Machine Translation

Session 10: Sequence-to-sequence with attention

Sharid Loáiciga — June 24th, 2020

Slides credits: Alessandro Raganato
(who credits Abigail See & Rico Sennrich)

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- Byte Pair Encoding (BPE) as a solution for Out-Of-Vocabulary (OOV) words

NMT course continues

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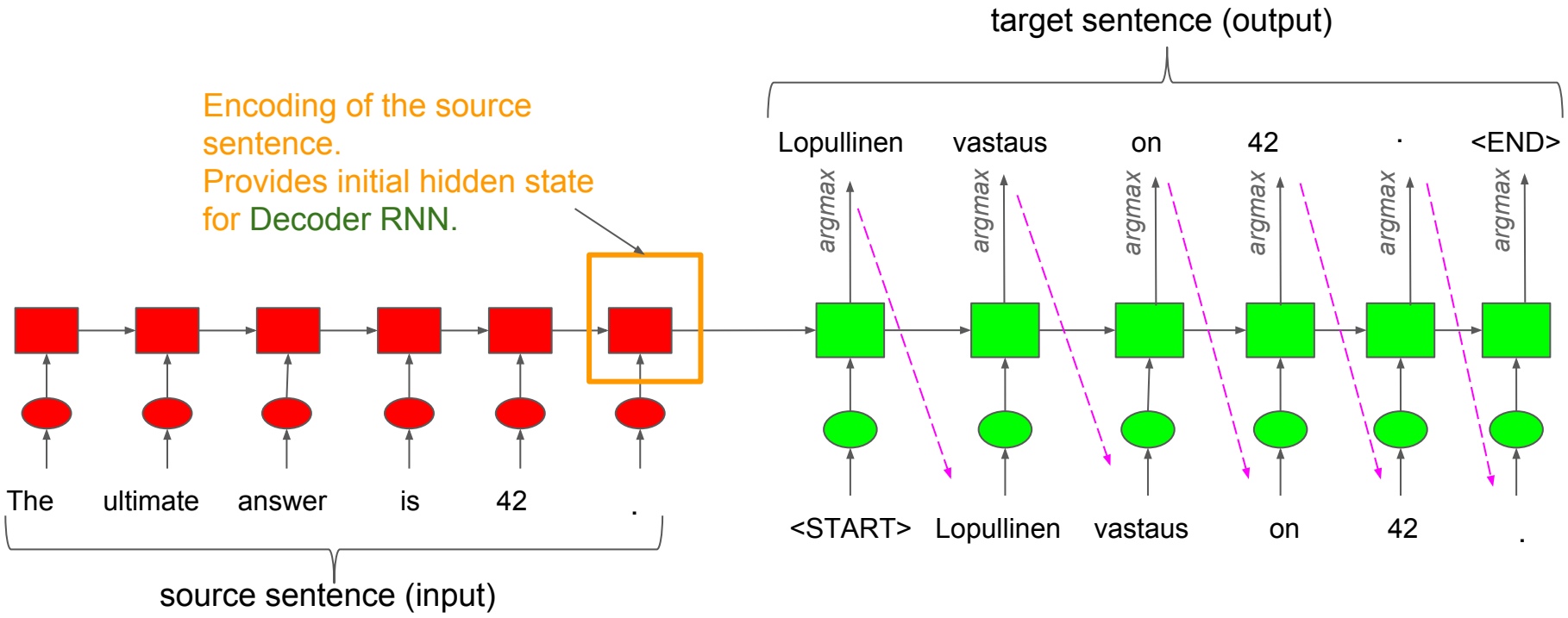

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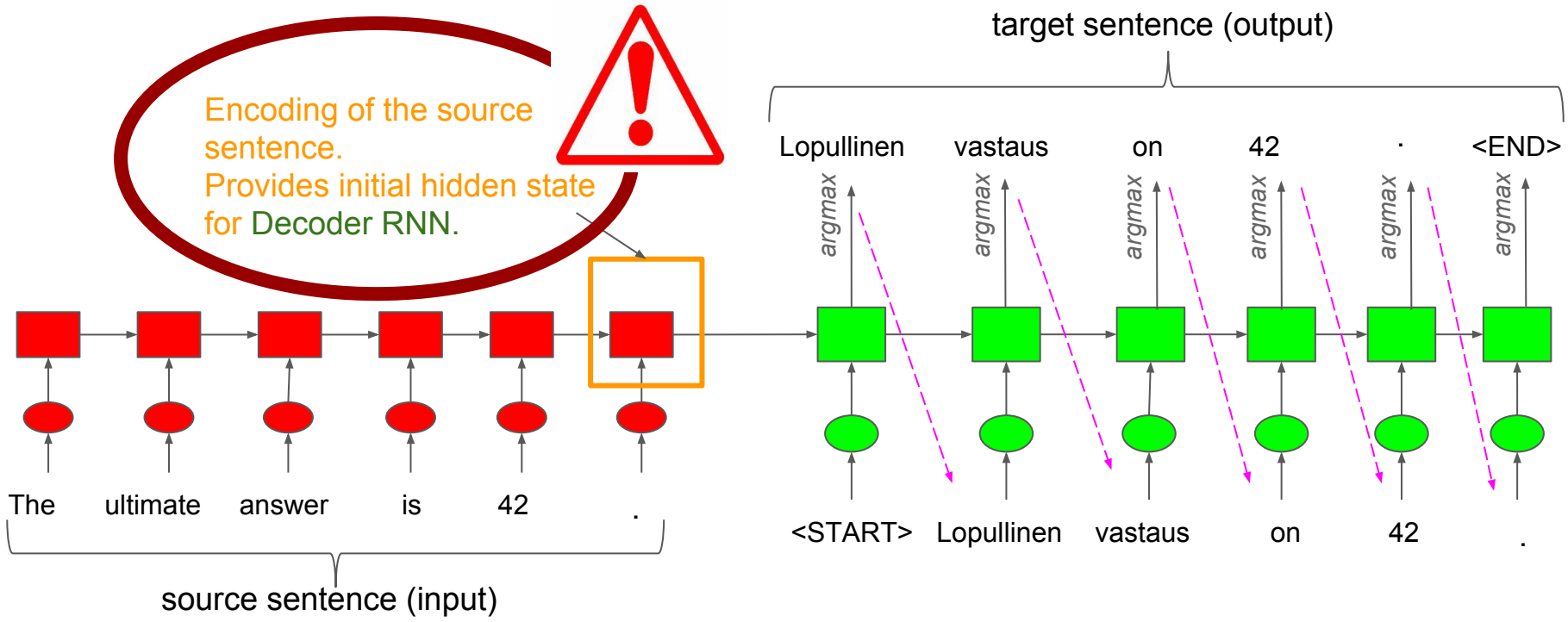

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Summary vector as information bottleneck

- Last encoder hidden-state “summarises” source sentence.
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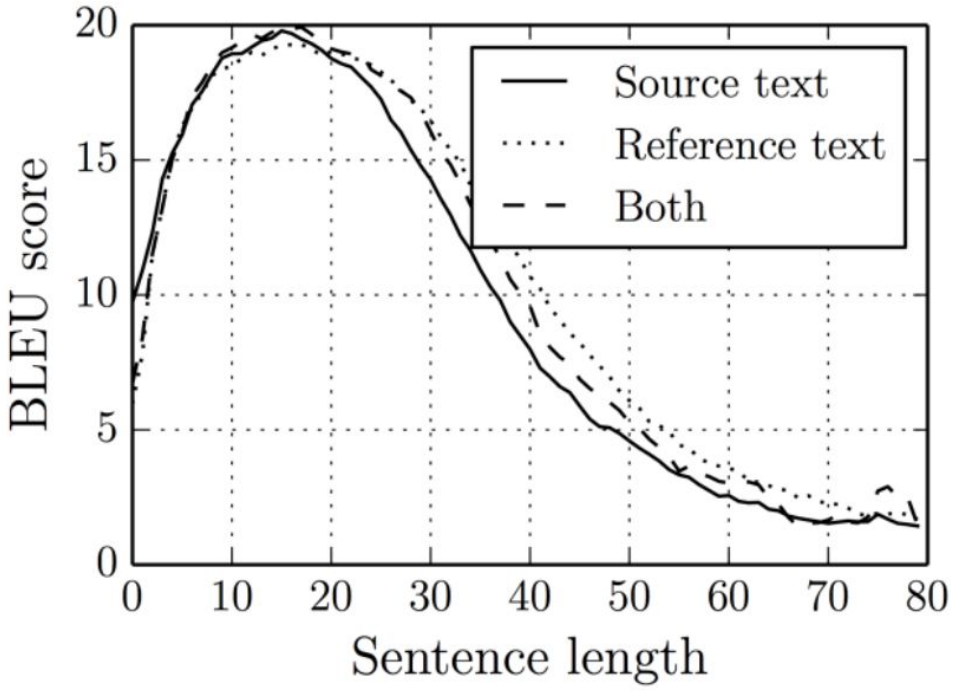
- **Problem**: *Information bottleneck!*
- Fixed sized representation degrades as sentence length increases



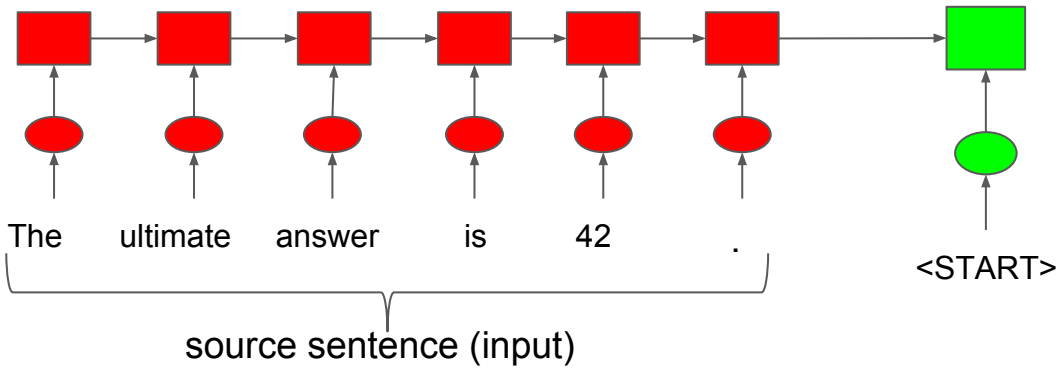
[Cho et al., 2014]

Attention

- **Attention** provides a solution to the bottleneck problem.

- Core idea: on each step of the decoder, use direct connection to the encoder to focus on a particular part of the source sequence

Sequence-to-sequence with attention



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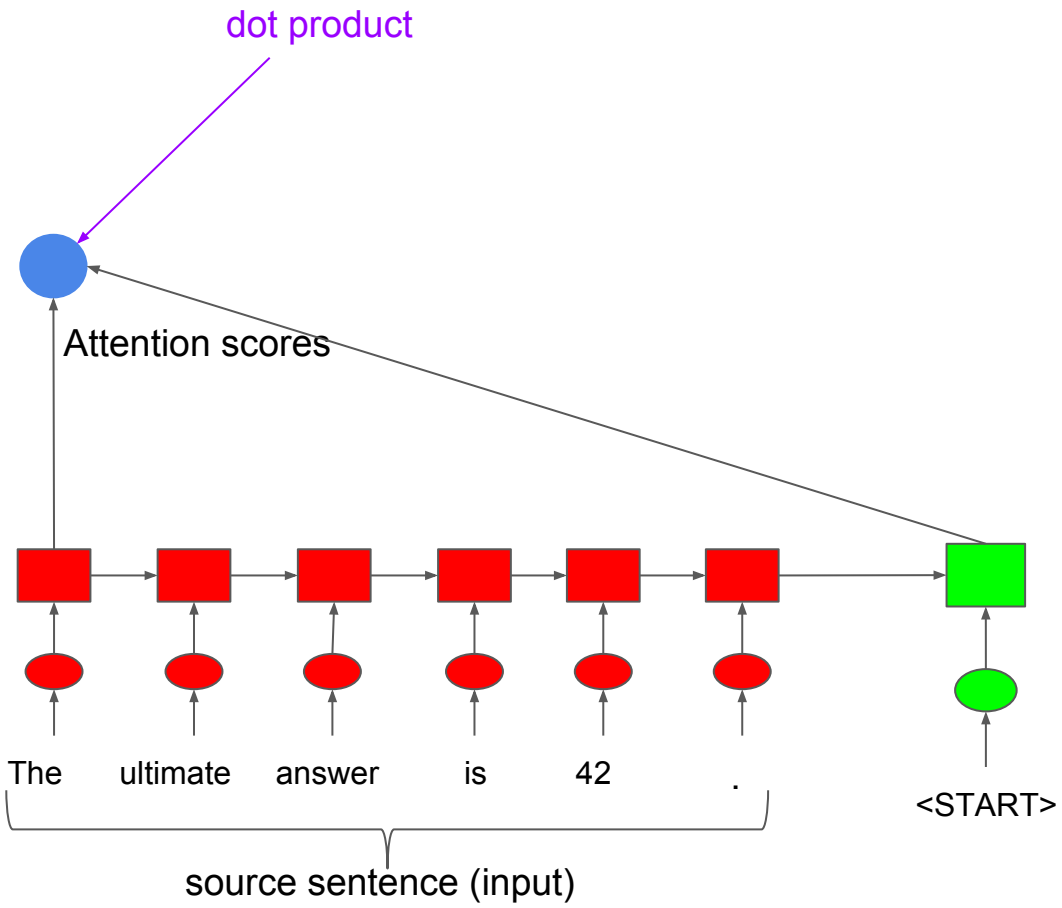

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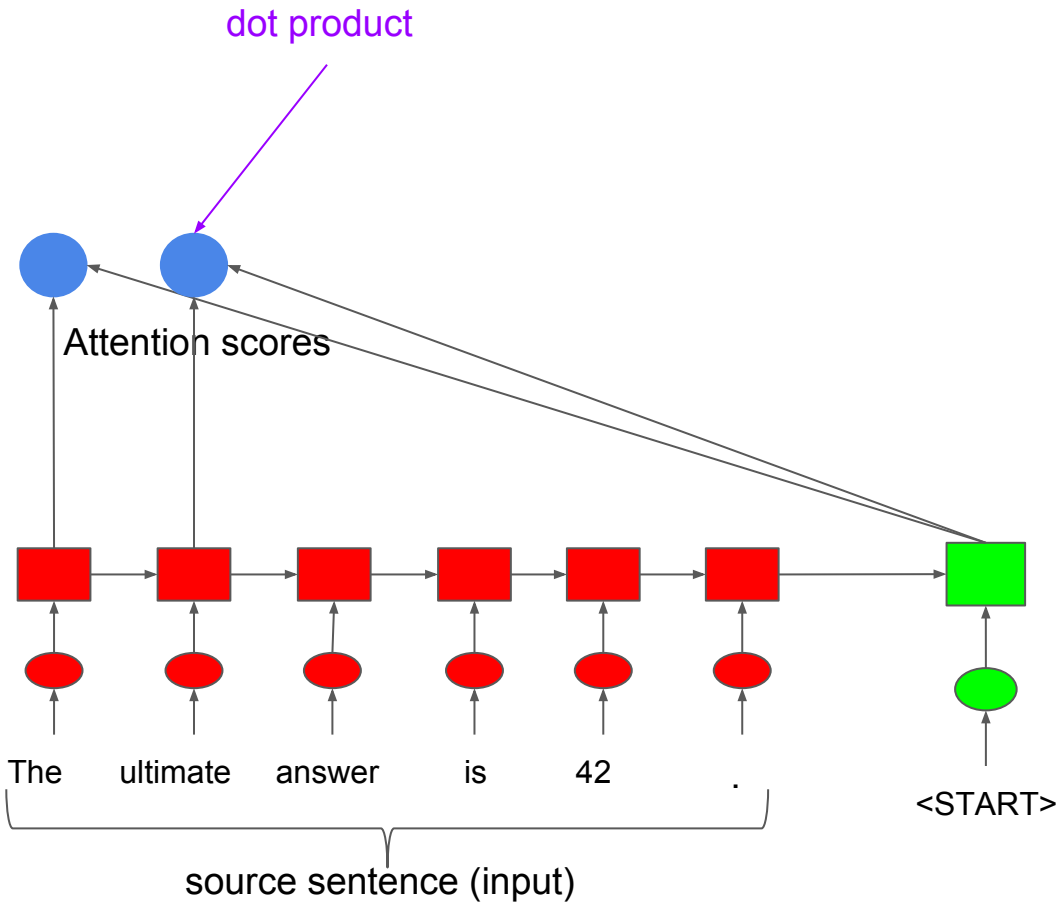

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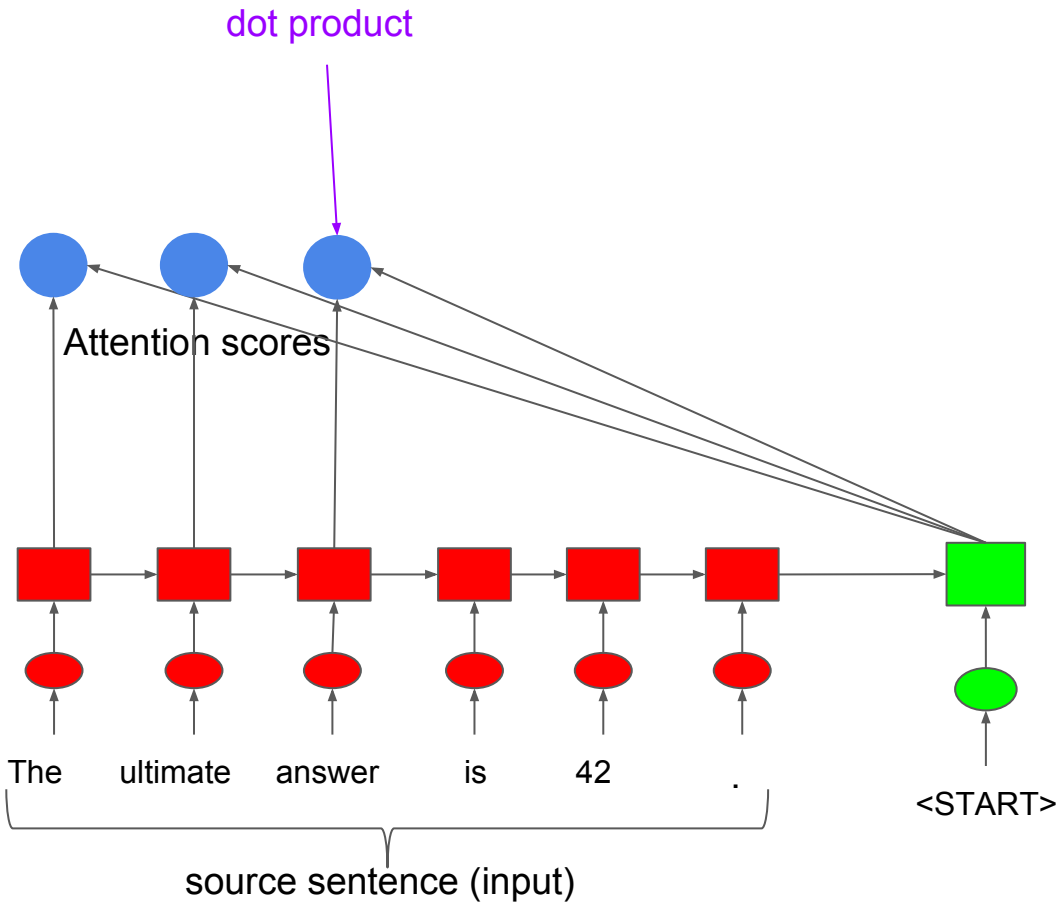

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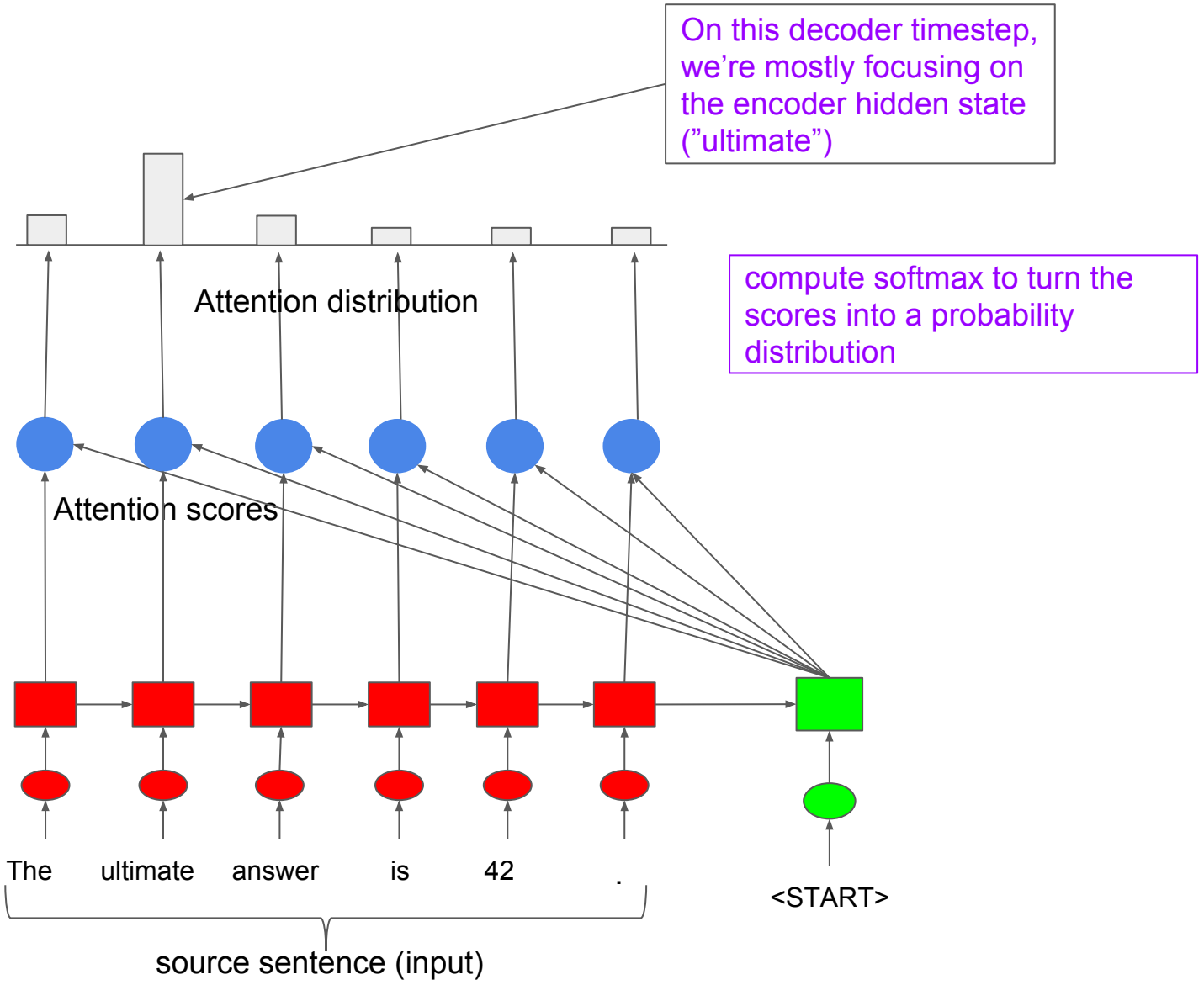

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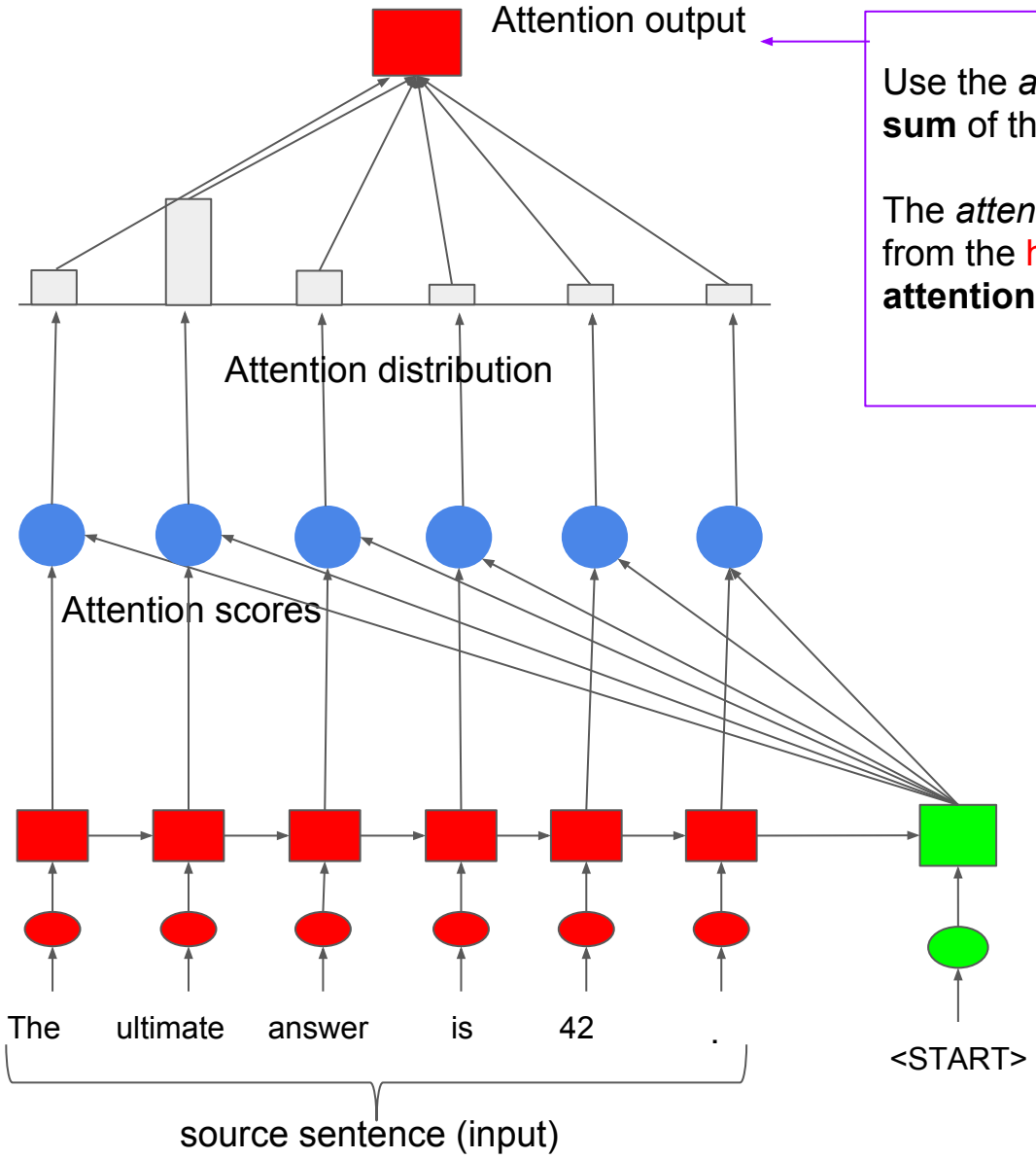
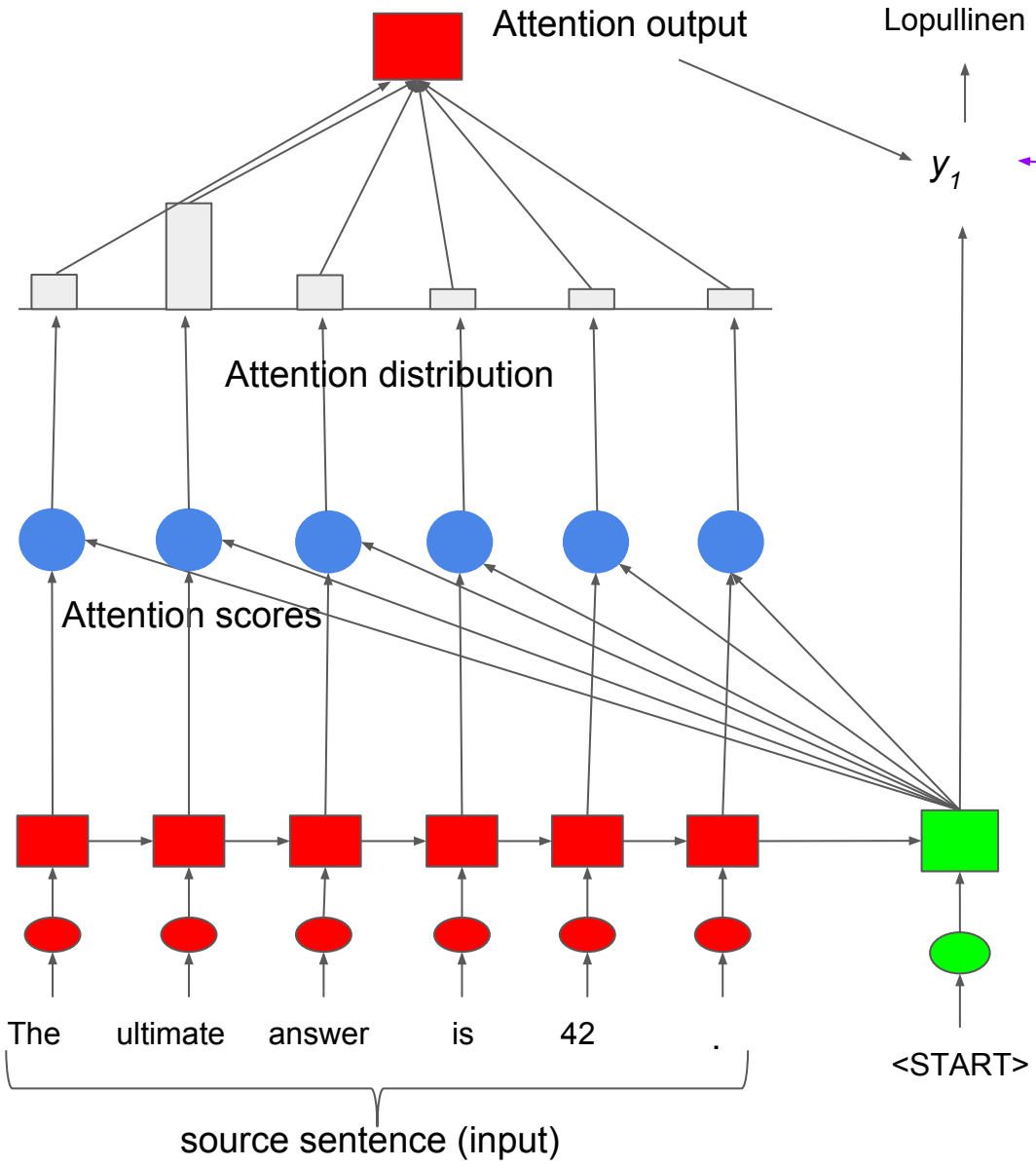


Use the *attention distribution* to take a **weighted sum** of the encoder hidden states.

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

Sequence-to-sequence with attention



Concatenate *attention output* with decoder hidden state, then use to compute y_1 as before

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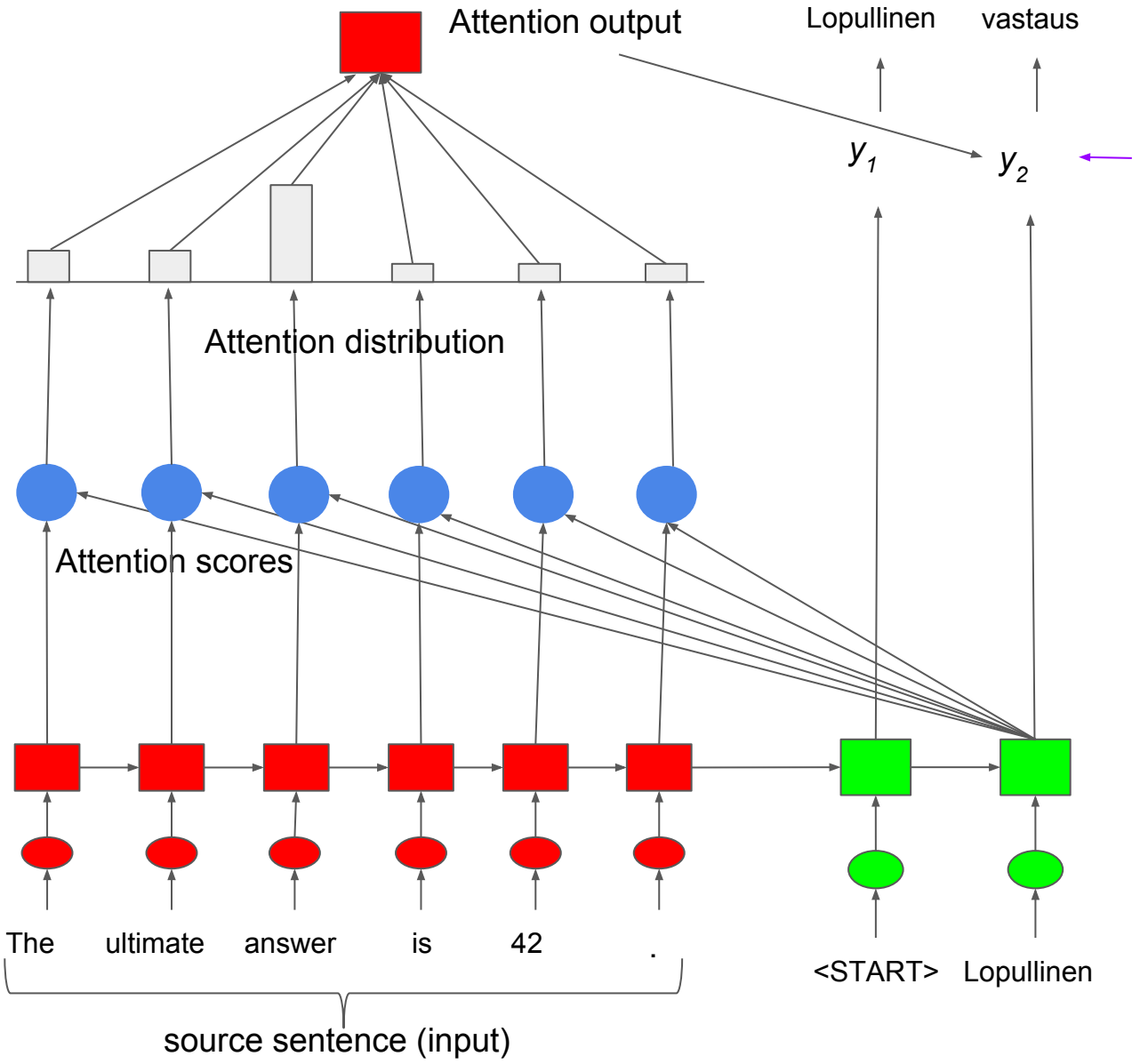

Concatenate *attention output* with decoder hidden state, then use to compute y_2 as before

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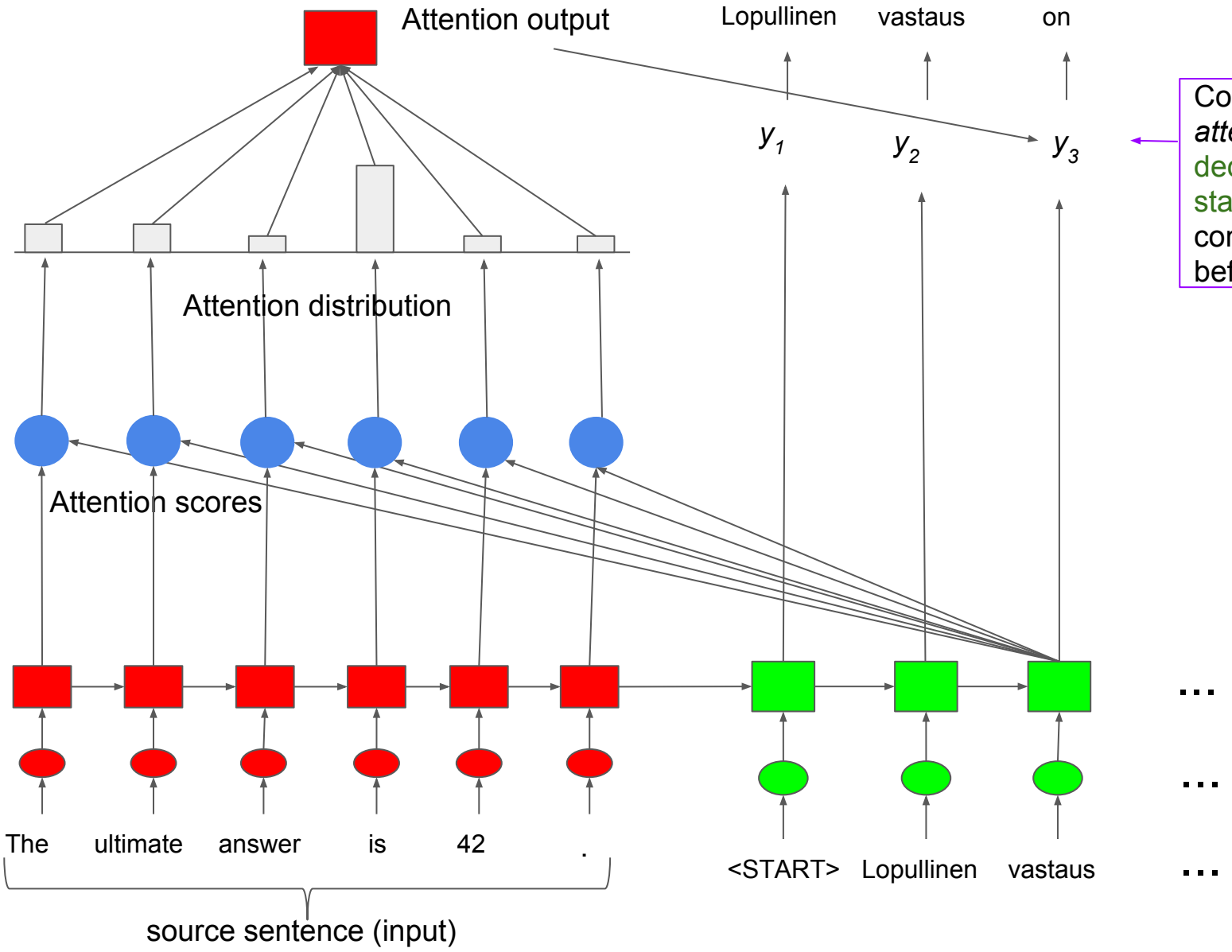

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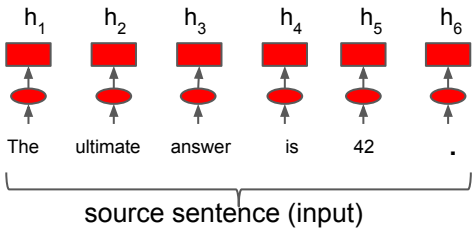

- We have encoder hidden states $h_1, \ldots, h_N \in \mathbb{R}^h$

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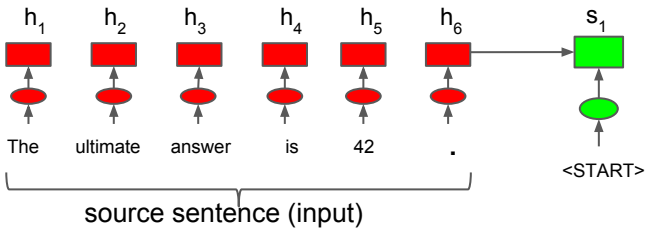

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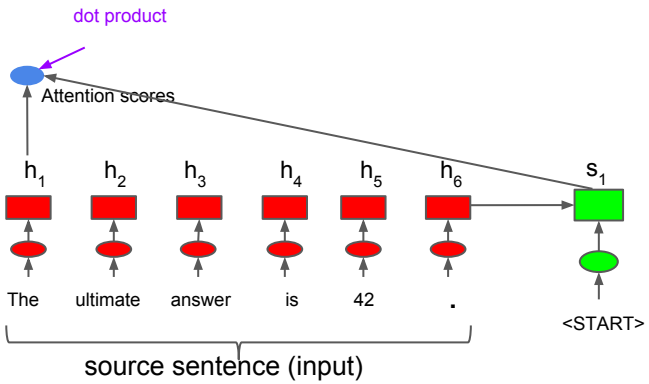

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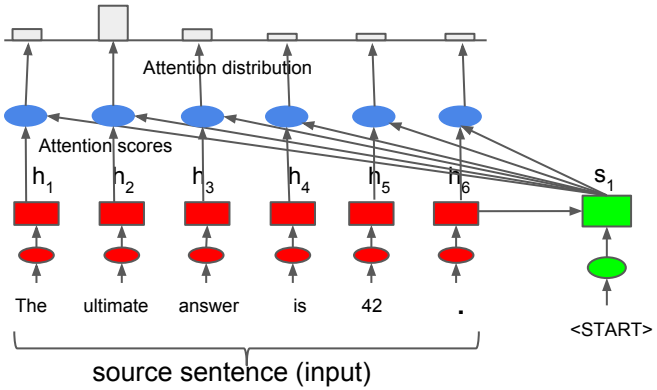

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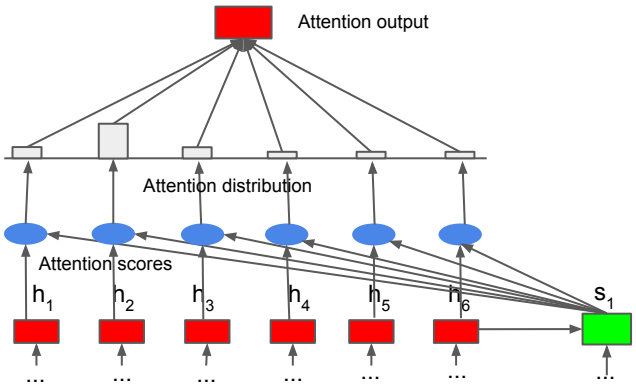

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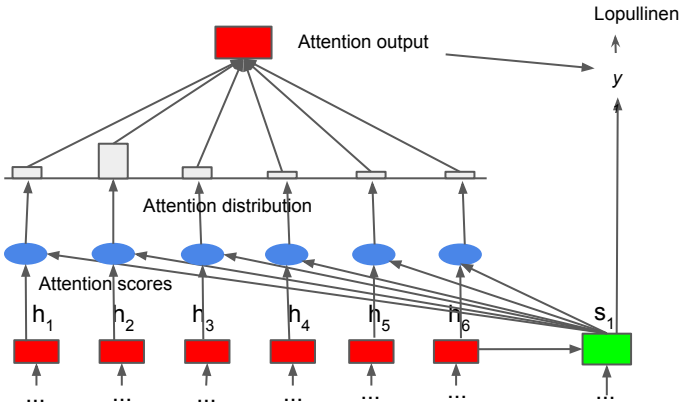

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- Finally we concatenate the *attention output* $\boldsymbol{a}_t$ with the decoder hidden state s_t and proceed as in the non-attention seq2seq model

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

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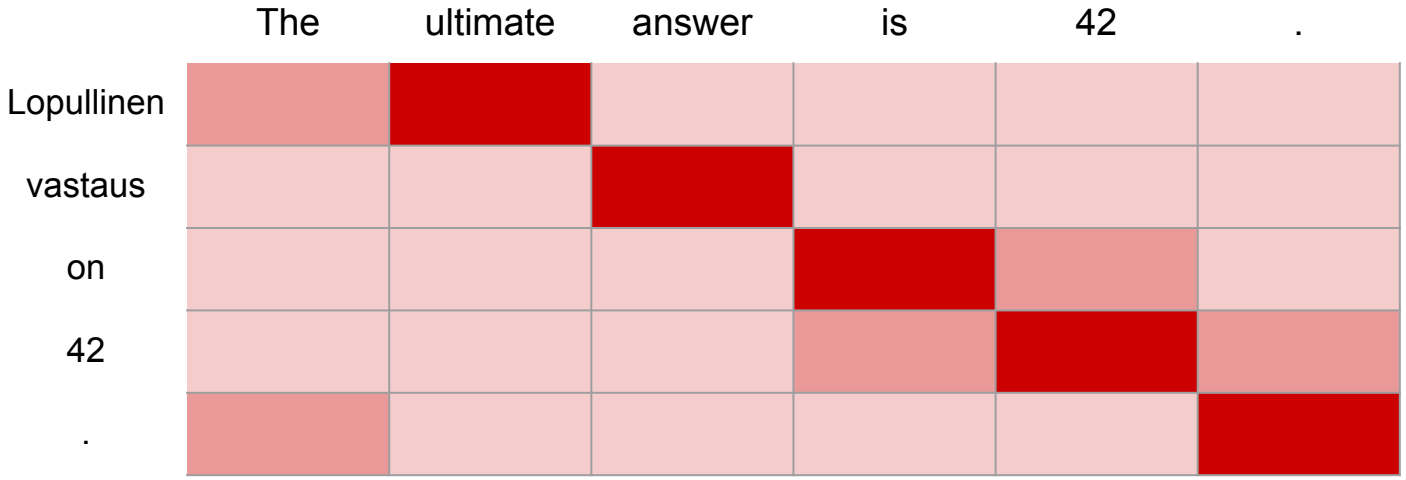
  - Attention allows decoder to look directly at source; bypass bottleneck
- Attention provides some interpretability:
  - By inspecting attention distribution, we can see what the decoder was focusing on
  - This is cool because we never explicitly trained an alignment system
  - The network just learned alignment by itself



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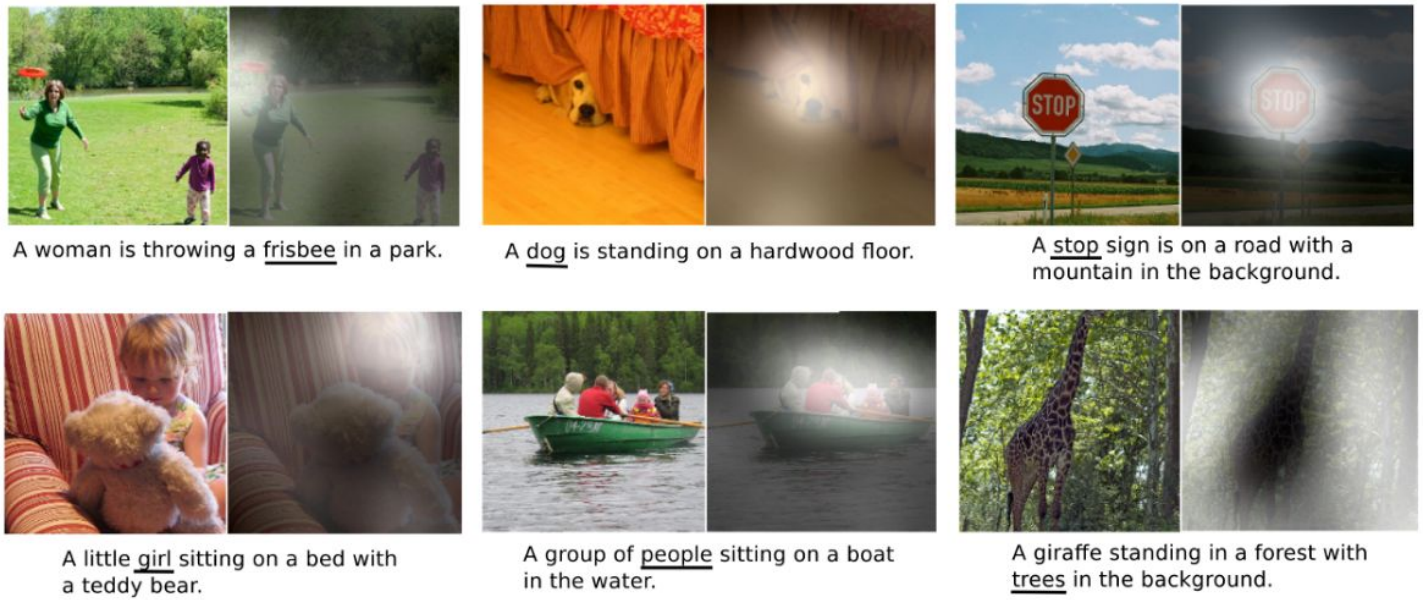

Fig. 5. Examples of the attention-based model attending to the correct object (*white* indicates the attended regions, *underlines* indicated the corresponding word) [22]

[Xu et al., 2015]

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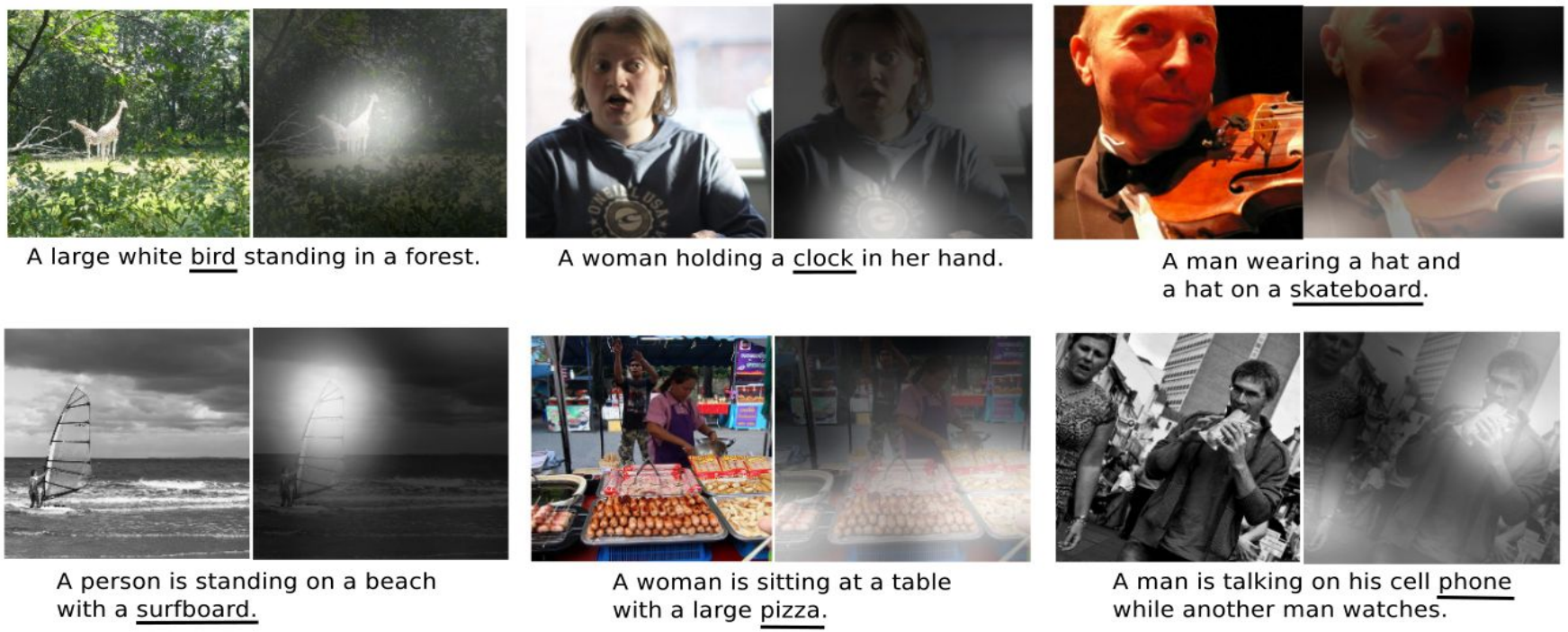
Figure 5. Examples of mistakes where we can use attention to gain intuition into what the model saw.



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- We sometimes say that the query *attends* to the values.
- For example, in the seq2seq + attention model, each decoder hidden state (**query**) *attends* to all the encoder hidden states (**values**).

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- **Intuition**:
  - The weighted sum is a selective summary of the information contained in the values, where the query determines which values to focus on.
  - Attention is a way to obtain a fixed-size representation of an arbitrary set of representations (the values), dependent on some other representation (the query).

There are *several* attention variants

- We have some *values* $\boldsymbol{h}_1, \ldots, \boldsymbol{h}_N \in \mathbb{R}^{d_1}$ and a *query* $\boldsymbol{s} \in \mathbb{R}^{d_2}$

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- Additive attention: $\boldsymbol{e}_i = \boldsymbol{v}^T \tanh(\boldsymbol{W}_1 \boldsymbol{h}_i + \boldsymbol{W}_2 \boldsymbol{s}) \in \mathbb{R}$
  - Where $\boldsymbol{W}_1 \in \mathbb{R}^{d_3 \times d_1}, \boldsymbol{W}_2 \in \mathbb{R}^{d_3 \times d_2}$ are weight matrices and $\boldsymbol{v} \in \mathbb{R}^{d_3}$ is a weight vector
  - d_3 (the attention dimensionality) is a hyperparameter

More information:

"Deep Learning for NLP Best Practices", Ruder, 2017. http://ruder.io/deep-learning-nlp-best-practices/index.html#attention

"Massive Exploration of Neural Machine Translation Architectures", Britz et al, 2017, https://arxiv.org/pdf/1703.03906.pdf

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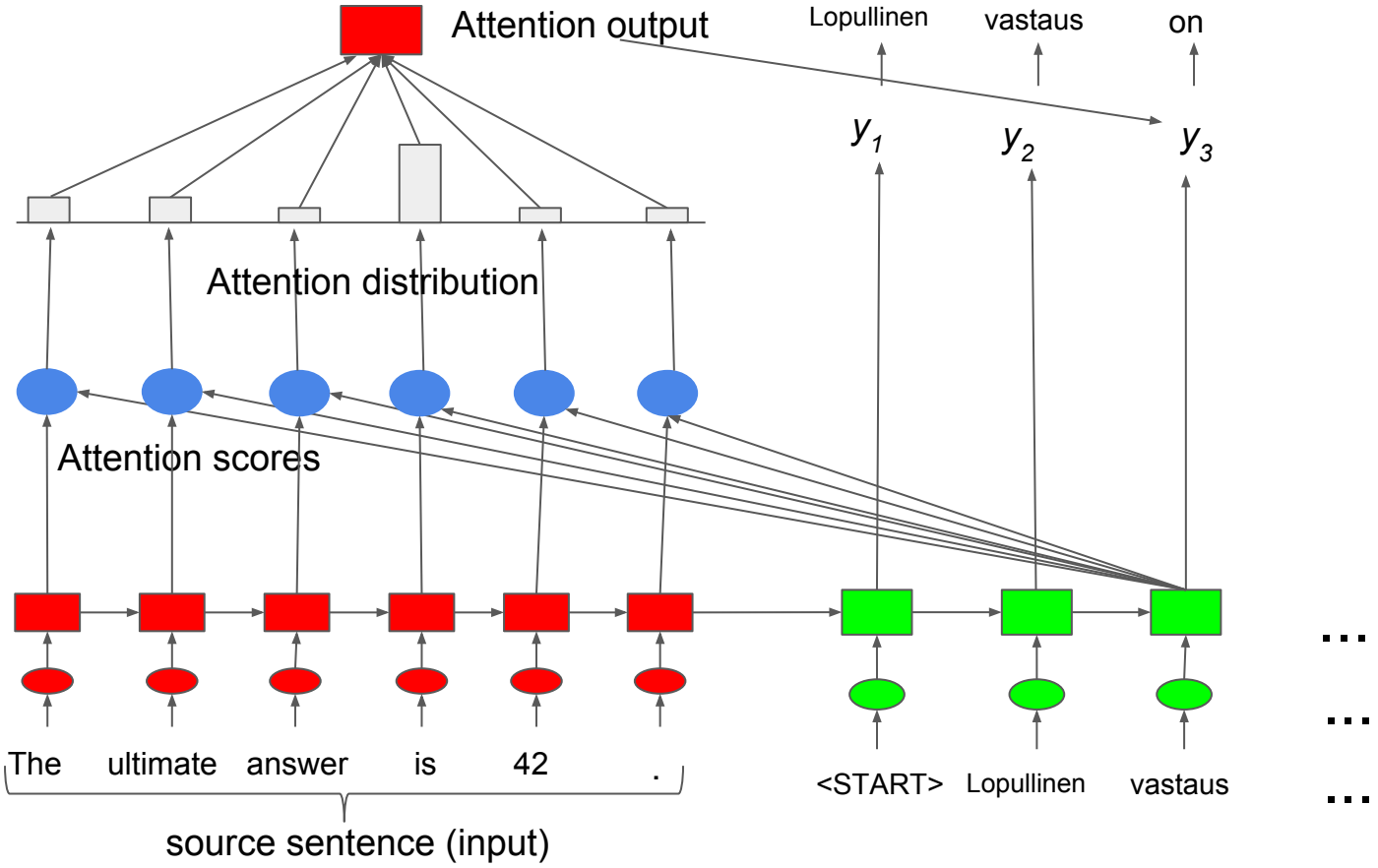

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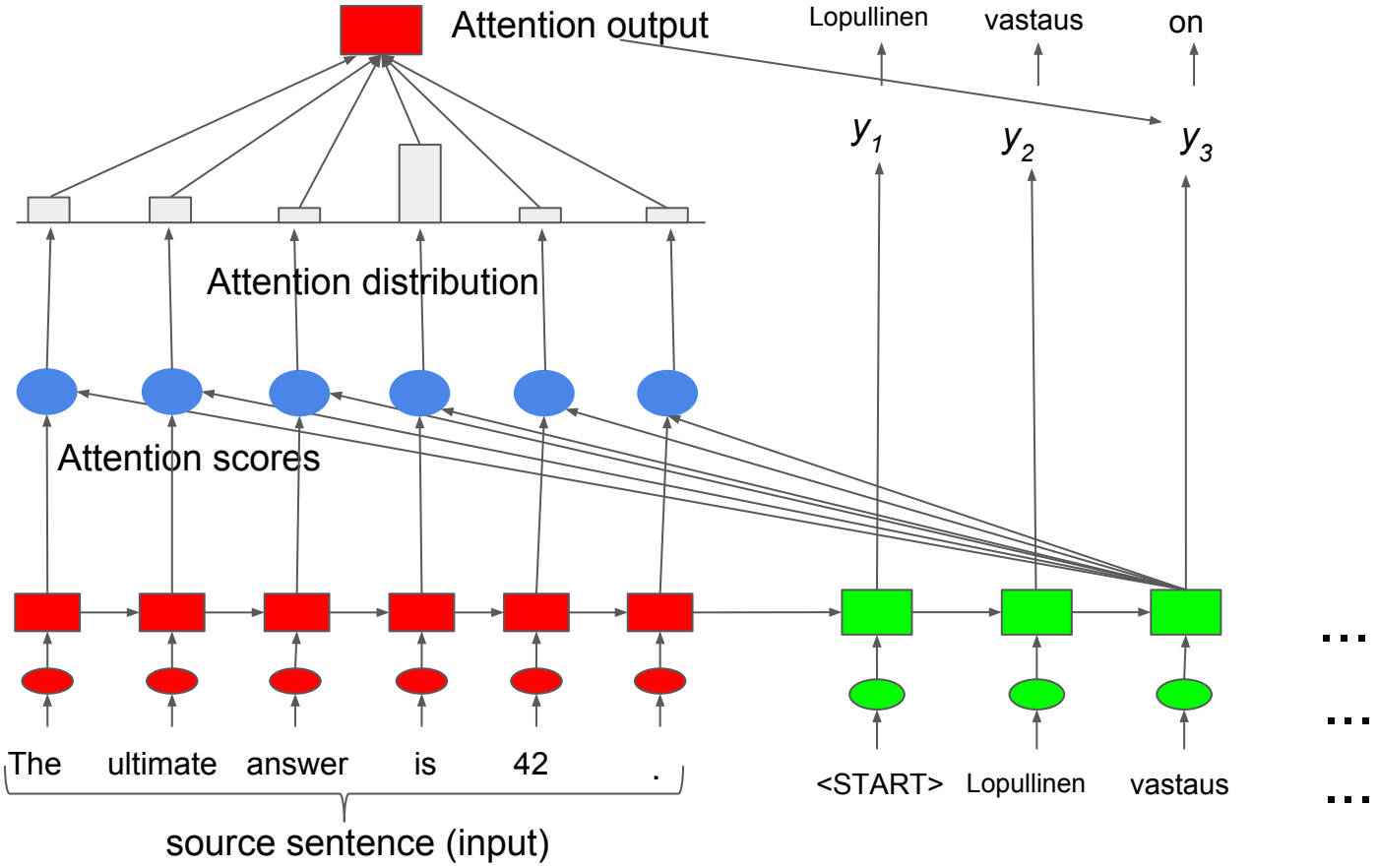
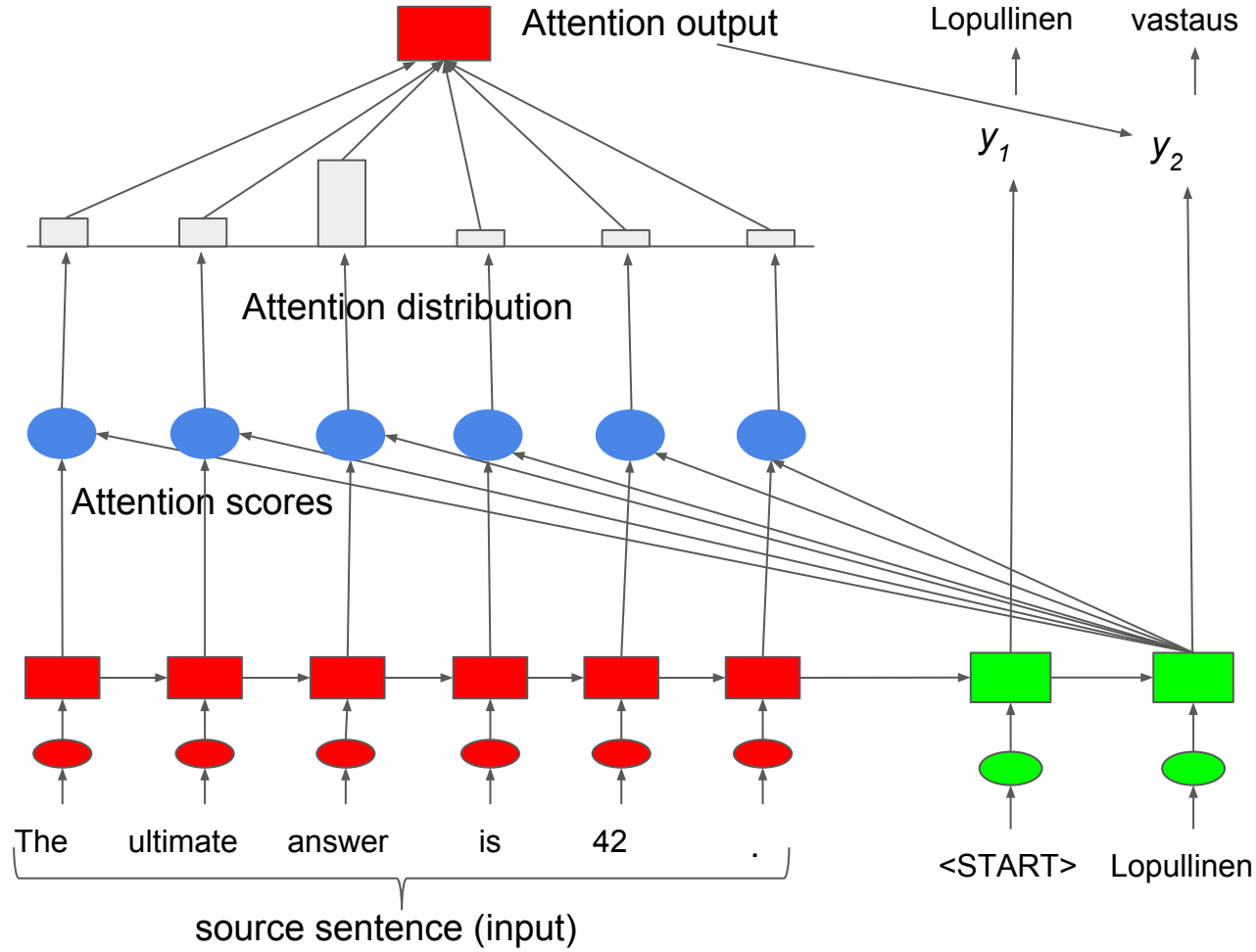


- <u>Are we forgetting something behind?</u>
  Attention decisions are made independently (which is *suboptimal*)

Input feeding

- Attention decisions should be made jointly taking into account past attention information.



Input feeding

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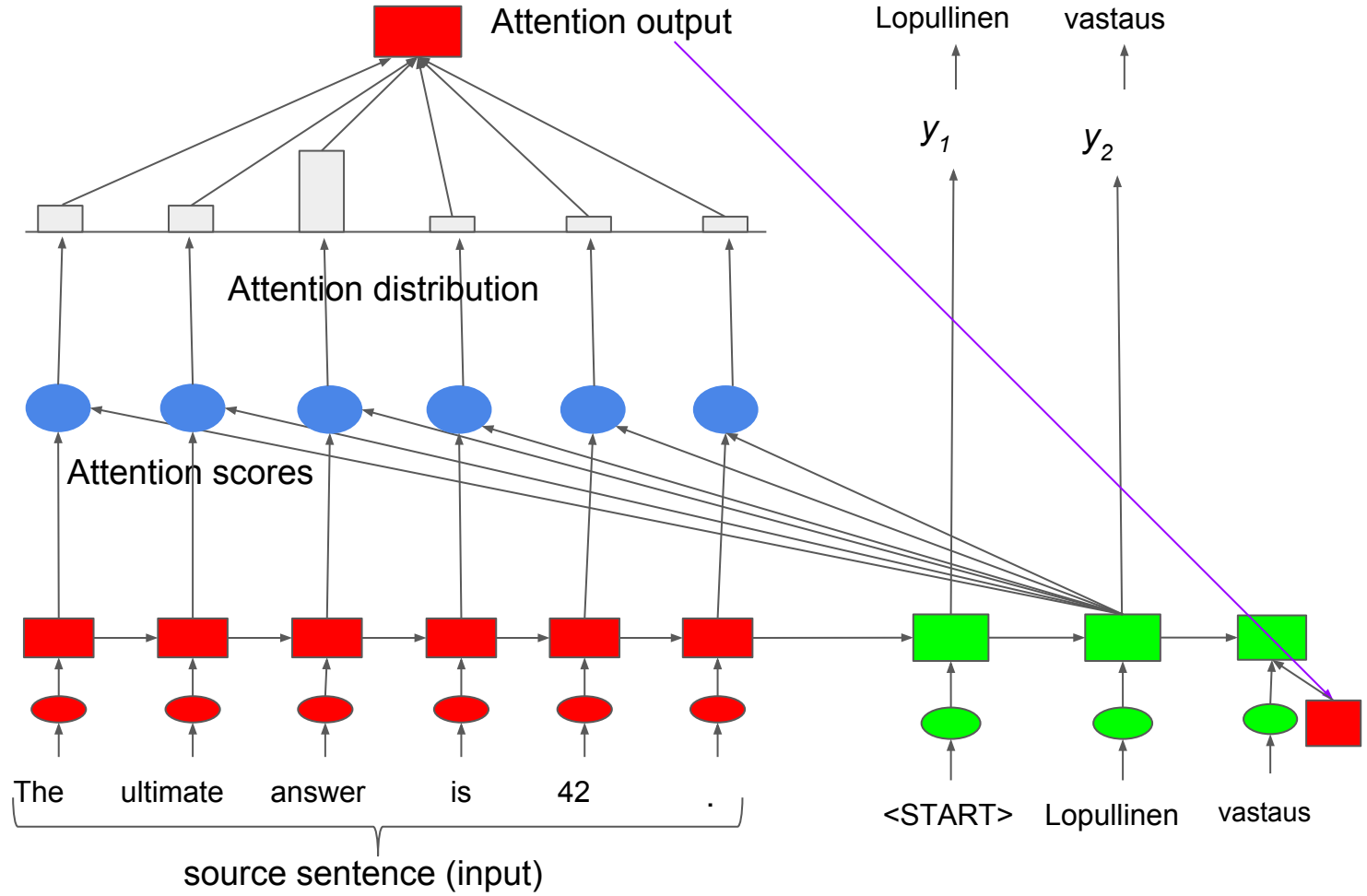
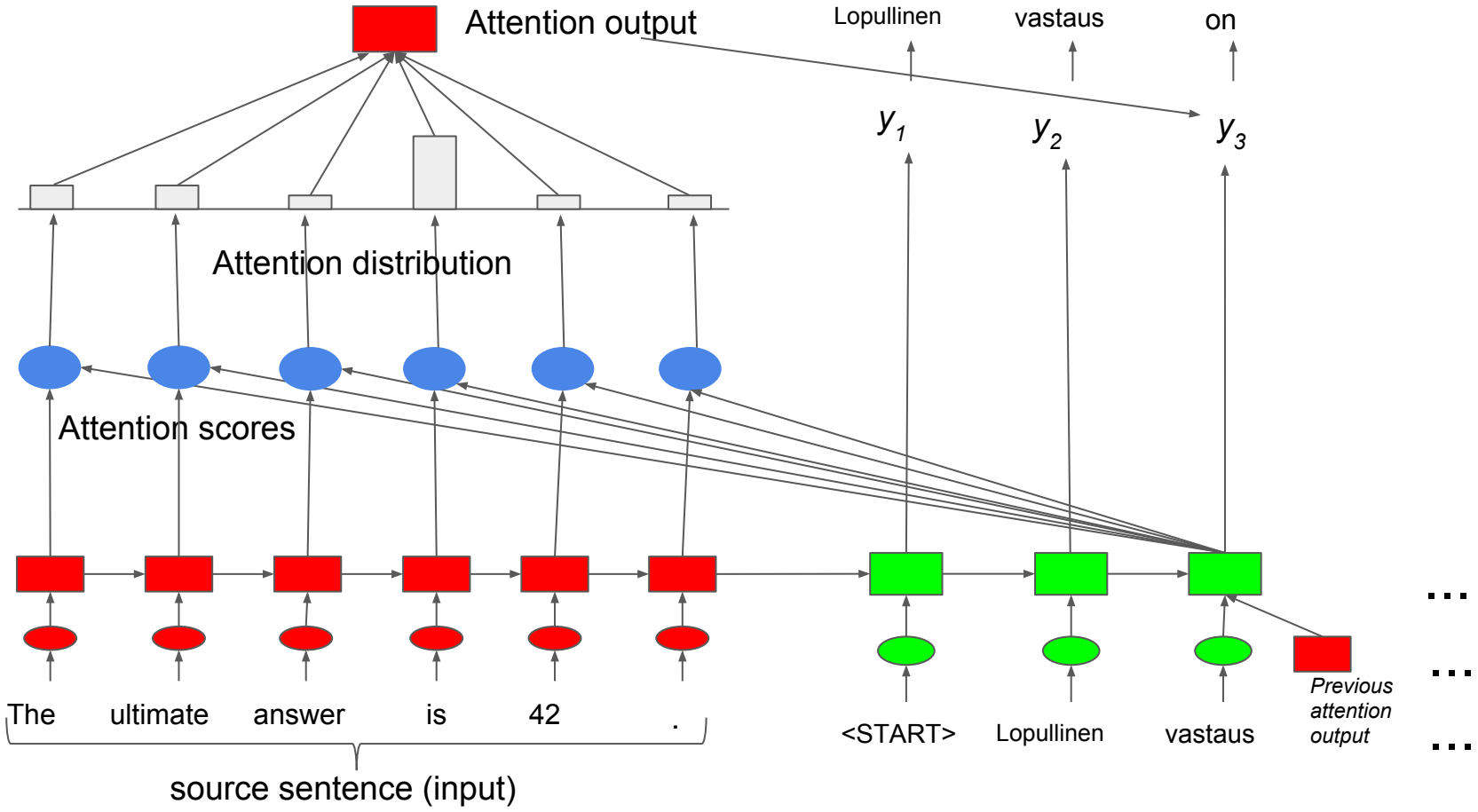


Input feeding

- Attention decisions should be made jointly taking into account past attention information:
  - we hope to make the model fully aware of previous attention choices
  - usually the attentional vector is concatenated with the input at the next time step



NMT research continues

NMT is the **flagship task** for Natural Language Processing (NLP) Deep Learning

- NMT research has pioneered many of the recent innovations of NLP Deep Learning

- In **2019**: NMT research continues to thrive
  - Researchers have found many, many improvements to the seq2seq NMT system
  - what we have seen today is considered the new "vanilla" seq2seq NMT architecture:
    - seq2seq + attention + input feeding

Readings

- Attention models:
  Bahdanau, Dzmitry, Kyunghyun Cho, and Yoshua Bengio. (2014)
  Neural machine translation by jointly learning to align and translate.
  https://arxiv.org/pdf/1409.0473.pdf

  Luong, T., Pham, H., and Manning, C. D. (2015).
  Effective Approaches to Attention-based Neural Machine Translation.
  https://aclweb.org/anthology/D15-1166

  Hamidreza Ghader and Christof Monz (2017)
  What does Attention in Neural Machine Translation Pay Attention to?
  https://arxiv.org/pdf/1710.03348.pdf

- BackTranslations:
  Rico Sennrich, Barry Haddow and Alexandra Birch (2016)
  Improving Neural Machine Translation Models with Monolingual Data
  https://arxiv.org/pdf/1511.06709.pdf

Readings

Xu, Kelvin, et al. (2015)
Show, attend and tell: Neural image caption generation with visual attention.
http://www.jmlr.org/proceedings/papers/v37/xuc15.pdf

Cho, Kyunghyun, et al. (2014)
On the properties of neural machine translation: Encoder-decoder approaches.
https://arxiv.org/pdf/1409.1259.pdf

Raganato, Alessandro, et al. (2018)
The University of Helsinki submissions to the WMT18 news task.
https://www.aclweb.org/anthology/W18-6425

Lample, Guillaume, et al. (2018)
Phrase-based & neural unsupervised machine translation.
https://arxiv.org/pdf/1804.07755.pdf

Artetxe, Mikel, Gorka Labaka, and Eneko Agirre. (2018)
Unsupervised statistical machine translation.
https://arxiv.org/pdf/1809.01272.pdf