Attention

Course Instructor: Chandresh
AI Lab Coordinator @IIT Indore

Course Content

Module I: History of Deep Learning, Sigmoid Neurons, Perceptrons, and learning algorithms. Multilayer Perceptrons (MLPs), Representation Power of MLPs,.

Module II: Feedforward Neural Networks. Backpropagation. first and second-order training methods. NN Training tricks, Regularization

Module III: Introduction to Autoencoders and their characteristics, relation to PCA, Regularization in autoencoders, and Types of autoencoders, Variational Autoencoder

Module IV: Architecture of Convolutional Neural Networks (CNN), types of CNNs. Image classification, Pre-training vs fine-tuning.- representation learning, Object Detection and Semantic Segmentation

Module V: Architecture of Recurrent Neural Networks (RNN), Word Embeddings,
Encoder-Decoder Models, **Attention Mechanism**. Advanced Topics: Transformers and BERT. Nodule VI: Gen AI- Deep generative models: VAE, GAN,

Acknowledgement

- Russ Salakhutdinov and Hugo Larochelle's class on Neural Networks
- Neural Networks and Deep Learning course by Danna Gurari University of Colorado Boulder

Today’s Topics

- Motivation: machine neural translation for long sentences
- Encoder
- Decoder: attention
- Performance evaluation

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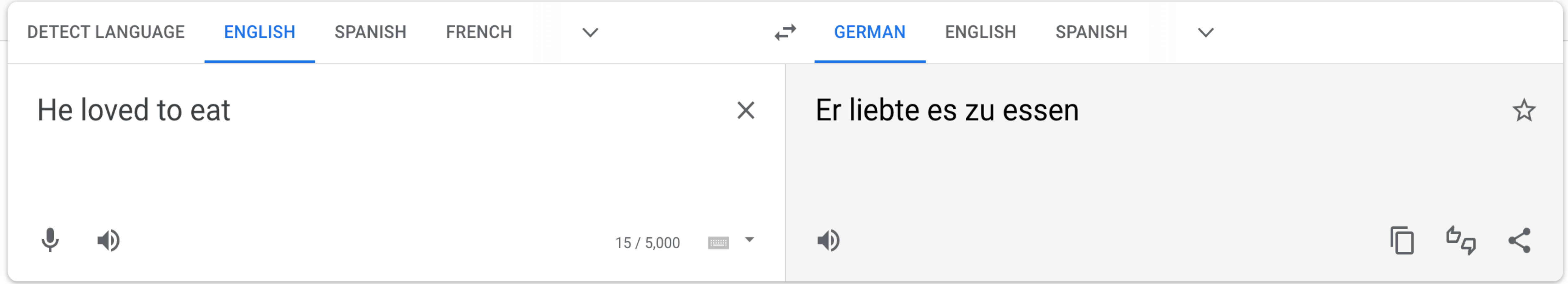
Task: Machine Translation



Which type of sequence problem is this: one-to-many, many-to-one, or many-to-many?

Pioneering Neural Network Approach

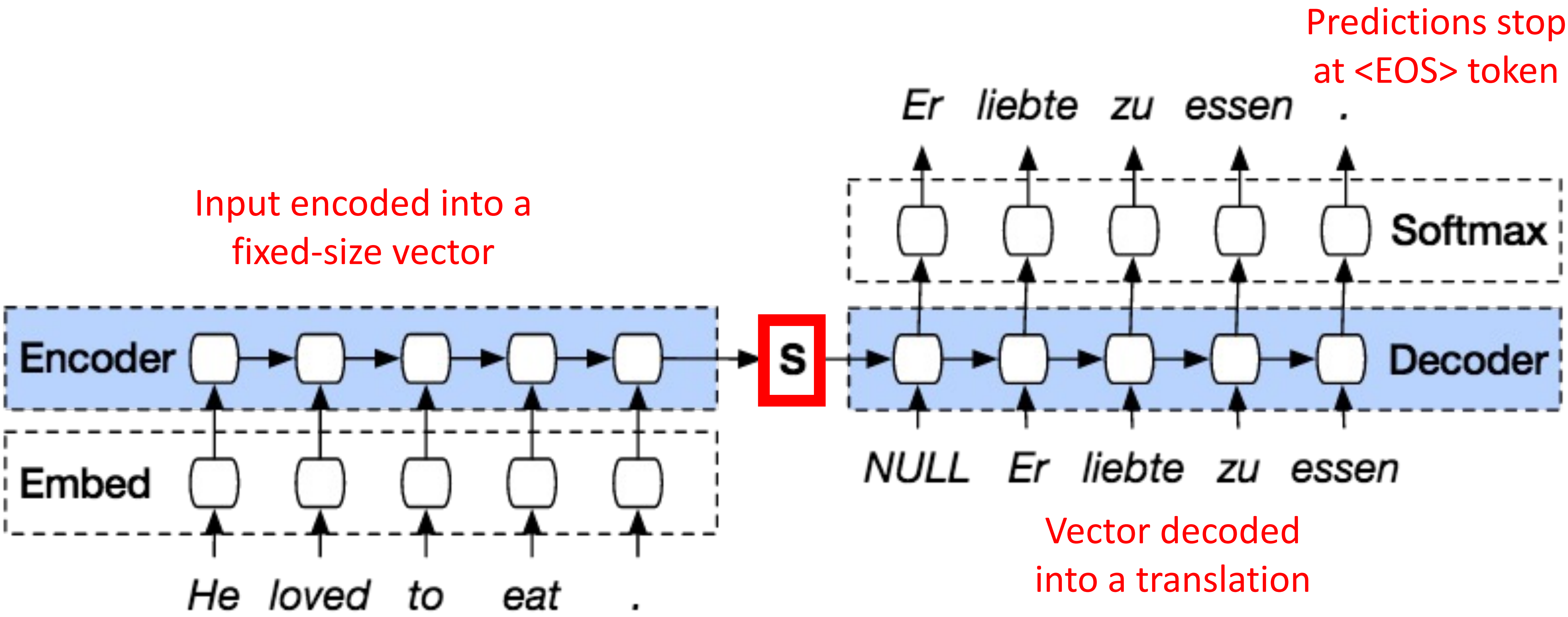
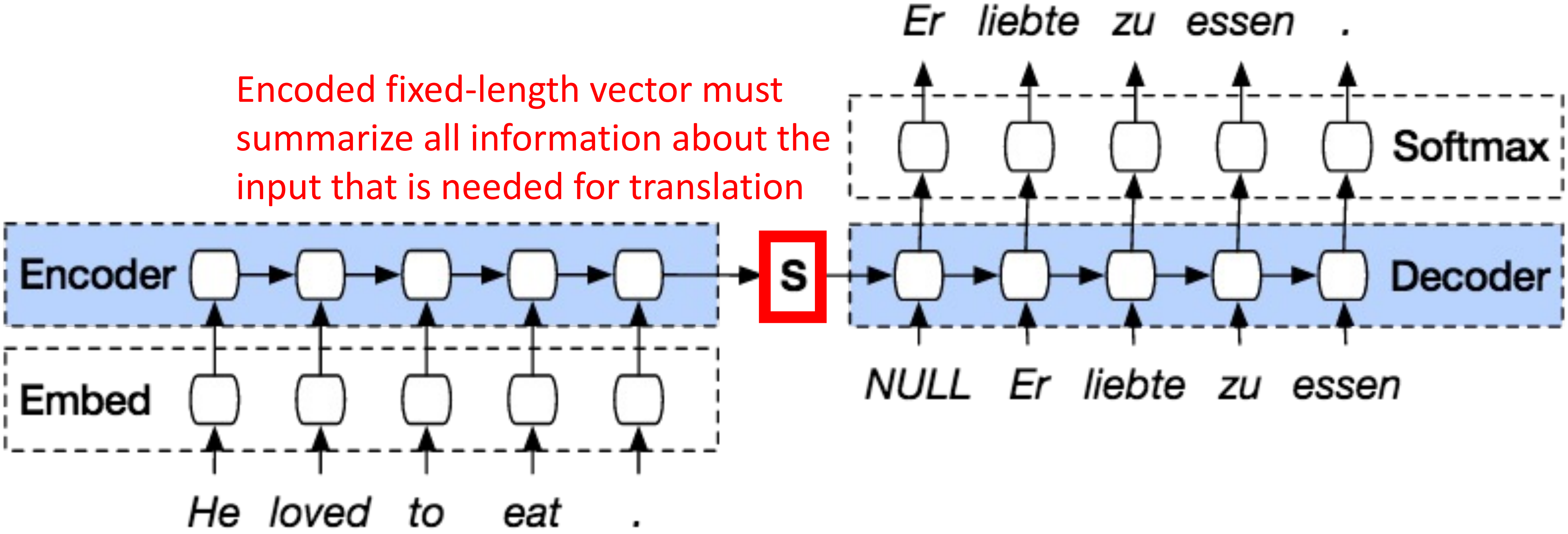


Image source: https://smerity.com/articles/2016/google_nmt_arch.html

seq2seq: Sutskever et al. Sequence to Sequence Learning with Neural Networks. Neurips 2014.

Pioneering Neural Network Approach

Encoded fixed-length vector must summarize all information about the input that is needed for translation



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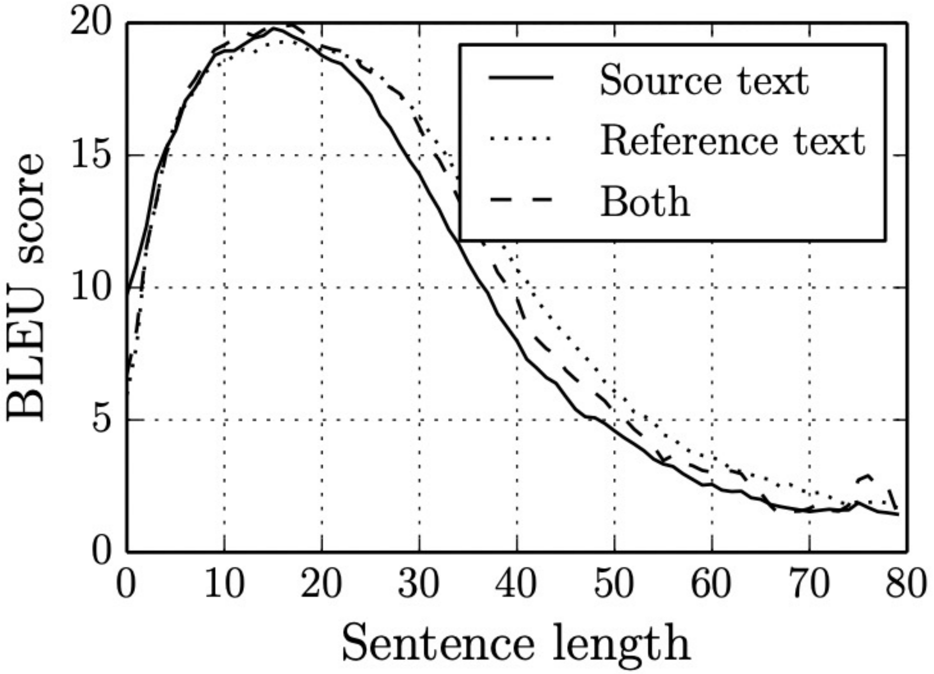
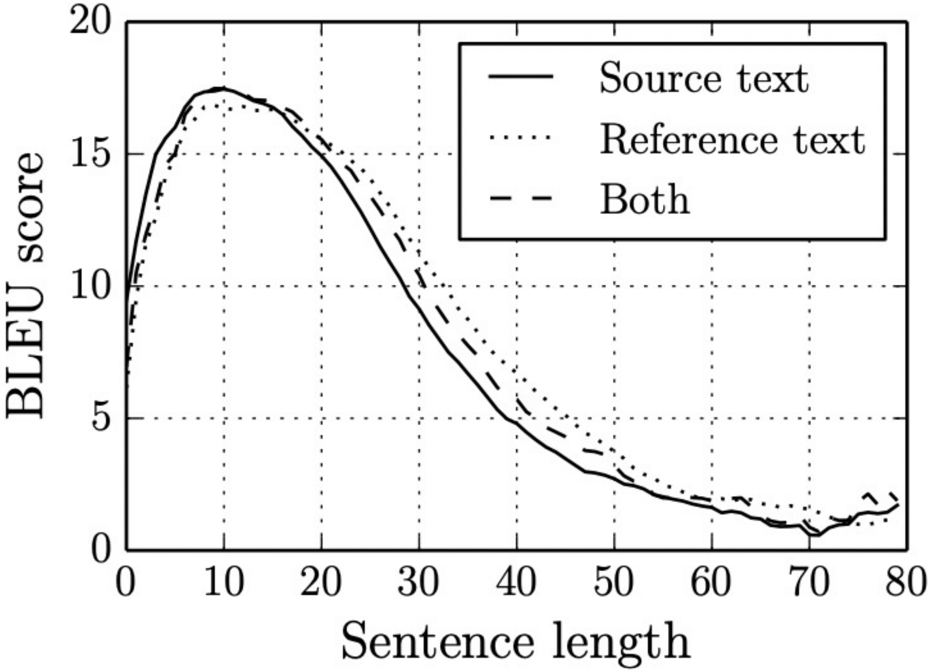
Analysis of Two Models

(larger scores are better)



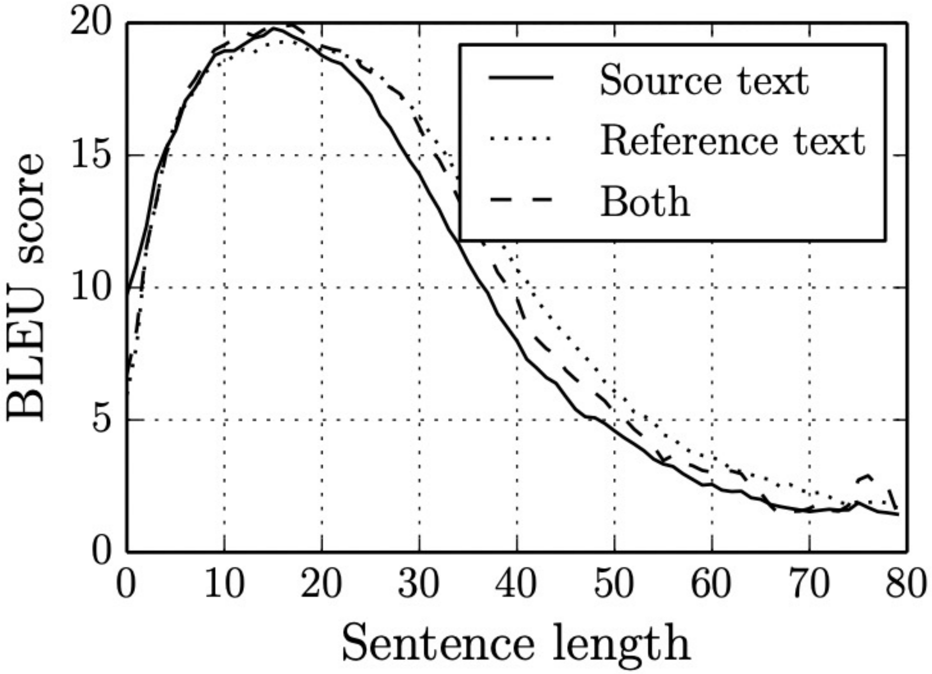


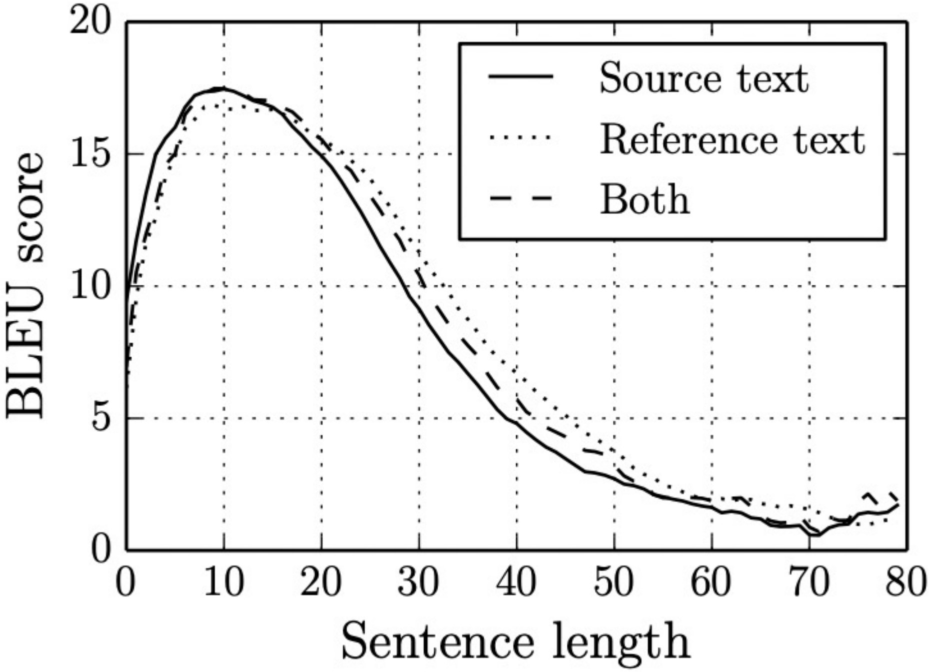
What performance trend is observed for inputs (source) and outputs (reference) as the number of words in each sentence grows?

Cho et al. On the Properties of Neural Machine Translation: Encoder–Decoder Approaches. SSST 2014.

Analysis of Two Models

(larger scores are better)



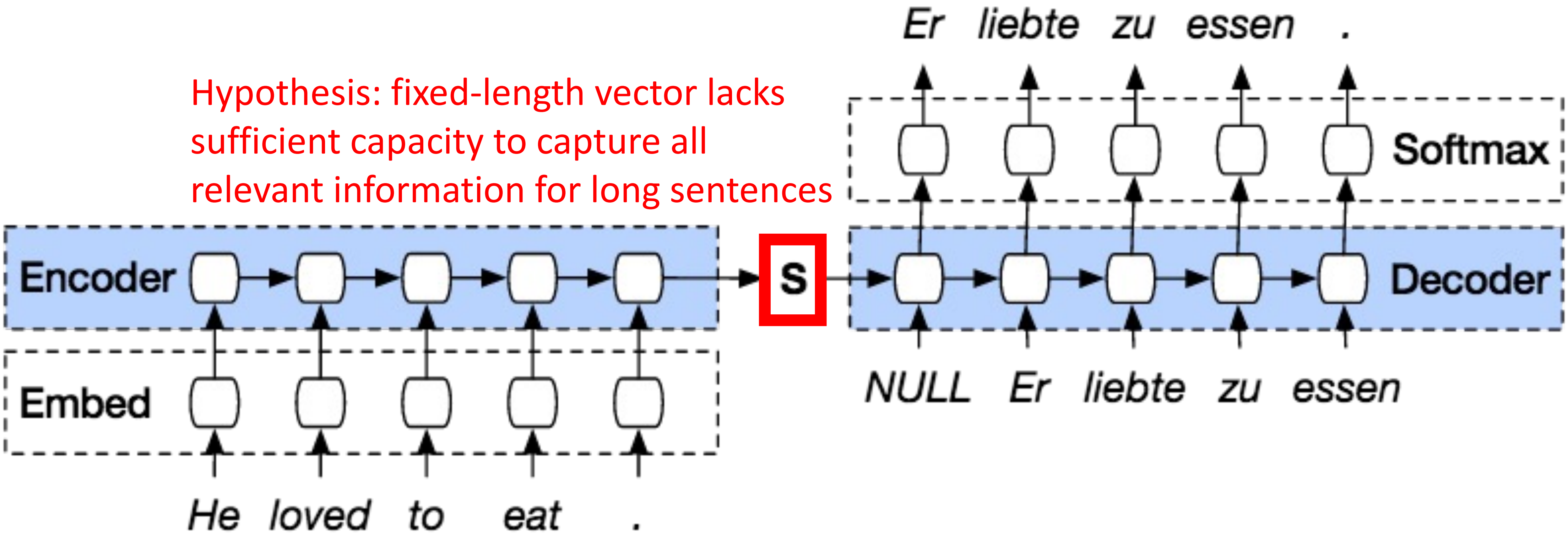


Performance drops for longer sentences!

Cho et al. On the Properties of Neural Machine Translation: Encoder–Decoder Approaches. SSST 2014.

Problem: Performance Drops As Sentence Length Grows

Hypothesis: fixed-length vector lacks sufficient capacity to capture all relevant information for long sentences



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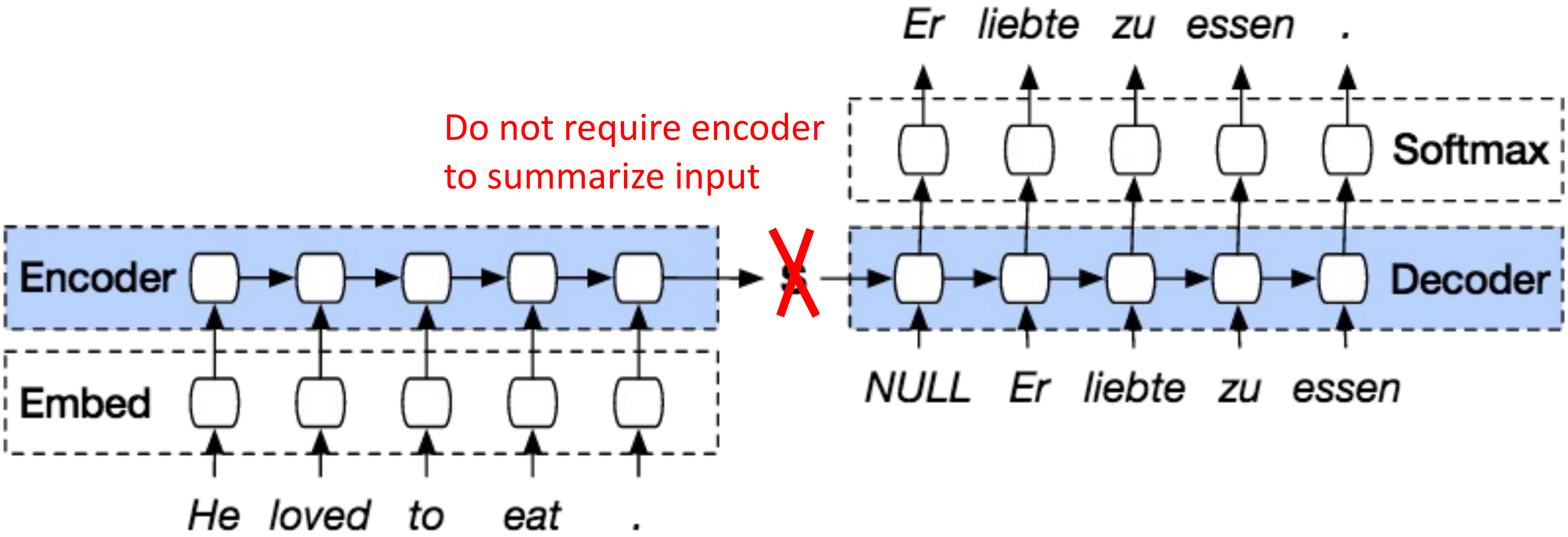
Idea to Preserve Performance for Long Sentences: **Attention**

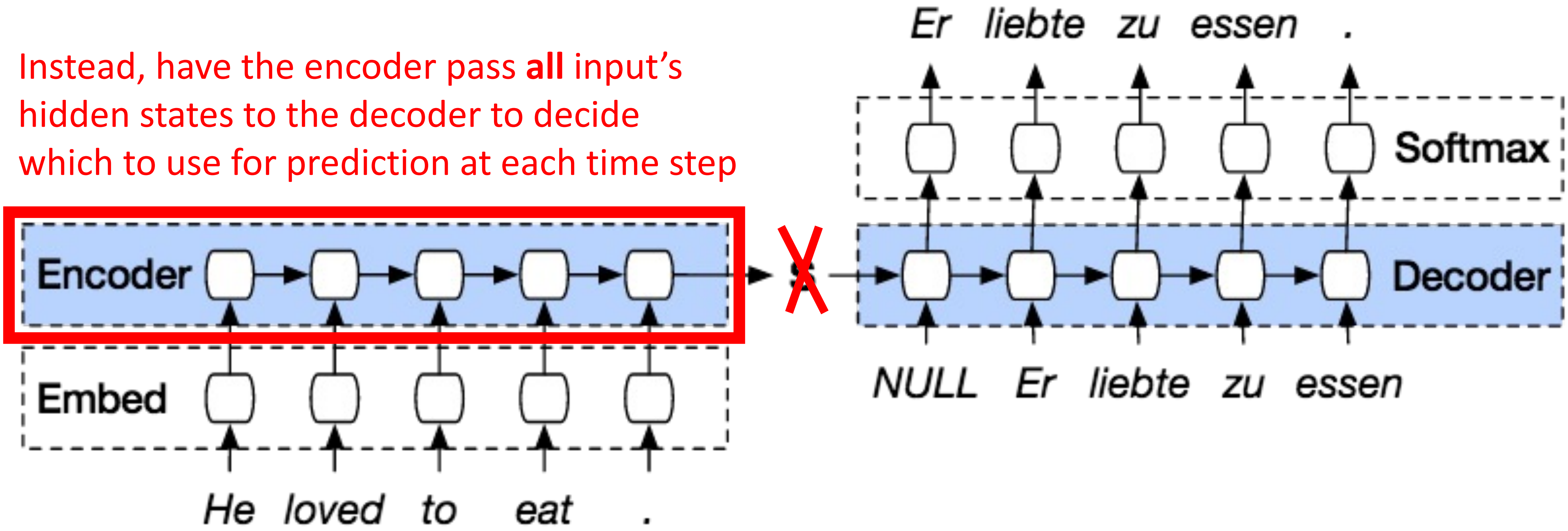


Do not require encoder to summarize input

Image source: https://smerity.com/articles/2016/google_nmt_arch.html

Idea to Preserve Performance for Long Sentences: **Attention**

Instead, have the encoder pass **all** input's hidden states to the decoder to decide which to use for prediction at each time step



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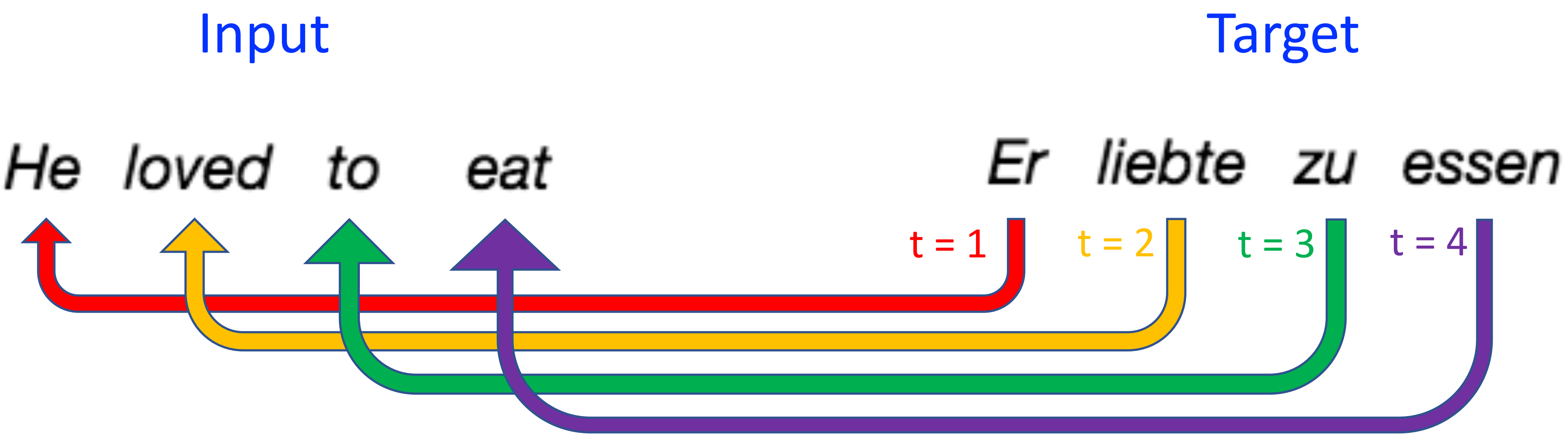
Idea to Preserve Performance for Long Sentences: **Attention**

Decoder decides which inputs are needed for prediction at each time step; e.g., "hard attention" focuses on one input



Note: while word order between the input and target align in this example, it can differ

https://deeplearning.cs.cmu.edu/F21/document/slides/lec18.attention.pdf

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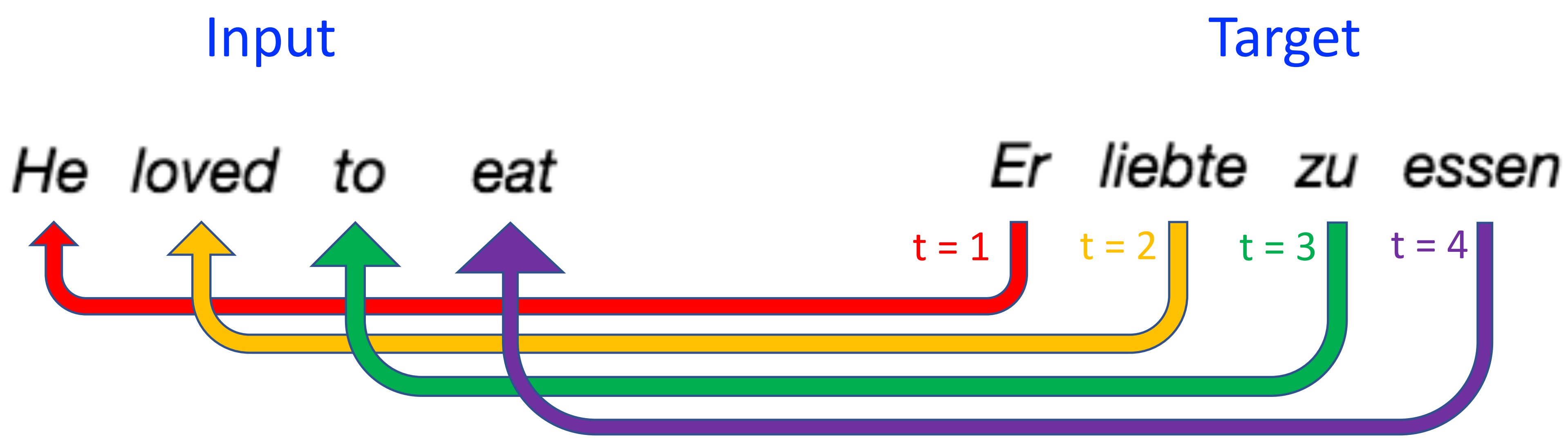


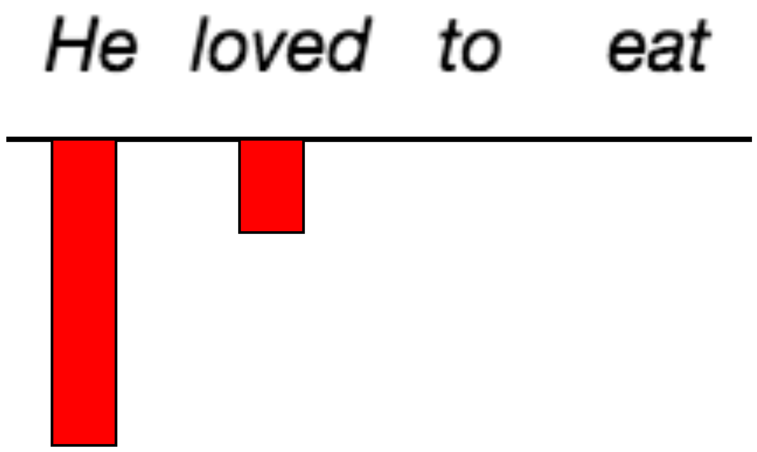
Limitations: a target word relies on information about one input word and "hard attention" is not differentiable

https://deeplearning.cs.cmu.edu/F21/document/slides/lec18.attention.pdf

Idea to Preserve Performance for Long Sentences: **Attention**

Decoder decides which inputs are needed for prediction at each time step; e.g., “soft attention” uses a weighted combination of the input

Input



Target

Er liebte zu essen

t = 1

Idea to Preserve Performance for Long Sentences: **Attention**

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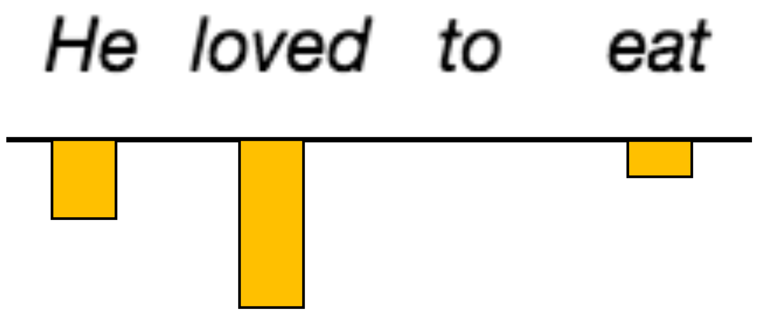
Input



Target

Er liebte zu essen

t = 1 t = 2

Idea to Preserve Performance for Long Sentences: **Attention**

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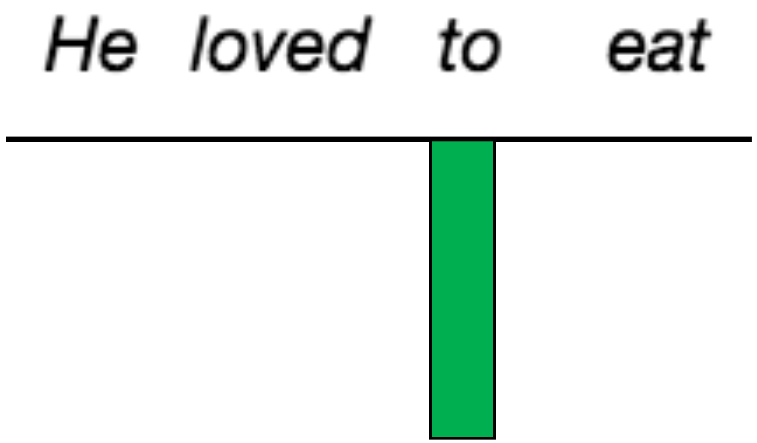
Input



Target

Er liebte zu essen

t = 1 t = 2 t = 3

Idea to Preserve Performance for Long Sentences: **Attention**

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Input

Target

“Soft” Attention: Challenge

Decoder decides which inputs are needed for prediction at each time step; e.g., “soft attention” uses a weighted combination of the input

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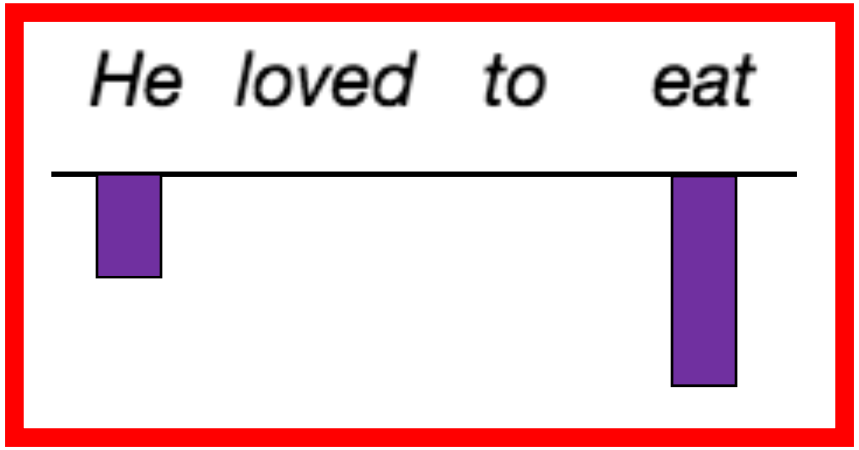

Target

Er liebte zu essen

t = 1 t = 2 t = 3 t = 4

How should weights be chosen for each input?

“Soft” Attention: Challenge

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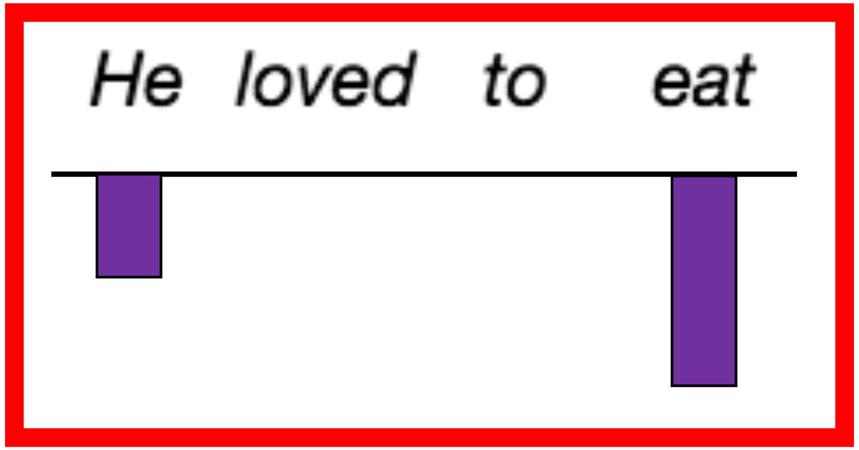
Input



Target

Er liebte zu essen

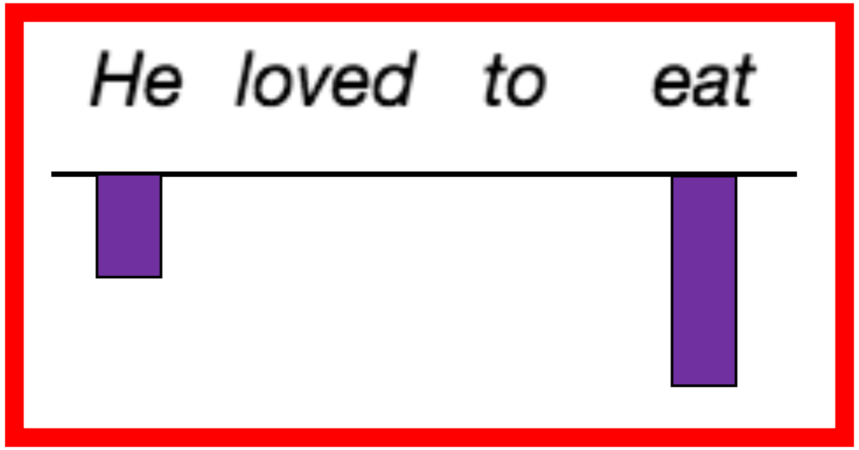
t = 1 t = 2 t = 3 t = 4

Could collect manual annotations and then incorporate into the loss function that predicted weights should match ground truth weights… but this approach is impractical

“Soft” Attention: Challenge

Decoder decides which inputs are needed for prediction at each time step; e.g., “soft attention” uses a weighted combination of the input

Input



Instead, have the model learn how to weight each input!

Target

Er liebte zu essen

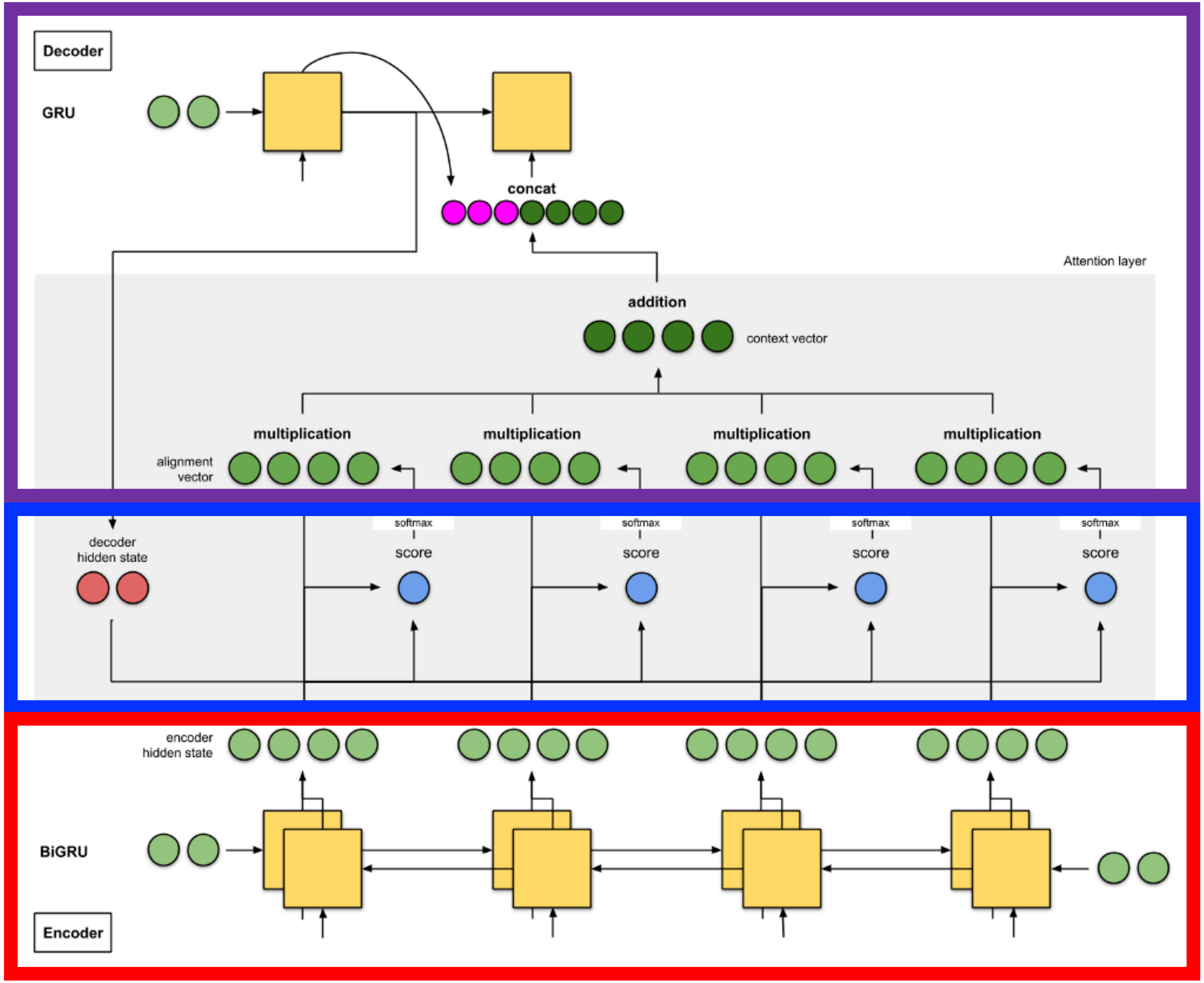
t = 1 t = 2 t = 3 t = 4

Solution

3. At each decoder time step, a prediction is made based on the weighted sum of the inputs

2. At each decoder time step, attention weights are computed that determine each input's relevance for the prediction

1. Encoder produces hidden state for every input



https://towardsdatascience.com/attn-illustrated-attention-5ec4ad276ee3

Today’s Topics

- Motivation: machine neural translation for long sentences
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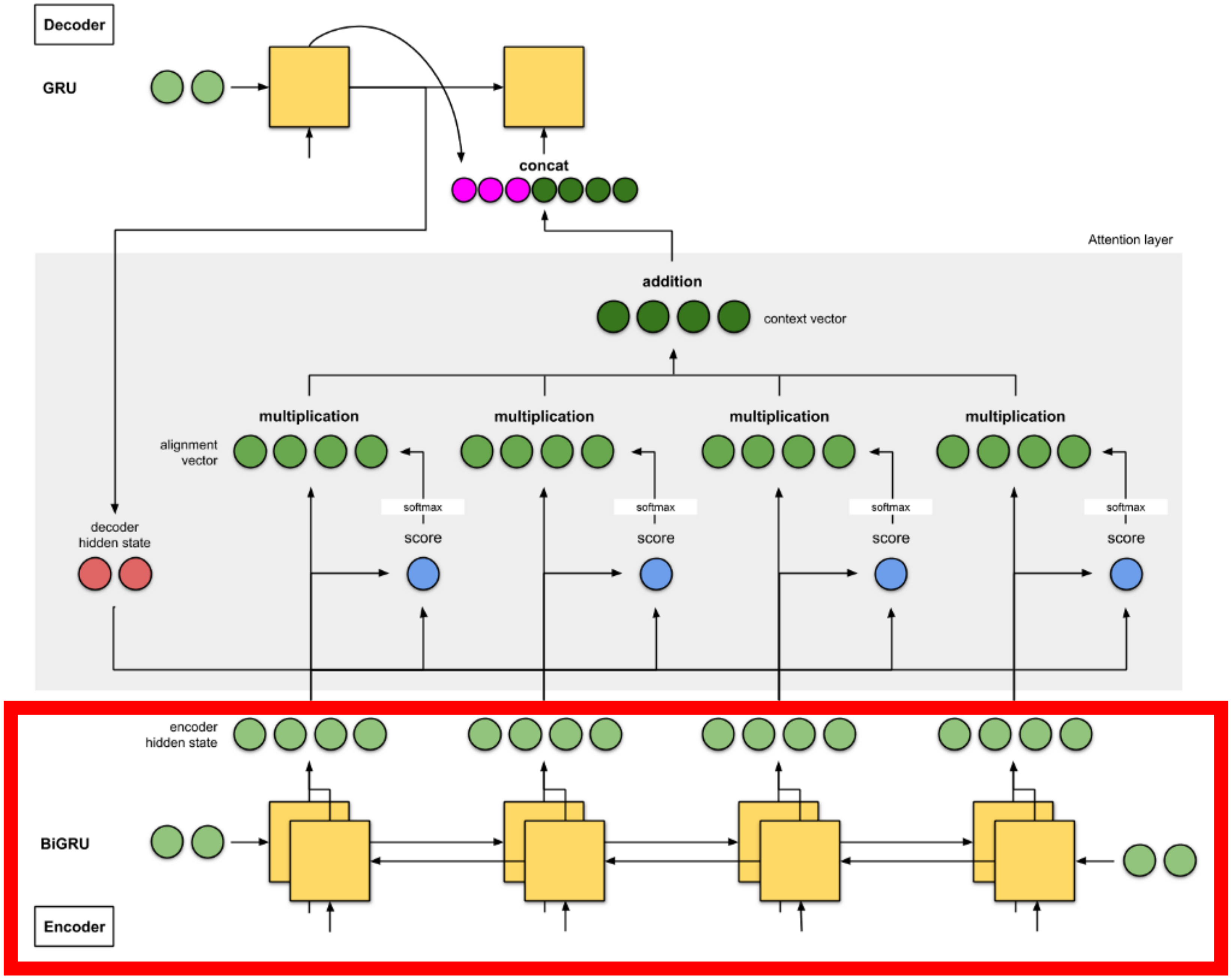

1. Encoder produces hidden state for every input

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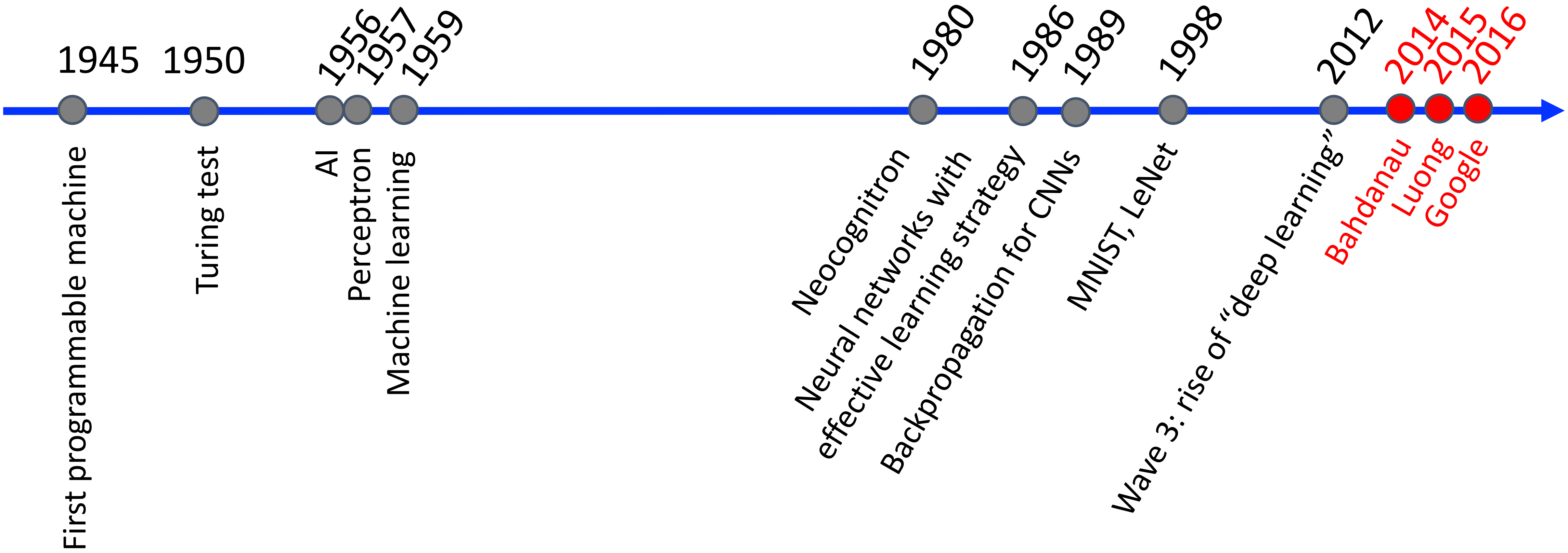
Popular Choices for Encoding Input

- Bi-directional RNN (Bahdanau)
- Stacked RNNs (Luong)
- Bi-directional and Stacked RNN (Google)

Historical Context



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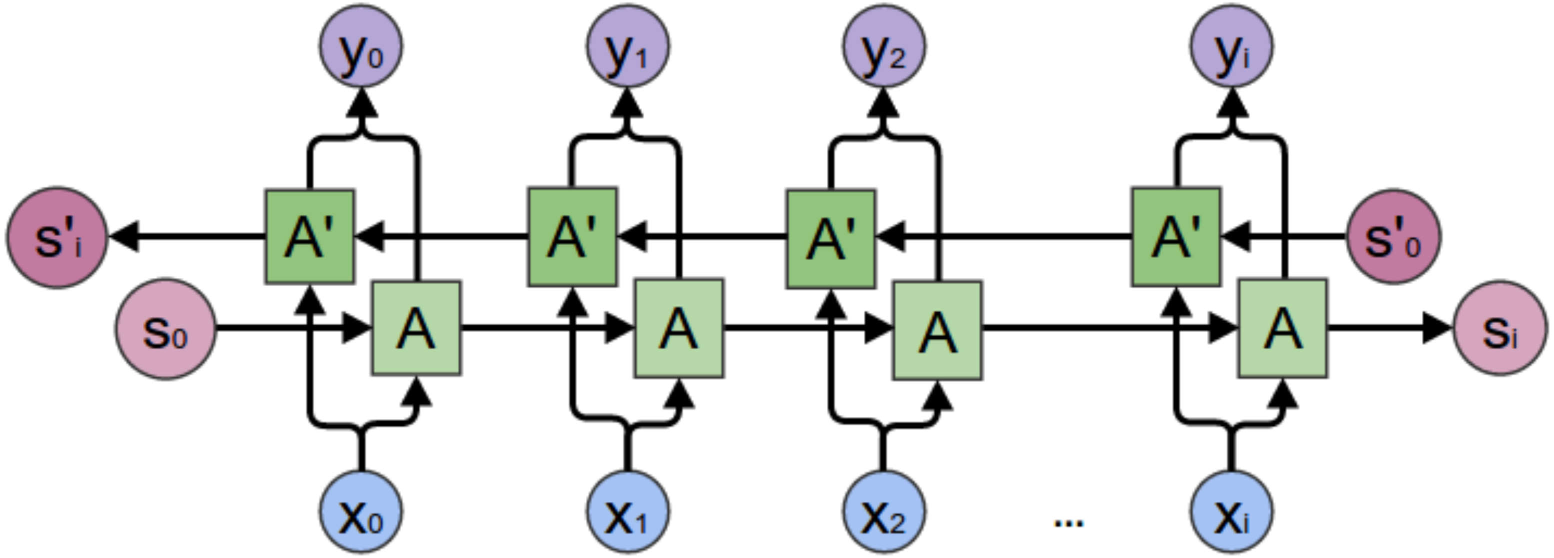
Bahdanau's Neural Machine Translation: Encoder

- Two RNNs where input is fed forward and backward respectively and then the hidden states (typically) are concatenated into a hidden state



What are advantages of a bi-directional RNN compared to a single RNN?

https://towardsdatascience.com/understanding-bidirectional-rnn-in-pytorch-5bd25a5dd66

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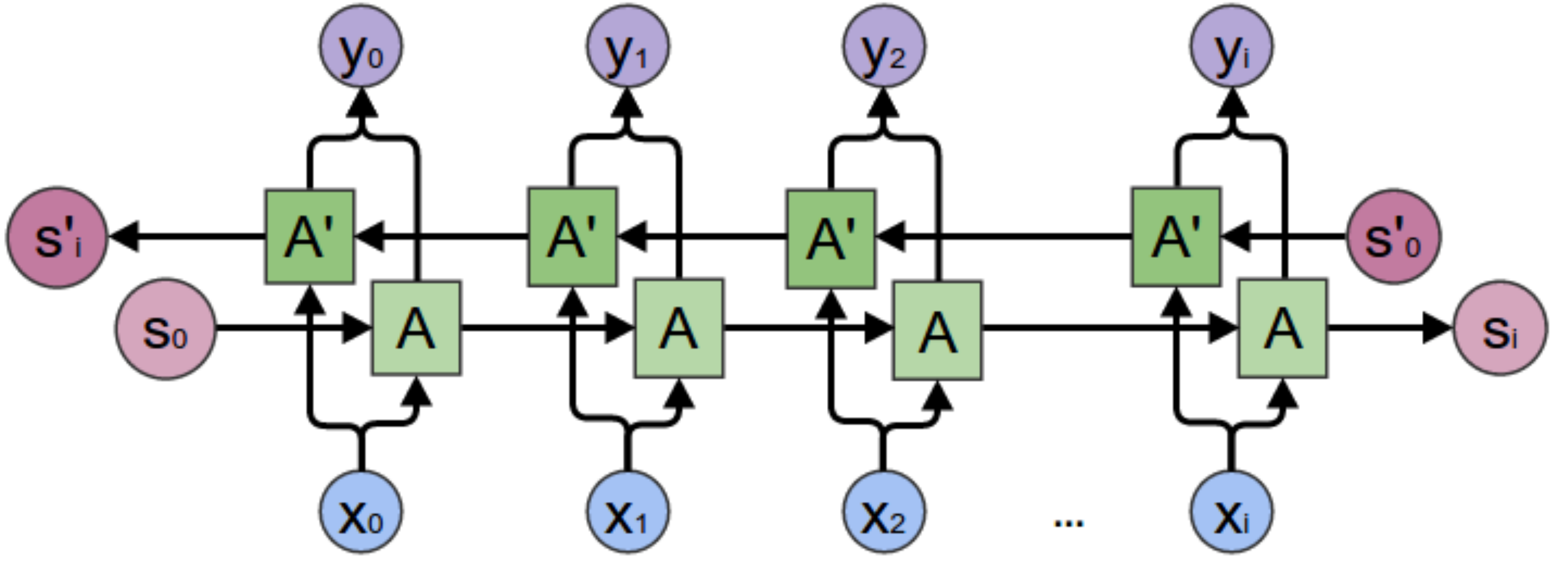

Can use information from the past and **future** to make predictions: e.g., can resolve for "Teddy is a …?" if Teddy refers to a "bear" or former US President Roosevelt

https://towardsdatascience.com/understanding-bidirectional-rnn-in-pytorch-5bd25a5dd66

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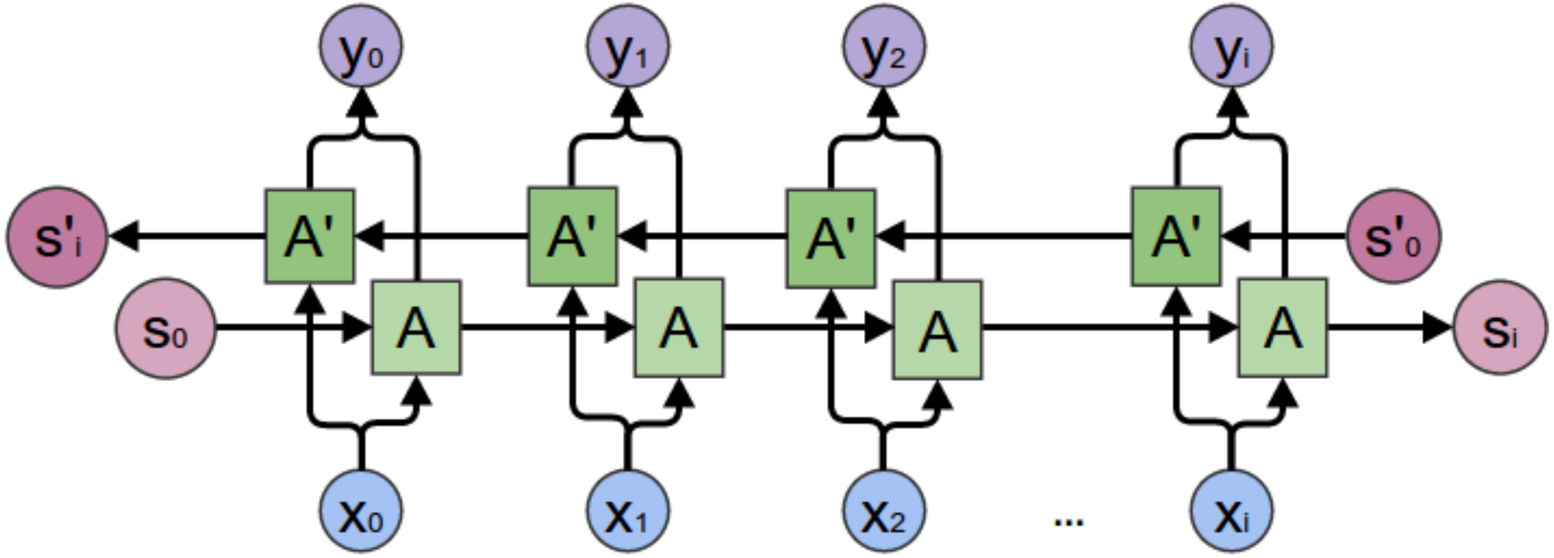

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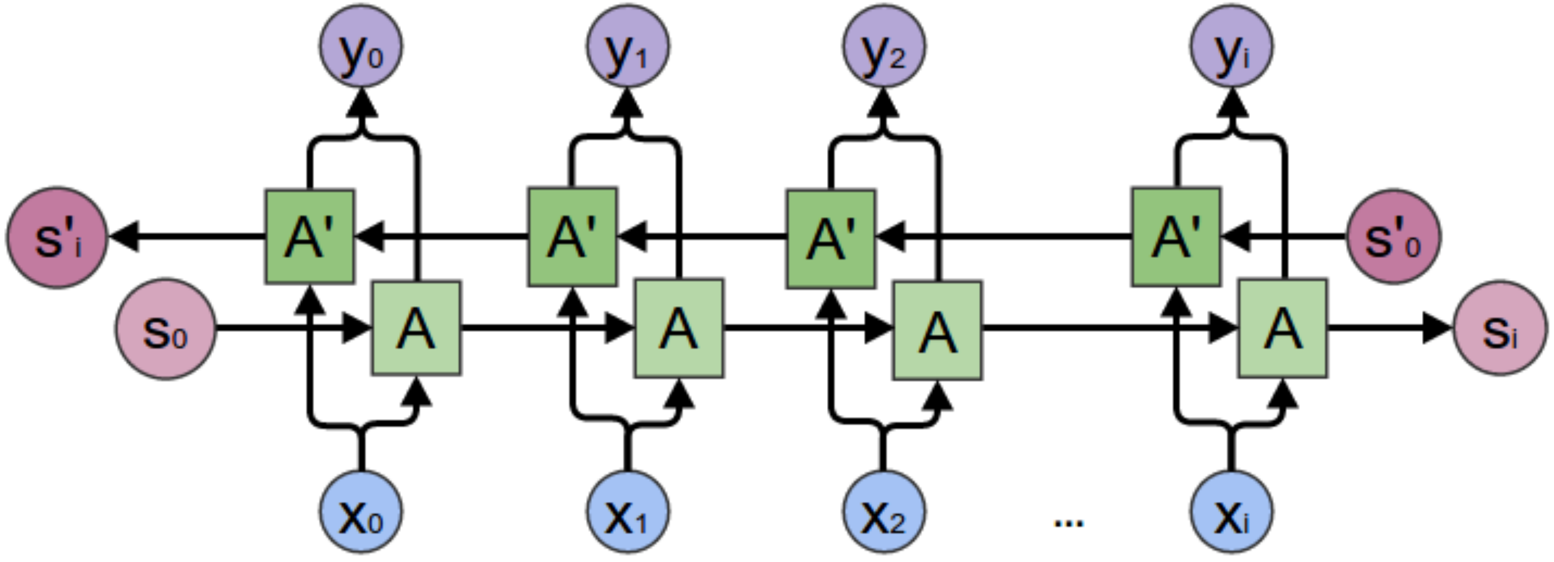

Entire sequence must be observed to make a prediction (e.g., unsuitable for text prediction)

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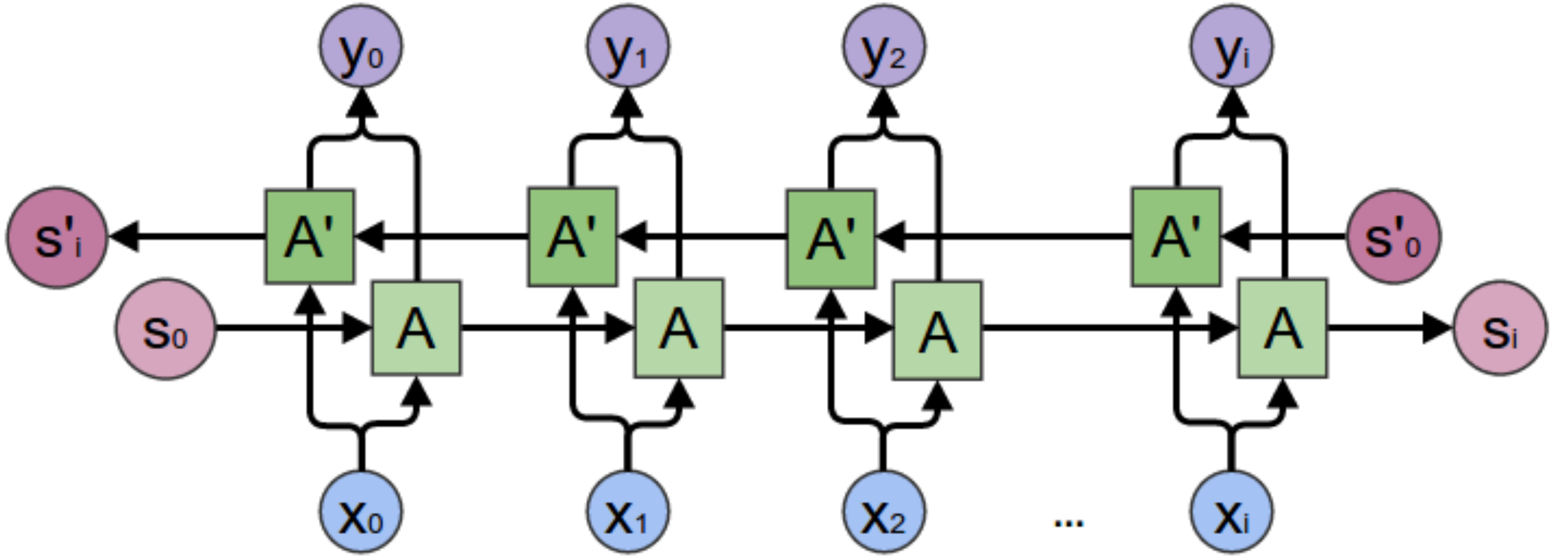

Bahdanau's method encodes input with a bidirectional GRU

https://towardsdatascience.com/understanding-bidirectional-rnn-in-pytorch-5bd25a5dd66

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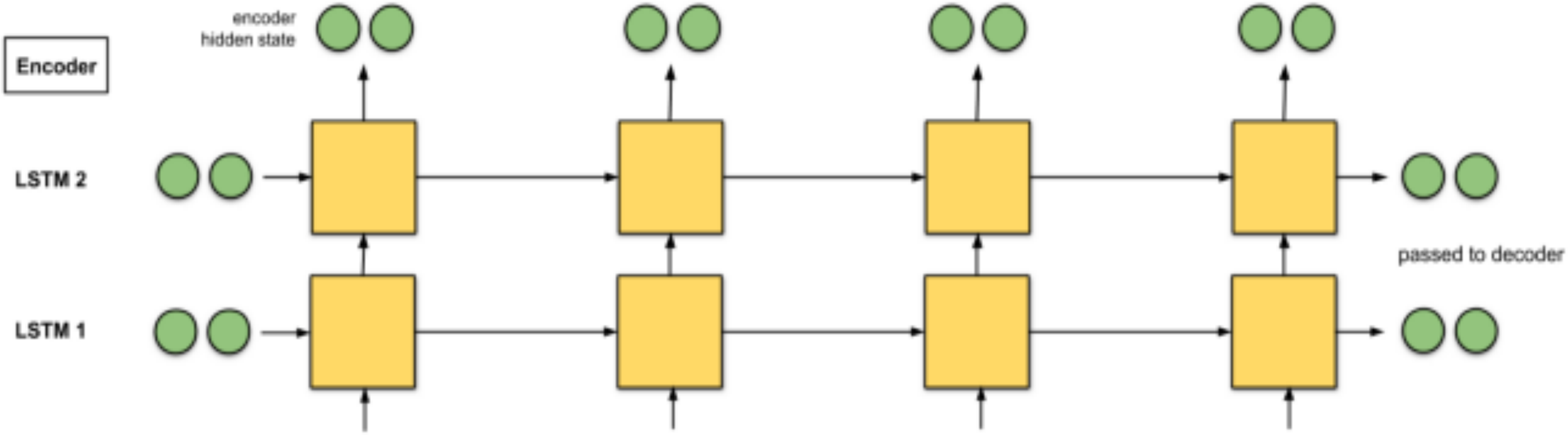
Luong’s Neural Machine Translation: Encoder



Luong’s method encodes input with a 2-layer stacked LSTM

Luong et al. Effective Approaches to Attention-based Neural Machine Translation. EMNLP 2015
https://towardsdatascience.com/attn-illustrated-attention-5ec4ad276ee3#df28

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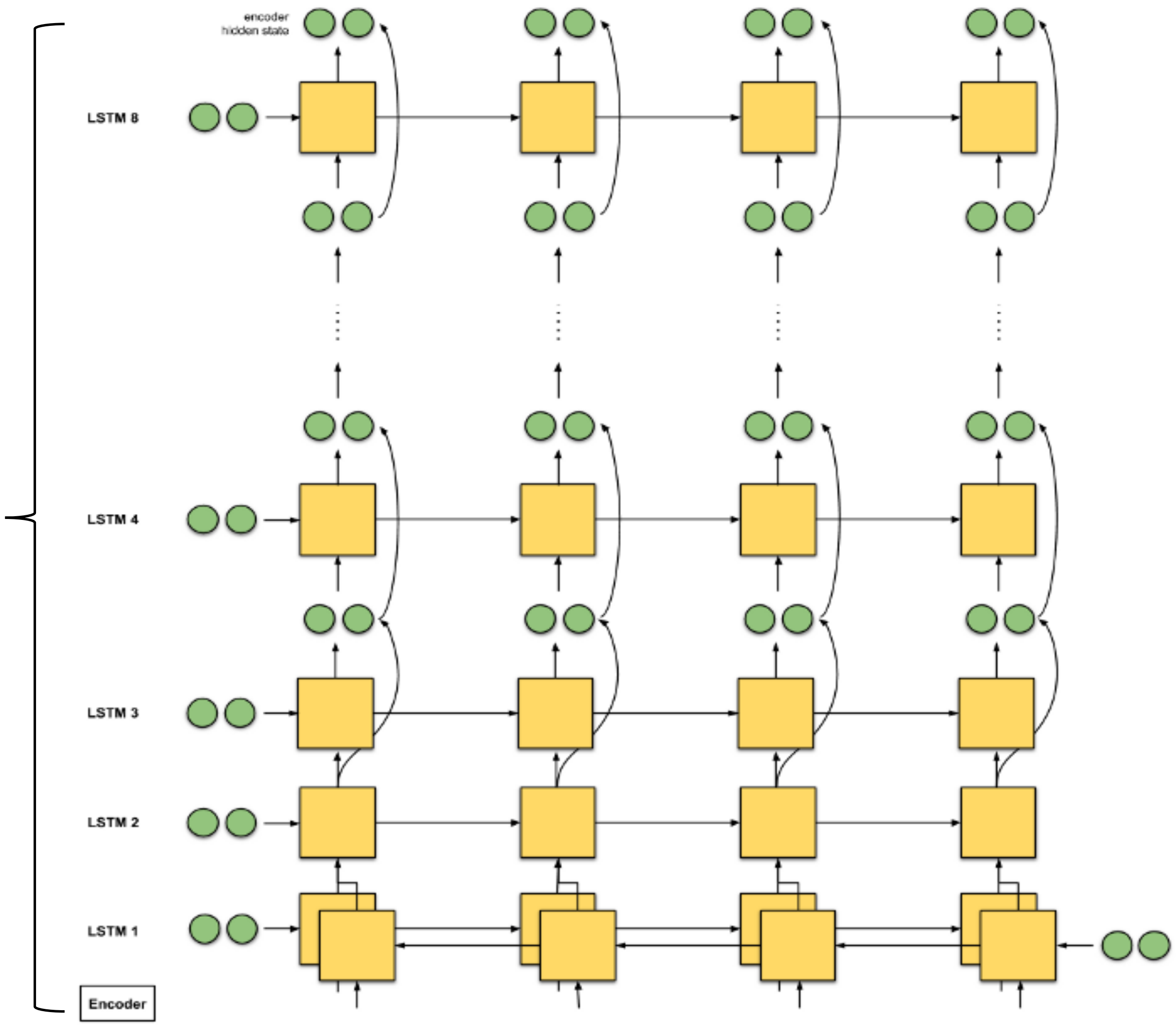
Google's Neural Machine Translation: Encoder

8 layers with 1rst layer bi-directional and skip connections between layers

(greater level of abstraction for input)



Wu et al. Google's Neural Machine Translation System: Bridging the Gap between Human and Machine Translation. arXiv 2016.
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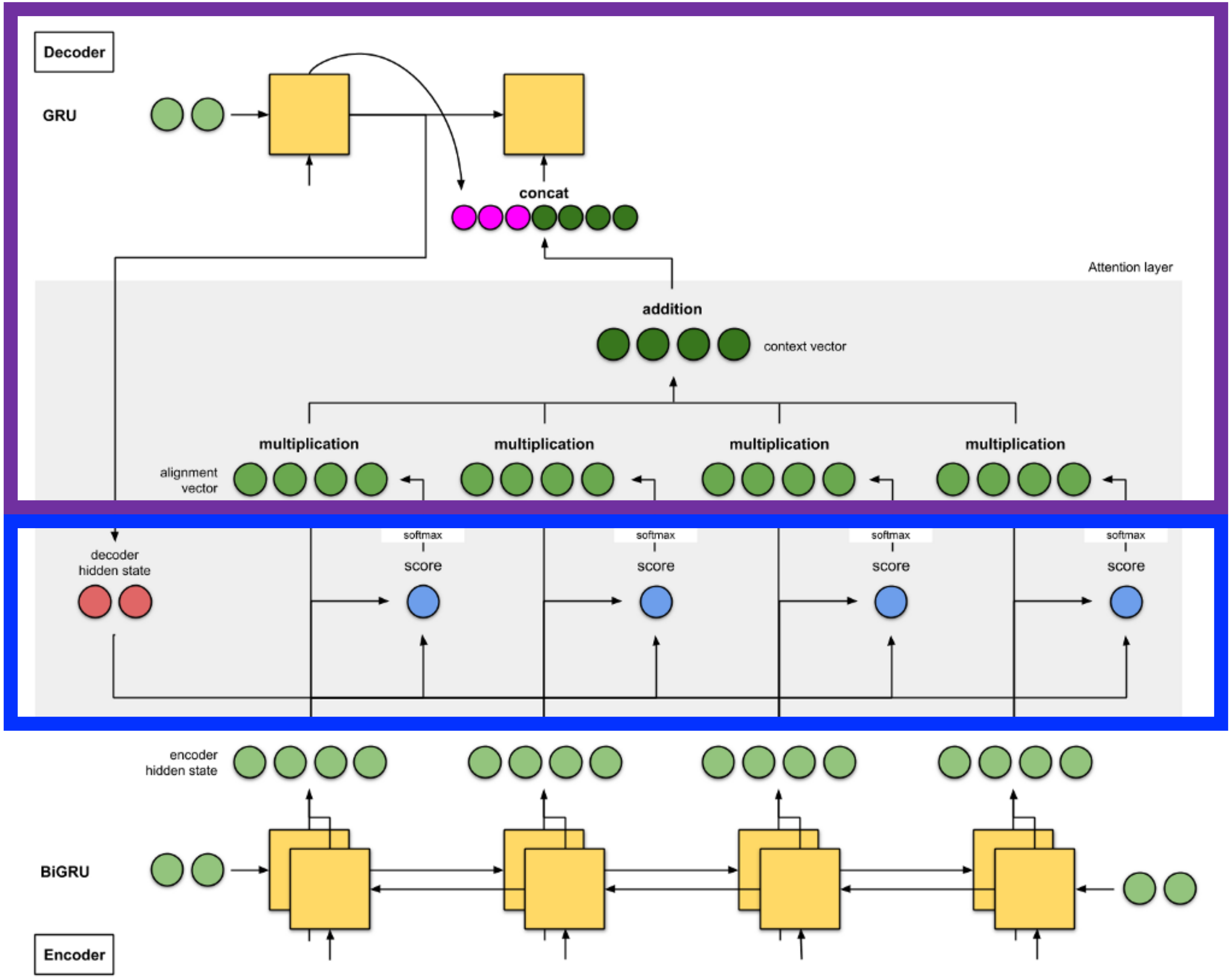

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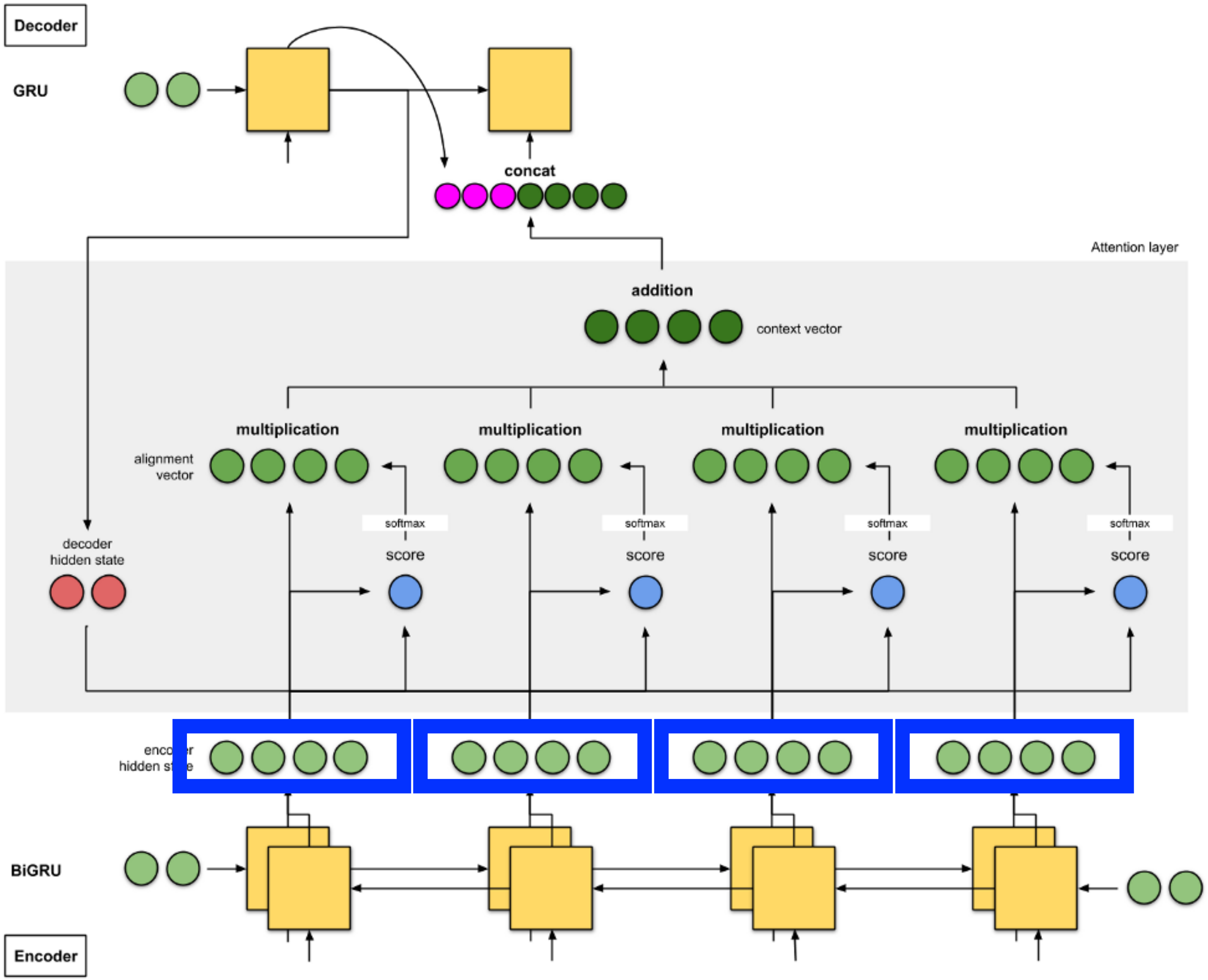
Measuring Each Input's Relevance on the Prediction

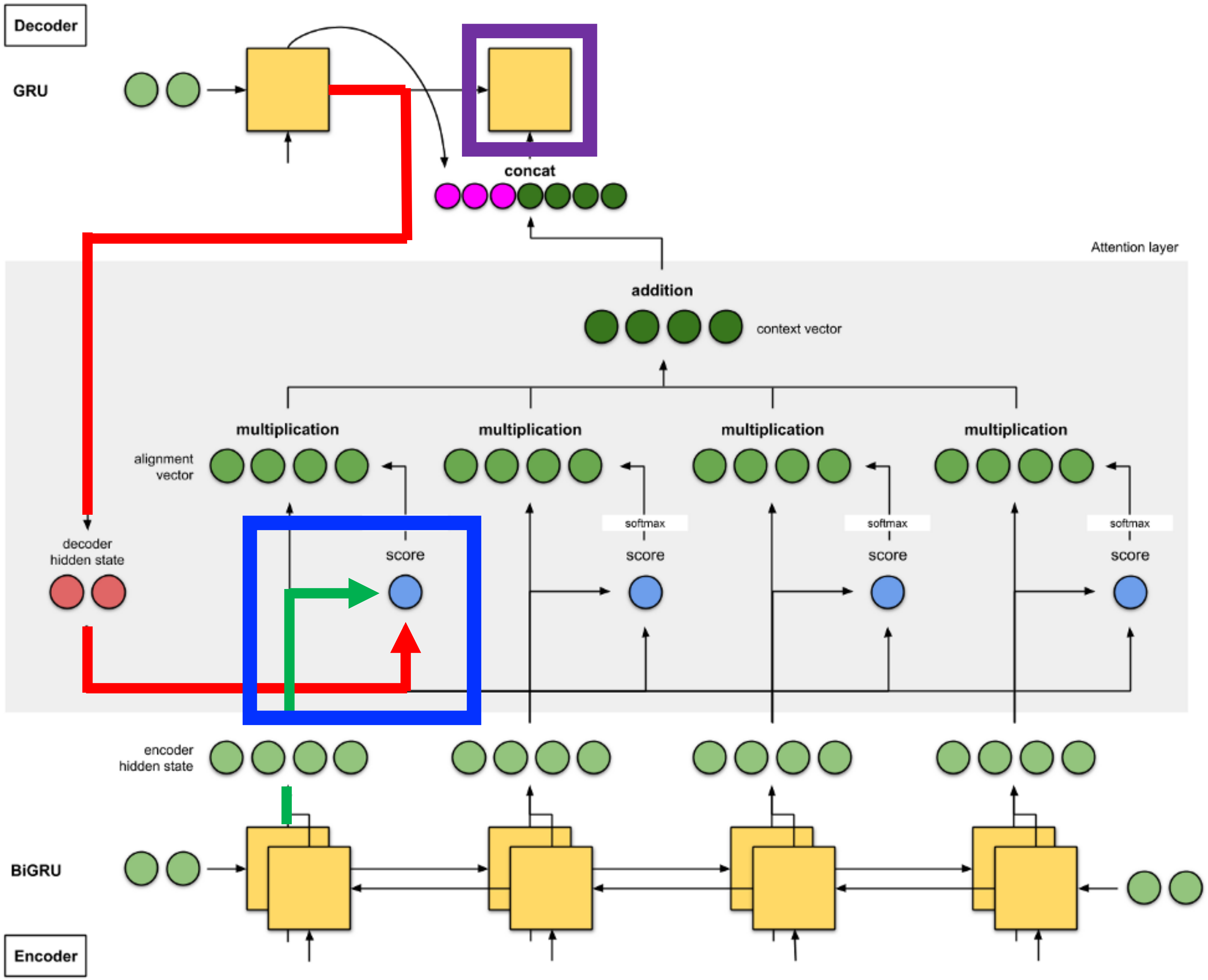


How many inputs are in this example?

https://towardsdatascience.com/attn-illustrated-attention-5ec4ad276ee3

Measuring Each Input's Relevance on the Prediction

At each decoder time step, the similarity between the decoder's hidden state and each input's hidden state is computed to decide each input's score at the time step



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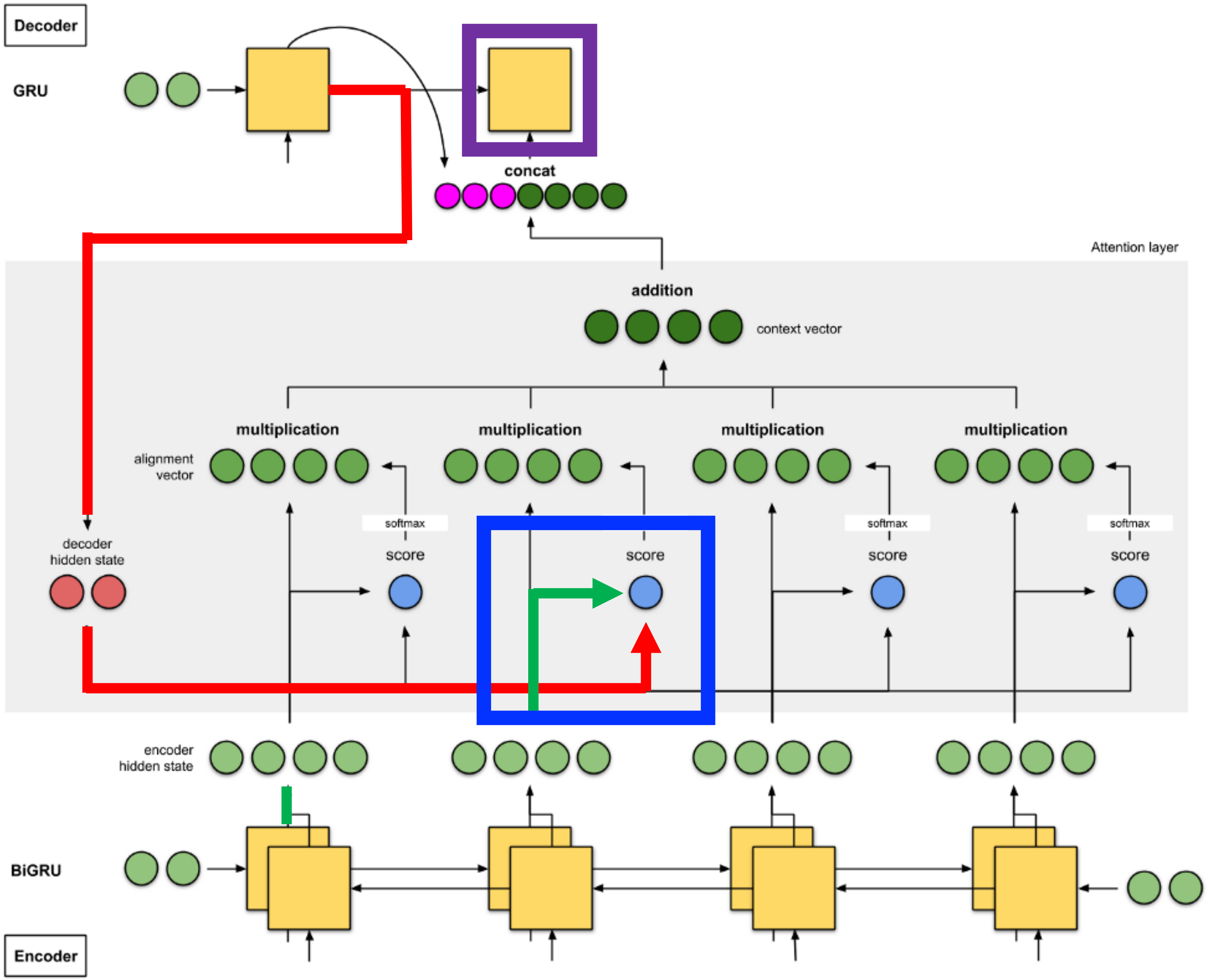

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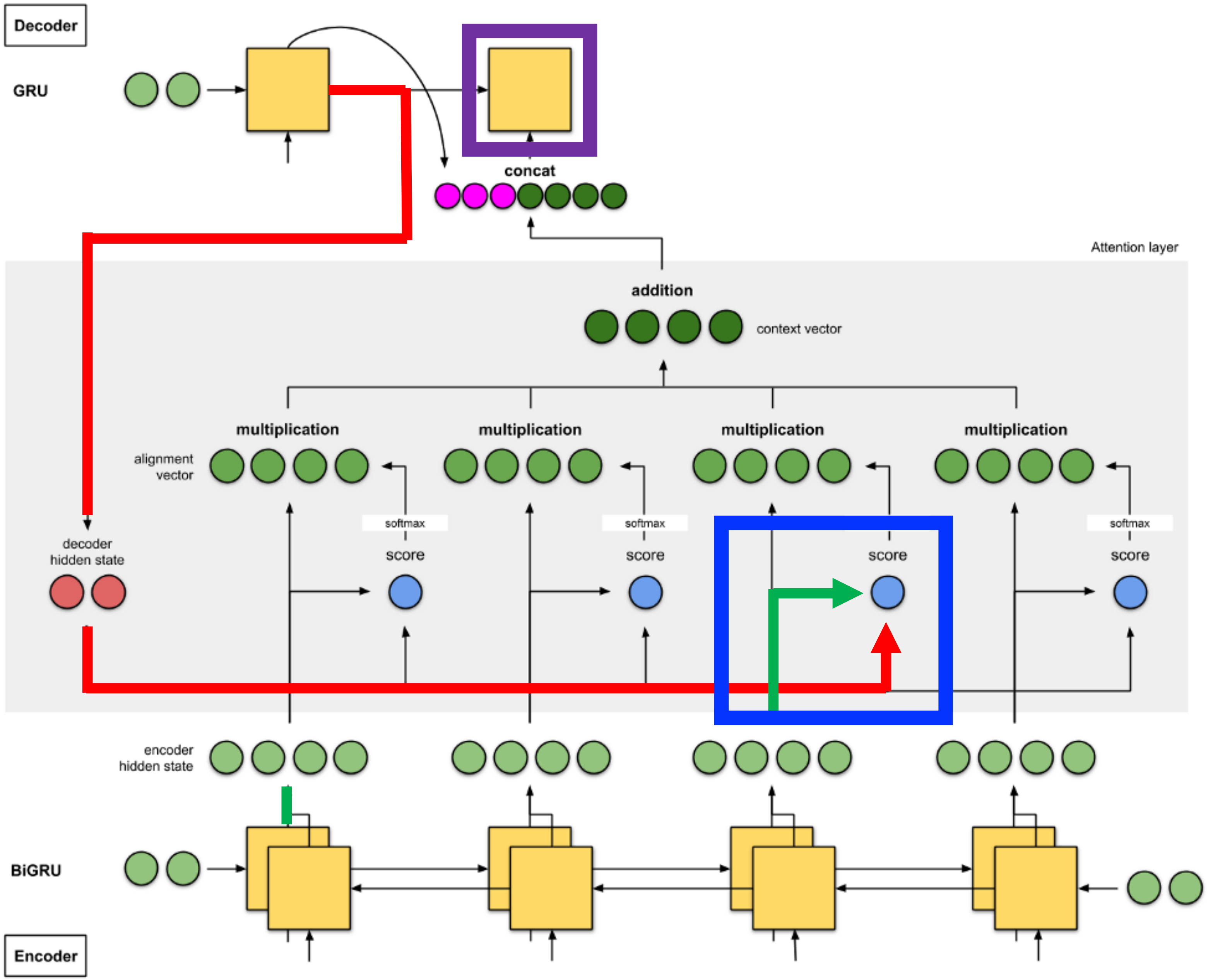

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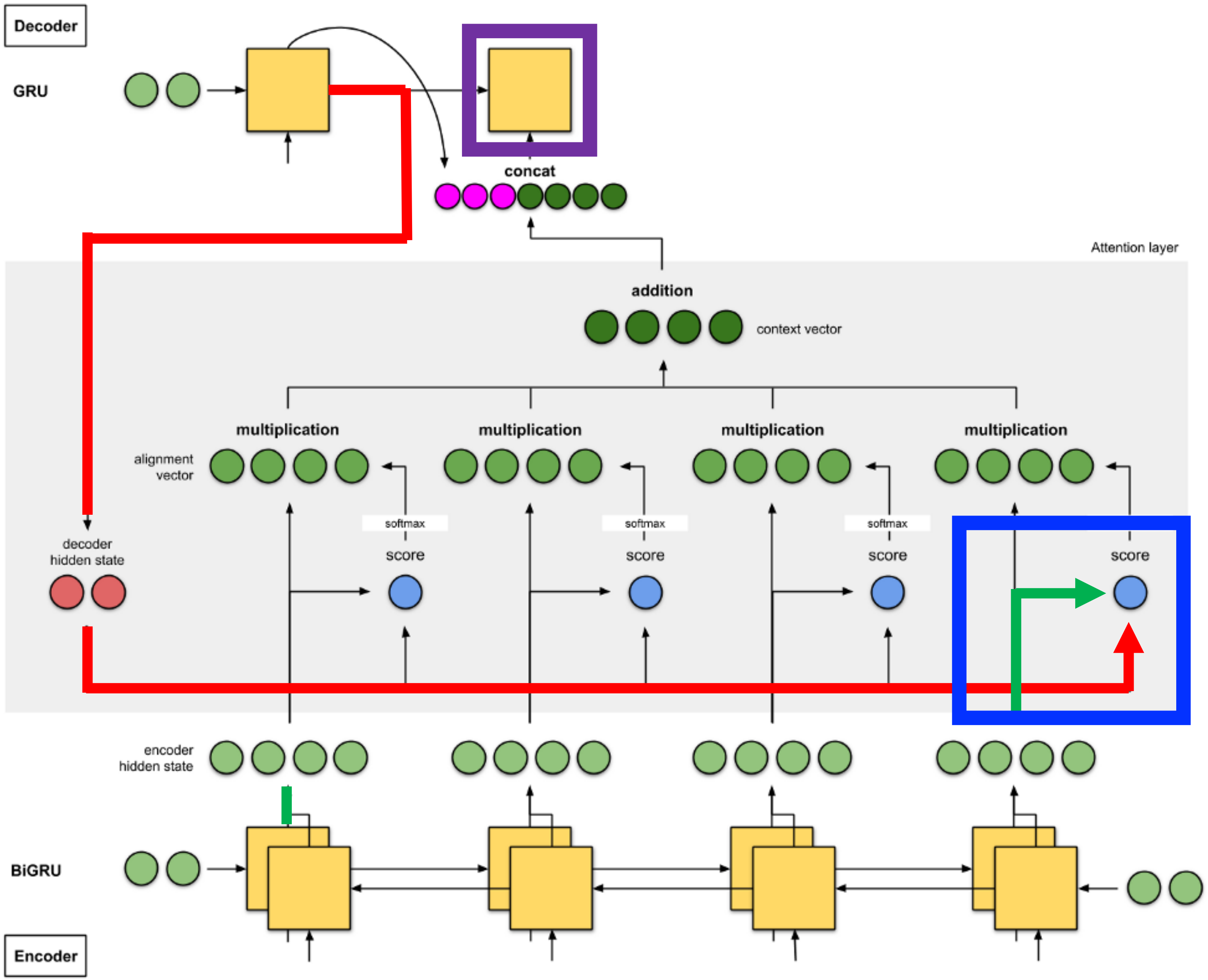

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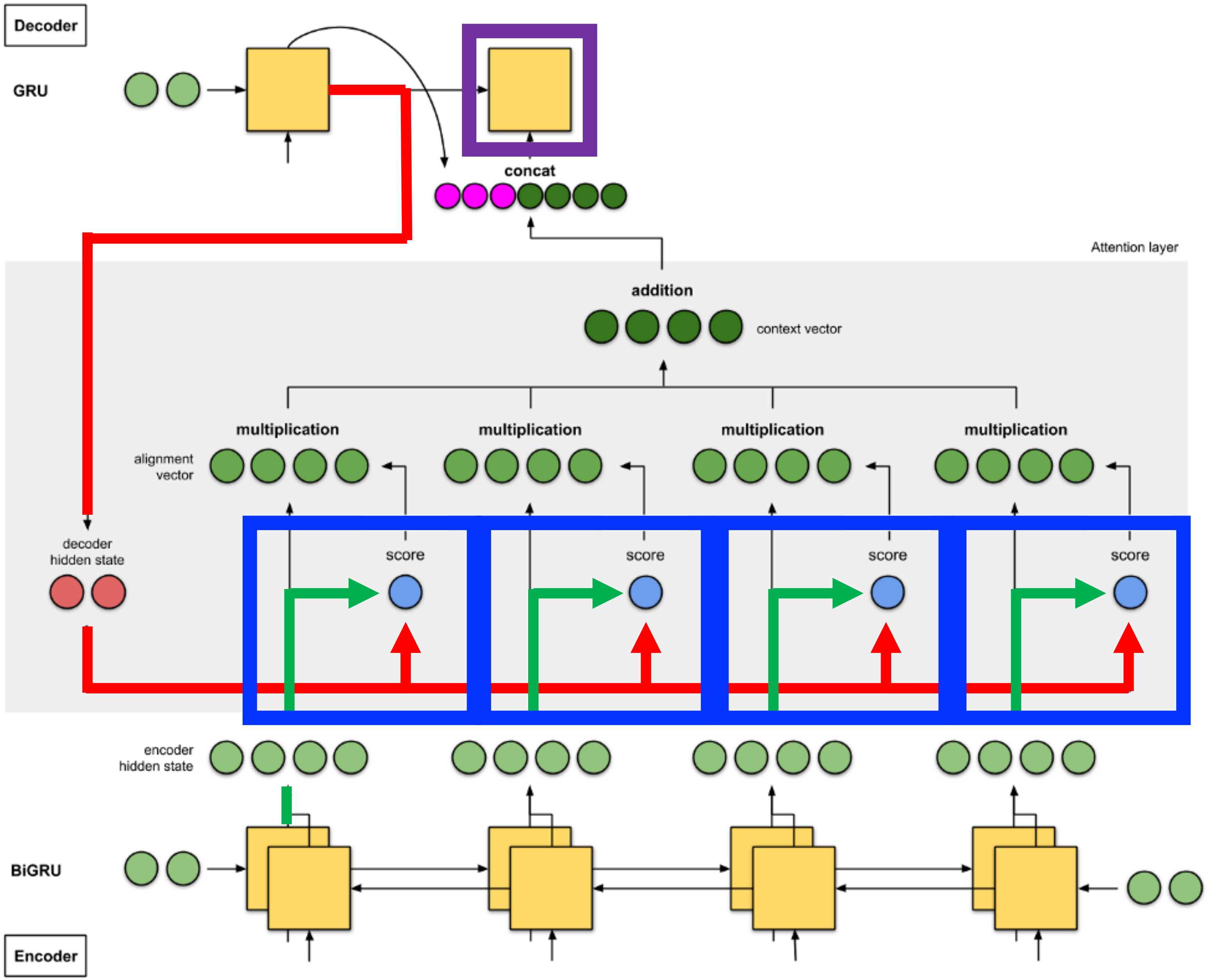
Measuring Each Input's Relevance on the Prediction

How to measure the similarity between hidden states of the decoder and input?



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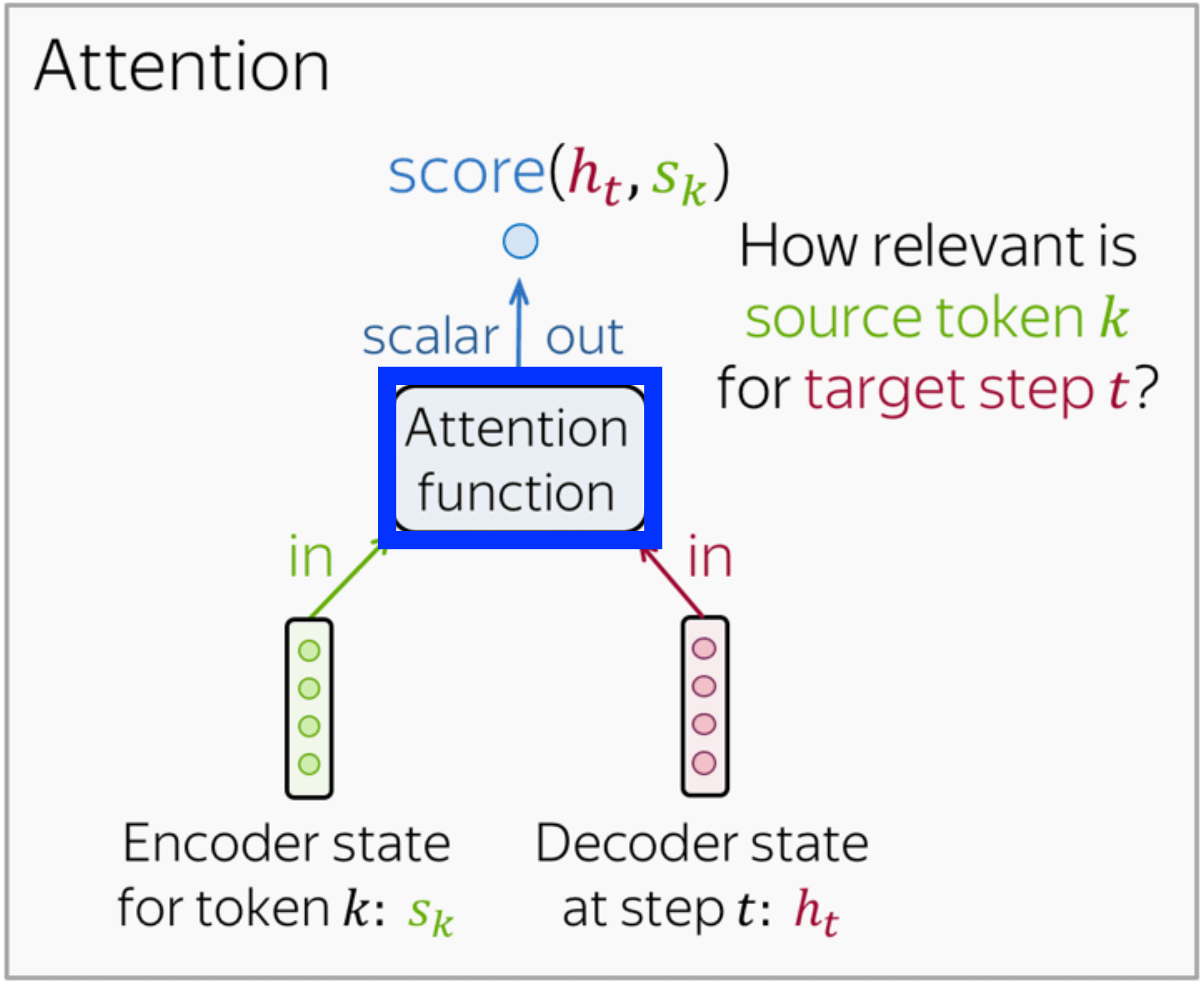
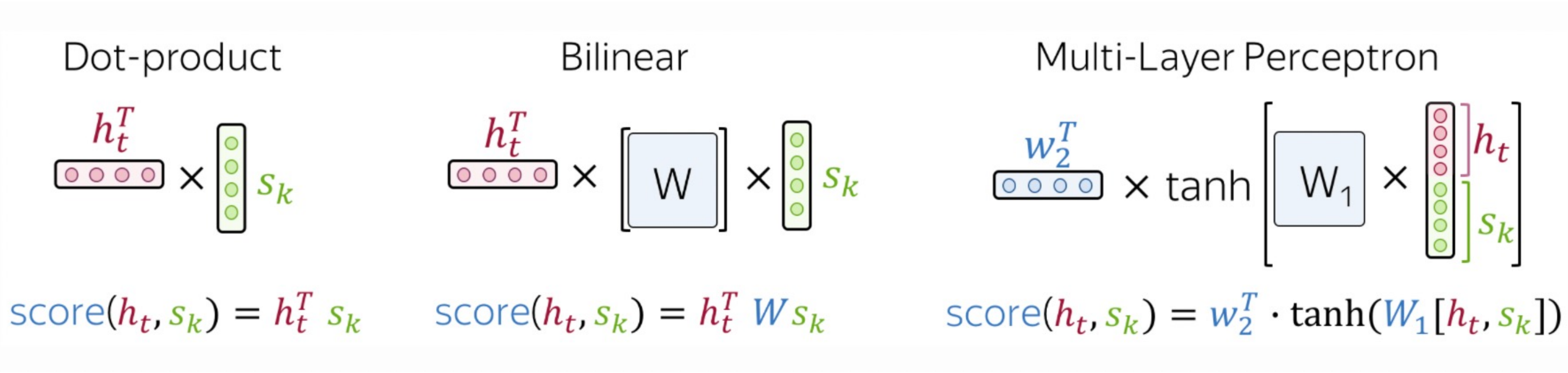
Similarity Measure for Hidden States of the Decoder and Encoder



https://lena-voita.github.io/nlp_course/seq2seq_and_attention.html

Similarity Measure for Hidden States of the Decoder and Encoder

- Many options (function should be differentiable)



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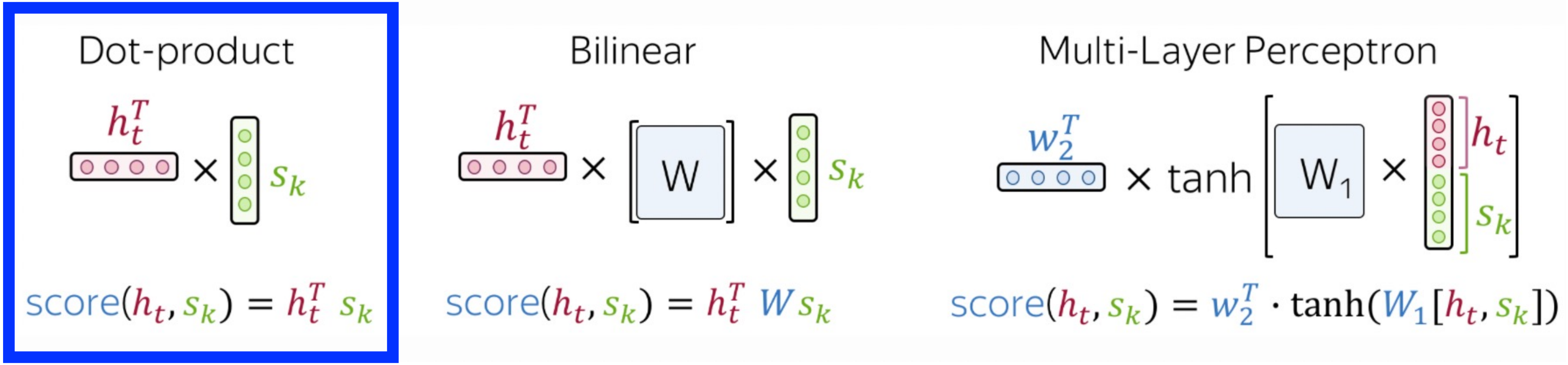
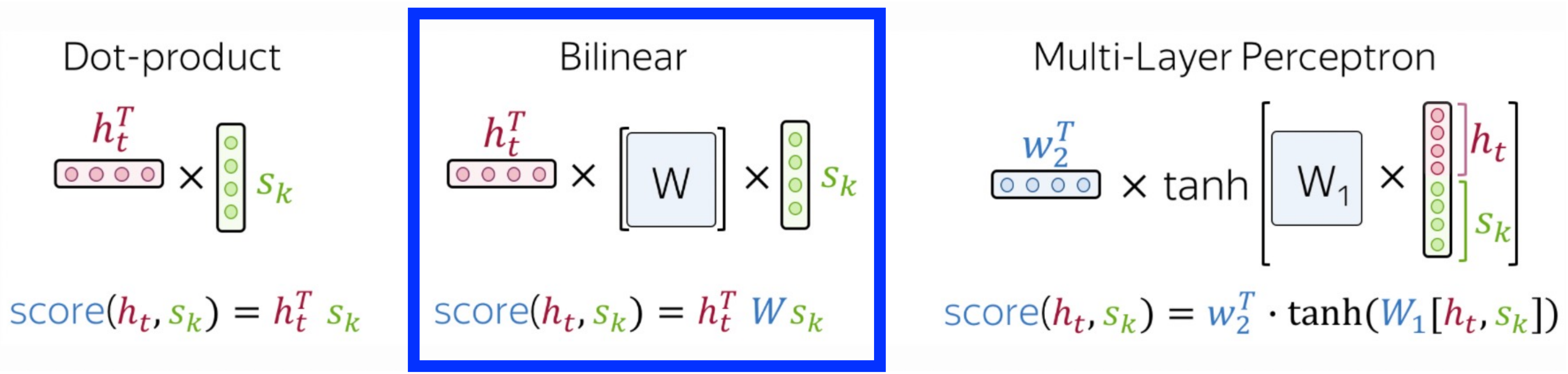


What model parameters must be learned when using dot-product?

https://lena-voita.github.io/nlp_course/seq2seq_and_attention.html

Similarity Measure for Hidden States of the Decoder and Encoder

- Many options (function should be differentiable)

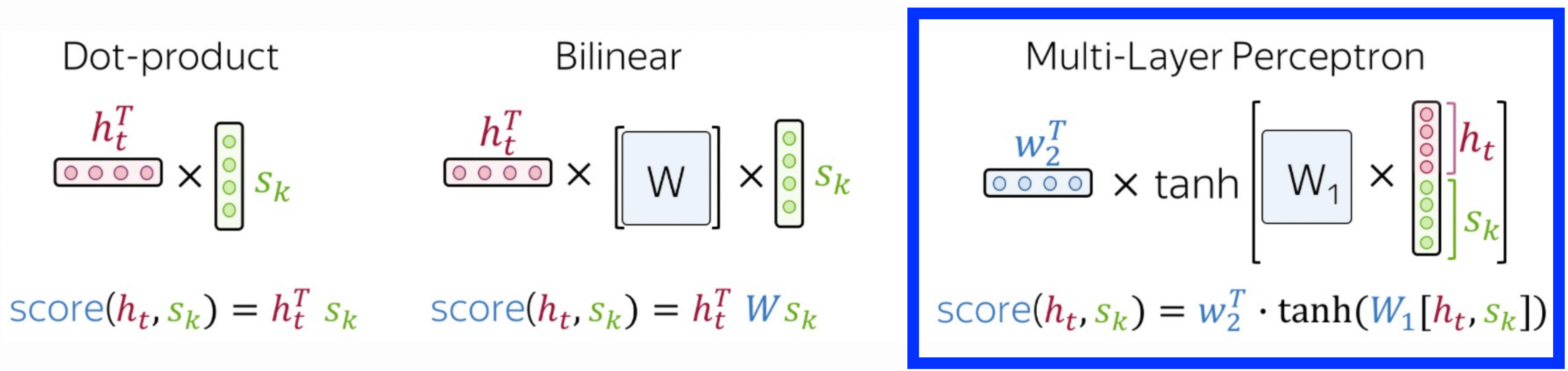


What model parameters must be learned when using bilinear?

https://lena-voita.github.io/nlp_course/seq2seq_and_attention.html

Similarity Measure for Hidden States of the Decoder and Encoder

- Many options (function should be differentiable)

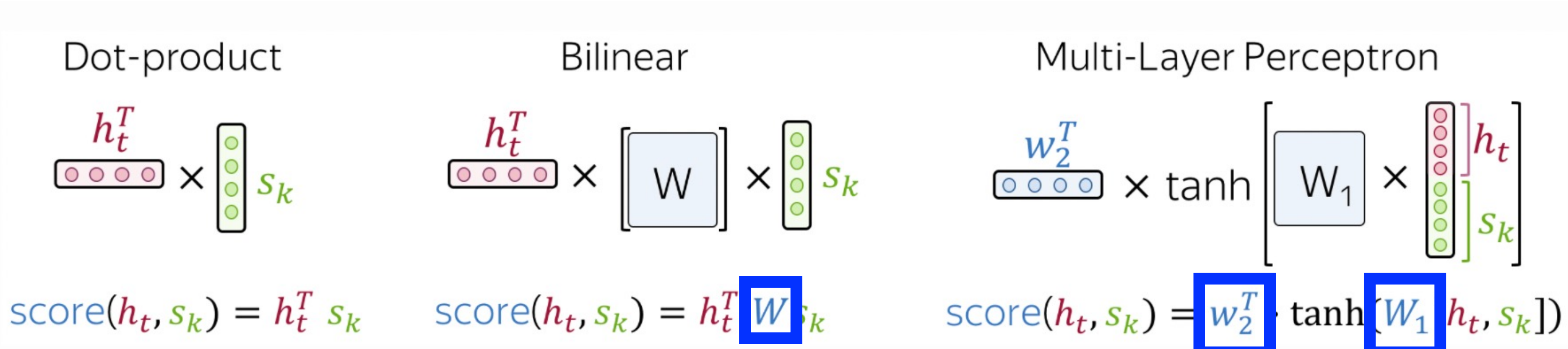


What model parameters must be learned when using multi-layer perceptron?

https://lena-voita.github.io/nlp_course/seq2seq_and_attention.html

Similarity Measure for Hidden States of the Decoder and Encoder

- Many options (function should be differentiable)



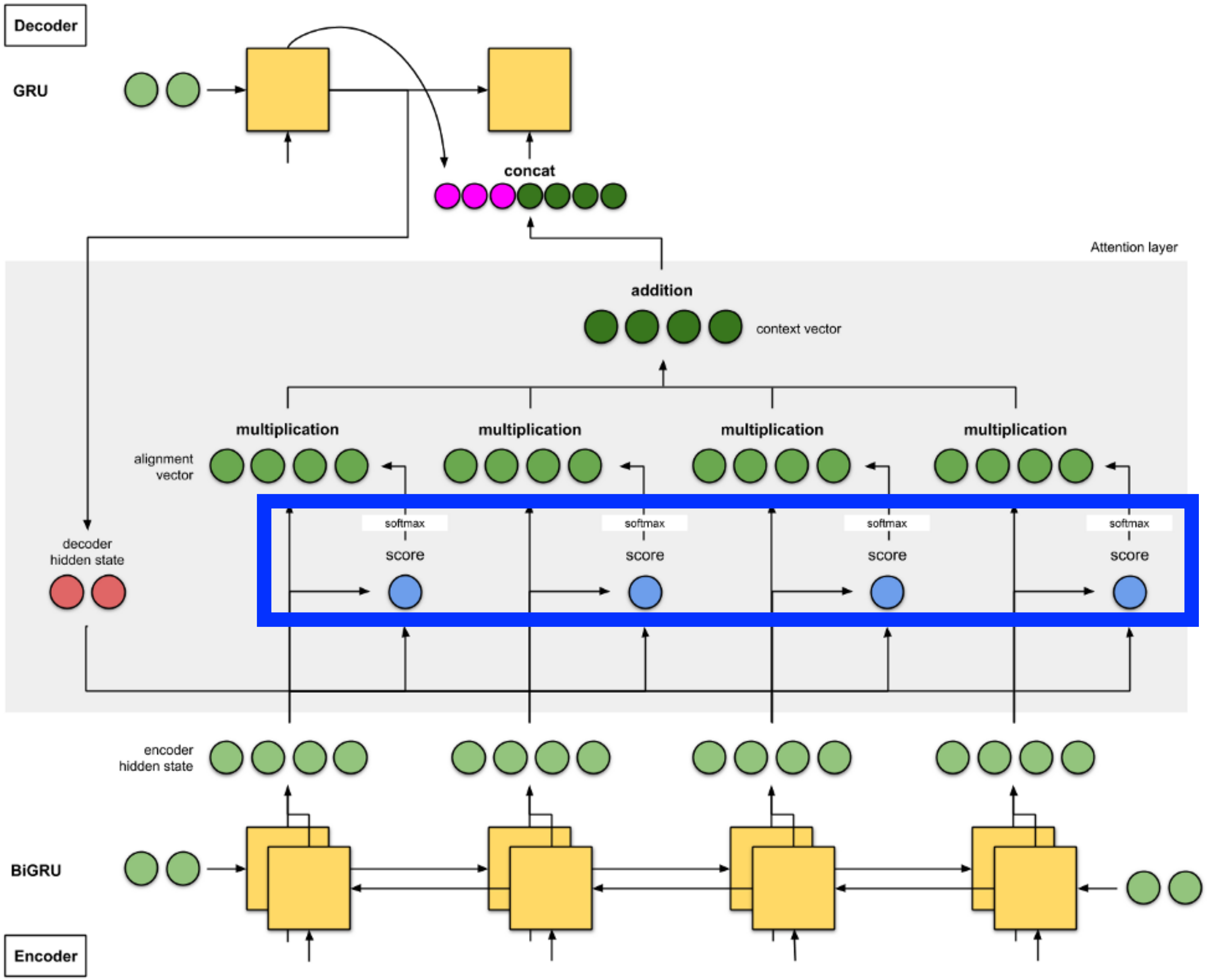
(no parameters)

Model parameters that must be learned

https://lena-voita.github.io/nlp_course/seq2seq_and_attention.html

Measuring Each Input's Influence on the Prediction

After computing the similarity scores for each input, then apply softmax to all scores so all inputs' weights sum to 1



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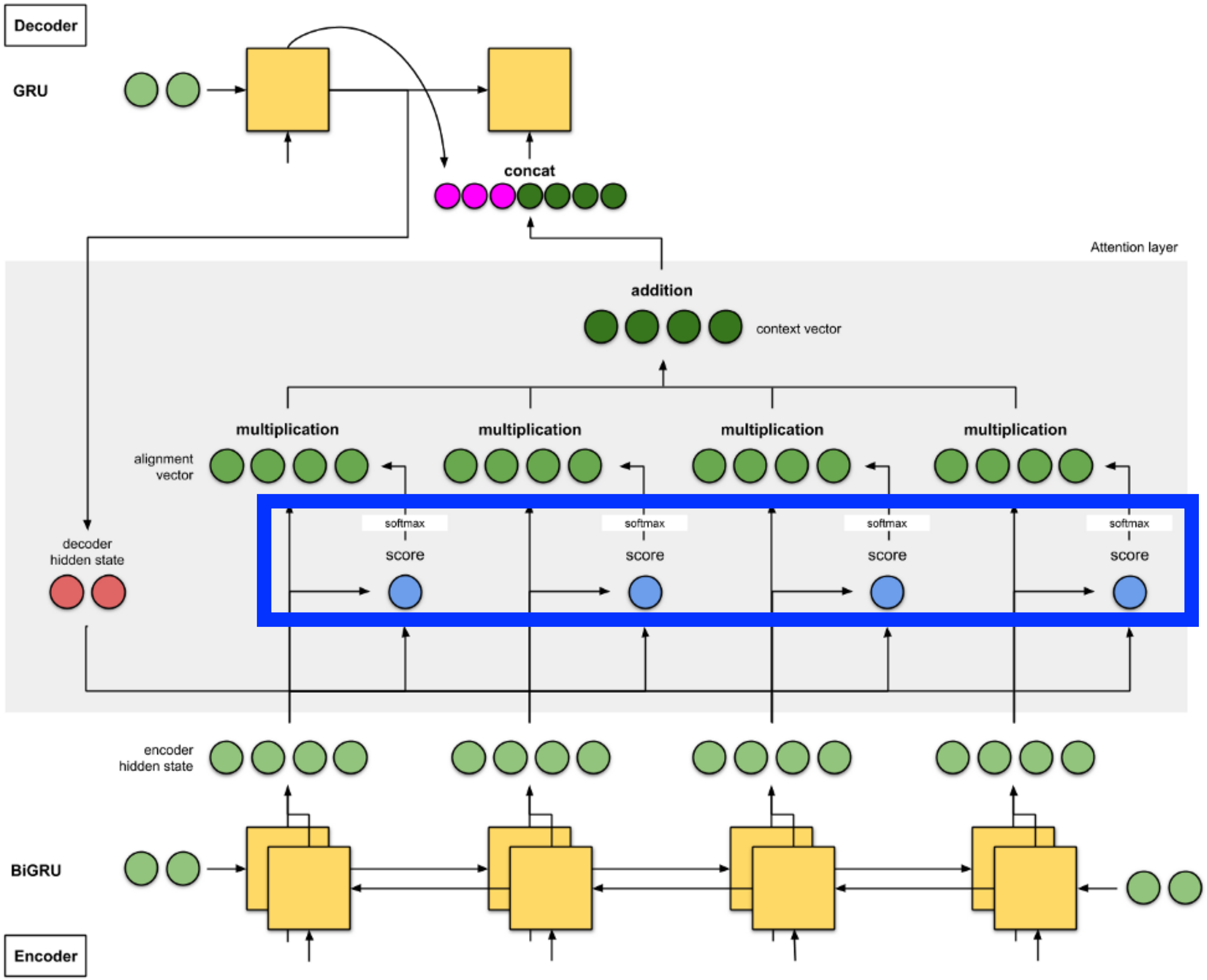
Measuring Each Input's Influence on the Prediction

We now have our attention weights!



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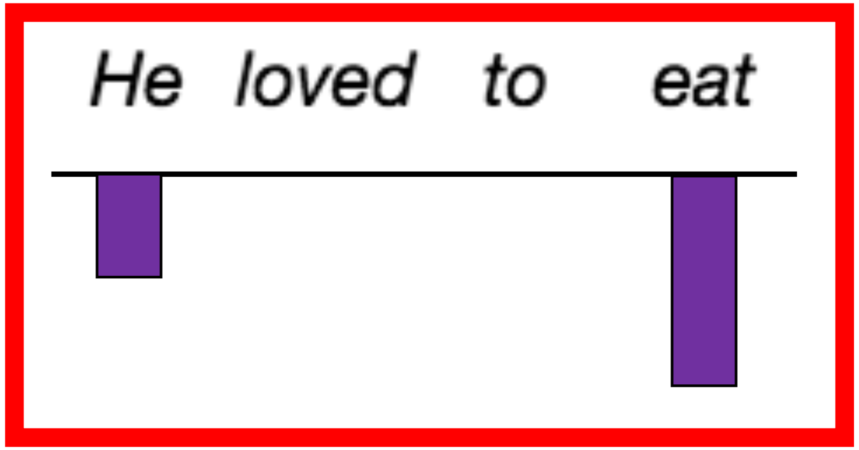
Measuring Each Input's Influence on the Prediction

Intuitively:

Input



The model can weight each input at each time step!

Target

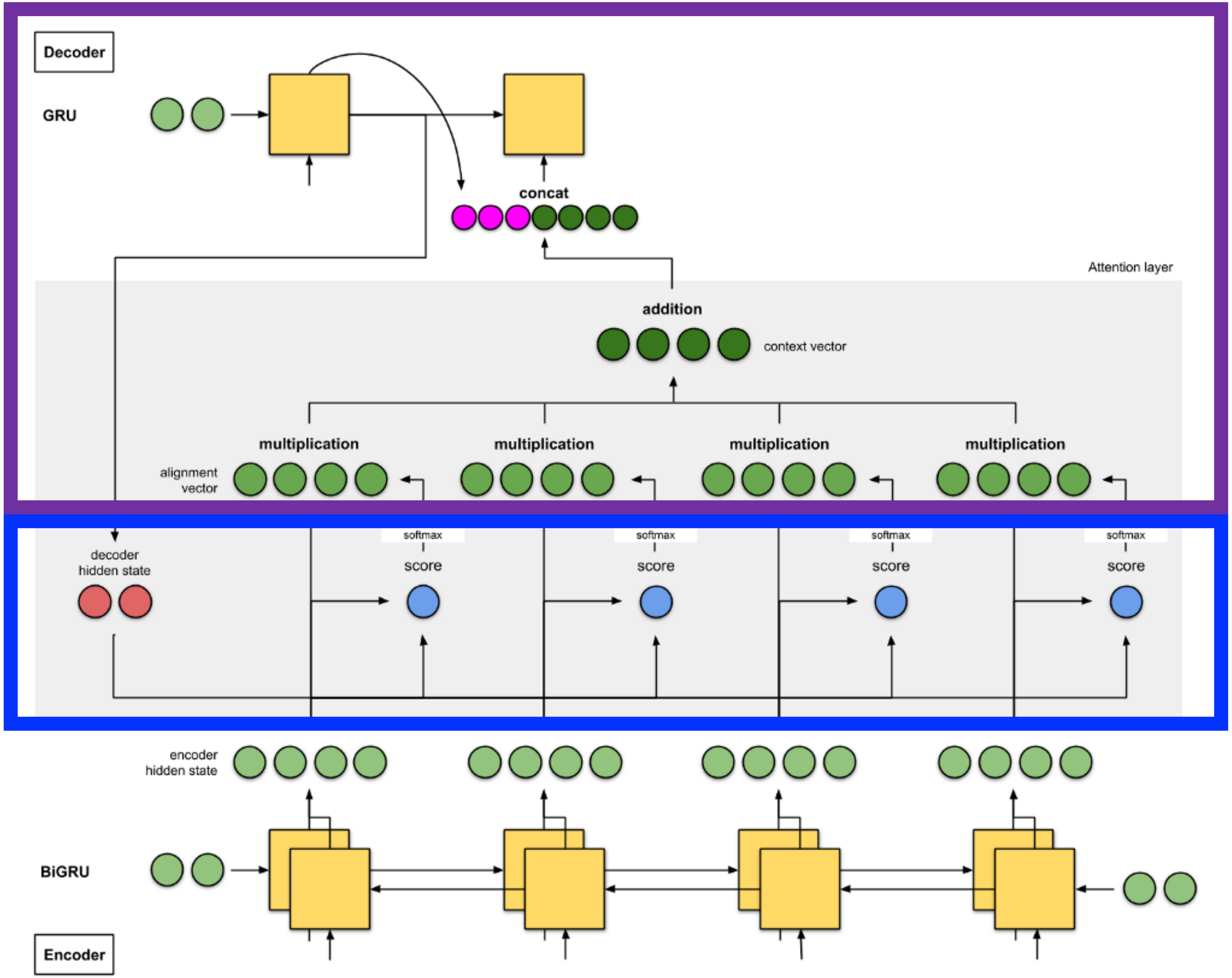
Er liebte zu essen

t = 4

Solution

3. At each decoder time step, a prediction is made based on the weighted sum of the inputs

2. At each decoder time step, attention weights are computed that determine each input's relevance for the prediction



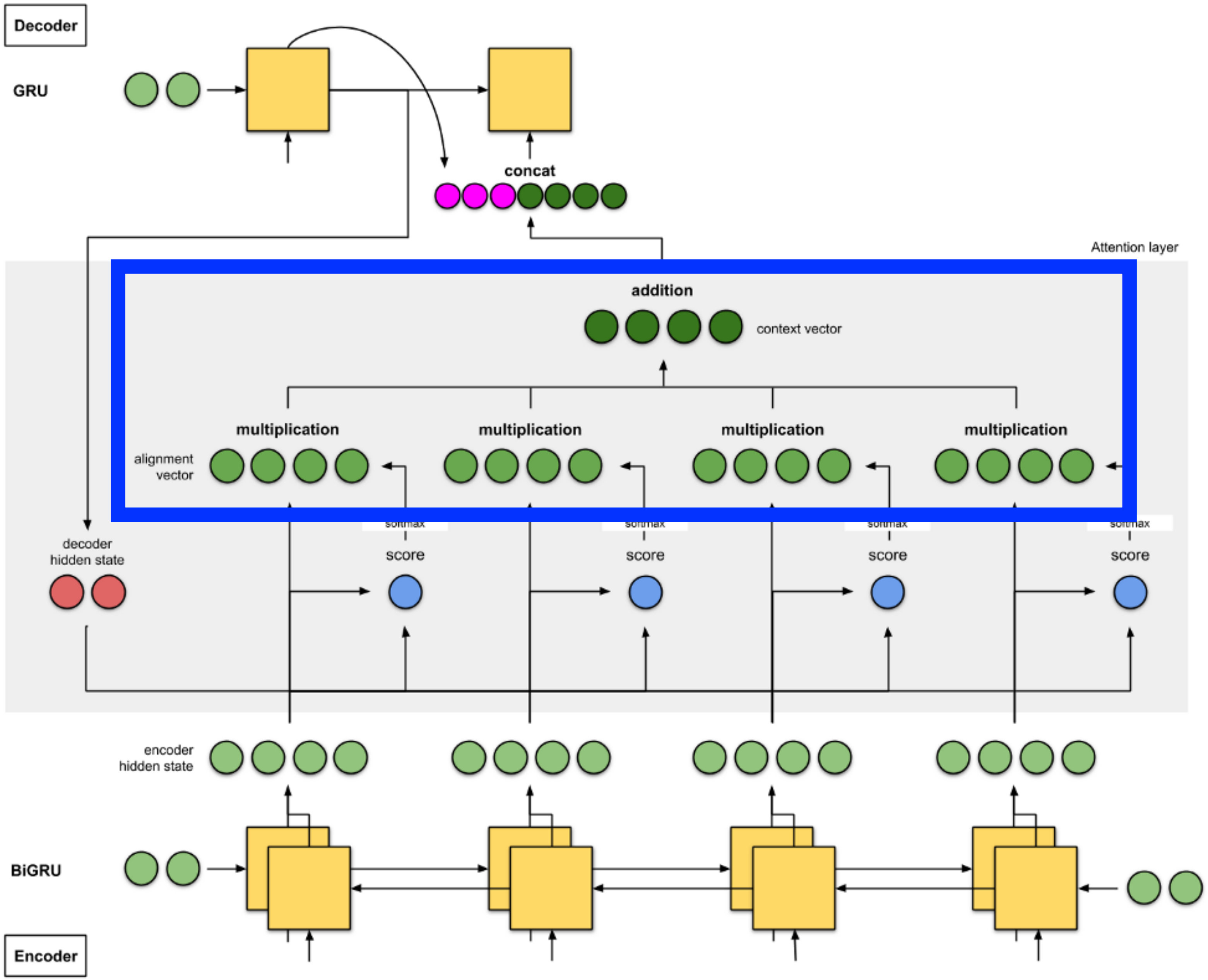
https://towardsdatascience.com/attn-illustrated-attention-5ec4ad276ee3

Word Prediction

We compute at time step *t* for all *n* inputs a weighted sum:

$$\mathbf{c}_t = \sum_{i=1}^{n} \alpha_{t,i} \boldsymbol{h}_i$$

The influence of inputs are **amplified** for large attention weights and repressed otherwise



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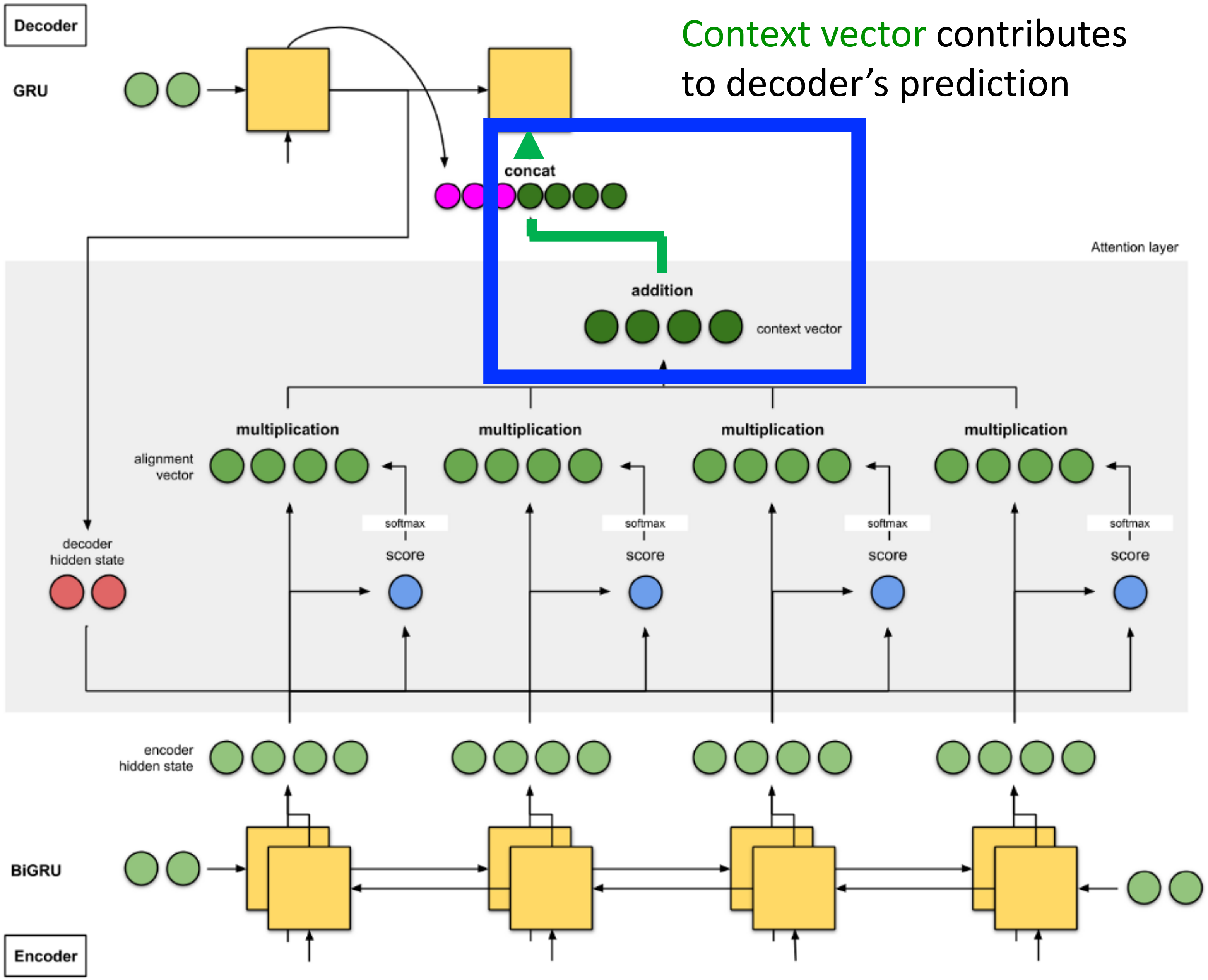
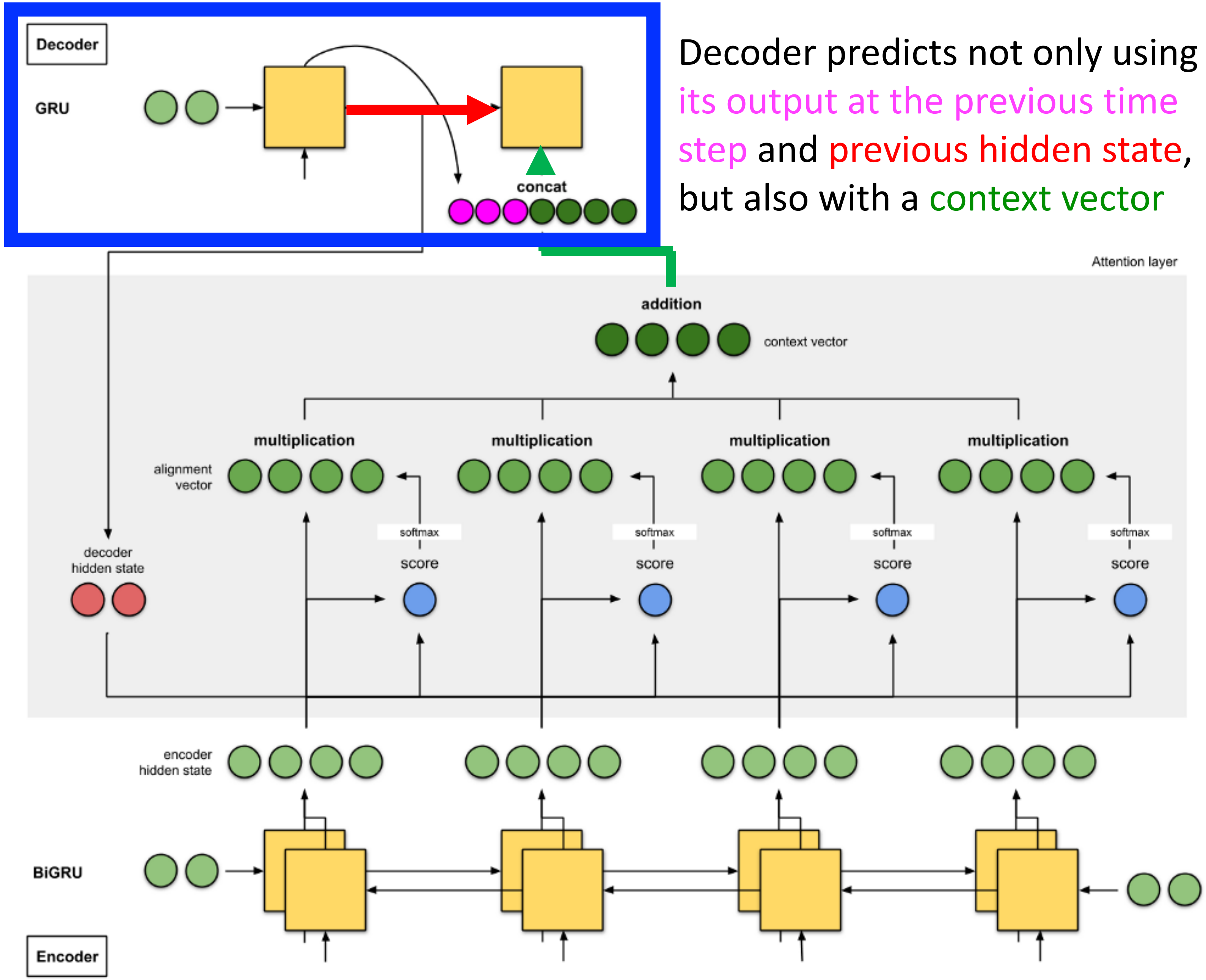
Word Prediction



Context vector contributes to decoder's prediction

https://towardsdatascience.com/attn-illustrated-attention-5ec4ad276ee3

Word Prediction

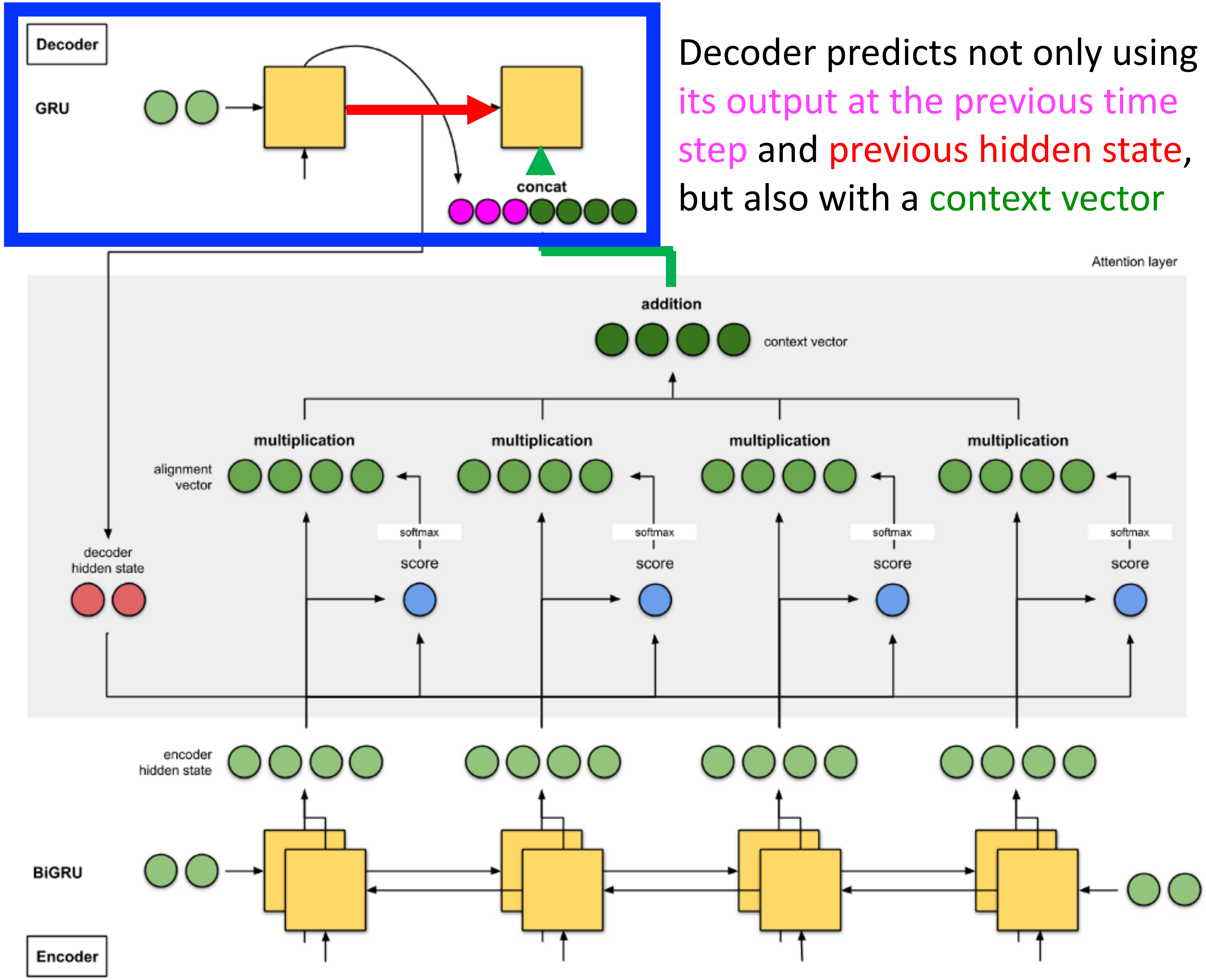


Decoder predicts not only using its output at the previous time step and previous hidden state, but also with a context vector

https://towardsdatascience.com/attn-illustrated-attention-5ec4ad276ee3

Bahdanau method

Many options exist for how to use the context vector with the decoder's output at the previous time step to produce an output at each decoder time step



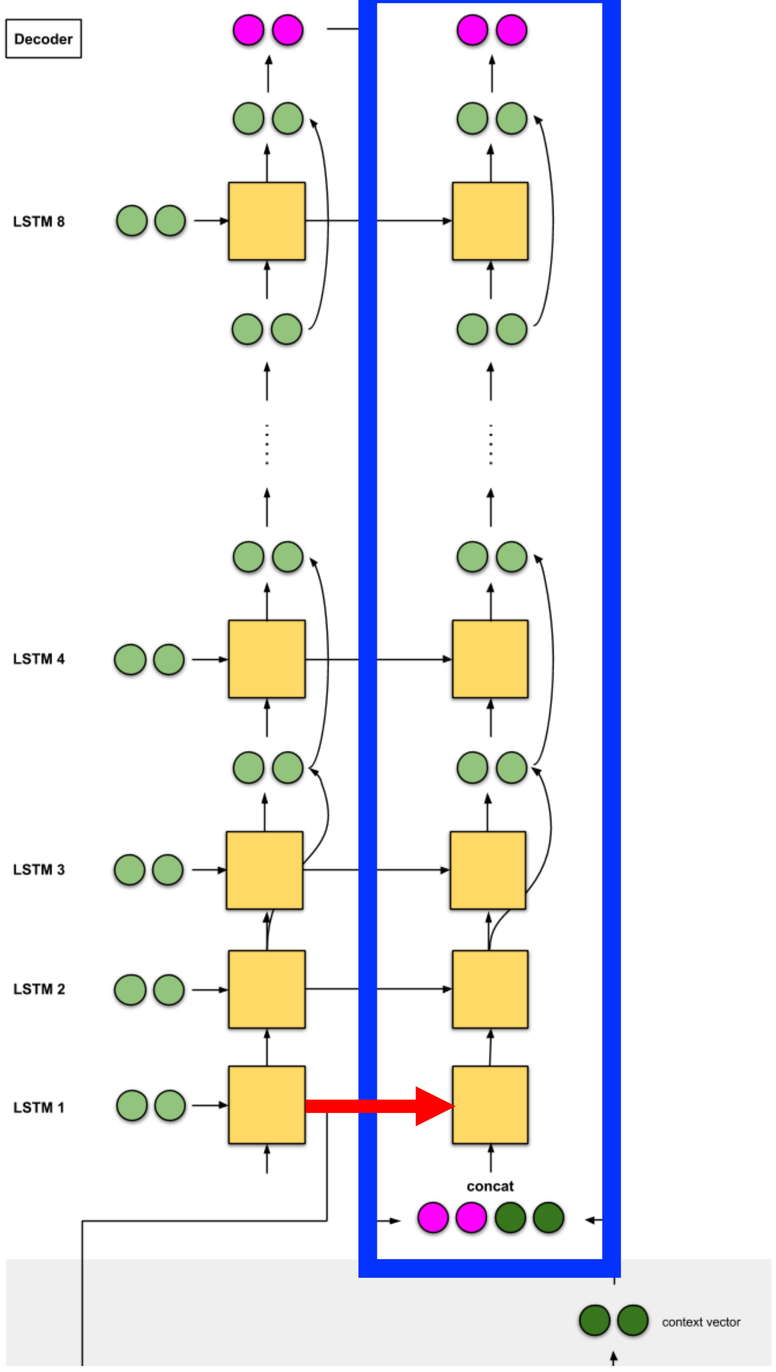
Decoder predicts not only using its output at the previous time step and previous hidden state, but also with a context vector

https://towardsdatascience.com/attn-illustrated-attention-5ec4ad276ee3

Google method

Many options exist for how to use the context vector with the decoder's output at the previous time step to produce an output at each decoder time step

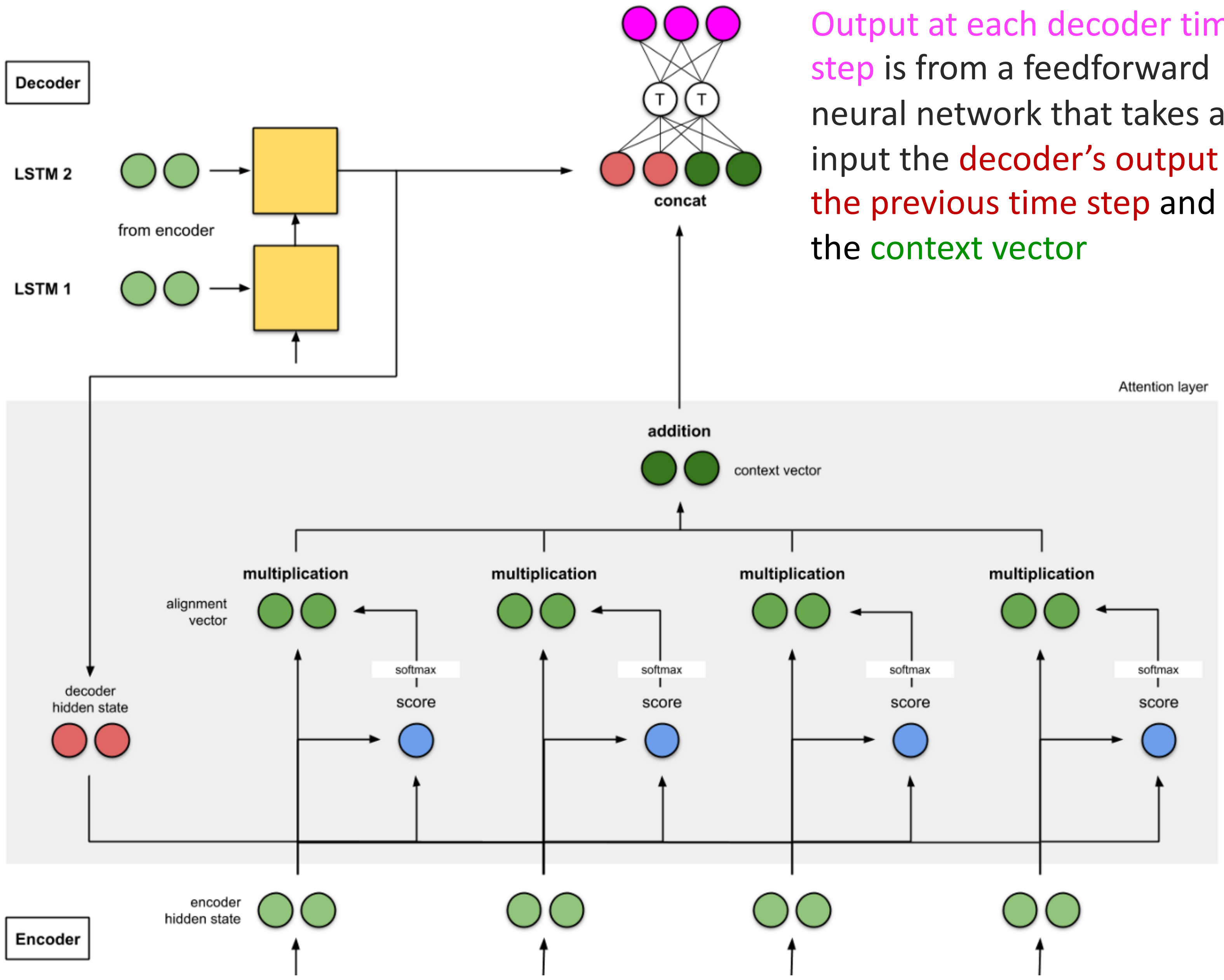
Decoder predicts not only using its output at the previous time step and previous hidden state, but also with a context vector



https://towardsdatascience.com/attn-illustrated-attention-5ec4ad276ee3

Luong method

Many options exist for how to use the context vector with the decoder’s output at the previous time step to produce an output at each decoder time step



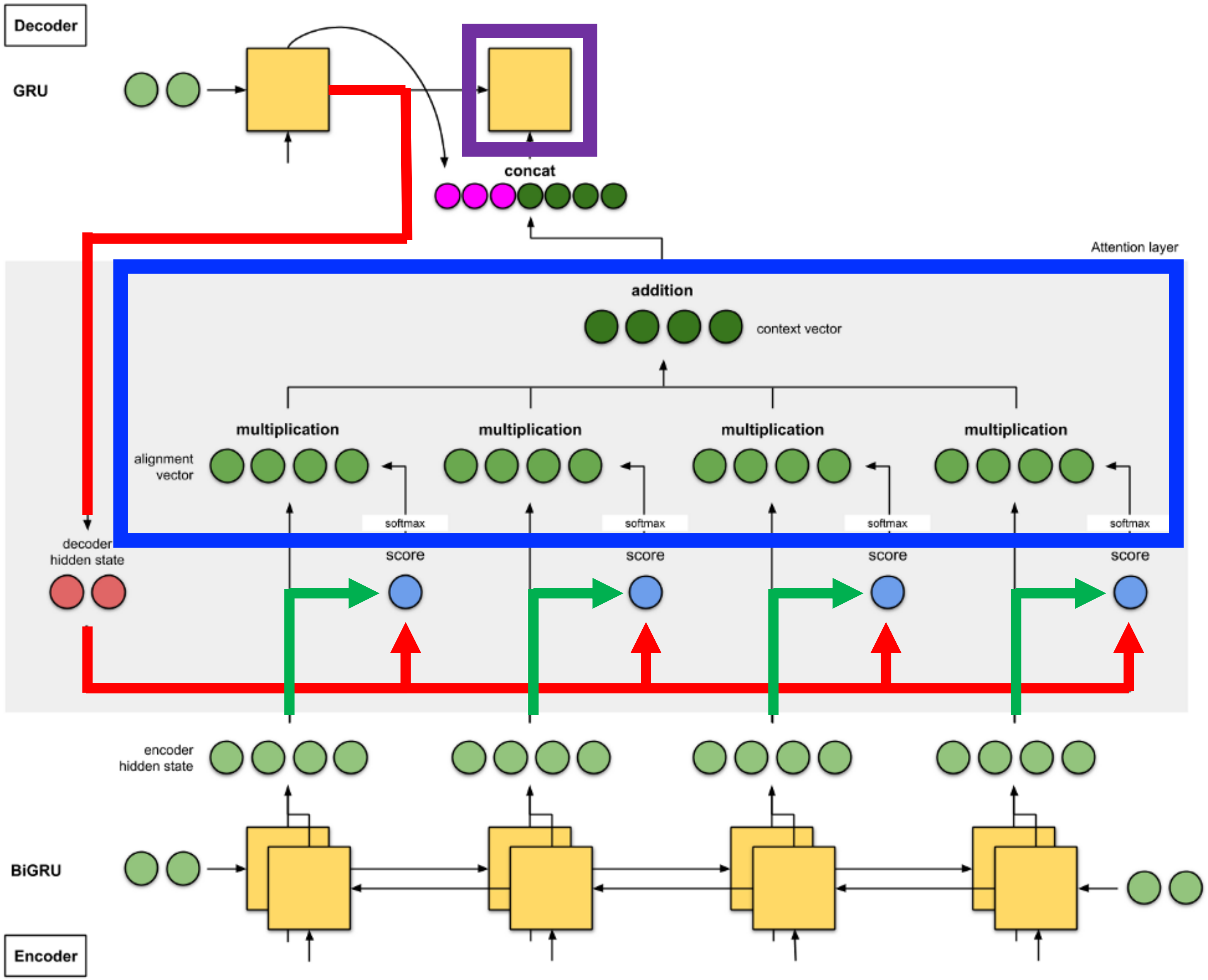
Output at each decoder time step is from a feedforward neural network that takes as input the decoder’s output at the previous time step and the context vector

https://towardsdatascience.com/attn-illustrated-attention-5ec4ad276ee3

Decoder

What stays the same at each decoder time step?
- input's hidden state

What changes at each decoder time step?
- decoder's hidden state
- (and so) attention weights and context vector
- decoder's output word at the previous time step



https://towardsdatascience.com/attn-illustrated-attention-5ec4ad276ee3

Summary: Attention (Computations at Each Decoder Step)

Decoder decides which inputs are needed for prediction at each time step with "soft attention", which results in a weighted combination of the input

Attention output

$$c^{(t)} = a_1^{(t)} s_1 + a_2^{(t)} s_2 + \dots + a_m^{(t)} s_m = \sum_{k=1}^{m} a_k^{(t)} s_k$$

"source context for decoder step t"

(weighted sum)

Attention weights

$$a_k^{(t)} = \frac{\exp(\mathrm{score}(h_t, s_k))}{\sum_{i=1}^{m} \exp(\mathrm{score}(h_t, s_i))}, \mathrm{k} = 1..\mathrm{m}$$

"attention weight for source token k at decoder step t"

(softmax)

Attention scores

$$\mathrm{score}(h_t, s_k), \mathrm{k} = 1..\mathrm{m}$$

"How relevant is source token k for target step t?"

Attention input

$s_1, s_2, \dots, s_m$ — all encoder states

h_t — one decoder state

https://lena-voita.github.io/nlp_course/seq2seq_and_attention.html

Summary: Attention (Computations at Each Decoder Step)

All parts are differentiable which means end-to-end training is possible

Attention output

$$c^{(t)} = a_1^{(t)} s_1 + a_2^{(t)} s_2 + \cdots + a_m^{(t)} s_m = \sum_{k=1}^{m} a_k^{(t)} s_k$$

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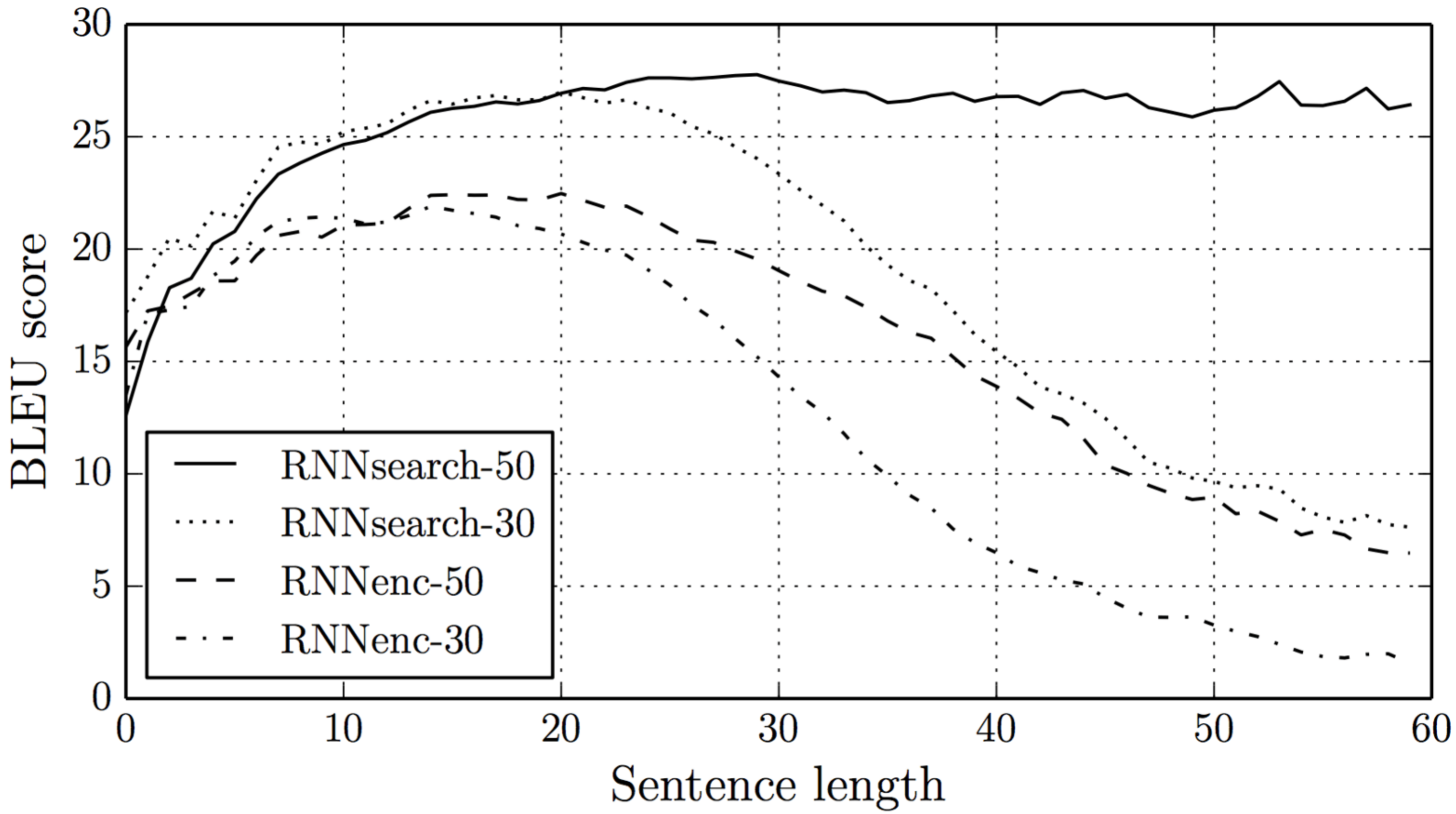
https://lena-voita.github.io/nlp_course/seq2seq_and_attention.html

Today’s Topics

- Motivation: machine neural translation for long sentences
- Encoder
- Decoder: attention
- Performance evaluation

Analysis of Attention Models

(larger scores are better)

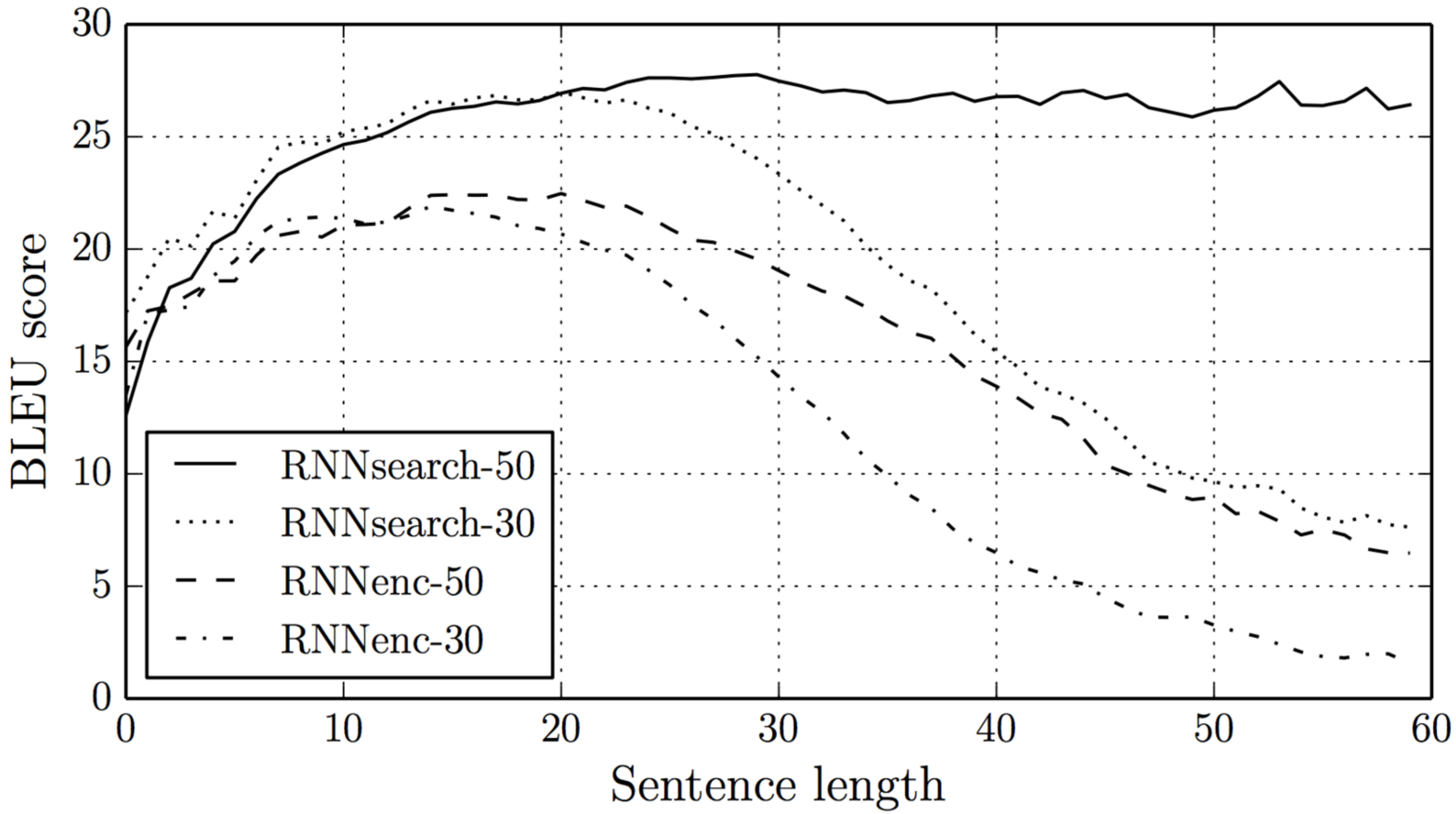


What performance trend is observed as the number of words in the input sentence grows?

Bahdanau et al. Neural Machine Translation by Jointly Learning to Align and Translate. ICLR 2015

Analysis of Attention Models

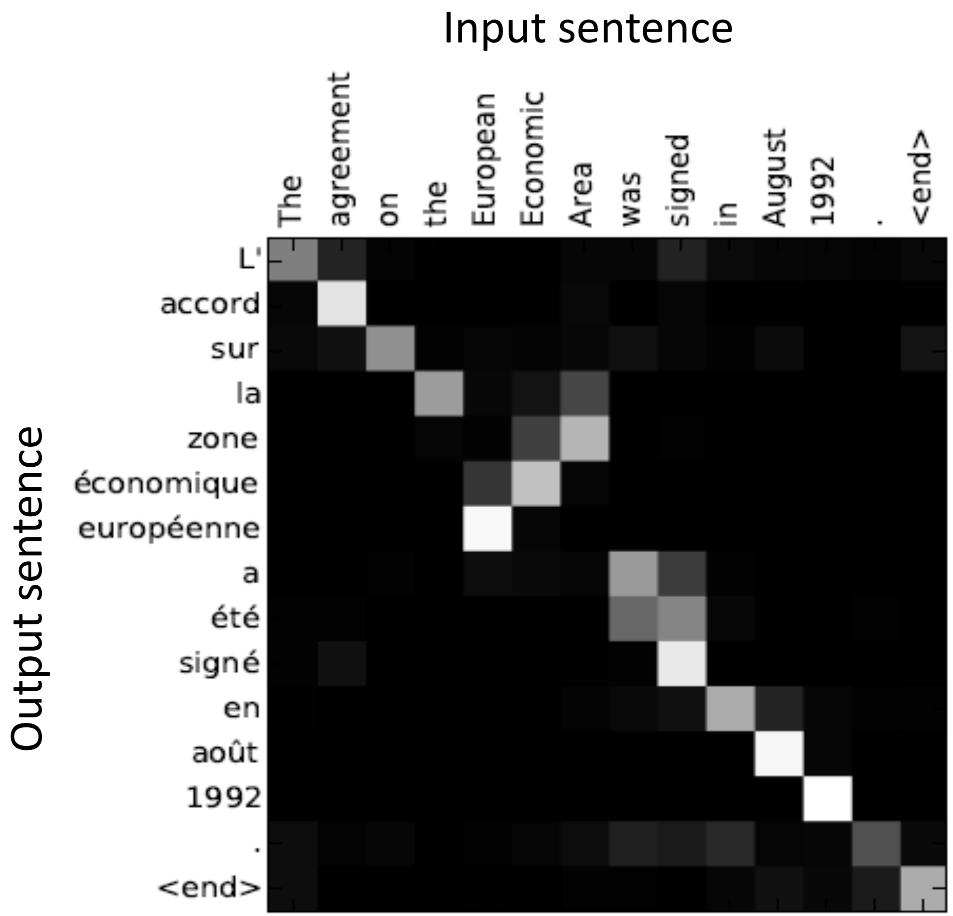
(larger scores are better)

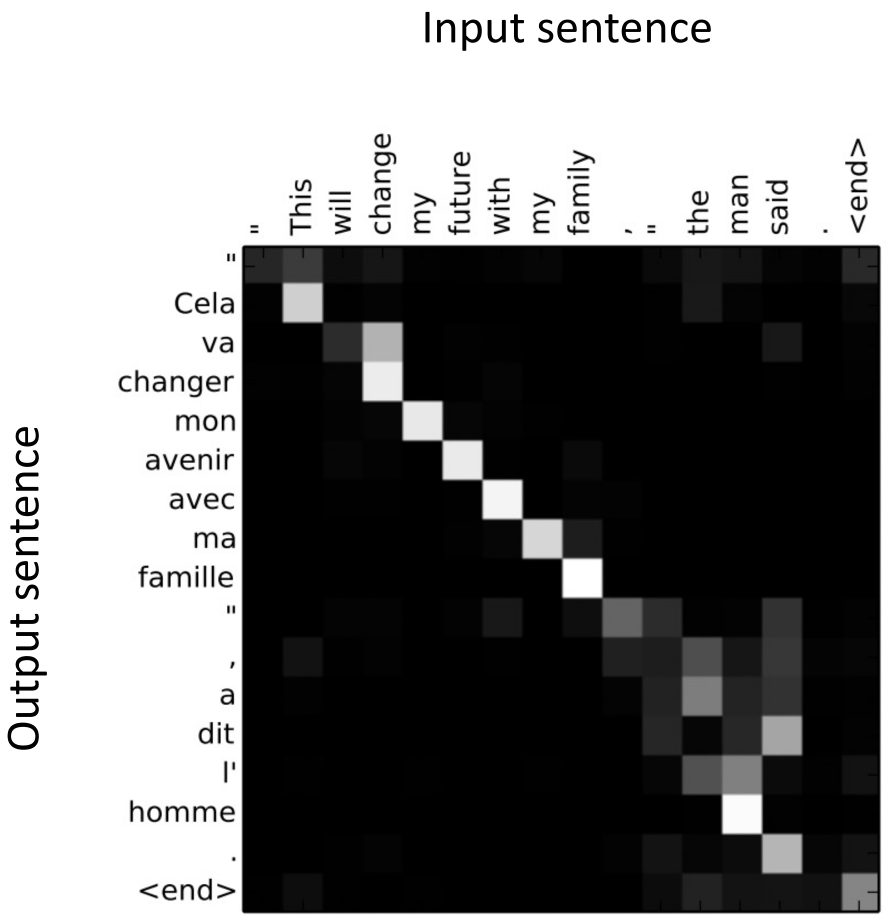


Performance no longer drops for longer sentences!

Bahdanau et al. Neural Machine Translation by Jointly Learning to Align and Translate. ICLR 2015

Visualizing Attention

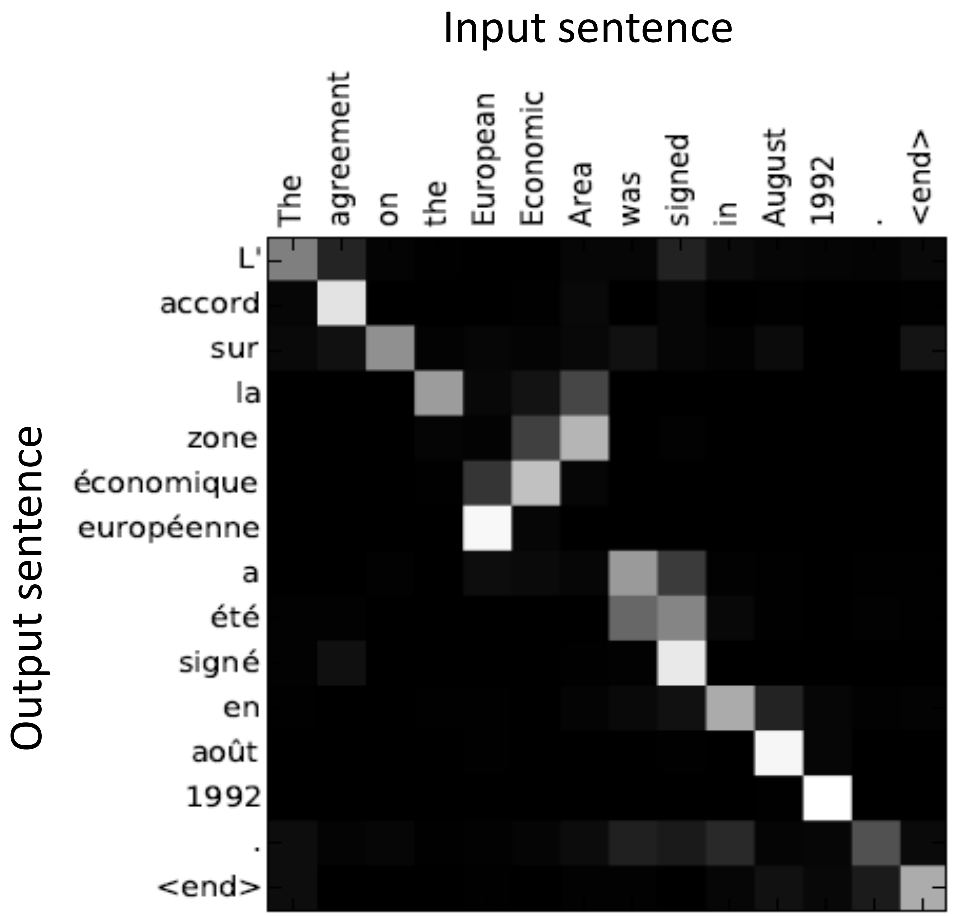


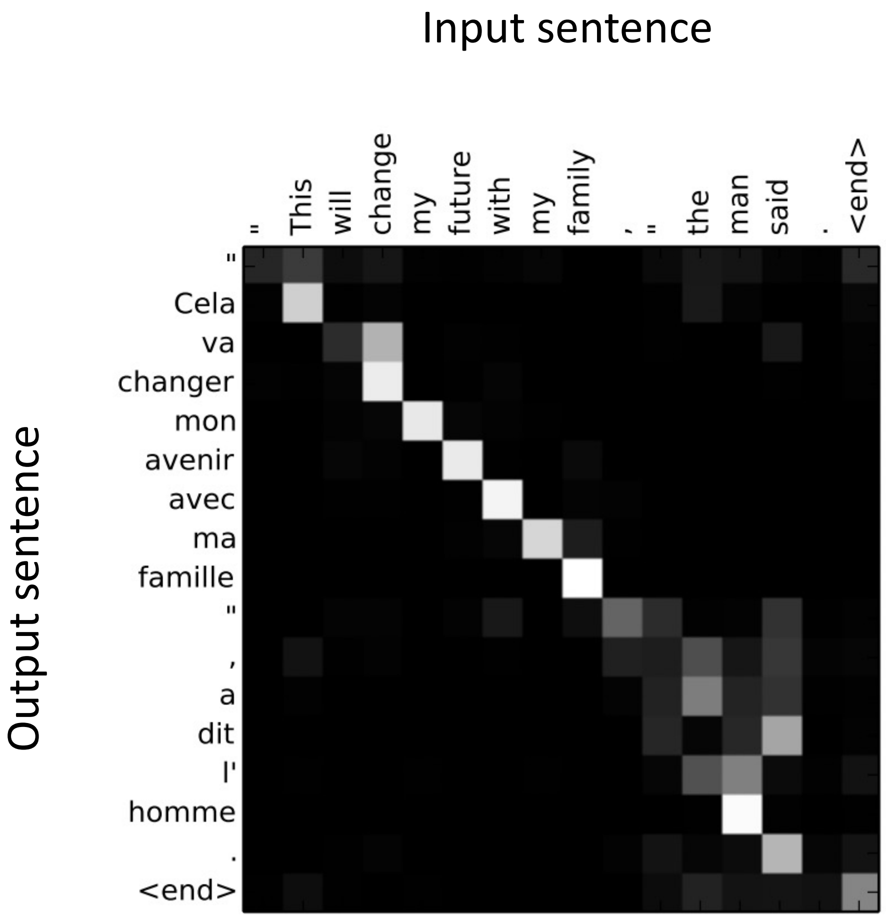


Values are 0 to 1, with whiter pixels indicating larger attention weights

Bahdanau et al. Neural Machine Translation by Jointly Learning to Align and Translate. ICLR 2015

Visualizing Attention

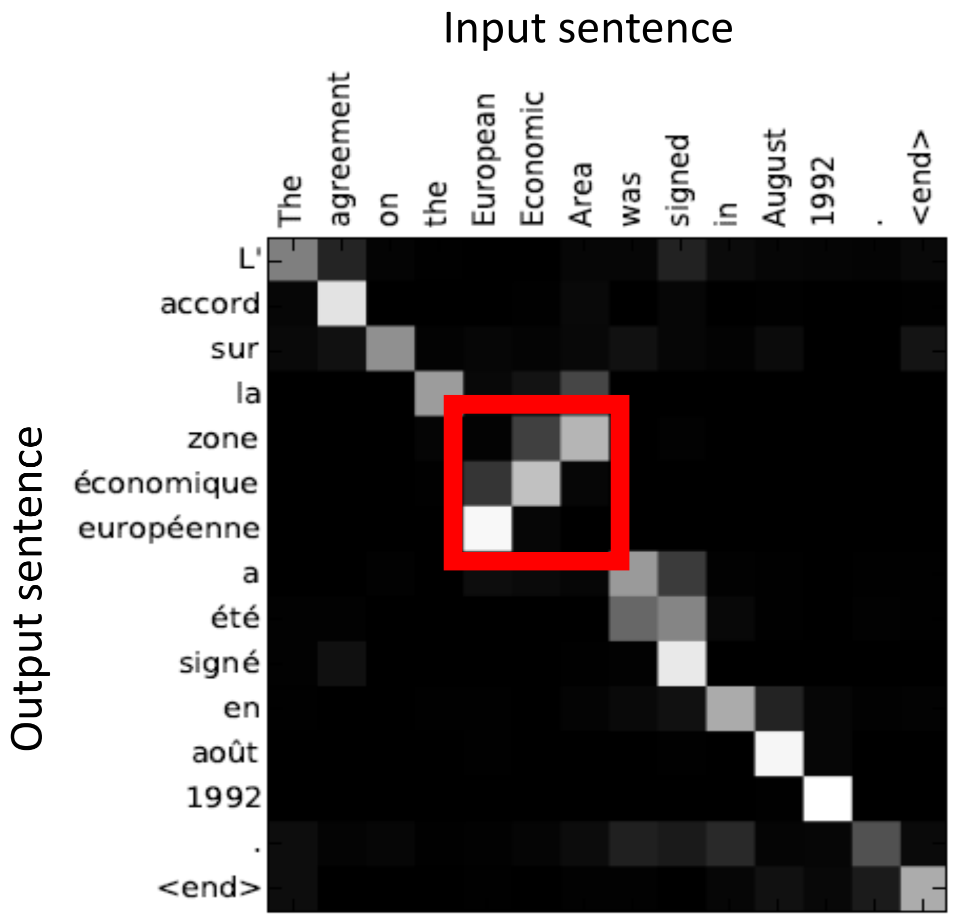


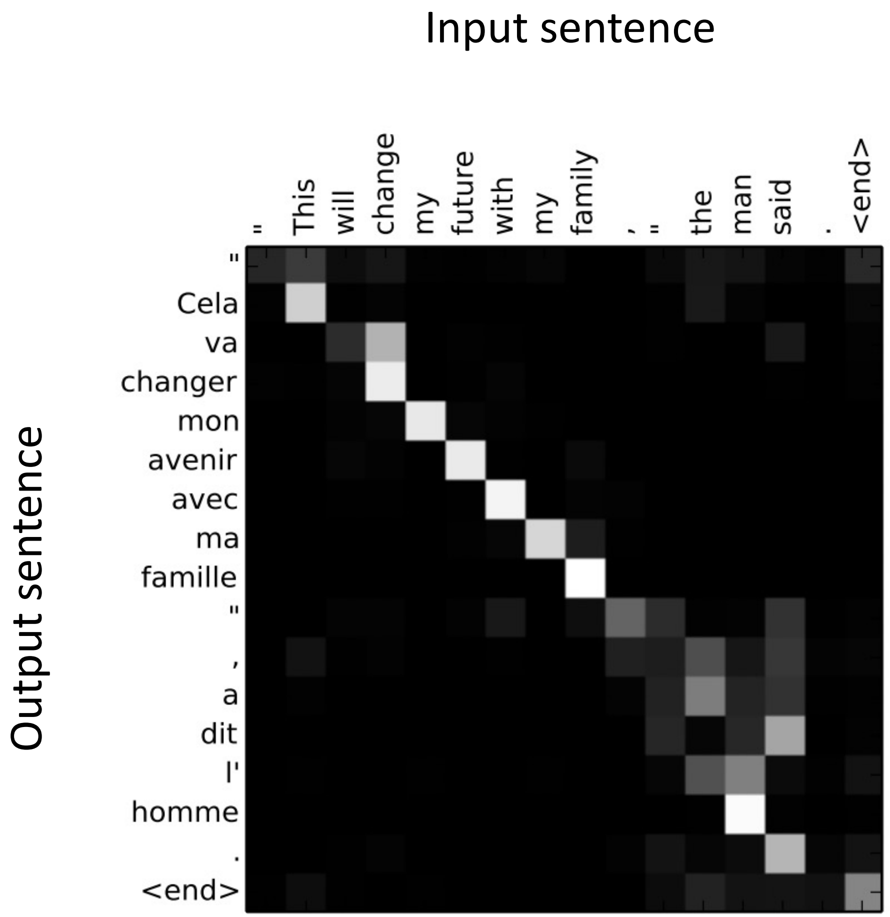


What insights can we glean from these examples?

Bahdanau et al. Neural Machine Translation by Jointly Learning to Align and Translate. ICLR 2015

Visualizing Attention

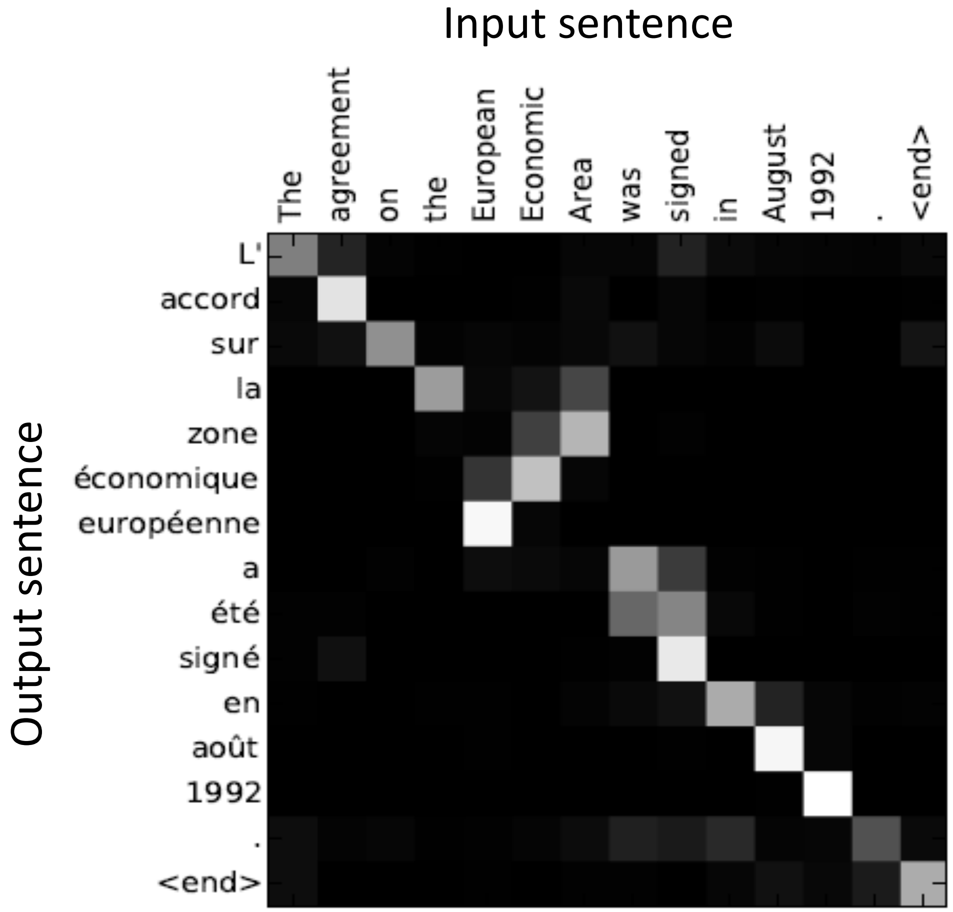


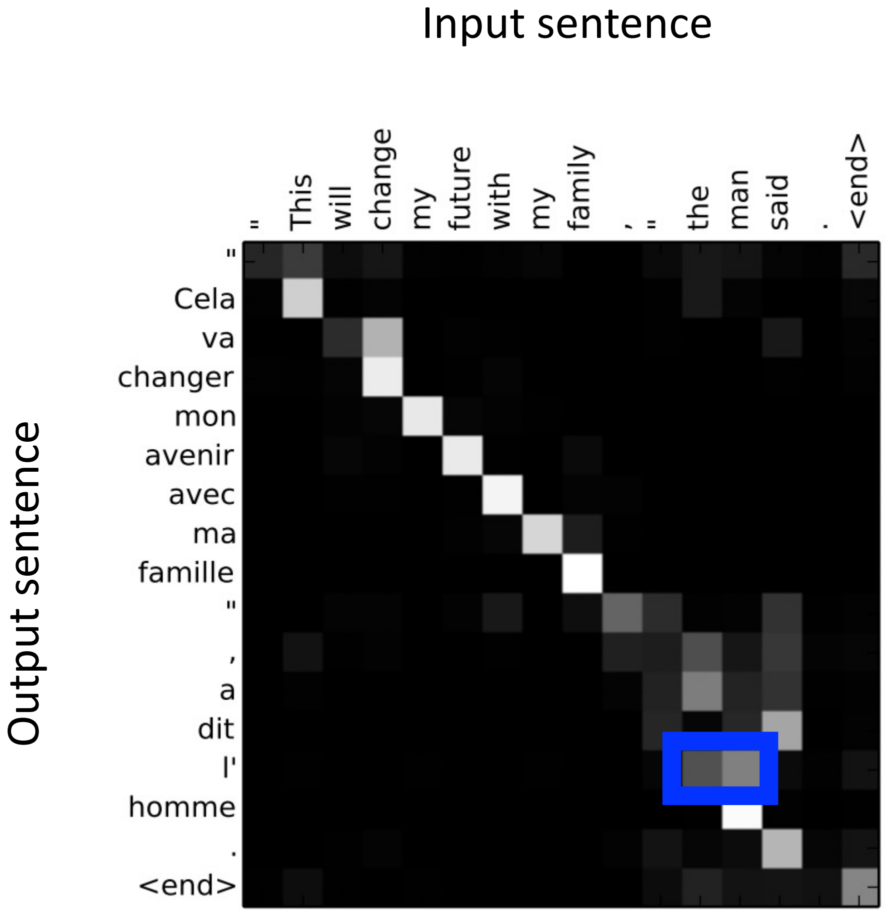


While a linear alignment between input and output sentences is common, there are exceptions (e.g., order of adjectives and nouns can differ)

Bahdanau et al. Neural Machine Translation by Jointly Learning to Align and Translate. ICLR 2015

Visualizing Attention

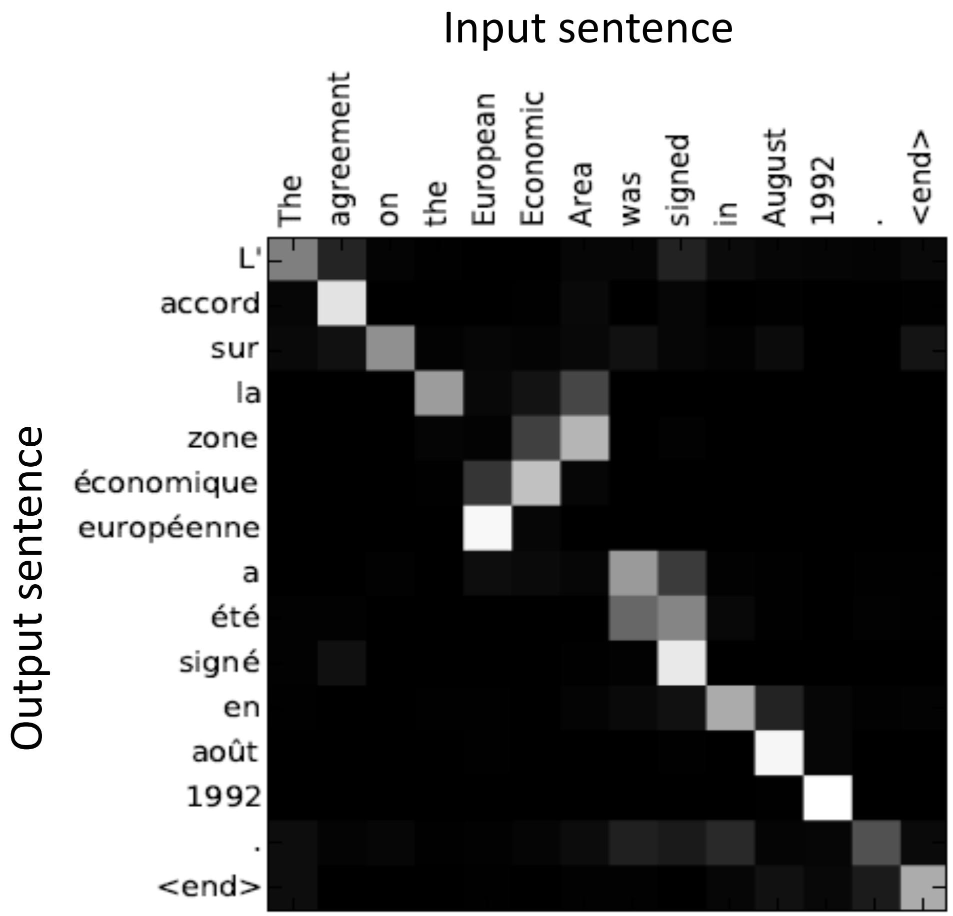


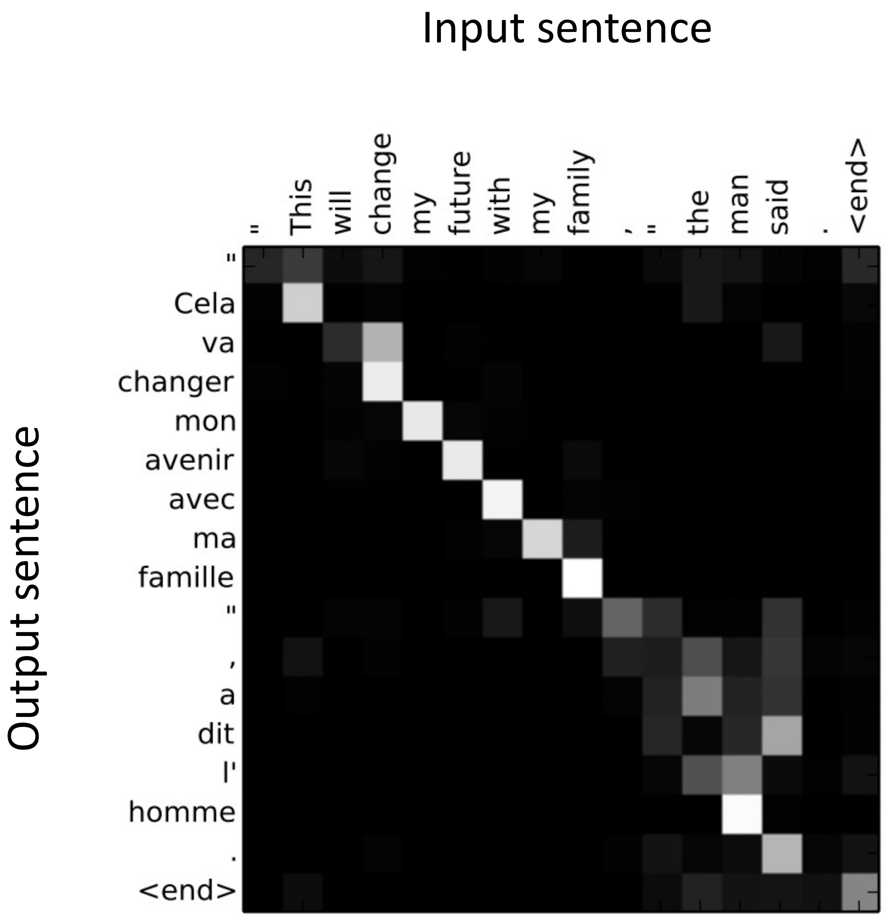


Output words are often informed by more than one input word;
e.g., "man" indicates translation of "the" to l' instead of le, la, or les

Bahdanau et al. Neural Machine Translation by Jointly Learning to Align and Translate. ICLR 2015

Visualizing Attention





It naturally handles different input and output lengths
(e.g., 1 extra output word for both examples)

Bahdanau et al. Neural Machine Translation by Jointly Learning to Align and Translate. ICLR 2015

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The End