Lecture 7
Vanishing gradient
Advanced RNN layers
CNNs for texts

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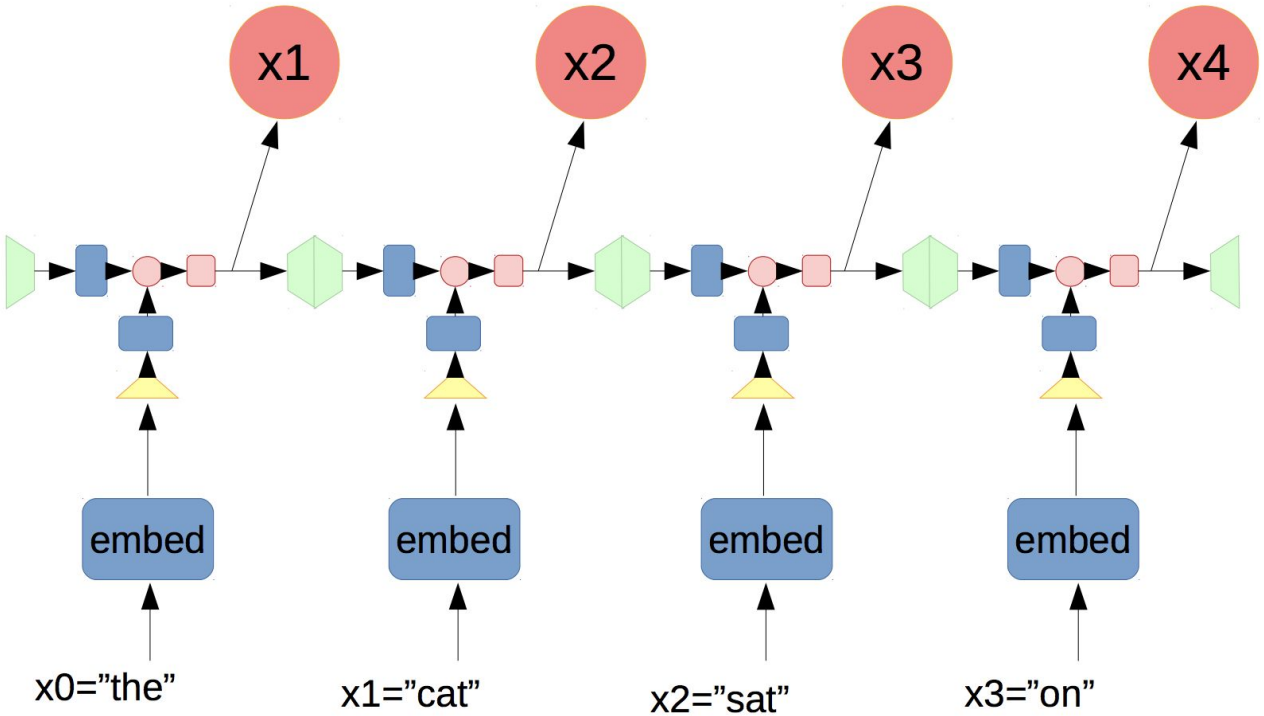
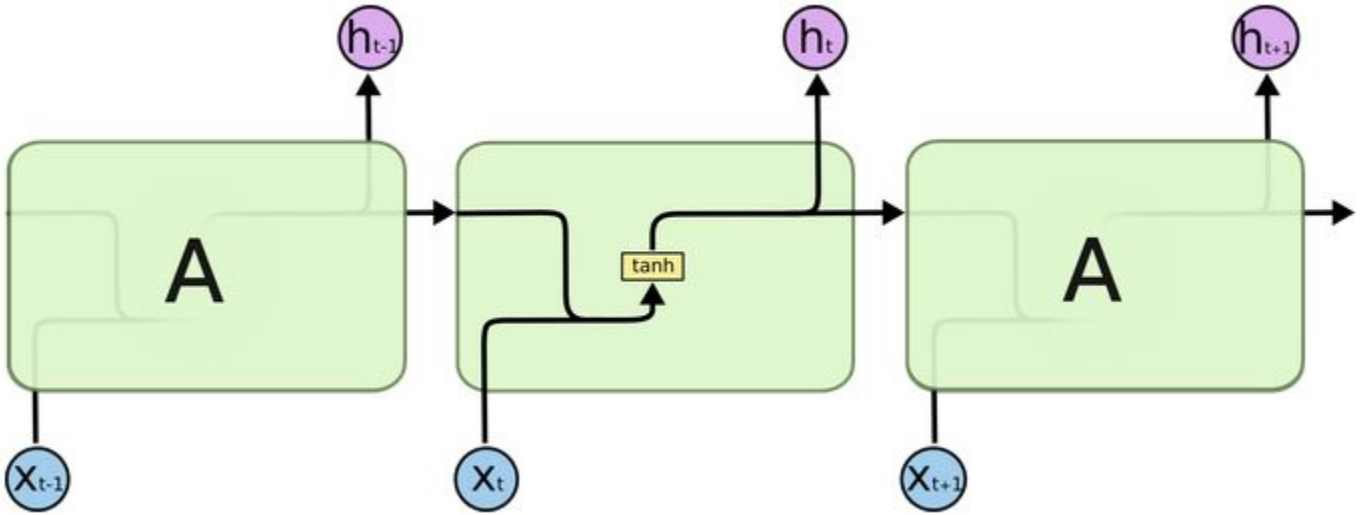
Outline

- Simple RNN recap
- Complex RNN:
  - Vanishing gradient
  - Exploding gradient
  - LSTM/GRU
  - Gradient clipping
  - Skip connections
  - Residual networks as ensembles
- CNNs for text

Recap: RNN

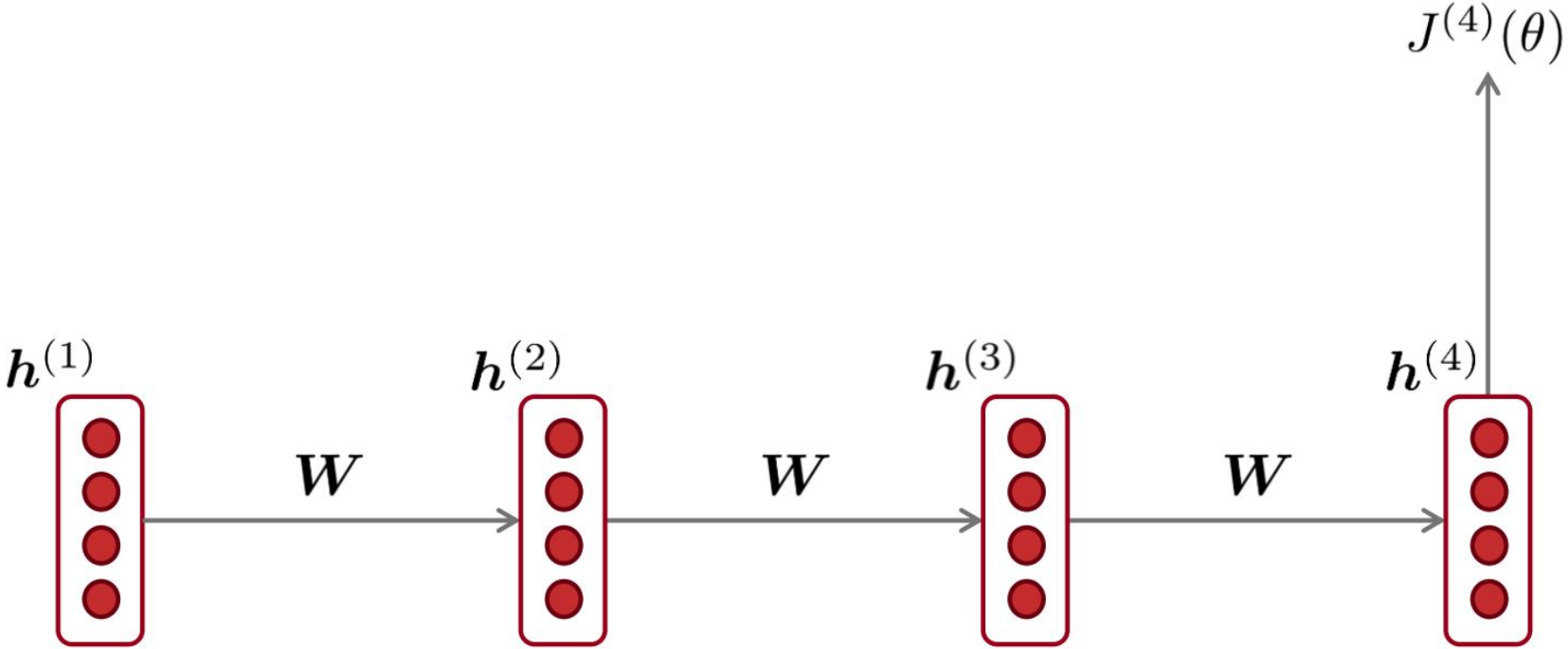


Recap: Vanilla RNN



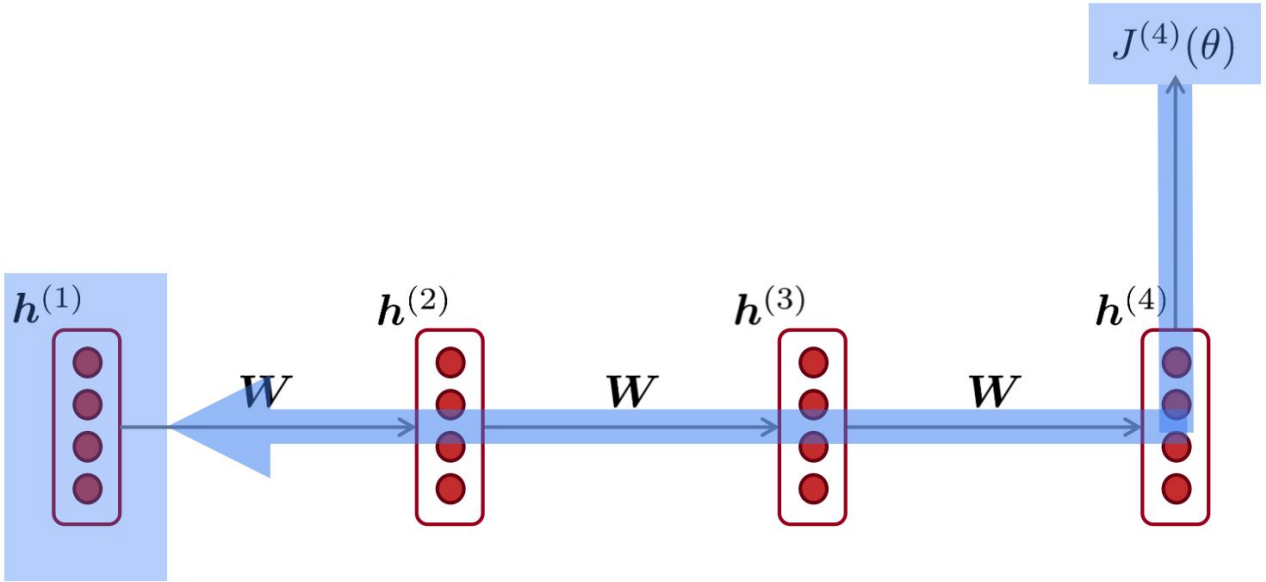
Source: https://colah.github.io/posts/2015-08-Understanding-LSTMs/

Vanishing gradient problem



Based on: Lecture by Abigail See, CS224n Lecture 7

Vanishing gradient problem



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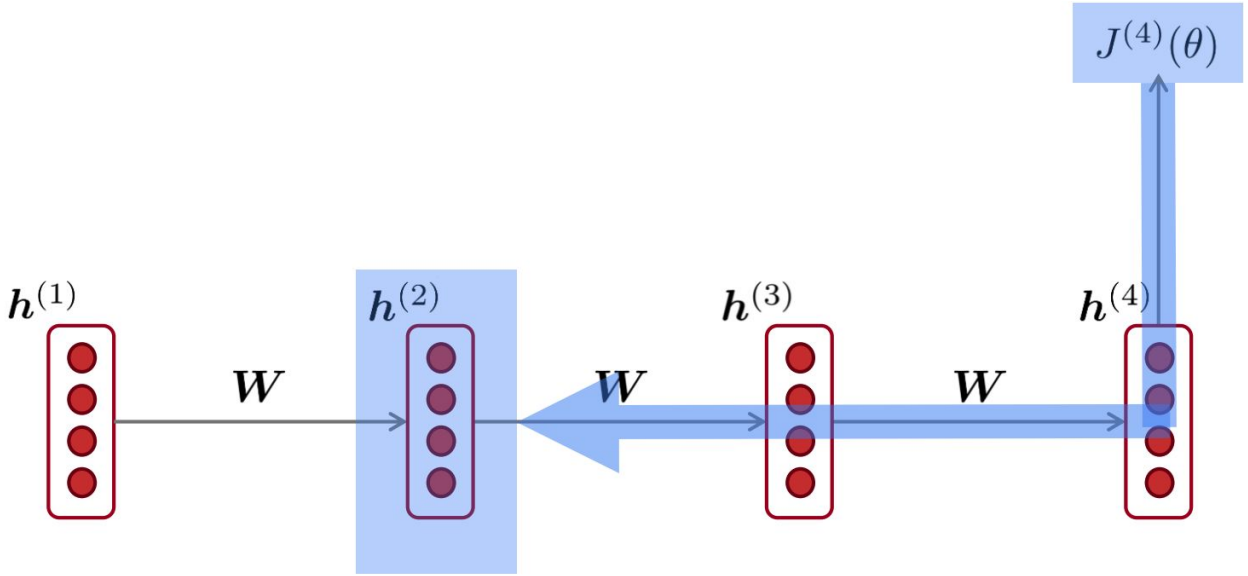
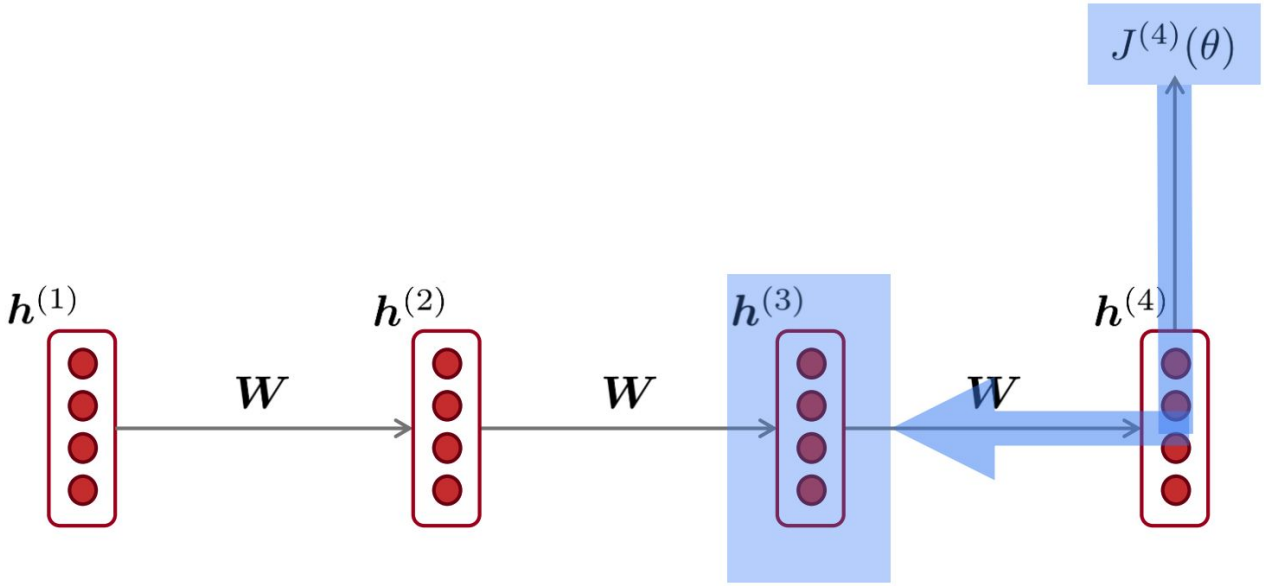


$$\frac{\partial J^{(4)}}{\partial \boldsymbol{h}^{(1)}} = \frac{\partial \boldsymbol{h}^{(2)}}{\partial \boldsymbol{h}^{(1)}} \times \frac{\partial J^{(4)}}{\partial \boldsymbol{h}^{(2)}}$$

chain rule!

Based on: Lecture by Abigail See, CS224n Lecture 7

Vanishing gradient problem



$$\frac{\partial J^{(4)}}{\partial h^{(1)}} = \frac{\partial h^{(2)}}{\partial h^{(1)}} \times \frac{\partial h^{(3)}}{\partial h^{(2)}} \times \frac{\partial J^{(4)}}{\partial h^{(3)}}$$

chain rule!

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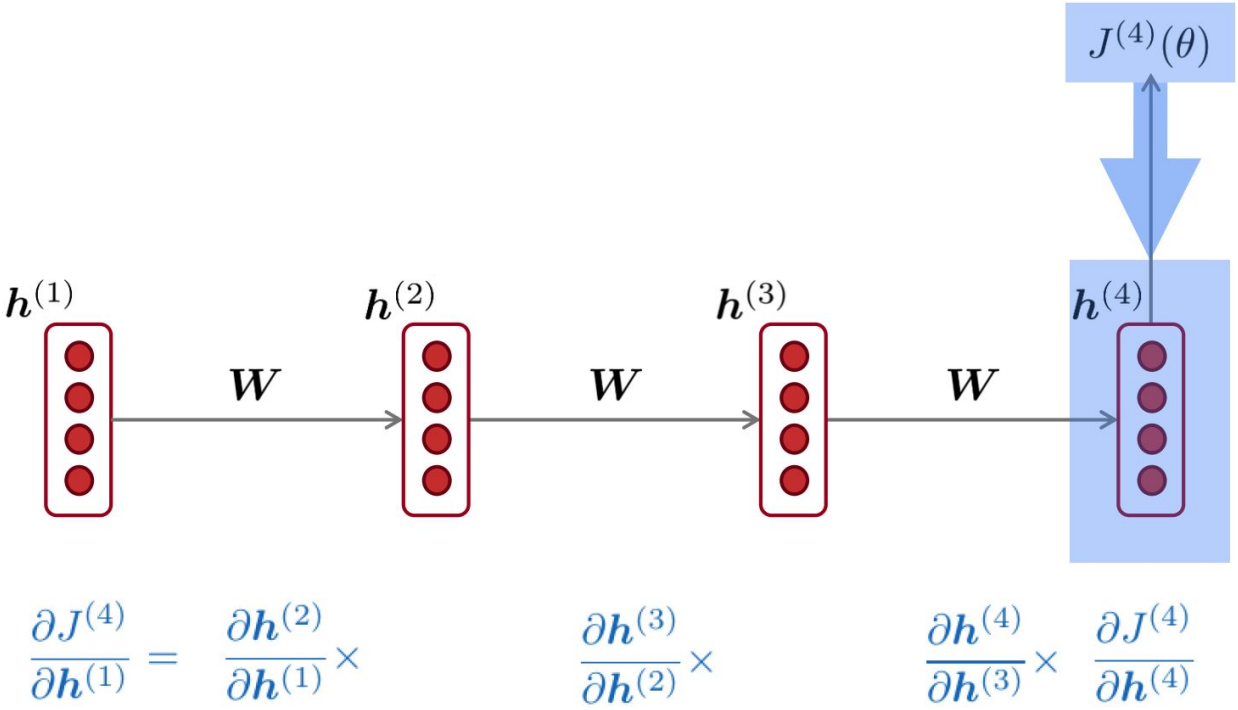
Vanishing gradient problem

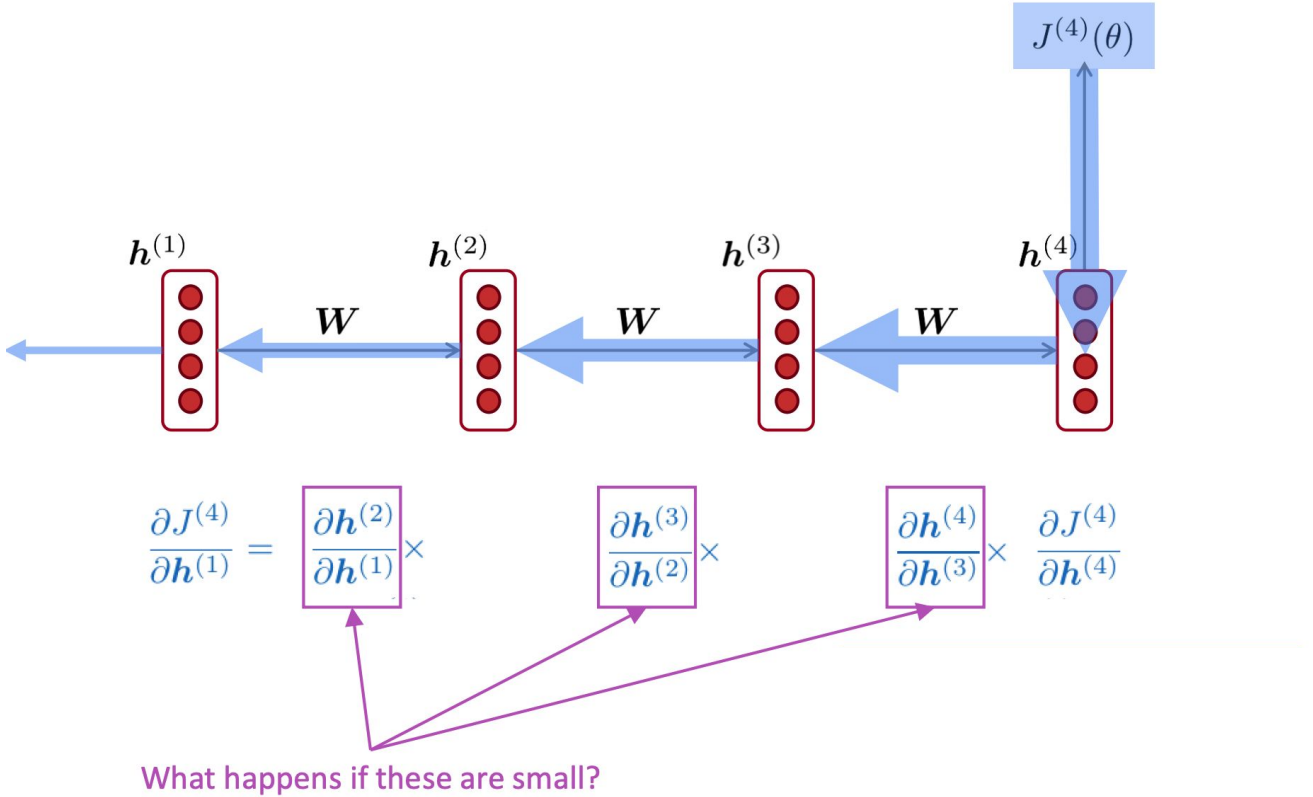


Based on: Lecture by Abigail See, CS224n Lecture 7

Vanishing gradient problem

Vanishing gradient problem:

When the derivatives are small, the gradient signal gets smaller and smaller as it backpropagates further

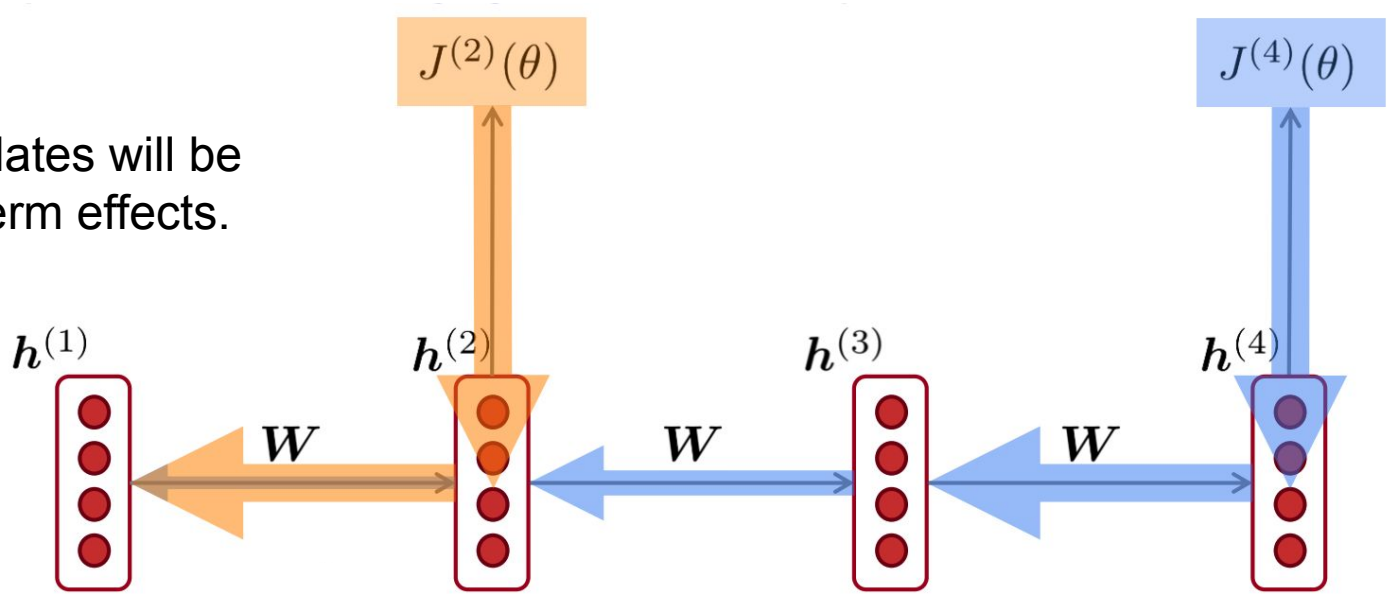


More info: "On the difficulty of training recurrent neural networks", Pascanu et al, 2013
http://proceedings.mlr.press/v28/pascanu13.pdf

Vanishing gradient problem

Gradient signal from far away is lost because it's much smaller than from close-by.

So model weights updates will be based only on short-term effects.



Based on: Lecture by Abigail See, CS224n Lecture 7

Exploding gradient problem

- If the gradient becomes too big, then the SGD update step becomes too big:

$$\theta^{new} = \theta^{old} - \underbrace{\overbrace{\alpha}^{\text{learning rate}}}_{\text{gradient}} \nabla_\theta J(\theta)$$

- This can cause bad updates: we take too large a step and reach a bad parameter configuration (with large loss)

- In the worst case, this will result in Inf or NaN in your network (then you have to restart training from an earlier checkpoint)

Based on: Lecture by Abigail See, CS224n Lecture 7

Exploding gradient solution

- Gradient clipping: if the norm of the gradient is greater than some threshold, scale it down before applying SGD update

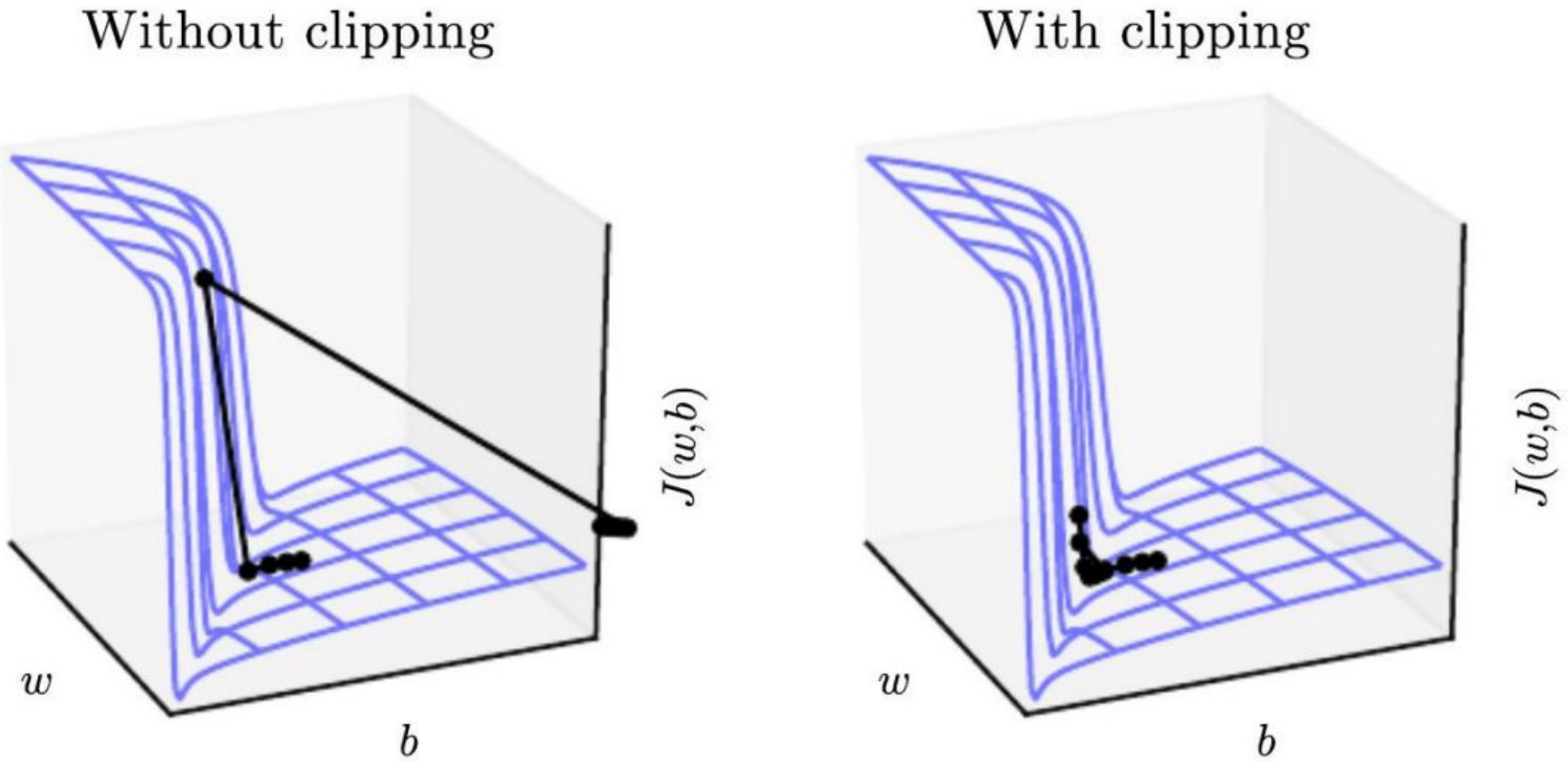
Algorithm 1 Pseudo-code for norm clipping

$\hat{\mathbf{g}} \leftarrow \frac{\partial \mathcal{E}}{\partial \theta}$
if $\|\hat{\mathbf{g}}\| \geq threshold$ **then**
  $\hat{\mathbf{g}} \leftarrow \frac{threshold}{\|\hat{\mathbf{g}}\|}\hat{\mathbf{g}}$
end if

- Intuition: take a step in the same direction, but a smaller step

Based on: Lecture by Abigail See, CS224n Lecture 7

Exploding gradient solution



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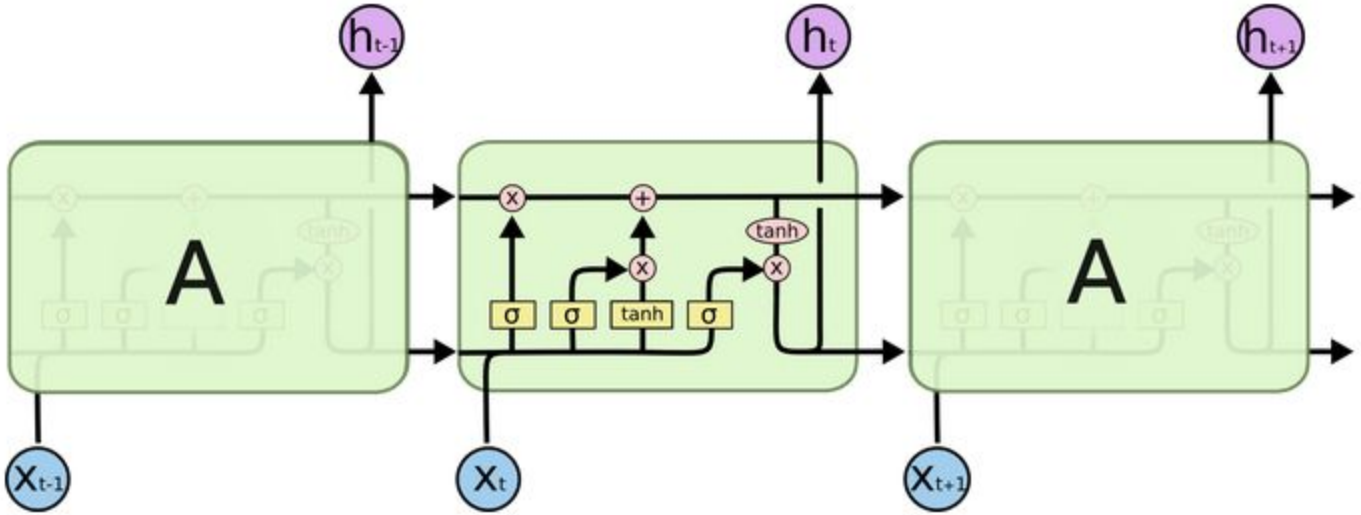
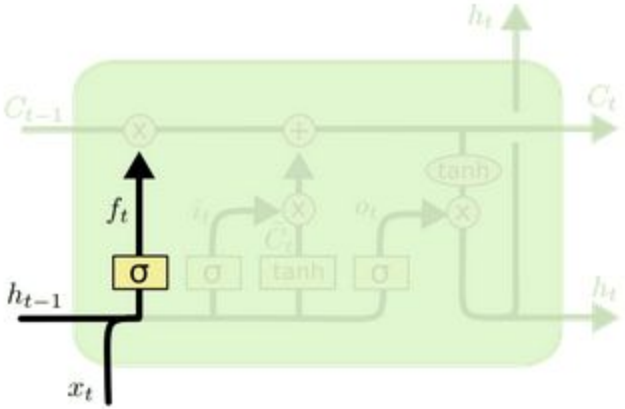
LSTM



Source: https://colah.github.io/posts/2015-08-Understanding-LSTMs/

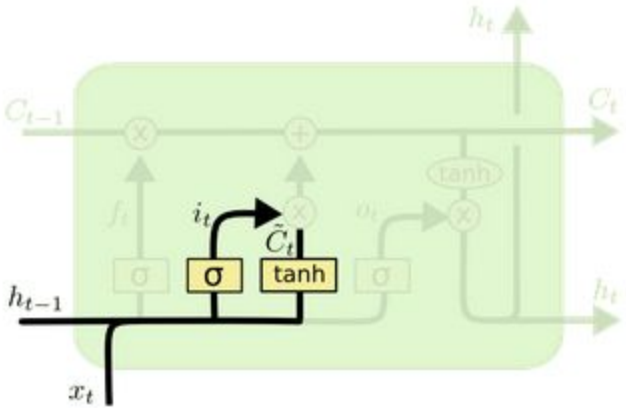
LSTM: quick overview



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

Source: https://colah.github.io/posts/2015-08-Understanding-LSTMs/

LSTM: quick overview

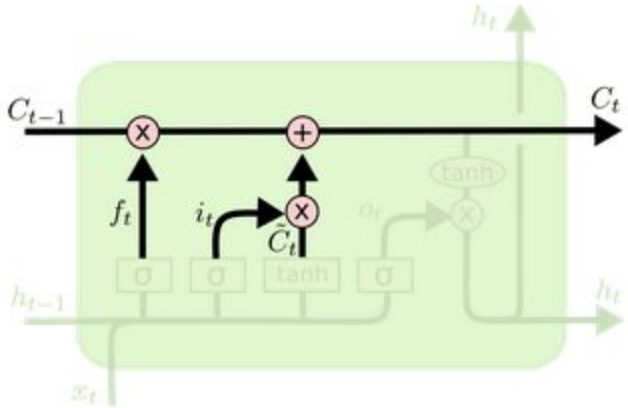


$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \; + \; b_i\right)$$

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

Source: https://colah.github.io/posts/2015-08-Understanding-LSTMs/

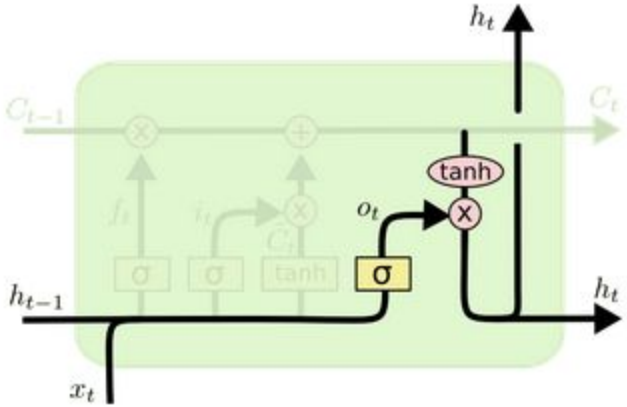
LSTM: quick overview



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

Source: https://colah.github.io/posts/2015-08-Understanding-LSTMs/

LSTM: quick overview

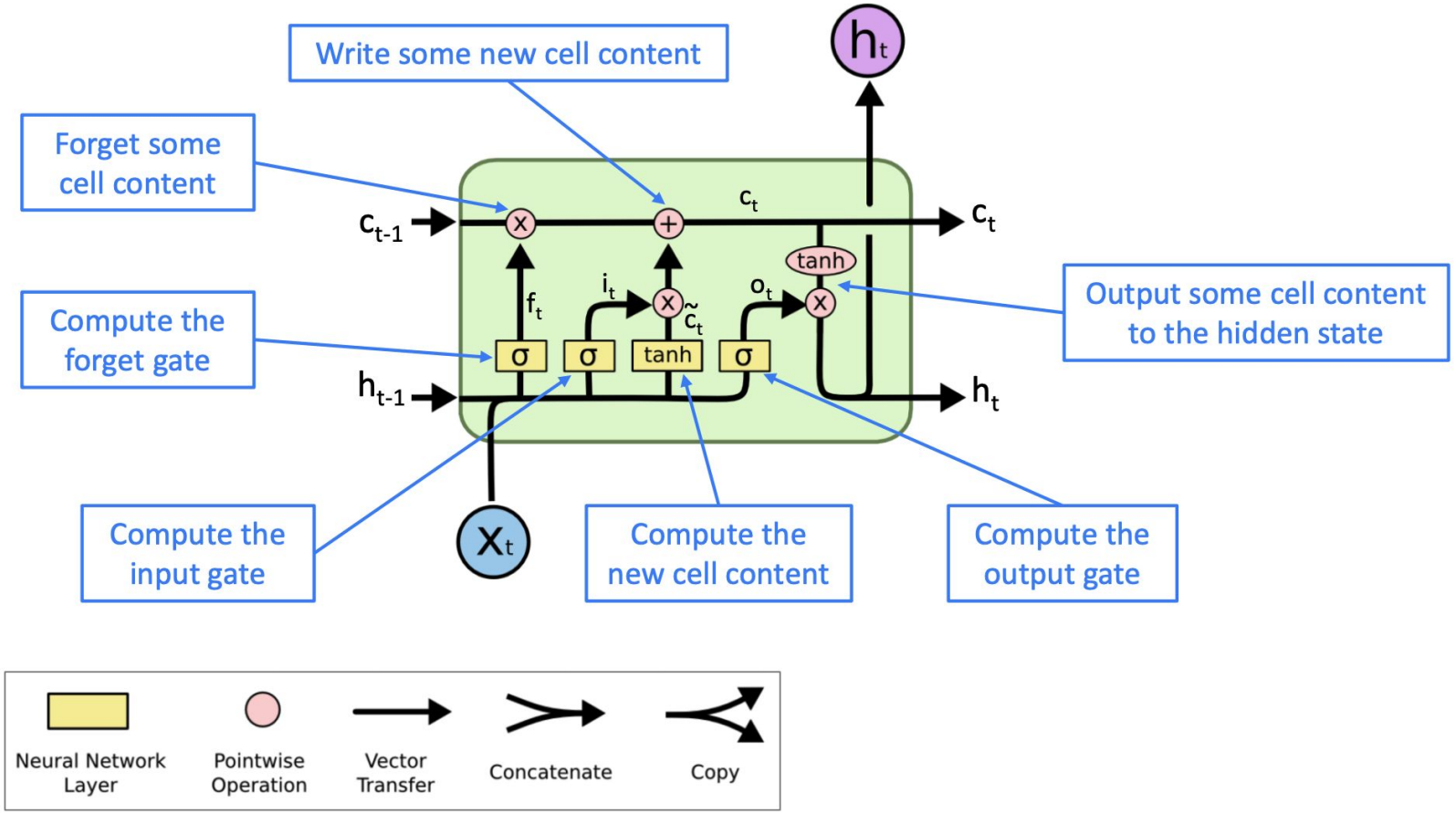


$$o_t = \sigma\left(W_o\left[h_{t-1}, x_t\right] + b_o\right)$$

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

Source: https://colah.github.io/posts/2015-08-Understanding-LSTMs/

Vanishing gradient: LSTM



Based on: Lecture by Abigail See, CS224n Lecture 7

Vanishing gradient: LSTM

Forget gate: controls what is kept vs forgotten, from previous cell state

Input gate: controls what parts of the new cell content are written to cell

Output gate: controls what parts of cell are output to hidden state

New cell content: this is the new content to be written to the cell

Cell state: erase ("forget") some content from last cell state, and write ("input") some new cell content

Hidden state: read ("output") some content from the cell

Sigmoid function: all gate values are between 0 and 1

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

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

$$\boldsymbol{o}^{(t)} = \sigma\left(\boldsymbol{W}_o\boldsymbol{h}^{(t-1)} + \boldsymbol{U}_o\boldsymbol{x}^{(t)} + \boldsymbol{b}_o\right)$$

$$\tilde{\boldsymbol{c}}^{(t)} = \tanh\left(\boldsymbol{W}_c\boldsymbol{h}^{(t-1)} + \boldsymbol{U}_c\boldsymbol{x}^{(t)} + \boldsymbol{b}_c\right)$$

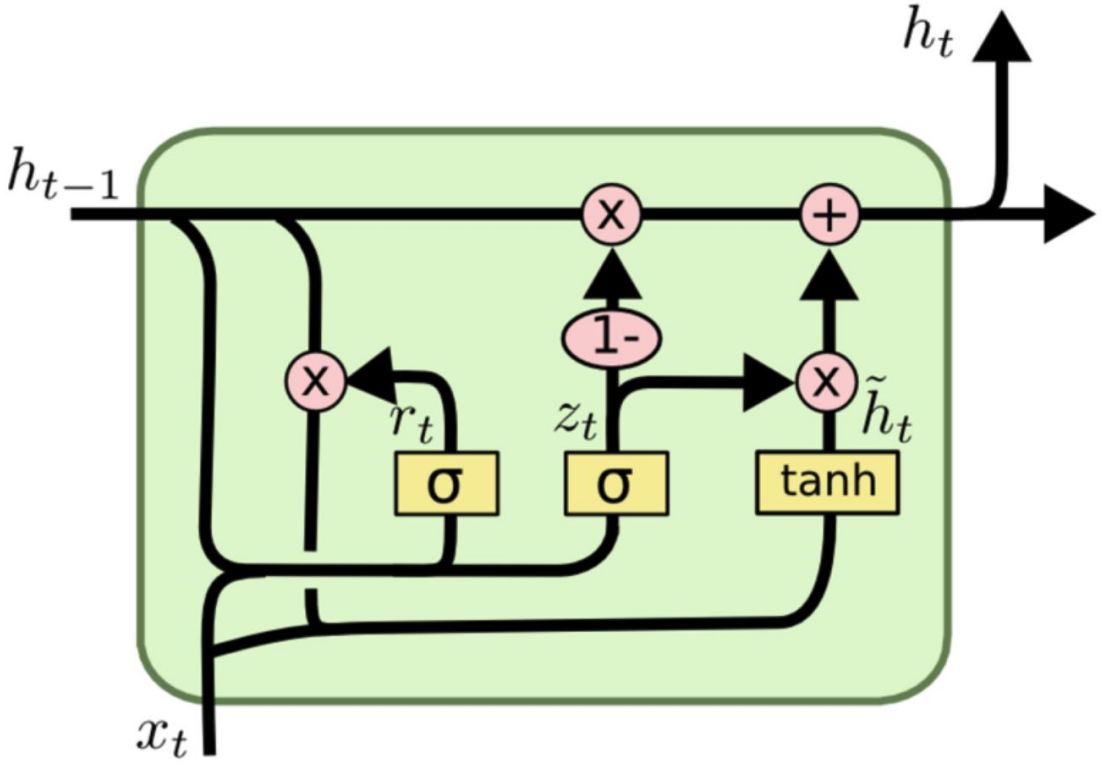
$$\boldsymbol{c}^{(t)} = \boldsymbol{f}^{(t)} \circ \boldsymbol{c}^{(t-1)} + \boldsymbol{i}^{(t)} \circ \tilde{\boldsymbol{c}}^{(t)}$$

$$\boldsymbol{h}^{(t)} = \boldsymbol{o}^{(t)} \circ \tanh \boldsymbol{c}^{(t)}$$

All these are vectors of same length *n*

Gates are applied using element-wise product

Vanishing gradient: GRU



Vanishing gradient: GRU

Update gate: controls what parts of hidden state are updated vs preserved

Reset gate: controls what parts of previous hidden state are used to compute new content

New hidden state content: reset gate selects useful parts of prev hidden state. Use this and current input to compute new hidden content.

Hidden state: update gate simultaneously controls what is kept from previous hidden state, and what is updated to new hidden state content

$$\boldsymbol{u}^{(t)} = \sigma\left(\boldsymbol{W}_u \boldsymbol{h}^{(t-1)} + \boldsymbol{U}_u \boldsymbol{x}^{(t)} + \boldsymbol{b}_u\right)$$

$$\boldsymbol{r}^{(t)} = \sigma\left(\boldsymbol{W}_r \boldsymbol{h}^{(t-1)} + \boldsymbol{U}_r \boldsymbol{x}^{(t)} + \boldsymbol{b}_r\right)$$

$$\tilde{\boldsymbol{h}}^{(t)} = \tanh\left(\boldsymbol{W}_h (\boldsymbol{r}^{(t)} \circ \boldsymbol{h}^{(t-1)}) + \boldsymbol{U}_h \boldsymbol{x}^{(t)} + \boldsymbol{b}_h\right)$$

$$\boldsymbol{h}^{(t)} = (1 - \boldsymbol{u}^{(t)}) \circ \boldsymbol{h}^{(t-1)} + \boldsymbol{u}^{(t)} \circ \tilde{\boldsymbol{h}}^{(t)}$$

How does this solve vanishing gradient?
Like LSTM, GRU makes it easier to retain info long-term (e.g. by setting update gate to 0)

Vanishing gradient: LSTM vs GRU

- LSTM and GRU are both great
  - GRU is quicker to compute and has fewer parameters than LSTM
  - There is no conclusive evidence that one consistently performs better than the other
  - LSTM is a good default choice (especially if your data has particularly long dependencies, or you have lots of training data)

Rule of thumb: start with LSTM, but switch to GRU if you want something more efficient

Vanishing gradient in non-RNN

Vanishing gradient is present in **all** deep neural network architectures.

- Due to chain rule / choice of nonlinearity function, gradient can become vanishingly small during backpropagation
- Lower levels are hard to train and are trained slower
- **Potential solution**: direct (or skip-) connections (just like in ResNet)

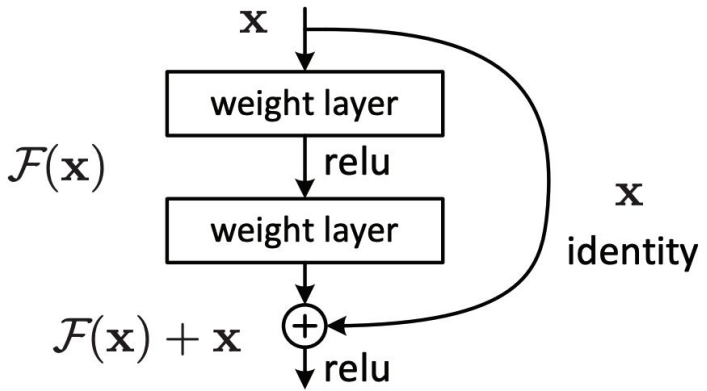


Figure 2. Residual learning: a building block.

Source: "Deep Residual Learning for Image Recognition", He et al, 2015. https://arxiv.org/pdf/1512.03385.pdf

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- Due to chain rule / choice of nonlinearity function, gradient can become vanishingly small during backpropagation
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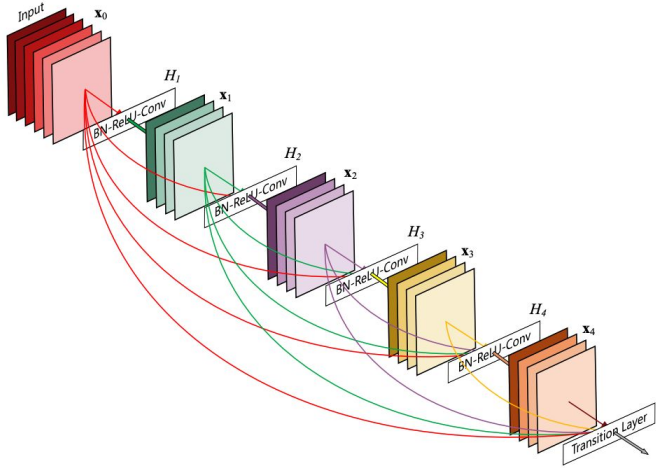
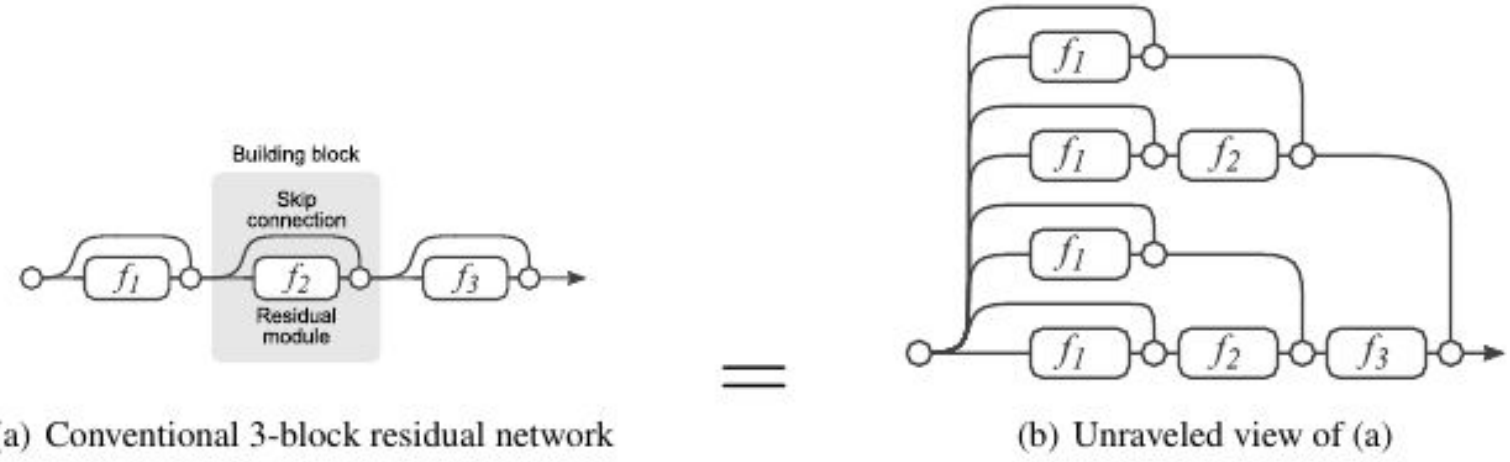
- **Potential solution**: dense connections (just like in DenseNet)



Source: ”Densely Connected Convolutional Networks", Huang et al, 2017 https://arxiv.org/pdf/1608.06993.pdf

Another view on ResNets and vanishing gradient

"**Residual Networks Behave Like Ensembles of Relatively Shallow Networks**"



(a) Conventional 3-block residual network

(b) Unraveled view of (a)

Source: https://arxiv.org/pdf/1605.06431.pdf

Vanishing gradient in non-RNN

Vanishing gradient is present in **all** deep neural network architectures.

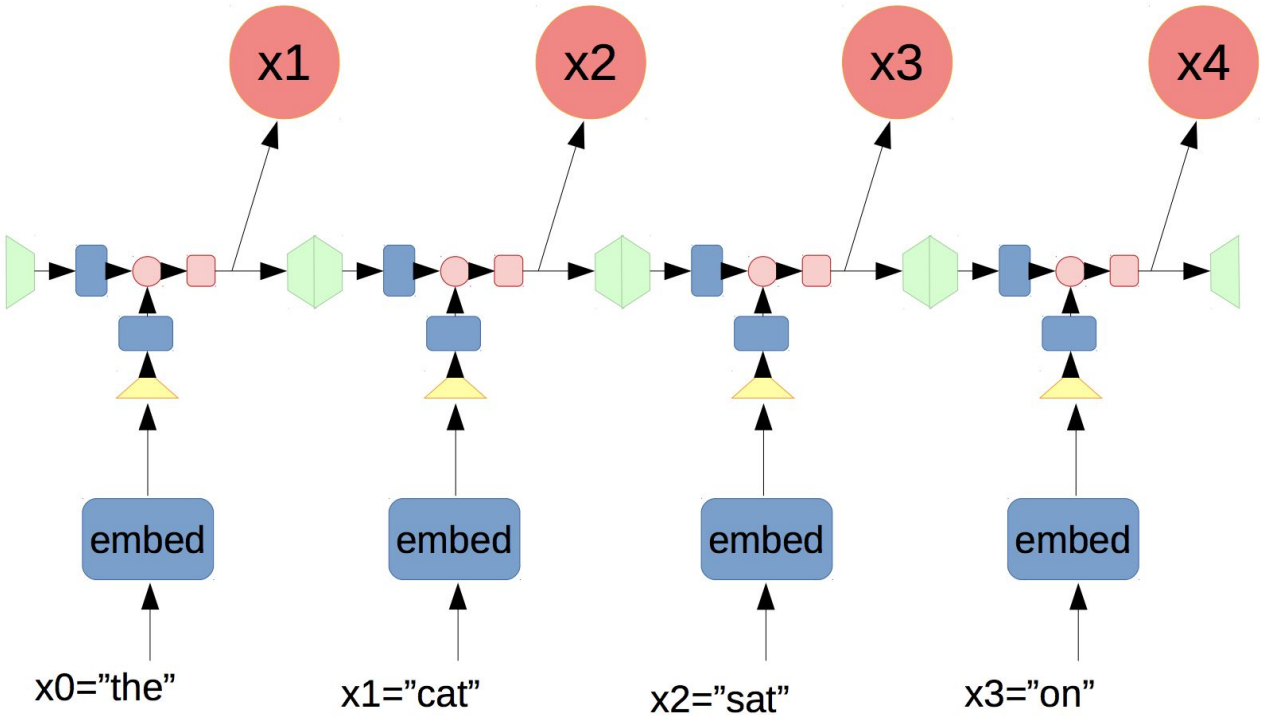
- Due to chain rule / choice of nonlinearity function, gradient can become vanishingly small during backpropagation
- Lower levels are hard to train and are trained slower
- **Potential solution(but not actually for that problem)**: dense connections (just like in DenseNet)

Conclusion:

Though vanishing/exploding gradients are a general problem, RNNs are particularly unstable due to the repeated multiplication by the same weight matrix [Bengio et al, 1994]. Gradients magnitude drops exponentially with connection length.

Source: ”Learning Long-Term Dependencies with Gradient Descent is Difficult", Bengio et al. 1994, http://ai.dinfo.unifi.it/paolo//ps/tnn-94-gradient.pdf

Recap: RNN



From RNN to CNN

- RNN: Get compositional vectors for grammatical phrases only

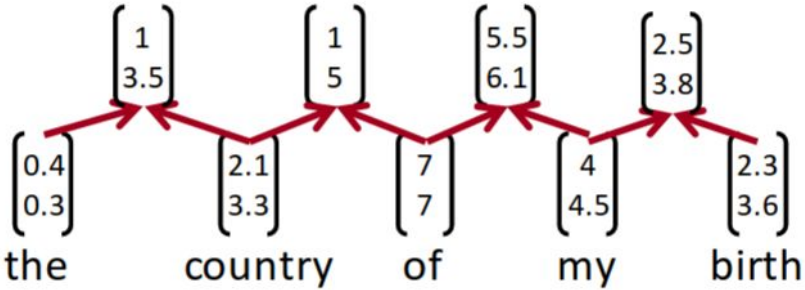
- CNN: What if we compute vectors for every possible phrase?
  - Example: *“the country of my birth”* computes vectors for:
    - *the country, country of, of my, my birth, the country of, country of my, of my birth, the country of my, country of my birth*

- Regardless of whether it is grammatical
- Wouldn’t need parser
- Not very linguistically or cognitively plausible

Based on: Lecture by Richard Socher 5/12/16, http://cs224d.stanford.edu

From RNN to CNN

- Imagine using only bigrams



- Same operation as in RNN, but for every pair

$$p = \tanh\left(W \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + b\right)$$

- Can be interpreted as convolution over the word vectors

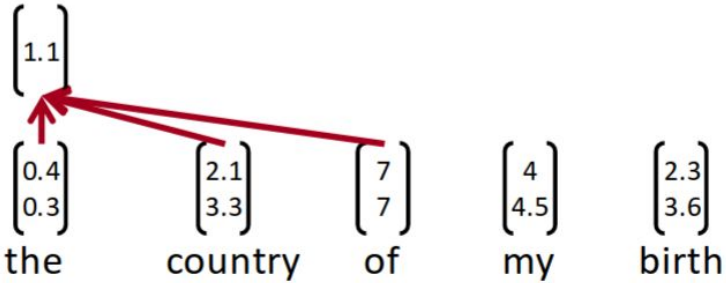
Based on: Lecture by Richard Socher 5/12/16, http://cs224d.stanford.edu

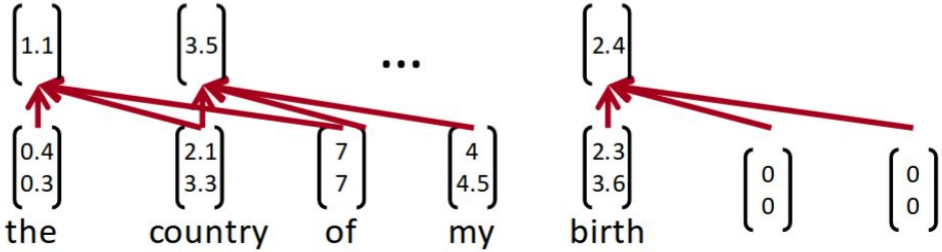
One layer CNN

- Simple convolution + pooling
- Window size may be different (2 or more)
- The feature map based on bigrams:

$$\mathbf{c} = [c_1, c_2, \ldots, c_{n-h+1}] \in \mathbb{R}^{n-h+1}$$

$$c_i = f(\mathbf{w}^T \mathbf{x}_{i:i+h-1} + b)$$





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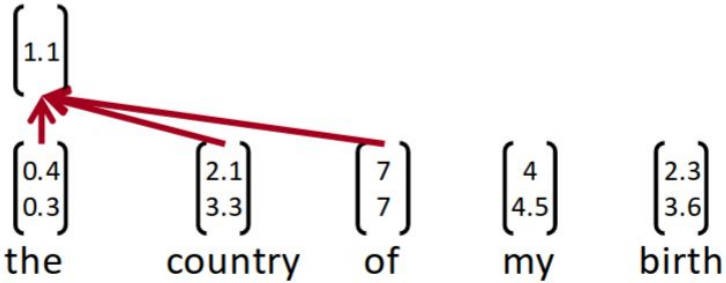
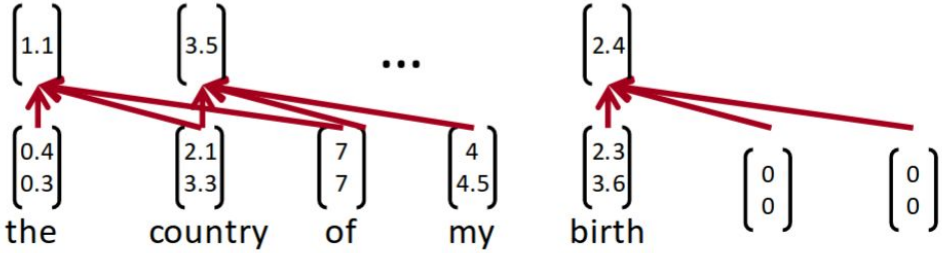
What's next?

$$c_i = f(\mathbf{w}^T \mathbf{x}_{i:i+h-1} + b)$$





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One layer CNN

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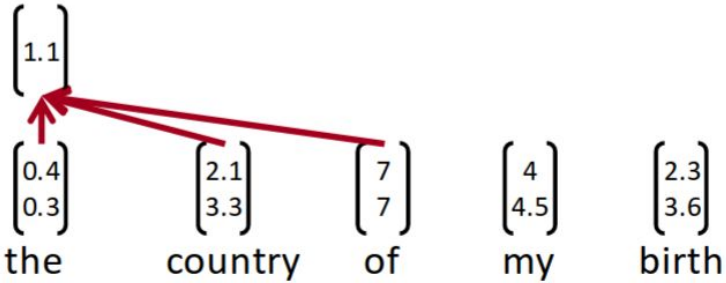
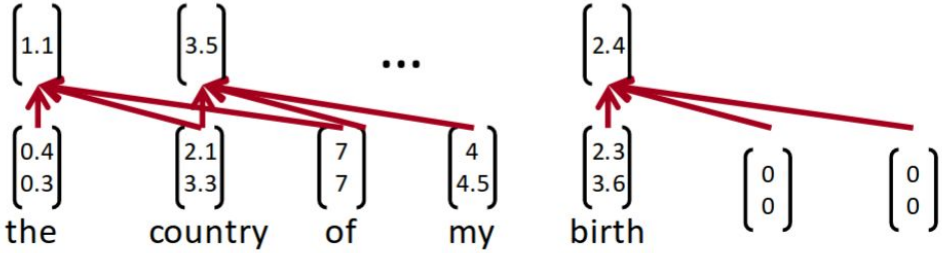
$$\mathbf{c} = [c_1, c_2, \ldots, c_{n-h+1}] \in \mathbb{R}^{n-h+1}$$

$$c_i = f(\mathbf{w}^T \mathbf{x}_{i:i+h-1} + b)$$



What's next?

We need more features!



Based on: Lecture by Richard Socher 5/12/16, http://cs224d.stanford.edu

One layer CNN

- Feature representation is based on some applied filter:

$$\mathbf{c} = [c_1, c_2, \ldots, c_{n-h+1}] \in \mathbb{R}^{n-h+1}$$

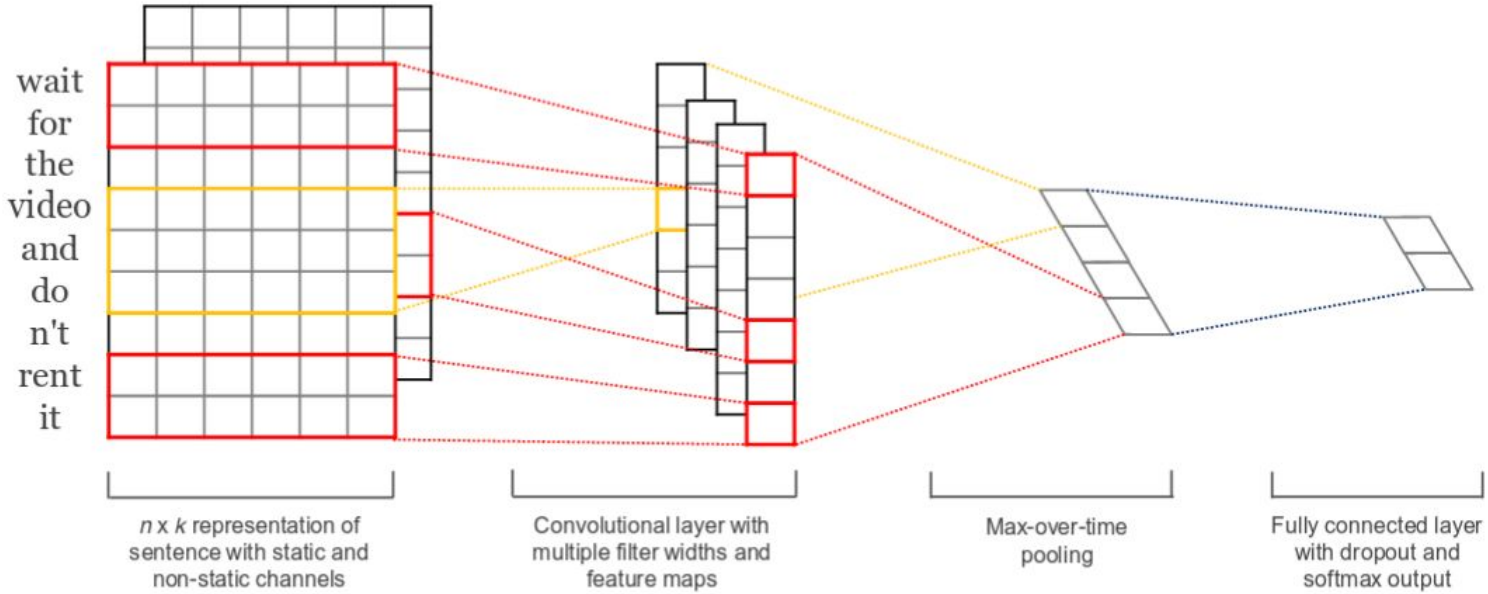
- Let's use pooling over the time axis: $\hat{c} = \max\{\mathbf{c}\}$

- Now the length of **c** is irrelevant!

- So we can use filters based on unigrams, bigrams, tri-grams, 4-grams, etc.

Based on: Lecture by Richard Socher 5/12/16, http://cs224d.stanford.edu

Another example from Kim (2014) paper



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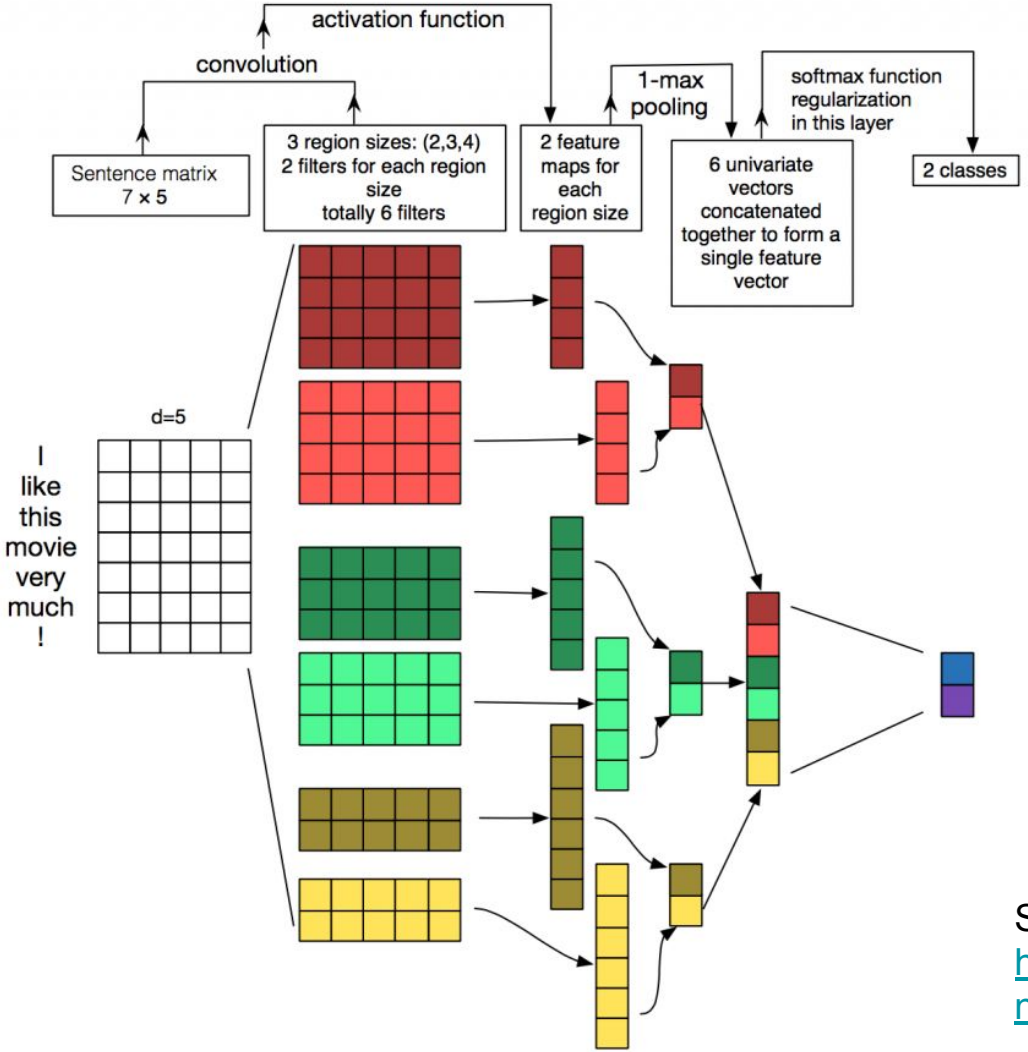
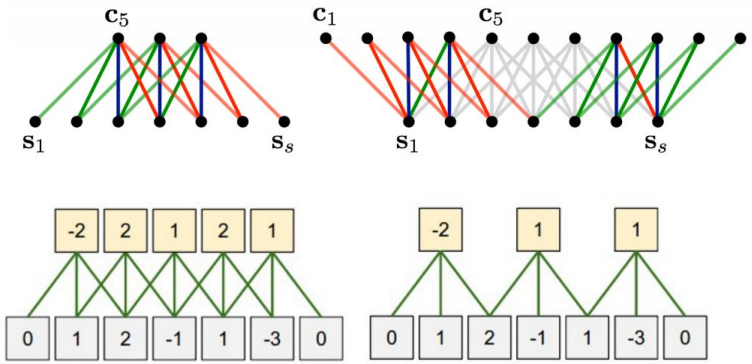
Example CNN structure



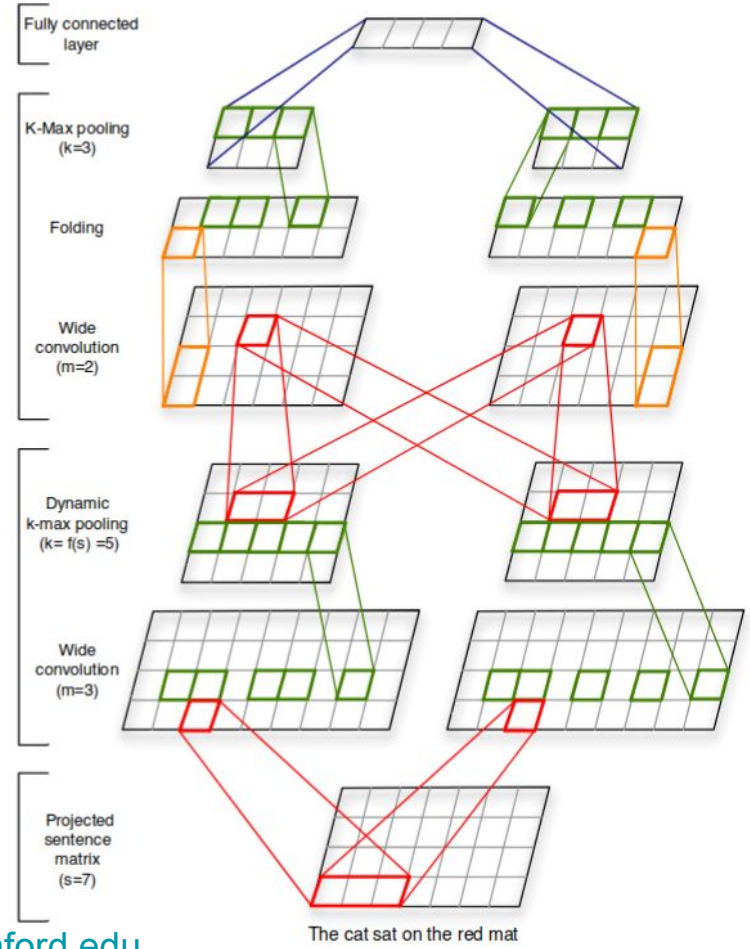
Source: http://www.wildml.com/2015/11/understanding-convolutional-neural-networks-for-nlp/

More about CNN

- Narrow vs wide convolution (stride and zero-padding)



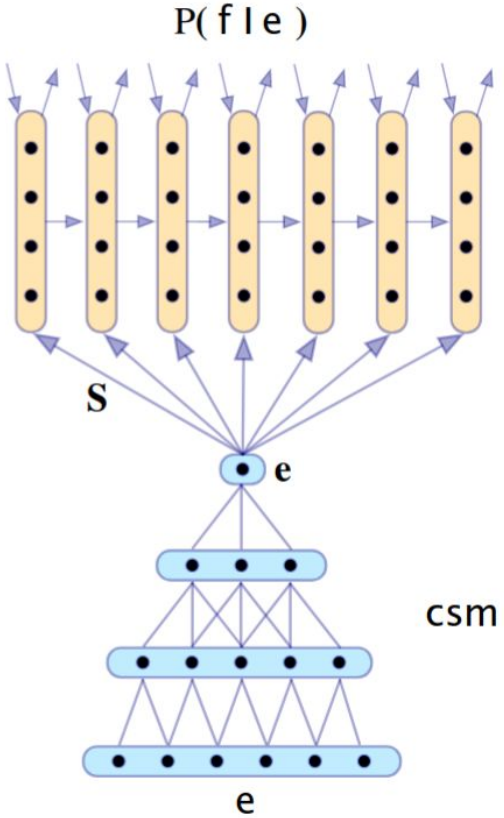
- Complex pooling schemes over sequences
- Great readings (e.g. Kalchbrenner et. al. 2014)



Based on: Lecture by Richard Socher 5/12/16, http://cs224d.stanford.edu

CNN applications

- Neural machine translation: CNN as encoder, RNN as decoder
- Kalchbrenner and Blunsom (2013) “Recurrent Continuous Translation Models”
- One of the first neural machine translation efforts



Based on: Lecture by Richard Socher 5/12/16, http://cs224d.stanford.edu

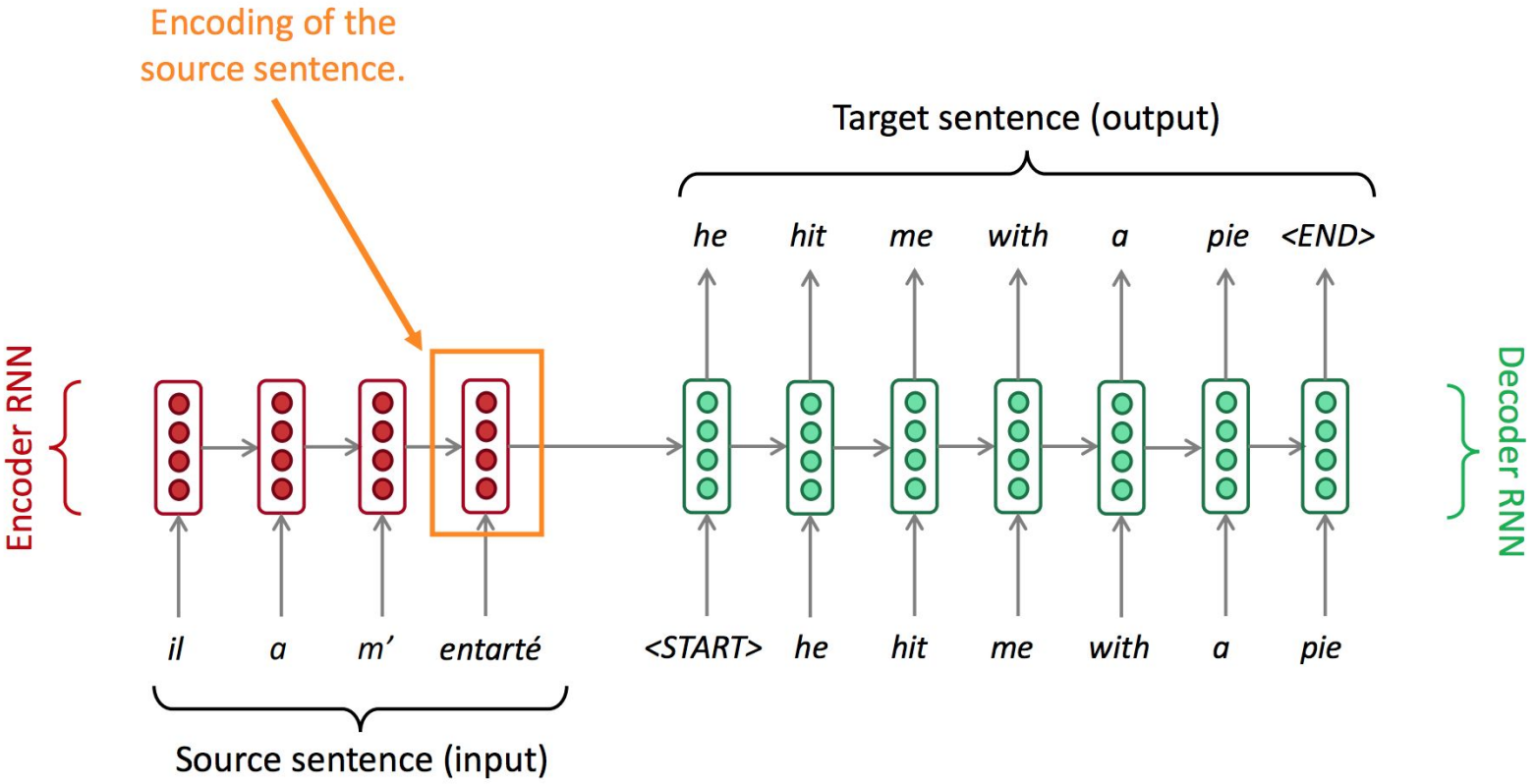
Outro and Q & A

- Vanishing gradient is present not only in RNNs
  - Use some kind of memory or skip-connections
- LSTM and GRU are both great
  - GRU is quicker, LSTM catch more complex dependencies
- Rule of thumb: start with LSTM, but switch to GRU if you want something more computationally efficient
- Clip your gradients
- Combining RNN and CNN worlds? Why not ;)

That’s all. Feel free to ask any questions.

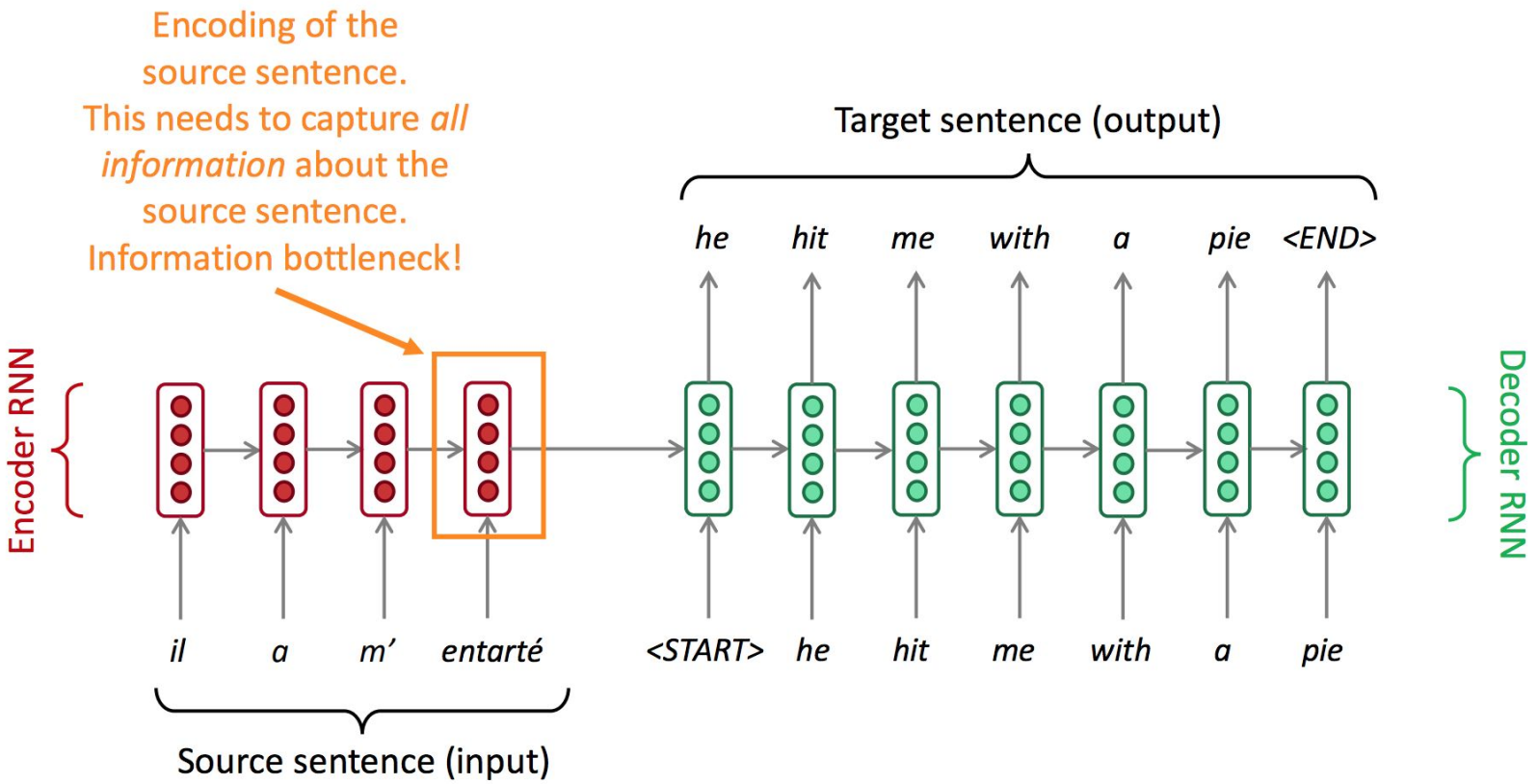
Backup

Seq2seq: the bottleneck problem



Problems with this architecture?

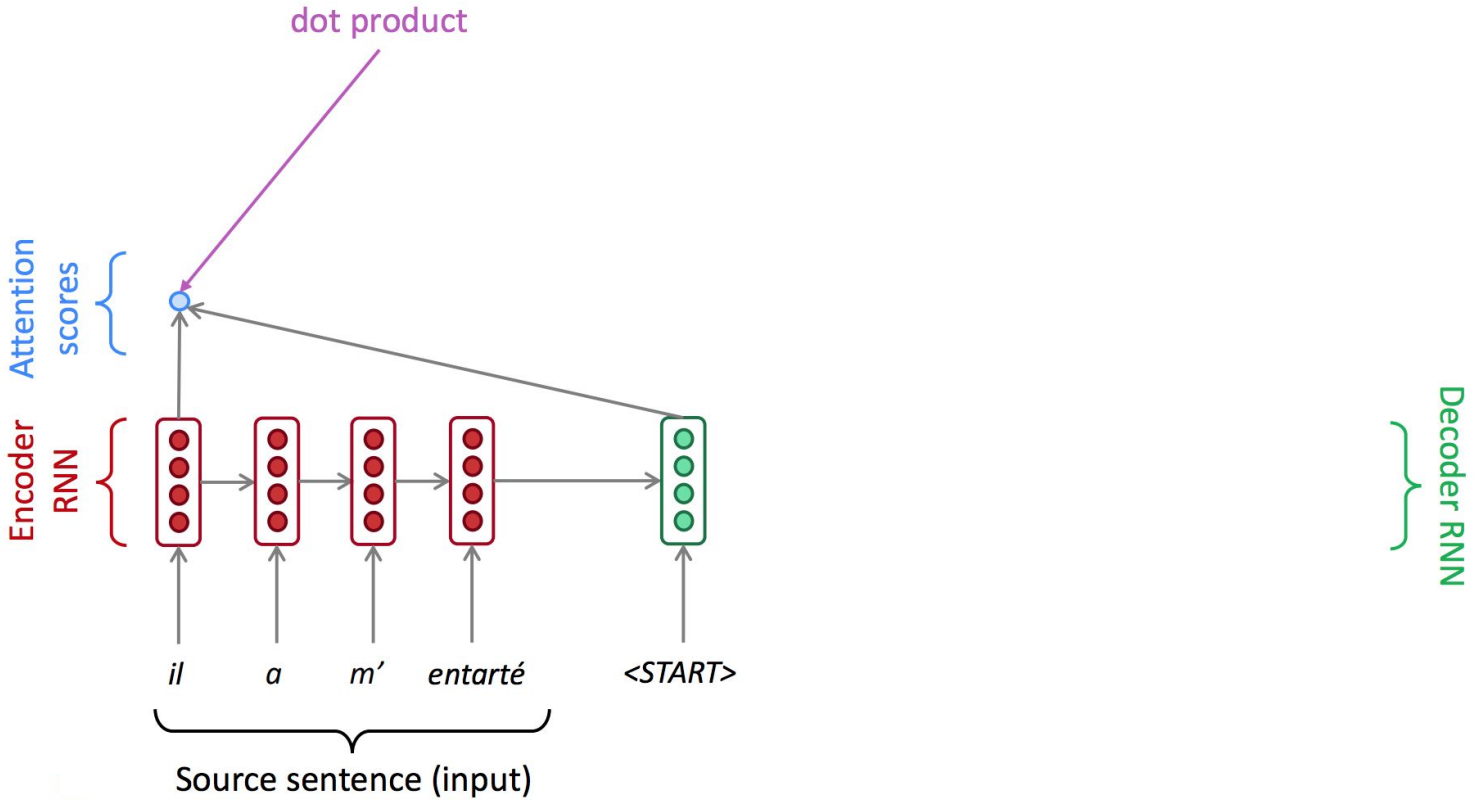
Seq2seq: the bottleneck problem



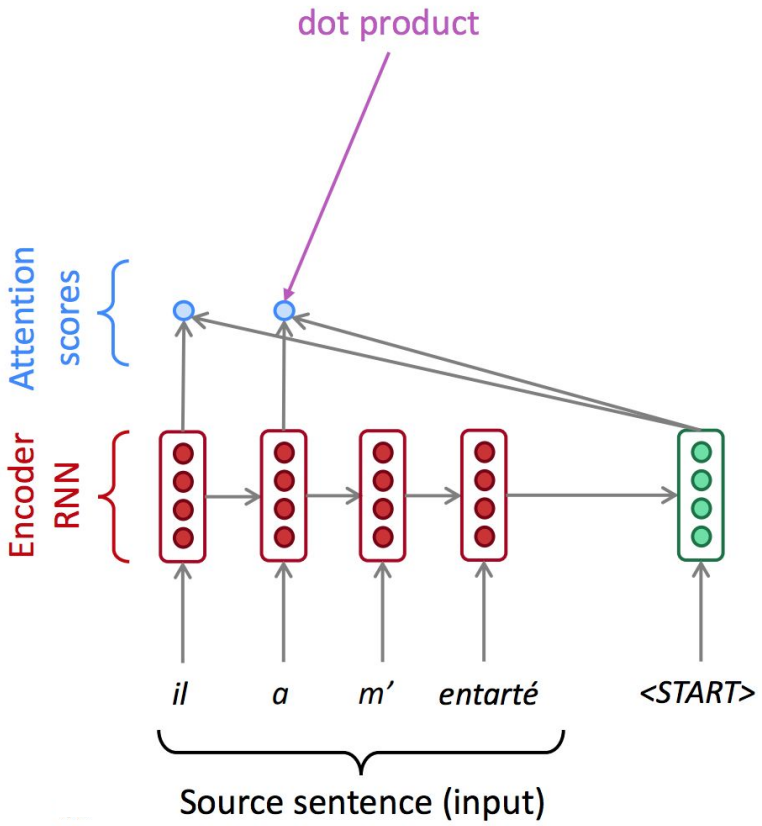
Attention

<u>Main idea:</u> on each step of the **decoder**, use **direct connection to the encoder** to focus on a particular part of the source sequence

Seq2seq with attention

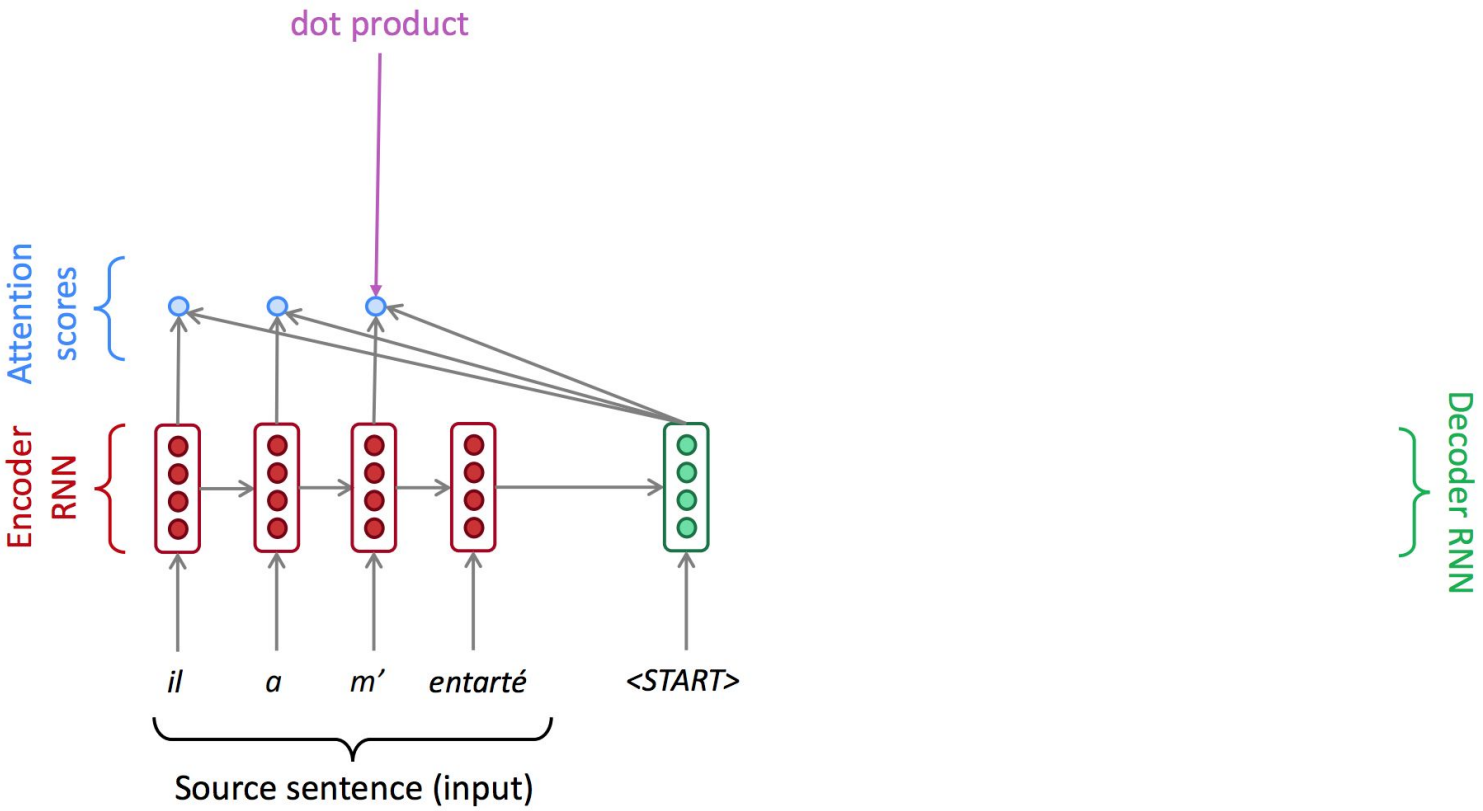


Seq2seq with attention

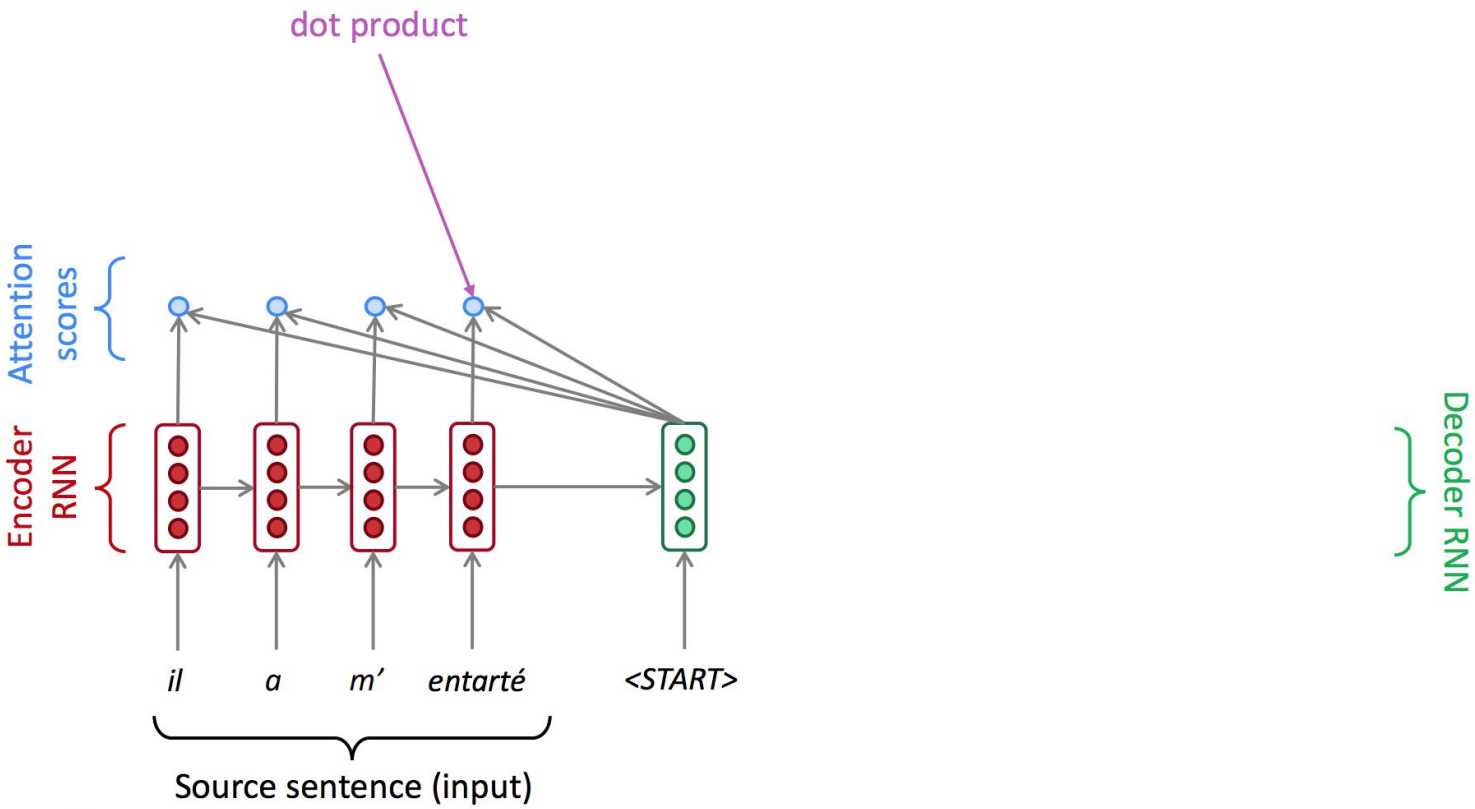


Decoder RNN

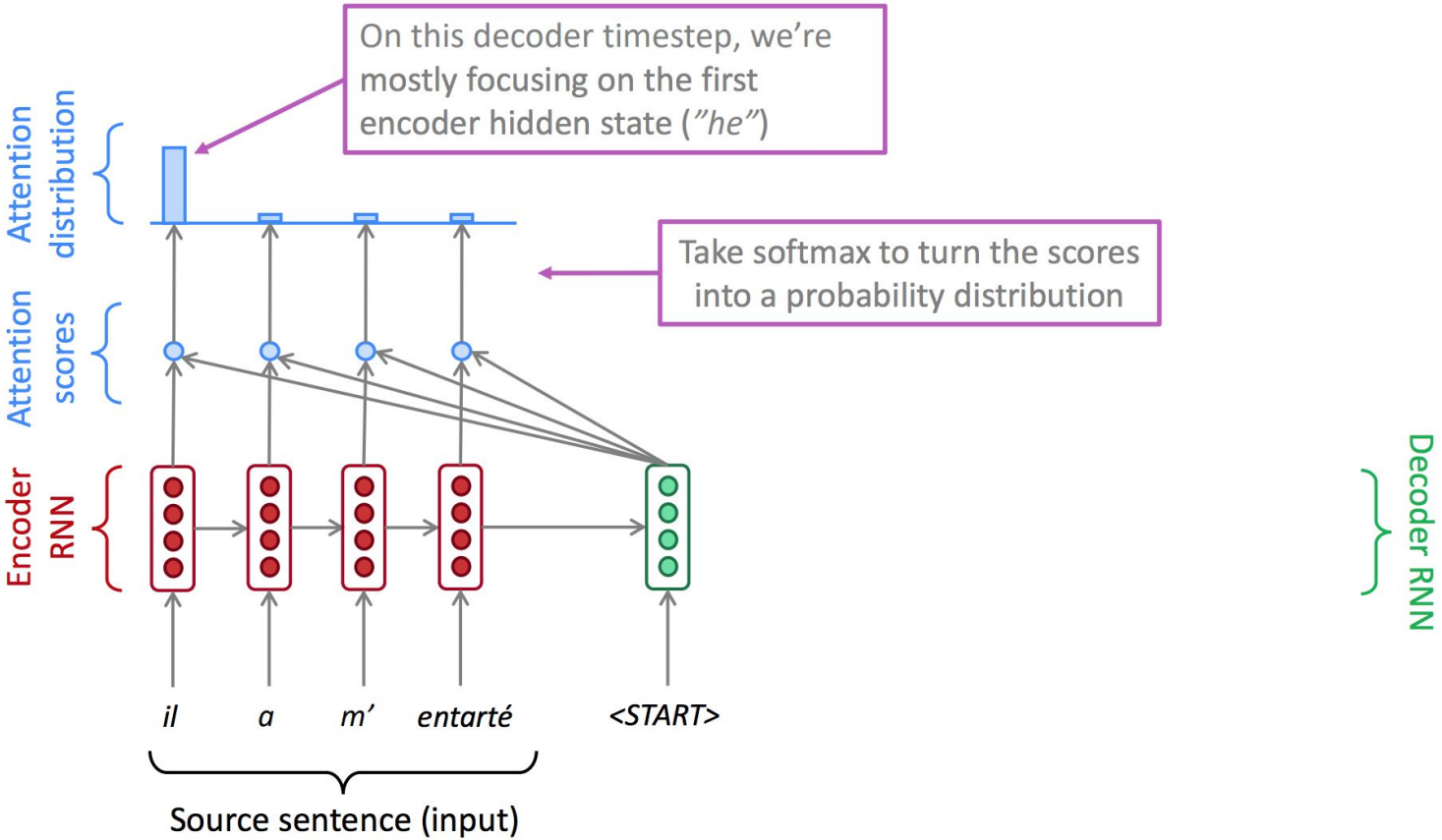
Seq2seq with attention



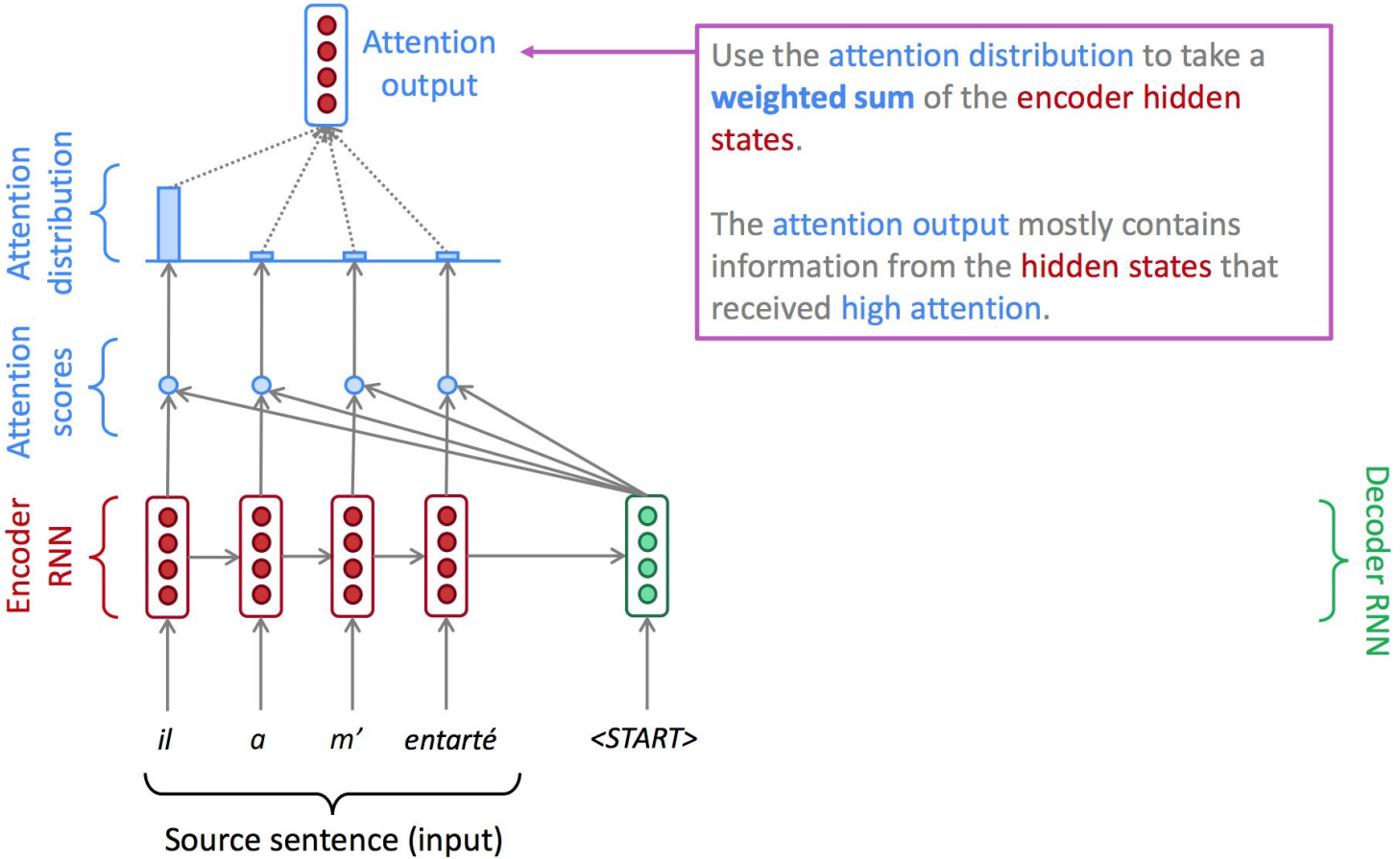
Seq2seq with attention



Seq2seq with attention



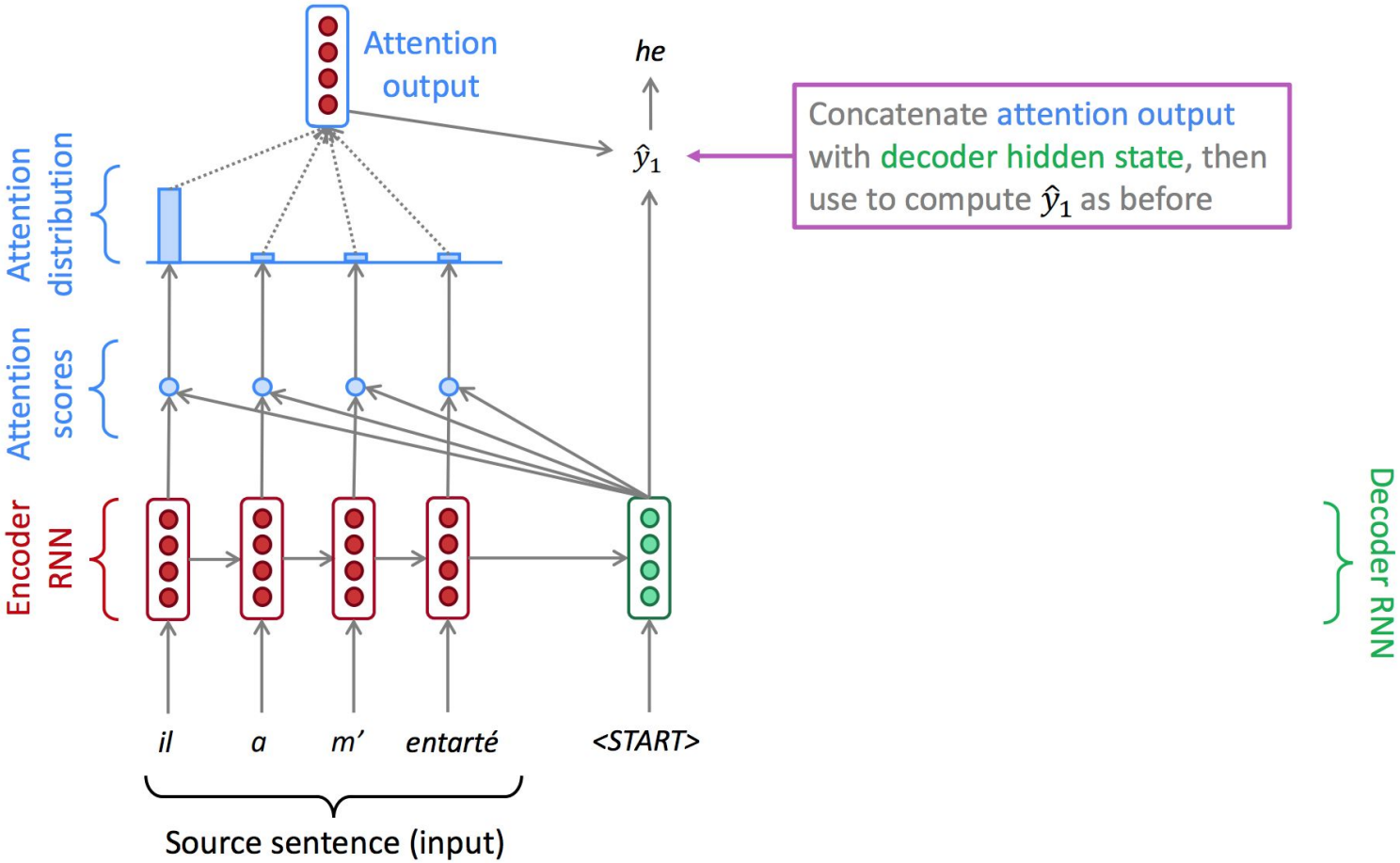
Seq2seq with attention



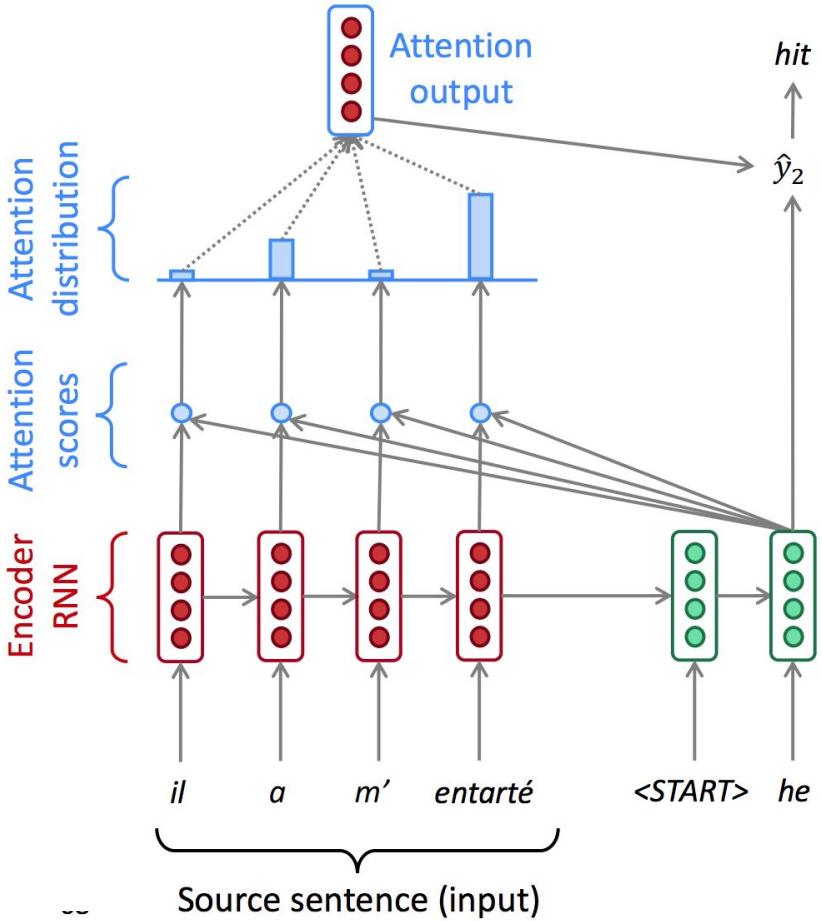
Use the attention distribution to take a **weighted sum** of the encoder hidden states.

The attention output mostly contains information from the hidden states that received high attention.

Seq2seq with attention



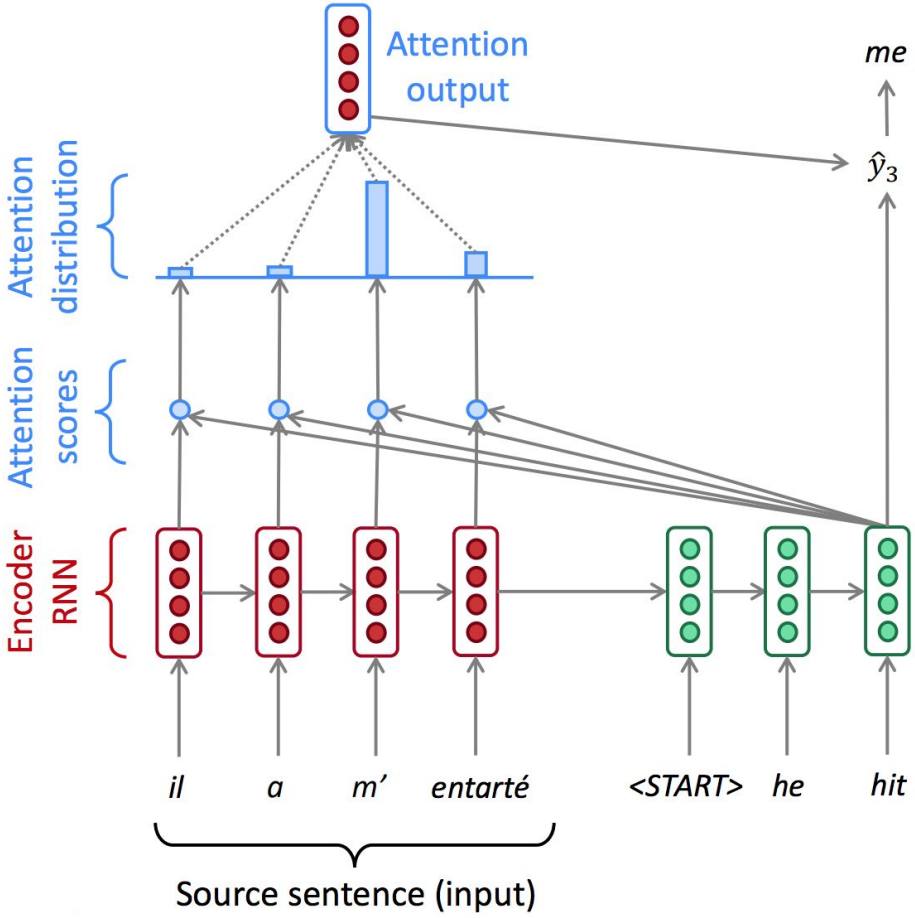
Seq2seq with attention



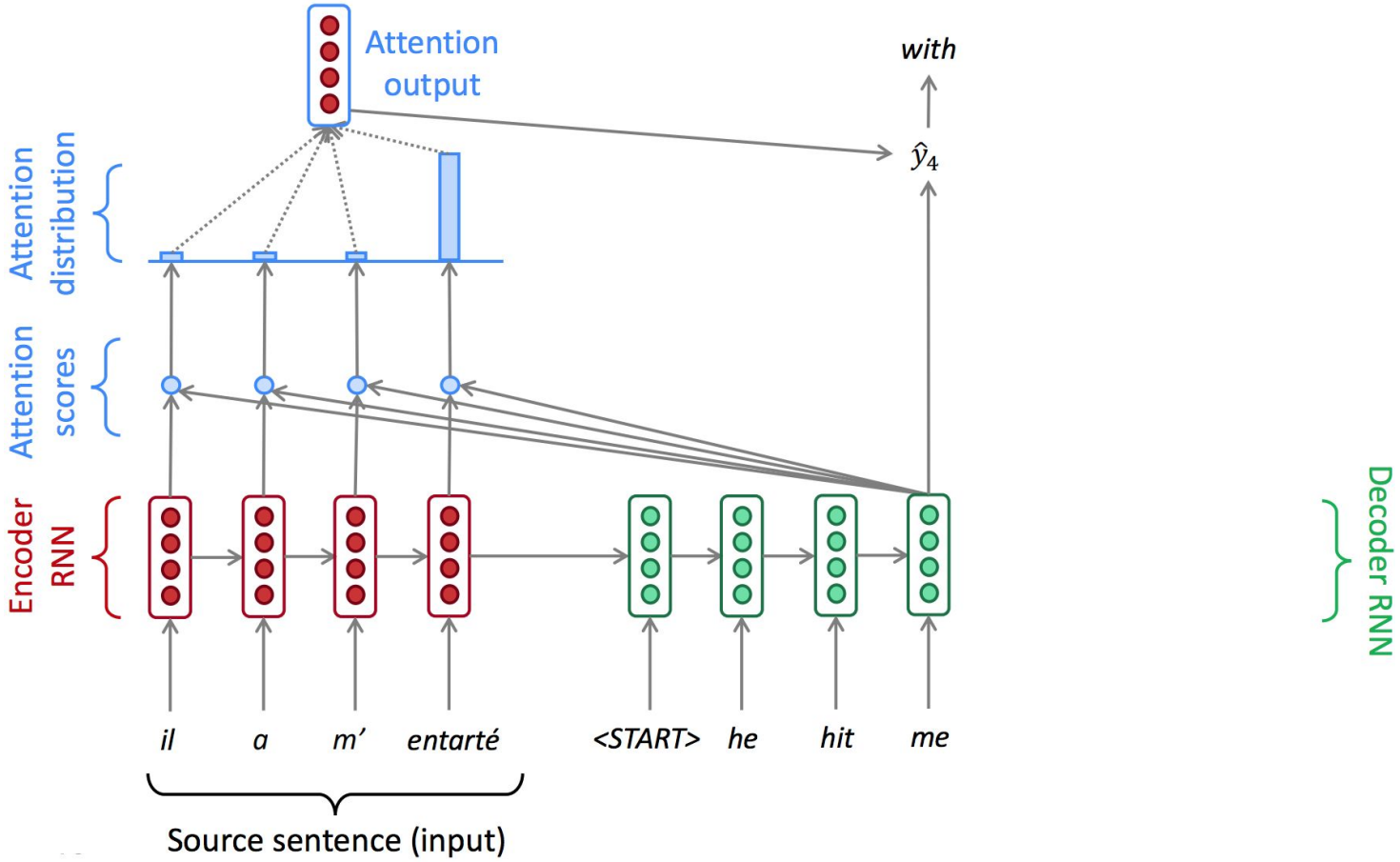
Sometimes we take the attention output from the previous step, and also feed it into the decoder (along with the usual decoder input). We do this in Assignment 4.

Decoder RNN

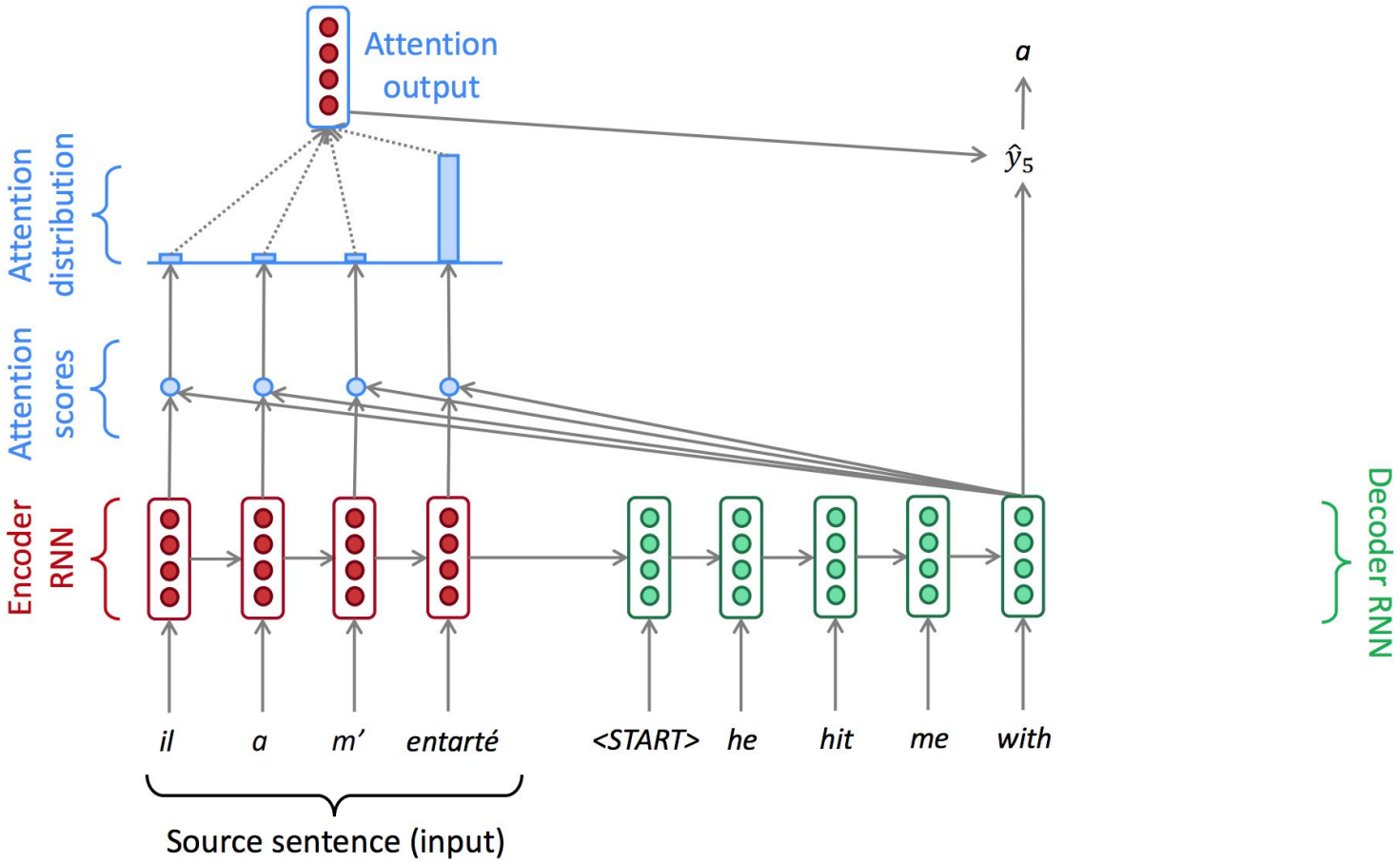
Seq2seq with attention



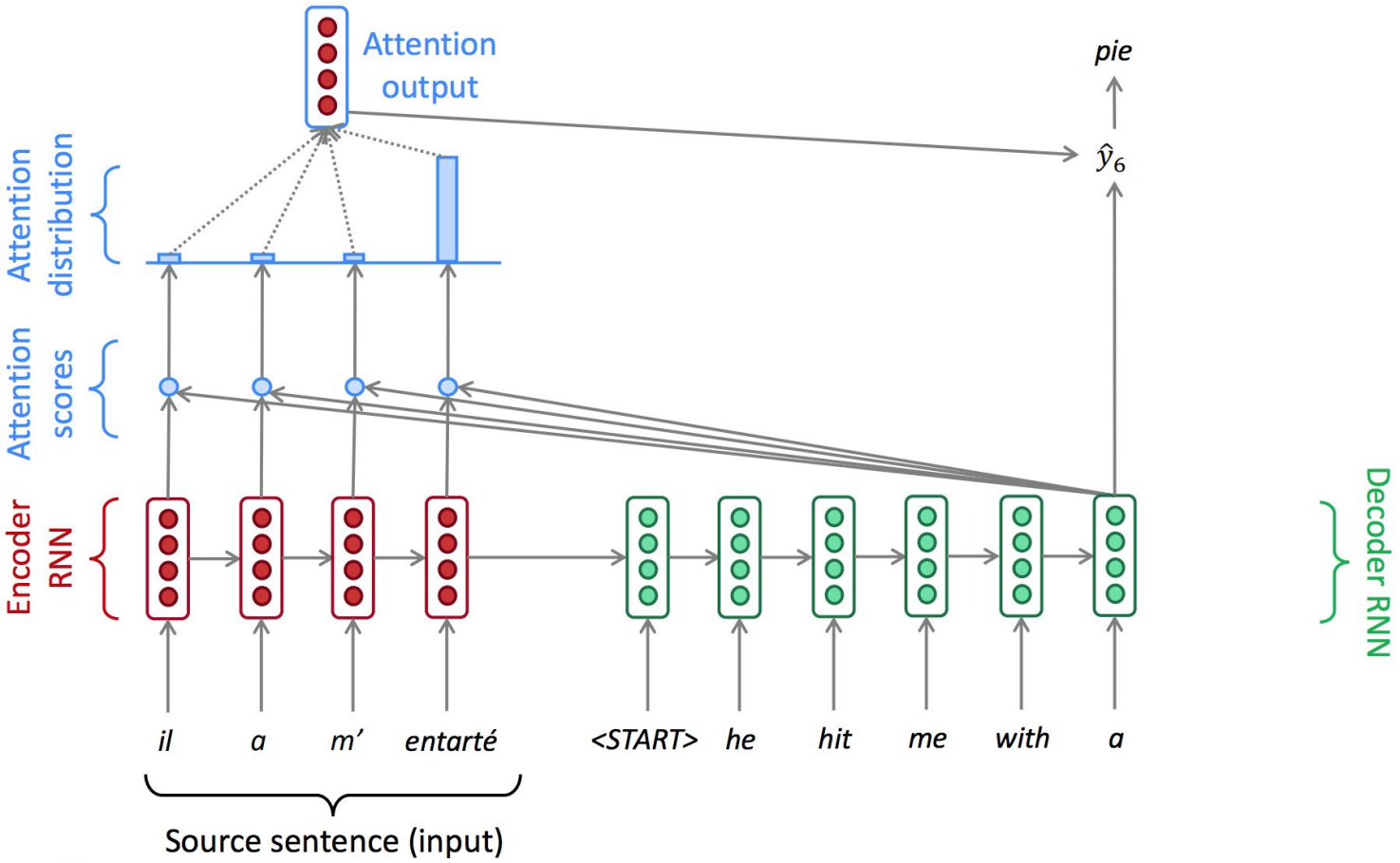
Seq2seq with attention



Seq2seq with attention



Seq2seq with attention



Attention in equations

We have encoder hidden states $h_1, \ldots, h_N \in \mathbb{R}^h$

On timestep *t*, we have decoder hidden state $s_t \in \mathbb{R}^h$

We get the attention scores $\boldsymbol{e}^t$ for this step:

$$\boldsymbol{e}^t = [\boldsymbol{s}_t^T \boldsymbol{h}_1, \ldots, \boldsymbol{s}_t^T \boldsymbol{h}_N] \in \mathbb{R}^N$$

We take softmax to get the attention distribution α^t for this step (this is a probability distribution and sums to 1)

$$\alpha^t = \text{softmax}(\boldsymbol{e}^t) \in \mathbb{R}^N$$

We use α^t to take a weighted sum of the encoder hidden states to get the attention output $\boldsymbol{a}_t$

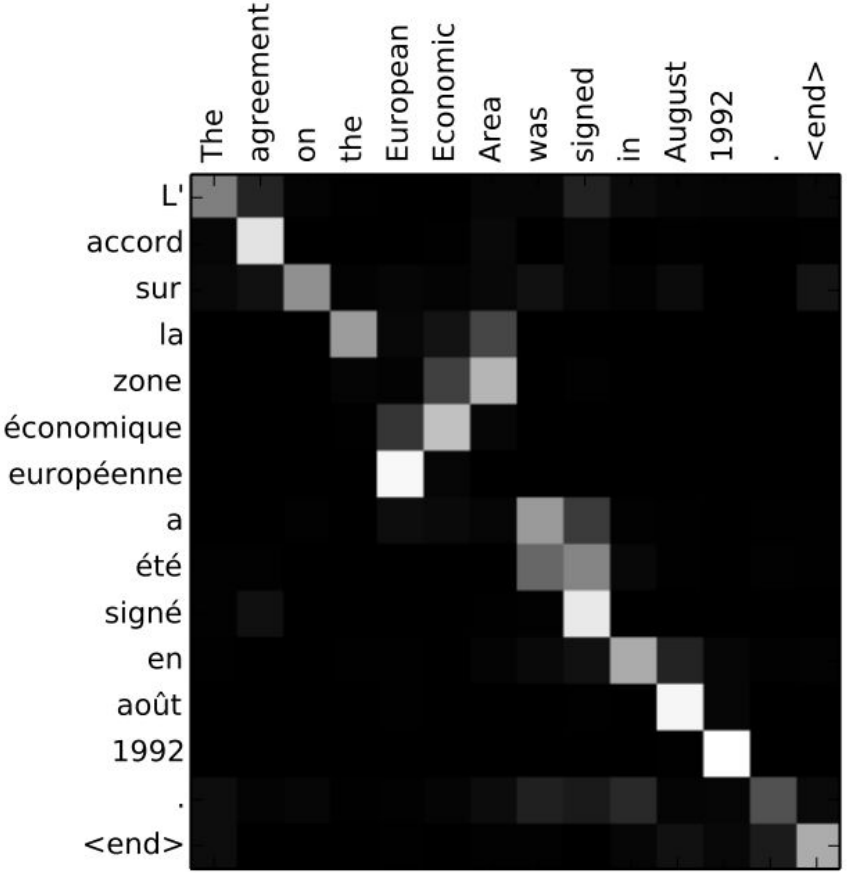
$$\boldsymbol{a}_t = \sum_{i=1}^{N} \alpha_i^t \boldsymbol{h}_i \in \mathbb{R}^h$$

Finally we concatenate the attention output $\boldsymbol{a}_t$ with the decoder hidden state s_t and proceed as in the non-attention seq2seq model

$$[\boldsymbol{a}_t; \boldsymbol{s}_t] \in \mathbb{R}^{2h}$$

Attention provides interpretability

- We may see what the decoder was focusing on
- We get word alignment for free!



Attention variants

- Basic dot-product (the one discussed before): $\boldsymbol{e}_i = \boldsymbol{s}^T \boldsymbol{h}_i \in \mathbb{R}$
- Multiplicative attention: $\boldsymbol{e}_i = \boldsymbol{s}^T \boldsymbol{W} \boldsymbol{h}_i \in \mathbb{R}$
  - $\boldsymbol{W} \in \mathbb{R}^{d_2 \times d_1}$ - weight matrix
- Additive attention: $\boldsymbol{e}_i = \boldsymbol{v}^T \tanh(\boldsymbol{W}_1 \boldsymbol{h}_i + \boldsymbol{W}_2 \boldsymbol{s}) \in \mathbb{R}$
  - $\boldsymbol{W}_1 \in \mathbb{R}^{d_3 \times d_1}, \boldsymbol{W}_2 \in \mathbb{R}^{d_3 \times d_2}$ - weight matrices
  - $\boldsymbol{v} \in \mathbb{R}^{d_3}$ - weight vector

Backup 2

Text augmentations

Like with images we can increase our training corpora size with augmentations.

Examples:

- Text deformations: mix some texts, change order…
- Reformulations
- Word dropout

Text segmentation

Open vocabulary problem: In NLP language vocabulary is usually very big. To produce a good quality with particular word the algorithm should see a lot of examples with it. This is a big problem for rare words.

There are two extreme approaches for vocabulary modelling:

- Char level: small vocabulary, a lot of examples with each element, slow training, long sequences during encoding and decoding
- Each word is a new item in vocabulary: Big vocabulary, small number of examples for rare words, fast training, short sequences during encoding and decoding

Text segmentation: Balance, BPE

We can balance vocabulary size with length of sequence

Bait Pair Encoding (BPE) (Sennrich et al.): Let's split rare words into subwords, while leave frequent sequences as a one token.

1) Compute merge table: Starting from characters let's one by one merge the most frequent symbols into one symbol until reaching desired vocabulary size.
2) During inference let's greedily (priority=number of step, when this pair was added in (1)) apply merge rules

https://arxiv.org/pdf/1508.07909.pdf

BPE Benefits

- We have not got out-of-vocabulary words, because we start from all characters.
- We can balance vocabulary size with decoding efficiency

  Example:

  “mother” -> (BPE) mother

  “sweetish” -> (BPE) sweet ish

  “asft” -> (BPE) as f t

https://arxiv.org/pdf/1508.07909.pdf