循环神经网络与长短时记忆

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主要内容

- 循环神经网络
  1. 场景与多种应用
  2. 层级结构
  3. 多种RNN
  4. BPTT算法
  5. 生成模型与图像描述
- LSTM
  1. 长时依赖问题
  2. “记忆细胞”与状态
  3. GRU
- 更多应用

循环神经网络与应用

模仿论文(连公式都格式很正确)

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 $X_{spaces,étale}$ 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 mext 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. □

循环神经网络与应用

□ 模仿linux内核代码“写程序”

```
/*
 * 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 << 12;
  return segtable;
}
```

循环神经网络与应用

模仿小四的作品

每个人，闭上眼睛的时候，才能真正面对光明

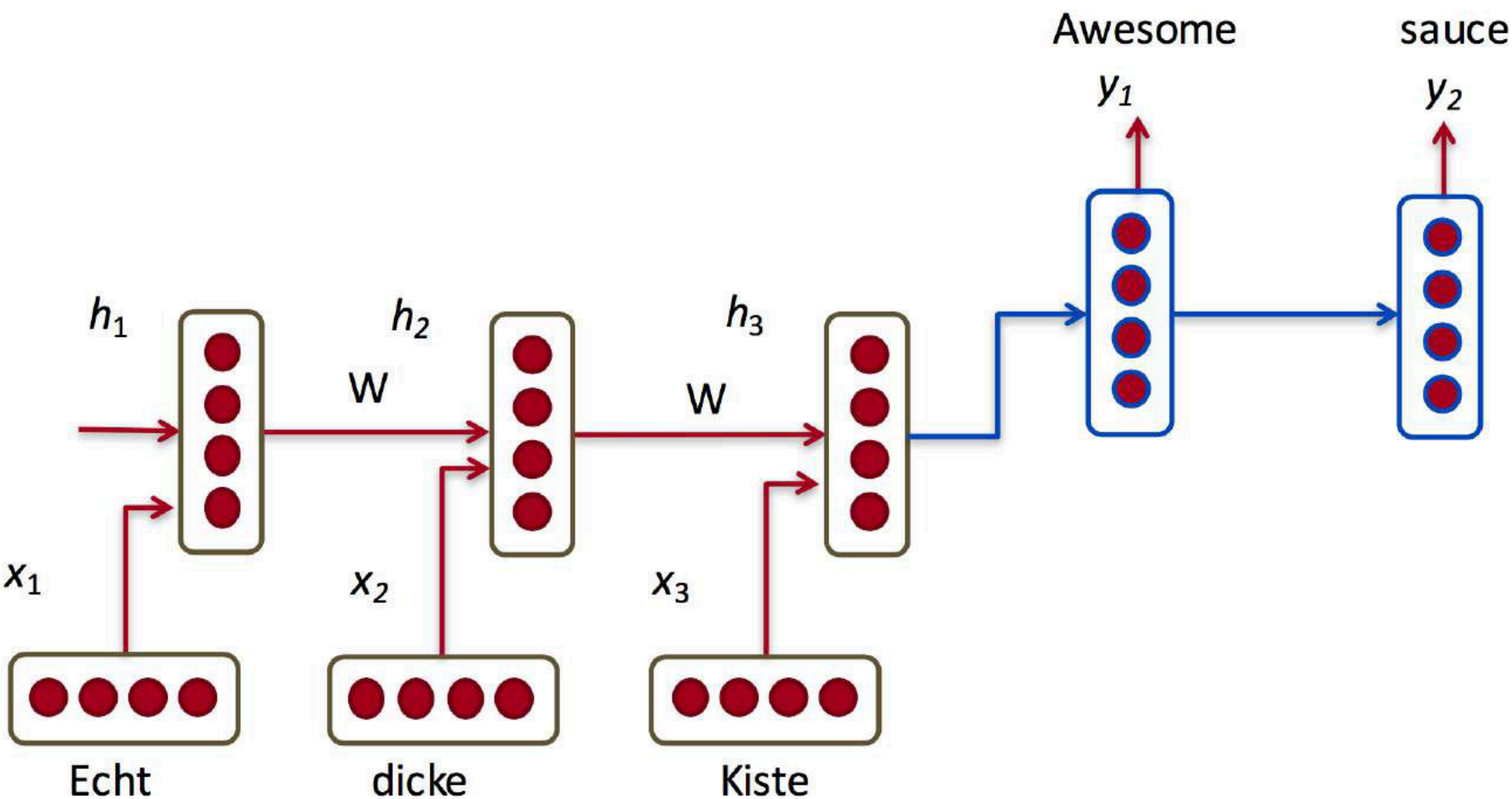
他们在吱呀作响的船舷上，静静看着世界，没有痛苦的声音，碎裂的海洋里摇晃出阵阵沉默，吞噬过来。他们的躯体，一点，一点，逐渐暗淡在

你们虔诚的看着远方，我抬起头，不经意间，目光划过你们的面庞，上面淡淡的倔强印，那么坚强

尘世凡间
沉睡亿万光年的年轻战士
萦绕不散的寂寞烟云中
静候在末世岛屿之上
守候，女王何时归来
你的目光延向她迟归的方向
缓缓推进的海浪
这最后一夜
荡漾

循环神经网络与应用

□ 机器翻译

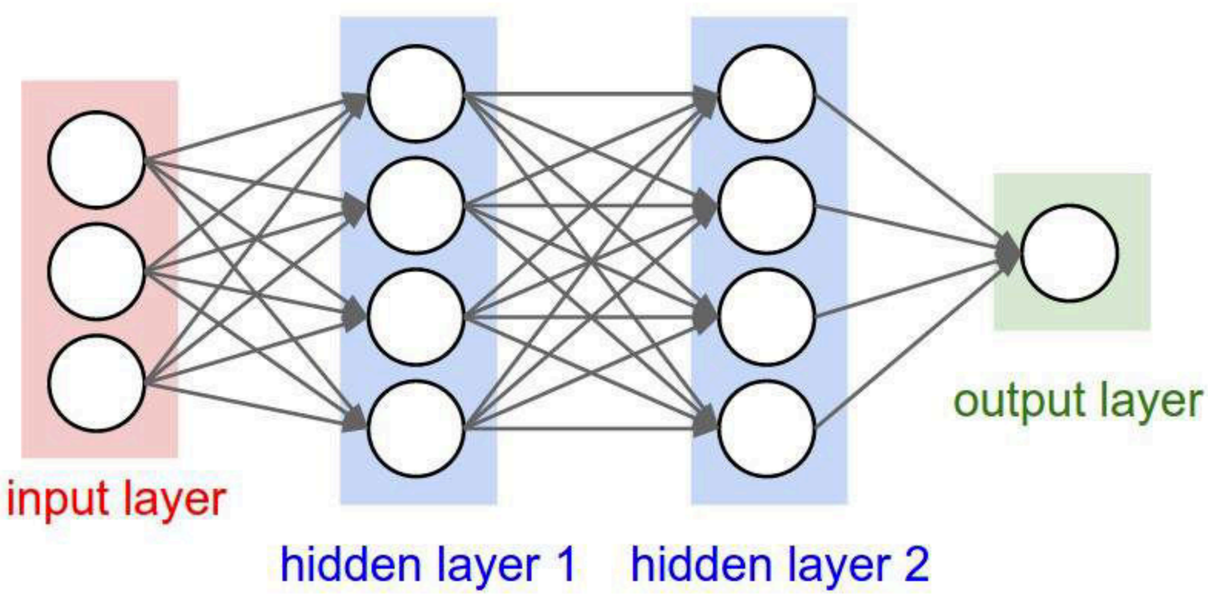


循环神经网络与应用

- 看图说话

神经网络到循环神经网络

- 我们知道神经网络结构如下



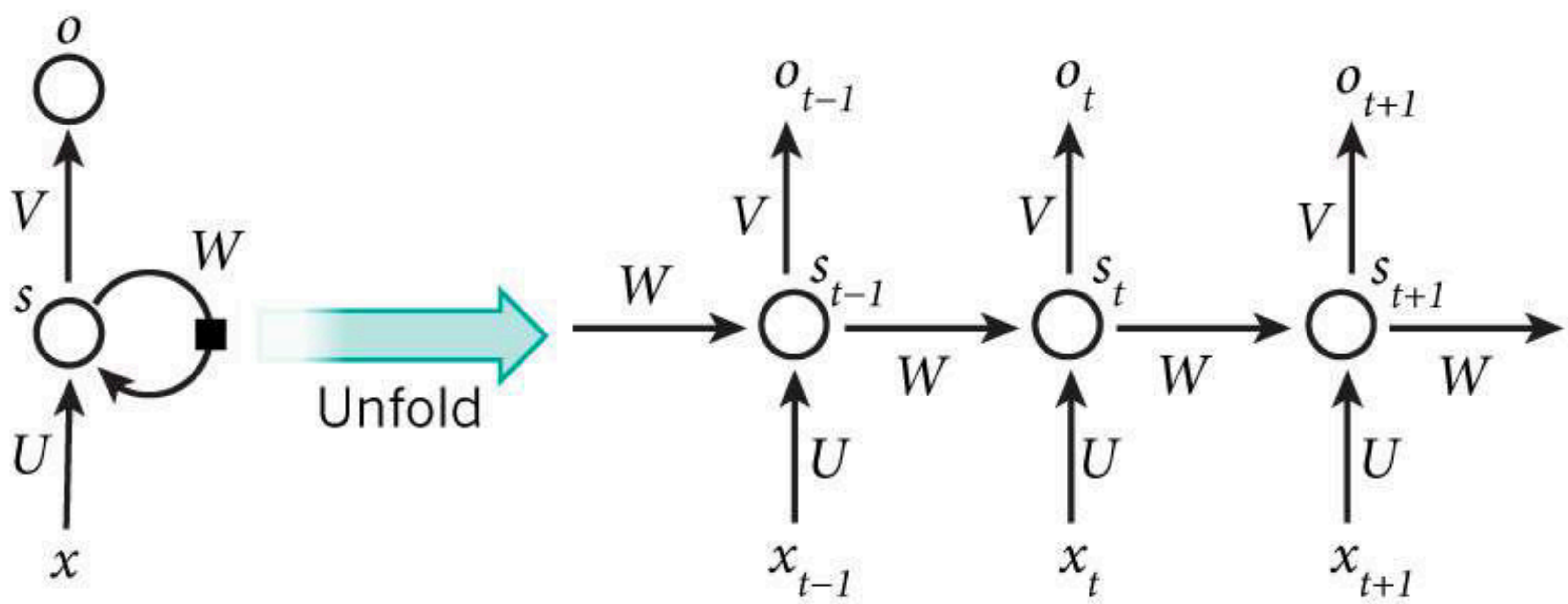
- 那循环神经网络和它是什么关系呢？

循环神经网络

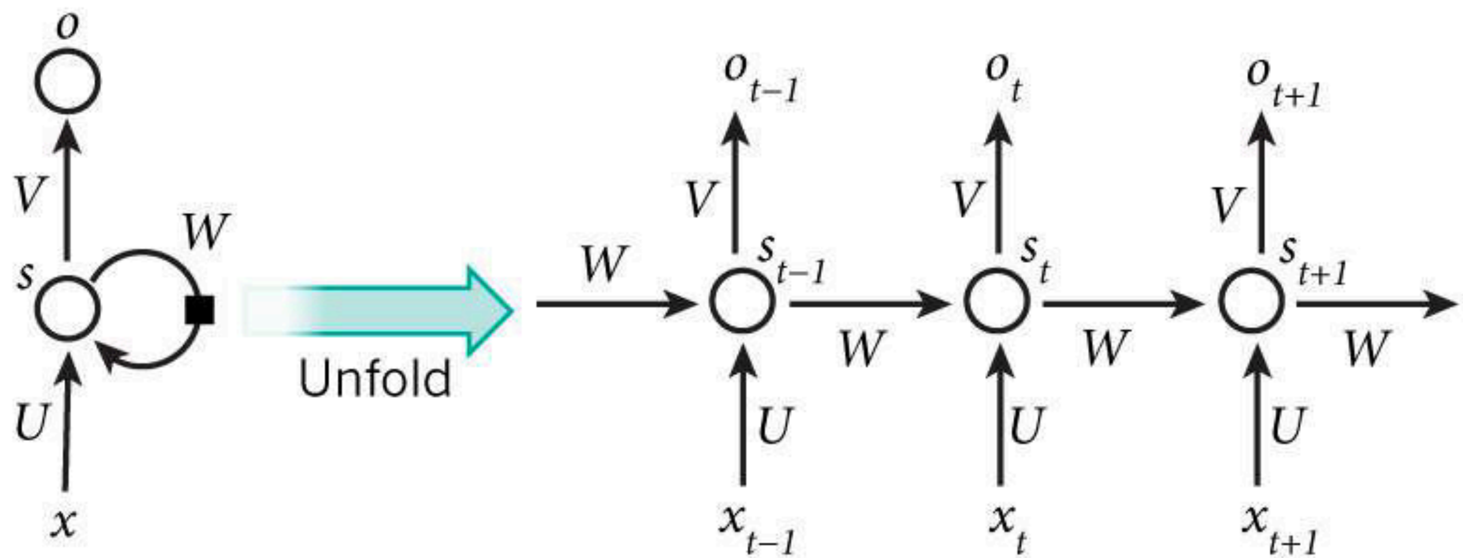
- 为什么有BP神经网络，CNN，还要RNN？
  - 传统神经网络(包括CNN)，输入和输出都是互相独立的。
    - 图像上的猫和狗是分隔开的，但有些任务，后续的输出和之前的内容是相关的。
    - “我是中国人，我的母语是___”
  - RNN引入“记忆”的概念
    - 循环2字来源于其每个元素都执行相同的任务。
    - 但是输出依赖于 输入 和 “记忆”

循环神经网络之 结构

- 简单来看，把序列按时间展开



循环神经网络之 结构



- X_t是时间t处的输入
- S_t是时间t处的“记忆”，$S_t=f(UX_t+WS_{t-1})$，f可以是tanh等
- O_t是时间t出的输出，比如是预测下个词的话，可能是softmax输出的属于每个候选词的概率，$O_t = \mathrm{softmax}(VS_t)$

循环神经网络之 结构细节

- 可以把隐状态S_t视作“记忆体”，捕捉了之前时间点上的信息。
- 输出O_t由当前时间及之前所有的“记忆”共同计算得到。
- 很可惜，实际应用中，S_t并不能捕捉和保留之前所有信息（记忆有限？）
- 不同于CNN，这里的RNN其实整个神经网络都共享一组参数（U,V,W），极大减小了需要训练和预估的参数量
- 图中的O_t在有些任务下是不存在的，比如文本情感分析，其实只需要最后的output结果就行

RNN
与
生成模型

```python
vocabulary_size = 8000
unknown_token = "UNKNOWN_TOKEN"
sentence_start_token = "SENTENCE_START"
sentence_end_token = "SENTENCE_END"

# 读取数据，添加SENTENCE_START和SENTENCE_END在开头和结尾
print "Reading CSV file..."
with open('data/reddit-comments-2015-08.csv', 'rb') as f:
    reader = csv.reader(f, skipinitialspace=True)
    reader.next()
    # 分句
    sentences = itertools.chain(*[nltk.sent_tokenize(x[0].decode('utf-8').lower()) for x in
    # 添加SENTENCE_START和SENTENCE_END
    sentences = ["%s %s %s" % (sentence_start_token, x, sentence_end_token) for x in sentenc
print "Parsed %d sentences." % (len(sentences))

# 分词
tokenized_sentences = [nltk.word_tokenize(sent) for sent in sentences]

# 统计词频
word_freq = nltk.FreqDist(itertools.chain(*tokenized_sentences))
print "Found %d unique words tokens." % len(word_freq.items())

# 取出高频词构建词到位置，和位置到词的索引
vocab = word_freq.most_common(vocabulary_size-1)
index_to_word = [x[0] for x in vocab]
index_to_word.append(unknown_token)
word_to_index = dict([(w,i) for i,w in enumerate(index_to_word)])

print "Using vocabulary size %d." % vocabulary_size
print "The least frequent word in our vocabulary is '%s' and appeared %d times." % (vocab[-1

# 把所有词表外的词都标记为unknown_token
for i, sent in enumerate(tokenized_sentences):
    tokenized_sentences[i] = [w if w in word_to_index else unknown_token for w in sent]

print "\nExample sentence: '%s'" % sentences[0]
print "\nExample sentence after Pre-processing: '%s'" % tokenized_sentences[0]

# 构建完整训练集
x_train = np.asarray([[word_to_index[w] for w in sent[:-1]] for sent in tokenized_sentences]
y_train = np.asarray([[word_to_index[w] for w in sent[1:]] for sent in tokenized_sentences])
```

RNN生成模型模仿语言风格例子

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

$$o_t = \mathrm{softmax}(Vs_t)$$

$$x_t \in \mathbb{R}^{8000}$$

$$o_t \in \mathbb{R}^{8000}$$

$$s_t \in \mathbb{R}^{100}$$

$$U \in \mathbb{R}^{100\times 8000}$$

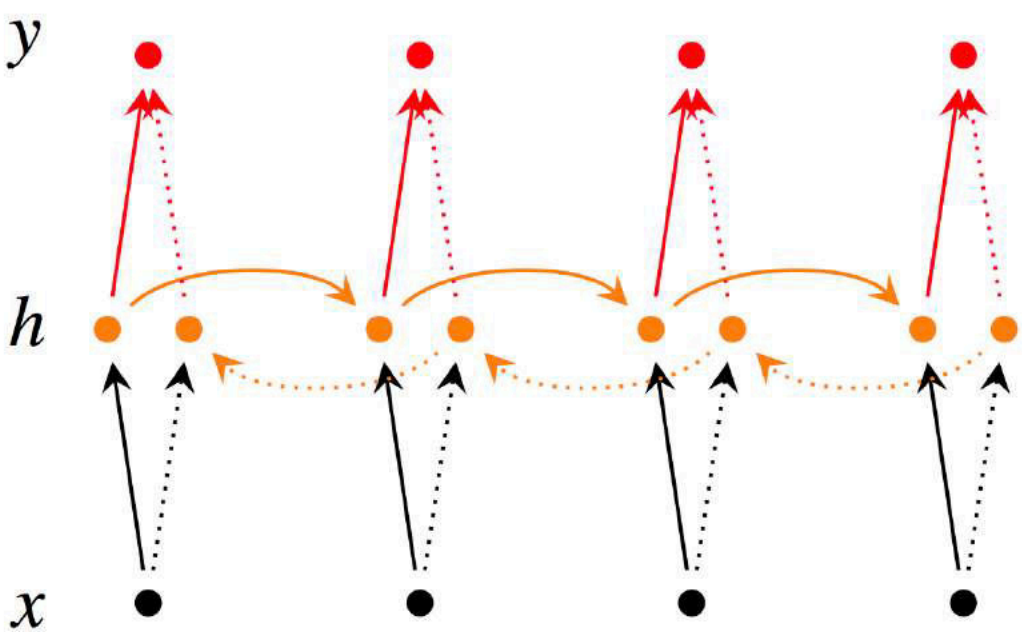
$$V \in \mathbb{R}^{8000\times 100}$$

$$W \in \mathbb{R}^{100\times 100}$$

- 详见代码

不同类型的RNN

- 双向RNN
  - 有些情况下，当前的输出不只依赖于之前的序列元素，还可能依赖之后的序列元素
  - 比如从一段话踢掉部分词，让你补全
  - 直观理解：双向RNN叠加



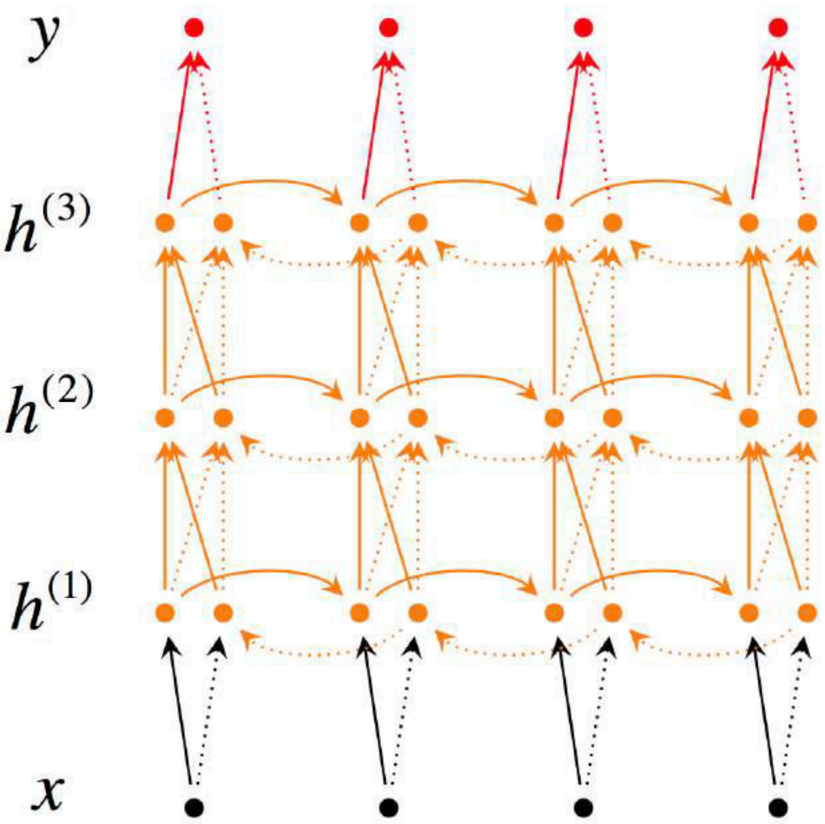
$$\overrightarrow{h}_t = f(\overrightarrow{W}x_t + \overrightarrow{V}\overrightarrow{h}_{t-1} + \overrightarrow{b})$$

$$\overleftarrow{h}_t = f(\overleftarrow{W}x_t + \overleftarrow{V}\overleftarrow{h}_{t+1} + \overleftarrow{b})$$

$$y_t = g(U[\overrightarrow{h}_t;\overleftarrow{h}_t]+c)$$

不同类型的RNN

- 深层双向RNN
  - 和双向RNN的区别是每一步/每个时间点我们设定多层结构



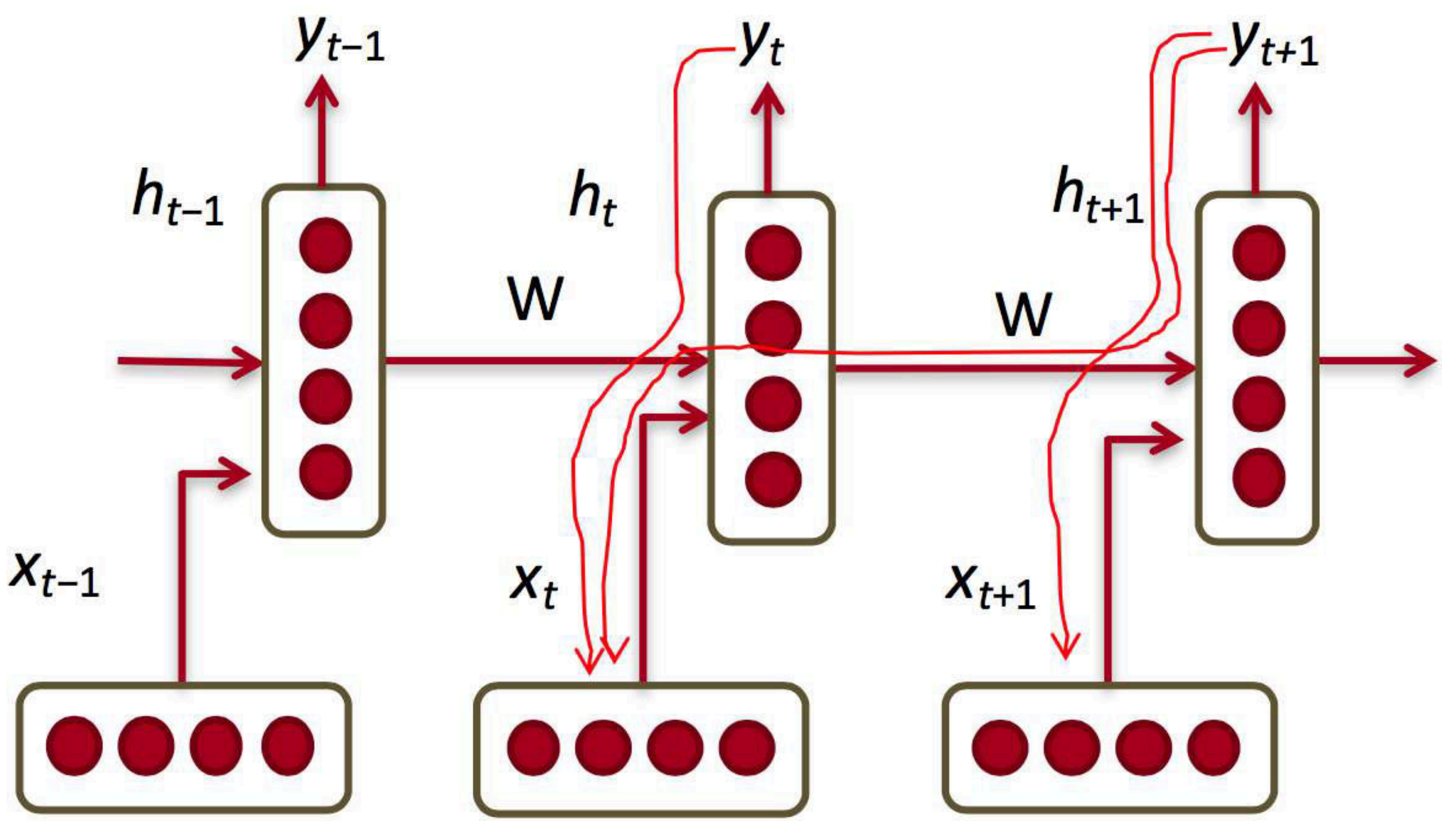
$$\overrightarrow{h}_t^{(i)} = f(\overrightarrow{W}^{(i)} h_t^{(i-1)} + \overrightarrow{V}^{(i)} \overrightarrow{h}_{t-1}^{(i)} + \overrightarrow{b}^{(i)})$$

$$\overleftarrow{h}_t^{(i)} = f(\overleftarrow{W}^{(i)} h_t^{(i-1)} + \overleftarrow{V}^{(i)} \overleftarrow{h}_{t+1}^{(i)} + \overleftarrow{b}^{(i)})$$

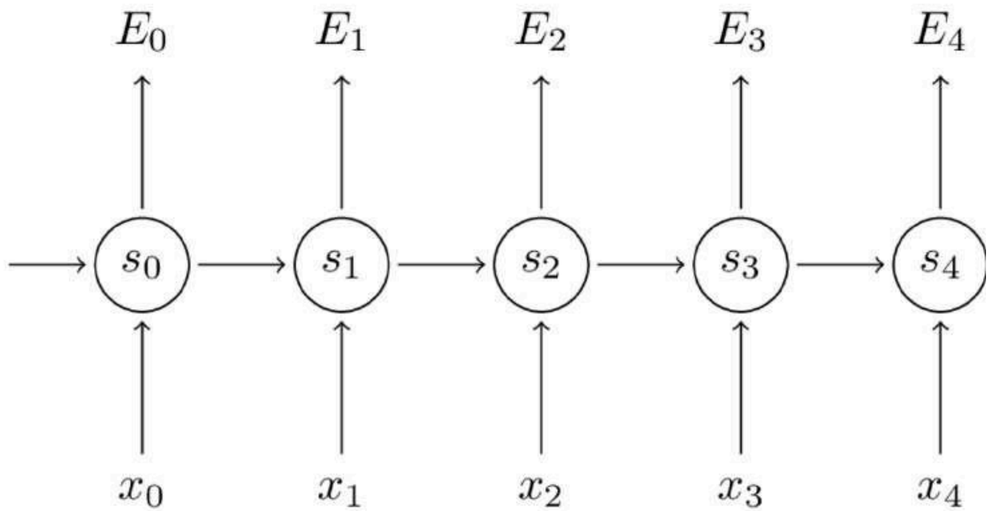
$$y_t = g(U[\overrightarrow{h}_t^{(L)}; \overleftarrow{h}_t^{(L)}] + c)$$

RNN与BPTT算法

- MLP(DNN)与CNN用BP算法求偏导
- BPTT和BP是一个思路，只不过既然有step，就和时间t有关系



RNN与BPTT算法



$$E_t(y_t, \hat{y}_t) = -y_t \log \hat{y}_t$$

$$E(y, \hat{y}) = \sum_t E_t(y_t, \hat{y}_t)$$
$$= -\sum_t y_t \log \hat{y}_t$$

$$\frac{\partial E}{\partial W} = \sum_t \frac{\partial E_t}{\partial W}.$$

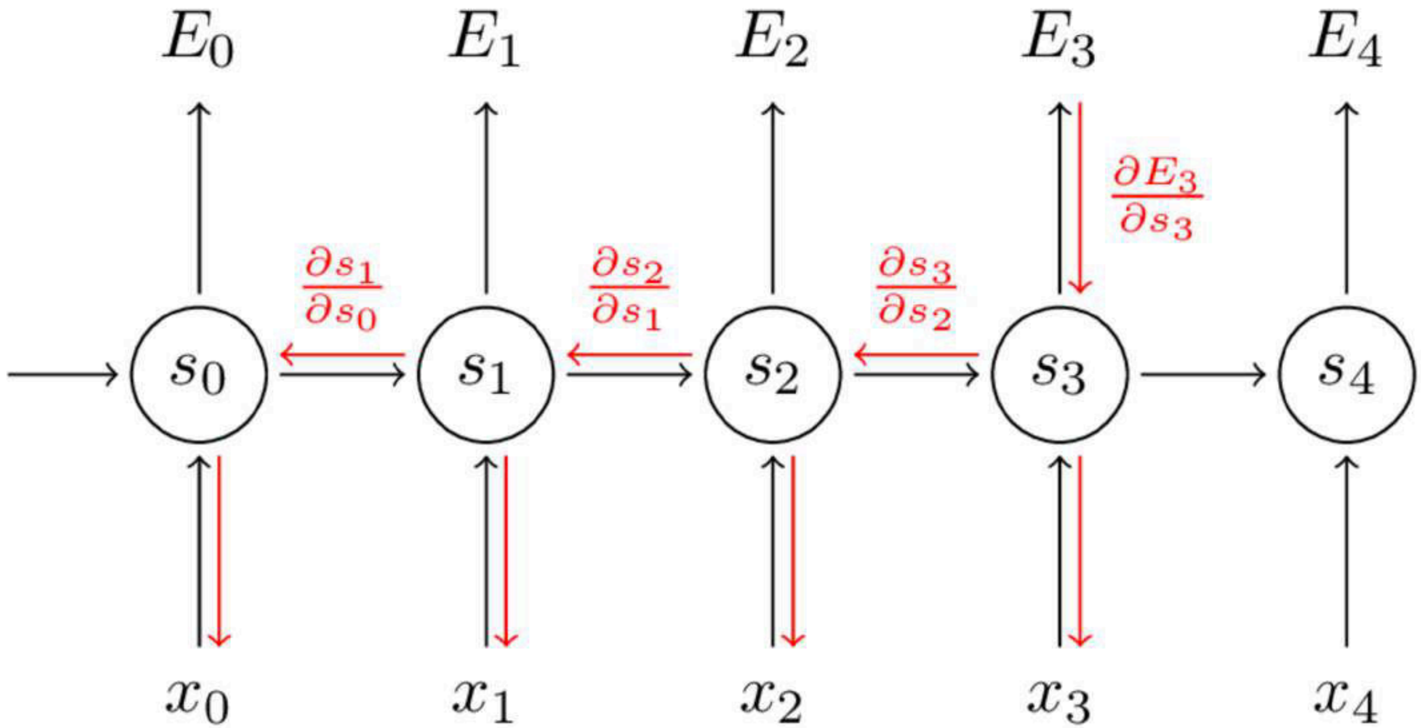
$$\frac{\partial E_3}{\partial W} = \frac{\partial E_3}{\partial \hat{y}_3}\frac{\partial \hat{y}_3}{\partial s_3}\frac{\partial s_3}{\partial W}$$

但是 $s_3 = \tanh(Ux_t + Ws_2)$ 依赖于s_2

链式法则

$$\frac{\partial E_3}{\partial W} = \sum_{k=0}^{3} \frac{\partial E_3}{\partial \hat{y}_3}\frac{\partial \hat{y}_3}{\partial s_3}\frac{\partial s_3}{\partial s_k}\frac{\partial s_k}{\partial W}$$

RNN与BPTT算法

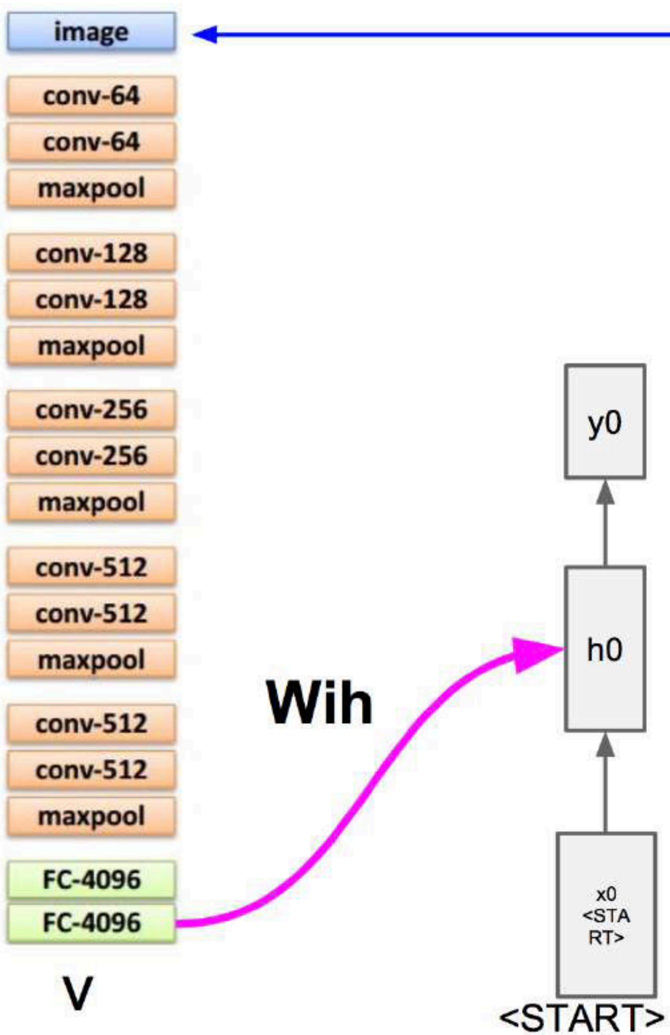


$$\frac{\partial E_3}{\partial W} = \sum_{k=0}^{3} \frac{\partial E_3}{\partial \hat{y}_3} \frac{\partial \hat{y}_3}{\partial s_3} \frac{\partial s_3}{\partial s_k} \frac{\partial s_k}{\partial W}$$

链式法则

$$\frac{\partial E_3}{\partial W} = \sum_{k=0}^{3} \frac{\partial E_3}{\partial \hat{y}_3} \frac{\partial \hat{y}_3}{\partial s_3} \left(\prod_{j=k+1}^{3} \frac{\partial s_j}{\partial s_{j-1}} \right) \frac{\partial s_k}{\partial W}$$

RNN与图片描述输出



test image

before:

h = tanh(Wxh * x + Whh * h)

now:

h = tanh(Wxh * x + Whh * h + Wih * v)

RNN与图片描述输出

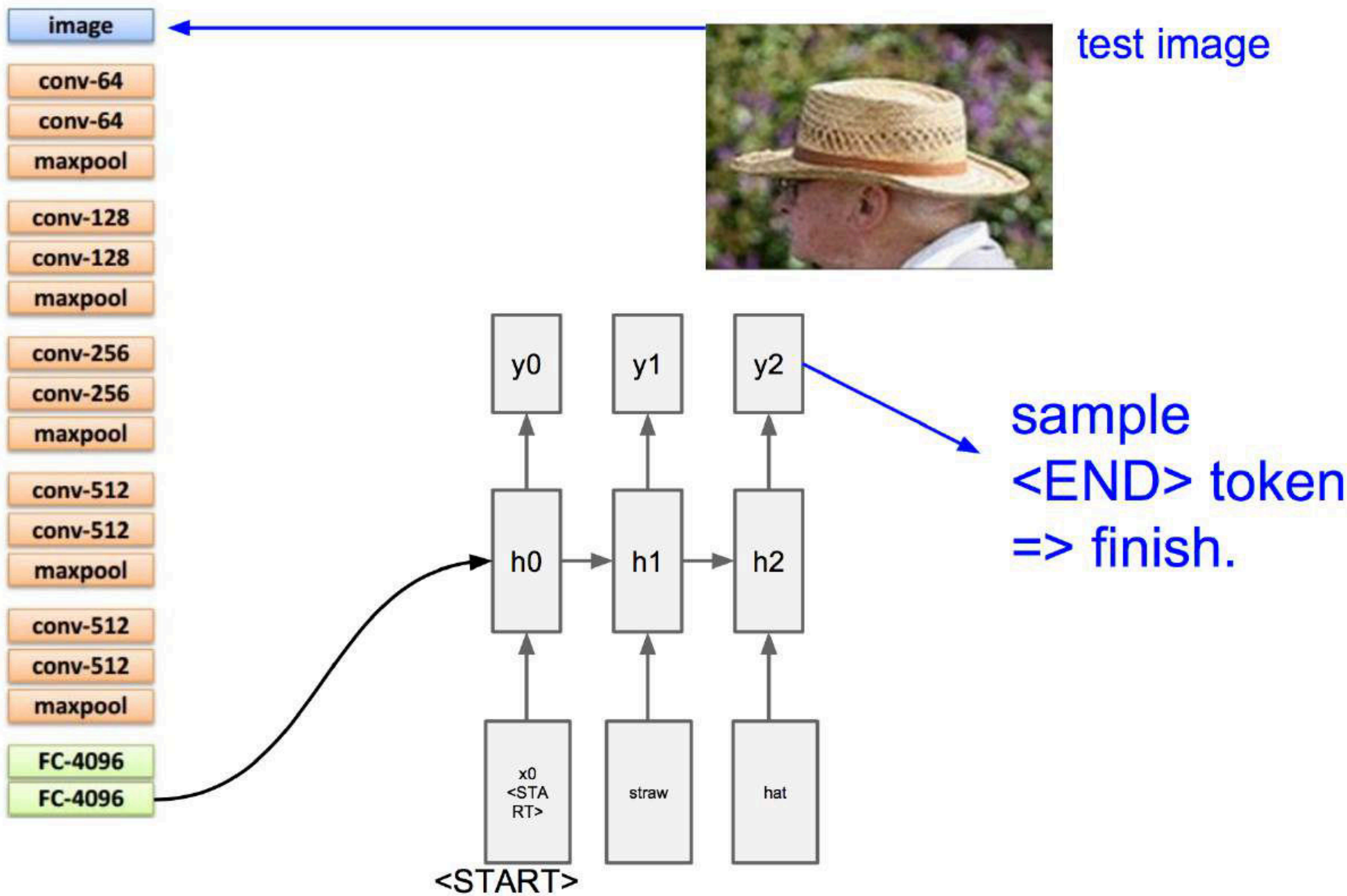
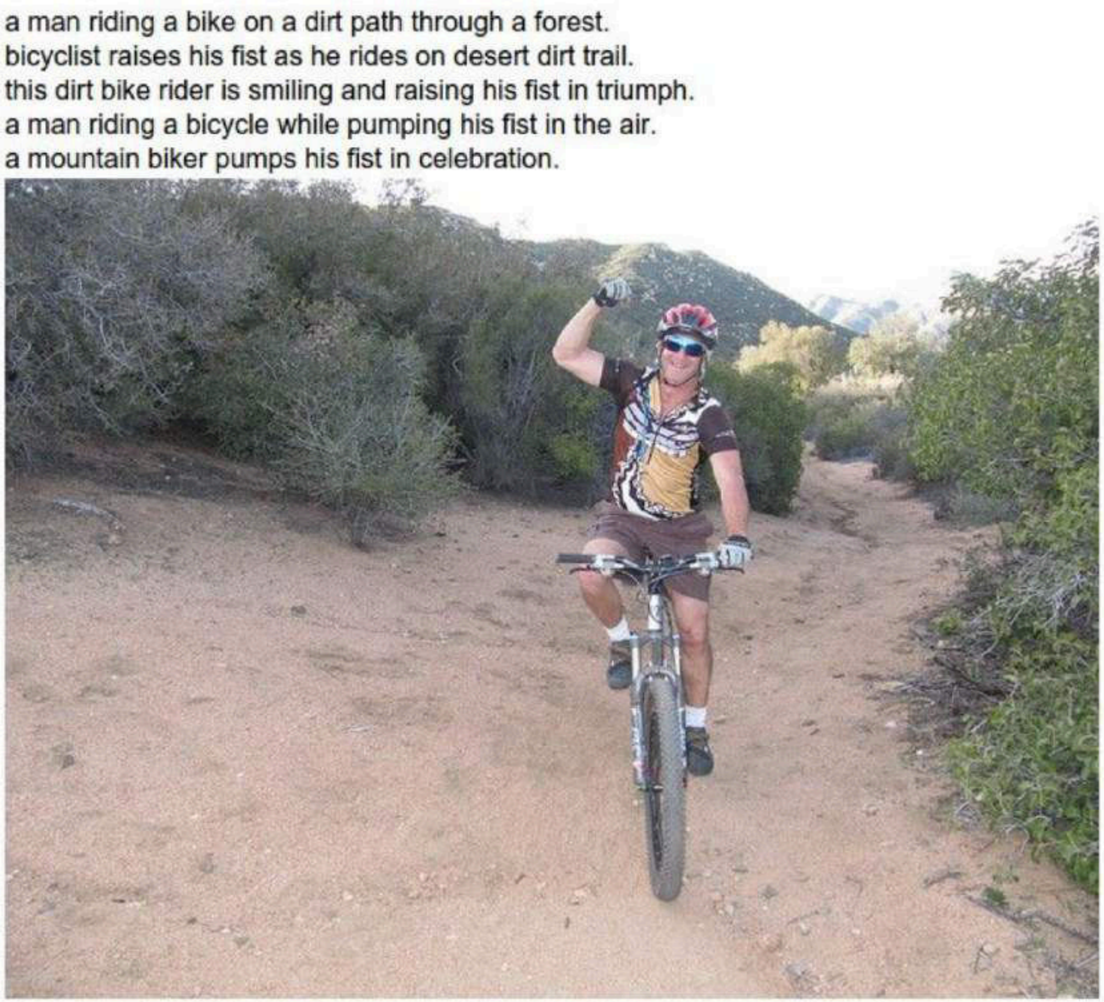


image
conv-64
conv-64
maxpool
conv-128
conv-128
maxpool
conv-256
conv-256
maxpool
conv-512
conv-512
maxpool
conv-512
conv-512
maxpool
FC-4096
FC-4096
test image
y0
y1
y2
h0
h1
h2
x0 <START>
straw
hat
<START>
sample <END> token => finish.

图片描述数据集

- Microsoft COCO数据集：http://mscoco.org

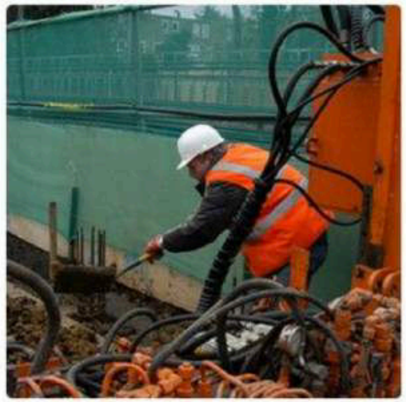


- 12w图片
- 5句话描述/每张图片

RNN与图片描述

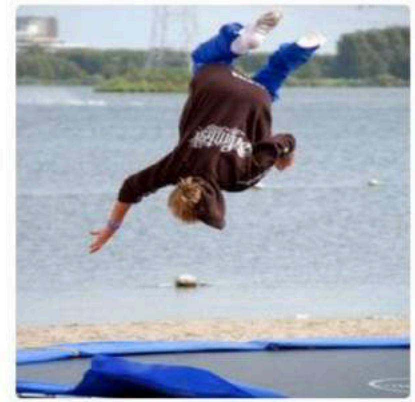
部分结果

"man in black shirt is playing guitar."



"construction worker in orange safety vest is working on road."

"two young girls are playing with lego toy."



"boy is doing backflip on wakeboard."

"a young boy is holding a baseball bat."

"a cat is sitting on a couch with a remote control."

"a woman holding a teddy bear in front of a mirror."

"a horse is standing in the middle of a road."

循环神经网络之 LSTM

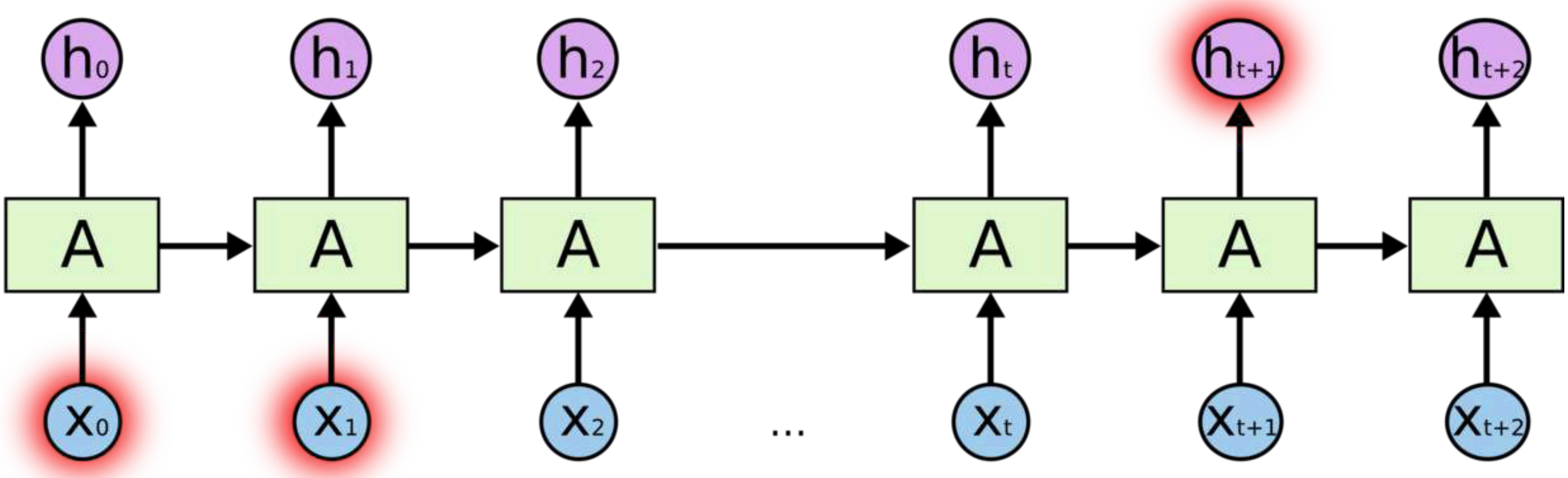
- 前面提到的RNN解决了，对之前的信息保存的问题
- 但是！存在长期依赖的问题。
  - 看电影的时候，某些情节的推断需要依赖很久以前的一些细节。
  - 很多其他的任务也一样。
  - 很可惜随着时间间隔不断增大时，RNN 会丧失学习到连接如此远的信息的能力。
  - 也就是说，记忆容量有限，一本书从头到尾一字不漏的去记，肯定离得越远的东西忘得越多。
  - 怎么办：LSTM

循环神经网络之LSTM

- LSTM是RNN一种，大体结构几乎一样。区别是?
  - 它的“记忆细胞”改造过。
  - 该记的信息会一直传递，不该记的会被“门”截断。

循环神经网络之 LSTM

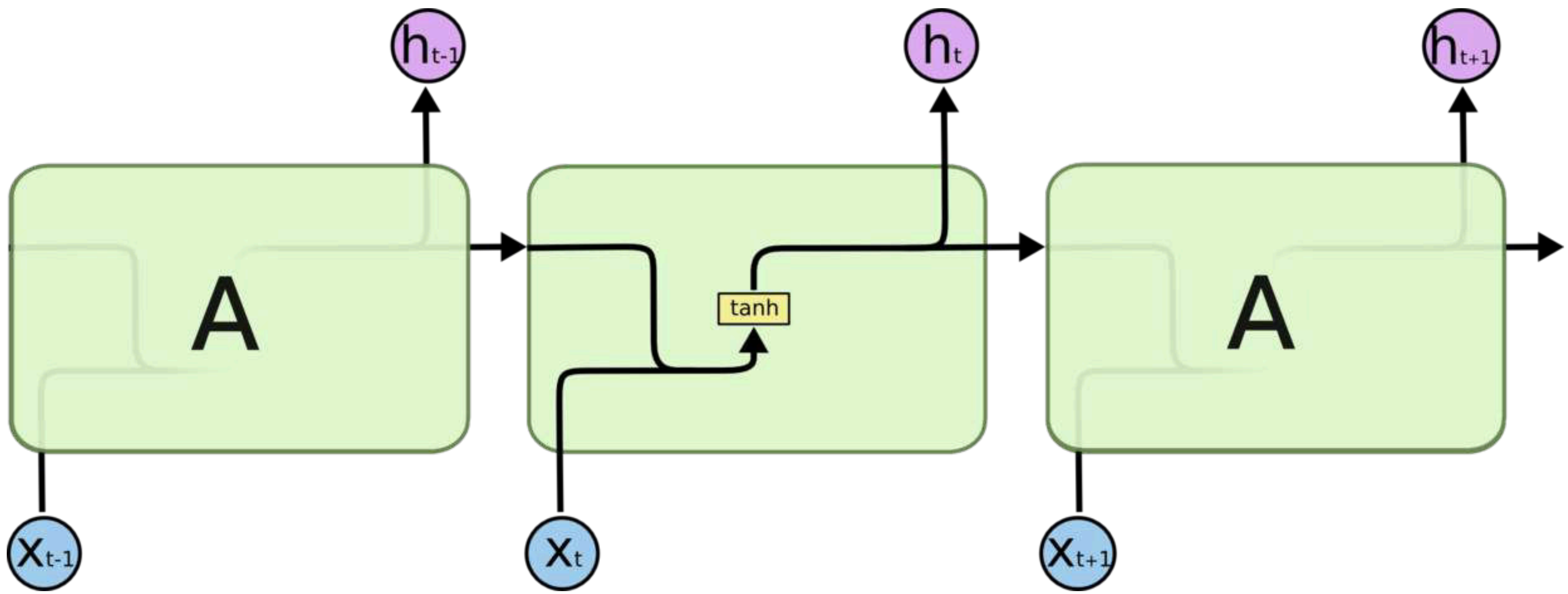
- 之前提到的RNN结构如下



Understanding LSTM Networks, colah, 2015

循环神经网络之LSTM

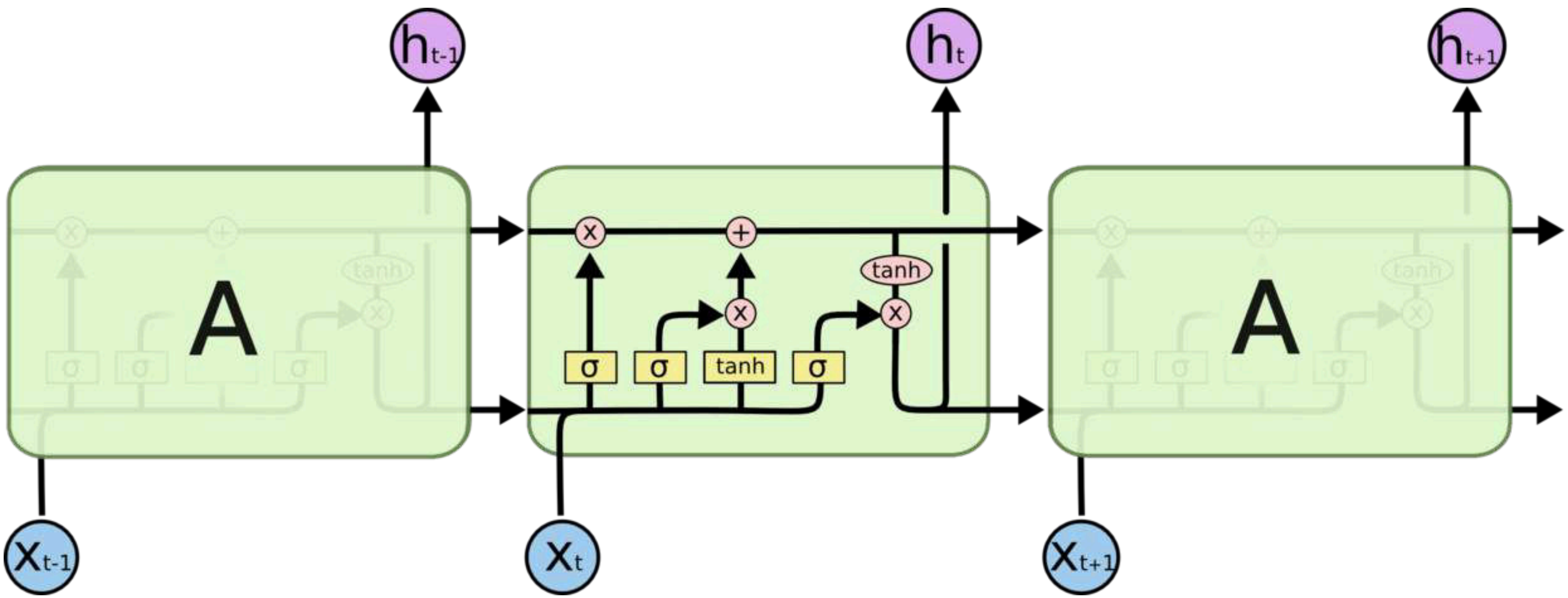
- 咱们把“记忆细胞”表示得炫酷一点



Understanding LSTM Networks, colah, 2015

循环神经网络之LSTM

- LSTM呢？
  - “记忆细胞”变得稍微复杂了一点点



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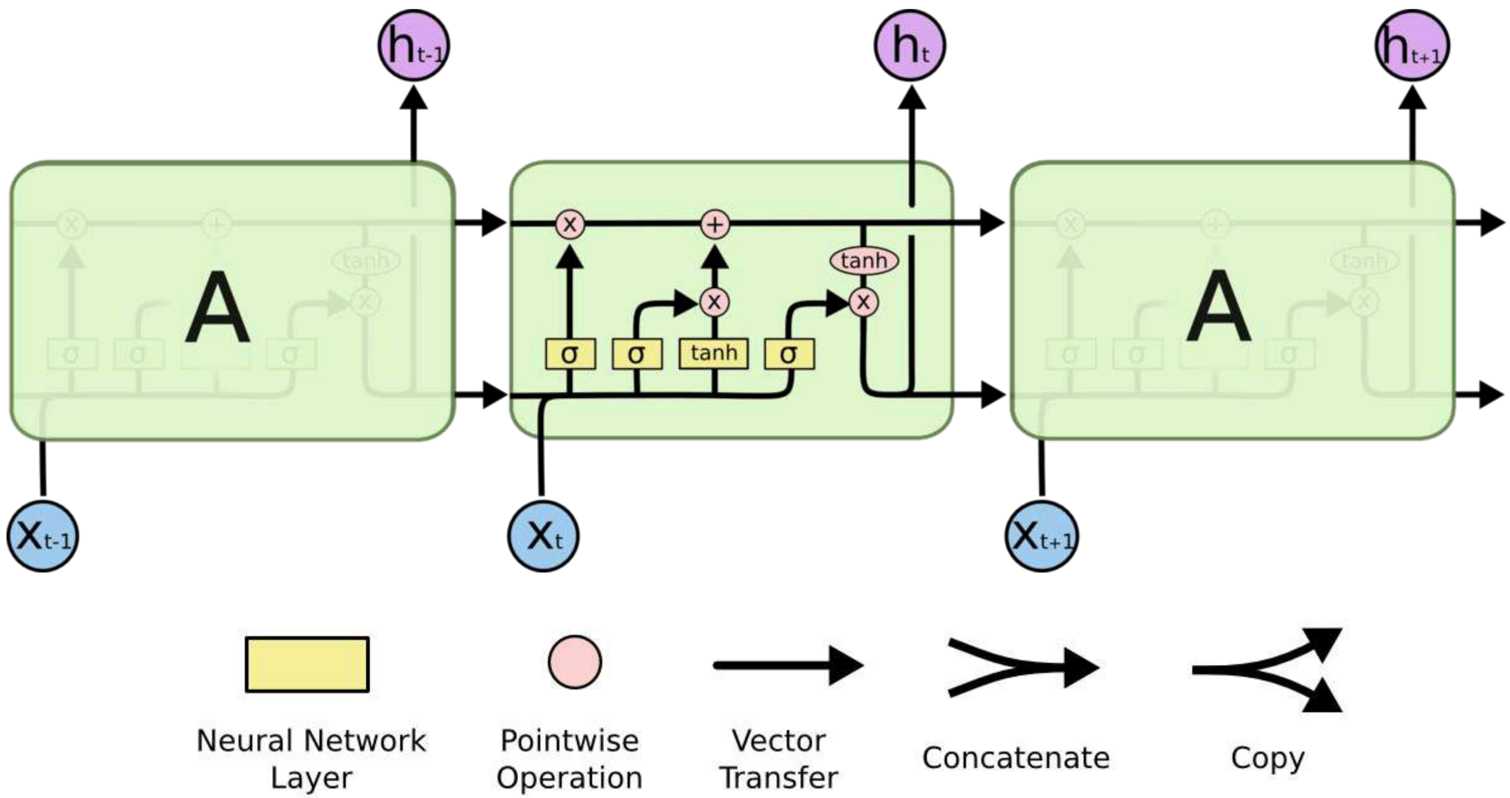
循环神经网络之 LSTM

- 图太复杂，细节看不懂？别着急，我们解释解释。



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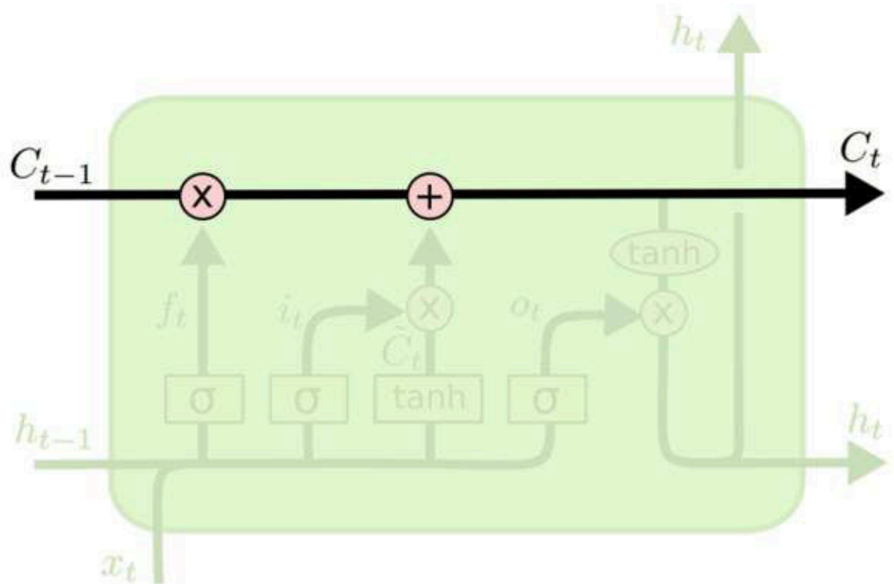
循环神经网络之 LSTM

- LSTM关键："细胞状态"
  - 细胞状态类似于传送带。直接在整个链上运行，只有一些少量的线性交互。信息在上面流传保持不变会很容易。



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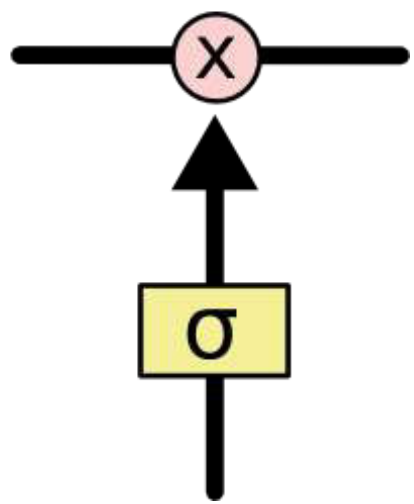
循环神经网络之LSTM

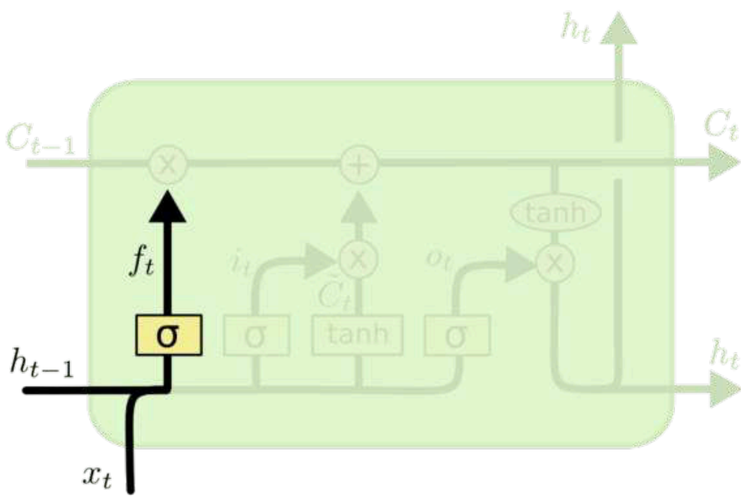
- LSTM怎么控制“细胞状态”？
  - 通过“门”让信息选择性通过，来去除或者增加信息到细胞状态
  - 包含一个sigmoid神经网络层 和 一个pointwise乘法操作
  - Sigmoid 层输出0到1之间的概率值，描述每个部分有多少量可以通过。0代表“不许任何量通过”，1就指“允许任意量通过”



Understanding LSTM Networks, colah, 2015

LSTM的几个关键“门”与操作

- 第1步：决定从“细胞状态”中丢弃什么信息 => “忘记门”
- 比如完形填空中填“他”或者“她”的问题，细胞状态可能包含当前主语的类别，当我们看到新的代词，我们希望忘记旧的代词。



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

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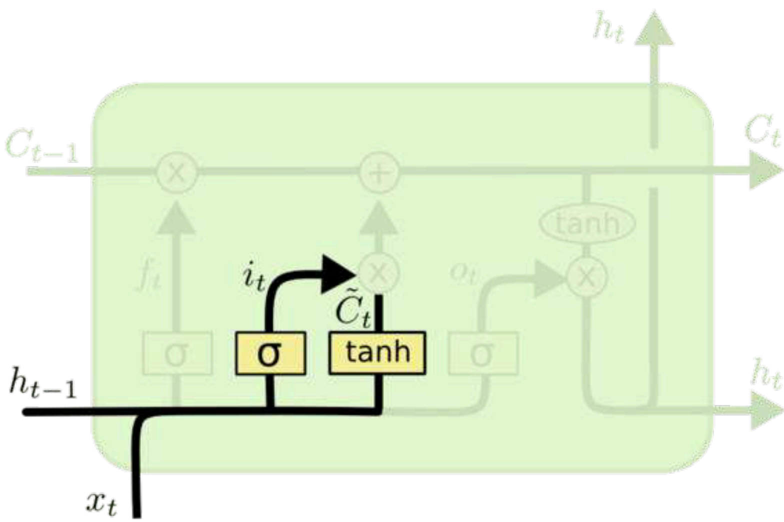
LSTM的几个关键"门"与操作

- 第2步：决定放什么新信息到"细胞状态"中
  1. Sigmoid层决定什么值需要更新
  2. Tanh层创建一个新的候选值向量 $\tilde{C}_t$
  3. 上述2步是为状态更新做准备



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

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

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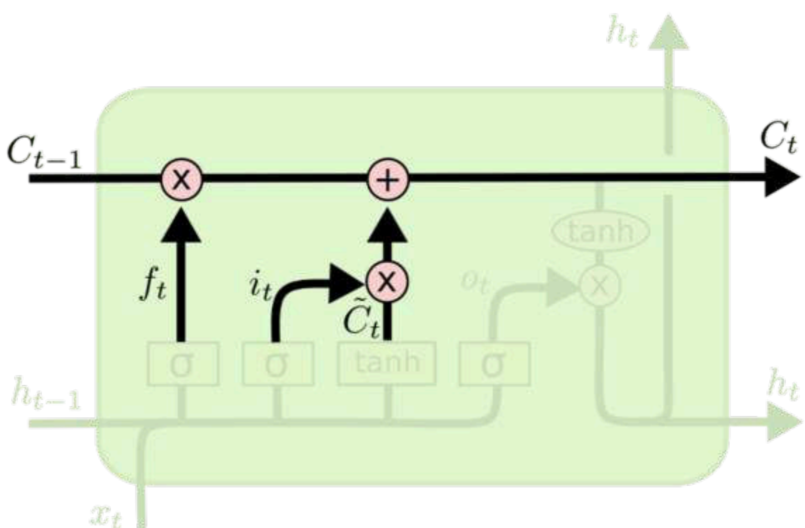
LSTM的几个关键“门”与操作

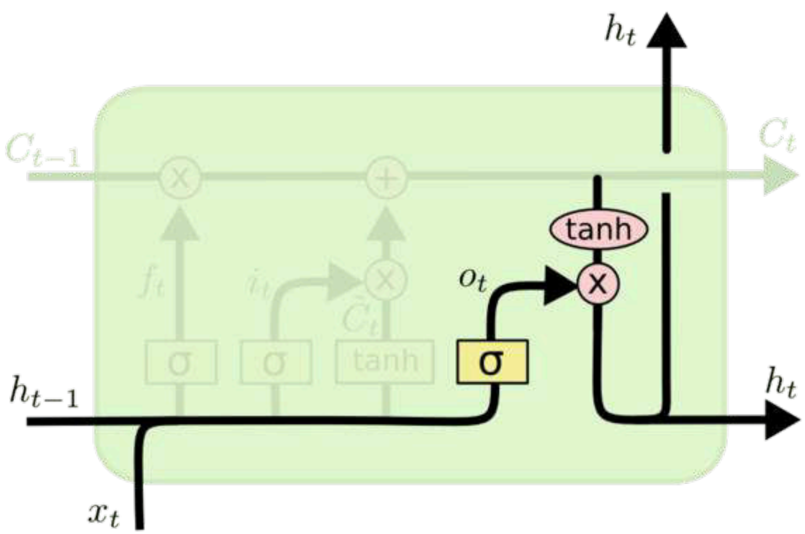
- 第3步：更新“细胞状态”
  1. 更新C_{t-1}为C_t
  2. 把旧状态与f_t相乘，丢弃掉我们确定需要丢弃的信息
  3. 加上$i_t * \tilde{C}_t$。这就是新的候选值，根据我们决定更新每个状态的程度进行变化。



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

LSTM的几个关键“门”与操作

- 第4步：基于“细胞状态”得到输出
  1. 首先运行一个sigmoid 层来确定细胞状态的哪个部分将输出
  2. 接着用tanh处理细胞状态(得到一个在-1到1之间的值)，再将它和sigmoid门的输出相乘，输出我们确定输出的那部分。
  3. 比如我们可能需要单复数信息来确定输出“他”还是“他们”



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

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

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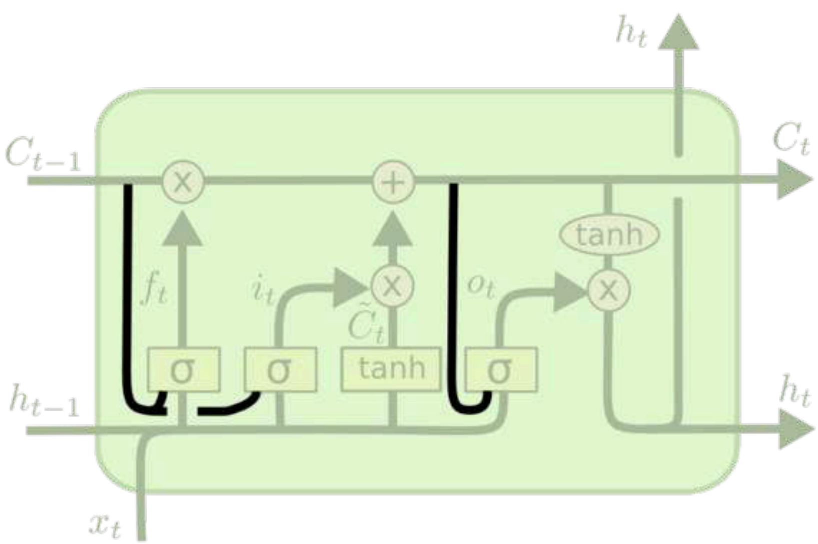
LSTM的变体

- 变种1
  - 增加“peephole connection”
  - 让 门层 也会接受细胞状态的输入。



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

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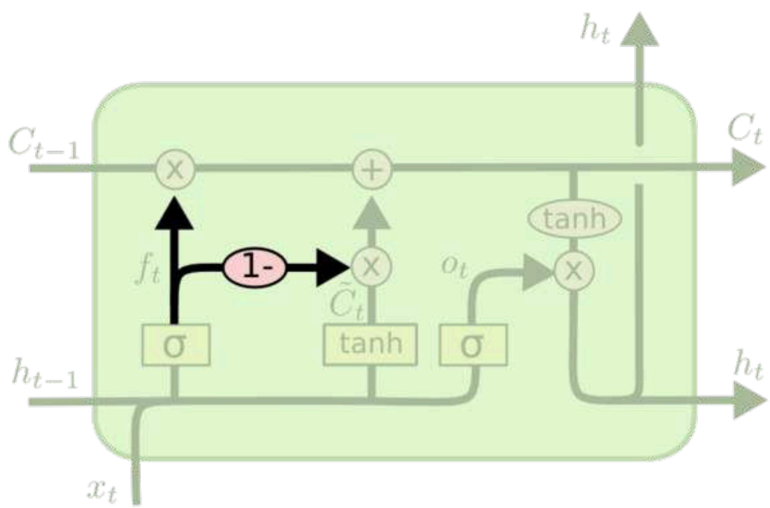
LSTM的变体

- 变种2
  - 通过使用 coupled 忘记和输入门
  - 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。



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

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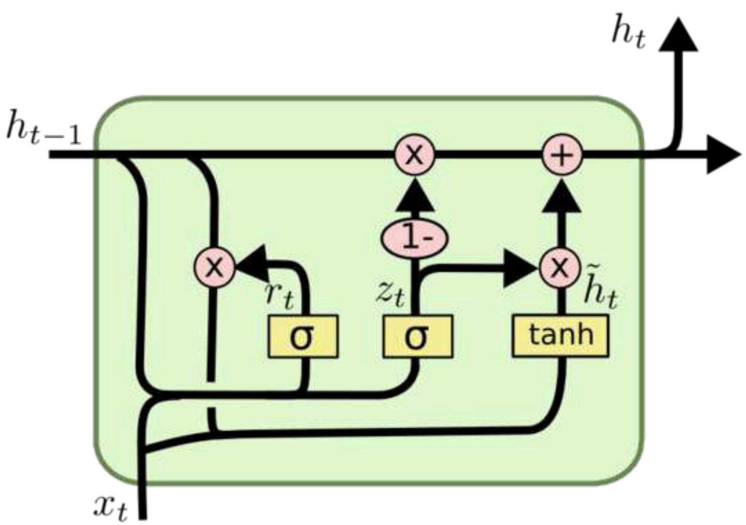
GRU

- Gated Recurrent Unit (GRU)，2014年提出
  - 将忘记门和输入门合成了一个单一的 更新门
  - 同样还混合了细胞状态和隐藏状态，和其他一些改动。
  - 比标准LSTM简单。



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

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

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

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

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RNN拓展

- 2015的paper《LSTM: A Search Space Odyssey》中，对各种变体做了对比，发现其实本质上它们大同小异。
- 2015的论文《An Empirical Exploration of Recurrent Network Architectures》中，google和facebook的大神尝试了非常多种RNN架构，发现并非所有任务上LSTM都表现最好。
- 现在有更多的RNN研究方向和应用(attention model, Grid LSTM等) 参见https://github.com/kjw0612/awesome-rnn

RNN生成模型仿照维基百科

- 数据请戳http://cs.stanford.edu/people/karpathy/char-rnn/wiki.txt

```
{ { cite journal | id=Cerling Nonforest Department|format=Newlymeslated|none } }
''www.e-complete''.

'''See also''': [[List of ethical consent processing]]

== See also ==
*[[Iender dome of the ED]]
*[[Anti-autism]]

===[[Religion|Religion]]===
*[[French Writings]]
*[[Maria]]
*[[Revelation]]
*[[Mount Agamul]]

== External links==
* [http://www.biblegateway.nih.gov/entrepre/ Website of the World Festival. The labour

==External links==
* [http://www.romanology.com/ Constitution of the Netherlands and Hispanic Competition
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RNN生成模型：到底发生了什么？

- 依旧是https://gist.github.com/karpathy/d4dee566867f8291f086

```
tyntd-iafhatawiaoihrdemot  lytdws  e ,tfti, astai f ogoh eoase rrranbyne 'nhthnee e
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```

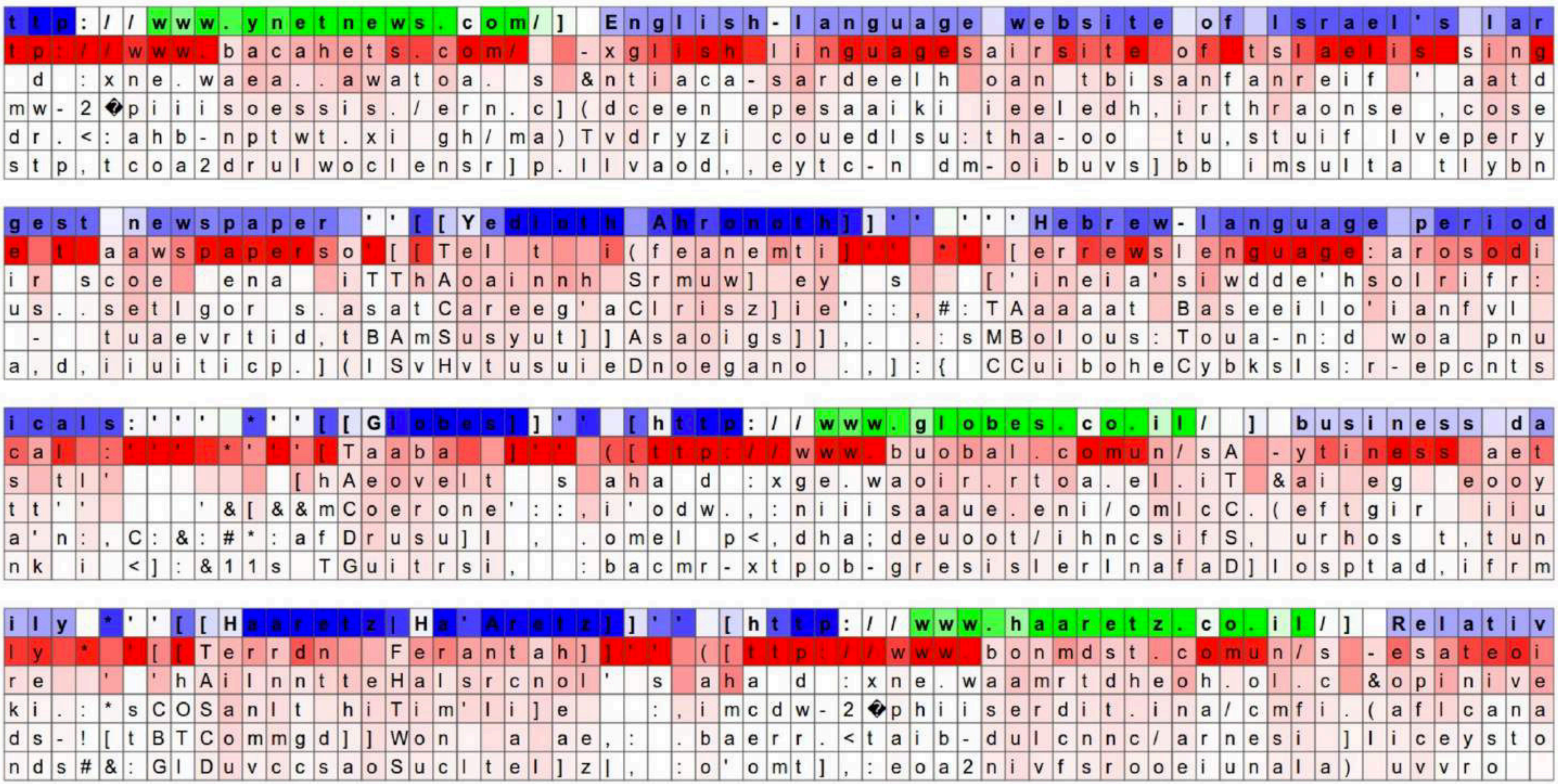
```
we counter. He stutn co des. His stanted out one ofler that concossions and was
to gearang reay Jotrets and with fre colt otf paitt thin wall. Which das stimn
```

```
"Kite vouch!" he repeated by her
door. "But I would be done and quarts, feeling, then, son is people...."
```

```
"Why do what that day," replied Natasha, and wishing to himself the fact the
princess, Princess Mary was easier, fed in had oftened him.
Pierre aking his soul came to the packs and drove up his father-in-law women.
```

RNN生成模型:到底发生了什么?

- 依旧是https://gist.github.com/karpathy/d4dee566867f8291f086



RNN生成模型“写”食谱？

- 案例https://gist.github.com/nylki/1efbaa36635956d35bcc
- 代码继续用https://gist.github.com/karpathy/d4dee566867f8291f086
- 数据请戳http://www.ffts.com/recipes/lg/lg32965.zip

```
MMMMM----- Recipe via Meal-Master (tm) v8.05

      Title: BARBECUE RIBS
 Categories: Chinese, Appetizers
      Yield: 4 Servings

      1 pk Seasoned rice
      1    Beer -- cut into
           -cubes
      1 ts Sugar
    3/4 c  Water
           Chopped finels,
           -up to 4 tblsp of chopped
      2 pk Yeast Bread/over
```

```
MMMMM-----------------------FILLING-----------------------------
      2 c  Pineapple, chopped
    1/3 c  Milk
    1/2 c  Pecans
           Cream of each
      2 tb Balsamic cocoa
      2 tb Flour
      2 ts Lemon juice
           Granulated sugar
      2 tb Orange juice
      1 c  Sherry wheated curdup
      1    Onion; sliced
      1 ts Salt
      2 c  Sugar
    1/4 ts Salt
    1/2 ts White pepper, freshly ground
           Sesame seeds
      1 c  Sugar
    1/4 c  Shredded coconut
    1/4 ts Cumin seeds

  Preheat oven to 350.  In a medium bowl, combine milk, the sugar, vanilla and seasoned
  flour and water and then cornstarch. add tomatoes, oregano, and
  nutmeg; serve.
```

模仿奥巴马演讲?

- https://medium.com/@samim/obama-rnn-machine-generated-political-speeches-c8abd18a2ea0#.9sb793kbm

Recurrent Neural Networks

Here is a selection of some of my favorite speeches the Obama-RNN generated so far. Keep in mind this is a just a quick hack project. With more time & effort the results can be improved.

SEED: Jobs

> *Good afternoon. God bless you.*
>
> *The United States will step up to the cost of a new challenges of the American people that will share the fact that we created the problem. They were attacked and so that they have to say that all the task of the final days of war that I will not be able to get this done. The promise of the men and women who were still going to take out the fact that the American people have fought to make sure that they have to be able to protect our part. It was a chance to stand together to completely look for the commitment to borrow from the American people. And the fact is the men and women in uniform and the millions of our country with the law system that we should be a strong stretcks of the forces that we can afford to increase our spirit of the American people and the leadership of our country who are on the Internet of American lives.*

合成音乐？

- 如果能把音乐的乐谱表示成文本形式，是不是可以借用RNN？
- https://highnoongmt.wordpress.com/2015/05/22/lisls-stis-recurrent-neural-networks-for-folk-music-generation/

- Abc notation转化，参见 http://abcnotation.com/blog/2010/01/31/how-to-understand-abc-the-basics/

```
X:1
T:Paddy O'Rafferty
C:Trad.
M:6/8
K:D
dff cee|def gfe|dff cee|dfe dBA|dff cee|def gfe|faf gfe|1 dfe dBA:|2 dfe dcB|]
~A3 B3|gfe fdB|AFA B2c|dfe dcB|~A3 ~B3|efe efg|faf gfe|1 dfe dcB:|2 dfe dBA|]
fAA eAA|def gfe|fAA eAA|dfe dBA|fAA eAA|def gfe|faf gfe|dfe dBA:|
```

感谢大家！

恳请大家批评指正！