RNN

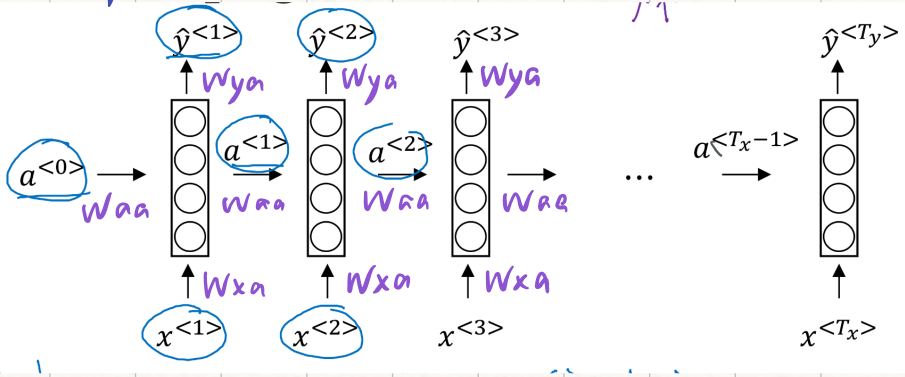
一. 循环序列模型 Sequence model

1. Notation

words: $x^{<1>}\ x^{<2>}\ \cdots\ x^{<t>}$ $T_x = 9$

diuts: $y^{<1>}\ y^{<2>}\ \cdots\ y^{<t>}$ $T_y = 9$

2. 循环神经网络 Recurrent Neural Network



考虑一句话中某个词语的前(后)文.

共用 Waa Wxa Wya

$$a^{<t>} = g(W_{aa}a^{<t-1>} + W_{ax}x^{<t>} + b_a)$$ tanh / relu

(100,100) 100 (100,10,000) 10,000

$$\hat{y}^{<t>} = g(W_{ya}a^{<t>} + b_y)$$ sigmoid

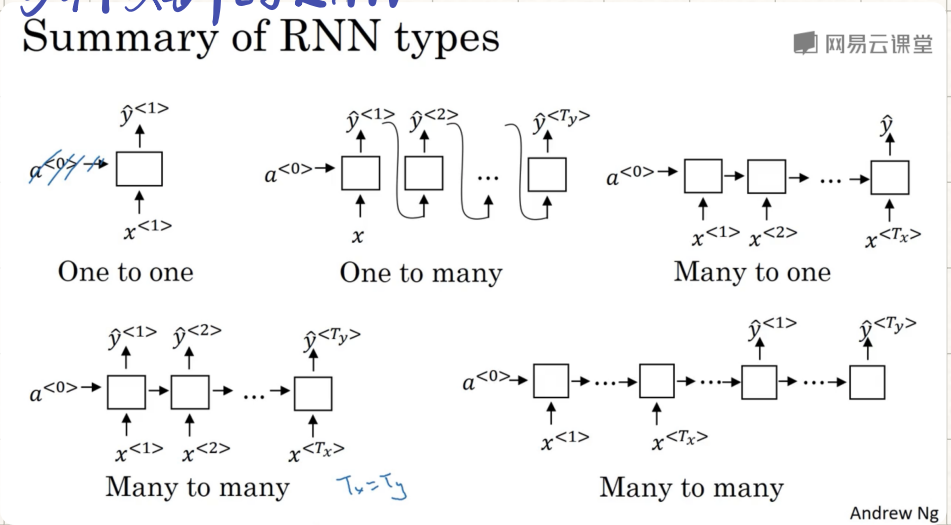
反向传播.

对 $\hat{y}^{<t>}$ 使用交叉熵损失 $(\text{logistic}) \Rightarrow L(t)$

$-\sum y \log(\hat{y})$

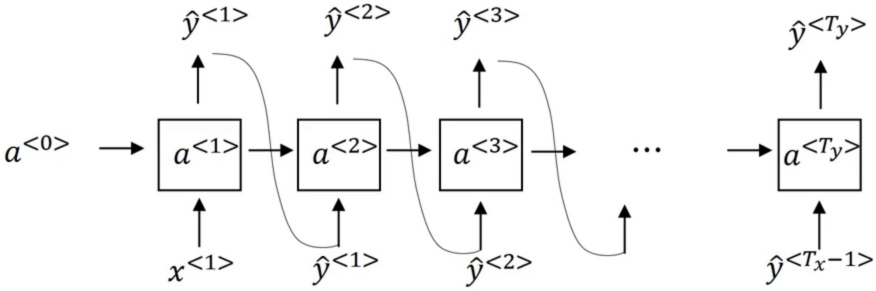
总损失 $L = \sum L(t)$. backprop through time

3. 多种类别的 RNN



4. 语言模型和序列生成

5. 新序列采样



{ 单词库，UNK，EOS.
字符库.

6. 梯度消失.

靠后的梯度很难影响靠前的层.

即句子后段的单词无法长期依赖前段的单词.

{ 梯度爆炸：剪枝
梯度消失：？（GRU）如何在长序列保持有效

6. GRU门控循环单元 gated recurrent unit

c = memory cell.

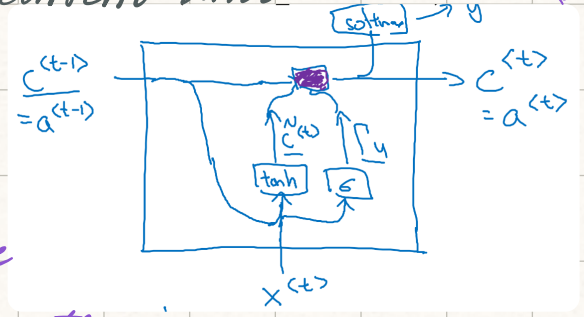
$\tilde{h}$ $\tilde{c}^{<t>} = \tanh(W_c[\Gamma_r * c^{<t-1>}, x^{<t>}] + b_c)$

u $\Gamma_u = \sigma(W_u[c^{<t-1>}, x^{<t>}] + b_u)$ update/optic gate

r $\Gamma_r = \sigma(W_r[c^{<t-1>}, x^{<t>}] + b_r)$ relevance

h $c^{<t>} = \Gamma_u * \tilde{c}^{<t>} + (1 - \Gamma_u) * c^{<t-1>}$

$a^{<t>} = c^{<t>}$



Γ_u 一般很小，因此 $c^{<t>}$ 可以记忆很久

用 c 代替 a.

7. LSTM 长短时记忆网络 Long Short Term Memory org

$\tilde{c}^{<t>} = \tanh(W_c[a^{<t-1>}, x^{<t>}] + b_c)$

$\Gamma_u = \sigma(W_u[a^{<t-1>}, x^{<t>}] + b_u)$ Update

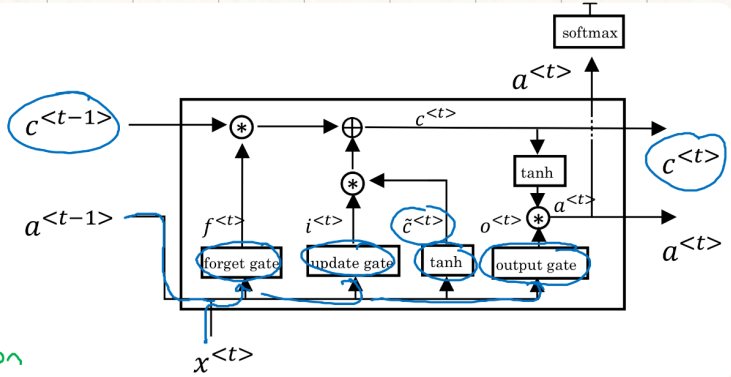
$\Gamma_f = \sigma(W_f[a^{<t-1>}, x^{<t>}] + b_f)$ Forget

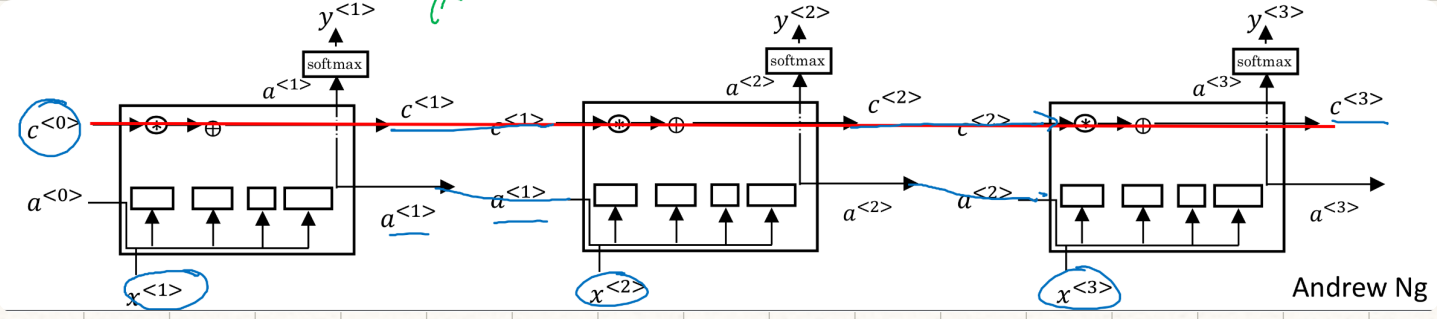
$\Gamma_o = \sigma(W_o[a^{<t-1>}, x^{<t>}] + b_o)$ Output

$c^{<t>} = \Gamma_u * \tilde{c}^{<t>} + \Gamma_f * c^{<t-1>}$

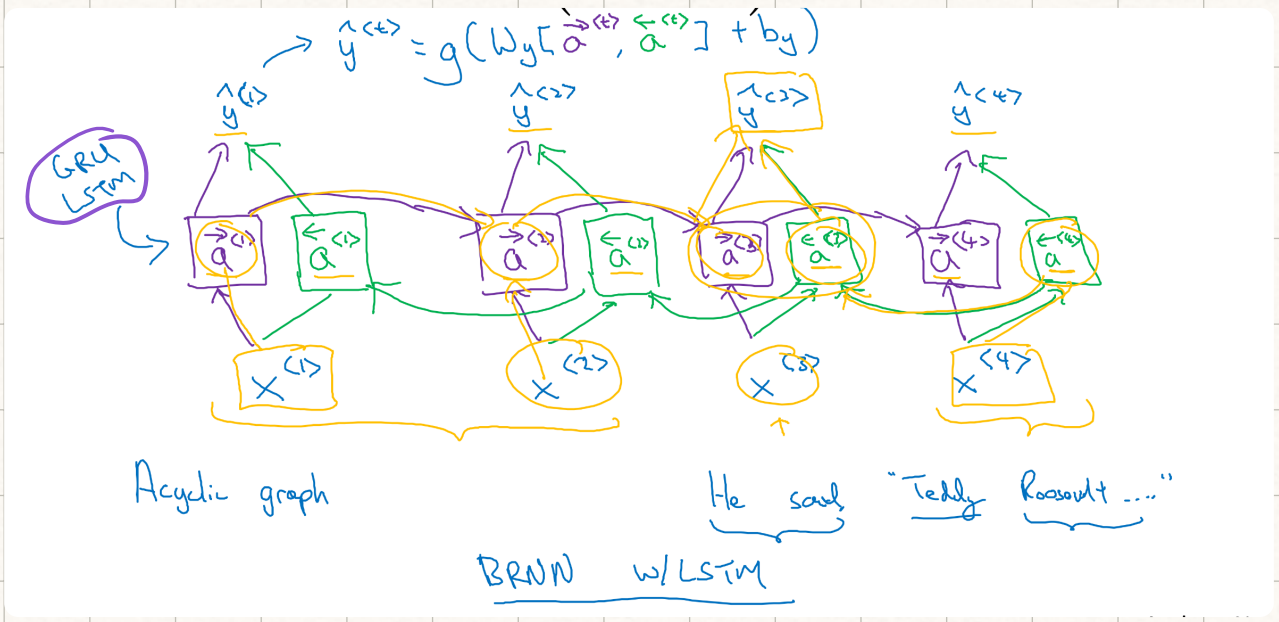
$a^{<t>} = \Gamma_o * c^{<t>}$

$c^{<t-1>}$ peephole connection



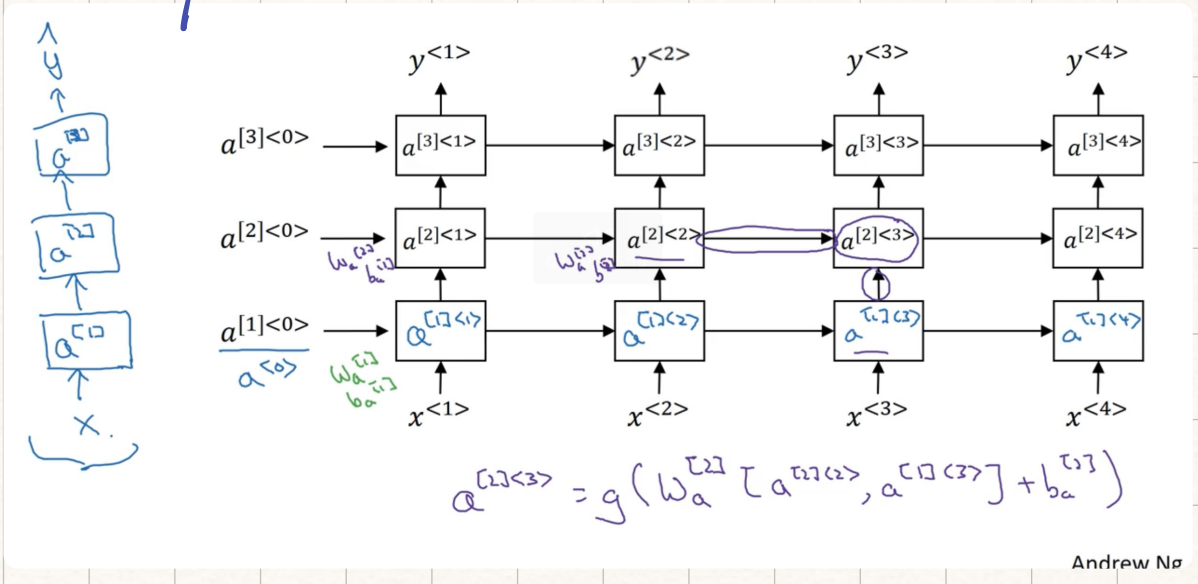


8. BRNN 双向循环网络 Bidirectional



同时考虑句子前后的信息来进行预测. 常用 BRNN + LSTM

9. Deep RNN

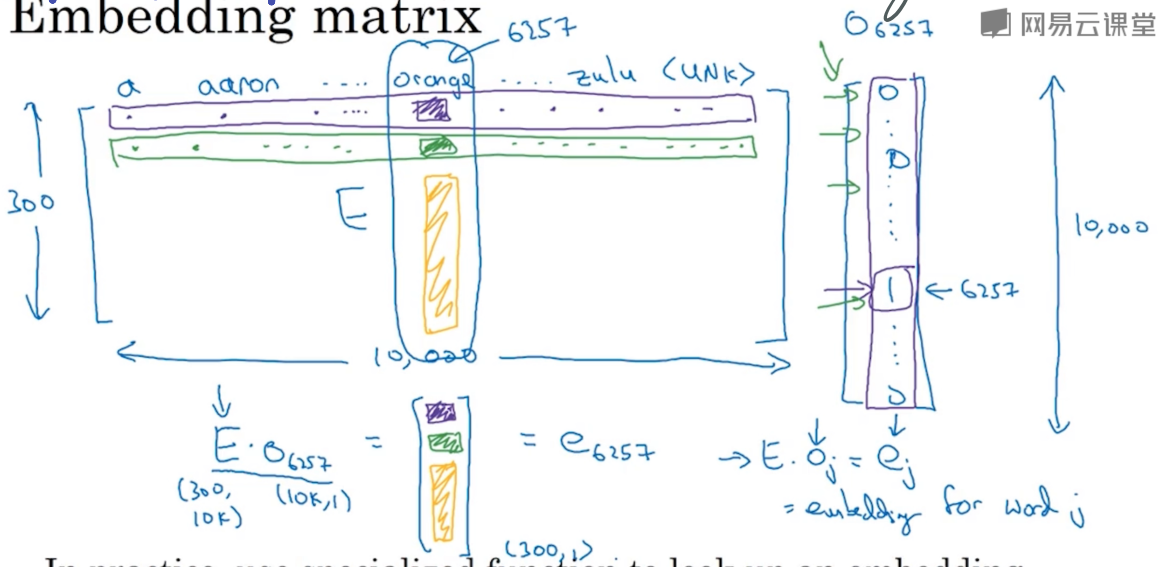


层数不会很深

二. 自然语言处理.

1. 词汇表征和词嵌入. Word Embedding

Embedding matrix



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In practice, use specialized function to look up an embedding.

但当你动手实现时
But if when you're implementing this,

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三. 序列模型和注意力机制

1. 基础模型. Seq2Seq.

Sequence to sequence model

$x^{<1>}$ $x^{<2>}$ $x^{<3>}$ $x^{<4>}$ $x^{<5>}$
Jane visite l'Afrique en septembre

→ Jane is visiting Africa in September.
$y^{<1>}$ $y^{<2>}$ $y^{<3>}$ $y^{<4>}$ $y^{<5>}$ $y^{<6>}$

机器翻译

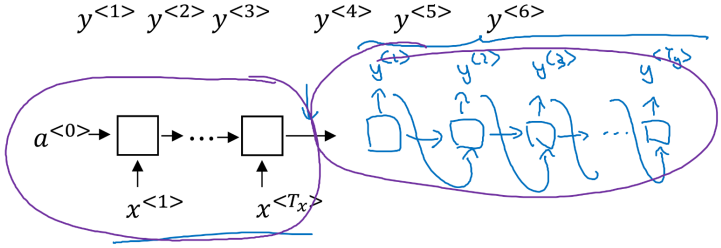
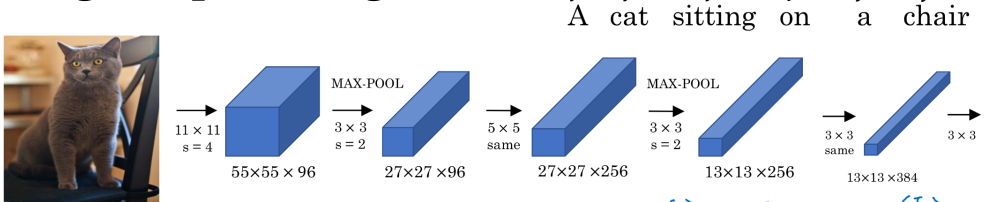
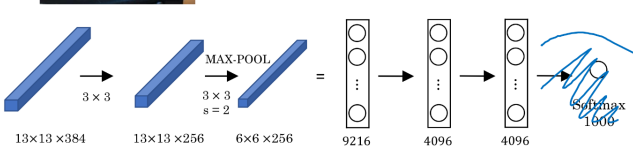
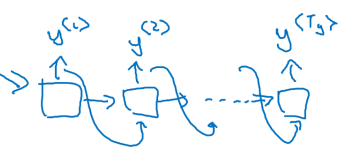


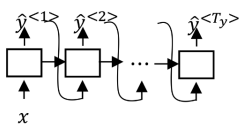
Image captioning

$y^{<1>}$ $y^{<2>}$ $y^{<3>}$ $y^{<4>}$ $y^{<5>}$ $y^{<6>}$
A cat sitting on a chair





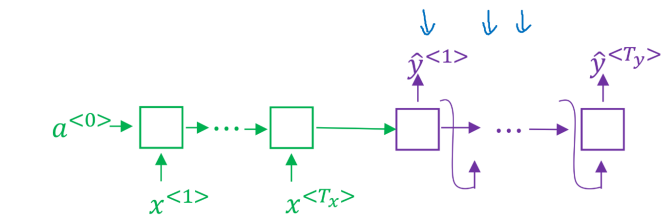




2. 选择最可能的句子.

Why not a greedy search?

$P(\hat{y}^{<1>}|x)$



10,000
10
$10{,}000^{10}$

$\arg\max_y P(\hat{y}^{<1>}, \hat{y}^{<2>}, \ldots, \hat{y}^{<T_y>}|x)$

$P(y|x)$

→ Jane is visiting Africa in September.

→ Jane is going to be visiting Africa in September.

$P(\text{Jane is going}|x) > P(\text{Jane is visiting}|x)$

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贪心算法会导致高数词汇次以及句子长度过长.

采用集束算法. 以3为例. 1) 每次保留概率最高的三组词句.

3. 改进定向搜索算法

Length normalization

$P(y^{<1>}\ldots y^{<T_y>}|x) = P(y^{<1>}|x)\,P(y^{<2>}|x, y^{<1>})\cdots P(y^{<T_y>}|x, y^{<1>}, \ldots, y^{<T_y-1>})$

$$\arg\max_y \prod_{t=1}^{T_y} P(y^{<t>}|x, y^{<1>}, \ldots, y^{<t-1>})$$

log

$\log P(y|x) \leftarrow$

$P(y|x) \leftarrow$

$$\arg\max_y \sum_{t=1}^{T_y} \log P(y^{<t>}|x, y^{<1>}, \ldots, y^{<t-1>})$$

$T_y = 1, 2, 3, \ldots, 30.$

$$\rightarrow \frac{1}{T_y^{\alpha}} \sum_{t=1}^{T_y} \log P(y^{<t>}|x, y^{<1>}, \ldots, y^{<t-1>})$$

$\alpha = 0.7$ $\alpha = 1$ $\alpha = 0$

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减少惩罚长句子 (再乘数倍向更短的句子).

4 Bleu Bilingual Evaluation Understudy

Bleu score on unigrams

Example: Reference 1: The cat is on the mat.

Reference 2: There is a cat on the mat.

MT output: The cat the cat on the mat. ($\hat{y}$)

$p_1 = \frac{\sum_{unigram \in \hat{y}} count_{clip}(unigram)}{\sum_{unigram \in \hat{y}} count(unigram)}$

$p_n = \frac{\sum_{ngram \in \hat{y}} count_{clip}(ngram)}{\sum_{ngram \in \hat{y}} count(ngram)}$

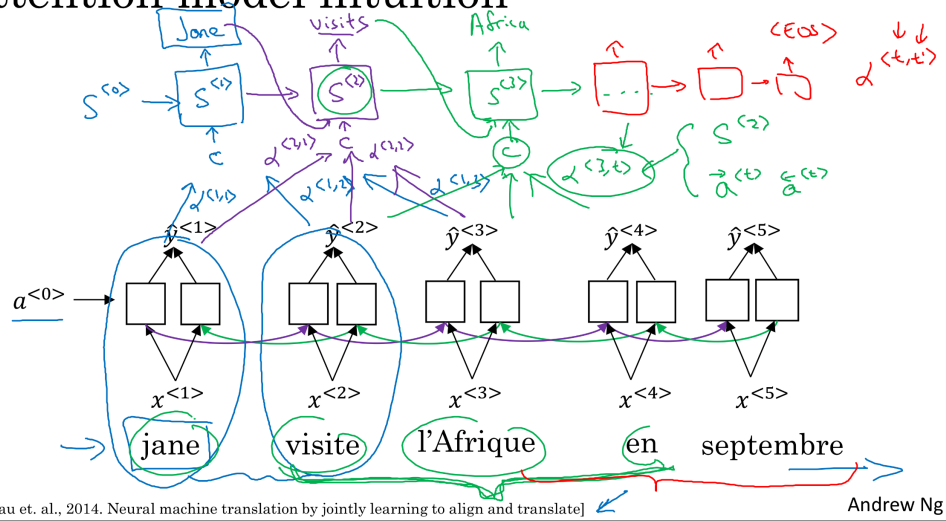
$p_1, p_2, \ldots = 1.0$

BP: $\exp\left(\frac{1}{n}\sum_{n=1} p_n\right)$

5. 注意力模型

长句中. Bleu会下降. 因此需要考虑全局.

Attention model intuition



[Bahdanau et. al., 2014. Neural machine translation by jointly learning to align and translate]

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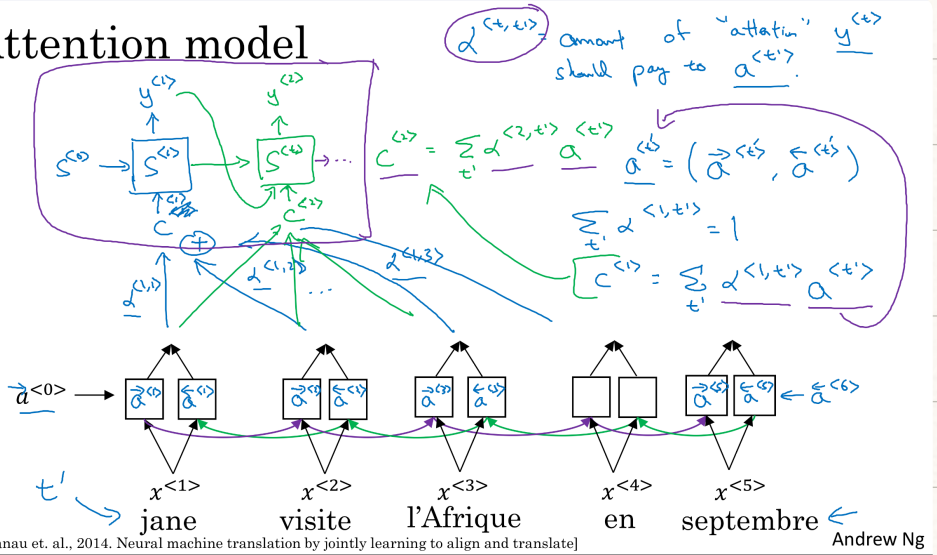
Attention model



[Bahdanau et. al., 2014. Neural machine translation by jointly learning to align and translate]

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Computing attention $\alpha^{<t,t'>}$

$\alpha^{<t,t'>}$ = amount of attention $y^{<t>}$ should pay to $a^{<t'>}$

$$\alpha^{<t,t'>} = \frac{\exp(e^{<t,t'>})}{\sum_{t'=1}^{T_x} \exp(e^{<t,t'>})}$$