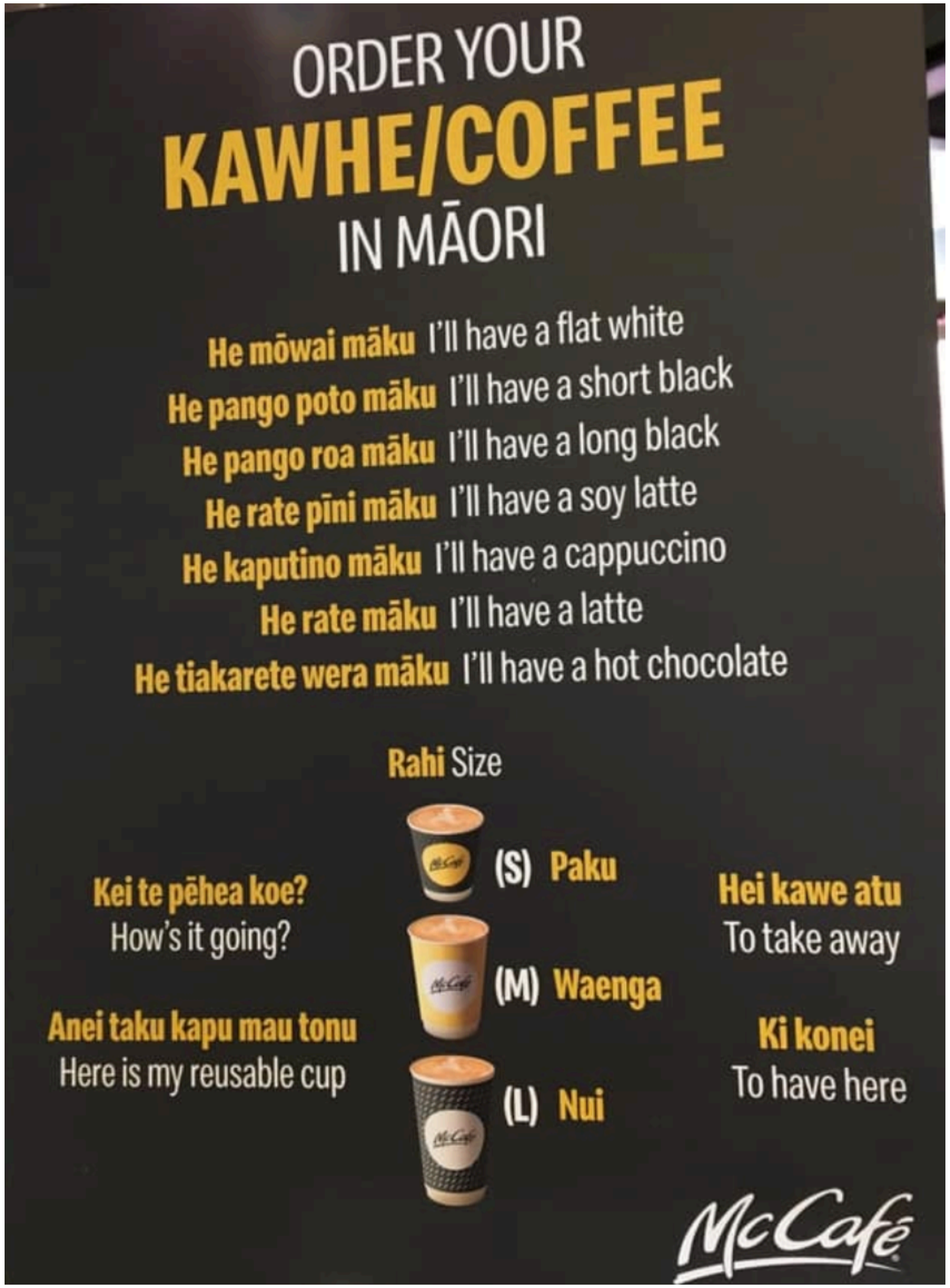

ORDER YOUR

KAWHE/COFFEE

IN MĀORI

He mōwai māku	I'll have a flat white
He pango poto māku	I'll have a short black
He pango roa māku	I'll have a long black
He rate pīni māku	I'll have a soy latte
He kaputino māku	I'll have a cappuccino
He rate māku	I'll have a latte
He tiakarete wera māku	I'll have a hot chocolate

Rahi Size

(S) **Paku**

(M) **Waenga**

(L) **Nui**

Kei te pēhea koe?
How's it going?

Anei taku kapu mau tonu
Here is my reusable cup

Hei kawe atu
To take away

Ki konei
To have here

McCafé

1. What's the Māori word for…
(a) "long"?
(b) "hot"?

2. How would you order a large cappuccino?

3. What's the word for chocolate?

AthNLP 2024

Machine Translation and Multilinguality

Antonis Anastasopoulos

NLP
GEORGE MASON

Acknowledgement: Many slides are taken from
Greg Durrett CS388@UT Austin,
Graham Neubig's Advanced NLP course@CMU
and Philipp Koehn's MT course@JHU

Machine Translation

Machine Translation

- Intro

Machine Translation

- Intro
- A historical note

Machine Translation

- Intro
- A historical note
    - Alignment and EM algorithm

Machine Translation

- Intro
- A historical note
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- MT Evaluation

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- Neural MT and LLM-based MT

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- Semi-supervised and Unsupervised MT

Machine translation

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- Machine Translation (MT) is the task of translating a sentence x from one language (the source language) to a sentence y in another language (the target language).

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Machine Translation

Machine Translation

- The classic test of language understanding!

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  - Both language analysis & generation

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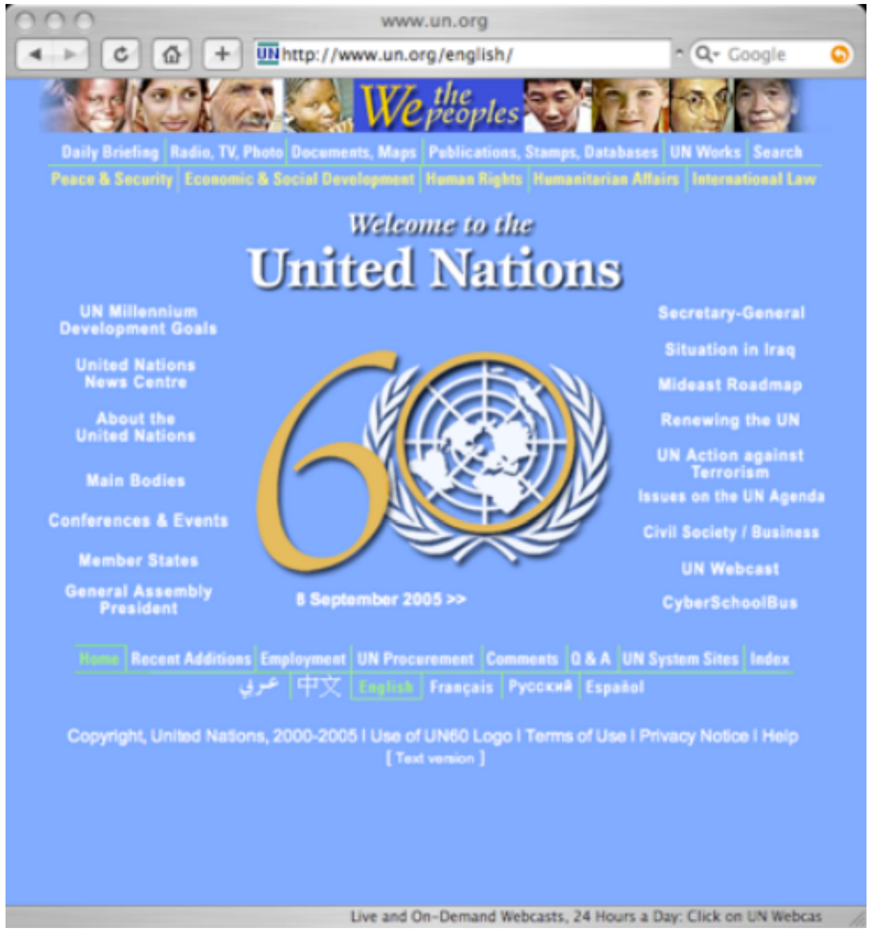
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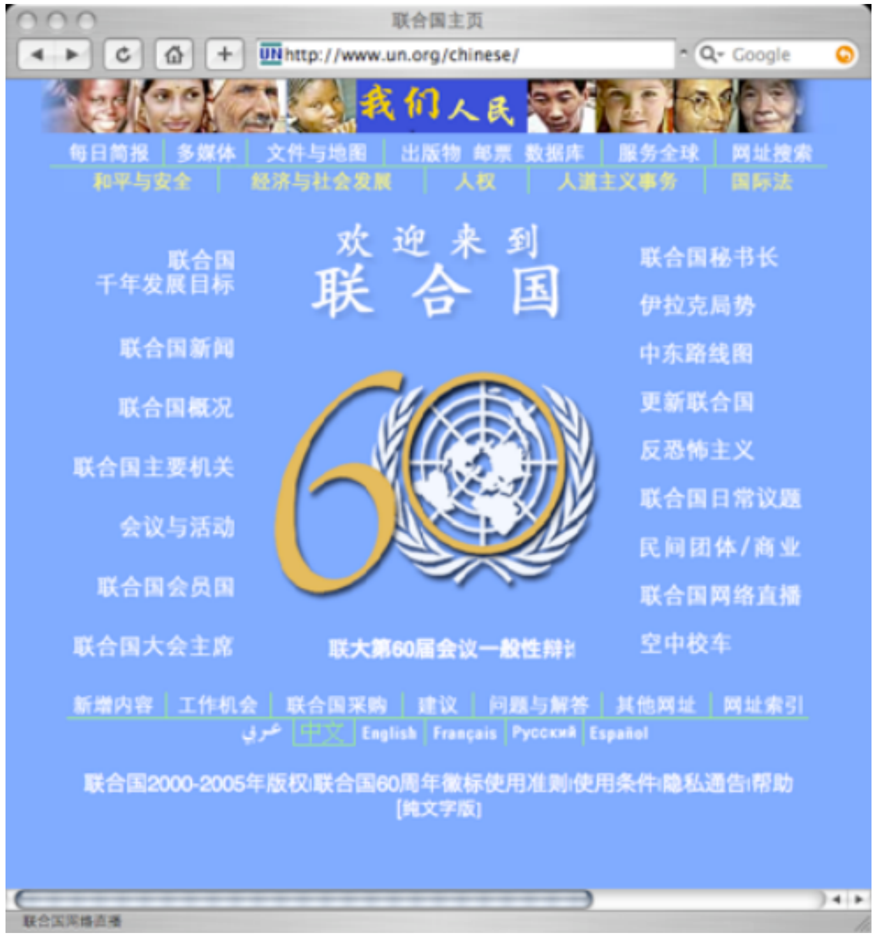
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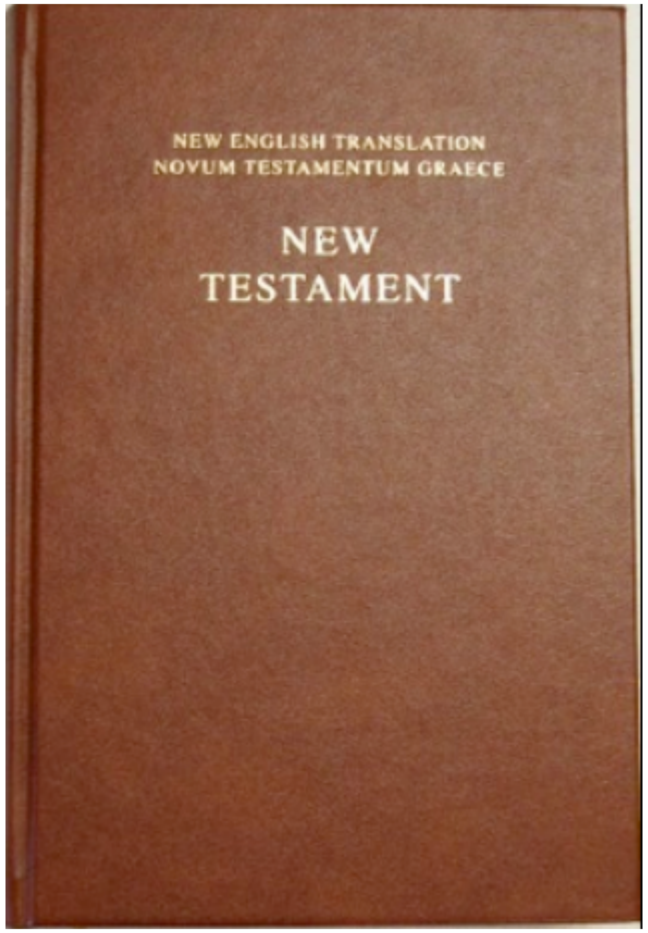
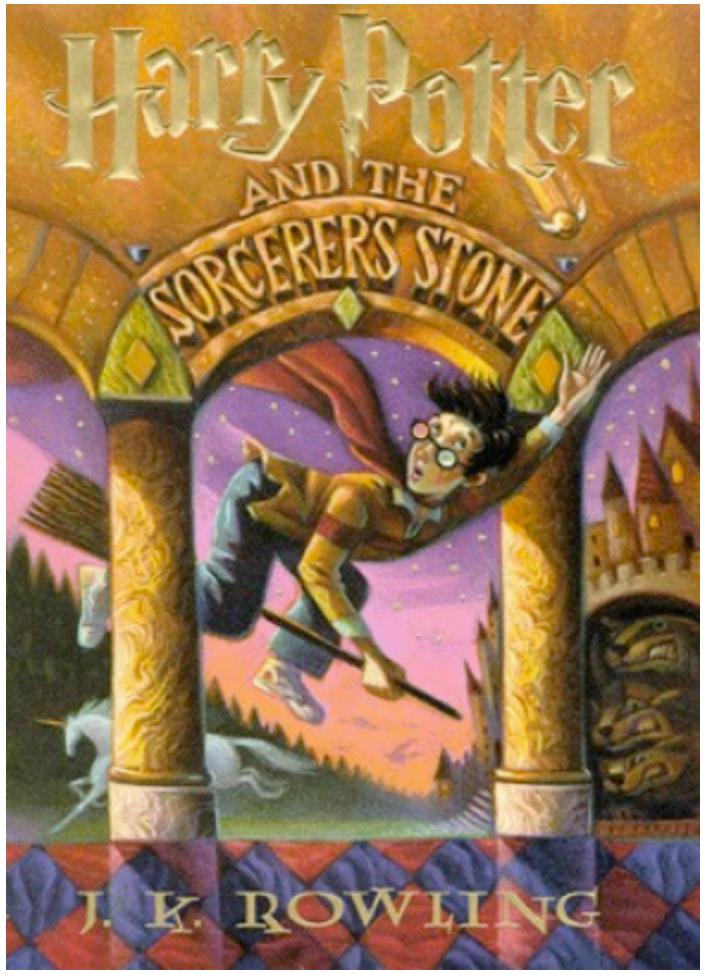

NEW ENGLISH TRANSLATION
NOVUM TESTAMENTUM GRAECE
NEW
TESTAMENT

聖經
■
尋道本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AND THE
SORCERER'S STONE
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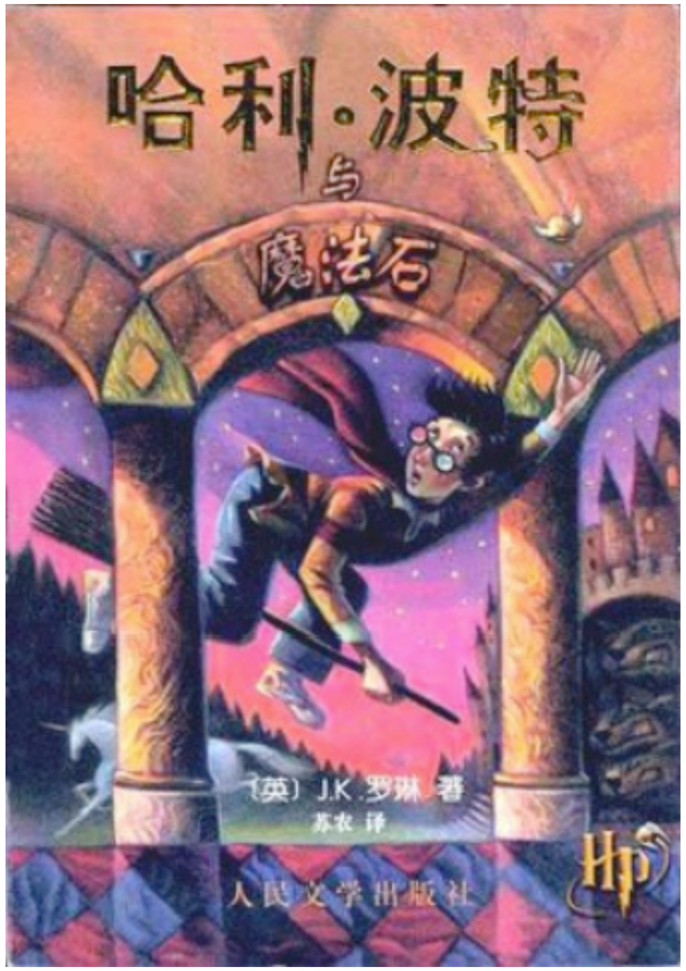
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CLASSIC SOUPS

			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

The need for Machine Translation

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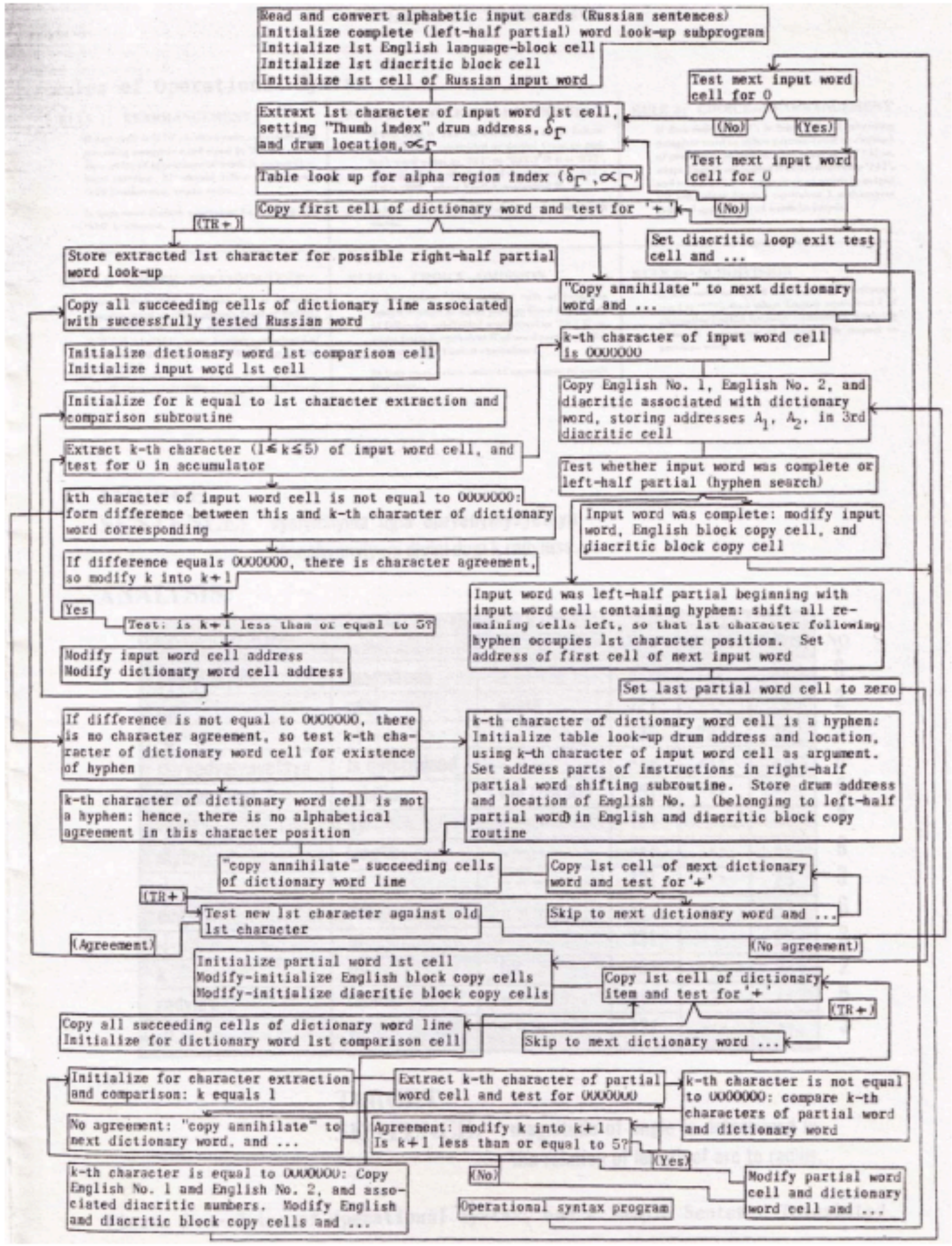
- NMT research has pioneered many of the recent innovations of NLP Deep Learning

A historical note

1950s: Early Machine Translation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Initialize 1st English language-block cell
Initialize 1st diacritic block cell
Initialize 1st cell of Russian input word
Test next input word cell for 0
(No)
(Yes)
Extraxt 1st character of input word 1st cell, setting "Thumb index" drum address, δ_Γ and drum location, α_Γ
Test next input word cell for 0
Table look up for alpha region index (δ_Γ, α_Γ)
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Copy first cell of dictionary word and test for '+'
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Set diacritic loop exit test cell and ...
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Initialize for k equal to 1st character extraction and comparison subroutine
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Test whether input word was complete or left-half partial (hyphen search)
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Input word was complete: modify input word, English block copy cell, and diacritic block copy cell
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Test: is k+1 less than or equal to 5?
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Operational syntax program

Fig. 7: Flowchart of part of the dictionary lookup procedures (from Sheridan 1955)

Flow chart of the dictionary look-up procedures (source)

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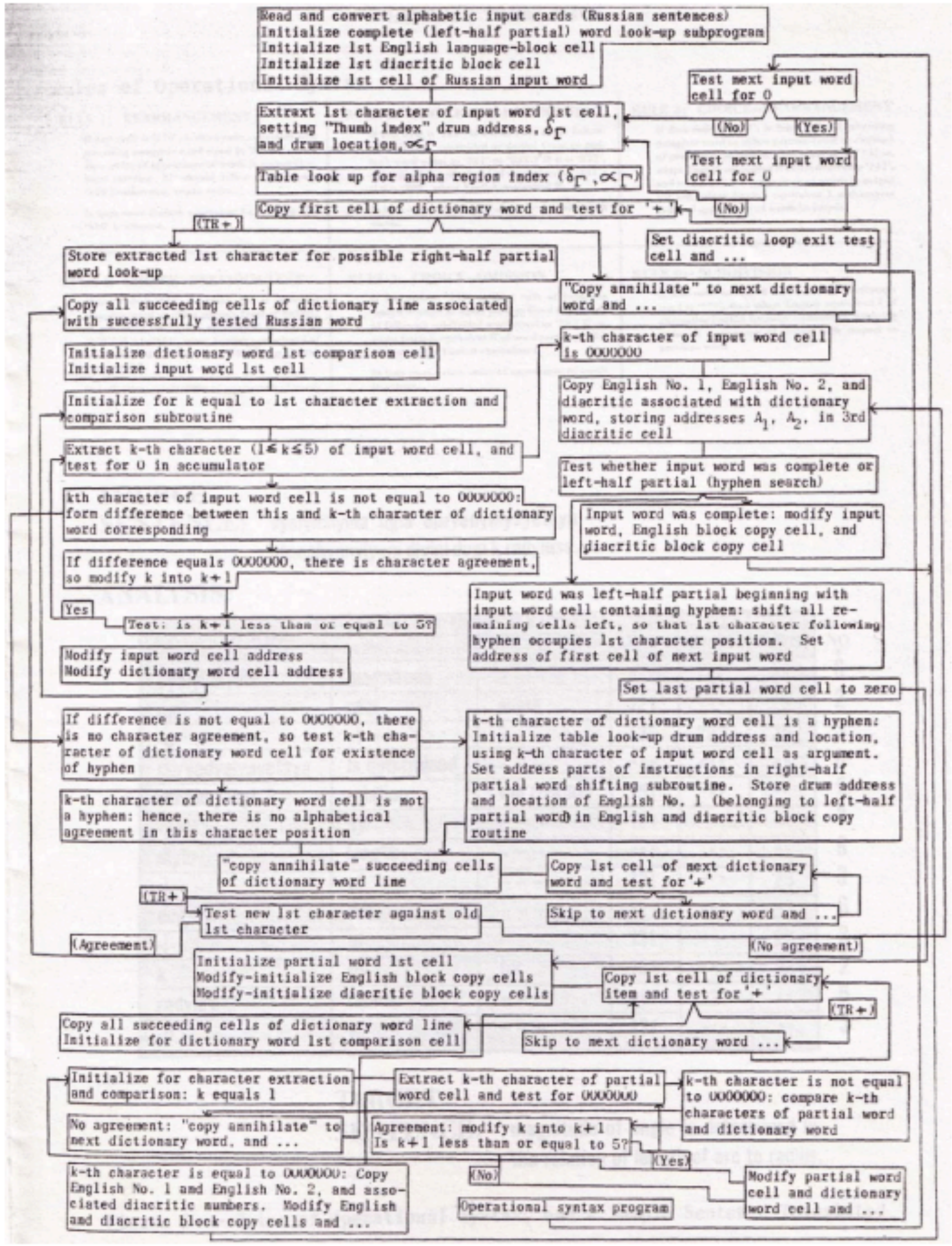
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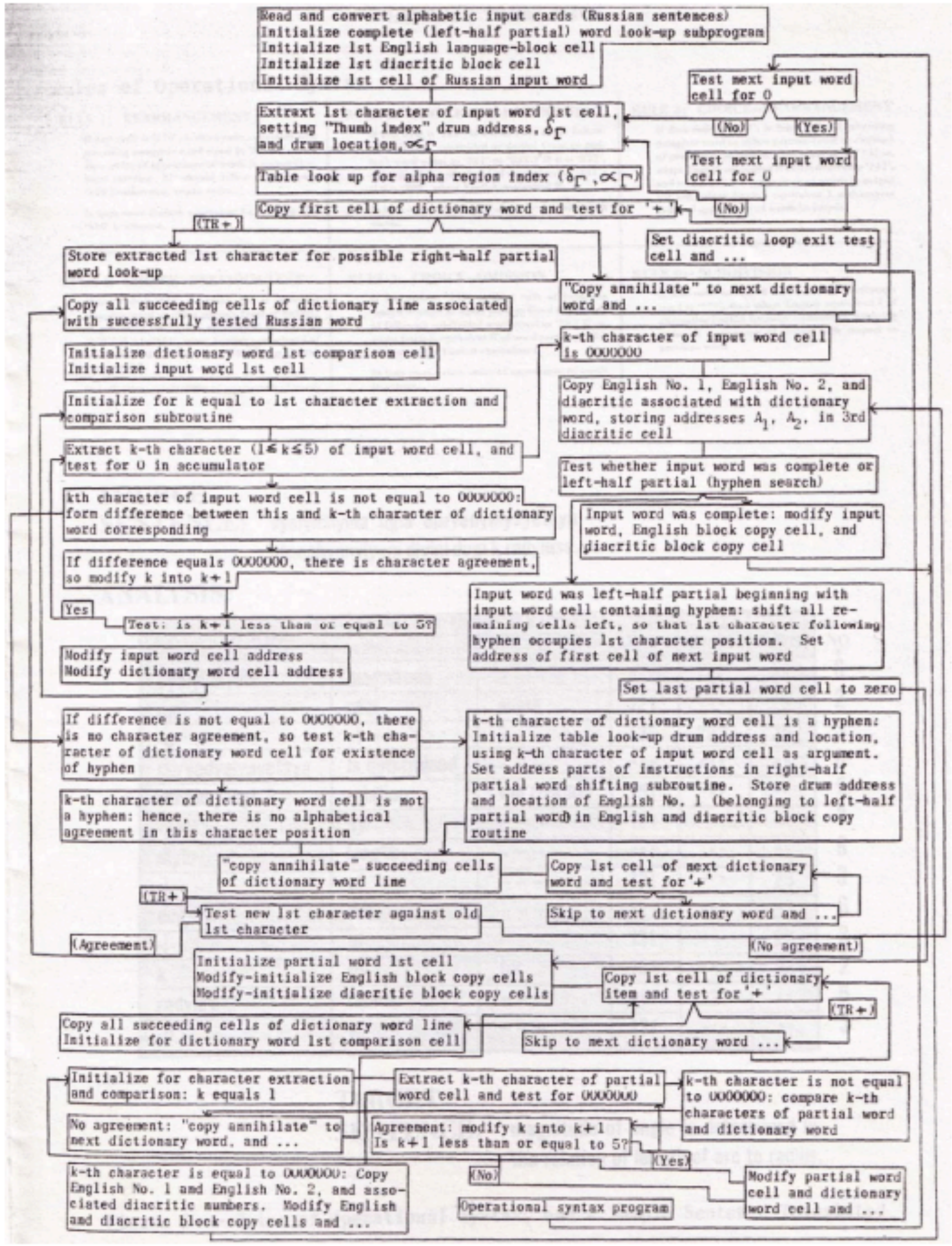
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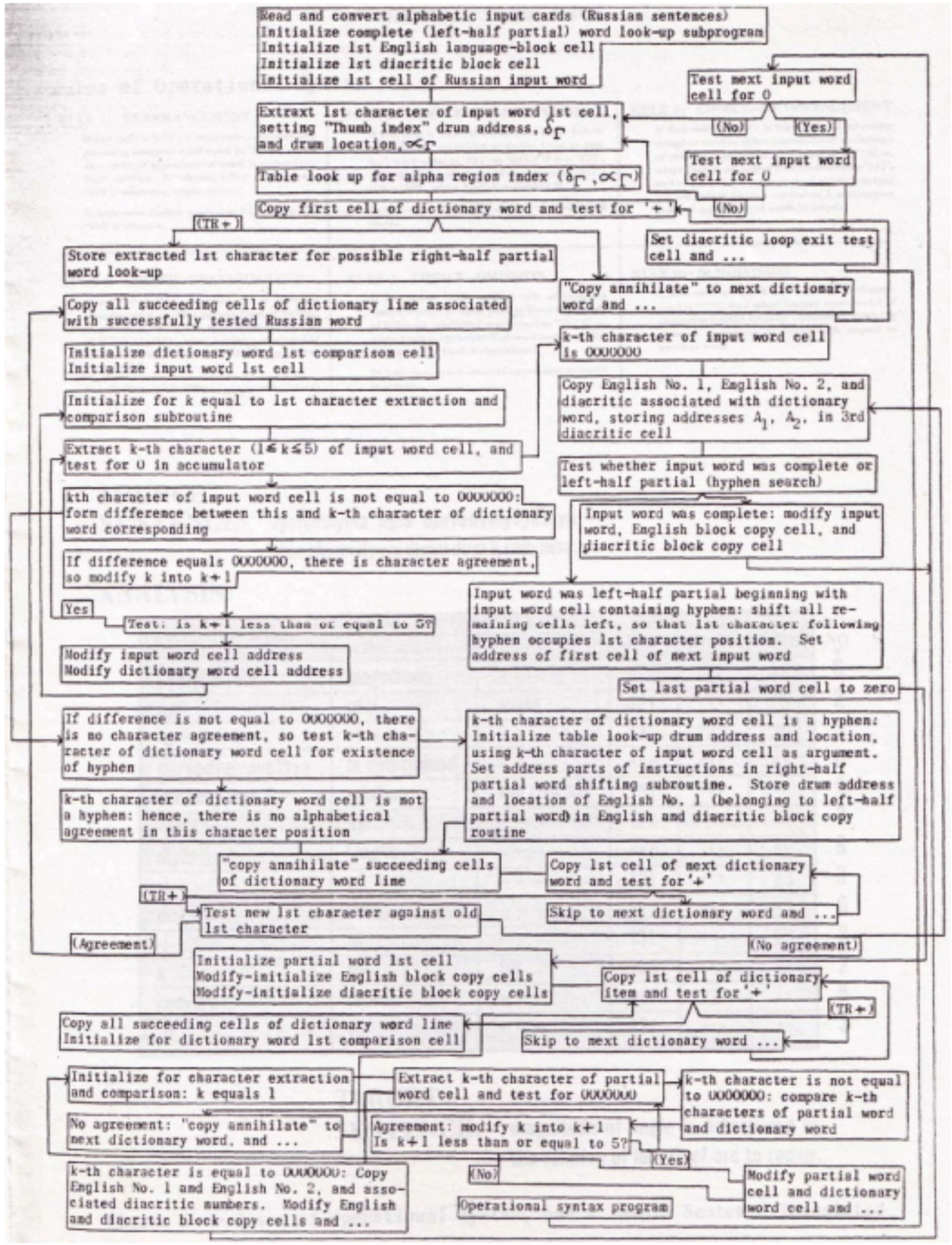

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  - Georgetown–IBM experiment (1954)
- Systems were mostly rule-based, using a bilingual dictionary to map Russian words to their English counterparts

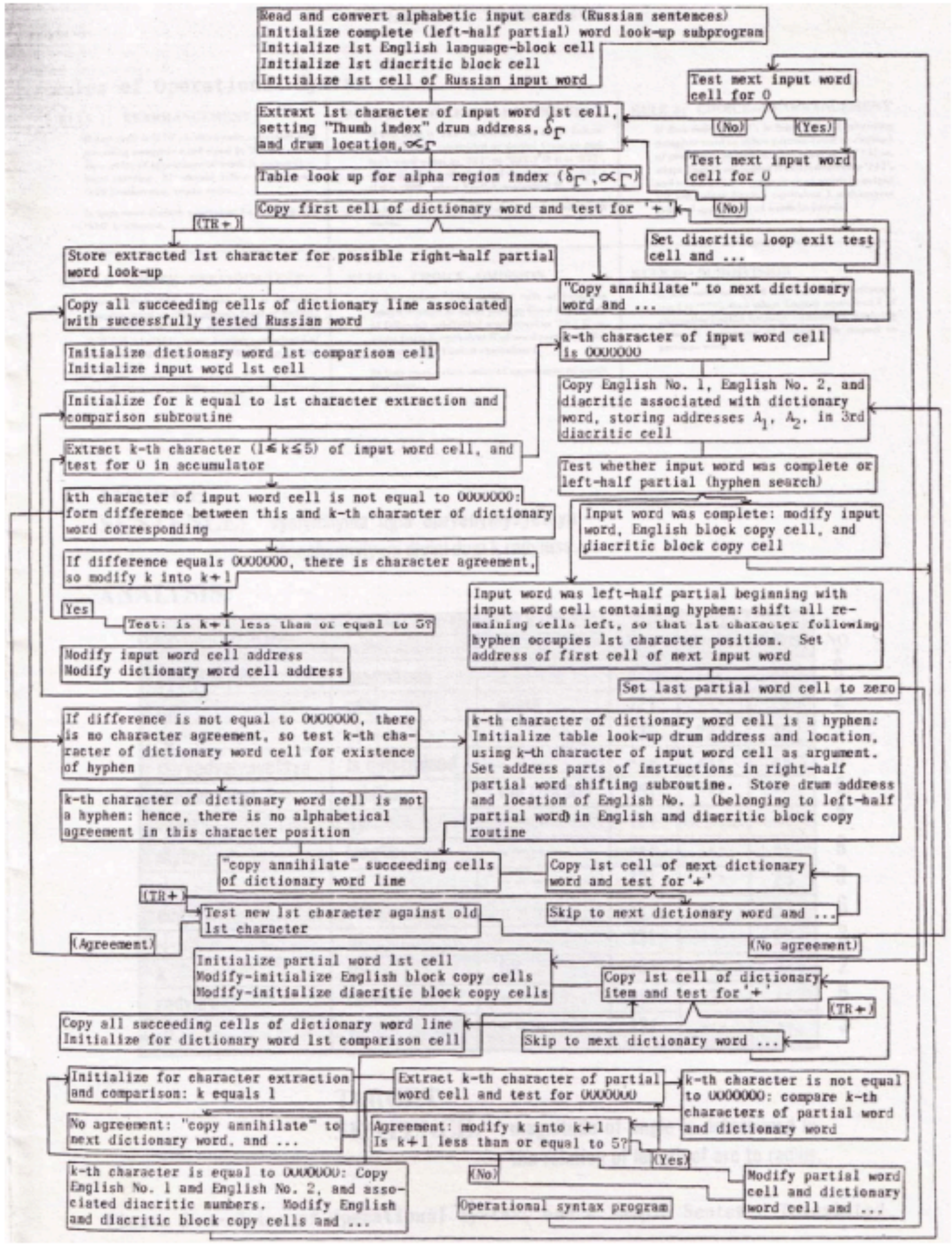
Read and convert alphabetic input cards (Russian sentences) Initialize complete (left-half partial) word look-up subprogram Initialize 1st English language-block cell Initialize 1st diacritic block cell Initialize 1st cell of Russian input word
Test next input word cell for 0
Extraxt 1st character of input word 1st cell, setting "Thumb index" drum address, δ_Γ and drum location, $\propto_\Gamma$
(No)
(Yes)
Test next input word cell for 0
Table look up for alpha region index (δ_Γ, $\propto_\Gamma$)
Copy first cell of dictionary word and test for '+'
(No)
(TR+)
Set diacritic loop exit test cell and ...
Store extracted 1st character for possible right-half partial word look-up
"Copy annihilate" to next dictionary word and ...
Copy all succeeding cells of dictionary line associated with successfully tested Russian word
k-th character of input word cell is 0000000
Initialize dictionary word 1st comparison cell Initialize input word 1st cell
Copy English No. 1, English No. 2, and diacritic associated with dictionary word, storing addresses A_1, A_2, in 3rd diacritic cell
Initialize for k equal to 1st character extraction and comparison subroutine
Extract k-th character (1≤k≤5) of input word cell, and test for 0 in accumulator
Test whether input word was complete or left-half partial (hyphen search)
kth character of input word cell is not equal to 0000000: form difference between this and k-th character of dictionary word corresponding
Input word was complete: modify input word, English block copy cell, and diacritic block copy cell
If difference equals 0000000, there is character agreement, so modify k into k+1
Input word was left-half partial beginning with input word cell containing hyphen: shift all remaining cells left, so that 1st character following hyphen occupies 1st character position. Set address of first cell of next input word
Yes
Test: is k+1 less than or equal to 5?
Modify input word cell address Modify dictionary word cell address
Set last partial word cell to zero
If difference is not equal to 0000000, there is no character agreement, so test k-th character of dictionary word cell for existence of hyphen
k-th character of dictionary word cell is a hyphen: Initialize table look-up drum address and location, using k-th character of input word cell as argument. Set address parts of instructions in right-half partial word shifting subroutine. Store drum address and location of English No. 1 (belonging to left-half partial word) in English and diacritic block copy routine
k-th character of dictionary word cell is not a hyphen: hence, there is no alphabetical agreement in this character position
"copy annihilate" succeeding cells of dictionary word line
Copy 1st cell of next dictionary word and test for '+'
(TR+)
Test new 1st character against old 1st character
Skip to next dictionary word and ...
(Agreement)
(No agreement)
Initialize partial word 1st cell Modify-initialize English block copy cells Modify-initialize diacritic block copy cells
Copy 1st cell of dictionary item and test for '+'
(TR+)
Copy all succeeding cells of dictionary word line Initialize for dictionary word 1st comparison cell
Skip to next dictionary word ...
Initialize for character extraction and comparison: k equals 1
Extract k-th character of partial word cell and test for 0000000
k-th character is not equal to 0000000: compare k-th characters of partial word and dictionary word
No agreement: "copy annihilate" to next dictionary word, and ...
Agreement: modify k into k+1 Is k+1 less than or equal to 5?
(Yes)
k-th character is equal to 0000000: Copy English No. 1 and English No. 2, and associated diacritic numbers. Modify English and diacritic block copy cells and ...
(No)
Modify partial word cell and dictionary word cell and ...
Operational syntax program

Fig. 7: Flowchart of part of the dictionary lookup procedures (from Sheridan 1955)

Flow chart of the dictionary look-up procedures (source)

1990s-2010s: Statistical Machine Translation

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- Core idea: Learn a probabilistic model from data

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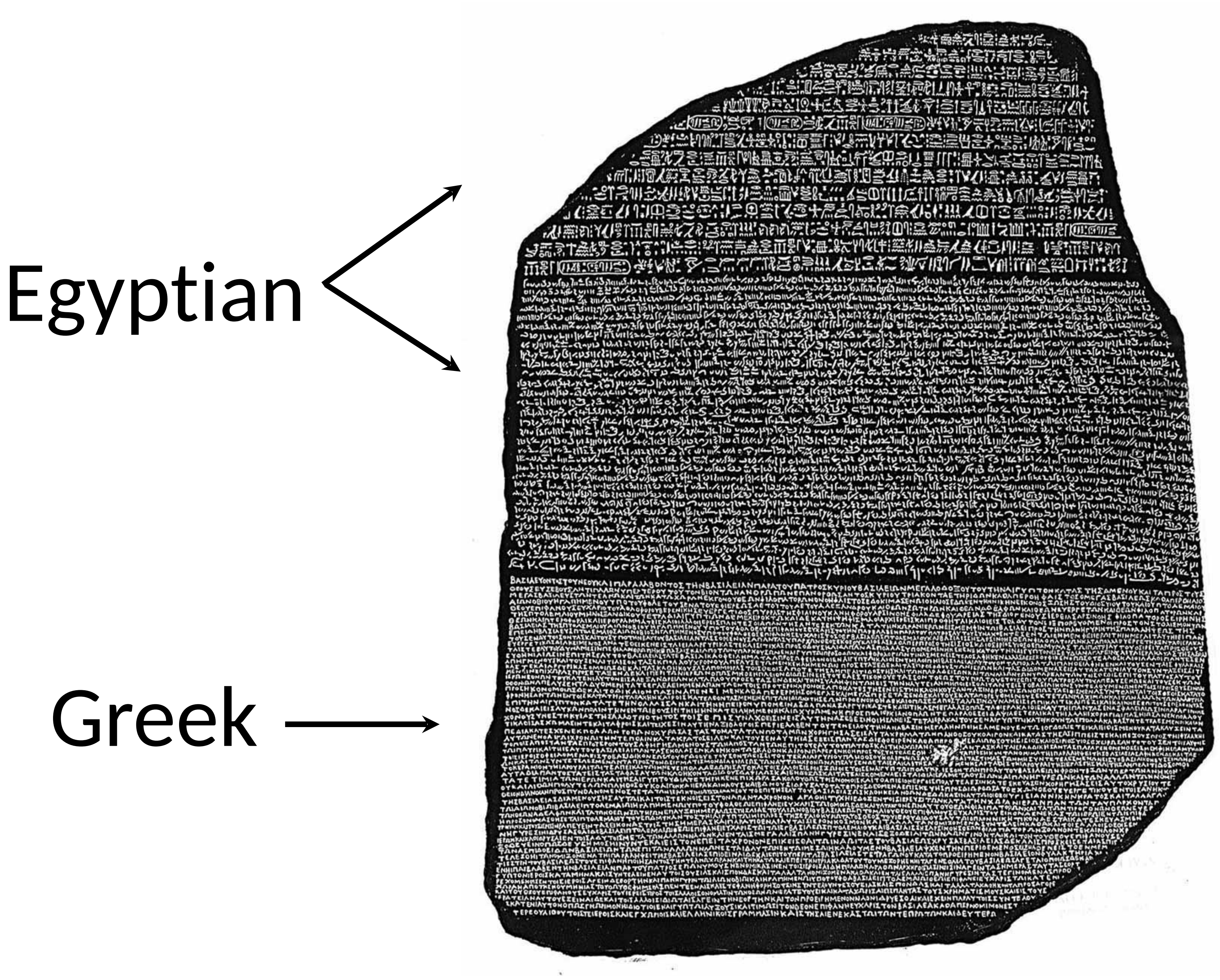
- Suppose we’re translating French → English.

1990s-2010s: Statistical Machine Translation

- Core idea: Learn a probabilistic model from data
- Suppose we’re translating French → English.
- We want to find best English sentence y, given French sentence x



Egyptian

Greek

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

Noisy Channel MT

We want a model of $p(\boldsymbol{e}|\boldsymbol{f})$

Noisy Channel MT

We want a model of $p(\boldsymbol{e}|\boxed{\boldsymbol{f}})$

Confusing foreign sentence

Noisy Channel MT

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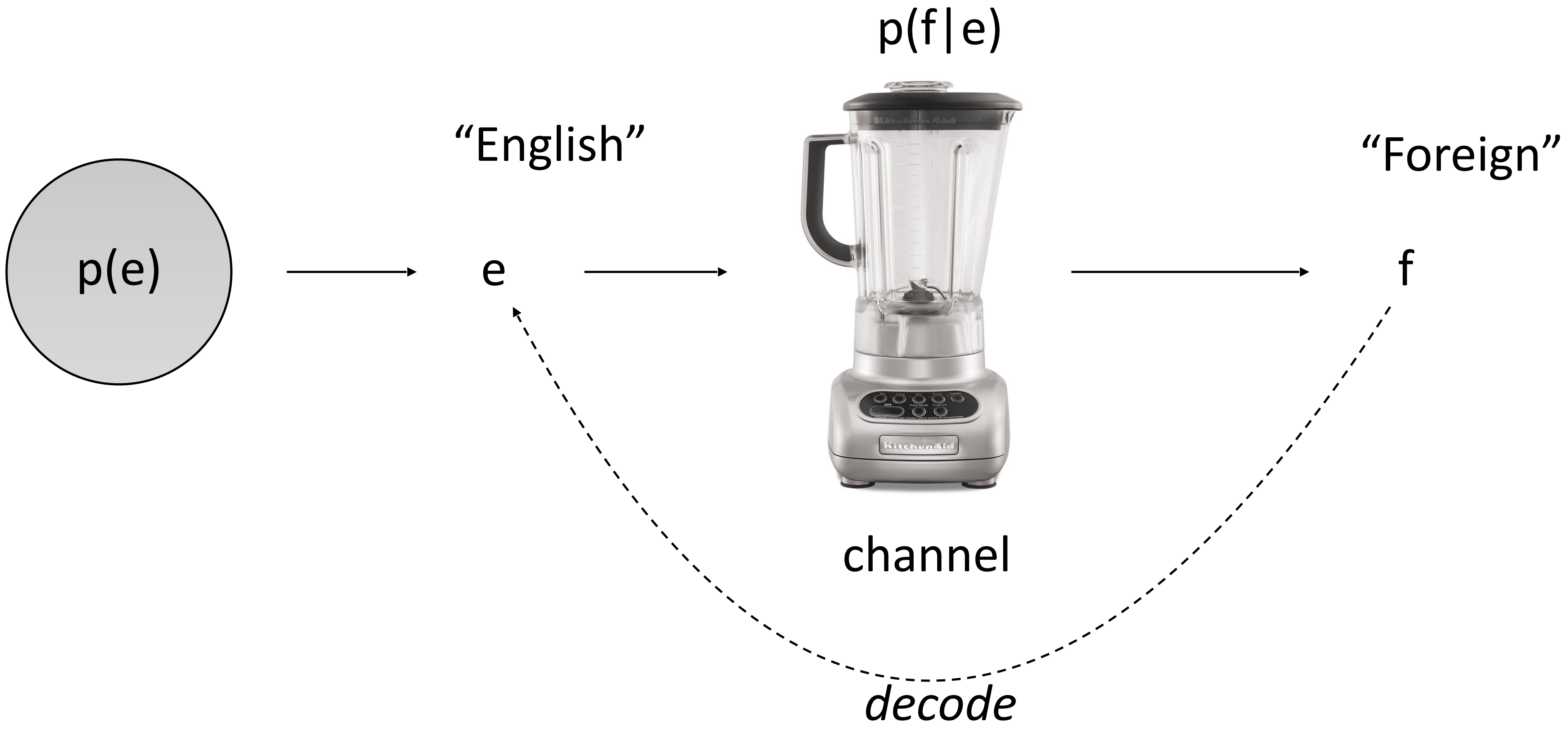
Possible English translation

Noisy Channel MT



p(f|e)

"English"

"Foreign"

p(e)

e

f

channel

decode

Noisy Channel MT

$$
\begin{aligned}
\hat{e} &= \arg\max_{e} p(e|f) \\
&= \arg\max_{e} \frac{p(e) \times p(f|e)}{p(f)} \\
&= \arg\max_{e} \underbrace{\boxed{p(e)}}_{\text{“Language Model”}} \times \underbrace{\boxed{p(f|e)}}_{\text{“Translation Model”}}
\end{aligned}
$$

Noisy Channel Division of Labor

- Language model – $p(\boldsymbol{e})$
  - is the translation fluent, grammatical, and idiomatic?
  - use any model of $p(\boldsymbol{e})$ – typically an *n*-gram model
- Translation model – $p(\boldsymbol{f}|\boldsymbol{e})$
  - translation probability
  - ensures adequacy of translation

Translation Model

- $p(\boldsymbol{f}\mid\boldsymbol{e})$ gives the channel probability – the probability of translating an English sentence into a foreign sentence

• $\boldsymbol{f}$ = je voudrais un peu de frommage	$p(\boldsymbol{f}\mid\boldsymbol{e})$
• $\mathbf{e}_1$ = I would like some cheese	0.4
$\mathbf{e}_2$ = I would like a little of cheese	0.5
$\mathbf{e}_3$ = There is no train to Barcelona	>0.00001

Translation Model

- How do we parameterize *p(**f**|**e**)*?

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

- There are a lot of sentences: this won’t generalize to new inputs

Lexical Translation

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- How do we translate a word? Look it up in a dictionary!

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Lexical Translation

- How do we translate a word? Look it up in a dictionary!

  Haus: house, home, shell, household

- Multiple translations
  - Different word senses, different registers, different inflections
  - *house, home* are common
  - *shell* is specialized (the Haus of a snail is its shell)

How common is each?

Translation	Count
house	5000
home	2000
shell	100
household	80

MLE

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

Lexical Translation

- Goal: a model $p(\boldsymbol{e}|\boldsymbol{f},m)$
- where **e** and **f** are complete English and Foreign sentences

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$$\mathbf{e} = \langle e_1, e_2, \ldots, e_m \rangle$$

Lexical Translation

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- where **e** and **f** are complete English and Foreign sentences

$$\mathbf{e} = \langle e_1, e_2, \ldots, e_m \rangle \quad \mathbf{f} = \langle f_1, f_2, \ldots, f_n \rangle$$

Lexical Translation

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  - Thus, we have a latent *alignment* $\mathbf{a}_i$ that indicates which word $\mathbf{e}_i$ "came from." Specifically it came from $\mathbf{f}_{\mathbf{a}_i}$.
  - Given the alignments **a**, translation decisions are conditionally independent of each other and depend *only* on the aligned source word $\mathbf{f}_{\mathbf{a}_i}$.

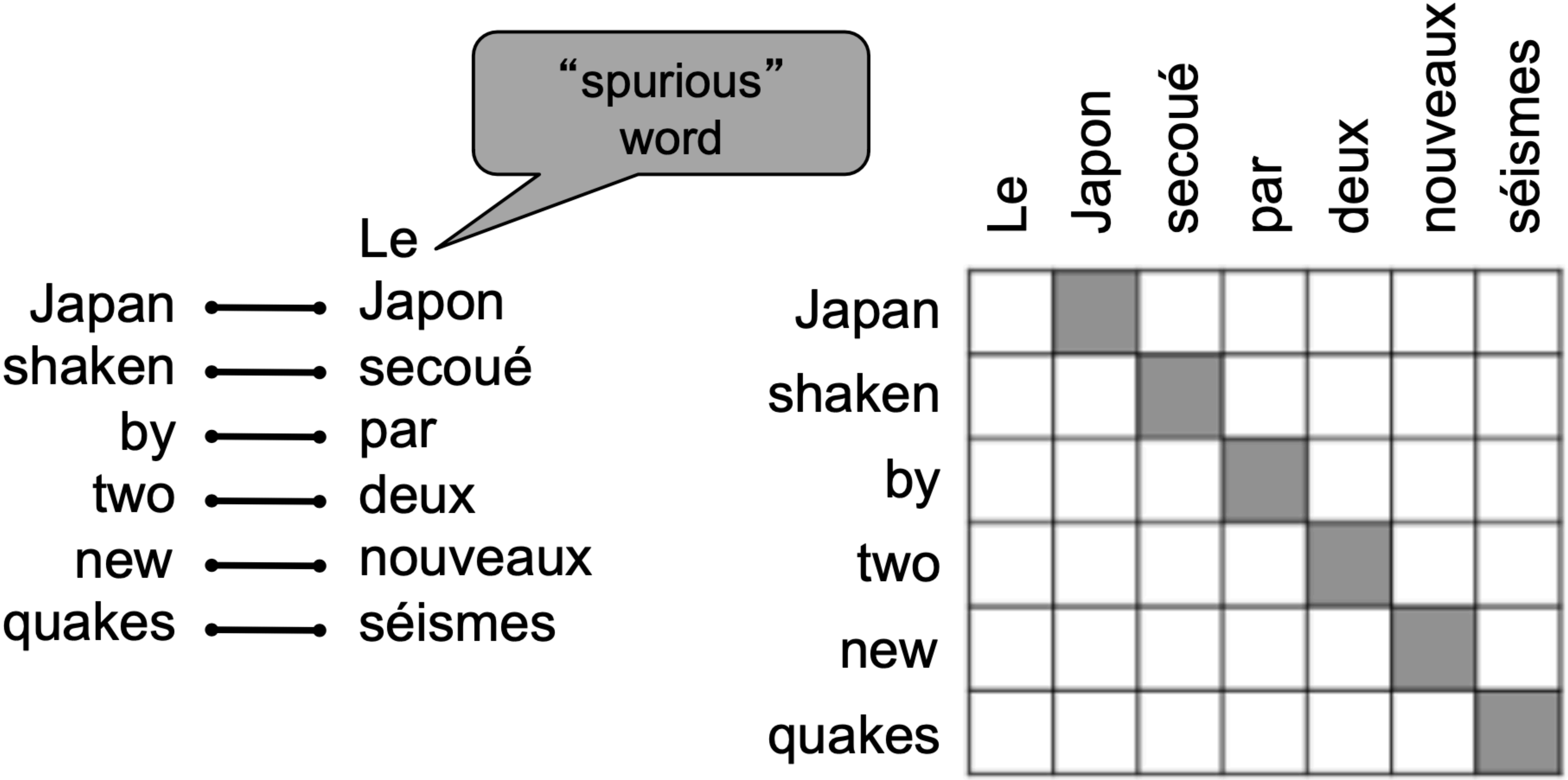
Lexical Translation

- Putting our assumptions together, we have:

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

What is alignment?

- Alignment is the correspondence between particular words in the translated sentence pair.



	Le	Japon	secoué	par	deux	nouveaux	séismes
Japan		▨					
shaken			▨				
by				▨			
two					▨		
new						▨	
quakes							▨

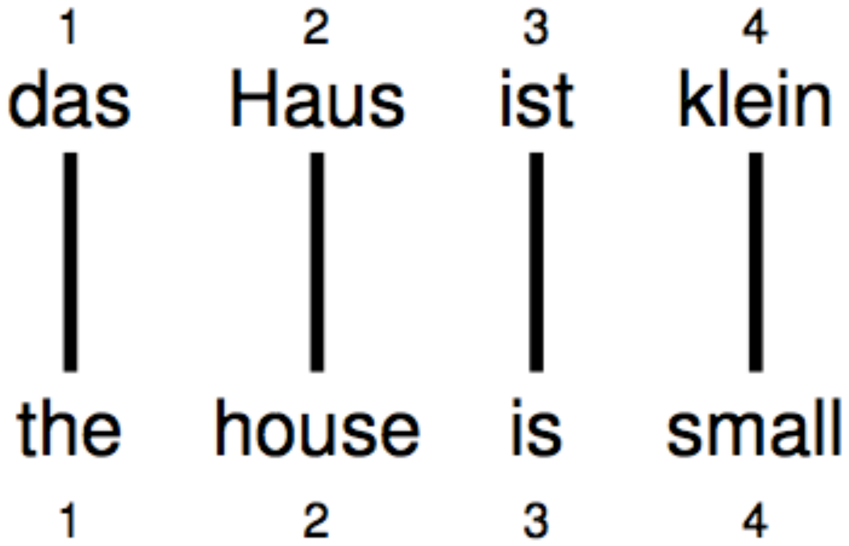
Alignment

$$p(\mathbf{a} \mid \mathbf{f}, m)$$

- Most of the action for the first 10 years of MT was here. Words weren't the problem. Word *order* was hard.

Alignment

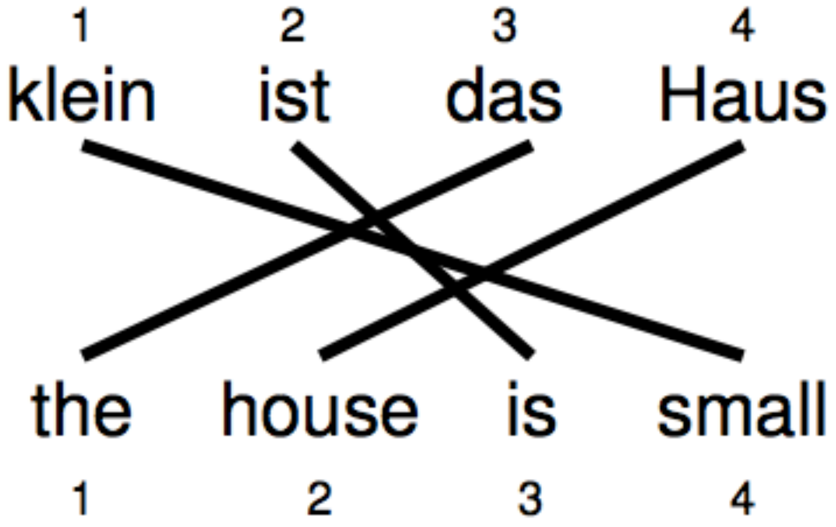
- Alignments can be visualized by drawing links between two sentences, and they are represented as vectors of positions:



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

Reordering

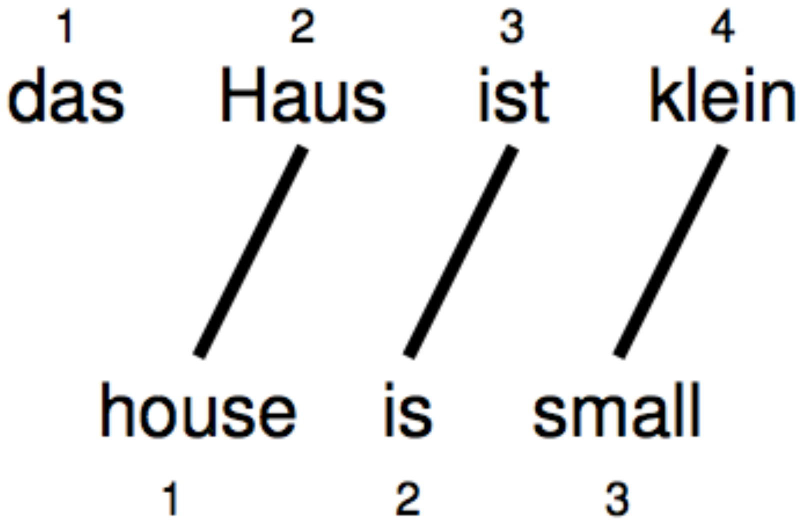
- Words may be reordered during translation



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

Word Dropping

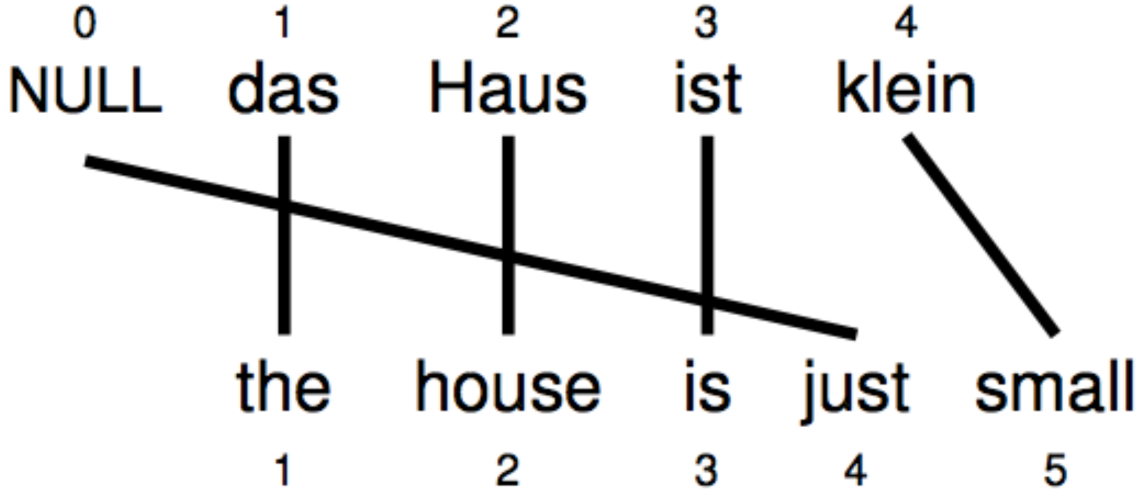
- A source word may not be translated at all



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

Word Insertion

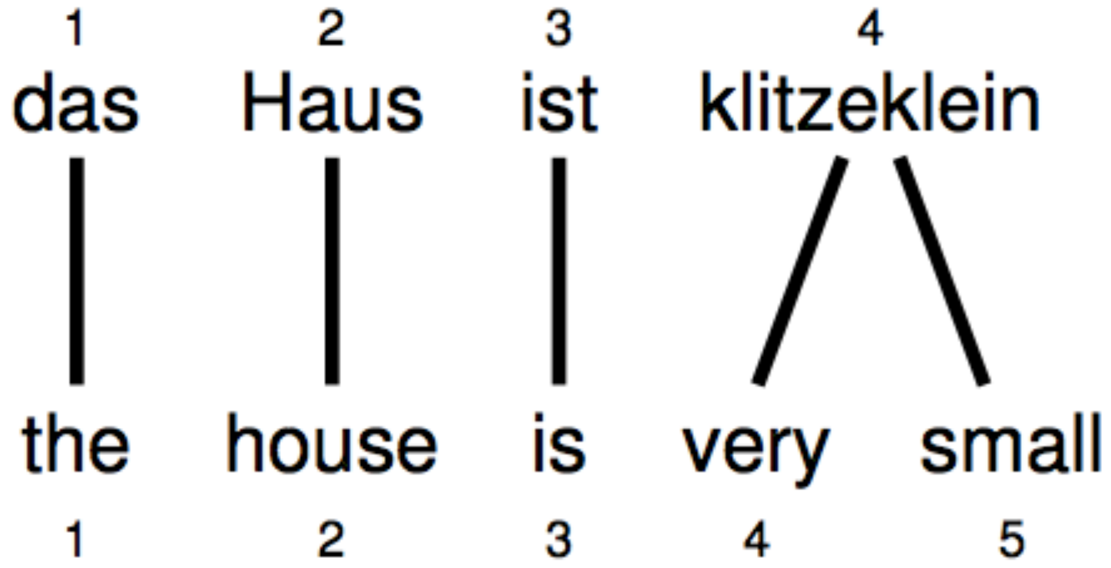
- Words may be inserted during translation
- E.g. English just does not have an equivalent
- But these words must be explained – we typically assume every source sentence contains a NULL token



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

One-to-many Translation

- A source word may translate into **more than one** target word



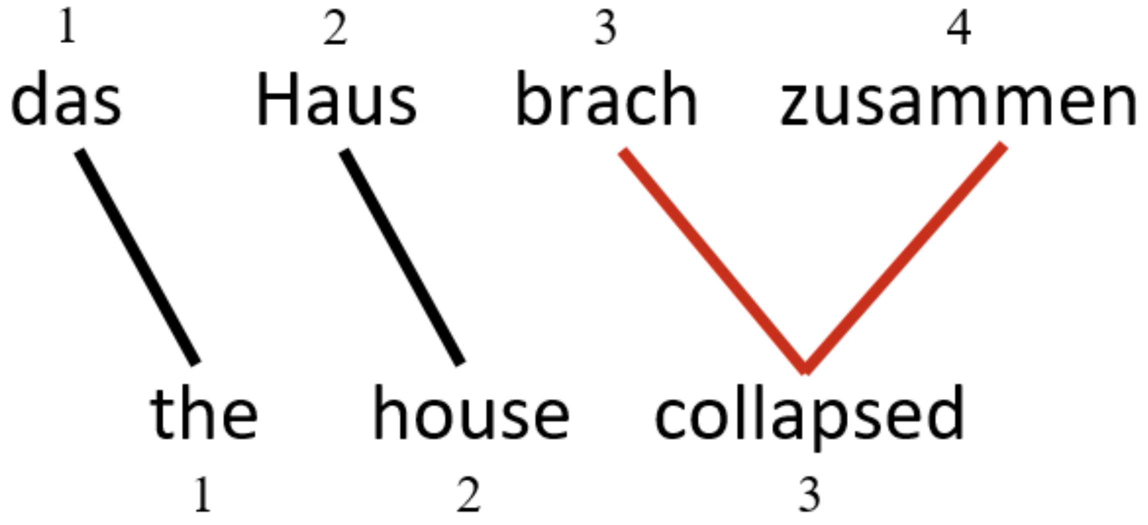
1 das 2 Haus 3 ist 4 klitzeklein

the 1 house 2 is 3 very 4 small 5

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

Many-to-one Translation

- More than one source word may **not** translate as a unit in lexical translation



1 das 2 Haus 3 brach 4 zusammen

the 1 house 2 collapsed 3

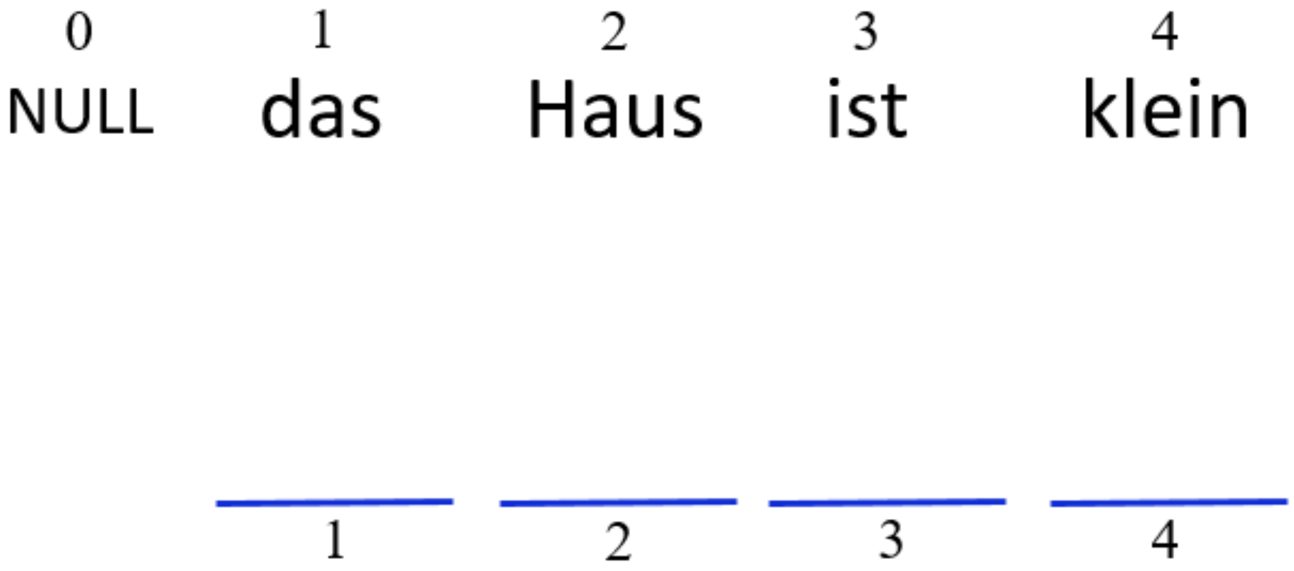
$\mathbf{a} = ???$ $\mathbf{a} = (1, 2, (3, 4)^\top)^\top$?

IBM Model 1

- Simplest possible lexical translation model
- Additional assumptions:
  - The *m* alignment decisions are independent
  - The alignment distribution for each $\mathbf{a}_i$ is uniform over all source words and NULL

$$
\begin{aligned}
&\text{for each } i \in [1, 2, \ldots, m] \\
&\qquad\qquad a_i \sim \text{Uniform}(0, 1, 2, \ldots, n) \\
&\qquad\qquad e_i \sim \text{Categorical}(\boldsymbol{\theta}_{f_{a_i}})
\end{aligned}
$$

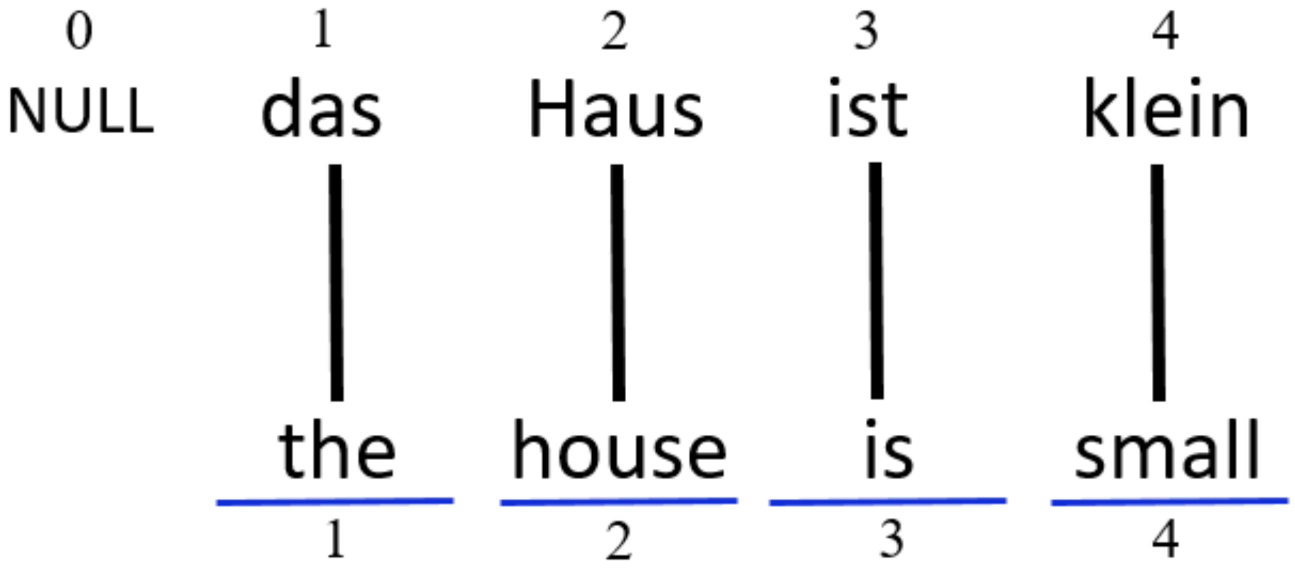
Translating with Model 1



0 NULL
1 das
2 Haus
3 ist
4 klein

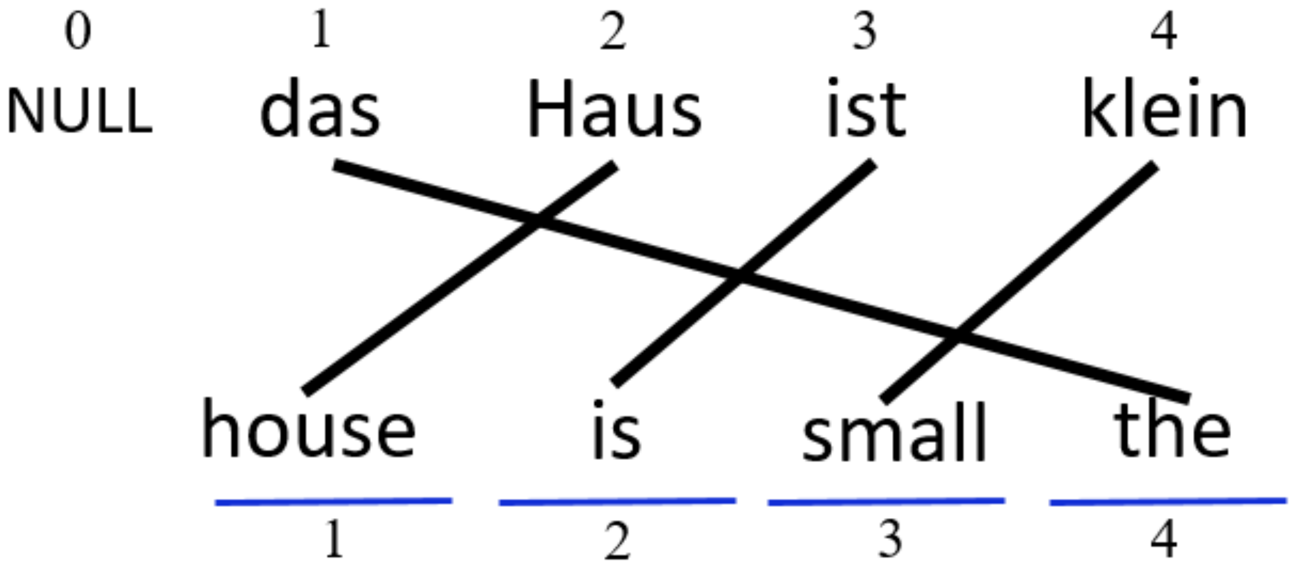
1 2 3 4

Translating with Model 1



Language model says: ☺

Translating with Model 1



Language model says: ☹

Learning Lexical Translation Models

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- How do we learn the parameters $p(e|f)$?

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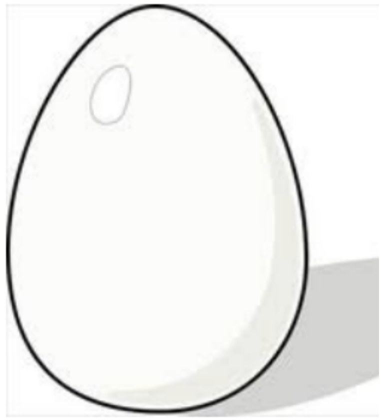

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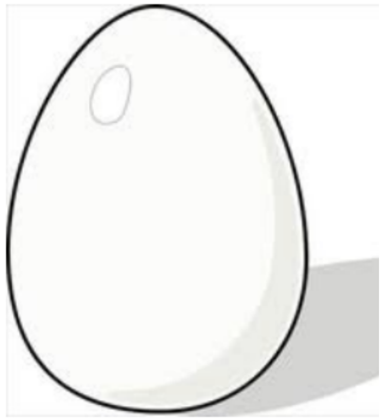

EM Algorithm

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    - Using the current parameters, compute “expected” alignments $p(\mathbf{a}_i | \mathbf{e}, \mathbf{f})$ for every target word token in the training data

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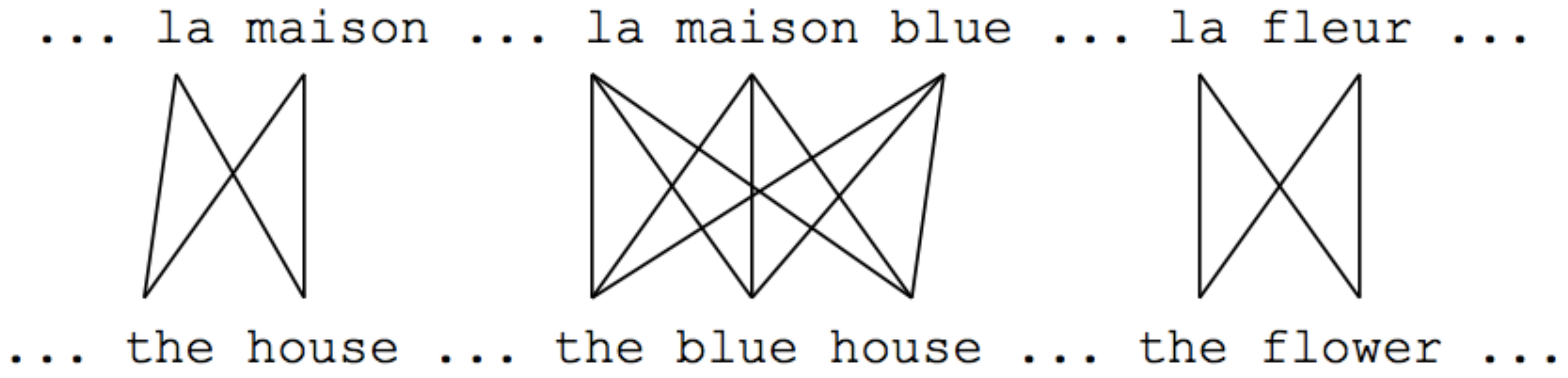
    - Keep track of the expected number of times *f* translates into *e* throughout the whole corpus
    - Keep track of the number of times *f* is used in the source of any translation
    - Use these estimates in the standard MLE equation to get a better set of parameters

EM for Model 1

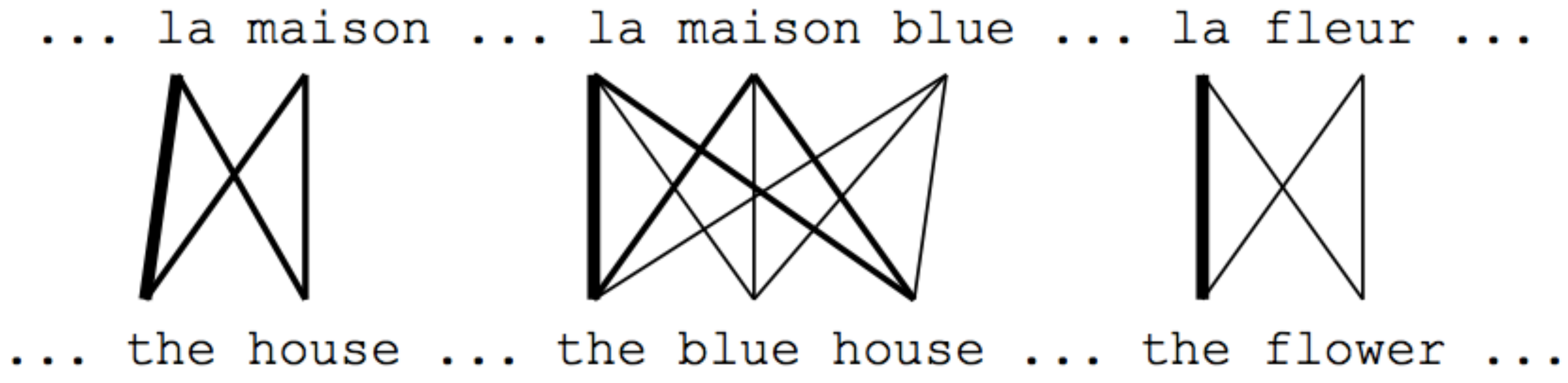


... la maison ... la maison blue ... la fleur ...

... the house ... the blue house ... the flower ...

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

EM for Model 1


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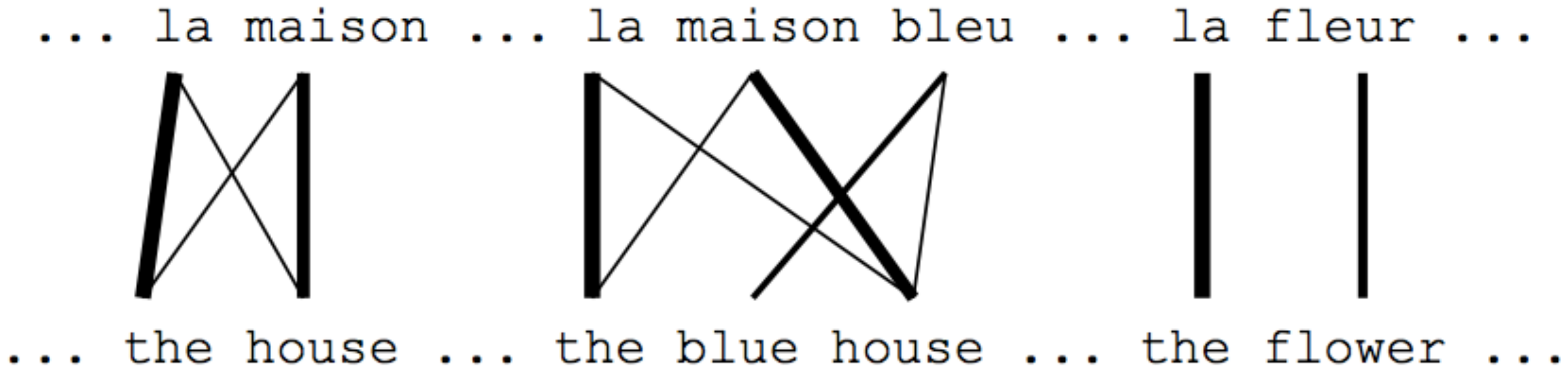
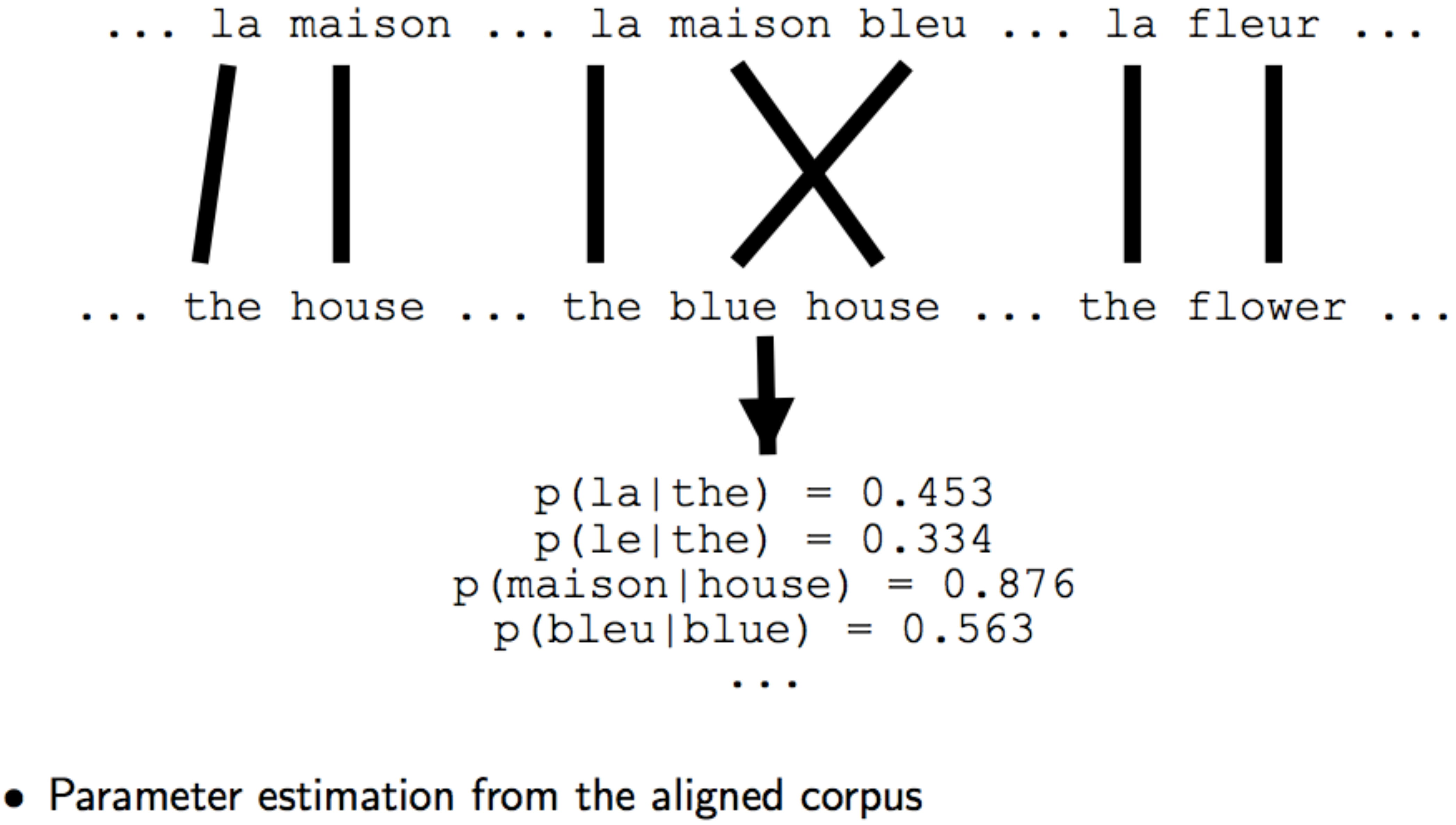
- After one iteration
- Alignments, e.g., between la and the are more likely

EM for Model 1


... la maison ... la maison bleu ... la fleur ...
... the house ... the blue house ... the flower ...

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

EM for Model 1



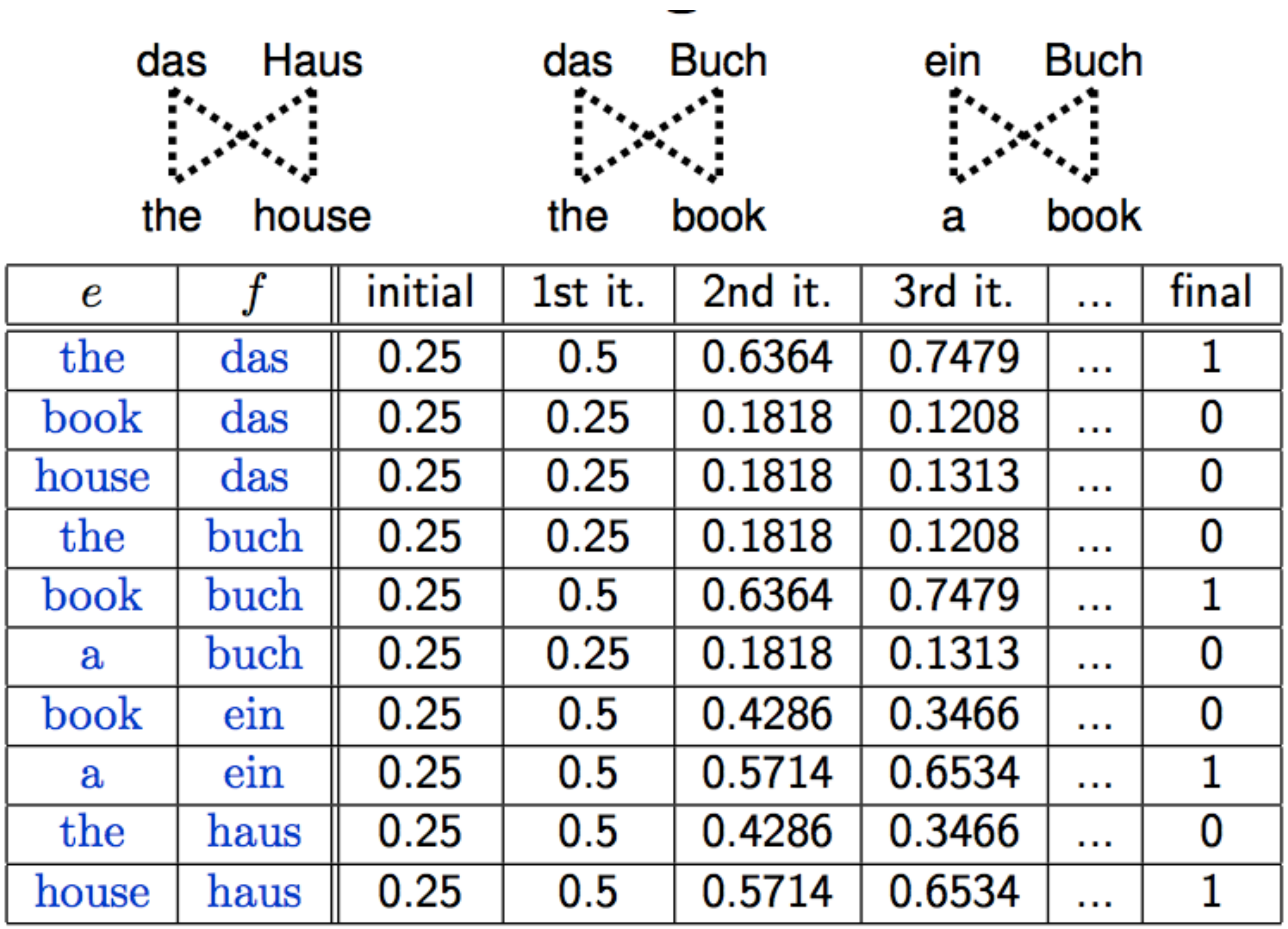
... la maison ... la maison bleu ... la fleur ...

... the house ... the blue house ... the flower ...

```
        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


das
Haus
the
house
das
Buch
the
book
ein
Buch
a
book

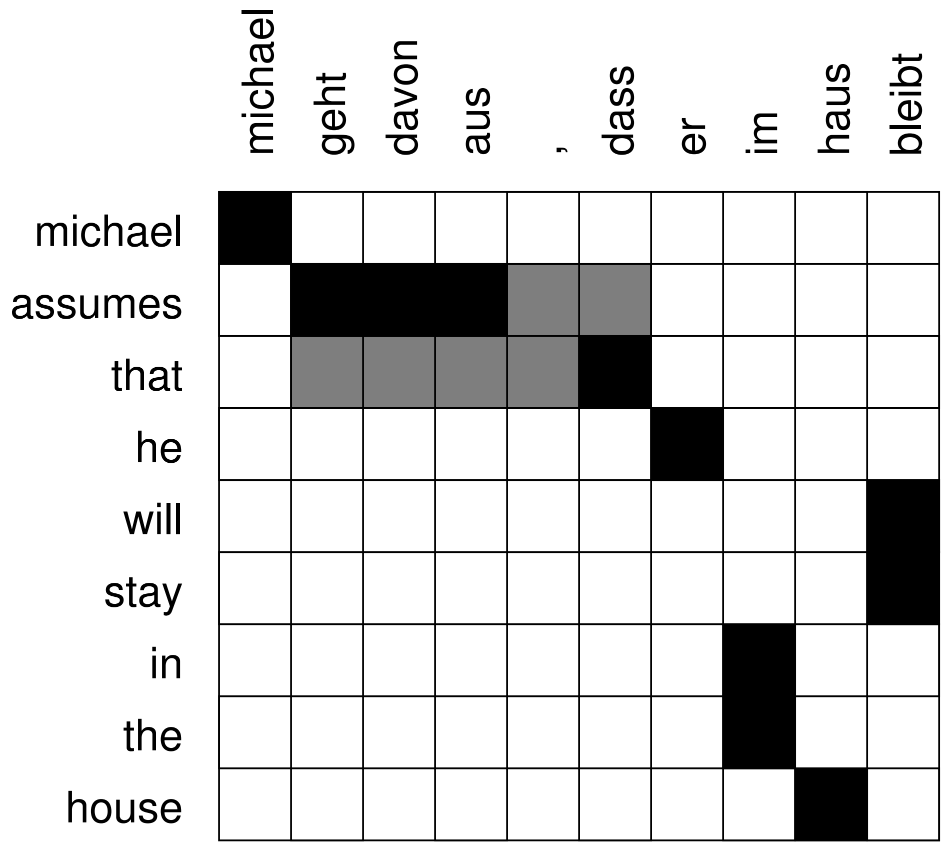
e	*f*	initial	1st it.	2nd it.	3rd it.	...	final
the	das	0.25	0.5	0.6364	0.7479	...	1
book	das	0.25	0.25	0.1818	0.1208	...	0
house	das	0.25	0.25	0.1818	0.1313	...	0
the	buch	0.25	0.25	0.1818	0.1208	...	0
book	buch	0.25	0.5	0.6364	0.7479	...	1
a	buch	0.25	0.25	0.1818	0.1313	...	0
book	ein	0.25	0.5	0.4286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

From words to phrases

Word Alignment

	michael	geht	davon	aus	,	dass	er	im	haus	bleibt
michael	■									
assumes		■	■	■						
that						■				
he							■			
will										■
stay										■
in								■		
the								■		
house									■	

Extracting Phrase Pairs

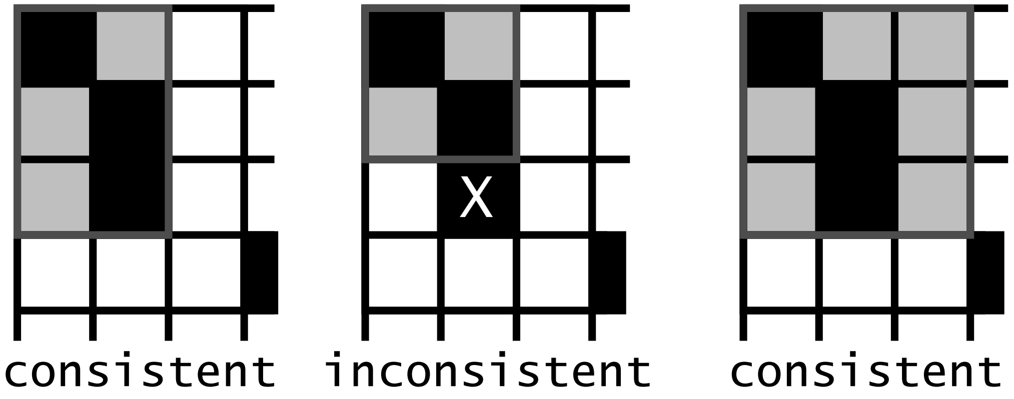


	michael	geht	davon	aus	,	dass	er	im	haus	bleibt
michael	■									
assumes		■	■	■	▨	▨				
that		▨	▨	▨	▨	■				
he							■			
will										■
stay										■
in								■		
the								■		
house									■	

extract phrase pair consistent with word alignment:

assumes that / geht davon aus , dass

Consistent



Phrase pair $(\bar{e}, \bar{f})$ consistent with an alignment A, if all words $f_1, ..., f_n$ in $\bar{f}$ that have alignment points in A have these with words $e_1, ..., e_n$ in $\bar{e}$ and vice versa:

$$(\bar{e}, \bar{f}) \text{ consistent with } A \Leftrightarrow$$

$$\forall e_i \in \bar{e} : (e_i, f_j) \in A \rightarrow f_j \in \bar{f}$$

$$\text{AND } \forall f_j \in \bar{f} : (e_i, f_j) \in A \rightarrow e_i \in \bar{e}$$

$$\text{AND } \exists e_i \in \bar{e}, f_j \in \bar{f} : (e_i, f_j) \in A$$

Phrase Pair Extraction

	michael	geht	davon	aus	,	dass	er	im	haus	bleibt
michael	■									
assumes		■	■	■						
that						■				
he							■			
will										■
stay										■
in								■		
the								■		
house									■	

Smallest phrase pairs:

michael — michael
assumes — geht davon aus / geht davon aus ,
that — dass / , dass
he — er
will stay — bleibt
in the — im
house — haus

unaligned words (here: German comma) lead to multiple translations

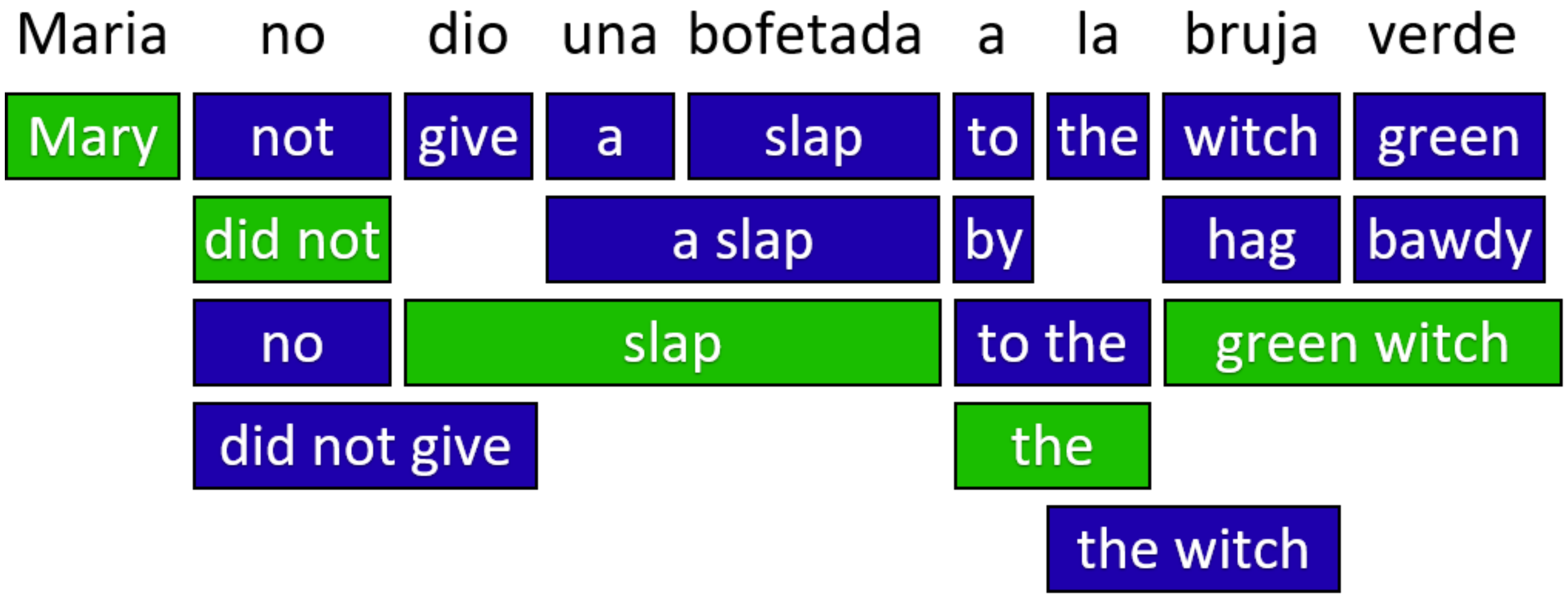
Larger Phrase Pairs

	michael	geht	davon	aus	,	dass	er	im	haus	bleibt
michael	■									
assumes		■	■	■						
that						■				
he							■			
will										■
stay										■
in								■		
the								■		
house									■	

michael assumes — michael geht davon aus / michael geht davon aus ,
assumes that — geht davon aus , dass ; assumes that he — geht davon aus , dass er
that he — dass er / , dass er ; in the house — im haus
michael assumes that — michael geht davon aus , dass
michael assumes that he — michael geht davon aus , dass er
michael assumes that he will stay in the house — michael geht davon aus , dass er im haus bleibt
assumes that he will stay in the house — geht davon aus , dass er im haus bleibt
that he will stay in the house — dass er im haus bleibt ; dass er im haus bleibt ,
he will stay in the house — er im haus bleibt ; will stay in the house — im haus bleibt

Extensions

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



Maria no dio una bofetada a la bruja verde

Mary not give a slap to the witch green

did not a slap by hag bawdy

no slap to the green witch

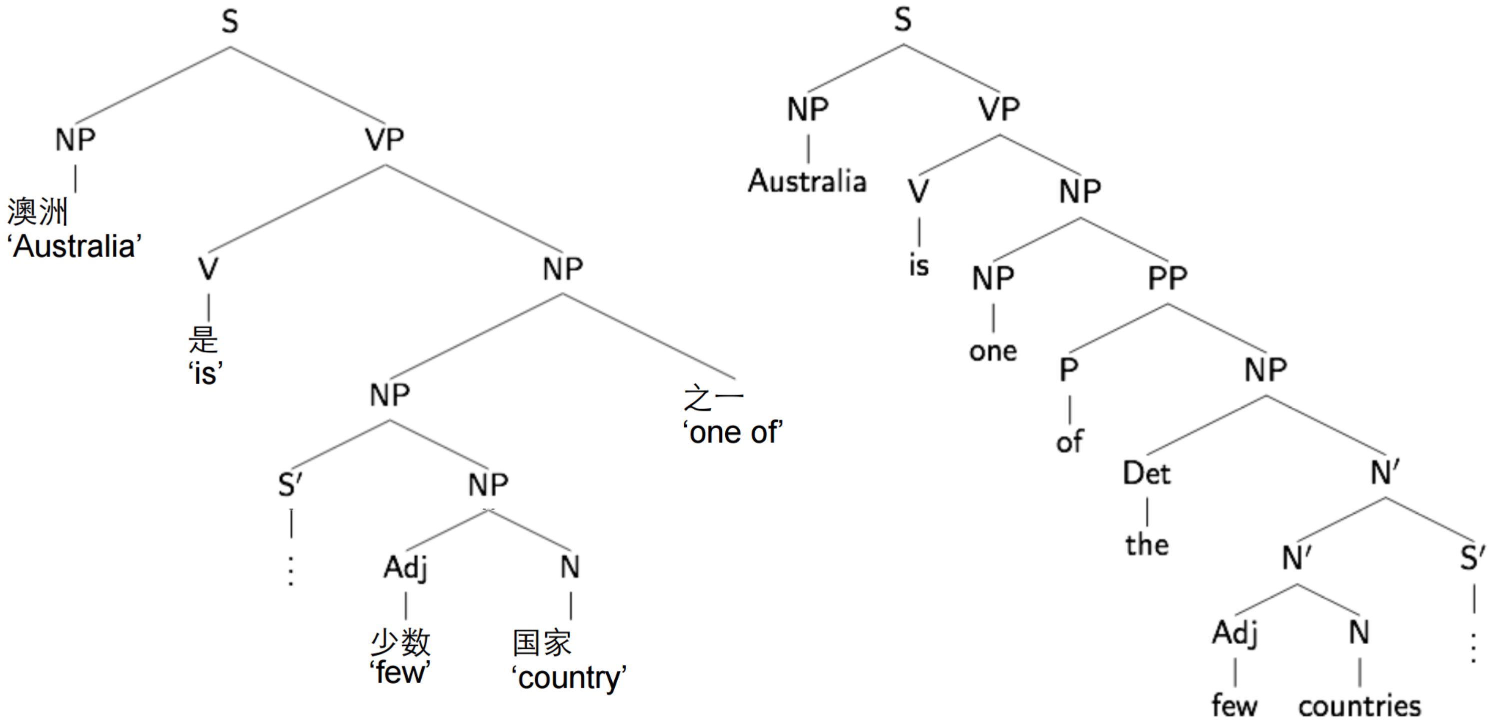
did not give the

the witch

Adapted from Koehn (2006)

Another Paradigm: Syntax-Based MT

- Syntactic structure
- Rules of the form:
- X之一 → one of the X

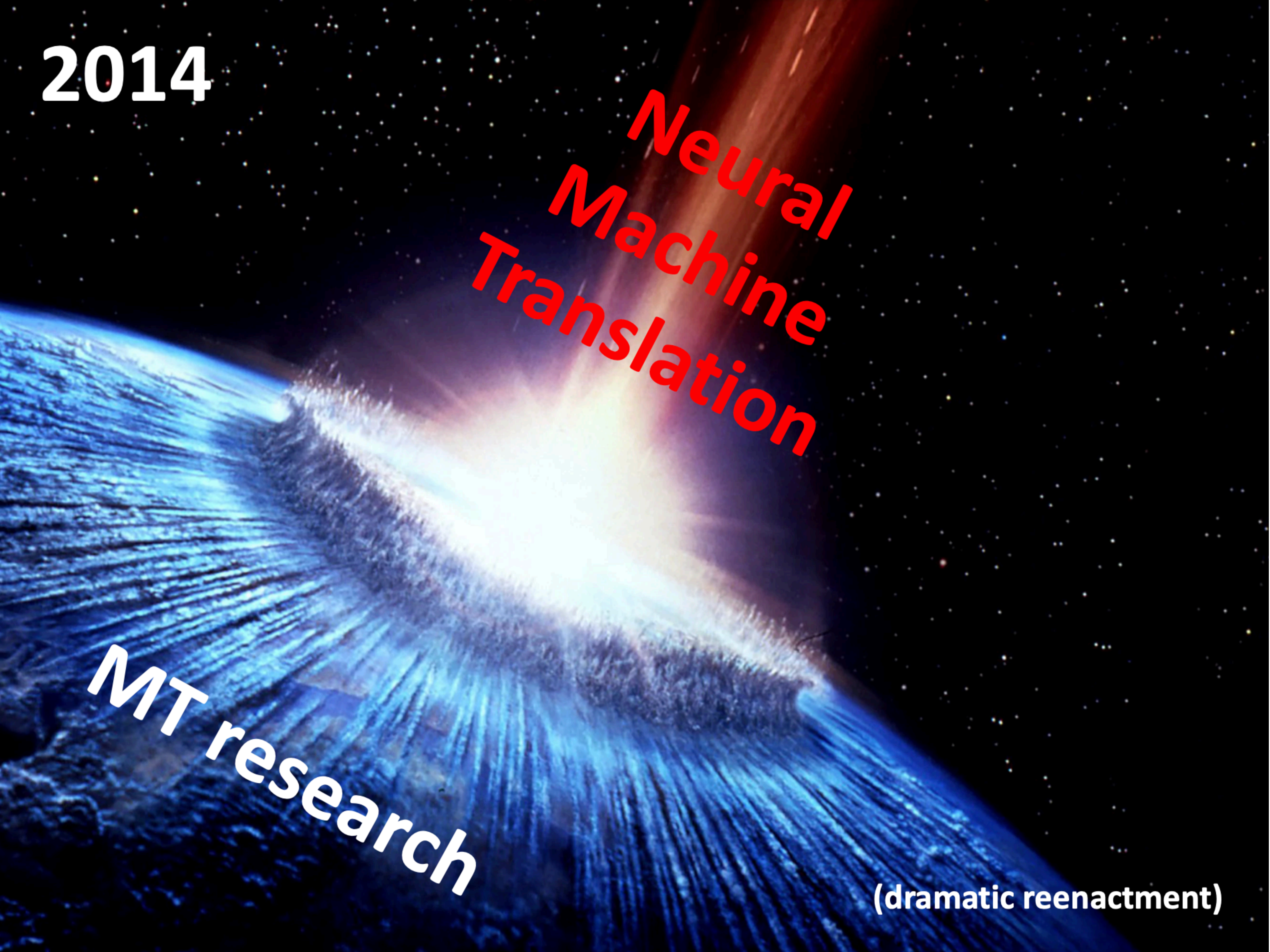


Chang (2005), Galley et al. (2

2014

(dramatic reenactment)

2014



(dramatic reenactment)

What is Neural Machine Translation?

- Neural Machine Translation (NMT) is a way to do Machine Translation with a single neural network
- The neural network architecture is called sequence-to-sequence (aka seq2seq) and it involves two RNNs.

Conditional Language Models

$$P(Y|X) = \prod_{j=1}^{J} P(y_j \mid X, y_1, \ldots, y_{j-1})$$

Conditional Language Models

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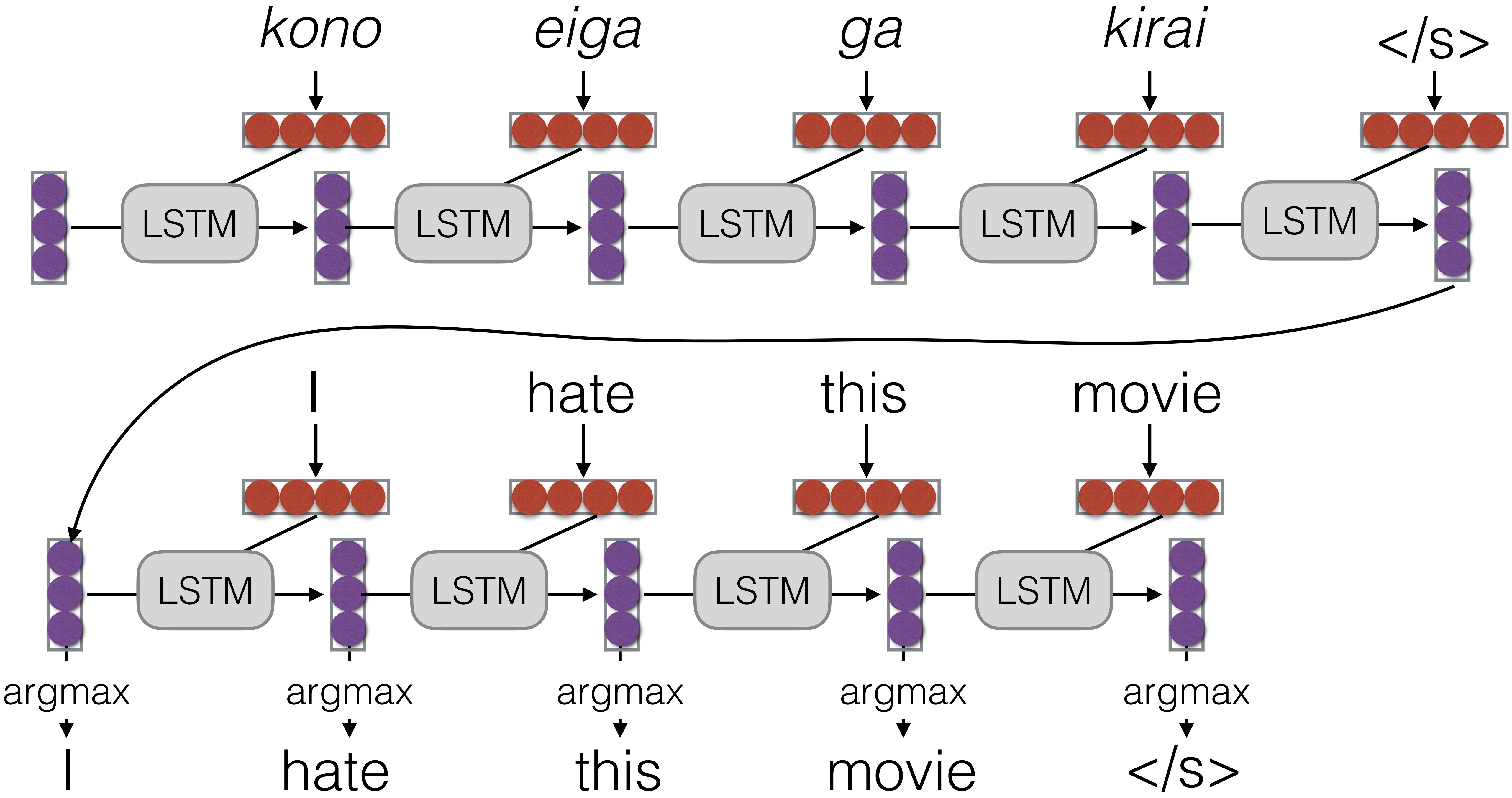
Added Context!

(One Type of) Conditional Language Model (Sutskever et al. 2014)



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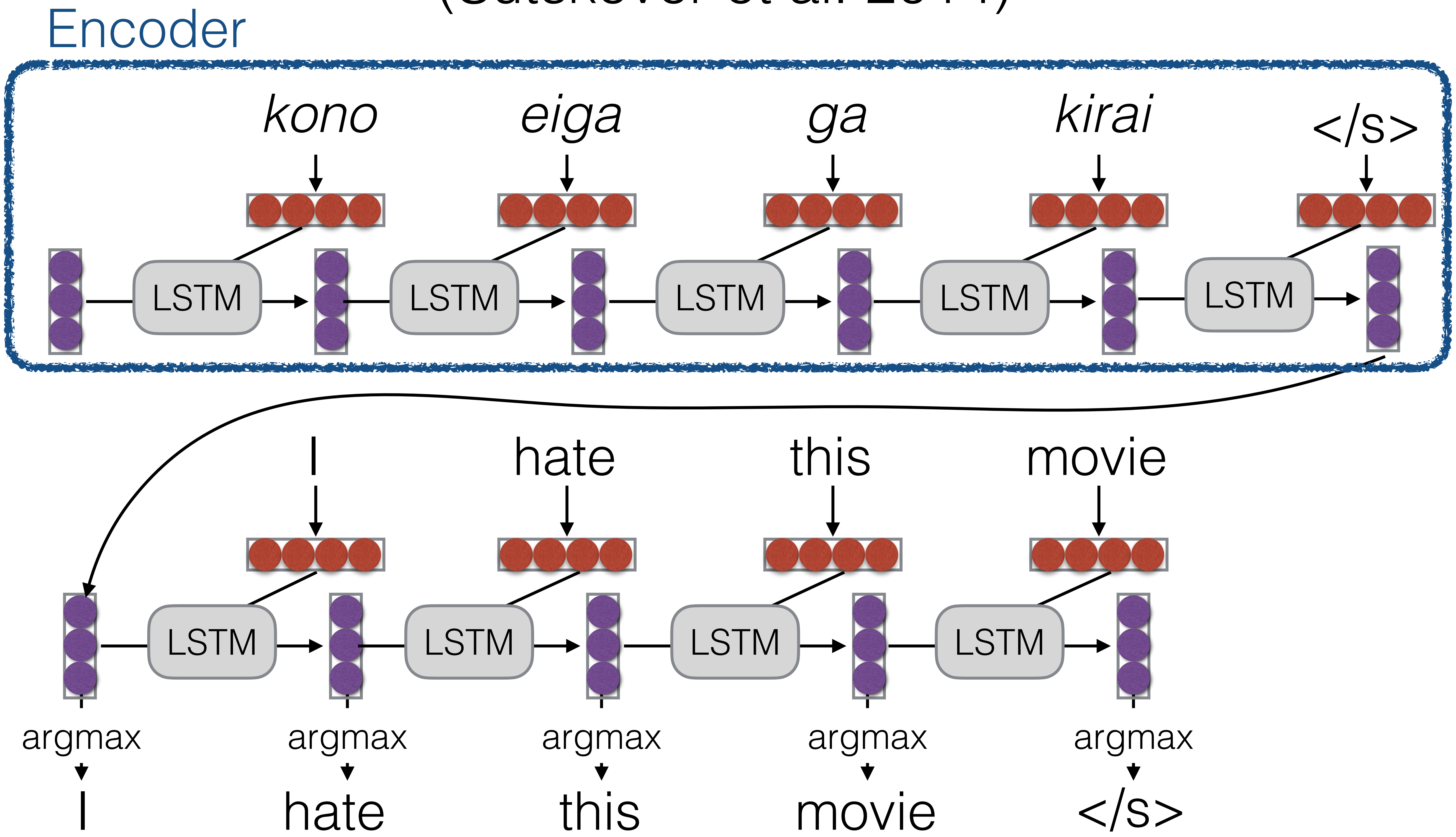

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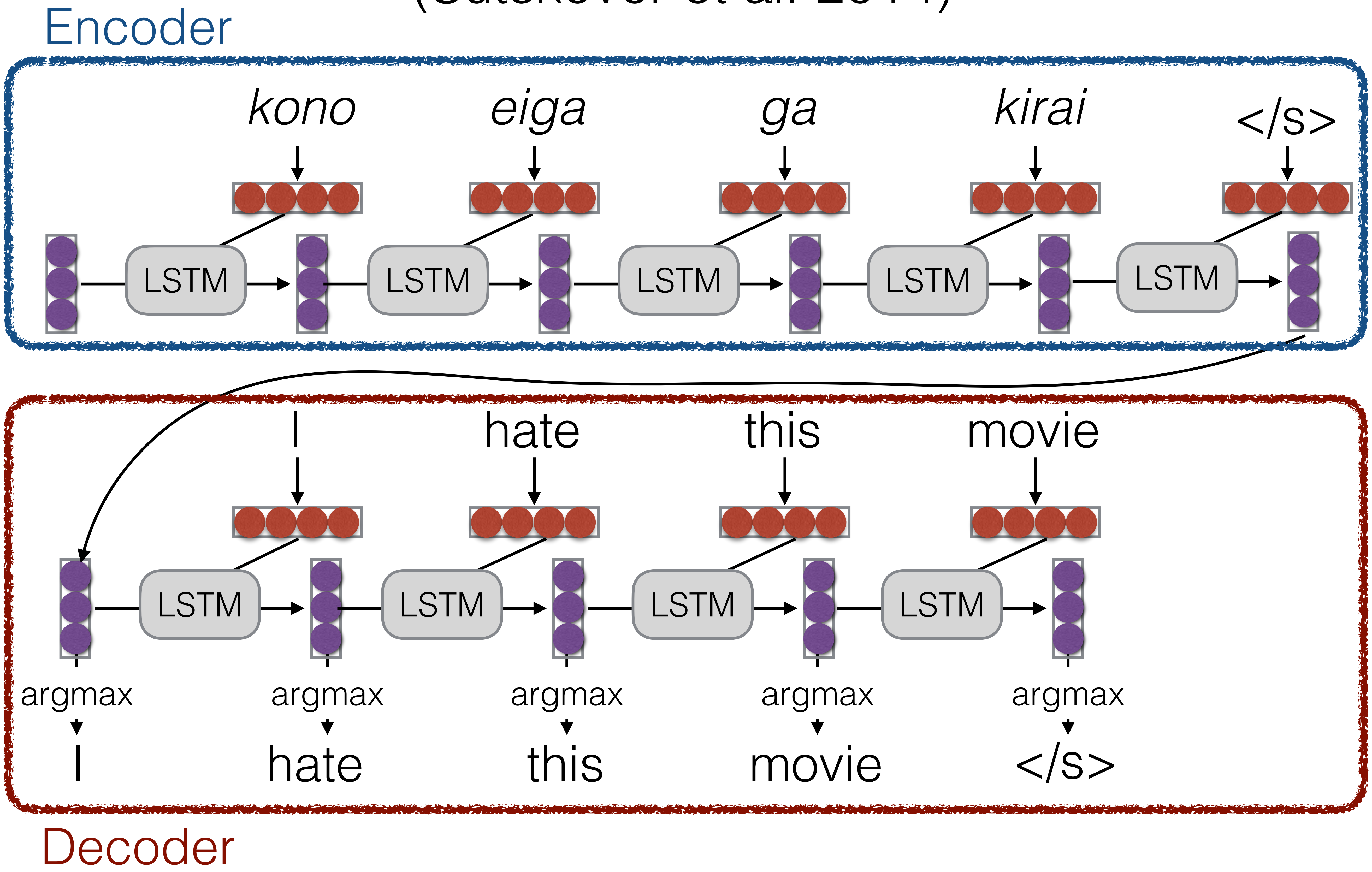
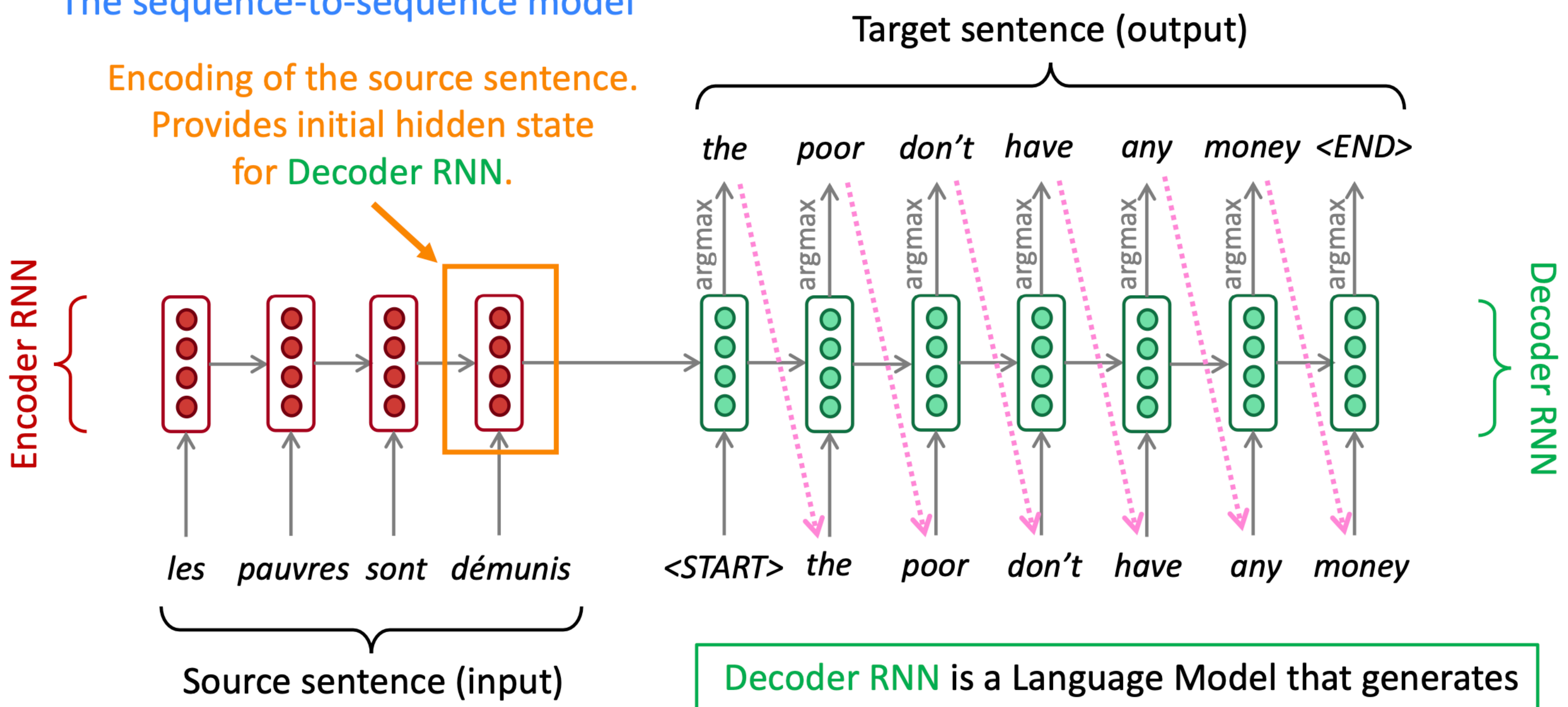


Neural Machine Translation (NMT)

The sequence-to-sequence model

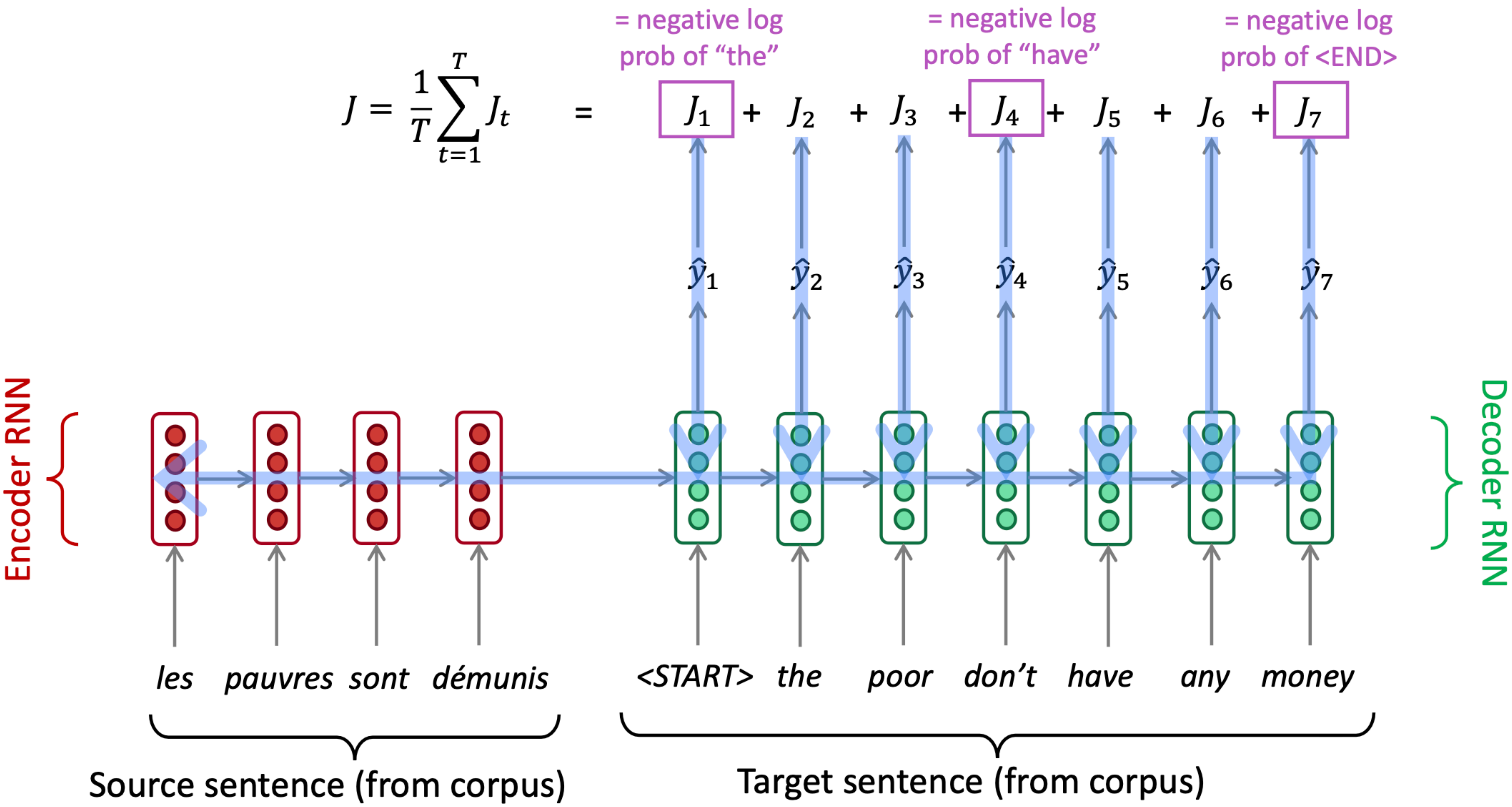


Decoder RNN is a Language Model that generates target sentence conditioned on encoding.

Encoder RNN produces an encoding of the source sentence.

Note: This diagram shows **test time** behavior: decoder output is fed in ·····> as next step's input

Neural Machine Translation (NMT)


= negative log prob of "the"
= negative log prob of "have"
= negative log prob of <END>
$J = \frac{1}{T}\sum_{t=1}^{T} J_t \quad = \quad \boxed{J_1} + J_2 + J_3 + \boxed{J_4} + J_5 + J_6 + \boxed{J_7}$
$\hat{y}_1$ $\hat{y}_2$ $\hat{y}_3$ $\hat{y}_4$ $\hat{y}_5$ $\hat{y}_6$ $\hat{y}_7$
Encoder RNN
Decoder RNN
les
pauvres
sont
démunis
<START>
the
poor
don't
have
any
money
Source sentence (from corpus)
Target sentence (from corpus)

Seq2seq is optimized as a **single system.**
Backpropagation operates *"end to end"*.

Advantages of NMT

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  - Better use of phrase similarities
- A single neural network to be optimized end-to-end
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- Requires much less human engineering effort
  - No feature engineering
  - Same method for all language pairs

Disadvantages of NMT?

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Compared to SMT:

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- NMT is less interpretable

Disadvantages of NMT?

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Disadvantages of NMT?

Compared to SMT:

- NMT is less interpretable
  - Hard to debug
- NMT is difficult to control
  - For example, can’t easily specify rules or guidelines for translation
  - Safety concerns!

Generation

Can we find the best (most likely) translation?

Generation through Sampling

No but we can approximate it!

Generating New Sentences

Generating New Sentences

- Generate sentences:

```
while didn’t choose end-of-sentence symbol:
    calculate probability of
$P(x_t | x_1, \ldots, x_{t-1})$
```

Greedy Decoding

- Generate next word conditioned on the context (i.e., the previously generated words)

- “Greedy”: always pick the most probable next word
$$x_t = argmax_{\hat{x}} P(\hat{x} \mid x_1, \ldots, x_{t-1})$$

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$$x_t = argmax_{\hat{x}} P(\hat{x} \mid x_1, \ldots, x_{t-1})$$

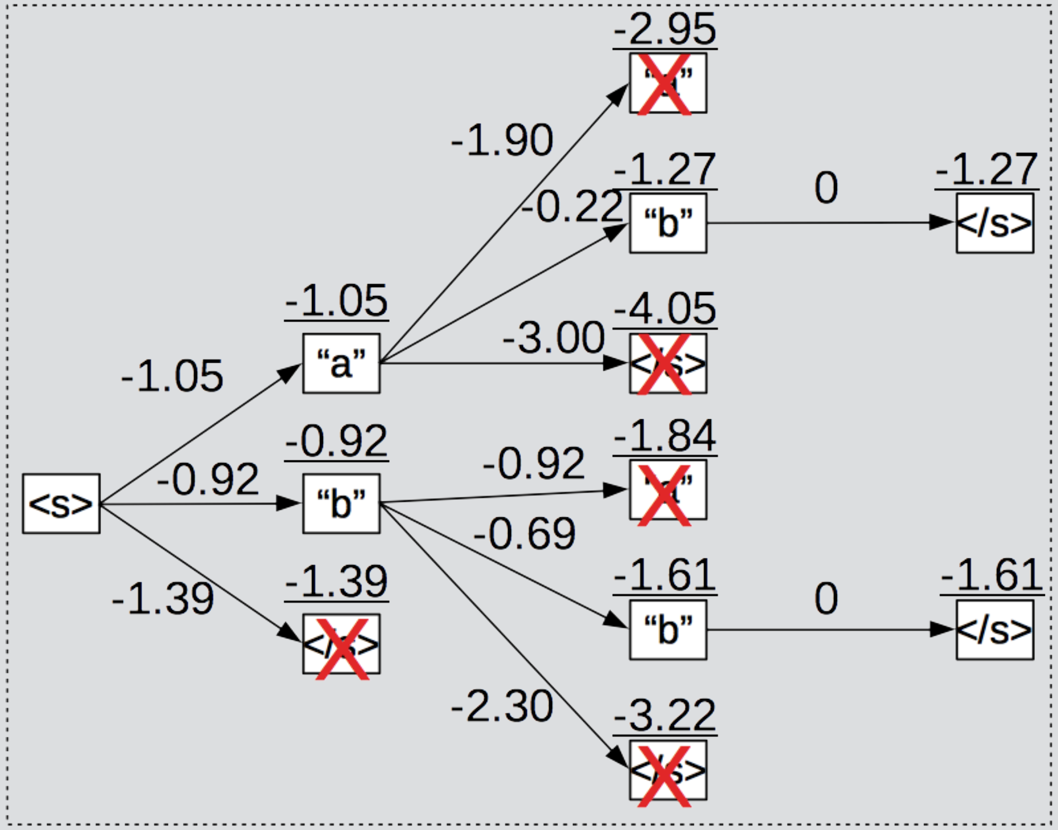
- Problem:
  - The most probable next word does not always lead to the most probable sentence;
  - We should be able to generate a diverse set of sentences!

Beam Search

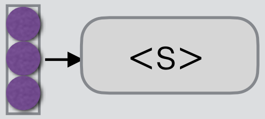
- Beam search: instead of picking one high-probability word, maintain several paths

Beam Search

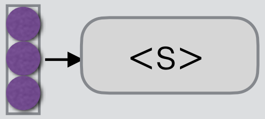
- Beam search: instead of picking one high-probability word, maintain several paths



Beam Search



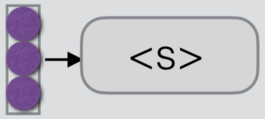
Beam Search



a	0.001
the	0.0002
I	0.12
you	0.04
cat	0.0004
movie	0.01
this	0.02
…	

Beam Search

k=2

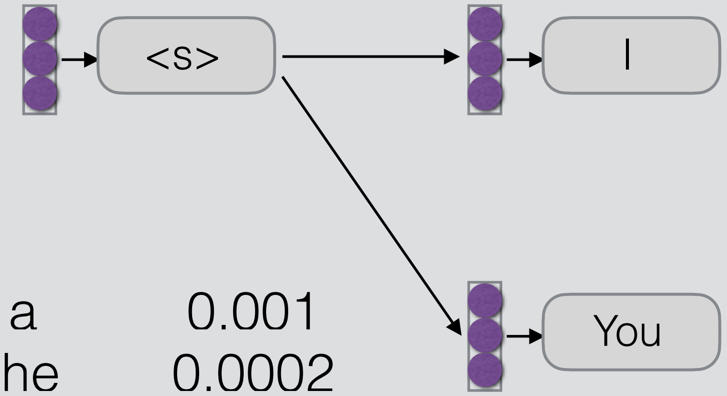


<s>

a	0.001
the	0.0002
I	0.12 ←
you	0.04 ←
cat	0.0004
movie	0.01
this	0.02
…	

Beam Search

k=2



a	0.001	
the	0.0002	
I	0.12	←
you	0.04	←
cat	0.0004	
movie	0.01	
this	0.02	
…		

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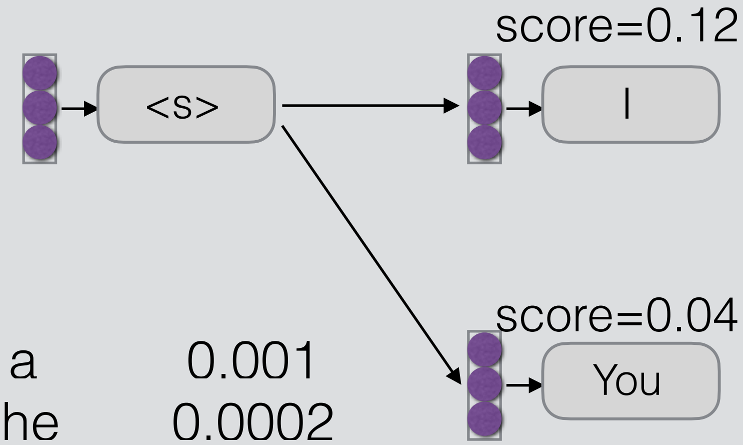

a	0.001
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I	0.12
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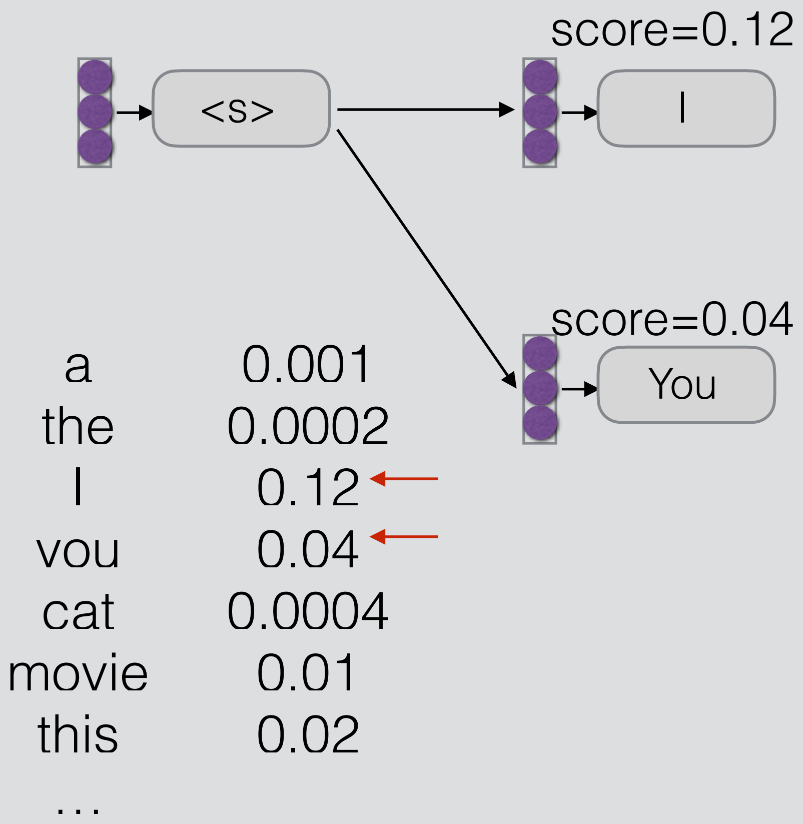
…	

Beam Search

k=2 Expand



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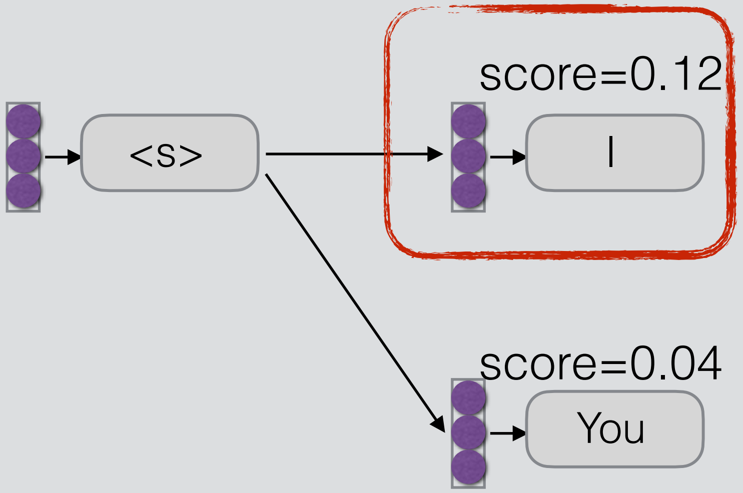
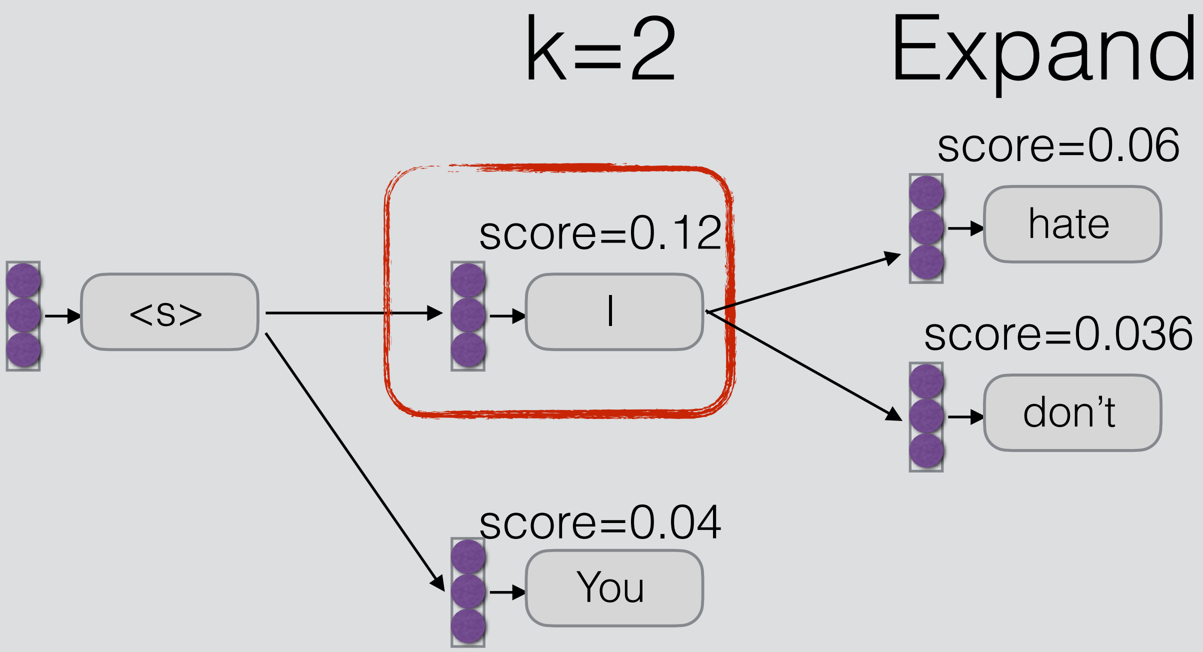
Beam Search

k=2 Expand



a	0.001
the	0.0002
hate	0.5 ←
this	0.001
cat	0.003
movie	0.07
don’t	0.3 ←
…	…

Beam Search



k=2

Expand

<s>

score=0.12

I

score=0.04

You

score=0.06

hate

score=0.036

don’t

a	0.001	
the	0.0002	
hate	0.5	←
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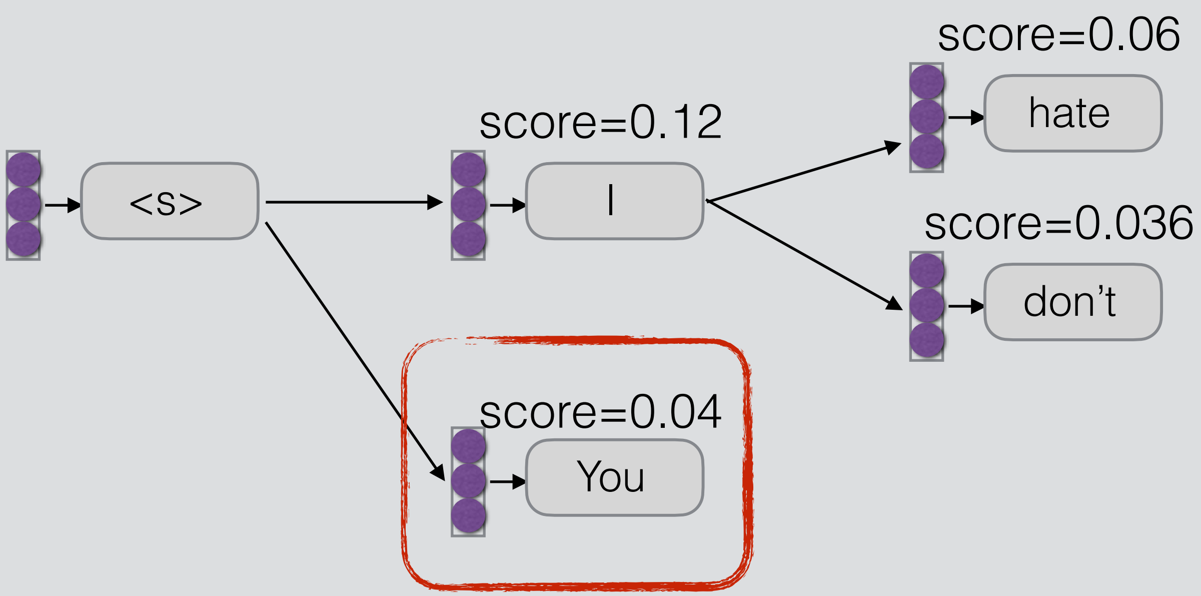
Beam Search

k=2

Expand



score=0.06

hate

score=0.12

<s>

I

score=0.036

don’t

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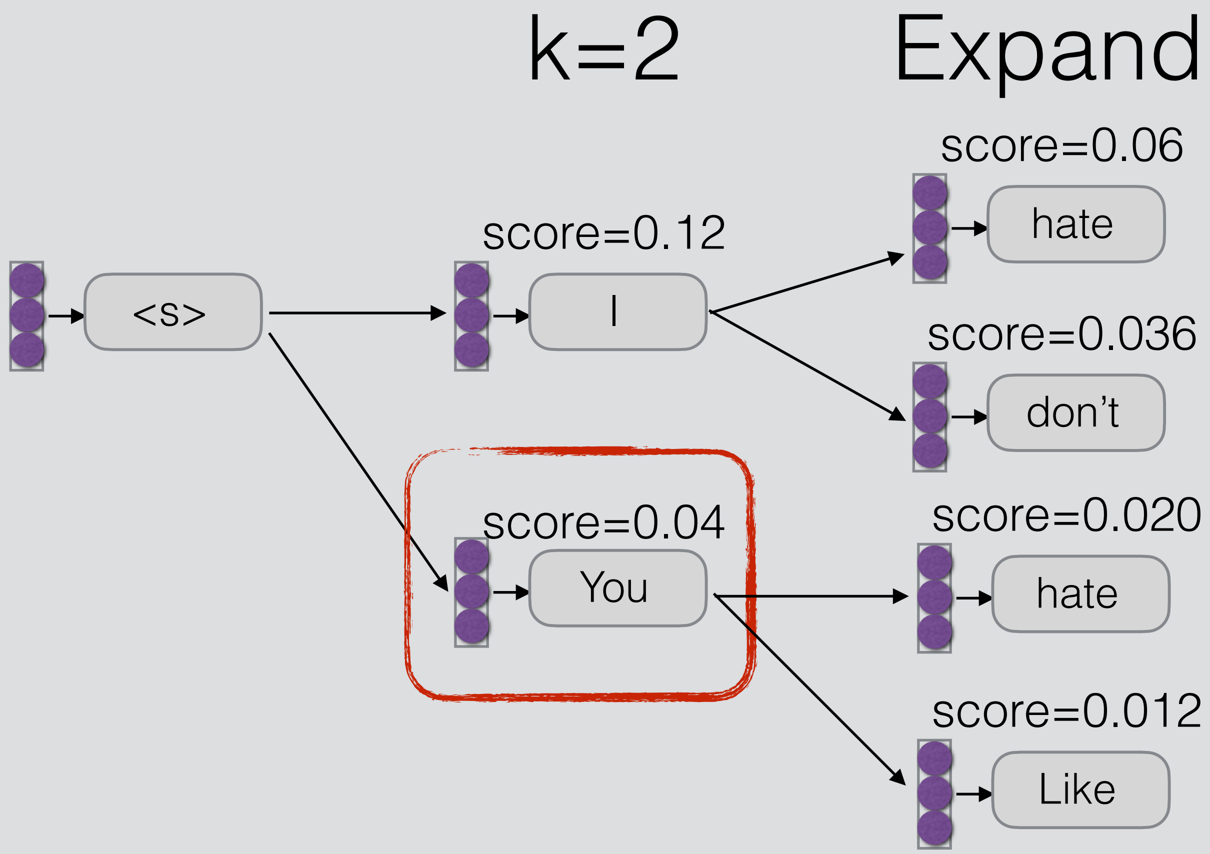
You

an	0.0012	
be	0.0002	
hate	0.5	←
these	0.001	
dog	0.003	
movie	0.07	
like	0.3	←
…	…	

Beam Search



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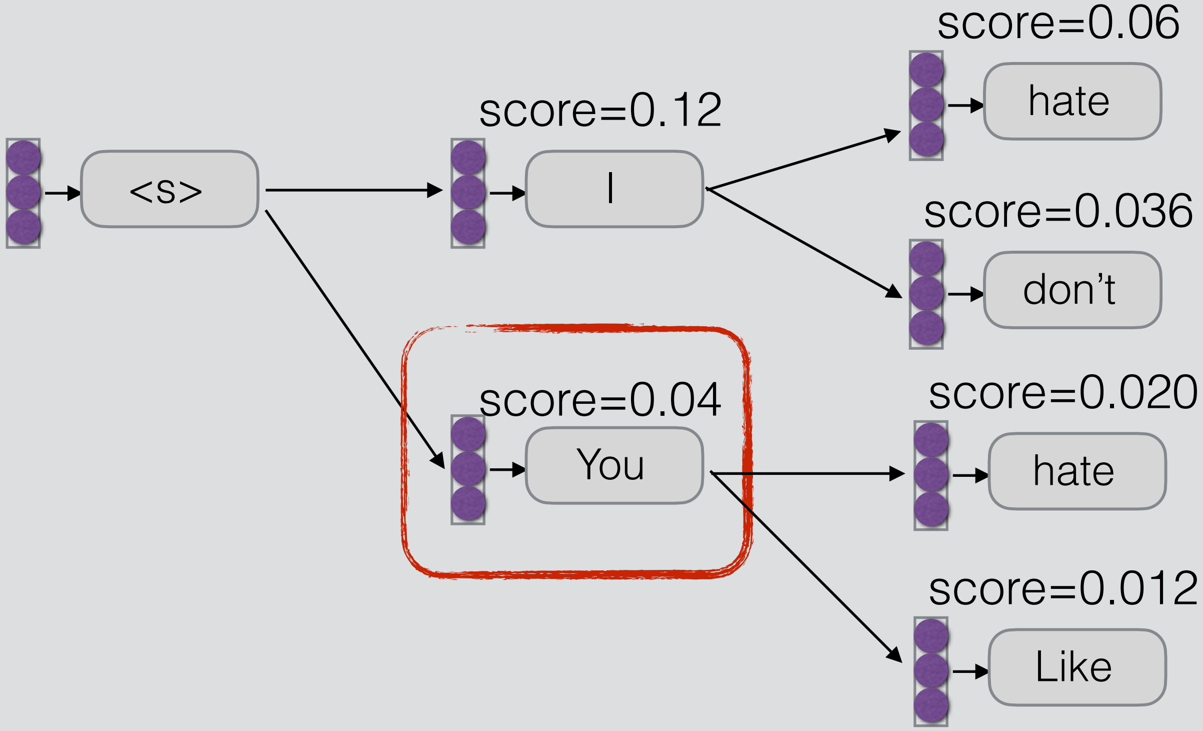
like	0.3	←
…	…	

Beam Search

k=2 Expand Prune



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like	0.3	←
…	…	

Beam Search

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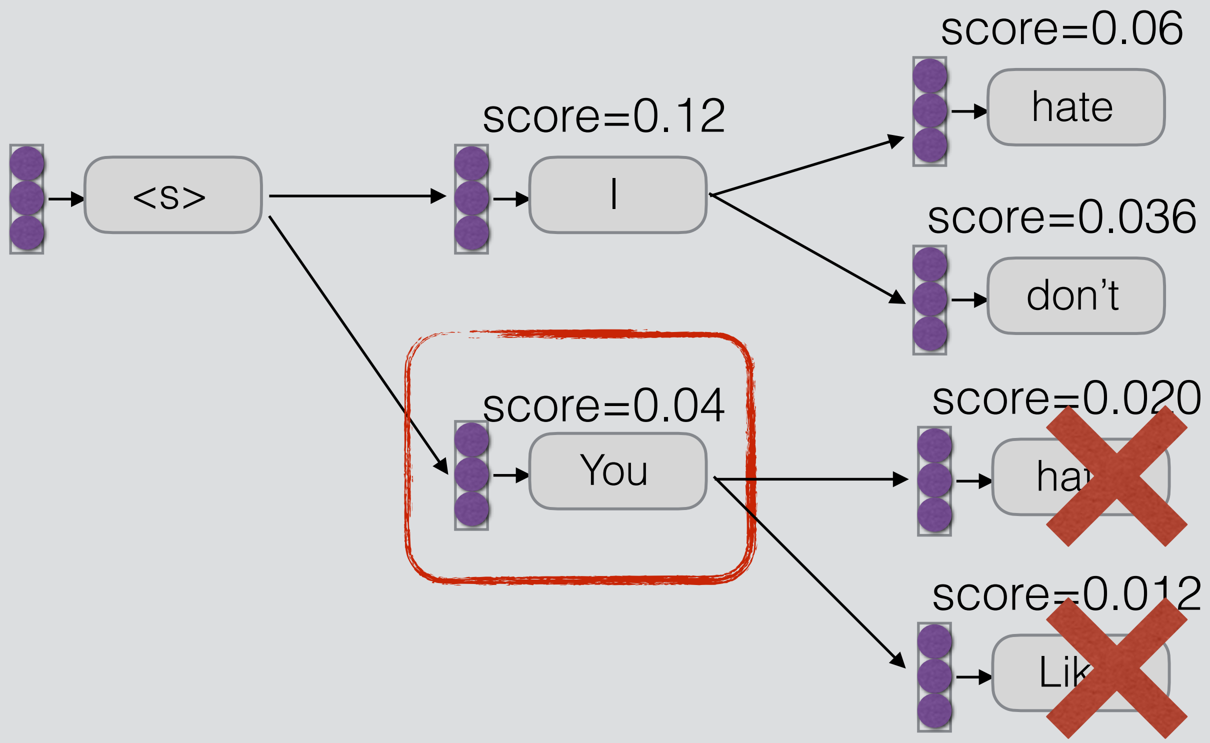

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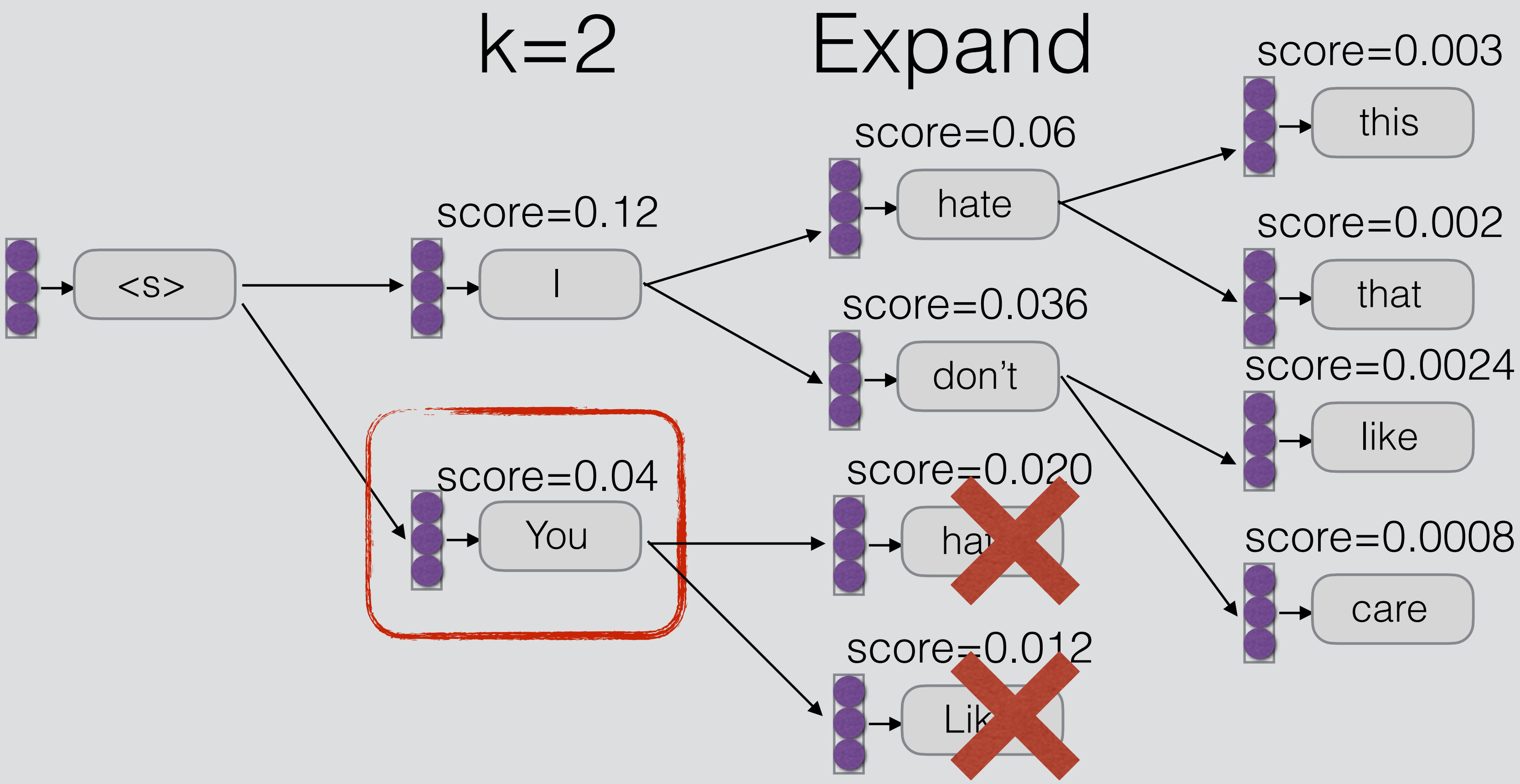
…	…	

Beam Search


k=2
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score=0.12
I
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don't
score=0.020
ha
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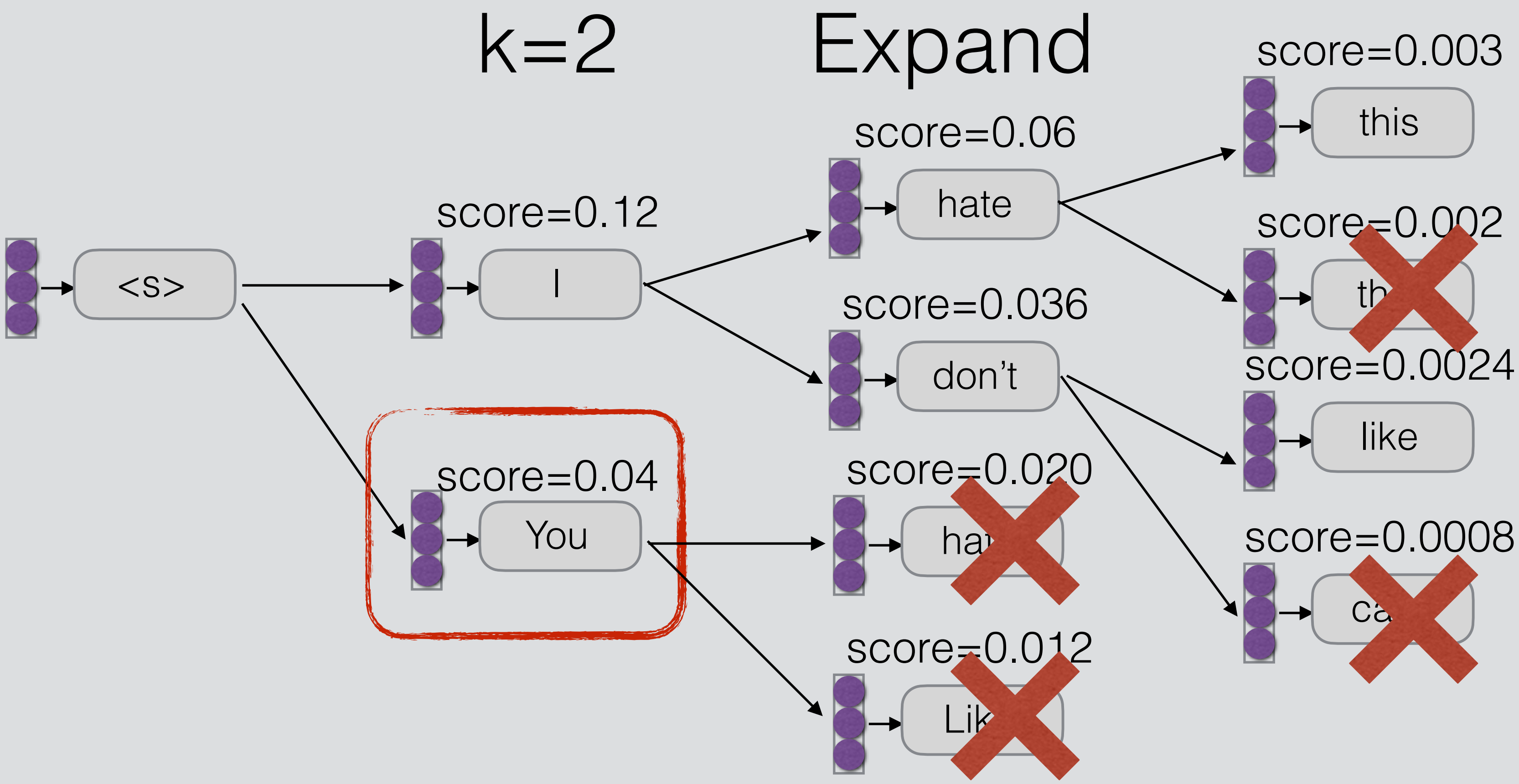
Lik
score=0.003
this
score=0.002
that
score=0.0024
like
score=0.0008
care

Beam Search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Lik

Evaluation

Machine Translation (reference based)

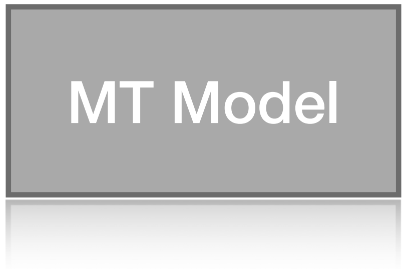
Mi piacerebbe un cappuccino freddo.

MT Model

I like one cold cappuccino.

Machine Translation (reference based)

Mi piacerebbe un cappuccino freddo.



I like one cold cappuccino.

reference: *I would like a cold cappuccino.*

Machine Translation (reference based)

Mi piacerebbe un cappuccino freddo.

MT Model

I like one cold cappuccino.

reference: *I would like a cold cappuccino.*

Compare the output with the reference!

How do we evaluate MT?

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BLEU (Bilingual Evaluation Understudy)

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- BLEU compares the machine-written translation to one or several human-written translation(s), and computes a similarity score based on:

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  - There are many valid ways to translate a sentence

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- BLEU compares the machine-written translation to one or several human-written translation(s), and computes a similarity score based on:
  - n-gram precision (usually up to 3 or 4-grams)
  - Penalty for too-short system translations
- BLEU is useful but imperfect
  - There are many valid ways to translate a sentence
  - So a good translation can get a poor BLEU score because it has low n-gram overlap with the human translation ☹️

Machine Translation: BLEU

reference: I would like a cold cappuccino

hypothesis: I like one cold cappuccino

Machine Translation: BLEU

reference: I would like a cold cappuccino

hypothesis: I like one cold cappuccino

Unigrams	4/5

Machine Translation: BLEU

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Unigrams	4/5
Bigrams	1/4

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→ **average**

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Unigrams	4/5
Bigrams	1/4
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4-grams	0/2

→ **average**

Can we cheat?

Machine Translation: BLEU

reference: I would like a cold cappuccino

hypothesis: I like like like like one cold cappuccino

Unigrams	7/8
Bigrams	1/7
3-grams	0/6
4-grams	0/5

Can we cheat?

Solution: Only count each word once.

Machine Translation: BLEU

reference: I would like a cold cappuccino

hypothesis: I would like

Unigrams	3/3
Bigrams	2/2
3-grams	1/1
4-grams	—

Can we cheat?

Solution: Brevity Penalty.

MT: Problems with BLEU

reference: I would like a cold cappuccino

hypothesis 1: *I would like one cold cappuccino*

These three hypotheses have the same BLEU score!

Solution: Use paraphrases, synonyms, etc (Meteor)

MT: Problems with BLEU

reference: I would like a cold cappuccino

hypothesis 1: *I would like one cold cappuccino*

hypothesis 2: *I would like a cold espresso*

These three hypotheses have the same BLEU score!

Solution: Use paraphrases, synonyms, etc (Meteor)

MT: Problems with BLEU

reference: I would like a cold cappuccino

hypothesis 1: *I would like one cold cappuccino*

hypothesis 2: *I would like a cold espresso*

hypothesis 3: *I would like a cold monk*

These three hypotheses have the same BLEU score!

Solution: Use paraphrases, synonyms, etc (Meteor)

MT: Problems with BLEU

source: ***behaving as if you are among those whom we could not civilize***

reference: *uygarlatıramadıklarımızdanmı¸ssınızcasına*

Languages with Rich Morphology: How dow we even evaluate this?

Solution: Use subwords, character-Fscore — chrF

MT: Human Evaluation

It is almost always better to ask humans!
e.g. in MT, we ask translators

Way 1:

We show system outputs to the annotators, and they provide a score (e.g. 1-5 Likert scale, or 0-100 score)

Way 2:

We show **2** system outputs to the annotators, and they annotate which one of the two they think is better.

Evaluation of Evaluation Metrics

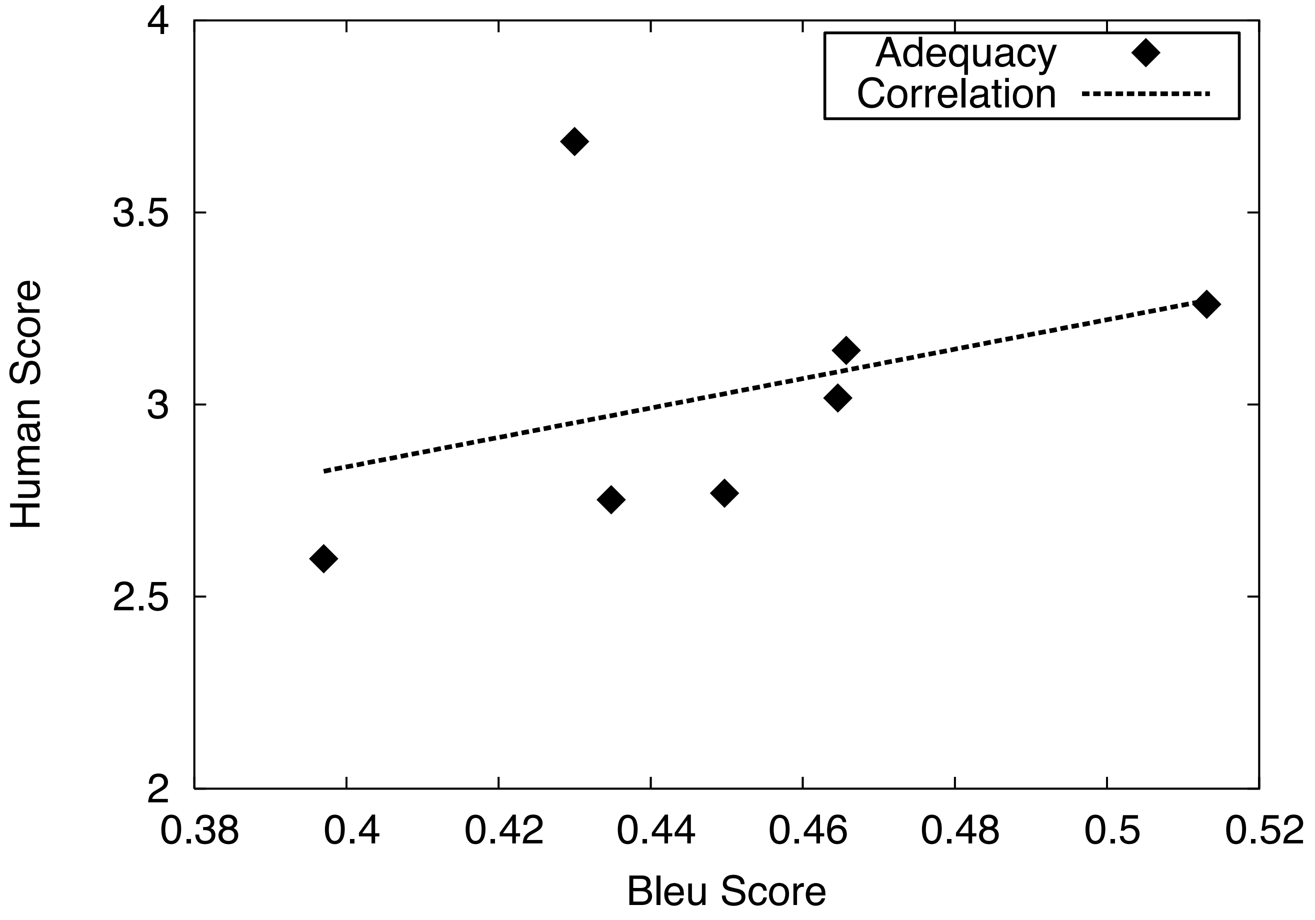
- Automatic metrics are low cost, tunable, consistent

- But are they correct?

→ Yes, if they correlate with human judgement

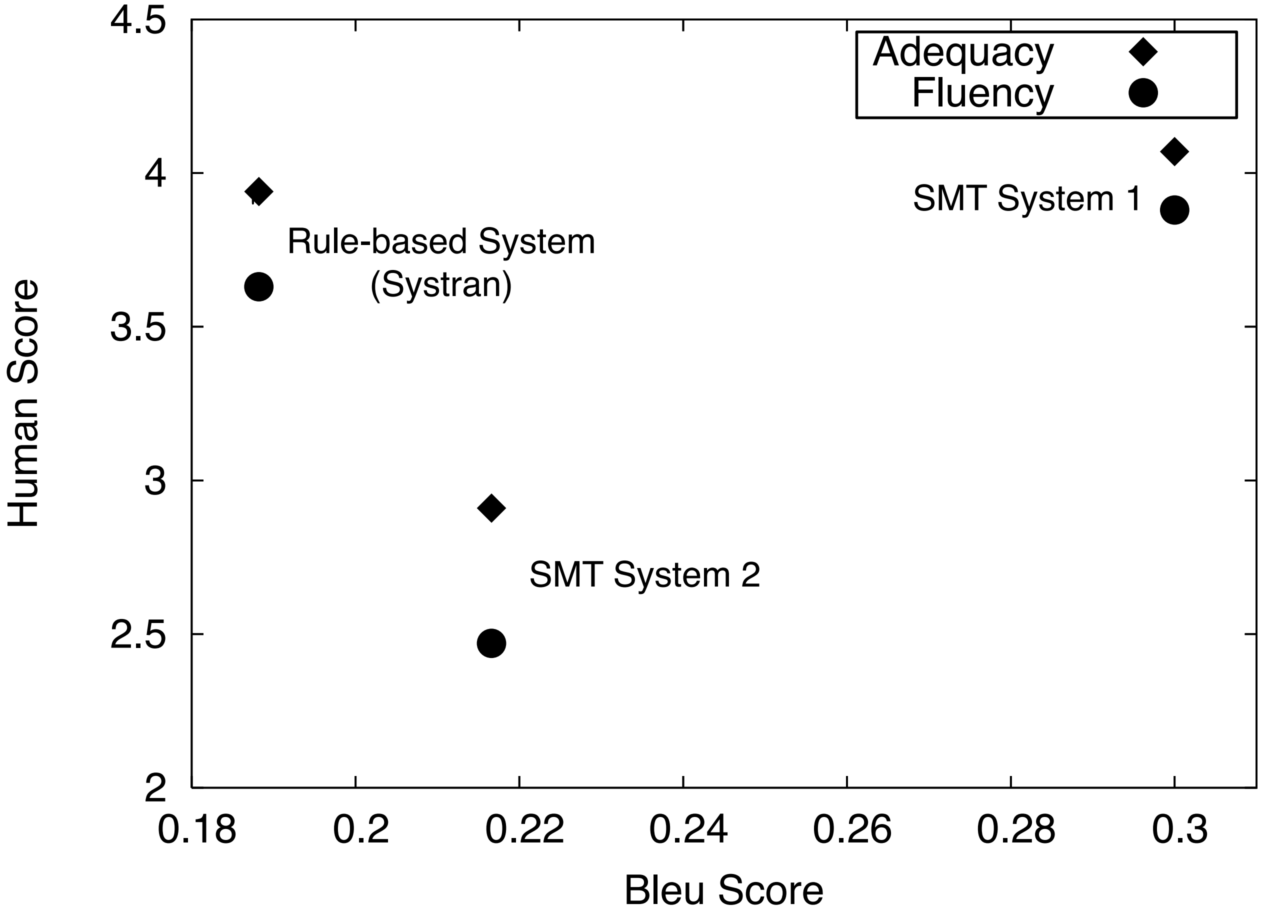
Evidence of Shortcomings of Automatic Metrics

Post-edited output vs. statistical systems (NIST 2005)



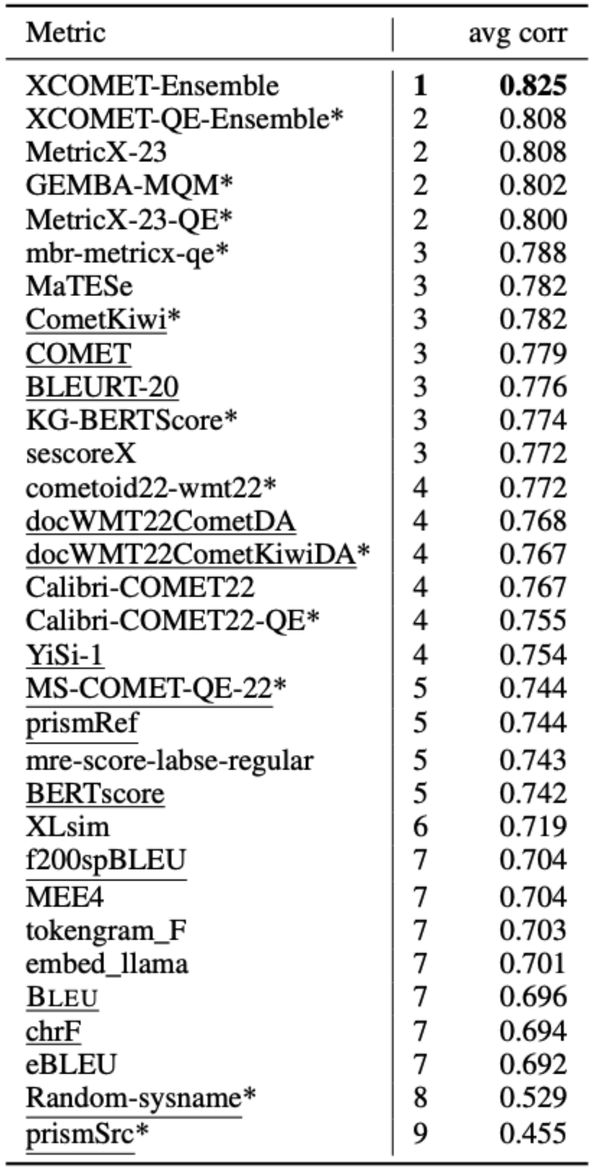
Evidence of Shortcomings of Automatic Metrics

Rule-based vs. statistical systems



WMT Metrics Shared Task

- Annual event to evaluate metrics
- Piggy-backs on the WMT General Translation Task
  - new test set every year
  - research systems and commercial systems
  - lately also large language models
  - human evaluation of automatic evaluations
- New metrics proposed
- Evaluation by correlation with human judgments



Metric		avg corr
XCOMET-Ensemble	**1**	**0.825**
XCOMET-QE-Ensemble*	2	0.808
MetricX-23	2	0.808
GEMBA-MQM*	2	0.802
MetricX-23-QE*	2	0.800
mbr-metricx-qe*	3	0.788
MaTESe	3	0.782
CometKiwi*	3	0.782
COMET	3	0.779
BLEURT-20	3	0.776
KG-BERTScore*	3	0.774
sescoreX	3	0.772
cometoid22-wmt22*	4	0.772
docWMT22CometDA	4	0.768
docWMT22CometKiwiDA*	4	0.767
Calibri-COMET22	4	0.767
Calibri-COMET22-QE*	4	0.755
YiSi-1	4	0.754
MS-COMET-QE-22*	5	0.744
prismRef	5	0.744
mre-score-labse-regular	5	0.743
BERTscore	5	0.742
XLsim	6	0.719
f200spBLEU	7	0.704
MEE4	7	0.704
tokengram_F	7	0.703
embed_llama	7	0.701
BLEU	7	0.696
chrF	7	0.694
eBLEU	7	0.692
Random-sysname*	8	0.529
prismSrc*	9	0.455

(WMT 2023)

Trained Metrics: COMET

- Two decades of evaluation campaigns for machine translation metrics
  → a lot of human judgment data

- Goal: automatic metric that correlates with human judgment

- Make it a machine learning problem
  - input: machine translation, reference translation
  - output: human annotation score

- COMET: Trained neural model for evaluation

Reference-Free Evaluation

- We have data in the form

  input, translation, human reference → human judgment

- We can also train a model on

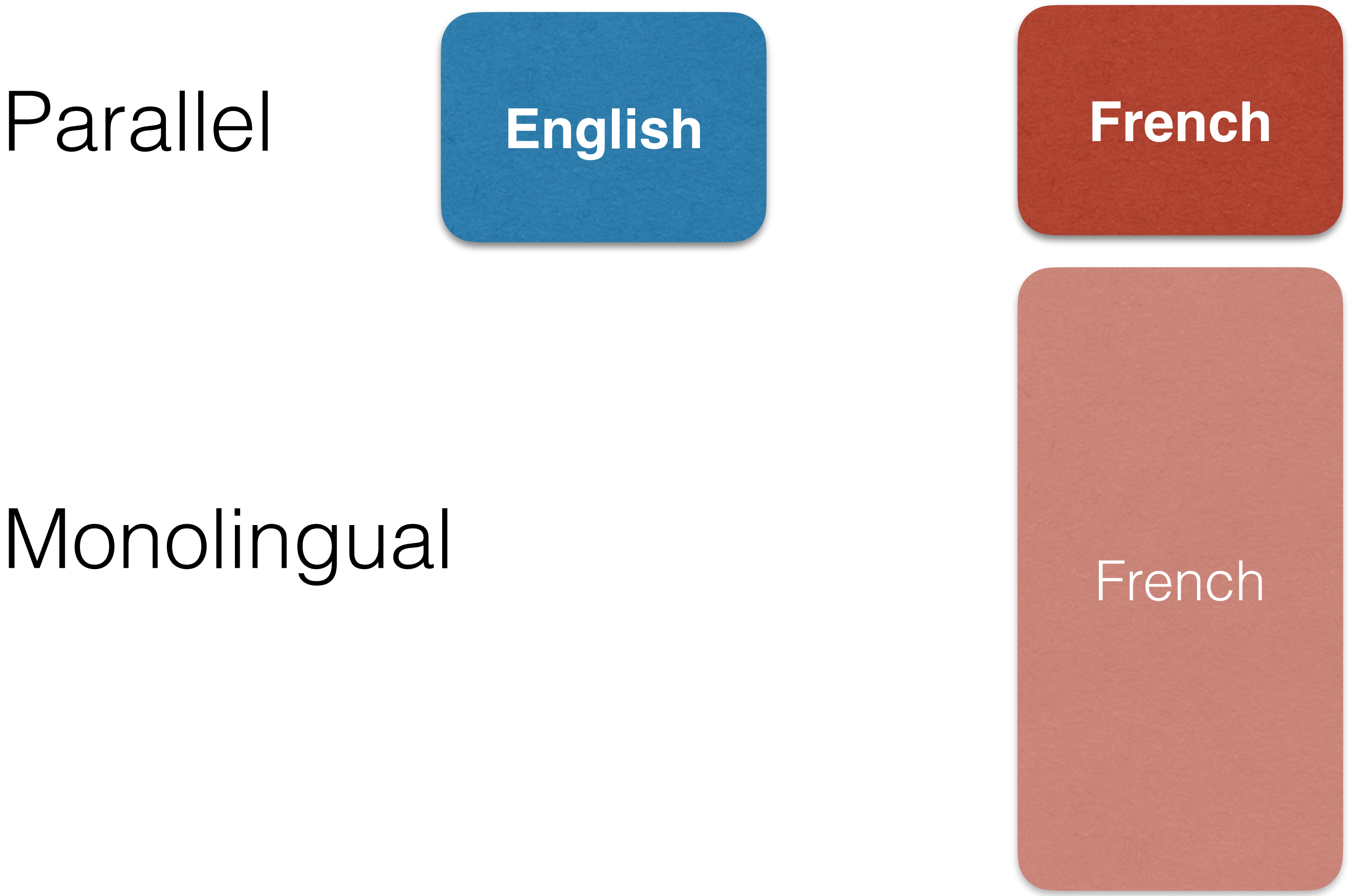
  input, translation → human judgment

- CometKiwi: trained evaluation model without references

- Also called **quality estimation** or **confidence estimation**

Semisupervised and Unsupervised Methods

On Using Monolingual Corpora in Neural Machine Translation (Gulcehre et al. 2015)



Parallel

English

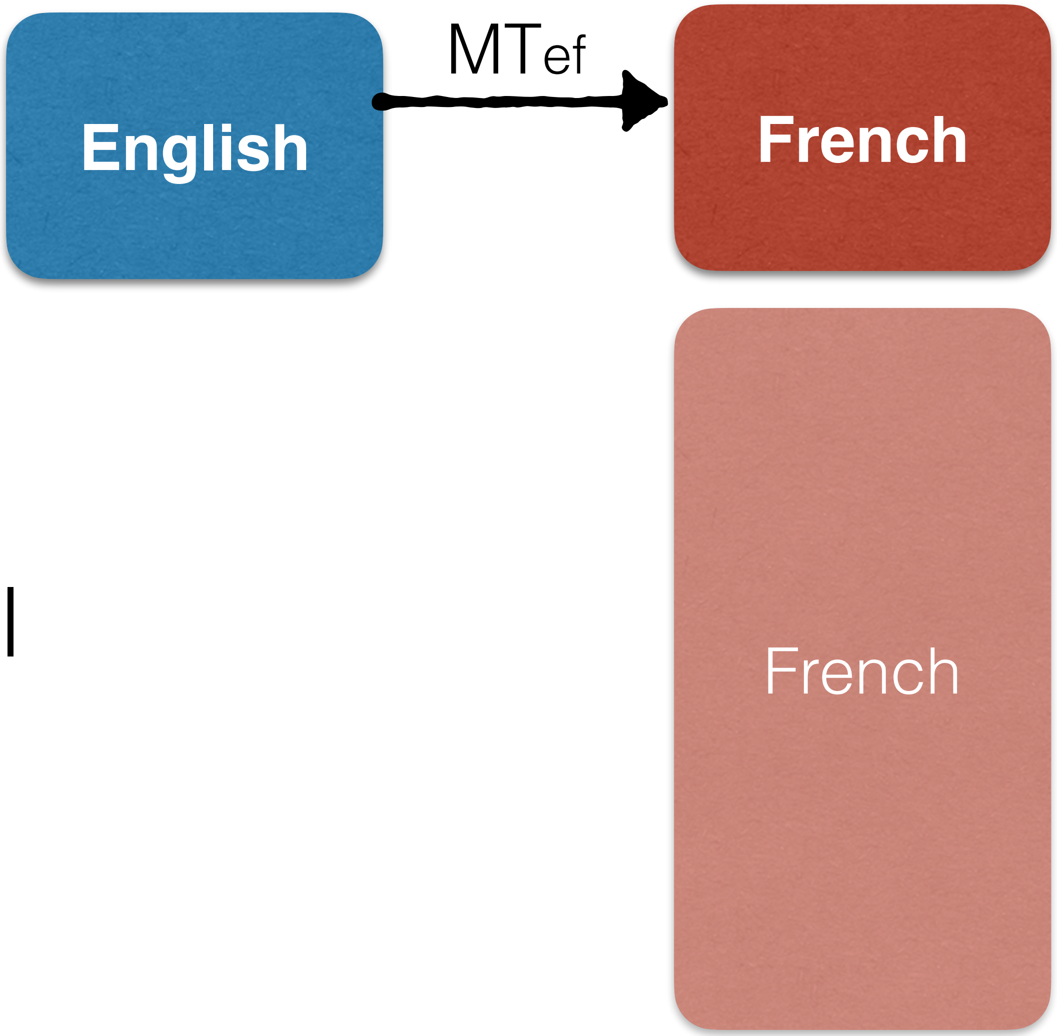
French

Monolingual

French

On Using Monolingual Corpora in Neural Machine Translation (Gulcehre et al. 2015)

Parallel



English

MT_{ef}

French

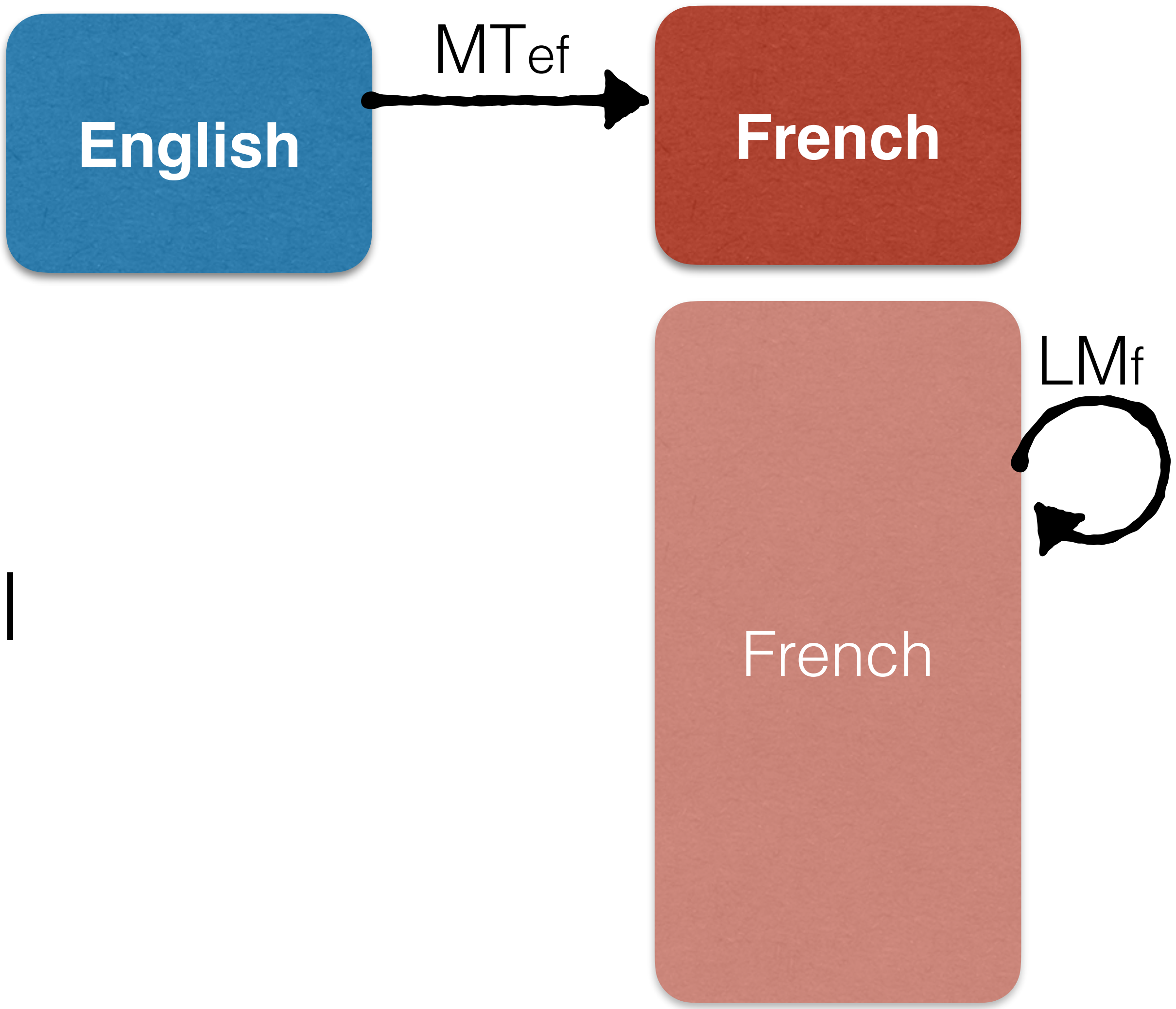
French

Train NMT

Monolingual

On Using Monolingual Corpora in Neural Machine Translation (Gulcehre et al. 2015)

Parallel



English

MT_{ef}

French

Train NMT

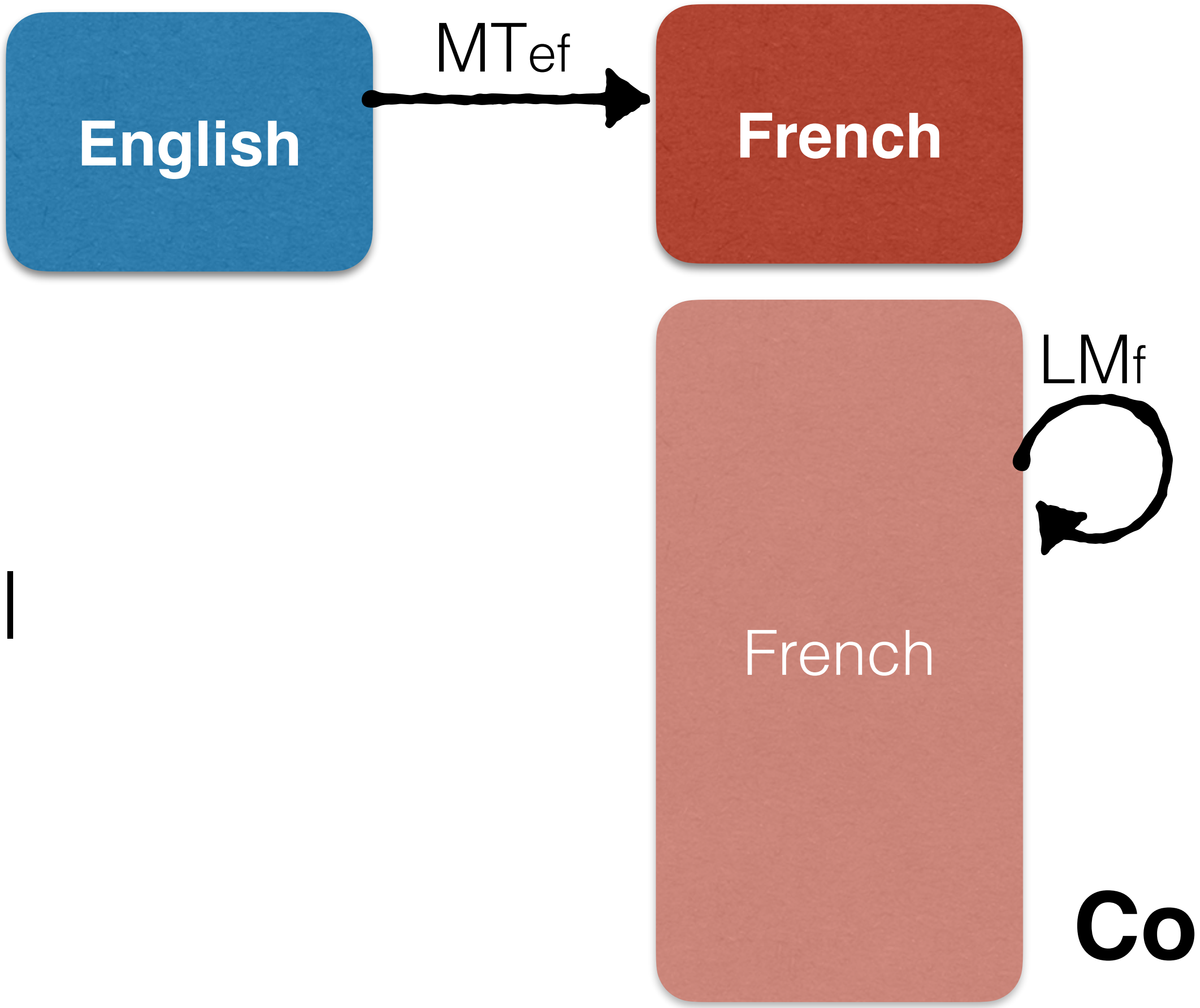
Monolingual

French

LM_f

Train LM

On Using Monolingual Corpora in Neural Machine Translation (Gulcehre et al. 2015)



Parallel

English $\xrightarrow{\text{MT}_{ef}}$ French

Train NMT

LM$_f$

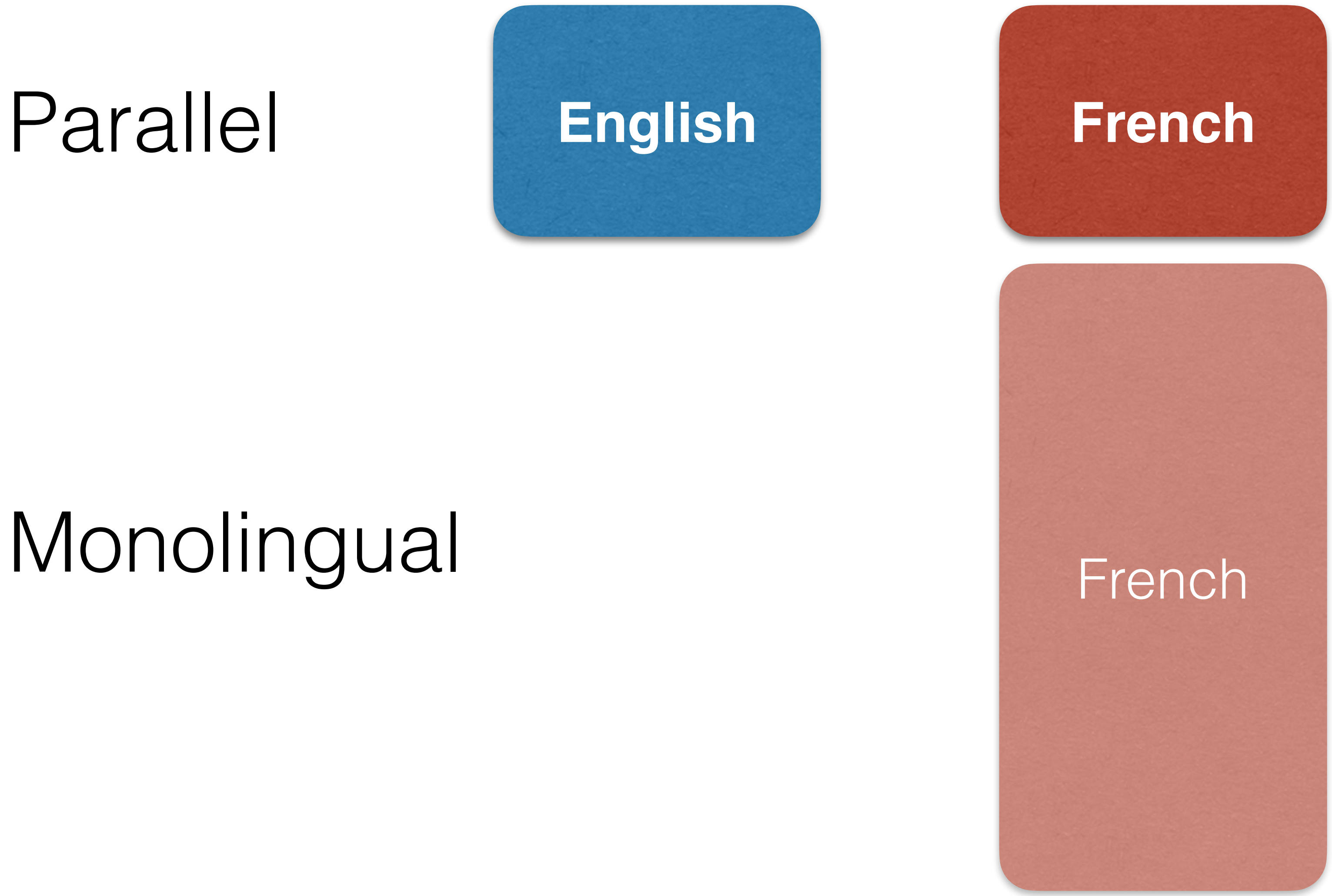
Monolingual

French

Train LM

Combine the two!

Back-translation (Sennrich et al. 2016)



Parallel

English

French

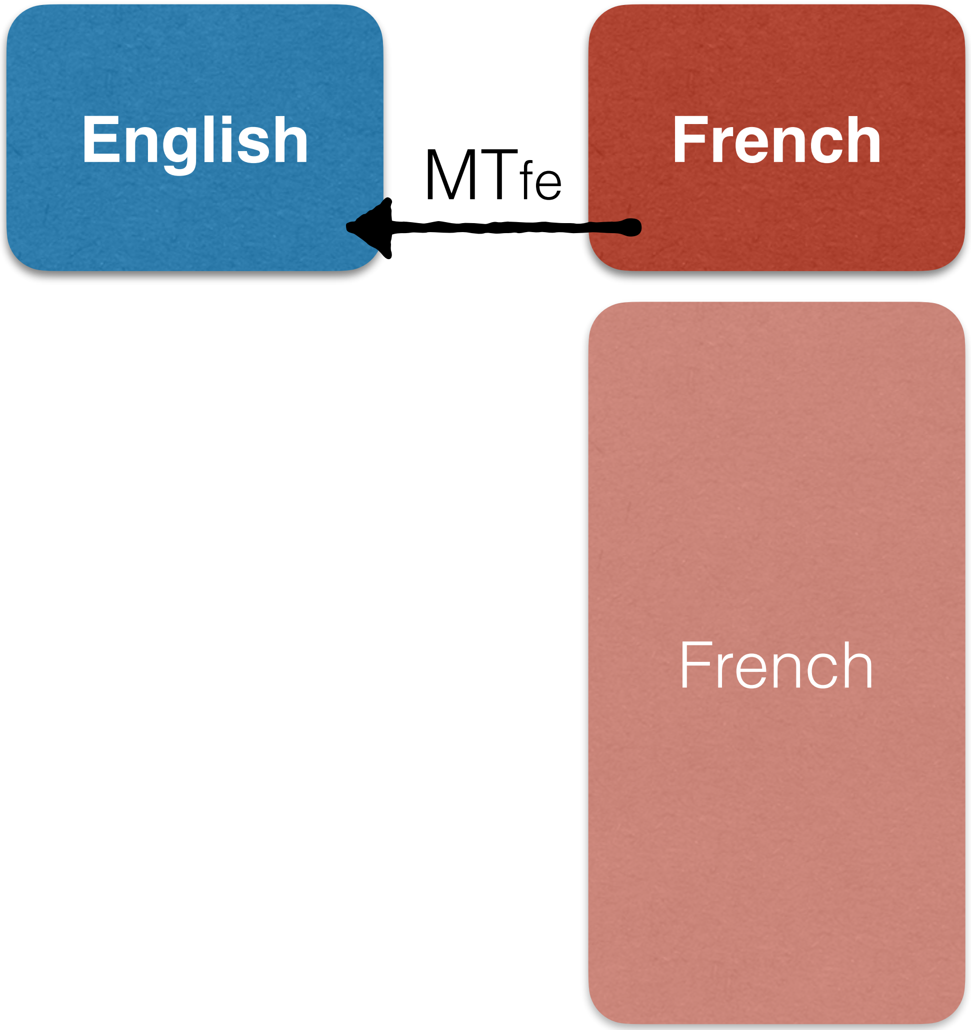
Monolingual

French

Back-translation (Sennrich et al. 2016)

Train French->English

Parallel



English

MT_{fe}

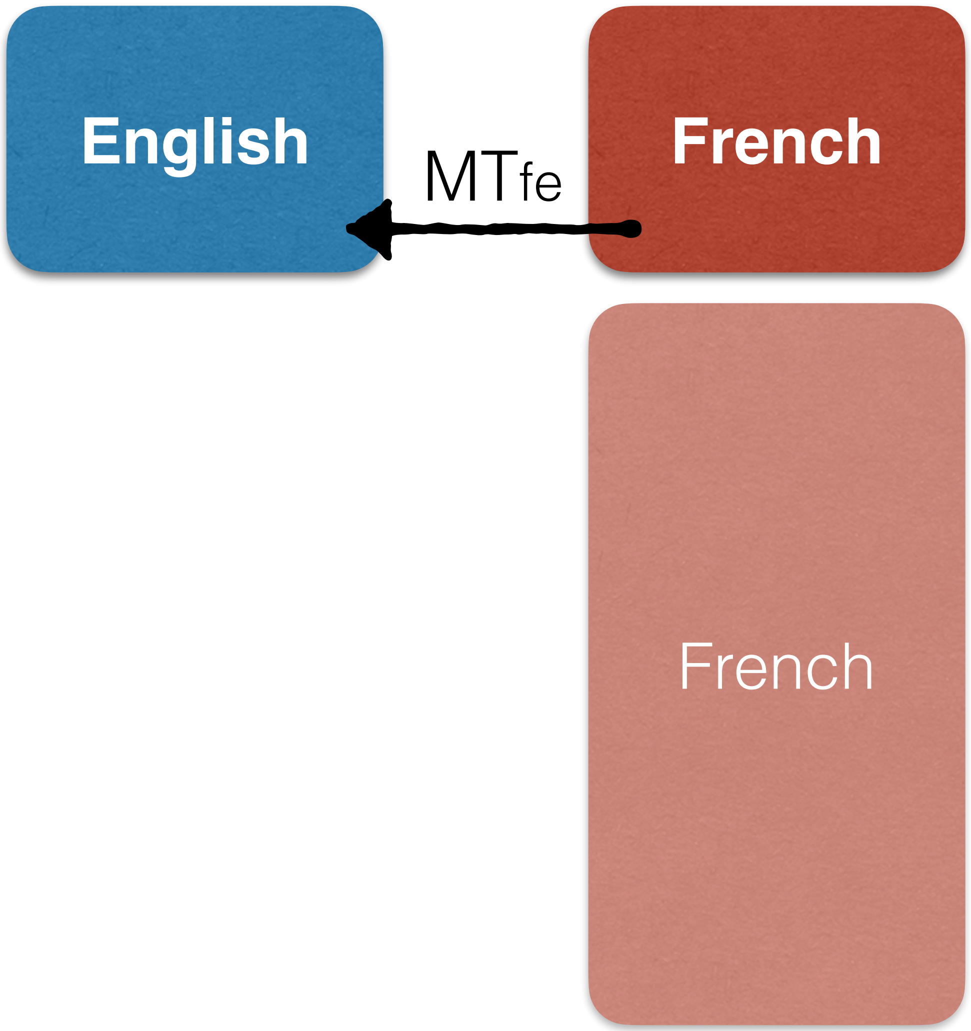
French

Monolingual

French

Back-translation (Sennrich et al. 2016)

Parallel



English

MT_{fe}

French

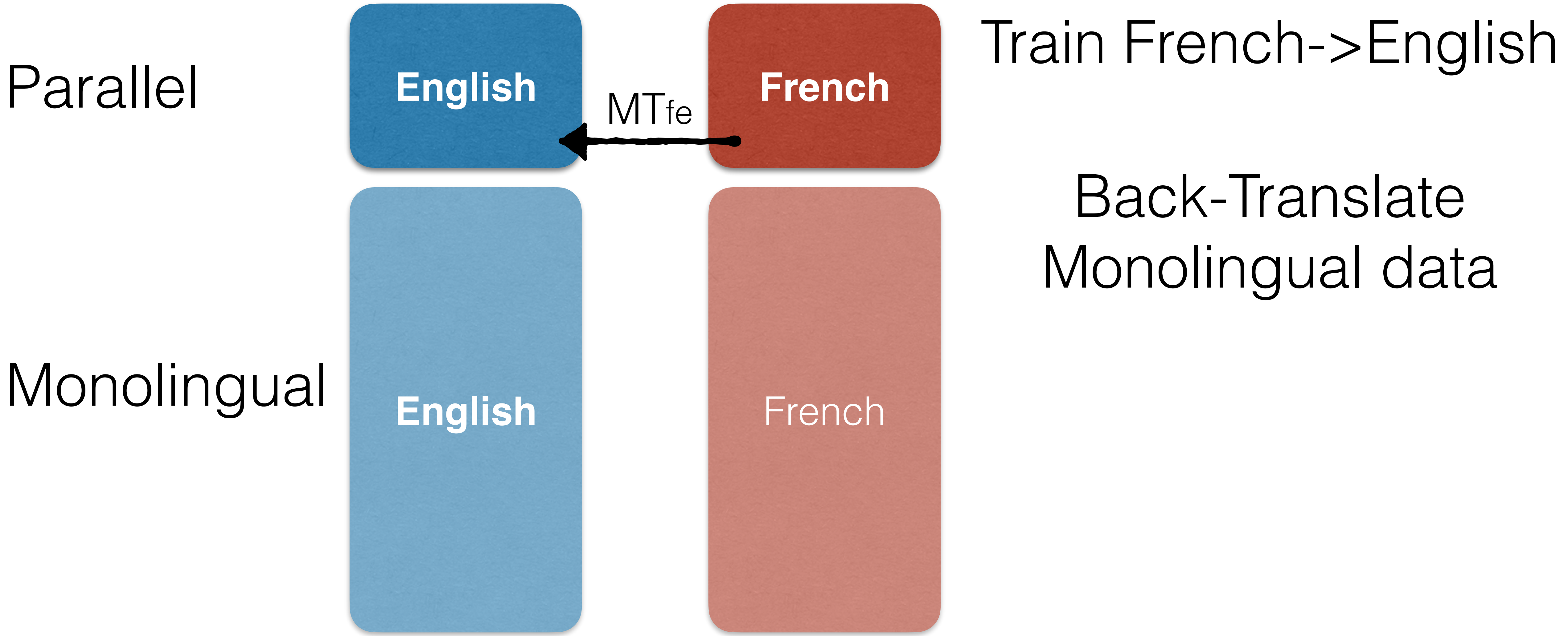
Train French->English

Back-Translate
Monolingual data

Monolingual

French

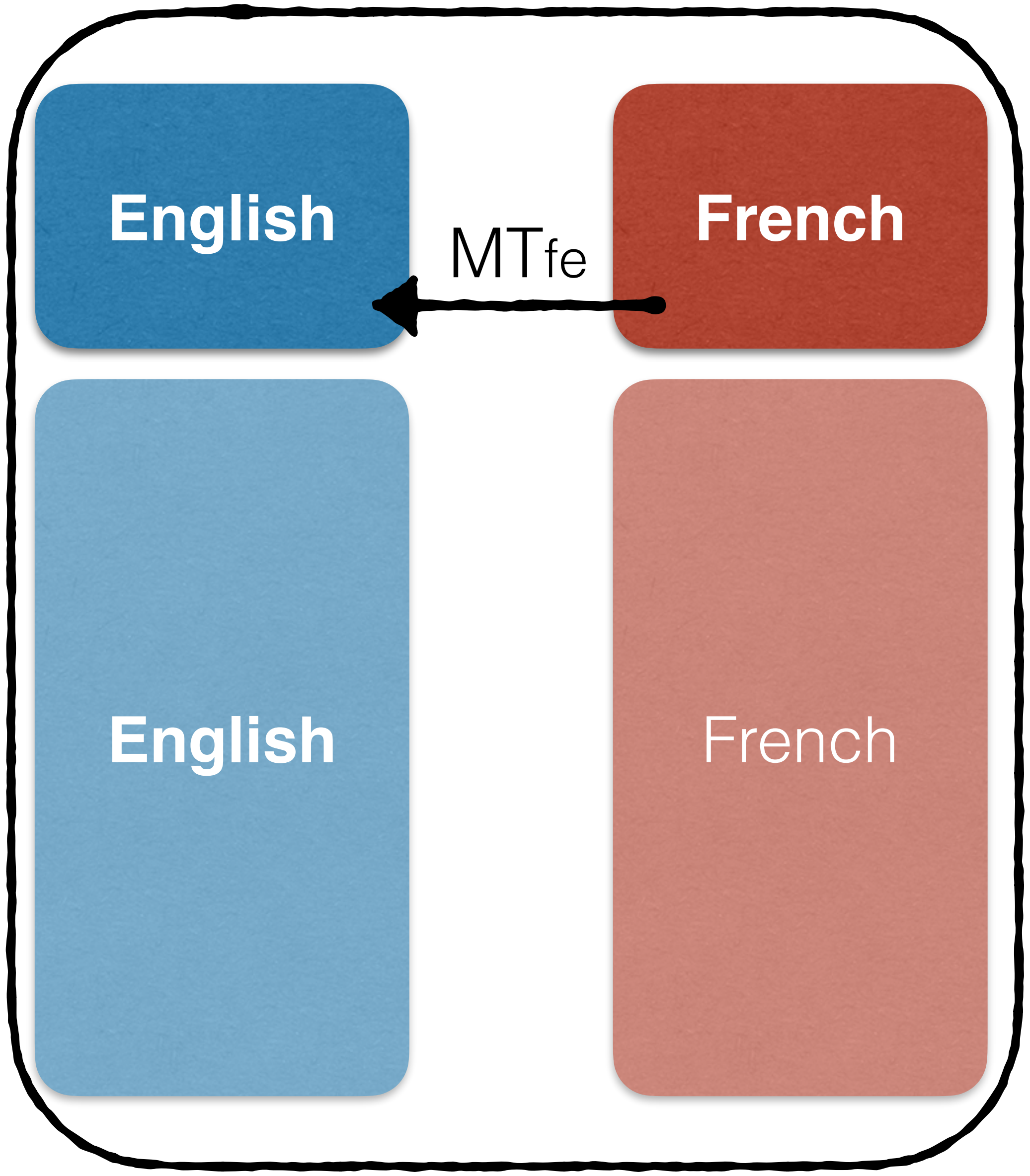
Back-translation (Sennrich et al. 2016)



Back-translation (Sennrich et al. 2016)

Parallel

Monolingual

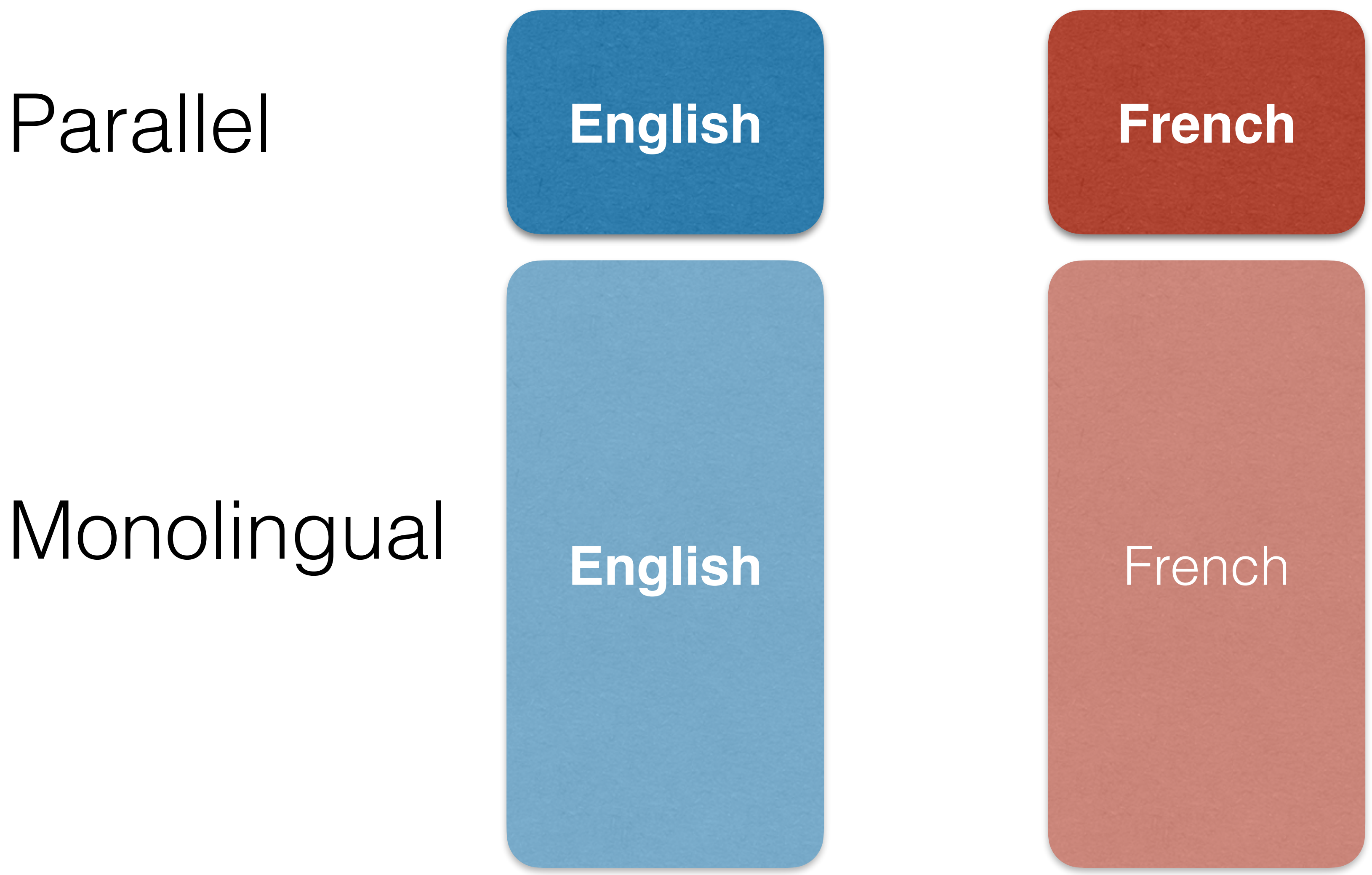


Train French->English

Back-Translate Monolingual data

Train English->French

Dual Learning (He et al. 2016)



Parallel

English

French

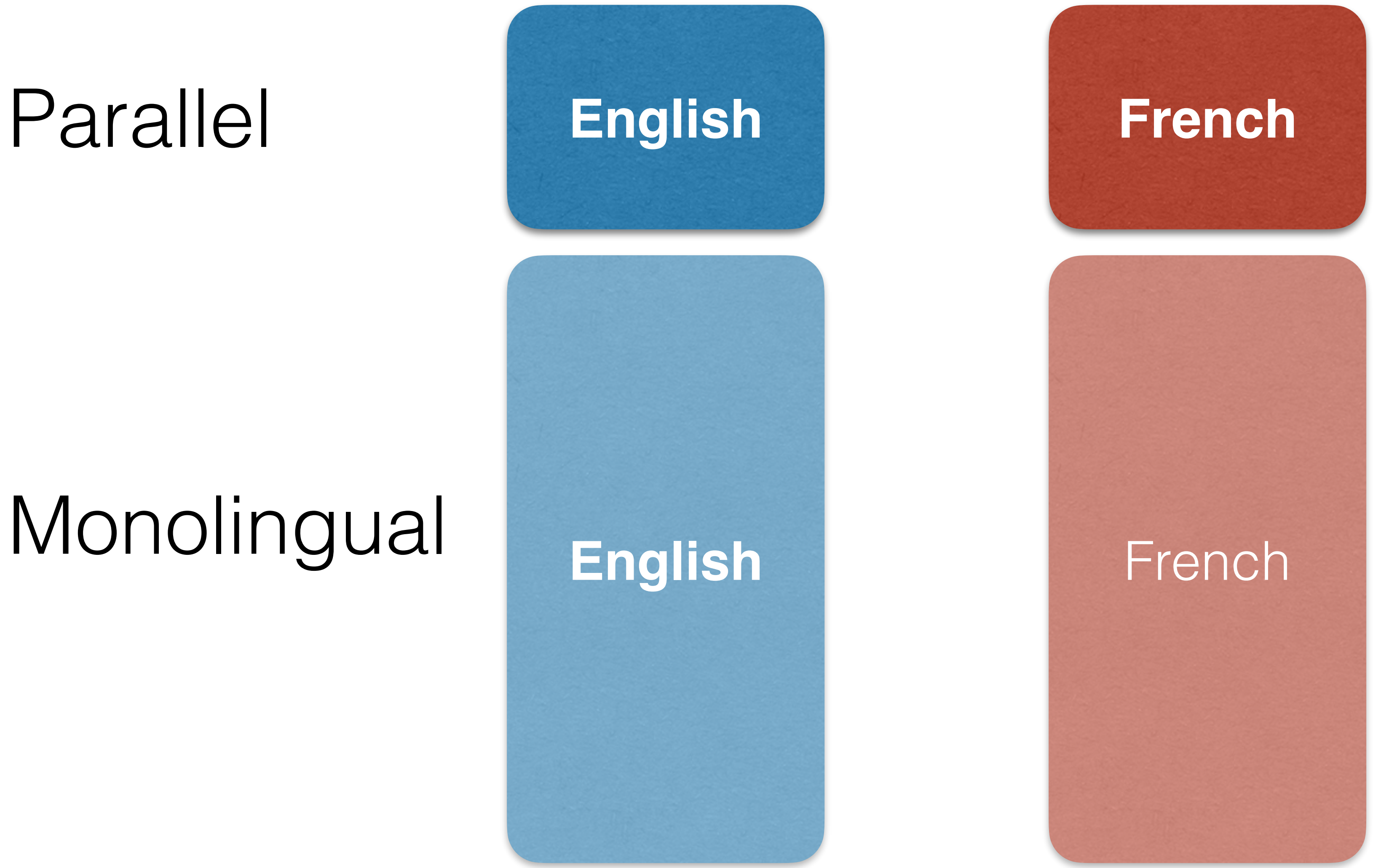
Monolingual

English

French

Dual Learning (He et al. 2016)

Assume MT_{ef}, MT_{fe}, LM_e, LM_f



Parallel

English

French

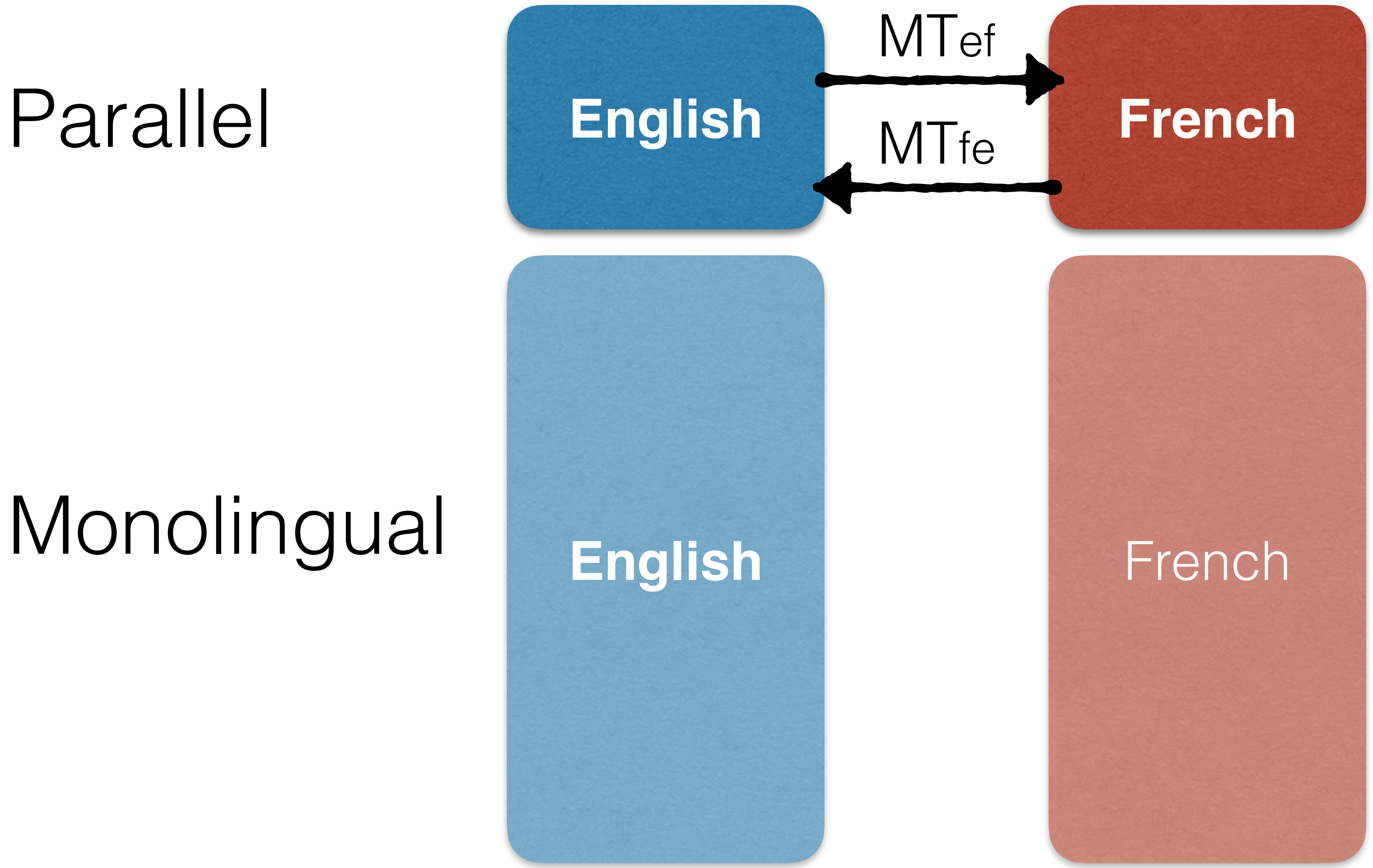
Monolingual

English

French

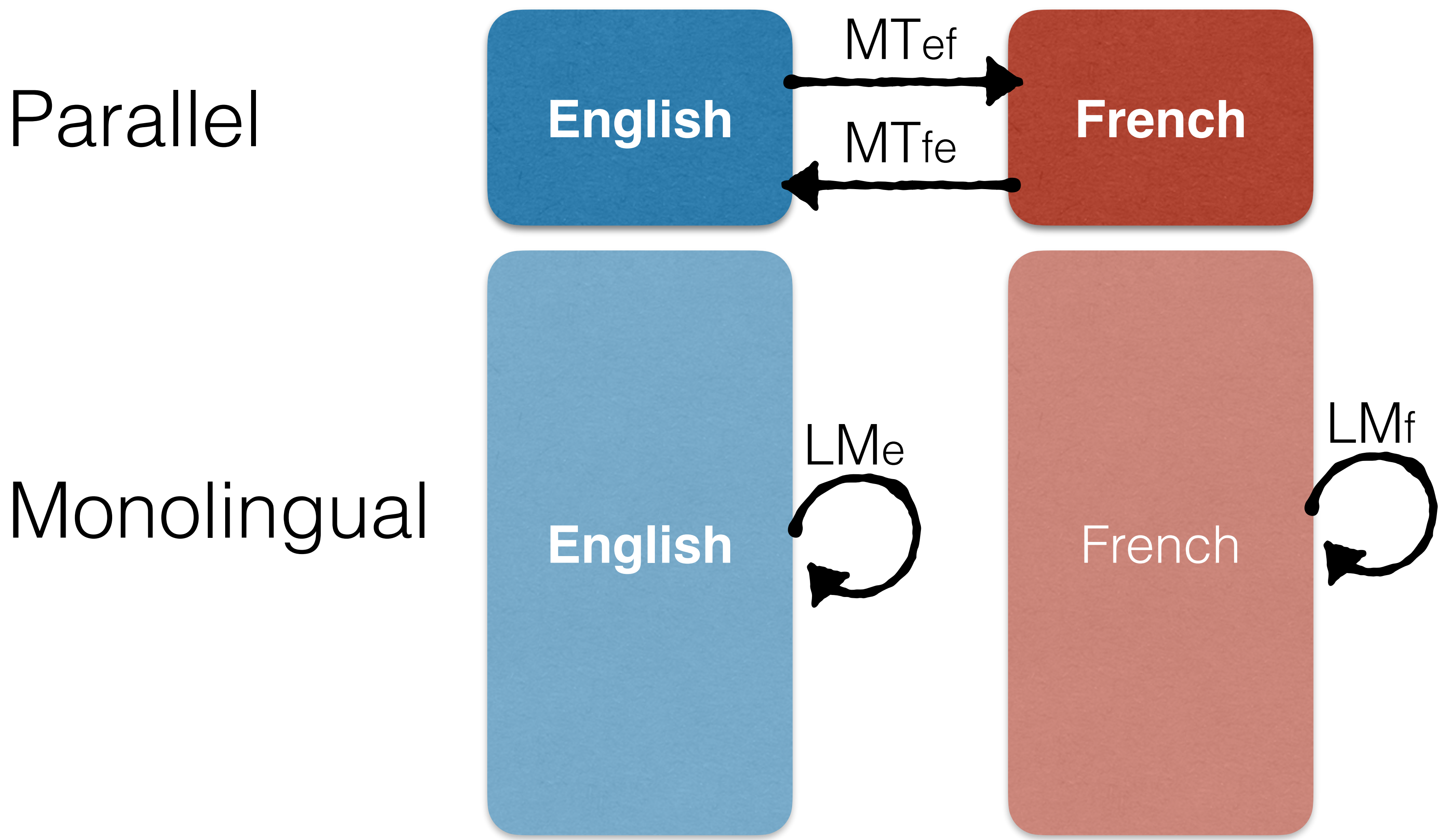
Dual Learning (He et al. 2016)

Assume MT_{ef}, MT_{fe}, LM_e, LM_f



Dual Learning (He et al. 2016)

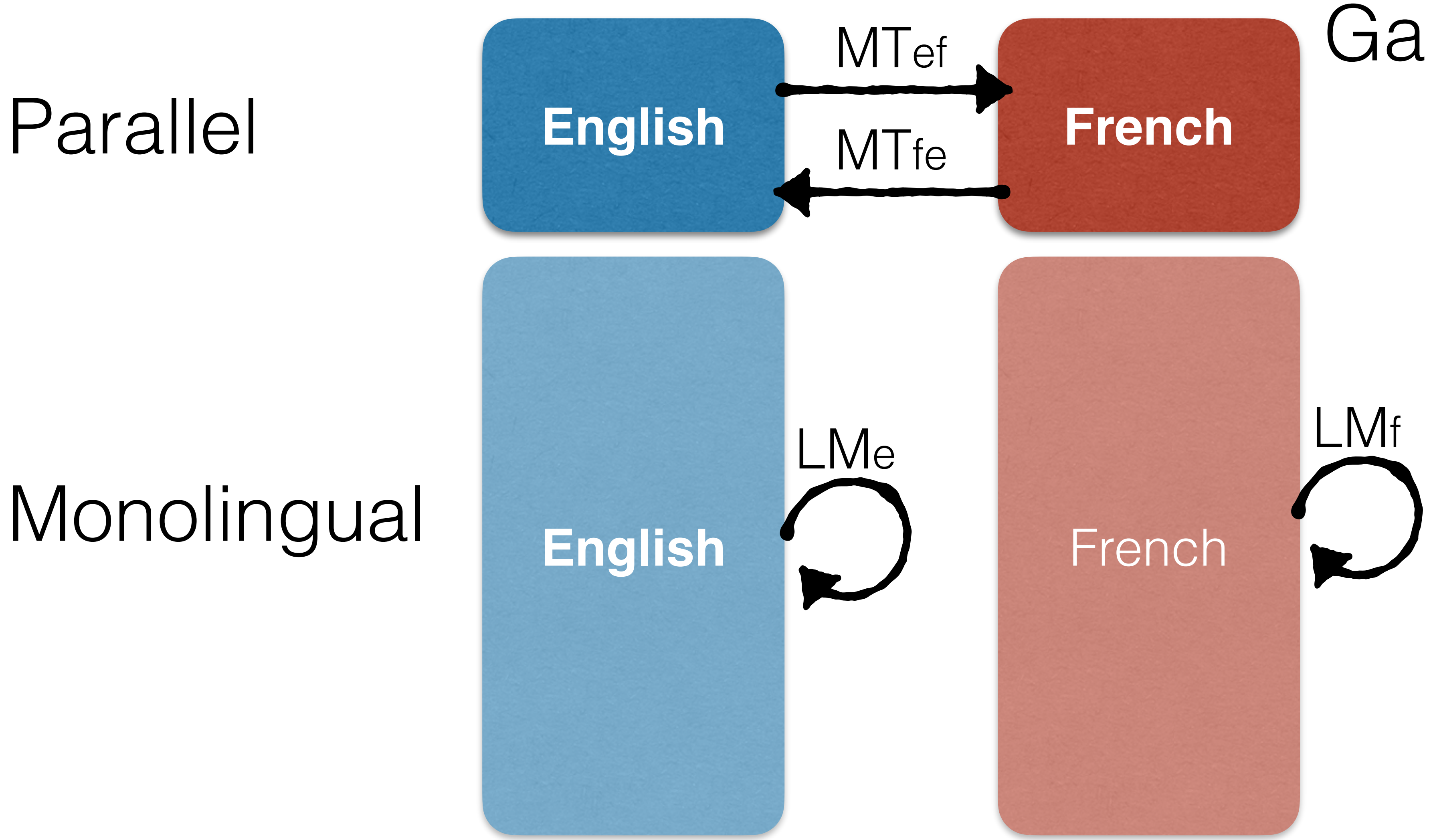
Assume MT_{ef}, MT_{fe}, LM_e, LM_f



Dual Learning (He et al. 2016)

Assume MT_{ef}, MT_{fe}, LM_e, LM_f

Game:



Parallel

English

MTef

MTfe

French

Monolingual

English

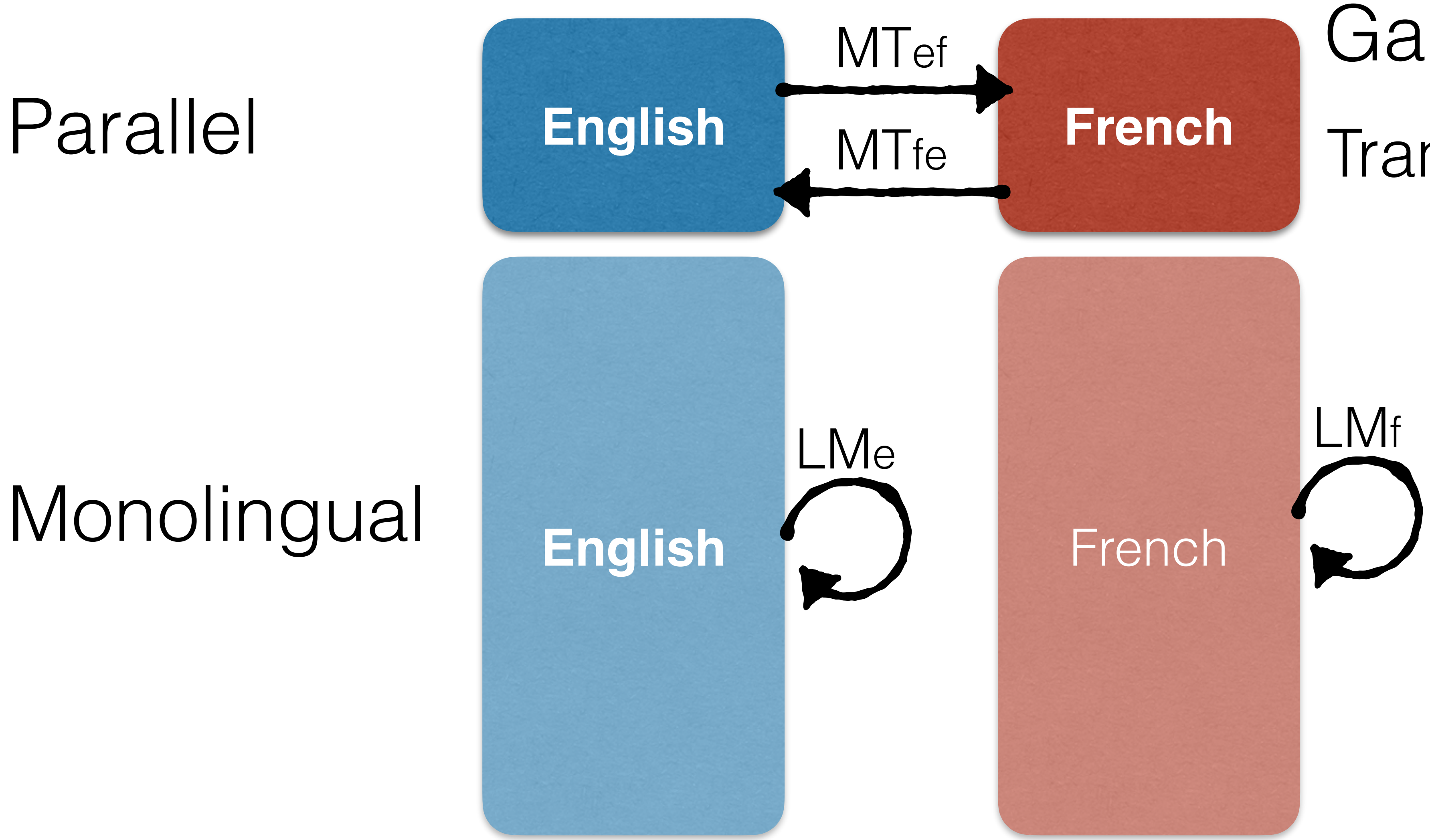
LMe

French

LMf

Dual Learning (He et al. 2016)

Assume MT_{ef}, MT_{fe}, LM_e, LM_f

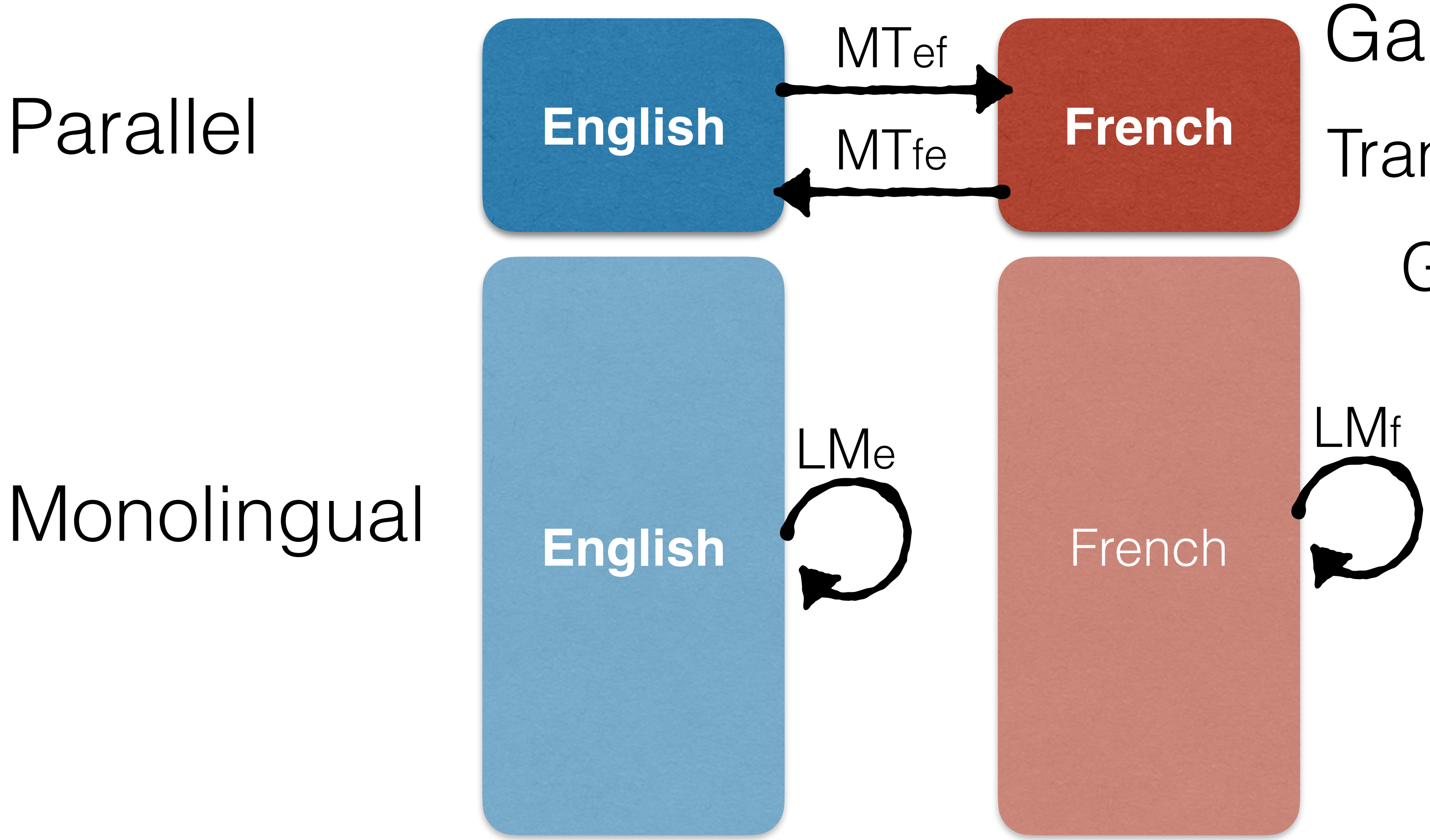


Game:

Translate sample with MT_{ef}

Dual Learning (He et al. 2016)

Assume MT_{ef}, MT_{fe}, LM_e, LM_f



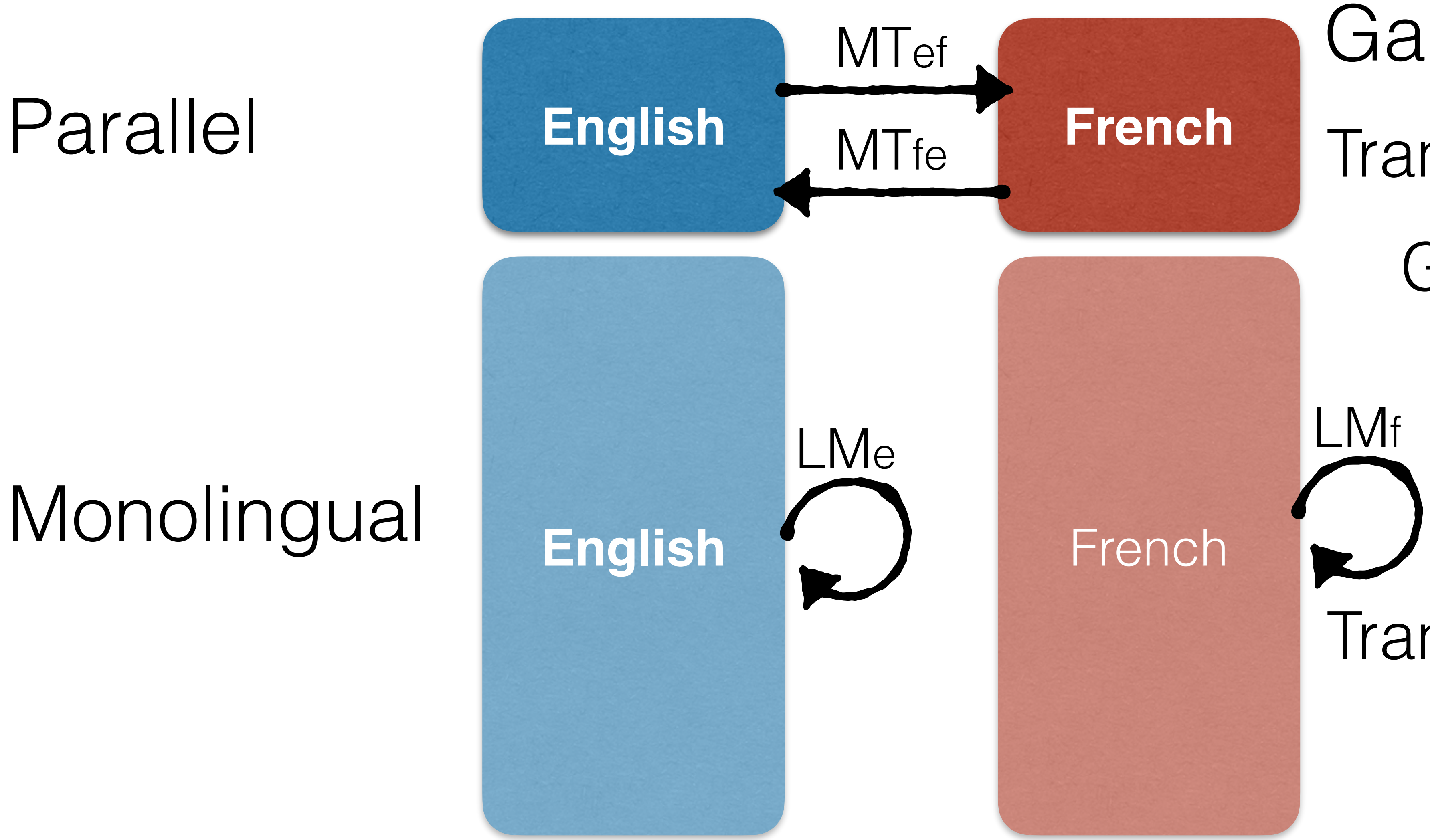
Game:

Translate sample with MT_{ef}

Get reward with LM_f

Dual Learning (He et al. 2016)

Assume MT_{ef}, MT_{fe}, LM_e, LM_f



Game:

Translate sample with MT_{ef}

Get reward with LM_f

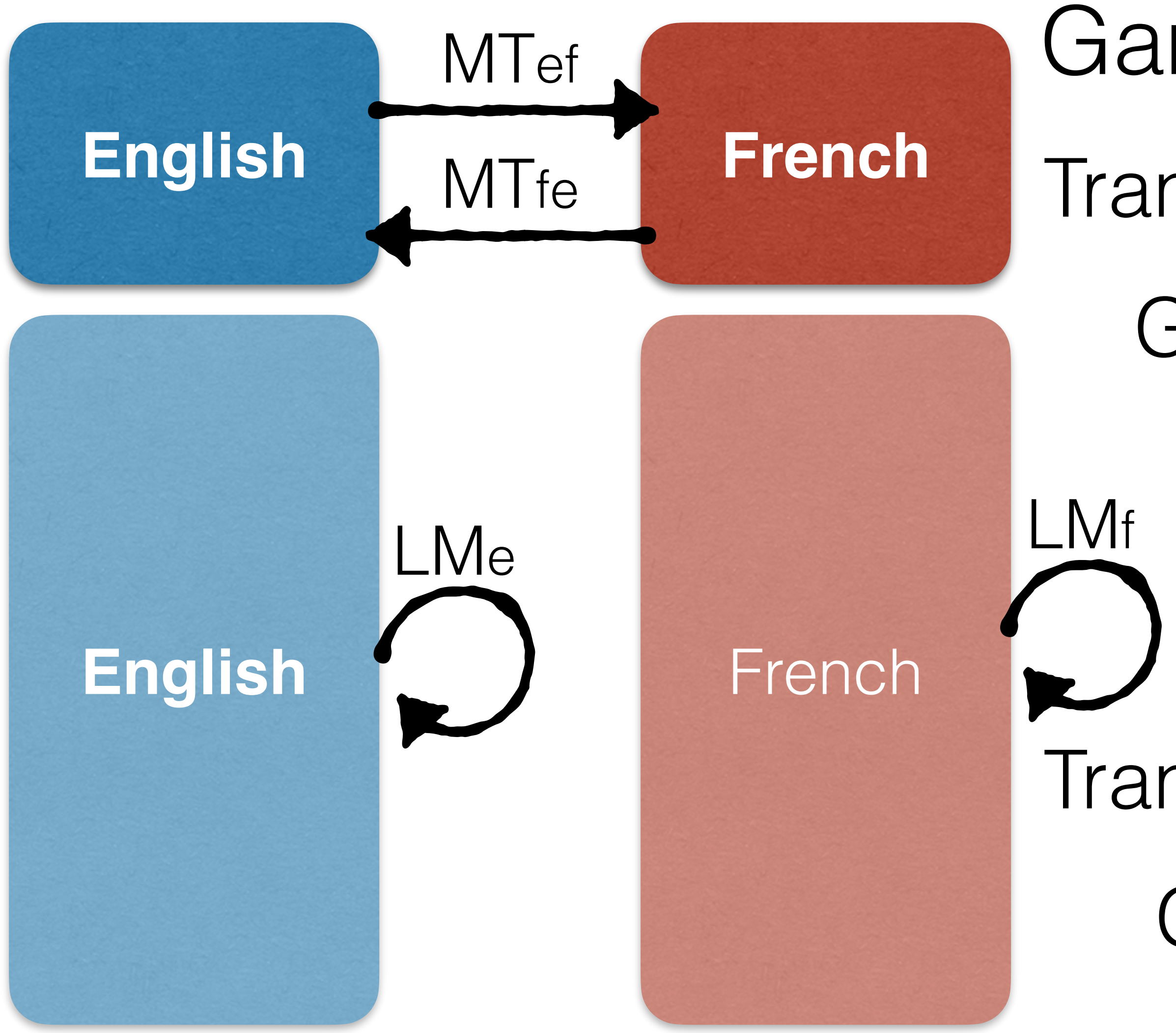
Translate sample with MT_{fe}

Dual Learning (He et al. 2016)

Assume MT_{ef}, MT_{fe}, LM_e, LM_f

Parallel

Monolingual



Game:

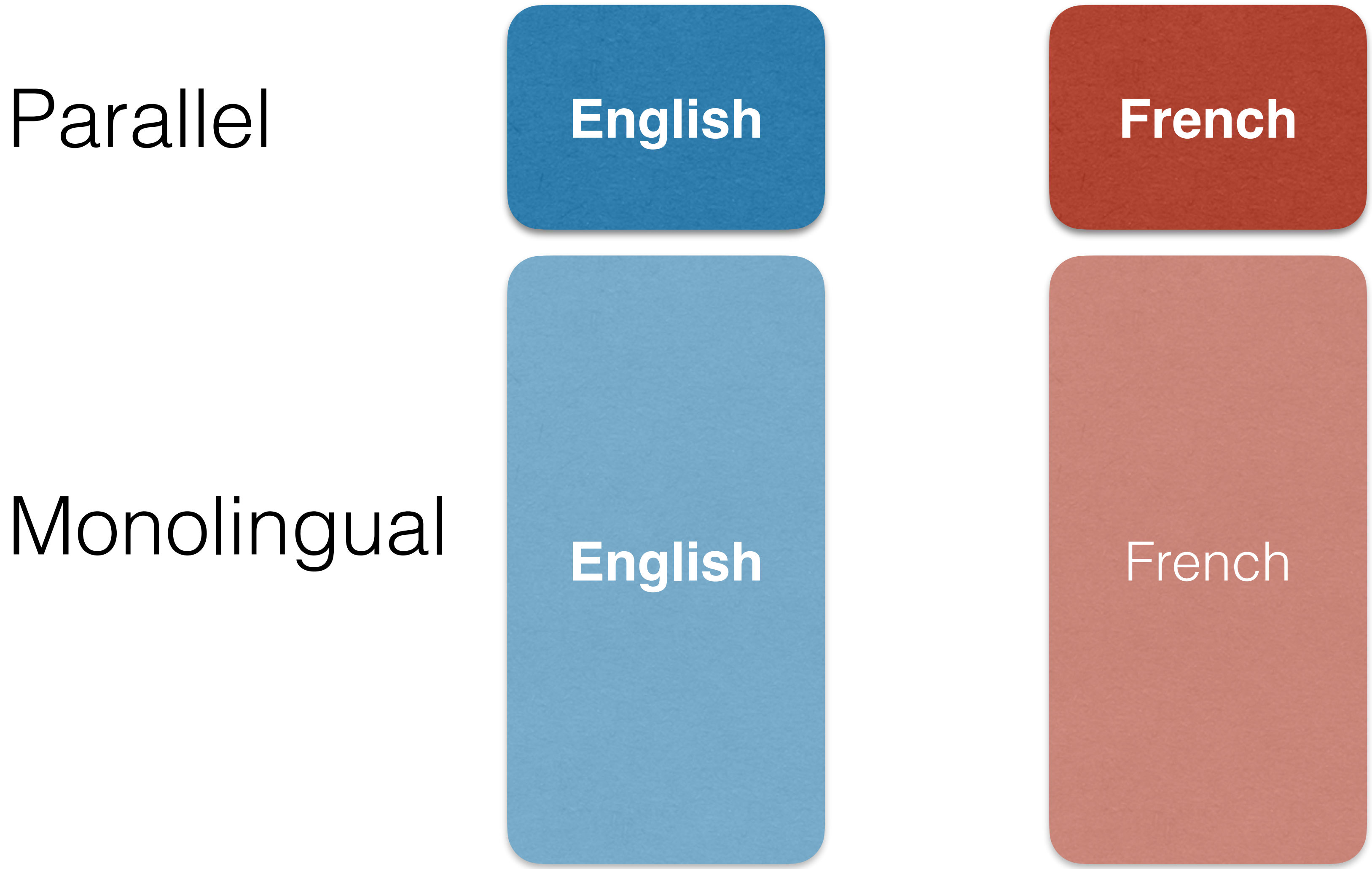
Translate sample with MT_{ef}

Get reward with LM_f

Translate sample with MT_{fe}

Get reward with LM_e

Semi-Supervised Learning for MT (Cheng et al. 2016)



Parallel

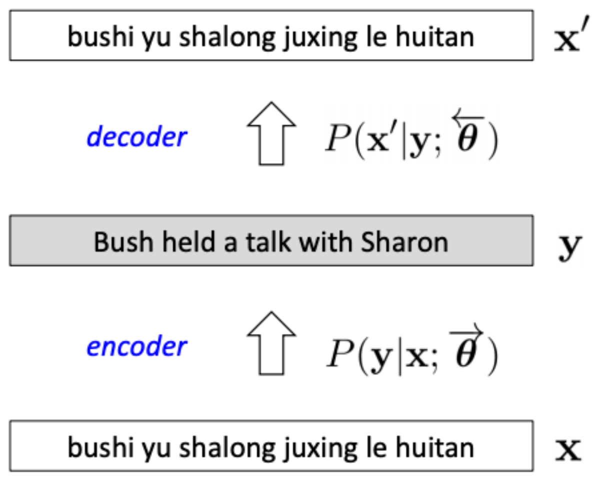
English

French

Monolingual

English

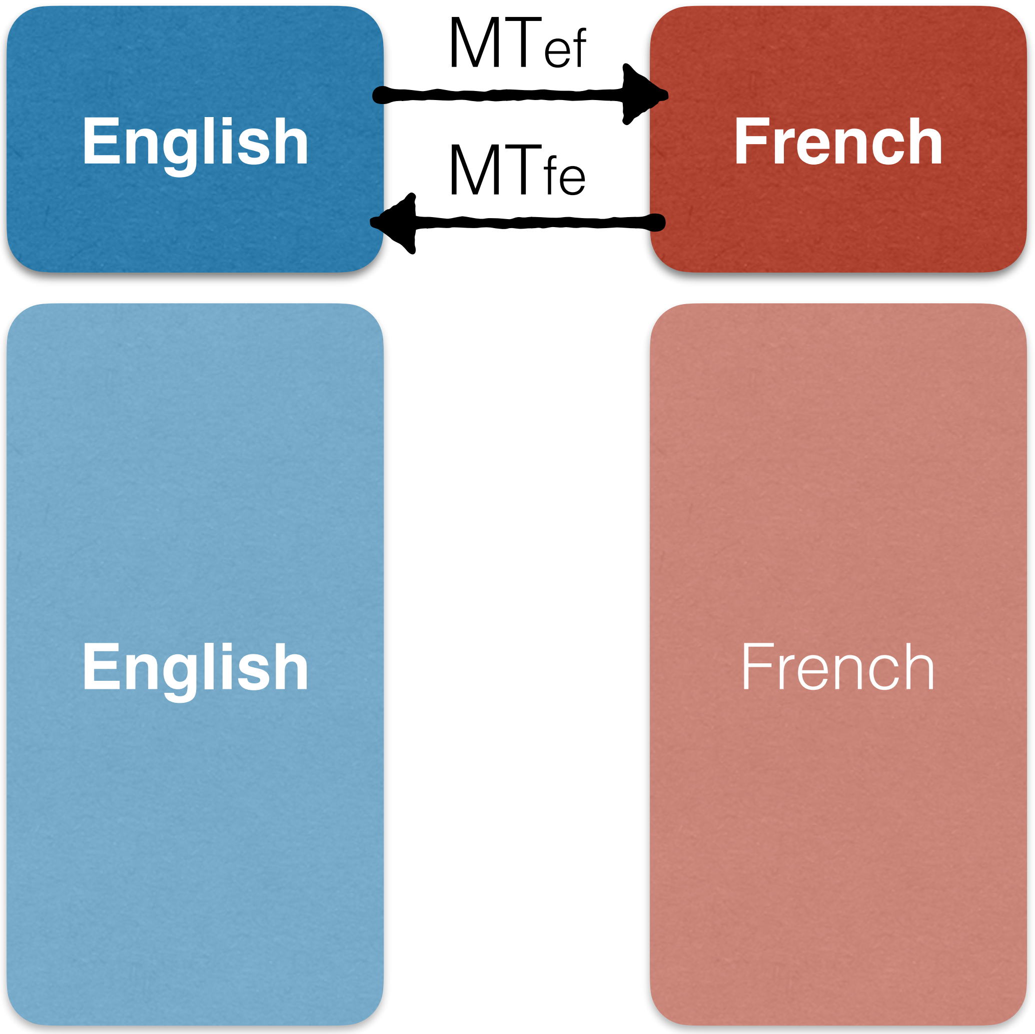
French

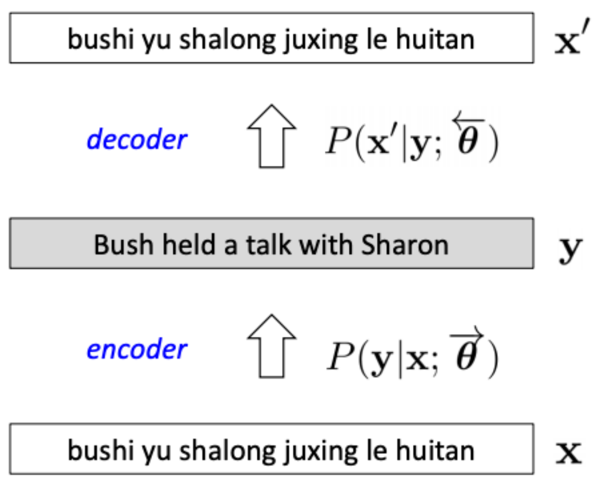

bushi yu shalong juxing le huitan $\mathbf{x}'$
decoder $P(\mathbf{x}'|\mathbf{y}; \overleftarrow{\boldsymbol{\theta}})$
Bush held a talk with Sharon $\mathbf{y}$
encoder $P(\mathbf{y}|\mathbf{x}; \overrightarrow{\boldsymbol{\theta}})$
bushi yu shalong juxing le huitan $\mathbf{x}$

Semi-Supervised Learning for MT (Cheng et al. 2016)

Parallel

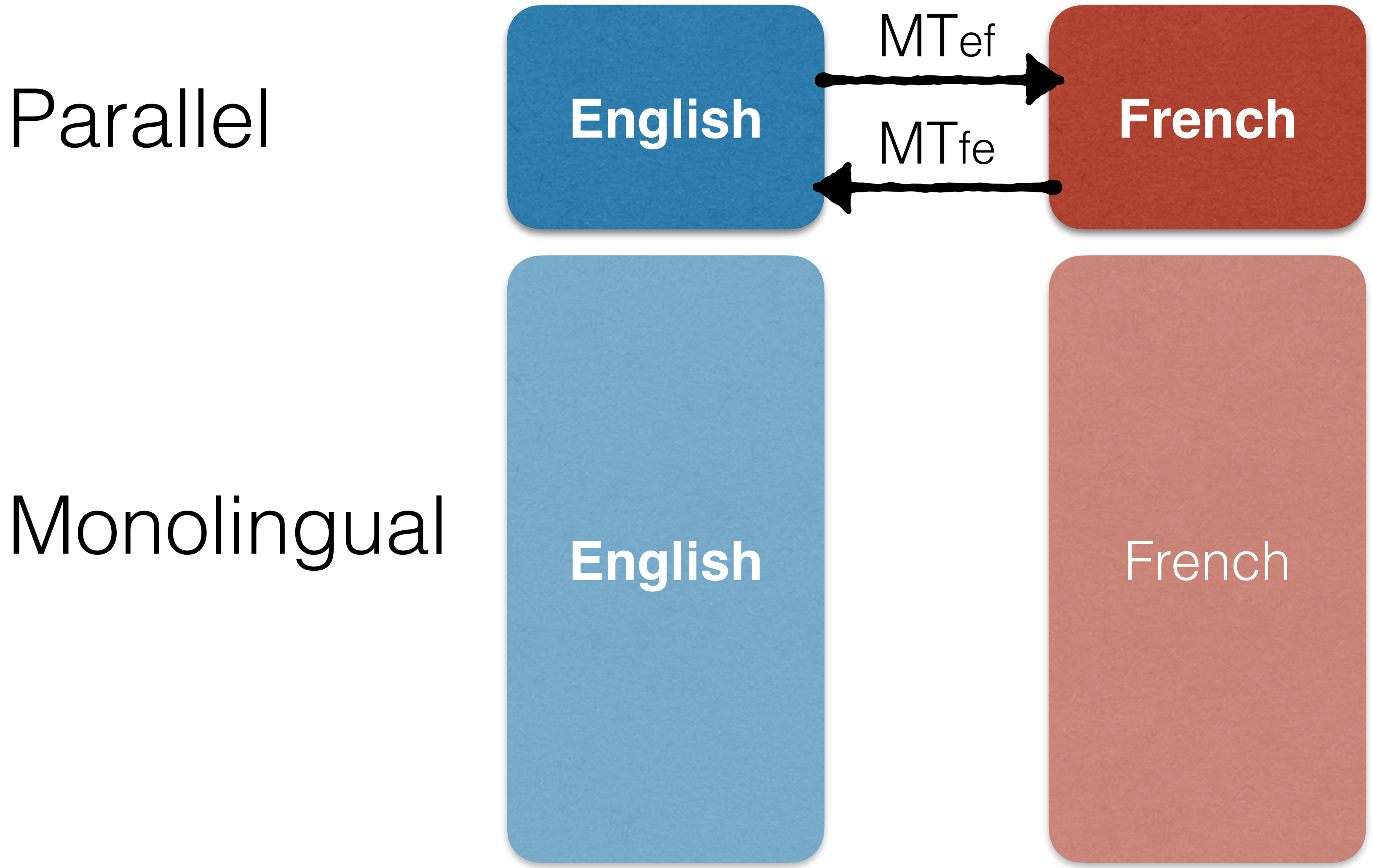
Monolingual

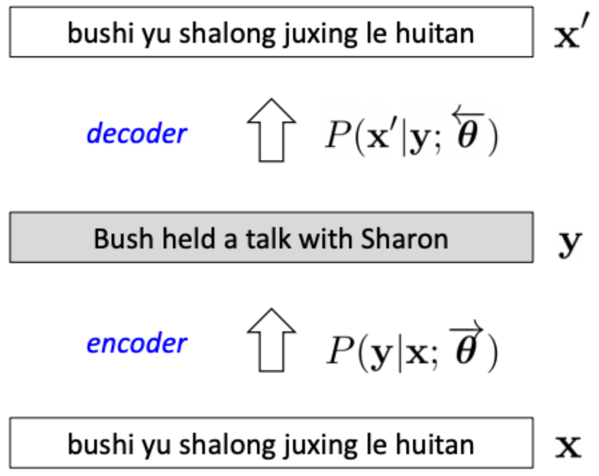



bushi yu shalong juxing le huitan
$\mathbf{x}'$
decoder
$P(\mathbf{x}'|\mathbf{y};\overleftarrow{\boldsymbol{\theta}})$
Bush held a talk with Sharon
$\mathbf{y}$
encoder
$P(\mathbf{y}|\mathbf{x};\overrightarrow{\boldsymbol{\theta}})$
bushi yu shalong juxing le huitan
$\mathbf{x}$

Semi-Supervised Learning for MT (Cheng et al. 2016)

Round-trip translation for supervision



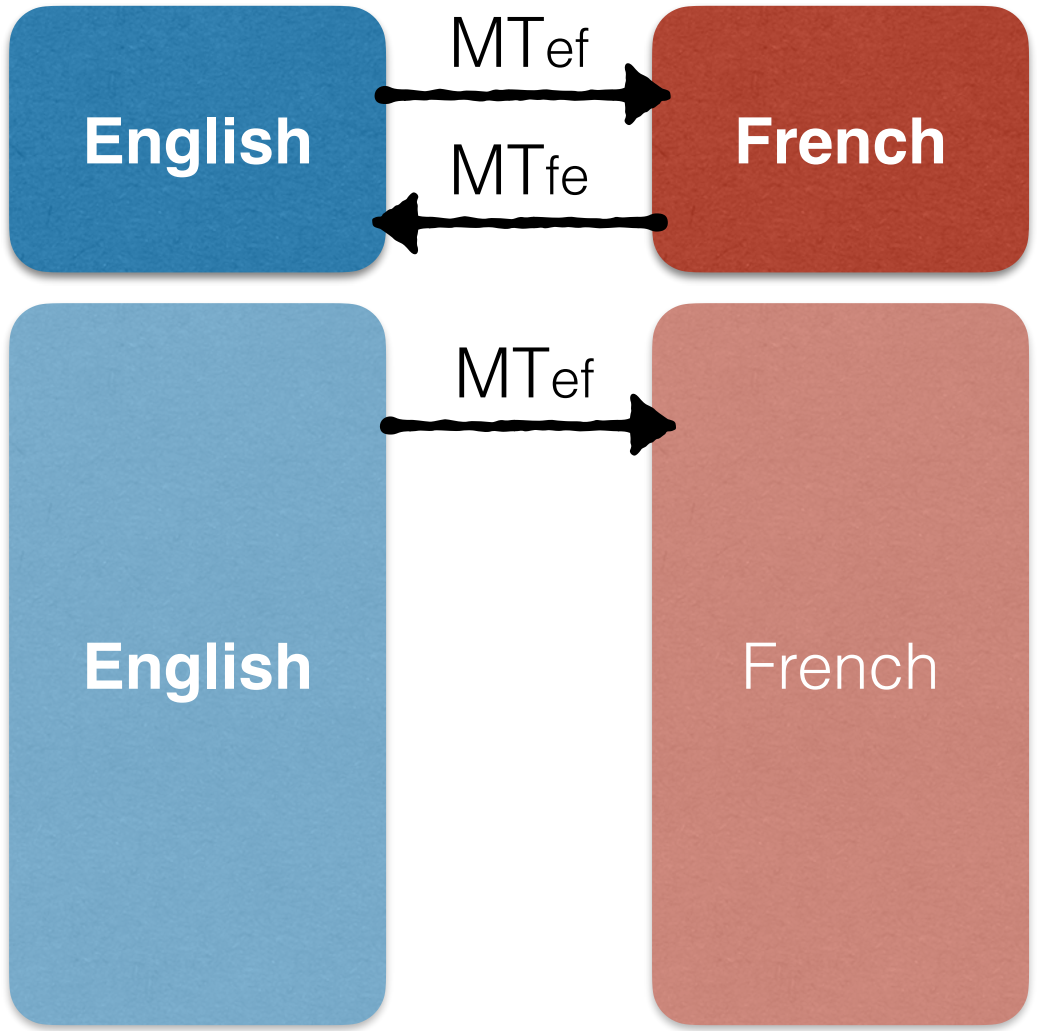

bushi yu shalong juxing le huitan
$\mathbf{x}'$
decoder
$P(\mathbf{x}'|\mathbf{y}; \overleftarrow{\boldsymbol{\theta}})$
Bush held a talk with Sharon
$\mathbf{y}$
encoder
$P(\mathbf{y}|\mathbf{x}; \overrightarrow{\boldsymbol{\theta}})$
bushi yu shalong juxing le huitan
$\mathbf{x}$

Semi-Supervised Learning for MT (Cheng et al. 2016)

Round-trip translation for supervision

Parallel

Monolingual



MT_{ef}

English

French

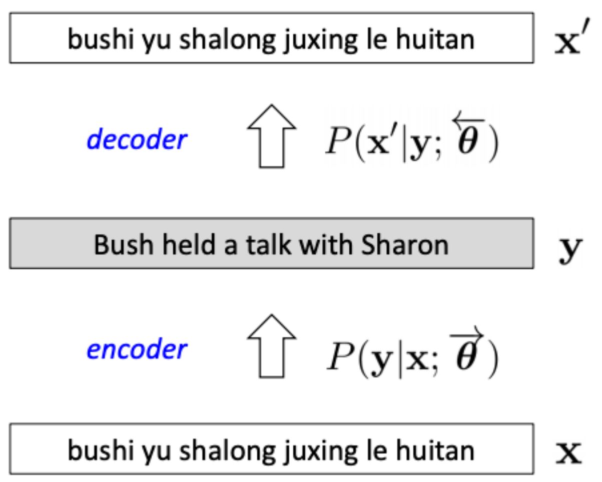
MT_{fe}

MT_{ef}

English

French

Translate *e* to *f'* with MT_{ef}

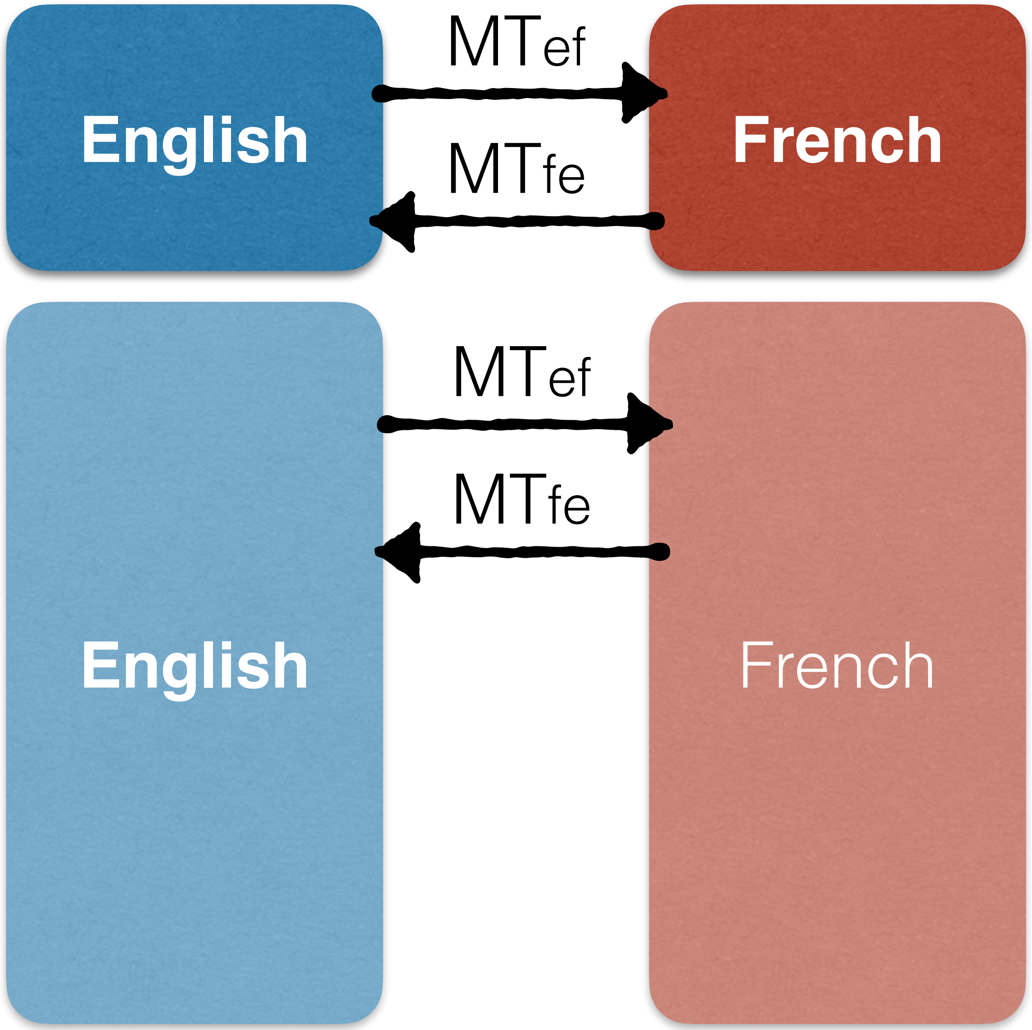

bushi yu shalong juxing le huitan
$\mathbf{x}'$
decoder
$P(\mathbf{x}'|\mathbf{y}; \overleftarrow{\boldsymbol{\theta}})$
Bush held a talk with Sharon
$\mathbf{y}$
encoder
$P(\mathbf{y}|\mathbf{x}; \overrightarrow{\boldsymbol{\theta}})$
bushi yu shalong juxing le huitan
$\mathbf{x}$

Semi-Supervised Learning for MT (Cheng et al. 2016)

Round-trip translation for supervision

Parallel

Monolingual


English

French

MTef

MTfe

English

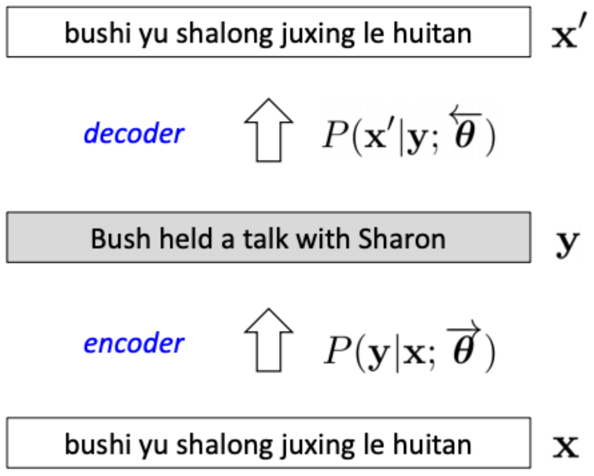
French

MTef

MTfe

Translate *e* to *f'* with MT_{ef}

Translate *f'* to *e'* with MT_{fe}


bushi yu shalong juxing le huitan $\mathbf{x}'$

decoder ⇧ $P(\mathbf{x}'|\mathbf{y};\overleftarrow{\boldsymbol{\theta}})$

Bush held a talk with Sharon $\mathbf{y}$

encoder ⇧ $P(\mathbf{y}|\mathbf{x};\overrightarrow{\boldsymbol{\theta}})$

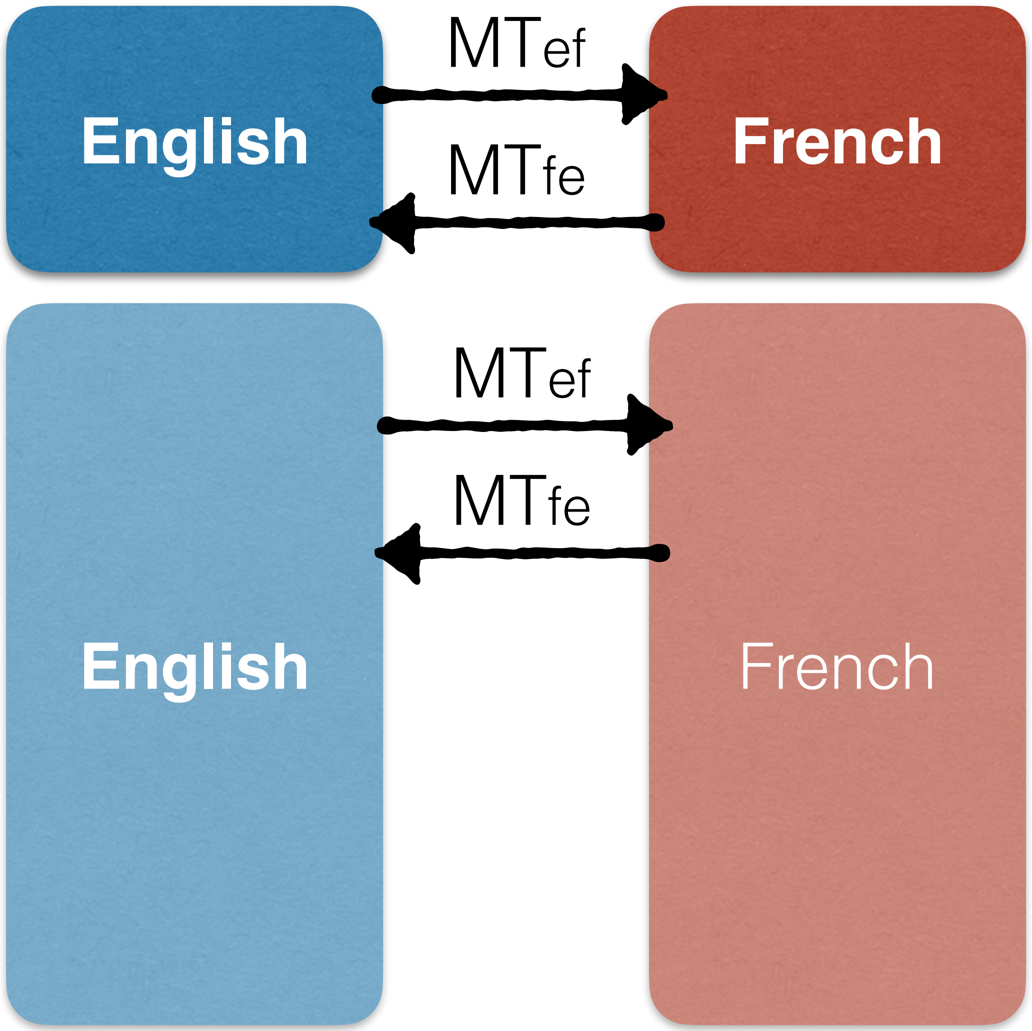
bushi yu shalong juxing le huitan $\mathbf{x}$

Semi-Supervised Learning for MT (Cheng et al. 2016)

Round-trip translation for supervision

Parallel

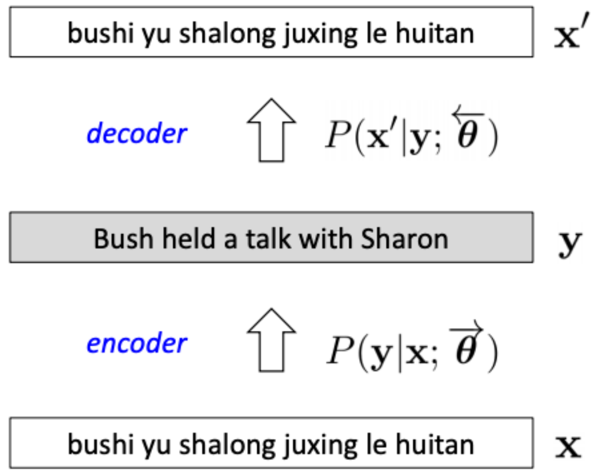
Monolingual



Translate *e* to *f'* with MT$_{ef}$

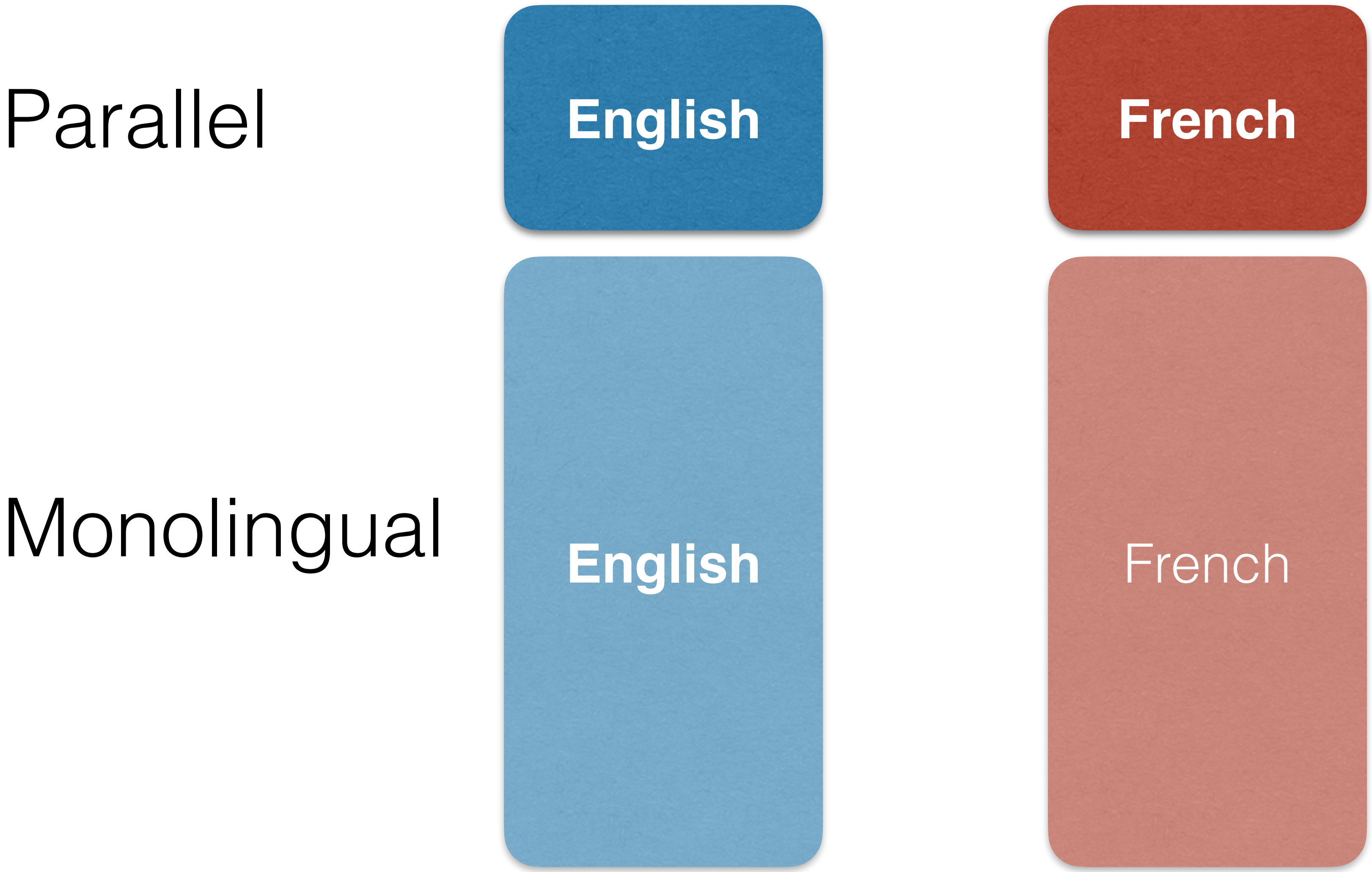
Translate *f'* to *e'* with MT$_{fe}$

Loss from *e* and *e'*



bushi yu shalong juxing le huitan
$\mathbf{x}'$
decoder
$P(\mathbf{x}'|\mathbf{y}; \overleftarrow{\boldsymbol{\theta}})$
Bush held a talk with Sharon
$\mathbf{y}$
encoder
$P(\mathbf{y}|\mathbf{x}; \overrightarrow{\boldsymbol{\theta}})$
bushi yu shalong juxing le huitan
$\mathbf{x}$

Another idea: use monolingual data to pretrain model components



Parallel

English

French

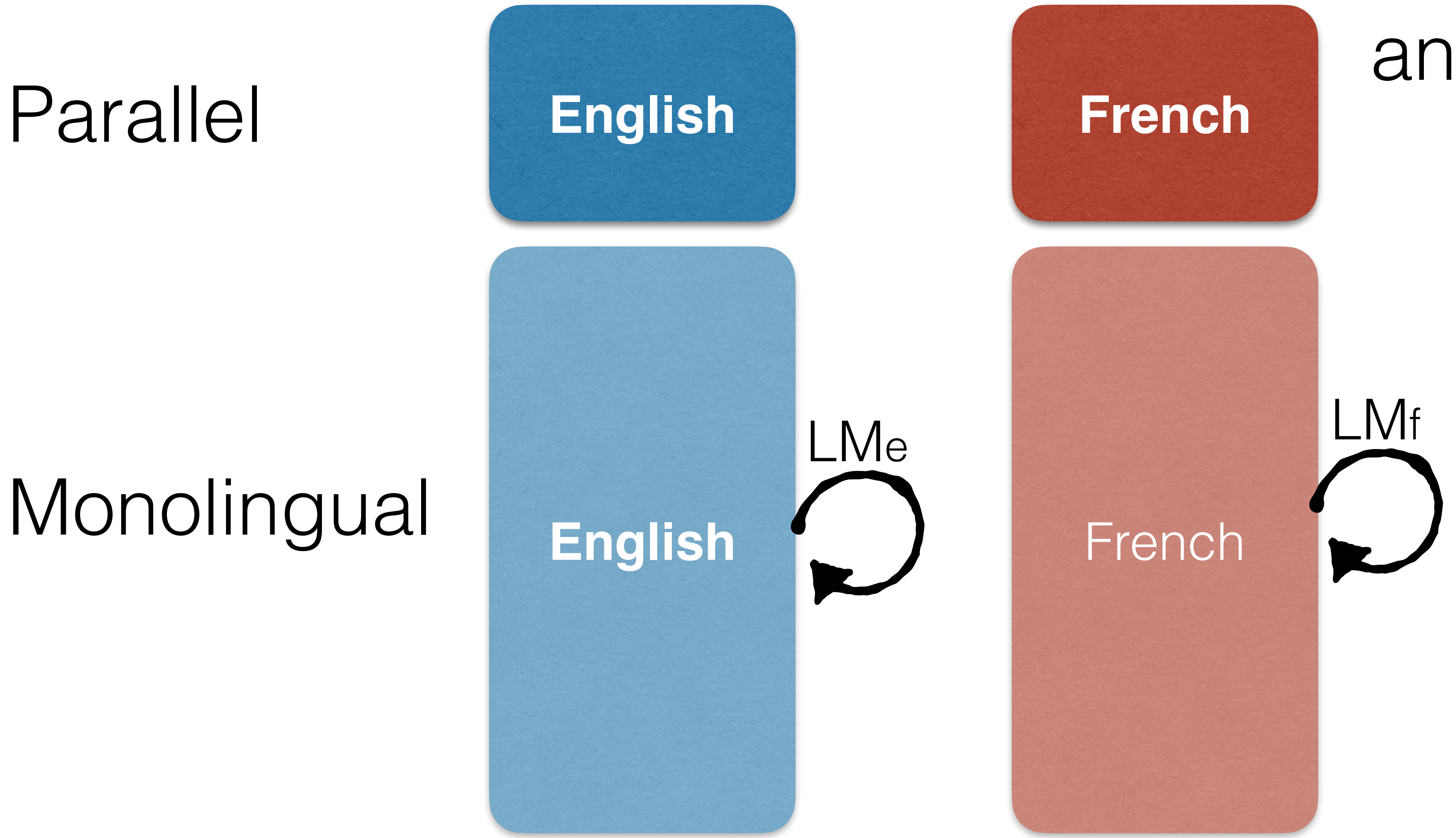
Monolingual

English

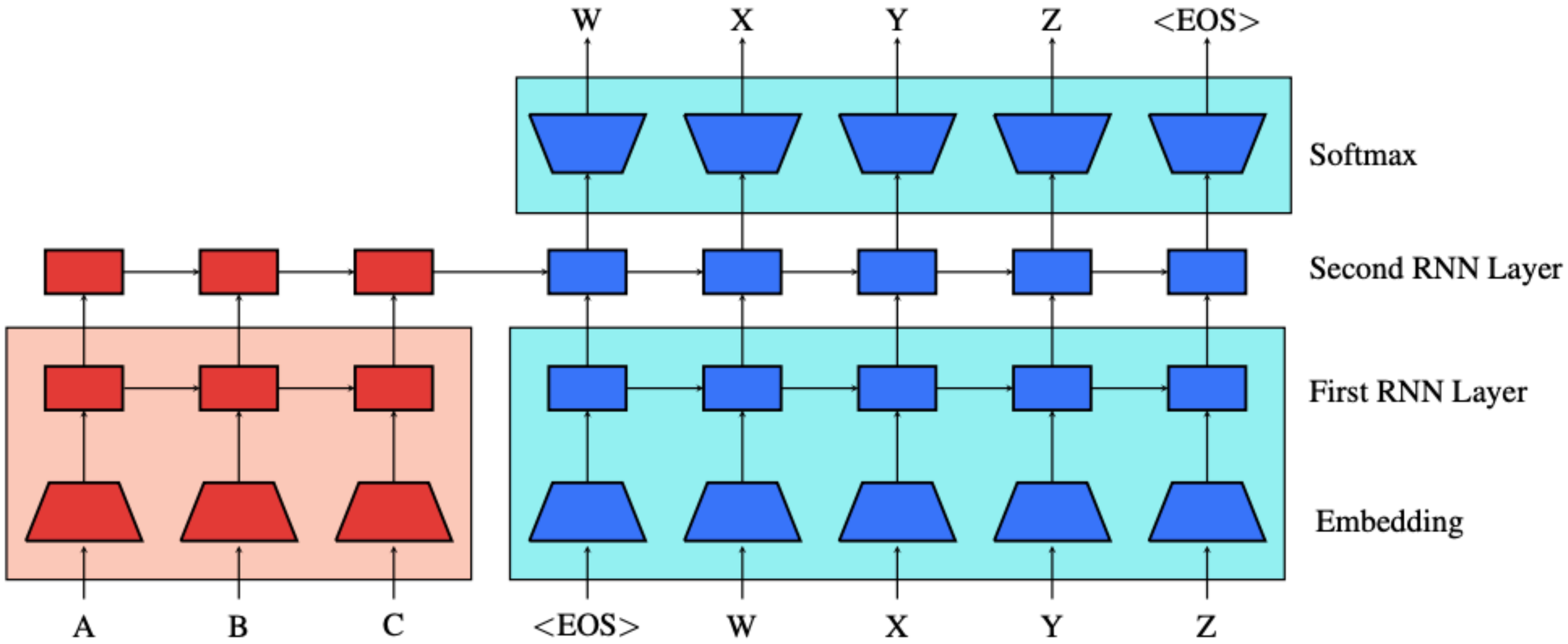
French

Another idea: use monolingual data to pretrain model components

Use the monolingual data to train the encoder and the decoder.



Another idea: use monolingual data to pretrain model components



Shaded regions are pre-trained

From "Unsupervised Pretraining for Sequence to Sequence Learning", Ramachadran et al. 2017.

Another idea: use monolingual data to pretrain model components

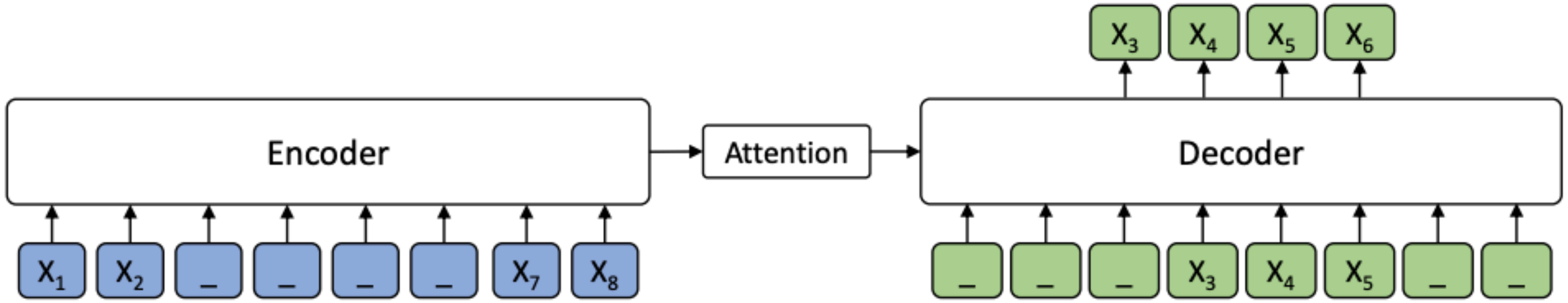
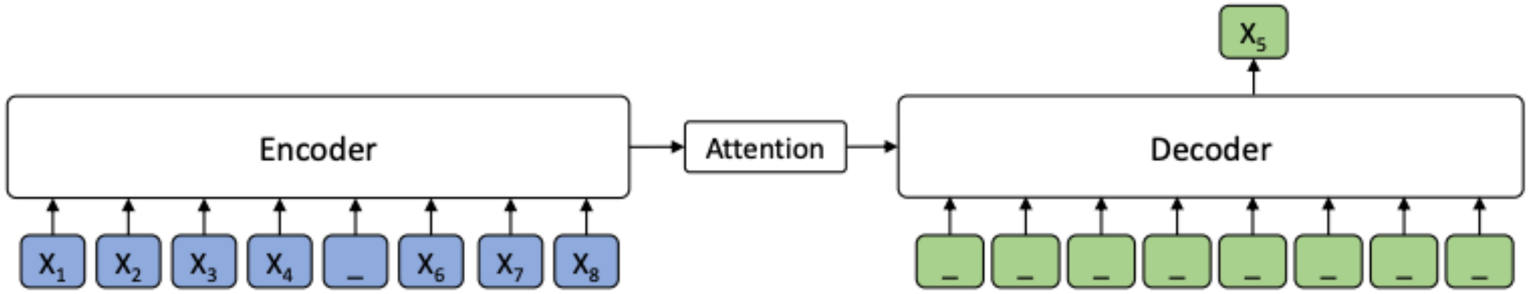


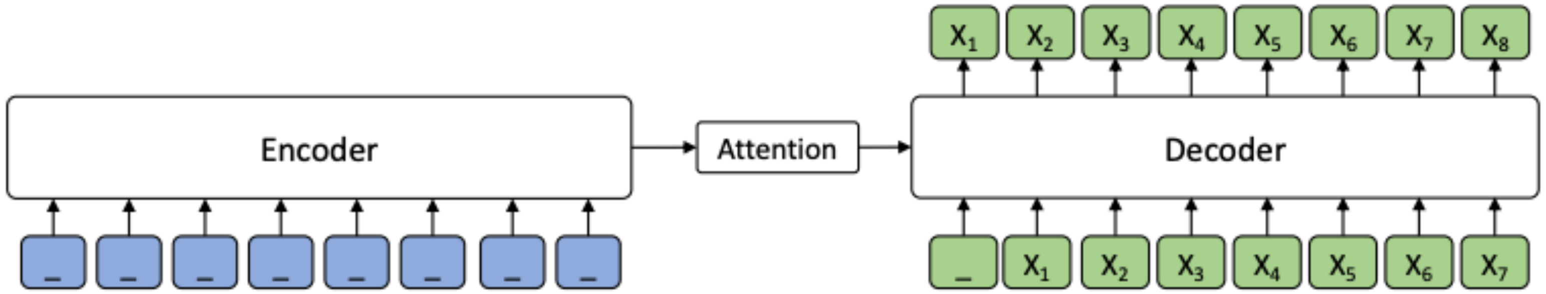
Figure 1. The encoder-decoder framework for our proposed MASS. The token "_" represents the mask symbol $[\mathbb{M}]$.

From "MASS: Masked Sequence to Sequence Pre-training for Language Generation", Song et al. 2019.

Another idea: use monolingual data to pretrain model components



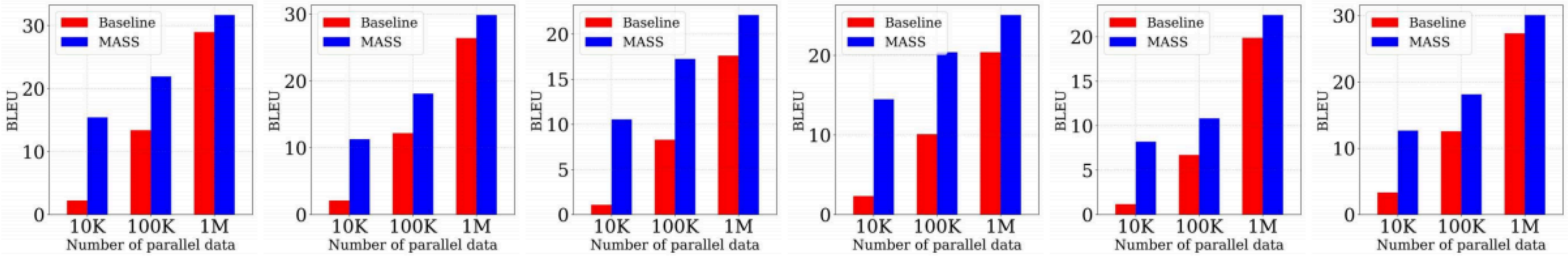
(a) Masked language modeling in BERT ($k = 1$)



(b) Standard language modeling ($k = m$)

From "MASS: Masked Sequence to Sequence Pre-training for Language Generation", Song et al. 2019.

Another idea: use monolingual data to pretrain model components



(a) en-fr (b) fr-en (c) en-de (d) de-en (e) en-ro (f) ro-en

Figure 3. The BLEU score comparisons between MASS and the baseline on low-resource NMT with different scales of paired data.

From "MASS: Masked Sequence to Sequence Pre-training for Language Generation", Song et al. 2019.

Unsupervised Translation

… at the core of it all: decipherment

French

$$\arg\max_{\theta} \prod_{f} P_{\theta}(f)$$

From "Deciphering Foreign Language", Ravi and Knight 2011.

… at the core of it all: decipherment

French

$$\arg\max_{\theta} \prod_{f} P_{\theta}(f)$$

Weaver (1955): *This is really English, encrypted in some strange symbols*

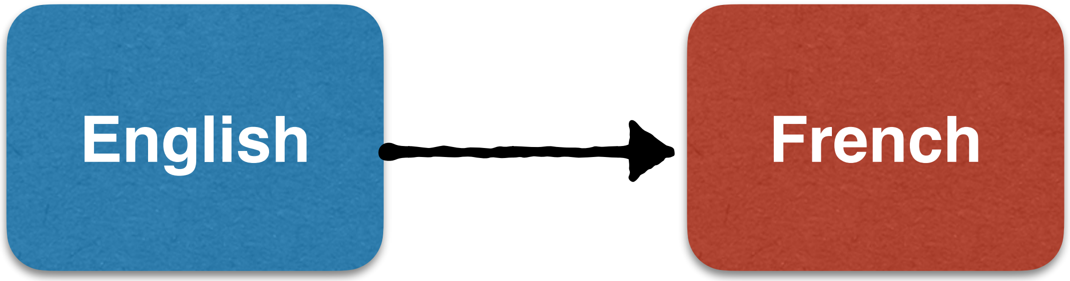
From "Deciphering Foreign Language", Ravi and Knight 2011.

… at the core of it all: decipherment

French

$$\arg\max_{\theta} \prod_{f} P_{\theta}(f)$$

Weaver (1955): *This is really English, encrypted in some strange symbols*



English

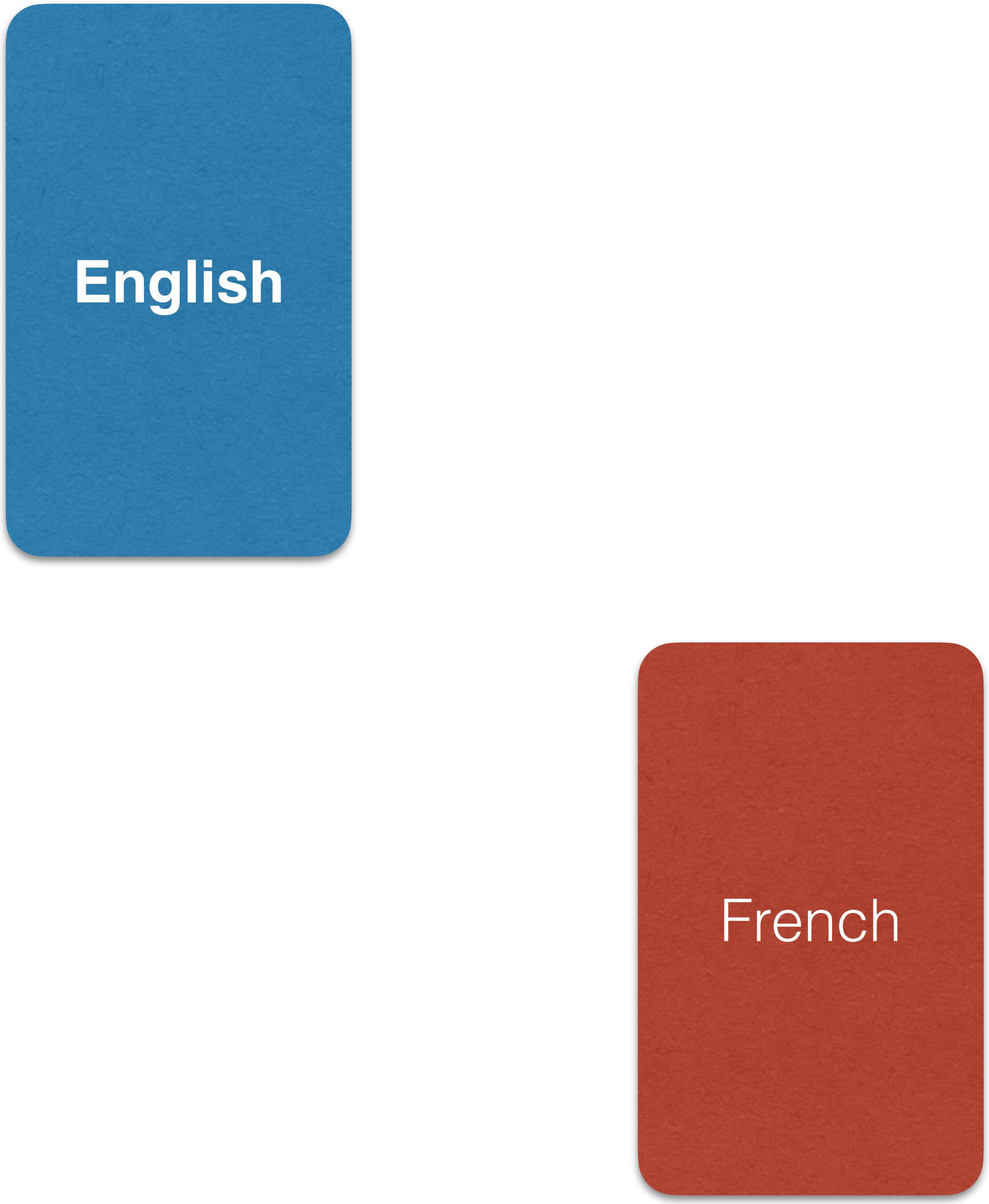
French

$$\arg\max_{\theta} \prod_{f} \sum_{e} P(e) \cdot P_{\theta}(f|e)$$

From "Deciphering Foreign Language", Ravi and Knight 2011.

Unsupervised MT
(Lample et al. and Artetxe et al. 2018)

Unsupervised MT
(Lample et al. and Artetxe et al. 2018)

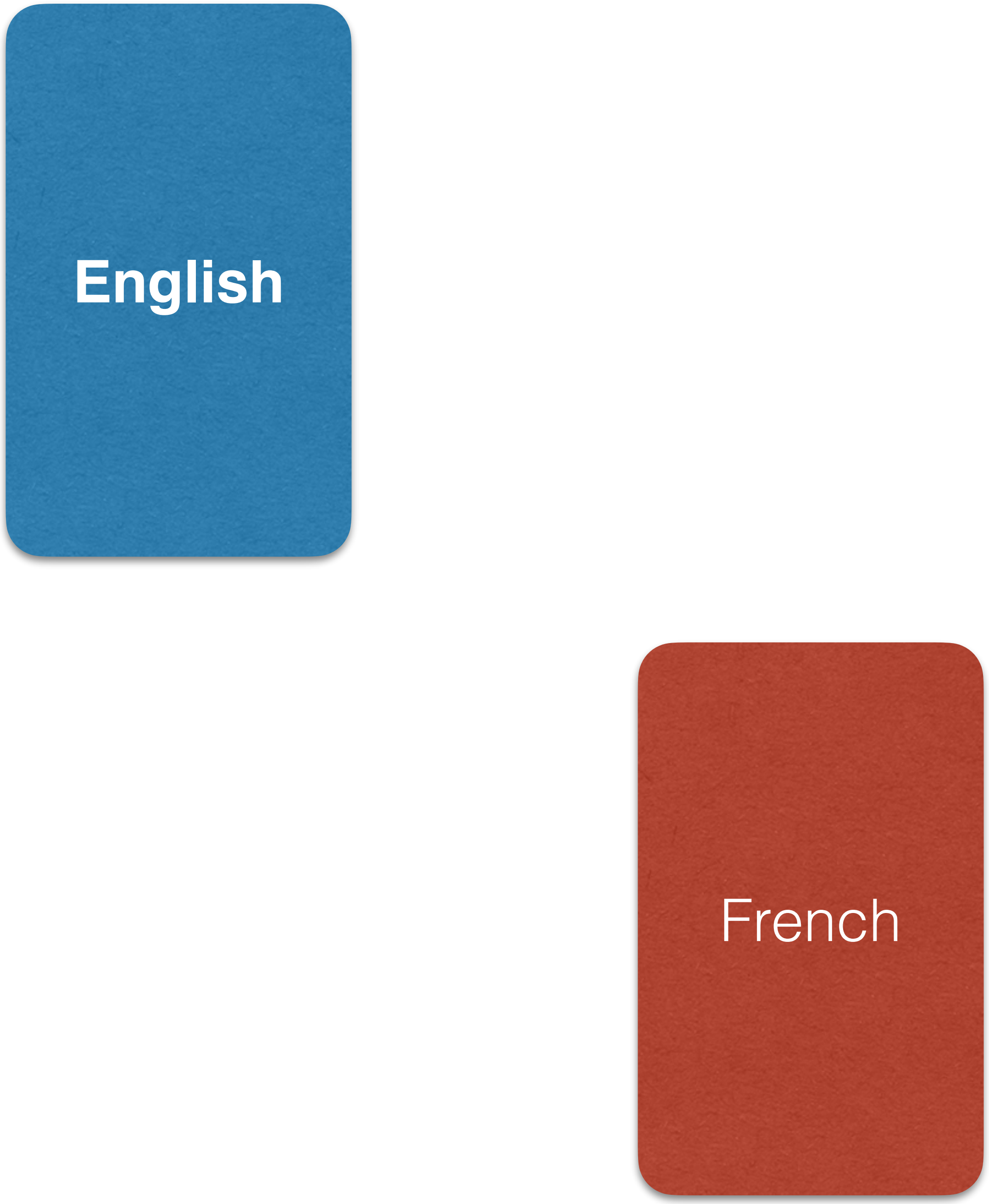


English

French

Unsupervised MT (Lampert et al. and Artetxe et al. 2018)

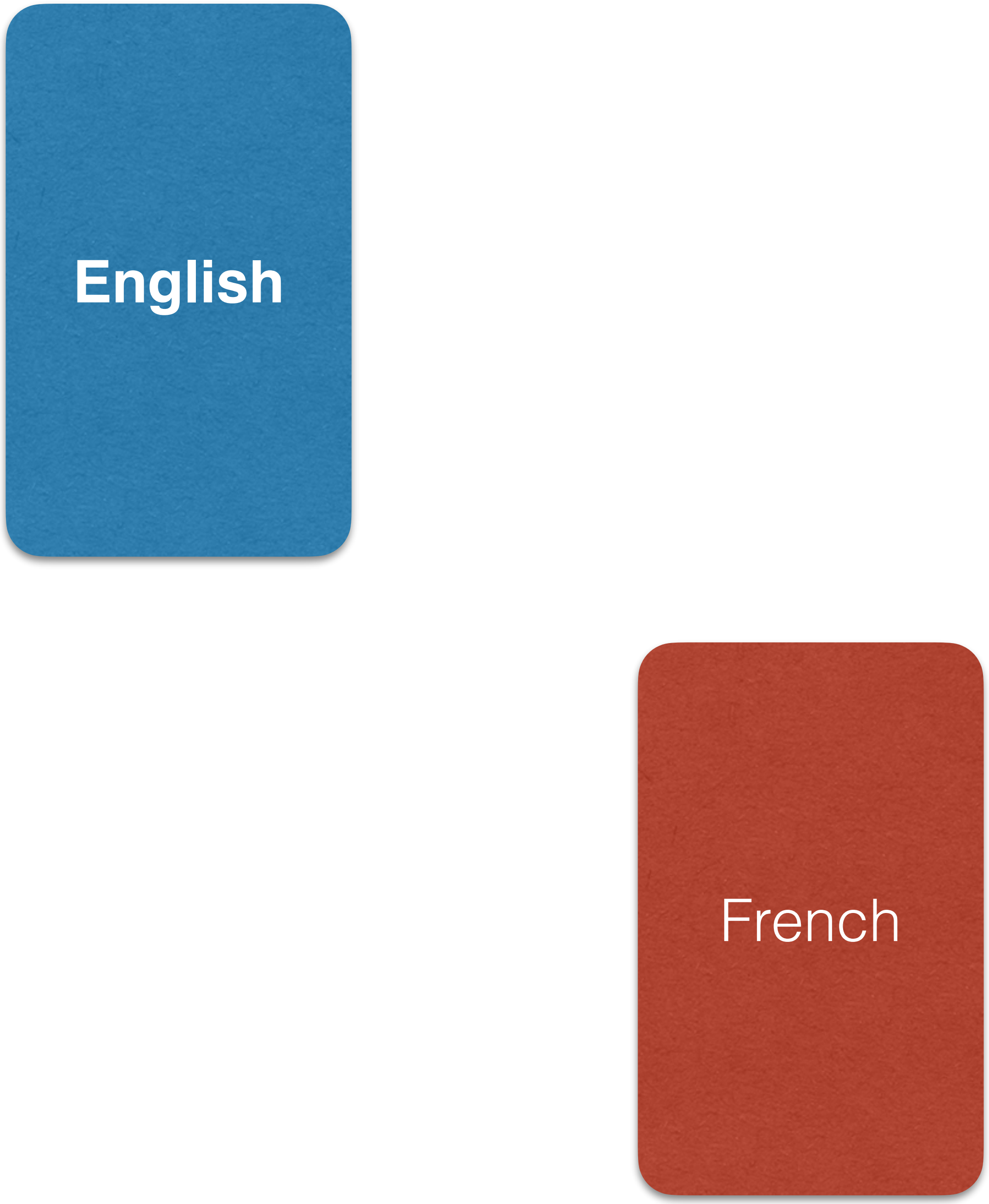
1. Embeddings + Unsup. BLI



Unsupervised MT
(Lample et al. and Artetxe et al. 2018)

1. Embeddings + Unsup. BLI

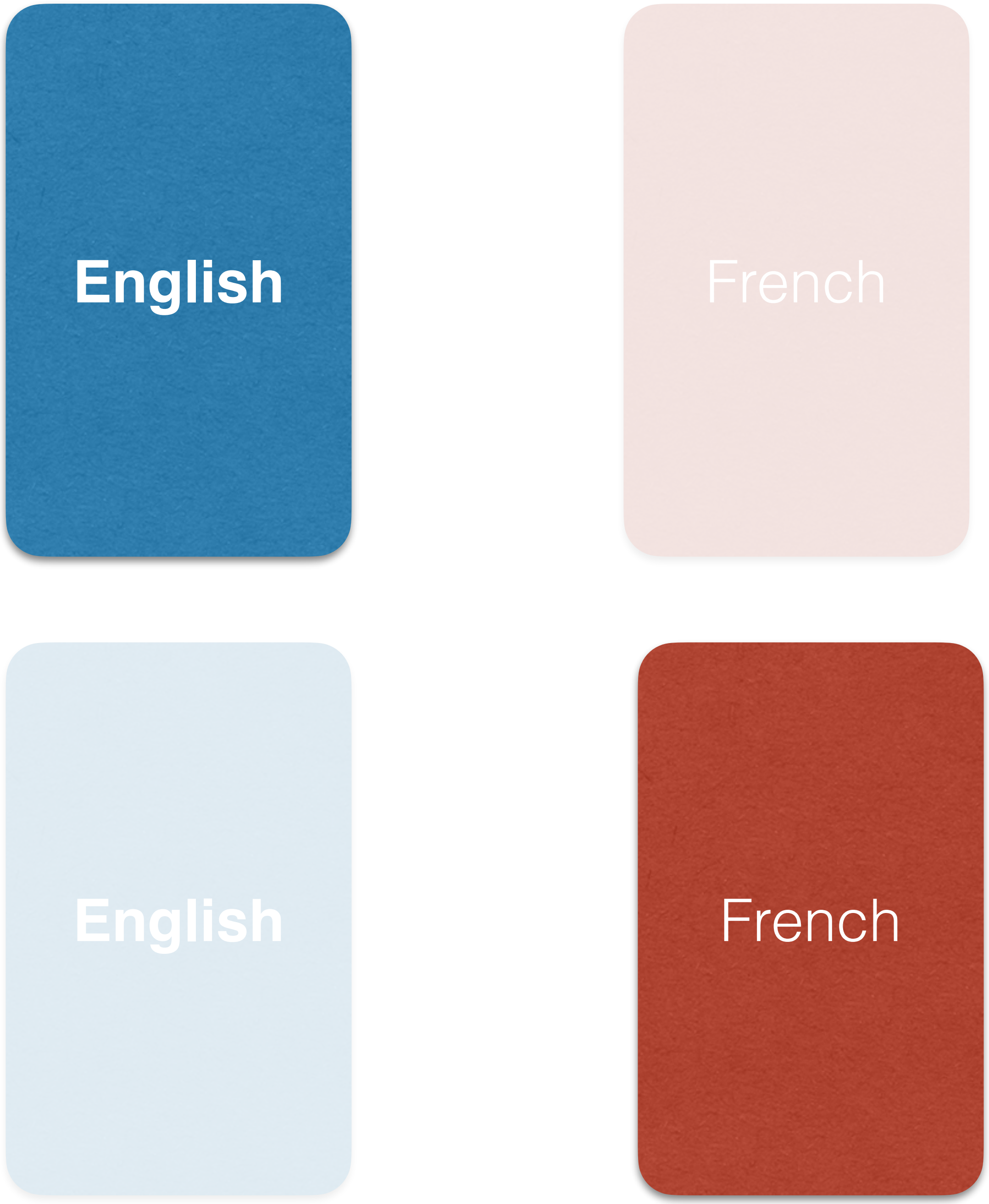
2. BLI —> Word Translations



English

French

Unsupervised MT
(Lample et al. and Artetxe et al. 2018)



English

French

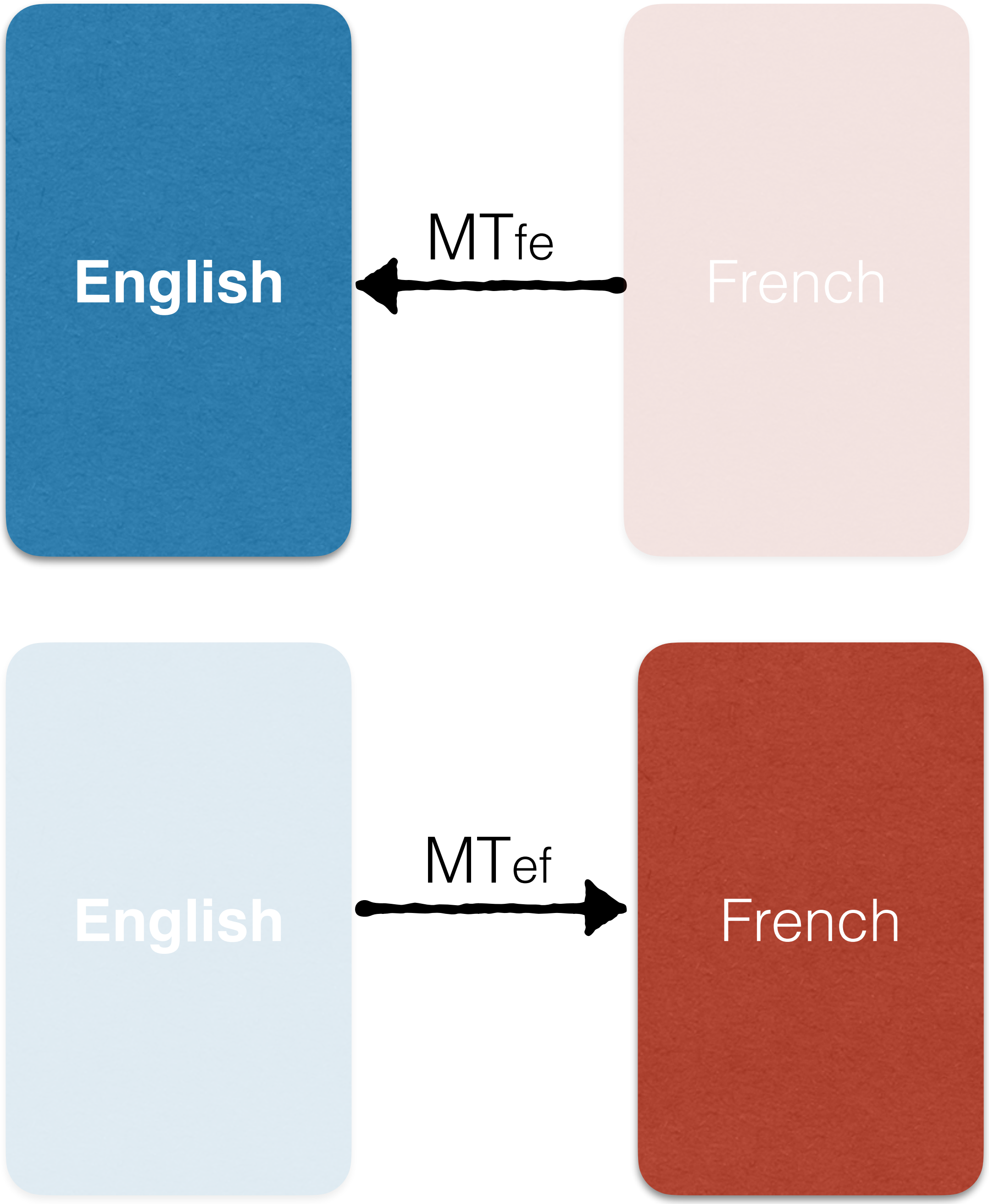
English

French

1. Embeddings + Unsup. BLI

2. BLI —> Word Translations

Unsupervised MT
(Lample et al. and Artetxe et al. 2018)

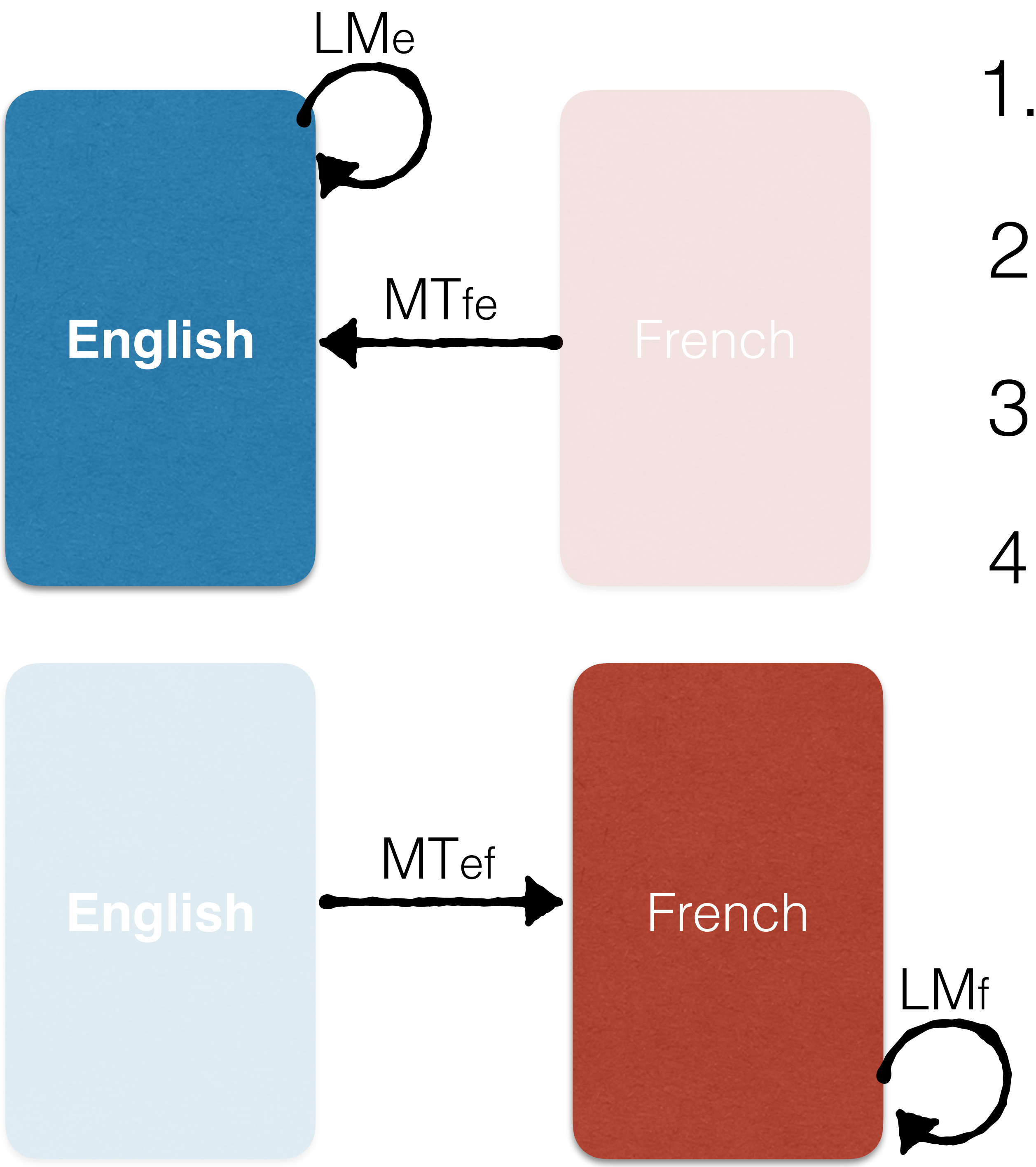


1. Embeddings + Unsup. BLI

2. BLI —> Word Translations

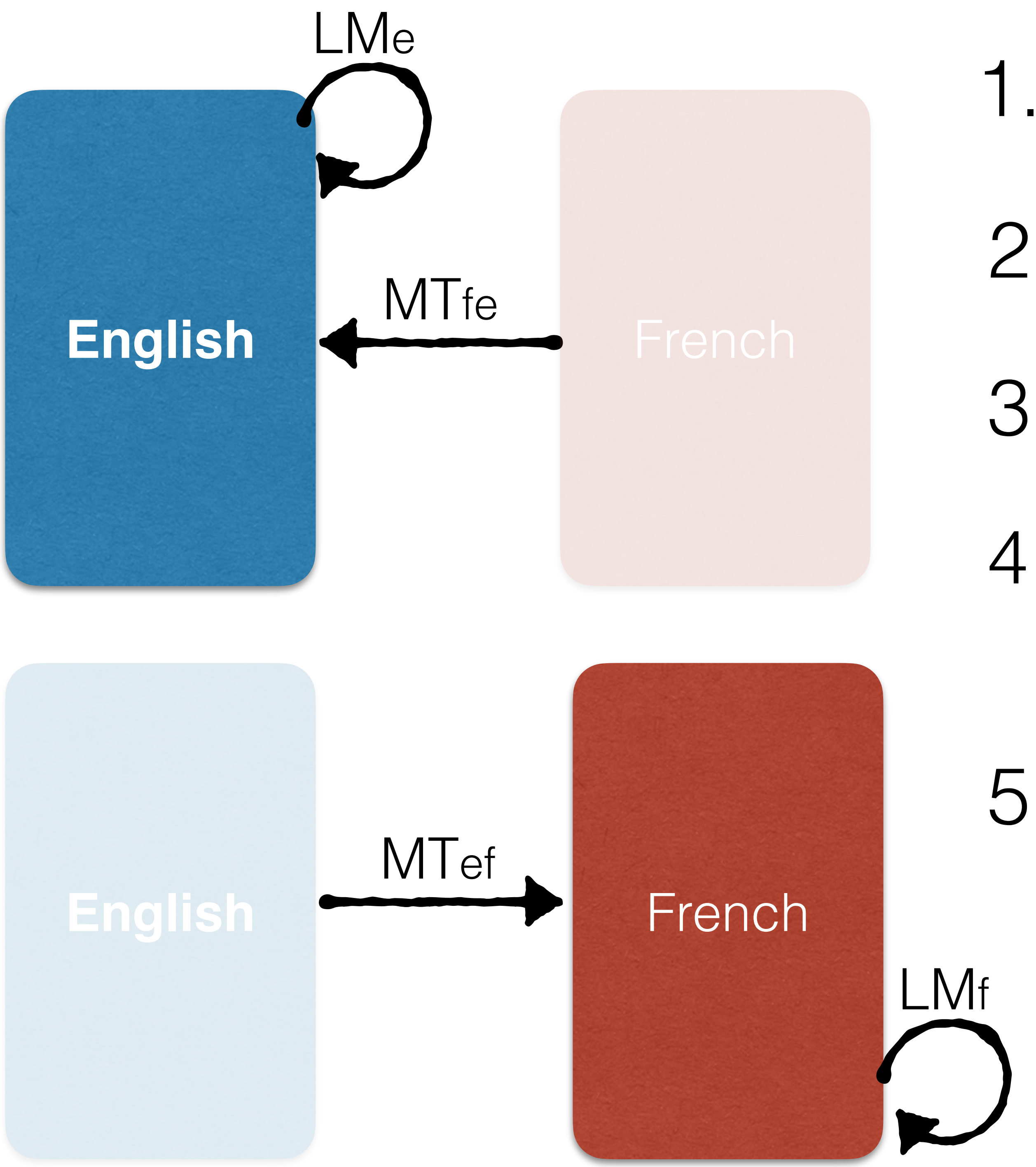
3. Train MT_{fe} and MT_{ef} systems

Unsupervised MT (Lample et al. and Artetxe et al. 2018)



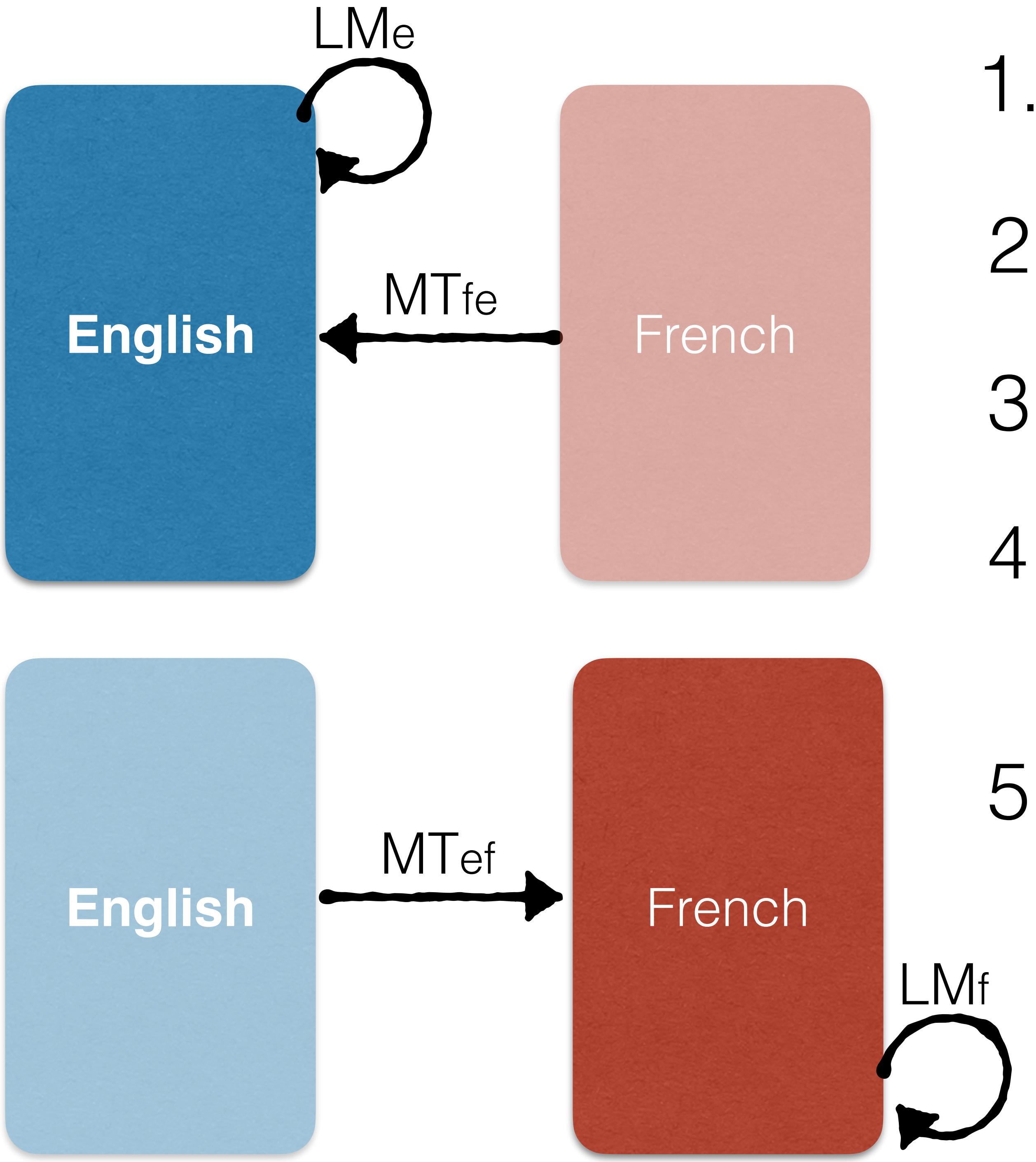
1. Embeddings + Unsup. BLI
2. BLI —> Word Translations
3. Train MT_{fe} and MT_{ef} systems
4. Meanwhile, use unsupervised objectives (denoising LM)

Unsupervised MT (Lampple et al. and Artetxe et al. 2018)



1. Embeddings + Unsup. BLI
2. BLI —> Word Translations
3. Train MT_{fe} and MT_{ef} systems
4. Meanwhile, use unsupervised objectives (denoising LM)
5. Iterate

Unsupervised MT (Lample et al. and Artetxe et al. 2018)



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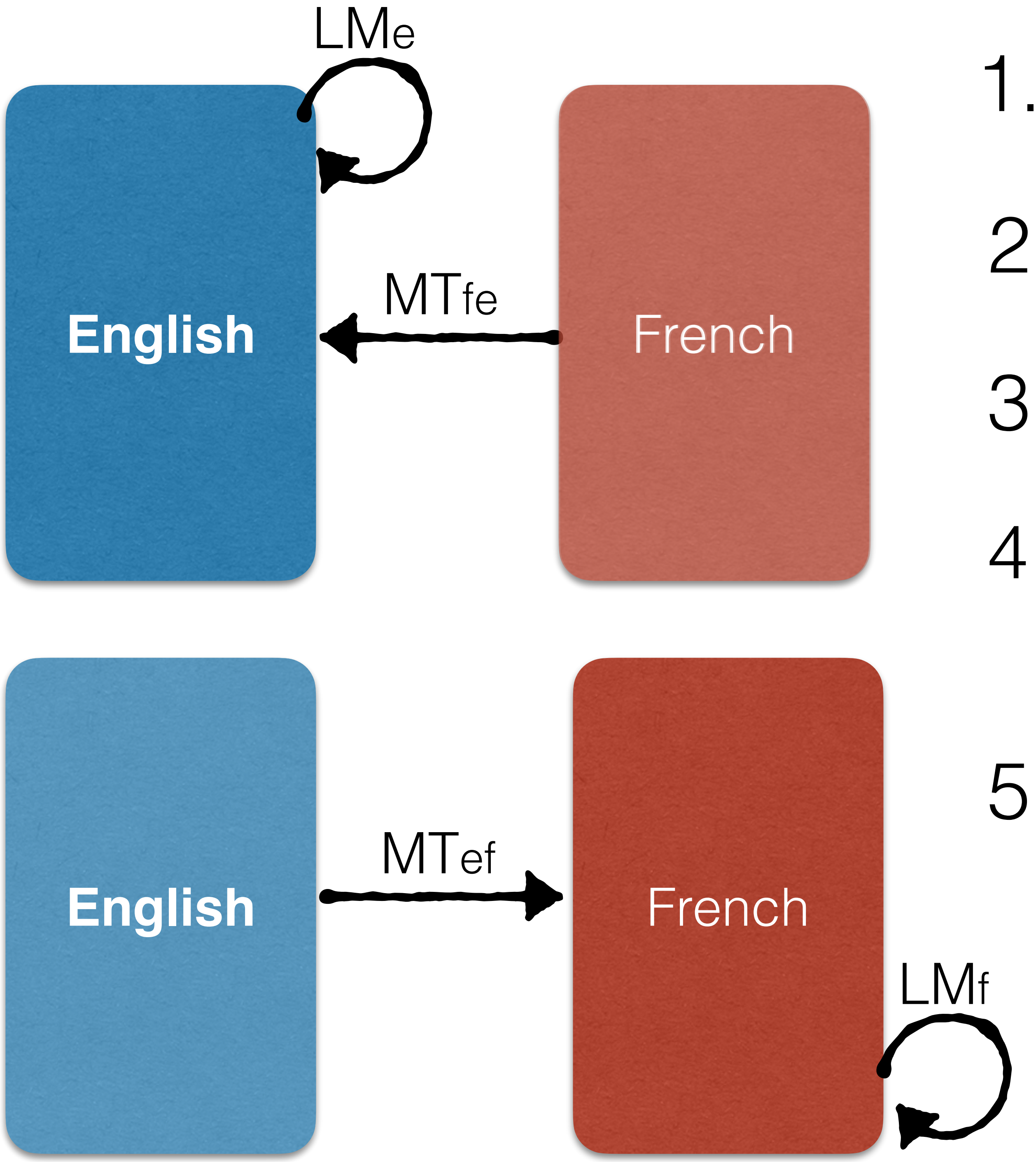

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NMT: the biggest success story of NLP Deep Learning

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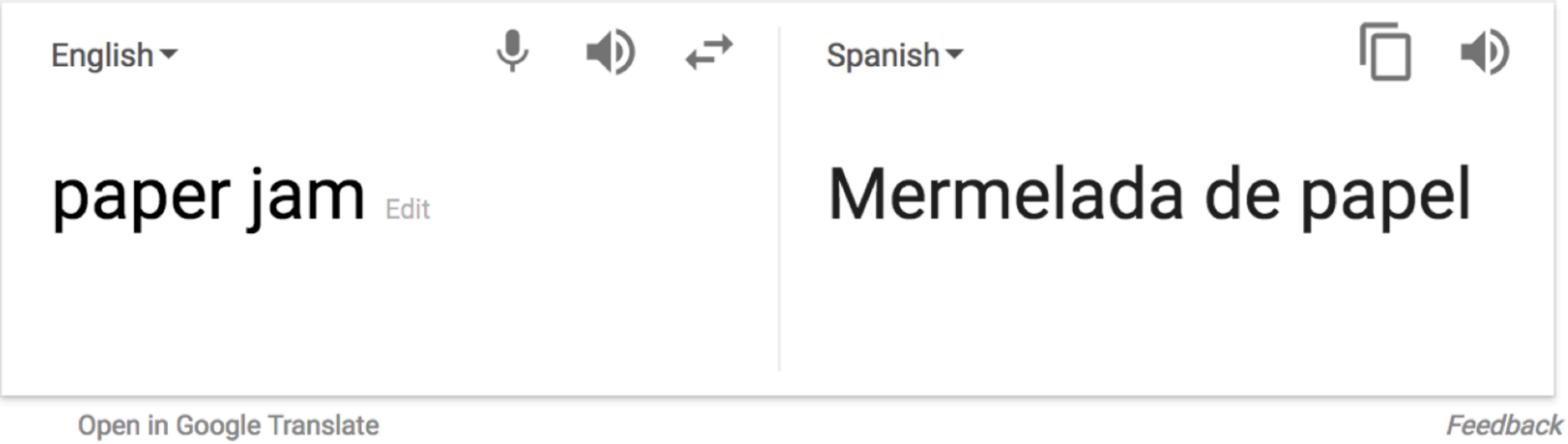
- **This is amazing!**
- SMT systems, built by hundreds of engineers over many years, outperformed by NMT systems trained by a handful of engineers in a few months

So is Machine Translation solved?

- Nope!
- Using common sense is still hard



English

paper jam

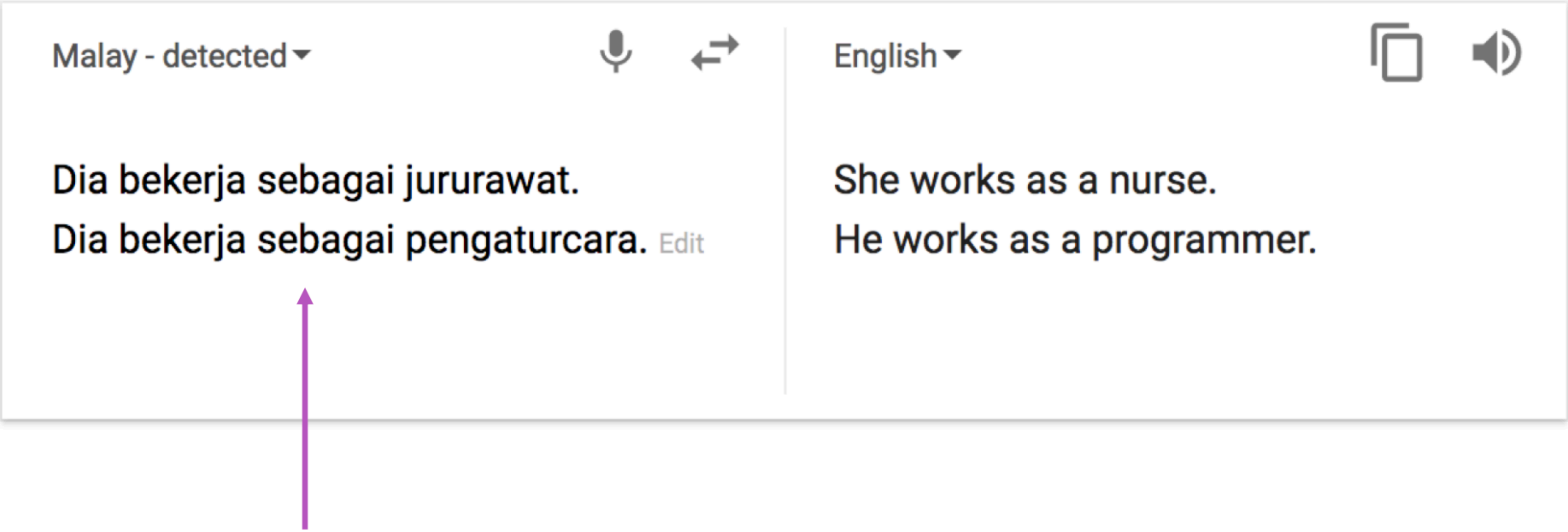
Spanish

Mermelada de papel

?

So is Machine Translation solved?

- Nope!
- NMT picks up biases in training data



Malay - detected

Dia bekerja sebagai jururawat.
Dia bekerja sebagai pengaturcara. Edit

English

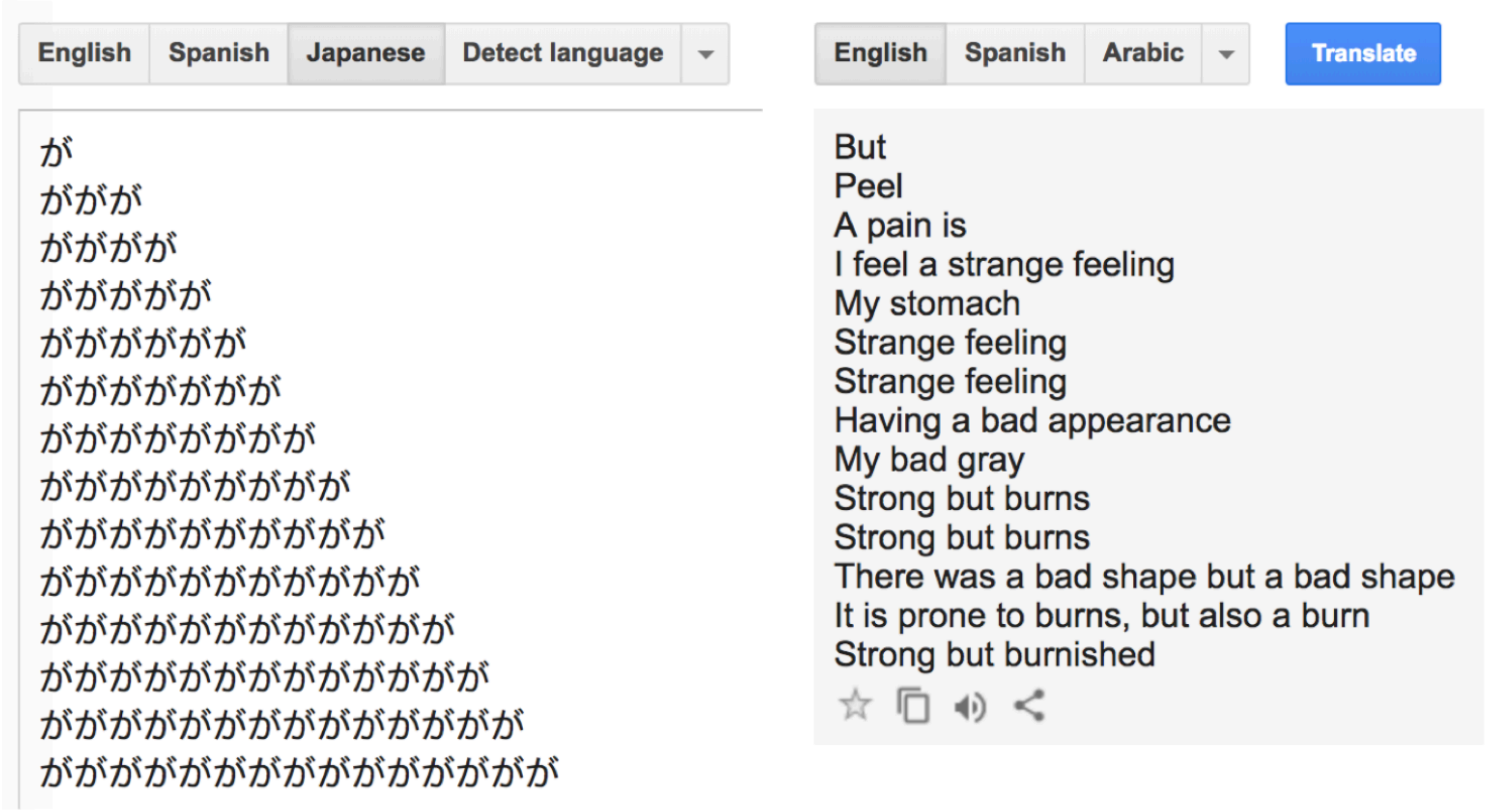
She works as a nurse.
He works as a programmer.

Didn’t specify gender

Source: https://hackernoon.com/bias-sexist-or-this-is-the-way-it-should-be-ce1f7c8c683c

So is Machine Translation solved?

- Nope!
- Uninterpretable systems do strange things



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But
Peel
A pain is
I feel a strange feeling
My stomach
Strange feeling
Strange feeling
Having a bad appearance
My bad gray
Strong but burns
Strong but burns
There was a bad shape but a bad shape
It is prone to burns, but also a burn
Strong but burnished

Source: http://languagelog.ldc.upenn.edu/nll/?p=35120#more-35120