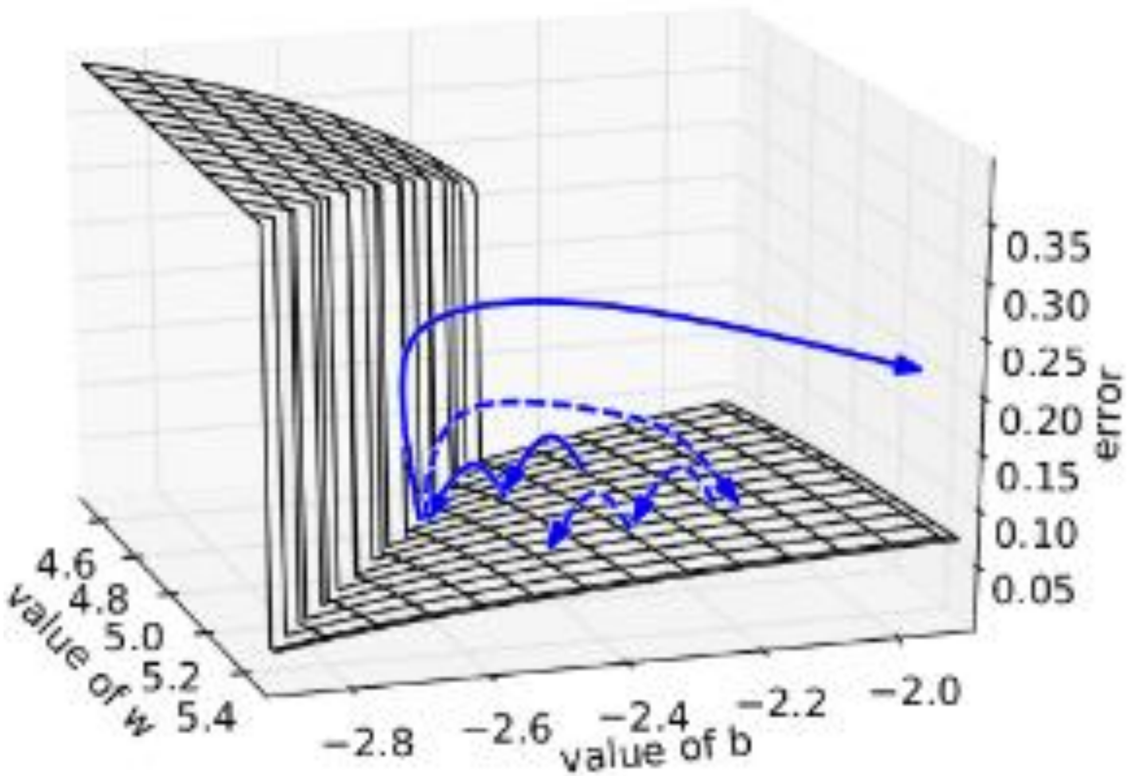
Let be $f: I=[0,T] \rightarrow R^n$ be a continuous curve, where $0<T<\infty$. Then, for an arbitrary $\varepsilon>0$, there exist an integer N and a recurrent networks with n outputs and N hidden units such that

$$\max_{t \in I} |f(t) - u(t)| < \varepsilon,$$

where $u(t)={}^t(u_1(t),\ldots u_n(t))$ is the internal state of output units of the network.

- Recurrent Neural Network循环神经网络
- 优点
  - 相比多层感知器，可以处理变长数据
- 缺点
  - Gradient Explosion （梯度爆炸）
  - Gradient Vanishing （梯度消失）

- Recurrent Neural Network循环神经网络
- 尝试
  - [2012] On the difficulty of training recurrent neural networks



历史& 基础知识

- 1997年Long Short-Term Memory Recurrent Neural Network (LSTM RNN)提出

- 当时神经网络正因为Support Vector Machine (SVM)支撑向量机的火爆而陷入低潮

- LSTM最初的提出有几个原因
  - 为了解决RNN的Gradient Explosion/Vanishing的问题
  - 为了得到能够学习如何学习的神经网络

- LSTM, 5000 weights, 5 months training: metalearns fast online learning algorithm for quadratic functions $f(x,y)=a_1x^2+a_2y^2+a_3xy+a_4x+a_5y+a_6$ Huge time lags.
- After metalearning, freeze weights.
- Now use net: Select new f, feed training exemplars ...data/target/data/target/data... into input units, one at a time. After 30 exemplars the net predicts target inputs before it sees them.

No weight changes! How?

- Metalearner也用RNN应用过，但没有LSTM如此好的效果
- LSTM的Memory存储了神奇的知识

历史& 基础知识

- 2006年，Deeplearning在ImageNet上取得巨大突破
- 深度学习开始火爆

历史& 基础知识

- 2013年，LSTM在Speech Recognition上取得很好的效果
  - SPEECH RECOGNITION WITH DEEP RECURRENT NEURAL NETWORKS
- 2014年，LSTM在Machine Translation上取得不错的效果，进入NLP领域
  - Sequence-to-sequence-learning-with-neural-networks
- 只要是和序列映射有关的，LSTM都可以做！
- LSTM开始火热

简介

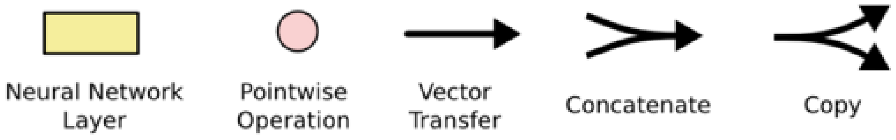
简介

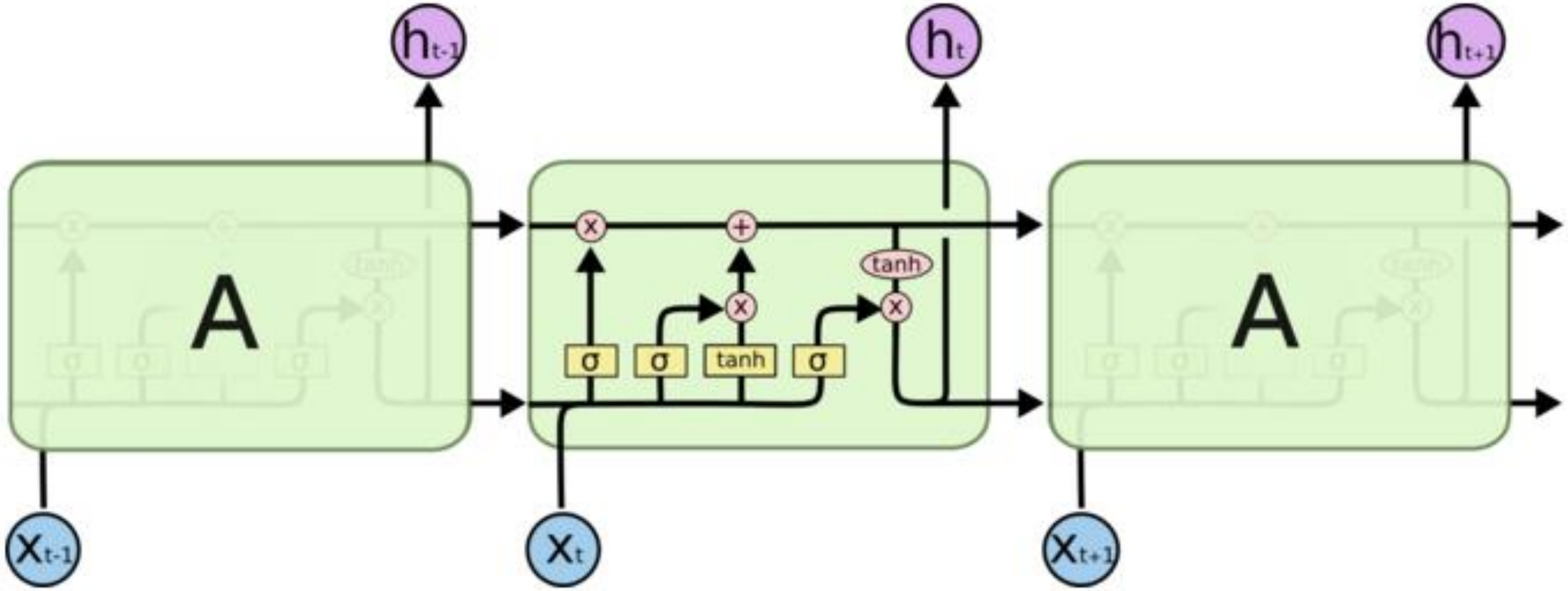
- LSTM的结构
- LSTM的思想
- 用LSTM实现Seq2Seq

简介

▶ 通用LSTM的结构

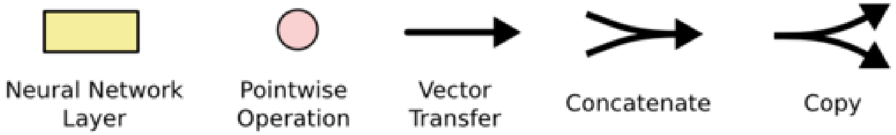
$$
\begin{aligned}
\bar{\mathbf{z}}^t &= \mathbf{W}_z\mathbf{x}^t + \mathbf{R}_z\mathbf{y}^{t-1} + \mathbf{b}_z \\
\mathbf{z}^t &= g(\bar{\mathbf{z}}^t) && \textit{block input} \\
\bar{\mathbf{i}}^t &= \mathbf{W}_i\mathbf{x}^t + \mathbf{R}_i\mathbf{y}^{t-1} + \mathbf{p}_i \odot \mathbf{c}^{t-1} + \mathbf{b}_i \\
\mathbf{i}^t &= \sigma(\bar{\mathbf{i}}^t) && \textit{input gate} \\
\bar{\mathbf{f}}^t &= \mathbf{W}_f\mathbf{x}^t + \mathbf{R}_f\mathbf{y}^{t-1} + \mathbf{p}_f \odot \mathbf{c}^{t-1} + \mathbf{b}_f \\
\mathbf{f}^t &= \sigma(\bar{\mathbf{f}}^t) && \textit{forget gate} \\
\mathbf{c}^t &= \mathbf{z}^t \odot \mathbf{i}^t + \mathbf{c}^{t-1} \odot \mathbf{f}^t && \textit{cell} \\
\bar{\mathbf{o}}^t &= \mathbf{W}_o\mathbf{x}^t + \mathbf{R}_o\mathbf{y}^{t-1} + \mathbf{p}_o \odot \mathbf{c}^t + \mathbf{b}_o \\
\mathbf{o}^t &= \sigma(\bar{\mathbf{o}}^t) && \textit{output gate} \\
\mathbf{y}^t &= h(\mathbf{c}^t) \odot \mathbf{o}^t && \textit{block output}
\end{aligned}
$$



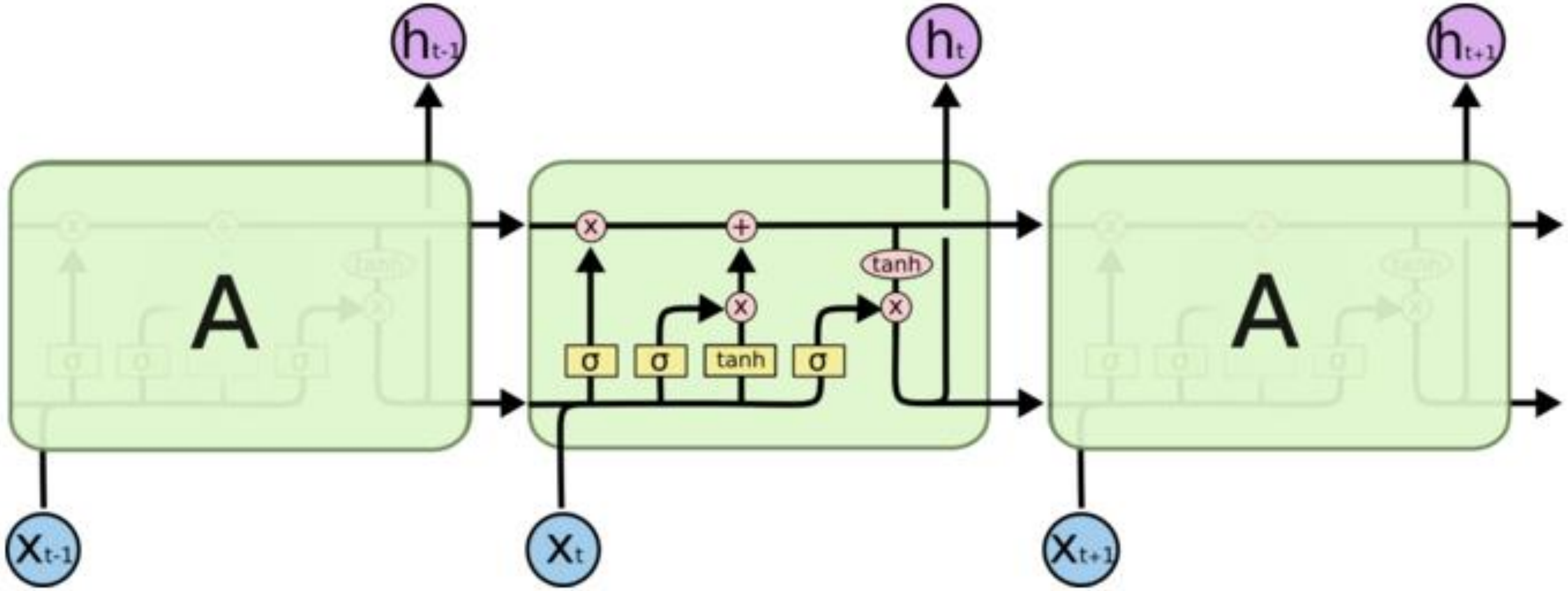


简介

▶ 常见LSTM结构



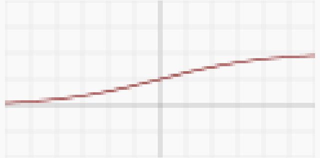
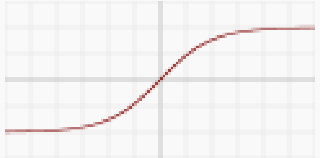
$$
\begin{aligned}
\bar{\mathbf{z}}^t &= \mathbf{W}_z\mathbf{x}^t + \mathbf{R}_z\mathbf{y}^{t-1} & \\
\mathbf{z}^t &= g(\bar{\mathbf{z}}^t) & \textit{block input} \\
\bar{\mathbf{i}}^t &= \mathbf{W}_i\mathbf{x}^t + \mathbf{R}_i\mathbf{y}^{t-1} & \\
\mathbf{i}^t &= \sigma(\bar{\mathbf{i}}^t) & \textit{input gate} \\
\bar{\mathbf{f}}^t &= \mathbf{W}_f\mathbf{x}^t + \mathbf{R}_f\mathbf{y}^{t-1} & \\
\mathbf{f}^t &= \sigma(\bar{\mathbf{f}}^t) & \textit{forget gate} \\
\mathbf{c}^t &= \mathbf{z}^t \odot \mathbf{i}^t + \mathbf{c}^{t-1} \odot \mathbf{f}^t & \textit{cell} \\
\bar{\mathbf{o}}^t &= \mathbf{W}_o\mathbf{x}^t + \mathbf{R}_o\mathbf{y}^{t-1} & \\
\mathbf{o}^t &= \sigma(\bar{\mathbf{o}}^t) & \textit{output gate} \\
\mathbf{y}^t &= h(\mathbf{c}^t) \odot \mathbf{o}^t & \textit{block output}
\end{aligned}
$$



简介

LSTM结构

- Gate是一种限制，代表一种选择（0或1）
- 不过为了保证可导，所以设置为Sigmoid函数σ(x)

Sigmoid		$f(x)=\frac{1}{1+e^{-x}}$	$f'(x)=f(x)(1-f(x))$
TanH		$f(x)=\tanh(x)=\frac{2}{1+e^{-2x}}-1$	$f'(x)=1-f(x)^2$

简介

LSTM结构

- Block input
- Input gate
- Forget gate
- Output gate

- Block output

- 输入为3gate，1input
- 存储为1memory
- 输出为1output

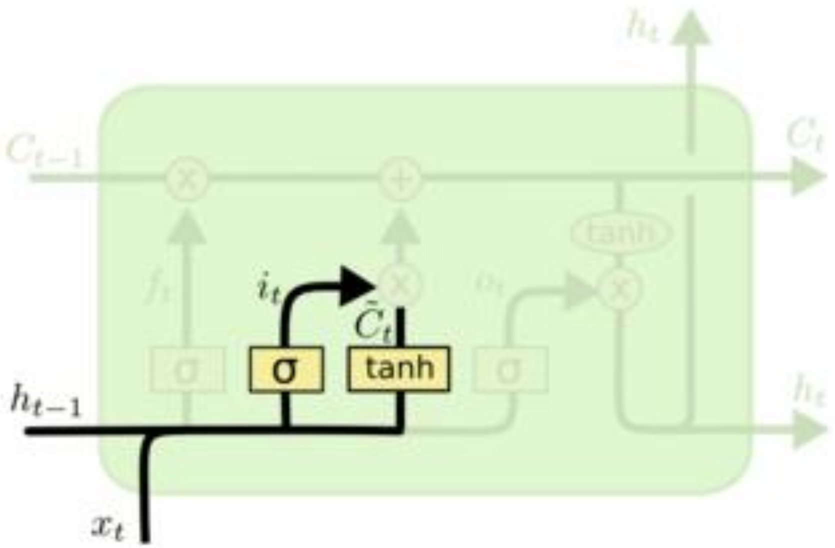
$$
\begin{aligned}
\bar{\mathbf{z}}^t &= \mathbf{W}_z \mathbf{x}^t + \mathbf{R}_z \mathbf{y}^{t-1} \\
\mathbf{z}^t &= g(\bar{\mathbf{z}}^t) && \textit{block input} \\
\bar{\mathbf{i}}^t &= \mathbf{W}_i \mathbf{x}^t + \mathbf{R}_i \mathbf{y}^{t-1} \\
\mathbf{i}^t &= \sigma(\bar{\mathbf{i}}^t) && \textit{input gate} \\
\bar{\mathbf{f}}^t &= \mathbf{W}_f \mathbf{x}^t + \mathbf{R}_f \mathbf{y}^{t-1} \\
\mathbf{f}^t &= \sigma(\bar{\mathbf{f}}^t) && \textit{forget gate} \\
\mathbf{c}^t &= \mathbf{z}^t \odot \mathbf{i}^t + \mathbf{c}^{t-1} \odot \mathbf{f}^t && \textit{cell} \\
\bar{\mathbf{o}}^t &= \mathbf{W}_o \mathbf{x}^t + \mathbf{R}_o \mathbf{y}^{t-1} \\
\mathbf{o}^t &= \sigma(\bar{\mathbf{o}}^t) && \textit{output gate} \\
\mathbf{y}^t &= h(\mathbf{c}^t) \odot \mathbf{o}^t && \textit{block output}
\end{aligned}
$$

简介

LSTM结构

- Block input
  - 代表输入信息
  - 结合上一时间的输出和当前输入
  - RNN中的原始结构

$$
\begin{aligned}
\bar{\mathbf{z}}^t &= \mathbf{W}_z \mathbf{x}^t + \mathbf{R}_z \mathbf{y}^{t-1} \\
\mathbf{z}^t &= g(\bar{\mathbf{z}}^t) && \textit{block input} \\
\bar{\mathbf{i}}^t &= \mathbf{W}_i \mathbf{x}^t + \mathbf{R}_i \mathbf{y}^{t-1} \\
\mathbf{i}^t &= \sigma(\bar{\mathbf{i}}^t) && \textit{input gate} \\
\bar{\mathbf{f}}^t &= \mathbf{W}_f \mathbf{x}^t + \mathbf{R}_f \mathbf{y}^{t-1} \\
\mathbf{f}^t &= \sigma(\bar{\mathbf{f}}^t) && \textit{forget gate} \\
\mathbf{c}^t &= \mathbf{z}^t \odot \mathbf{i}^t + \mathbf{c}^{t-1} \odot \mathbf{f}^t && \textit{cell} \\
\bar{\mathbf{o}}^t &= \mathbf{W}_o \mathbf{x}^t + \mathbf{R}_o \mathbf{y}^{t-1} \\
\mathbf{o}^t &= \sigma(\bar{\mathbf{o}}^t) && \textit{output gate} \\
\mathbf{y}^t &= h(\mathbf{c}^t) \odot \mathbf{o}^t && \textit{block output}
\end{aligned}
$$



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

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

LSTM结构

Input gate

- 是否需要加入新信息？
- （比如情感分析中的'the'就可以直接无视了）

$$\bar{\mathbf{z}}^t = \mathbf{W}_z\mathbf{x}^t + \mathbf{R}_z\mathbf{y}^{t-1}$$

$$\mathbf{z}^t = g(\bar{\mathbf{z}}^t) \qquad \textit{block input}$$

$$\boxed{\begin{aligned}\bar{\mathbf{i}}^t &= \mathbf{W}_i\mathbf{x}^t + \mathbf{R}_i\mathbf{y}^{t-1}\\ \mathbf{i}^t &= \sigma(\bar{\mathbf{i}}^t) \qquad \textit{input gate}\end{aligned}}$$

$$\bar{\mathbf{f}}^t = \mathbf{W}_f\mathbf{x}^t + \mathbf{R}_f\mathbf{y}^{t-1}$$

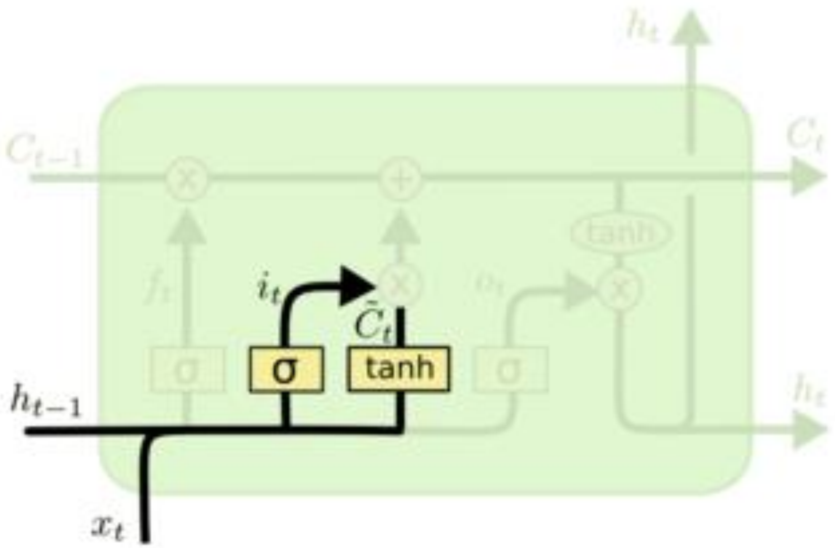
$$\mathbf{f}^t = \sigma(\bar{\mathbf{f}}^t) \qquad \textit{forget gate}$$

$$\mathbf{c}^t = \mathbf{z}^t \odot \mathbf{i}^t + \mathbf{c}^{t-1} \odot \mathbf{f}^t \qquad \textit{cell}$$

$$\bar{\mathbf{o}}^t = \mathbf{W}_o\mathbf{x}^t + \mathbf{R}_o\mathbf{y}^{t-1}$$

$$\mathbf{o}^t = \sigma(\bar{\mathbf{o}}^t) \qquad \textit{output gate}$$

$$\mathbf{y}^t = h(\mathbf{c}^t) \odot \mathbf{o}^t \qquad \textit{block output}$$



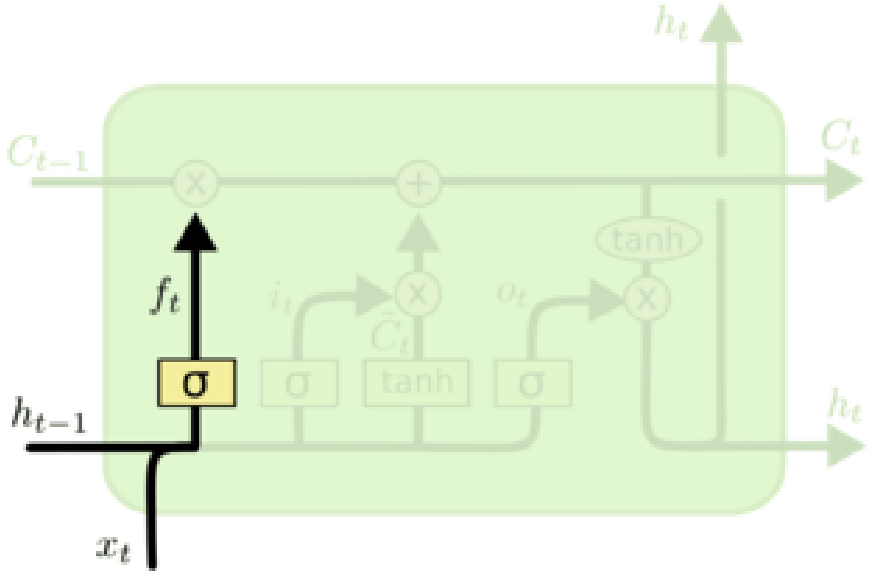
$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t]\ \right)$$

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

LSTM结构

- Forget gate
    - 是否需要记住/忘记之前的信息？
    - （比如在情感分析中，看到'but'这种转折词就忘记之前的内容，看到'the'这类无关的词就记住）

$$
\begin{aligned}
\bar{\mathbf{z}}^t &= \mathbf{W}_z\mathbf{x}^t + \mathbf{R}_z\mathbf{y}^{t-1} & \\
\mathbf{z}^t &= g(\bar{\mathbf{z}}^t) & \textit{block input} \\
\bar{\mathbf{i}}^t &= \mathbf{W}_i\mathbf{x}^t + \mathbf{R}_i\mathbf{y}^{t-1} & \\
\mathbf{i}^t &= \sigma(\bar{\mathbf{i}}^t) & \textit{input gate} \\
\bar{\mathbf{f}}^t &= \mathbf{W}_f\mathbf{x}^t + \mathbf{R}_f\mathbf{y}^{t-1} & \\
\mathbf{f}^t &= \sigma(\bar{\mathbf{f}}^t) & \textit{forget gate} \\
\mathbf{c}^t &= \mathbf{z}^t \odot \mathbf{i}^t + \mathbf{c}^{t-1} \odot \mathbf{f}^t & \textit{cell} \\
\bar{\mathbf{o}}^t &= \mathbf{W}_o\mathbf{x}^t + \mathbf{R}_o\mathbf{y}^{t-1} & \\
\mathbf{o}^t &= \sigma(\bar{\mathbf{o}}^t) & \textit{output gate} \\
\mathbf{y}^t &= h(\mathbf{c}^t) \odot \mathbf{o}^t & \textit{block output}
\end{aligned}
$$



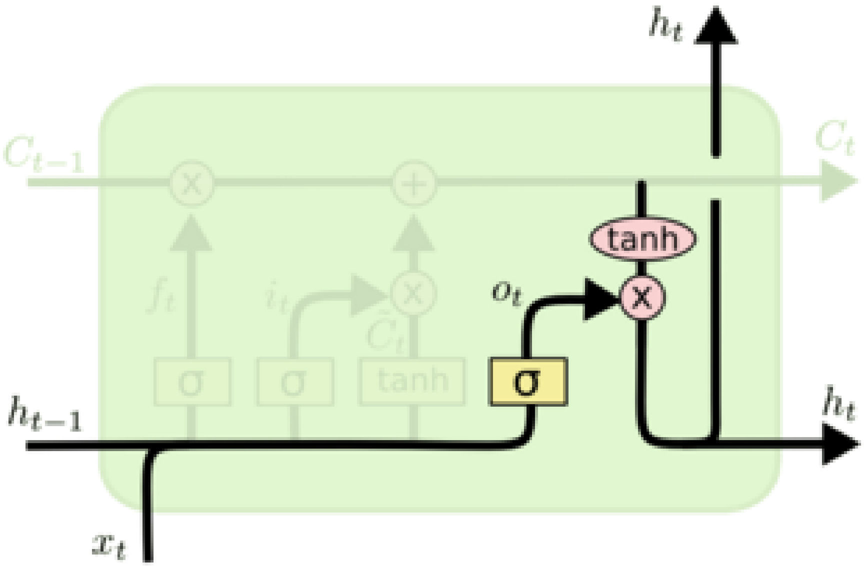
$$
f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t]\right)
$$

LSTM结构

Output gate

- 选取特定记忆影响这次的结果和控制下次的gate

$$
\begin{aligned}
\bar{\mathbf{z}}^t &= \mathbf{W}_z \mathbf{x}^t + \mathbf{R}_z \mathbf{y}^{t-1} && \\
\mathbf{z}^t &= g(\bar{\mathbf{z}}^t) && \textit{block input} \\
\bar{\mathbf{i}}^t &= \mathbf{W}_i \mathbf{x}^t + \mathbf{R}_i \mathbf{y}^{t-1} && \\
\mathbf{i}^t &= \sigma(\bar{\mathbf{i}}^t) && \textit{input gate} \\
\bar{\mathbf{f}}^t &= \mathbf{W}_f \mathbf{x}^t + \mathbf{R}_f \mathbf{y}^{t-1} && \\
\mathbf{f}^t &= \sigma(\bar{\mathbf{f}}^t) && \textit{forget gate} \\
\mathbf{c}^t &= \mathbf{z}^t \odot \mathbf{i}^t + \mathbf{c}^{t-1} \odot \mathbf{f}^t && \textit{cell} \\
\bar{\mathbf{o}}^t &= \mathbf{W}_o \mathbf{x}^t + \mathbf{R}_o \mathbf{y}^{t-1} && \\
\mathbf{o}^t &= \sigma(\bar{\mathbf{o}}^t) && \textit{output gate} \\
\mathbf{y}^t &= h(\mathbf{c}^t) \odot \mathbf{o}^t && \textit{block output}
\end{aligned}
$$



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

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

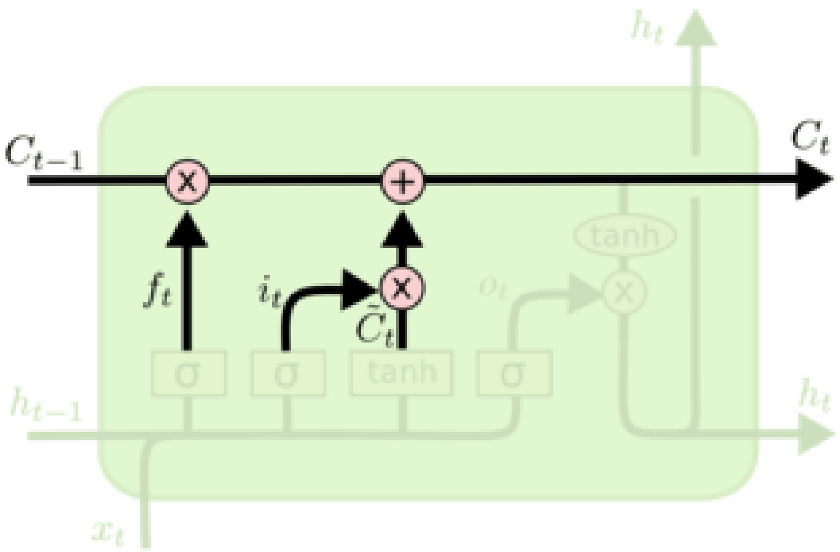
简介

▶ LSTM结构

- Cell

- 记忆即存储
- 抹去一些记忆后加入新信息

$$
\begin{aligned}
\bar{\mathbf{z}}^t &= \mathbf{W}_z\mathbf{x}^t + \mathbf{R}_z\mathbf{y}^{t-1} & \\
\mathbf{z}^t &= g(\bar{\mathbf{z}}^t) & \textit{block input} \\
\bar{\mathbf{i}}^t &= \mathbf{W}_i\mathbf{x}^t + \mathbf{R}_i\mathbf{y}^{t-1} & \\
\mathbf{i}^t &= \sigma(\bar{\mathbf{i}}^t) & \textit{input gate} \\
\bar{\mathbf{f}}^t &= \mathbf{W}_f\mathbf{x}^t + \mathbf{R}_f\mathbf{y}^{t-1} & \\
\mathbf{f}^t &= \sigma(\bar{\mathbf{f}}^t) & \textit{forget gate} \\
\mathbf{c}^t &= \mathbf{z}^t \odot \mathbf{i}^t + \mathbf{c}^{t-1} \odot \mathbf{f}^t & \textit{cell} \\
\bar{\mathbf{o}}^t &= \mathbf{W}_o\mathbf{x}^t + \mathbf{R}_o\mathbf{y}^{t-1} & \\
\mathbf{o}^t &= \sigma(\bar{\mathbf{o}}^t) & \textit{output gate} \\
\mathbf{y}^t &= h(\mathbf{c}^t) \odot \mathbf{o}^t & \textit{block output}
\end{aligned}
$$



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

简介

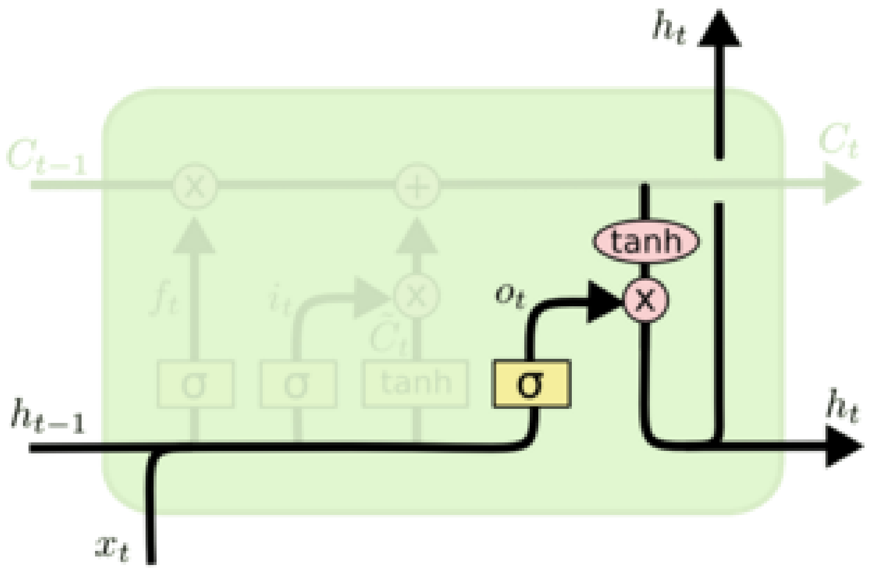
▶ LSTM结构

- Block output

- 利用记忆产生行为

以及改变下一次的控制

$$
\begin{aligned}
\bar{\mathbf{z}}^t &= \mathbf{W}_z\mathbf{x}^t + \mathbf{R}_z\mathbf{y}^{t-1} \\
\mathbf{z}^t &= g(\bar{\mathbf{z}}^t) && \textit{block input} \\
\bar{\mathbf{i}}^t &= \mathbf{W}_i\mathbf{x}^t + \mathbf{R}_i\mathbf{y}^{t-1} \\
\mathbf{i}^t &= \sigma(\bar{\mathbf{i}}^t) && \textit{input gate} \\
\bar{\mathbf{f}}^t &= \mathbf{W}_f\mathbf{x}^t + \mathbf{R}_f\mathbf{y}^{t-1} \\
\mathbf{f}^t &= \sigma(\bar{\mathbf{f}}^t) && \textit{forget gate} \\
\mathbf{c}^t &= \mathbf{z}^t \odot \mathbf{i}^t + \mathbf{c}^{t-1} \odot \mathbf{f}^t && \textit{cell} \\
\bar{\mathbf{o}}^t &= \mathbf{W}_o\mathbf{x}^t + \mathbf{R}_o\mathbf{y}^{t-1} \\
\mathbf{o}^t &= \sigma(\bar{\mathbf{o}}^t) && \textit{output gate} \\
\mathbf{y}^t &= h(\mathbf{c}^t) \odot \mathbf{o}^t && \textit{block output}
\end{aligned}
$$



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

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

简介

LSTM结构总结

- 选择性输入
- 选择性记忆
- 记忆和输入合并
- 记忆选择性输出

$$\bar{\mathbf{z}}^t = \mathbf{W}_z\mathbf{x}^t + \mathbf{R}_z\mathbf{y}^{t-1}$$

$$\mathbf{z}^t = g(\bar{\mathbf{z}}^t) \qquad \textit{block input}$$

$$\bar{\mathbf{i}}^t = \mathbf{W}_i\mathbf{x}^t + \mathbf{R}_i\mathbf{y}^{t-1}$$

$$\mathbf{i}^t = \sigma(\bar{\mathbf{i}}^t) \qquad \textit{input gate}$$

$$\bar{\mathbf{f}}^t = \mathbf{W}_f\mathbf{x}^t + \mathbf{R}_f\mathbf{y}^{t-1}$$

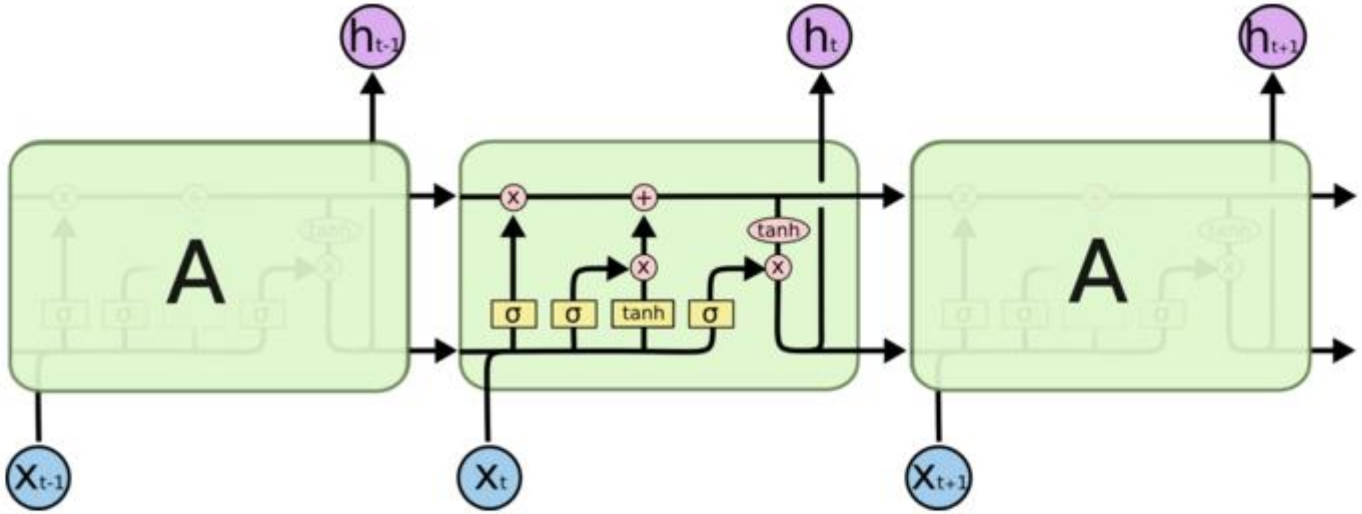
$$\mathbf{f}^t = \sigma(\bar{\mathbf{f}}^t) \qquad \textit{forget gate}$$

$$\mathbf{c}^t = \mathbf{z}^t \odot \mathbf{i}^t + \mathbf{c}^{t-1} \odot \mathbf{f}^t \qquad \textit{cell}$$

$$\bar{\mathbf{o}}^t = \mathbf{W}_o\mathbf{x}^t + \mathbf{R}_o\mathbf{y}^{t-1}$$

$$\mathbf{o}^t = \sigma(\bar{\mathbf{o}}^t) \qquad \textit{output gate}$$

$$\mathbf{y}^t = h(\mathbf{c}^t) \odot \mathbf{o}^t \qquad \textit{block output}$$



简介

- LSTM思想
  - 记忆 Memory
  - 选择 Gate

- LSTM思想
  - 记忆 Memory

  - RNN不具备很强的记忆性，所以LSTM弥补了这一点
  - 利用强制的记忆结构

  - 实际上RNN在经过适当的初始化(Recurrent矩阵类似I矩阵)后，也可以达到类似效果
    - [2015] A Simple Way to Initialize Recurrent Networks of Rectified Linear Units

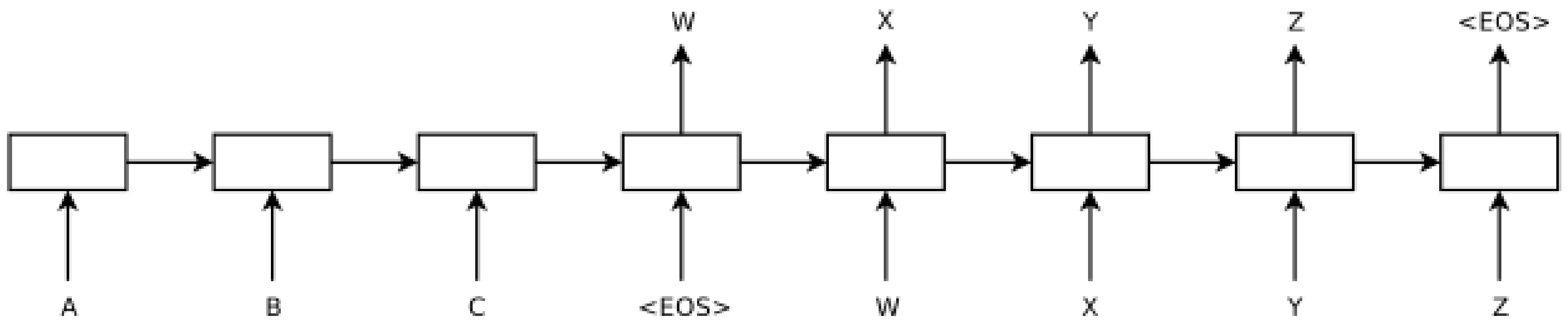
- LSTM思想
  - 选择 Gate

- LSTM让RNN有了选择信息的能力，更容易排除冗余信息，找到时序依赖关系
- 实验表明，情感分析中'the', 'an', 'he', 'she'的input gate基本都为0，而强情感词语如'good', 'bad', 'excellent'的input gate基本都为1

简介

- LSTM实现Seq2Seq
  - 为什么LSTM这么火？
    - 处理Sequence序列之间映射关系的强大工具
      - 句子
      - 语音
      - 代码
      - 视频
      - 轨迹
      - ……(只要是Sequence都能试一试)

- LSTM实现Seq2Seq
  - [2014] Sequence-to-sequence-learning-with-neural-networks



优化

Bidirectional LSTM(双向LSTM)

- 单向LSTM不能很好处理未来信息对当前预测的影响
- 双向LSTM可以缓解这一问题，实际中效果也确实好
- 就是暴力把正向和逆向的输出向量拼在一起

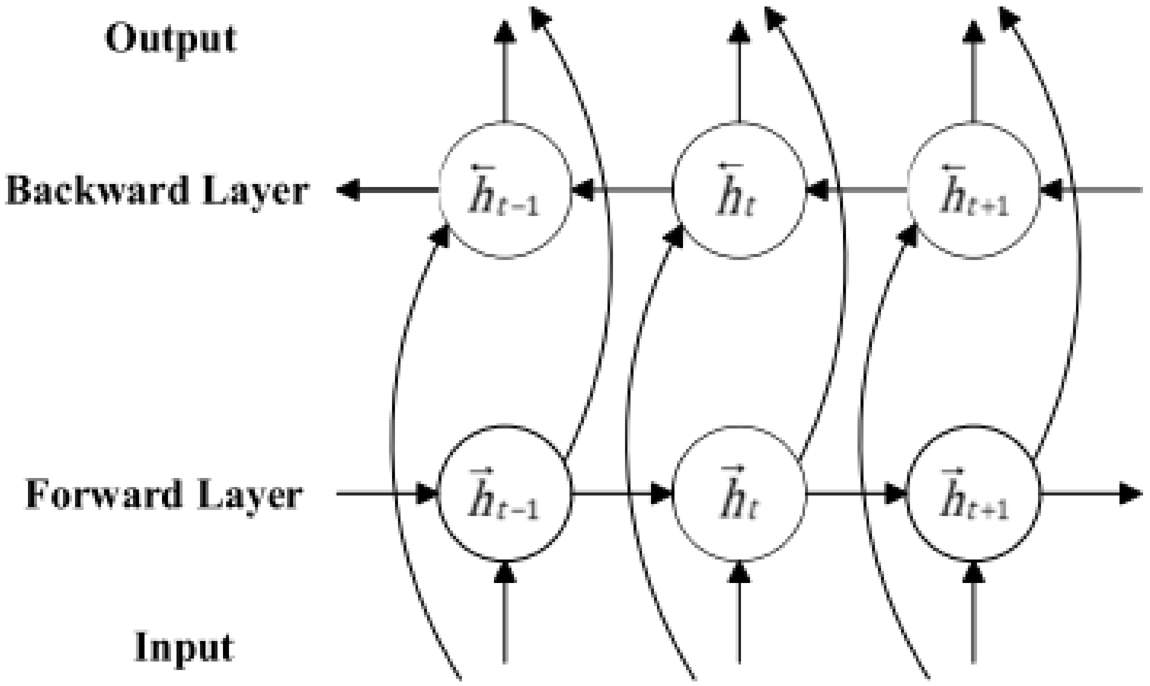


Fig.2. Bidirectional RNN

Gated Recurrent Unit(GRU)

- LSTM训练非常慢，GRU对此做了优化
- 减少一个Gate，速度快25%，

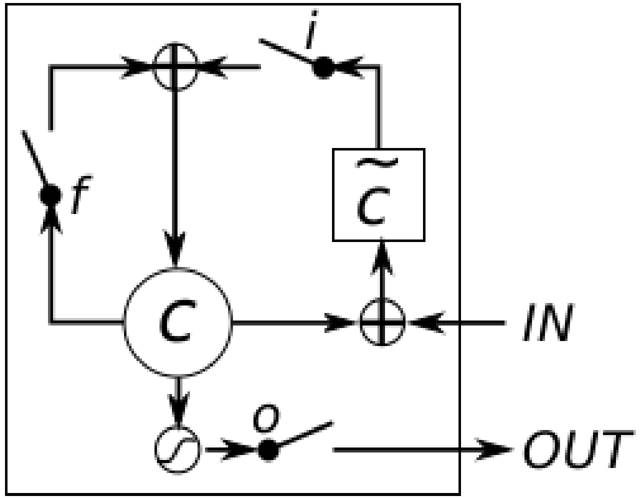
效果没有明显下降

$$\tilde{h}_t^j = \tanh\left(W\mathbf{x}_t + U\left(\mathbf{r}_t \odot \mathbf{h}_{t-1}\right)\right)^j,$$
block input

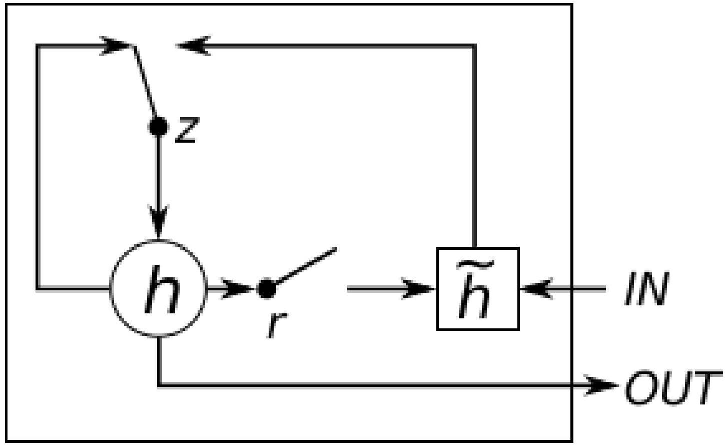
$$z_t^j = \sigma\left(W_z\mathbf{x}_t + U_z\mathbf{h}_{t-1}\right)^j.$$
update gate

$$r_t^j = \sigma\left(W_r\mathbf{x}_t + U_r\mathbf{h}_{t-1}\right)^j.$$
reset gate

$$h_t^j = (1 - z_t^j)h_{t-1}^j + z_t^j\tilde{h}_t^j,$$
output/memory



(a) Long Short-Term Memory



(b) Gated Recurrent Unit

优化

Gated Recurrent Unit(GRU)

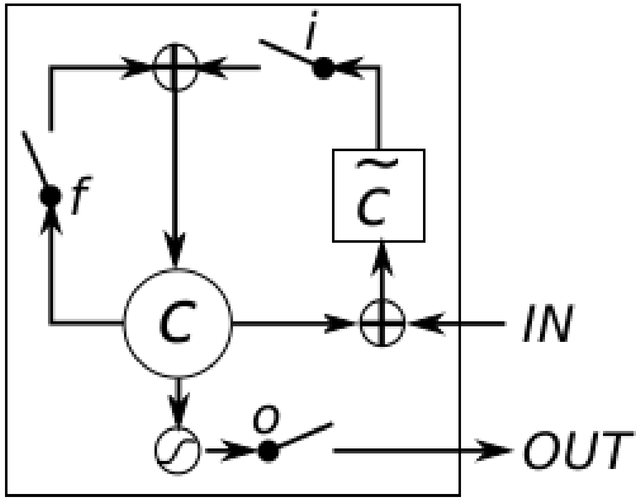
- 主要合并了input gate和forget gate
- 另外还合并了隐层和记忆

$$\tilde{h}_t^j = \tanh\left(W\mathbf{x}_t + U\left(\mathbf{r}_t \odot \mathbf{h}_{t-1}\right)\right)^j,$$ block input

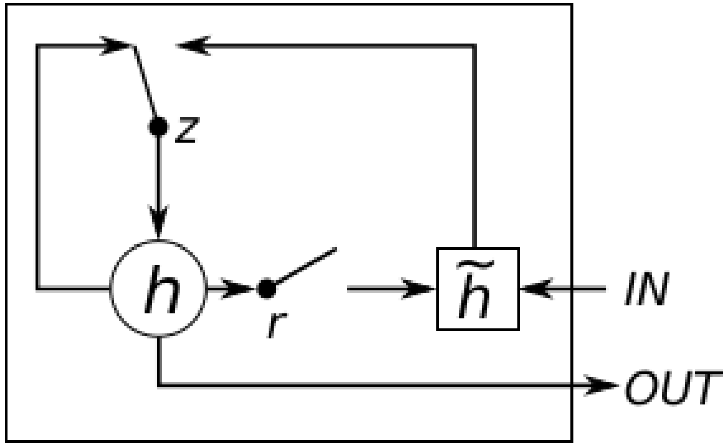
$$z_t^j = \sigma\left(W_z\mathbf{x}_t + U_z\mathbf{h}_{t-1}\right)^j.$$ update gate

$$r_t^j = \sigma\left(W_r\mathbf{x}_t + U_r\mathbf{h}_{t-1}\right)^j.$$ reset gate

$$h_t^j = (1 - z_t^j)h_{t-1}^j + z_t^j\tilde{h}_t^j,$$ output/memory



(a) Long Short-Term Memory



(b) Gated Recurrent Unit

Multilayer LSTM(多层次LSTM)

- 对深度的无限追求（RNN本身横着就够深了，现在竖着也要变深）
- 正常2~3层都会有提升，4层以上就不好说了

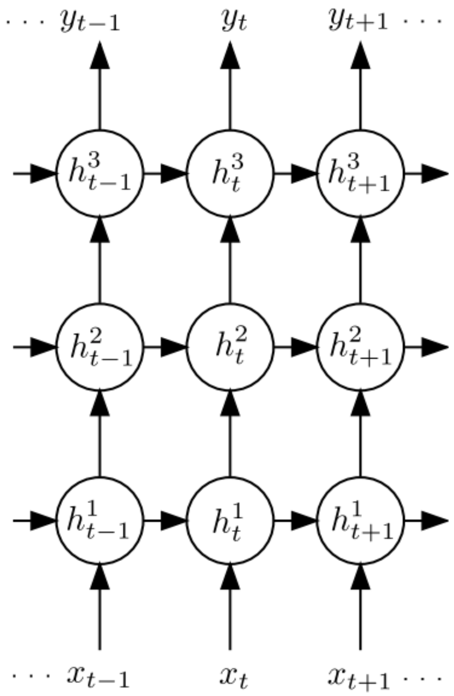
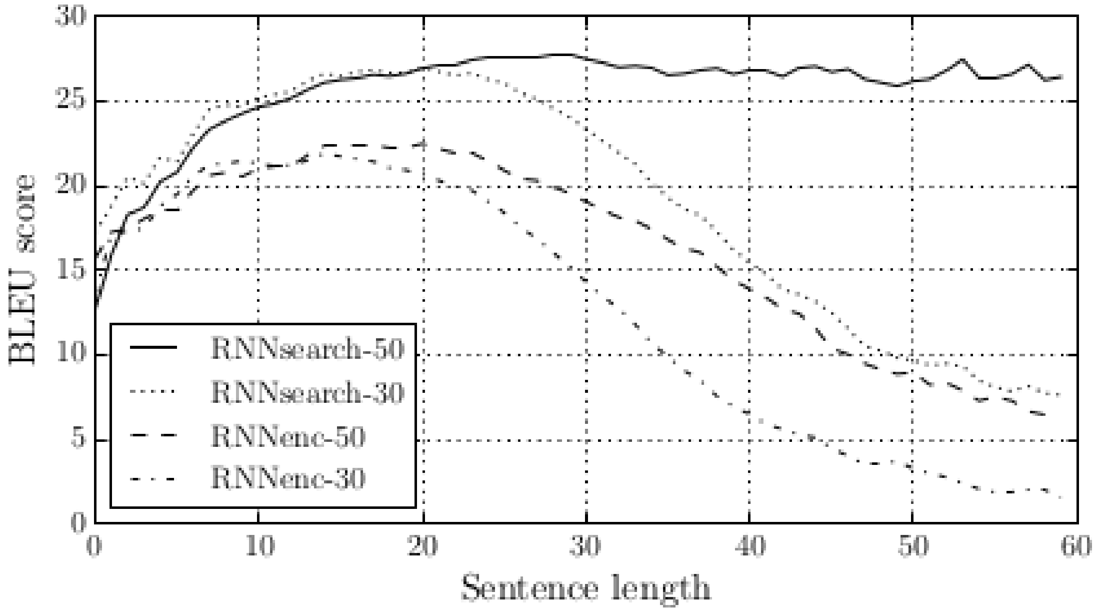
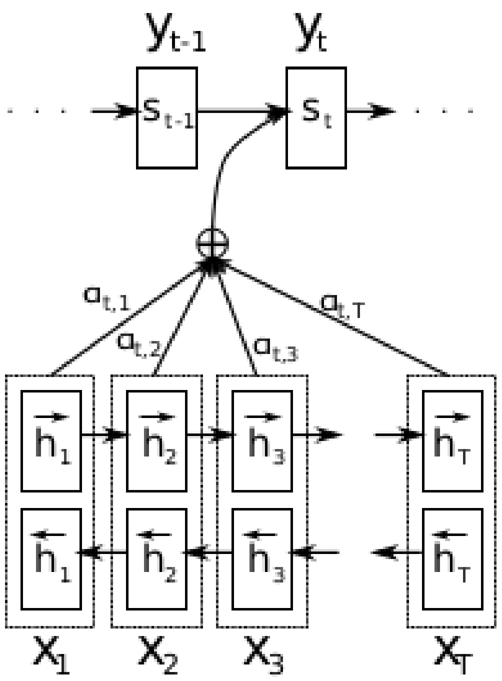


Fig. 3. Deep Recurrent Neural Network

Attention-based LSTM (基于注意力的LSTM)

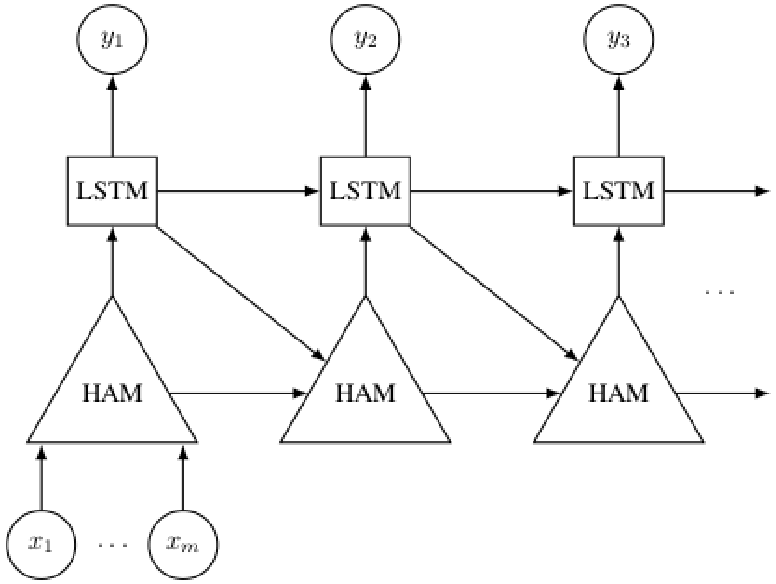
- LSTM记忆力不好
- 训练用30长度的句子，测试用50长度的，效果就不行
- Attention-based把句子全给LSTM连上，让他挑看着顺眼的最匹配的

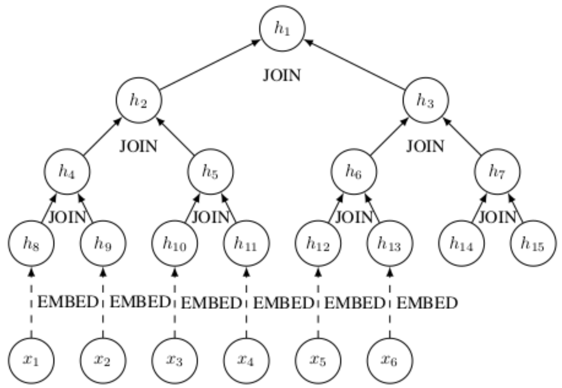


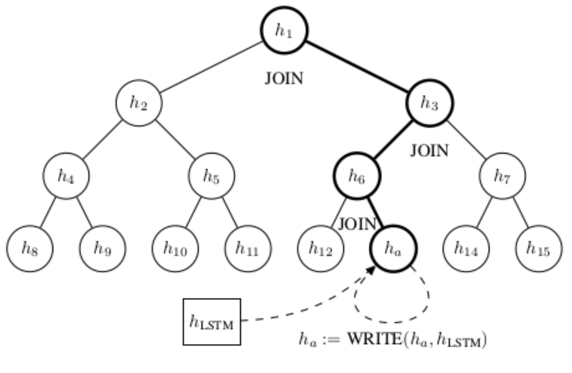


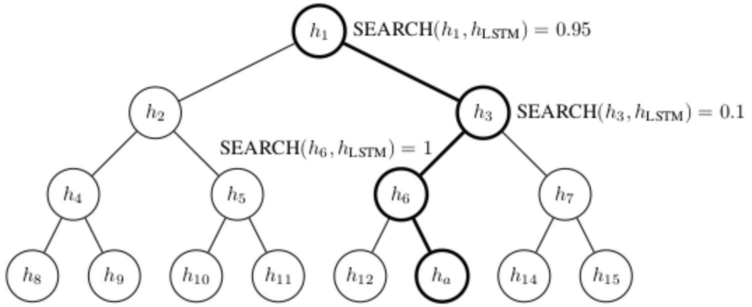
Hierarchical Attentive Memory

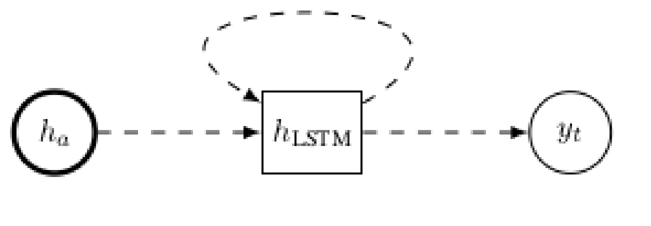
- Attention机制的升级版，将输入组织成二叉树，有效提高了效率
- 泛化能力增强：在训练数据为长度32的序列时，给长度在64-128的序列排序取得0.24%的错误率（同样情况下使用纯attention机制错误率为100%）











应用

应用

- Sentiment classification情感分析
  - [2015] Improved semantic representations from tree-structured long short-term memory networks
- Language Modeling语言模型
  - [2015] Character-Aware Neural Language Models
- Sequence Generation 序列生成
  - http://karpathy.github.io/2015/05/21/rnn-effectiveness/
- Speech Recognition 语音识别
  - [2013] SPEECH RECOGNITION WITH DEEP RECURRENT NEURAL NETWORKS
- Machine Translation 机器翻译
  - [2014] Neural machine translation by jointly learning
- Question Answering 问答系统
  - [2015] Neural Responding Machine for Short-Text Conversation

应用

- 我说这是LSTM生成的你信吗？

"The surprised in investors weren't going to raise money. I'm not the company with the time there are all interesting quickly, don't have to get off the same programmers. There's a super-angel round fundraising, why do you can do. If you have a different physical investment are become in people who reduced in a startup with the way to argument the acquirer could see them just that you're also the founders will part of users' affords that and an alternation to the idea. [2] Don't work at first member to see the way kids will seem in advance of a bad successful startup. And if you have to act the big company too."

应用

- 我说这是LSTM生成的你信吗？

For $\bigoplus_{n=1,\dots,m}$ where $\mathcal{L}_{m_\bullet} = 0$, hence we can find a closed subset $\mathcal{H}$ in $\mathcal{H}$ and any sets $\mathcal{F}$ on X, U is a closed immersion of S, then $U \to T$ is a separated algebraic space.

Proof. Proof of (1). It also start we get

$$S = \mathrm{Spec}(R) = U \times_X U \times_X U$$

and the comparicoly in the fibre product covering we have to prove the lemma generated by $\coprod Z \times_U U \to V$. Consider the maps M along the set of points Sch_{fppf} and $U \to U$ is the fibre category of S in U in Section, ?? and the fact that any U affine, see Morphisms, Lemma ??. Hence we obtain a scheme S and any open subset $W \subset U$ in $Sh(G)$ such that $\mathrm{Spec}(R') \to S$ is smooth or an

$$U = \bigcup U_i \times_{S_i} U_i$$

which has a nonzero morphism we may assume that f_i is of finite presentation over S. We claim that $\mathcal{O}_{X,x}$ is a scheme where $x, x', s'' \in S'$ such that $\mathcal{O}_{X,x'} \to \mathcal{O}'_{X',x'}$ is separated. By Algebra, Lemma ?? we can define a map of complexes $\mathrm{GL}_{S'}(x'/S'')$ and we win. □

To prove study we see that $\mathcal{F}|_U$ is a covering of $\mathcal{X}'$, and $\mathcal{T}_i$ is an object of $\mathcal{F}_{X/S}$ for $i > 0$ and $\mathcal{F}_p$ exists and let $\mathcal{F}_i$ be a presheaf of $\mathcal{O}_X$-modules on $\mathcal{C}$ as a $\mathcal{F}$-module. In particular $\mathcal{F} = U/\mathcal{F}$ we have to show that

$$\widetilde{M}^\bullet = \mathcal{I}^\bullet \otimes_{\mathrm{Spec}(k)} \mathcal{O}_{S,s} - i_X^{-1}\mathcal{F})$$

is a unique morphism of algebraic stacks. Note that

$$\mathrm{Arrows} = (Sch/S)^{opp}_{fppf}, (Sch/S)_{fppf}$$

and

$$V = \Gamma(S, \mathcal{O}) \longmapsto (U, \mathrm{Spec}(A))$$

is an open subset of X. Thus U is affine. This is a continuous map of X is the inverse, the groupoid scheme S.

Proof. See discussion of sheaves of sets. □

The result for prove any open covering follows from the less of Example ??. It may replace S by $X_{spaces,\acute{e}tale}$ which gives an open subspace of X and T equal to S_{Zar}, see Descent, Lemma ??. Namely, by Lemma ?? we see that R is geometrically regular over S.

Lemma 0.1. *Assume (3) and (3) by the construction in the description.*

Suppose $X = \lim |X|$ (by the formal open covering X and a single map $\underline{Proj}_X(\mathcal{A}) = \mathrm{Spec}(B)$ over U compatible with the complex

$$Set(\mathcal{A}) = \Gamma(X, \mathcal{O}_{X,\mathcal{O}_X}).$$

When in this case of to show that $\mathcal{Q} \to \mathcal{C}_{Z/X}$ is stable under the following result in the second conditions of (1), and (3). This finishes the proof. By Definition ?? (without element is when the closed subschemes are catenary. If T is surjective we may assume that T is connected with residue fields of S. Moreover there exists a closed subspace $Z \subset X$ of X where U in X' is proper (some defining as a closed subset of the uniqueness it suffices to check the fact that the following theorem

(1) *f is locally of finite type. Since $S = \mathrm{Spec}(R)$ and $Y = \mathrm{Spec}(R)$.*

Proof. This is form all sheaves of sheaves on X. But given a scheme U and a surjective étale morphism $U \to X$. Let $U \cap U = \coprod_{i=1,\dots,n} U_i$ be the scheme X over S at the schemes $X_i \to X$ and $U = \lim_i X_i$. □

The following lemma surjective restrocomposes of this implies that $\mathcal{F}_{x_0} = \mathcal{F}_{x_0} = \mathcal{F}_{X,\dots,0}$.

Lemma 0.2. *Let X be a locally Noetherian scheme over S, $E = \mathcal{F}_{X/S}$. Set $\mathcal{I} = \mathcal{J}_1 \subset \mathcal{I}'_n$. Since $\mathcal{I}^n \subset \mathcal{I}^n$ are nonzero over $i_0 \leq \mathfrak{p}$ is a subset of $\mathcal{J}_{n,0} \circ \overline{A}_2$ works.*

Lemma 0.3. *In Situation ??. Hence we may assume $\mathfrak{q}' = 0$.*

Proof. We will use the property we see that $\mathfrak{p}$ is the next functor (??). On the other hand, by Lemma ?? we see that

$$D(\mathcal{O}_{X'}) = \mathcal{O}_X(D)$$

where K is an F-algebra where δ_{n+1} is a scheme over S. □

- 我说这是LSTM生成的你信吗？

```c
/*
 * Increment the size file of the new incorrect UI_FILTER group information
 * of the size generatively.
 */
static int indicate_policy(void)
{
  int error;
  if (fd == MARN_EPT) {
    /*
     * The kernel blank will coeld it to userspace.
     */
    if (ss->segment < mem_total)
      unblock_graph_and_set_blocked();
    else
      ret = 1;
    goto bail;
  }
  segaddr = in_SB(in.addr);
  selector = seg / 16;
  setup_works = true;
  for (i = 0; i < blocks; i++) {
    seq = buf[i++];
    bpf = bd->bd.next + i * search;
    if (fd) {
      current = blocked;
    }
  }
  rw->name = "Getjbbregs";
  bprm_self_clearl(&iv->version);
  regs->new = blocks[(BPF_STATS << info->historidac)] | PFMR_CLOBATHINC_SECONDS << 1
  return segtable;
}
```

应用

- 但这还远远没有结束……
- Sorting 排序!?
  - [2014] Neural Turing Machine
- Taxi Destination Prediction的士目的预测!?
  - [2015] Artificial Neural Networks Applied to Taxi Destination Prediction
- Python Interpreter Python解释器!?
  - [2014] Learn to execute
- 写简单的程序!?
  - [2015] Neural Programmer-Interpreters

实现细节

实现细节

- 一些小Trick
  - 初始化矩阵都在[-0.01, 0.01]比较好，均匀分布
  - Peephole和bias不要比较好（常用版本LSTM）
  - GRU很好用
  - 用GPU训练，多GPU更好
  - Learning rate学习率开始可以比较大，之后可以变小
  - 用Gradient Clipping防止梯度爆炸
  - 在适当的地方放Dropout防止Overfitting
  - Mini-batch，不然GPU没法加速，batch大小很讲究
  - 使用Momentum加速收敛
  - 在训练时往Gradient里加高斯noise

实现细节

- 梯度更新方法
  - 不同task不同，大概有以下几种
    - 裸的SGD
    - 前期learning rate很大，过一段时间后逐渐减少
    - AdaGrad
    - Rmsprop
    - AdaDelta
    - AdaM

工具库

工具库

- Theano
  - Python前端，C++实现
  - 自动求导
  - 将图结构编译成GPU流，存储时间都有优化
- Torch7
  - Lua前端，C/CUDA实现
  - 嵌入式支持得很好
- TensorFlow
  - Google第二代深度学习系统
- MXNet
  - 结合命令式语言（如Caffe）和符号式语言（如Theano）
  - 对多GPU有一定支持

……

工具库

- 后端库（想自己实现的请看这里）
- CUDA
  - 非常容易上手的GPU编程语言
  - 然而Parallel programming is easy as long as you don't care about performance
- CUBLAS
  - 支持大部分矩阵/向量操作，已经做过大量底层优化
- CUDNN
  - 支持神经网络的常用操作，已经做过大量底层优化
- CUSPARSE
  - 支持一部分稀疏矩阵/向量操作，已经做过大量底层优化

工具库

- LSTM已经有大量现成实现
  - C++
  - Python
  - Matlab

  ……

- 所以没事千万别自己实现

- (用Theano只要5行我会乱说？)

- 当前工具库的评价
  - [2015] Comparative Study of Caffe, Neon, Theano, and Torch for Deep Learning
  - 目前还没有通用的支持多机多GPU的框架出现

展望

展望

- LSTM存在的问题
  - 记忆力不足
  - 只能处理序列映射
  - 理论基础仍缺乏，调参手段一大堆
  - 结合更多类型数据

展望

- 继LSTM之后又一火爆话题
  - Attention-based mechanism 注意力机制
    - [2014] Neural machine translation by jointly learning
    - 论如何用一个模型达到Google Translation的效果

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Q&A