Cross-linguality and machine translation without bilingual data

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

http://ixa.eus

Motivation

Cross-lingual word representations:

- **Word embeddings key** for Natural Language Processing
- **Mapped embeddings** represent languages in a single space
  - Depend on seed **bilingual dictionaries**
- **Exciting results** in dictionary induction, transfer learning, crosslingual applications, interlingual semantic representations

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Our focus: **extend mappings to any pair of languages**

- Most language pairs have **very few bilingual resources**
- Key research area for **wide adoption** of NLP tools

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Our focus: **extend mappings to any pair of languages**

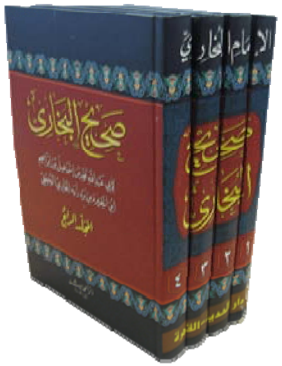
- Most language pairs have **very few bilingual resources**
- Key research area for **wide adoption** of NLP tools

In particular: **no bilingual resources at all**

- **Unsupervised** embedding mappings
- **Unsupervised** neural machine translation

Overview

<u>Arabic monolingual corpora</u>



Arabic embeddings

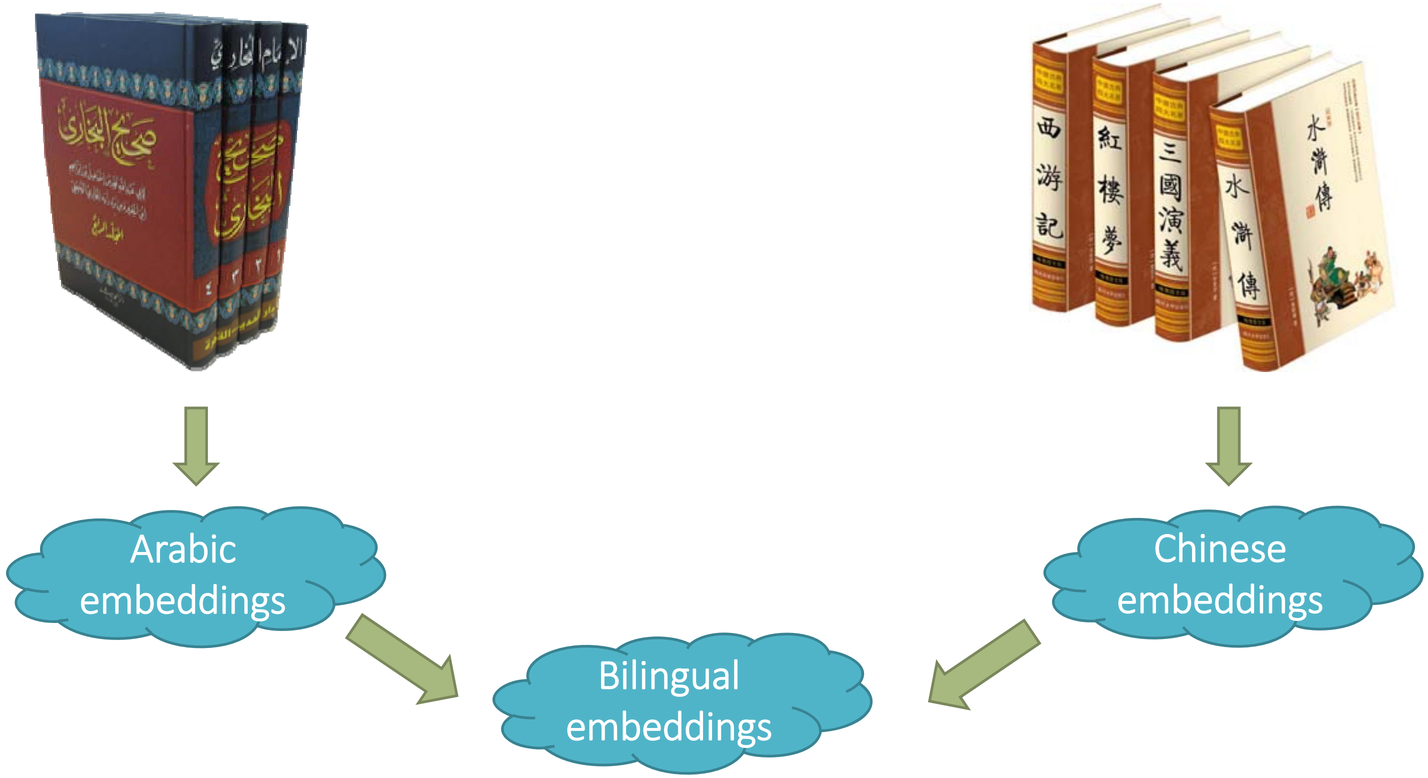
<u>Chinese monolingual corpora</u>

Chinese embeddings

Overview

Arabic monolingual corpora

Chinese monolingual corpora



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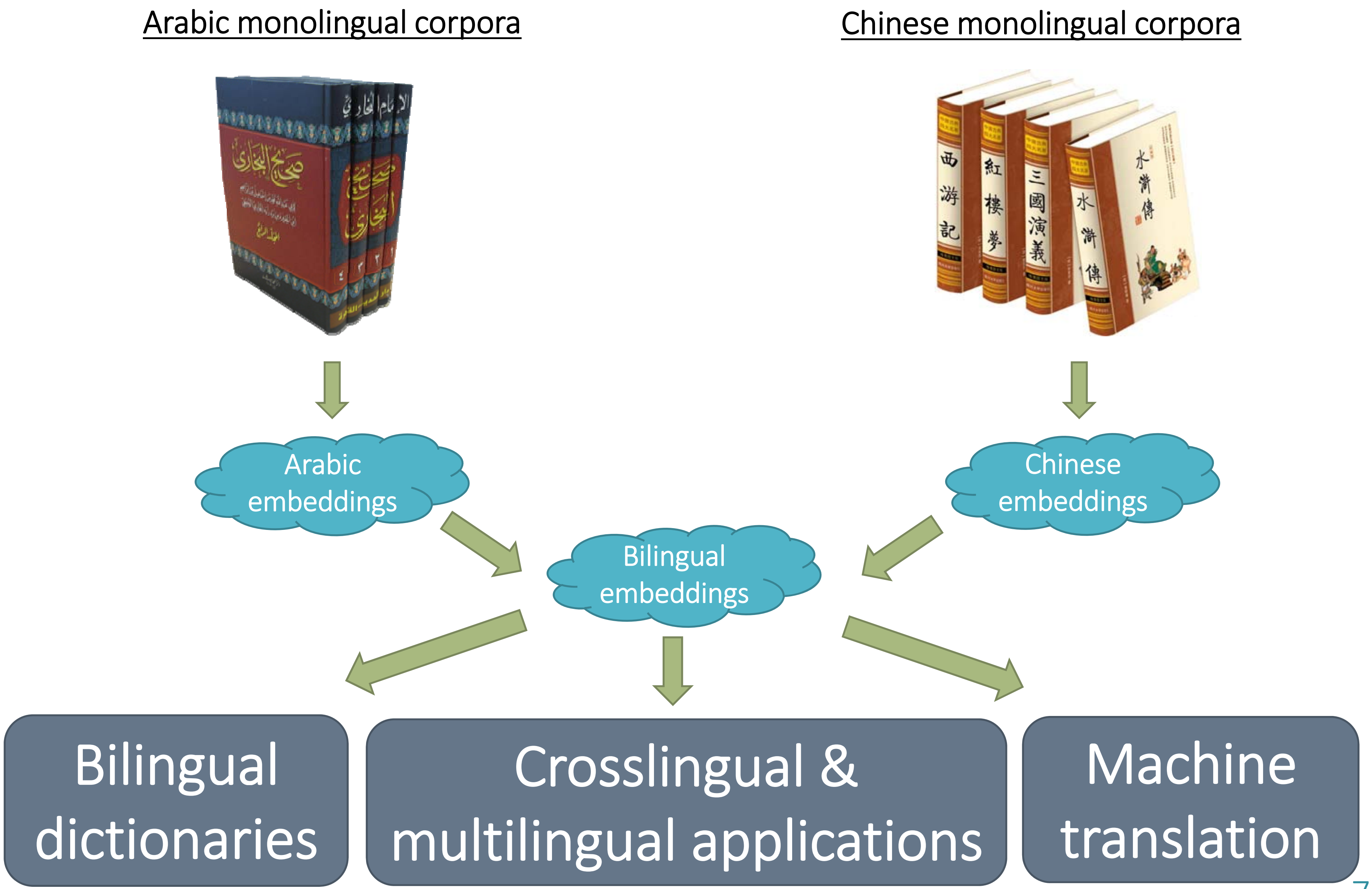
Arabic monolingual corpora
Chinese monolingual corpora
西游記
紅樓夢
三國演義
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Arabic embeddings
Chinese embeddings
Bilingual embeddings
Bilingual dictionaries
Crosslingual & multilingual applications
Machine translation

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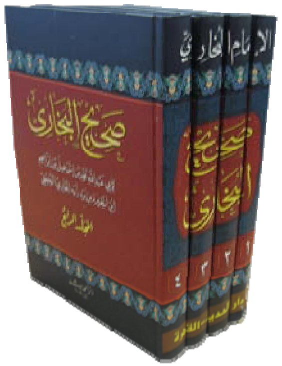

Chinese monolingual corpora

No bilingual resource

Arabic embeddings

Chinese embeddings

Bilingual embeddings

Bilingual dictionaries

Crosslingual & multilingual applications

Machine translation

Outline

- Bilingual embedding mappings
  - *Introduction to vector space models (embeddings)*
  - *Bilingual embedding mappings (AAAI18)*
  - *Reduced supervision*
    - Self-learning, semi-supervised (ACL17)
    - Self-learning, fully unsupervised (ACL18)
  - *Conclusions*
- Unsupervised neural machine translation
  - *Introduction to NMT*
  - *From bilingual embeddings to uNMT (ICLR18)*
  - *Unsupervised statistical MT (EMNLP18)*
  - *Conclusions*

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Introduction to vector space models

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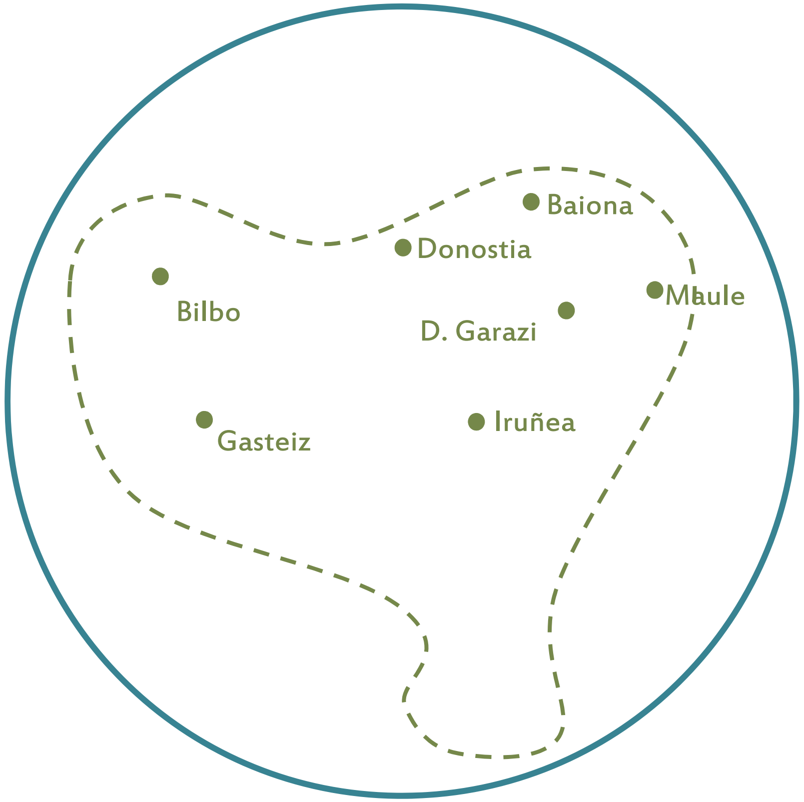

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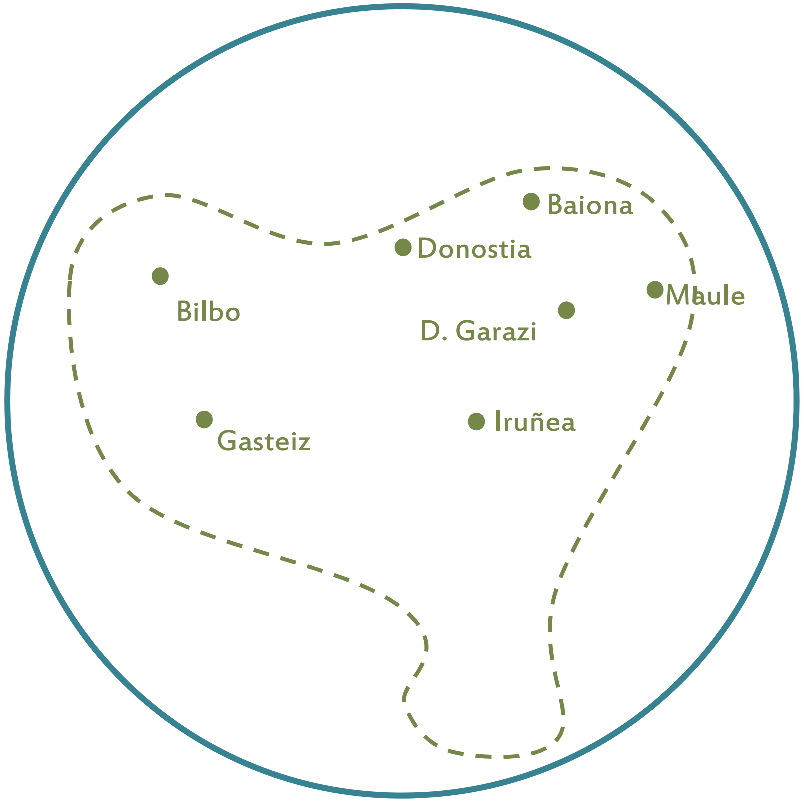


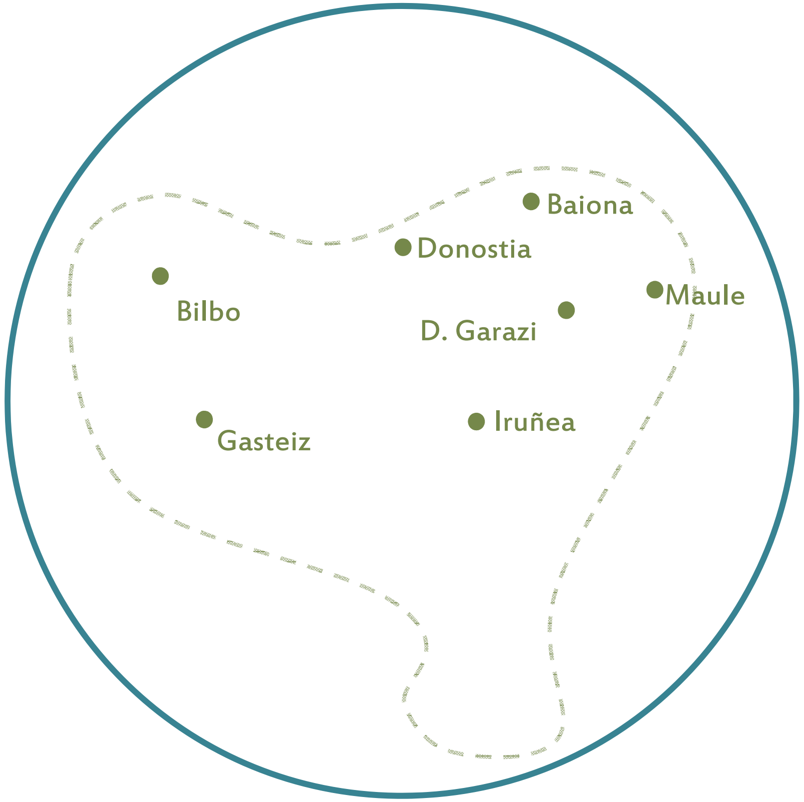
Geographical space

Introduction to vector space models

Geographical space

- Cities

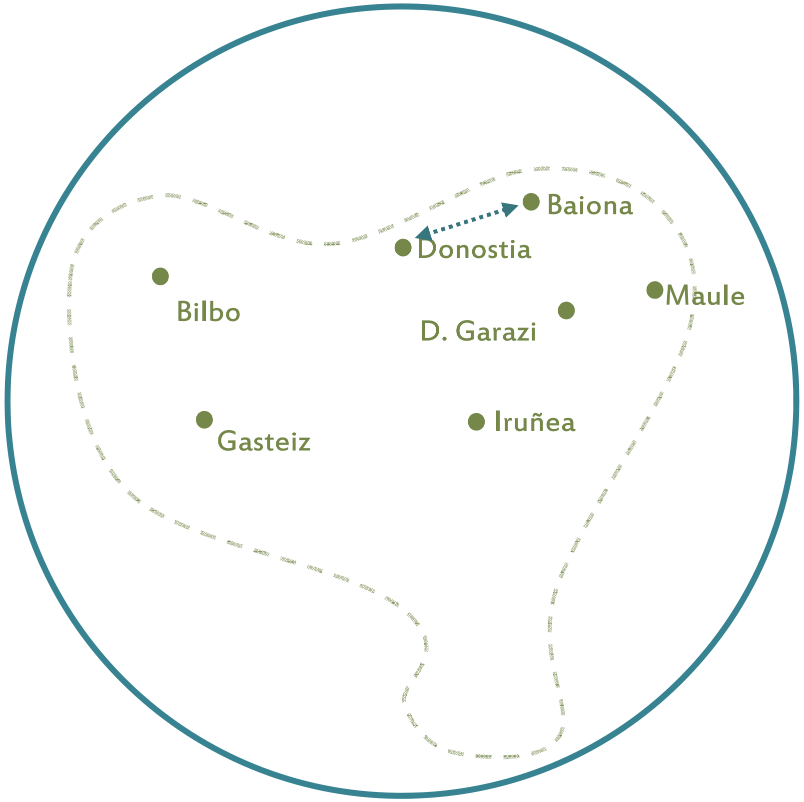
Introduction to vector space models



Geographical space

- Cities
- Meaningful distances

Introduction to vector space models



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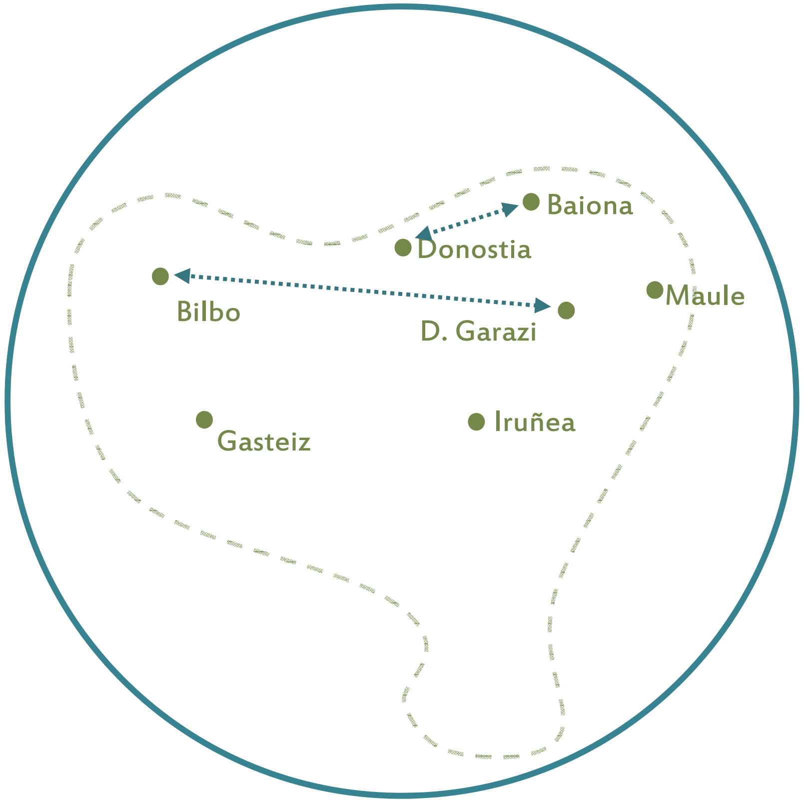

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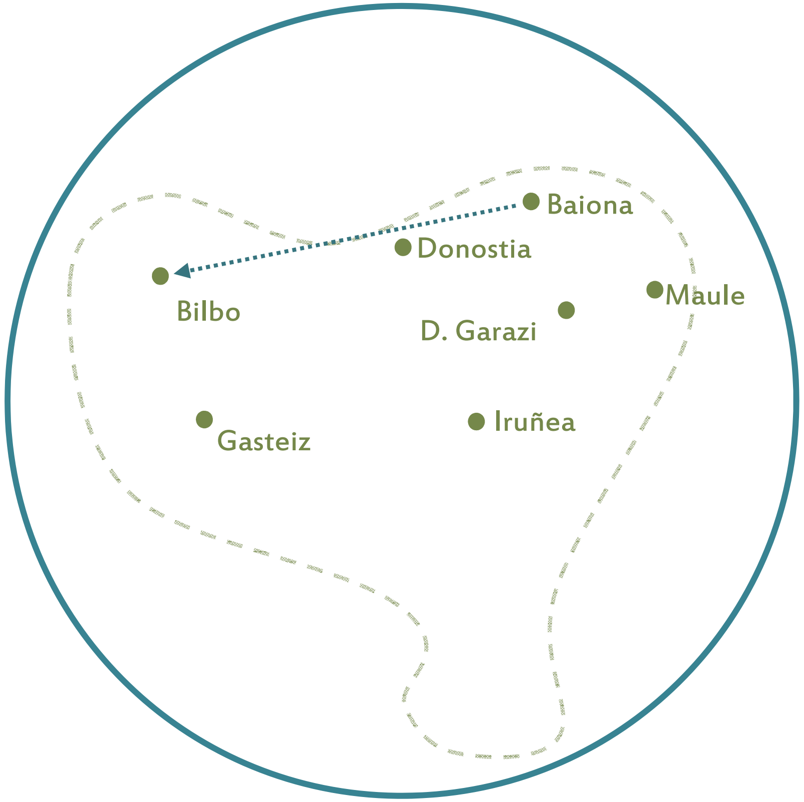

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Introduction to vector space models

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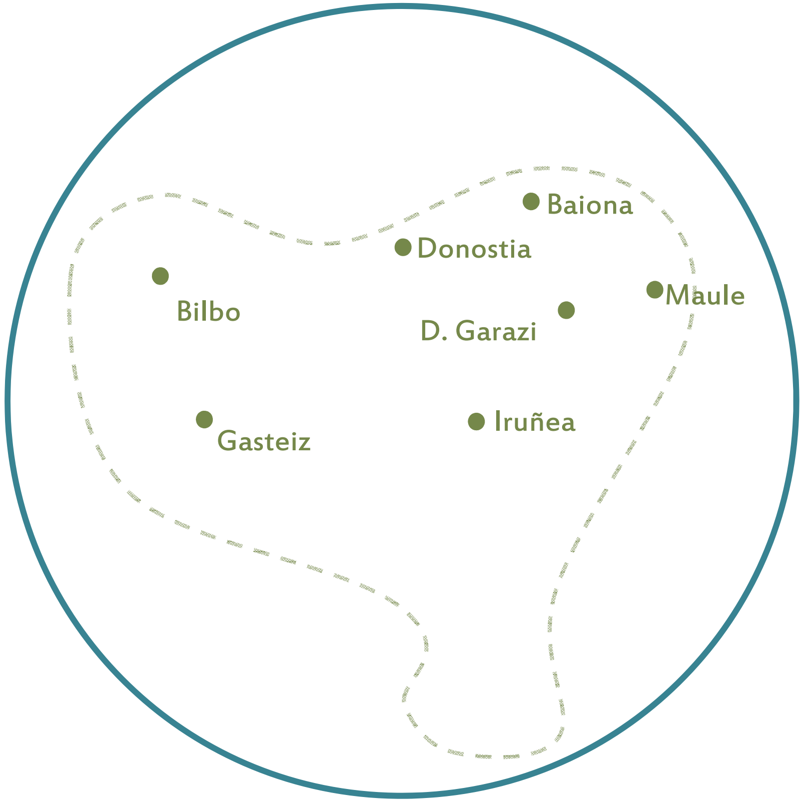

<u>Geographical space</u>

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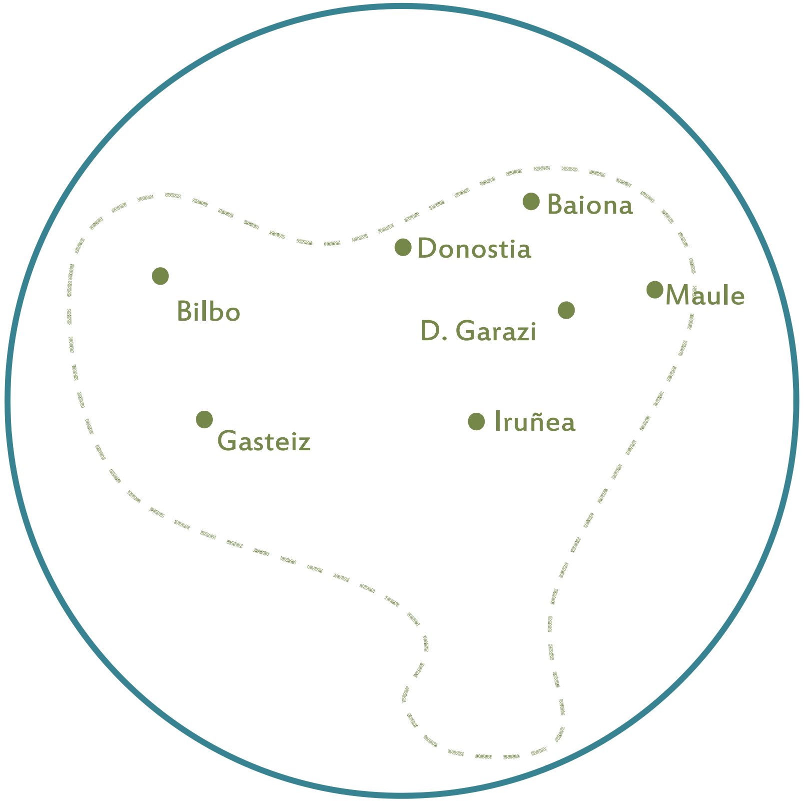

Geographical space

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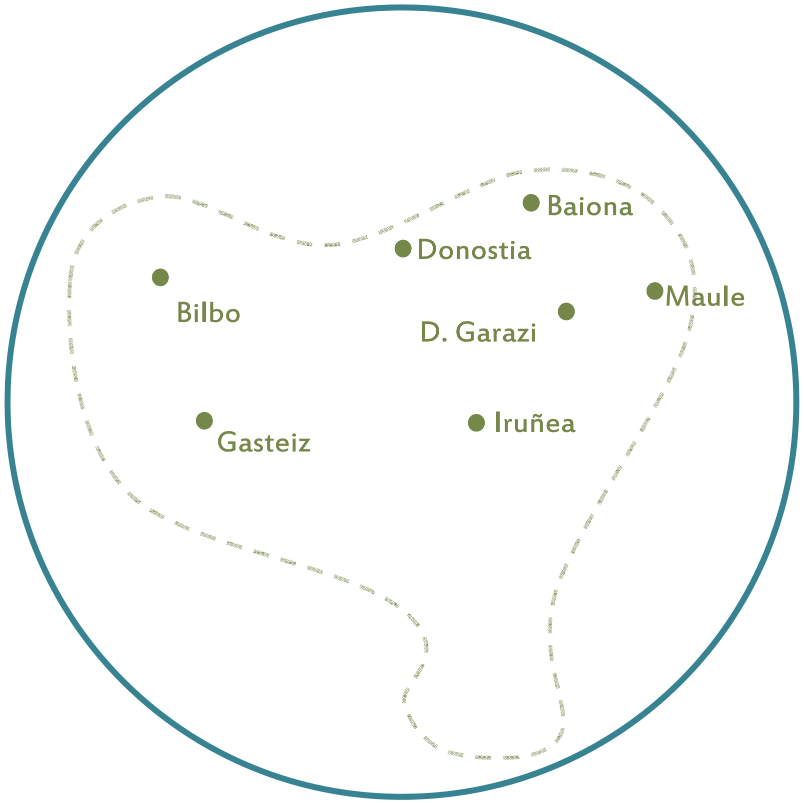
Semantic space

Introduction to vector space models



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Semantic space

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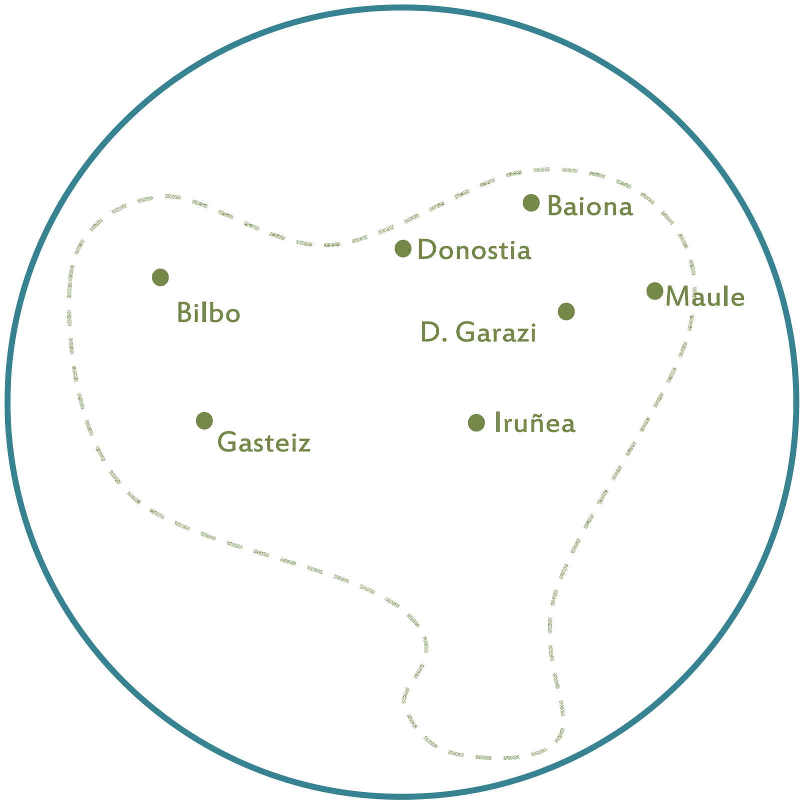

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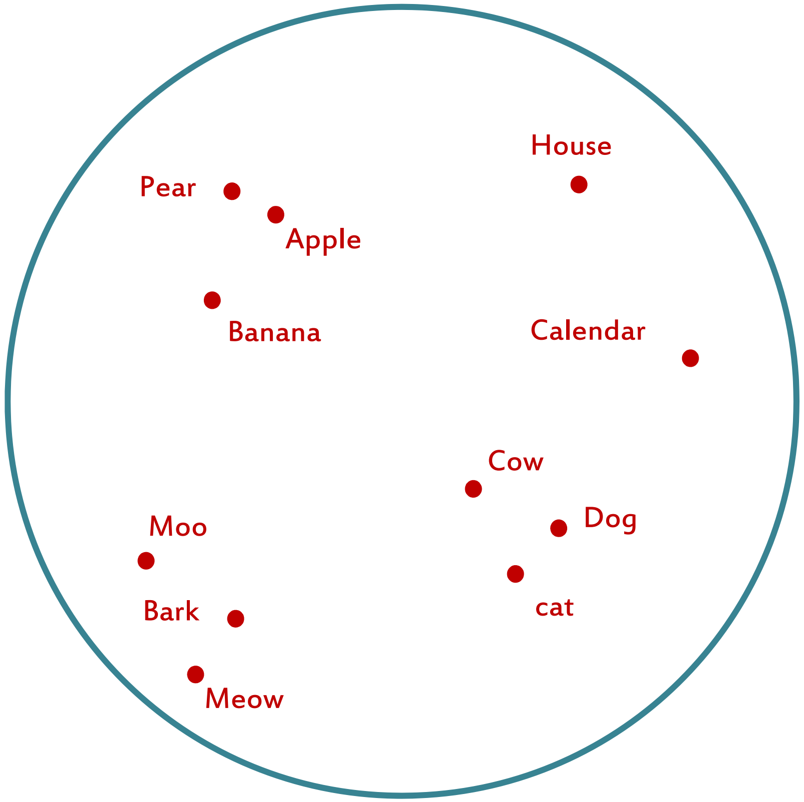

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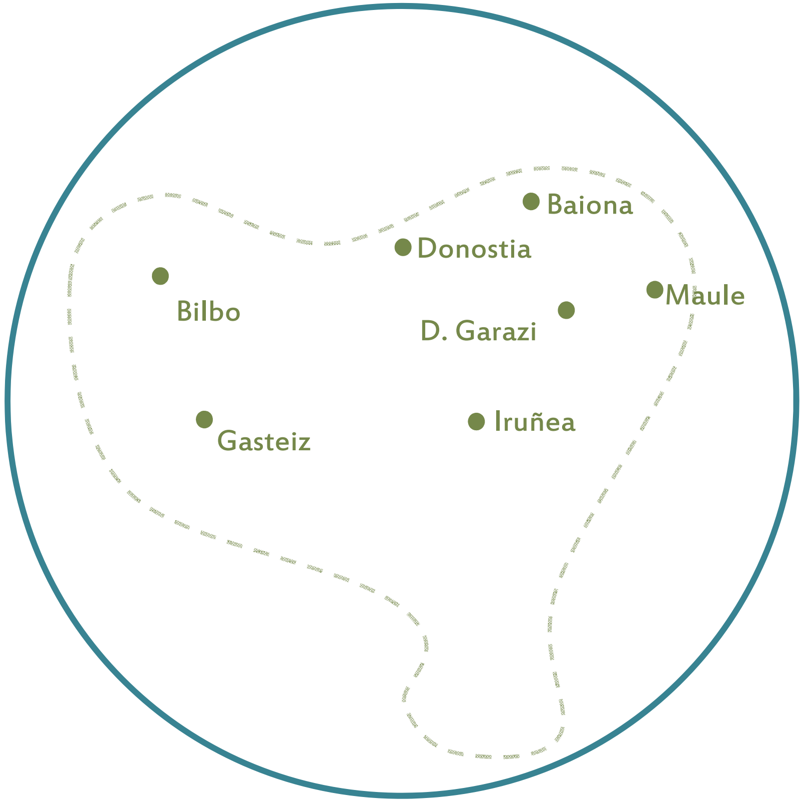

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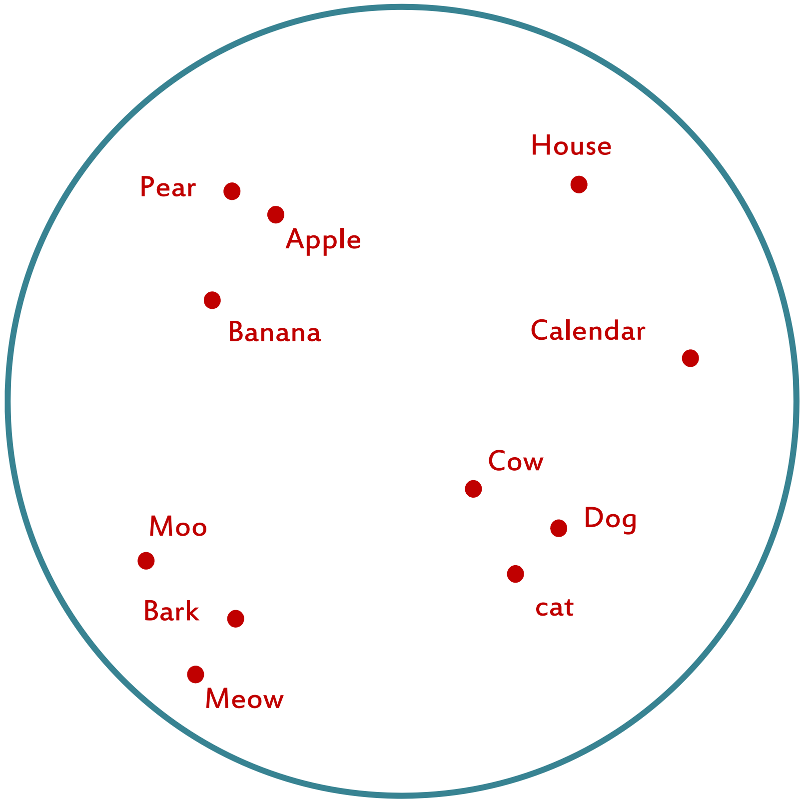

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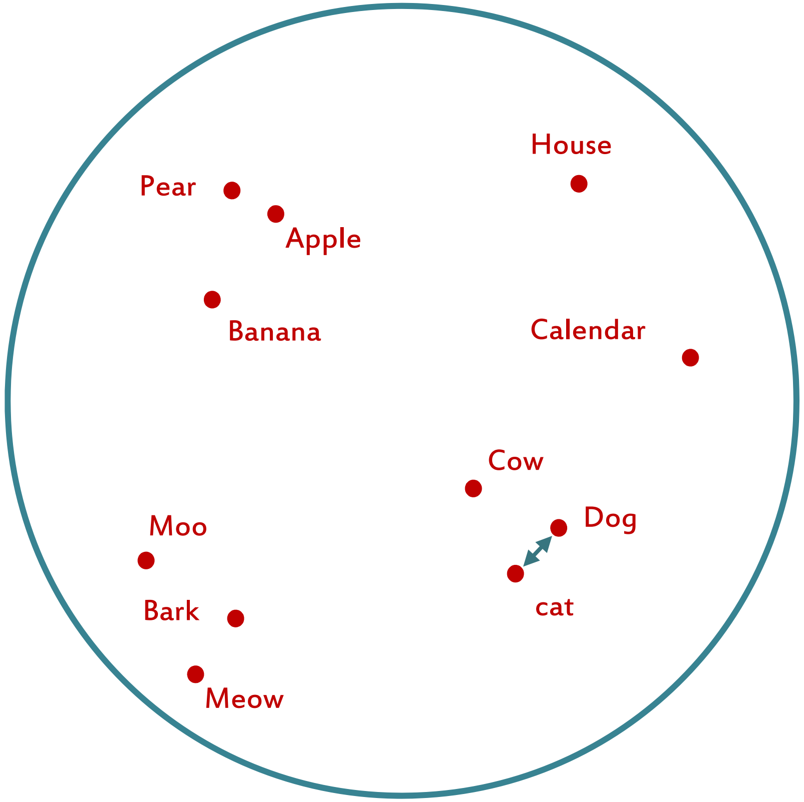

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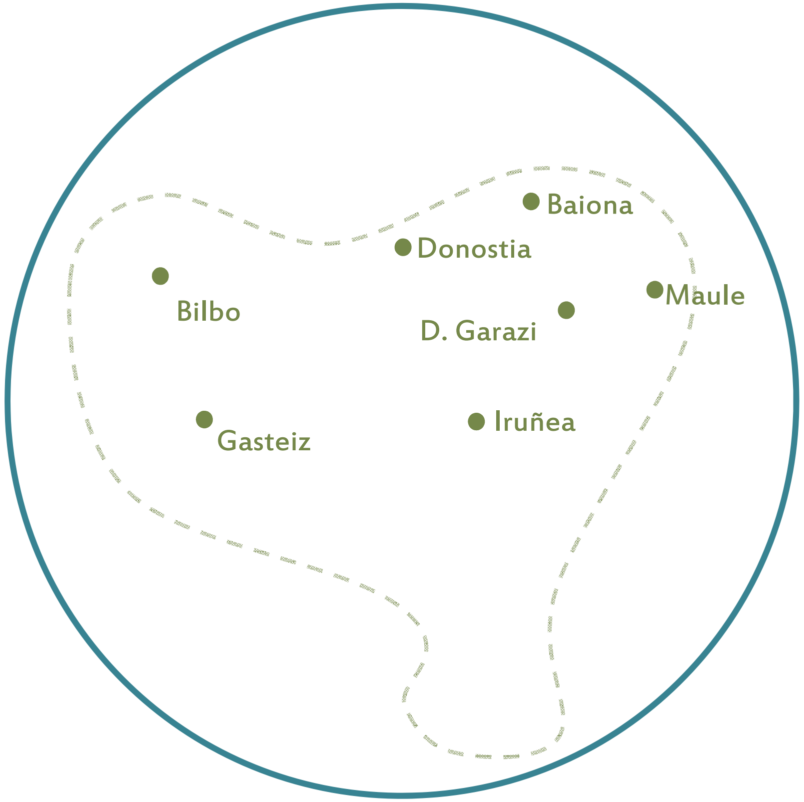

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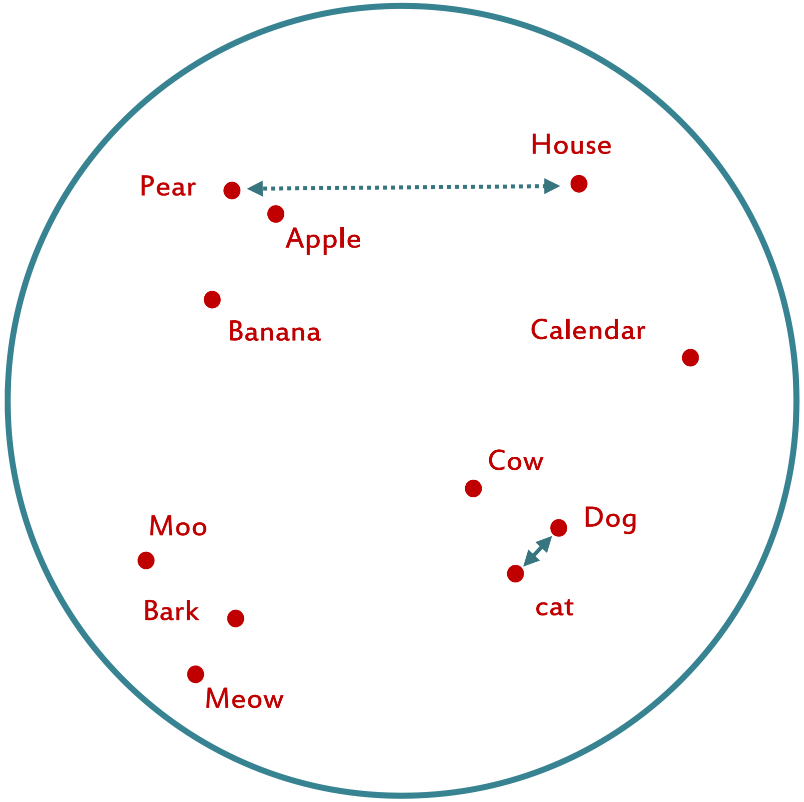

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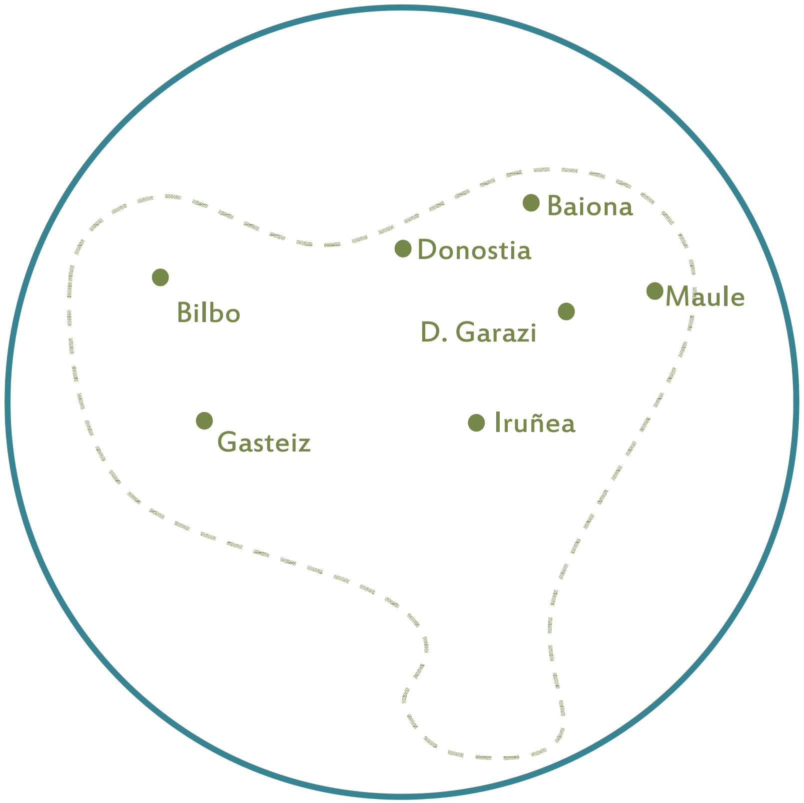

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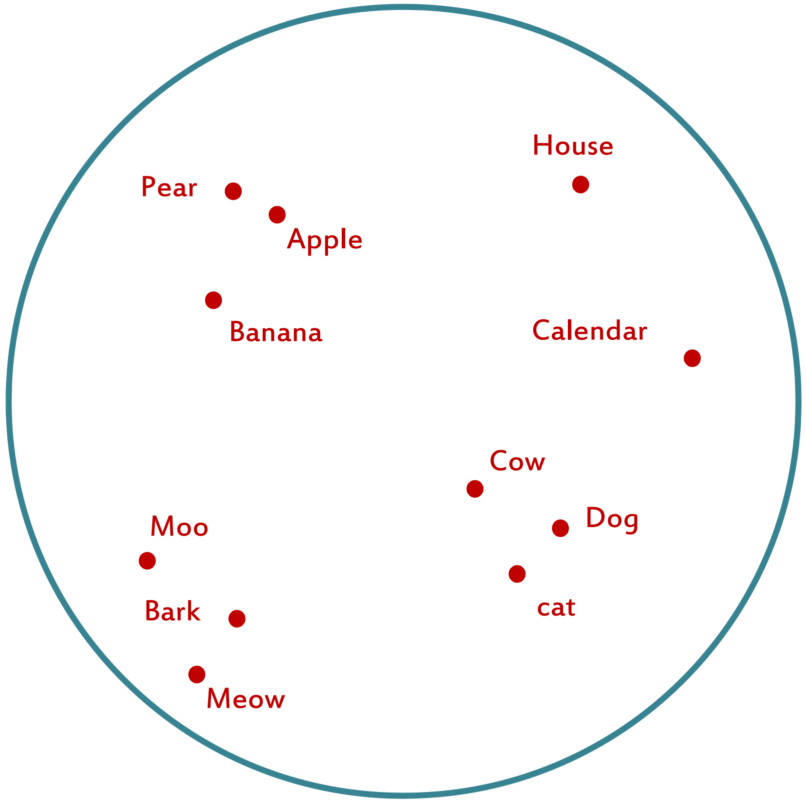

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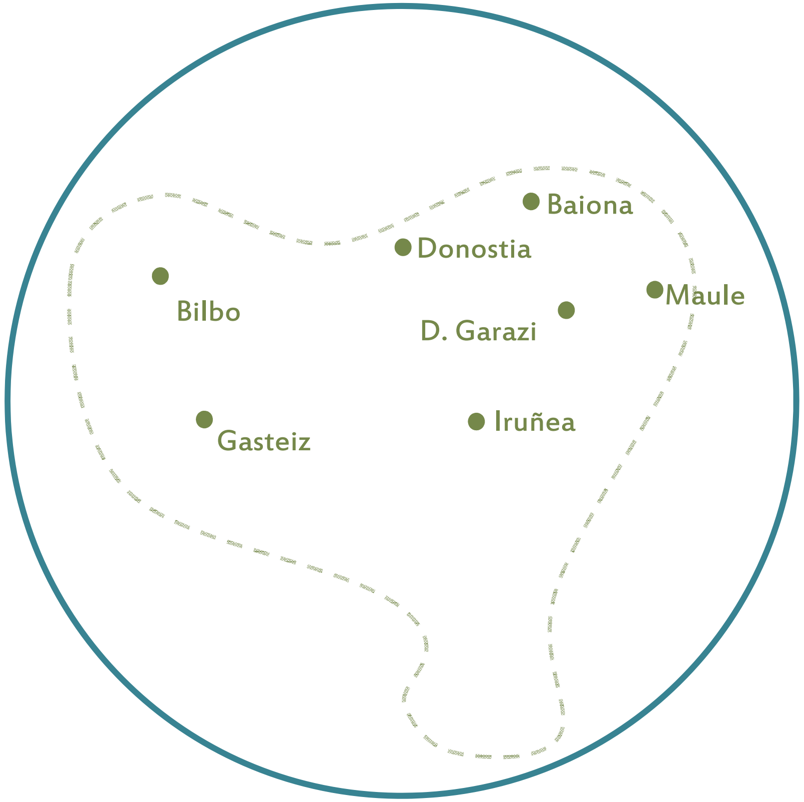

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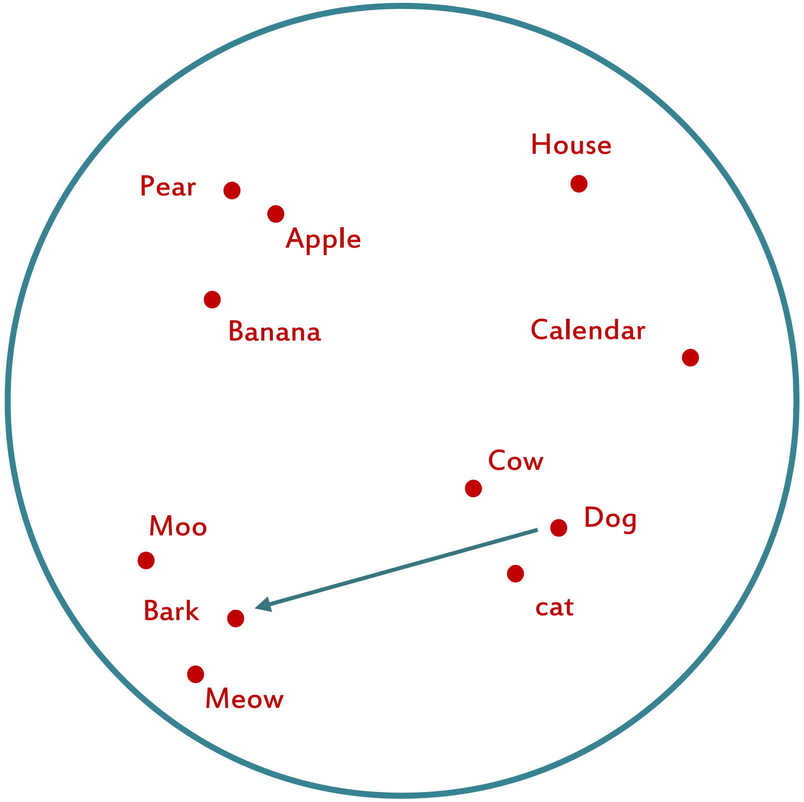

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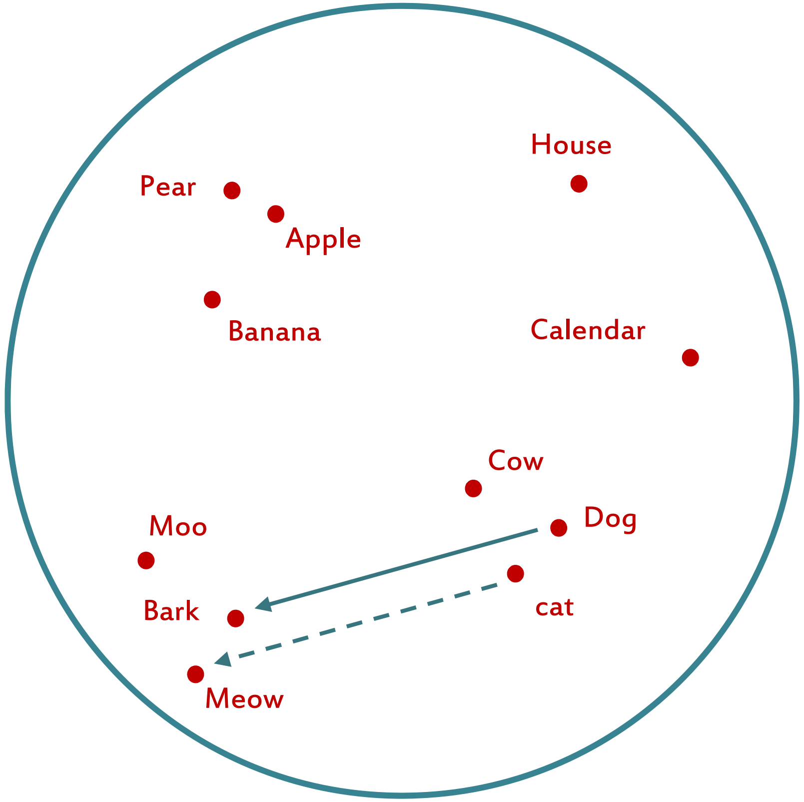

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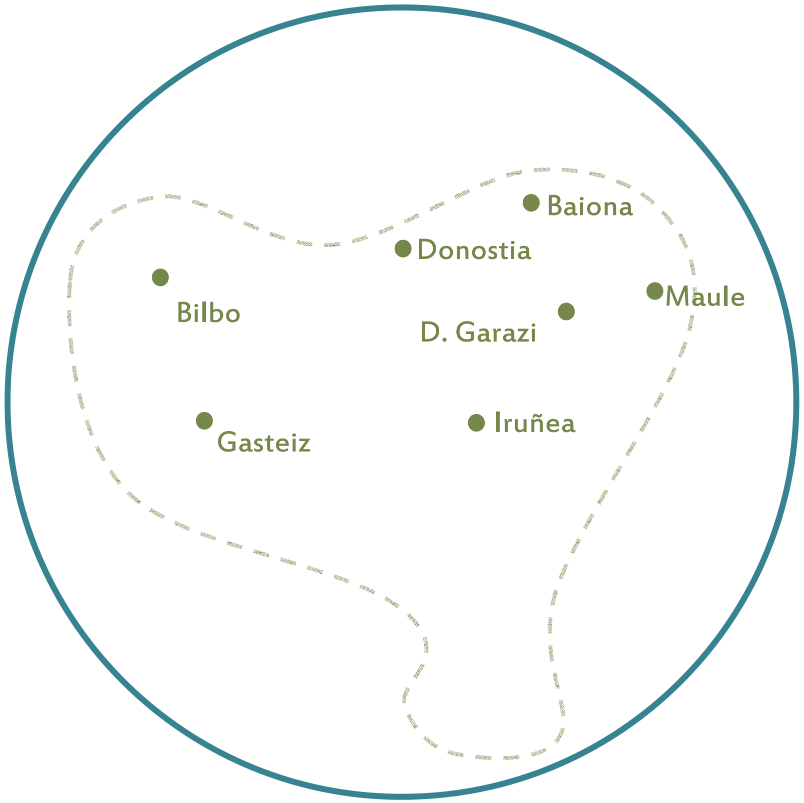

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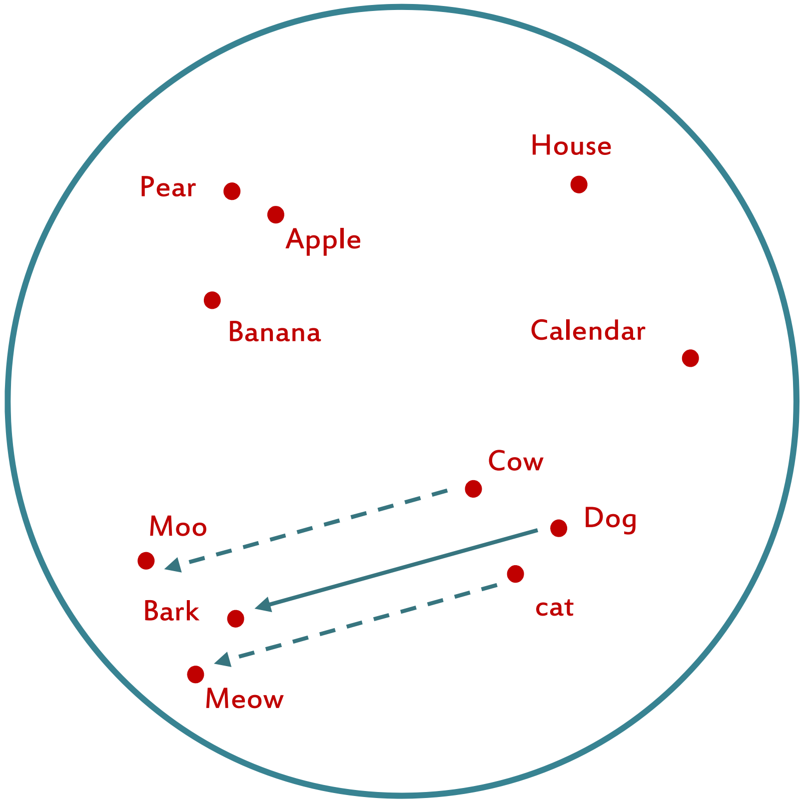

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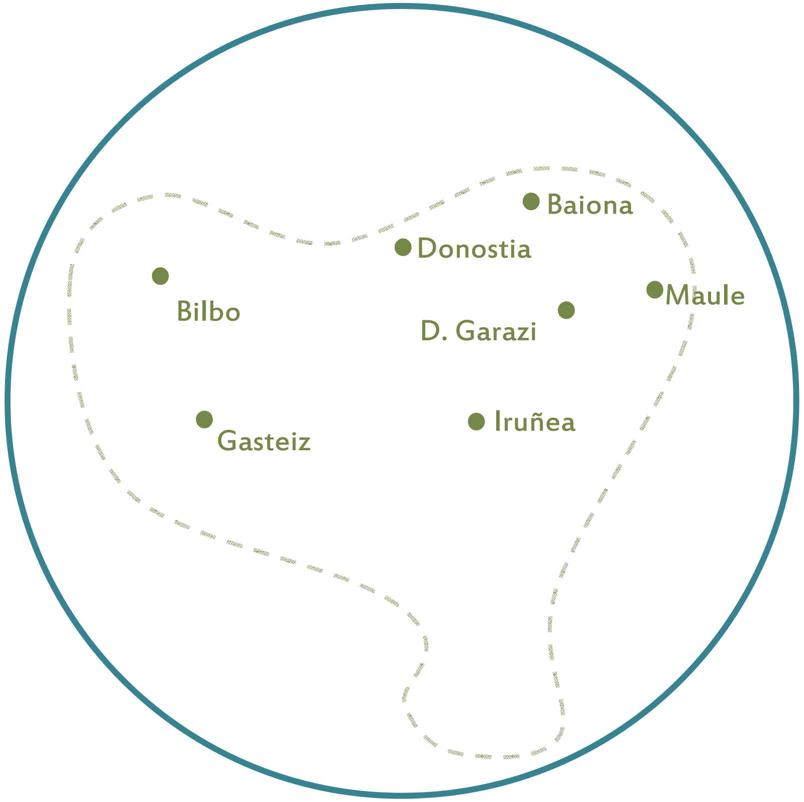

Geographical space

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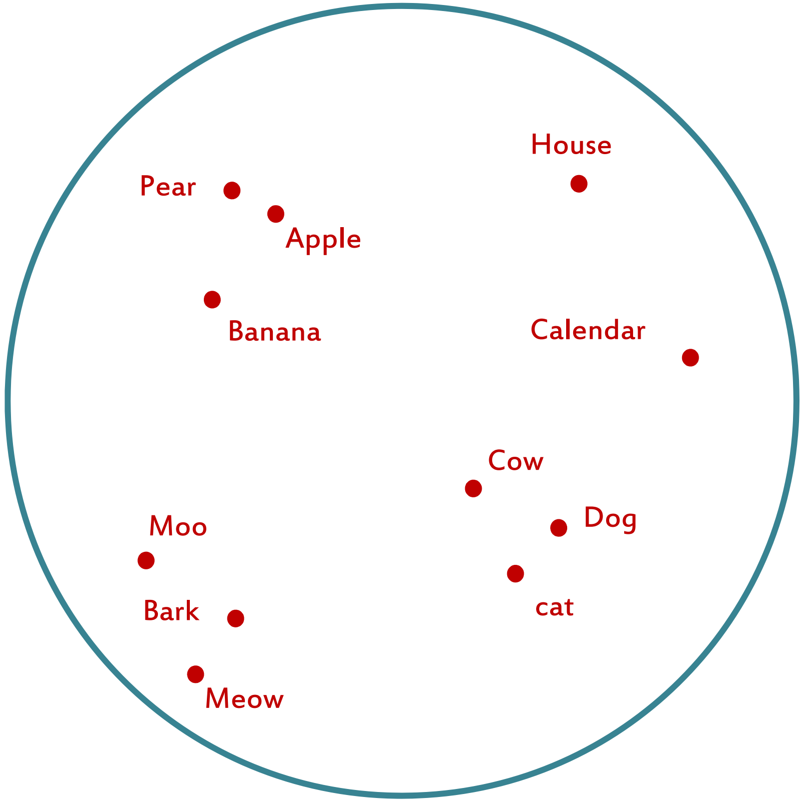
Semantic space

- Words
- Meaningful distances
- Meaningful relations
- 300 dimensions



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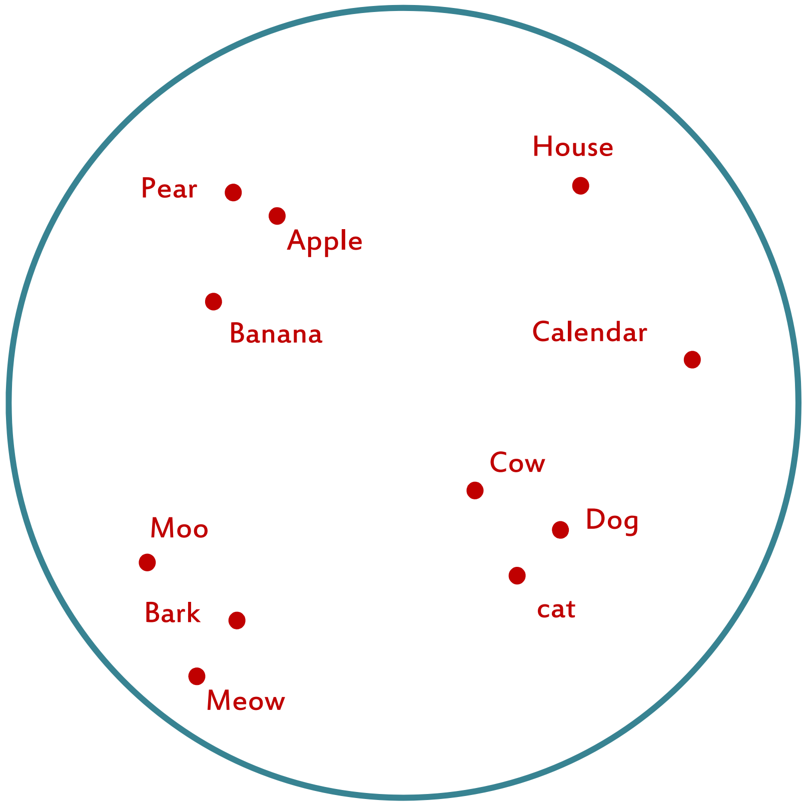
Semantic space

- Words
- Meaningful distances
- Meaningful relations
- 300 dimensions
- Neural networks / linear algebra from co-occurrence counts



Introduction to embedding mappings

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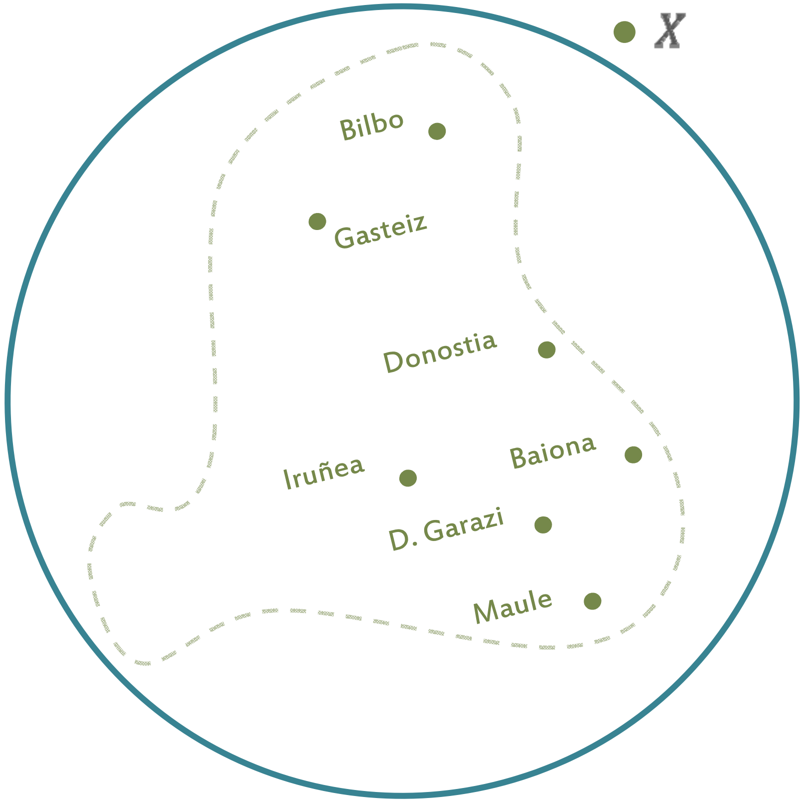

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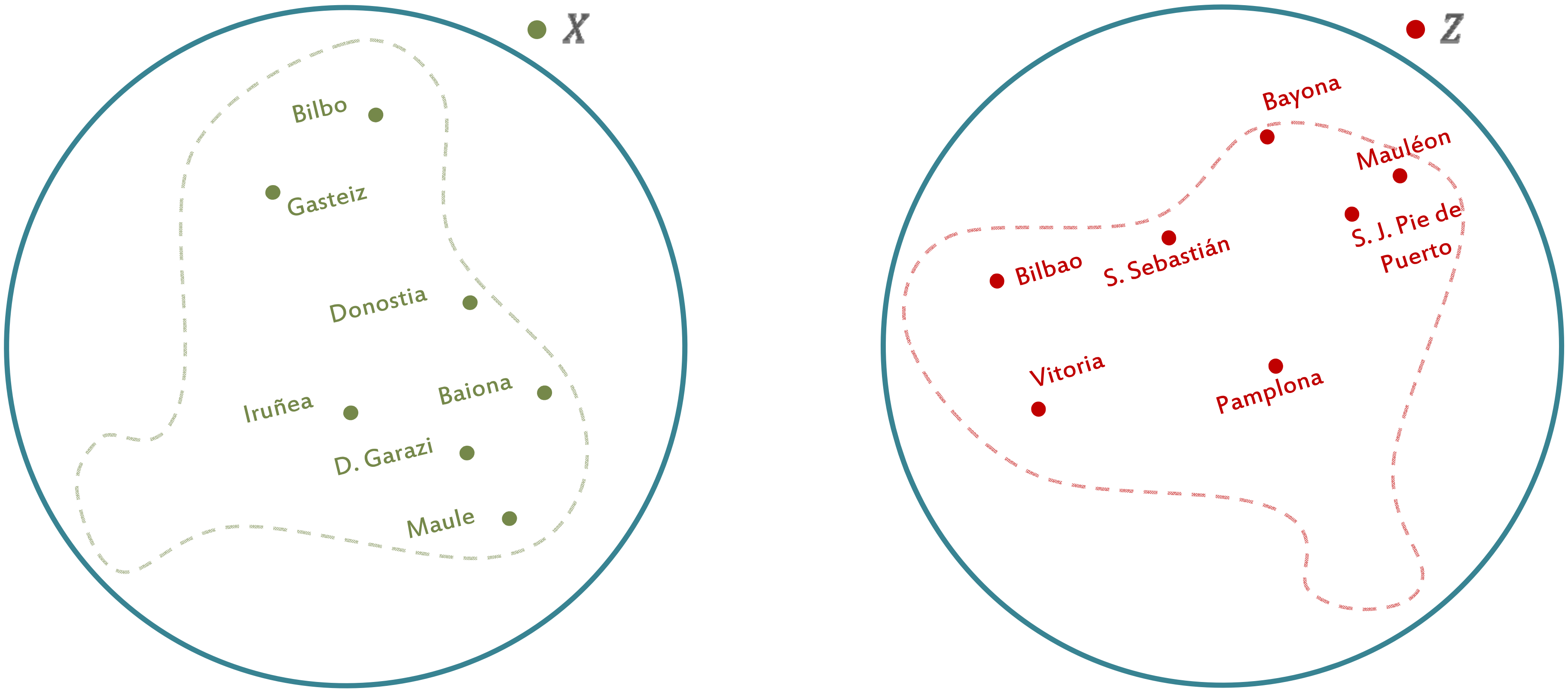

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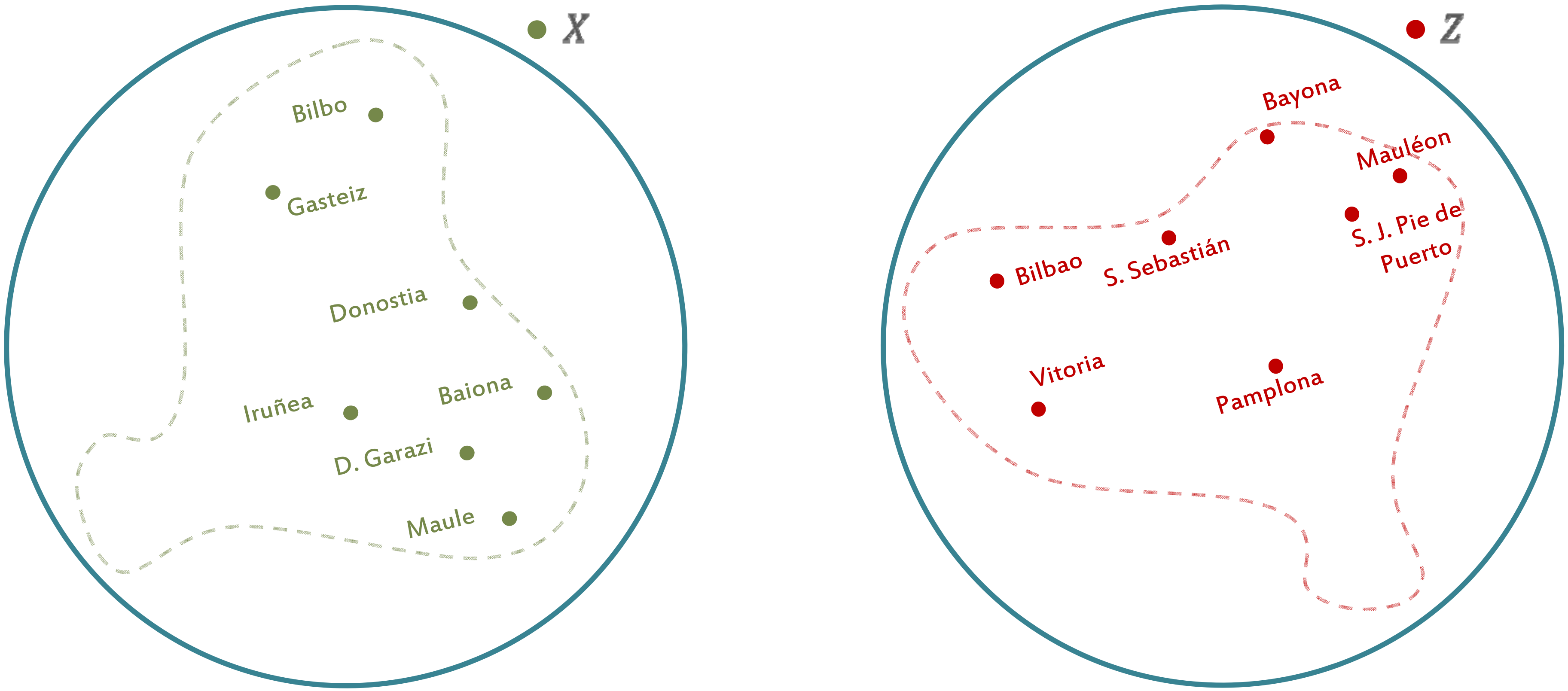
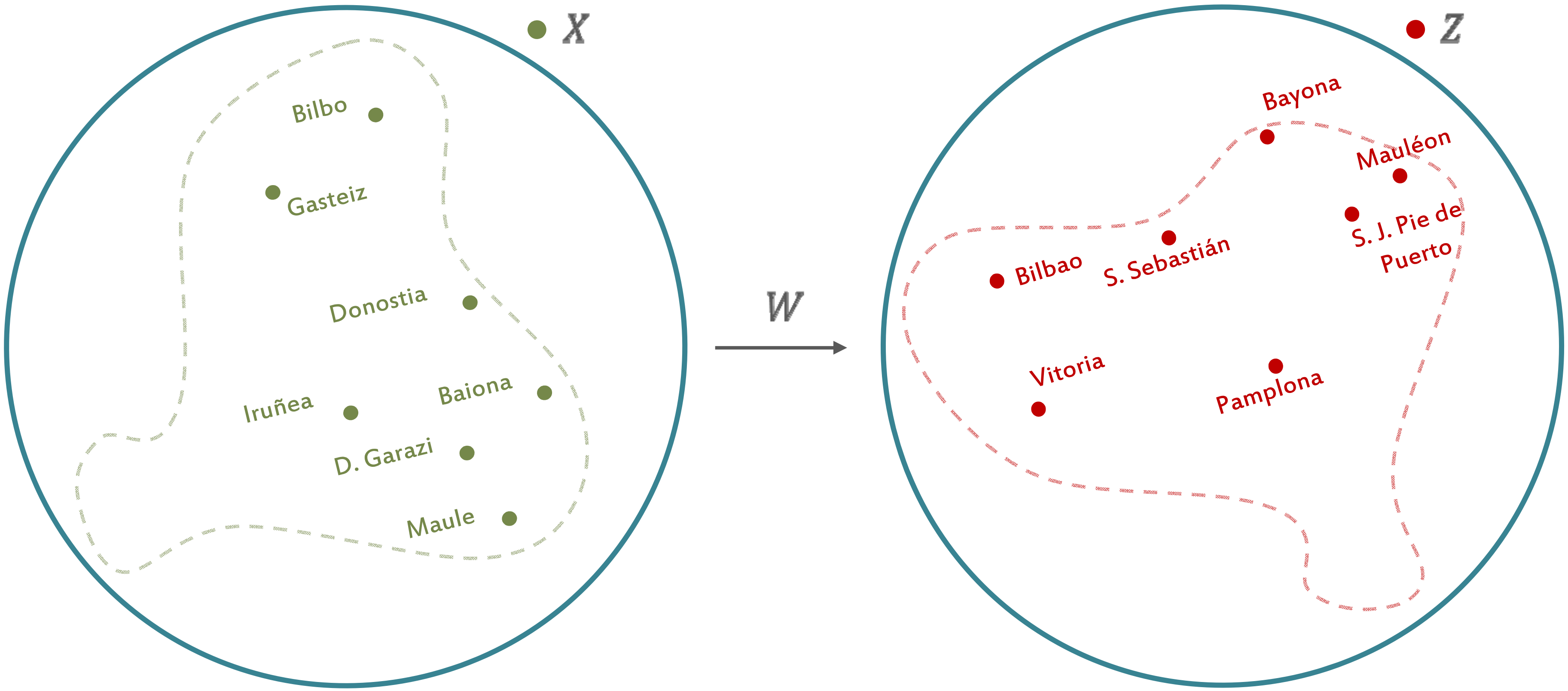


Bilbo	Bilbao
Baiona	Bayona
Iruñea	Pamplona

Introduction to embedding mappings



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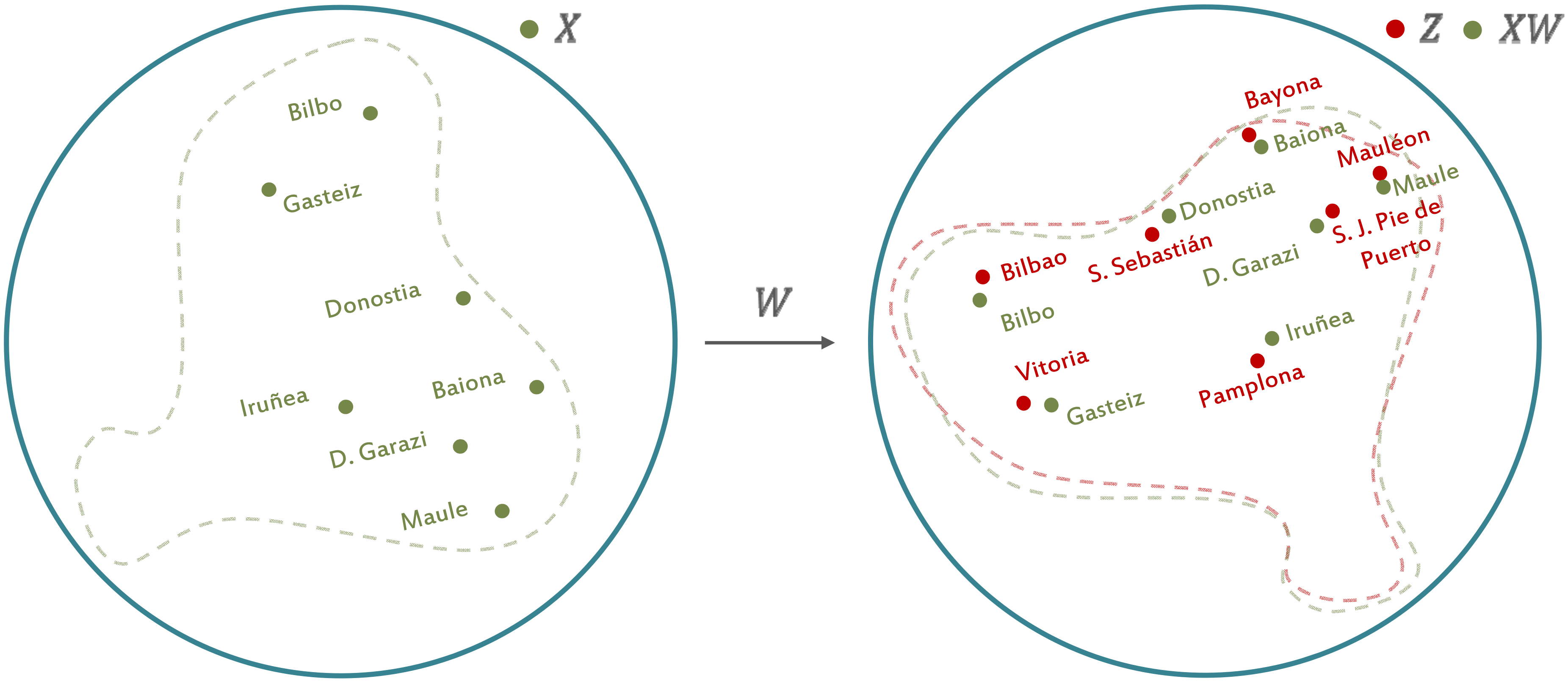

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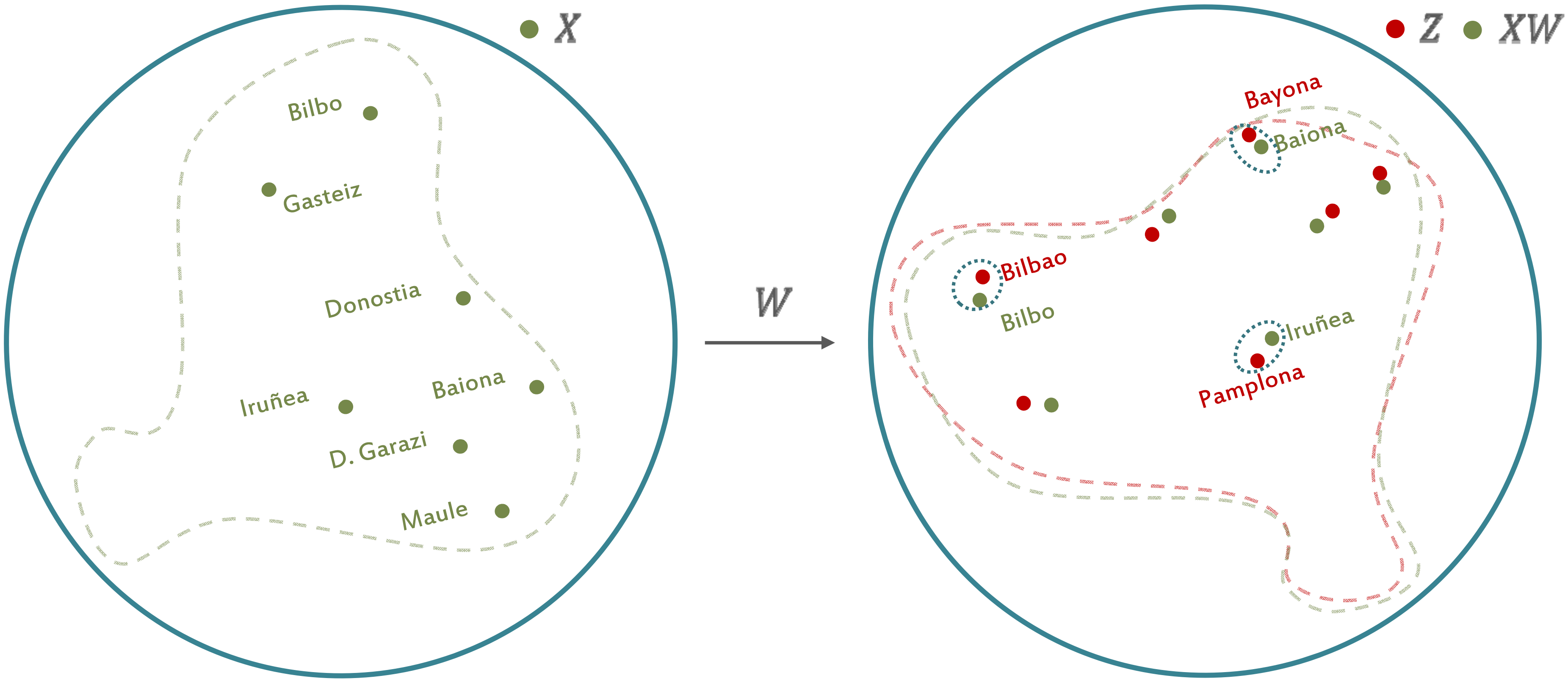

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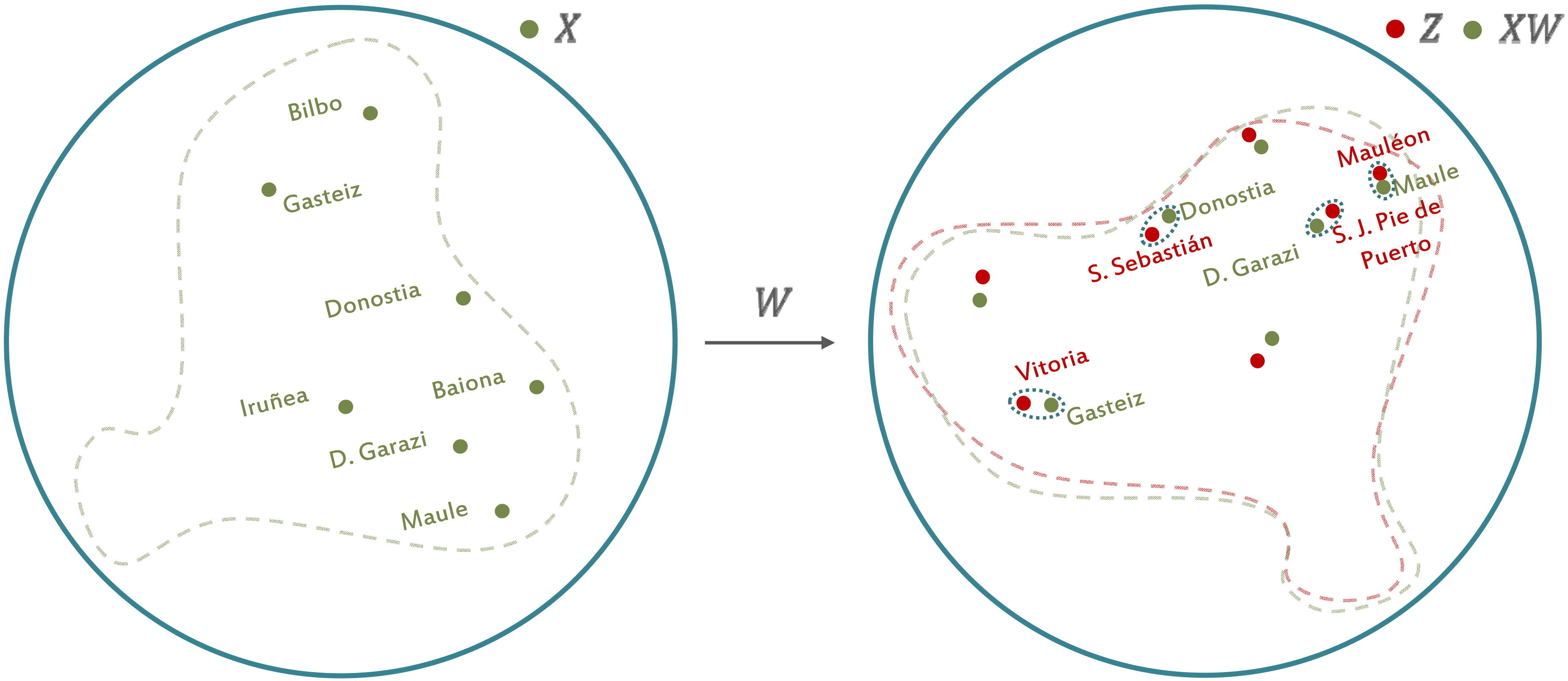

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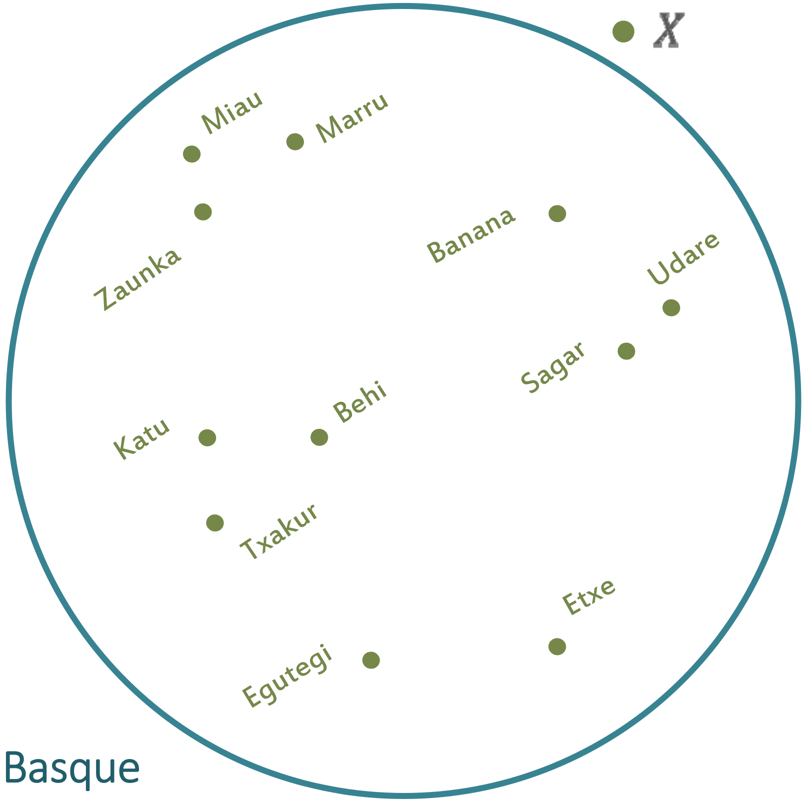

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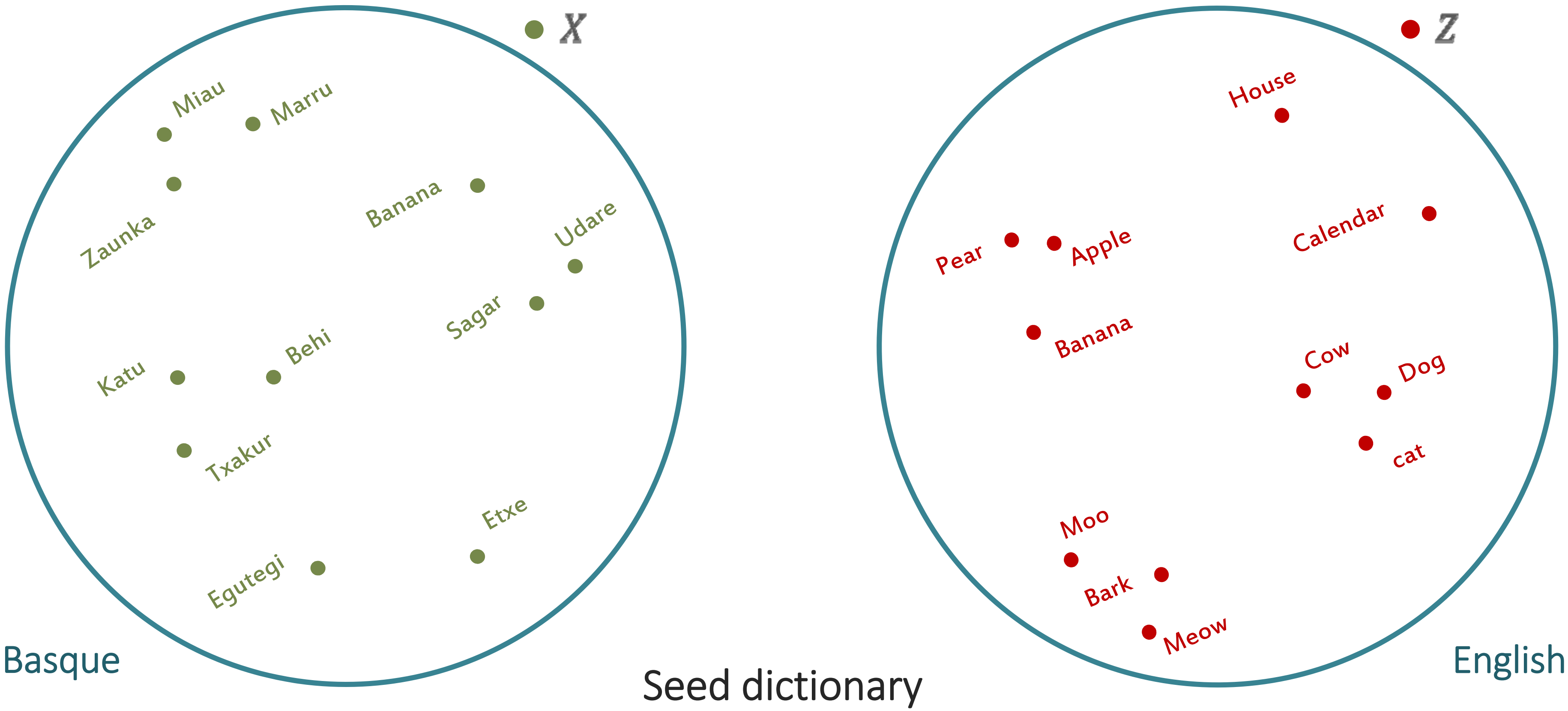

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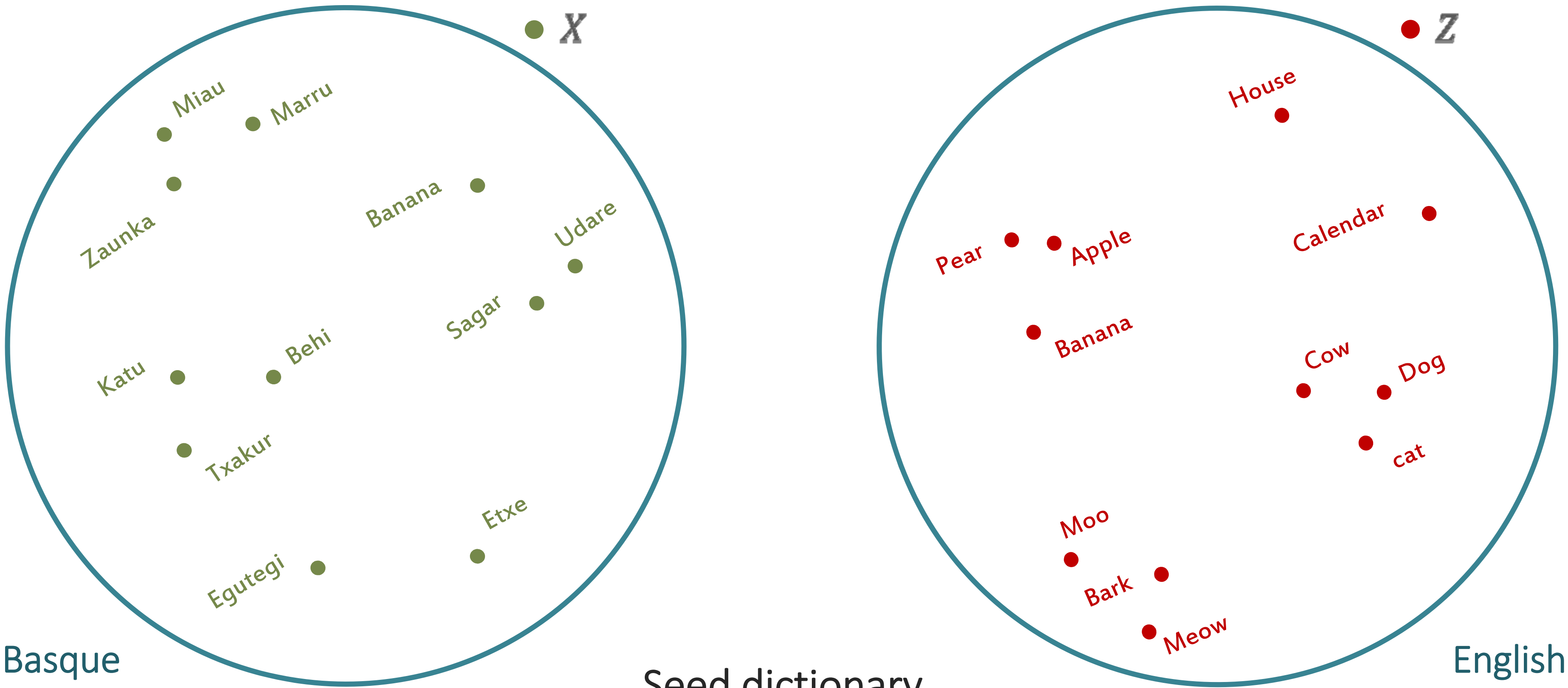

Seed dictionary

Txakur	Dog
Sagar	Apple
⋮	⋮
Egutegi	Calendar

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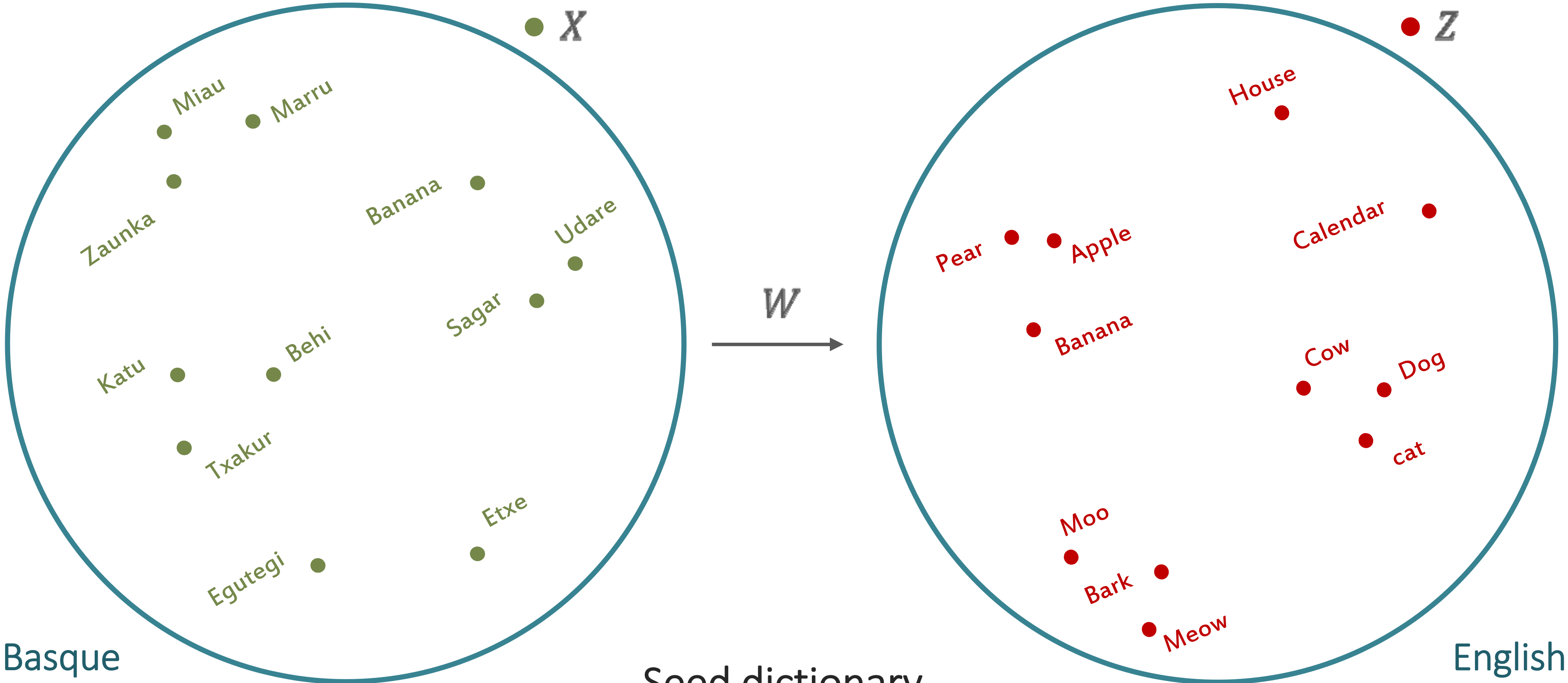

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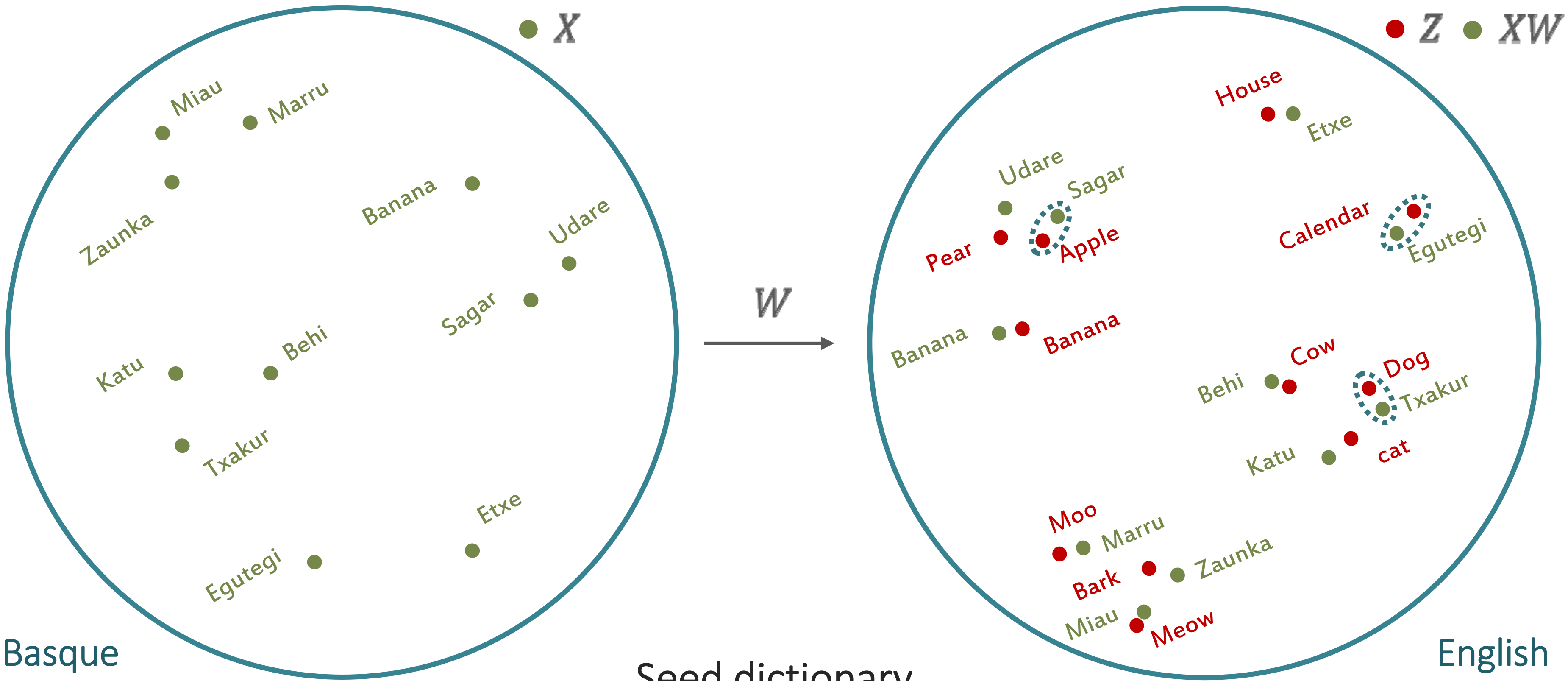

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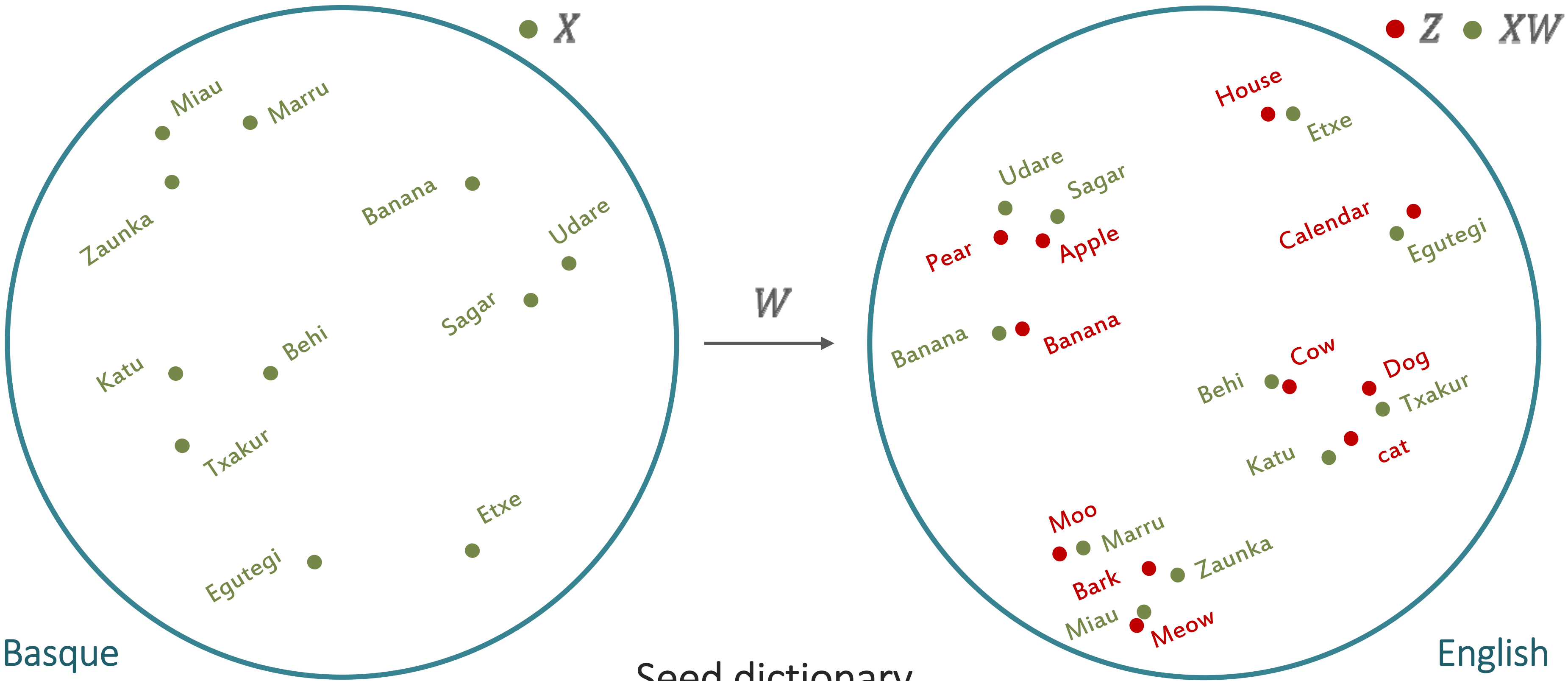

Seed dictionary

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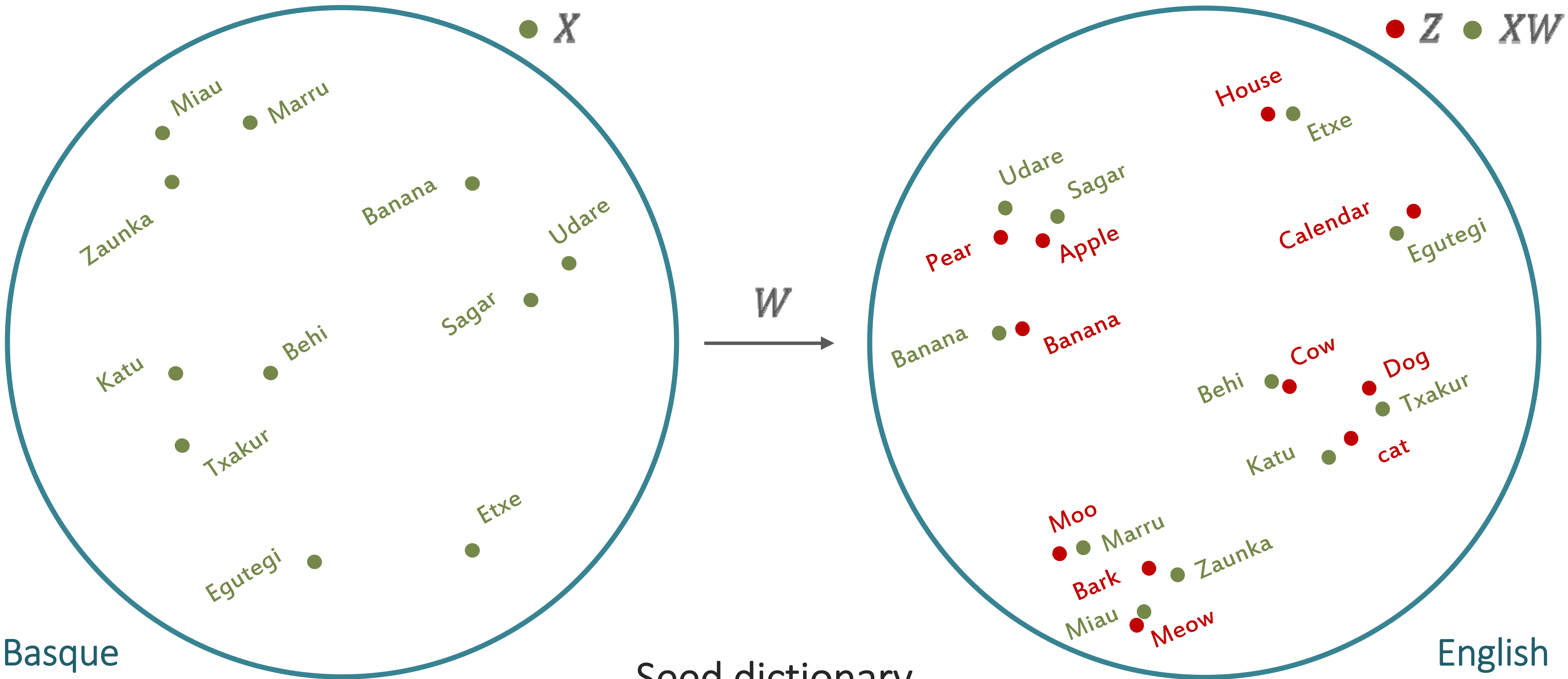

Seed dictionary

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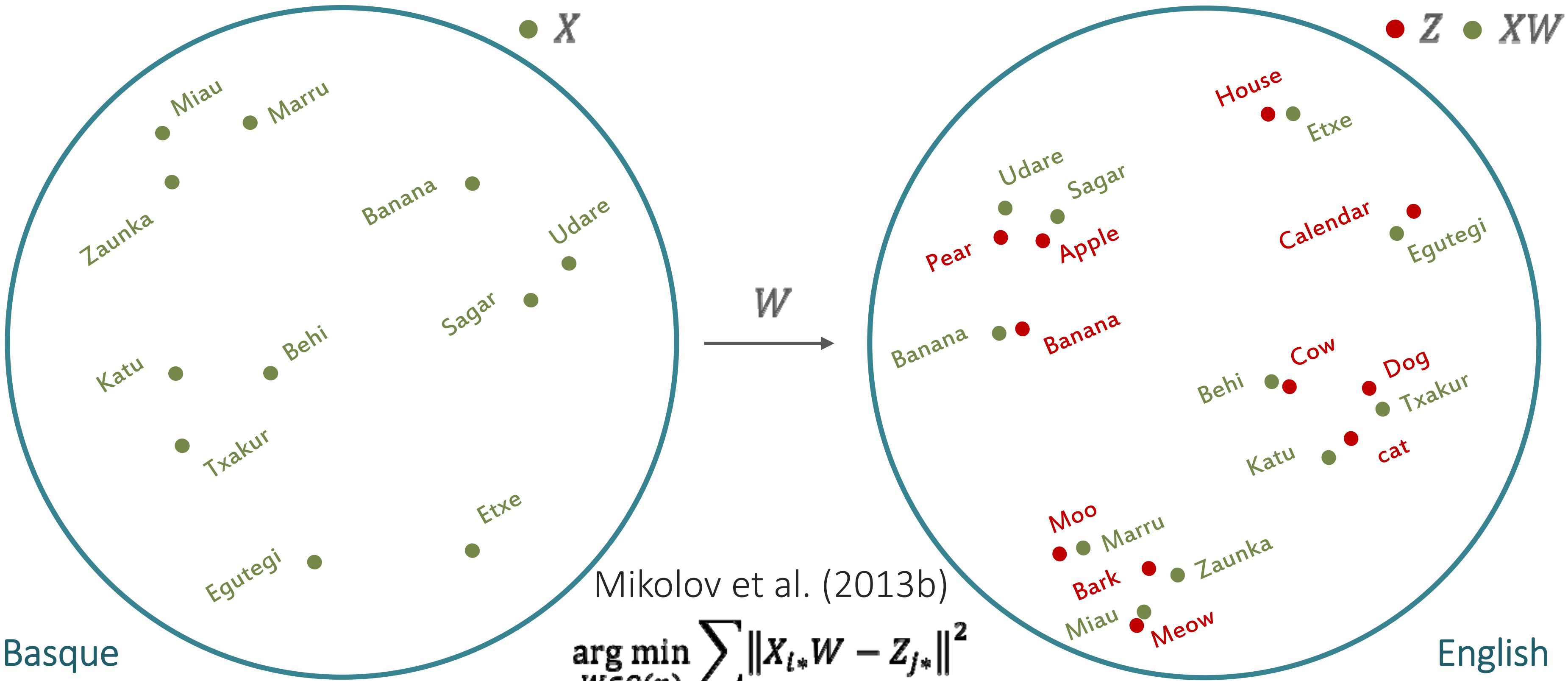

Mikolov et al. (2013b)

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

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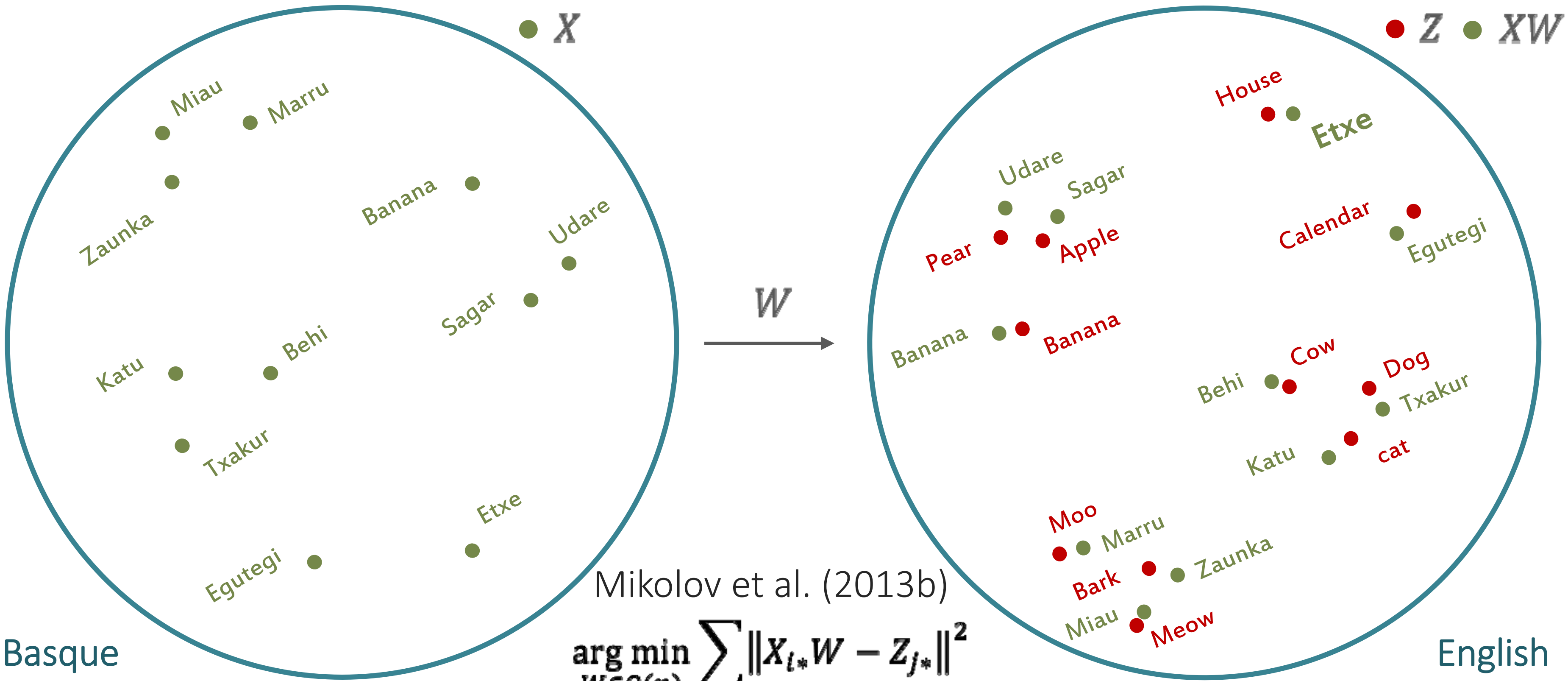

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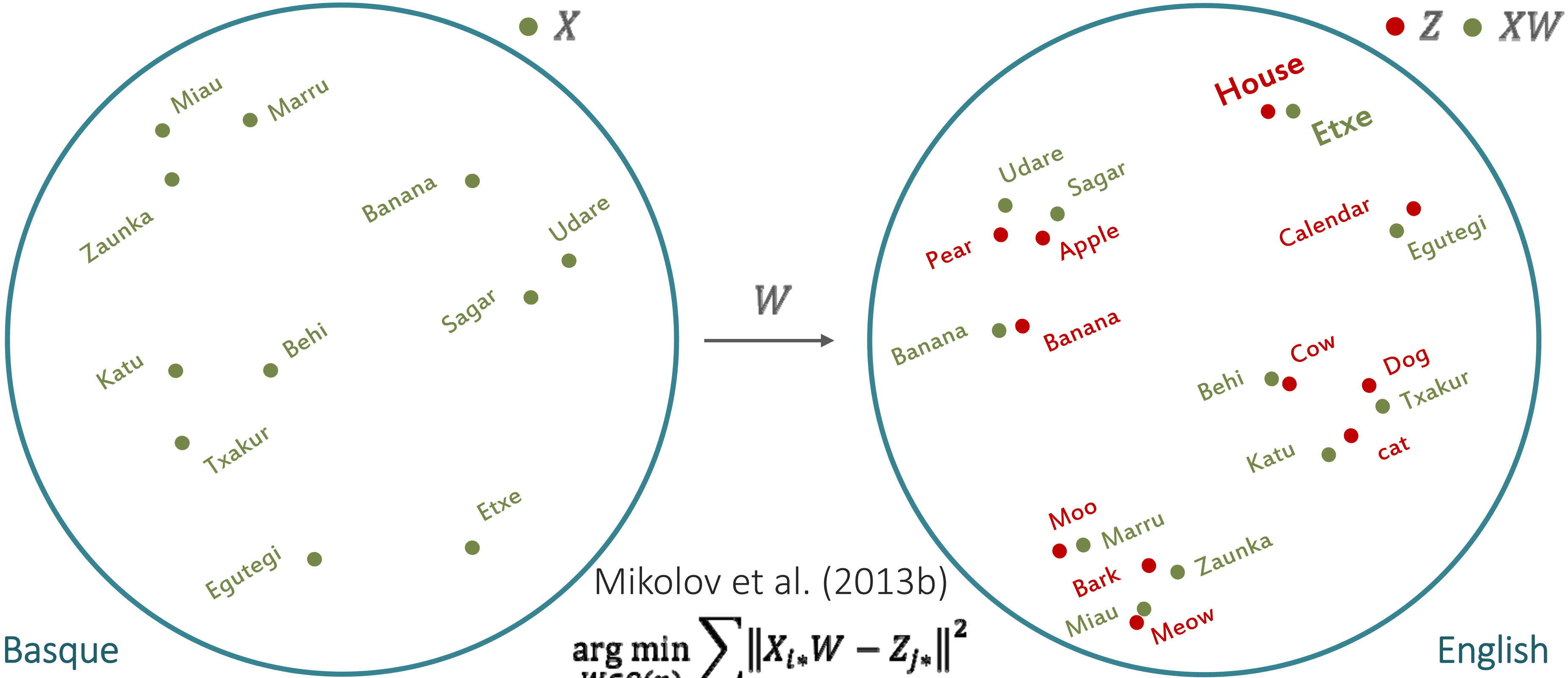

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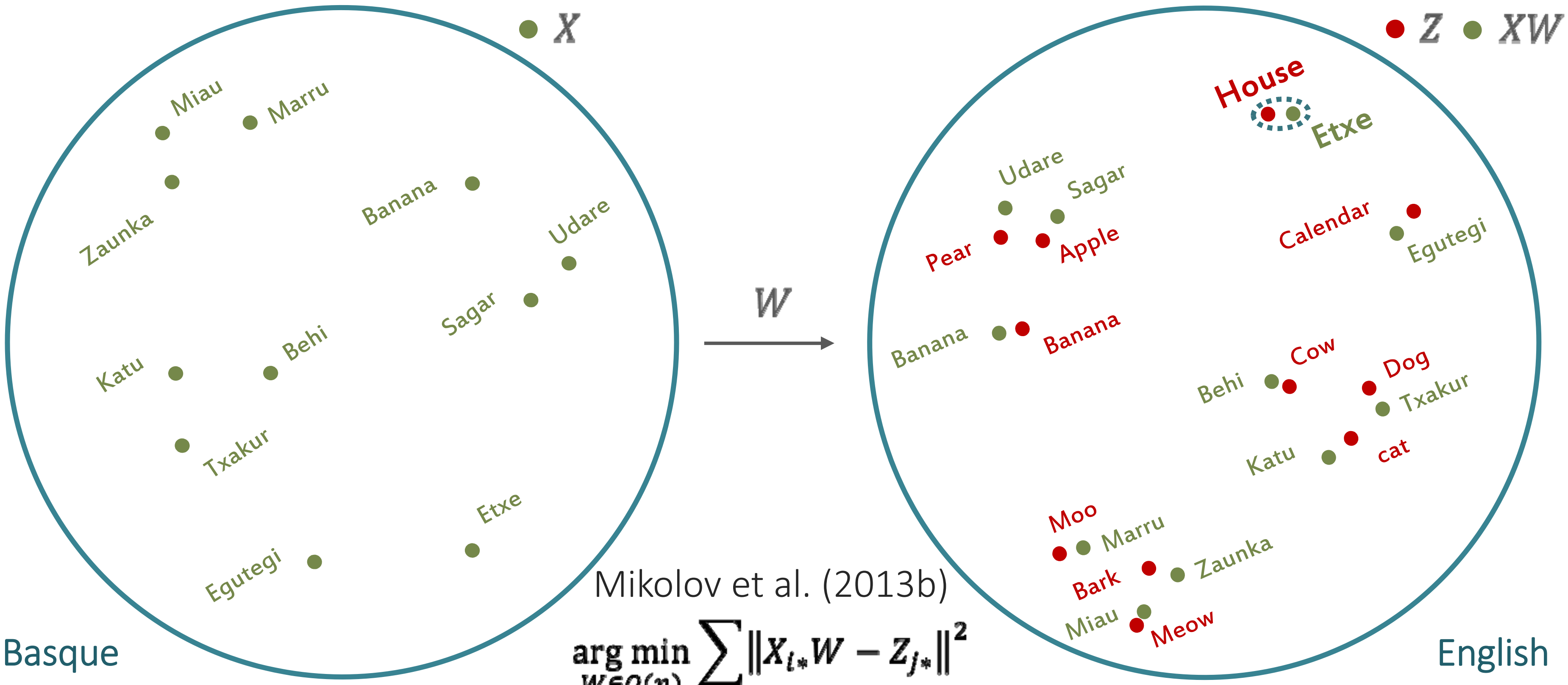

Mikolov et al. (2013b)

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

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

State-of-the-art in **supervised** mappings Artetxe et al. AAAI 2018

- Use 5000 sized seed bilingual dictionary
- Framework subsuming previous work that learns two mappings W_X W_Z as **sequences of (optional) linear mappings**:

    (opt.) Pre-process

    1. (opt.) Whitening
    2. **Orthogonal mapping**
    3. (opt.) Re-weighting
    4. (opt.) De-whitening

- The optional steps, properly combined, bring up to 5 points improvement

State-of-the-art in **supervised** mappings

S0 (opt.) Pre-processing: length normalization, mean centering

State-of-the-art in **supervised** mappings

Two sequences of (optional) linear transformations:

$$W_X = \prod_i W_{X(i)} \quad W_Z = \prod_i W_{Z(i)}$$

S0 (opt.) Pre-processing: length normalization, mean centering

State-of-the-art in **supervised** mappings

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$$W_X = \prod_i W_{X(i)} \quad W_Z = \prod_i W_{Z(i)}$$

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S1 (opt.) Whitening : turn covariance matrices into the identity matrix

$$W_{X(1)} = (X^T X)^{-0.5}$$
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S2 Orthogonal mapping: map into a shared space (Procrustes)

$$W_{X(2)} = U \quad W_{Z(2)} = V \quad USV^T = X_{(1)}^T Z_{(1)}$$

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S3 (opt.) Re-weight each component according to its cross-correlation $\quad W_{X(3)} = S,\ W_{Z(3)} = I$; $W_{X(3)} = I,\ W_{Z(3)} = S$

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$$W_{X(3)} = S, \; W_{Z(3)} = I$$
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$$W_{A(4)} = W_{B(2)}^T W_{B(1)}^{-1} W_{B(2)}$$

State-of-the-art in supervised mappings

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S5 (opt) Dimensionality reduction: keep the first *n* components only

$$W_{X(5)} = W_{Z(5)} = (I_n\ 0)^T$$

State-of-the-art in **supervised** mappings

		S0 (l)	S0 (m)	S1	S2	S3	S4 (src)	S4 (trg)	S5
OLS	Mikolov et al. (2013)			x	x	src	trg	trg	
	Shigeto et al. (2015)			x	x	trg	src	src	
CCA	Faruqui and Dyer (2014)	x	x	x	x				x
Orth.	Xing et al. (2015)	x			x				
	Artetxe et al. (2016)	x	x		x				
	Zhang et al. (2016)				x				
	Smith et al. (2017)	x			x				x

State-of-the-art in **supervised** mappings

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Orth.	Xing et al. (2015)	x			x				
	Artetxe et al. (2016)	x	x		x				
	Zhang et al. (2016)				x				
	Smith et al. (2017)	x			x				x
	Our method (AAAI18)	x	x	x	x	trg	src	trg	x

Evaluating via Bilingual Dictionary induction

Dataset by Dinu et al. (2015) extended to German, Finnish, Spanish

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$\Rightarrow$ Monolingual embeddings (CBOW + negative sampling)

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⇒ Seed dictionary: 5,000 word pairs

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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†
Artetxe et al. (2016)	39.27	41.87*	30.62*	31.40*
Zhang et al. (2016)	36.73†	40.80†	28.16†	31.07†
Smith et al. (2017)	43.1	43.33†	29.42†	35.13†

† our publicly available reimplementation

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Our method (AAAI18)	**45.27**	**44.13**	**32.94**	**36.60**

Why does it work?

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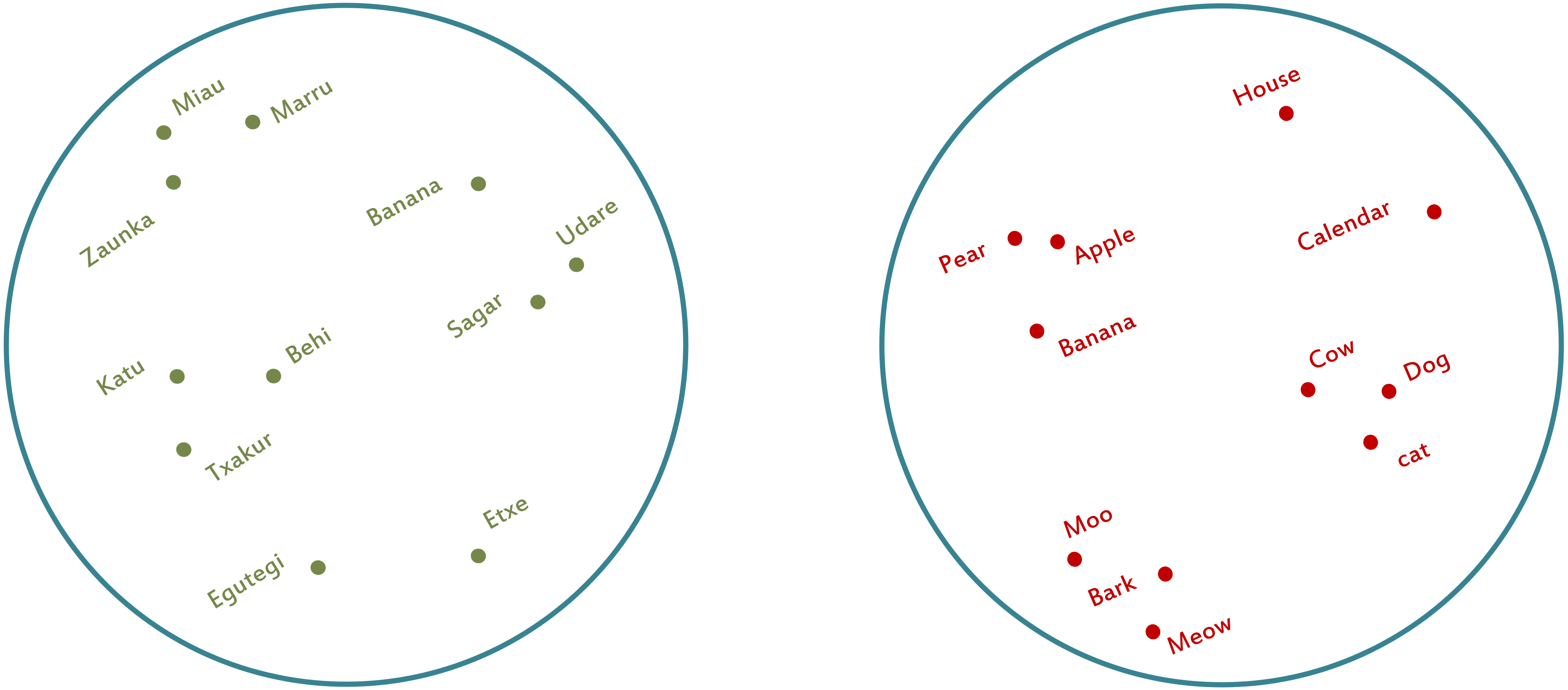

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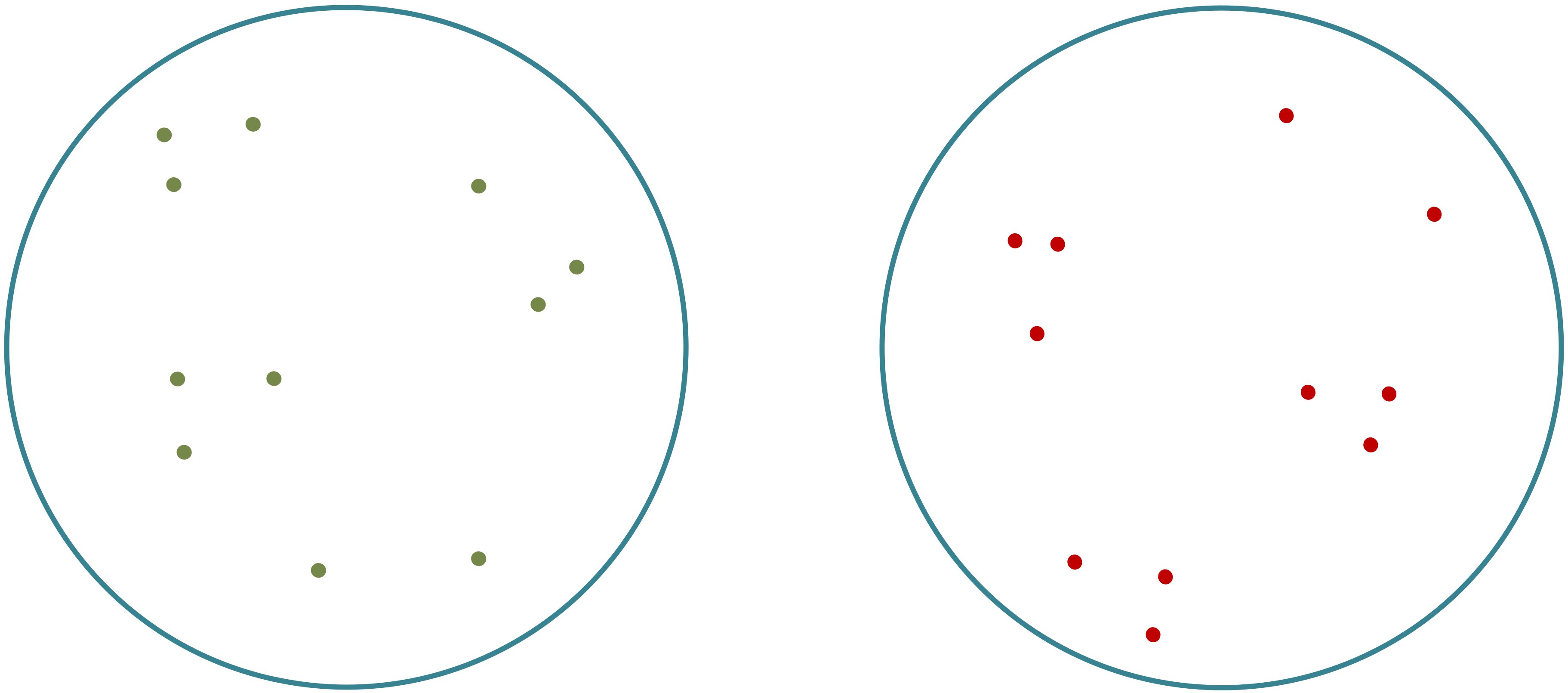

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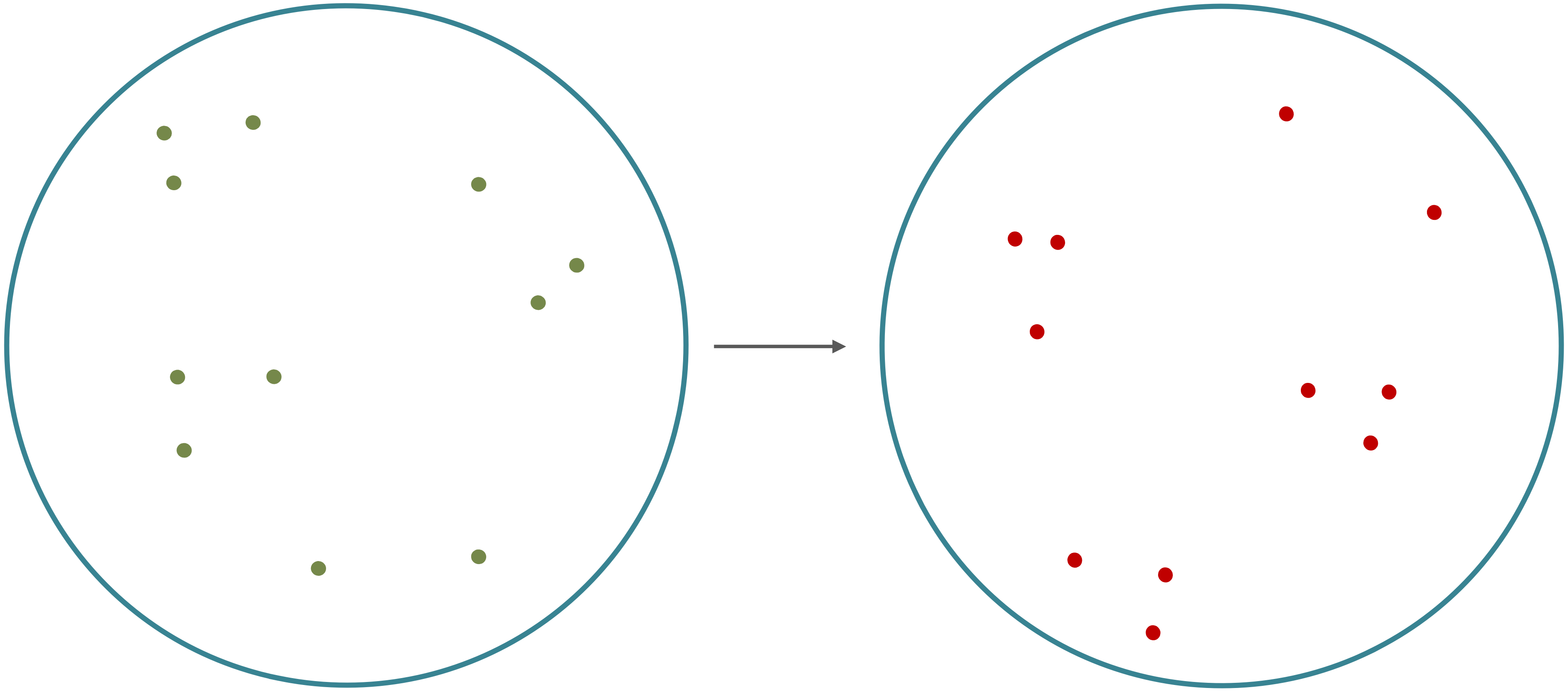

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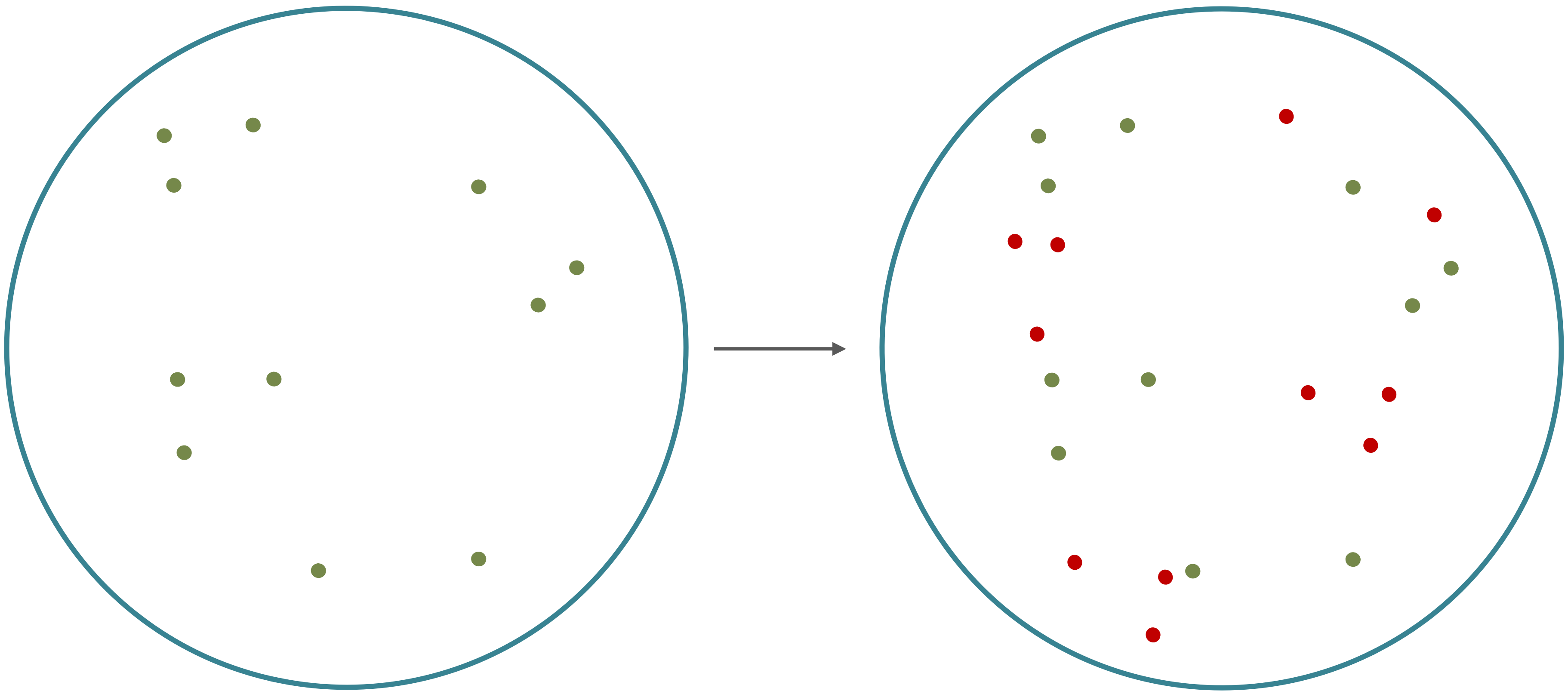

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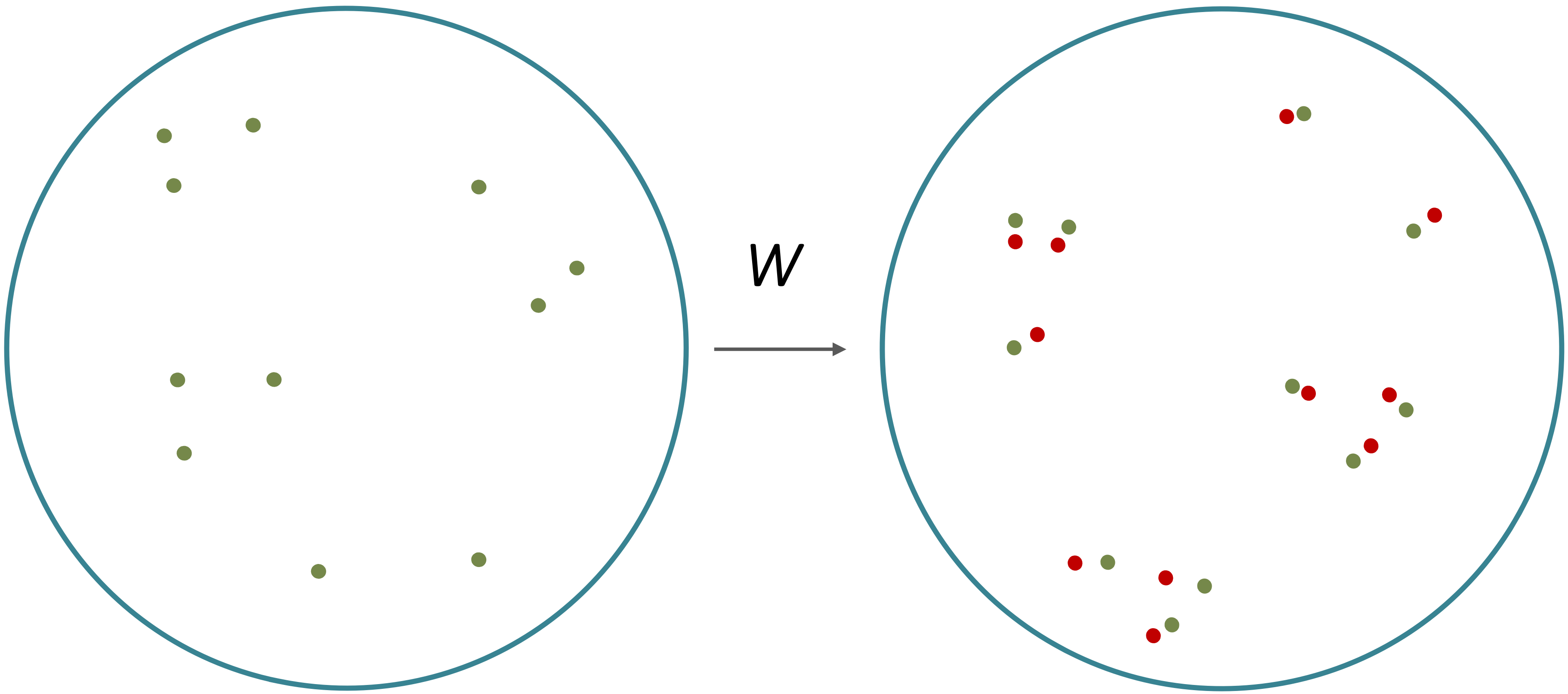
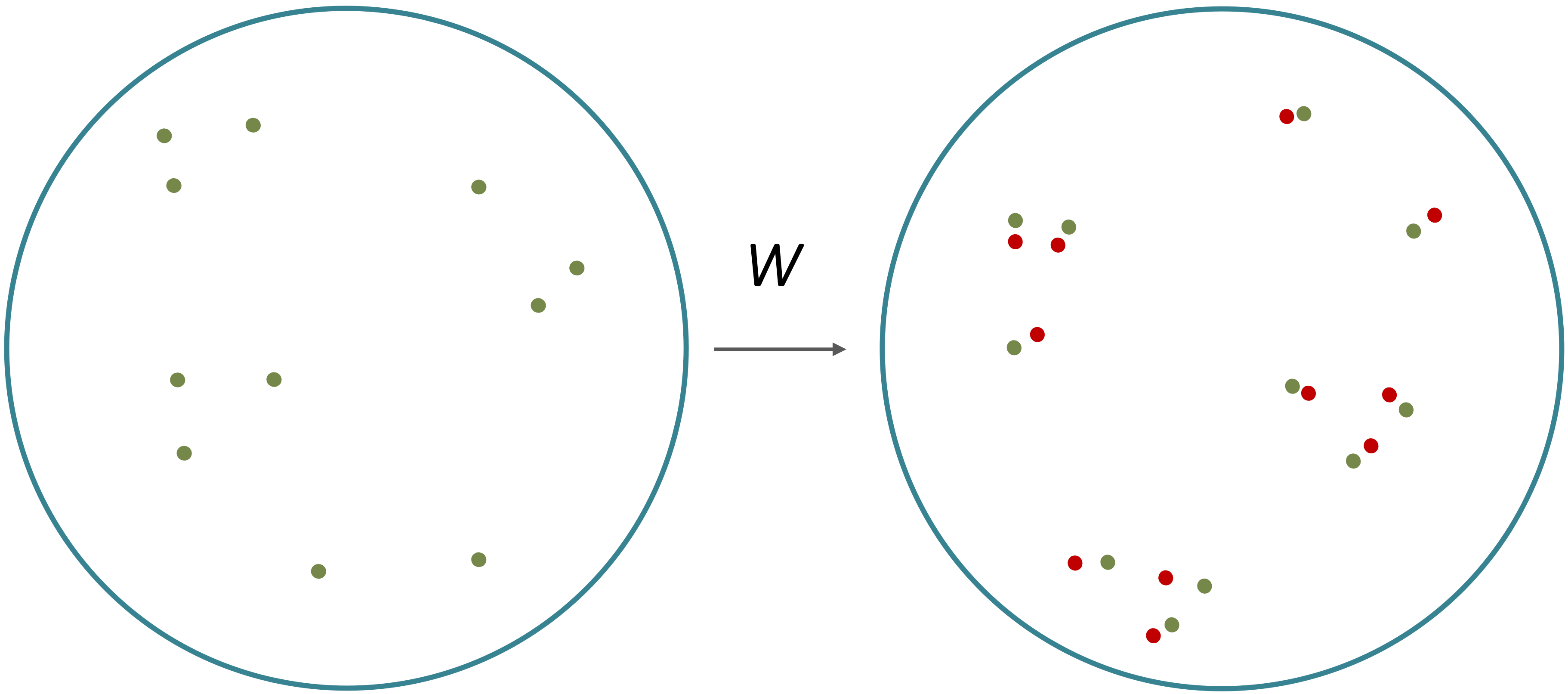


Why does it work?

Languages are (to a large extent)
isometric in word embedding space (!)

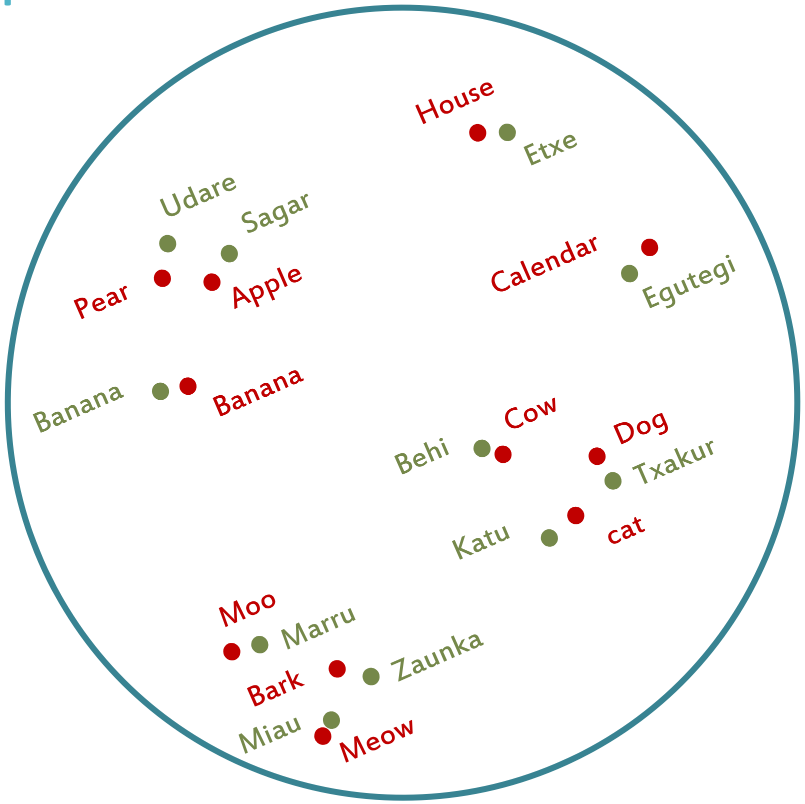


Outline

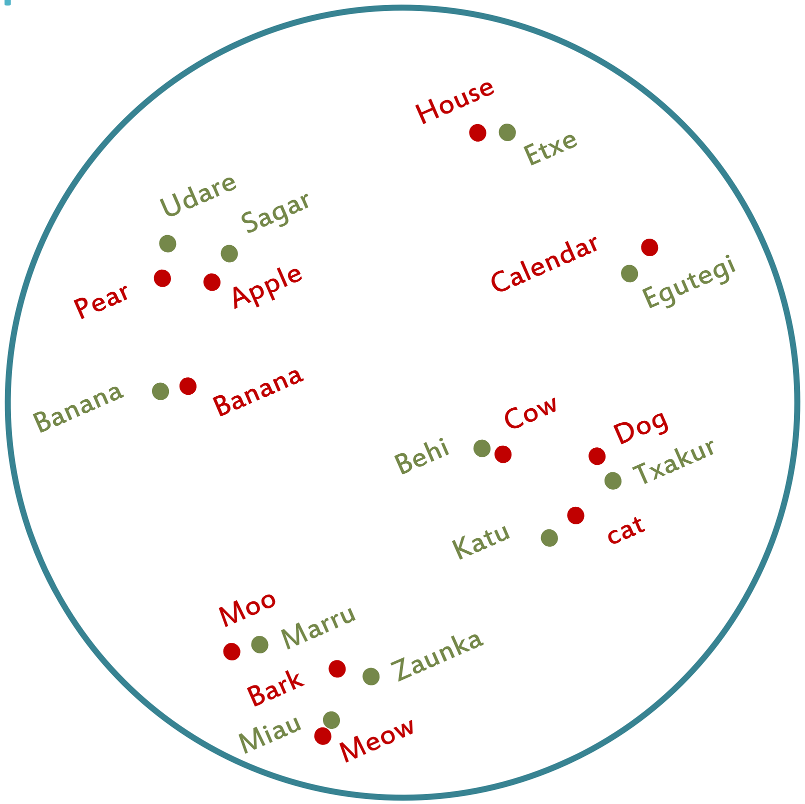
- Bilingual embedding mappings
  - *Introduction to vector space models (embeddings)*
  - *Bilingual embedding mappings (AAAI18)*
  - *Reduced supervision*
    - Self-learning, semi-supervised (ACL17)
    - Self-learning, fully unsupervised (ACL18)
  - *Conclusions*
- Unsupervised neural machine translation
  - *Introduction to NMT*
  - *From bilingual embeddings to uNMT (ICLR18)*
  - *Unsupervised statistical MT (EMNLP18)*
  - *Conclusions*

Reducing supervision

Reducing supervision



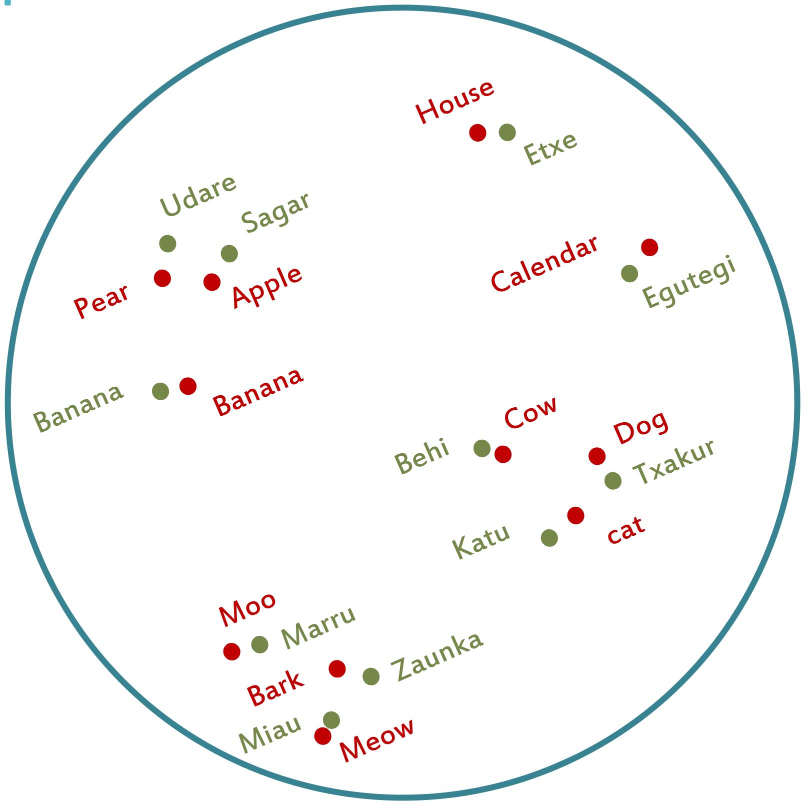
Reducing supervision



bilingual signal for training

Previous work

Reducing supervision

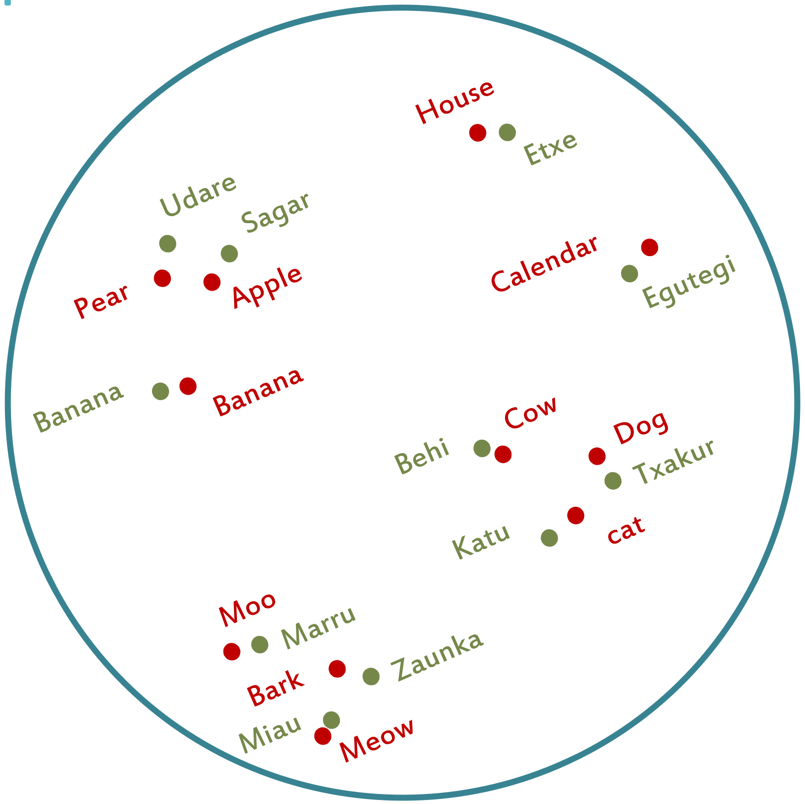


bilingual signal for training

<u>Previous work</u>

- parallel corpora
- comparable corpora
- (big) dictionaries

Reducing supervision



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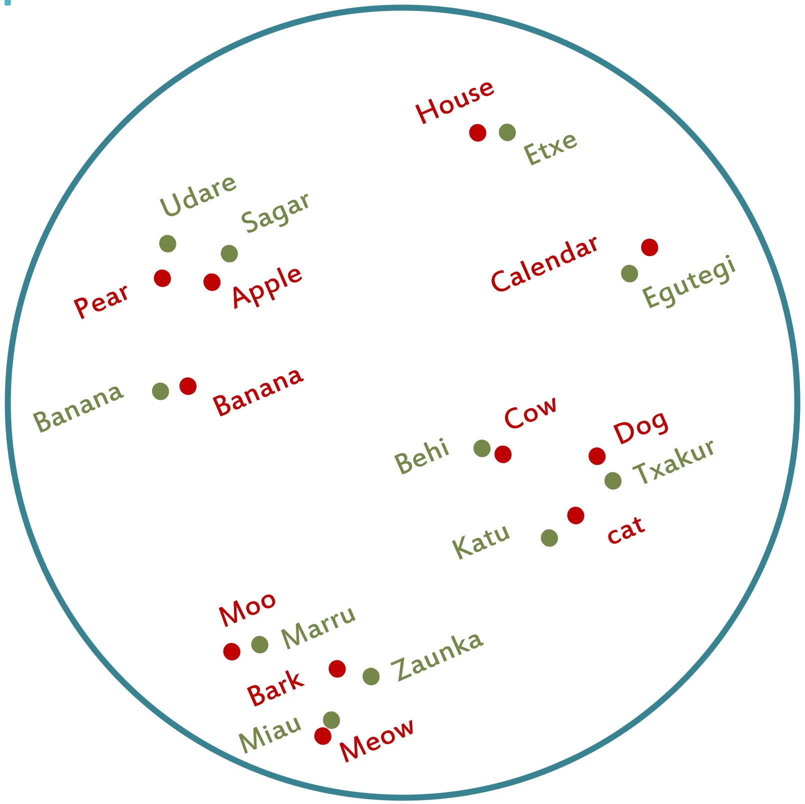


bilingual signal for training

~~Previous work~~	Our work
~~- parallel corpora~~	- 25 word dictionary
~~- comparable corpora~~	- numerals (1, 2, 3…)
~~- (big) dictionaries~~	- nothing

Self-learning

Self-learning

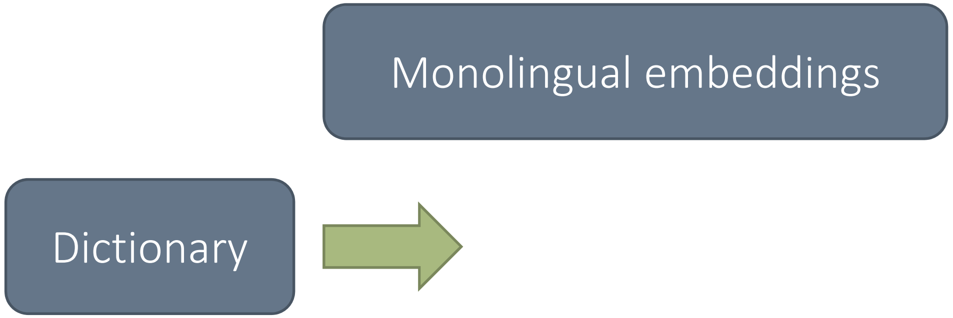
Monolingual embeddings

Self-learning

Monolingual embeddings

Dictionary

Self-learning



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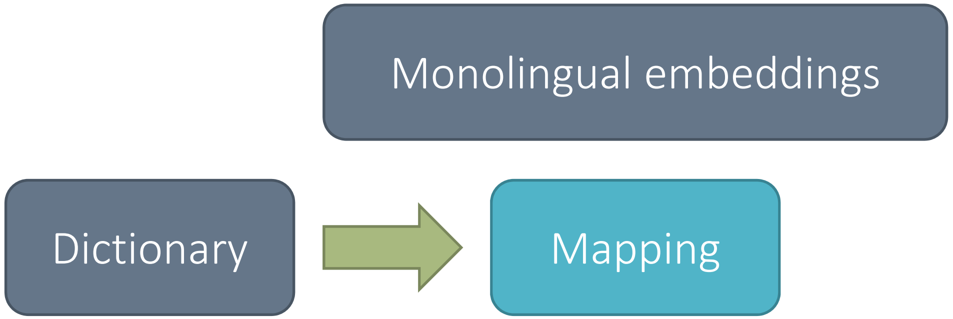

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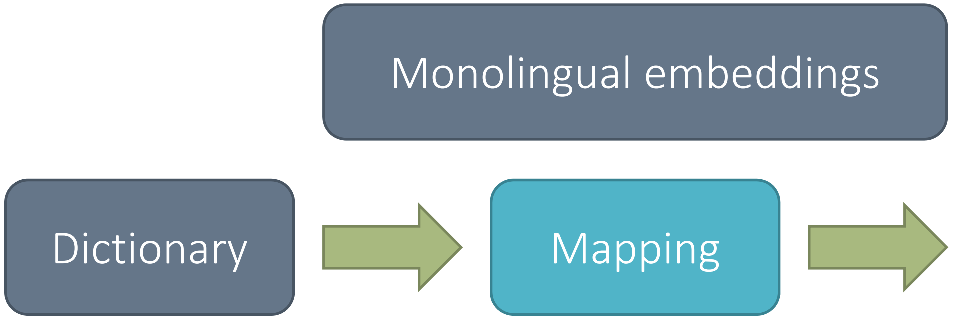

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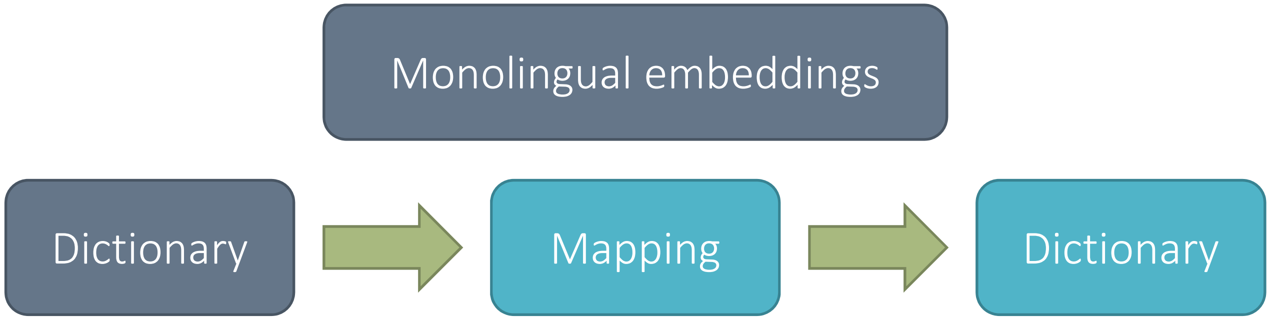

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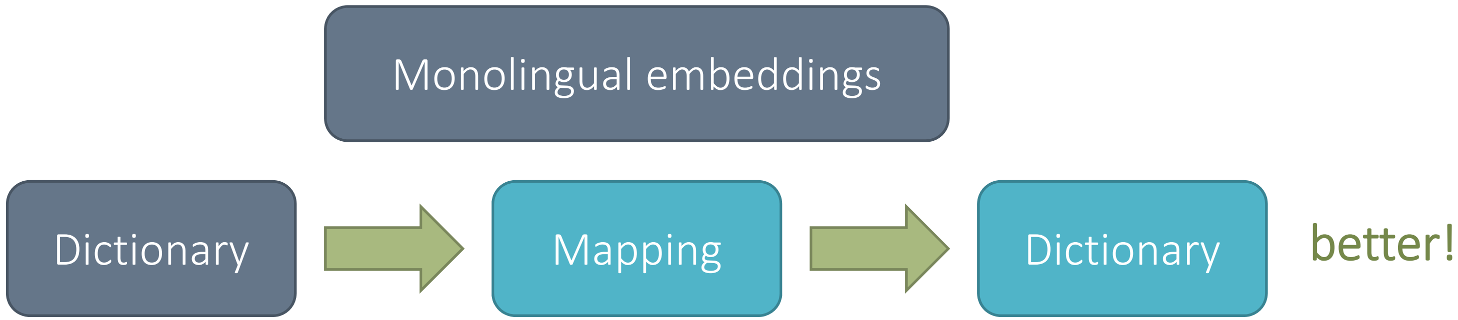

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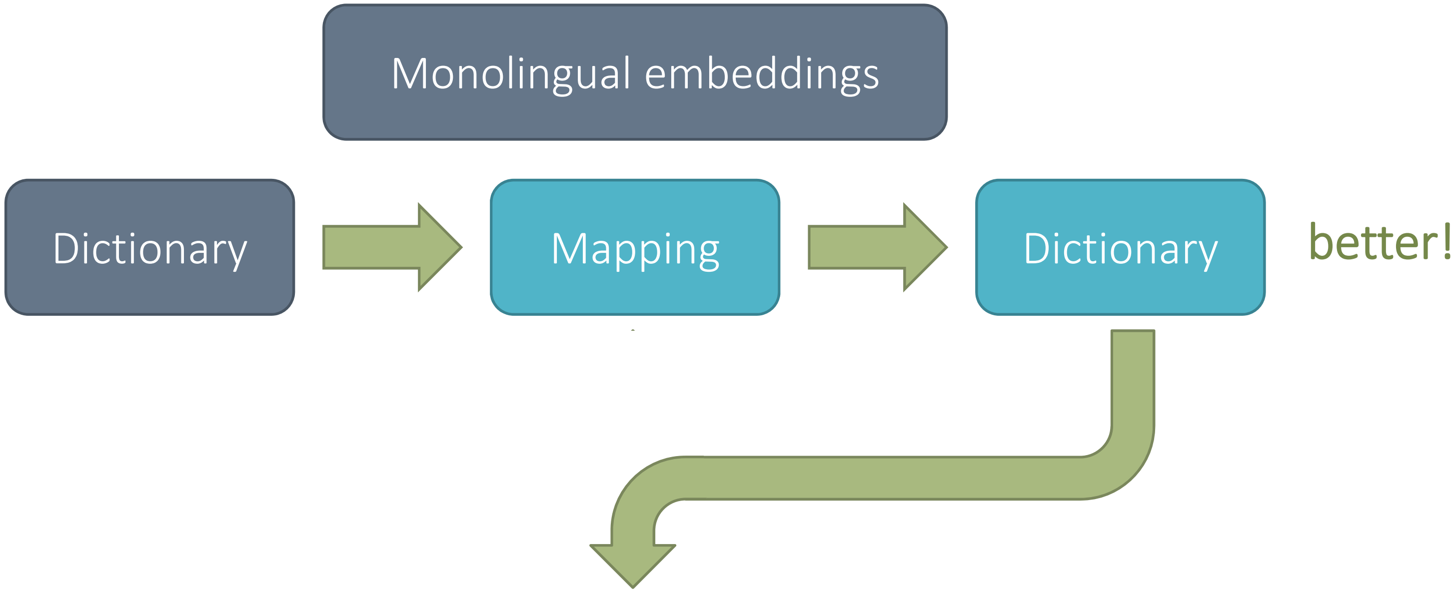

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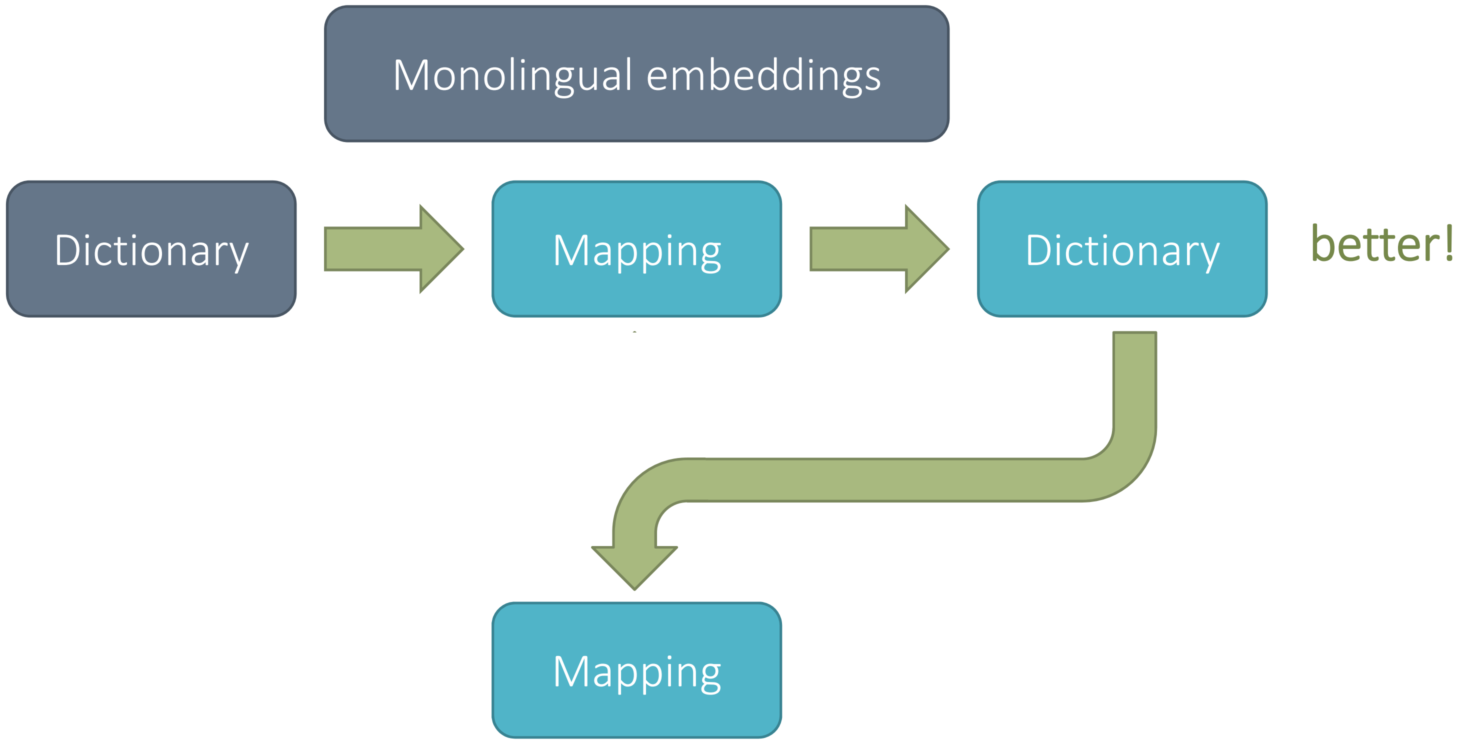

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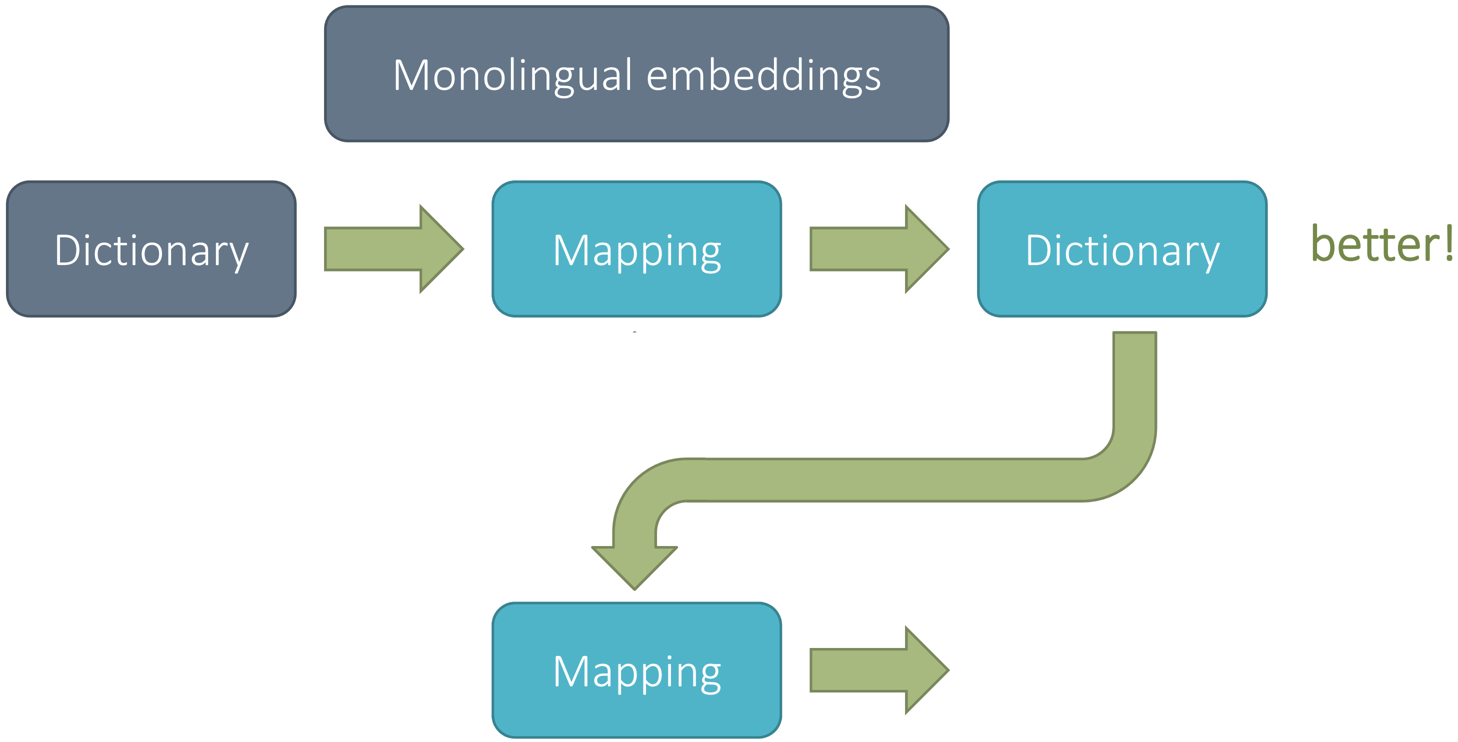

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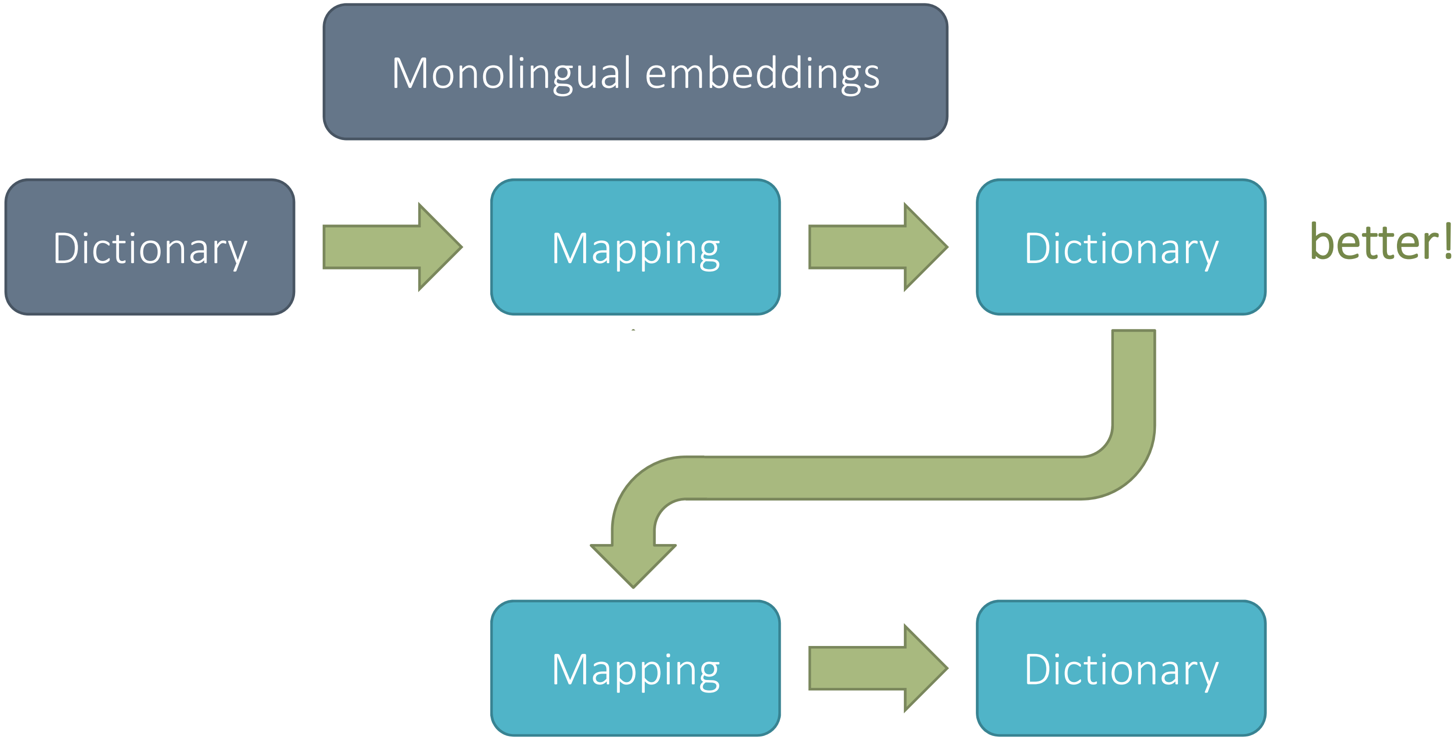

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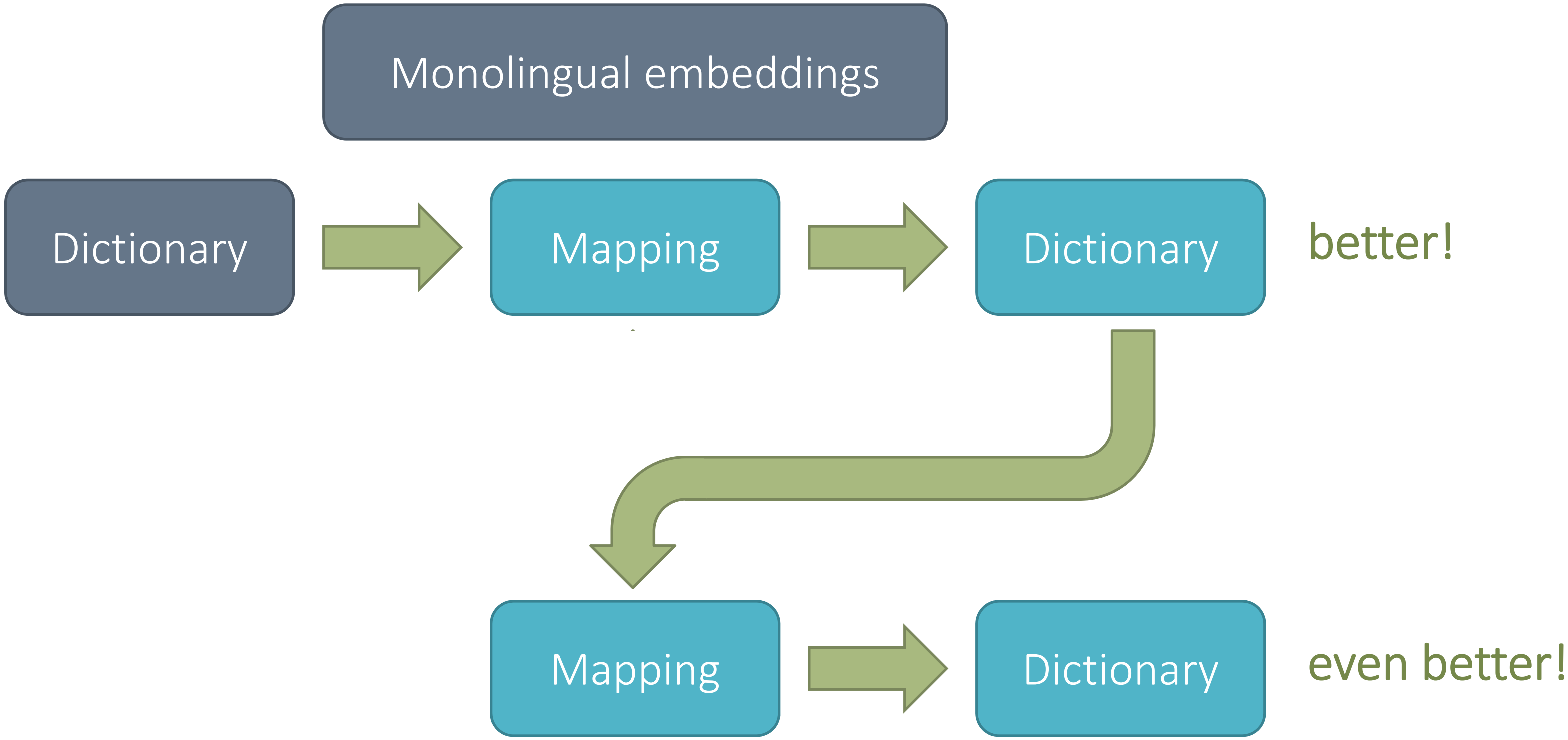

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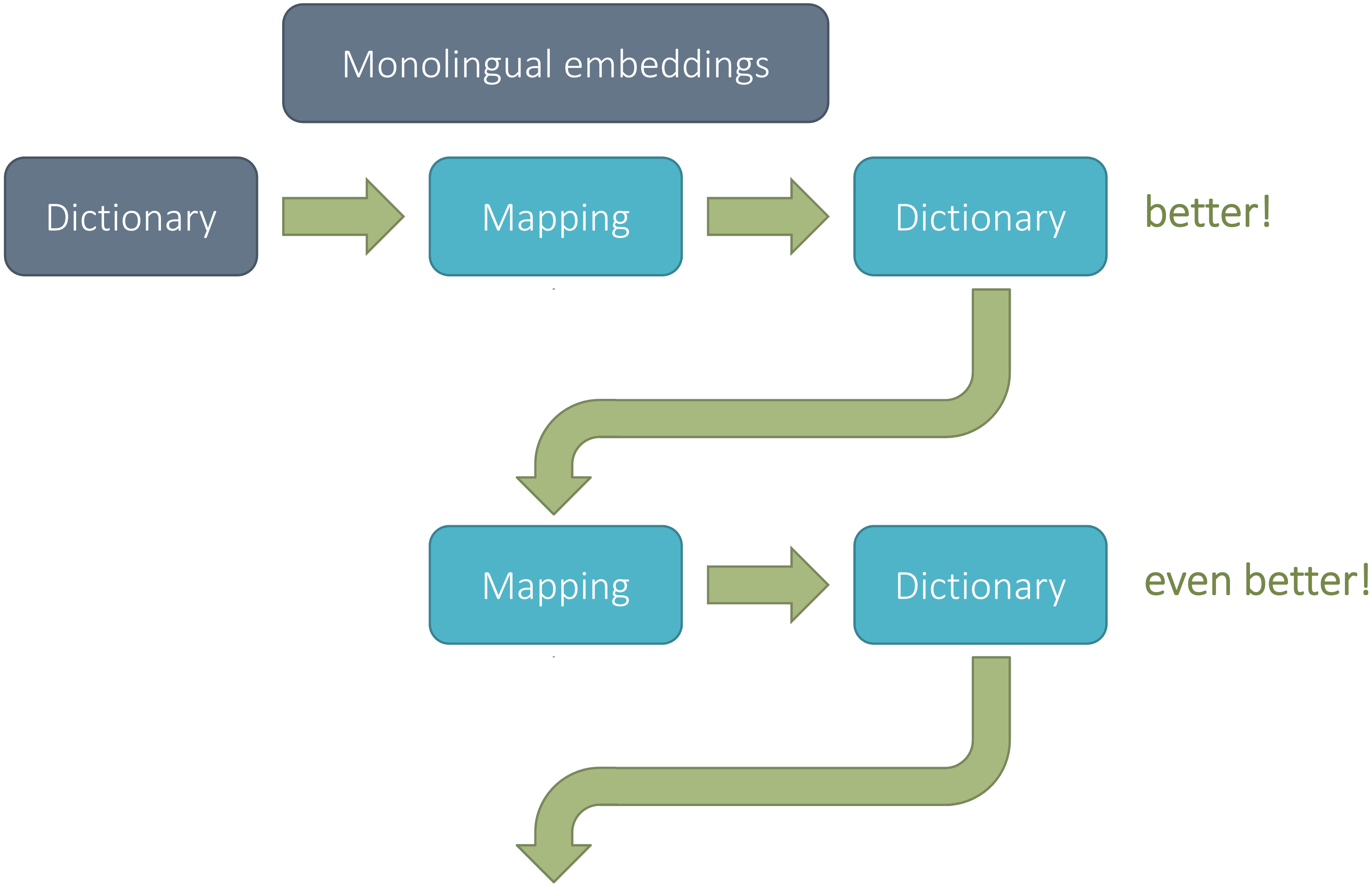

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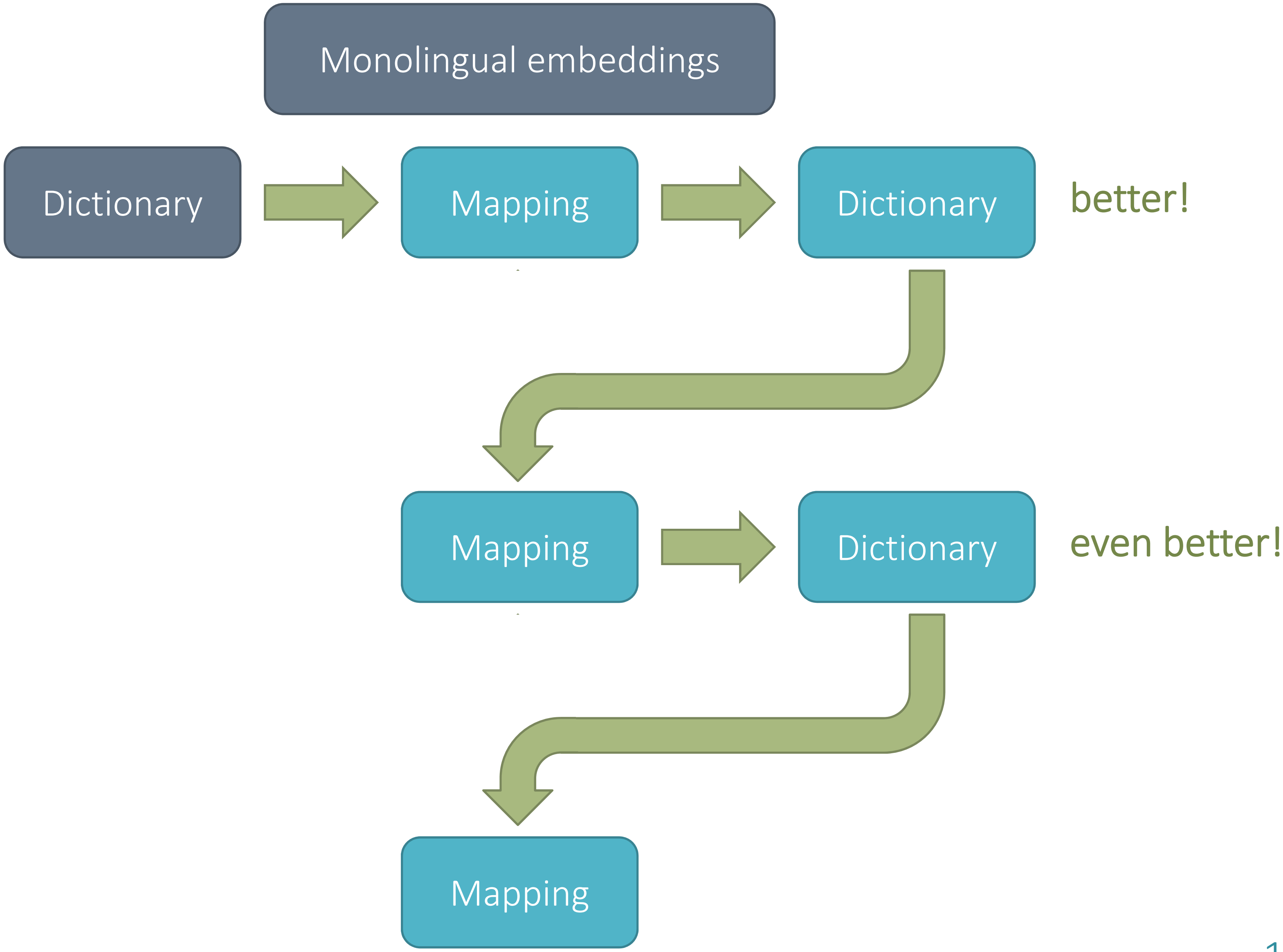

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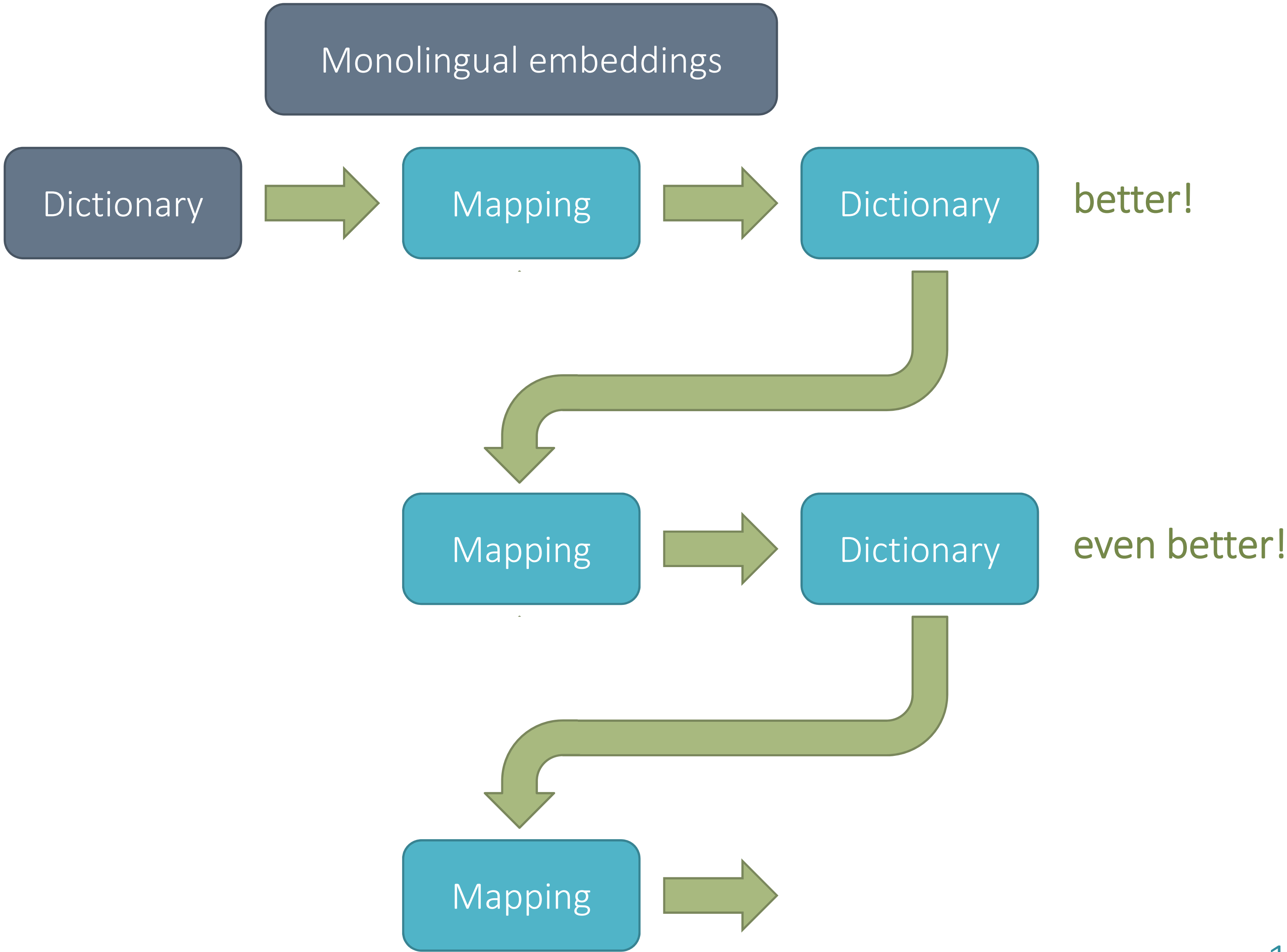

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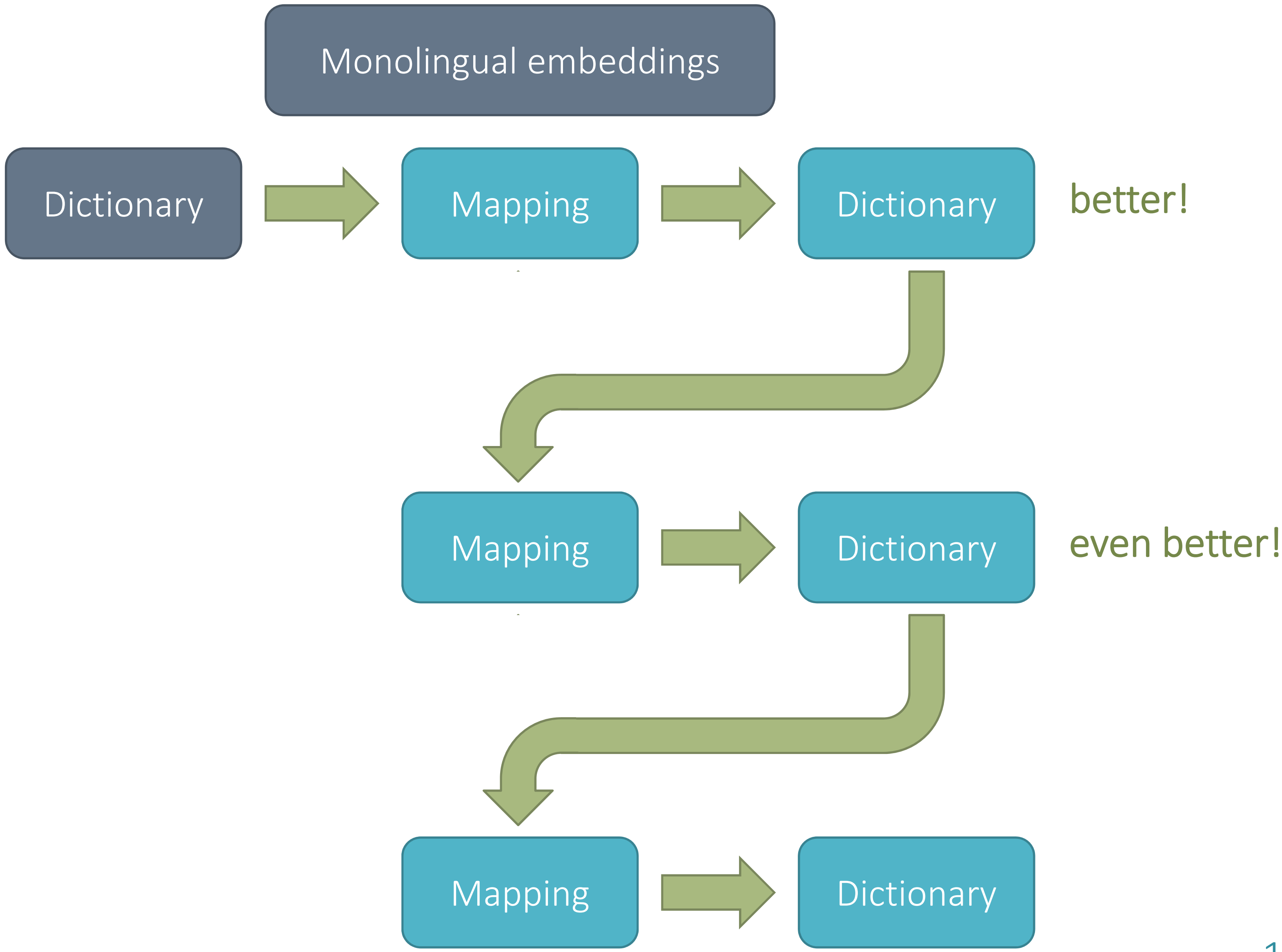

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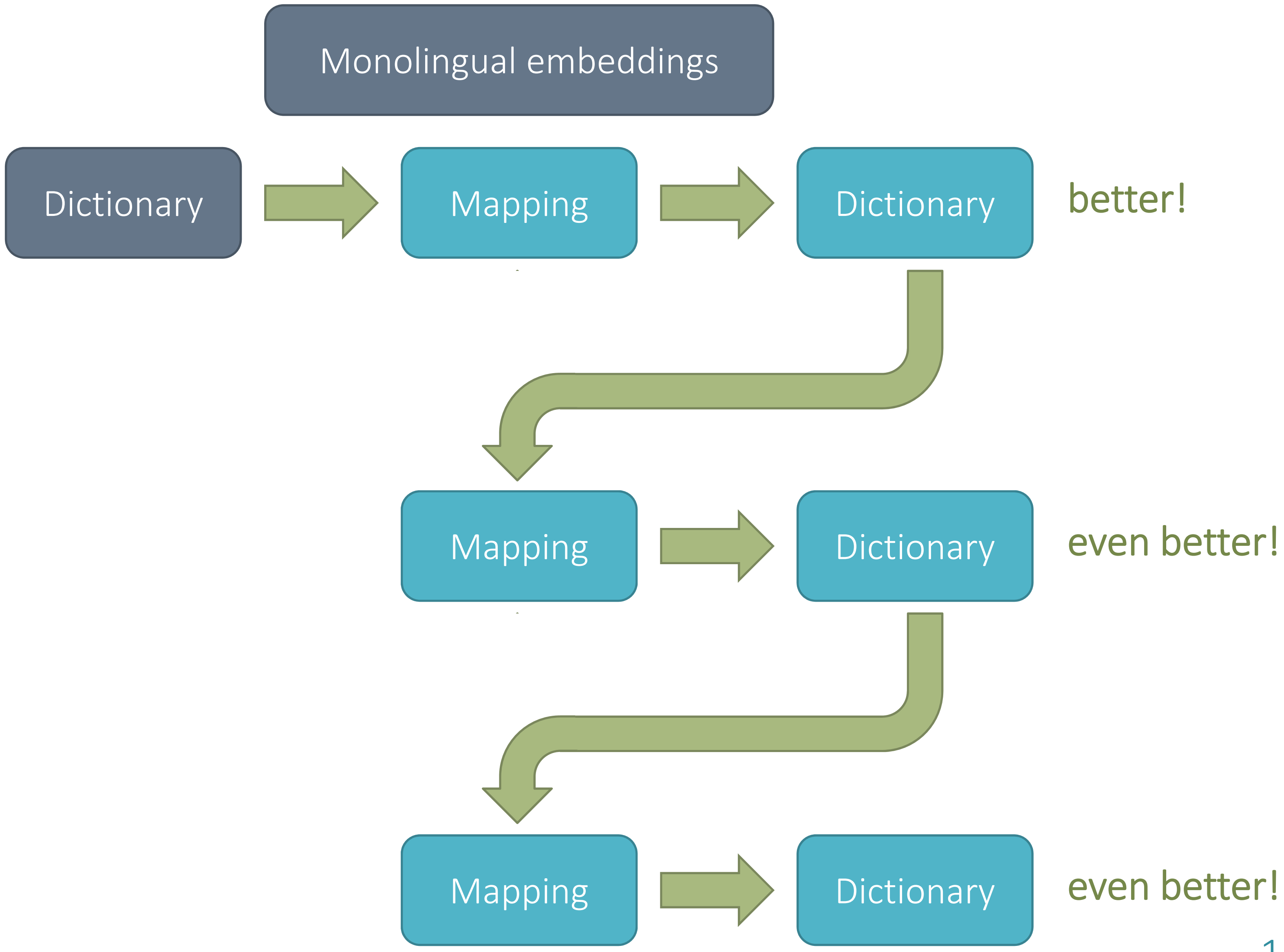

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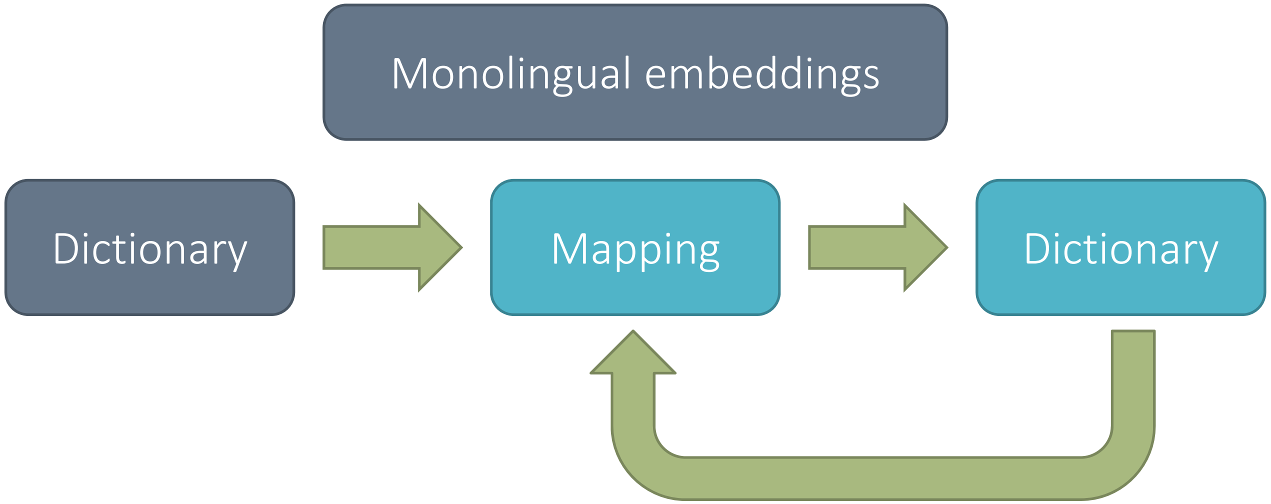

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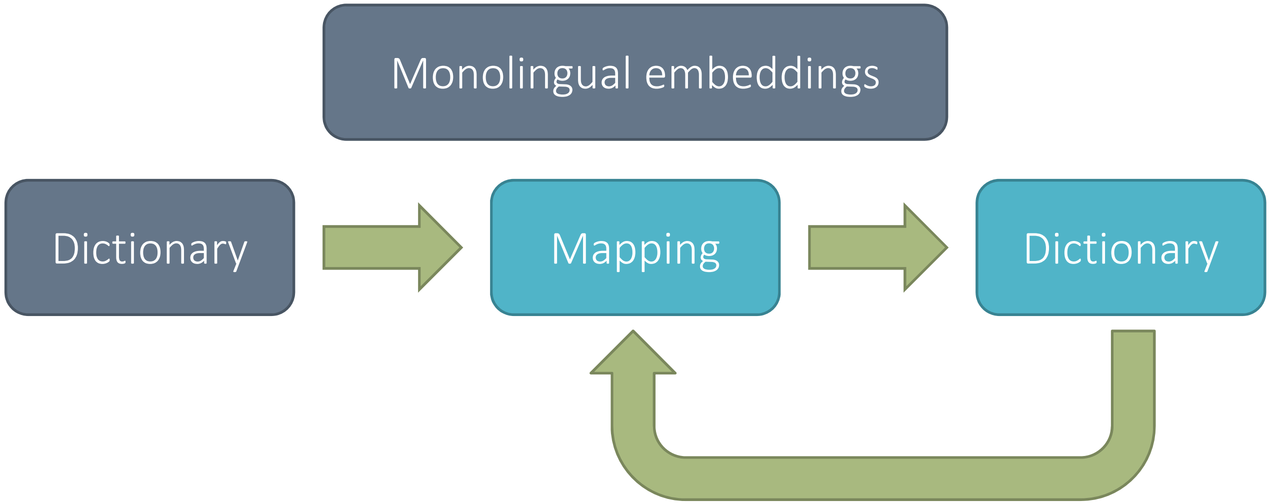

<u>proposed self-learning method</u>

Too good to be true?

Semi-supervised experiments (ACL17)

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- Given monolingual embeddings
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Semi-supervised experiments (ACL17)

- Given monolingual embeddings plus seed bilingual dictionary (*train* dictionary):
  - 25 word pairs
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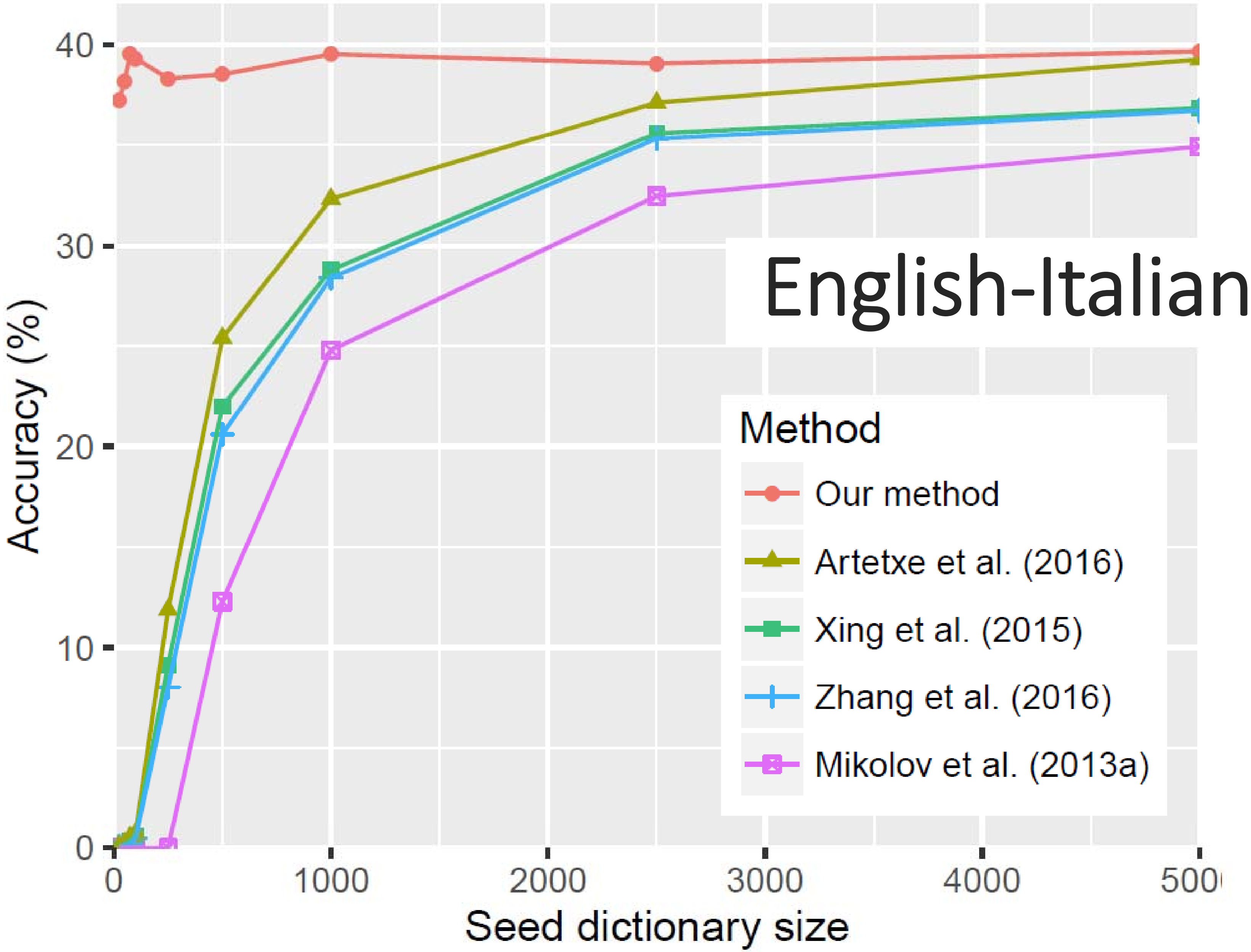
- Induce bilingual dictionary using self-learning for full vocabulary
- Evaluation
  - Compare translations to existing bilingual dictionary (*test* dictionary)
  - Accuracy

Semi-supervised experiments (ACL17)



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<u>Implicit objective</u>: $W^* = \arg\max_W \sum_i \max_j (X_{i*}W) \cdot Z_{j*} \quad \text{s.t.} \quad WW^T = W^TW = I$

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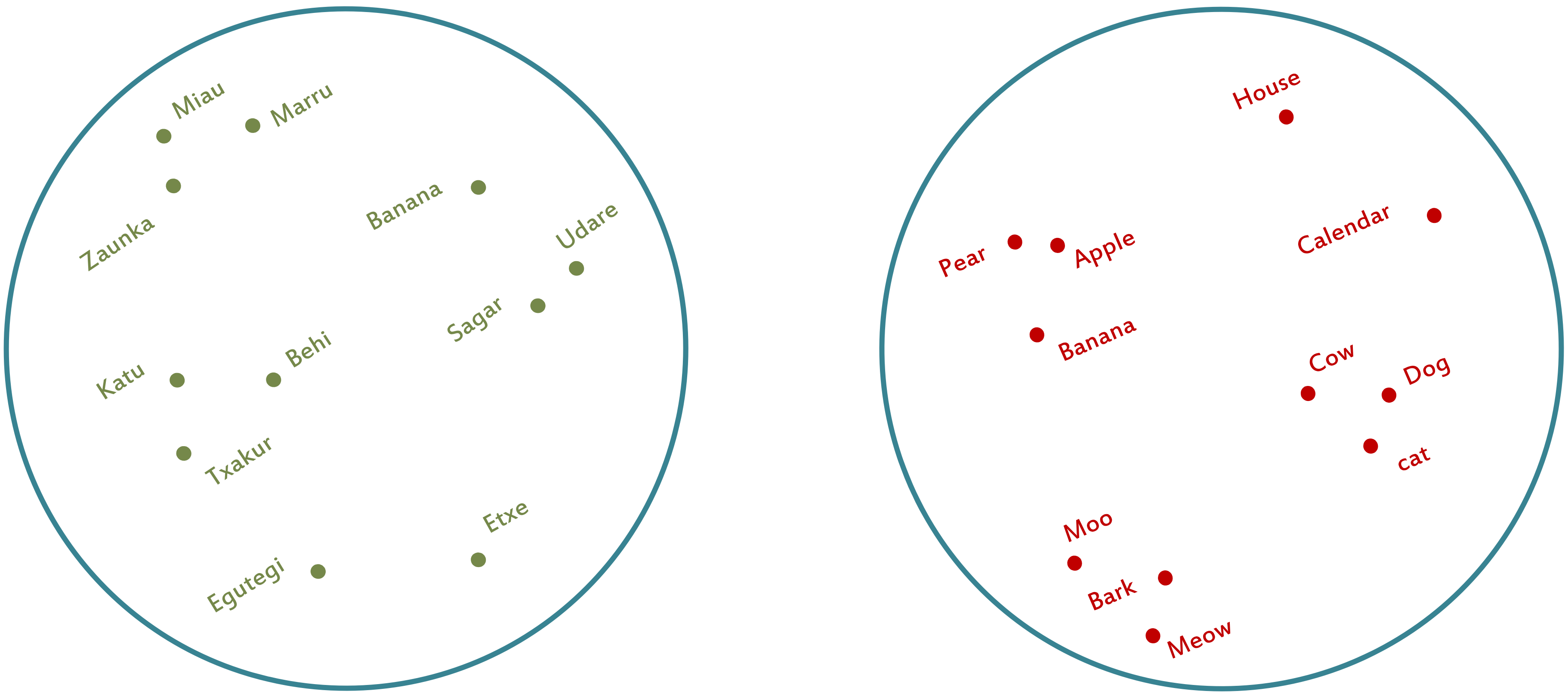

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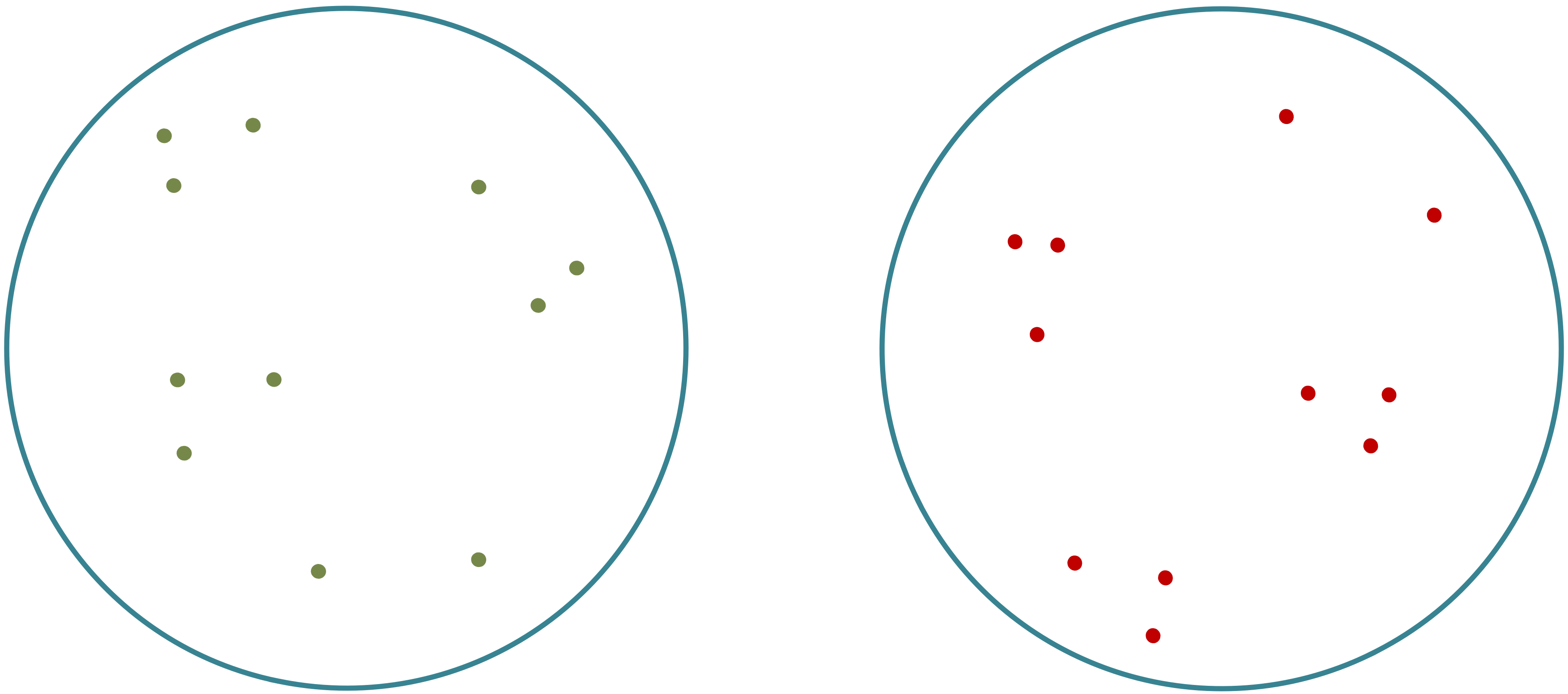

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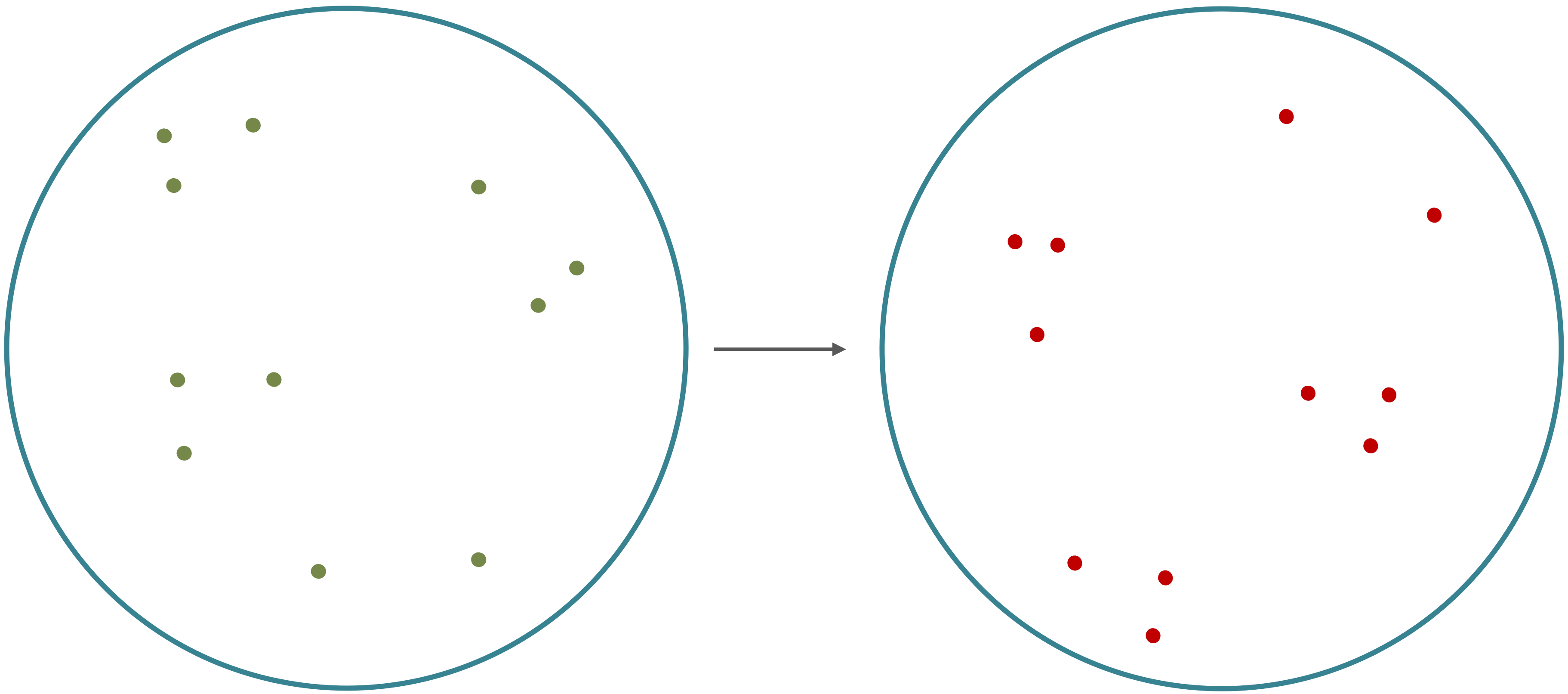

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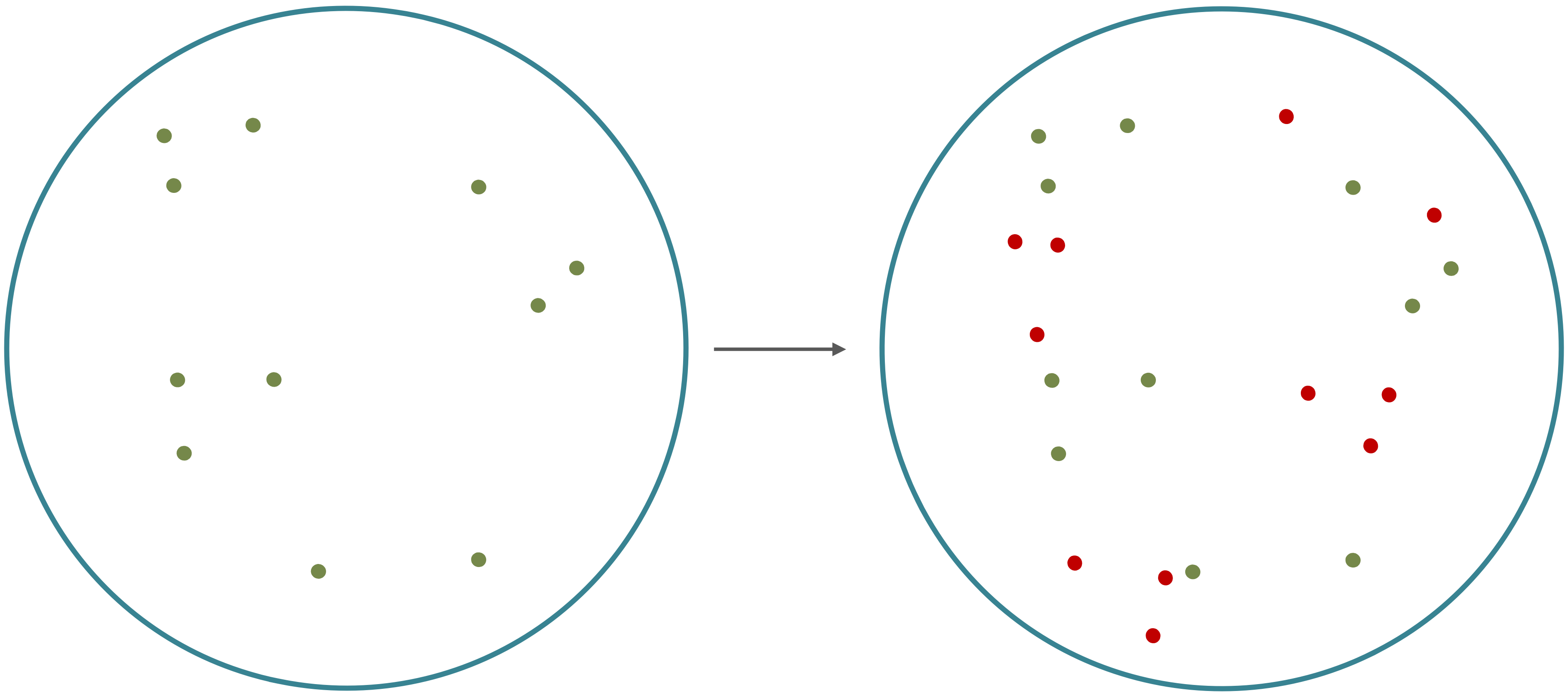

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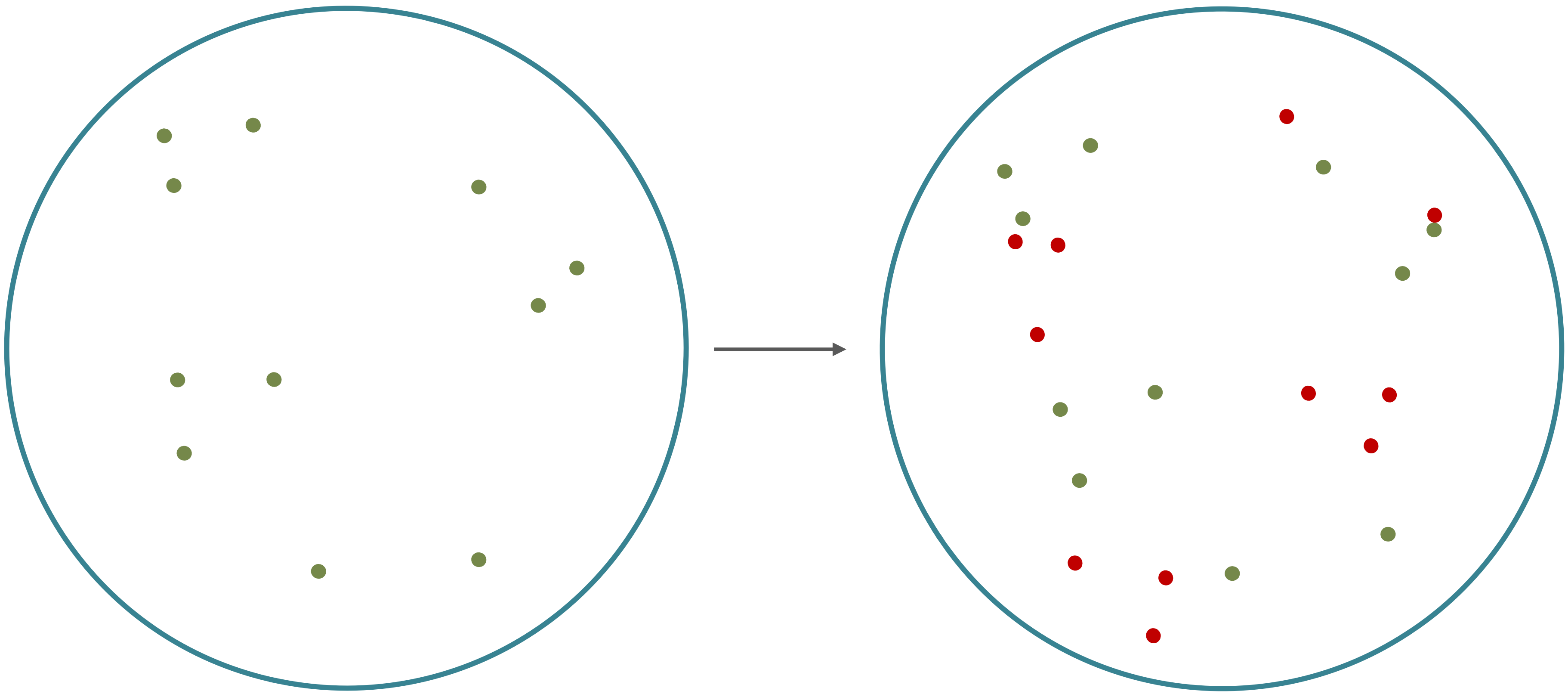

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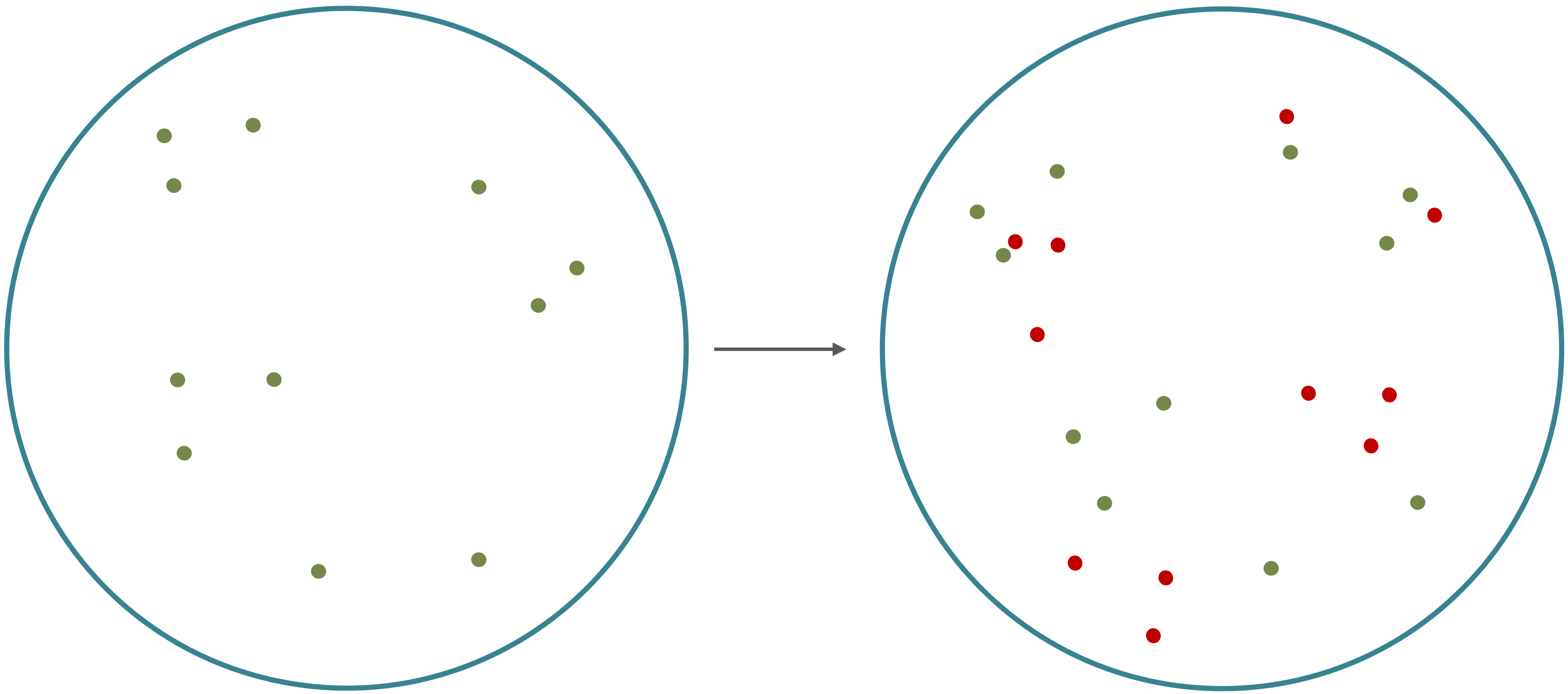

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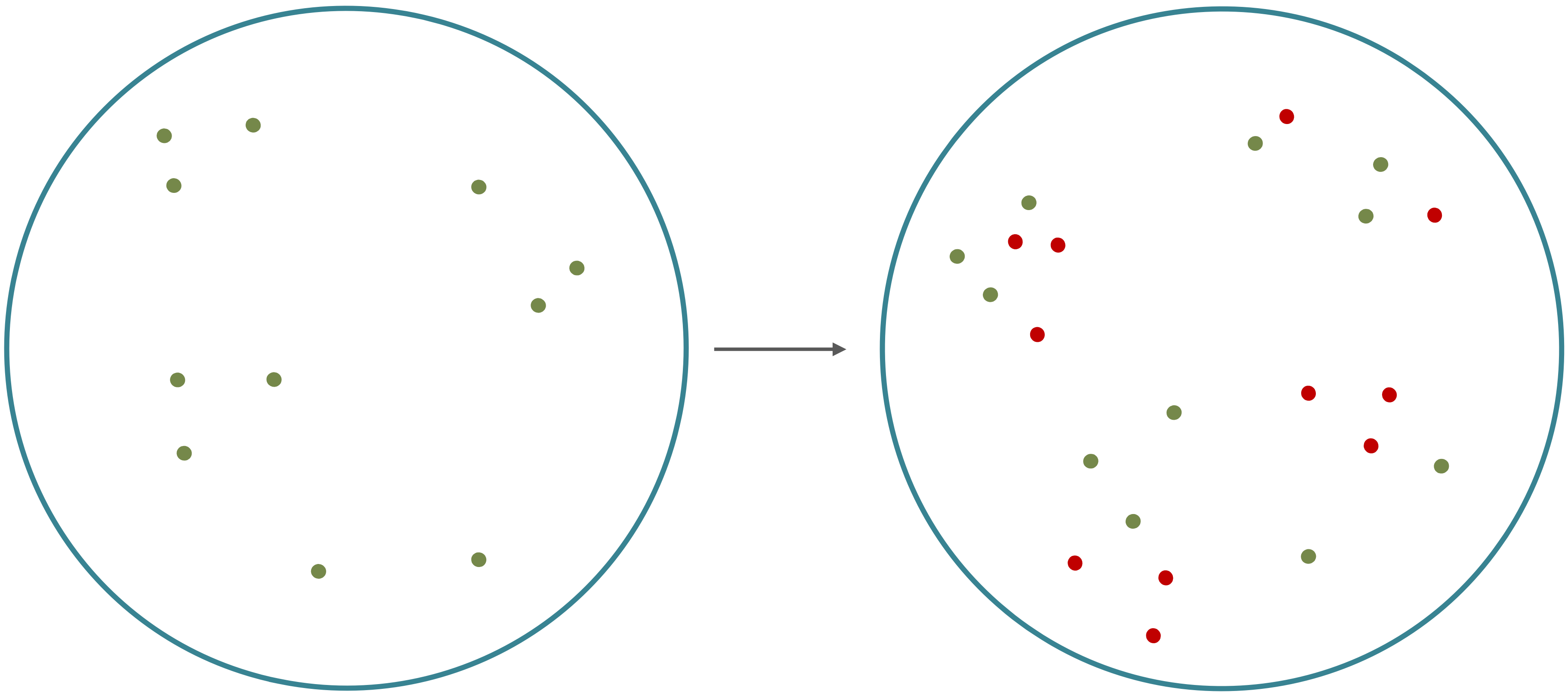

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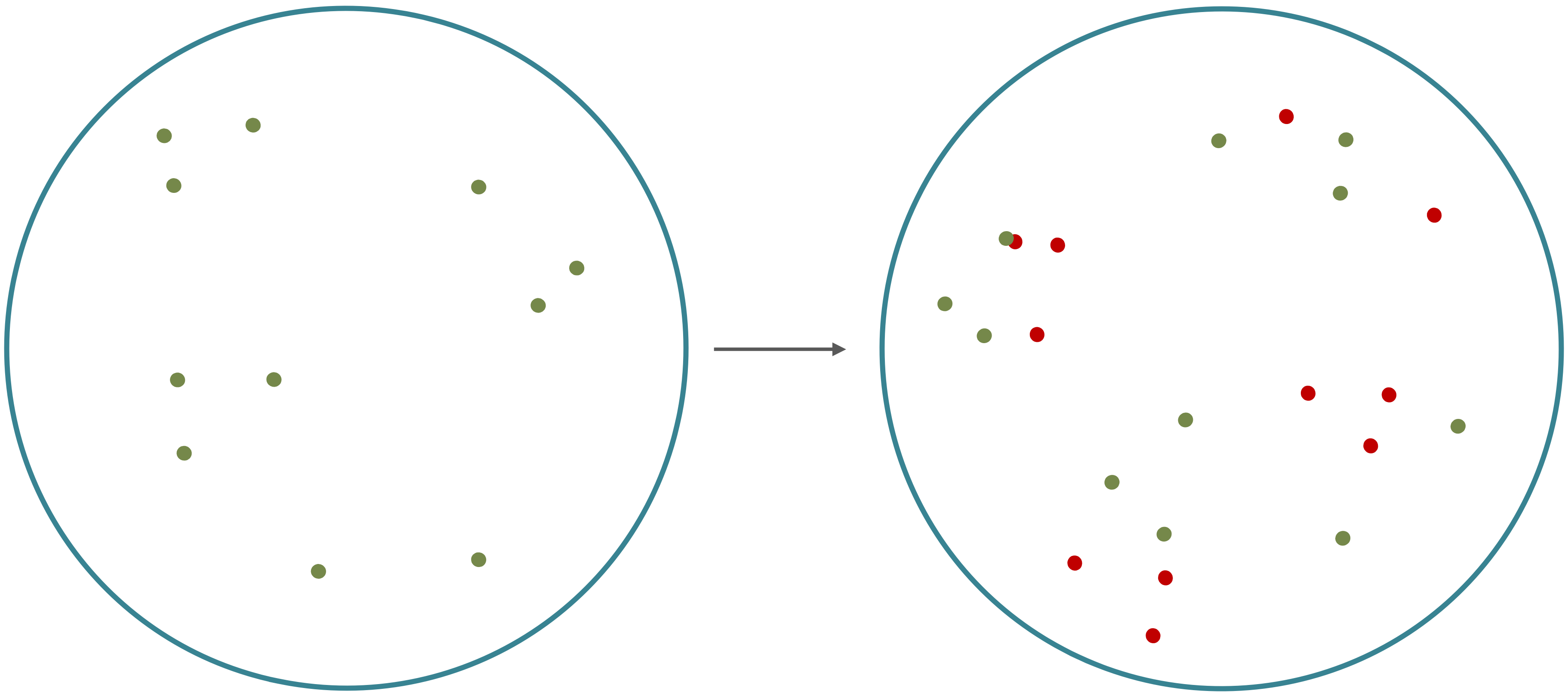
Implicit objective: $W^* = \arg\max_W \sum_i \max_j (X_{i*}W) \cdot Z_{j*}$ s.t. $WW^T = W^TW = I$



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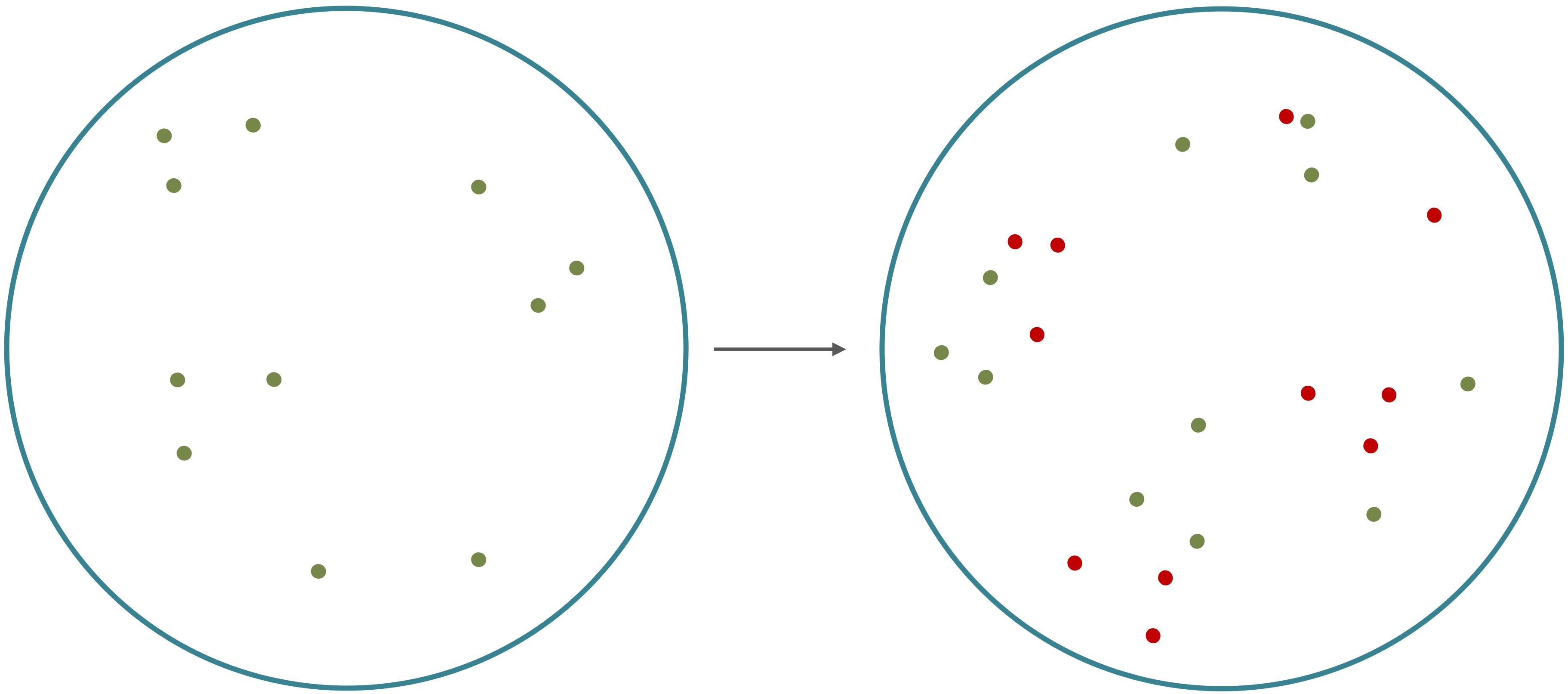

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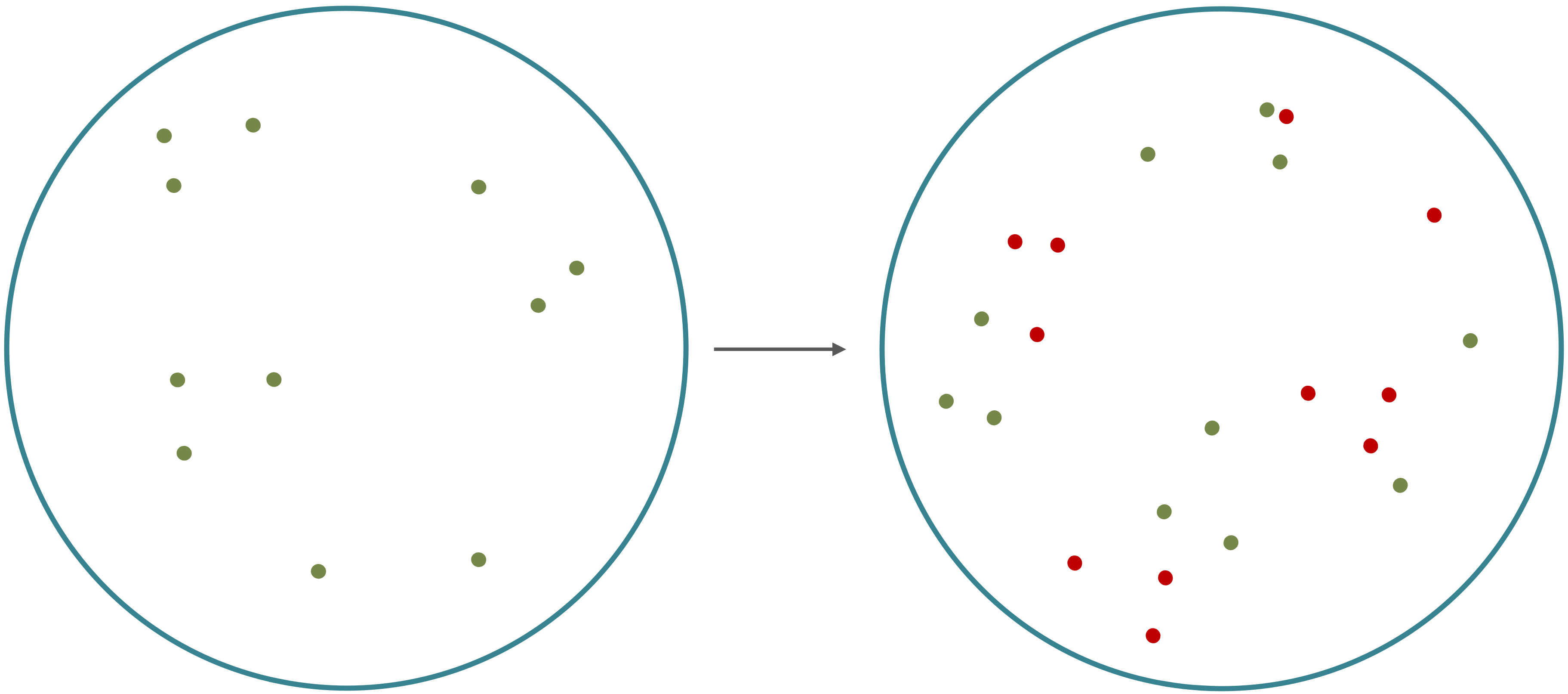

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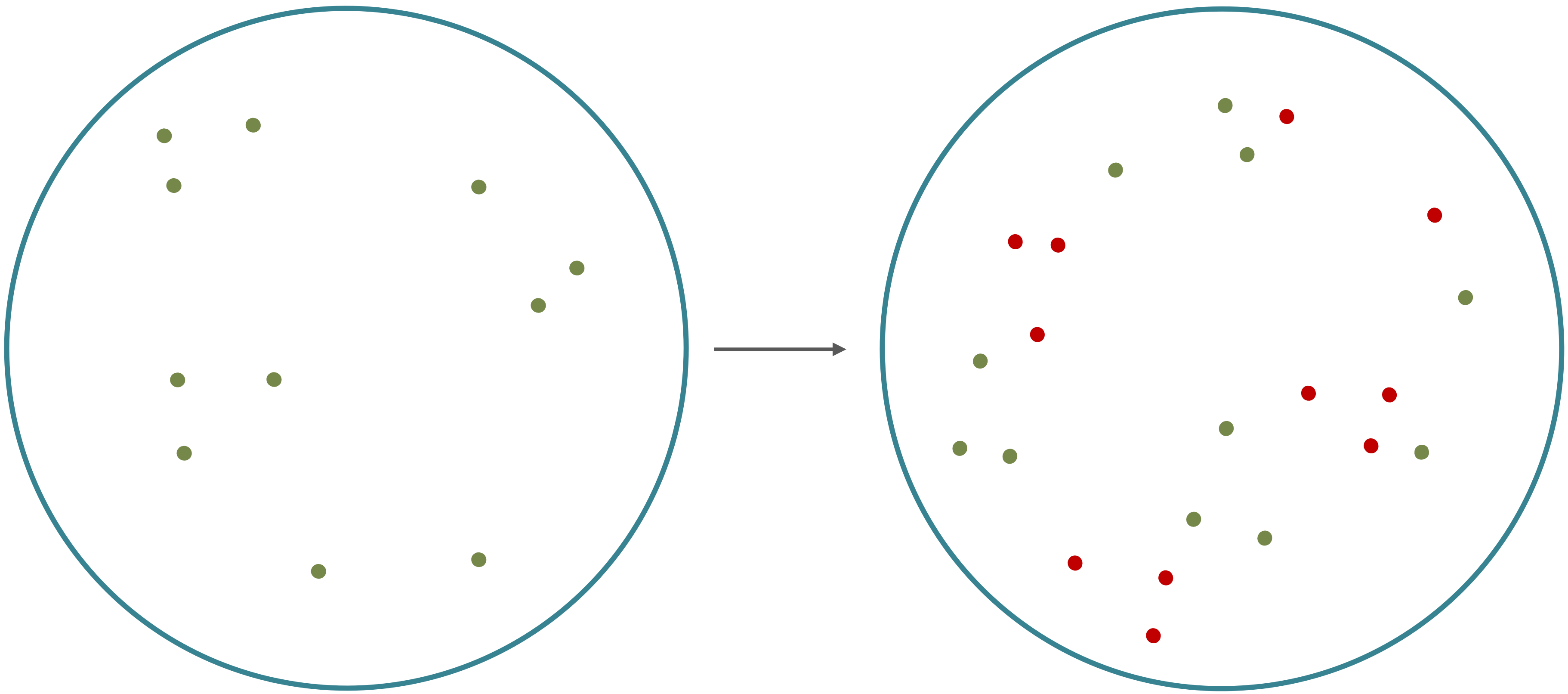

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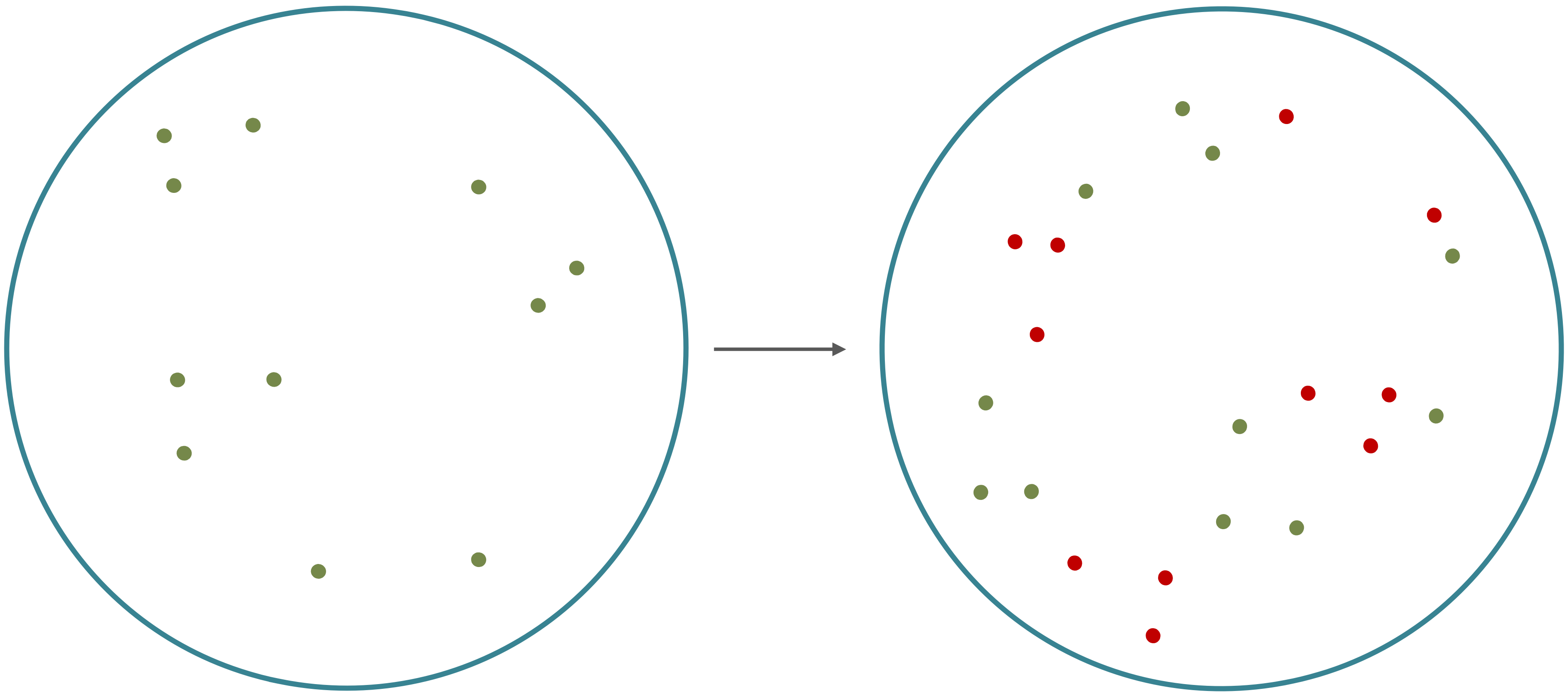

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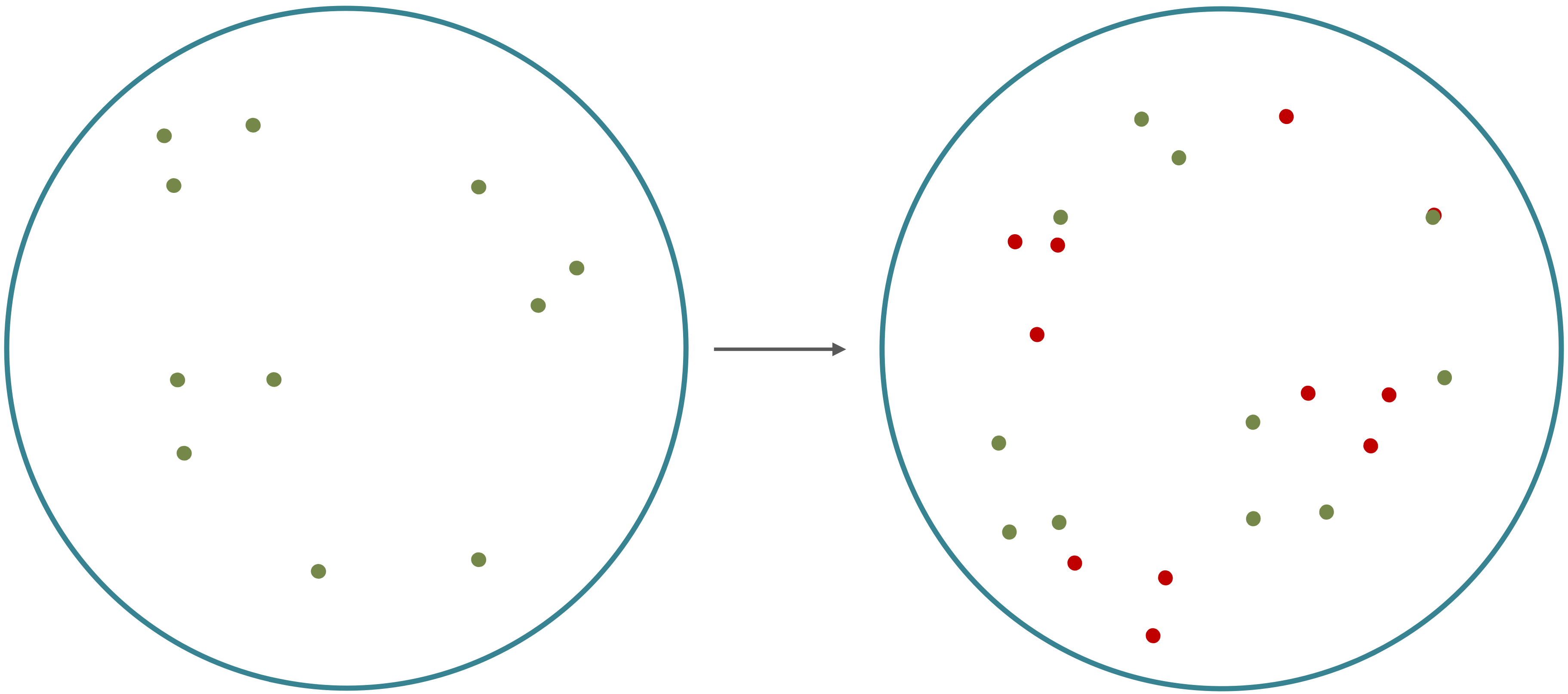

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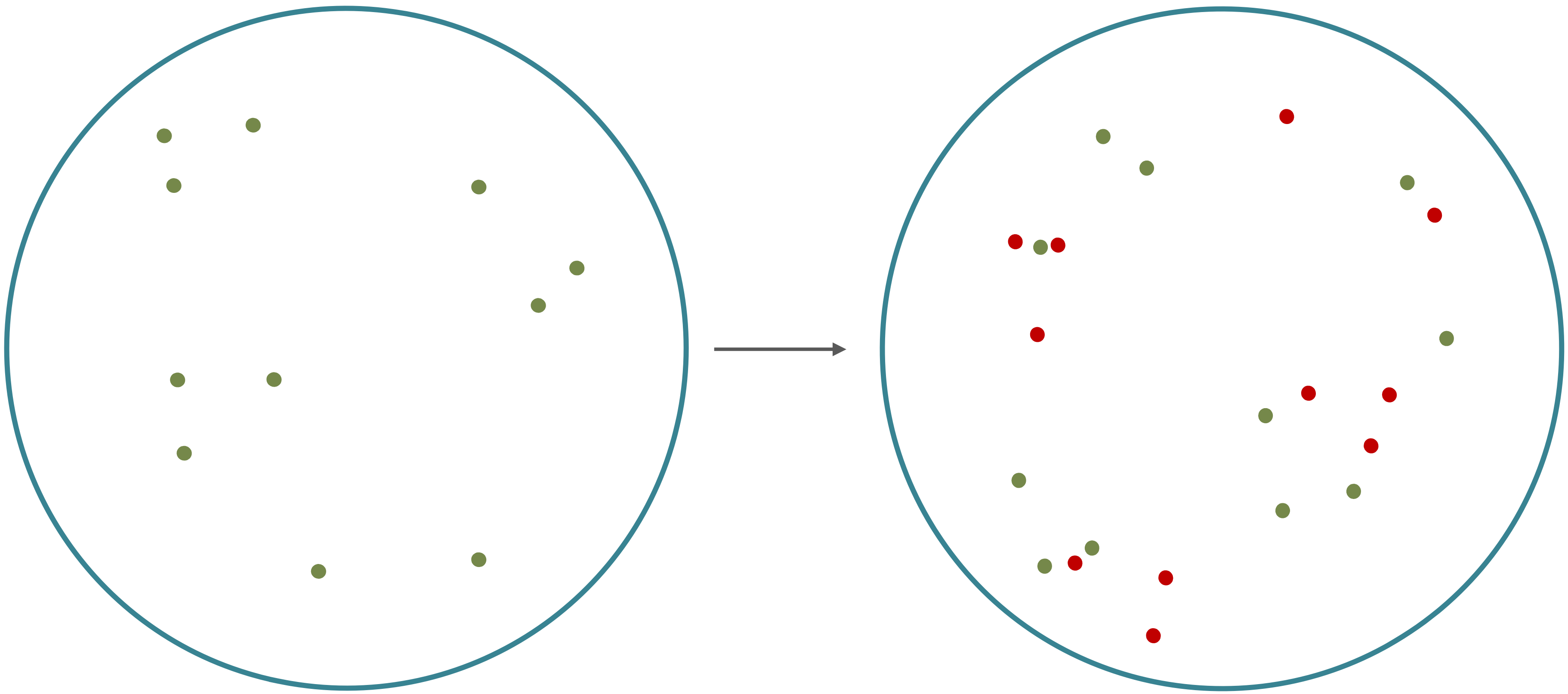

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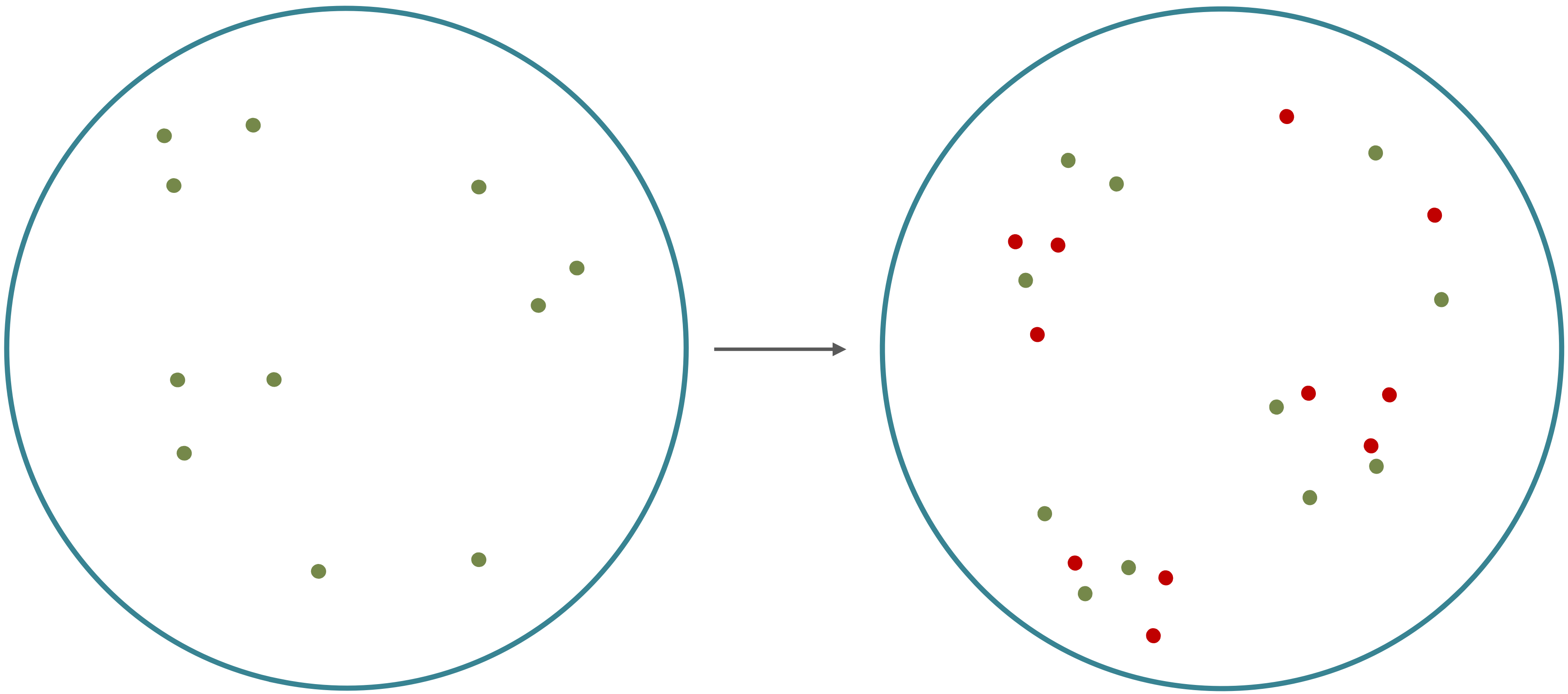

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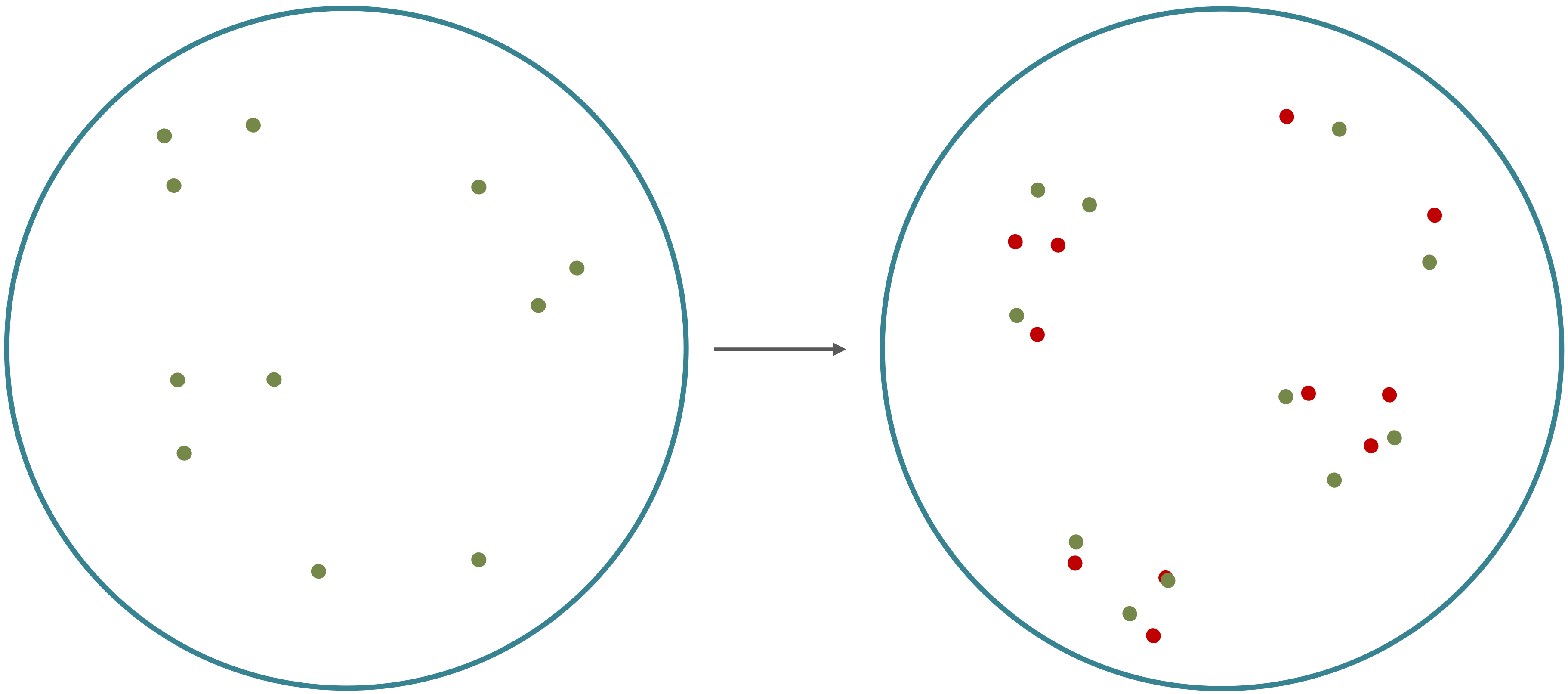

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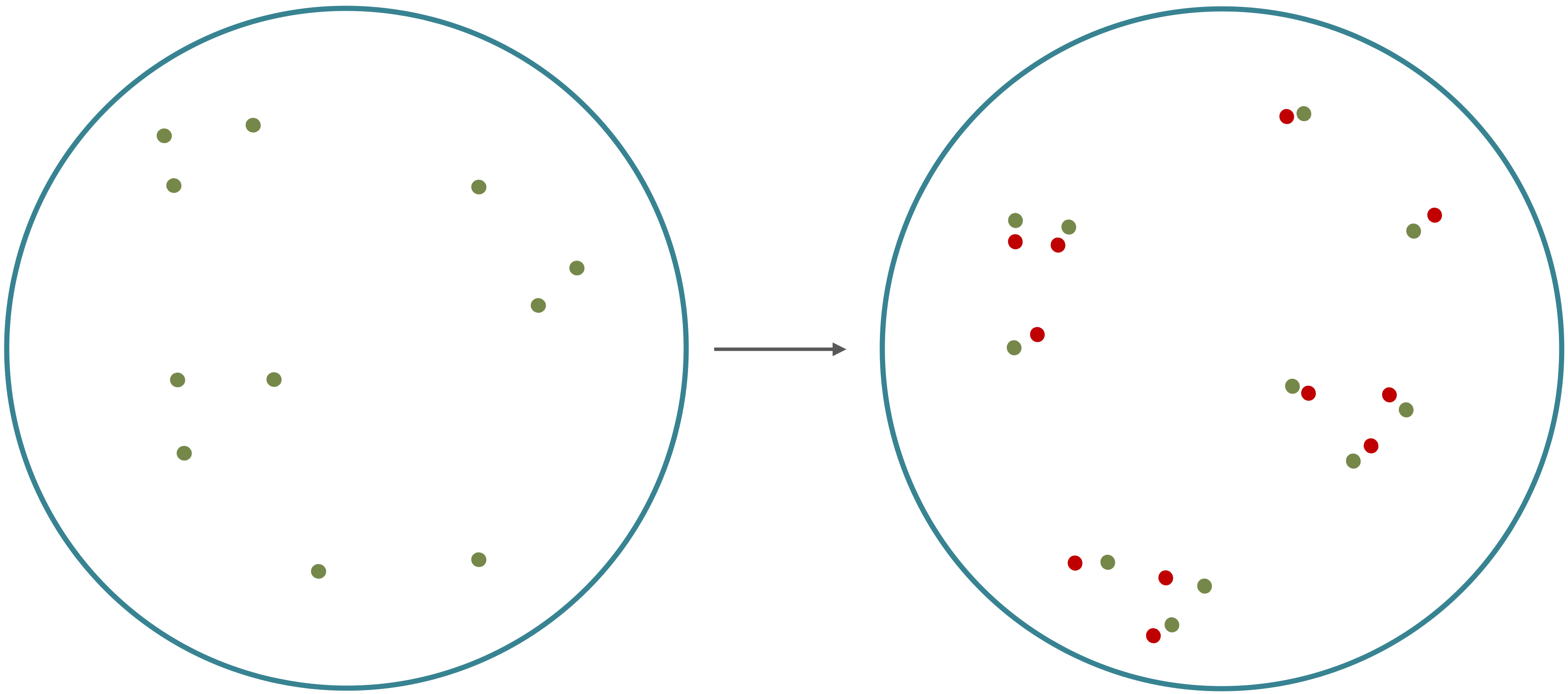

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Independent from seed dictionary!

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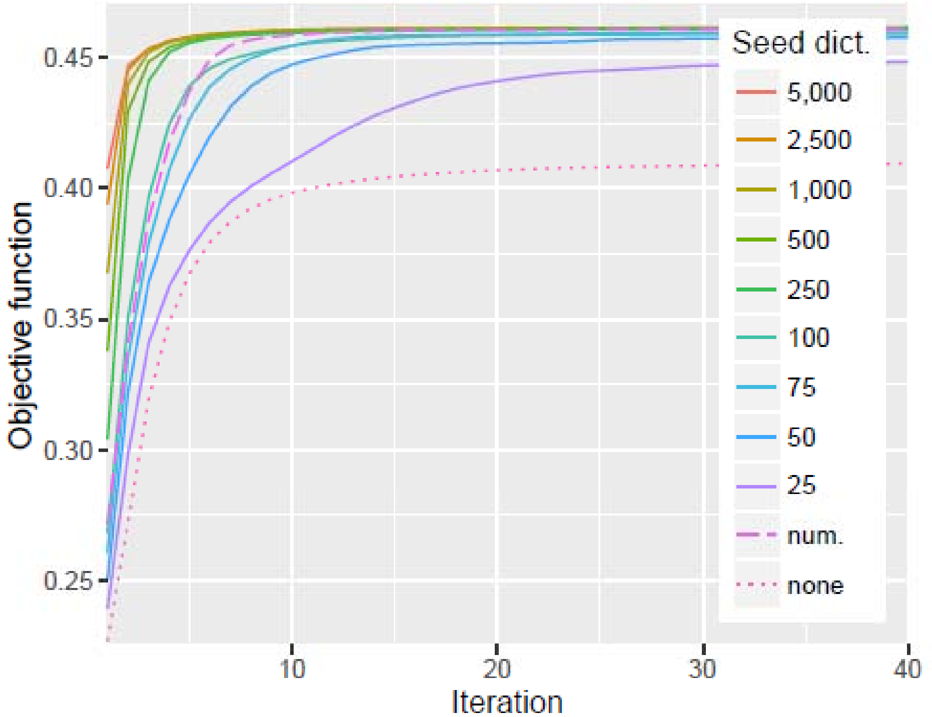

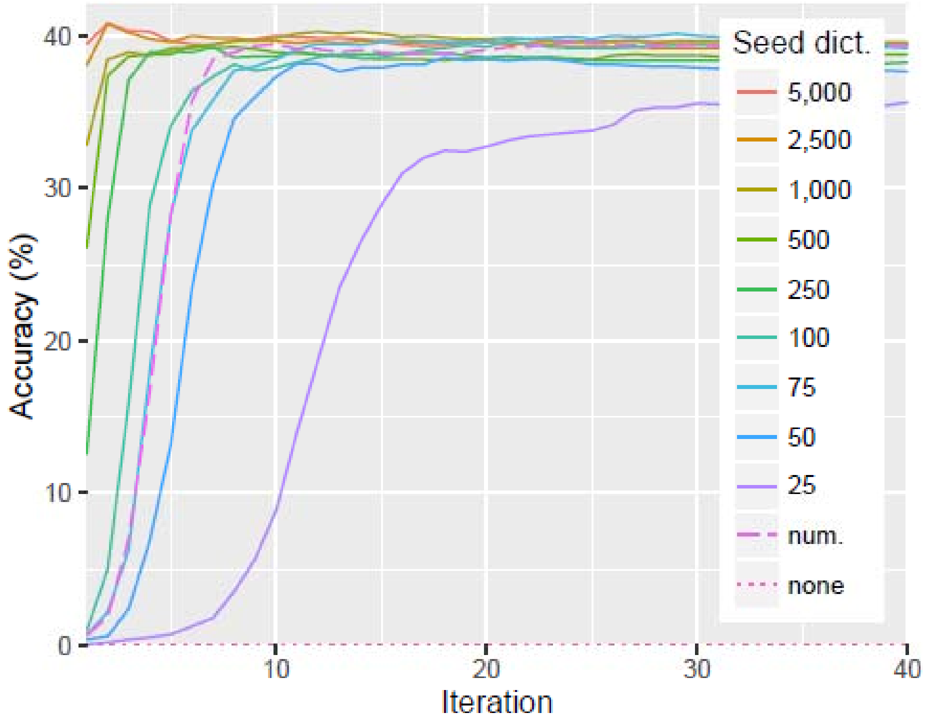

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<u>Implicit objective</u>: $W^* = \arg\max_W \sum_i \max_j (X_{i*}W) \cdot Z_{j*} \quad \text{s.t.} \quad WW^T = W^TW = I$

Independent from seed dictionary!

So why do we need a seed dictionary?

Avoid poor local optima!

Why does it work?

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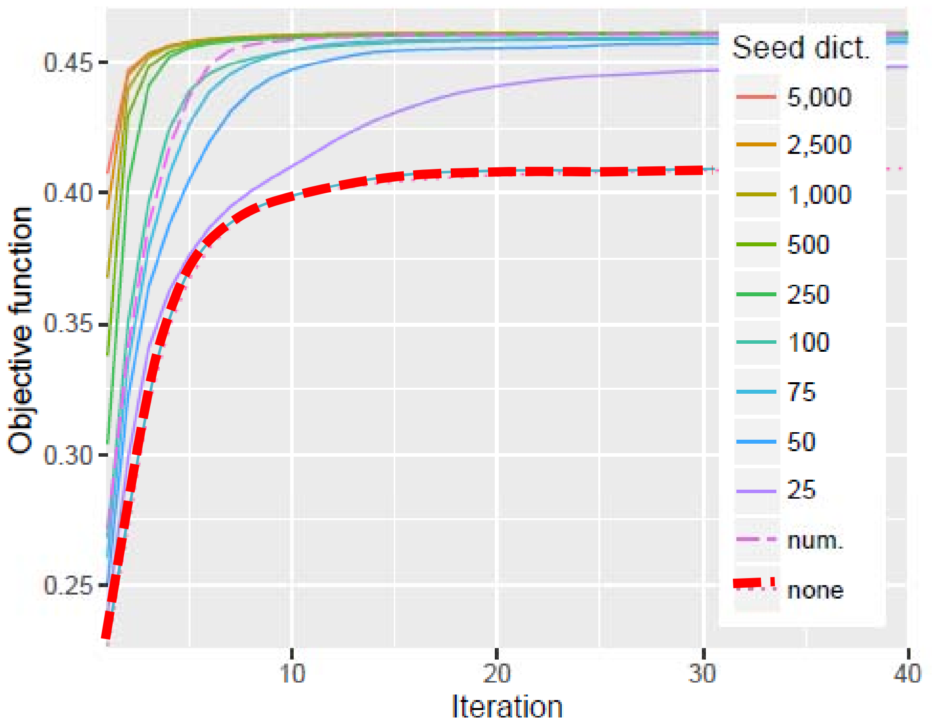

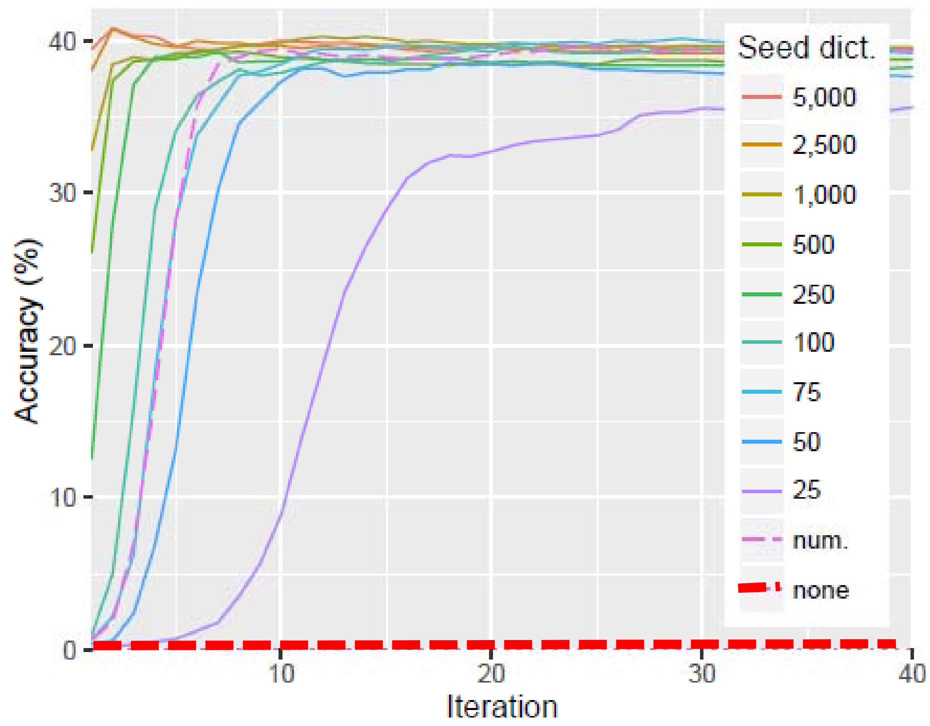

Next steps

Is there a way we can avoid the seed dictionary?

Would an initial noisy initialization suffice?

Unsupervised experiments (ACL18)

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Initial dictionary:

1. Compute intra-language similarity
2. Words which are translations of each other
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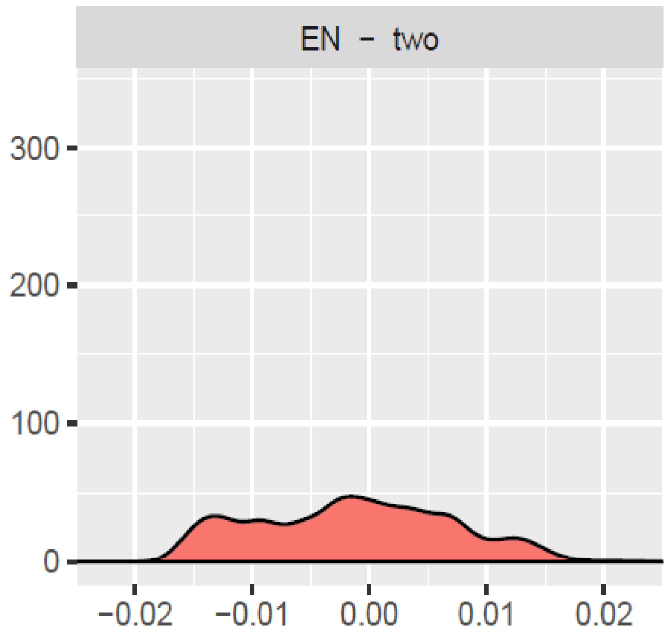

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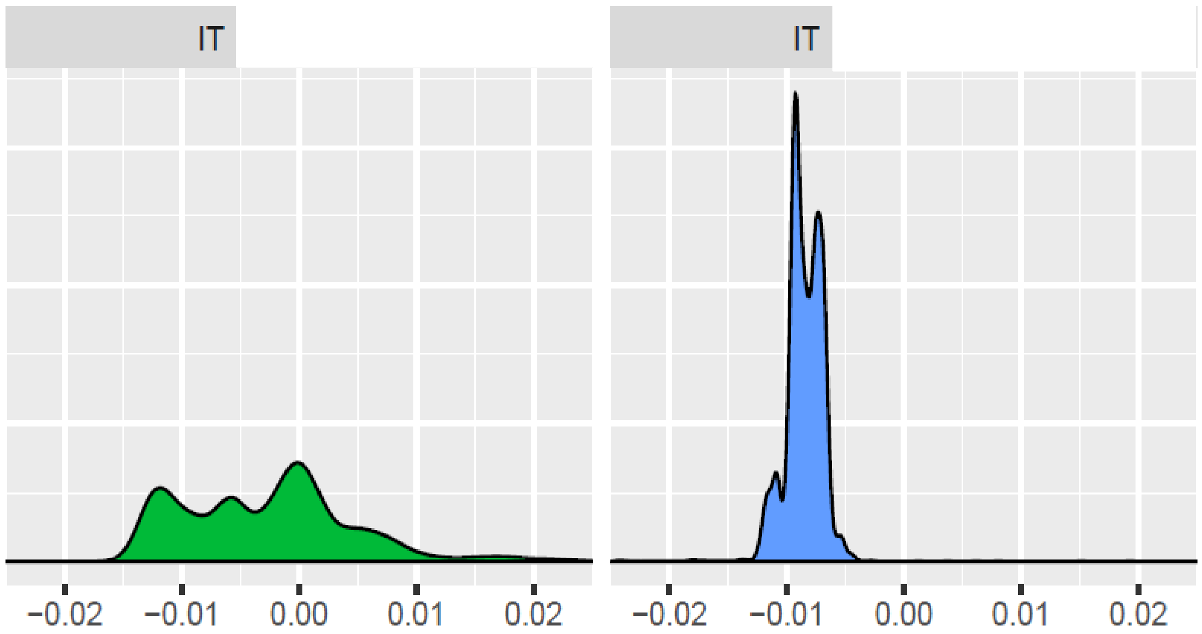

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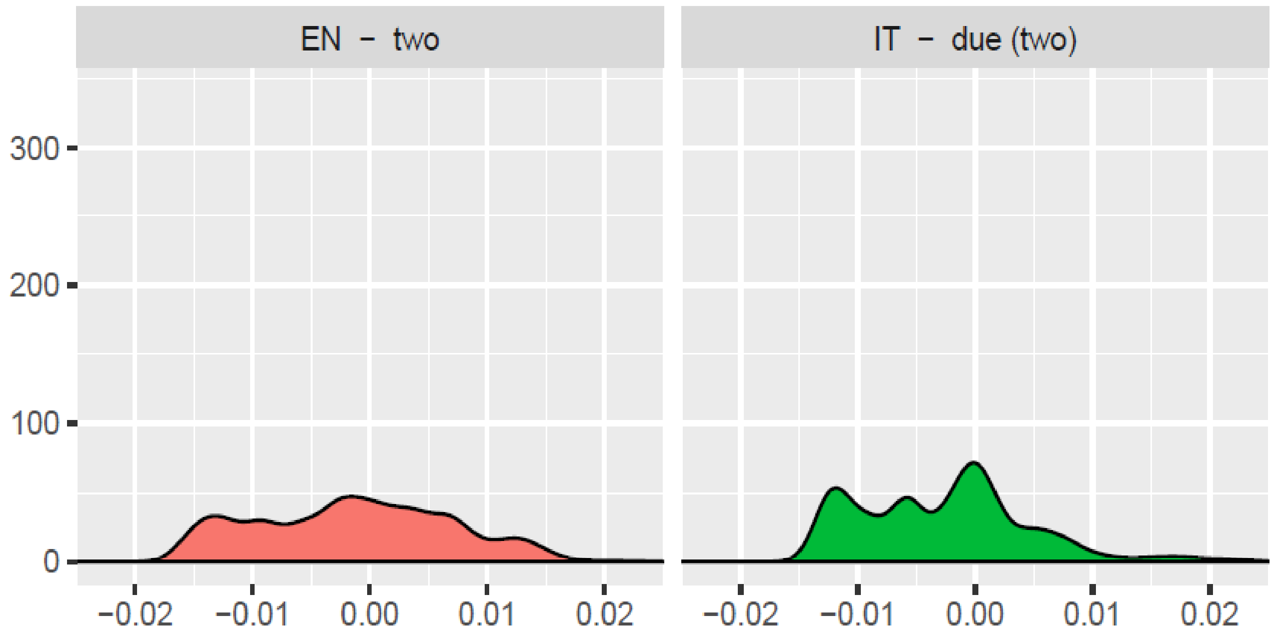

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It works, but very weak: Accuracy 0.52%

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For self-learning to work we had to add:

1. Stochastic dictionary induction
2. Frequency-based vocabulary cut-off
3. Hubness problem: Instead of inducing dictionary with nearest-neighbour use CSLS (Lample et al. 2018)

$$2cos(x,y) - mnn_T(x) - mnn_S(y)$$

$$mnn_T(x) = \frac{1}{K}\sum_{i=1}^{K} cos(x, nn_i)$$

Unsupervised experiments (ACL18)

- Dataset by Dinu et al. (2015) extended German, Finnish, Spanish

Supervision	Method	EN-IT	EN-DE	EN-FI	EN-ES

Unsupervised experiments (ACL18)

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Supervision	Method	EN-IT	EN-DE	EN-FI	EN-ES
5k dict.					
25 dict.					
None					

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Supervision	Method	EN-IT	EN-DE	EN-FI	EN-ES
5k dict.	Mikolov et al. (2013)	34.93†	35.00†	25.91†	27.73†
	Artetxe et al. (2016)	39.27	41.87*	30.62*	31.40*
	Smith et al. (2017)	43.1	43.33†	29.42†	35.13†
	Our method (AAAI18)	**45.27**	**44.13**	**32.94**	**36.60**
25 dict.					

None

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Previous work convergence problems!
Also observed by Sogard et al. (2018)

Supervision	Method	EN-IT	EN-DE	EN-FI	EN-ES
5k dict.					
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None	Zhang et al. (2017)	0.00	0.00	0.01	0.01
	Conneau et al. (2018)	13.55	42.15	0.38	21.23

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- Shows that languages share “semantic” structure to a large degree

References: cross-lingual mappings

- Mikel Artetxe, Gorka Labaka, and Eneko Agirre. 2018. **Generalizing and Improving Bilingual Word Embedding Mappings with a Multi-Step Framework of Linear Transformations**. In *AAAI-2018.*

- Mikel Artetxe, Gorka Labaka, and Eneko Agirre. 2017. **Learning bilingual word embeddings with (almost) no bilingual data**. In *ACL-2017*.

- Mikel Artetxe, Gorka Labaka, and Eneko Agirre. 2018. **A robust self-learning method for fully unsupervised cross-lingual mappings of word embeddings**. In *ACL-2018*.

Outline

- Bilingual embedding mappings
  - *Introduction to vector space models (embeddings)*
  - *Bilingual embedding mappings (AAAI18)*
  - *Reduced supervision*
    - Self-learning, semi-supervised (ACL17)
    - Self-learning, fully unsupervised (ACL18)
  - *Conclusions*
- Unsupervised neural machine translation
  - *Introduction to NMT*
  - *From bilingual embeddings to uNMT (ICLR18)*
  - *Unsupervised statistical MT (EMNLP18)*
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Introduction to (supervised) NMT

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- Given pairs of sentences with known translation $(x_1 \ldots x_n, y_1 \ldots y_m)$

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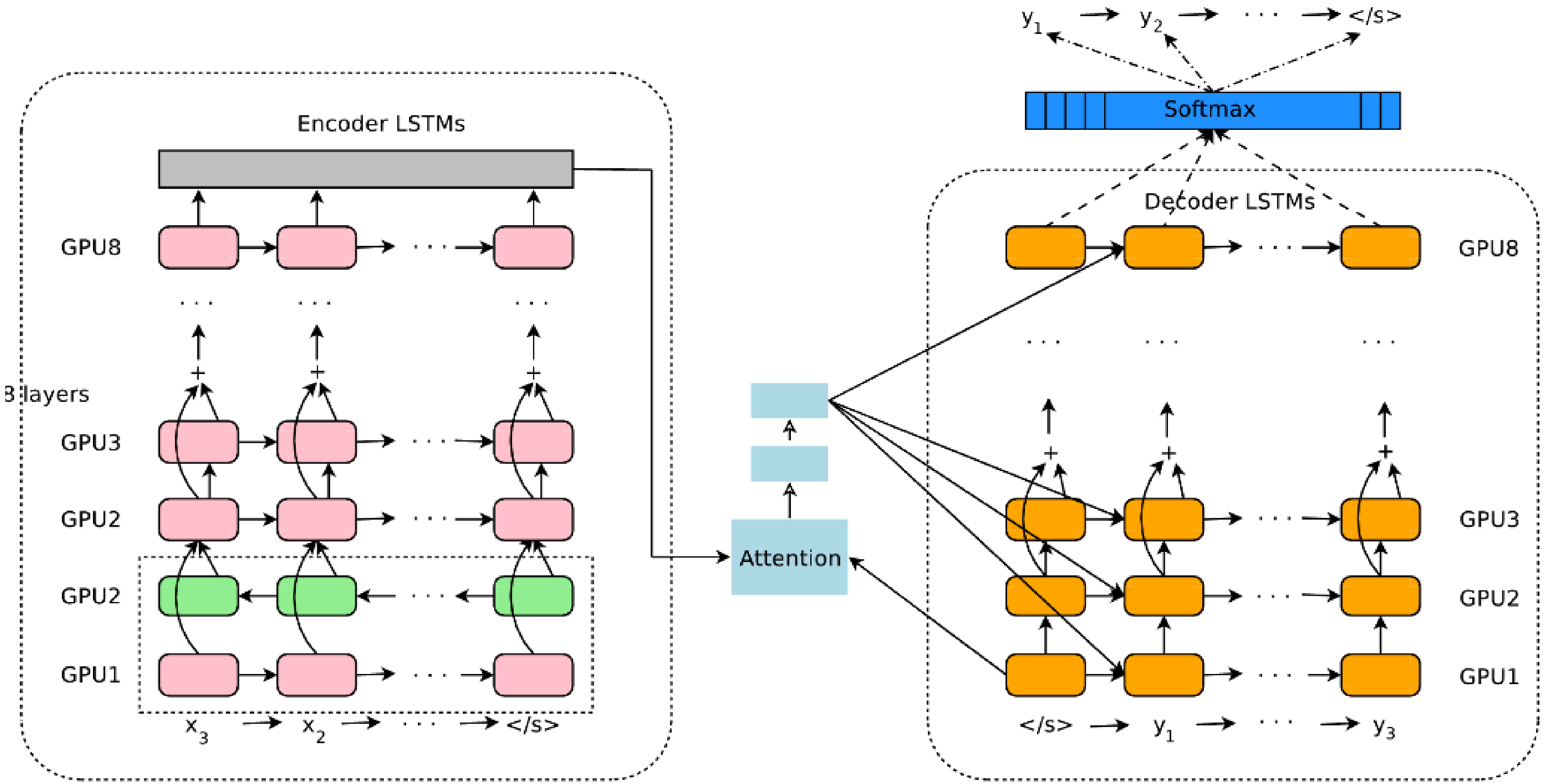
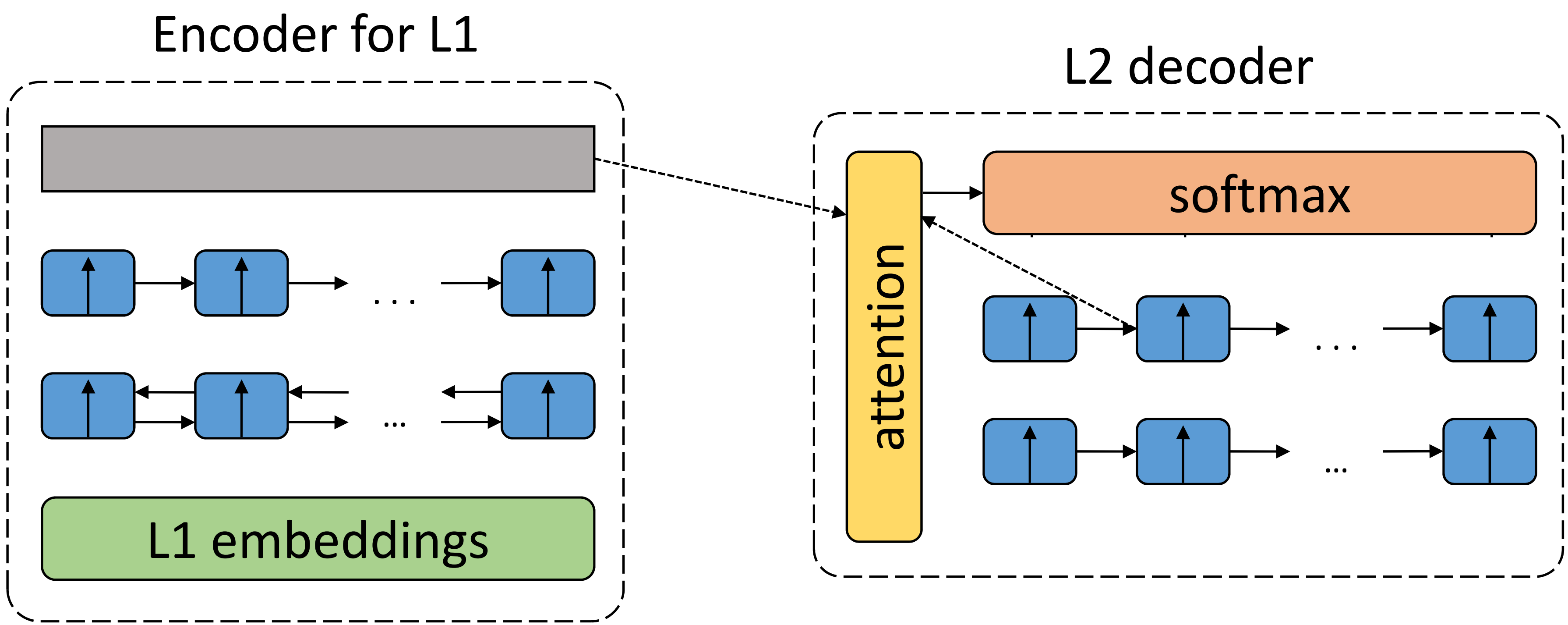
End-to-end training

Introduction to (supervised) NMT



Source: Wu et al. 2016 (~ 30 authors – Also known as Google NMT)

Introduction to (supervised) NMT



Unsupervised neural machine translation

- Now that we **can represent words in two languages in the same embeddings space** without bilingual dictionaries…

  … what can we do?

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- We change the **architecture of the NMT system**:
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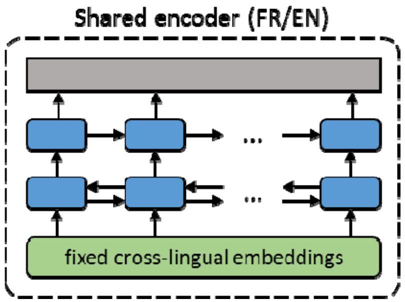

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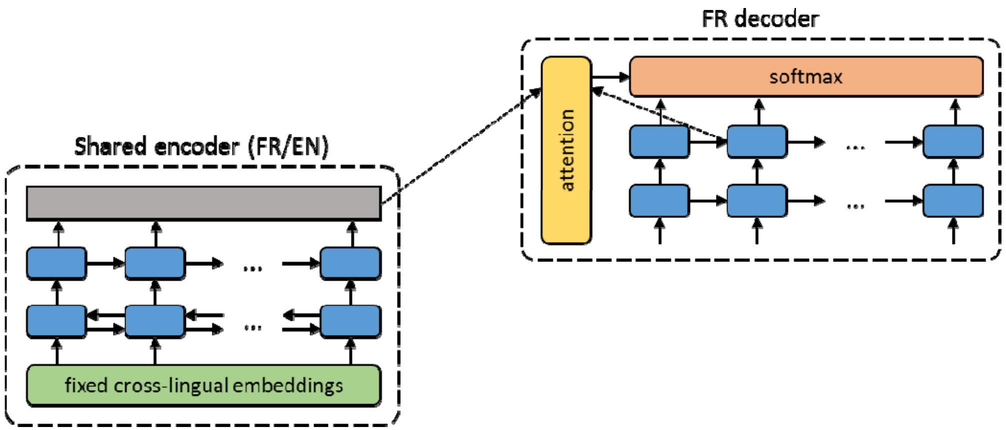

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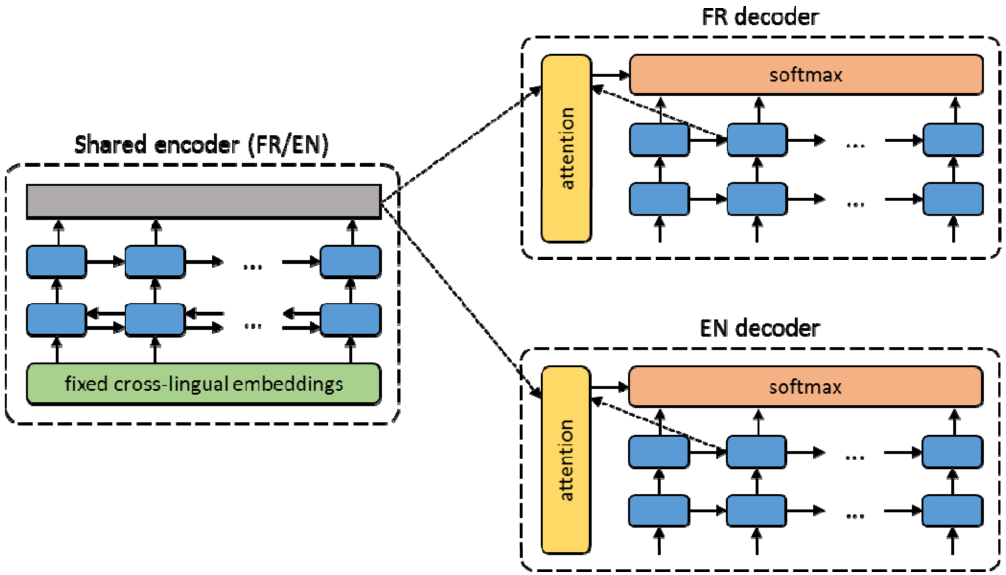

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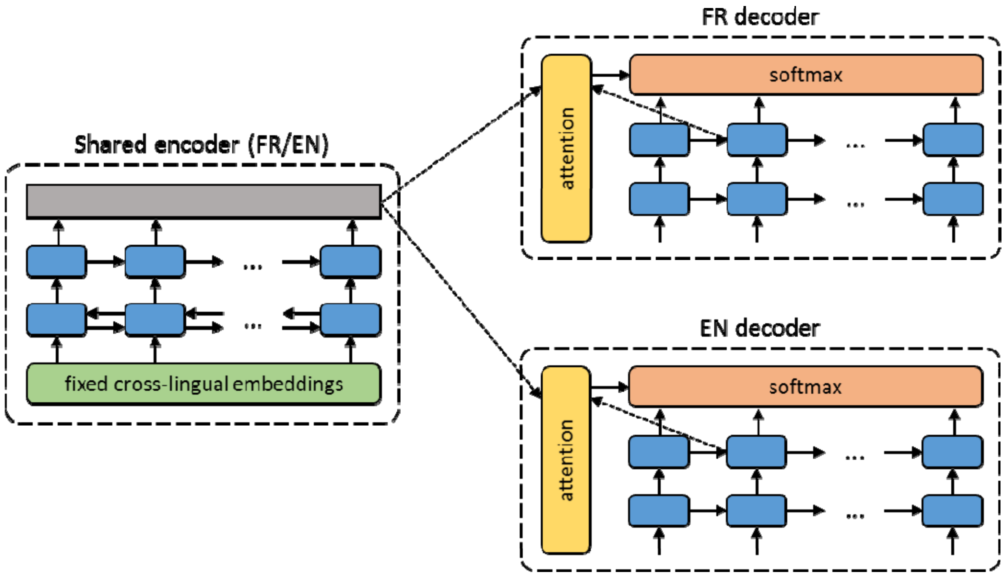
- We change the **training regime, mixing mini-batches**:
  - Denoising autoencoder: noisy input in L1, output in the same language (E+D1)
  - Denoising autoencoder: noisy input in L2, output in the same language (E+D2)
  - Backtranslation: input in L1, translate E+D2, translate E+D1, output in L1
  - Backtranslation: input in L2, translate E+D1, translate E+D2, output in L2

Unsupervised neural machine translation

Training



Unsupervised neural machine translation

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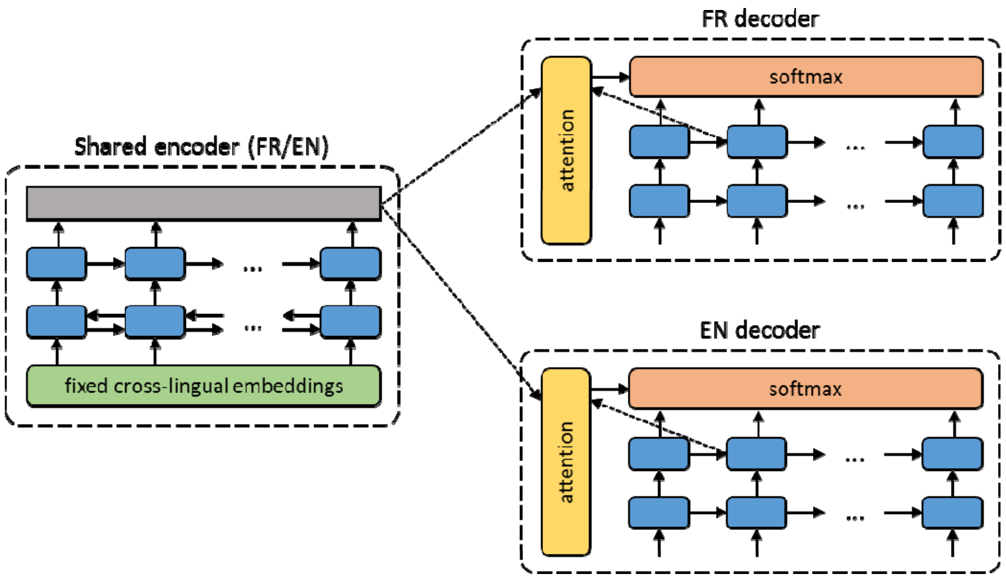
Une fusillade a eu lieu à l'aéroport international de Los Angeles.



Unsupervised neural machine translation

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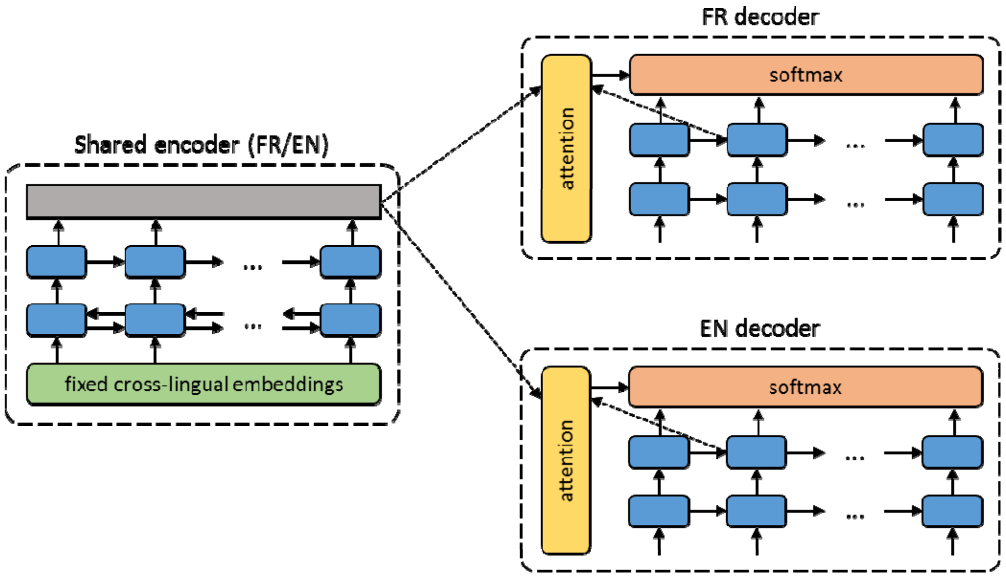

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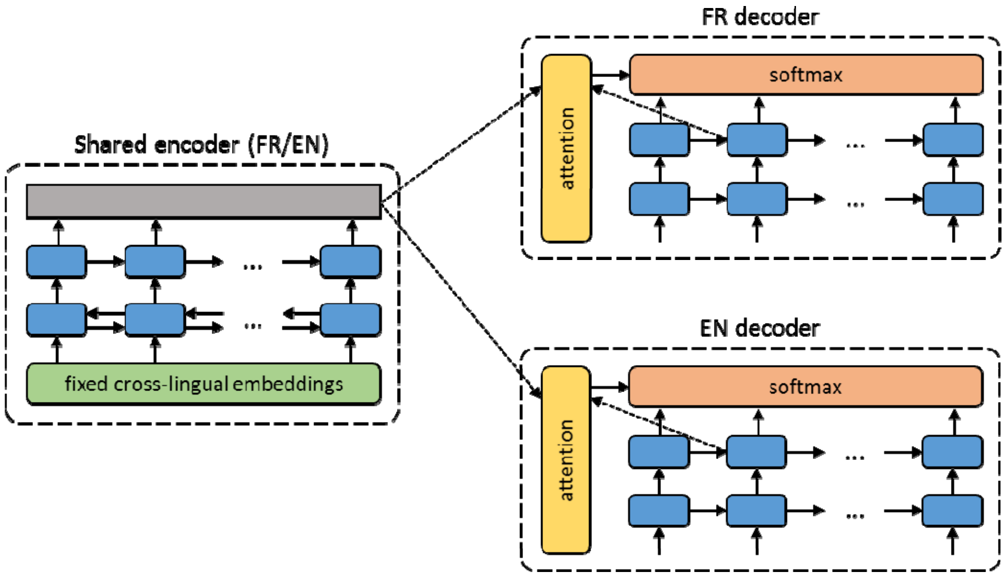

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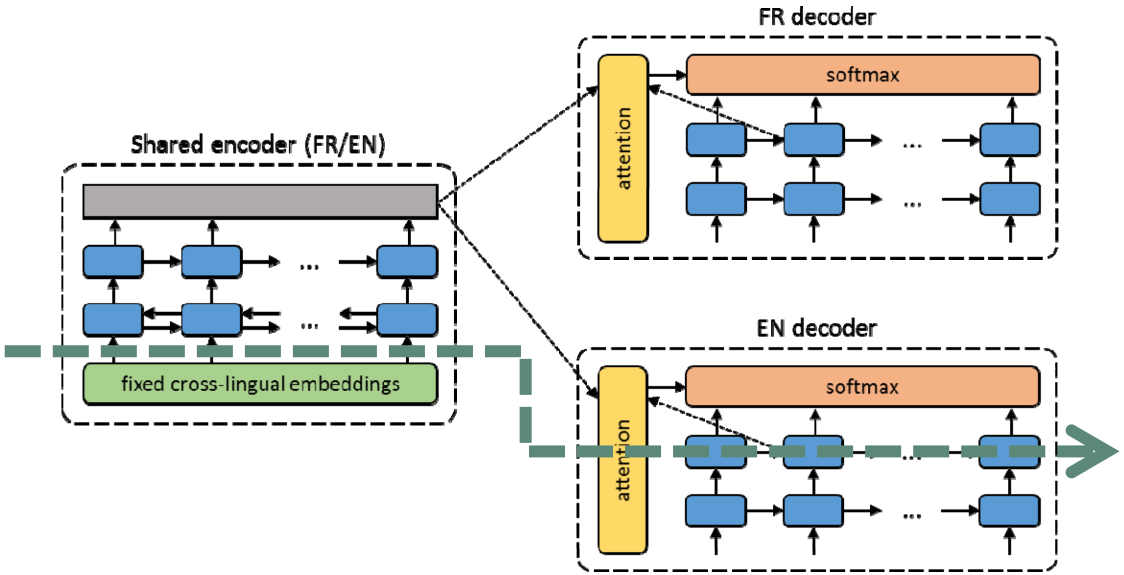

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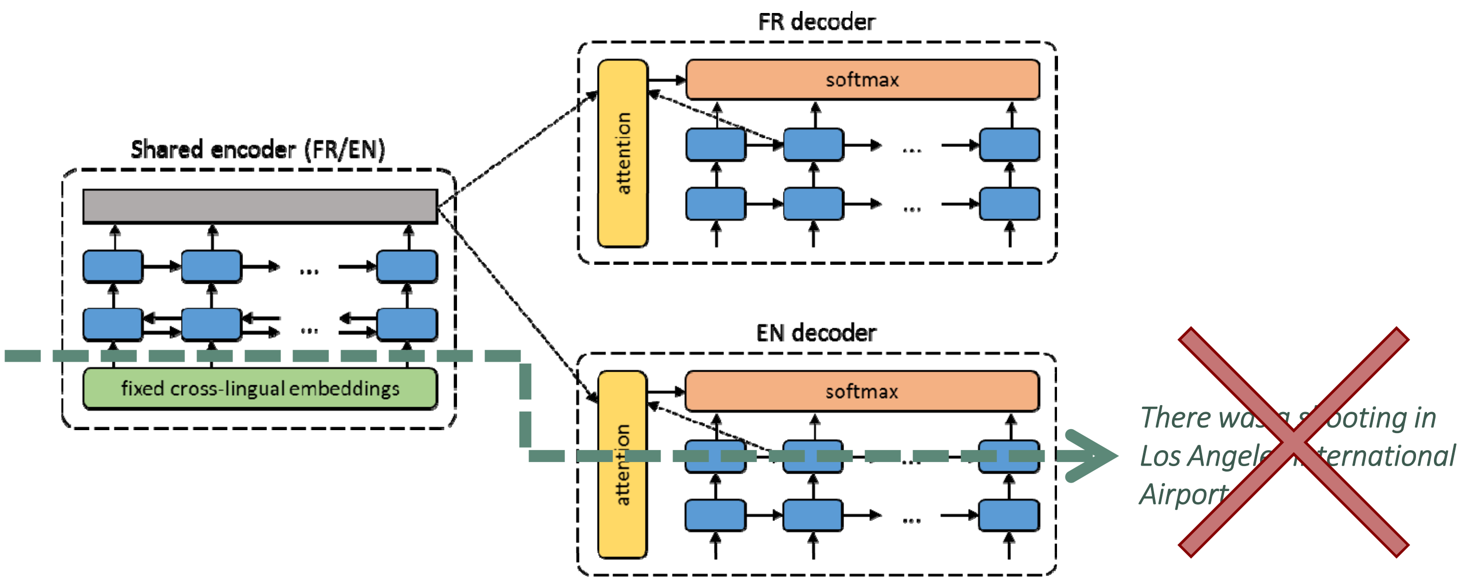

Unsupervised neural machine translation

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- ~~Supervised~~

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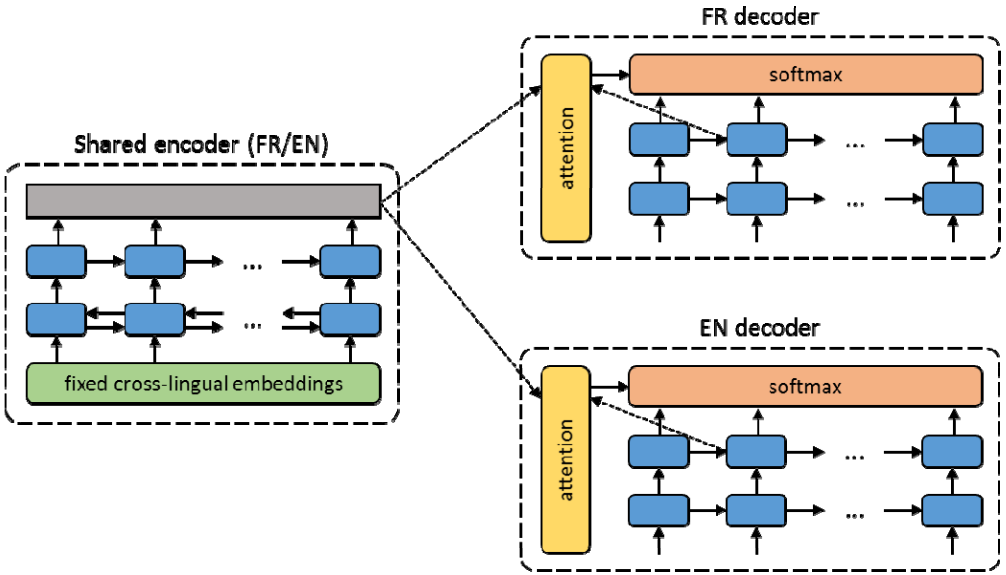

Unsupervised neural machine translation

Training

- ~~Supervised~~
- Autoencoder

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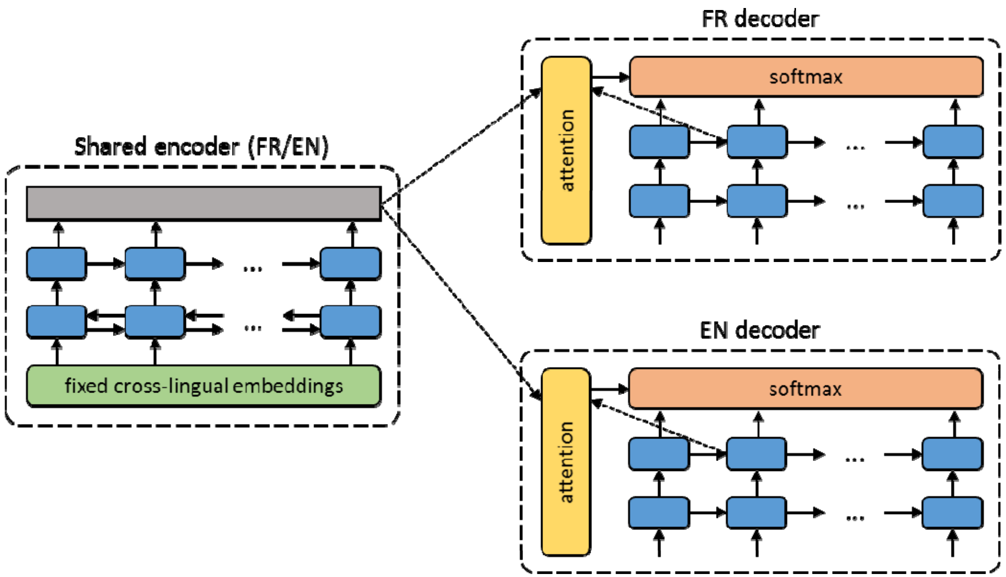

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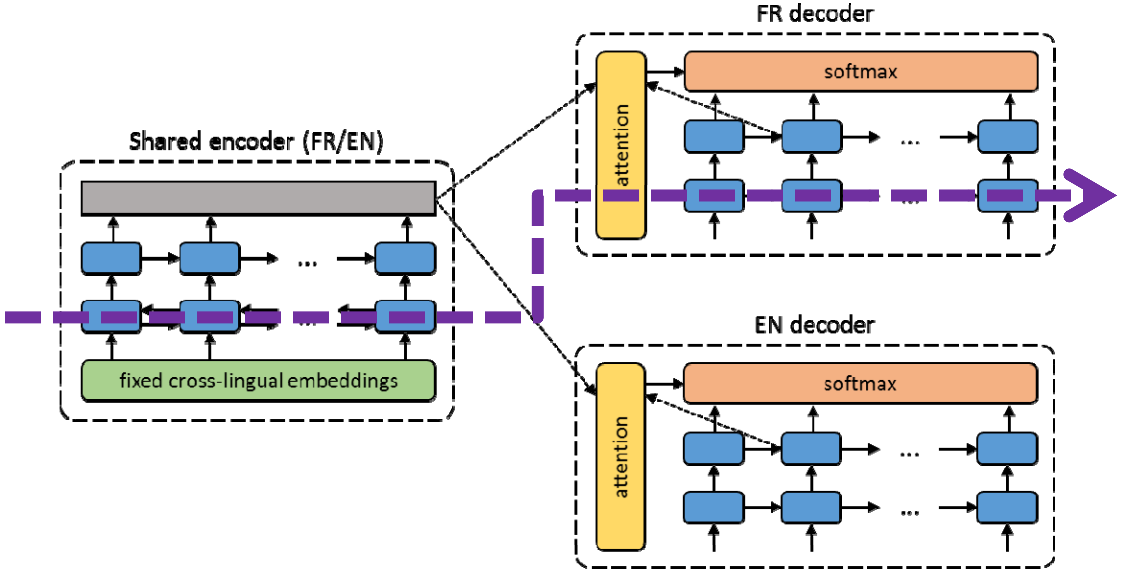

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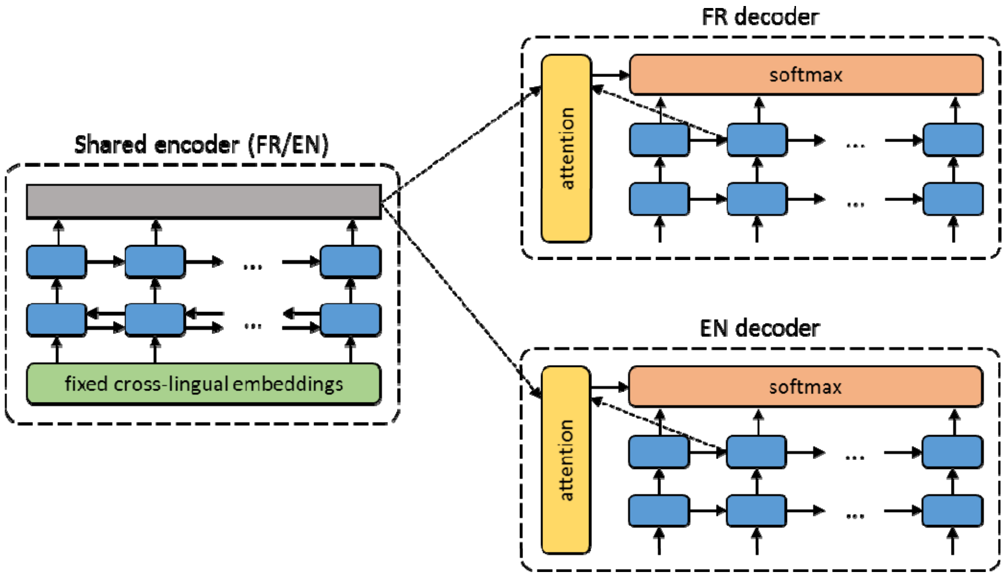

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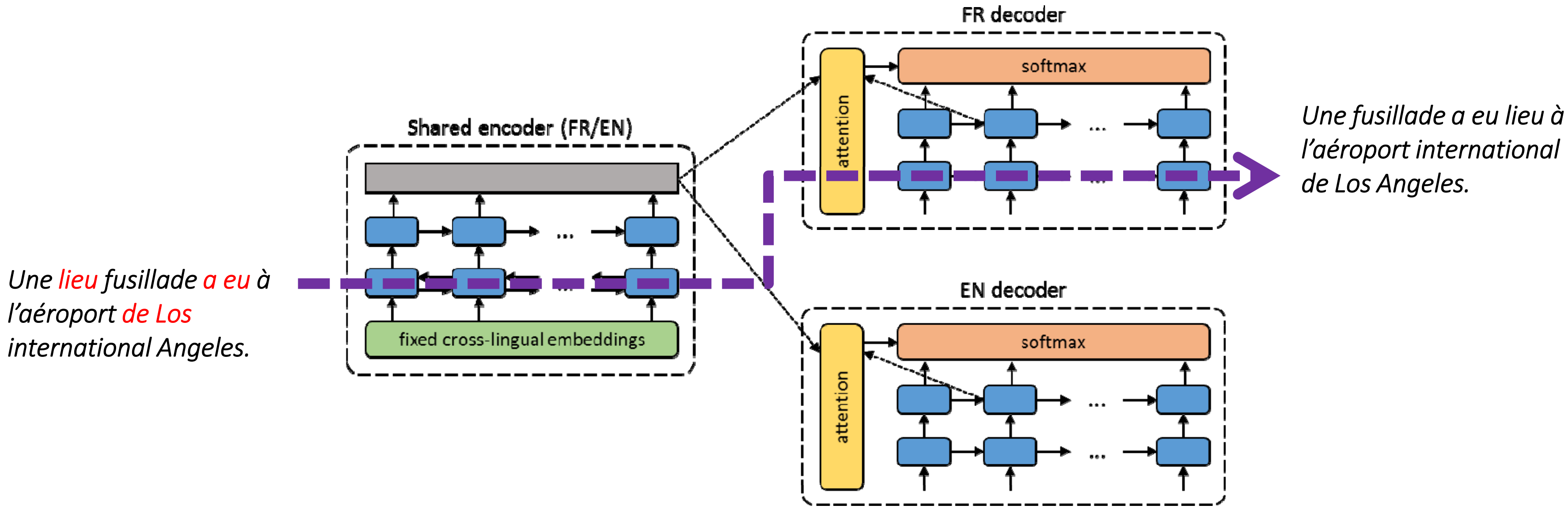

Unsupervised neural machine translation

Training

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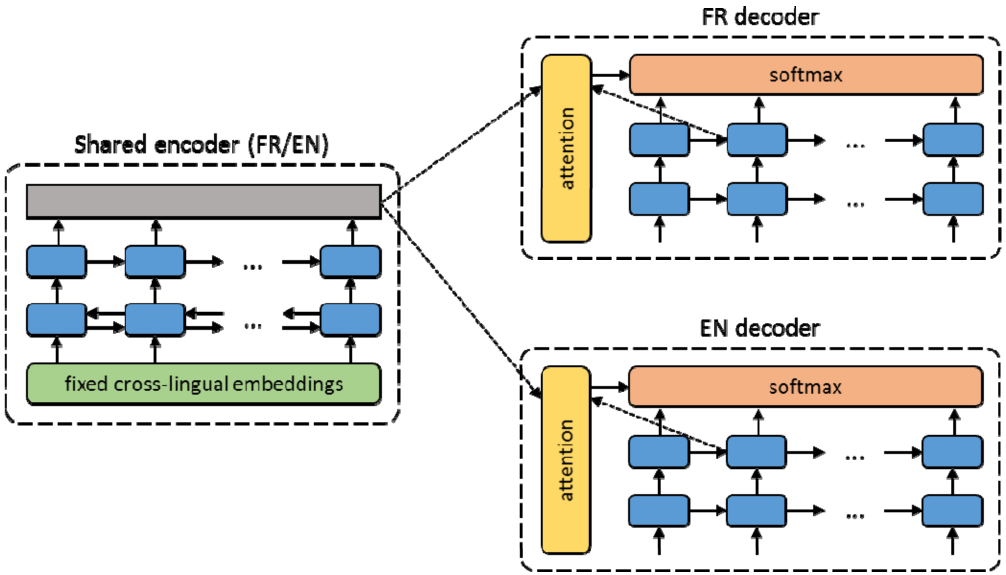
There a shooting was in Airport Los Angeles International.



There was a shooting in Los Angeles International Airport.

Unsupervised neural machine translation

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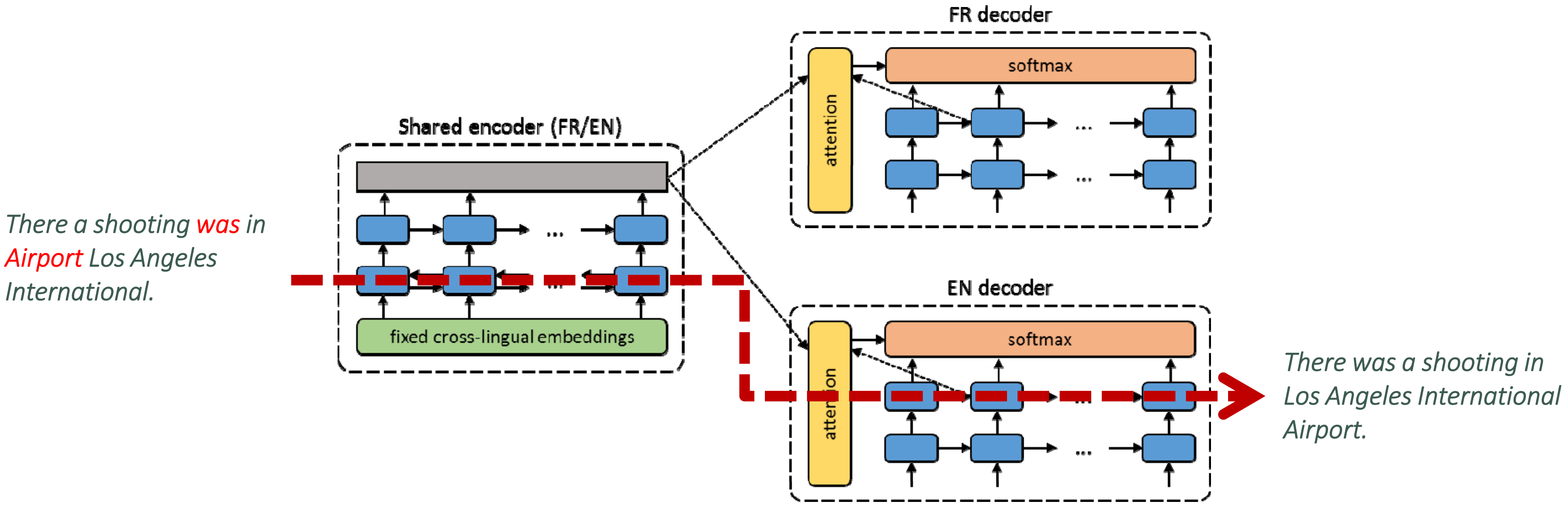

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Training

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- Backtranslation

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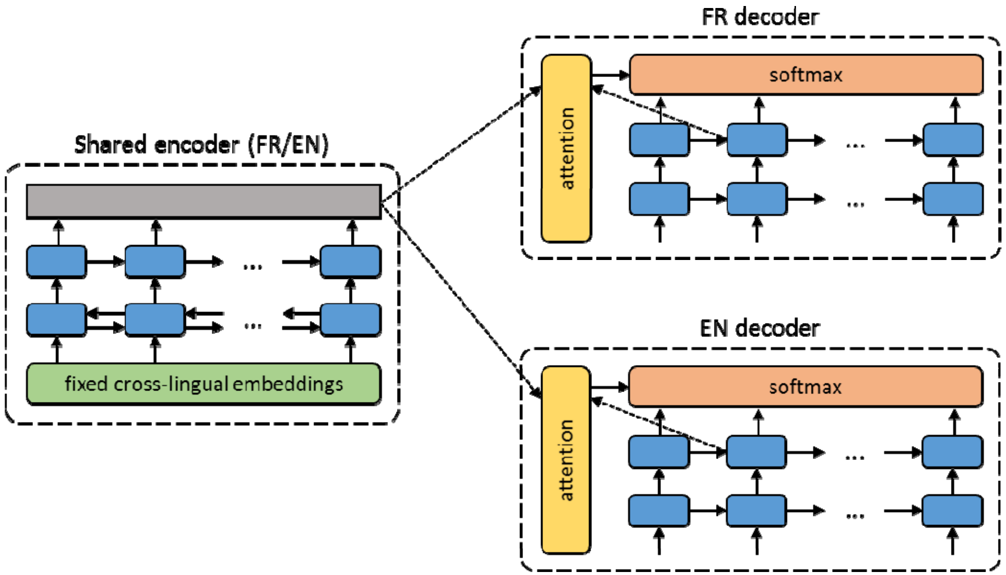

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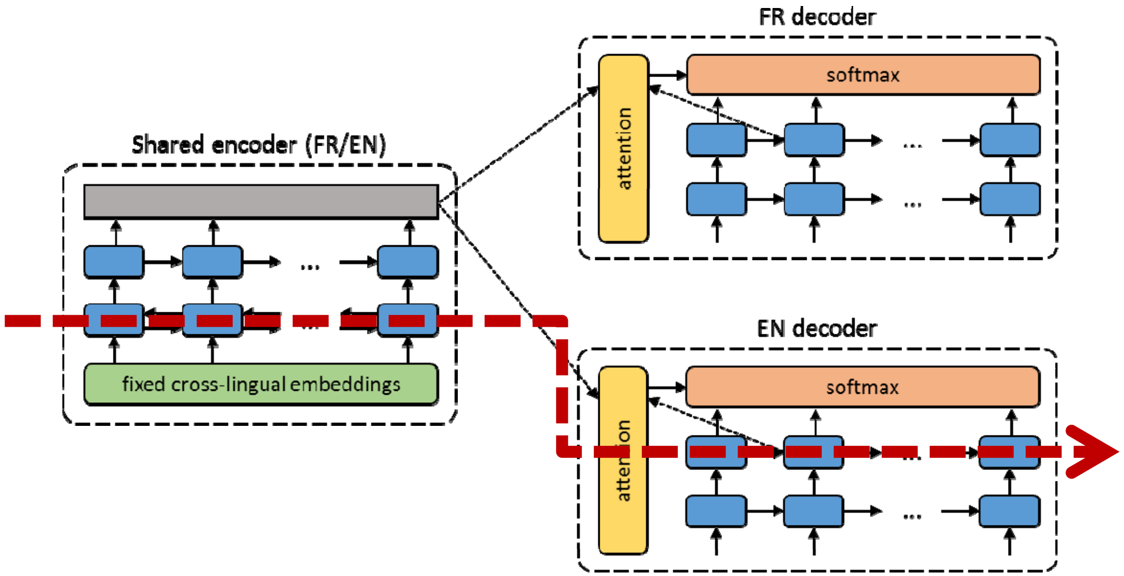

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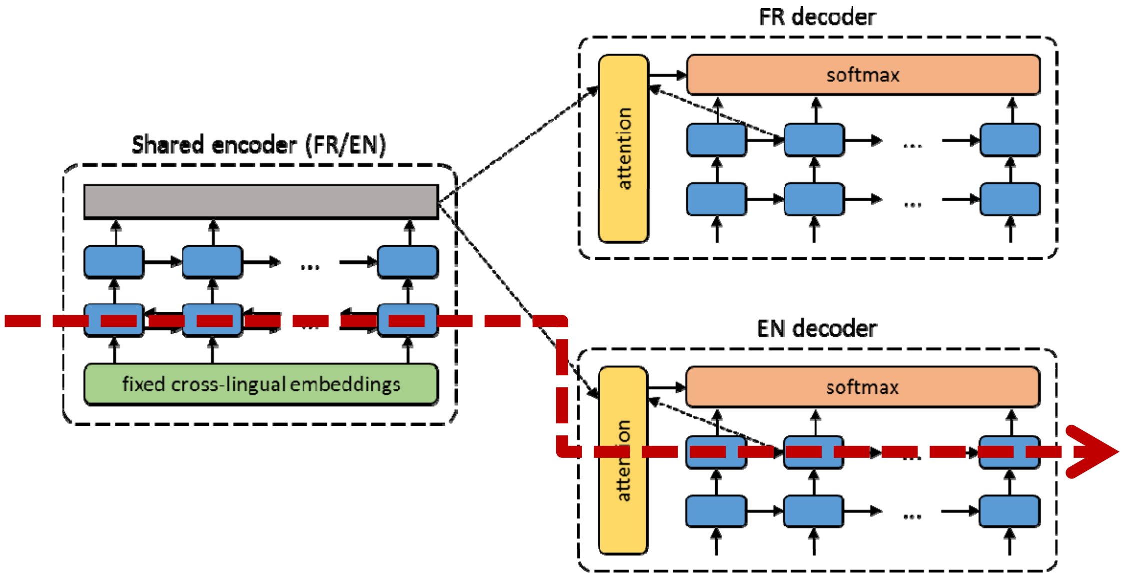

A shooting has had place in airport international of Los Angeles.

Unsupervised neural machine translation

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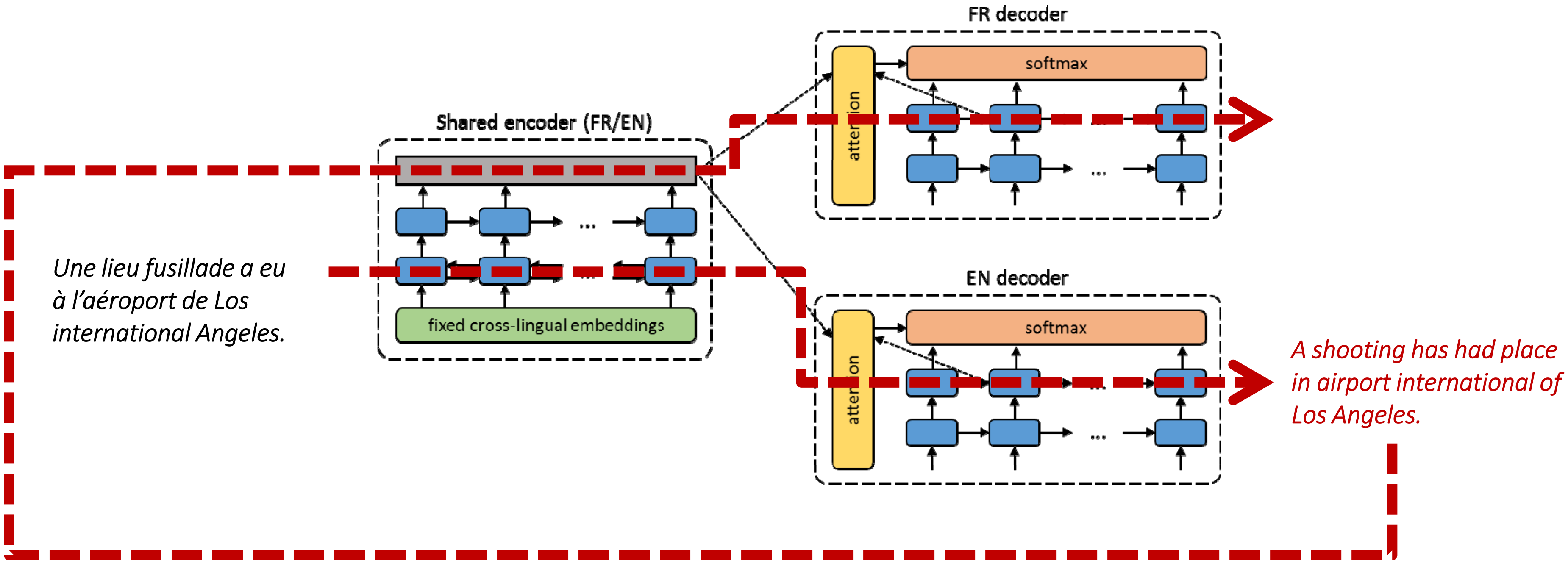

Unsupervised neural machine translation

Training

- Supervised ~~Supervised~~
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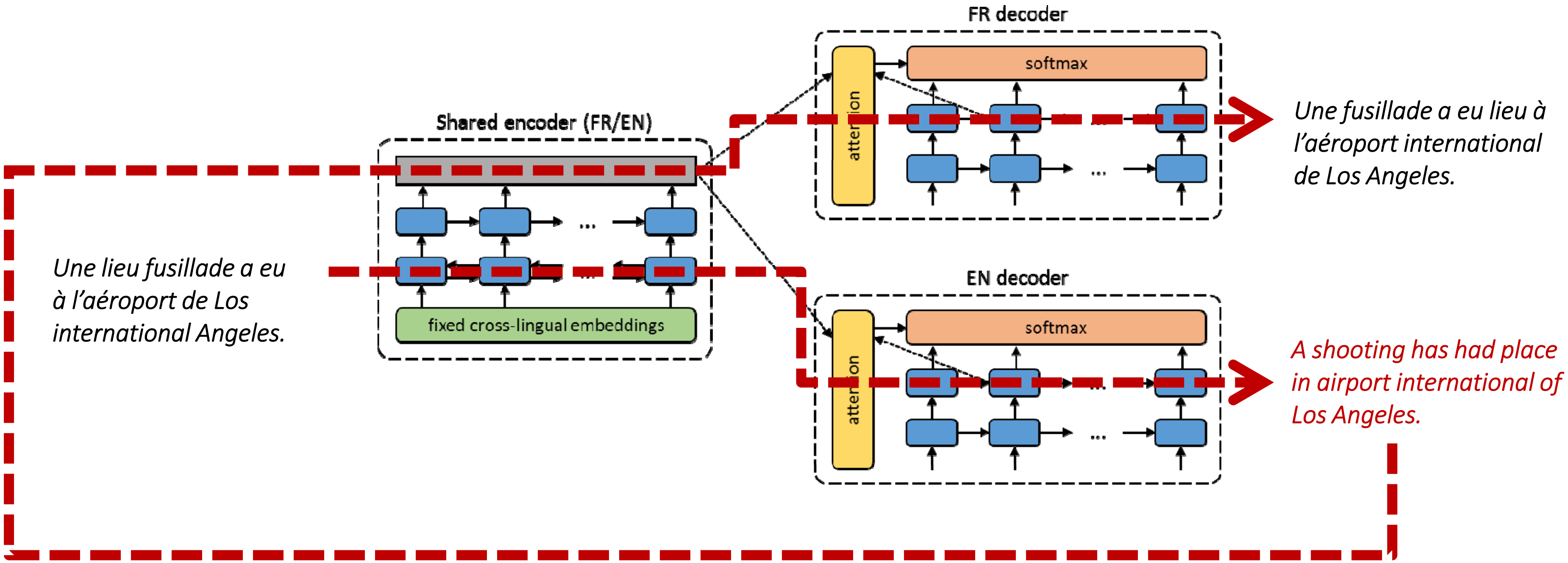

Unsupervised neural machine translation

- We change the **architecture of the NMT system**:
  - Handle both directions together (L1 -> L2, L2 -> L1)
  - Shared encoder for the two languages (E)
  - Two decoders for each language (D1, D2)
  - Fixed embeddings

- We change the **training regime, mixing mini-batches**:
  - Denoising autoencoder: noisy input in L1, output in the same language (E+D1)
  - Denoising autoencoder: noisy input in L2, output in the same language (E+D2)
  - Backtranslation: input in L1, translate E+D2, translate E+D1, output in L1
  - Backtranslation: input in L2, translate E+D1, translate E+D2, output in L2

Unsupervised neural machine translation

Test on WMT released data (test and monolingual corpora)

	FR-EN	EN-FR	DE-EN	EN-DE
Unsupervised NMT				

Unsupervised neural machine translation

Test on WMT released data (test and monolingual corpora)

		FR-EN	EN-FR	DE-EN	EN-DE
Unsupervised NMT	Baseline (emb. nearest neighbor)	9.98	6.25	7.07	4.39

Unsupervised neural machine translation

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Unsupervised neural machine translation

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	Proposed (+backtranslation)	**15.56**	**15.13**	**10.21**	**6.55**

It works!

Unsupervised neural machine translation

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Semi-supervised NMT	Proposed (full) + 10k parallel	**18.57**	**17.34**	**11.47**	**7.86**
	Proposed (full) + 100k parallel	**21.81**	**21.74**	**15.24**	**10.95**

It can be easily combined with training data (interesting for low resource MT)

Unsupervised neural machine translation

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	Lample et al. 2018 (Same conference!)	14.31	15.06	-	-

State-of-the-art (not anymore…)

Unsupervised neural machine translation

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	Lample et al. 2018b				

Lample et al. 2018b (EMNLP)

- No embedding mappings
- BPE jointly over monolingual corpora. Fails for less related languages (Russian).
- Shared decoder for both languages
- Transformer (instead of LSTM)

Unsupervised neural machine translation

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Unsupervised statistical machine translation

Unsupervised statistical machine translation

Artetxe et al. 2018b (EMNLP)

- Estimate PBMT parameters
    - Learn monolingual embeddings for bigrams and trigrams
    - Initialize phrase table using prob. estimates from cross-lingual mappings
    - Unsupervised tuning based on back-translation
- Use backtranslation and train reverse PBMT from scratch. Iterate.

Unsupervised statistical machine translation

Test on WMT released data (test and monolingual corpora). WMT14 and WMT16

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Unsupervised PBMT	Artetxe et al. 2018b	25.87	26.22	17.43	14.08	23.05	18.23

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Unsupervised machine translation

Getting closer to supervised machine translation!

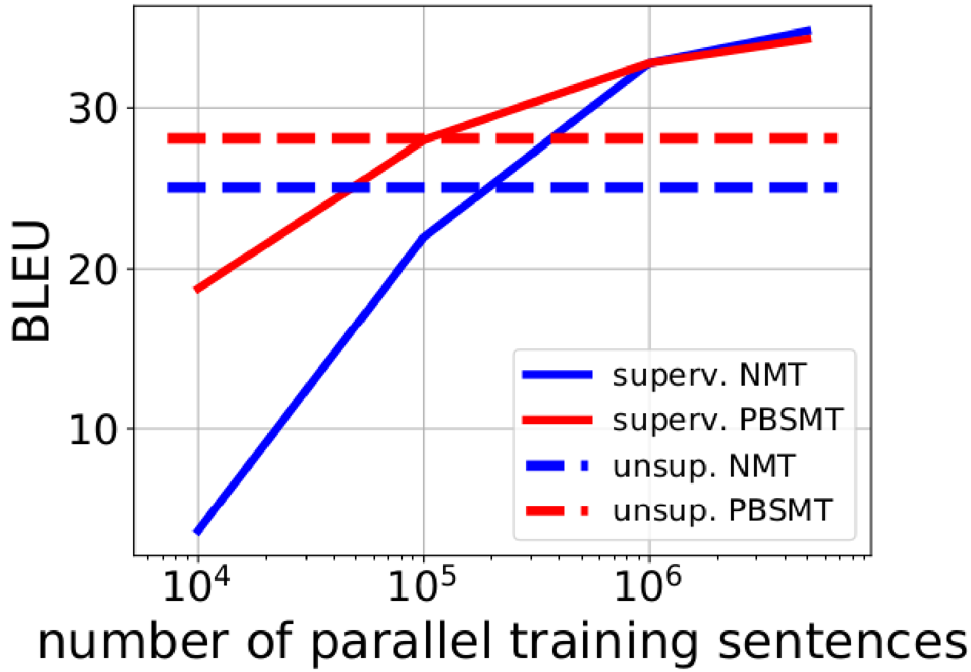

Figure 2: Comparison between supervised and unsupervised approaches on WMT'14 En-Fr, as we vary the number of parallel sentences for the supervised methods.

Source: (Lample et al. 2018)

Unsupervised machine translation

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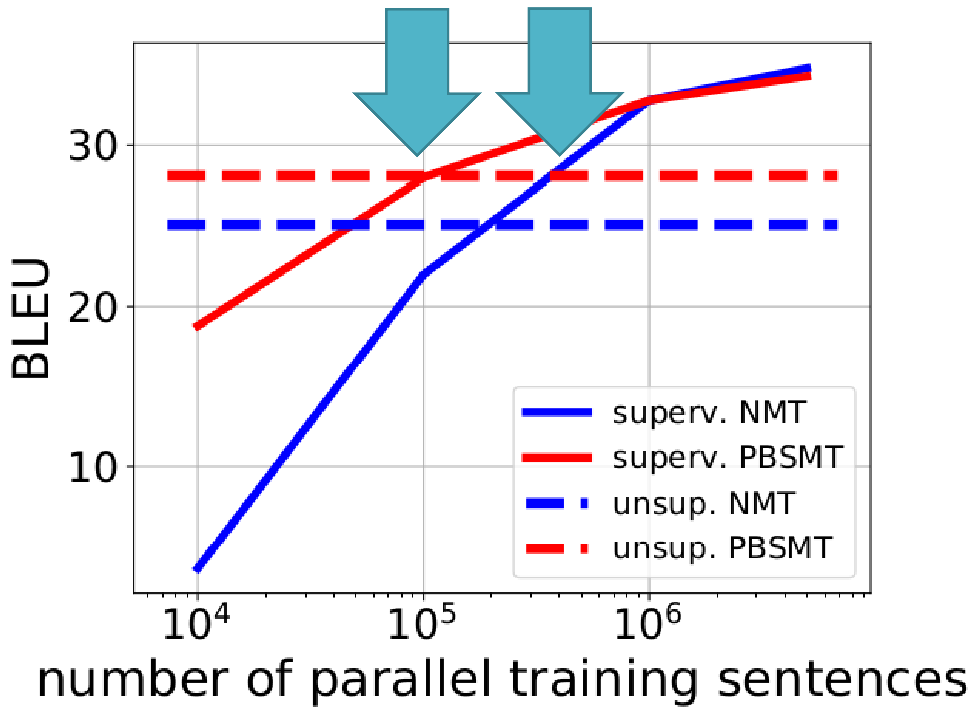

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Why does it work?

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Early to say… but intuition:

Why does it work?

Early to say… but intuition:

- Mapped embedding space provides information for k-best possible translations
- NMT / PBMT figures out how to best “combine” them

Conclusions

- New research area – unsupervised Machine Translation

  The main Machine Translation competition (WMT18) has now an **unsupervised track**

- Performance up, 28 BLEU En-Fr

- Plenty of margin for improvement

- Code for replicability

  `https://github.com/artetxem/undreamt`
  `https://github.com/artetxem/monoses (soon)`

References: unsupervised MT

- Mikel Artetxe, Gorka Labaka, and Eneko Agirre. 2017. Unsupervised Neural Machine Translation. In *ICLR-2018*.

- Mikel Artetxe, Gorka Labaka, and Eneko Agirre. 2018. Unsupervised Statistical Machine Translation. In *EMNLP-2018*.

Final words

- **Word embeddings key** for Natural Language Processing
- Mappings represent **languages in common space**
  - Most of language pairs have **very few resources**
  - New research area: **only monolingual resources**

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- **Cross-lingual unsupervised mappings** enabled breakthroughs in
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  - Unsupervised machine translation
  - Confirmed in (Conneau et al. 2018; Lample et al. 2018)
- Unexplored area in its **infancy**
  - Potential for **MT in low resource languages and domains**
  - Potential for **transforming the NLP landscape**
    - From monolingual NLP (e.g. English) to **multilingual tools**
    - **Universal sentence representations**

Thank you!

@eagirre
http://ixa2.si.ehu.eus/eneko

https://github.com/artetxem/vecmap
https://github.com/artetxem/undreamt
https://github.com/artetxem/monoses