CS769 Advanced NLP

Machine Translation and Multilingual NLP

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Slides adapted from Austin

https://junjiehu.github.io/cs769-fall25/

Goal for Today

- Background & Parallel Corpus
- **Noisy Channel MT (SMT, non-parametric models)**
    - Lexical Translation
    - Word Alignment
- **Neural Machine Translation (parametric models)**
    - Architecture: LSTM, CNN, Transformer
    - Multilingual NMT
- **Hybrid MT (non-parametric + parametric MT)**
    - Interpolation / Retrieval MT
    - Prompt MT

One naturally wonders if the problem of translation could conceivably be treated as a problem in cryptography. When I look at an article in Russian, I say: '**This is really written in English, but it has been coded in some strange symbols. I will now proceed to decode**.'

Warren Weaver to Norbert Wiener, March, 1947

Parallel Corpus

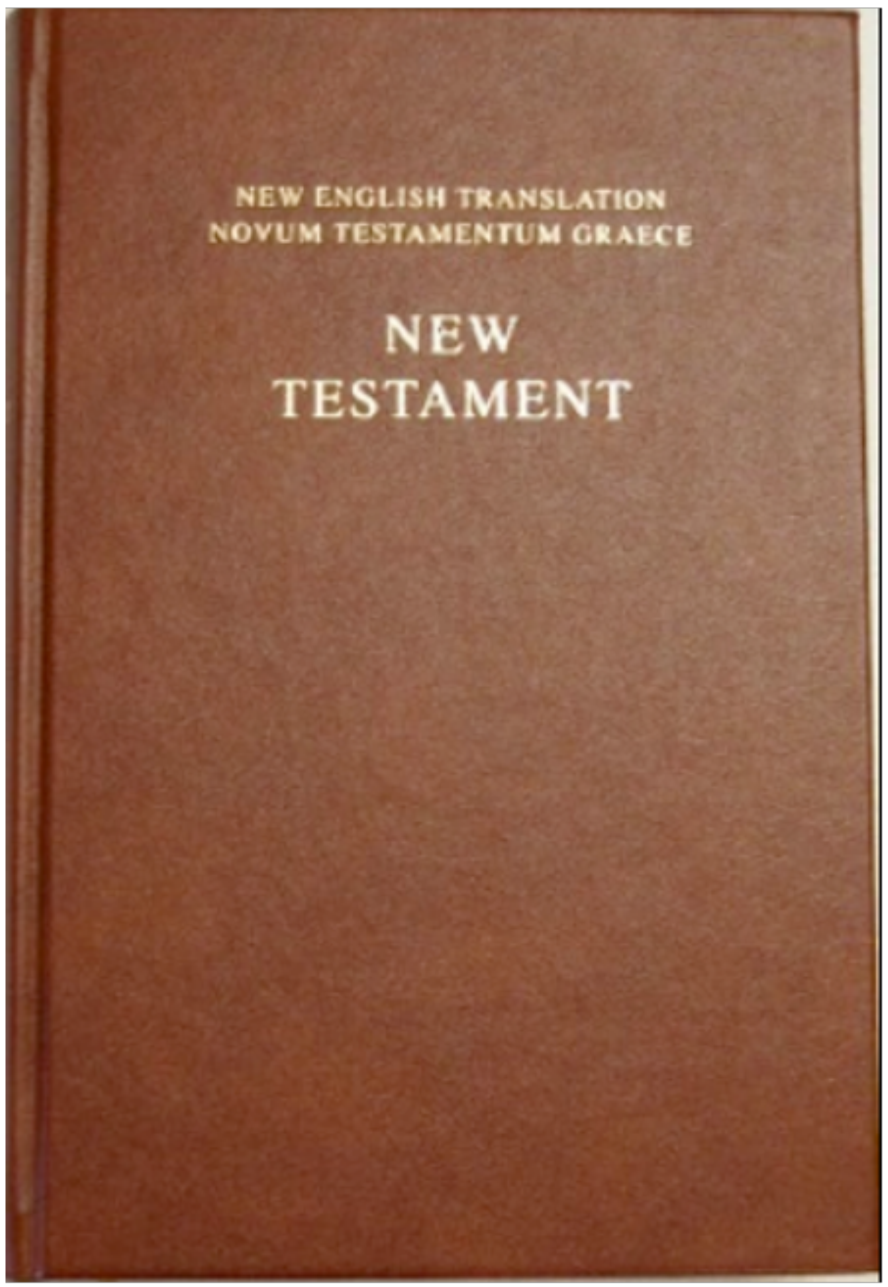
- We are given a corpus of sentence pairs in two languages to train our machine translation models.
- Source language is also called foreign language, denoted as **f**.
- Conventionally (in earlier studies before NMT) target language is usually referred to English, denoted as **e**.

Parallel Corpus

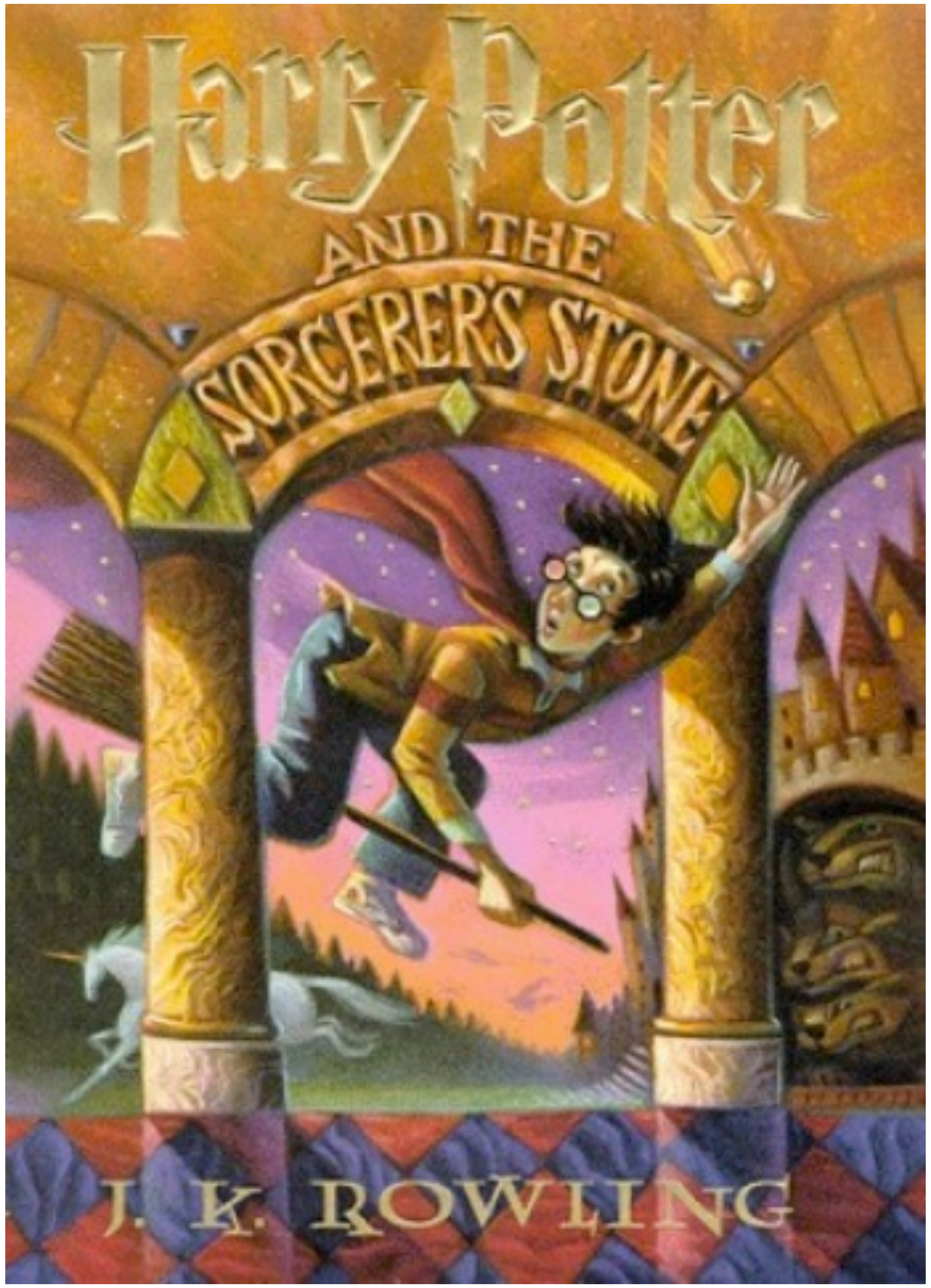
		CLASSIC SOUPS	Sm.	Lg.
清燉雞湯	57.	House Chicken Soup (Chicken, Celery, Potato, Onion, Carrot)	1.50	2.75
雞飯湯	58.	Chicken Rice Soup	1.85	3.25
雞麵湯	59.	Chicken Noodle Soup	1.85	3.25
廣東雲吞	60.	Cantonese Wonton Soup	1.50	2.75
蕃茄蛋湯	61.	Tomato Clear Egg Drop Soup	1.65	2.95
雲吞湯	62.	Regular Wonton Soup	1.10	2.10
酸辣湯	63.	Hot & Sour Soup	1.10	2.10
蛋花湯	64.	Egg Drop Soup	1.10	2.10
雲蛋湯	65.	Egg Drop Wonton Mix	1.10	2.10
豆腐菜湯	66.	Tofu Vegetable Soup	NA	3.50
雞玉米湯	67.	Chicken Corn Cream Soup	NA	3.50
蟹肉玉米湯	68.	Crab Meat Corn Cream Soup	NA	3.50
海鮮湯	69.	Seafood Soup	NA	3.50

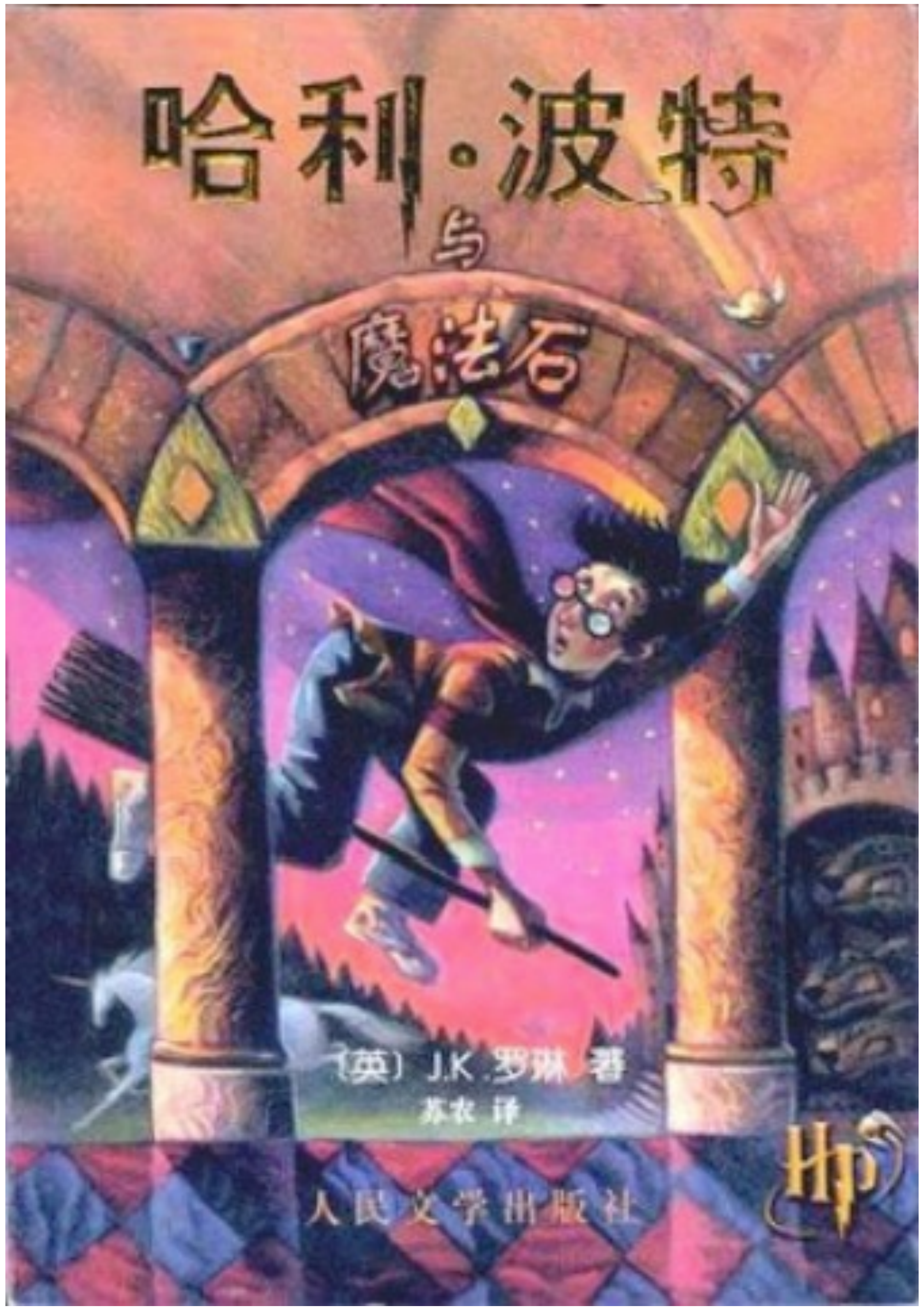
Parallel Corpus

Parallel Corpus



Parallel Corpus

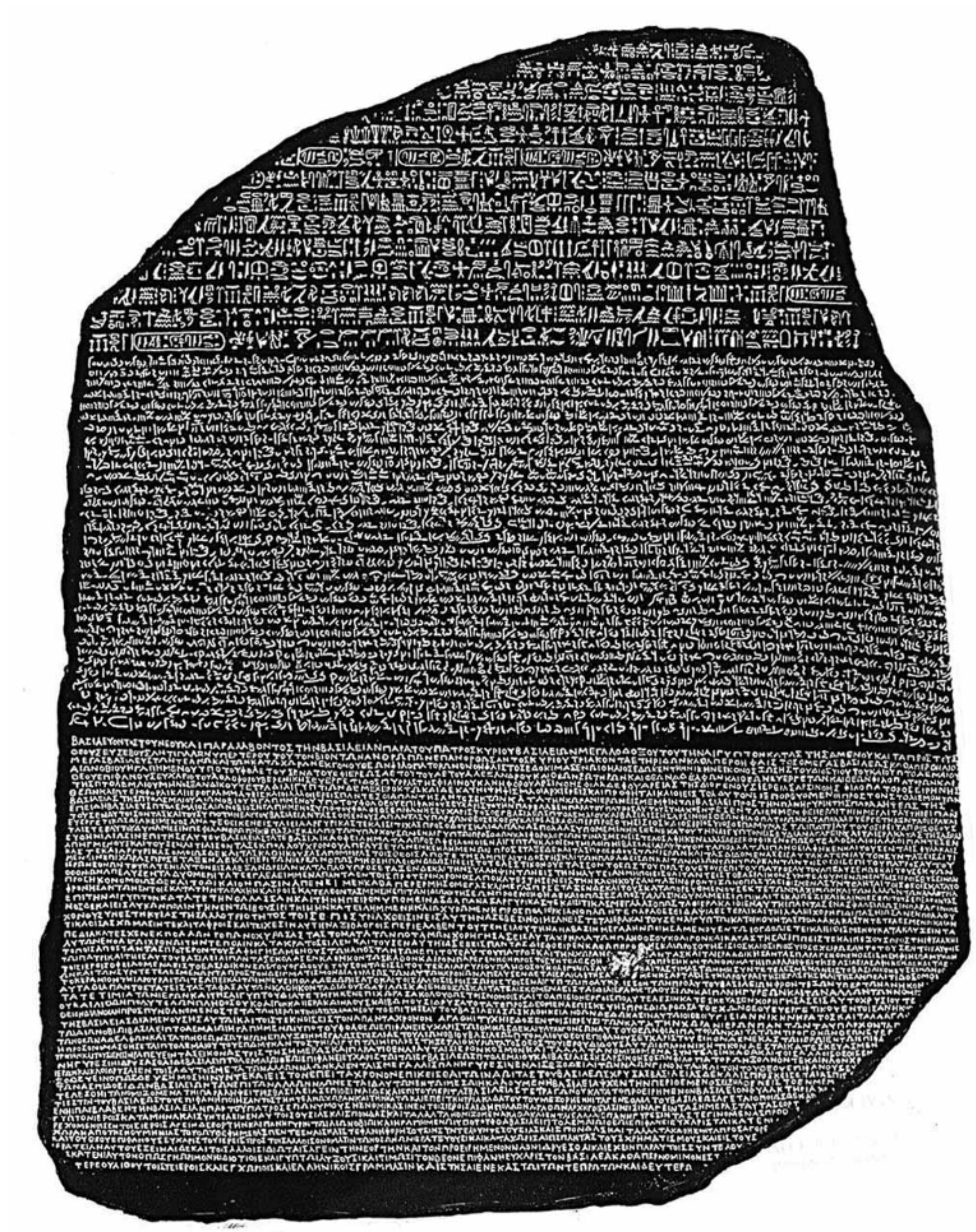




Parallel Corpus

Egyptian

Greek



WMT

- Annual conference for Machine Translation (2006-now)

- Many shared tasks:

  - **Translation** tasks: News, Biomedical articles, Translate similar languages, low-resource MT, large-scale multilingual MT, triangular MT, efficiency, terminology, unsupervised MT, lifelong learning

  - **Evaluation** tasks: quality estimation, metrics

  - **Other** tasks: automatic post-editing

https://www.statmt.org/wmt21/

OPUS Parallel Corpus

- OPUS (Tiedemann 2012) is a growing collection of translated texts from the web.
- Preprocessed parallel texts in tmx, moses format

OPUS

Search & download resources: de (German) en (English) all ☐ show all versions

Language resources: click on [tmx | moses | xces | lang-id] to download the data! (raw = untokenized, ud = parsed with universal dependencies, alg = word alignments and phrase tables)

corpus	doc's	sent's	de tokens	en tokens	XCES/XML	raw	TMX	Moses	mono	raw	ud	alg	dic	freq			other files
CCMatrix v1	1	247.5M	3.8G	3.9G	xces de en	de en	tmx	moses	de en	de en				de en		sample	
WikiMatrix v1	1	6.2M	443.1M	1.0G	xces de en	de en	tmx	moses	de en	de en				de en		sample	
ParaCrawl v8	364	36.3M	450.7M	478.7M	xces de en	de en	tmx	moses	de en	de en				de en			
EUbookshop v2	15373	9.6M	337.4M	380.2M	xces de en	de en	tmx	moses	de en	de en		alg	dic	de en	query	sample	moses/strict
EuroPat v3	1	12.6M	318.2M	387.8M	xces de en	de en	tmx	moses	de en	de en				de en		sample	
wikimedia v20210402	1	0.1M	11.0M	349.2M	xces de en	de en	tmx	moses	de en	de en				de en		sample	
CCAligned v1	1852	15.3M	150.8M	159.5M	xces de en	de en	tmx	moses	de en	de en				de en		sample	
TildeMODEL v2018	7	4.3M	108.8M	131.4M	xces de en	de en	tmx	moses	de en	de en		alg smt	dic	de en		sample	
DGT v2019	38675	3.6M	66.0M	73.3M	xces de en	de en	tmx	moses	de en	de en		alg smt	dic	de en		sample	

https://opus.nlpl.eu/

Noisy Channel MT
(Statistic Machine Translation)

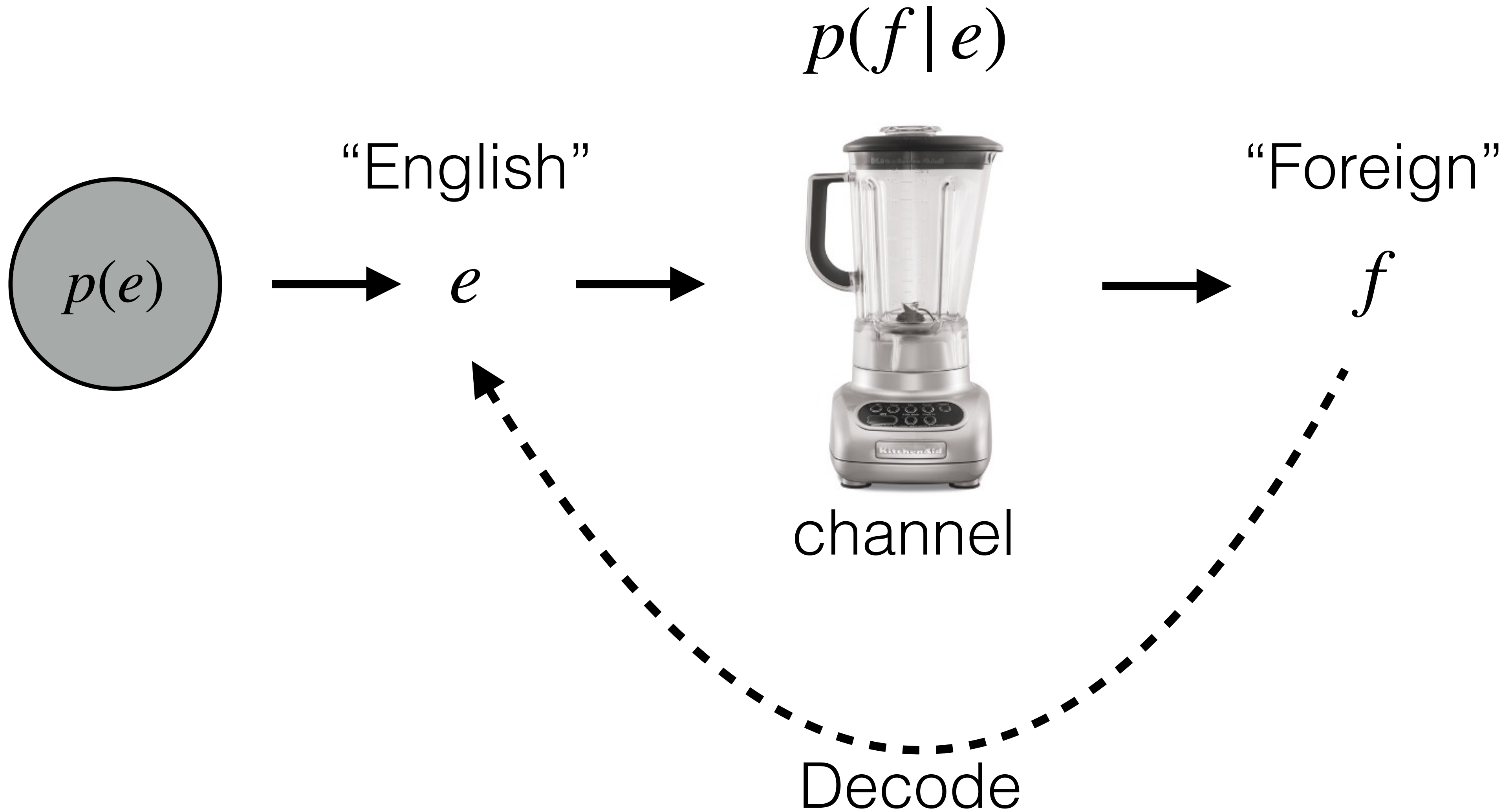
f-to-e Translation

- We want a model of $p(e \mid f)$

Possible English sentence — Confusing foreign sentence

Noisy Channel MT

- **Speaker**: Have an English sentence in mind, encrypt it through a noisy channel, and speak the sentence in a foreign language
- **Listener**: Decode what they hear to the original English sentence.



Noisy Channel MT

(Forward) Translation Model

$$\hat{e} = \arg\max_e \underbrace{p(e|f)}$$

$$= \arg\max_e \frac{p(e) \times p(f|e)}{p(f)}$$

$$= \arg\max_e \underbrace{p(e)} \times \underbrace{p(f|e)}$$

Language Model

(Backward) Translation Model
i.e., Noisy Channel

What's the benefit of the Noisy Channel decomposition in stead of modeling the forward translation directly?

Noisy Channel Division of Labor

- Language model $p(e)$
  - Is the translation fluent, grammatical, and idiomatic?
  - Use any LMs trained on large datasets
- Translation model $p(f \mid e)$
  - (Backward) translation probability
  - Ensures adequacy of translation

Training Noisy Channel MT

- Training LMs is simple (refer to the LM lecture)
- Estimating $p(f \mid e)$ is a bit harder
  - $f =$ ie voudrais un peu de frommage $\qquad p(f \mid e)$
  - $e_1 =$ I would like some cheese $\qquad$ 0.4
  - $e_2 =$ I would like a little of cheese $\qquad$ 0.5
  - $e_3 =$ There is no train to Barcelona $\qquad$ >0.00001

Estimate Channel Translation Model

- How do we parameterize $p(f \mid e)$?

$$p(f \mid e) = \frac{\text{count}(f, e)}{\text{count}(e)} \quad ?$$

- There are a lot of possible sentences
  - We can only count the sentences in our training data
  - This won't generalize to new inputs
- Can we break the sentence probability into lexical (word-level) translation probability?

Lexical Translation

- How do we translate a word? Look it up in a dictionary!
  - e.g., Haus (German): house, home, shell, household

Translation	Count
house	5000
home	2000
shell	100
household	80

Maximum Likelihood Estimation (MLE)

$$\hat{p}_{\mathrm{MLE}}(e \mid \texttt{Haus}) = \begin{cases} 0.696 & \text{if } e = \texttt{house} \\ 0.279 & \text{if } e = \texttt{home} \\ 0.014 & \text{if } e = \texttt{shell} \\ 0.011 & \text{if } e = \texttt{household} \\ 0 & \text{otherwise} \end{cases}$$

Lexical Translation

- Goal: a model $p(\mathbf{f} \mid \mathbf{e}, m)$, where $\mathbf{e} = \langle e_1, e_2, \ldots, e_l \rangle$ and $\mathbf{f} = \langle f_1, f_2, \ldots, f_m \rangle$, assuming that there is some distribution $p(m \mid l)$ that models $\mathbf{f}$'s length conditioned on $\mathbf{e}$'s length.

- Lexical translation makes the following assumptions:

    1. Each word f_i is generated from exactly one word in $\mathbf{e}$

    2. Thus, we have a latent alignment a_i that indicates which English word e_{a_i} generates f_i.

    3. Given the alignments $\mathbf{a}$, translation decisions are conditionally independent of each other and depend only on the aligned English word e_{a_i}

Lexical Translation

- Putting our assumptions together, we have:

$$p(\mathbf{f} \mid \mathbf{e}, m) = \underbrace{\sum_{\mathbf{a} \in [0,l]^m} p(\mathbf{a} \mid \mathbf{e}, m)}_{\text{p(Alignment)}} \times \underbrace{\prod_{i=1}^{m} p(f_i \mid e_{a_i})}_{\text{p(Translation|Alignment)}}$$

where $\mathbf{a}$ is an m-dimensional latent vector with each element a_i in the range of $[0,l]$

Word Alignment

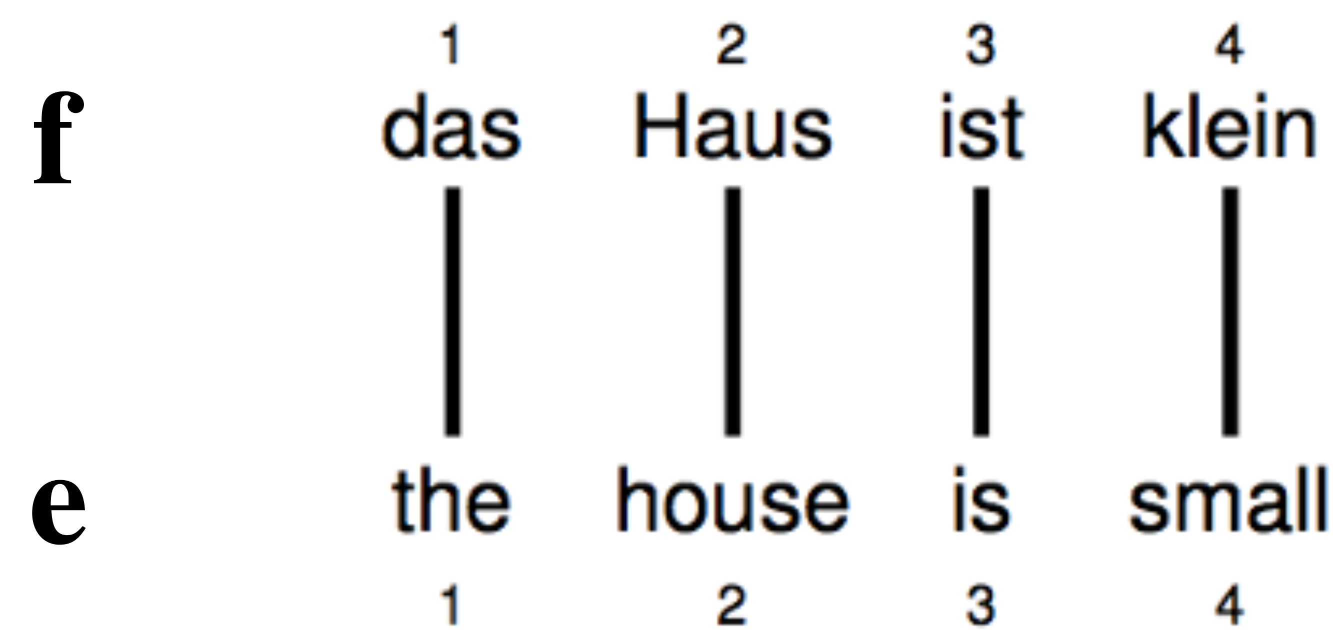
- Most of the research for the first 10 years of SMT was focusing on improving word alignment. Word translations weren't hard (with MLE), but predicting word order was hard.
- E.g. IBM Model 1, 2, 3, Giza++, FastAlign

$$p(\mathbf{a} \mid \mathbf{e}, m) = \prod_{i=1}^{m} p(a_i \mid i, l, m)$$

where $|\mathbf{e}| = l$, $|\mathbf{f}| = m$, f_i is aligned to e_{a_i} , $a_i \in [0, l]$

Word Alignment

- Alignments can be visualized by drawing links between two sentences, and they are represented as vectors of positions:

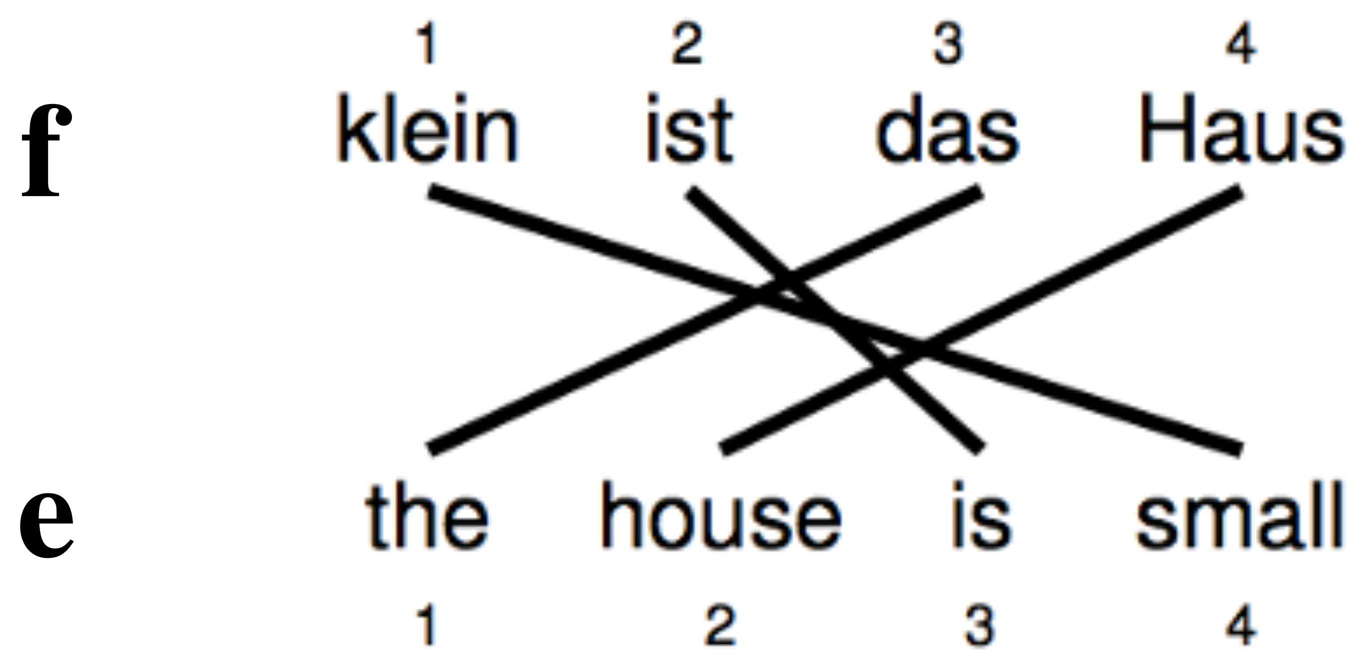


$$\mathbf{a} = (1,2,3,4)^{\mathsf{T}}$$

Reordering

- Words may be reordered during translation

$$\mathbf{a} = (4,3,1,2)^{\mathsf{T}}$$



Word Dropping

- A source word may not be translated at all

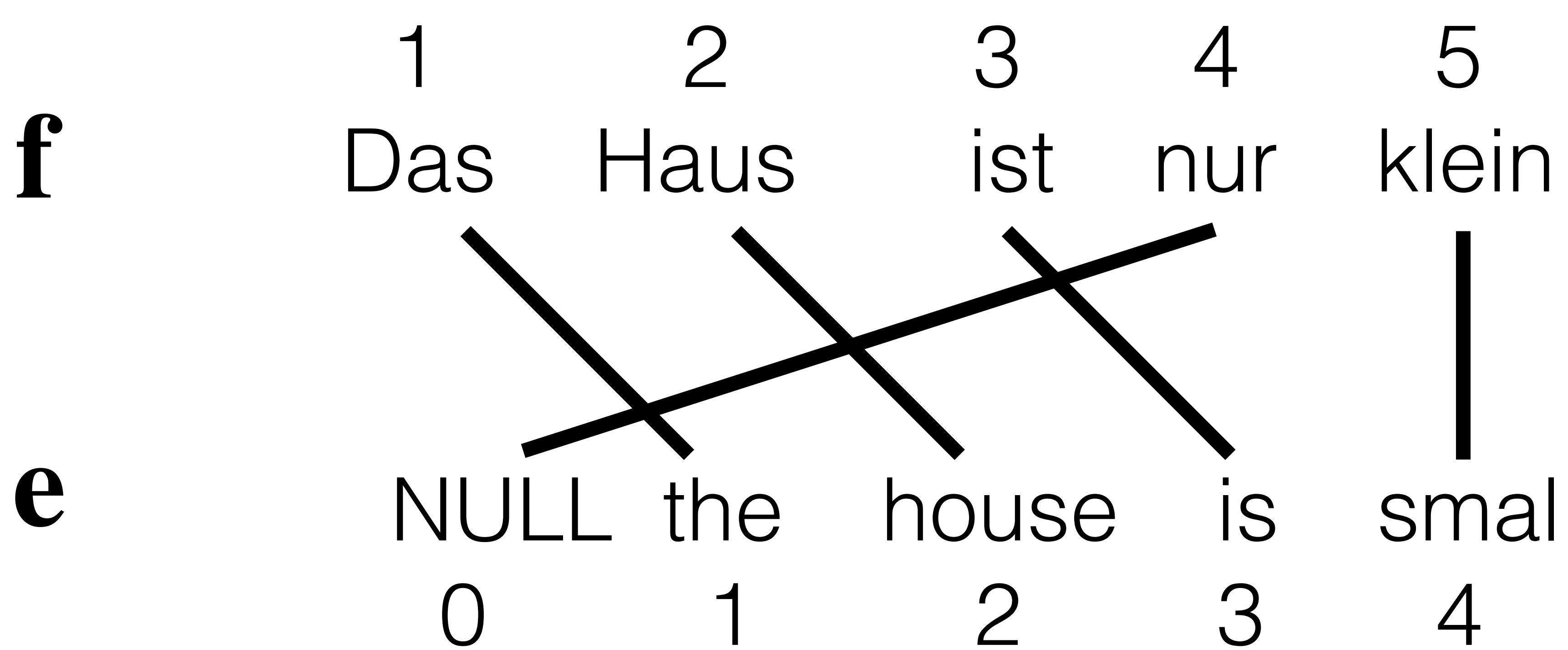
$$\mathbf{a} = (2,3,4)^{\mathsf{T}}$$

	1	2	3	
$\mathbf{f}$	Haus	ist	klein	
$\mathbf{e}$	the	house	is	small
	1	2	3	4

Word Insertion

- Words may be inserted during translation
- e.g., English just does not have an equivalent
- But these words must be explained—we typically assume every source sentence contains a NULL token

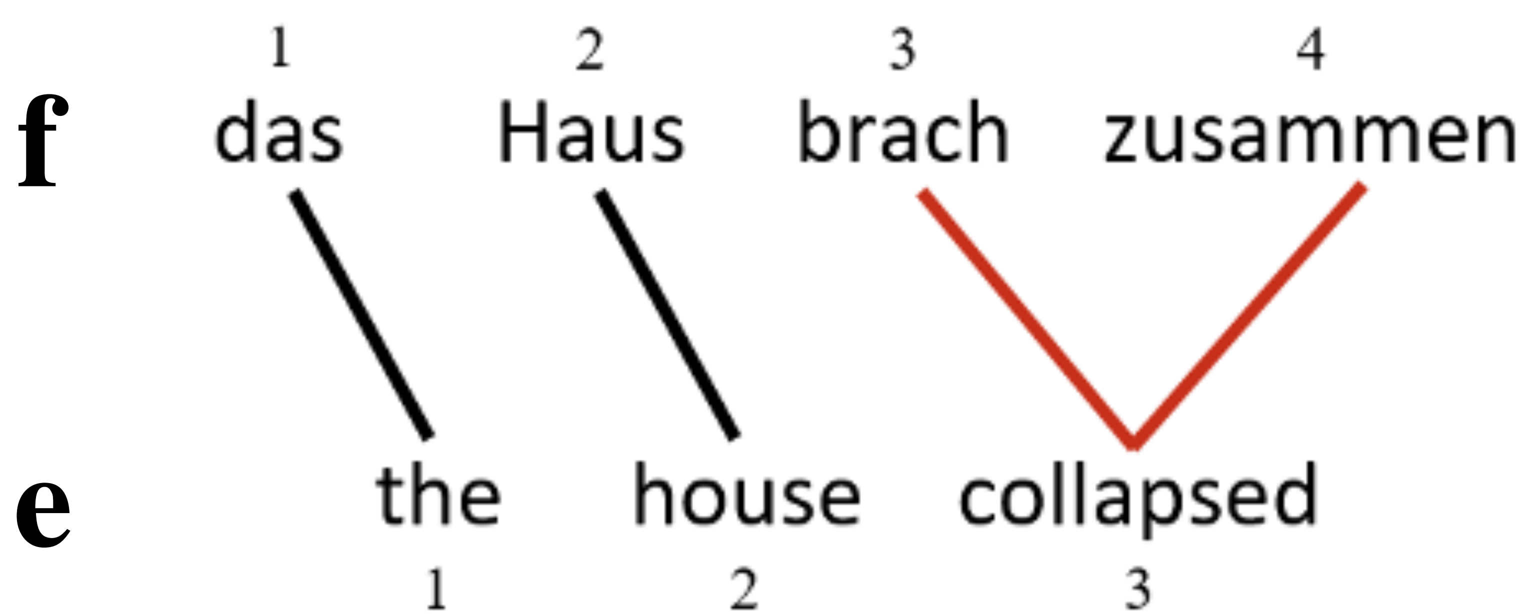
$$\mathbf{a} = (1,2,3,0,4)^{\mathsf{T}}$$



One-to-many Translation

- A source word may be translated into more than one target word

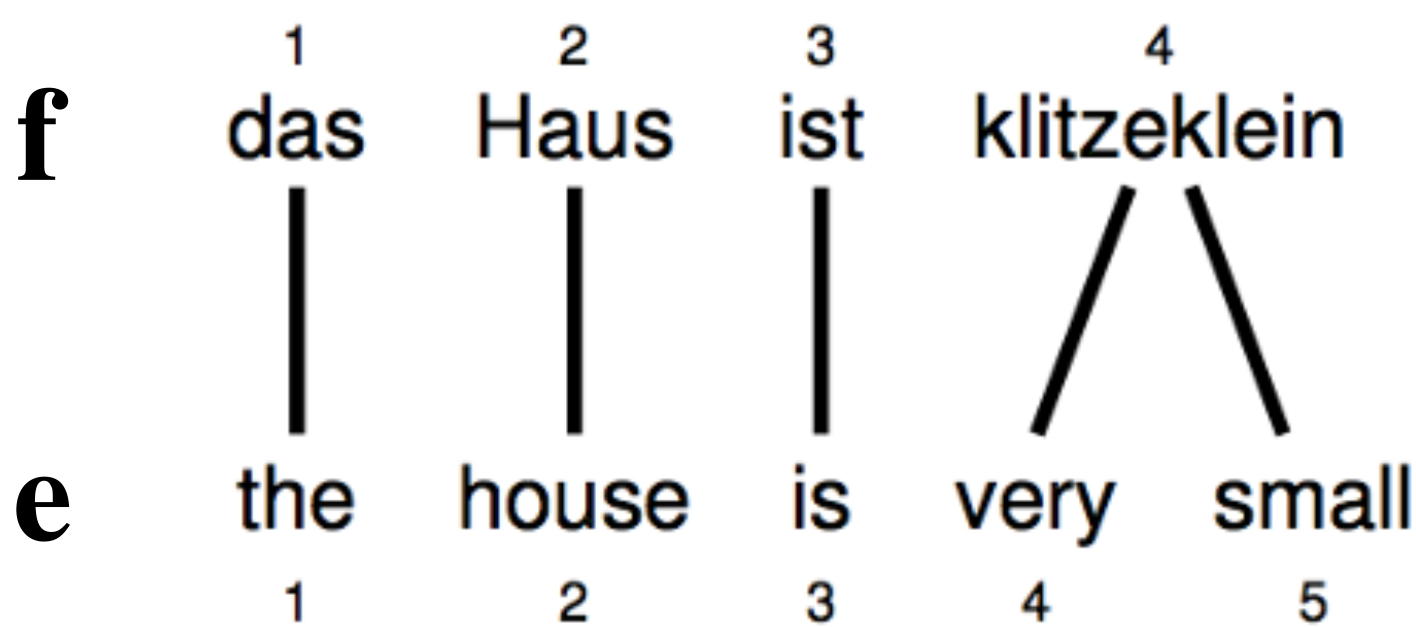
$$\mathbf{a} = (1,2,3,3)^{\mathsf{T}}$$



Many-to-one Translation

- More than one source word may not be translated as a unit in lexical translation

$$\mathbf{a} = ???\qquad \mathbf{a} = (1,2,3,(4,5)^{\top})^{\top}\ ?$$



This could be addressed by considering phrase-level alignment instead of word level.

Learn alignment & translation together

- How do we learn from training corpus of $(\mathbf{f}, \mathbf{e})$ pairs?

$$p(\mathbf{f} \mid \mathbf{e}, m) = \sum_{\mathbf{a} \in [0,l]^m} p(\mathbf{a} \mid \mathbf{e}, m) \times \prod_{i=1}^{m} p(f_i \mid e_{a_i})$$

$$= \sum_{\mathbf{a} \in [0,l]^m} \prod_{i=1}^{m} \underbrace{p(a_i \mid i, l, m)}_{\text{p(Alignment)}} \times \underbrace{p(f_i \mid e_{a_i})}_{\text{p(Translation|Alignment)}}$$

p(Alignment) p(Translation|Alignment)

- MLE of two probability with the latent alignment

$$p(a_i \mid i, l, m) = \frac{\text{count}(a_i \mid i, l, m)}{\text{count}(i, l, m)} \qquad p(f_i \mid e_{a_i}) = \frac{\text{count}(f_i, e_{a_i})}{\text{count}(e_{a_i})}$$

count$(a_i \mid i, l, m)$ is the no. time f_i is aligned to e_{a_i} in the training set. count(i, l, m) is the no. time we see a foreign sentence f of length m and an English sentence e of length l

Learn alignment & translation together

- How do we learn from training corpus of $(\mathbf{f}, \mathbf{e})$ pairs?
- "Chicken and egg" problem:
  - **If we had the good alignments**, we could estimate the translation probabilities by MLE (i.e., counting)

$$p(f_i \mid e_{a_i}) = \frac{\text{count}(f_i, e_{a_i})}{\text{count}(e_{a_i})}$$

  - **If we had the good translation probabilities**, we could find the most likely alignments greedily by taking the word pairs with the largest probability

$$a_i = \arg\max_{j \in [0,l]} p(a_i \mid i, l, m)$$

Expectation-Maximization (EM) Algorithm

- Pick some random (or uniform) starting parameters (i.e., counts)
- Repeat until converged

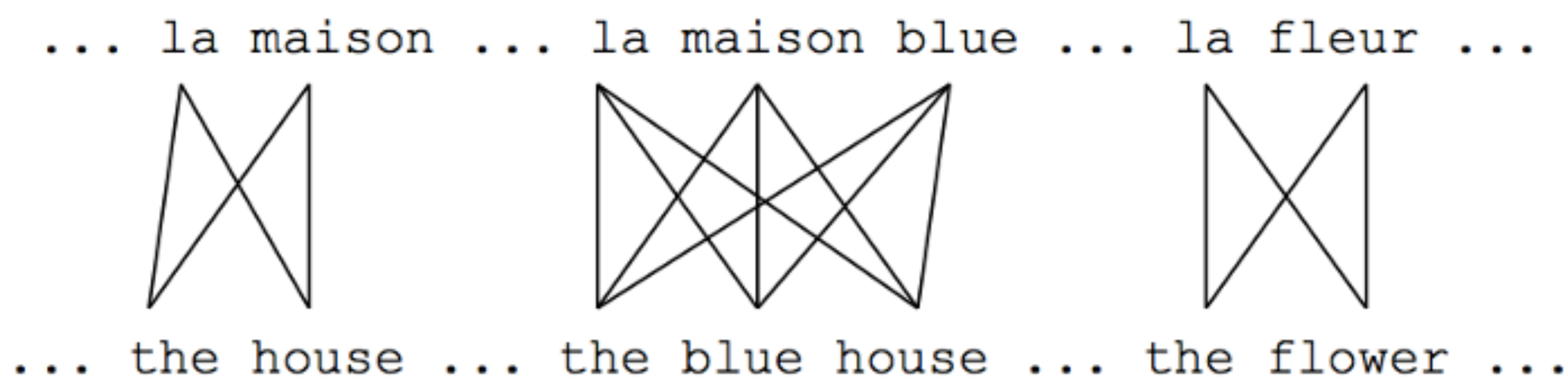
1. **E- Step**: use the current parameters to compute "expected" alignments

2. Update the no. of times e_{a_i} is translated to f_i i.e., count(e_{a_i}, f_i), and keep track of no. of times e_{a_i} is used in the training corpus count(e_{a_i}).

3. **M-Step:** use MLE to update translation probability

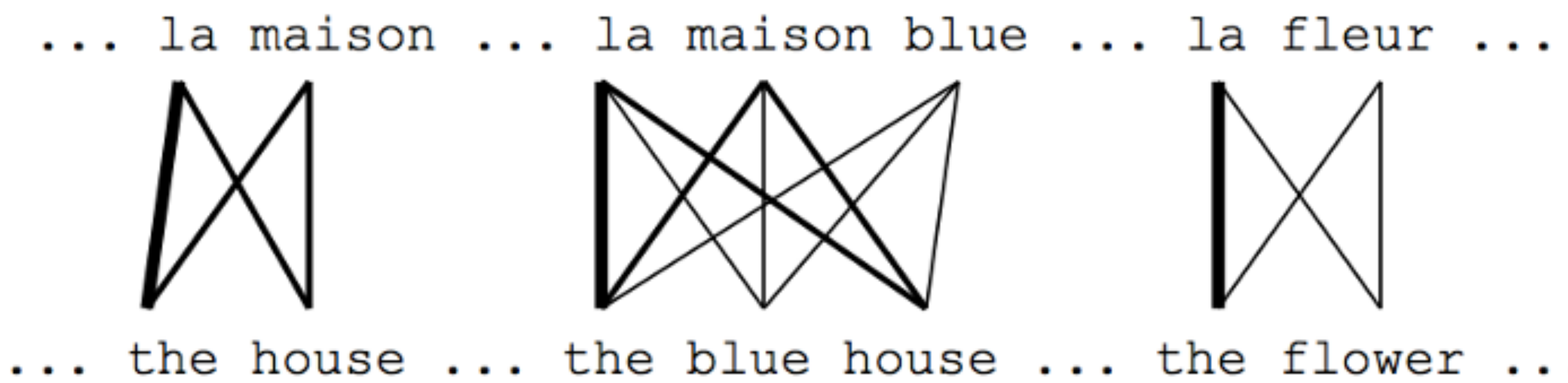
$$p(f_i \mid e_{a_i}) = \frac{\text{count}(f_i, e_{a_i})}{\text{count}(e_{a_i})}$$

EM for IBM Model 1



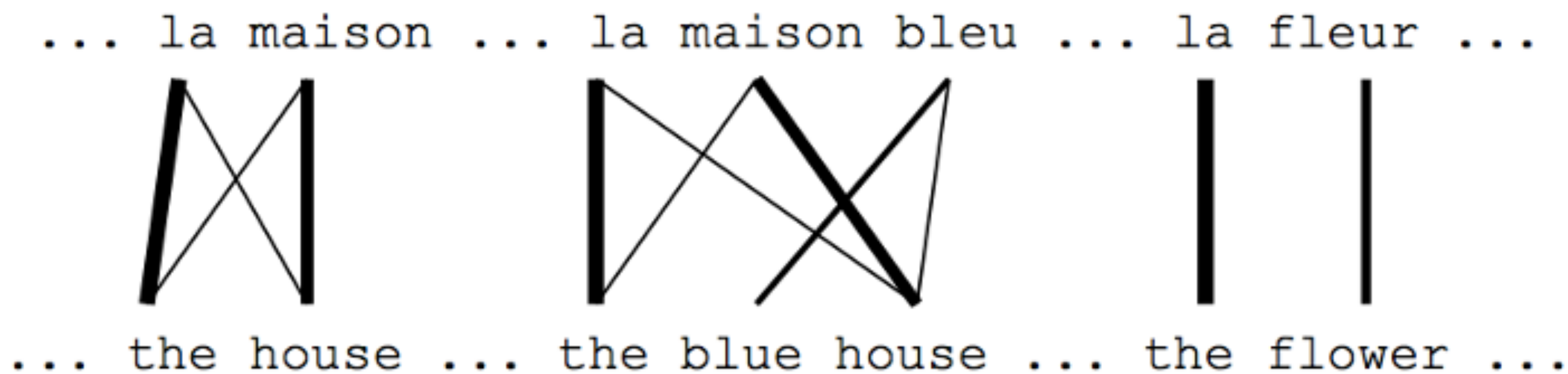
- Initial step: all alignments equally likely
- Model learns that, e.g., la is often aligned with the

EM for IBM Model 1



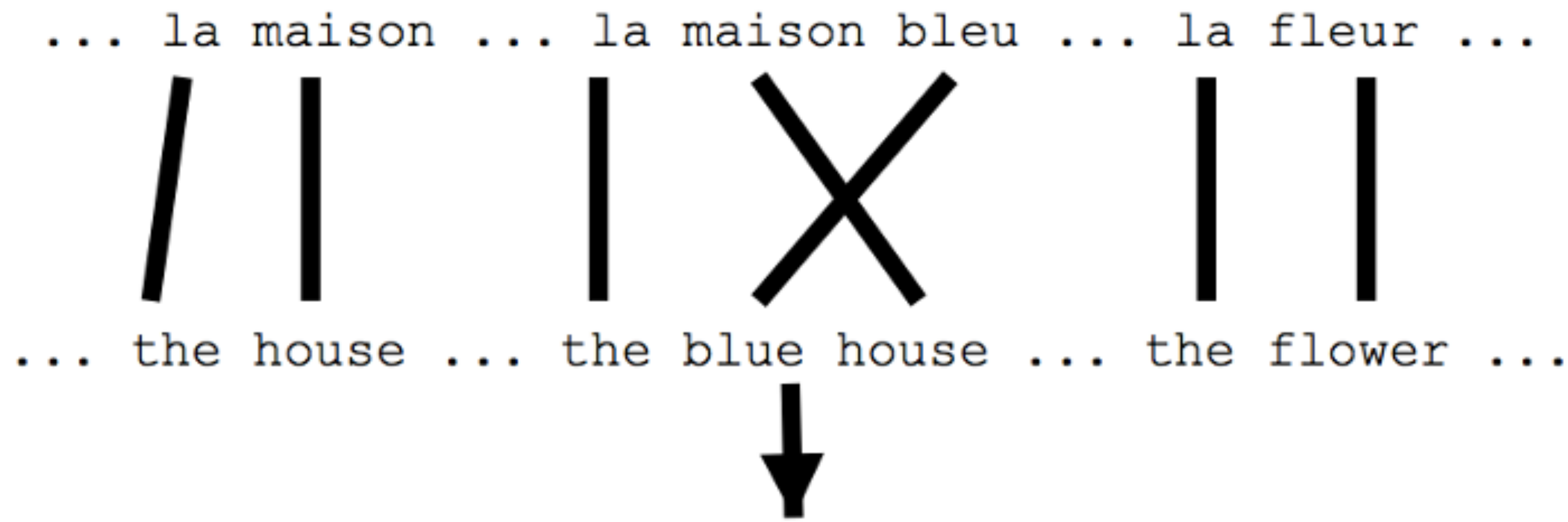
- After one iteration
- Alignments, e.g., between la and the are more likely

EM for IBM Model 1



- After another iteration
- It becomes apparent that alignments, e.g., between fleur and flower are more likely (pigeon hole principle)

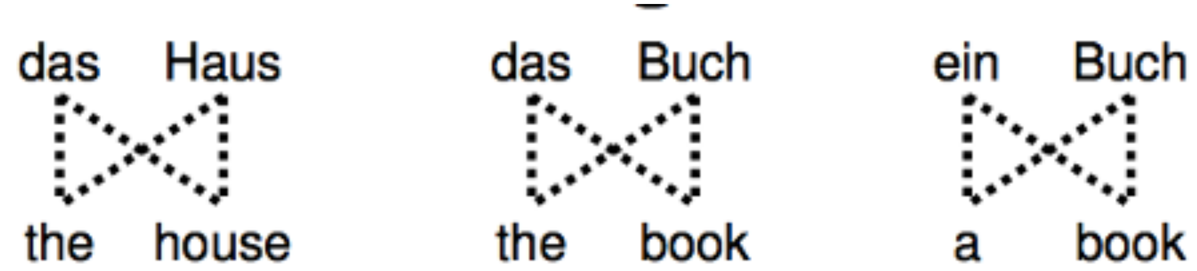
EM for IBM Model 1




```
p(la|the) = 0.453
p(le|the) = 0.334
p(maison|house) = 0.876
p(bleu|blue) = 0.563
...
```

- Parameter estimation from the aligned corpus

Convergence



e	f	initial	1st it.	2nd it.	3rd it.	...	final
the	das	0.25	0.5	0.6364	0.7479	...	1
book	das	0.25	0.25	0.1818	0.1208	...	0
house	das	0.25	0.25	0.1818	0.1313	...	0
the	buch	0.25	0.25	0.1818	0.1208	...	0
book	buch	0.25	0.5	0.6364	0.7479	...	1
a	buch	0.25	0.25	0.1818	0.1313	...	0
book	ein	0.25	0.5	0.4286	0.3466	...	0
a	ein	0.25	0.5	0.5714	0.6534	...	1
the	haus	0.25	0.5	0.4286	0.3466	...	0
house	haus	0.25	0.5	0.5714	0.6534	...	1

Whole Pipeline of SMT

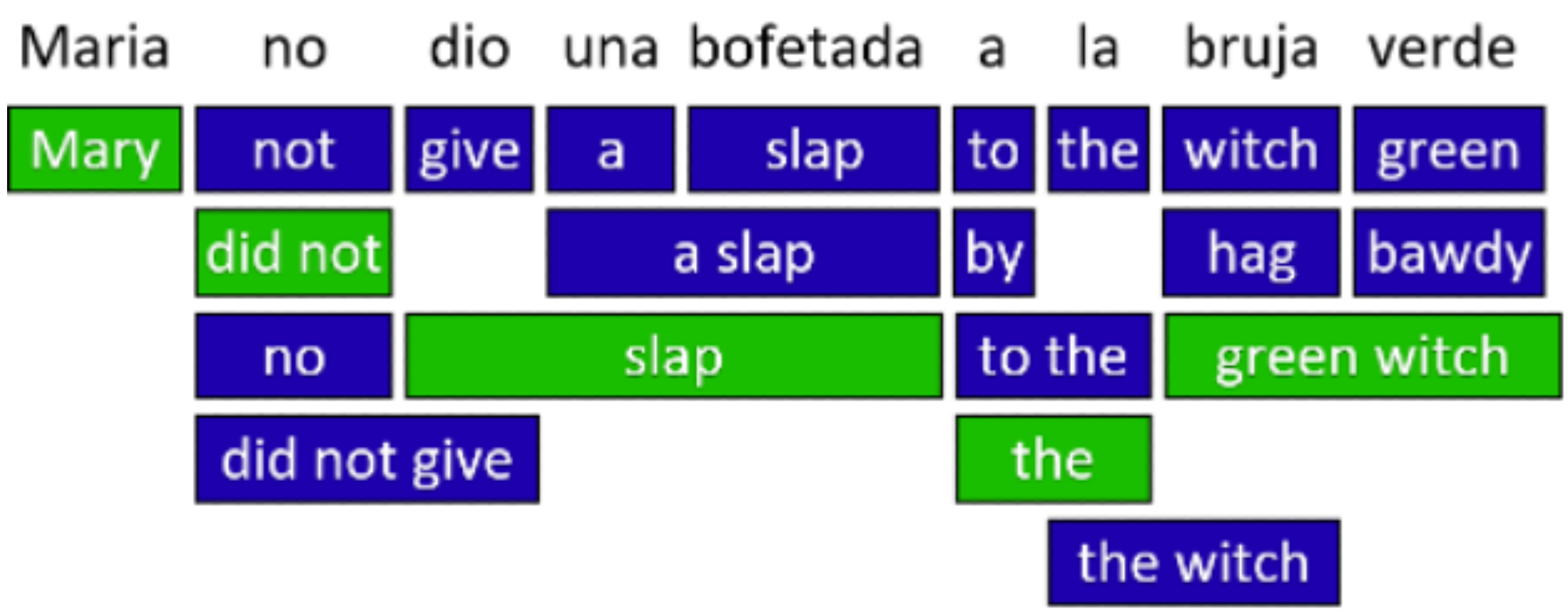
- Moses (Koehn 2009)

1 Prepare data
2 Run GIZA
3 Align words
4 Lexical translation
5 Extract phrases
6 Score phrases
7 Reordering model
8 Generation model
9 Configuration file

EM algorithms to align & translate words

Extensions: Lexical to Phrase Translation

- Phrase-based MT:
  - Allow multiple words to translate as chunks (including many-to-one)
  - Introduce **another latent variable**, the **source segmentation**



Adapted from Koehn (2006)

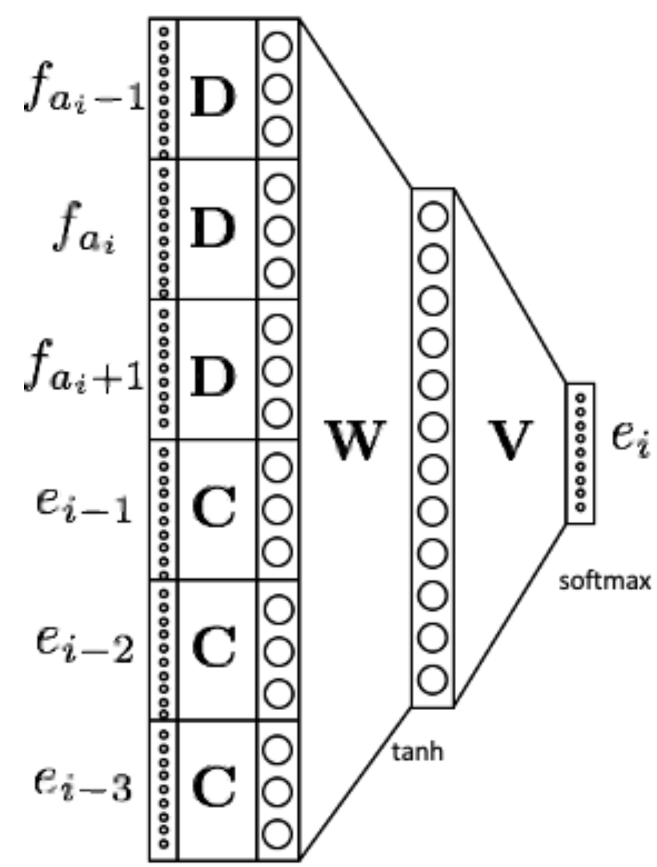
Neural Machine Translation

Neural Features for Translation

- Inspired by Neural n-gram LMs, use a conditional model to generate the next English word conditioned on
    - The previous *n* English words that have been generated
    - The aligned source word and its *m* neighbors

$$p(\mathbf{e} \mid \mathbf{f}, \mathbf{a}) = \prod_{i=1}^{|\mathbf{e}|} p(e_i \mid e_{i-2}, e_{i-1}, f_{a_i-1}, f_{a_i}, f_{a_i+1})$$

$$p(e_i \mid e_{i-2}, e_{i-1}, f_{a_i-1}, f_{a_i}, f_{a_i+1}) =$$



Devlin et al. 2014

Neural Features for Translation

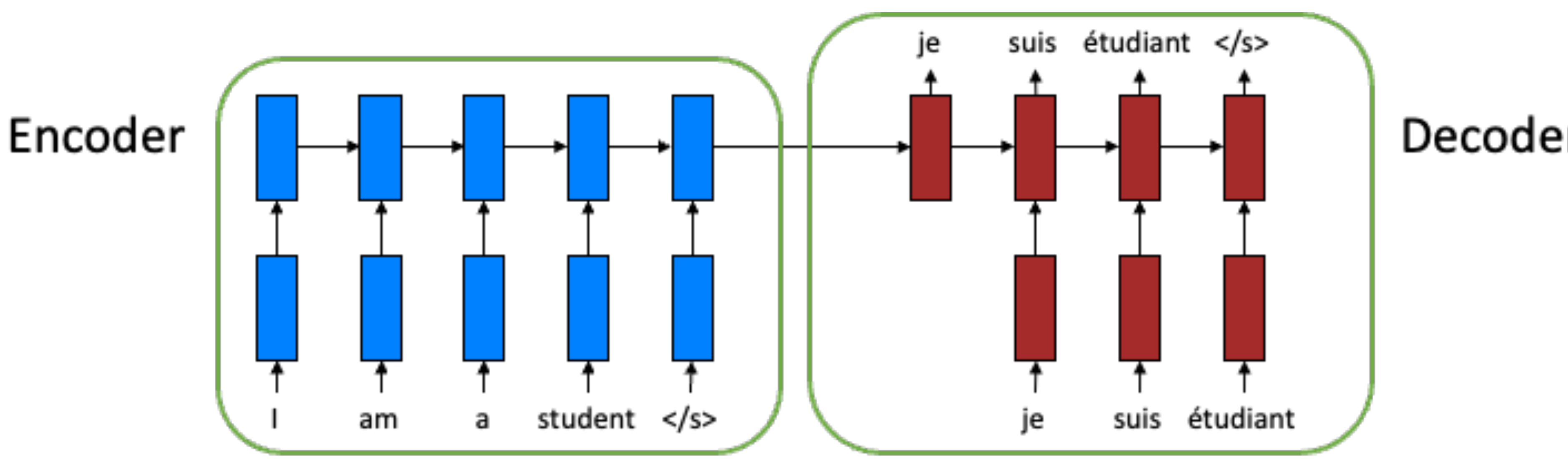
- Word alignment is still needed.
- Improves over SMT

BOLT Test		
	Ar-En	
	BLEU	% Gain
"Simple Hier." Baseline	33.8	-
S2T/L2R NNJM (Dec)	38.4	100%
Source Window=7	38.3	98%
Source Window=5	38.2	96%
Source Window=3	37.8	87%
Source Window=0	35.3	33%
Layers=384x768x768	38.5	102%
Layers=192x512	38.1	93%
Layers=128x128	37.1	72%
Vocab=64,000	38.5	102%
Vocab=16,000	38.1	93%
Vocab=8,000	37.3	83%
Activation=Rectified Lin.	38.5	102%
Activation=Linear	37.3	76%

Devlin et al. 2014

Fully Neural Translation

- Fully end-to-end RNN-based MT model
- Encode the source sentence using one RNN
- Generate the target sentence one word at a time using another RNN



Sutskever et al. 2014

Attention MT Models

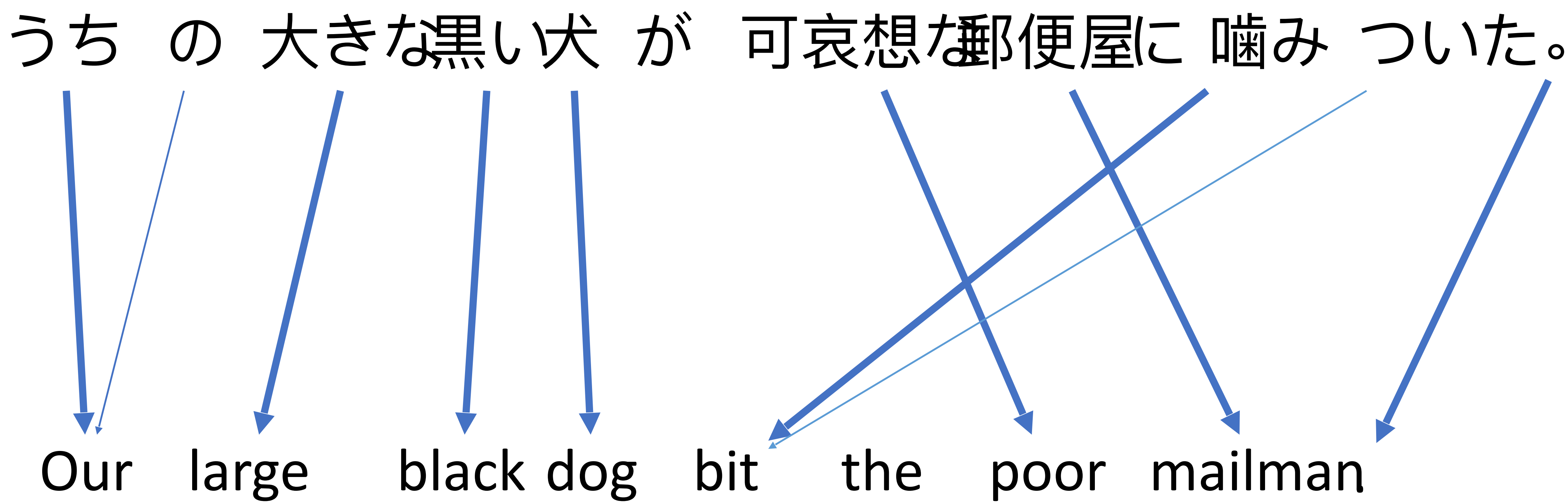
- The encoder-decoder model struggles with long sentences

- An RNN is trying to compress an arbitrarily long sentence into a finite-length word vector

- What if we only look at one (or a few) source words when we generate each output word?

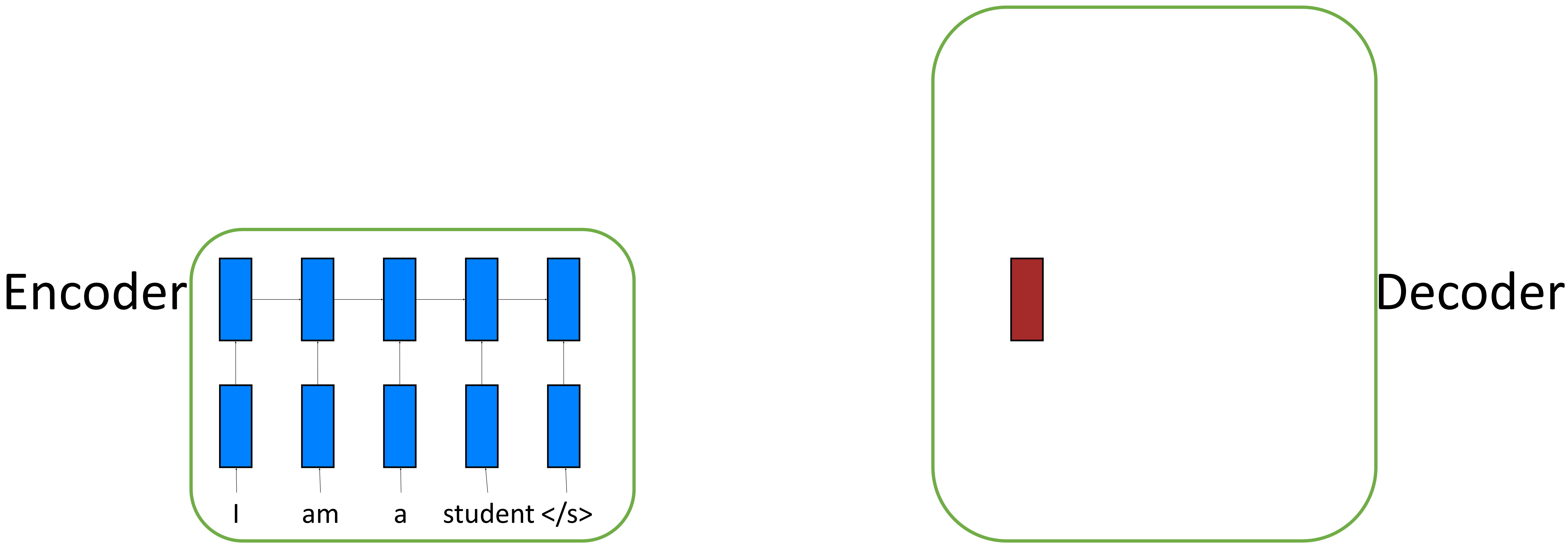
Bahdanau et al. 2014

Intuition



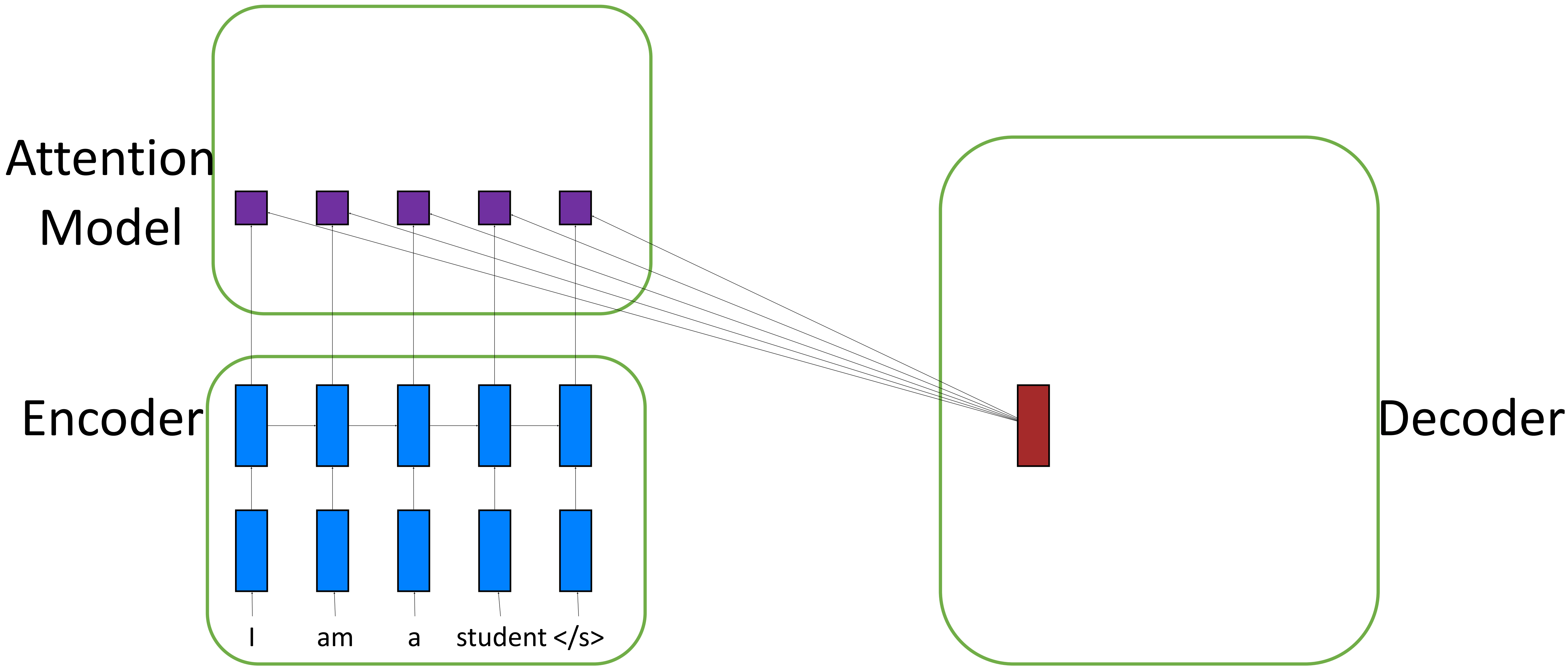
Bahdanau et al. 2014

Attention MT Models



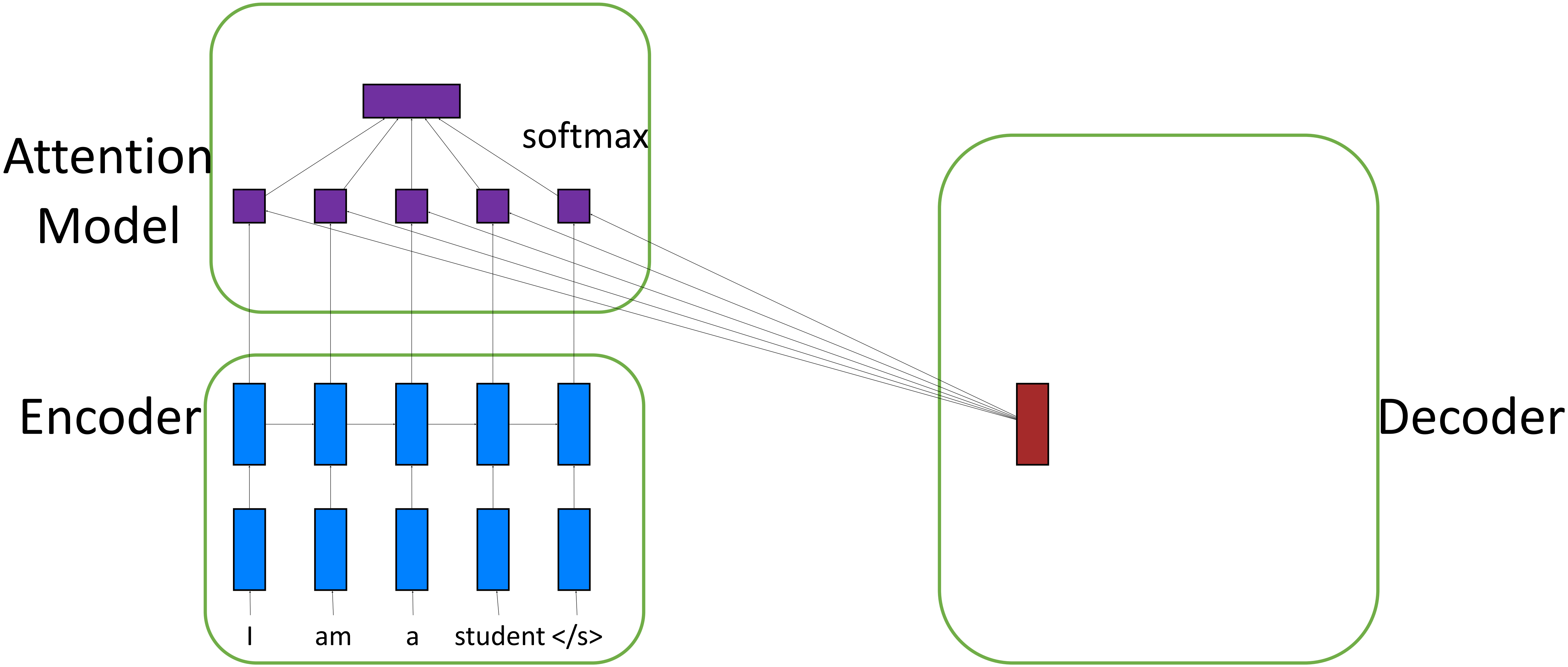
Bahdanau et al. 2014

Attention MT Models



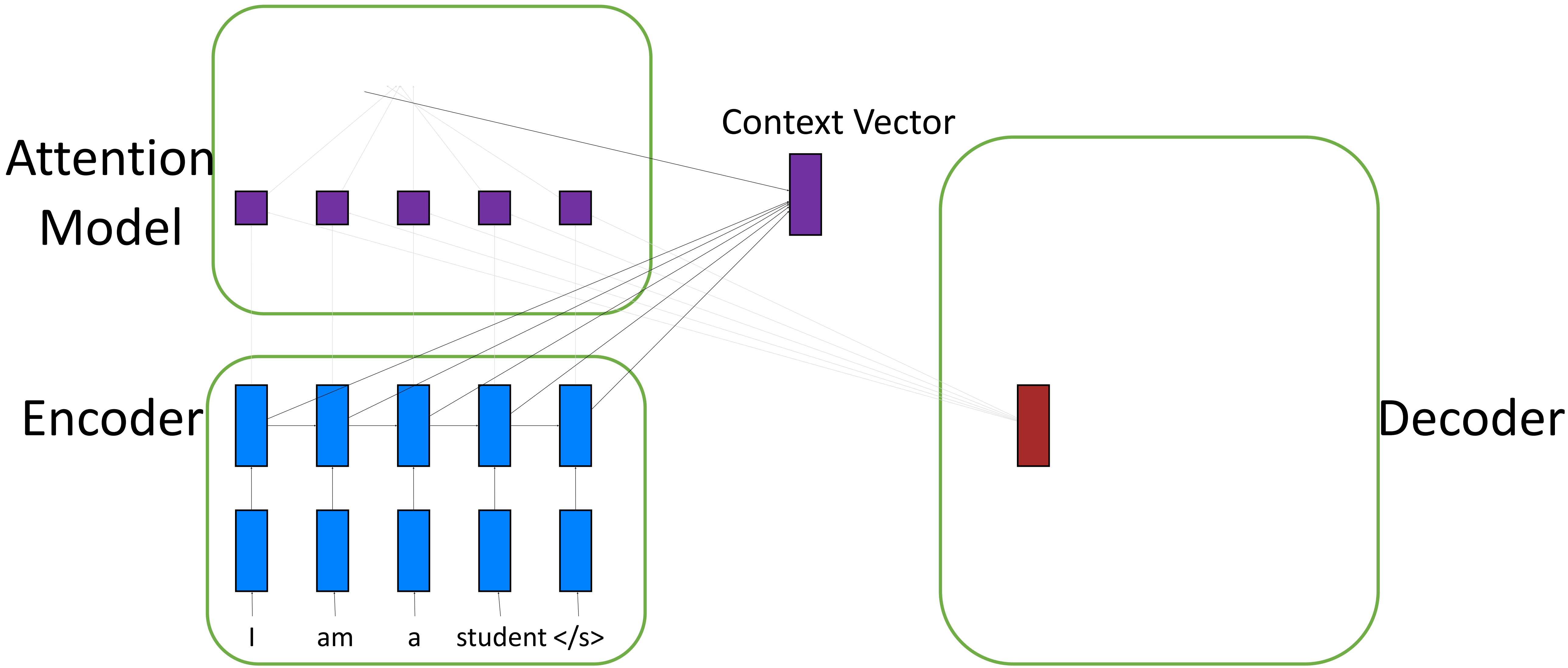
Bahdanau et al. 2014

Attention MT Models



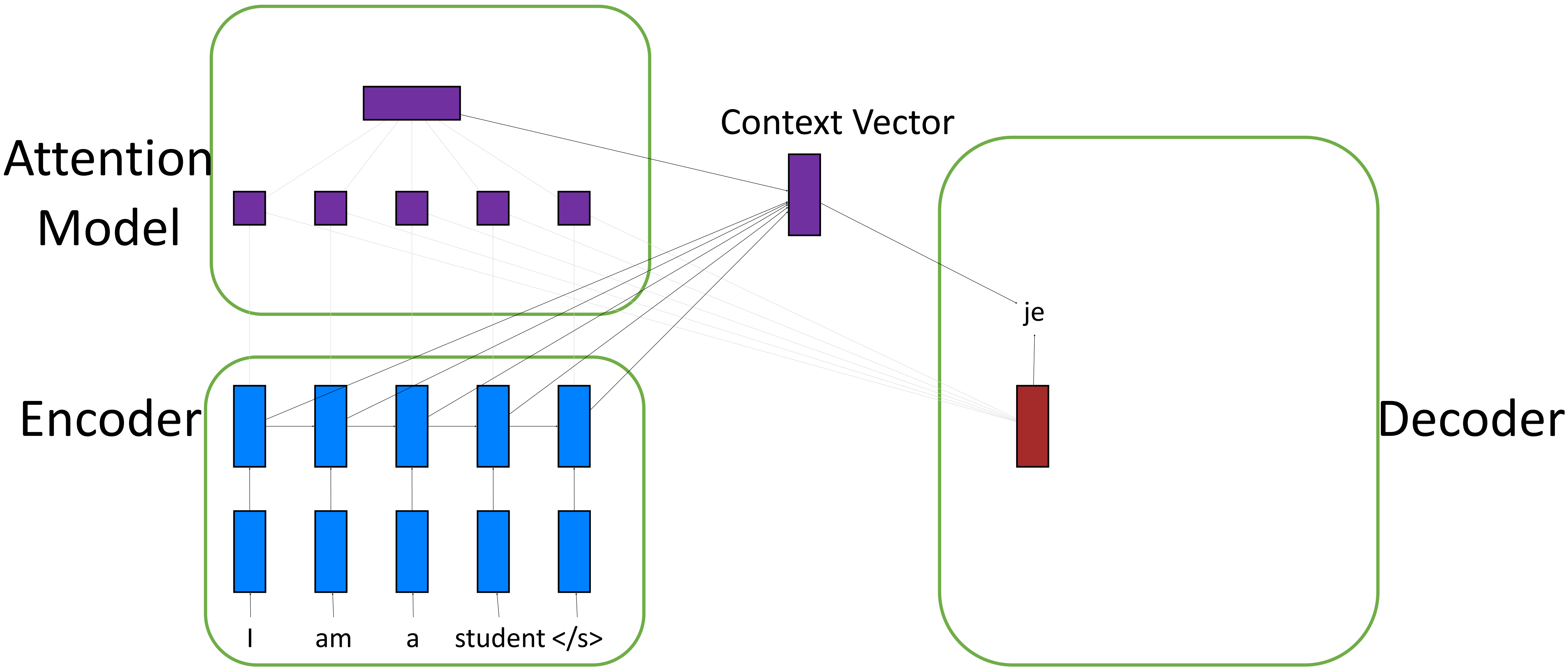
Bahdanau et al. 2014

Attention MT Models



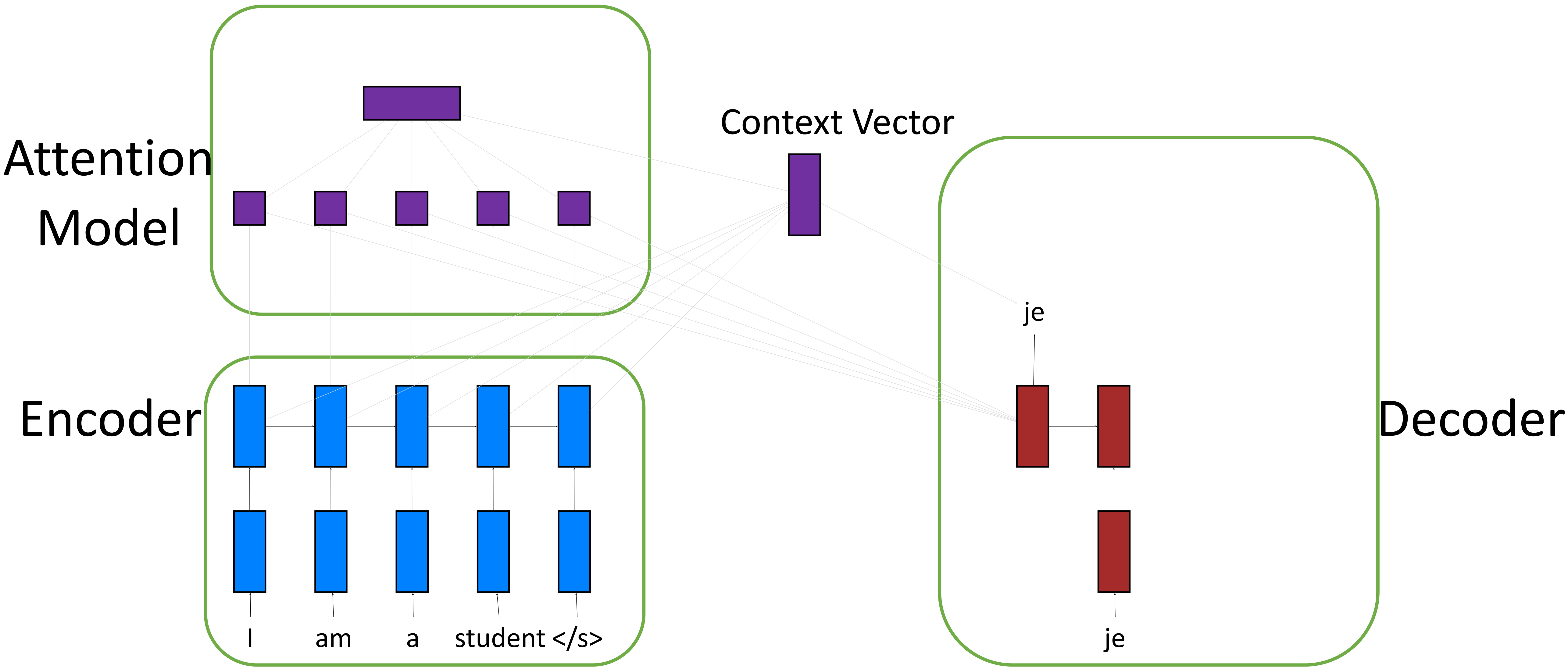
Bahdanau et al. 2014

Attention MT Models



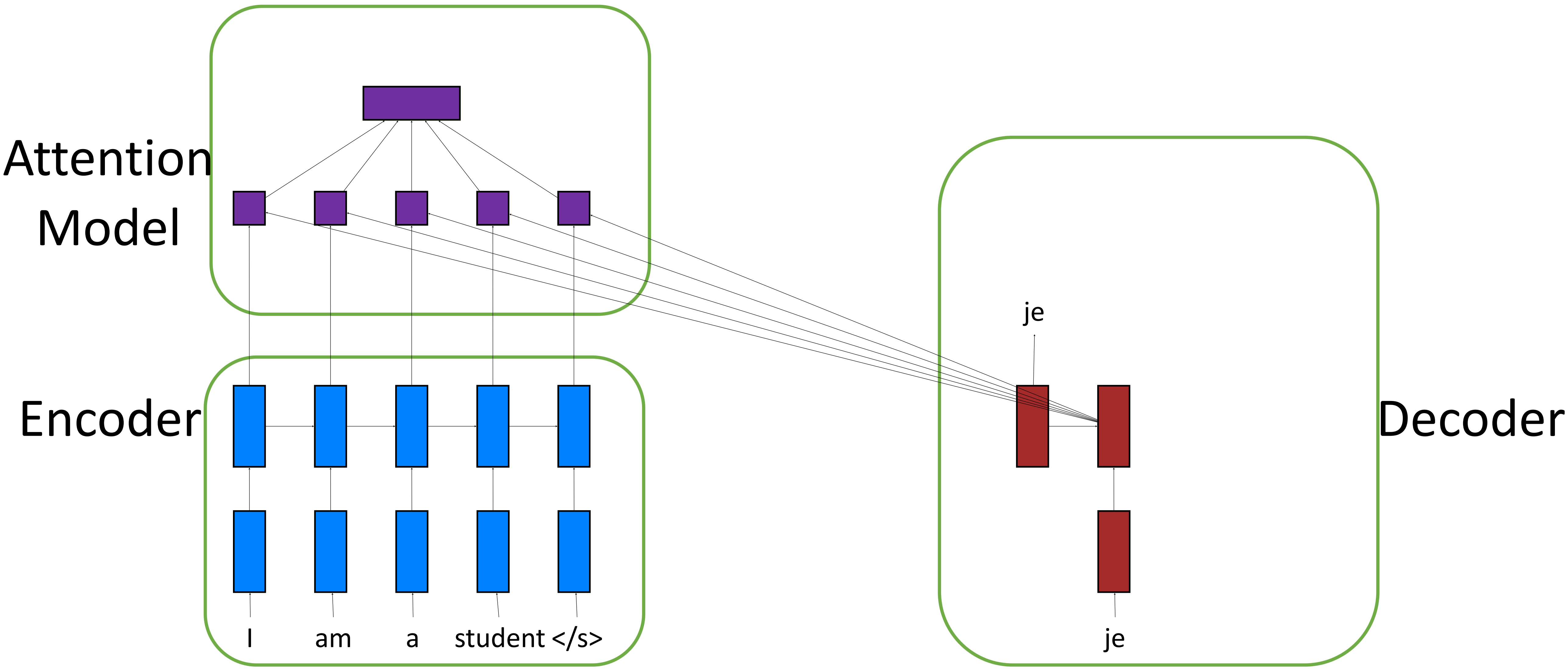
Bahdanau et al. 2014

Attention MT Models



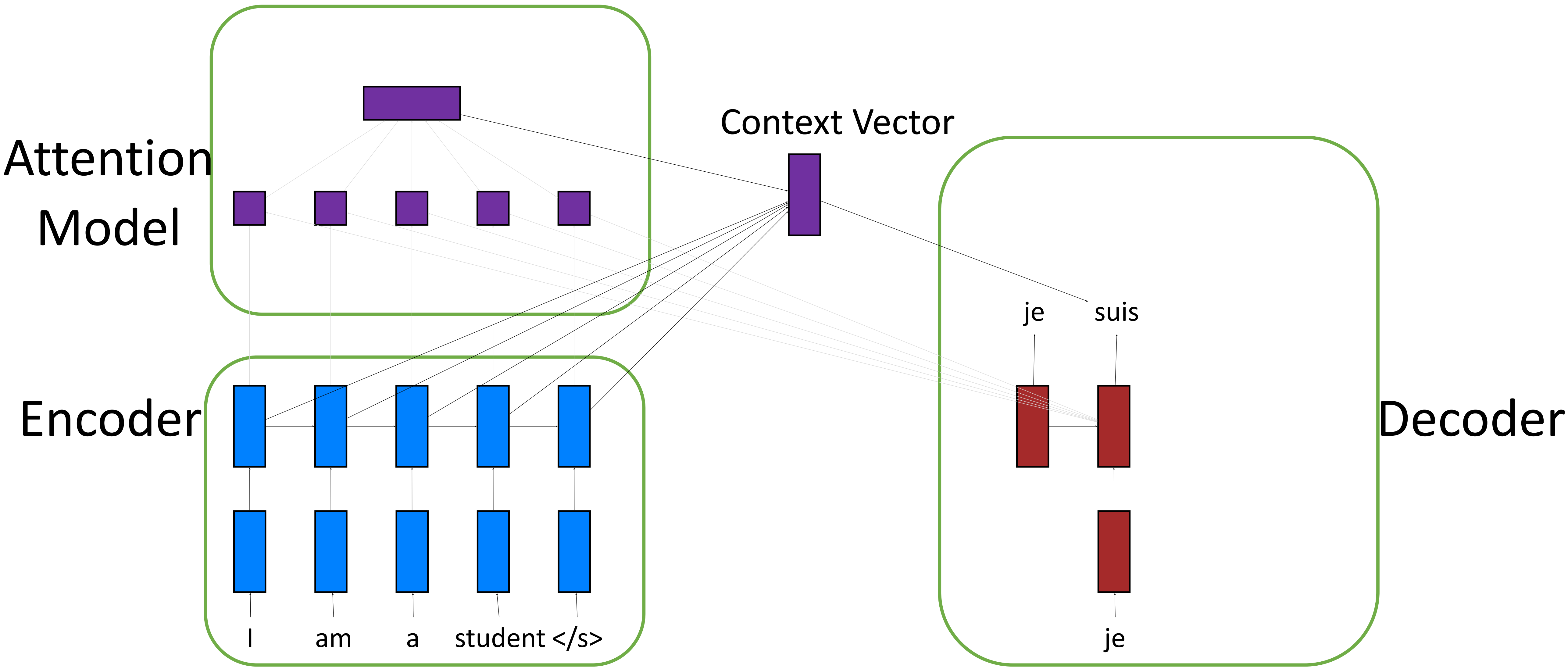
Bahdanau et al. 2014

Attention MT Models



Bahdanau et al. 2014

Attention MT Models



Bahdanau et al. 2014

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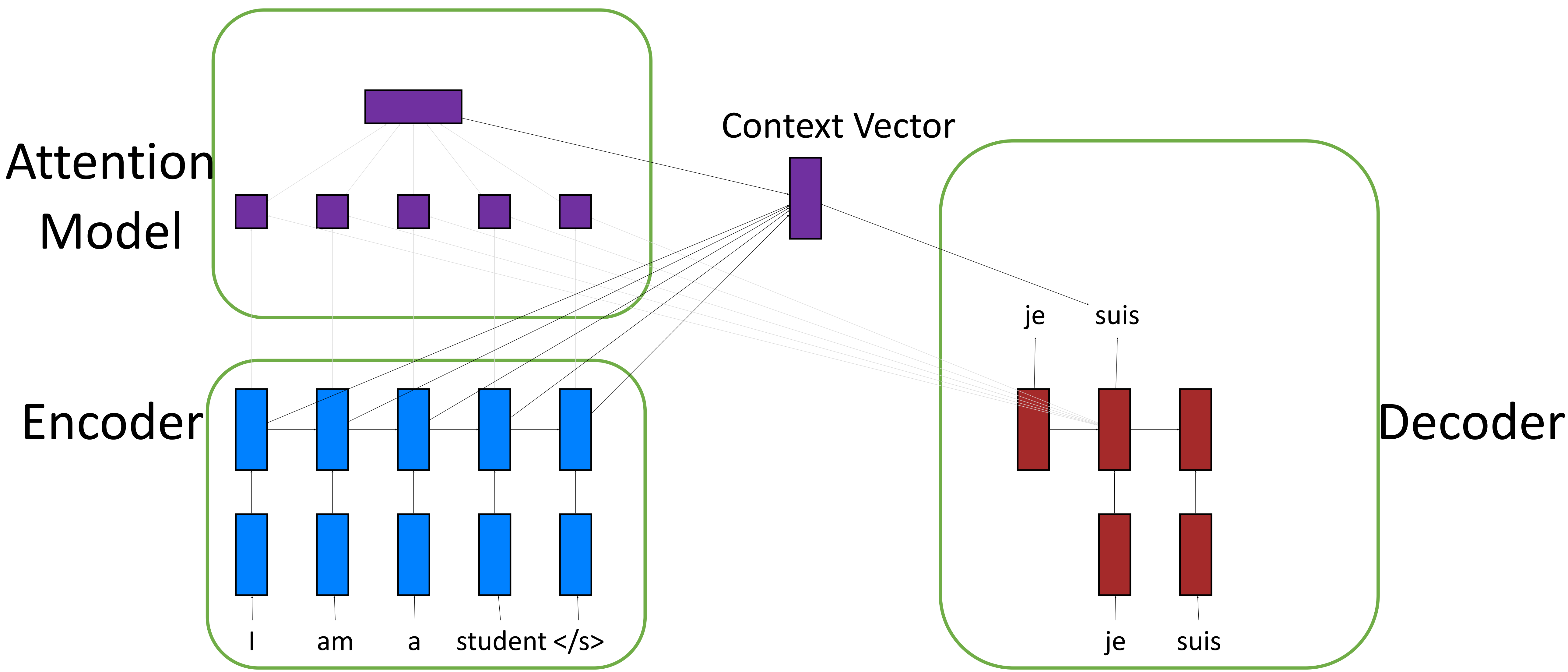
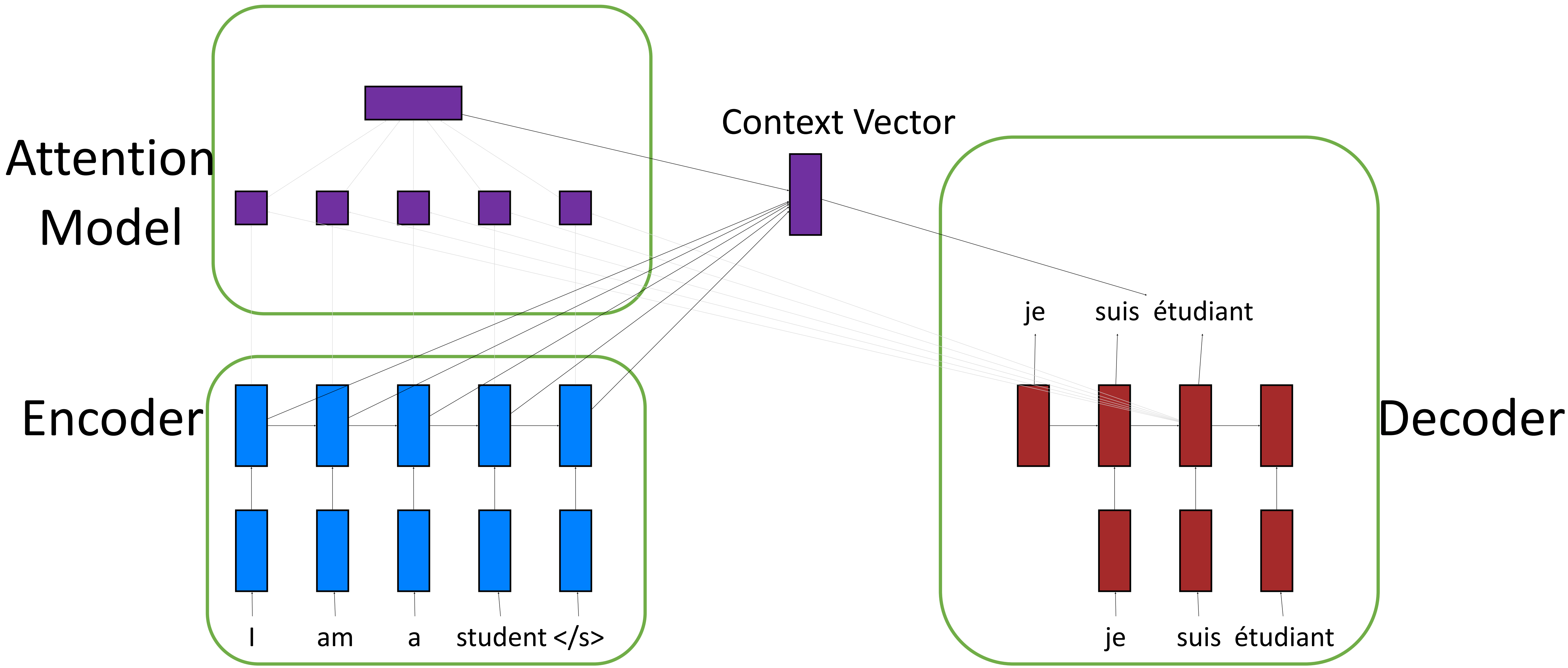


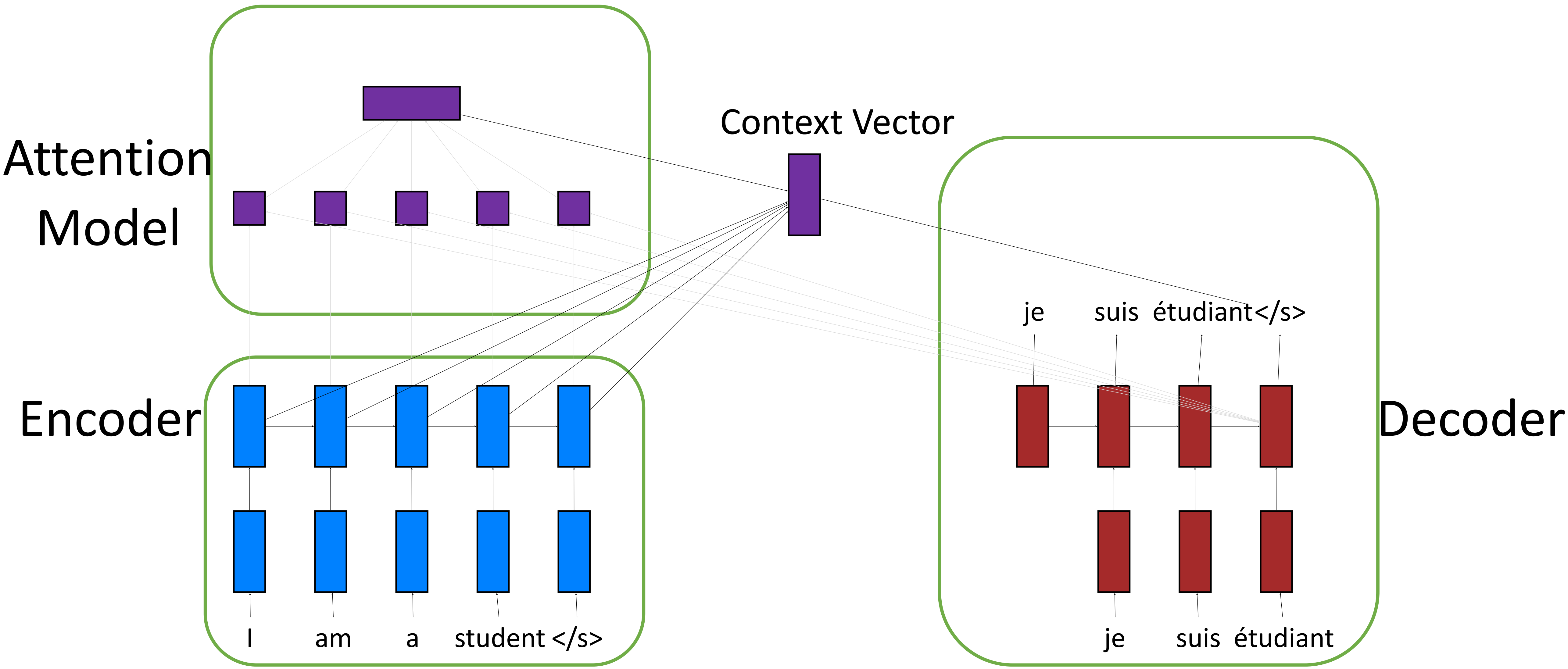
Bahdanau et al. 2014

Attention MT Models



Bahdanau et al. 2014

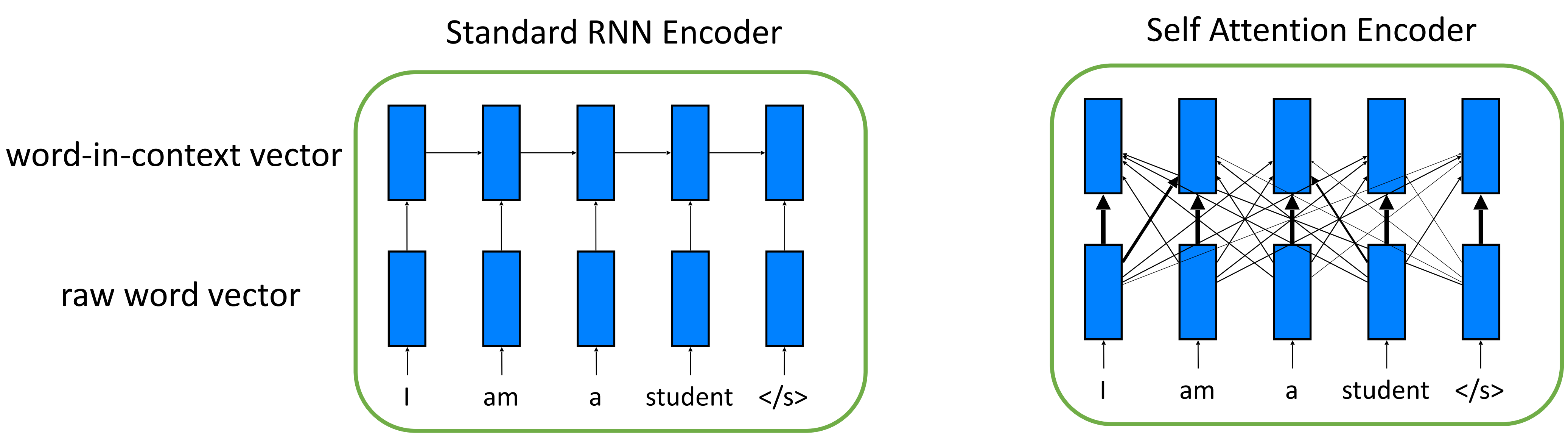
Attention MT Models



Bahdanau et al. 2014

Transformer

- Idea: Instead of using an RNN to encode the source sentence and the partial target sentence, use self-attention!



Vaswani et al. 2017

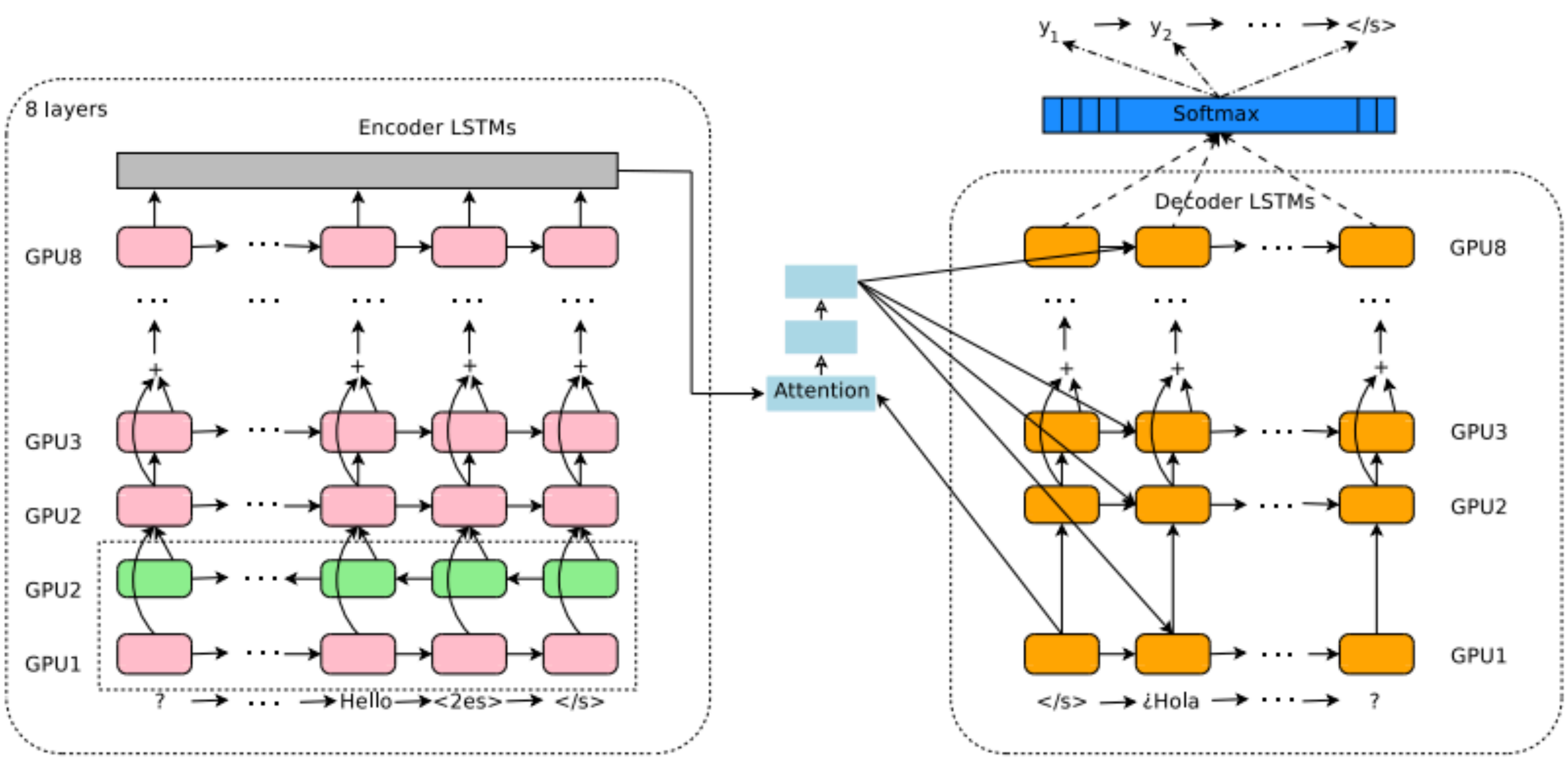
Transformer

- Computation is easily parallelizable
- Shorter path from each target word to each source word -> stronger gradient signals
- Empirically stronger translation performance
- Empirically trains substantially faster than more serial models

Model	BLEU		Training Cost (FLOPs)	
	EN-DE	EN-FR	EN-DE	EN-FR
ByteNet [17]	23.75			
Deep-Att + PosUnk [37]		39.2		$1.0 \cdot 10^{20}$
GNMT + RL [36]	24.6	39.92	$2.3 \cdot 10^{19}$	$1.4 \cdot 10^{20}$
ConvS2S [9]	25.16	40.46	$9.6 \cdot 10^{18}$	$1.5 \cdot 10^{20}$
MoE [31]	26.03	40.56	$2.0 \cdot 10^{19}$	$1.2 \cdot 10^{20}$
Deep-Att + PosUnk Ensemble [37]		40.4		$8.0 \cdot 10^{20}$
GNMT + RL Ensemble [36]	26.30	41.16	$1.8 \cdot 10^{20}$	$1.1 \cdot 10^{21}$
ConvS2S Ensemble [9]	26.36	**41.29**	$7.7 \cdot 10^{19}$	$1.2 \cdot 10^{21}$
Transformer (base model)	27.3	38.1	$\mathbf{3.3 \cdot 10^{18}}$	
Transformer (big)	**28.4**	**41.0**	$2.3 \cdot 10^{19}$	

Google's Multilingual NMT

- Stack 8-layers of LSTM encoder, and 8-layers of LSTM decoder
- Only use the last layer of encoder LSTM to perform target-to-source attention -> Re-use the context vector for each decoder layer
- Use the language code to indicate which target language to translate



Johnson et al. 2016

Google's Multilingual NMT

- Add the target language code to the start of the source sentence, which enables sharing parameters for different language pairs (**many-to-one, one-to-many, zero-shot translation**)

```
Hello, how are you? -> Hola, ¿cómo estás?

<2es> Hello, how are you? -> Hola, ¿cómo estás?
```

Table 5: Portuguese→Spanish BLEU scores using various models.

	Model	Zero-shot	BLEU
(a)	PBMT bridged	no	28.99
(b)	NMT bridged	no	30.91
(c)	NMT Pt→Es	no	31.50
(d)	Model 1 (Pt→En, En→Es)	yes	21.62
(e)	Model 2 (En↔{Es, Pt})	yes	24.75
(f)	Model 2 + incremental training	no	31.77

Johnson et al. 2016

Google's Multilingual NMT

- Interpolate the language code embeddings

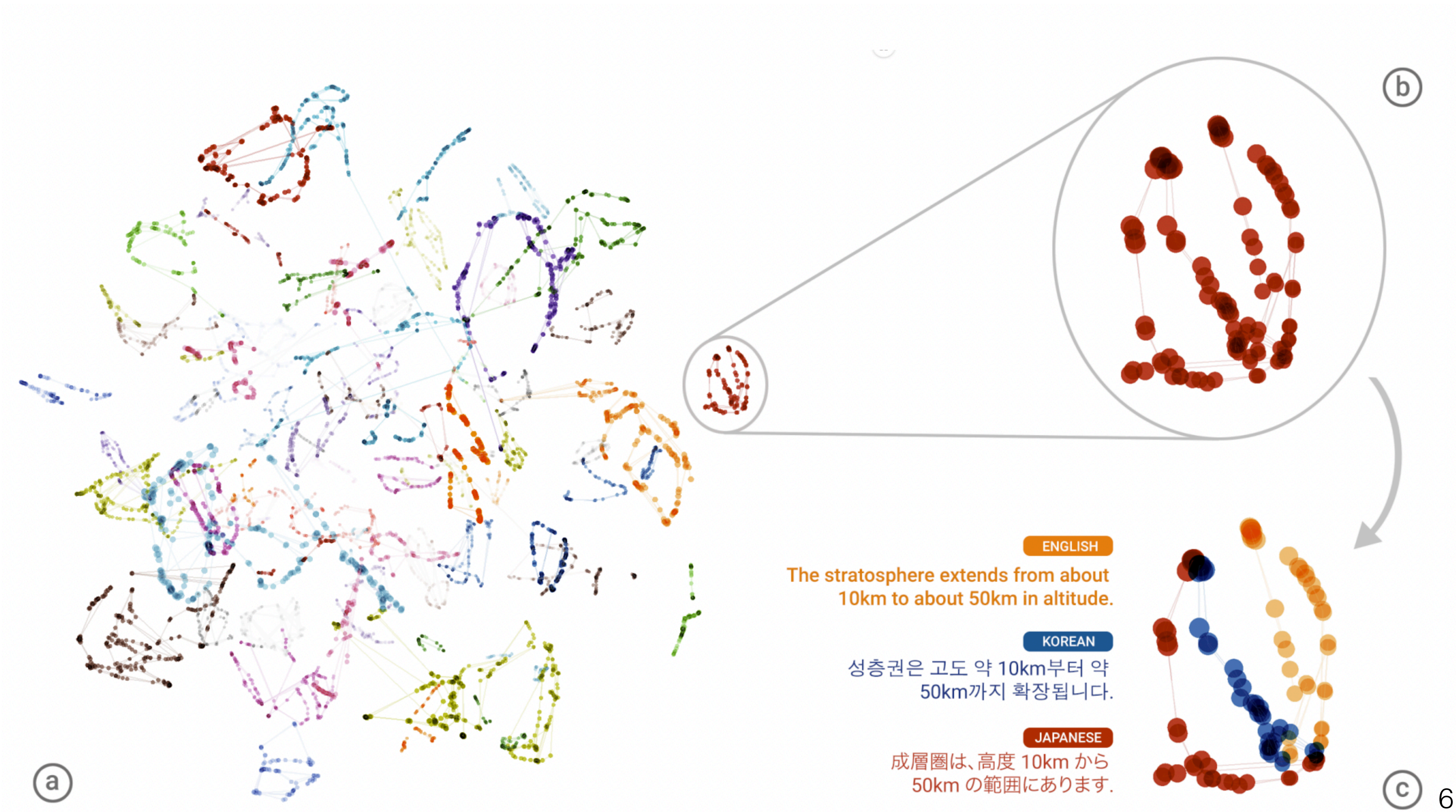
$$(1 - w)<\text{2ja}> + w<\text{2ko}>$$

Russian/Belarusian:	I wonder what they'll do next!
$w_{be} = 0.00$	Интересно, что они сделают дальше!
$w_{be} = 0.20$	Интересно, что они сделают дальше!
$w_{be} = 0.30$	Цікаво, что они будут делать дальше!
$w_{be} = 0.44$	Цікаво, що вони будуть робити далі!
$w_{be} = 0.46$	Цікаво, що вони будуть робити далі!
$w_{be} = 0.48$	Цікаво, што яны зробяць далей!
$w_{be} = 0.50$	Цікава, што яны будуць рабіць далей!
$w_{be} = 1.00$	Цікава, што яны будуць рабіць далей!

Japanese/Korean:	I must be getting somewhere near the centre of the earth.
$w_{ko} = 0.00$	私は地球の中心の近くにどこかに行っているに違いない。
$w_{ko} = 0.40$	私は地球の中心近くのどこかに着いているに違いない。
$w_{ko} = 0.56$	私は地球の中心の近くのどこかになっているに違いない。
$w_{ko} = 0.58$	私は지구の中心의가까이에어딘가에도착하고있어야한다。
$w_{ko} = 0.60$	나는지구의센터의가까이에어딘가에도착하고있어야한다。
$w_{ko} = 0.70$	나는지구의중심근처어딘가에도착해야합니다。
$w_{ko} = 0.90$	나는어딘가지구의중심근처에도착해야합니다。
$w_{ko} = 1.00$	나는어딘가지구의중심근처에도착해야합니다。

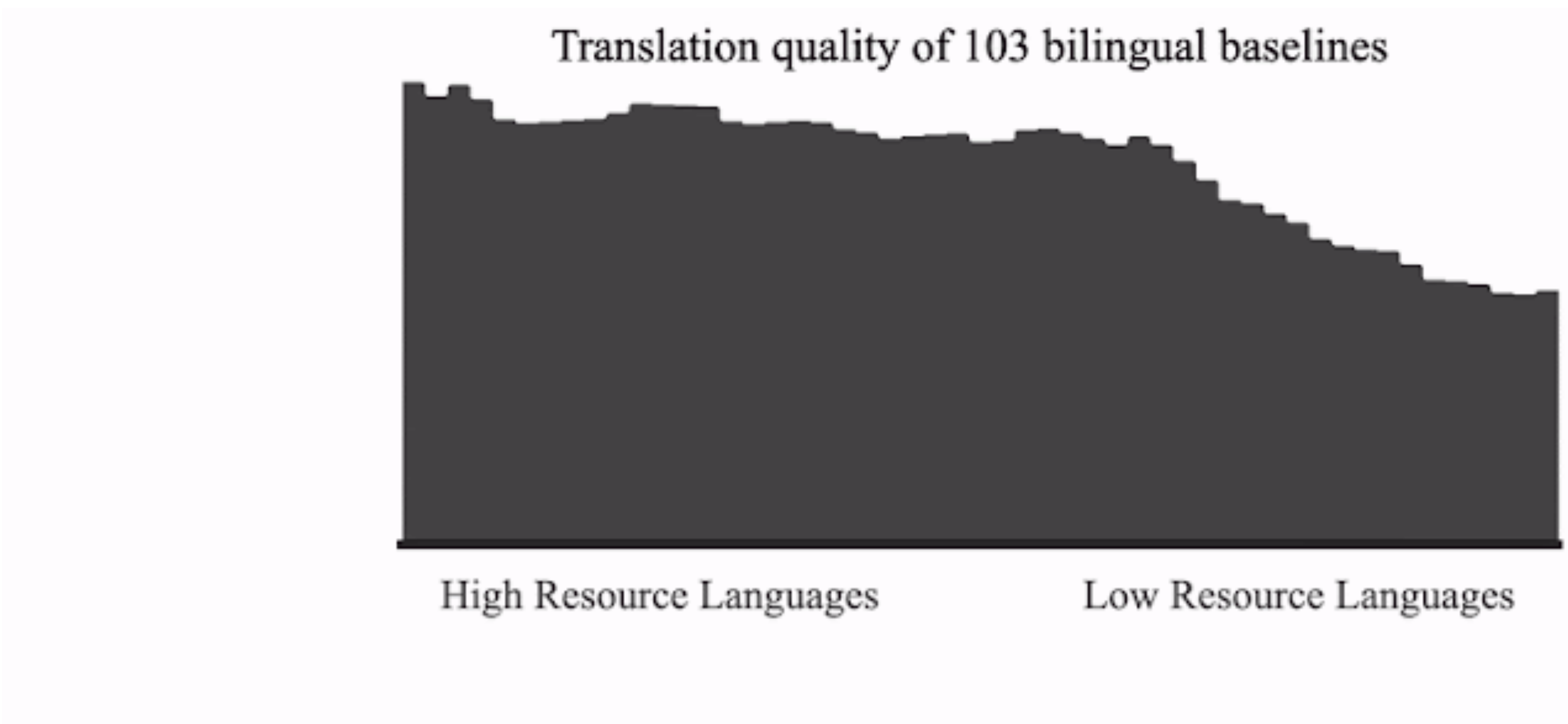
Google's Multilingual NMT

- Sentence embeddings learned by MNMT are clustered by languages

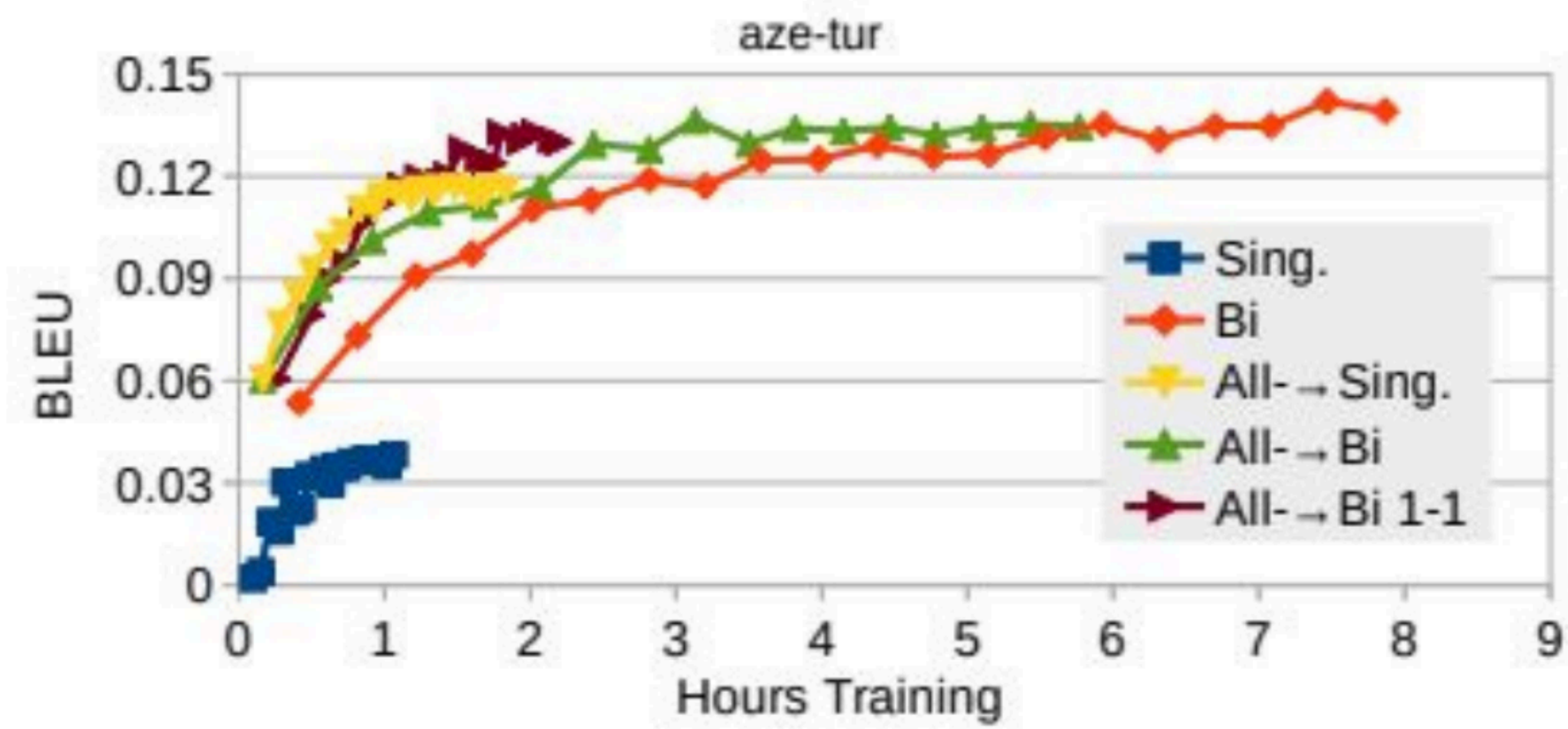


Multilingual vs Bilingual

- Multilingual NMT especially improves low-resource language translation



Rapid Adaptation to New Languages

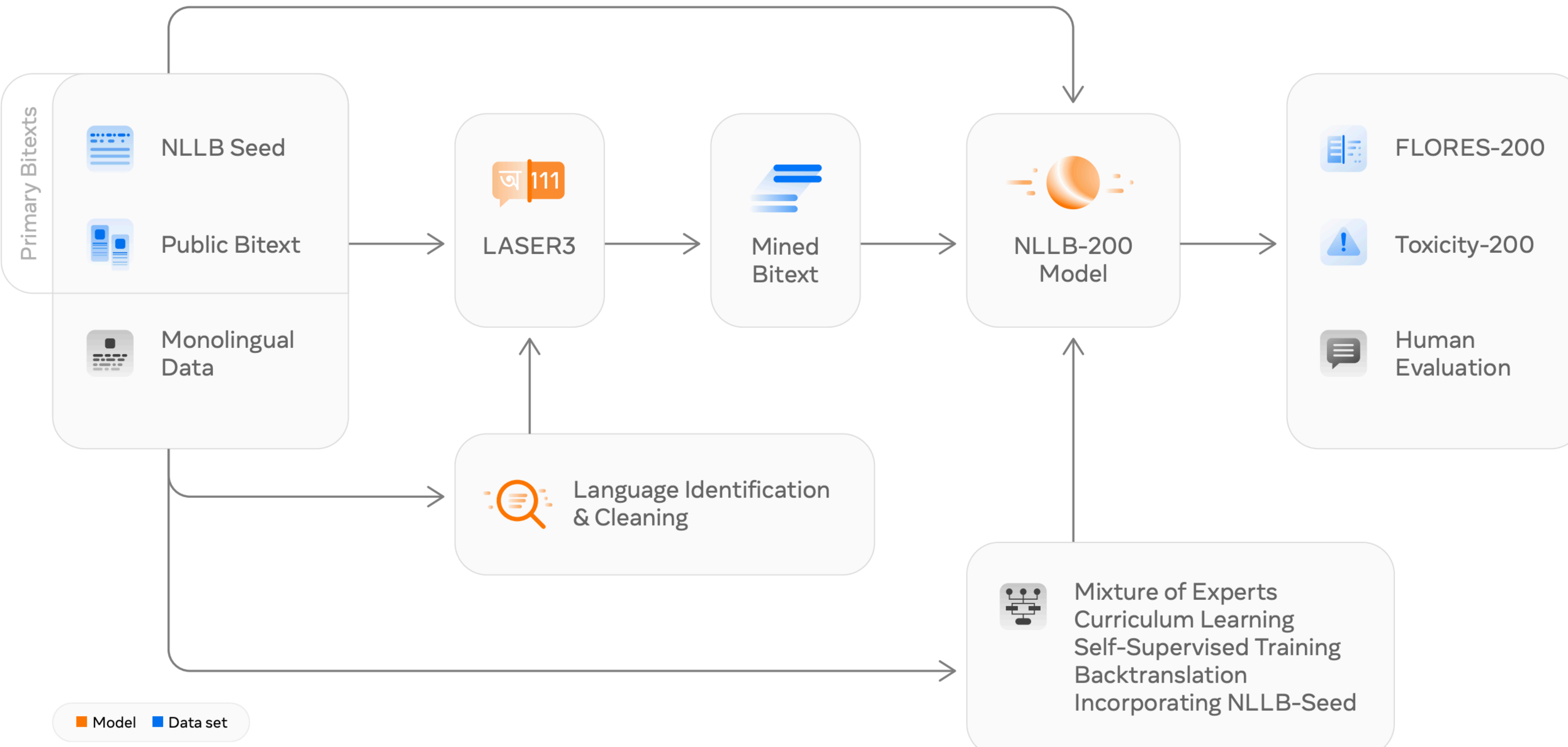


- ➔ All- -> xx models: adapting from a multilingual makes convergence faster
- ➔ Regularized fine-tuning leads to better final performance

Rapid adaptation of Neural Machine Translation to New Languages. Neubig and Hu. 2018

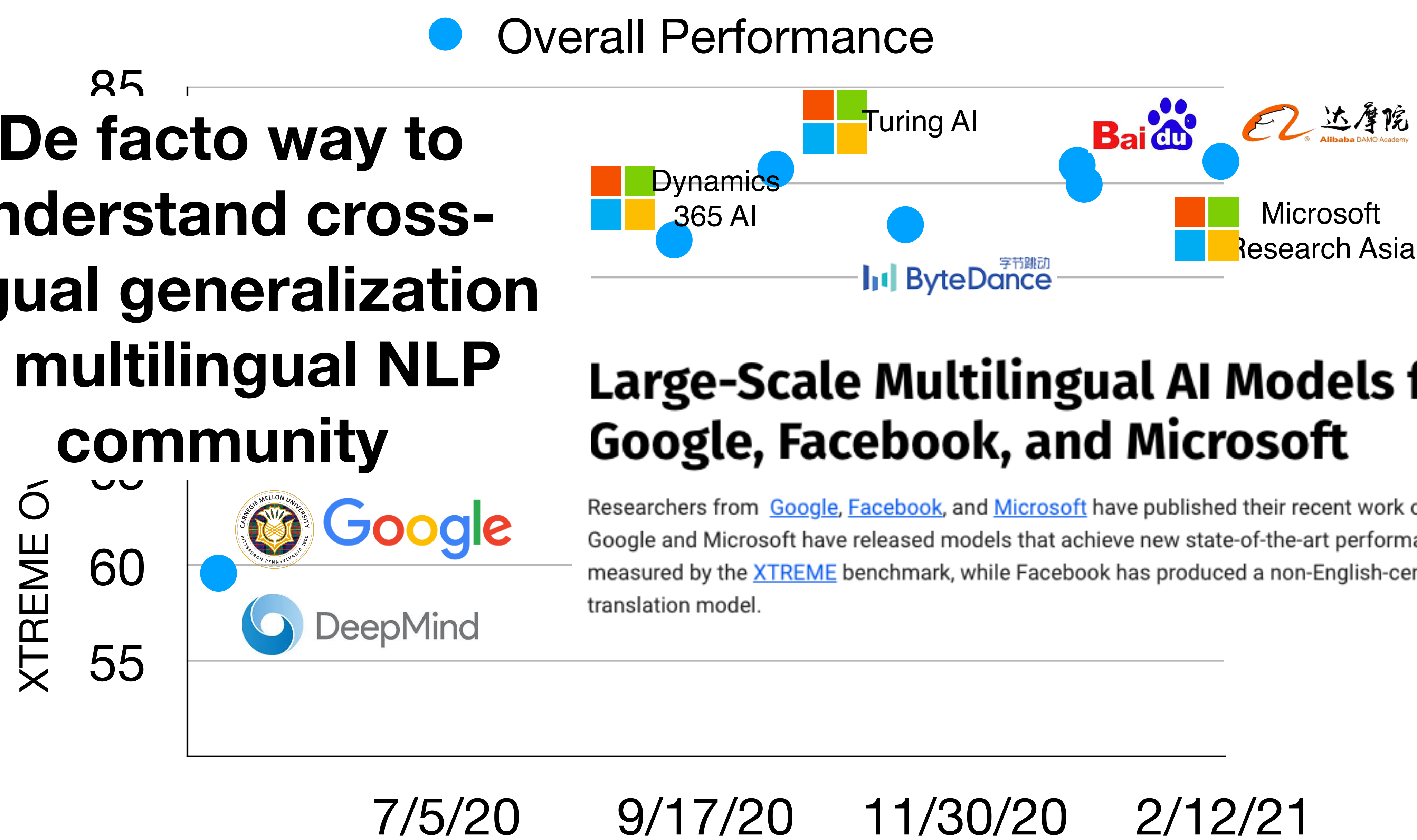
Supervised NMT: NLLB

- SOTA encoder-decoder MT models over 40,000 translation directions
- 3.3 B & 1.3 B Transformer model + mixture of experts (MOE)



No Language Left Behind: Scaling Human-Centered Machine Translation
https://github.com/facebookresearch/fairseq/tree/nllb

XTREME: Massive Zero-shot Cross-lingual Transfer Learning



De facto way to understand cross-lingual generalization in multilingual NLP community

Large-Scale Multilingual AI Models from Google, Facebook, and Microsoft

Researchers from Google, Facebook, and Microsoft have published their recent work on multilingual AI models. Google and Microsoft have released models that achieve new state-of-the-art performance on NLP tasks measured by the XTREME benchmark, while Facebook has produced a non-English-centric many-to-many translation model.

Hu et al. XTREME: A Massively Multilingual Multi-task Benchmark for Evaluating Cross-lingual Generalization. ICML 2020.

Hybrid MT

Incorporating Discrete Translation Lexicons in Neural Machine Translation

- Estimate the probability of translation lexicons (a.k.a translation phrases) $p_l(\cdot)$

- Integrate this lexicon probability $p_l(\cdot)$ with NMT probability $p_m(\cdot)$
  - Add them as a bias to the NMT's softmax output

$$p_b(e_i|F, e_1^{i-1}) = \textbf{softmax}(W_s\boldsymbol{\eta}_i + b_s + \log(p_l(e_i|F, e_1^{i-1}) + \epsilon)).$$

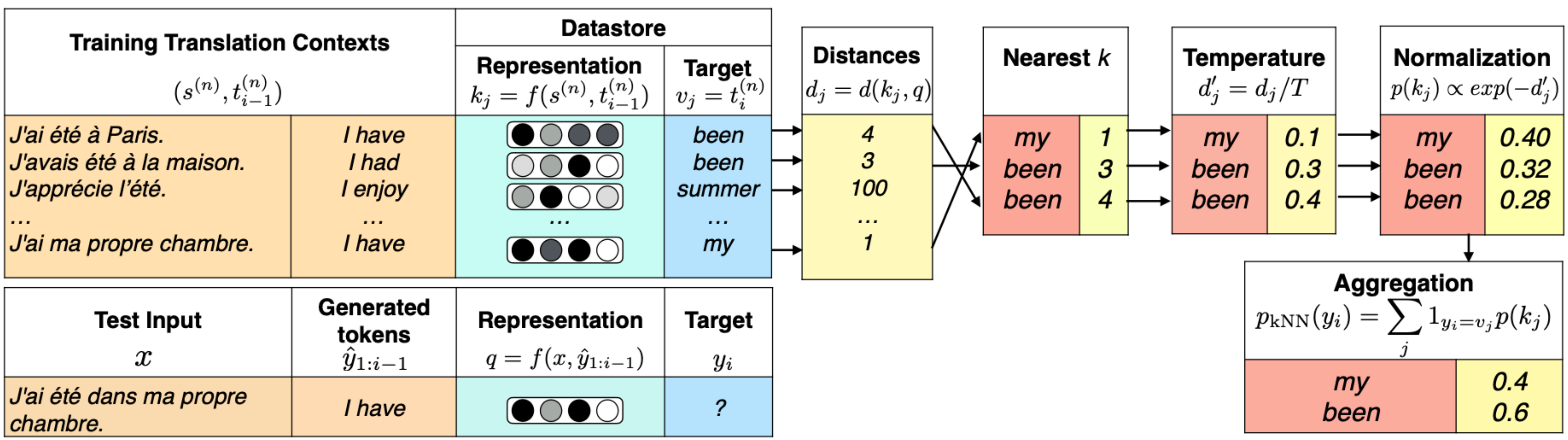
  - Linear interpolation

$$p_o(e_i|F, e_1^{i-1}) = \lambda p_l(e_i|F, e_1^{i-1}) + (1-\lambda)p_m(e_i|F, e_1^{i-1})$$

Arthur et al NAACL 2016. Incorporating Discrete Translation Lexicons in Neural Machine Translation

KNN-MT

- Construct a datastore (e.g., phrase table in SMT), and perform KNN retrieval to get related phrases for a test input



$$p(y_i|x, \hat{y}_{1:i-1}) = \lambda\, p_{\text{kNN}}(y_i|x, \hat{y}_{1:i-1}) + (1-\lambda)\, p_{\text{MT}}(y_i|x, \hat{y}_{1:i-1})$$

Khandelwal et al ICLR 2021. Nearest Neighbor Machine Translation

Prompt-based MT

- Given a **translation instruction** and **few-shot examples**, ask a LLM to perform MT

Zero-shot

The model predicts the answer given only a natural language description of the task. No gradient updates are performed.

```
Translate English to French:     ← task description
cheese => .....................  ← prompt
```

Few-shot

In addition to the task description, the model sees a few examples of the task. No gradient updates are performed.

```
Translate English to French:          ← task description
sea otter => loutre de mer            ← examples
peppermint => menthe poivrée          ←
plush girafe => girafe peluche        ←
cheese => .........................   ← prompt
```

Brown et al. NeurIPS 2019. GPT-3: Language Models are Few-Shot Learners

Prompt-based MT

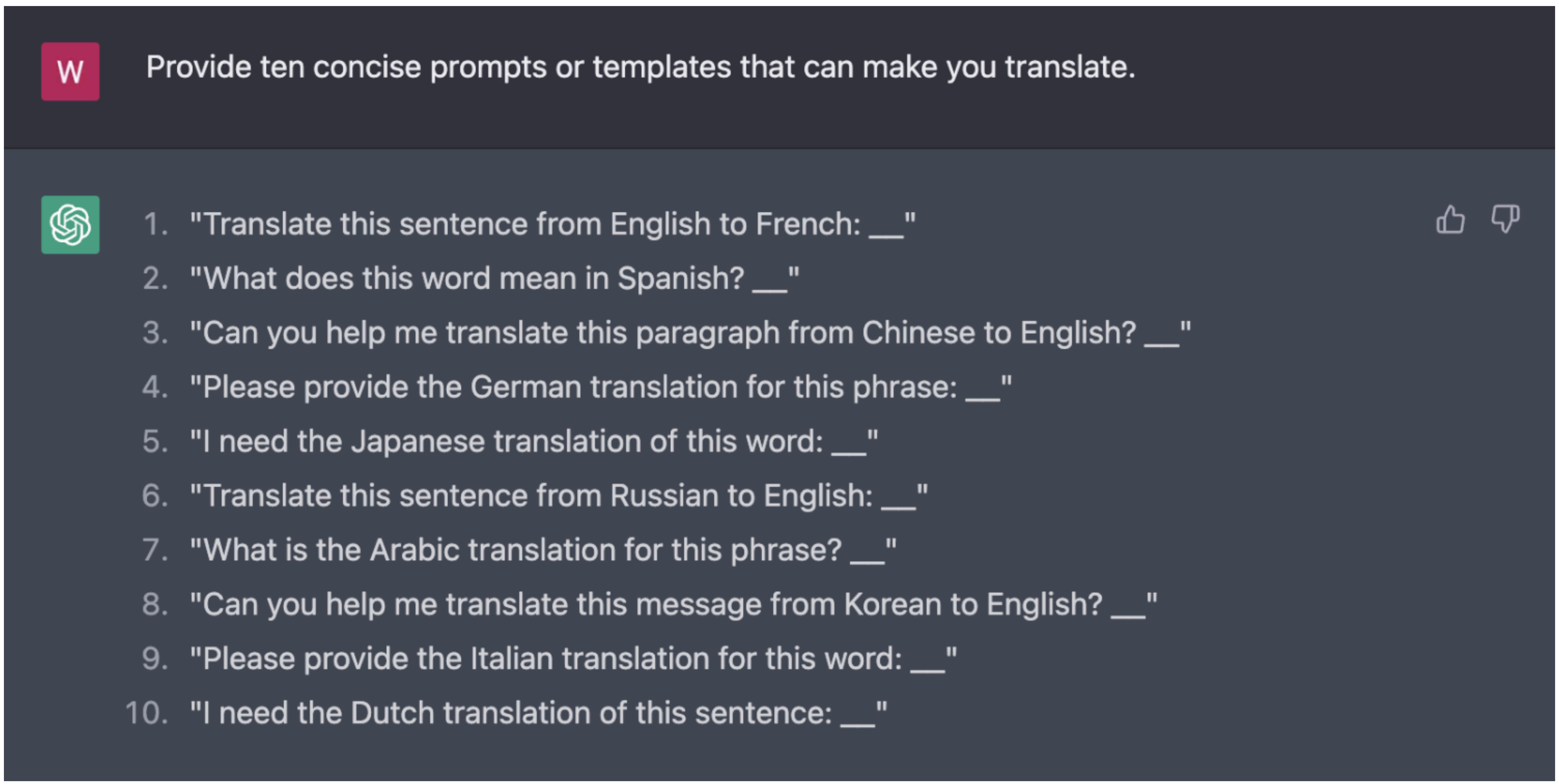
- Perform comparable or even better at XX-English translation, but still far behind at English-XX translation
- GPT-3's training data (93% by word count) is still English

Setting	En→Fr	Fr→En	En→De	De→En	En→Ro	Ro→En
SOTA (Supervised)	**45.6**[a]	35.0 [b]	**41.2**[c]	40.2[d]	**38.5**[e]	**39.9**[e]
XLM [LC19]	33.4	33.3	26.4	34.3	33.3	31.8
MASS [STQ+19]	<u>37.5</u>	34.9	28.3	35.2	<u>35.2</u>	33.1
mBART [LGG+20]	-	-	<u>29.8</u>	34.0	35.0	30.5
GPT-3 Zero-Shot	25.2	21.2	24.6	27.2	14.1	19.9
GPT-3 One-Shot	28.3	33.7	26.2	30.4	20.6	38.6
GPT-3 Few-Shot	32.6	<u>39.2</u>	29.7	<u>40.6</u>	21.0	<u>39.5</u>

Brown et al. NeurIPS 2019. GPT-3: Language Models are Few-Shot Learners

Prompt-based MT

- Ask ChatGPT to create prompts for MT



Jiao et al. 2023 Is ChatGPT A Good Translator? Yes With GPT-4 As The Engine

"Data Contamination" in Common English Corpus

- Most pretraining data contain non-English texts

- Use a language identification (LID) tool based on FastText to check if a line of text contains non-English words.

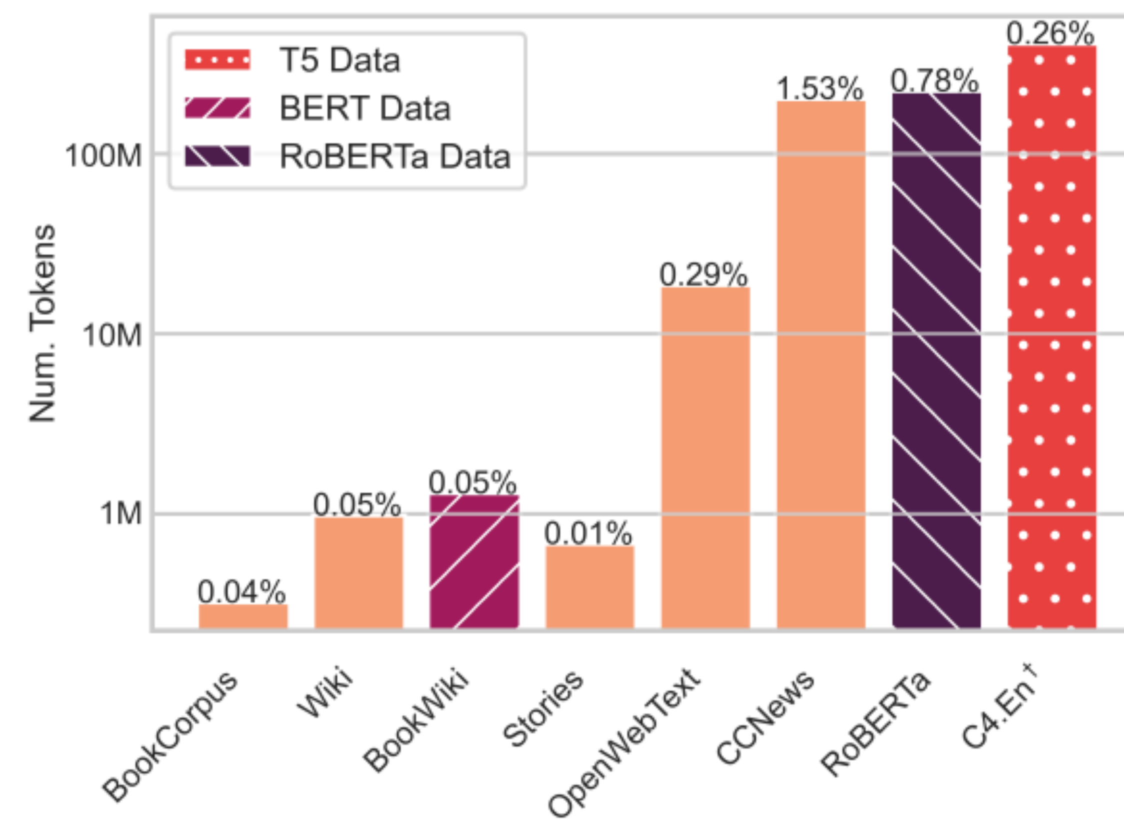
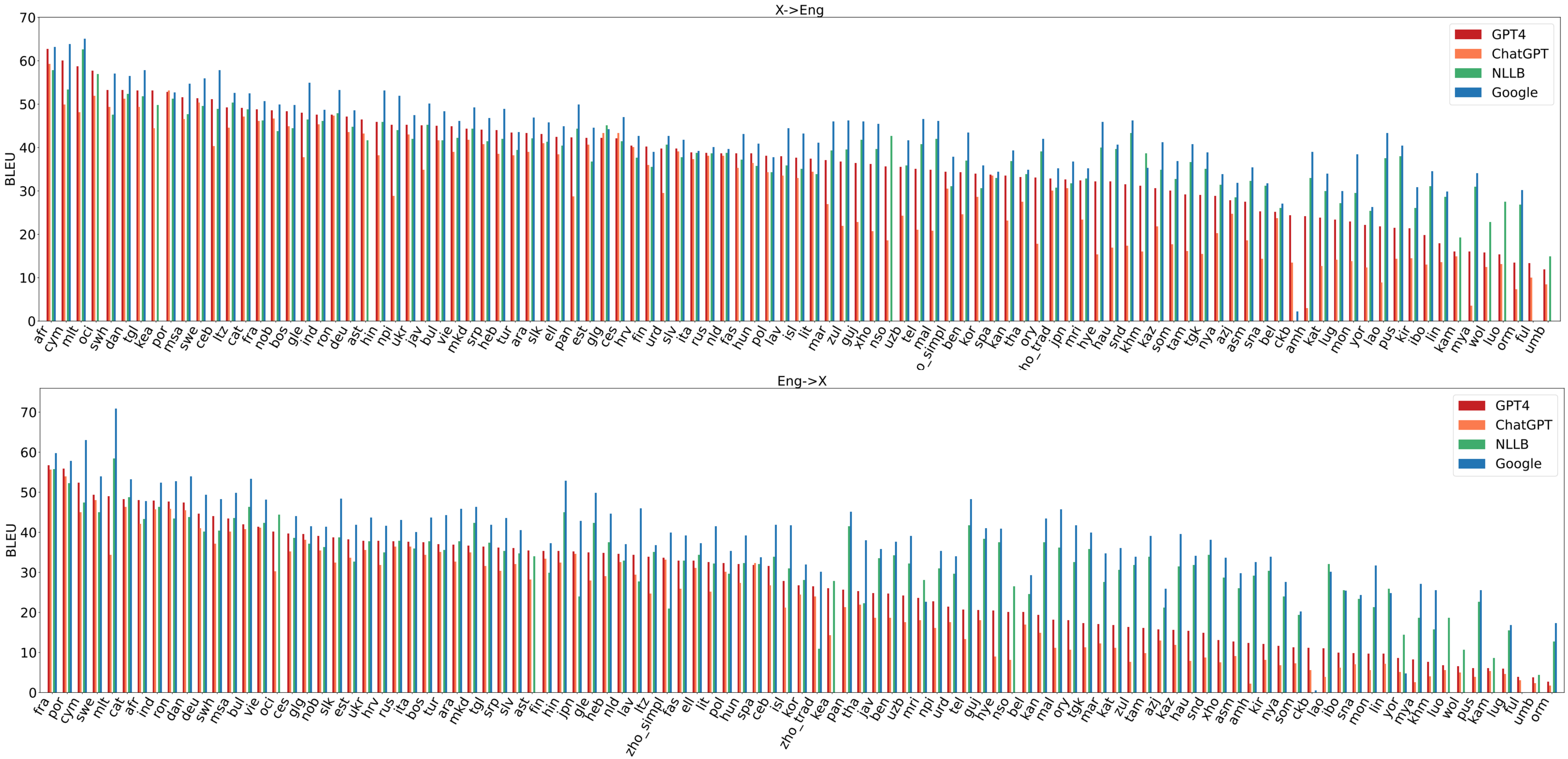


Figure 1: Estimated non-English data in English pre-training corpora (token count and total percentage); even small percentages lead to many tokens. C4.En (†) is estimated from the first 50M examples in the corpus.

LLM-MT vs NMT

- High-resourced language pairs: comparable
- Low-resourced language pairs: Google Translate >= NLLB >> LLM-MT



Zhu et al 2023. Multilingual Machine Translation with Large Language Models: Empirical Results and Analysis

Comparison between SMT and NMT

- **SMT** (non-parametric model)
  - Explicitly store translation phrase pairs
  - High precision, but low coverage, thus poor generation
  - Easy manipulation (insert/delete/update pairs in the translation phrase table)

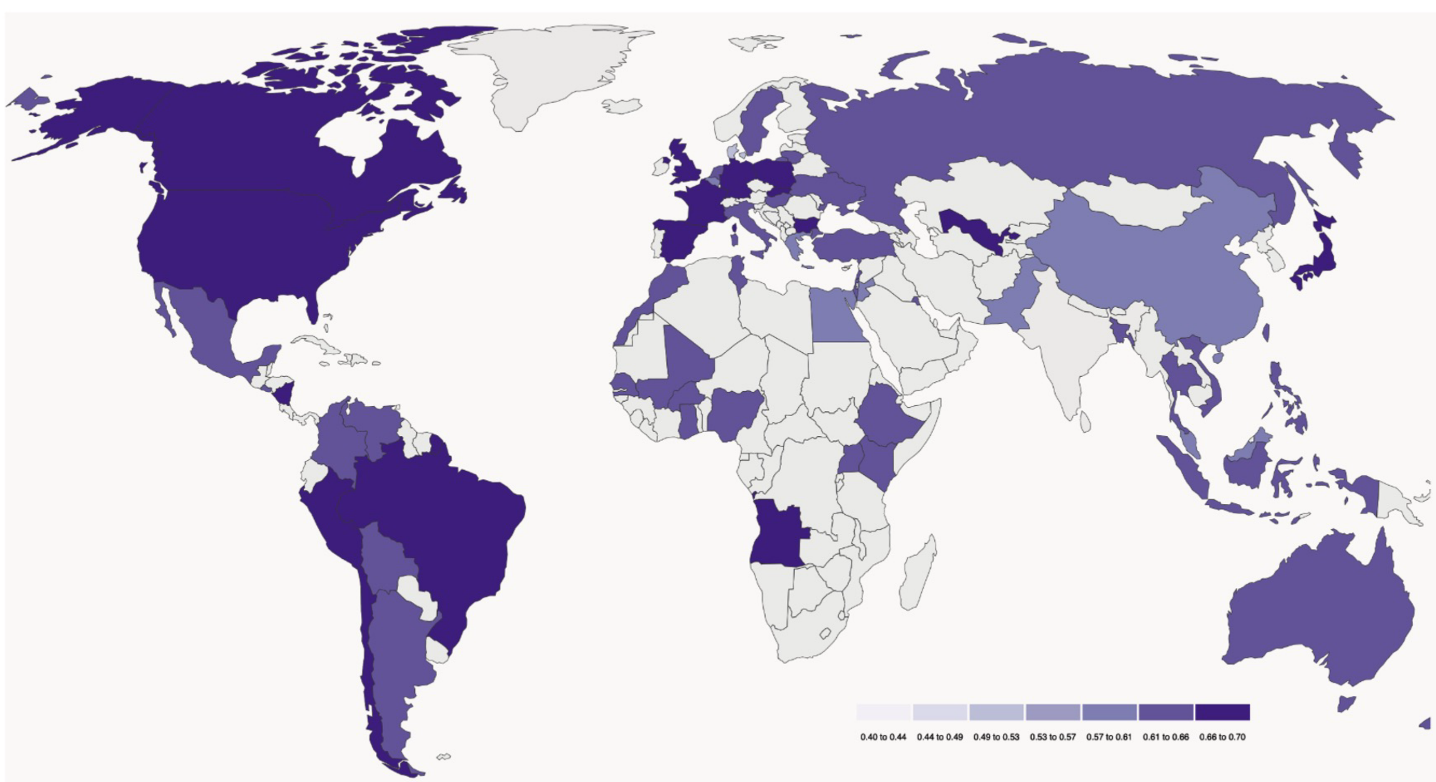
- **NMT** (over-parametric model)
  - Implicitly store translation phrase pairs in model parameters
  - Better generation, but data-hungry
  - Hard manipulation (catastrophic forgetting after fine-tuning, domain adaptation issues)

- **Hybrid MT** (e.g., Retrieval-MT, Prompt-based MT)
  - Leverage both neural network parameters and retrieved translation phrase pairs
  - Perform better than NMT on domain adaptation when providing new domain information from retrieval.

Future Research

Pragmatic *Pluralism*

Language models cannot adopt a **uniform** strategy to effectively serve individuals across **diverse sociocultural** contexts.

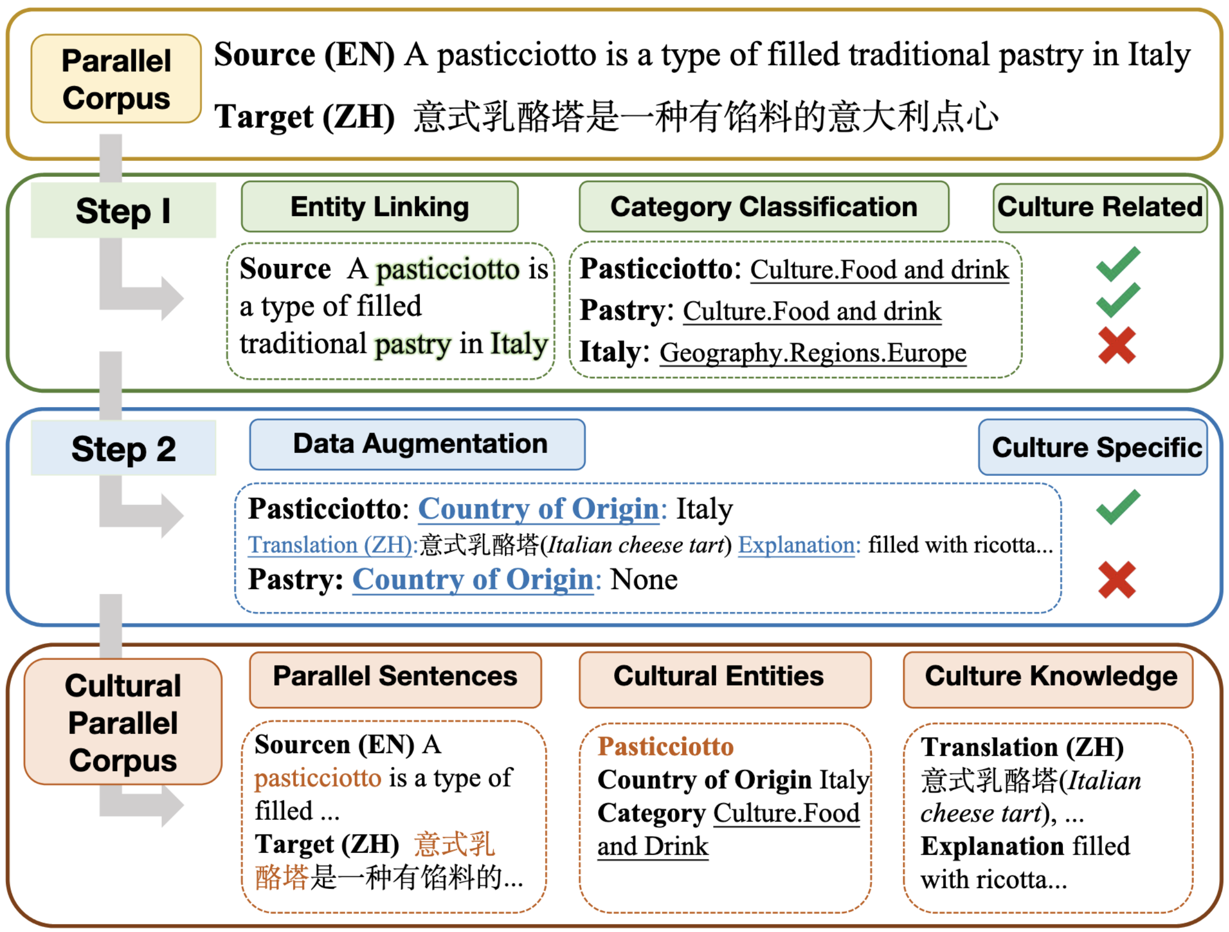


The responses from the LLM are more similar to the opinions of respondents from certain populations such as north America. (Durmus, et al., 2024)

Challenges of Culturally-aware Machine Translation

- **Data Scarcity**: Many **CSIs** often lack viable translations across languages, making it difficult to collect high-quality and diverse parallel corpora with CSI annotations at scale, hindering a systematic evaluation of the cultural awareness of MT systems
- **Evaluation Metric Insufficiency**: Existing evaluation metrics mainly focus on **semantic-level** accuracy between the source and target texts. However, in the context of CSI translation where translation quality is tightly associated with target culture, **pragmatic translation quality** becomes crucial.

Cultural Parallel Corpus Construction Pipeline



Overview of the Data Construction Pipeline

- The pipeline leverages Wikipedia as a knowledge base to create a parallel corpus with CSI annotations automatically.
- The resulting corpus, called **Culturally-Aware Machine Translation (CAMT)**, has **6** language pairs, covering **6,983** CSIs across **18** concept categories from **235** countries and regions.

Yao et al. Benchmarking Machine Translation with Cultural Awareness, EMNLP Findings 2024

Questions?