CS60050 Machine learning

Neural Network Architectures
LSTM, Attention

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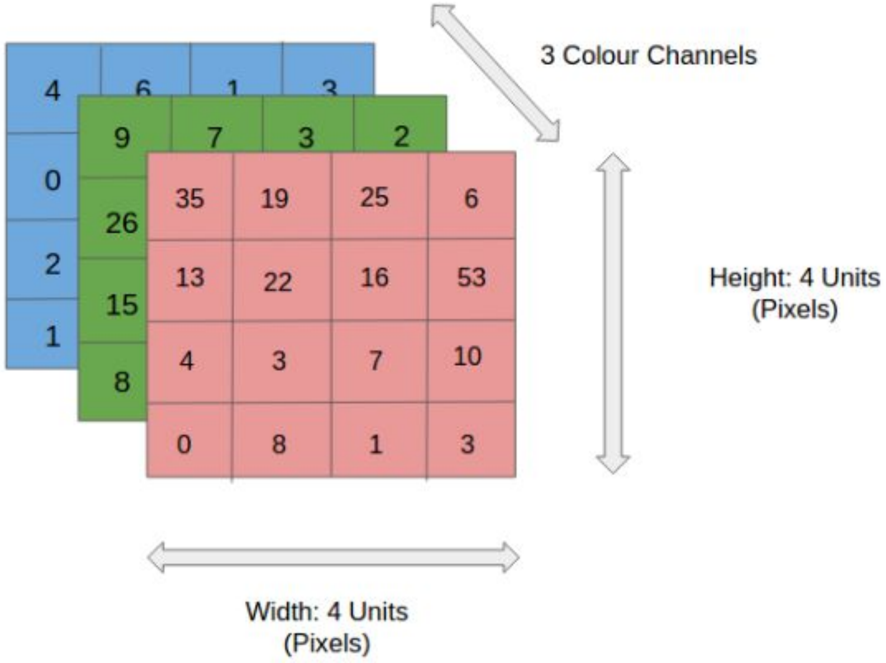
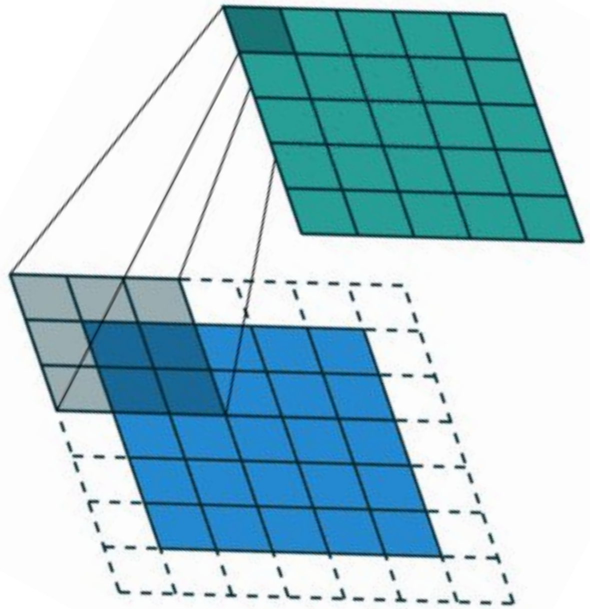
- Slide Courtesy: Prof. Chris Manning, Prof. Li Fei Fei, Prof. Yunzhu Li, Prof. Ruohan Gao (Stanford Univ)

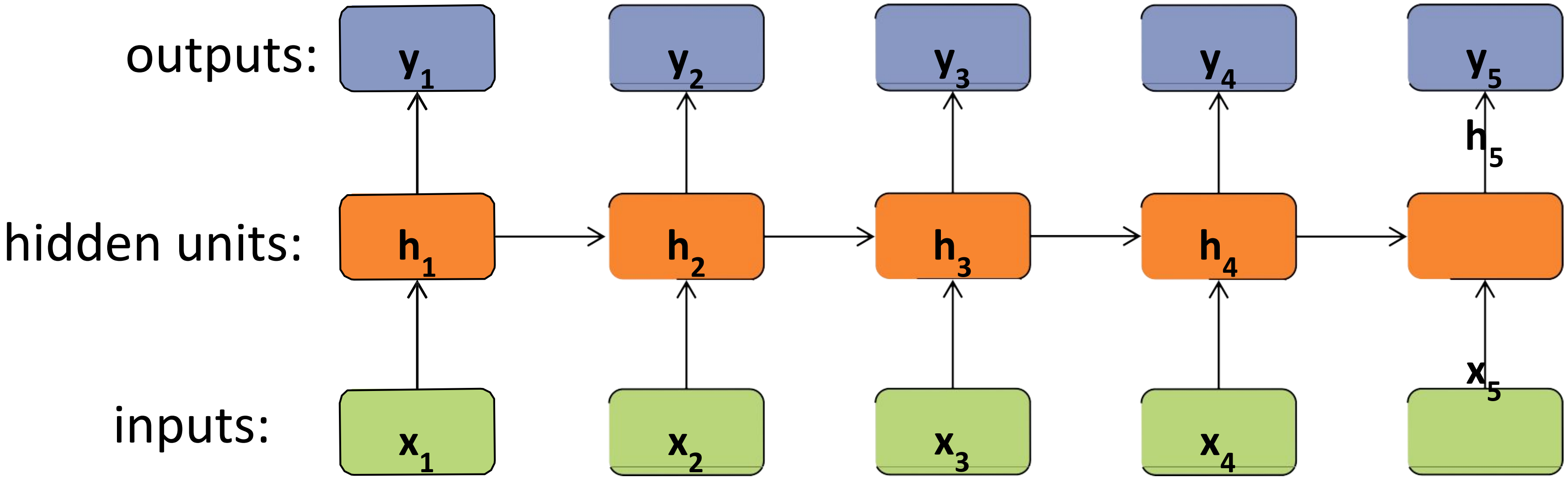
CNN and Convolution



Kernel Size: 3x3x1
Stride: 1
Zero-Padding



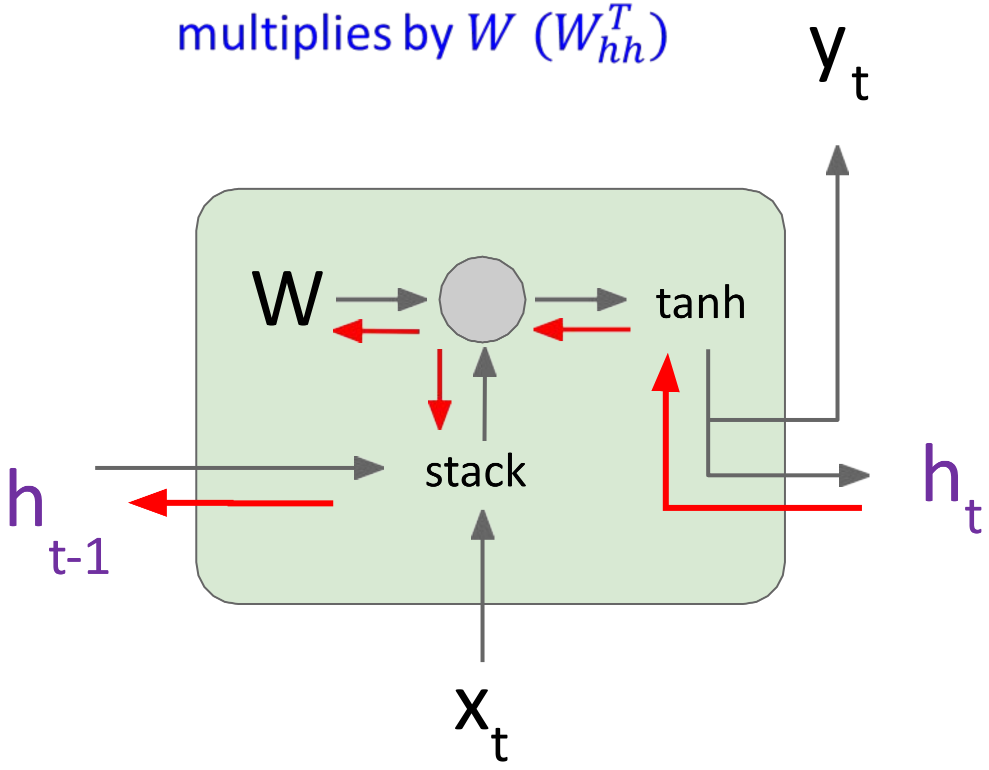
Recurrent Neural Networks (RNNs)



$$h_t = g\left(W_{xh} x_t + W_{hh} h_{t-1} + b_h\right)$$
$$y_t = W_{hy} h_t + b_y$$

Vanilla RNN Gradient Flow

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



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

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

RNN 2.0: Long short-term Memory (LSTM)

- Hidden State: holds previous information (Short-term memory)
- Cell State: memory of the network (Long-term memory)

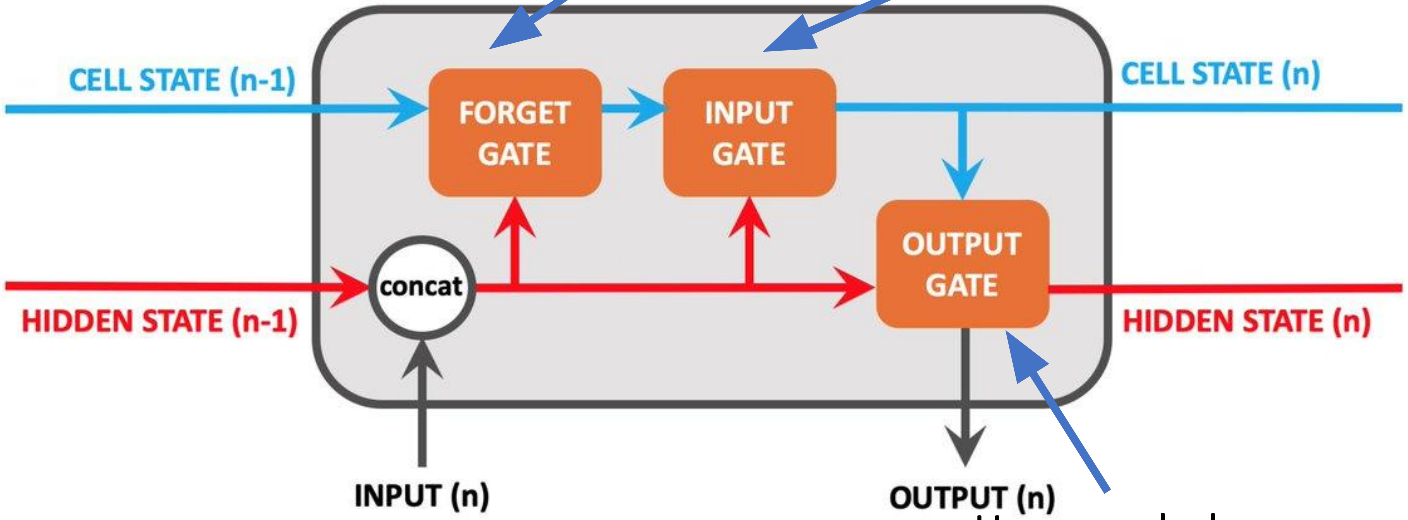
What should be forget in cell state

How much new data should be taken

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

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

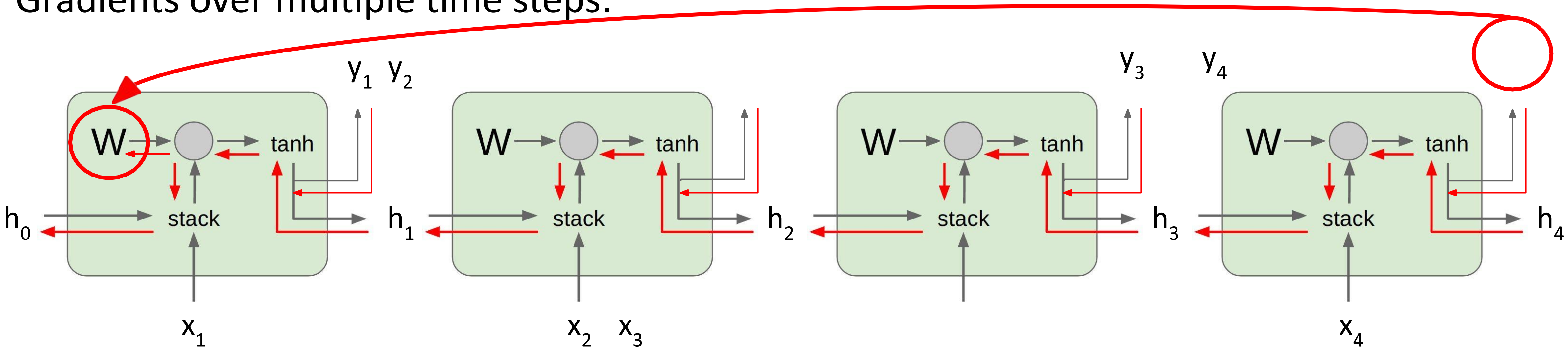
$$h_t = o \odot \tanh(c_t)$$



How much does memory affect output

Revisiting Vanilla RNN Gradient Flow

Gradients over multiple time steps:



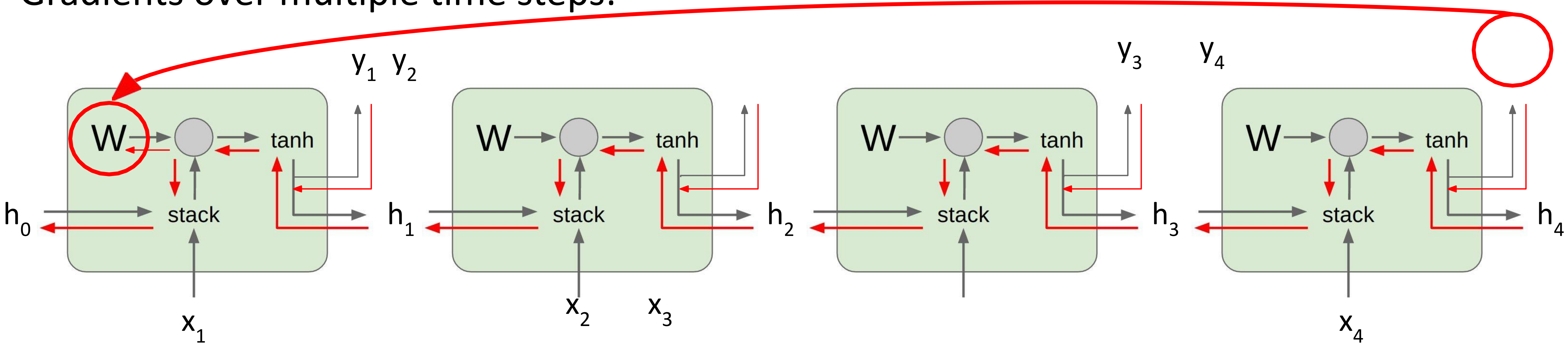
Computing gradient of h_0
Involves many factors of W
and repeated tanh

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

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

Revisiting Vanilla RNN Gradient Flow

Gradients over multiple time steps:



What if we assumed no non-linearity?

Computing gradient of h_0 Involves many factors of W and repeated tanh

Largest singular value > 1: **Exploding gradients** → **Gradient clipping**: Scale gradient if its norm is too big

Largest singular value < 1: **Vanishing gradients** → Change RNN architecture

Long Short Term Memory (LSTM)

Vanilla RNN   LSTM

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

Four gates

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

Cell state

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

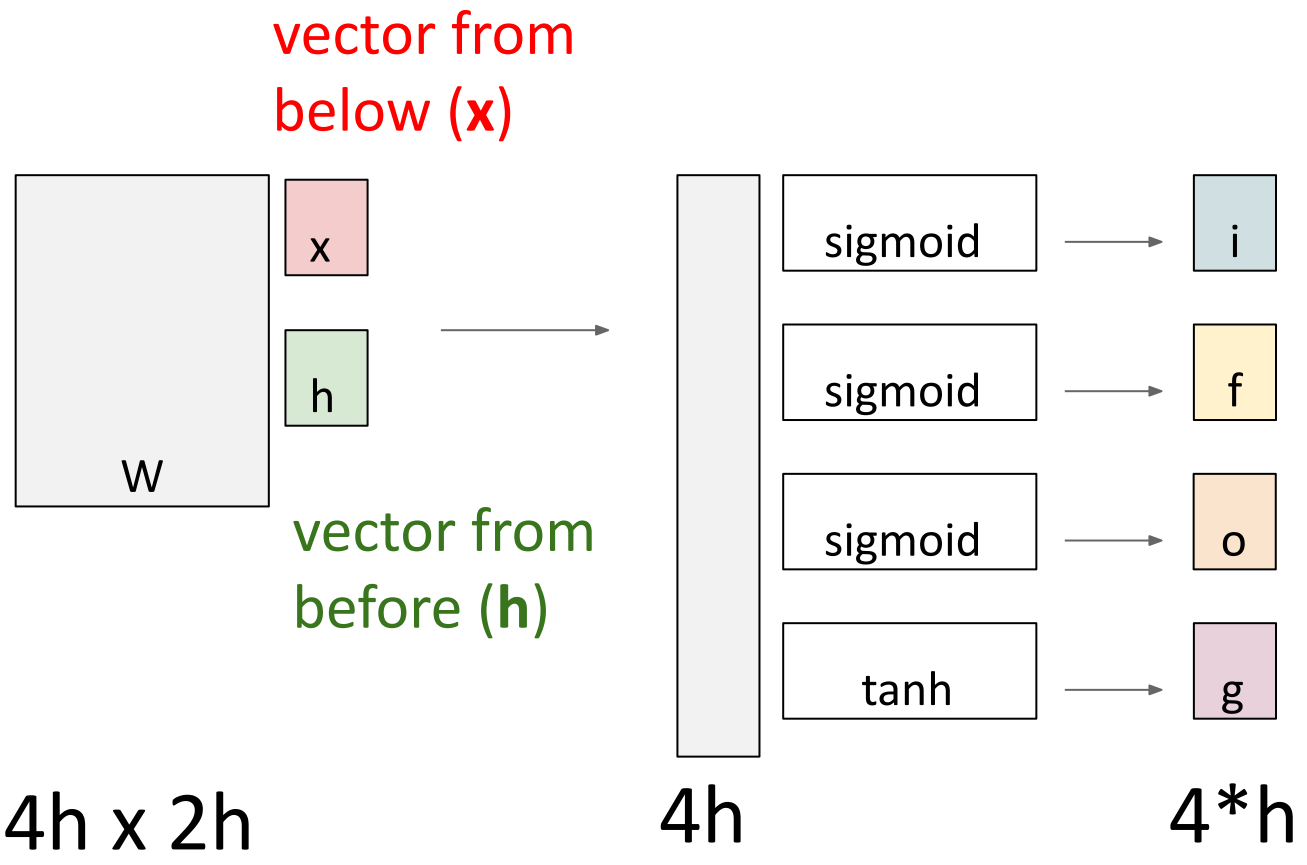
Hidden state

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

Hochreiter and Schmidhuber, "Long Short Term Memory", Neural Computation 1997

Long Short Term Memory (LSTM)

[Hochreiter et al., 1997]



g: <u>Gate</u>(?), How much to write to cell

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

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

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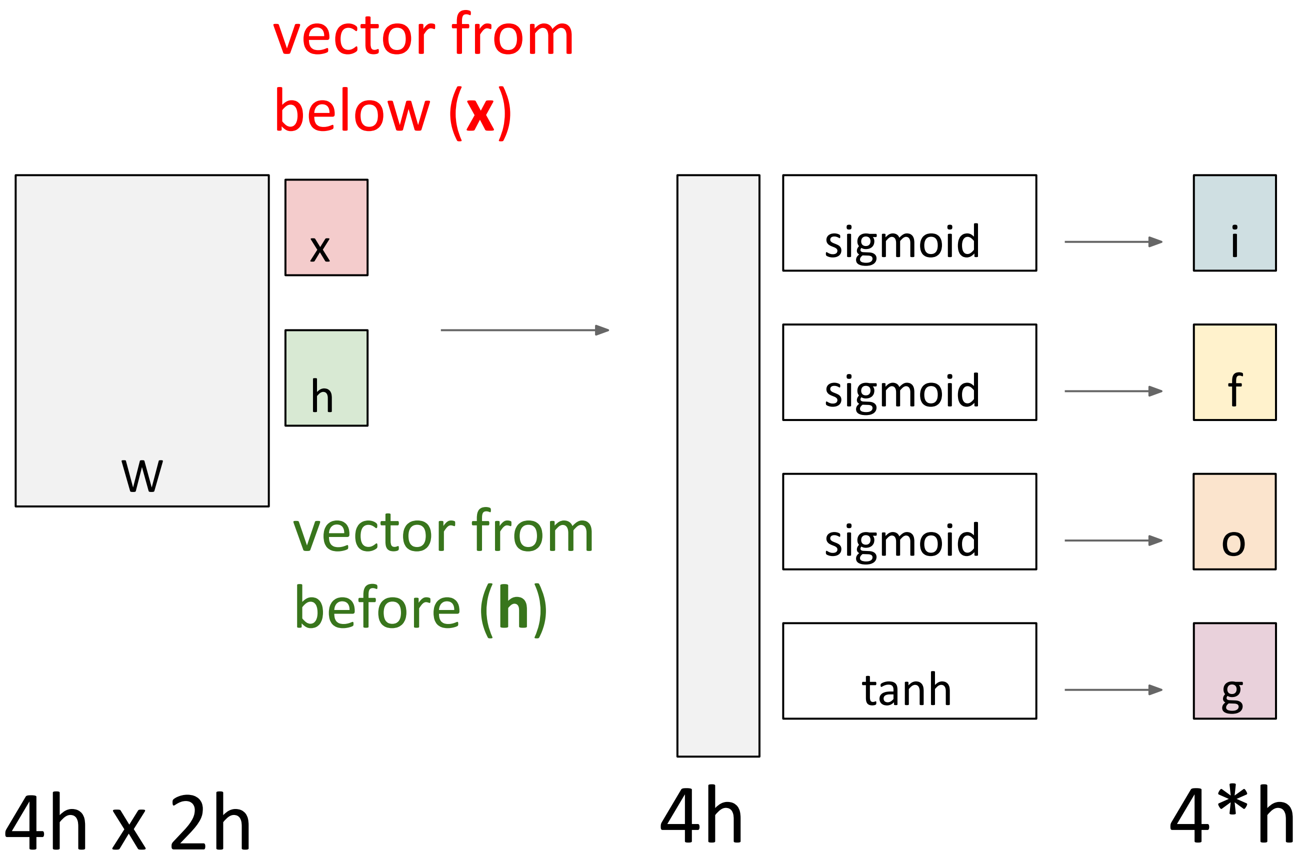
Long Short Term Memory (LSTM)

[Hochreiter et al., 1997]



i: Input gate, whether to write to cell

g: Gate (?), How much to write to cell

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

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

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

Long Short Term Memory (LSTM)

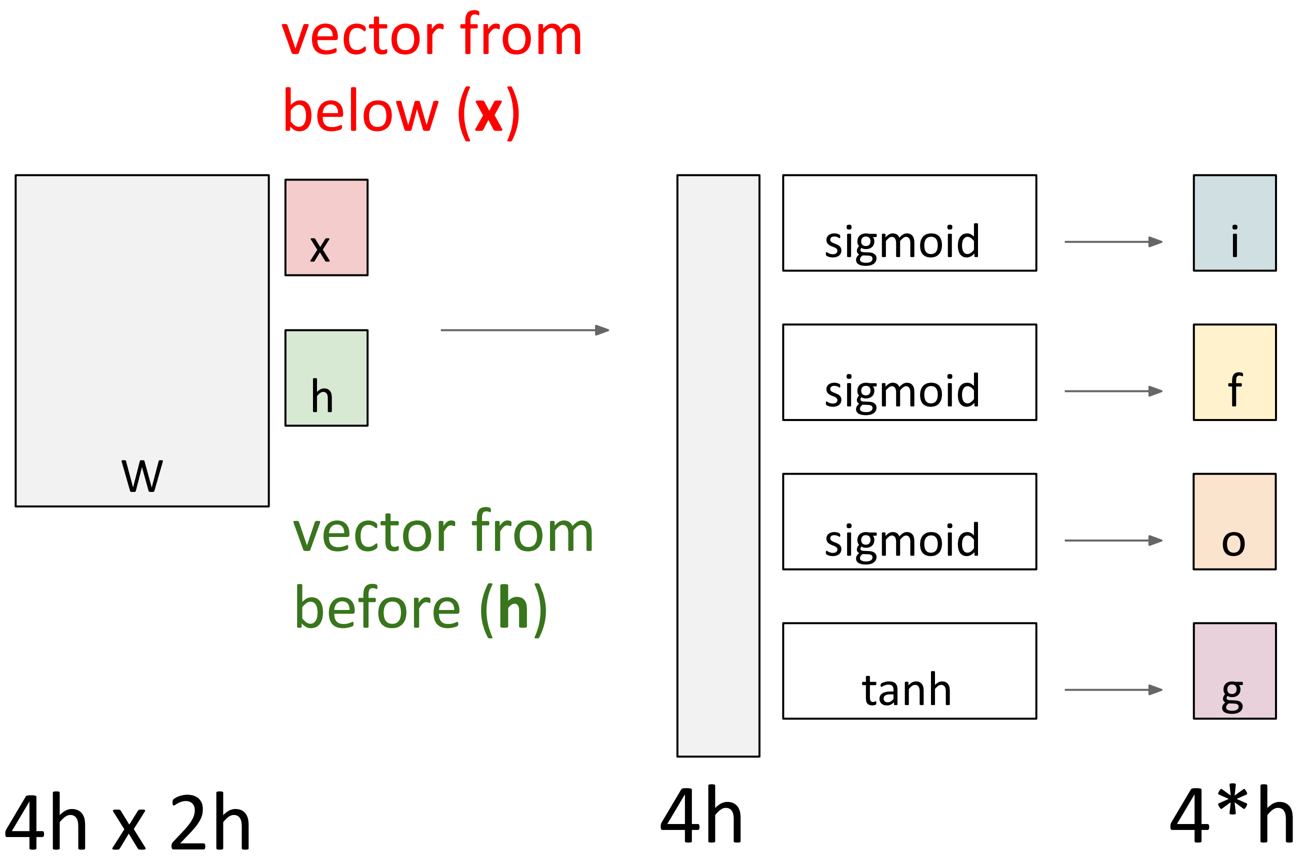
[Hochreiter et al., 1997]

i: Input gate, whether to write to cell

f: Forget gate, Whether to erase cell

o: Output gate, How much to reveal cell

g: Gate (?), How much to write to cell



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

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

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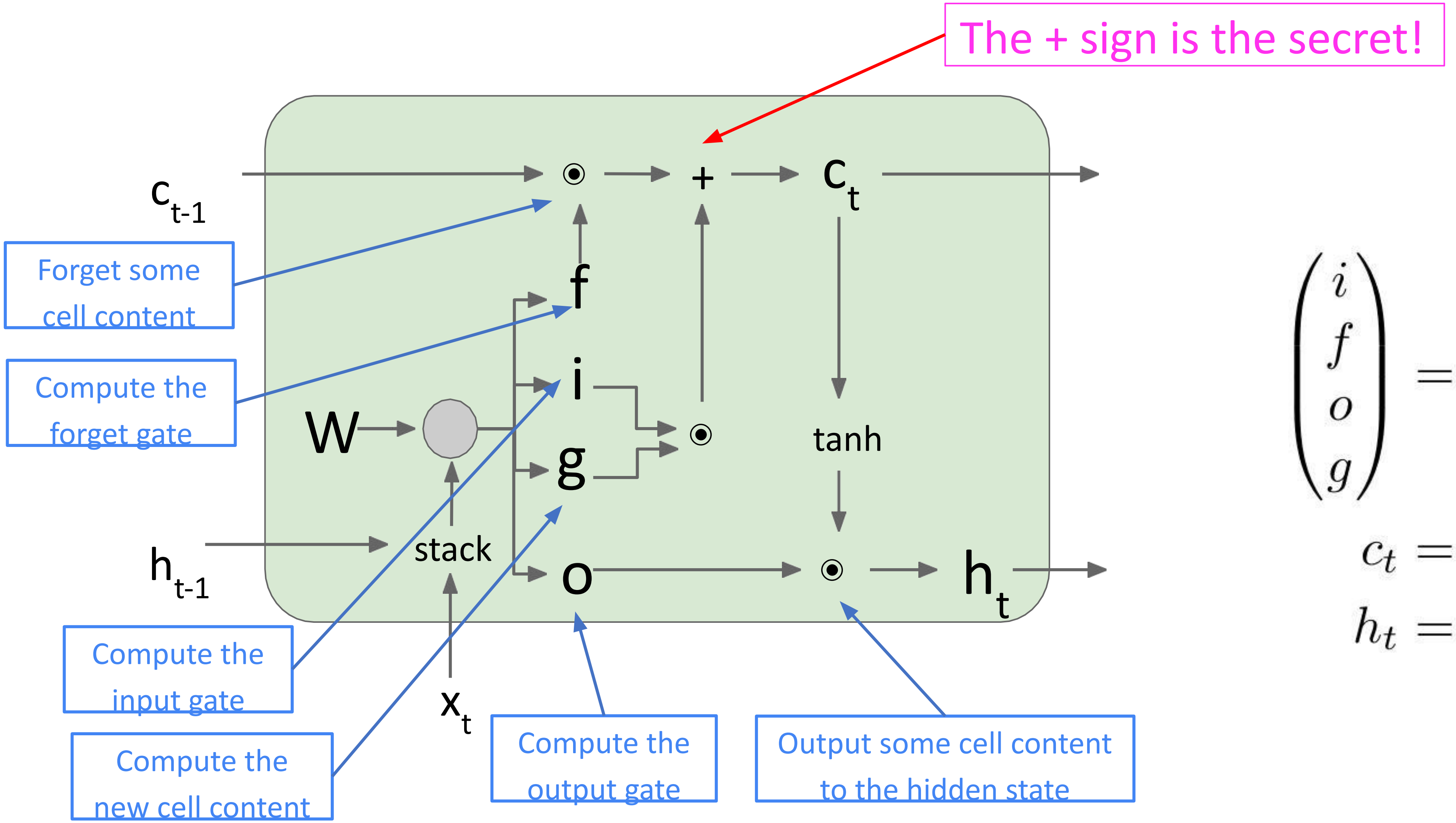

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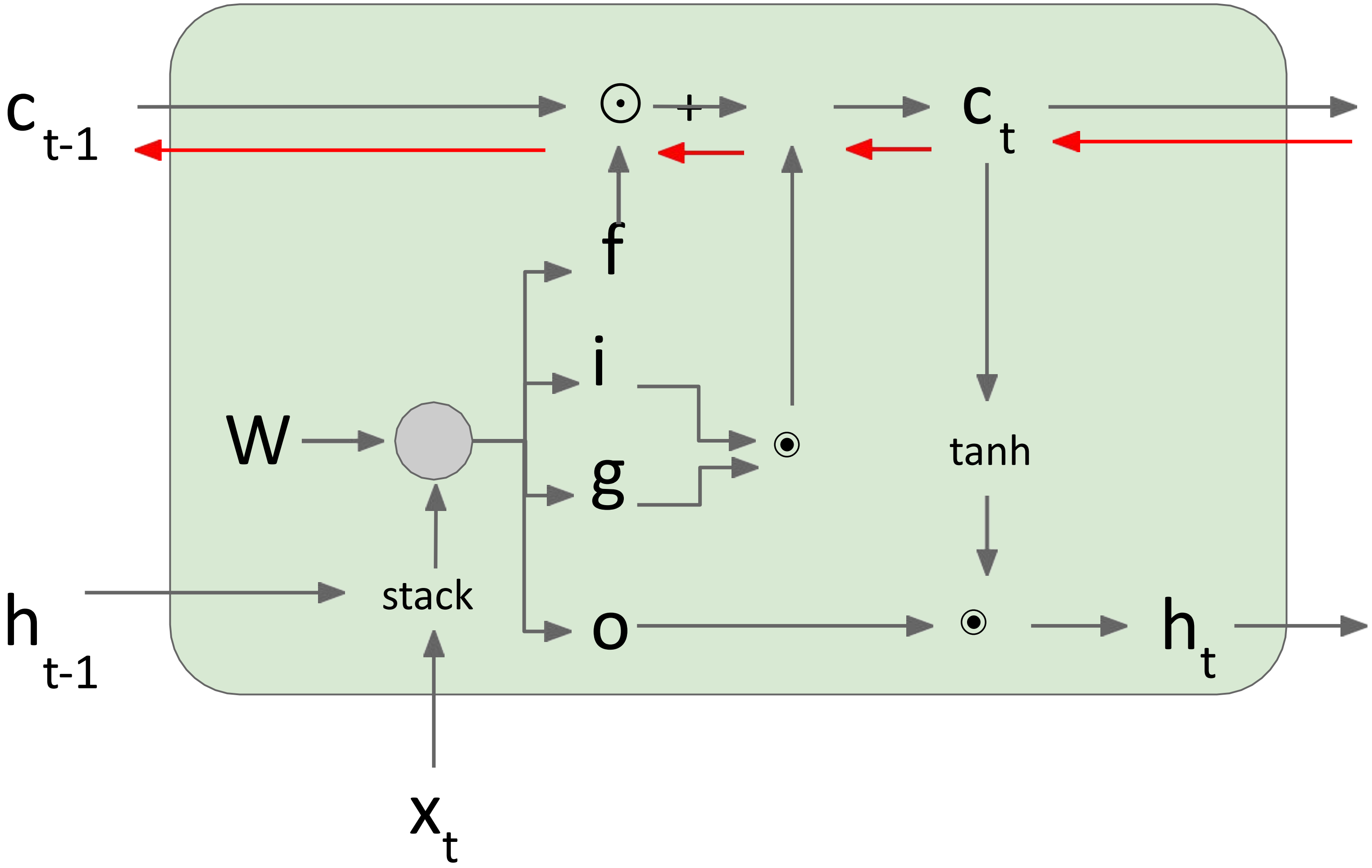
Long Short Term Memory (LSTM): Gradient Flow



Backpropagation from c_t to c_{t-1} only elementwise multiplication by f, no matrix multiply by W

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

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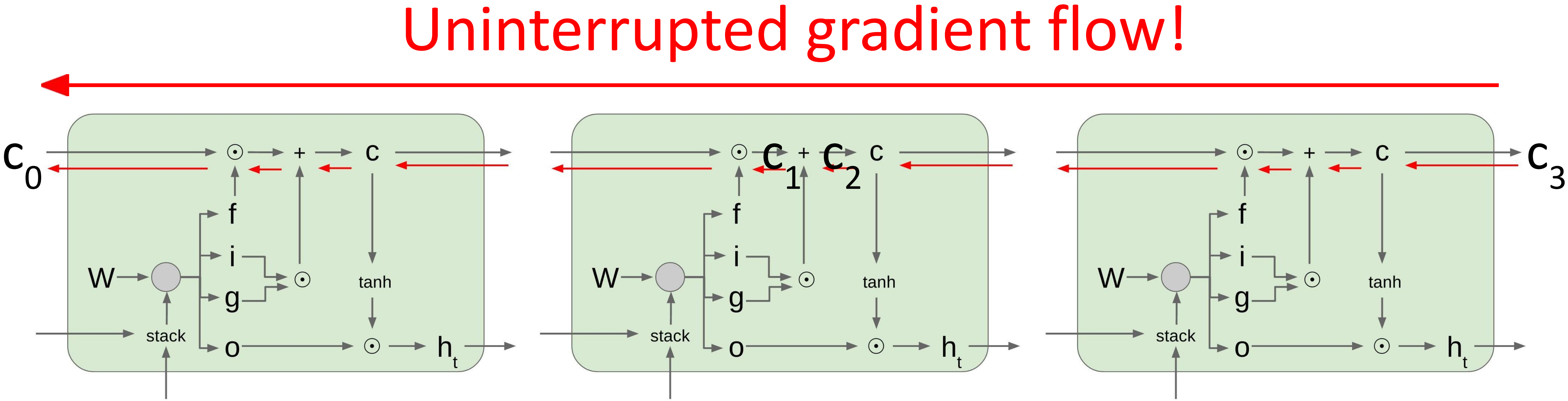
Long Short Term Memory (LSTM): Gradient Flow

[Hochreiter et al., 1997]



Do LSTMs solve the vanishing gradient problem?

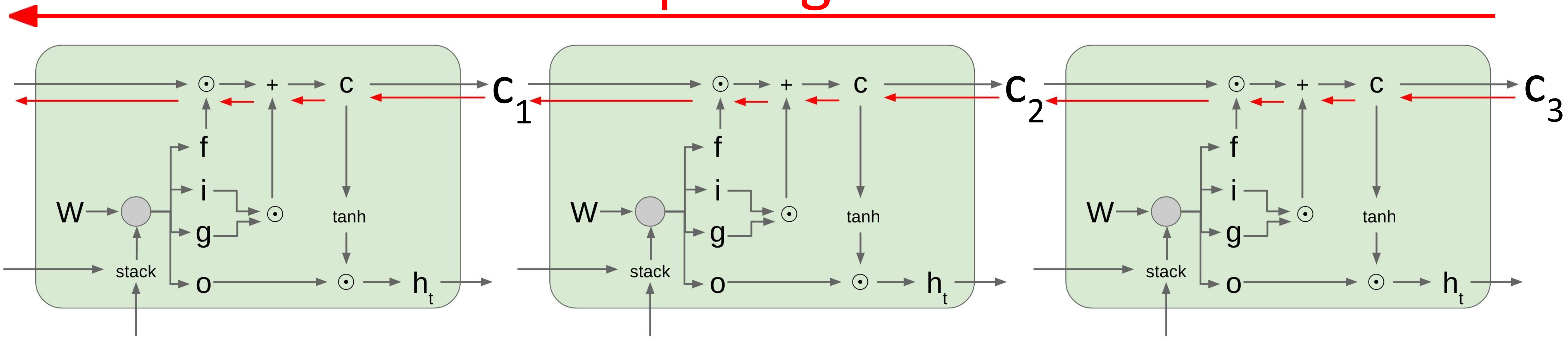
The LSTM architecture makes it easier for the RNN to preserve information over many timesteps

- e.g. **if the f = 1 and the i = 0**, then the information of that cell is preserved indefinitely.
- By contrast, it's harder for vanilla RNN to learn a recurrent weight matrix Wh that preserves info in hidden state

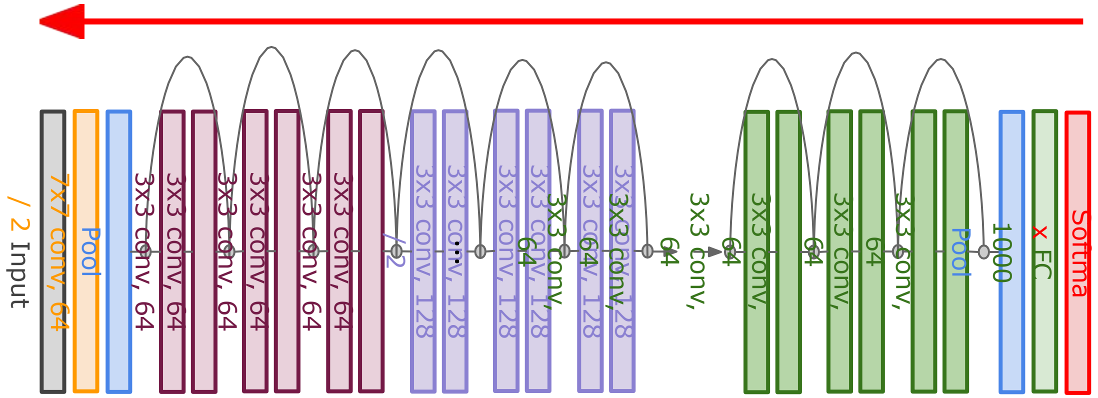
LSTM **doesn't guarantee** that there is no vanishing/exploding gradient, but it does provide an easier way for the model to learn long-distance dependencies

Long Short Term Memory (LSTM): Gradient Flow

Uninterrupted gradient flow!



Similar to ResNet!



In between:

Highway Networks

$$g = T(x, W_T)$$

$$y = g \odot H(x, W_H) + (1 - g) \odot x$$

Srivastava et al, “Highway Networks”, ICML DL Workshop 2015

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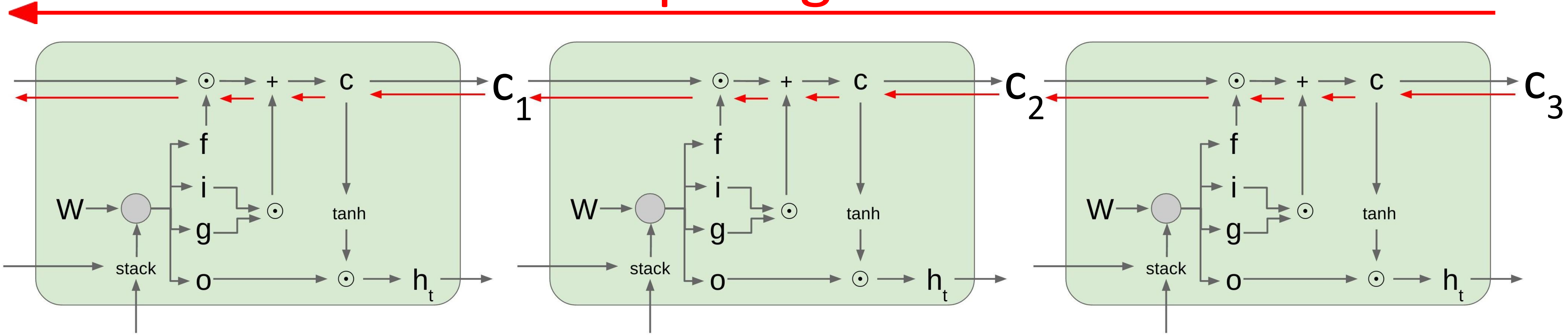
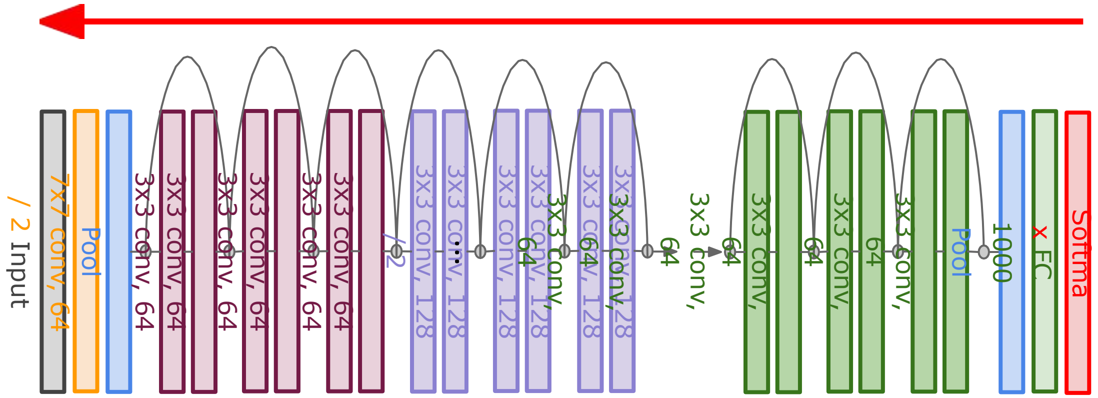


Similar to ResNet!



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$$g = T(x, W_T)$$

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Other RNN Variants

GRU [*Learning phrase representations using rnn encoder-decoder for statistical machine translation*, Cho et al. 2014]

$$r_t = \sigma(W_{xr}x_t + W_{hr}h_{t-1} + b_r)$$
$$z_t = \sigma(W_{xz}x_t + W_{hz}h_{t-1} + b_z)$$
$$\tilde{h}_t = \tanh(W_{xh}x_t + W_{hh}(r_t \odot h_{t-1}) + b_h)$$
$$h_t = z_t \odot h_{t-1} + (1 - z_t) \odot \tilde{h}_t$$

[*LSTM: A Search Space Odyssey*, Greff et al., 2015]

[*An Empirical Exploration of Recurrent Network Architectures*, Jozefowicz et al., 2015]

MUT1:

$$\begin{aligned} z &= \mathrm{sigm}(W_{\mathrm{xz}}x_t + b_{\mathrm{z}}) \\ r &= \mathrm{sigm}(W_{\mathrm{xr}}x_t + W_{\mathrm{hr}}h_t + b_{\mathrm{r}}) \\ h_{t+1} &= \tanh(W_{\mathrm{hh}}(r \odot h_t) + \tanh(x_t) + b_{\mathrm{h}}) \odot z \\ &+ h_t \odot (1 - z) \end{aligned}$$

MUT2:

$$\begin{aligned} z &= \mathrm{sigm}(W_{\mathrm{xz}}x_t + W_{\mathrm{hz}}h_t + b_{\mathrm{z}}) \\ r &= \mathrm{sigm}(x_t + W_{\mathrm{hr}}h_t + b_{\mathrm{r}}) \\ h_{t+1} &= \tanh(W_{\mathrm{hh}}(r \odot h_t) + W_{xh}x_t + b_{\mathrm{h}}) \odot z \\ &+ h_t \odot (1 - z) \end{aligned}$$

MUT3:

$$\begin{aligned} z &= \mathrm{sigm}(W_{\mathrm{xz}}x_t + W_{\mathrm{hz}}\tanh(h_t) + b_{\mathrm{z}}) \\ r &= \mathrm{sigm}(W_{\mathrm{xr}}x_t + W_{\mathrm{hr}}h_t + b_{\mathrm{r}}) \\ h_{t+1} &= \tanh(W_{\mathrm{hh}}(r \odot h_t) + W_{xh}x_t + b_{\mathrm{h}}) \odot z \\ &+ h_t \odot (1 - z) \end{aligned}$$

Summary

- RNNs allow a lot of flexibility in architecture design
- Vanilla RNNs are simple but don’t work very well
- Common to use LSTM or GRU: their additive interactions improve gradient flow
- Backward flow of gradients in RNN can explode or vanish. Exploding is controlled with gradient clipping. Vanishing is controlled with additive interactions (LSTM)
- Better understanding (both theoretical and empirical) is needed.

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$$
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Sequence to Sequence with Attention

A Language Modeling perspective and a precursor to Transformers

What is a Language Model?

An LM is

- a probability distribution over sequence of words.
- a way to predict the next word

For a sentence S consisting of m words

$$S = w_1 w_2 w_3 \ldots \ldots . . w_m$$

In Language Model, we assume:

$$P(S) = P(w_1 w_2 w_3 \ldots \ldots . . w_m)$$

$$= P(w_1) \times P(w_2|w_1) \times \cdots \times P(w_m|w_{m-1} \ldots w_1)$$

What is a Language Model?

Using LM, we can find out

- If a sentence S_1 is more likely than another S_2 (conditioned on q, but ignore for now).

For example:

- S_1: Virat Kohli plays cricket for India.
- S_2: plays Kohli cricket for India Virat.
- S_3: Virat Kohli plays plays for India.

Which is more likely?

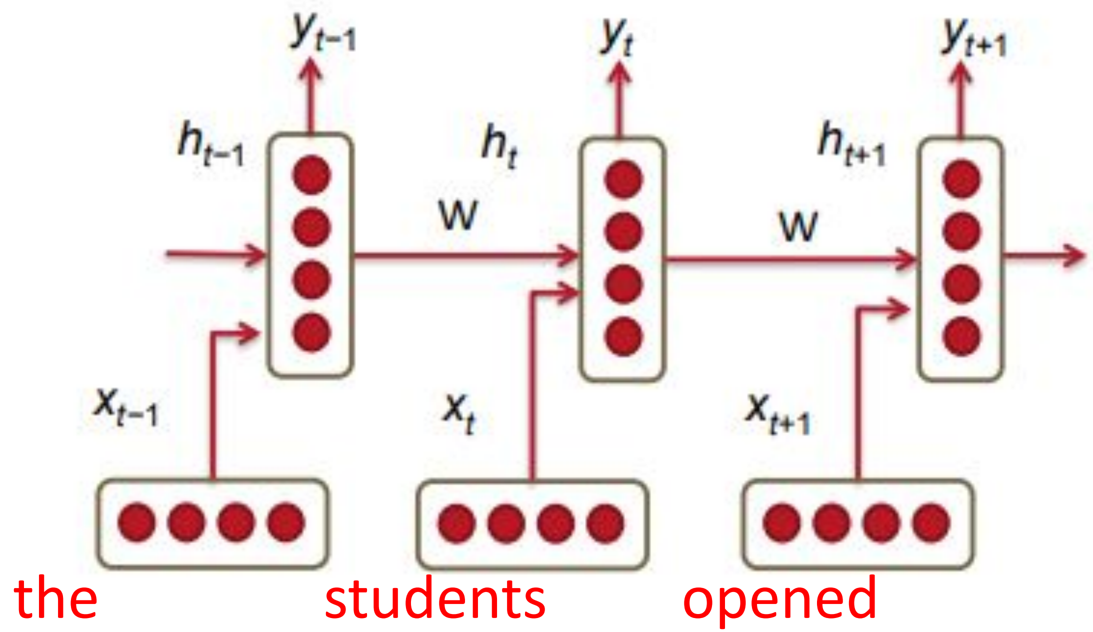
Obviously S_1. Hence our LM should say **$P(S_1) > P(S_2)$** and **$P(S_1) > P(S_3)$**.

Recurrent Neural Networks - LM

Recurrent Neural Networks (RNN)

- Each word depends on all previous words in the "sentence/paragraph".
- ***RNNs add the immediate past to the present.***

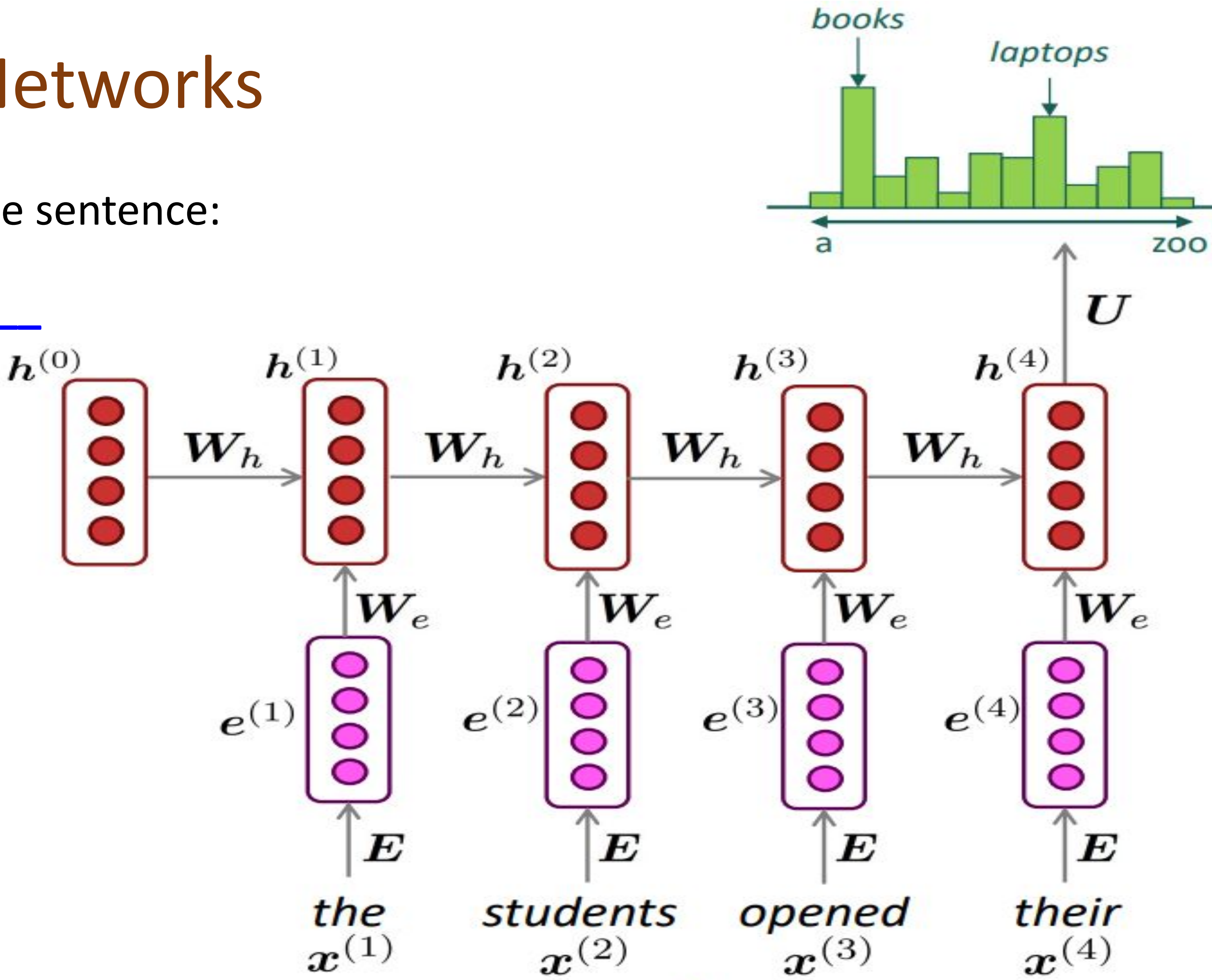
Here, is a simple architecture of RNN:



Recurrent Neural Networks

Working of RNN for the example sentence:

the students opened their _____



Evaluating Language Models

- The standard evaluation metric for Language Models is perplexity.

$$\text{perplexity} = \underbrace{\prod_{t=1}^{T} \left(\frac{1}{P_{\text{LM}}(\boldsymbol{x}^{(t+1)} | \, \boldsymbol{x}^{(t)}, \ldots, \boldsymbol{x}^{(1)})} \right)}_{\text{Inverse probability of corpus, according to Language Model}}^{1/T}$$

Normalized by number of words

- This is equal to the exponential of the cross-entropy loss $J(\theta)$:

$$= \prod_{t=1}^{T} \left(\frac{1}{\hat{\boldsymbol{y}}^{(t)}_{\boldsymbol{x}_{t+1}}} \right)^{1/T} = \exp\left(\frac{1}{T} \sum_{t=1}^{T} -\log \hat{\boldsymbol{y}}^{(t)}_{\boldsymbol{x}_{t+1}} \right) = \exp(J(\theta))$$

Lower perplexity is better!

RNNs greatly improved perplexity over what came before

n-gram model →

Increasingly complex RNNs

Model	Perplexity
Interpolated Kneser-Ney 5-gram (Chelba et al., 2013)	67.6
RNN-1024 + MaxEnt 9-gram (Chelba et al., 2013)	51.3
RNN-2048 + BlackOut sampling (Ji et al., 2015)	68.3
Sparse Non-negative Matrix factorization (Shazeer et al., 2015)	52.9
LSTM-2048 (Jozefowicz et al., 2016)	43.7
2-layer LSTM-8192 (Jozefowicz et al., 2016)	30
Ours small (LSTM-2048)	43.9
Ours large (2-layer LSTM-2048)	39.8

Perplexity improves (lower is better)

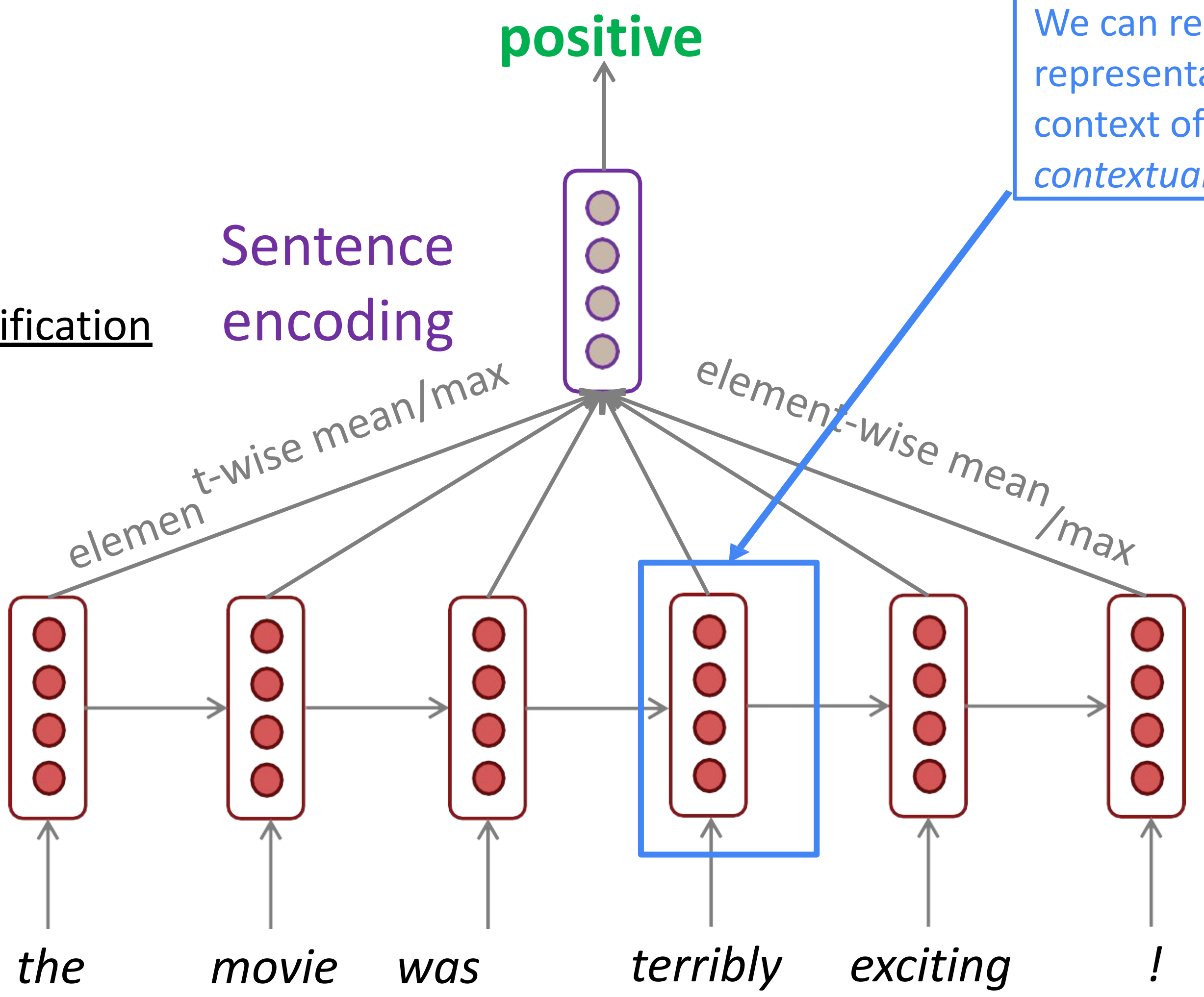
Source: https://research.fb.com/building-an-efficient-neural-language-model-over-a-billion-words/

In Summary …

- **Language Model**: A system that predicts the next word
- Recurrent Neural Network $\neq$ Language Model
  - RNNs can be used for many other things (see later)
- Language Modeling is a traditional subcomponent of many NLP tasks, all those involving generating text or estimating the probability of text.
- In practical tasks:
  - Both left and right context is necessary to model. Bidirectional RNNs
  - Need to remember distant Past. LSTM does NOT FULLY solve this. Attention!

Bidirectional RNNs: motivation

<u>Task: Sentiment</u> <u>Classification</u>



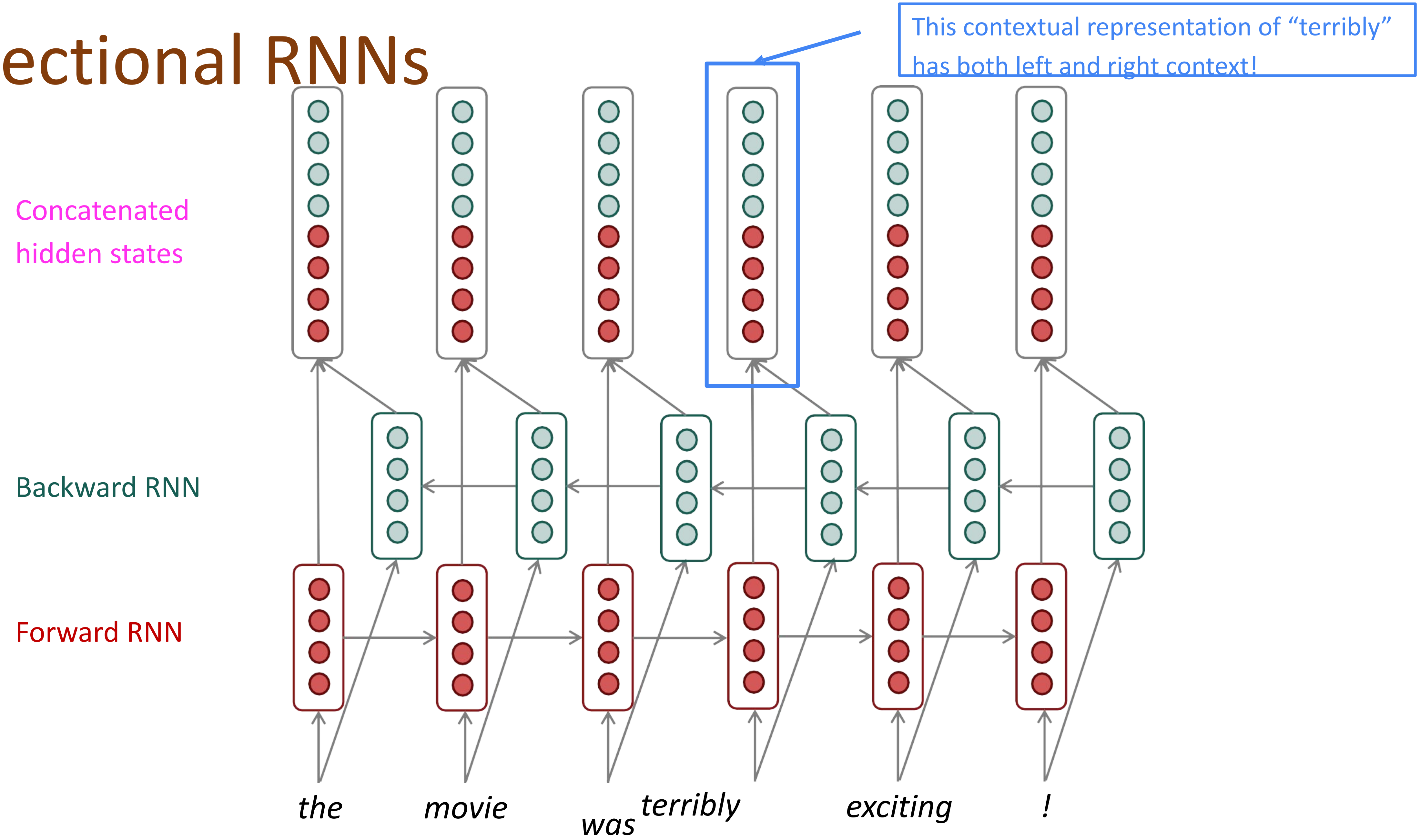
We can regard this hidden state as a representation of the word *"terribly"* in the context of this sentence. We call this a *contextual representation.*

These contextual representations only contain information about the *left* context (e.g. *"the movie was"*).

What about *right* context?

In this example, *"exciting"* is in the right context and this modifies the meaning of *"terribly"* (from negative to positive)

Bidirectional RNNs



Bidirectional RNNs

On timestep *t*:

This is a general notation to mean "compute one forward step of the RNN" – it could be a simple RNN or LSTM computation.

Forward RNN $\overrightarrow{\boldsymbol{h}}^{(t)} = \boxed{\mathrm{RNN}_{\mathrm{FW}}}(\overrightarrow{\boldsymbol{h}}^{(t-1)}, \boldsymbol{x}^{(t)})$

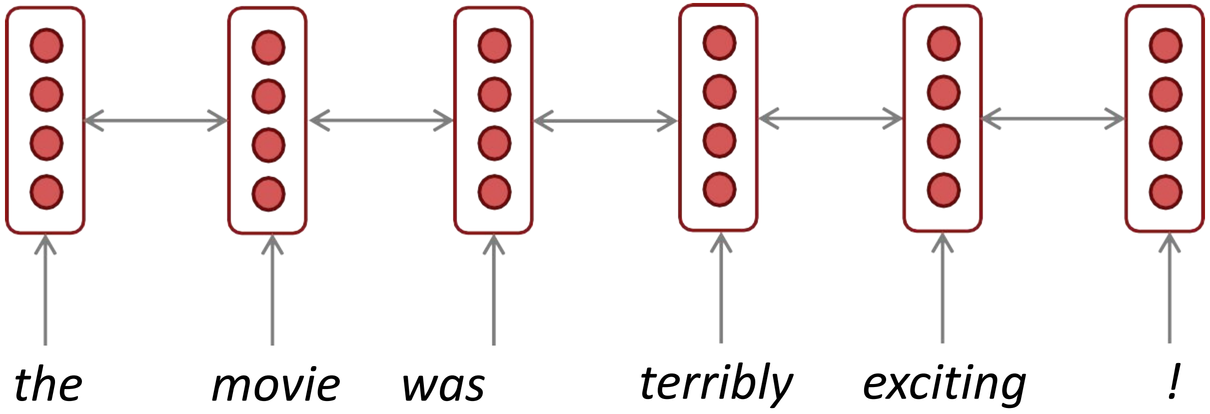
Backward RNN $\overleftarrow{\boldsymbol{h}}^{(t)} = \mathrm{RNN}_{\mathrm{BW}}(\overleftarrow{\boldsymbol{h}}^{(t+1)}, \boldsymbol{x}^{(t)})$

Generally, these two RNNs have separate weights

Concatenated hidden states $\boxed{\boldsymbol{h}^{(t)}} = [\overrightarrow{\boldsymbol{h}}^{(t)}; \overleftarrow{\boldsymbol{h}}^{(t)}]$

We regard this as "the hidden state" of a bidirectional RNN. This is what we pass on to the next parts of the network.

Bidirectional RNNs: simplified diagram



The two-way arrows indicate bidirectionality and the depicted hidden states are assumed to be the concatenated forwards+backwards states

Bidirectional RNNs

- Note: bidirectional RNNs are only applicable if you have access to the entire input sequence
  - They are **not** applicable to Language Modeling, because in LM you *only* have left context available.

- If you do have entire input sequence (e.g., any kind of encoding), bidirectionality is powerful (you should use it by default).

- For example, BERT (**Bidirectional** Encoder Representations from Transformers) is a powerful pretrained contextual representation system built on bidirectionality.

Will revisit this in Transformers!

Multi-layer RNNs

- RNNs are already “deep” on one dimension (they unroll over many timesteps)

- We can also make them “deep” in another dimension by applying multiple RNNs – this is a multi-layer RNN.

- This allows the network to compute more complex representations
  - The lower RNNs should compute lower-level features and the higher RNNs should compute higher-level features.

These concepts would be useful in Transformers!

Sequence to Sequence Model

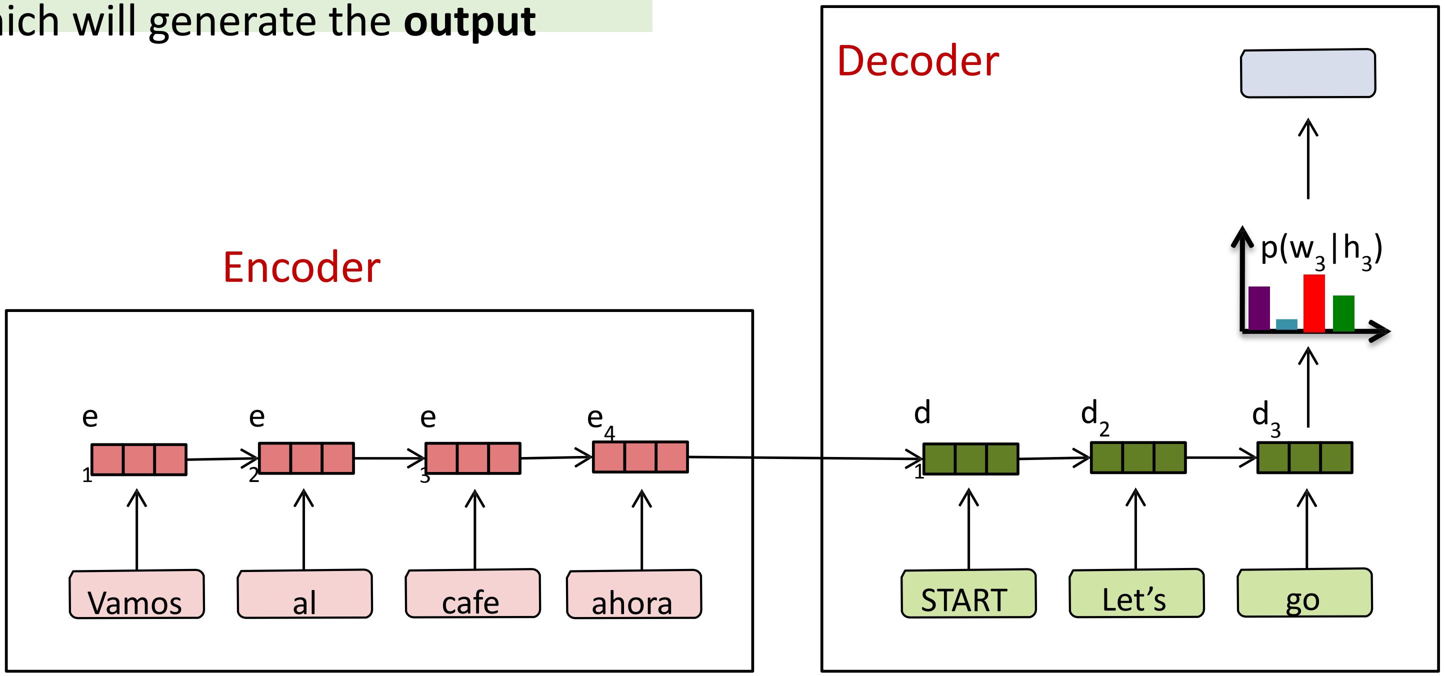
Suppose you want generate a sequence conditioned on another input

Key Idea:

1. Use an **encoder** model to generate a vector representation of the **input**
2. Feed the output of the encoder to a **decoder** which will generate the **output**

Applications:

- translation: Spanish to English
- summarization: article to summary
- speech recognition: speech signal to transcription

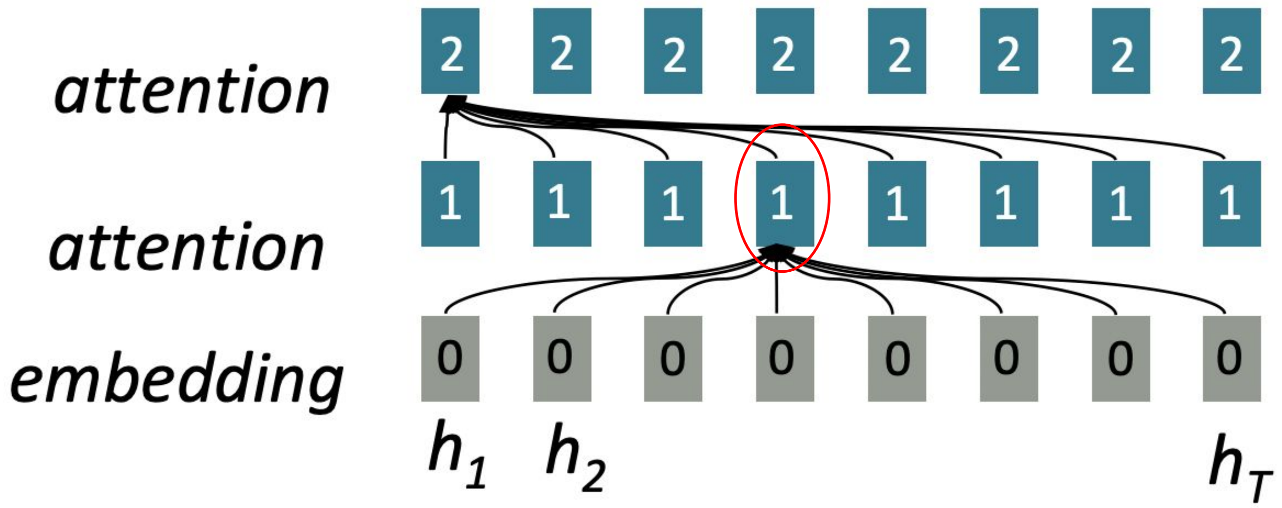


Recurrence to Attention

- Attention treats each word's representation as a query to access and incorporate information from a set of values.
  - For example, Layer 2 each node j computes

$$\sum_{i=1}^{T} \alpha_i w_{ij} h_i, \text{ s.t. } \Sigma_i \alpha_i = 1$$

- Max. interaction distance: O(1).



Sequence to Sequence with RNNs

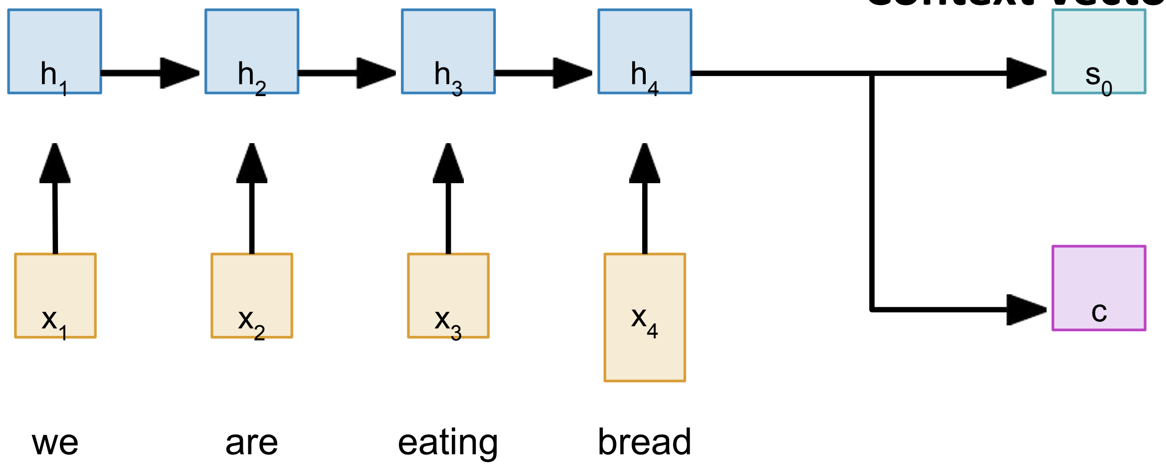
Input: Sequence $x_1, \ldots x_T$
Output: Sequence $y_1, \ldots, y_{T'}$

Encoder: $h_t = f_W(x_t, h_{t-1})$

From final hidden state predict:

Initial decoder state s_0

Context vector c (often $c=h_T$)



Sutskever et al, “Sequence to sequence learning with neural networks”, NeurIPS 2014

Sequence to Sequence with RNNs

Input: Sequence $x_1, \ldots x_T$
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Decoder: $s_t = g_U(y_{t-1}, s_{t-1}, c)$

Encoder: $h_t = f_W(x_t, h_{t-1})$

From final hidden state predict:
Initial decoder state s_0
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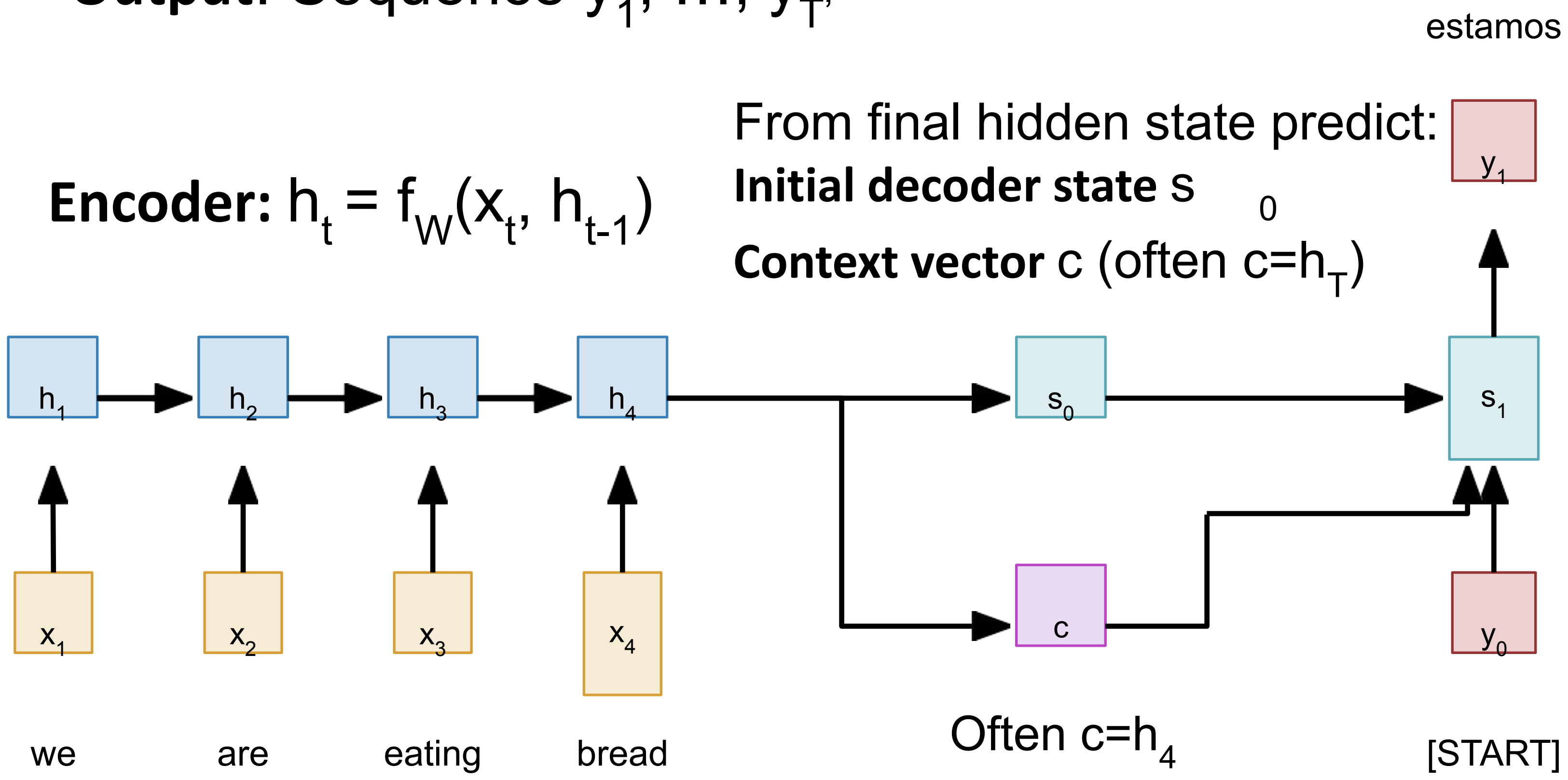

Sutskever et al, "Sequence to sequence learning with neural networks", NeurIPS 201

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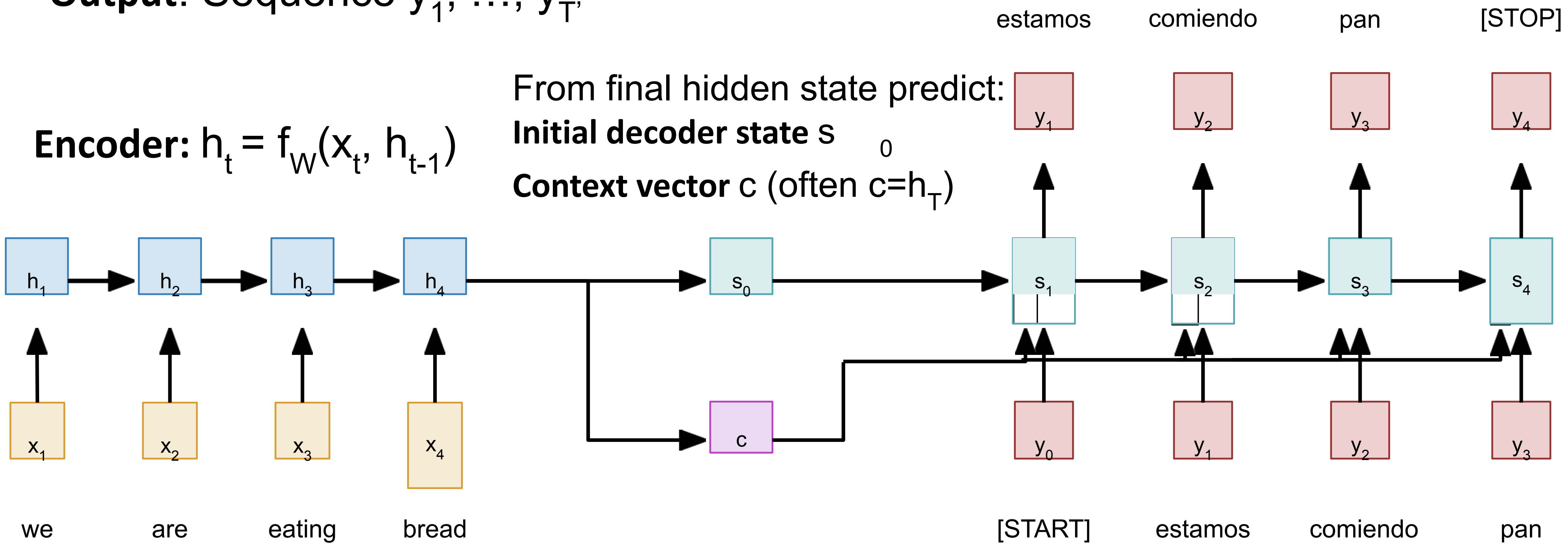

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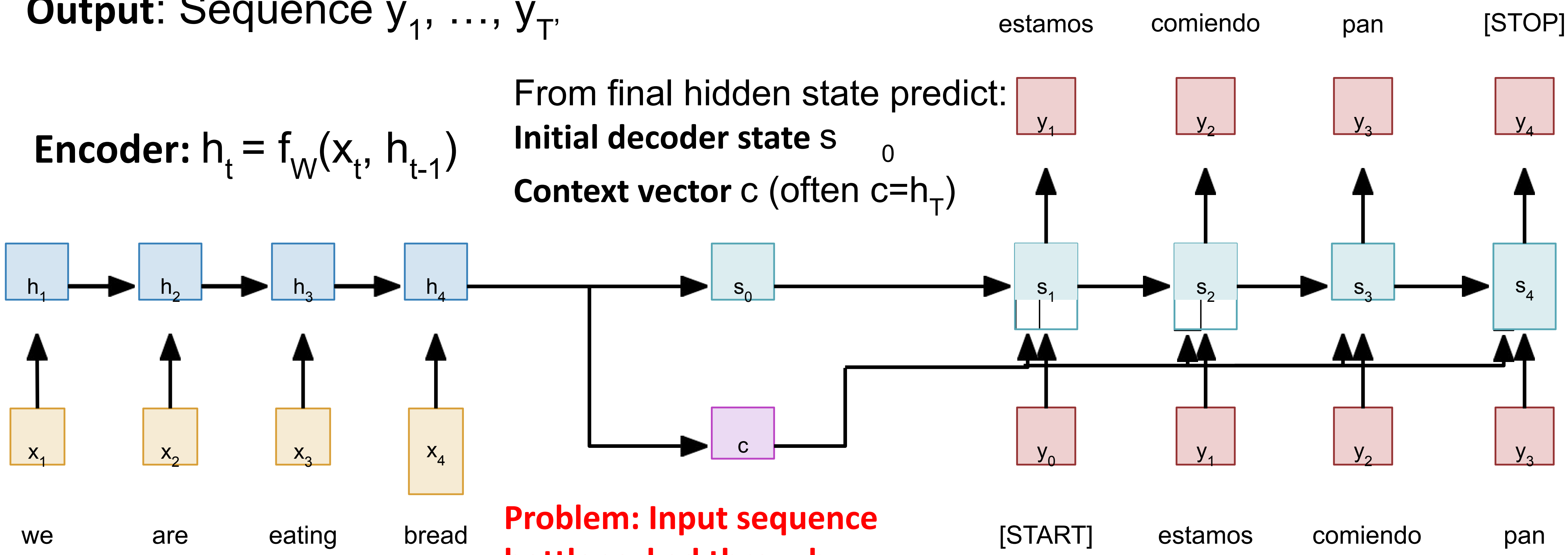

Problem: Input sequence bottlenecked through fixed-sized vector. What if T=1000?

Idea: use new context vector at each step of decoder!

Sutskever et al, "Sequence to sequence learning with neural networks",

Sequence to Sequence with RNNs and Attention

Input: Sequence $x_1, \ldots x_T$
Output: Sequence $y_1, \ldots, y_{T'}$

Encoder: $h_t = f_W(x_t, h_{t-1})$

From final hidden state:
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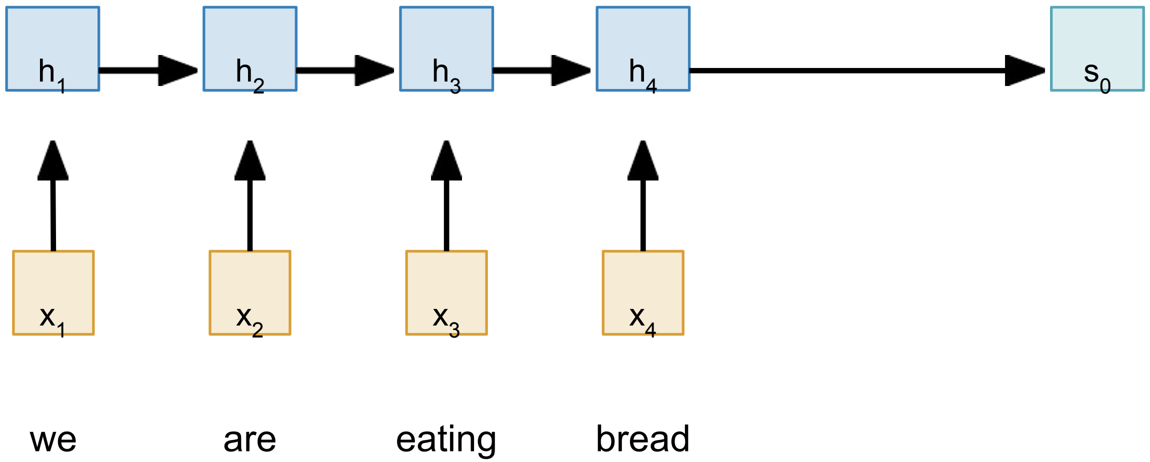


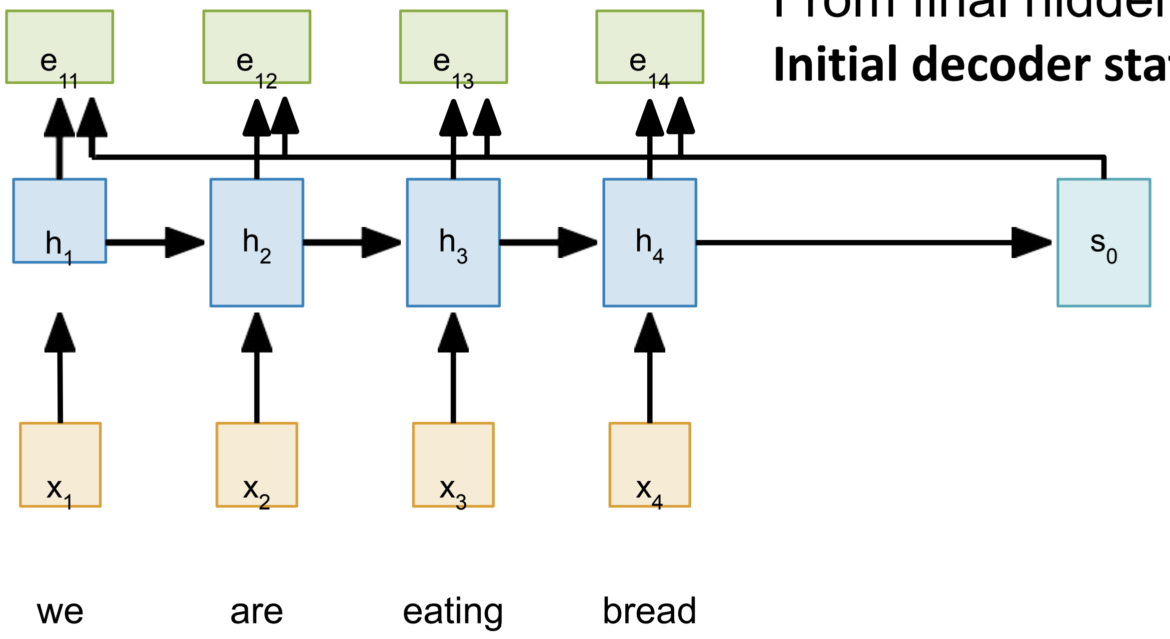
Bahdanau et al, "Neural machine translation by jointly learning to align and translate", ICLR 2015

Sequence to Sequence with RNNs and Attention

Compute (scalar) **alignment scores**

$e_{t,i} = f_{att}(s_{t-1}, h_i)$ (f_{att} is an MLP)

From final hidden state:
Initial decoder state s_0



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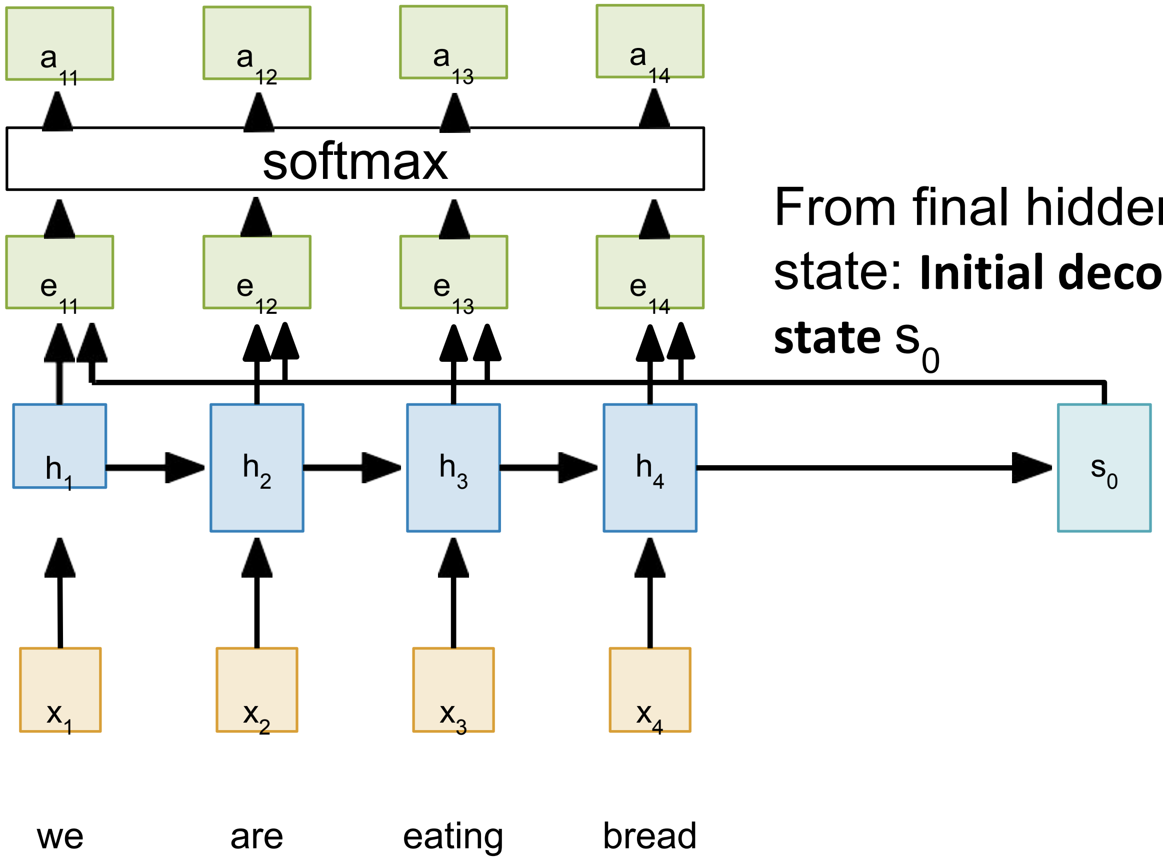
Sequence to Sequence with RNNs and Attention



From final hidden state: **Initial decoder state** s_0

Compute (scalar) **alignment scores**

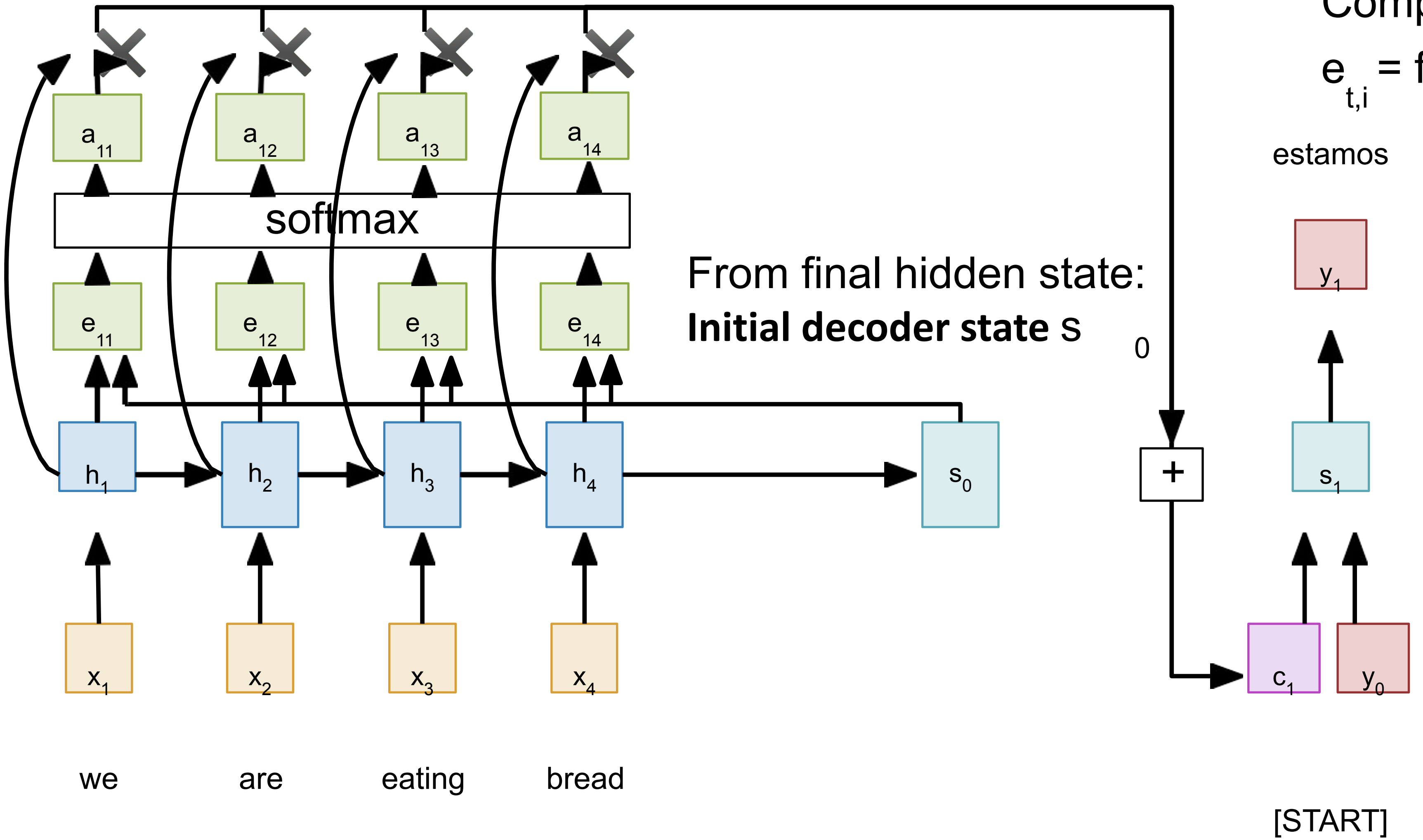
$e_{t,i} = f_{att}(s_{t-1}, h_i)$ (f_{att} is an MLP)

Normalize alignment scores to get **attention weights**

$0 < a_{t,i} < 1$ $\sum_i a_{t,i} = 1$

Bahdanau et al, “Neural machine translation by jointly learning to align and translate”, ICLR 2015

Sequence to Sequence with RNNs and Attention



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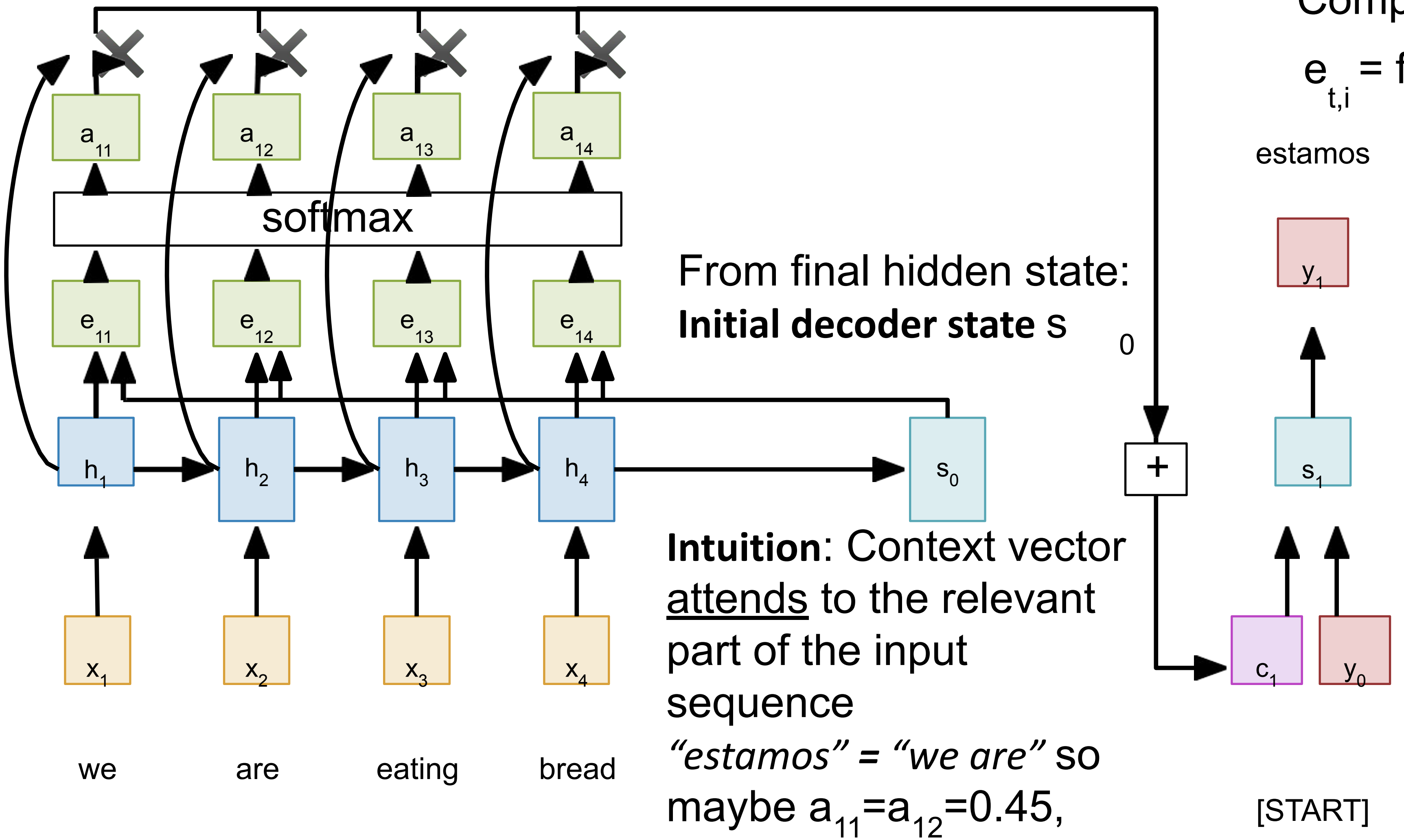
Compute context vector as linear combination of hidden states

$c_t = \sum_i a_{t,i} h_i$

Bahdanau et al, "Neural machine translation by jointly learning to align and translate", ICLR 2015

Sequence to Sequence with RNNs and Attention



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$0 < a_{t,i} < 1$ $\sum_i a_{t,i} = 1$

Compute context vector as linear combination of hidden states

$c_t = \sum_i a_{t,i} h_i$

Use context vector in decoder: $s_t = g_U(y_{t-1}, s_{t-1}, c_t)$

Intuition: Context vector <u>attends</u> to the relevant part of the input sequence

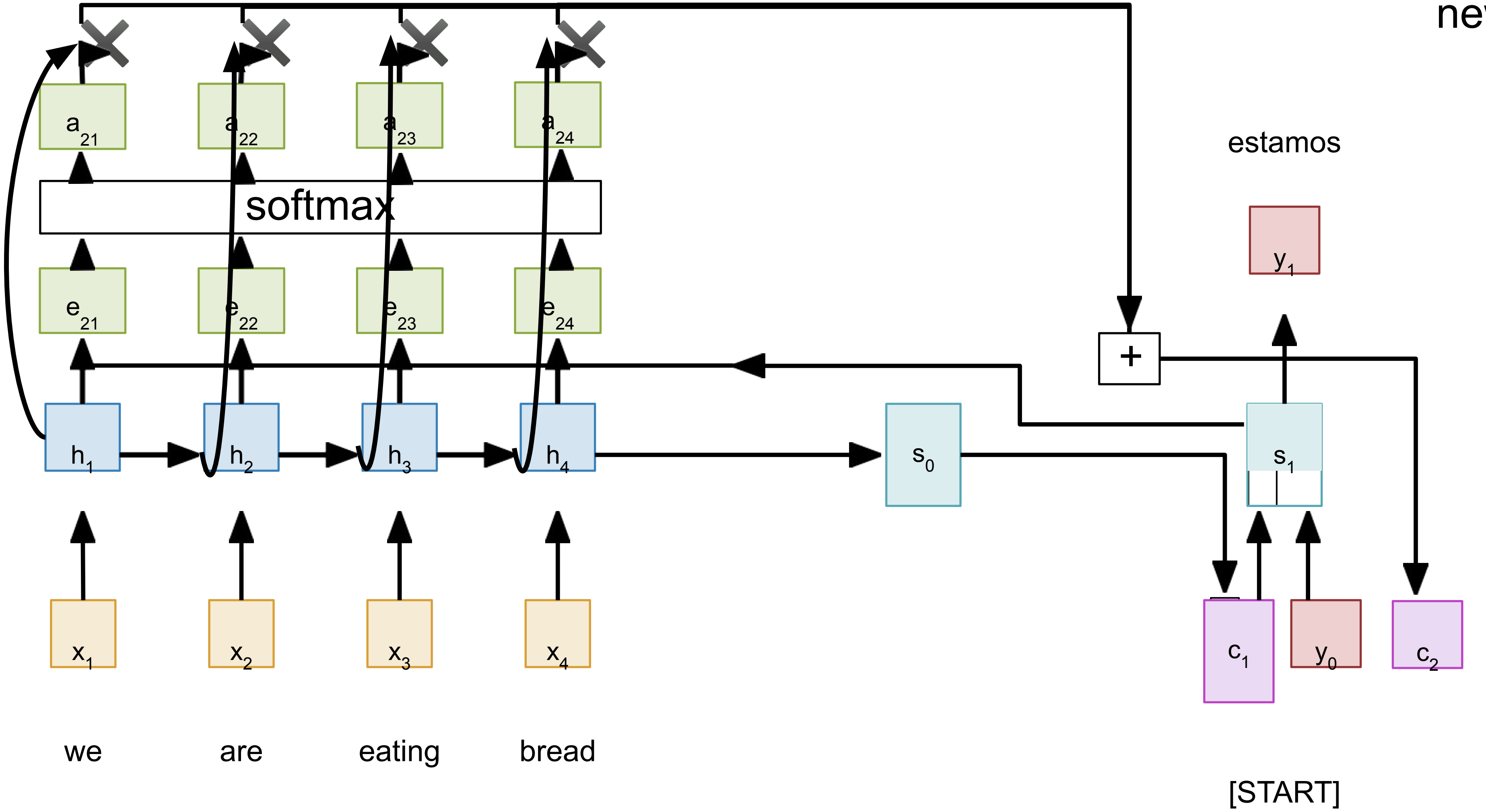
"estamos" = "we are" so maybe $a_{11}=a_{12}=0.45$, $a_{13}=a_{14}=0.05$

This is all differentiable! No supervision on attention weights – backprop through everything

Bahdanau et al, "Neural machine translation by jointly learning to align and translate", ICLR 2015

Sequence to Sequence with RNNs and Attention

Repeat: Use s_1 to compute new context vector c_2

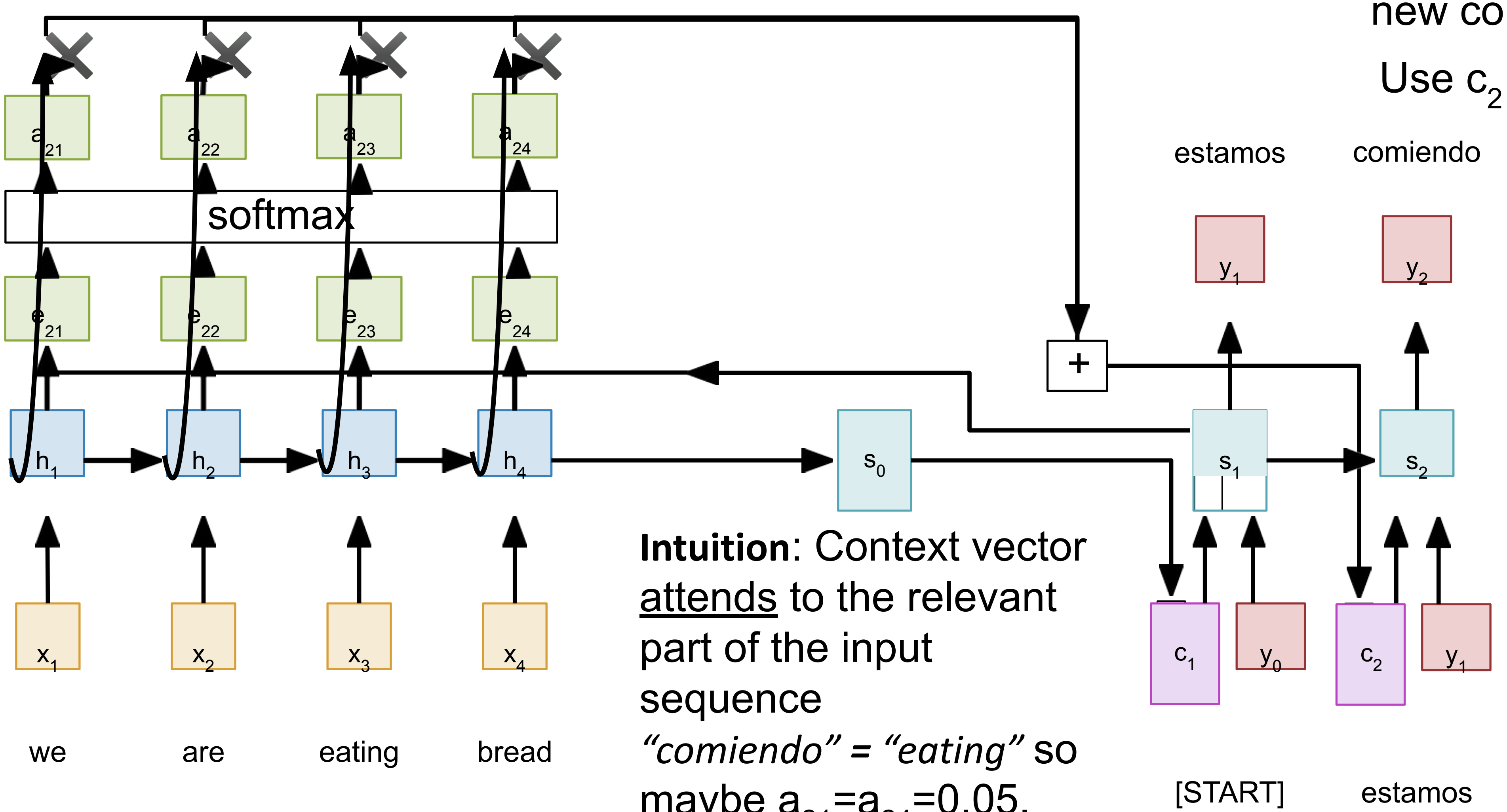


Bahdanau et al, “Neural machine translation by jointly learning to align and translate”, ICLR 2015

Sequence to Sequence with RNNs and Attention

Repeat: Use s_1 to compute new context vector c_2

Use c_2 to compute s_2, y_2



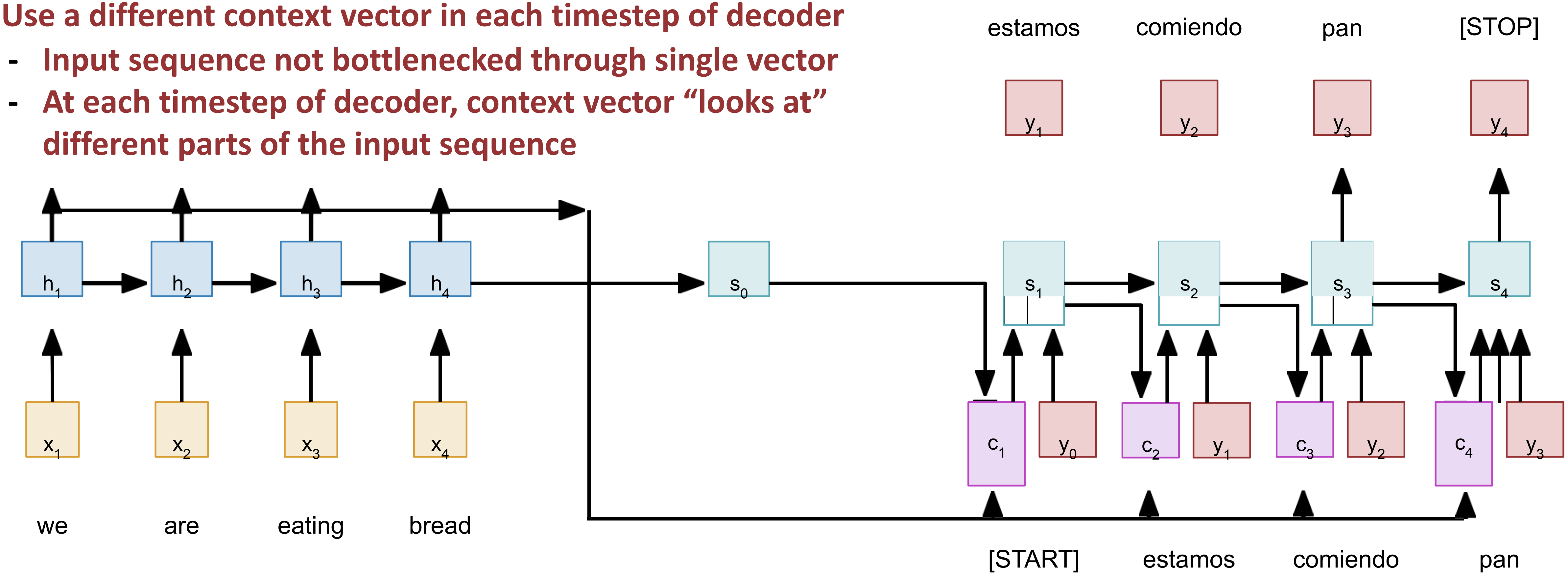
Intuition: Context vector attends to the relevant part of the input sequence

"comiendo" = "eating" so maybe $a_{21}=a_{24}=0.05$, $a_{22}=0.1$, $a_{23}=0.8$

Sequence to Sequence with RNNs and Attention

Use a different context vector in each timestep of decoder

- **Input sequence not bottlenecked through single vector**
- **At each timestep of decoder, context vector "looks at" different parts of the input sequence**



Bahdanau et al, "Neural machine translation by jointly learning to align and translate", ICLR 2015

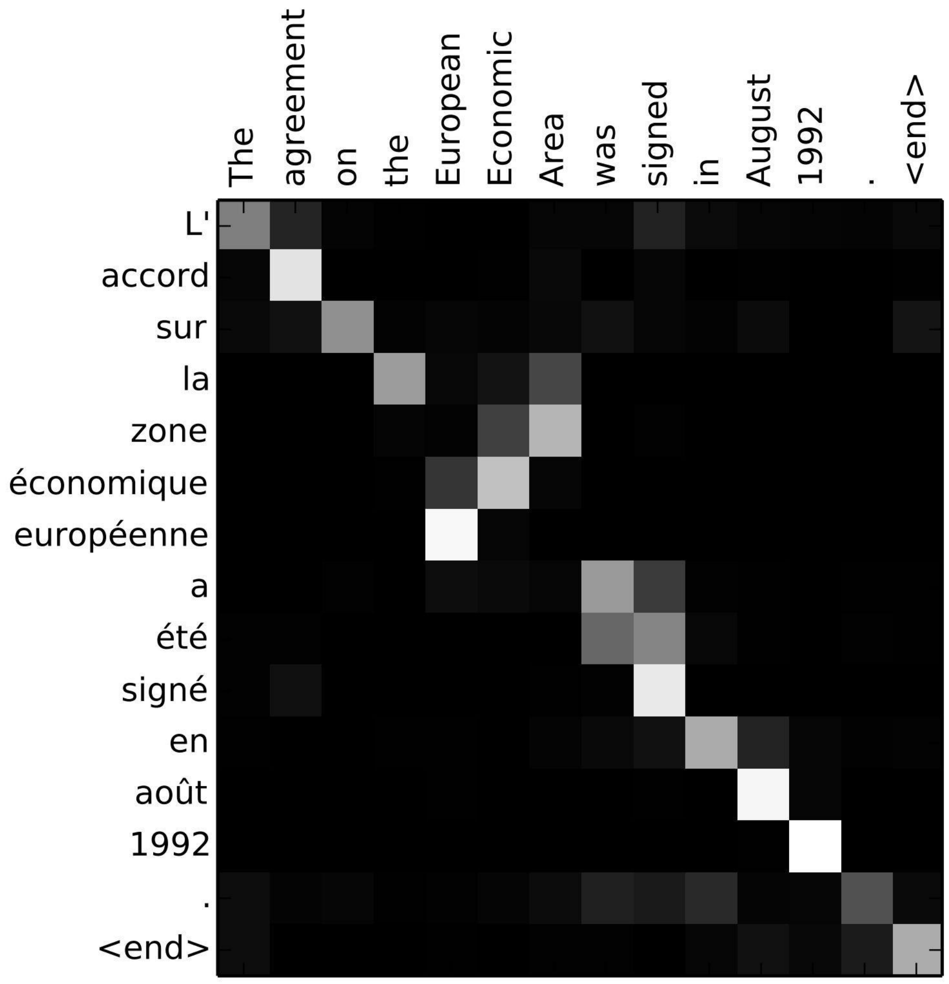
Sequence to Sequence with RNNs and Attention

Example: English to French translation

Input: “The agreement on the European Economic Area was signed in August 1992.”

Output: “L’accord sur la zone économique européenne a été signé en août 1992.”

Visualize attention weights $a_{t,i}$



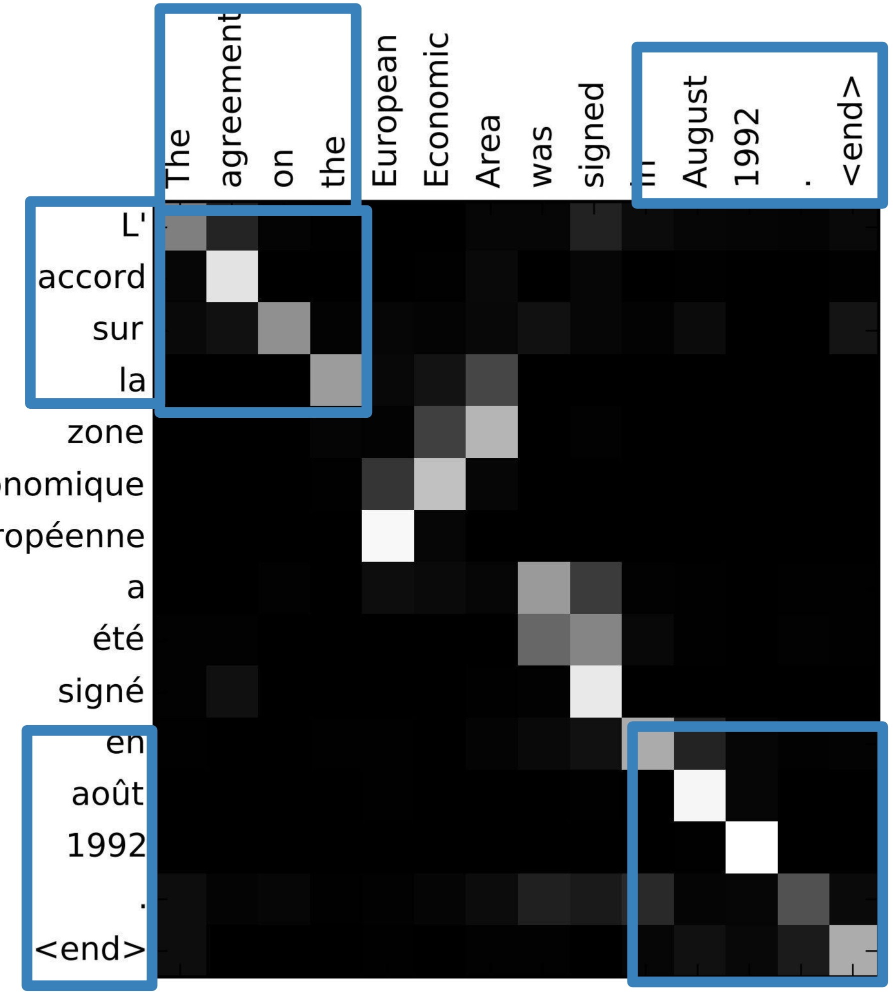
Sequence to Sequence with RNNs and Attention

Example: English to French translation

Input: "**The agreement on the** European Economic Area was signed **in August 1992**."

Output: "**L'accord sur la** zone économique européenne a été signé **en août 1992**."

Visualize attention weights $a_{t,i}$



Diagonal attention means words correspond in order

Diagonal attention means words correspond in order

Sequence to Sequence with RNNs and Attention

Example: English to French translation

Input: "The agreement on the European Economic Area was signed in August 1992."

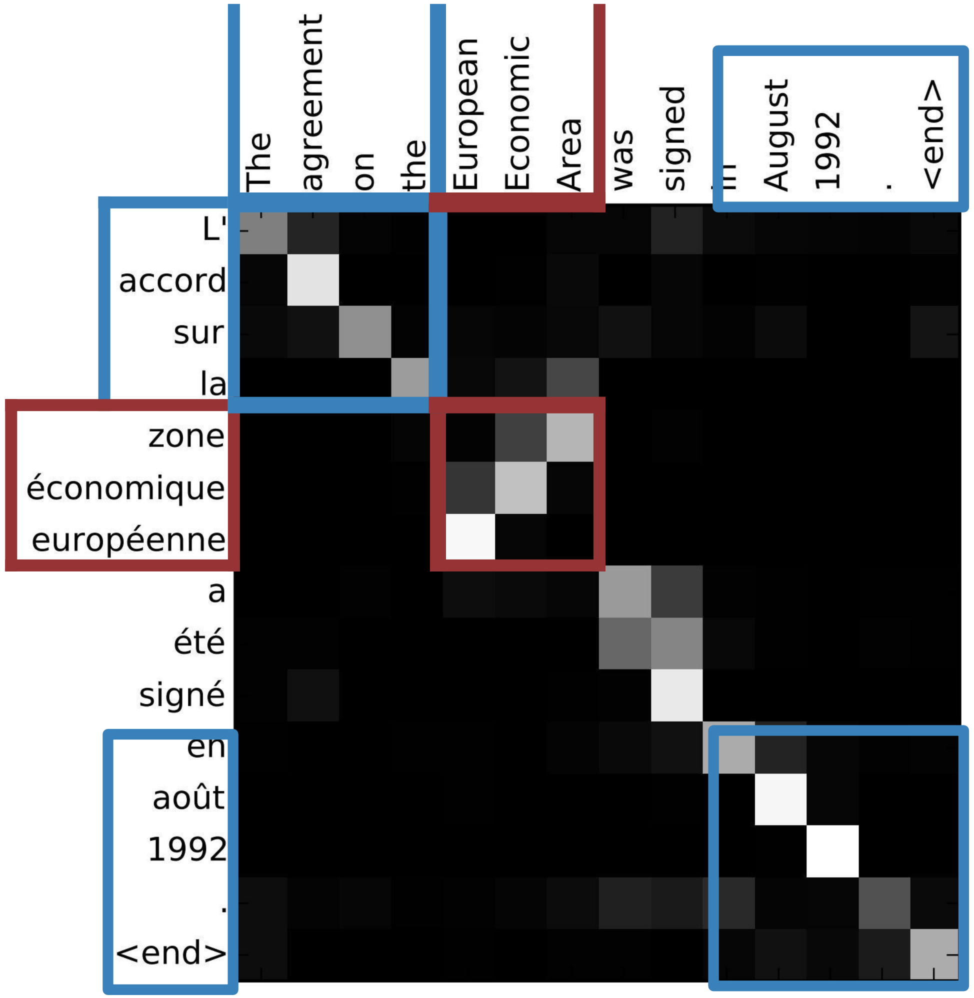
Output: "L'accord sur la zone économique européenne a été signé en août 1992."

Diagonal attention means words correspond in order

Attention figures out different word orders

Diagonal attention means words correspond in order

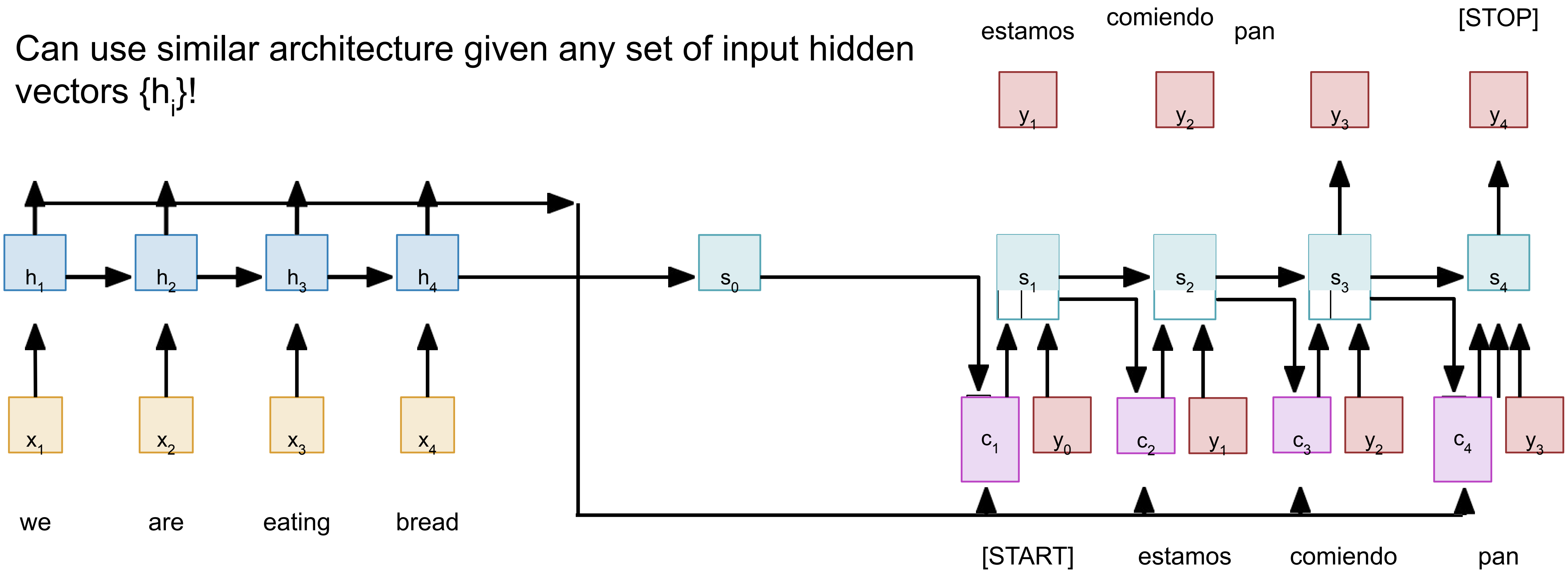
Visualize attention weights $a_{t,i}$



Sequence to Sequence with RNNs and Attention

The decoder doesn't use the fact that h_i form an ordered sequence – it just treats them as an unordered set $\{h_i\}$

Can use similar architecture given any set of input hidden vectors $\{h_i\}$!

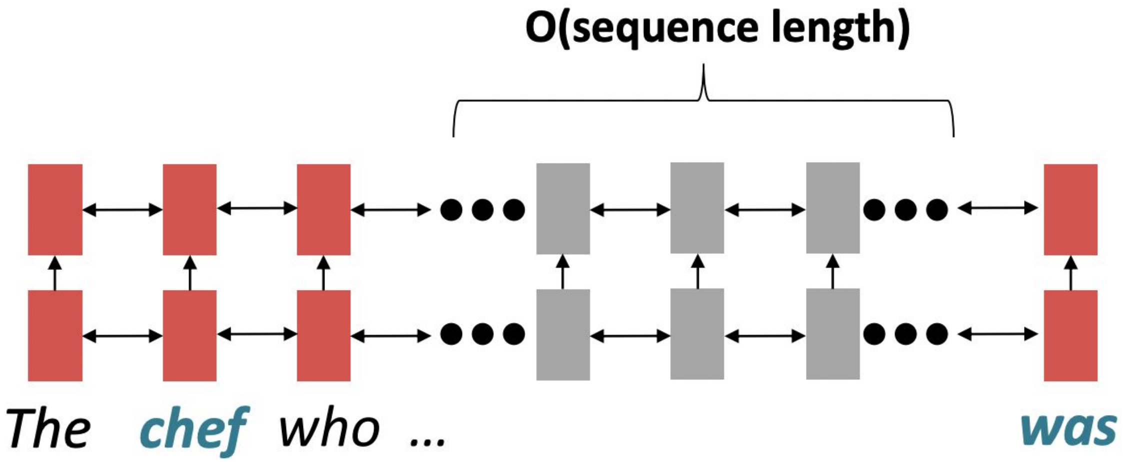


Transformers - Motivation

RNN – Linear Interaction Distance/Non-parallelizable

- RNNs are unrolled “left-to-right”.
- Useful: Nearby words often affect each other’s meanings

- Problem: RNNs take O(sequence length) steps for distant word pairs to interact
- Problem: Linear Order is “baked in”. Not sure that is best.
  - Right-to-left
  - Left-to-right
  - Bi-directional RNNs.

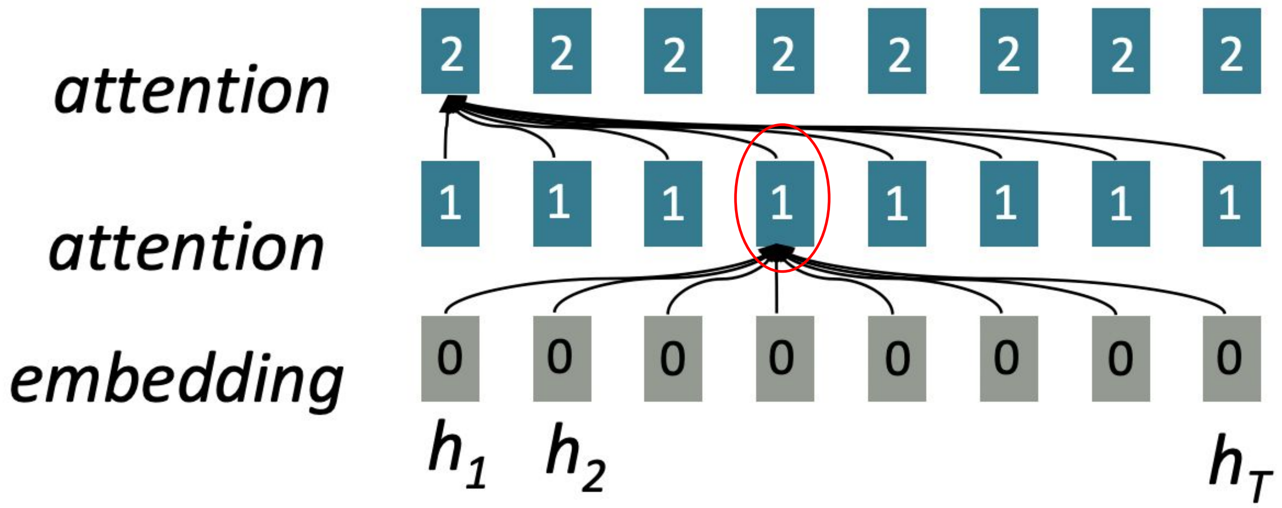


Recurrence to Attention

- Attention treats each word's representation as a query to access and incorporate information from a set of values.
  - For example, Layer 2 each node j computes

$$\sum_{i=1}^{T} \alpha_i w_{ij} h_i, \text{ s.t. } \Sigma_i \alpha_i = 1$$

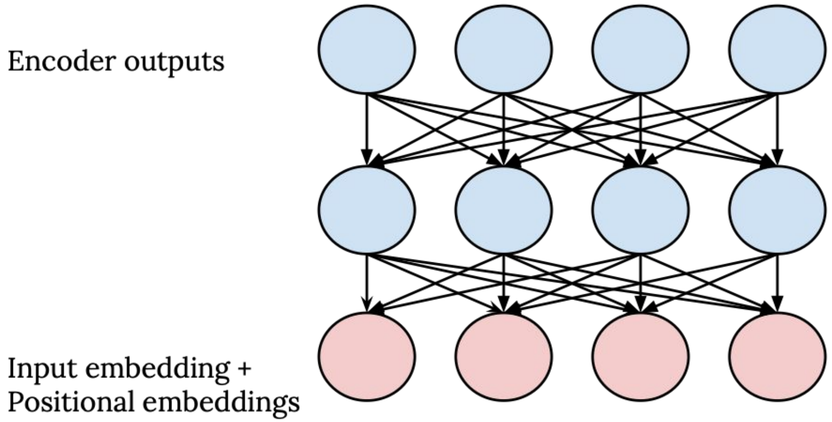
- Max. interaction distance: O(1).



Transformers - Motivation

How can we speed up the encoding process of sequences?

- Remove the recurrent connection (from RNNs)
- Only use attention

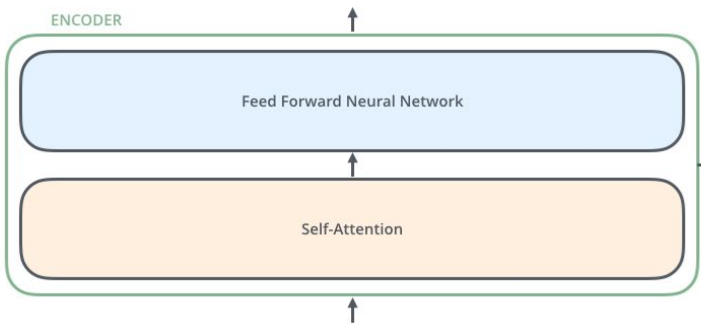


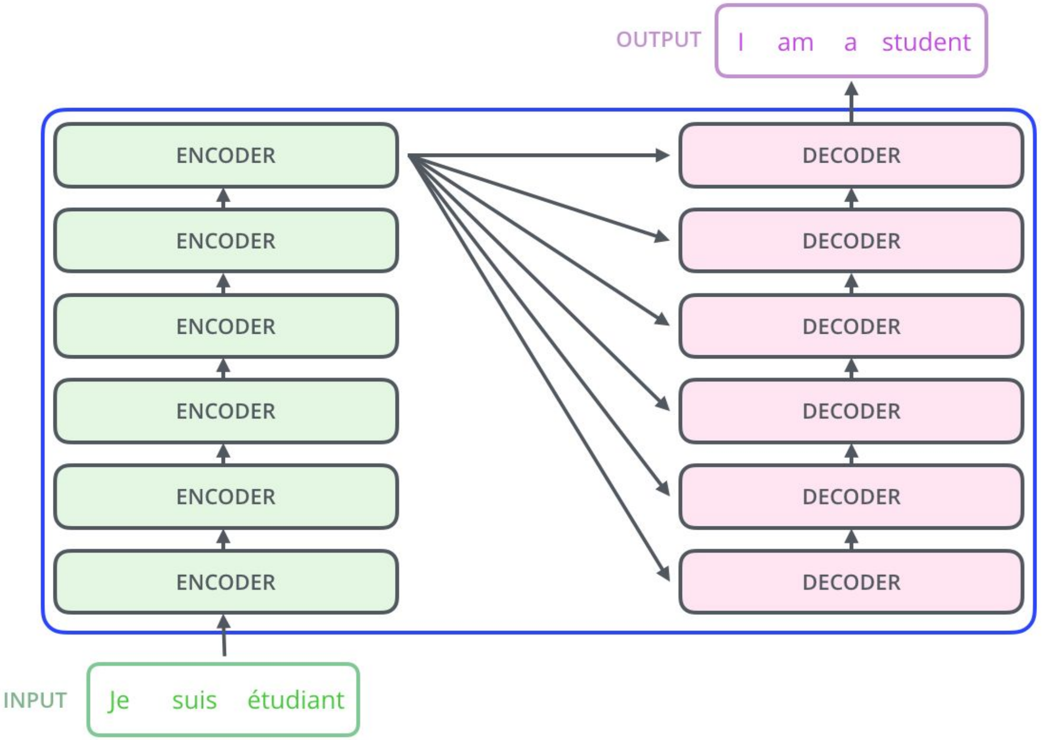
- But No order?
- No nonlinearities. Just weighted average

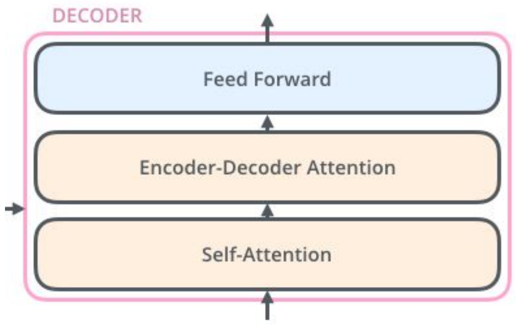
Solution:

- Positional Embeddings (encode positions as vectors)
- Add non-linearities using separate layers
  FFN+BatchNorm

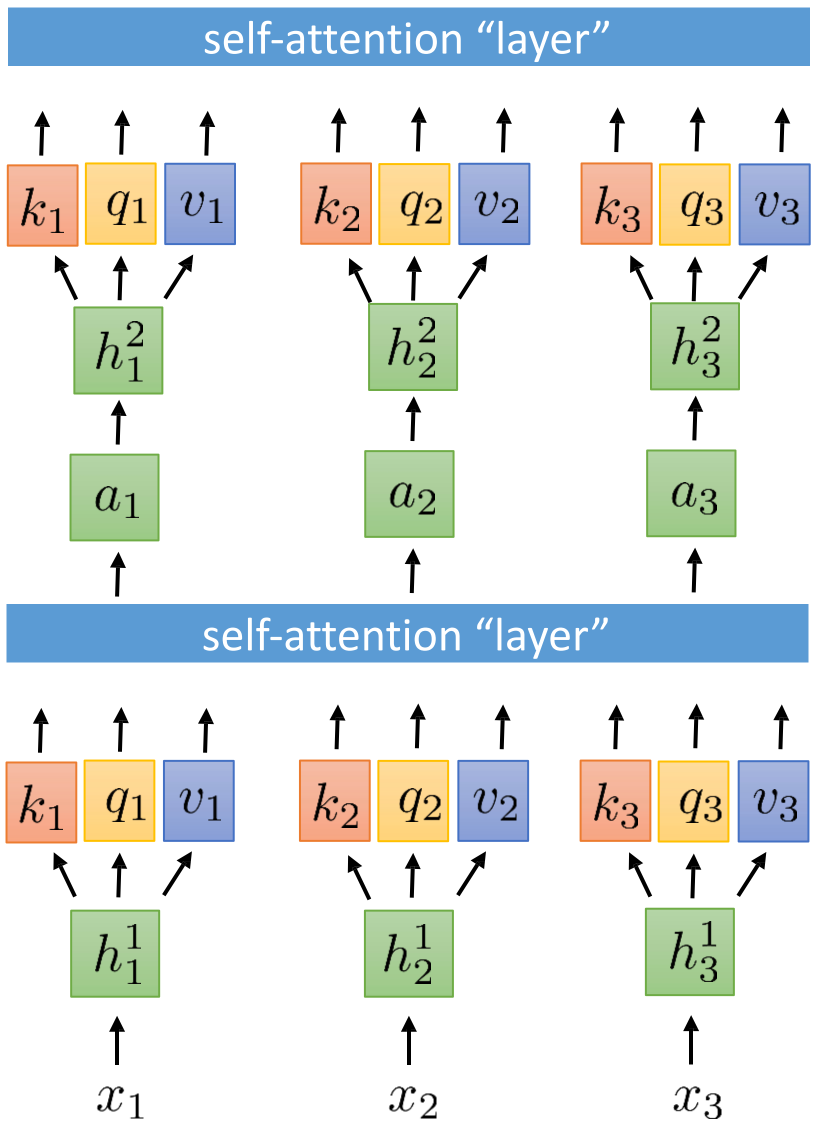
Transformer: Structure







Transformer summary



- Alternate self-attention "layers" with nonlinear position-wise feedforward networks (to get nonlinear transformations)
- Use positional encoding to make the model aware of relative positions of tokens
- Use multi-head attention
- Use masked attention if you want to use the model for decoding.

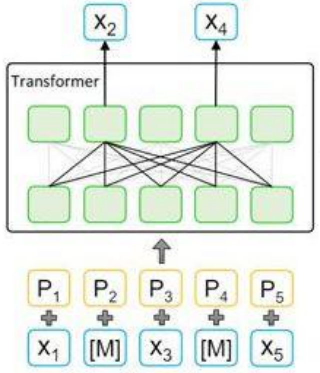
Self-supervised Models (Unsupervised Pretraining)

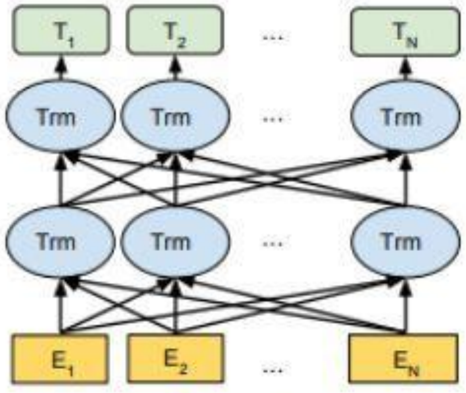
Incorporating context into word embeddings

a watershed idea in NLP

- BERT, 2018: Bidirectional Encoder Representations from Transformers (BERT, 2018)
- GPT

Led to significant improvements on virtually every NLP task.

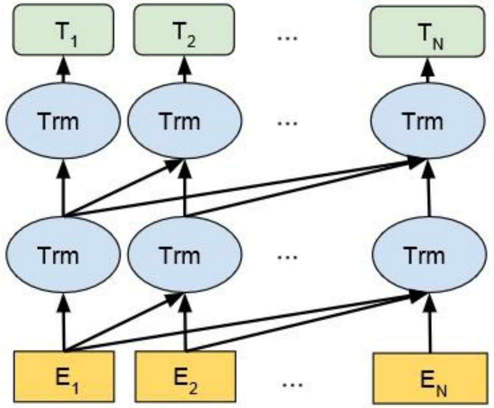




BERT Architecture

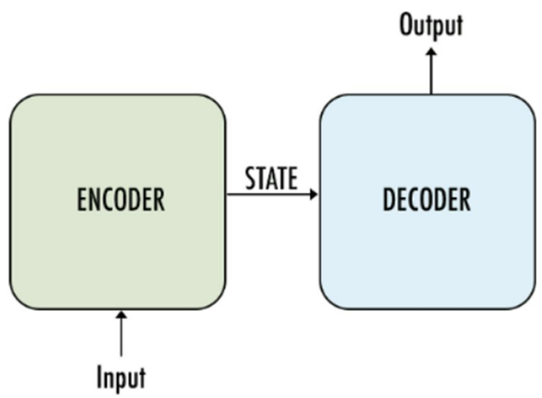
NLP

- Masked language modeling
- Predict the next word
- Next sentence prediction

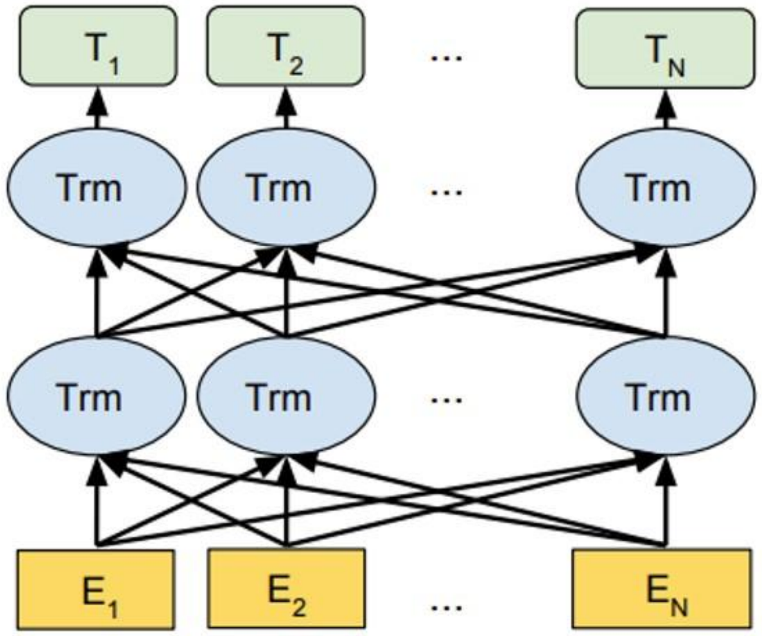


1. Build background knowledge
2. Approximate a form of common sense in AI systems.

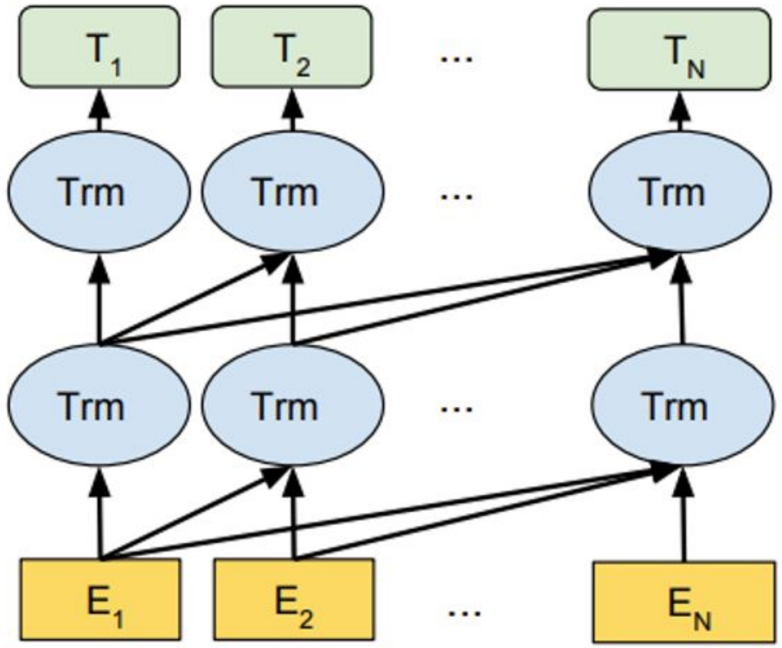
Self-attention encoder decoder



Parametric architectures for sentence denoising: Encoder

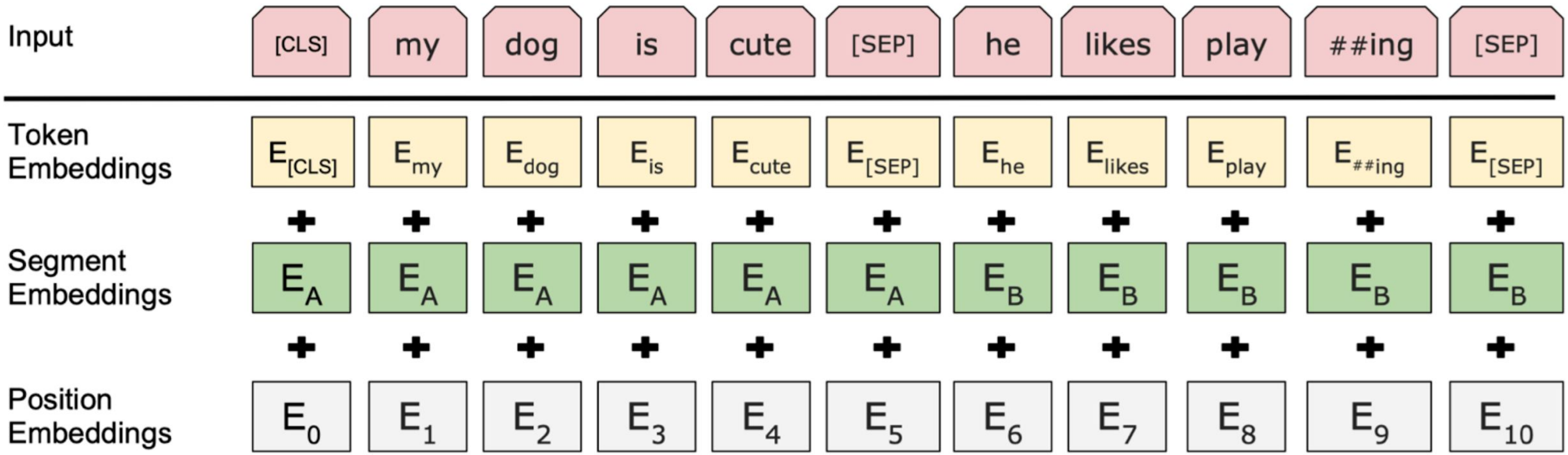


Parametric architectures for text completion: Decoder

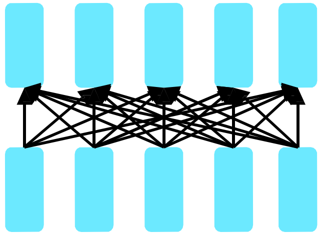


BERT

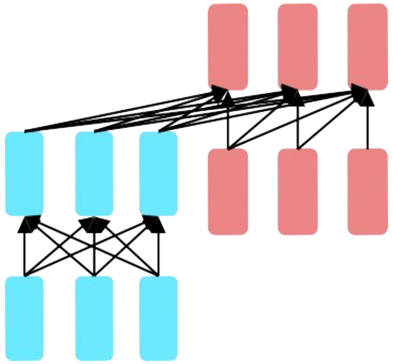
- multi-layer self-attention (Transformer)
- Input: a sentence or a pair of sentences with a separator and subword representation



Large Language Models

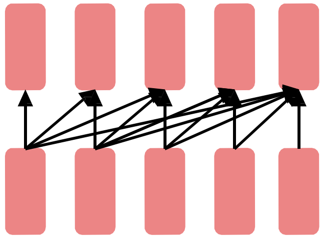


Encoders



Encoder-

Decoders



Decoders

A language model
- Models language
- Assigns probability to a sequence of words

- Encoder only models: BERT, RoBERTa, Electra
- Decoder only models: GPT-n
- Encoder-decoder models: full encoder, autoregressive decoder : T5, BART

Trained by Self-supervised learning on a huge corpus.

Pre-training allows language models to learn robust task-agnostic features

May be followed by

•Supervised fine-tuning for tasks

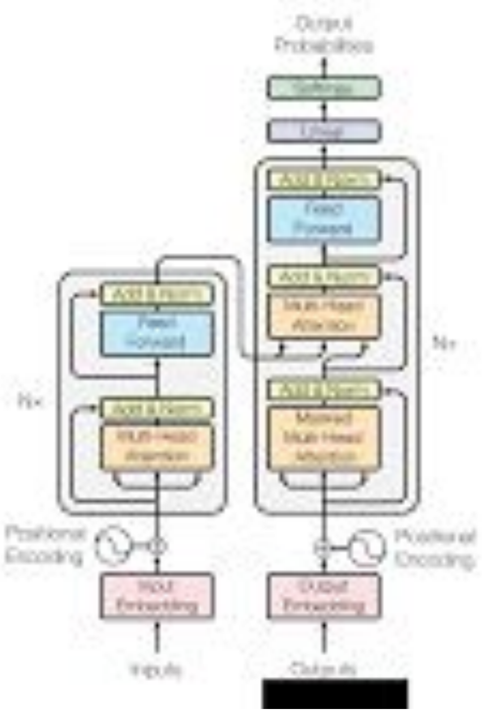
•Reinforcement learning with human feedback

The promise : One single model for many tasks

Three types of LLMs

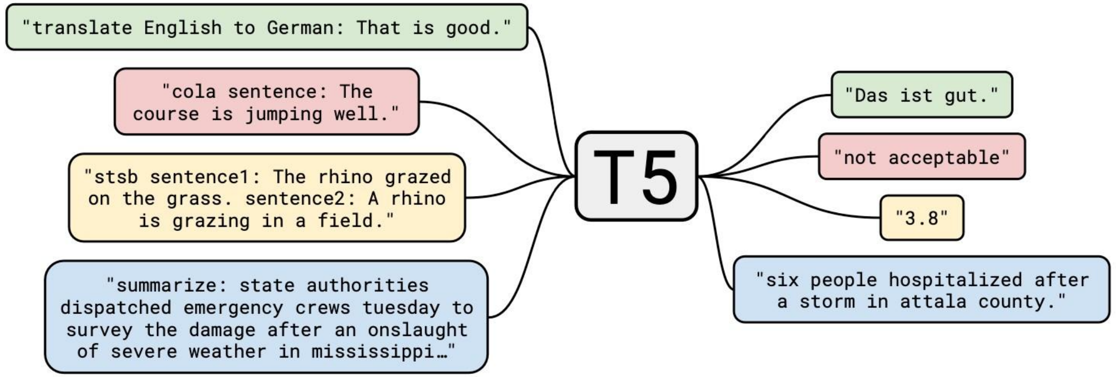
BERT

Encoder

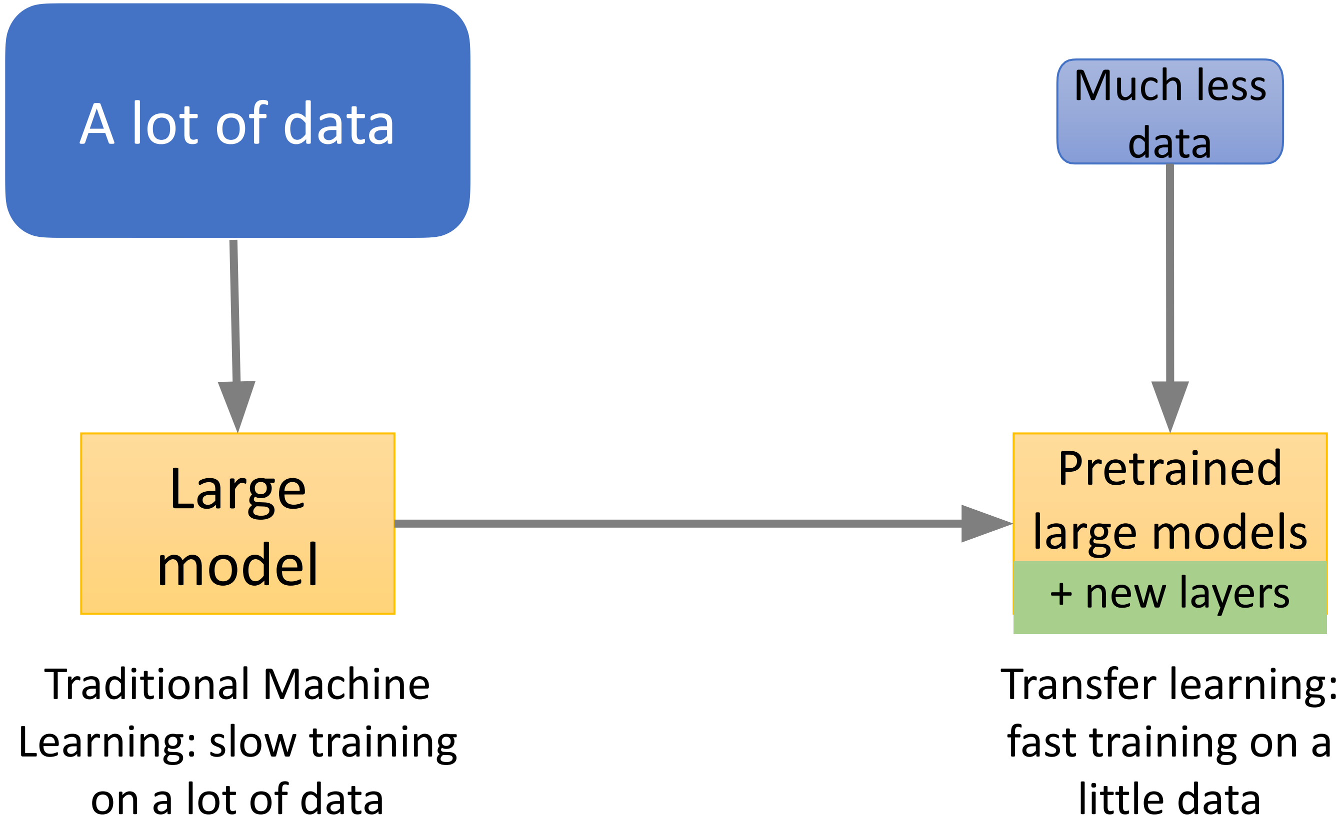


GPT

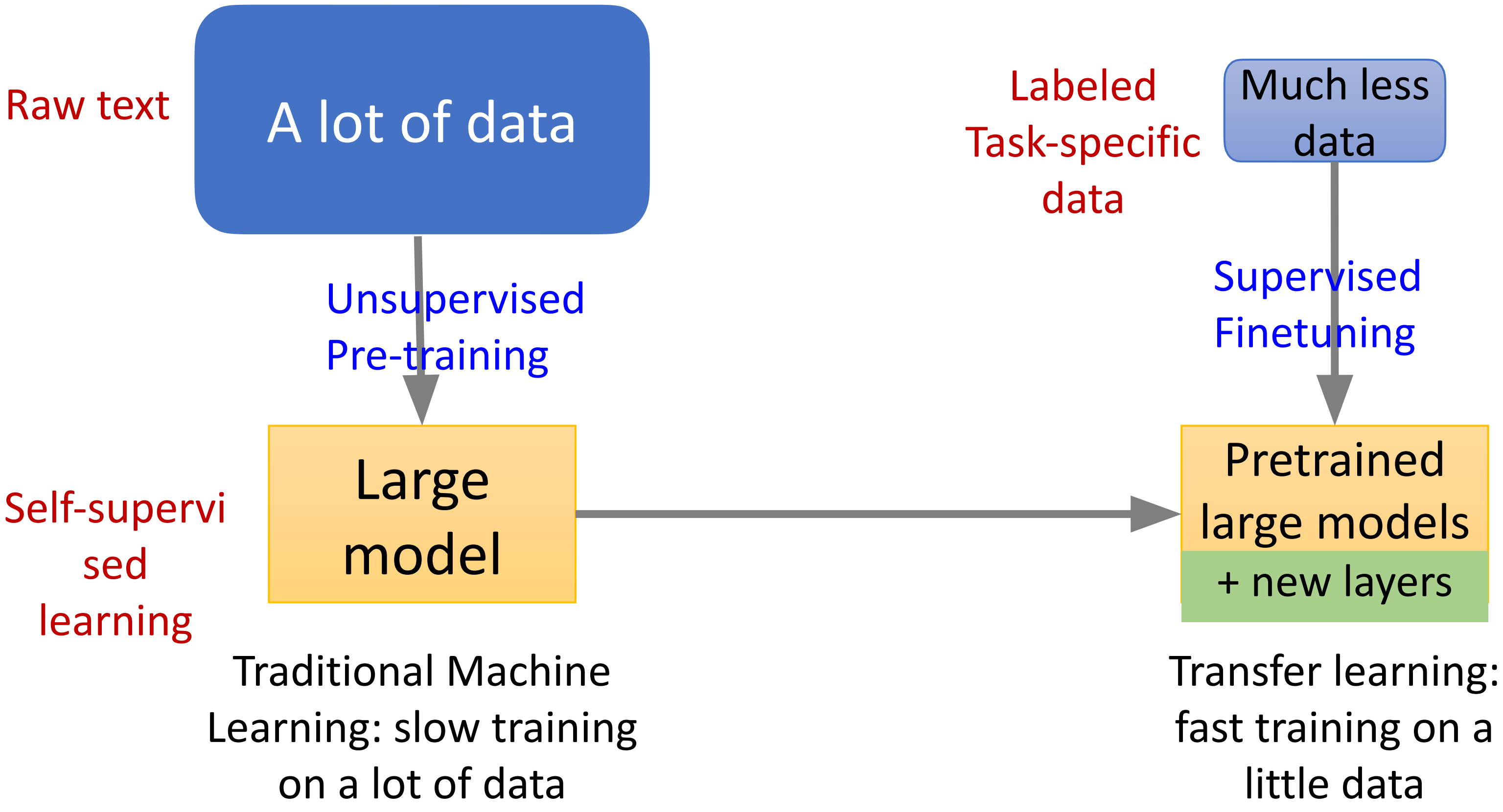
Decoder



Transfer Learning



Transfer Learning in NLP



How are LLMs applied in various tasks/domains?

- Previously
  - By adding task-specific layers on top of LLMs and fine-tuning them on labeled data of such tasks
  - Examples: Text classification, language translation, question-answering

- More recently
  - By prompt engineering/tuning, **without** changing LLM params
  - Design a prompt that elicits the desired output from the LLM
  - Example (English->French translation):

Translate the following English sentence [sentence input] *to French:* [model output]

Slide credit: Yuxiong Wang