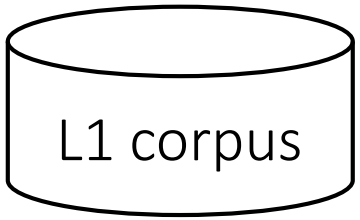
Unsupervised Machine Translation

Mikel Artetxe

IXA NLP group – University of the Basque Country (UPV/EHU)

Introduction

Introduction



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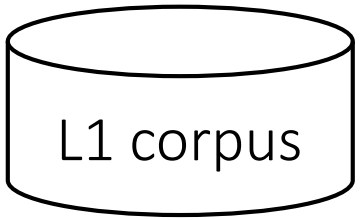

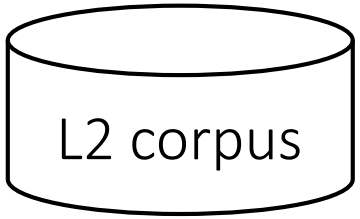

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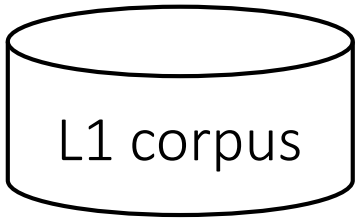

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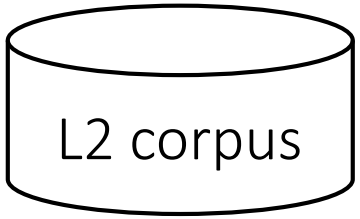

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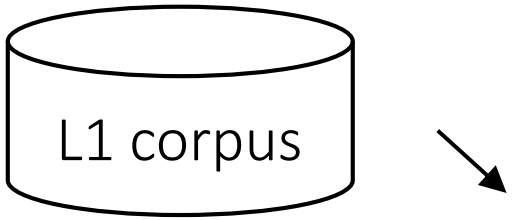

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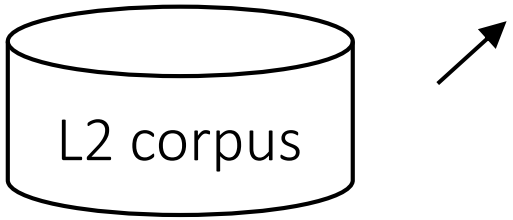

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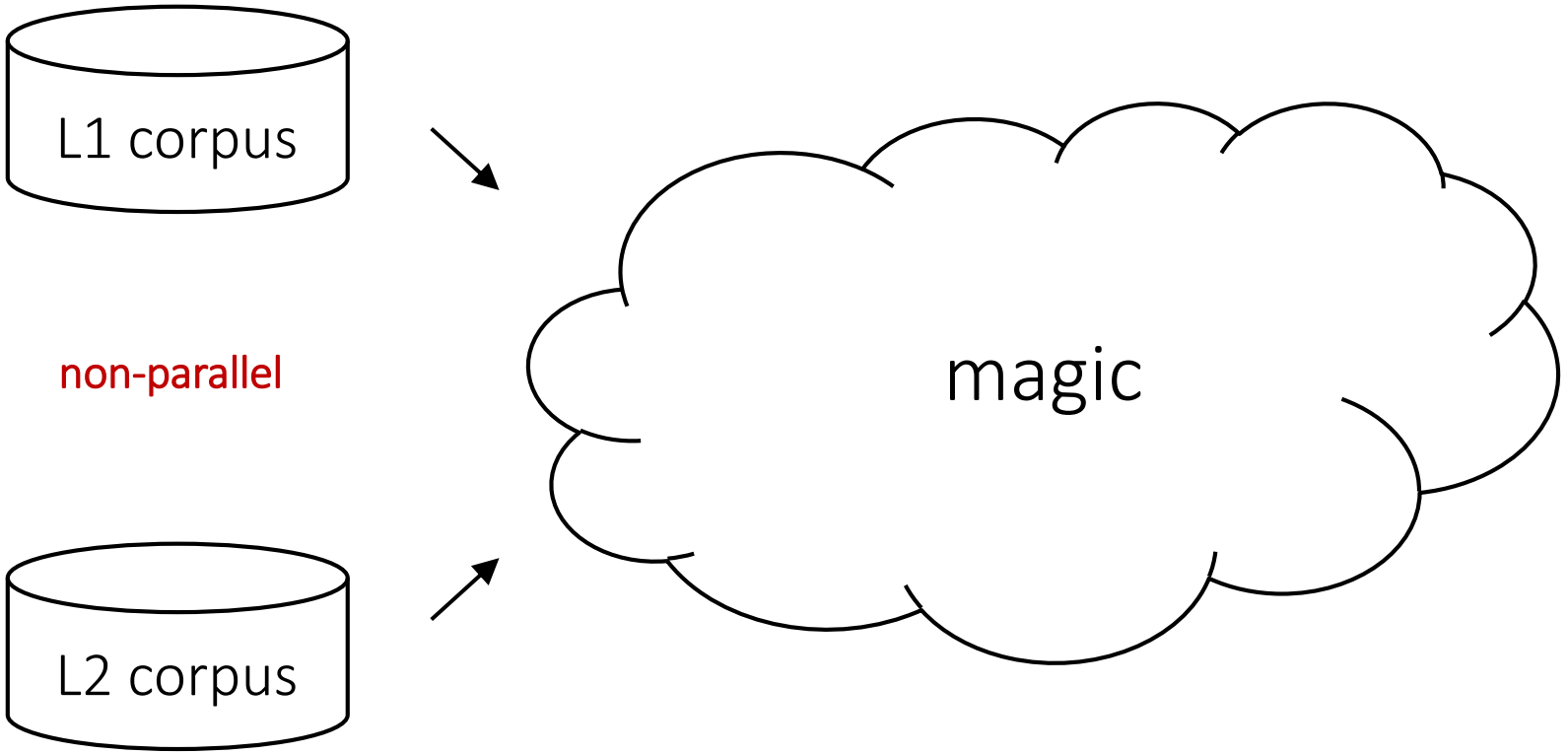

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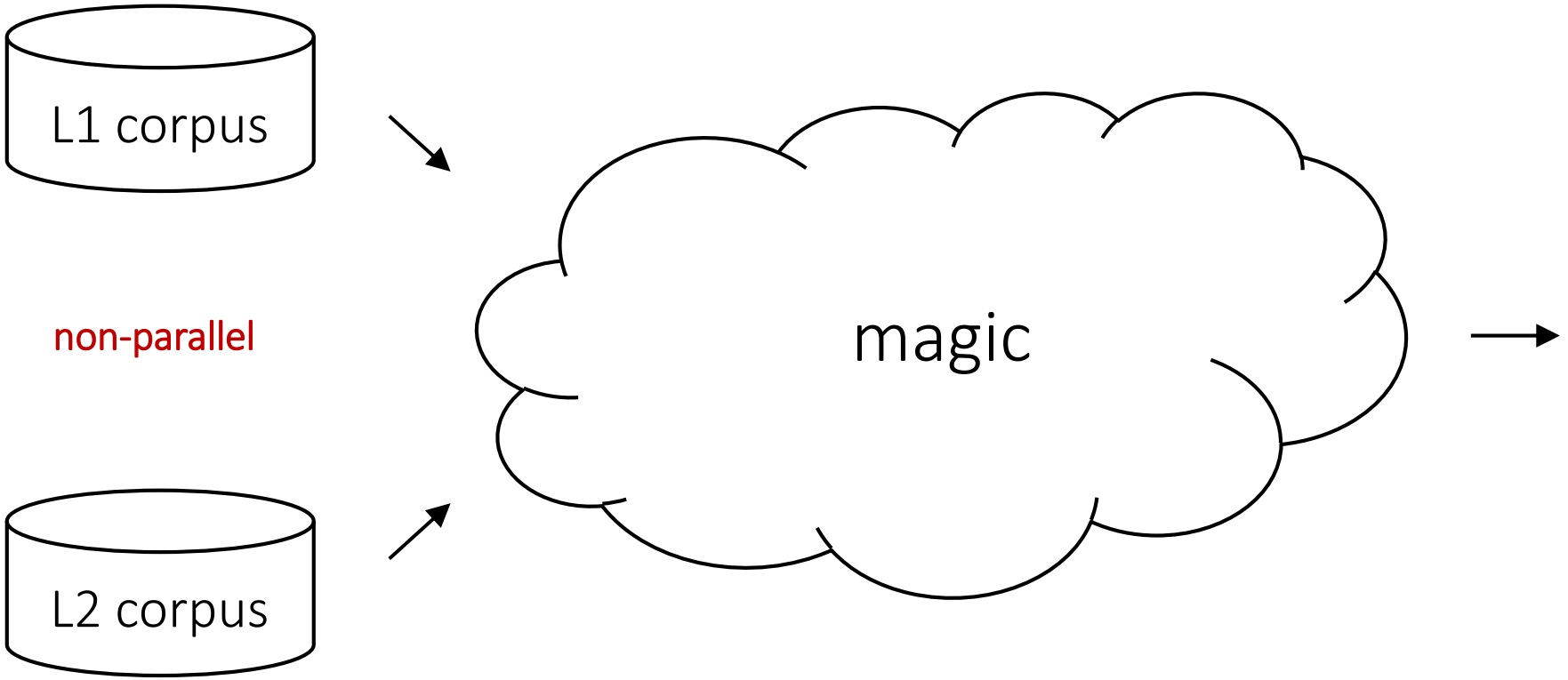

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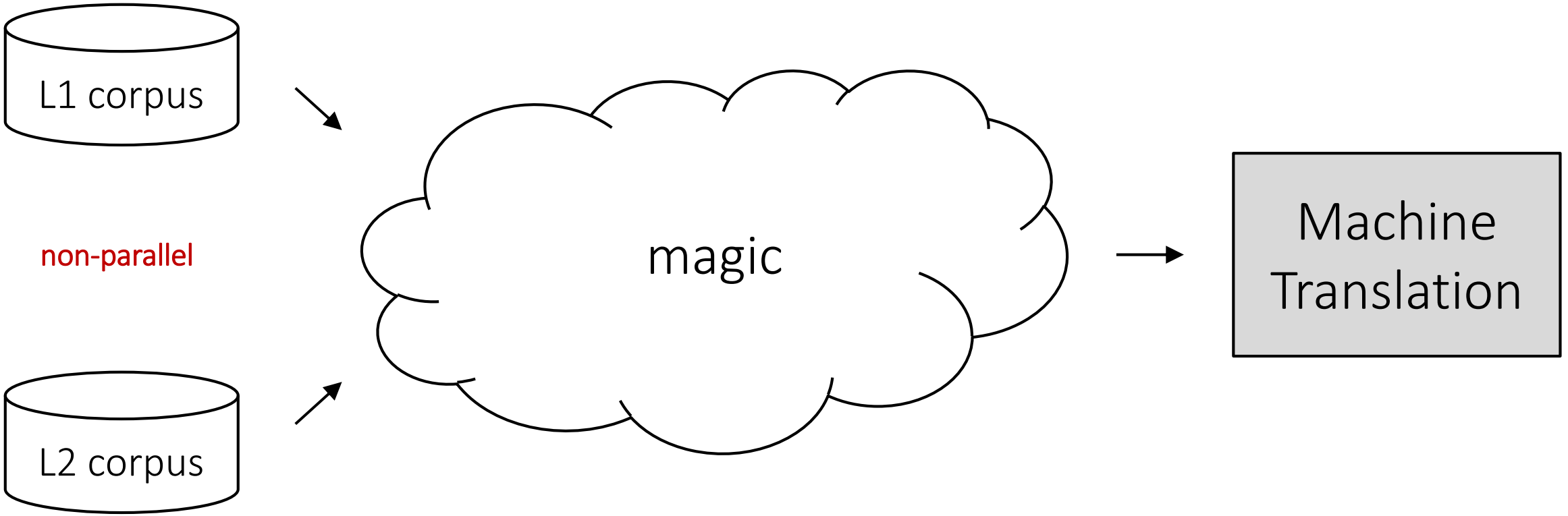

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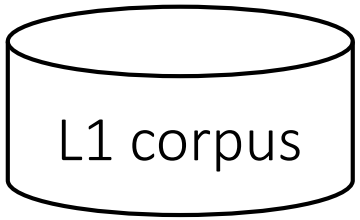

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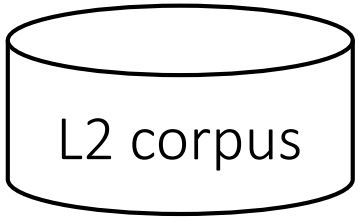

Machine Translation

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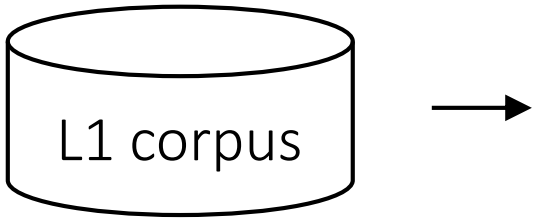

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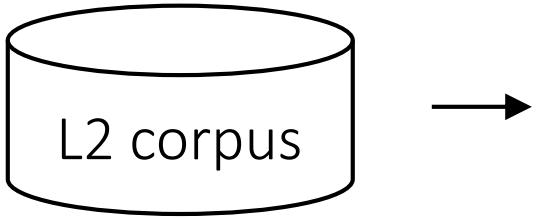
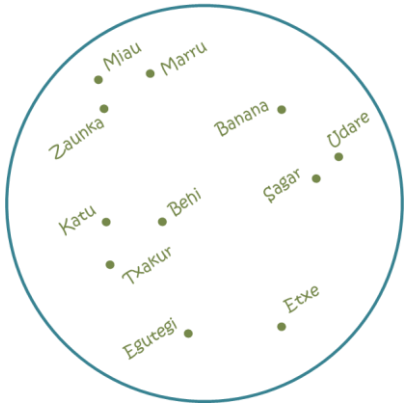


Machine Translation

Introduction

L1 corpus



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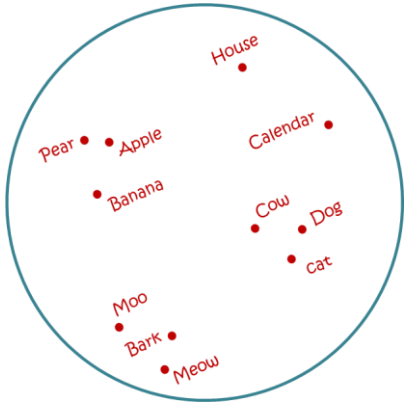
L2 corpus



Machine Translation

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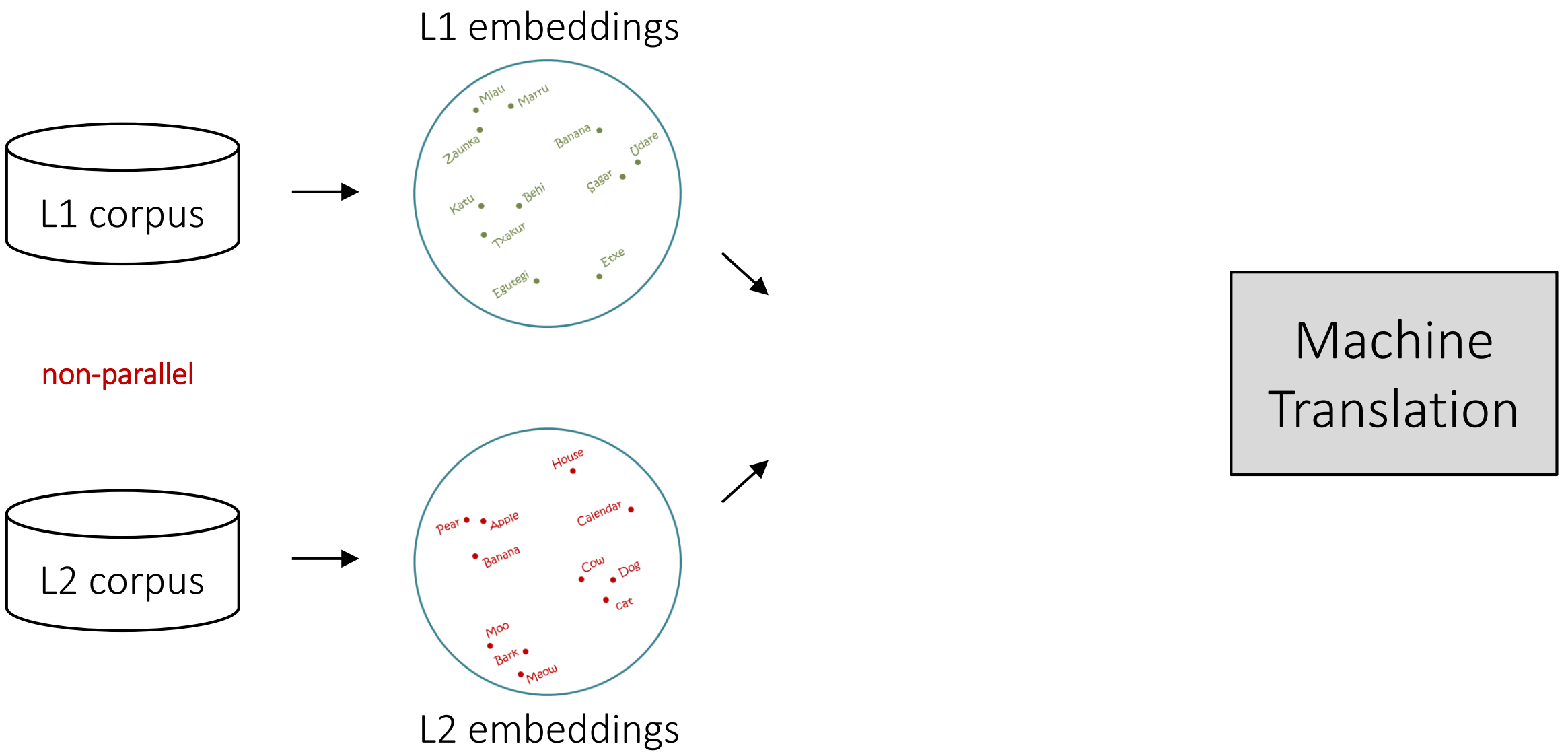

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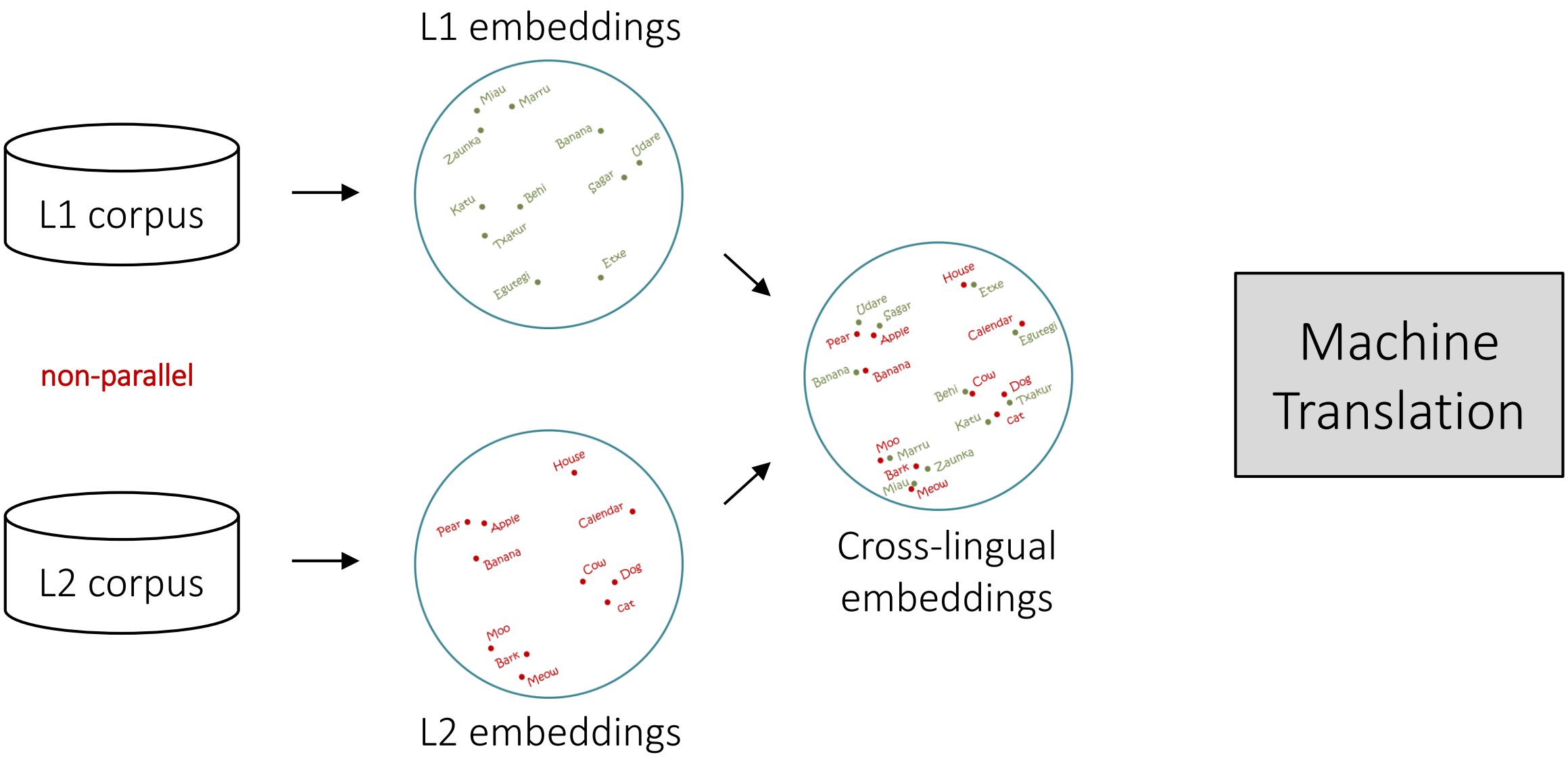

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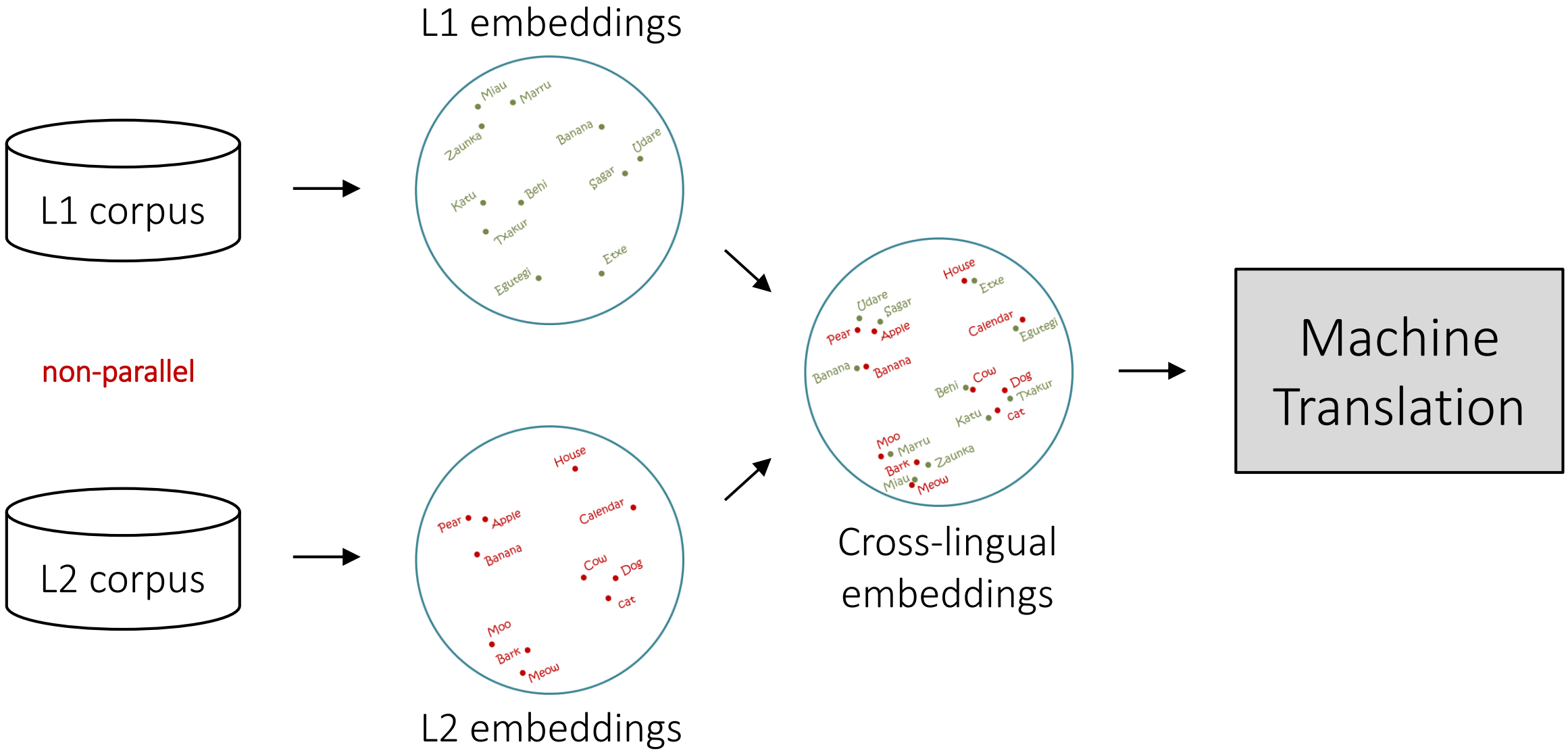

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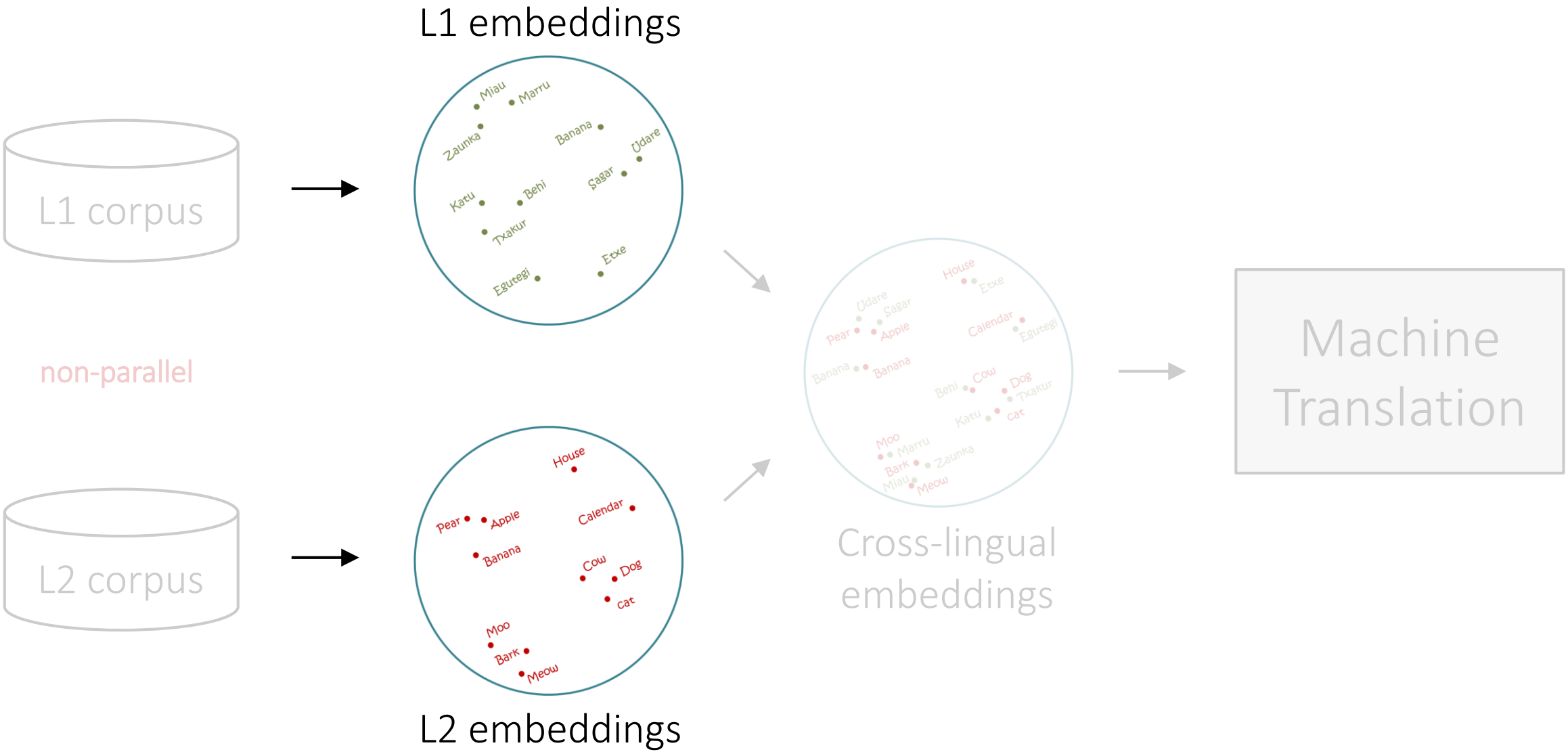

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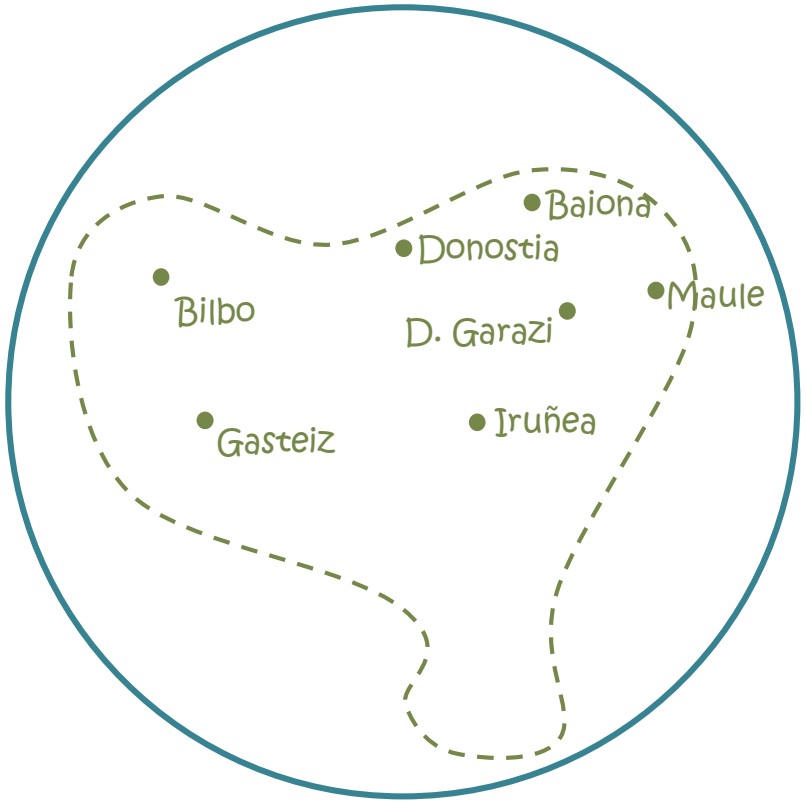

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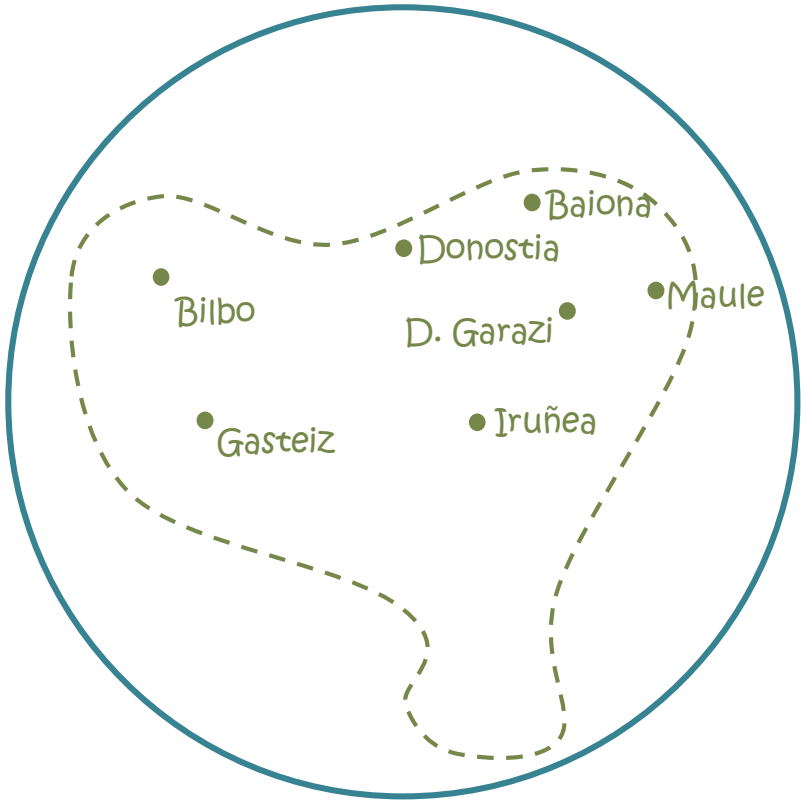
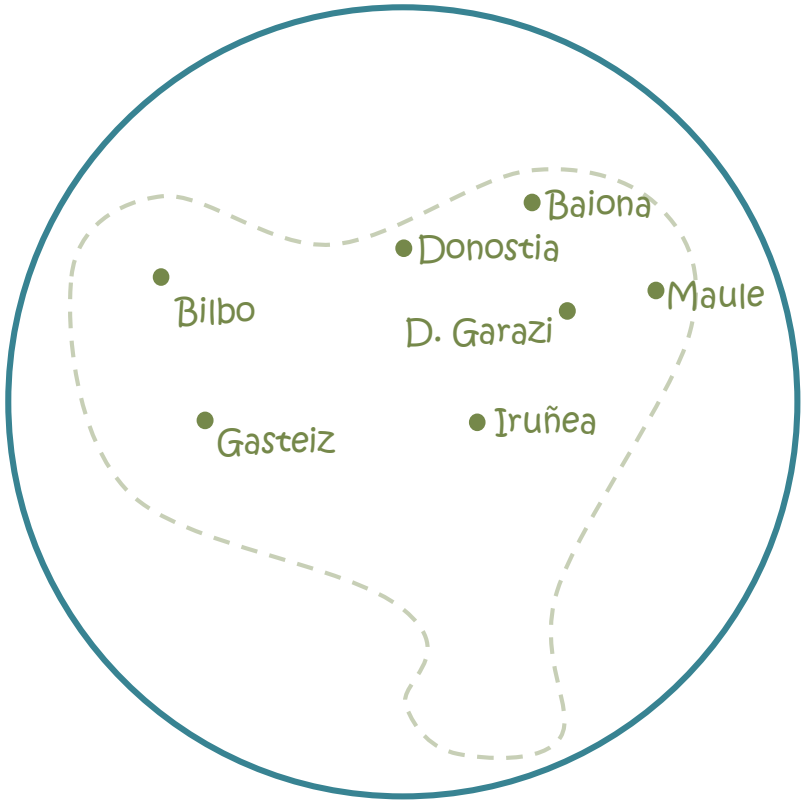


Geographical space

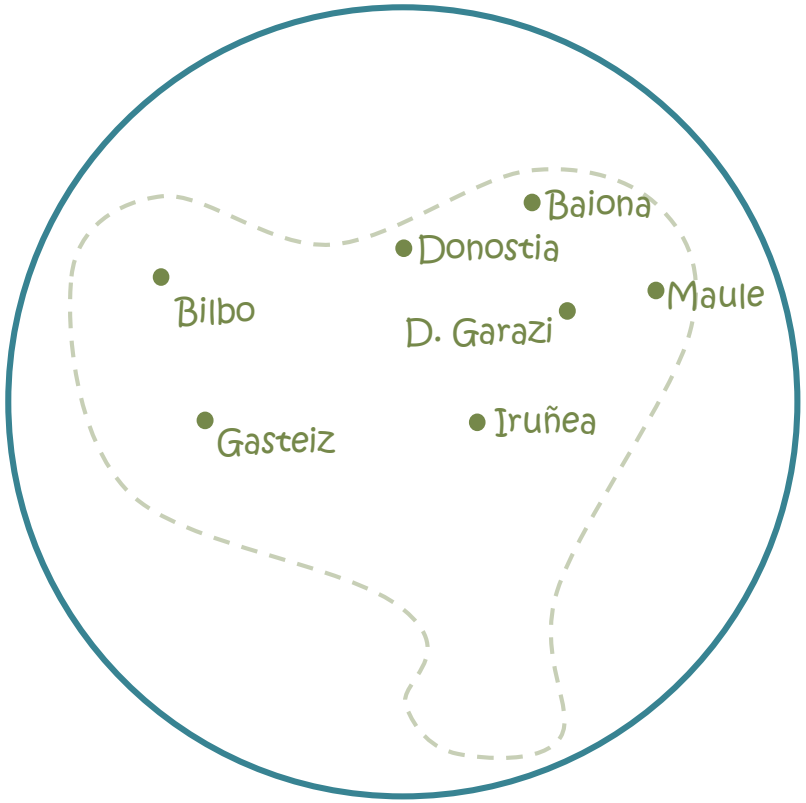
Embeddings



Geographical space

- Cities

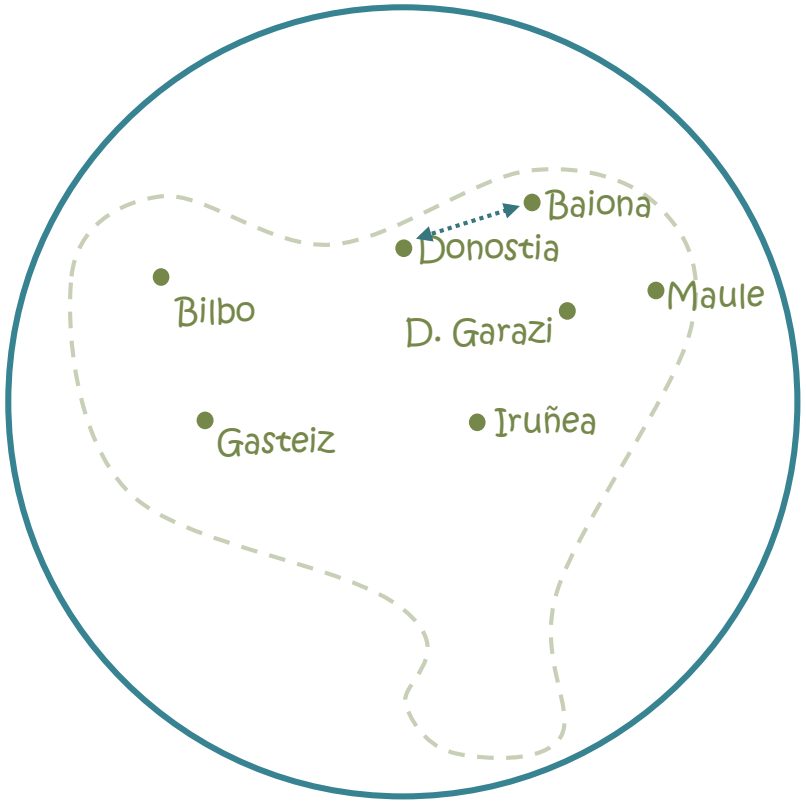
Embeddings



Geographical space

- Cities
- Meaningful distances

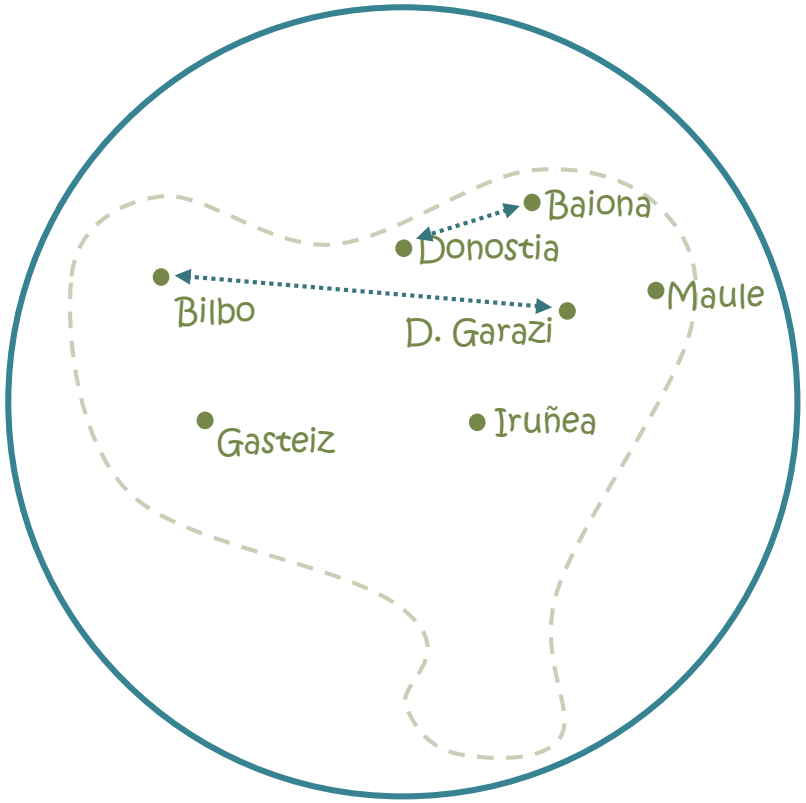
Embeddings



Geographical space

- Cities
- Meaningful distances

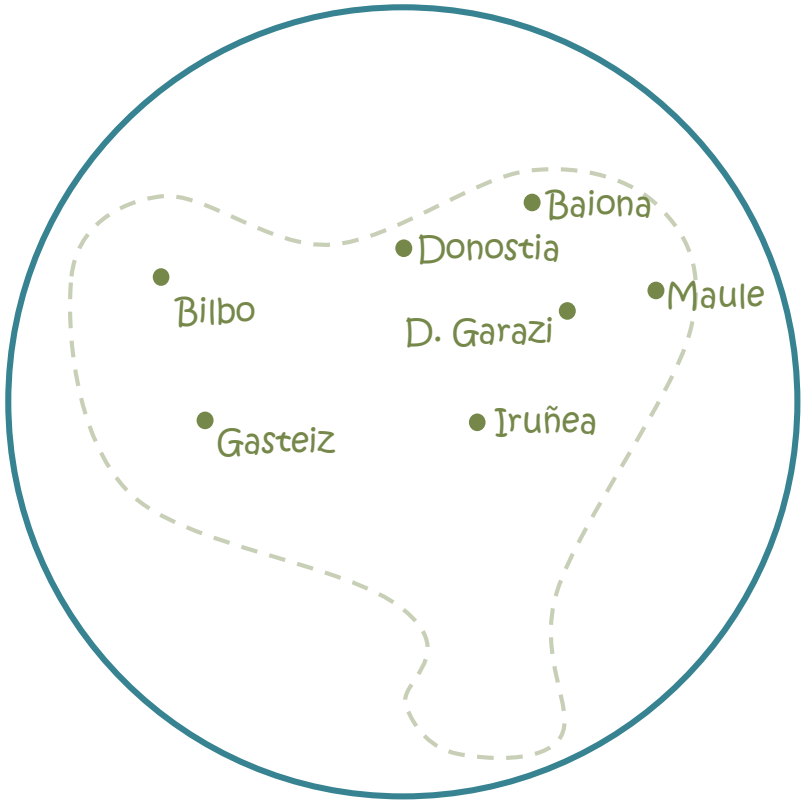
Embeddings



Geographical space

- Cities
- Meaningful distances

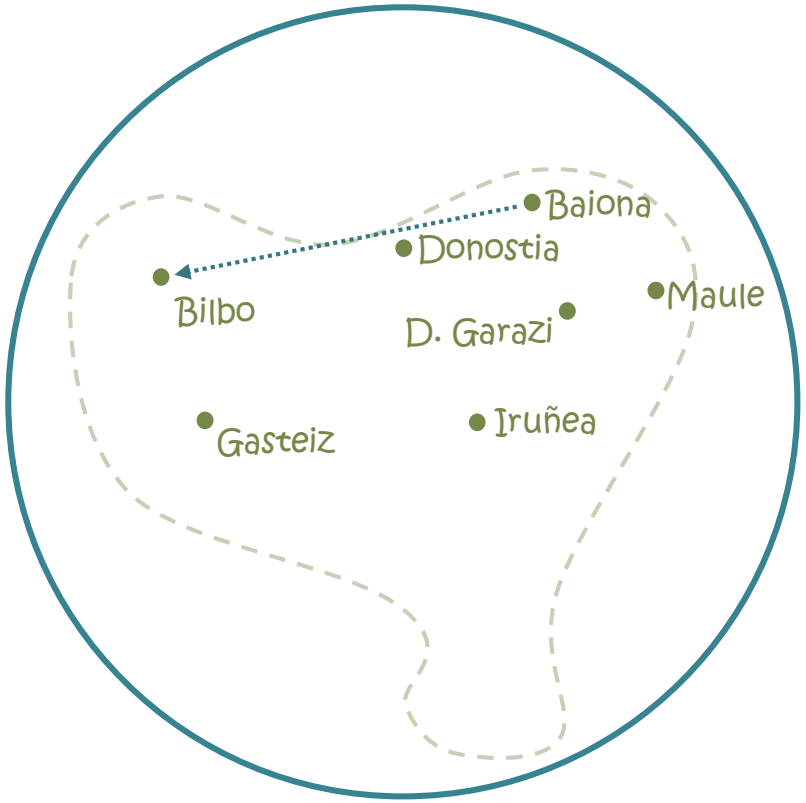
Embeddings



Geographical space

- Cities
- Meaningful distances
- Meaningful relations

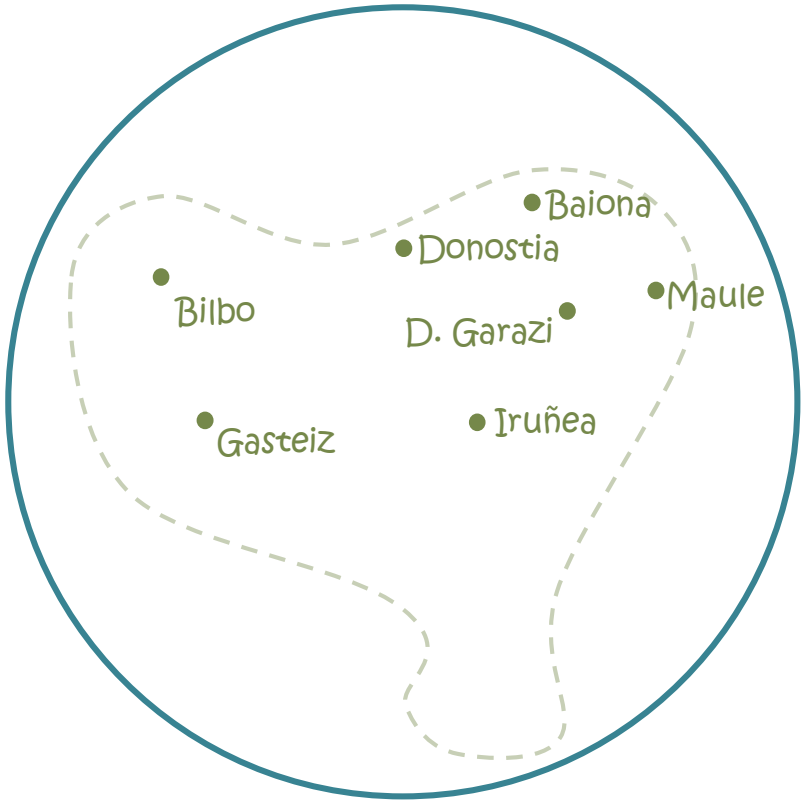
Embeddings



Geographical space

- Cities
- Meaningful distances
- Meaningful relations

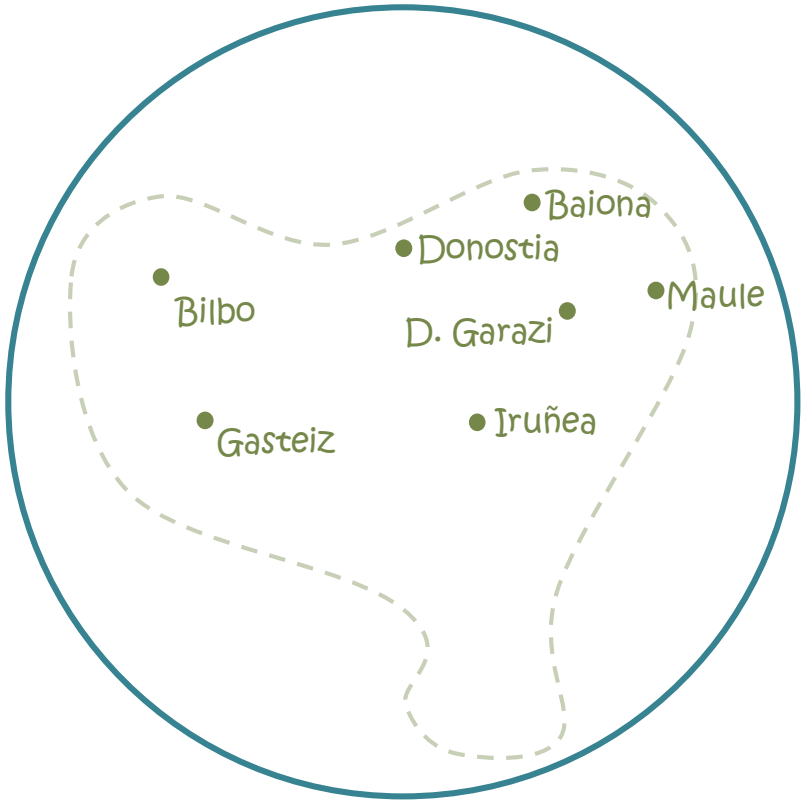
Embeddings



Geographical space

- Cities
- Meaningful distances
- Meaningful relations
- 2 dimensions

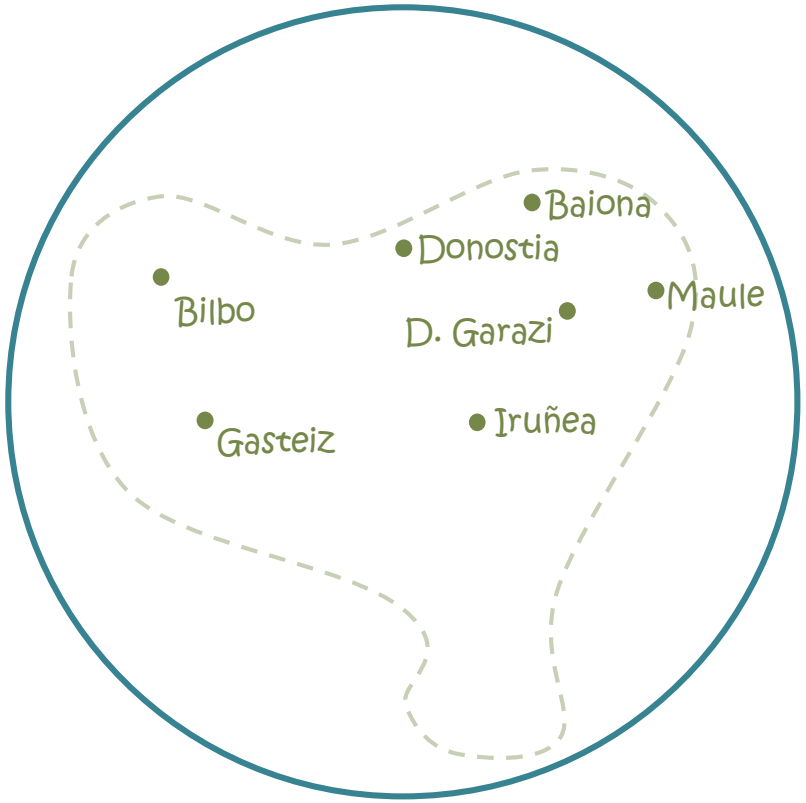
Embeddings



Geographical space

- Cities
- Meaningful distances
- Meaningful relations
- 2 dimensions
- Cartographers from 3D world

Embeddings

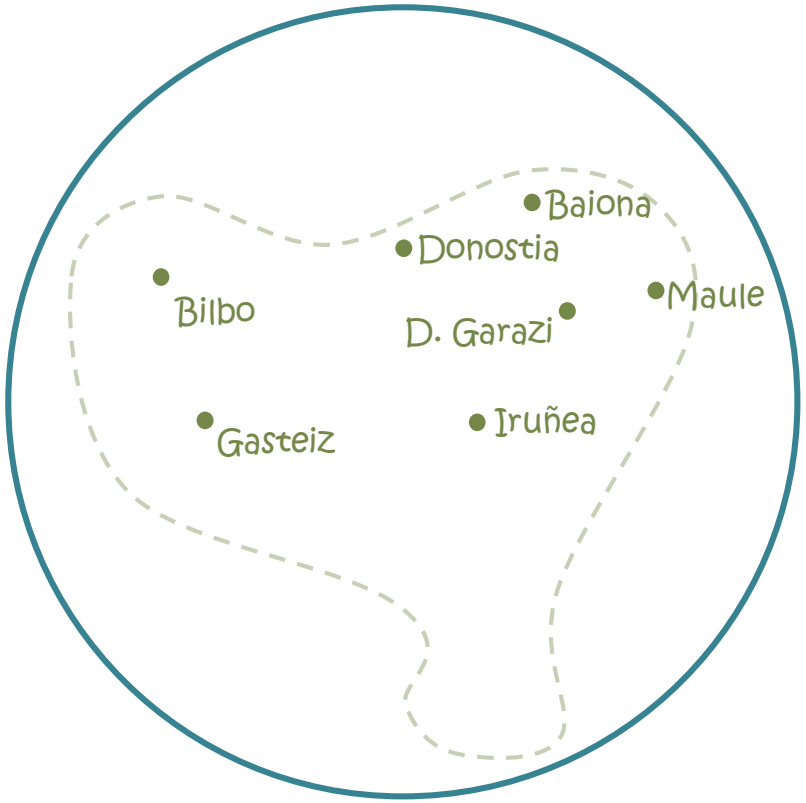


Geographical space

- Cities
- Meaningful distances
- Meaningful relations
- 2 dimensions
- Cartographers from 3D world

Semantic space

Embeddings



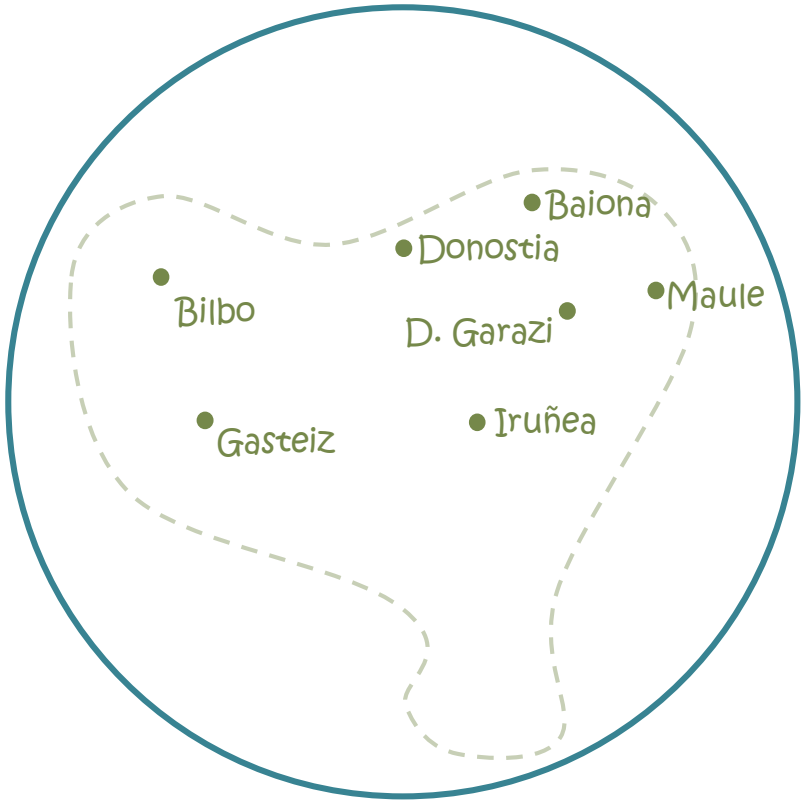
Geographical space

- Cities
- Meaningful distances
- Meaningful relations
- 2 dimensions
- Cartographers from 3D world

Semantic space

- Words

Embeddings

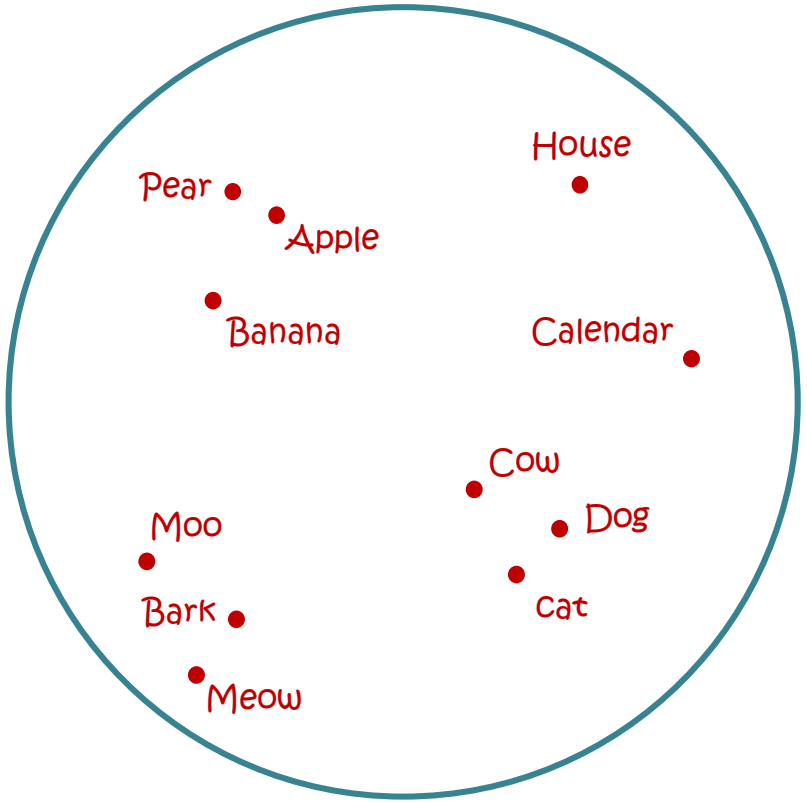


Geographical space

- Cities
- Meaningful distances
- Meaningful relations
- 2 dimensions
- Cartographers from 3D world

Semantic space

- Words



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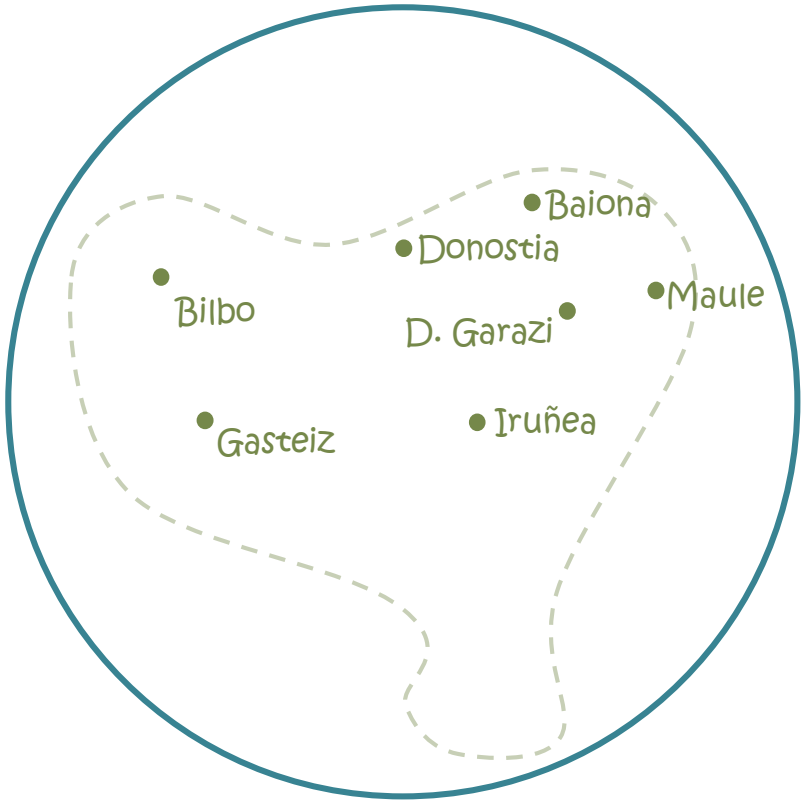

Geographical space

- Cities
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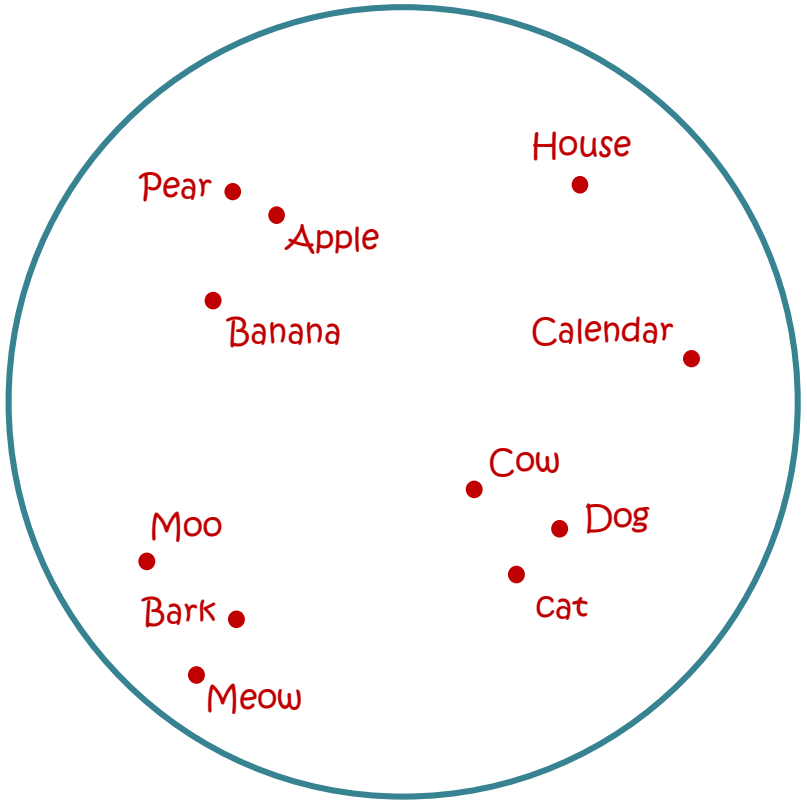
- Meaningful relations
- 2 dimensions
- Cartographers from 3D world

Semantic space

- Words
- Meaningful distances



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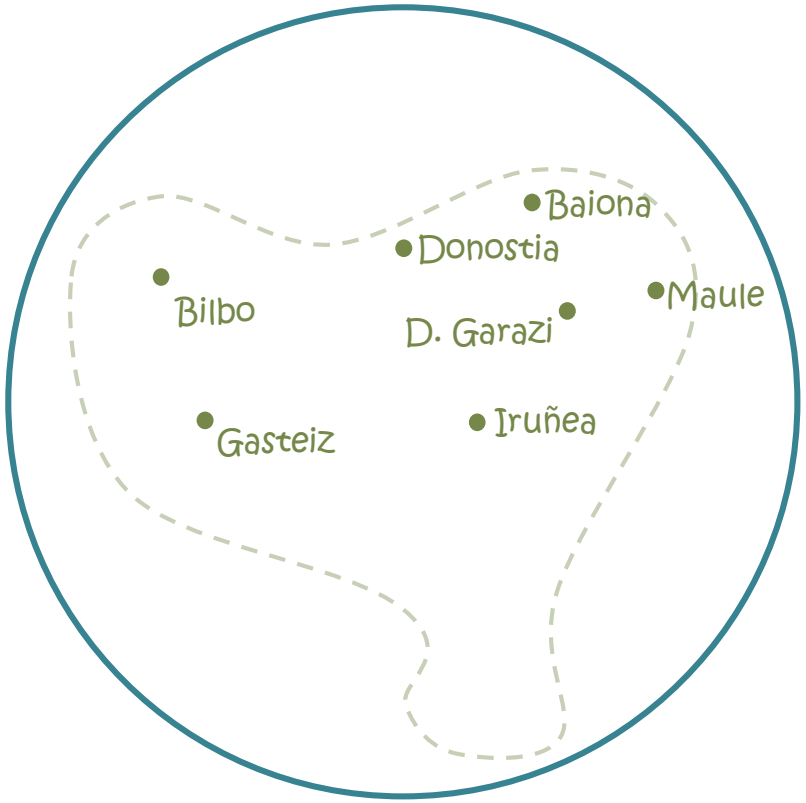
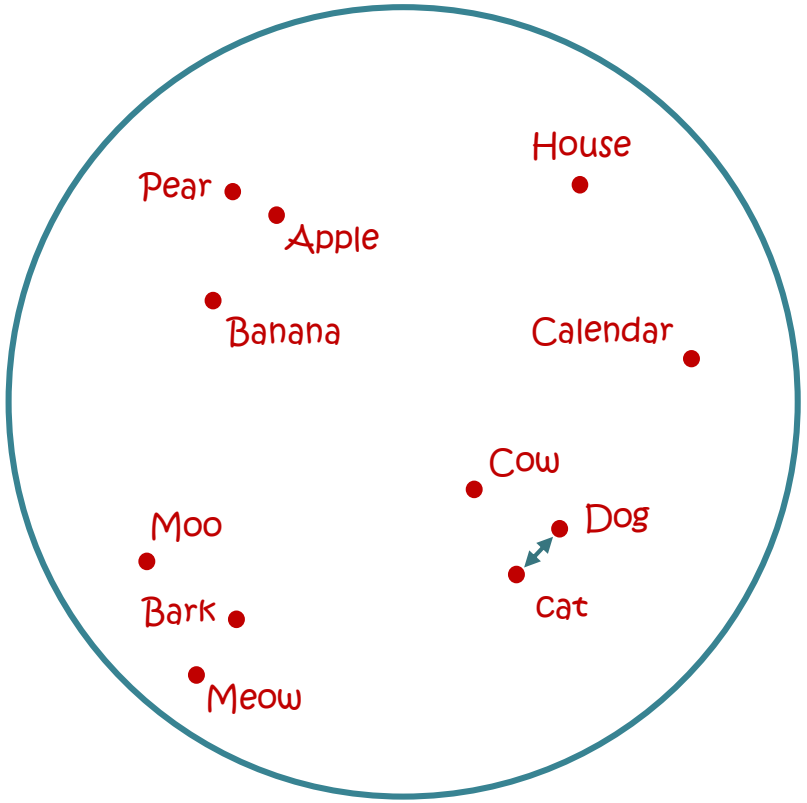


Geographical space

- Cities
- Meaningful distances
- Meaningful relations
- 2 dimensions
- Cartographers from 3D world

Semantic space

- Words
- Meaningful distances



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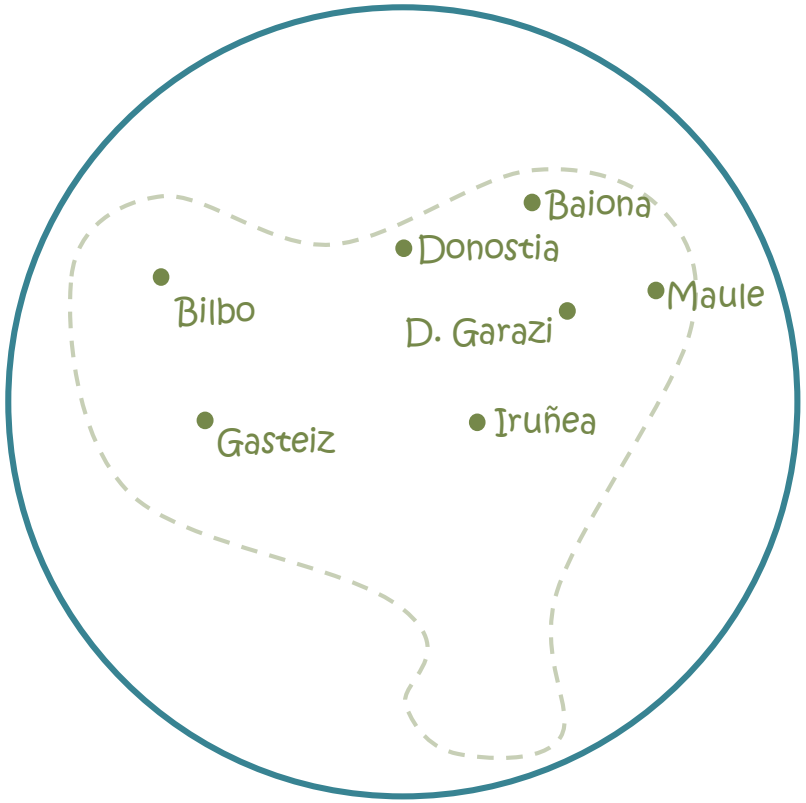

Geographical space

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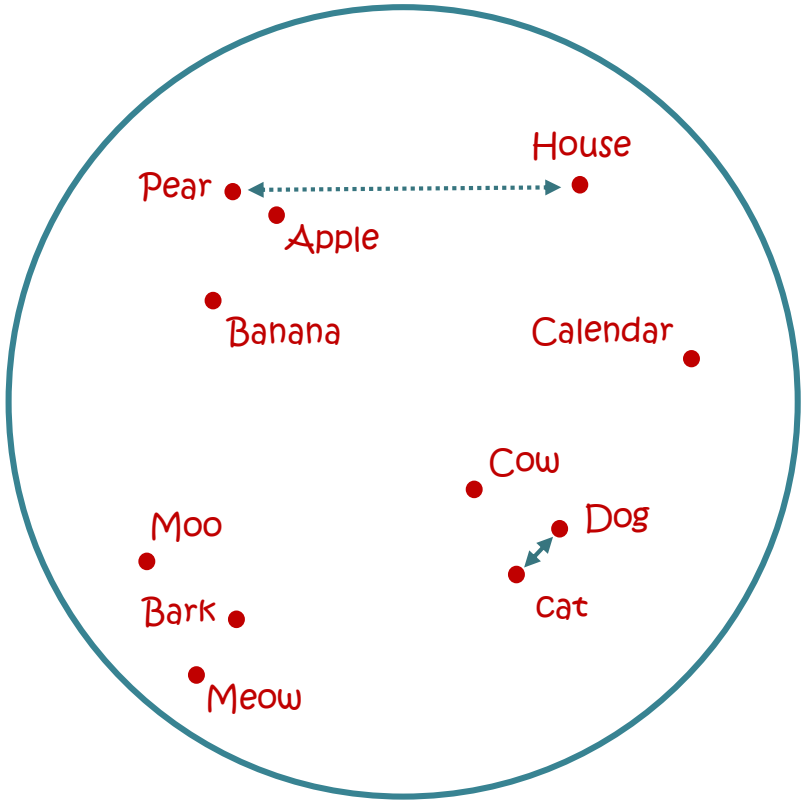
- 2 dimensions
- Cartographers from 3D world

Semantic space

- Words
- Meaningful distances



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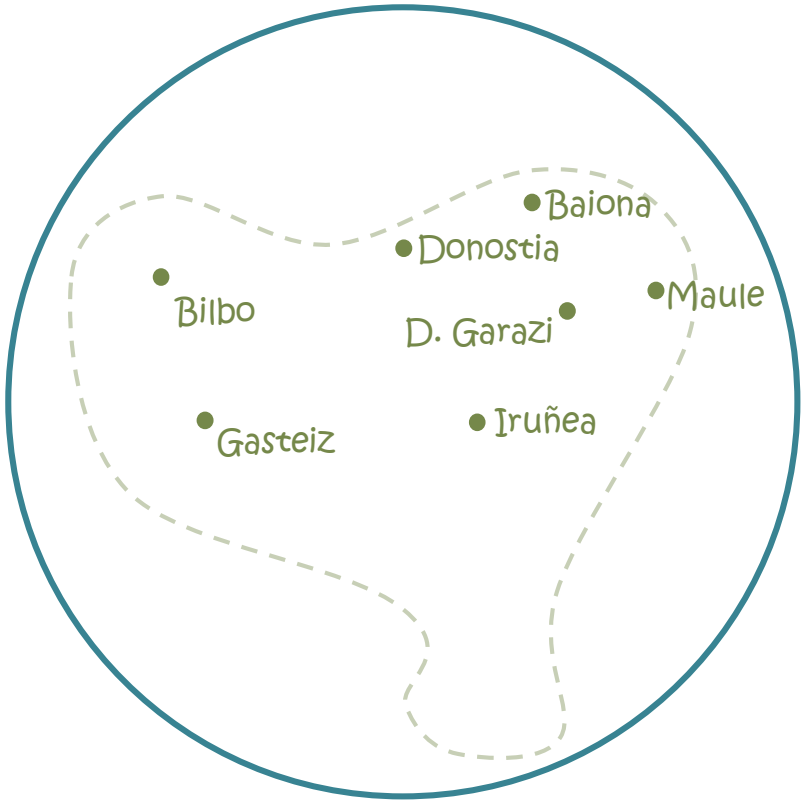

Geographical space

- Cities
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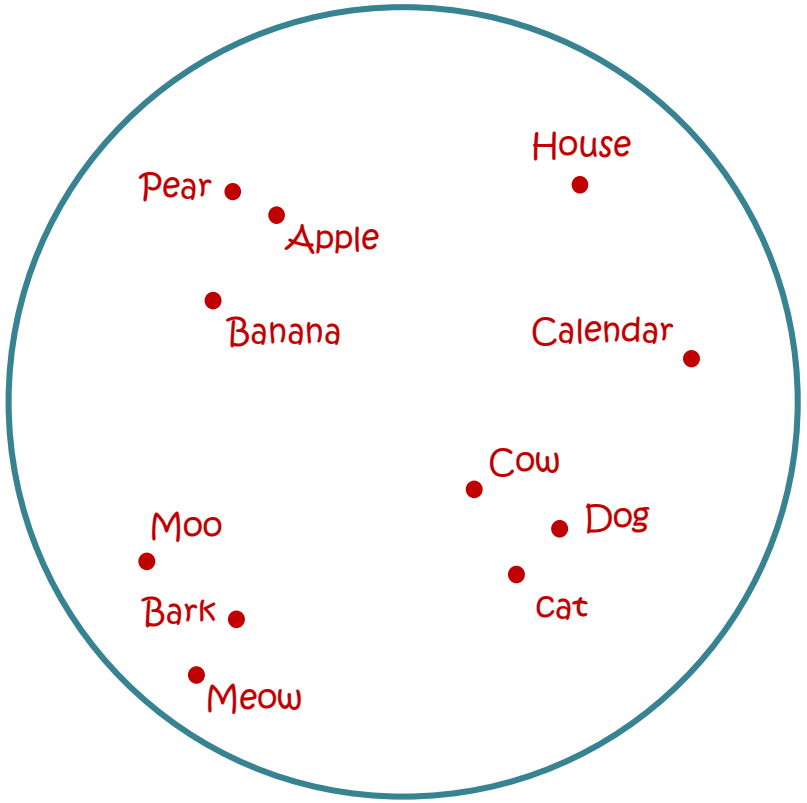
- 2 dimensions
- Cartographers from 3D world

Semantic space

- Words
- Meaningful distances
- Meaningful relations



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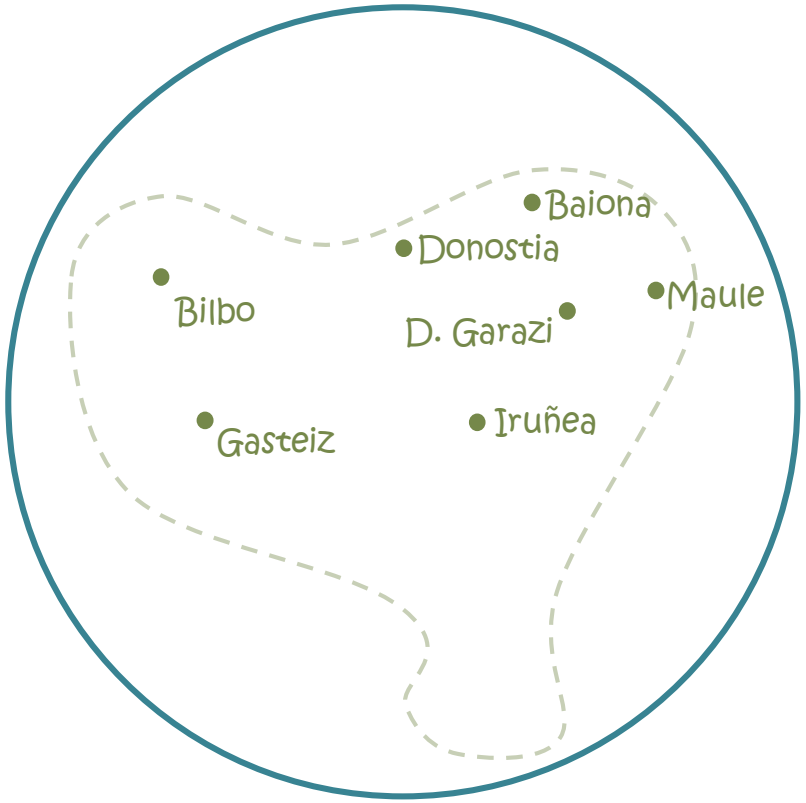

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- Meaningful relations
- 2 dimensions
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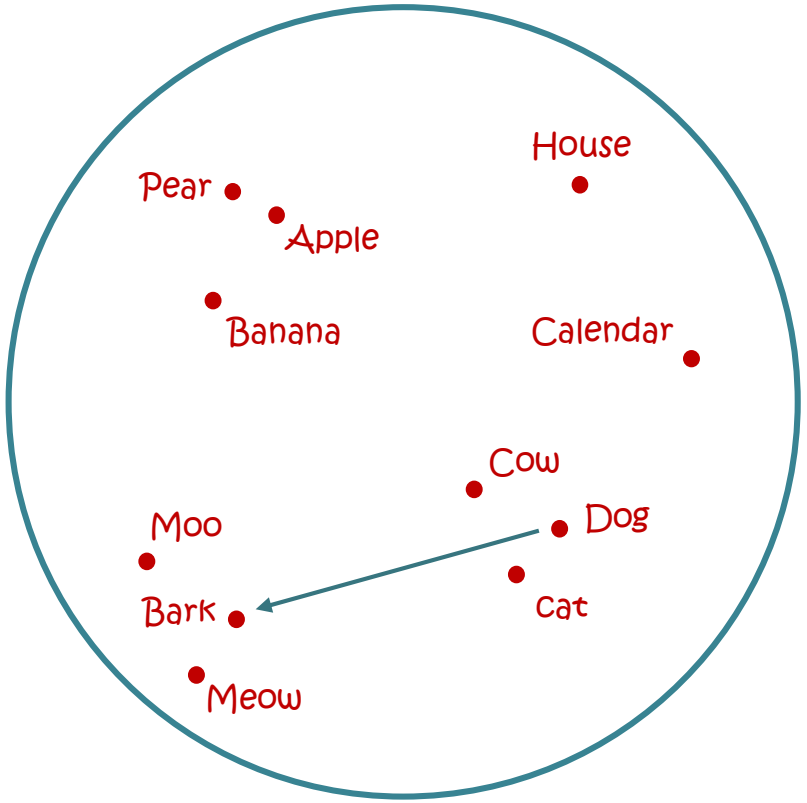
Semantic space

- Words
- Meaningful distances
- Meaningful relations



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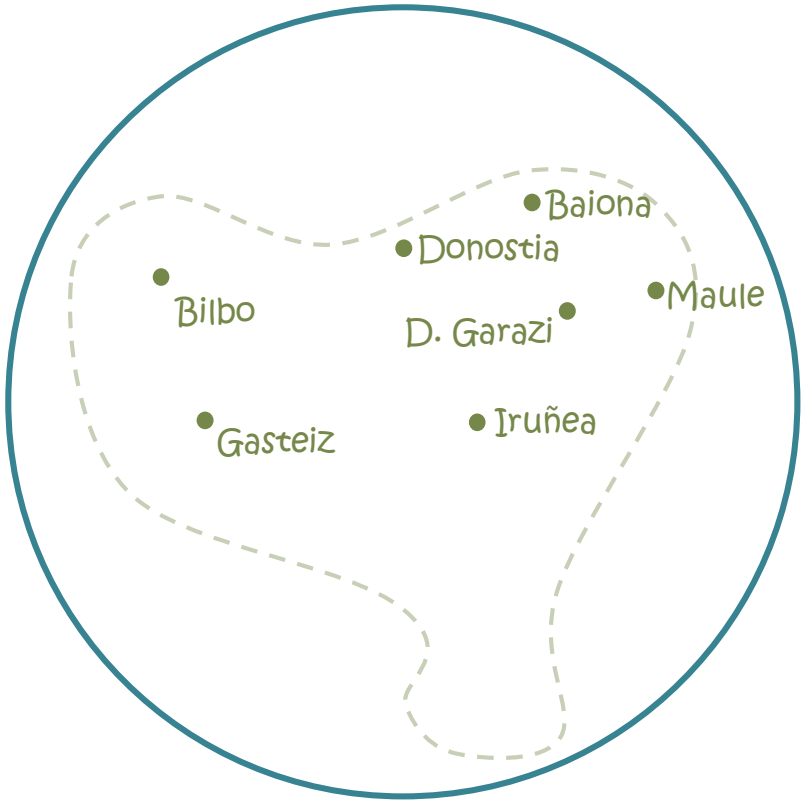
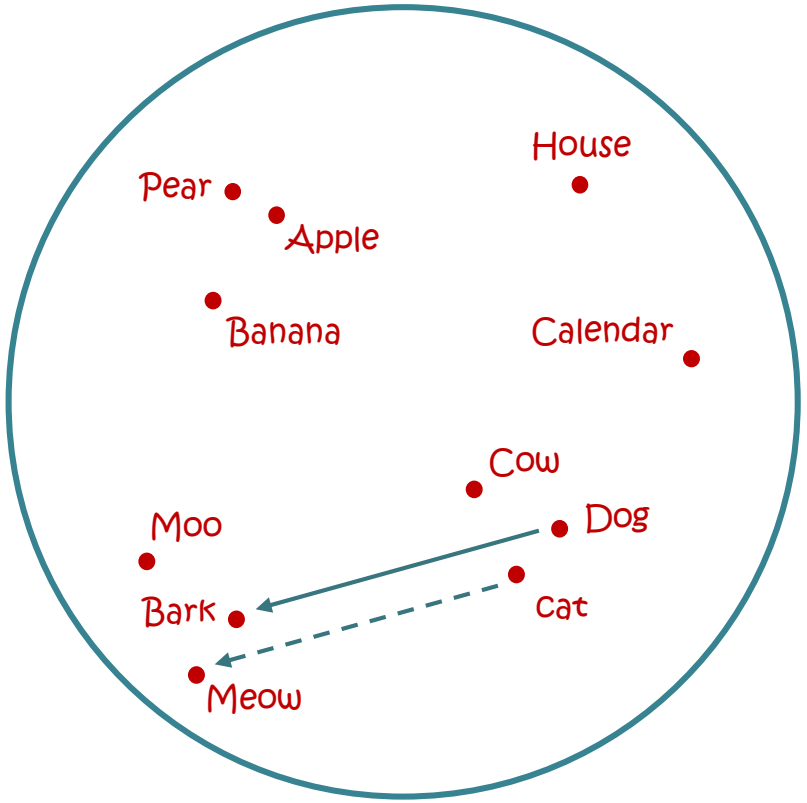


Geographical space

- Cities
- Meaningful distances
- Meaningful relations
- 2 dimensions
- Cartographers from 3D world

Semantic space

- Words
- Meaningful distances
- Meaningful relations



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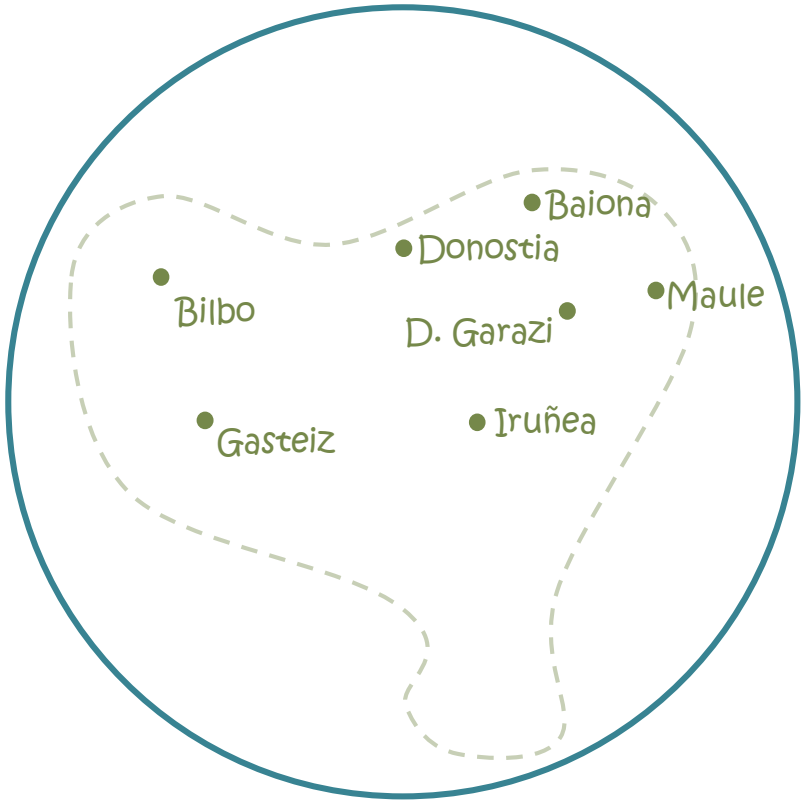
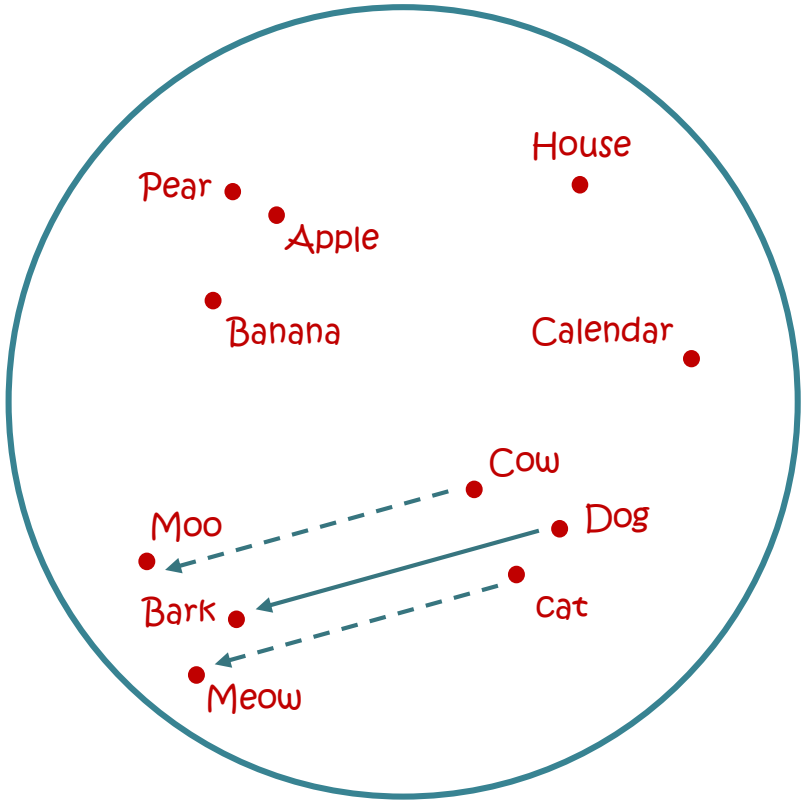


Geographical space

- Cities
- Meaningful distances
- Meaningful relations
- 2 dimensions
- Cartographers from 3D world

Semantic space

- Words
- Meaningful distances
- Meaningful relations



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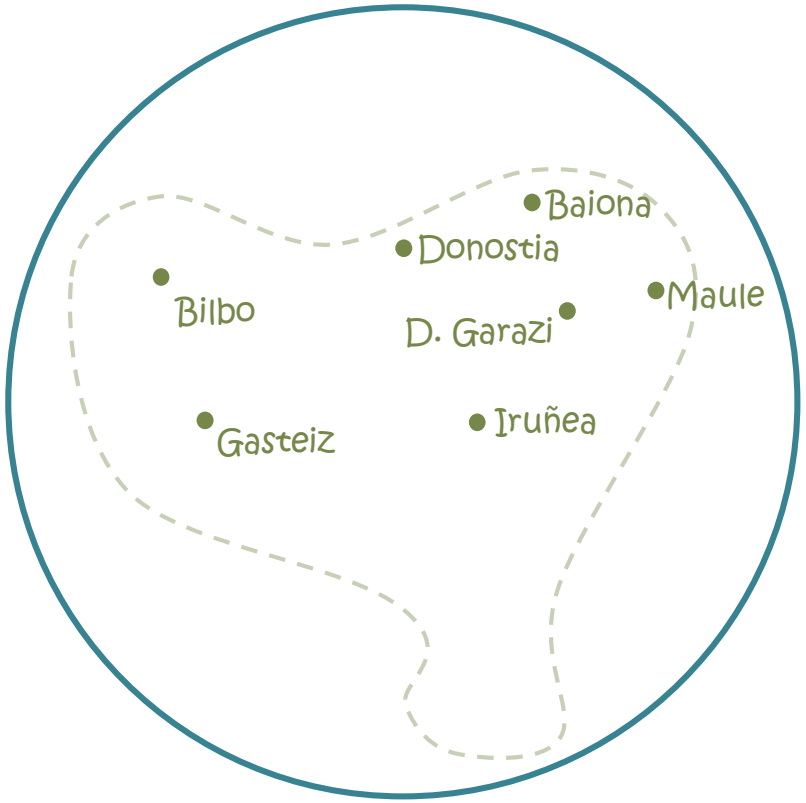
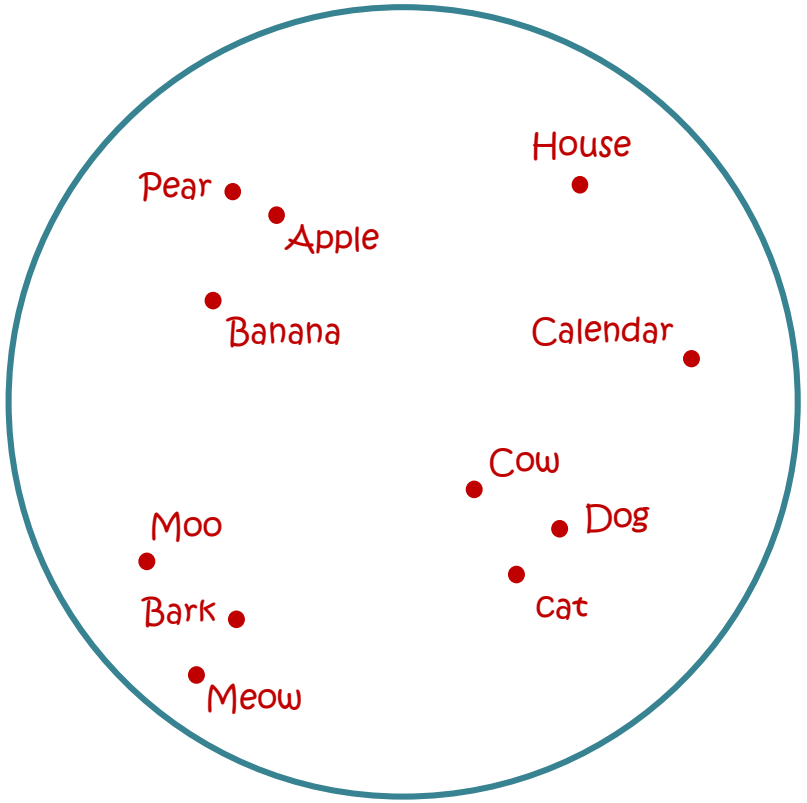


Geographical space

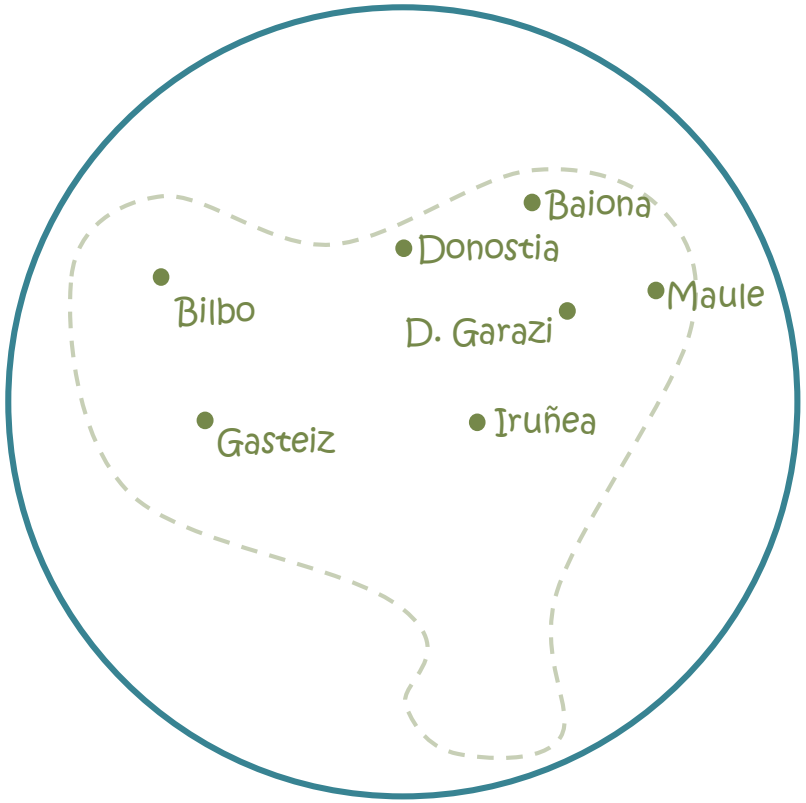
- Cities
- Meaningful distances
- Meaningful relations
- 2 dimensions
- Cartographers from 3D world

Semantic space

- Words
- Meaningful distances
- Meaningful relations
- 300 dimensions



Embeddings

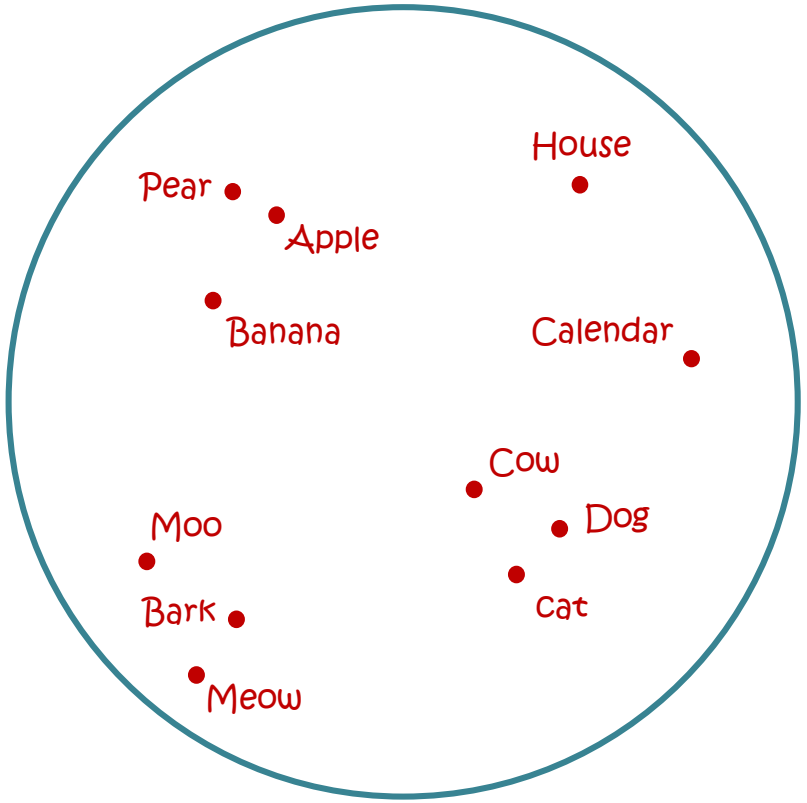


Geographical space

- Cities
- Meaningful distances
- Meaningful relations
- 2 dimensions
- Cartographers from 3D world

Semantic space

- Words
- Meaningful distances
- Meaningful relations
- 300 dimensions
- Machine learning / linear algebra from co-occurrence counts



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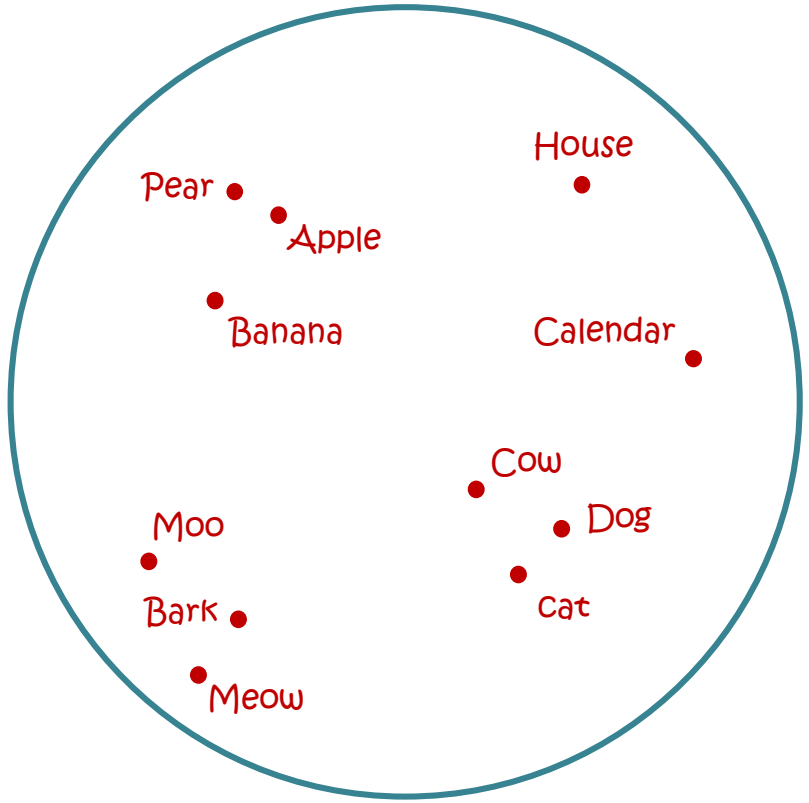

Embeddings

Traditional vector space models:

Semantic space

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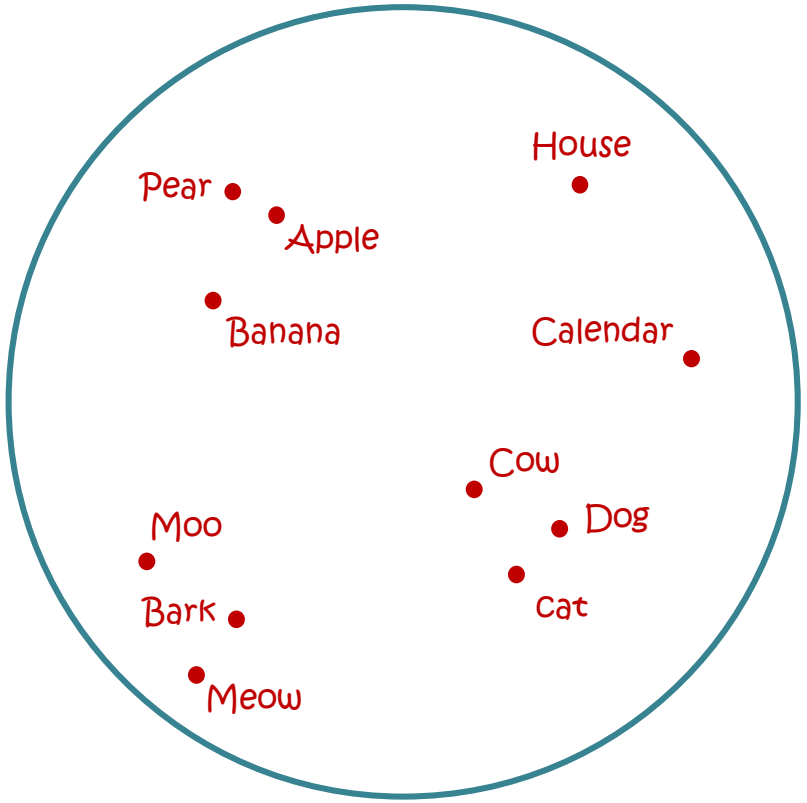

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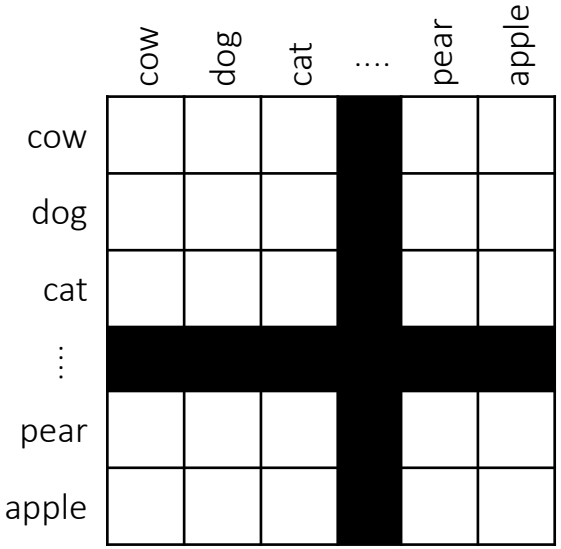

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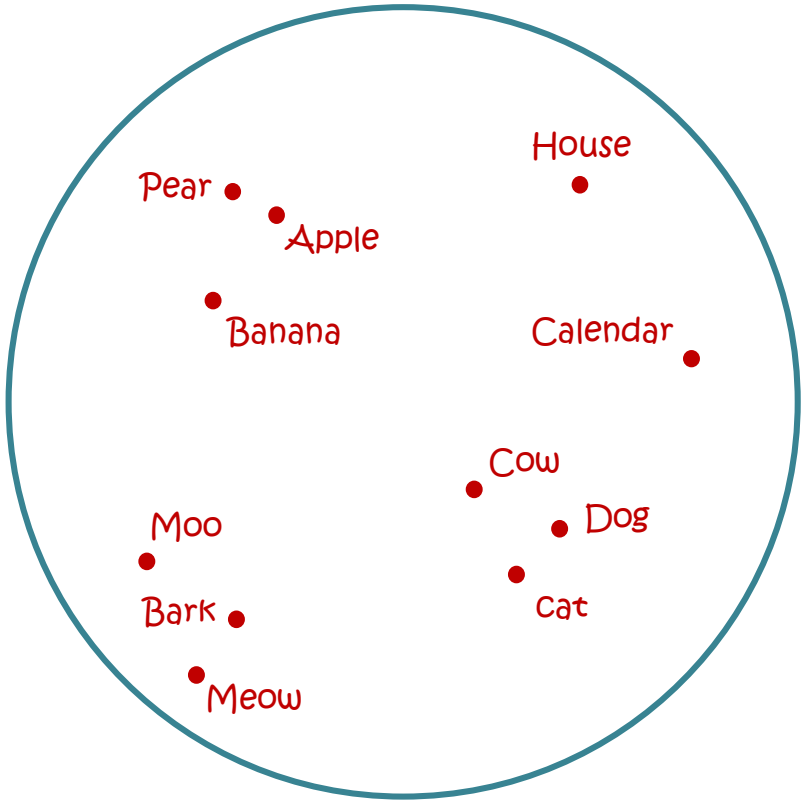

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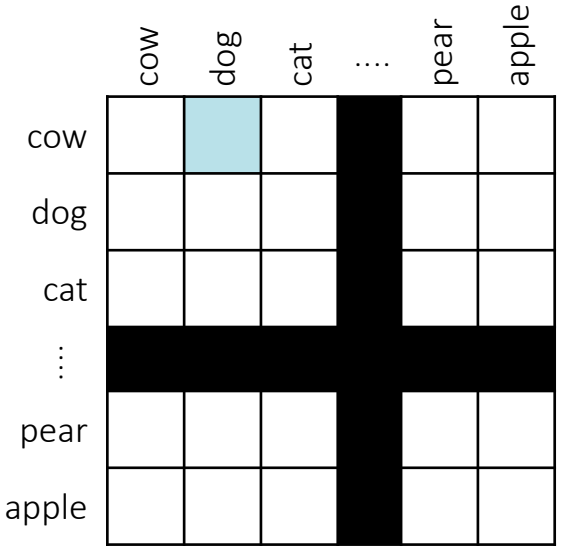

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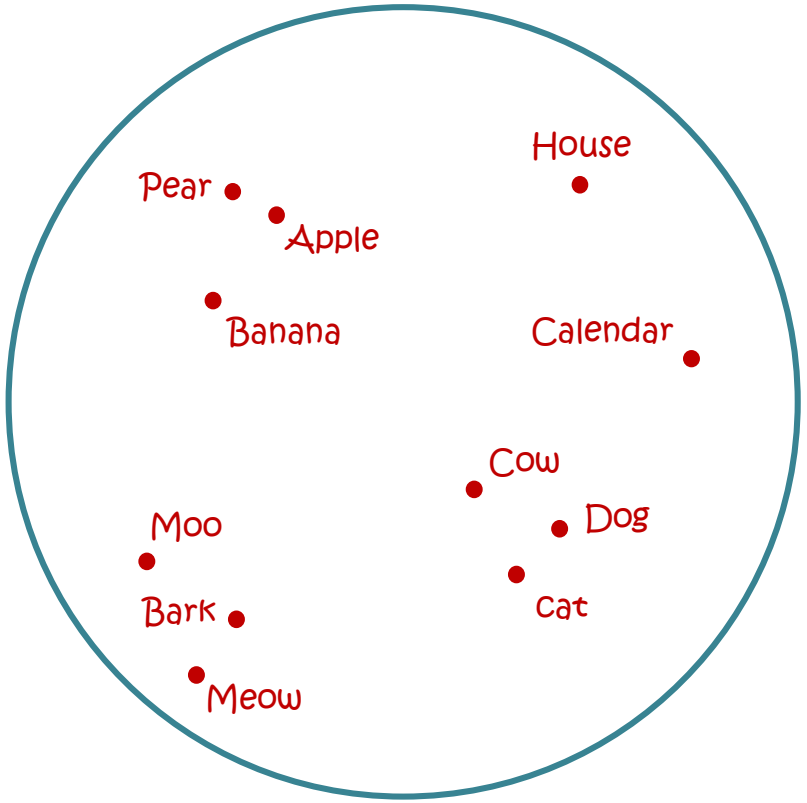

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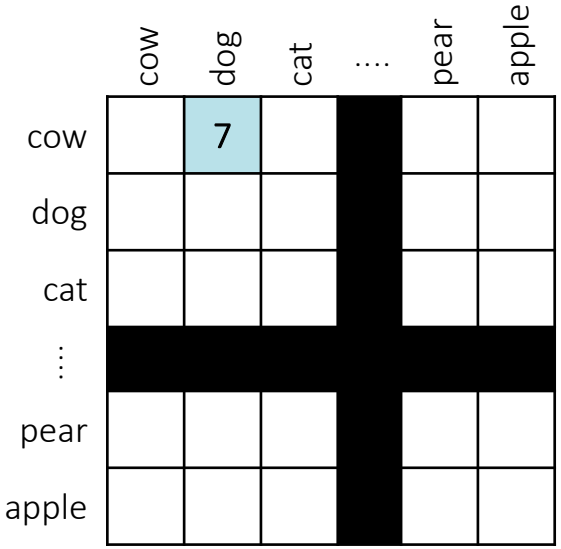

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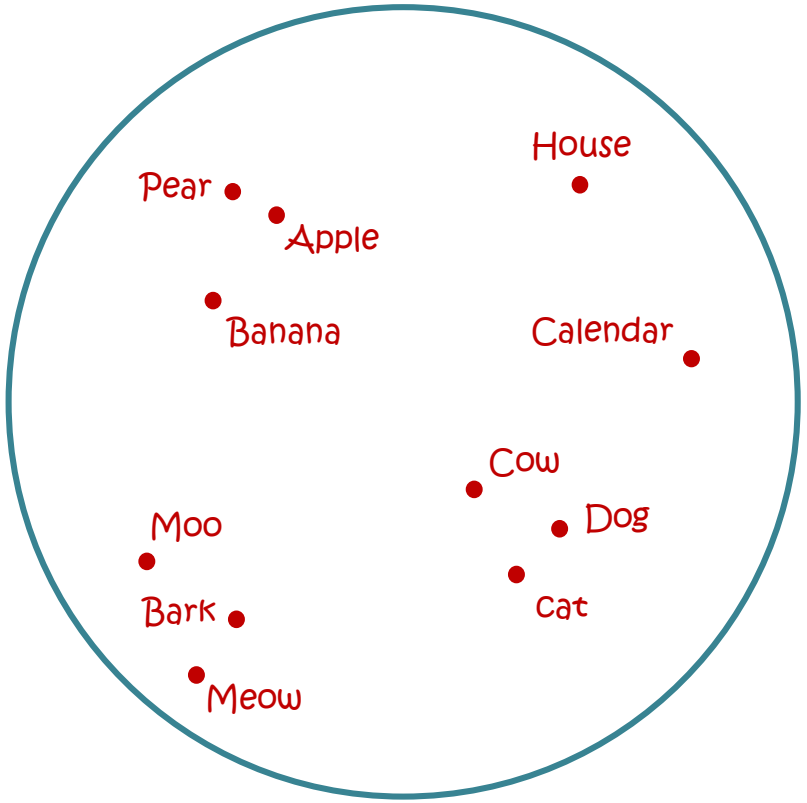

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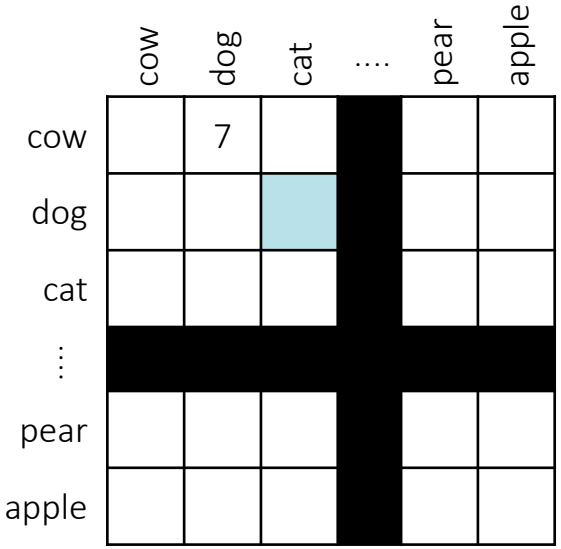

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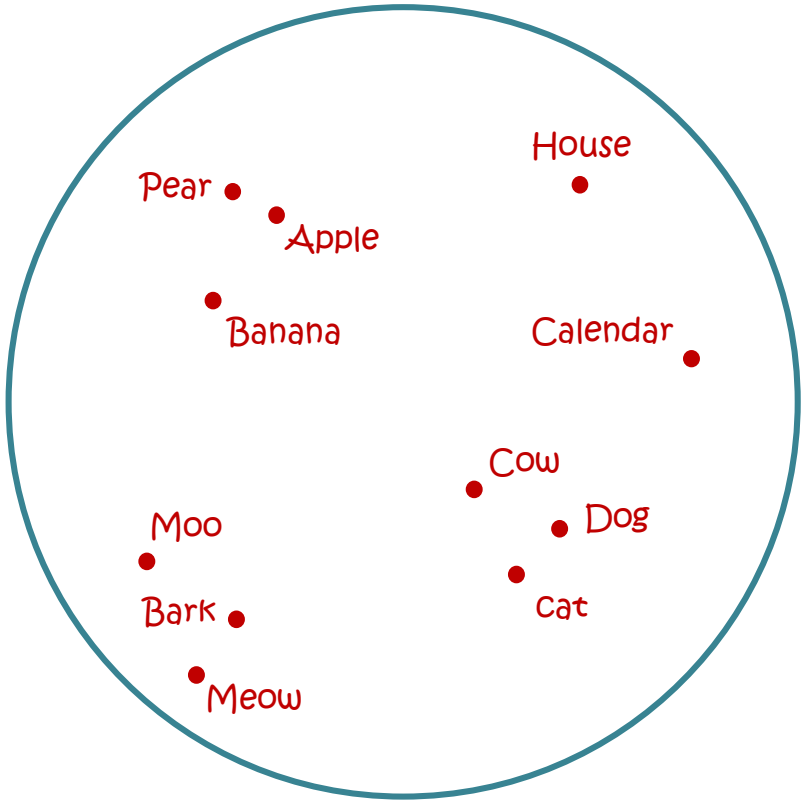

Embeddings

Traditional vector space models:

	cow	dog	cat	....	pear	apple
cow		7				
dog			24			
cat						
⋮						
pear						
apple						

Semantic space

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- Meaningful distances
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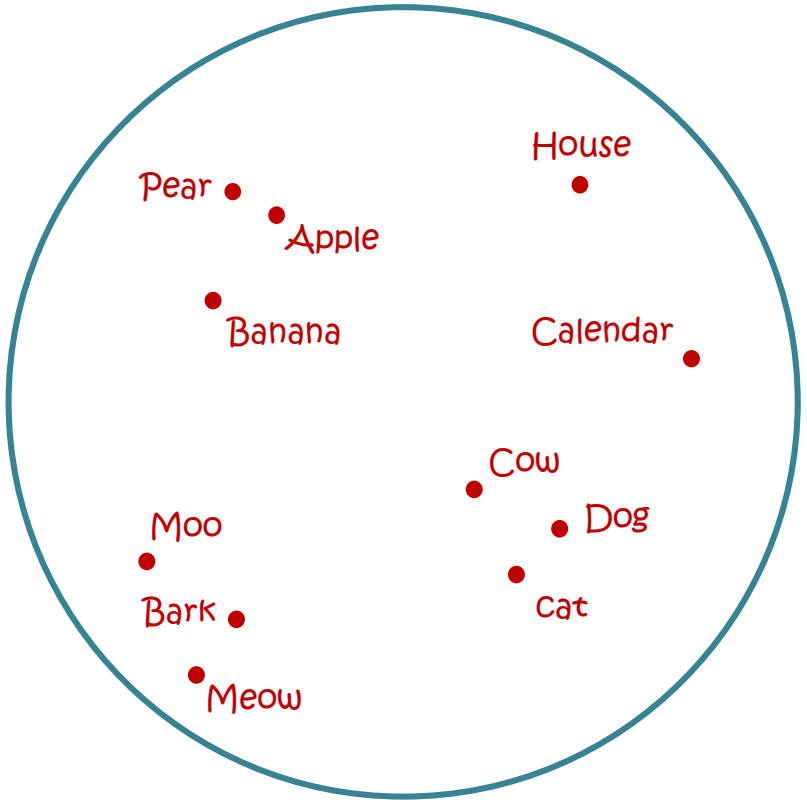

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	cow	dog	cat	....	pear	apple
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dog	7	34	24		2	3
cat	4	24	27		2	1
⋮						
pear	1	2	2		19	21
apple	2	3	1		21	28

Semantic space

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- Meaningful distances
- Meaningful relations
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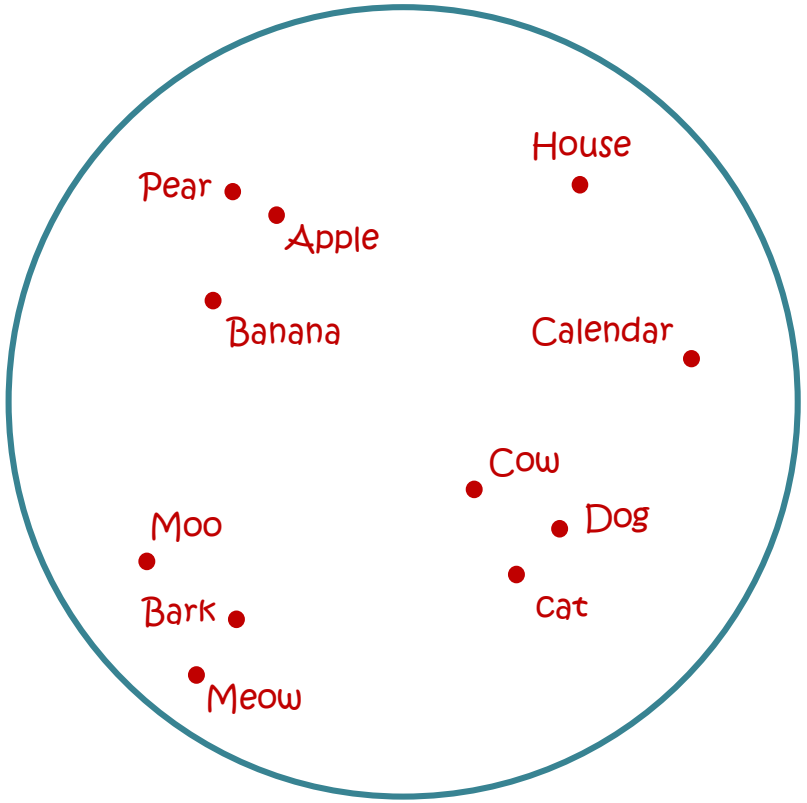

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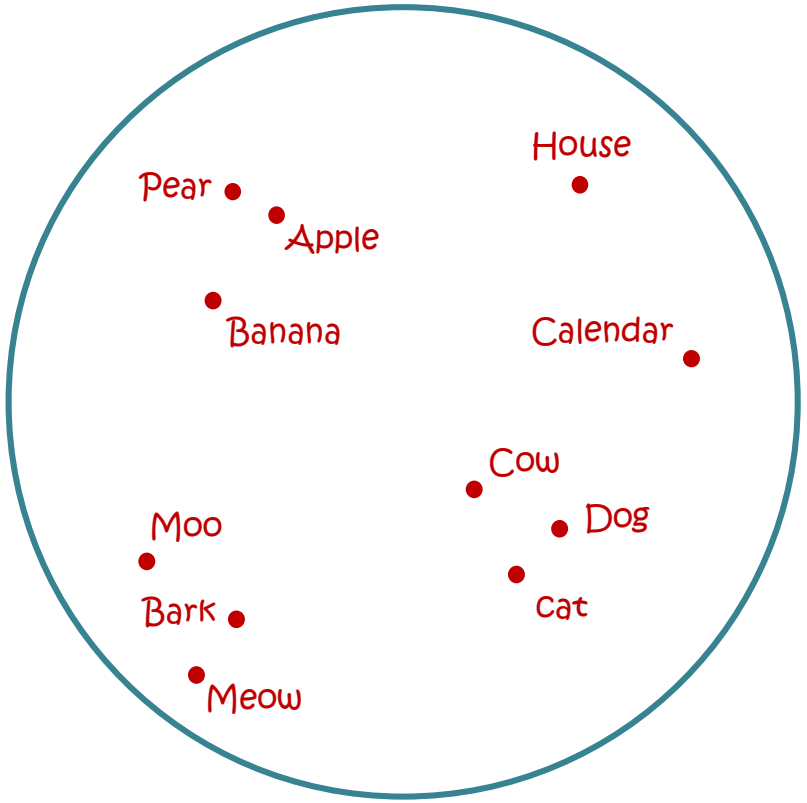

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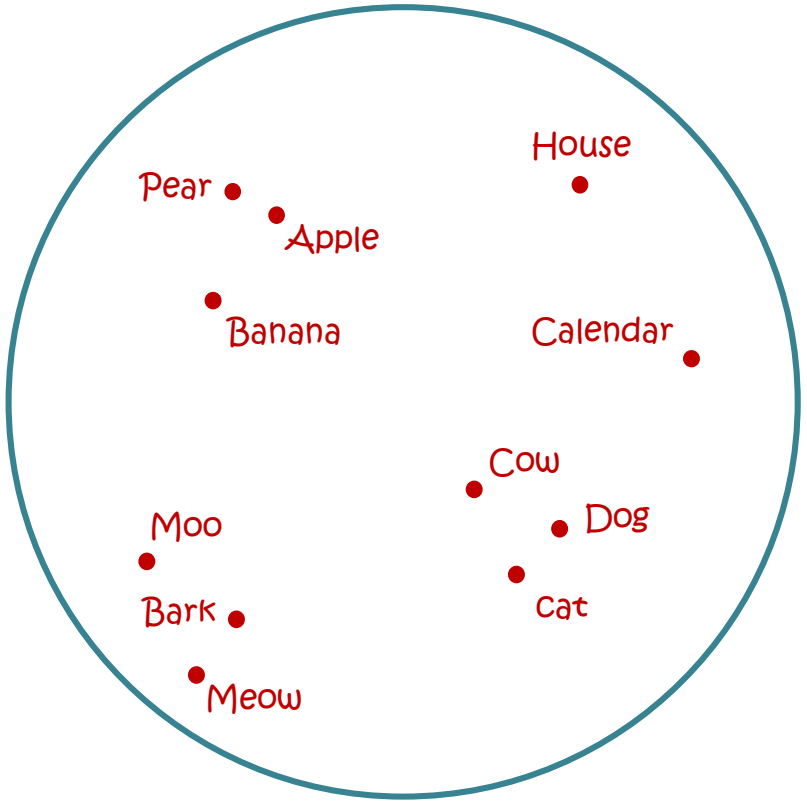

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cow: (23, 7, 4, …, 1, 2)

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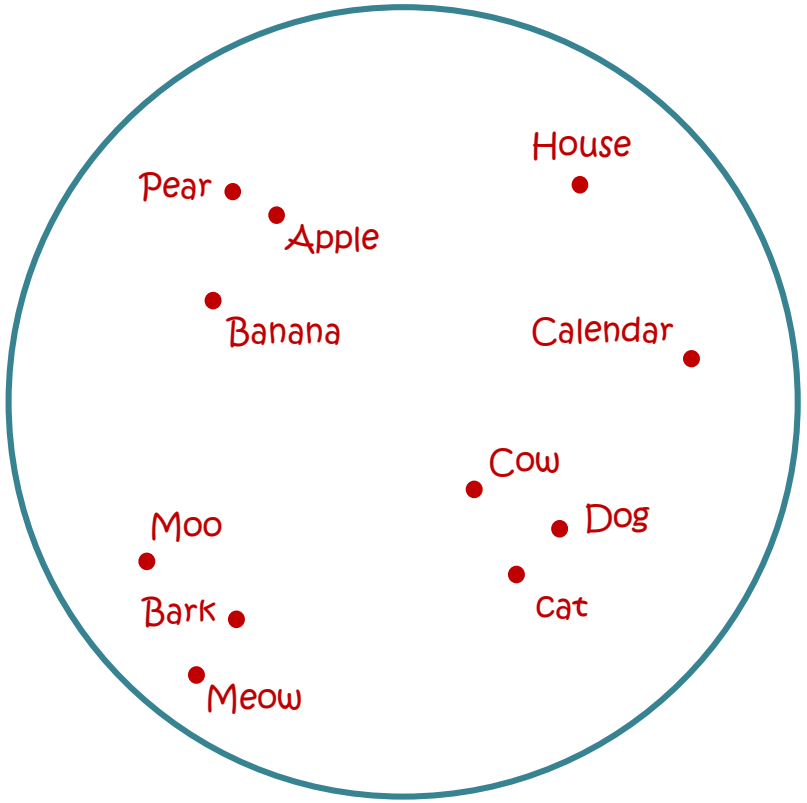

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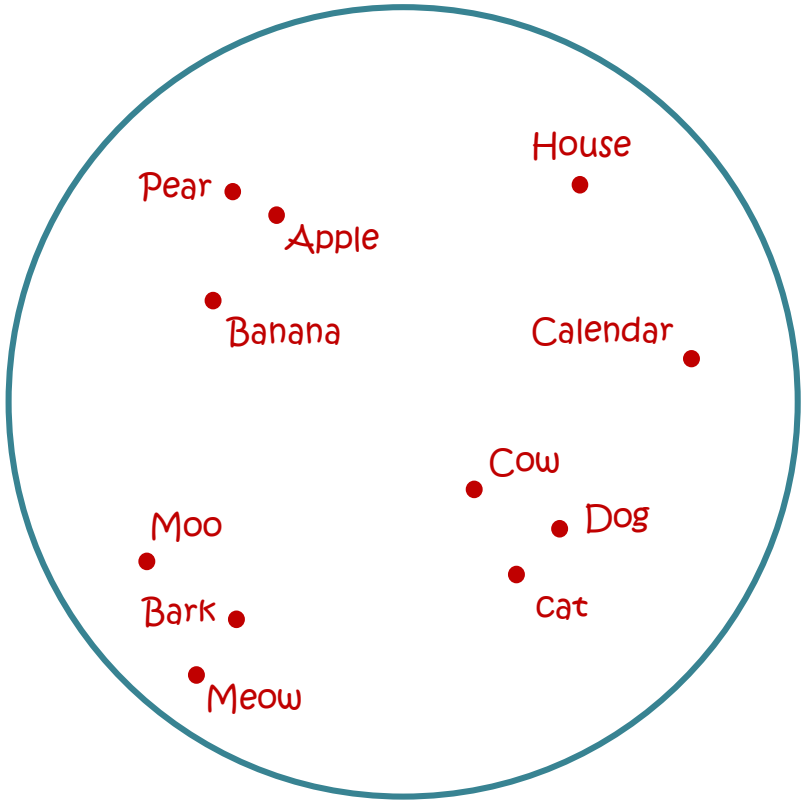
PCA

Semantic space

- Words
- Meaningful distances
- Meaningful relations
- 300 dimensions
- Machine learning / linear algebra from co-occurrence counts



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PCA

Semantic space

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- Meaningful distances
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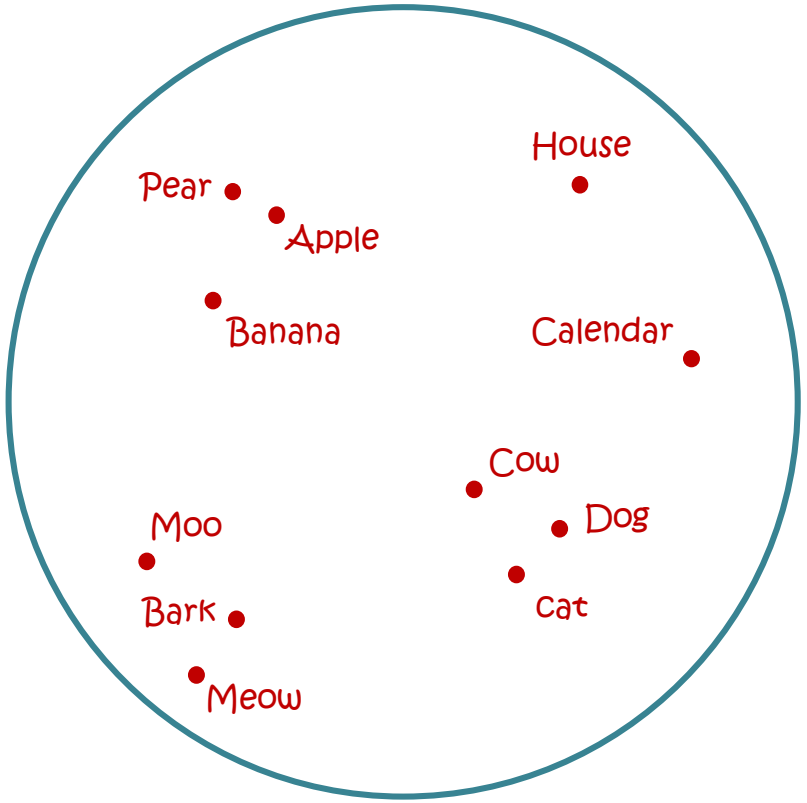

Embeddings

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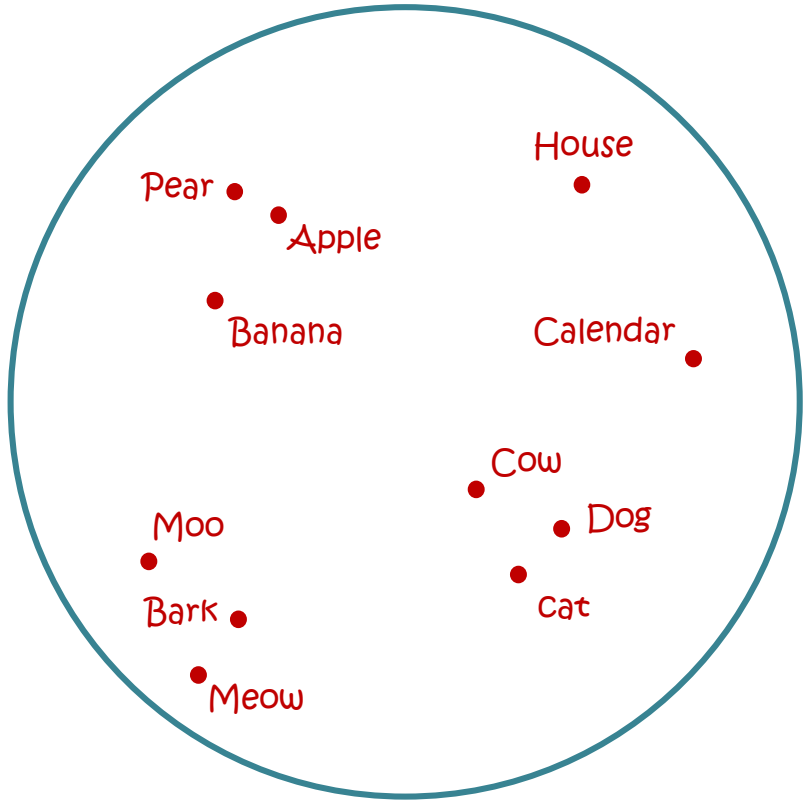
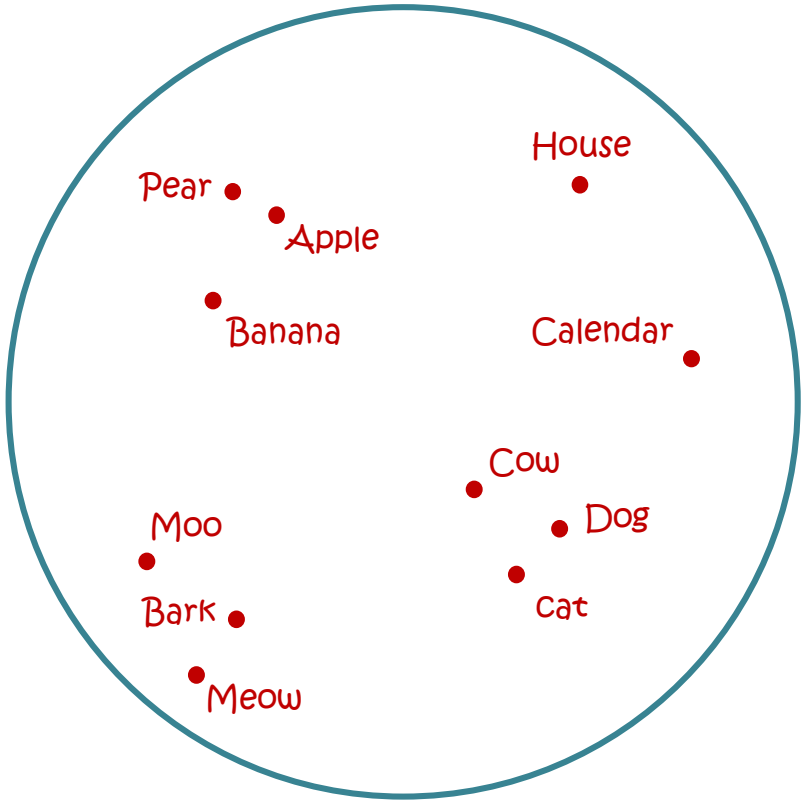


Embeddings

Skip-gram with negative sampling:

Semantic space

- Words
- Meaningful distances
- Meaningful relations
- 300 dimensions
- Machine learning / linear algebra from co-occurrence counts



Embeddings

Skip-gram with negative sampling:

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

Semantic space

- Words
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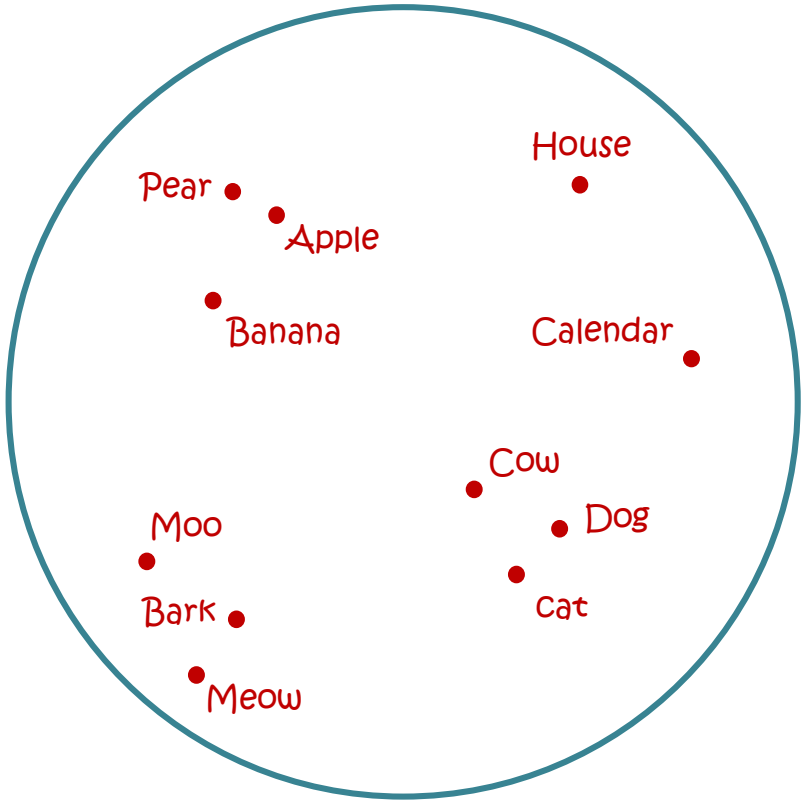

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I will go to New York by plane .

Semantic space

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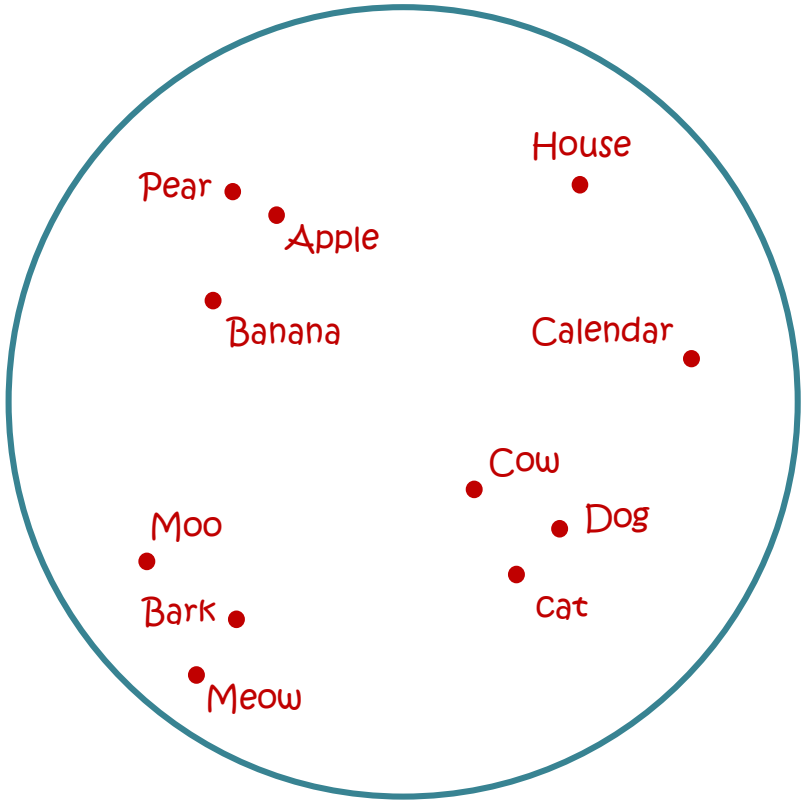

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I will $\underset{w}{\underline{go}}$ *to New York by plane .*

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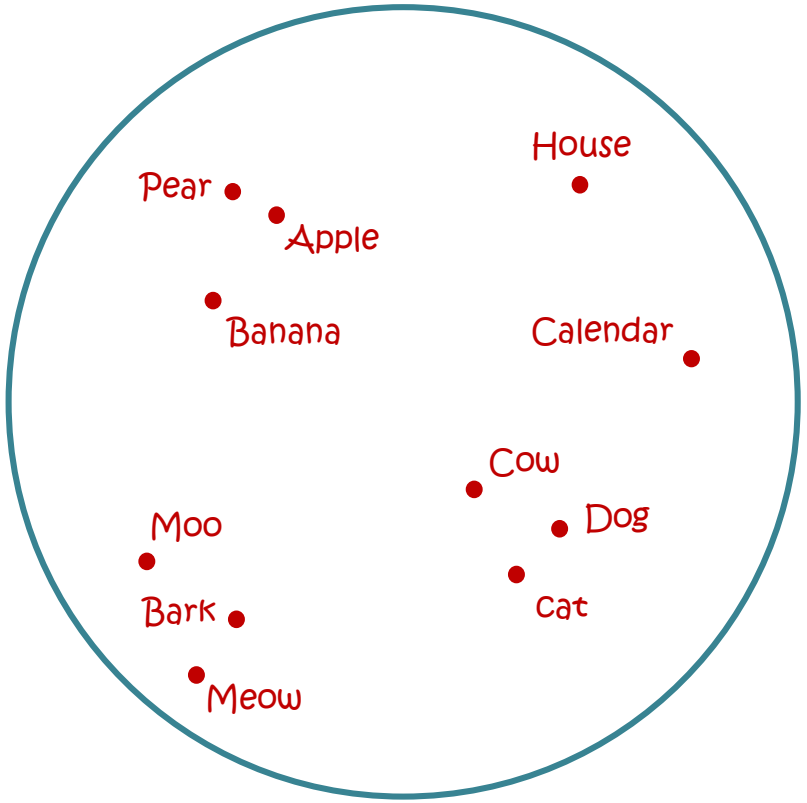

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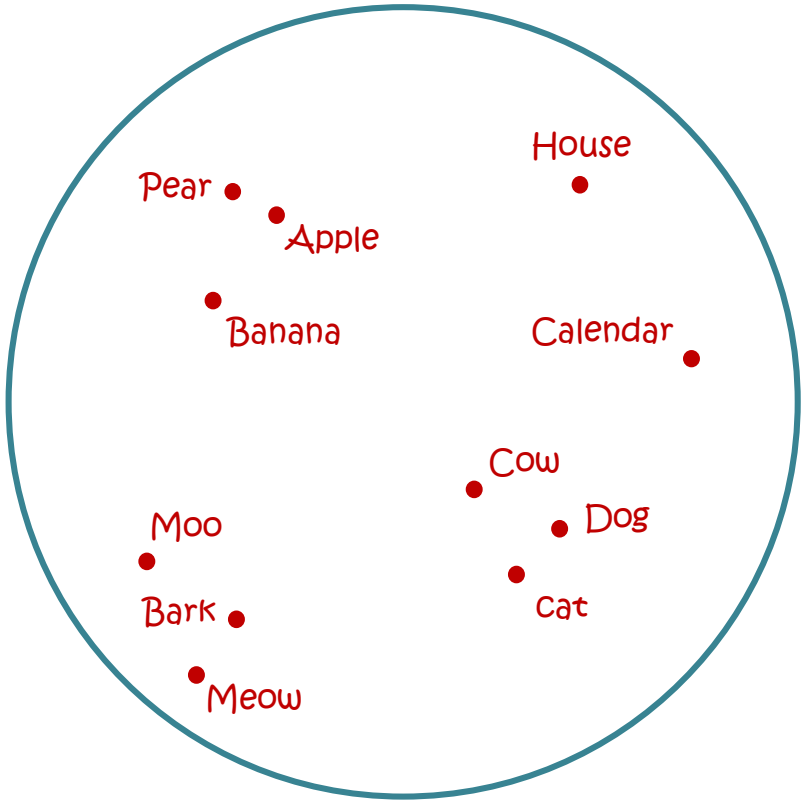

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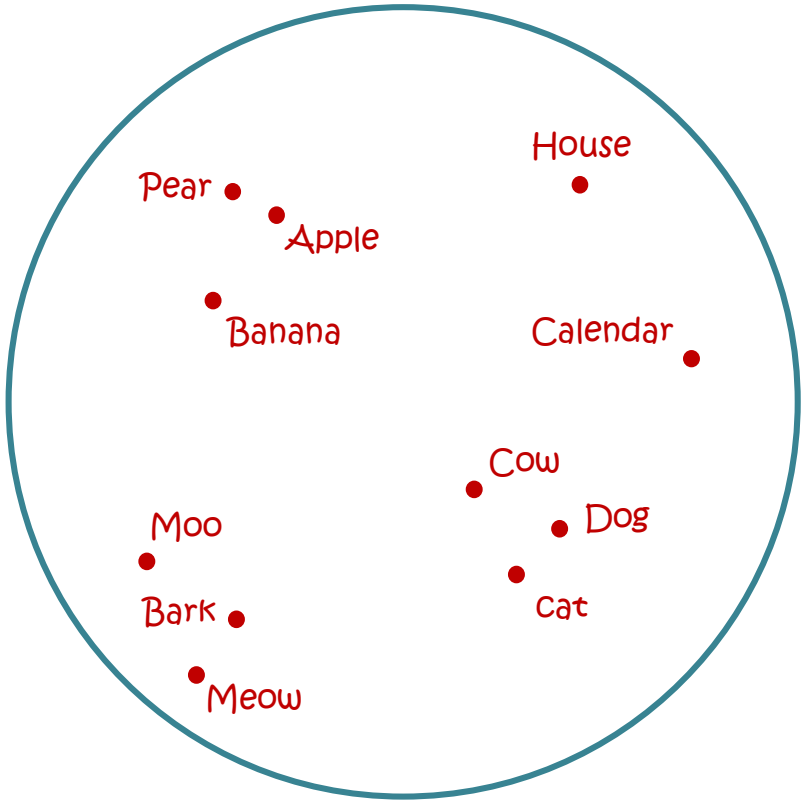

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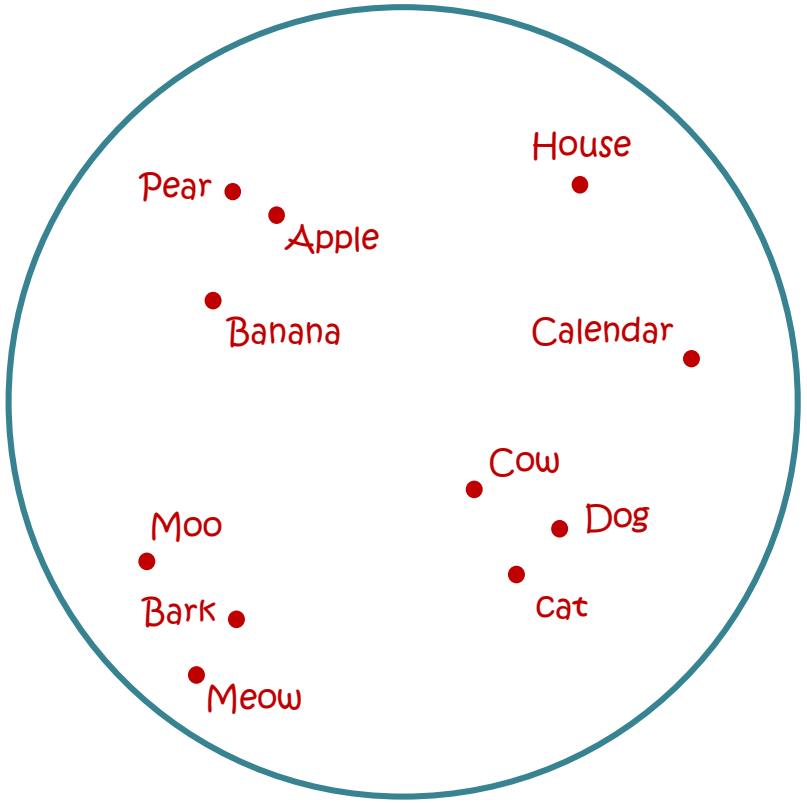

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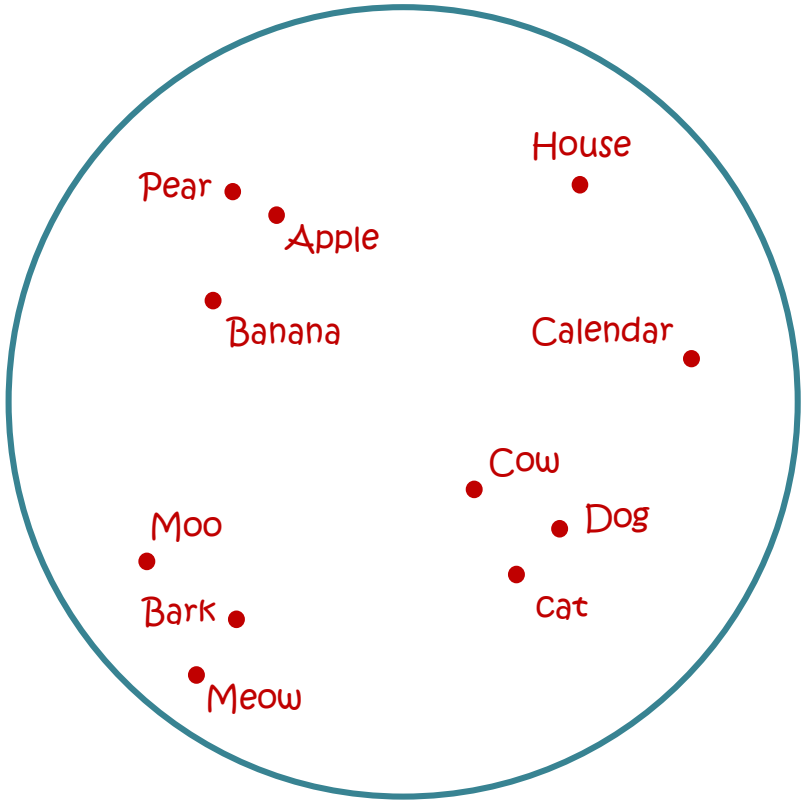
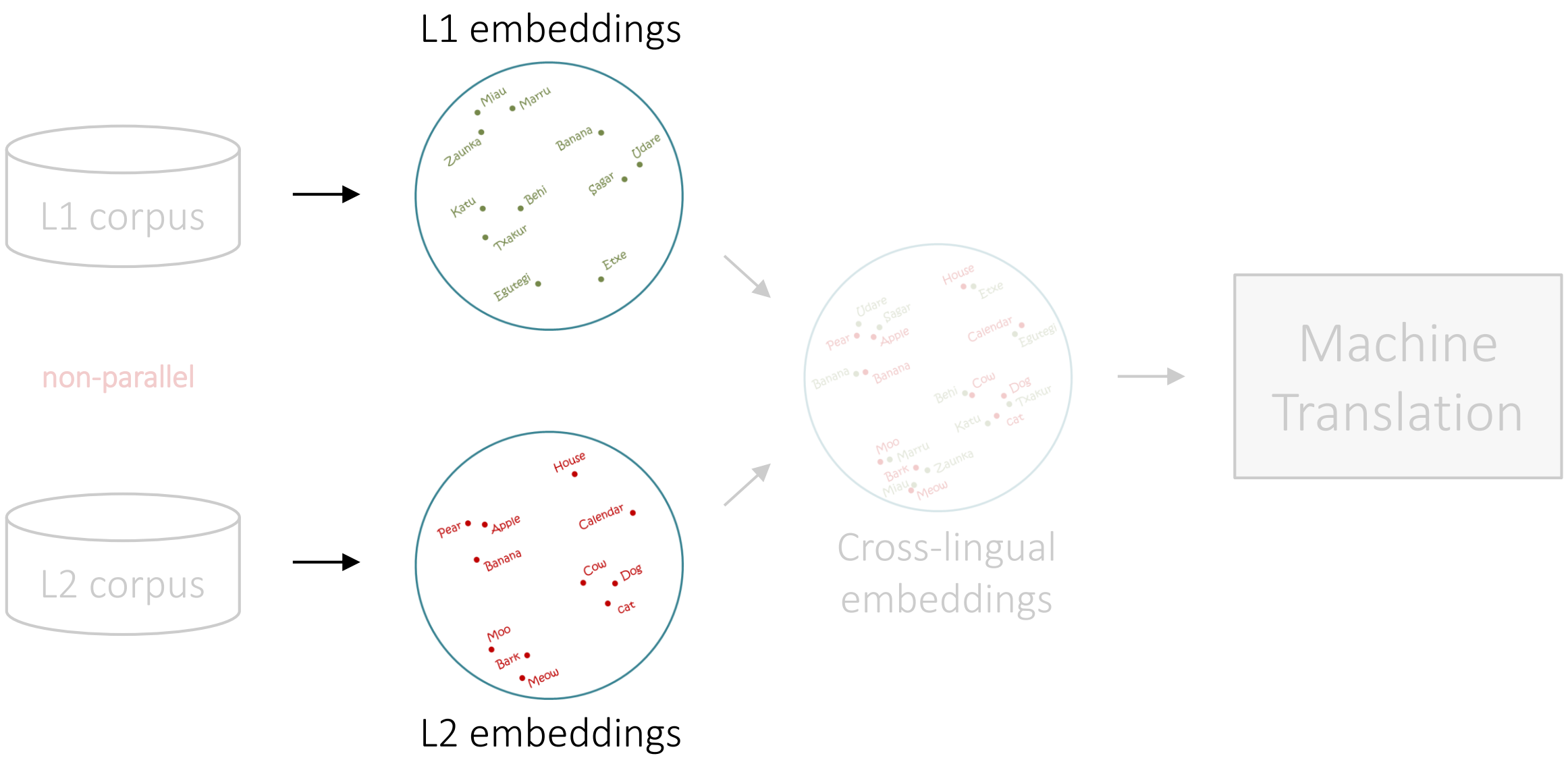
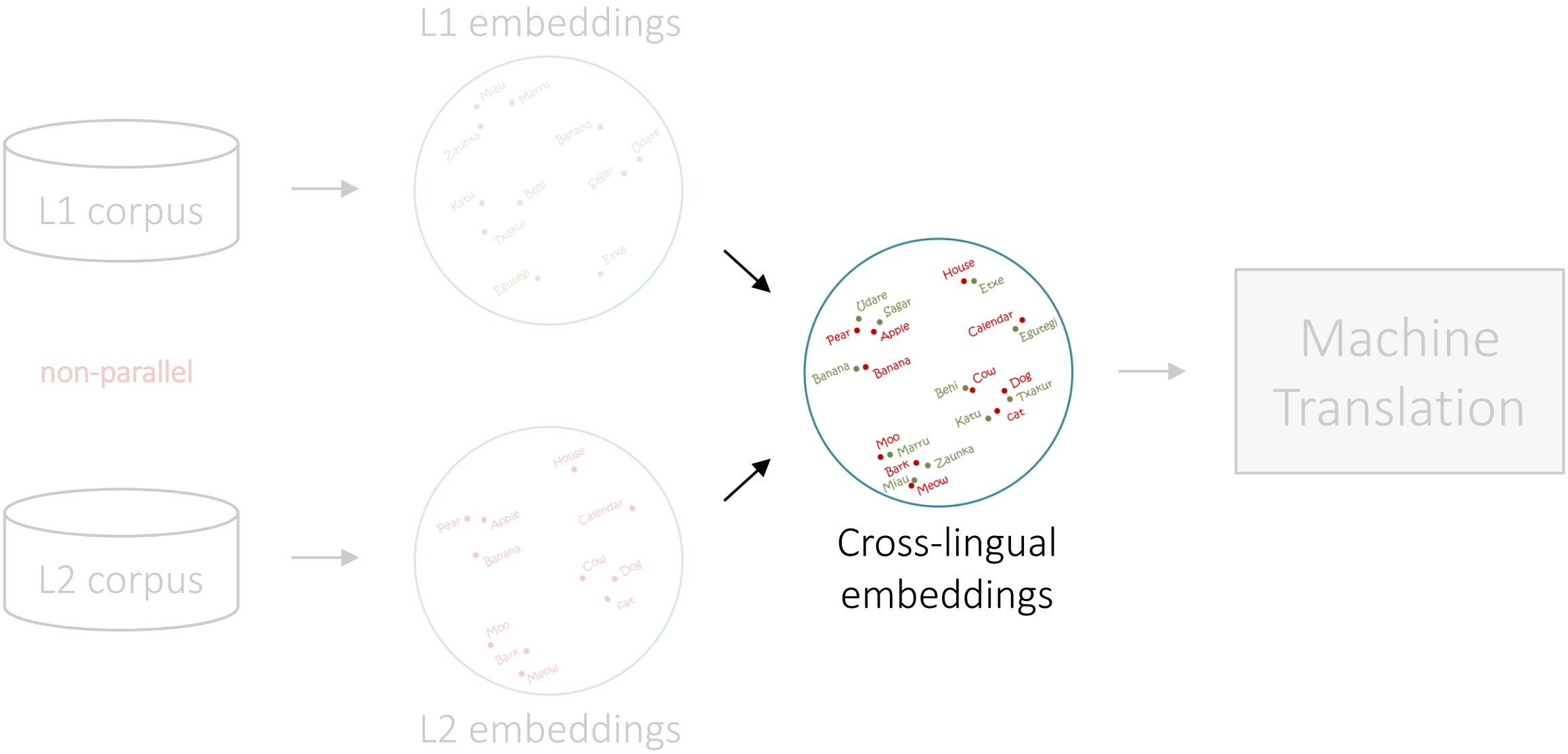


Outline


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

Outline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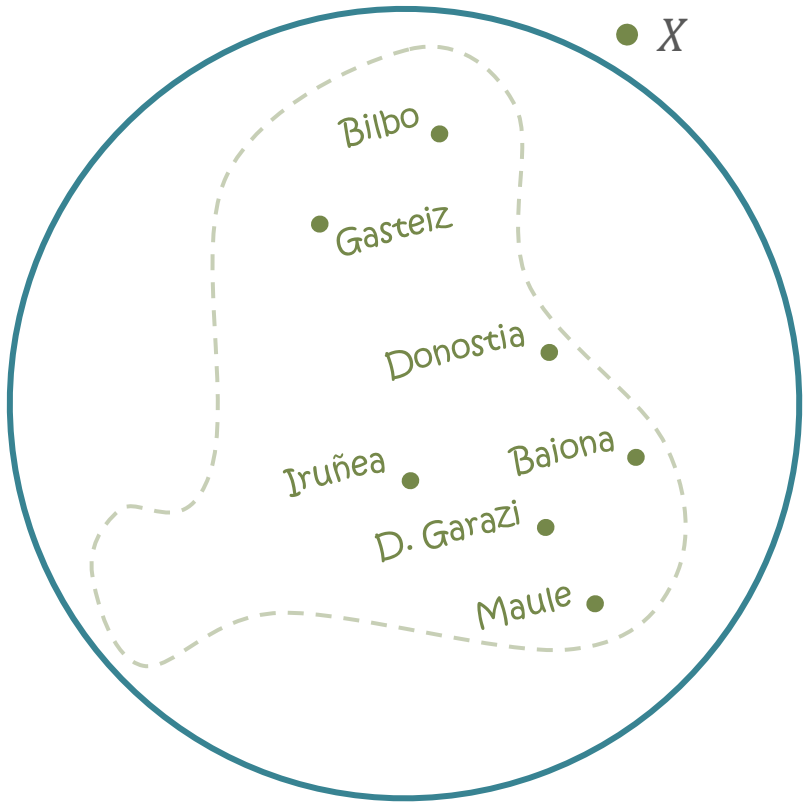
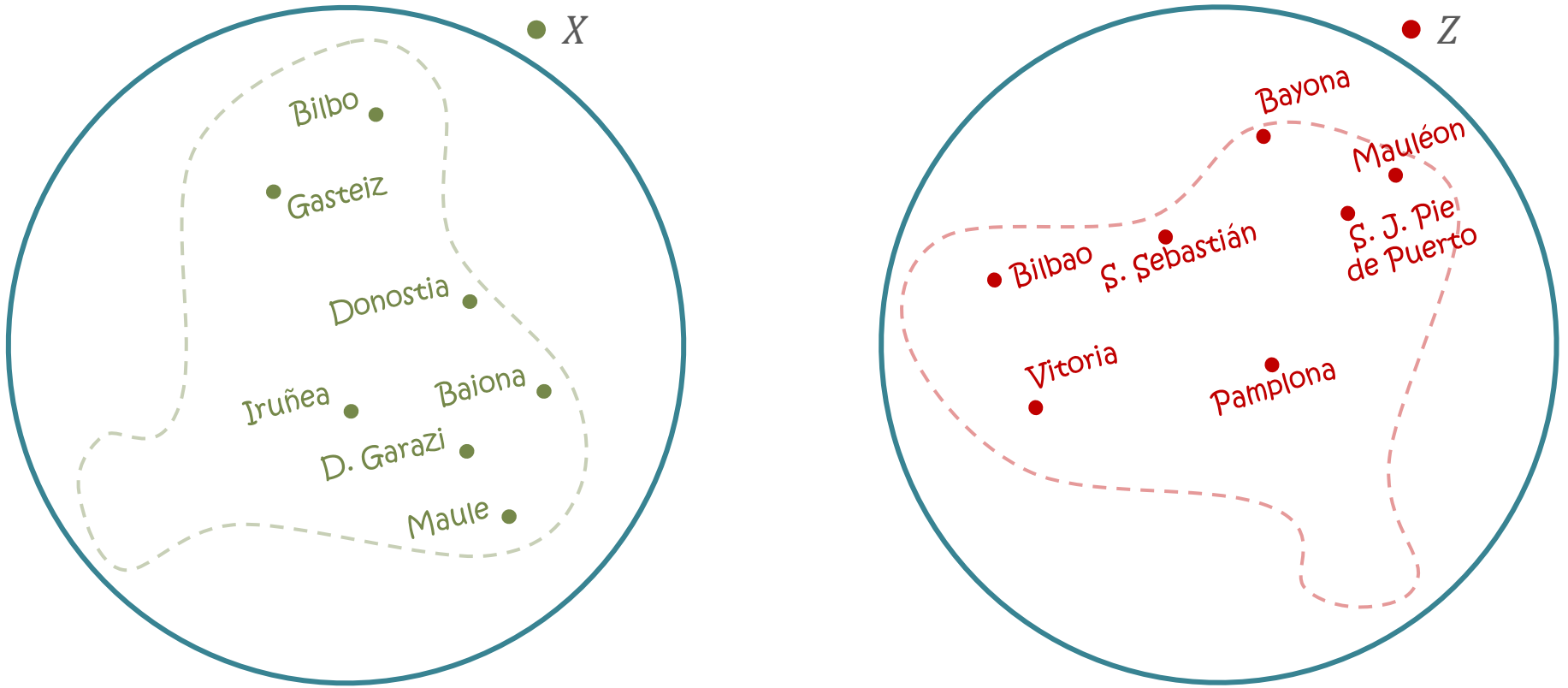
Cross-lingual embedding mappings

Cross-lingual embedding mappings



Cross-lingual embedding mappings



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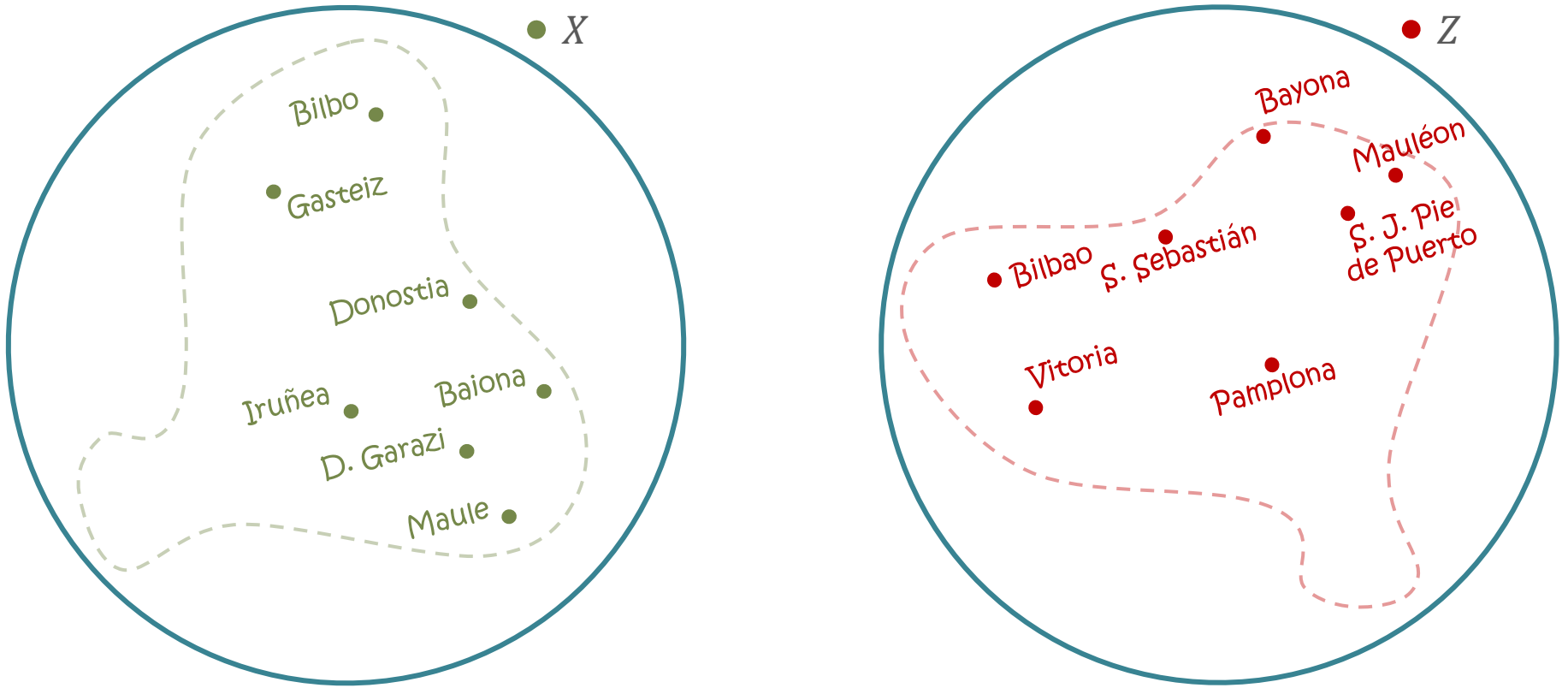
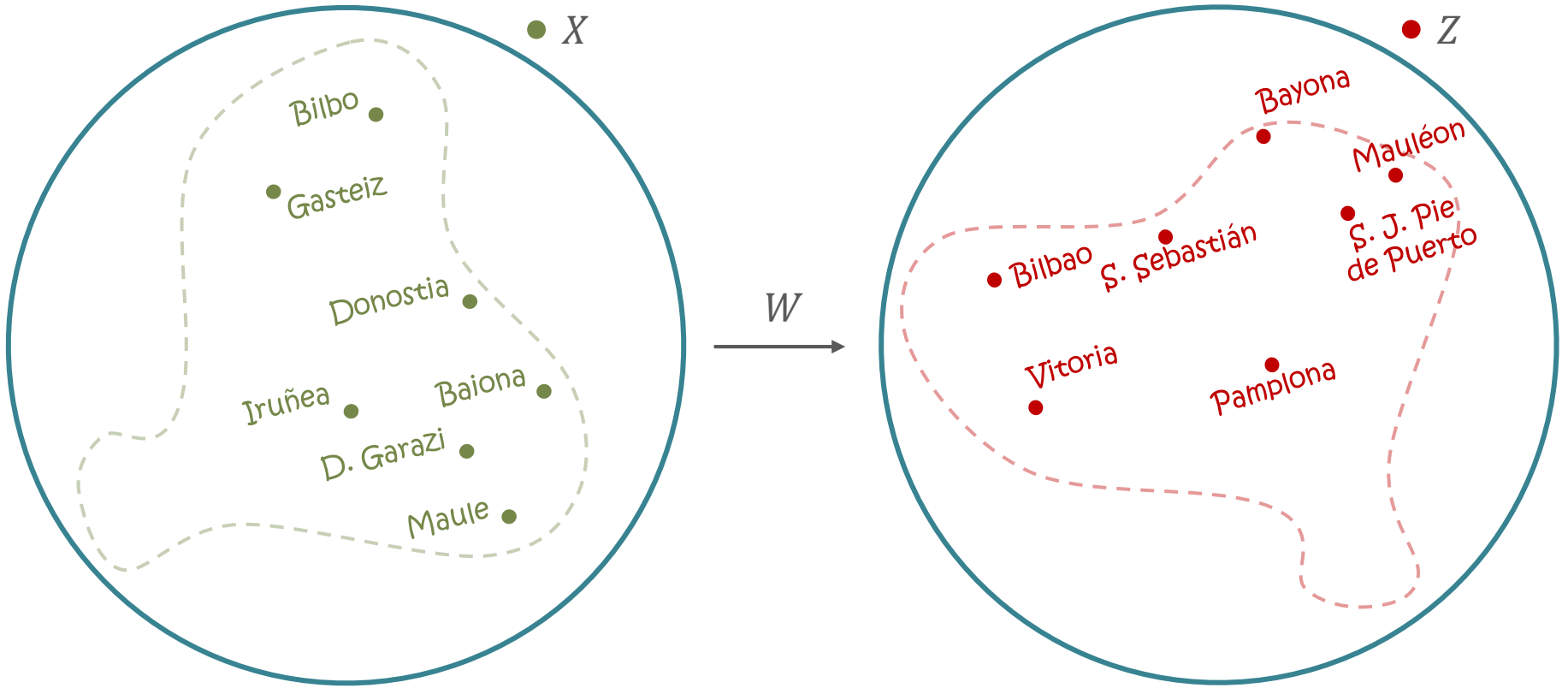


Bilbo	Bilbao
Baiona	Bayona
Iruñea	Pamplona

Cross-lingual embedding mappings



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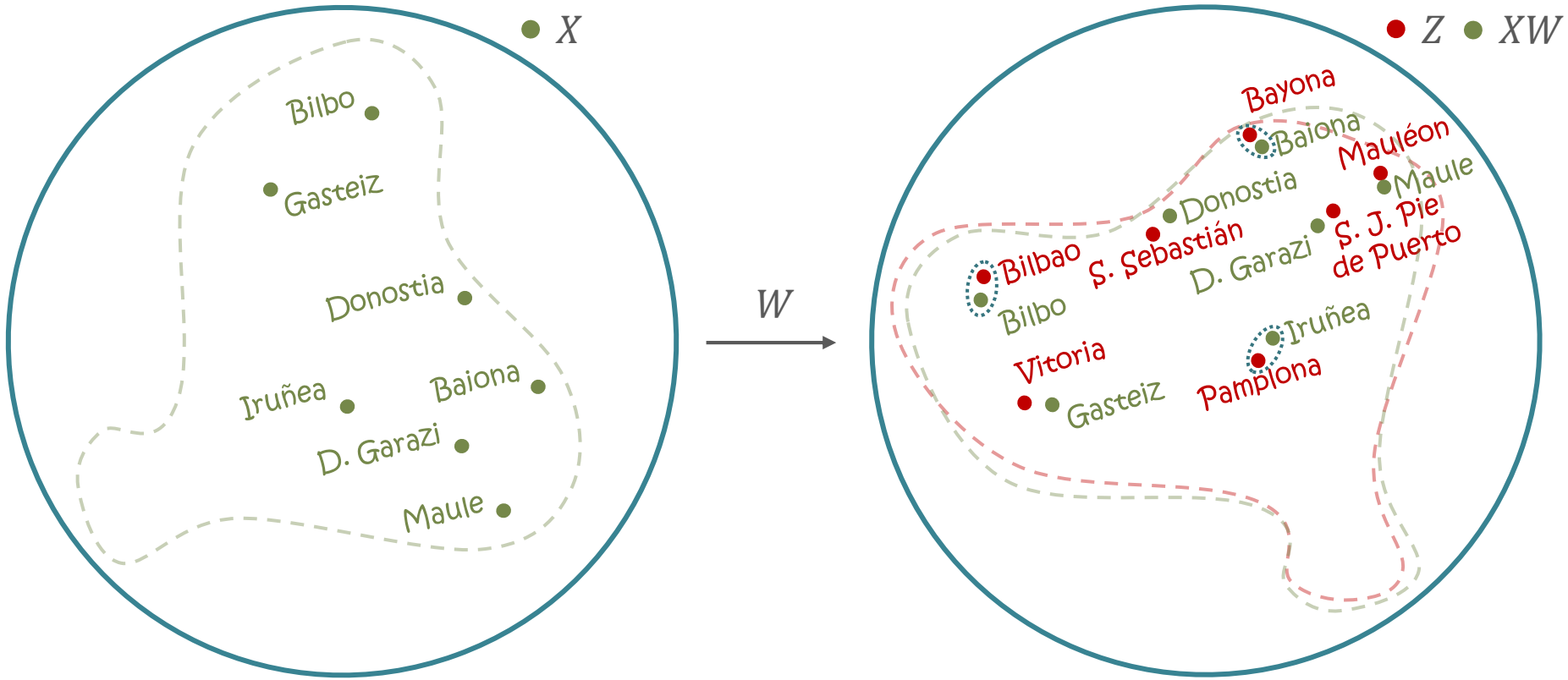

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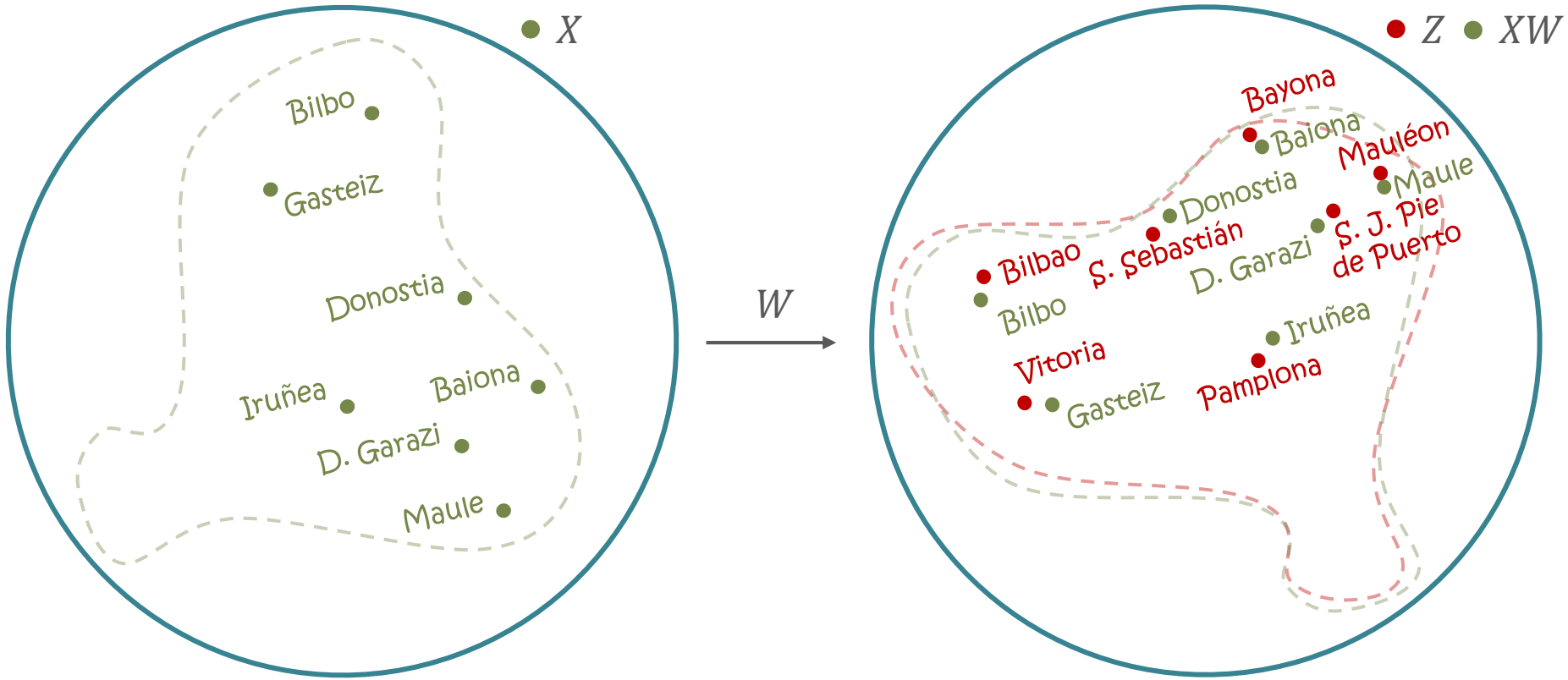

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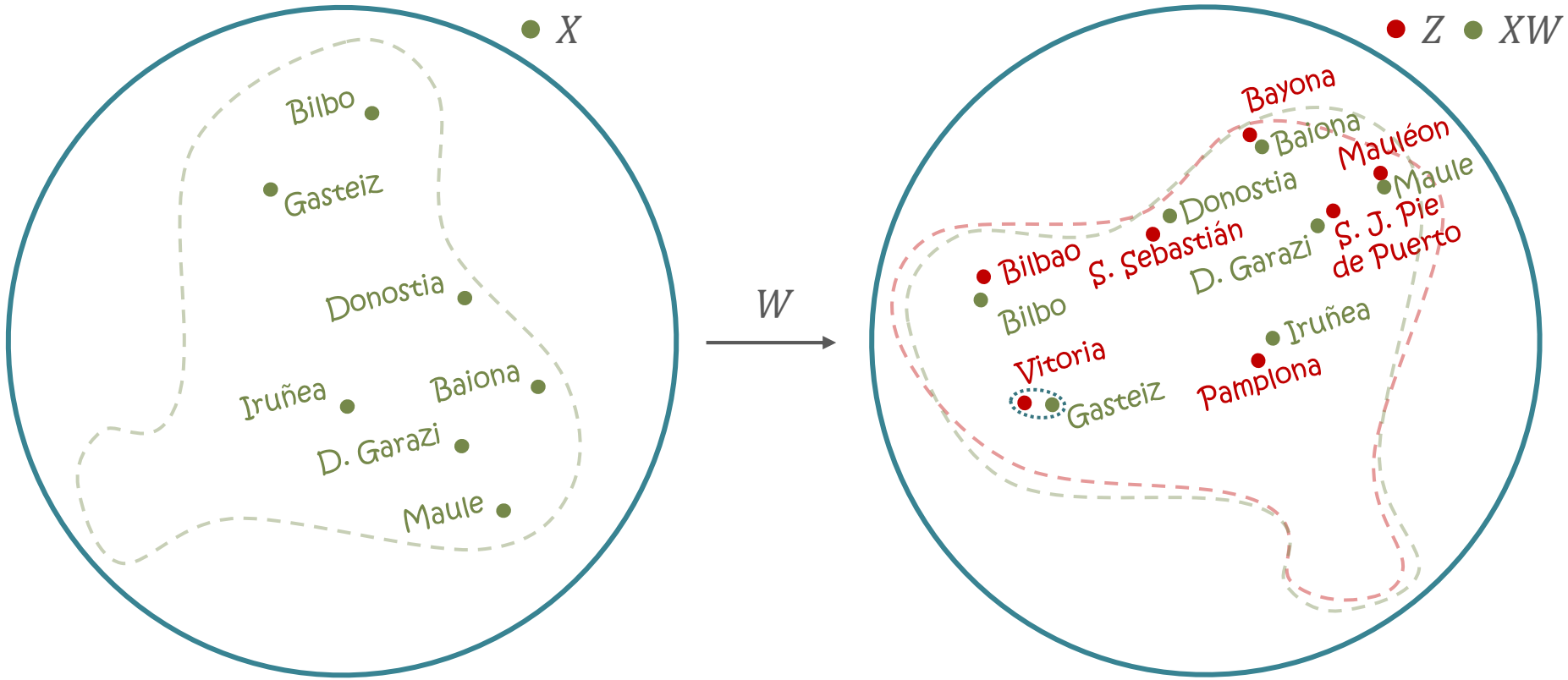

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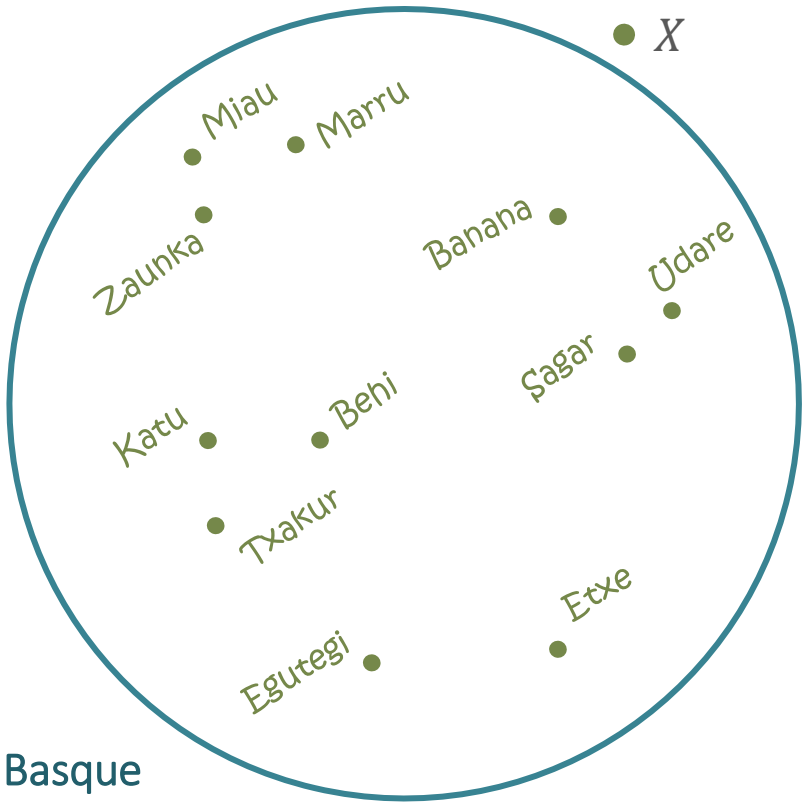
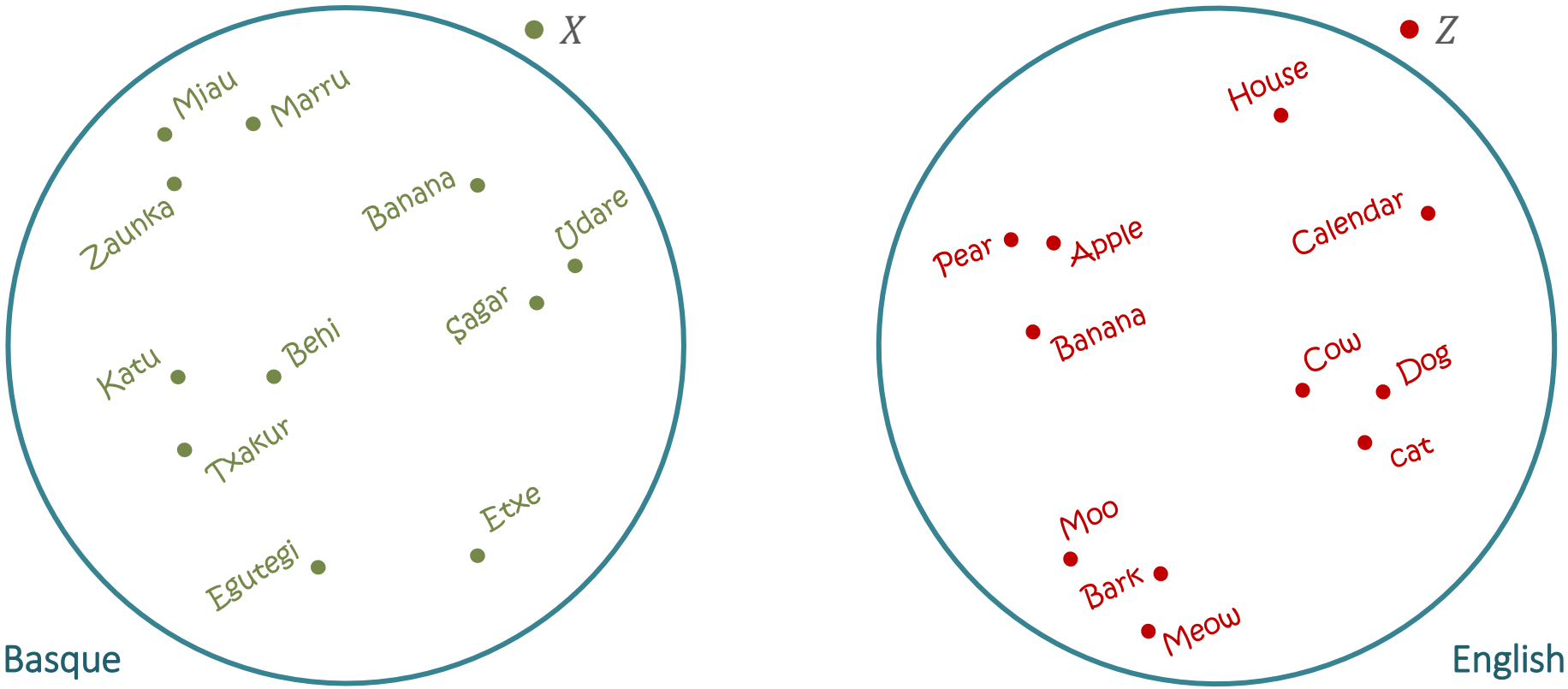
Iruñea	Pamplona

Cross-lingual embedding mappings

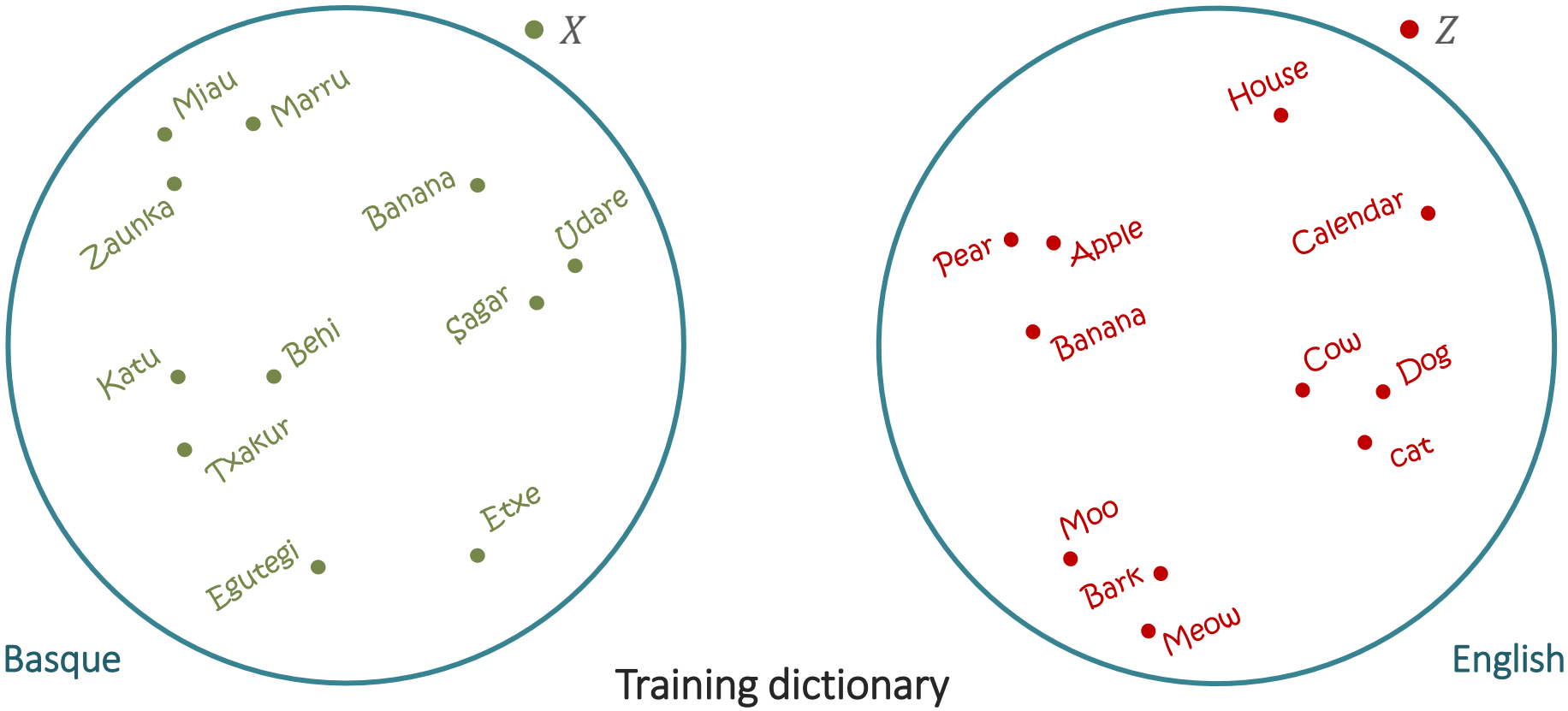
Cross-lingual embedding mappings



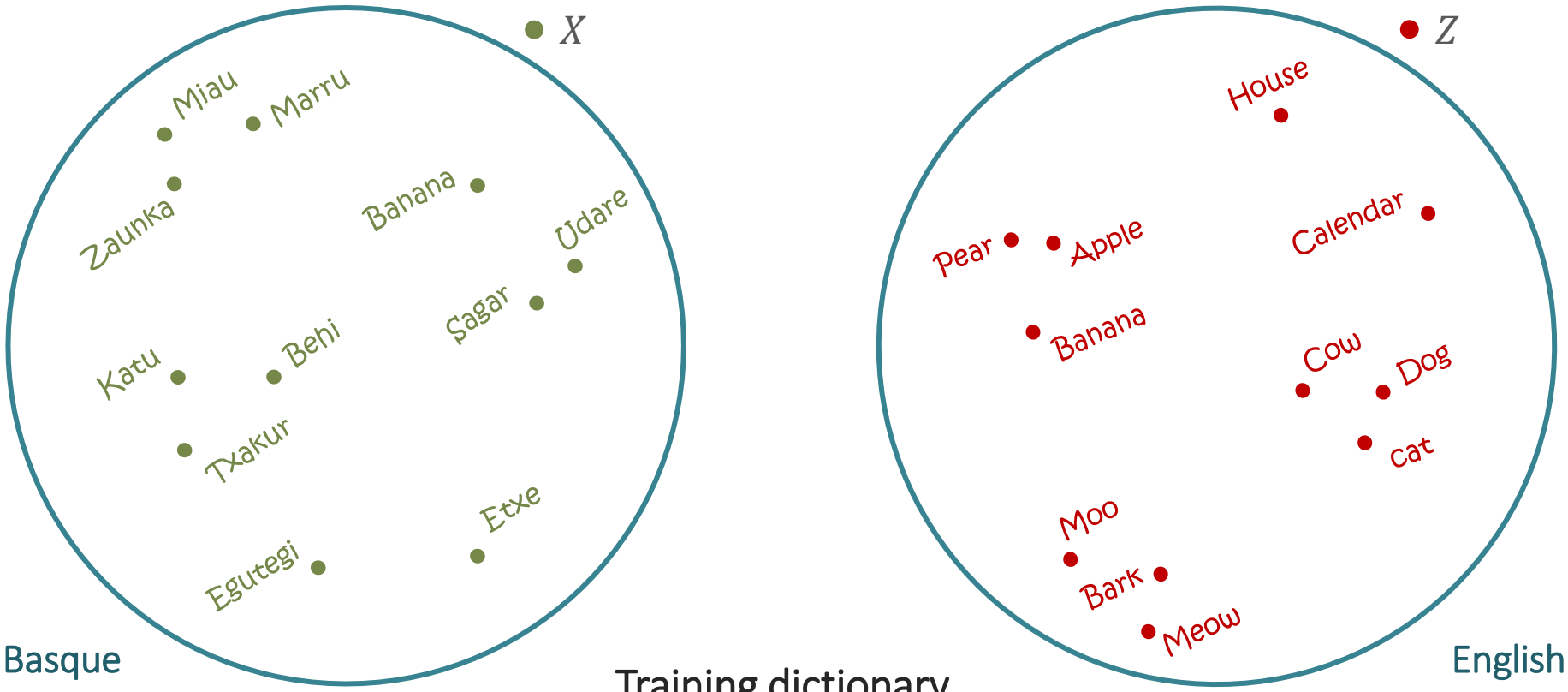
Cross-lingual embedding mappings



Cross-lingual embedding mappings



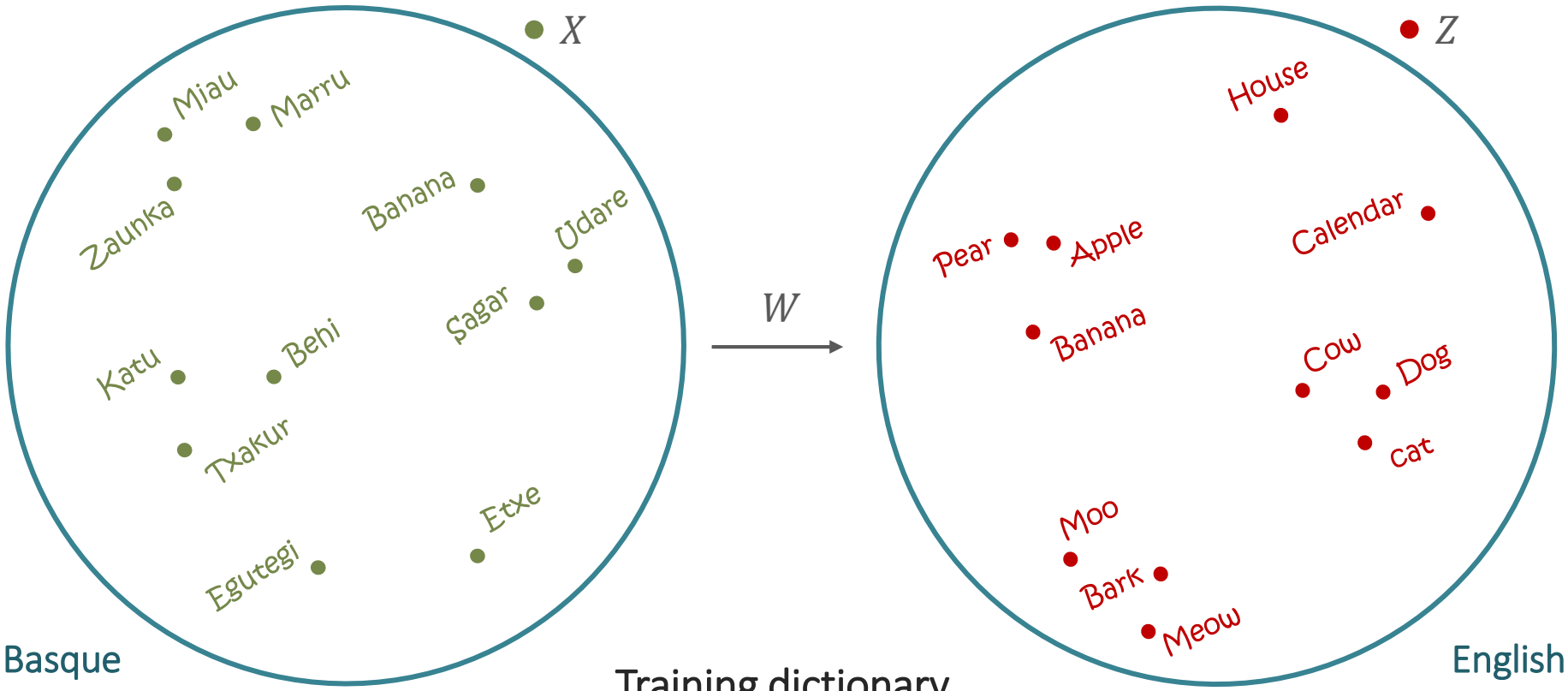
Cross-lingual embedding mappings



Training dictionary

Txakur	Dog
Sagar	Apple
⋮	⋮
Egutegi	Calendar

Cross-lingual embedding mappings



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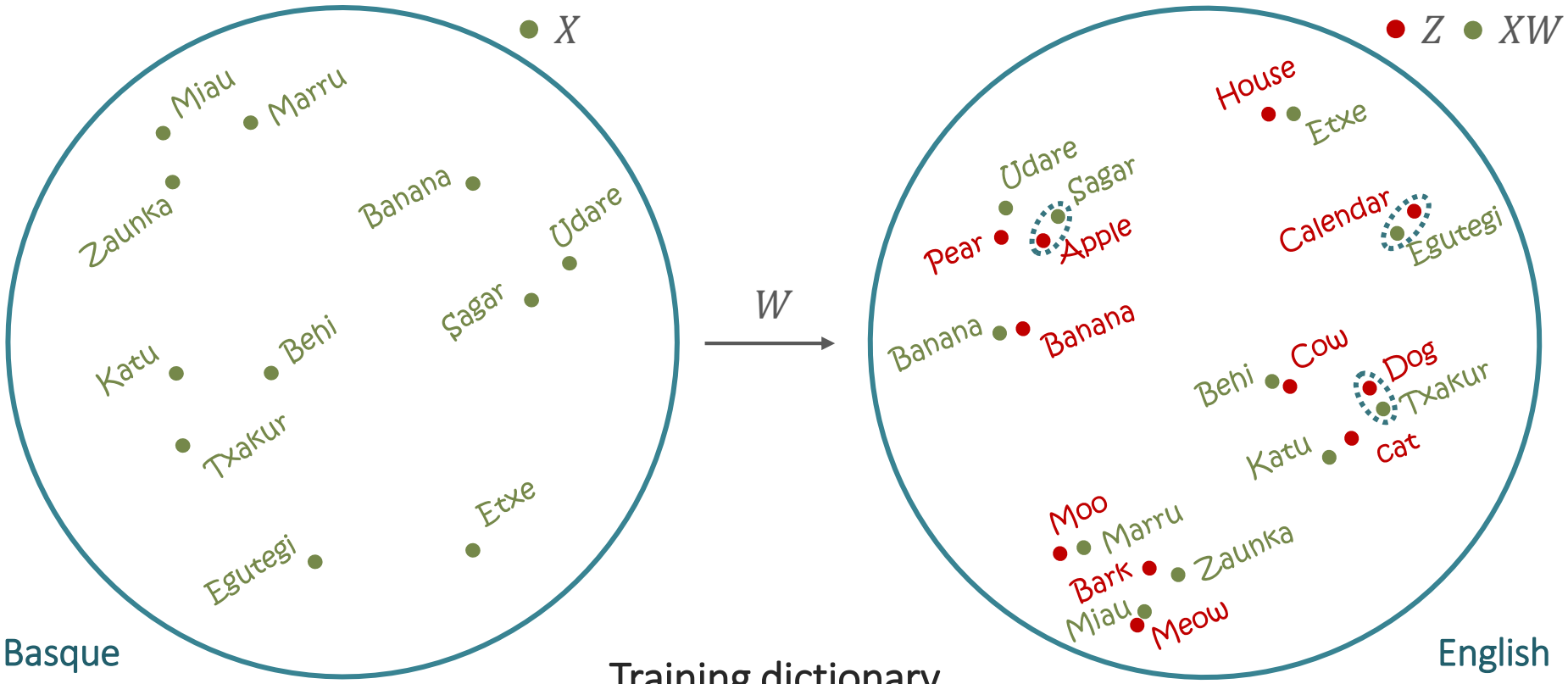

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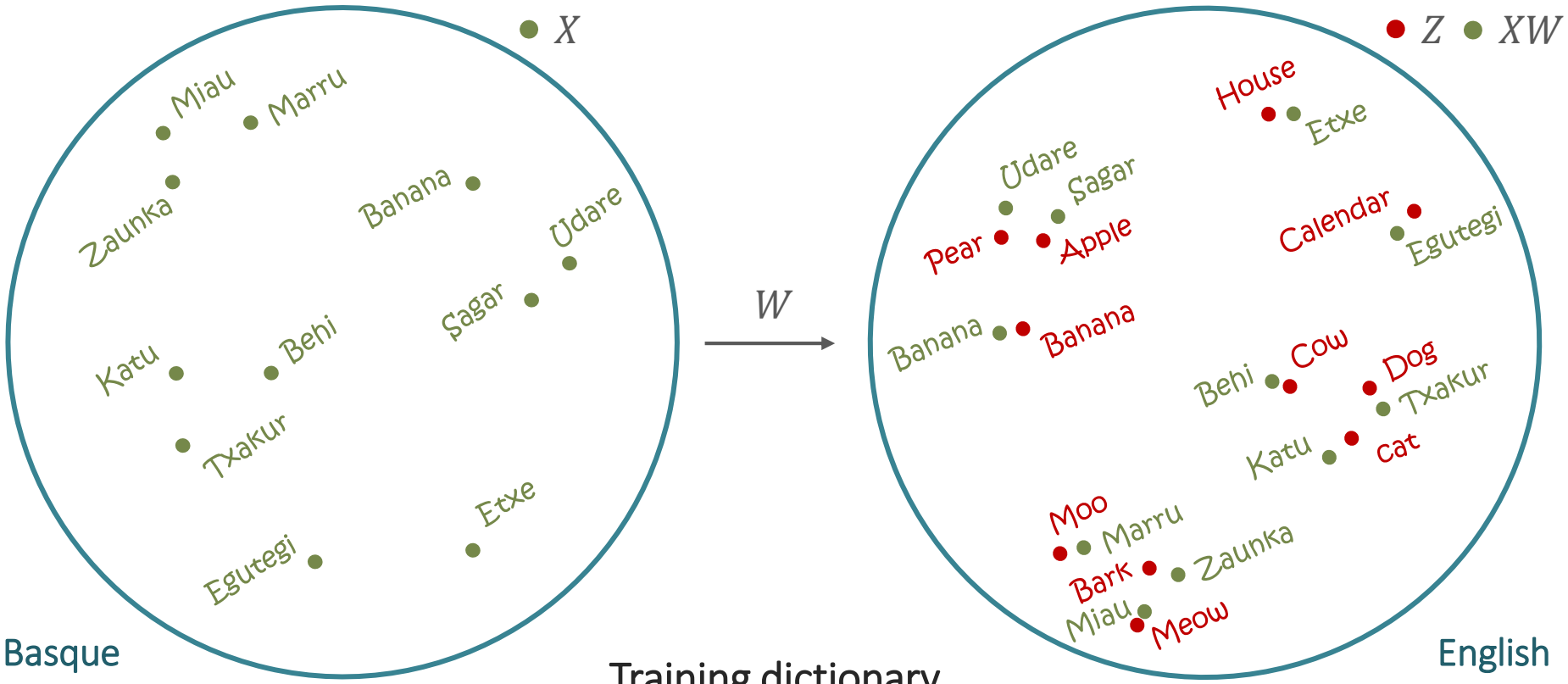

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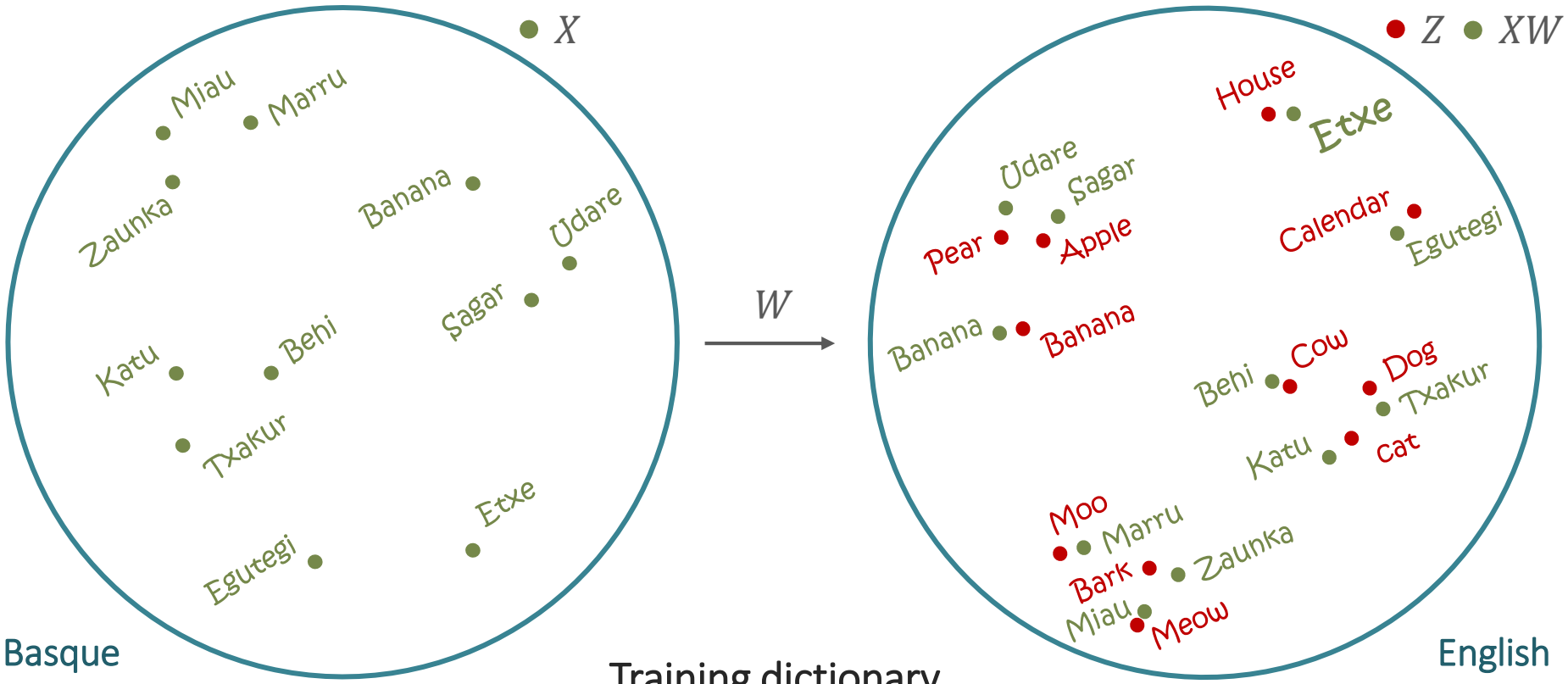
Cross-lingual embedding mappings



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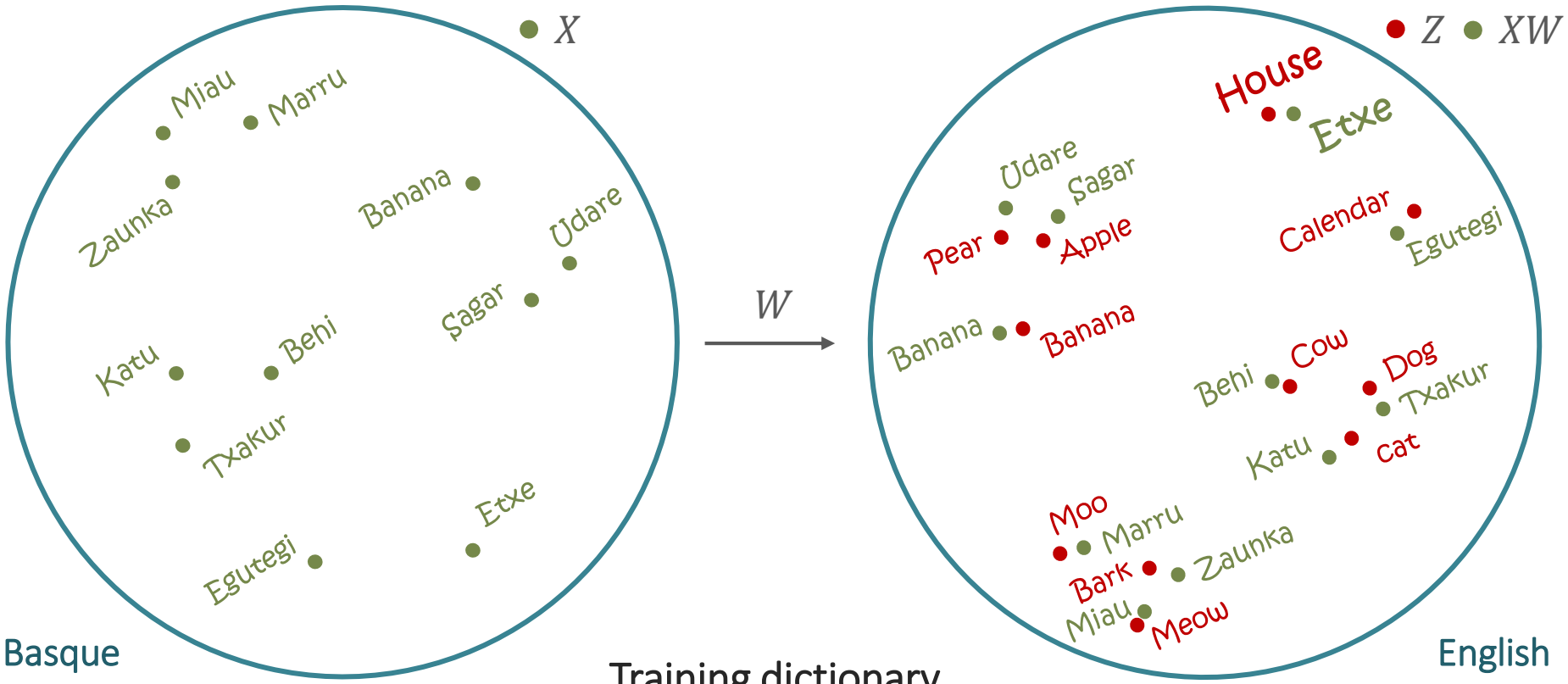
Cross-lingual embedding mappings



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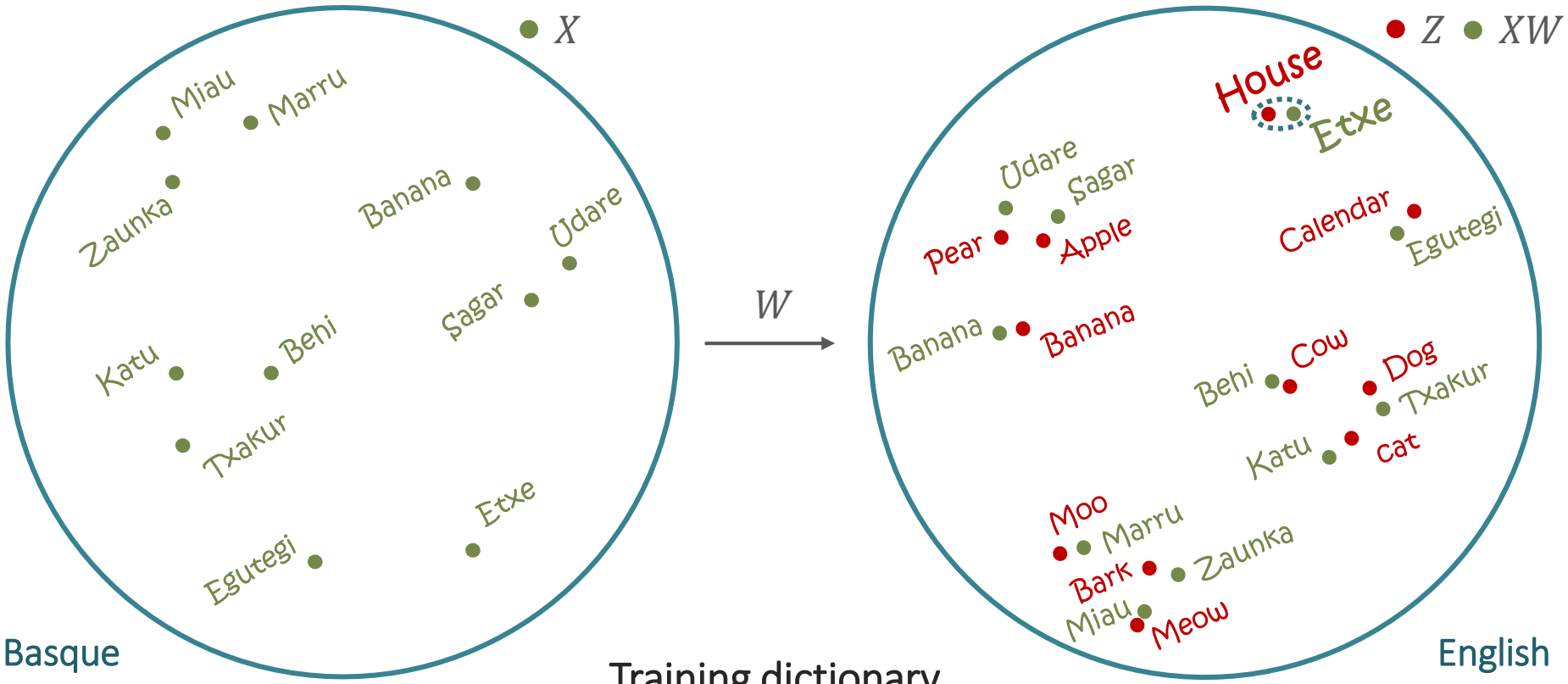
Cross-lingual embedding mappings



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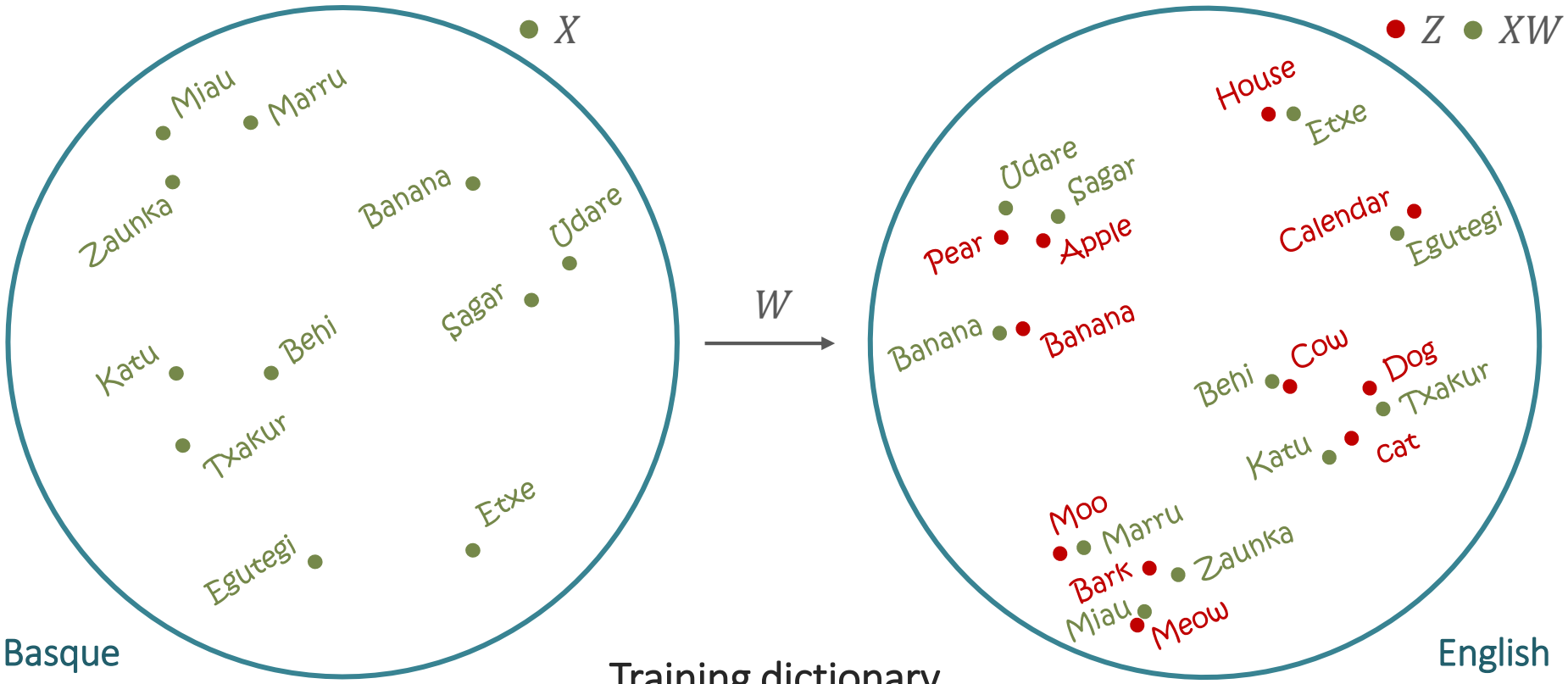
Cross-lingual embedding mappings



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Txakur	Dog
Sagar	Apple
⋮	⋮
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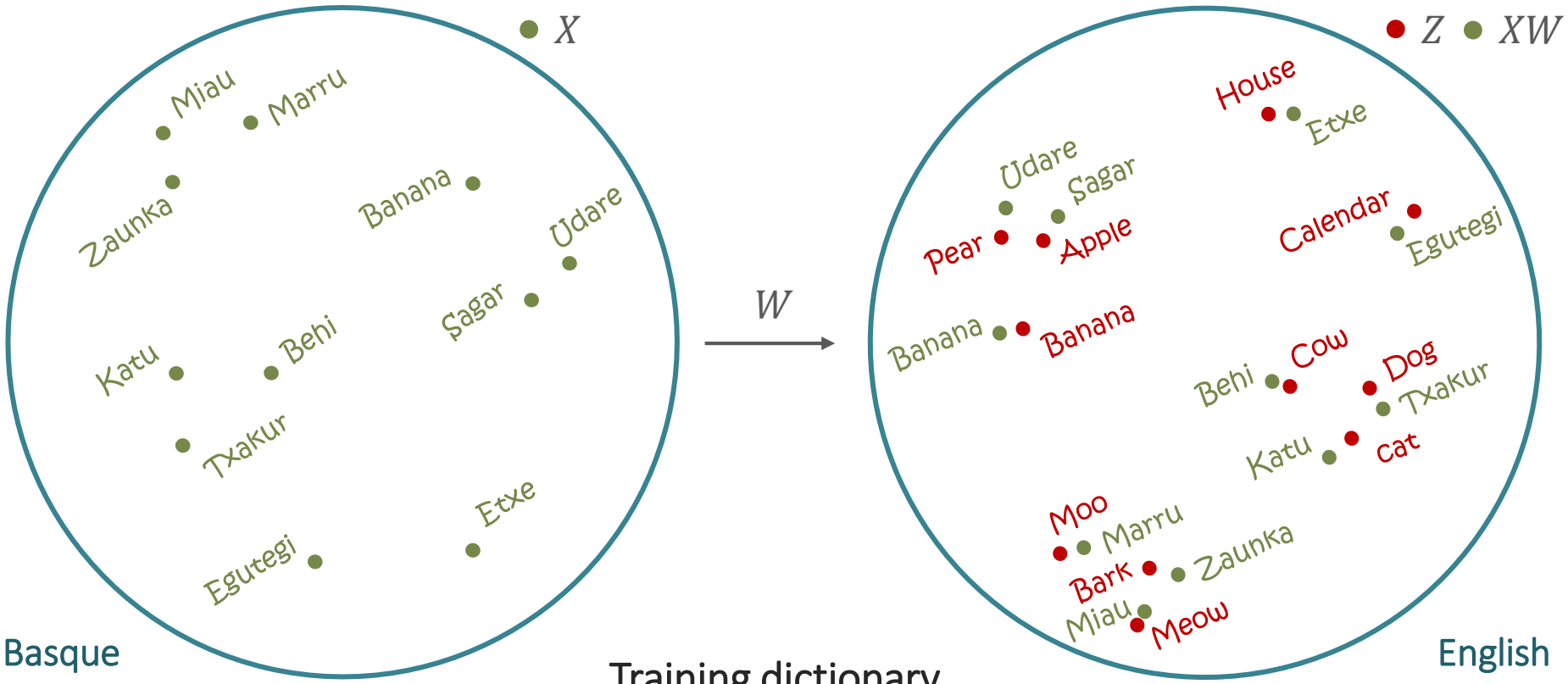
Cross-lingual embedding mappings



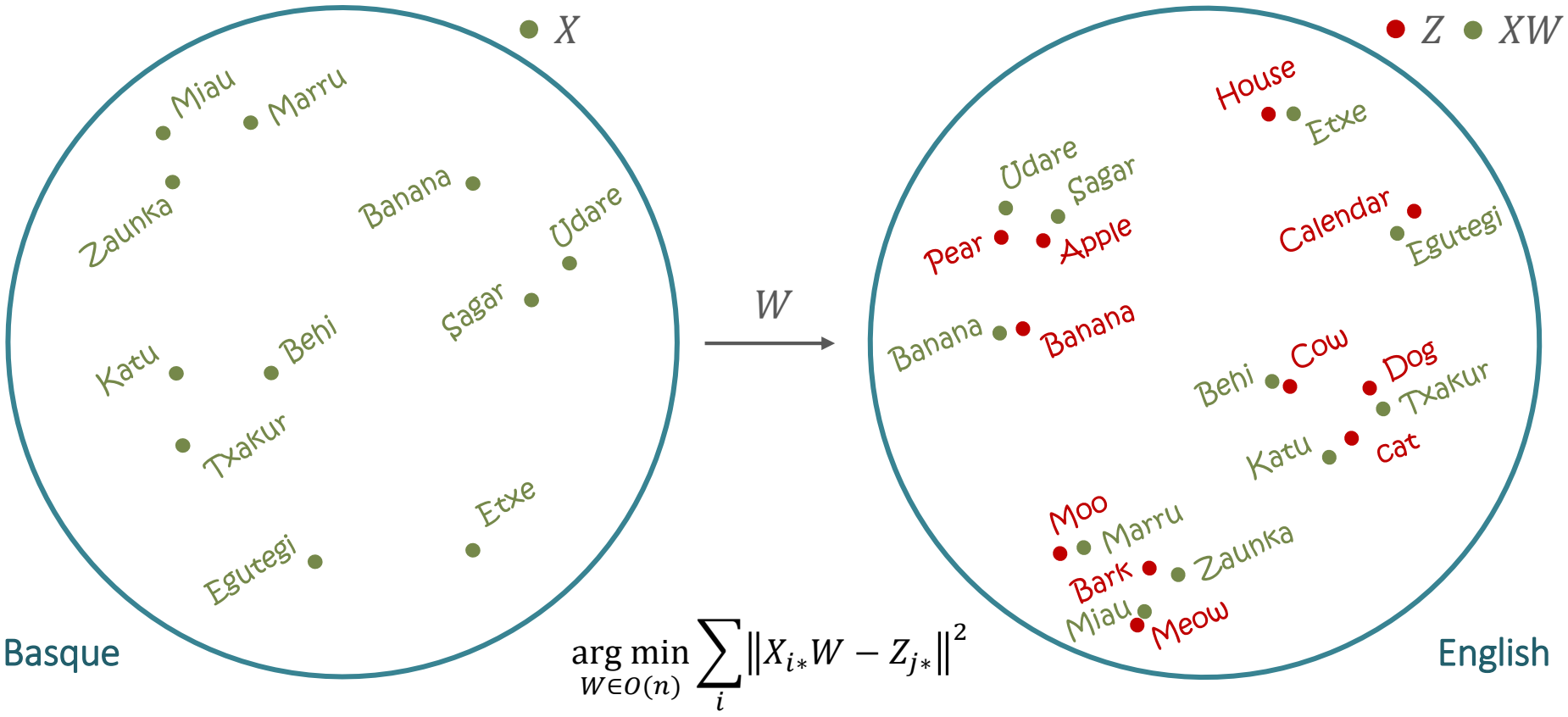
Training dictionary

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

Cross-lingual embedding mappings

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

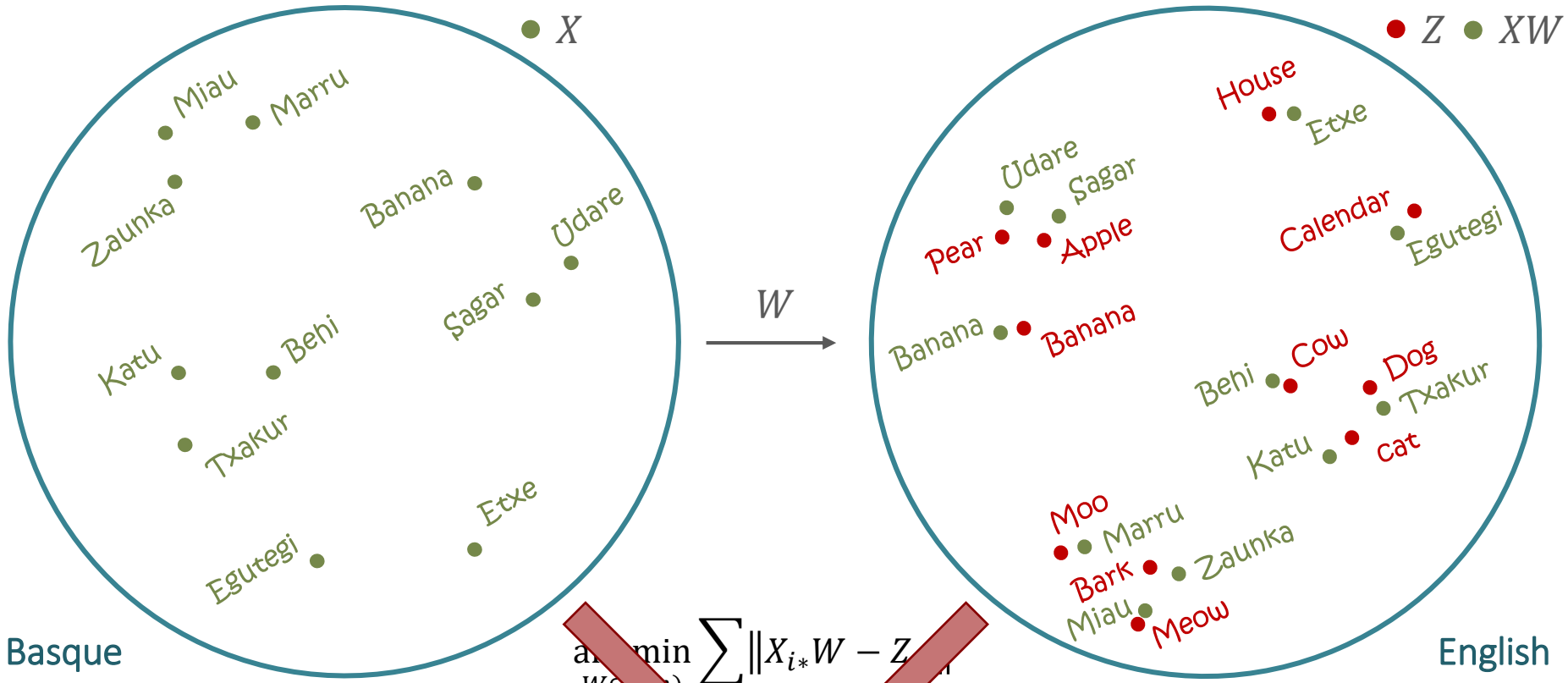
Cross-lingual embedding mappings



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

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

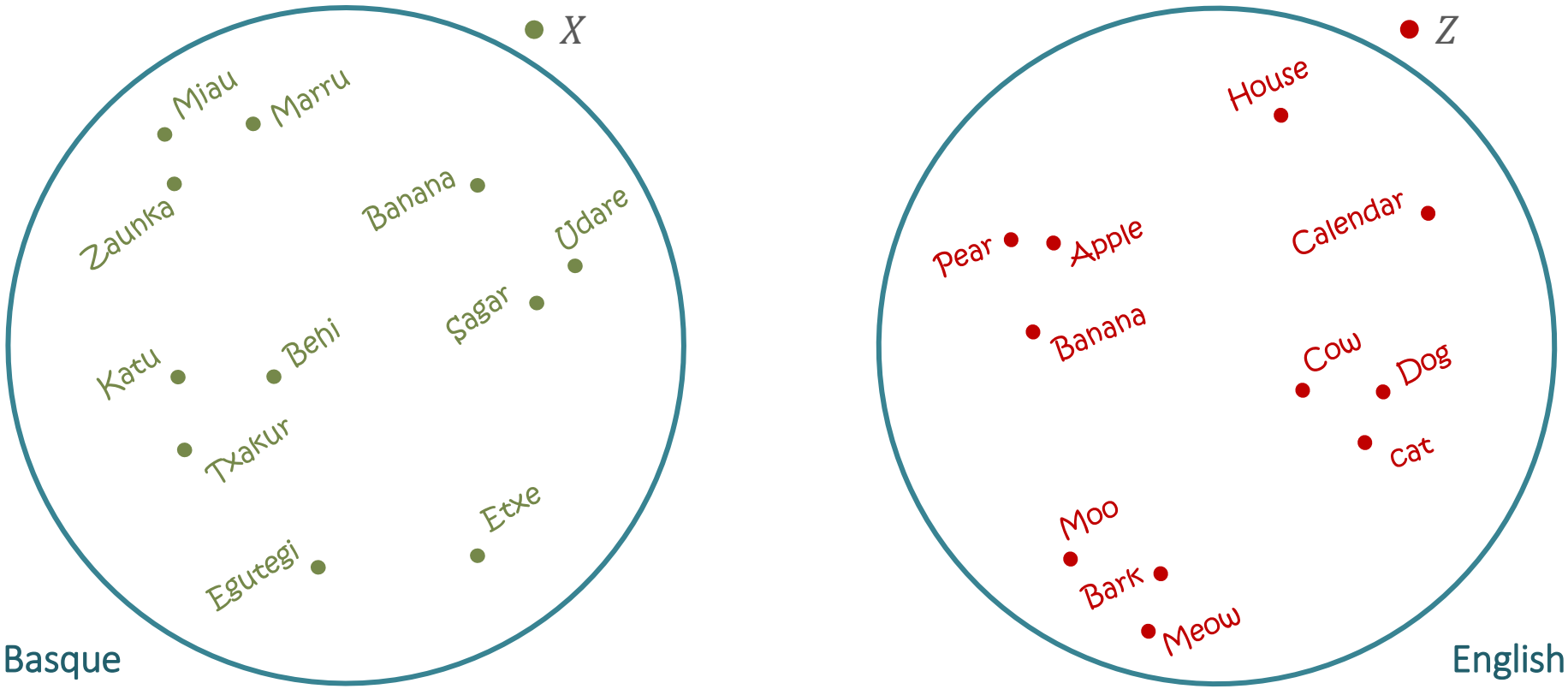
Cross-lingual embedding mappings



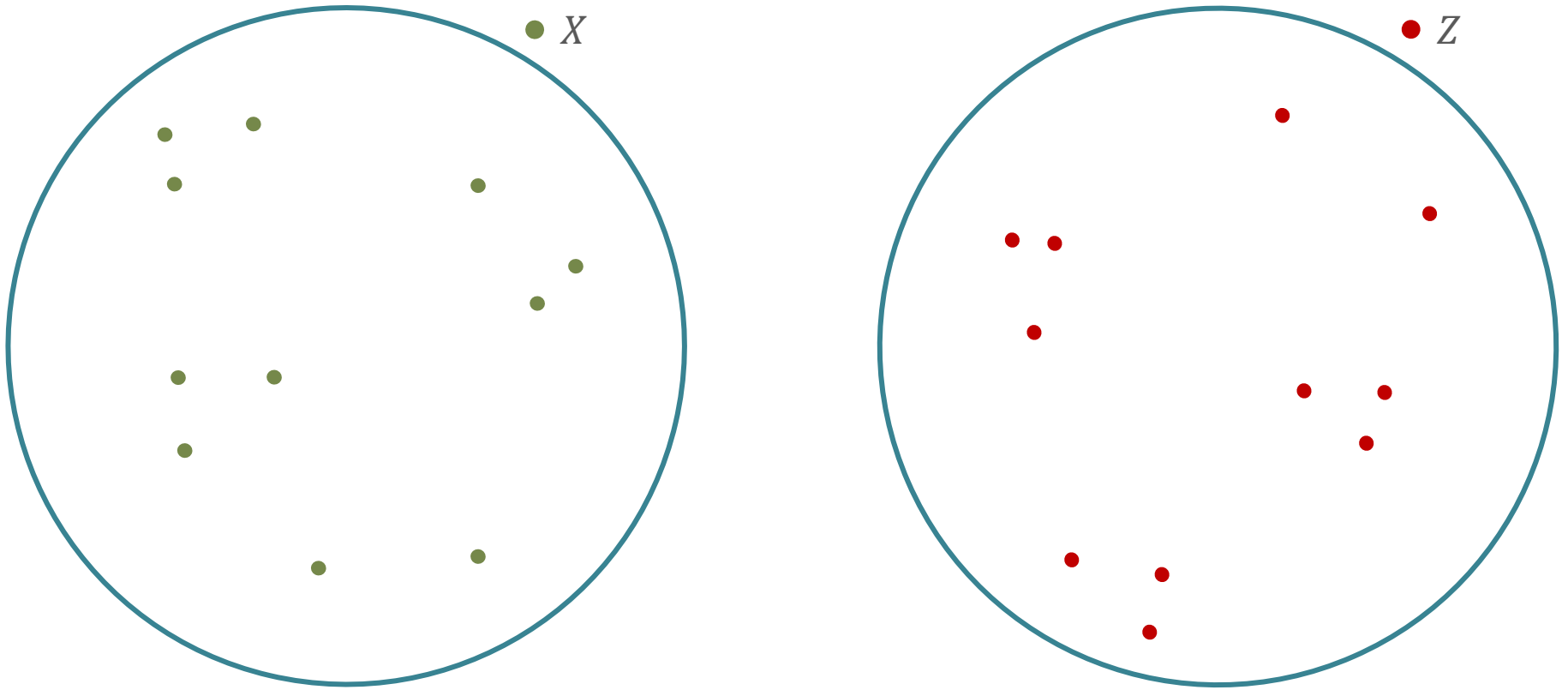
$$\min_{W} \sum_{i} \|X_{i*}W - Z_{i*}\|$$

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

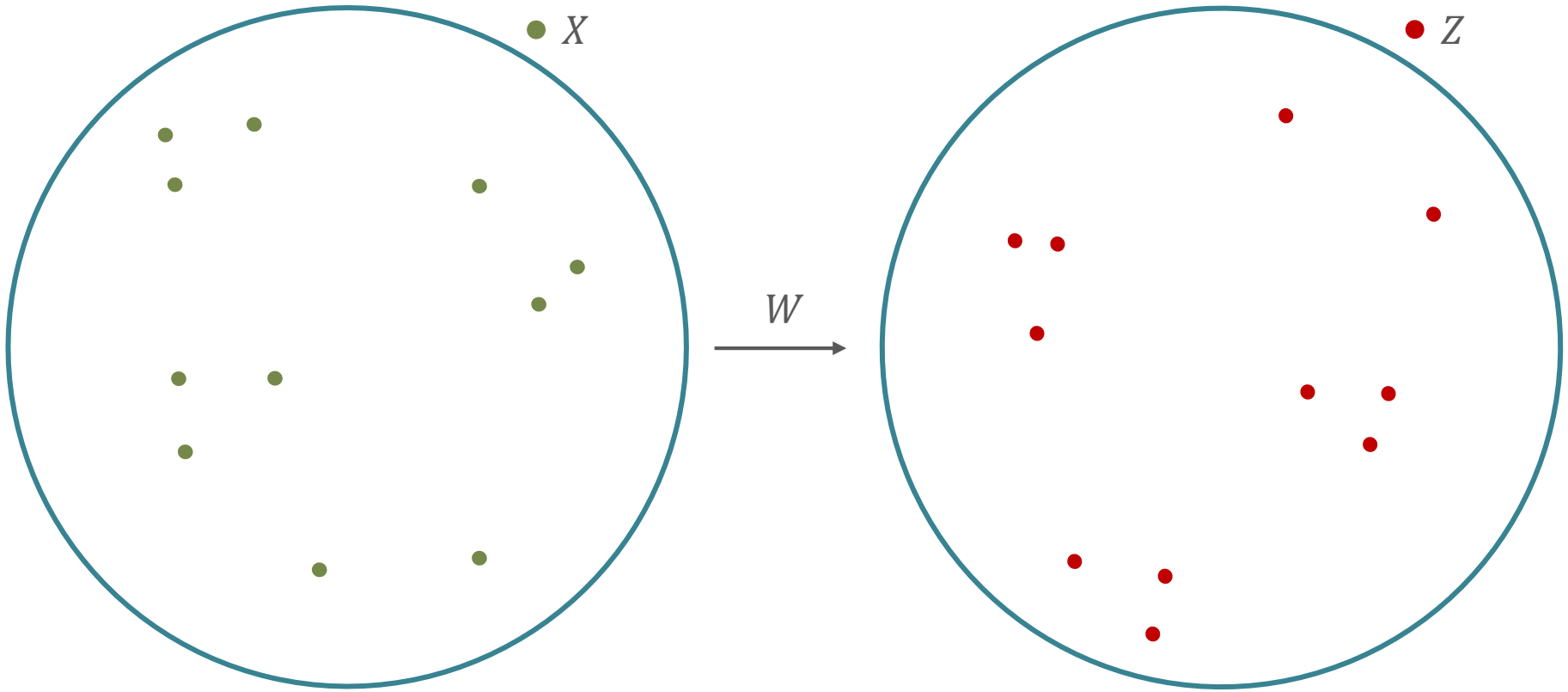
Cross-lingual embedding mappings



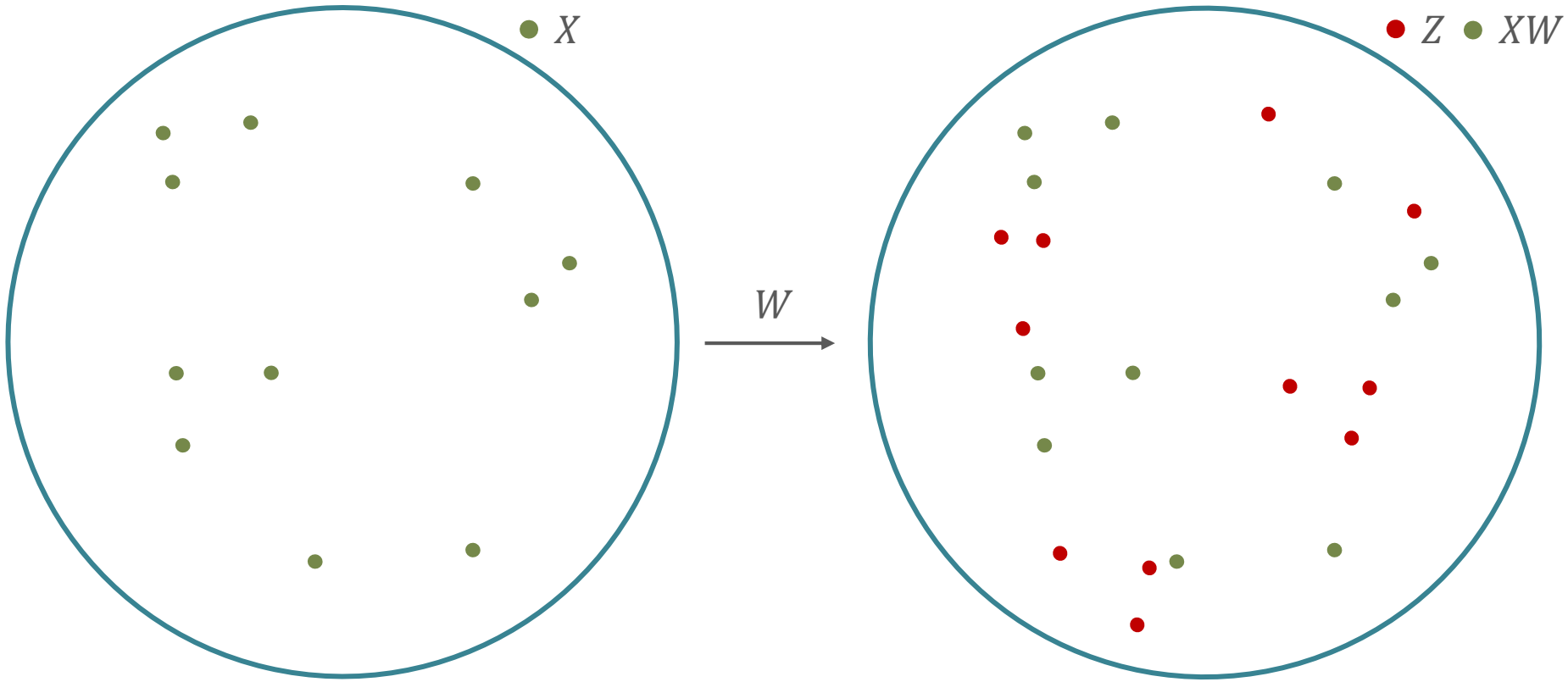
Cross-lingual embedding mappings



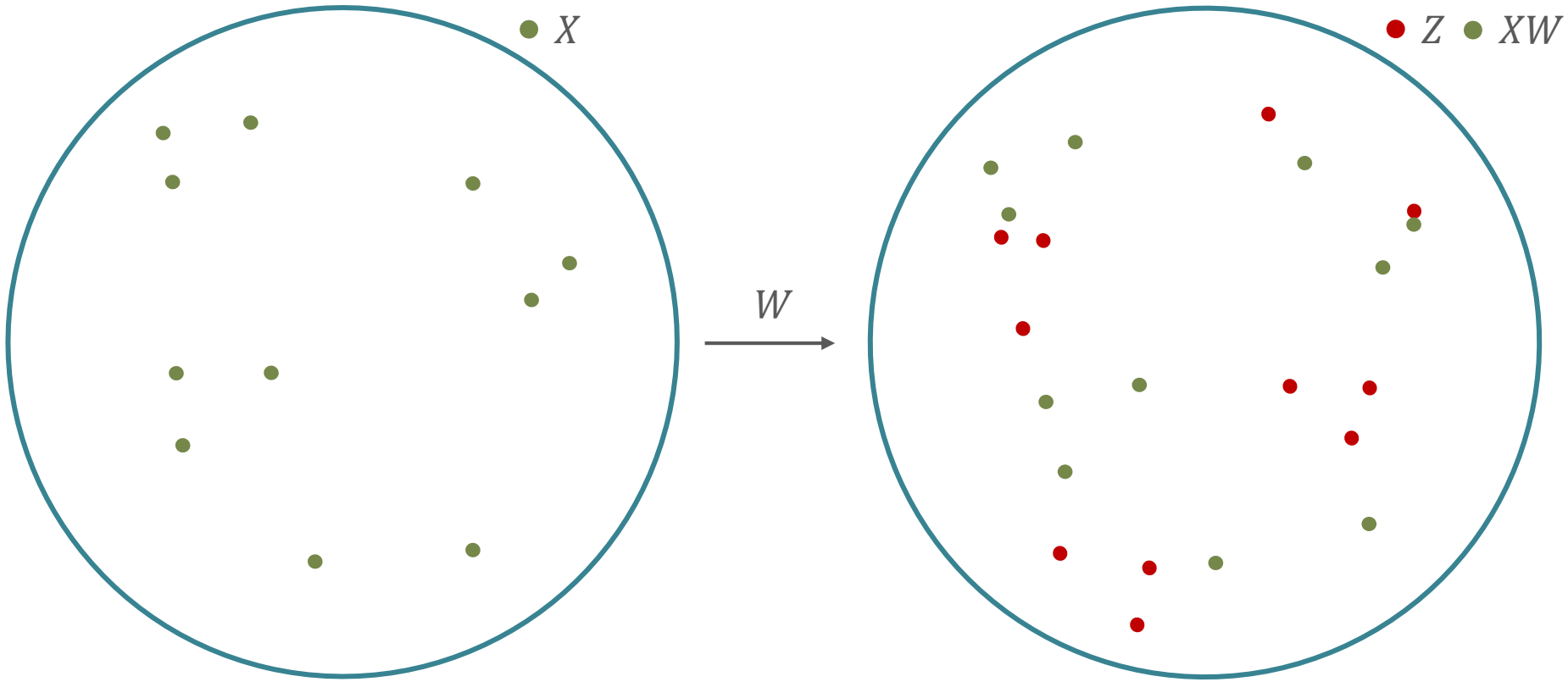
Cross-lingual embedding mappings



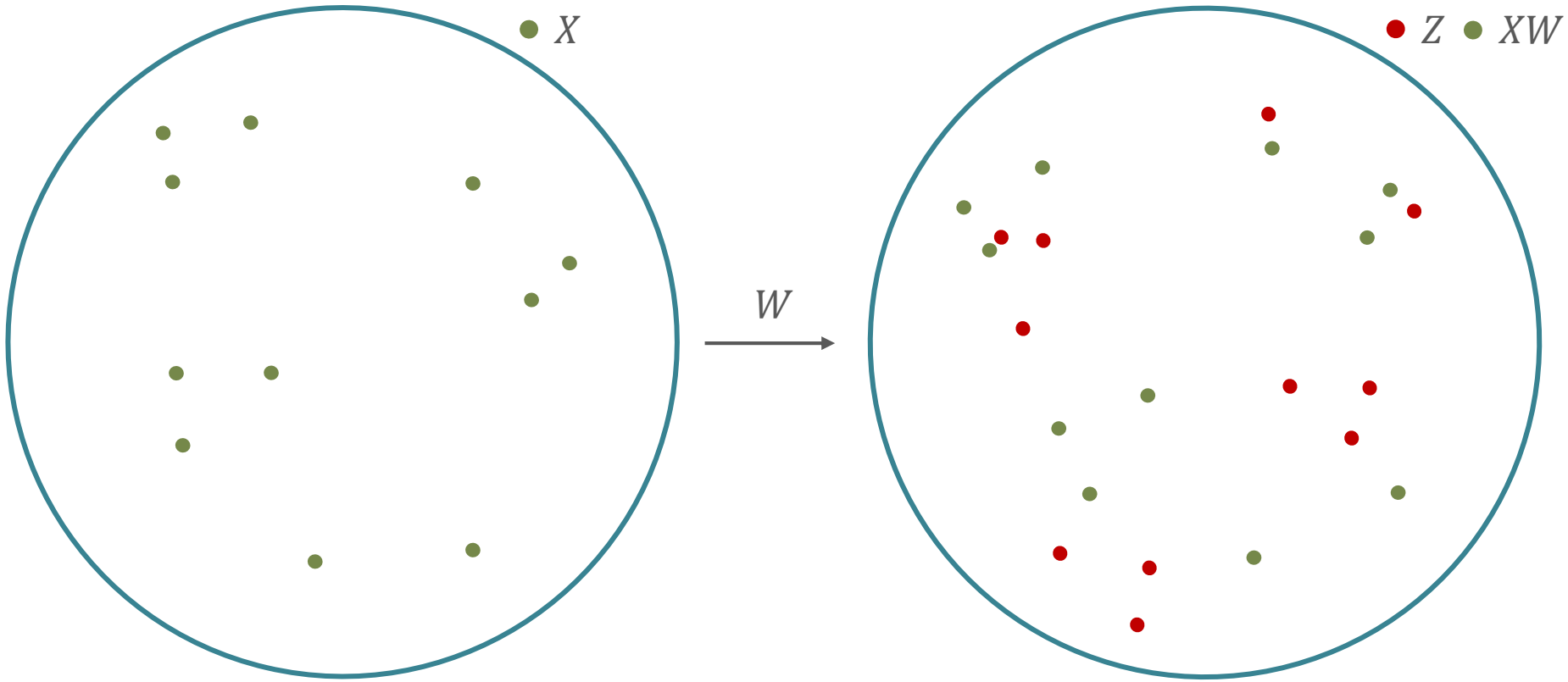
Cross-lingual embedding mappings



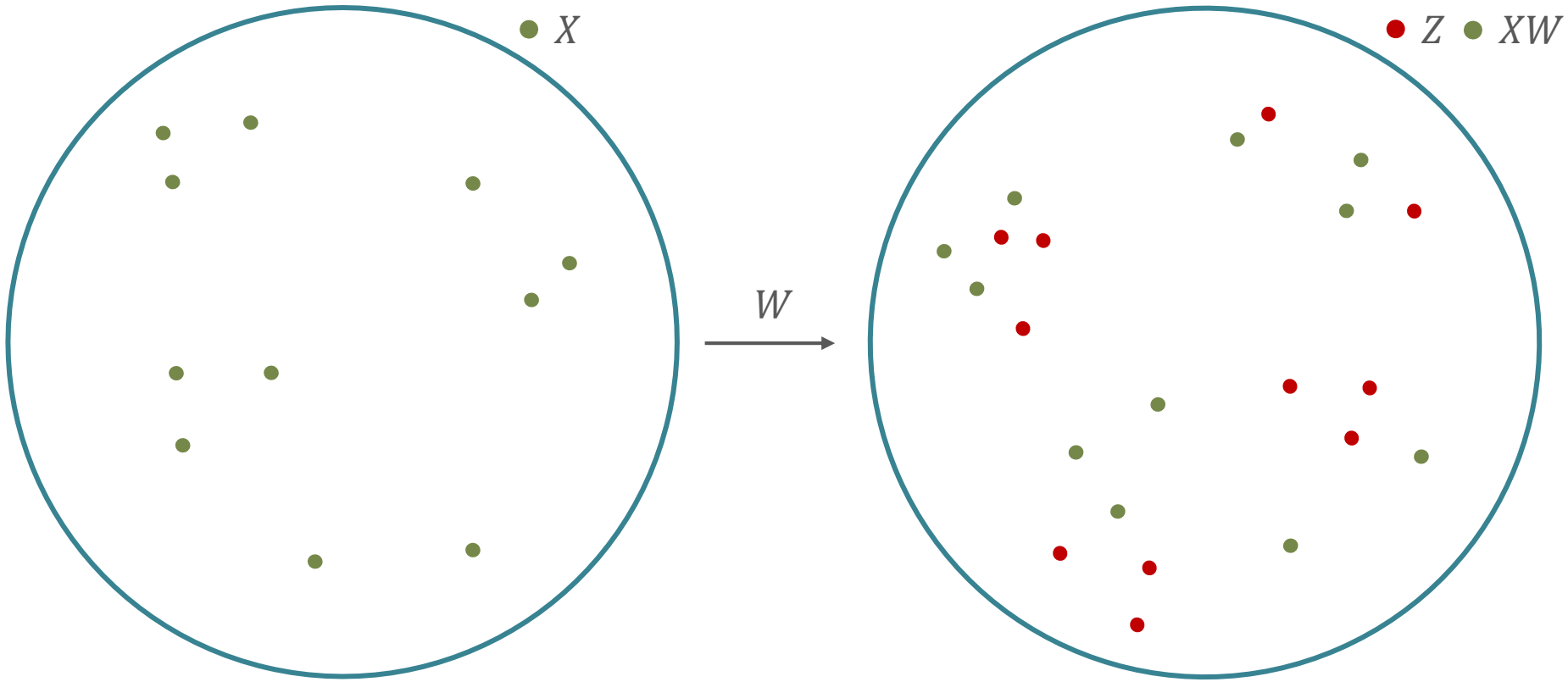
Cross-lingual embedding mappings



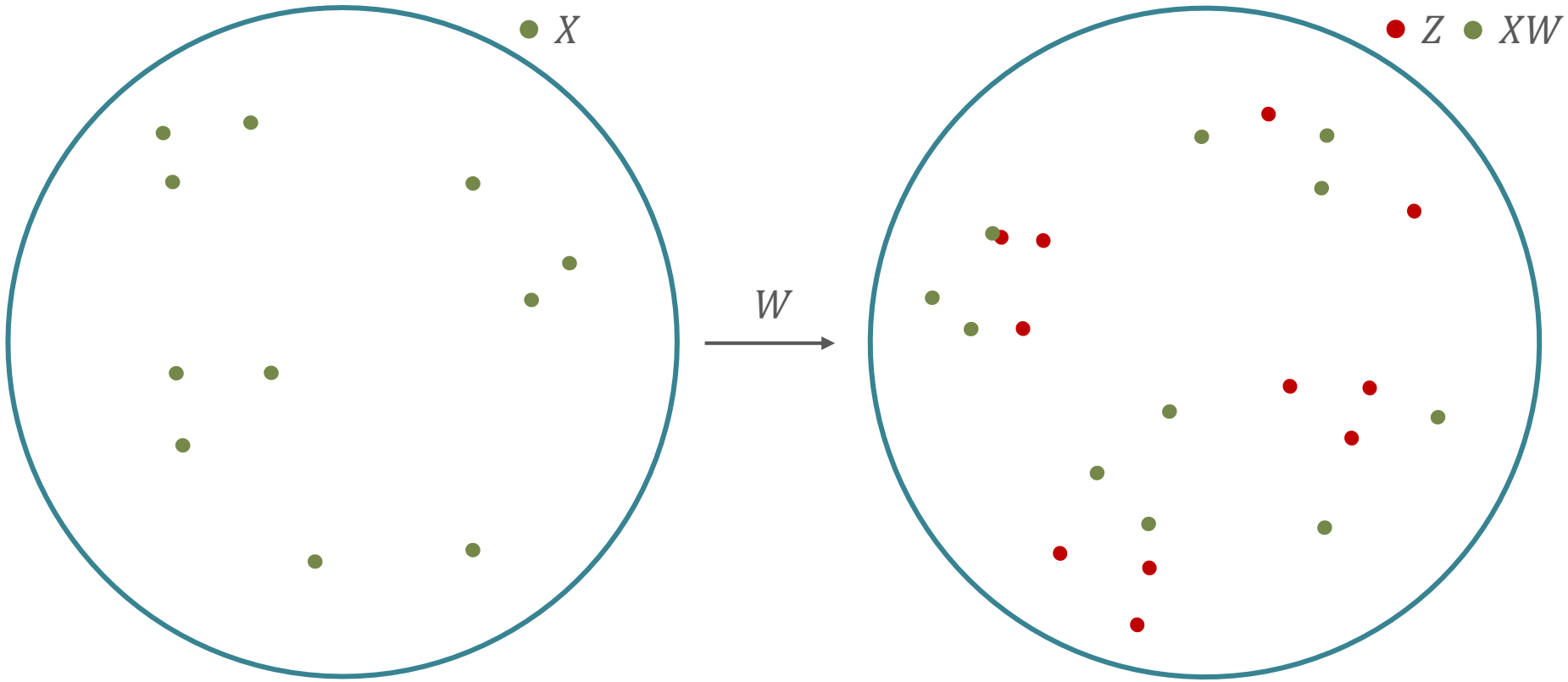
Cross-lingual embedding mappings



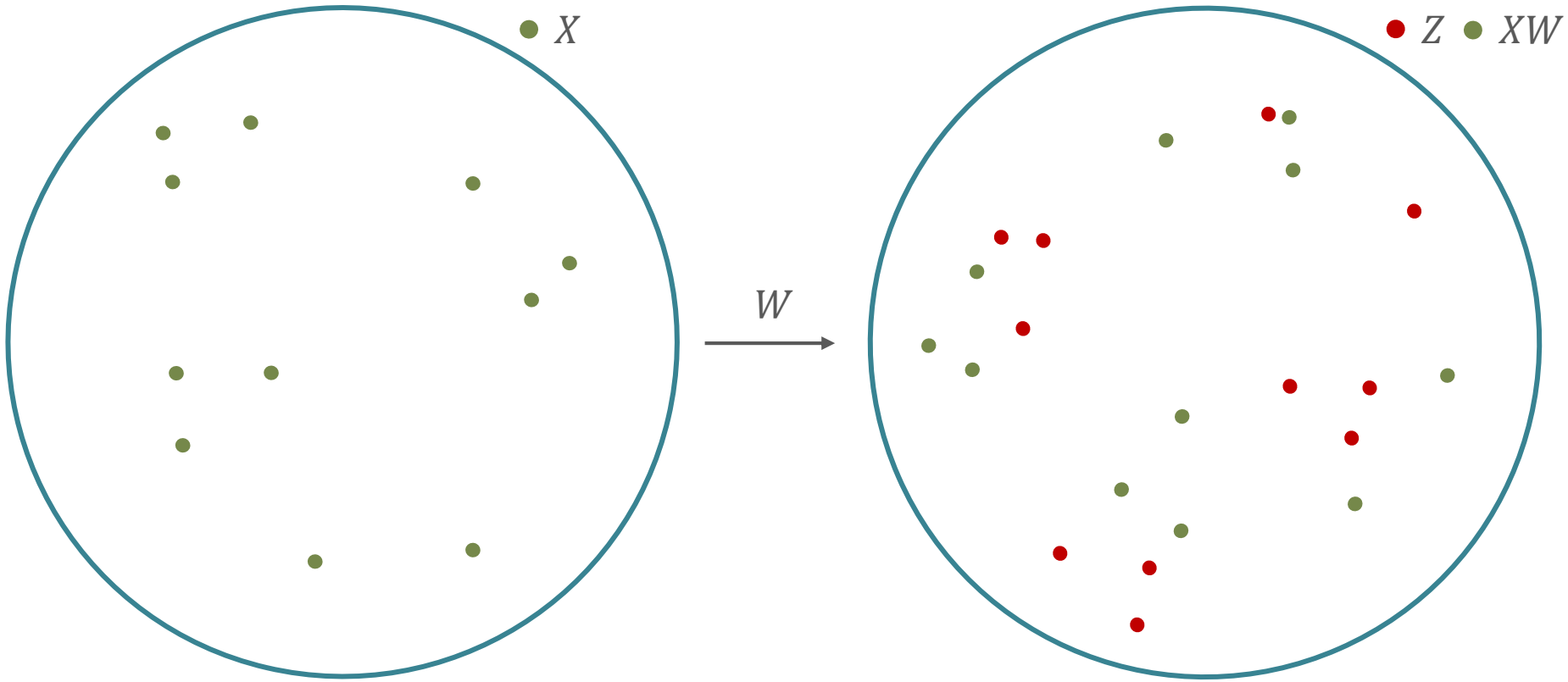
Cross-lingual embedding mappings



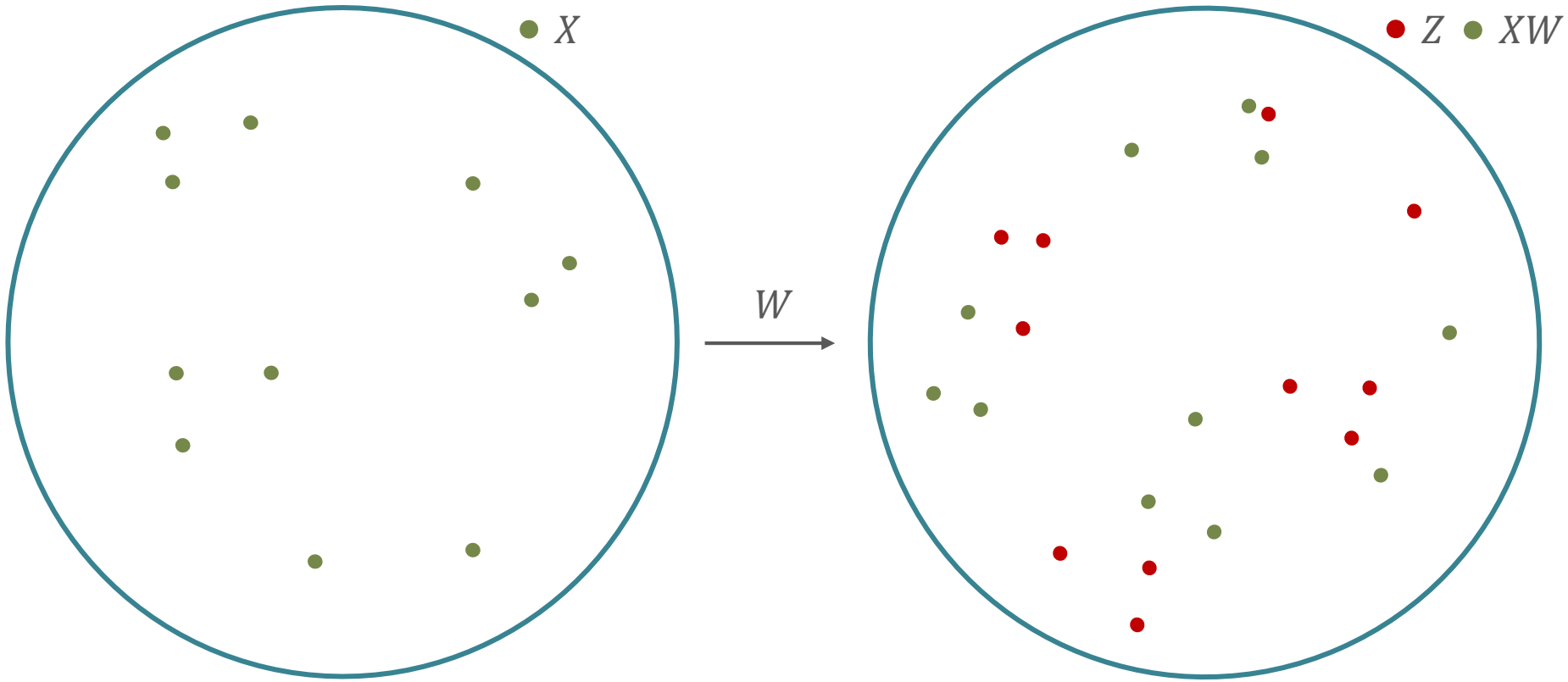
Cross-lingual embedding mappings



Cross-lingual embedding mappings



Cross-lingual embedding mappings



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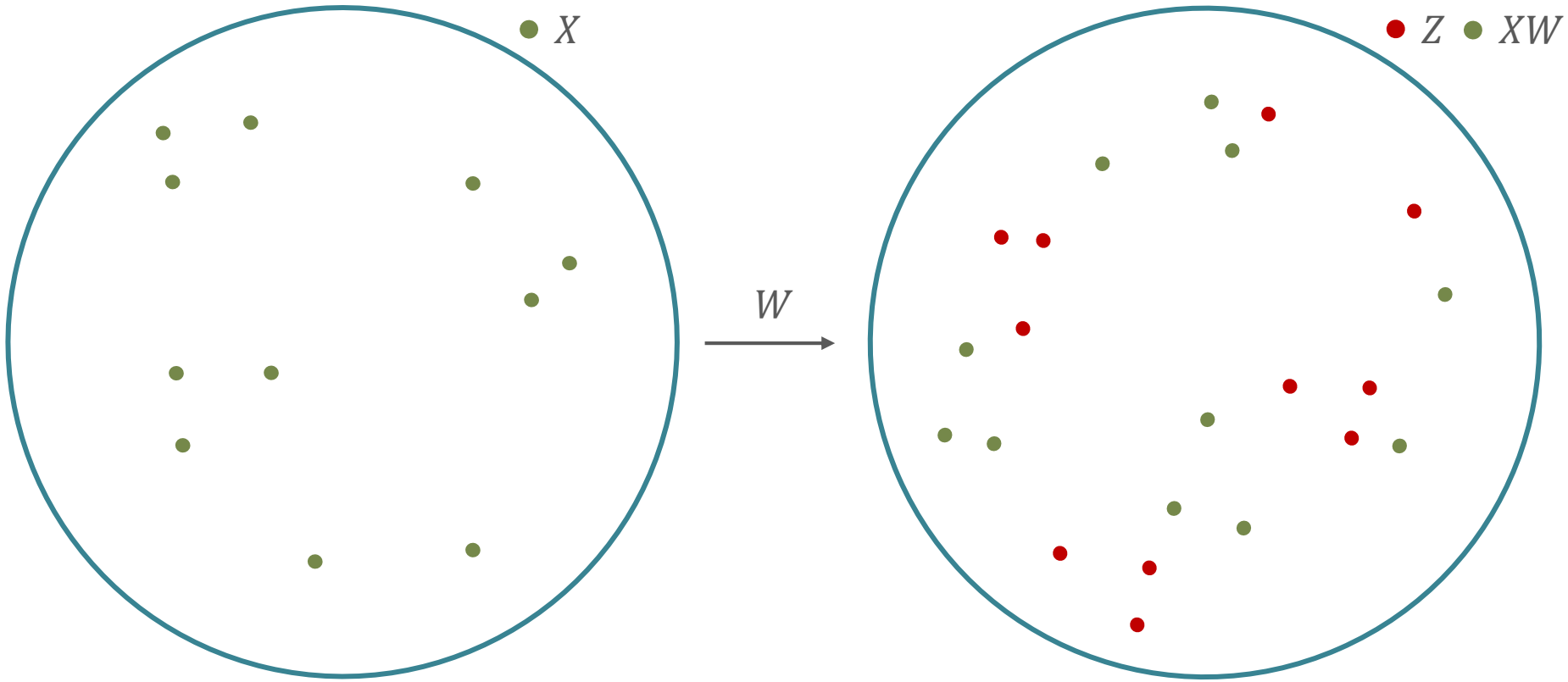

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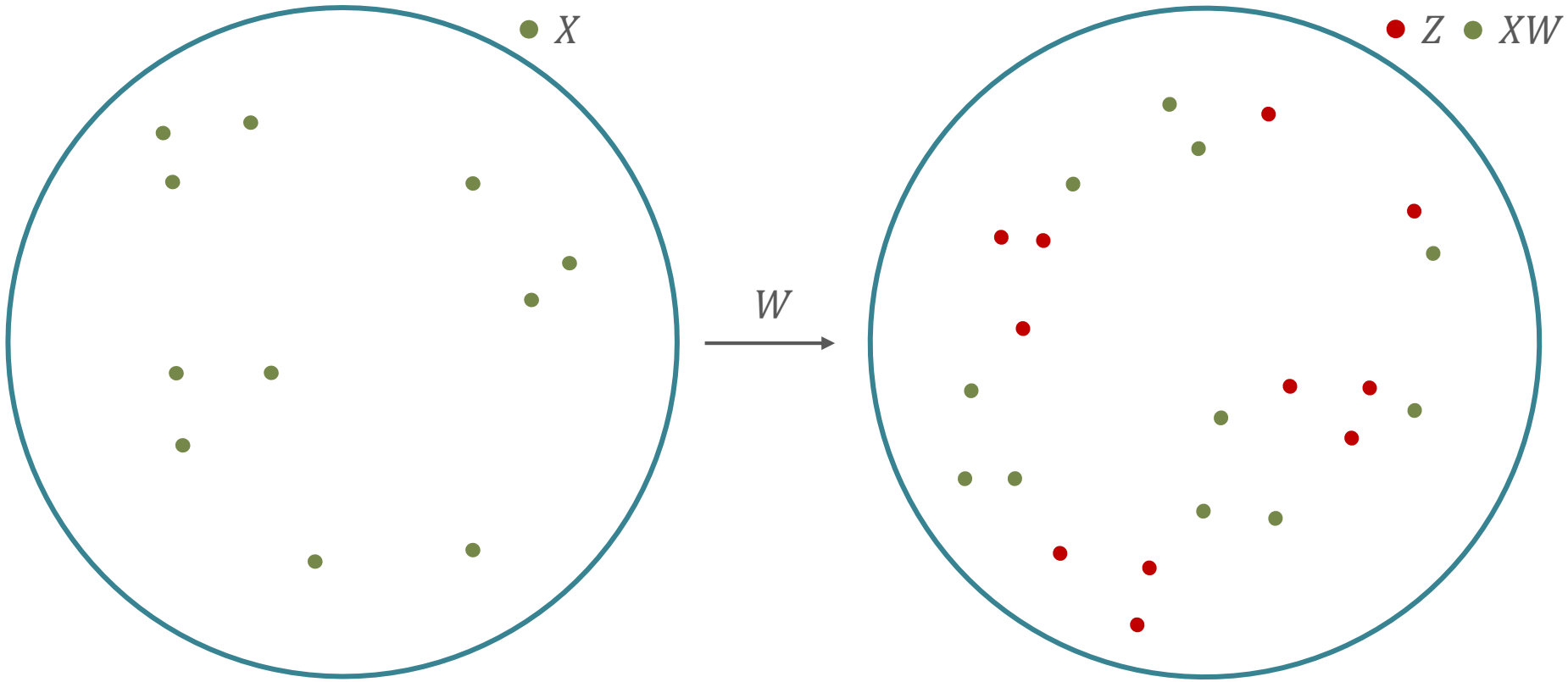

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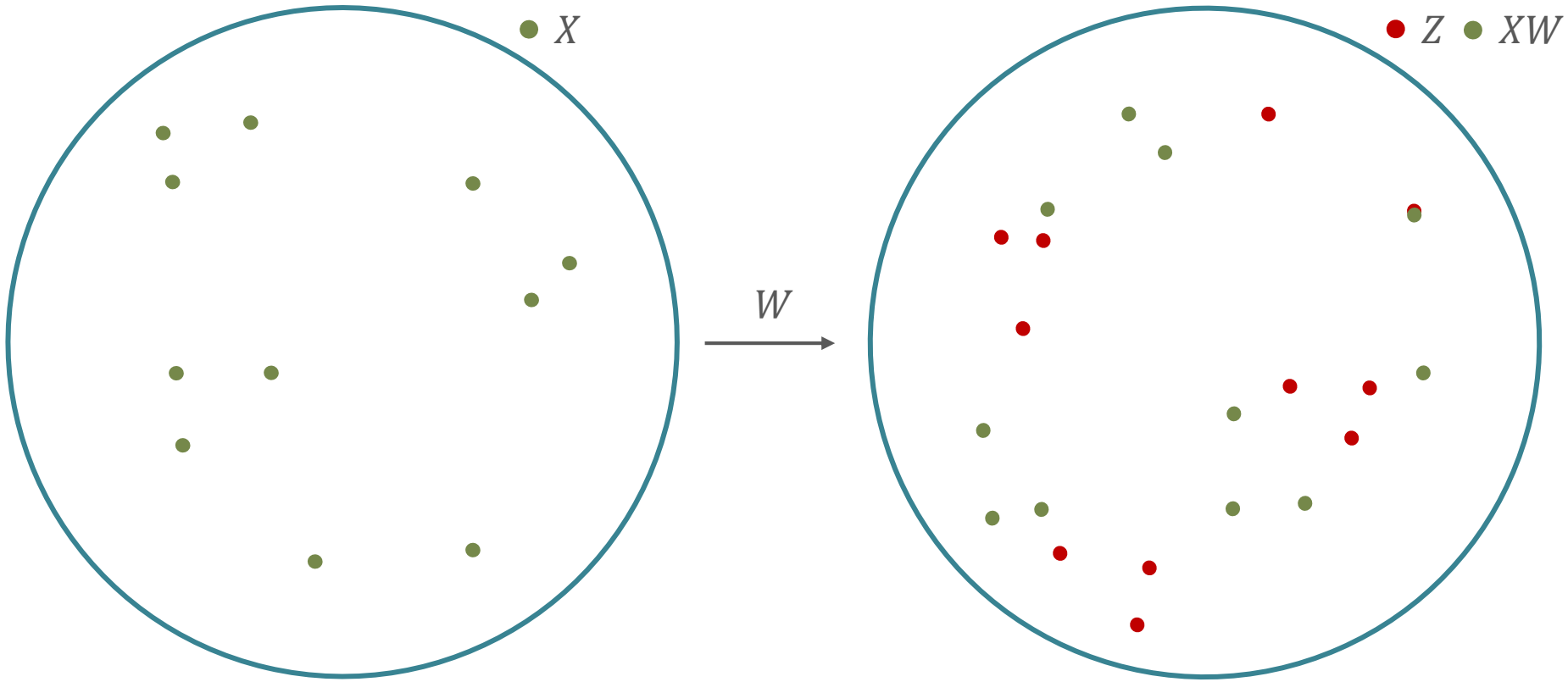

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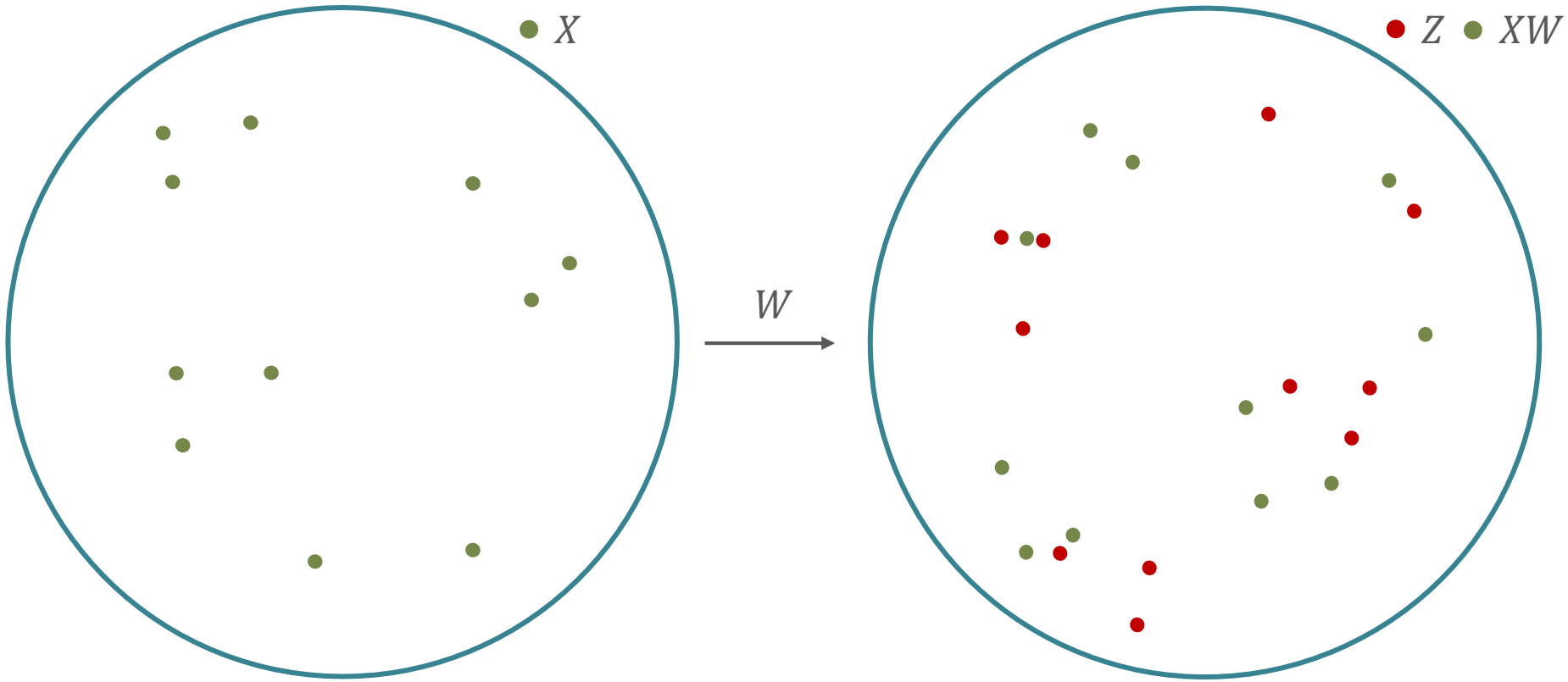

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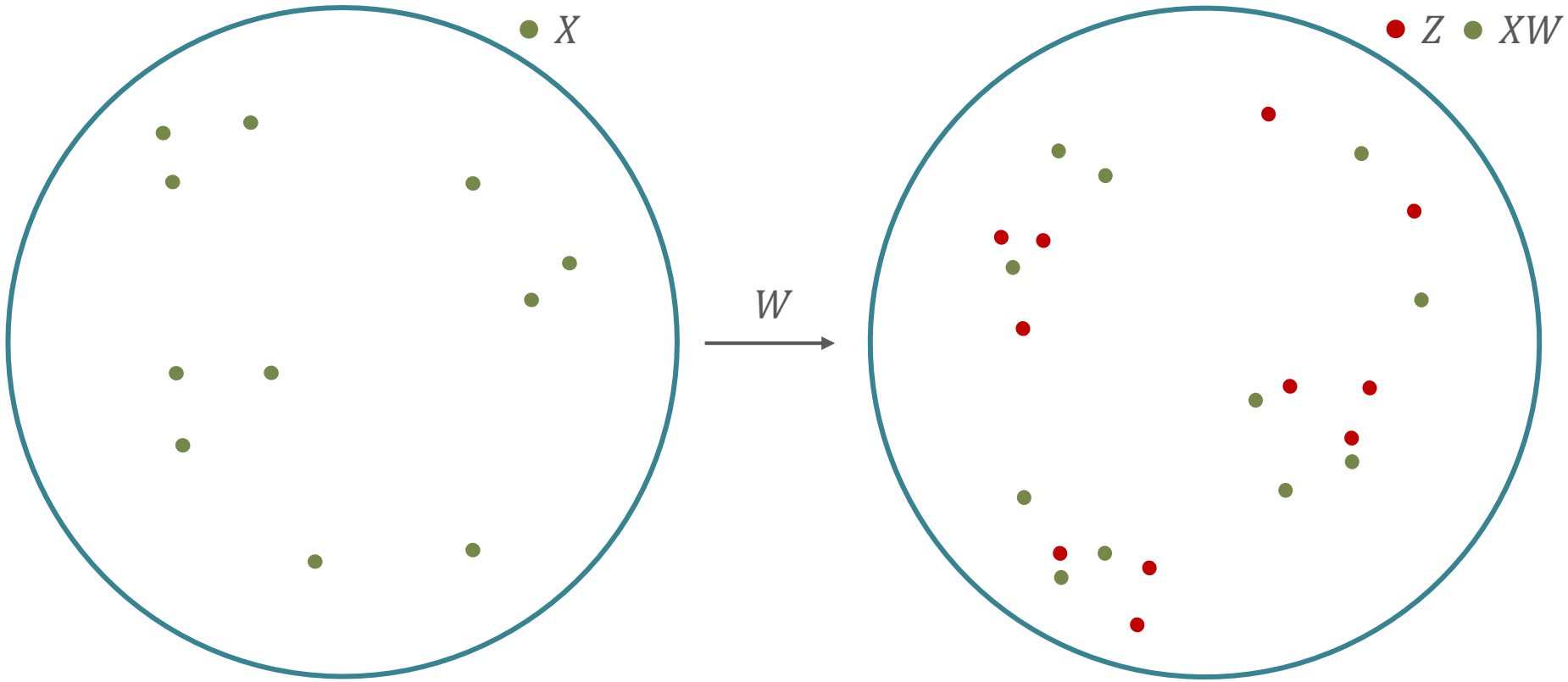

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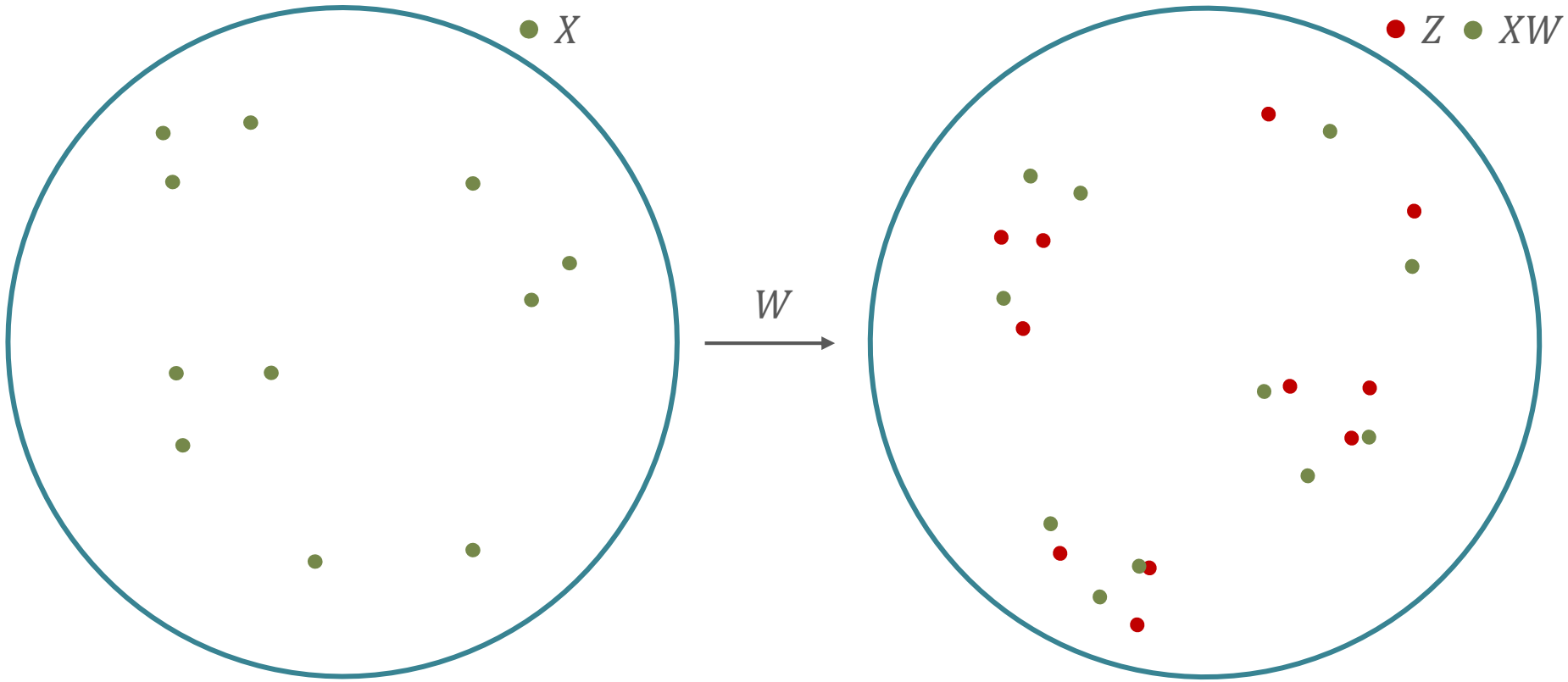

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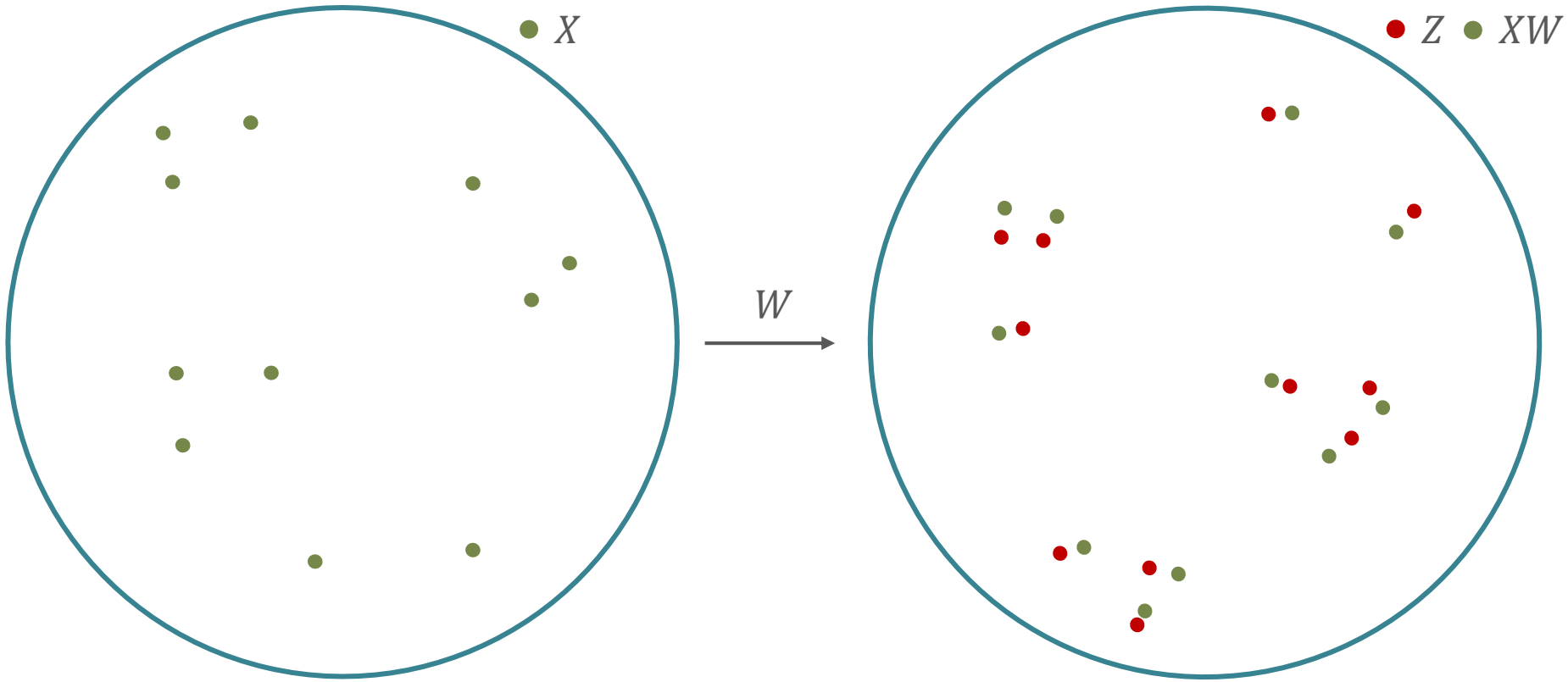

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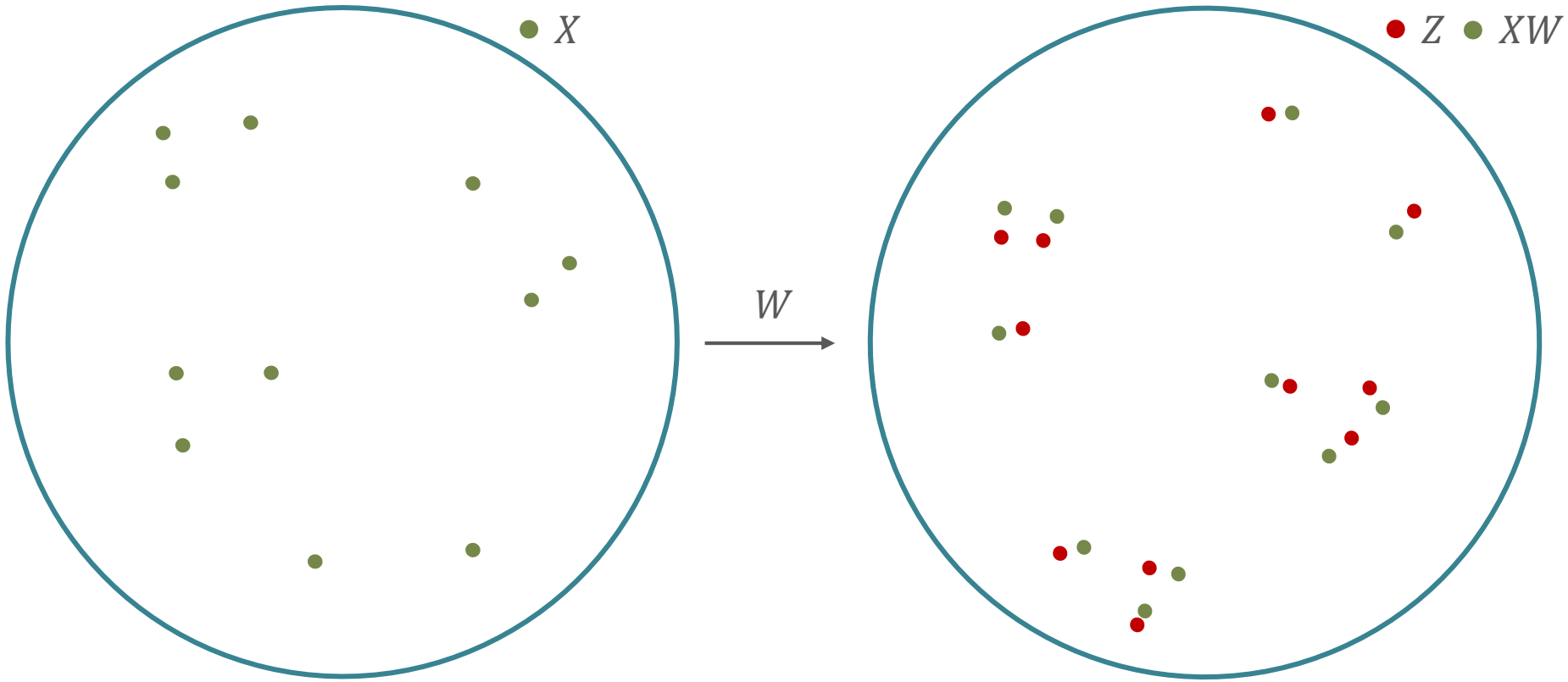


$$W^* = \arg\min_{W \in O(n)} \sum_i \min_j \left\| X_{i*} W - Z_{j*} \right\|^2$$

Cross-lingual embedding mappings

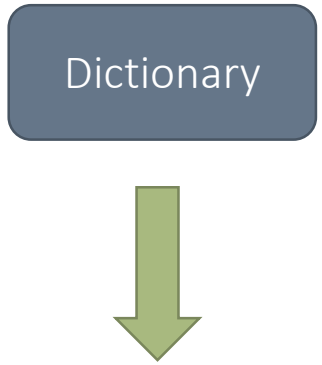
$$W^* = \arg\min_{W \in O(n)} \sum_i \min_j \left\| X_{i*} W - Z_{j*} \right\|^2$$

Cross-lingual embedding mappings

Dictionary

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

Cross-lingual embedding mappings



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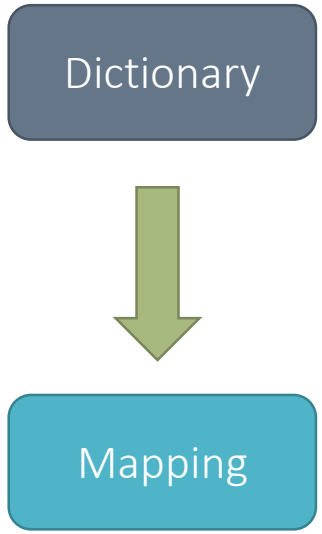

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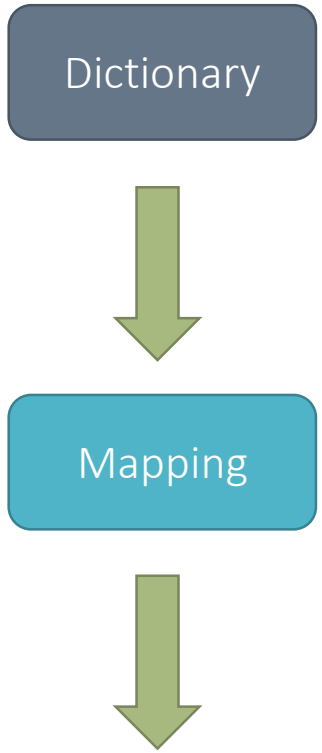

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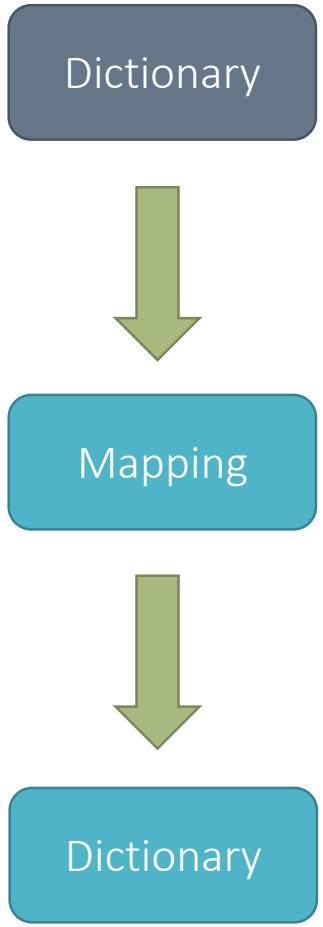

Cross-lingual embedding mappings

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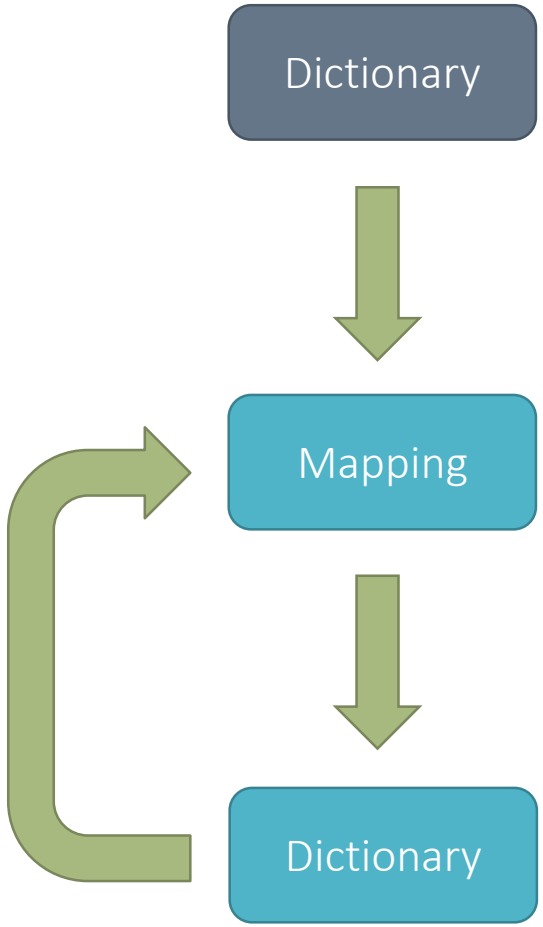
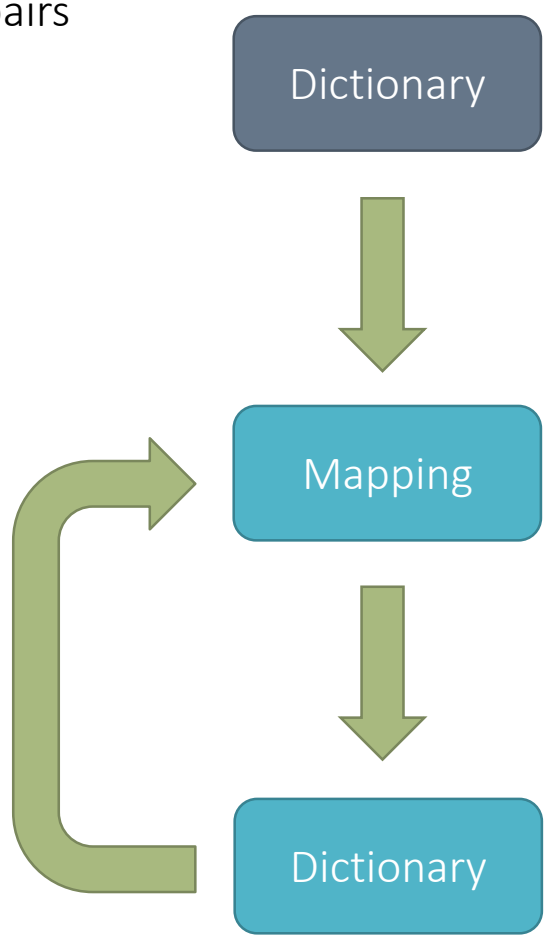


Cross-lingual embedding mappings

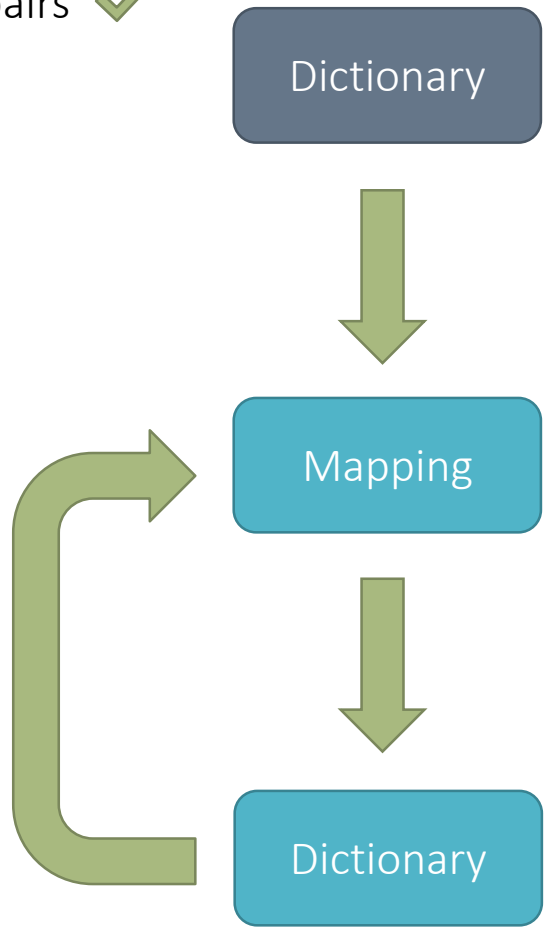
- 25 word pairs

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



Cross-lingual embedding mappings

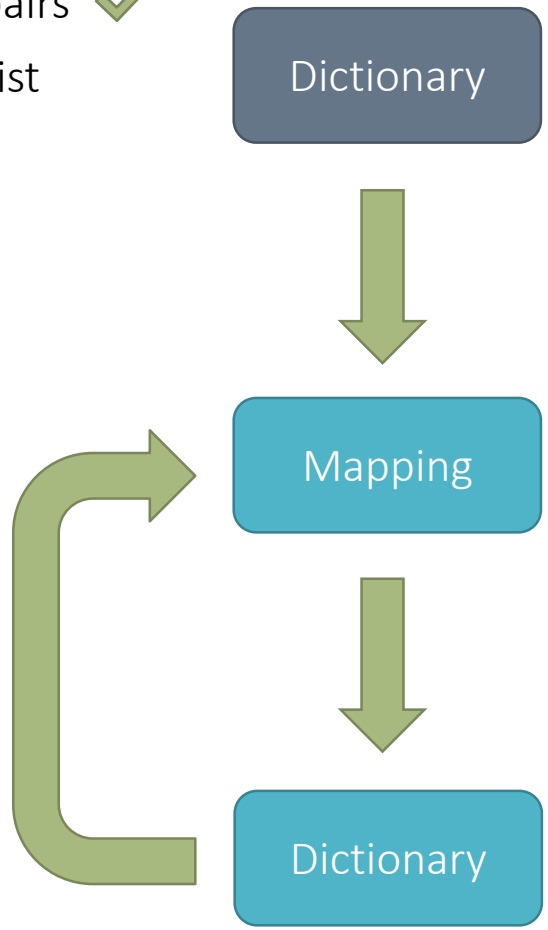
- 25 word pairs ✓



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

Cross-lingual embedding mappings

- 25 word pairs ✓
- Numeral list



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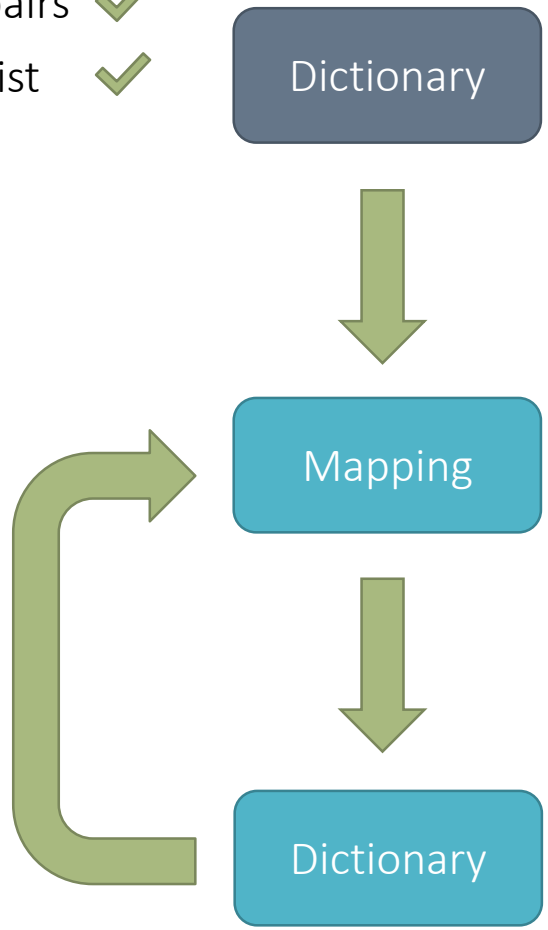
Cross-lingual embedding mappings

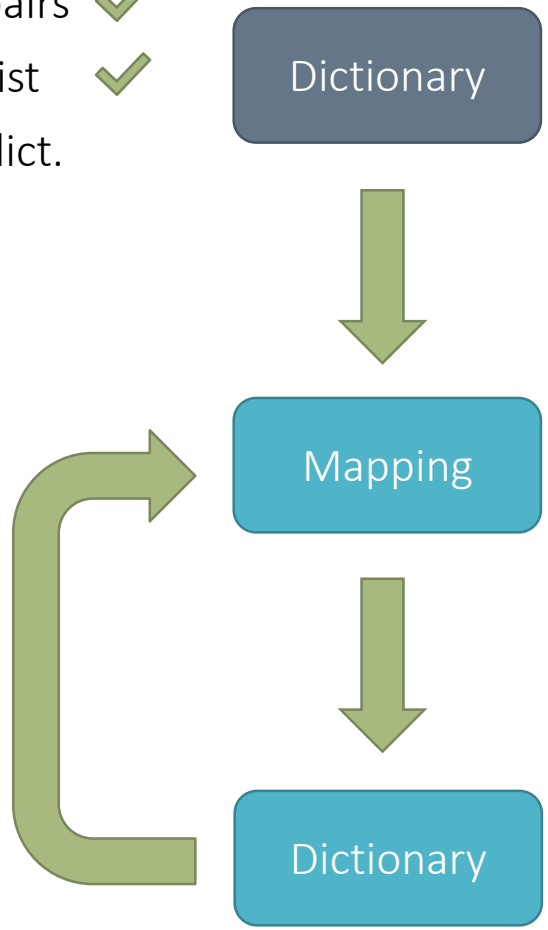
- 25 word pairs ✓
- Numeral list ✓



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

Cross-lingual embedding mappings

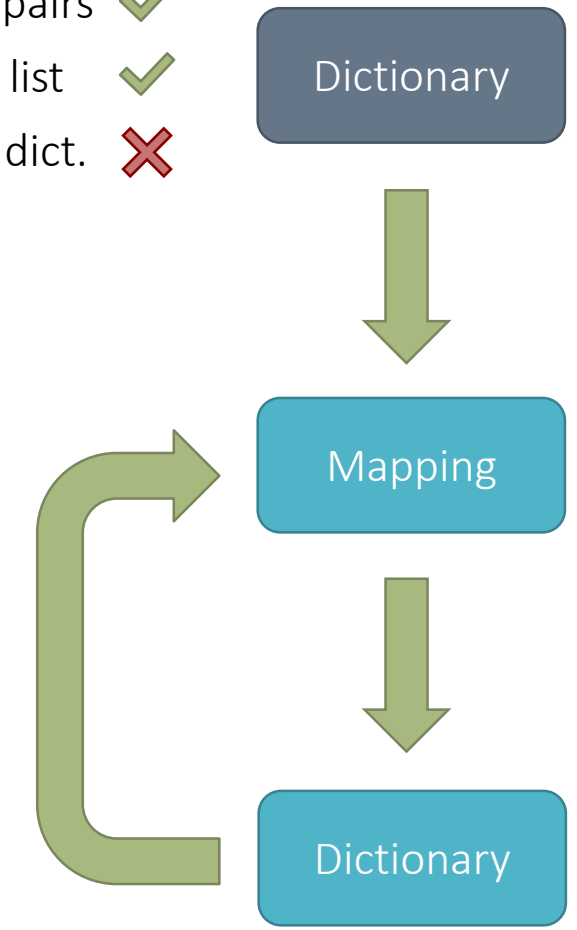
- 25 word pairs ✓
- Numeral list ✓
- Random dict.



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

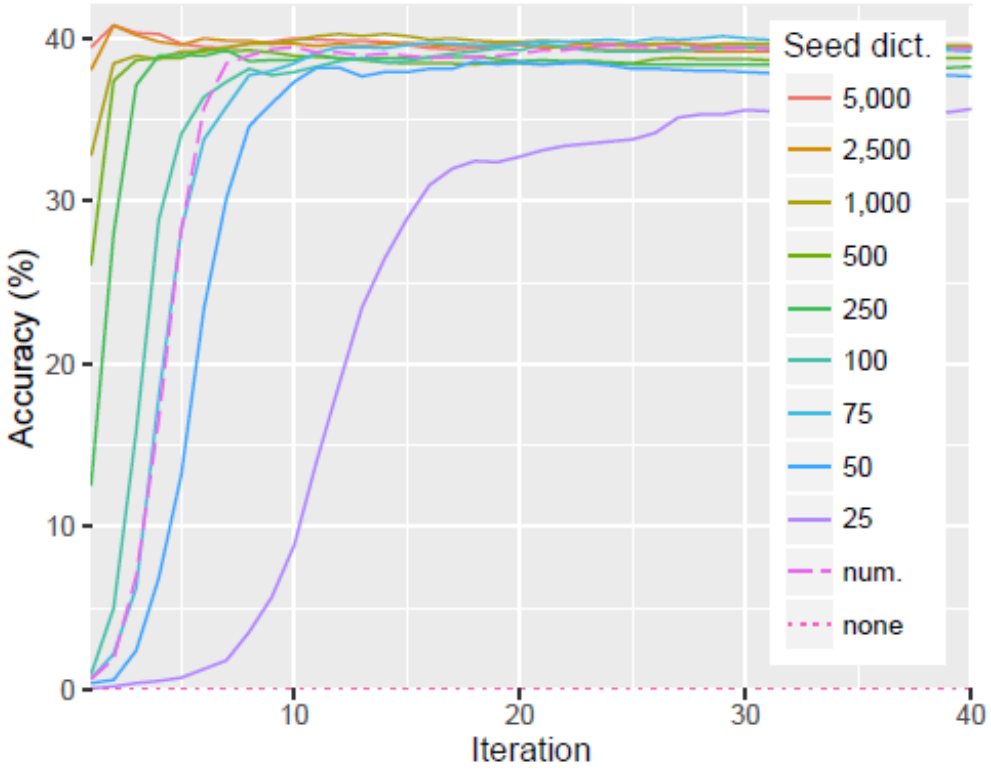
Cross-lingual embedding mappings

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

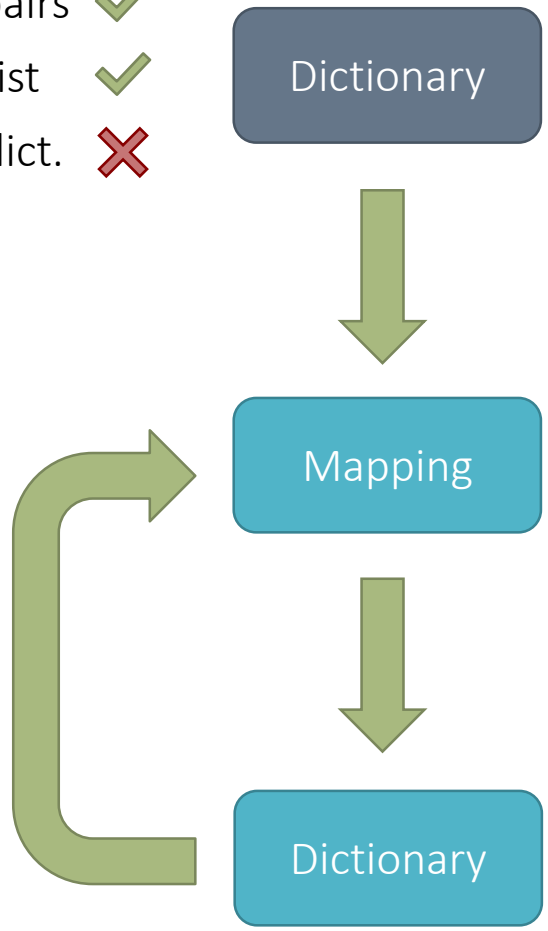


$$W^* = \arg\min_{W \in O(n)} \sum_i \min_j \left\| X_{i*} W - Z_{j*} \right\|^2$$

Cross-lingual embedding mappings



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



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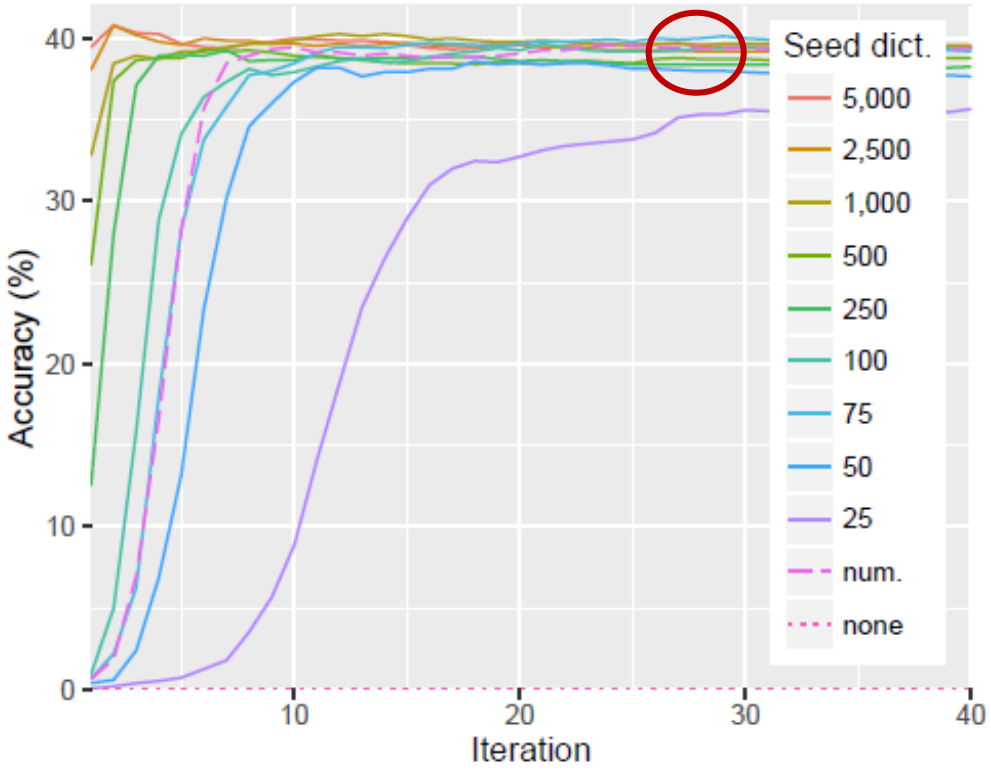
Cross-lingual embedding mappings



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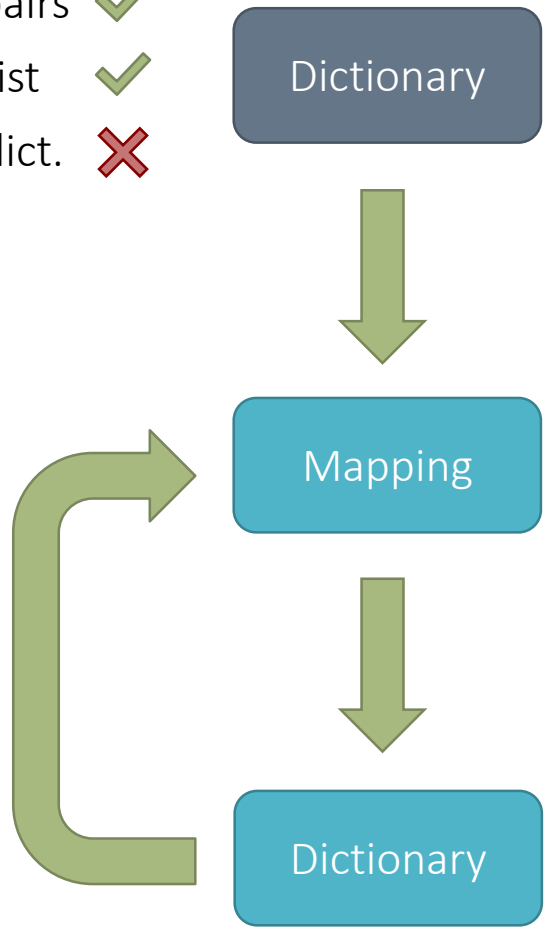

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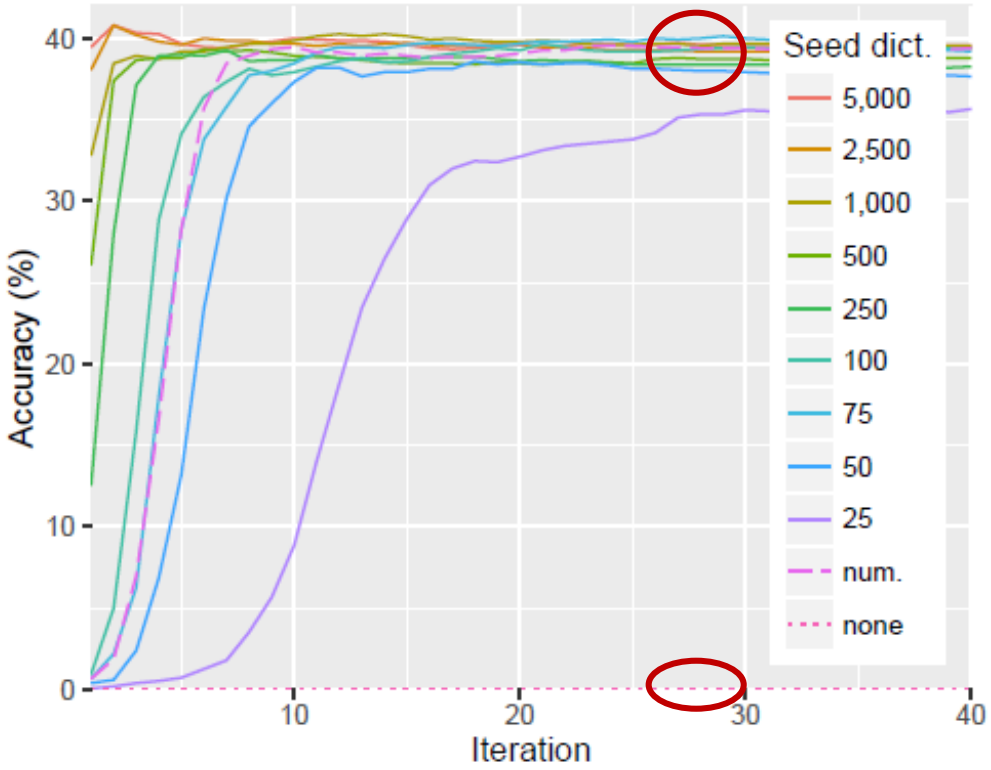
Cross-lingual embedding mappings



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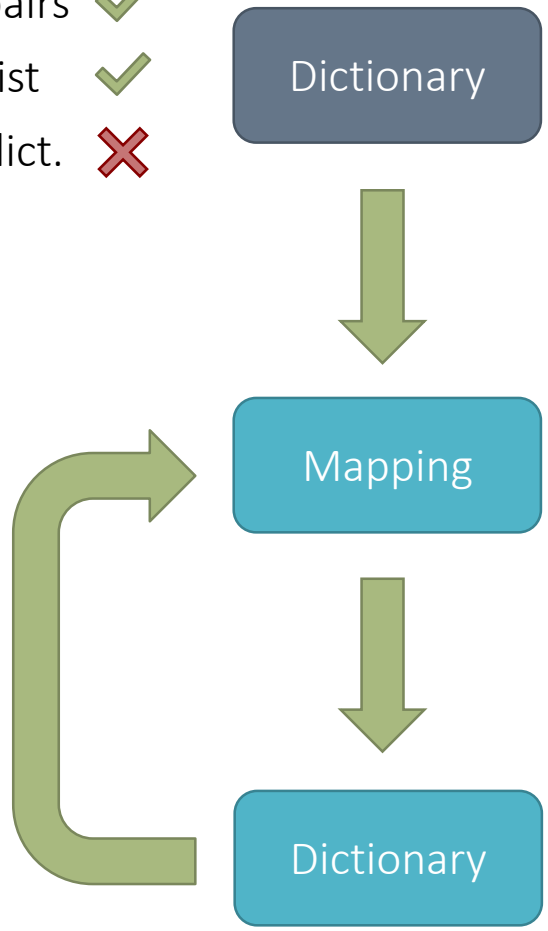

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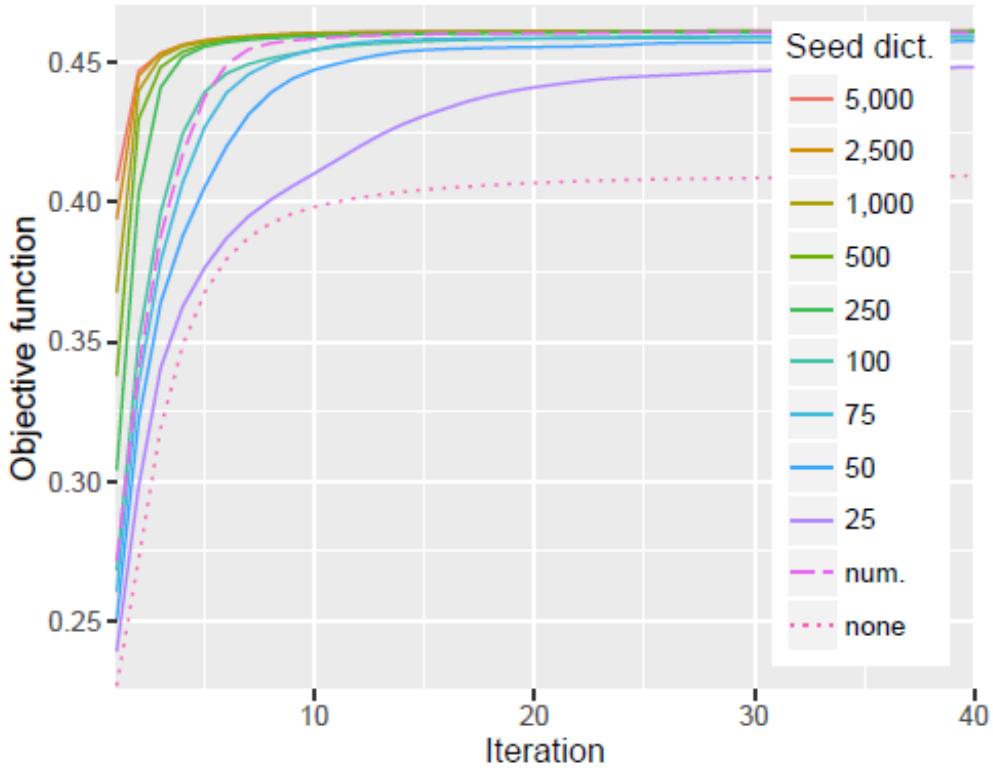
Cross-lingual embedding mappings



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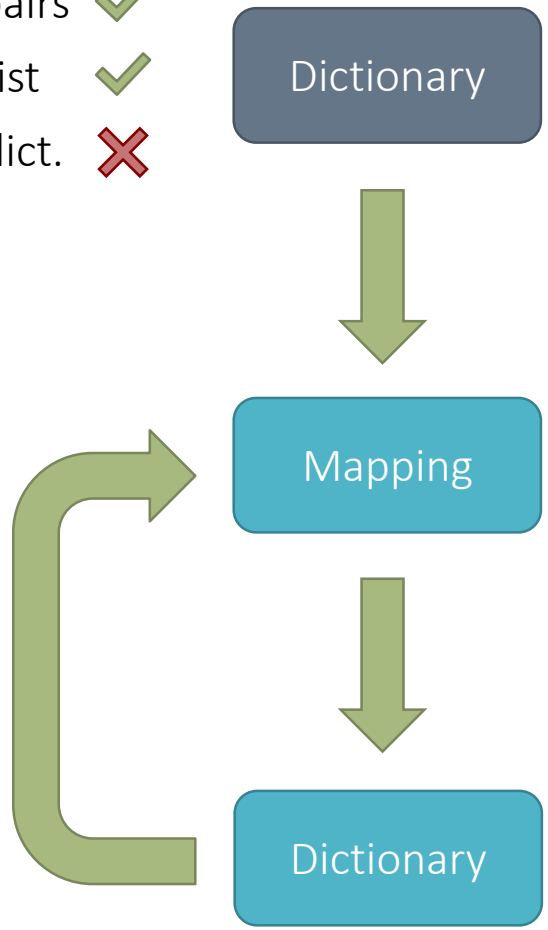

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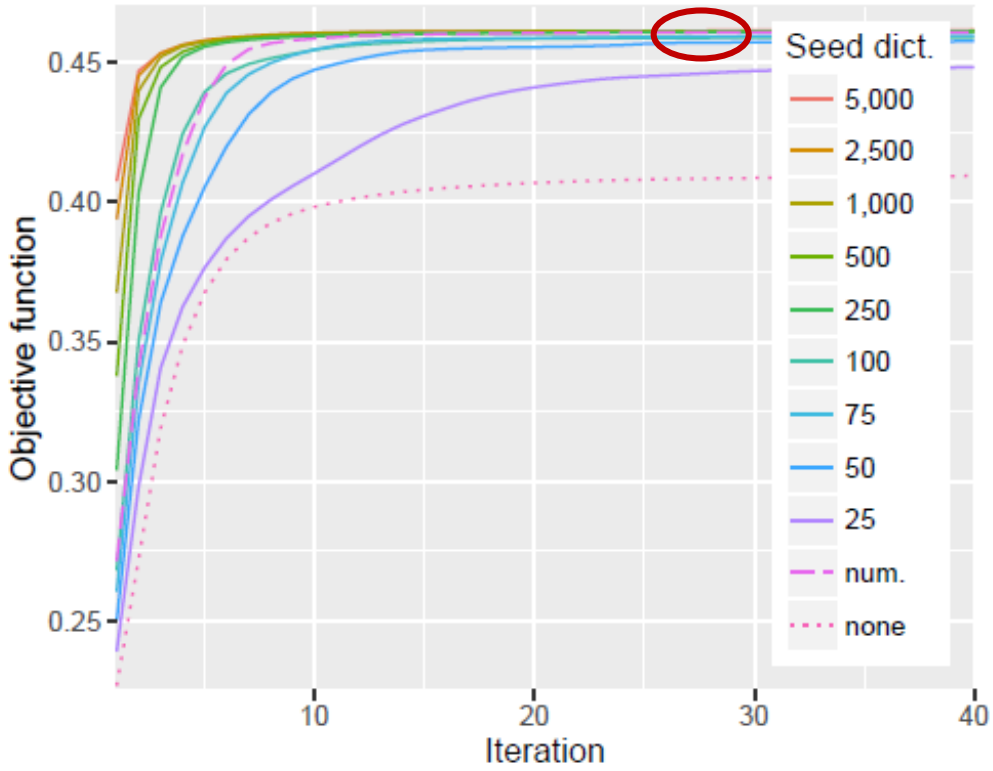
Cross-lingual embedding mappings



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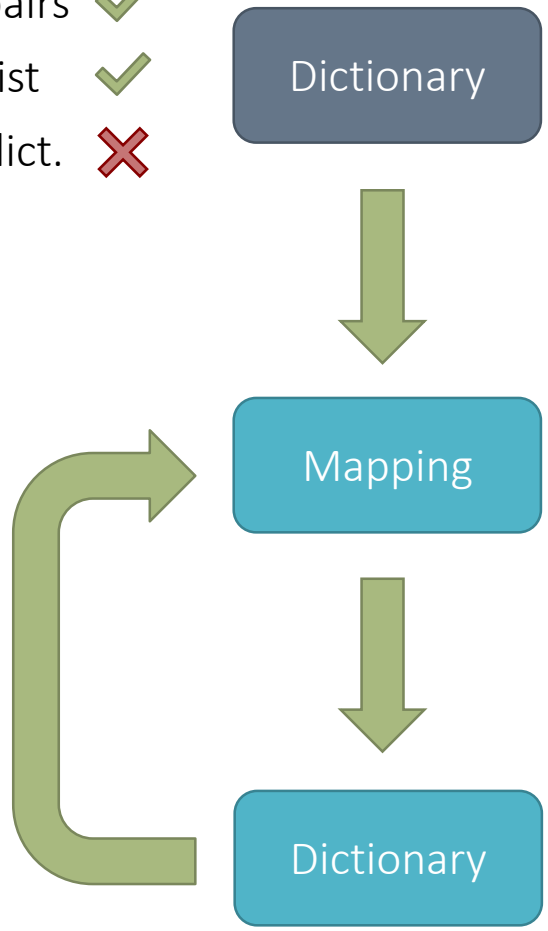

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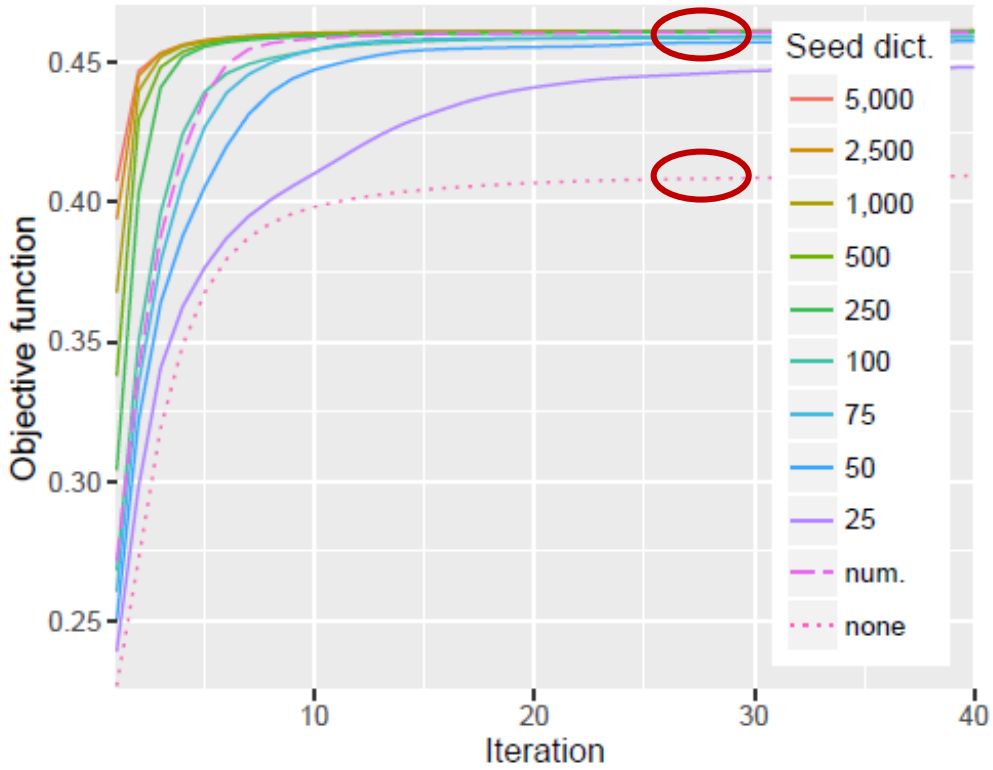
Cross-lingual embedding mappings



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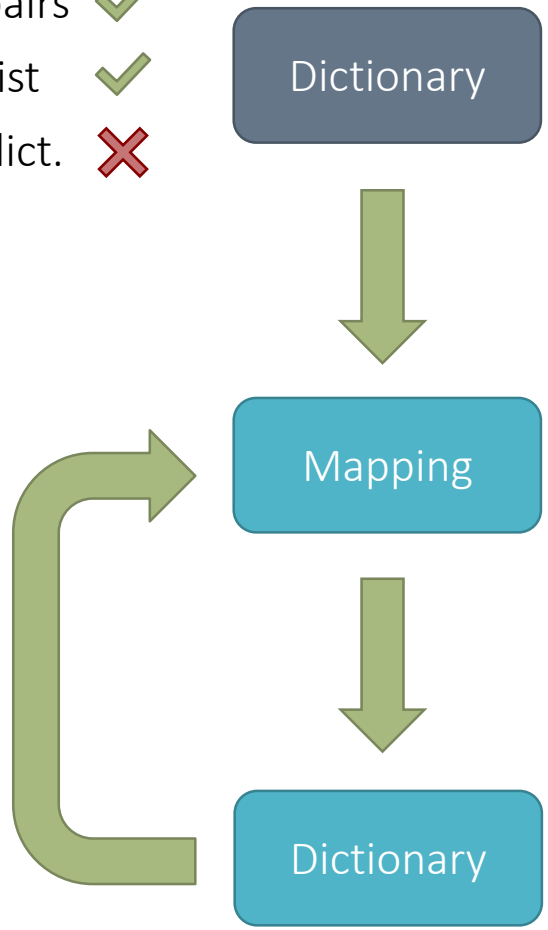
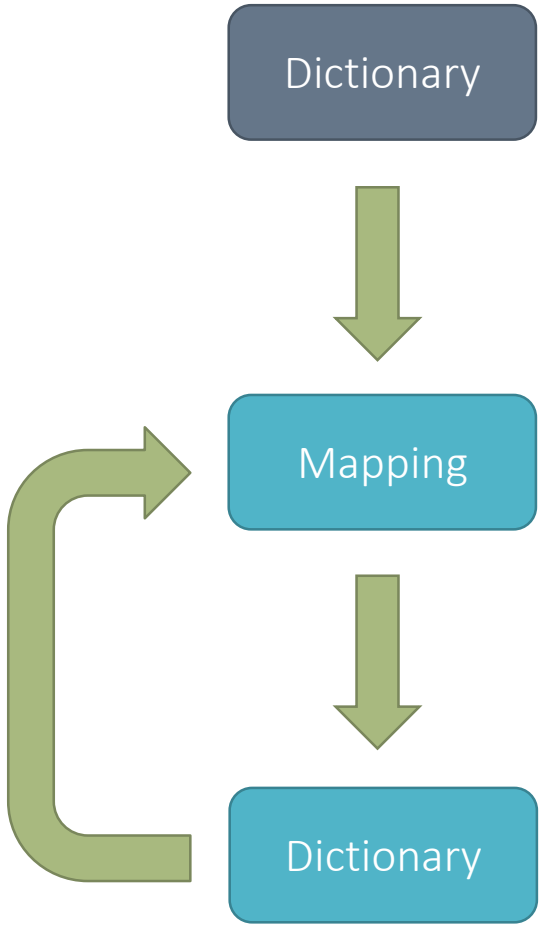


$$W^* = \arg\min_{W \in O(n)} \sum_i \min_j \left\| X_{i*} W - Z_{j*} \right\|^2$$

Cross-lingual embedding mappings

Intra-lingual similarity distribution

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

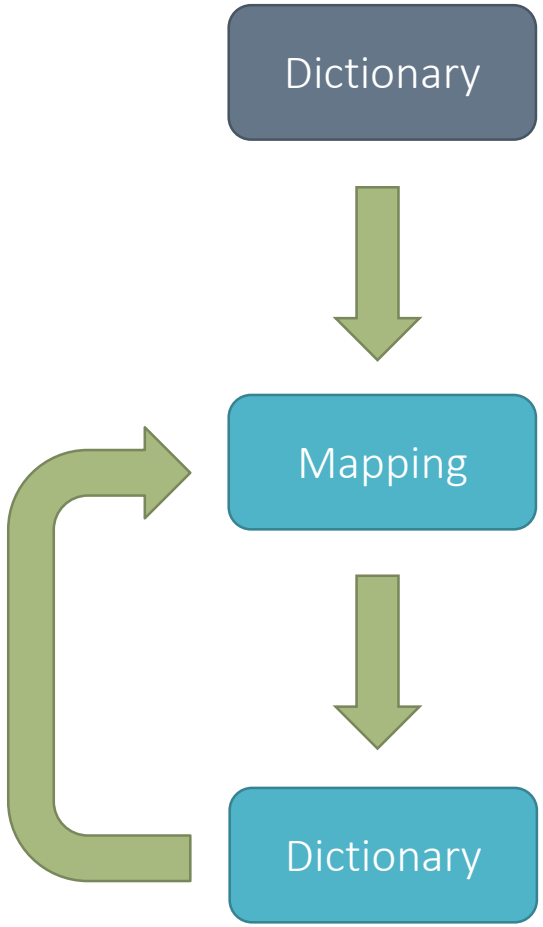


Cross-lingual embedding mappings

English

Intra-lingual similarity distribution

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



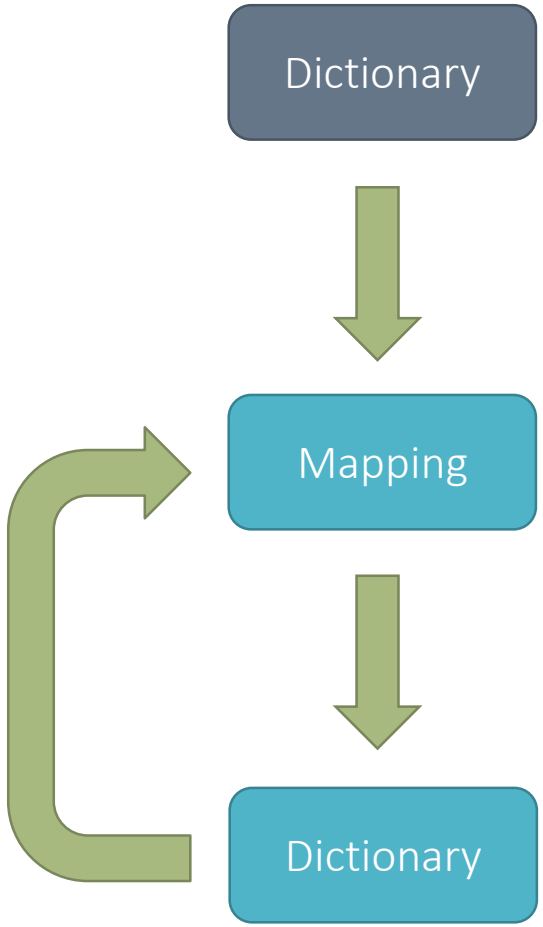
Cross-lingual embedding mappings

English

two

Intra-lingual similarity distribution

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



Cross-lingual embedding mappings

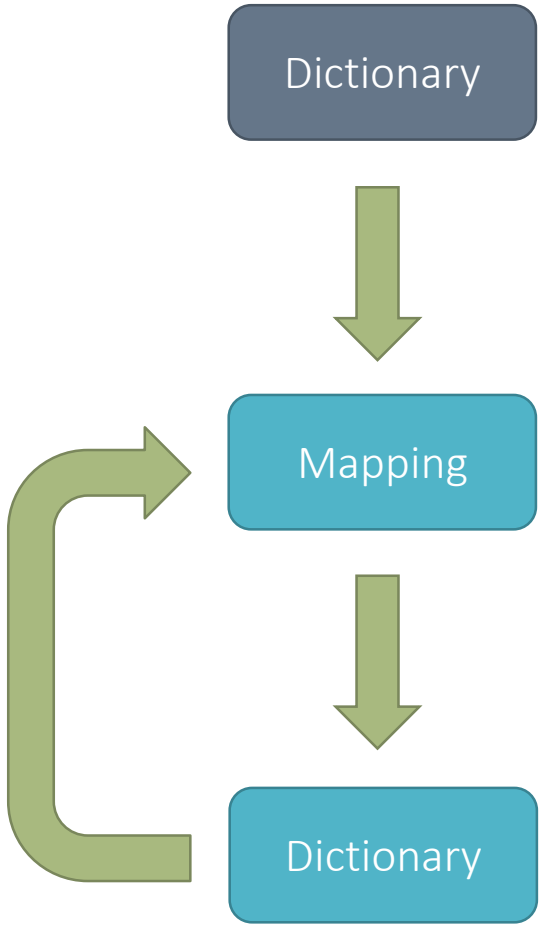
English

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

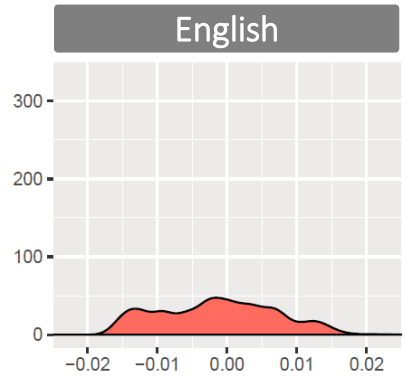
two

Intra-lingual similarity distribution

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



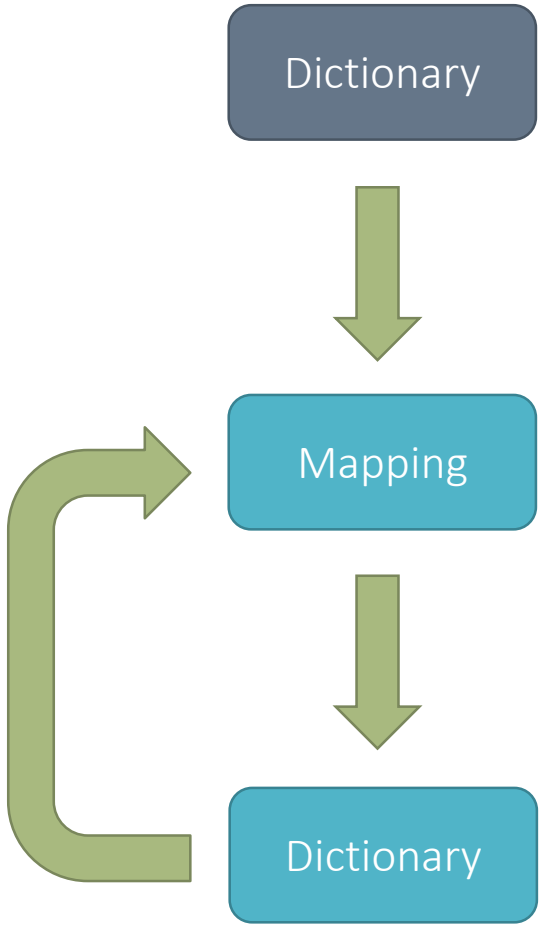
Cross-lingual embedding mappings



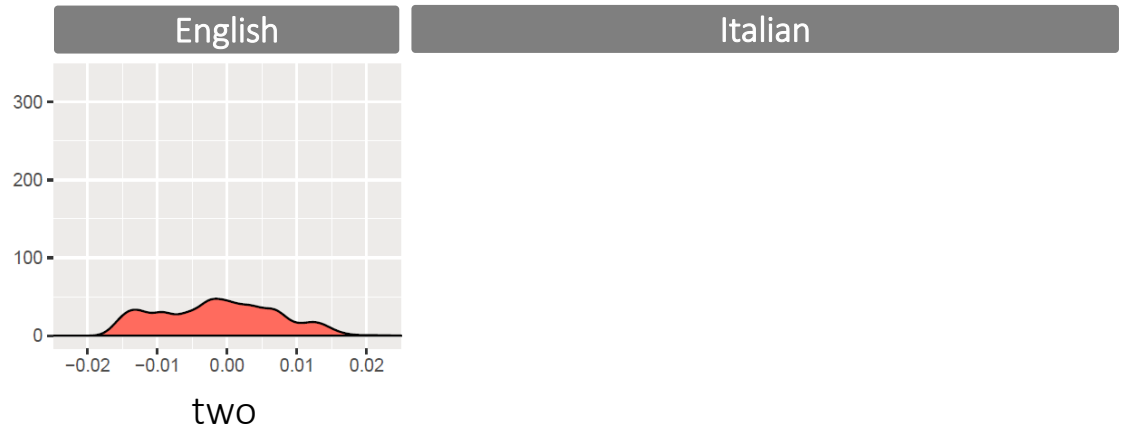
two

Intra-lingual similarity distribution

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



Cross-lingual embedding mappings



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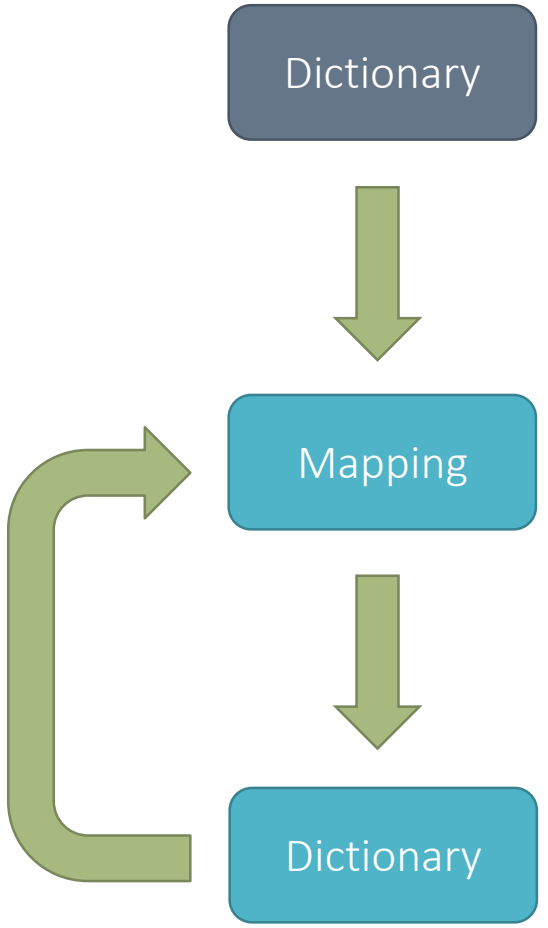
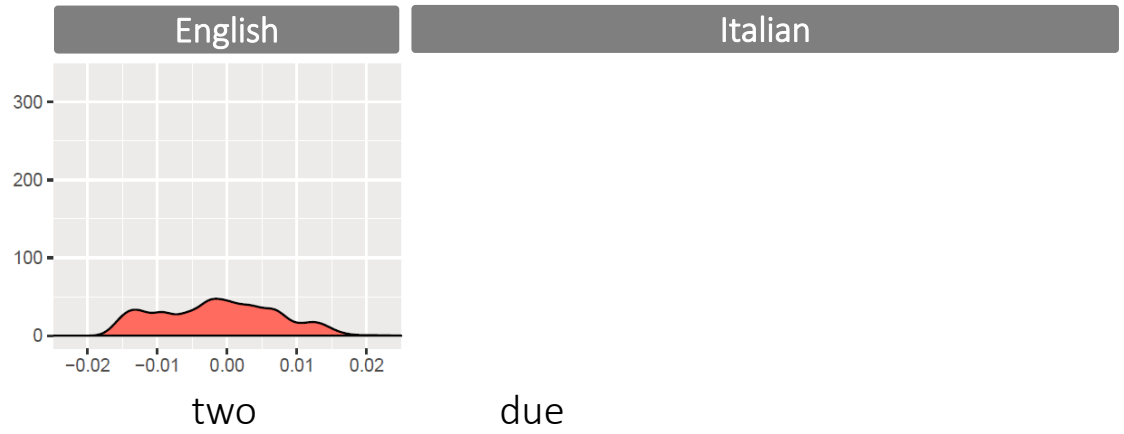


Cross-lingual embedding mappings



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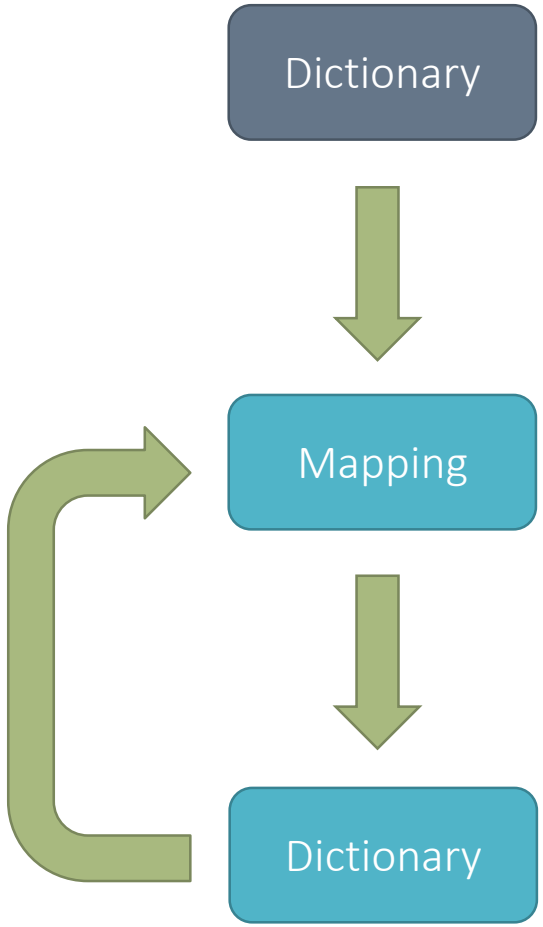
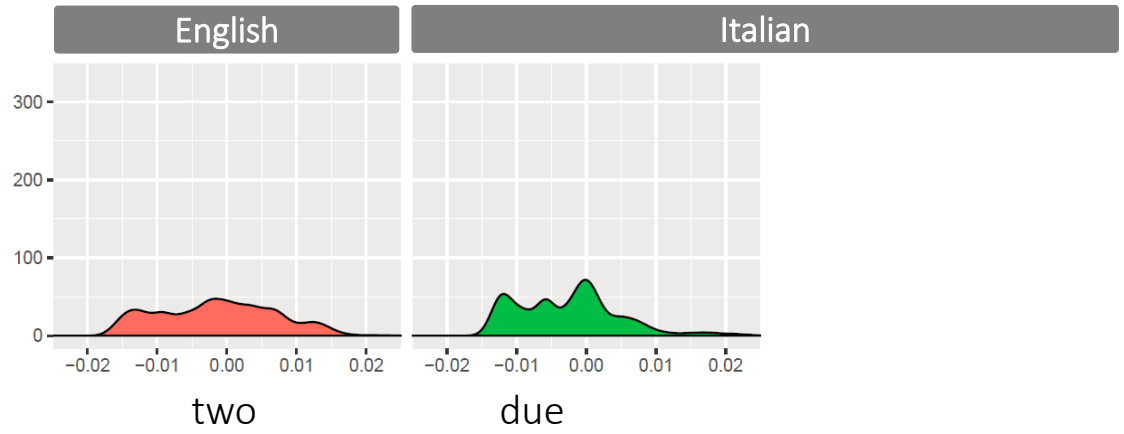


Cross-lingual embedding mappings



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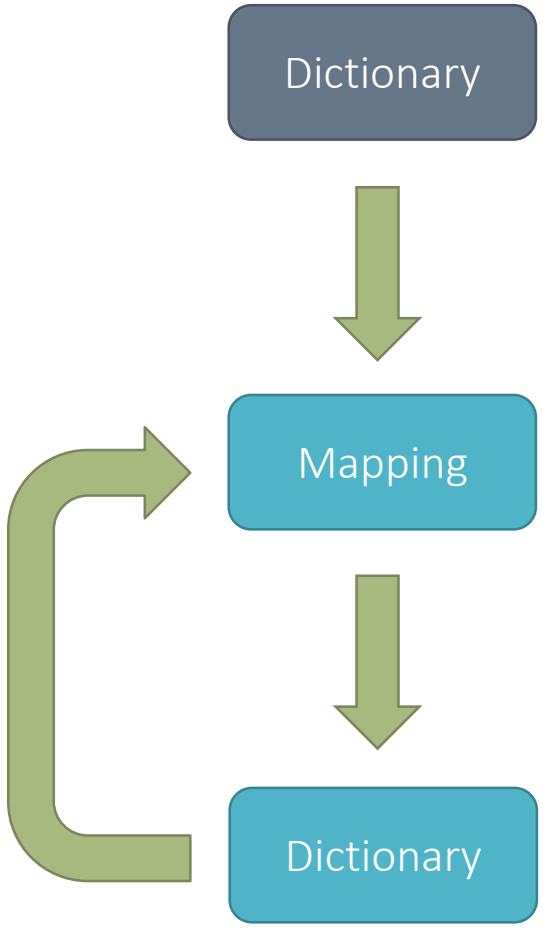
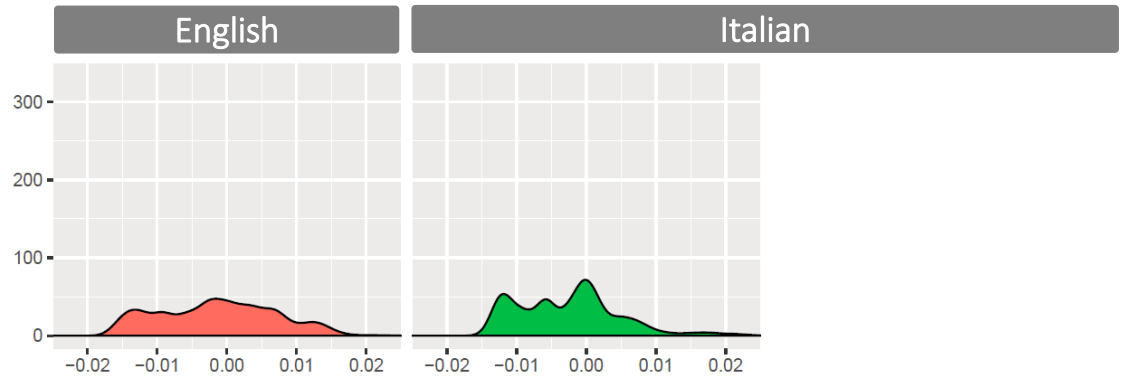


Cross-lingual embedding mappings



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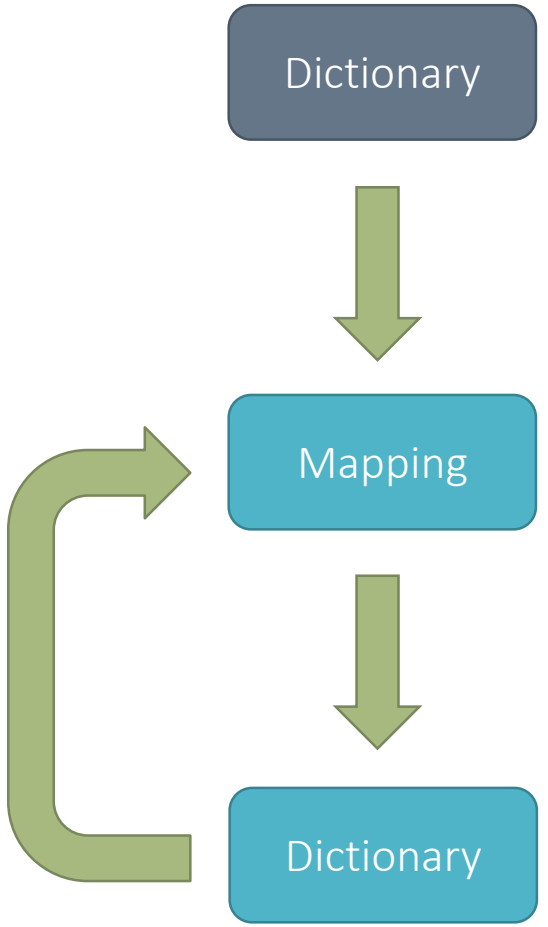
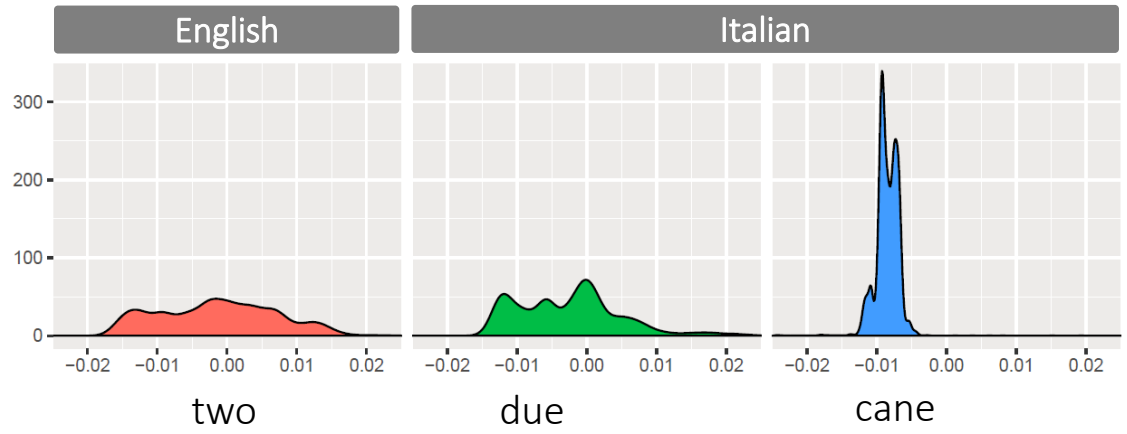


Cross-lingual embedding mappings



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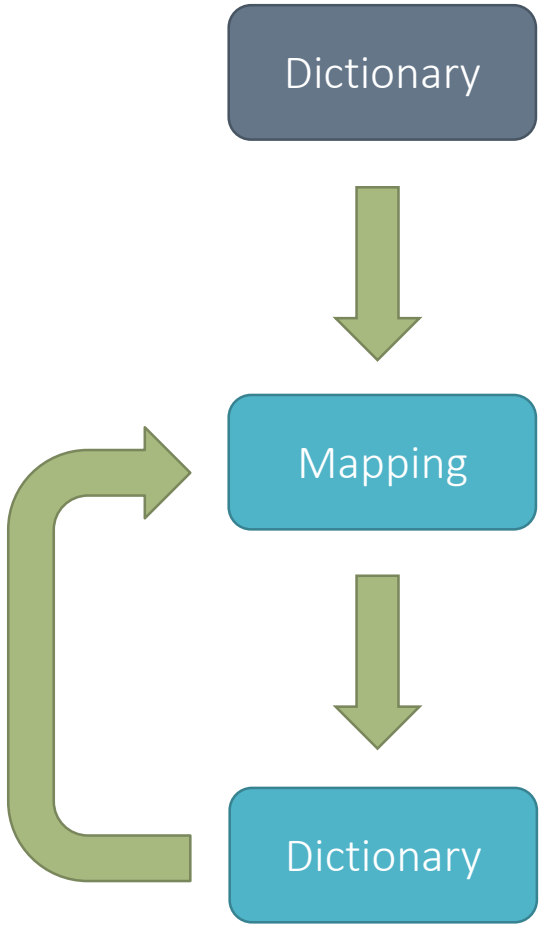
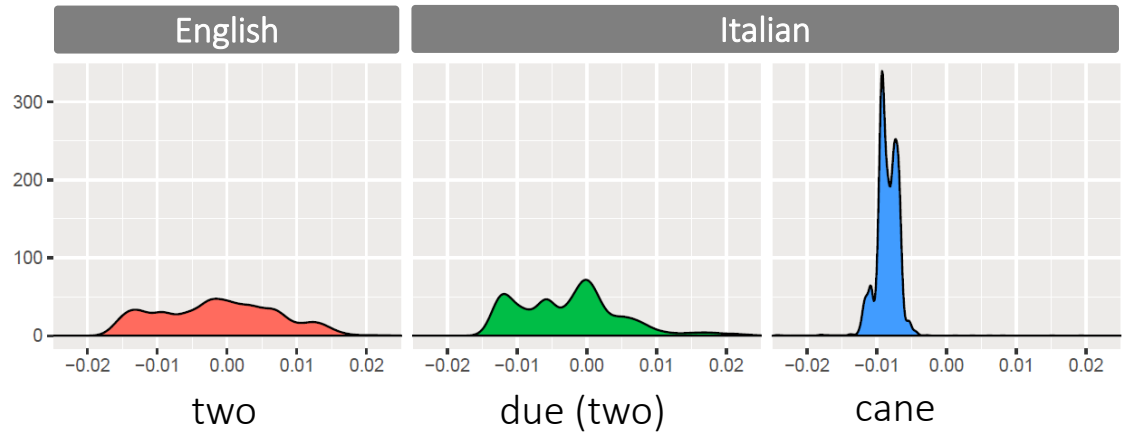


Cross-lingual embedding mappings



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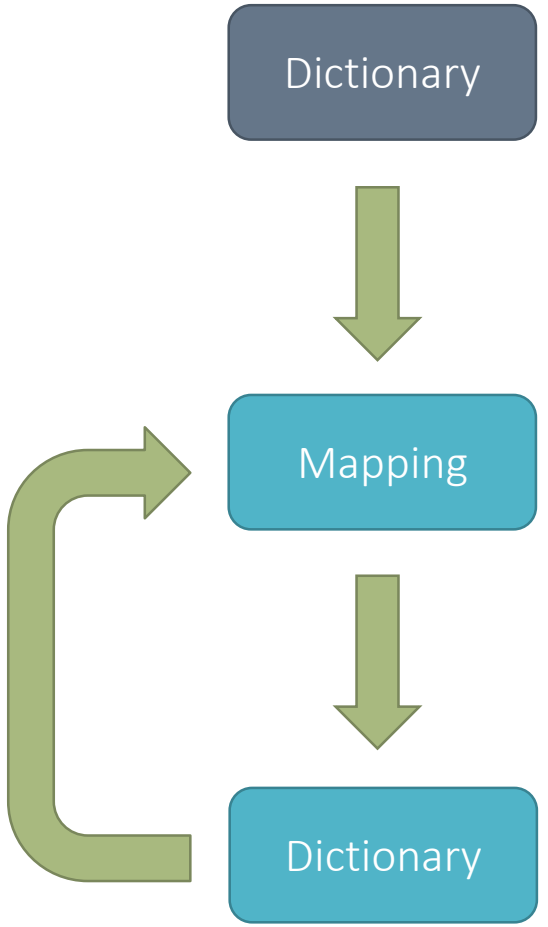
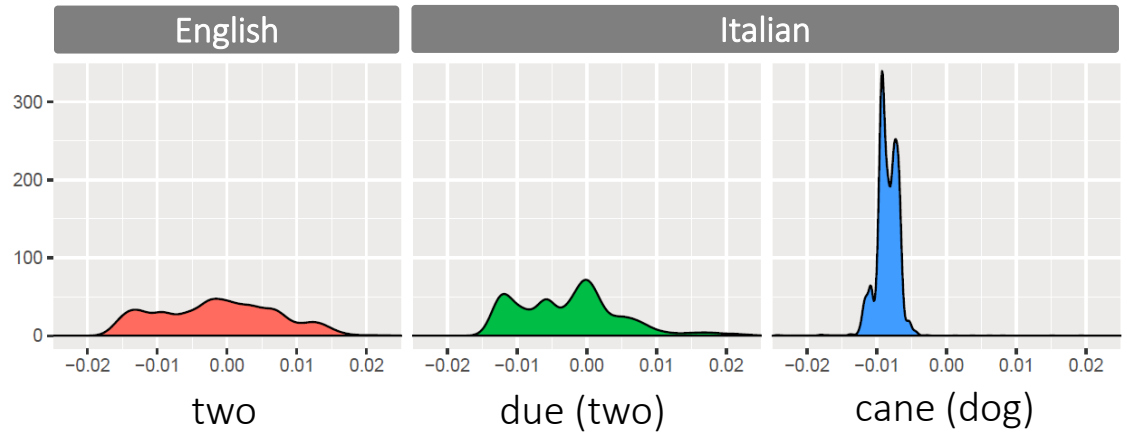


Cross-lingual embedding mappings



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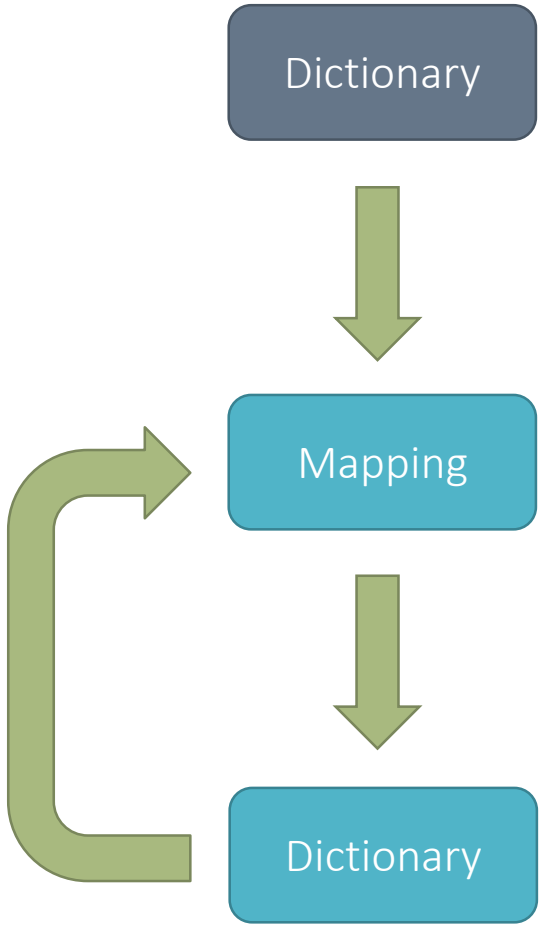
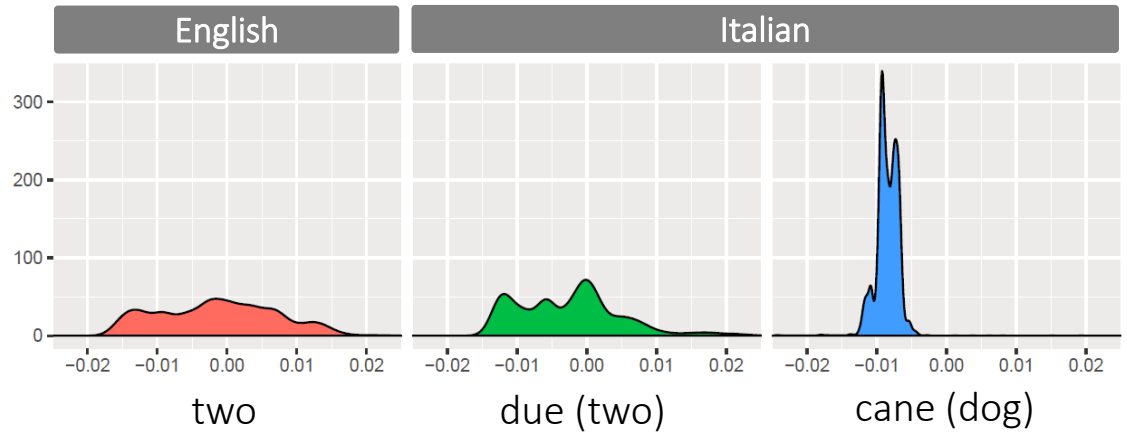


Cross-lingual embedding mappings



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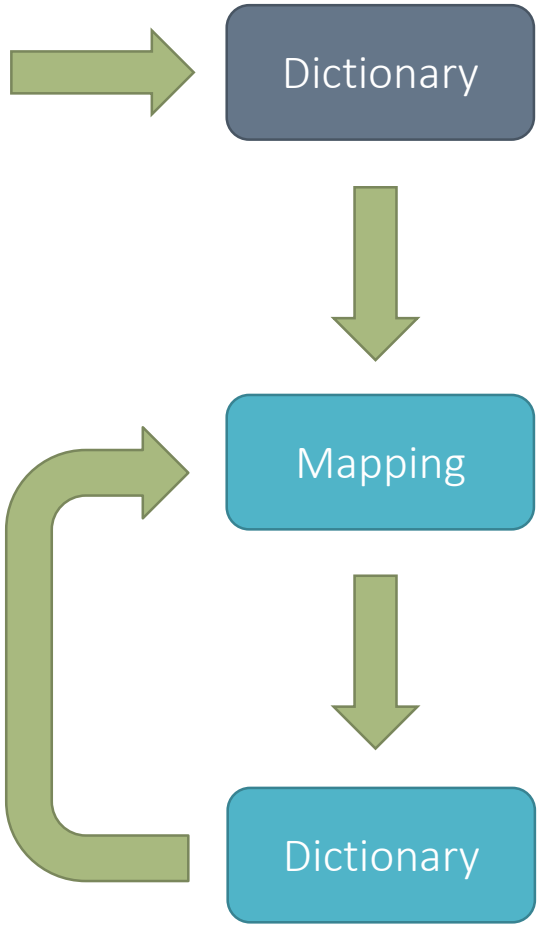
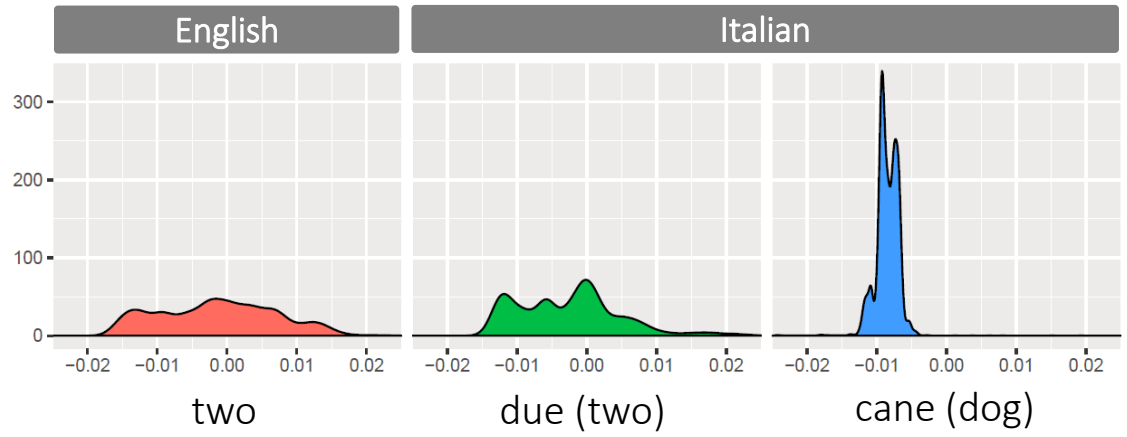


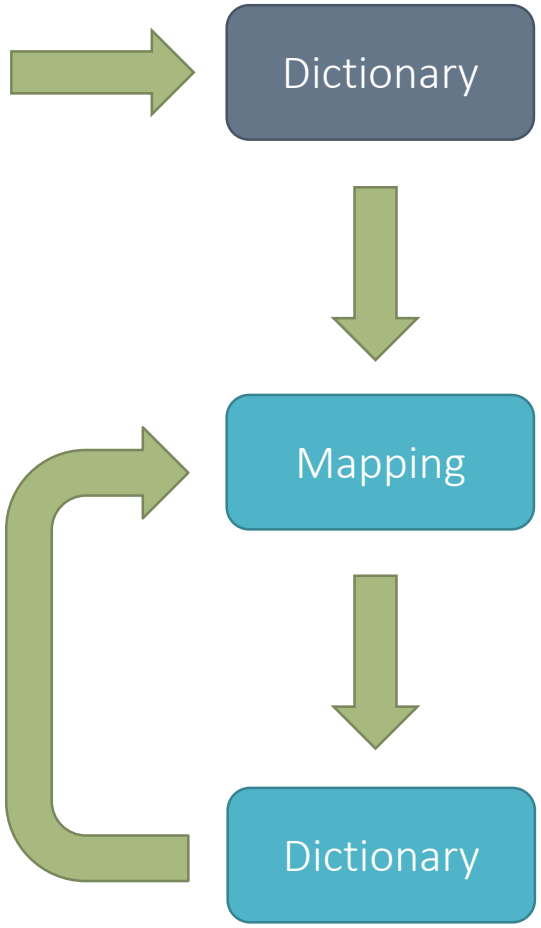
Cross-lingual embedding mappings



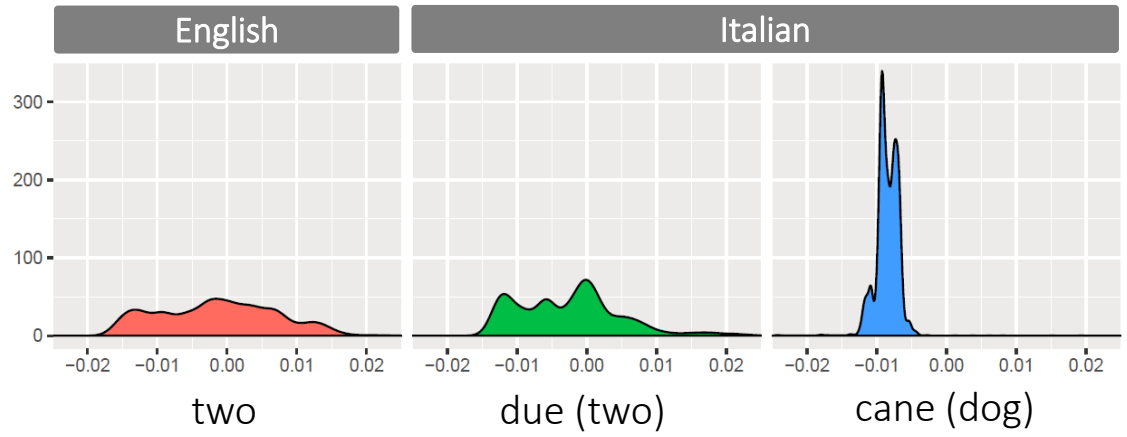
Intra-lingual similarity distribution

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

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



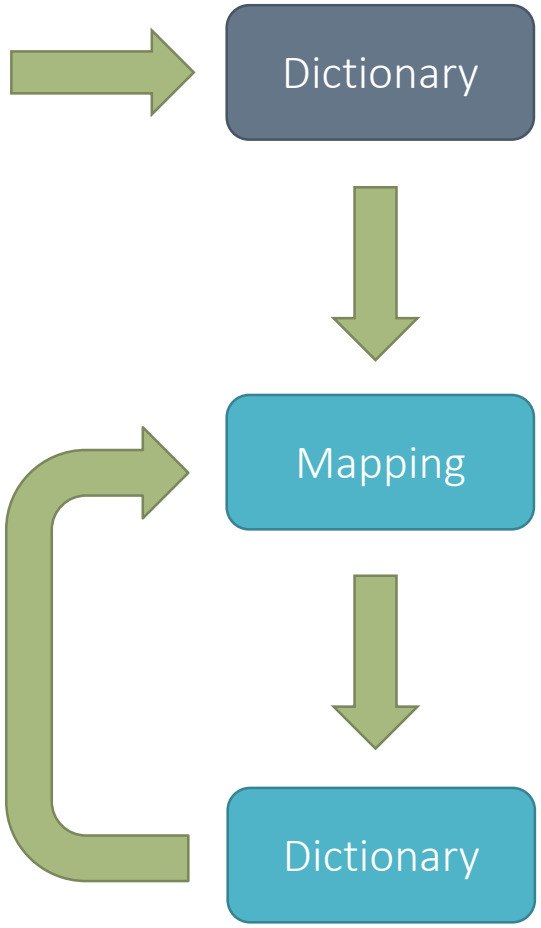
Cross-lingual embedding mappings



Intra-lingual similarity distribution

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

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



Cross-lingual embedding mappings

Cross-lingual embedding mappings

Supervision	Method

Cross-lingual embedding mappings

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 embedding mappings

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)
25 dict.	**Artetxe et al. (2017)**

Cross-lingual embedding mappings

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)
25 dict.	**Artetxe et al. (2017)**
Init. heurist.	Smith et al. (2017), cognates
	Artetxe et al. (2017), num.

Cross-lingual embedding mappings

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)
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 embedding mappings

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 embedding mappings

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*
	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 embedding mappings

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*
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None	Zhang et al. (2017), $\lambda = 1$	0.00*	0.00*	0.00*	0.00*
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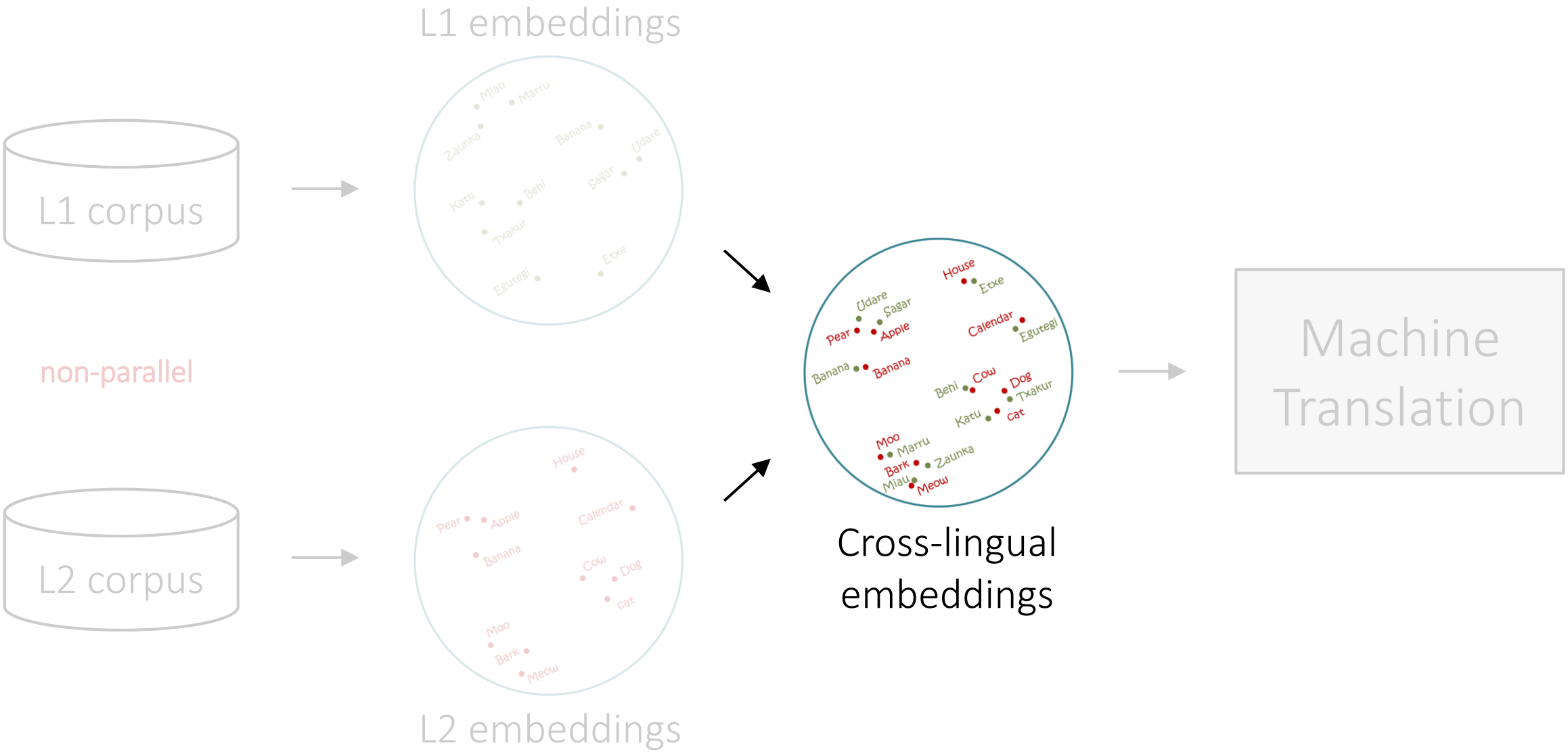
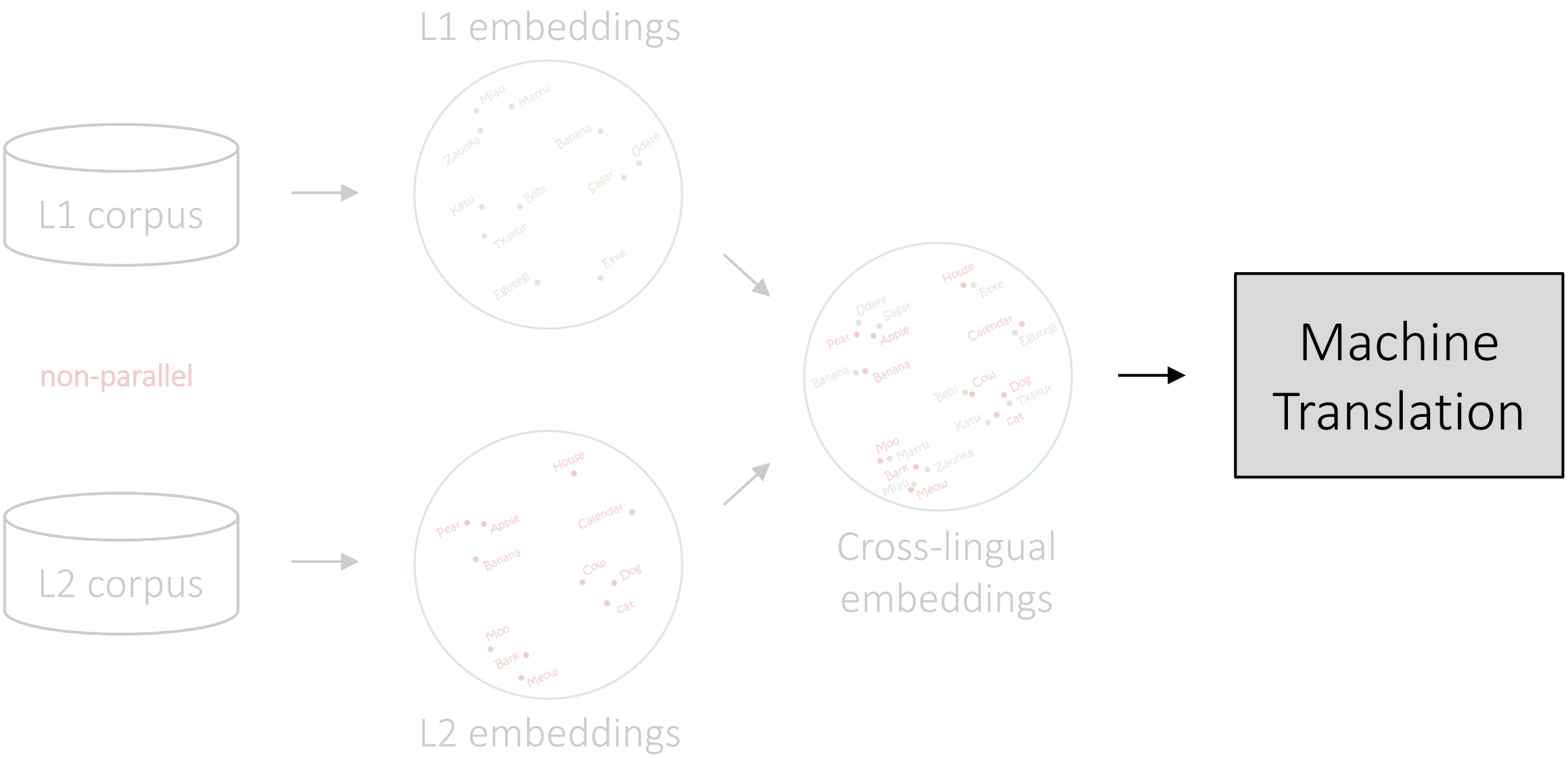
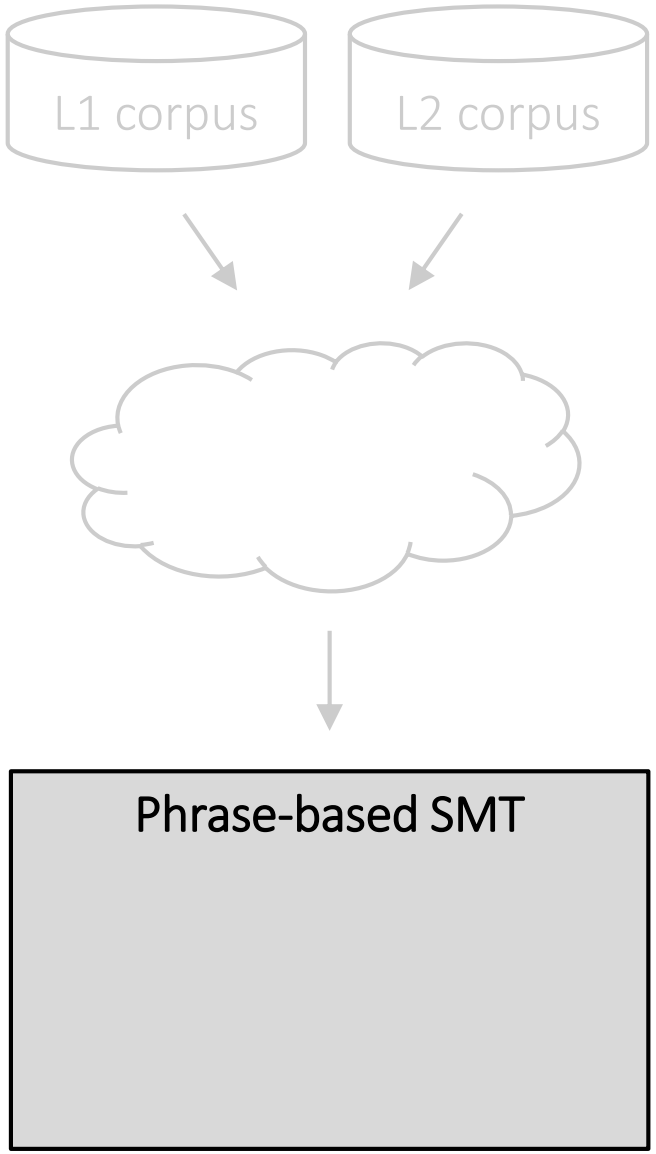
Outline

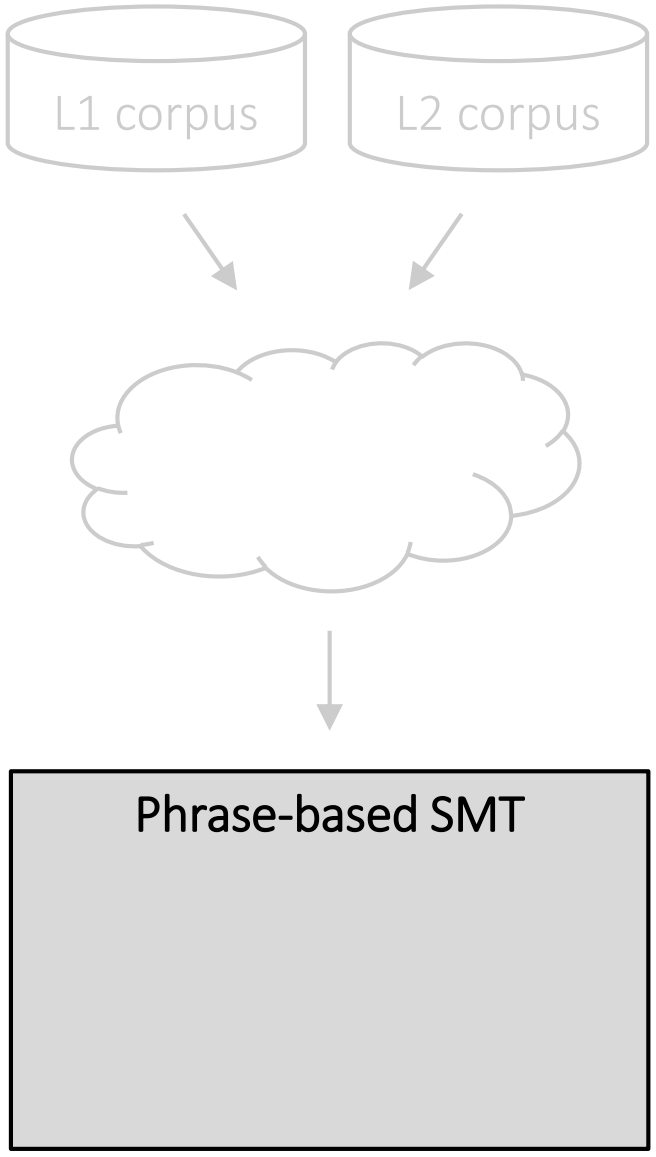

L1 embeddings
L1 corpus
non-parallel
L2 corpus
L2 embeddings
Cross-lingual embeddings
Machine Translation

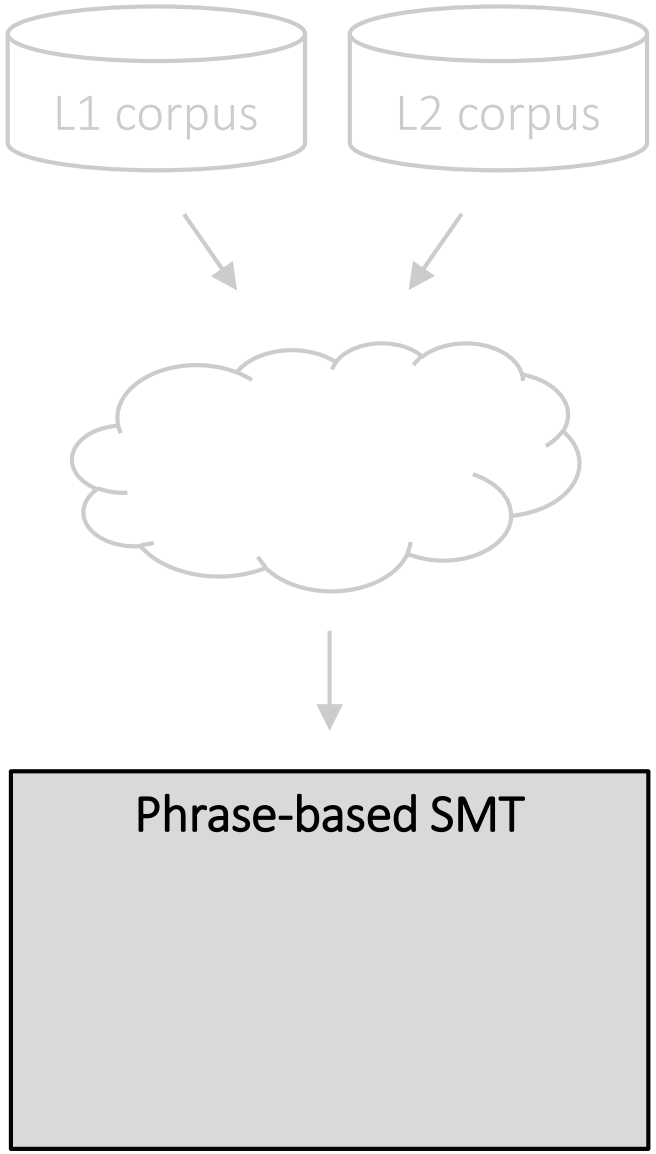
Outline


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


L1 corpus
L2 corpus
Phrase-based SMT

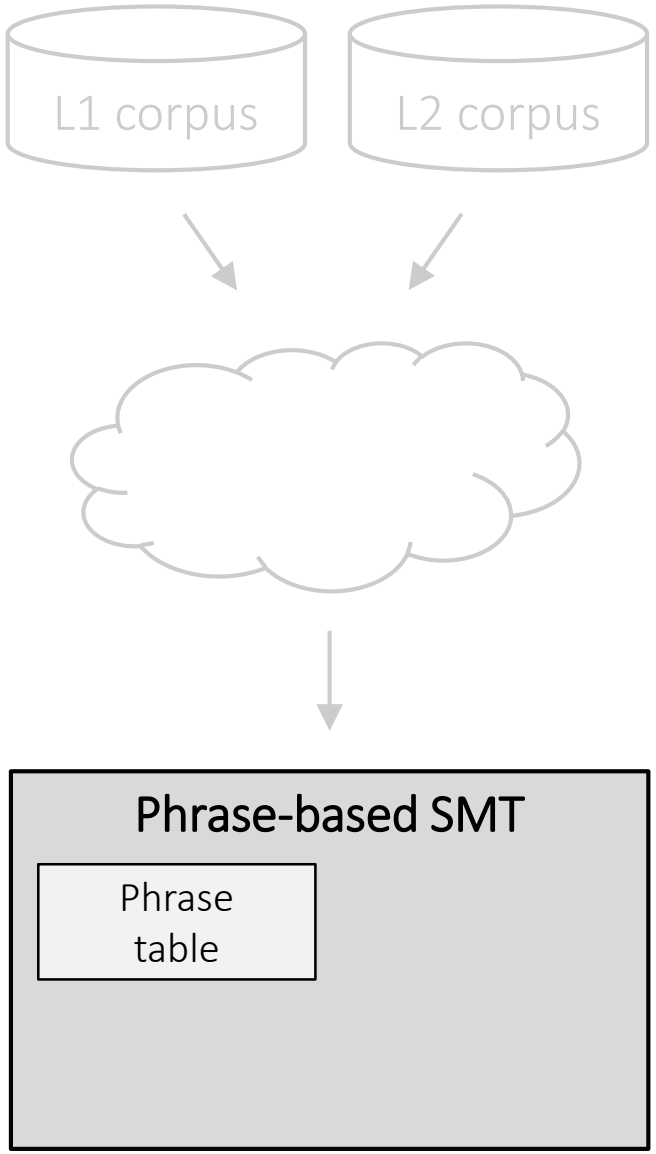
Phrase-based SMT





Phrase-based SMT

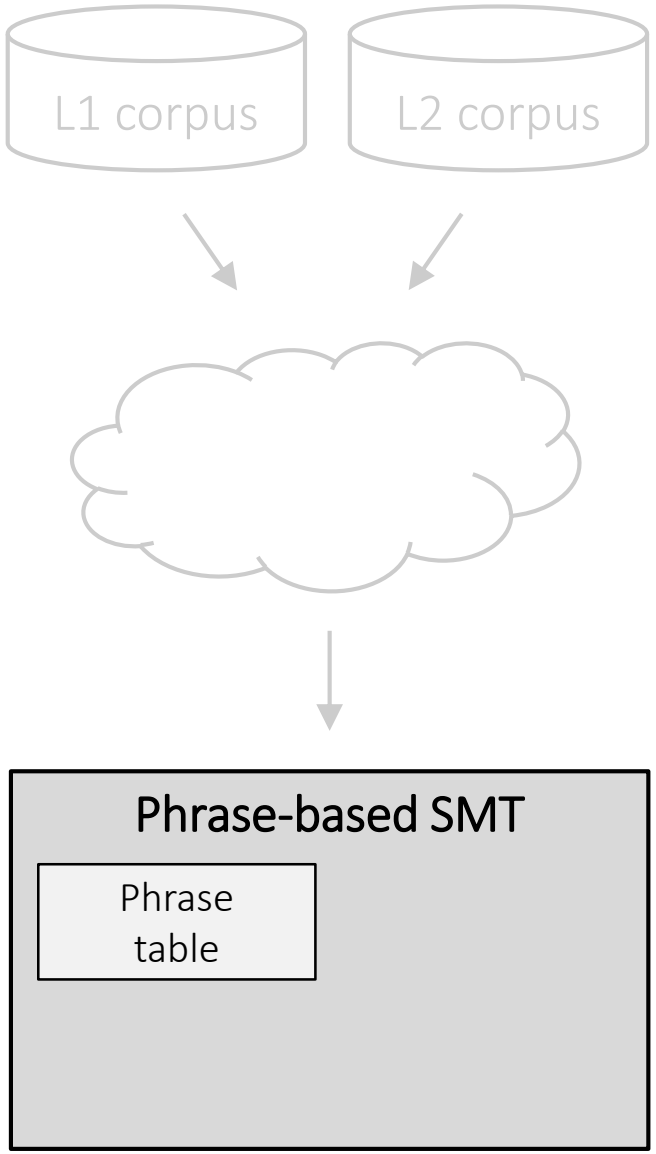
Log-linear model combining



Phrase-based SMT

Log-linear model combining

- Phrase table



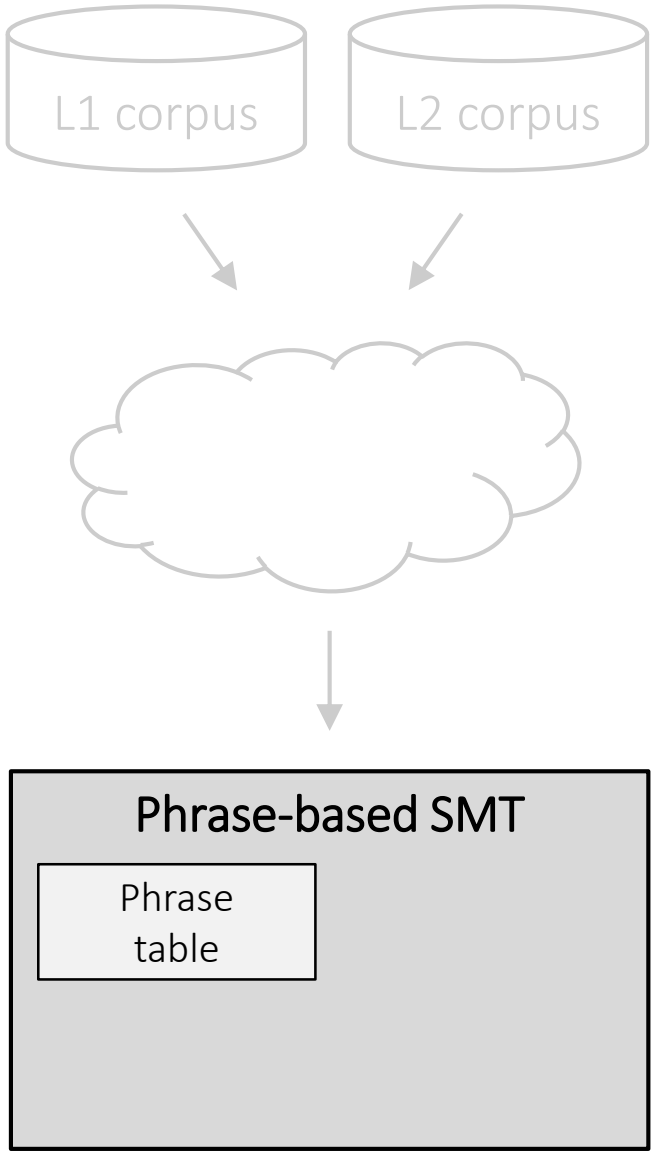
Phrase-based SMT

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

⋮



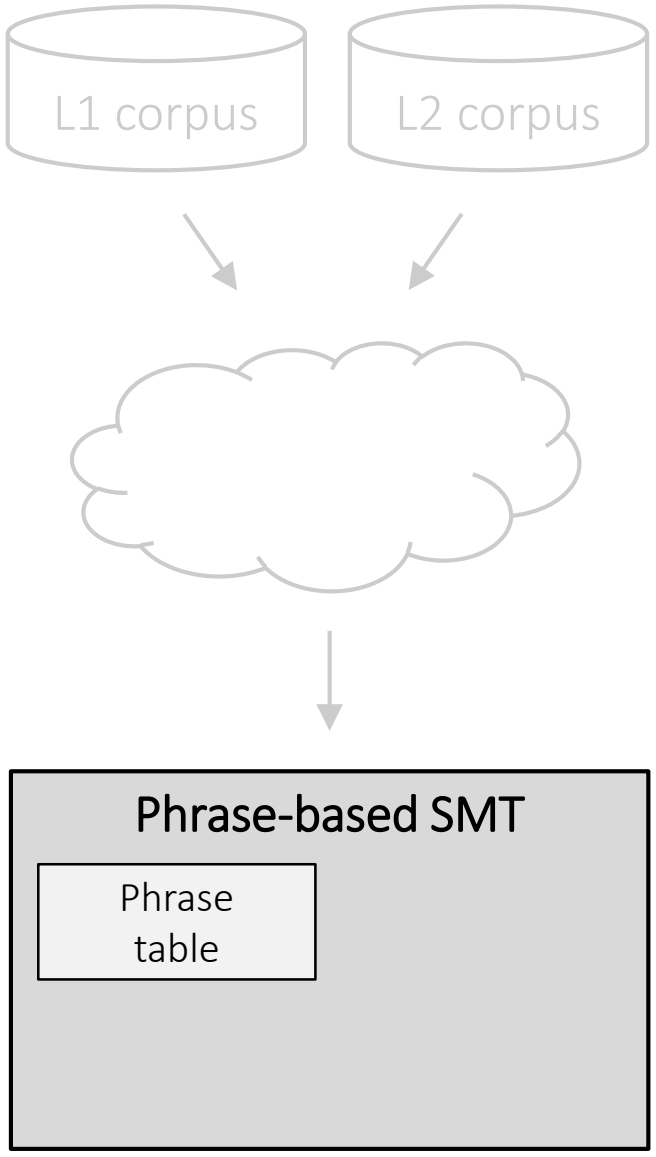
Phrase-based SMT

Log-linear model combining

- Phrase table
  - Direct/inverse translation probabilities

		$\phi(\bar{f}\|\bar{e})$	$\phi(\bar{e}\|\bar{f})$
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

⋮



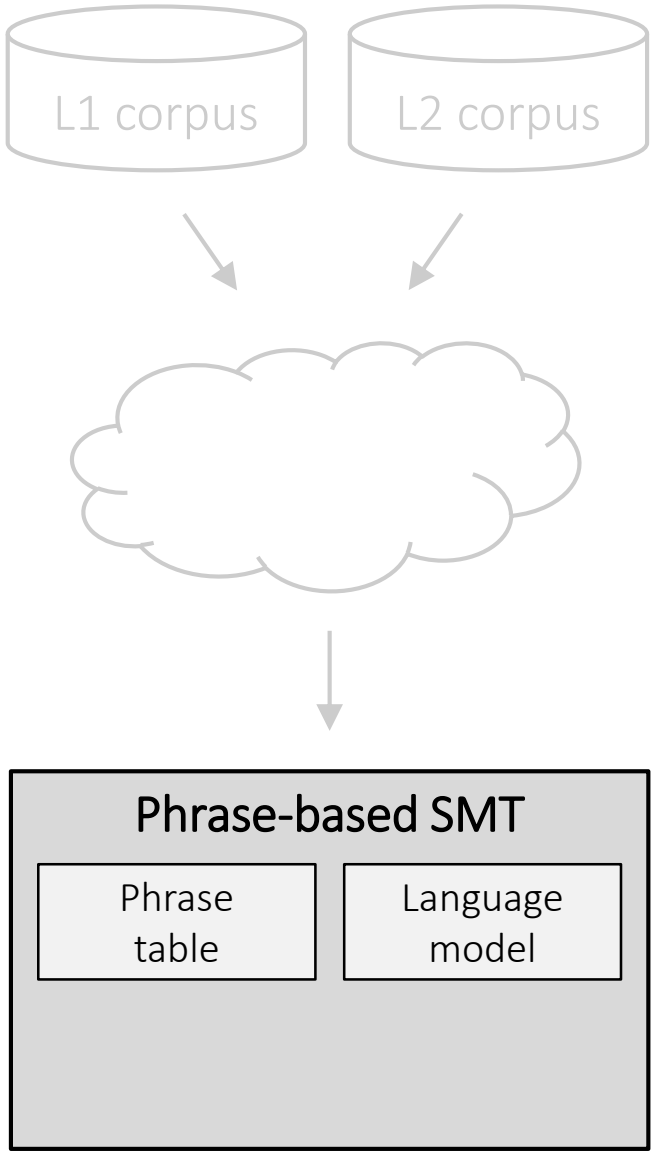
Phrase-based SMT

Log-linear model combining

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

		$\phi(\bar{f}\|\bar{e})$	$\phi(\bar{e}\|\bar{f})$	$\mathbf{lex}(\bar{f}\|\bar{e})$	$\mathbf{lex}(\bar{e}\|\bar{f})$
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

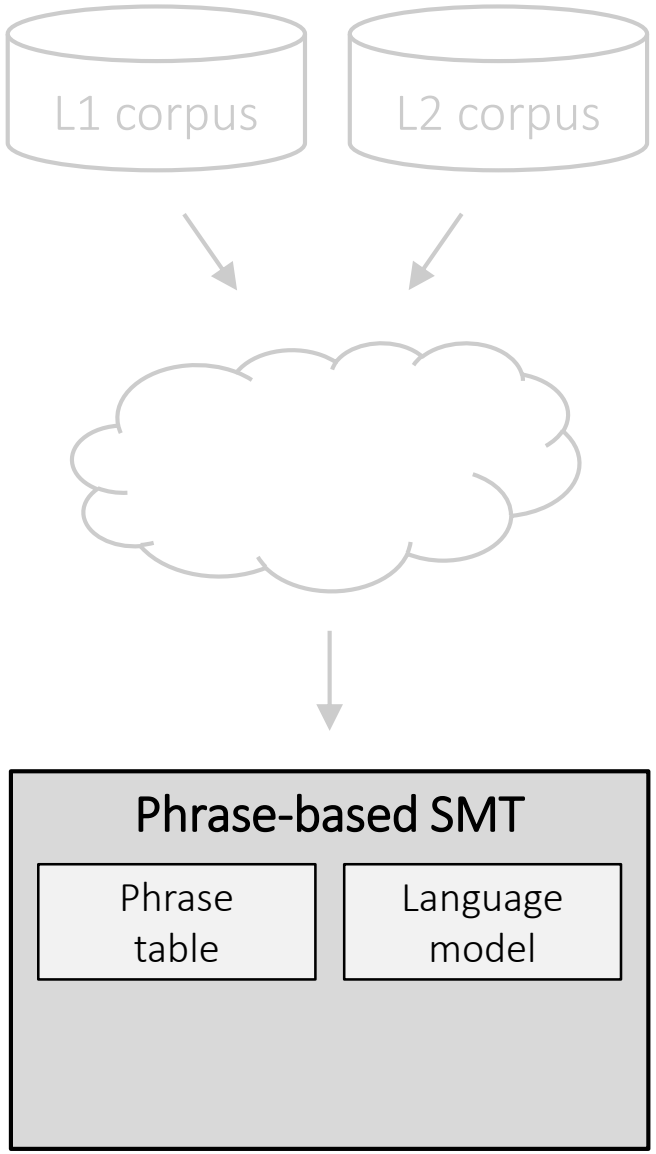
⋮



Phrase-based SMT

Log-linear model combining

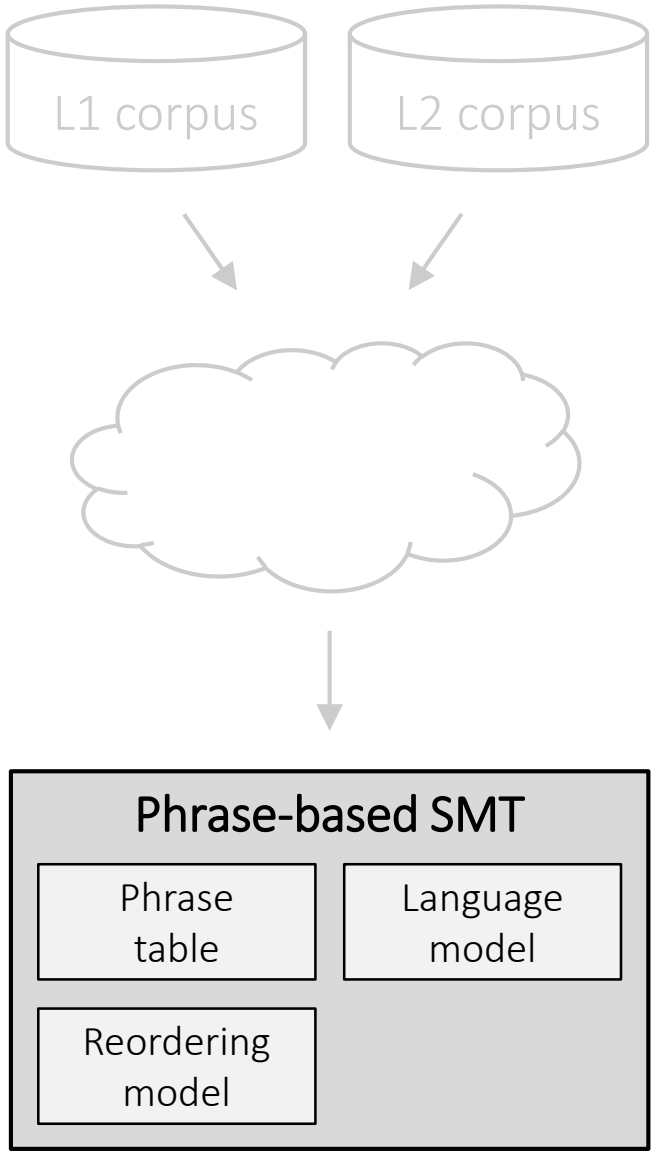
- Phrase table
  - Direct/inverse translation probabilities
  - Direct/inverse lexical weightings
- Language model



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
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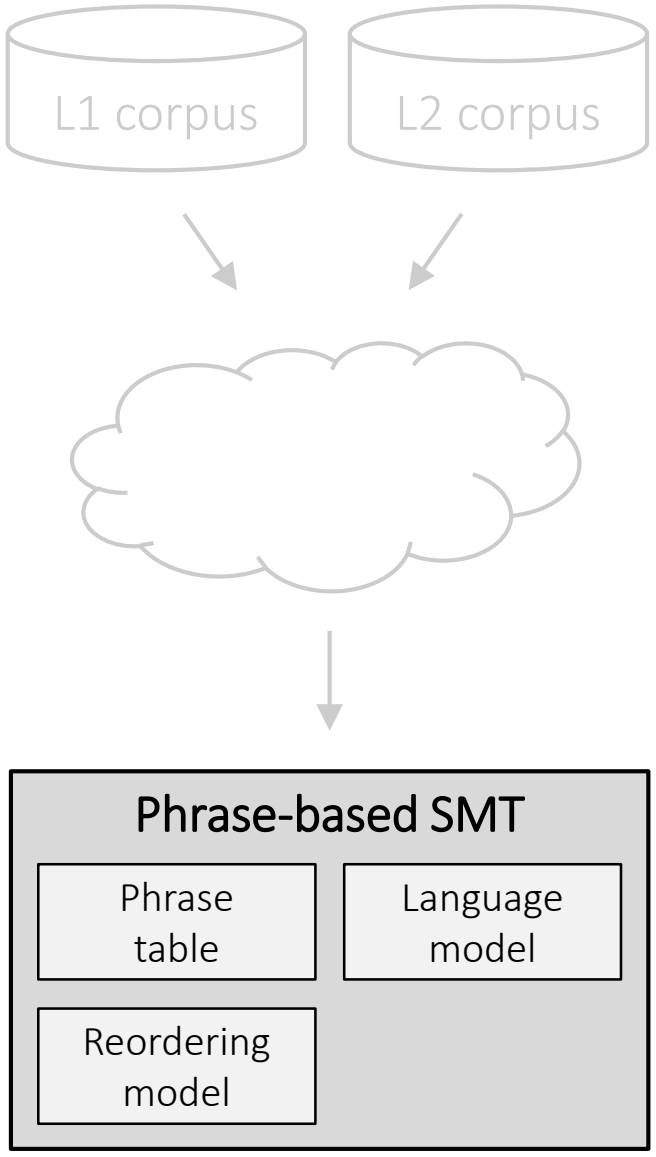
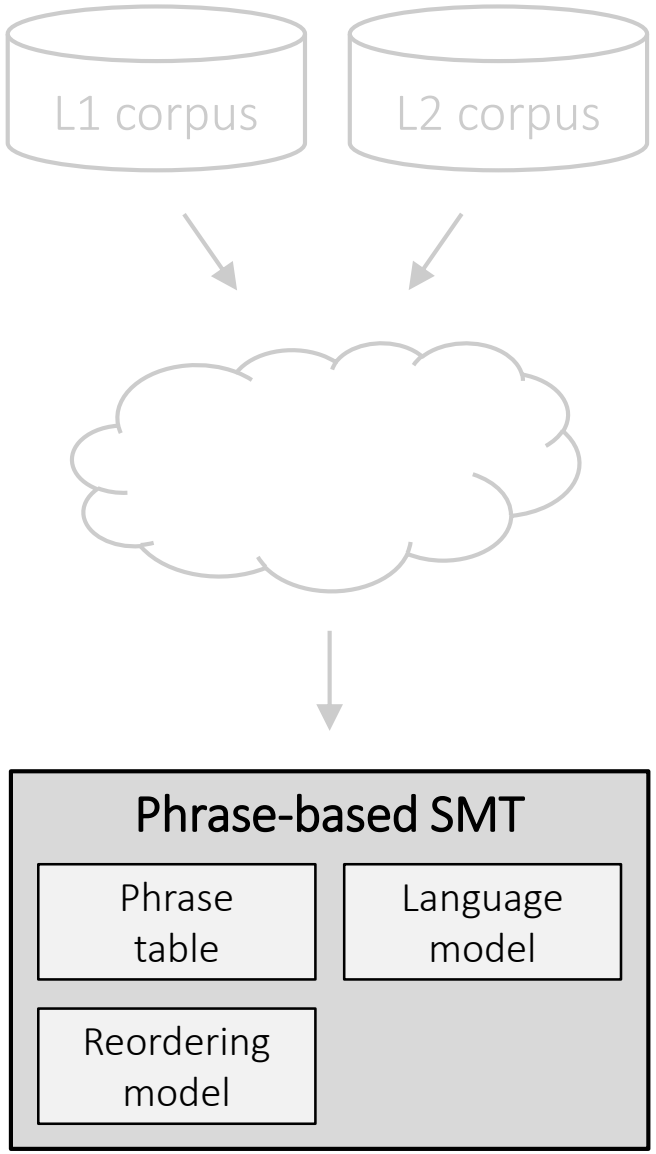
- Language model
  - N-gram frequency counts with back-off and smoothing
- Reordering model



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
- Reordering model
  - Distortion model (distance based)



Phrase-based SMT

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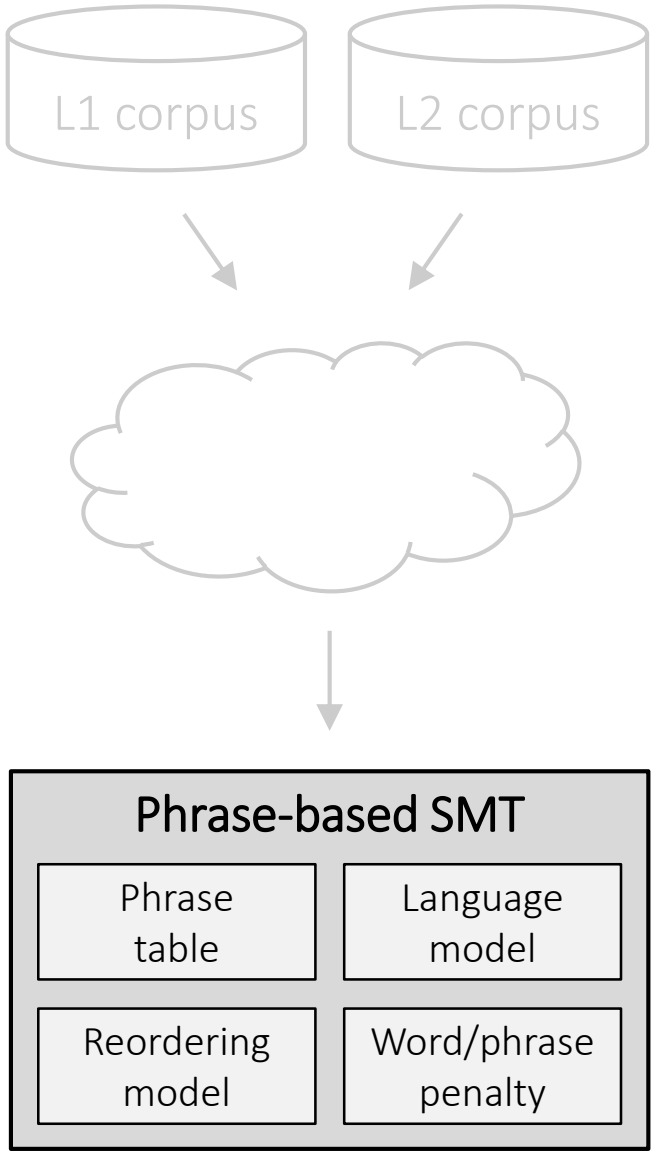
  - Distortion model (distance based)
  - Lexical reordering model



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Log-linear model combining

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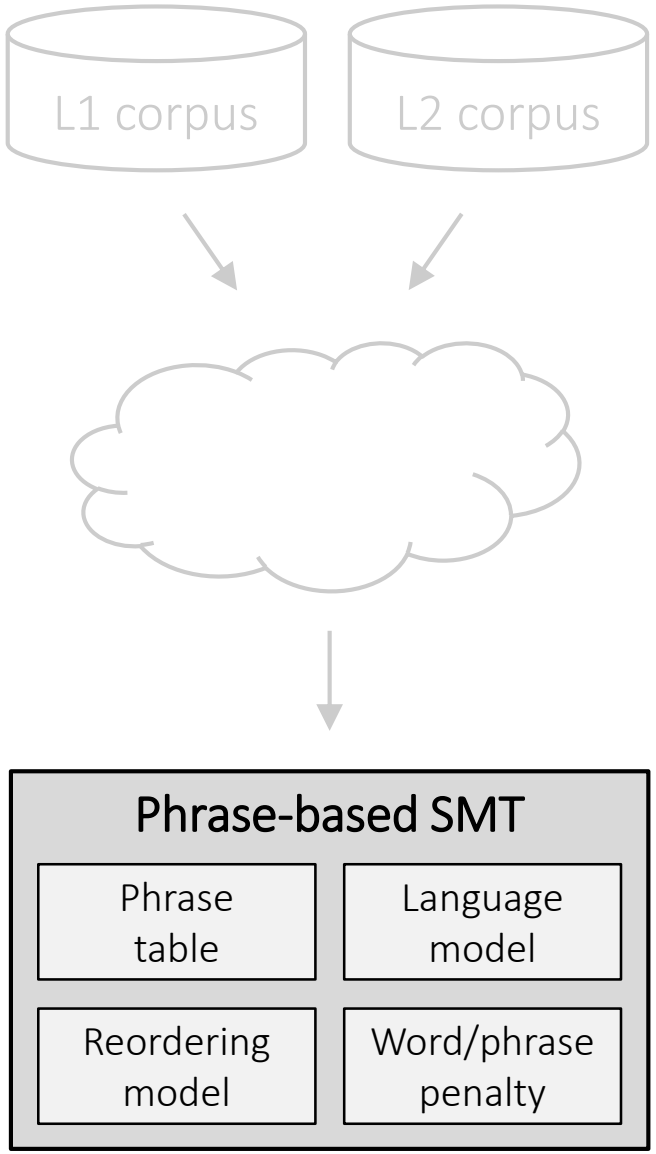
- Word/phrase penalty



Phrase-based SMT

Log-linear model combining

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

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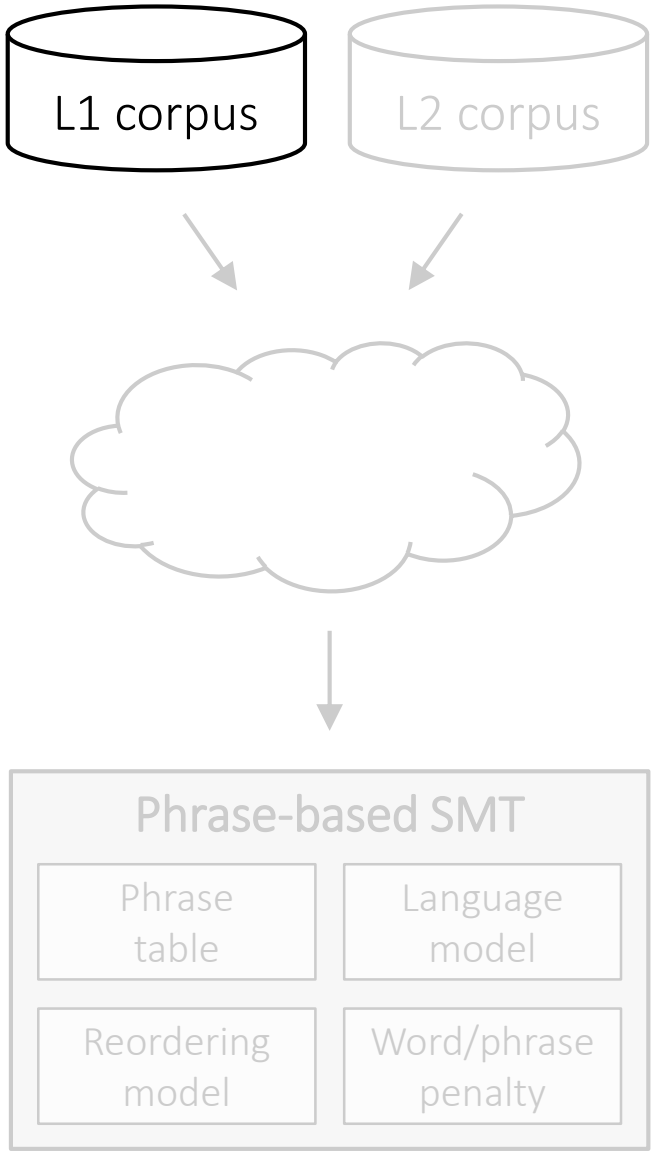

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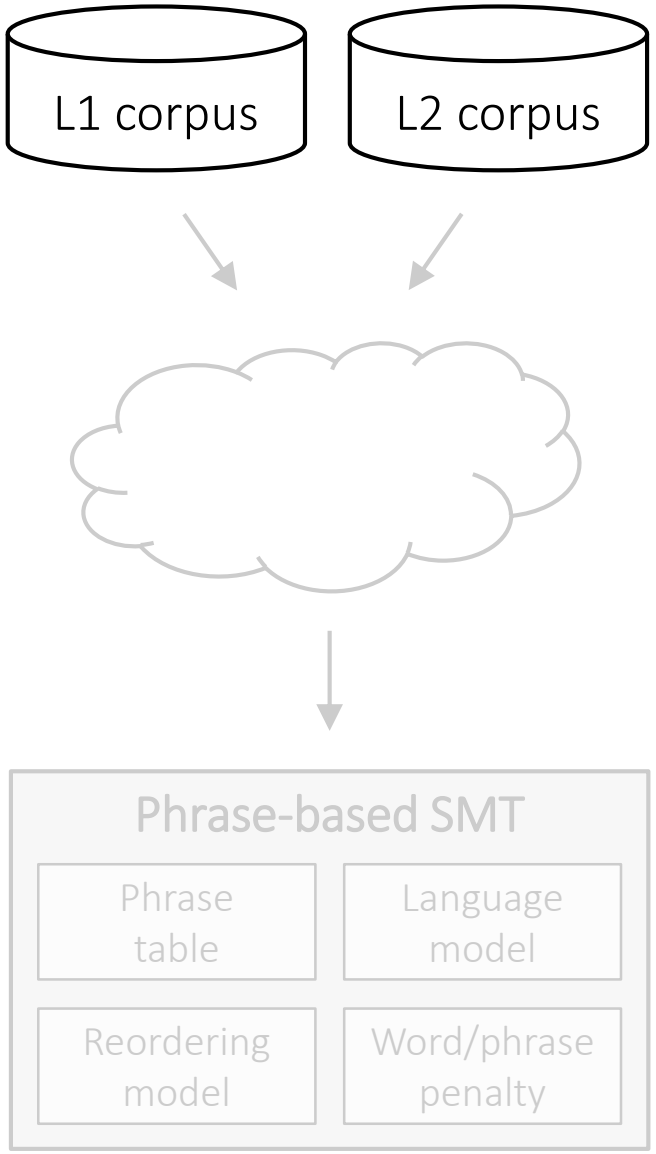

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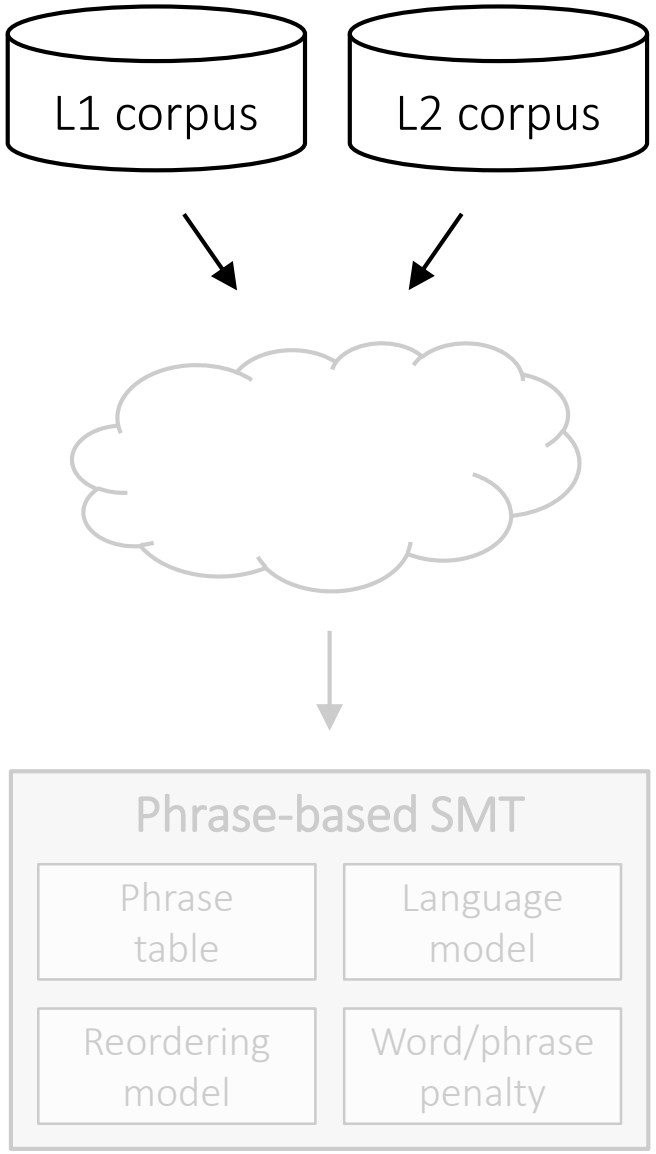

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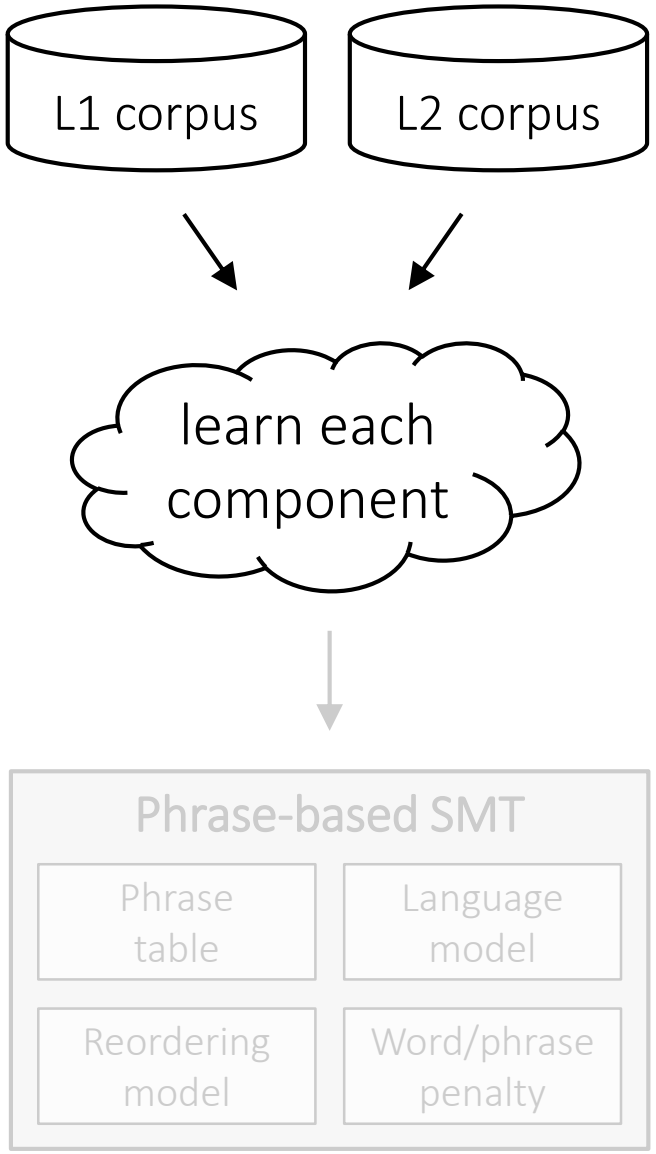

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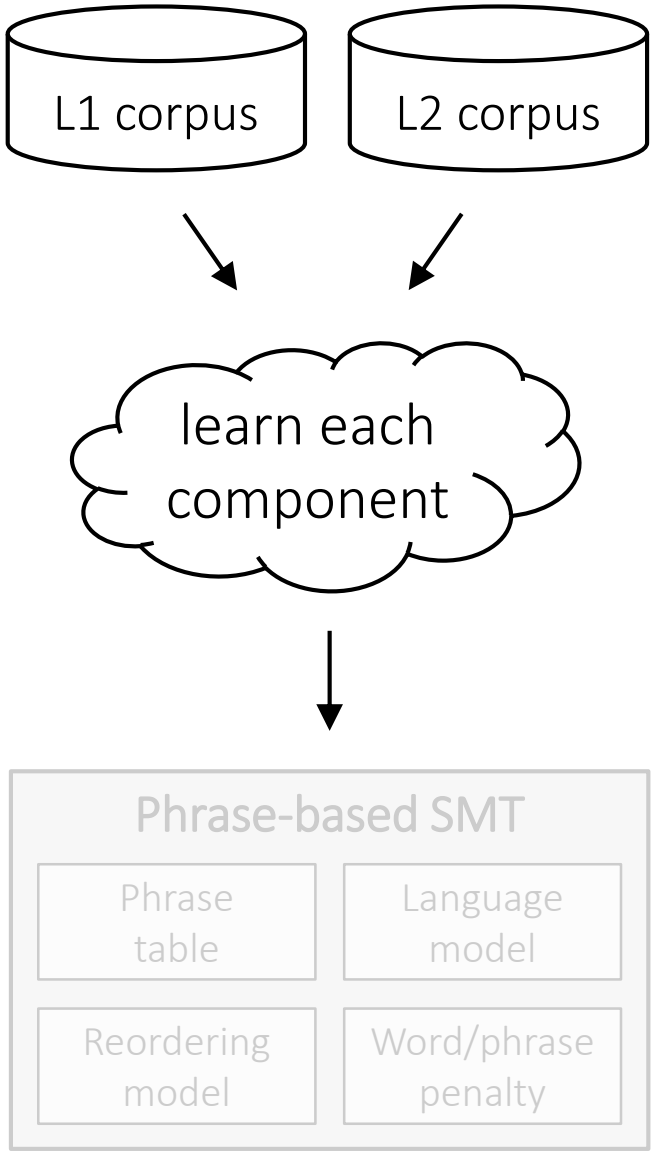

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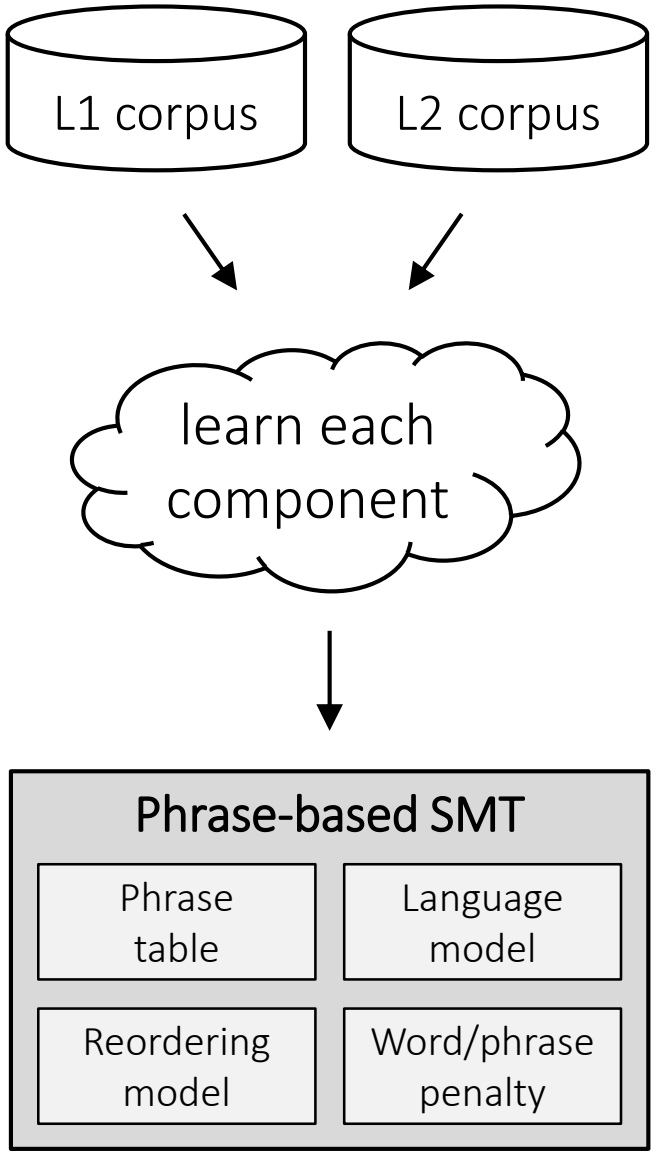

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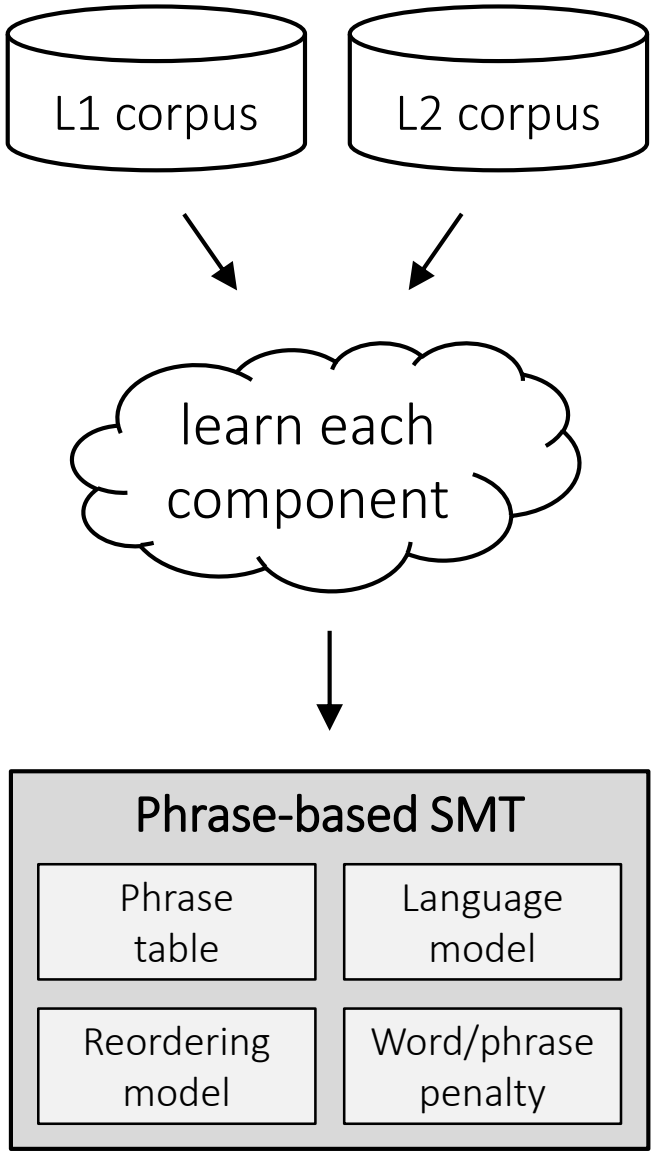
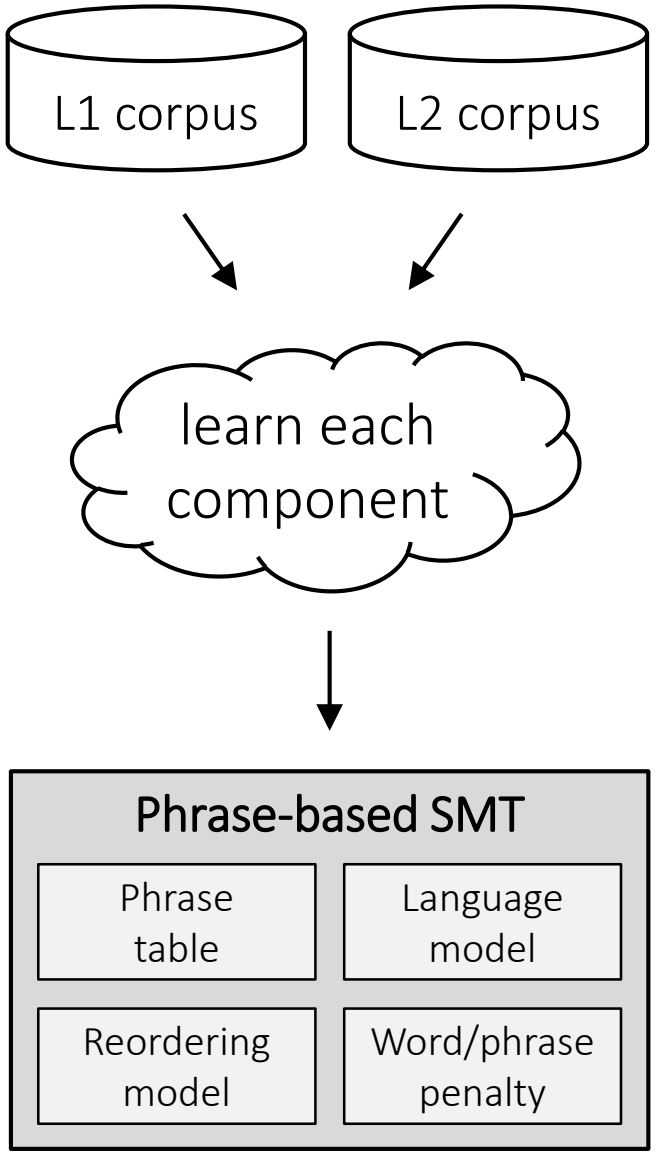


Unsupervised phrase-based SMT

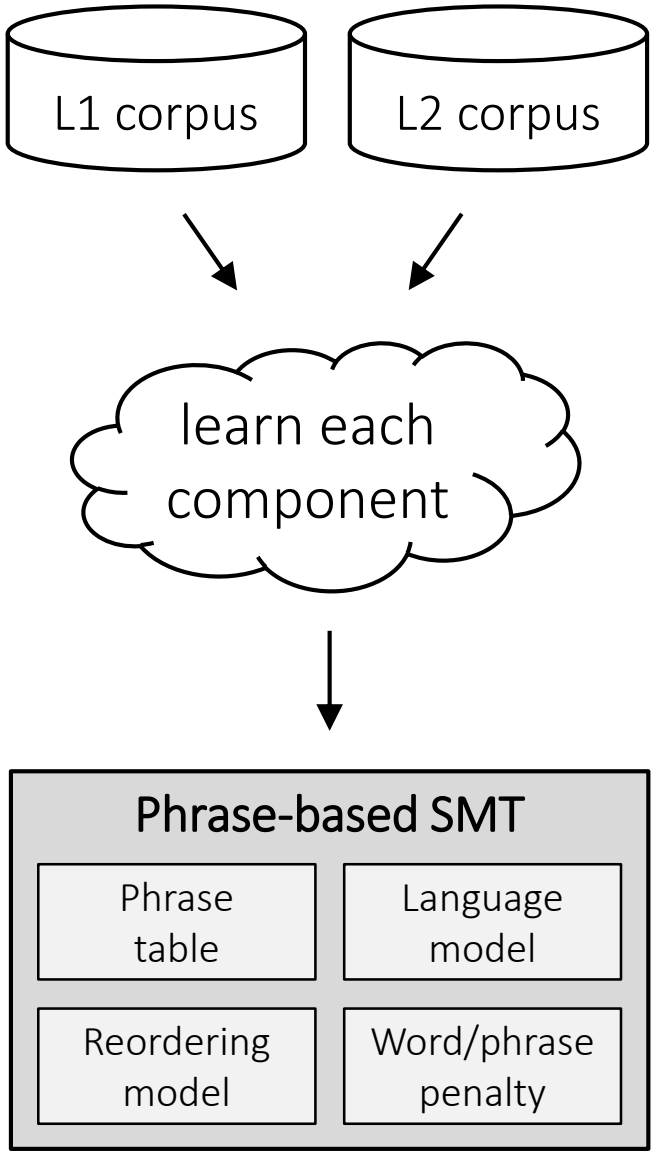
- Phrase table
  - Direct/inverse translation probabilities
  - Direct/inverse lexical weightings
- Language model
  - N-gram frequency counts with back-off and smoothing
- Reordering model
  - Distortion model (distance based)
  - Lexical reordering model
- Word/phrase penalty
  - Fixed score to control the length of the output



Unsupervised phrase-based SMT

Learn components from monolingual corpora

- Phrase table
  - Direct/inverse translation probabilities
  - Direct/inverse lexical weightings
- Language model
  - N-gram frequency counts with back-off and smoothing
- Reordering model
  - Distortion model (distance based)
  - Lexical reordering model
- Word/phrase penalty
  - Fixed score to control the length of the output



Unsupervised phrase-based SMT

Learn components from monolingual corpora

- Phrase table
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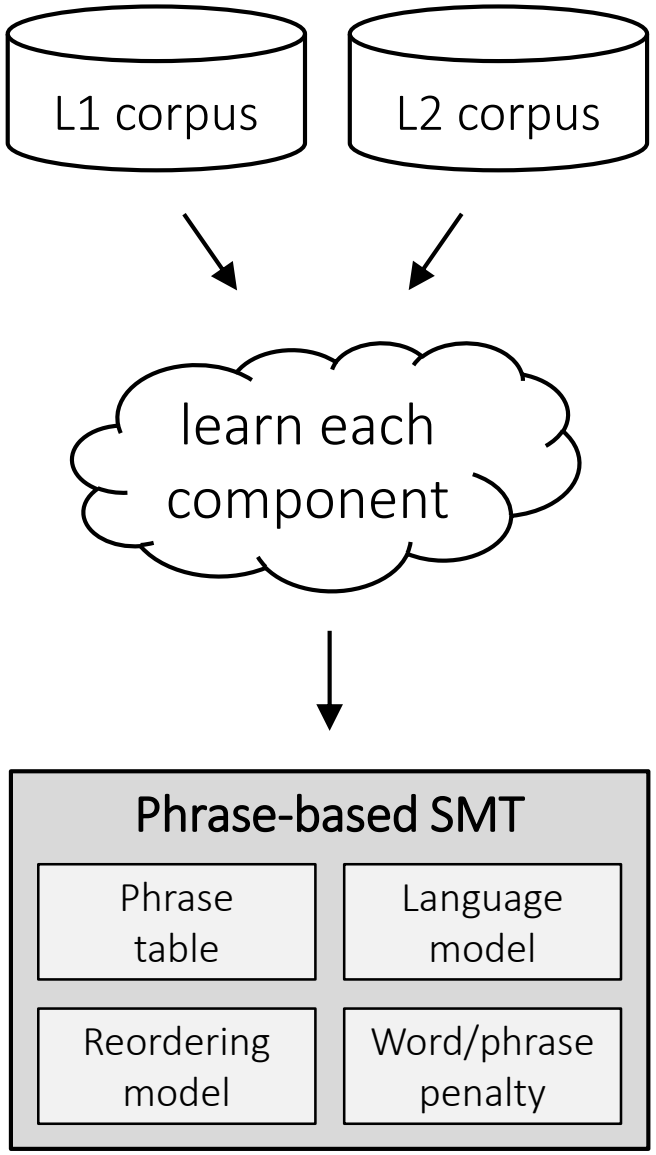

Unsupervised phrase-based SMT

Learn components from monolingual corpora

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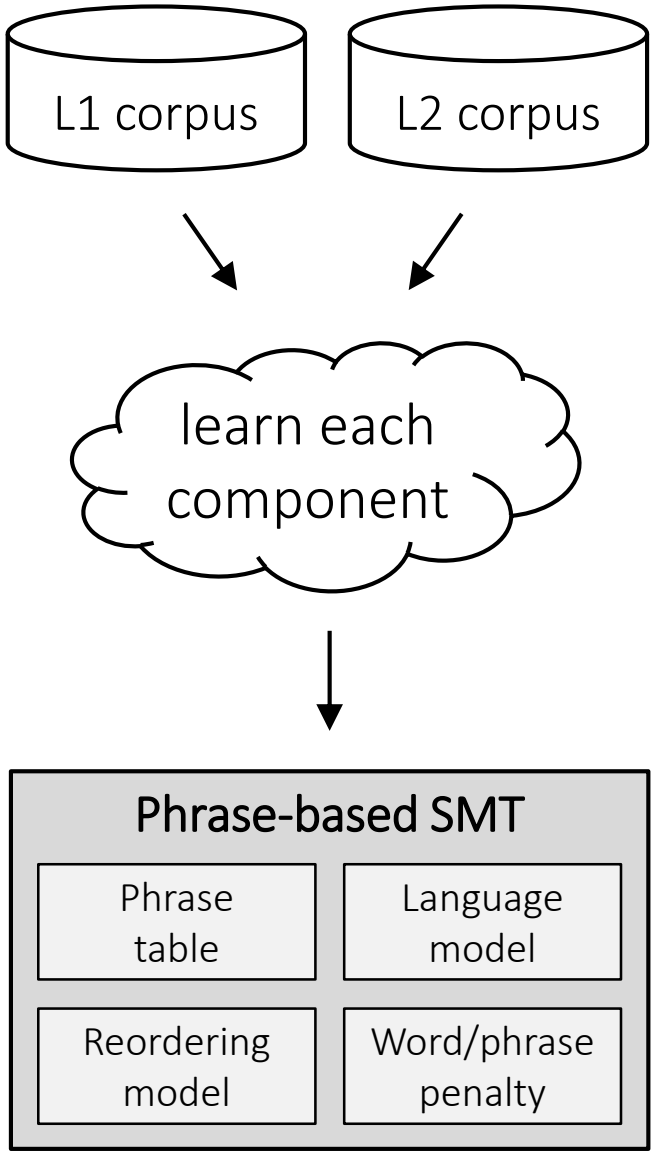

Unsupervised phrase-based SMT

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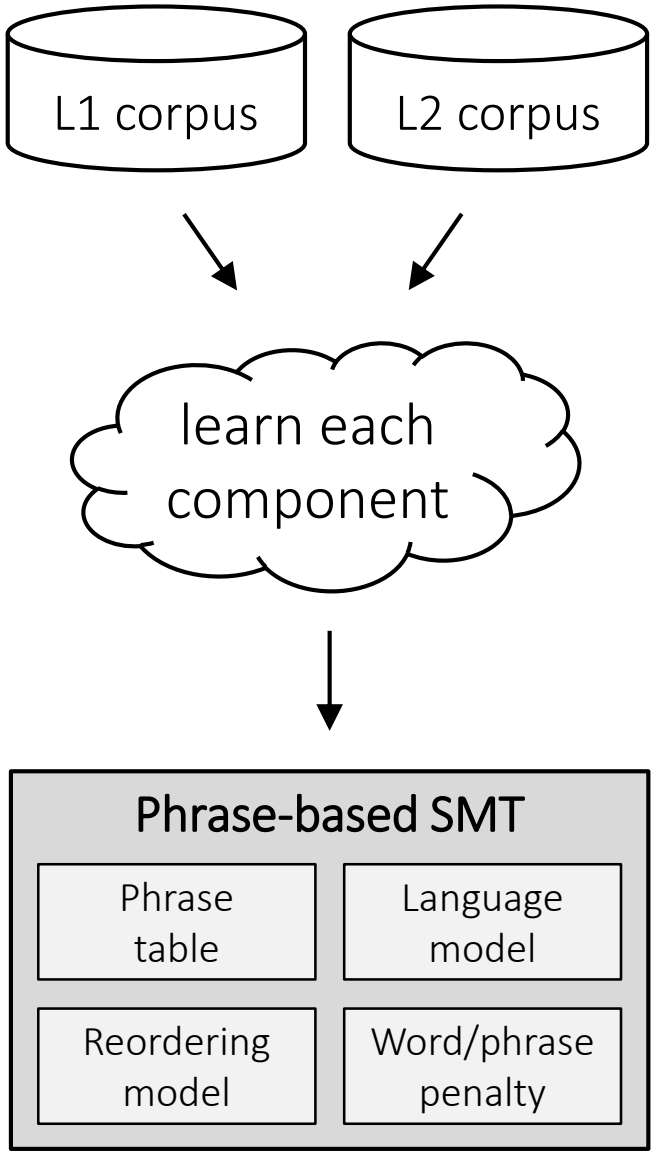

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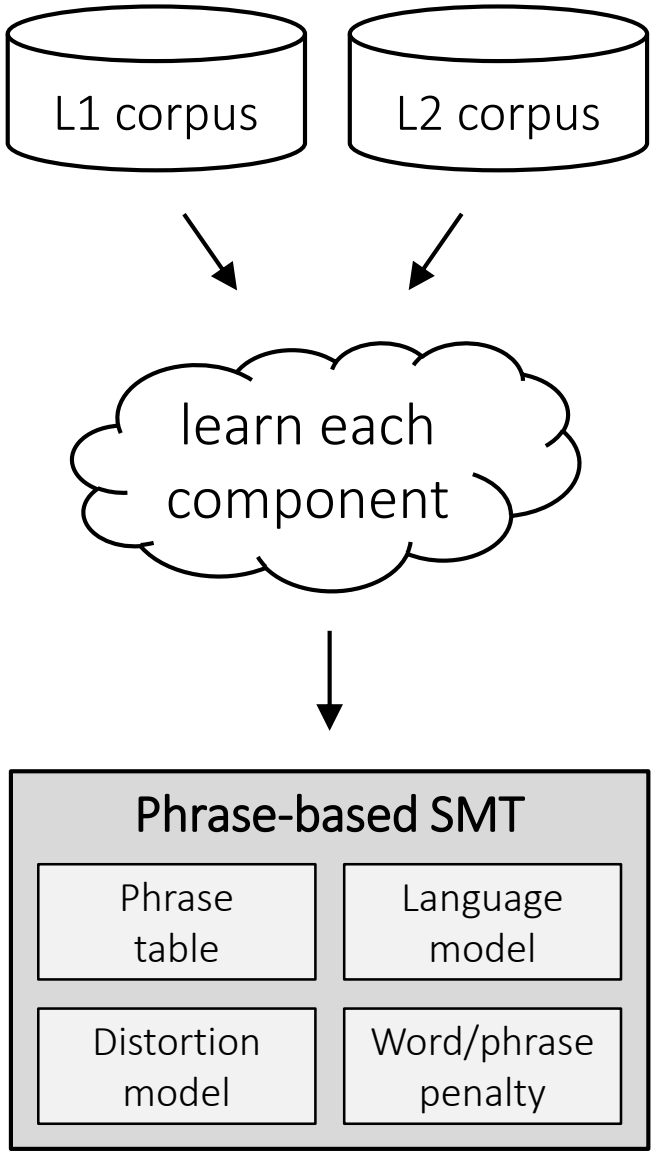

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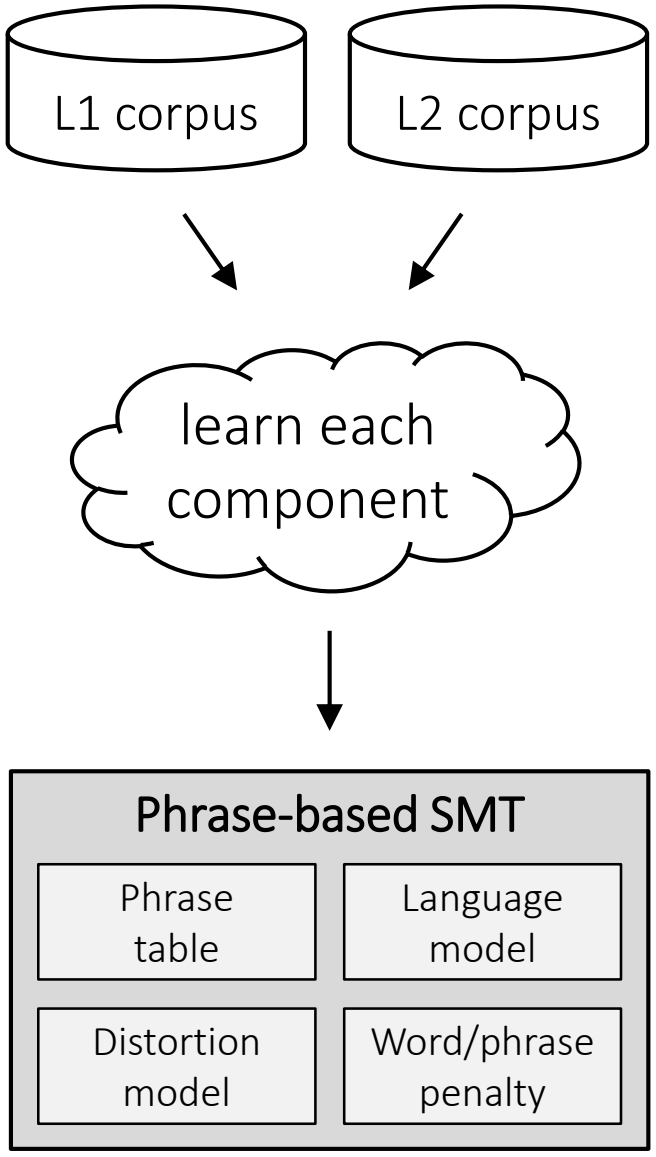

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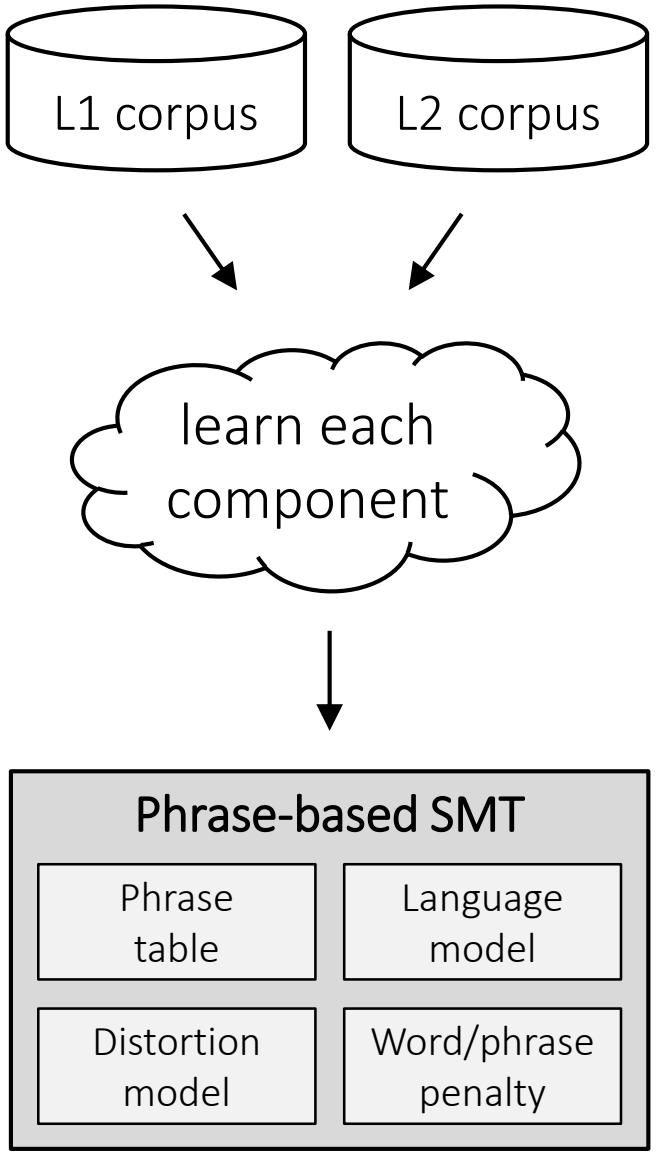

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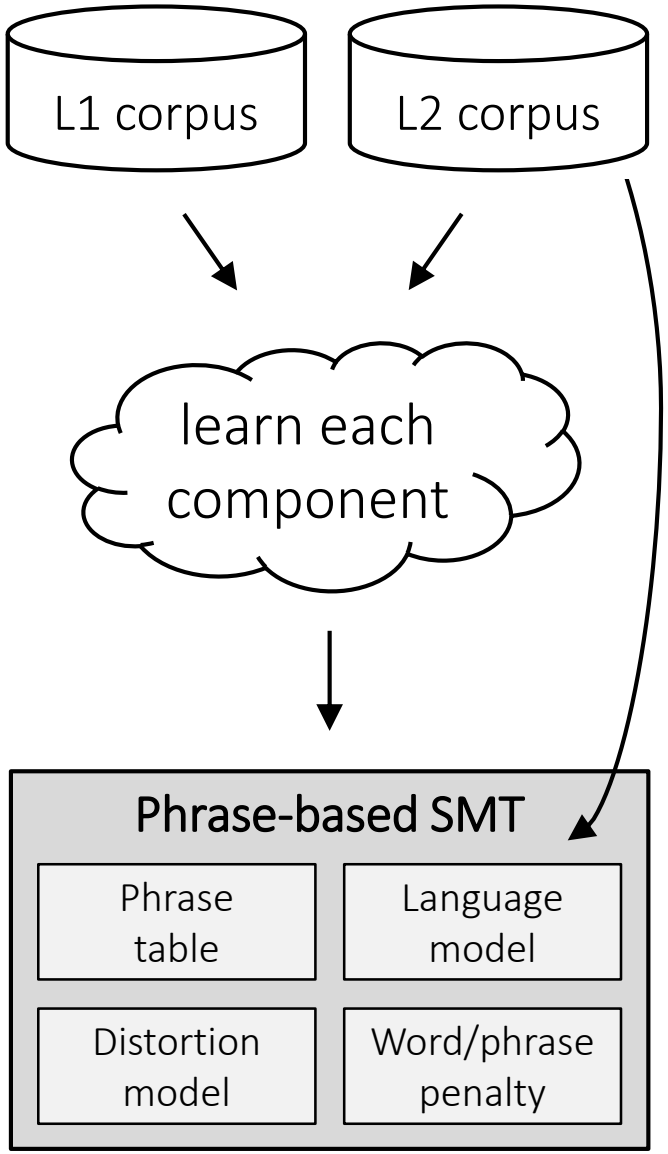

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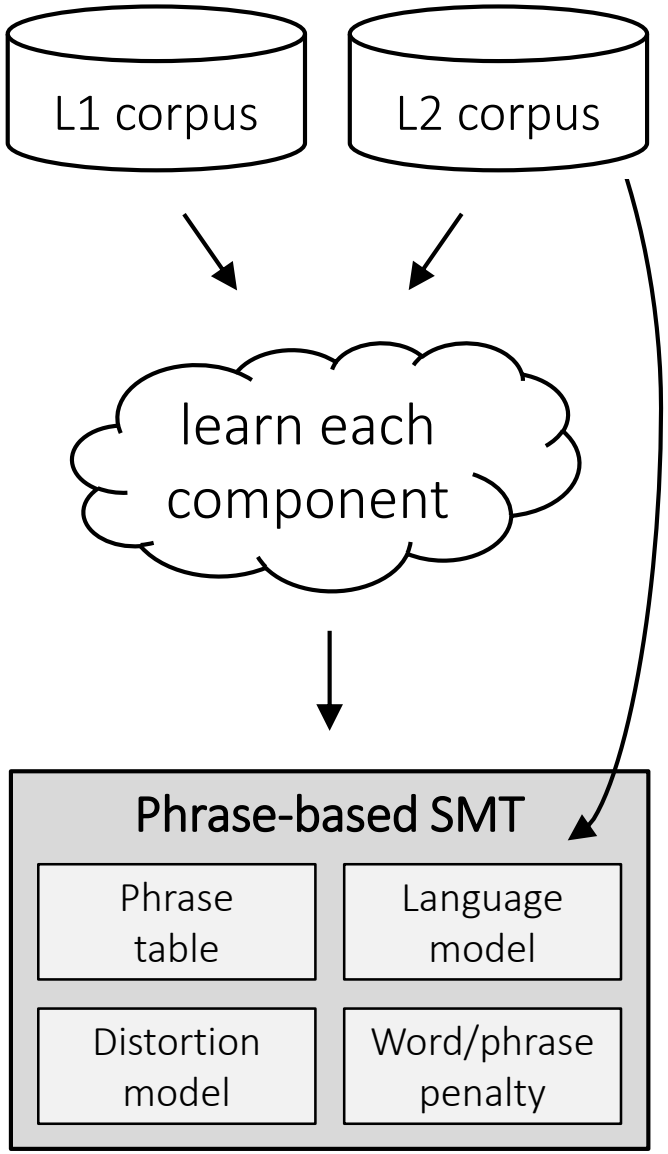

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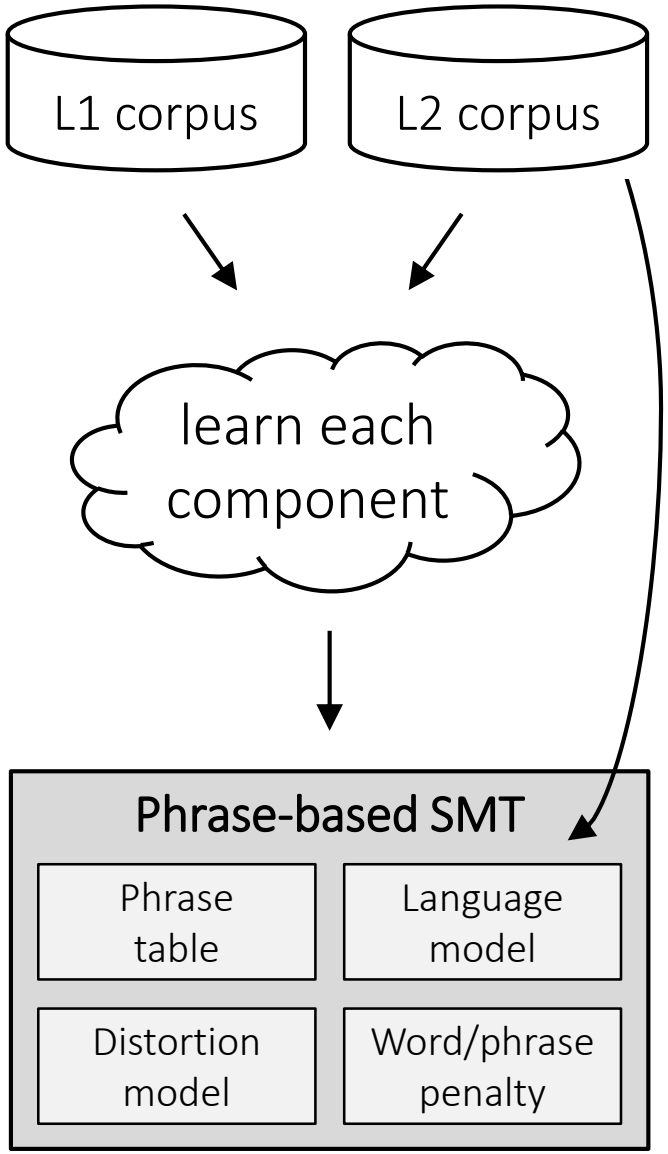

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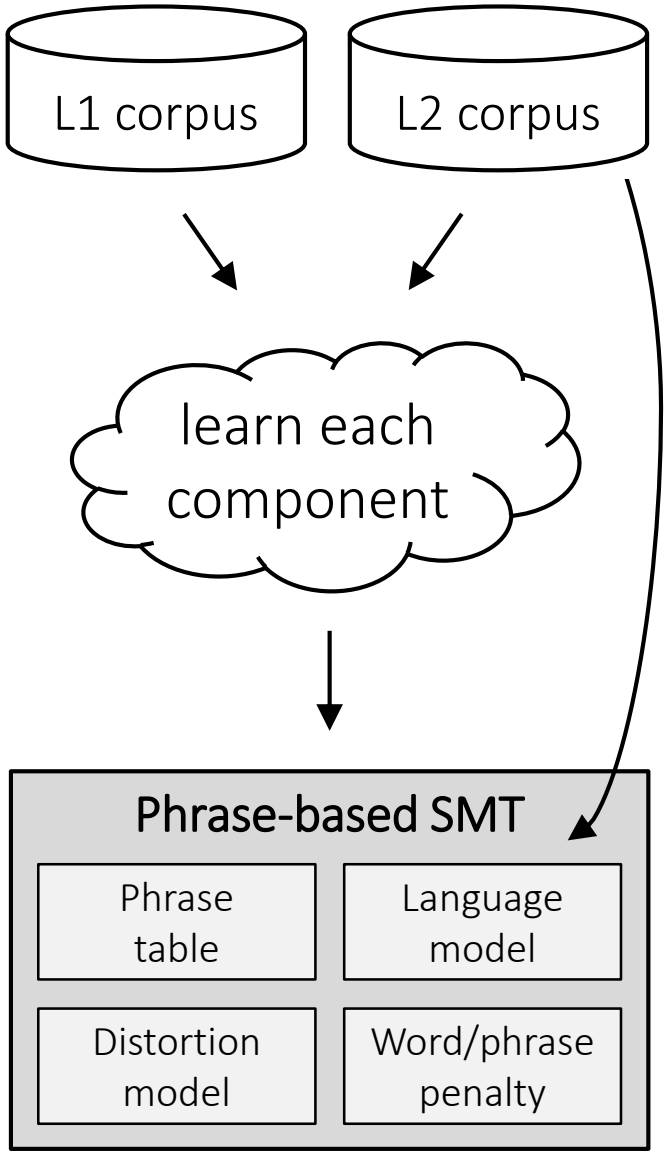

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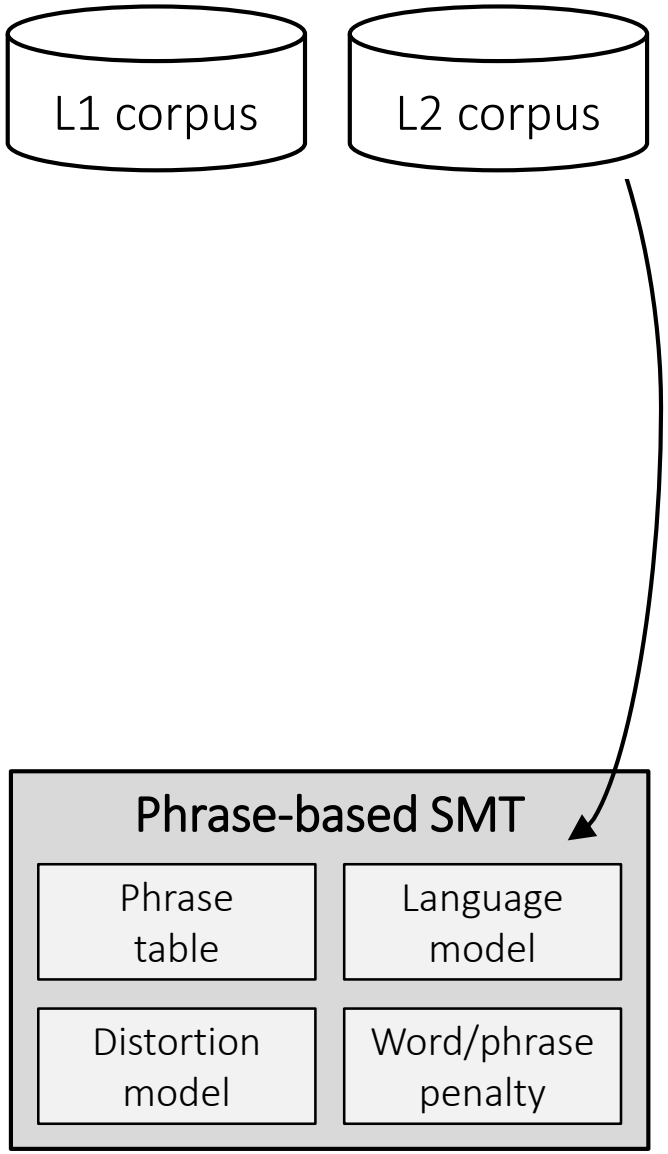

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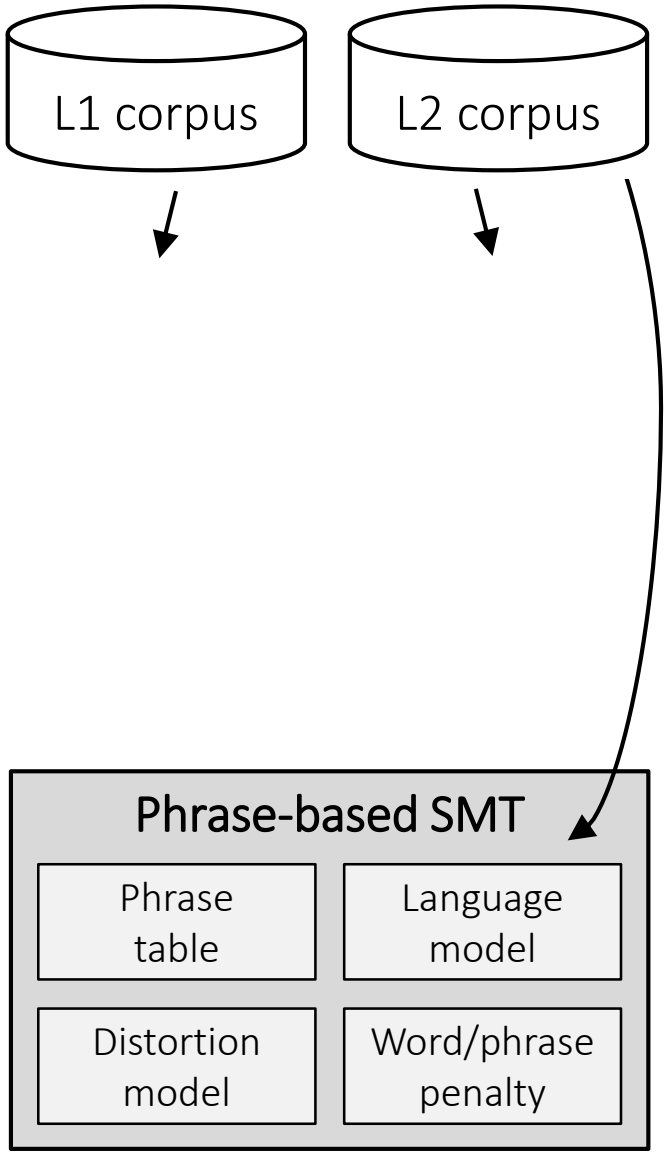

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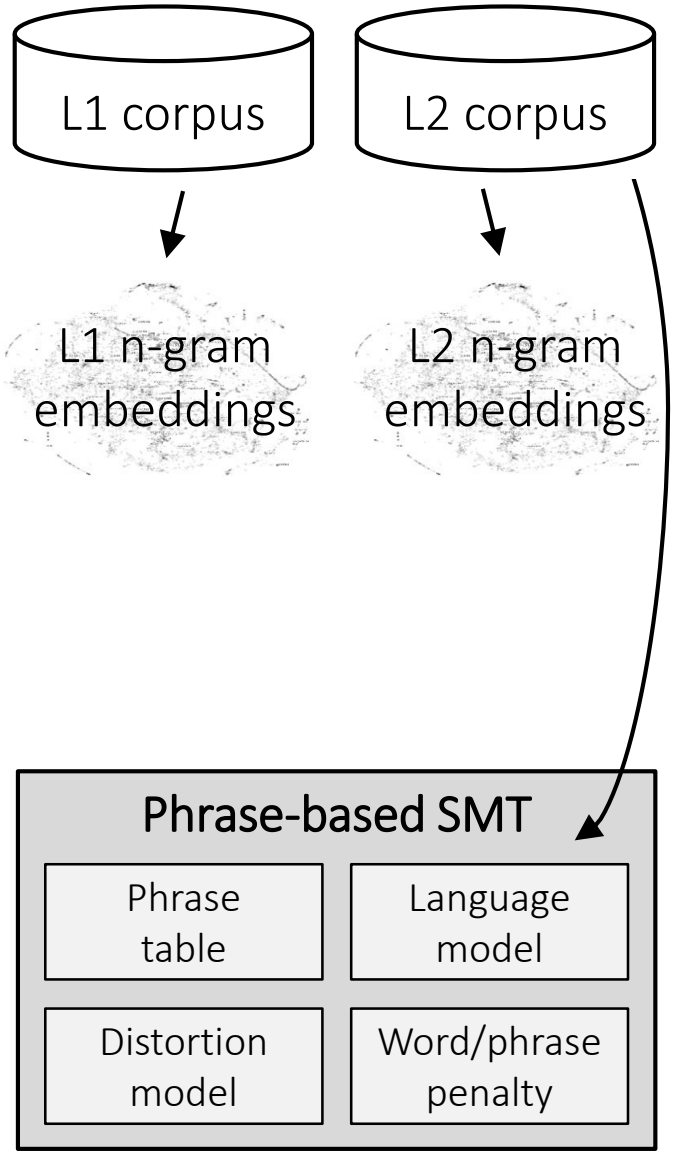

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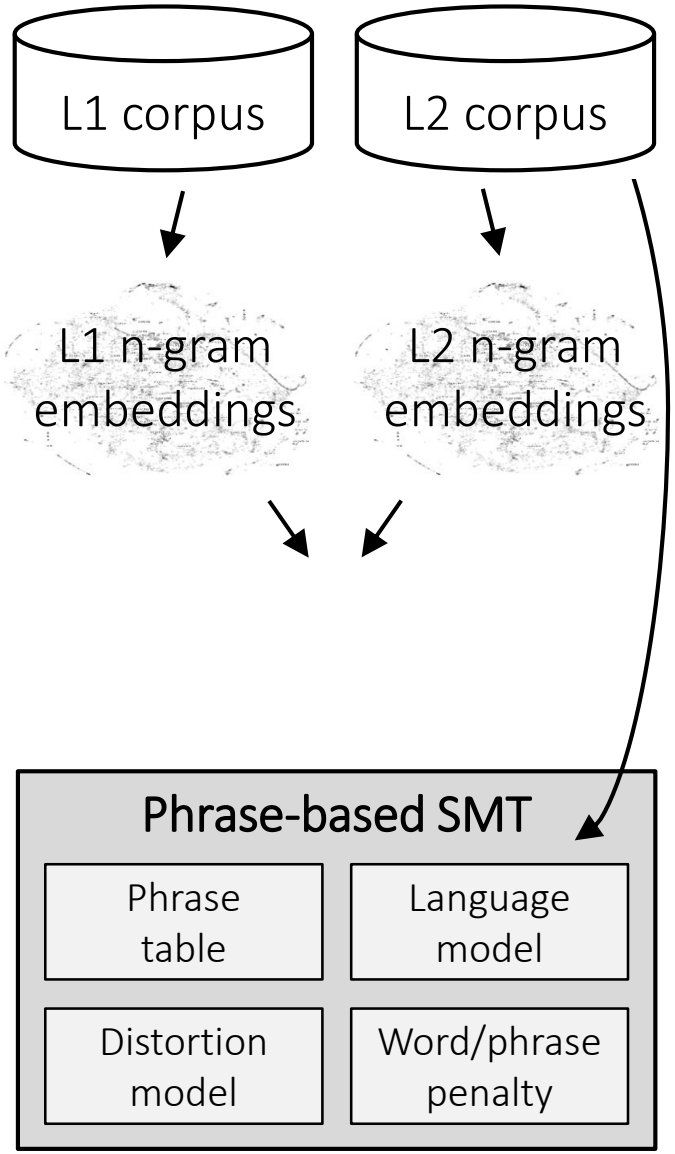

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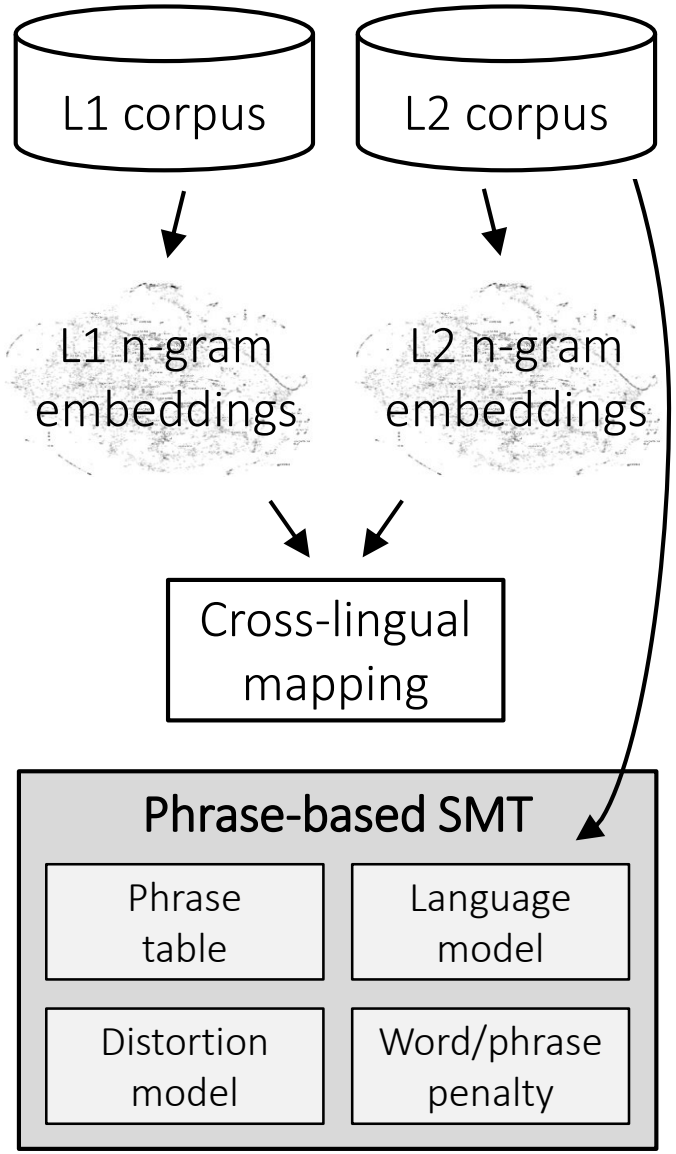

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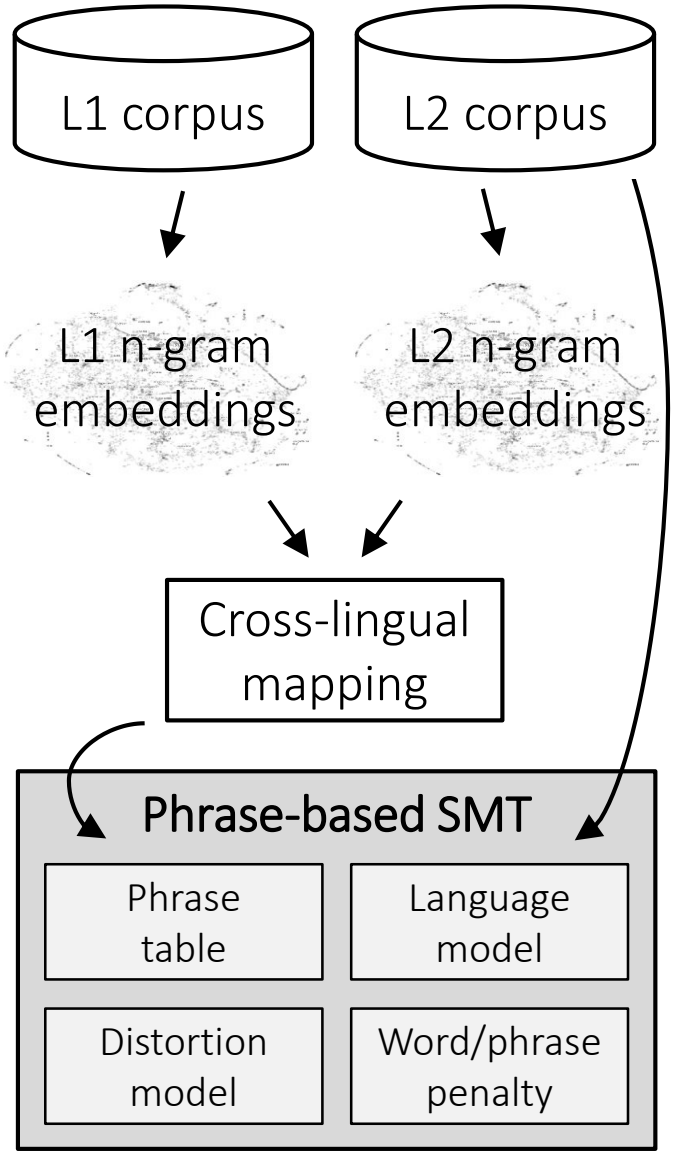

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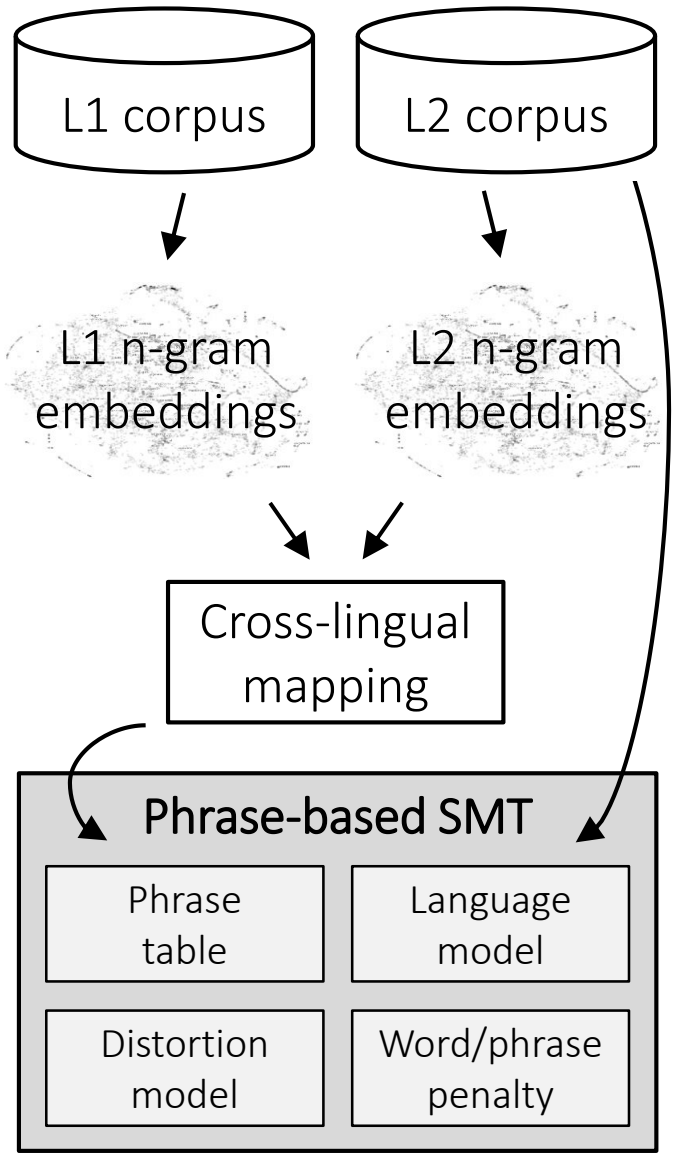

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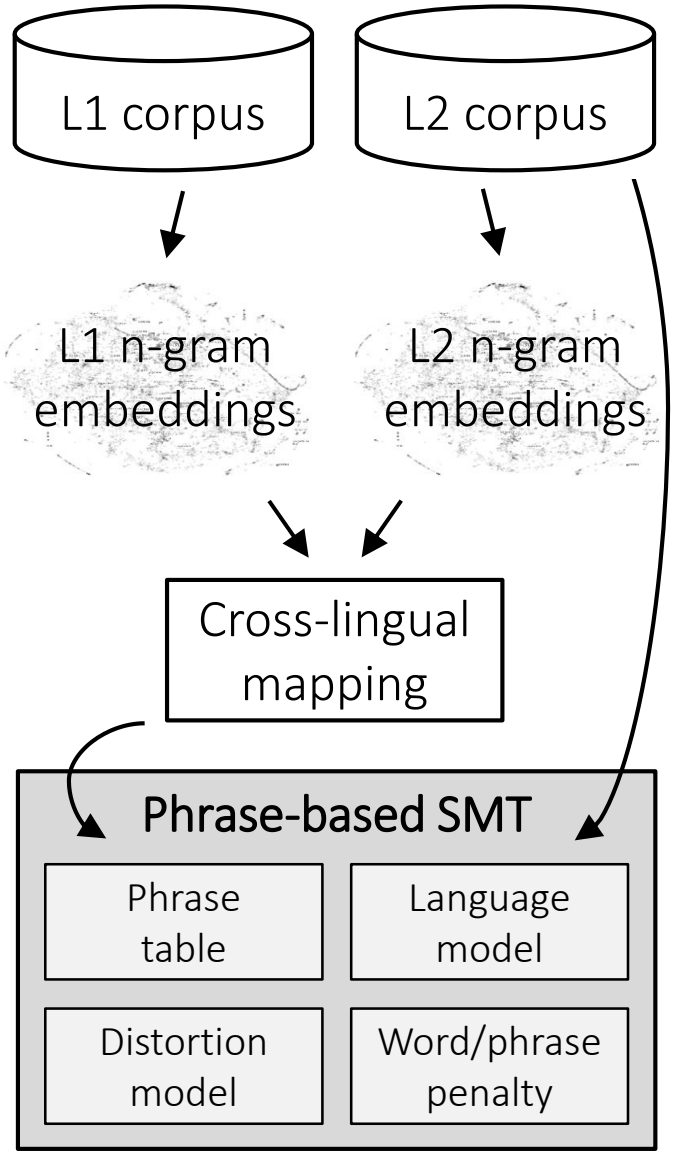

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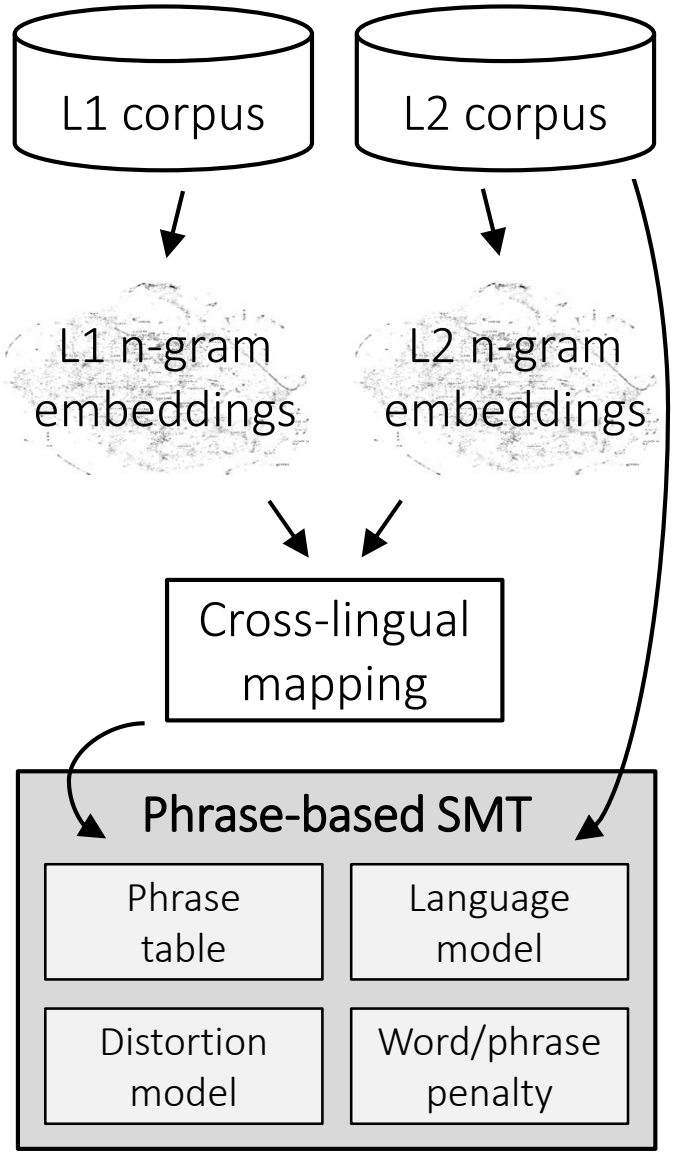
I will go to New York by plane .



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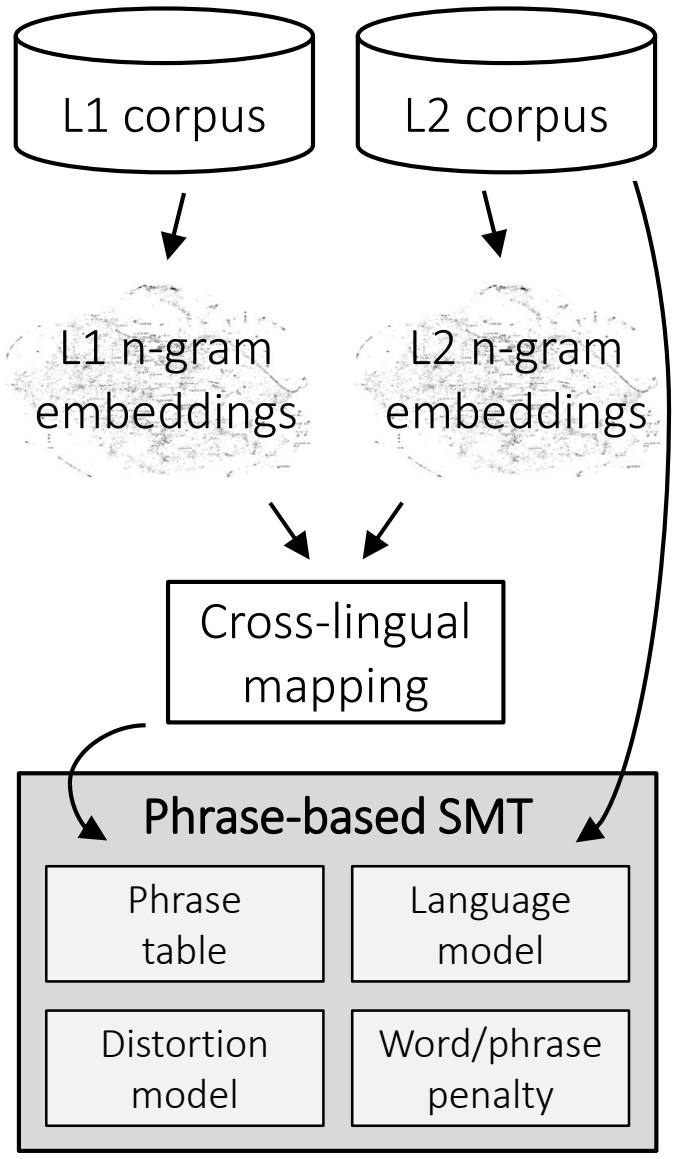
$$I \ will \ \underset{w}{\underline{go}} \ to \ New \ York \ by \ plane \ .$$



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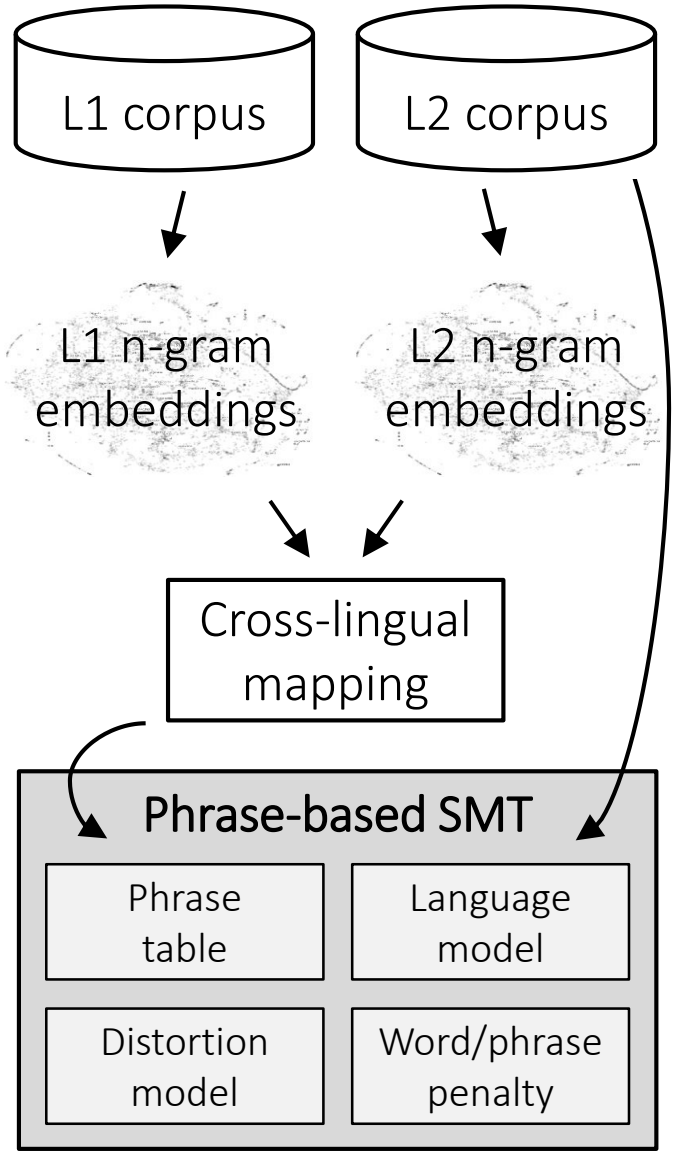

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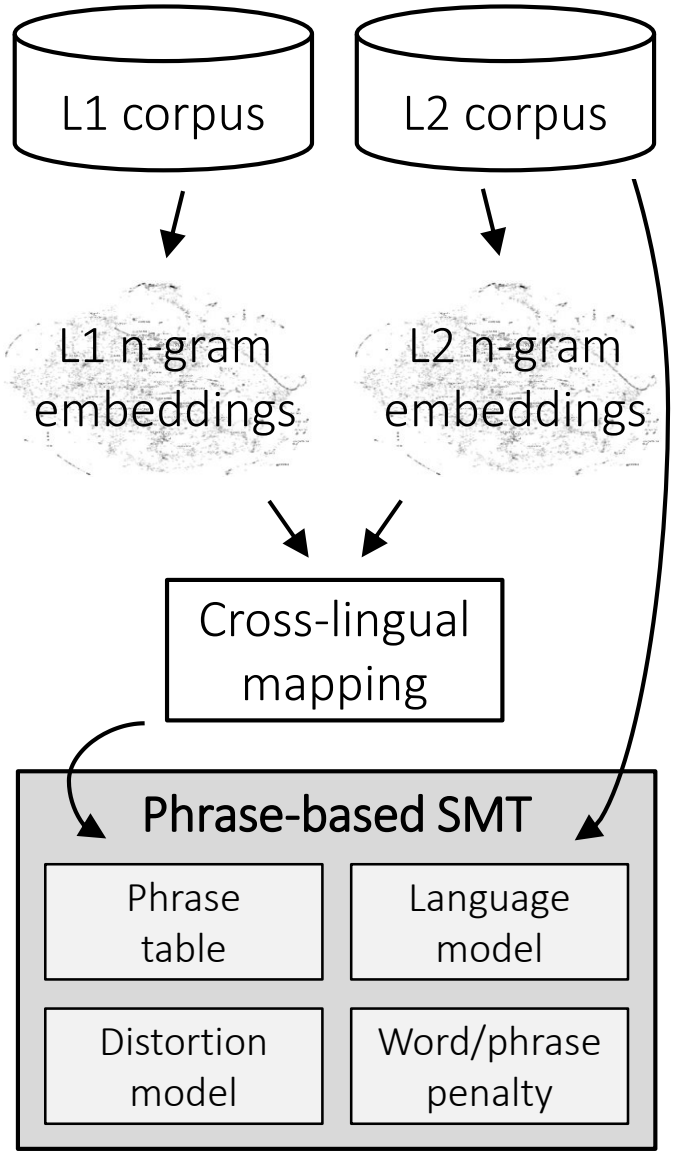
I will $\underbrace{go}_{w}$ $\underbrace{to}_{c}$ *New York by plane .*



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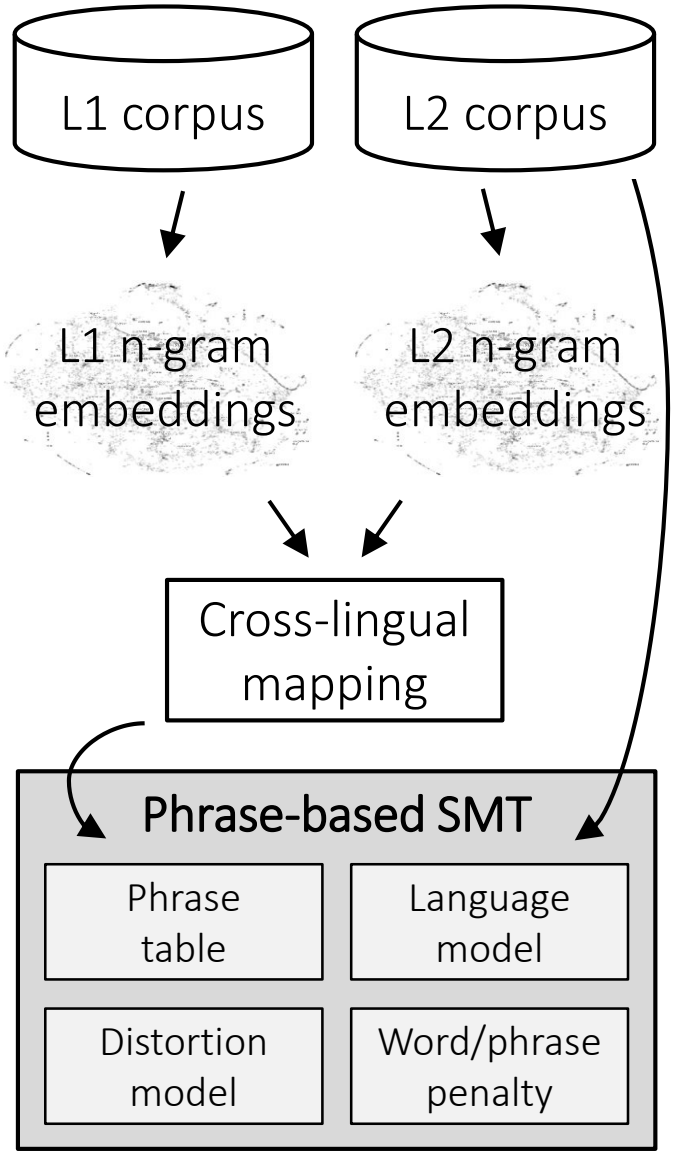
w c



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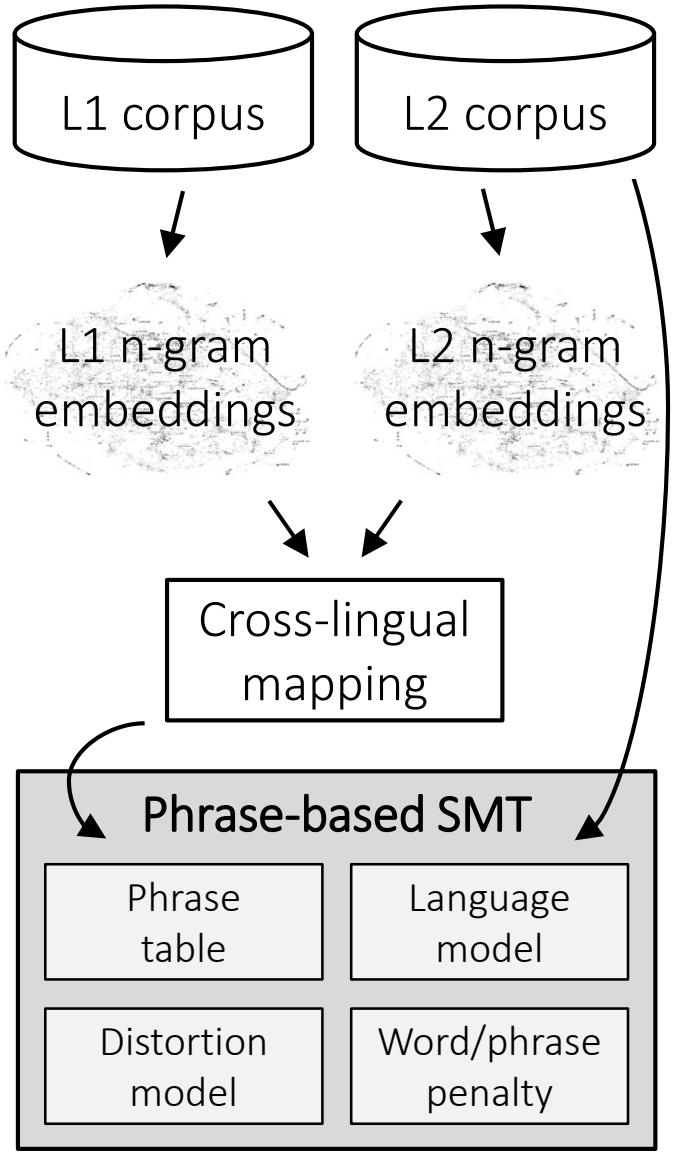

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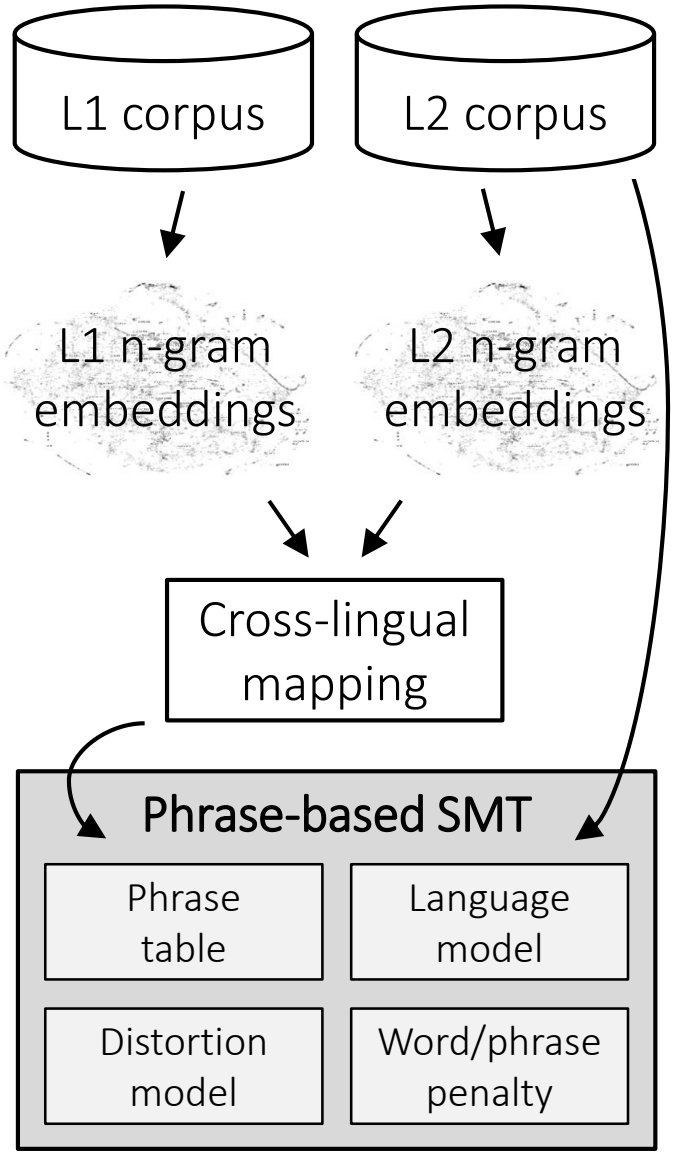

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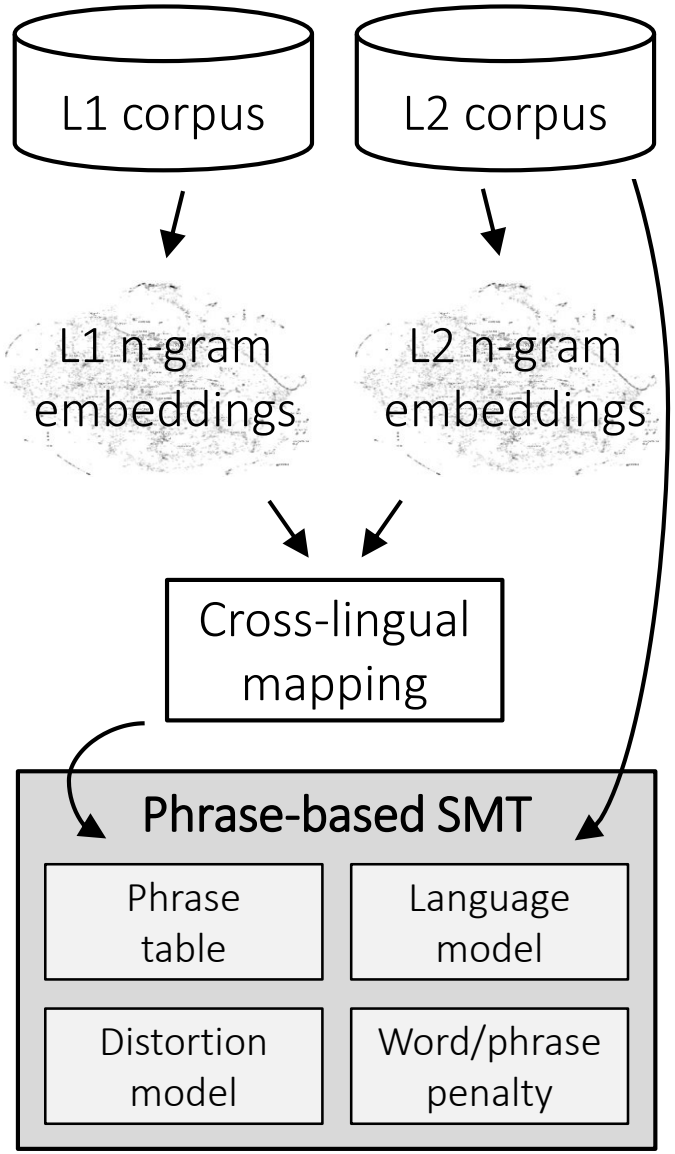

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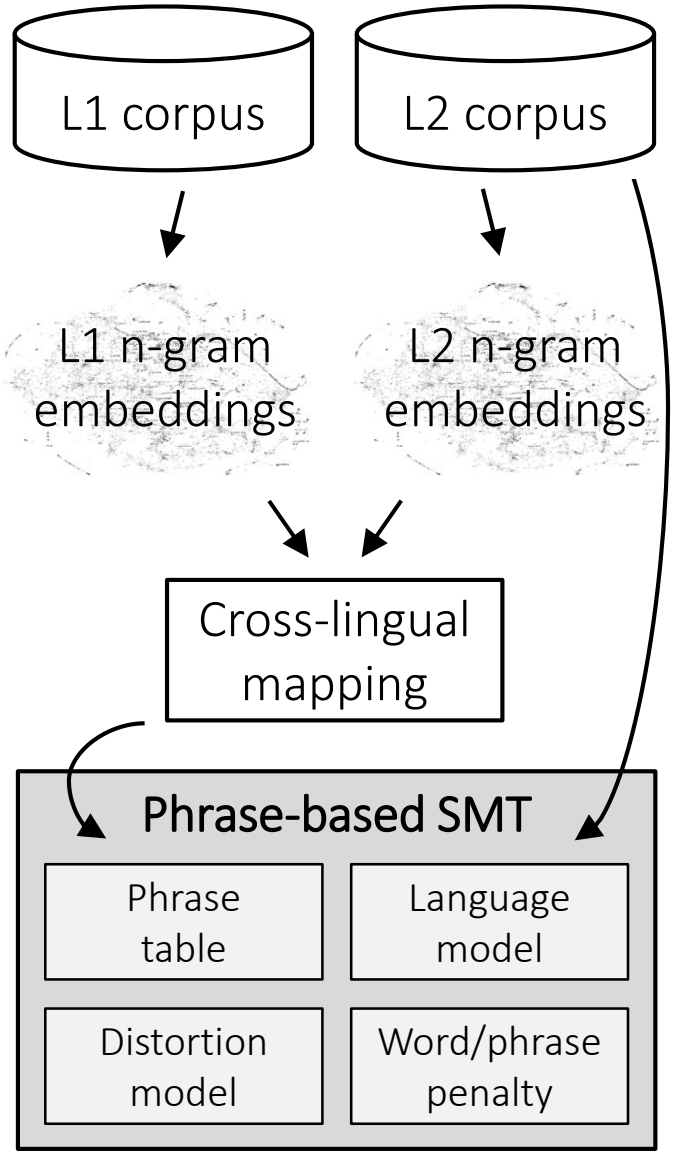

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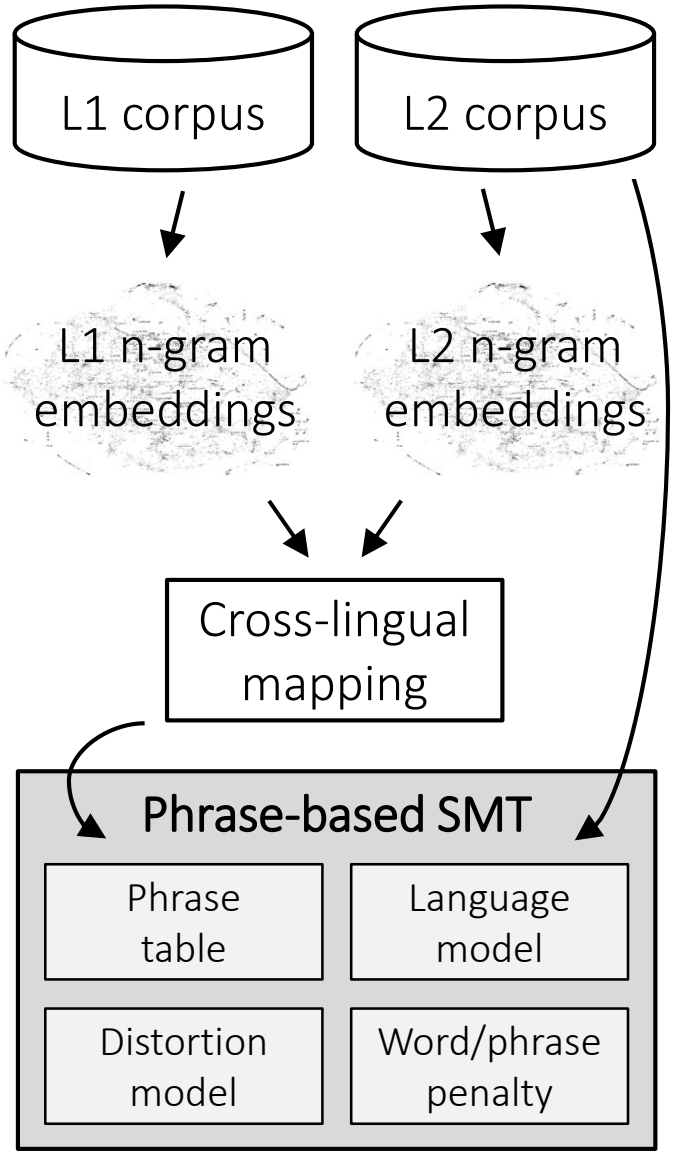

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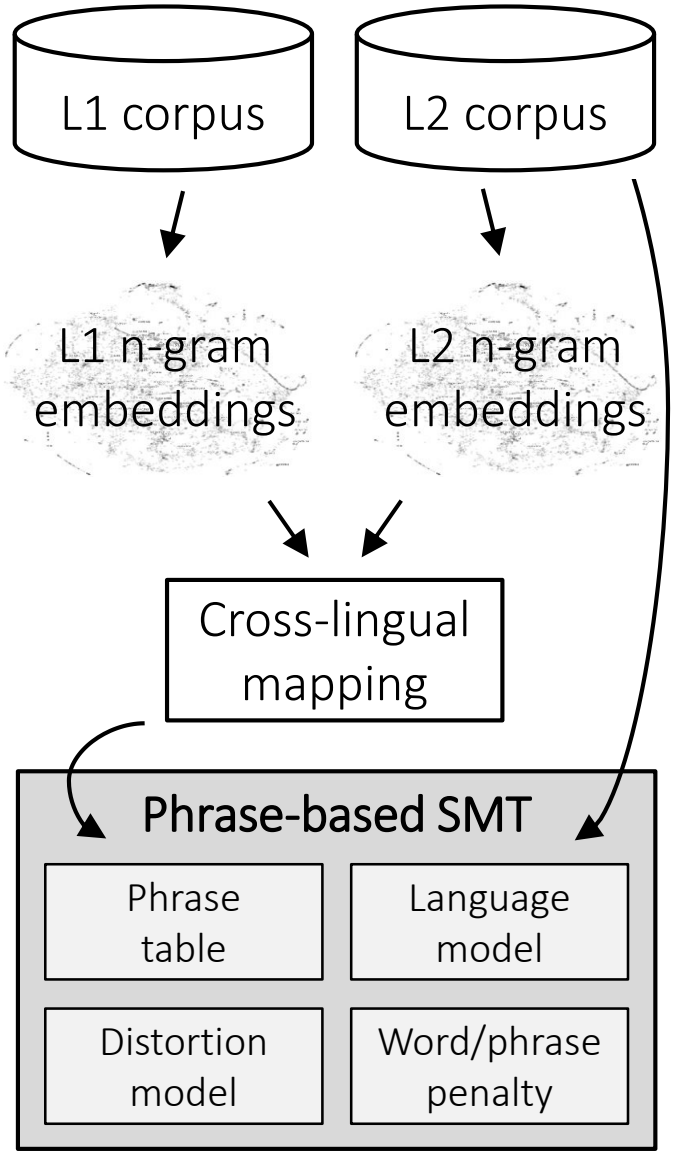

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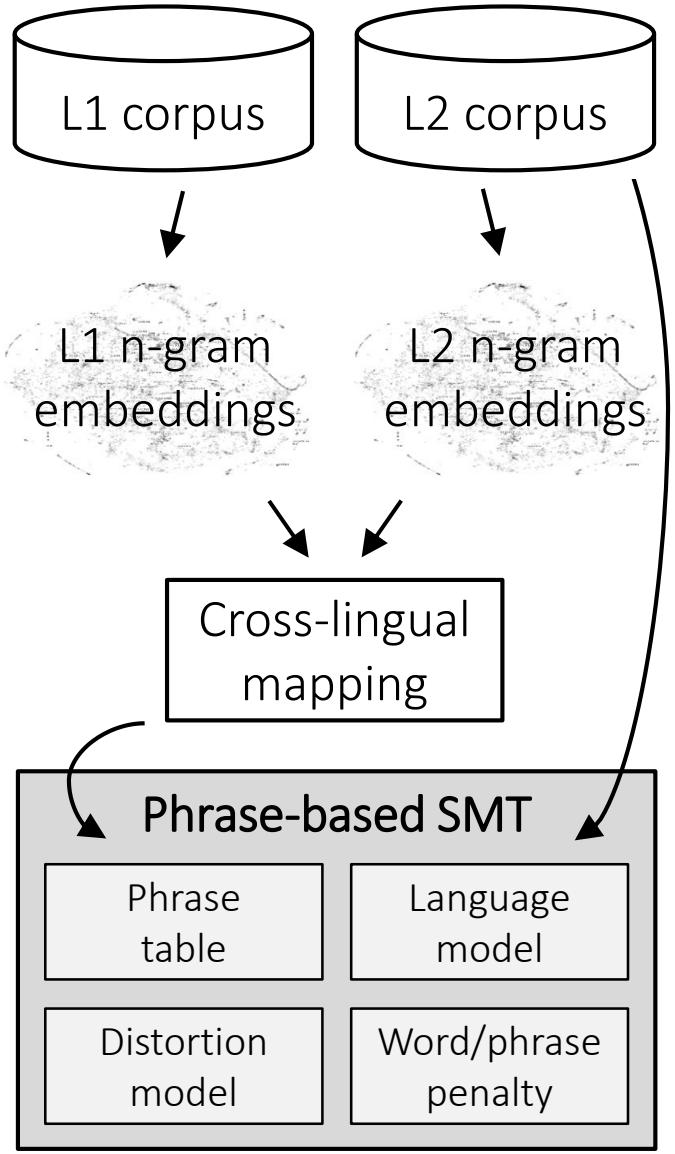
$$\phi(\bar{f}|\bar{e}) = \frac{e^{\cos(\bar{e},\bar{f})/\tau}}{\sum_{\bar{f}'} e^{\cos(\bar{e},\bar{f}')/\tau}}$$



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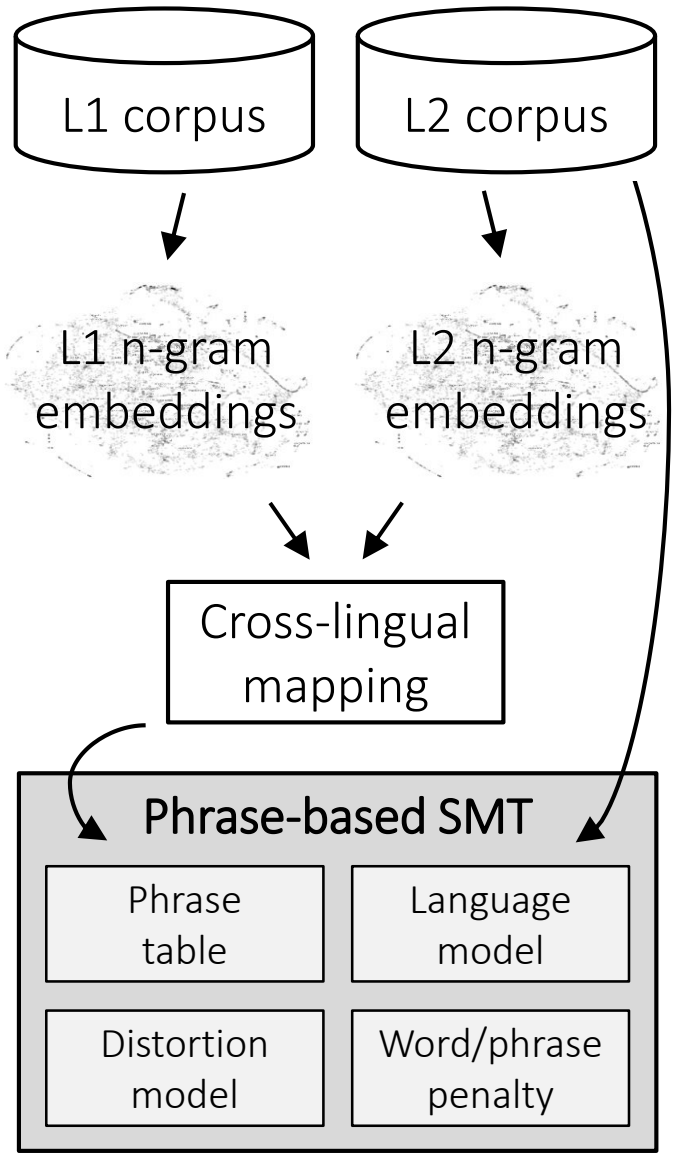
  - Distortion model (distance based)
  - ~~Lexical reordering model~~
- Word/phrase penalty EASY!!!
  - Fixed score to control the length of the output

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

$$\phi(\bar{f}|\bar{e}) = \frac{e^{\cos(\bar{e},\bar{f})/\tau}}{\sum_{\bar{f}'} e^{\cos(\bar{e},\bar{f}')/\tau}} \qquad \min_{\tau} \sum_{\bar{f}} \log \phi\left(\bar{f}|\mathrm{NN}_{\bar{e}}(\bar{f})\right) + \sum_{\bar{e}} \log \phi\left(\bar{e}|\mathrm{NN}_{\bar{f}}(\bar{e})\right)$$



Unsupervised phrase-based SMT

Learn components from monolingual corpora

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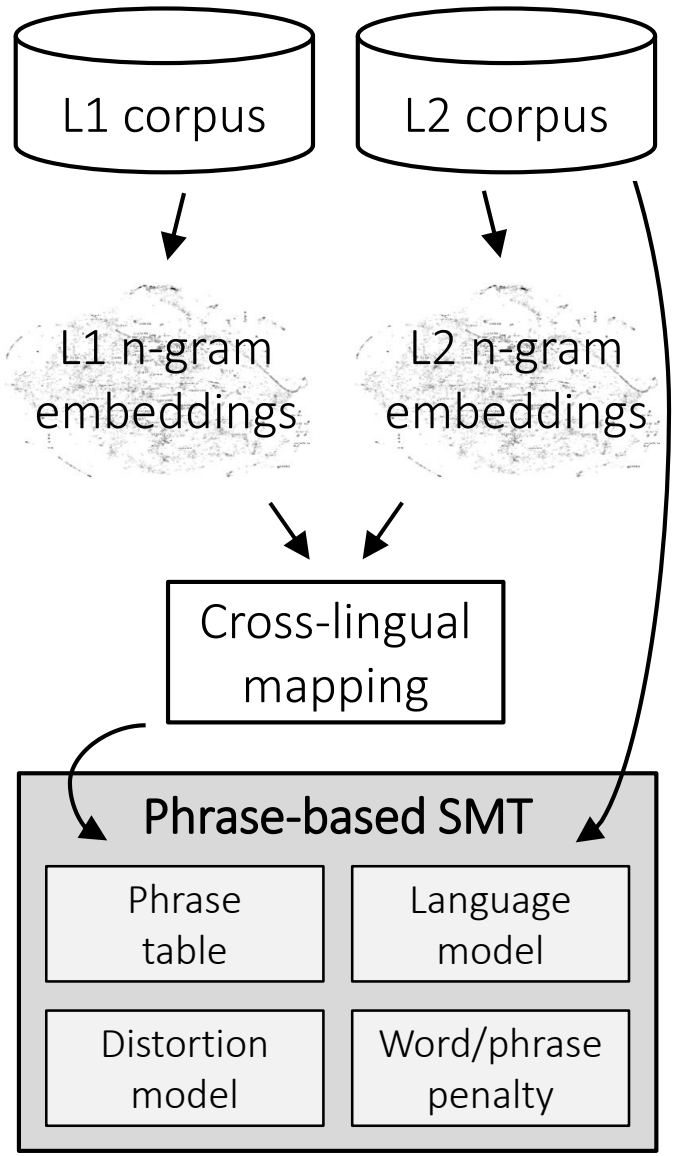

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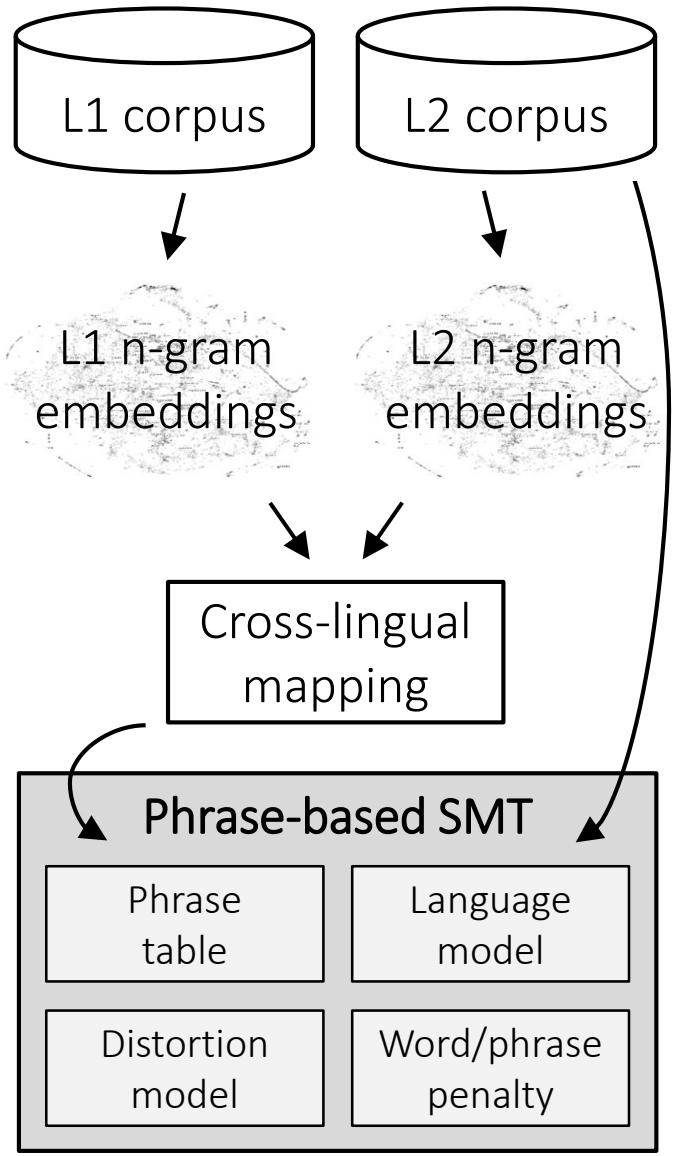

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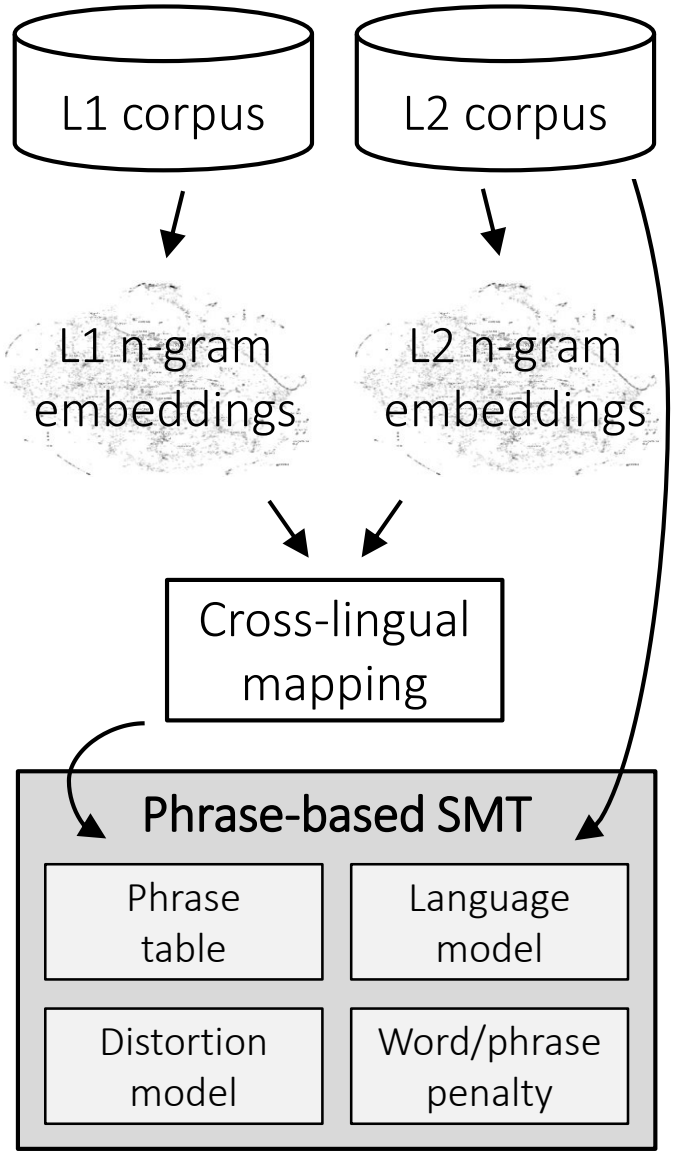
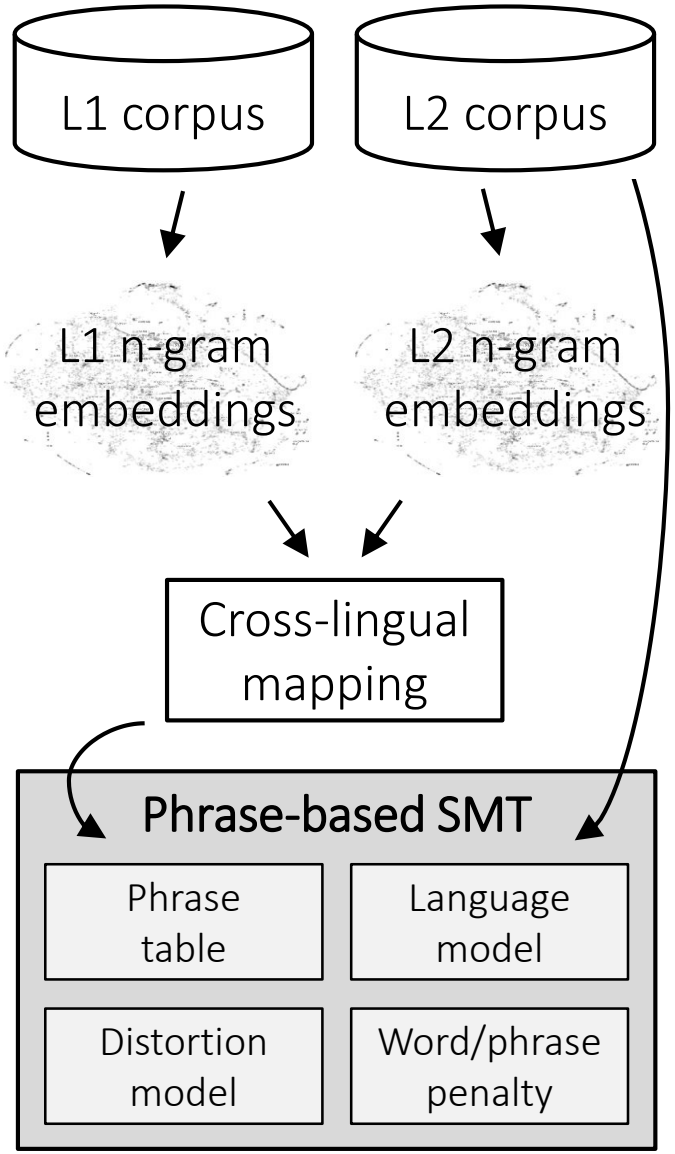
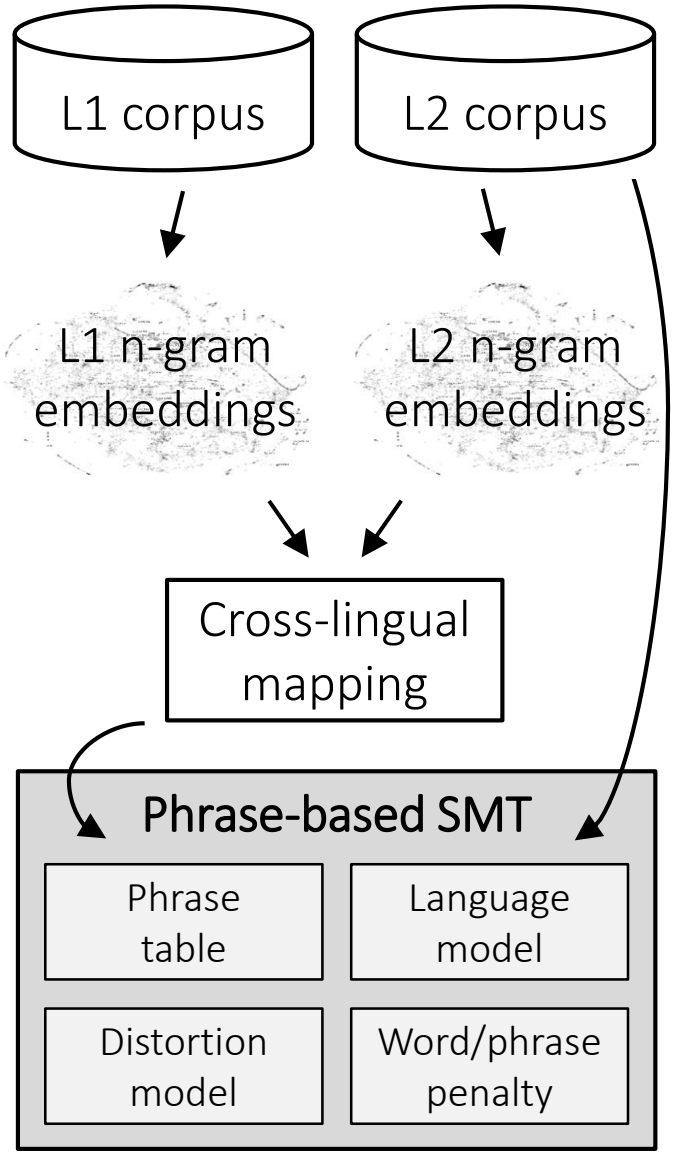
Unsupervised phrase-based SMT



Unsupervised phrase-based SMT



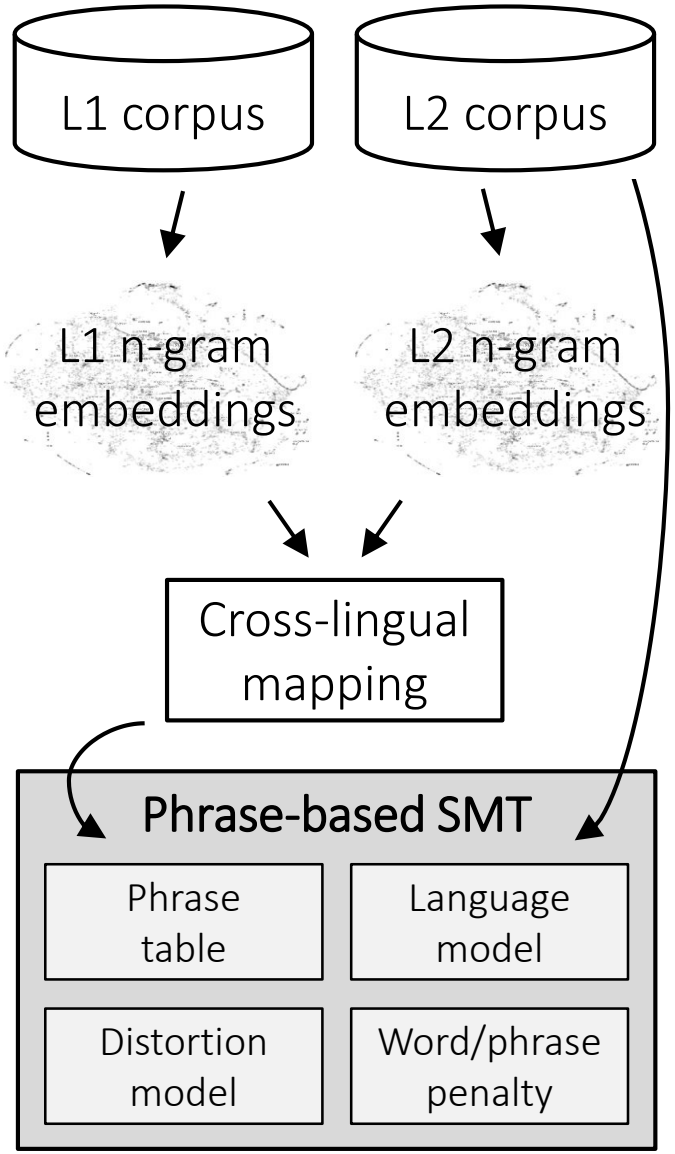
EXPERIMENTS



Unsupervised phrase-based SMT

EXPERIMENTS

- Languages: French-English, German-English



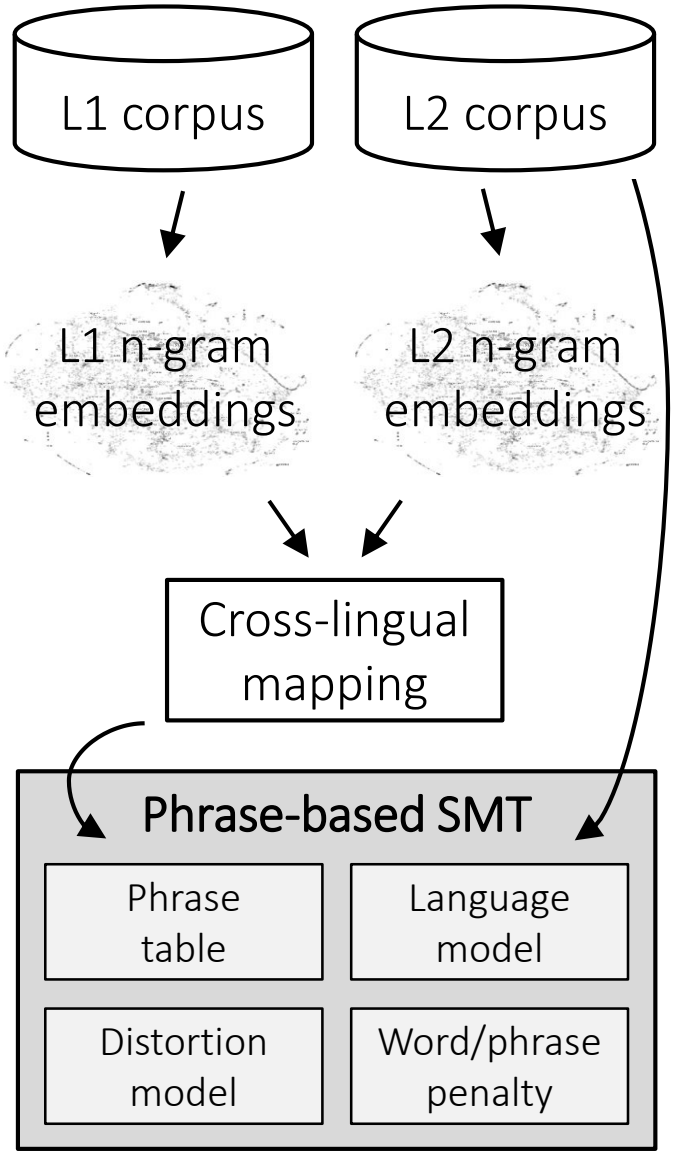
Unsupervised phrase-based SMT

EXPERIMENTS

- Languages: French-English, German-English

- Training: WMT-14 News Crawl

Unsupervised phrase-based SMT



EXPERIMENTS

- Languages: French-English, German-English
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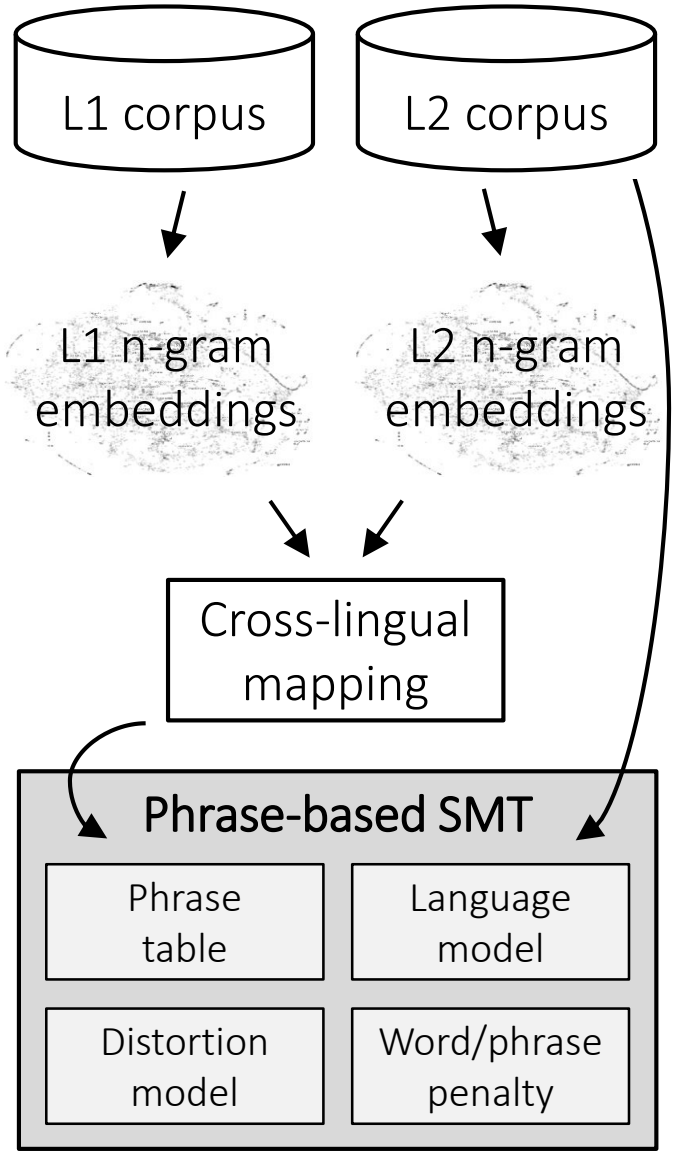
- Test set: WMT-14 newstest (BLEU)



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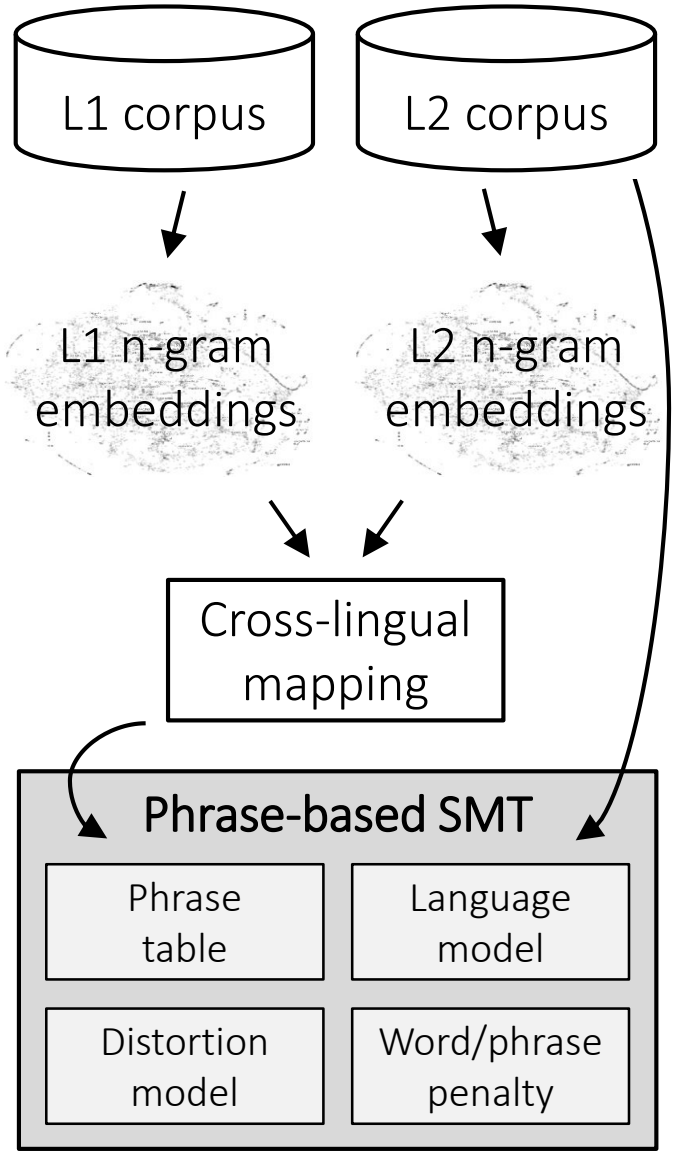
FR-EN	EN-FR	DE-EN	EN-DE



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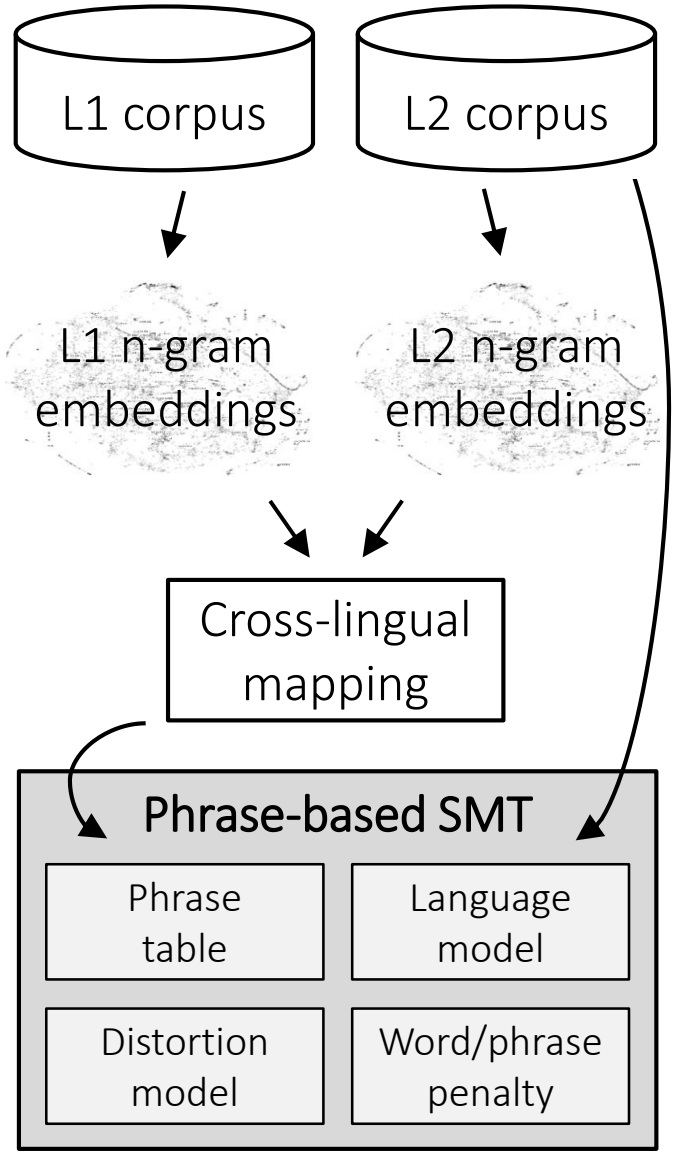
Unsupervised phrase-based SMT



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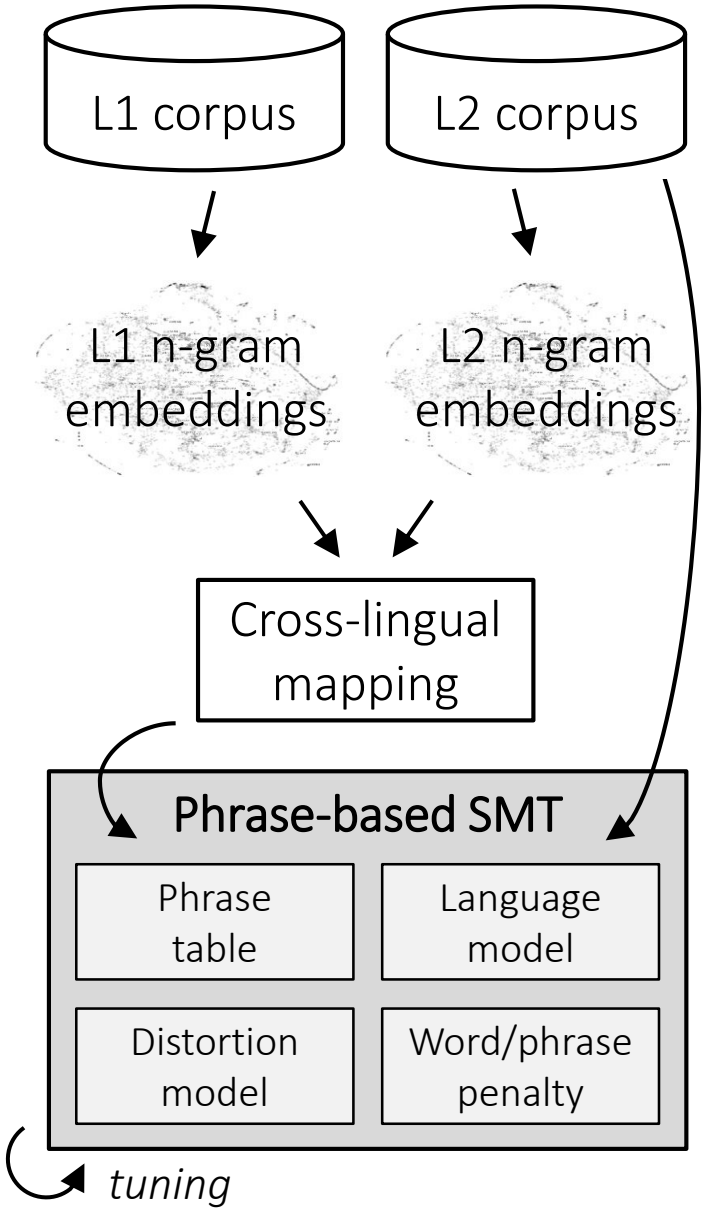

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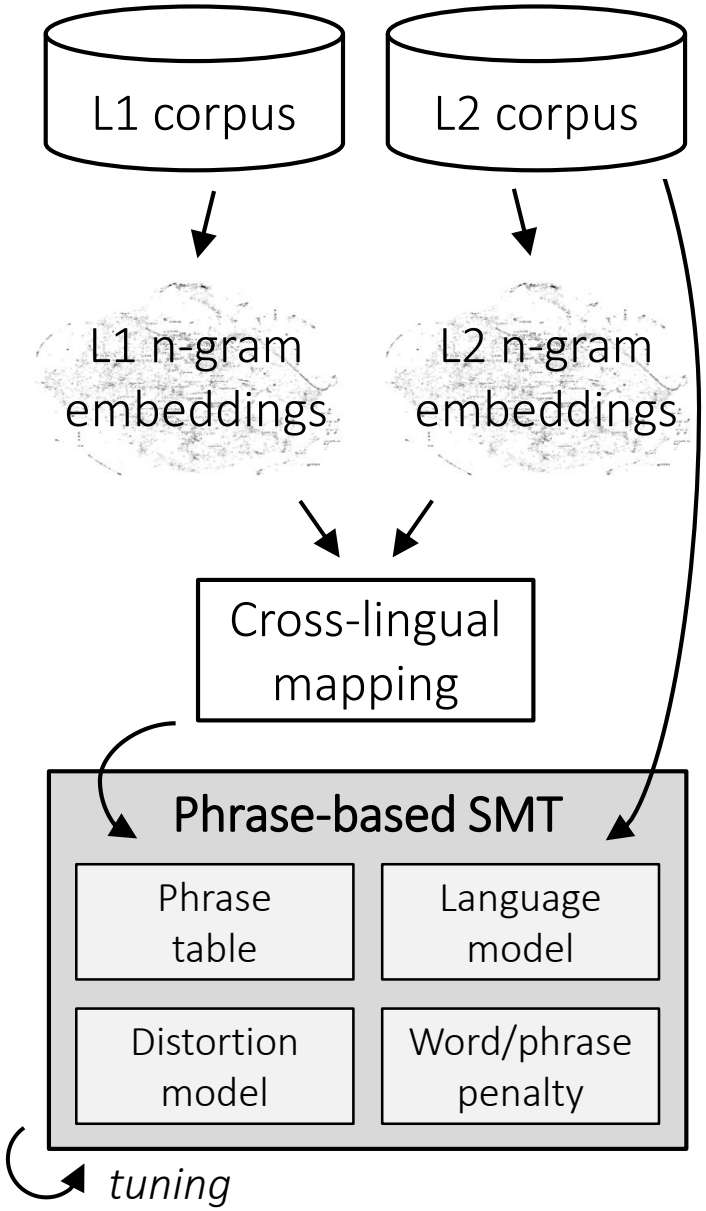
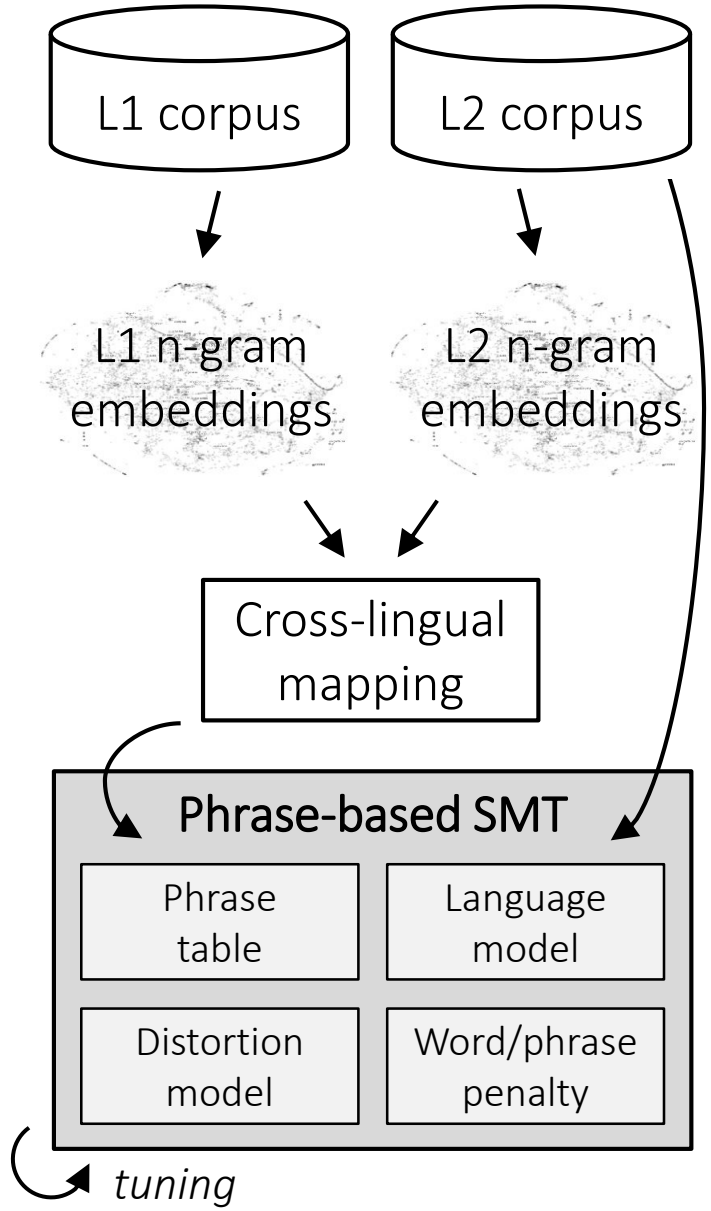


$$L = L_{cycle}(E) + L_{cycle}(F) + L_{lm}(E) + L_{lm}(F)$$



Unsupervised phrase-based SMT

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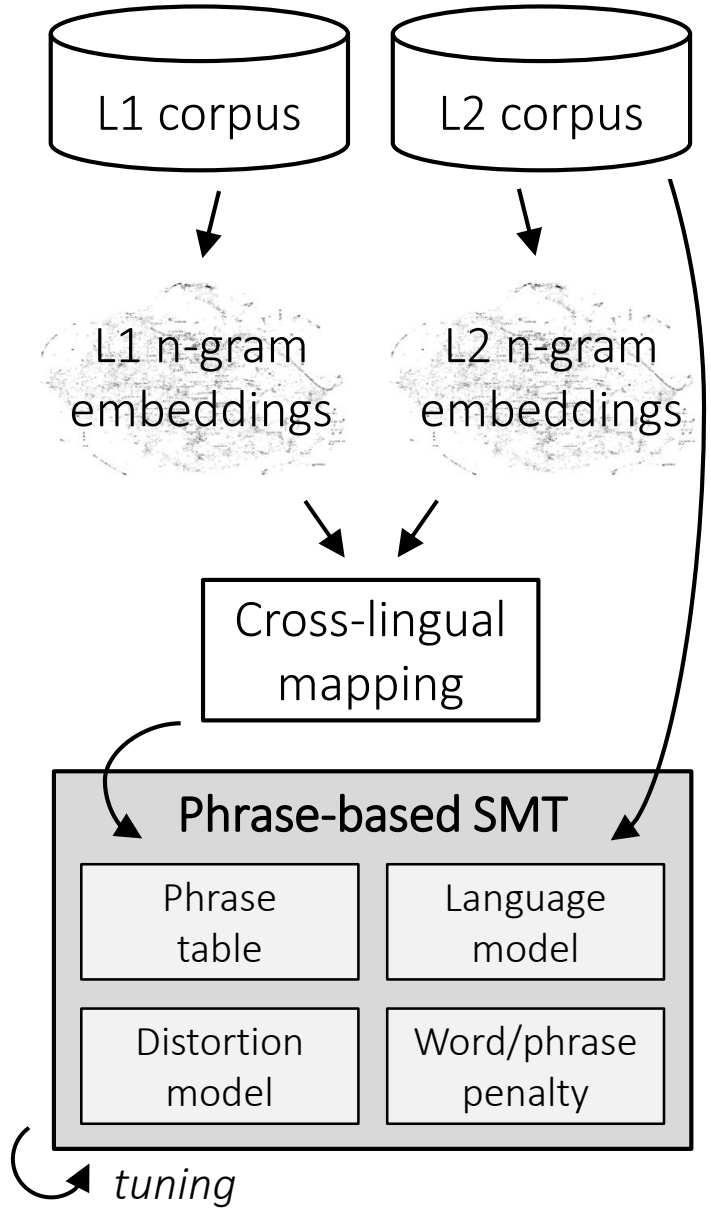

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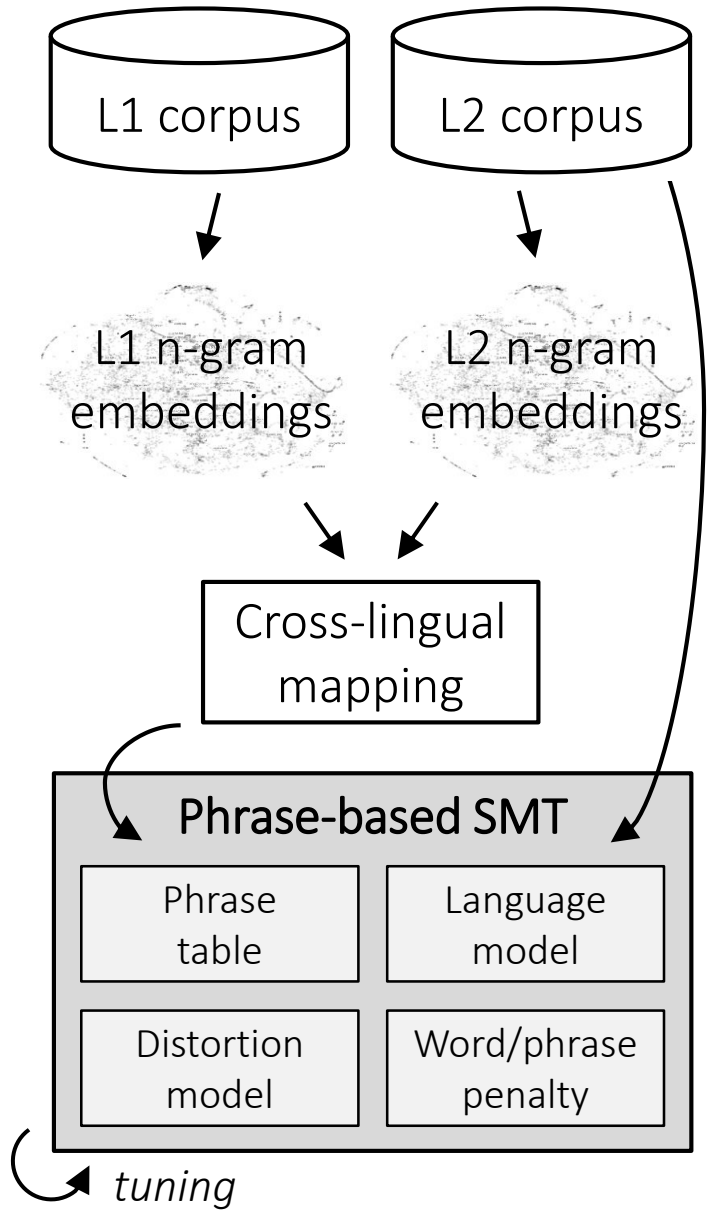

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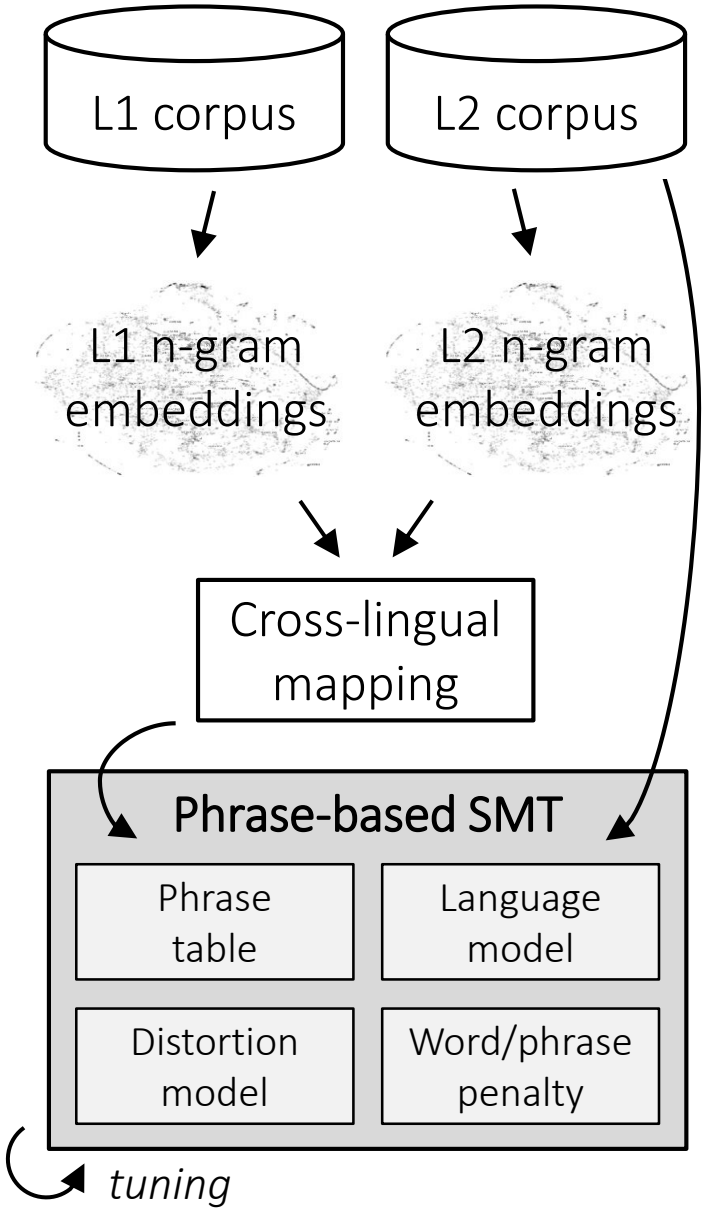

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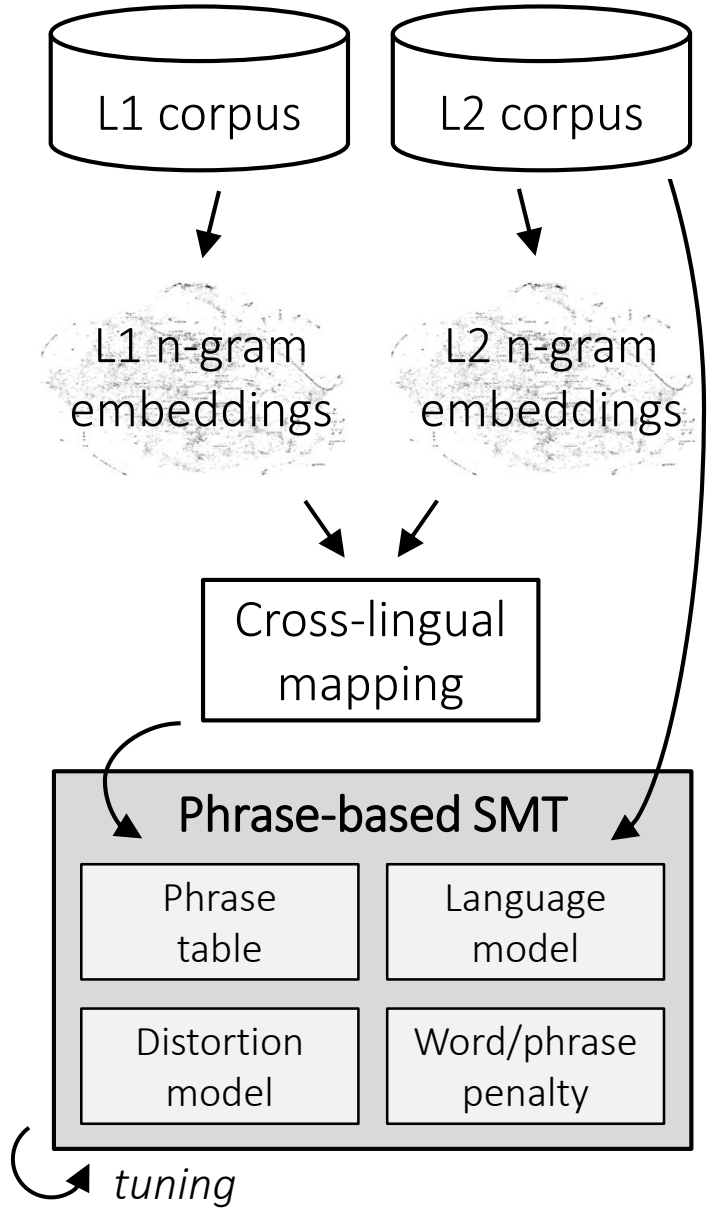
Alternating optimization



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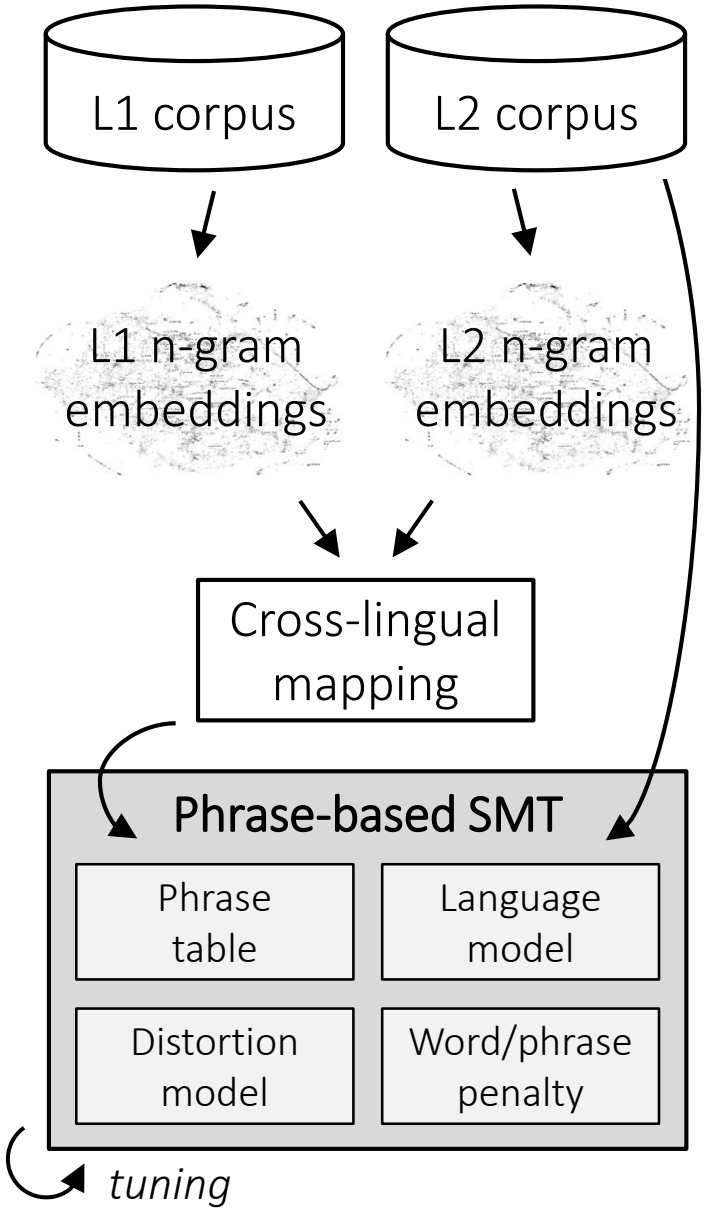
Alternating optimization

- Fix $\mathrm{T}_{F\to E}$ and optimize $\mathrm{T}_{E\to F}$ using MERT



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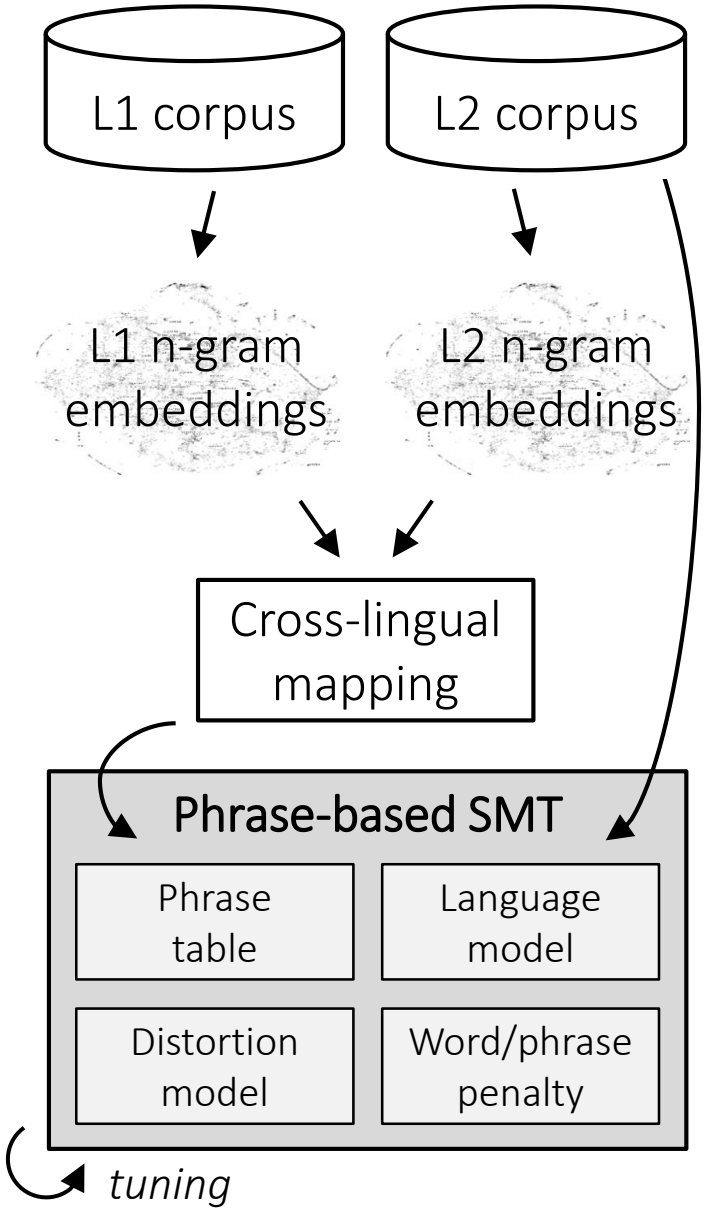

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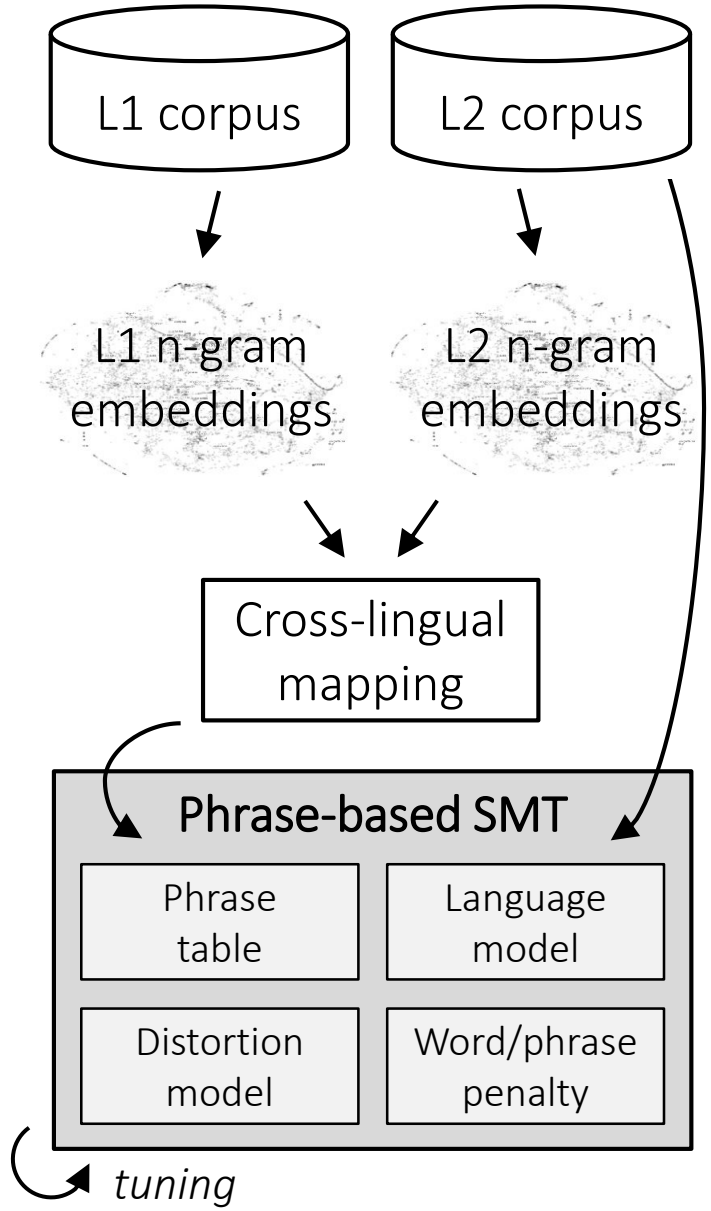
- Iterate until convergence

Unsupervised phrase-based SMT



EXPERIMENTS

- Languages: French-English, German-English
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- Test set: WMT-14 newstest (BLEU)

	FR-EN	EN-FR	DE-EN	EN-DE
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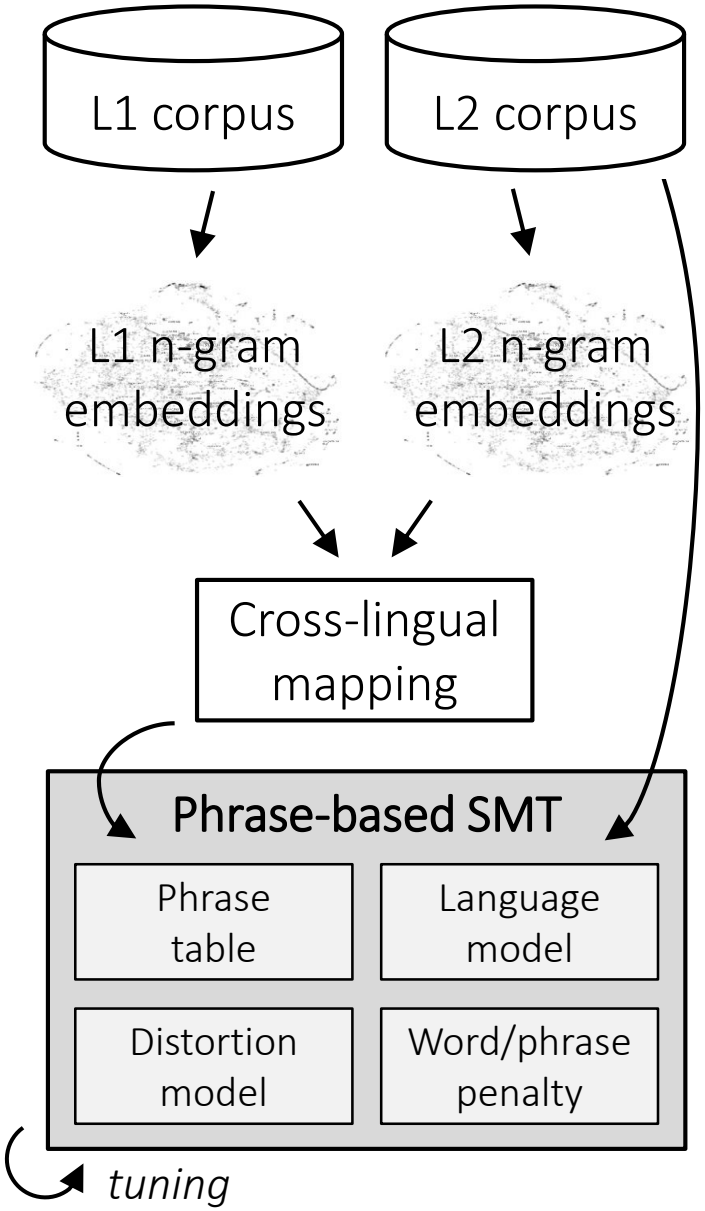
Unsupervised phrase-based SMT



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+ Tuning	23.4	21.9	15.4	11.2

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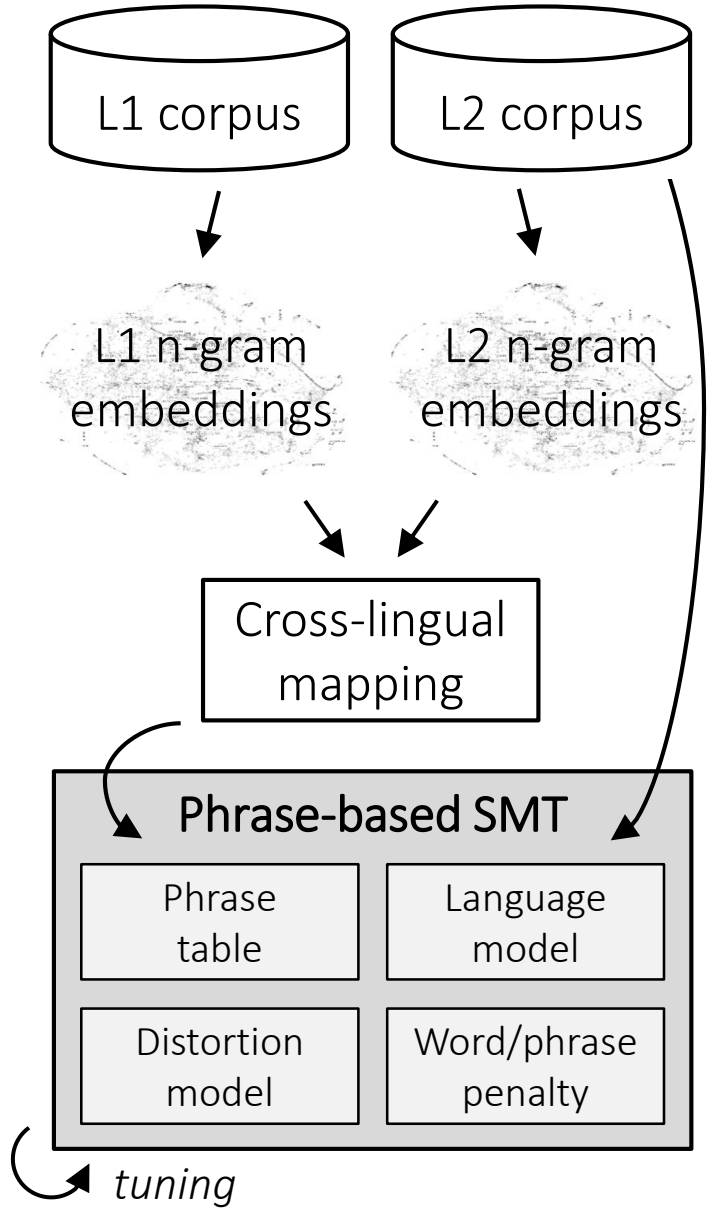

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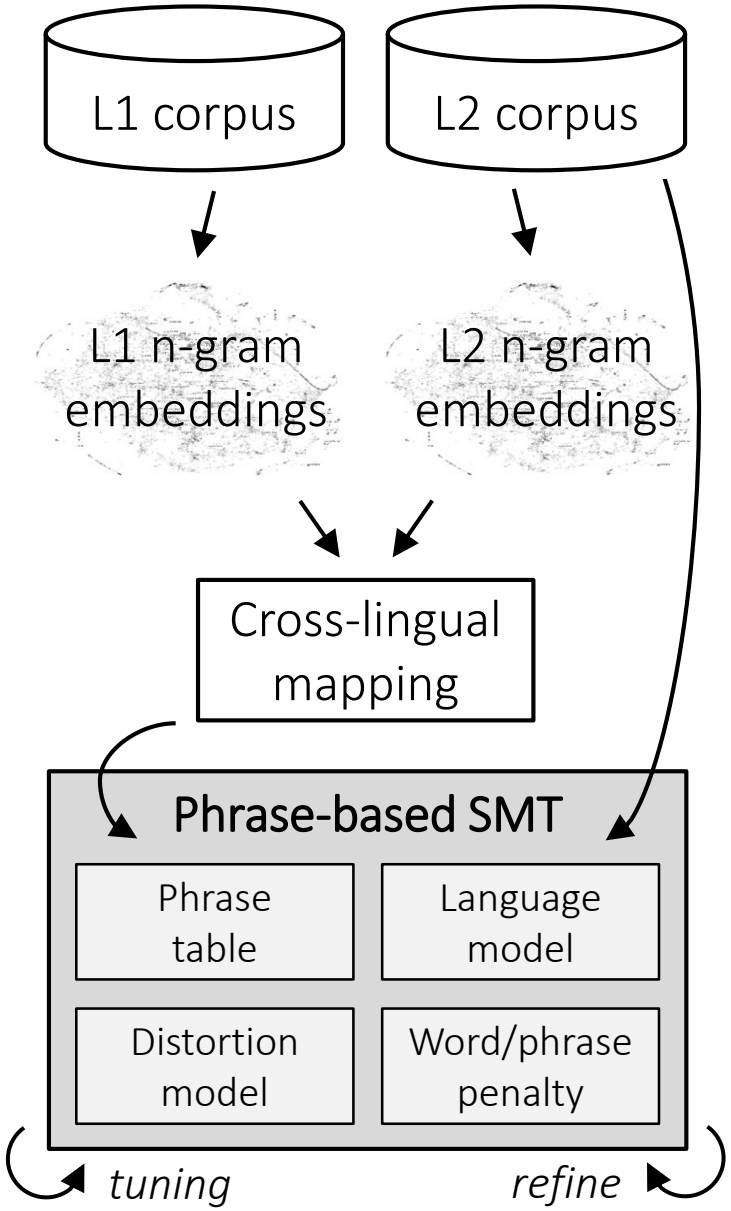

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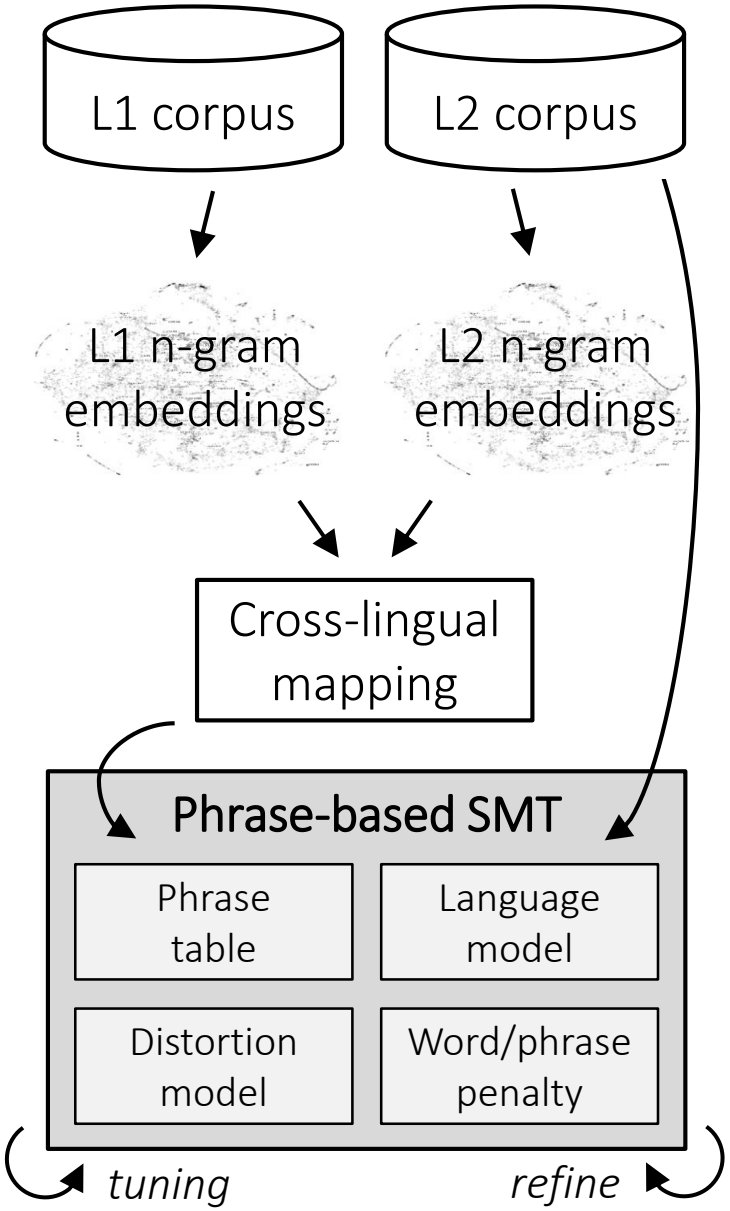
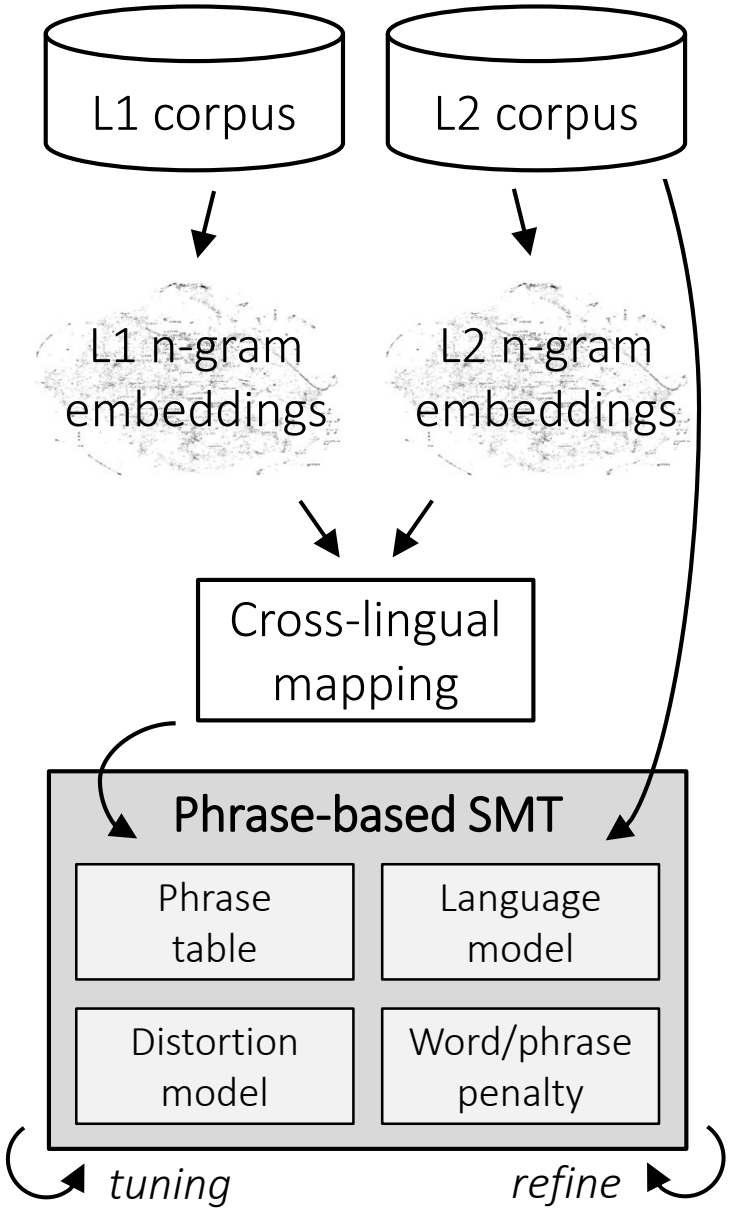


L1 train

L2 train

Unsupervised phrase-based SMT

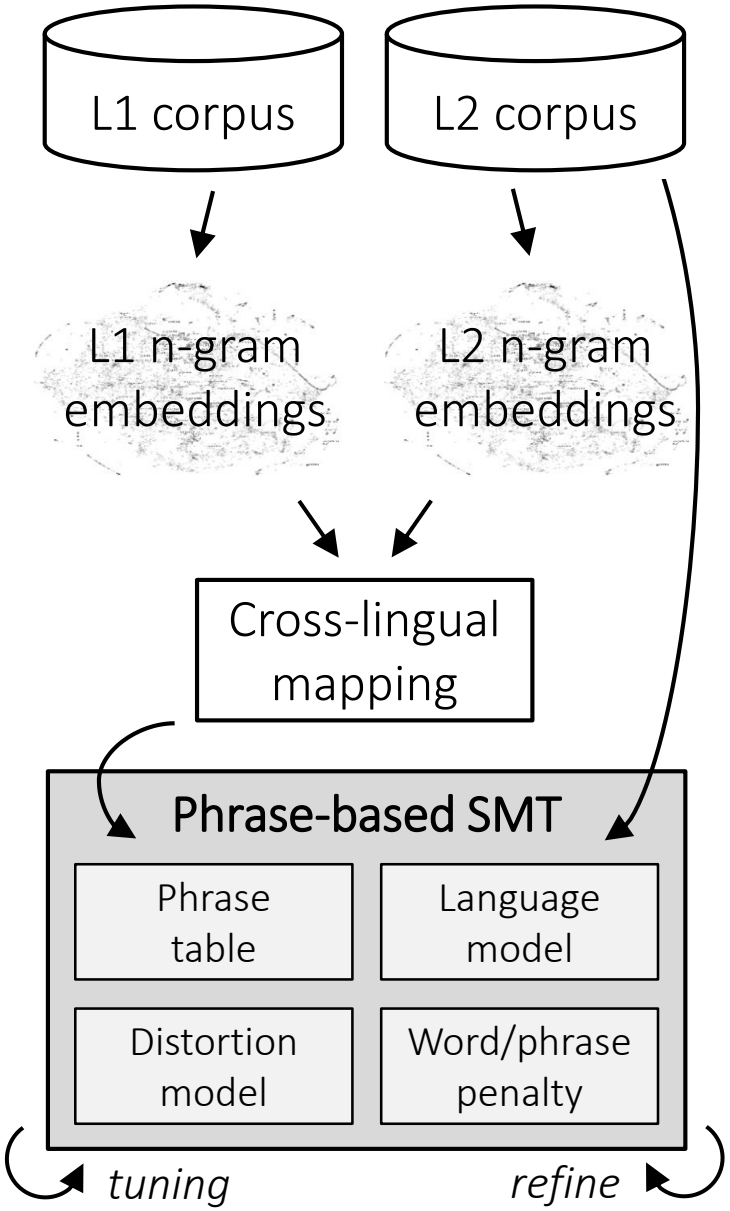


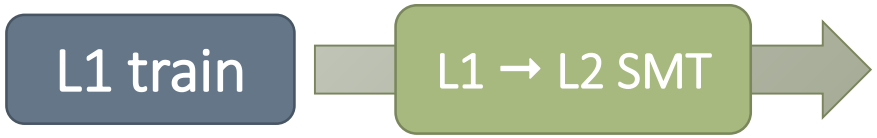
L1 train

L1 → L2 SMT

L2 train

Unsupervised phrase-based SMT





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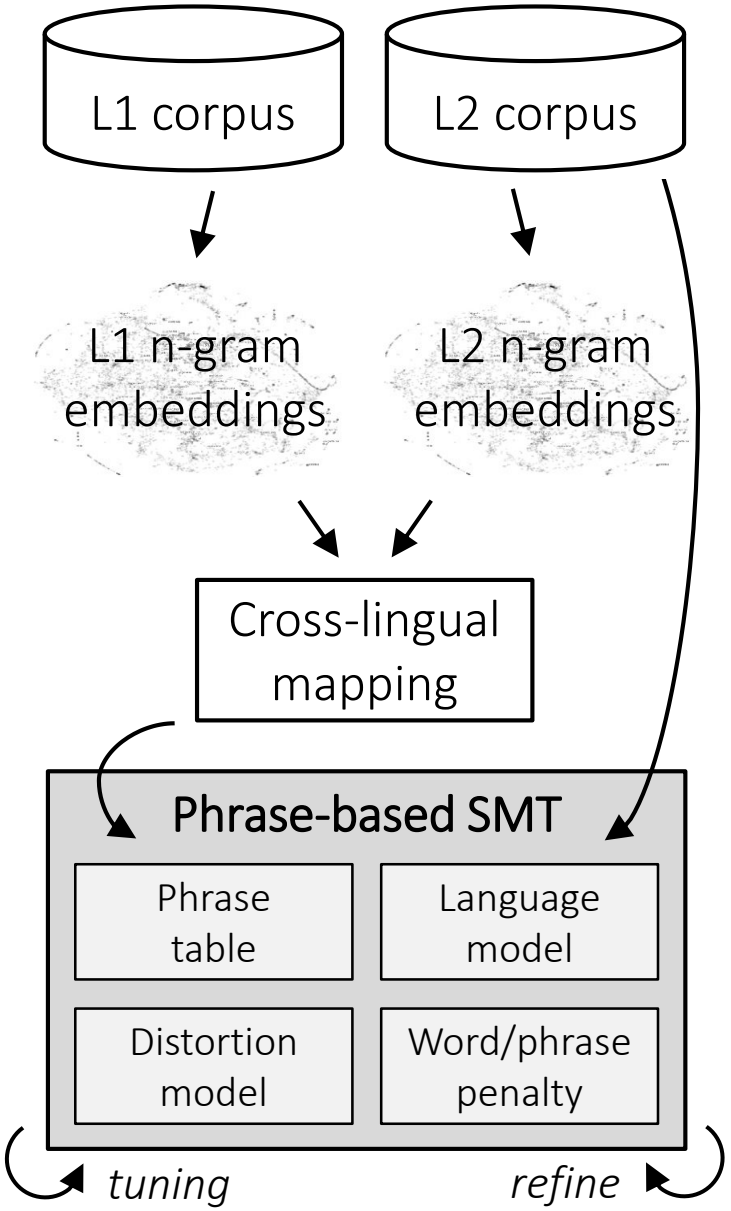

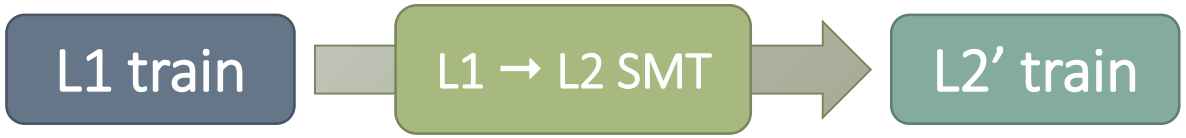

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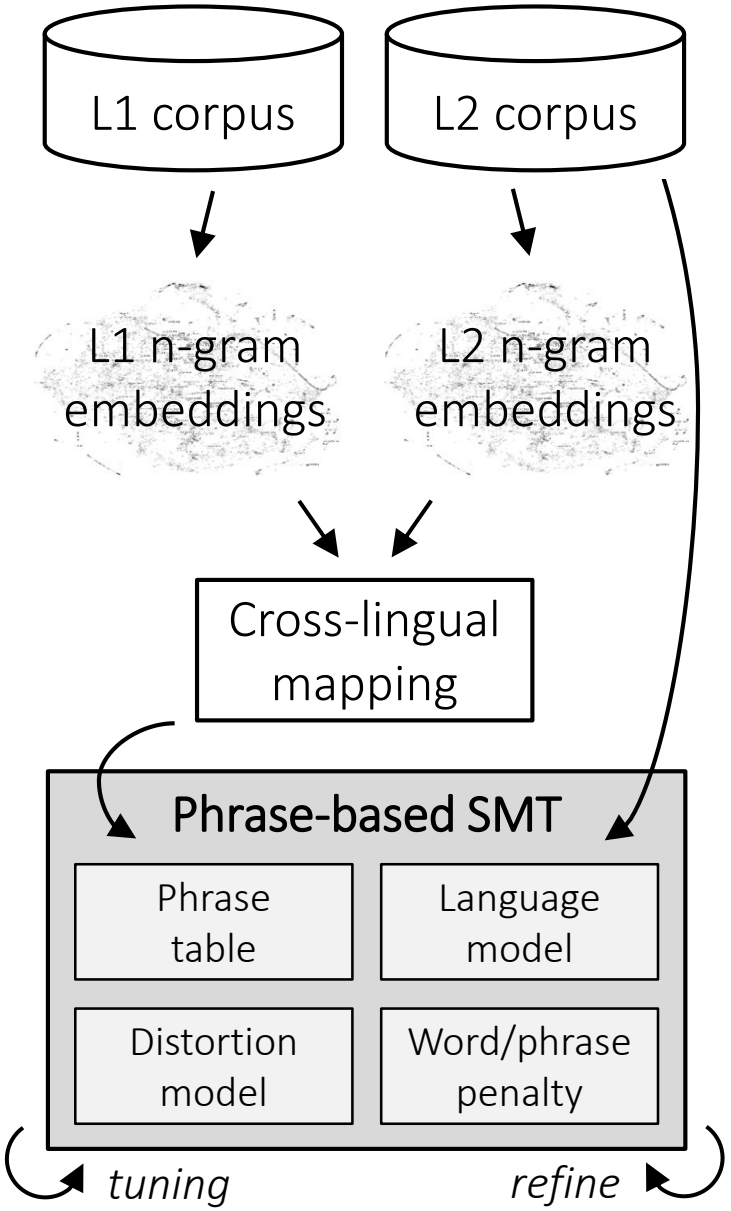
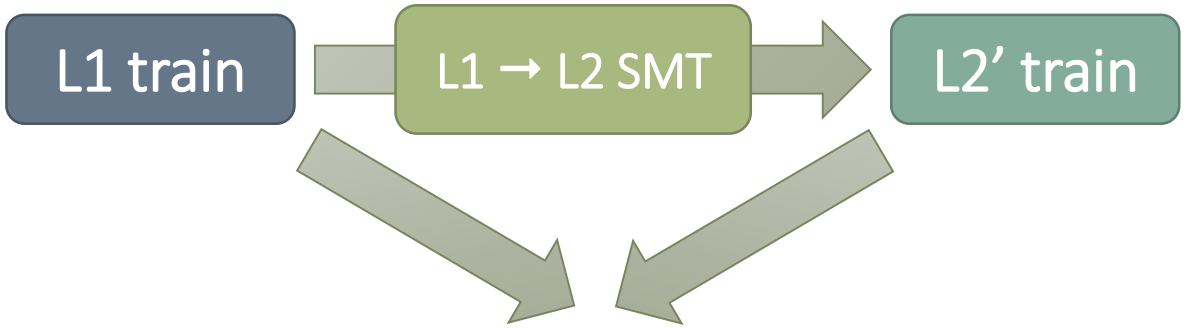
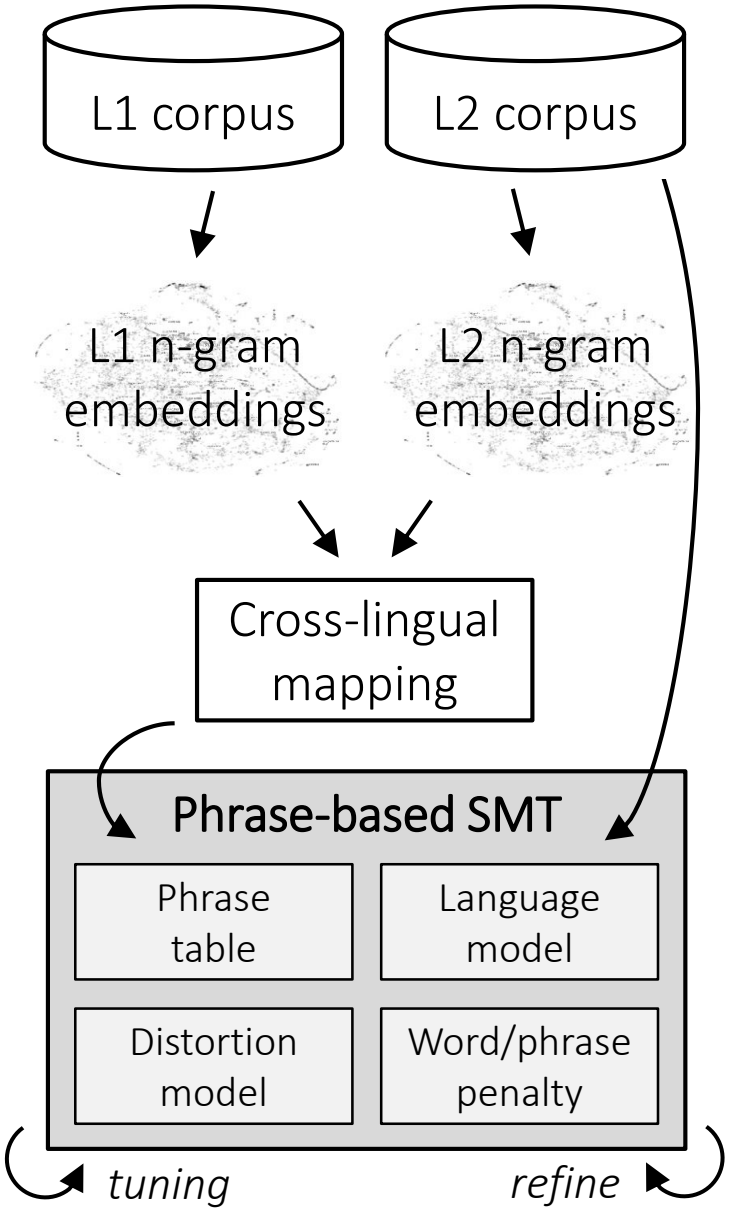
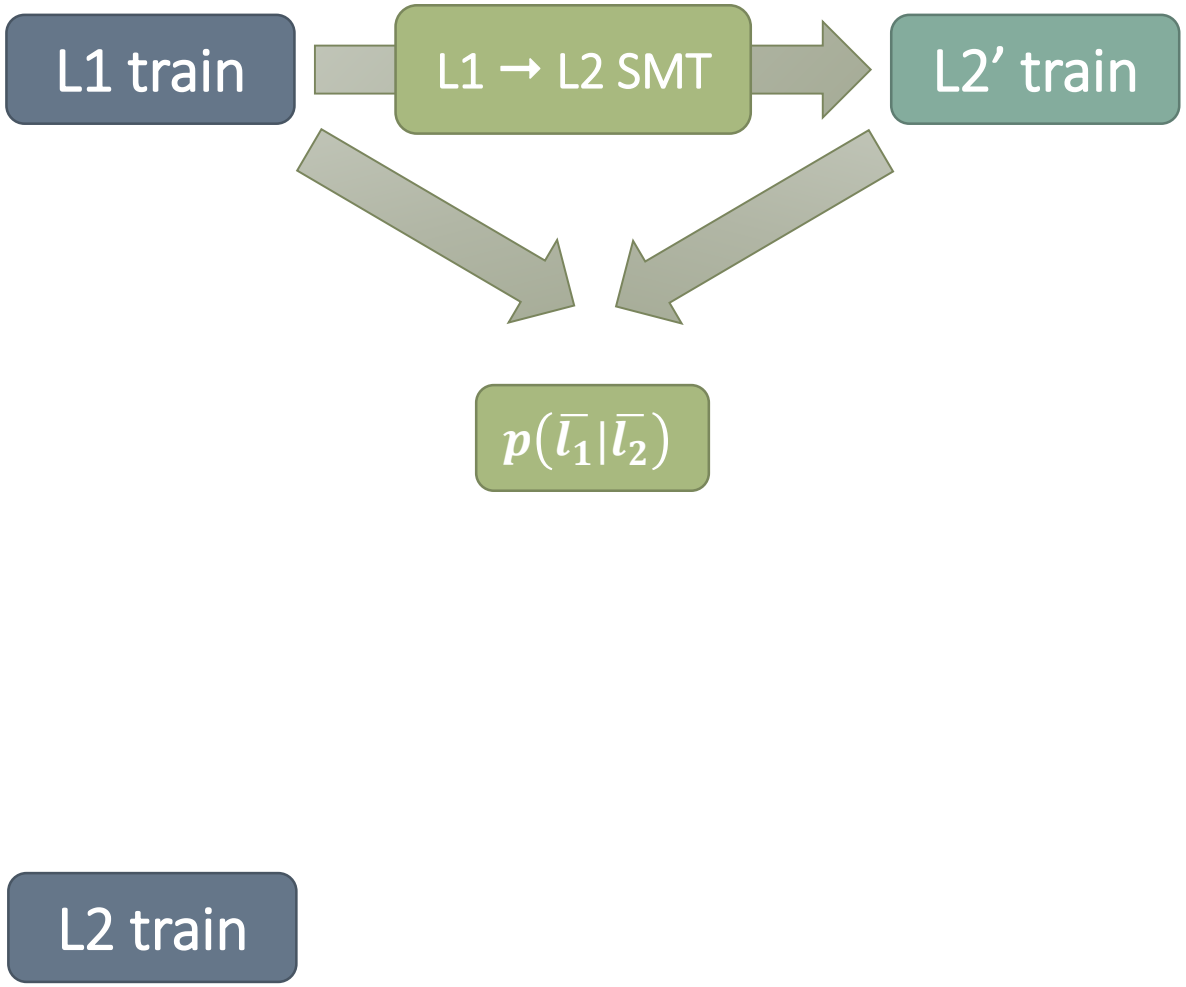




L2 train

Unsupervised phrase-based SMT





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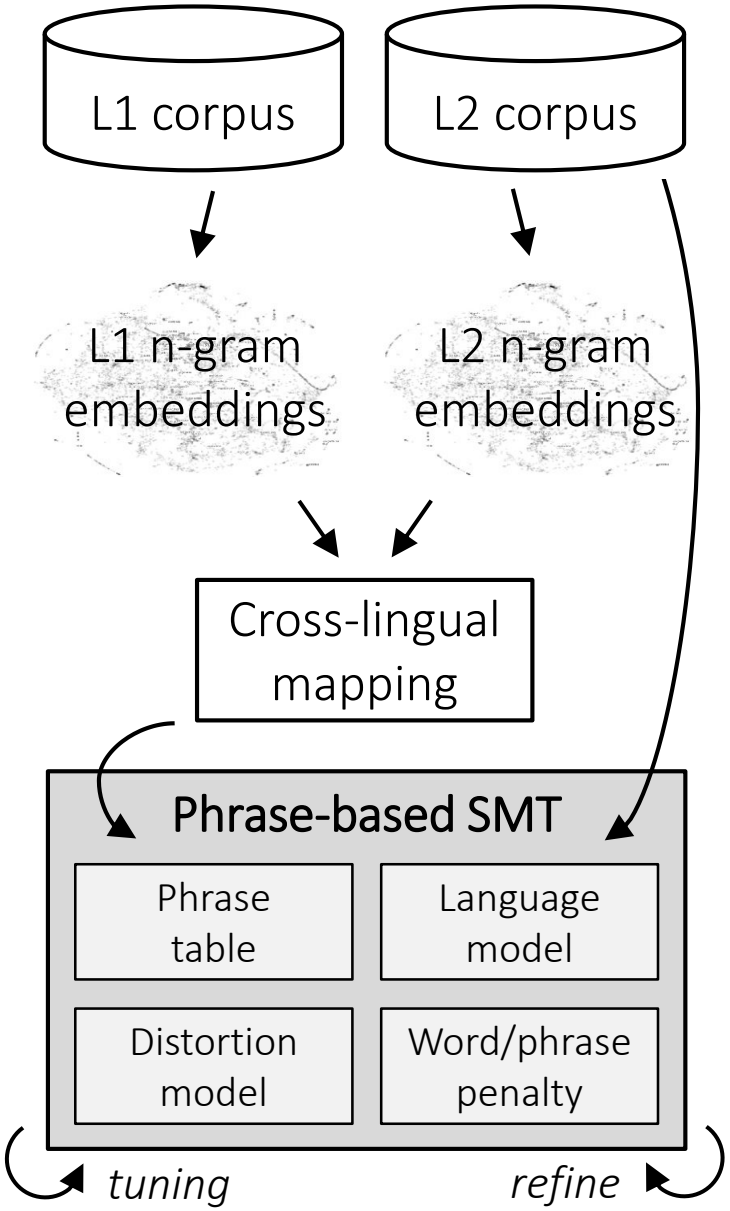
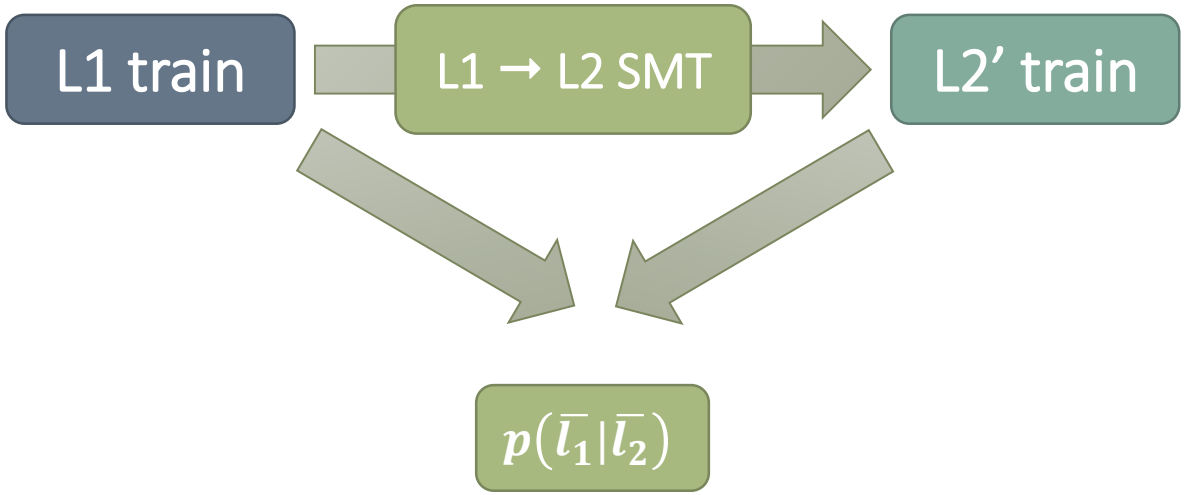
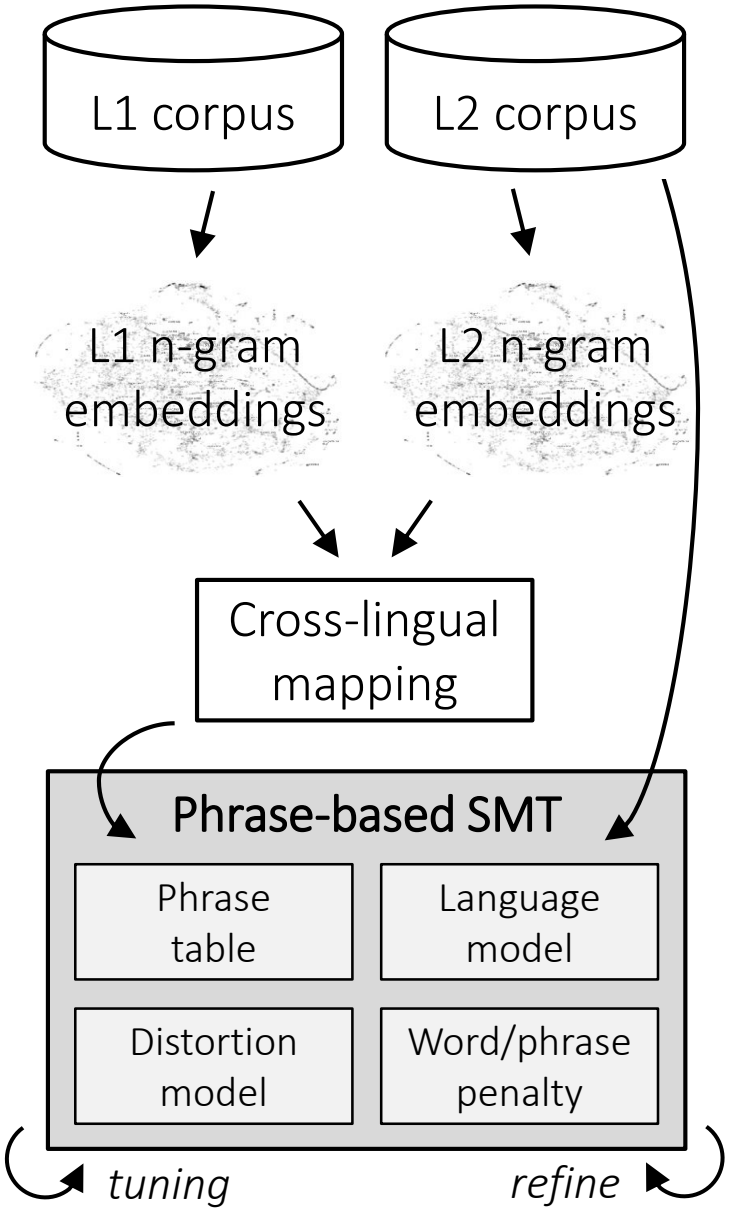
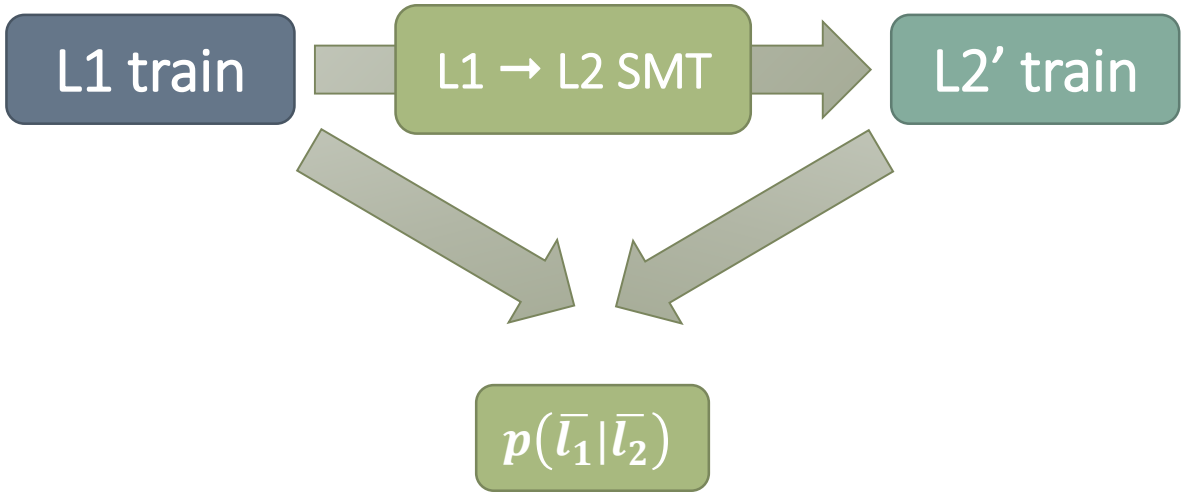
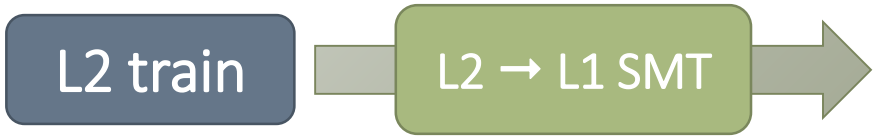




Unsupervised phrase-based SMT







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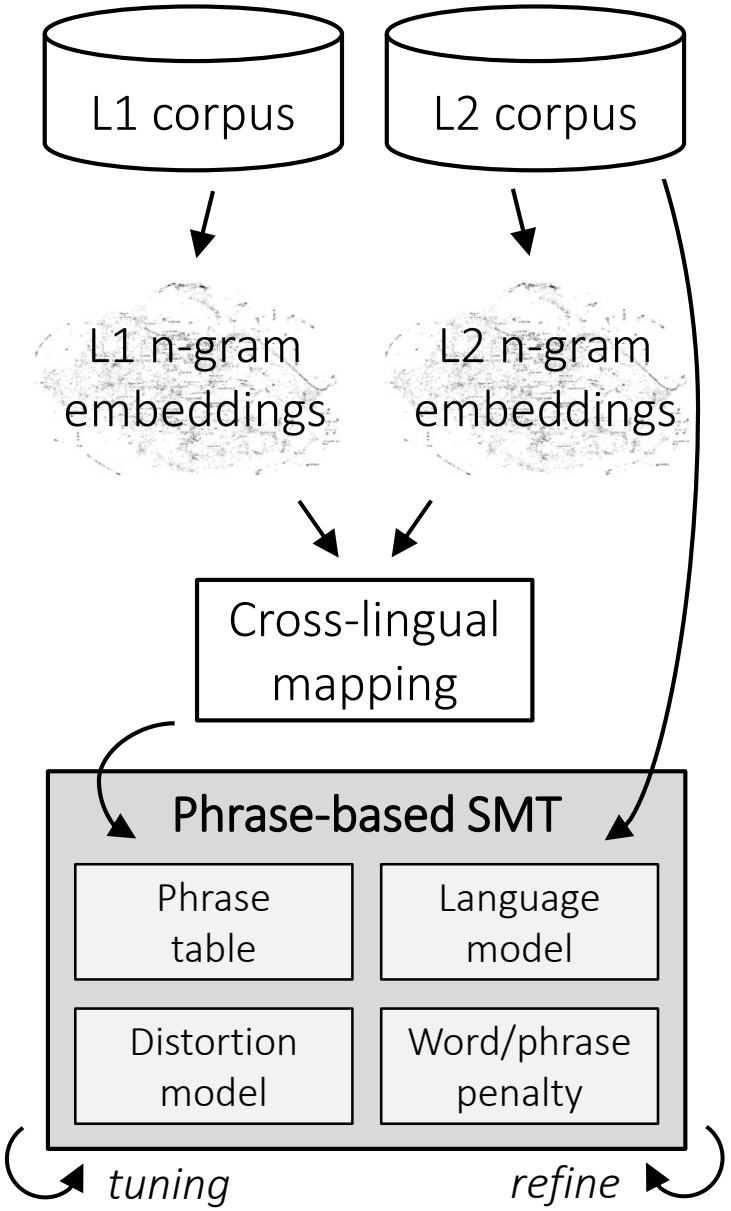

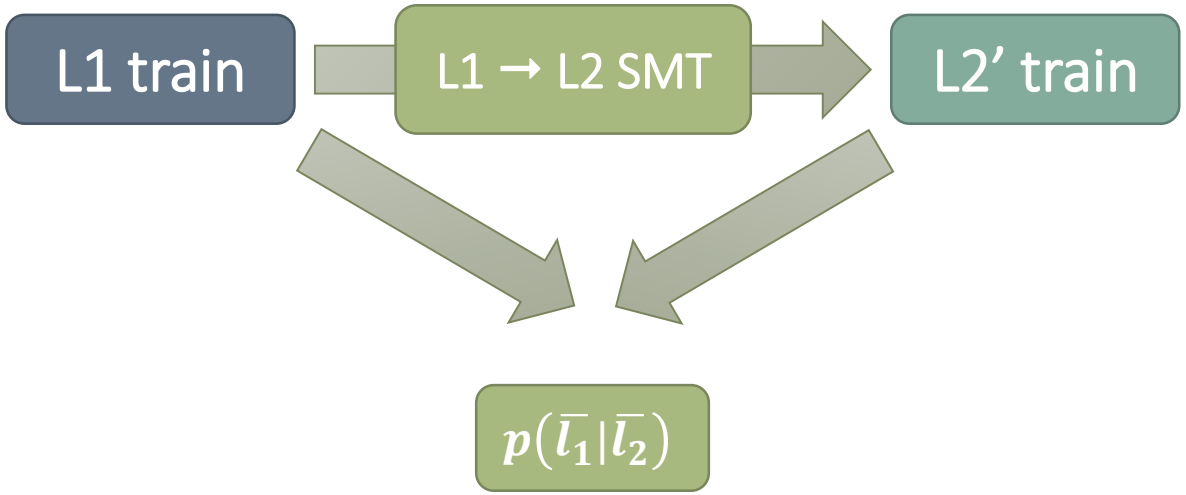

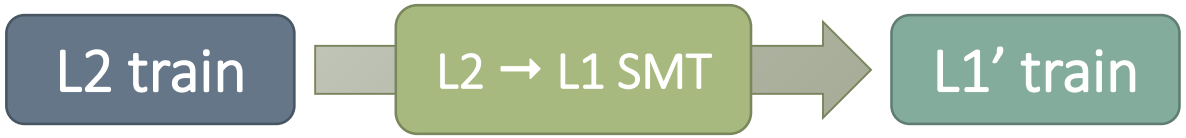

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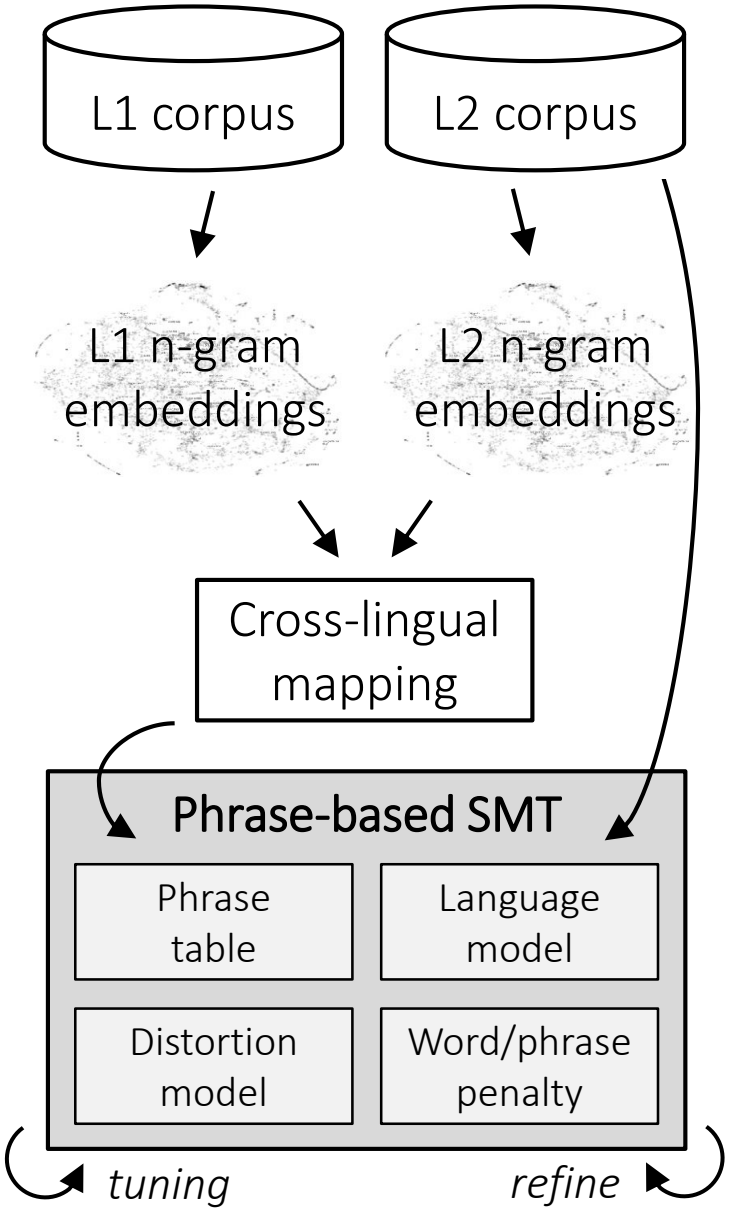

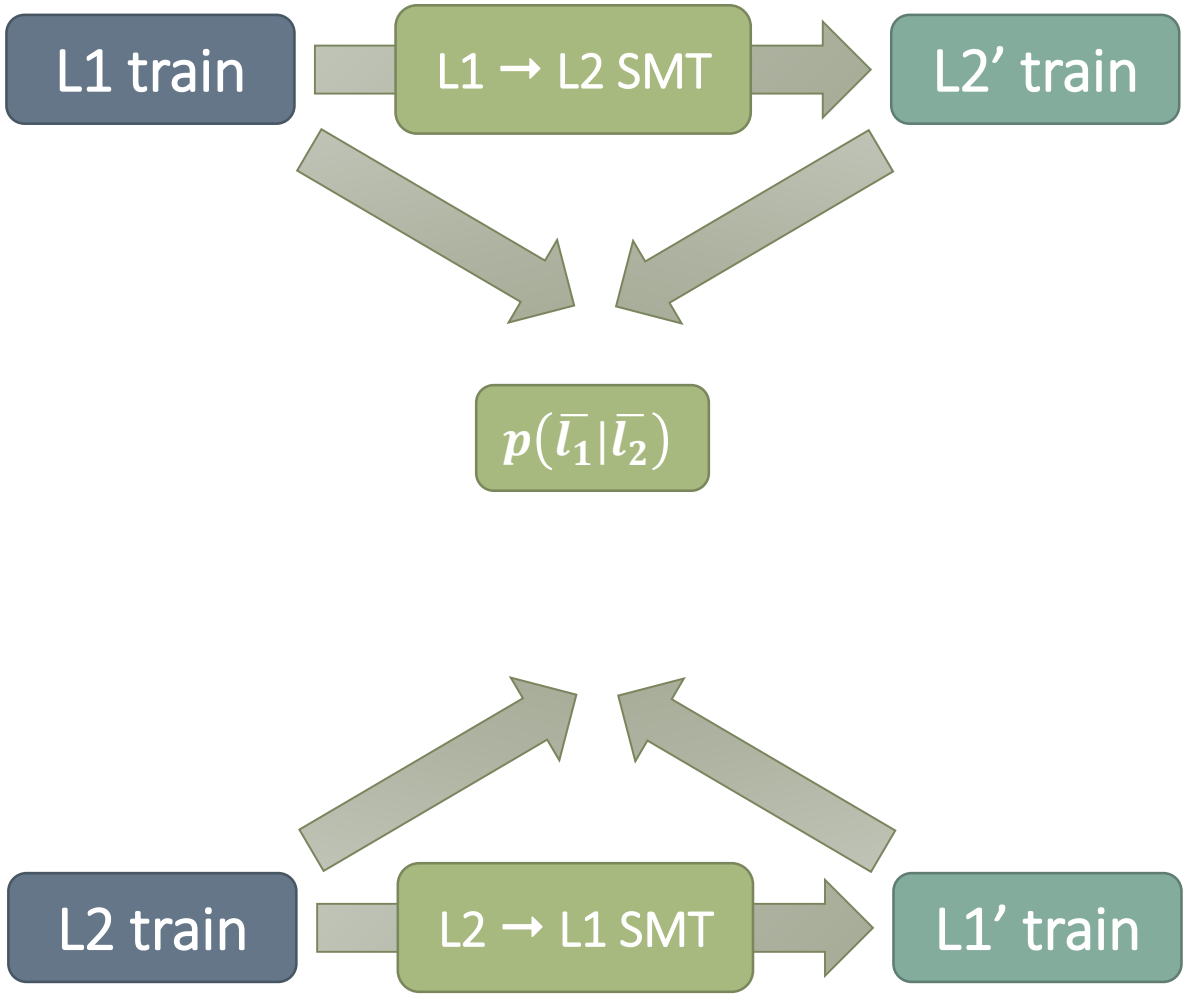

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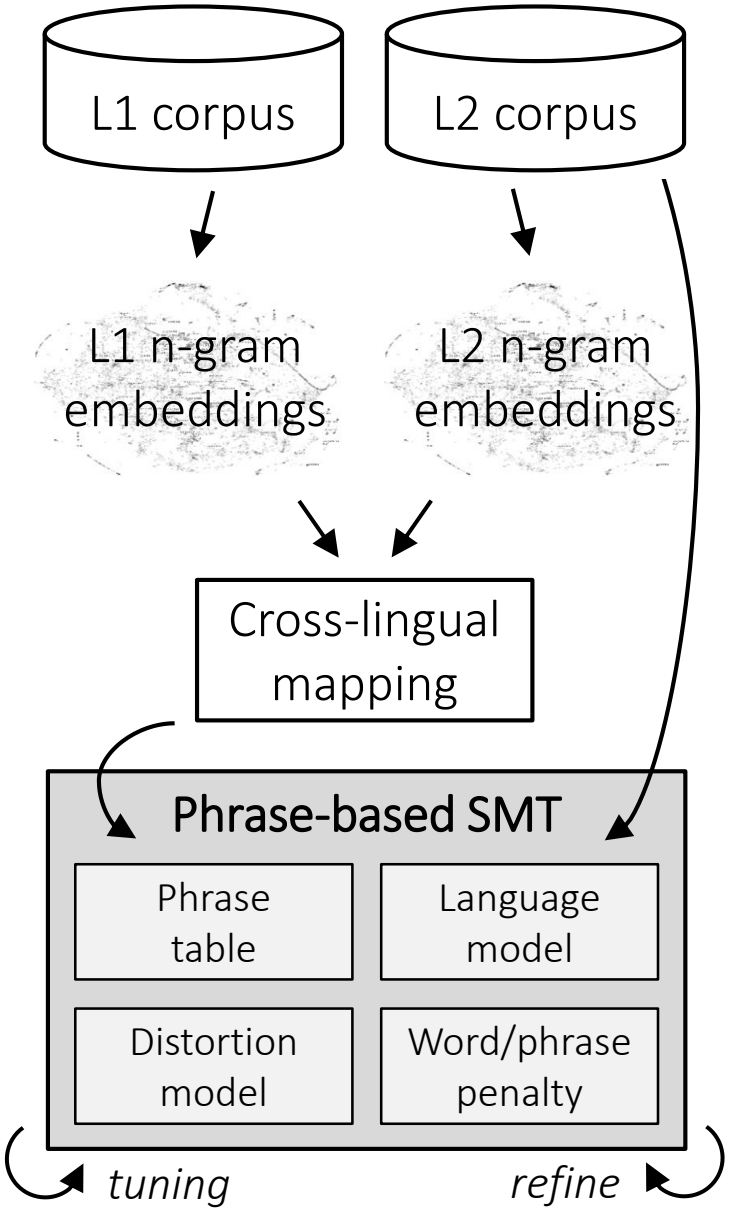

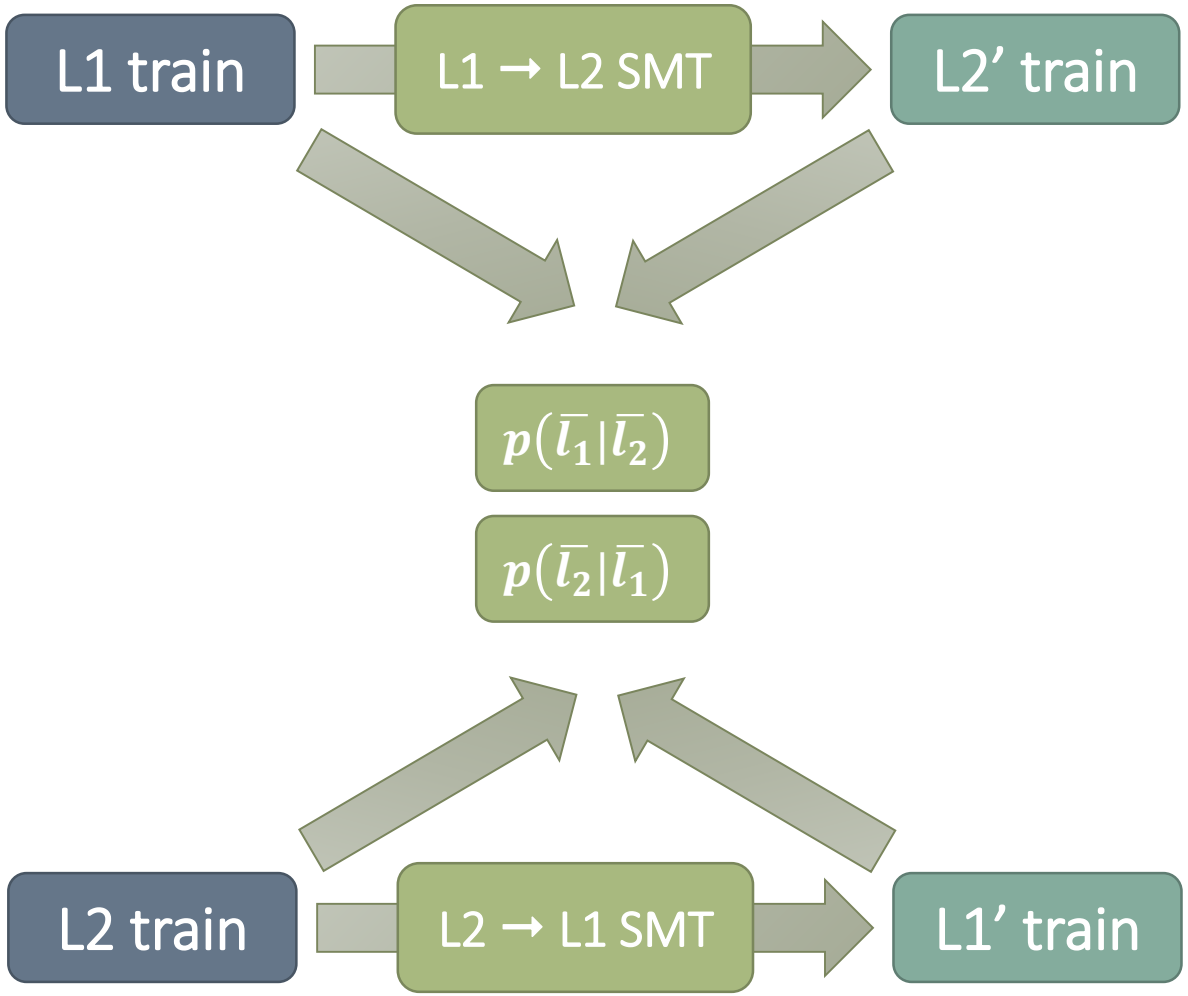

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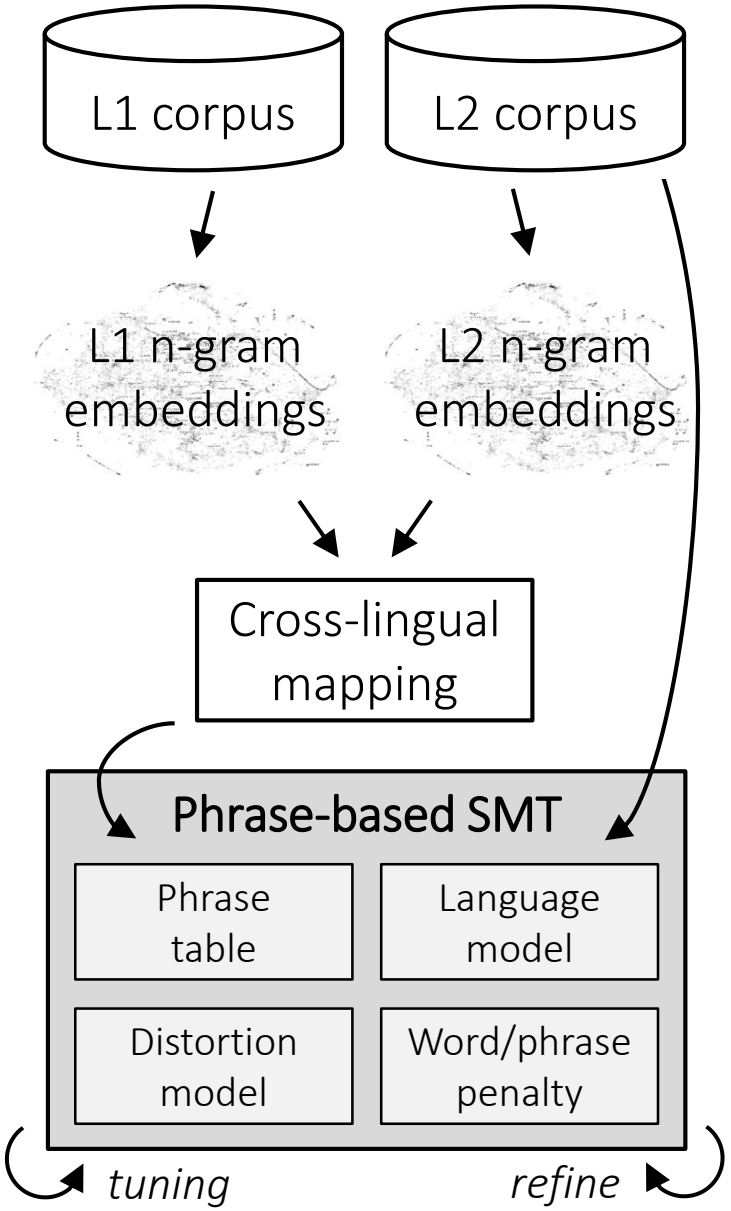

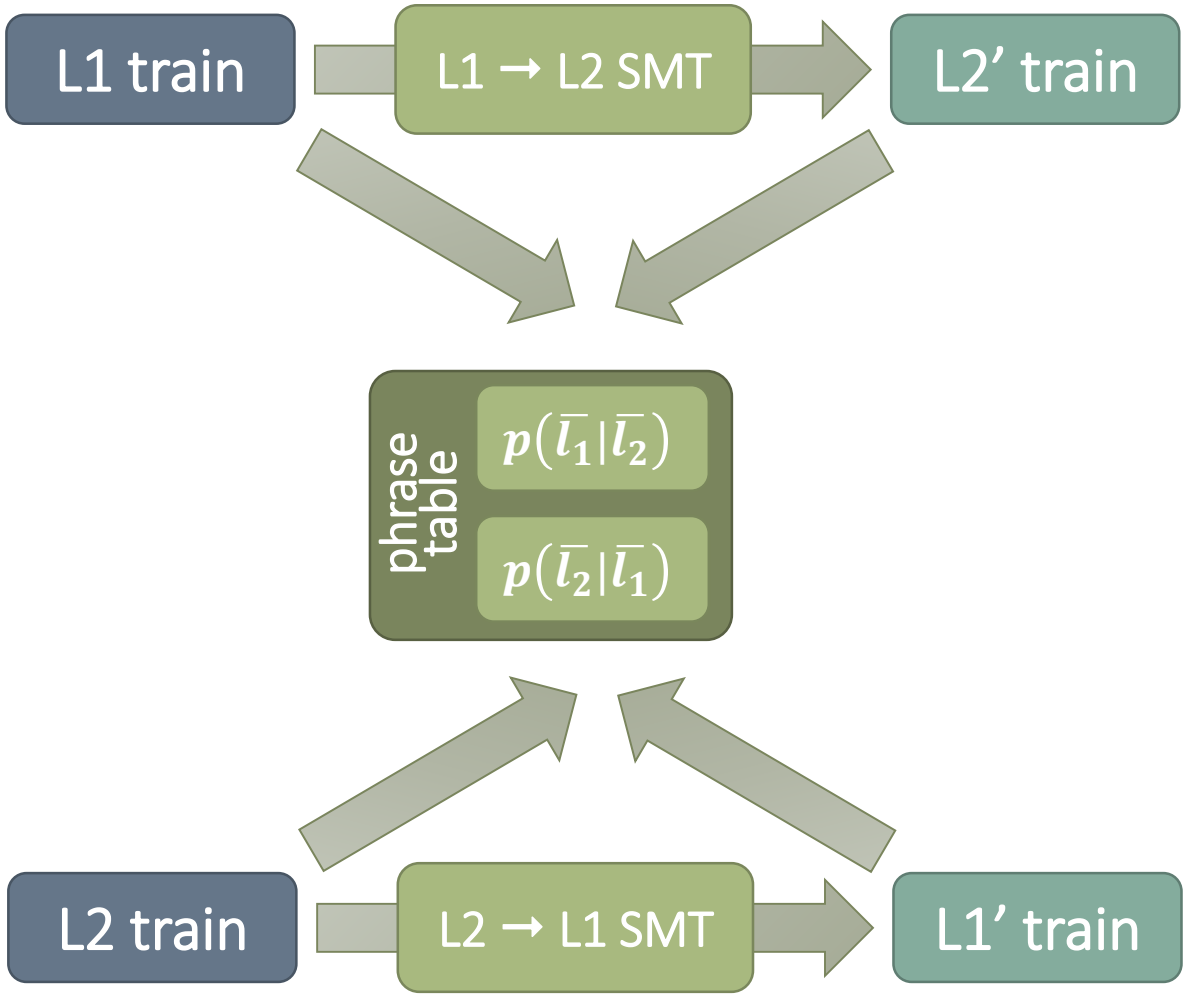

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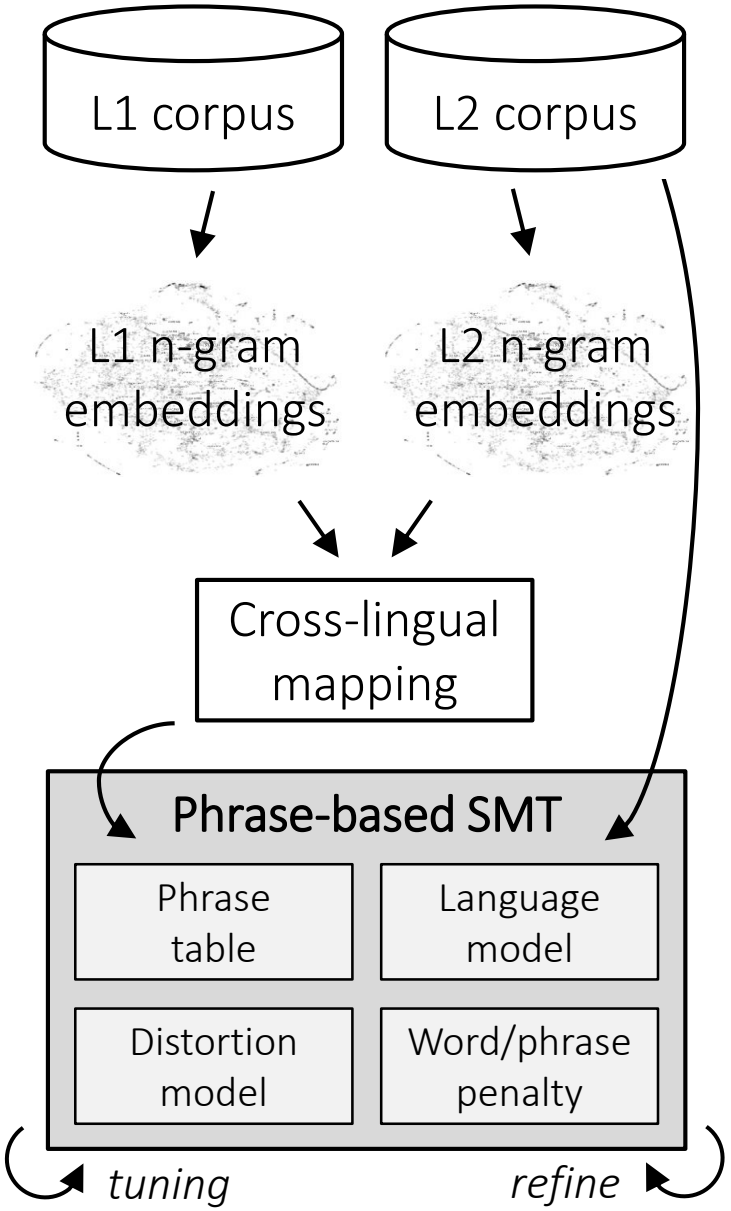

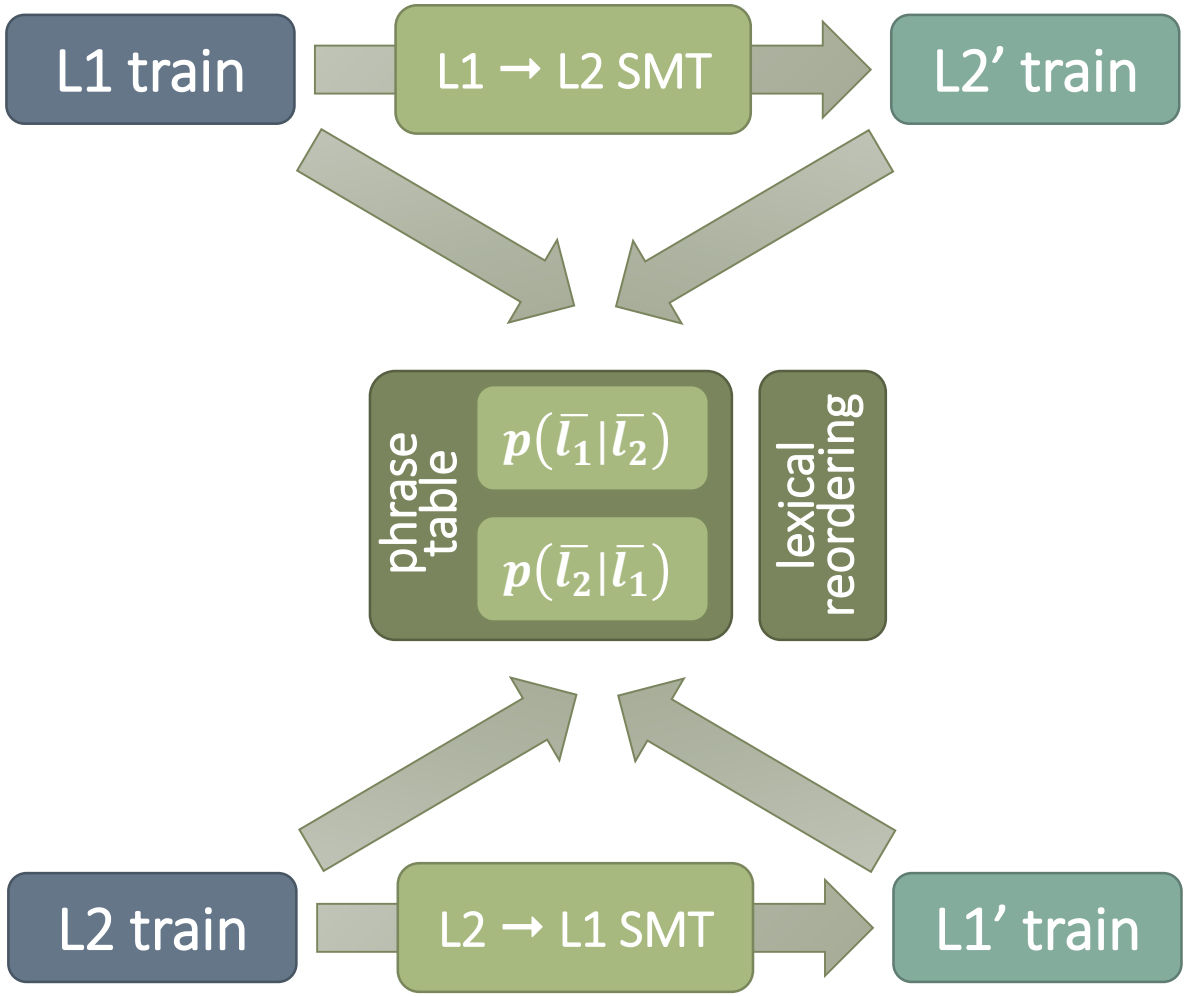

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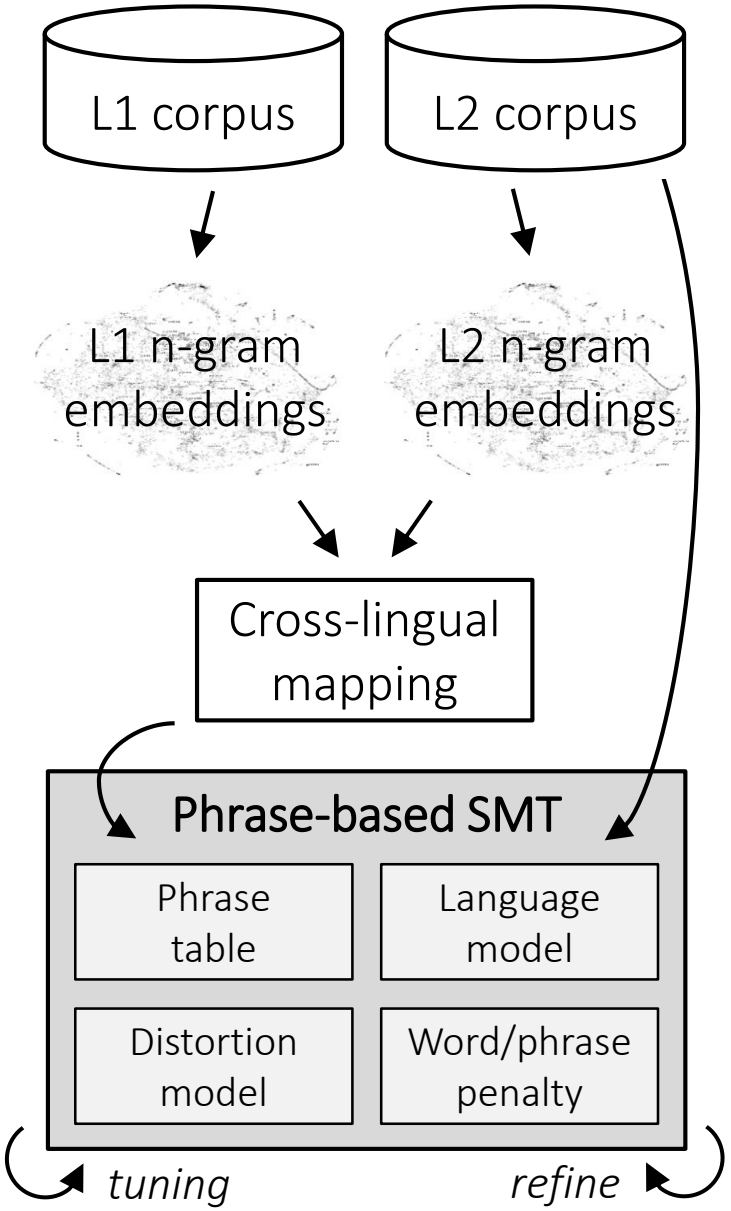

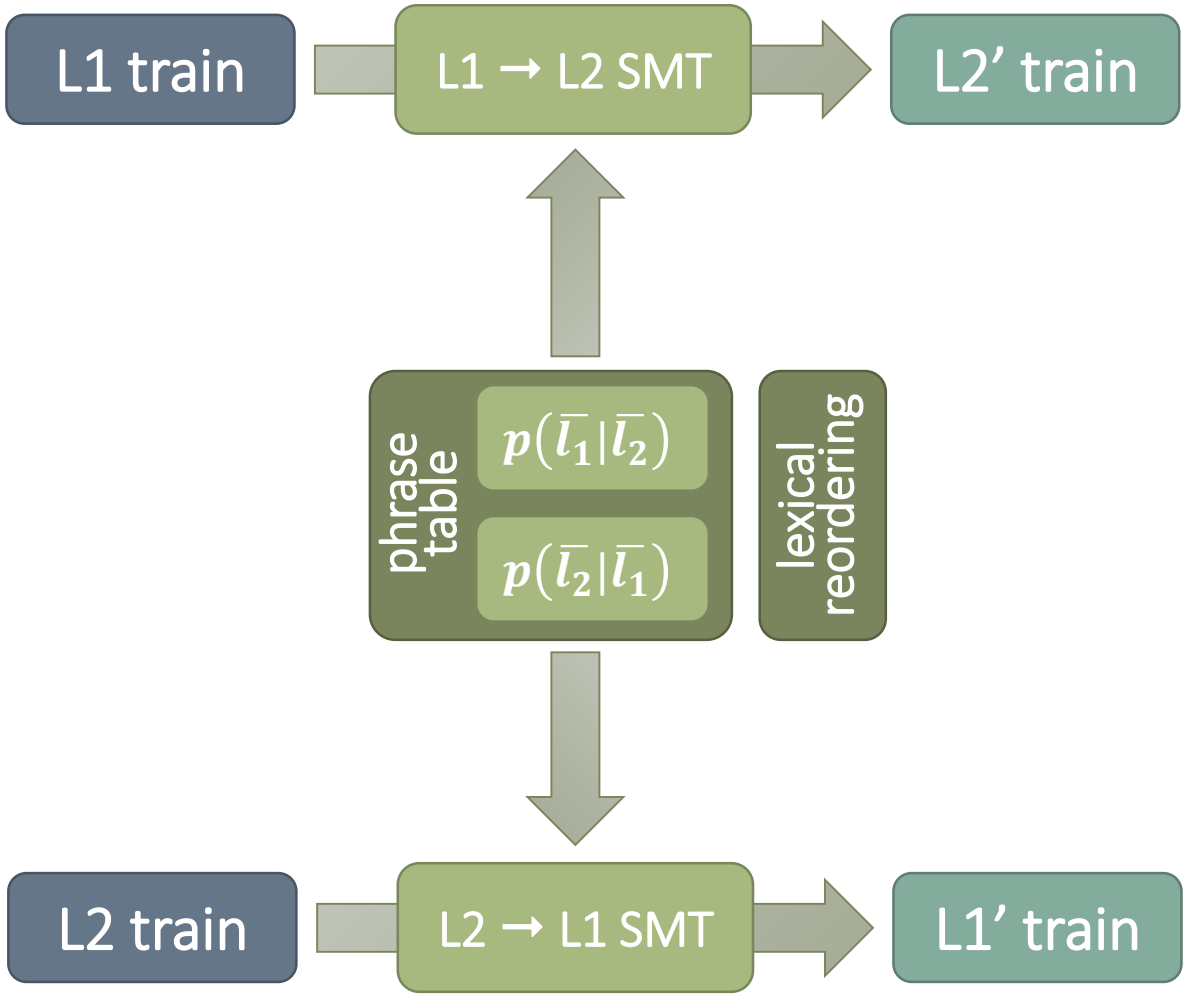

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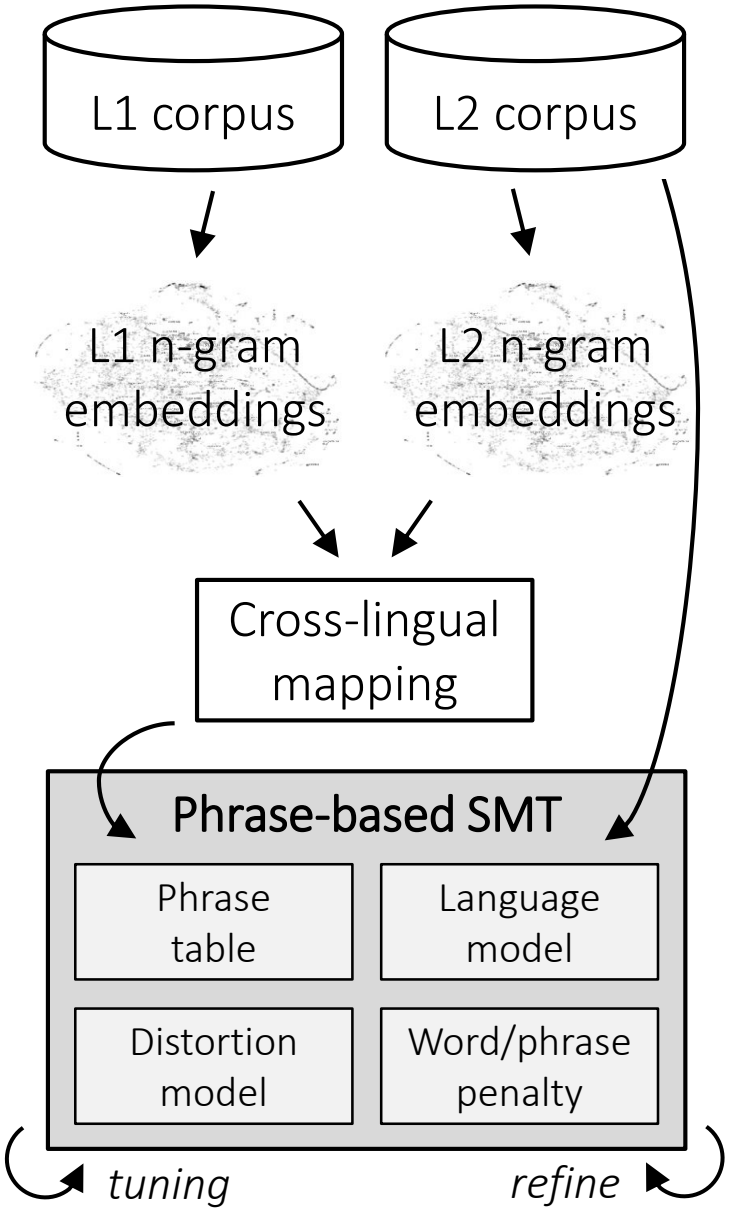
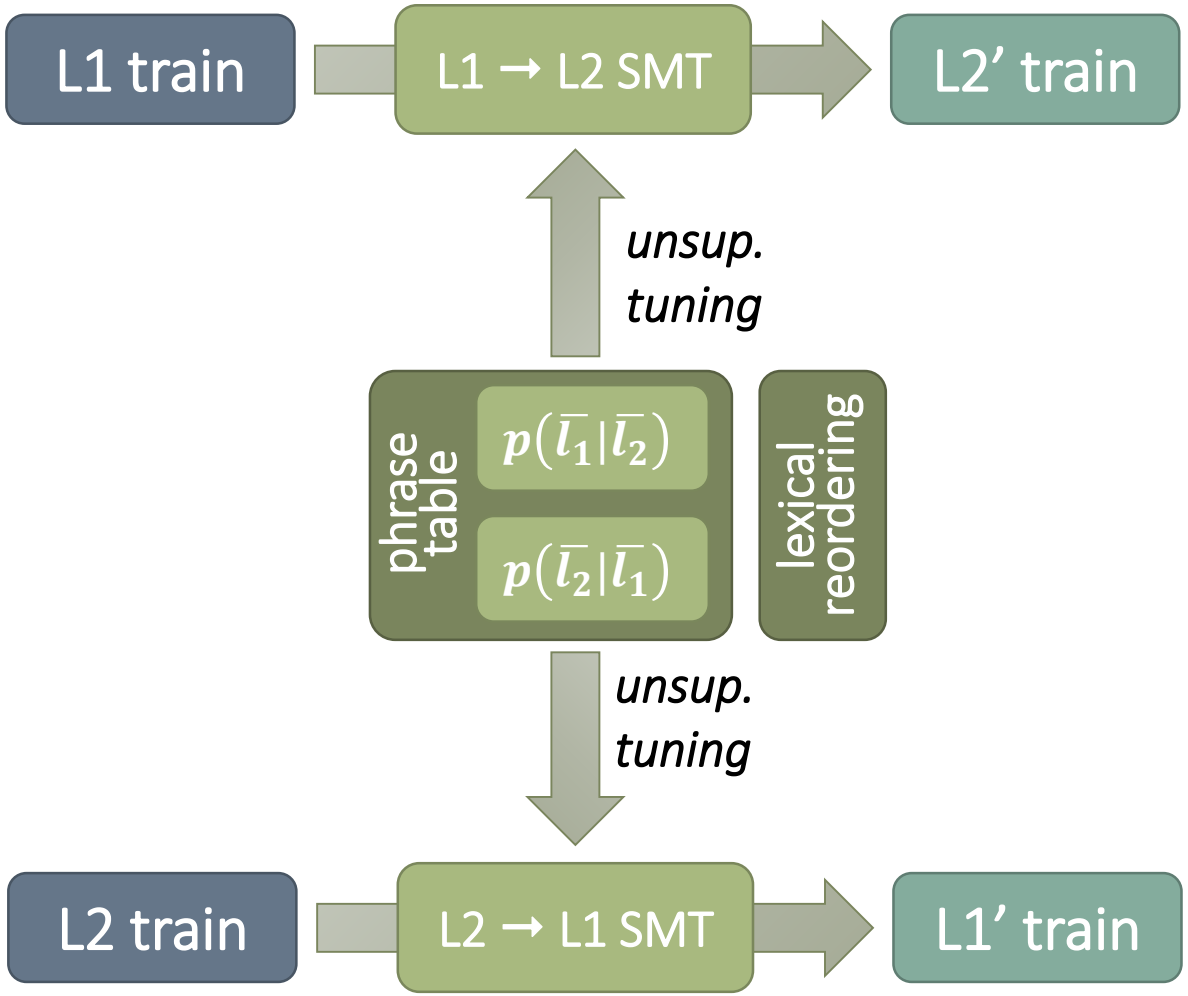
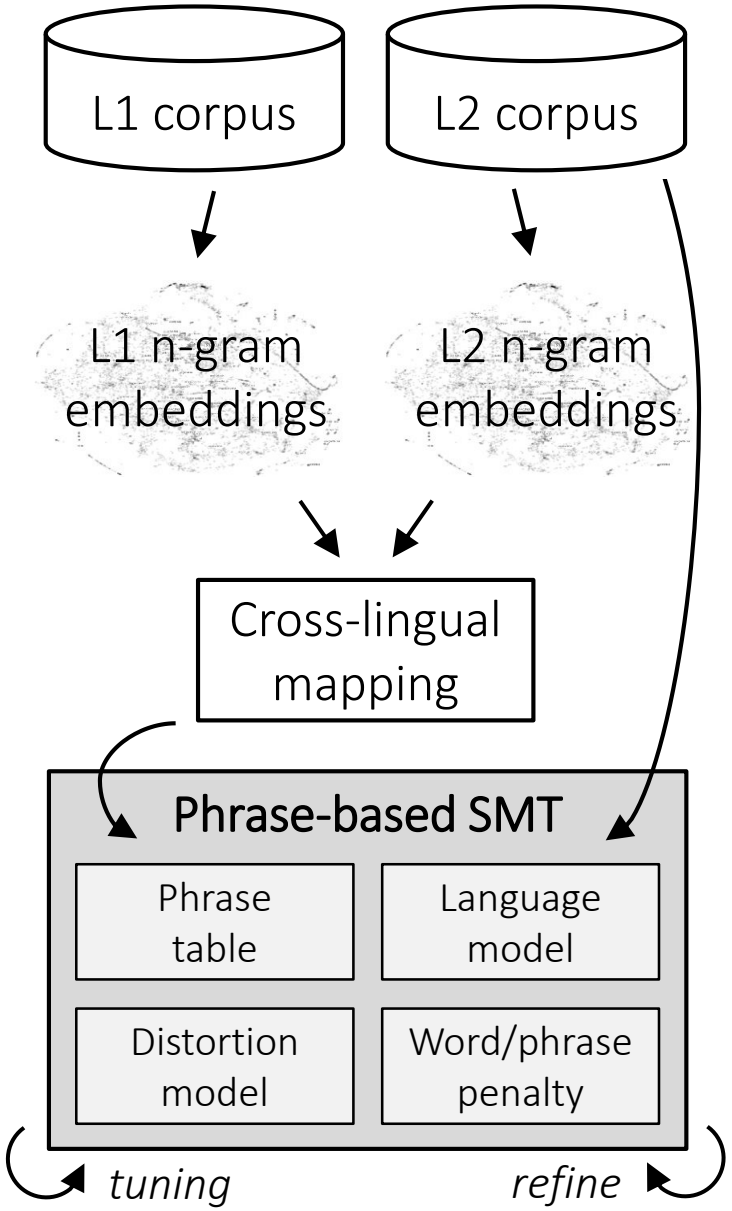






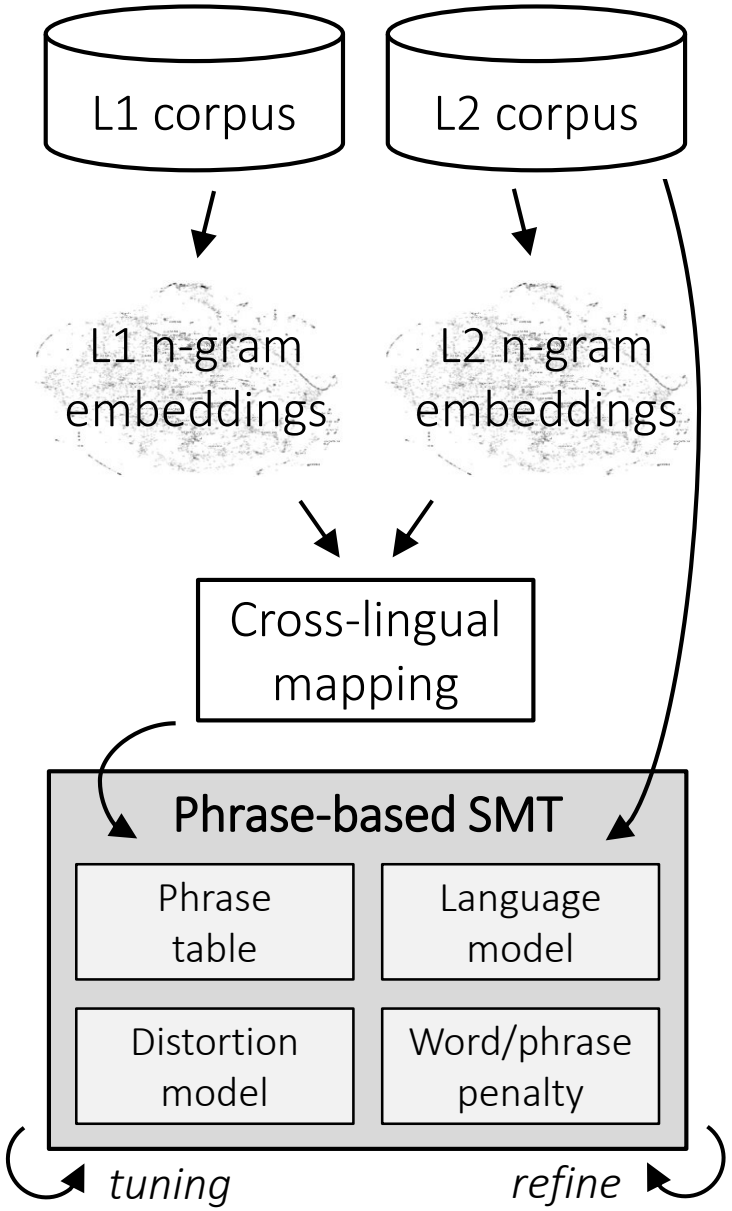
Unsupervised phrase-based SMT

EXPERIMENTS

- Languages: French-English, German-English
- Training: WMT-14 News Crawl
- Test set: WMT-14 newstest (BLEU)

	FR-EN	EN-FR	DE-EN	EN-DE
Initial SMT	22.4	19.6	15.3	11.0
+ Tuning	23.4	21.9	15.4	11.2

Unsupervised phrase-based SMT



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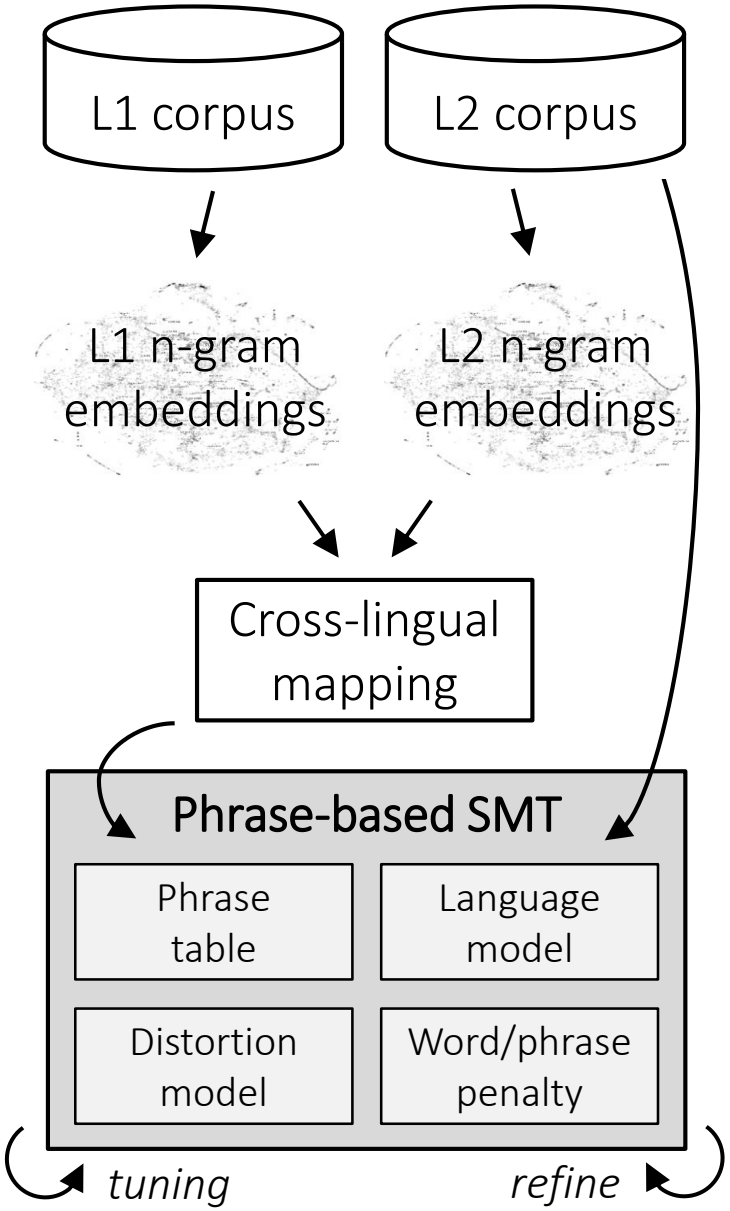
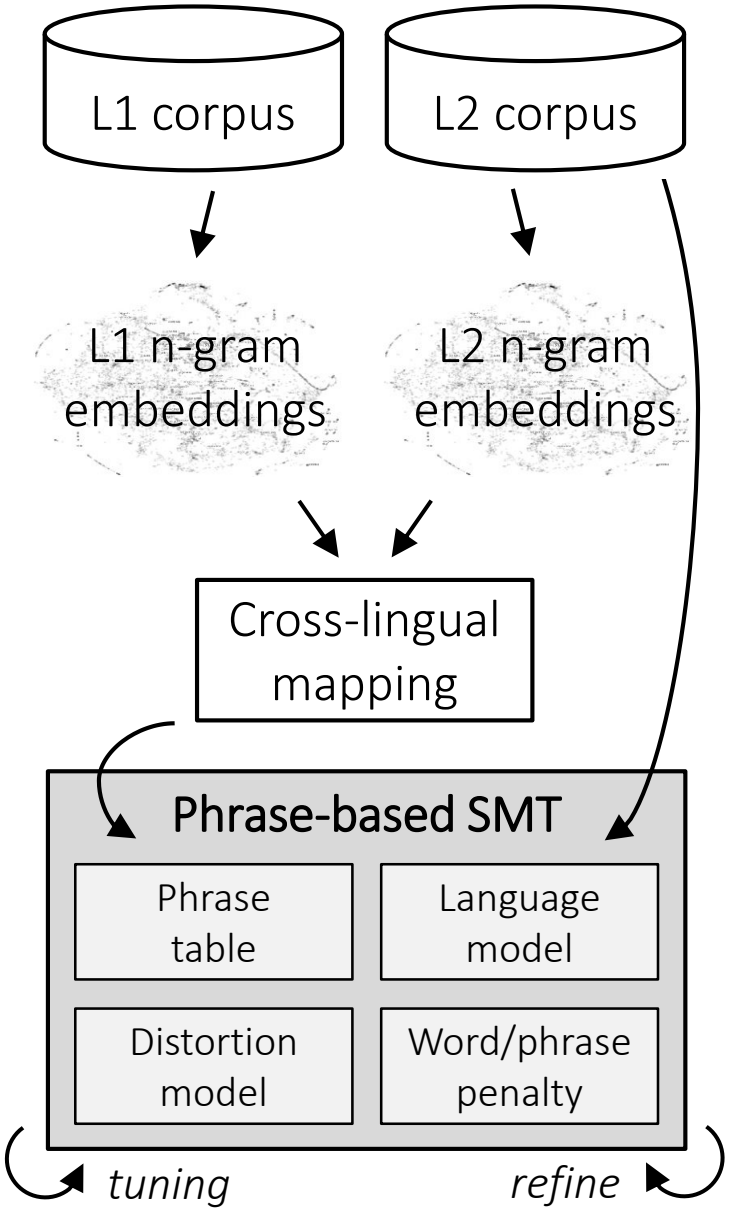
+ Refinement	27.9	27.8	19.7	14.7


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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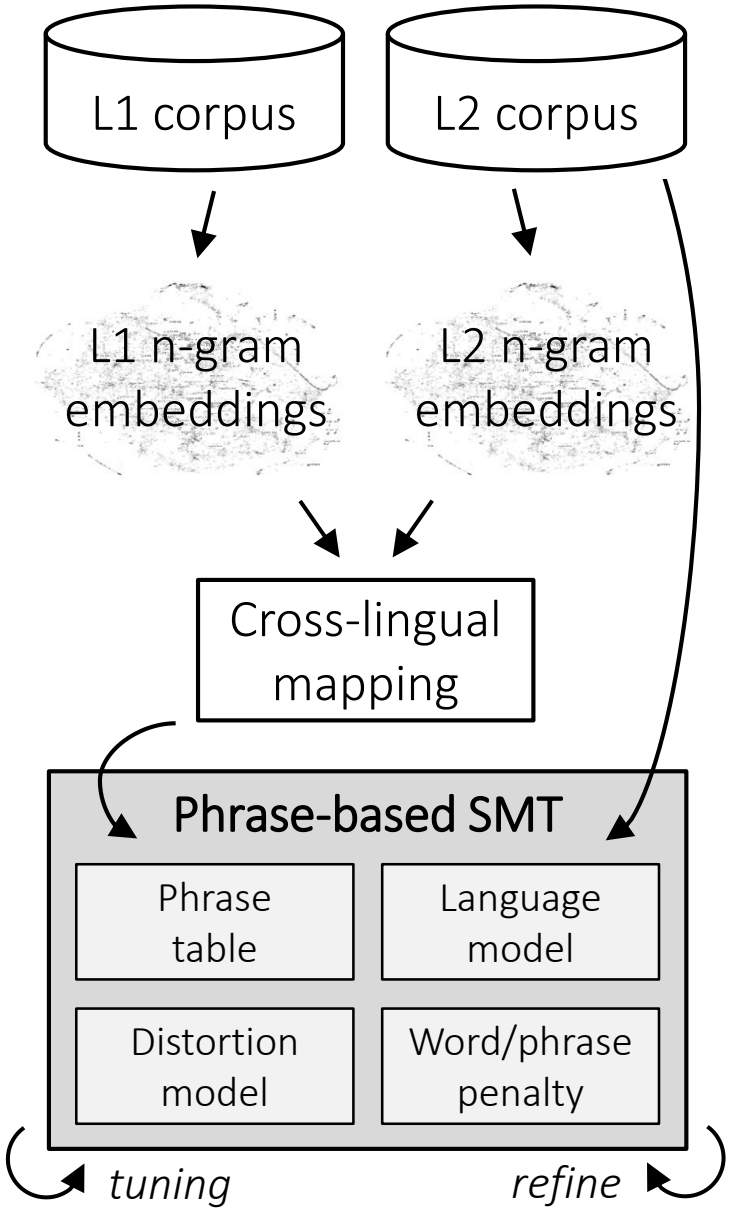
but…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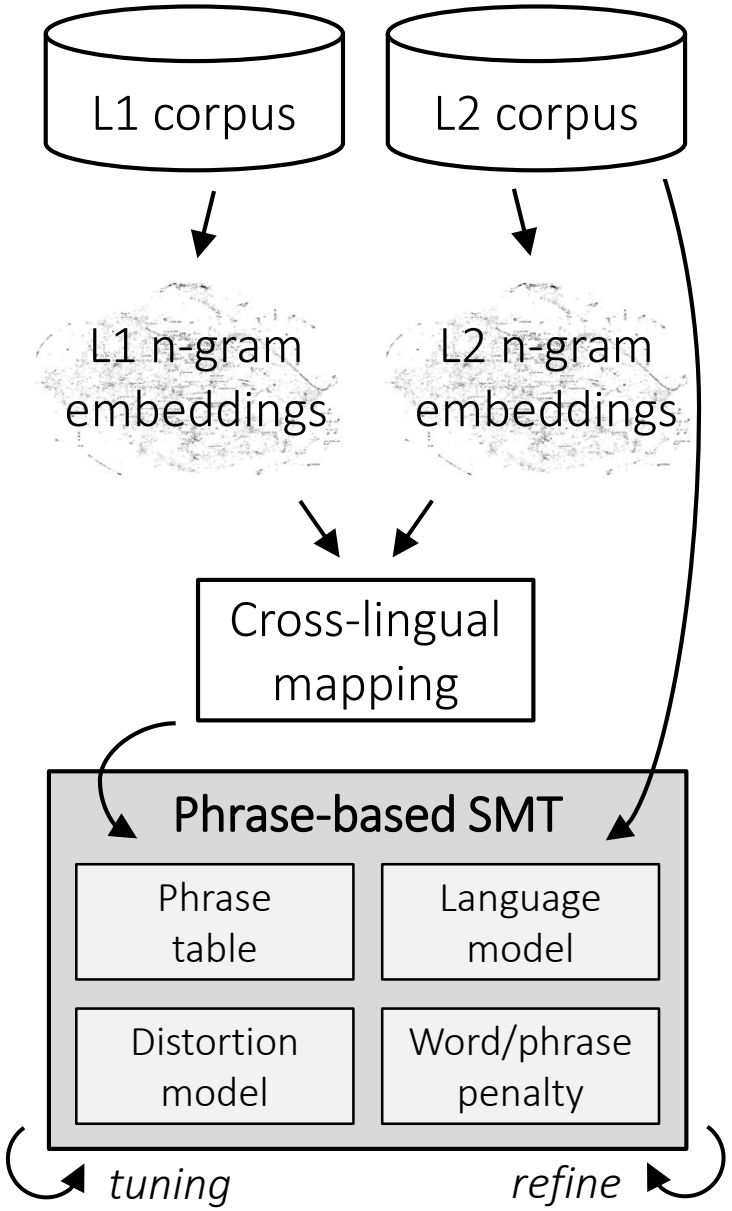
but…

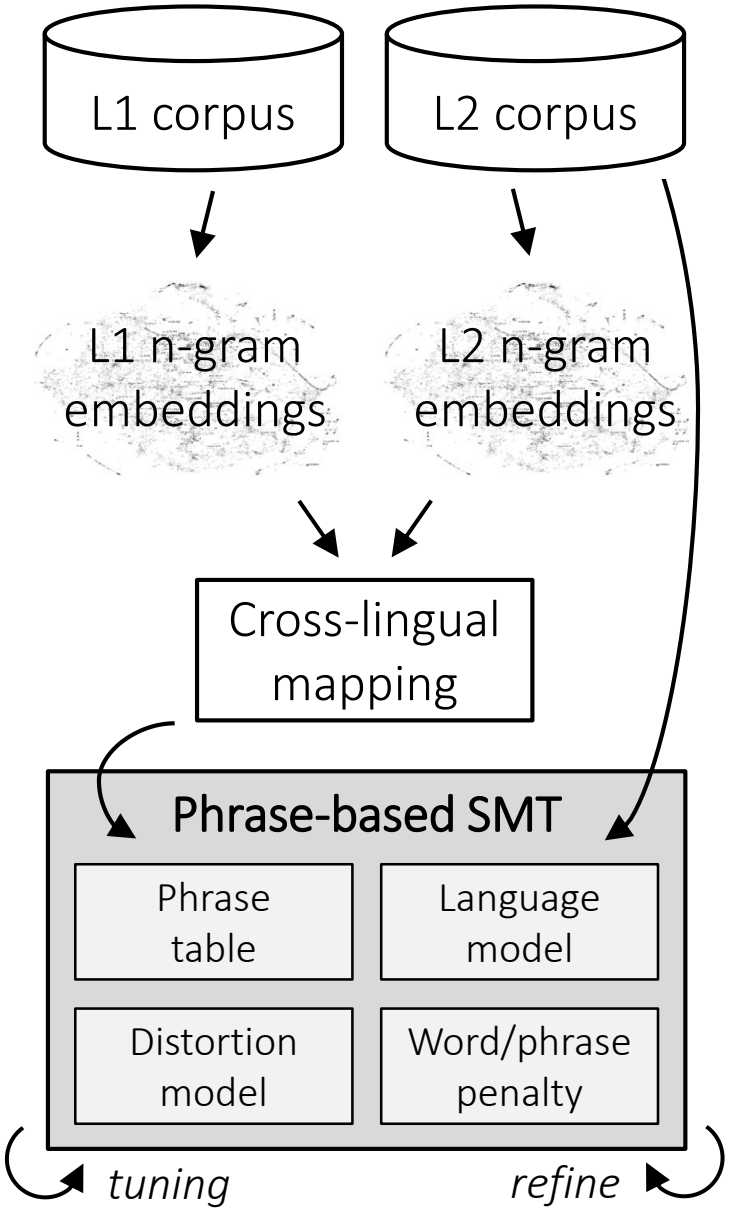
NMT >> SMT



but…

NMT >> SMT

(unsupervised) SMT has a hard ceiling!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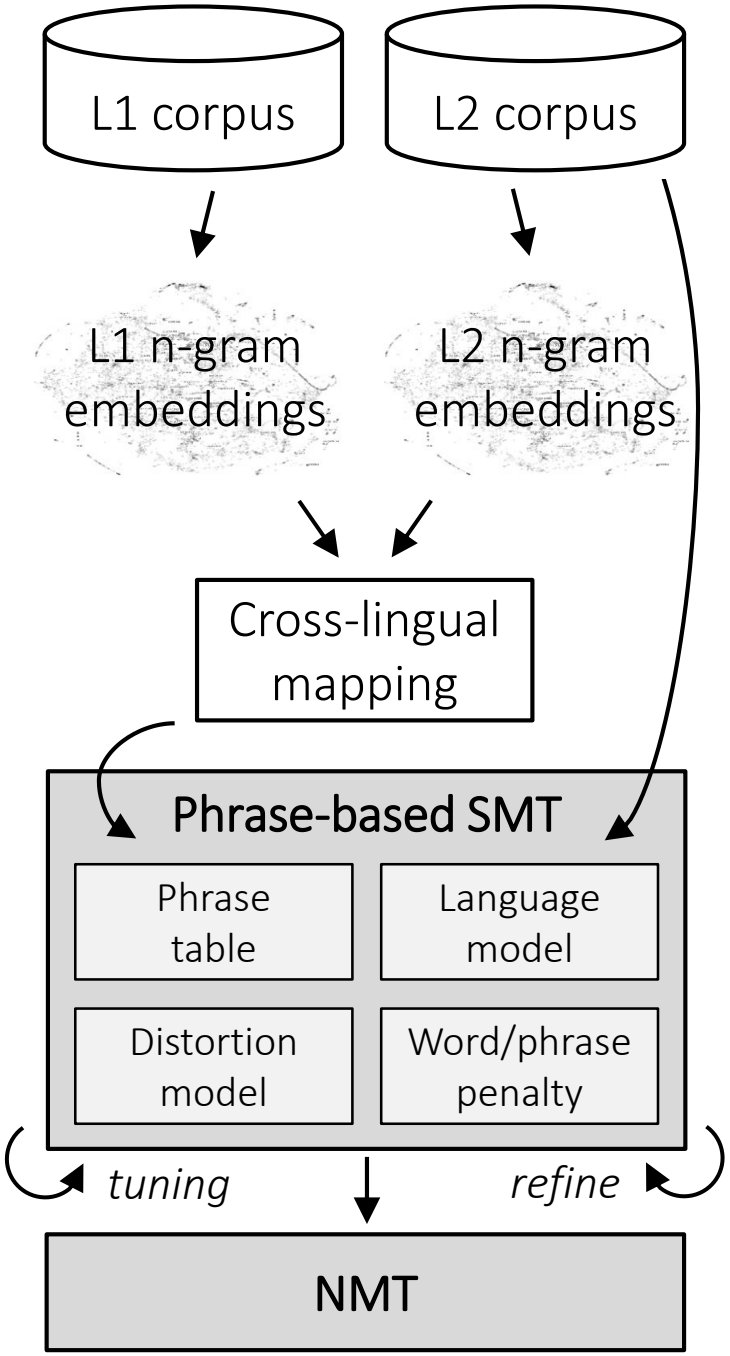
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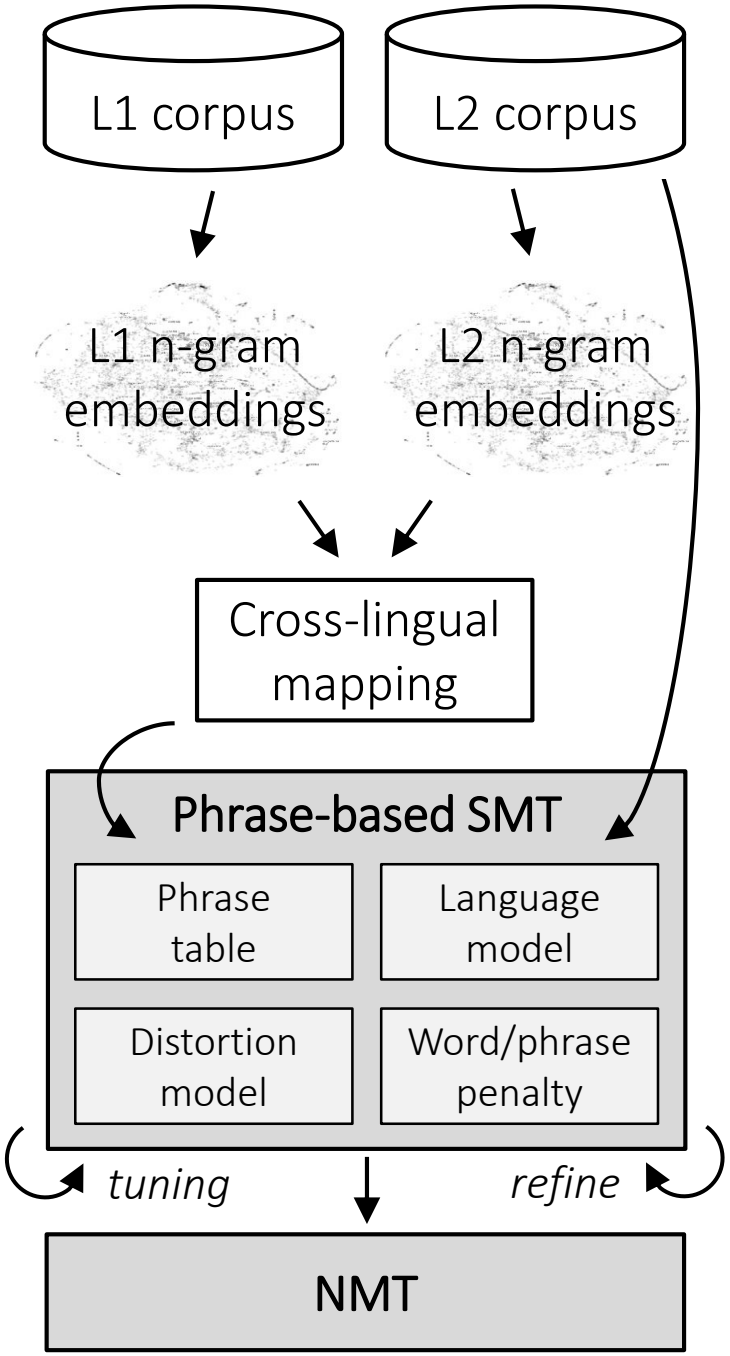
NMT hybridization



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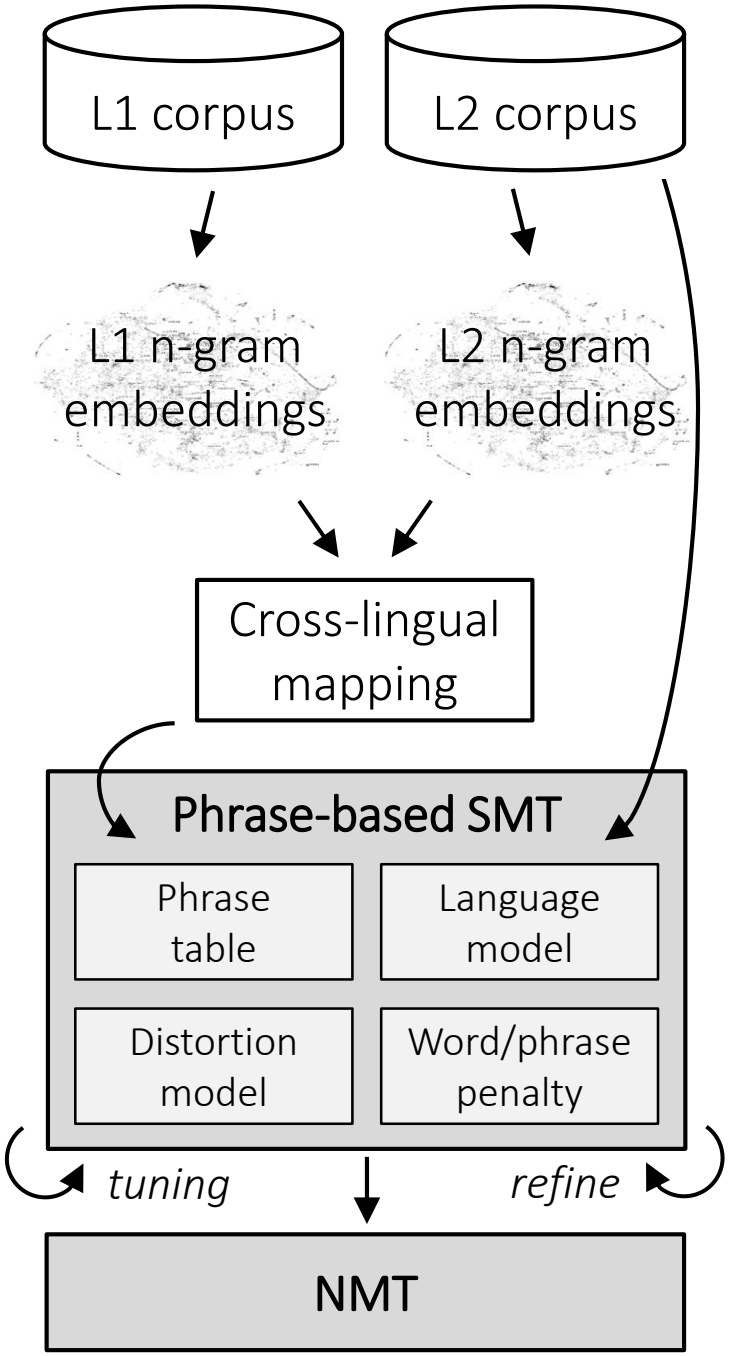

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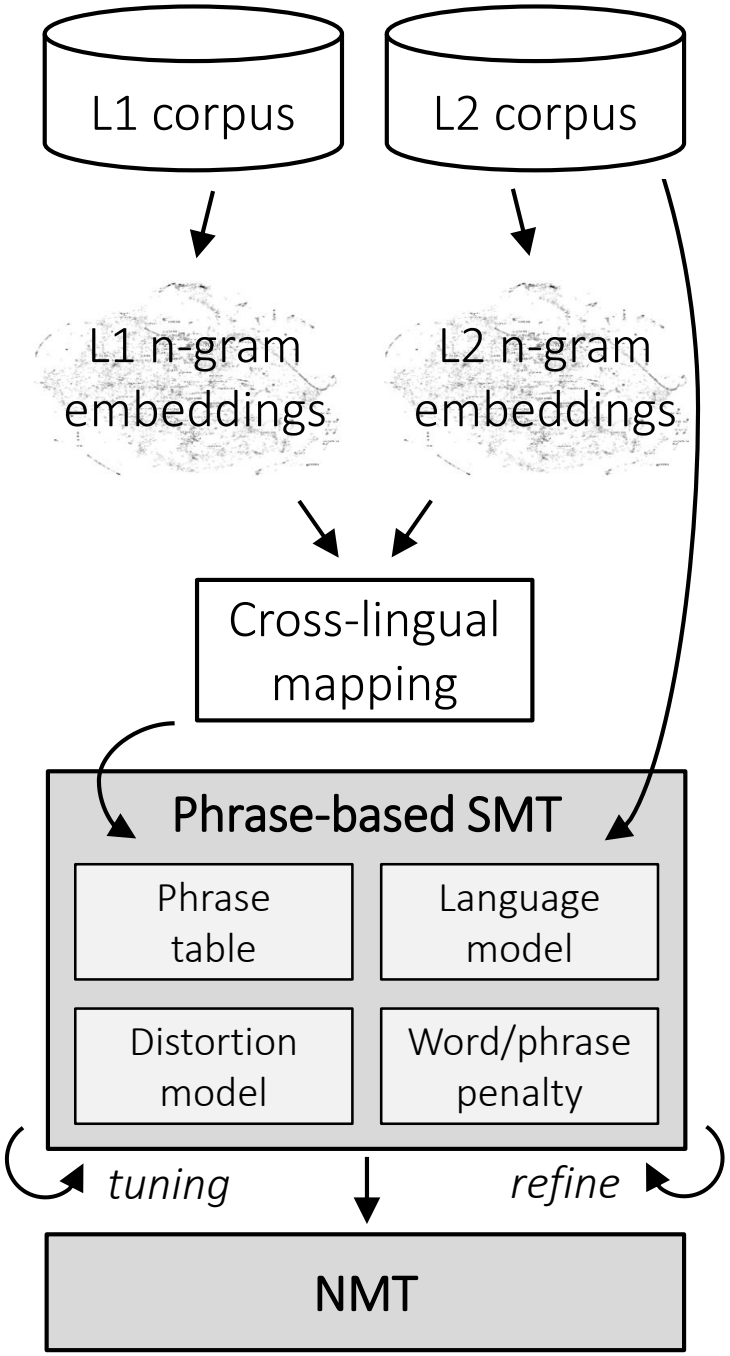

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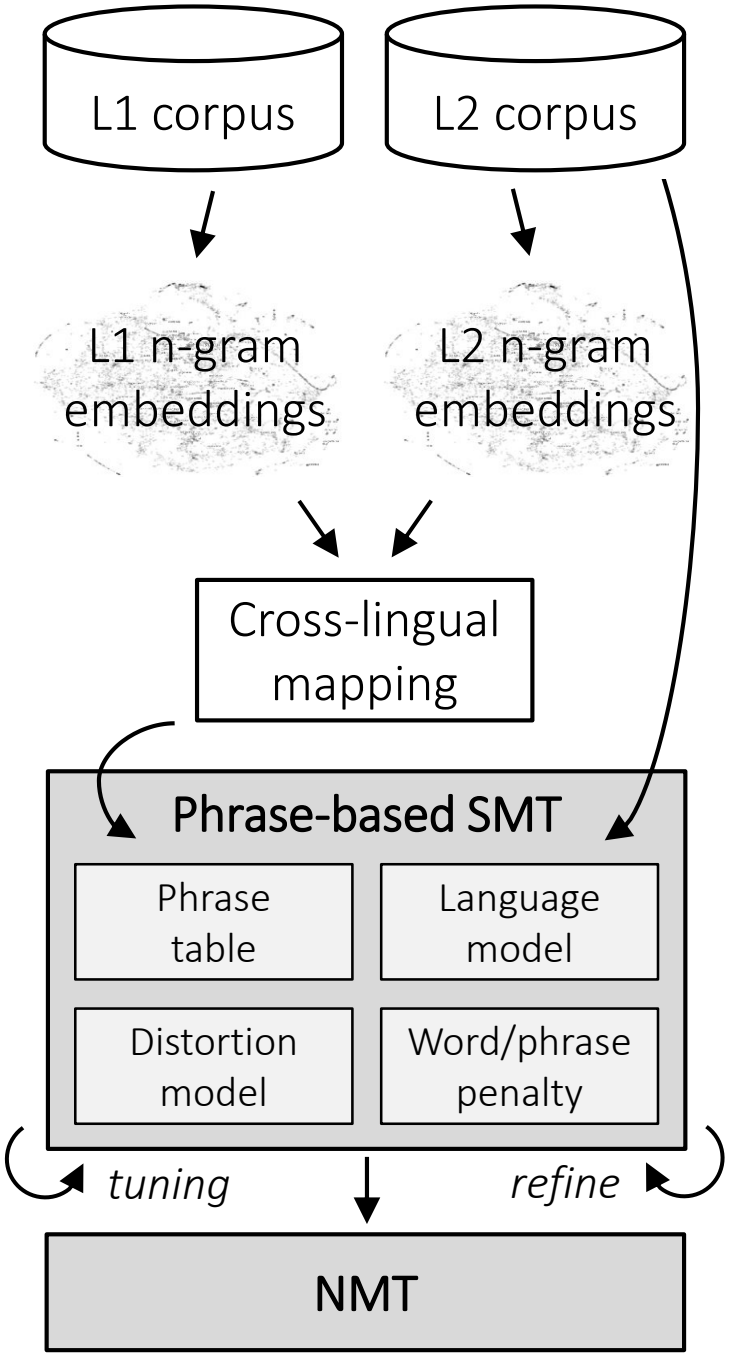

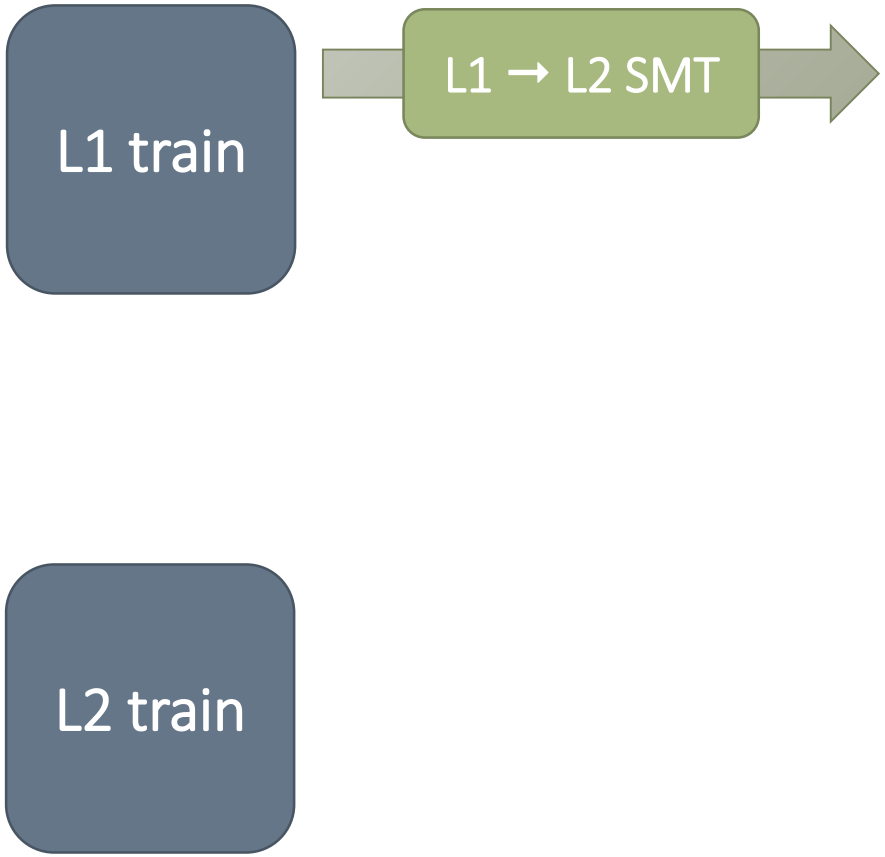

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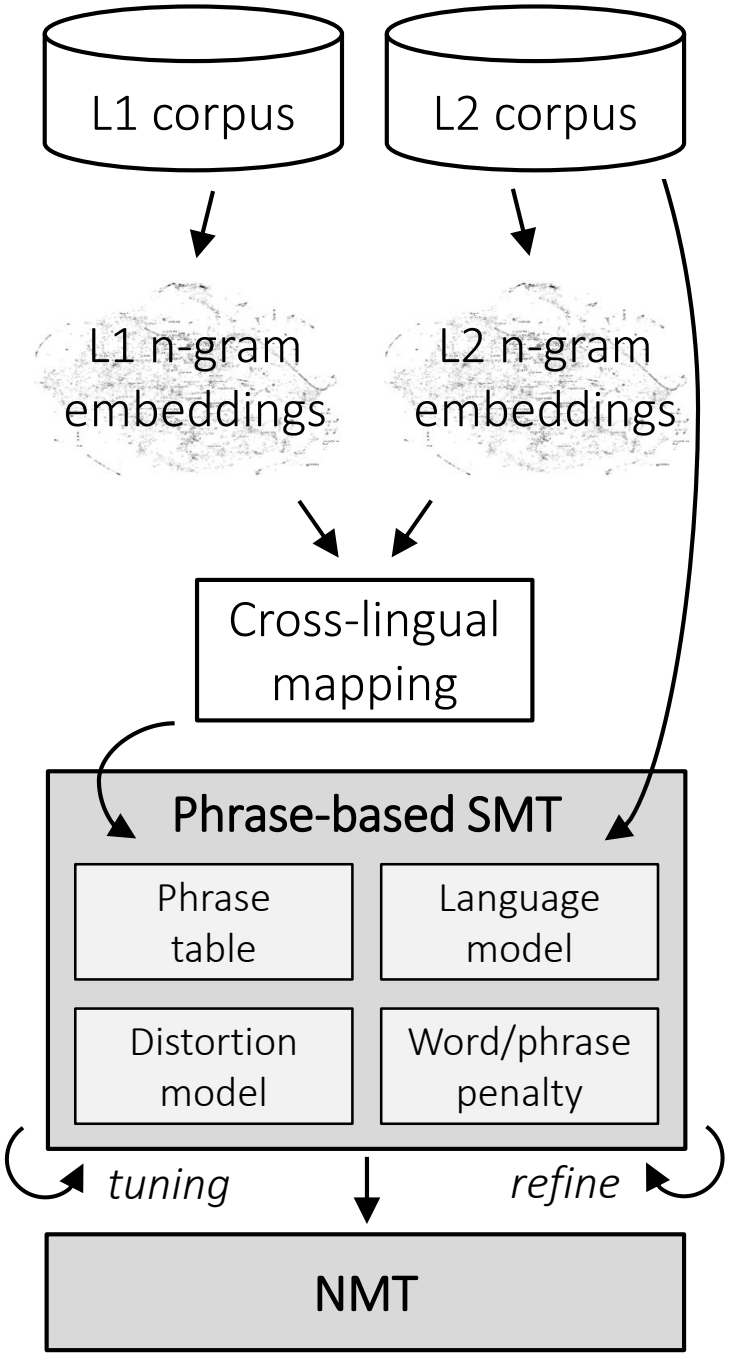

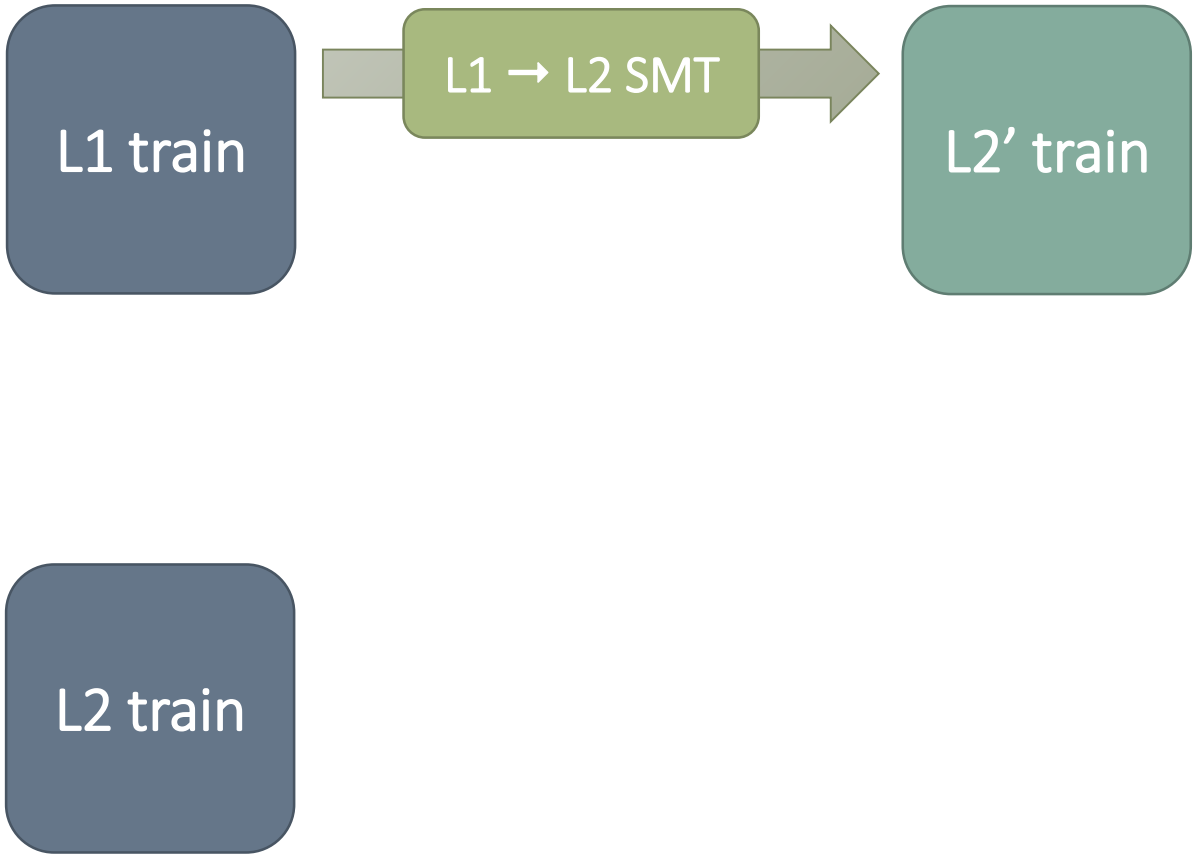

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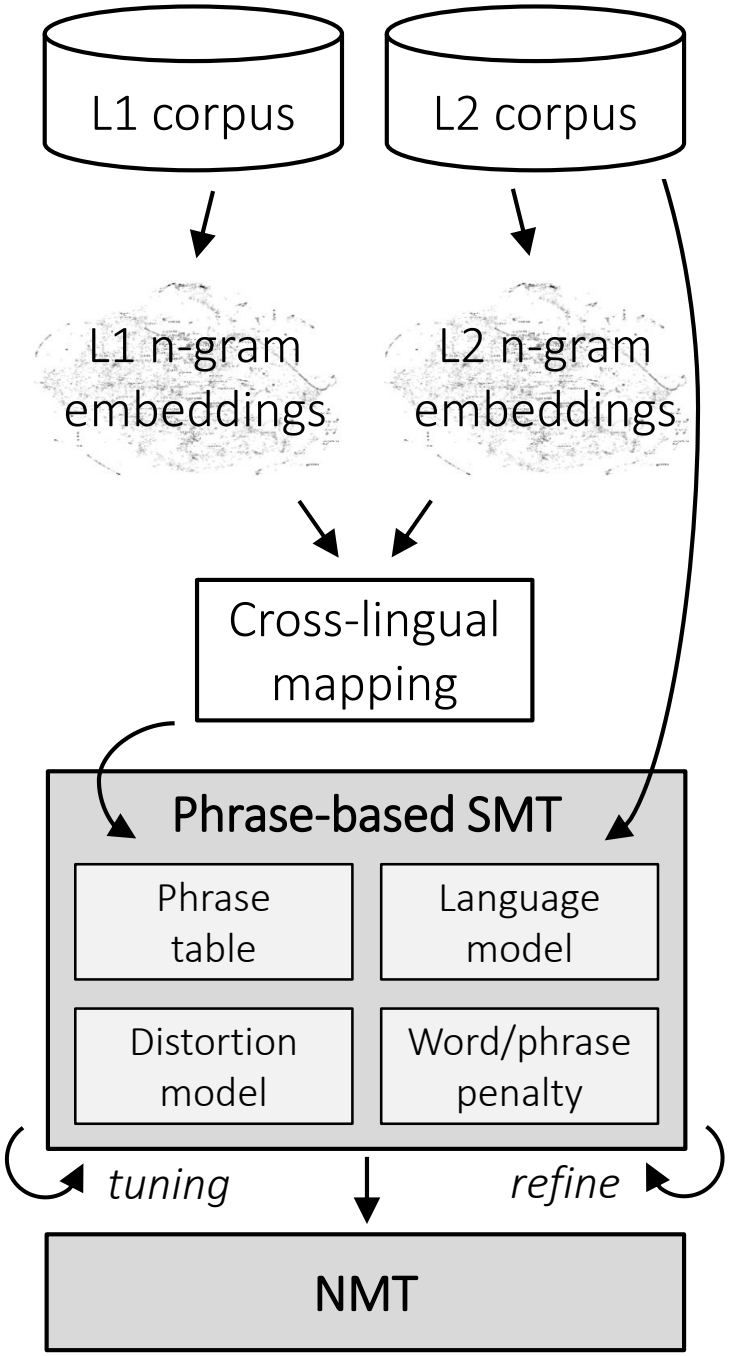

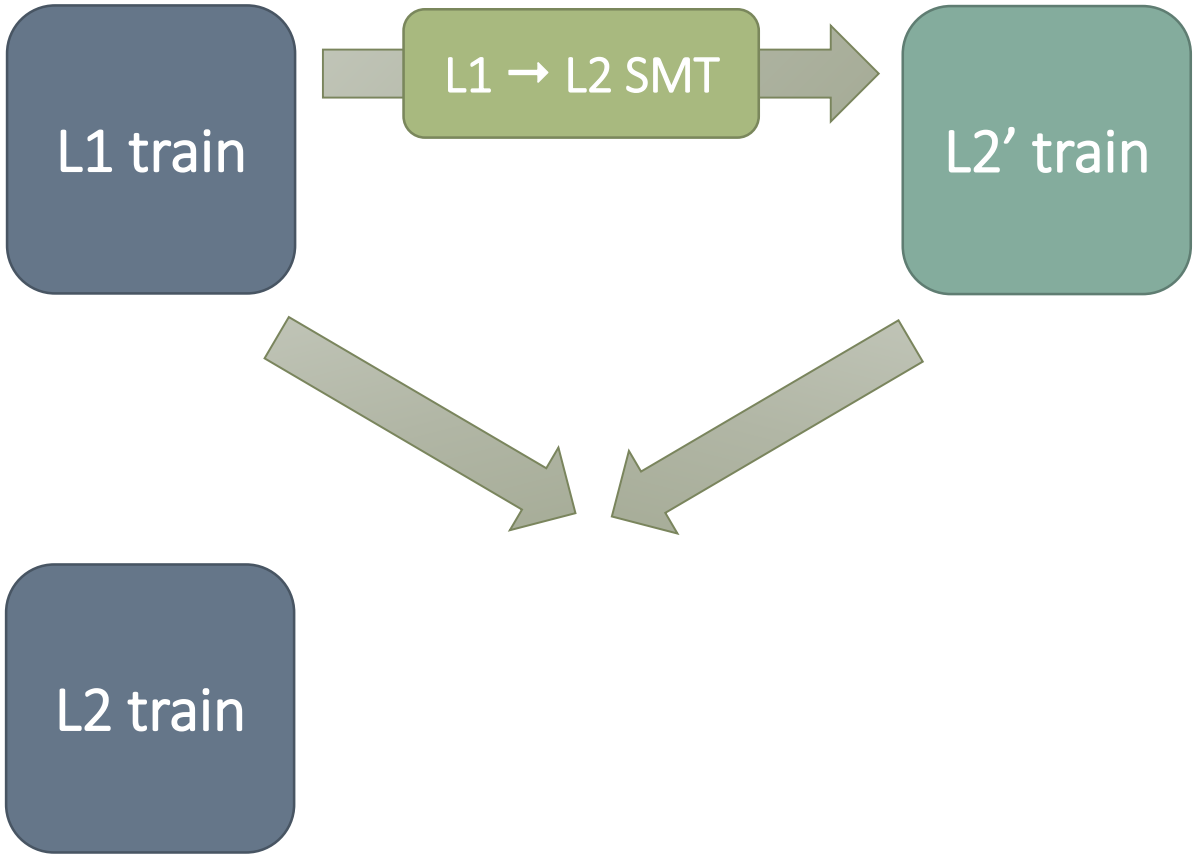

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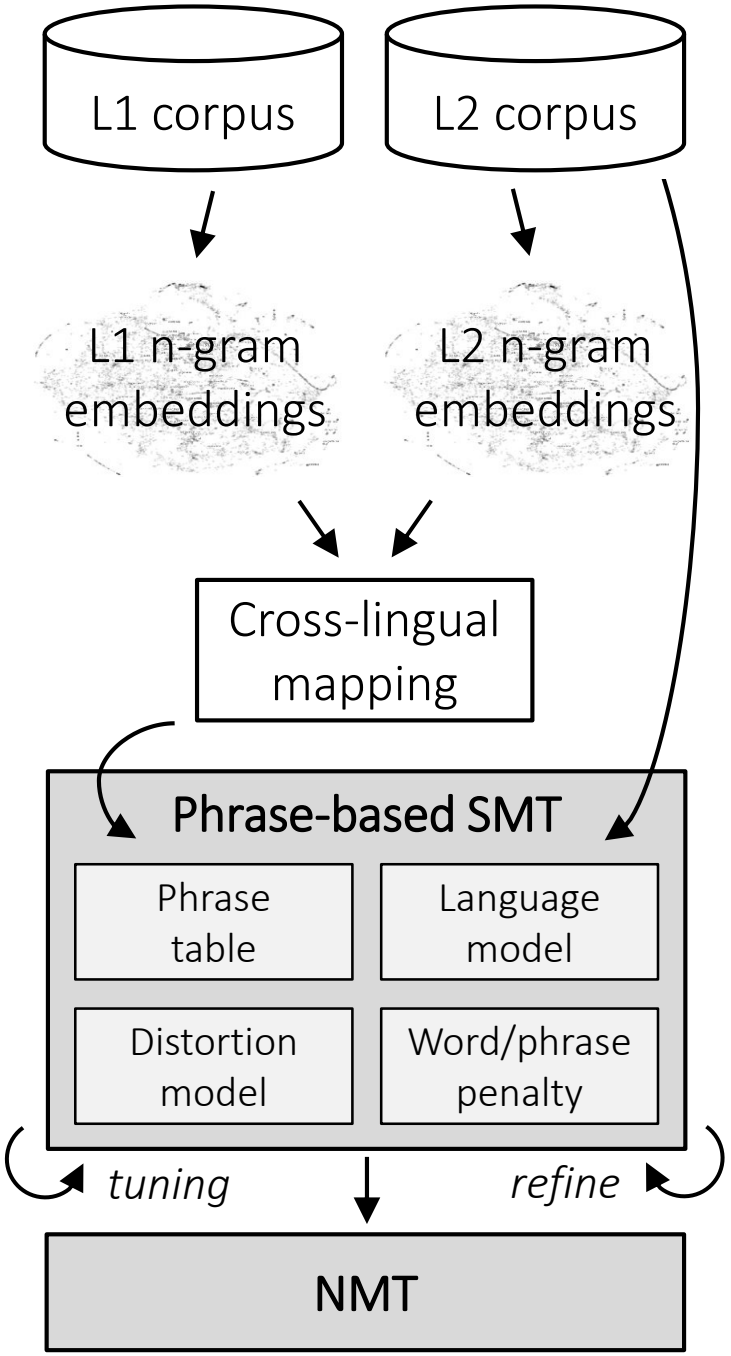

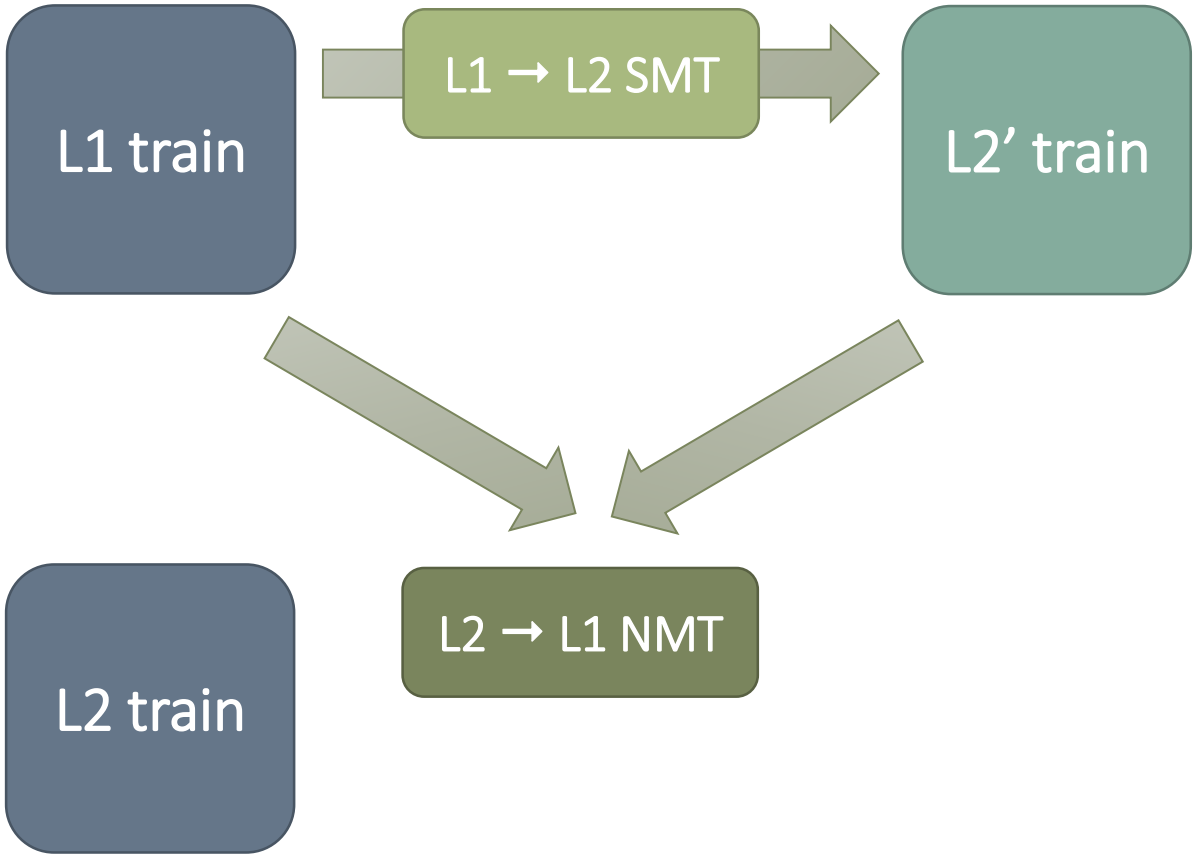

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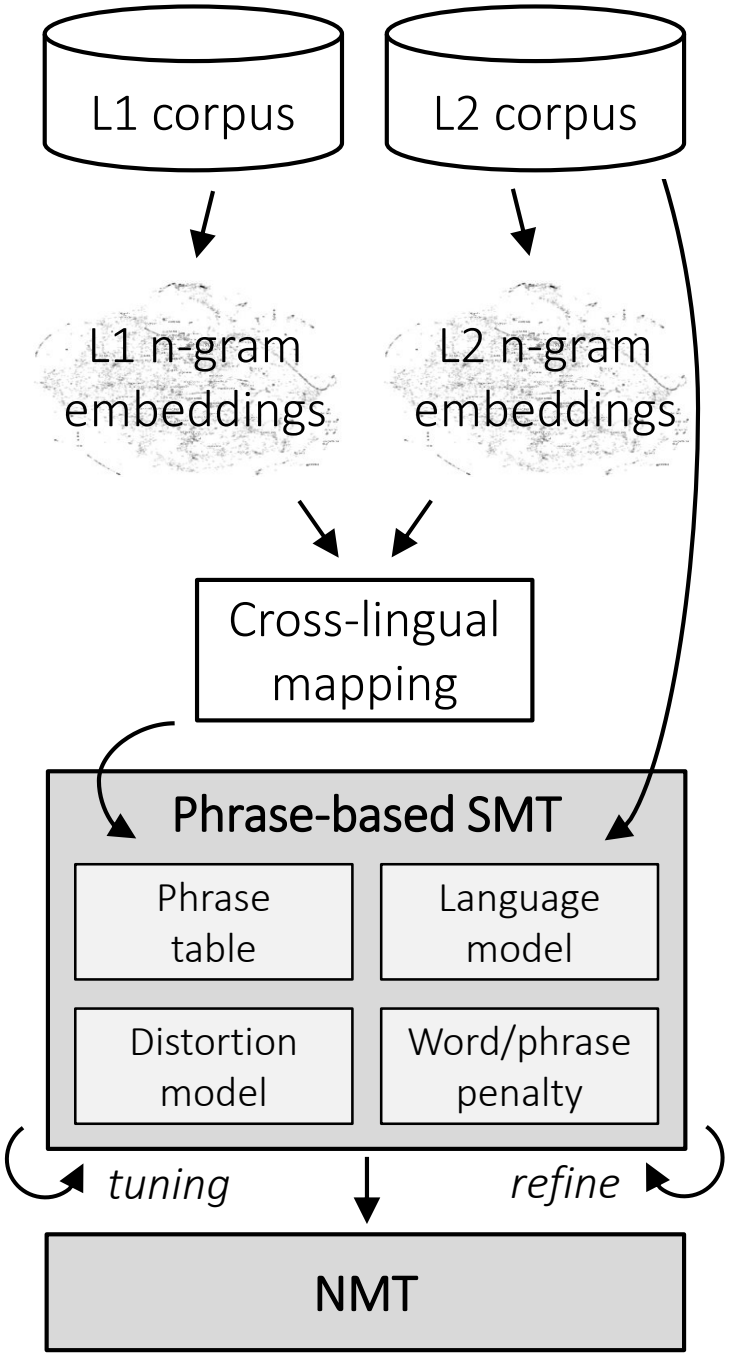

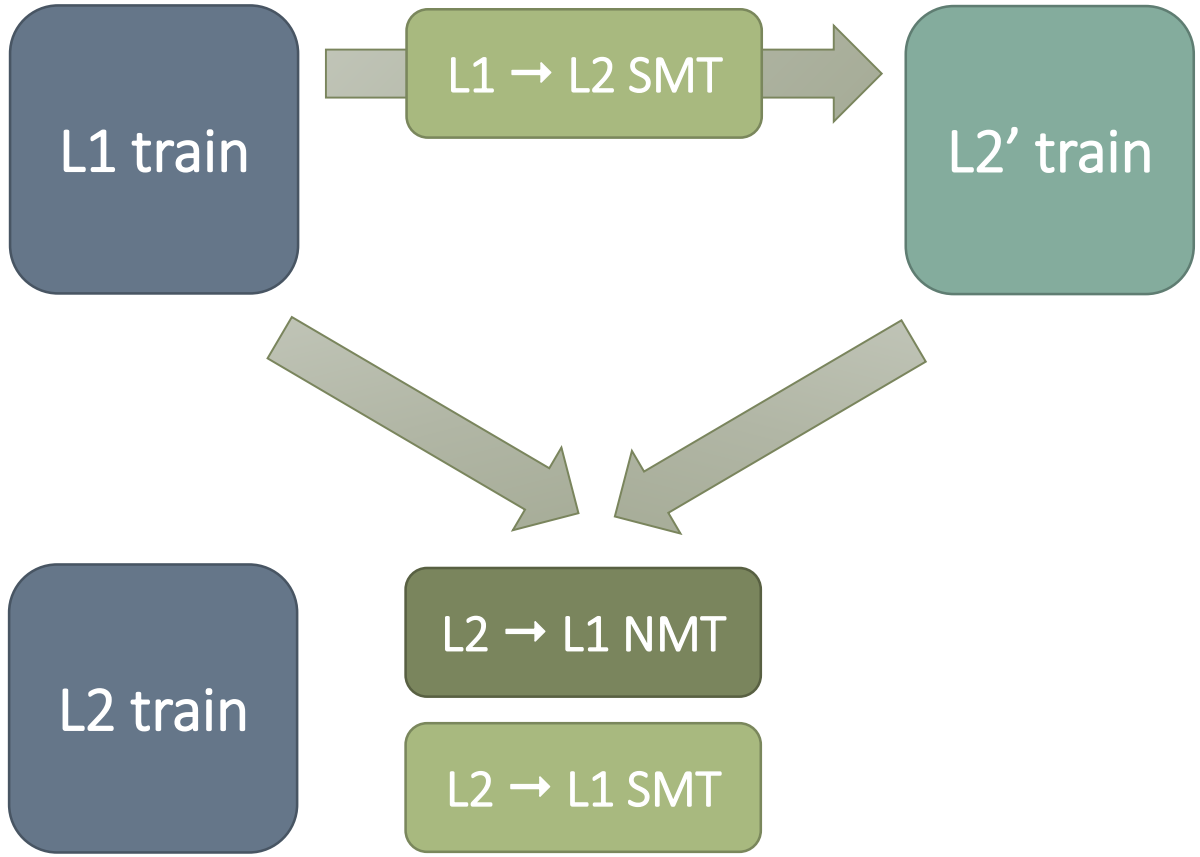

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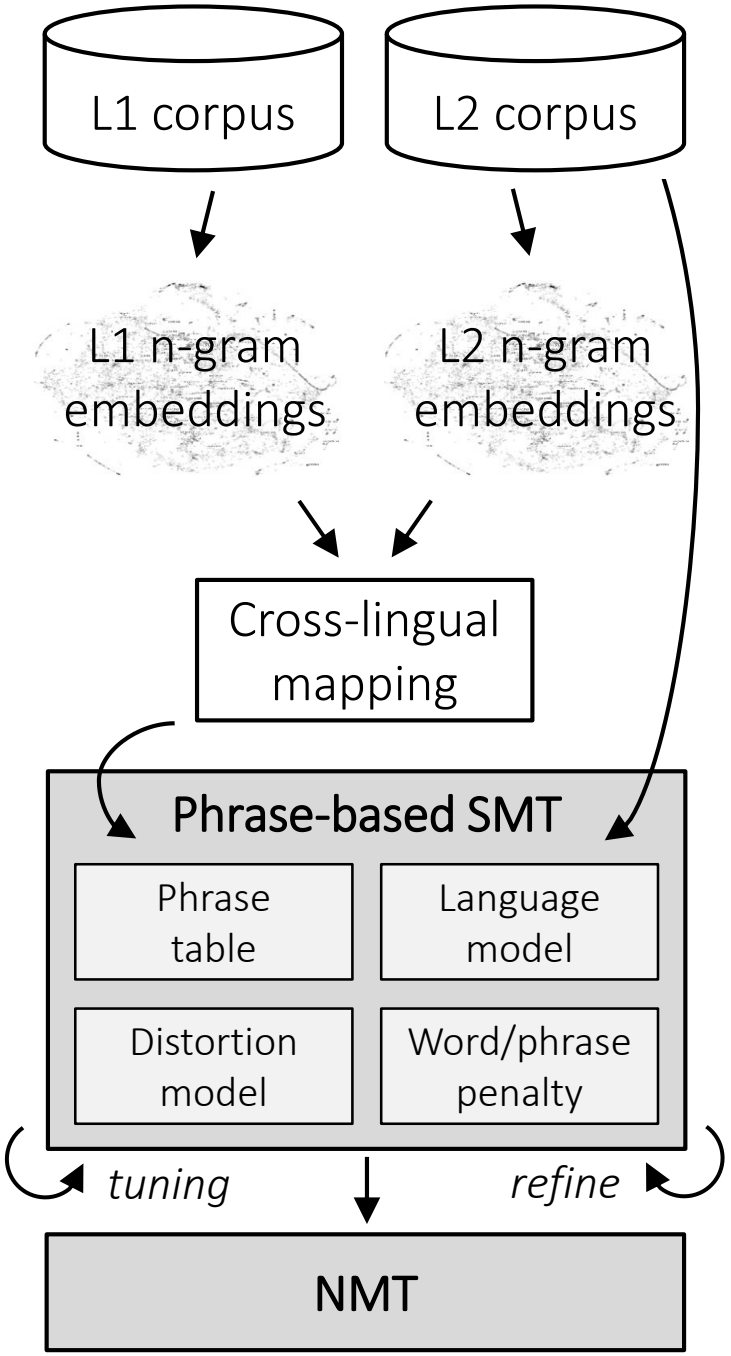

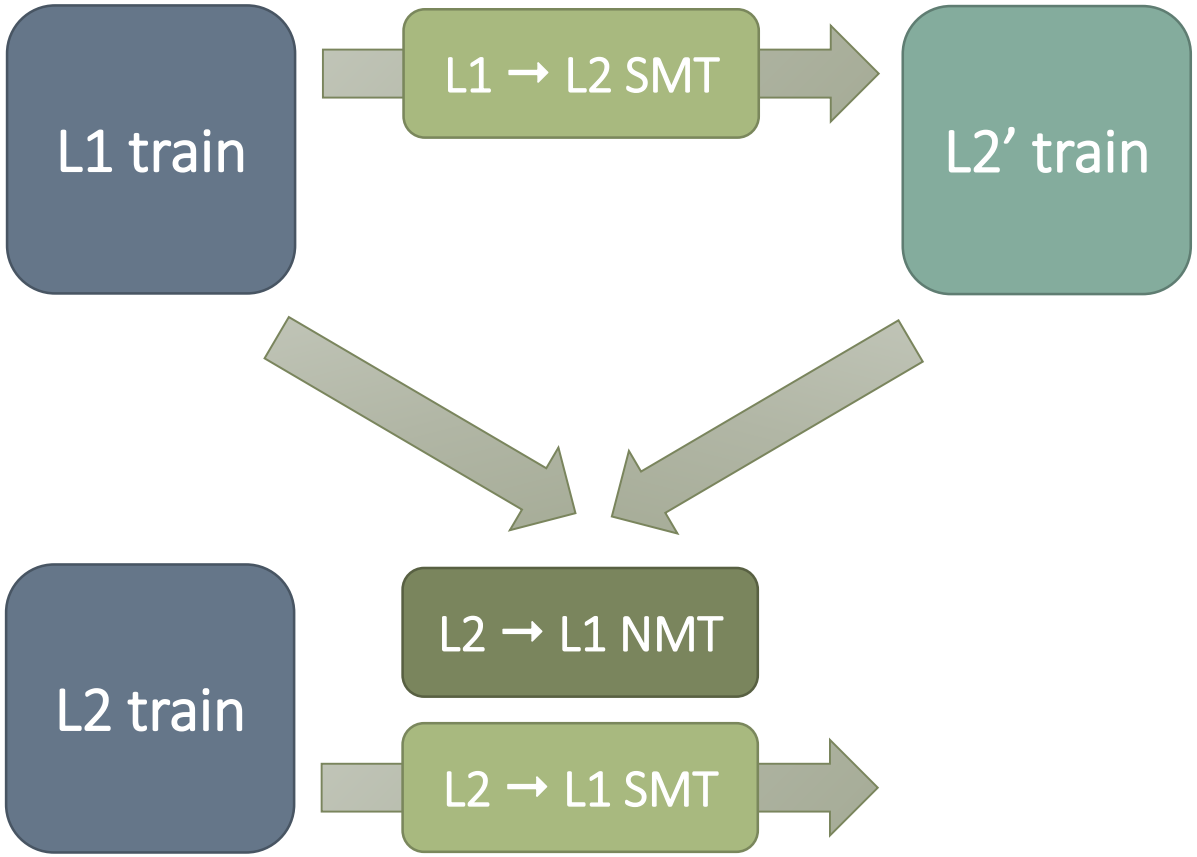

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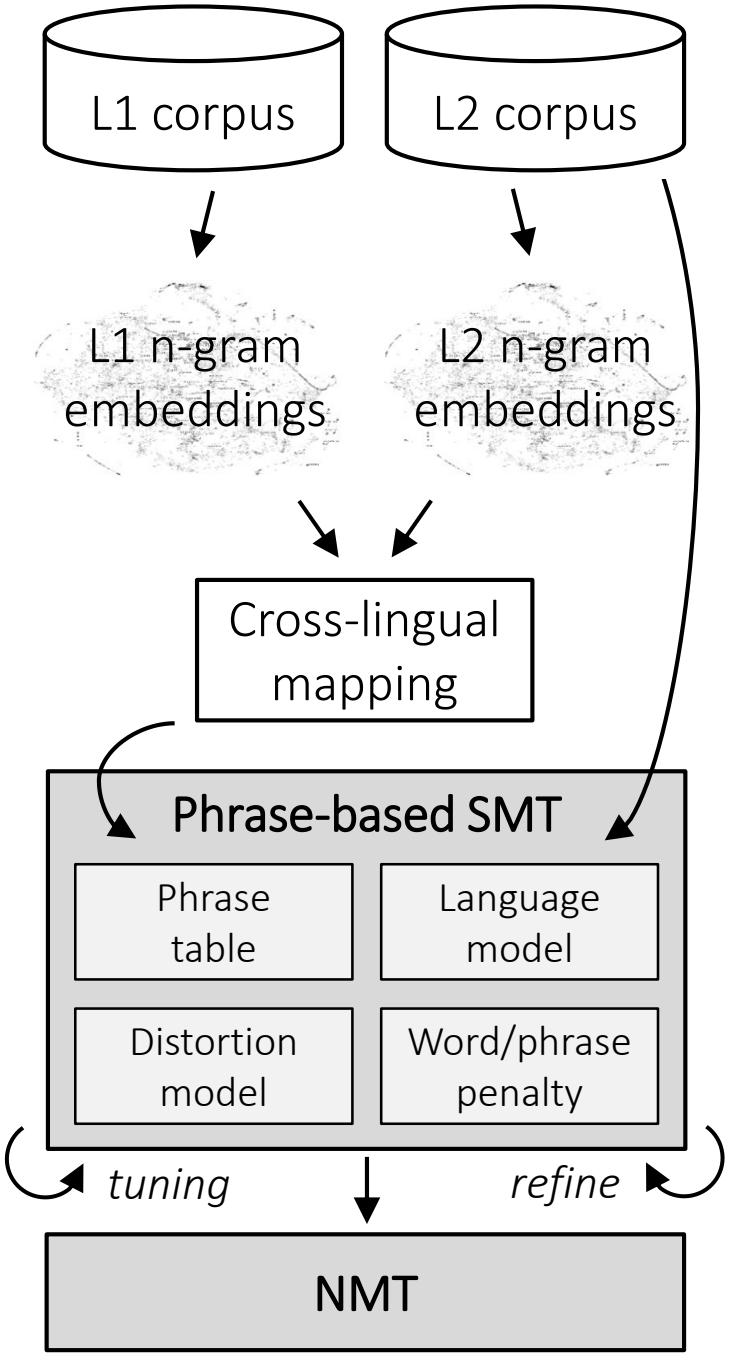

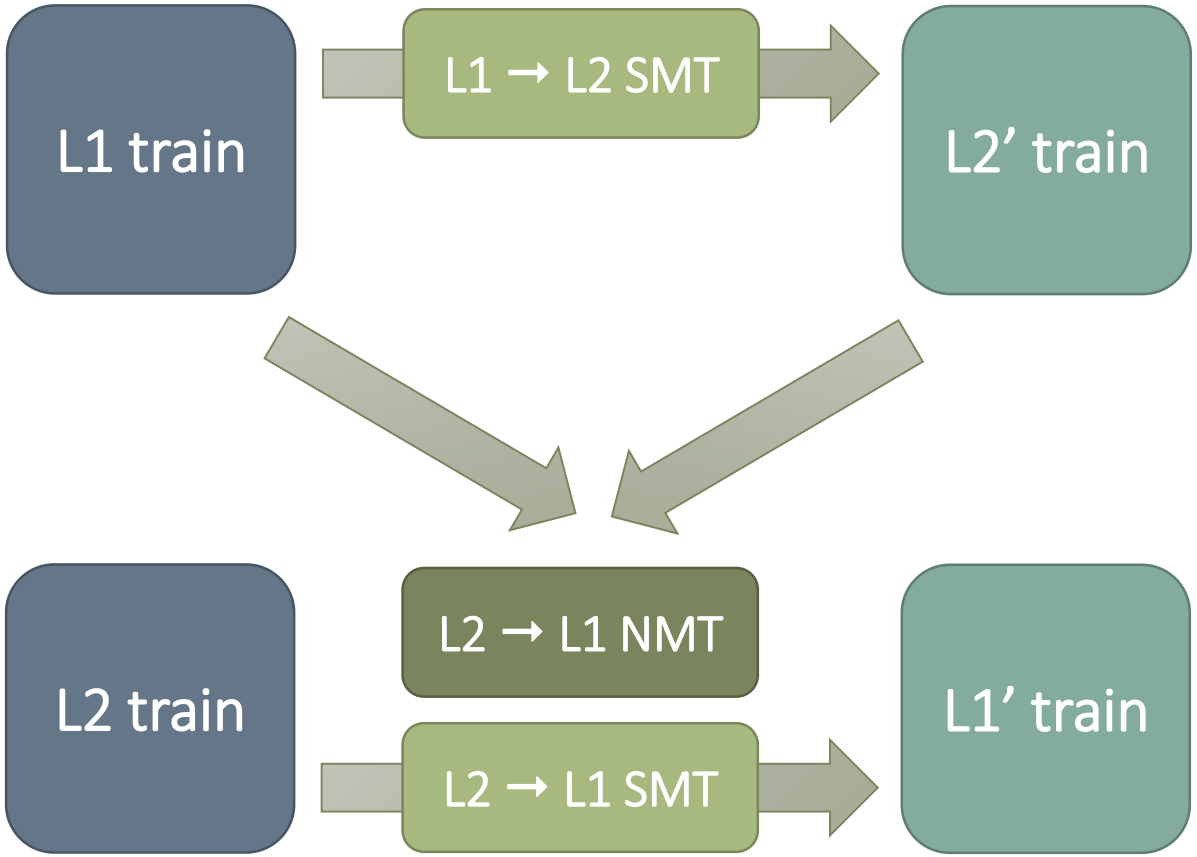

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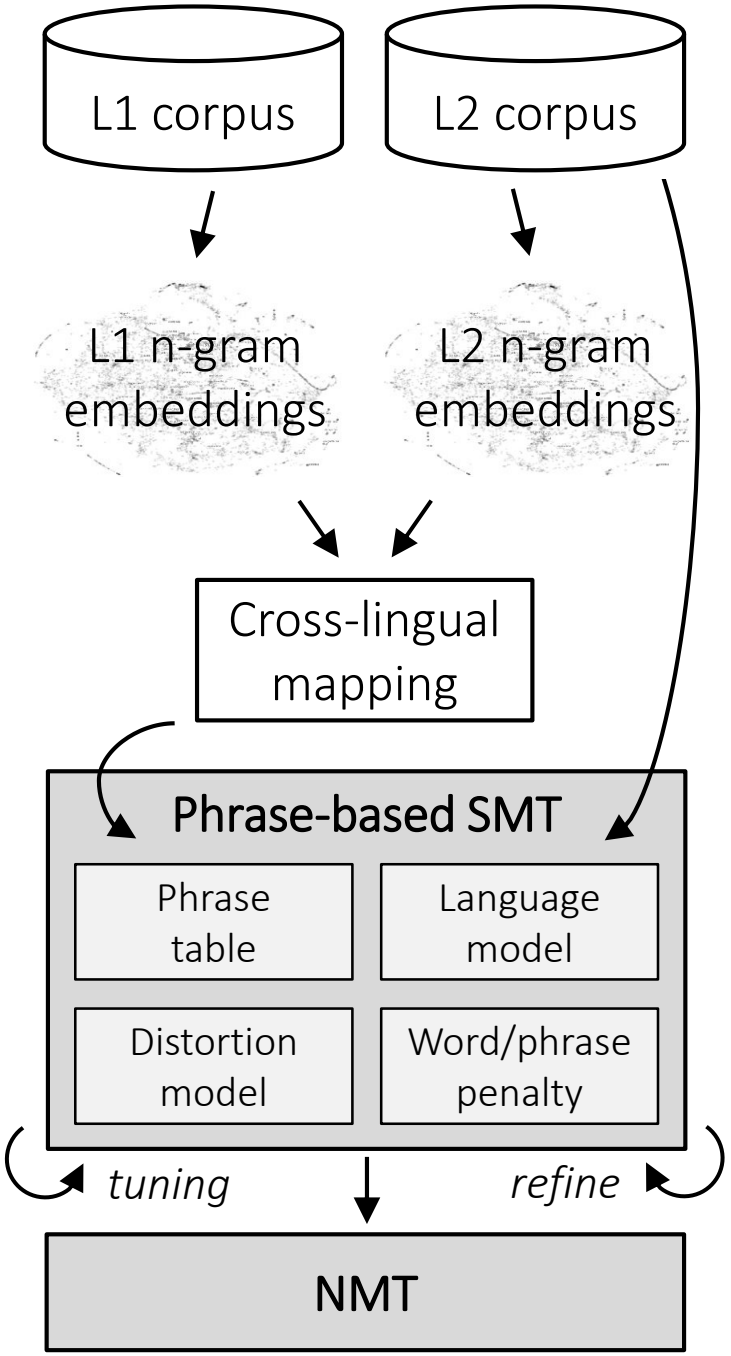

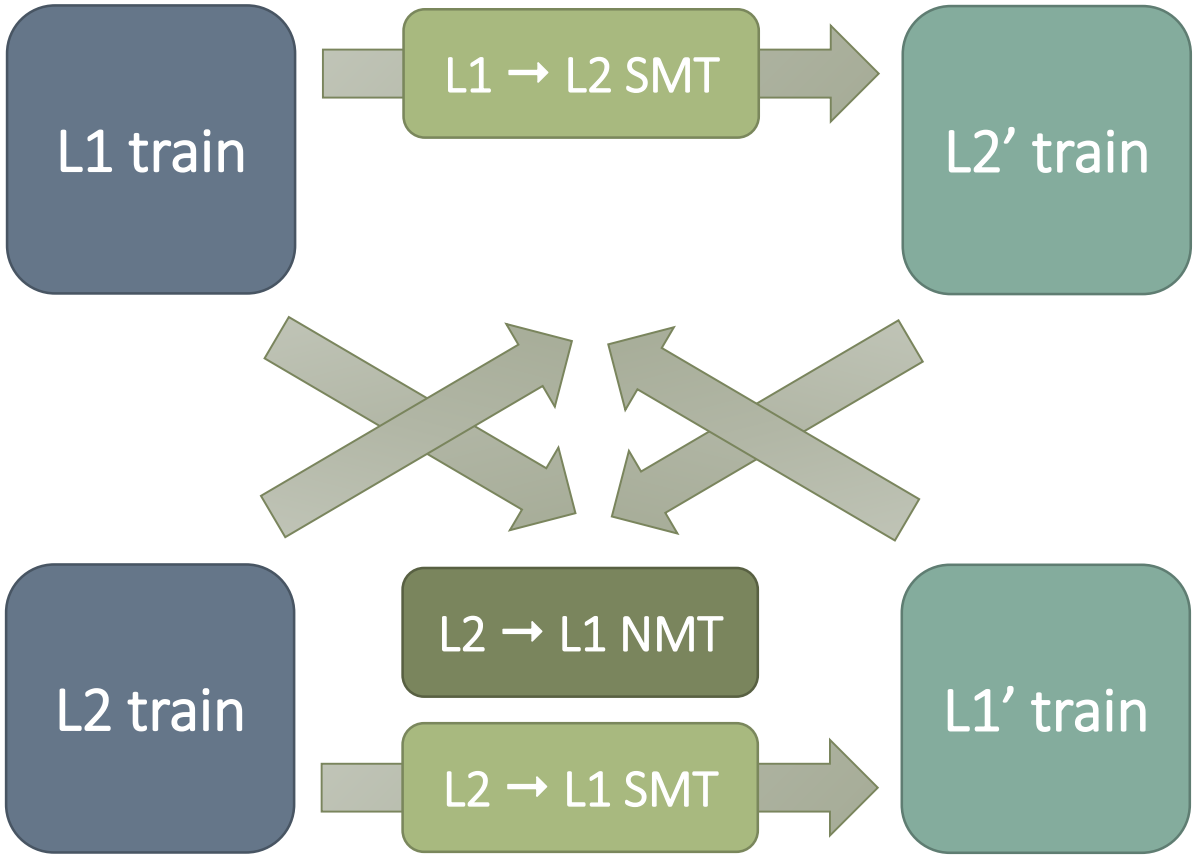

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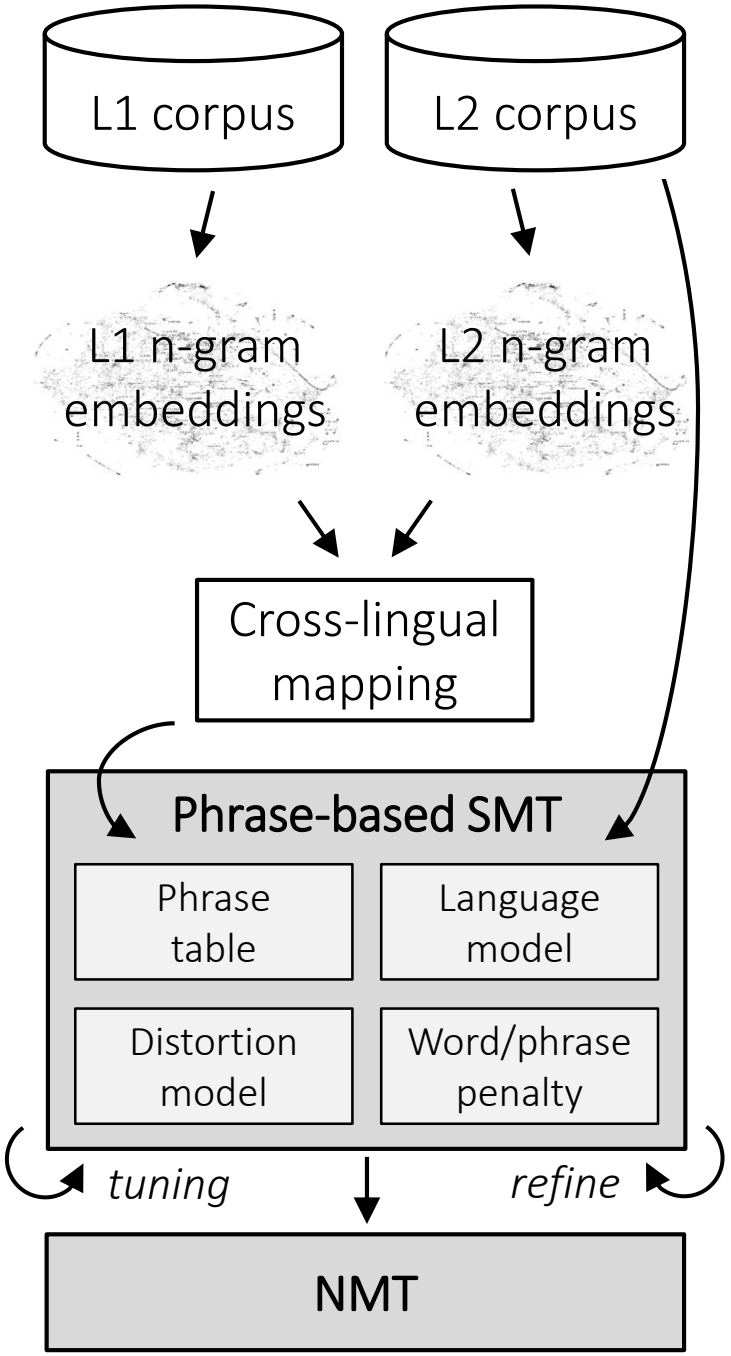

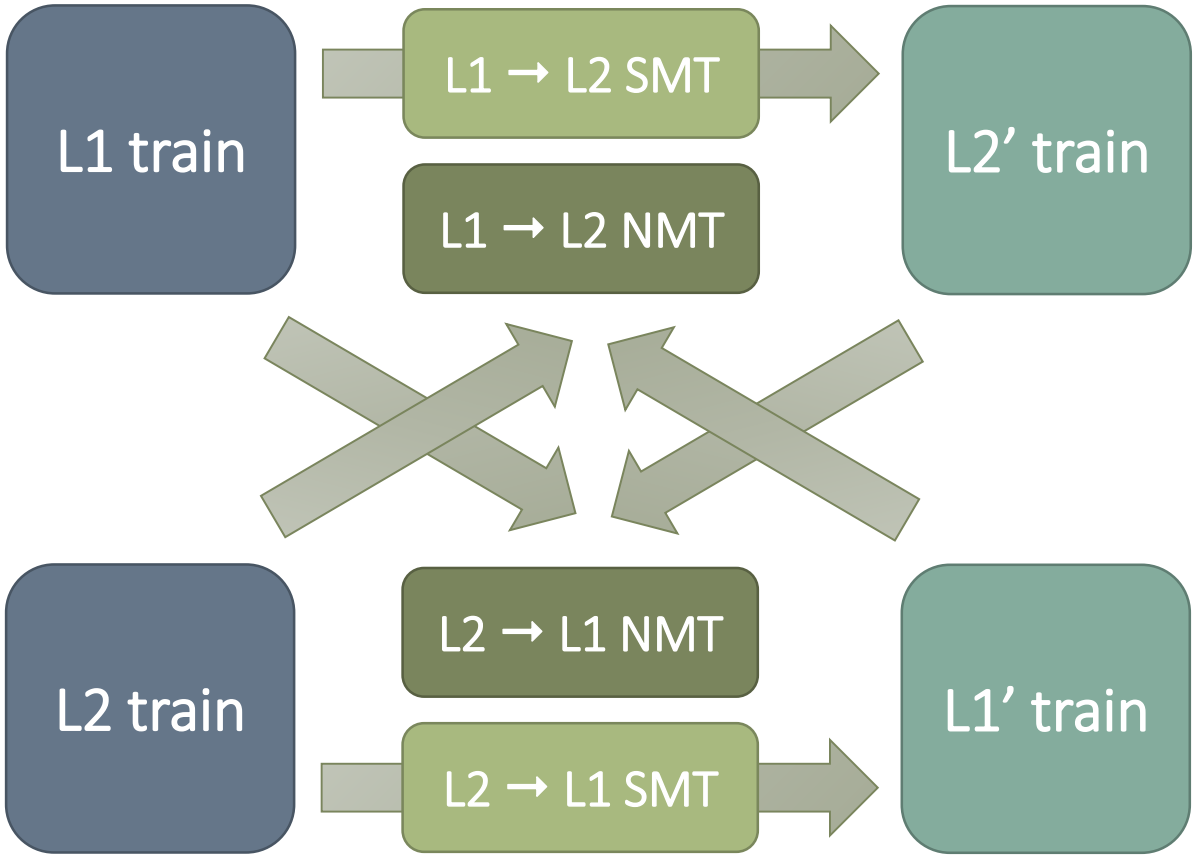

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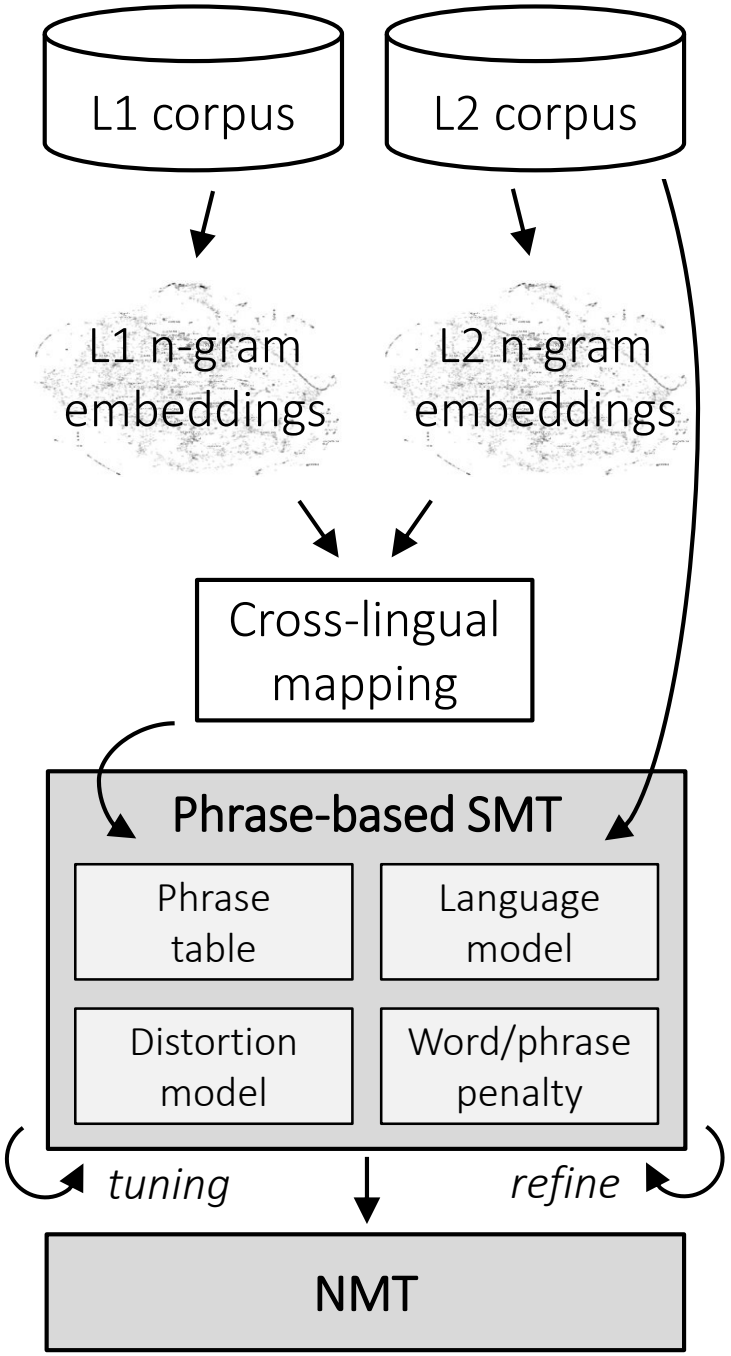

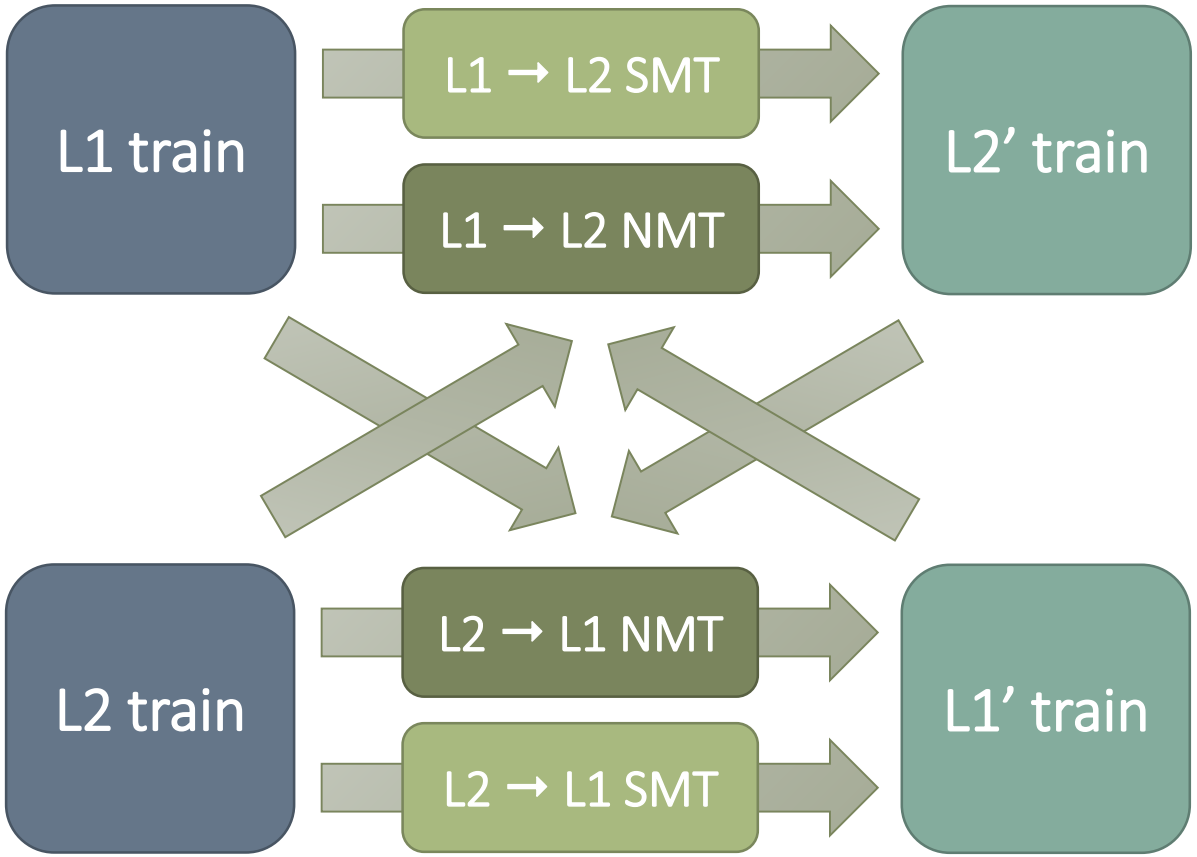

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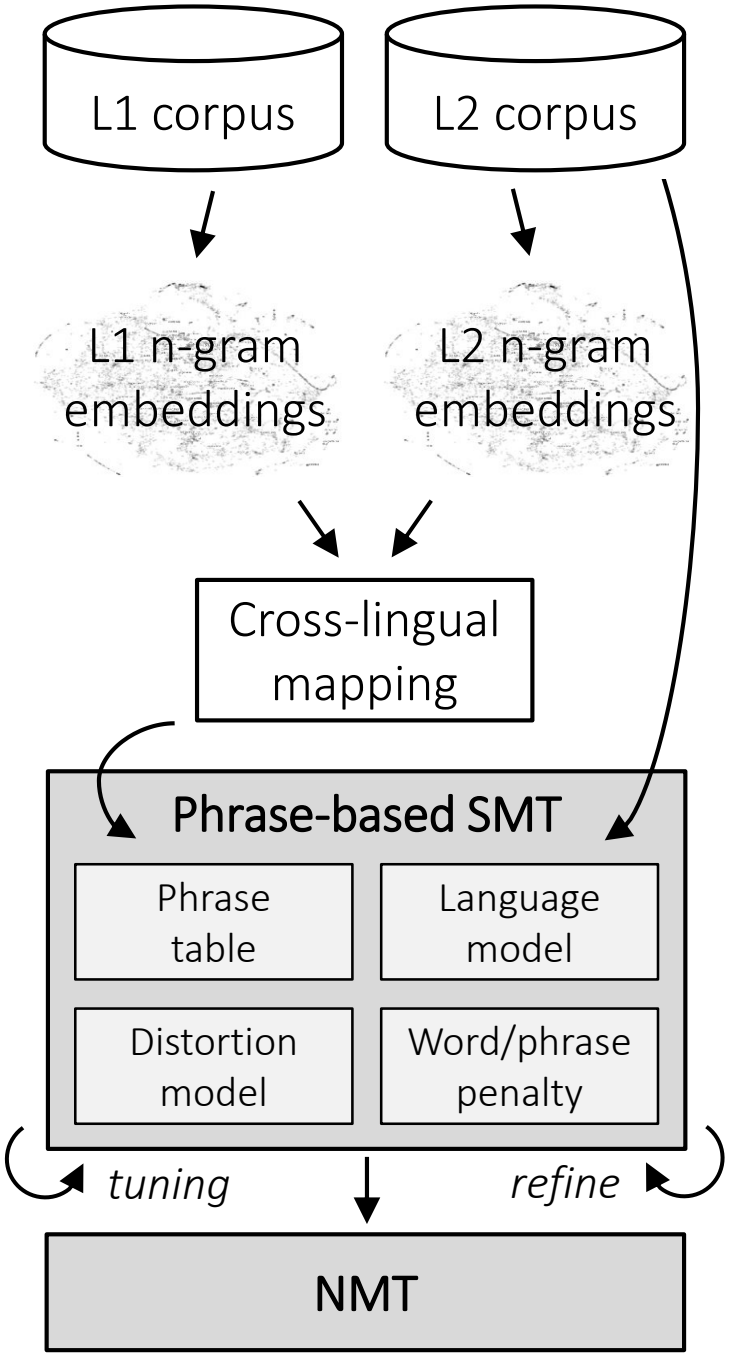
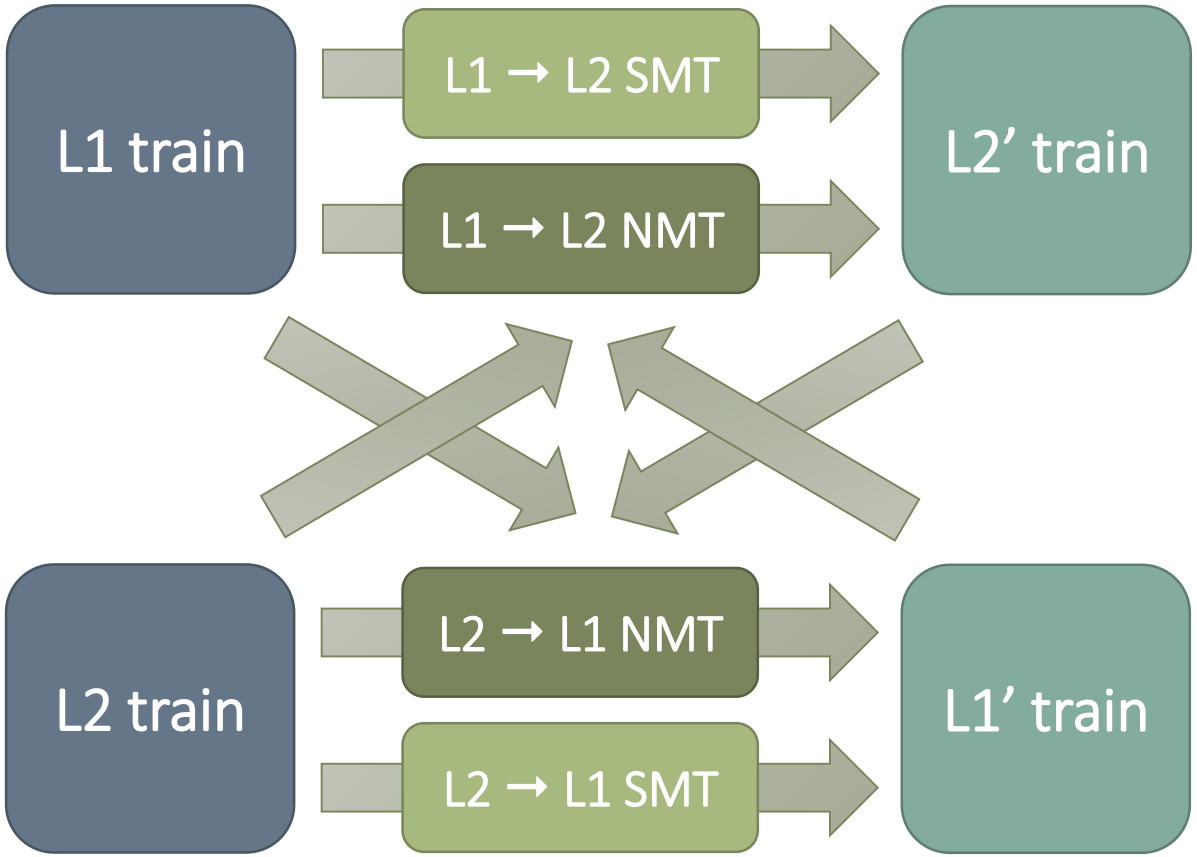
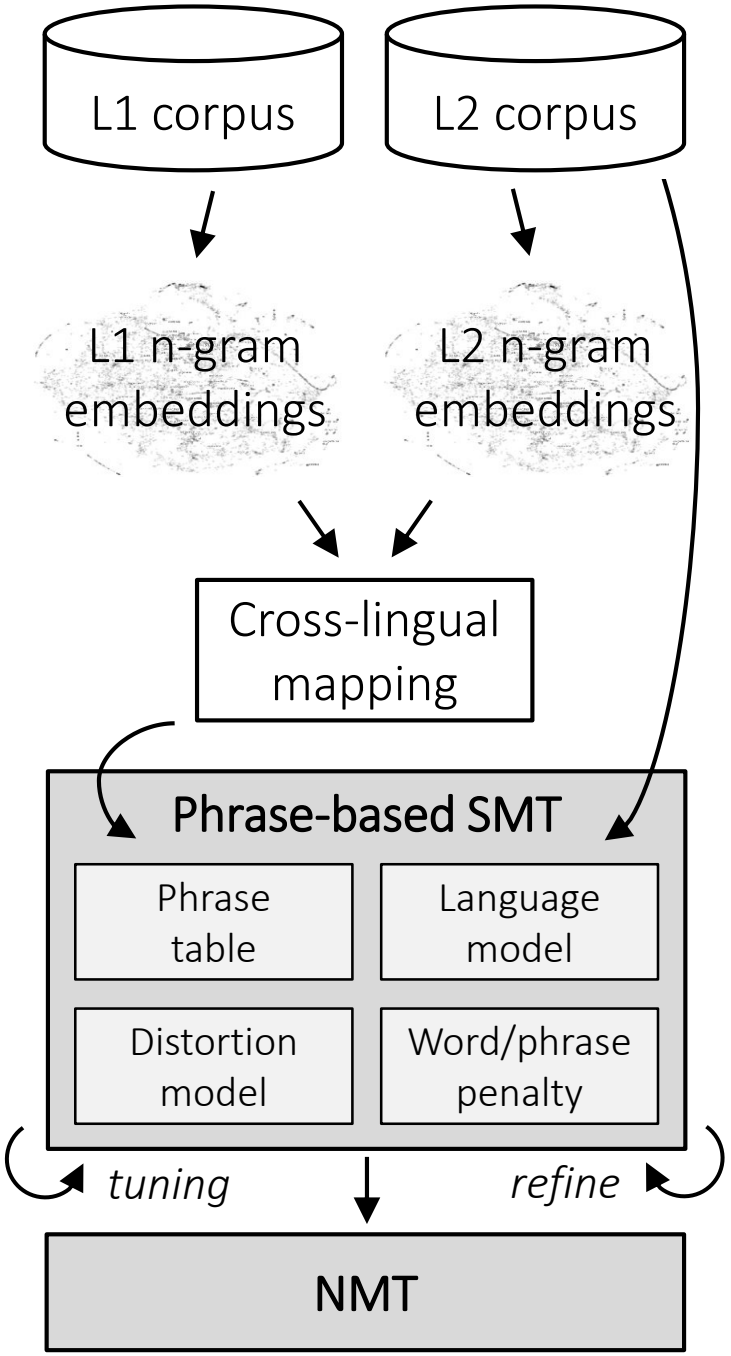
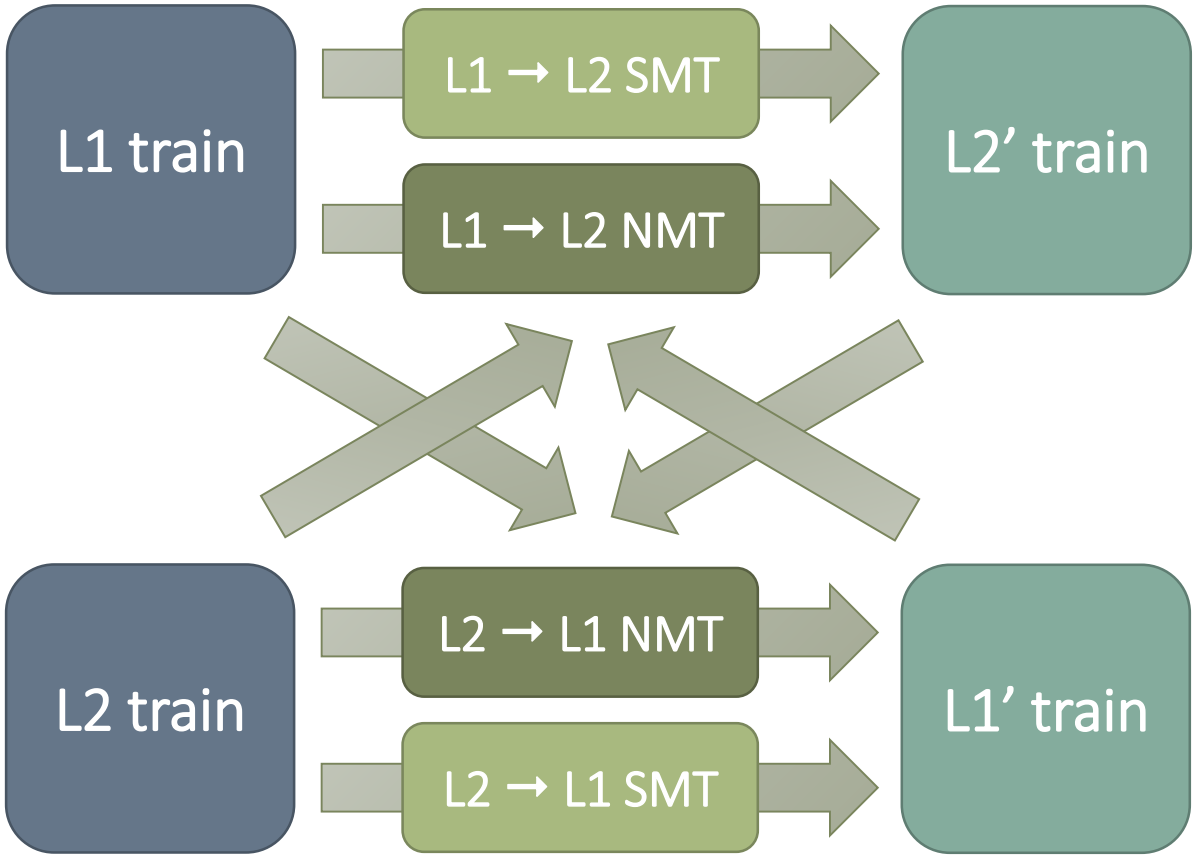




$$N_{SMT} = N \cdot \max(0, 1 - t/a)$$

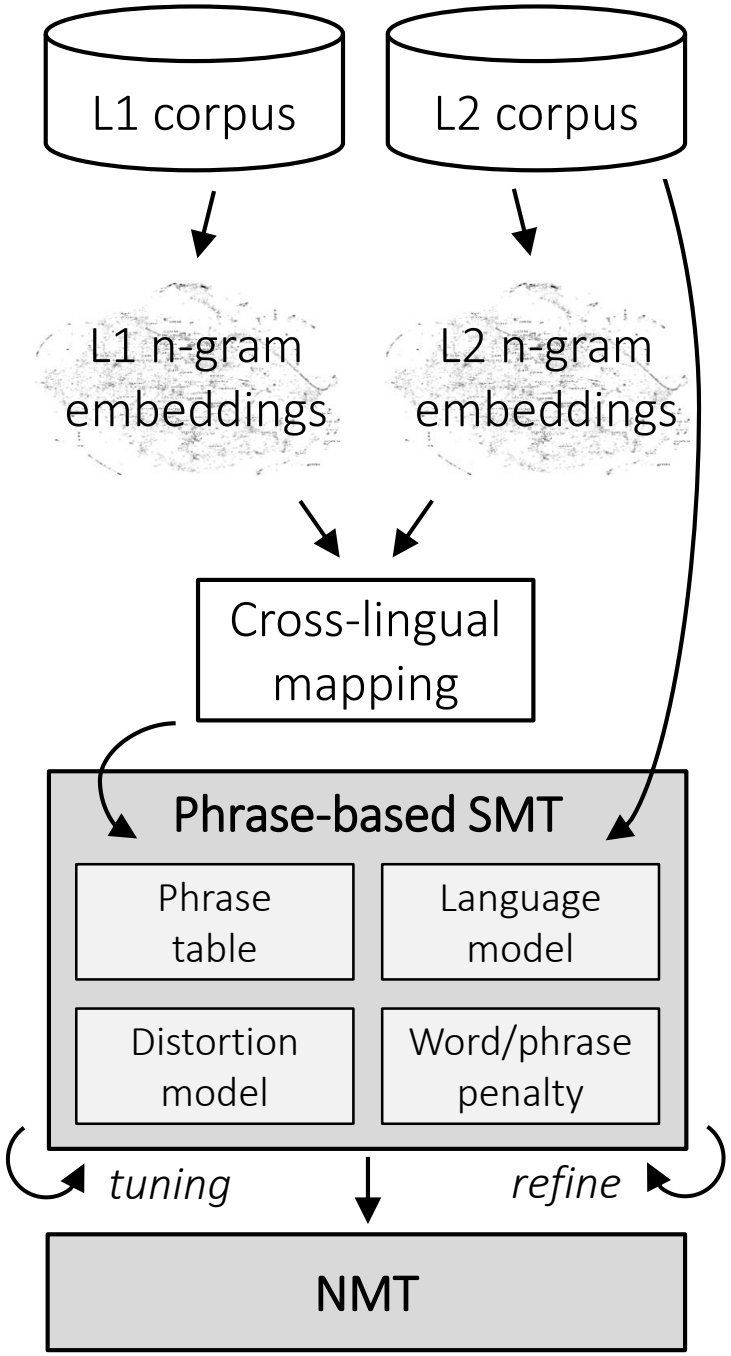
NMT hybridization





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

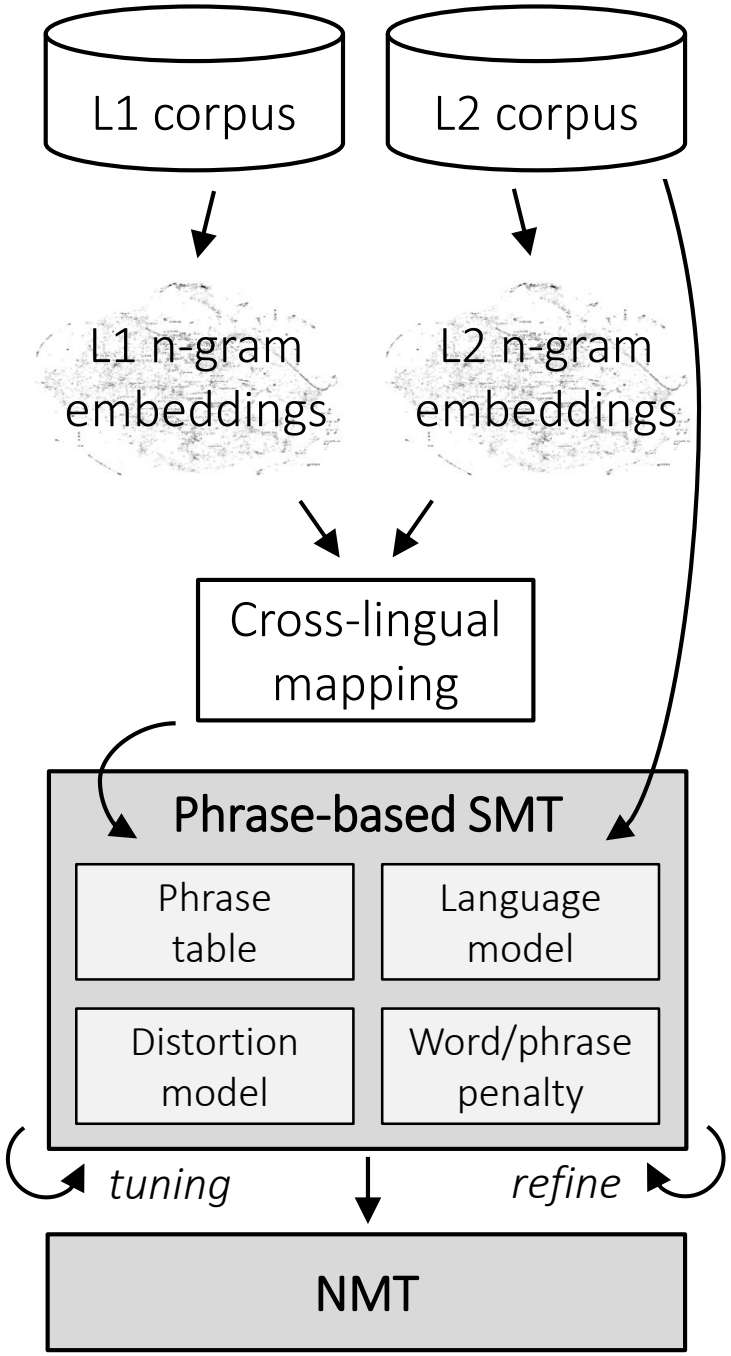
NMT hybridization



EXPERIMENTS

- Languages: French-English, German-English
- Training: WMT-14 News Crawl
- Test set: WMT-14 newstest (BLEU)

	FR-EN	EN-FR	DE-EN	EN-DE
Initial SMT	22.4	19.6	15.3	11.0
+ Tuning	23.4	21.9	15.4	11.2
+ Refinement	27.9	27.8	19.7	14.7



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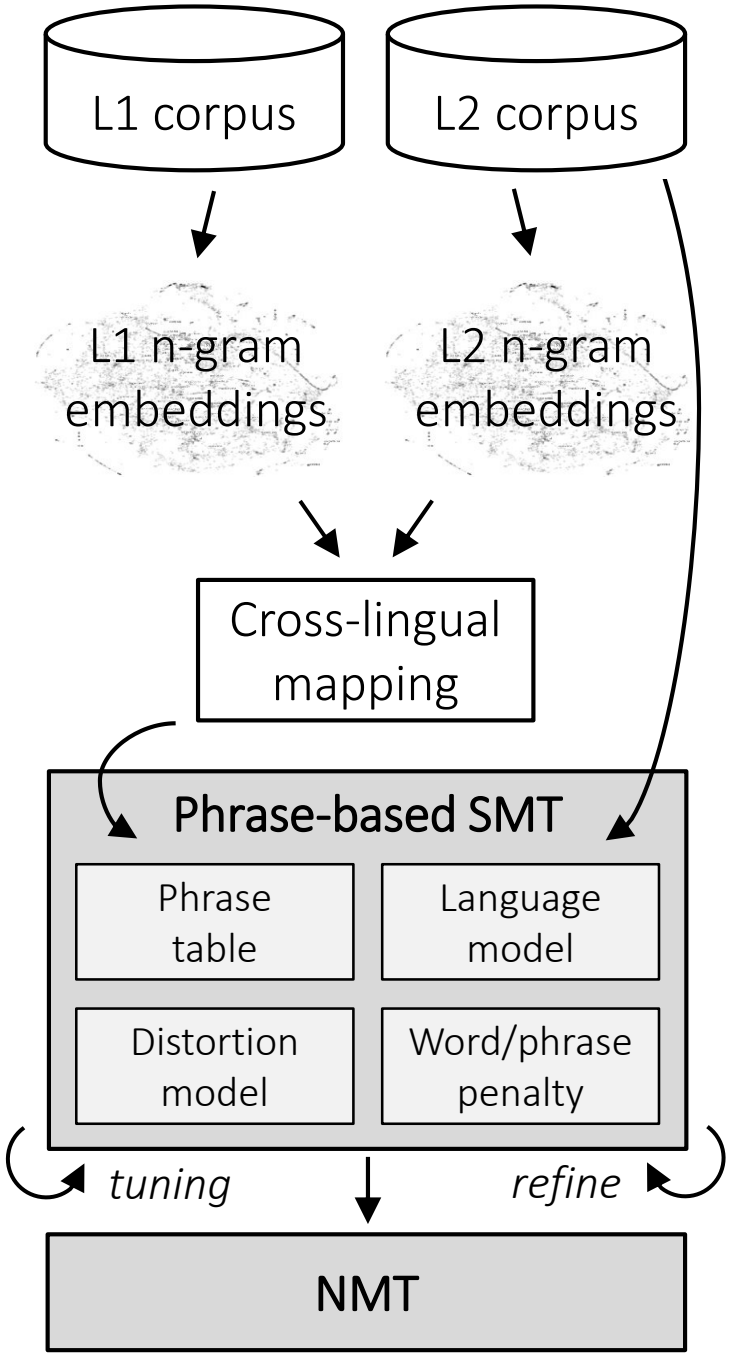
NMT hybridization



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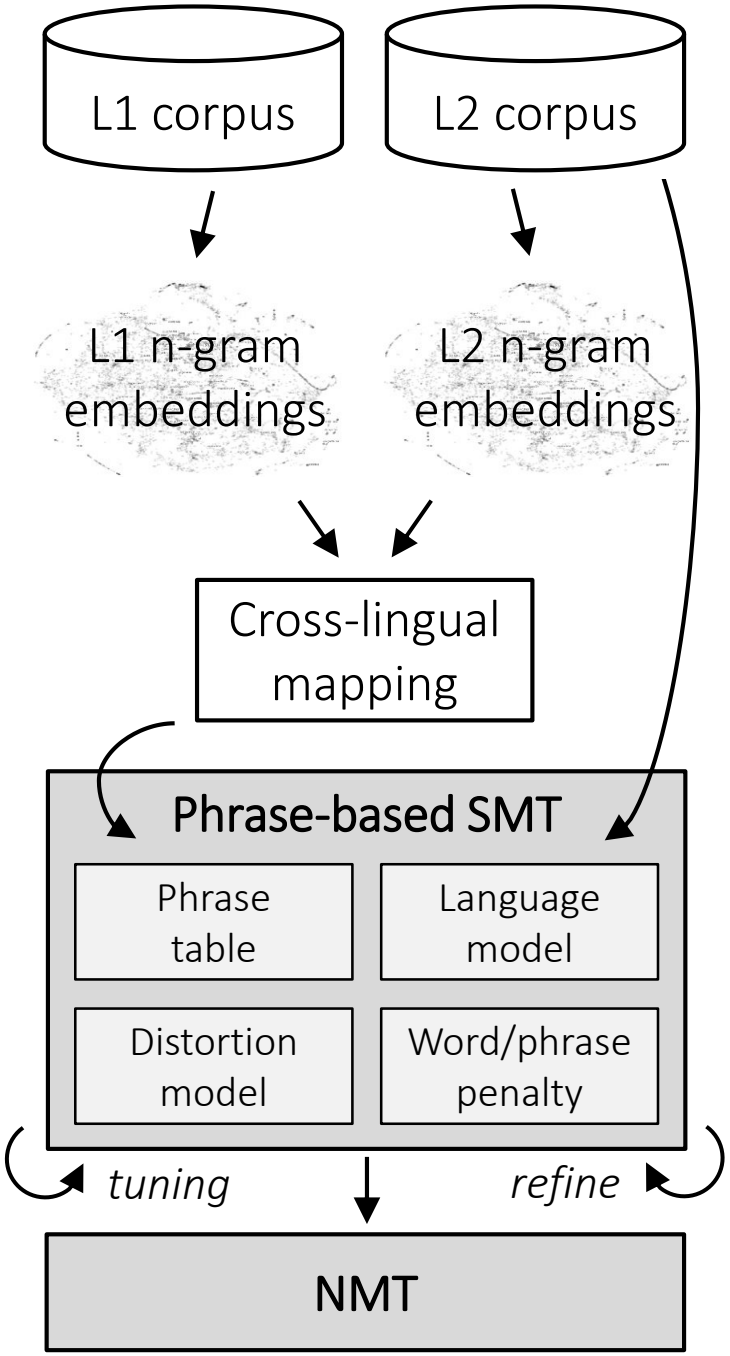
NMT hybridization

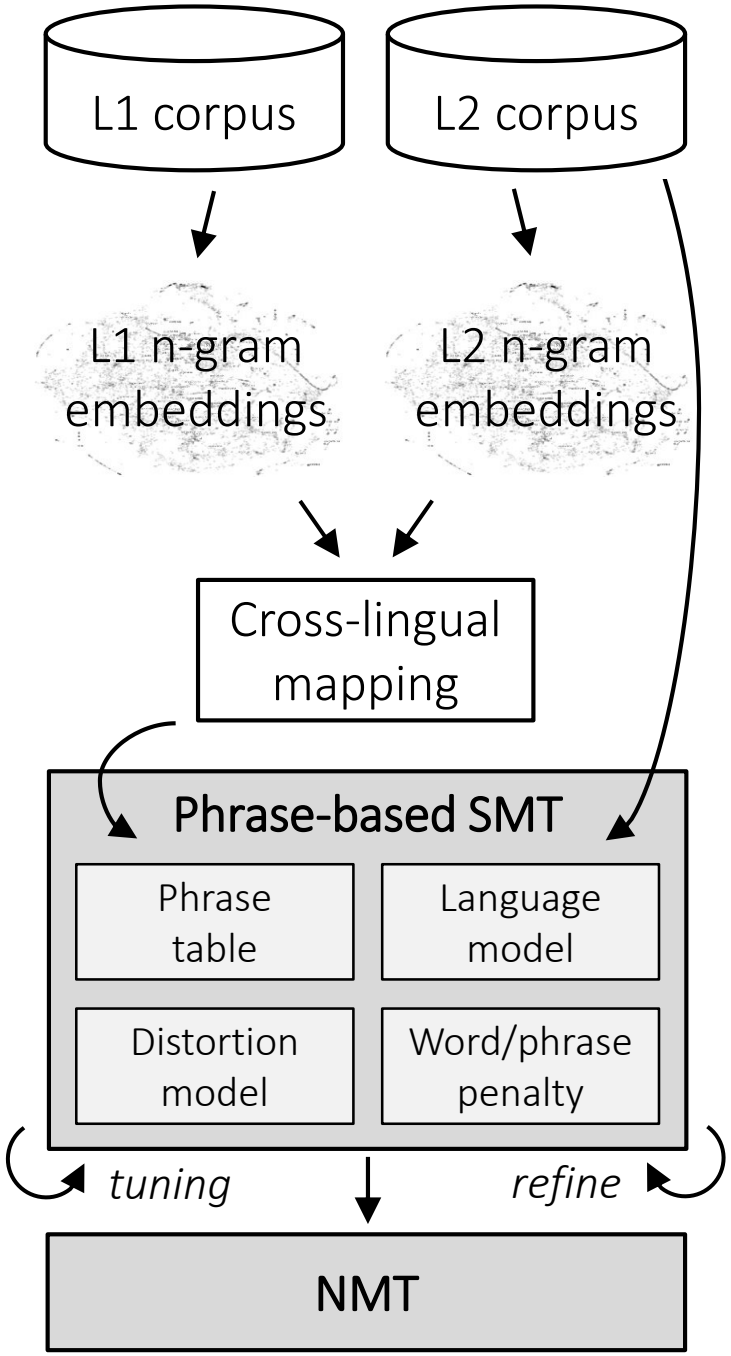


EXPERIMENTS

- Languages: French-English, German-English
- Training: WMT-14 News Crawl
- Test set: WMT-14 newstest (BLEU)

		FR-EN	EN-FR	DE-EN	EN-DE
Unsup.	Initial SMT	22.4	19.6	15.3	11.0
	+ Tuning	23.4	21.9	15.4	11.2
	+ Refinement	27.9	27.8	19.7	14.7
	+ NMT hybrid	33.2	33.6	26.4	21.2
Supervised					

NMT hybridization



EXPERIMENTS

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- Test set: WMT-14 newstest (BLEU)

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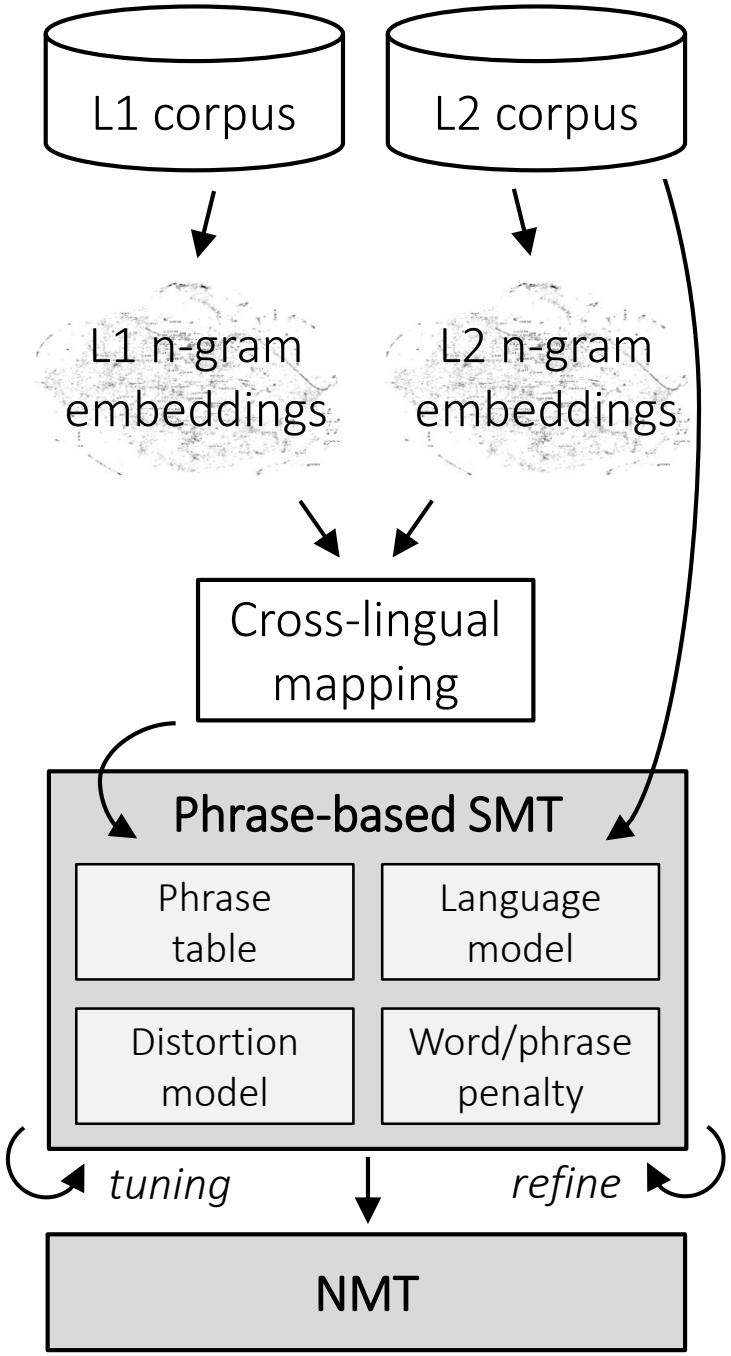
	+ NMT hybrid	33.2	33.6	26.4	21.2
Supervised	WMT winner	35.0	35.8	29.0	20.6

NMT hybridization



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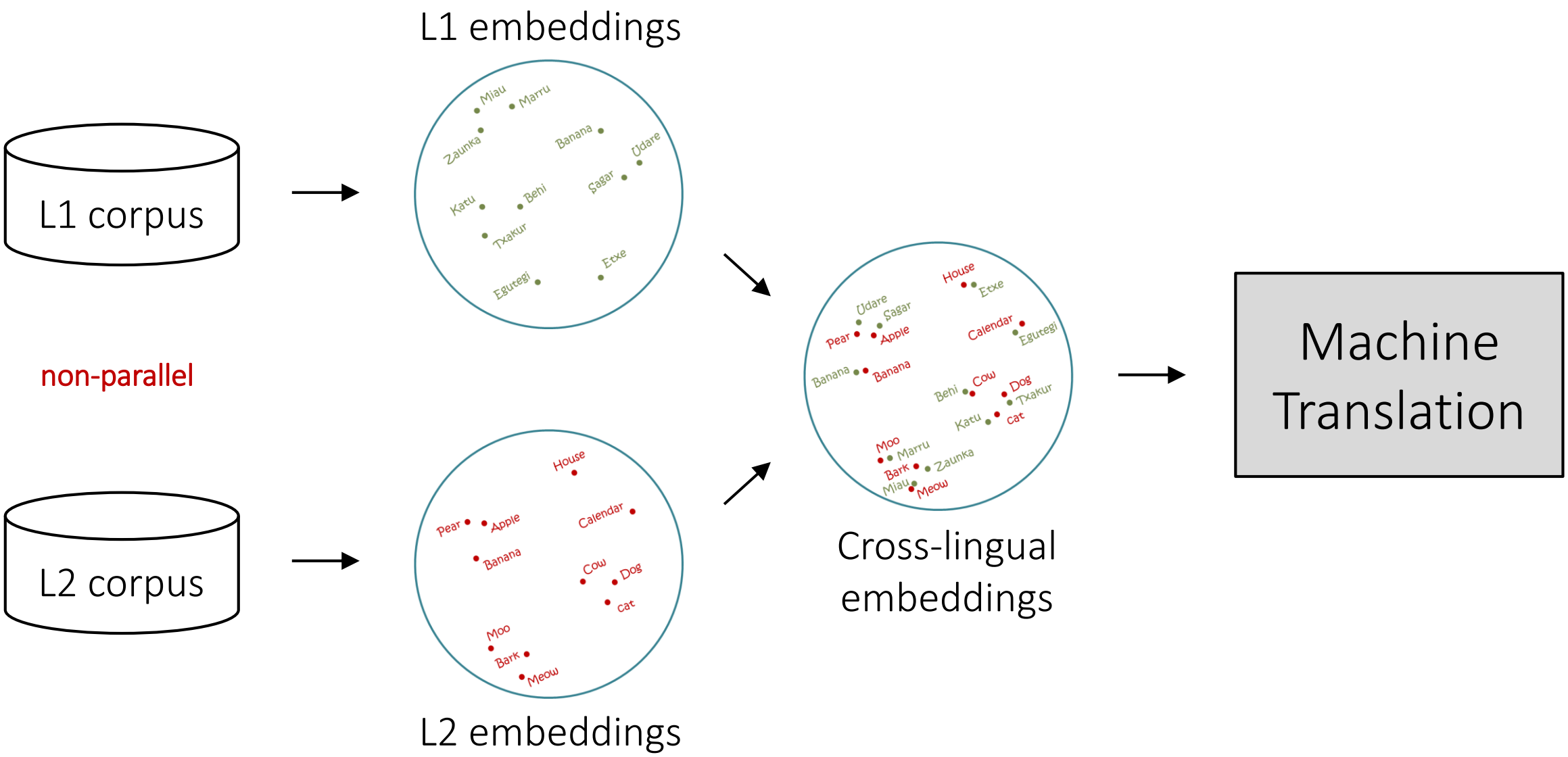
	+ NMT hybrid	33.2	33.6	26.4	21.2
Supervised	WMT winner	35.0	35.8	29.0	20.6
	Current SOTA	-	43.8	-	33.8

Outline


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

Publications

Publications

- Cross-lingual embedding mappings

Publications

- Cross-lingual embedding mappings
  - *Generalize & Improve*

Publications

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    - Normalization & Orthogonality (EMNLP’16)

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    - NMT based (ICLR'18)

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    - SMT based (EMNLP'18)

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    - Joint learning vs offline mapping on parallel corpora (under review)
    - Bilingual lexicon induction through unsupervised machine translation (under review)
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  - SMT based (EMNLP'18)
  - Improve SMT based + NMT (arXiv'19, under review)
  - Understanding iterative back-translation (under review)

Publications

- Tailoring word embeddings (CoNLL'18)

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  - Parallel corpus mining (arXiv'18, under review)

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  - Cross-lingual transfer learning (arXiv'18, under review)