Massively Multilingual Neural Machine Translation

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Joint work with Melvin Johnson, Orhan Firat
Google Translate

DL Course

Google Translate

B I U
N L P

Some (Israeli) History

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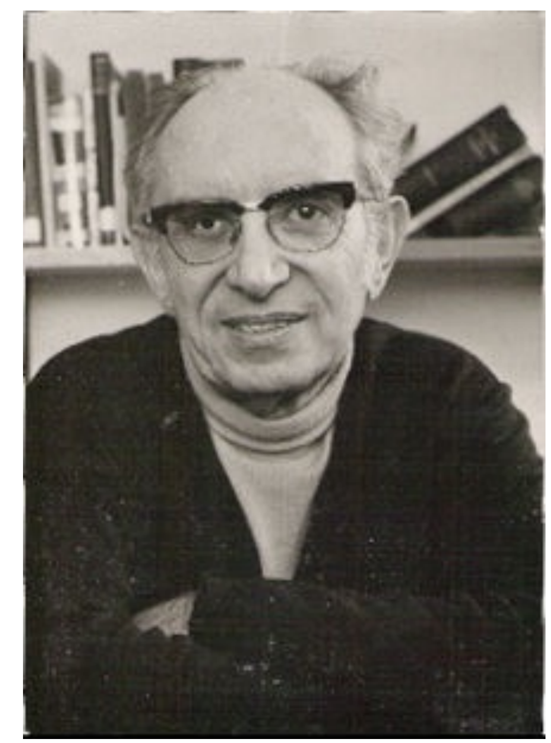
- “Since thinking in terms of machines might perhaps be difficult for the reader, let him imagine an **utterly moronic student** without the slightest knowledge of either the source-language or the target-language…” Bar Hillel, 1953



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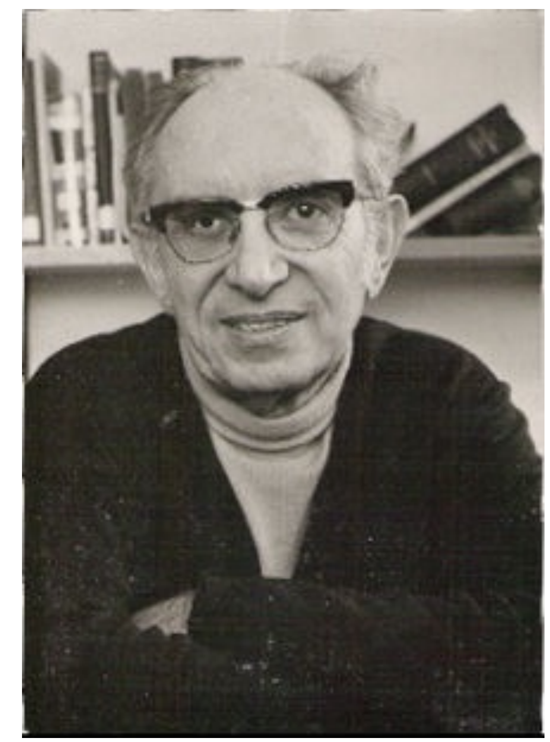

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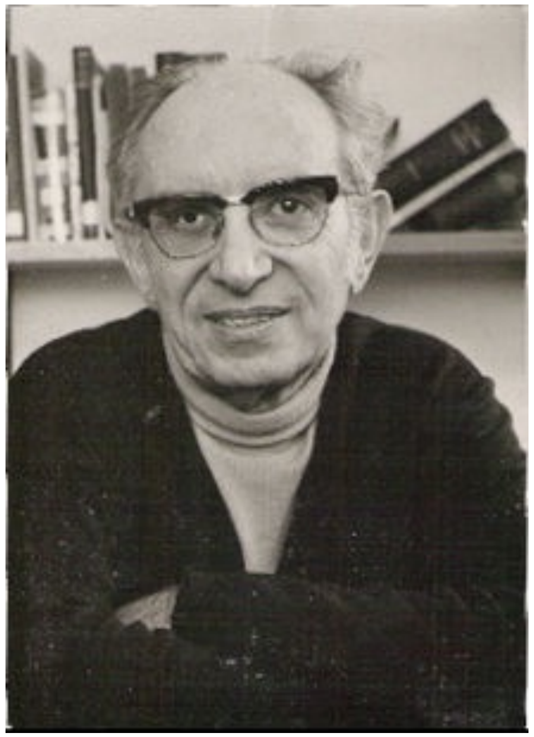
- Wer’e trying to make computers translate for more than 70 years!



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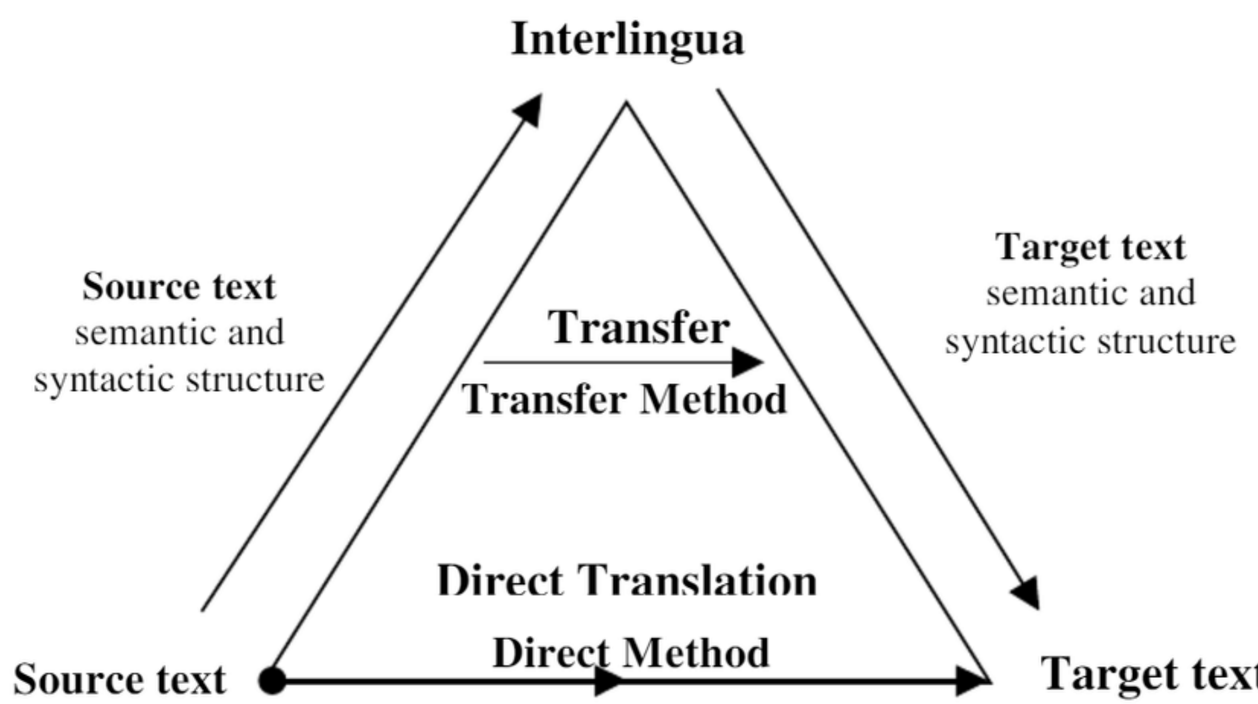

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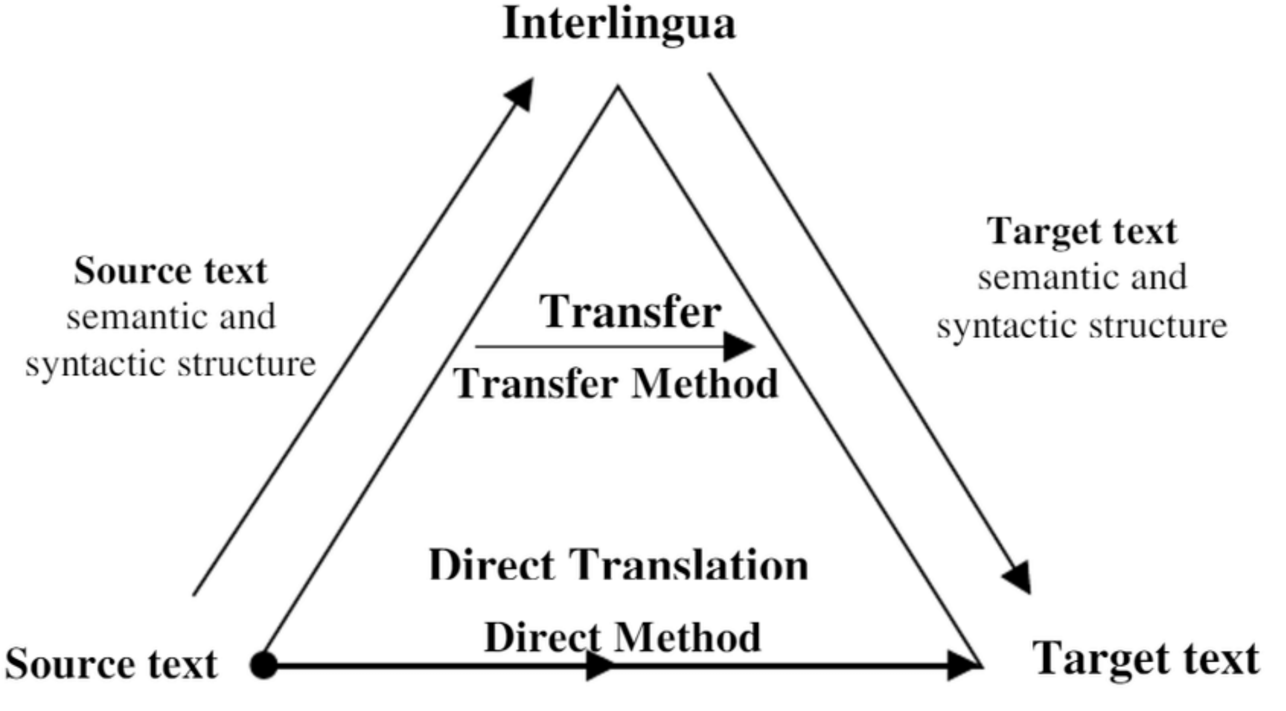

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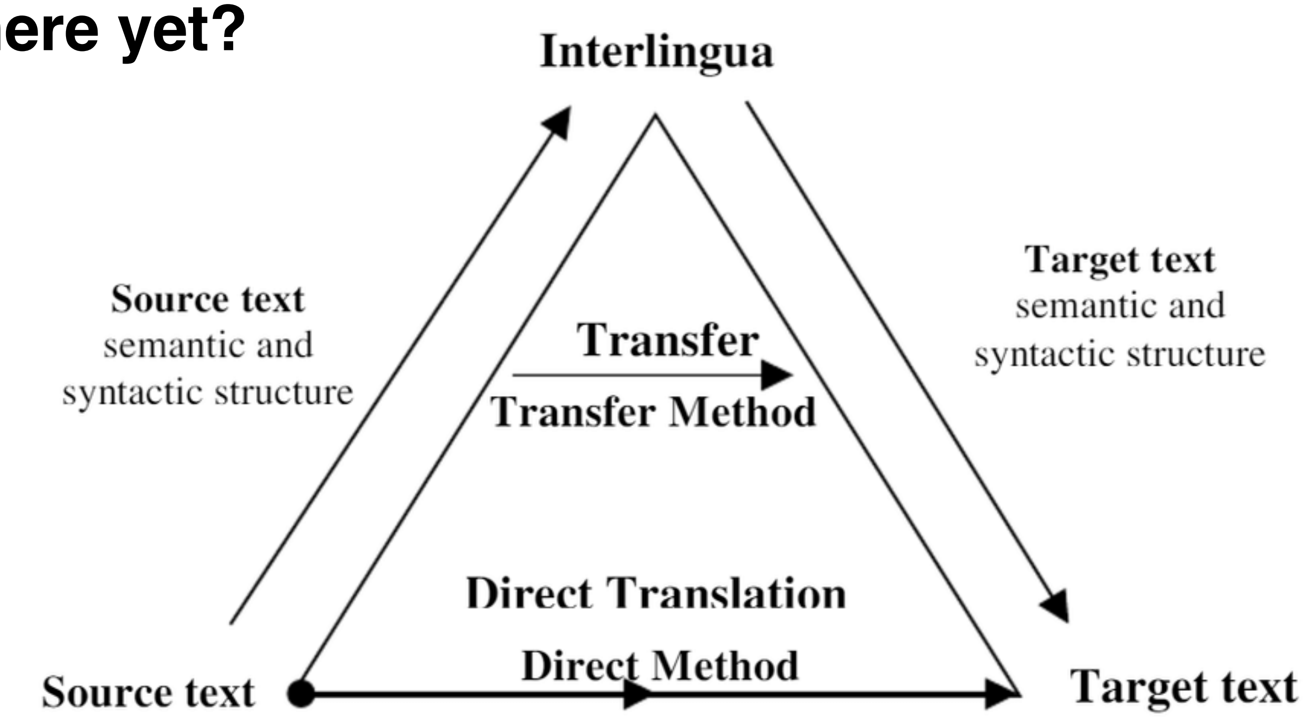
  - **Are we there yet?**



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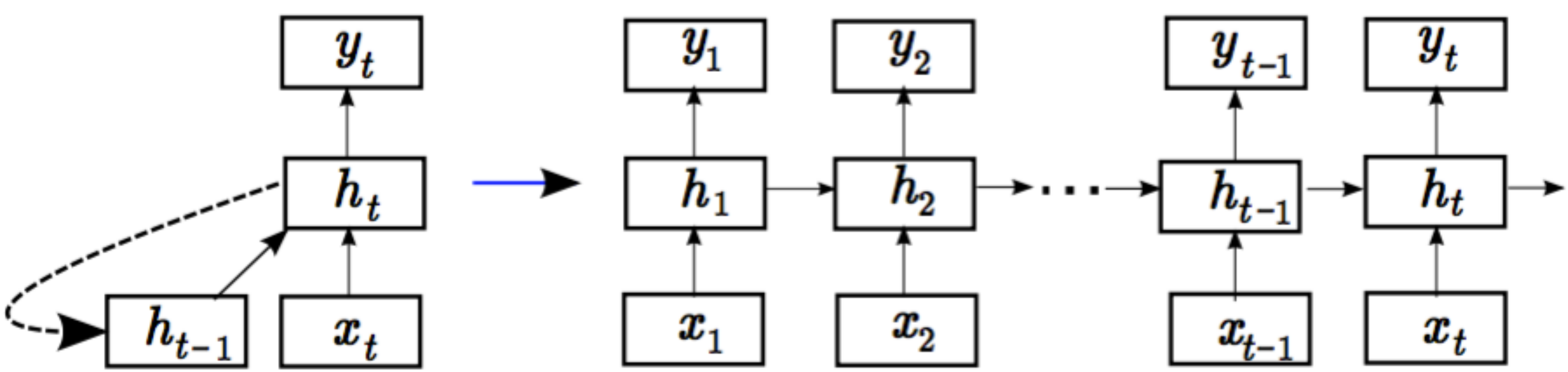
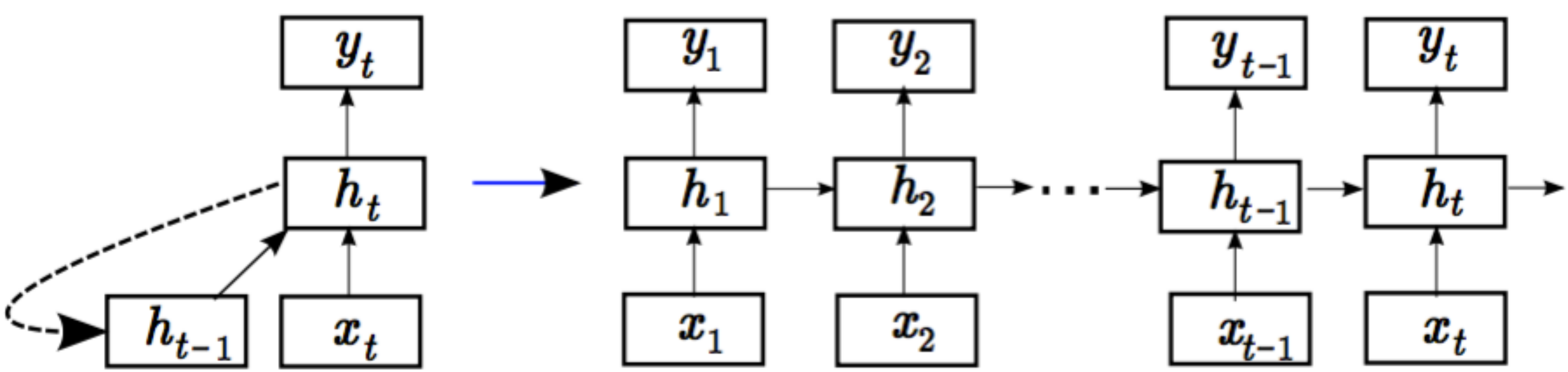
- First, lets recap on…

Recurrent Neural Networks (RNN’s)



Recurrent Neural Networks (RNN's)

- "Horizontally deep" architecture



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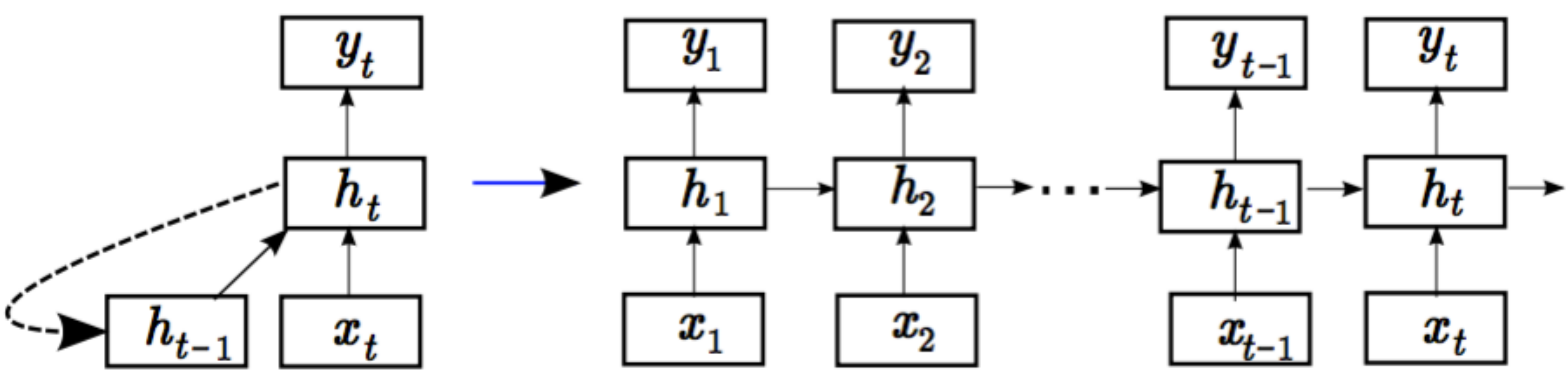

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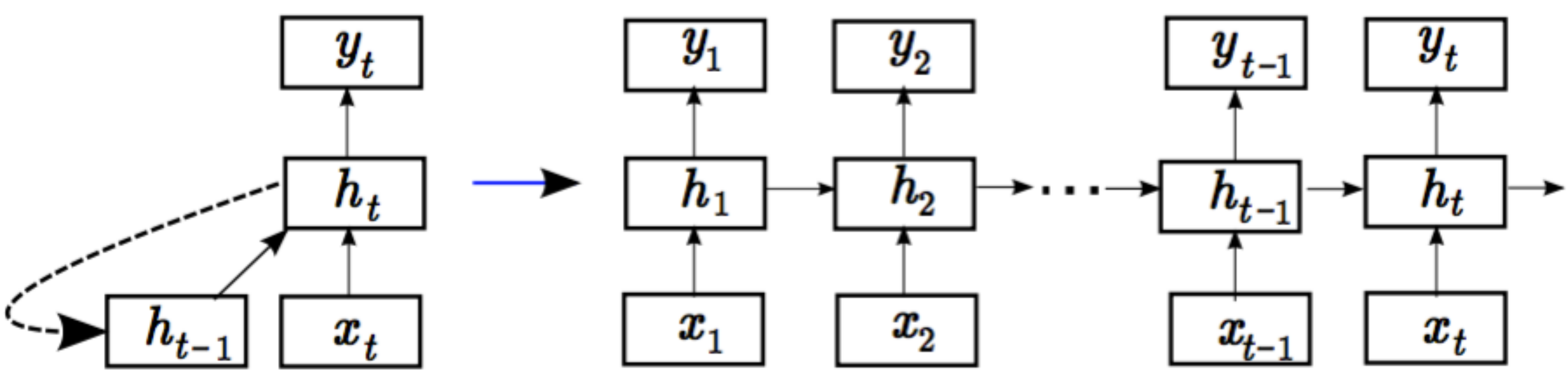

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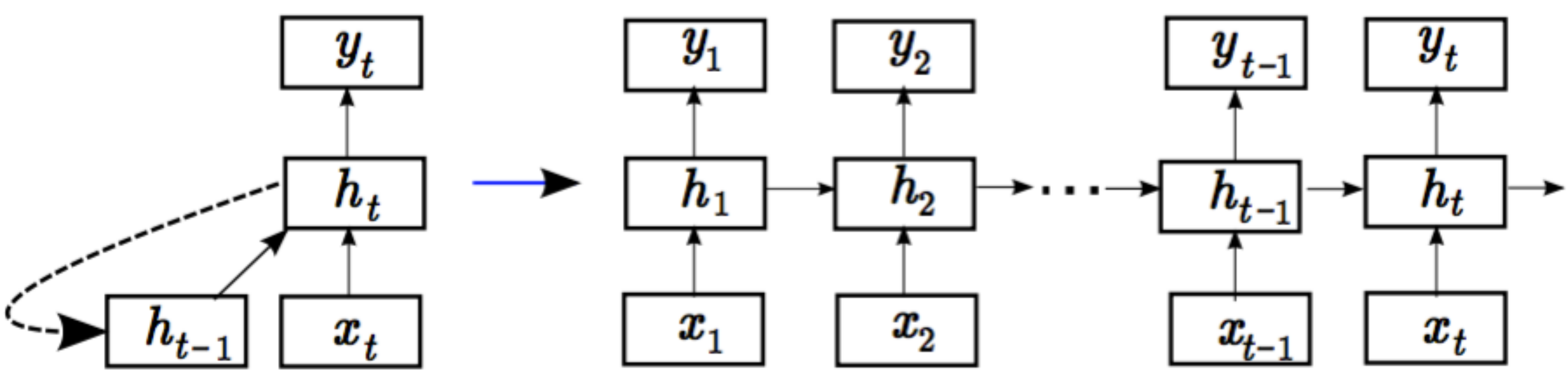

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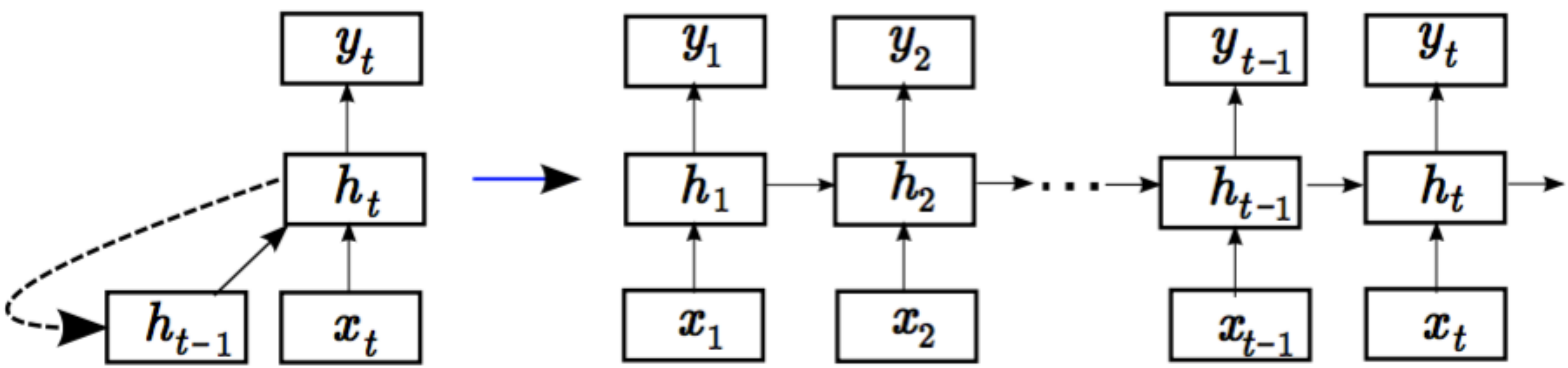
  - How can we predict a sentence with an RNN?



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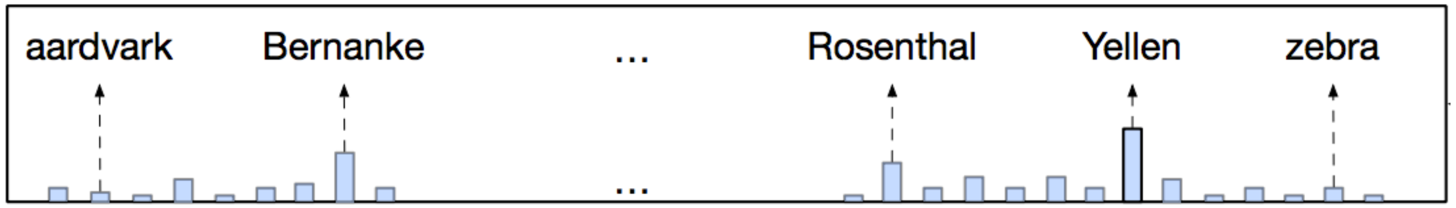
$$p(x = i) = \frac{e^{y_i}}{\sum_{j=1}^{k} e^{y_j}}$$



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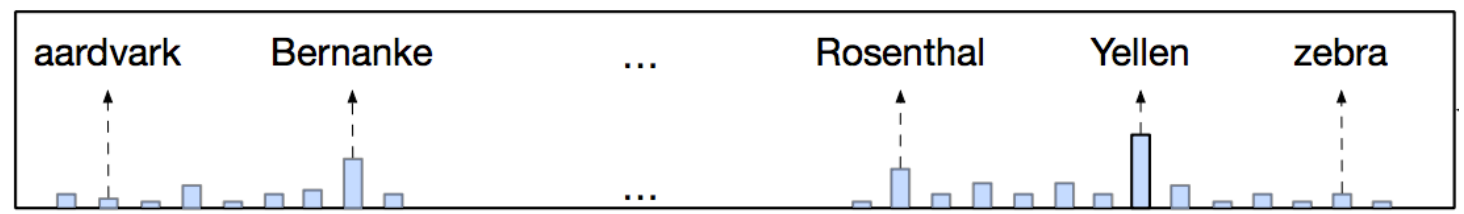
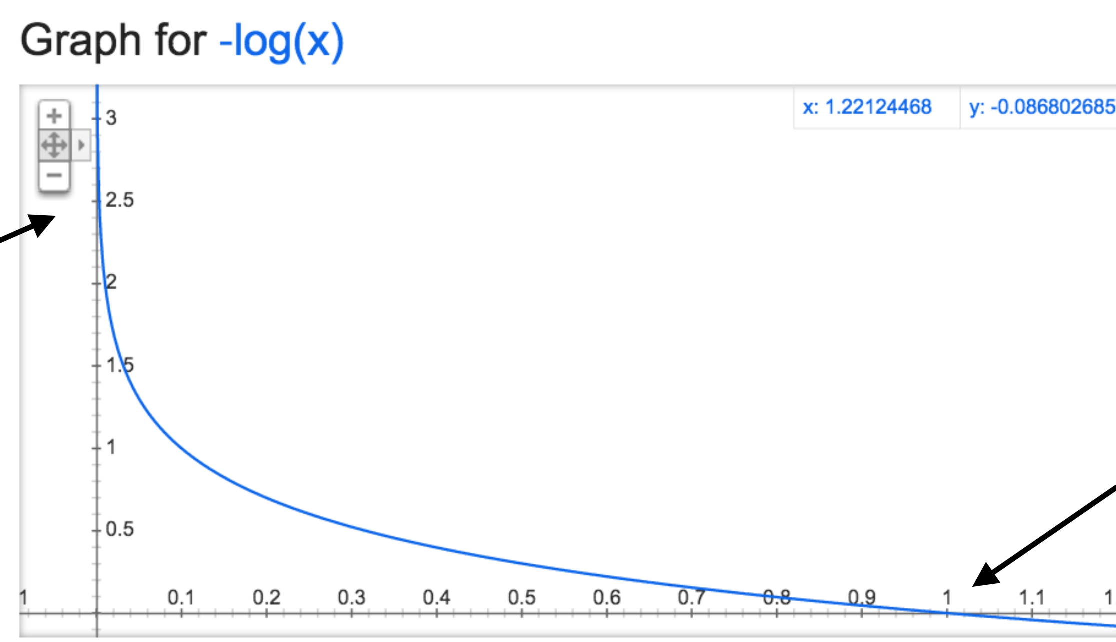


- The network's loss function is usually the sum of **negative log softmax** values for the **correct sequence**

wrong prediction - large loss value



correct prediction - zero loss

Sequence 2 Sequence Learning

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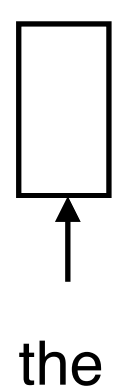

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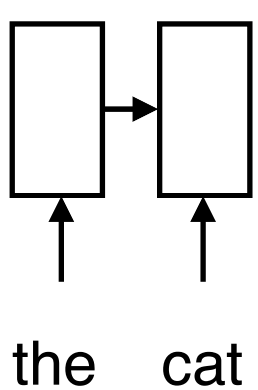

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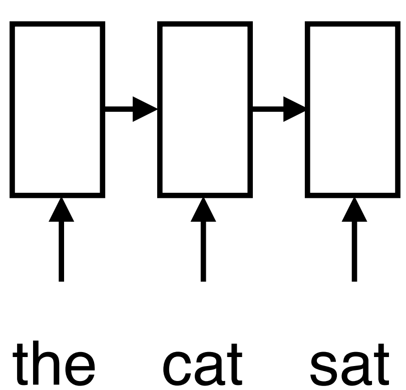

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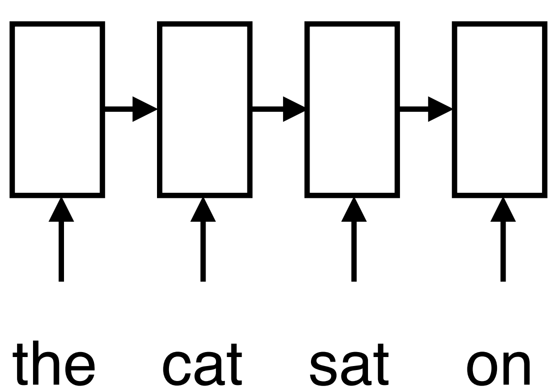

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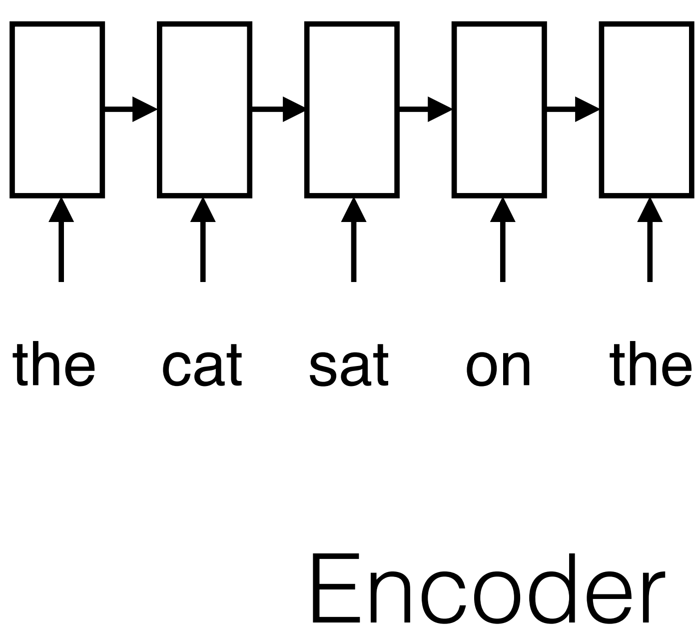

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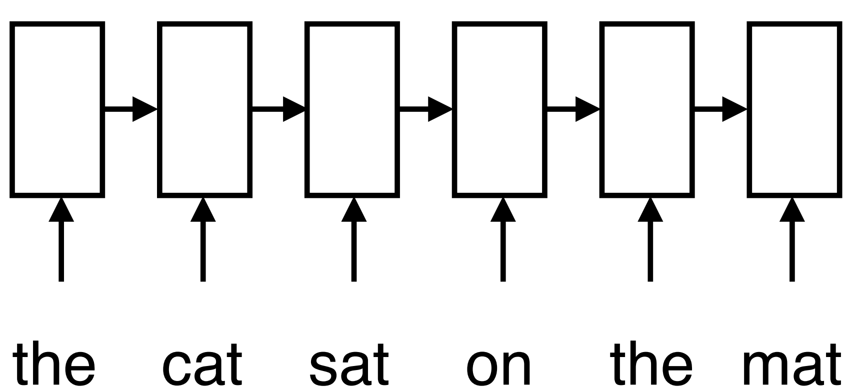

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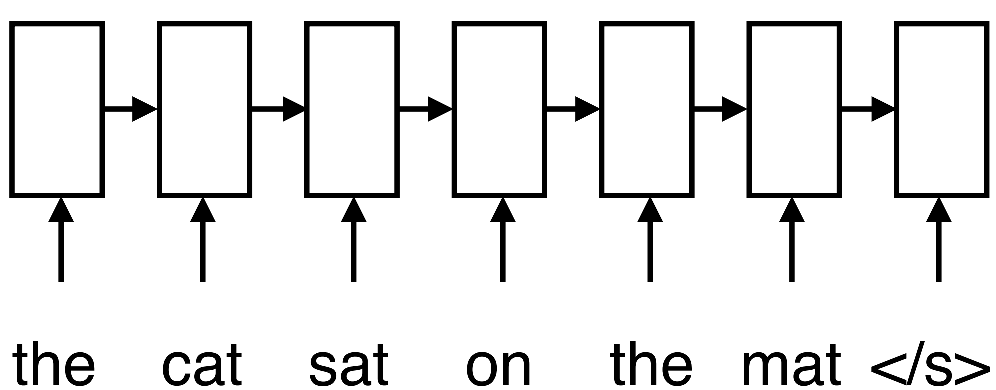

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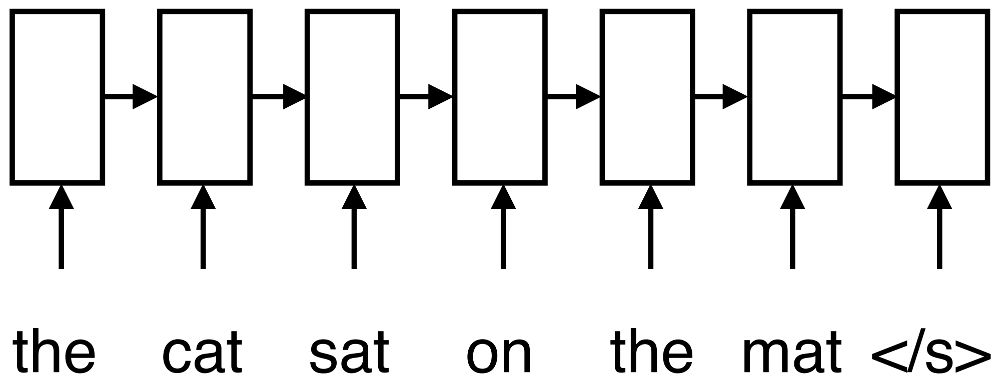

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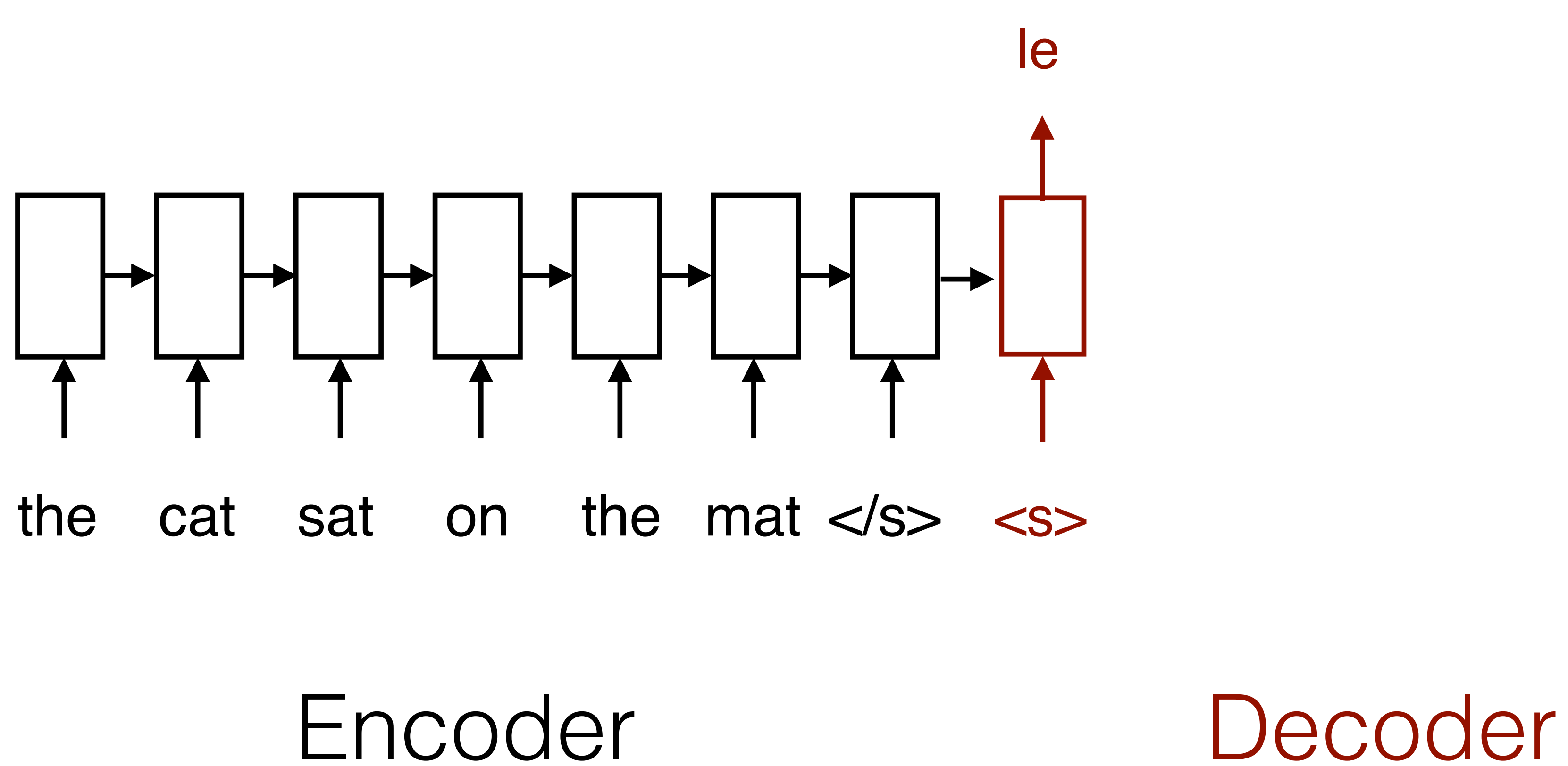

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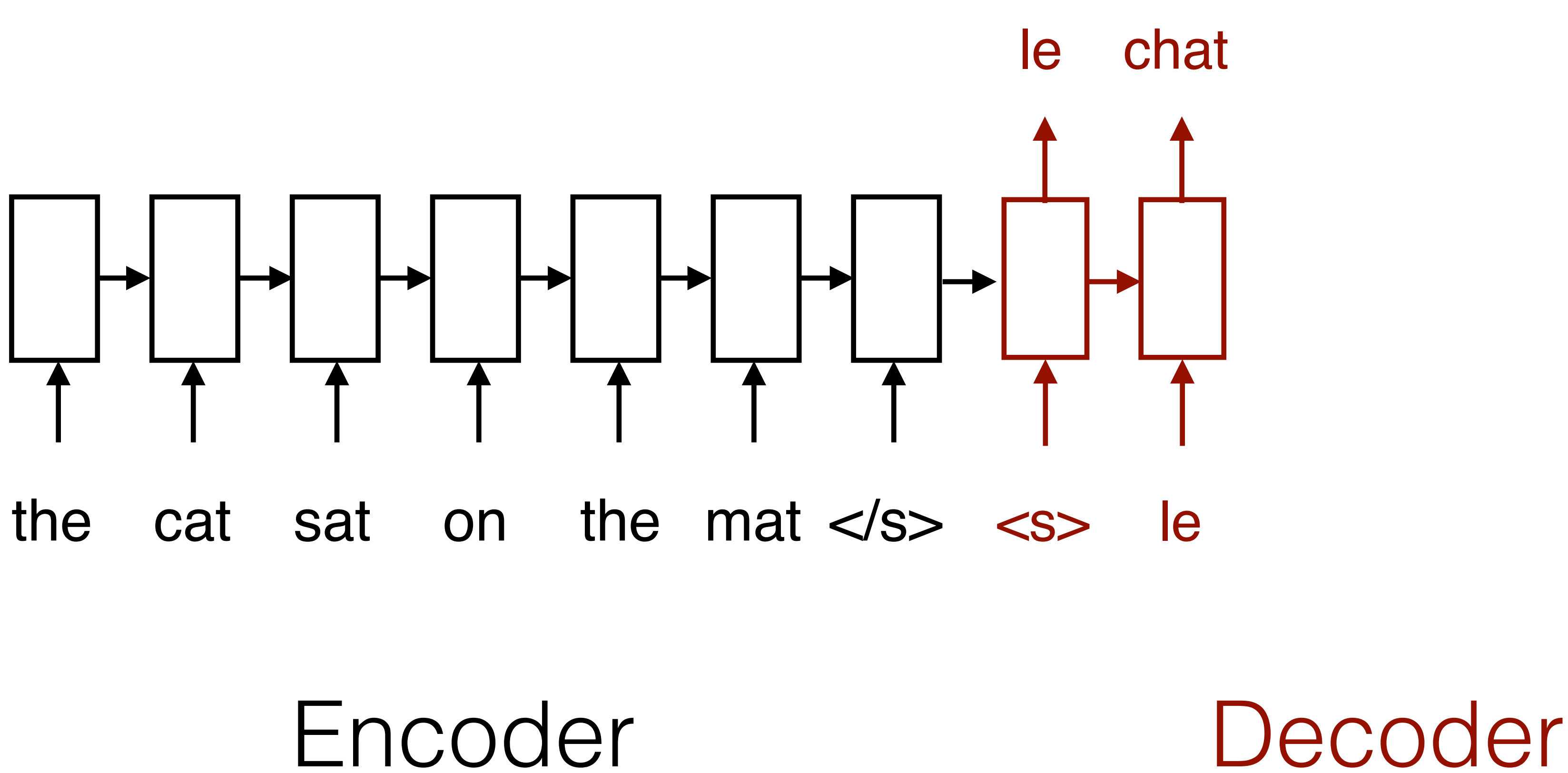

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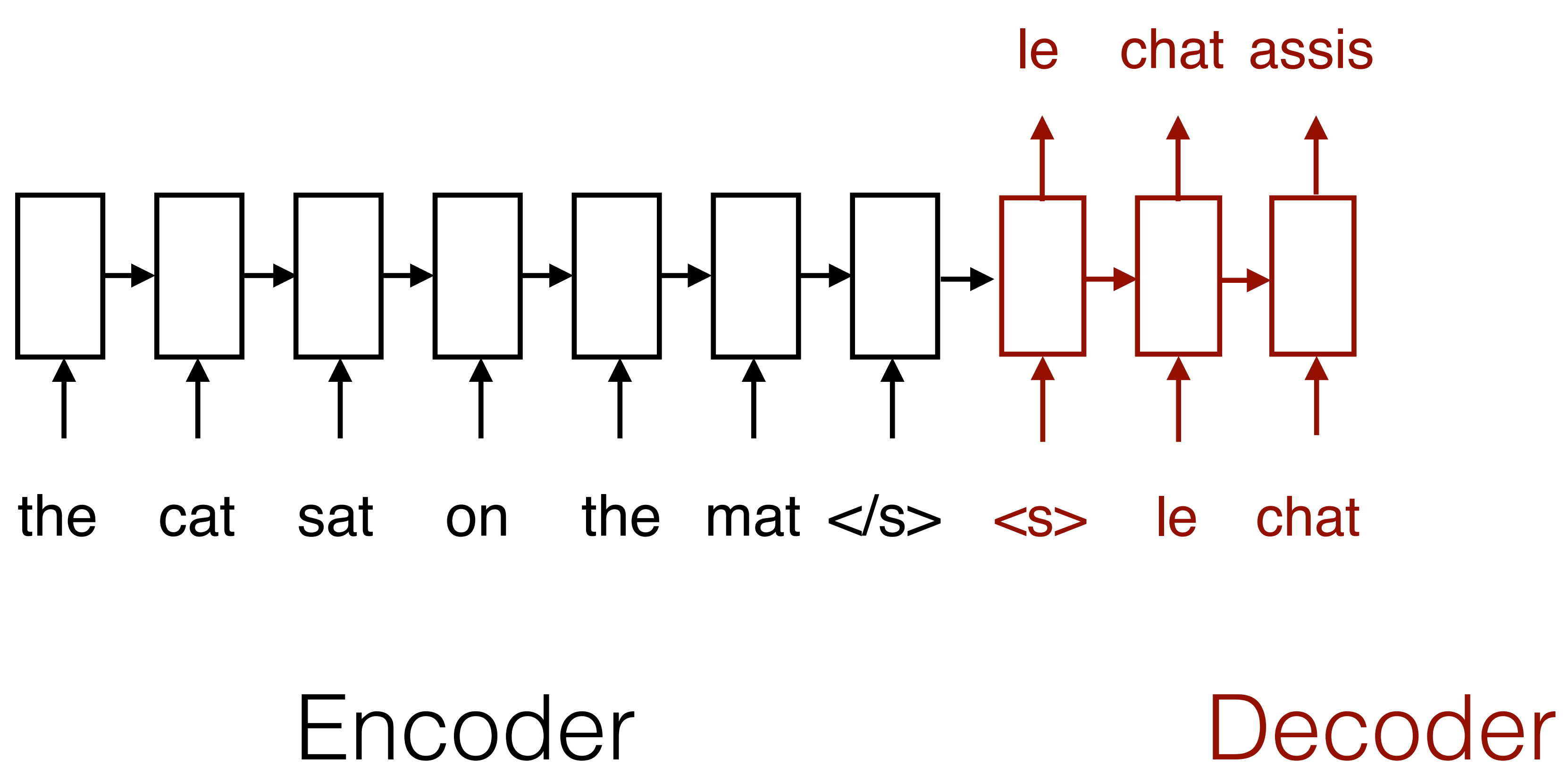

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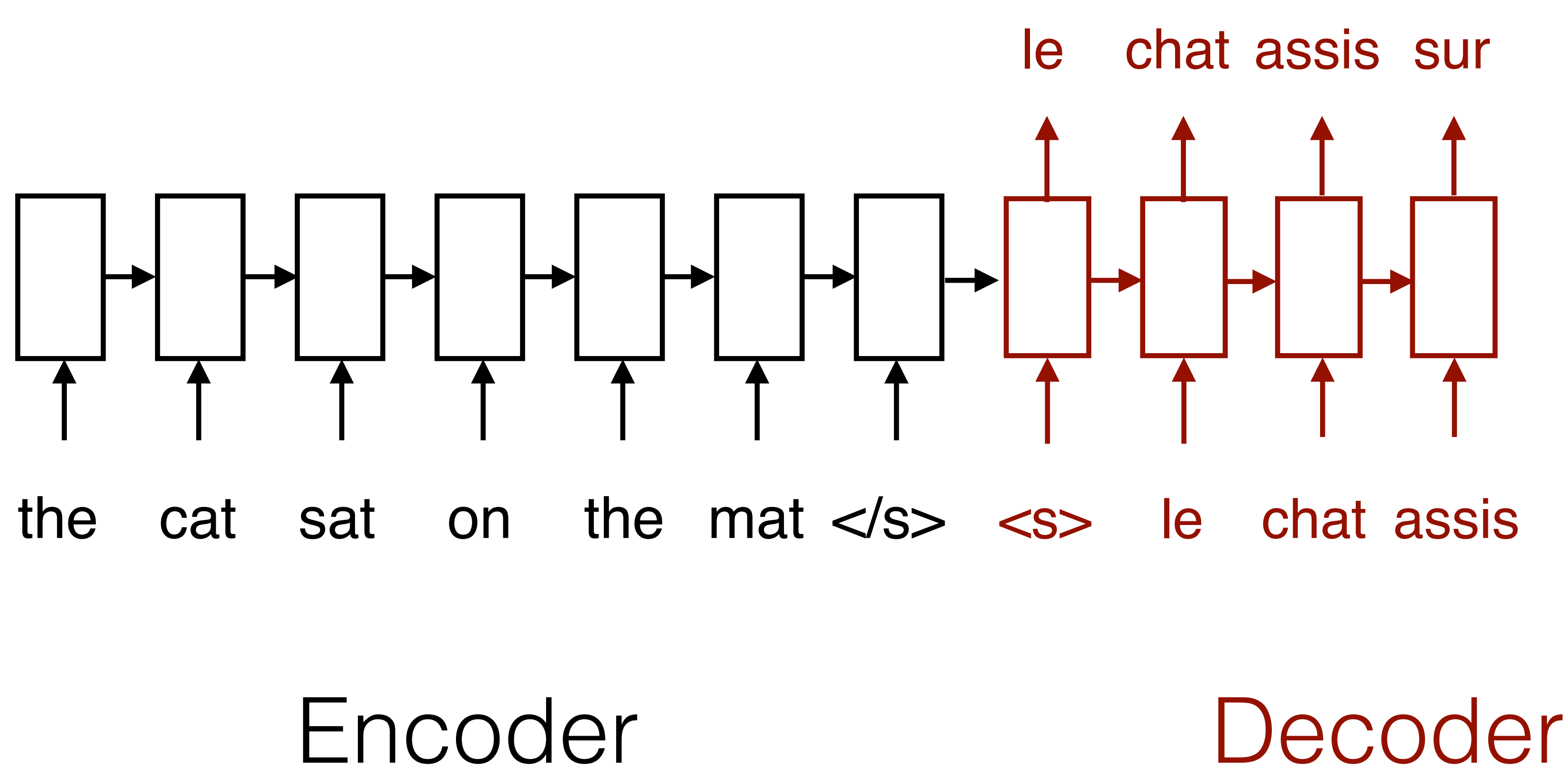

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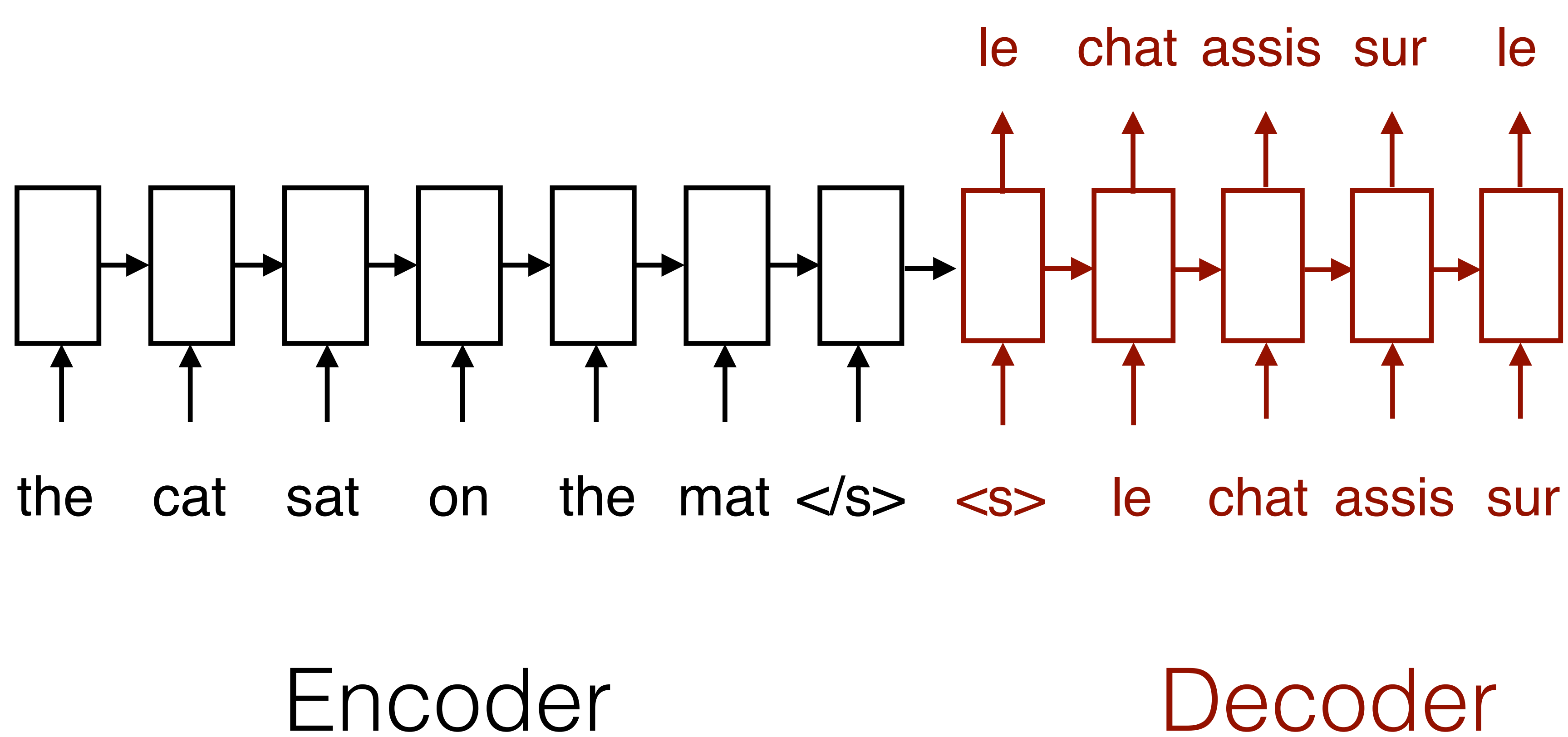

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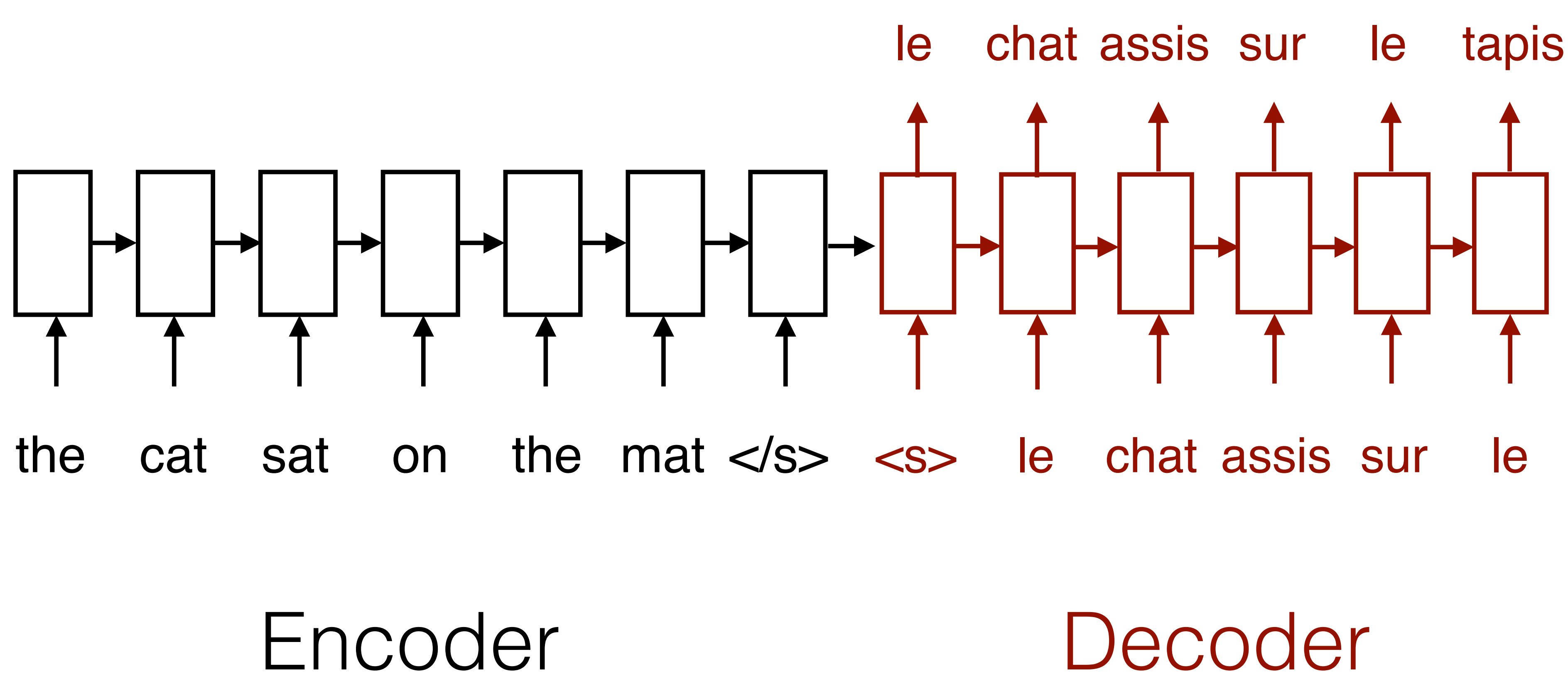

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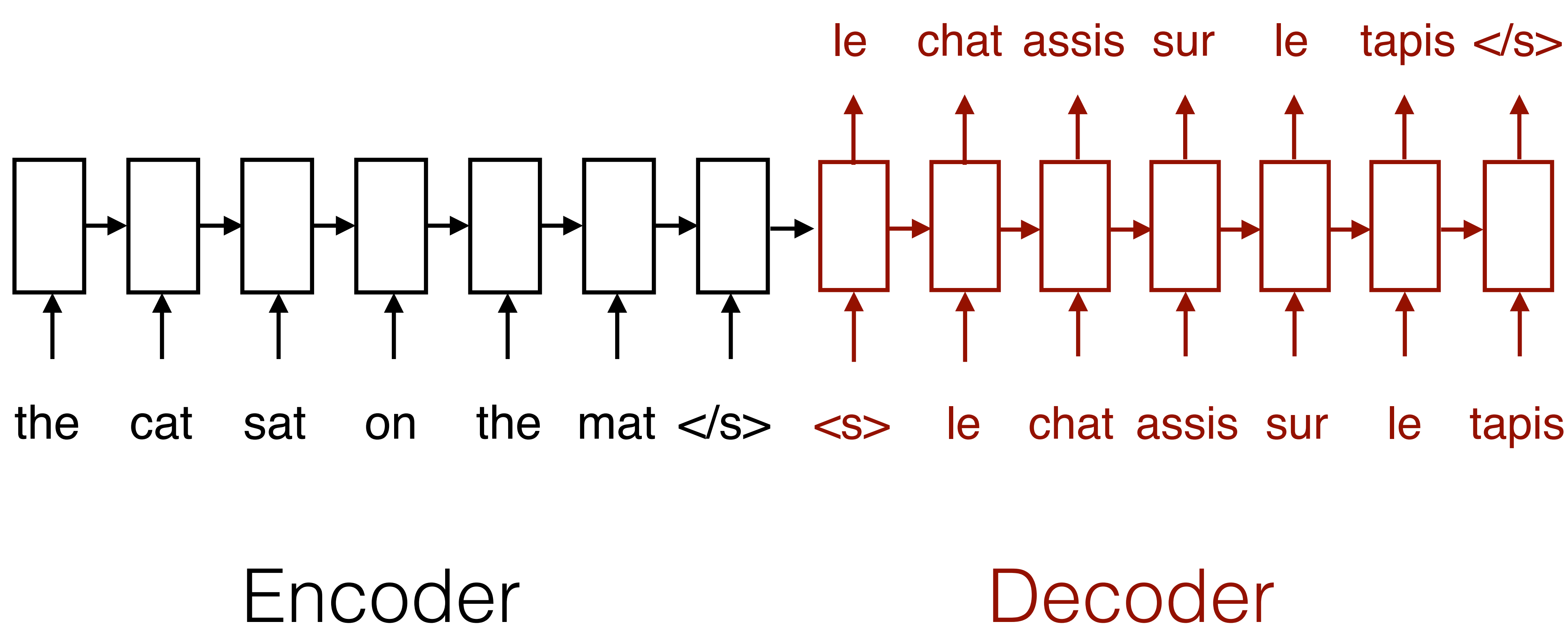

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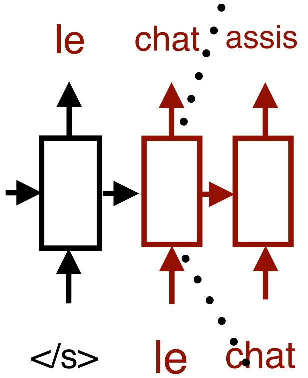
$$p(y_i = word_k|y_{<i}, x) = softmax_k(NN_\Theta(y_{<i}, x))$$

Seq2Seq decoder step - Zoom-In

“chat”



“le”

Seq2Seq decoder step - Zoom-In

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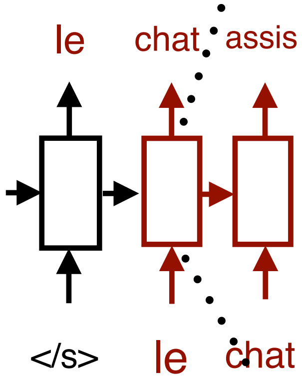
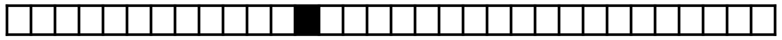


1-hot vec
for symbol
at time *t*



“le”

input vocabulary
size

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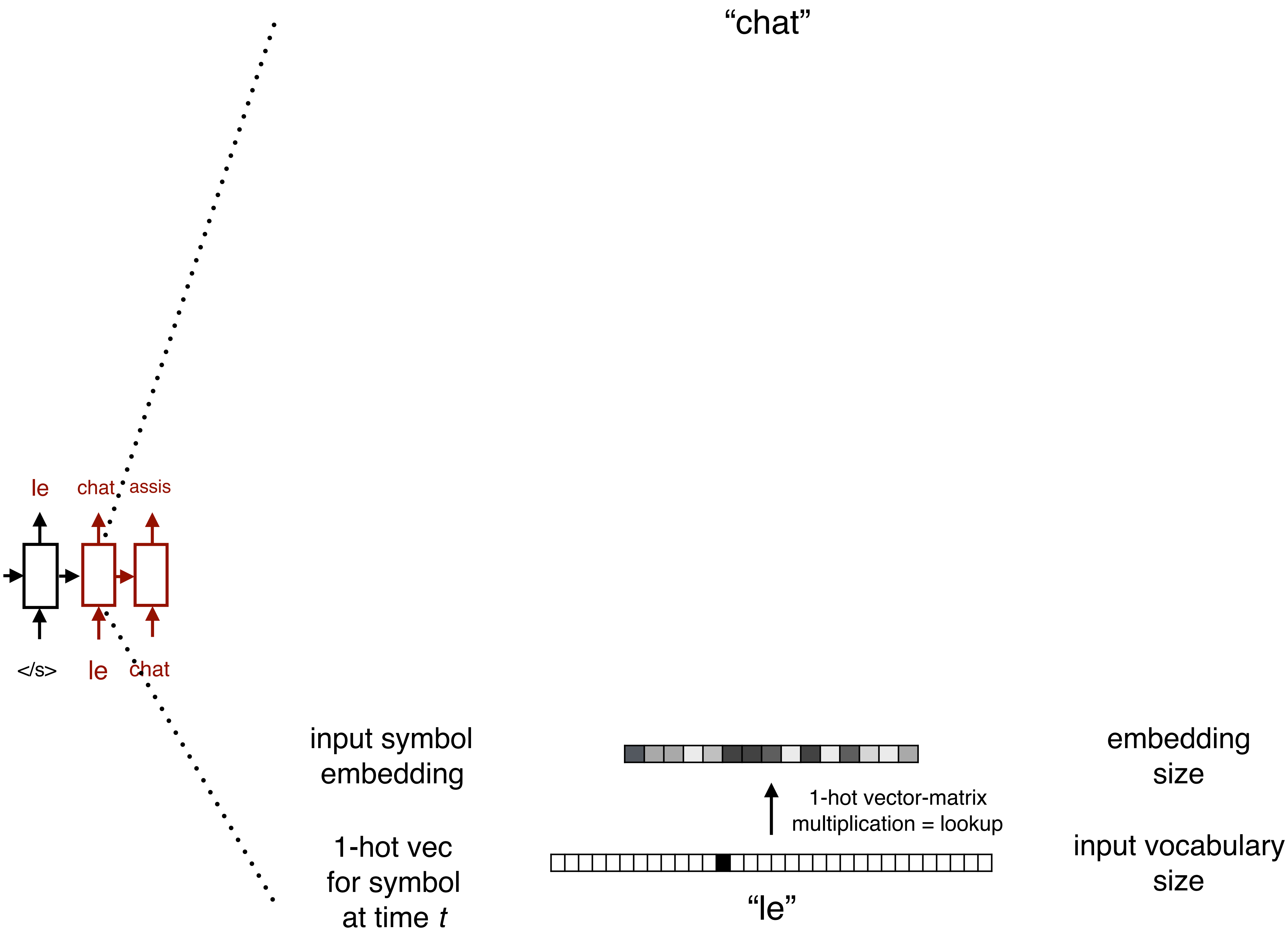

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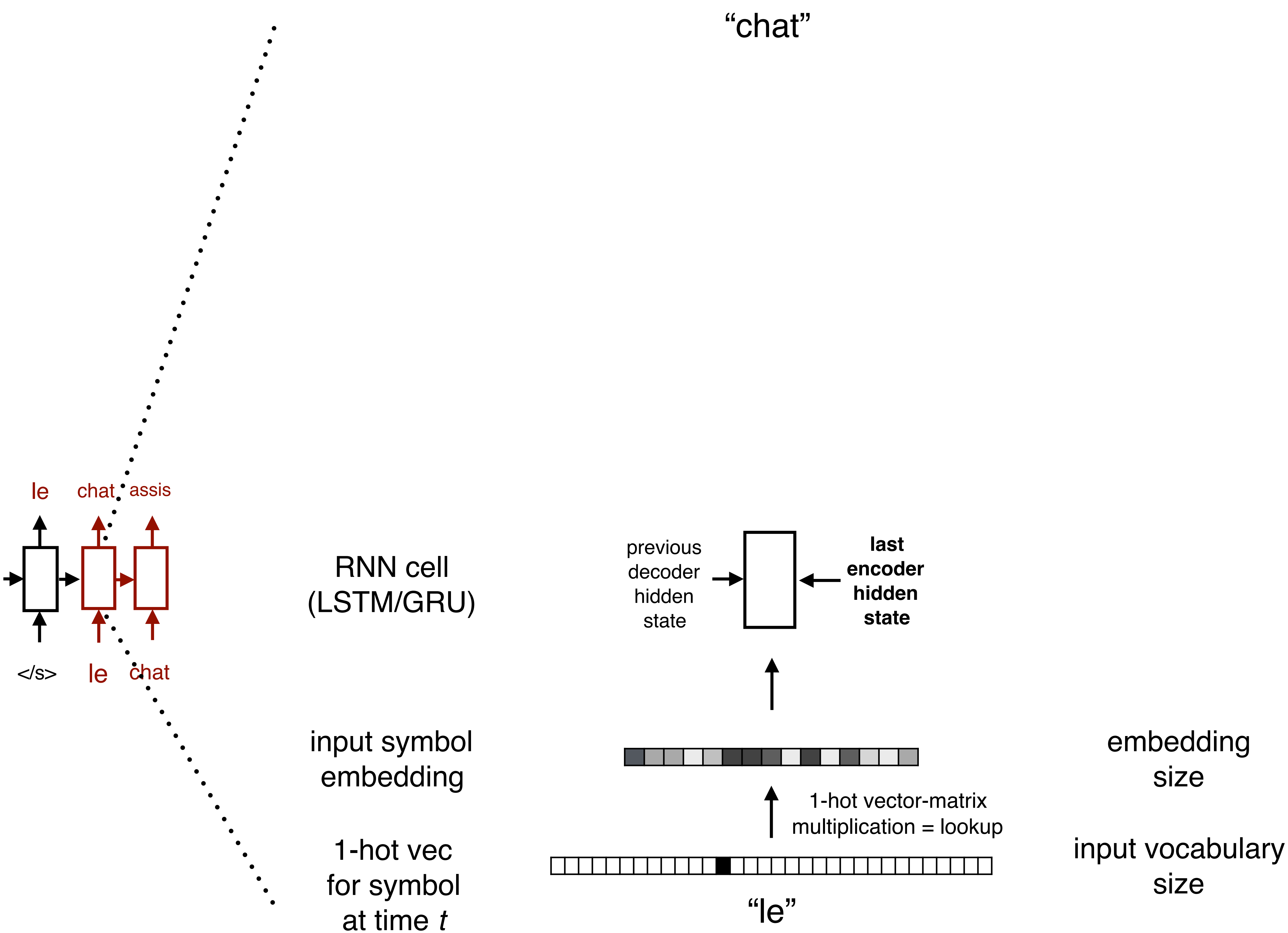

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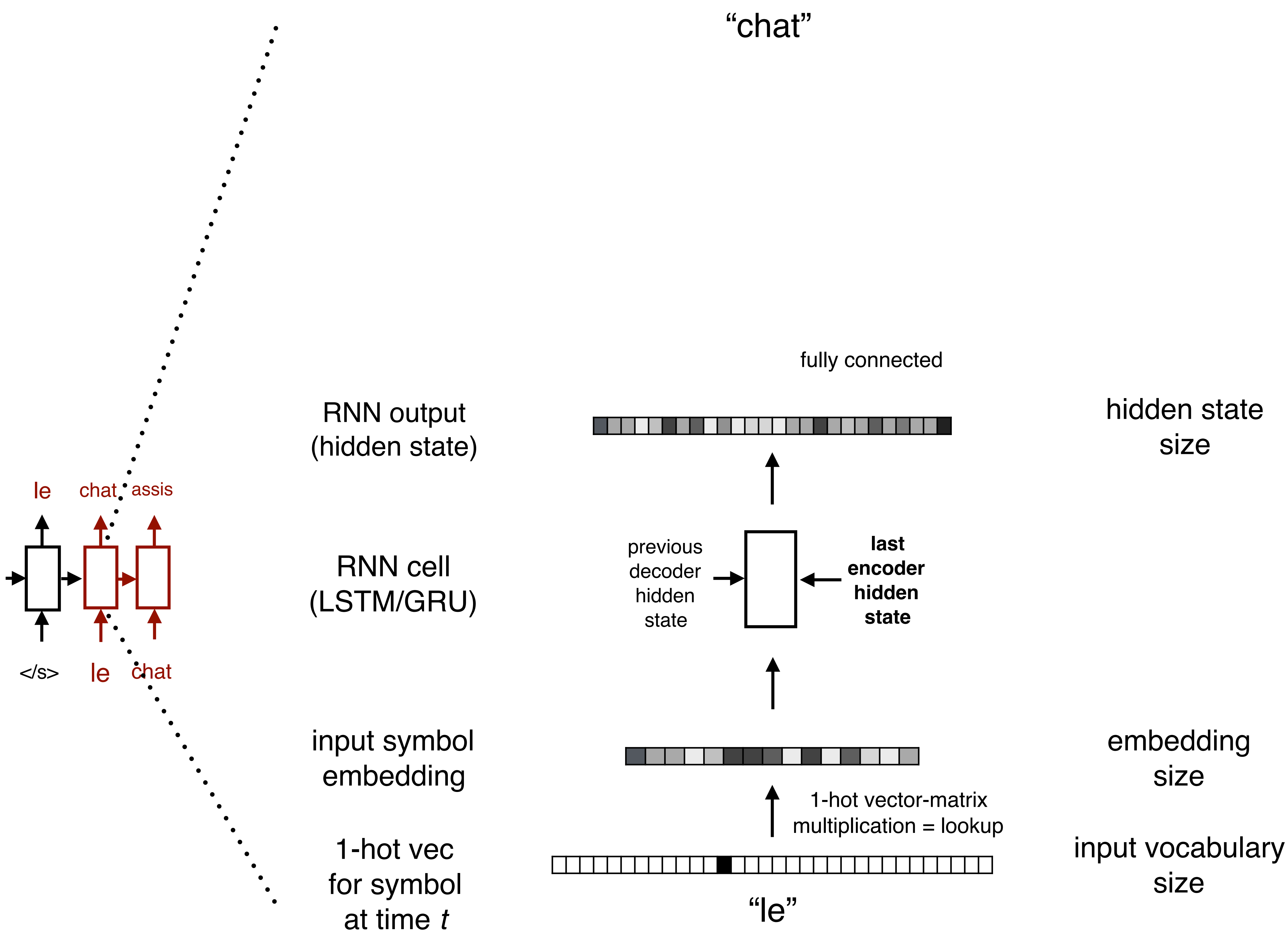

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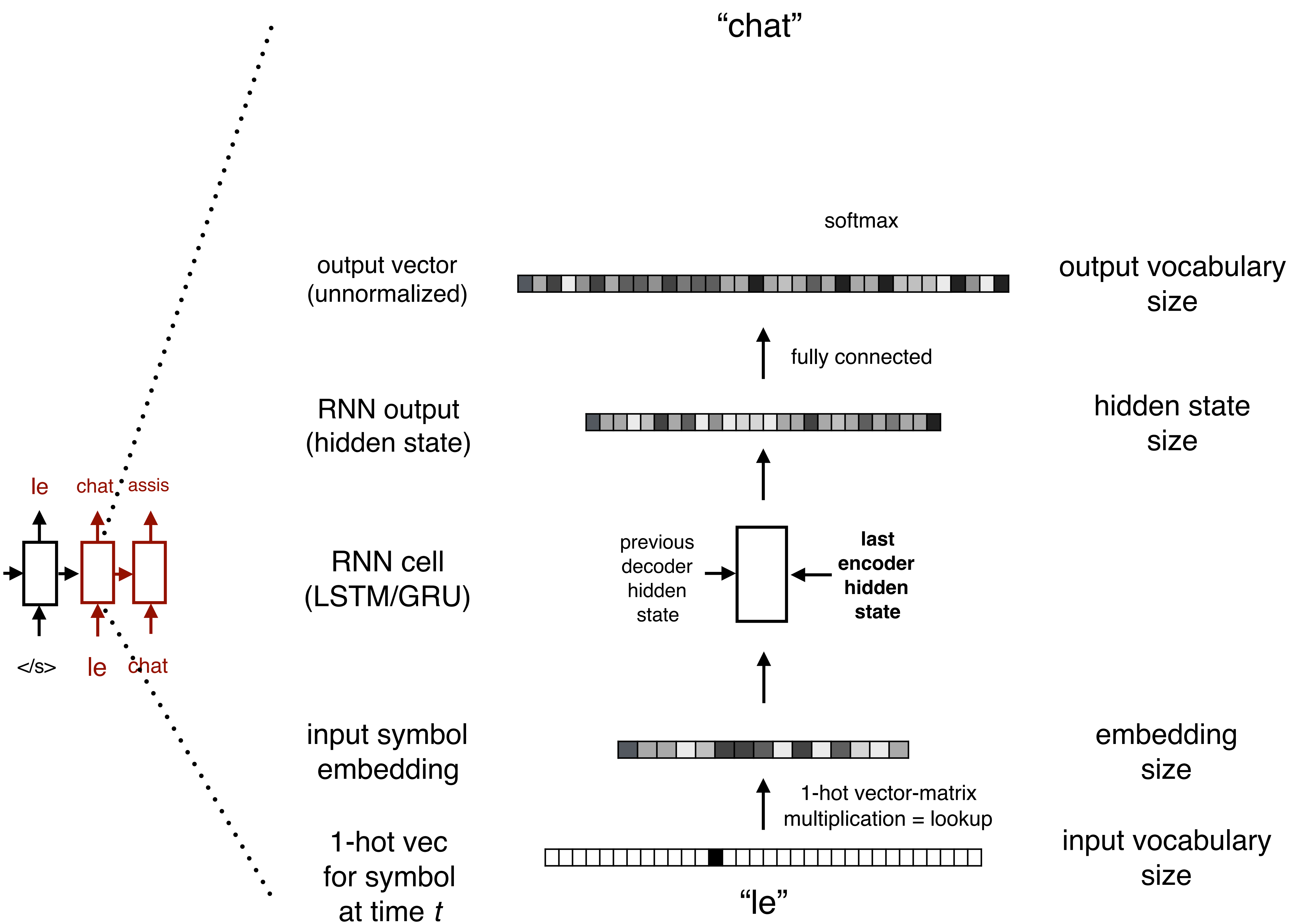

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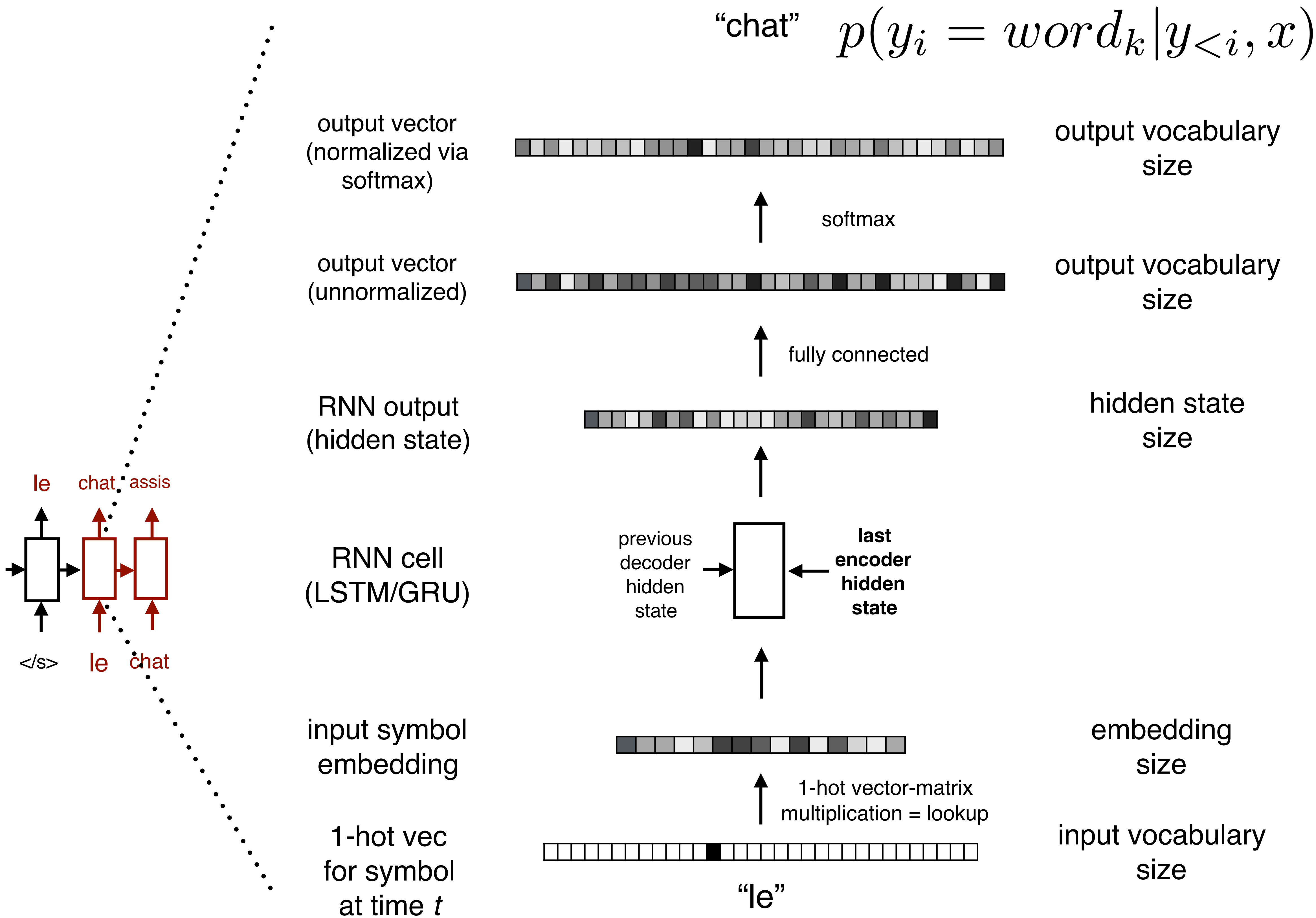

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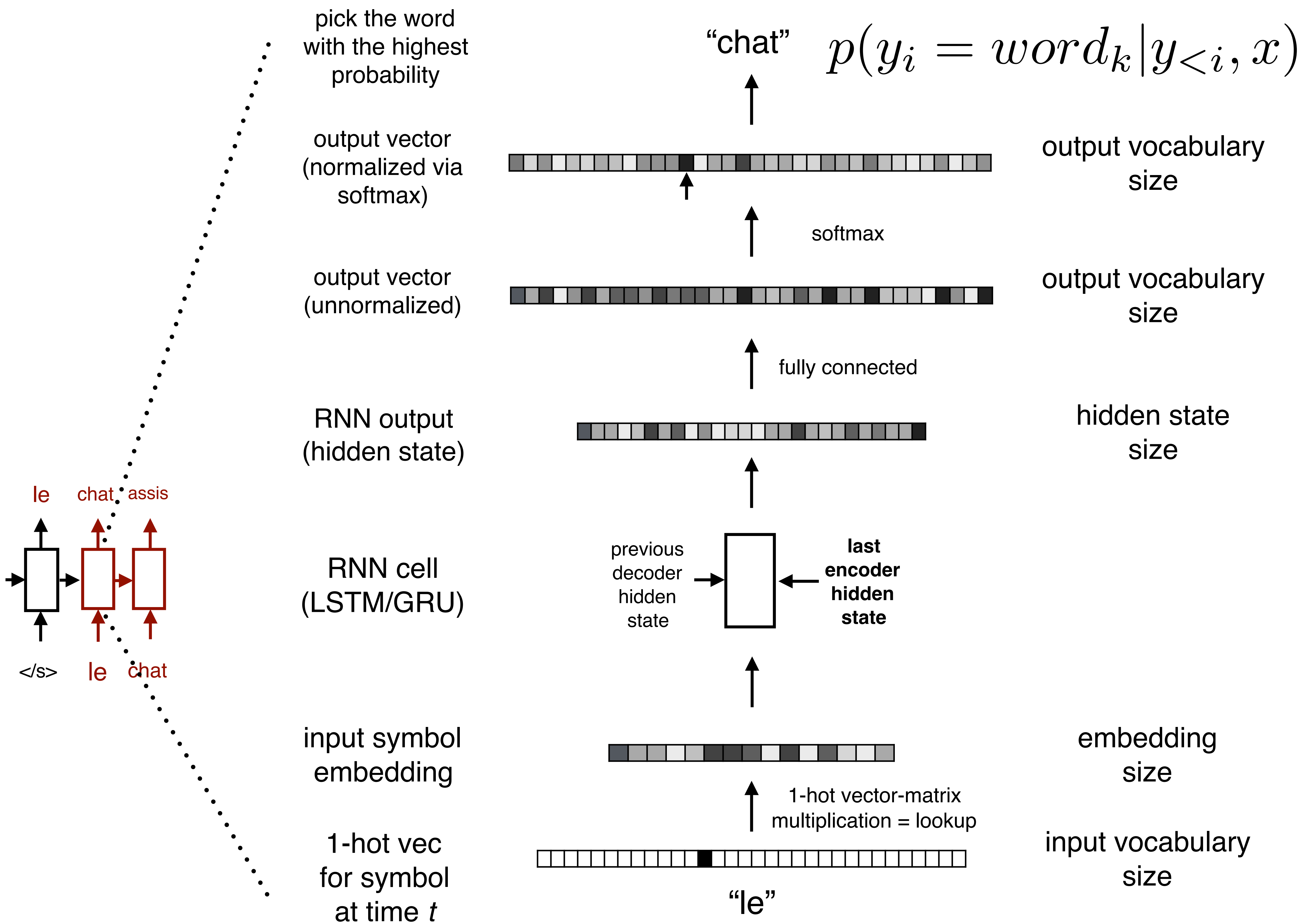
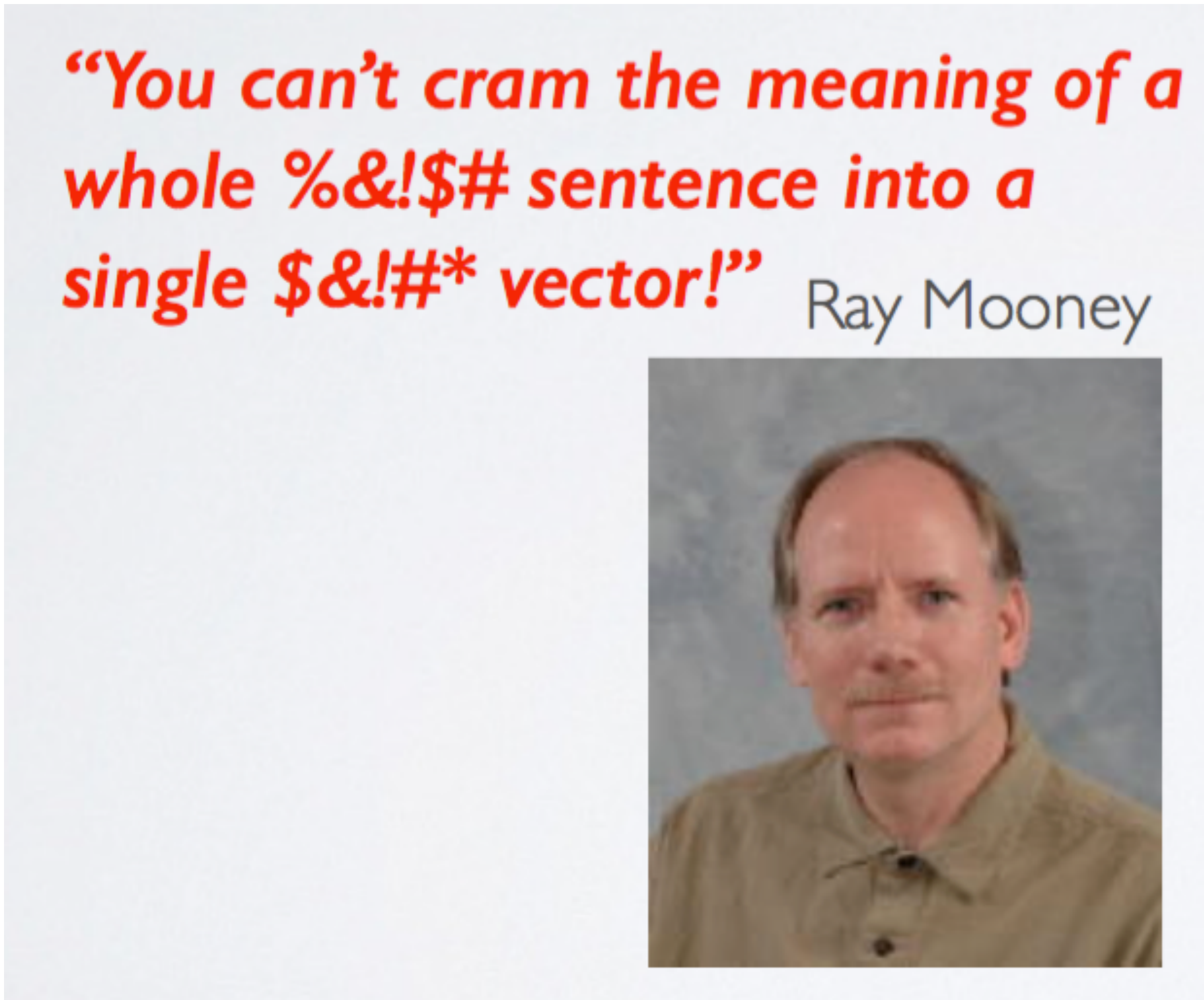


The problem with “vanilla” seq2seq



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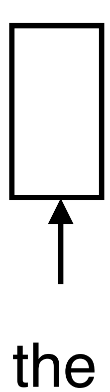

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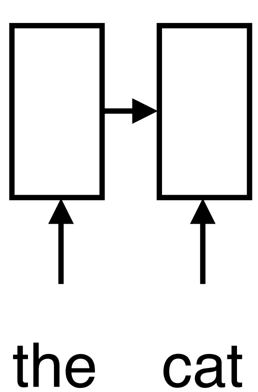

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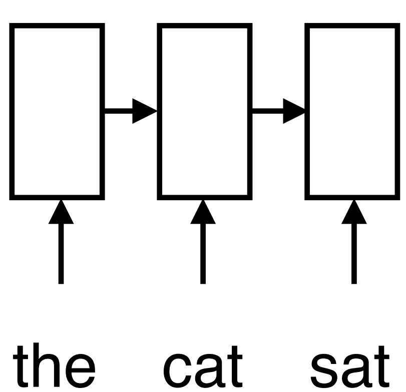

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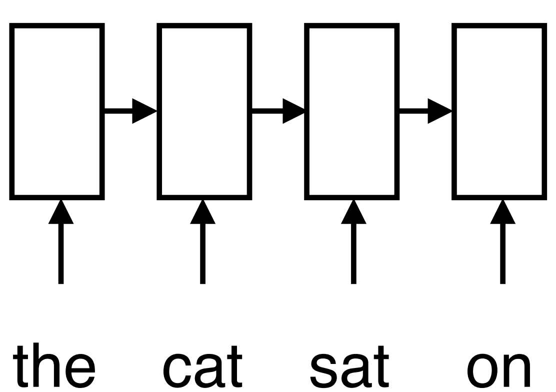

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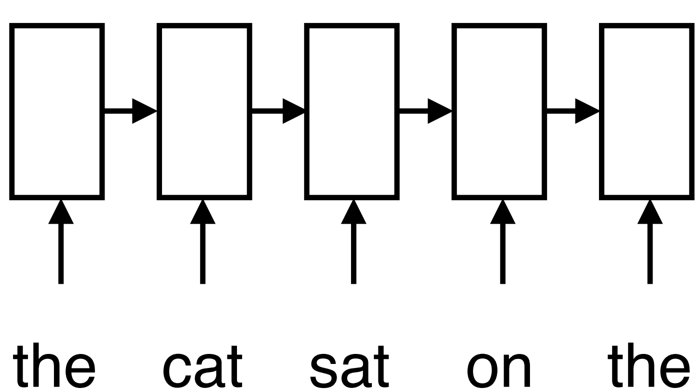

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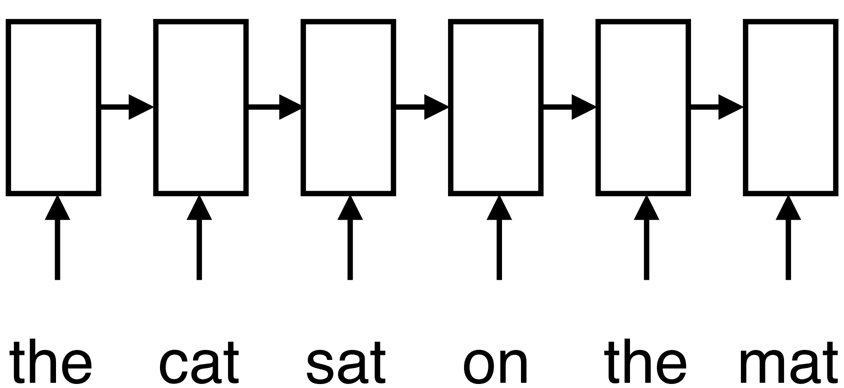

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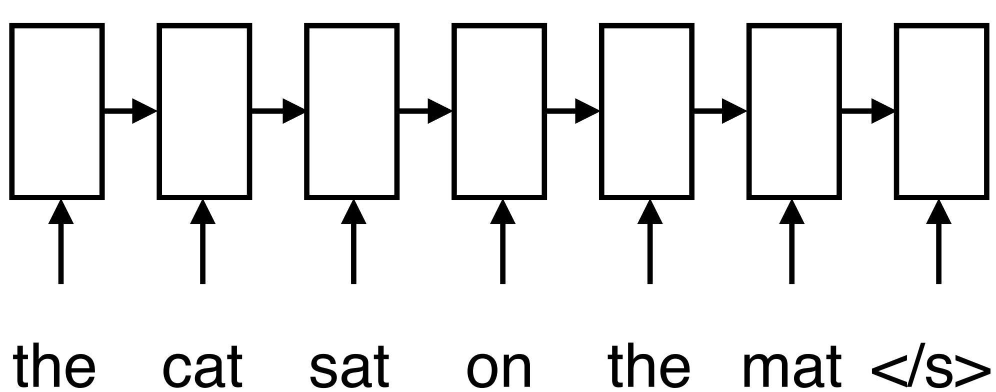

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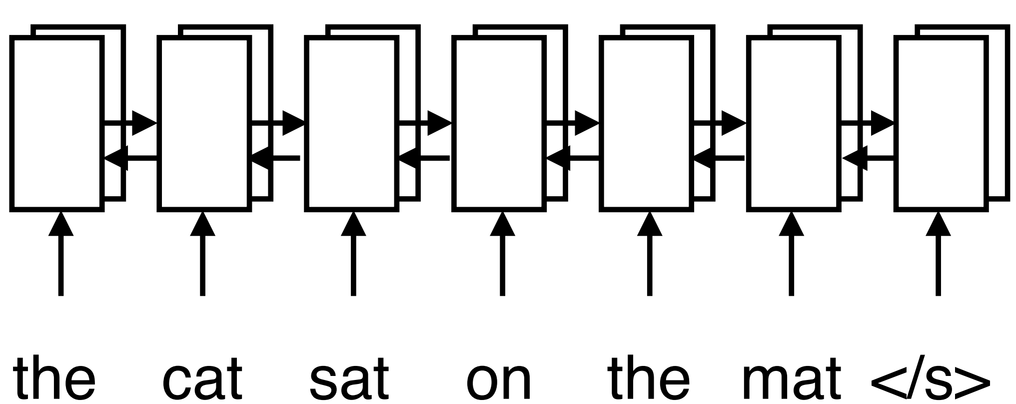

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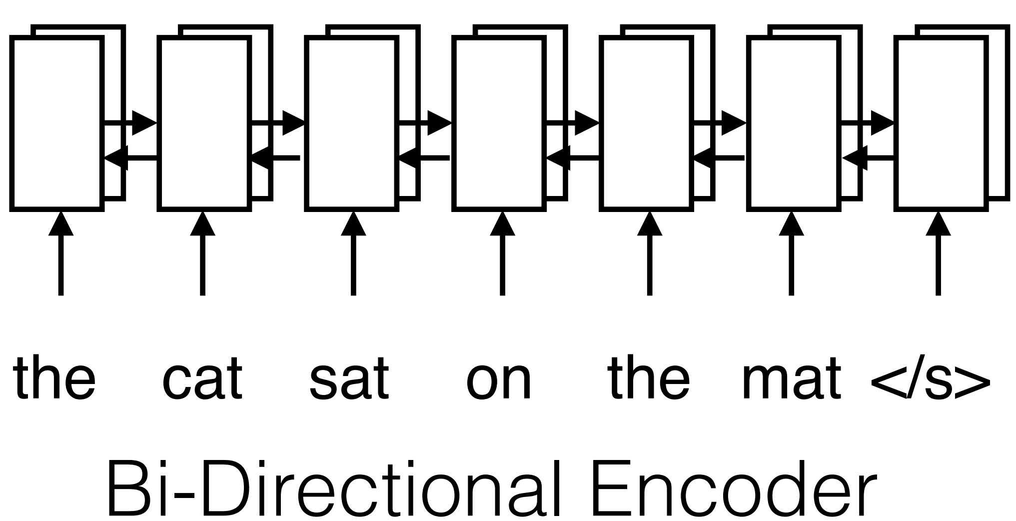

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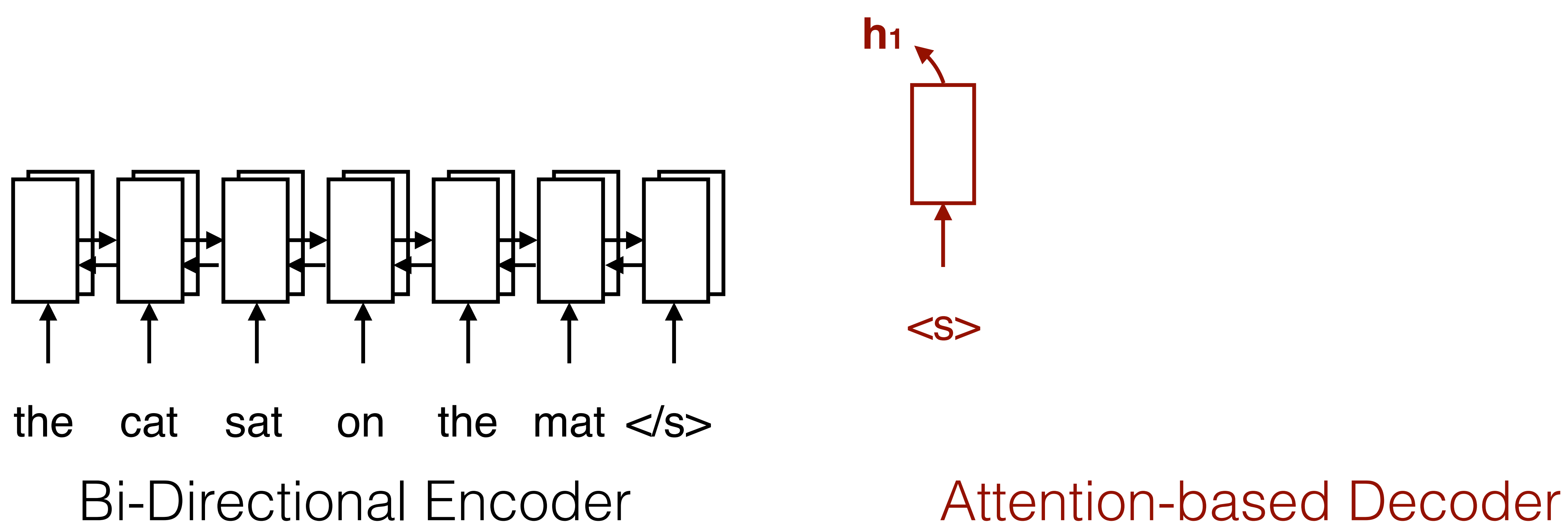

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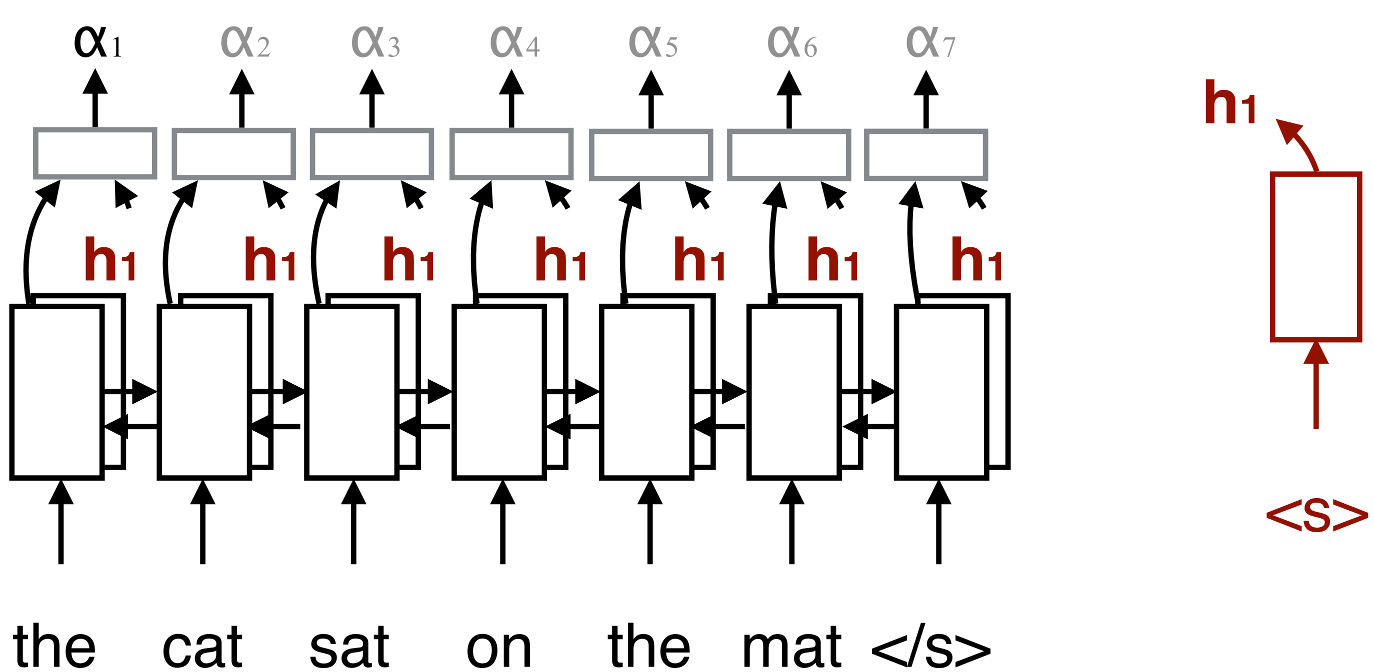

Bi-Directional Encoder

Attention-based Decoder

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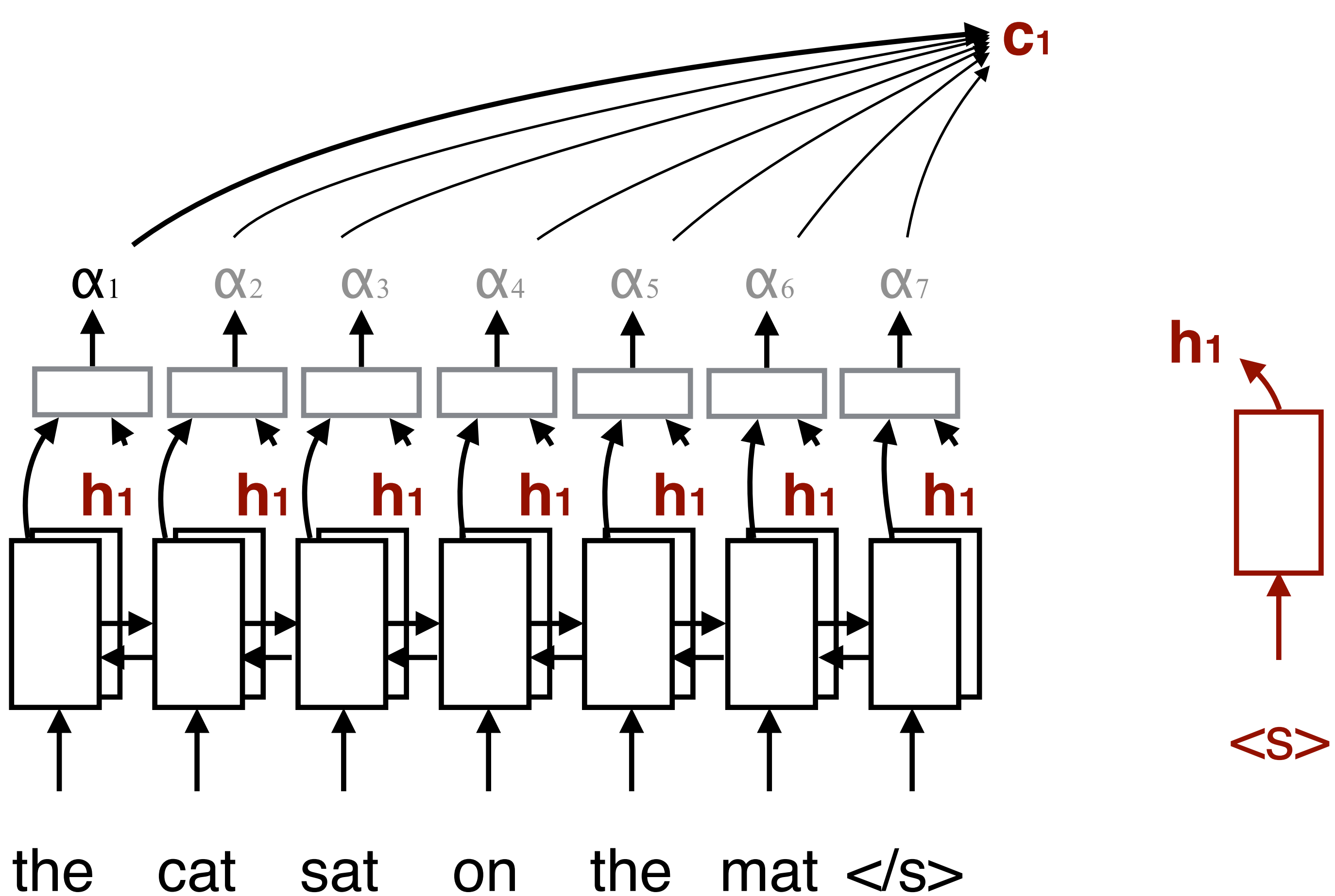

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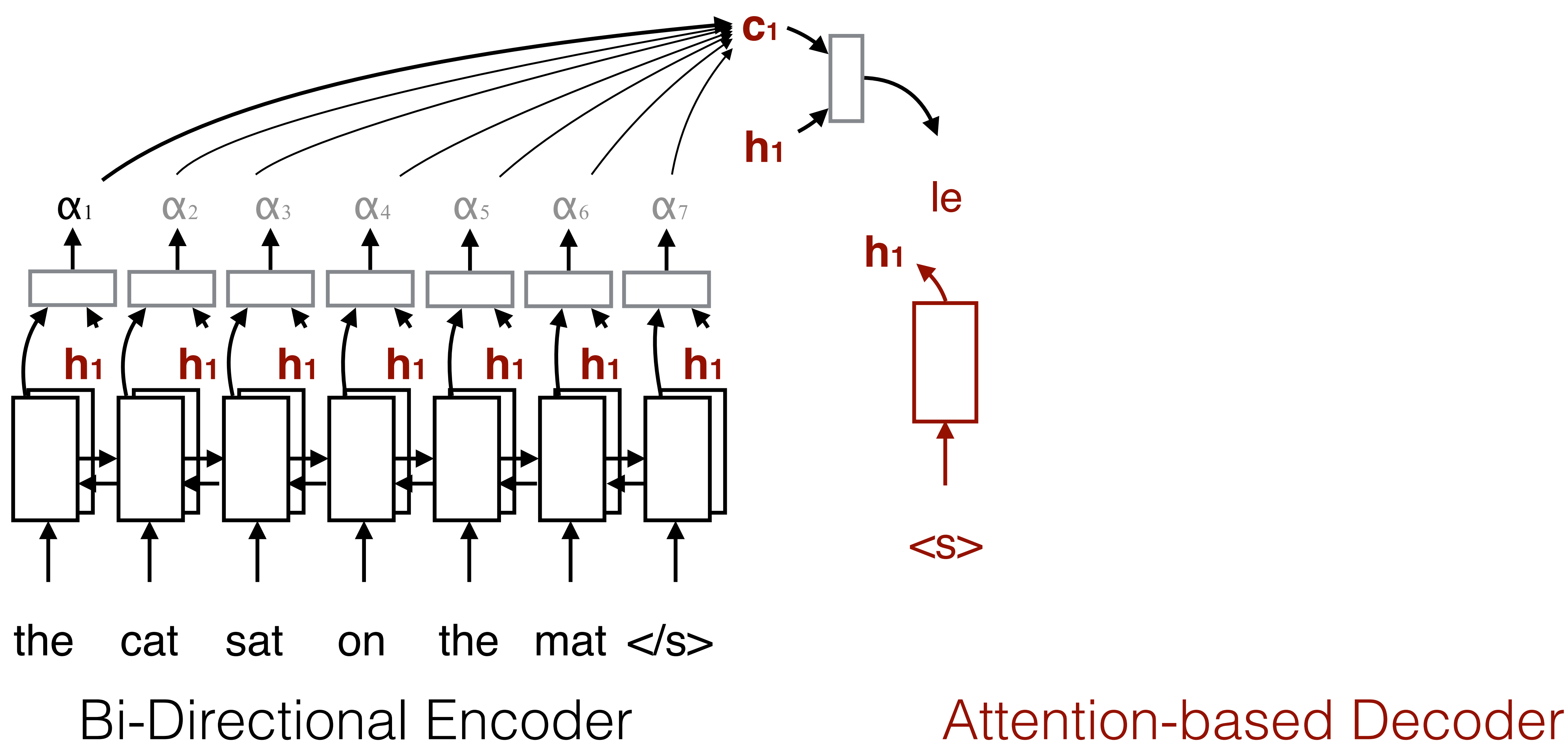

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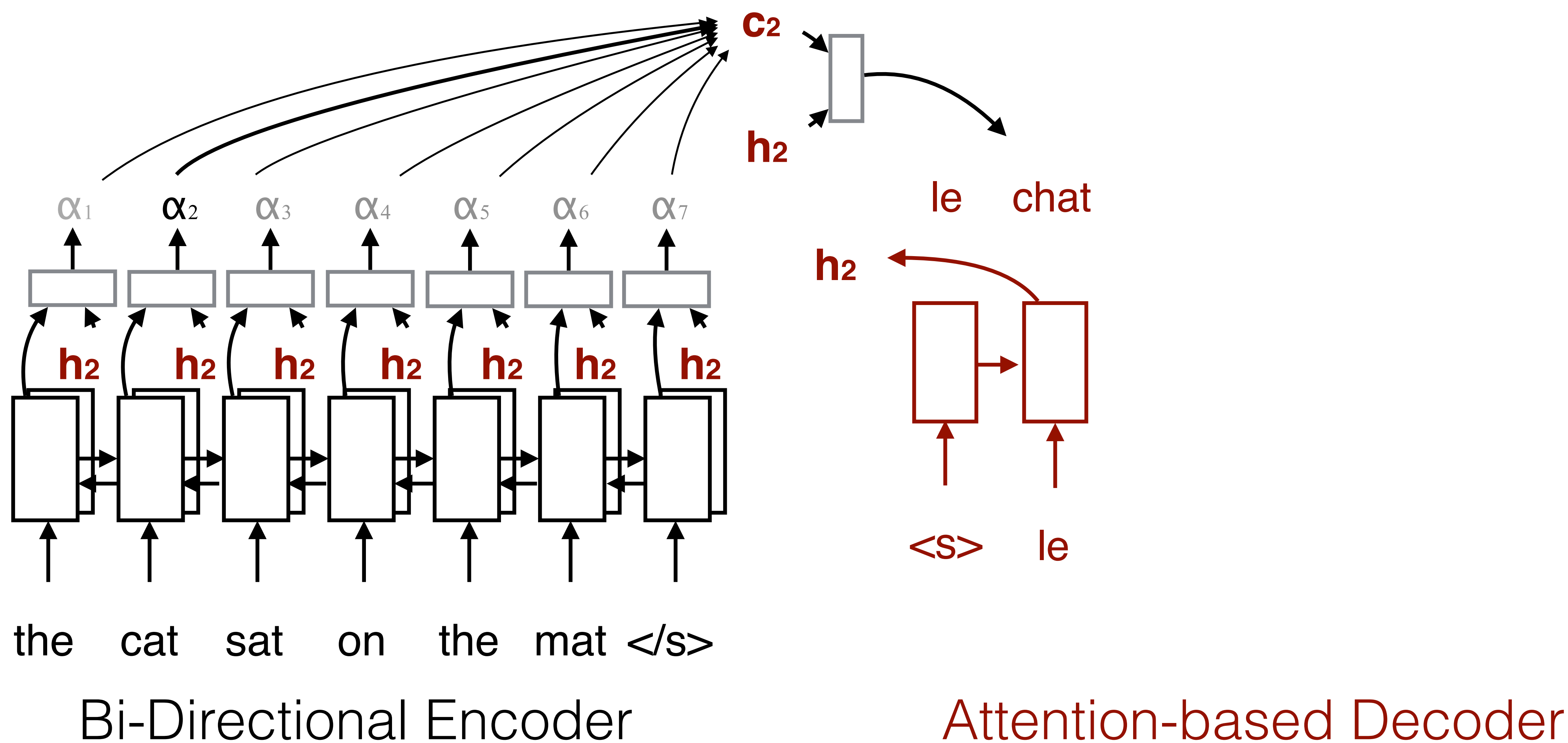

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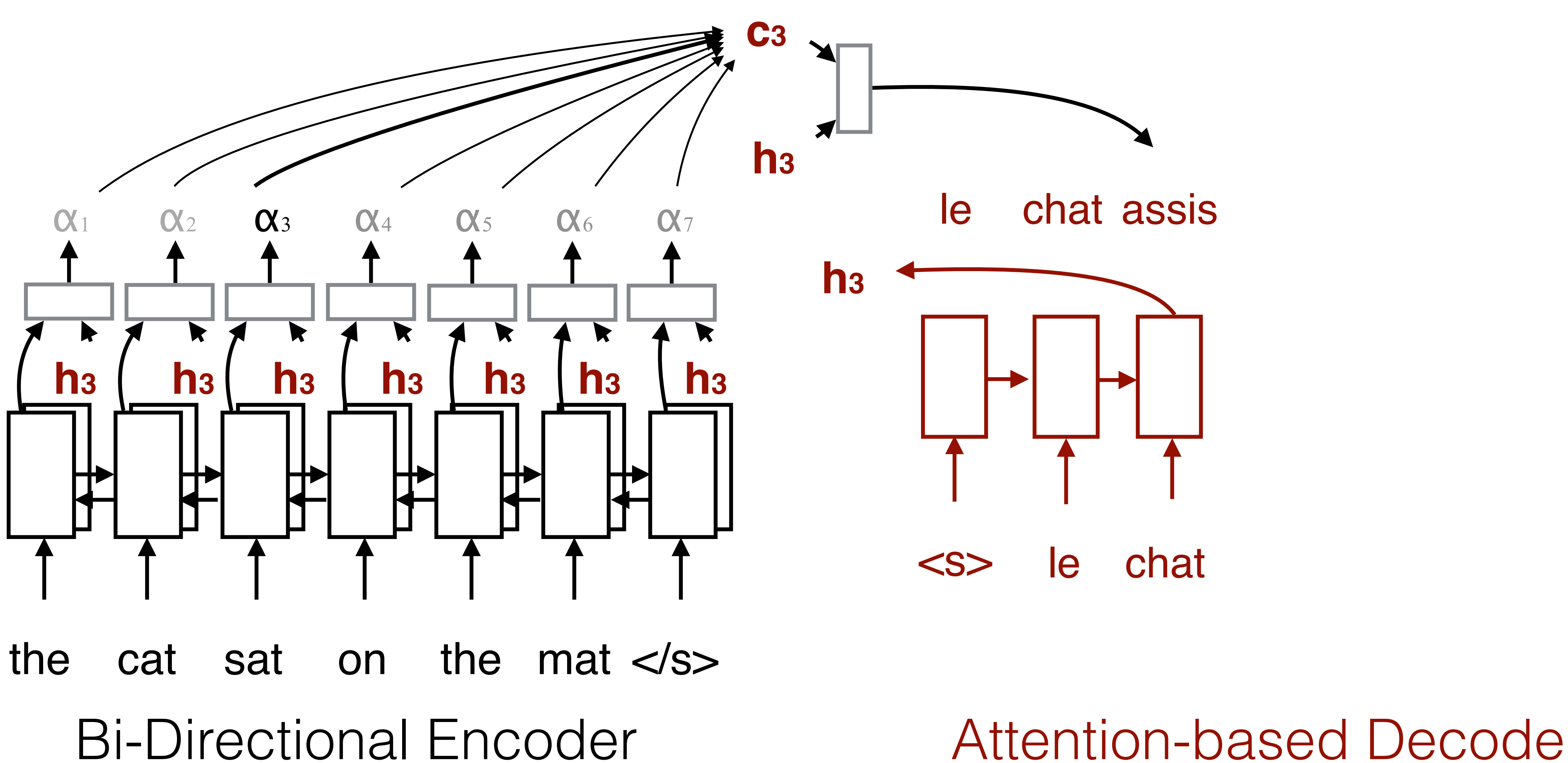

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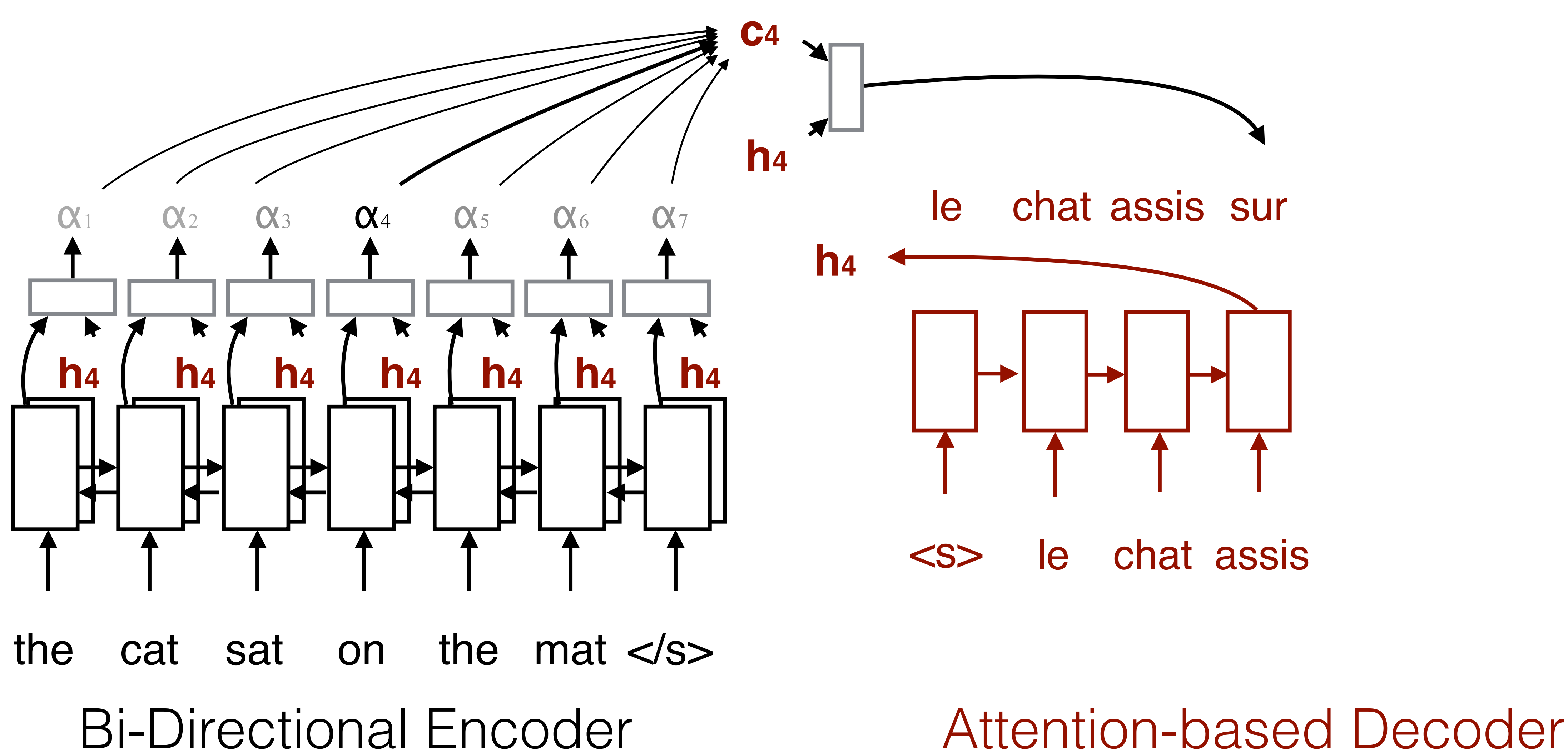

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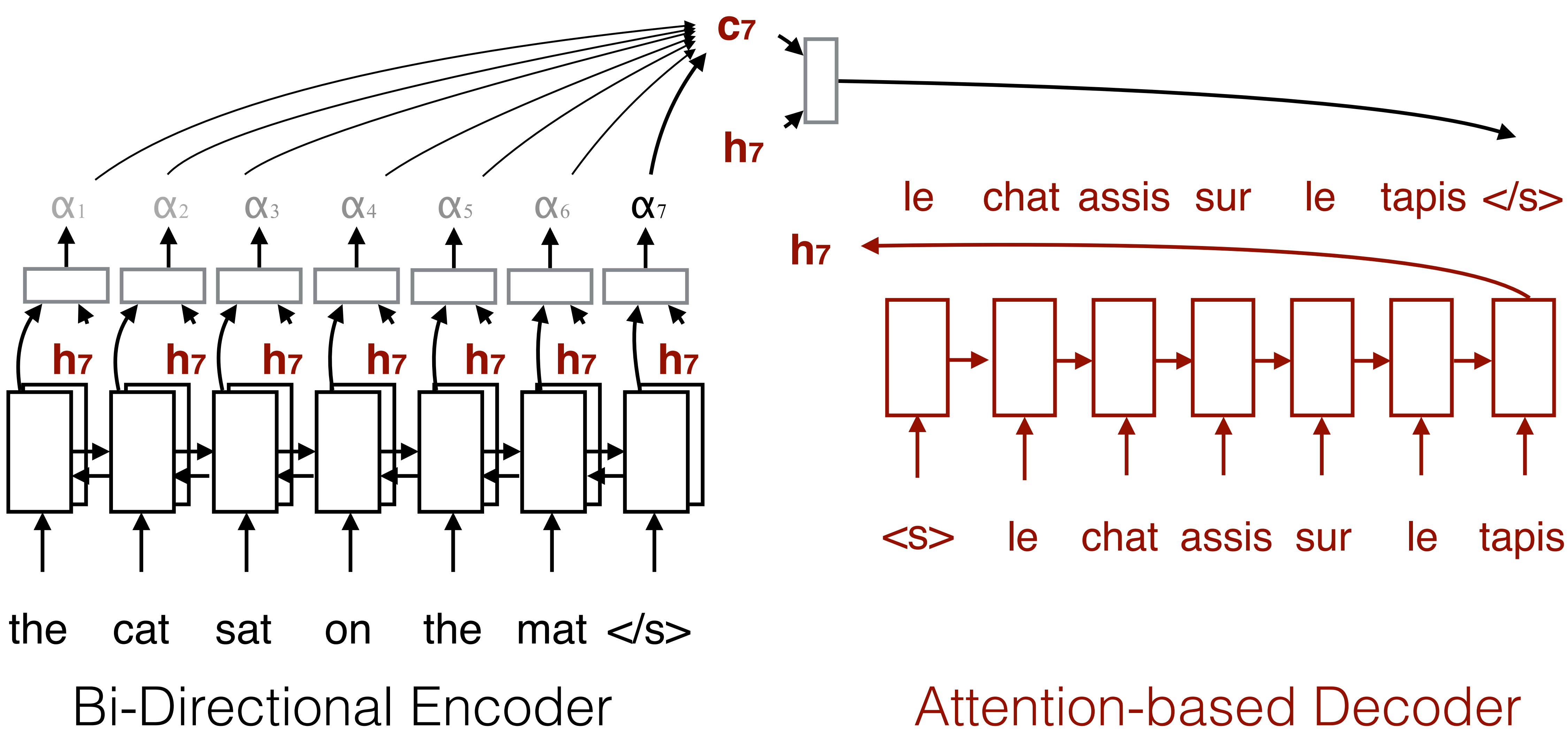

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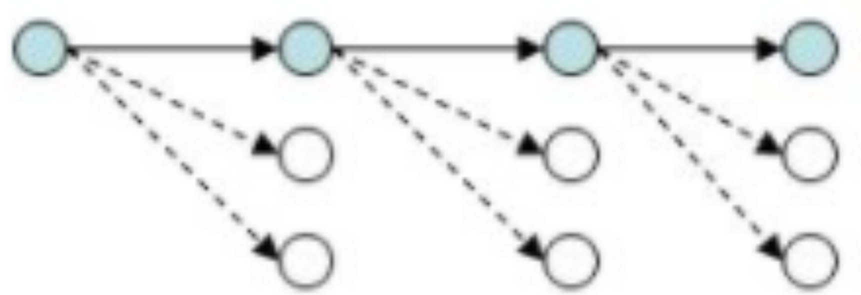
  - Compute output probability distribution:

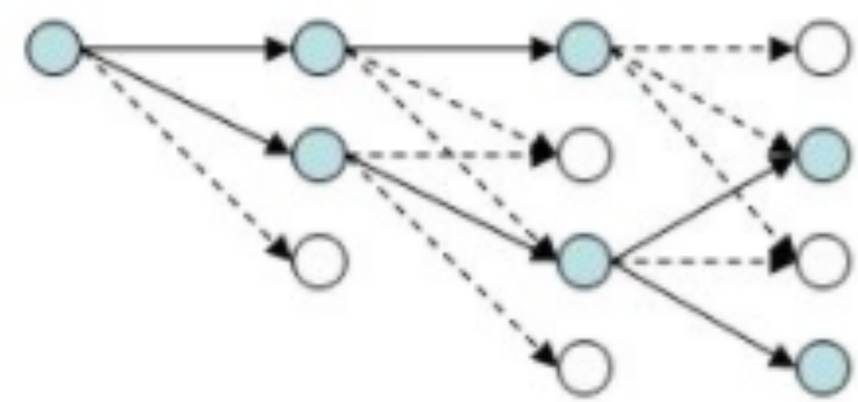
$$p(y_t | y_{<t}, x) = \mathrm{softmax}(\boldsymbol{W_s} \tilde{\boldsymbol{h}}_t)$$

Decoding with Beam Search

- Instead of keeping one best option on each time step, keep k best options which are updated as-you-go
- Usually a small beam size is enough (5-12)

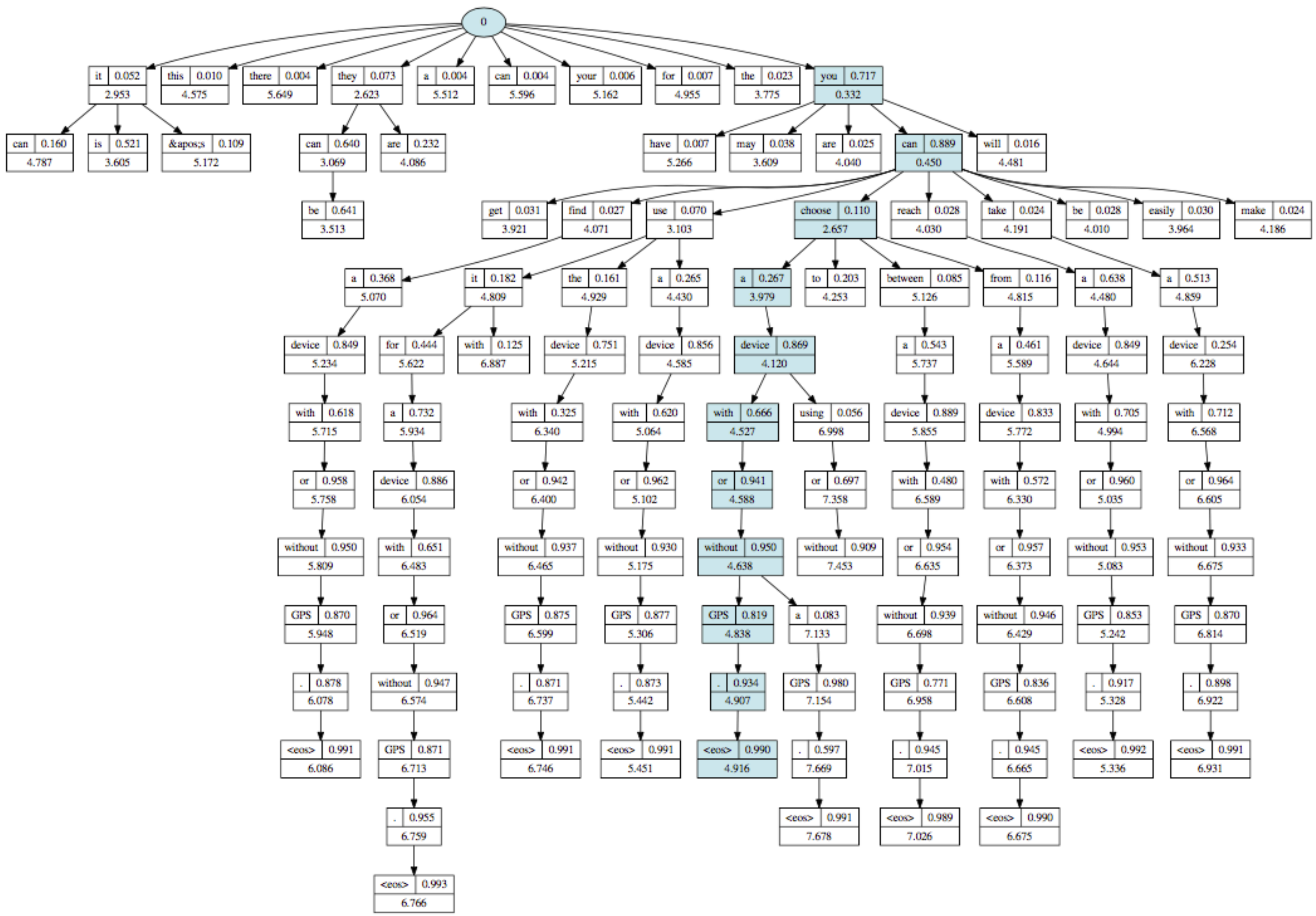


Greedy Search



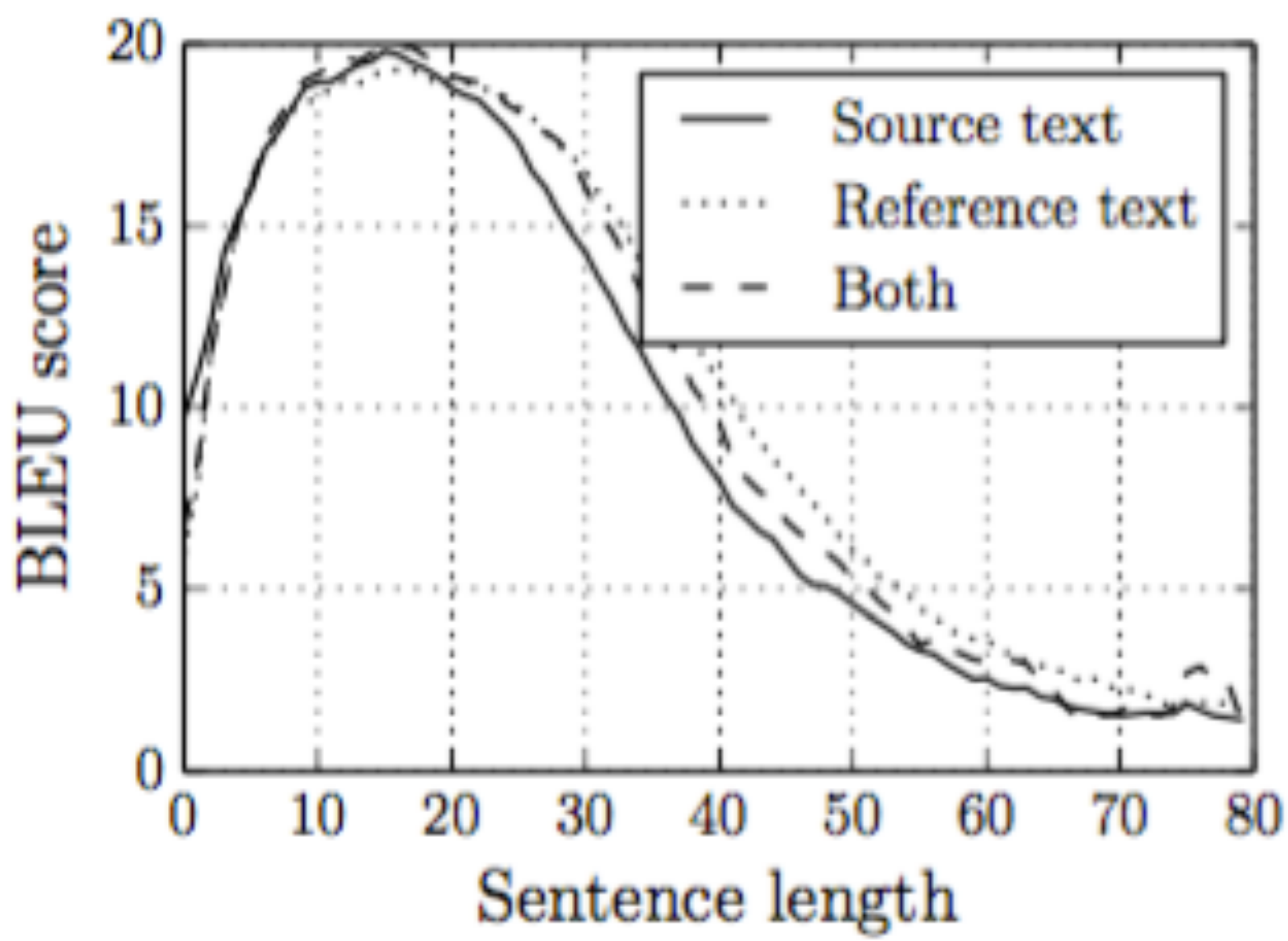
Beam Search (k=2)

Decoding with Beam Search



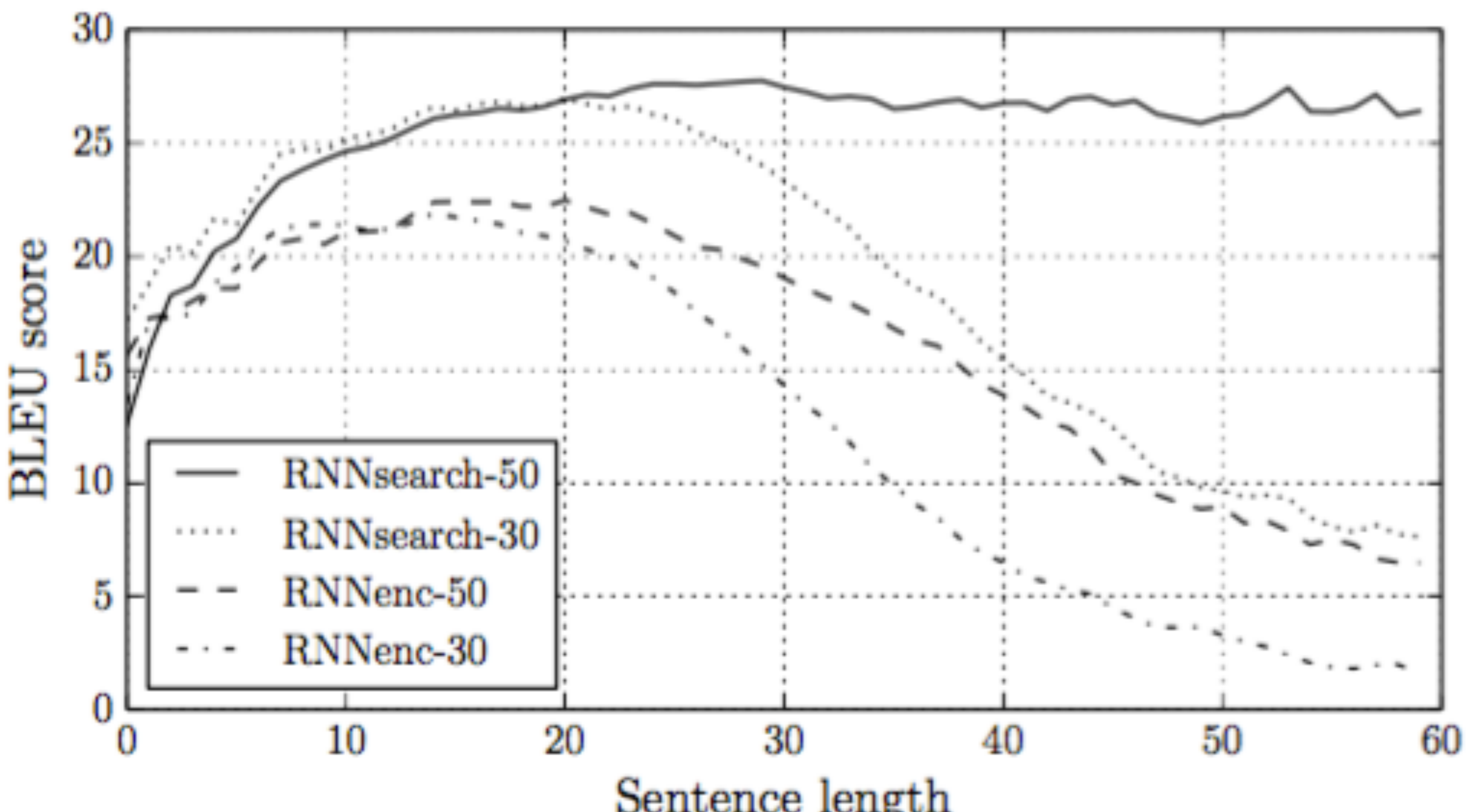
BLEU by Sentence Length - No Attention

- Long sentences are very hard as they are "compressed" to a fixed length vector



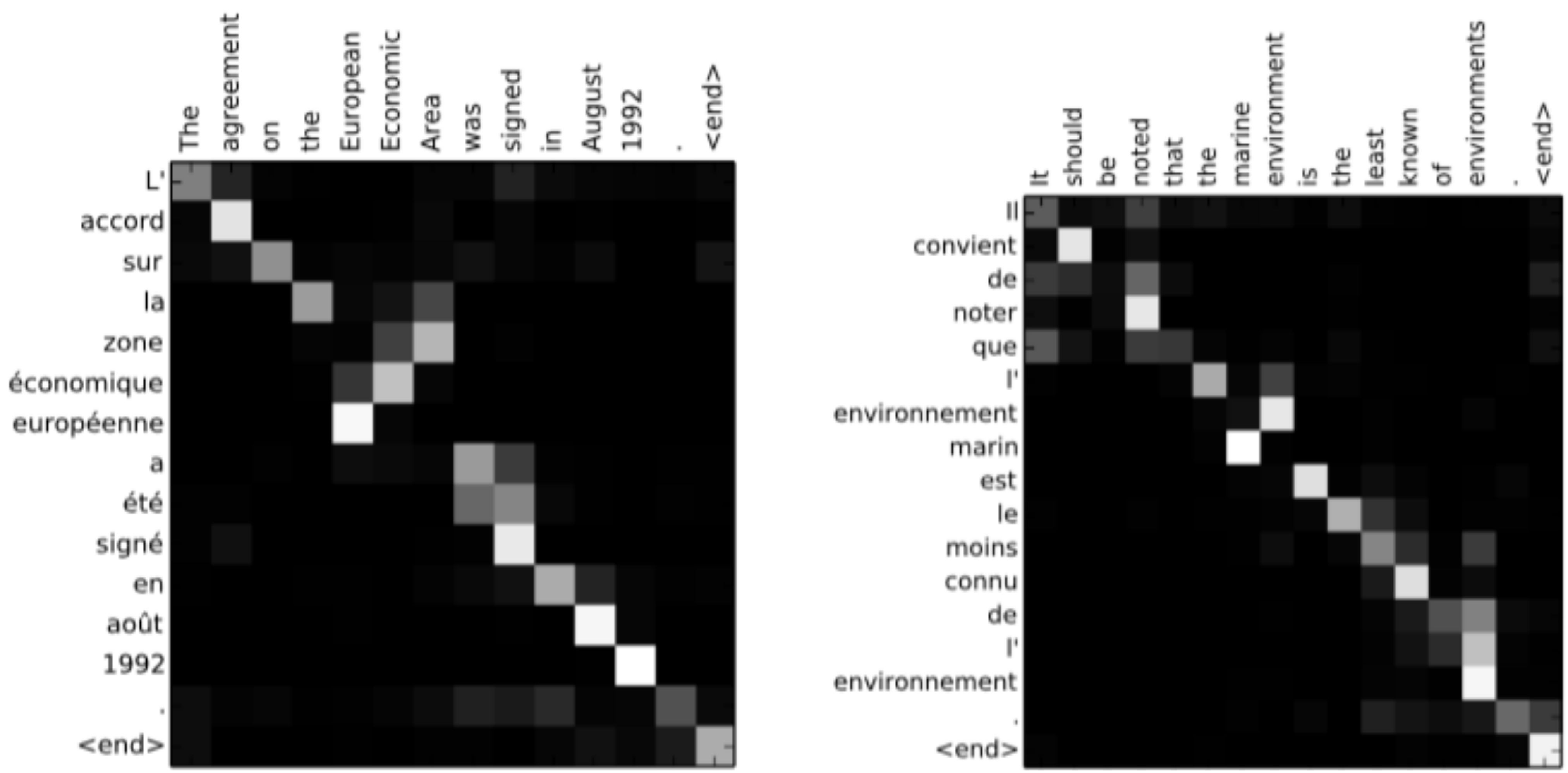
BLEU by Sentence Length - With Attention

- The attention mechanism overcomes the issue

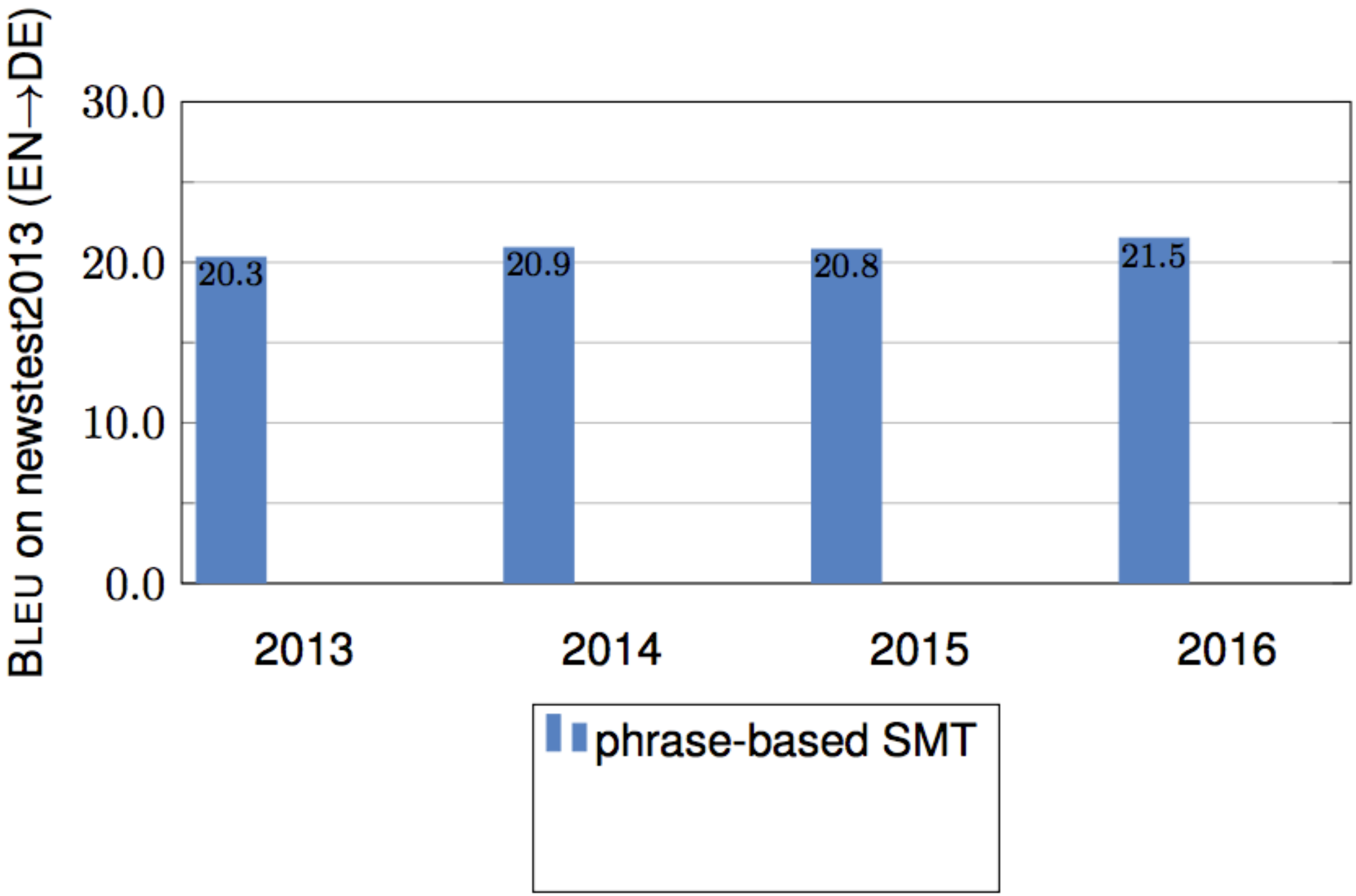


Results - With Attention

- The model learns nice alignments as a by-product (important for **interpretation**):



Edinburgh's* WMT results over the years



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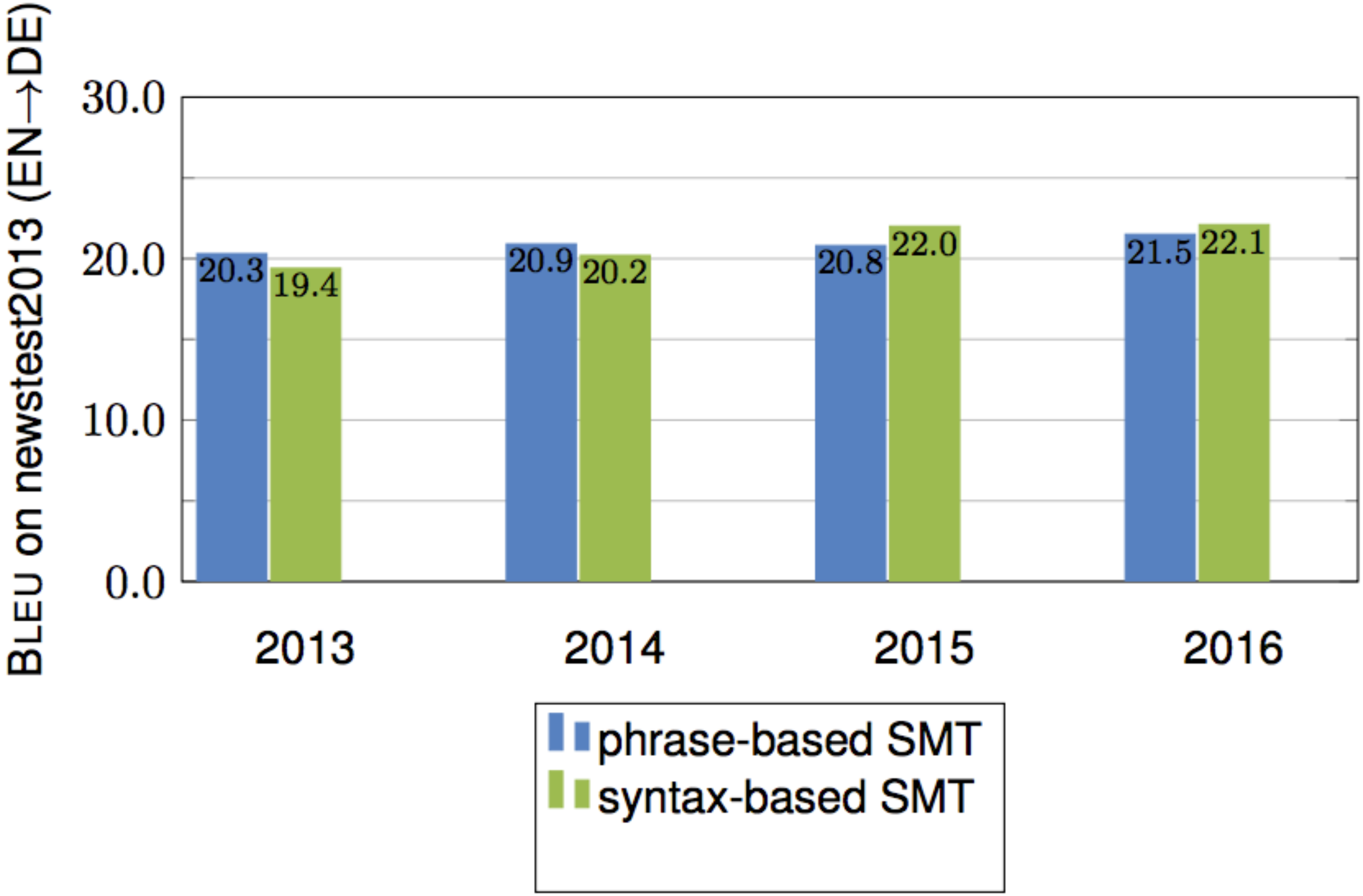

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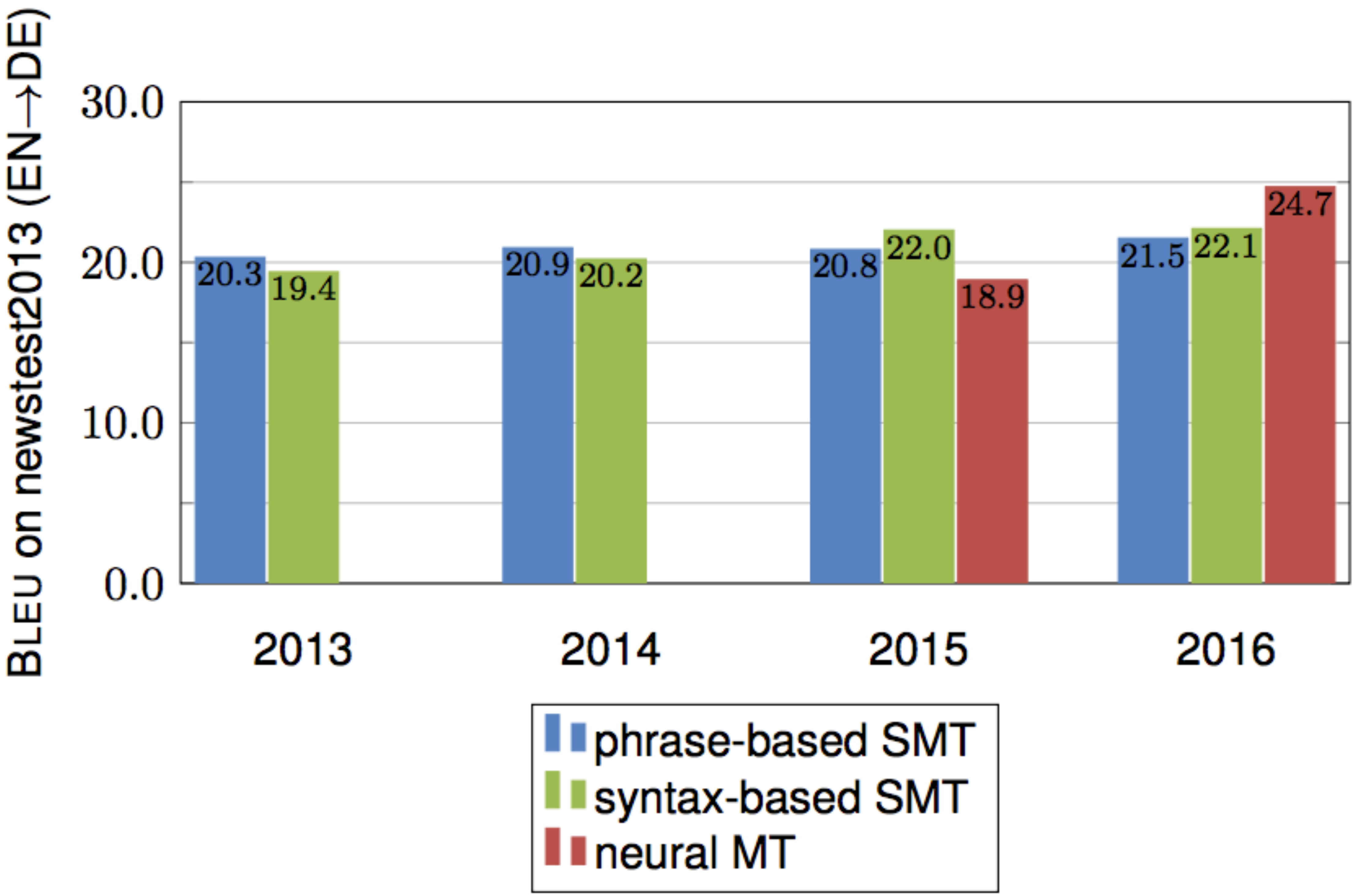

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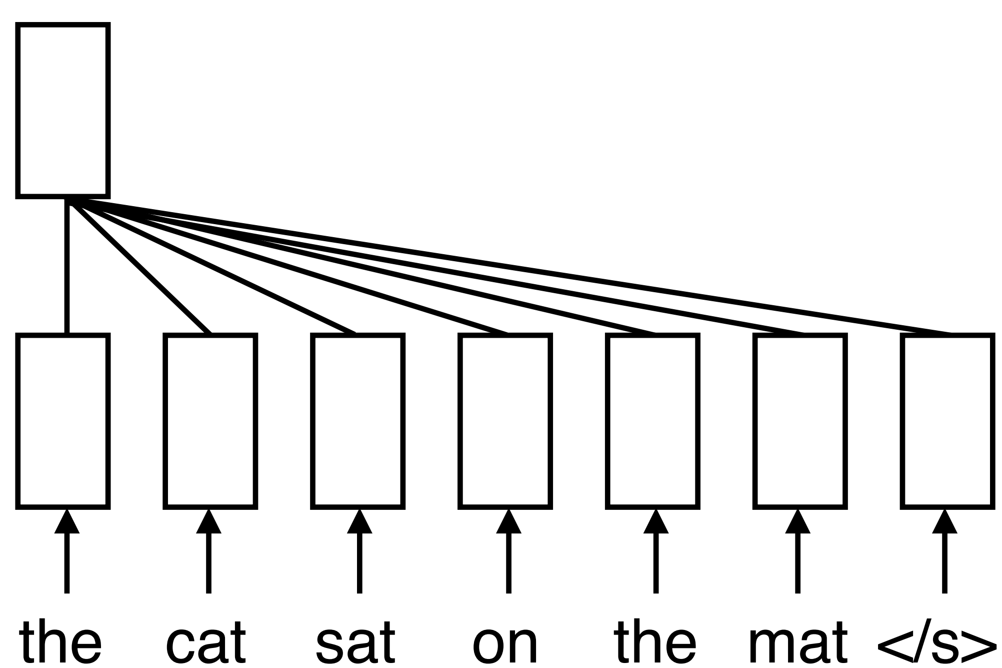

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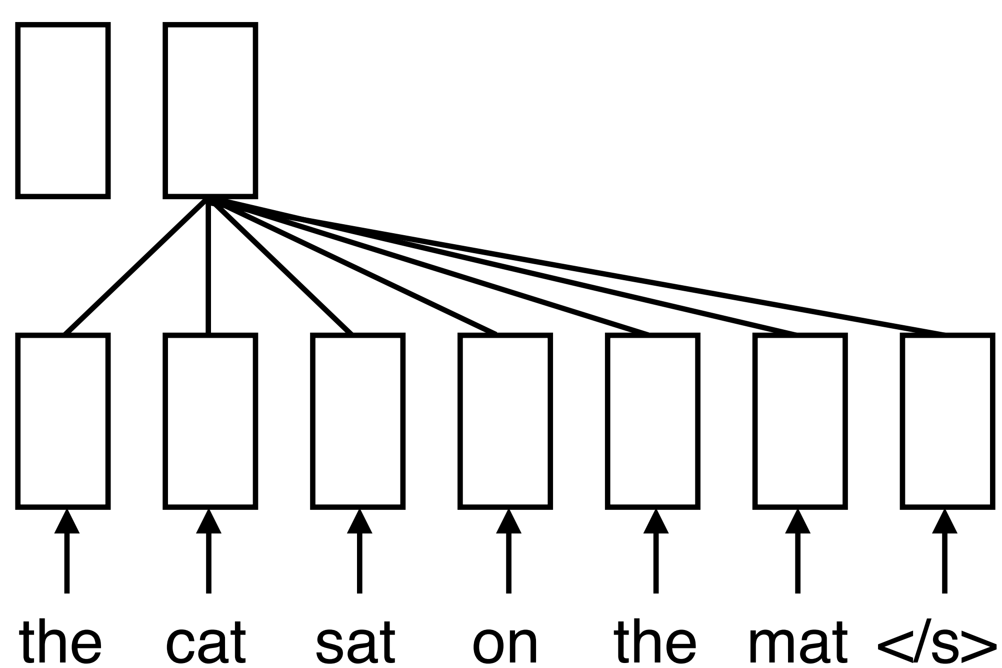

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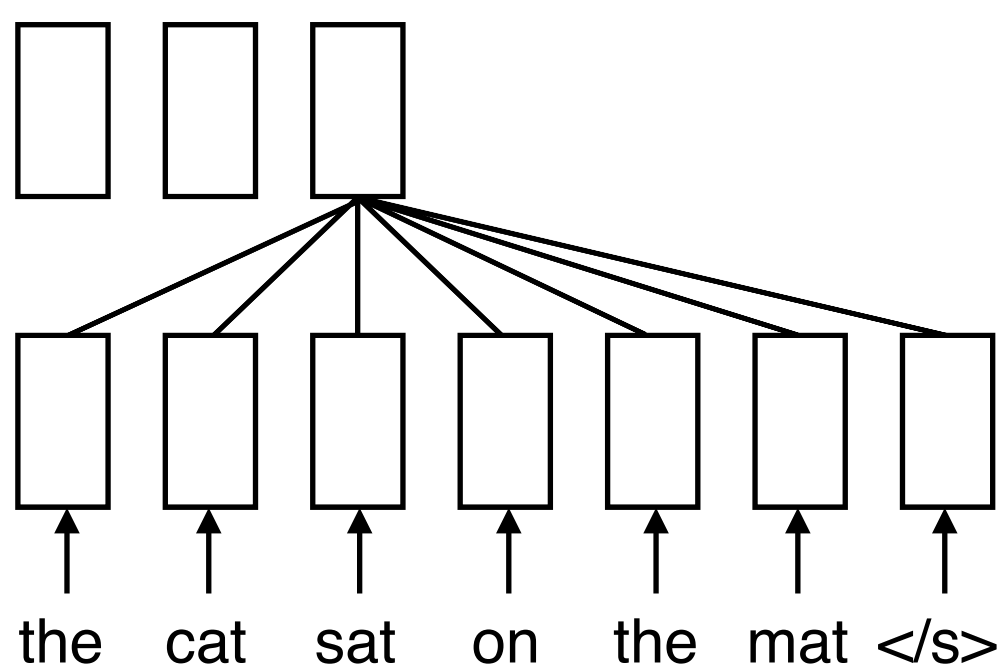

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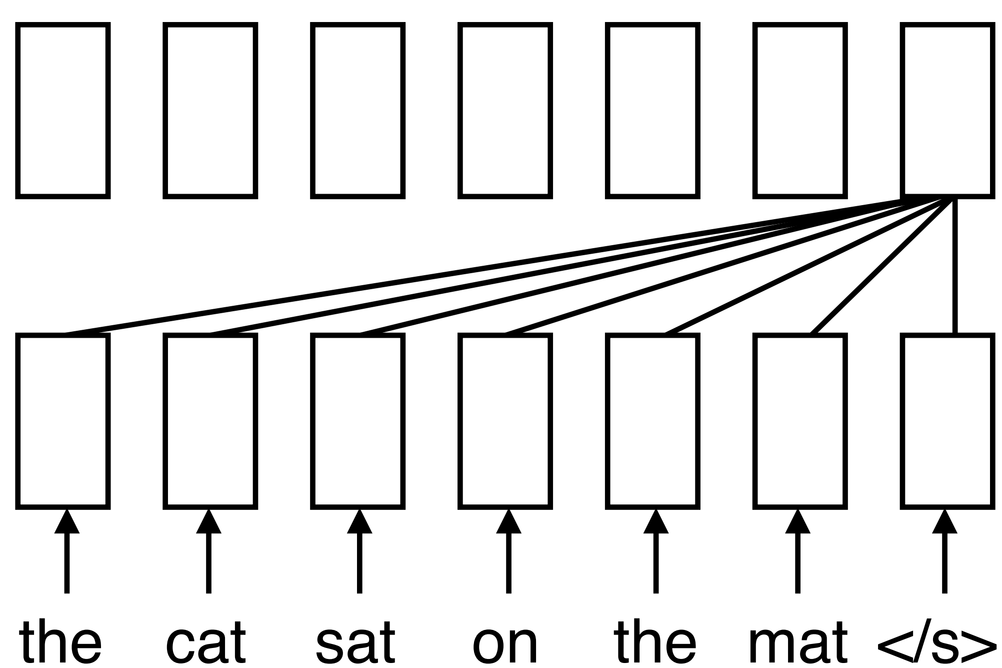
- Similar representation power as a bi-LSTM (both left and right context)
- Can be **parallelized** at the sequence level - faster training



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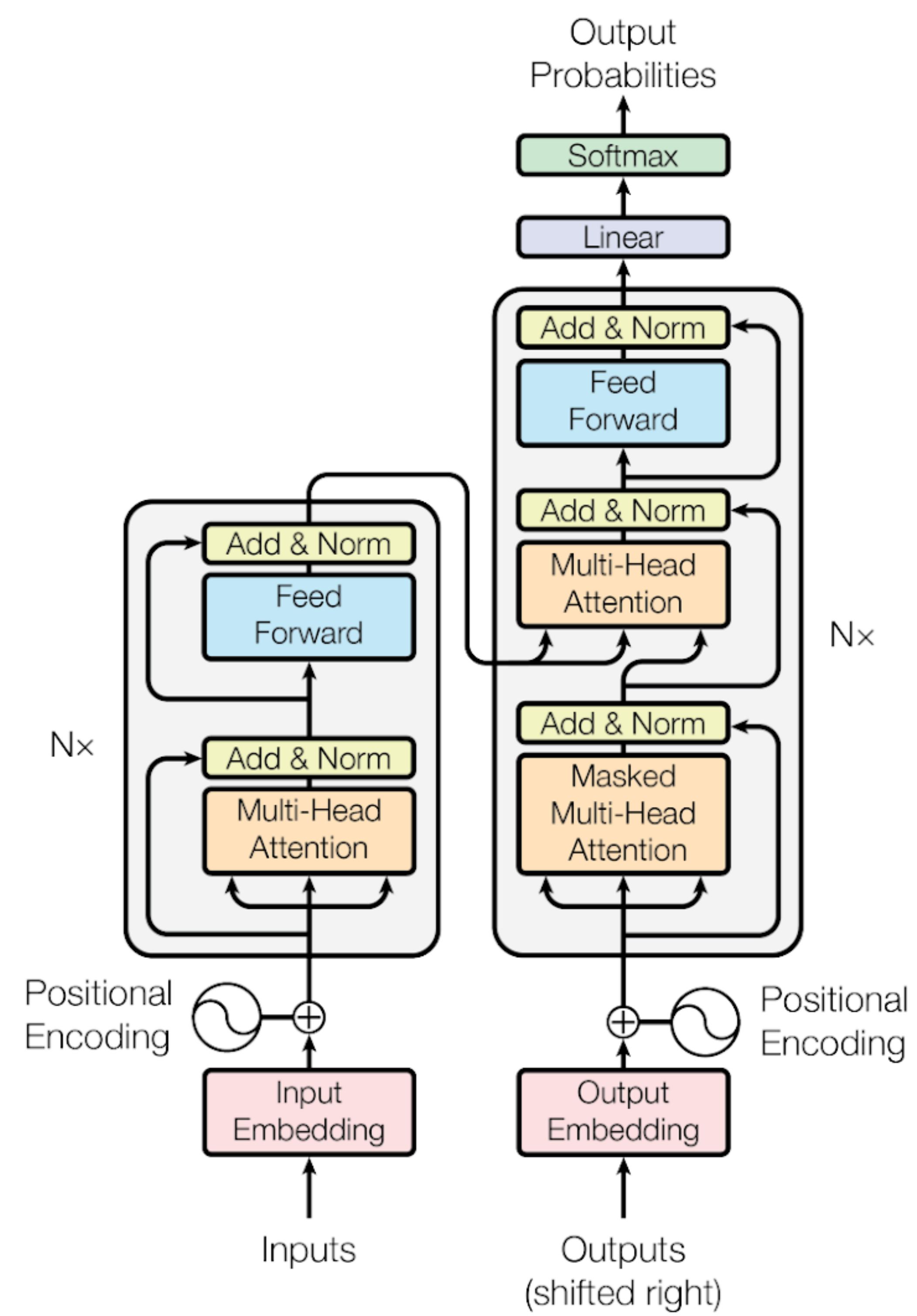

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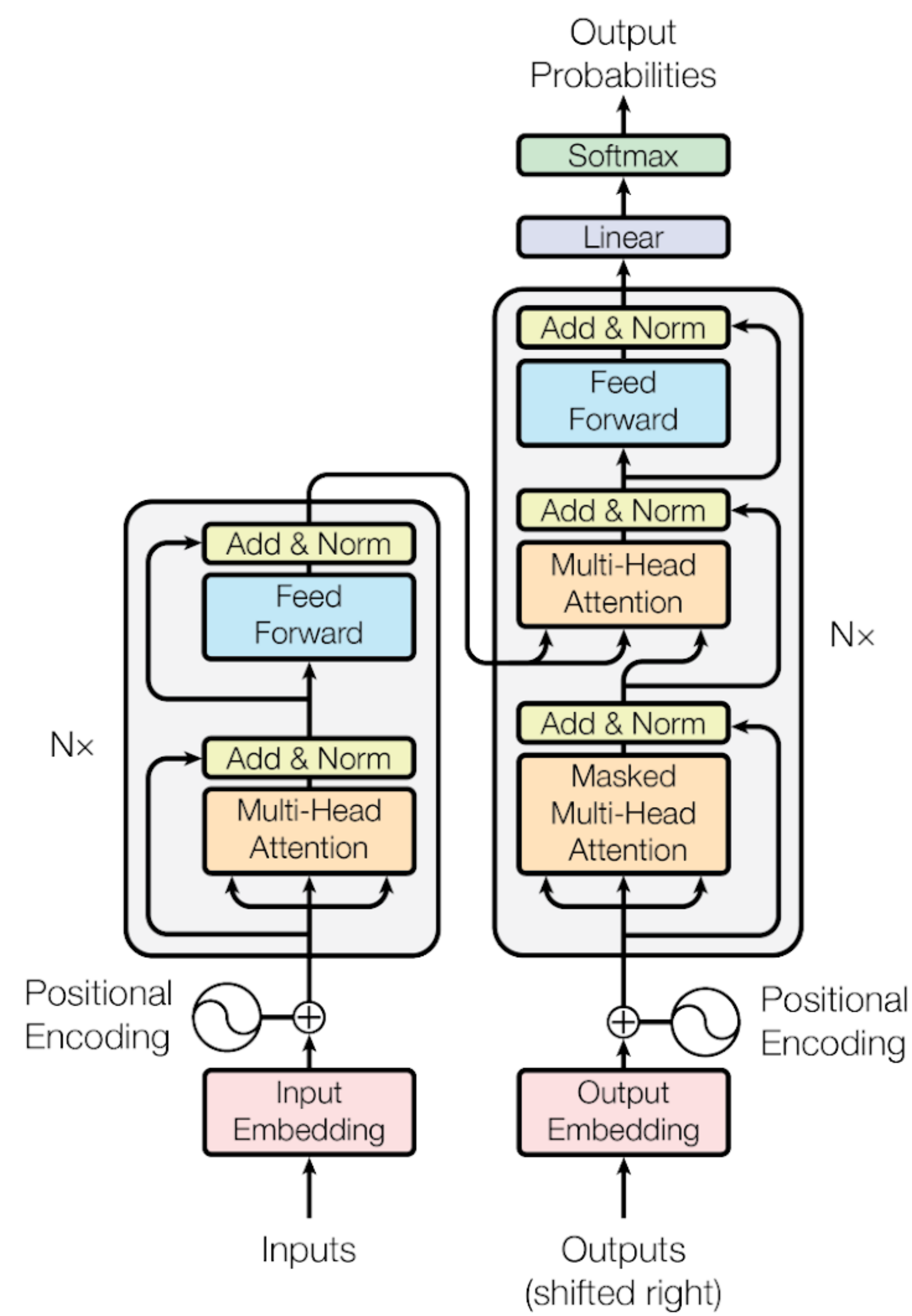

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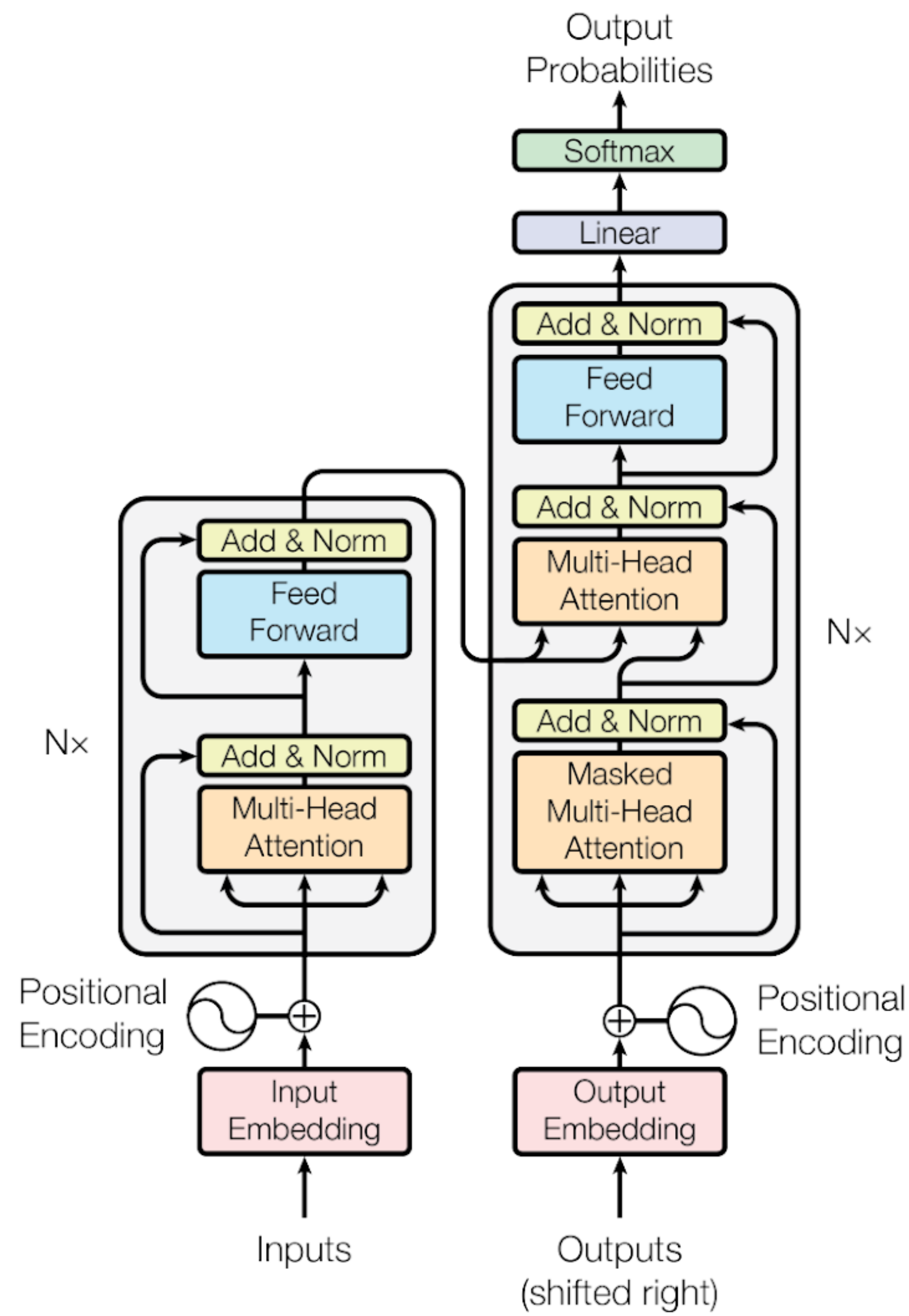

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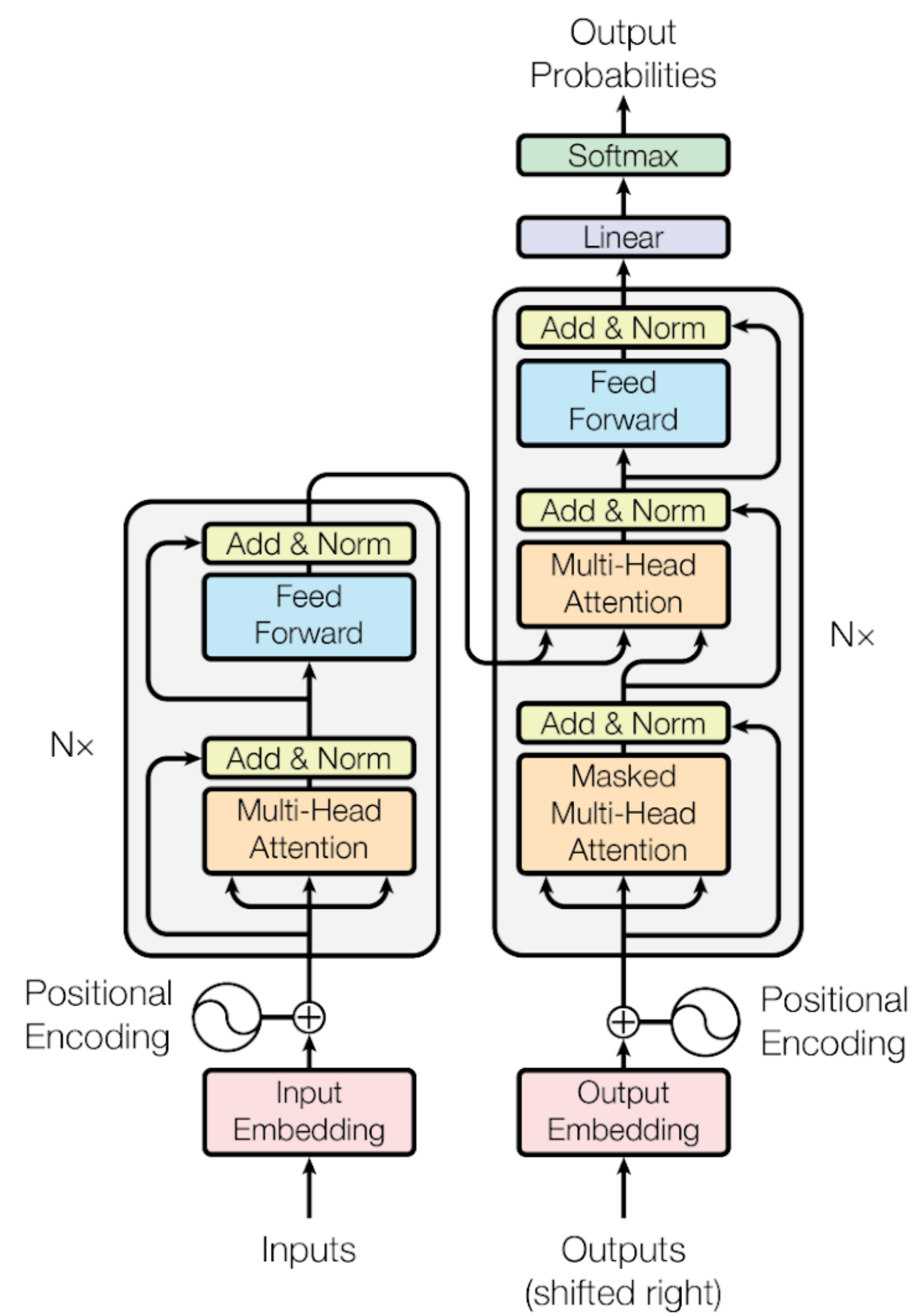

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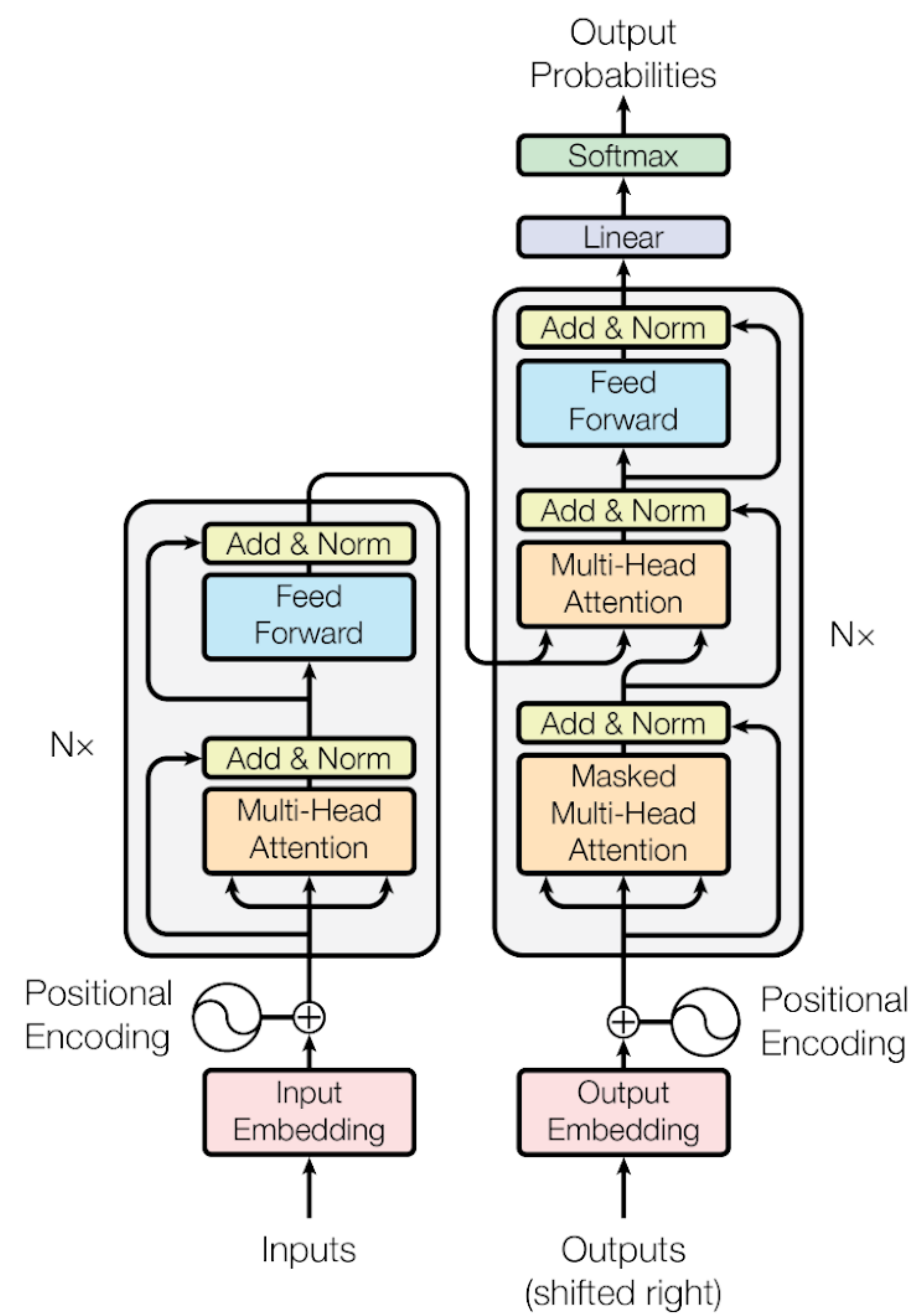

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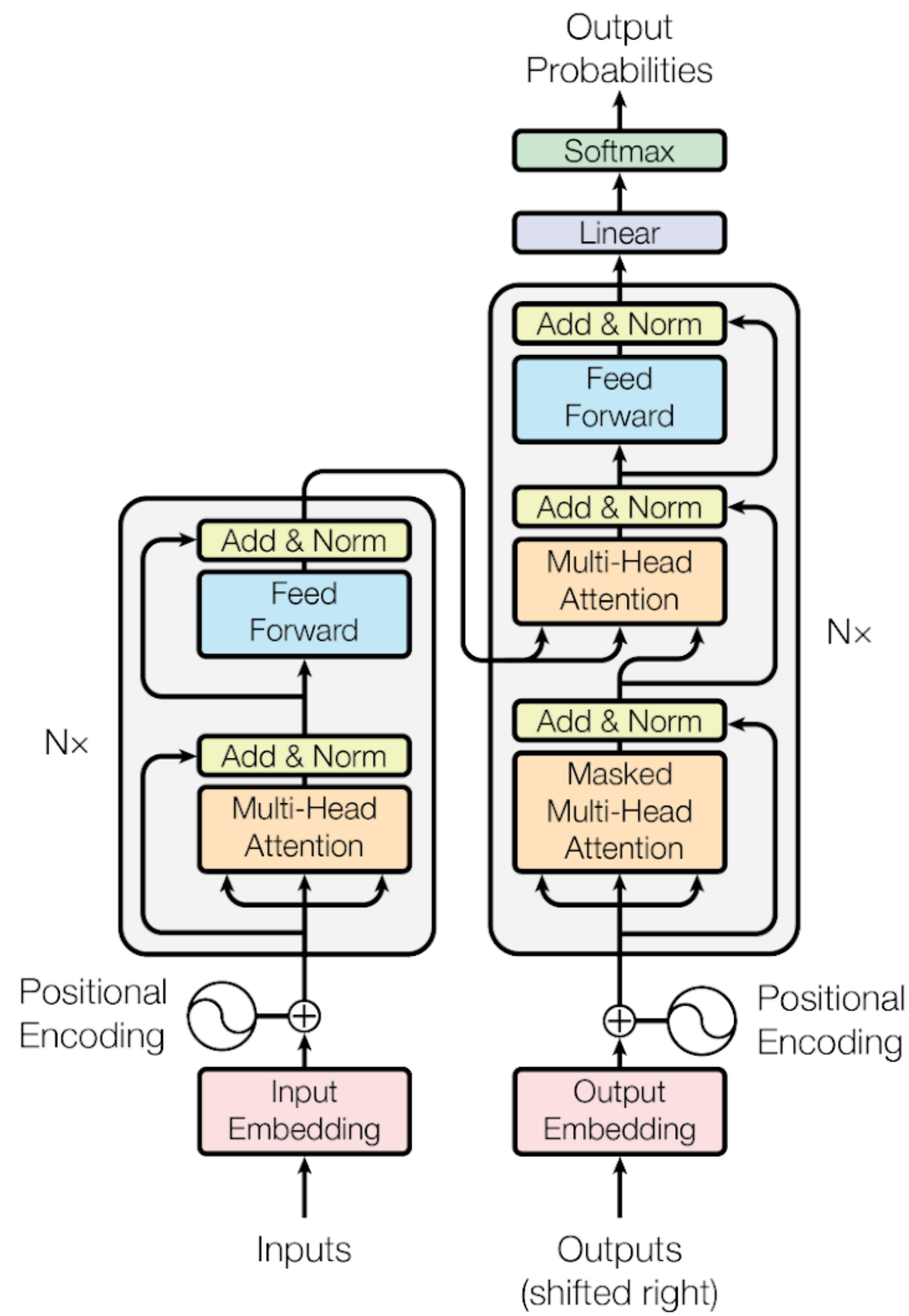

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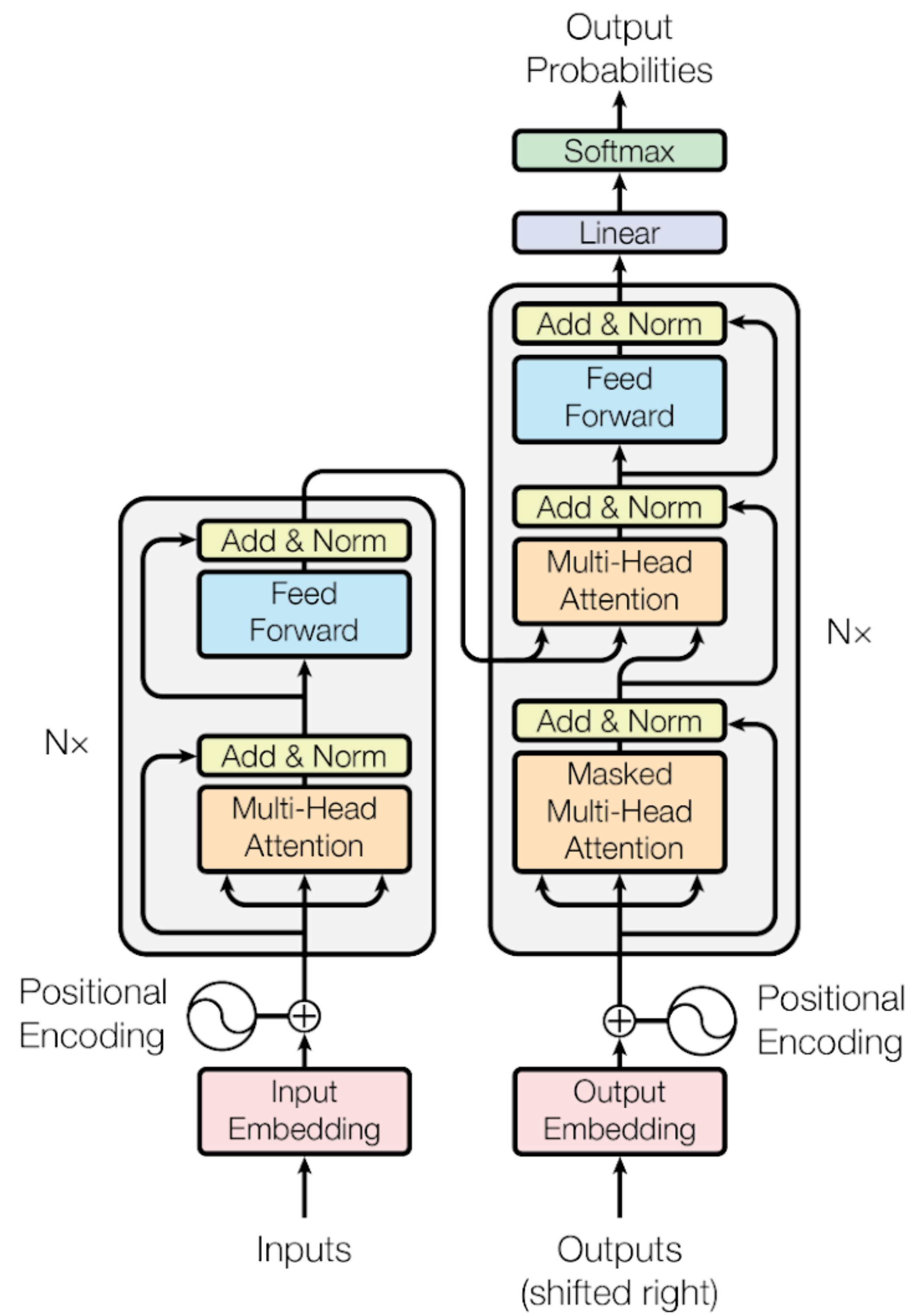

Other Important Details

- Positional encodings
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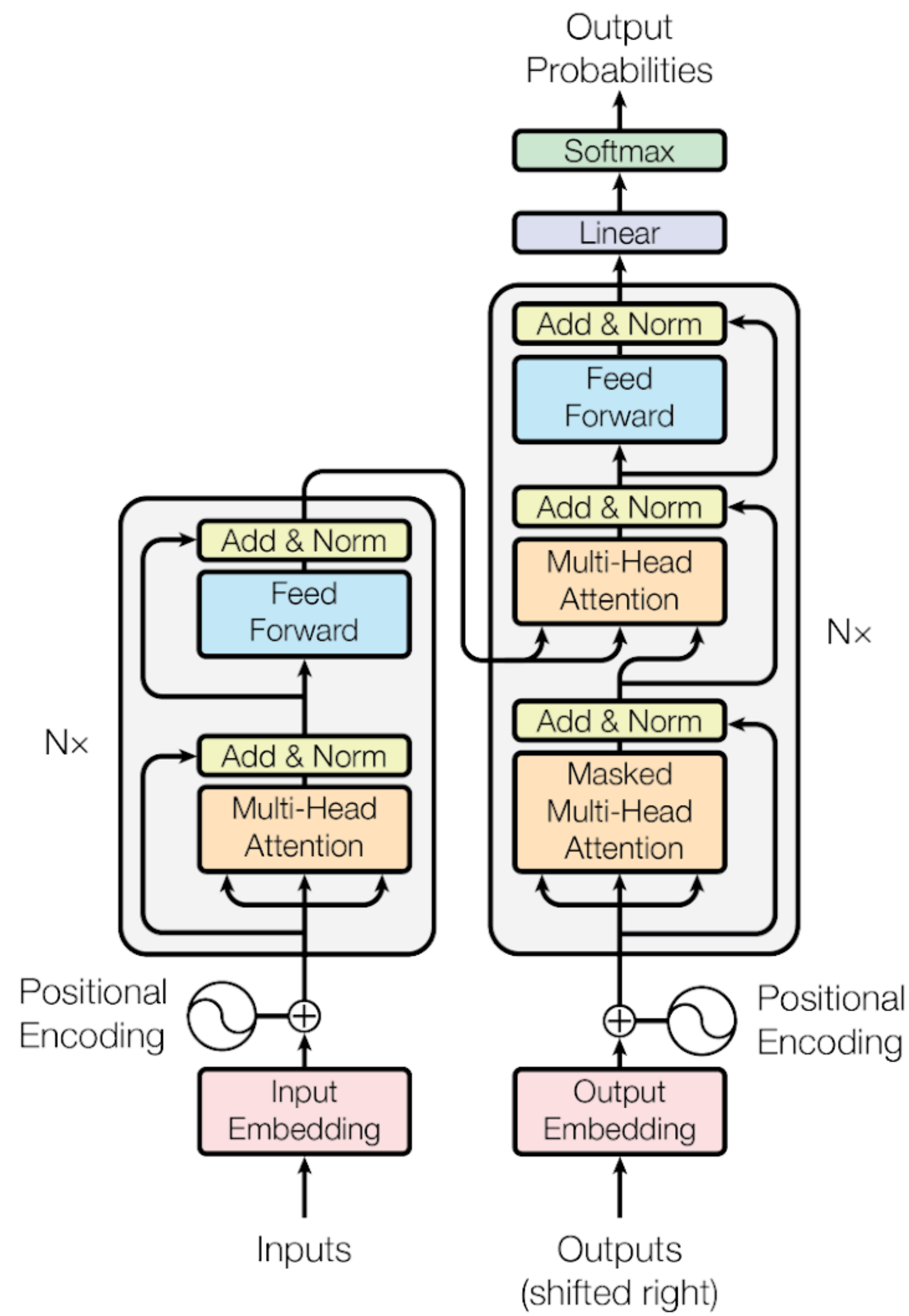

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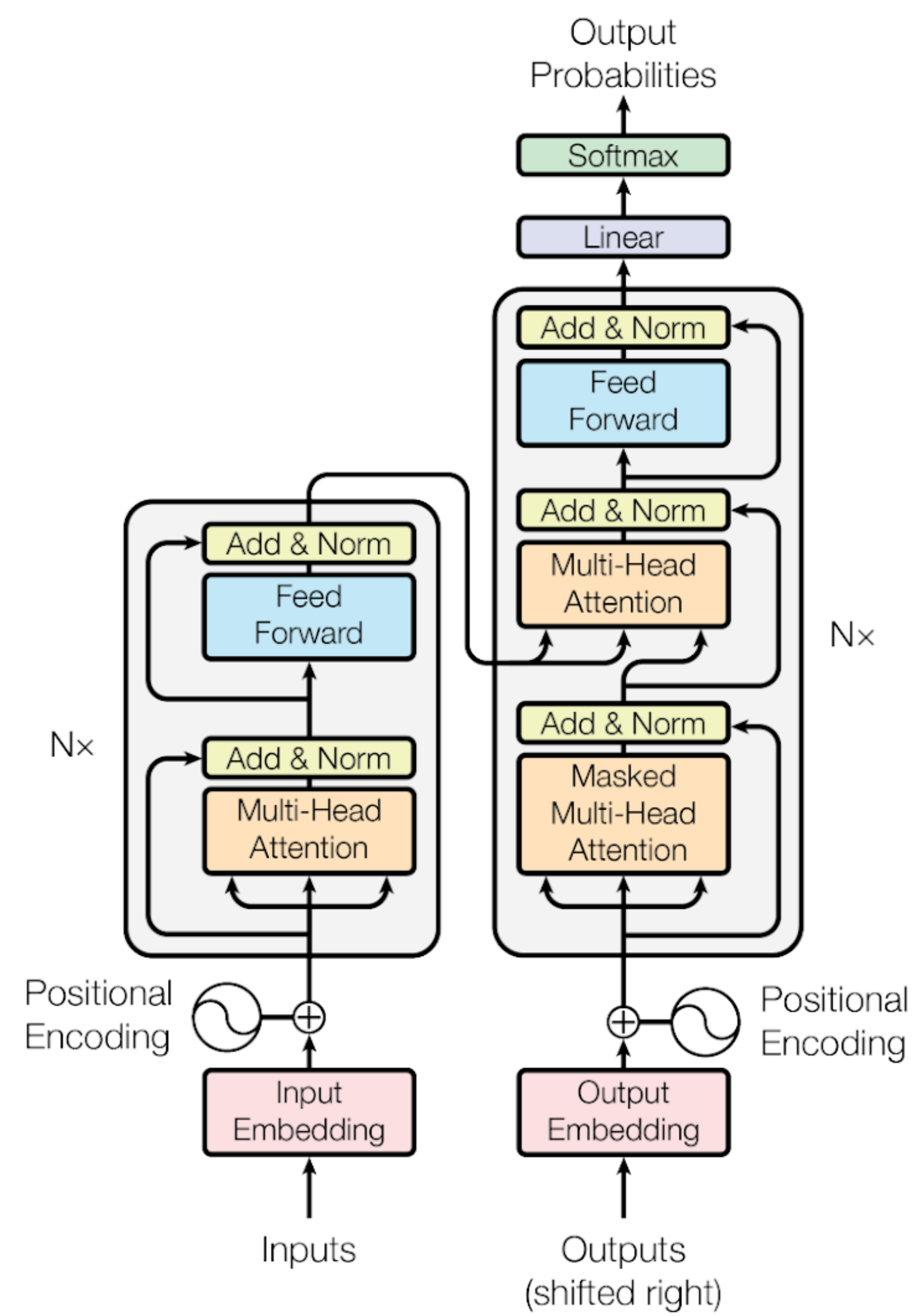

Multilingual Neural Machine Translation

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  - Reduces hardware requirements: much simpler deployment

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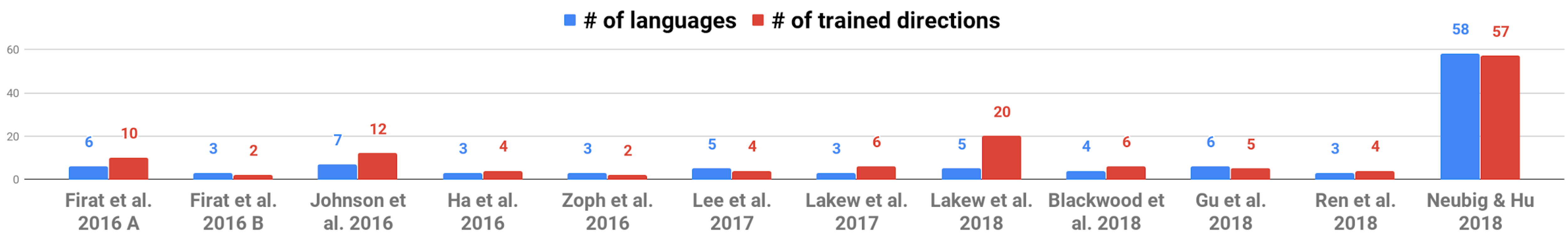

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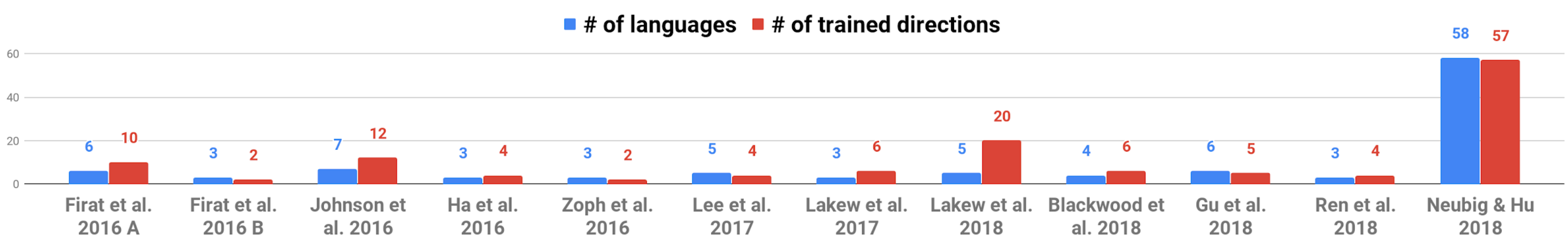
- Up to 5 languages and 20 translation directions



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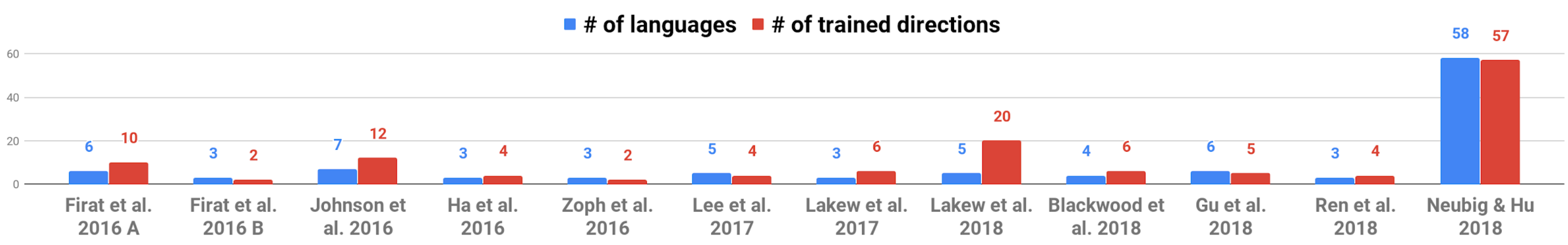

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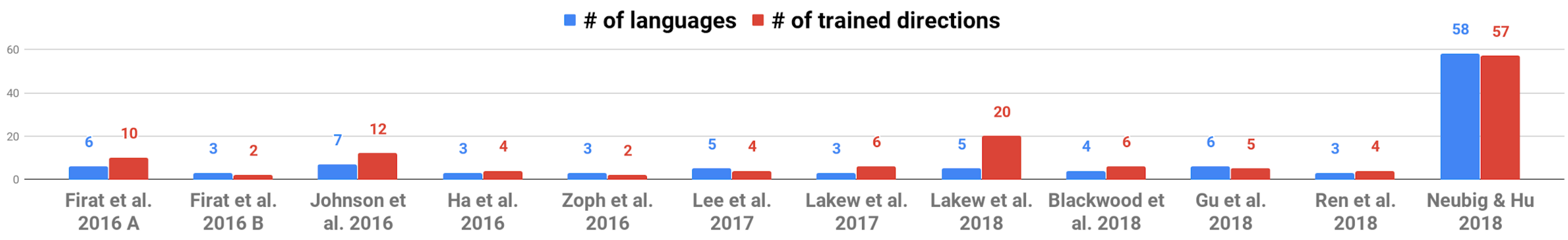
- Why stop here?



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- Effective in low resource settings - state of the art results with 58 languages in a single model

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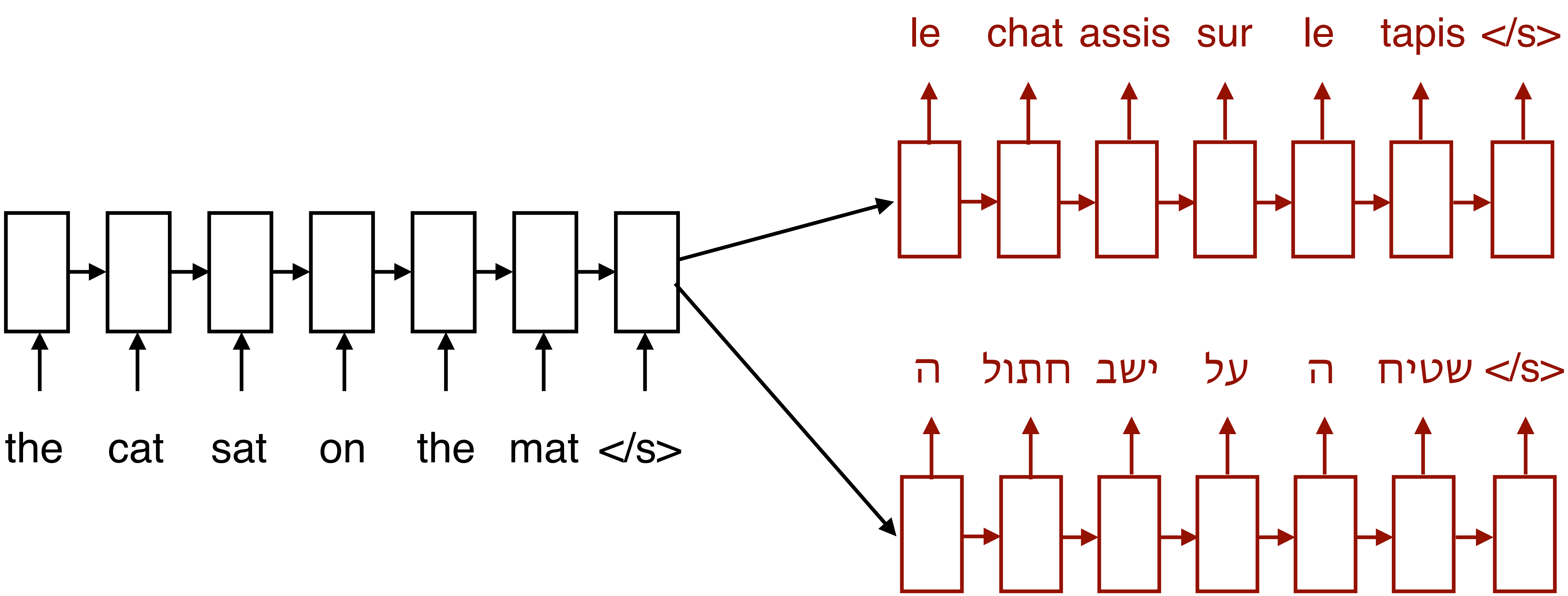
- **Loss Functions** - tailored multilingual loss functions?
- **Optimization** - Individual pair in a single batch or mixed batches?

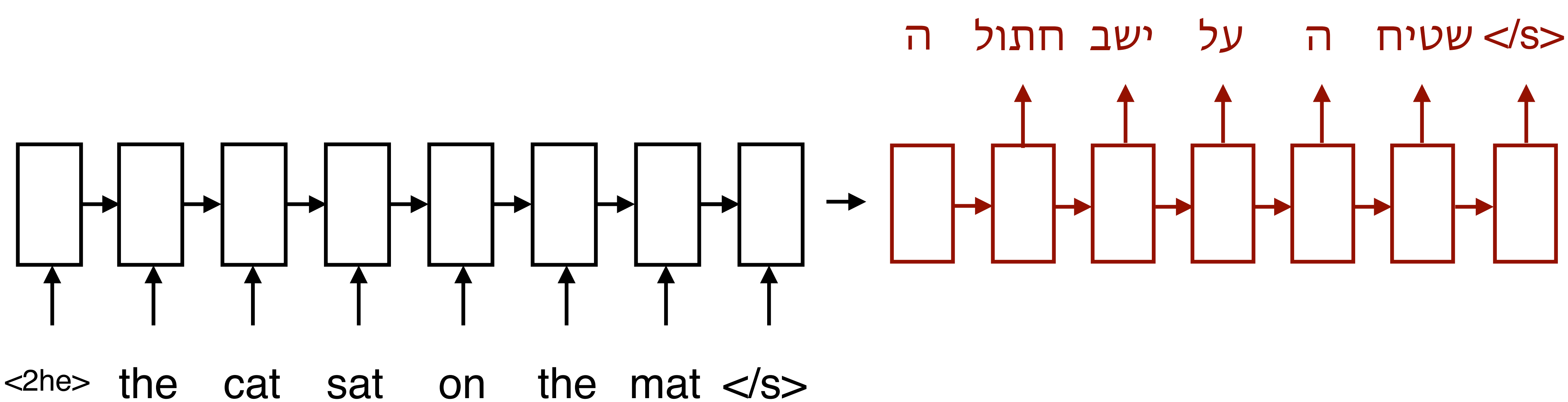
Multilingual NMT Methods

- **Separate** Encoder/Decoder per language (Dong et al. 2015, Firat et al. 2016)
    - Pros - each language its own parameters, no interference
    - Cons - complex models, less parameter sharing



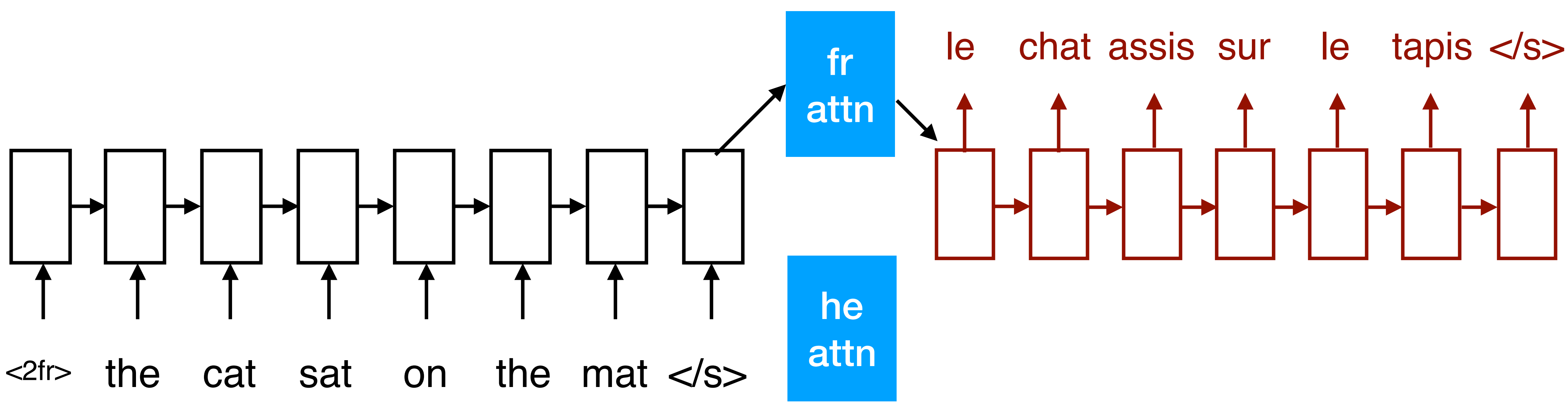
Multilingual NMT Methods

- **Joint** Encoder/Decoder/Attention model (Ha et al. 2016, Johnson et al. 2017)
  - Use a special “language token”
  - Pros - Full parameter sharing, simple (unchanged) model
  - Cons - Languages may interfere each other



Multilingual NMT Methods

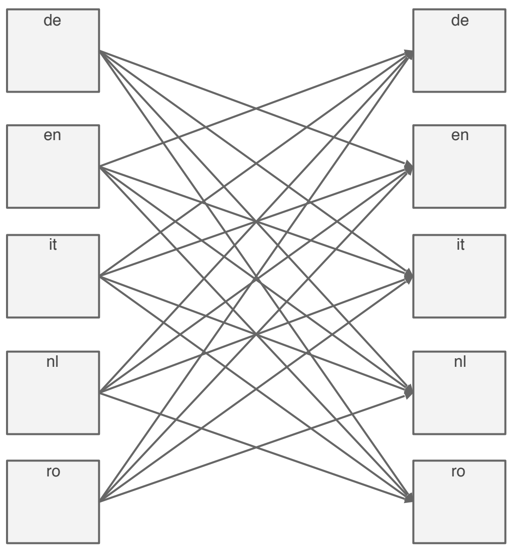
- **“In Between”** Share only some of the parameters, i.e. all but the attention mechanism (i.e. Blackwood et al. 2018, Sachan & Neubig 2018)
  - Pros - may reduce interference
  - Cons - adds implementation complexity



Data Settings

Many-to-Many

Fully-Supervised



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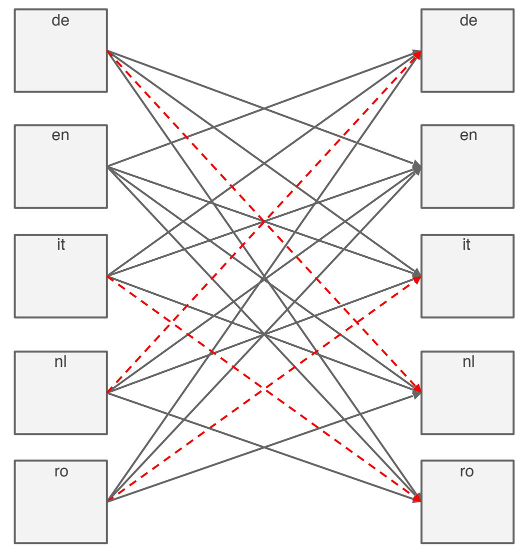
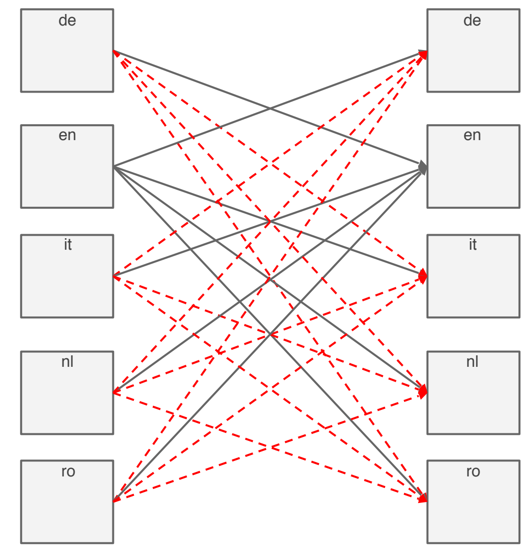


“English Centric”



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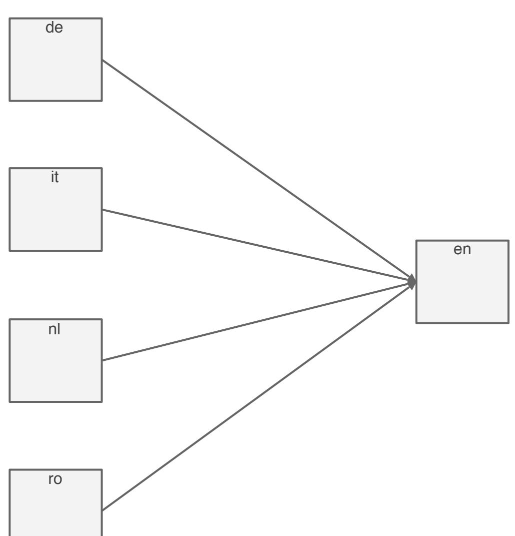
all-en



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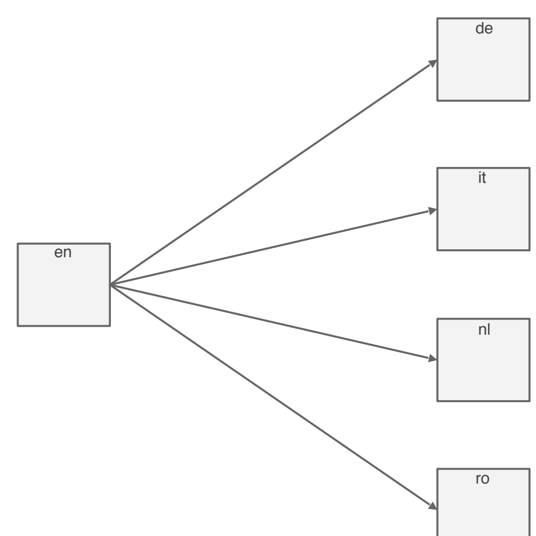

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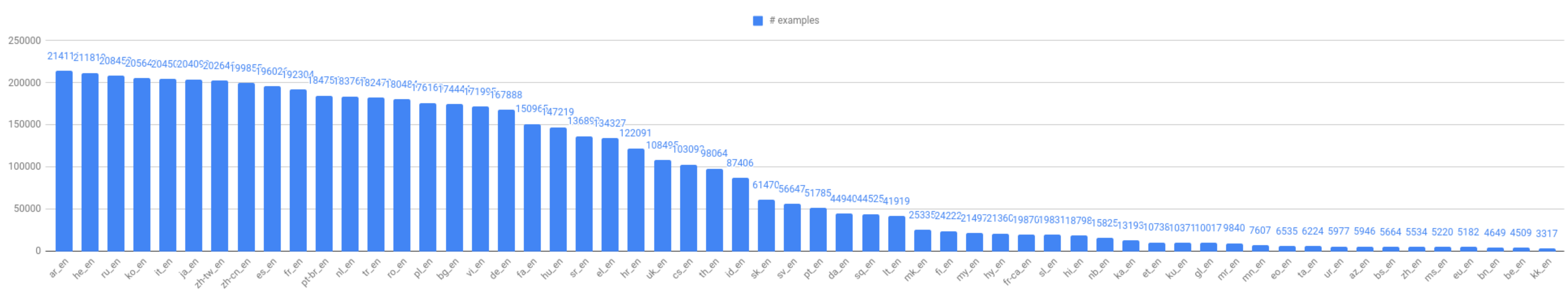

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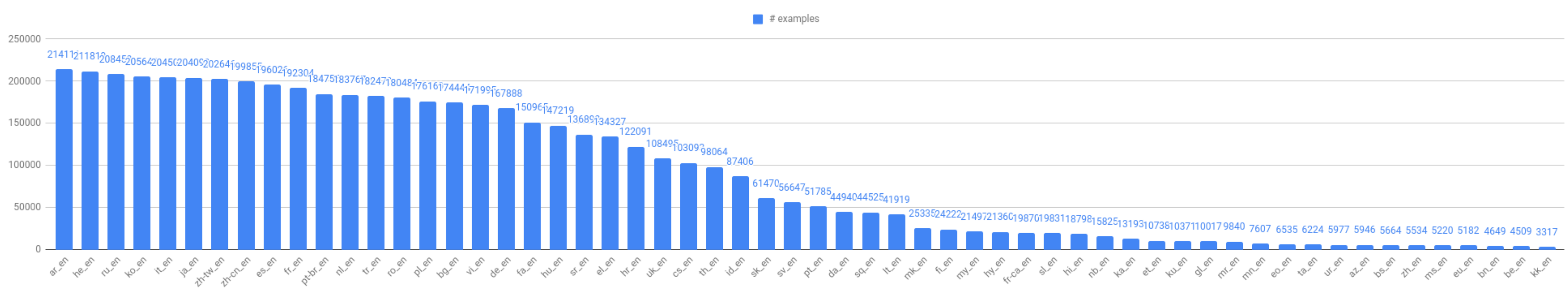

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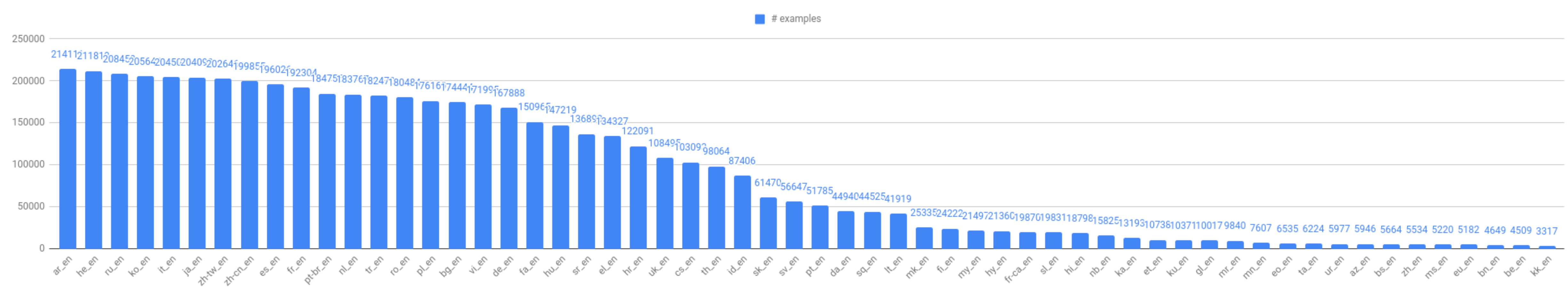

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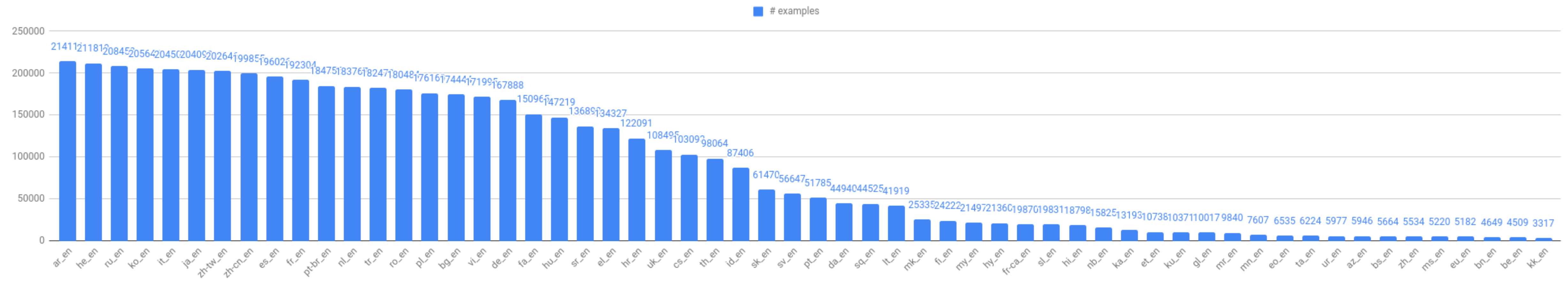

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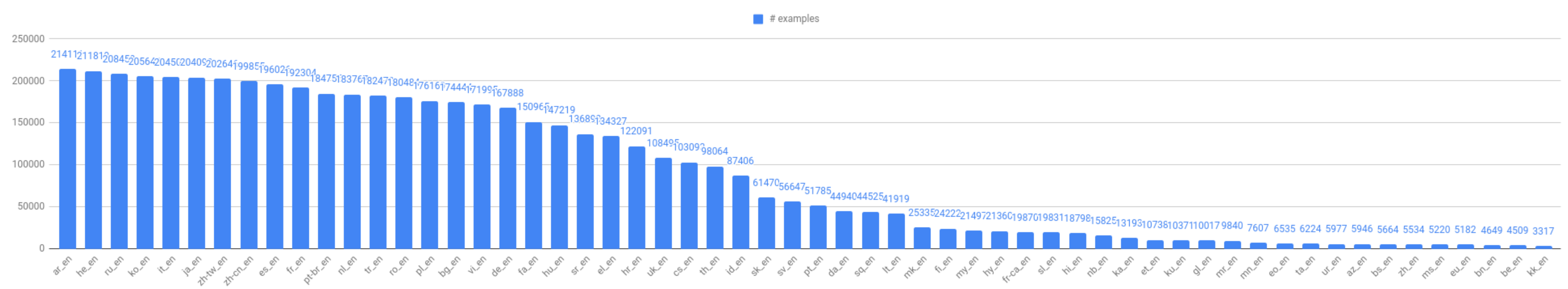

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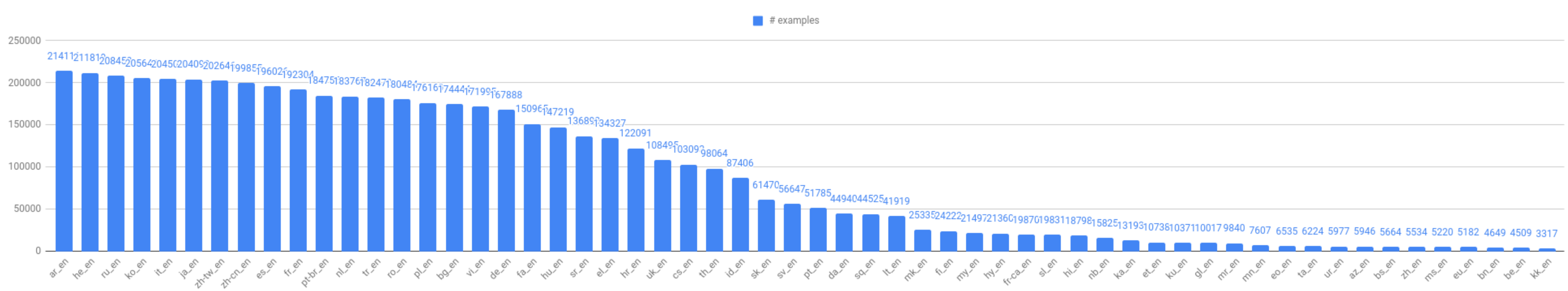

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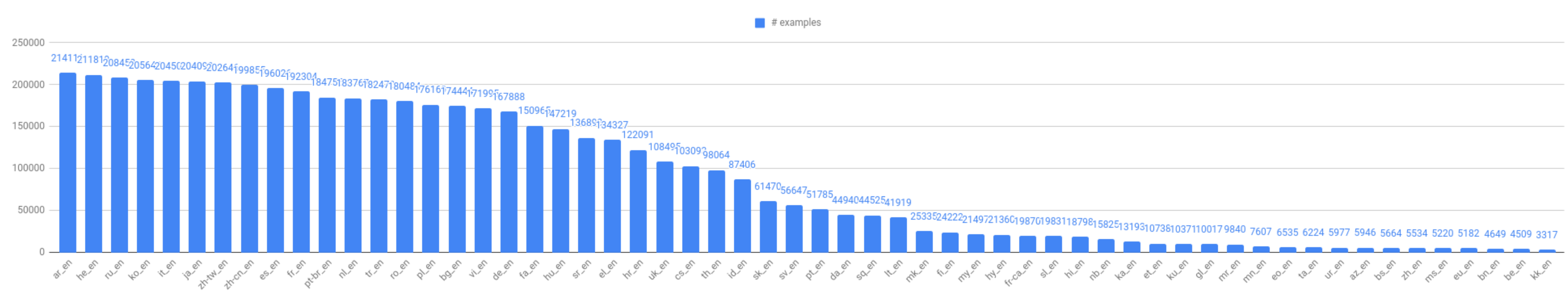

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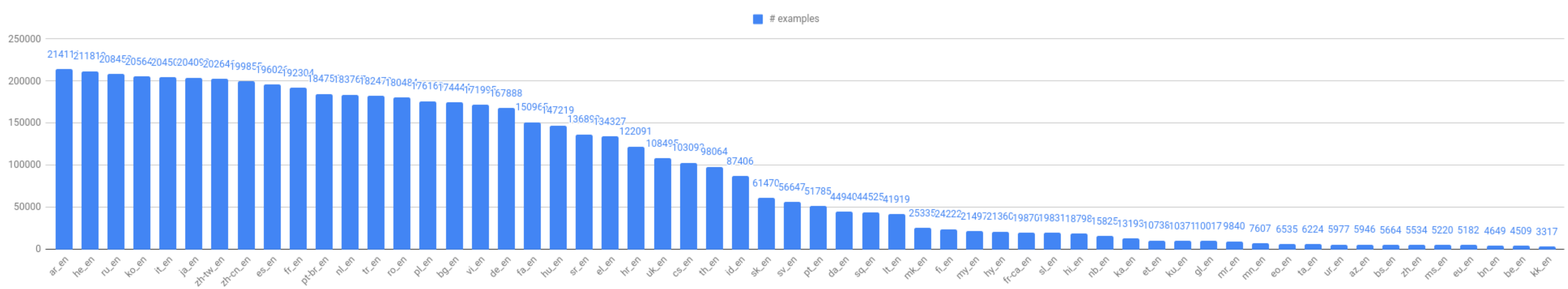

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# of examples	5.9k	4.5k	10k	61k	20.3k
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baselines	2.7	2.8	16.2	24	11.42
many-to-one	11.7	18.3	29.1	28.3	21.85
Ours					
many-to-one	11.24	18.28	28.63	26.78	21.23
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# of examples	213k	167k	211k	203k	198.5k
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many-to-one	25.93	28.87	30.19	32.42	29.35
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- Why? many-to-many is “harder”

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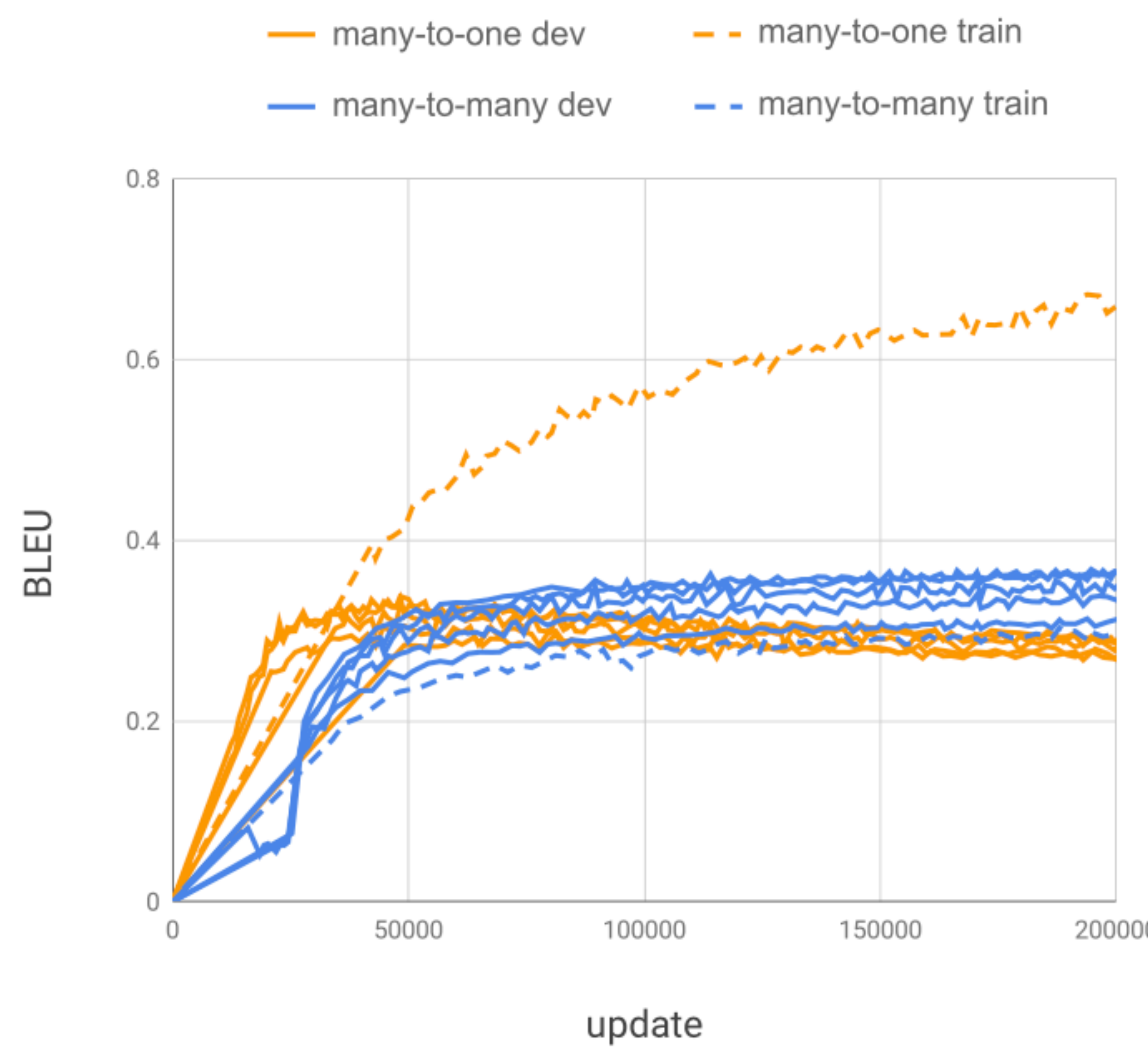

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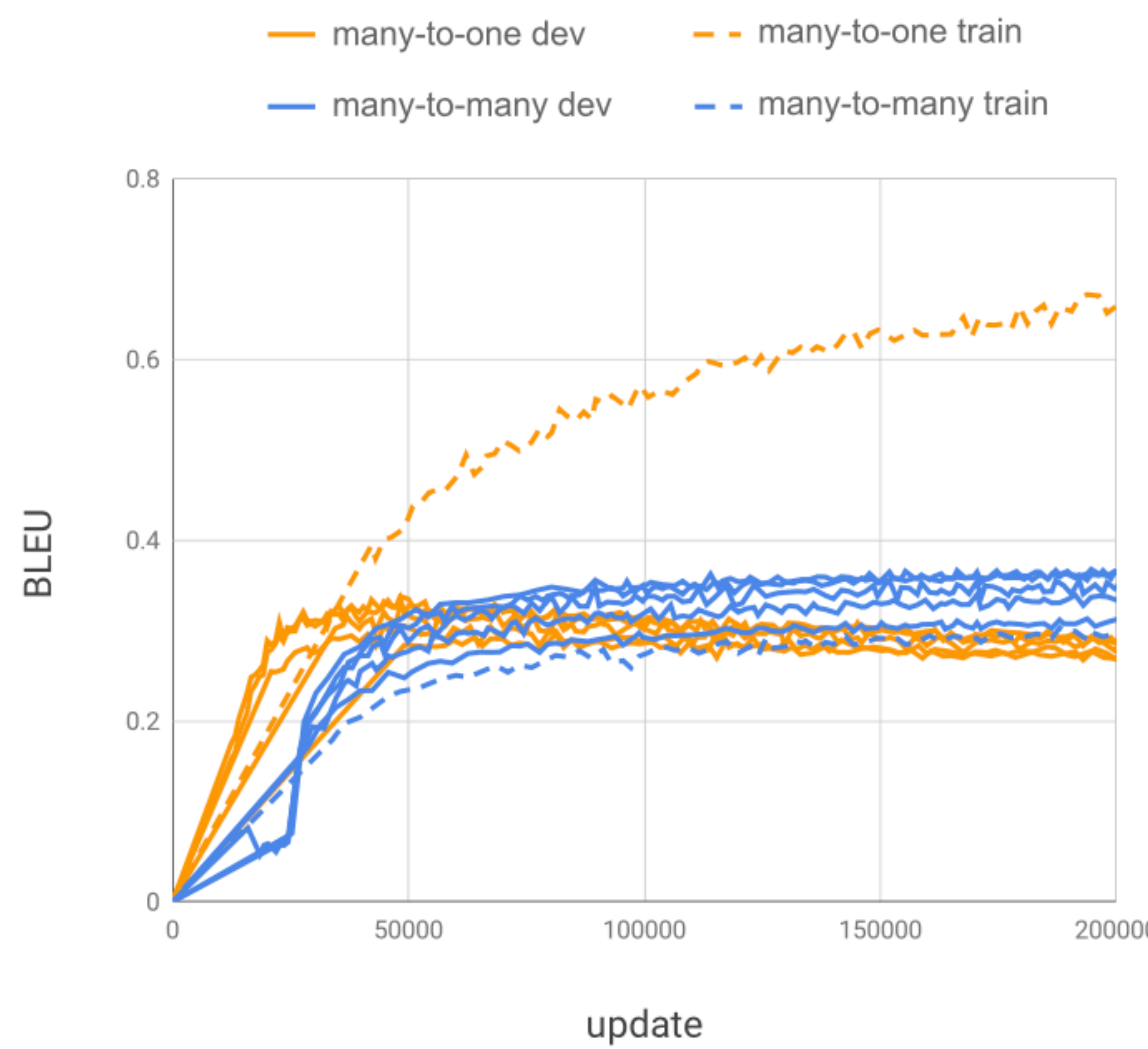

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	En-Az	En-Be	En-Gl	En-Sk	Avg.
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baselines	2.16	2.47	3.26	5.8	3.42
one-to-many	**5.06**	**10.72**	**26.59**	**24.52**	**16.72**
many-to-many	3.9	7.24	23.78	21.83	14.19

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  - With larger, balanced, “real-world” datasets?

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Results - Into English

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baselines	23.34	16.3	21.93	30.18	31.83	**36.47**	36.12	34.59	24.01	27.13	28.19
many-to-one	**26.04**	**23.68**	**25.36**	35.05	**33.61**	35.69	**36.28**	36.33	28.35	**29.75**	**31.01**
many-to-many	22.17	21.45	23.03	**37.06**	30.71	35.0	36.18	**36.57**	**29.87**	27.64	29.97

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    - When the data is large enough and not multi-way-parallel, memorization is not an issue and “less is more”

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    - When the data is large enough and not multi-way-parallel, memorization is not an issue and “less is more”
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Results - Into English

	Ar	Az	Be	De	He	It	Nl	Ro	Sk	Tr	Avg.
baselines	23.34	16.3	21.93	30.18	31.83	**36.47**	36.12	34.59	24.01	27.13	28.19
many-to-one	**26.04**	**23.68**	**25.36**	35.05	**33.61**	35.69	**36.28**	36.33	28.35	**29.75**	**31.01**
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  - When the data is large enough and not multi-way-parallel, memorization is not an issue and “less is more”
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Results - Out of English

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baselines	10.57	8.07	15.3	23.24	19.47	31.42	28.68	27.92	11.08	15.54	19.13
one-to-many	**12.08**	**9.92**	**15.6**	**31.39**	**20.01**	**33**	**31.06**	**28.43**	**17.67**	**17.68**	**21.68**
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- Less burden, not biased towards English

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  - Both supervised and Zero-Shot
- Keep model fixed, measure performance on 5 languages while varying the number of additional languages

Analysis - Supervised Directions

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	Ar-En	En-Ar	Fr-En	En-Fr	Ru-En	En-Ru	Uk-En	En-Uk	Avg.
5-to-5	**23.87**	**12.42**	**38.99**	**37.3**	29.07	**24.86**	**26.17**	16.48	**26.14**
25-to-25	23.43	11.77	38.87	36.79	**29.36**	23.24	25.81	**17.17**	25.8
50-to-50	23.7	11.65	37.81	35.83	29.22	21.95	26.02	15.32	25.18
75-to-75	22.23	10.69	37.97	34.35	28.55	20.7	25.89	14.59	24.37
103-to-103	21.16	10.25	35.91	34.42	27.25	19.9	24.53	13.89	23.41

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- Maybe we need even bigger models? 1M examples per language pair is not very large… (in MT scale)

Analysis - Zero-Shot Directions

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- 50-to-50 strikes a good balance between capacity and generalization

	Ar-Fr	Fr-Ar	Ru-Uk	Uk-Ru	Avg.
5-to-5	1.66	4.49	3.7	3.02	3.21
25-to-25	1.83	**5.52**	**16.67**	4.31	7.08
50-to-50	**4.34**	4.72	15.14	**20.23**	**11.1**
75-to-75	1.85	4.26	11.2	15.88	8.3
103-to-103	2.87	3.05	12.3	18.49	9.17

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Analysis - Zero-Shot Directions

- 50-to-50 strikes a good balance between capacity and generalization
- Similar languages are much easier
- General trend - more languages, more generalization (interlingua?)

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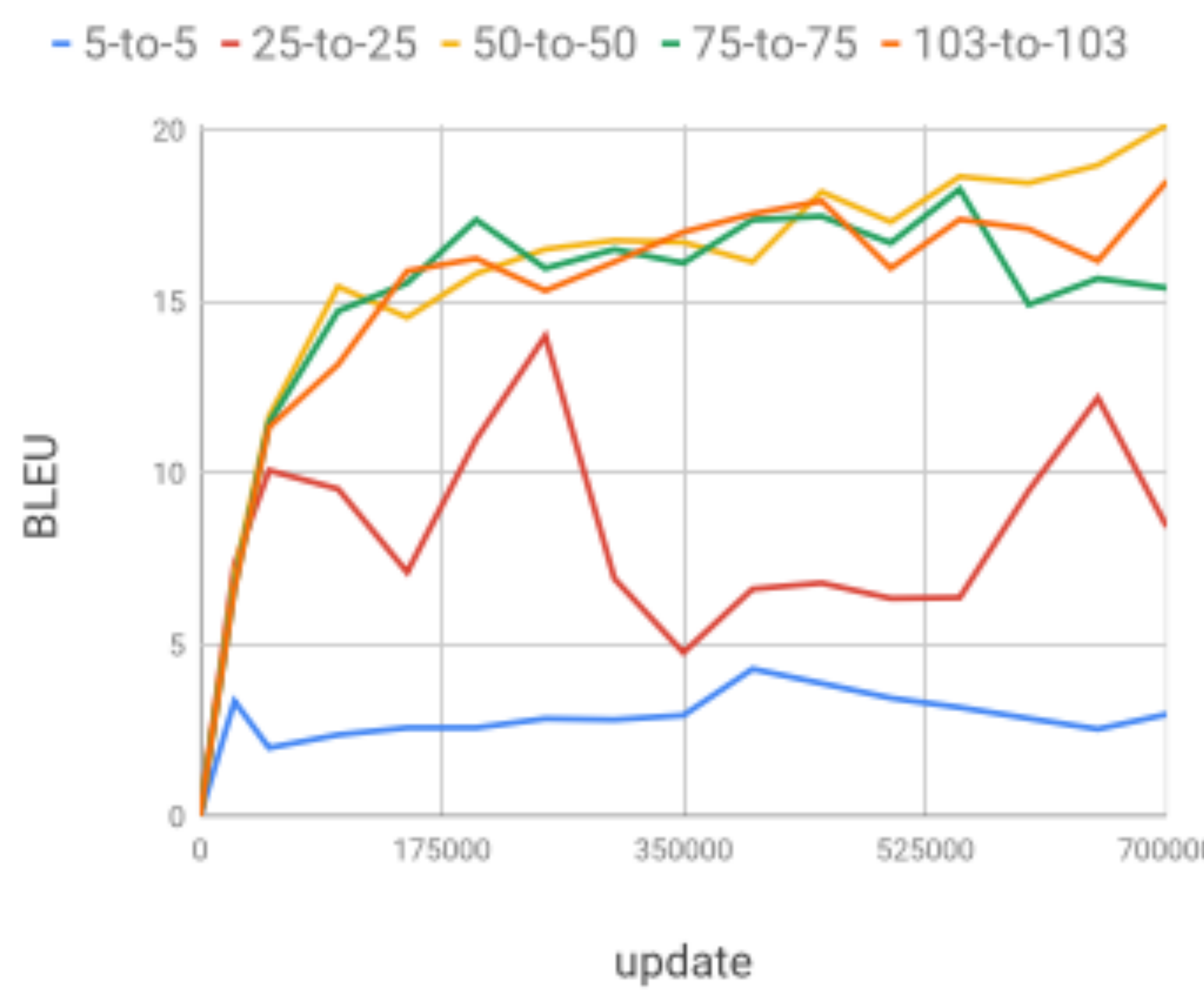

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- Especially helpful in low-resource settings
- Can scale to high resource settings, 100+ languages (with some trade-off)
- Zero-shot analysis: more languages - more generalization?

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- Improving zero-shot performance with interlingual-losses

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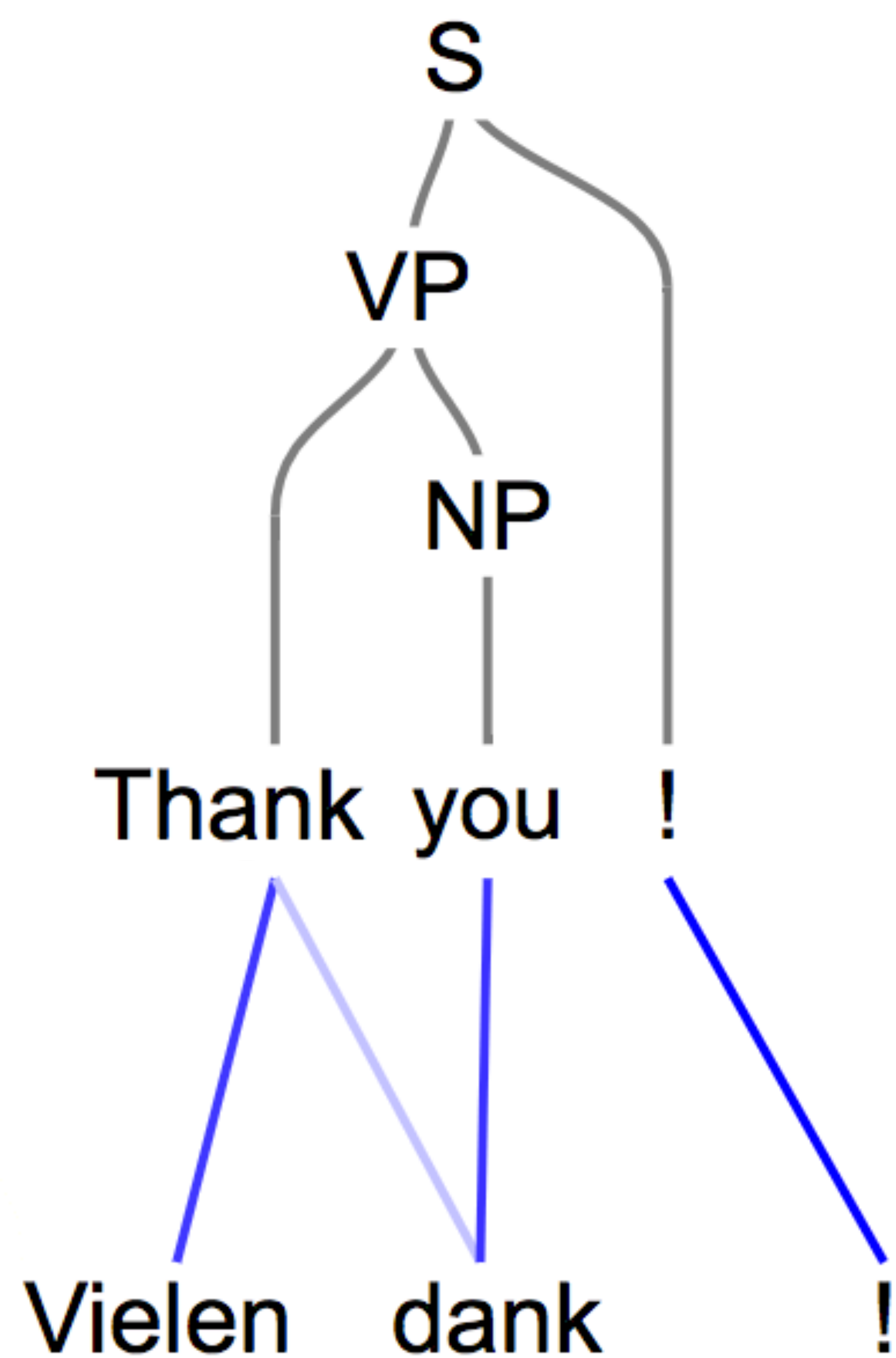
  - Multilingual BERT
  - Zero-shot Transfer Learning (Eriguchi et al 2018, Artetxe et al 2019)


S
VP
NP
Thank
you
!
Vielen
dank
!