Unsupervised Machine Translation

Mikel Artetxe

Facebook AI Research

Introduction

Introduction

WMT 2019 English-German

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System	Score
Facebook FAIR	0.347
Microsoft sent-doc	0.311
Microsoft doc-level	0.296
HUMAN	0.240
MSRA-MADL	0.214
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super-human performance

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NMT trained on 27.7M parallel sentence pairs

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In my opinion, this exposes a serious inconsistency in industrial…
En mi opinión, esto representa una grave inconsistencia entre…

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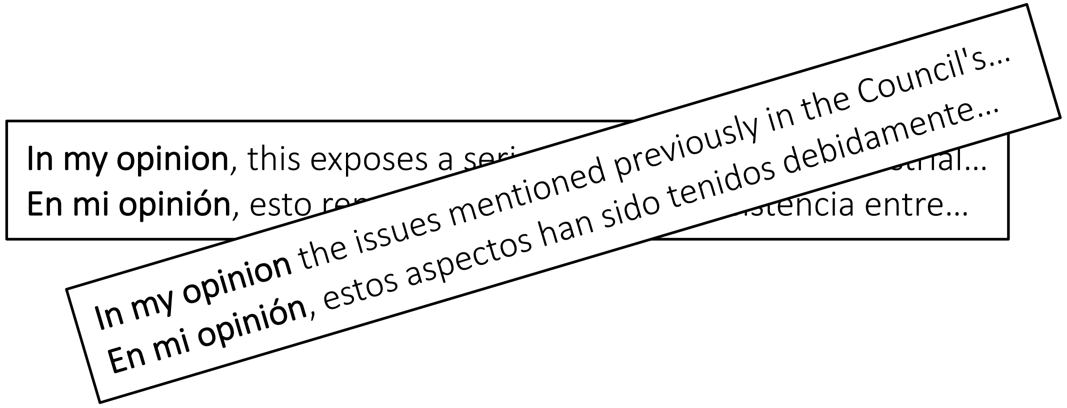

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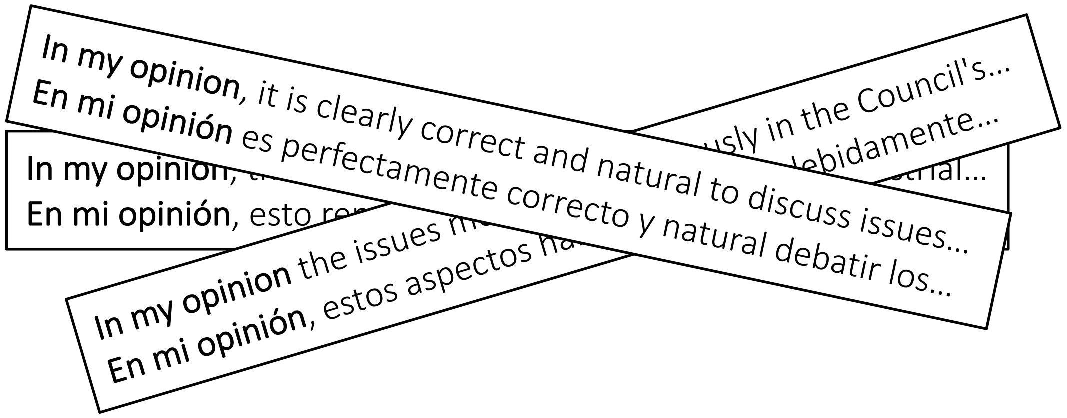

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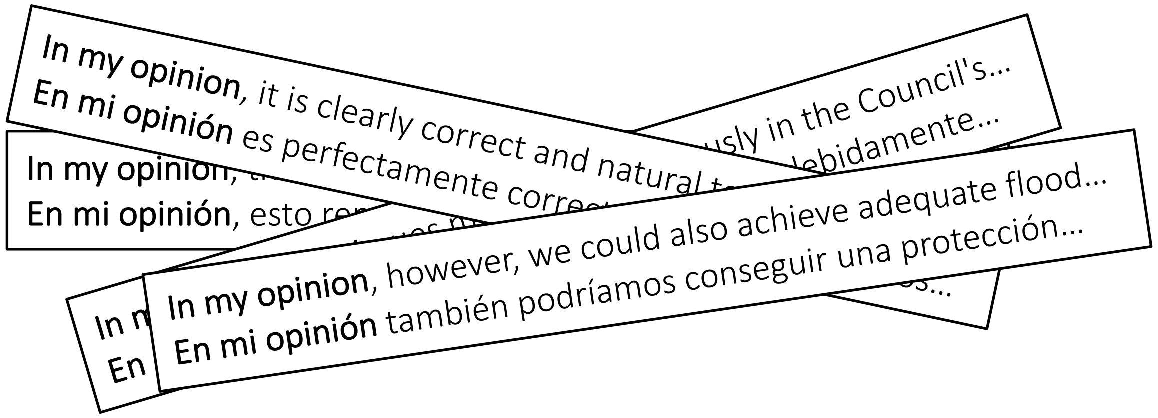

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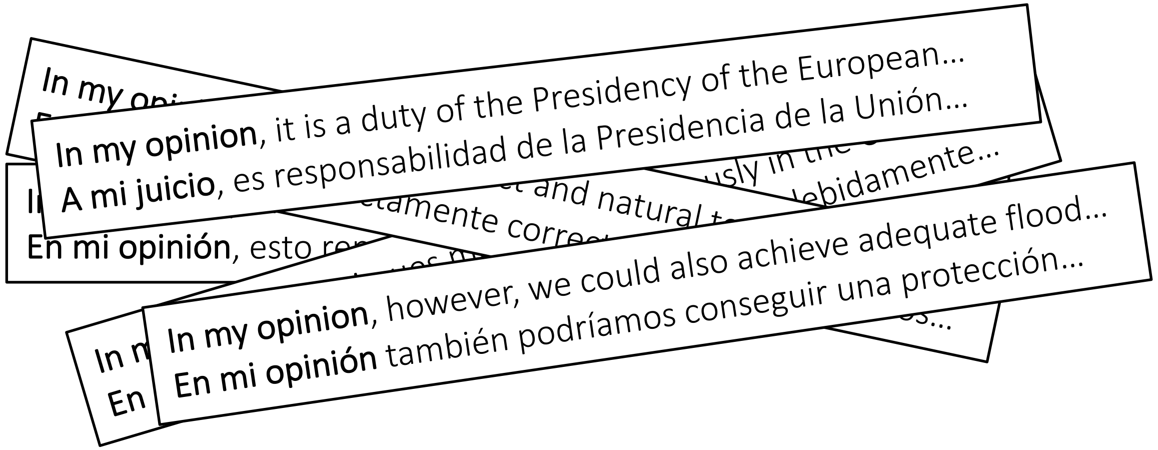

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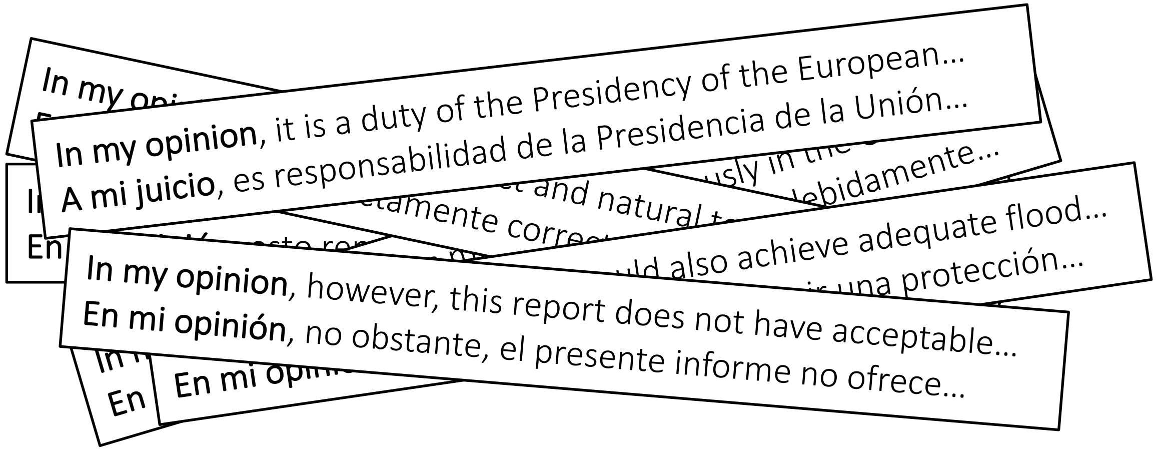

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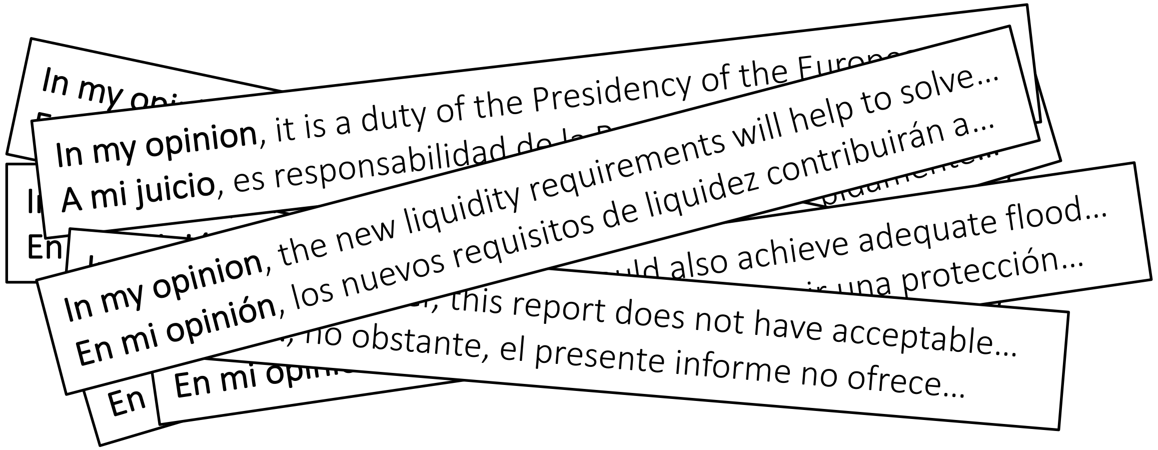

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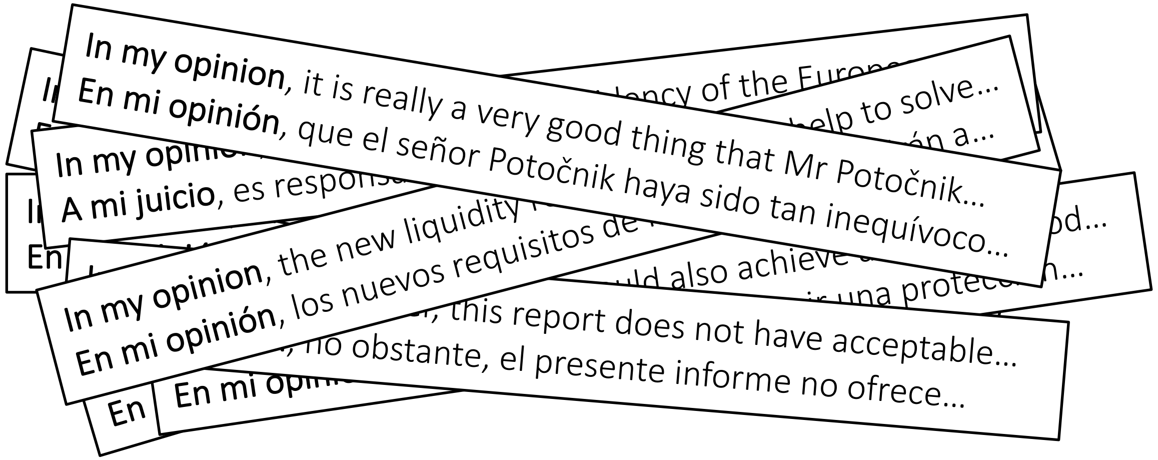

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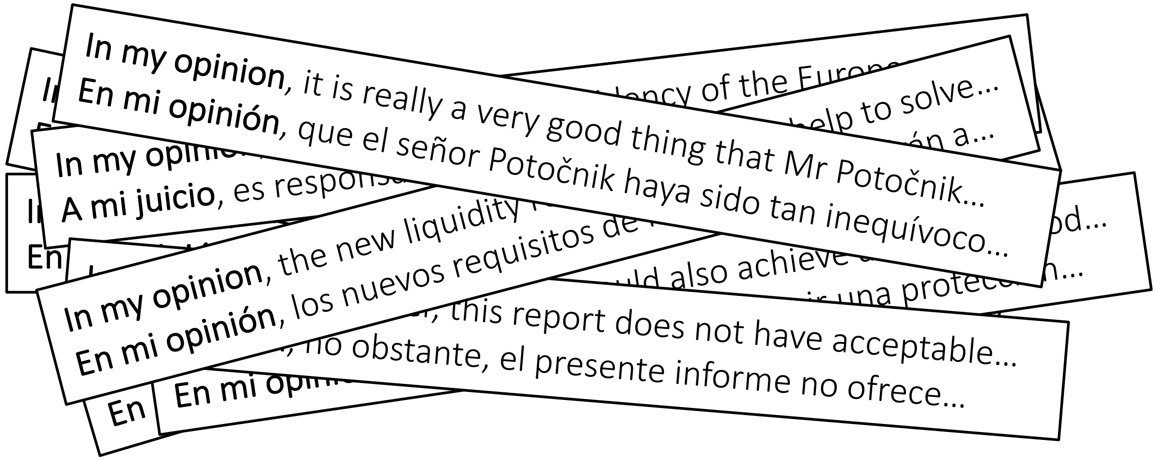

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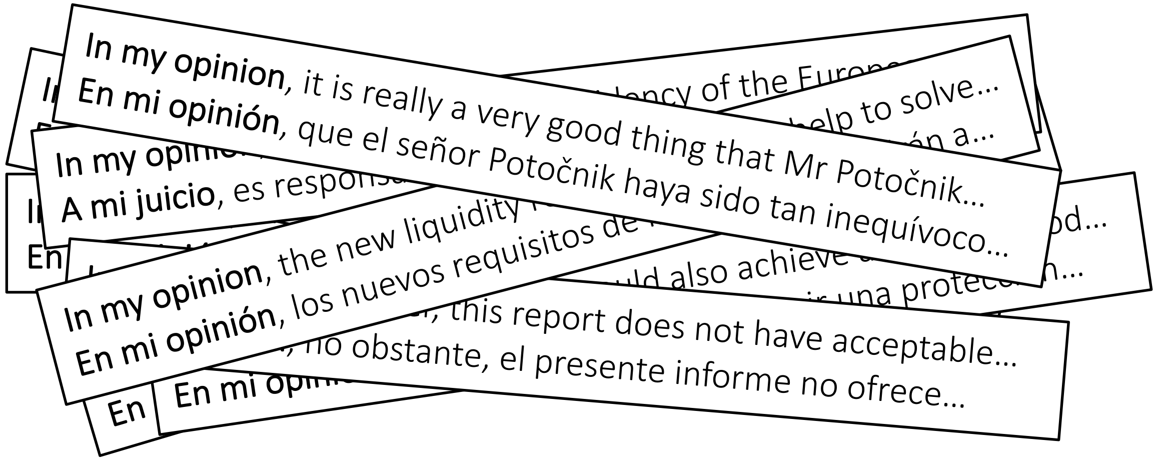

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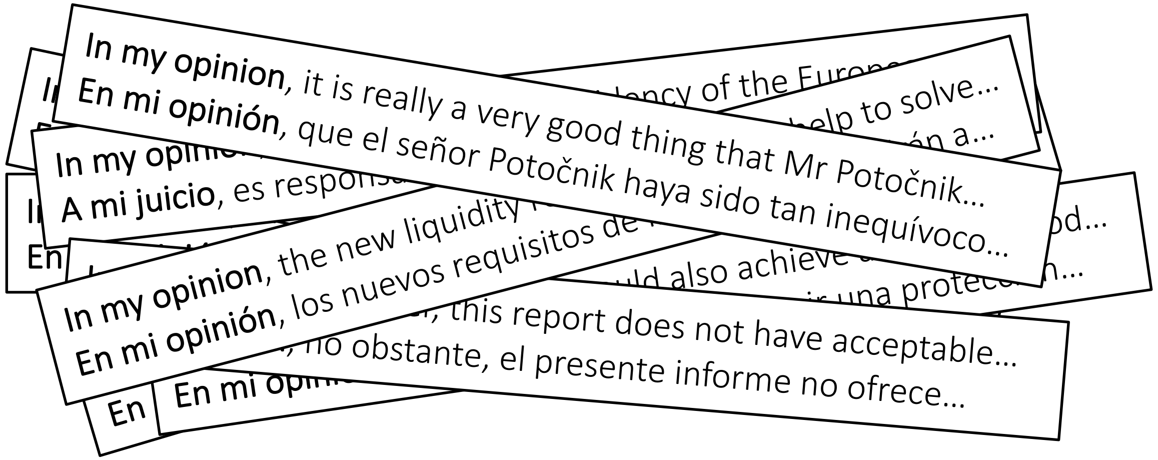

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En mi opinion, ...

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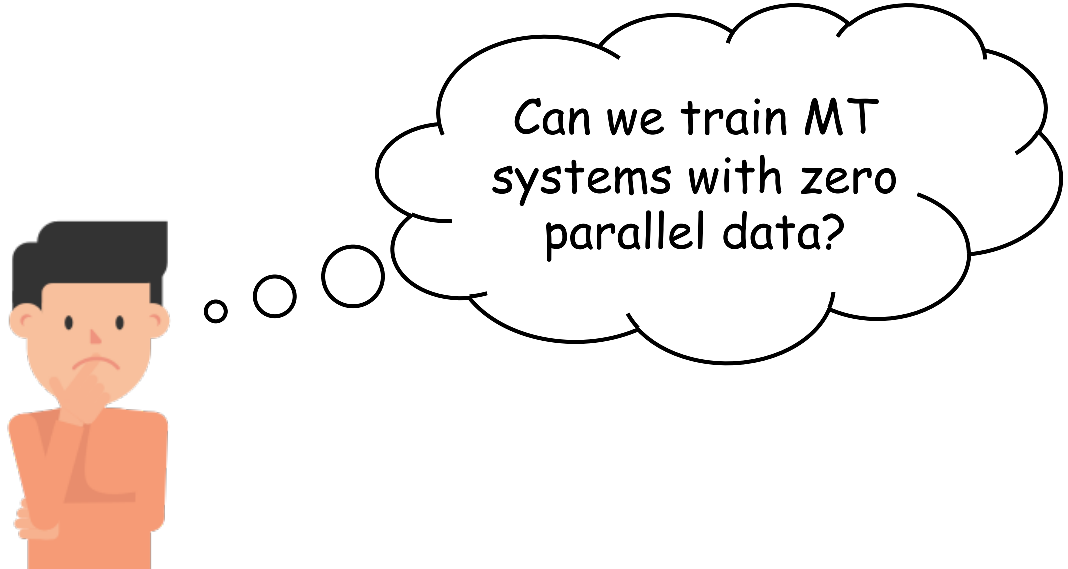

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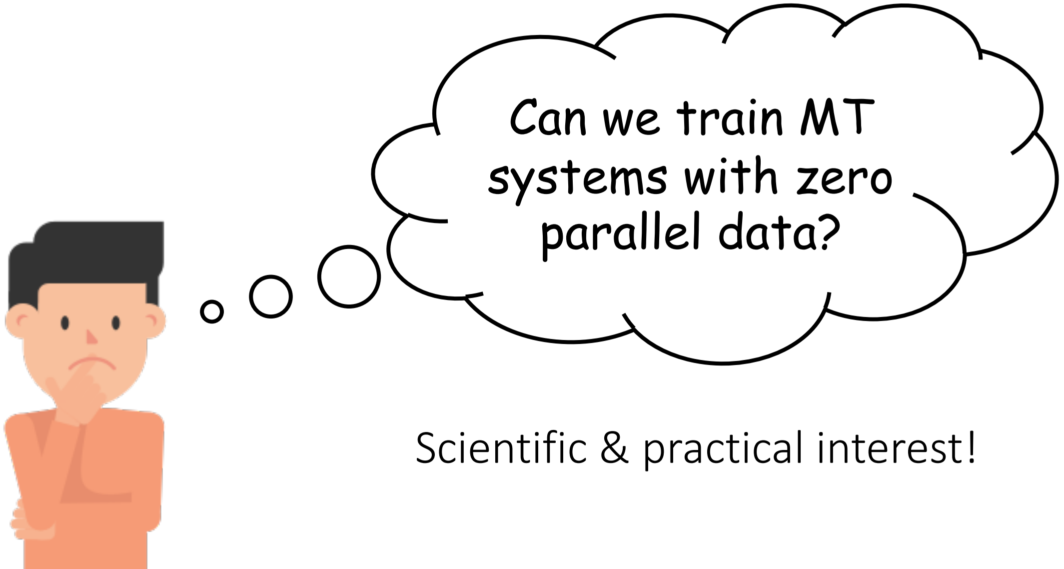

Scientific & practical interest!

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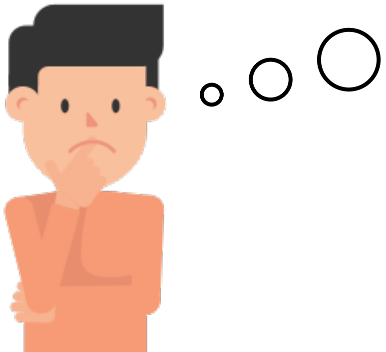

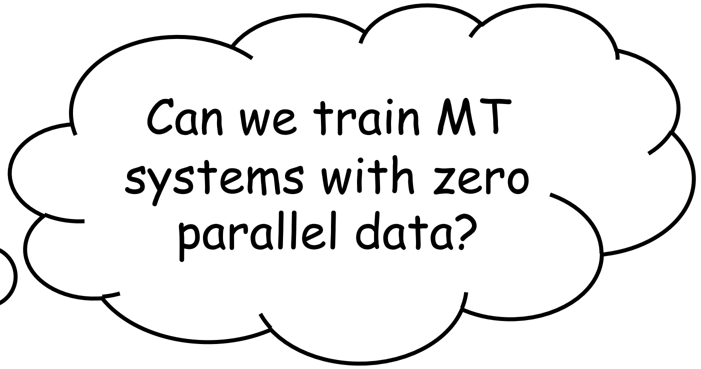

Scientific & practical interest!

Previously explored in statistical decipherment

(Knight et al., ACL'06; Ravi & Knight, ACL'11; Dou et al., ACL'15; *inter alia*)

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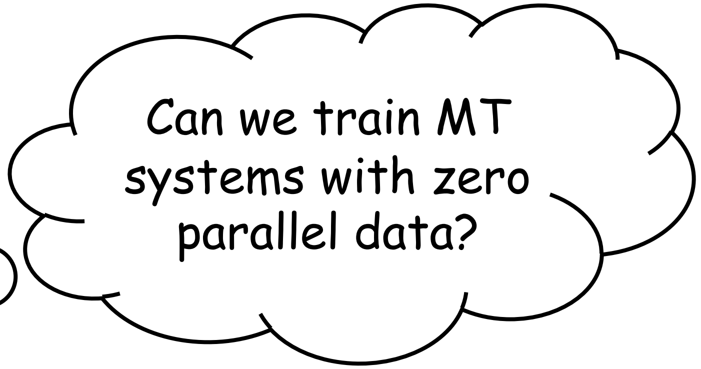

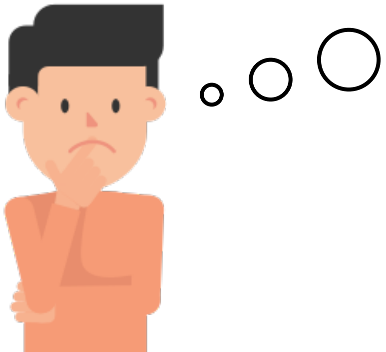

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…but strong limitations…

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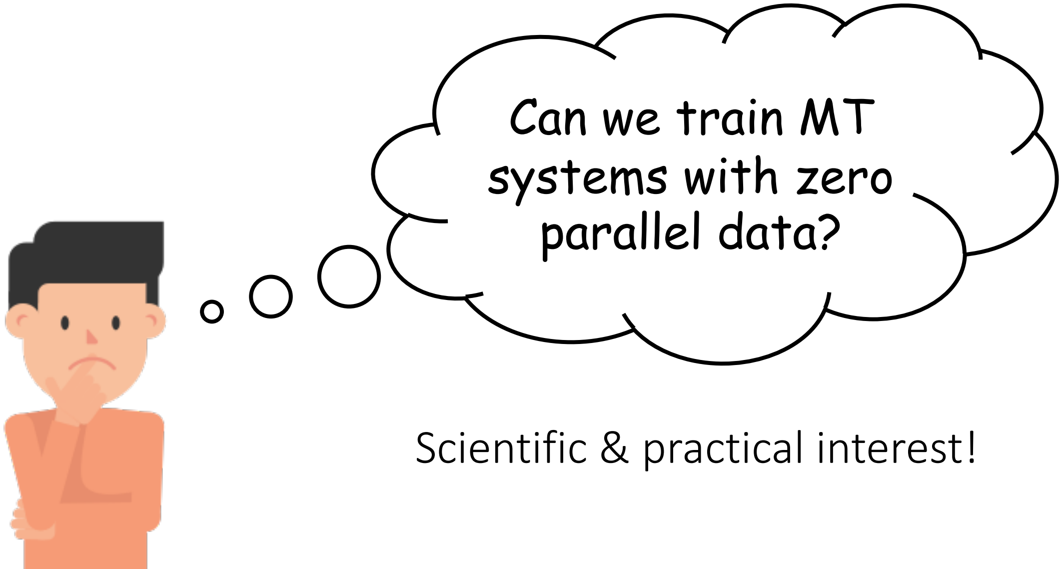

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IMPRESSIVE PROGRESS IN THE LAST 2-3 YEARS!

Outline

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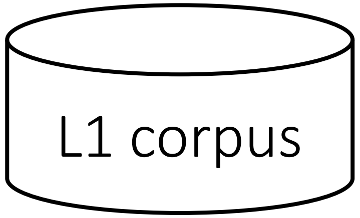

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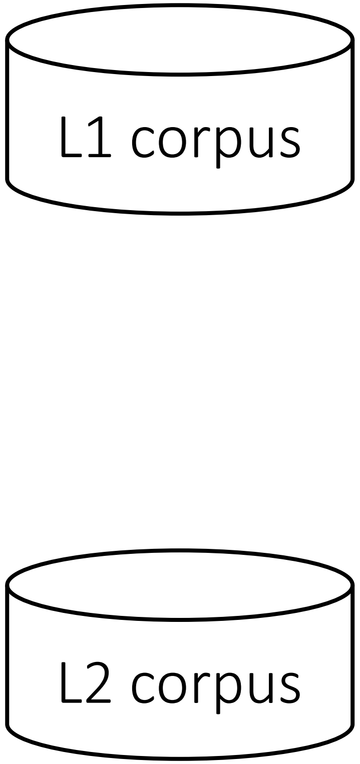

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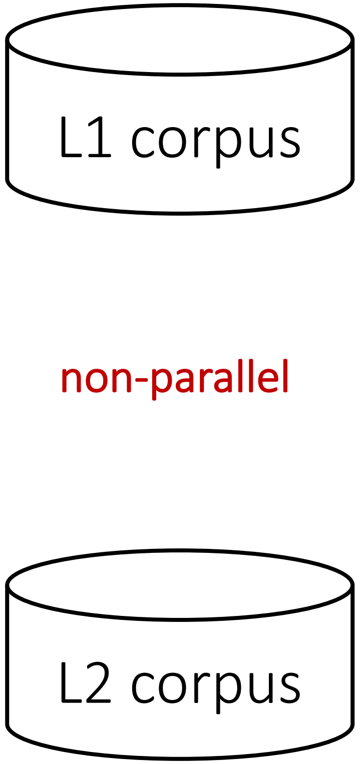

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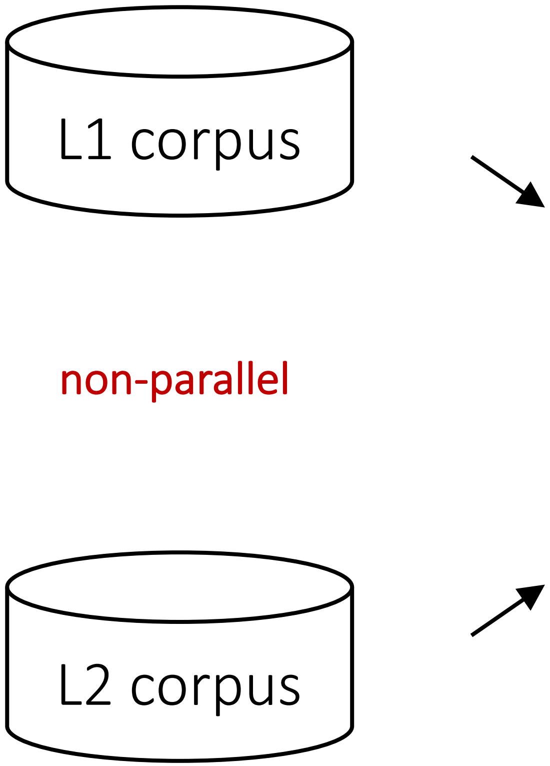

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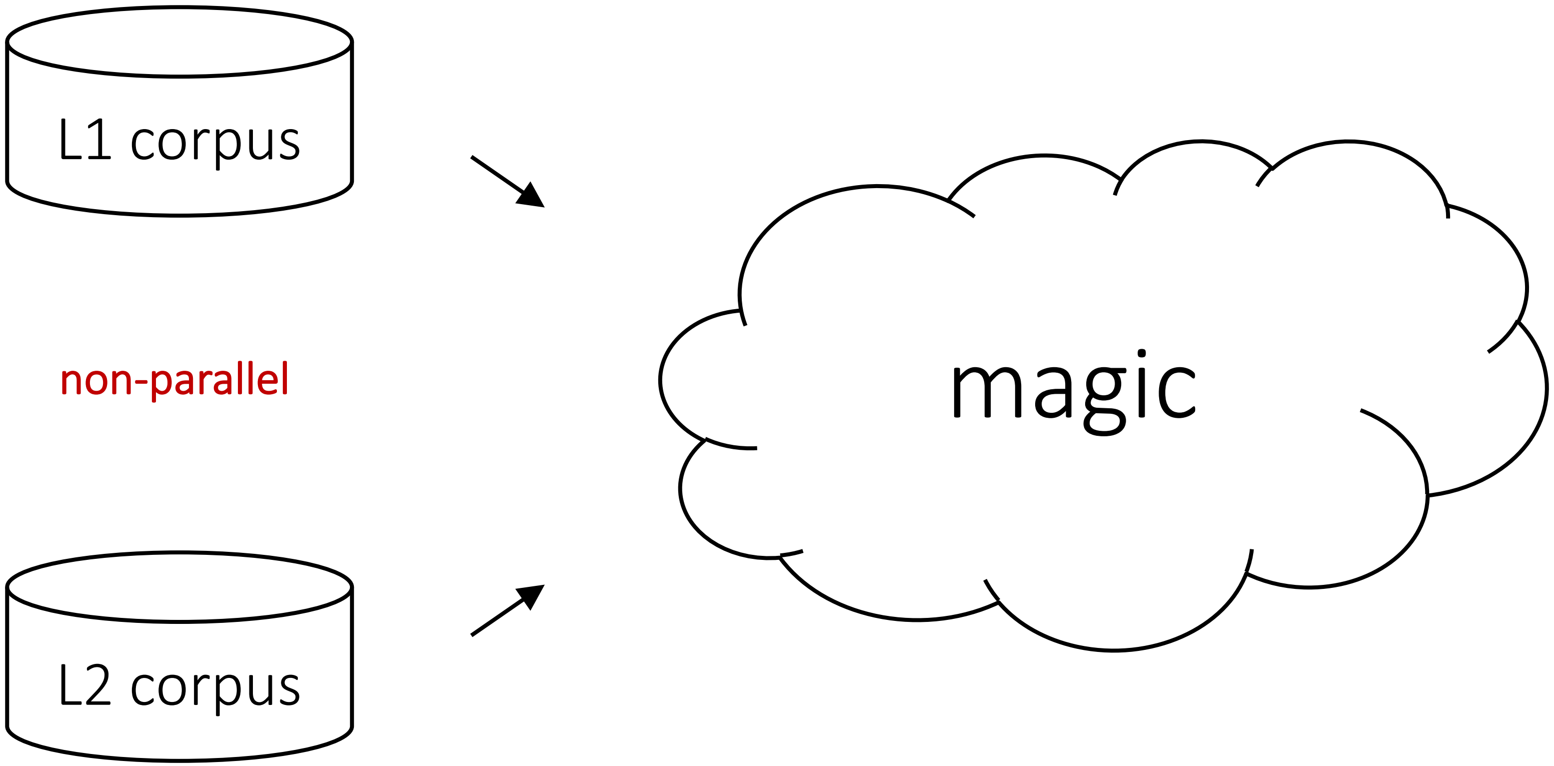

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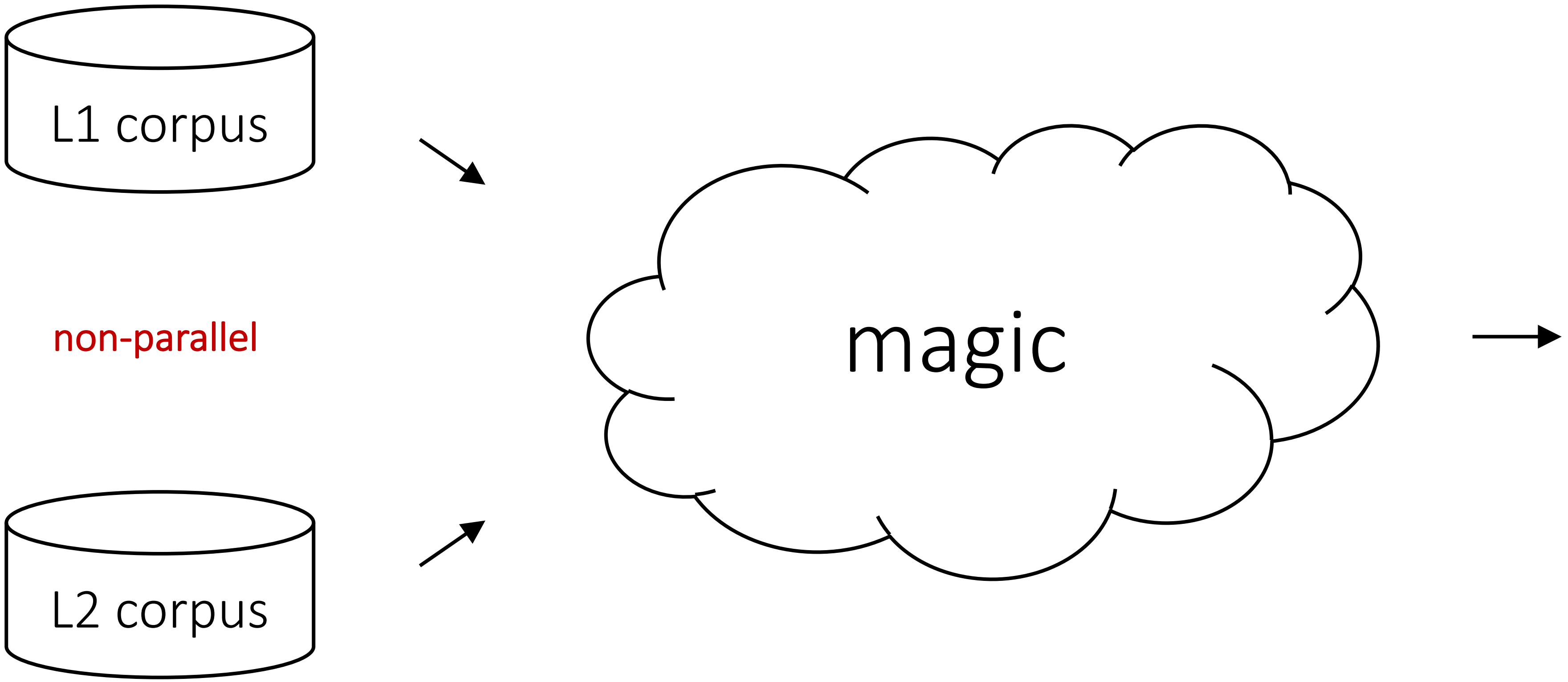

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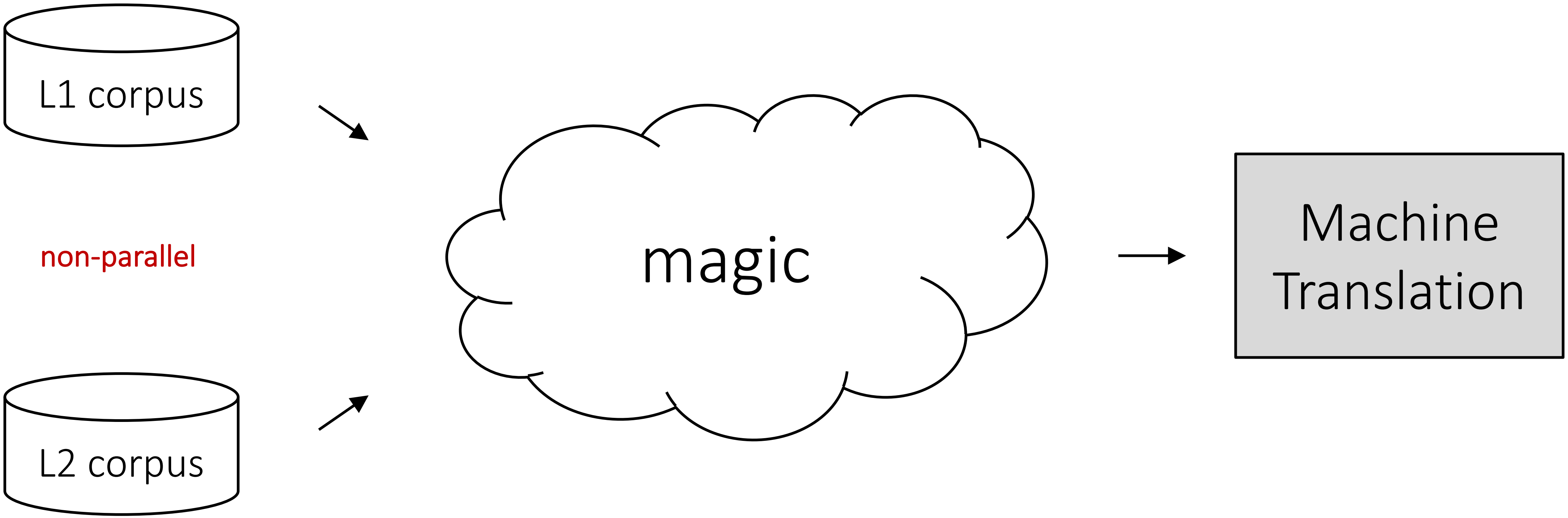
L1 corpus
non-parallel
L2 corpus
magic
Machine Translation

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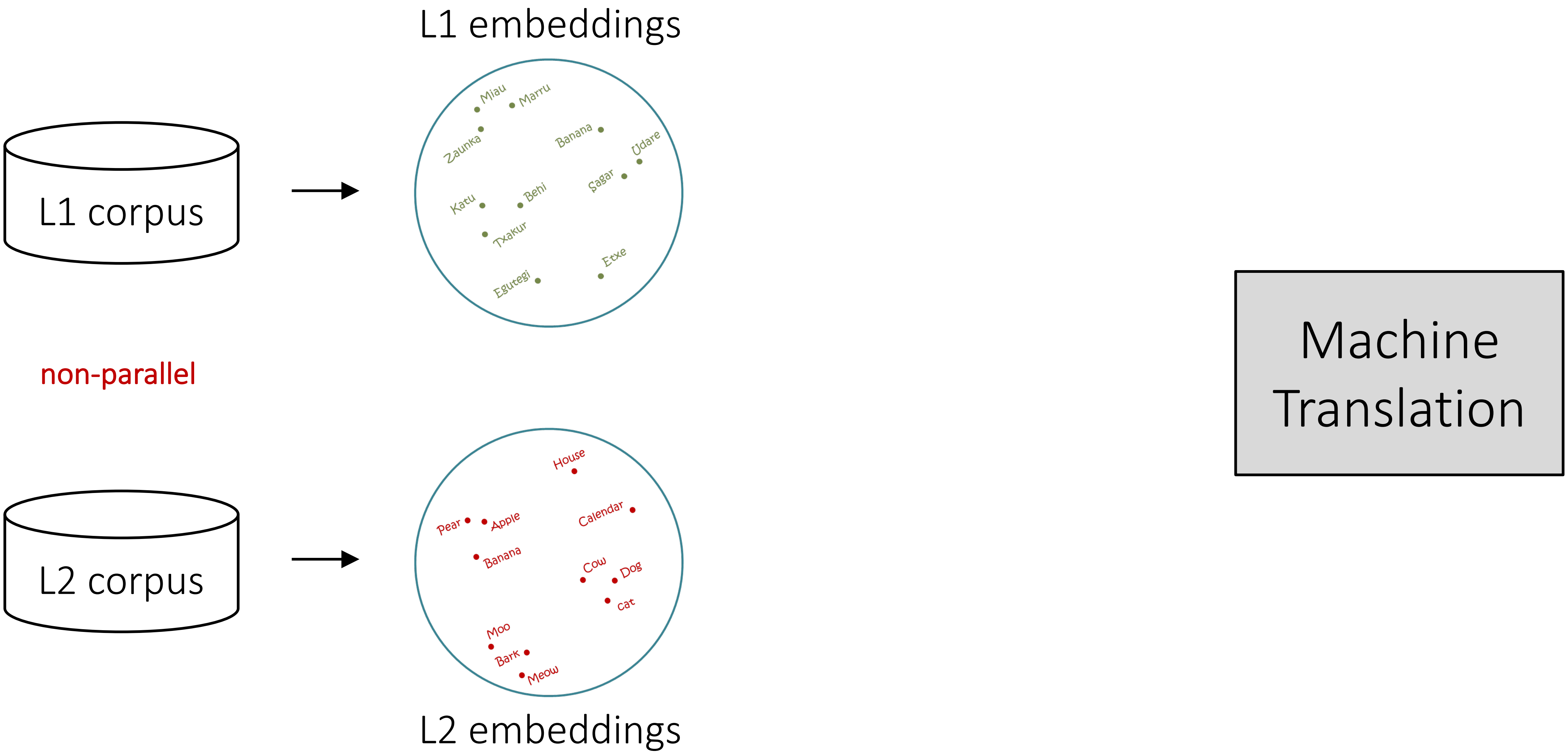

L1 embeddings
L1 corpus
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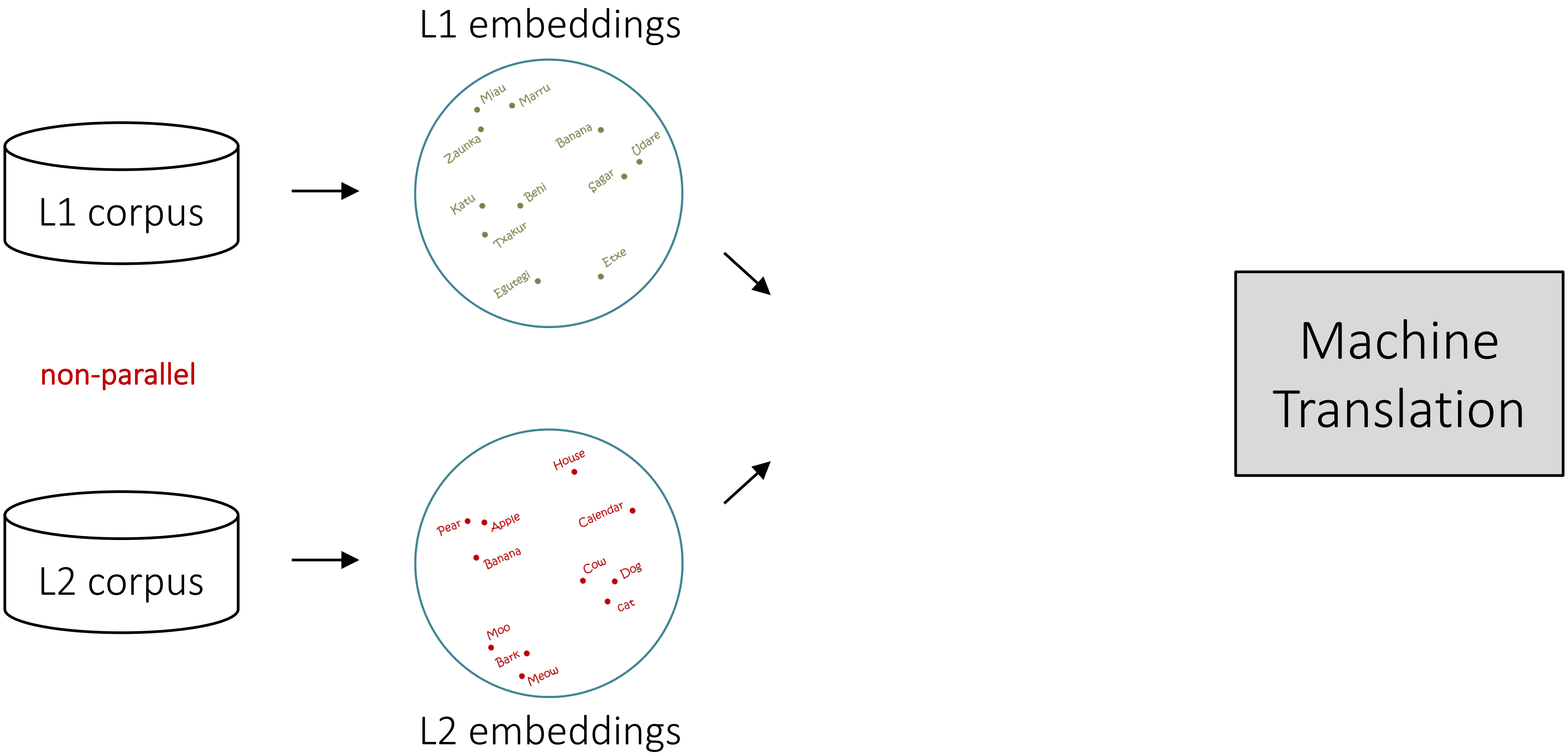
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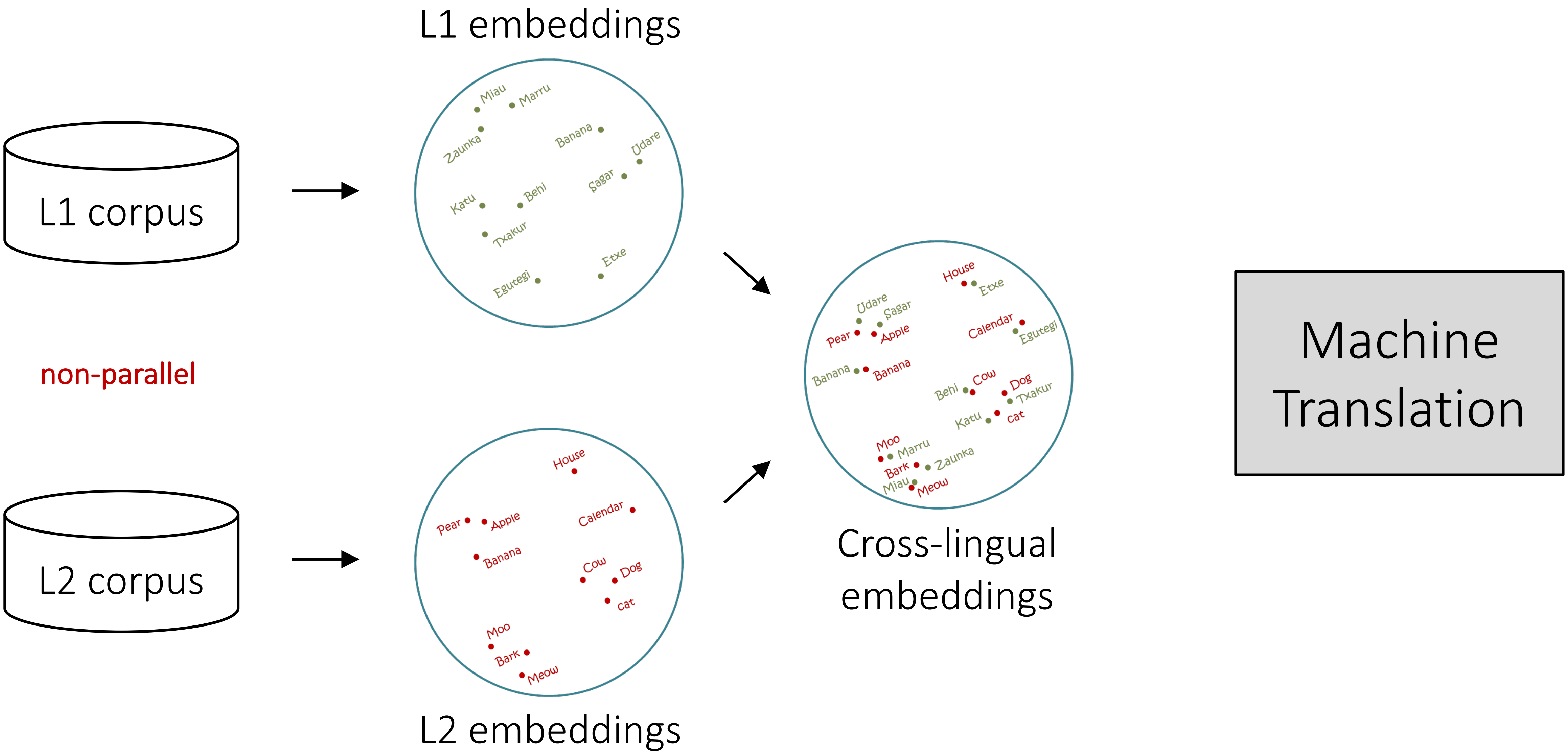
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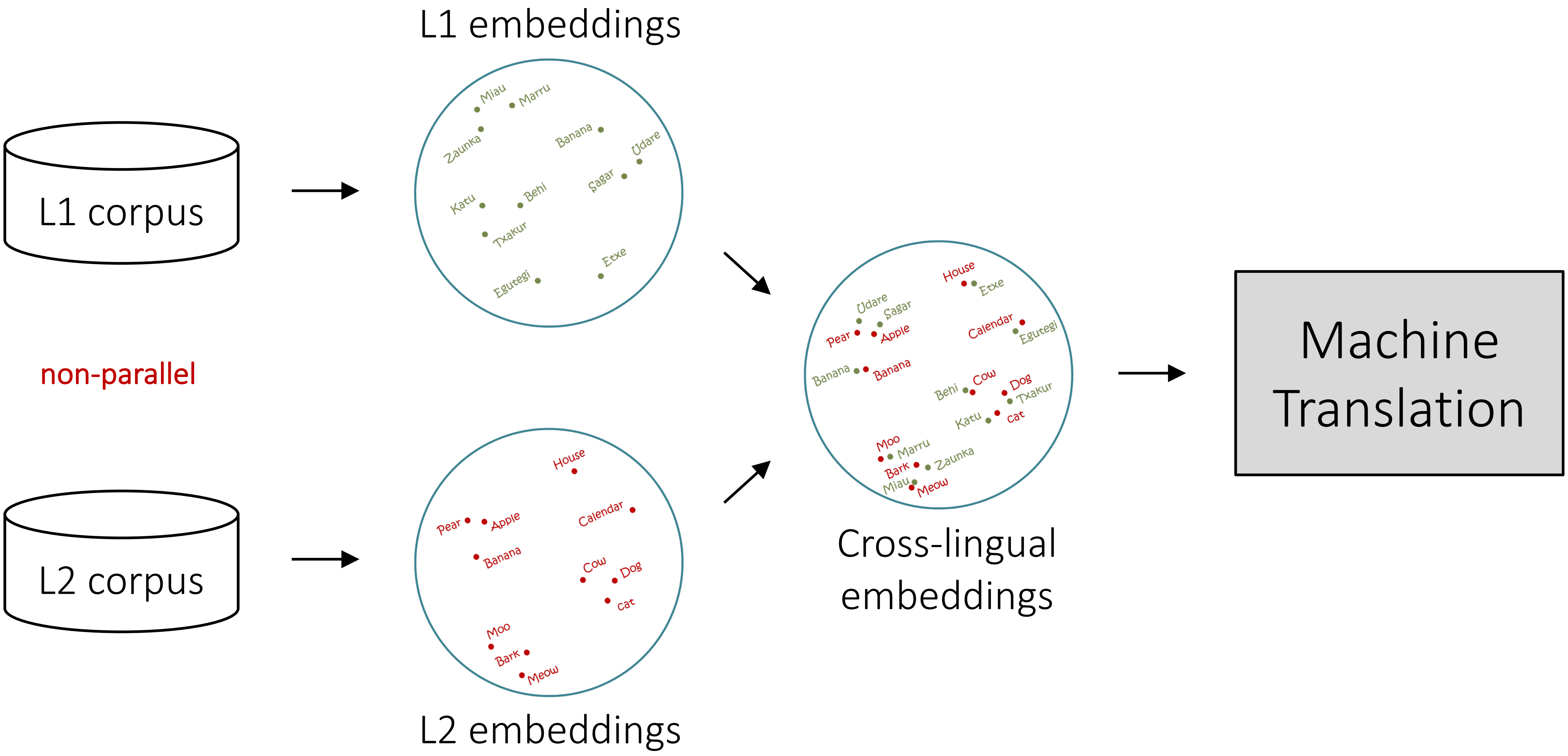
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Dog
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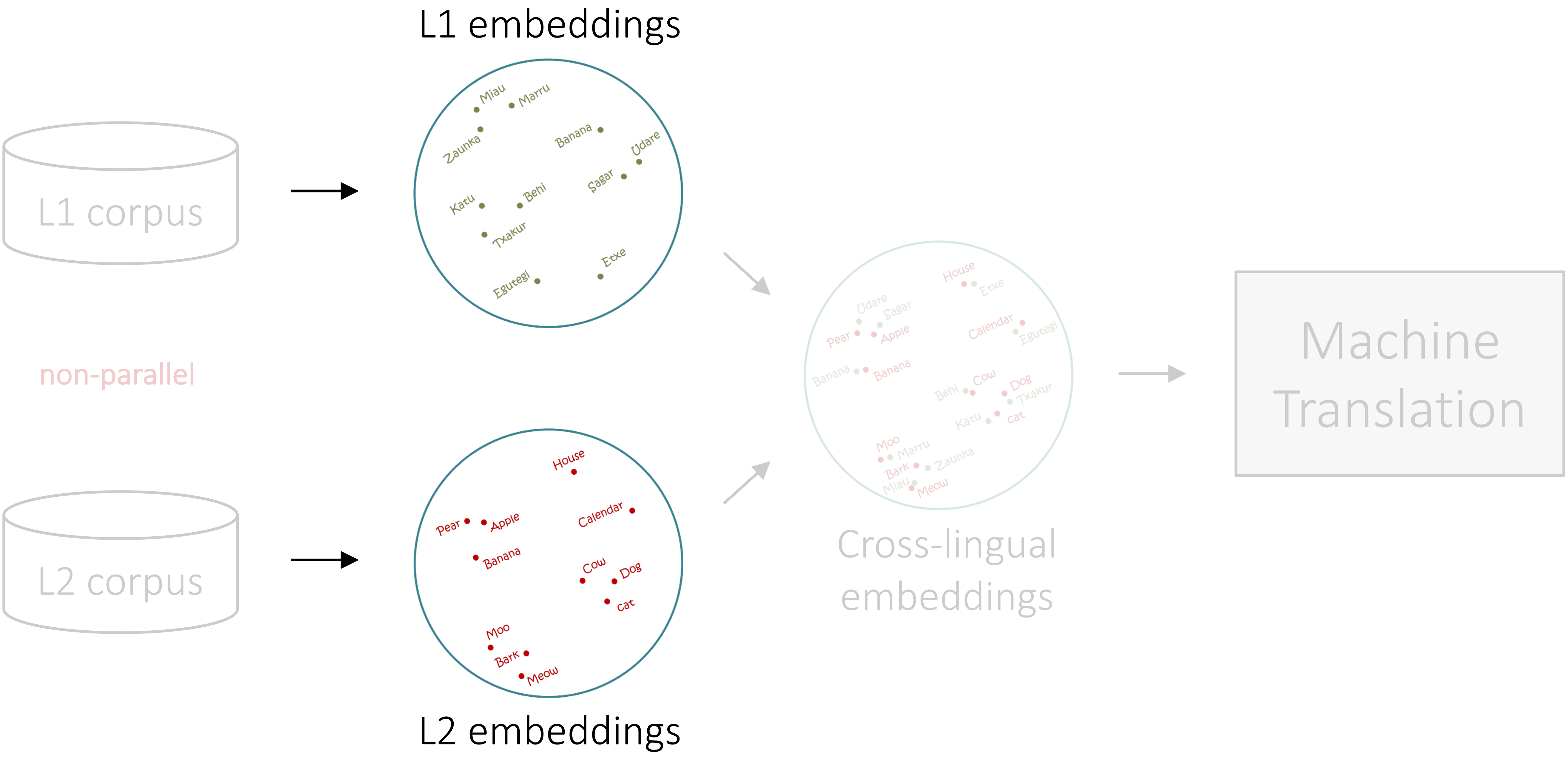

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non-parallel
L2 corpus
House
Pear
Apple
Calendar
Banana
Cow
Dog
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Word embeddings

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Distributed representations of words

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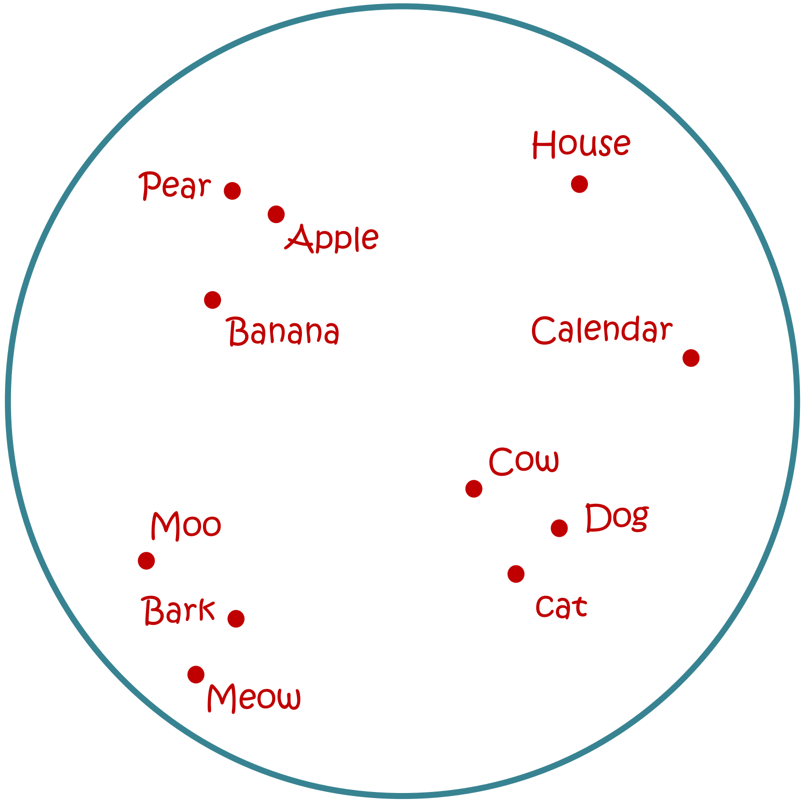
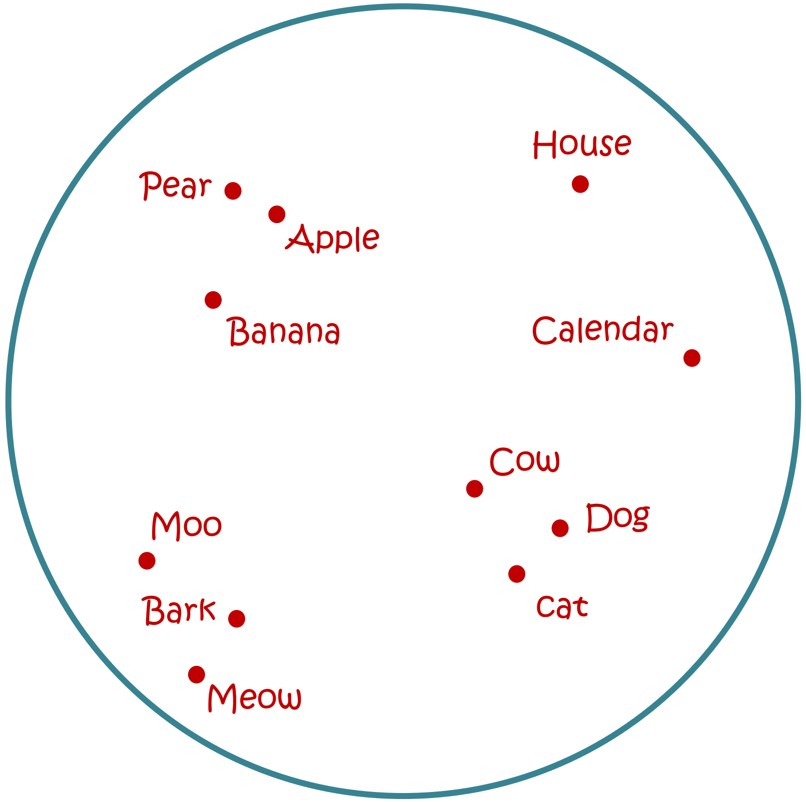


Word embeddings

Distributed representations of words



$$\mathrm{sim}(cow, cat) \approx \cos(w_{cow}, w_{cat}) = \frac{w_{cow} \cdot w_{cat}}{\|w_{cow}\| \|w_{cat}\|}$$

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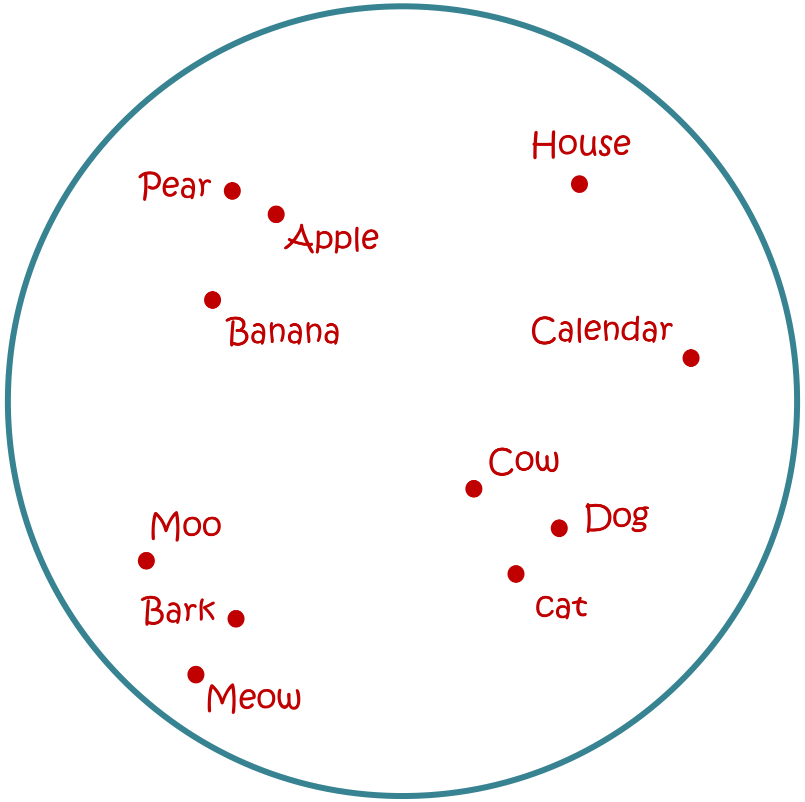

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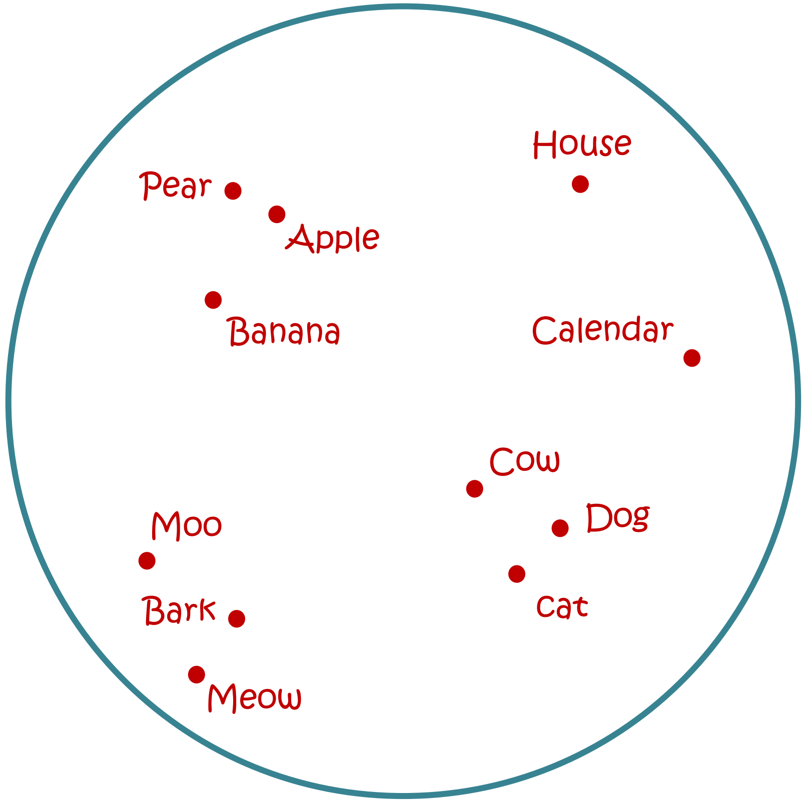

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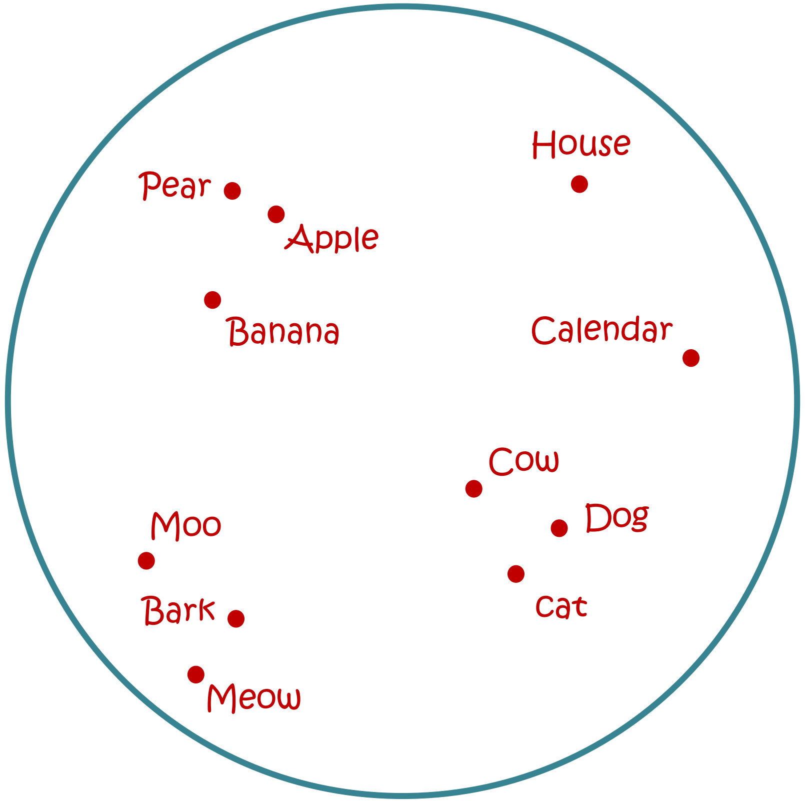

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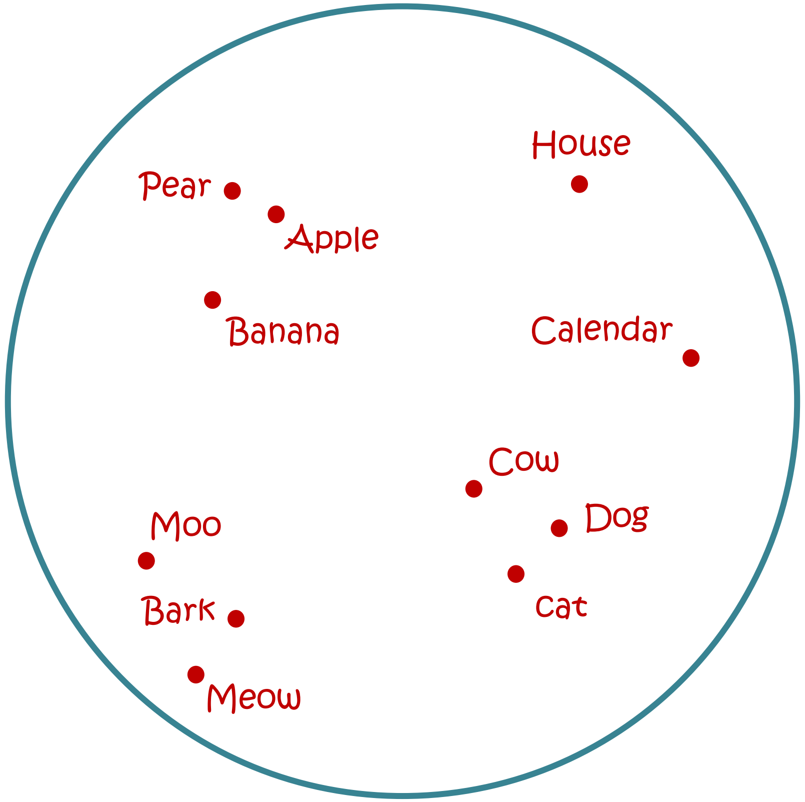
e.g. skip-gram with negative sampling
(Mikolov et al., NIPS'13)

Word embeddings

Distributed representations of words



$$\mathrm{sim}(cow, cat) \approx \cos(w_{cow}, w_{cat}) = \frac{w_{cow} \cdot w_{cat}}{\|w_{cow}\|\|w_{cat}\|}$$

Learned from co-occurrence patterns in a monolingual corpus

e.g. skip-gram with negative sampling
(Mikolov et al., NIPS'13)

$$\log \sigma(w \cdot c) + \sum_{i=1}^{k} \mathbb{E}_{c_N \sim P_D}[\log \sigma(-w \cdot c_N)]$$

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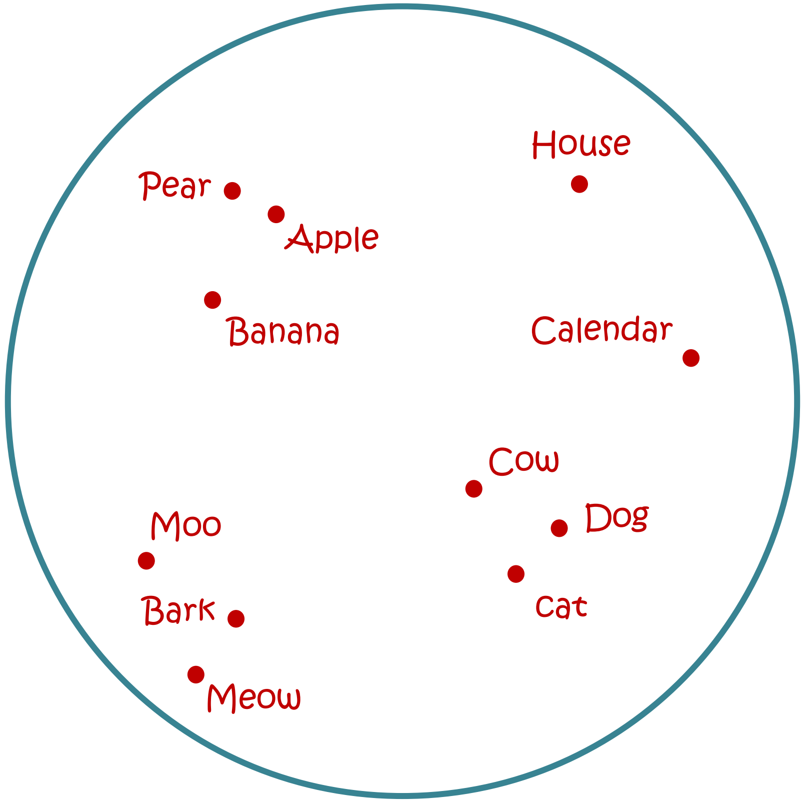

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I will go to New York by plane .

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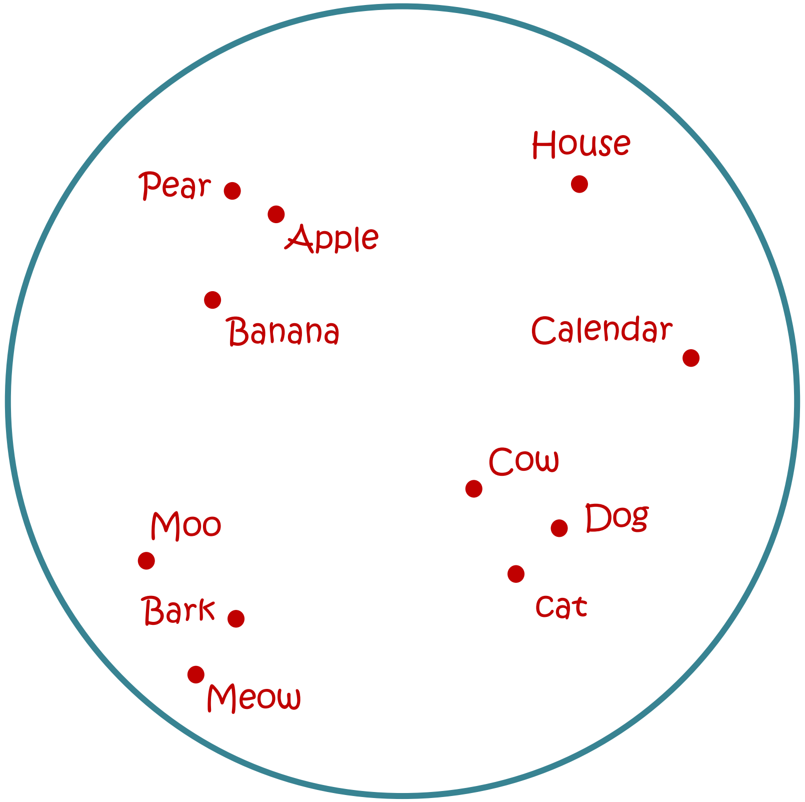

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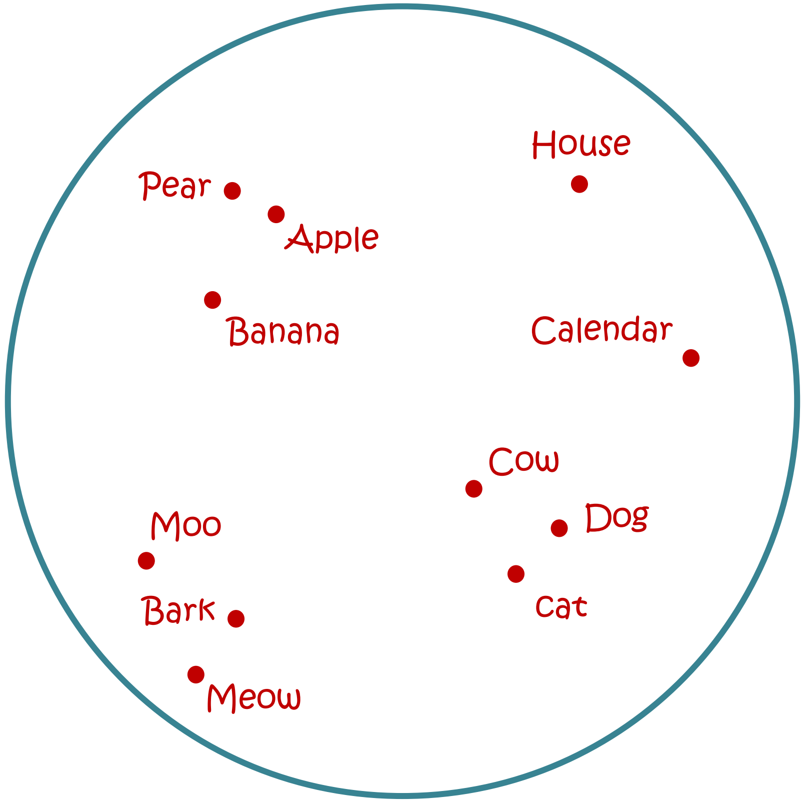

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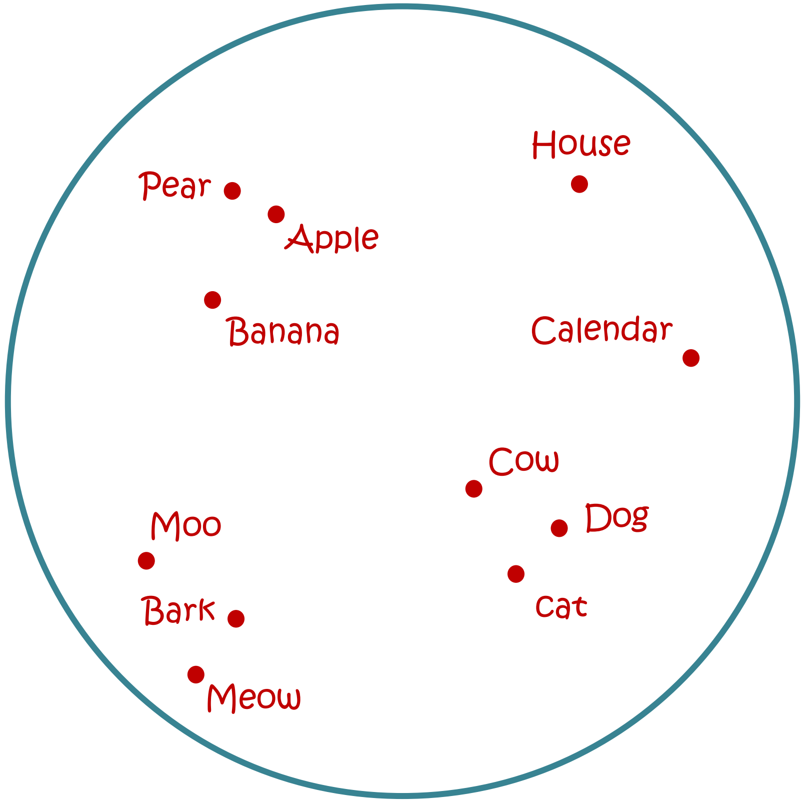

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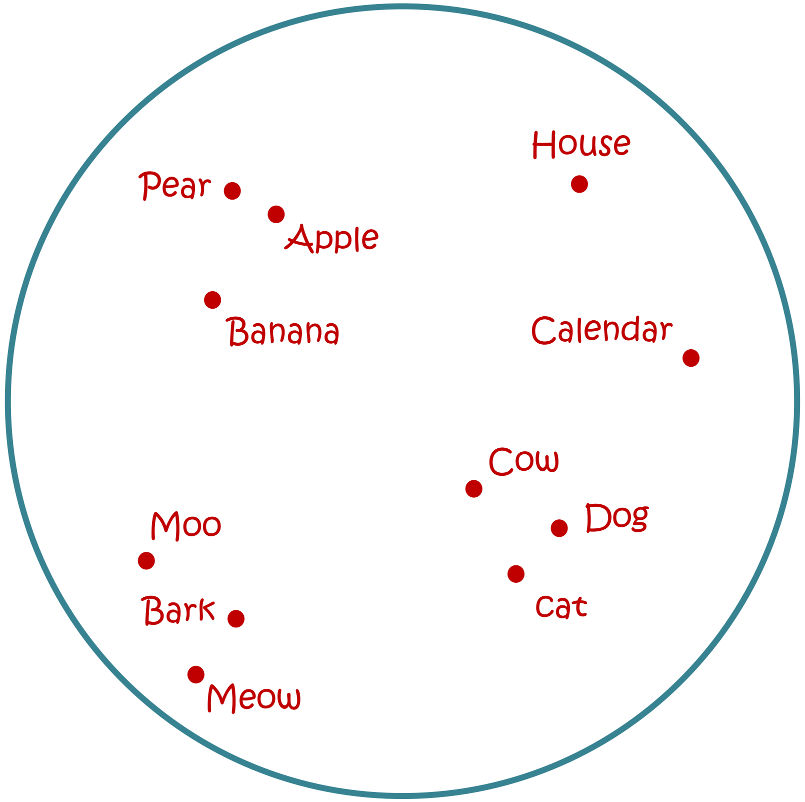

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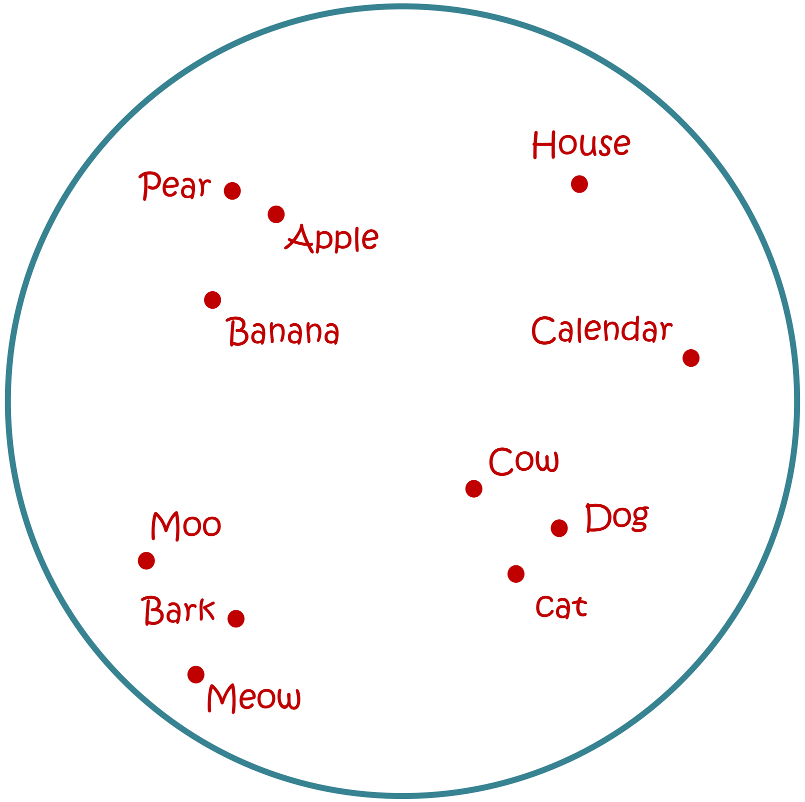

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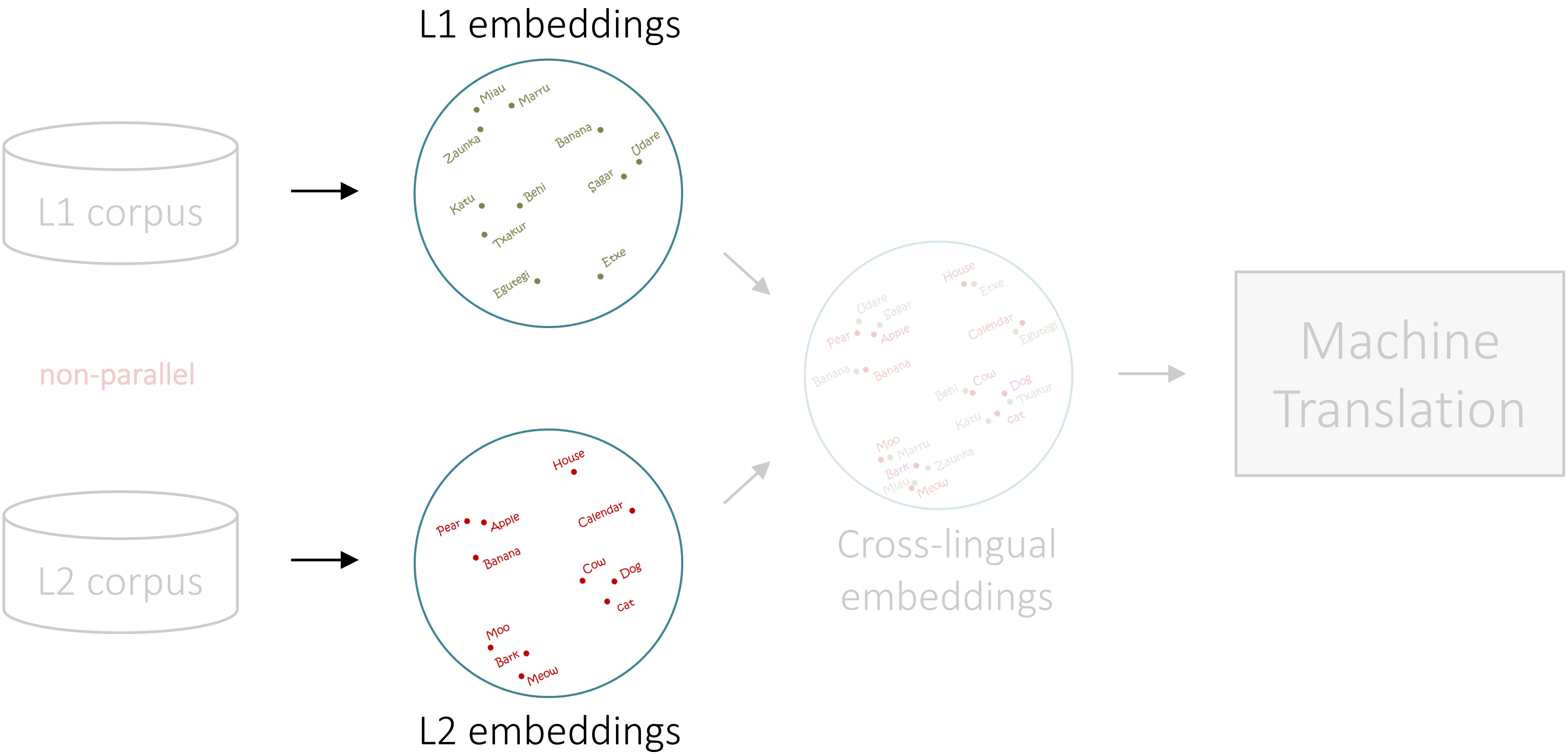
Outline



L1 embeddings
L1 corpus
Miau
Marru
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Banana
Udare
Katu
Behi
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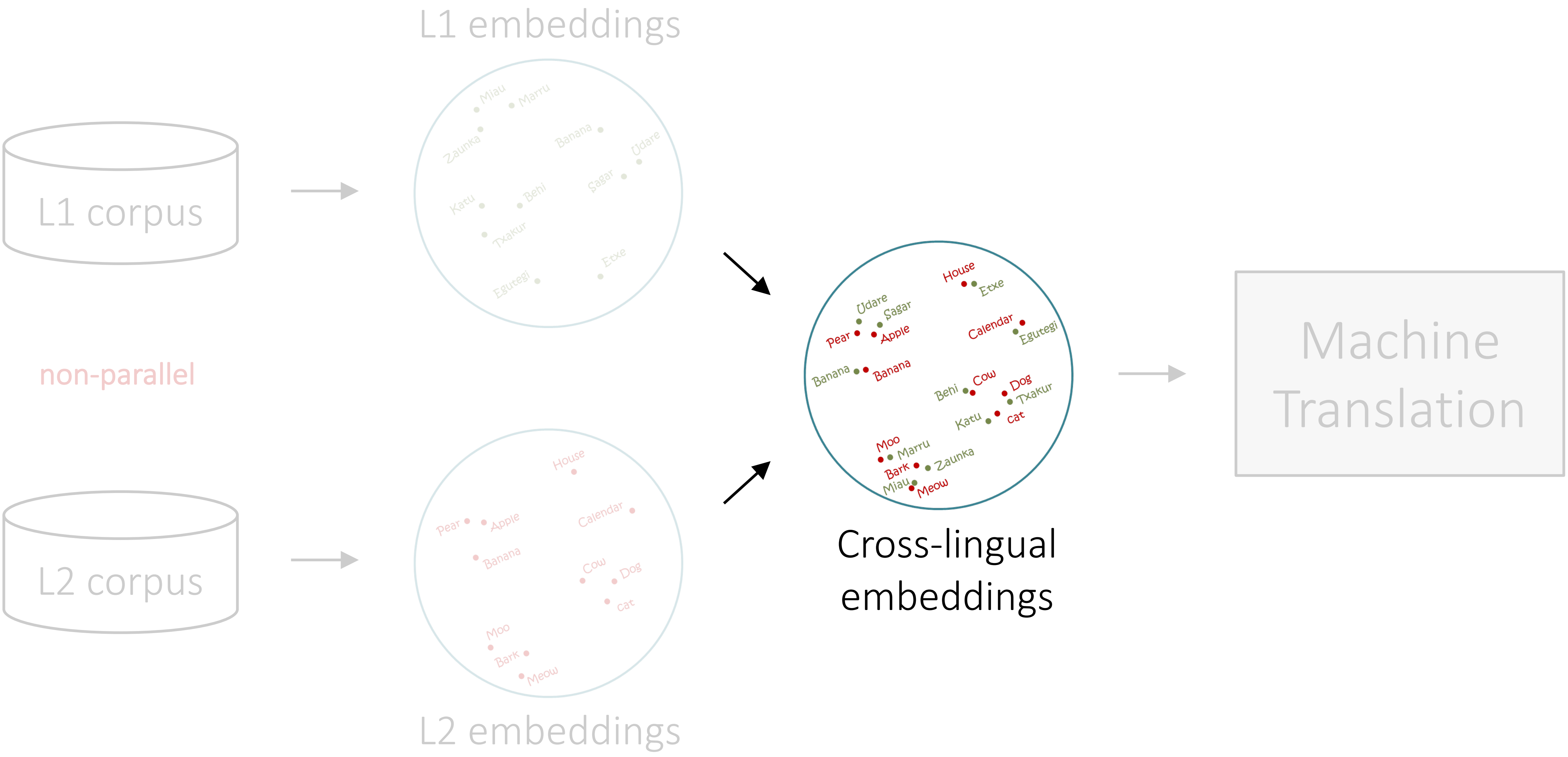
Txakur
Etxe
Egutegi
non-parallel
L2 corpus
House
Pear
Apple
Calendar
Banana
Cow
Dog
Cat
Moo
Bark
Meow
L2 embeddings
Cross-lingual embeddings
Machine Translation

Outline



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Cross-lingual word embedding alignment

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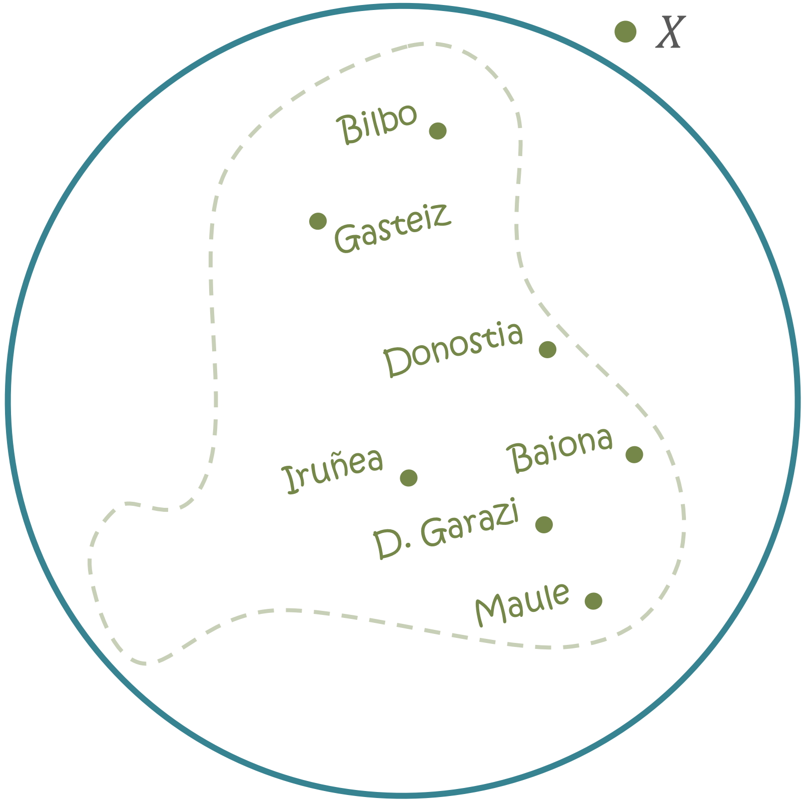

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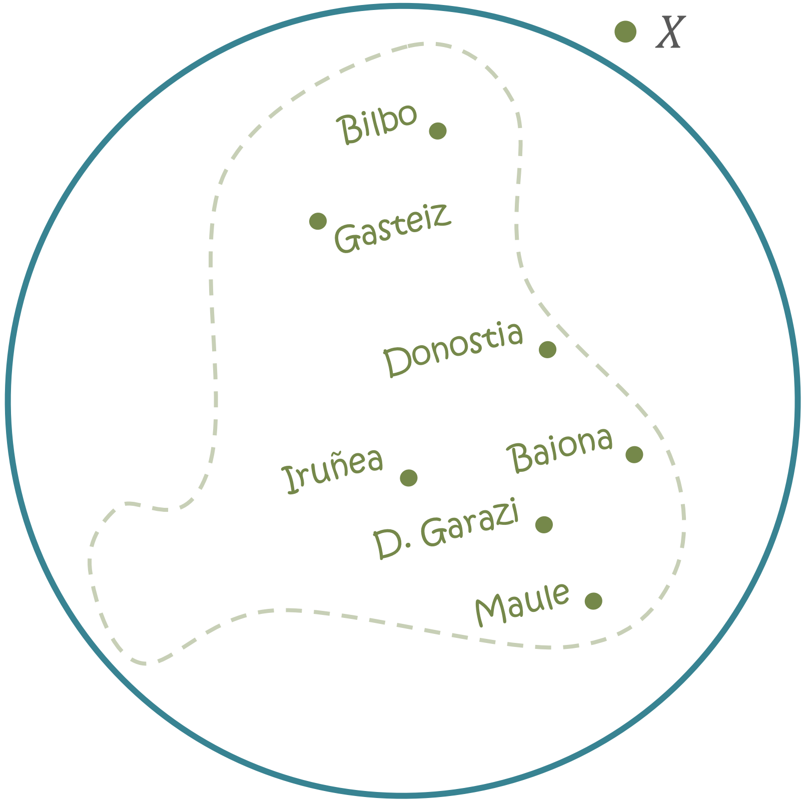

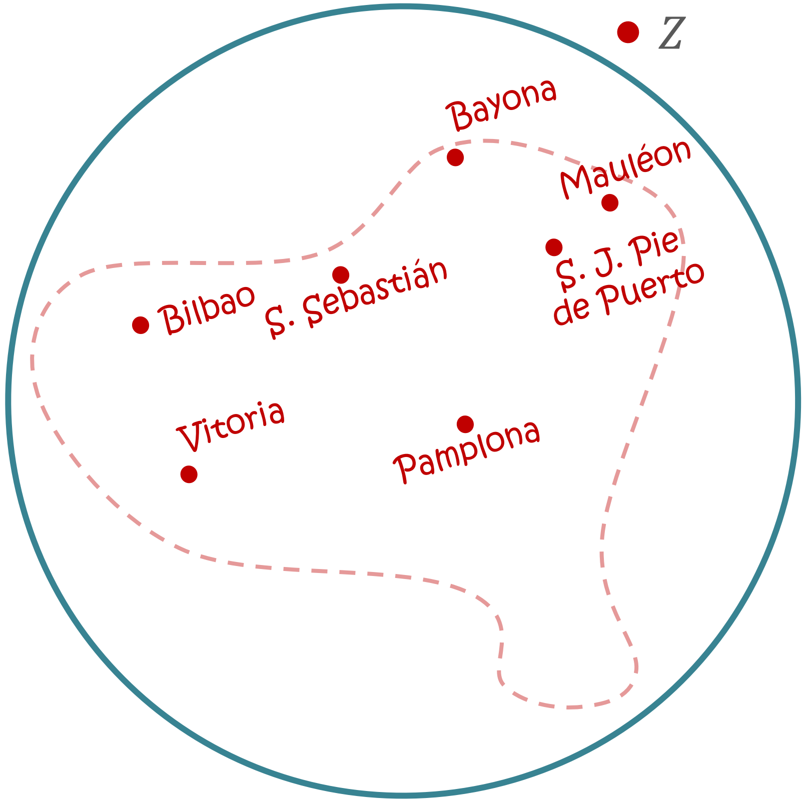

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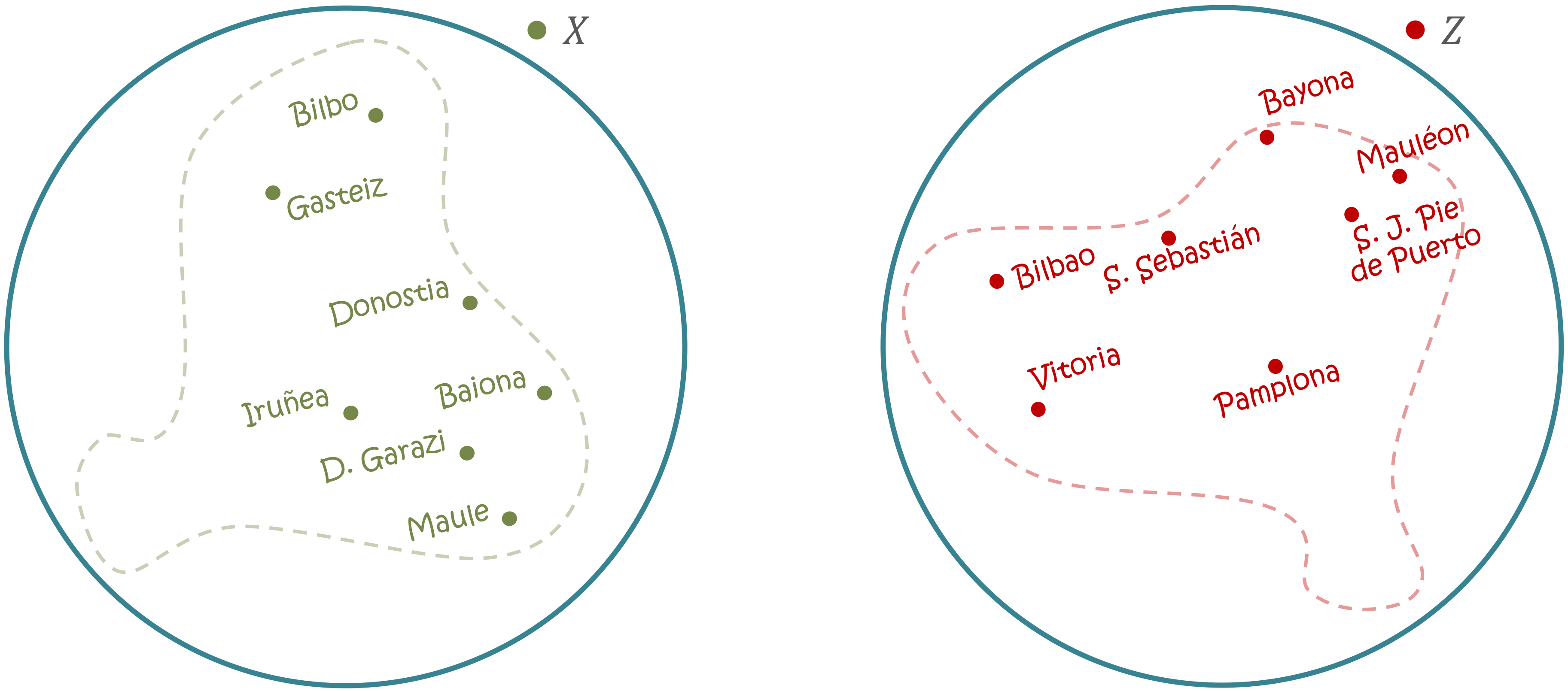
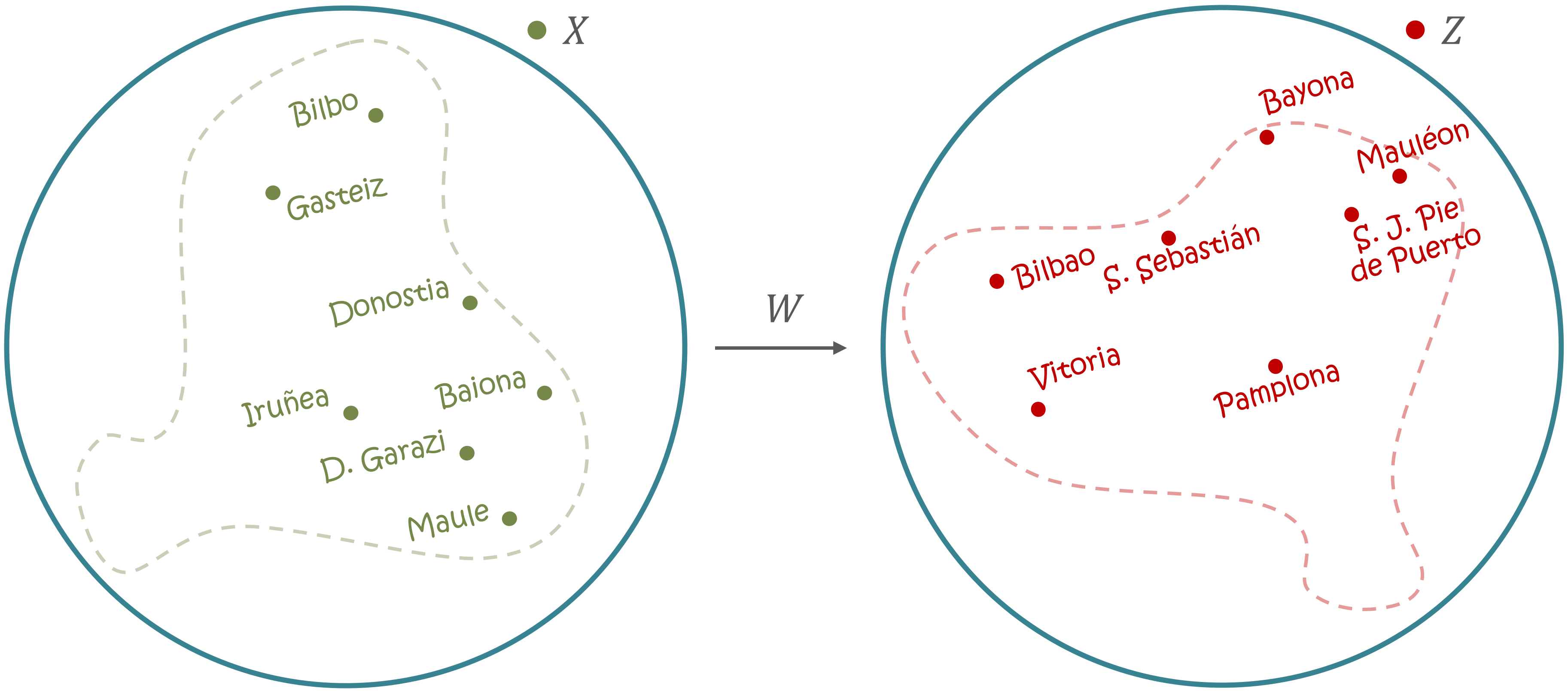


Bilbo	Bilbao
Baiona	Bayona
Iruñea	Pamplona

Cross-lingual word embedding alignment



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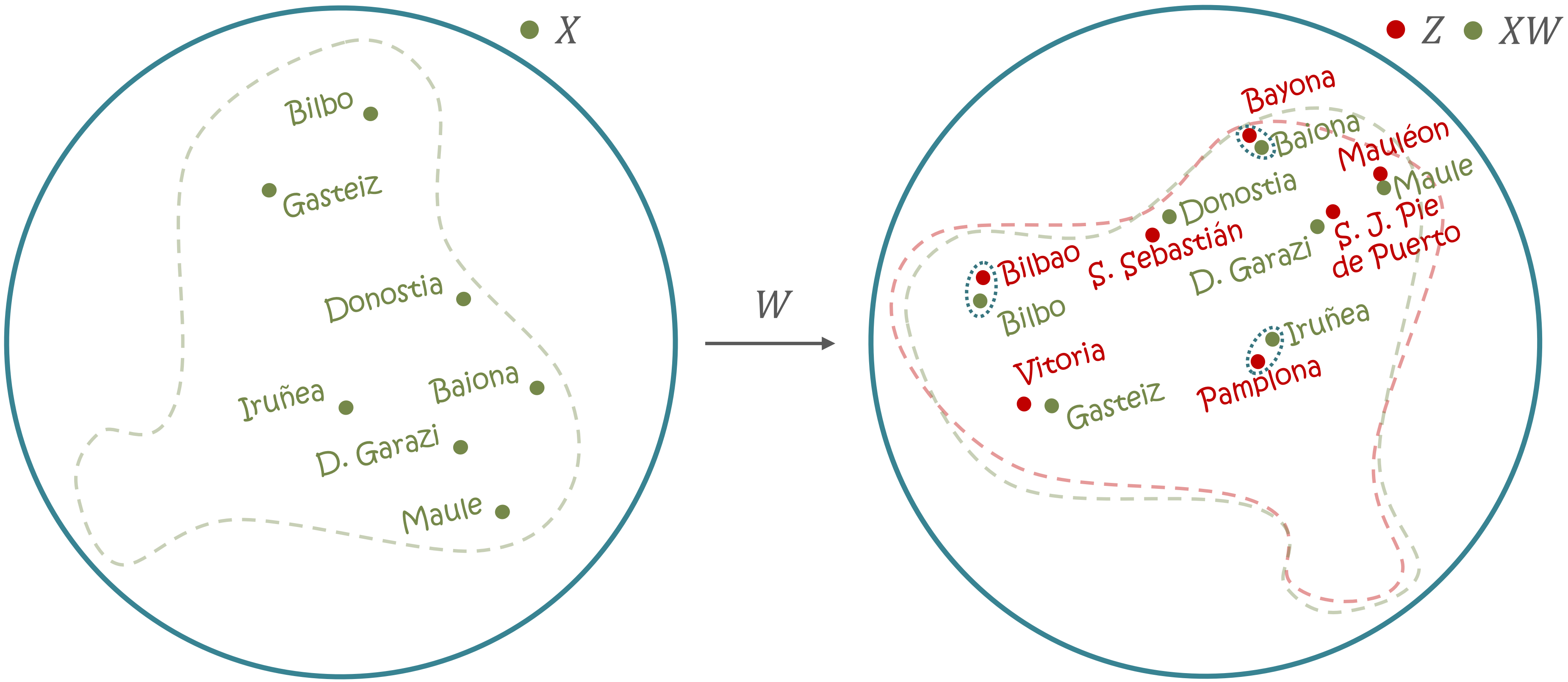

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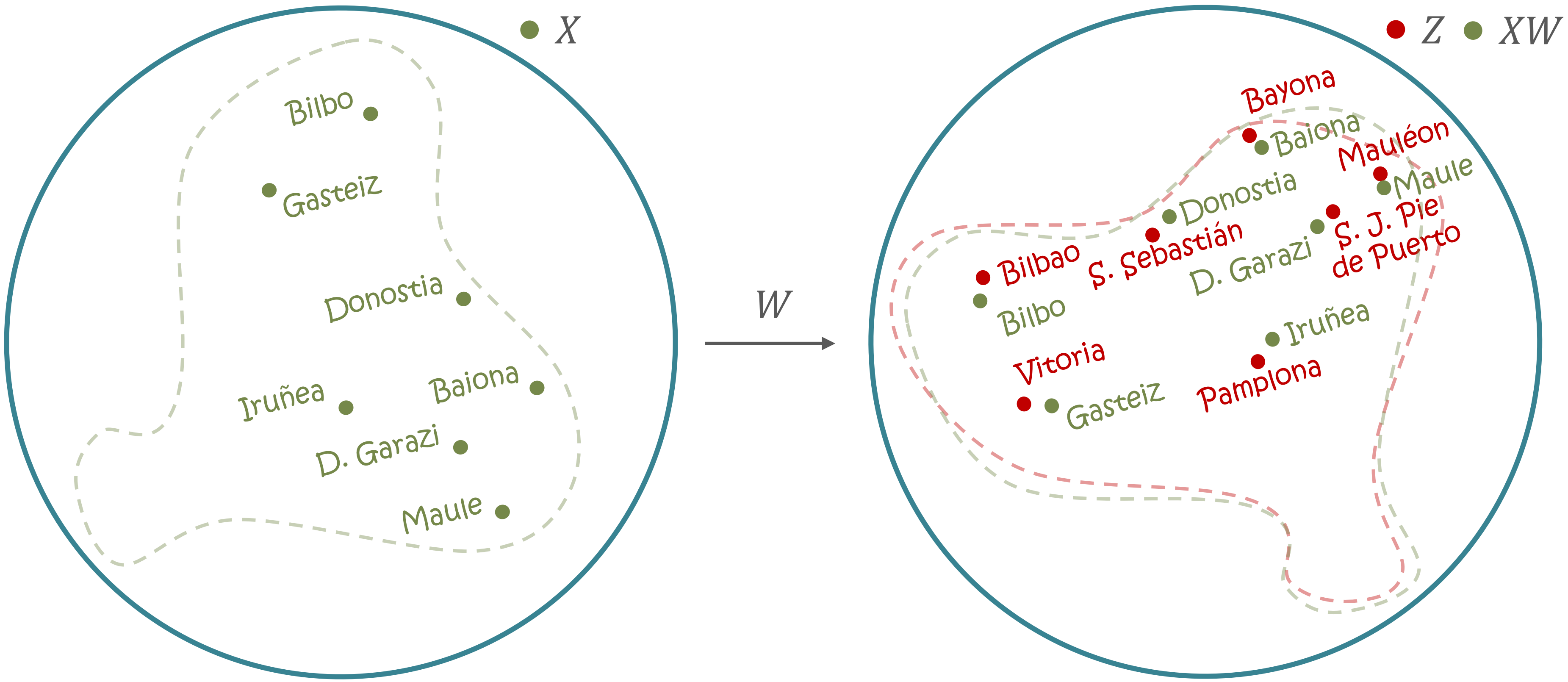

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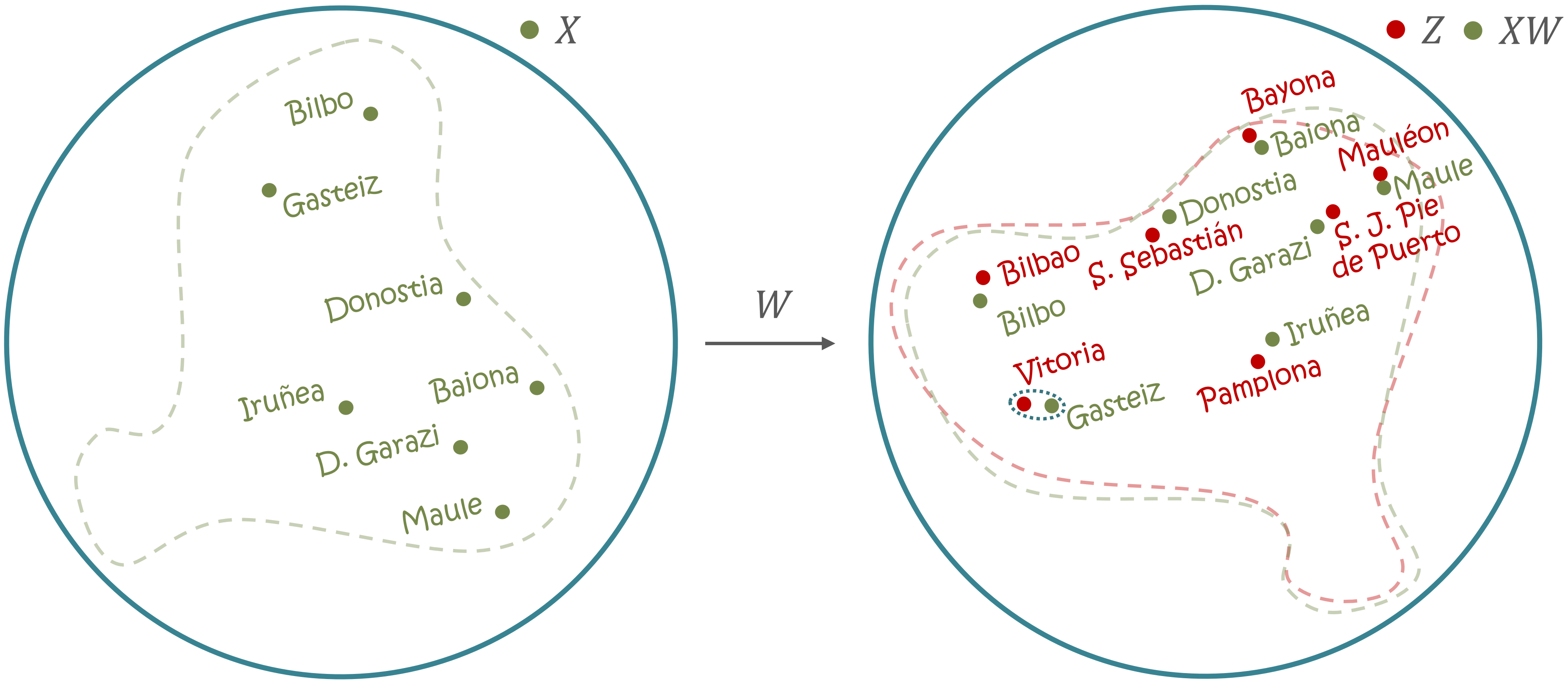

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Mikolov et al. (arXiv'13)

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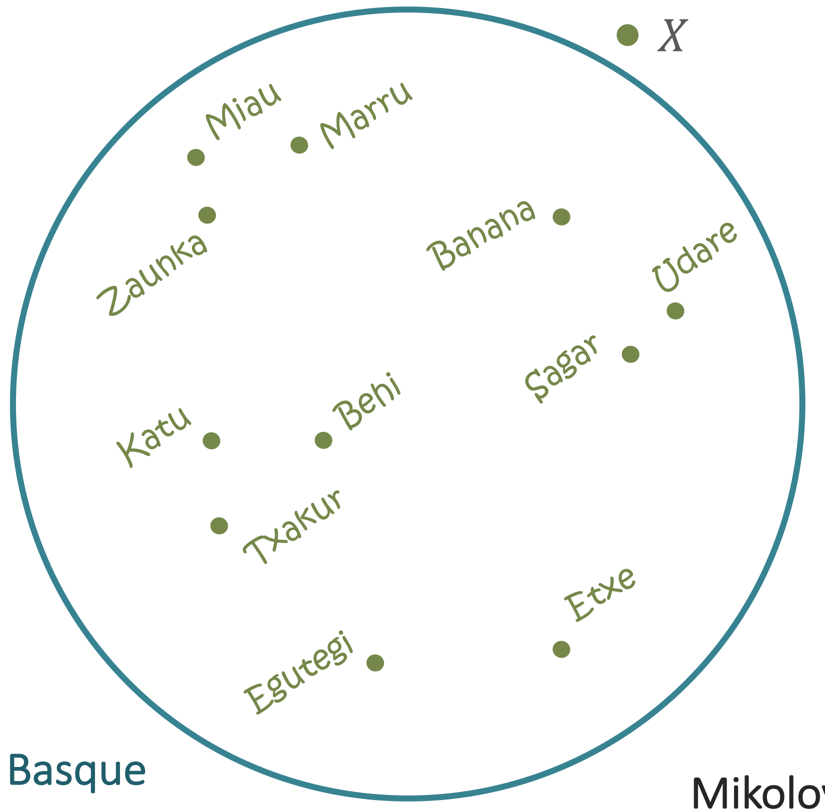

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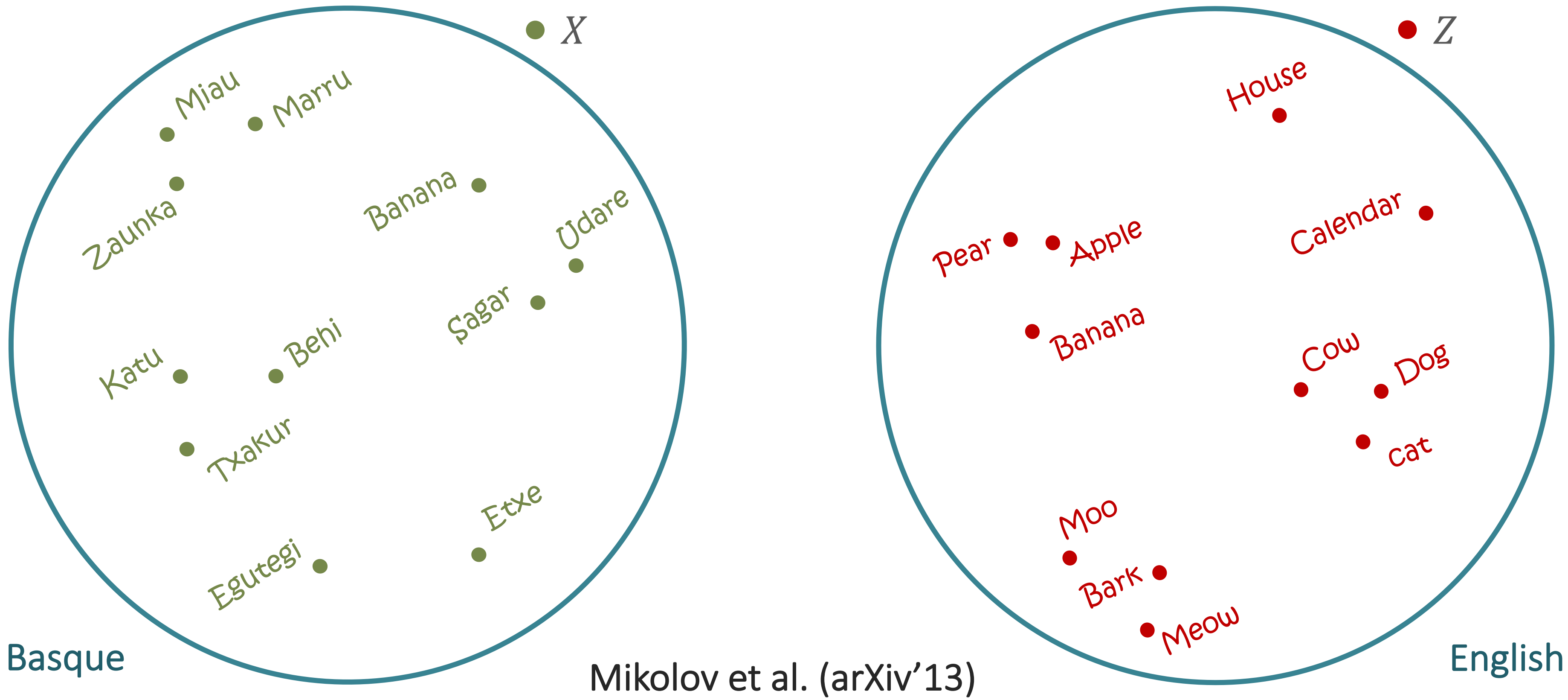

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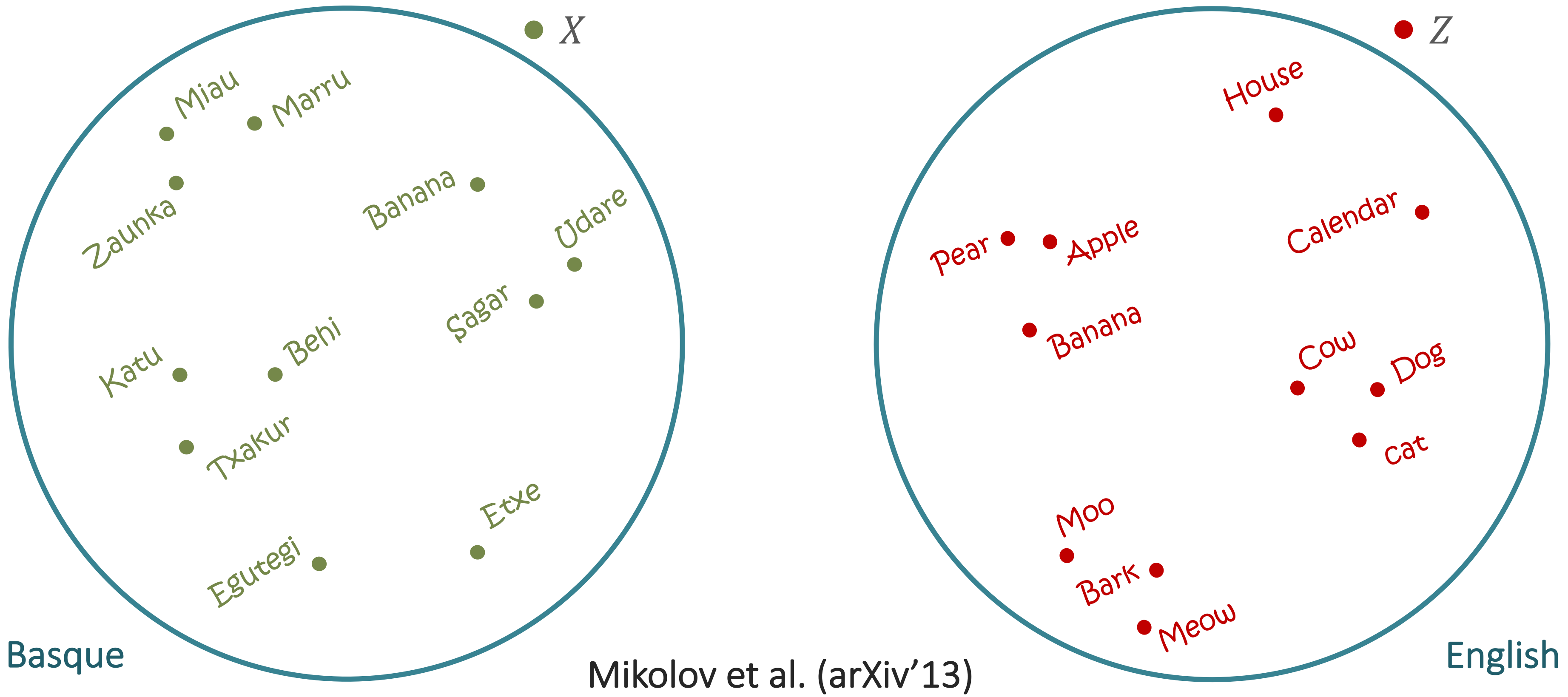
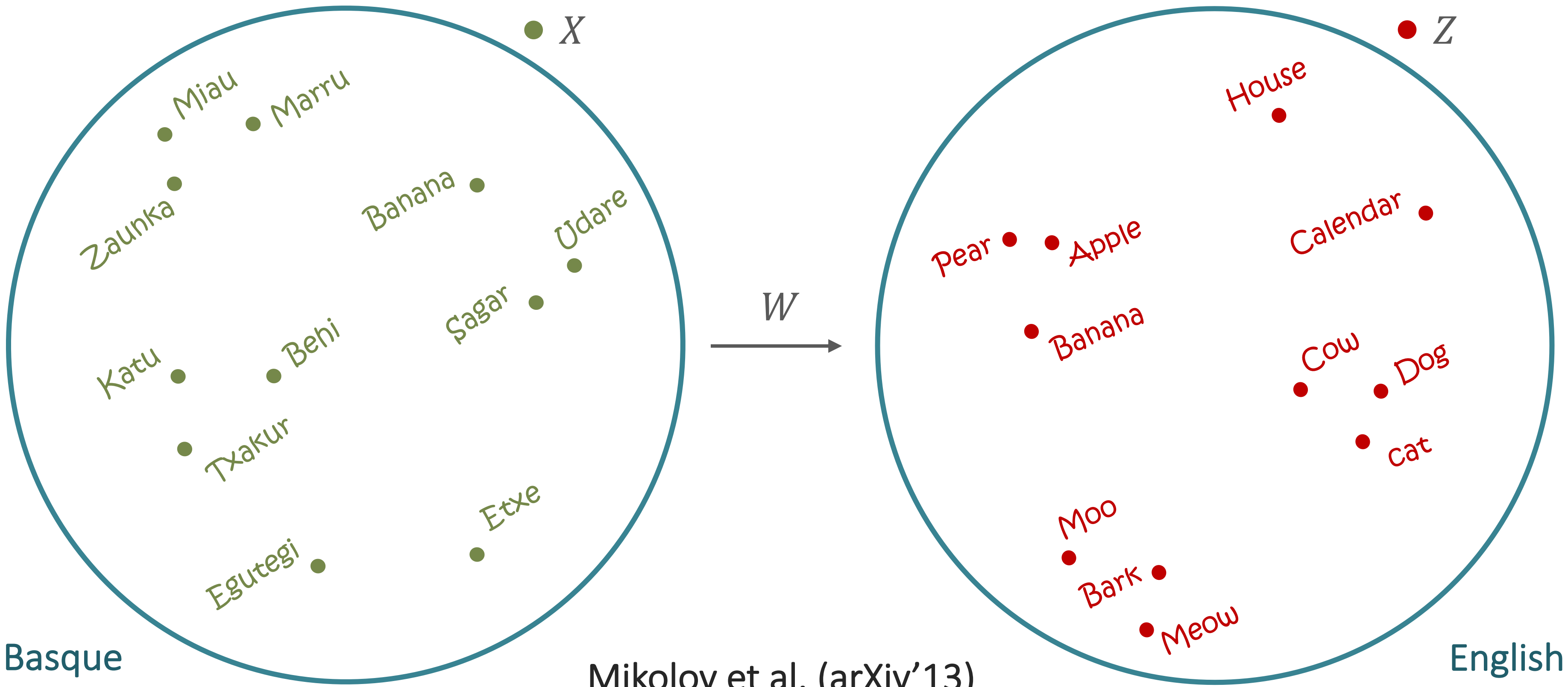


Mikolov et al. (arXiv'13)

Txakur	Dog
Sagar	Apple
⋮	⋮
Egutegi	Calendar

Cross-lingual word embedding alignment



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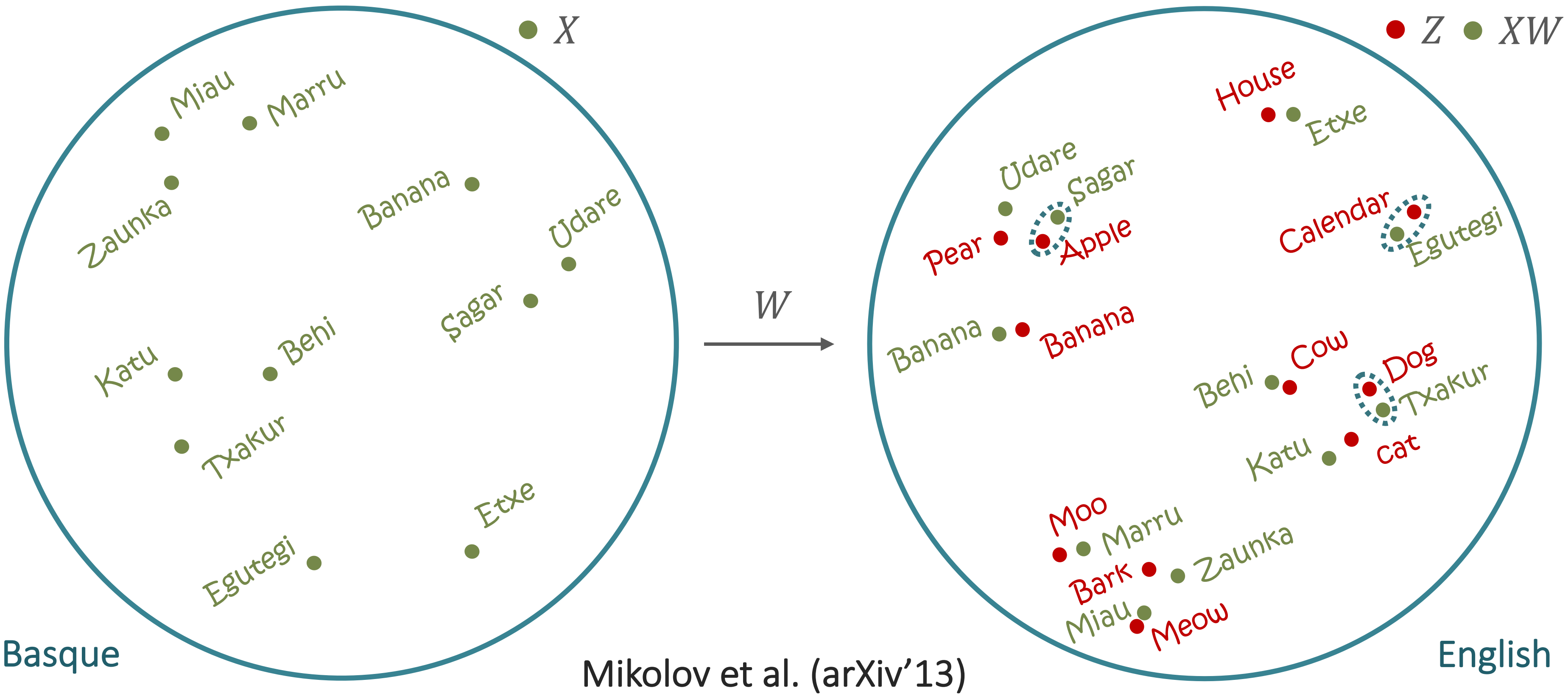

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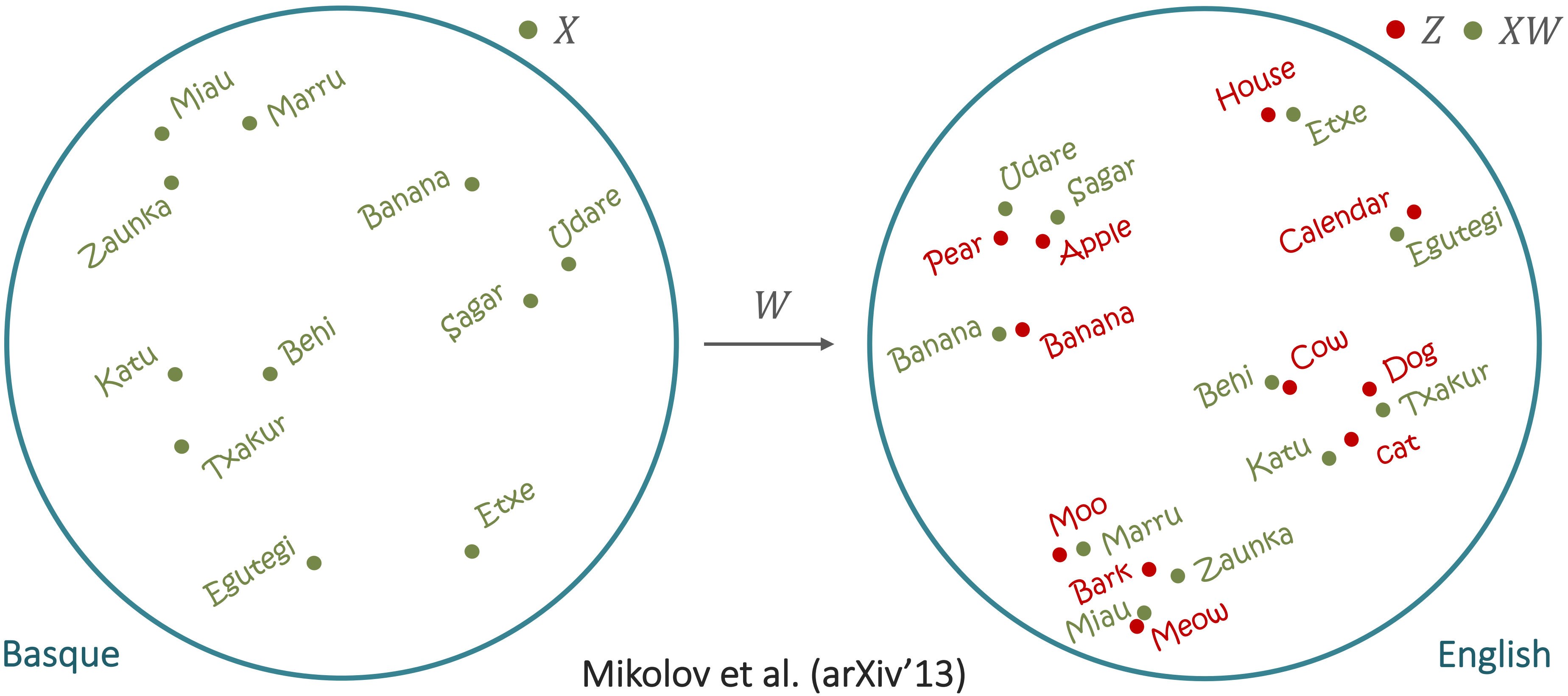

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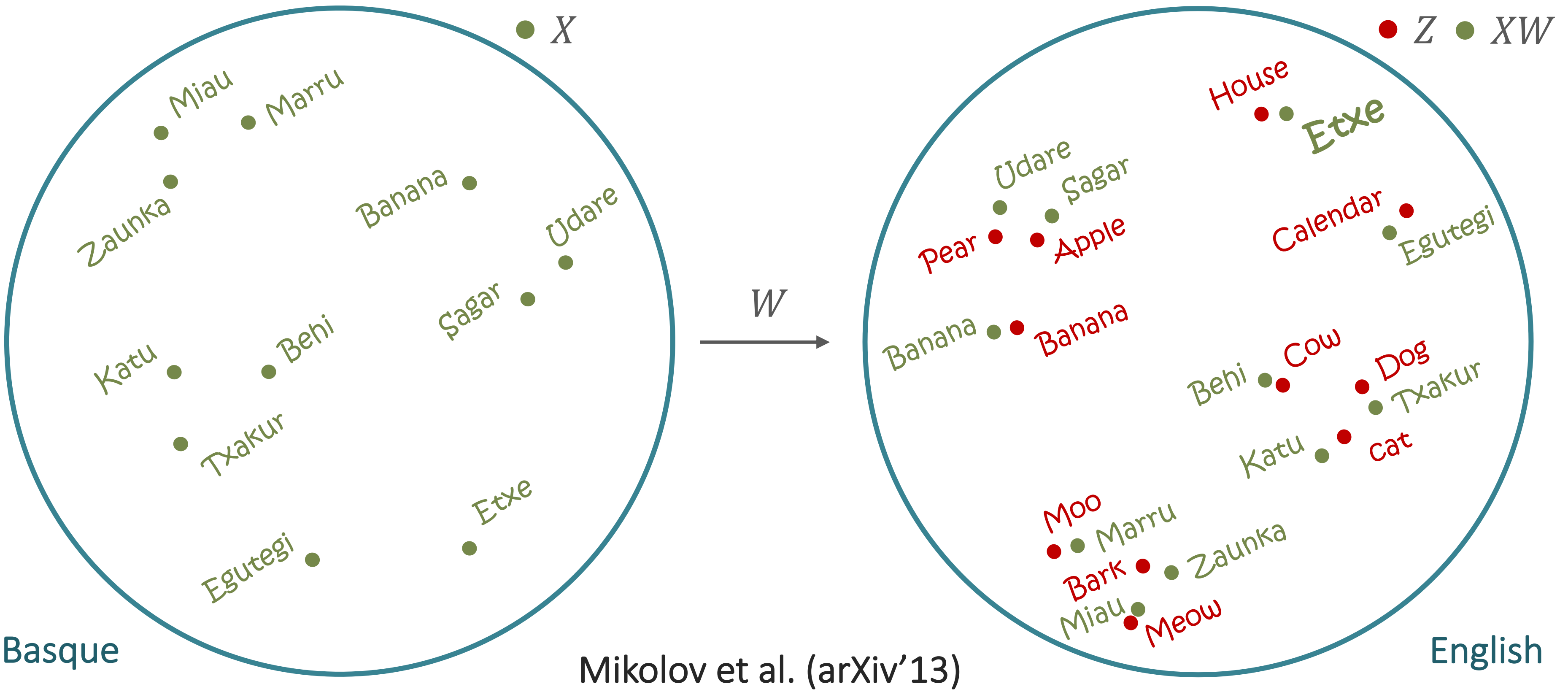

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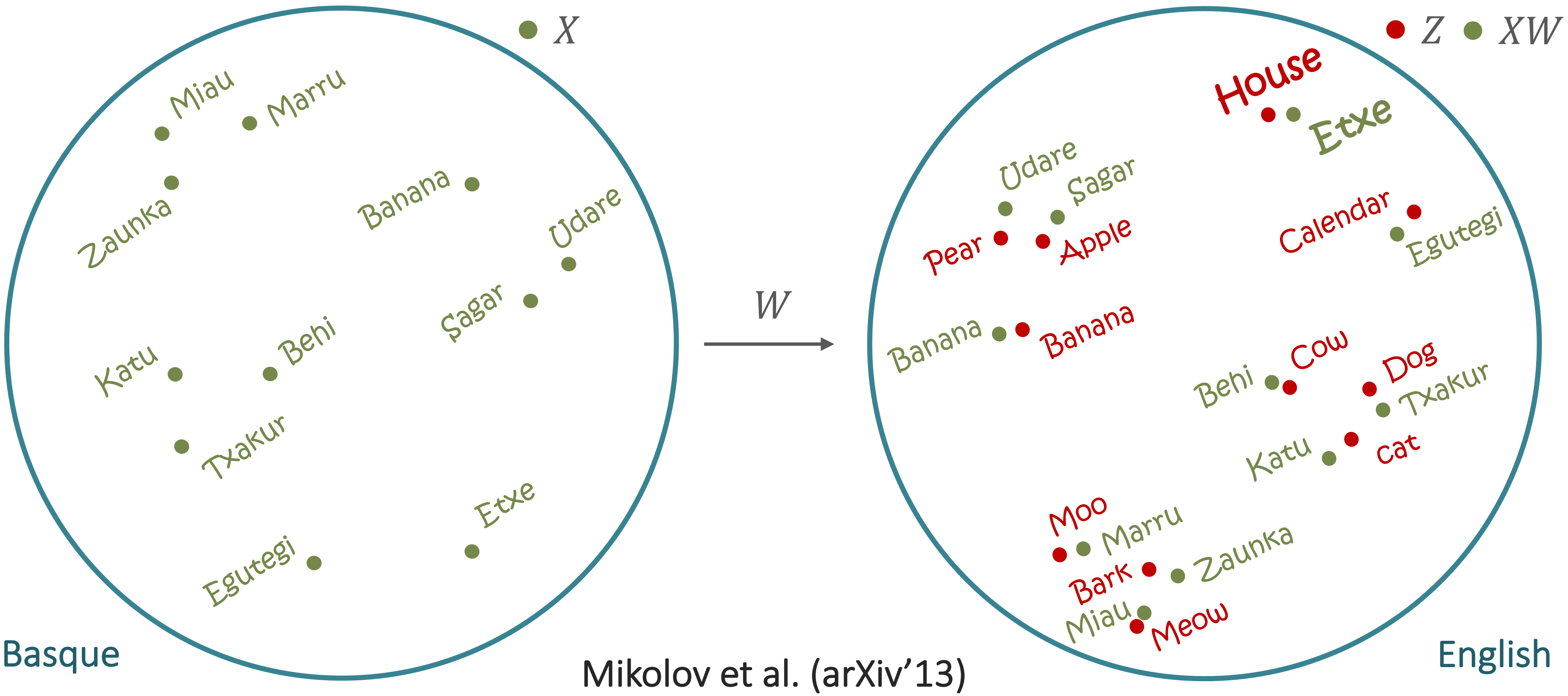

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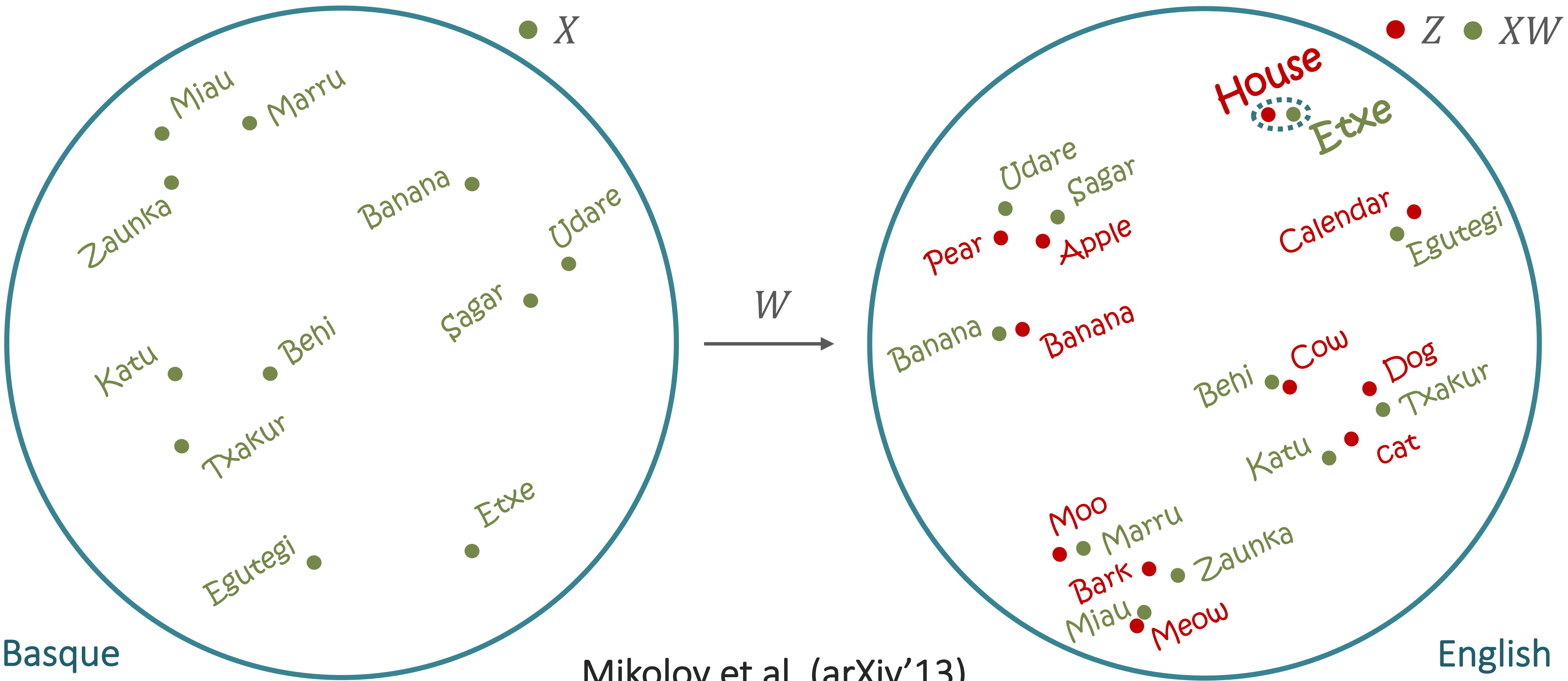

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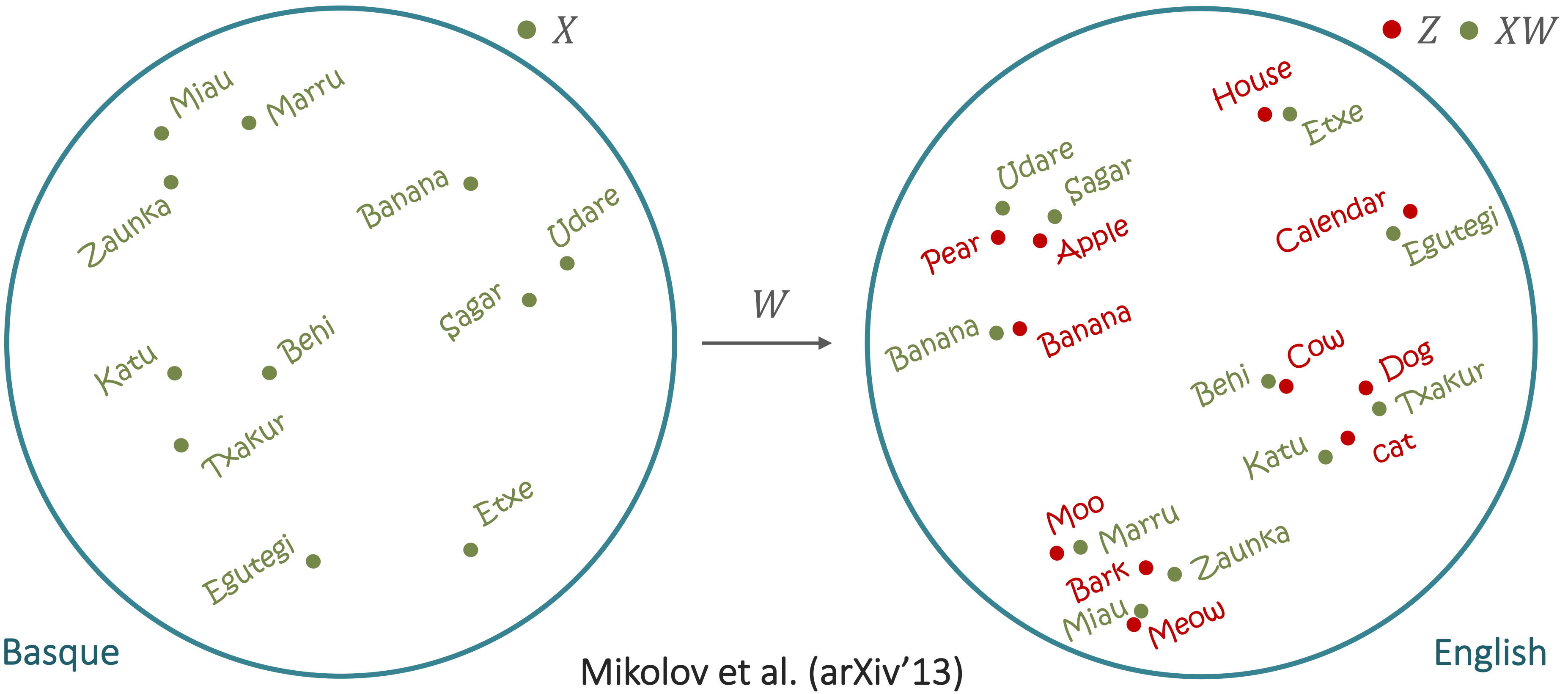

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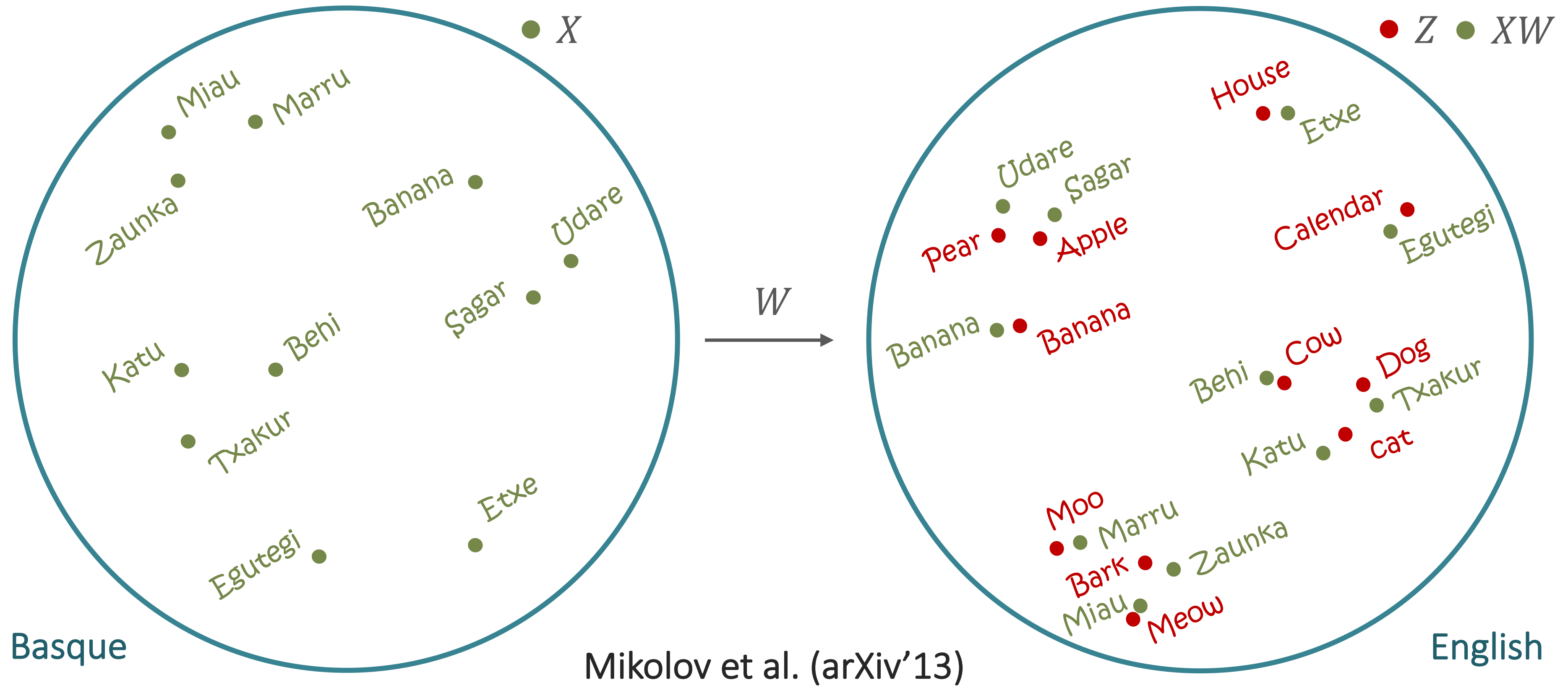

Mikolov et al. (arXiv'13)

$$\begin{array}{r} \text{Txakur} \\ \text{Sagar} \\ \vdots \\ \text{Egutegi} \end{array} \begin{bmatrix} X_{1,*} \\ X_{2,*} \\ \vdots \\ X_{n,*} \end{bmatrix} \quad \Bigg| \quad \begin{bmatrix} Z_{1,*} \\ Z_{2,*} \\ \vdots \\ Z_{n,*} \end{bmatrix} \begin{array}{l} \text{Dog} \\ \text{Apple} \\ \vdots \\ \text{Calendar} \end{array}$$

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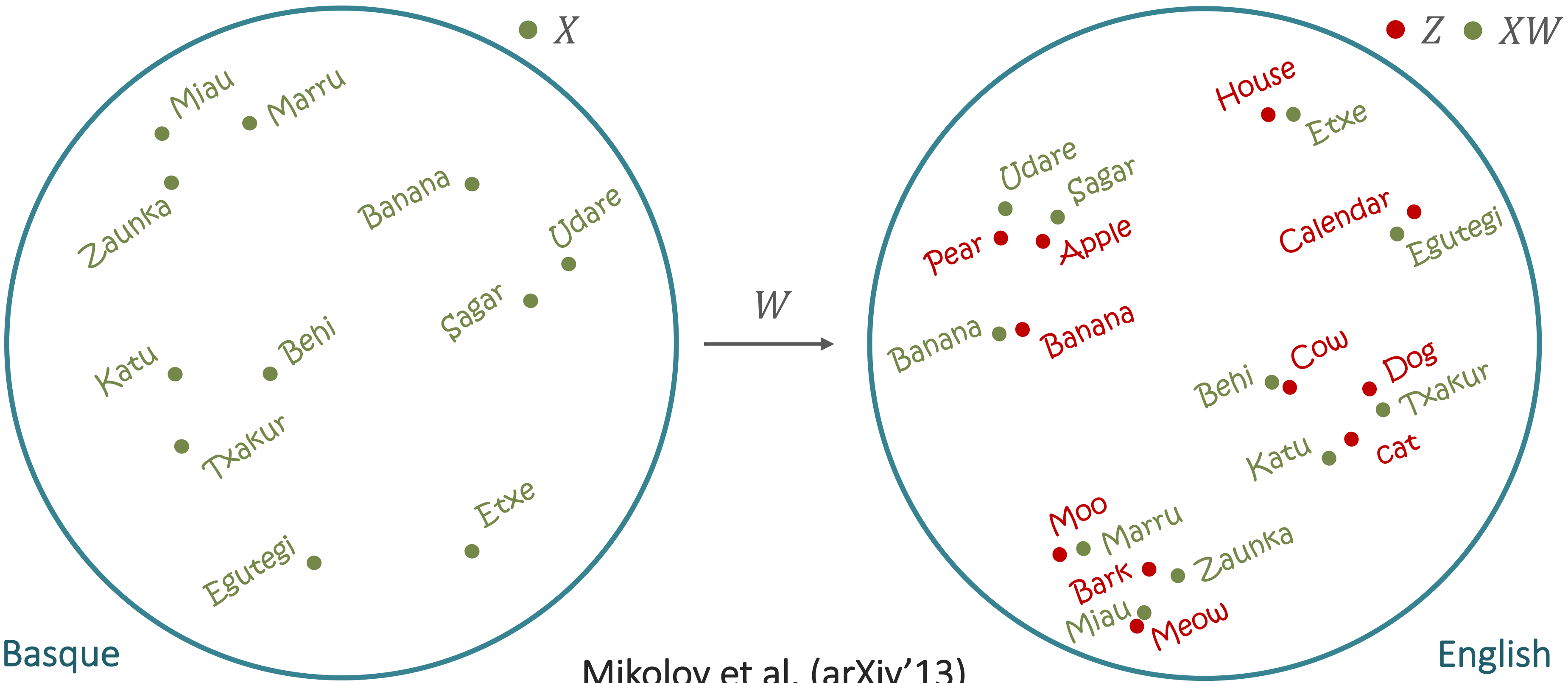

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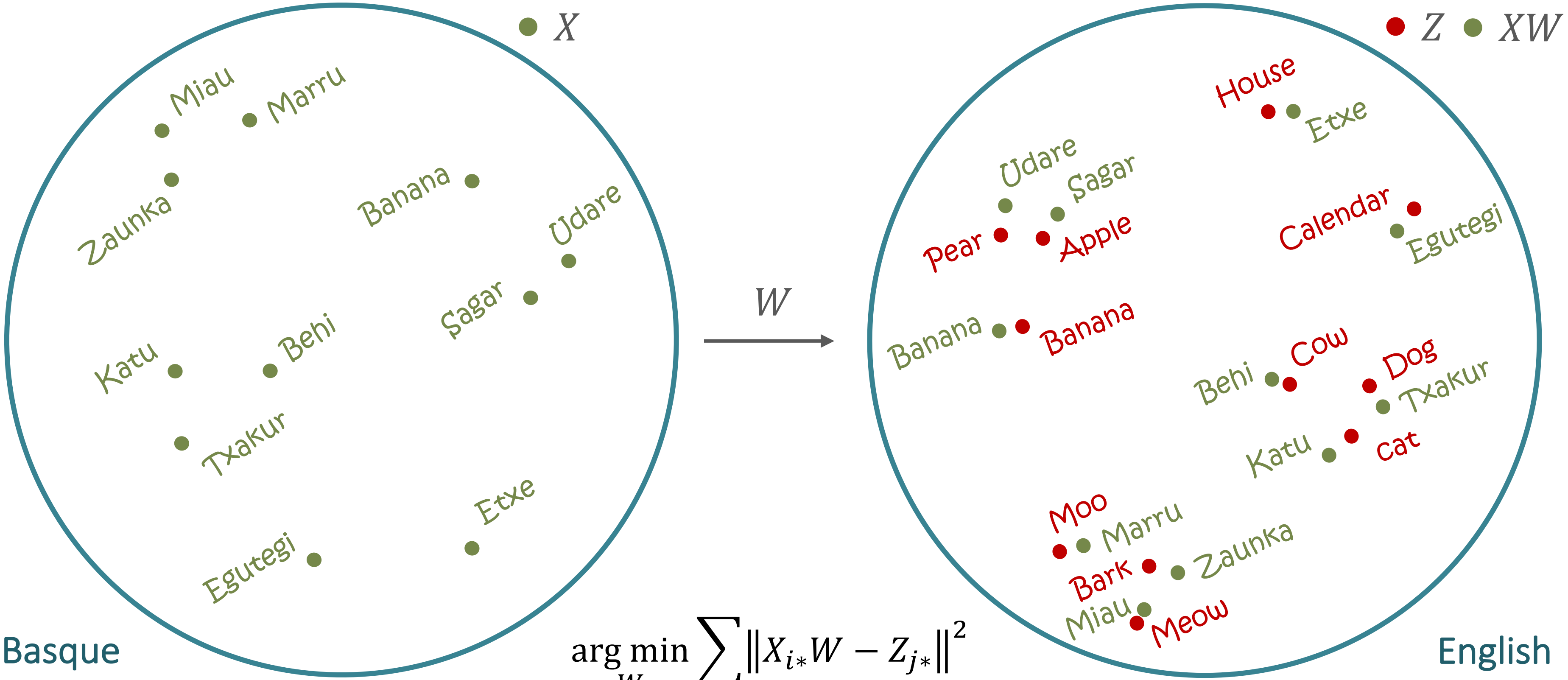

$$\arg\min_W \sum_i \left\| X_{i*} W - Z_{j*} \right\|^2$$

$$\begin{array}{r} \text{Txakur} \\ \text{Sagar} \\ \vdots \\ \text{Egutegi} \end{array} \begin{bmatrix} X_{1,*} \\ X_{2,*} \\ \vdots \\ X_{n,*} \end{bmatrix} [W] \approx \begin{bmatrix} Z_{1,*} \\ Z_{2,*} \\ \vdots \\ Z_{n,*} \end{bmatrix} \begin{array}{l} \text{Dog} \\ \text{Apple} \\ \vdots \\ \text{Calendar} \end{array}$$

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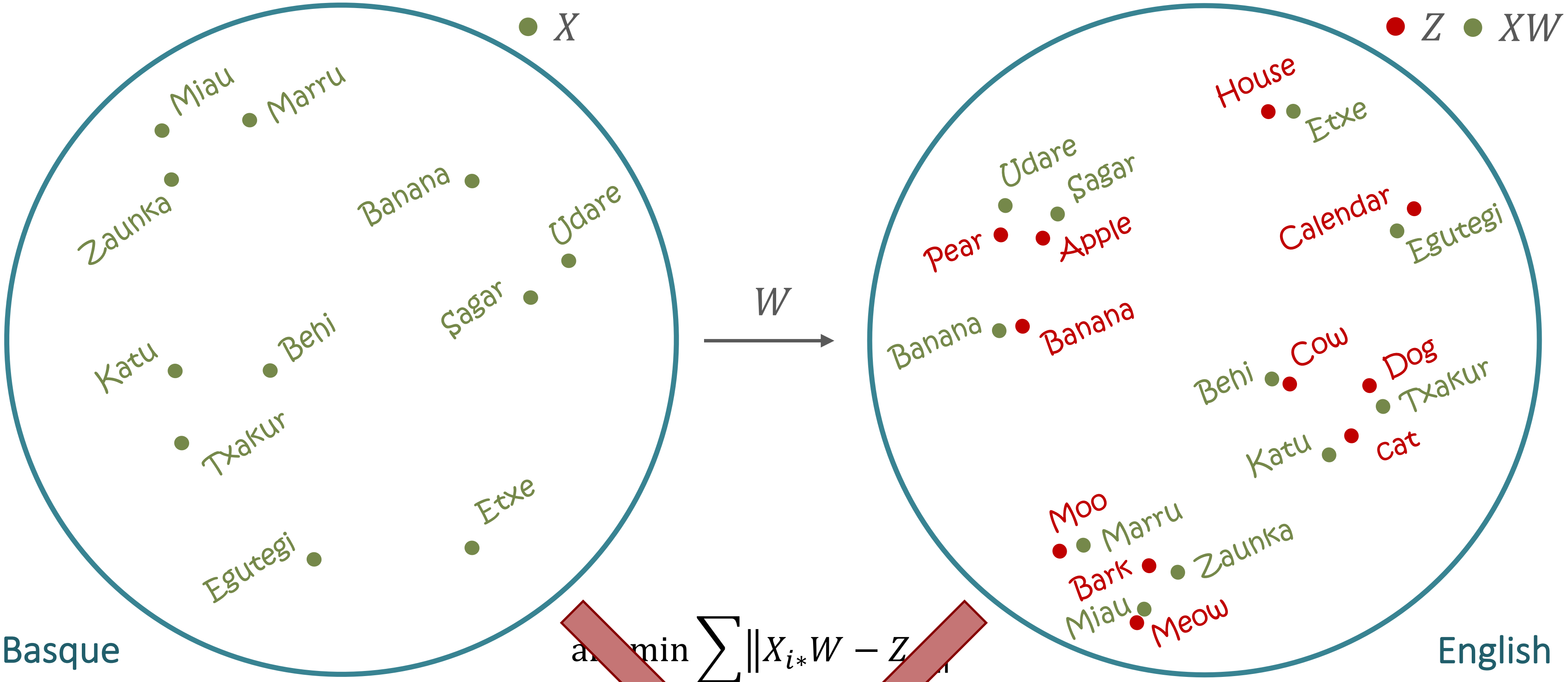

$$\arg\min_{W} \sum_i \|X_{i*}W - Z_{i*}\|$$

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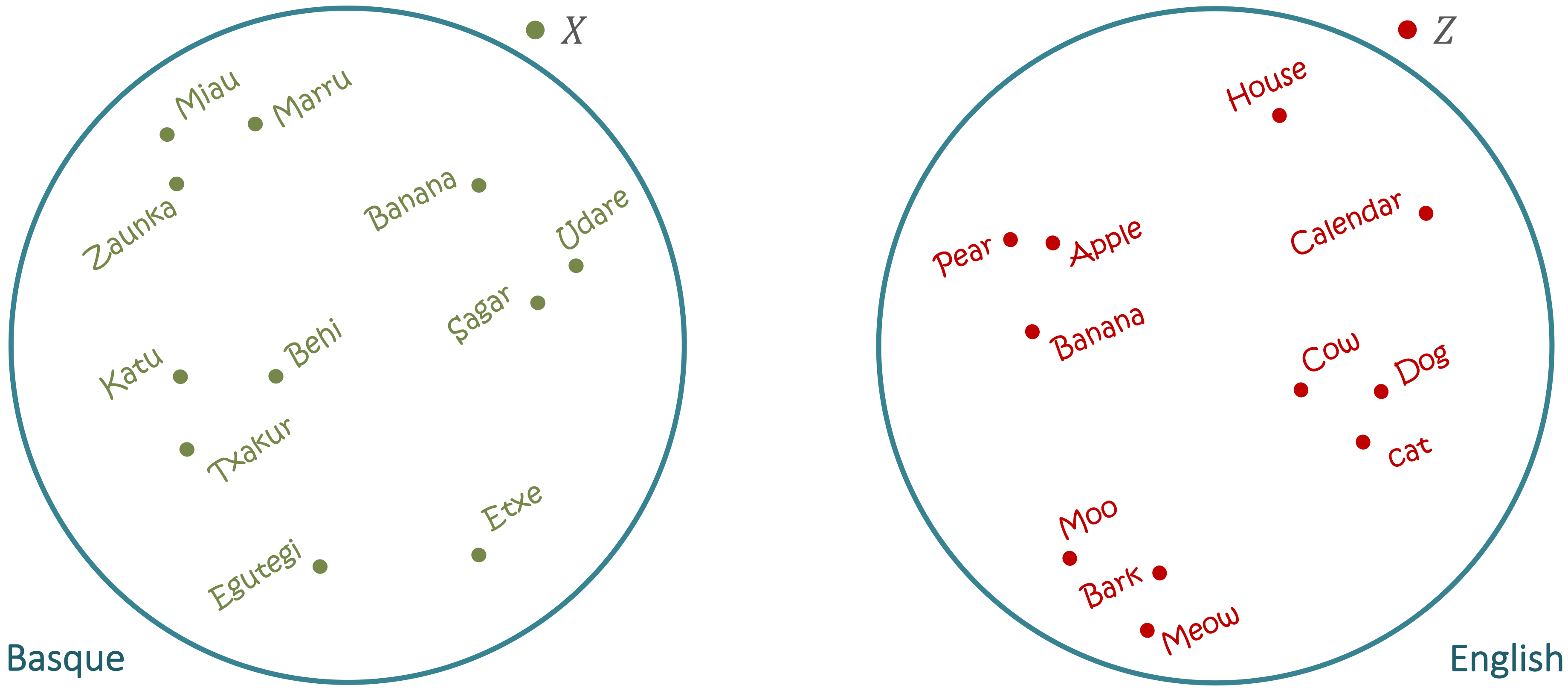

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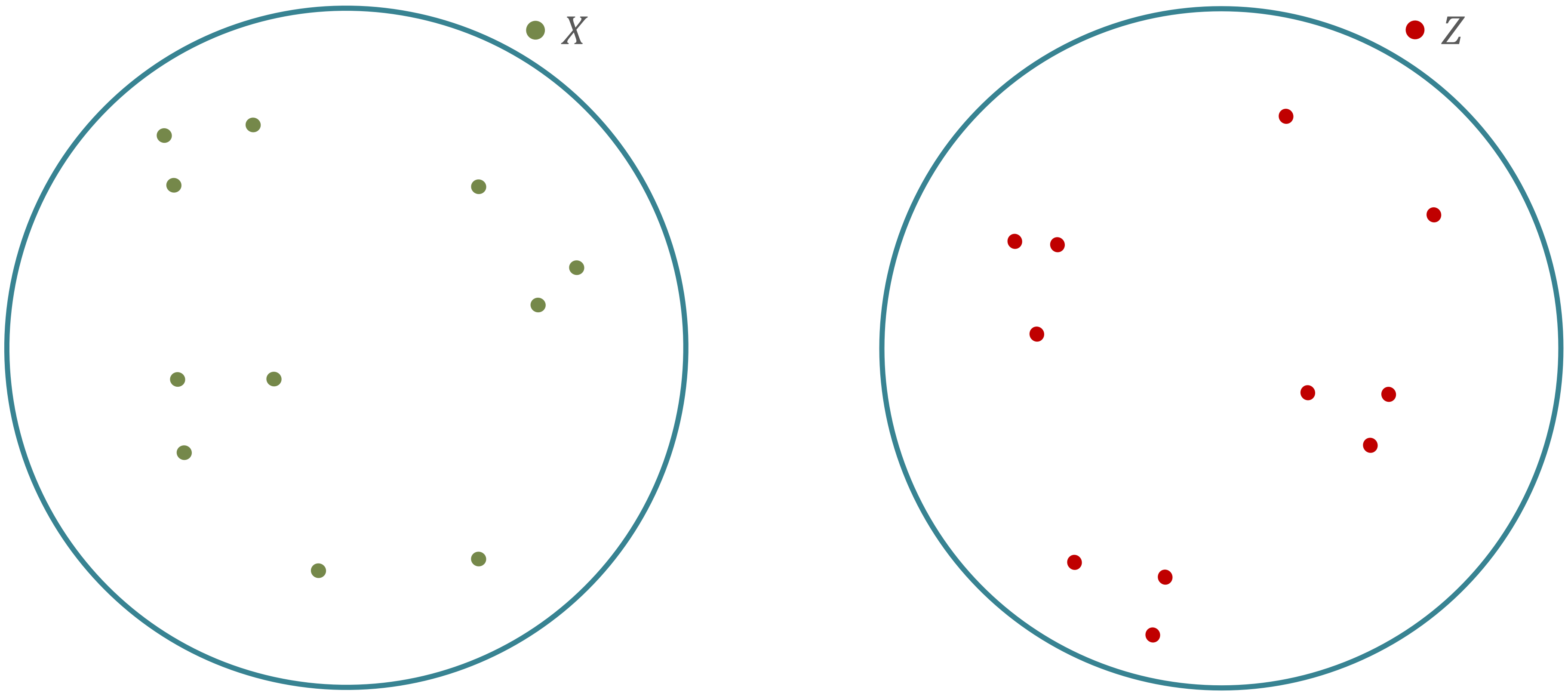

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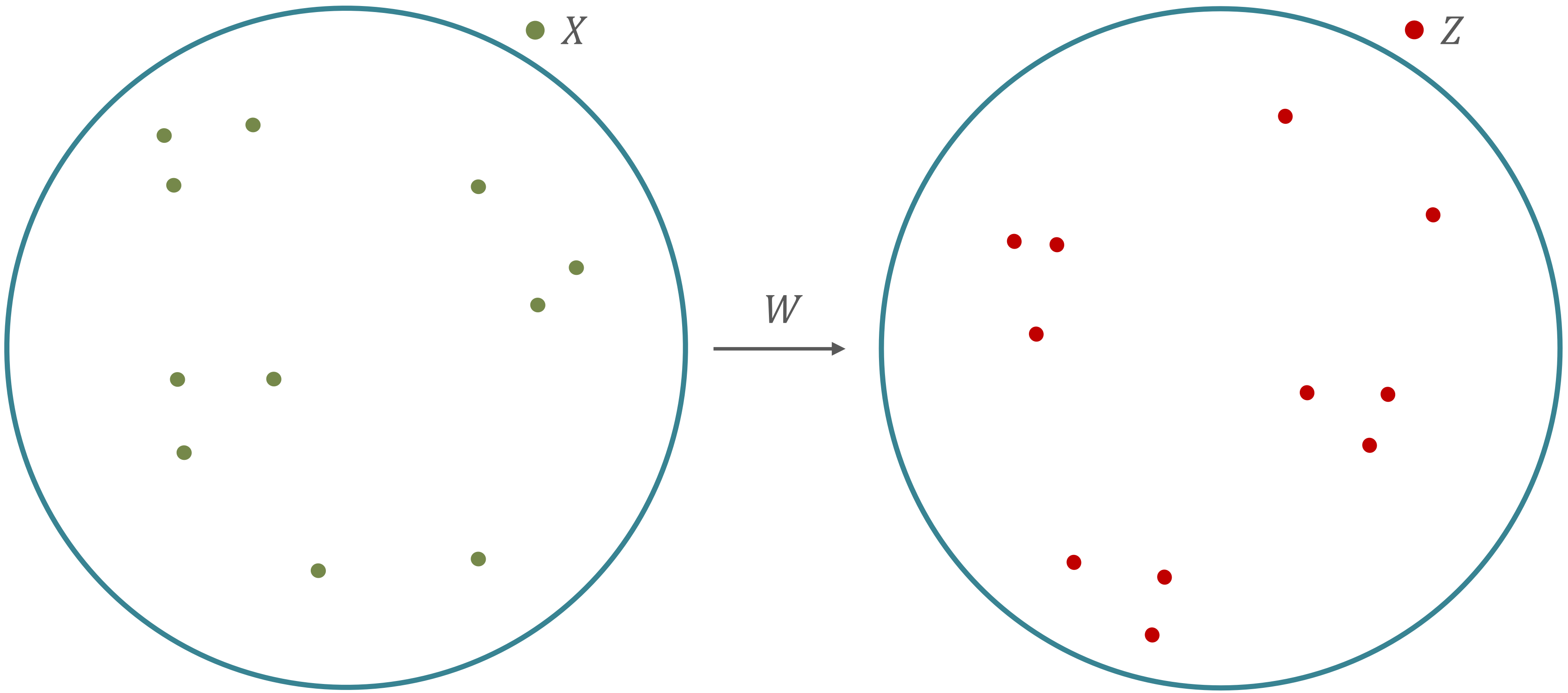

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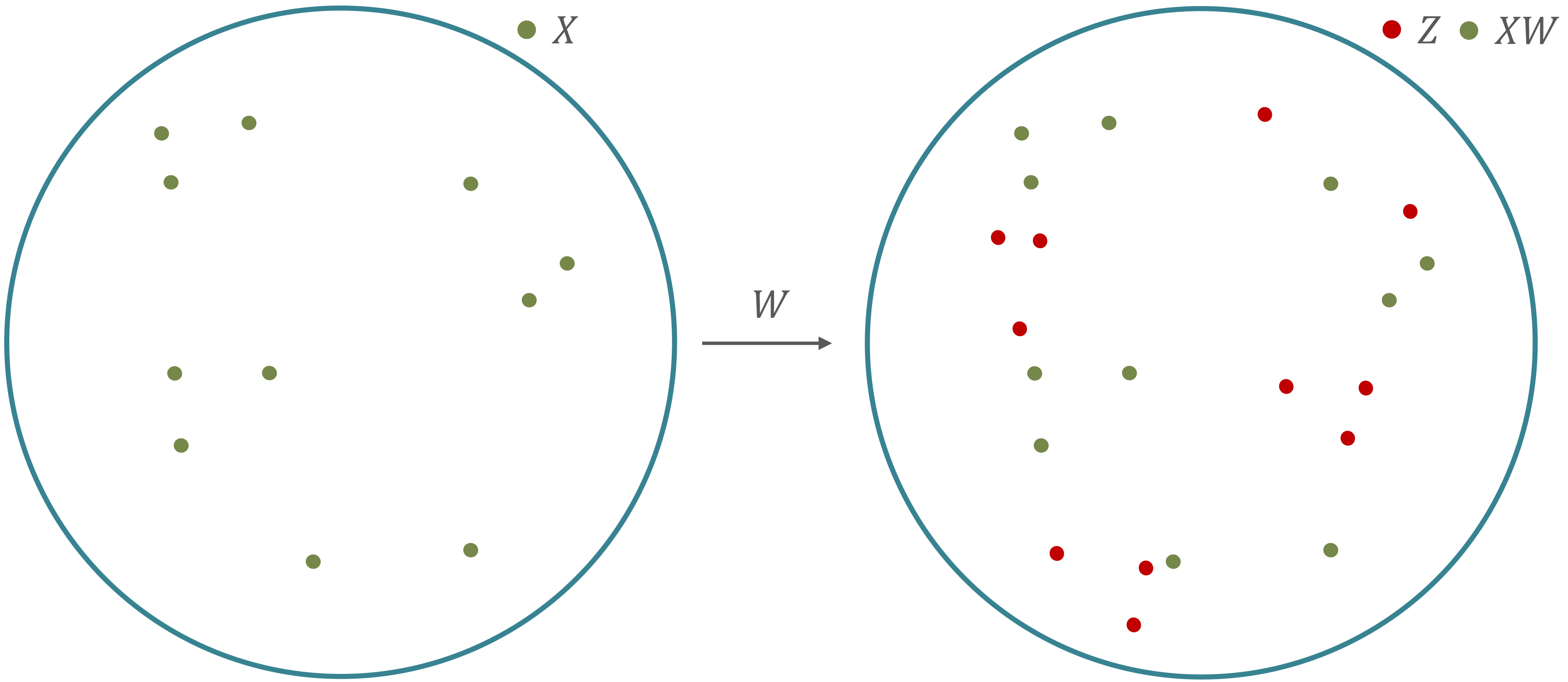

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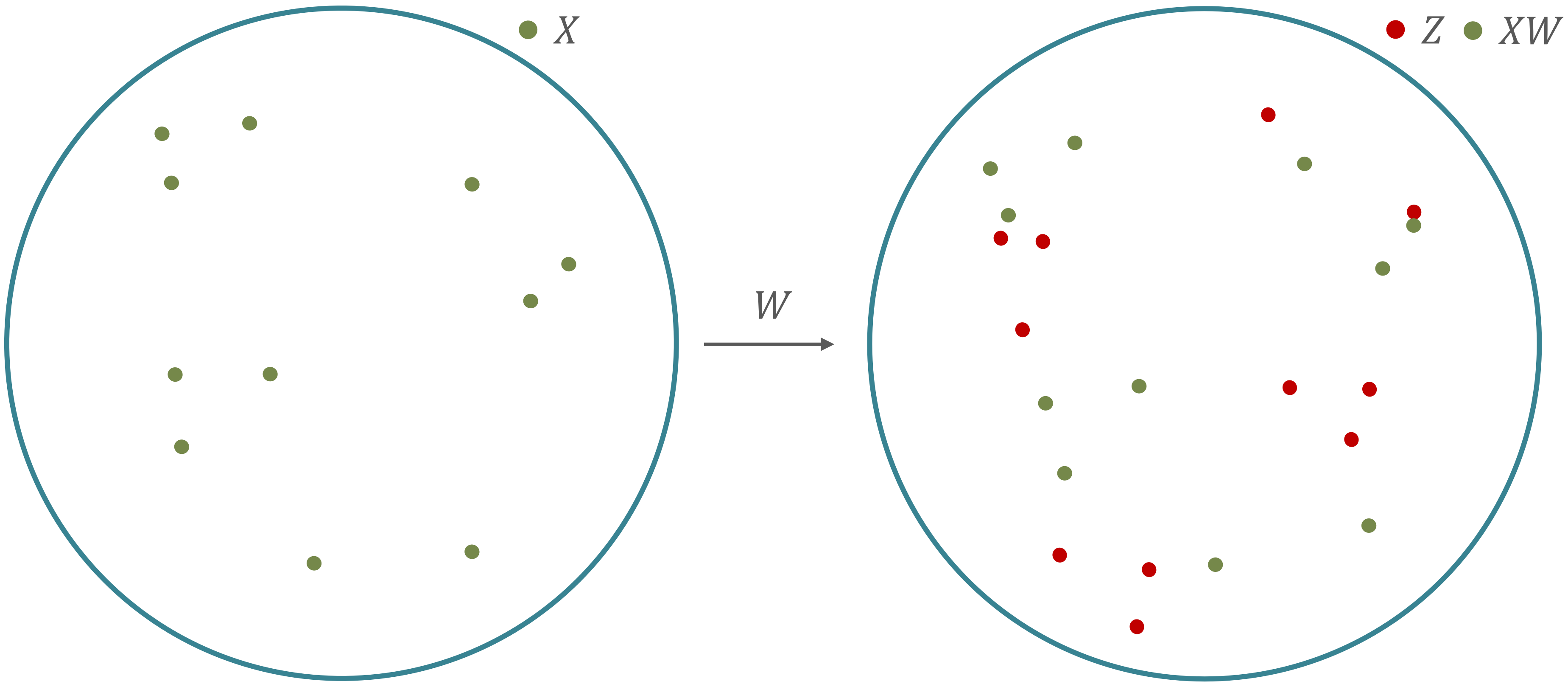

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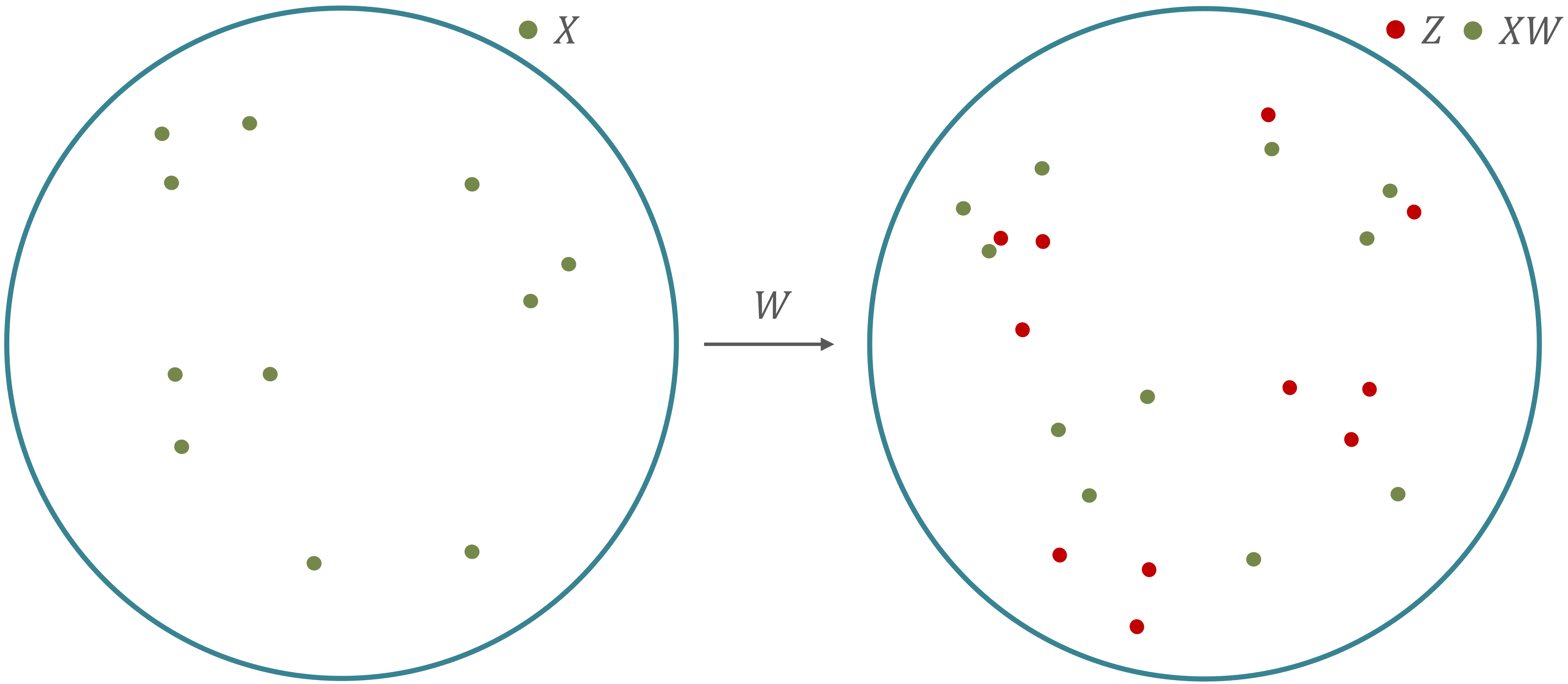

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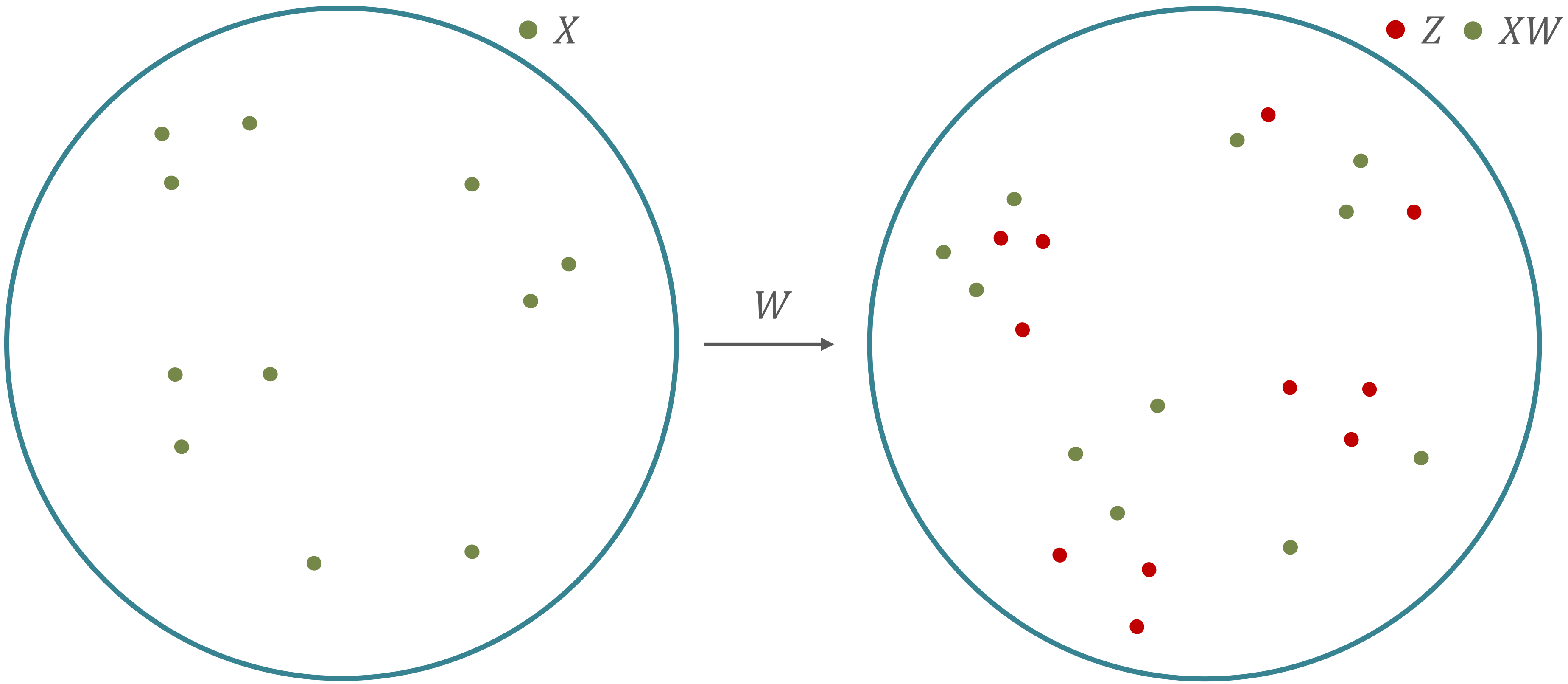

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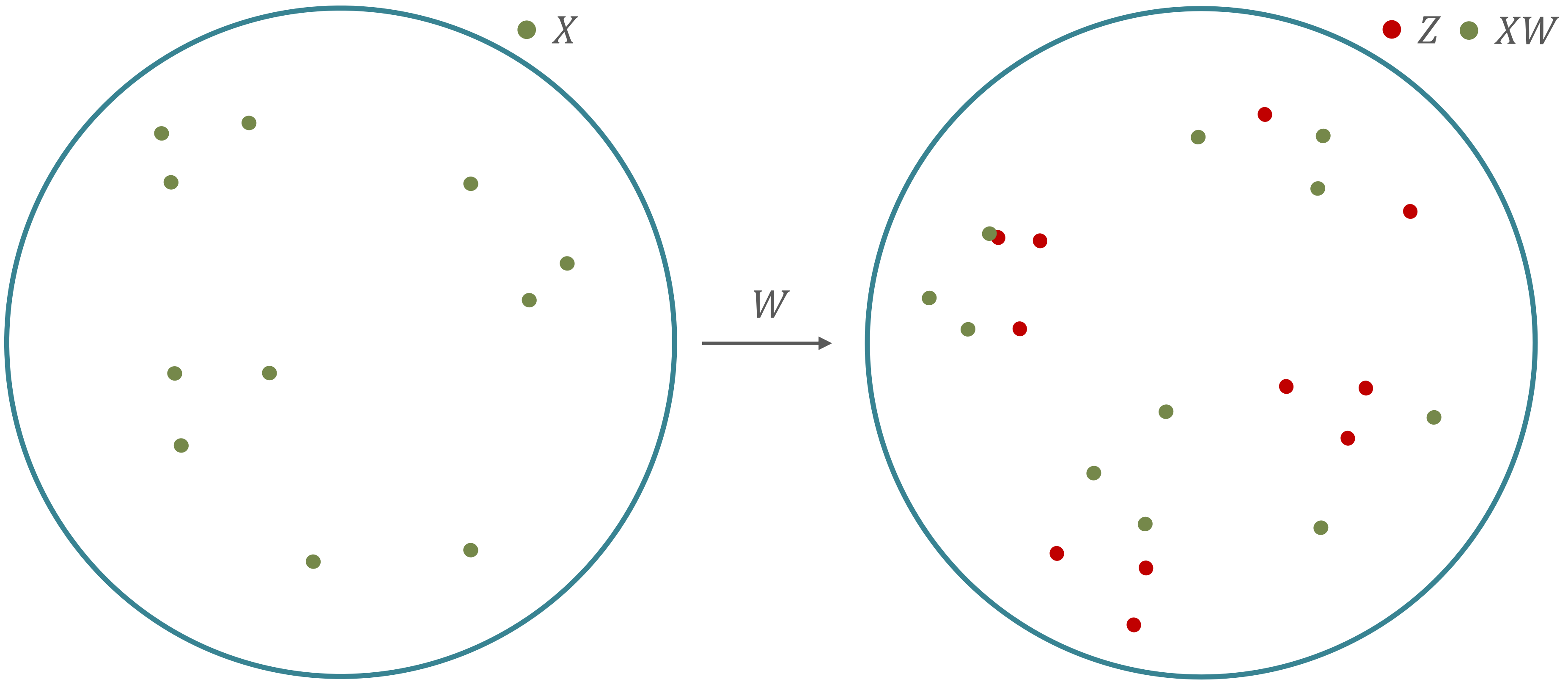

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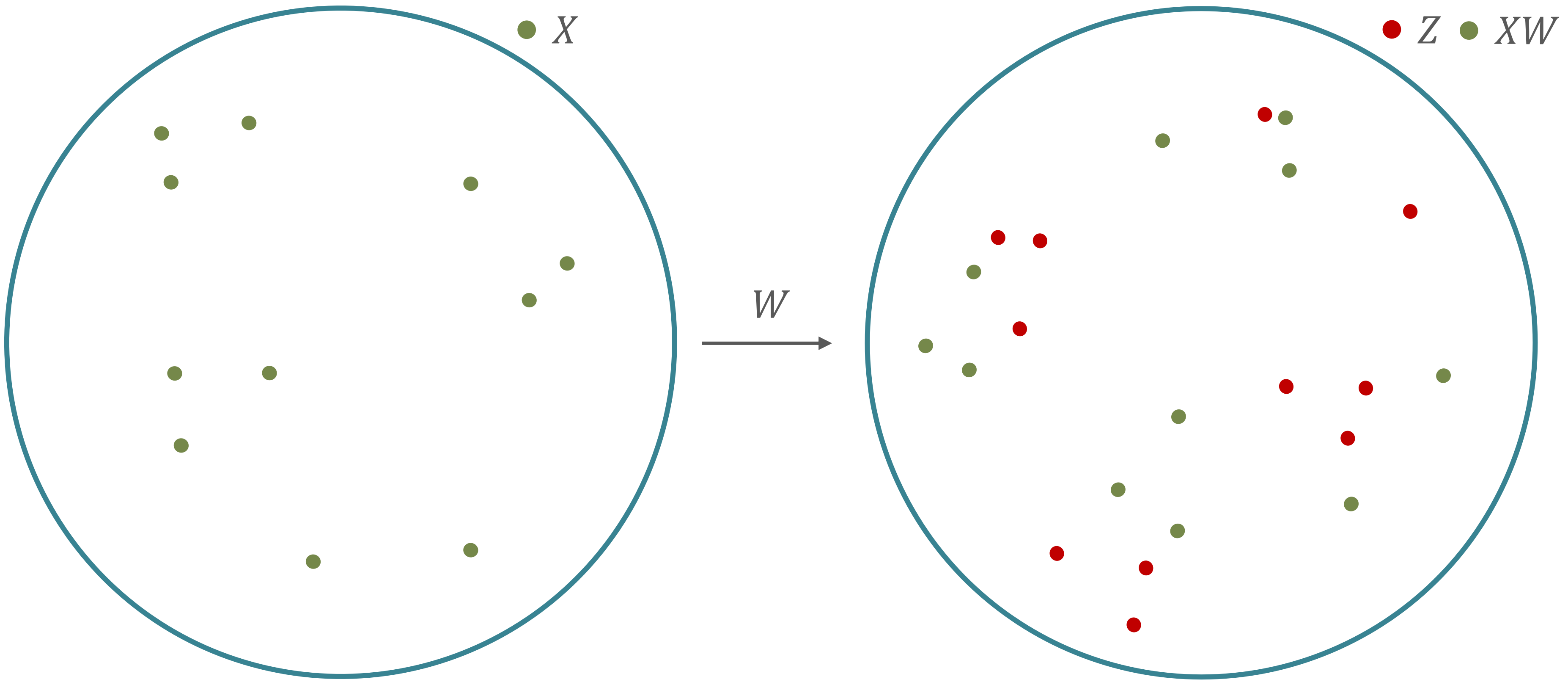

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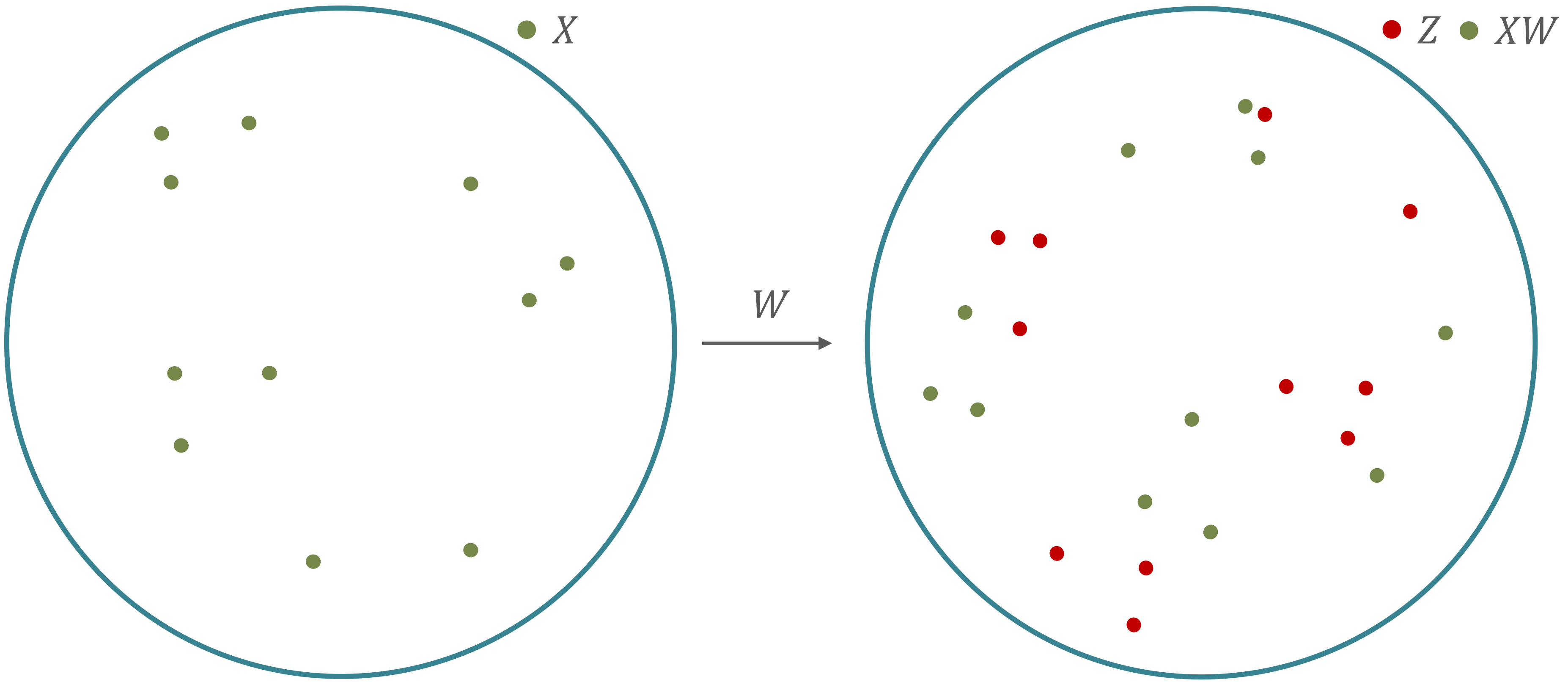

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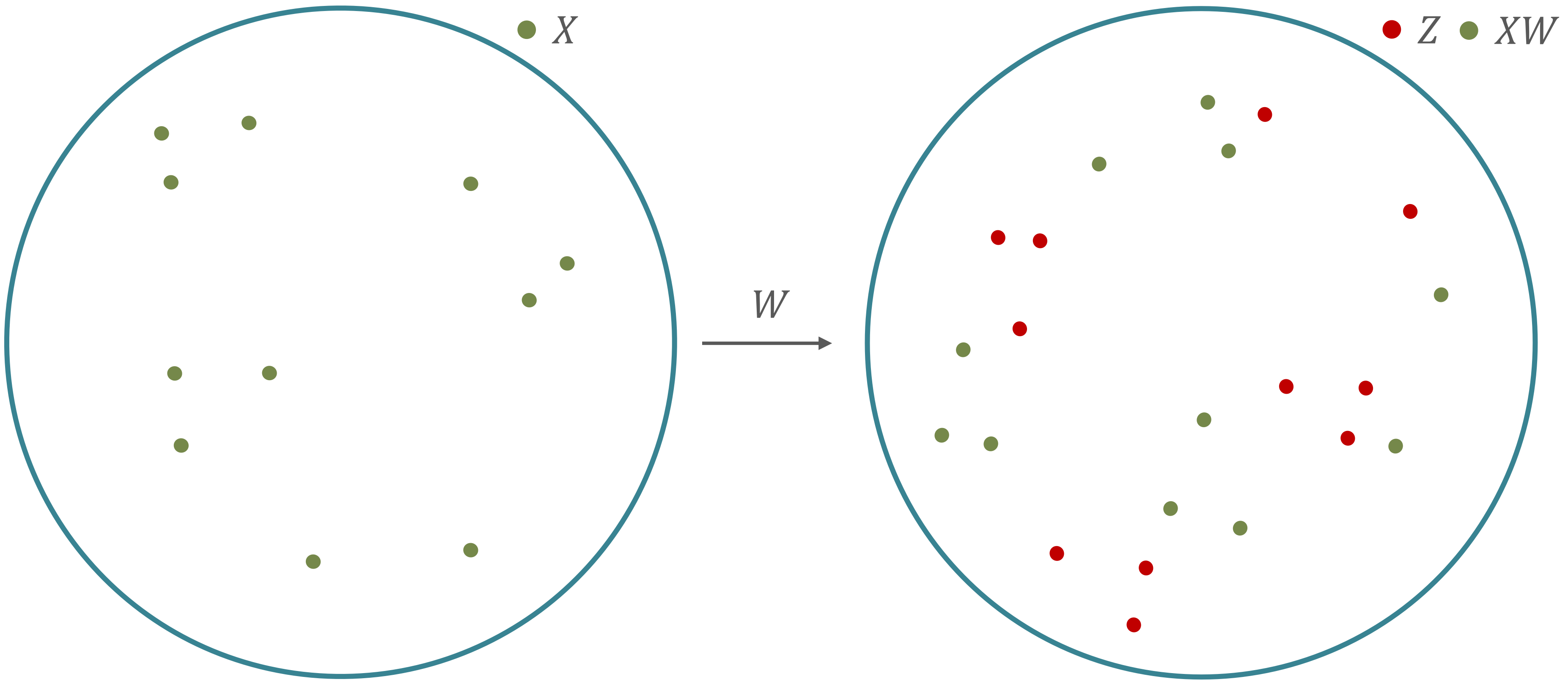

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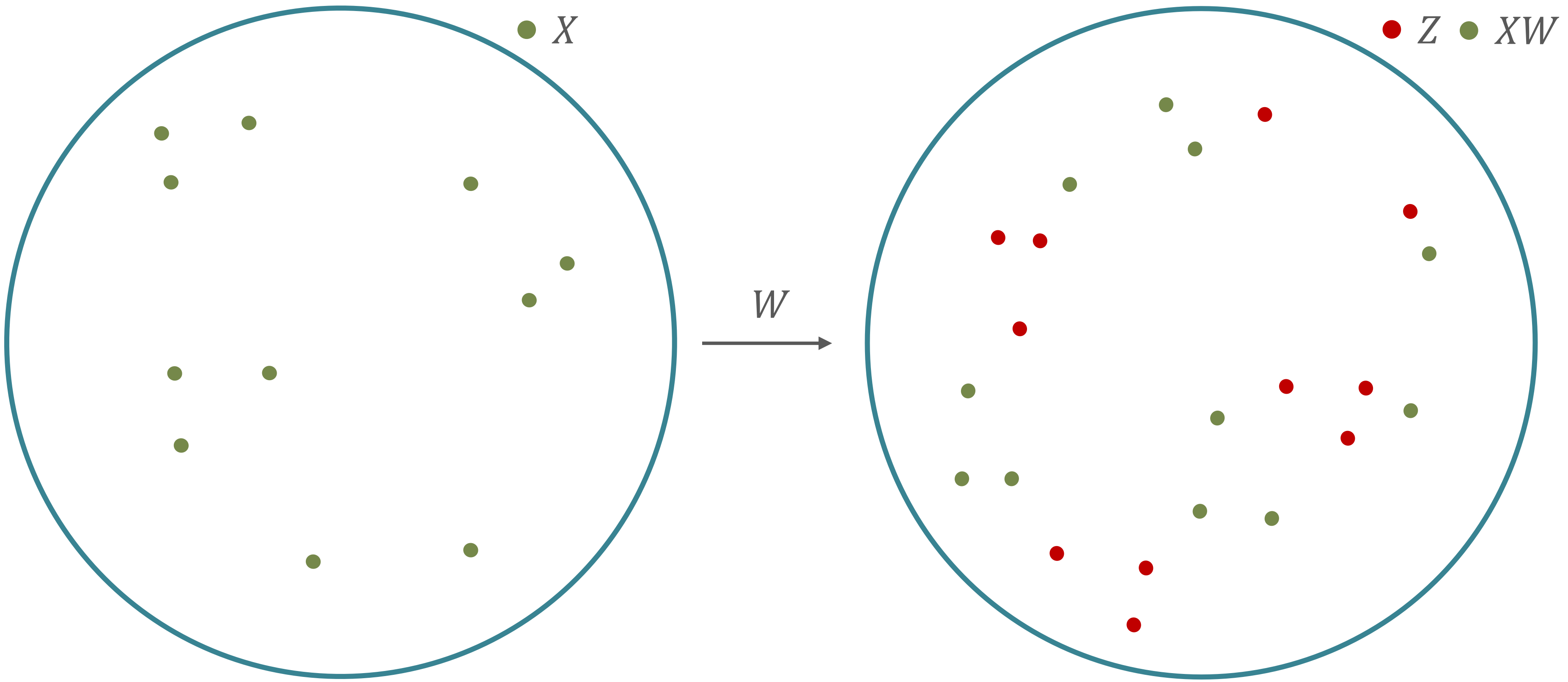

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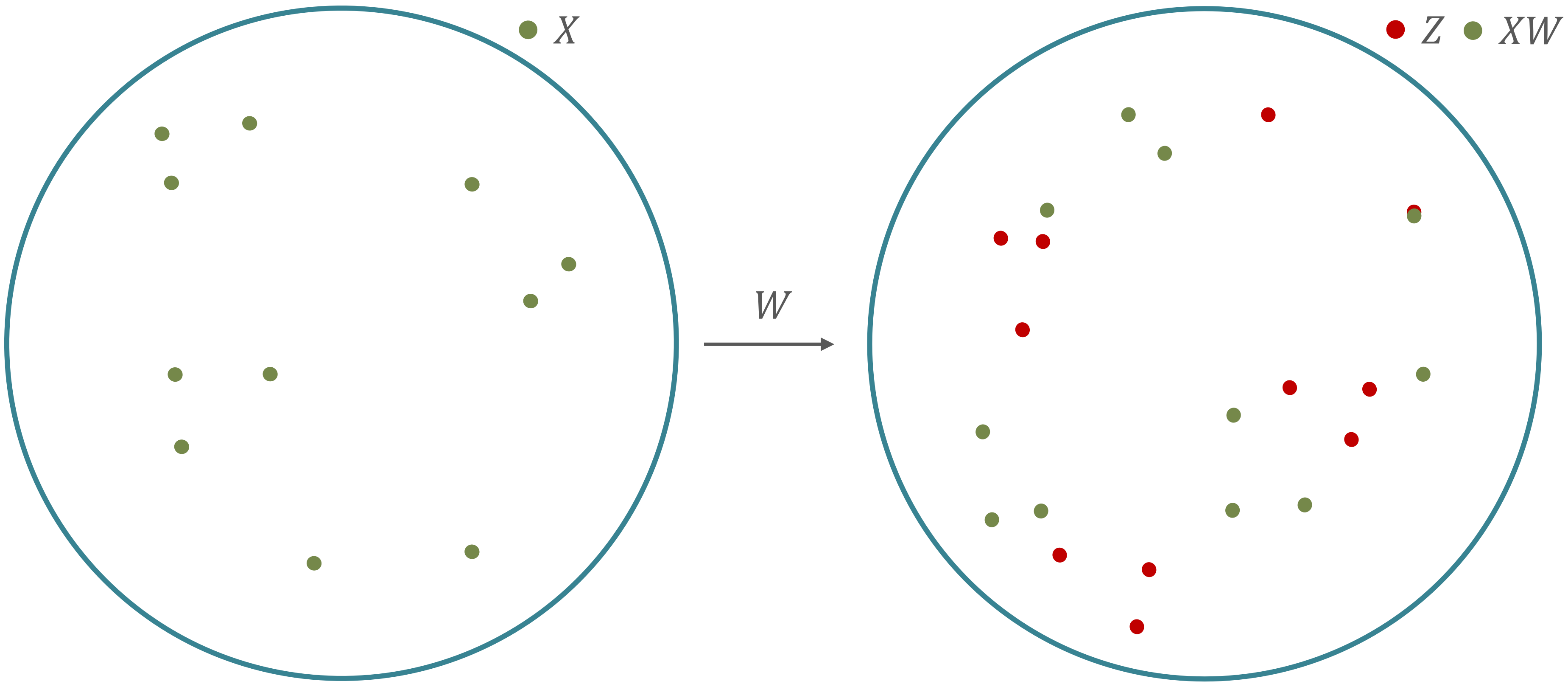

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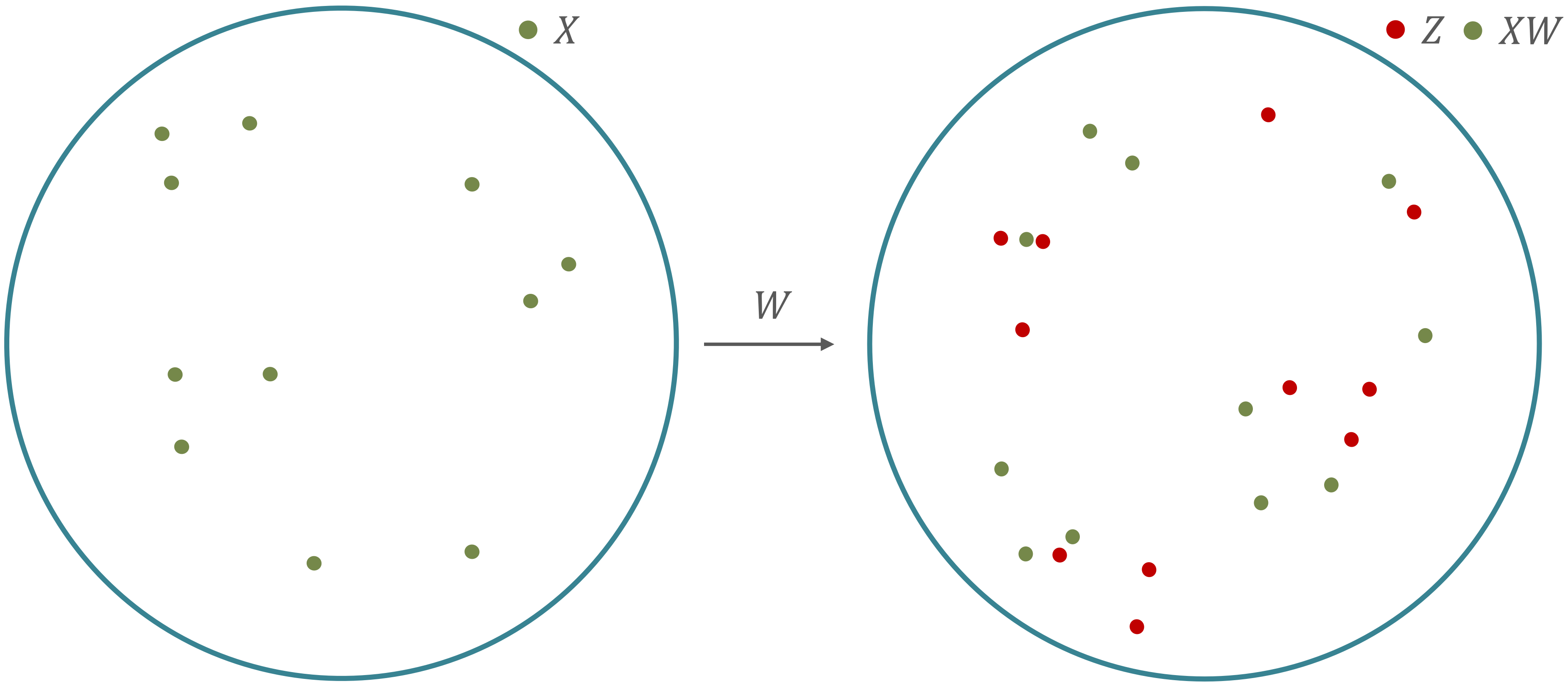

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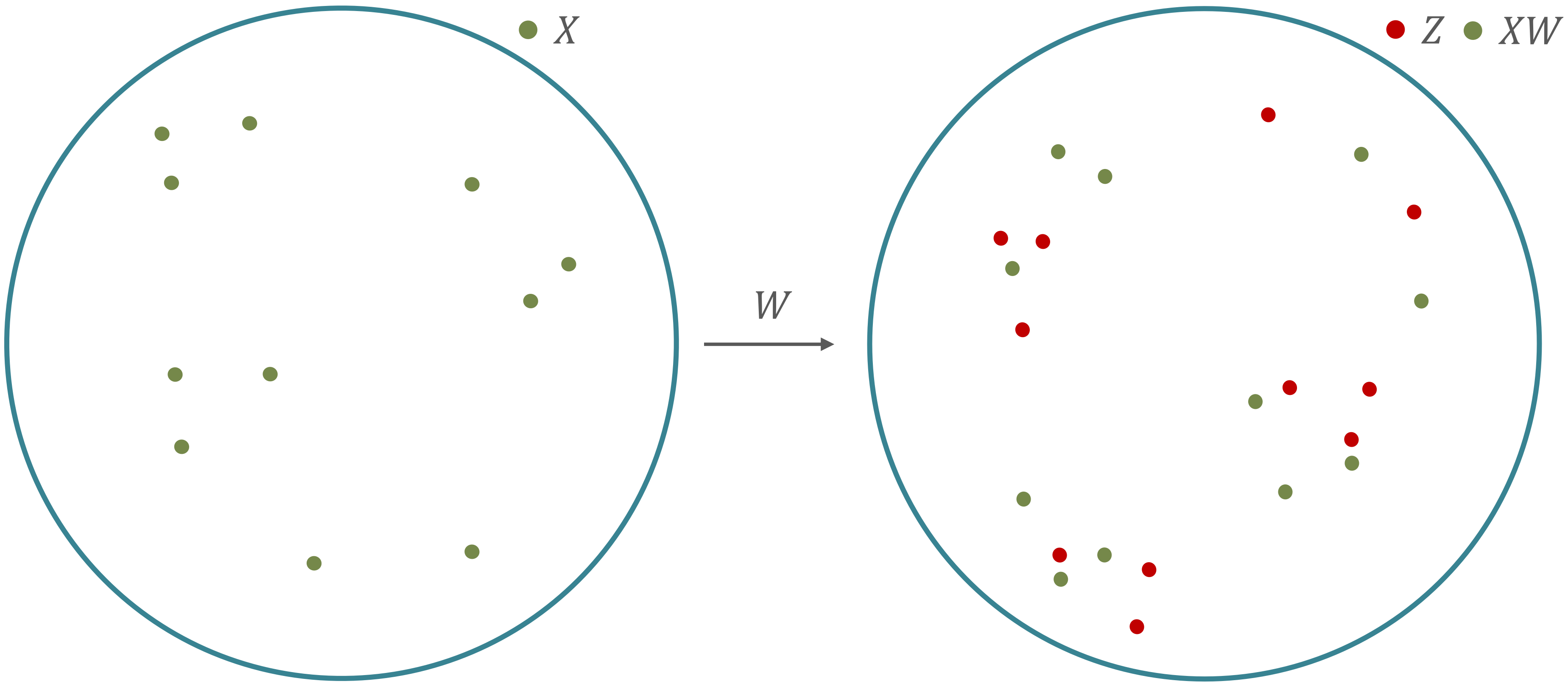

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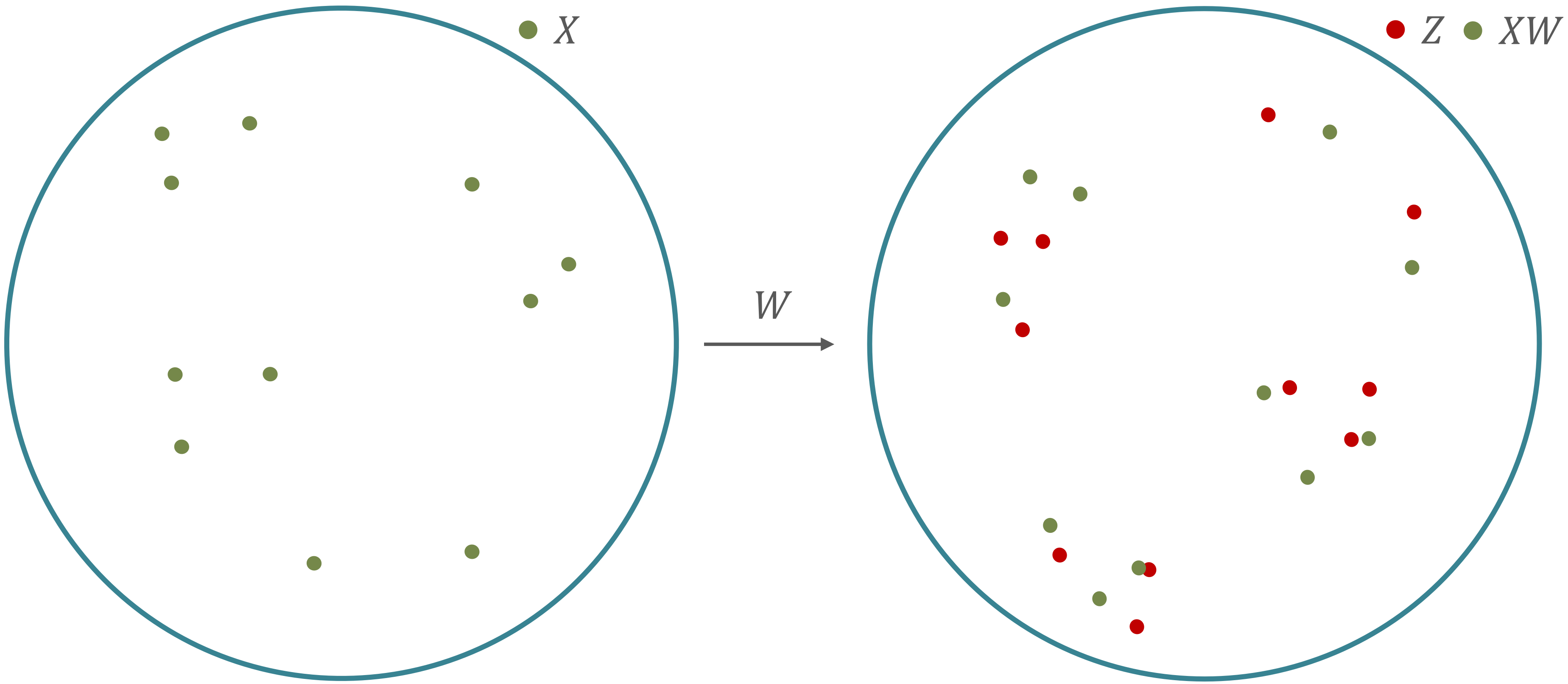

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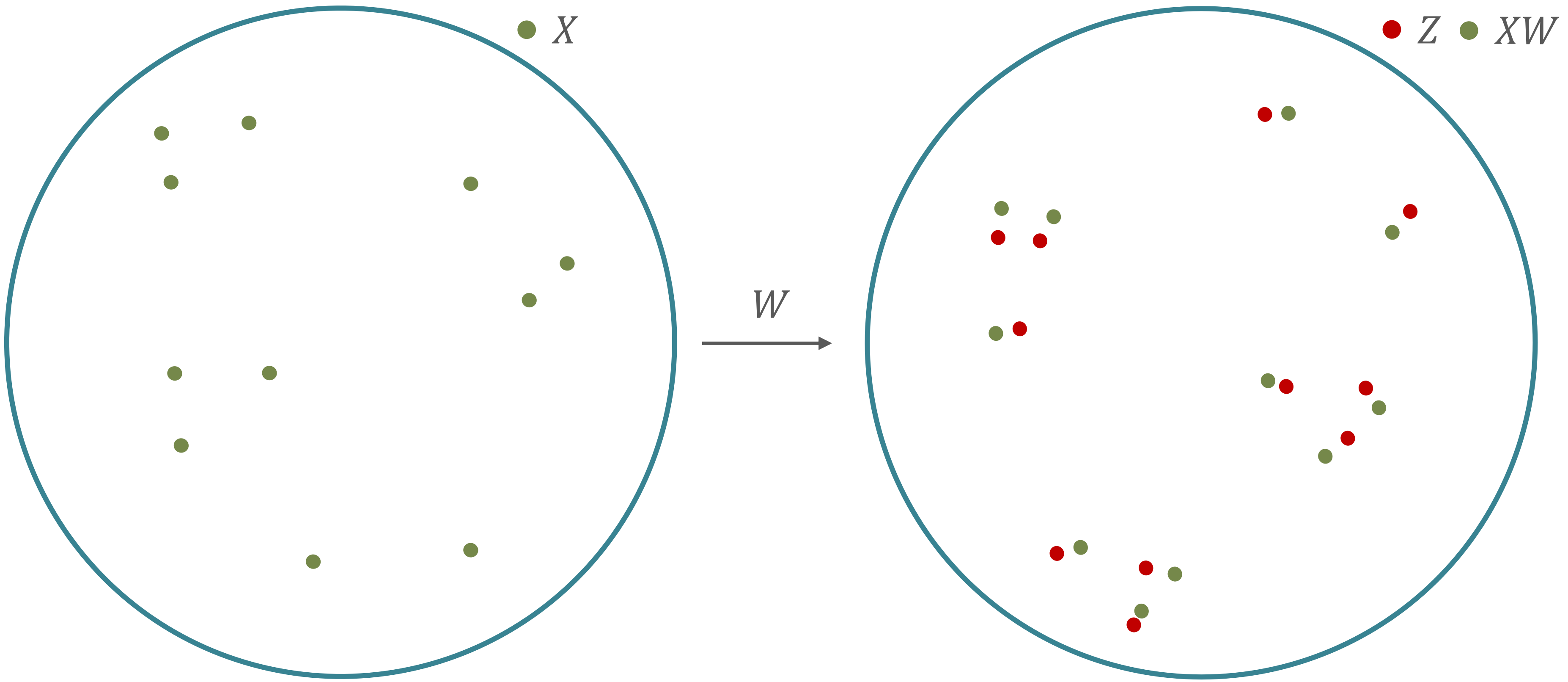
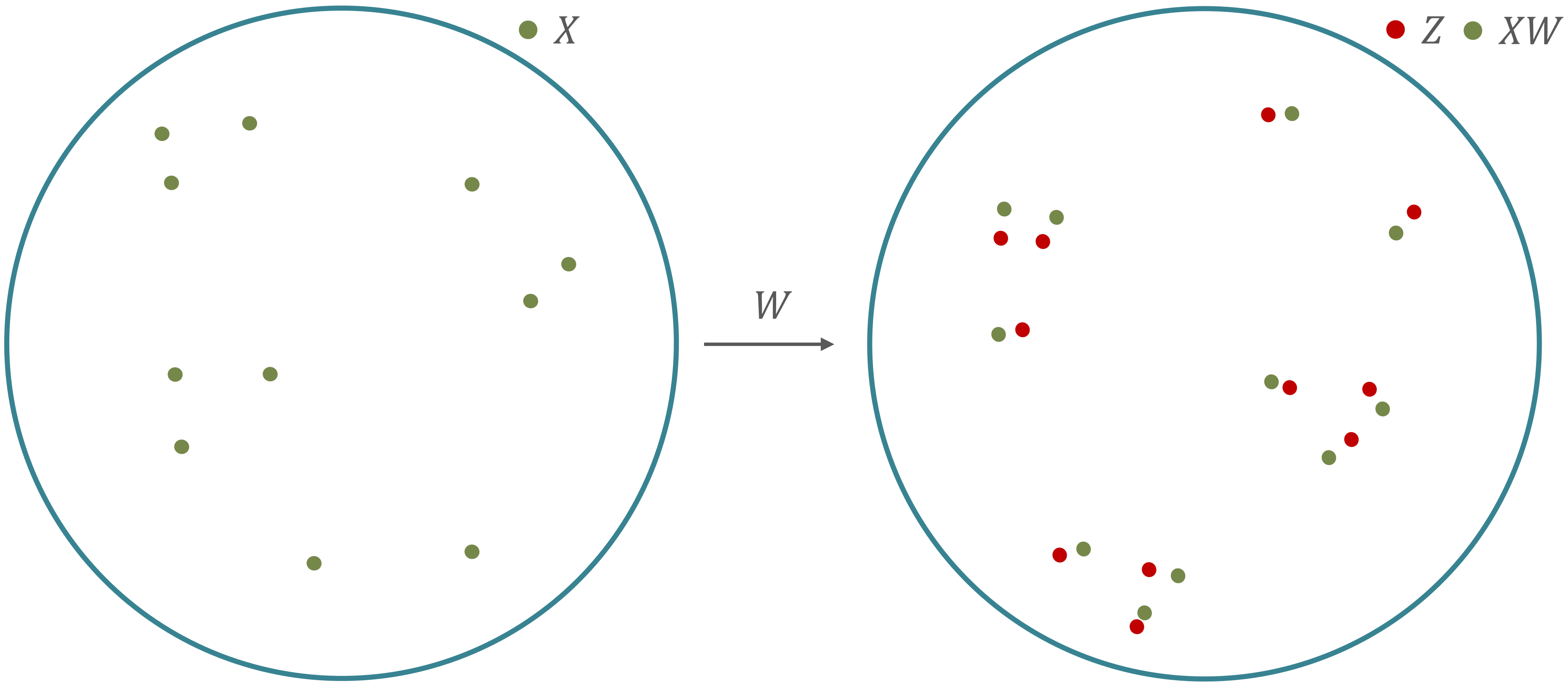


Cross-lingual word embedding alignment



$$W^* = \underset{W \in O(n)}{\arg\min} \sum_i \min_j \left\| X_{i*}W - Z_{j*} \right\|^2$$

Cross-lingual word embedding alignment

$$W^* = \underset{W \in O(n)}{\arg\min} \sum_i \min_j \left\| X_{i*} W - Z_{j*} \right\|^2$$

Cross-lingual word embedding alignment

Self-learning

$$W^* = \underset{W \in O(n)}{\arg\min} \sum_i \min_j \left\| X_{i*} W - Z_{j*} \right\|^2$$

Cross-lingual word embedding alignment

Self-learning

Dictionary

$$W^* = \underset{W \in O(n)}{\arg\min} \sum_i \min_j \left\| X_{i*} W - Z_{j*} \right\|^2$$

Cross-lingual word embedding alignment

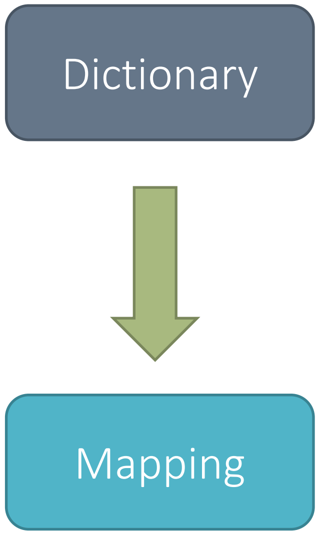
Self-learning

Dictionary

$$W^* = \underset{W \in O(n)}{\arg\min} \sum_i \min_j \left\| X_{i*}W - Z_{j*} \right\|^2$$

Cross-lingual word embedding alignment

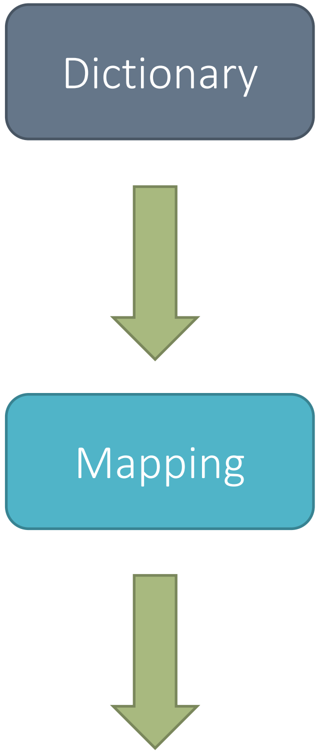
Self-learning



$$W^* = \underset{W \in O(n)}{\arg\min} \sum_i \min_j \left\| X_{i*} W - Z_{j*} \right\|^2$$

Cross-lingual word embedding alignment

Self-learning



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Cross-lingual word embedding alignment

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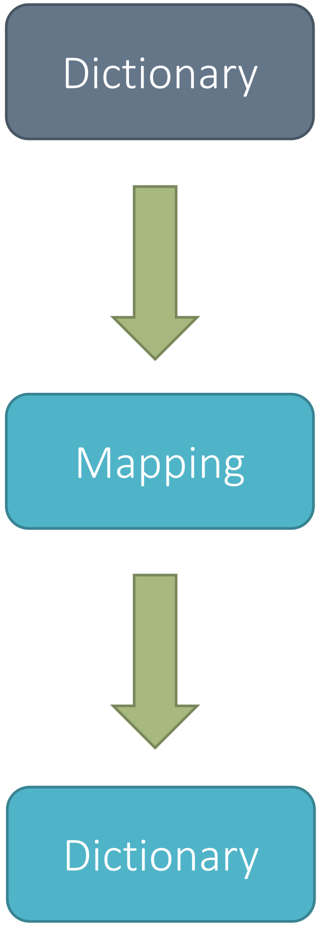
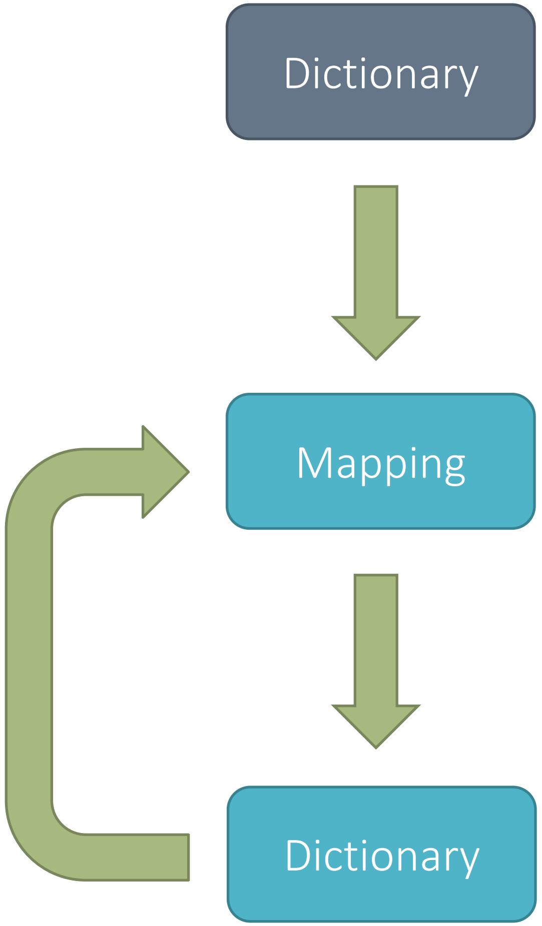


Cross-lingual word embedding alignment

<u>Self-learning</u>

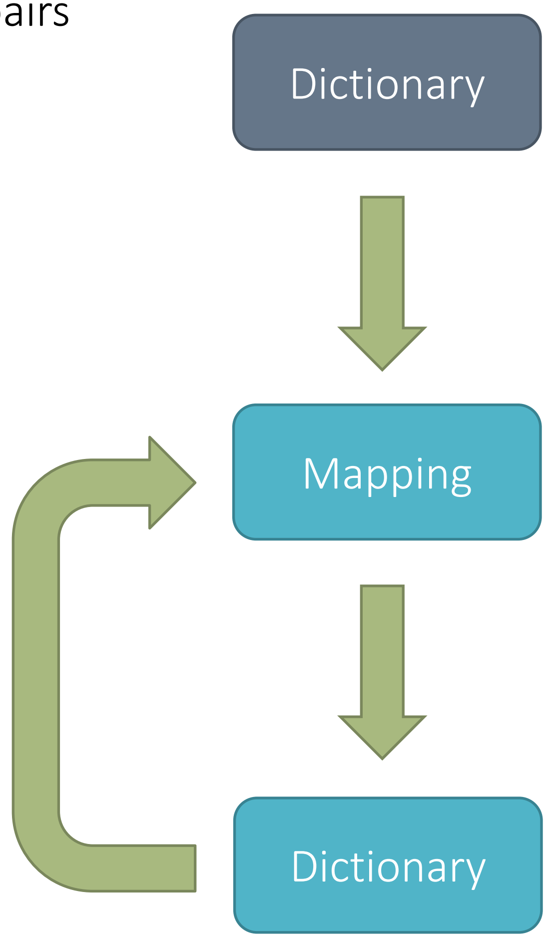
$$W^* = \underset{W \in O(n)}{\arg\min} \sum_i \min_j \|X_{i*}W - Z_{j*}\|^2$$



Cross-lingual word embedding alignment

Self-learning

- 25 word pairs

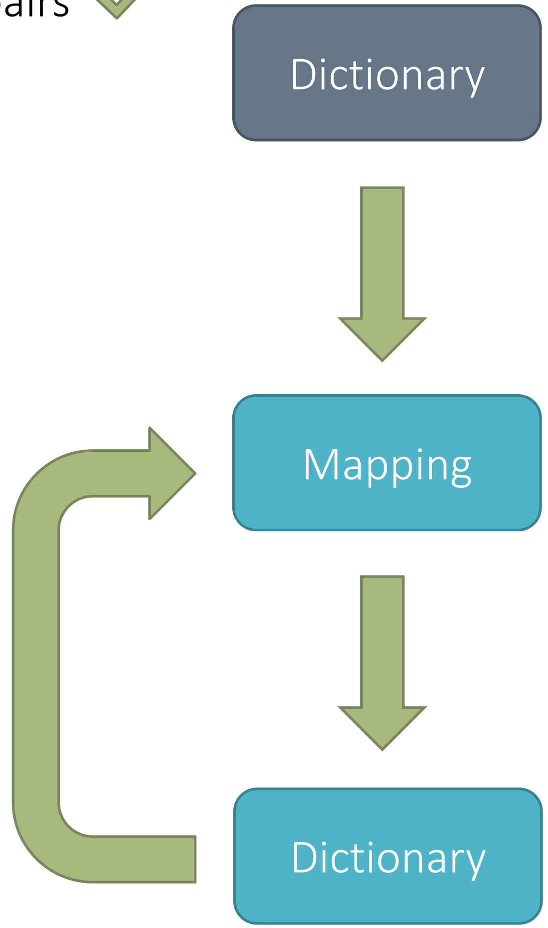


$$W^* = \underset{W \in O(n)}{\arg\min} \sum_i \min_j \left\| X_{i*} W - Z_{j*} \right\|^2$$

Cross-lingual word embedding alignment

Self-learning

- 25 word pairs ✓

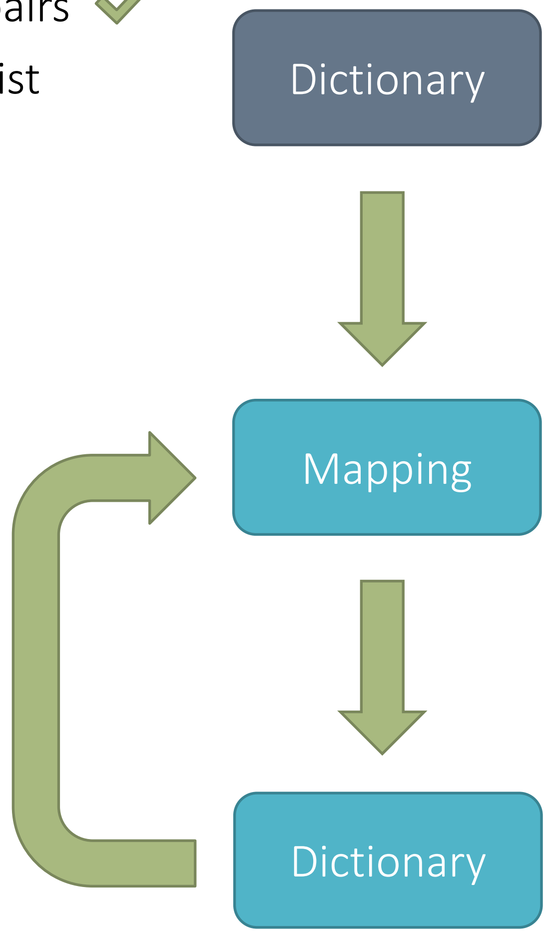


$$W^* = \underset{W \in O(n)}{\arg\min} \sum_i \min_j \|X_{i*}W - Z_{j*}\|^2$$

Cross-lingual word embedding alignment

Self-learning

- 25 word pairs
- Numeral list

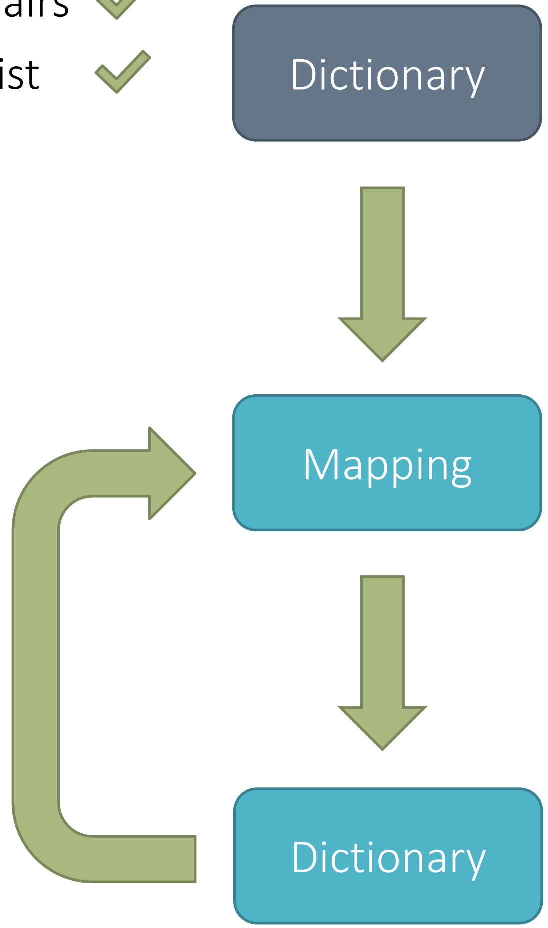


$$W^* = \underset{W \in O(n)}{\arg\min} \sum_i \min_j \|X_{i*}W - Z_{j*}\|^2$$

Cross-lingual word embedding alignment

Self-learning

- 25 word pairs
- Numeral list

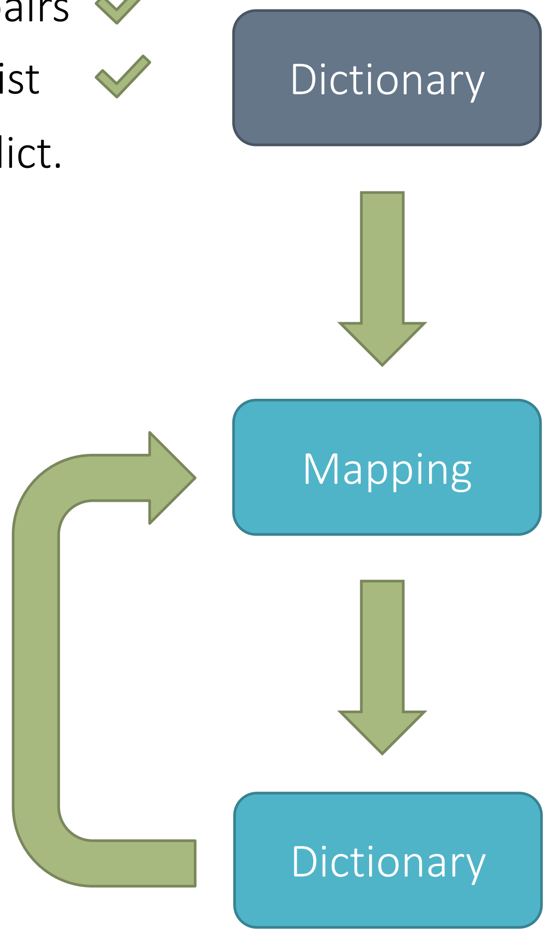


$$W^* = \underset{W \in O(n)}{\arg\min} \sum_i \min_j \|X_{i*}W - Z_{j*}\|^2$$

Cross-lingual word embedding alignment

Self-learning

- 25 word pairs ✓
- Numeral list ✓
- Random dict.

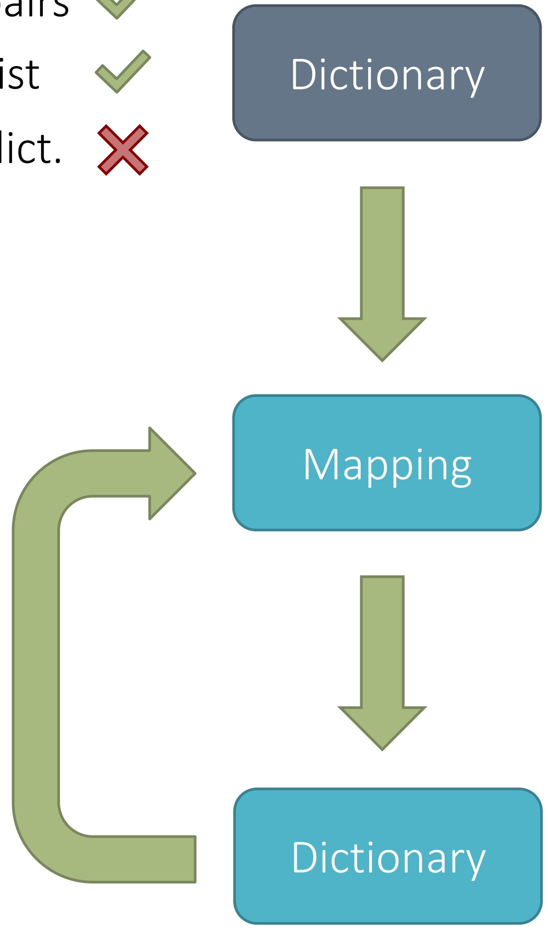


$$W^* = \underset{W \in O(n)}{\arg\min} \sum_i \min_j \lVert X_{i*}W - Z_{j*} \rVert^2$$

Cross-lingual word embedding alignment

Self-learning

- 25 word pairs ✓
- Numeral list ✓
- Random dict. ✗



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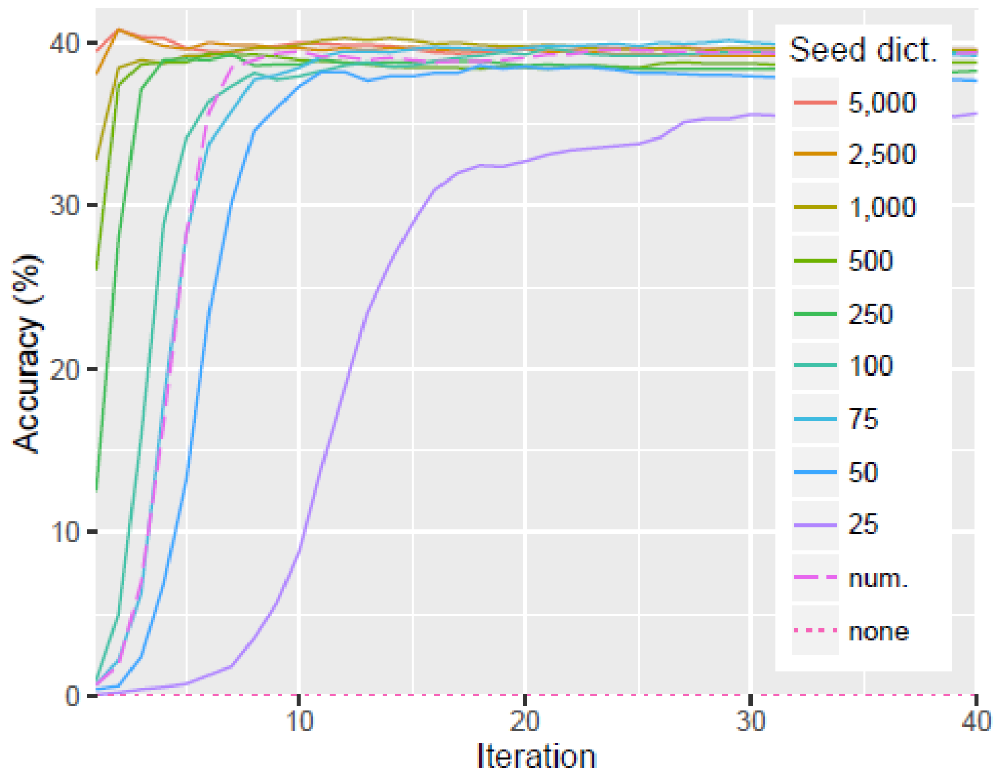
Cross-lingual word embedding alignment



- 25 word pairs ✓
- Numeral list ✓
- Random dict. ✗

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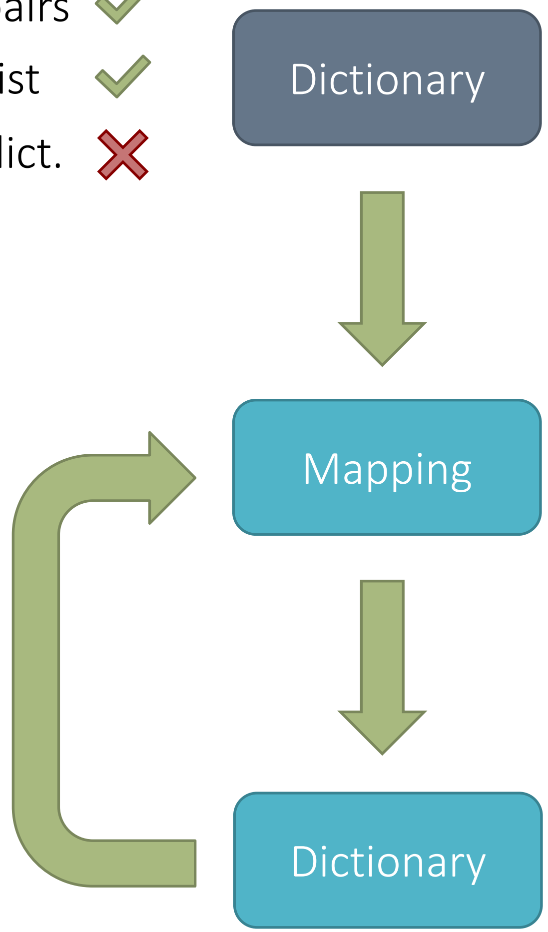
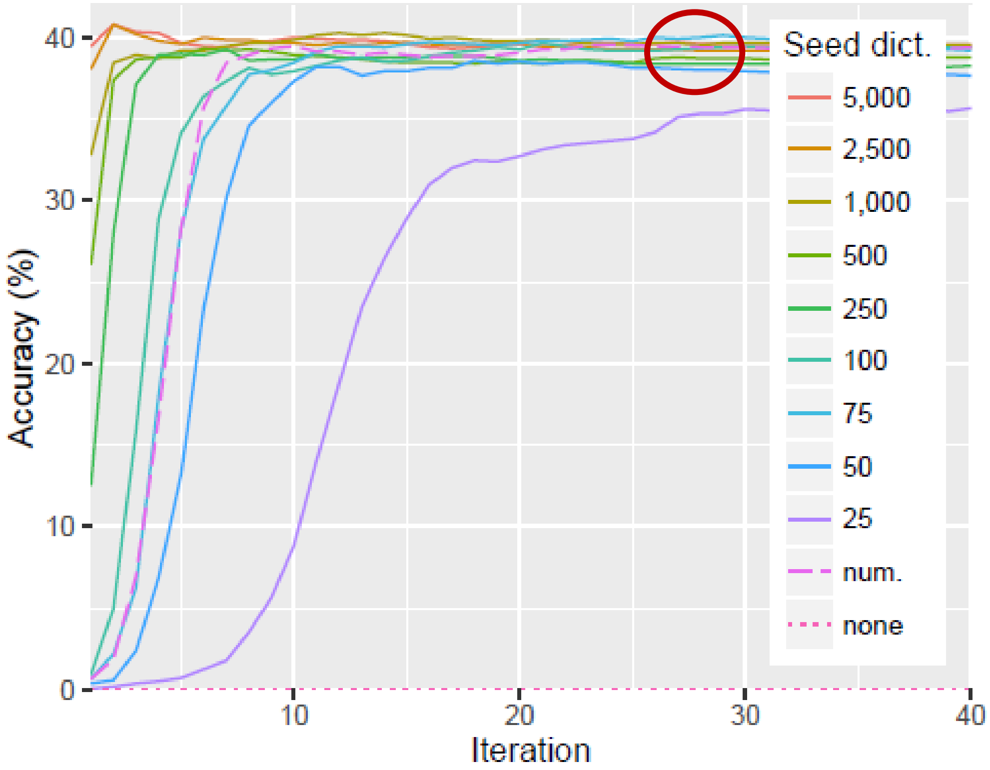
Self-learning



Cross-lingual word embedding alignment



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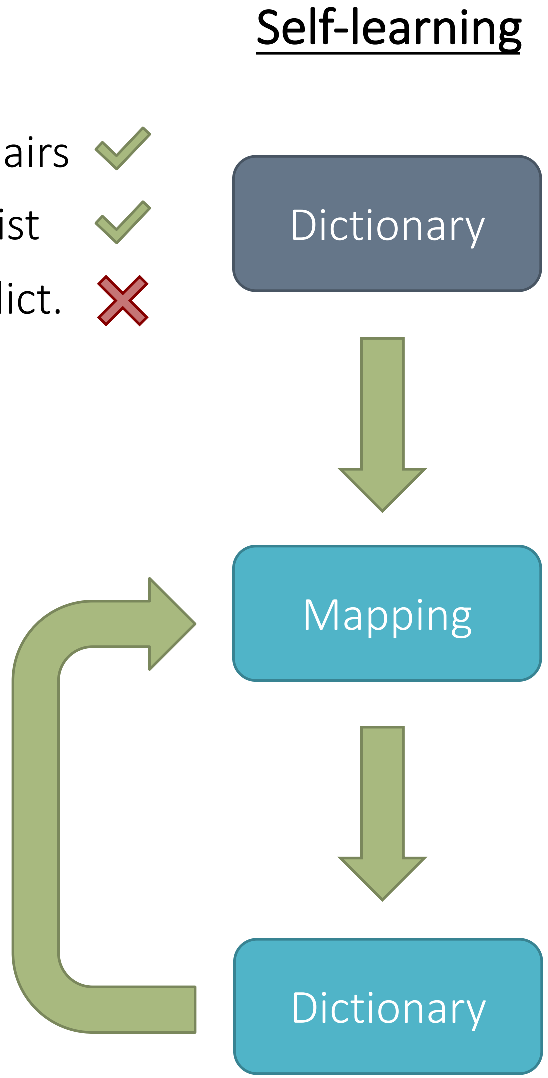
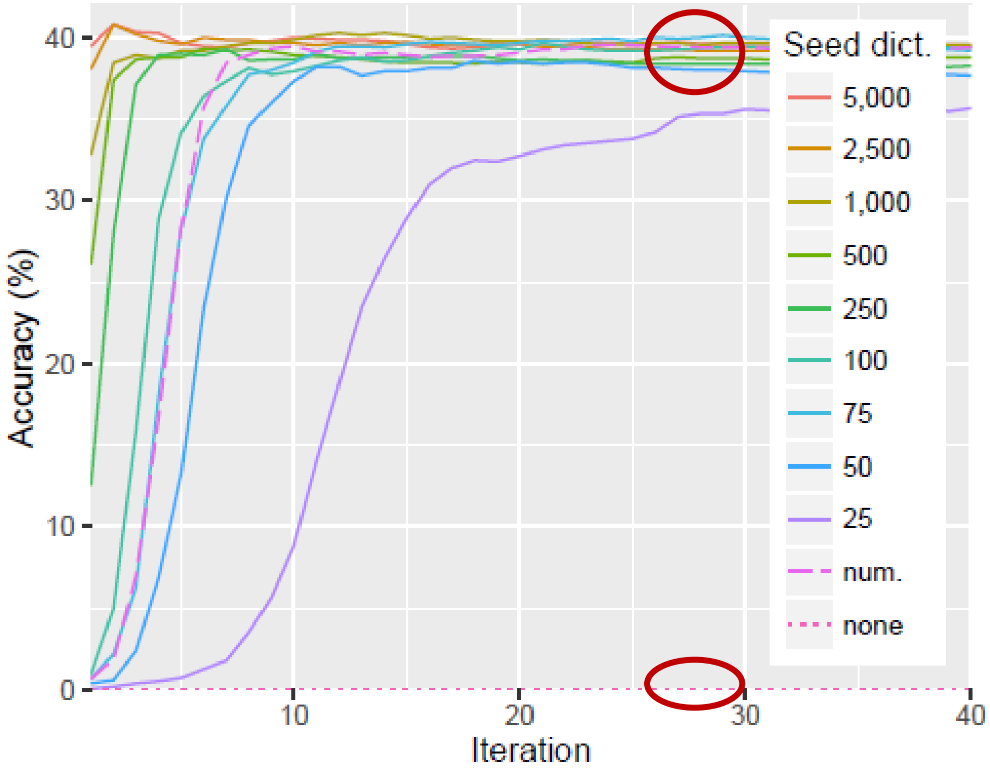


Cross-lingual word embedding alignment



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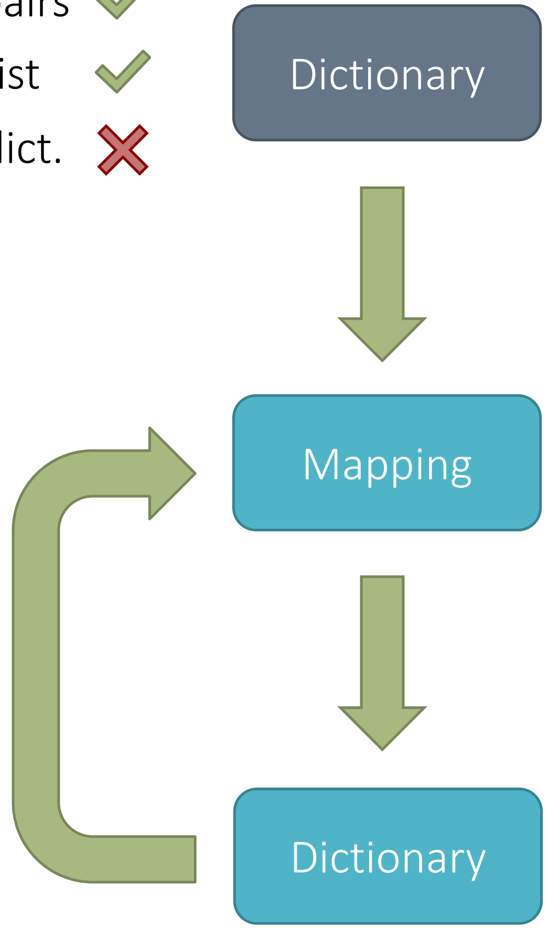
$$W^* = \underset{W \in O(n)}{\arg\min} \sum_i \min_j \|X_{i*}W - Z_{j*}\|^2$$

Self-learning



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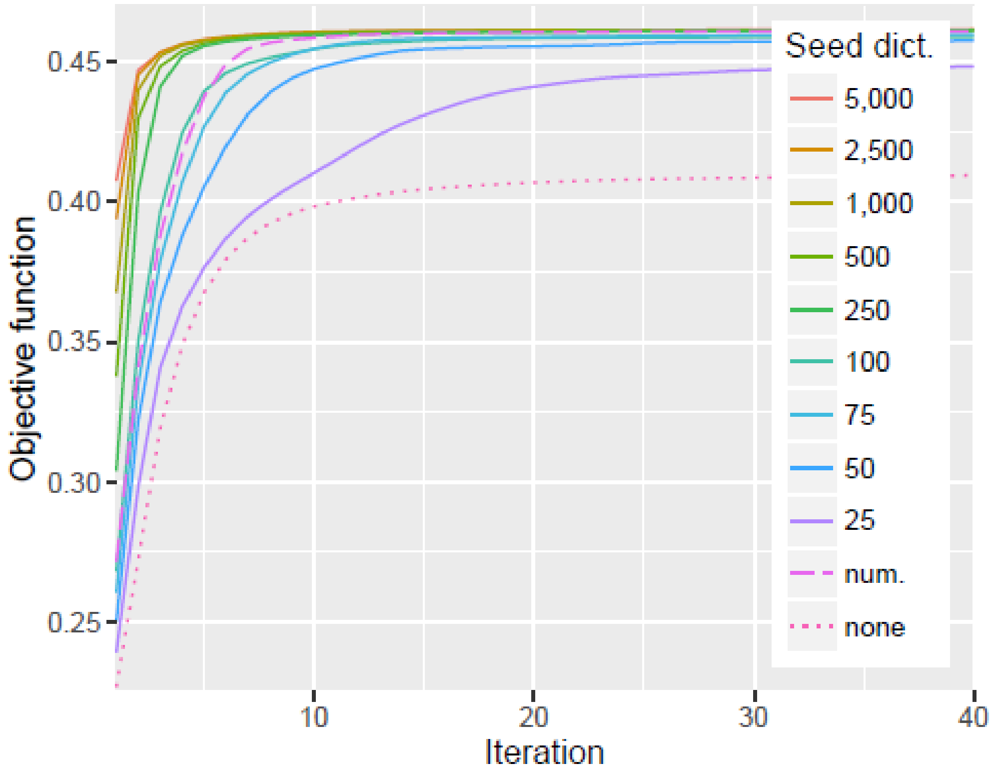

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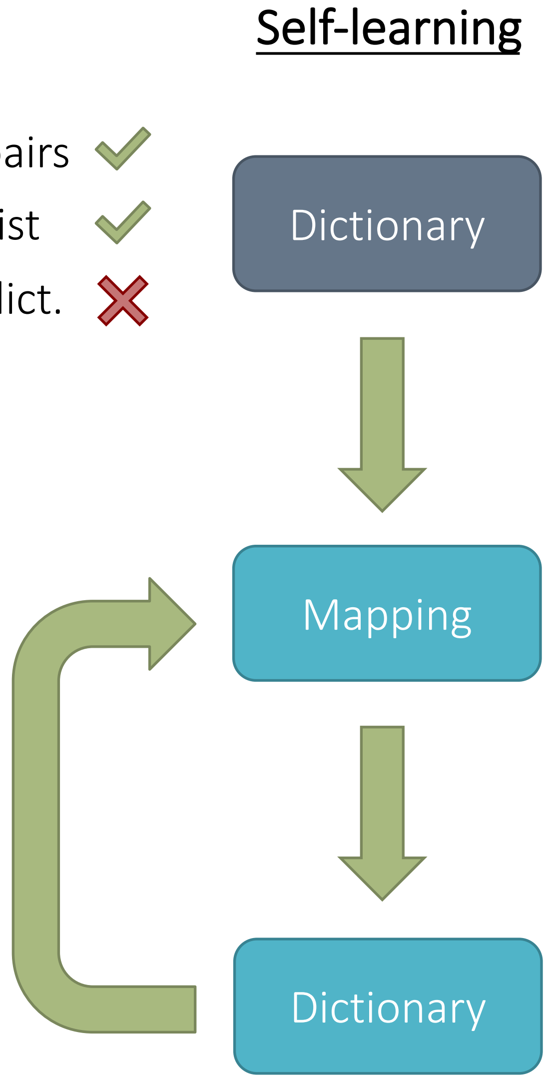
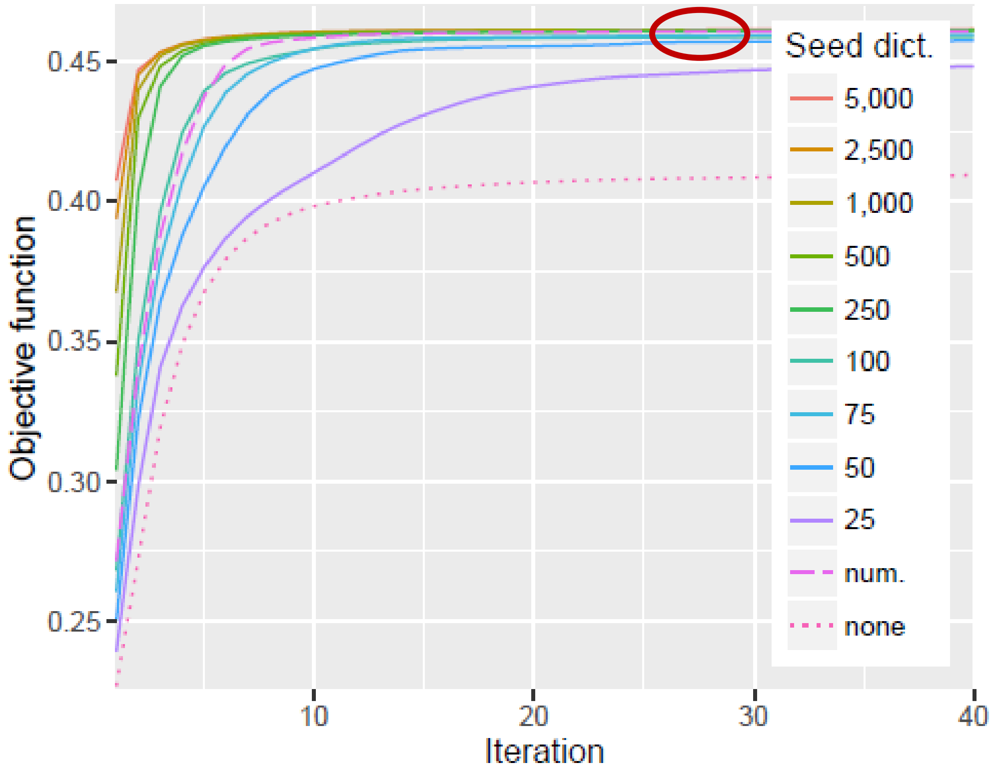


Cross-lingual word embedding alignment



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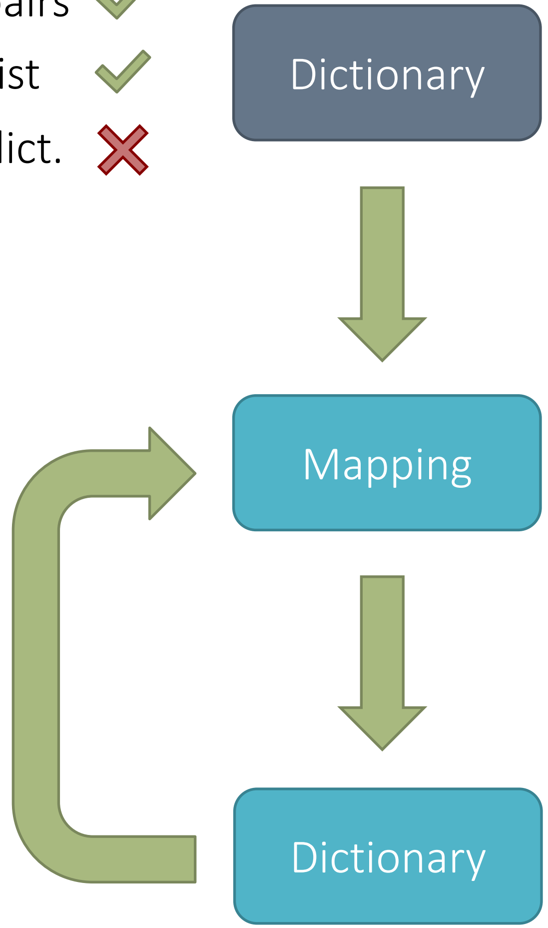
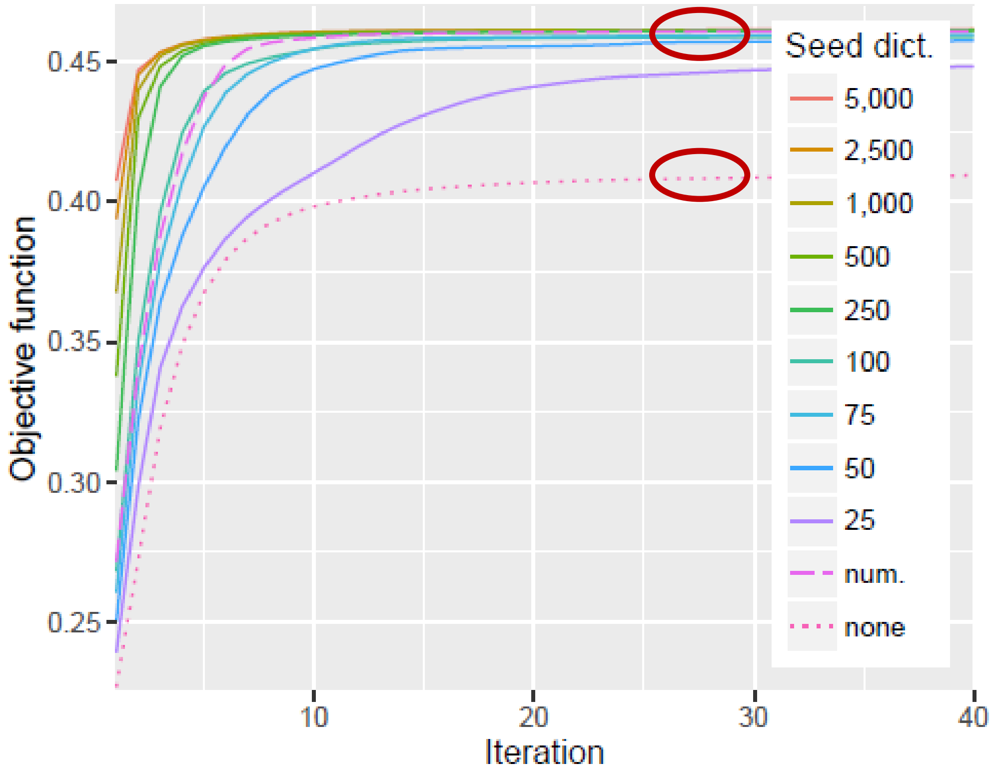
Self-learning



Cross-lingual word embedding alignment



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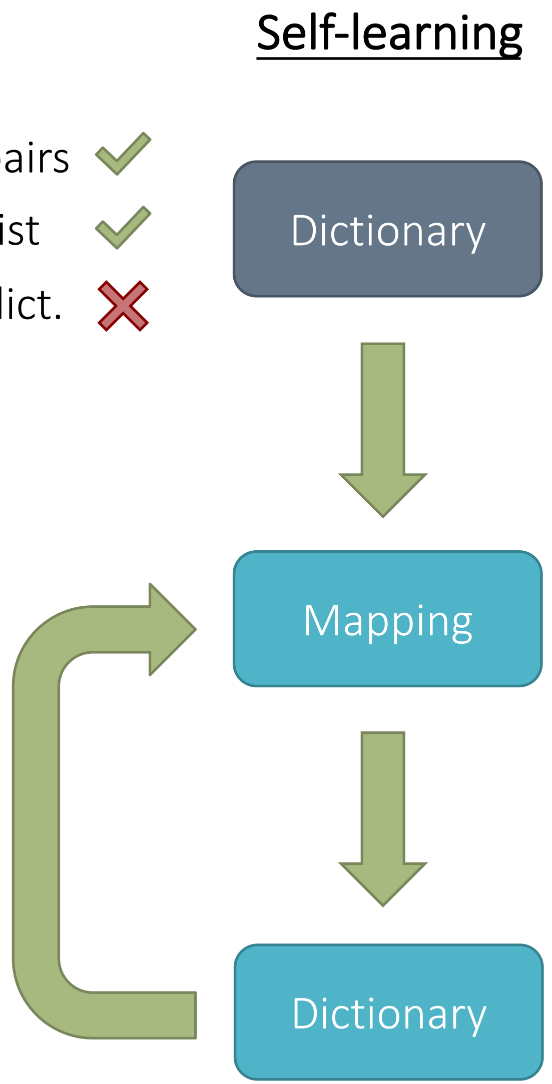
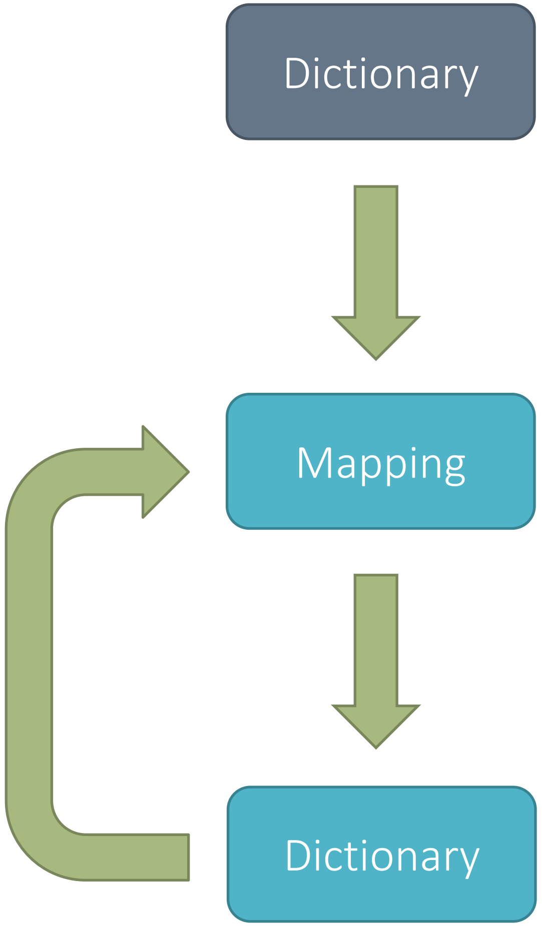


Cross-lingual word embedding alignment

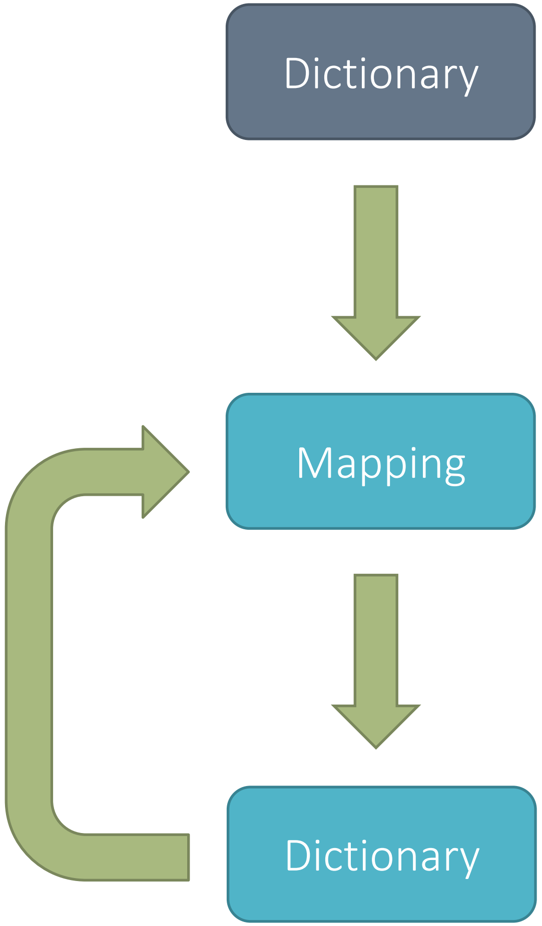
Intra-lingual similarity distribution



Cross-lingual word embedding alignment

English

<u>Intra-lingual similarity distribution</u>

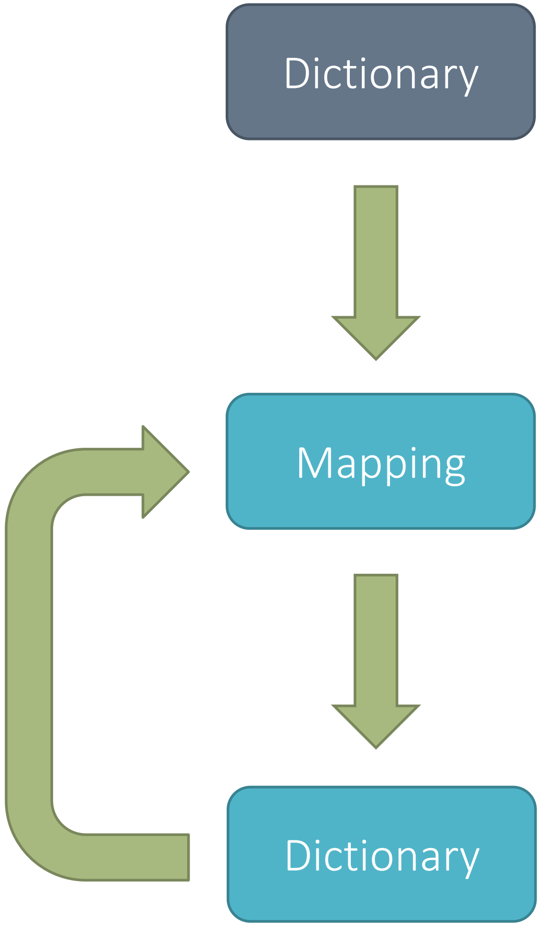


Cross-lingual word embedding alignment

English

two

Intra-lingual similarity distribution



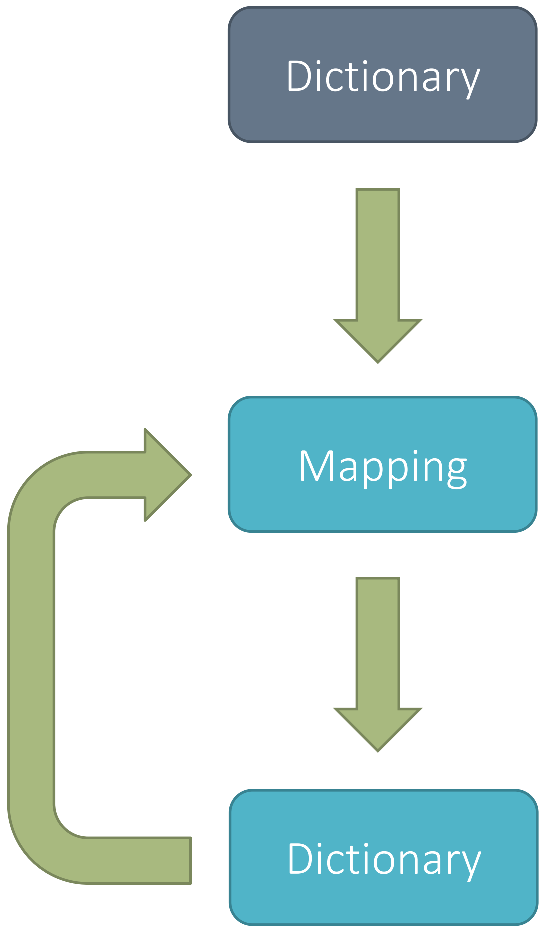
Cross-lingual word embedding alignment

English

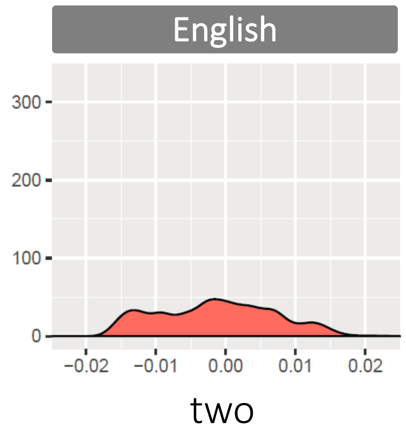
```
for x in vocab:
    sim("two", x)
```

two

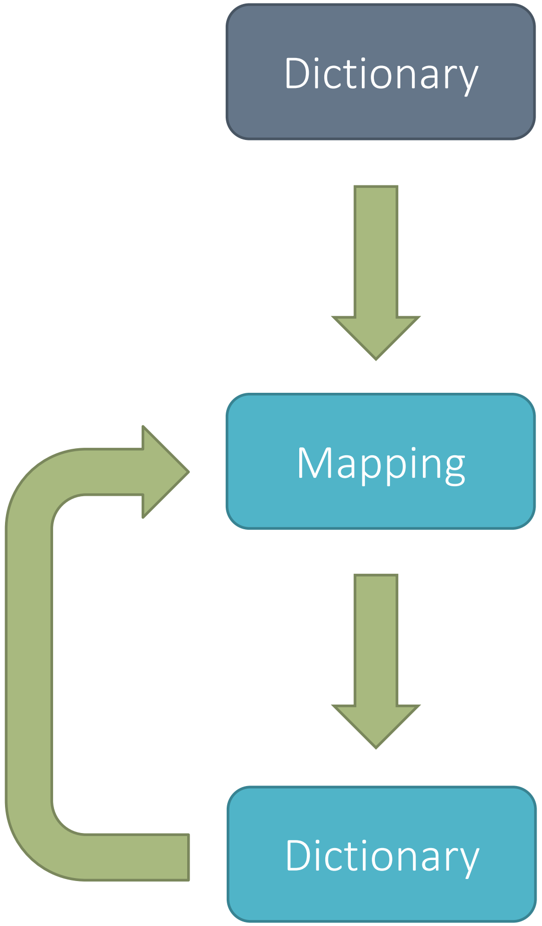
<u>Intra-lingual similarity distribution</u>



Cross-lingual word embedding alignment



Intra-lingual similarity distribution



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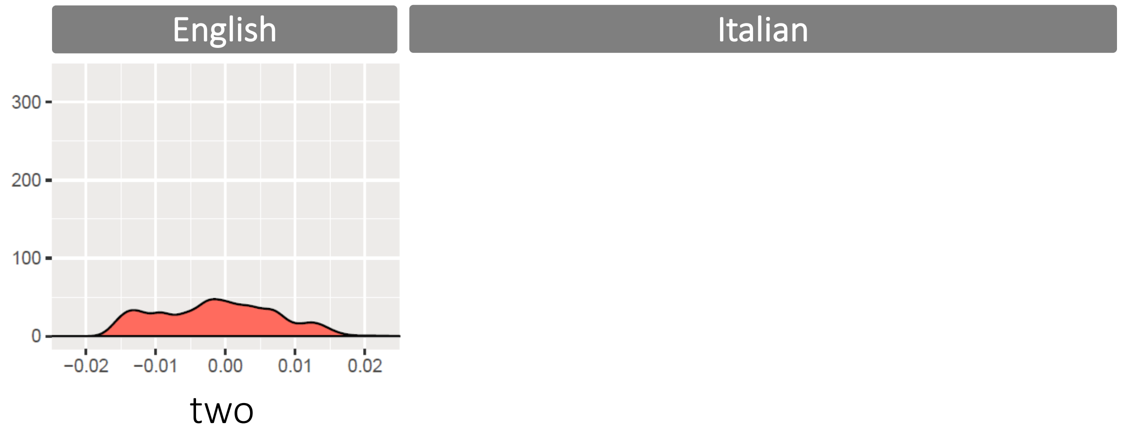
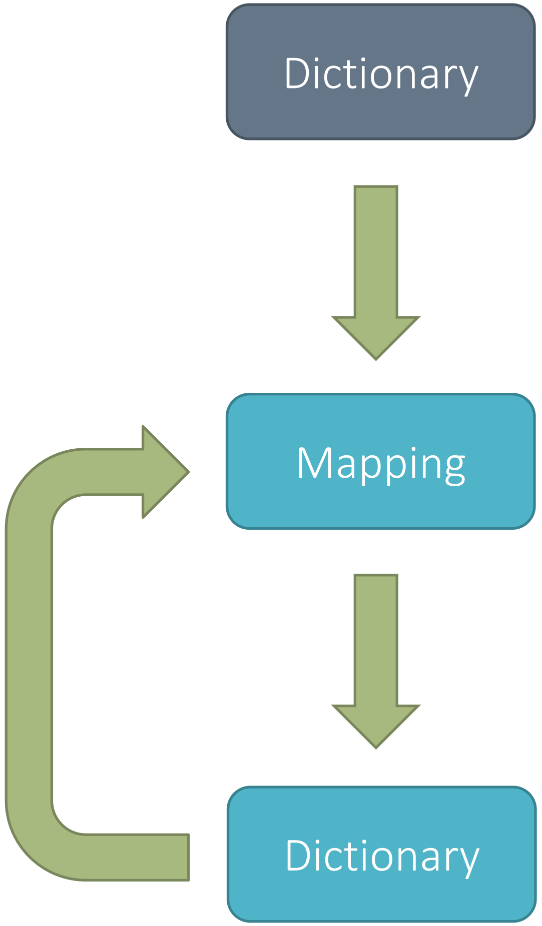


<u>Intra-lingual similarity distribution</u>



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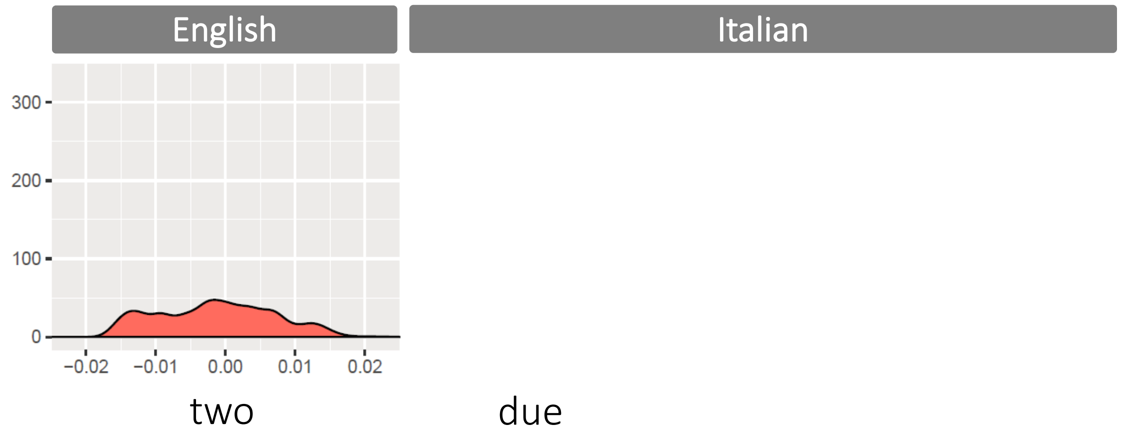
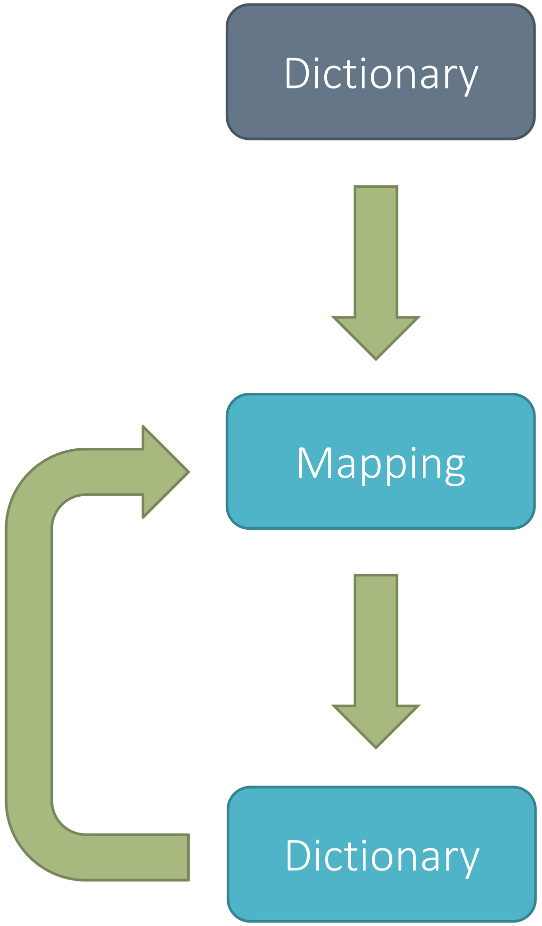


Intra-lingual similarity distribution



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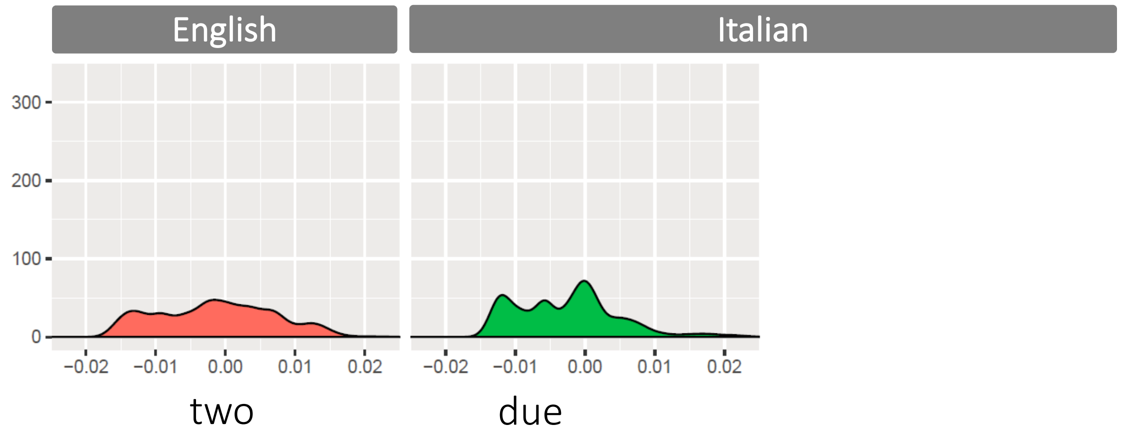
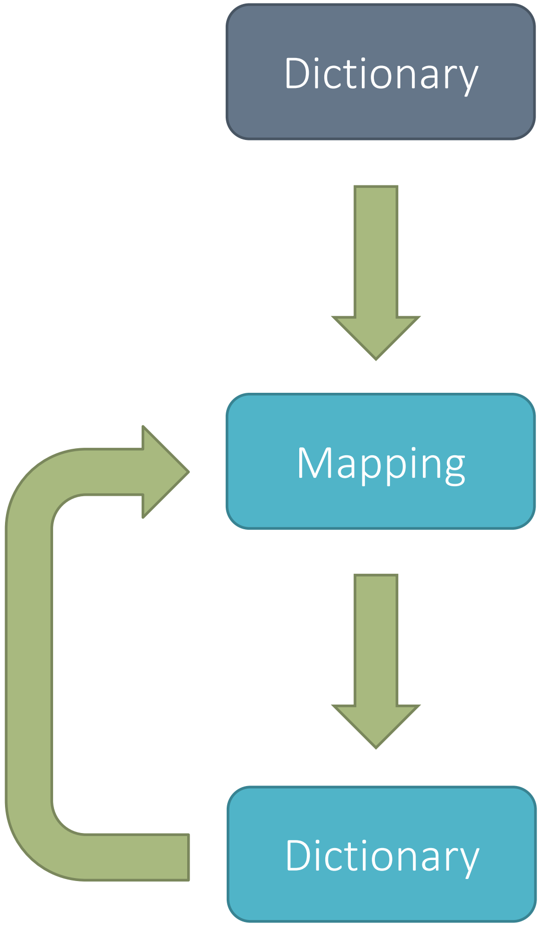


Intra-lingual similarity distribution



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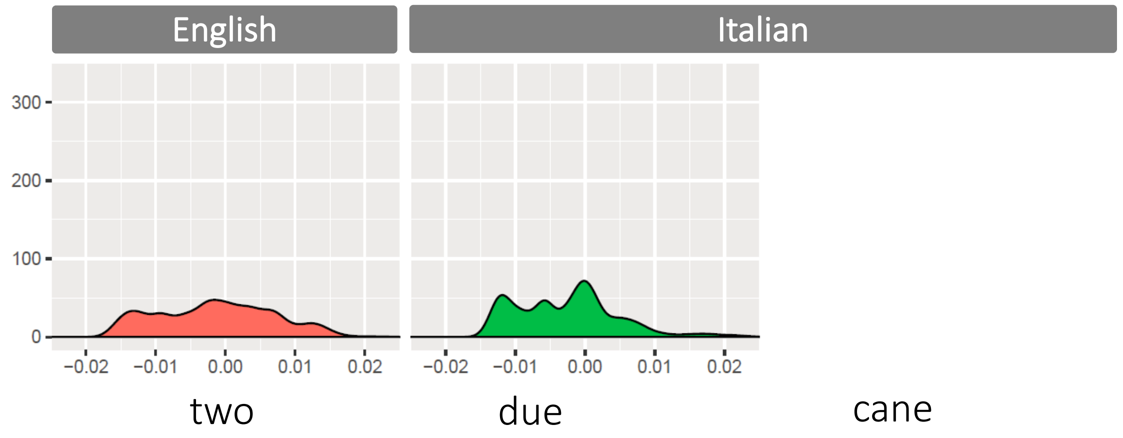
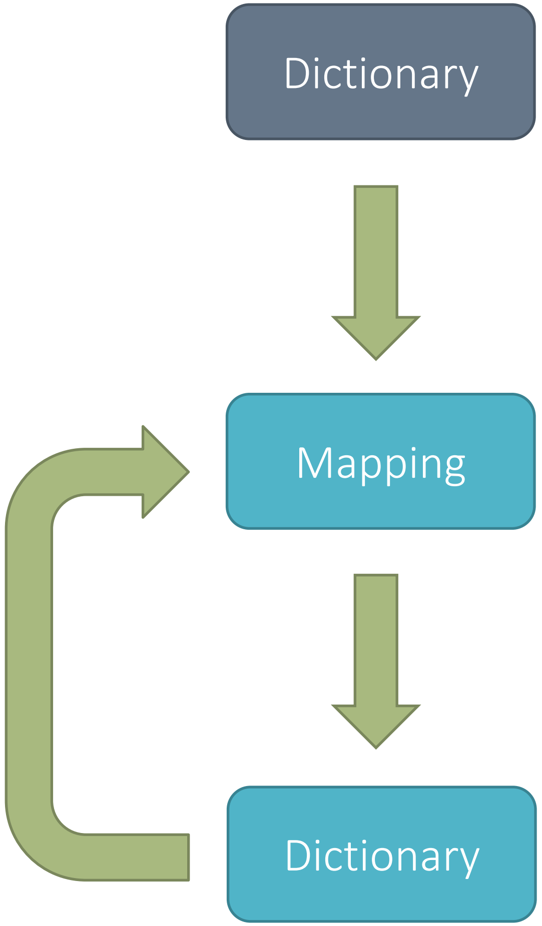
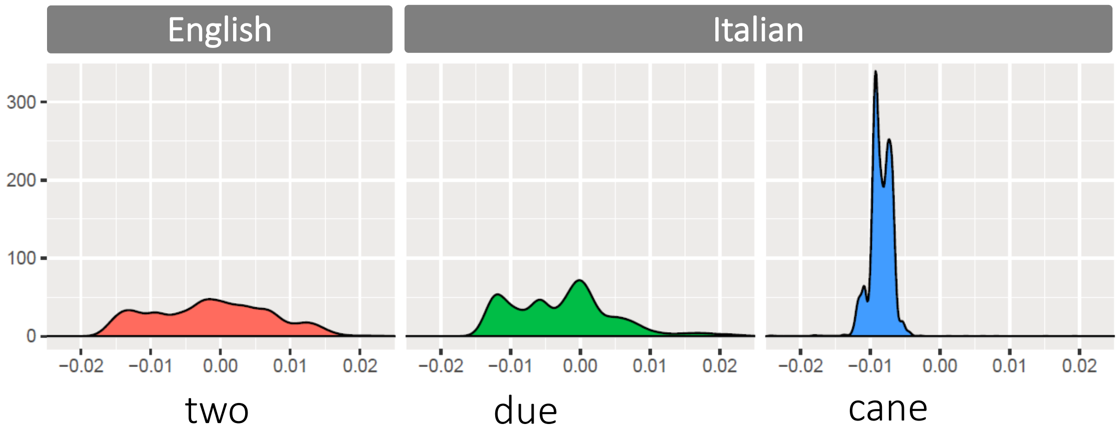


Intra-lingual similarity distribution



Cross-lingual word embedding alignment



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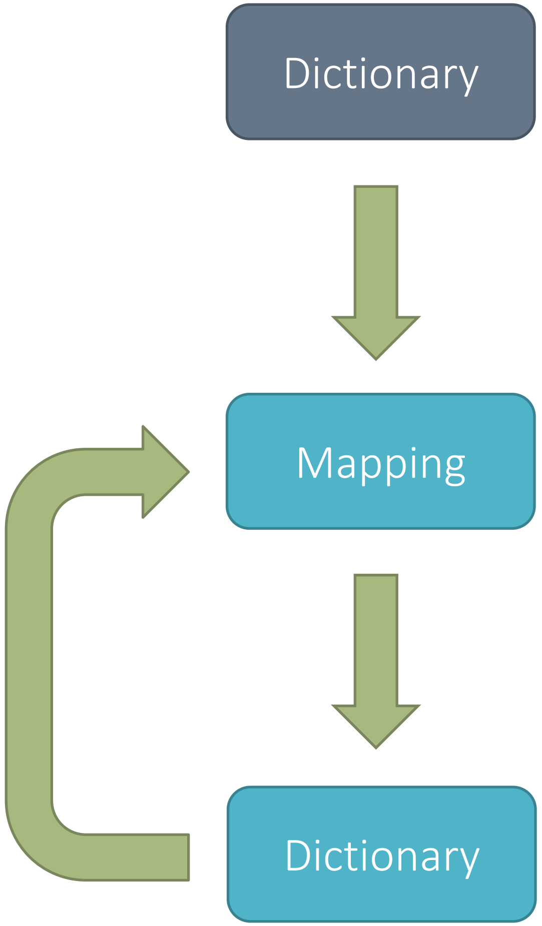
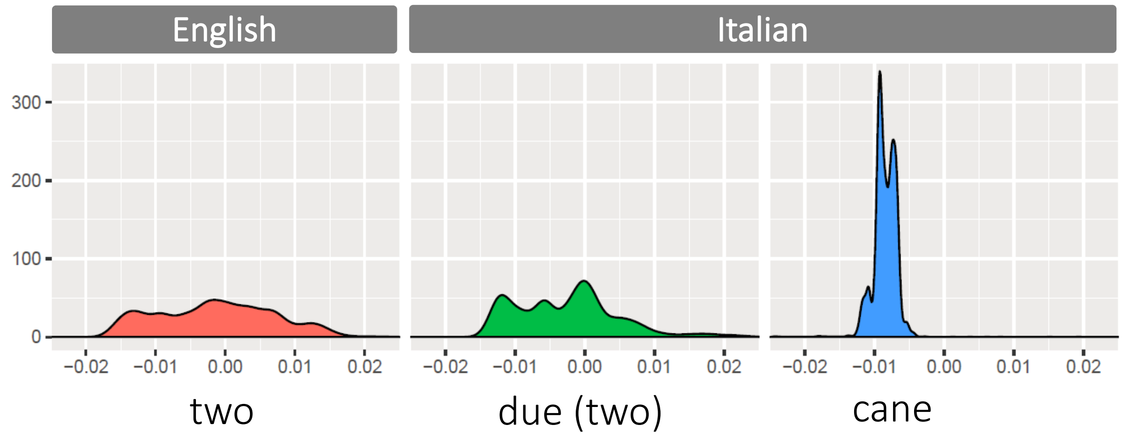
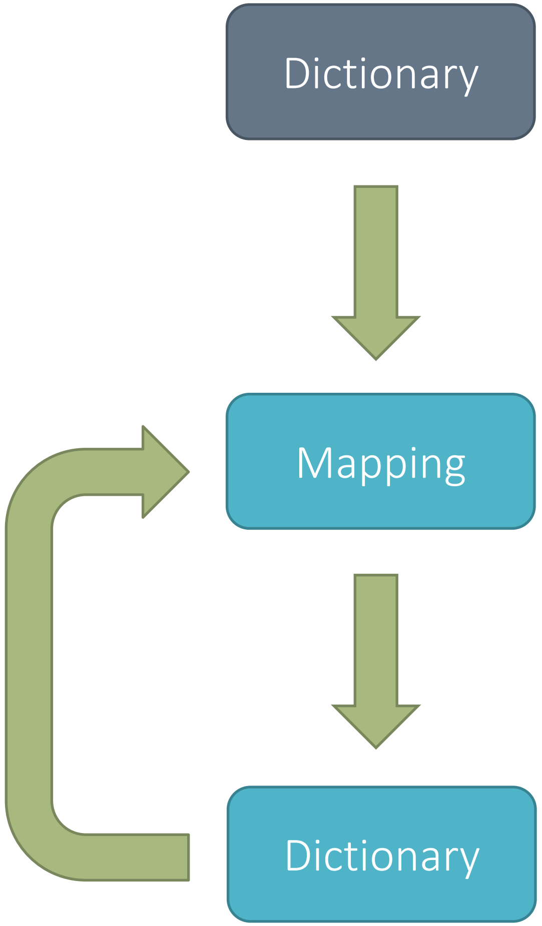


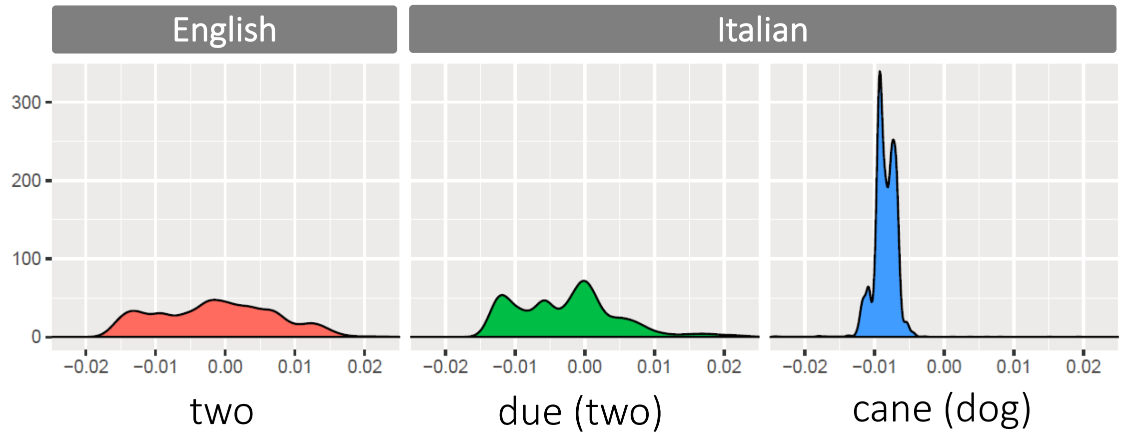
Cross-lingual word embedding alignment



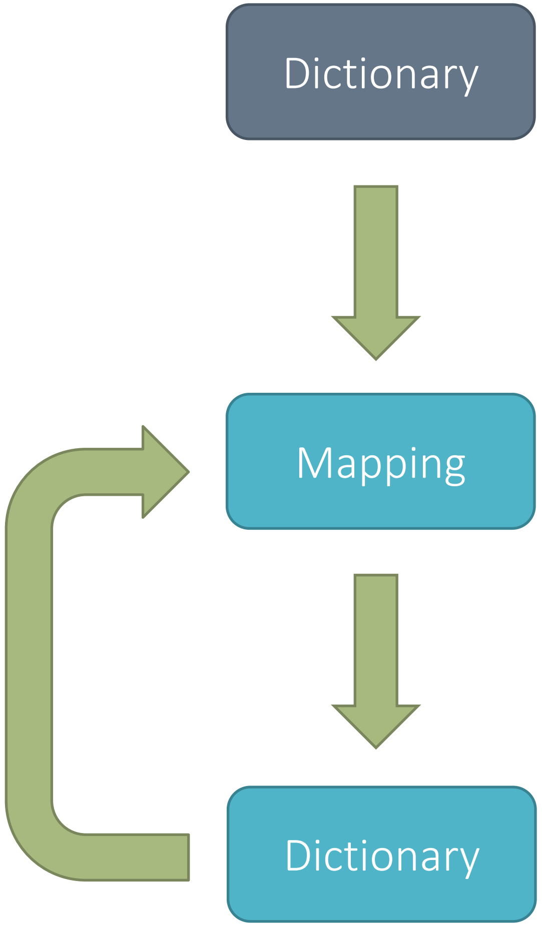
Intra-lingual similarity distribution



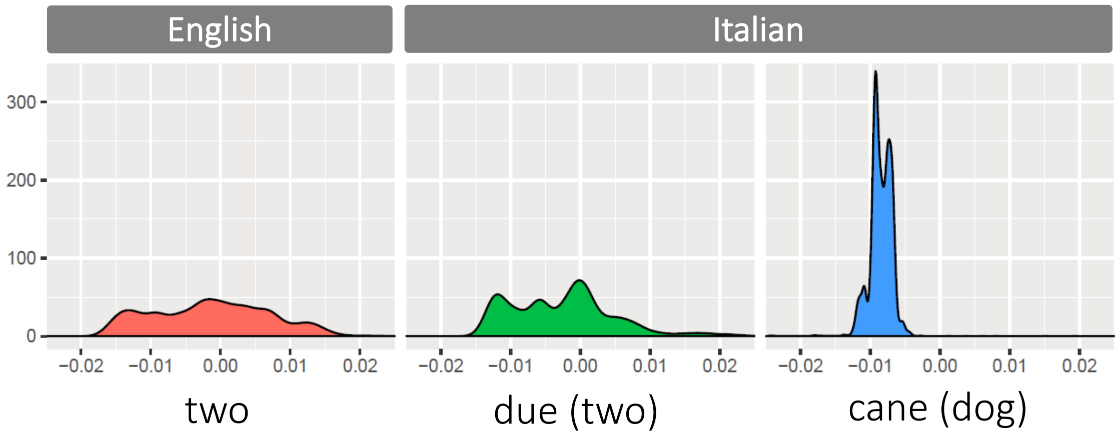
Cross-lingual word embedding alignment



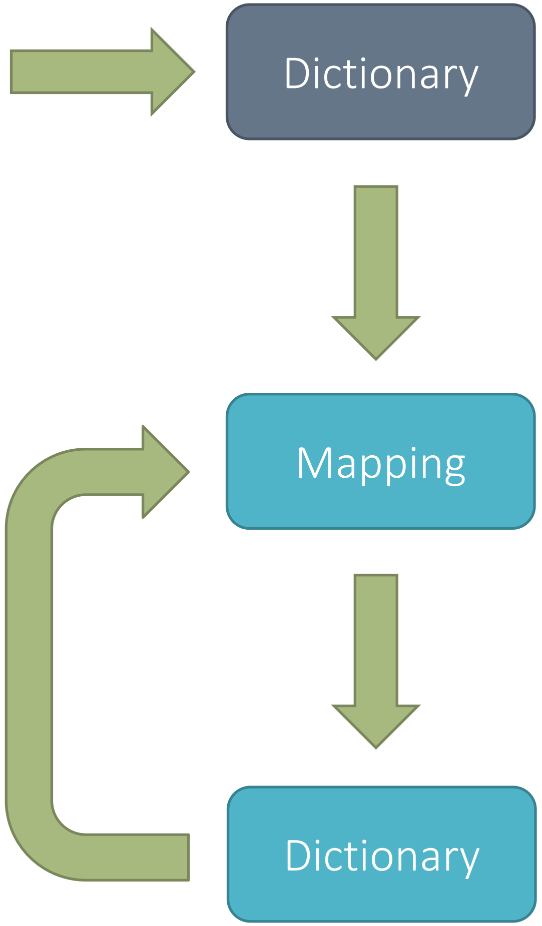
Intra-lingual similarity distribution



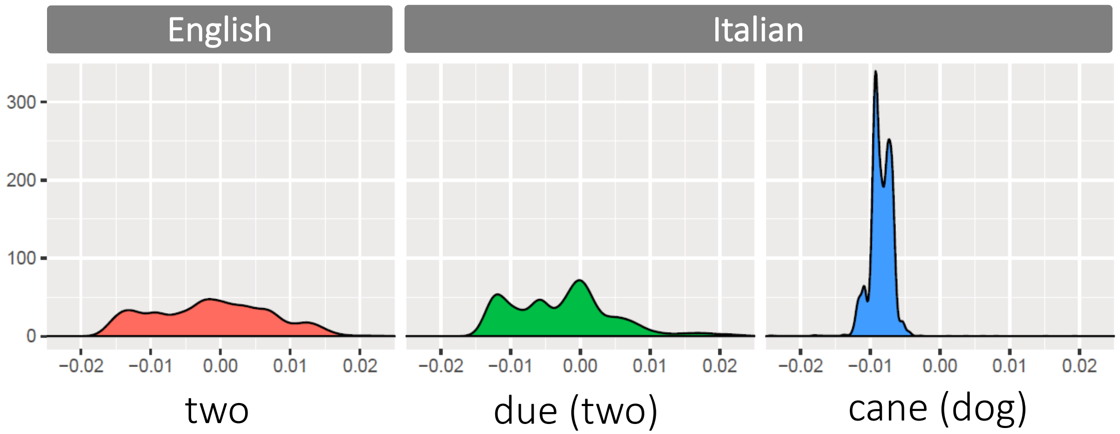
Cross-lingual word embedding alignment



Intra-lingual similarity distribution

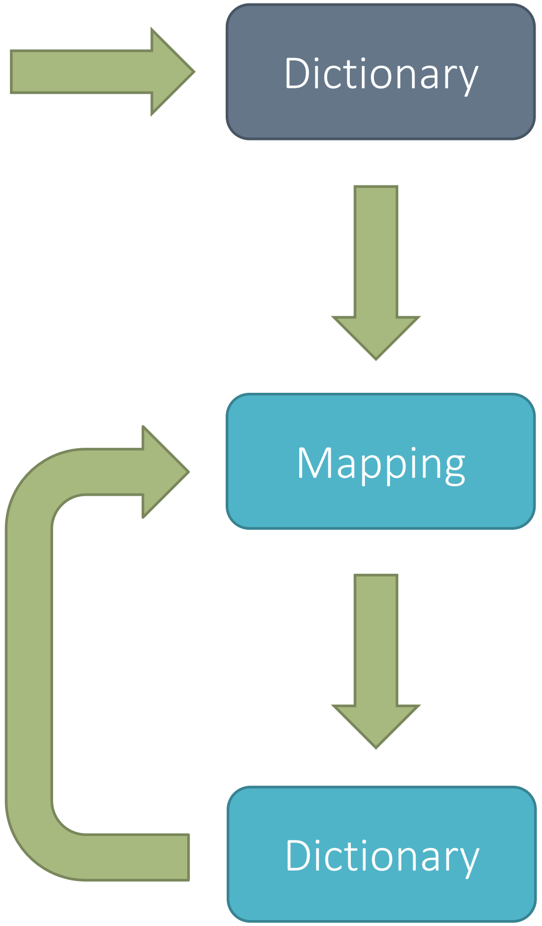


Cross-lingual word embedding alignment

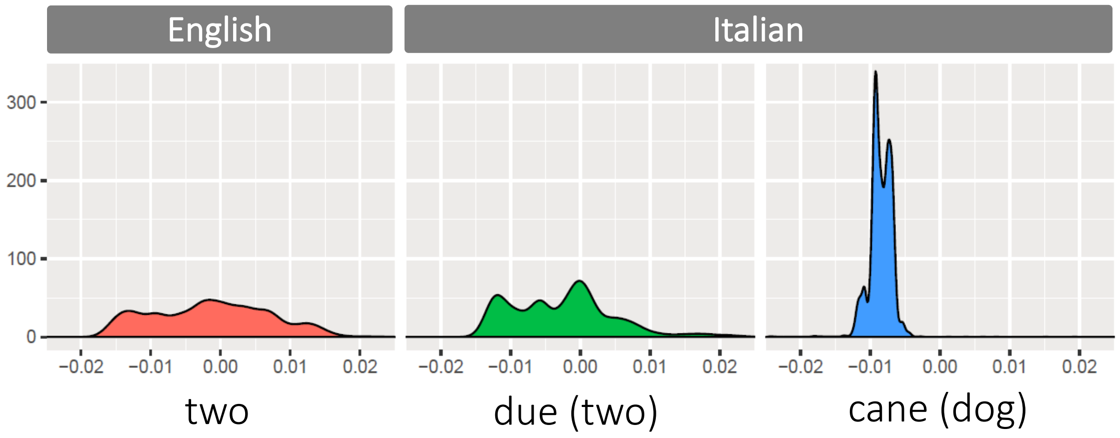


Intra-lingual similarity distribution

$$X' = \text{sorted}\left(\sqrt{XX^T}\right)$$

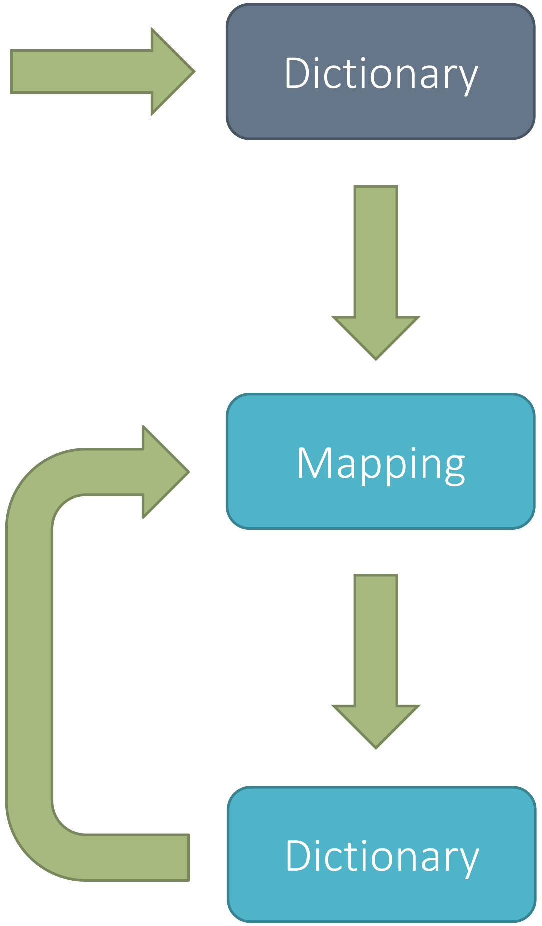


Cross-lingual word embedding alignment

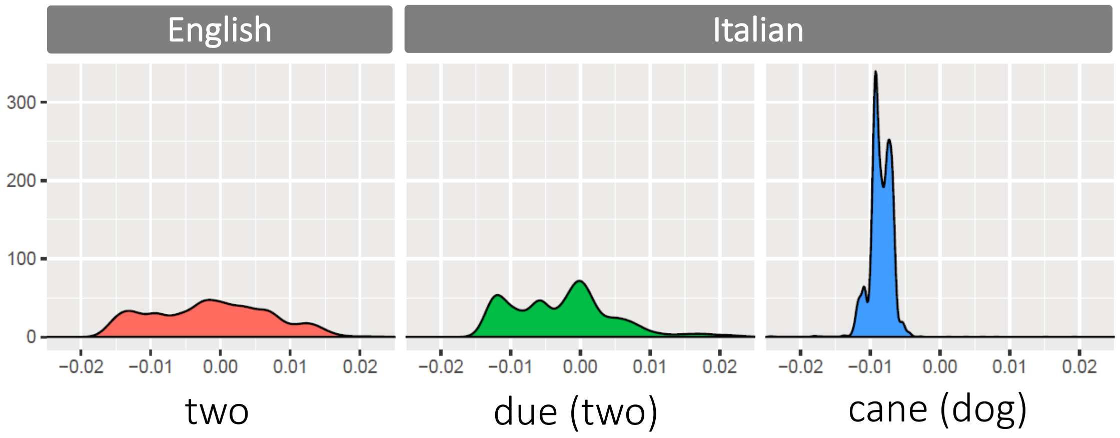


Intra-lingual similarity distribution

$$X' = \text{sorted}\left(\sqrt{XX^T}\right) \quad Z' = \text{sorted}\left(\sqrt{ZZ^T}\right)$$



Cross-lingual word embedding alignment



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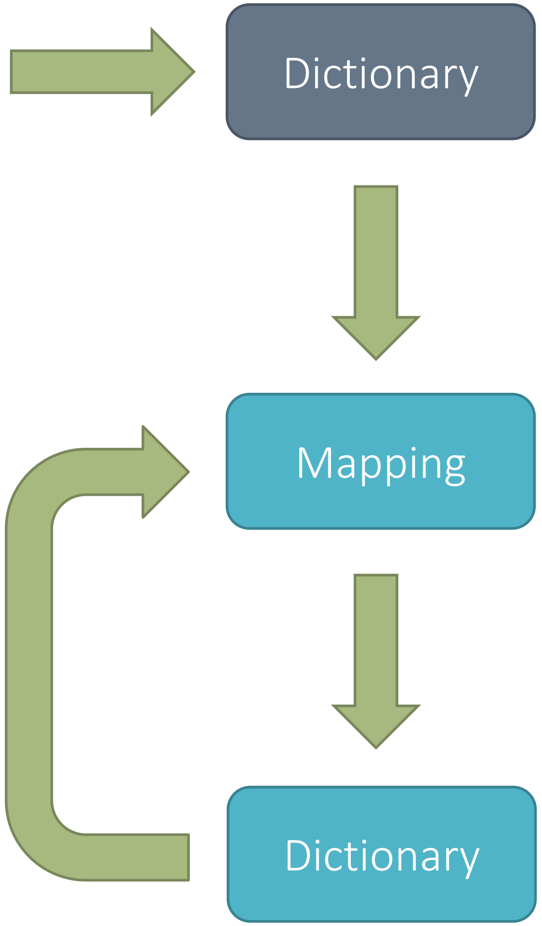
+



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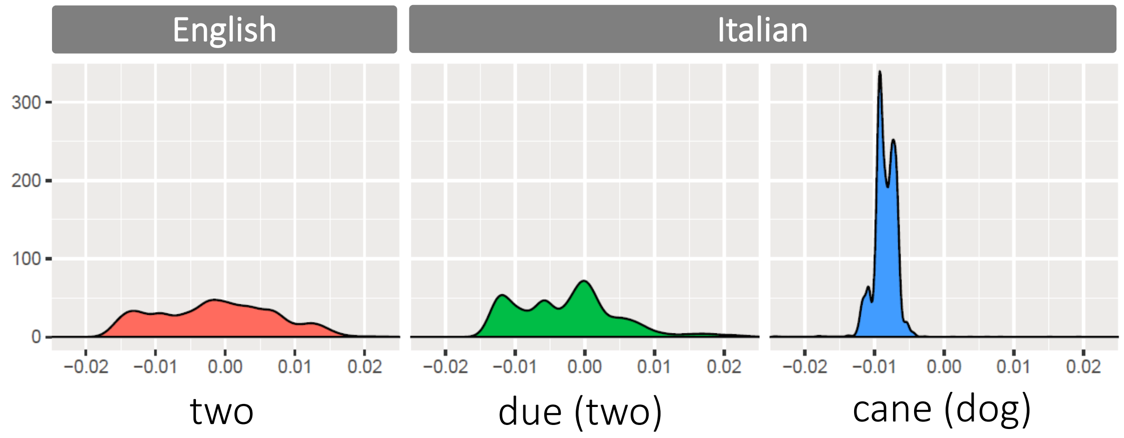

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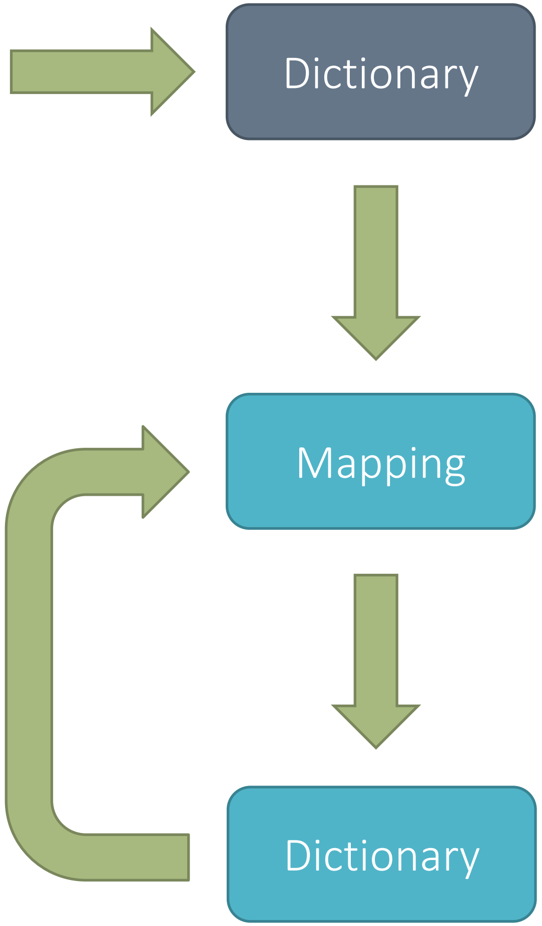
+

Robust self-learning



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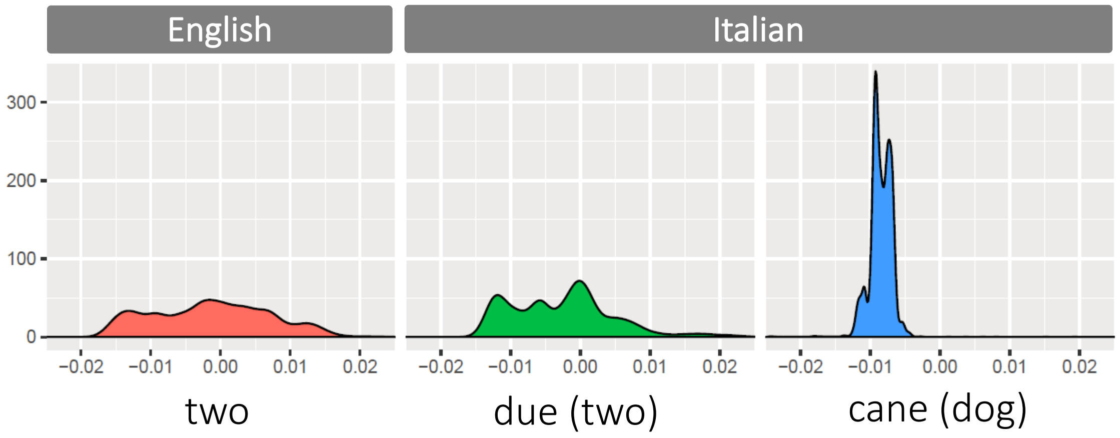


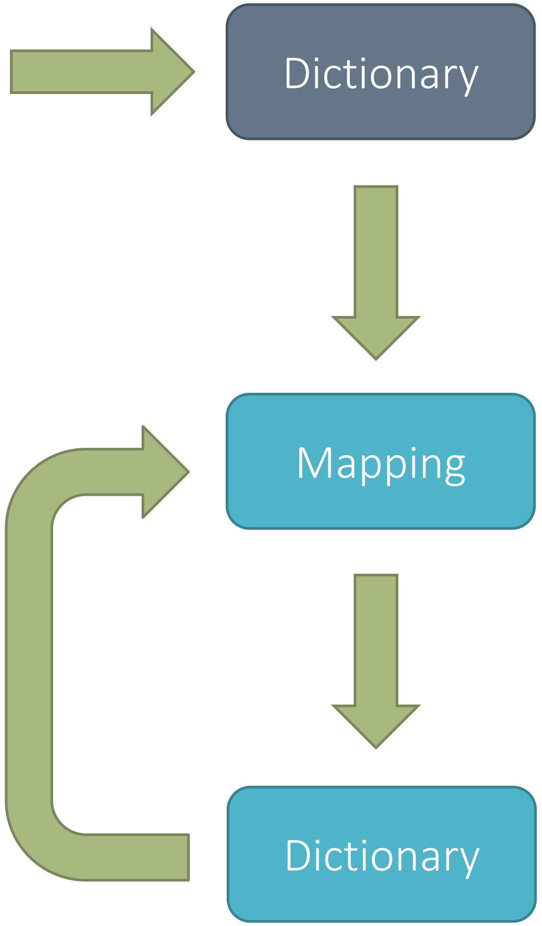
<u>Intra-lingual similarity distribution</u>

$$X' = \text{sorted}\left(\sqrt{XX^T}\right) \quad Z' = \text{sorted}\left(\sqrt{ZZ^T}\right)$$

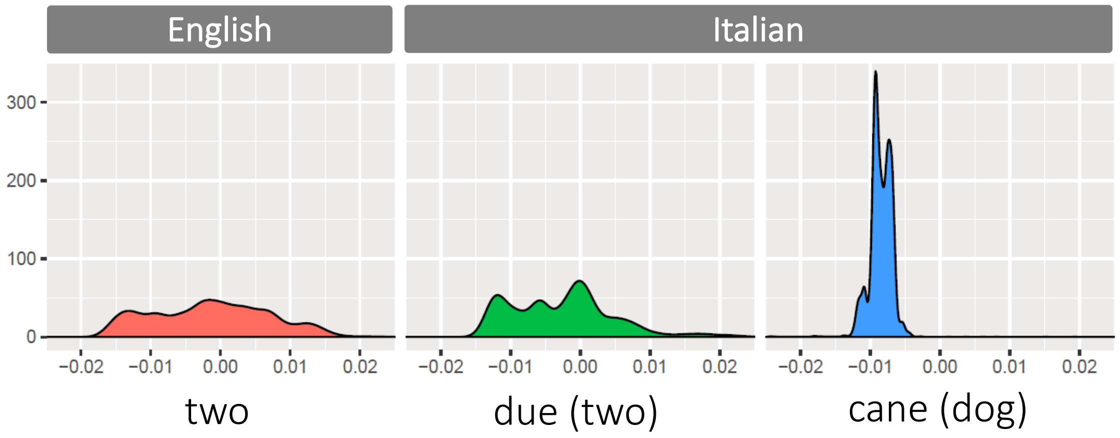
+

<u>Robust self-learning</u>

- Stochastic dictionary induction



Cross-lingual word embedding alignment



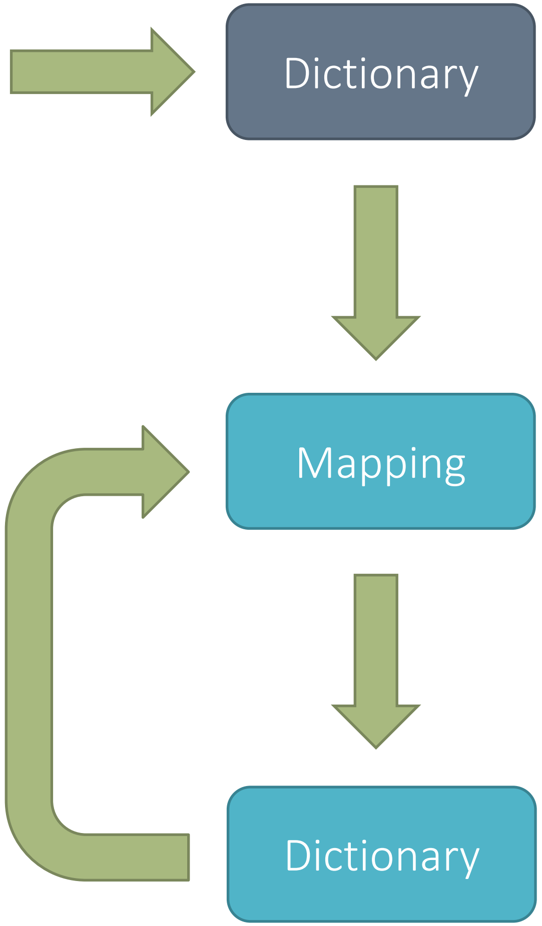
<u>Intra-lingual similarity distribution</u>

$$X' = \text{sorted}\left(\sqrt{XX^T}\right) \quad Z' = \text{sorted}\left(\sqrt{ZZ^T}\right)$$

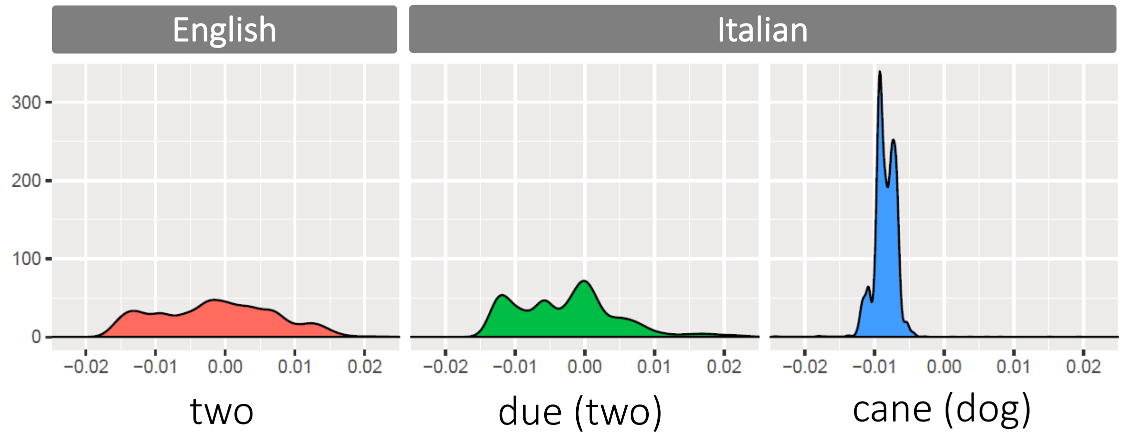
+

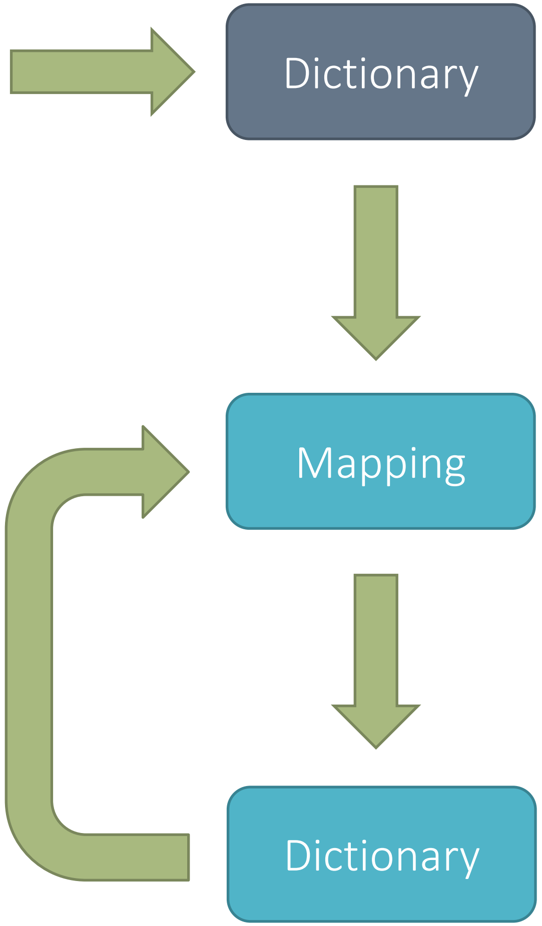
<u>Robust self-learning</u>

- Stochastic dictionary induction
- Frequency-based vocabulary cutoff



Cross-lingual word embedding alignment





Intra-lingual similarity distribution

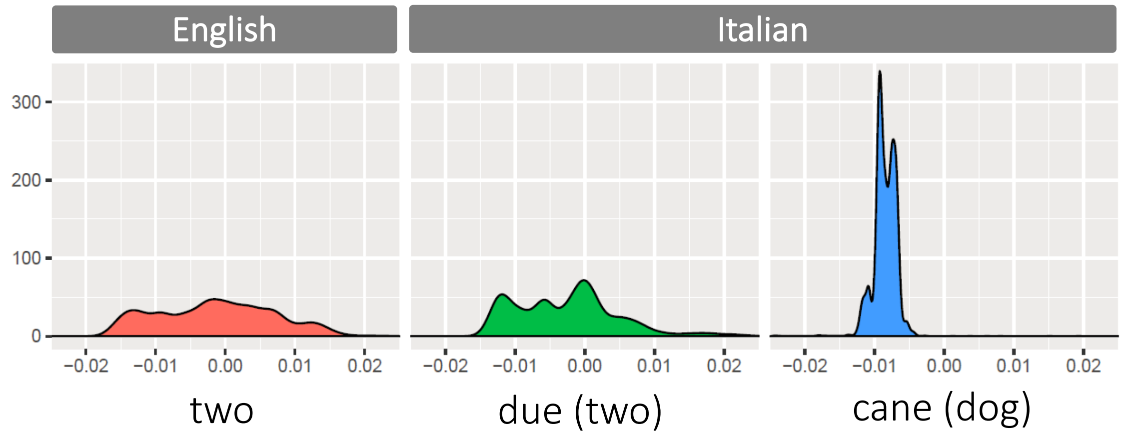
$$X' = \text{sorted}\left(\sqrt{XX^T}\right) \quad Z' = \text{sorted}\left(\sqrt{ZZ^T}\right)$$

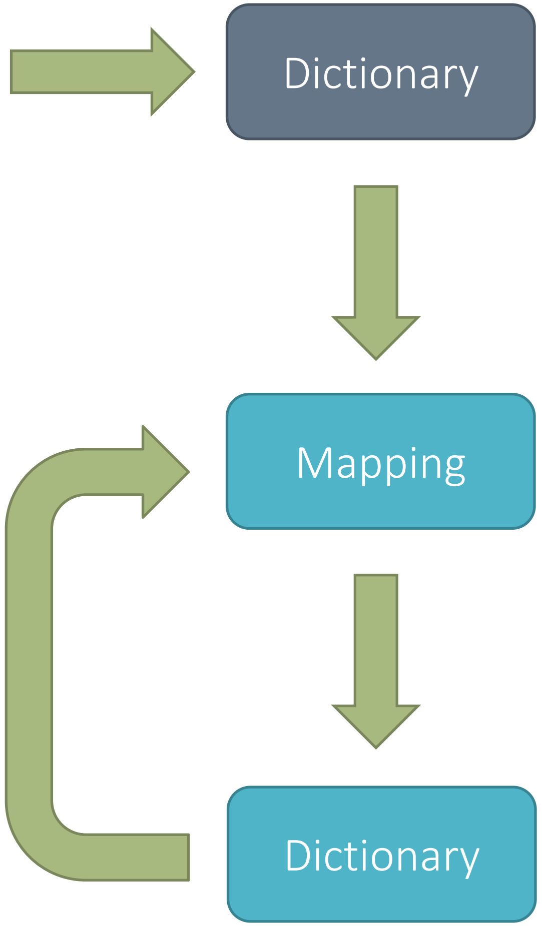
+

Robust self-learning

- Stochastic dictionary induction
- Frequency-based vocabulary cutoff
- CSLS retrieval (Conneau et al., ICLR’18)

Cross-lingual word embedding alignment





Intra-lingual similarity distribution

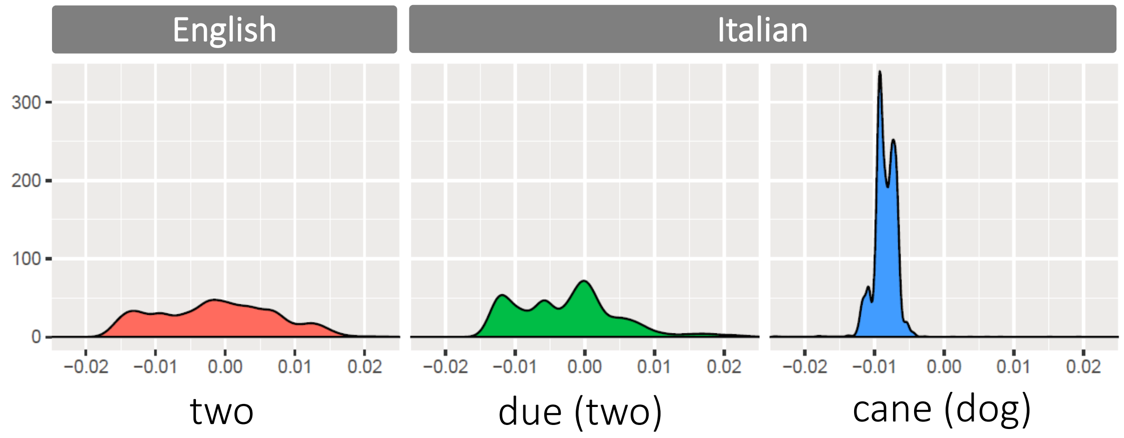
$$X' = \text{sorted}\left(\sqrt{XX^T}\right) \quad Z' = \text{sorted}\left(\sqrt{ZZ^T}\right)$$

+

Robust self-learning

- Stochastic dictionary induction
- Frequency-based vocabulary cutoff
- CSLS retrieval (Conneau et al., ICLR'18)
- Bidirectional dictionary induction

Cross-lingual word embedding alignment



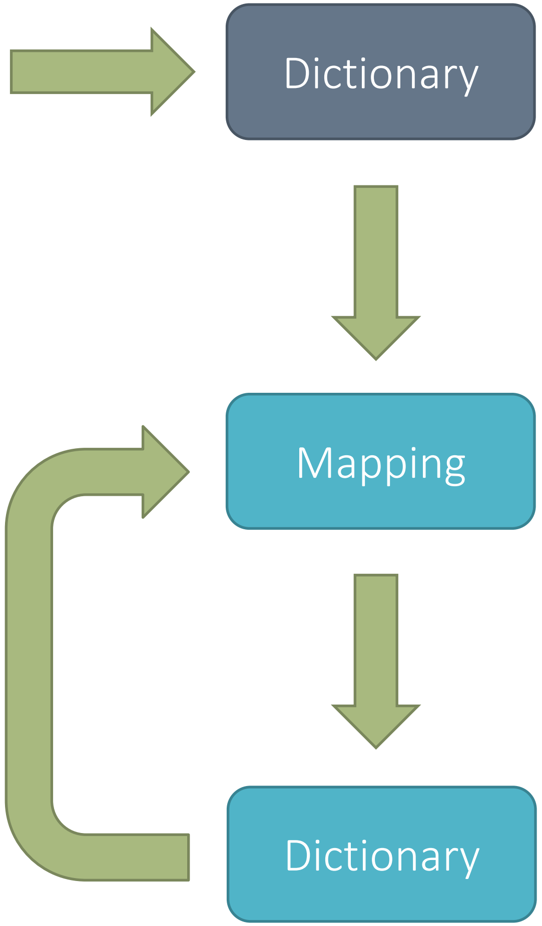
Intra-lingual similarity distribution

$$X' = \text{sorted}\left(\sqrt{XX^T}\right) \quad Z' = \text{sorted}\left(\sqrt{ZZ^T}\right)$$

+

Robust self-learning

- Stochastic dictionary induction
- Frequency-based vocabulary cutoff
- CSLS retrieval (Conneau et al., ICLR'18)
- Bidirectional dictionary induction
- Final symmetric re-weighting



Cross-lingual word embedding alignment

Cross-lingual word embedding alignment

Supervision	Method

Cross-lingual word embedding alignment

Supervision	Method
5k dict.	Mikolov et al. (2013)
	Faruqui and Dyer (2014)
	Shigeto et al. (2015)
	Dinu et al. (2015)
	Lazaridou et al. (2015)
	Xing et al. (2015)
	Zhang et al. (2016)
	Artetxe et al. (2016)
	Smith et al. (2017)
	Artetxe et al. (2018a)

Cross-lingual word embedding alignment

Supervision	Method
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	Lazaridou et al. (2015)
	Xing et al. (2015)
	Zhang et al. (2016)
	Artetxe et al. (2016)
	Smith et al. (2017)
	Artetxe et al. (2018a)
25 dict.	**Artetxe et al. (2017)**

Cross-lingual word embedding alignment

Supervision	Method
5k dict.	Mikolov et al. (2013)
	Faruqui and Dyer (2014)
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	Xing et al. (2015)
	Zhang et al. (2016)
	Artetxe et al. (2016)
	Smith et al. (2017)
	Artetxe et al. (2018a)
25 dict.	**Artetxe et al. (2017)**
Init. heurist.	Smith et al. (2017), cognates
	Artetxe et al. (2017), num.

Cross-lingual word embedding alignment

Supervision	Method
5k dict.	Mikolov et al. (2013)
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	Lazaridou et al. (2015)
	Xing et al. (2015)
	Zhang et al. (2016)
	Artetxe et al. (2016)
	Smith et al. (2017)
	Artetxe et al. (2018a)
25 dict.	**Artetxe et al. (2017)**
Init. heurist.	Smith et al. (2017), cognates
	Artetxe et al. (2017), num.
None	Zhang et al. (2017), $\lambda = 1$
	Zhang et al. (2017), $\lambda = 10$
	Conneau et al. (2018), code‡
	Conneau et al. (2018), paper‡
	Artetxe et al. (2018b)

Cross-lingual word embedding alignment

Supervision	Method	EN-IT	EN-DE	EN-FI	EN-ES
5k dict.	Mikolov et al. (2013)				
	Faruqui and Dyer (2014)				
	Shigeto et al. (2015)				
	Dinu et al. (2015)				
	Lazaridou et al. (2015)				
	Xing et al. (2015)				
	Zhang et al. (2016)				
	Artetxe et al. (2016)				
	Smith et al. (2017)				
	Artetxe et al. (2018a)				
25 dict.	**Artetxe et al. (2017)**				
Init. heurist.	Smith et al. (2017), cognates				
	Artetxe et al. (2017), num.				
None	Zhang et al. (2017), $\lambda = 1$				
	Zhang et al. (2017), $\lambda = 10$				
	Conneau et al. (2018), code‡				
	Conneau et al. (2018), paper‡				
	Artetxe et al. (2018b)				

Cross-lingual word embedding alignment

Supervision	Method	EN-IT	EN-DE	EN-FI	EN-ES
5k dict.	Mikolov et al. (2013)	$34.93^{\dagger}$	$35.00^{\dagger}$	$25.91^{\dagger}$	$27.73^{\dagger}$
	Faruqui and Dyer (2014)	38.40^{*}	37.13^{*}	27.60^{*}	26.80^{*}
	Shigeto et al. (2015)	$41.53^{\dagger}$	$43.07^{\dagger}$	$31.04^{\dagger}$	$33.73^{\dagger}$
	Dinu et al. (2015)	37.7	38.93^{*}	29.14^{*}	30.40^{*}
	Lazaridou et al. (2015)	40.2	-	-	-
	Xing et al. (2015)	$36.87^{\dagger}$	$41.27^{\dagger}$	$28.23^{\dagger}$	$31.20^{\dagger}$
	Zhang et al. (2016)	$36.73^{\dagger}$	$40.80^{\dagger}$	$28.16^{\dagger}$	$31.07^{\dagger}$
	Artetxe et al. (2016)	39.27	41.87^{*}	30.62^{*}	31.40^{*}
	Smith et al. (2017)	43.1	$43.33^{\dagger}$	$29.42^{\dagger}$	$35.13^{\dagger}$
	Artetxe et al. (2018a)	45.27	44.13	**32.94**	36.60
25 dict.	**Artetxe et al. (2017)**	37.27	39.60	28.16	-
Init. heurist.	Smith et al. (2017), cognates	39.9	-	-	-
	Artetxe et al. (2017), num.	39.40	40.27	26.47	-
None	Zhang et al. (2017), $\lambda = 1$	0.00^{*}	0.00^{*}	0.00^{*}	0.00^{*}
	Zhang et al. (2017), $\lambda = 10$	0.00^{*}	0.00^{*}	0.01^{*}	0.01^{*}
	Conneau et al. (2018), code‡	45.15^{*}	46.83^{*}	0.38^{*}	35.38^{*}
	Conneau et al. (2018), paper‡	45.1	0.01^{*}	0.01^{*}	35.44^{*}
	Artetxe et al. (2018b)	**48.13**	**48.19**	32.63	**37.33**

Cross-lingual word embedding alignment

Supervision	Method	EN-IT	EN-DE	EN-FI	EN-ES
5k dict.	Mikolov et al. (2013)	34.93†	35.00†	25.91†	27.73†
	Faruqui and Dyer (2014)	38.40*	37.13*	27.60*	26.80*
	Shigeto et al. (2015)	41.53†	43.07†	31.04†	33.73†
	Dinu et al. (2015)	37.7	38.93*	29.14*	30.40*
	Lazaridou et al. (2015)	40.2	-	-	-
	Xing et al. (2015)	36.87†	41.27†	28.23†	31.20†
	Zhang et al. (2016)	36.73†	40.80†	28.16†	31.07†
	Artetxe et al. (2016)	39.27	41.87*	30.62*	31.40*
	Smith et al. (2017)	43.1	43.33†	29.42†	35.13†
	Artetxe et al. (2018a)	45.27	44.13	**32.94**	36.60
25 dict.	**Artetxe et al. (2017)**	37.27	39.60	28.16	-
Init. heurist.	Smith et al. (2017), cognates	39.9	-	-	-
	Artetxe et al. (2017), num.	39.40	40.27	26.47	-
None	Zhang et al. (2017), $\lambda = 1$	0.00*	0.00*	0.00*	0.00*
	Zhang et al. (2017), $\lambda = 10$	0.00*	0.00*	0.01*	0.01*
	Conneau et al. (2018), code‡	45.15*	46.83*	0.38*	35.38*
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None	Zhang et al. (2017), $\lambda = 1$	0.00*	0.00*	0.00*	0.00*
	Zhang et al. (2017), $\lambda = 10$	0.00*	0.00*	0.01*	0.01*
	Conneau et al. (2018), code‡	45.15*	46.83*	0.38*	35.38*
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Cross-lingual word embedding alignment

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	Conneau et al. (2018), paper‡	45.1	0.01*	0.01*	35.44*
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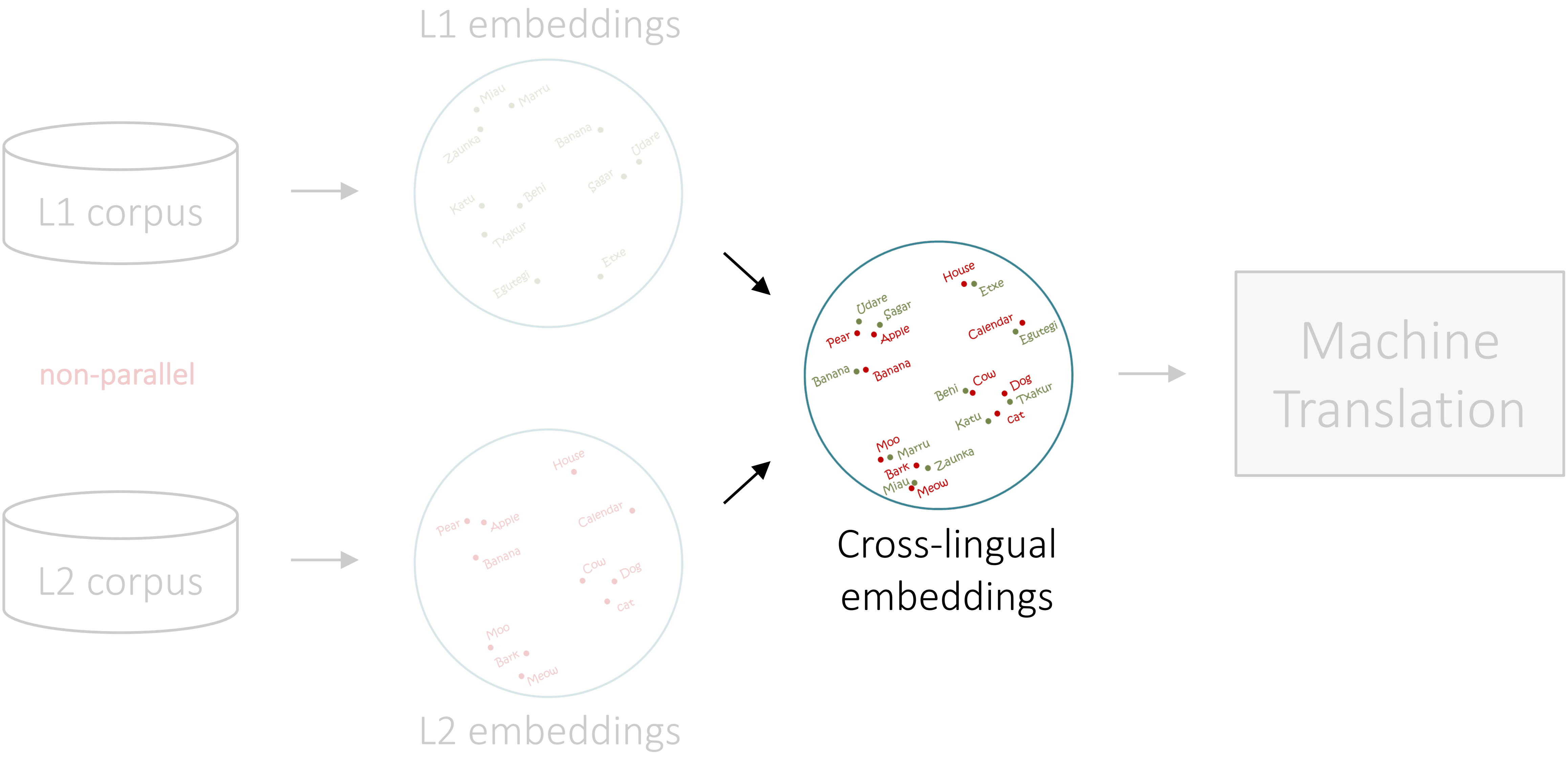
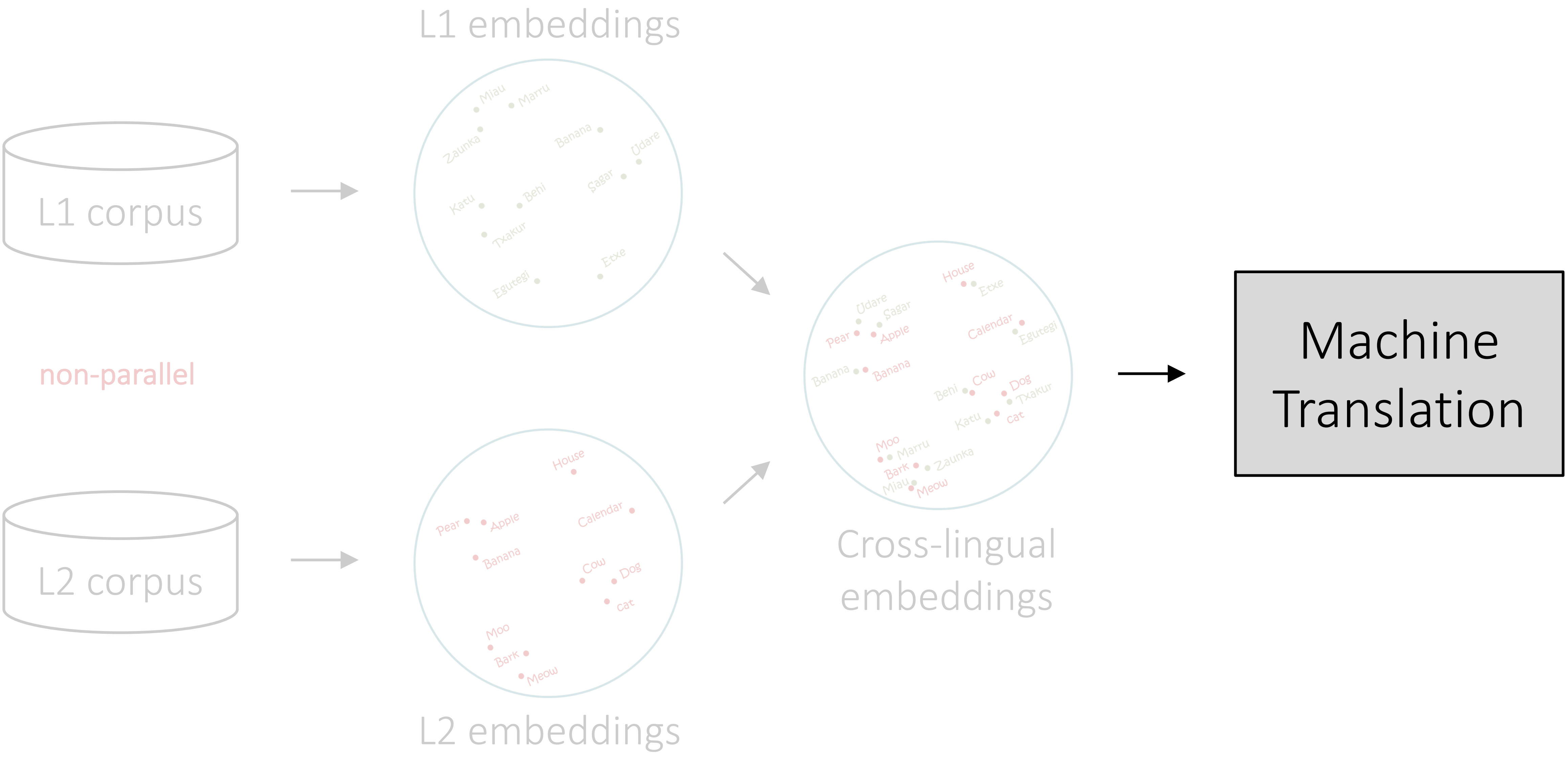
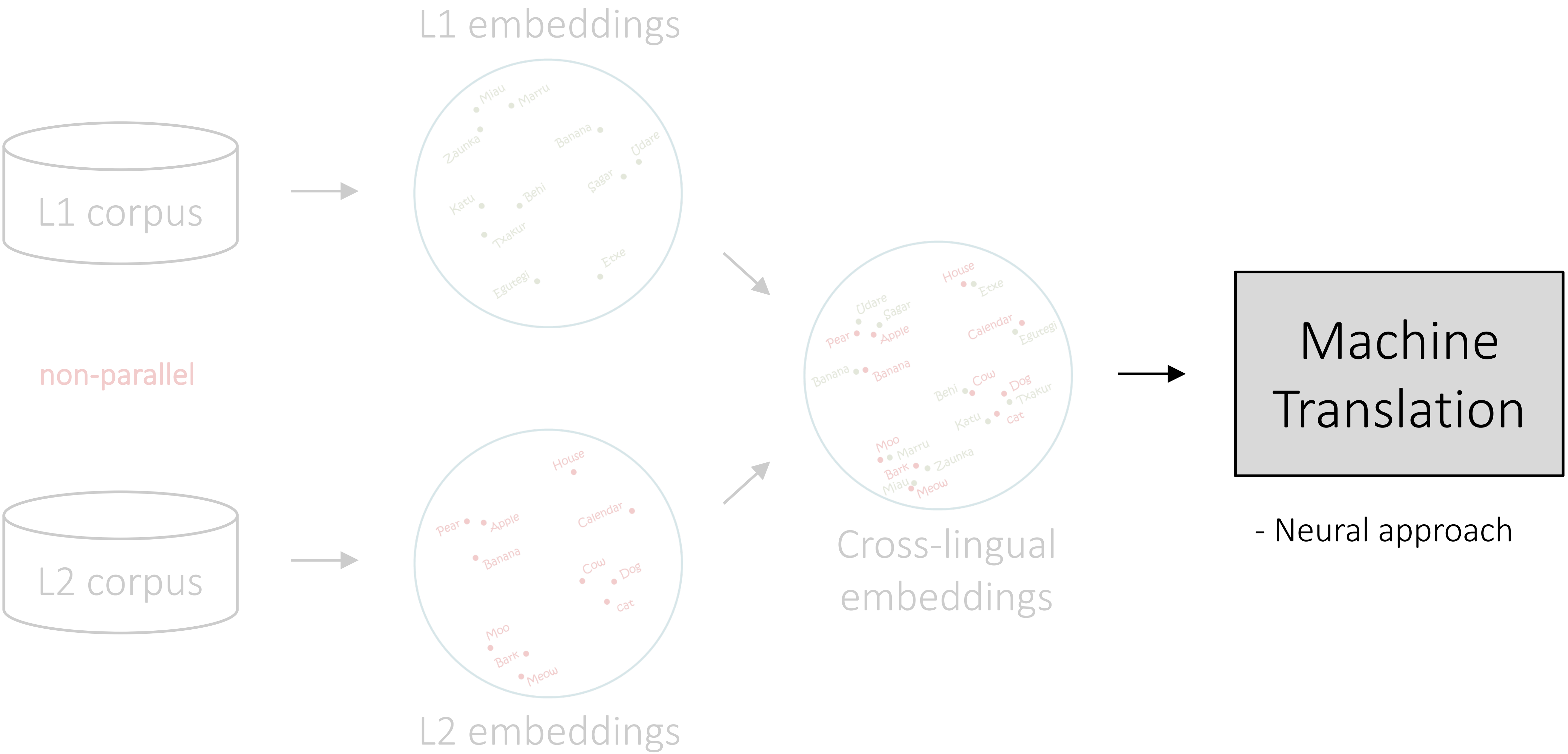
Outline


L1 embeddings
L1 corpus
non-parallel
L2 corpus
L2 embeddings
House
Etxe
Udare
Sagar
Pear
Apple
Calendar
Egutegi
Banana
Banana
Behi
Cow
Dog
Txakur
Katu
Cat
Moo
Marru
Bark
Zaunka
Miau
Meow
Cross-lingual embeddings
Machine Translation

Outline

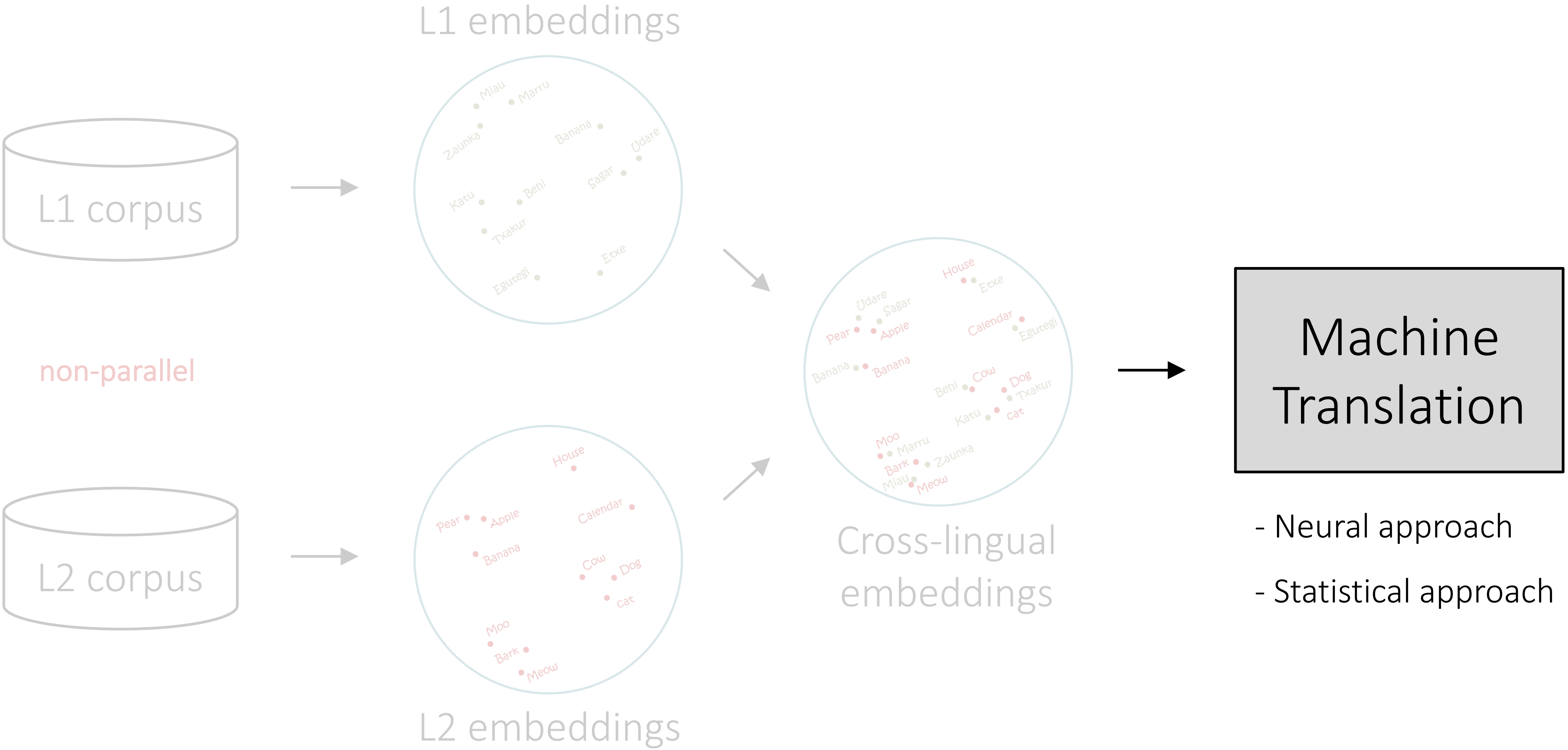

L1 embeddings
L1 corpus
non-parallel
L2 corpus
L2 embeddings
Cross-lingual embeddings
Machine Translation

Outline

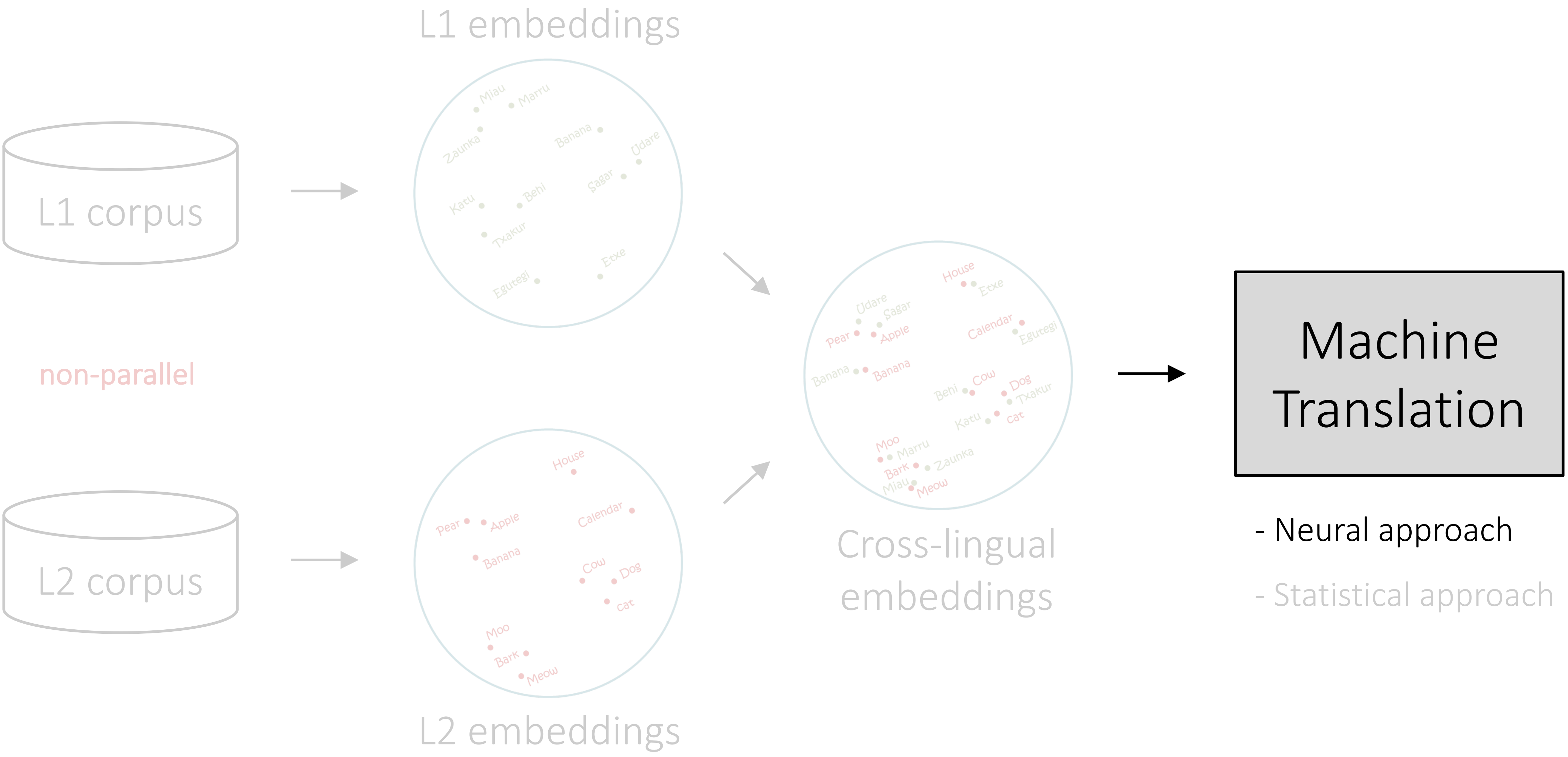


L1 embeddings
L1 corpus
Miau
Marru
Zaunka
Banana
Udare
Katu
Beni
Sagar
Txakur
Etxe
Egutegi
non-parallel
L2 corpus
House
Pear
Apple
Calendar
Banana
Cow
Dog
Cat
Moo
Bark
Meow
L2 embeddings
Cross-lingual
embeddings
Machine
Translation
- Neural approach

Outline


L1 embeddings
L1 corpus
non-parallel
L2 corpus
L2 embeddings
Cross-lingual embeddings
Machine Translation
- Neural approach
- Statistical approach

Outline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Machine Translation
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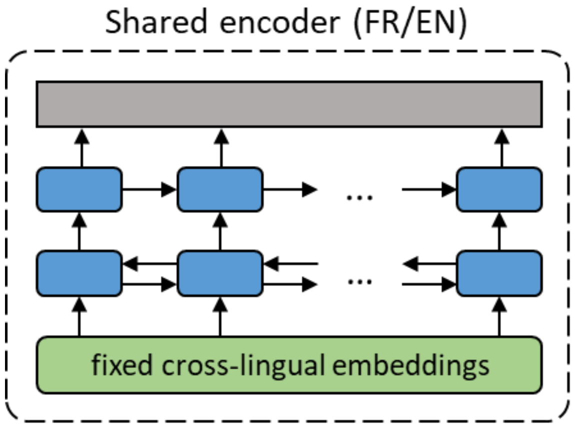
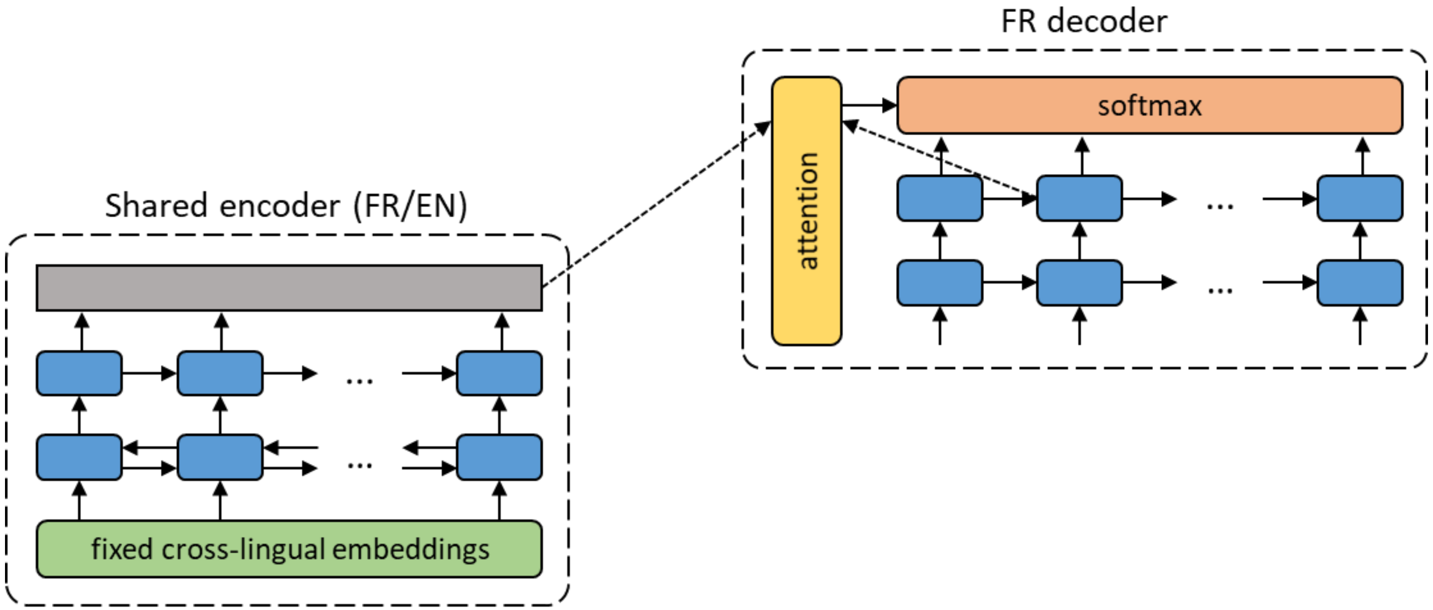
- Statistical approach

Unsupervised neural machine translation

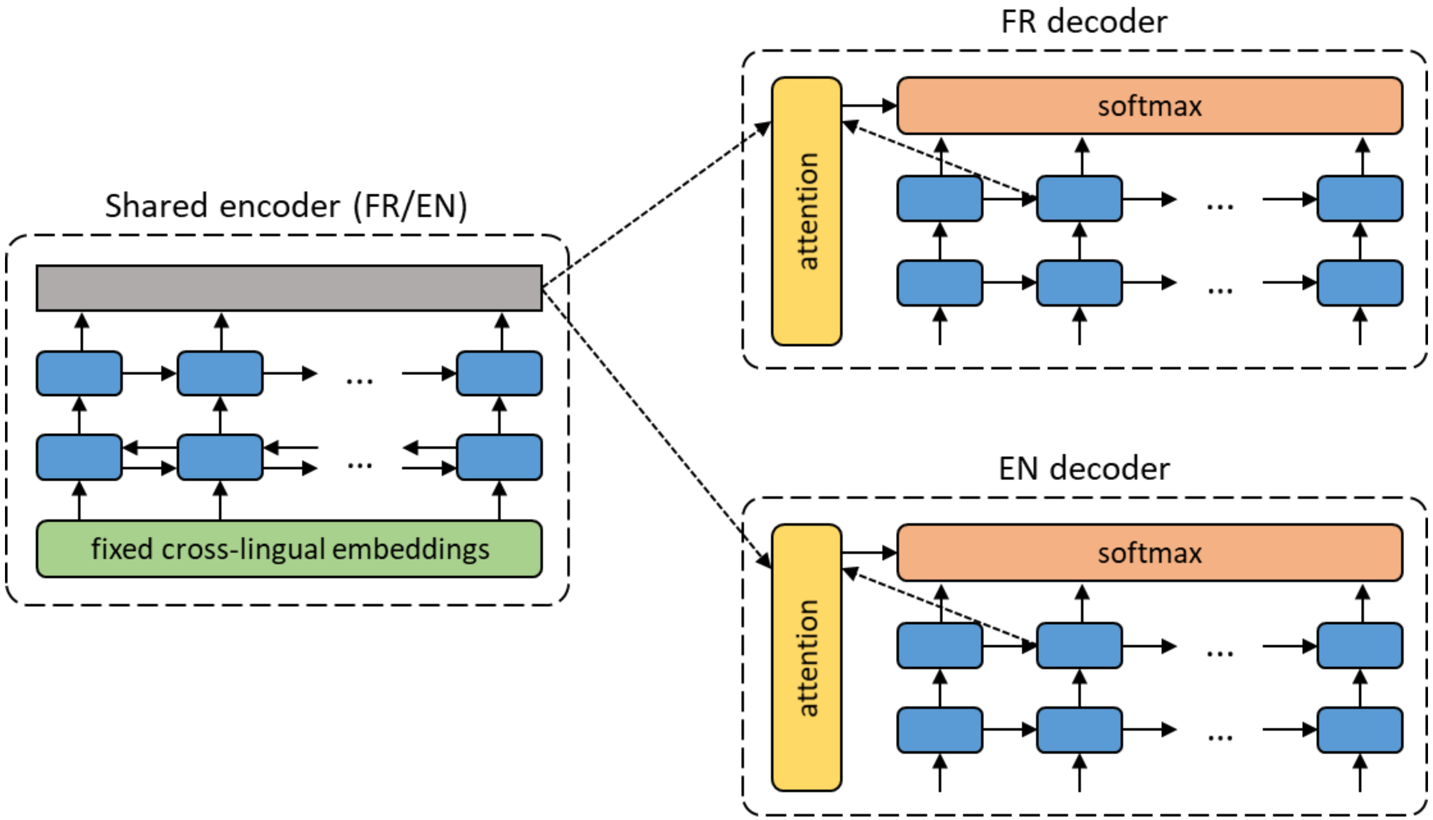
Unsupervised neural machine translation



Unsupervised neural machine translation

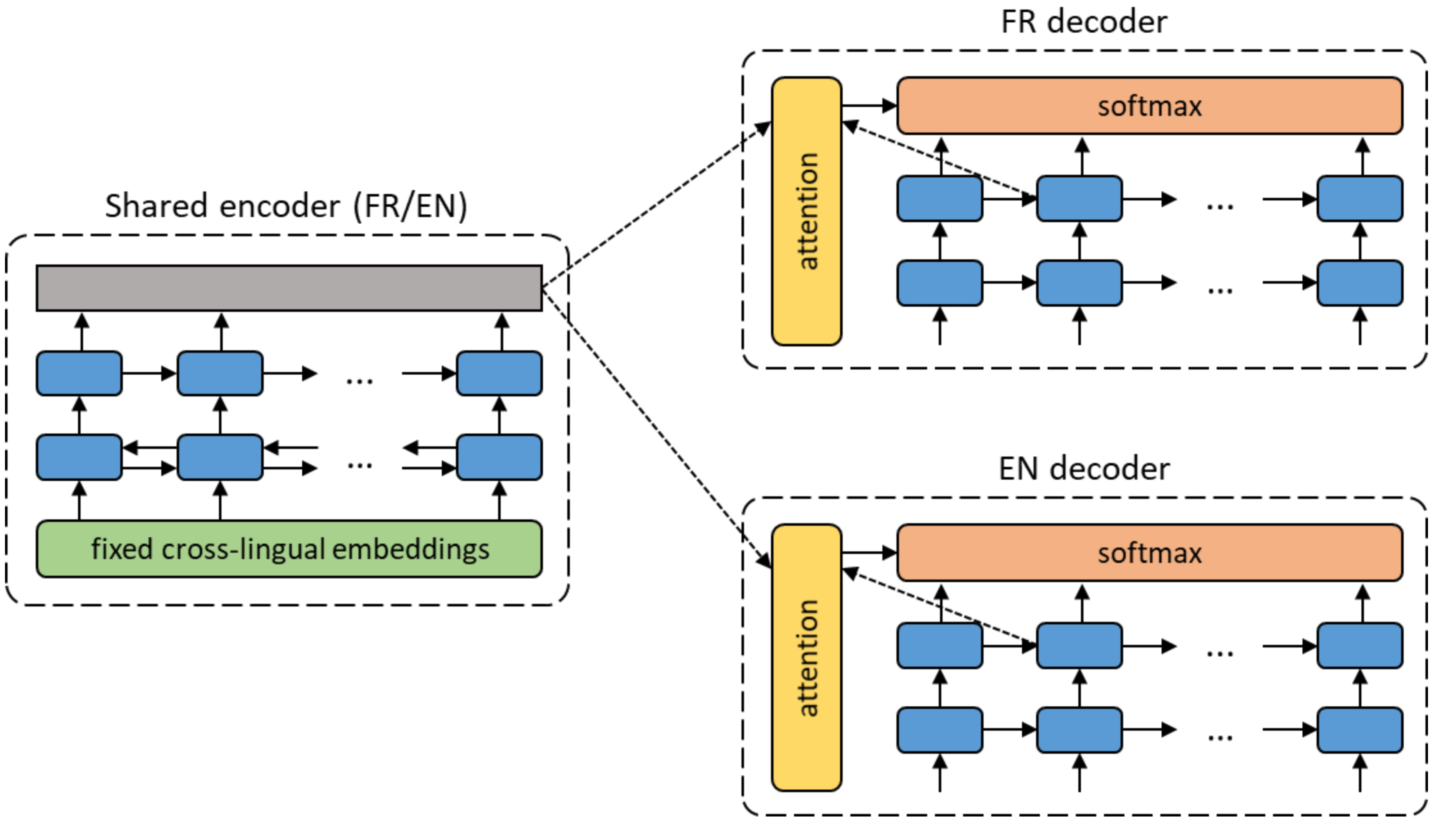


Unsupervised neural machine translation



Unsupervised neural machine translation

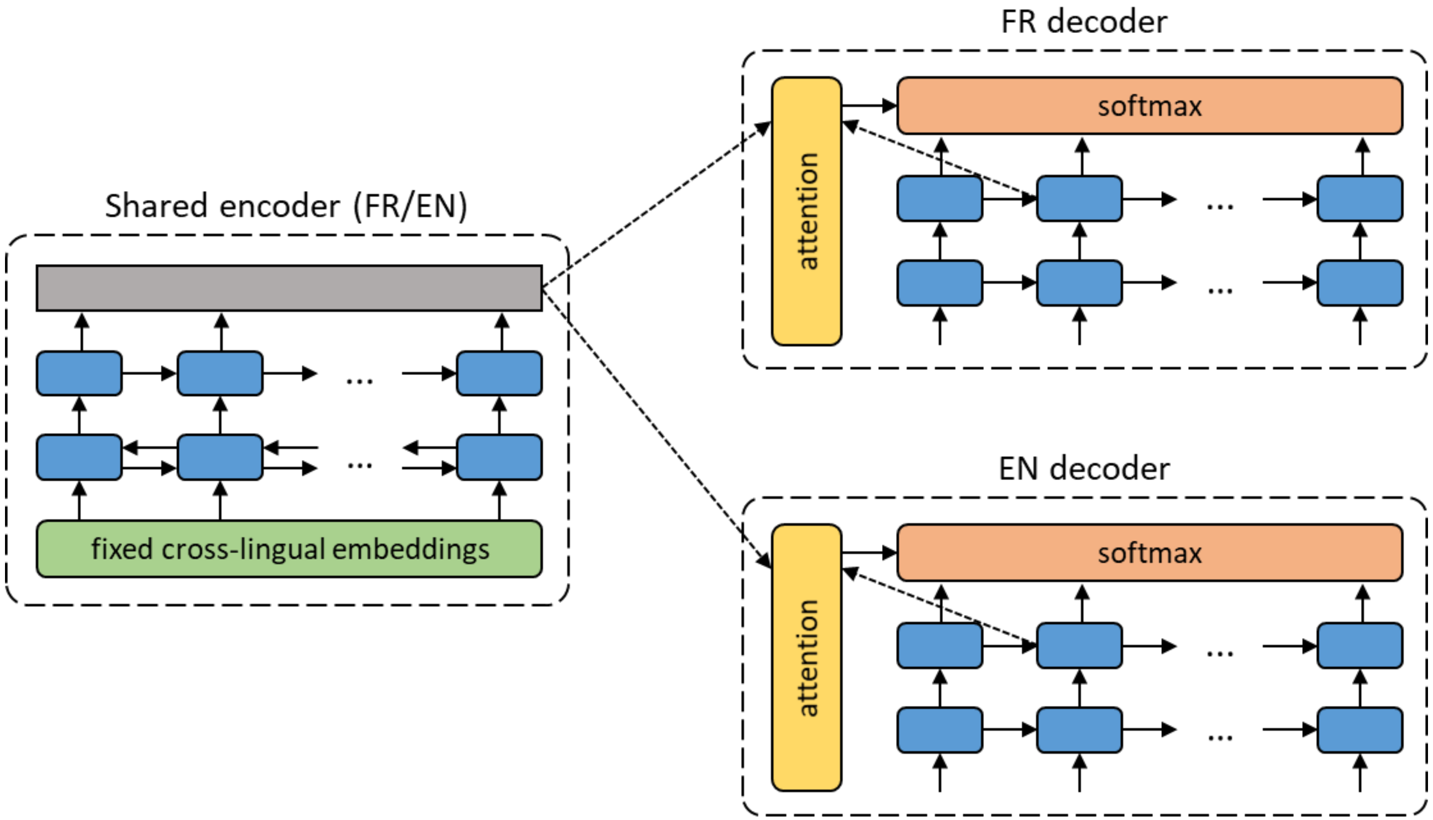
Training



Unsupervised neural machine translation

Training

Une fusillade a eu lieu à l'aéroport international de Los Angeles.

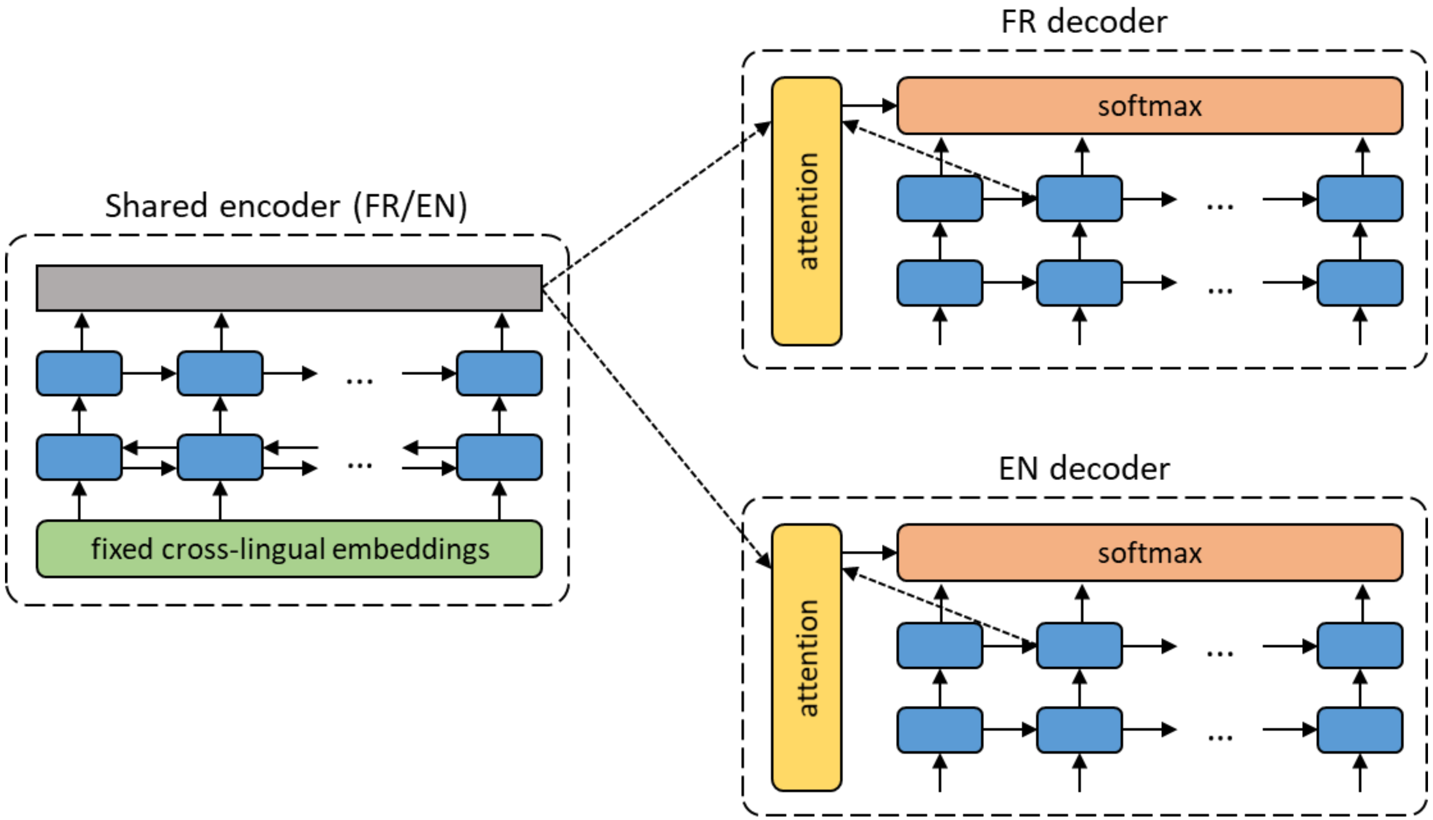


Unsupervised neural machine translation

Training

- Supervised

Une fusillade a eu lieu à l'aéroport international de Los Angeles.



Unsupervised neural machine translation

Training

- Supervised

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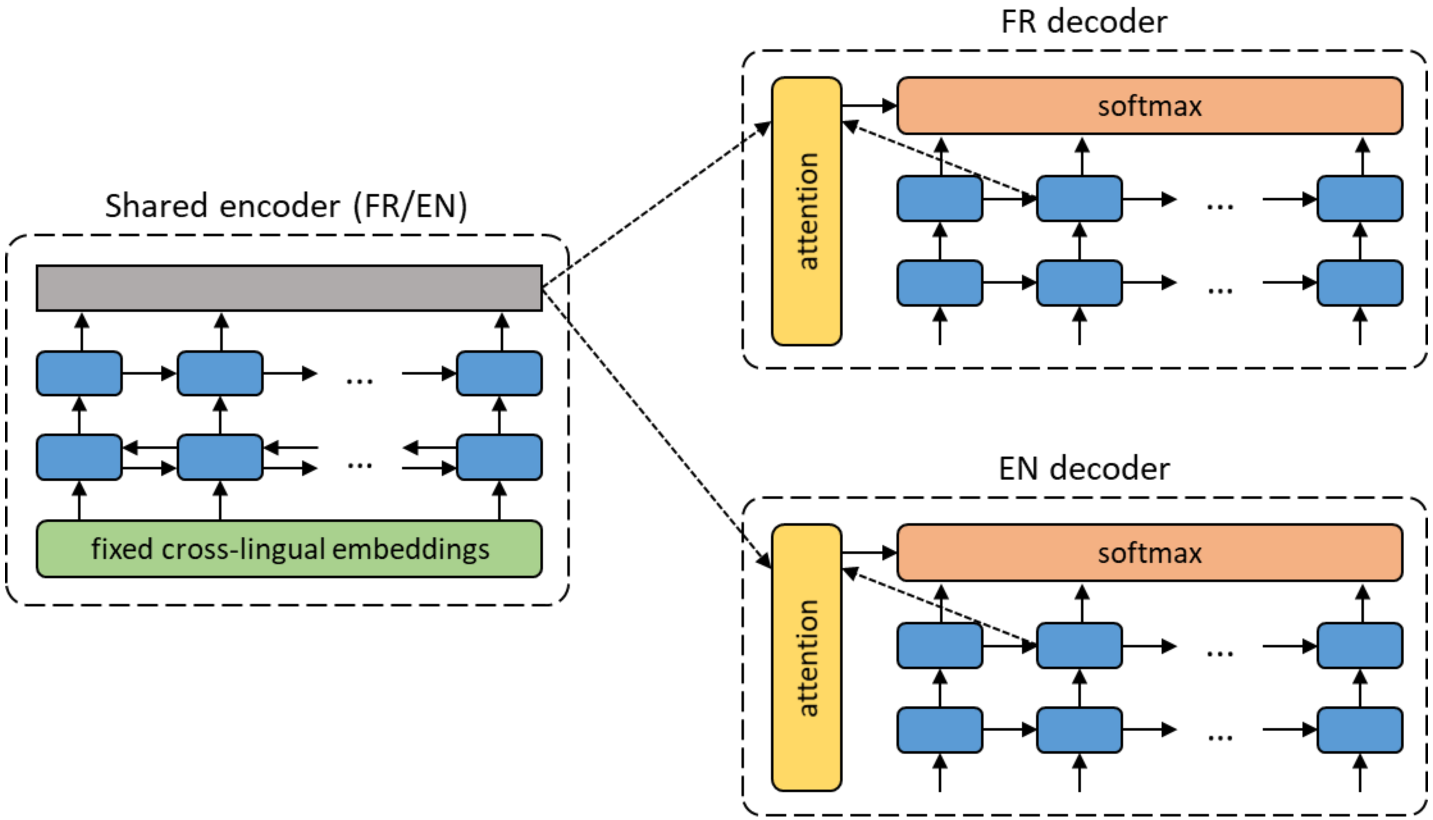


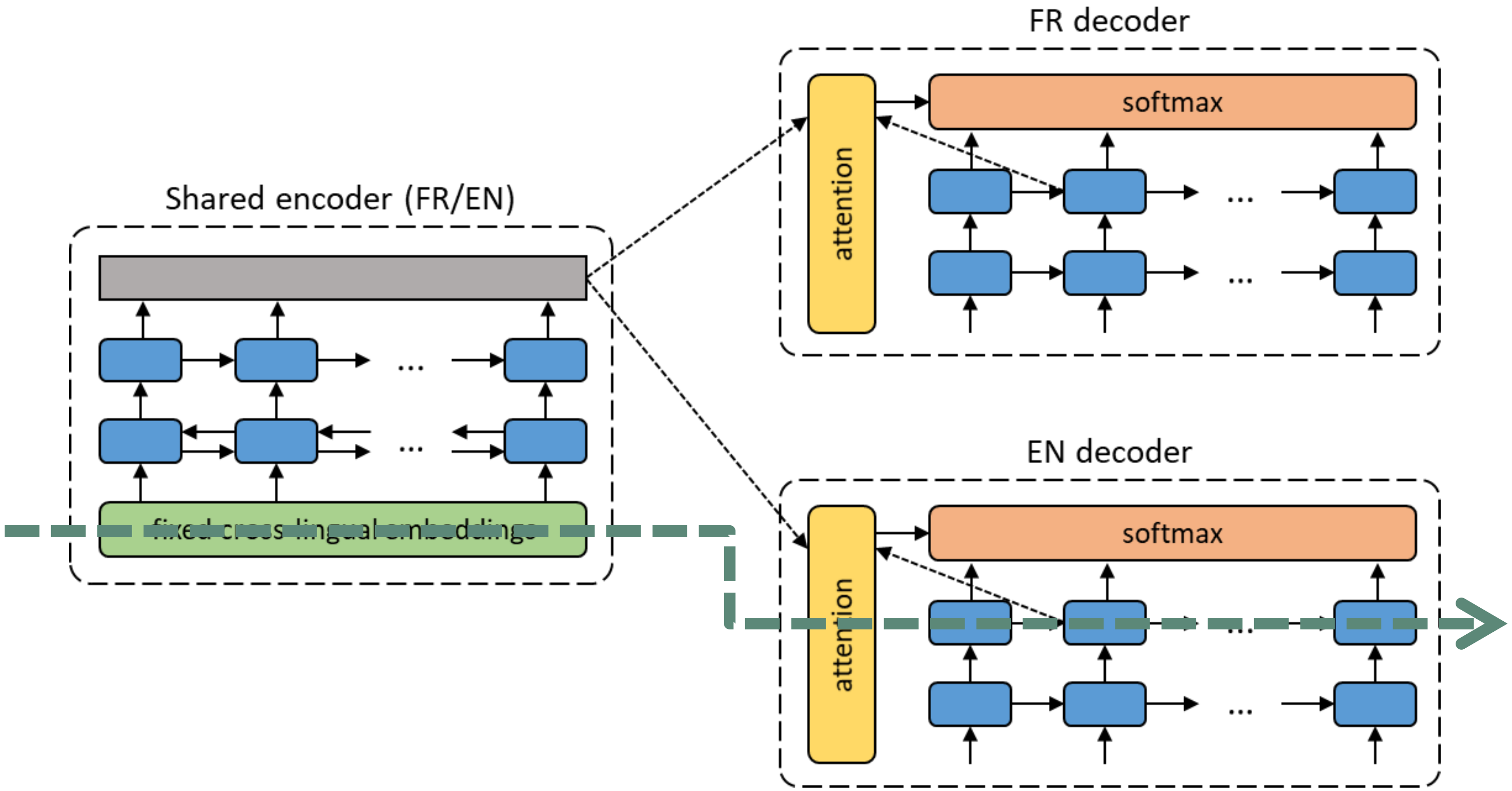
There was a shooting in Los Angeles International Airport.

Unsupervised neural machine translation

Training

- Supervised

Une fusillade a eu lieu à l'aéroport international de Los Angeles.



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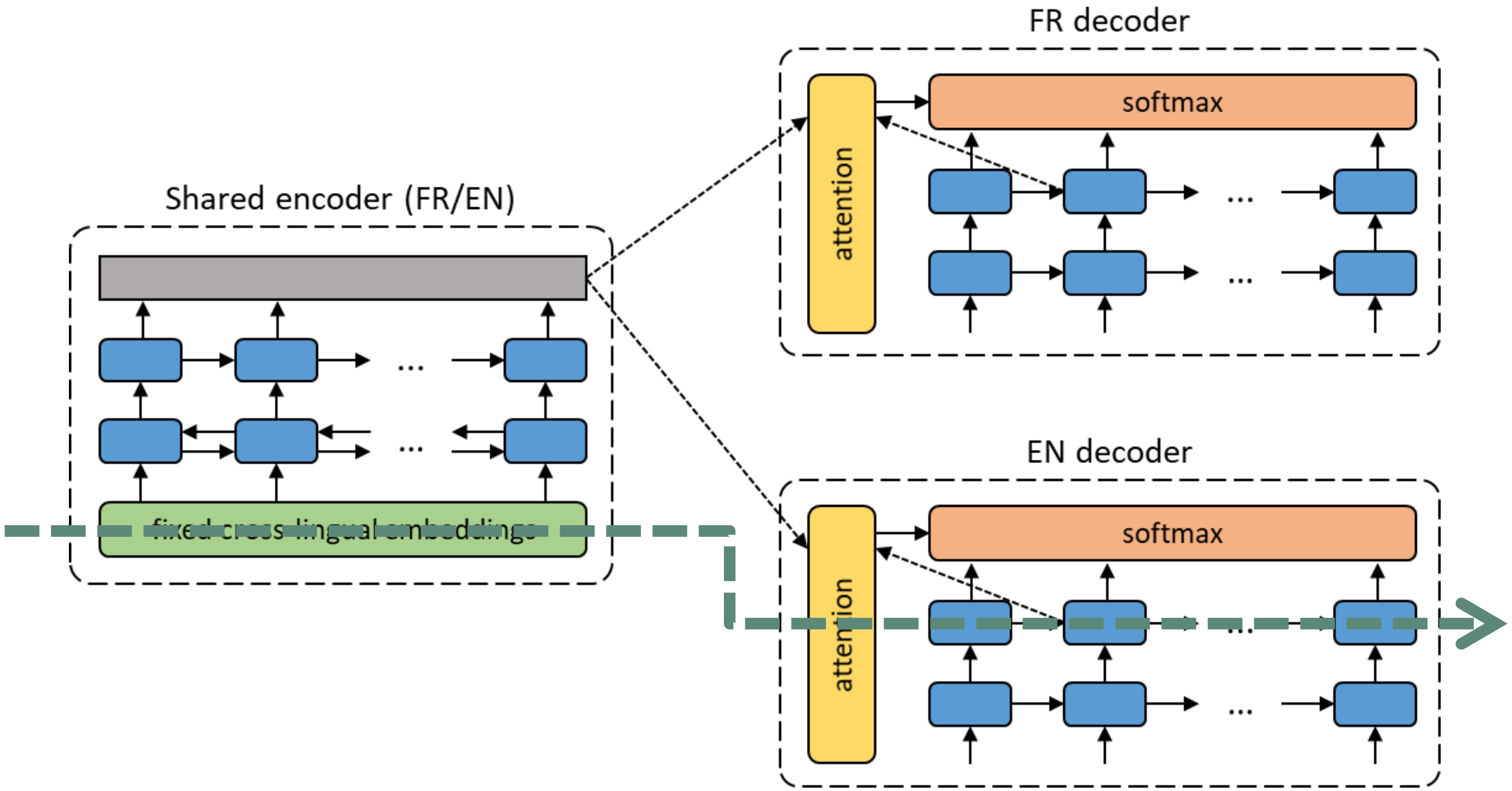
Unsupervised neural machine translation

Training

- Supervised

Une fusillade a eu lieu à l'aéroport international de Los Angeles.



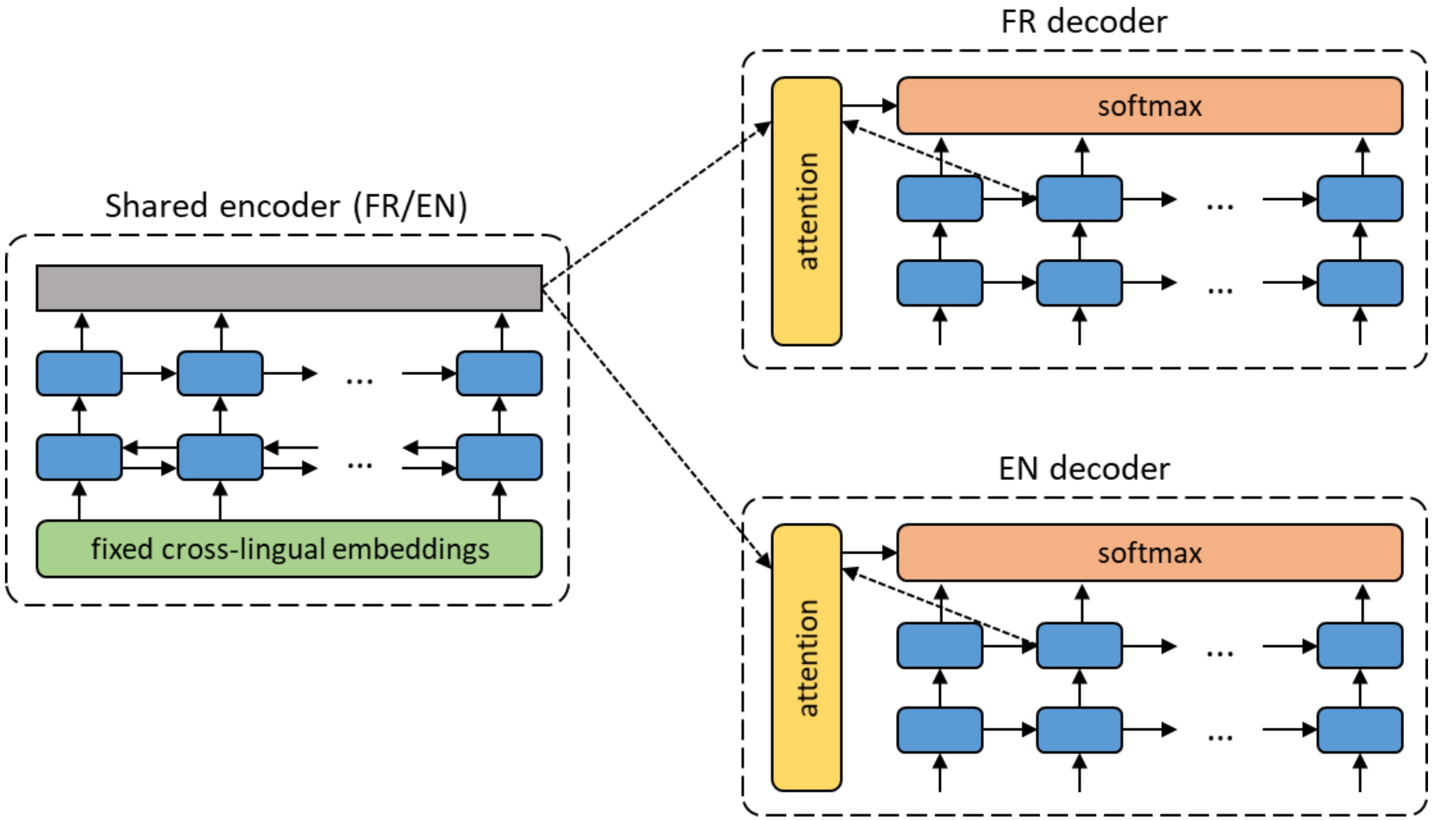
~~There was a shooting in Los Angeles International Airport.~~

Unsupervised neural machine translation

Training

- Supervised

Une fusillade a eu lieu à l'aéroport international de Los Angeles.

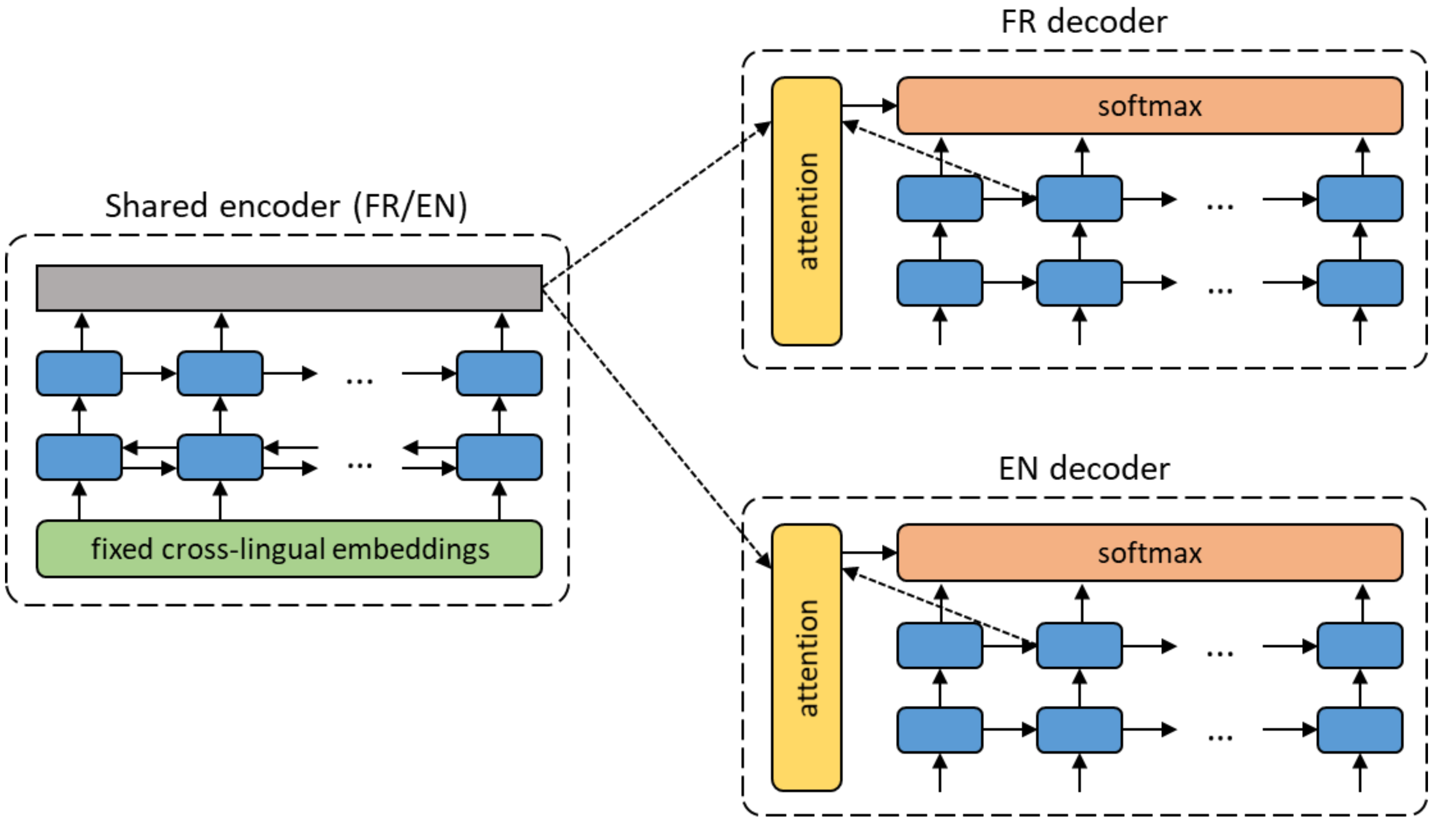


Unsupervised neural machine translation

Training

- ~~Supervised~~

Une fusillade a eu lieu à l'aéroport international de Los Angeles.

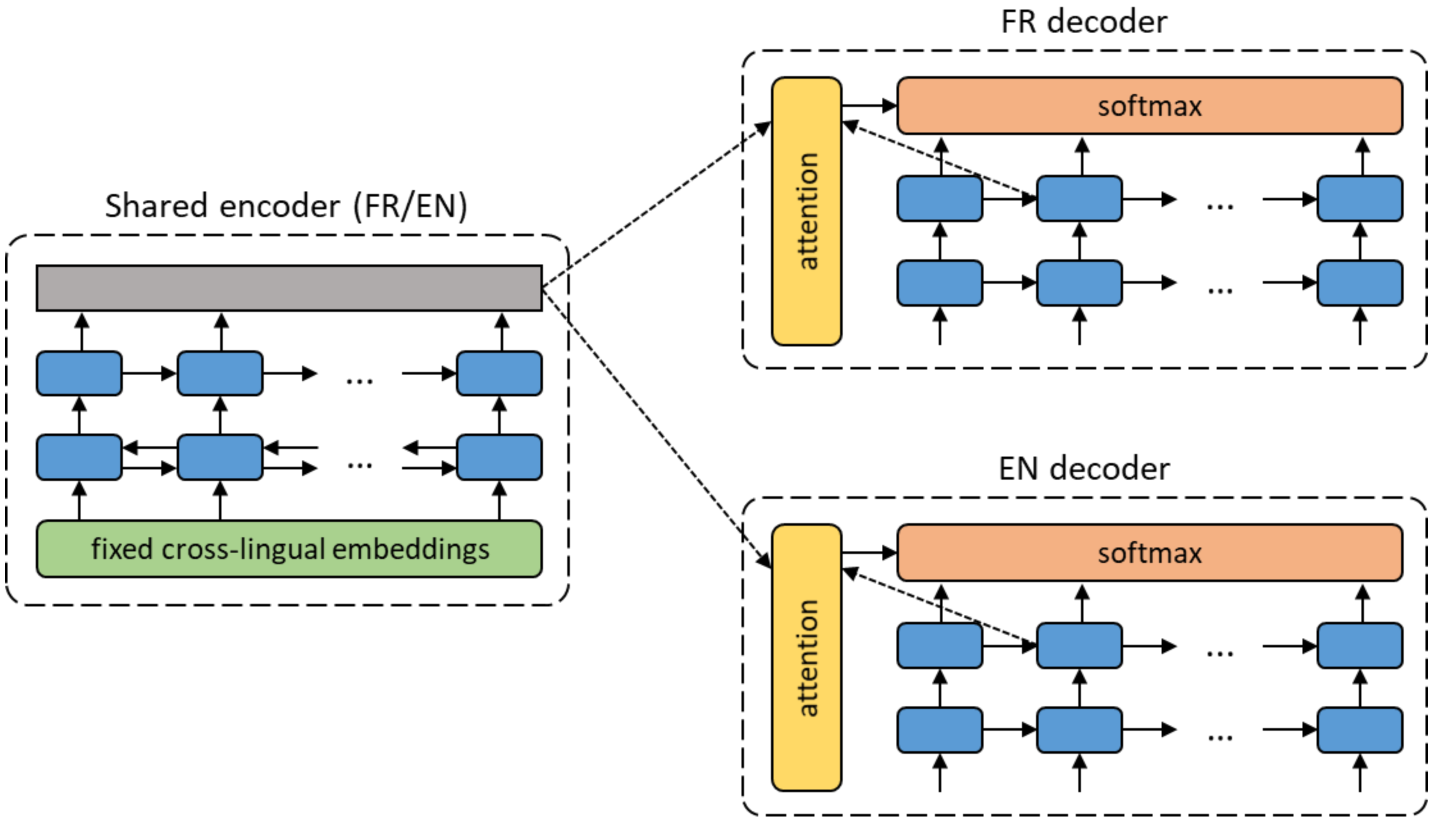


Unsupervised neural machine translation

Training

- ~~Supervised~~

Une fusillade a eu lieu à l'aéroport international de Los Angeles.



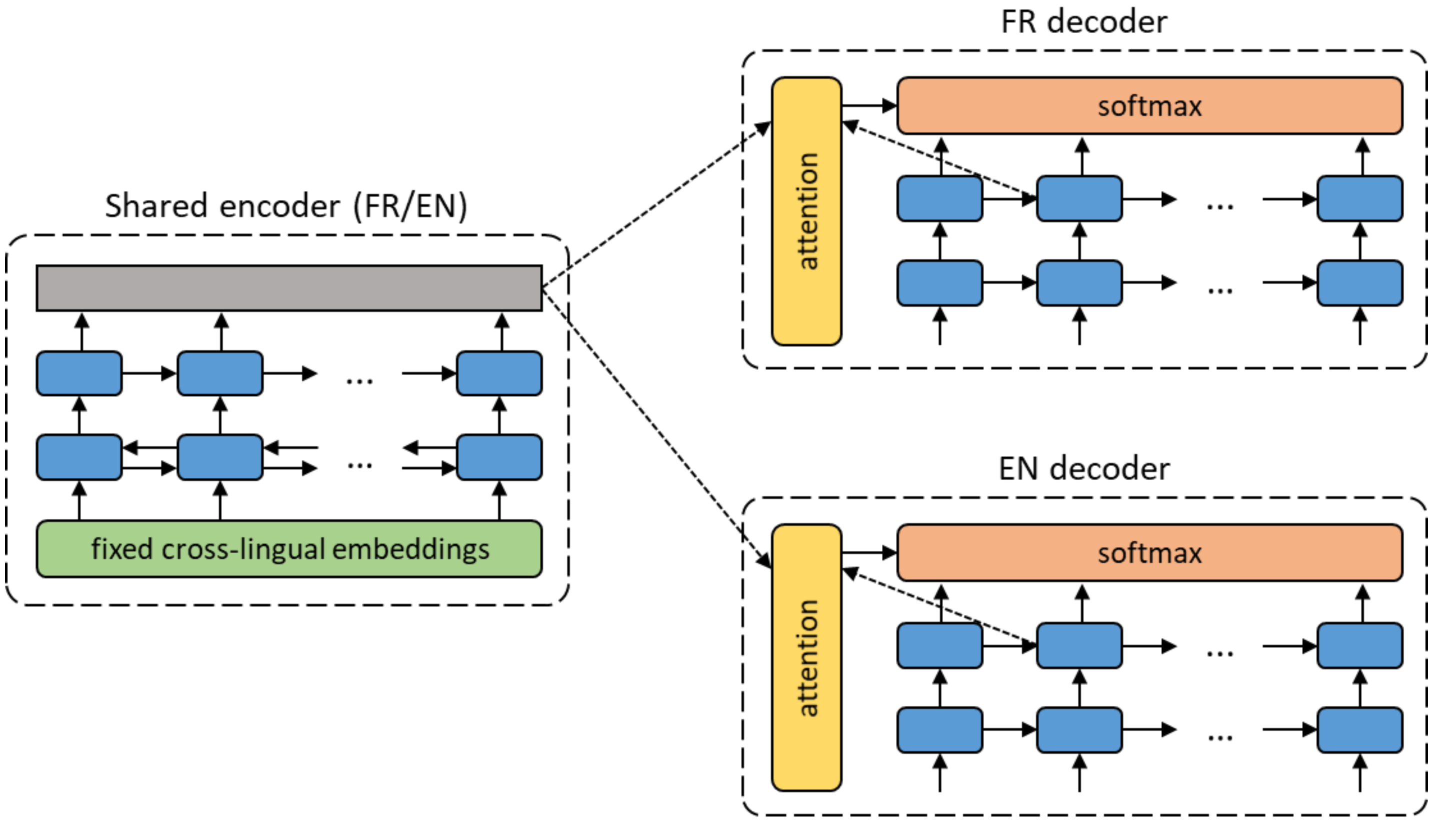
Une fusillade a eu lieu à l'aéroport international de Los Angeles.

Unsupervised neural machine translation

Training

- ~~Supervised~~
- Denoising

Une fusillade a eu lieu à l'aéroport international de Los Angeles.



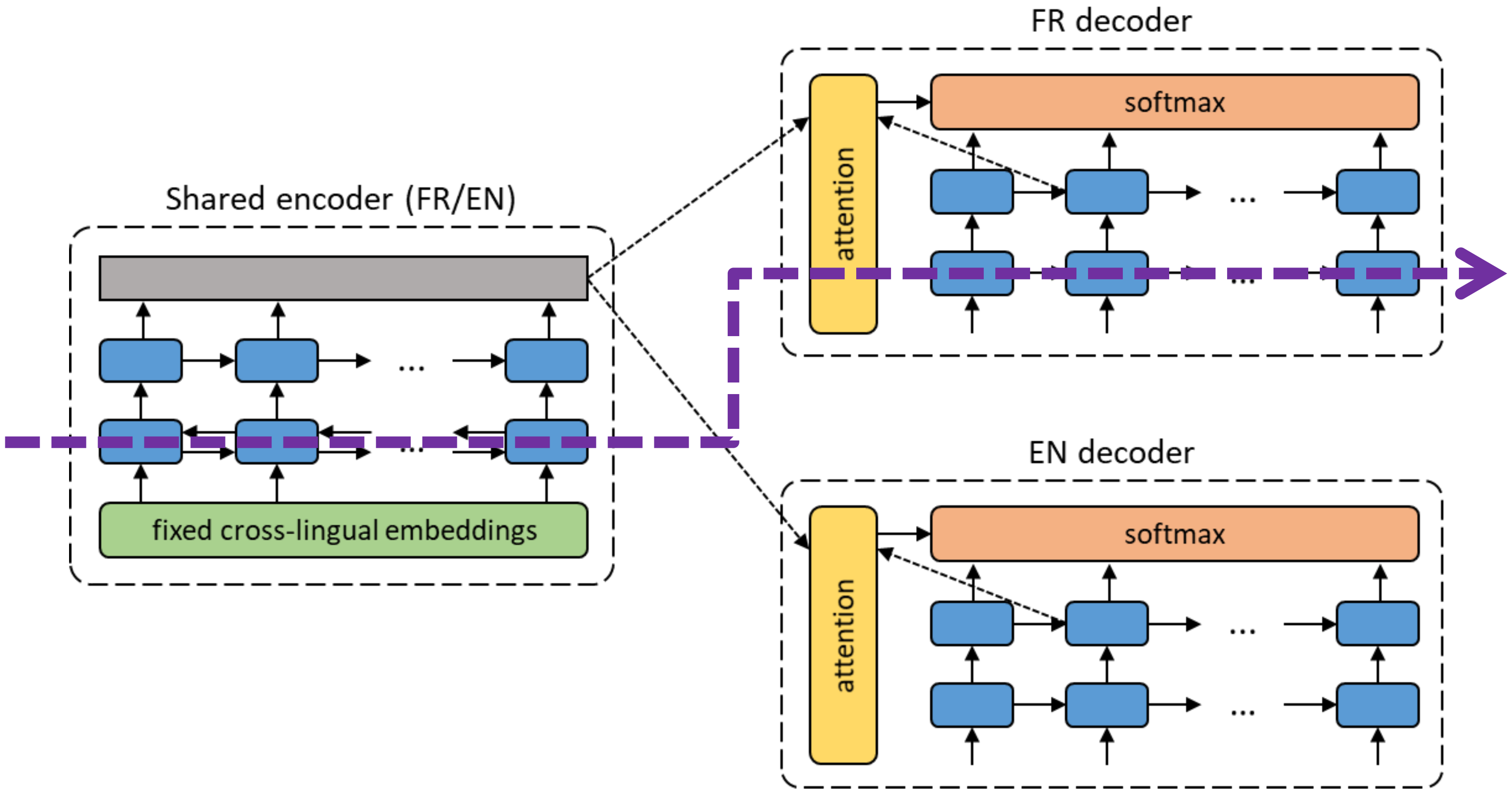
Une fusillade a eu lieu à l'aéroport international de Los Angeles.

Unsupervised neural machine translation

Training

- ~~Supervised~~
- Denoising

Une fusillade a eu lieu à l'aéroport international de Los Angeles.



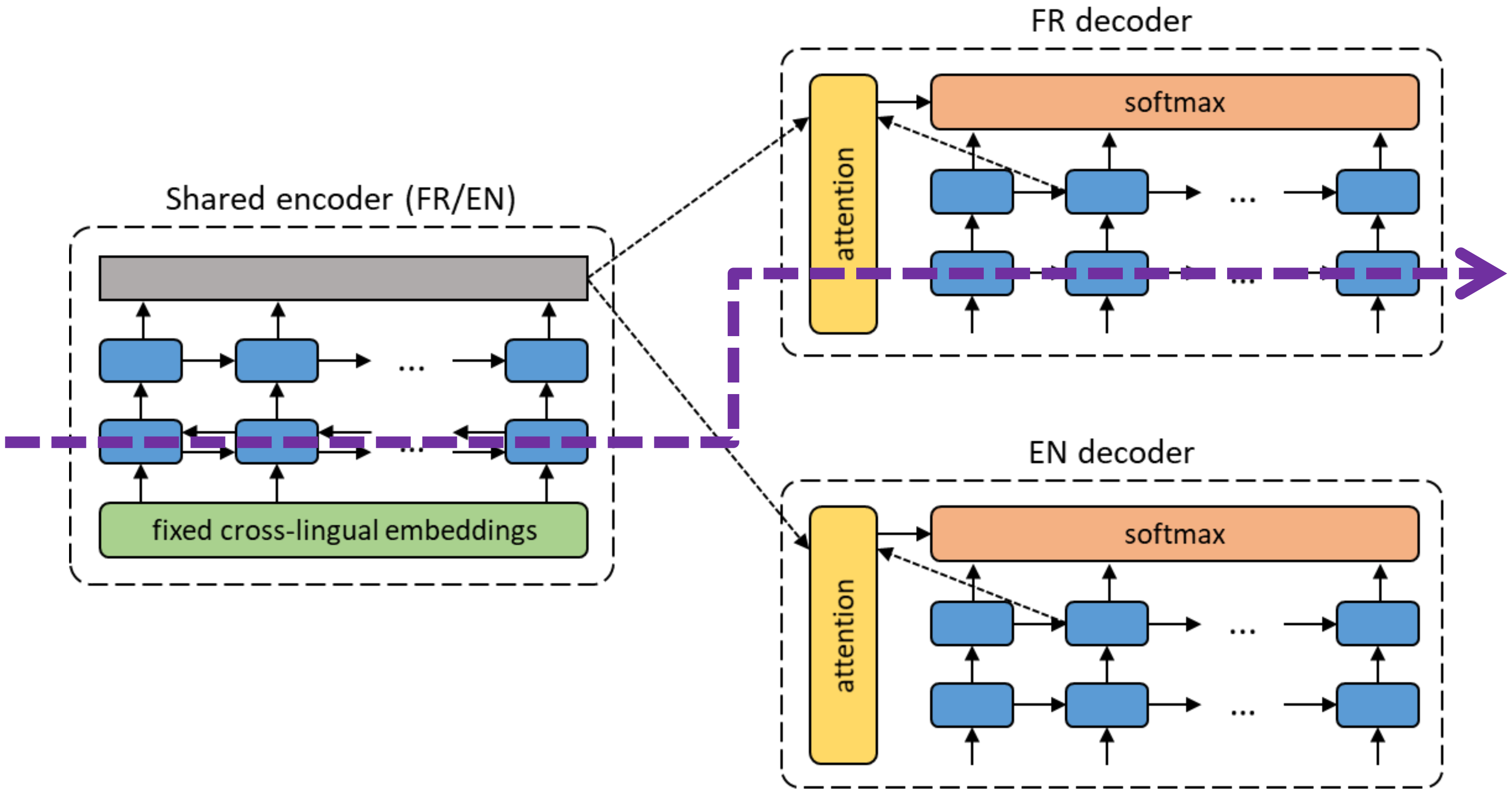
Une fusillade a eu lieu à l'aéroport international de Los Angeles.

Unsupervised neural machine translation

Training

- ~~Supervised~~
- Denoising

Une lieu fusillade a eu à l'aéroport de Los international Angeles.



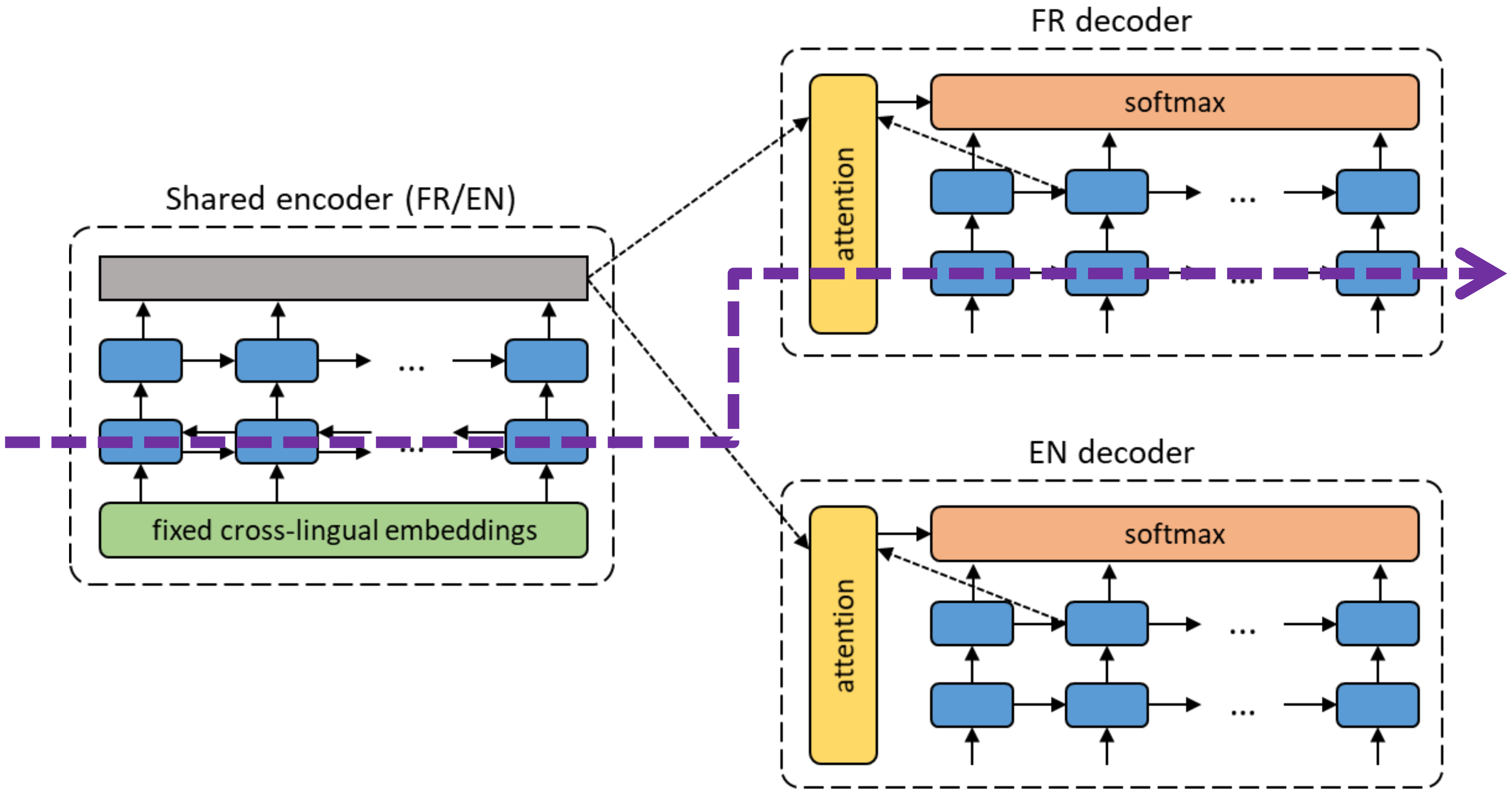
Une fusillade a eu lieu à l'aéroport international de Los Angeles.

Unsupervised neural machine translation

Training

- ~~Supervised~~
- Denoising
- Backtranslation

Une lieu fusillade a eu à l'aéroport de Los international Angeles.



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Unsupervised neural machine translation

Training

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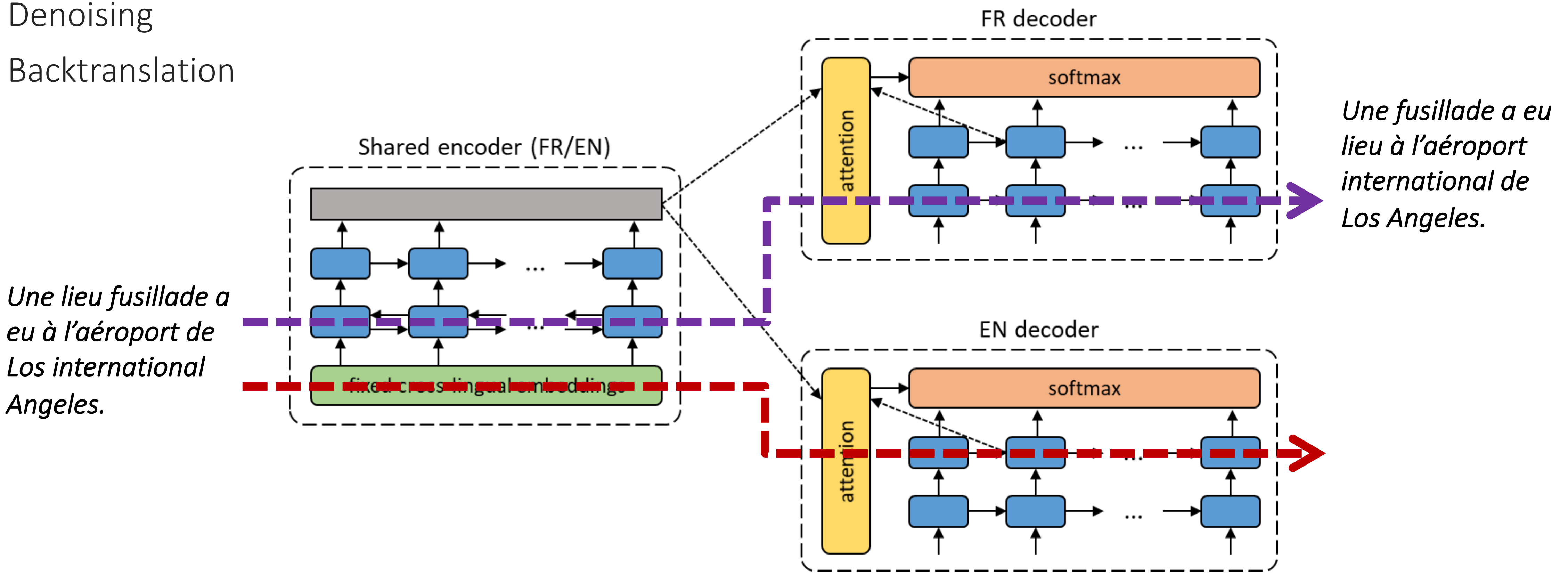
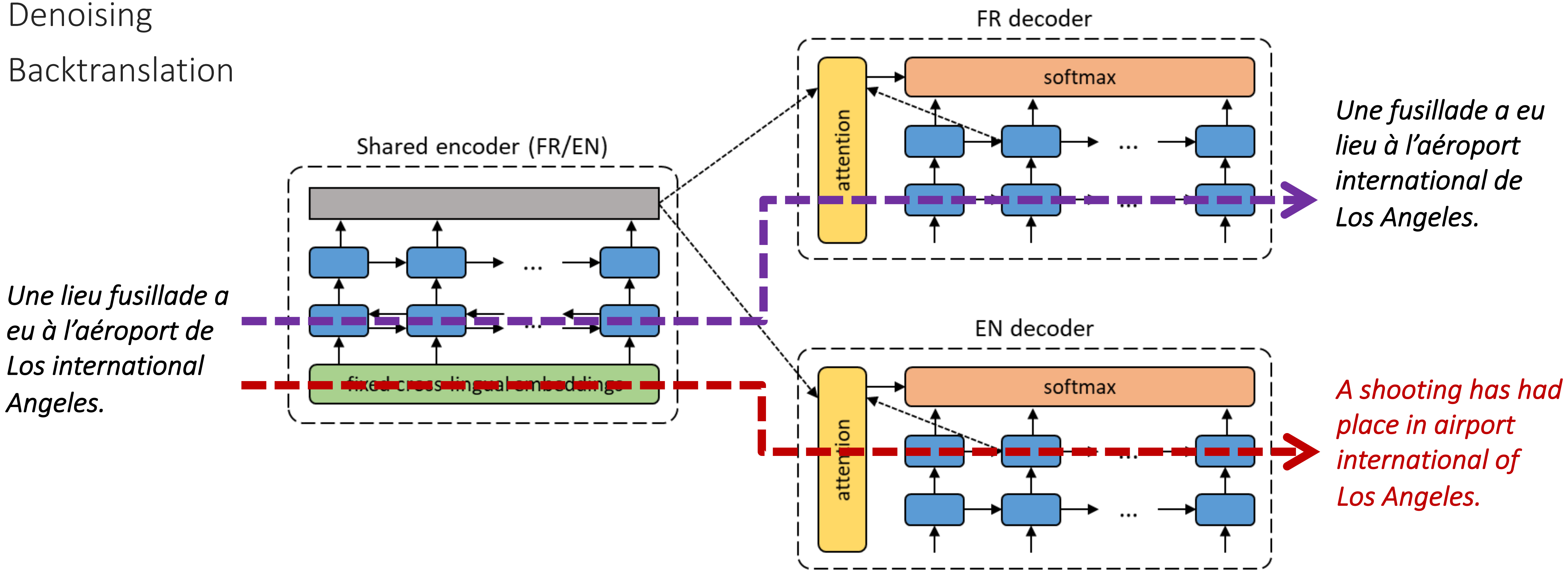
- Denoising
- Backtranslation



Unsupervised neural machine translation

Training

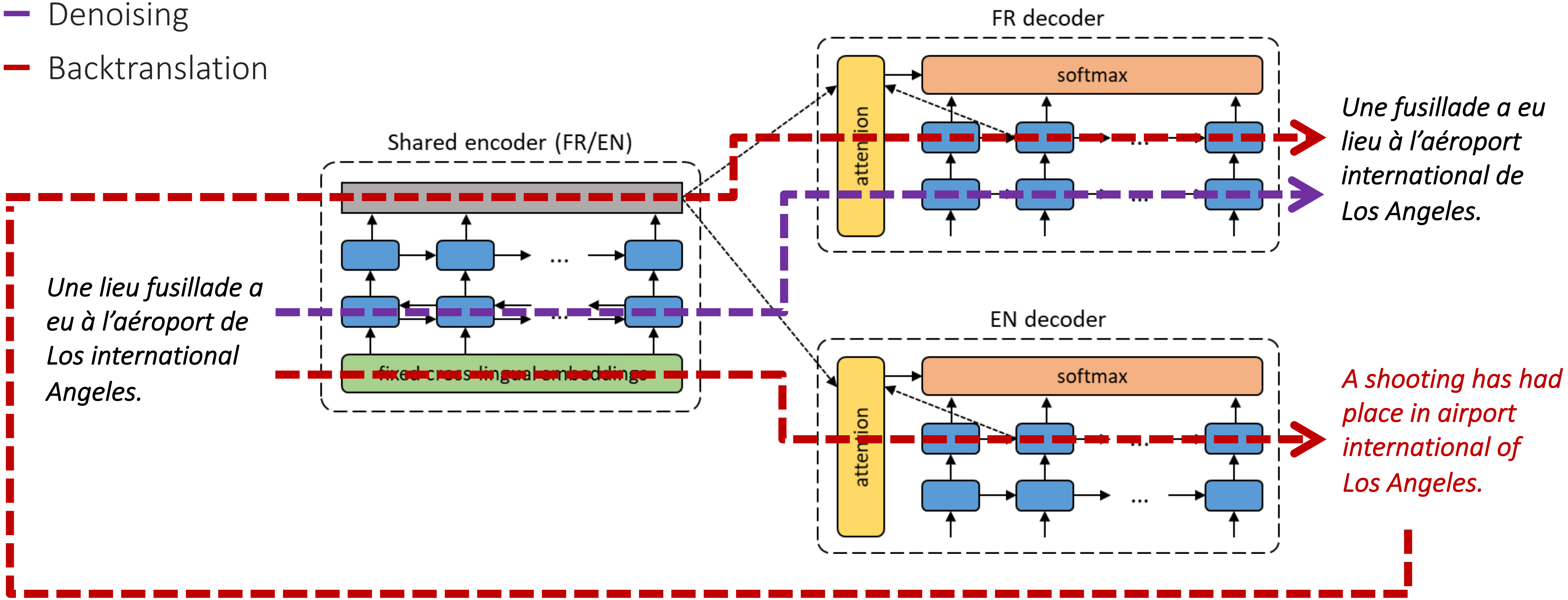
- ~~Supervised~~
- Denoising
- Backtranslation



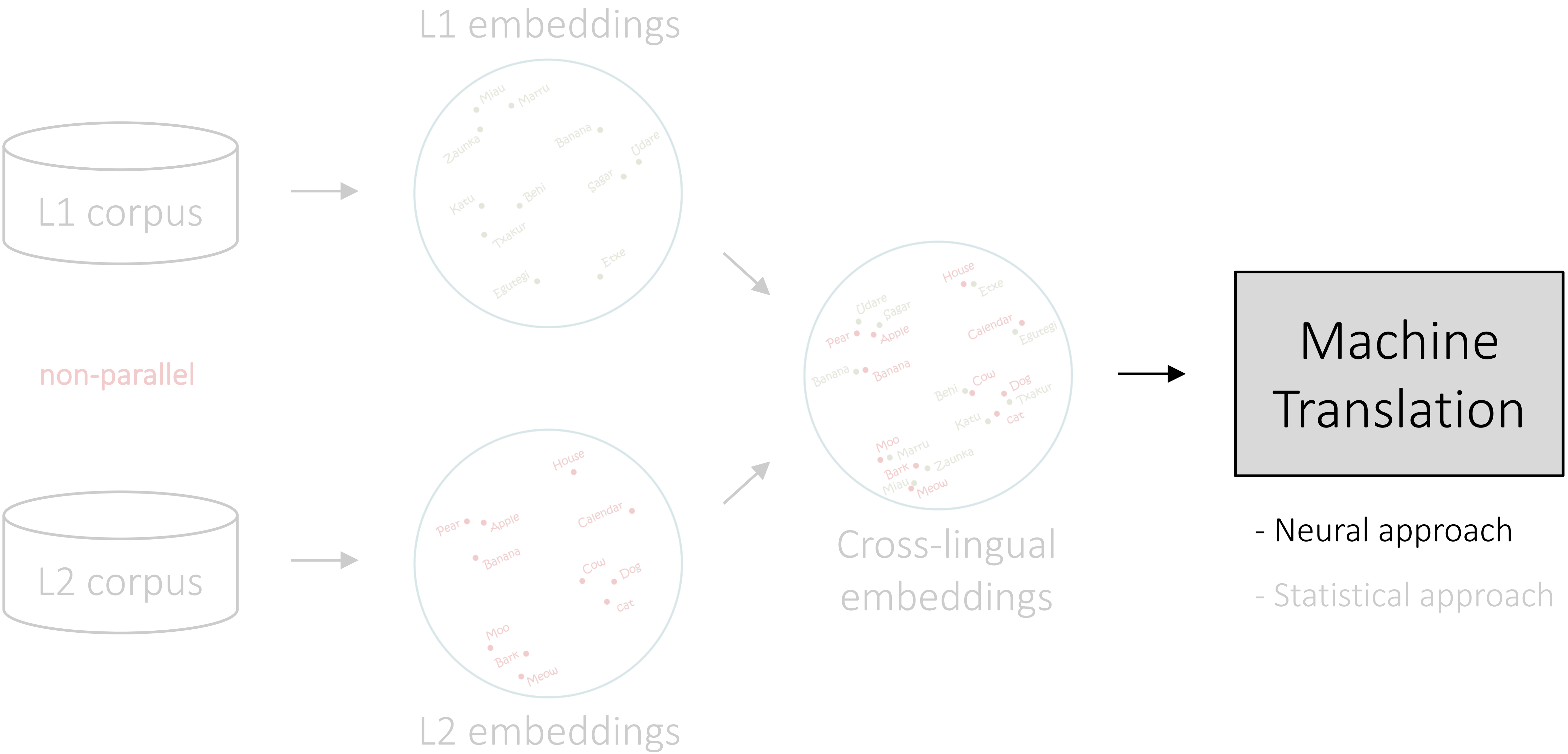
Unsupervised neural machine translation

Training

- ~~Supervised~~
- Denoising
- Backtranslation

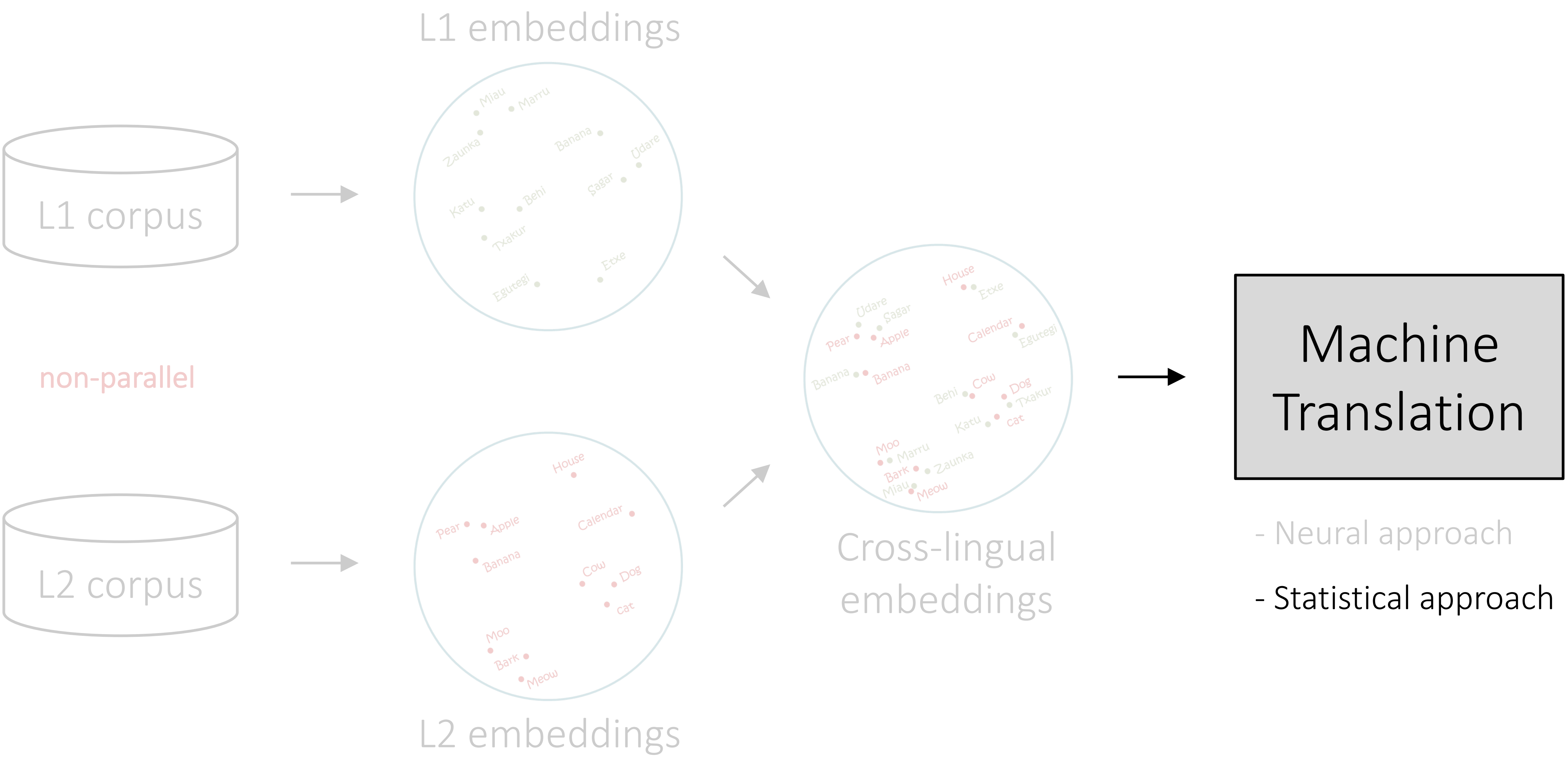


Outline



L1 embeddings
L1 corpus
non-parallel
L2 corpus
L2 embeddings
Cross-lingual embeddings
Machine Translation
- Neural approach
- Statistical approach

Outline


L1 embeddings
L1 corpus
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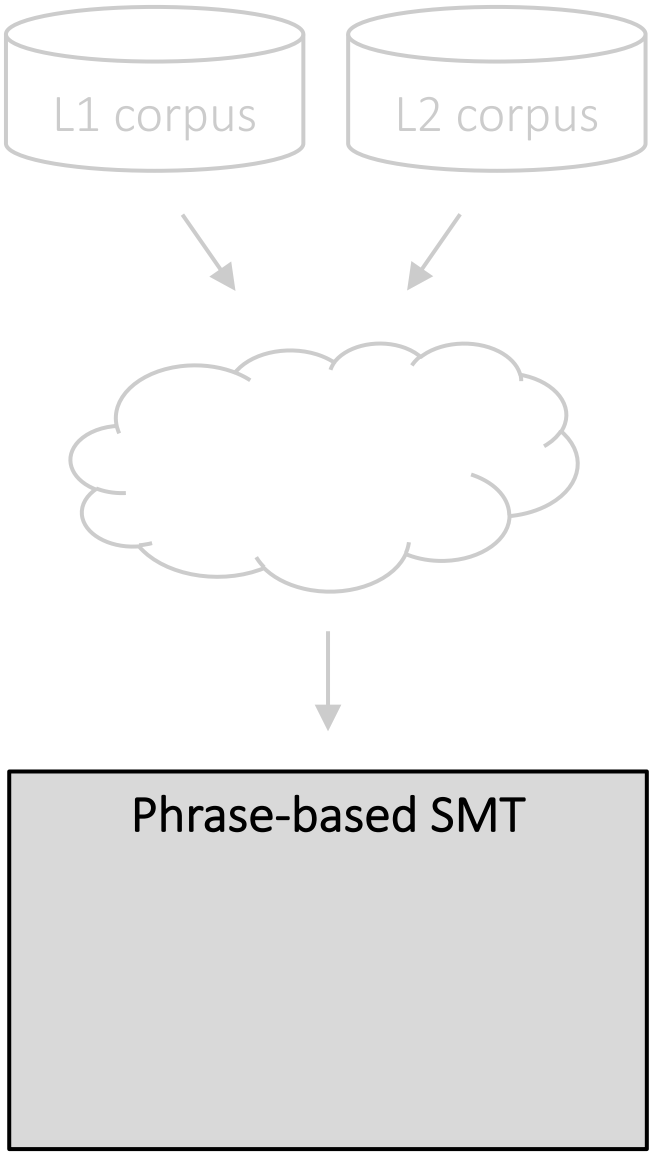
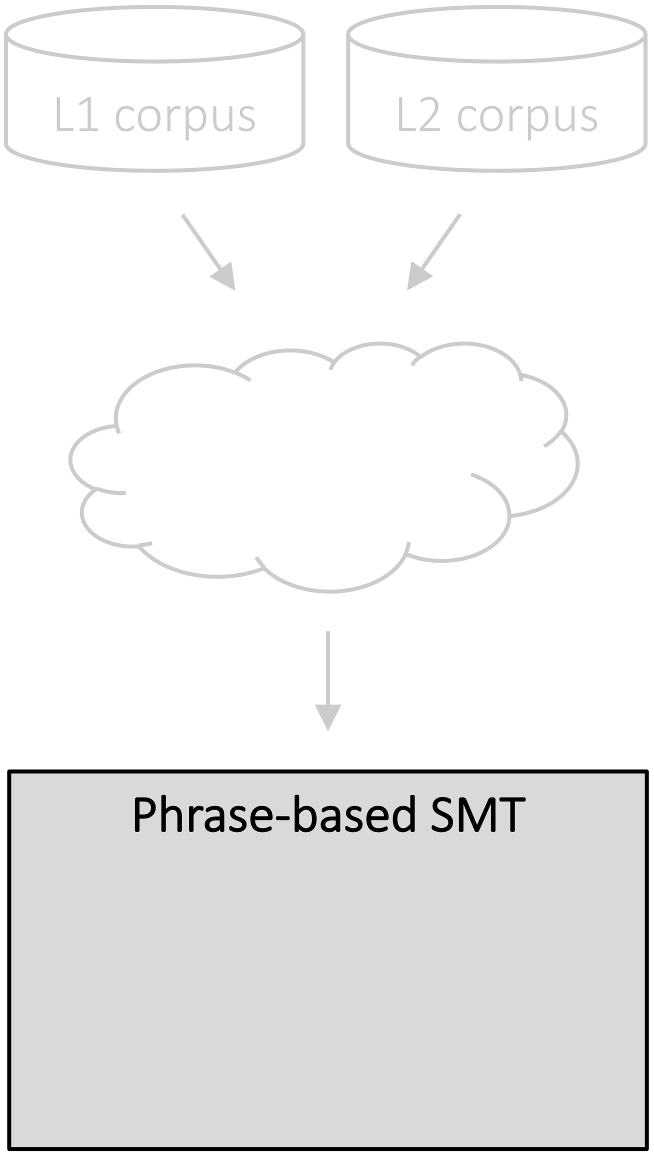
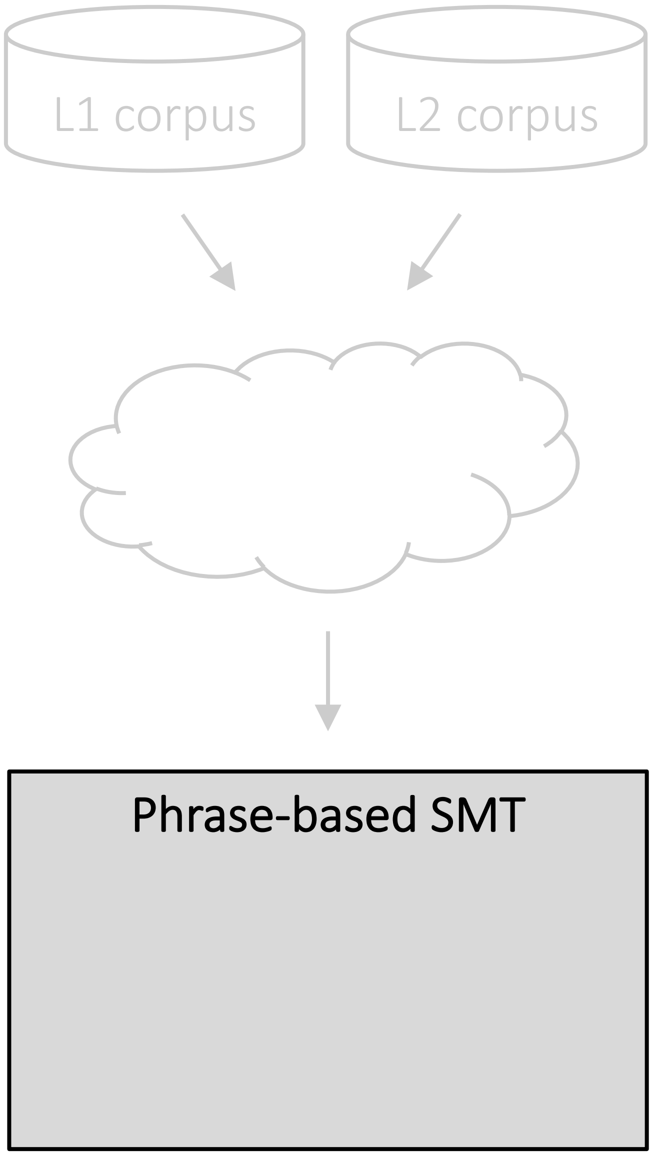
L2 embeddings
Cross-lingual embeddings
Machine Translation
- Neural approach
- Statistical approach


L1 corpus
L2 corpus
Phrase-based SMT

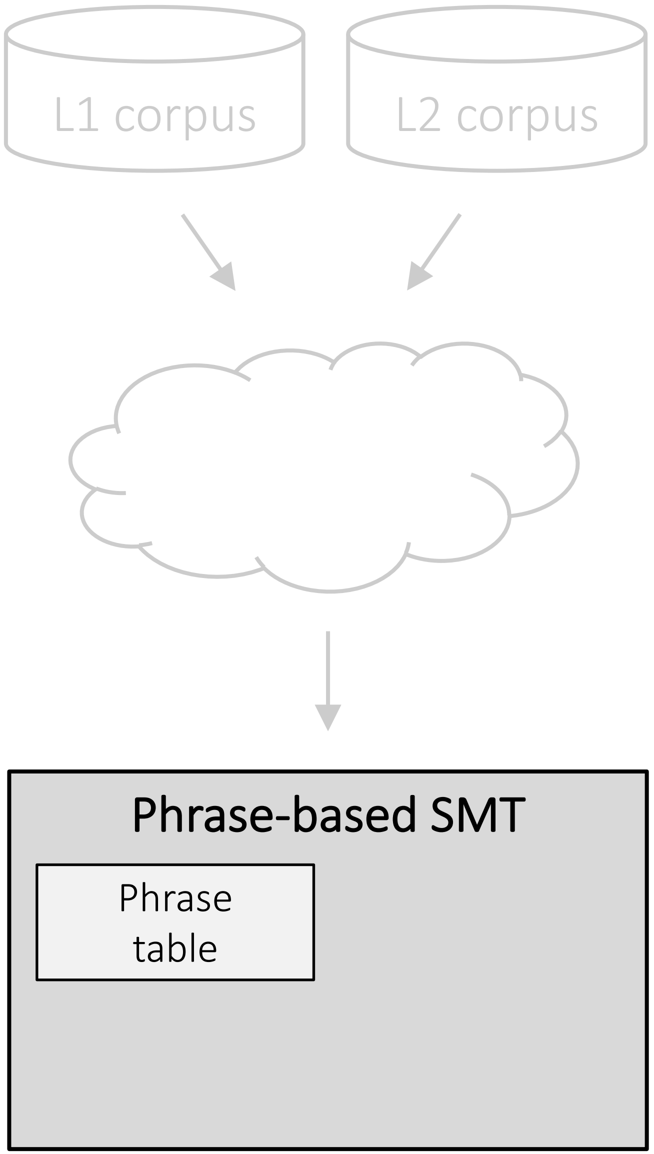
Phrase-based SMT





Phrase-based SMT

Log-linear model combining

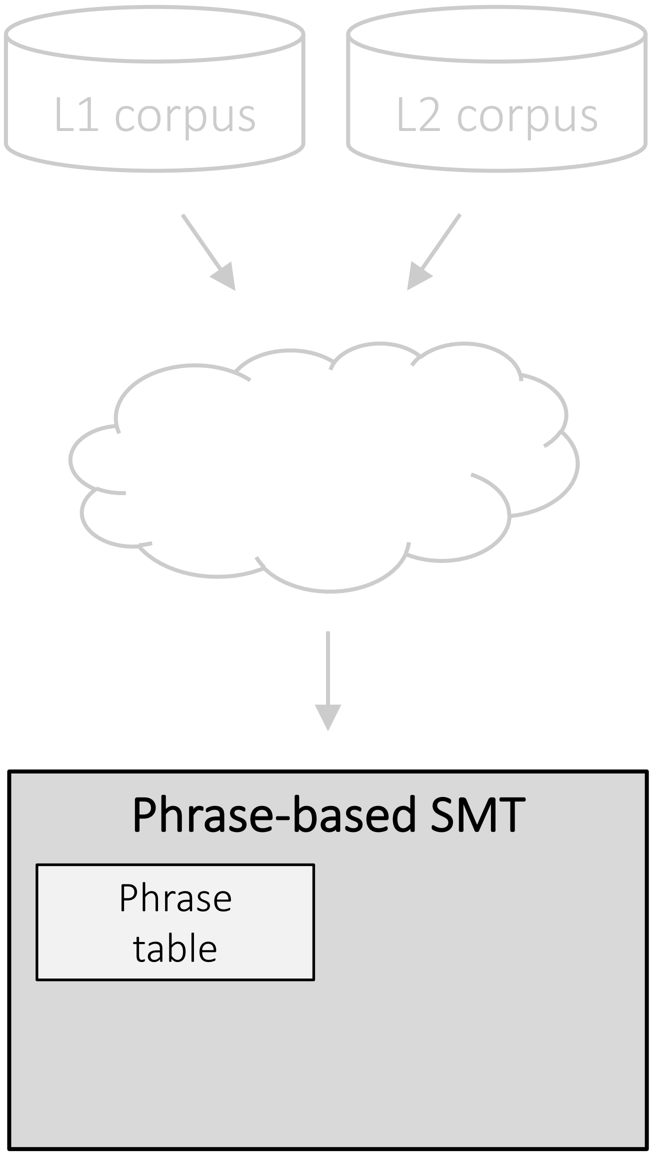


Phrase-based SMT

Log-linear model combining

- Phrase table

Phrase-based SMT

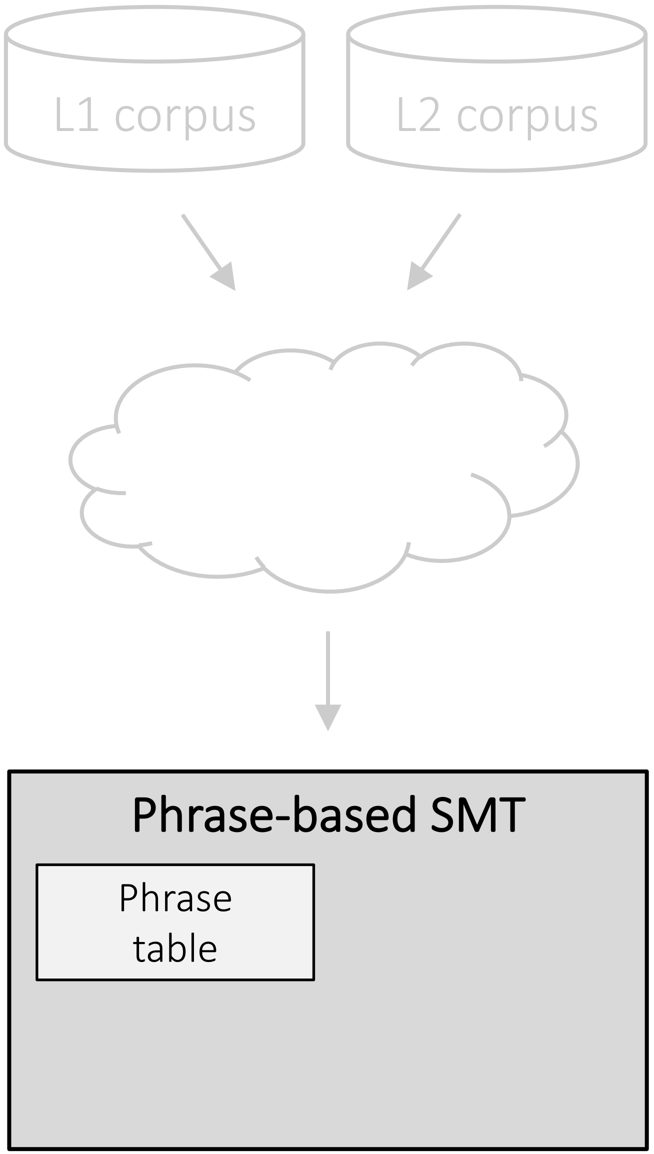


Log-linear model combining

- Phrase table

nire iritziz	in my opinion
nire iritziz	in my view
nire iritziz	I think
opari bat	a present
opari bat	one present
opari bat	a gift

⋮



Phrase-based SMT

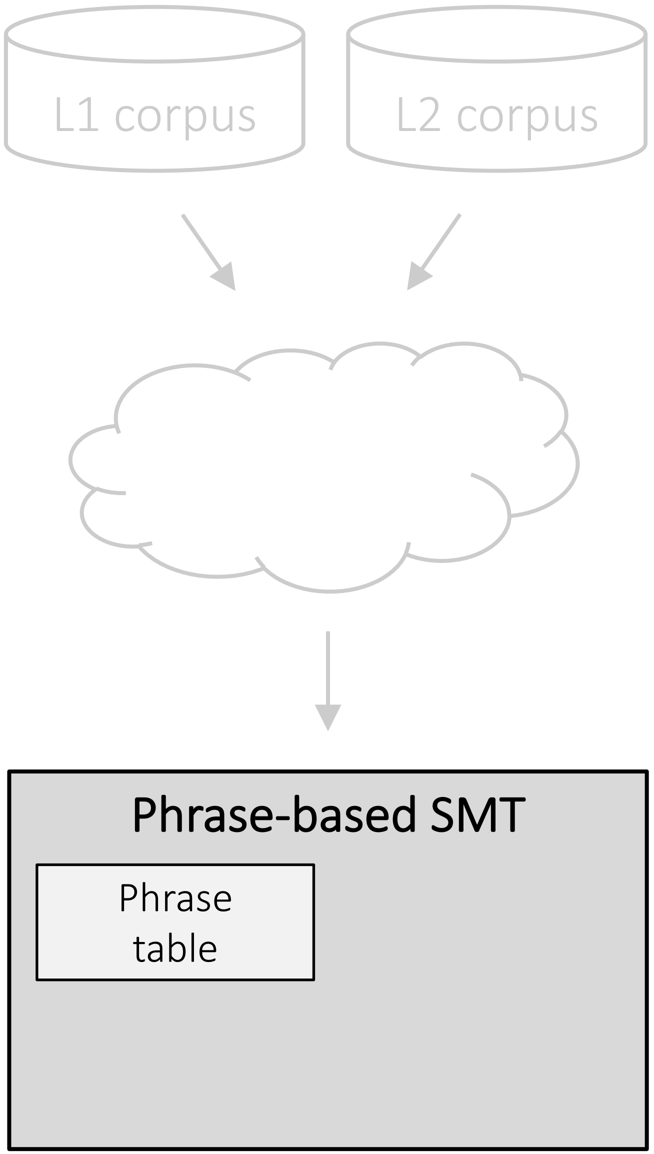
Log-linear model combining

- Phrase table
  - Direct/inverse translation probabilities

		$\phi(\bar{f}\vert\bar{e})$	$\phi(\bar{e}\vert\bar{f})$
nire iritziz	in my opinion	0.54	0.63
nire iritziz	in my view	0.32	0.68
nire iritziz	I think	0.11	0.09
opari bat	a present	0.32	0.56
opari bat	one present	0.14	0.73
opari bat	a gift	0.11	0.49

⋮

Phrase-based SMT

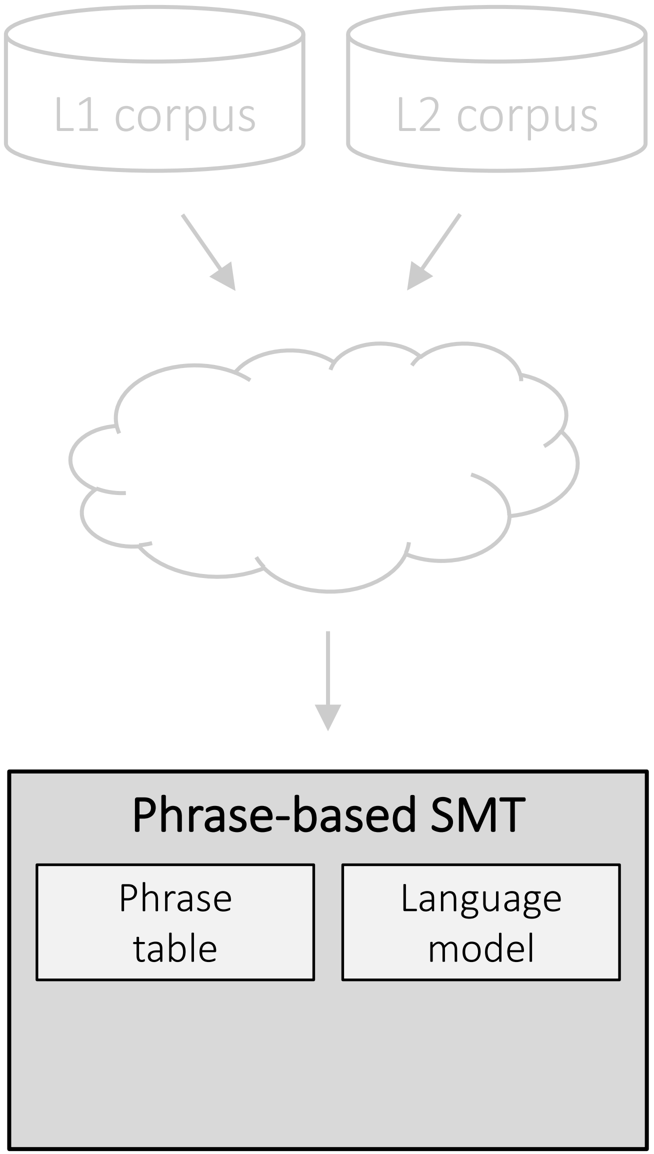


Log-linear model combining

- Phrase table
  - Direct/inverse translation probabilities
  - Direct/inverse lexical weightings

		$\phi(\bar{f}\|\bar{e})$	$\phi(\bar{e}\|\bar{f})$	$\mathrm{lex}(\bar{f}\|\bar{e})$	$\mathrm{lex}(\bar{e}\|\bar{f})$
nire iritziz	in my opinion	0.54	0.63	0.12	0.15
nire iritziz	in my view	0.32	0.68	0.09	0.16
nire iritziz	I think	0.11	0.09	0.04	0.02
opari bat	a present	0.32	0.56	0.21	0.22
opari bat	one present	0.14	0.73	0.18	0.32
opari bat	a gift	0.11	0.49	0.11	0.13

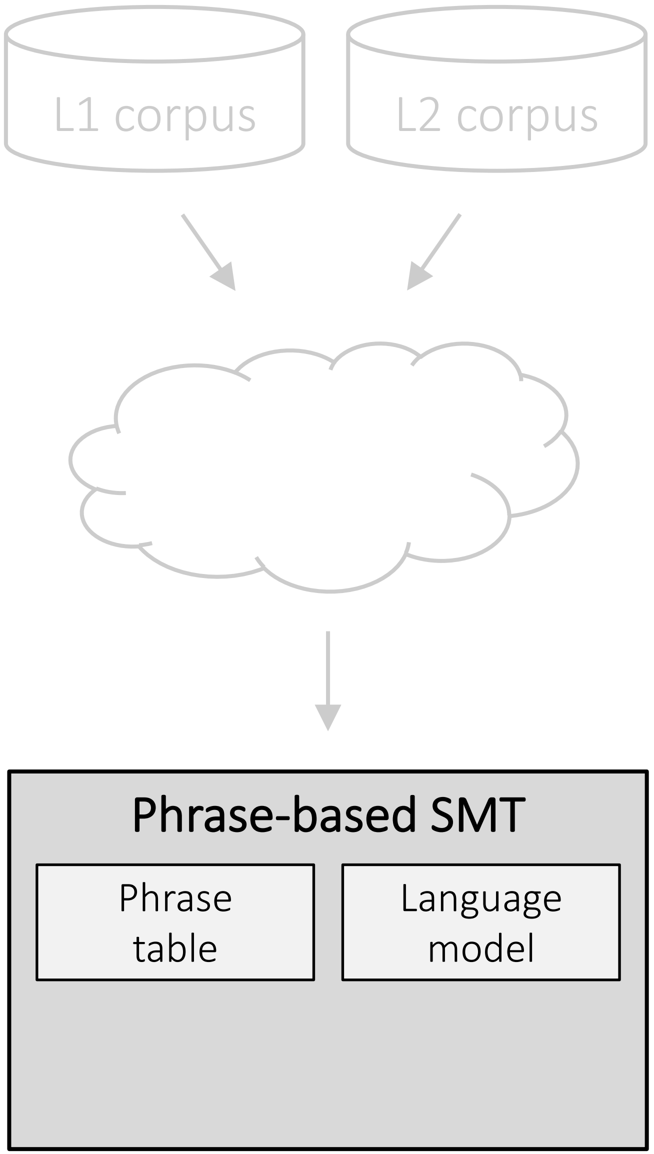
⋮



Phrase-based SMT

Log-linear model combining

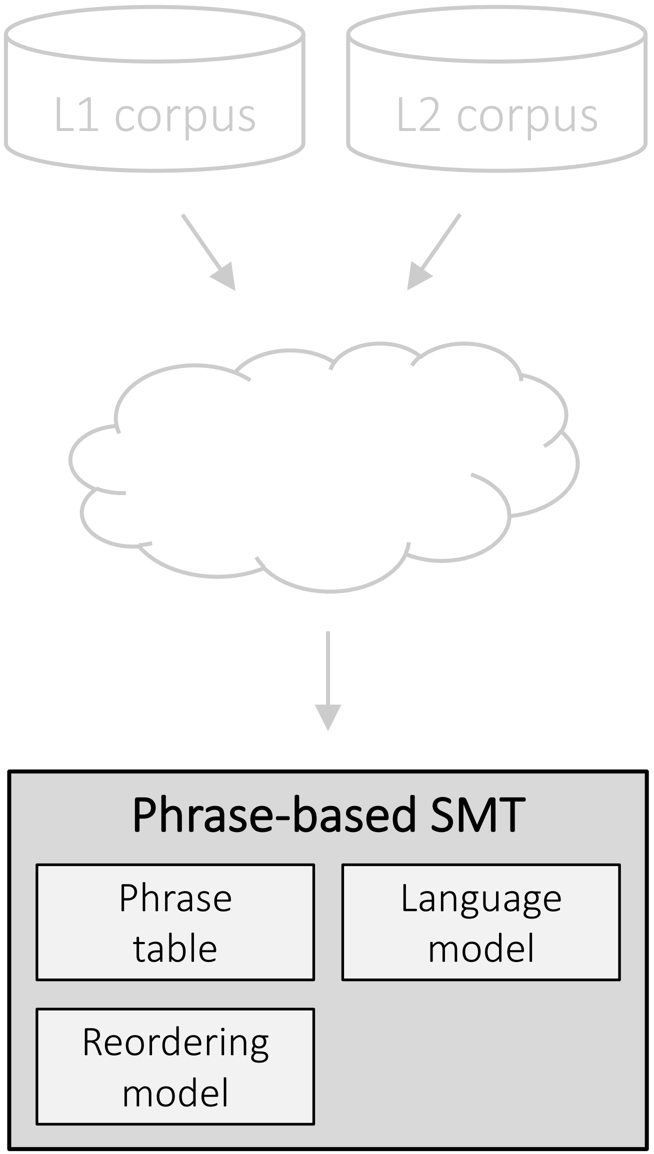
- Phrase table
  - Direct/inverse translation probabilities
  - Direct/inverse lexical weightings
- Language model



Phrase-based SMT

Log-linear model combining

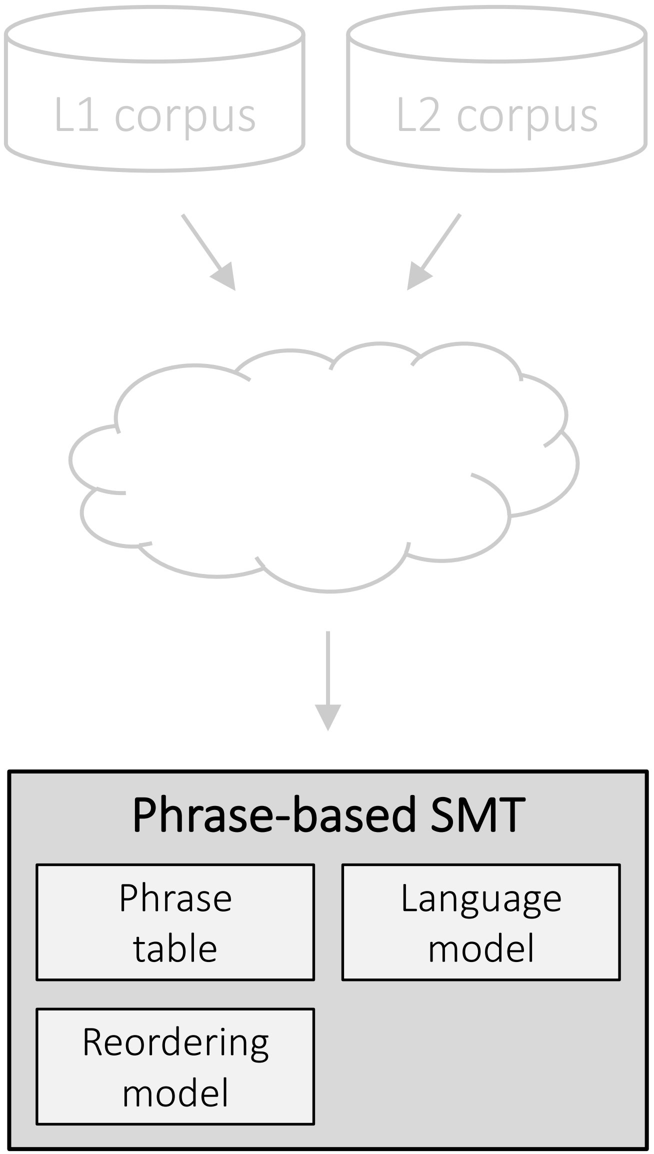
- Phrase table
  - Direct/inverse translation probabilities
  - Direct/inverse lexical weightings
- Language model
  - N-gram frequency counts with back-off and smoothing



Phrase-based SMT

Log-linear model combining

- Phrase table
  - Direct/inverse translation probabilities
  - Direct/inverse lexical weightings
- Language model
  - N-gram frequency counts with back-off and smoothing
- Reordering model



Phrase-based SMT

Log-linear model combining

- Phrase table
  - Direct/inverse translation probabilities
  - Direct/inverse lexical weightings
- Language model
  - N-gram frequency counts with back-off and smoothing
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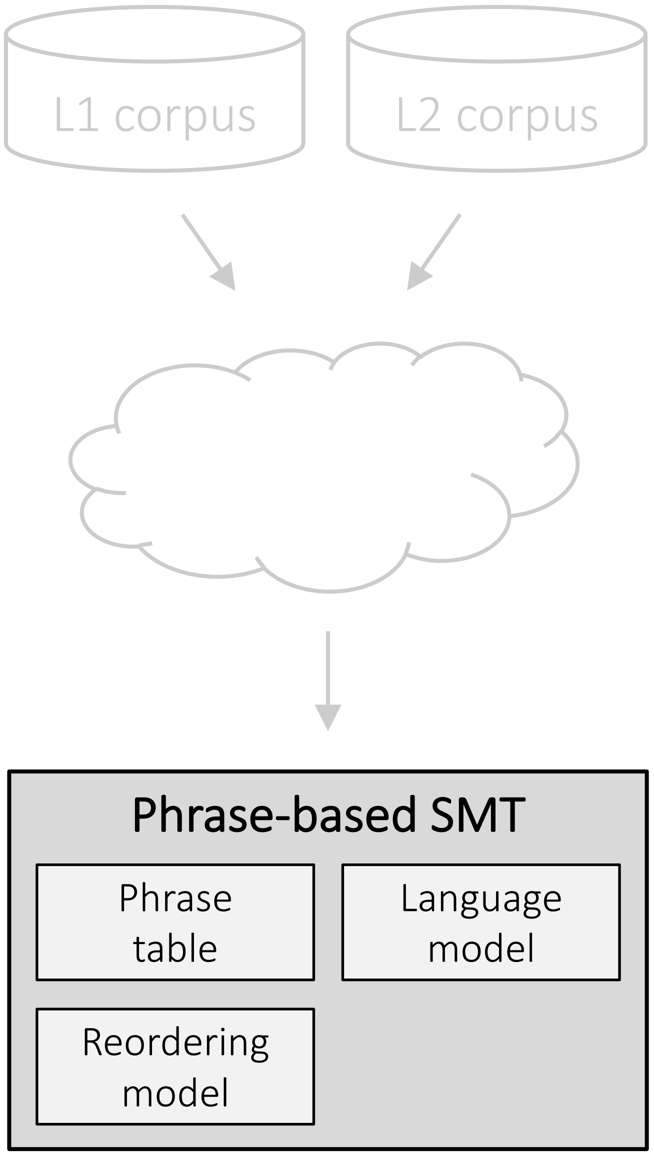
  - Distortion model (distance based)



Phrase-based SMT

Log-linear model combining

- Phrase table
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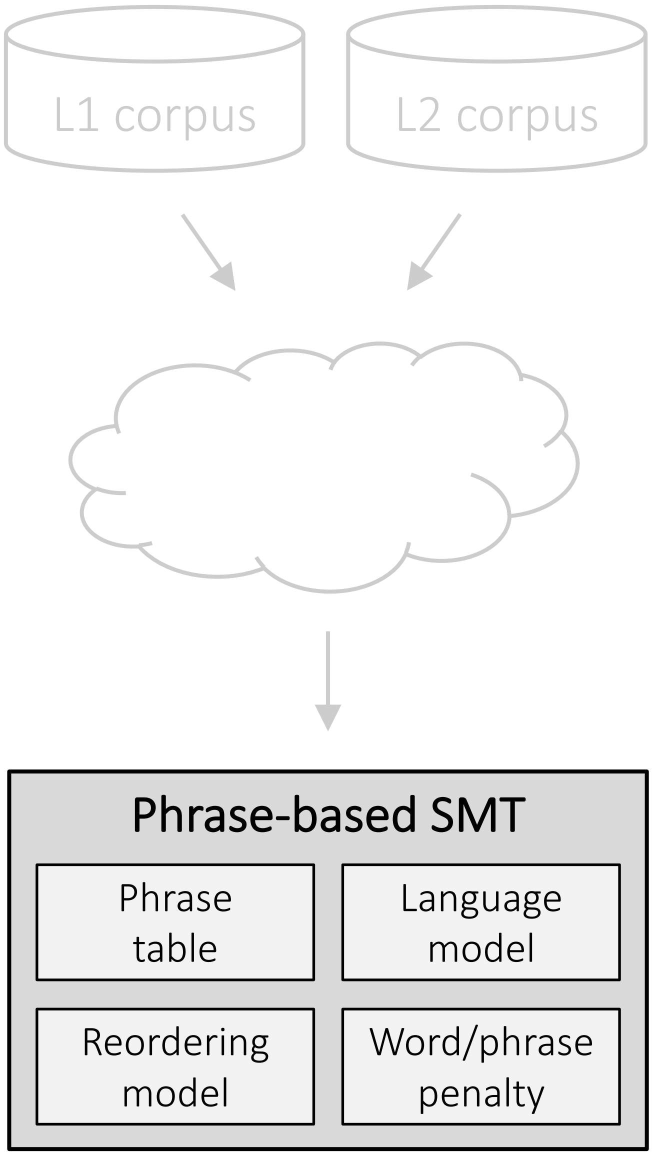
  - Distortion model (distance based)
  - Lexical reordering model



Phrase-based SMT

Log-linear model combining
- Phrase table
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- Language model
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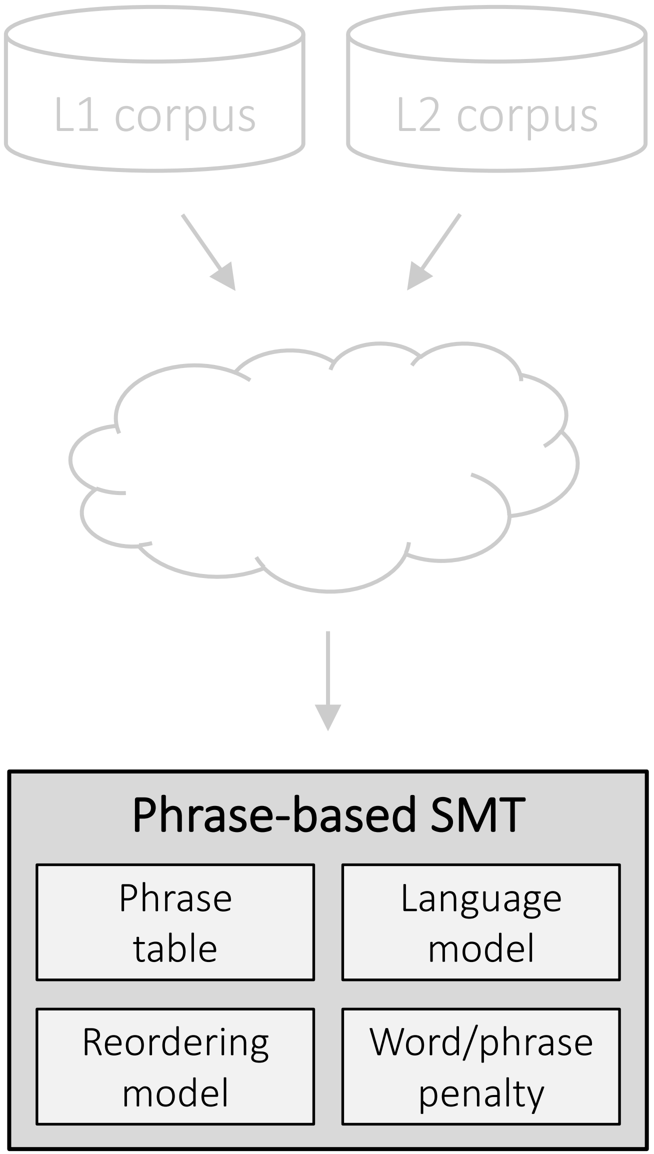
- Word/phrase penalty

Phrase-based SMT



Log-linear model combining

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- Word/phrase penalty
  - Fixed score to control the length of the output

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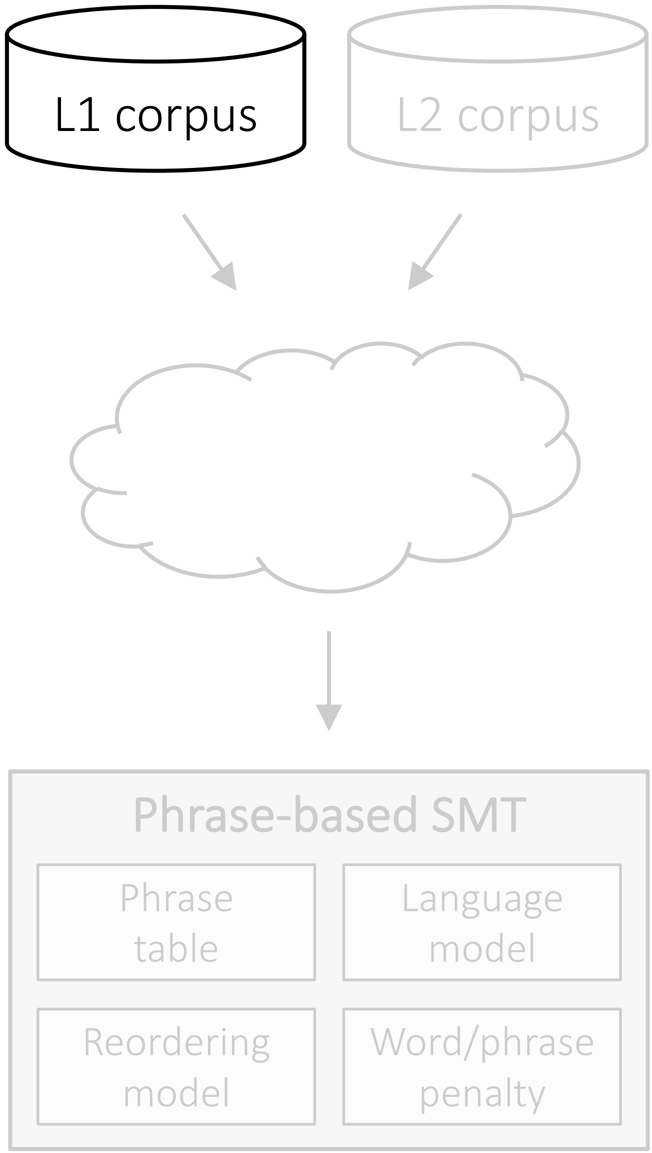

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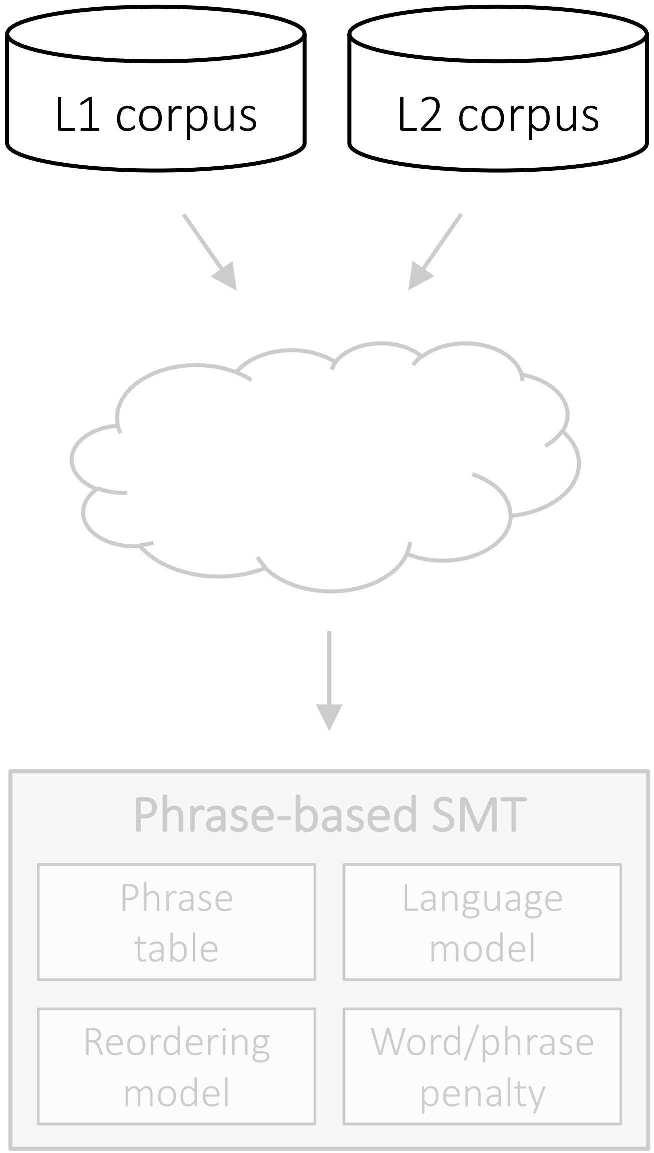

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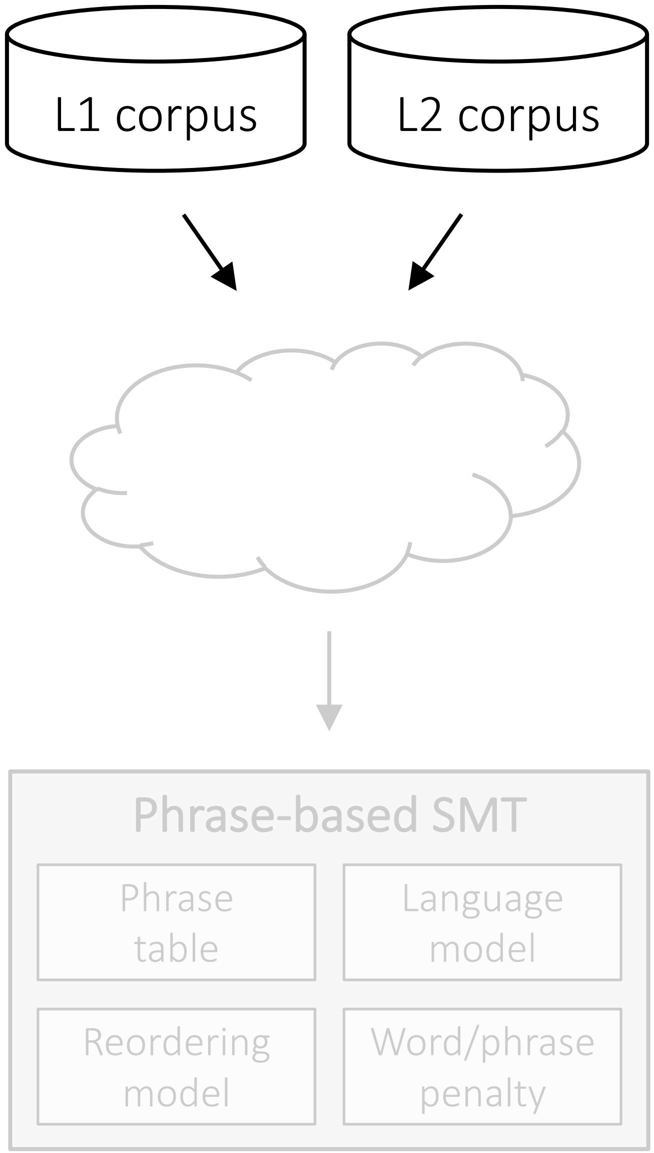

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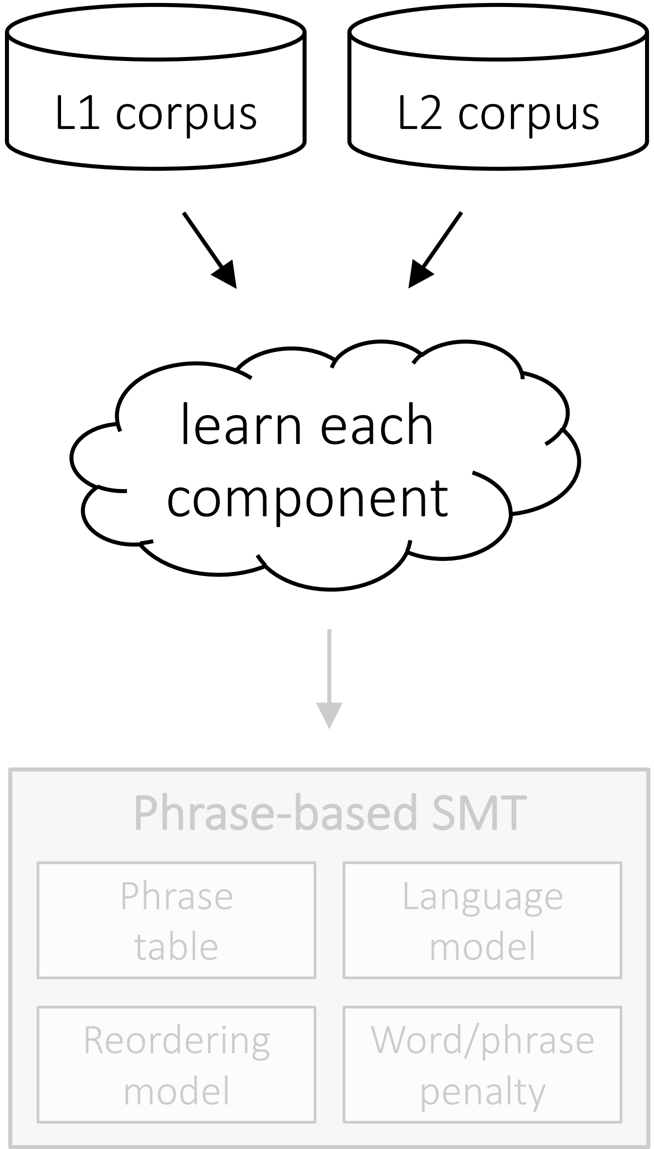

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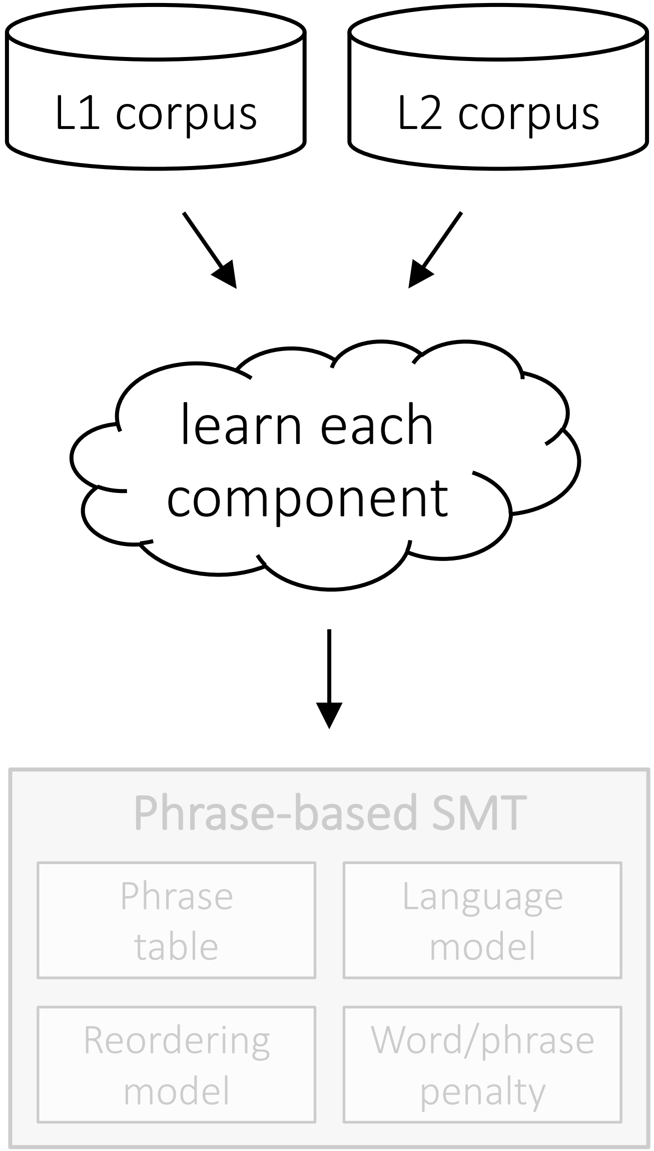

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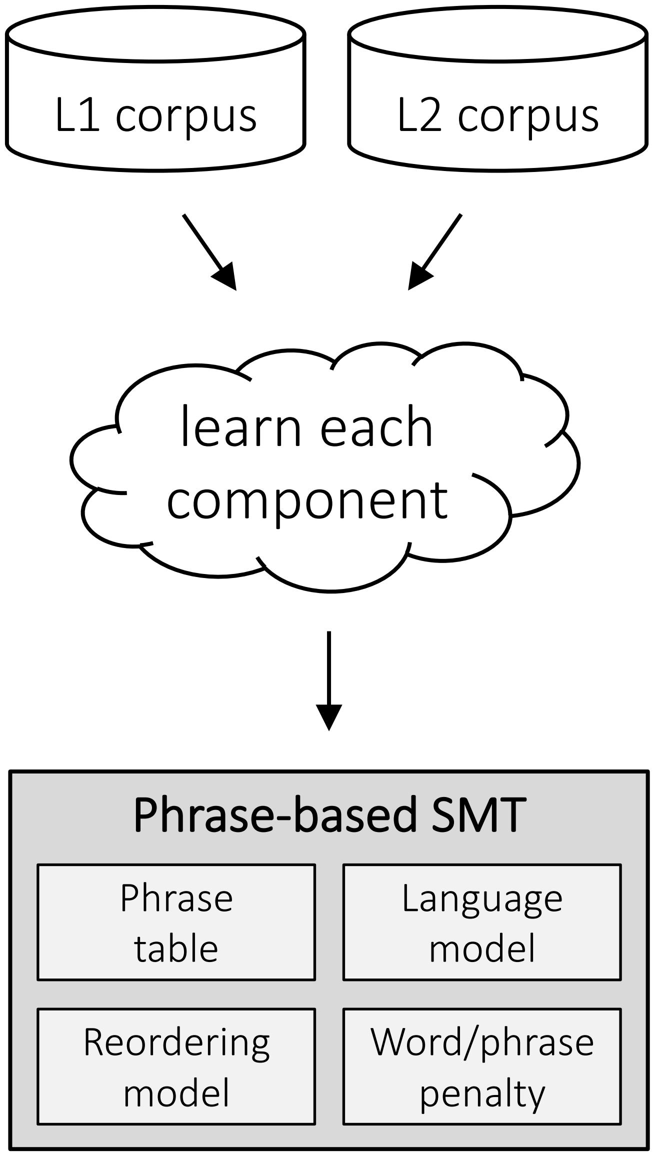

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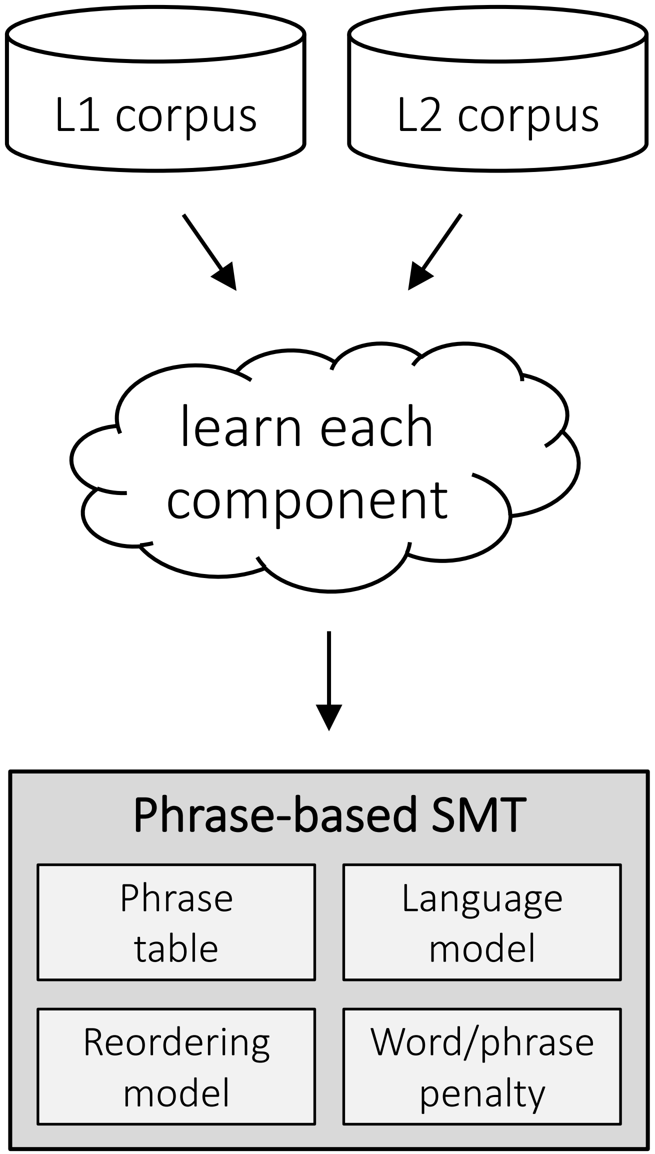
Unsupervised phrase-based SMT



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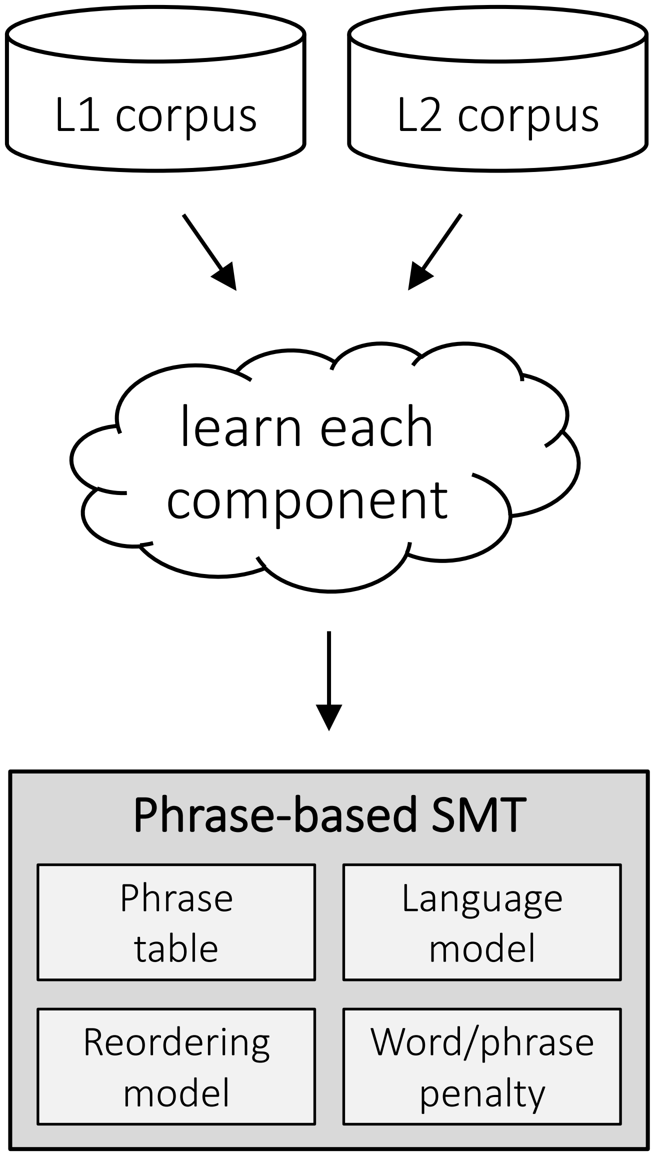

Unsupervised phrase-based SMT

Learn components from monolingual corpora

- Phrase table
  - Direct/inverse translation probabilities
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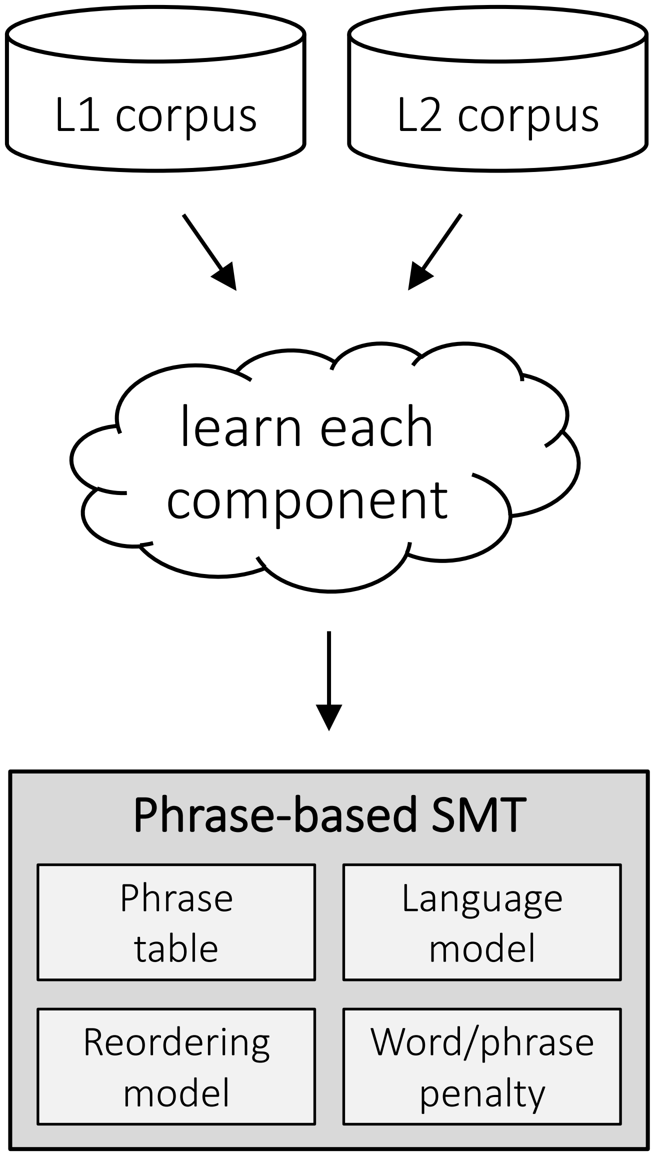

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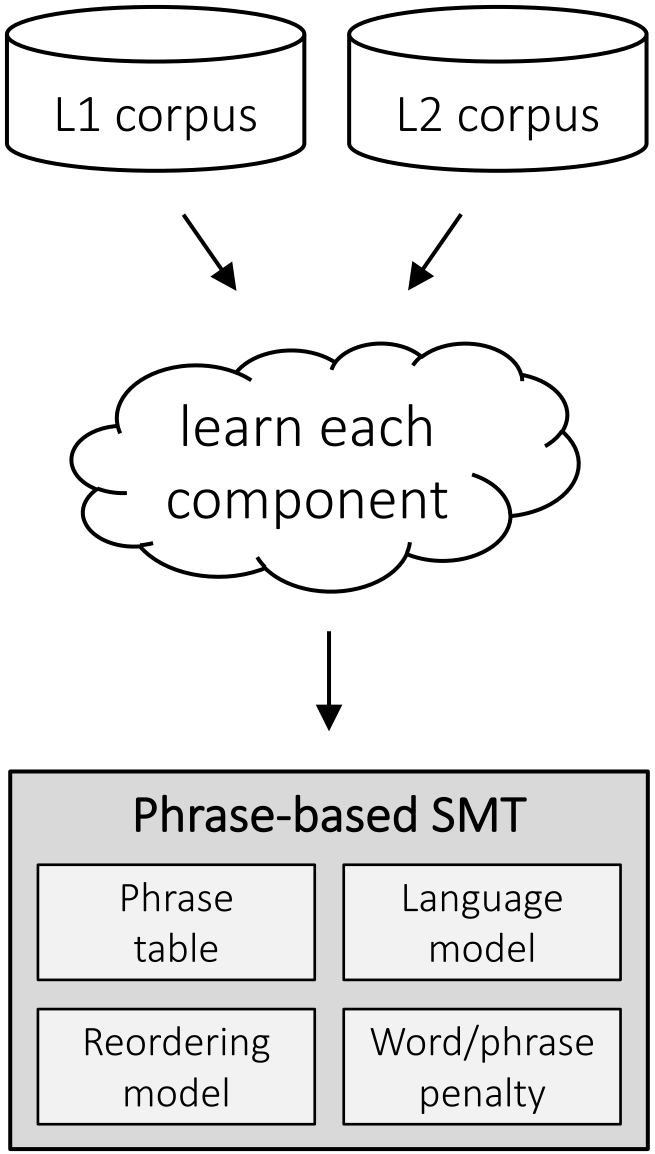

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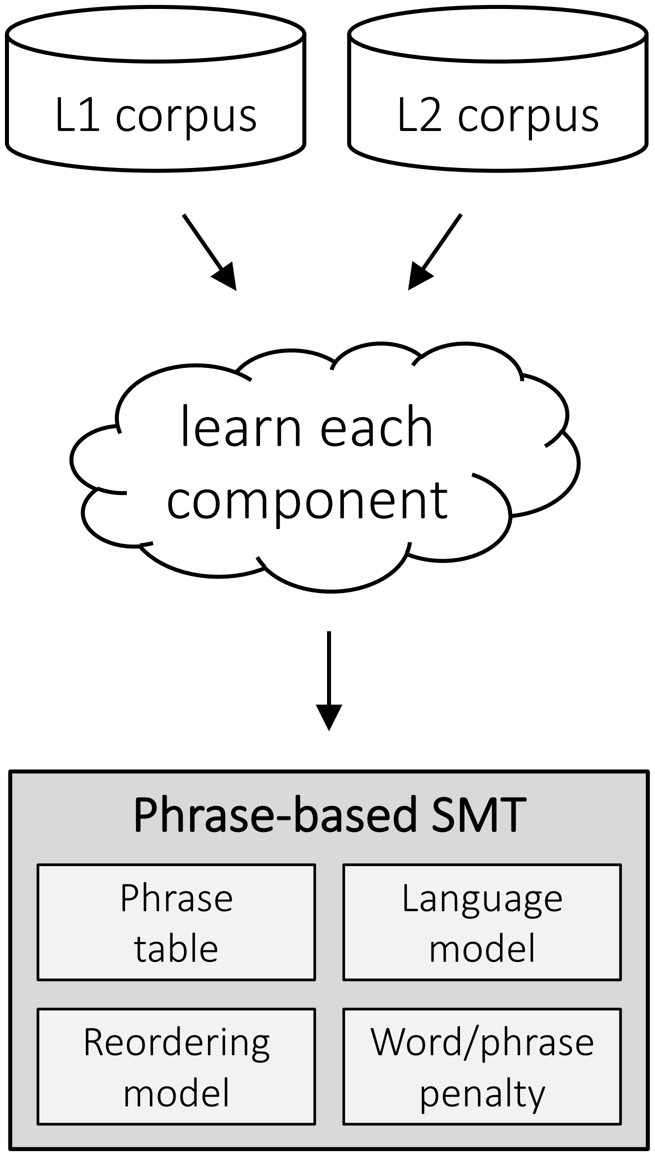

Unsupervised phrase-based SMT

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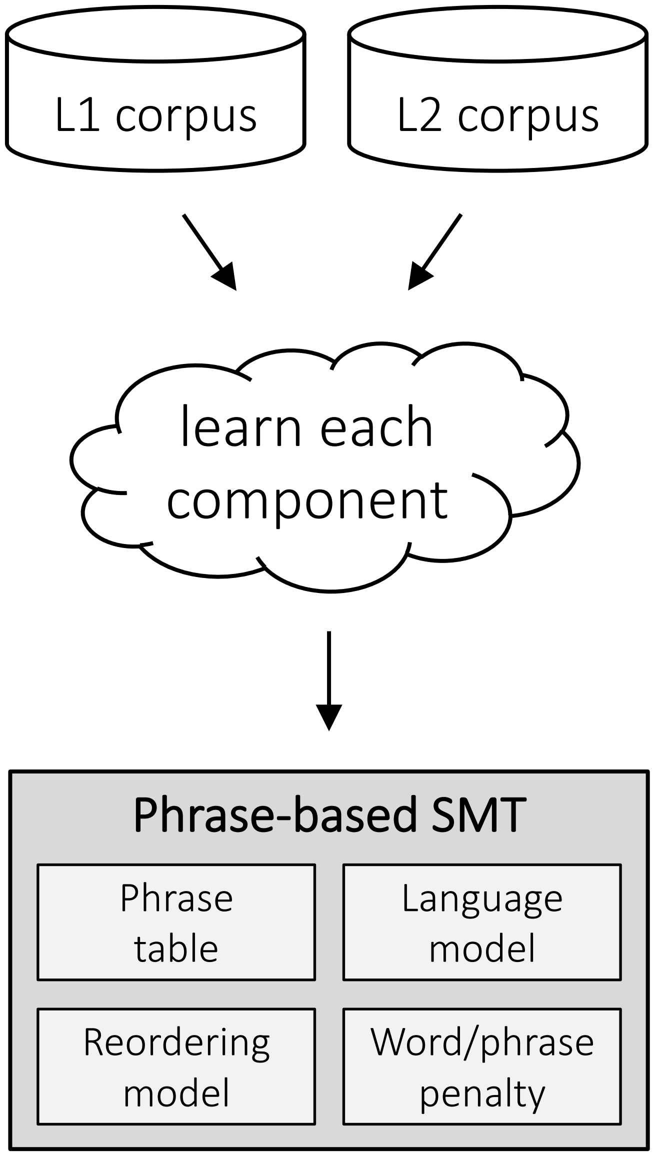

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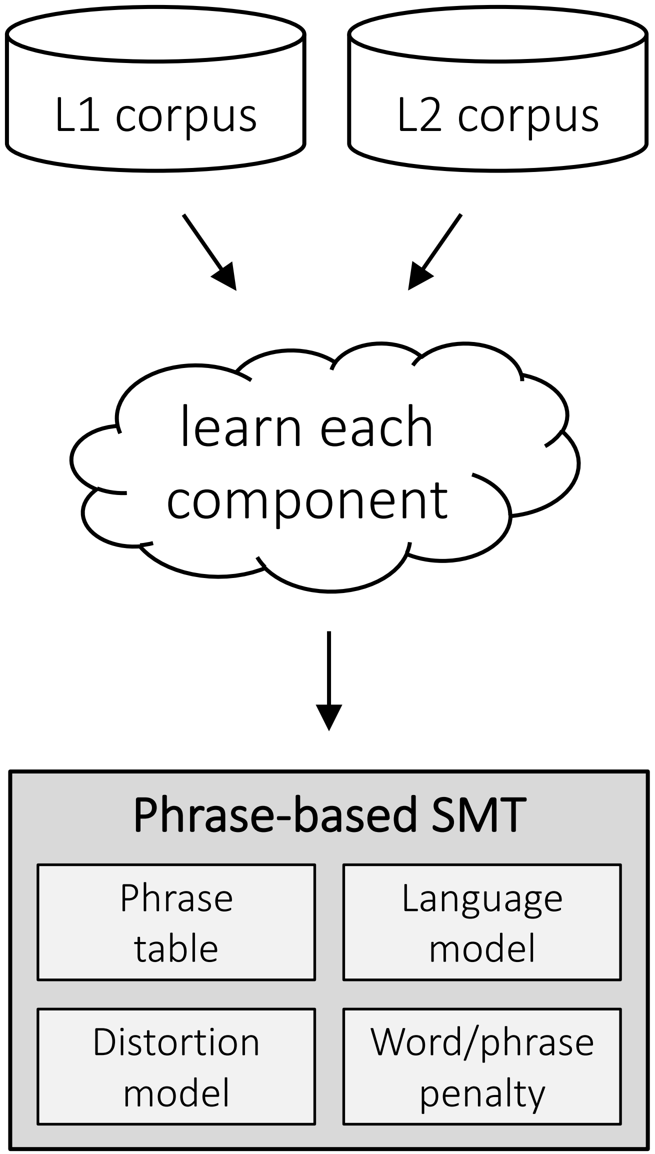

Unsupervised phrase-based SMT

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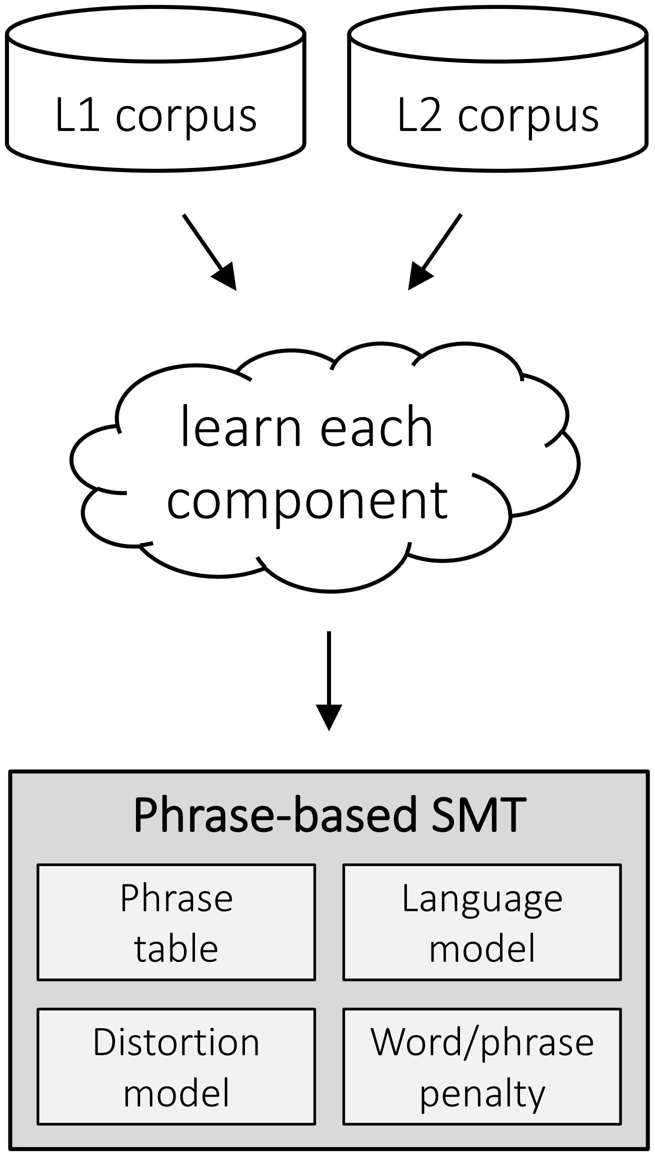

Unsupervised phrase-based SMT

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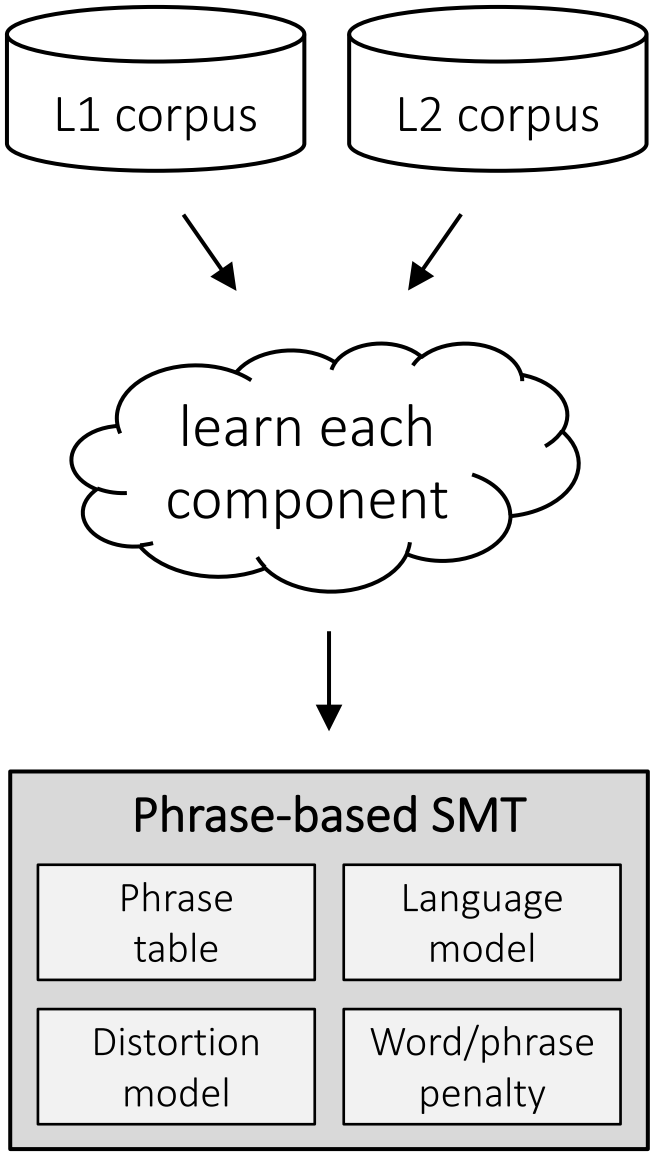

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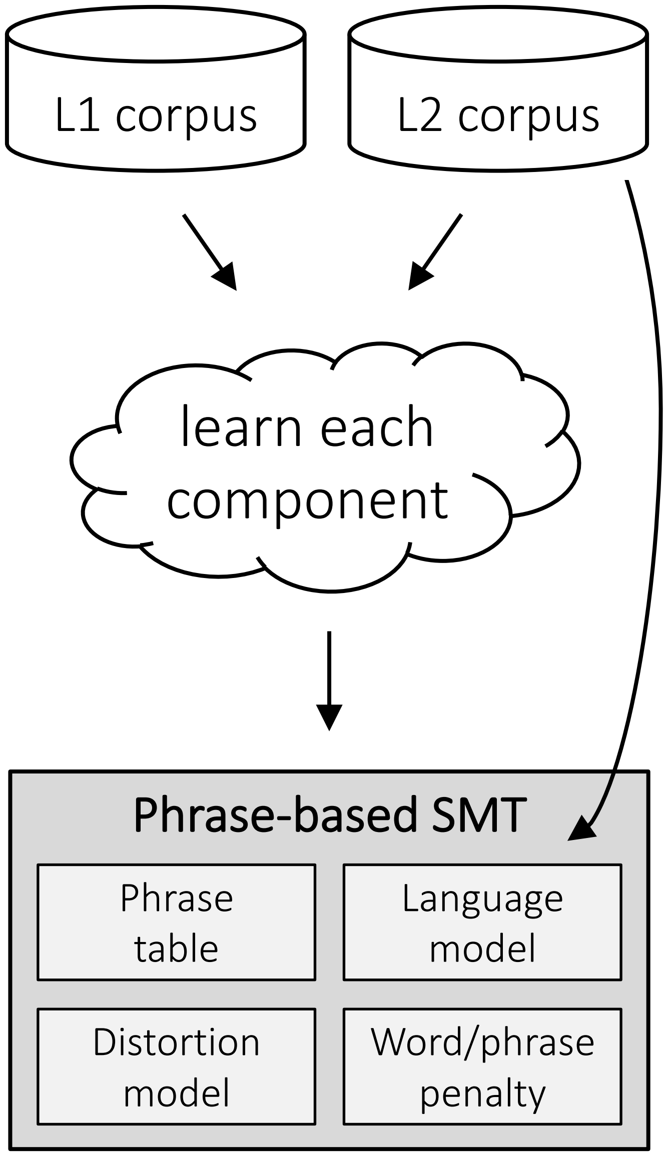

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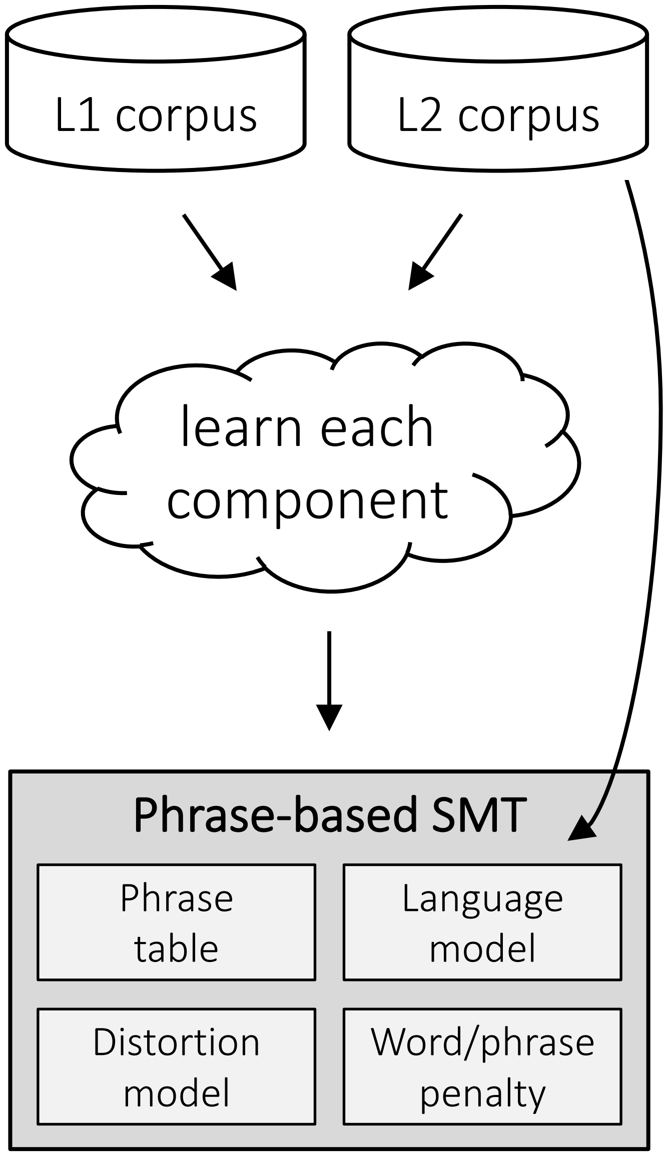

Unsupervised phrase-based SMT

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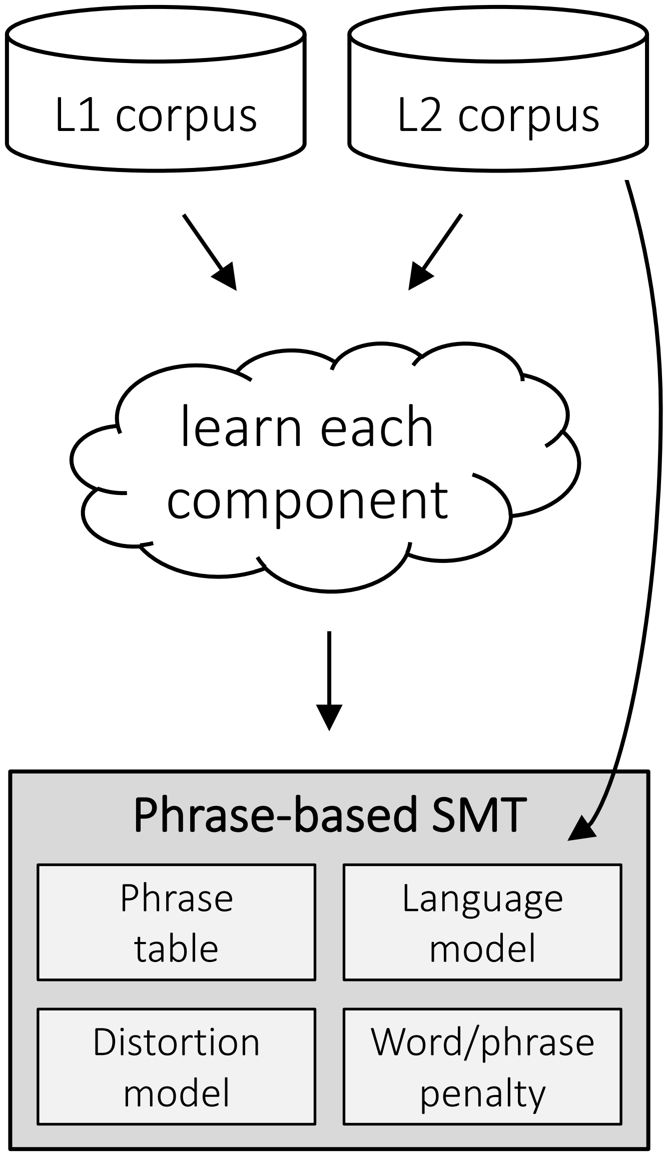

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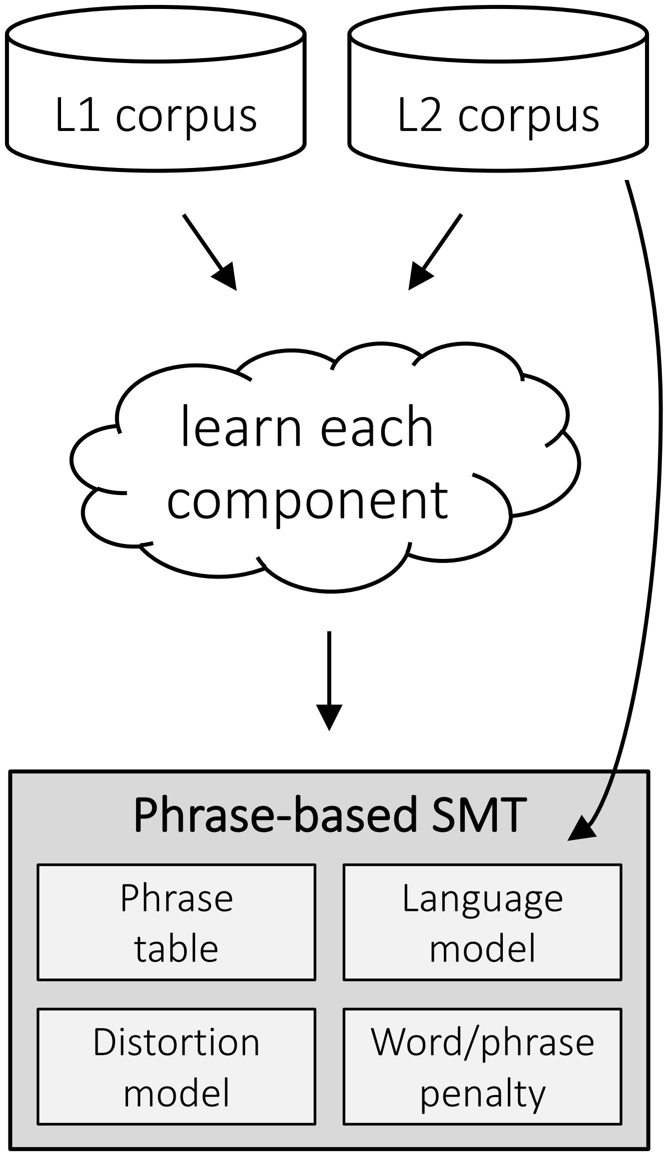

Unsupervised phrase-based SMT

Learn components from monolingual corpora

- Phrase table TRICKY…
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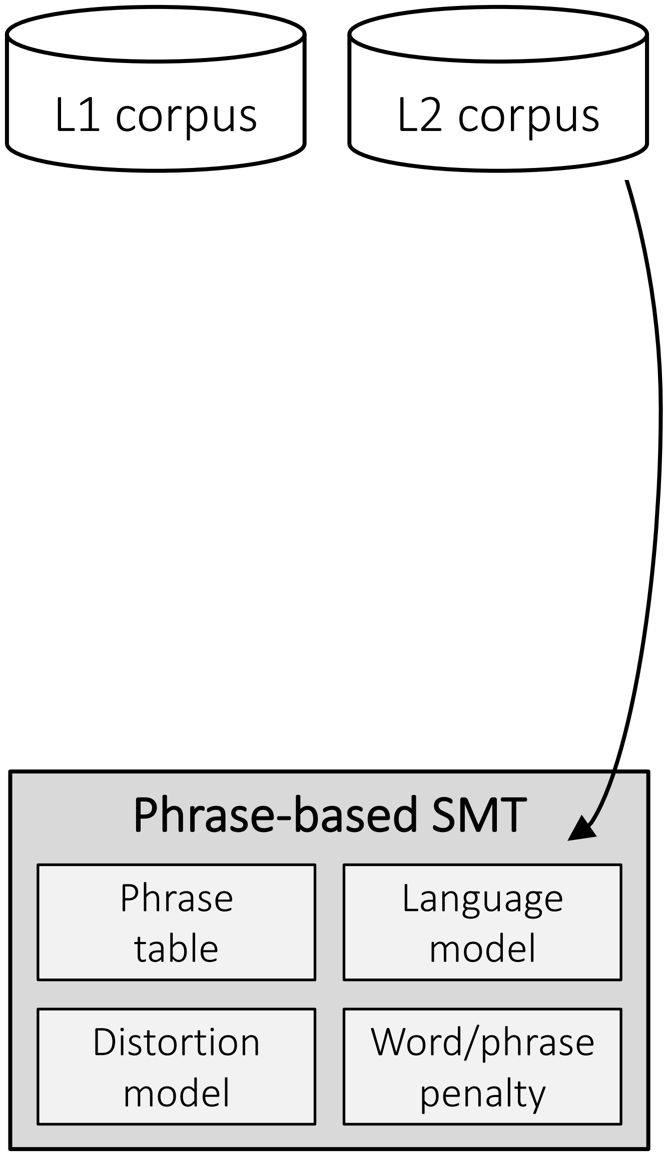

Unsupervised phrase-based SMT

Learn components from monolingual corpora

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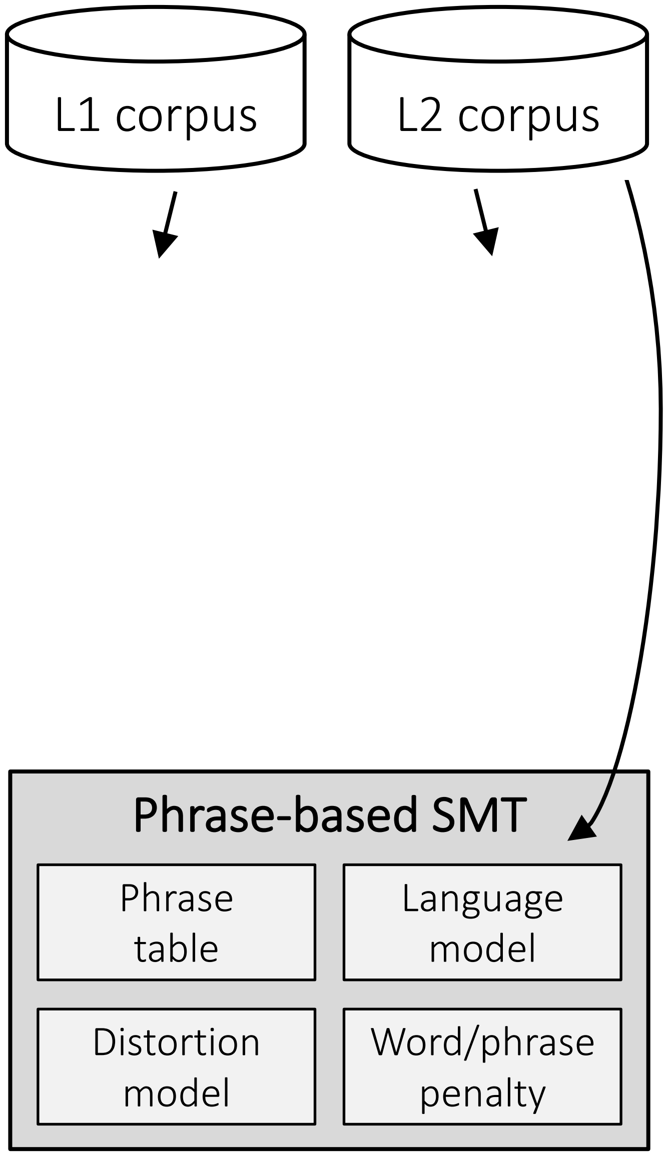

Unsupervised phrase-based SMT

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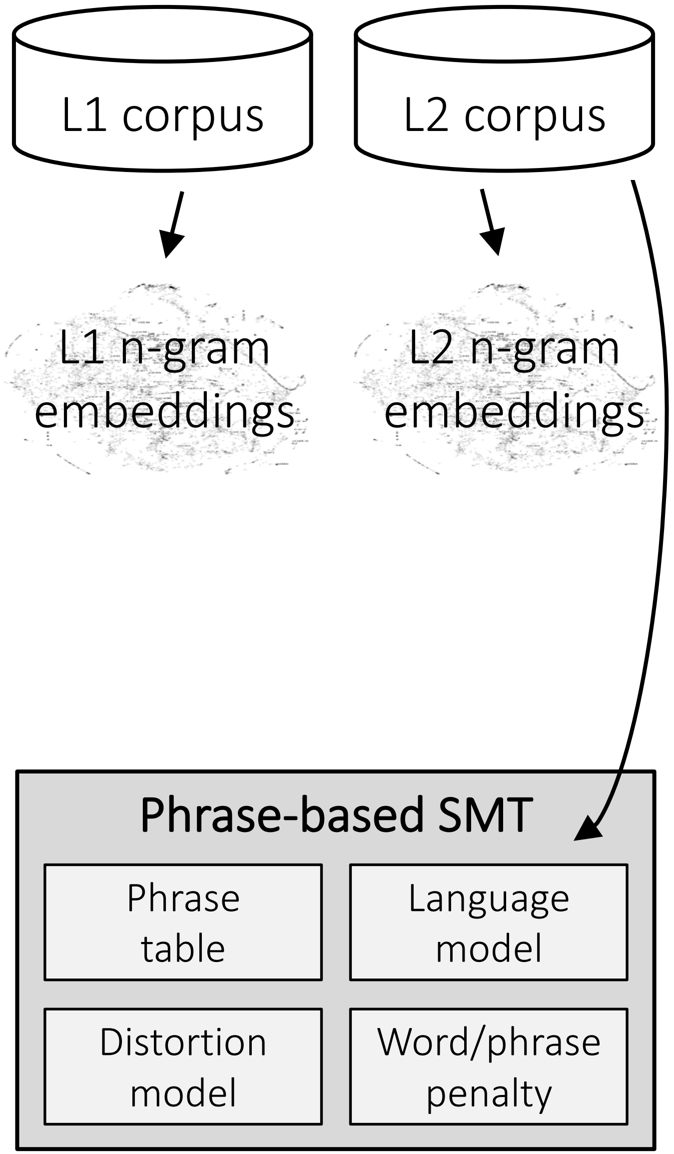

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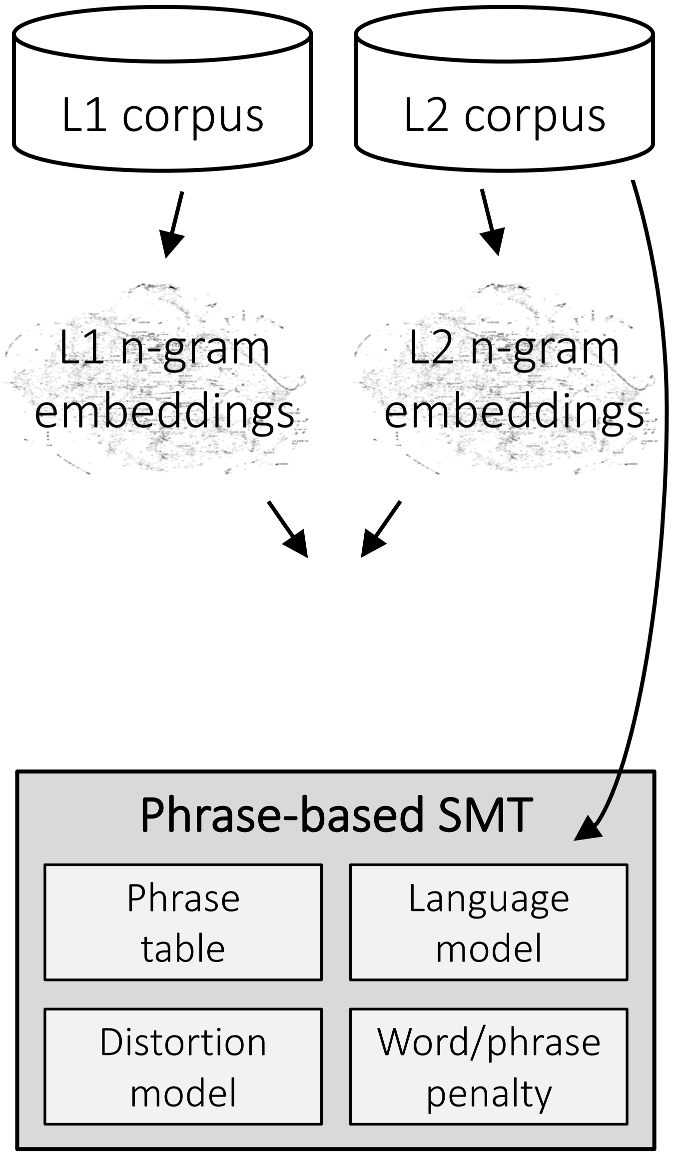

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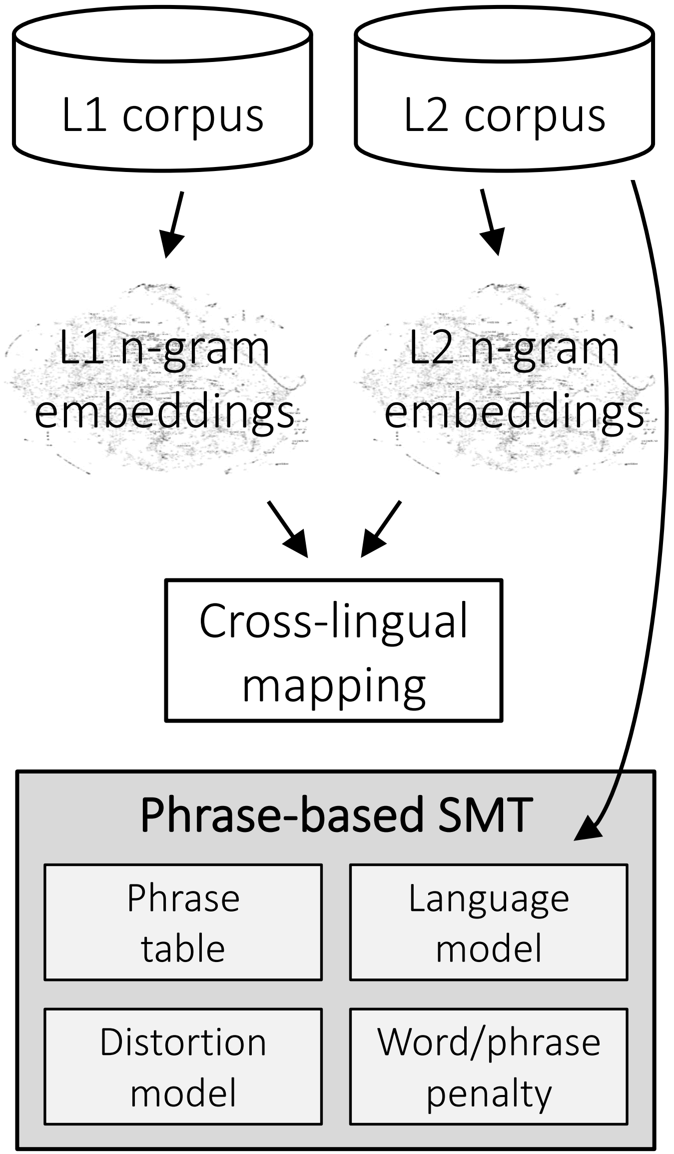

Unsupervised phrase-based SMT

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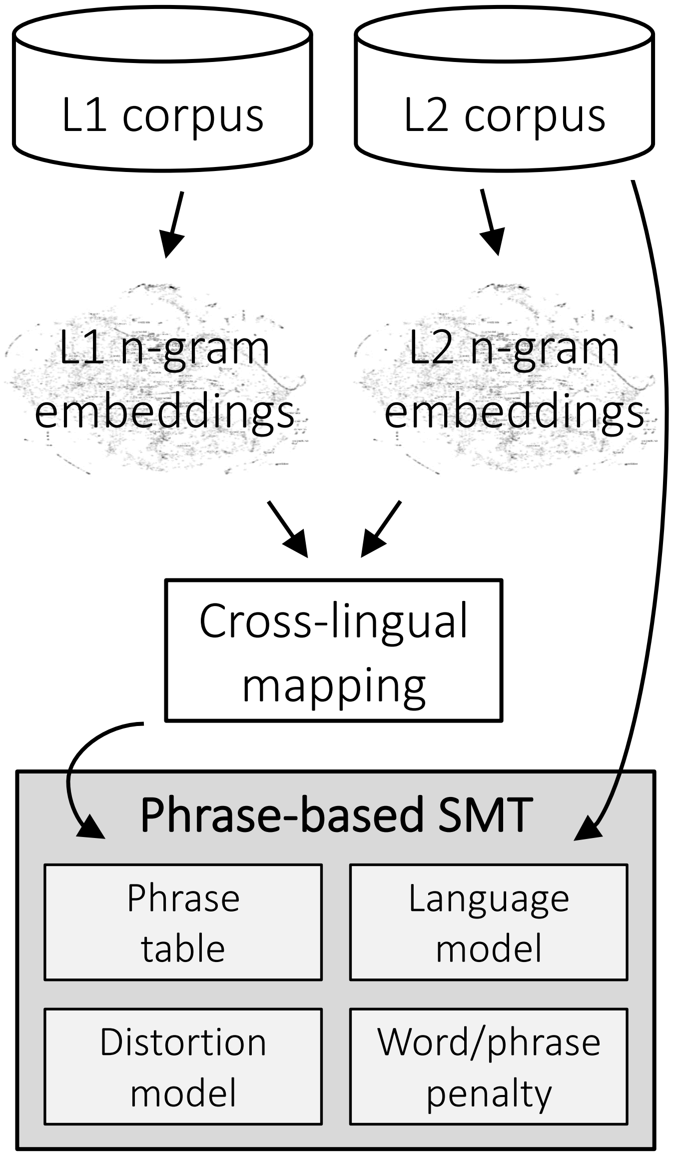

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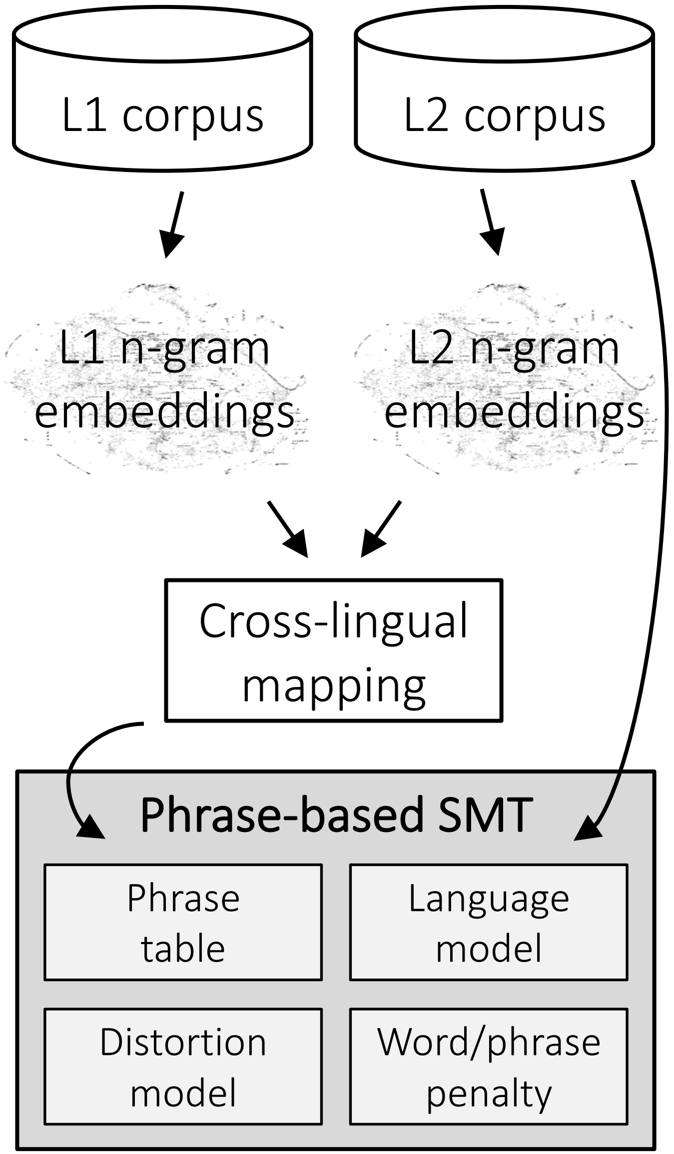

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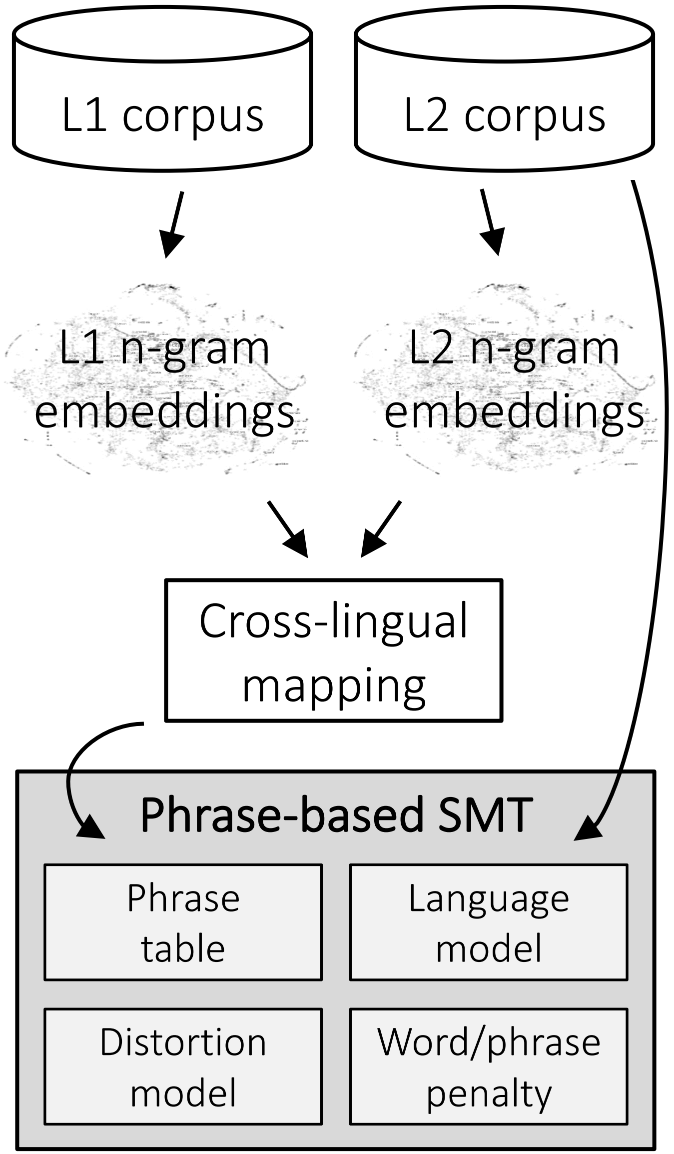

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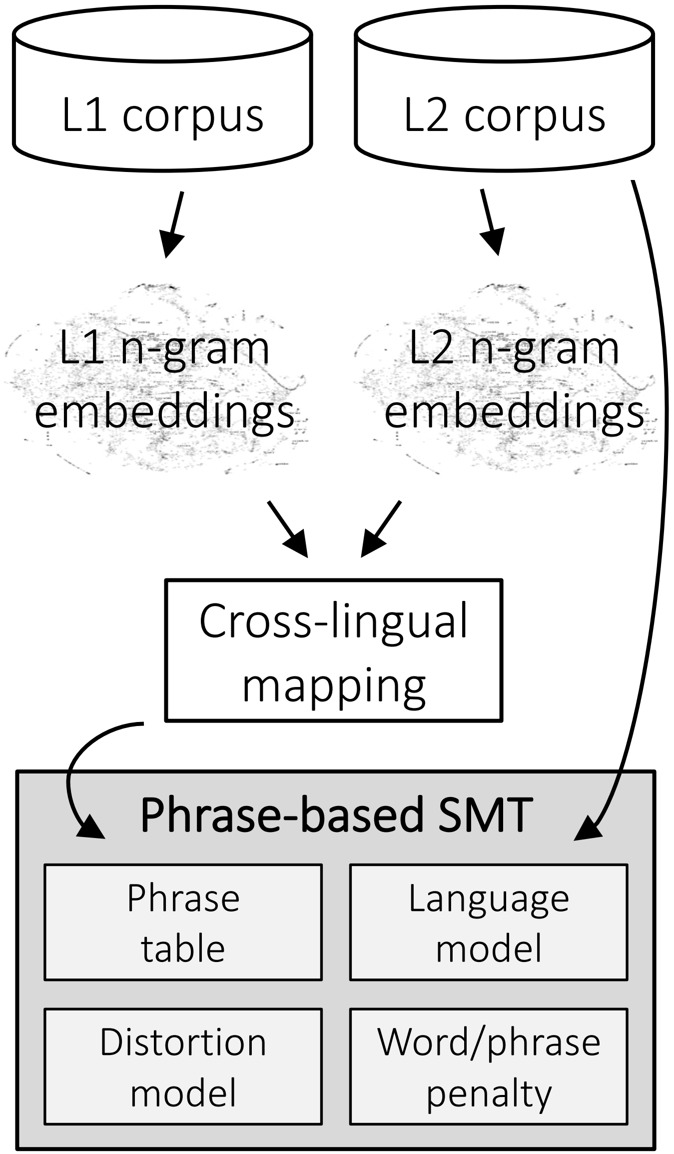
I will go to New York by plane .



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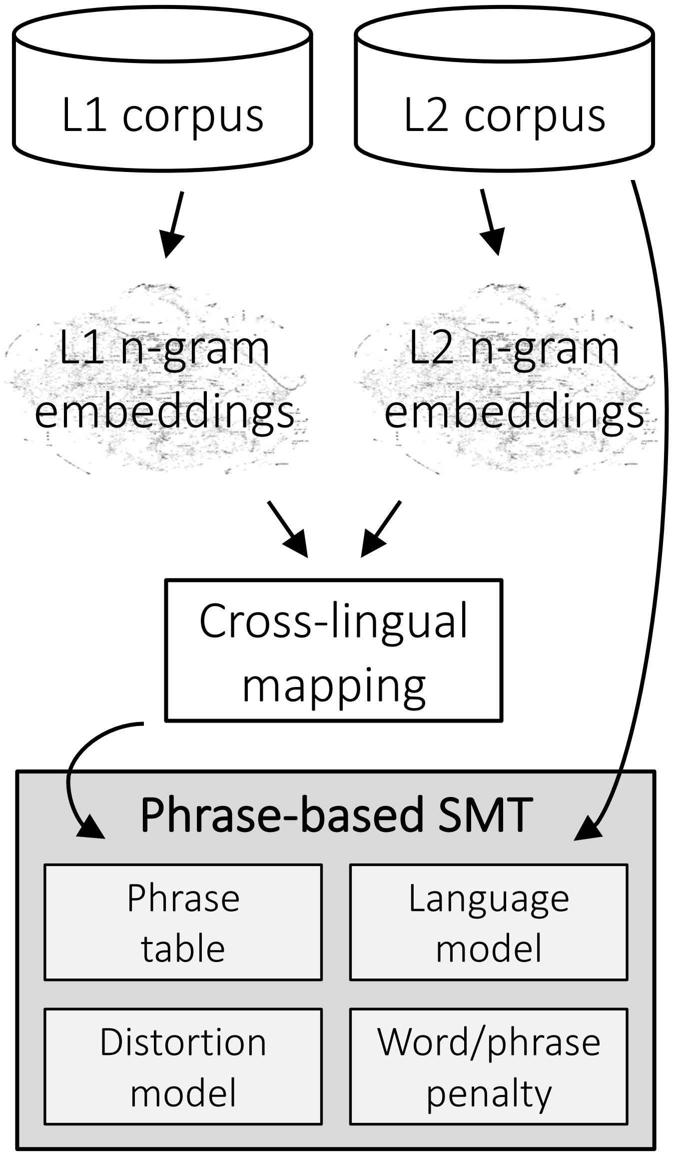
I will $\underbrace{\textit{go}}_{w}$ *to New York by plane .*



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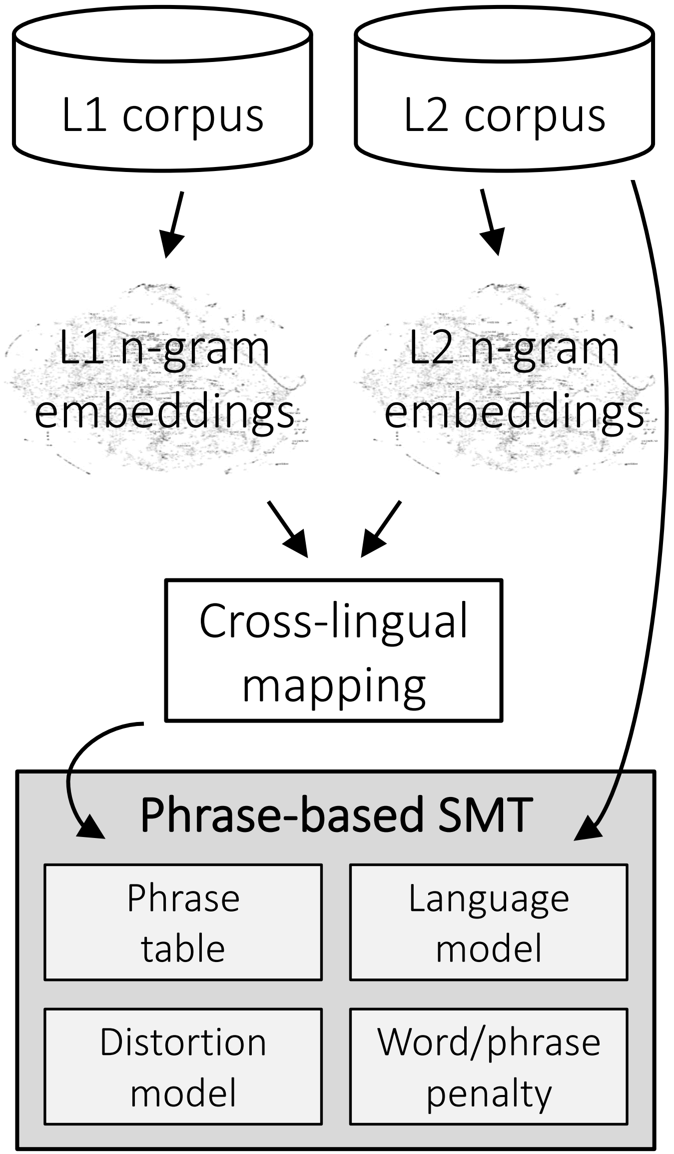
I will go to New York by plane .

w



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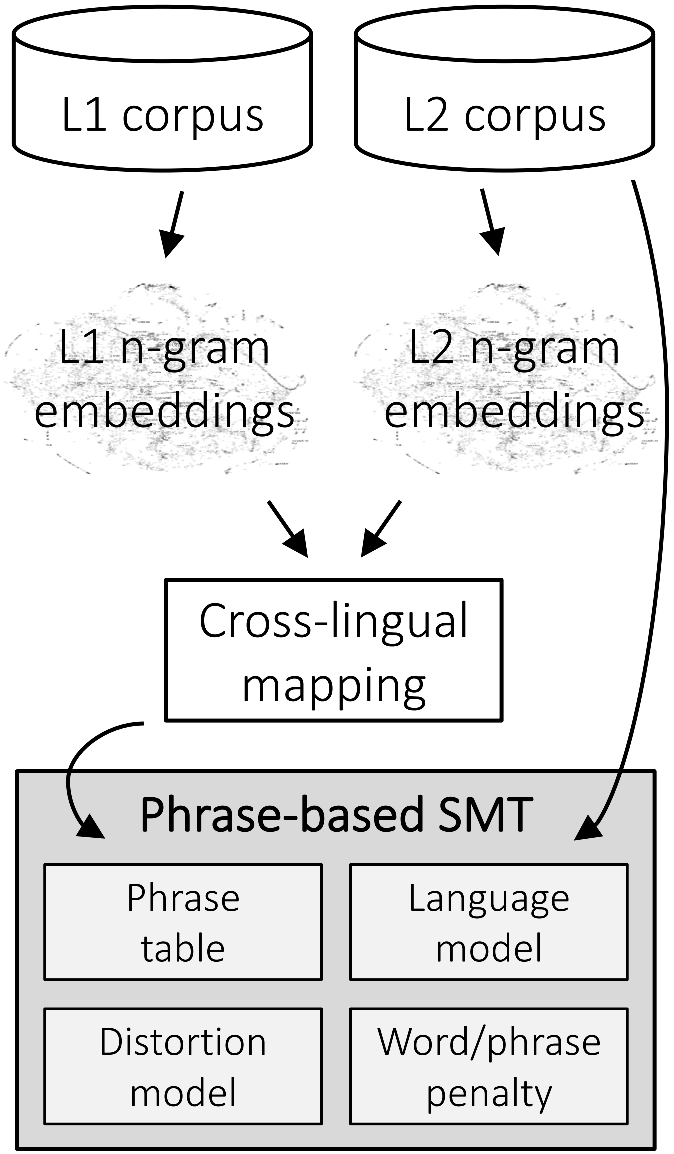
I will $\underbrace{\textit{go}}_{w}$ $\underbrace{\textit{to}}_{c}$ New York by plane .



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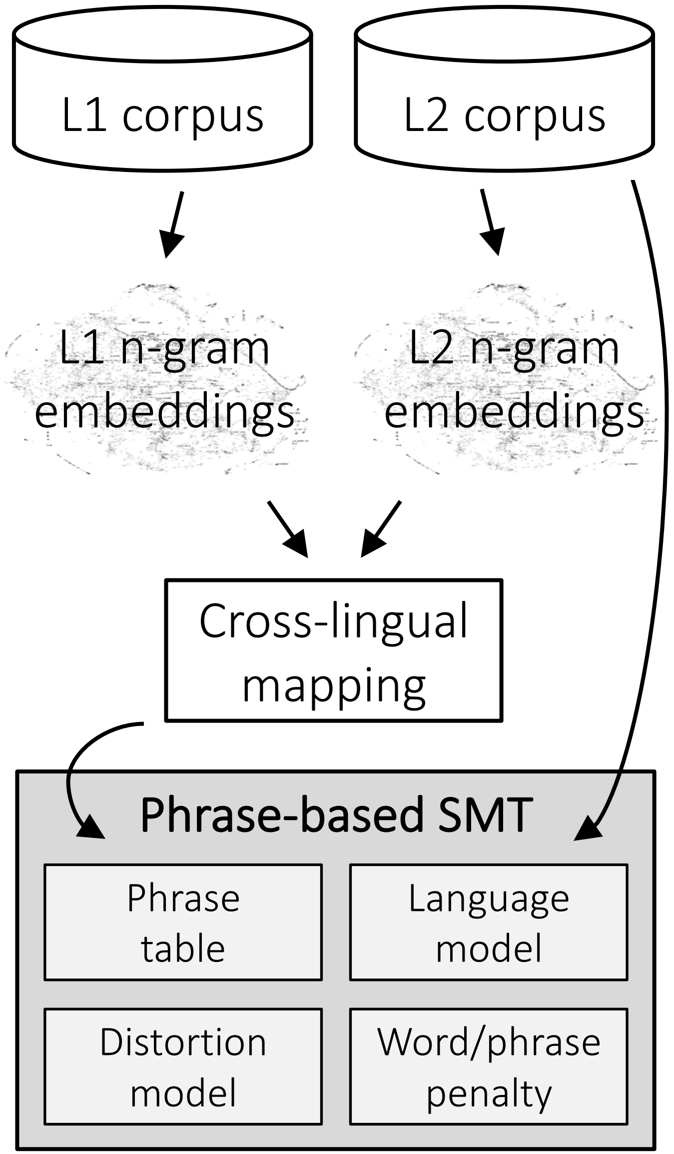
I will $\underbrace{\textit{go}}_{w}$ *to* $\underbrace{\textit{New}}_{c}$ *York by plane .*



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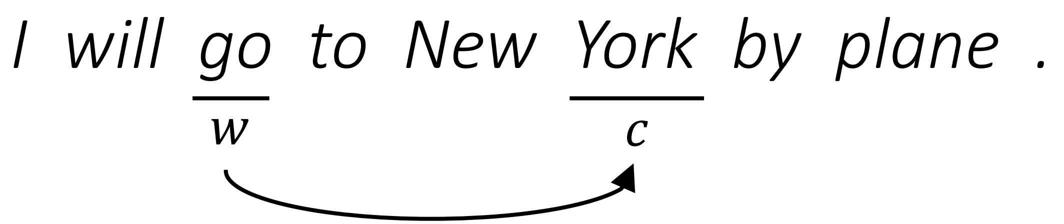

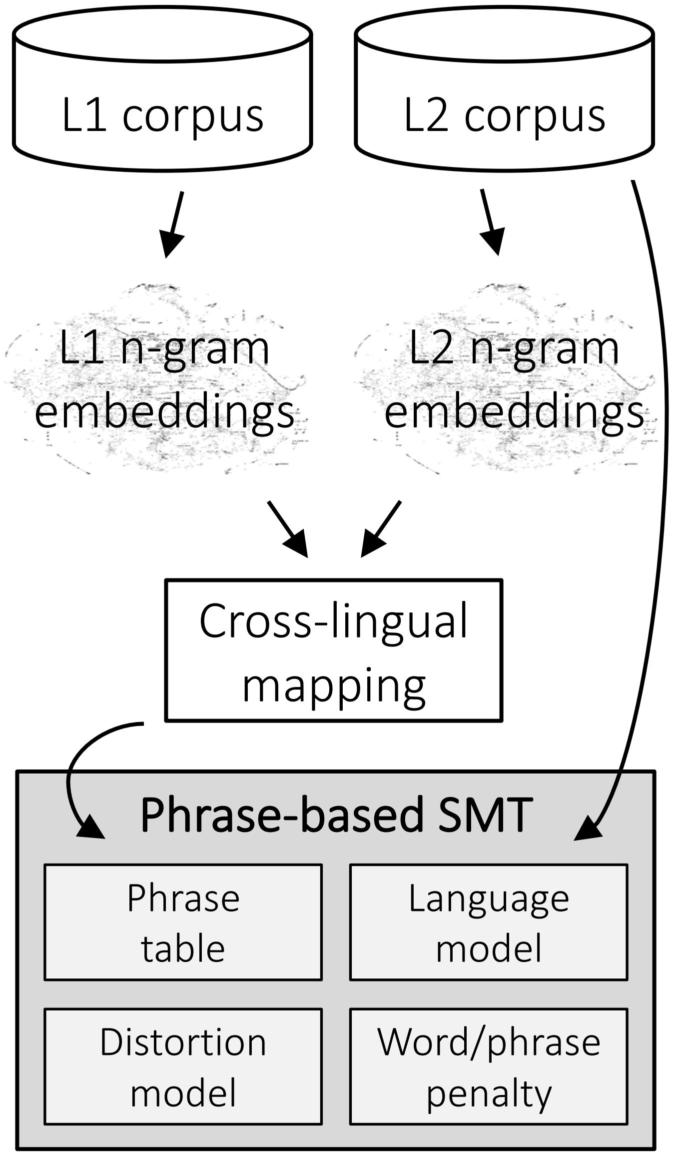

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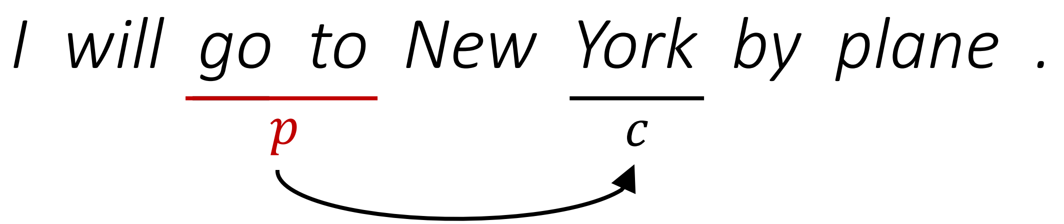

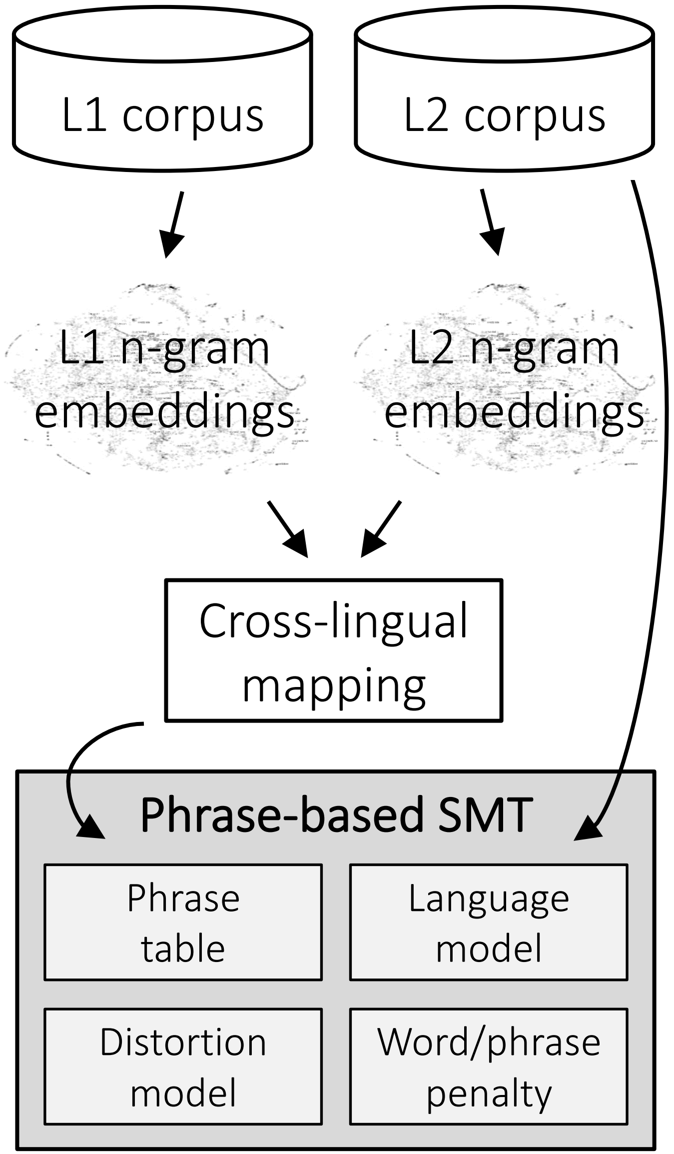

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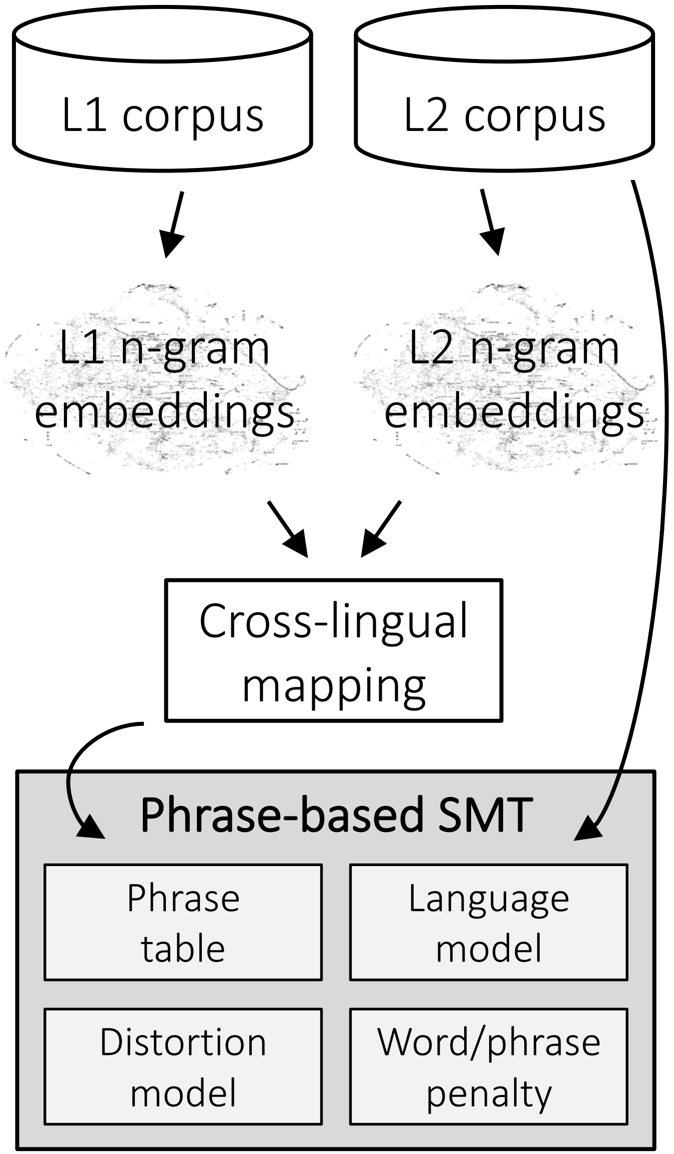

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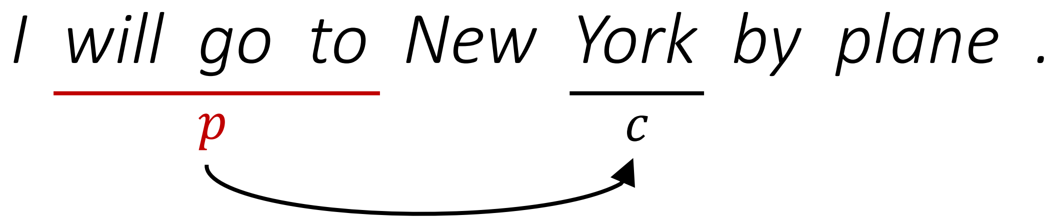

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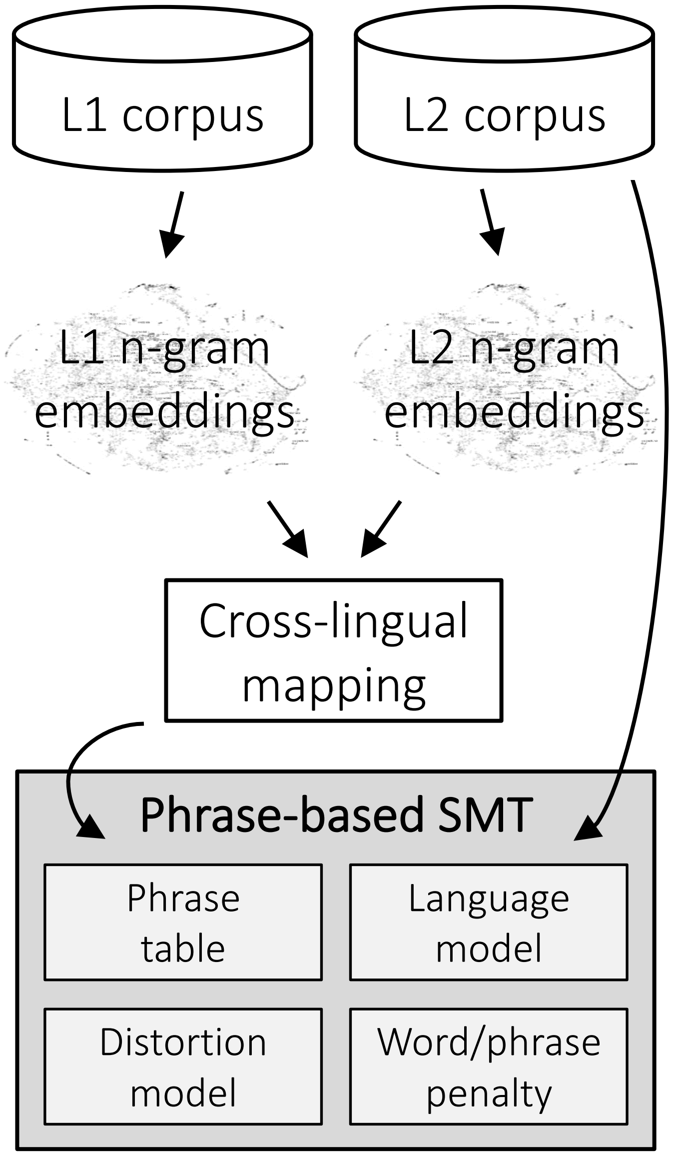

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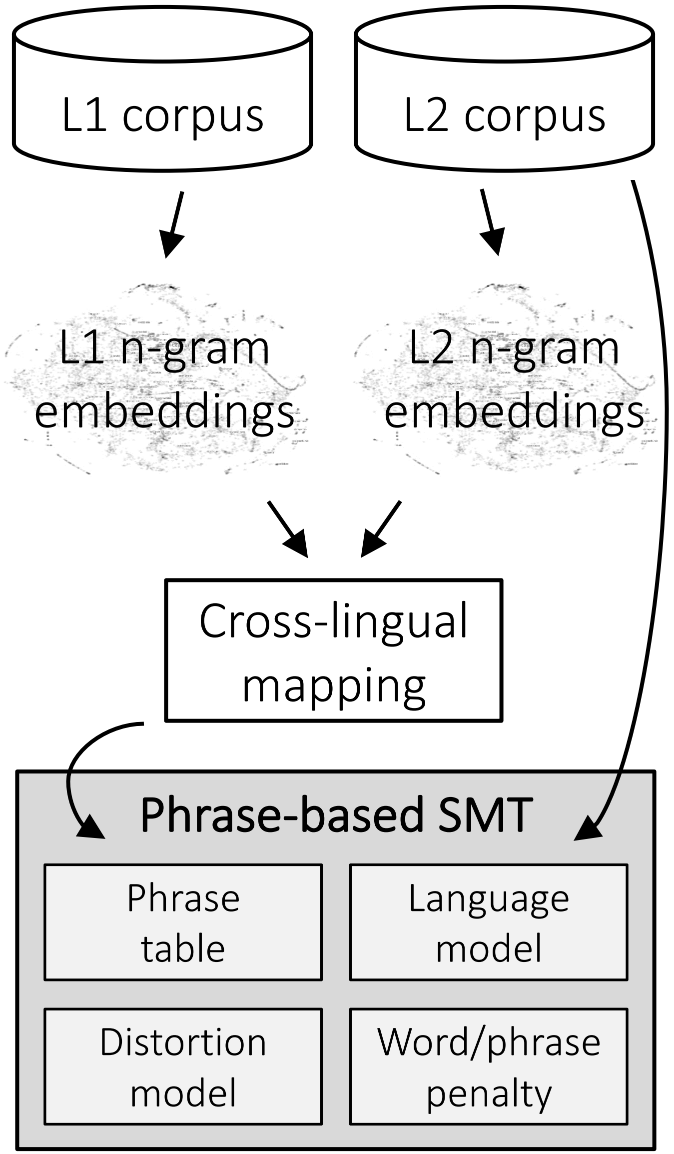

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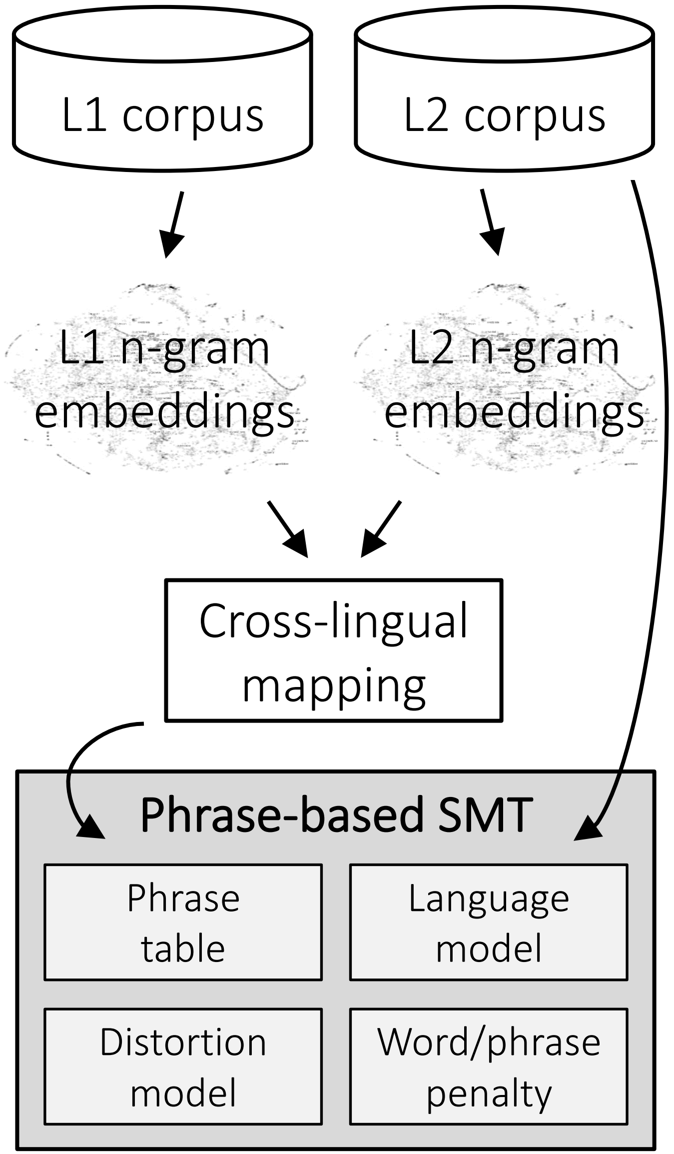
For each $\bar{e}$, estimate $\phi(\bar{f}|\bar{e})$ for 100-NN:



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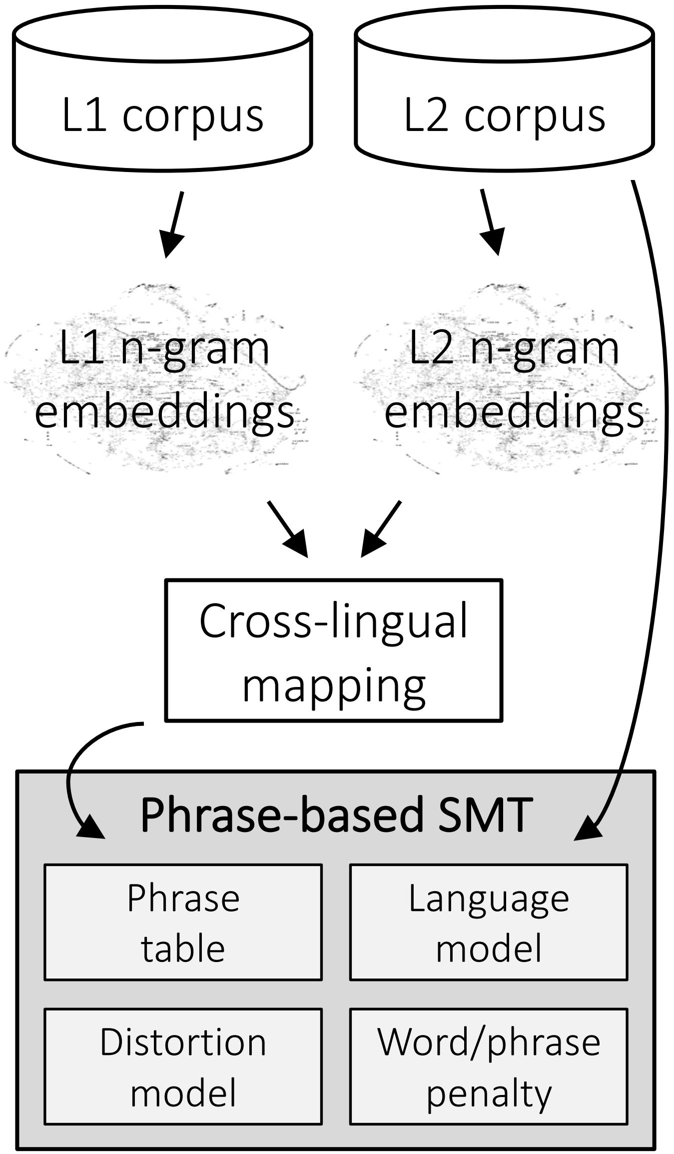
$$\phi(\bar{f}|\bar{e}) = \frac{e^{\cos(\bar{e},\bar{f})/\tau}}{\sum_{\overline{f'}} e^{\cos(\bar{e},\overline{f'})/\tau}}$$



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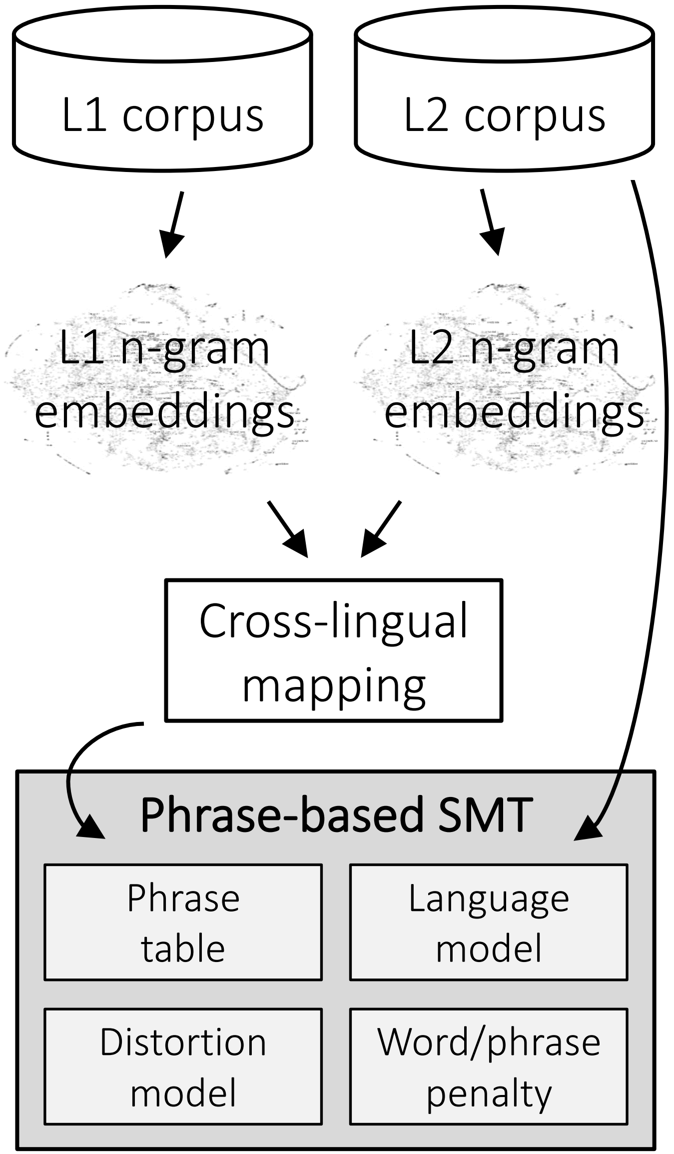
$$\min_{\tau} \sum_{\bar{f}} \log \phi\left(\bar{f}|\mathrm{NN}_{\bar{e}}(\bar{f})\right) + \sum_{\bar{e}} \log \phi\left(\bar{e}|\mathrm{NN}_{\bar{f}}(\bar{e})\right)$$



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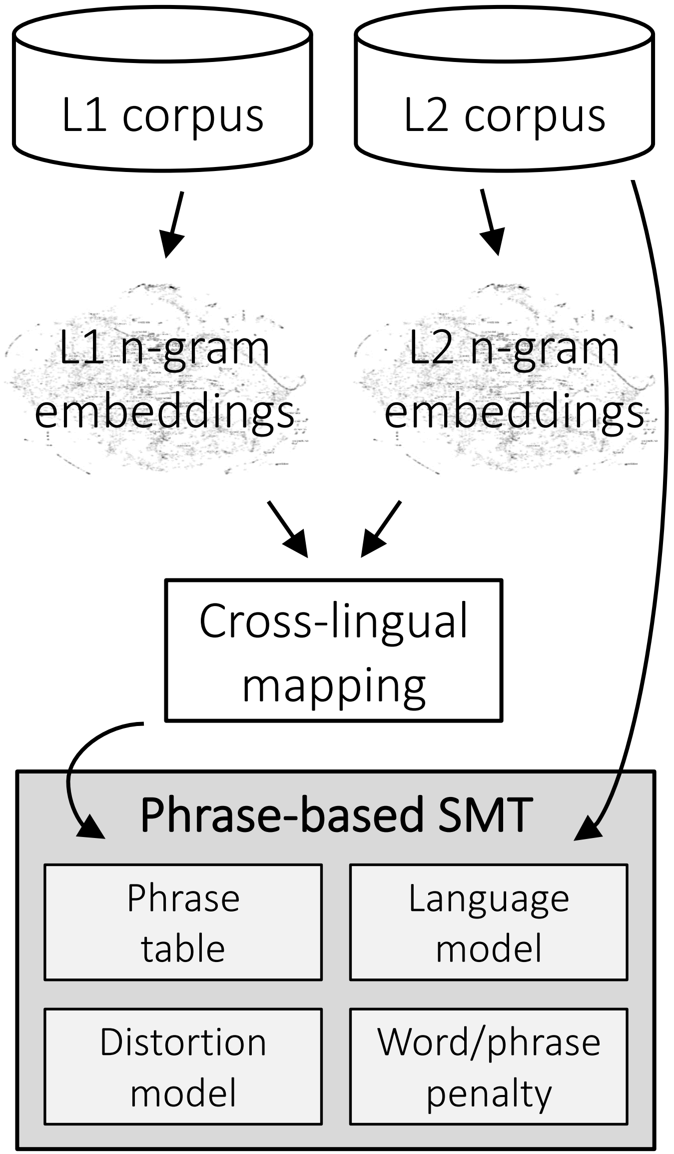

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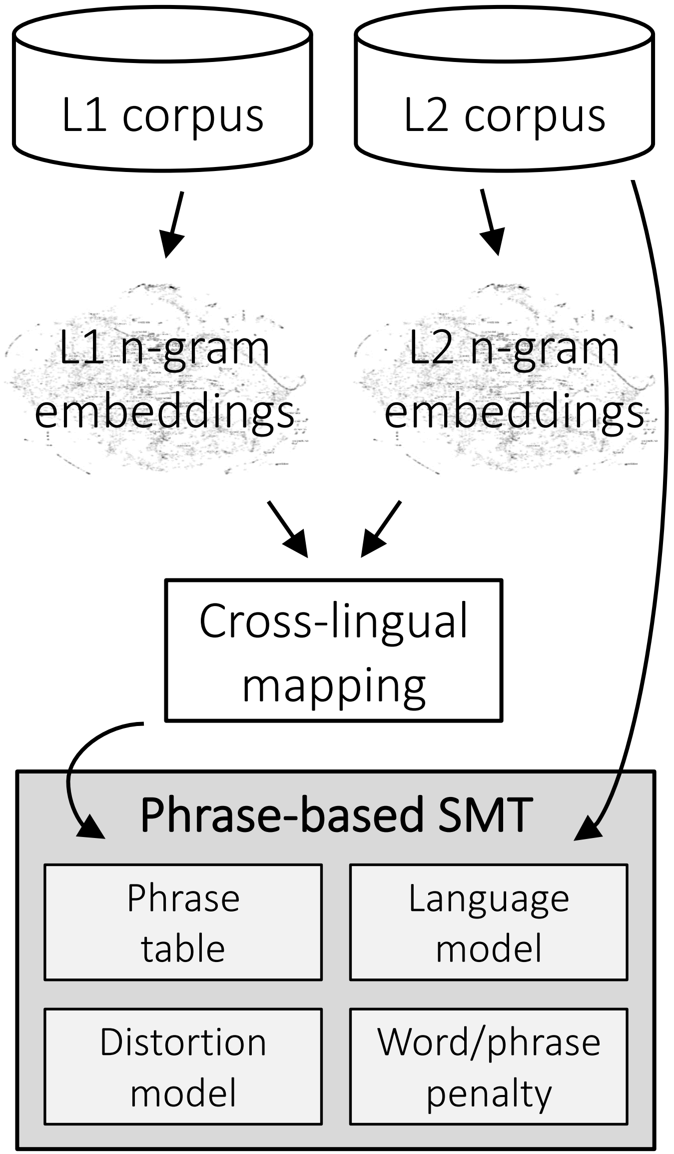

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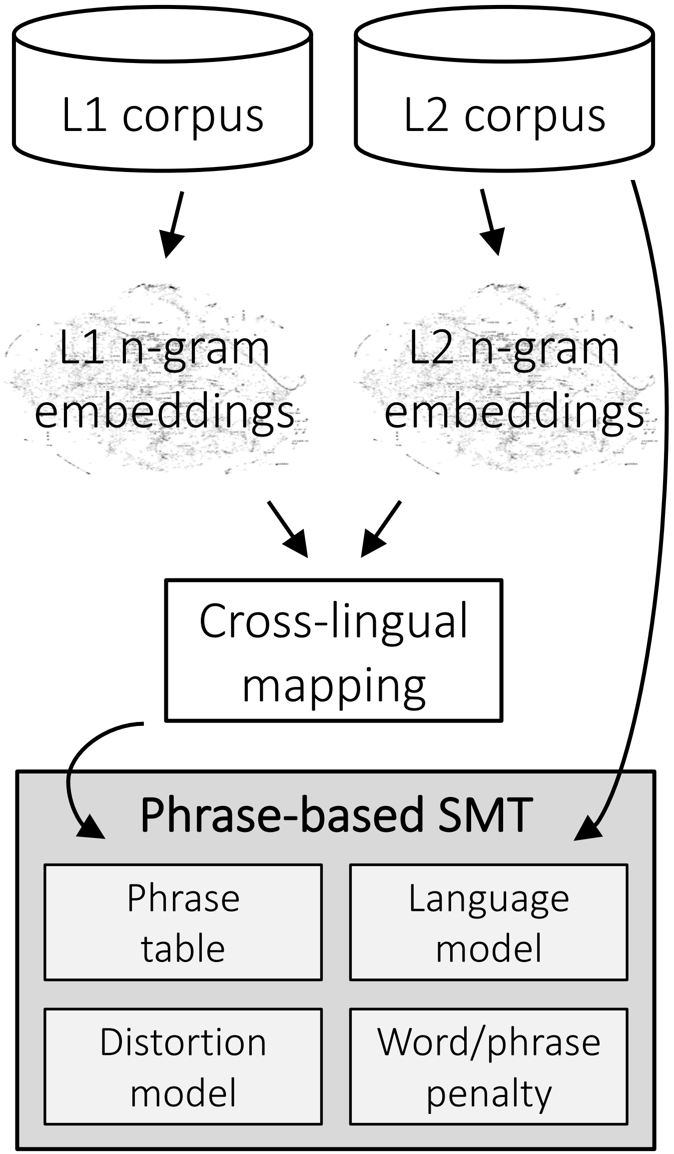

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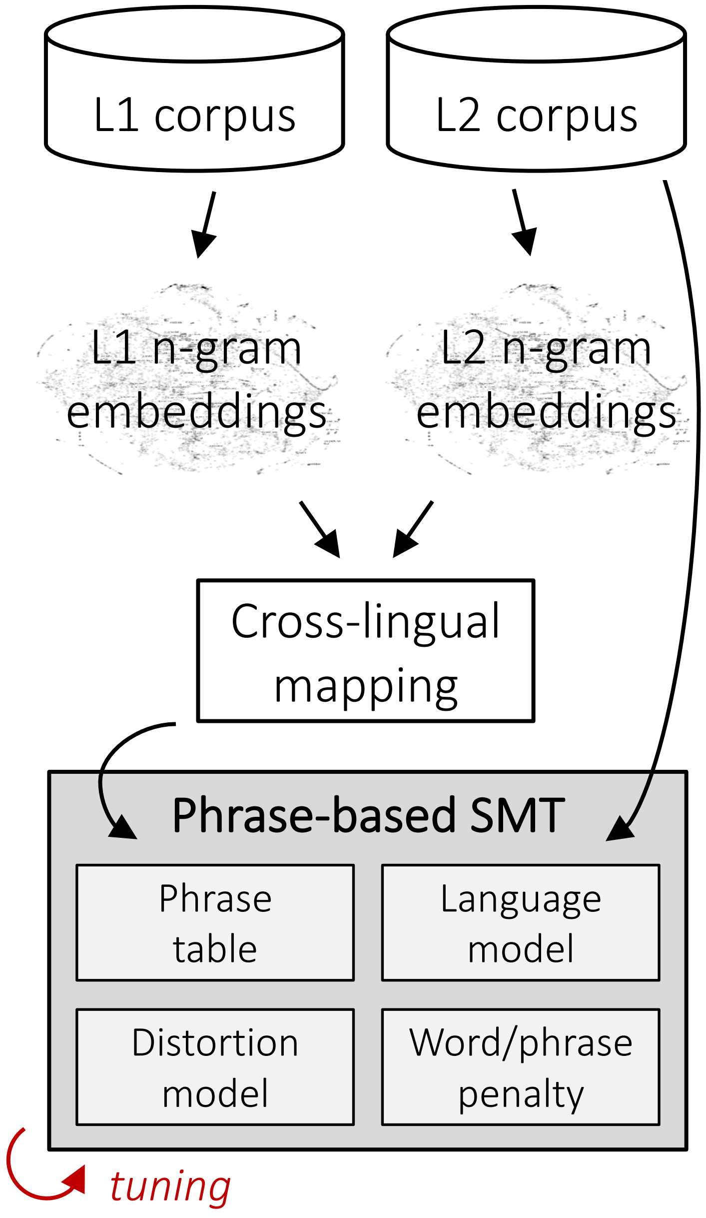

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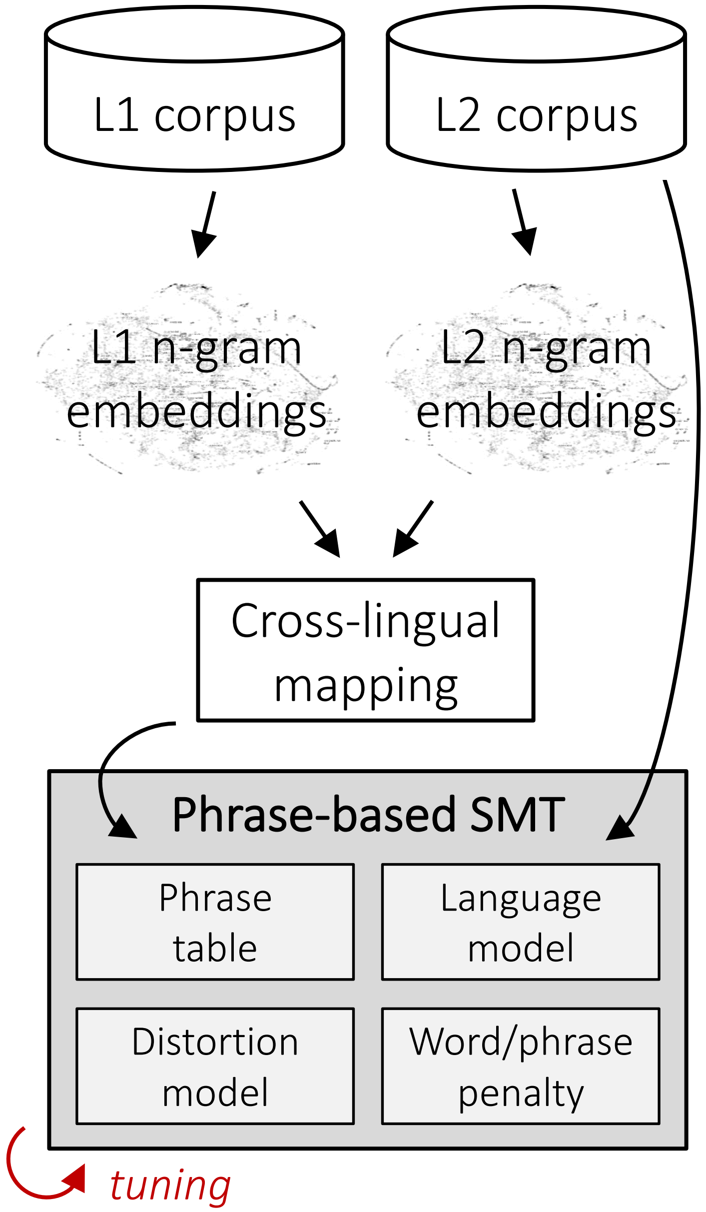
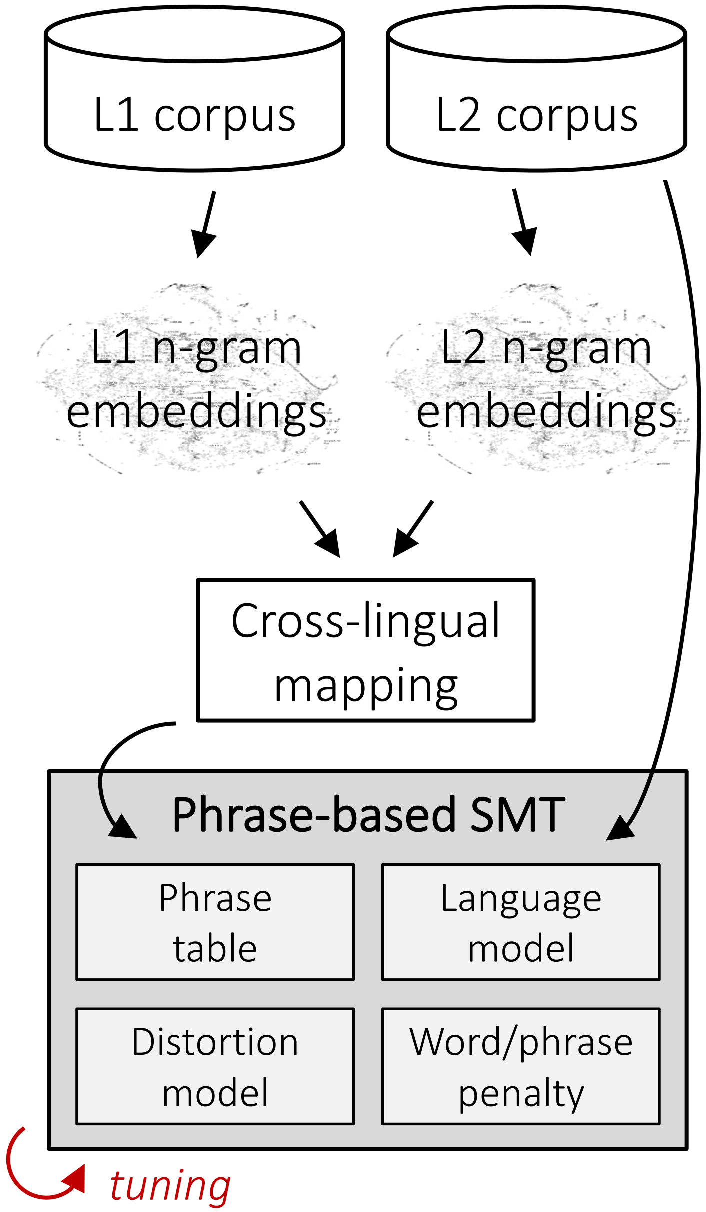


Goal: Adjust the weights of the resulting log-linear model to optimize some evaluation metric (e.g. BLEU)



Unsupervised phrase-based SMT

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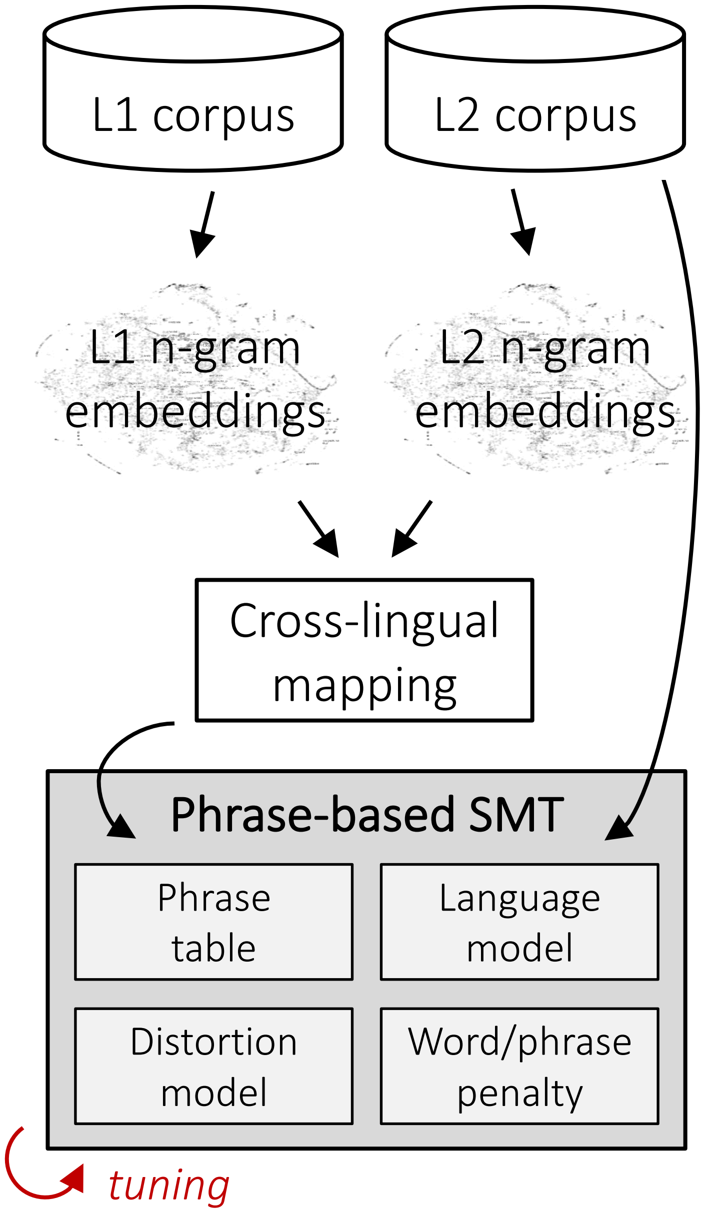
... but we don't have a parallel development set!



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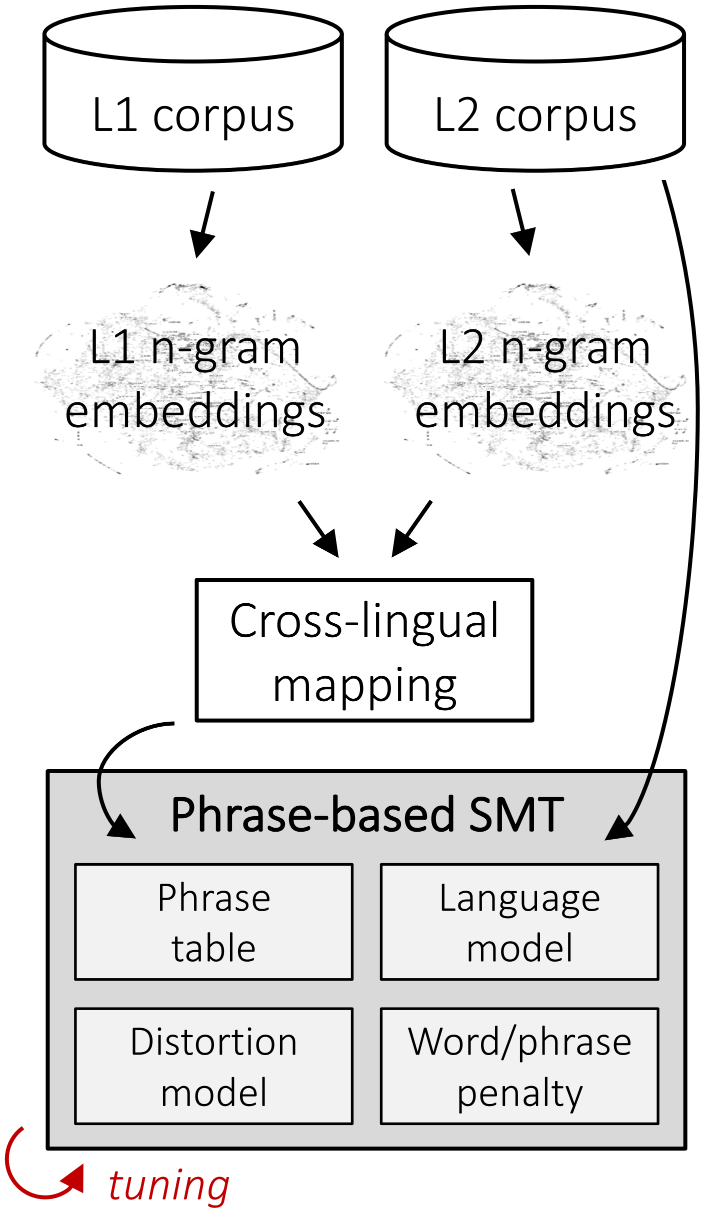

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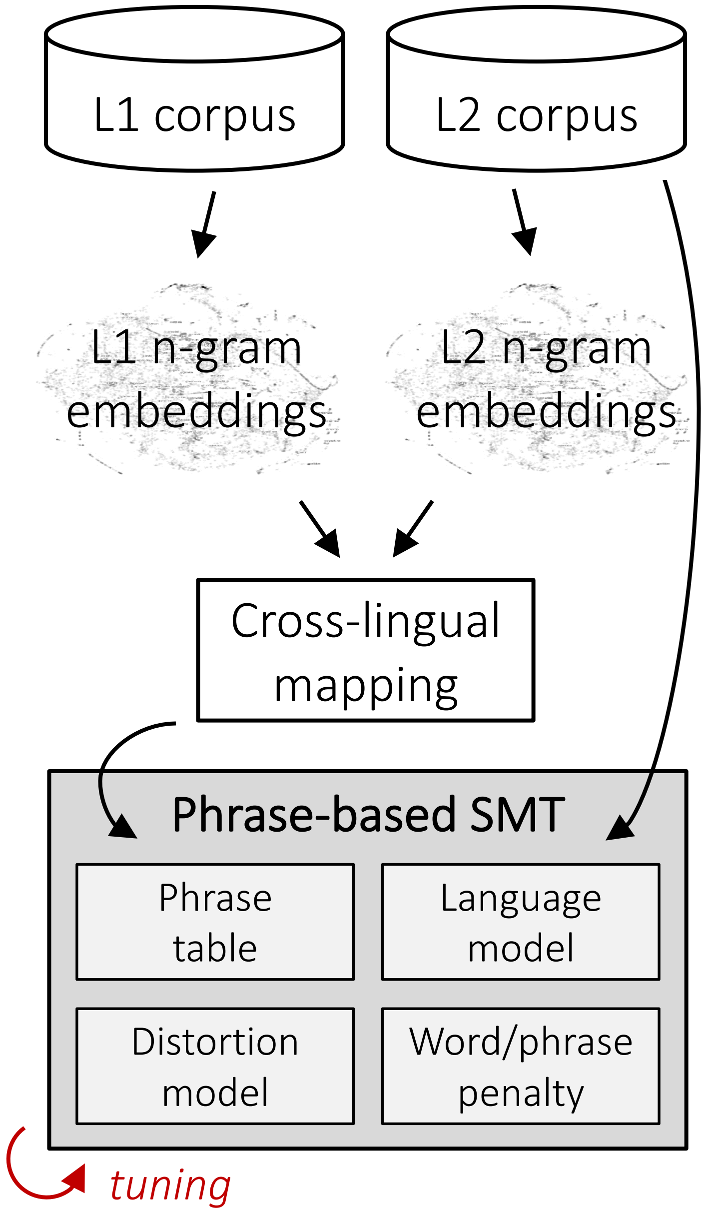
- Default weights without tuning (Lample et al., EMNLP'18)



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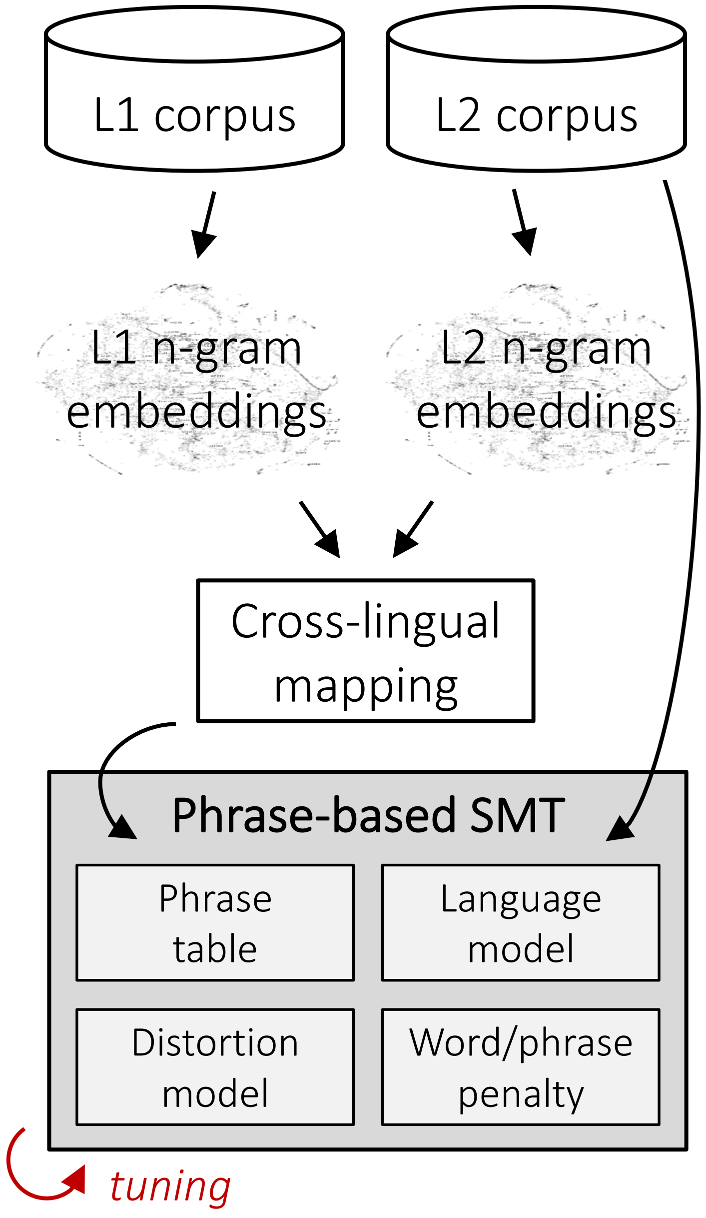
- Alternating optimization with back-translation (Artetxe et al., EMNLP'18)



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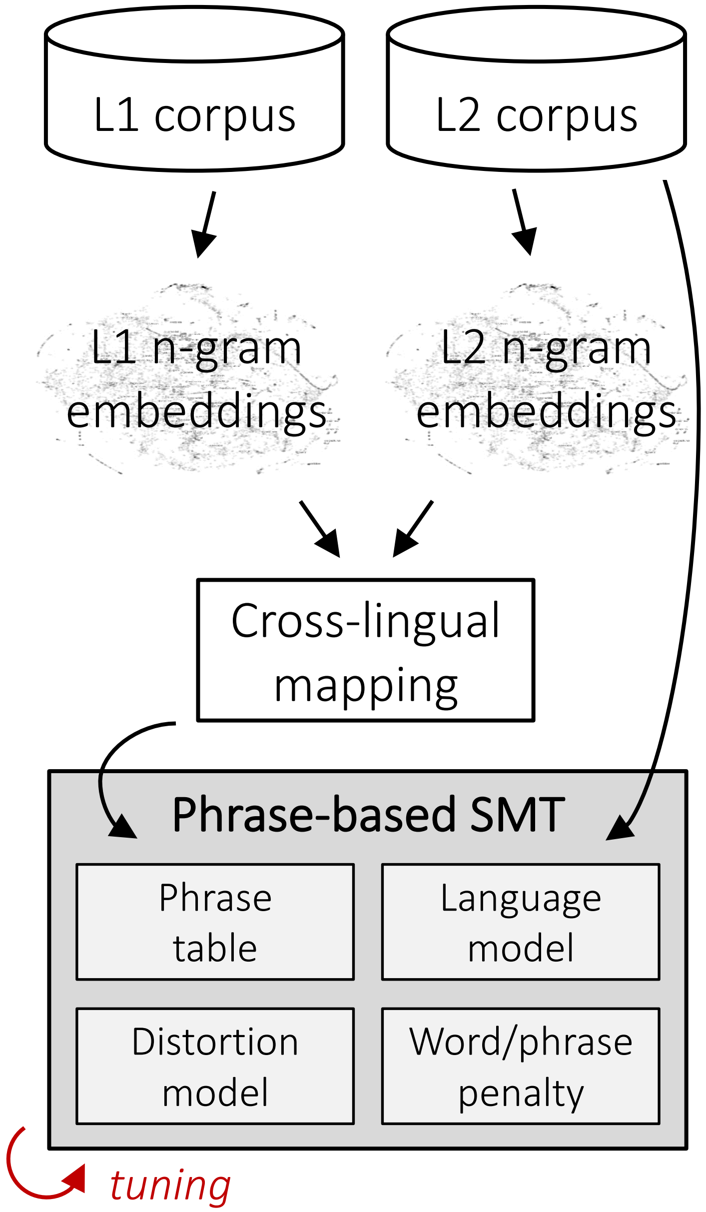

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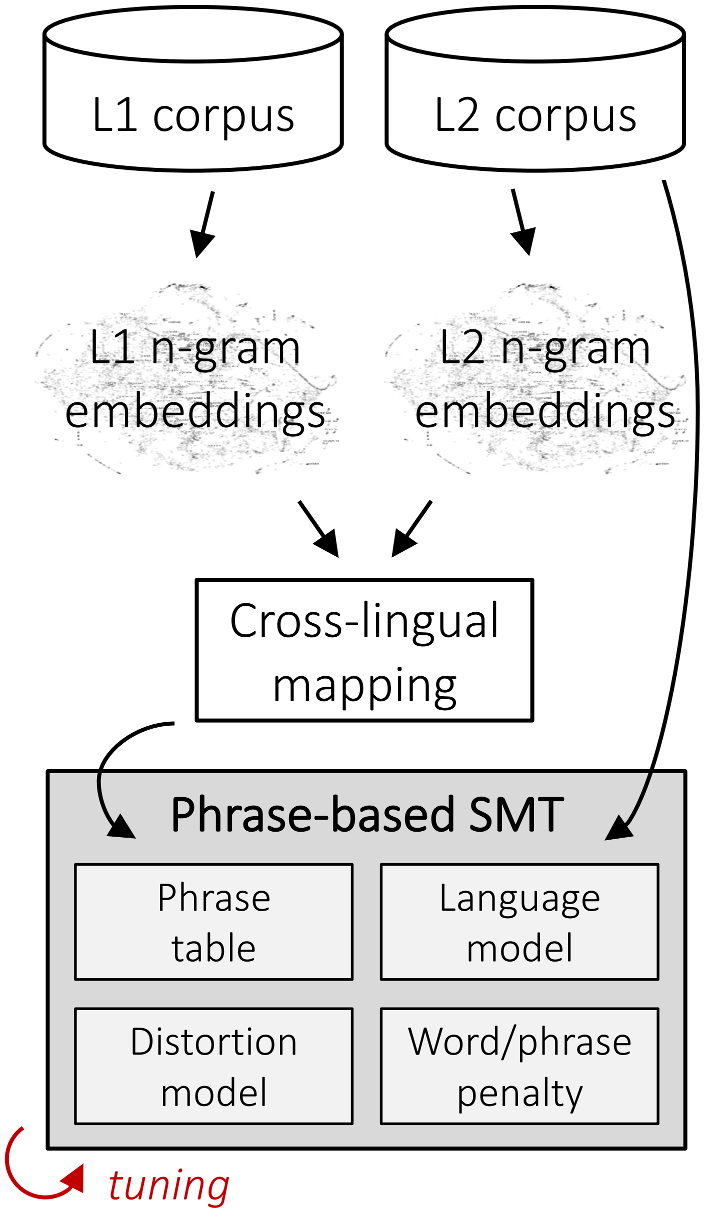
$$L = L_{cycle}(E) + L_{cycle}(F) + L_{lm}(E) + L_{lm}(F)$$



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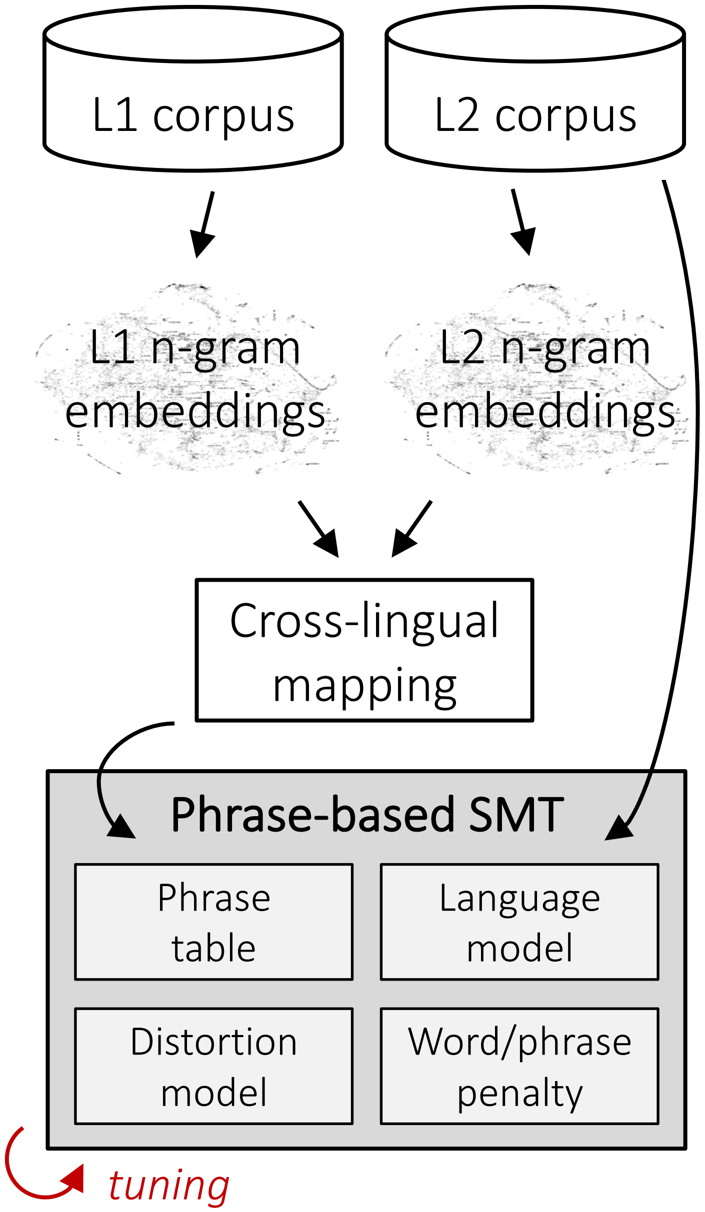
$$L = L_{cycle}(E) + L_{cycle}(F) + L_{lm}(E) + L_{lm}(F)$$

- $L_{cycle}(E) = 1 - \mathrm{BLEU}\big(\mathrm{T}_{F\rightarrow E}\big(\mathrm{T}_{E\rightarrow F}(E)\big), E\big)$



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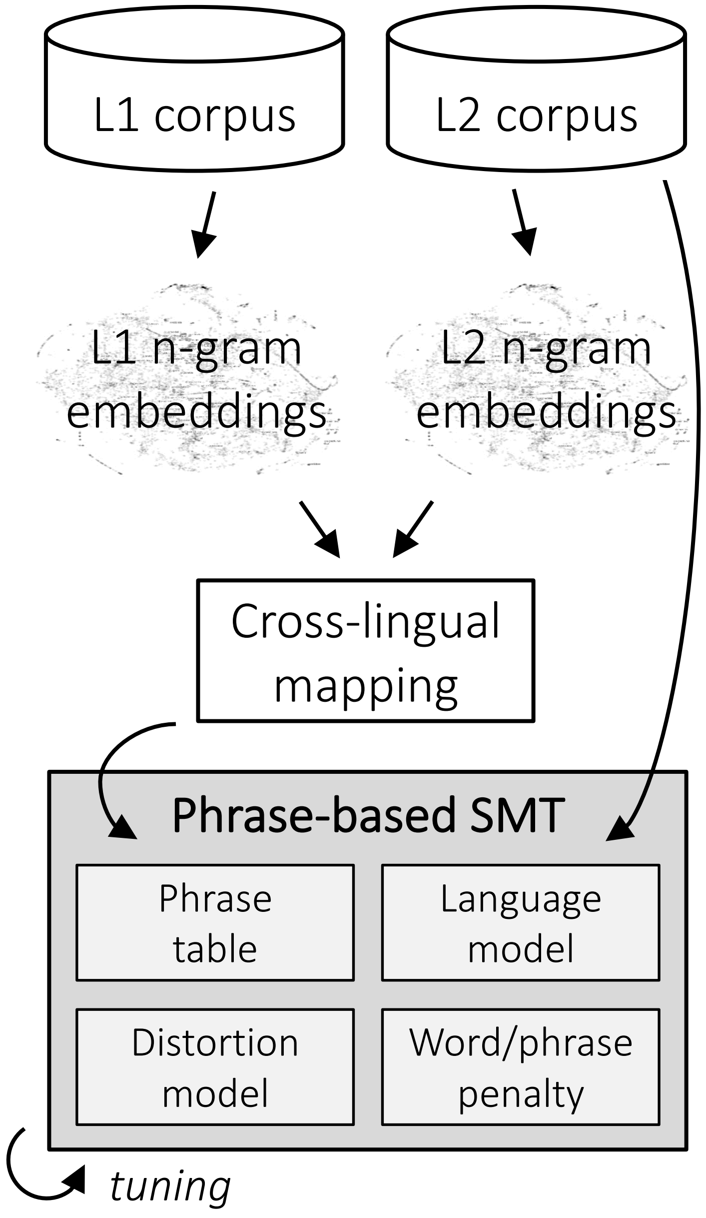
- $L_{cycle}(E) = 1 - \mathrm{BLEU}\big(\mathrm{T}_{F\rightarrow E}\big(\mathrm{T}_{E\rightarrow F}(E)\big), E\big)$
- $L_{lm}(E) = \max\Big(0, \mathrm{H}(F) - \mathrm{H}\big(\mathrm{T}_{E\rightarrow F}(E)\big)\Big)^2 \cdot \mathrm{LP}$

$$\mathrm{LP} = \mathrm{LP}(E) \cdot \mathrm{LP}(F)\,, \quad \mathrm{LP}(E) = \max\left(1, \frac{\mathrm{len}\big(\mathrm{T}_{F\rightarrow E}(\mathrm{T}_{E\rightarrow F}(E))\big)}{\mathrm{len}(E)}\right)$$

Unsupervised phrase-based SMT



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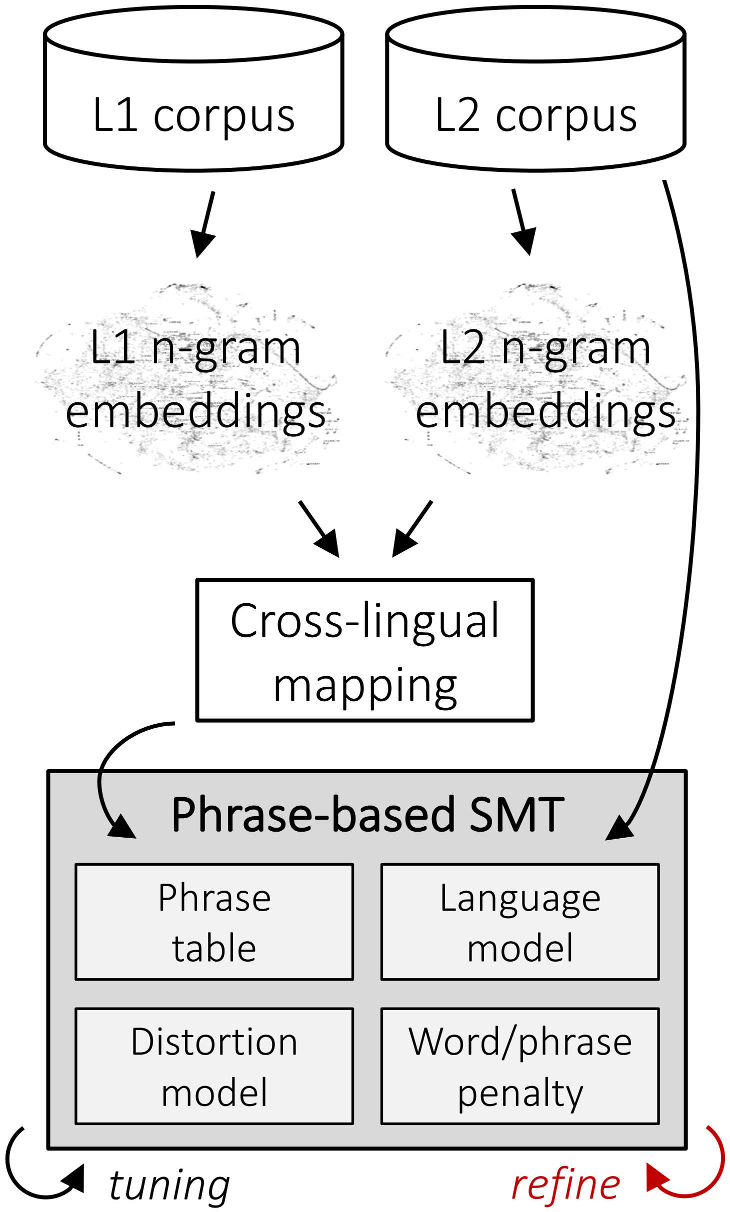

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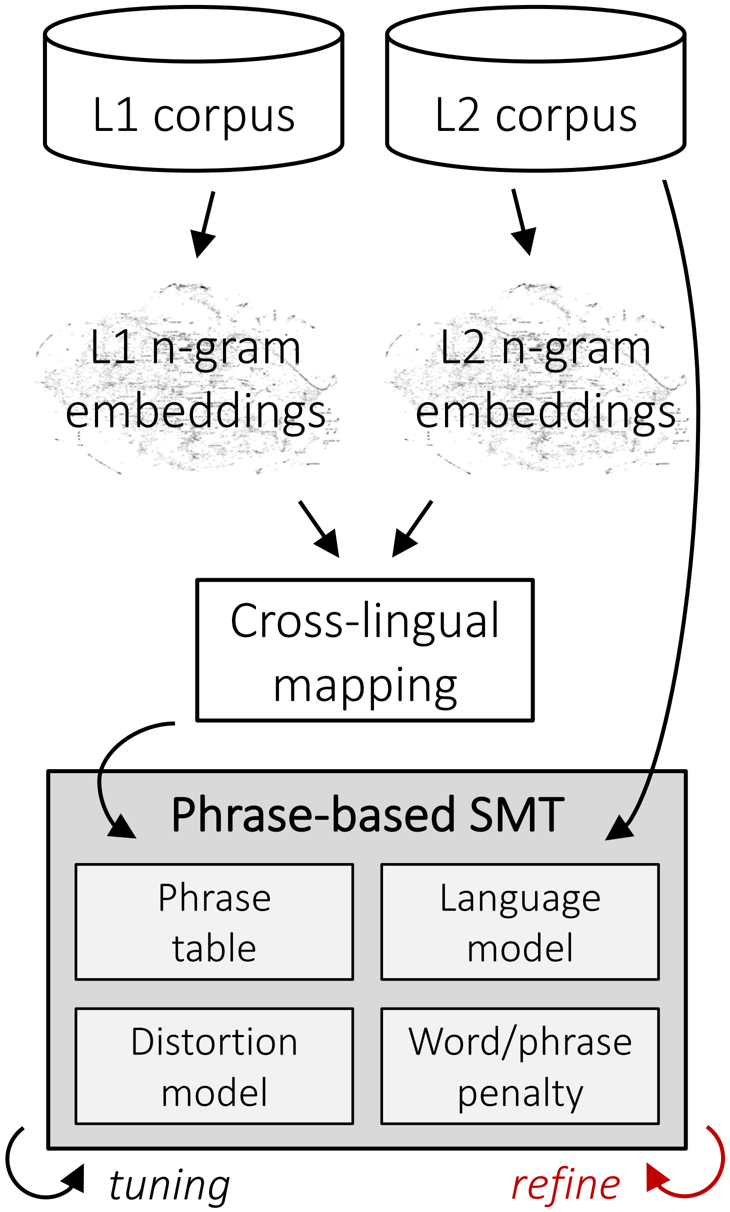
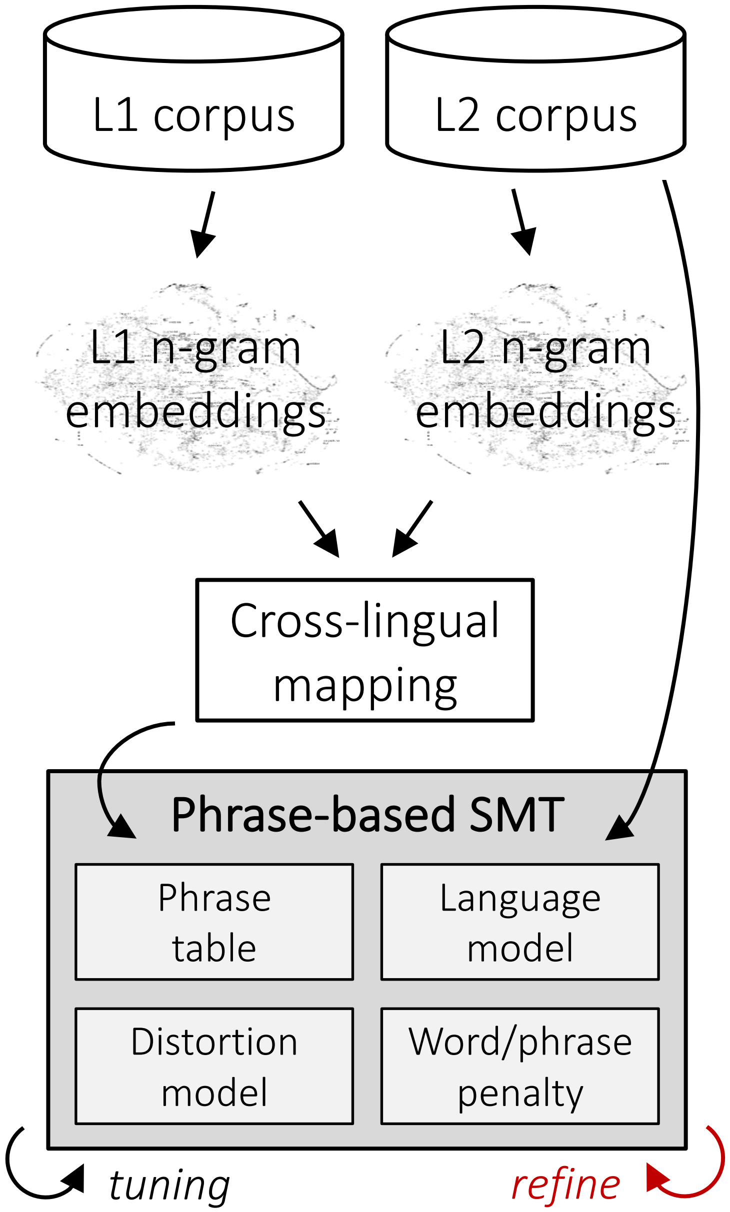


L1 train

Unsupervised phrase-based SMT



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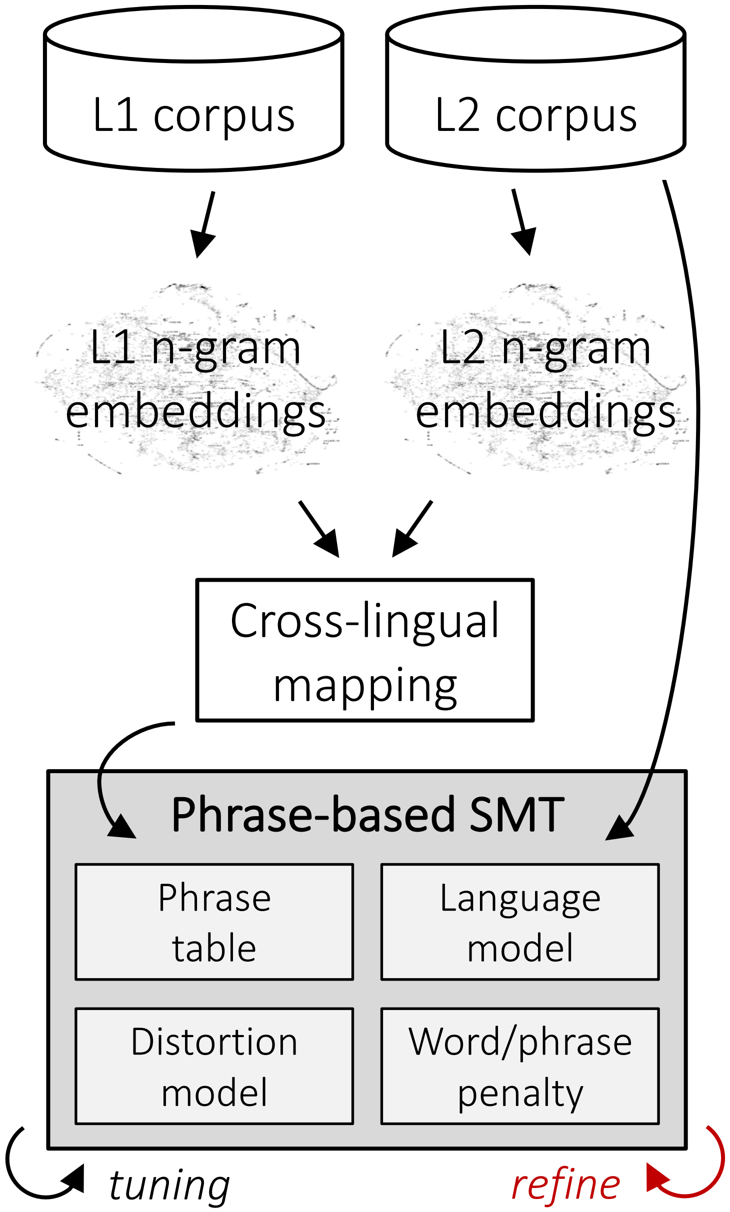

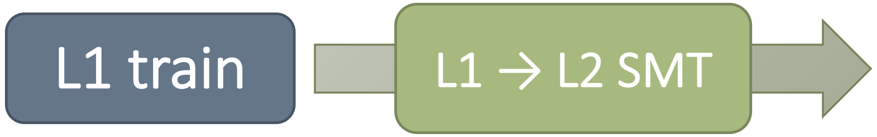

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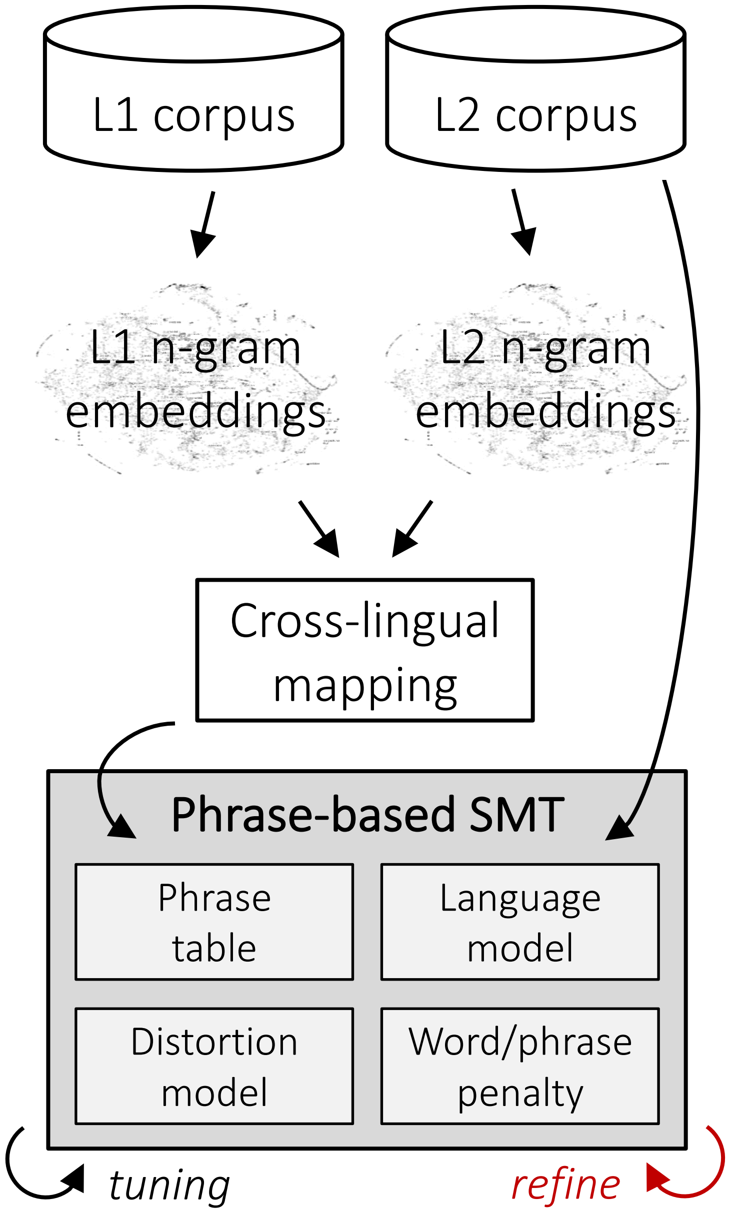

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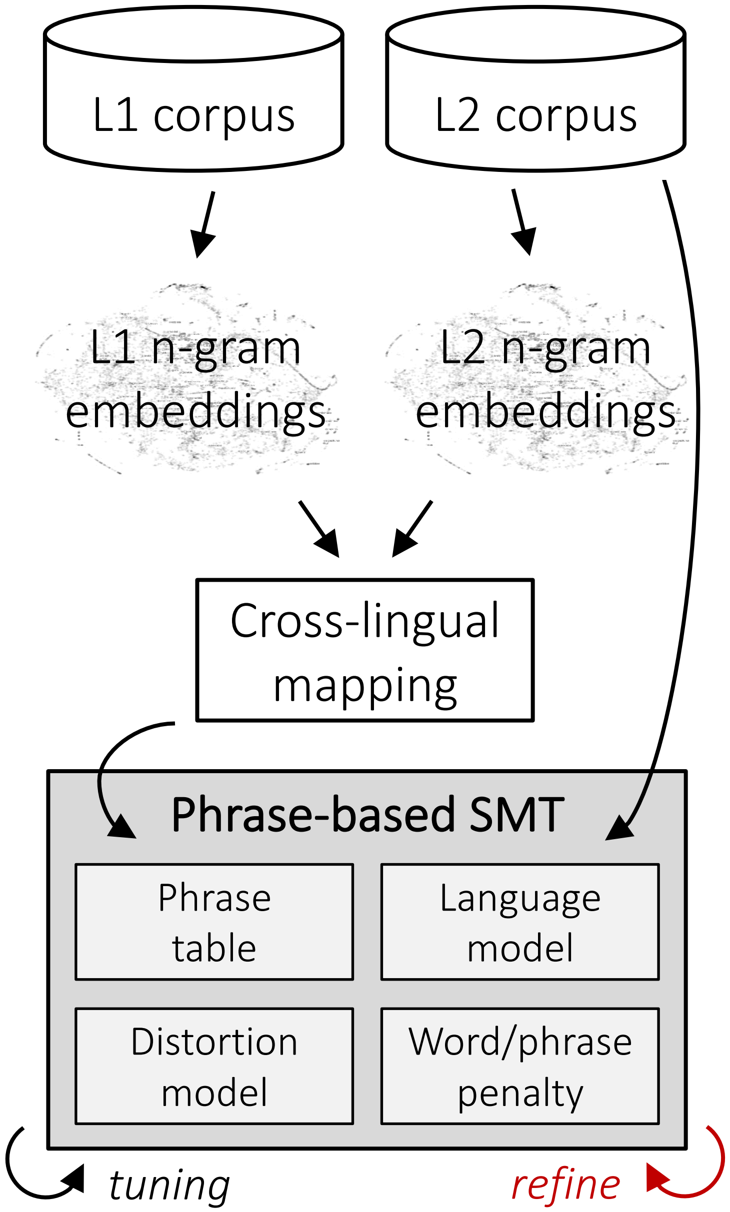

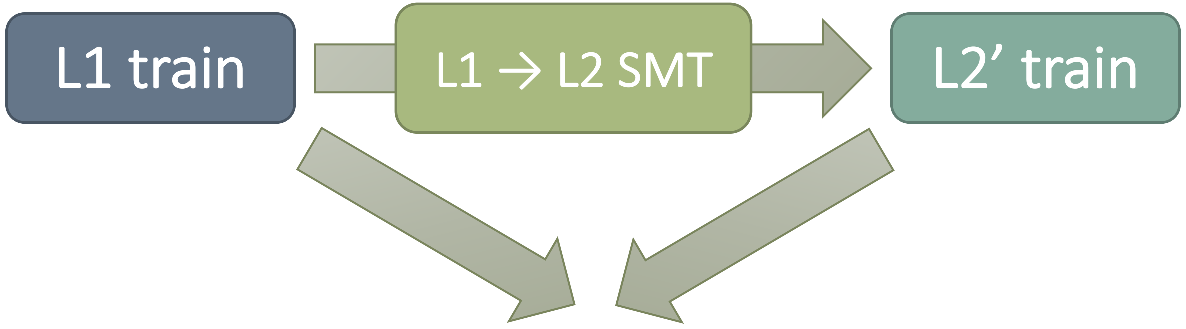

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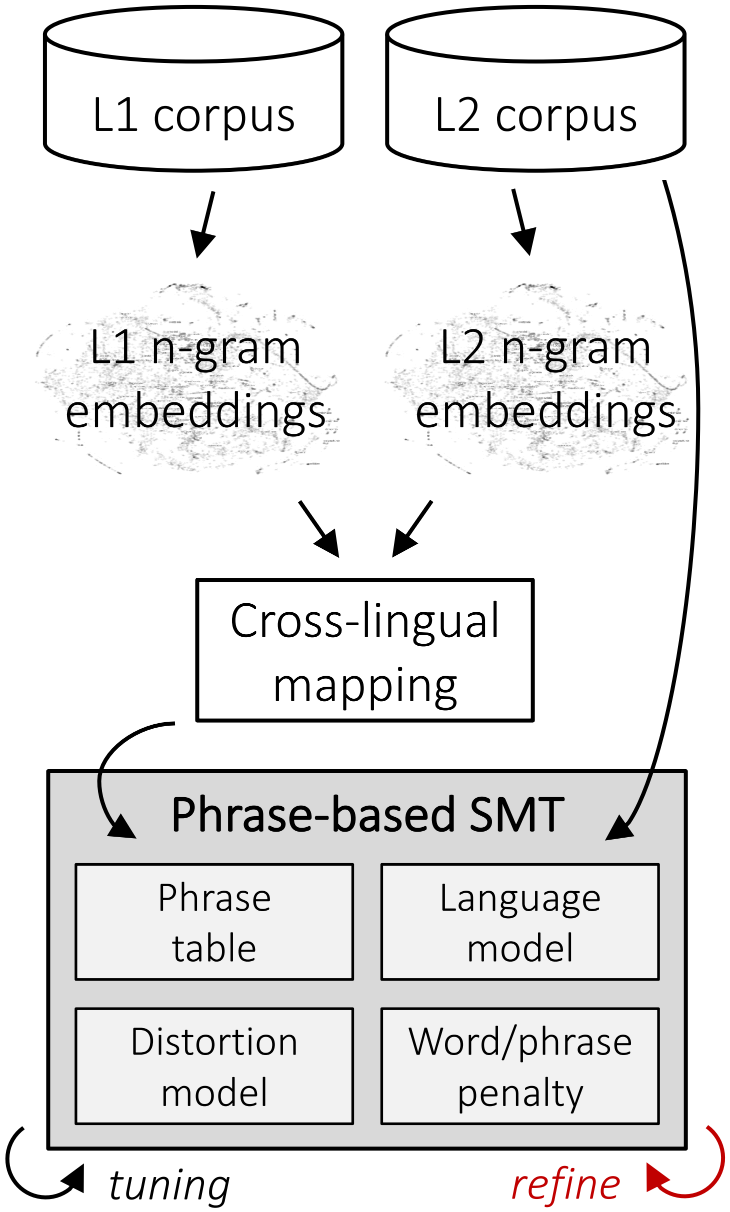

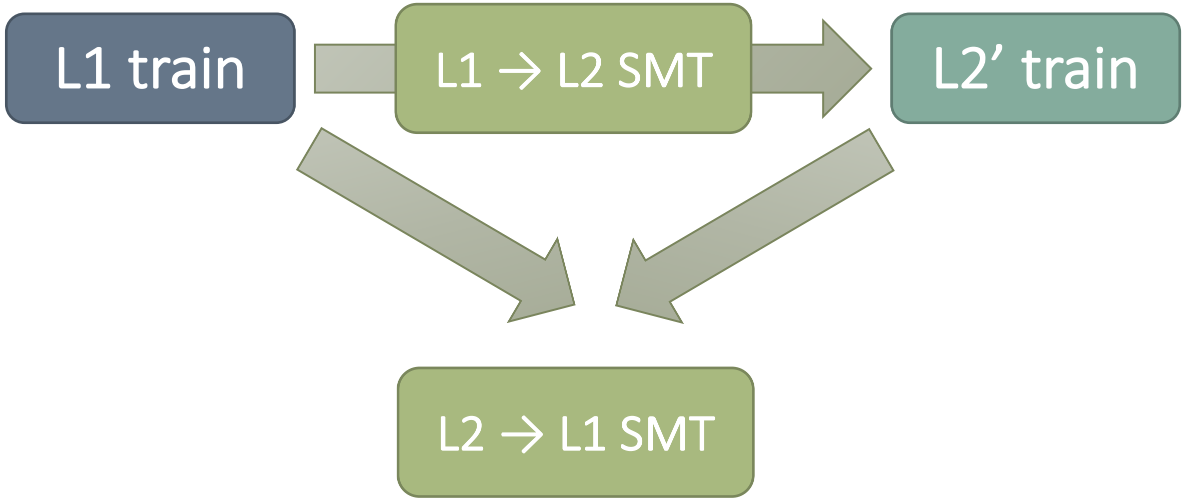

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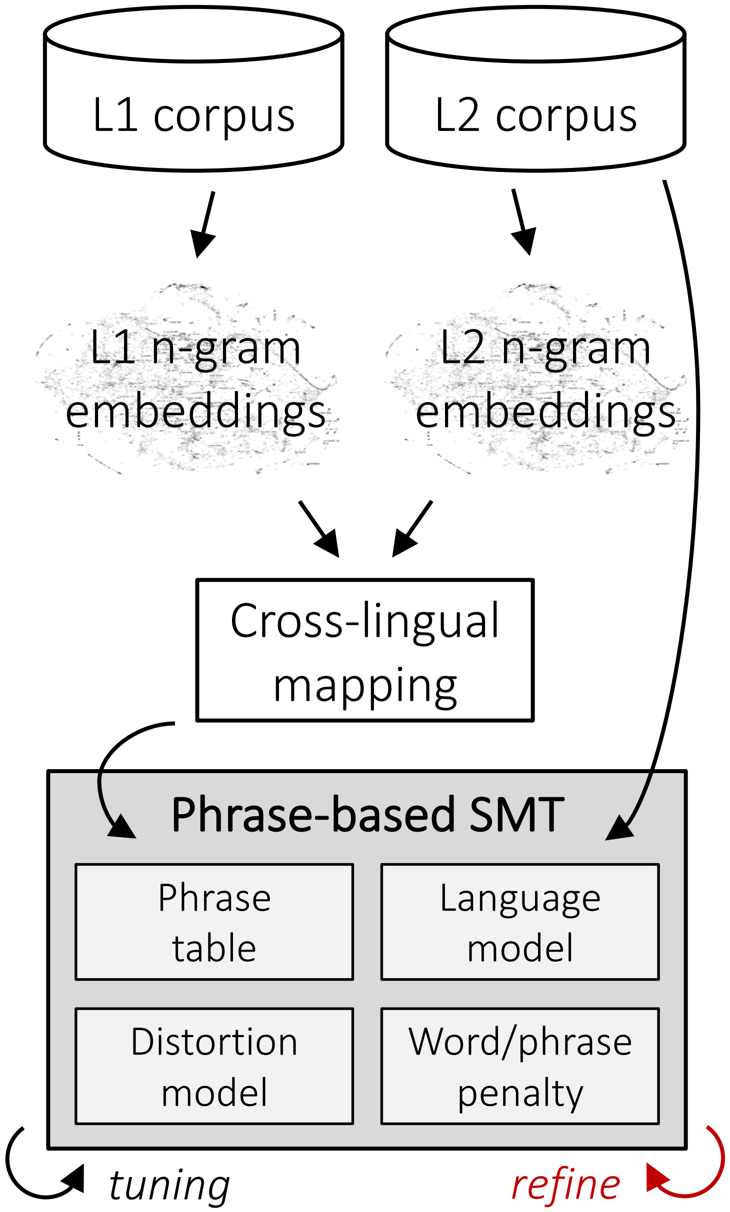

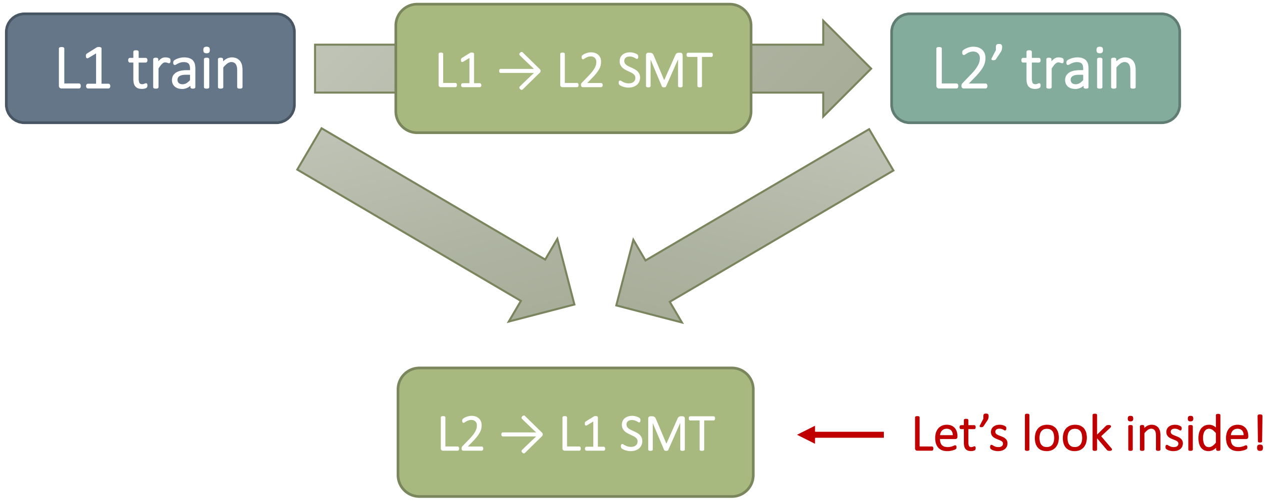

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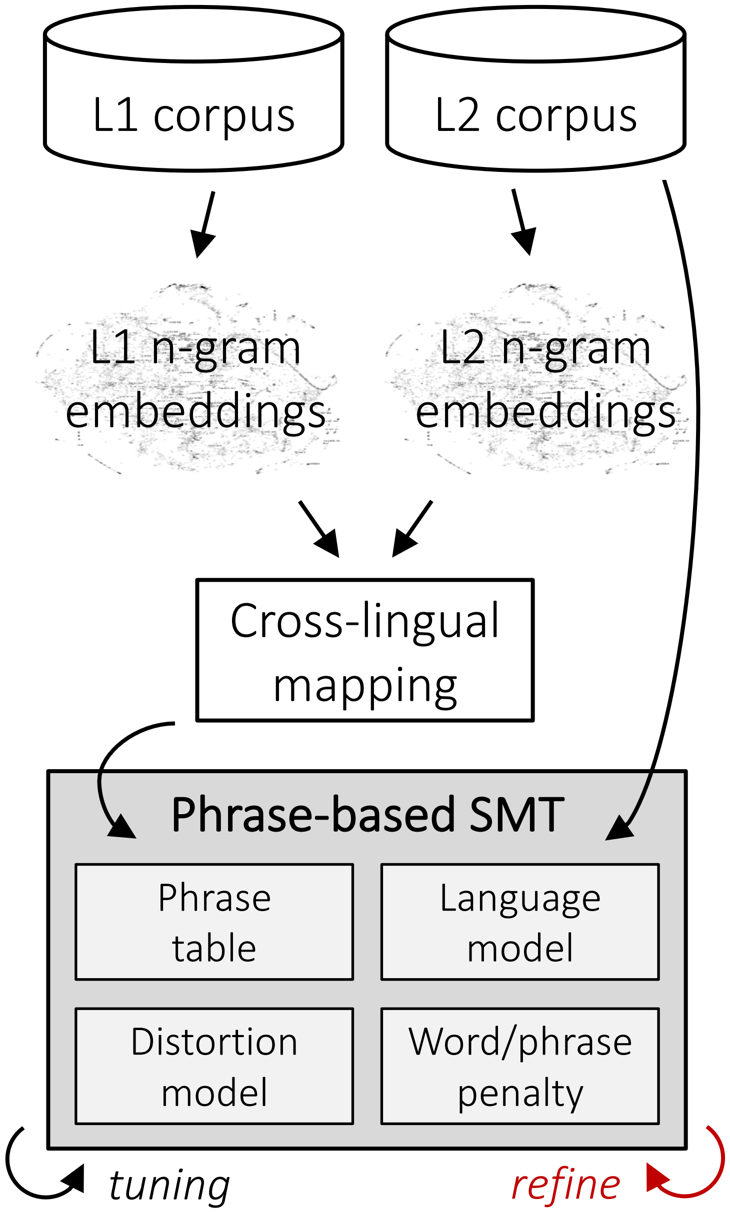

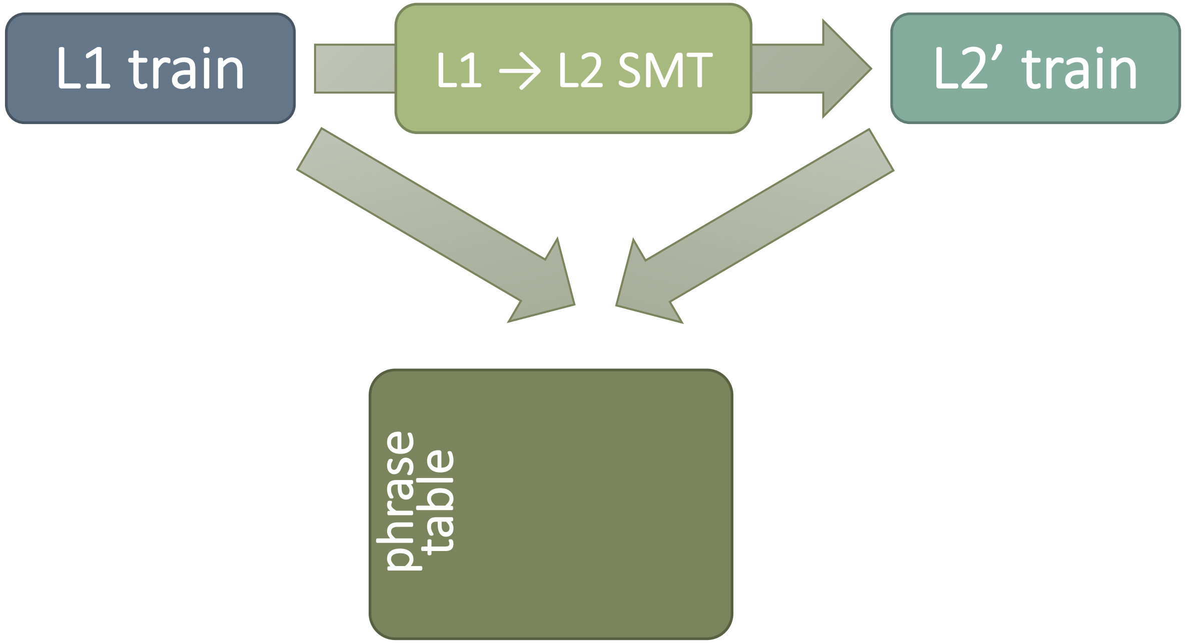

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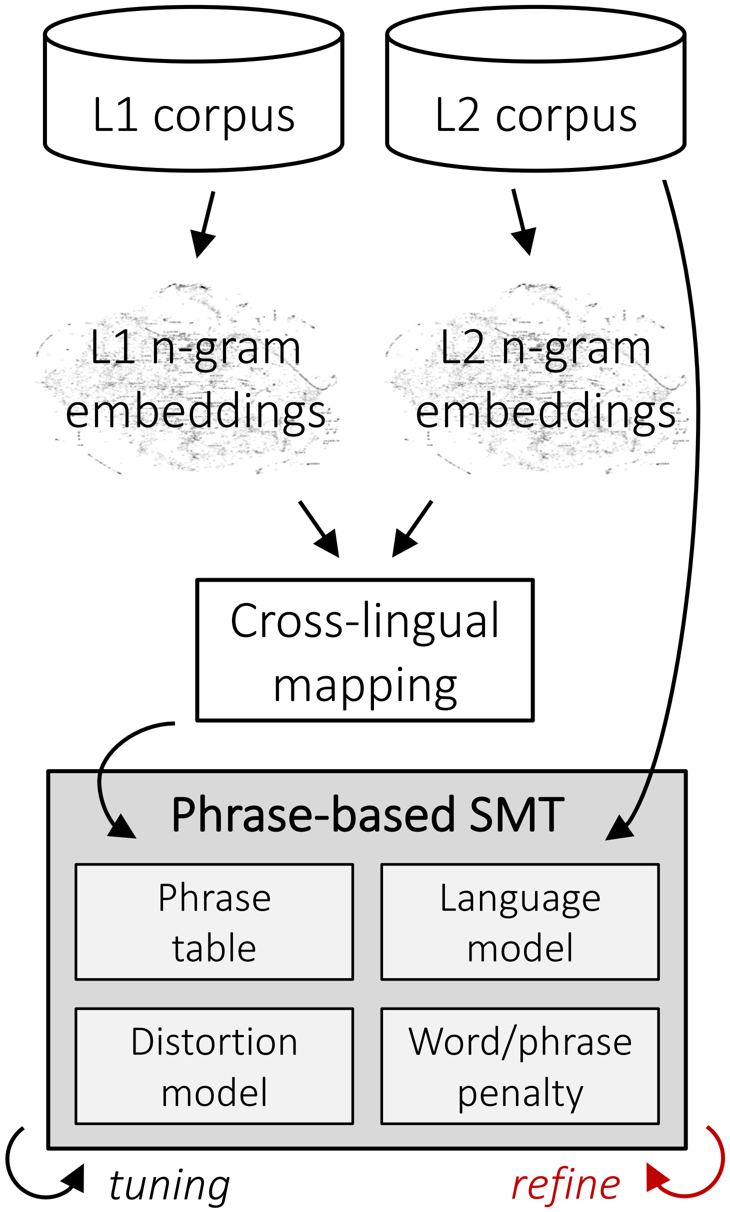

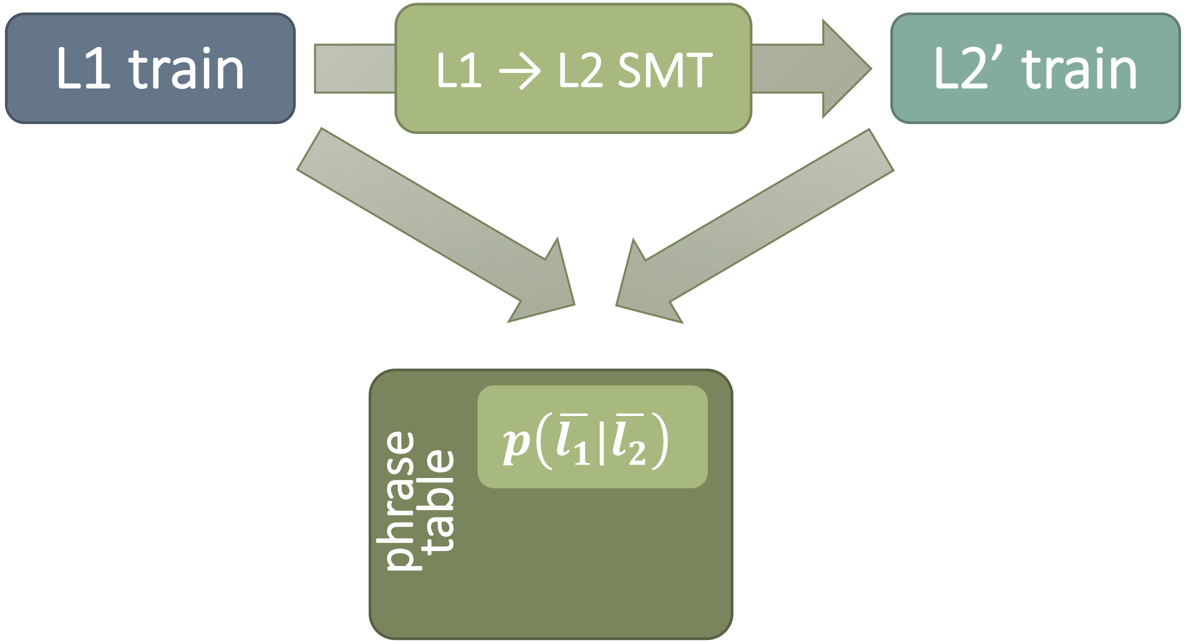

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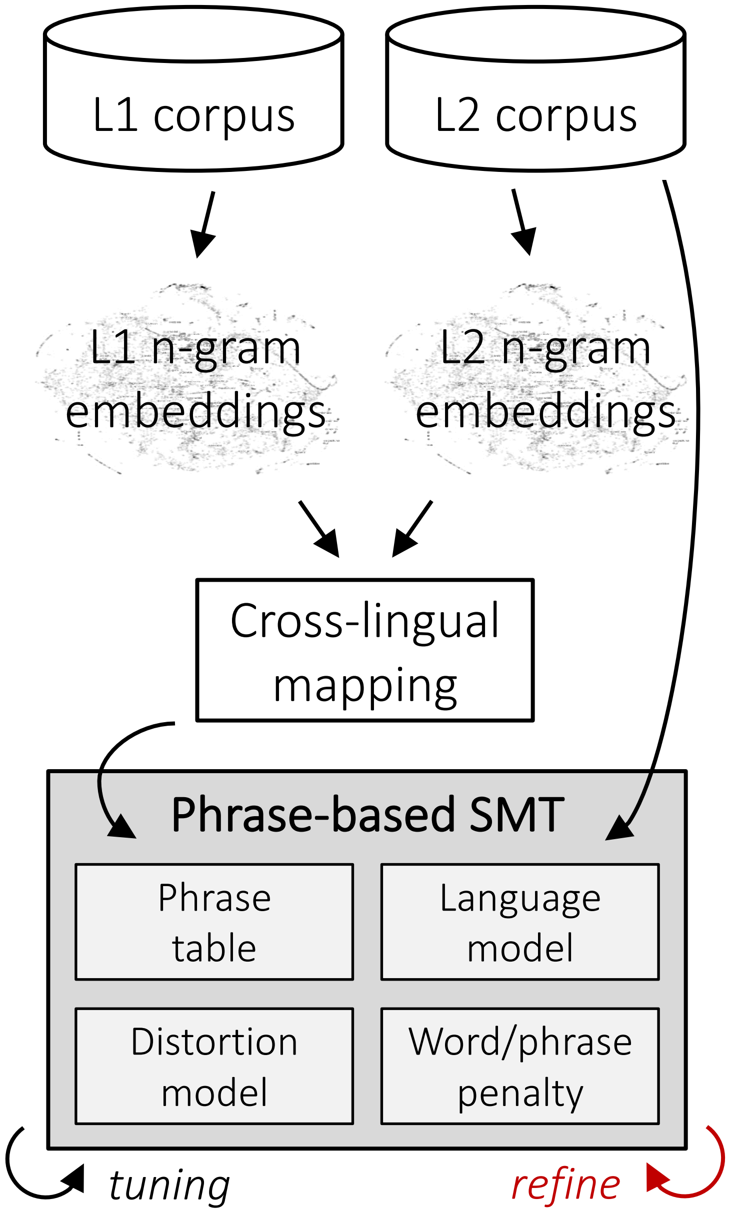

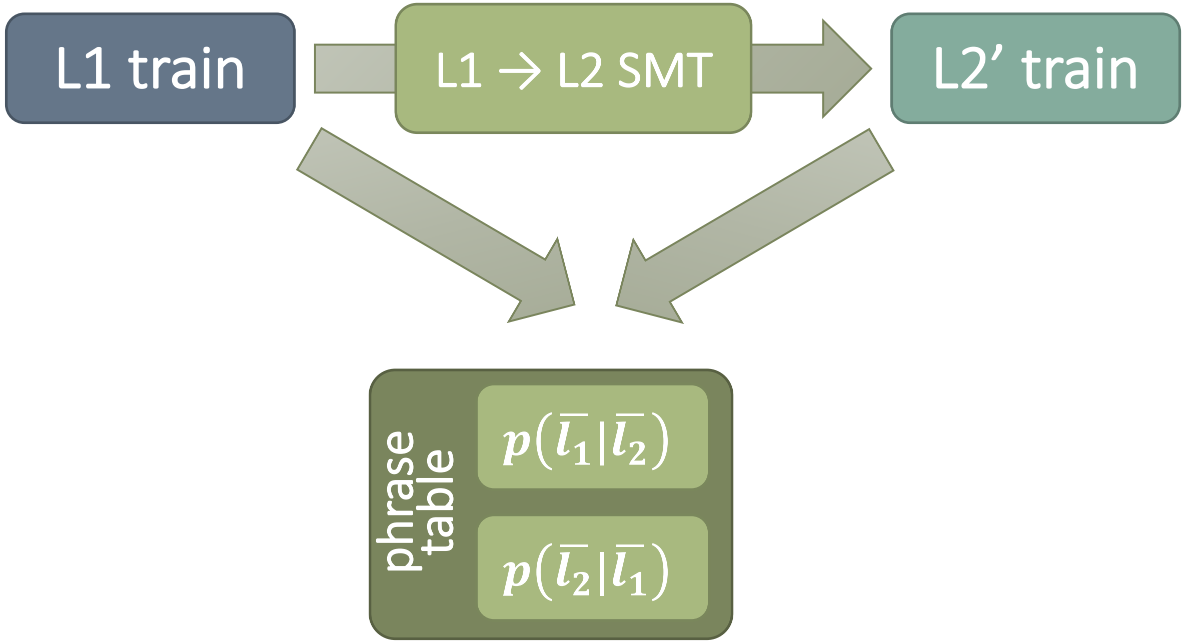

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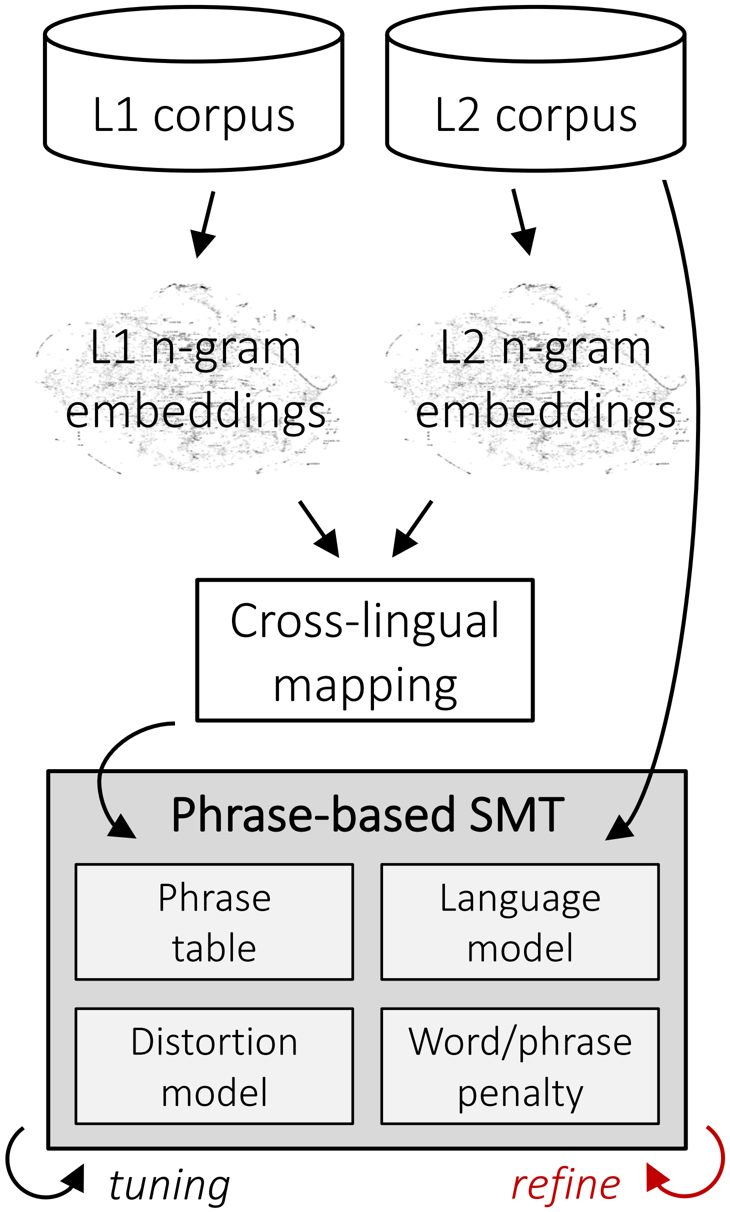

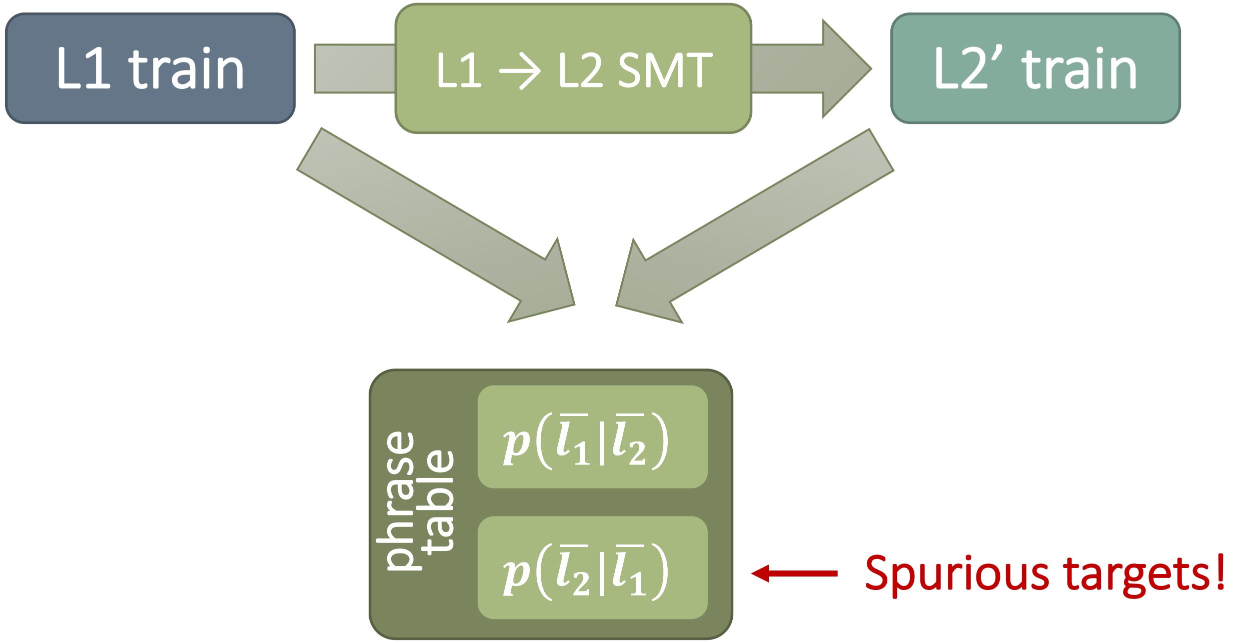

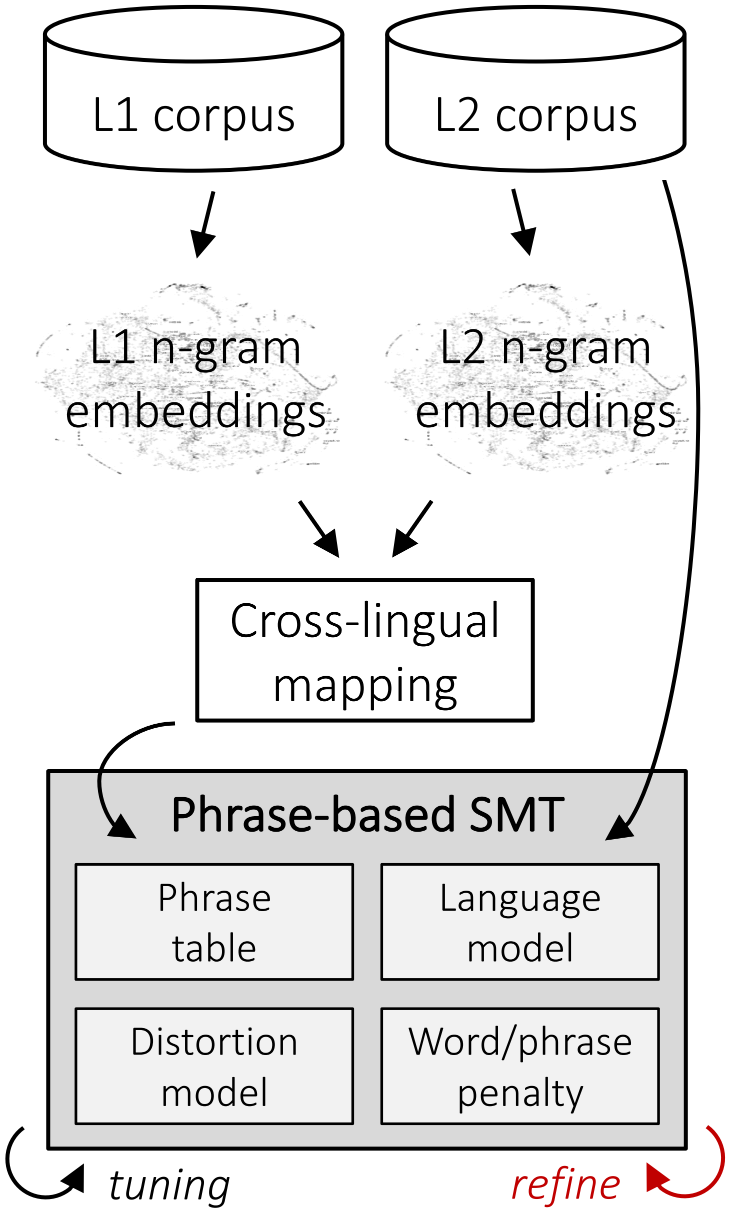

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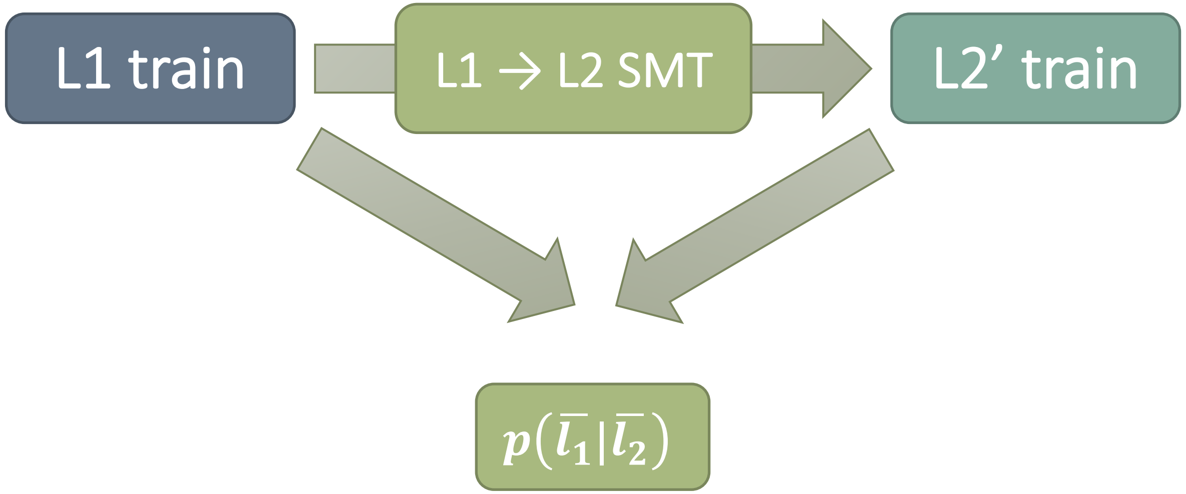

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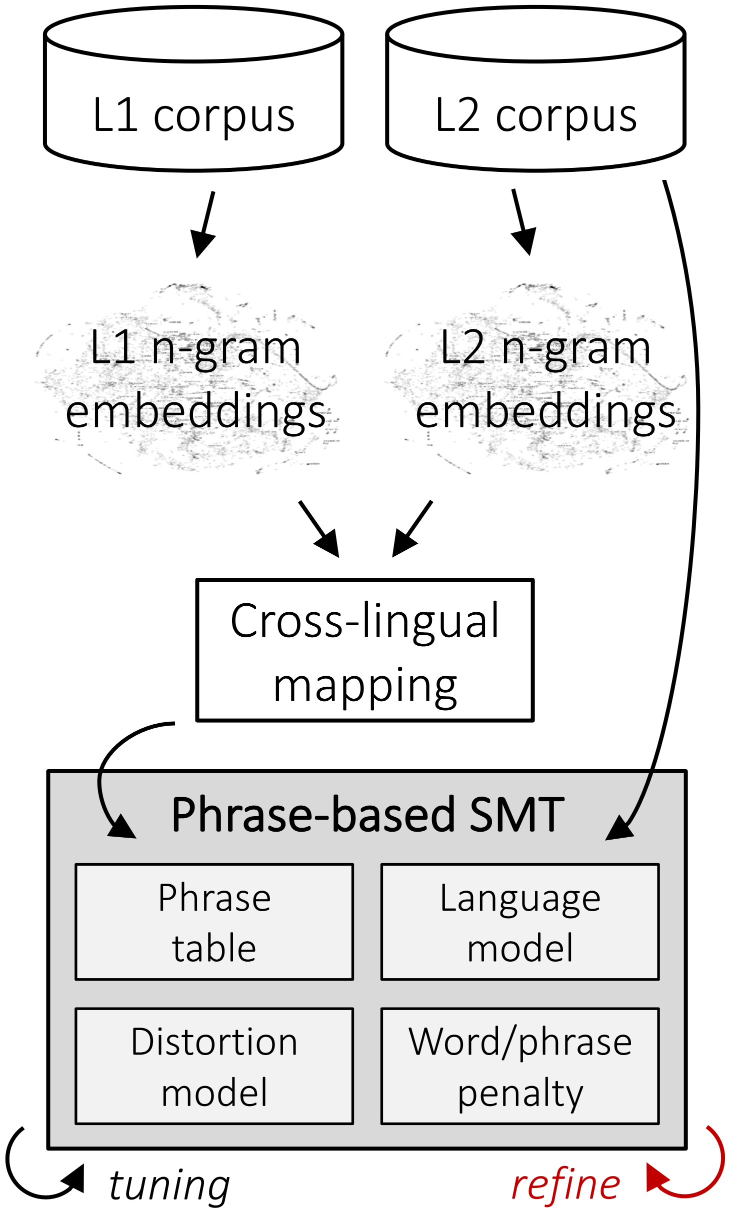

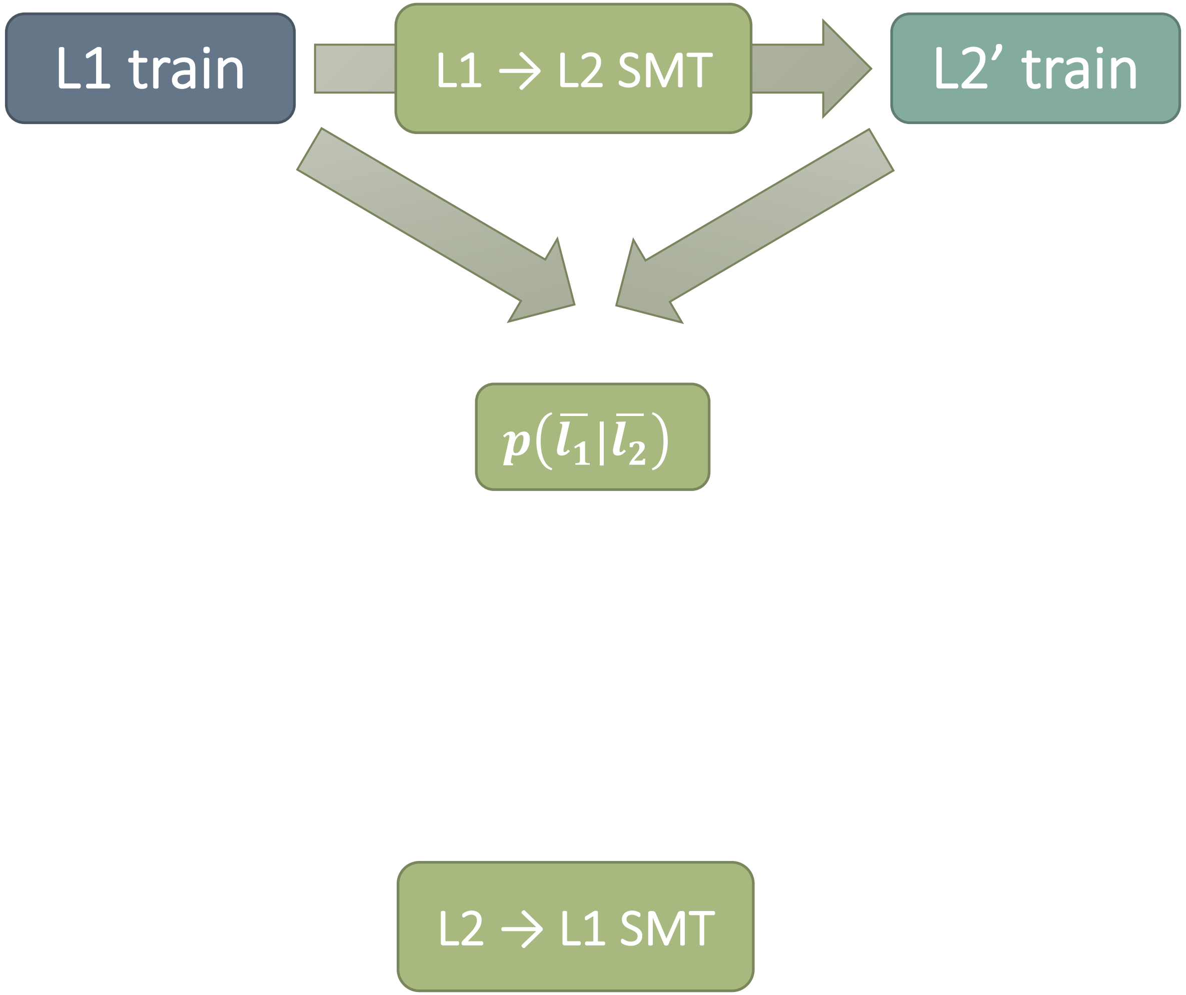

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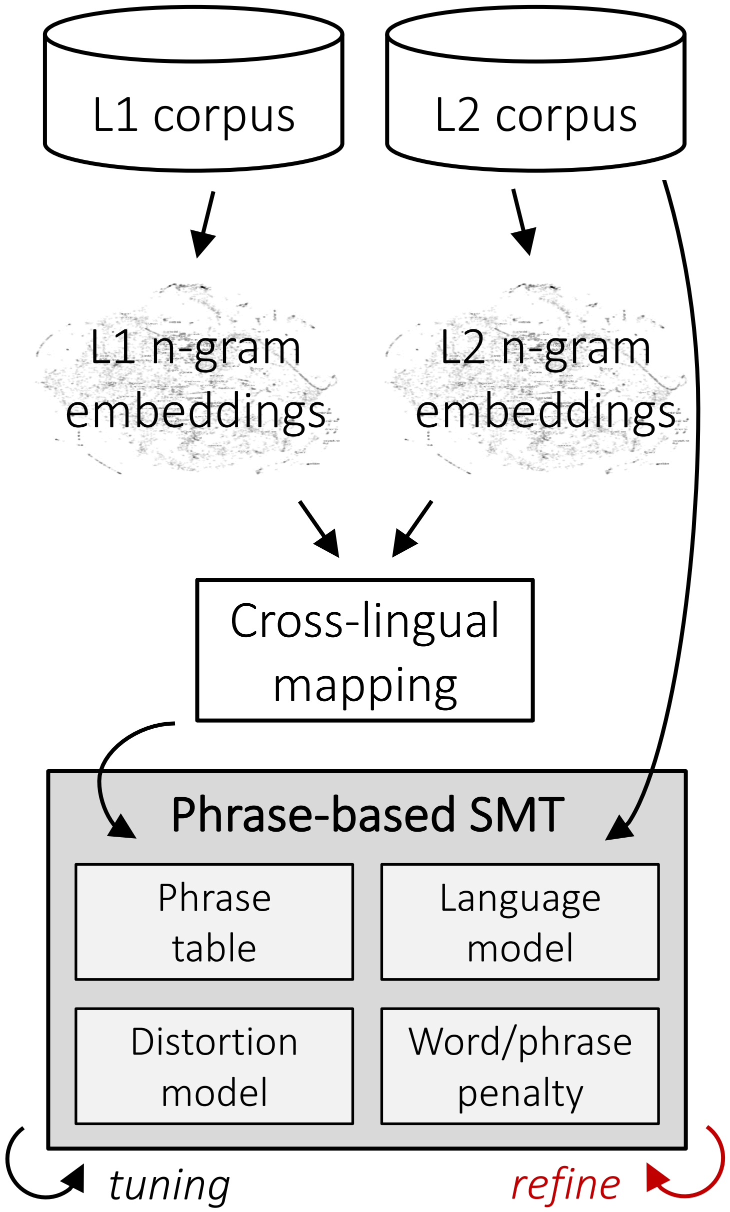

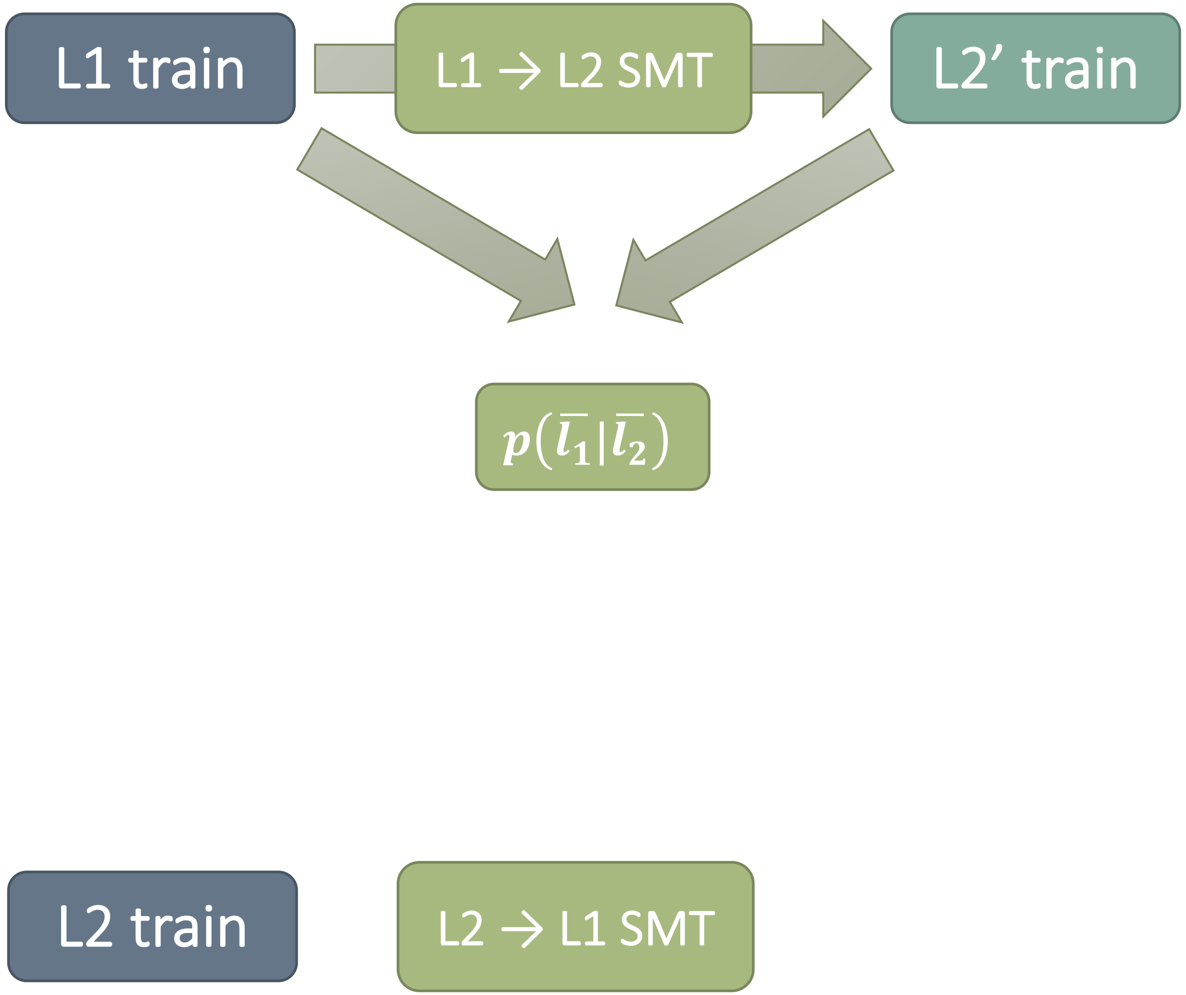

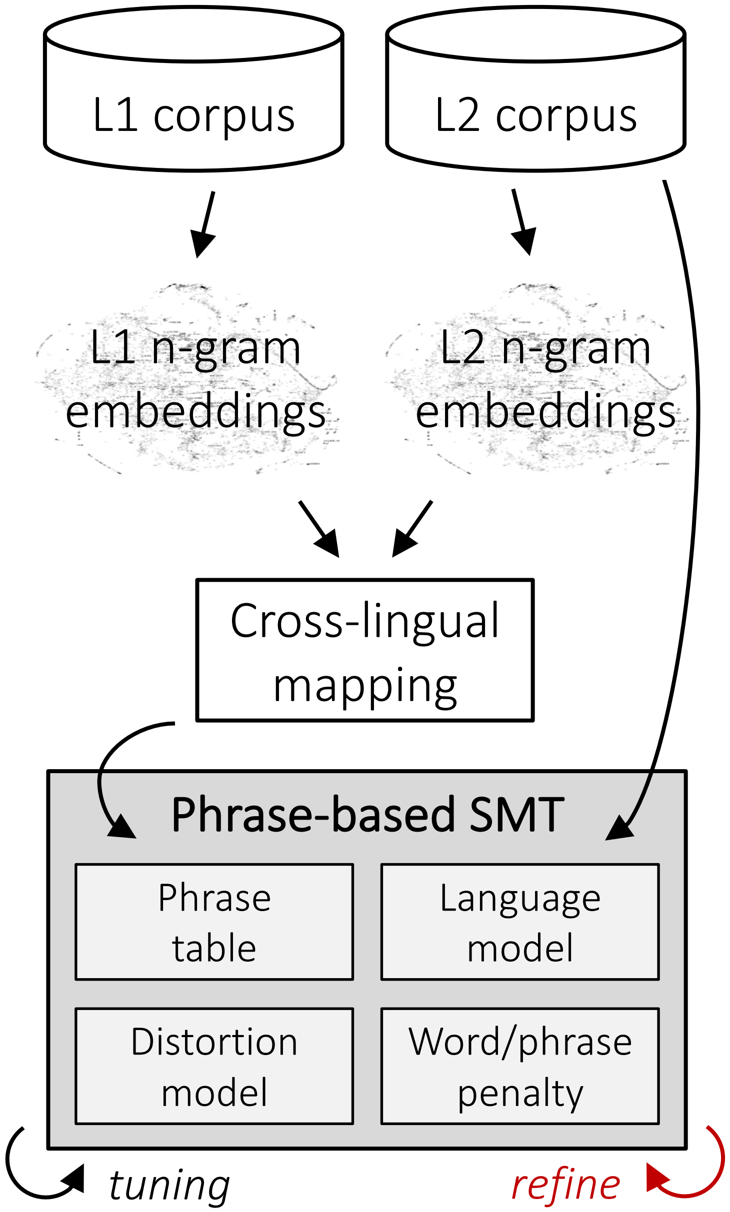

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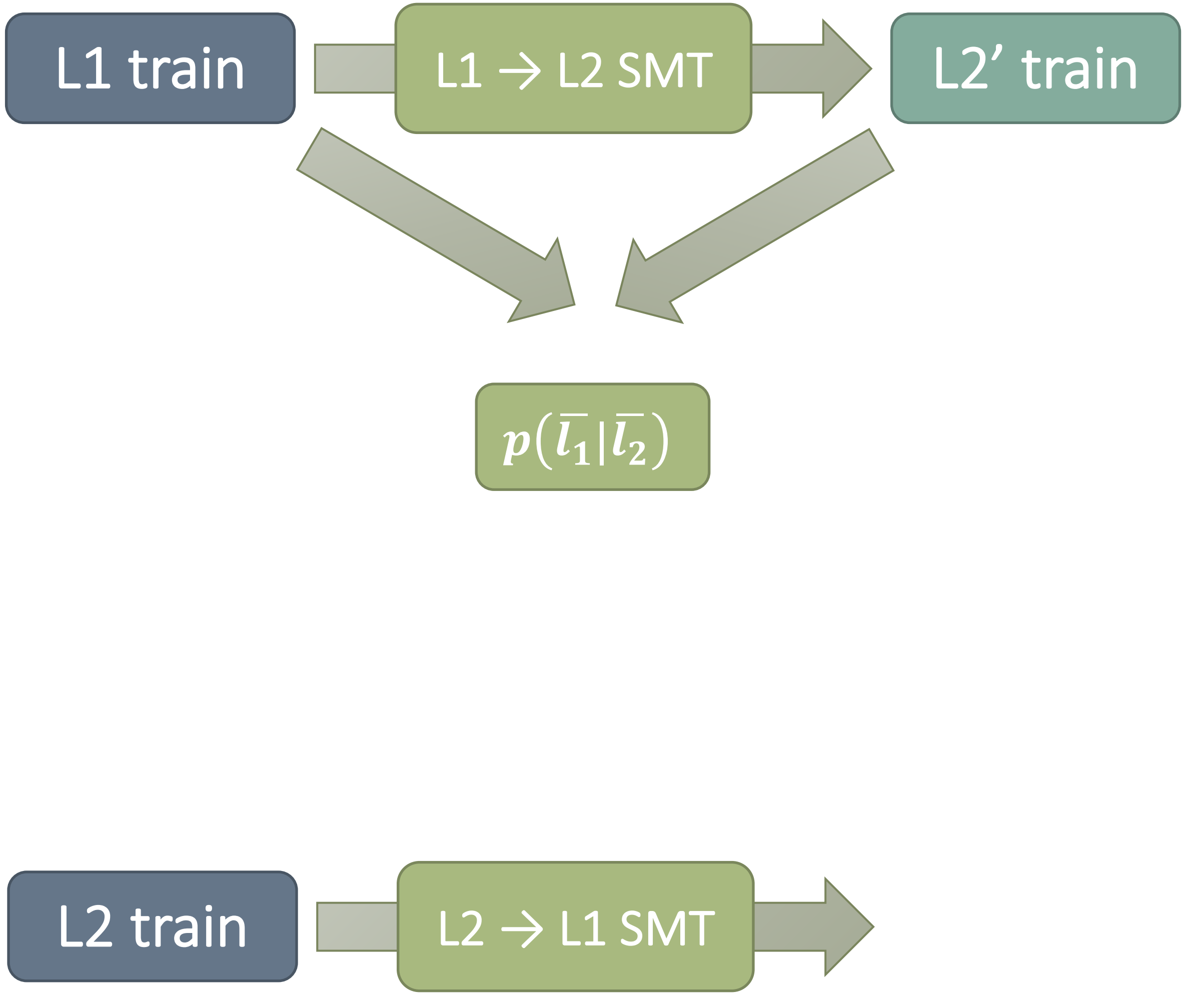

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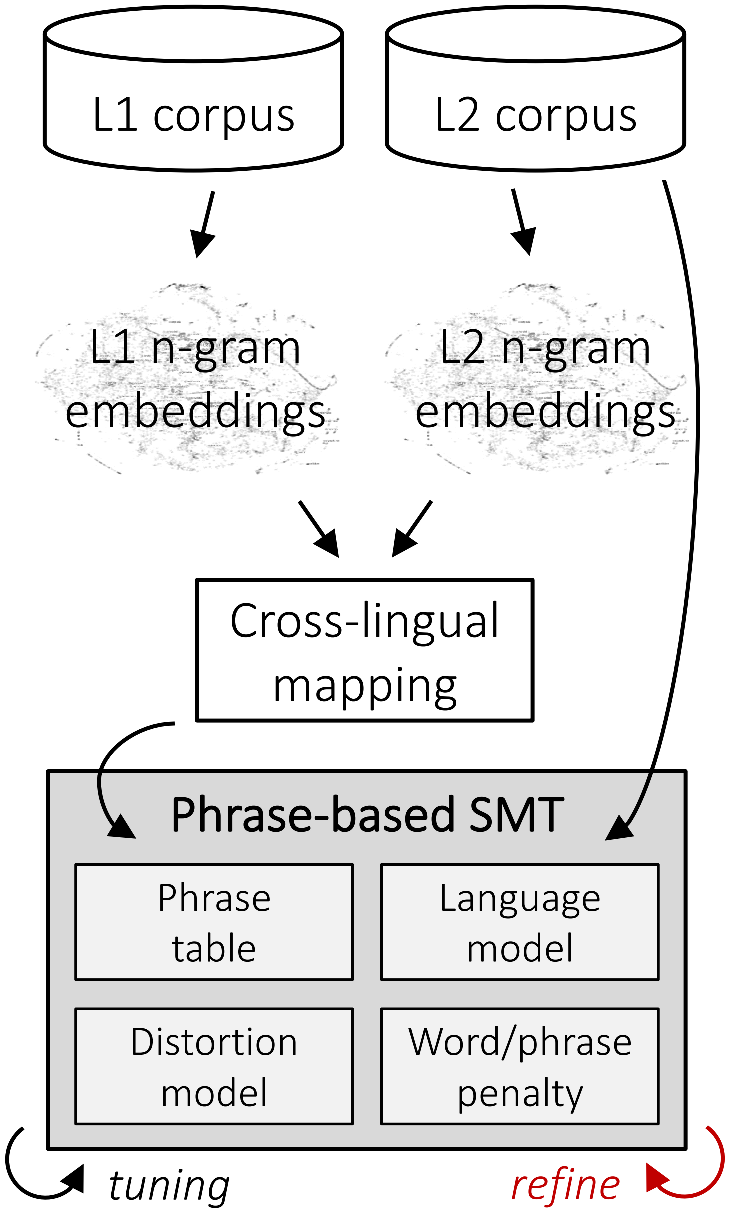

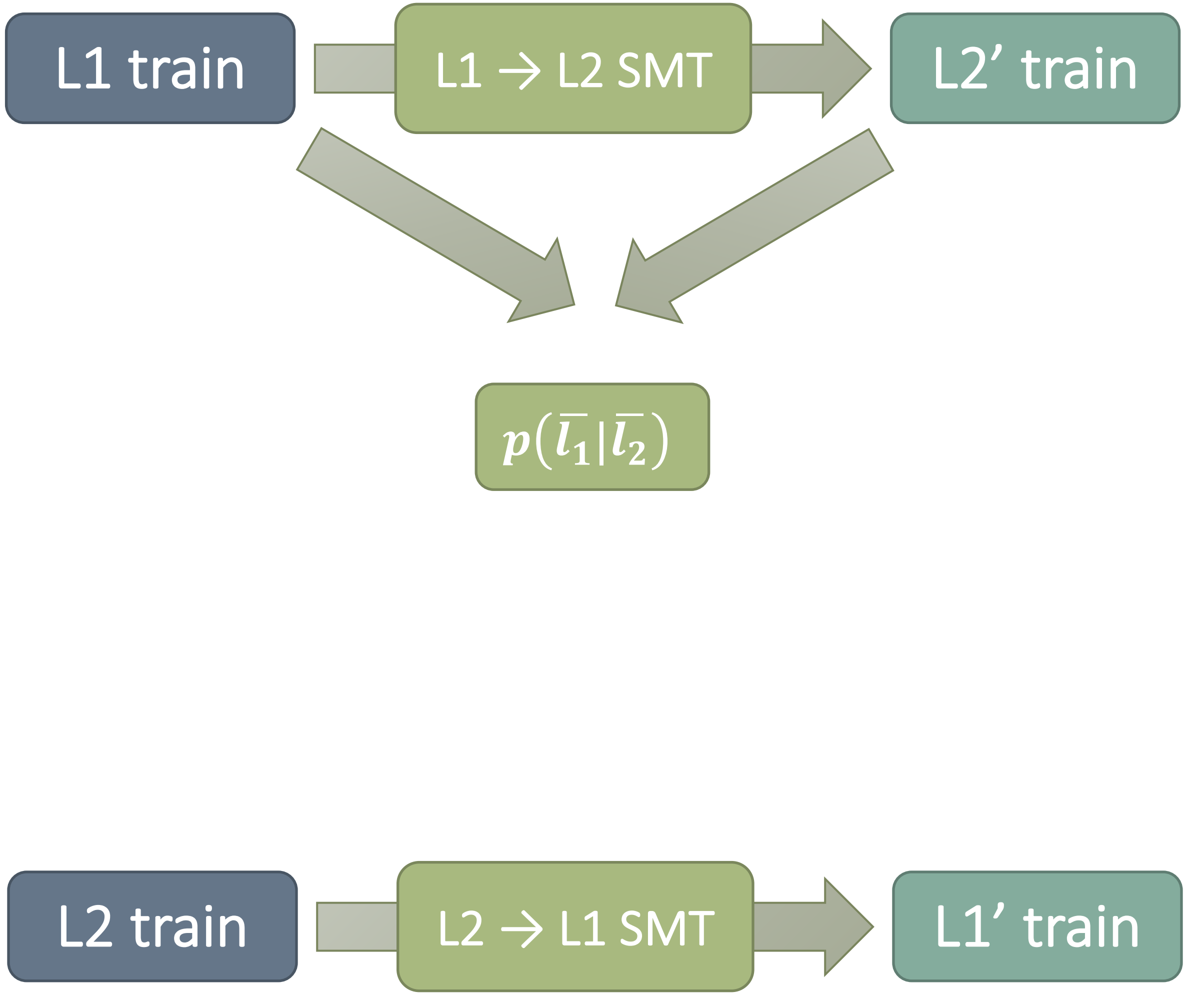

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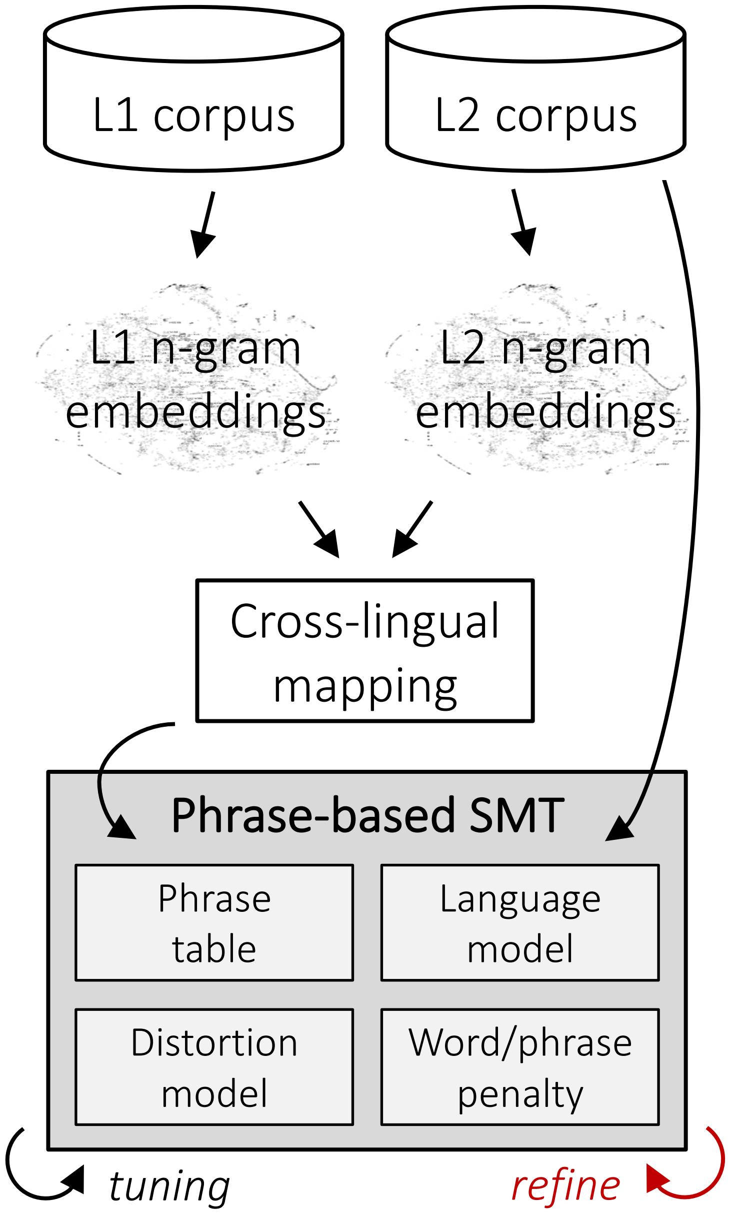

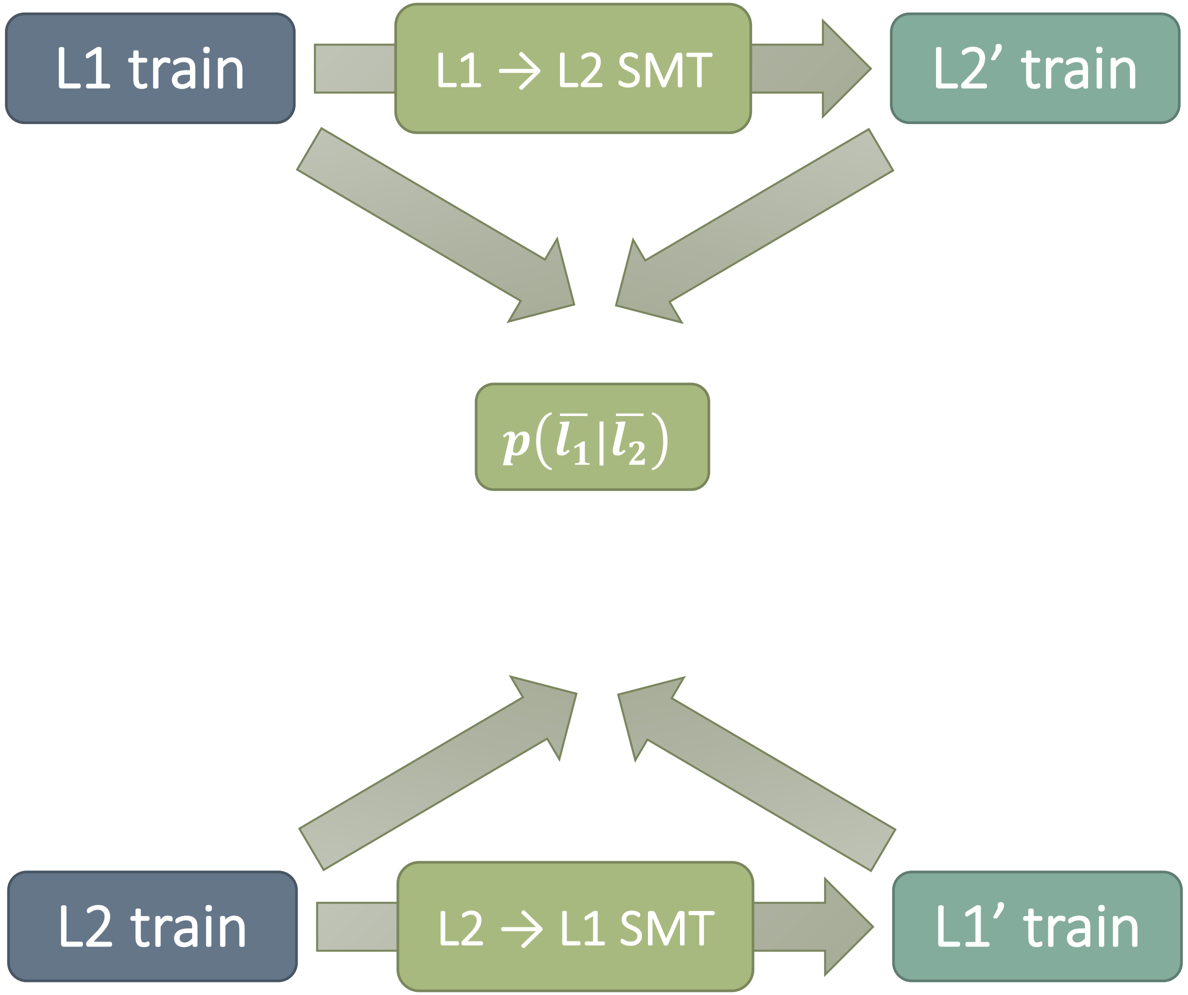

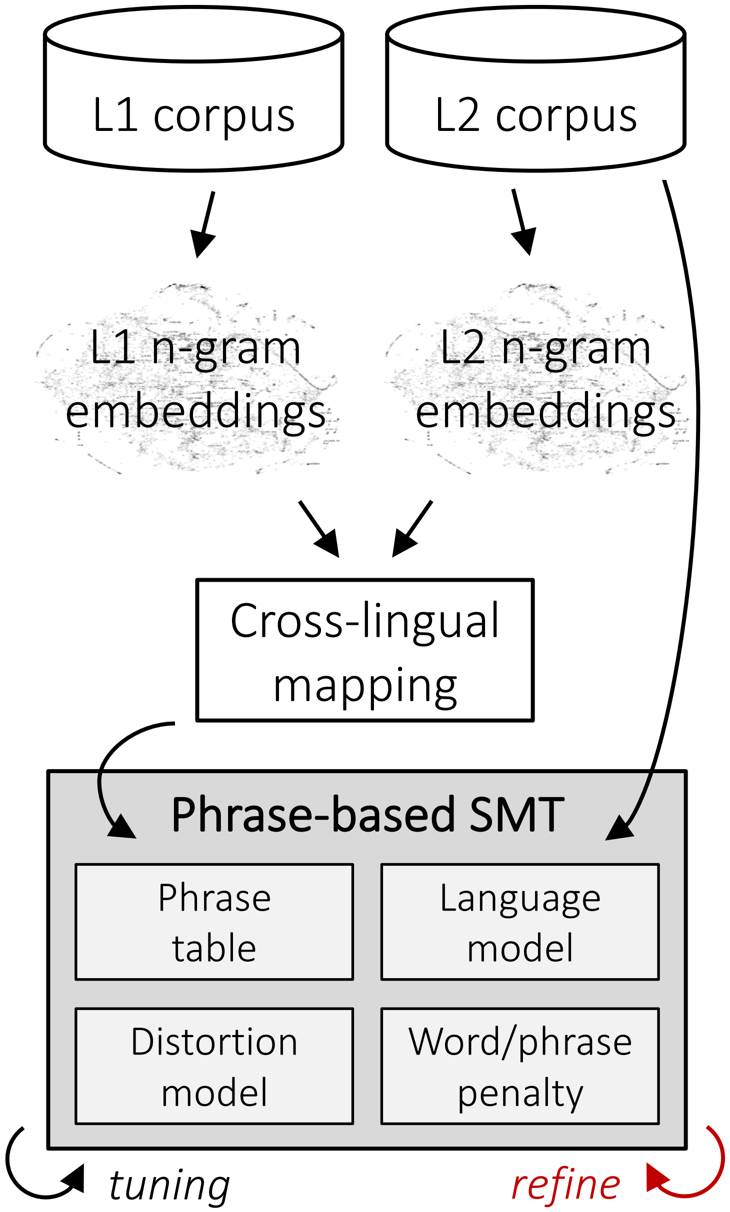

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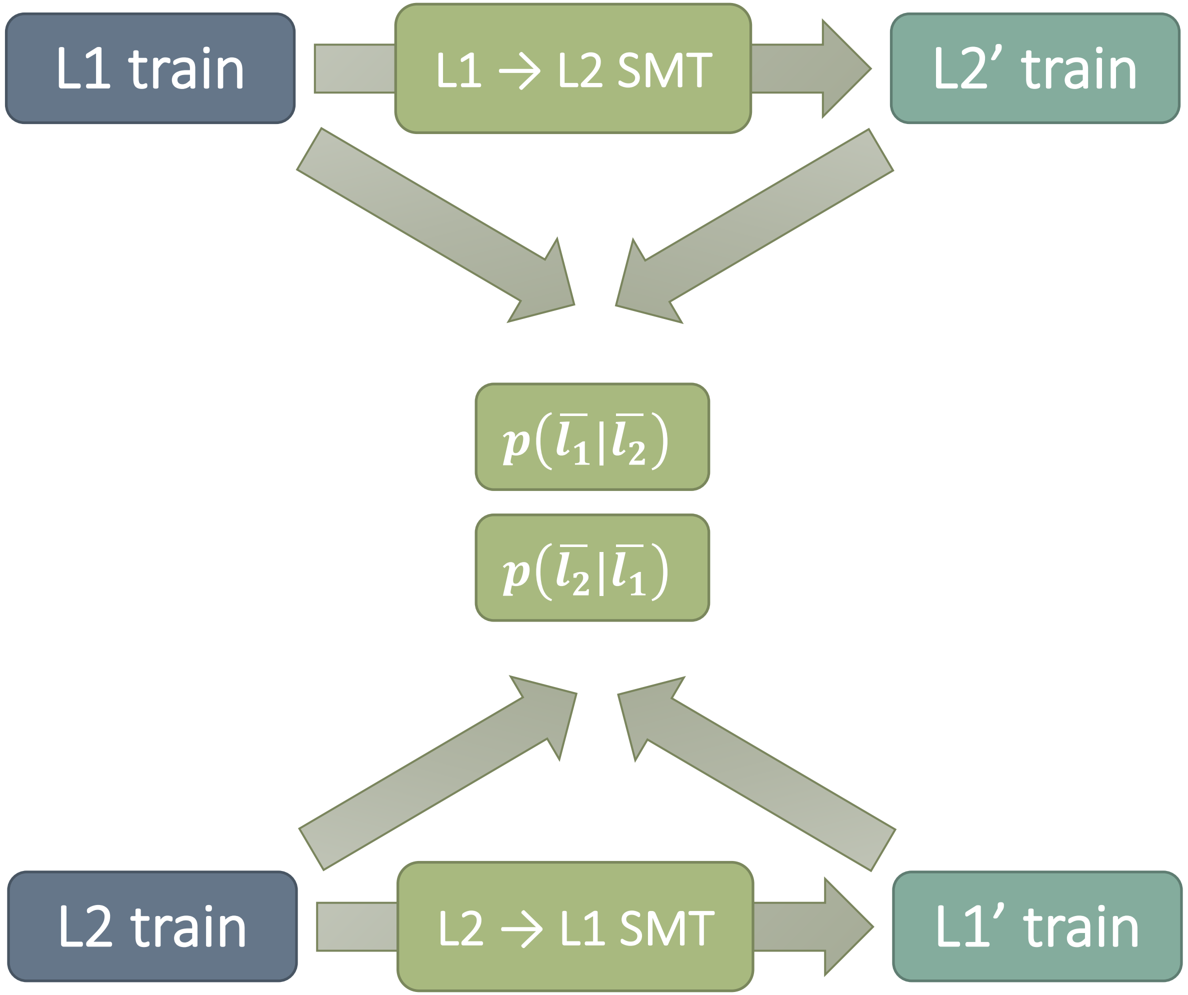

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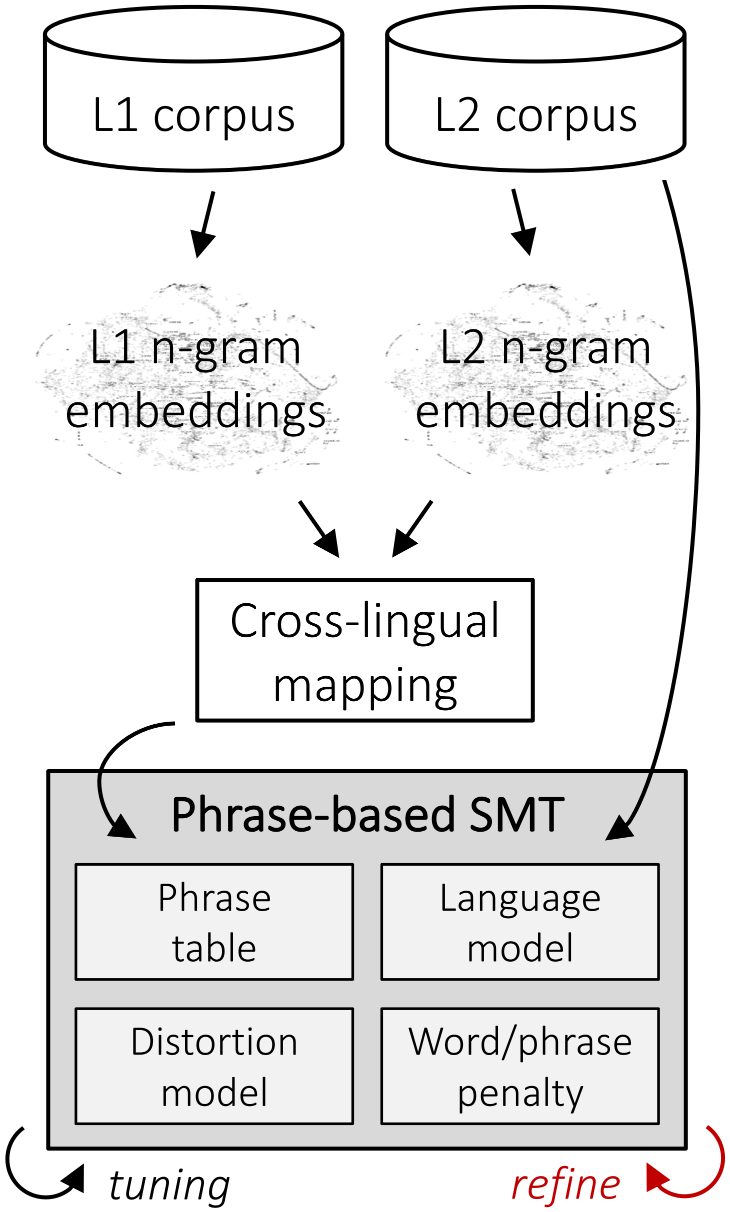

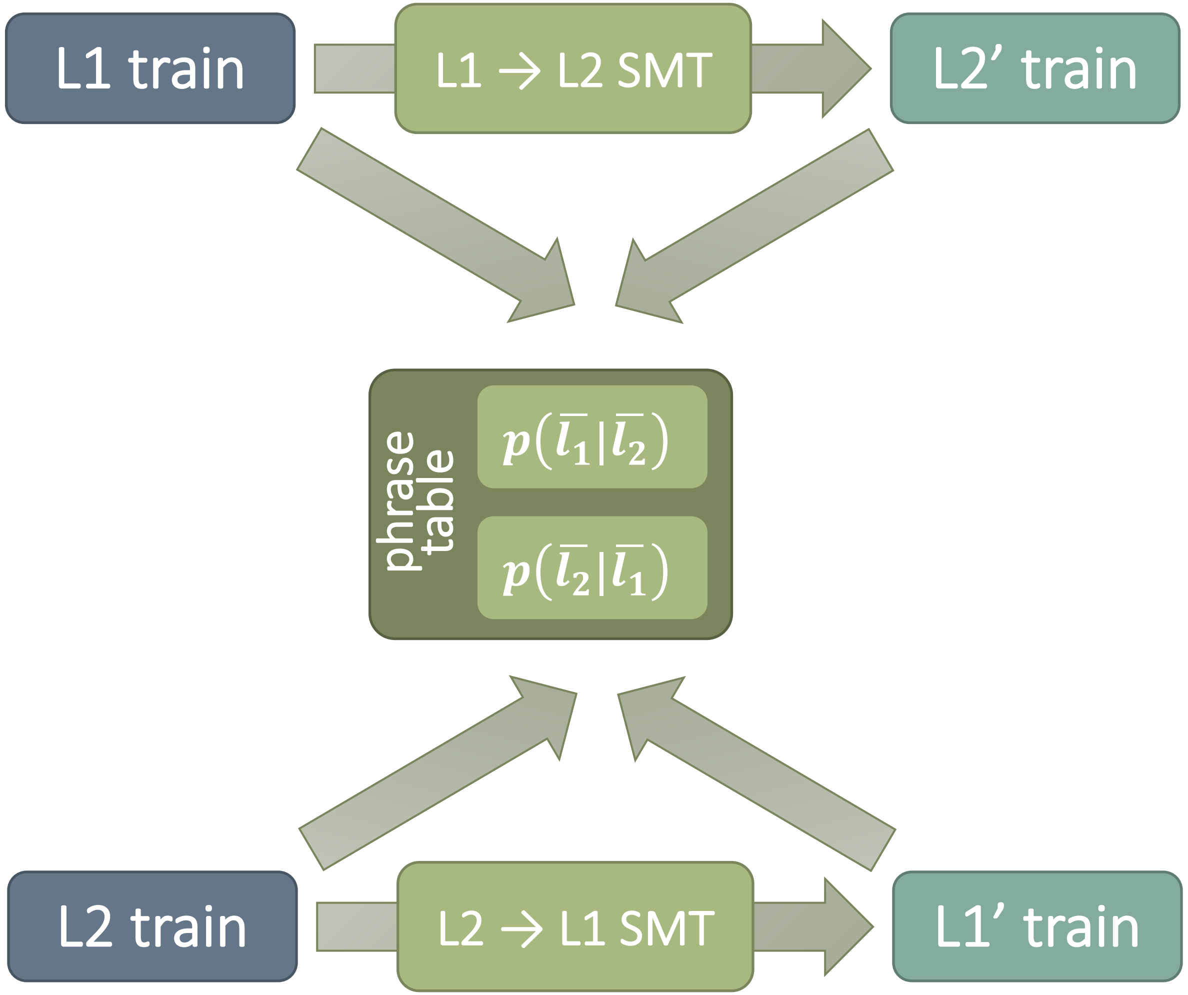

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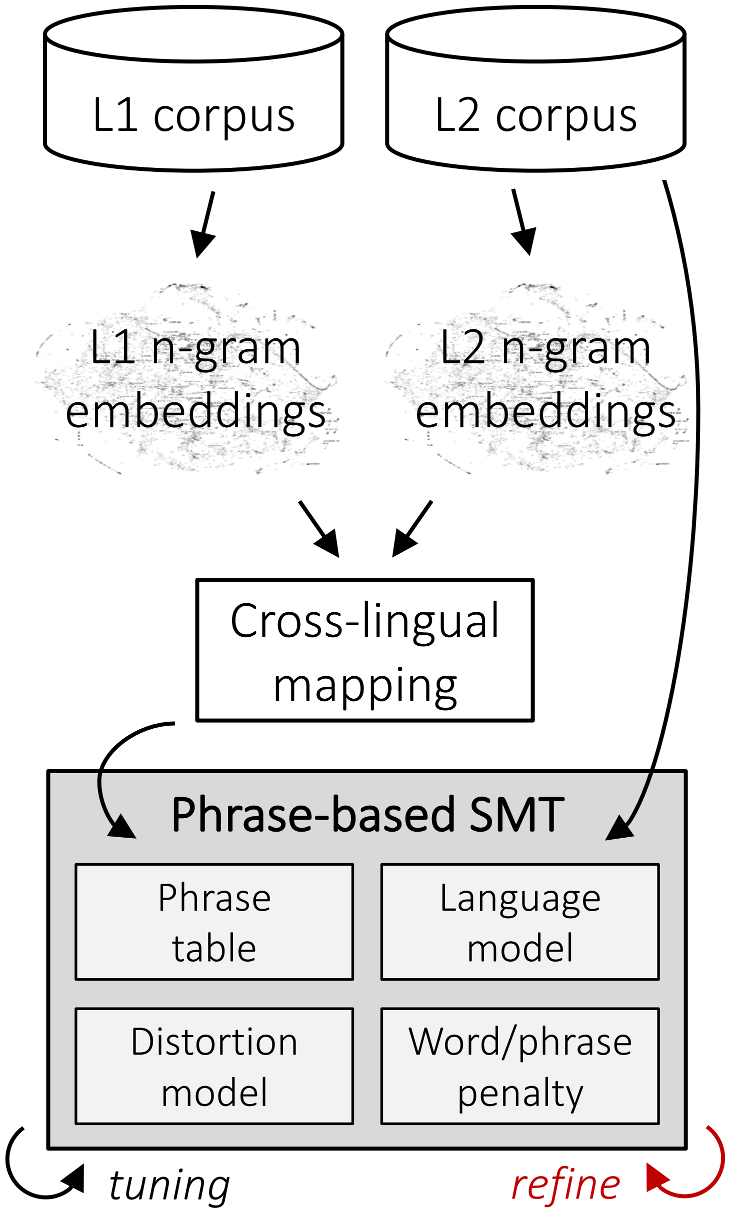

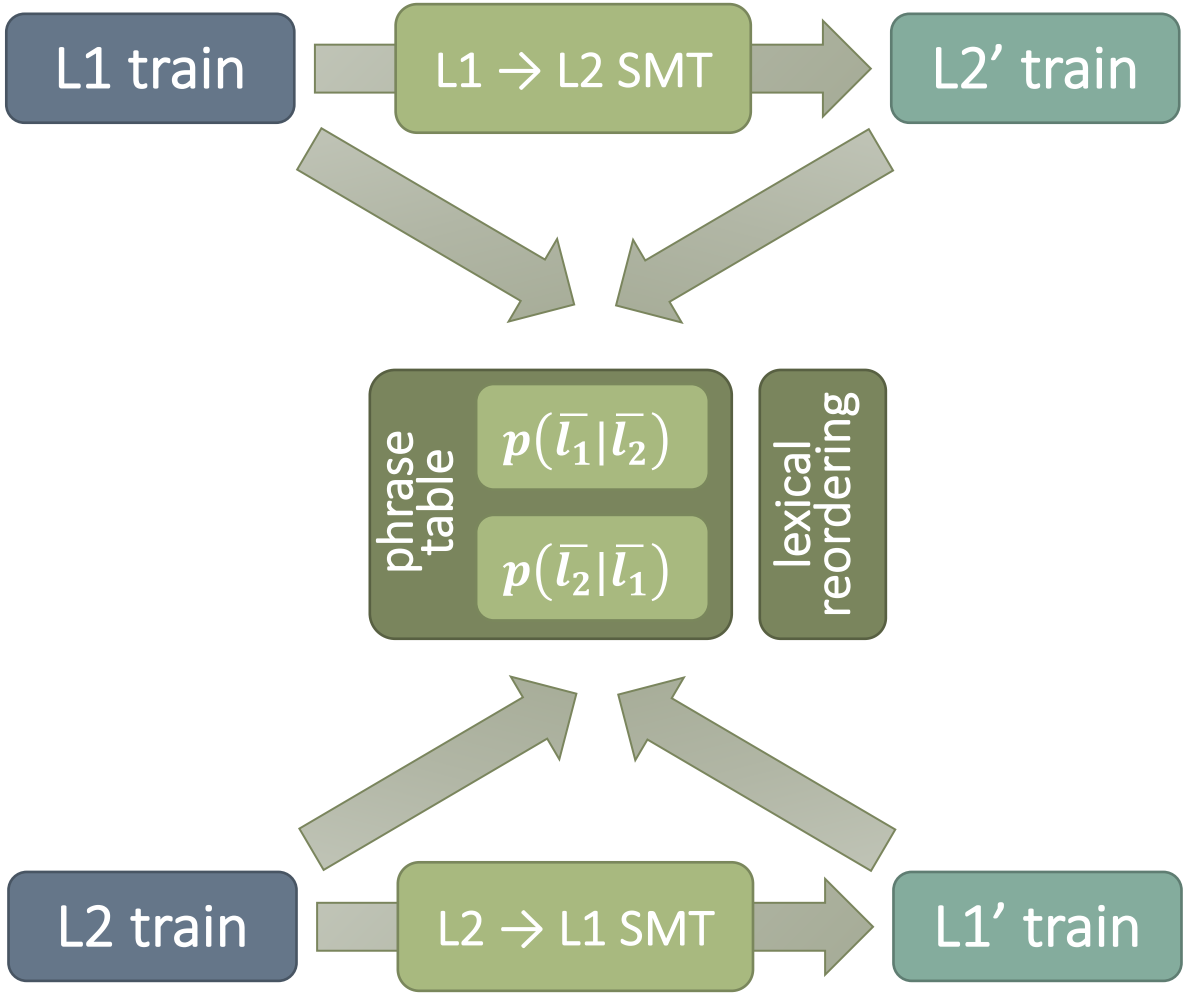

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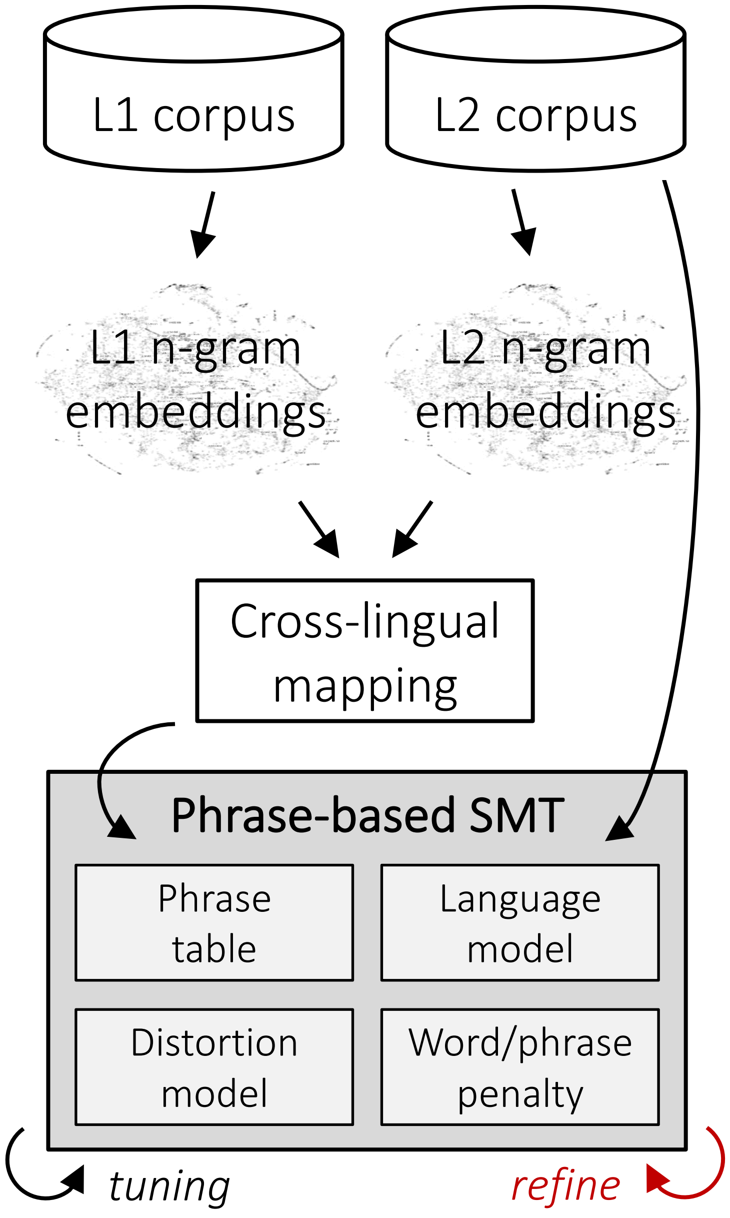

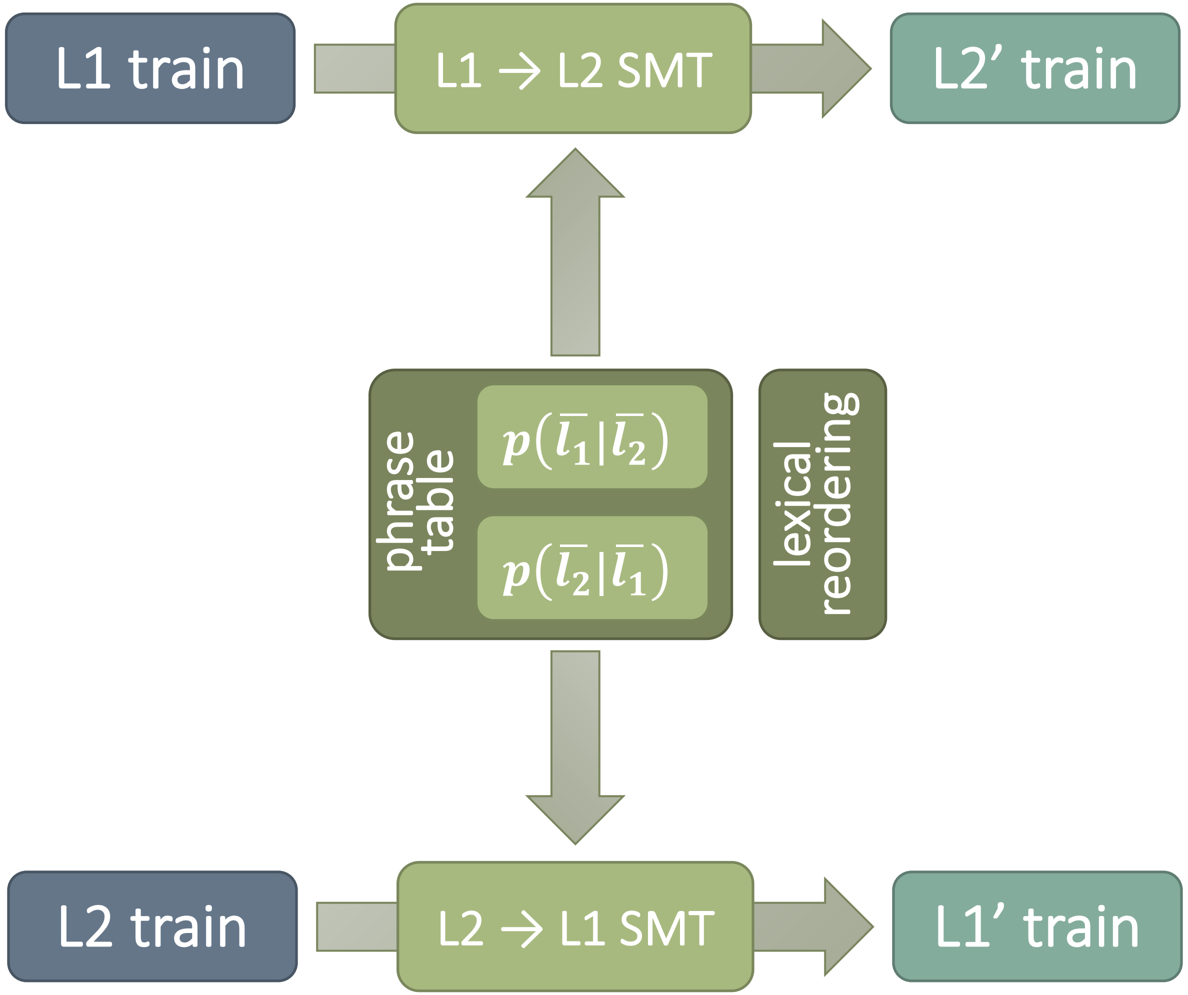

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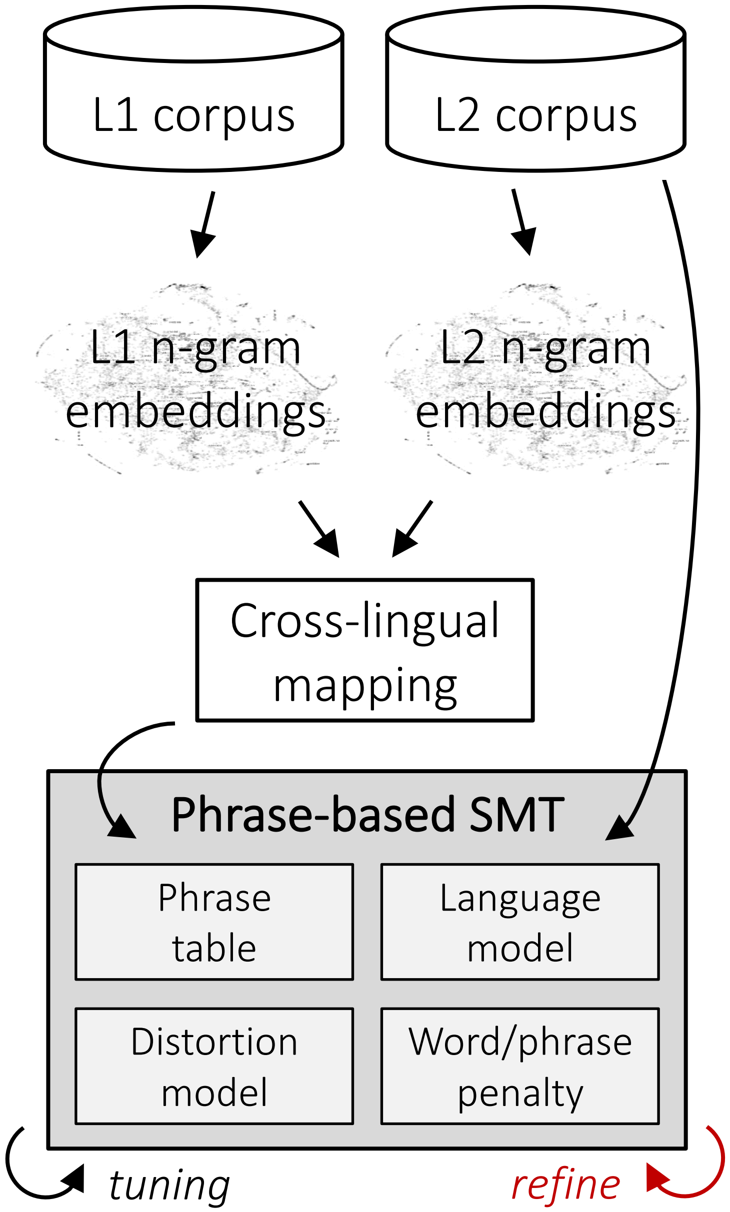
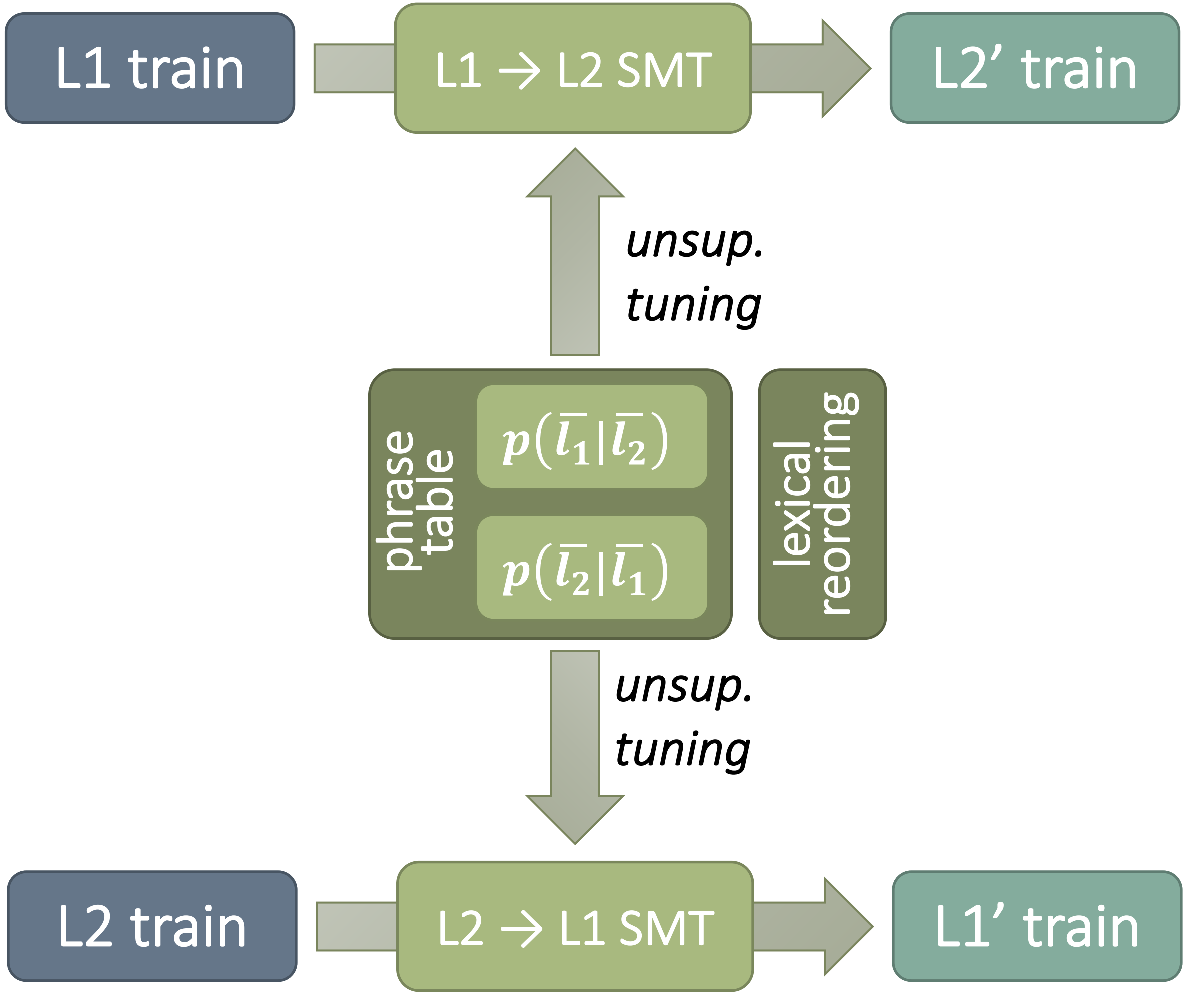
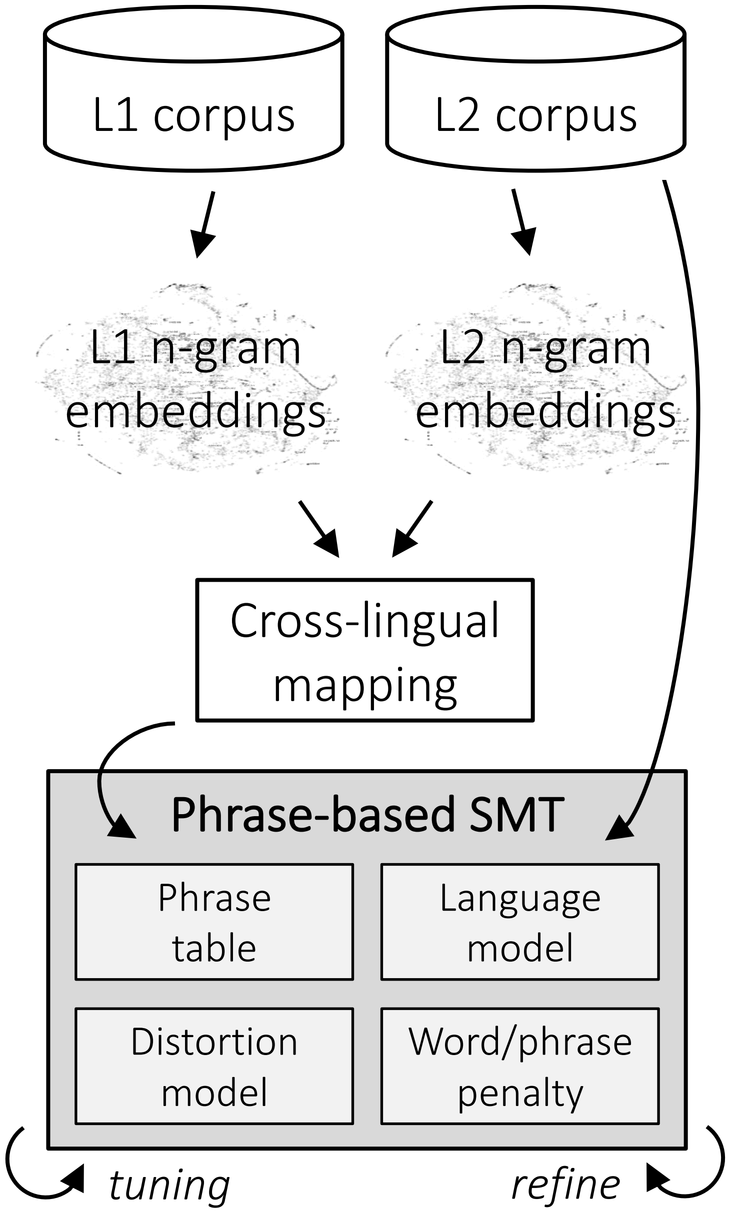
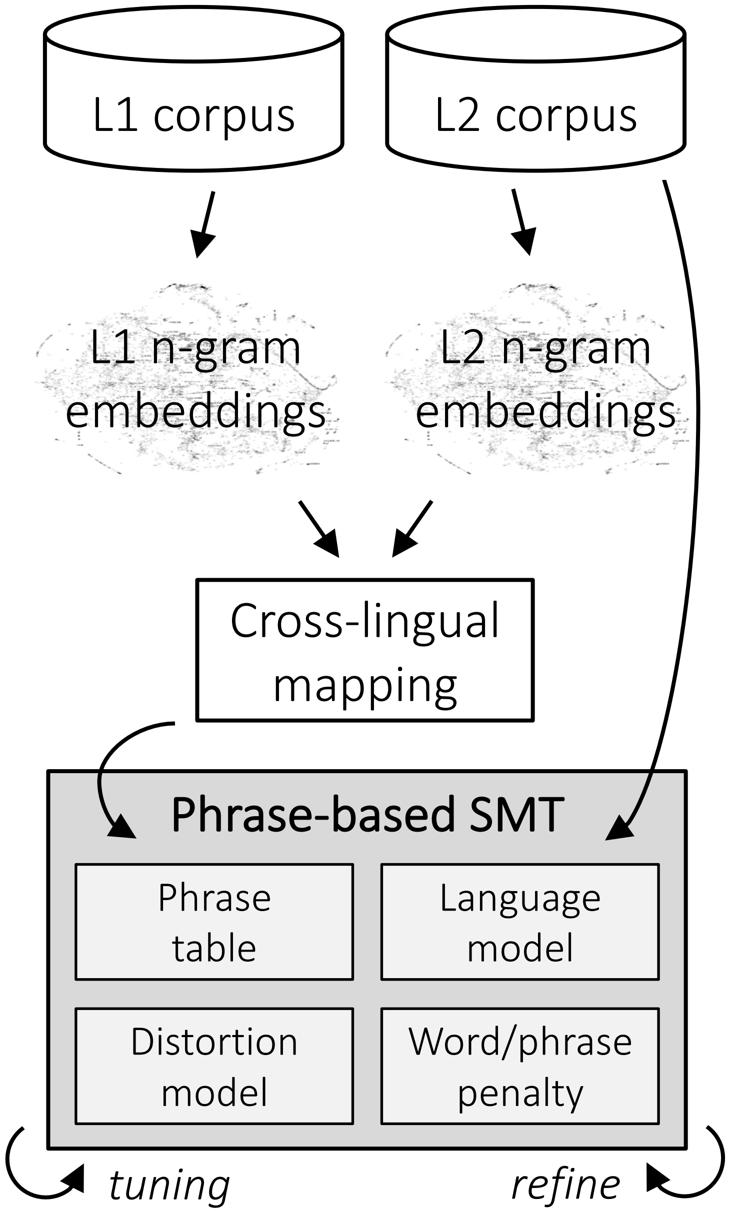





L1 corpus
L2 corpus
L1 n-gram embeddings
L2 n-gram embeddings
Cross-lingual mapping
Phrase-based SMT
Phrase table
Language model
Distortion model
Word/phrase penalty
tuning
refine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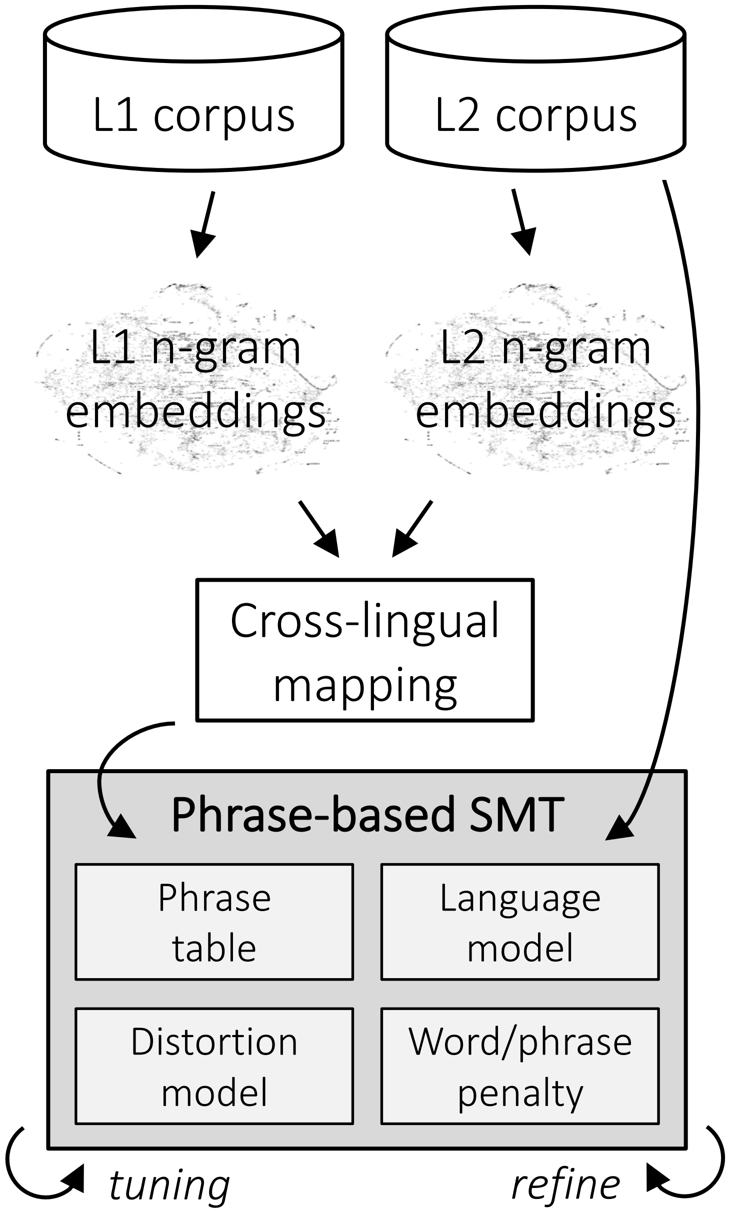
but…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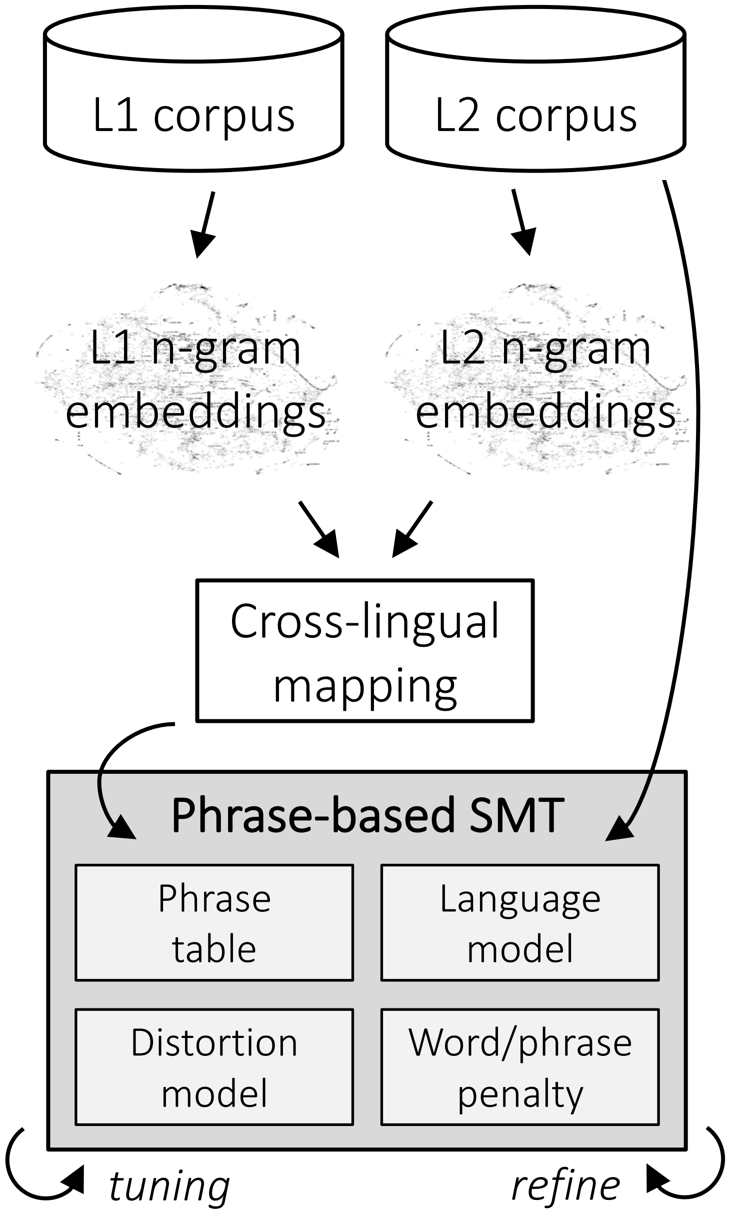
but…

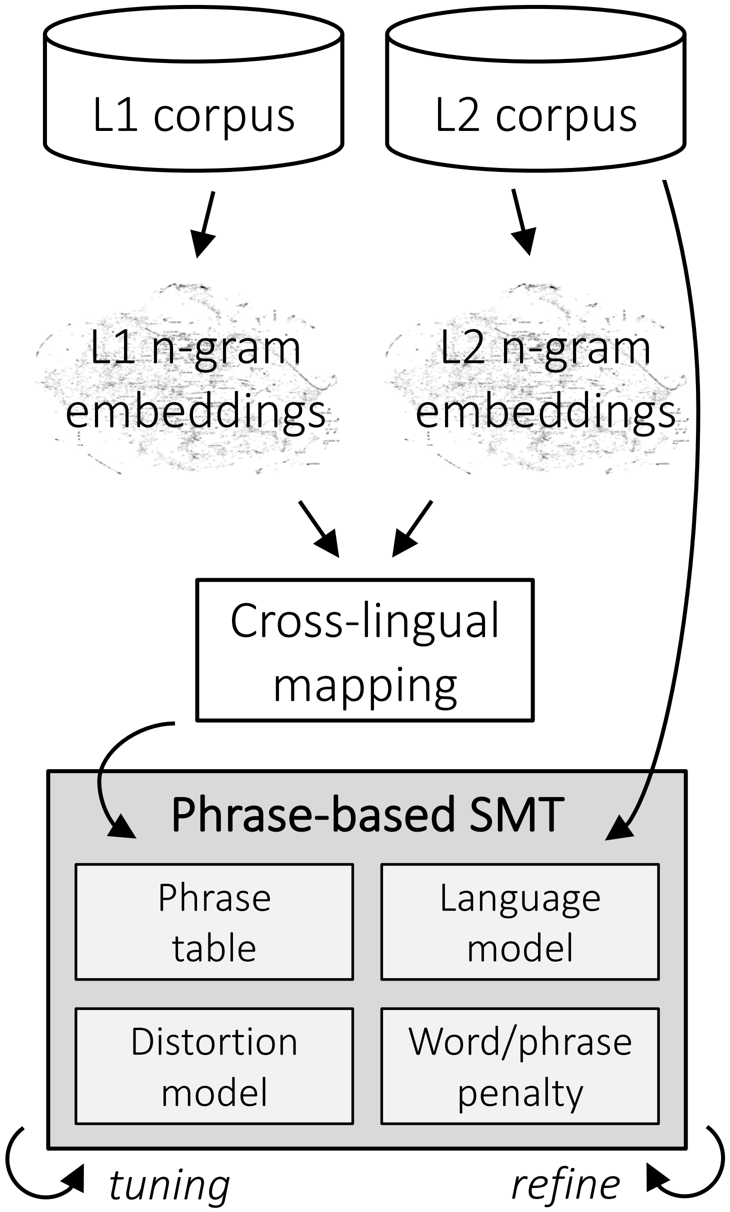
NMT >> SMT



but…

NMT >> SMT

(unsupervised) SMT has a hard ceiling!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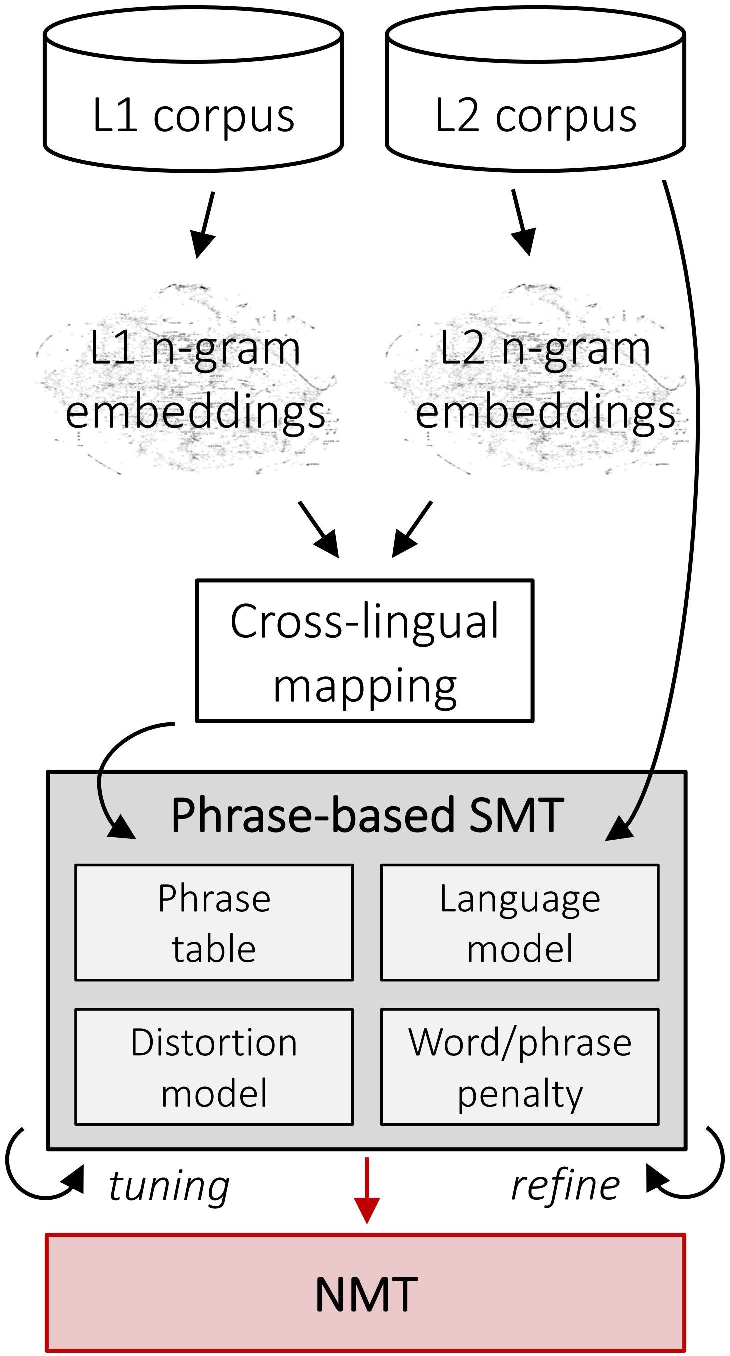
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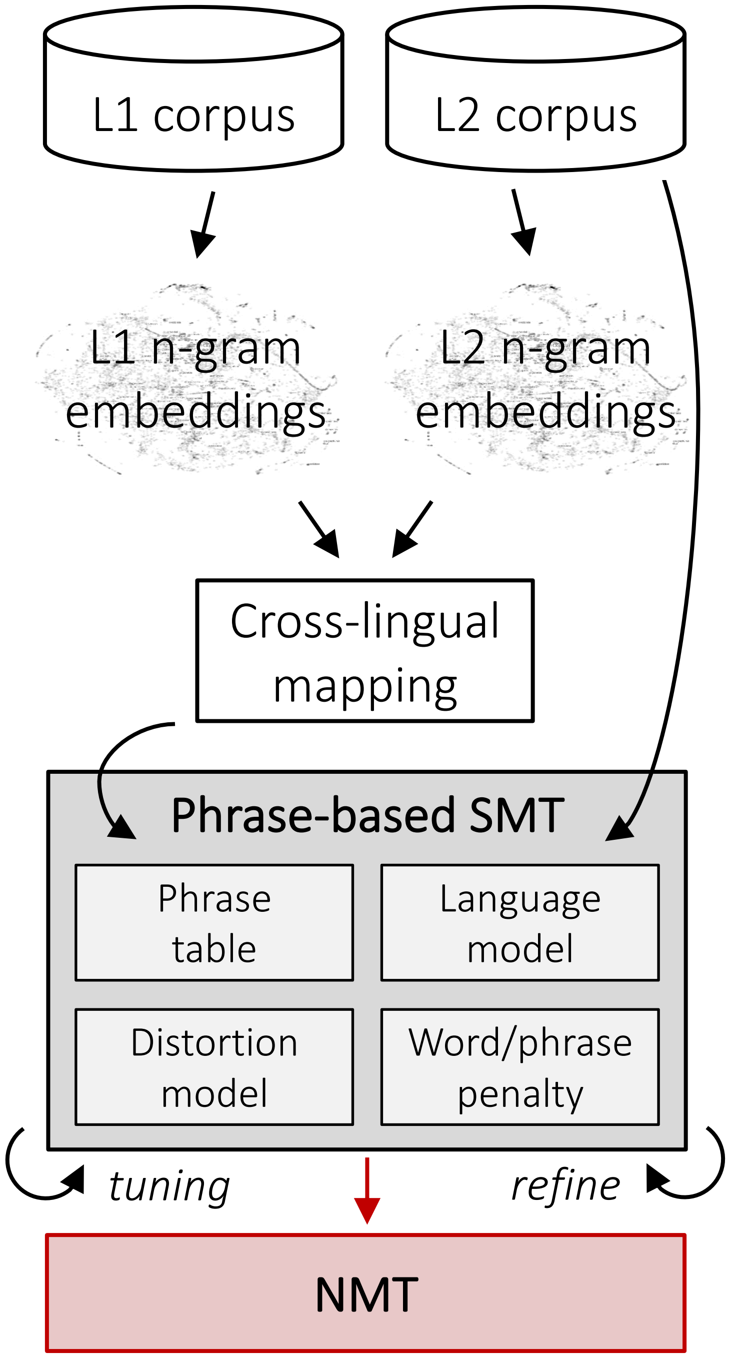
NMT

NMT hybridization



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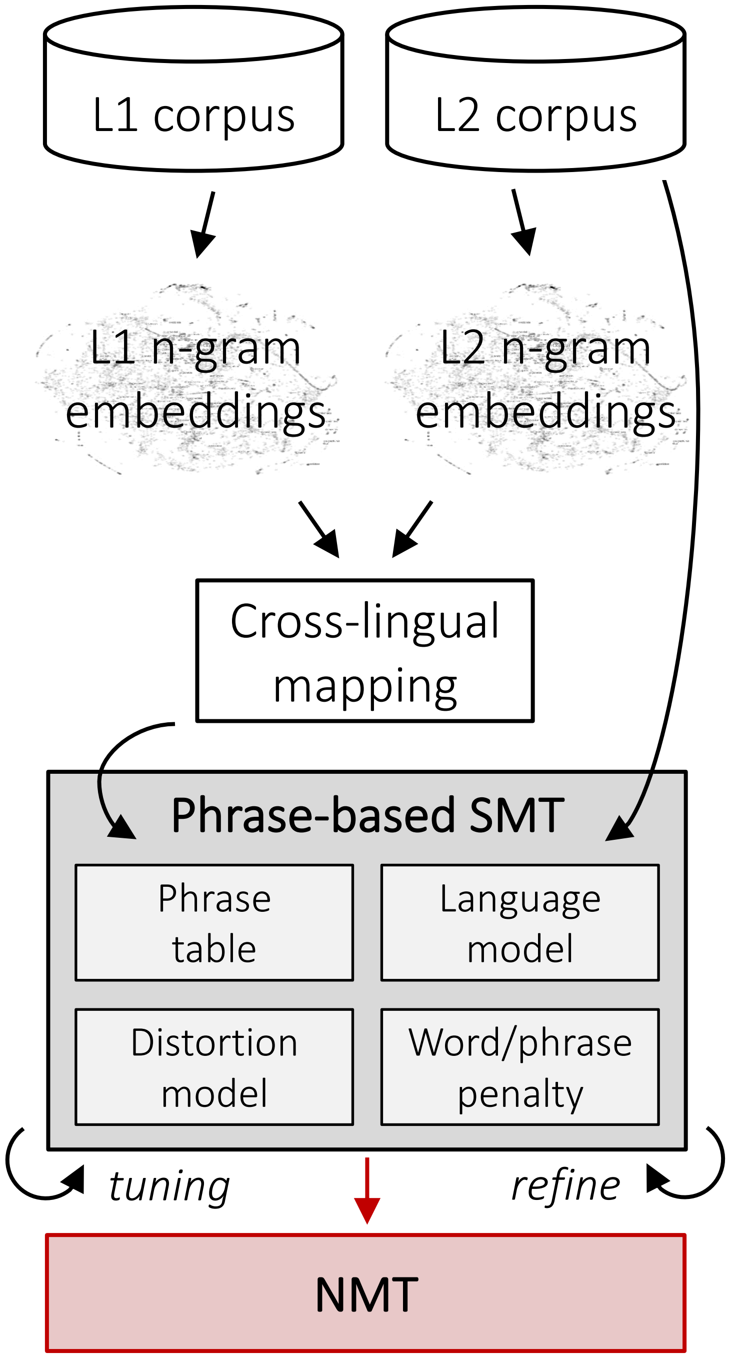

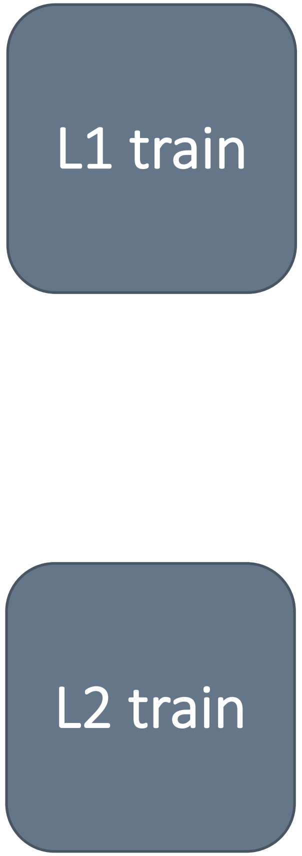

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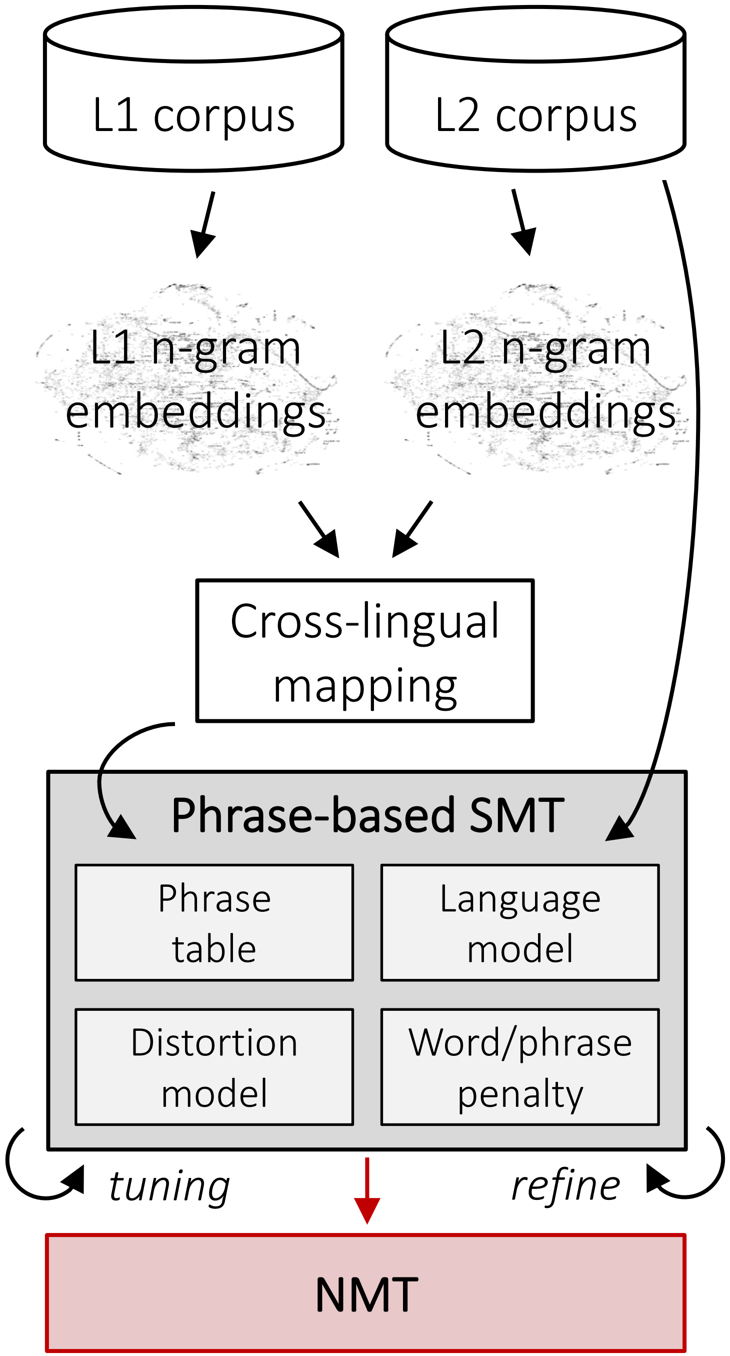

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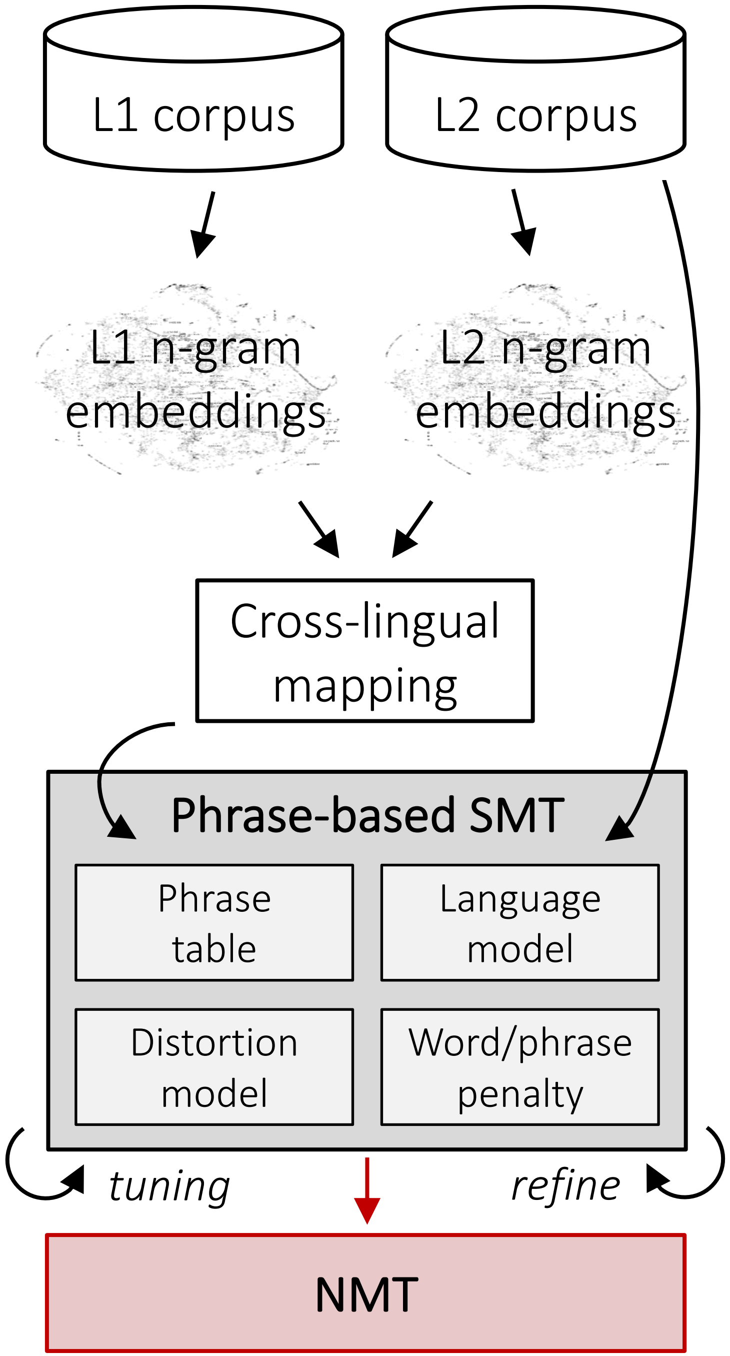

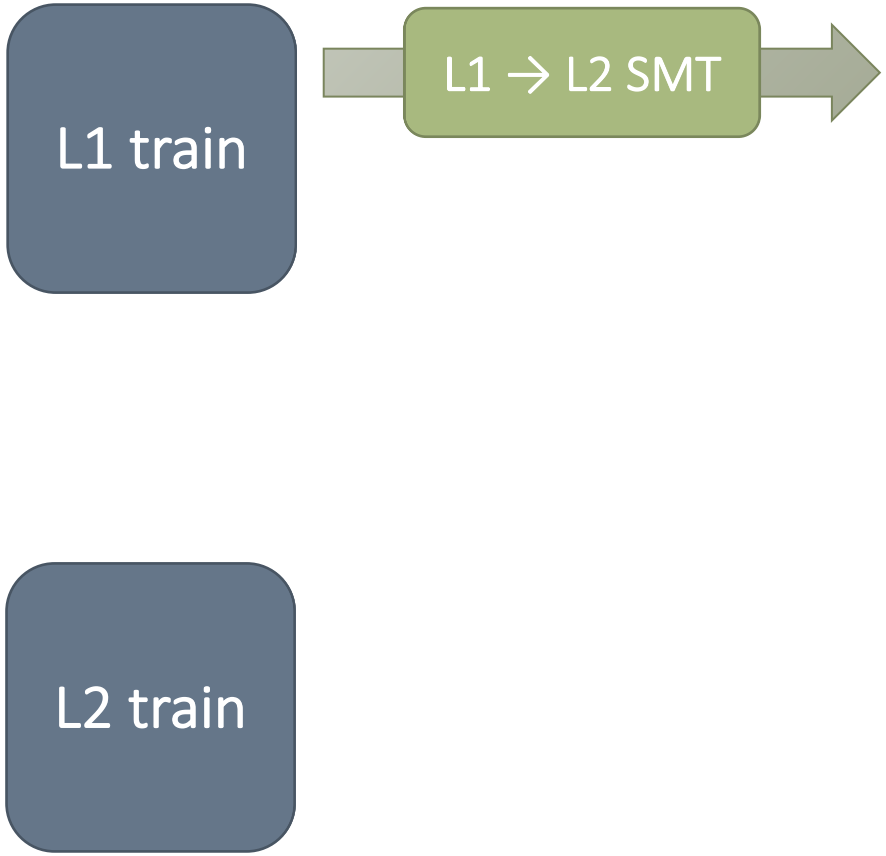

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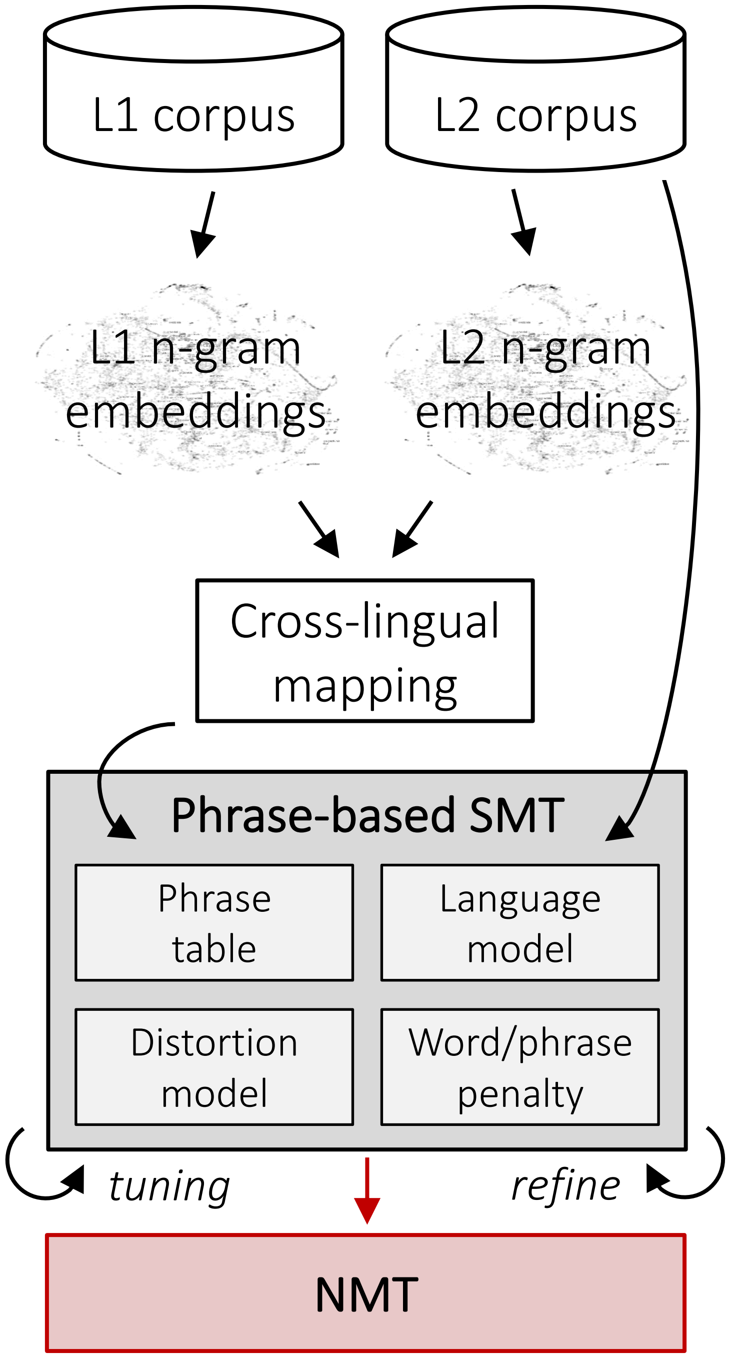

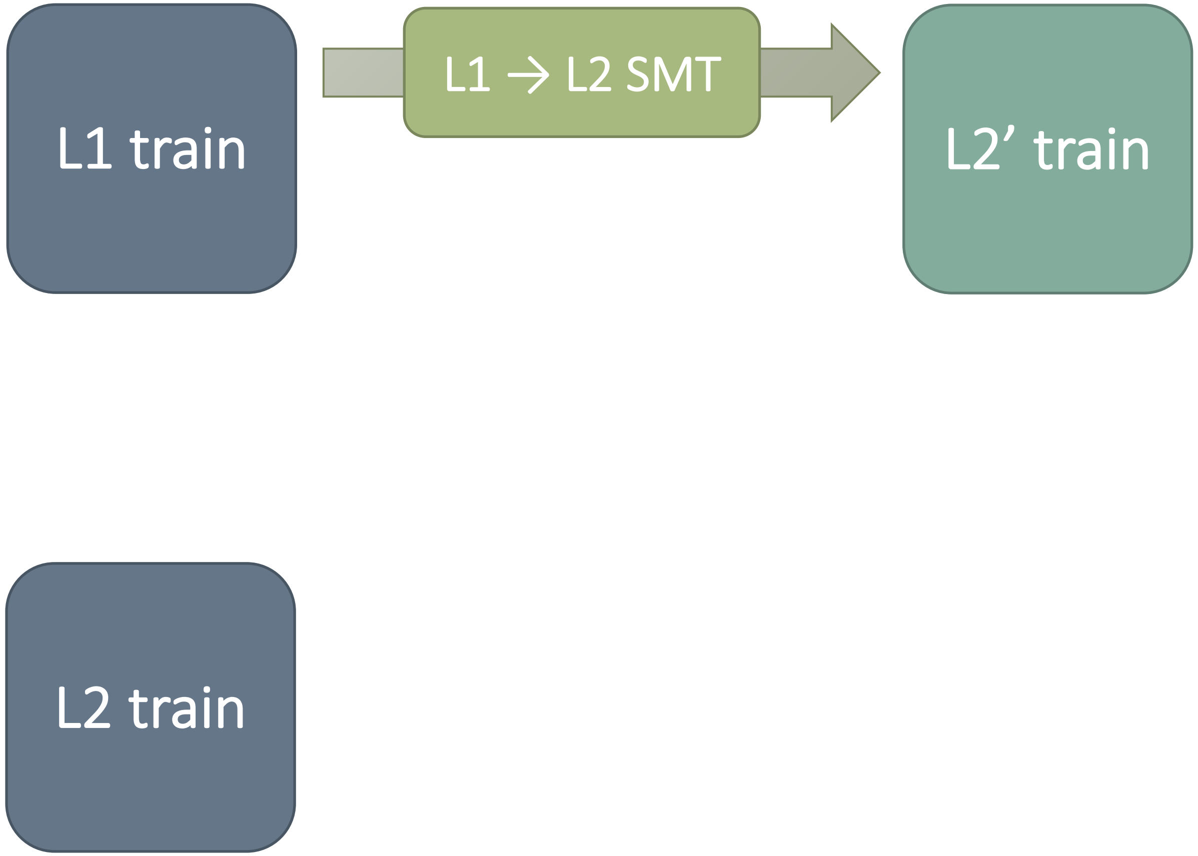

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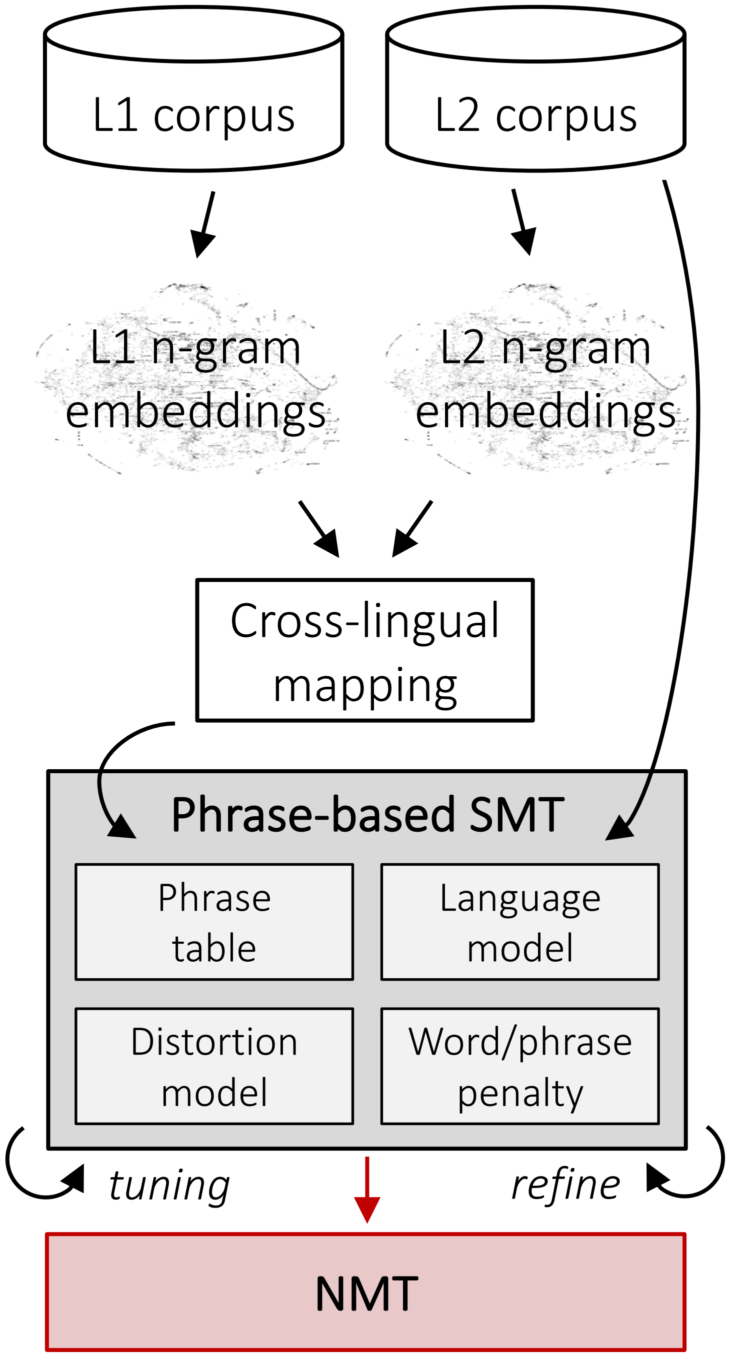

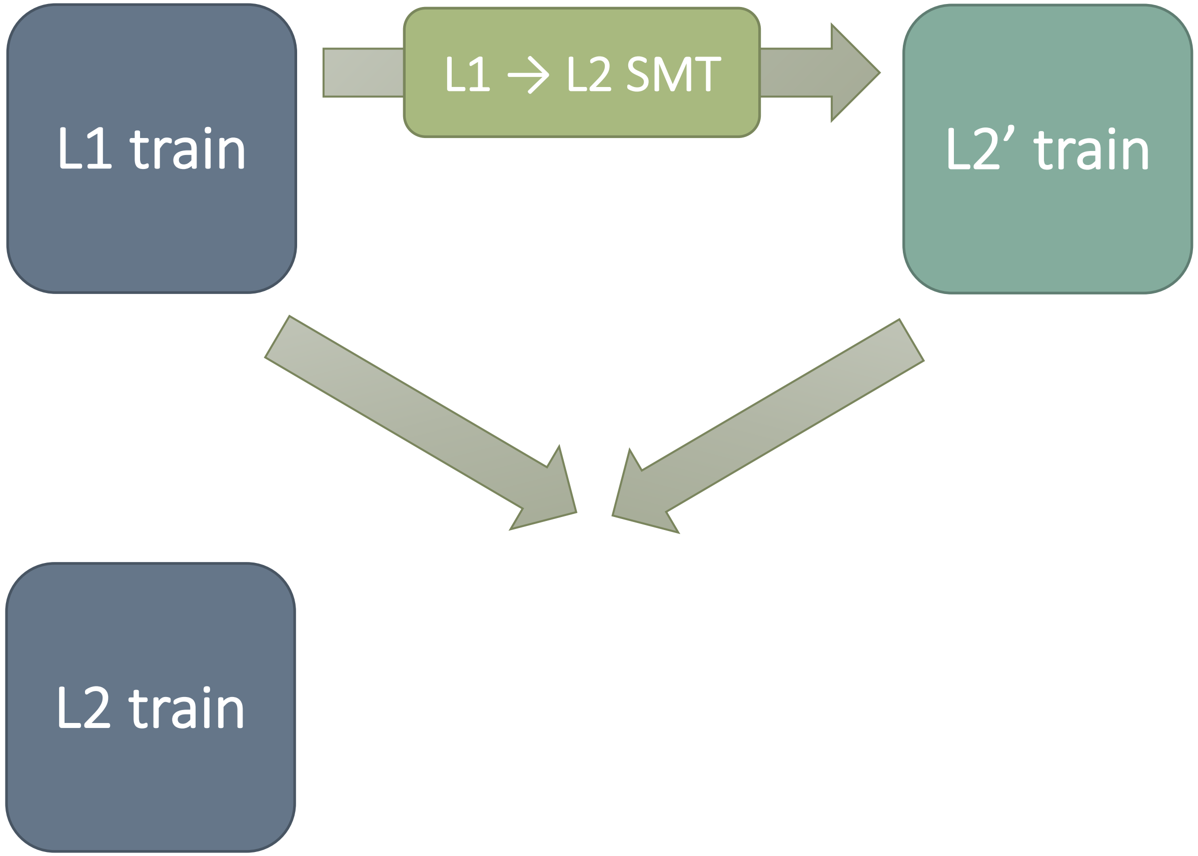

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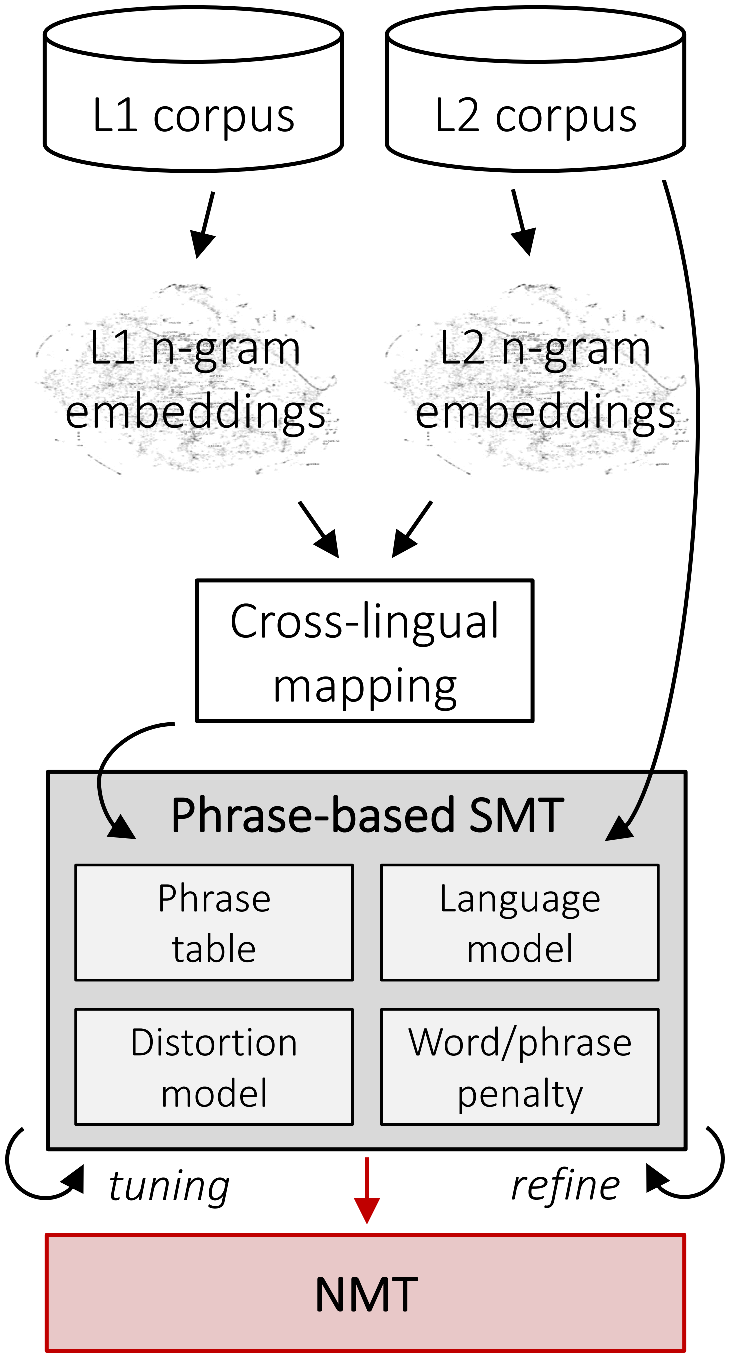

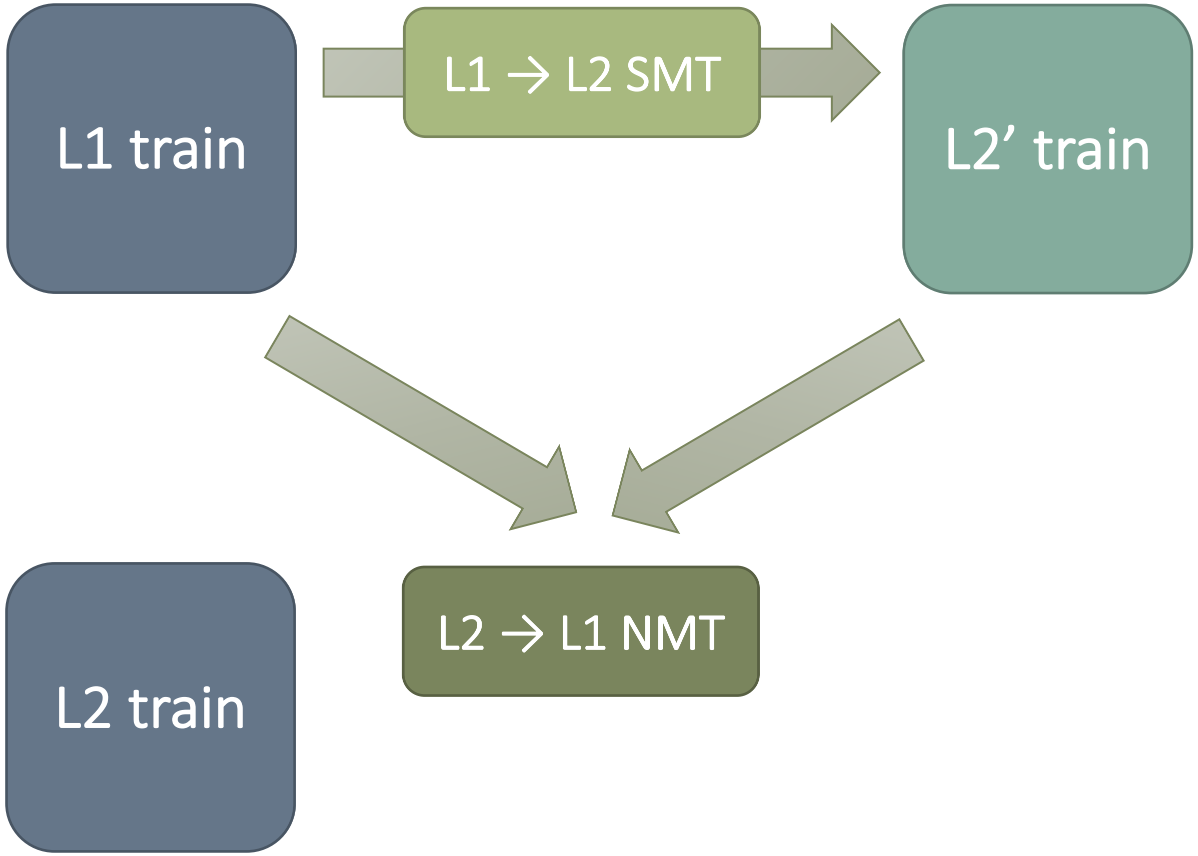

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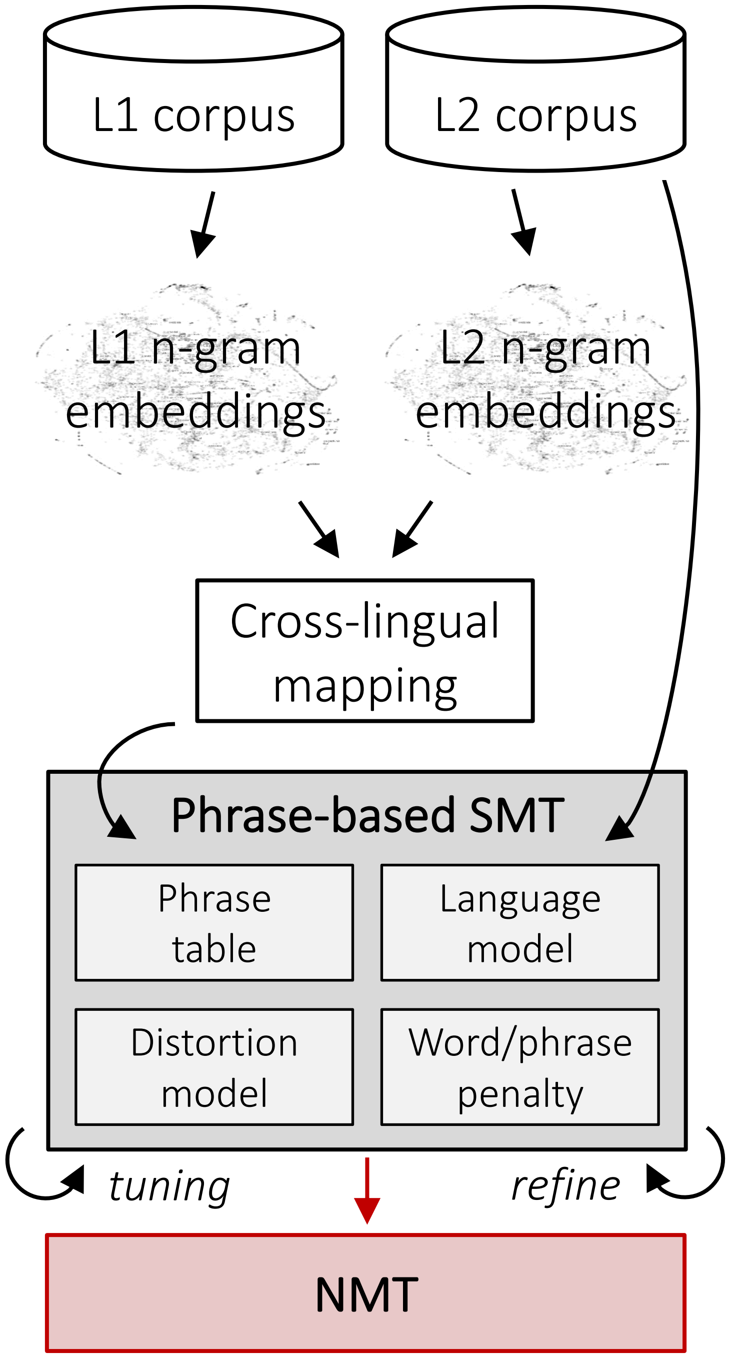

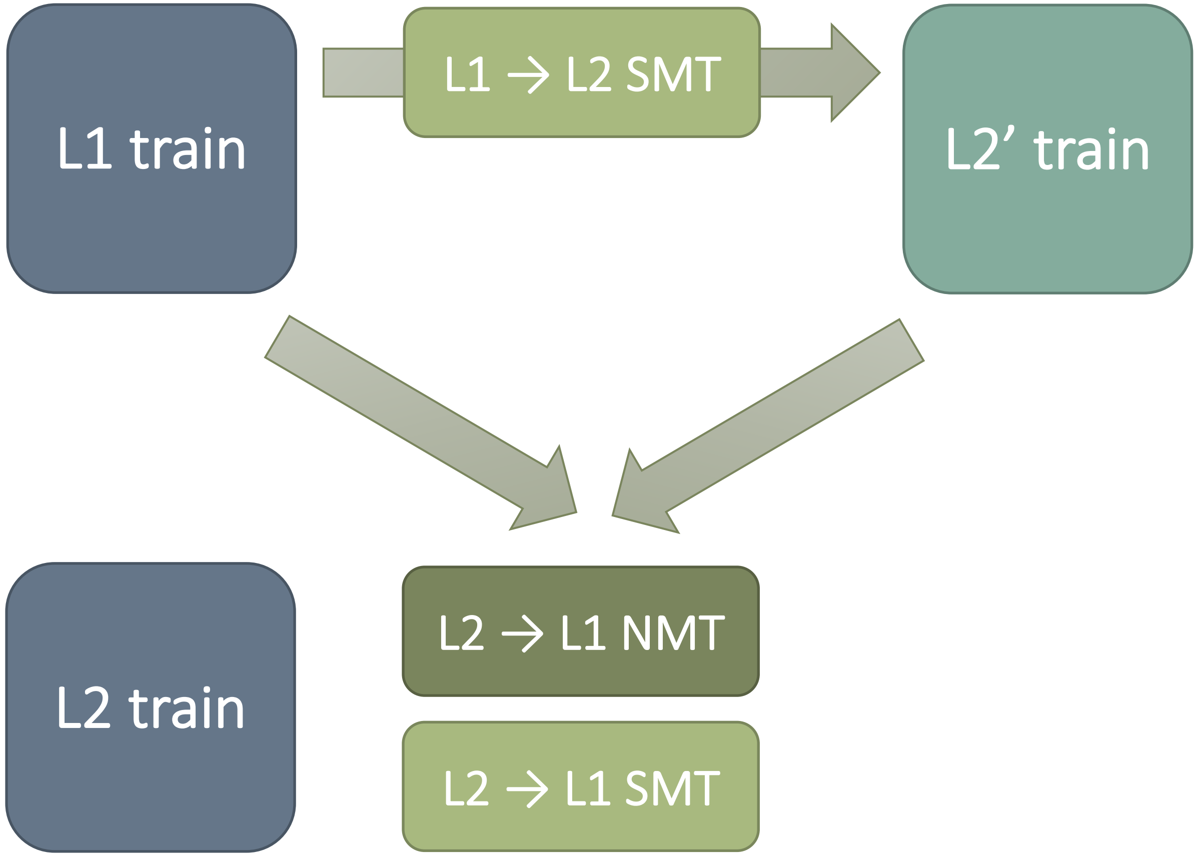

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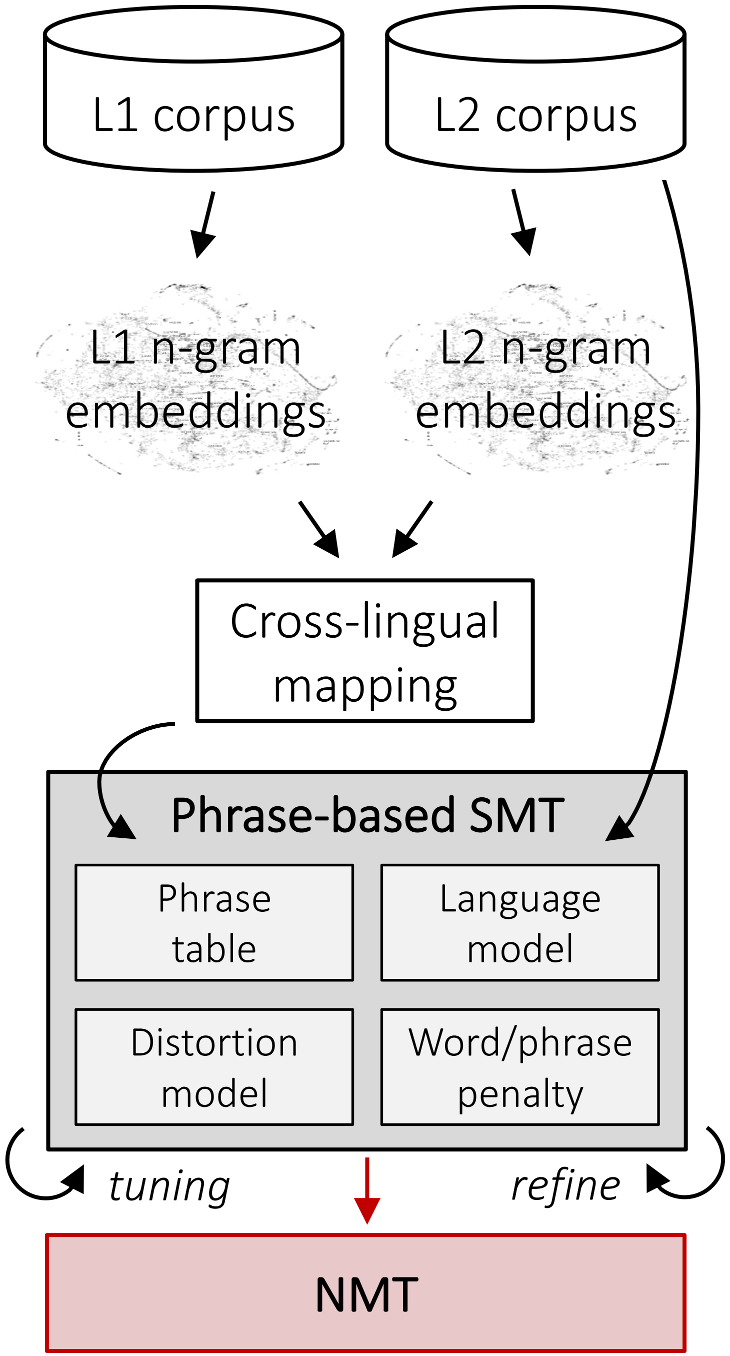

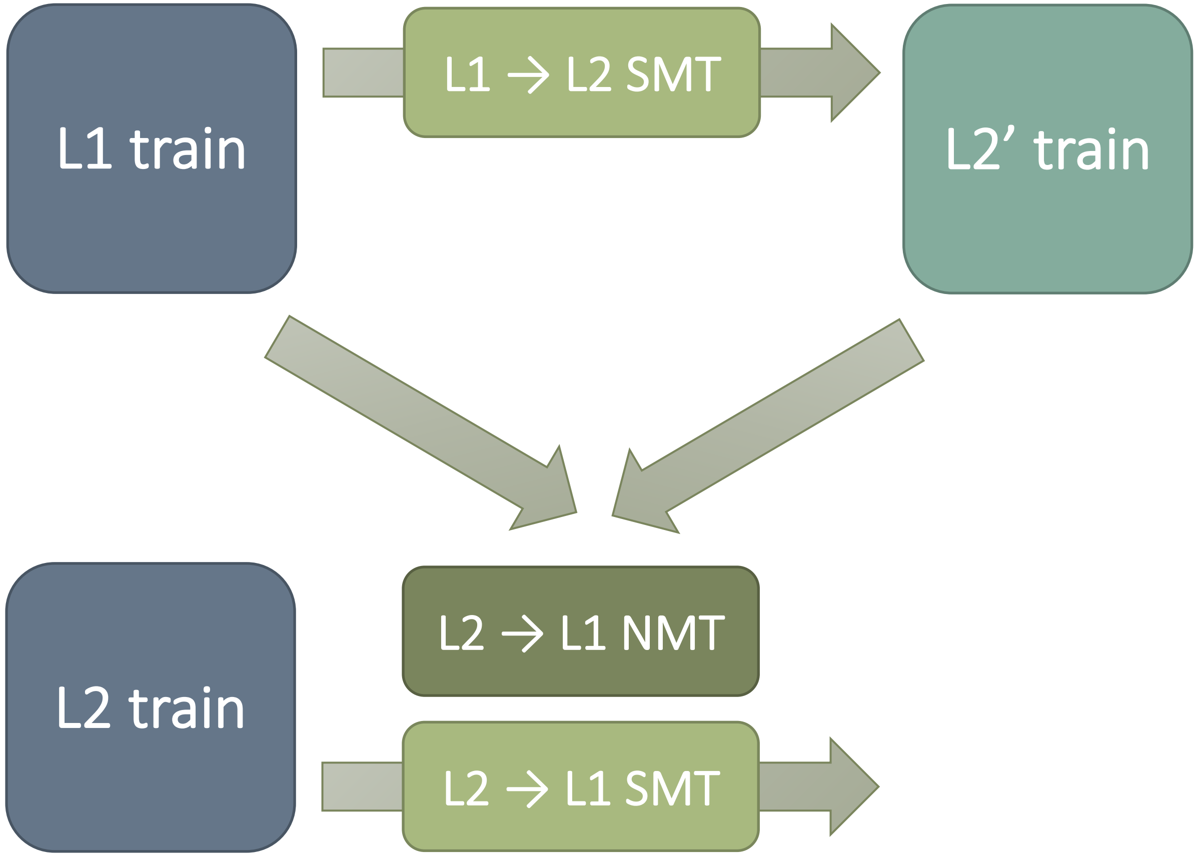

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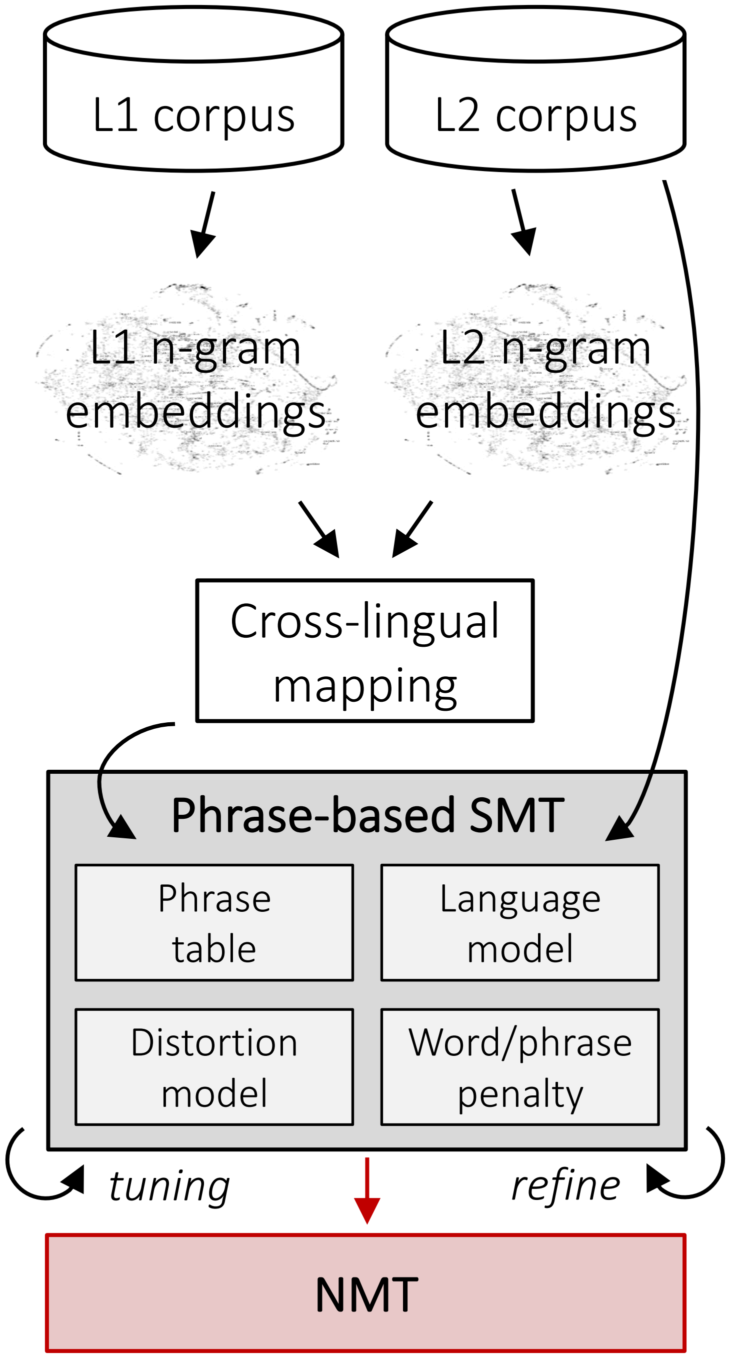

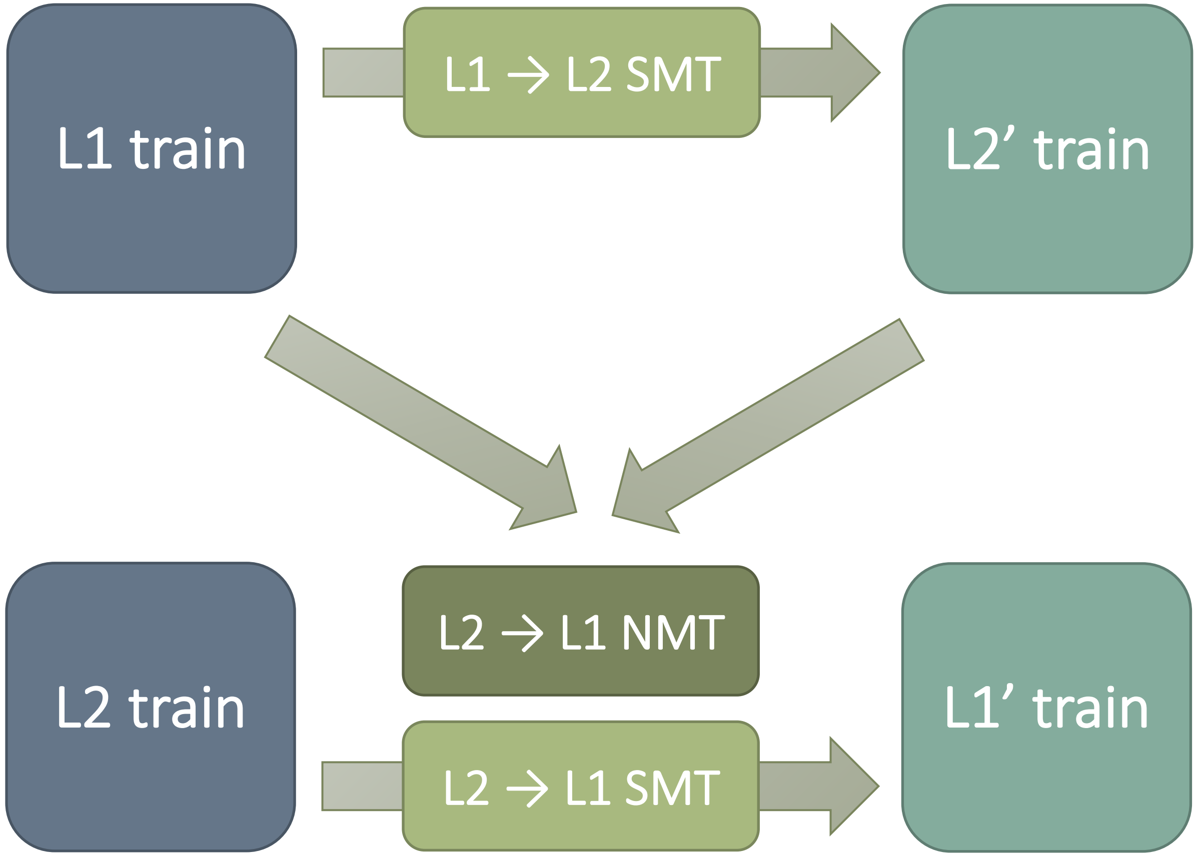

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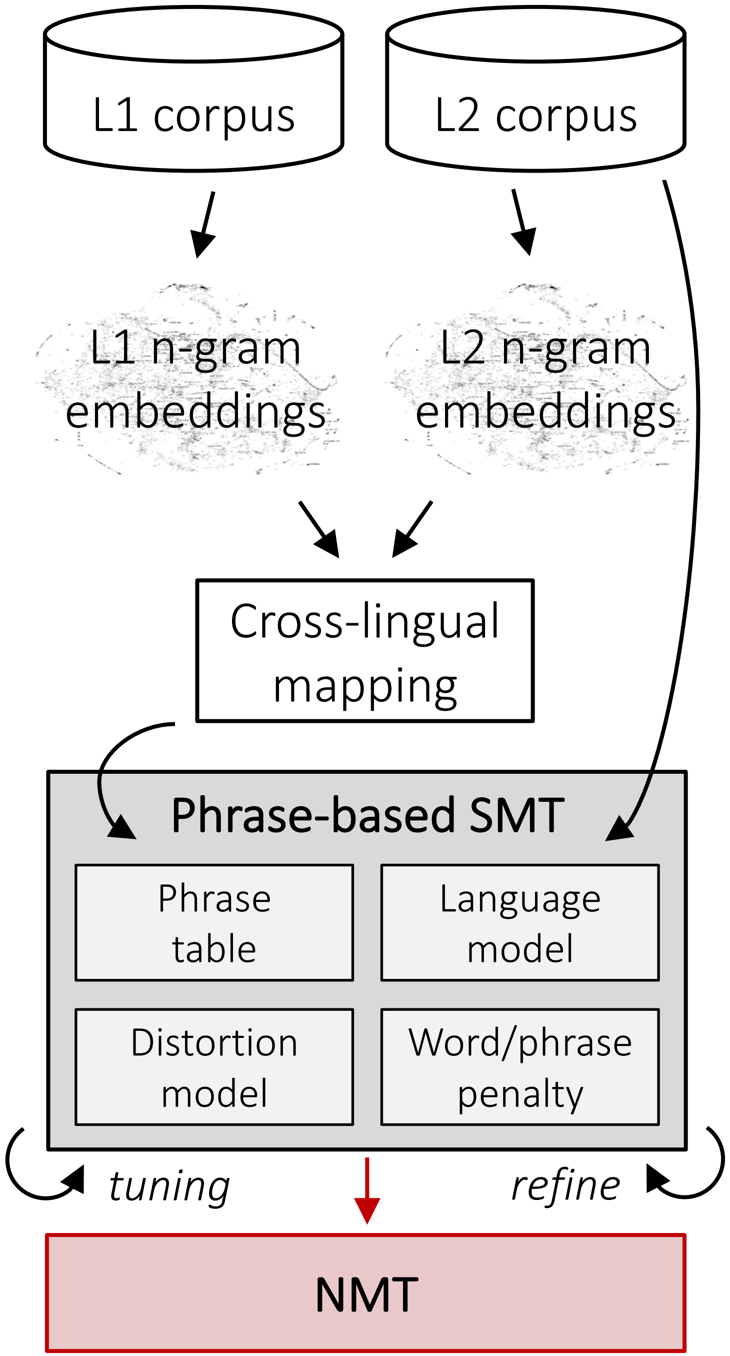

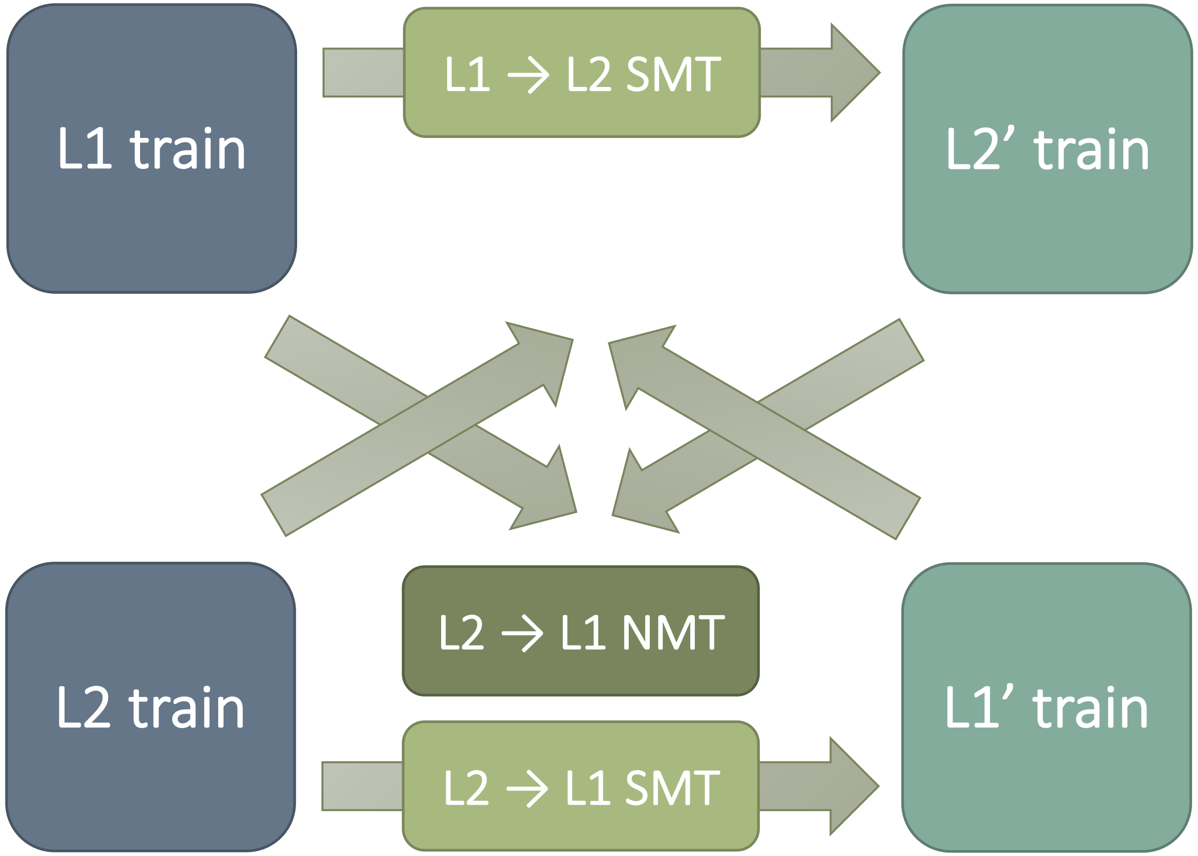

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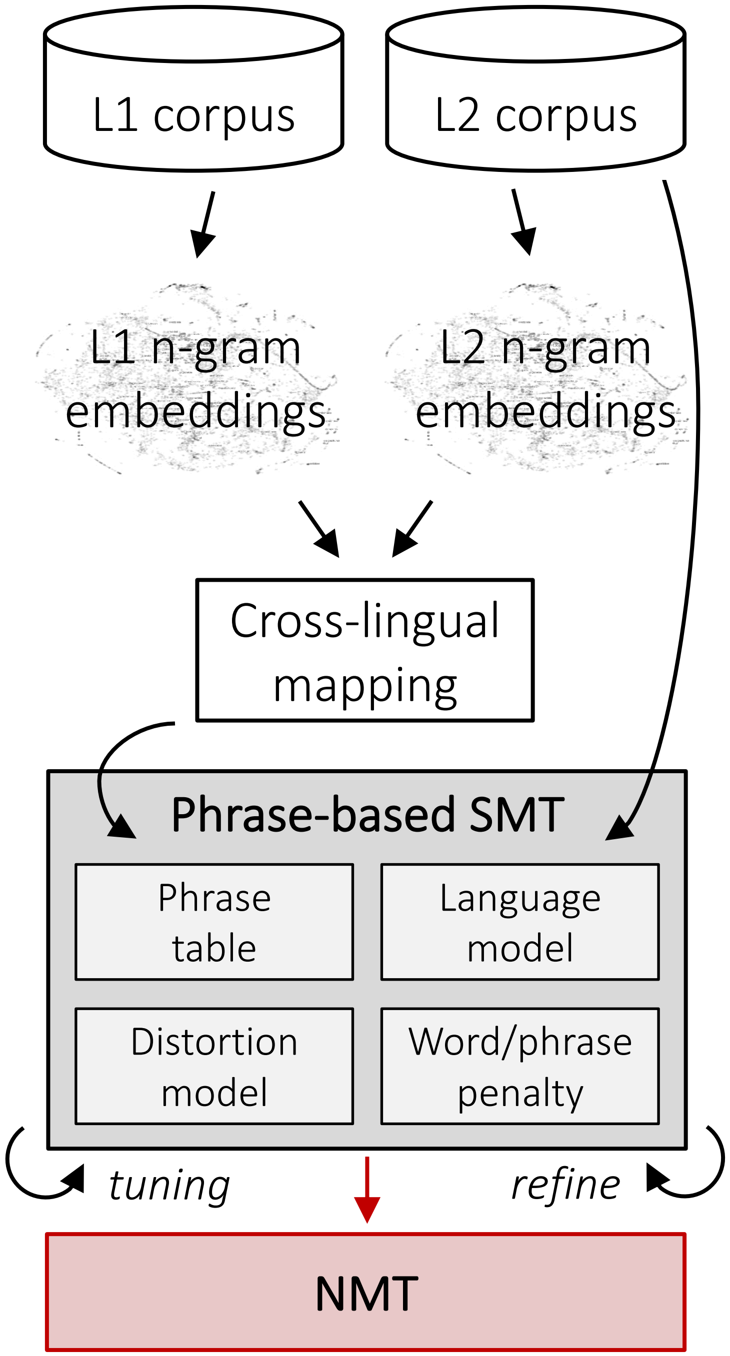

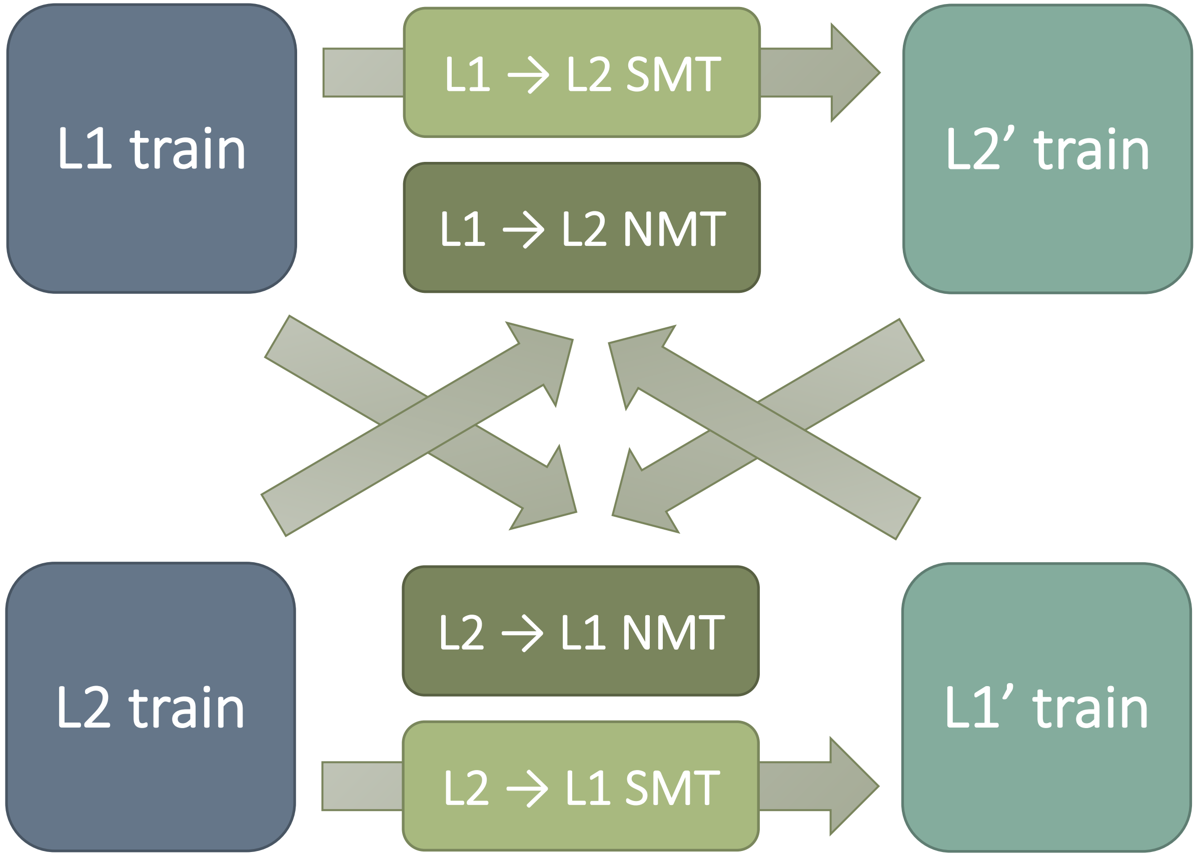

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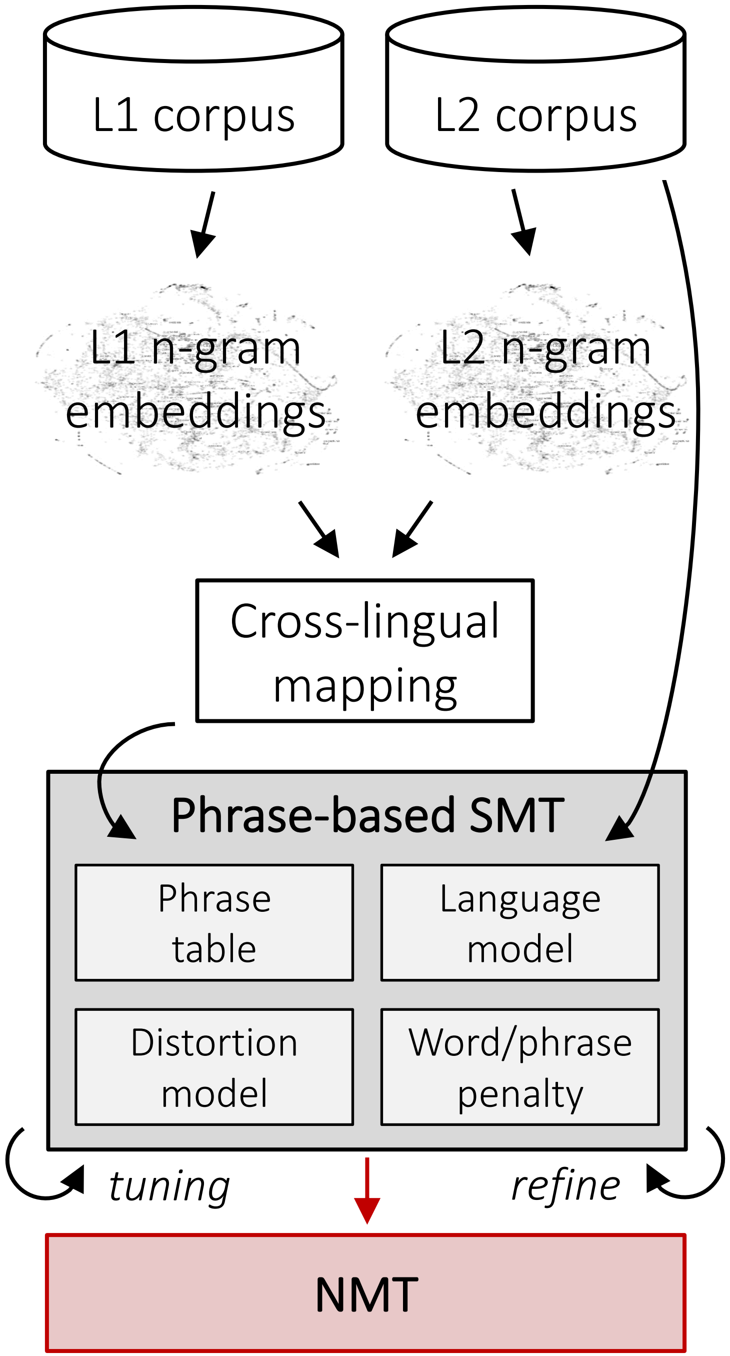

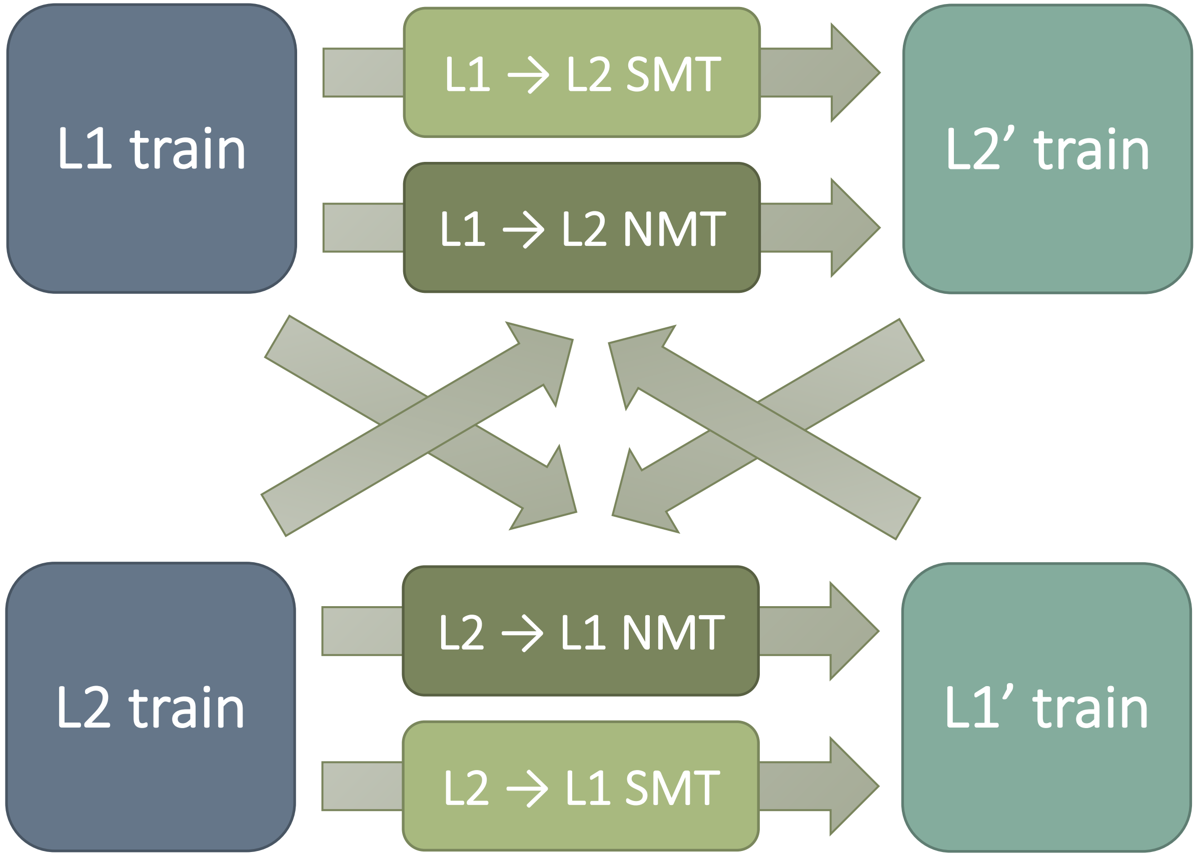

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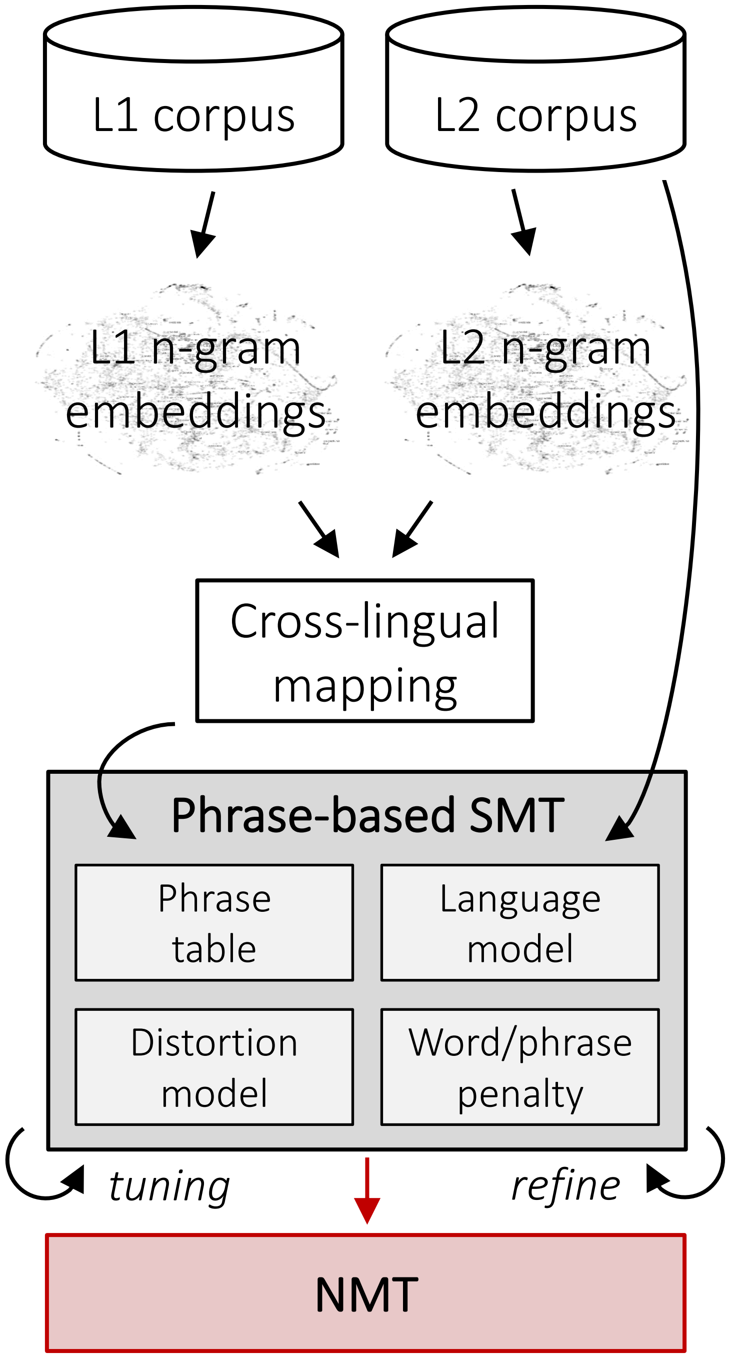
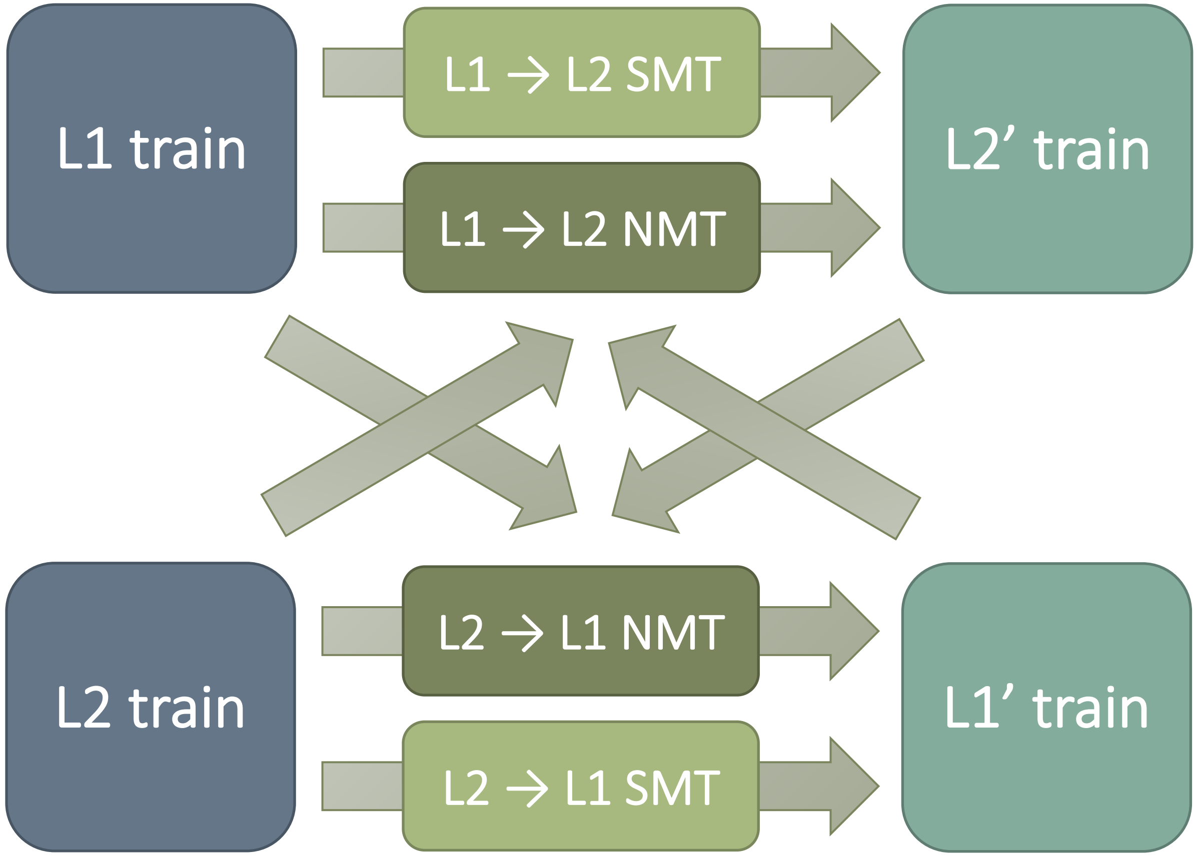
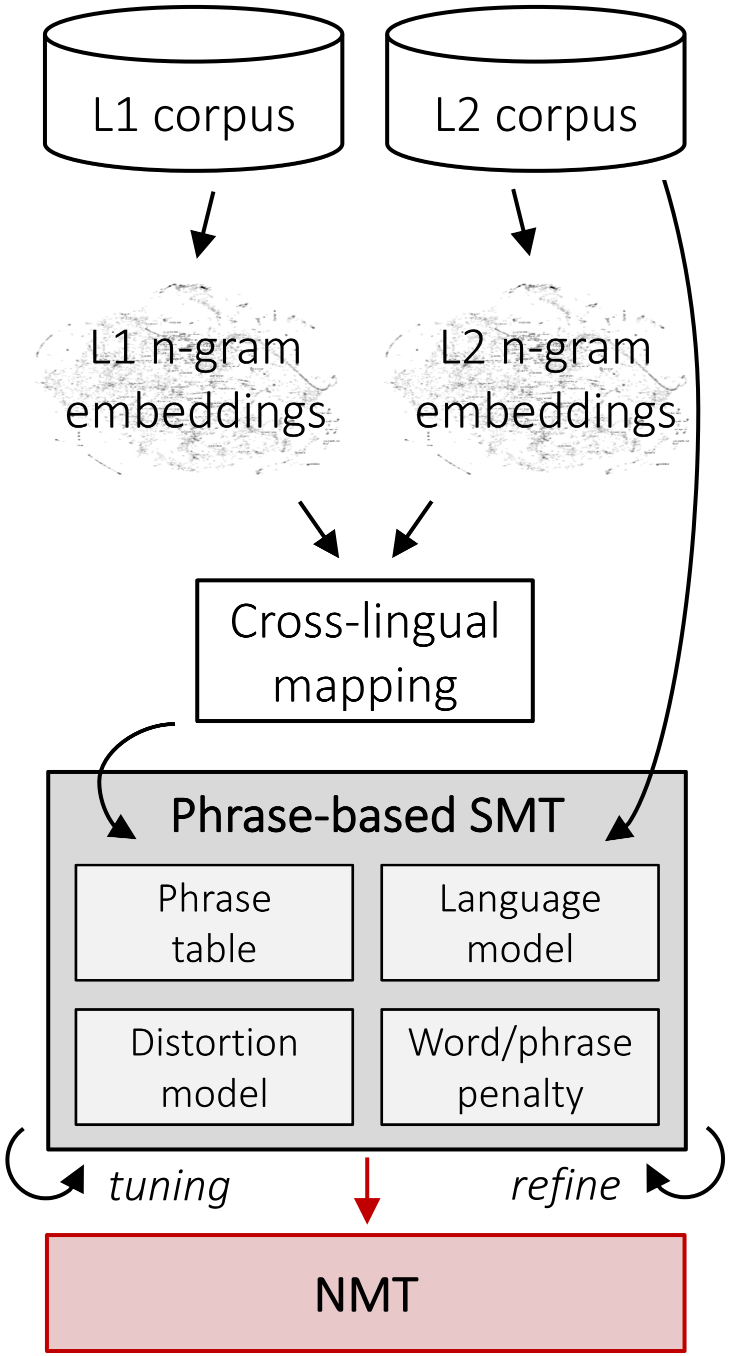
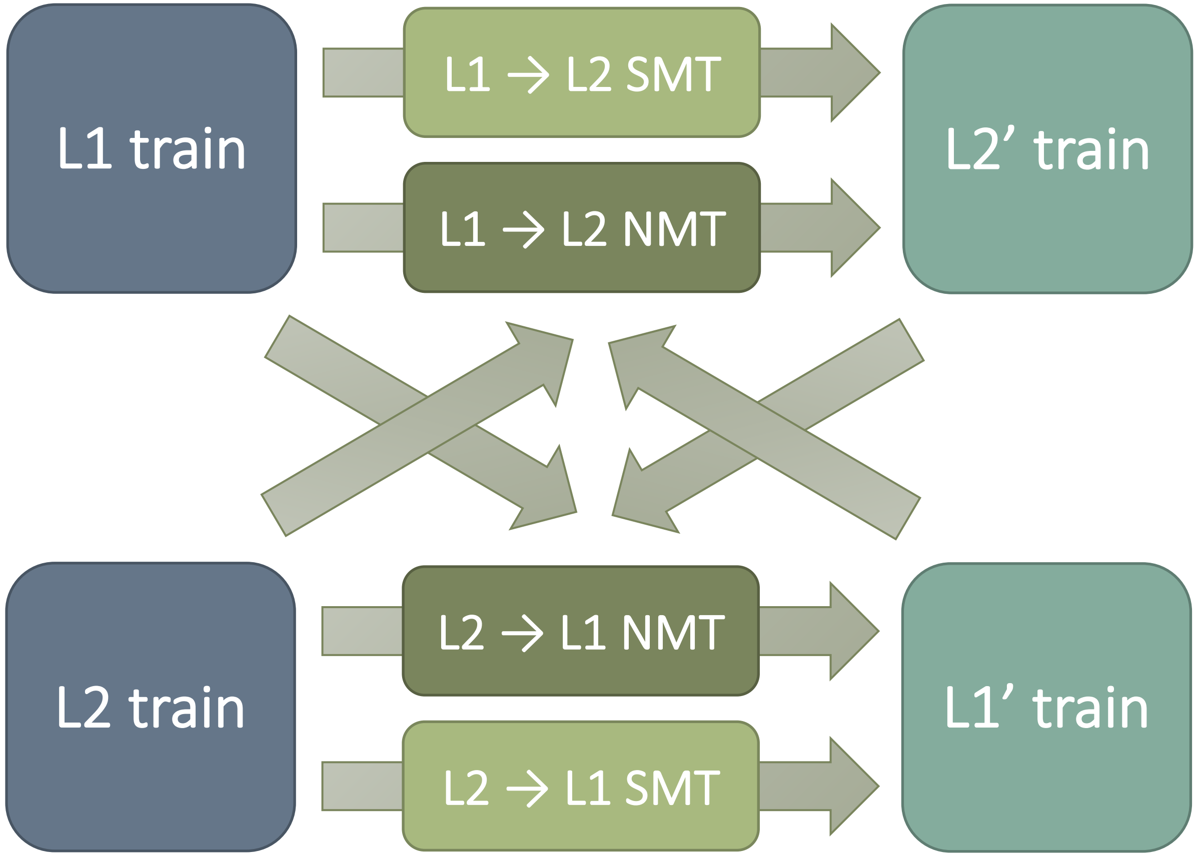




$$N_{SMT} = N \cdot \max(0, 1 - t/a)$$

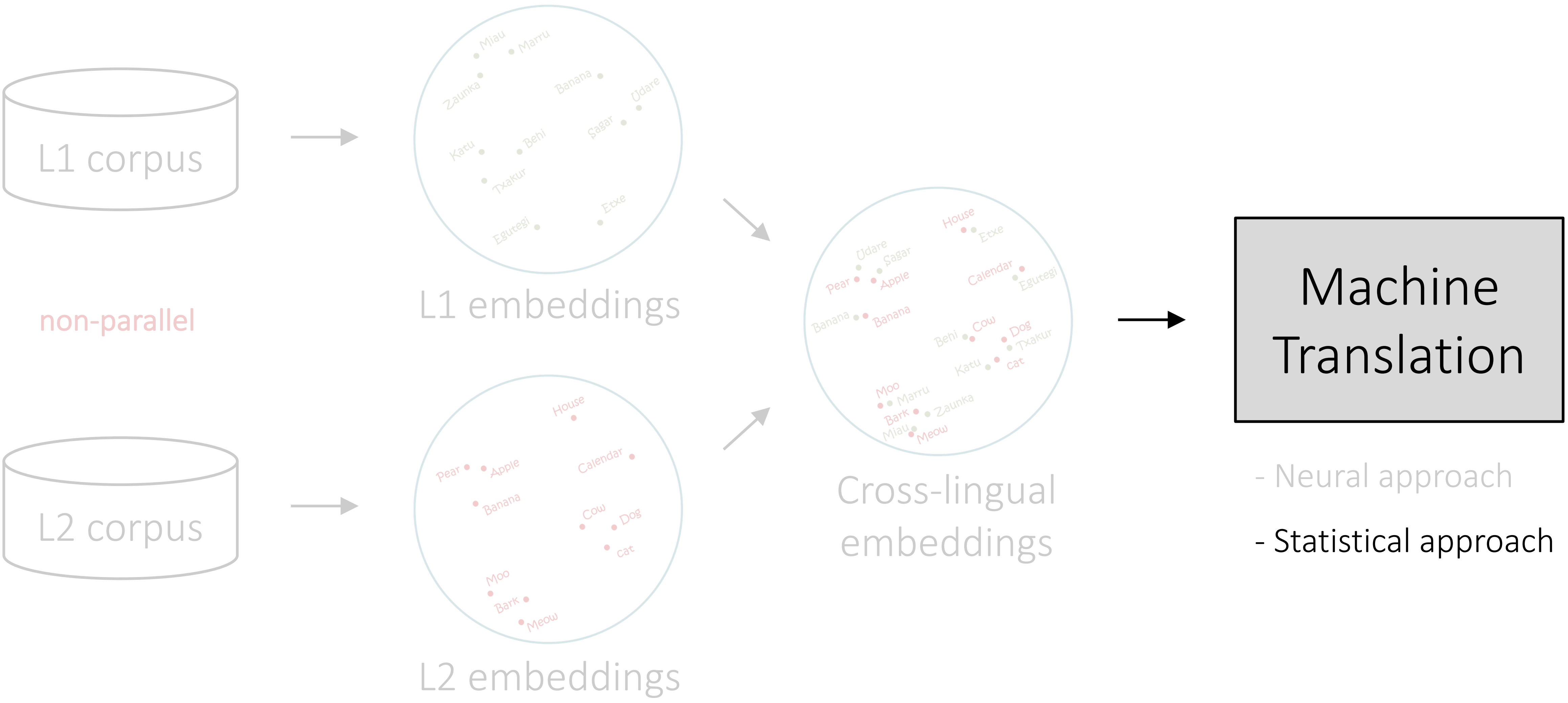
NMT hybridization



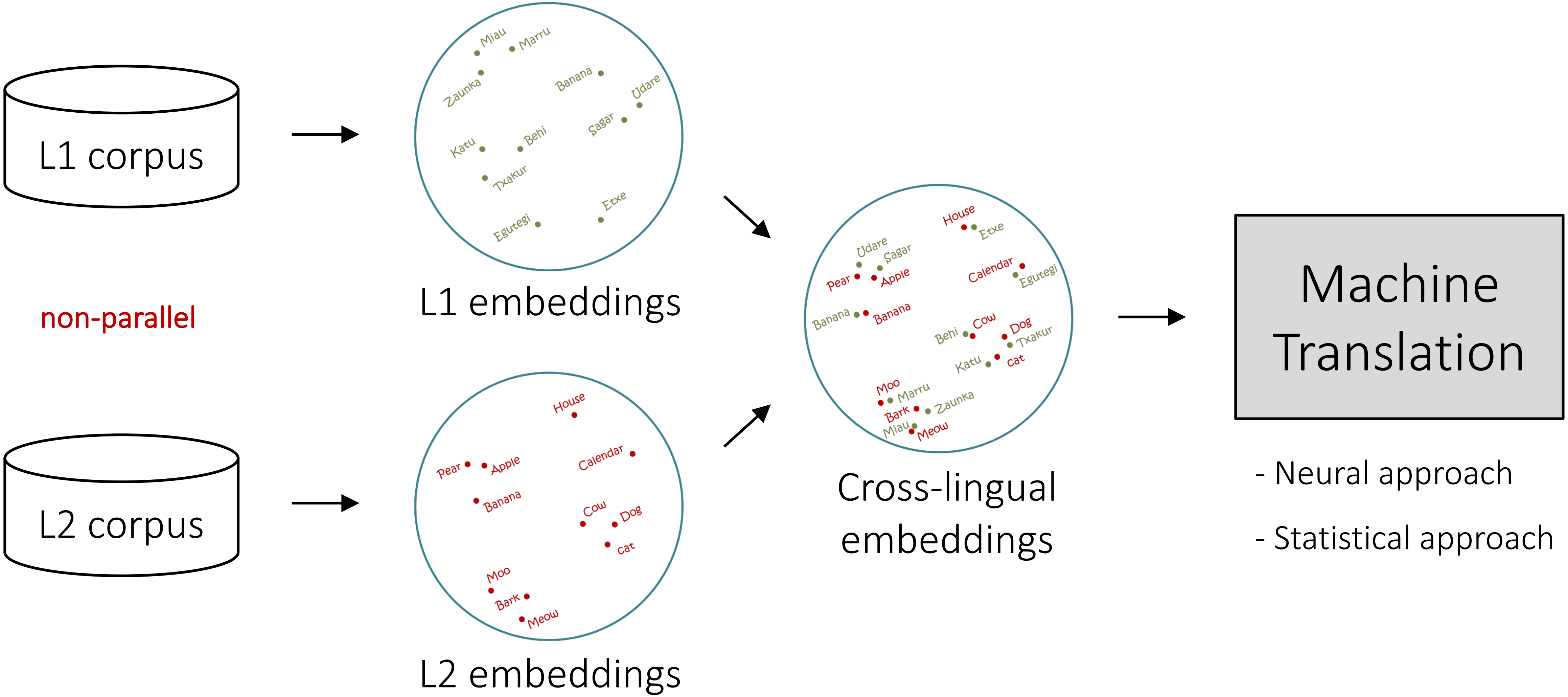


$$N_{SMT} = N \cdot \max(0, 1 - t/a)$$
$$N_{NMT} = N - N_{SMT}$$

Outline


L1 corpus
L2 corpus
non-parallel
L1 embeddings
L2 embeddings
Cross-lingual embeddings
Machine Translation
- Neural approach
- Statistical approach

Outline


L1 corpus
non-parallel
L2 corpus
Miau
Marru
Zaunka
Banana
Udare
Katu
Behi
Sagar
Txakur
Etxe
Egutegi
L1 embeddings
House
Pear
Apple
Calendar
Banana
Cow
Dog
Cat
Moo
Bark
Meow
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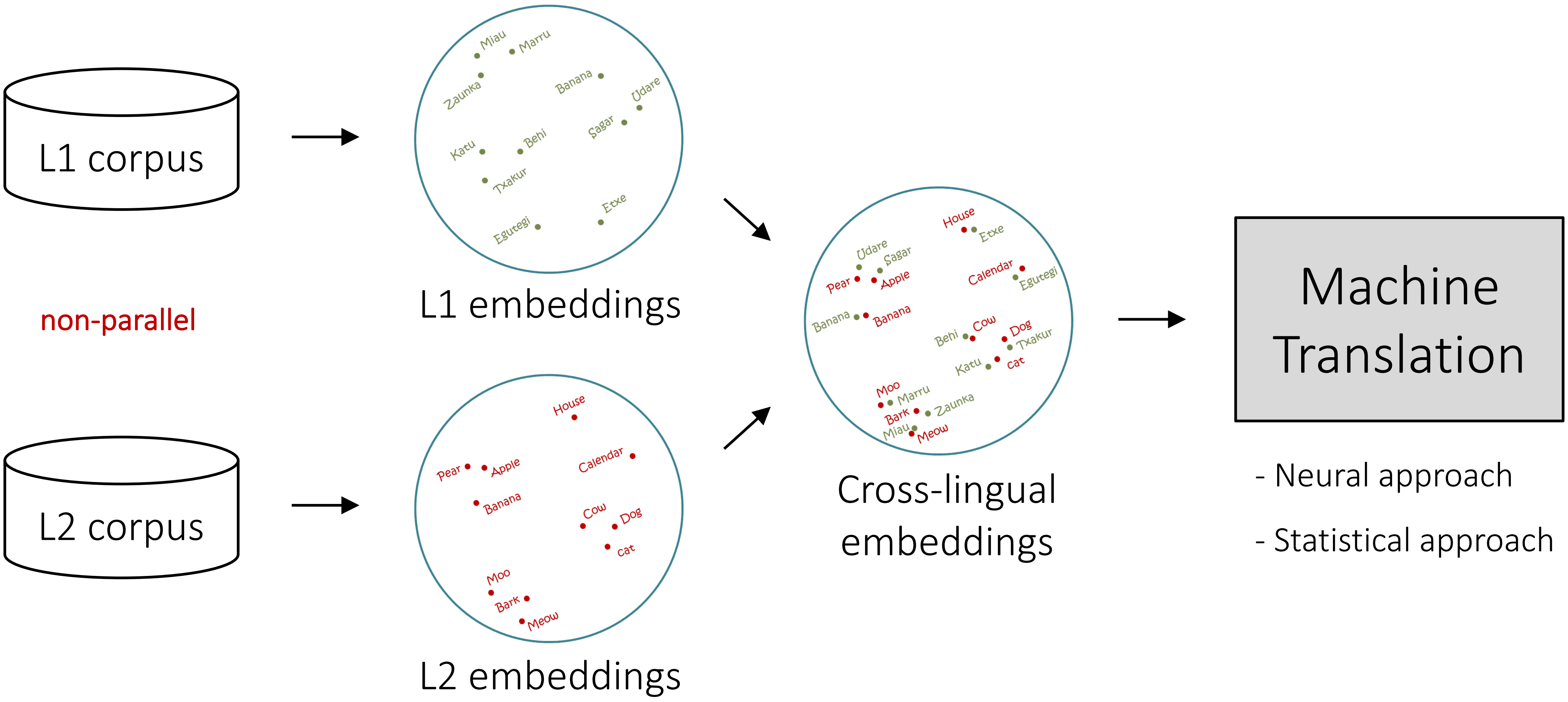
General recipe



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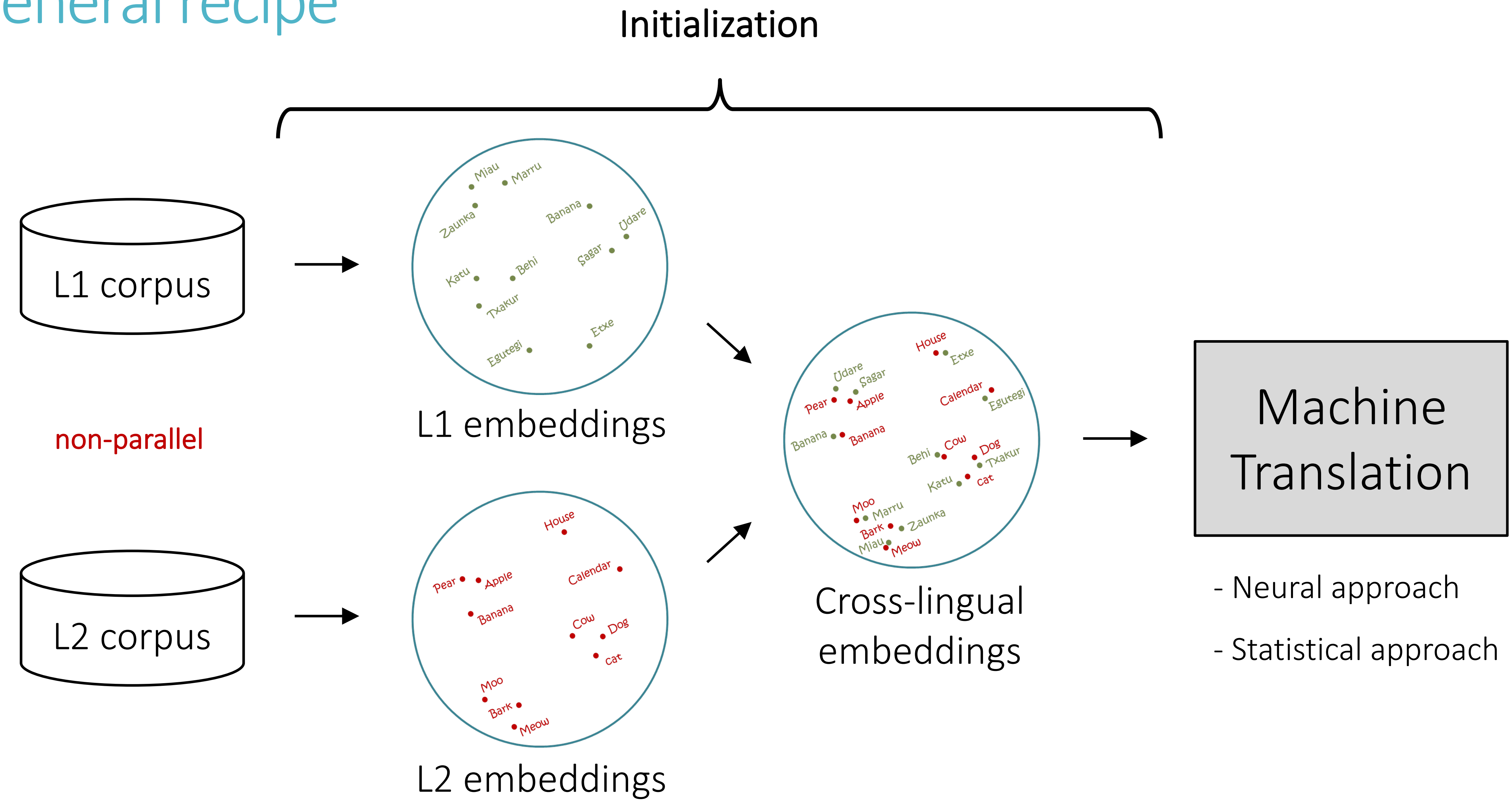

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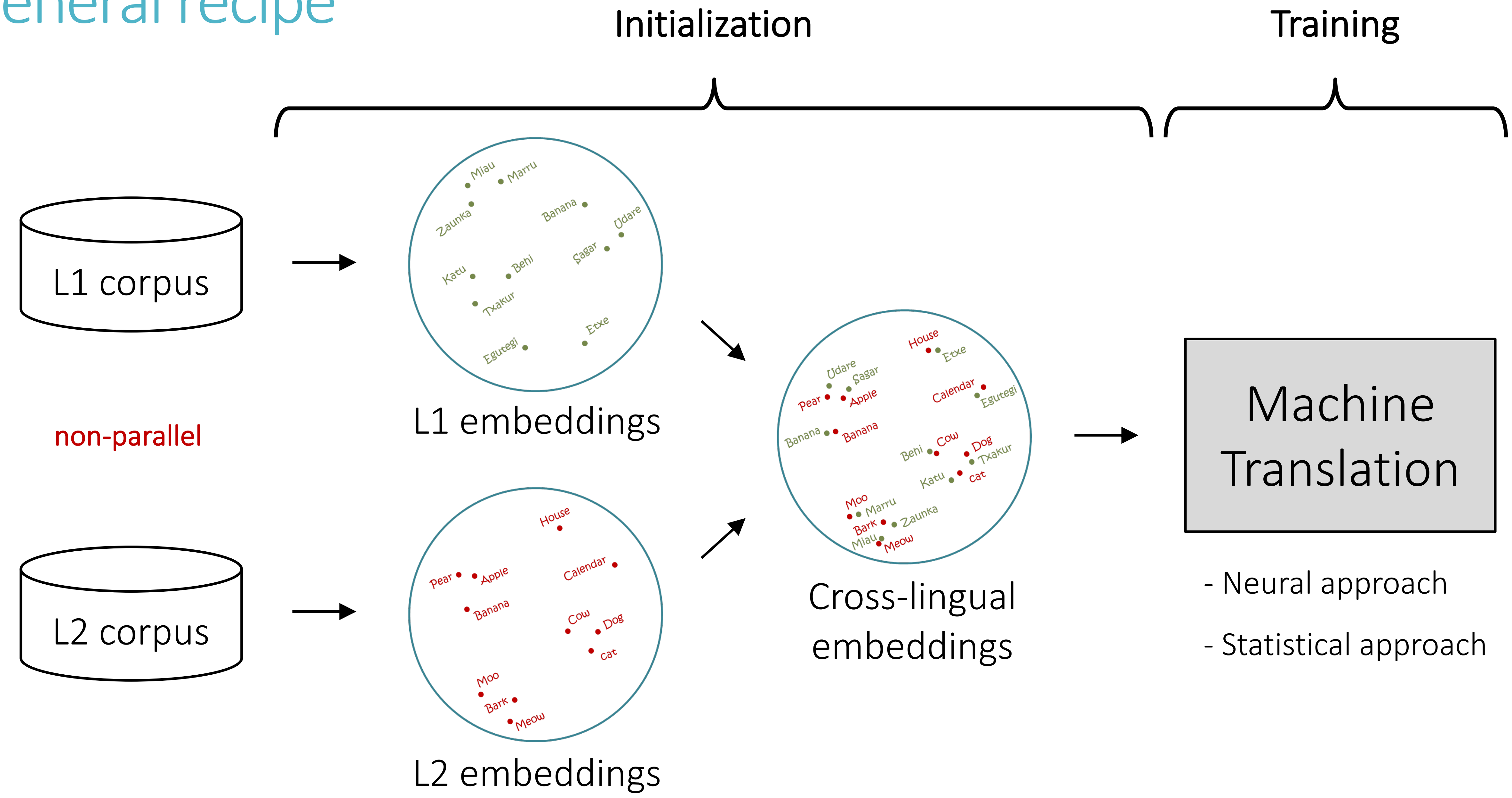
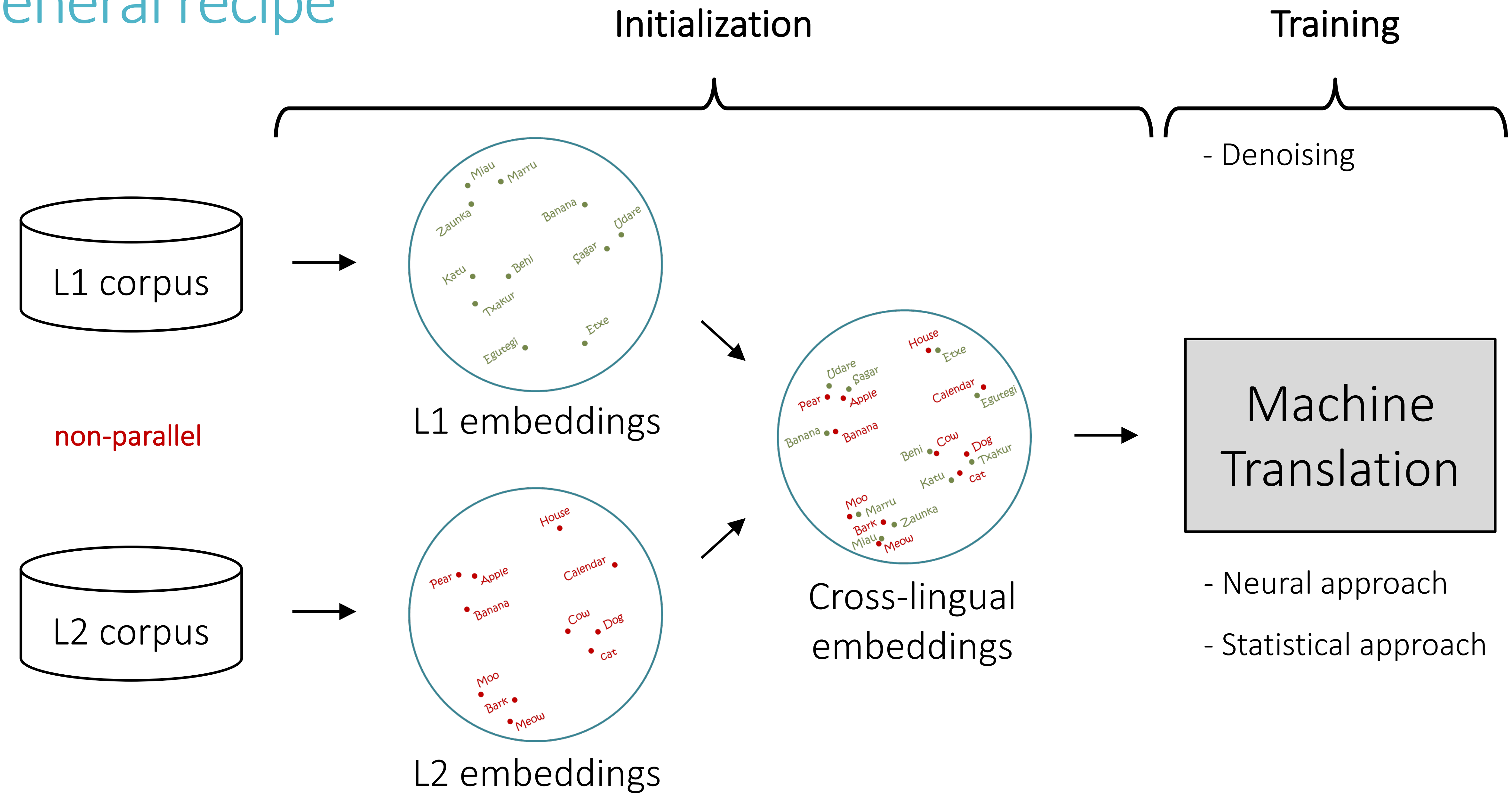


General recipe



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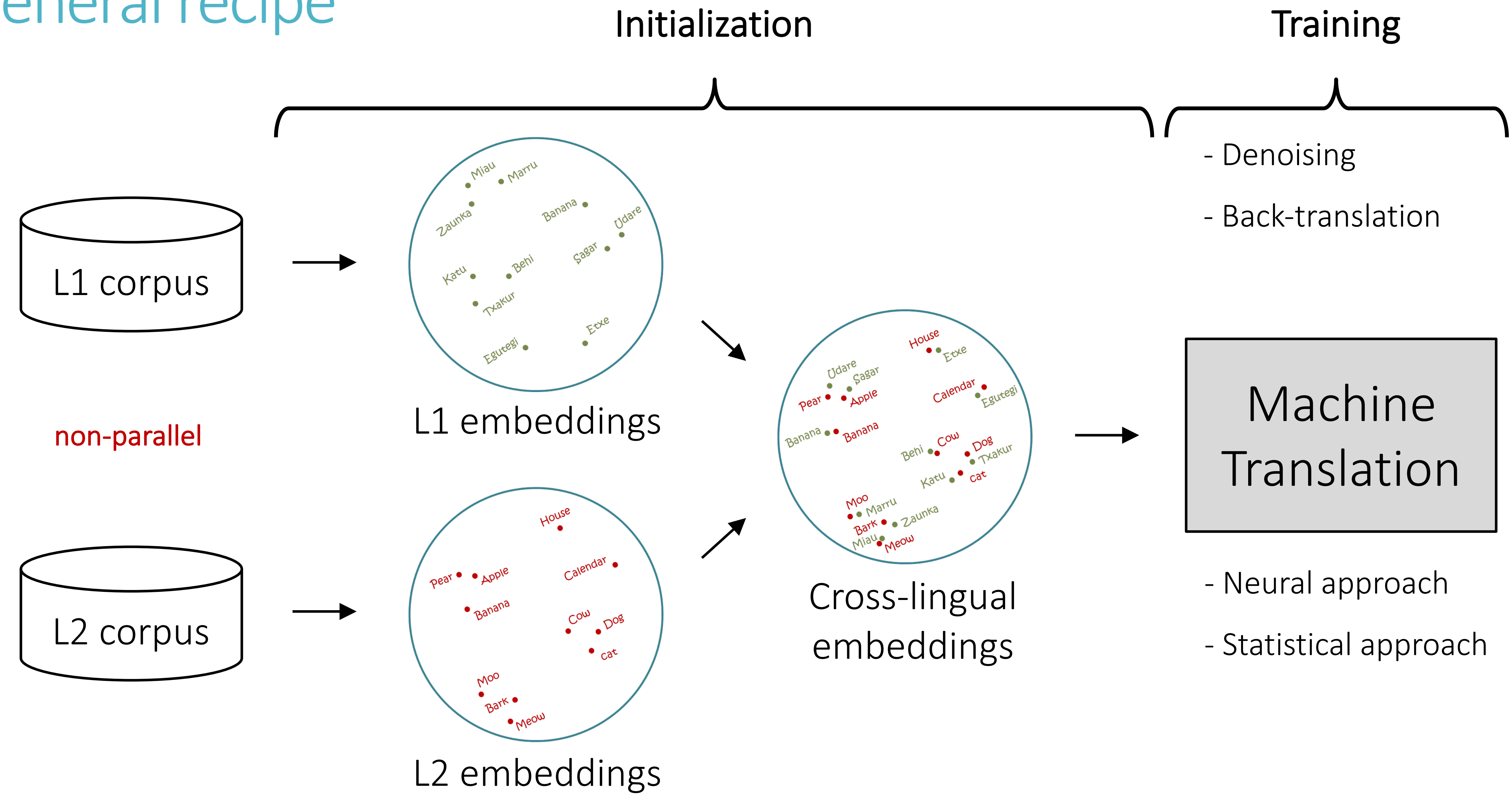

General recipe

Initialization

Training

- Denoising
- Back-translation

L1 corpus

L1 embeddings

non-parallel

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Cross-lingual embeddings

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General recipe

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- Cross-lingual word embeddings *(Artetxe et al., ICLR'18; Lample et al., ICLR'18)*

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  - Pretrain the full network through masked language modeling (e.g., multilingual BERT, XLM, MASS, mBART)

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  - <u>Basic</u>: word-for-word translation using cross-lingual word embeddings

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  - Better: Unsupervised statistical machine translation

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Results

Results

- <u>Languages</u>: French-English, German-English

Results

- Languages: French-English, German-English
- Training: WMT-14 News Crawl

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	FR-EN	EN-FR	DE-EN	EN-DE

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	FR-EN	EN-FR	DE-EN	EN-DE
Cross-lingual embs. (Artetxe et al., ICLR'18)*	15.6	15.1	10.2	6.6

*Tokenized BLEU (about 1-2 points higher)

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	Original transformer (Vaswani et al., NIPS'17)*	-	41.0	-	28.4

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Supervised	WMT winner	35.0	35.8	29.0	20.6
	Original transformer (Vaswani et al., NIPS'17)*	-	41.0	-	28.4
	Large scale back-translation (Edunov et al., EMNLP'18)	-	43.8	-	33.8

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Conclusions

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Unsupervised machine translation is a reality!

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- General recipe: back-translation + smart initialization

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What's next?

Thank you!

Twitter: @artetxem
Email: artetxe@fb.com