Sequence to Sequence (seq2seq) + Attention

LING 575K Deep Learning for NLP

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Announcements

- HW2 grades coming soon; good job!
  - Not too much “tea leaf reading” on the 2D vectors: small scale, small data, etc
  - When in doubt, show more work / every step
- HW3 ref code available in hw3/ref on dropbox
- Edugrad, numpy, etc:
  - Numpy *only* inside of backward/forward methods of an Operation
  - @tensor_op: your Operations becomes methods that take Tensor arguments
  - With Tensors: must use these methods, not numpy
- Broadcasting/shapes in edugrad (lack thereof :))
  - Remember: annotate shapes!!
- Adagrad:
  - param._grad_hist: this is $G_{t,i}$
  - Order of operations: first update $G_{t,i}$, then apply update rule

```python
@tensor_op
class sigmoid(Operation):
    @staticmethod
    def forward(ctx, a):
        value = 1 / (1 + np.exp(-a))
        ctx.append(value)
        return value

    @staticmethod
    def backward(ctx, grad_output):
        value = ctx[-1]
        return [value * (1 - value) * grad_output]
```

```python
# [batch_size, embedding_dim]
target_vectors = self.embeddings(target_indices)
# [batch_size, embedding_dim]
context_vectors = self.context_embeddings(context_indices)
# [batch_size]
similarities = dot_product_rows(target_vectors, context_vectors)
# [batch_size]
probabilities = ops.sigmoid(similarities)
return probabilities
```

Today's Plan

- Last time: RNNs for sequence processing
  - Motivation (long-distance dependencies), Vanilla/Elman, stacked/bidirectional, classification and LM
- Today:
  - Vanishing gradient problem for vanilla RNNs
  - *Gating* mechanisms / fancier RNNs to overcome this (LSTM, GRU)
  - Sequence-to-sequence tasks/models
    - Attention mechanism

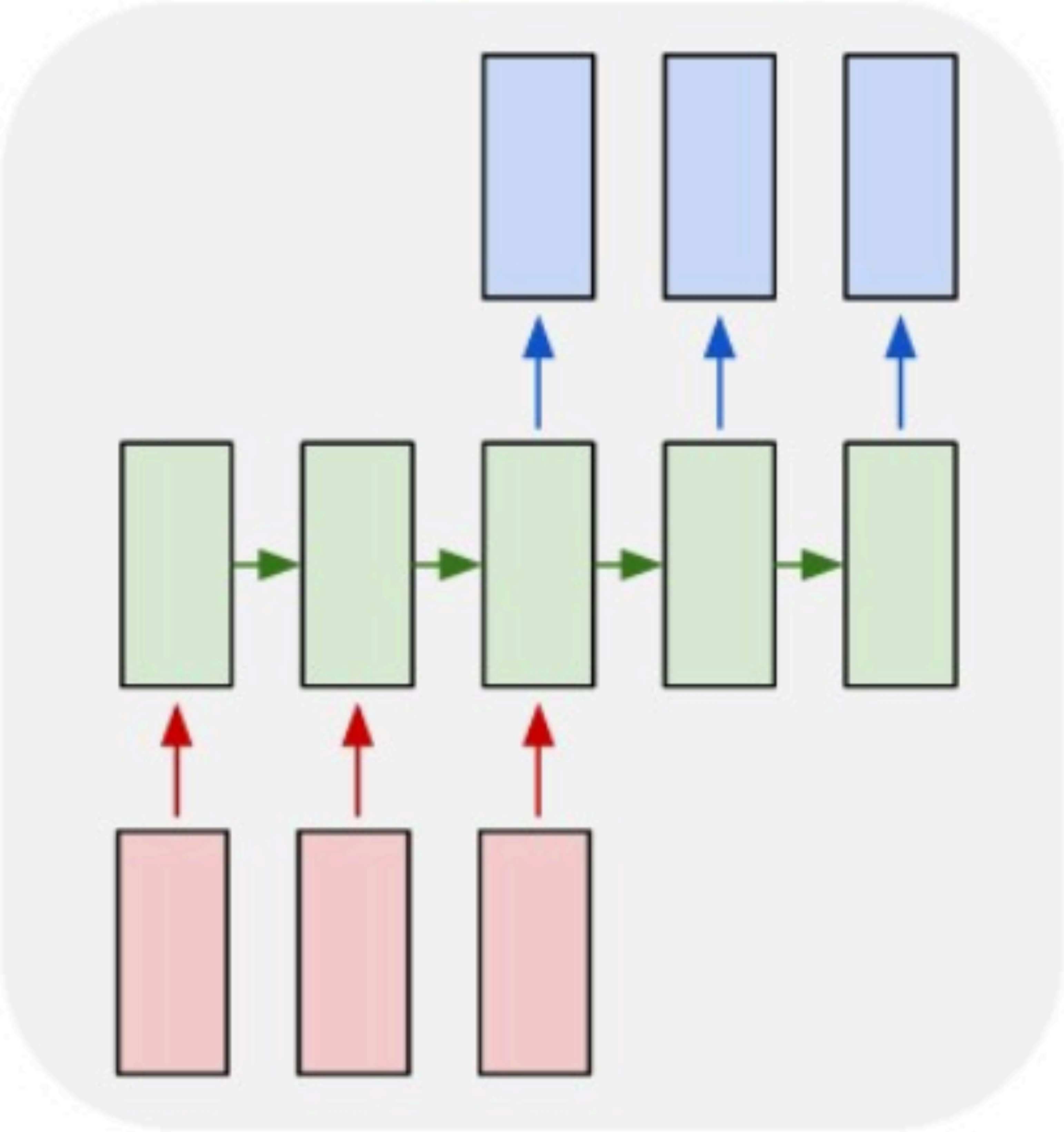
seq2seq: Overview

Sequence to sequence problems

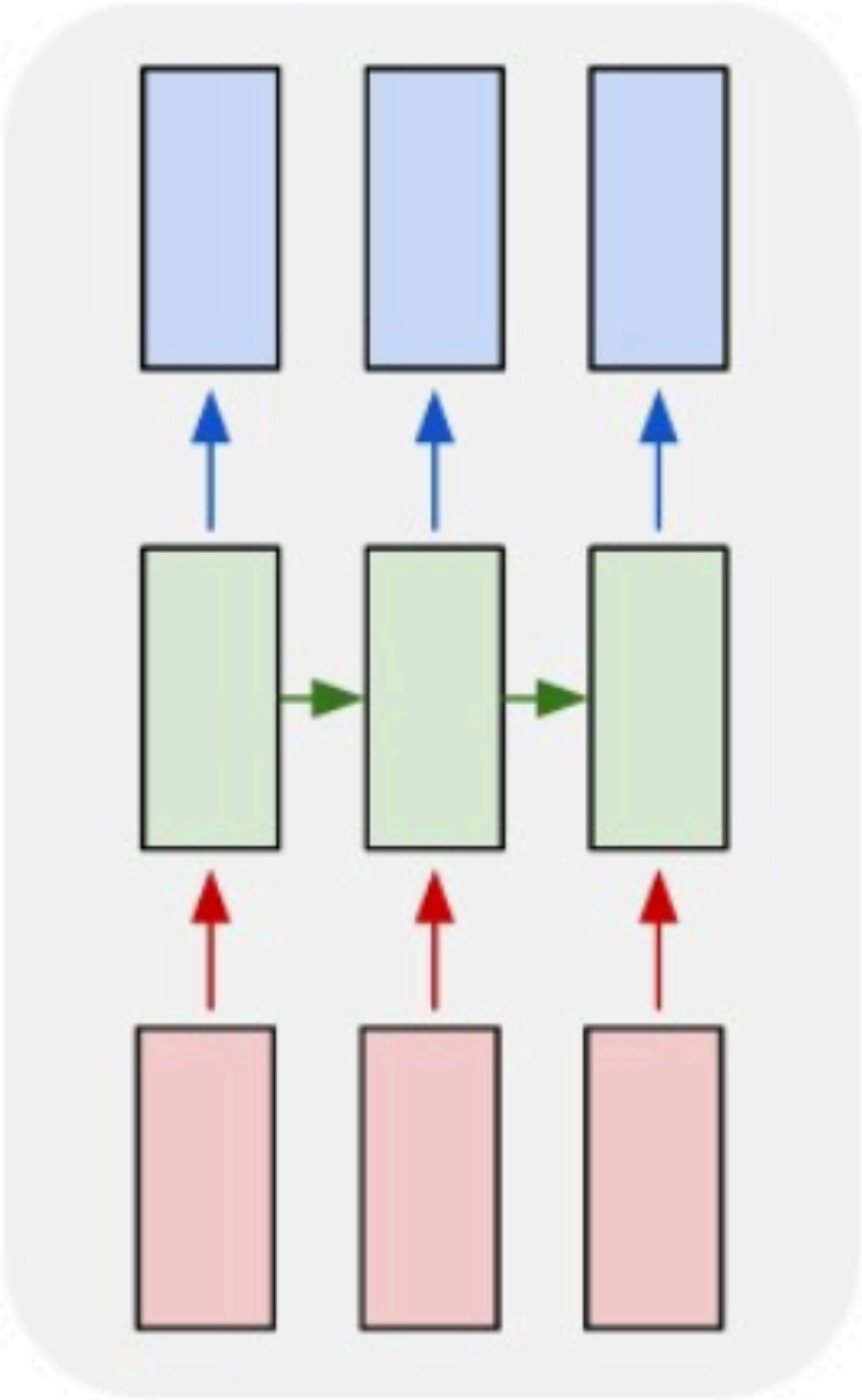
- Many NLP tasks can be construed as *sequence-to-sequence* problems
  - Machine translations: sequence of source lang tokens to sequence of target lang tokens
  - Parsing: “Shane talks.” —> “(S (NP (N Shane)) (VP V talks))”
    - Incl semantic parsing
  - Summarization
  - …
- NB: not the same as *tagging*, which assigns a label to each position in a given sequence

Seq2seq vs Tagging

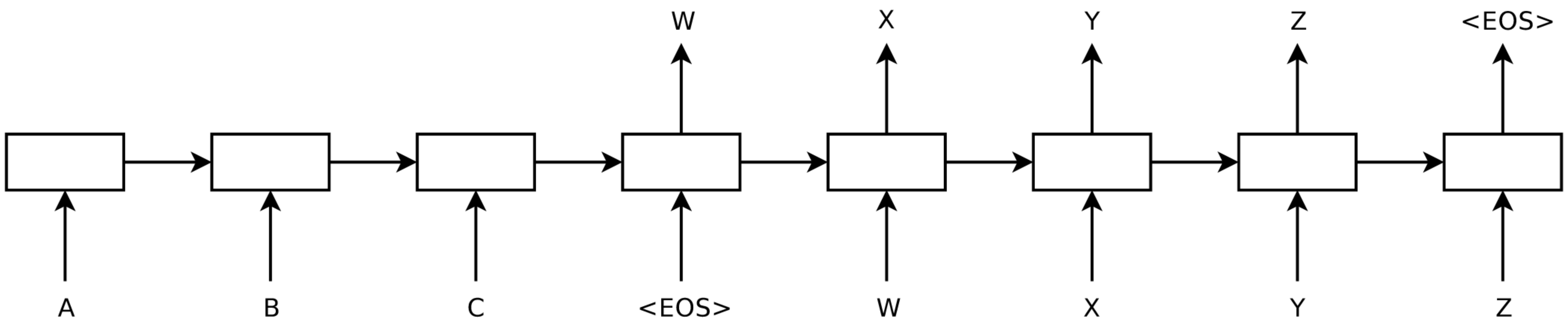
many to many



many to many



seq2seq architecture [e.g. NMT]



Sutskever et al 2013

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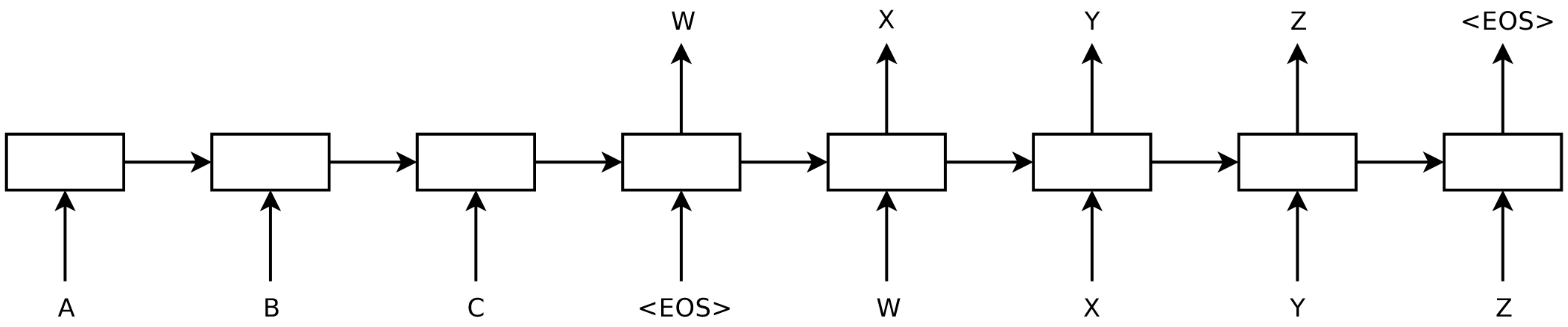

encoder

Sutskever et al 2013

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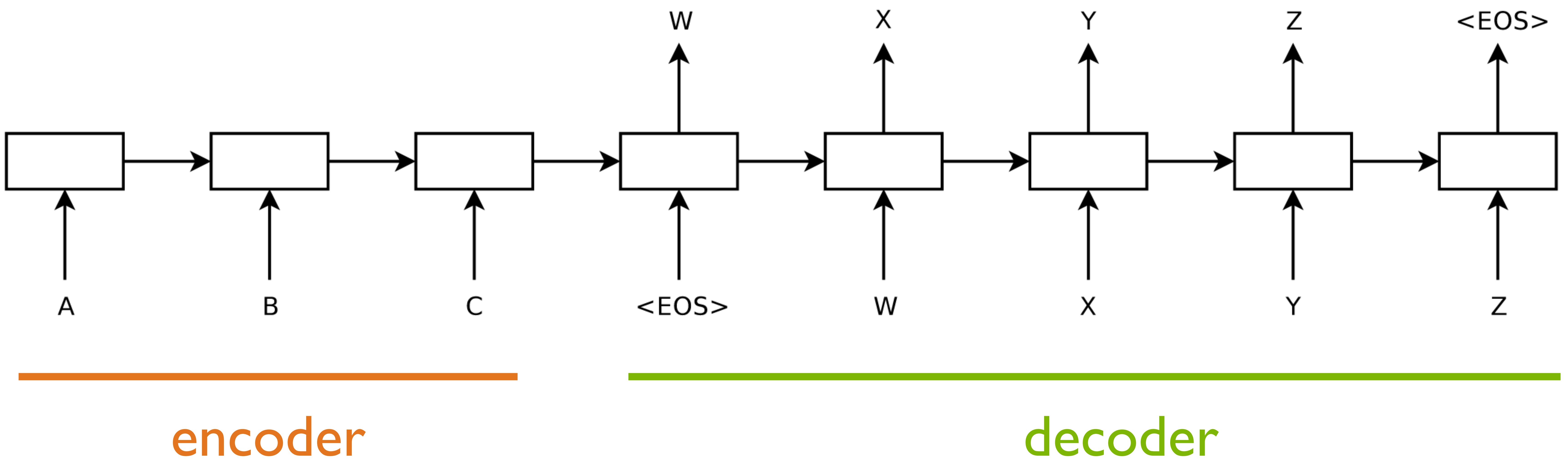

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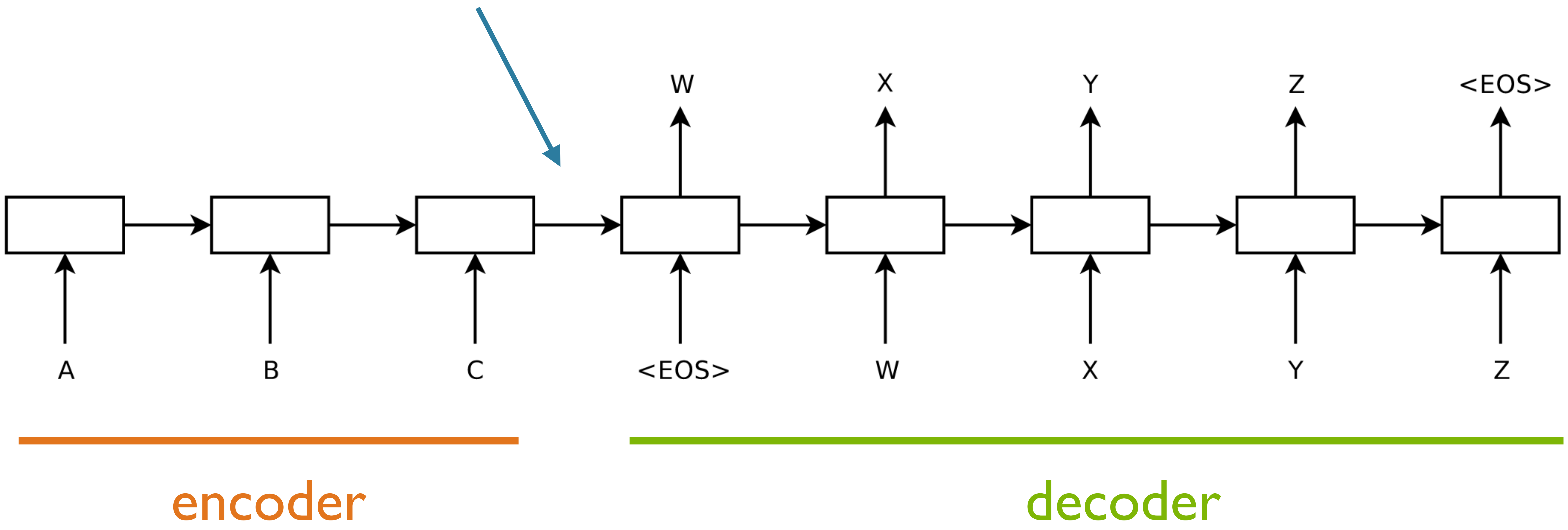
seq2seq architecture [e.g. NMT]

Initial hidden state of decoder =
final hidden state of encoder



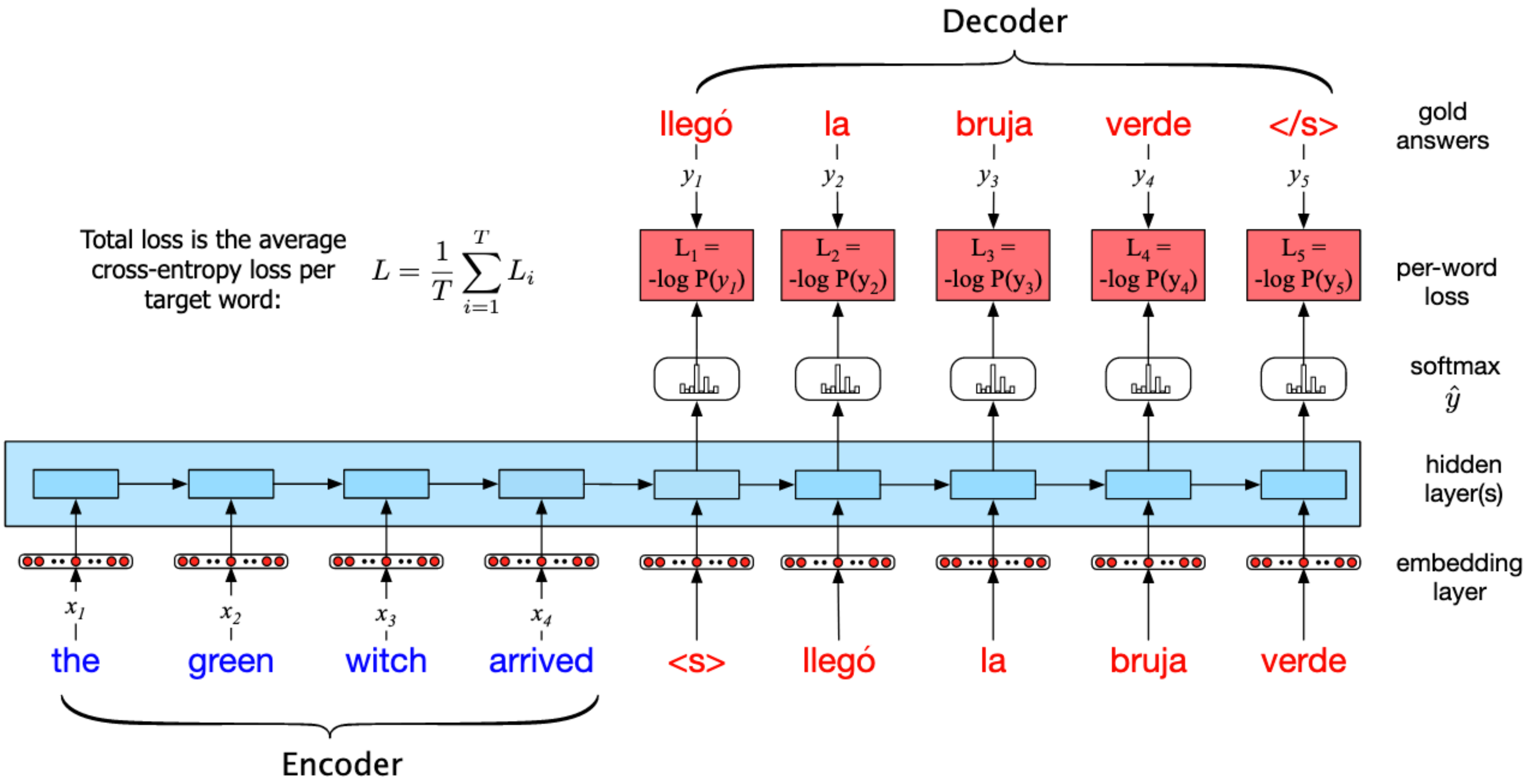
Sutskever et al 2013

seq2seq architecture

- Two components:
  - Encoder
    - Input sequence —> vector representation ("context" vector)
  - Decoder
    - Vector ("context" vector) —> Output sequence

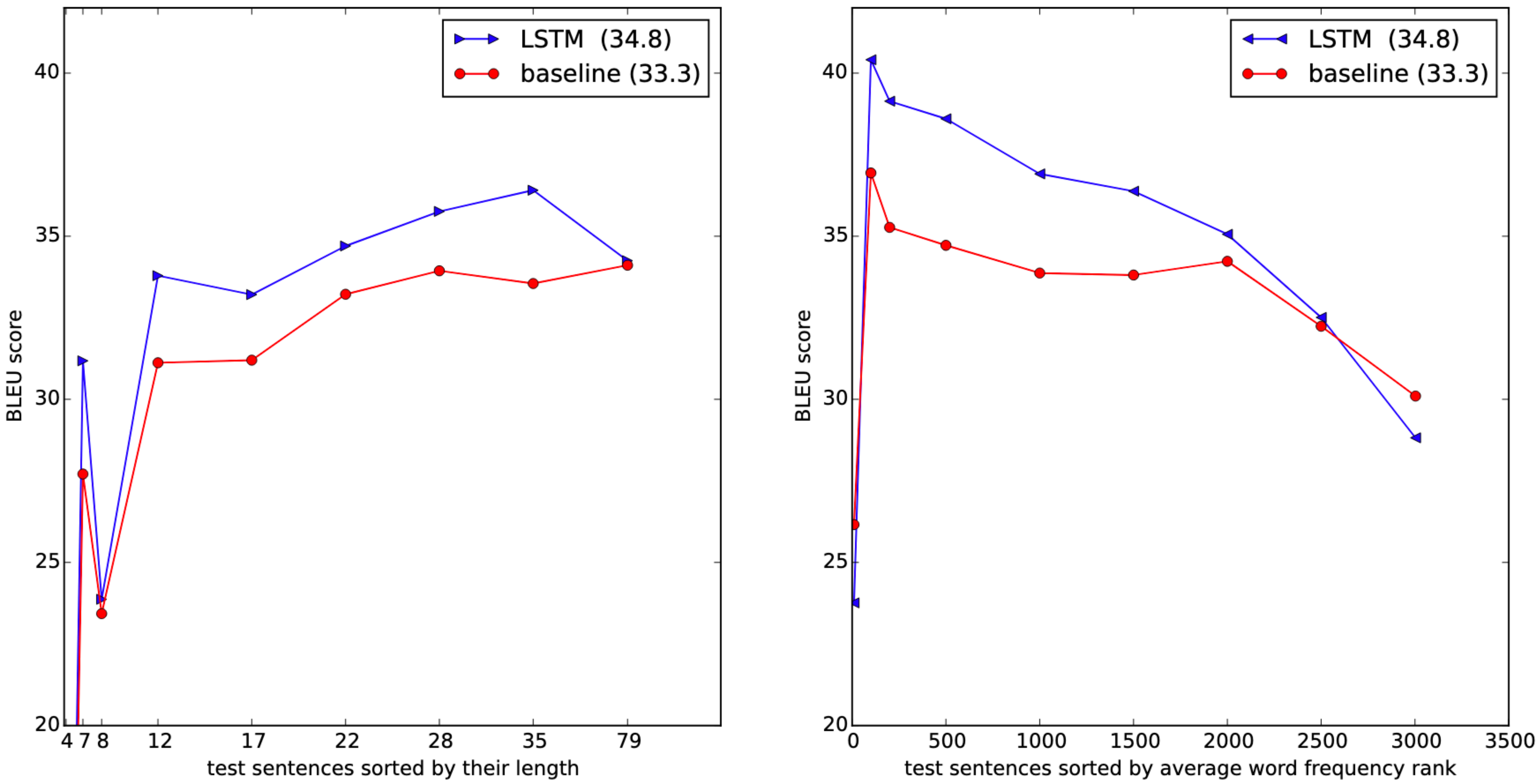
- High-level "API": encoder/decoder can be different architectures (LSTM, GRU, Transformer, convolutional, …)

Training an encoder-decoder RNN

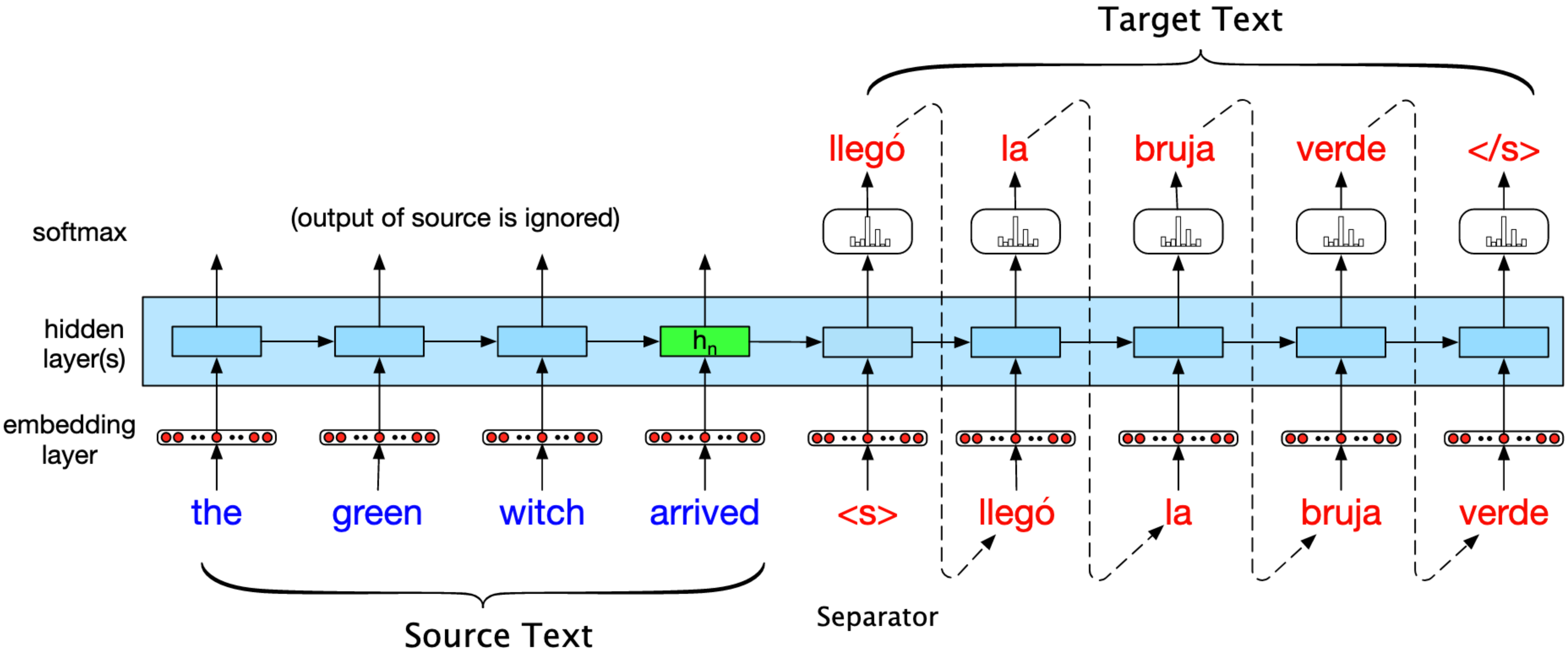


JM 11.3.1

seq2seq initial results



Inference / Generation



Seq2seq interim summary

- Effectively, a seq2seq model is a *conditional* language model: the same kind of language model that we have seen, but conditioned on the context of the input sequence

$$P(y \mid x) = \prod_{i=1}^{|y|} P(y_i \mid x, y_{<i})$$

NMT Evaluation

- "Ideal": human evaluation (fluency, adequacy, ranking)
- BLEU (BiLingual Evaluation Understudy): roughly, n-gram overlap between reference translations and machine translations
  - Penalizes synonymous translations
    - METEOR, BERTScore attempt to alleviate
  - Low correlation with human ratings
- chrF++
  - Refinement of *character* n-gram F1 score
  - Seems to have better correlations
- In general: still no perfect solution

Source

la verdad, cuya madre es la historia, émula del tiempo, depósito de las acciones, testigo de lo pasado, ejemplo y aviso de lo presente, advertencia de lo por venir.

Reference

truth, whose mother is history, rival of time, storehouse of deeds, witness for the past, example and counsel for the present, and warning for the future.

Candidate 1

truth, whose mother is history, voice of time, deposit of actions, witness for the past, example and warning for the present, and warning for the future

Candidate 2

the truth, which mother is the history, émula of the time, deposition of the shares, witness of the past, example and notice of the present, warning of it for coming

JM S11.8

Outstanding Issues in NMT

- Evaluation: automated metrics are all flawed
  - "Tangled Up in BLEU"
- Low-resource / unsupervised MT
  - Can we build good translation models in the absence of huge amounts of parallel text?
    - Common technique: *backtranslation*
  - http://www.statmt.org/wmt20/unsup_and_very_low_res/
  - http://turing.iimas.unam.mx/americasnlp/st.html
  - https://www.aclweb.org/anthology/2020.acl-main.560/

Statistical Machine Translation: Alignment

Statistical Machine Translation (90s-2010s)

- Goal: find best translation *y* (e.g. English) of source sentence *x* (e.g. French)

$$\arg\max_y P(y \mid x)$$

- Use Bayes to decompose into two components:

$$\arg\max_y P(x \mid y) P(y)$$

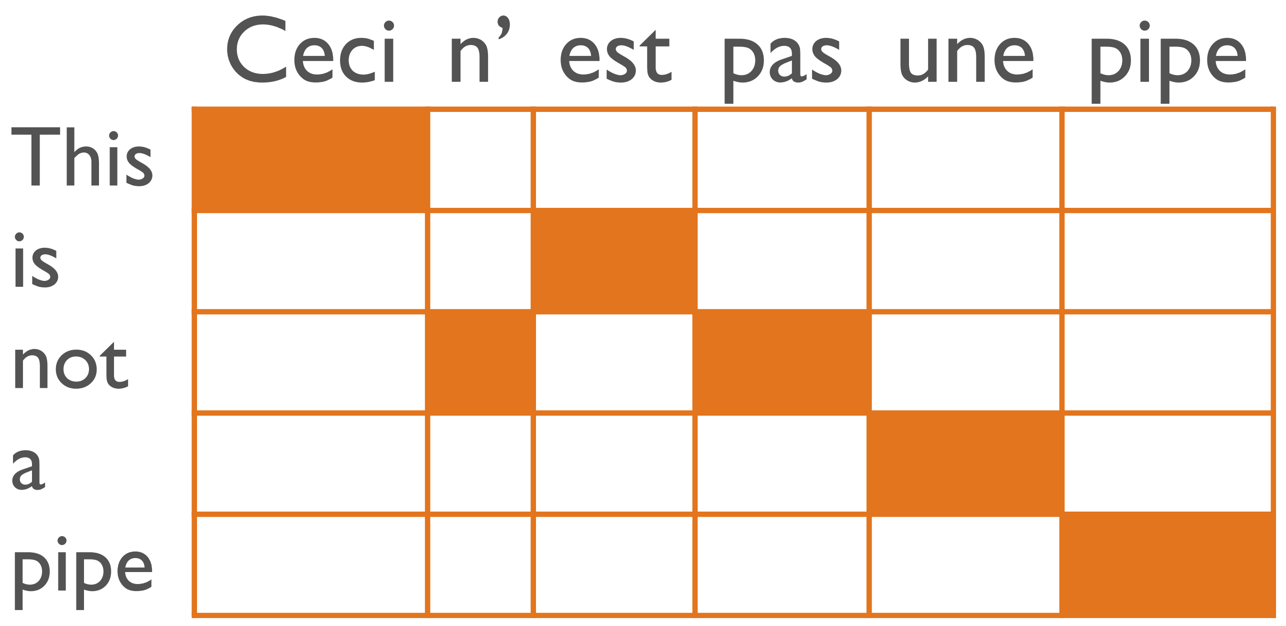
  - Core translation model P(x|y)
  - Language model P(y): produce good / fluent target language text (e.g. English)

Alignment

- Most SMT systems factored through an *alignment*
  - Correspondence between words/phrases in source and target sentence
  - Typologically different languages have, e.g., very different word order (see JM 11.1 for more examples)
- Add alignment as a latent variable:

$$P(x, a \mid y)$$

Alignment, example



Alignment, example

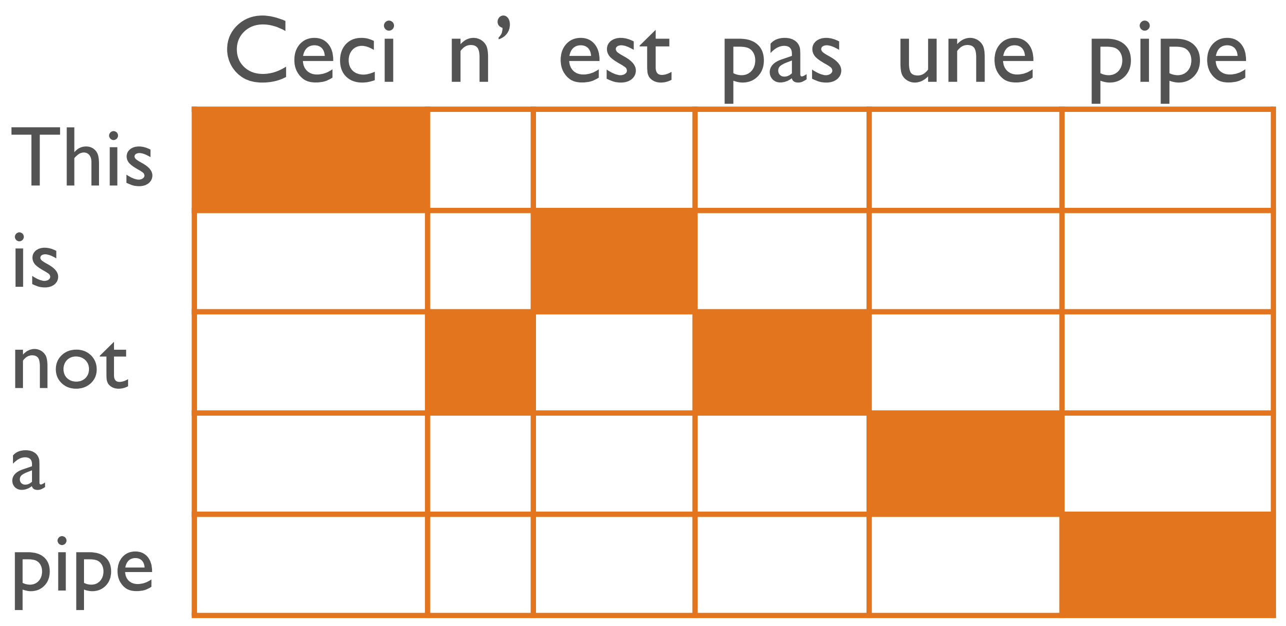
Ceci n’ est pas une pipe

	Ceci	n’	est	pas	une	pipe
This	■					
is			■			
not		■		■		
a					■	
pipe						■

Alignment, example

Ceci n’ est pas une pipe

This is not a pipe



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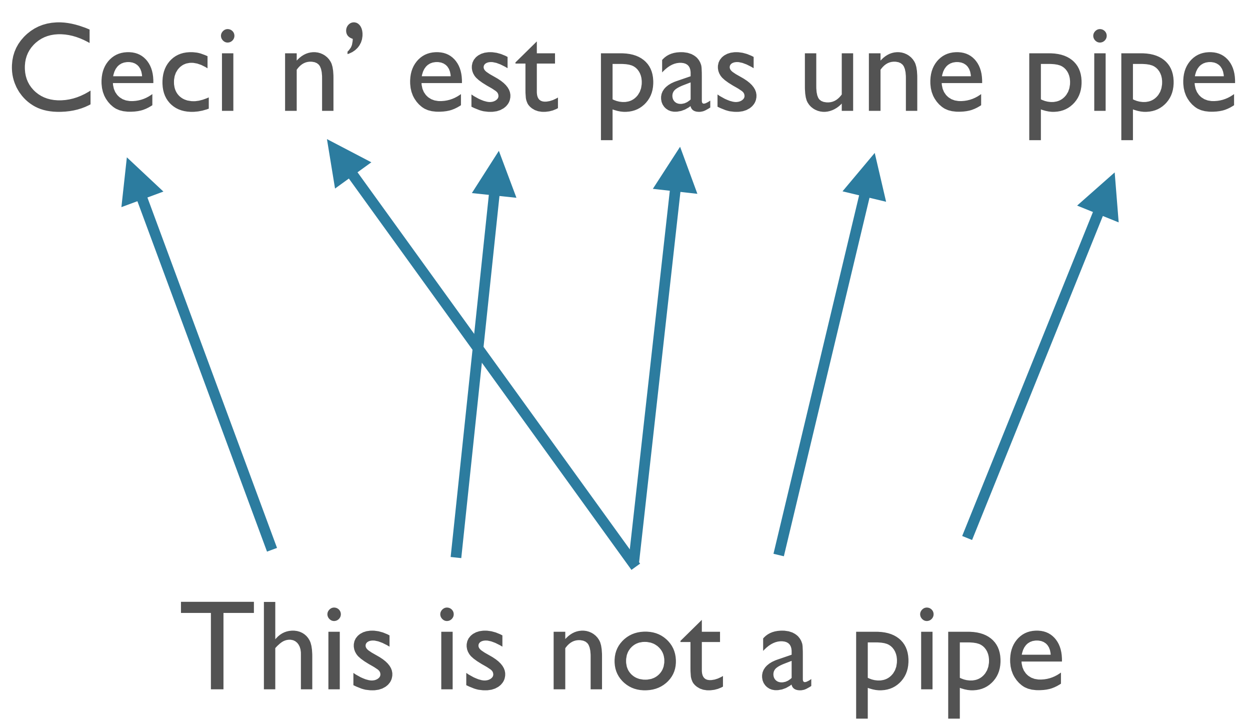
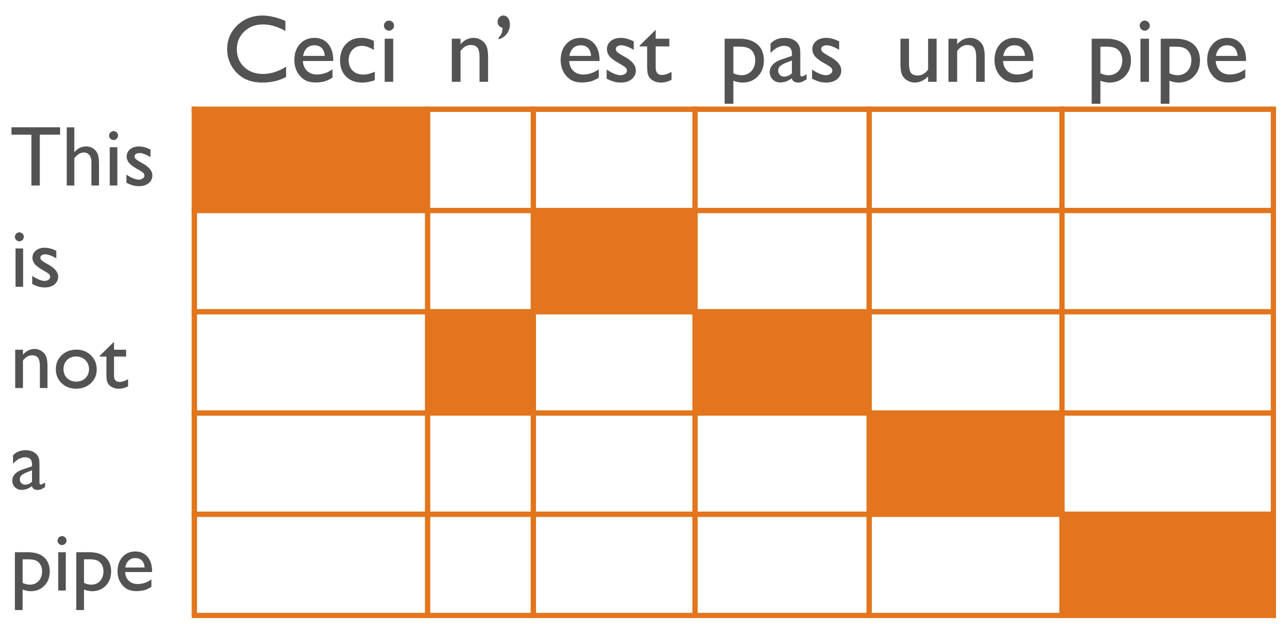


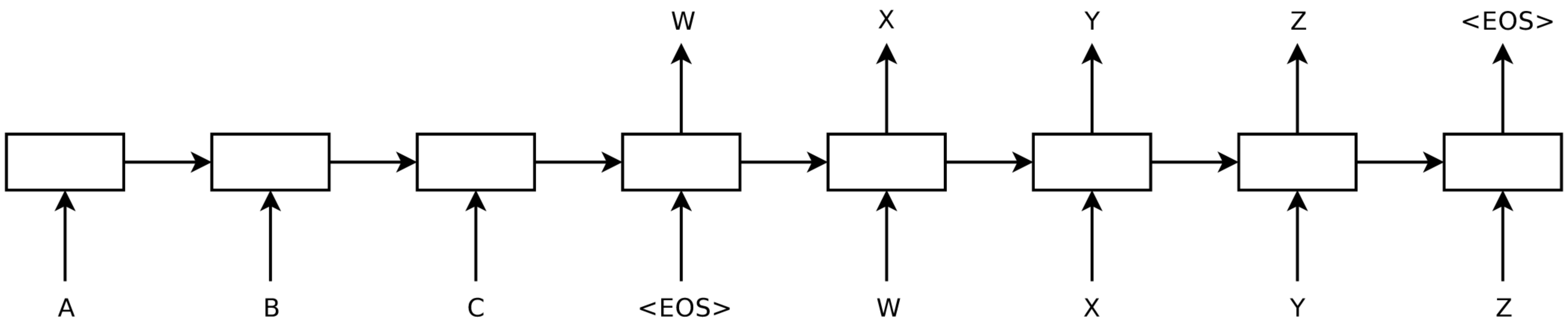


SMT Difficulties

- Features for alignment:
  - Probability of particular pairs aligning (lexicon / bilingual dictionary)
  - Probability of a word aligning to a phrase (in general)
- More generally:
  - Huge amounts of feature engineering
  - Reliance on human curated resources like dictionaries
  - Most of the above are *language-pair-specific*, have to be repeated
- NMT was one of the first major success stories of neural methods in NLP:
  - End-to-end systems, “language-agnostic” models, equal/better performance

Attention

seq2seq architecture: problem



Sutskever et al 2013

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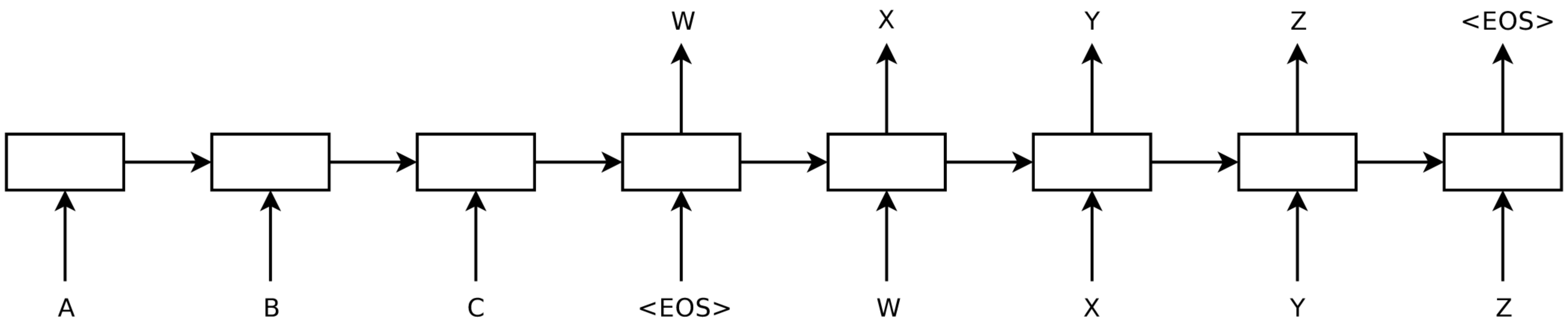

encoder

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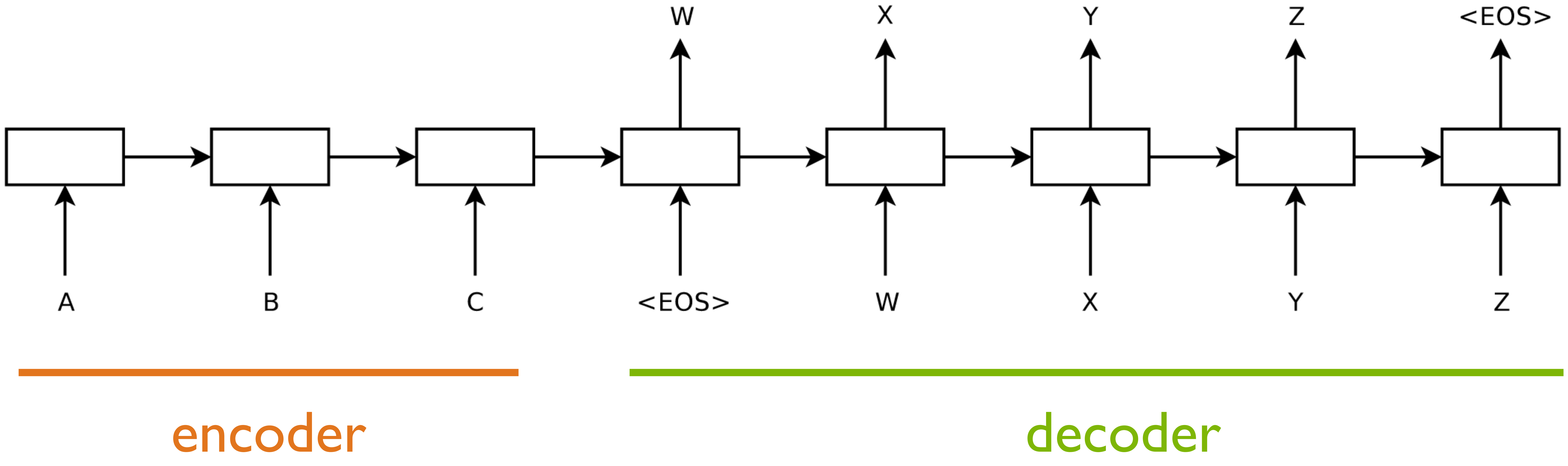

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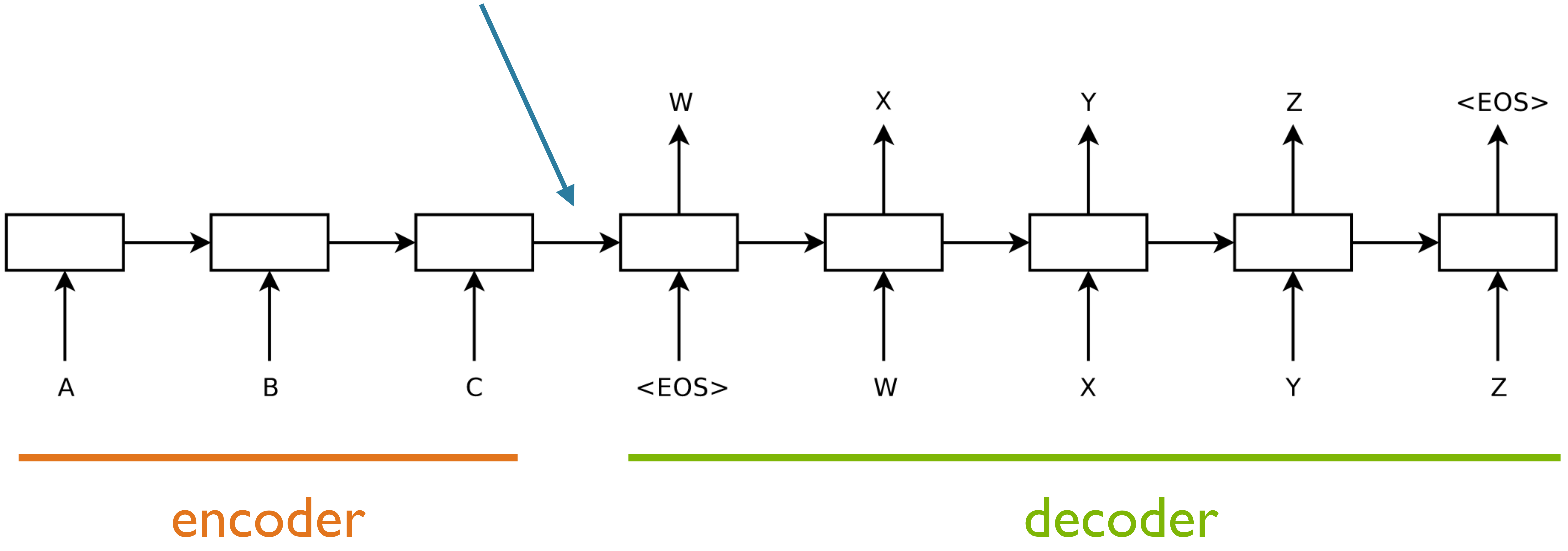
seq2seq architecture: problem

Decoder can only see info in this one vector
all info about source must be "crammed" into here



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seq2seq architecture: problem

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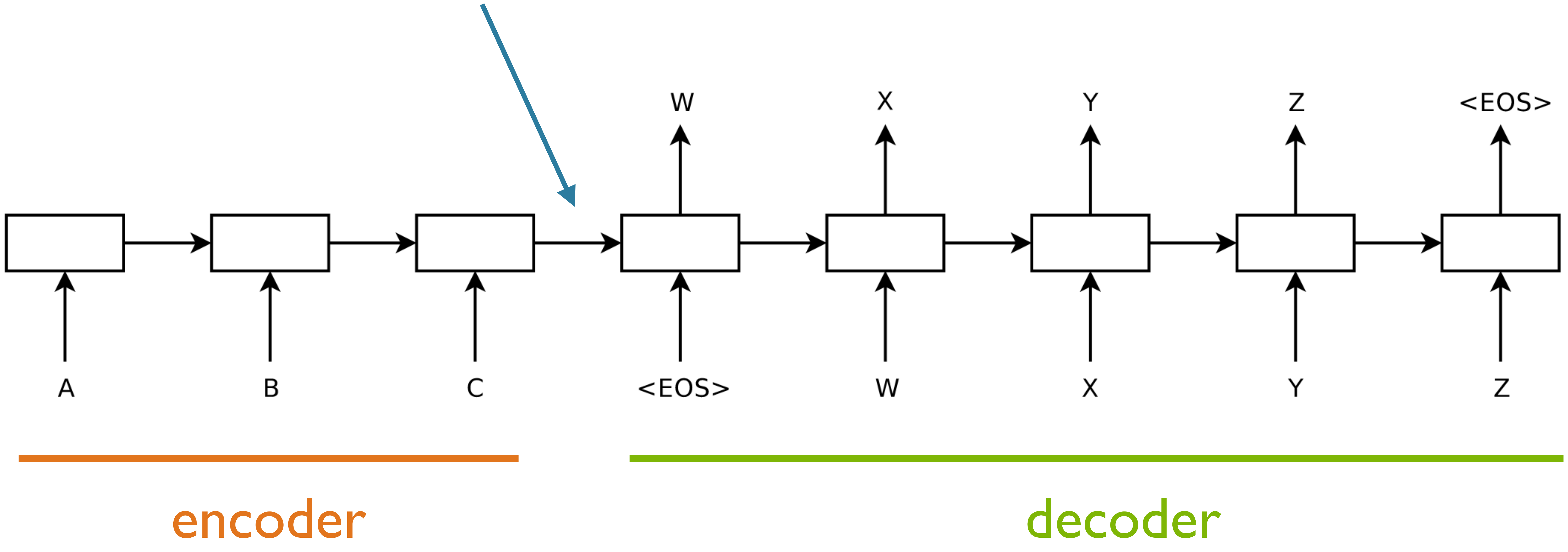
Mooney 2014: "You can't cram the meaning of a whole %&!$# sentence into a single $&!#* vector!"



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NEURAL MACHINE TRANSLATION BY JOINTLY LEARNING TO ALIGN AND TRANSLATE

Dzmitry Bahdanau
Jacobs University Bremen, Germany

KyungHyun Cho **Yoshua Bengio***
Université de Montréal

ABSTRACT

Neural machine translation is a recently proposed approach to machine translation. Unlike the traditional statistical machine translation, the neural machine translation aims at building a single neural network that can be jointly tuned to maximize the translation performance. The models proposed recently for neural machine translation often belong to a family of encoder–decoders and encode a source sentence into a fixed-length vector from which a decoder generates a translation. In this paper, we conjecture that the use of a fixed-length vector is a bottleneck in improving the performance of this basic encoder–decoder architecture, and propose to extend this by allowing a model to automatically (soft-)search for parts of a source sentence that are relevant to predicting a target word, without having to form these parts as a hard segment explicitly. With this new approach, we achieve a translation performance comparable to the existing state-of-the-art phrase-based system on the task of English-to-French translation. Furthermore, qualitative analysis reveals that the (soft-)alignments found by the model agree well with our intuition.

source

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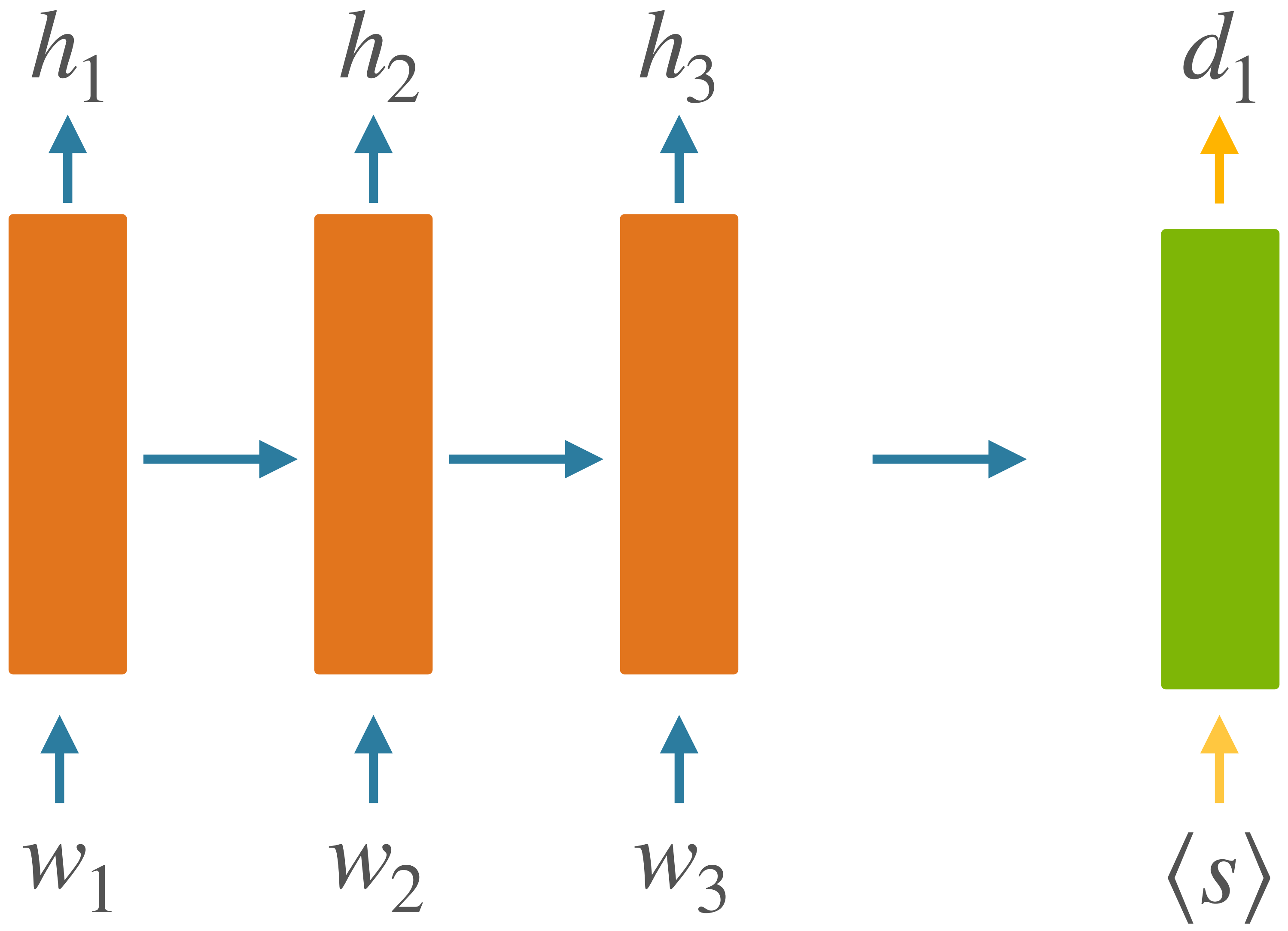

Badhanau et al 2014
Luong et al 2015

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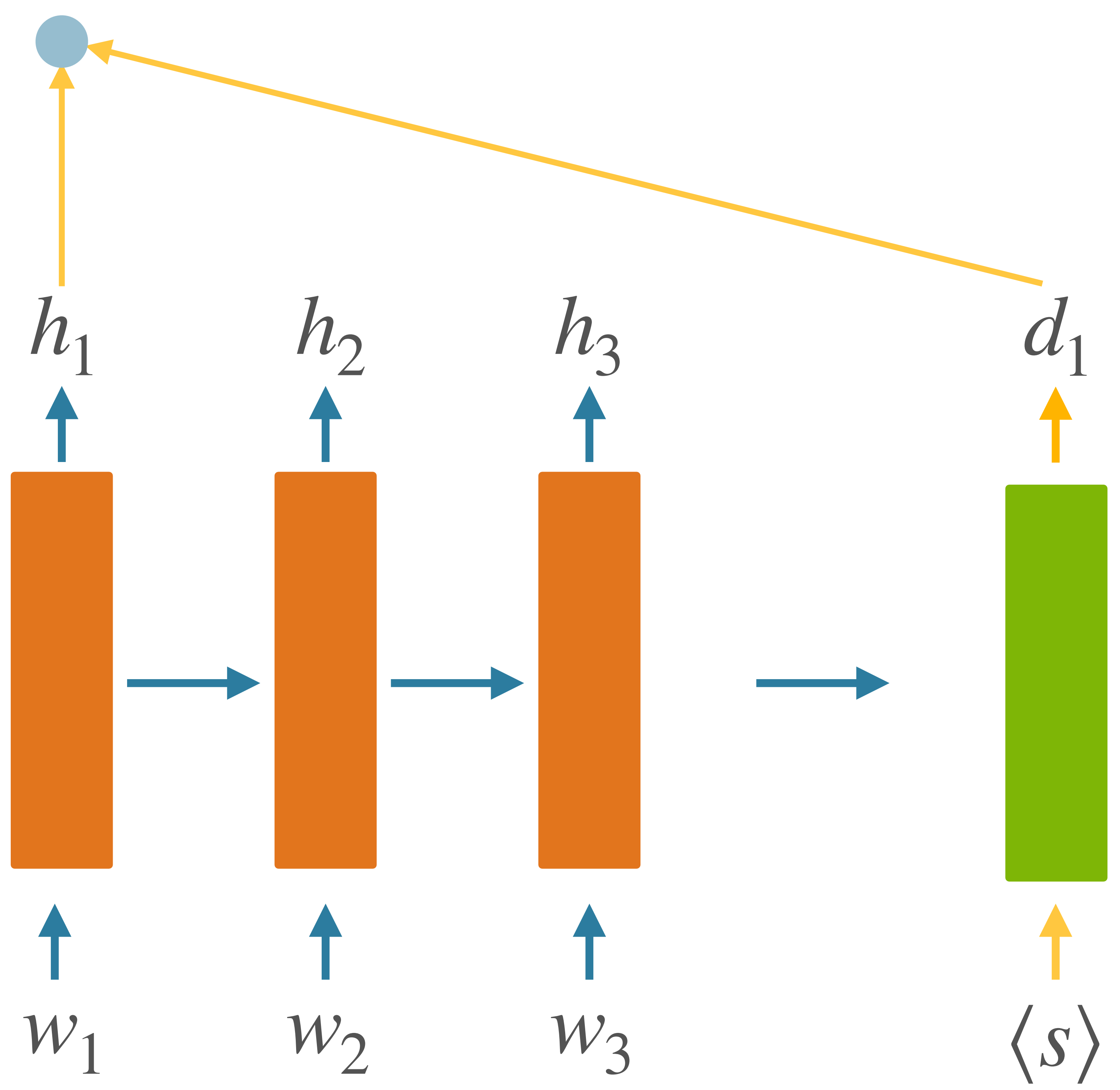

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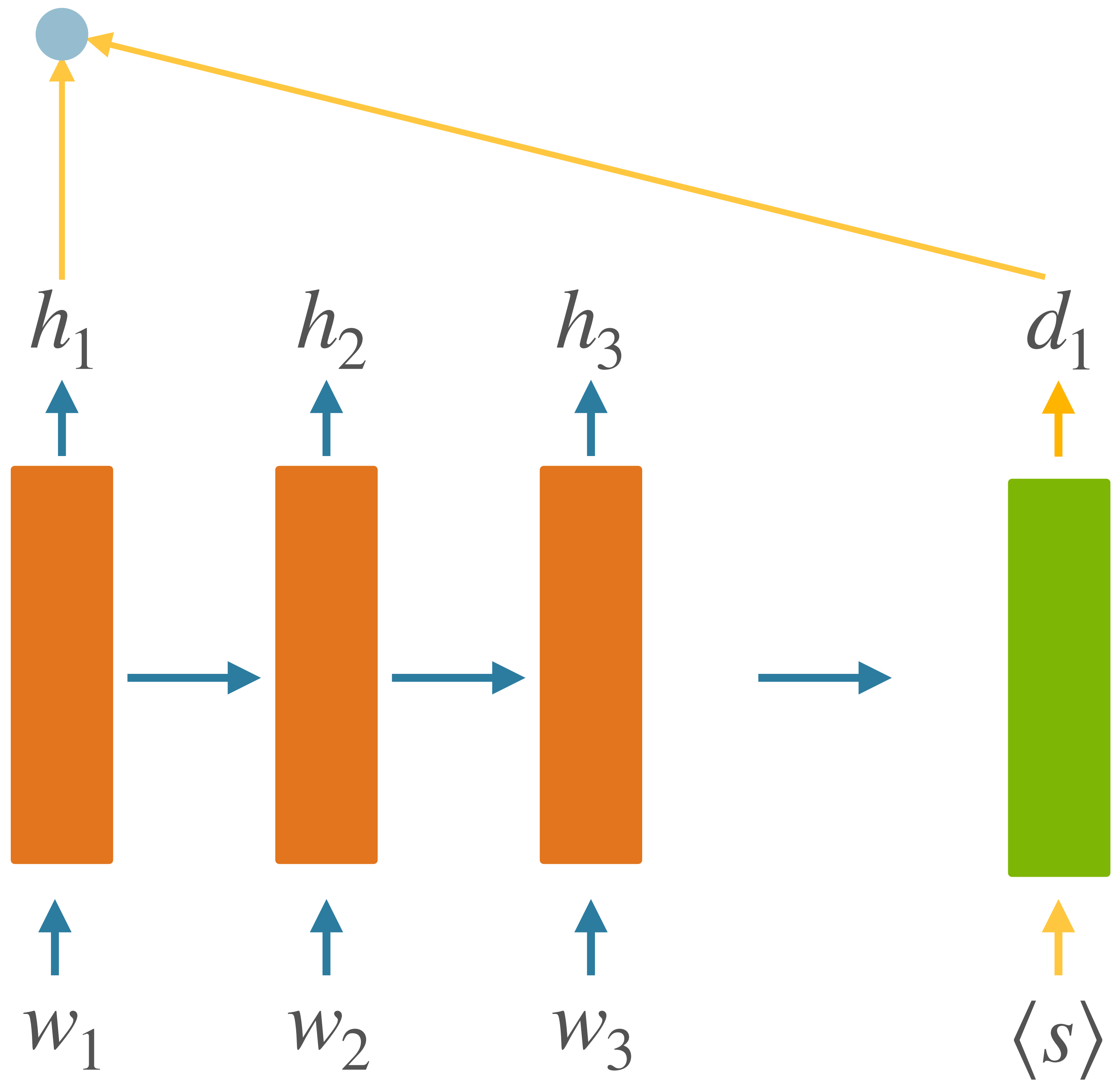
Luong et al 2015

Adding Attention

$\alpha_{ij} = a(h_j, d_i)$
(dot product usually)



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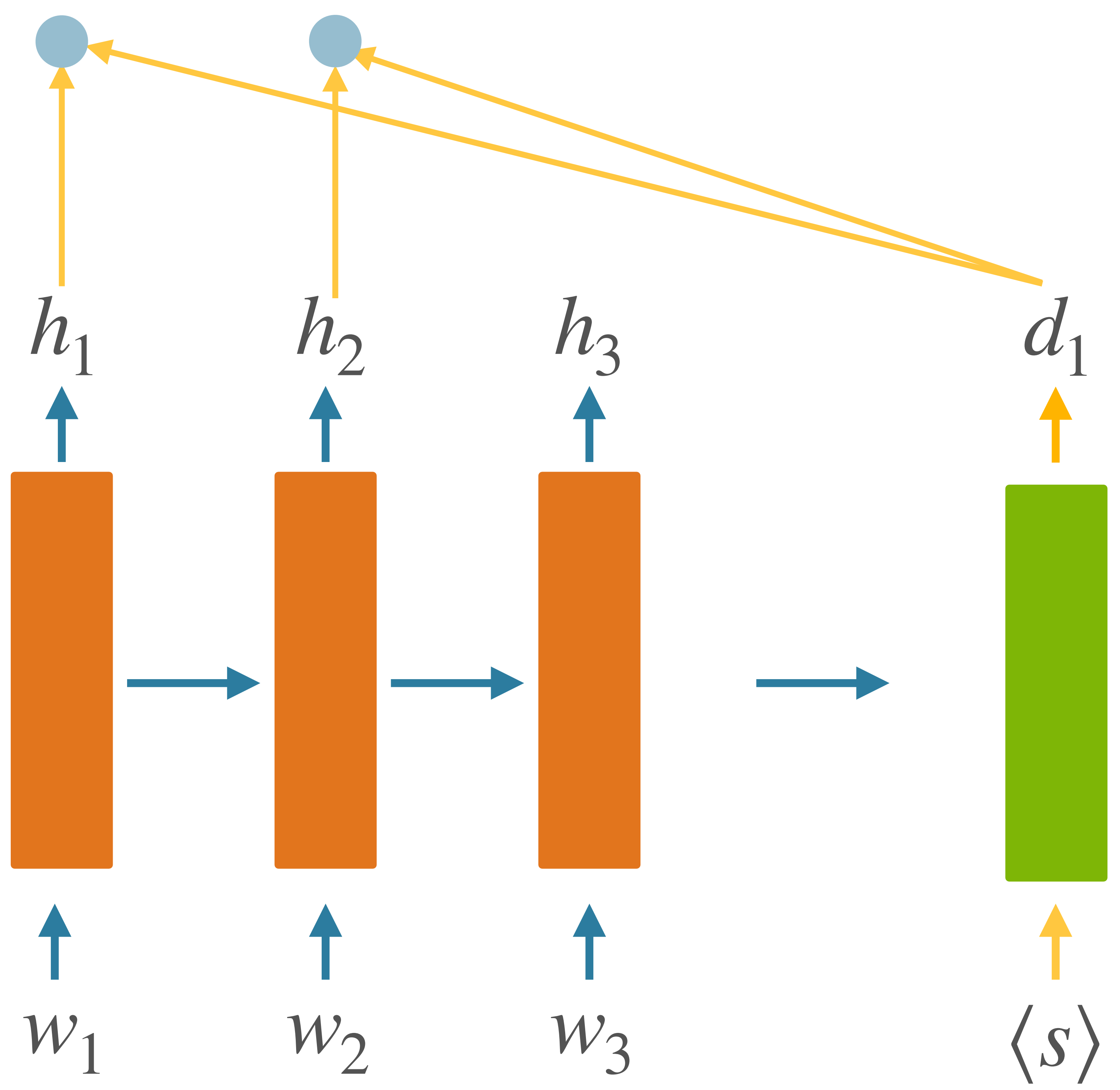

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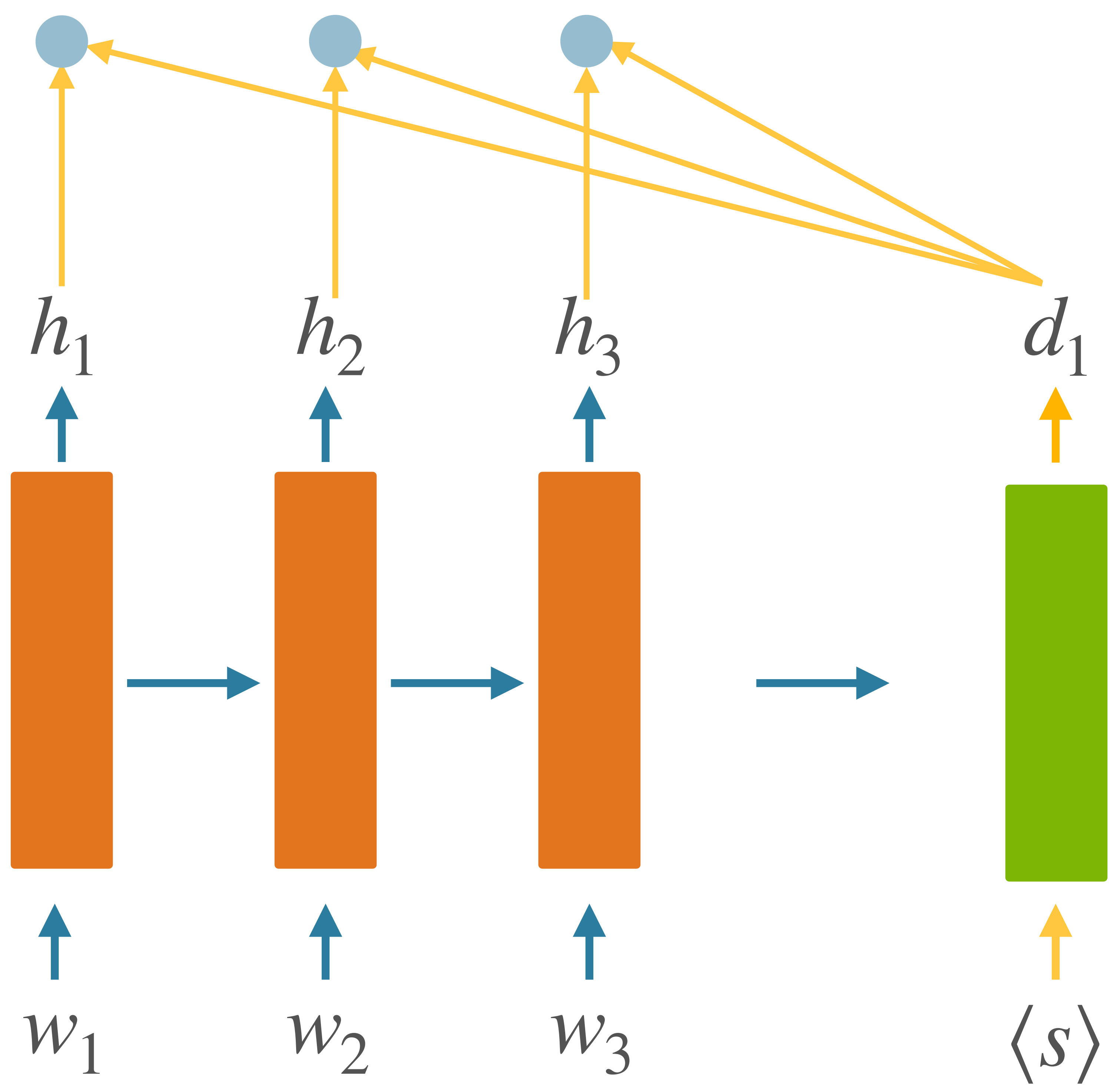

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Adding Attention

$e_{ij} = \text{softmax}(\alpha)_j$

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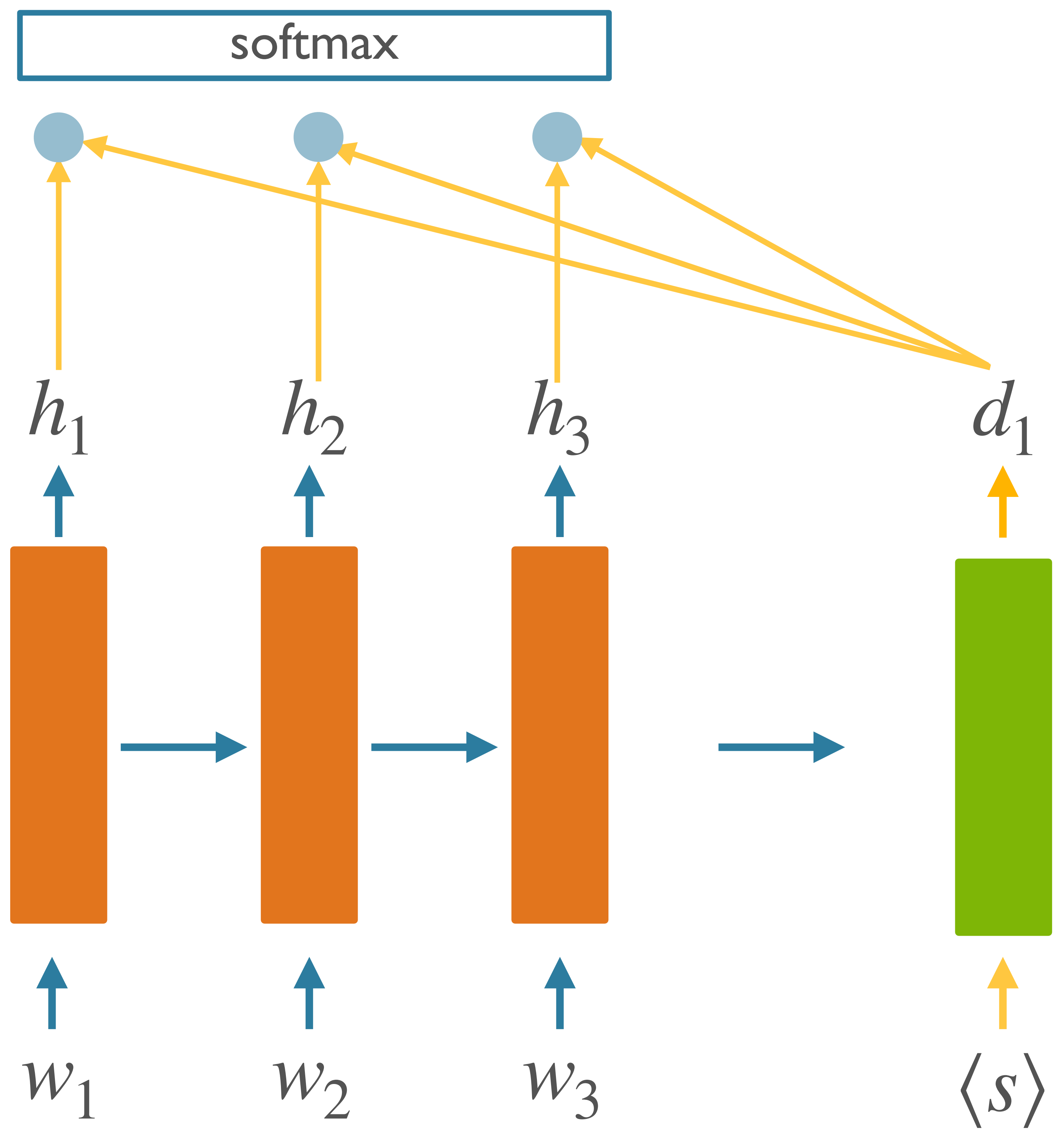

Badhanau et al 2014
Luong et al 2015

Adding Attention

$c_i = \Sigma_j e_{ij} h_j$

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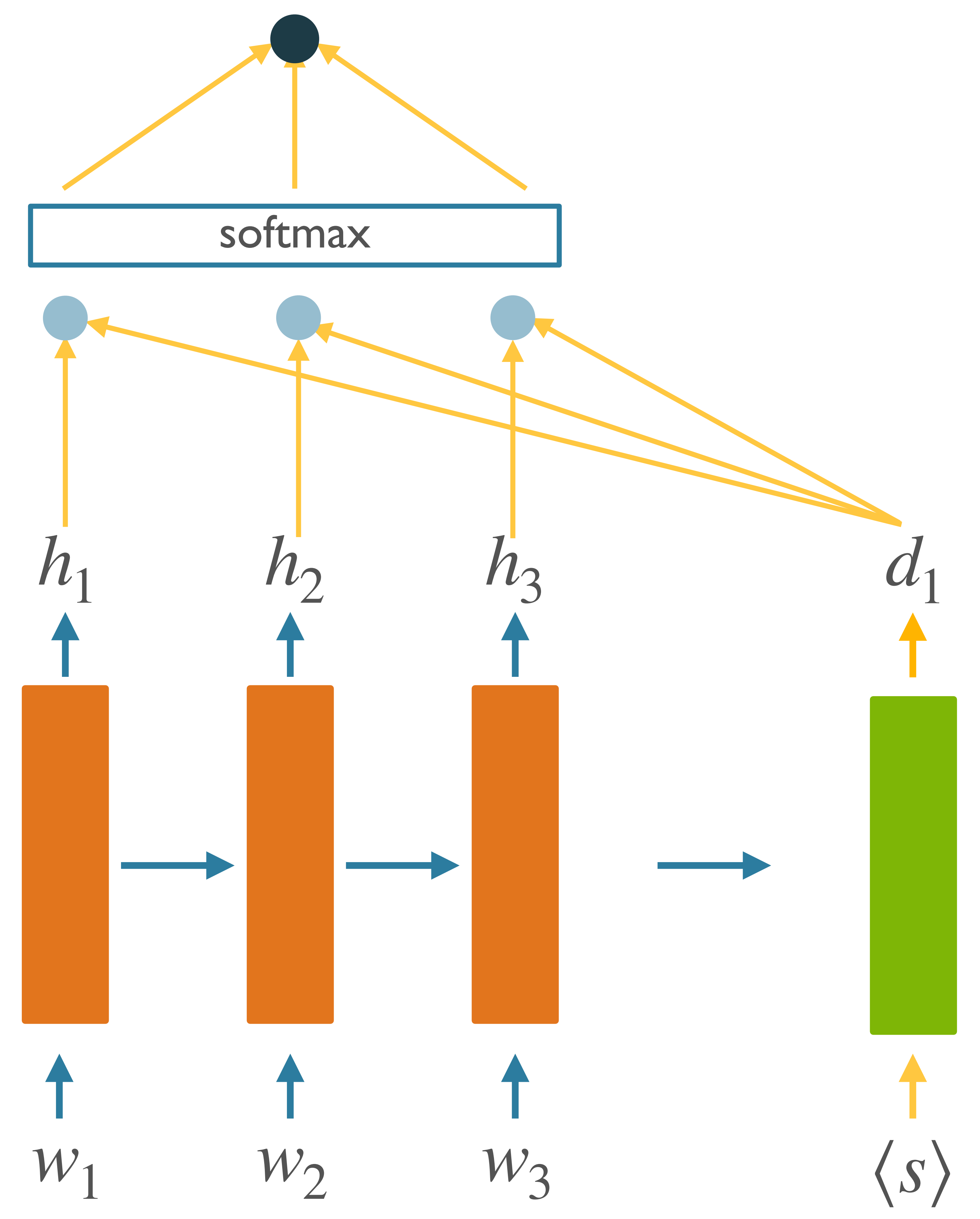

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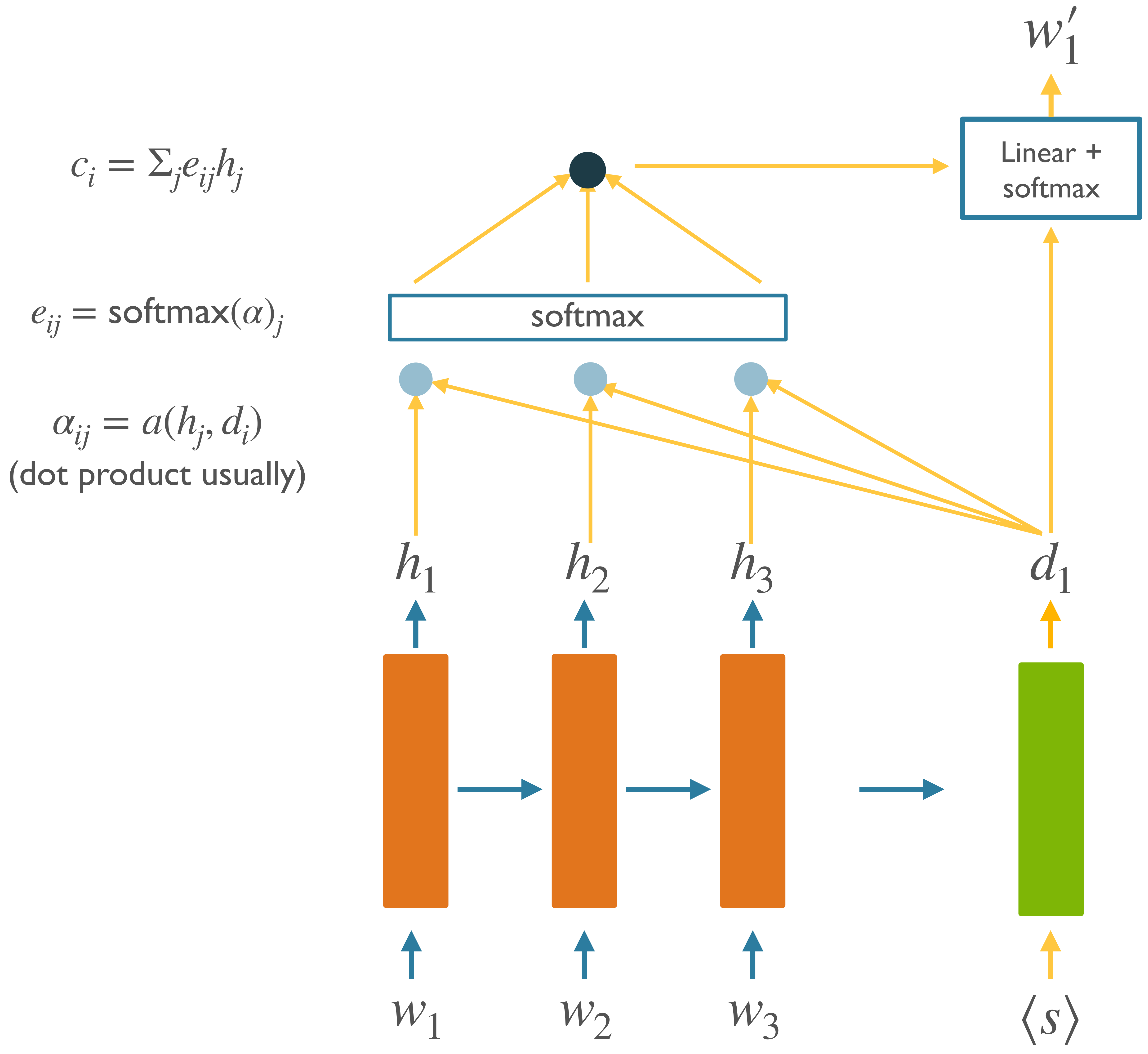

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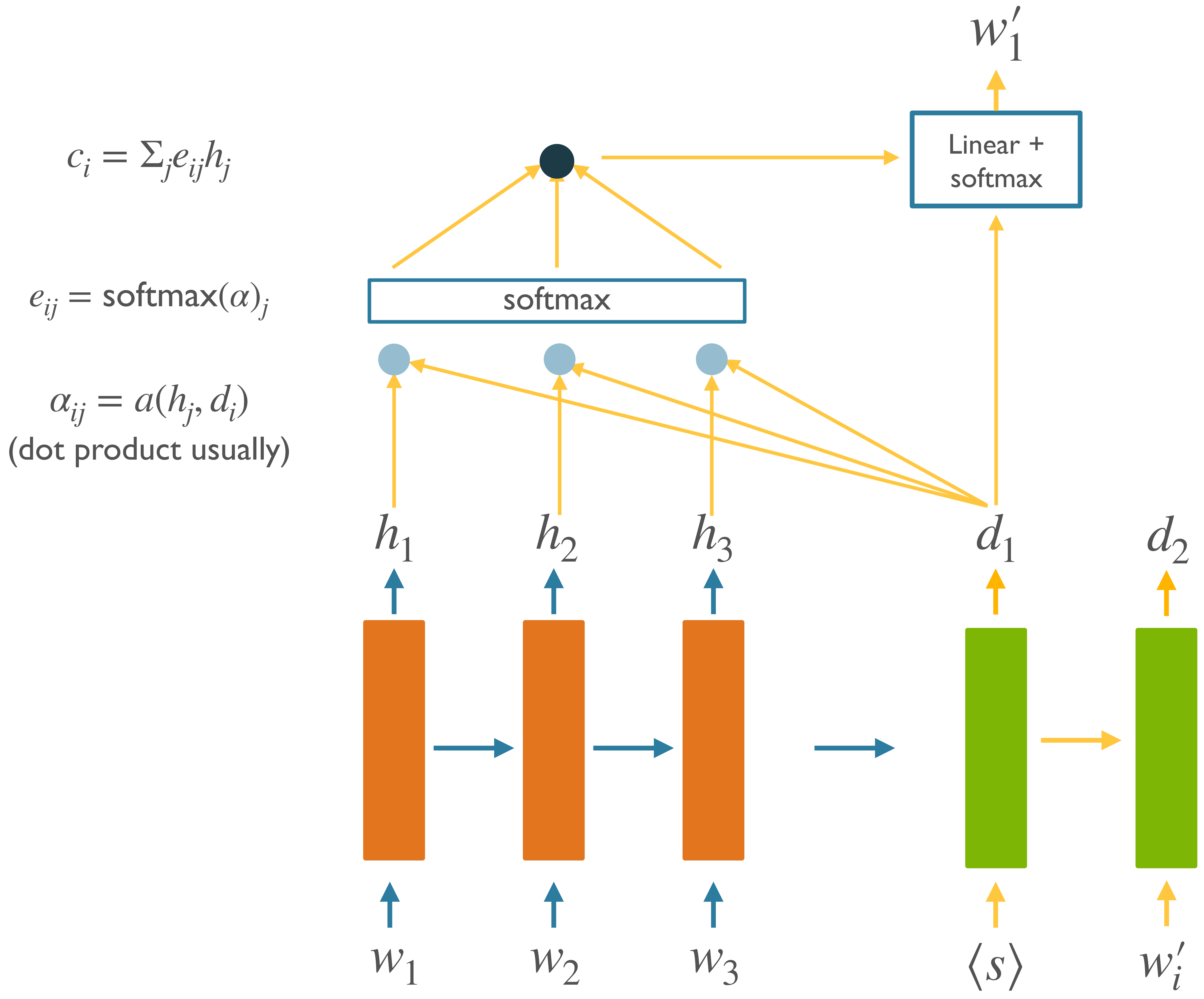

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$$\alpha_j = q \cdot k_j$$
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- In the previous example: encoder hidden states played *both* the keys and the values roles.

Why attention?

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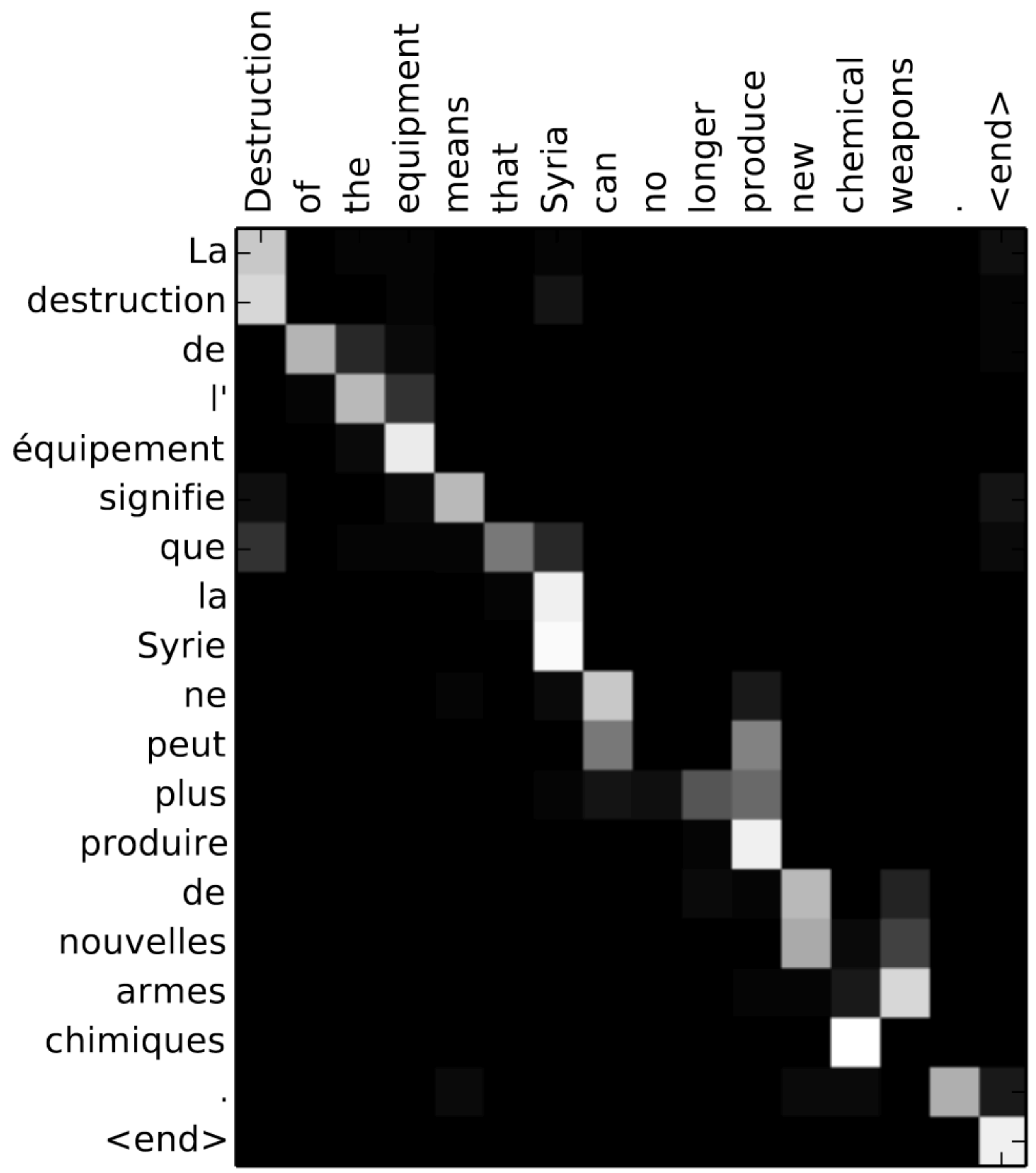

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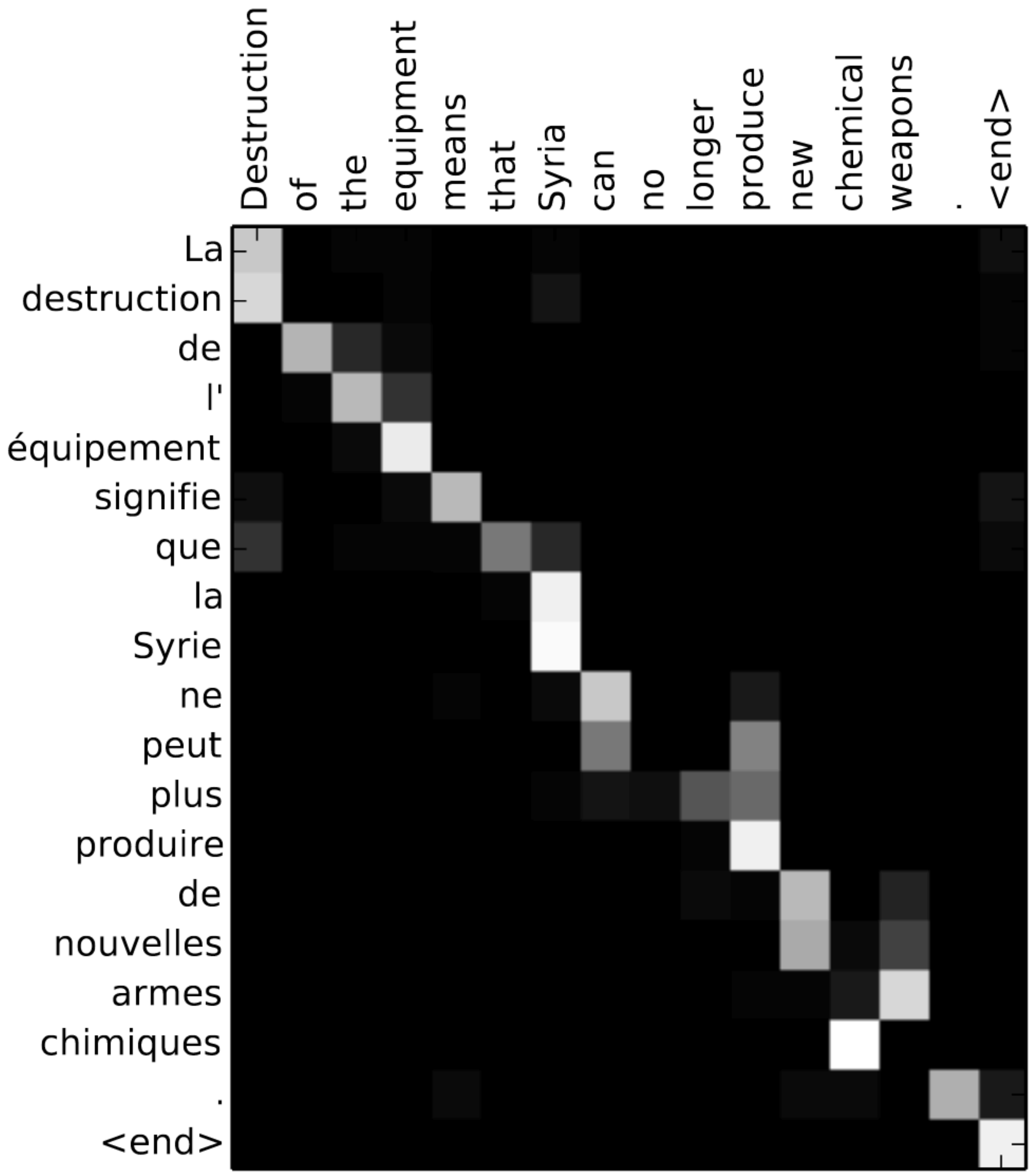

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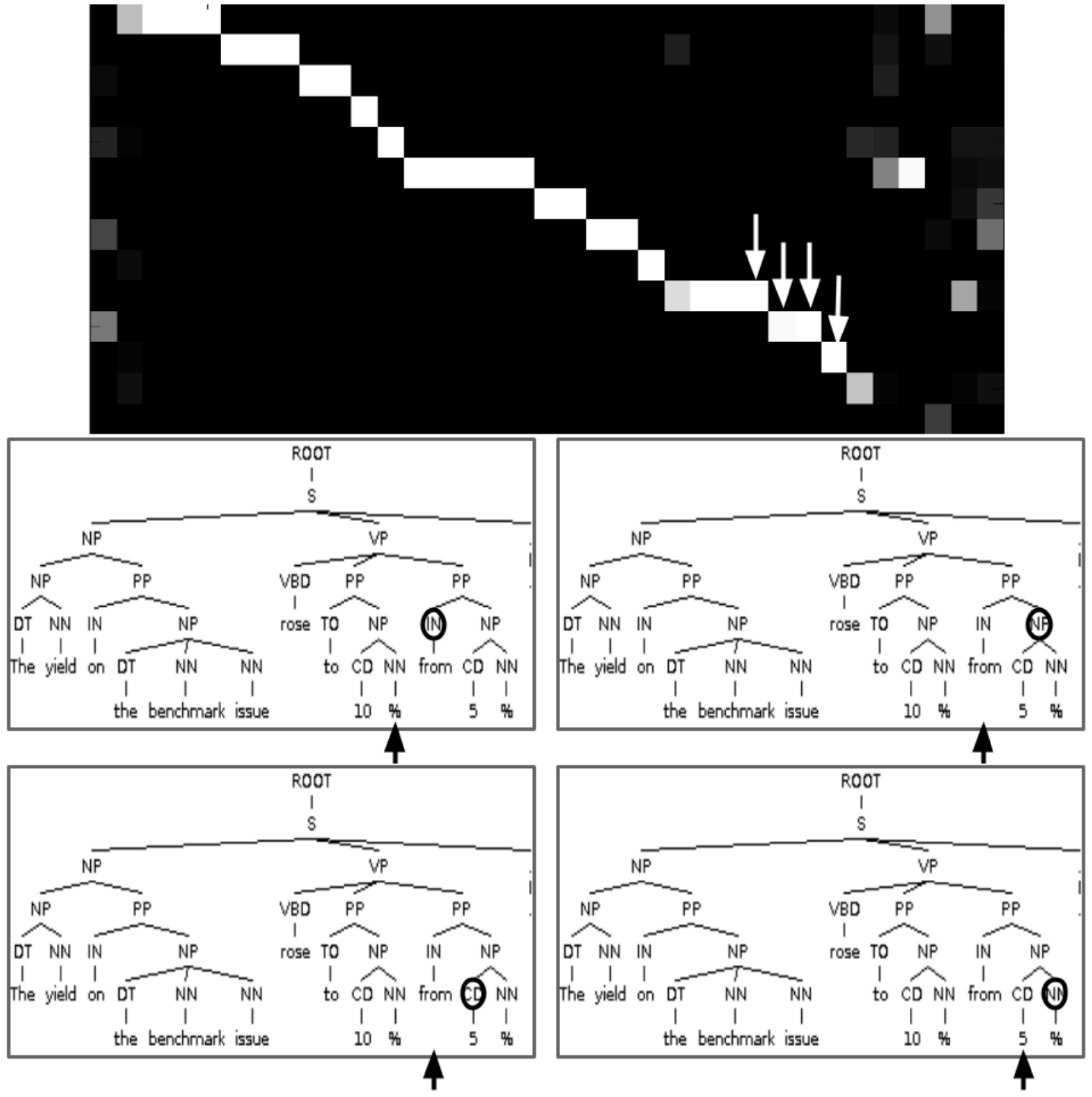

[Vinyals et al 2015]

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- Aids interpretability (maybe)
- A general technique for combining representations, applications in:
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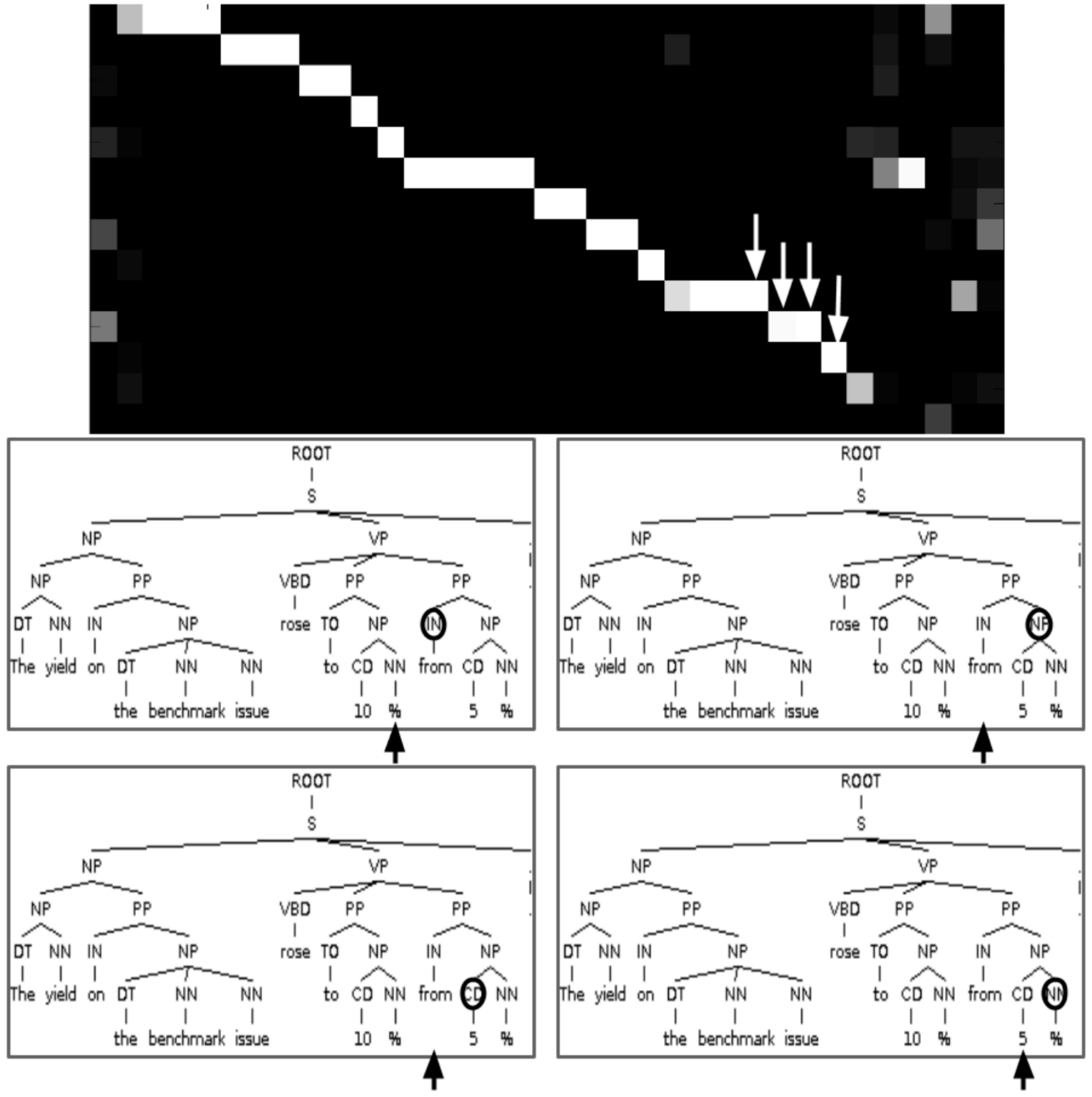
- Conceptually, let the model *learn to align* representations
  - “Soft” alignment, just like gates = “soft” masks



Vinyals et al 2015

Next Time

- Introduction to the *Transformer* architecture
  - Hint:

Next Time

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  - Hint:

Attention Is All You Need

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Abstract

The dominant sequence transduction models are based on complex recurrent or convolutional neural networks that include an encoder and a decoder. The best performing models also connect the encoder and decoder through an attention mechanism. We propose a new simple network architecture, the Transformer, based solely on attention mechanisms, dispensing with recurrence and convolutions entirely. Experiments on two machine translation tasks show these models to be superior in quality while being more parallelizable and requiring significantly