Ten Pairs to Tag – Multilingual POS Tagging via Coarse Mapping between Embeddings

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Multilingual Transfer of POS Tagging

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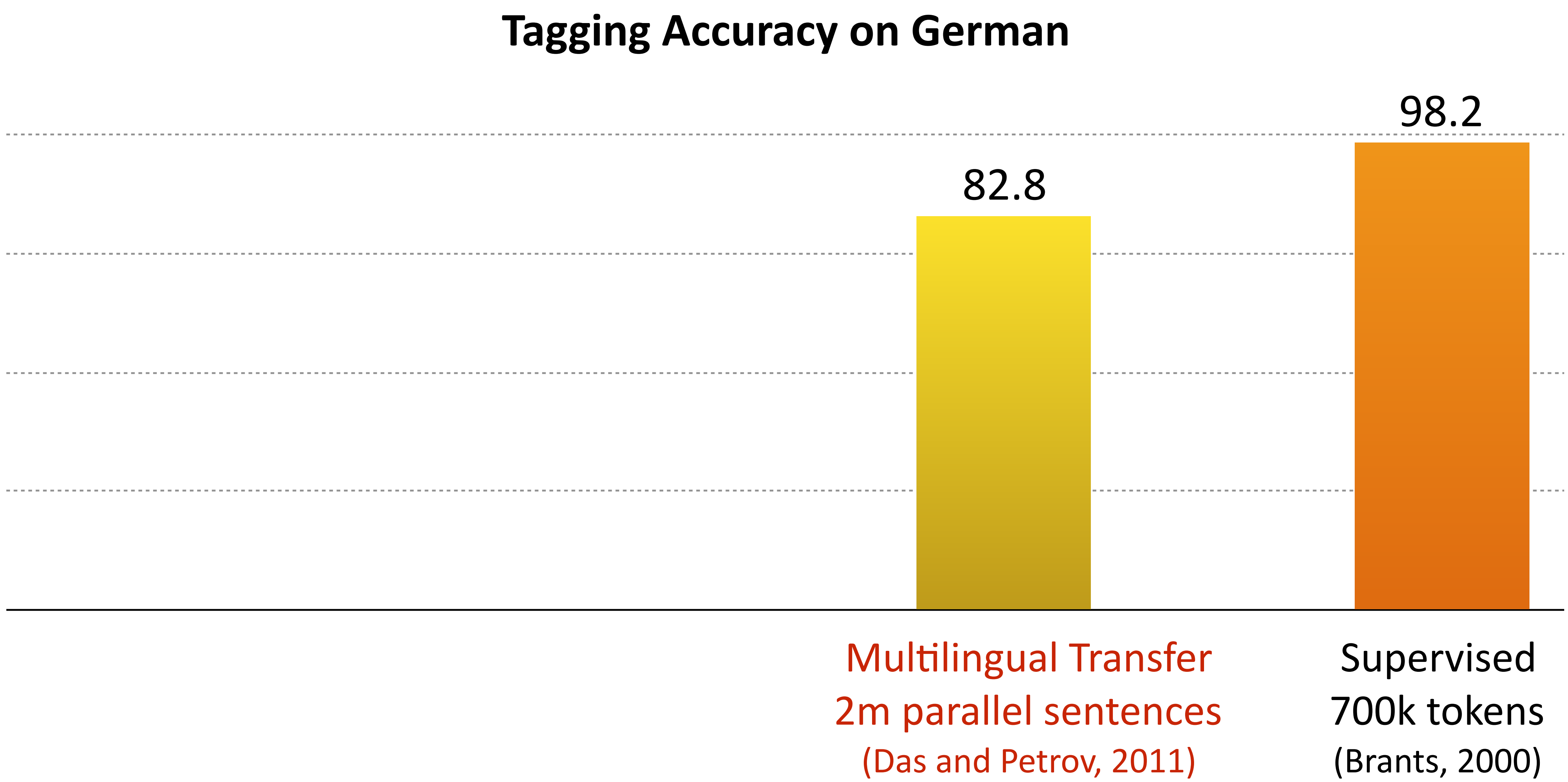

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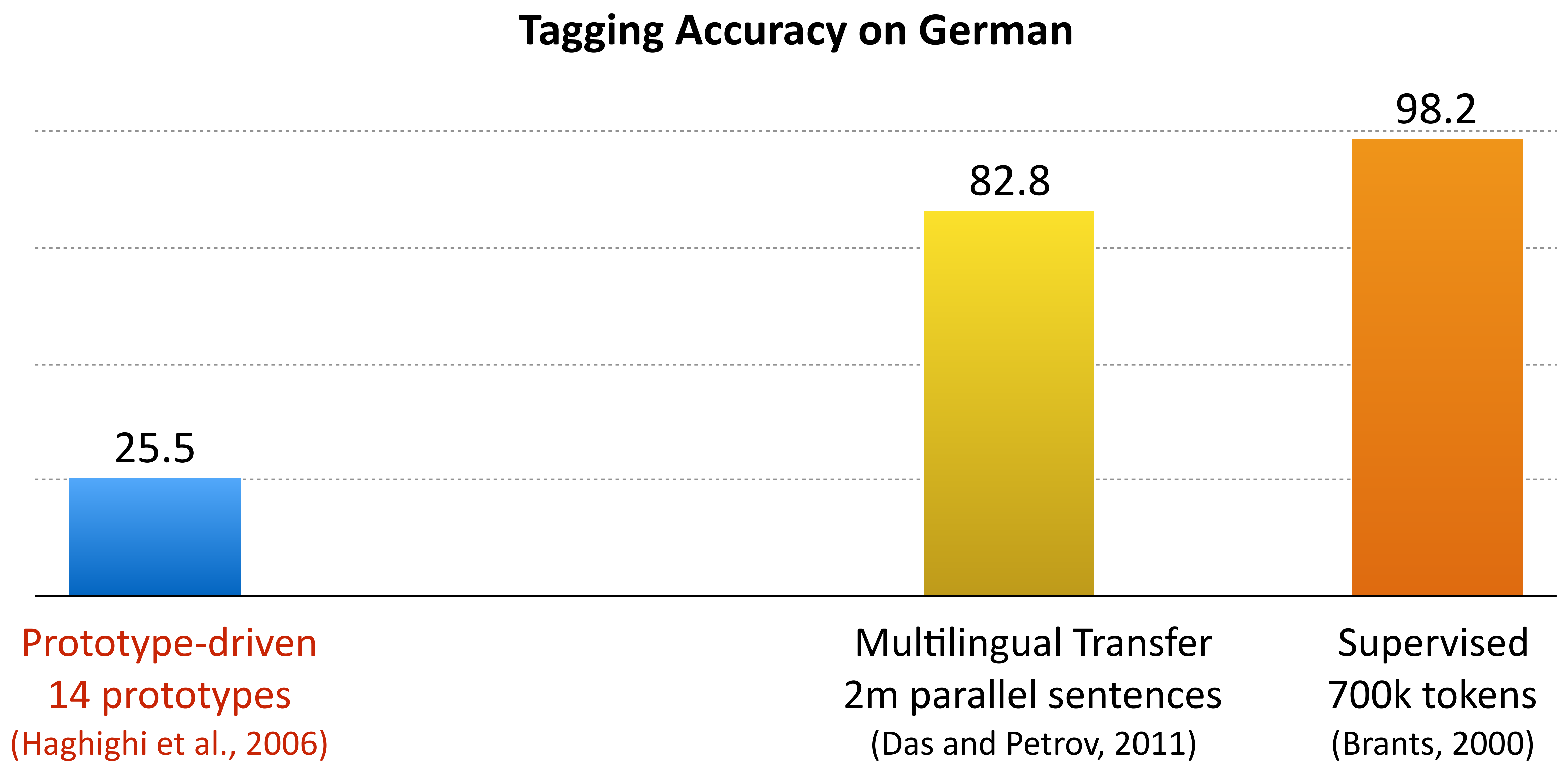
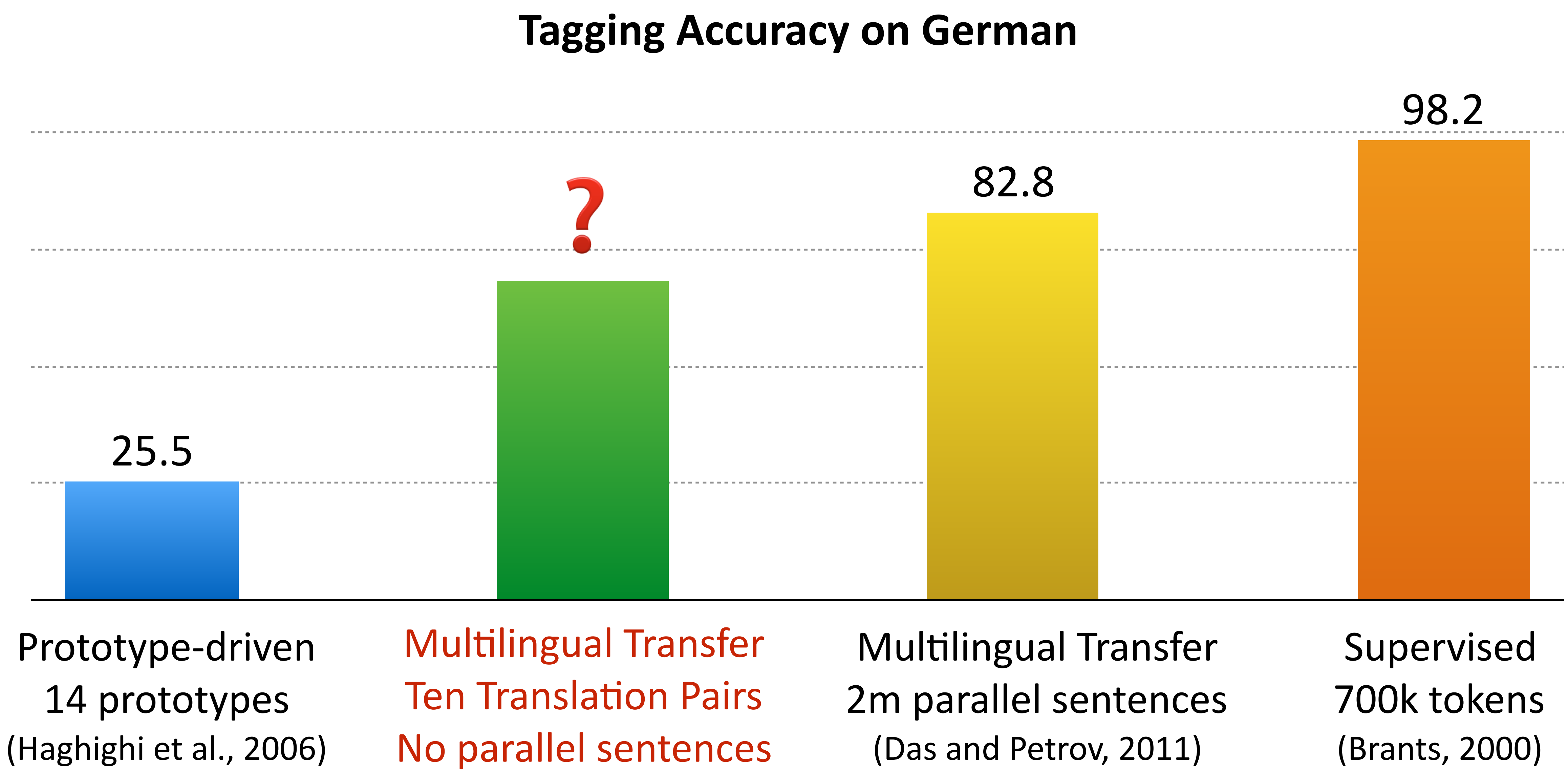


Multilingual Transfer of POS Tagging



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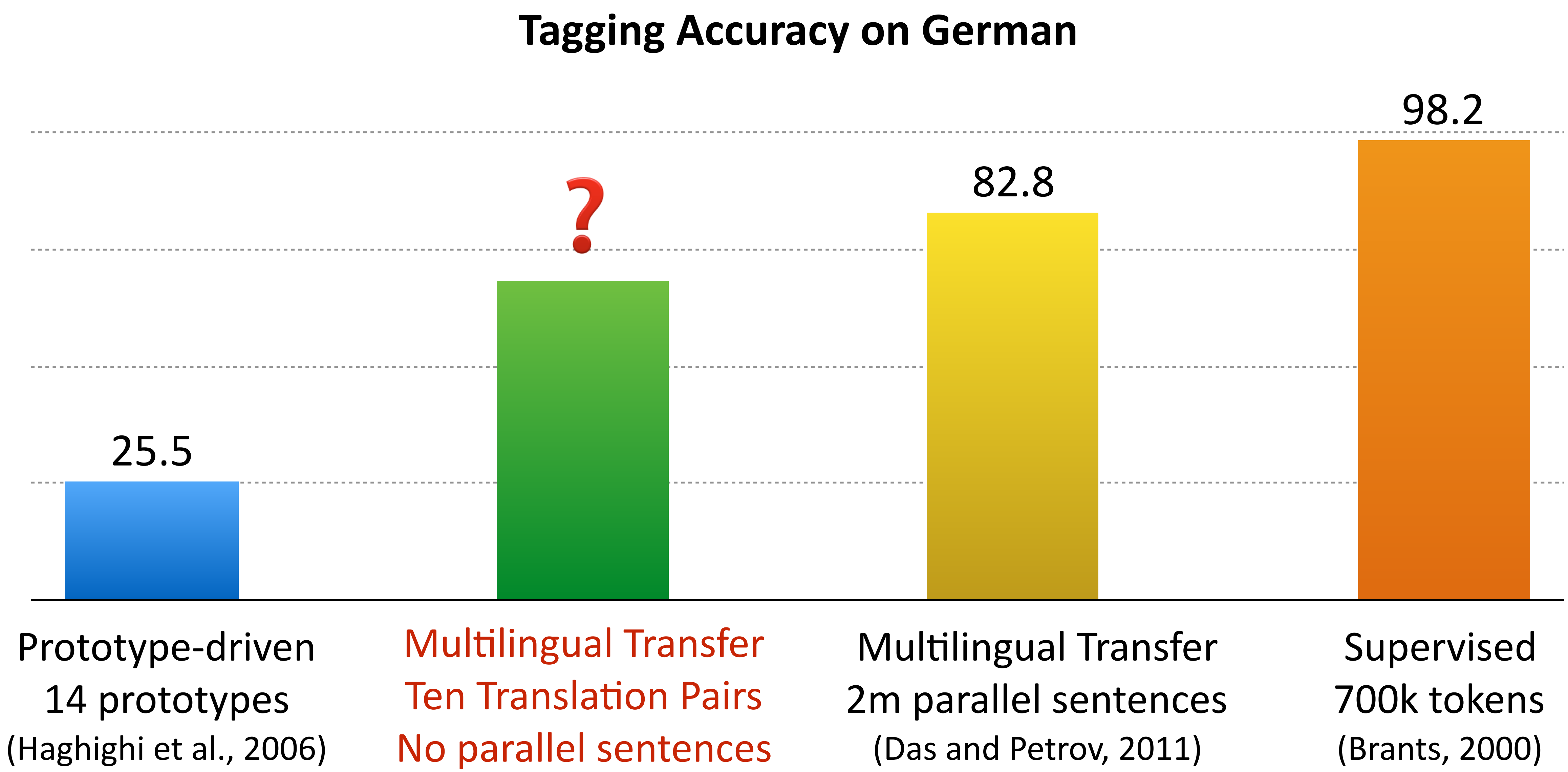

How little parallel data is necessary to enable multilingual transfer?

Our Work

- Task: multilingual transfer of part-of-speech (POS) tagging
- Data:

	Source	Target
Labeled	✓	✗
Unlabeled	✓	✓ *(non-parallel data)*

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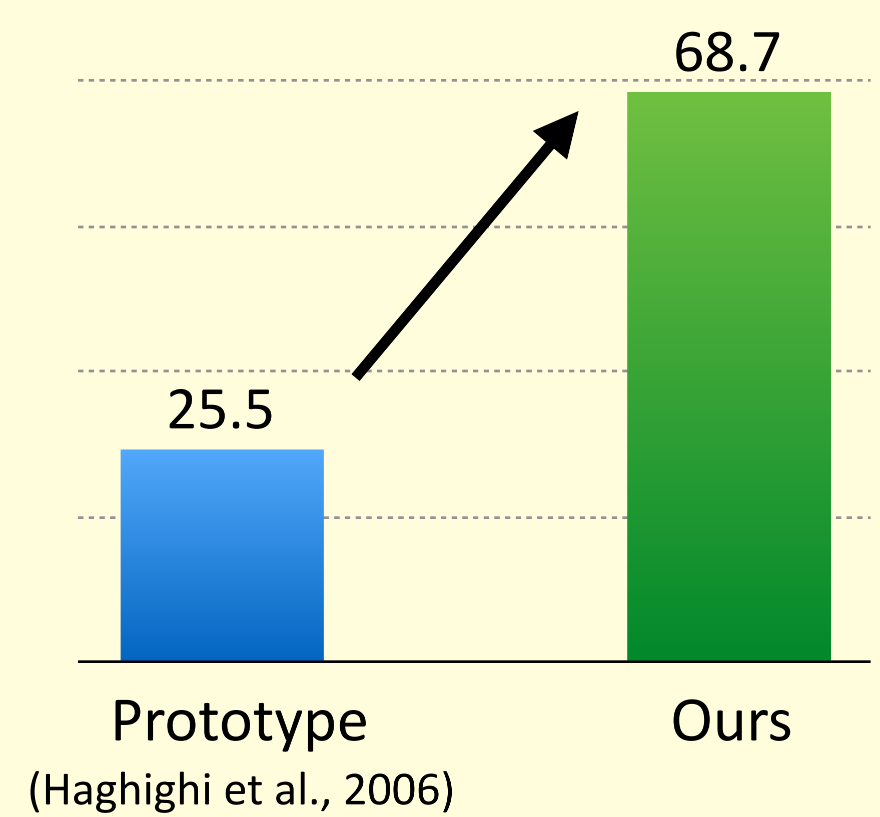
POS Accuracy on German



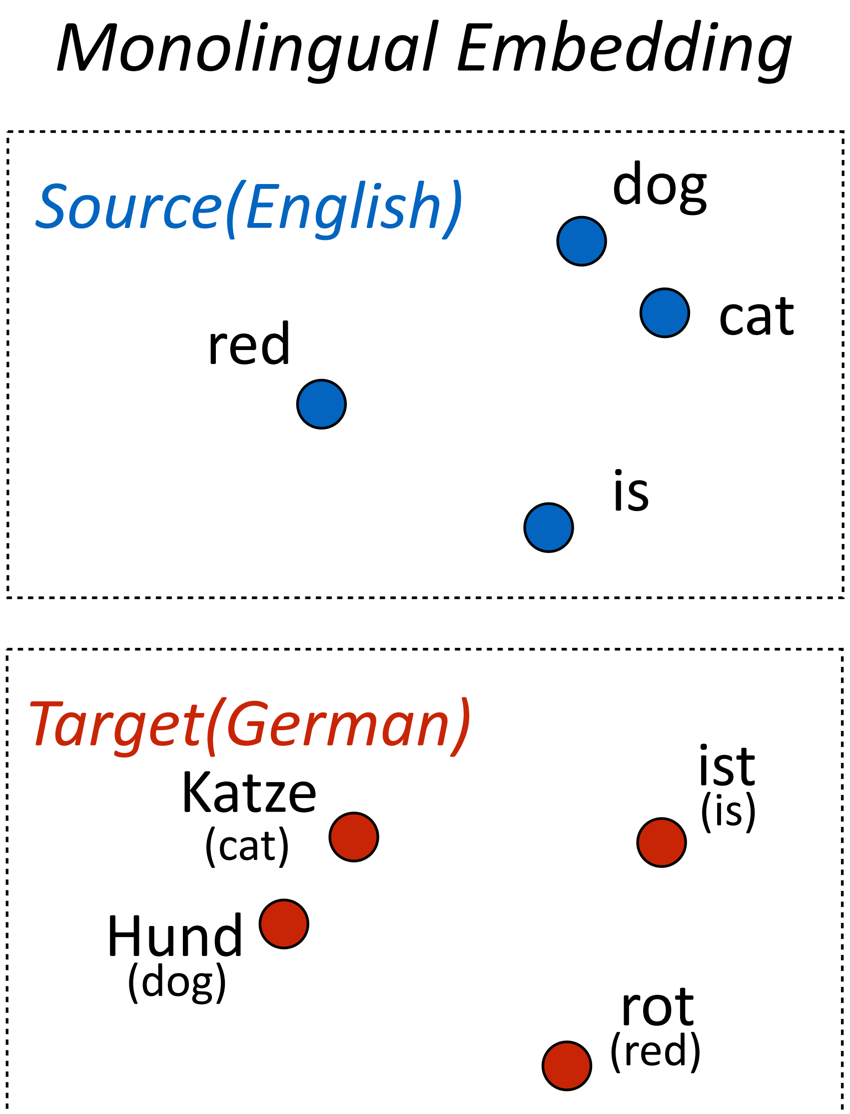
Our Two-phase Method

1. Learn coarse mapping between embeddings via ten translation pairs

2. Refine embedding transformations and model parameters via unsupervised learning on the target language

Coarse Mapping between Embeddings

- Goal: find a linear transformation from target to source embedding space
- Objective: minimize the distance between translation pairs



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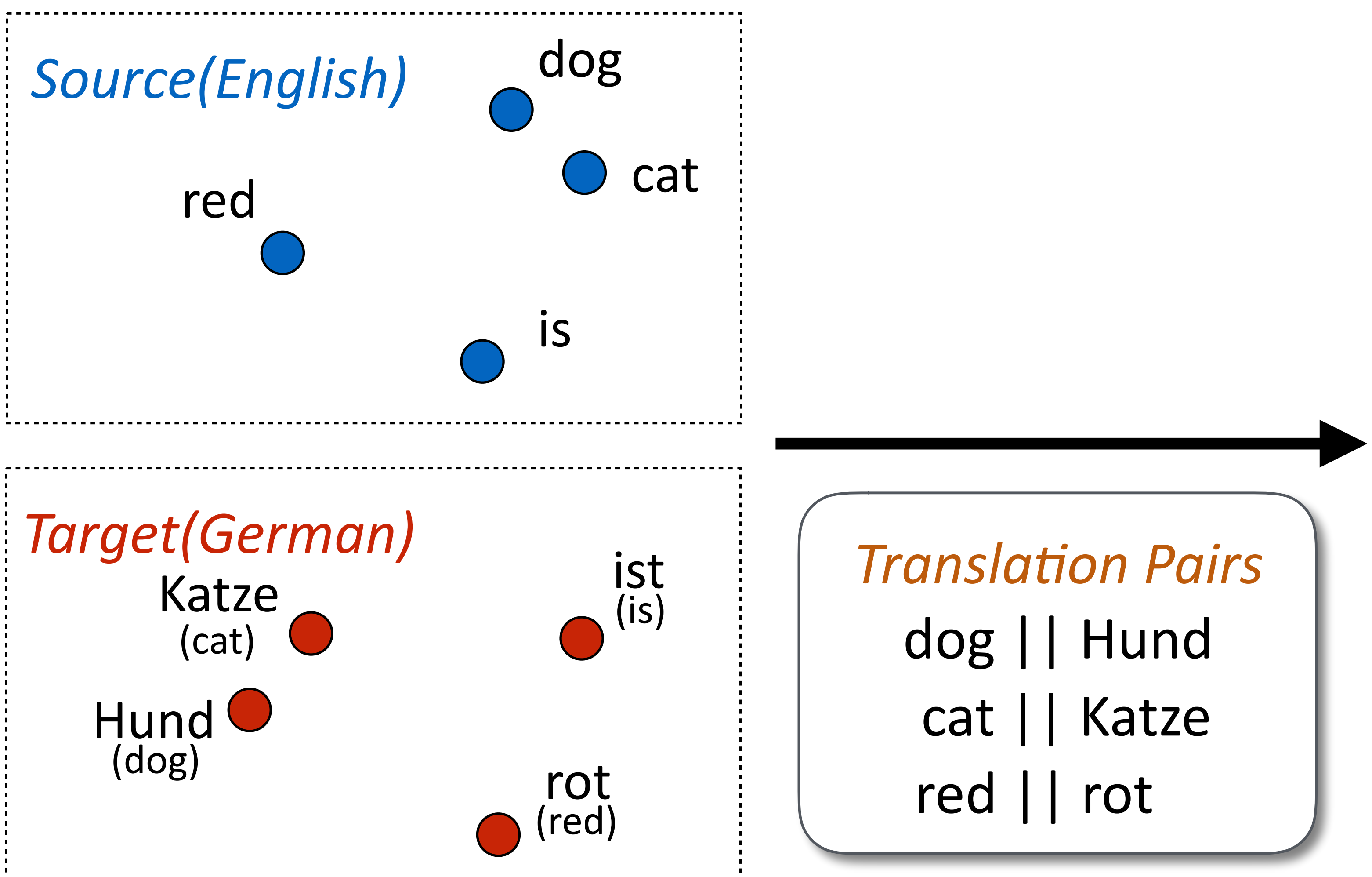
Monolingual Embedding



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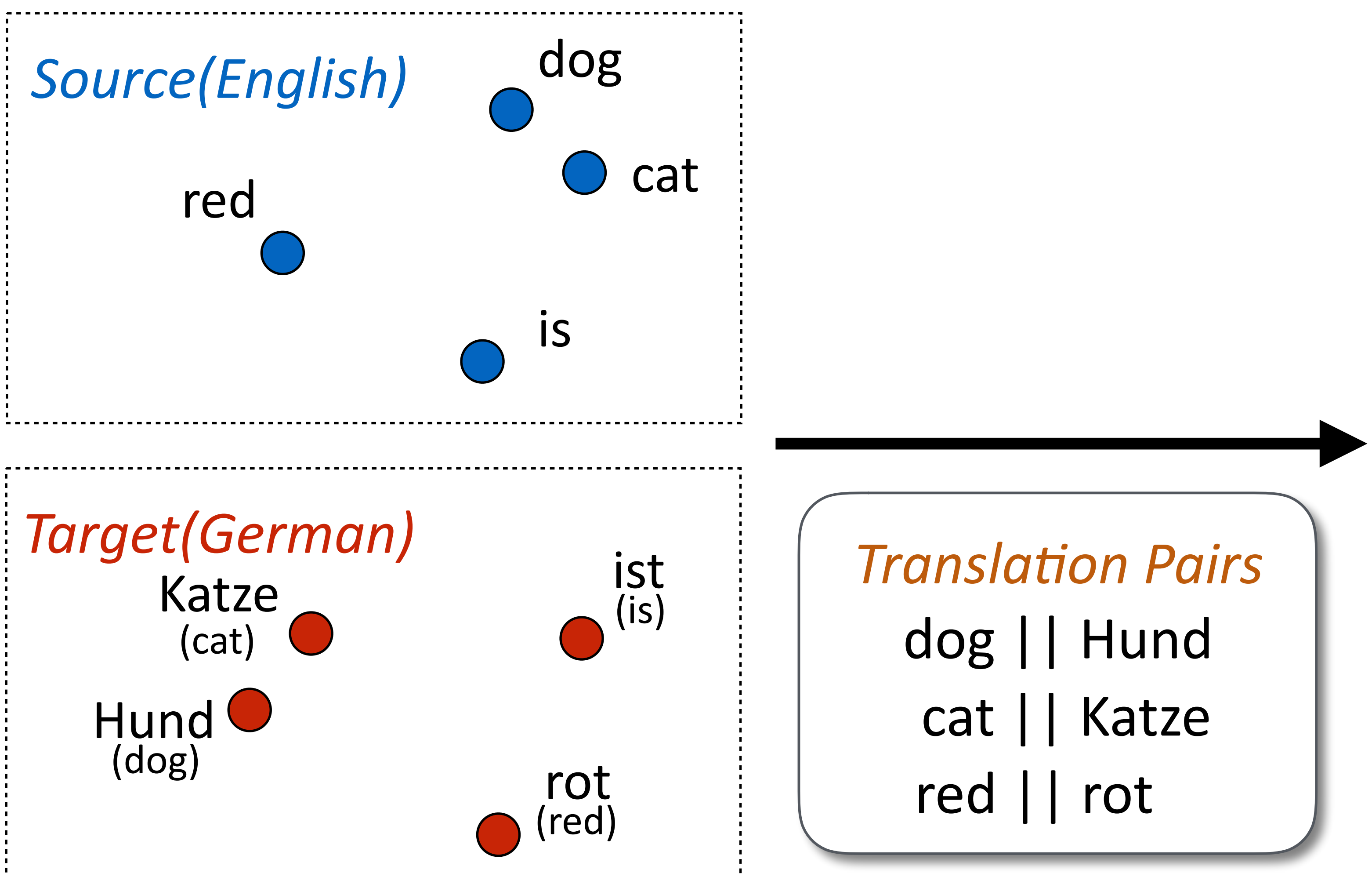

Too many degrees of freedom

dimension:	20
# pairs:	10
degree of freedom:	10

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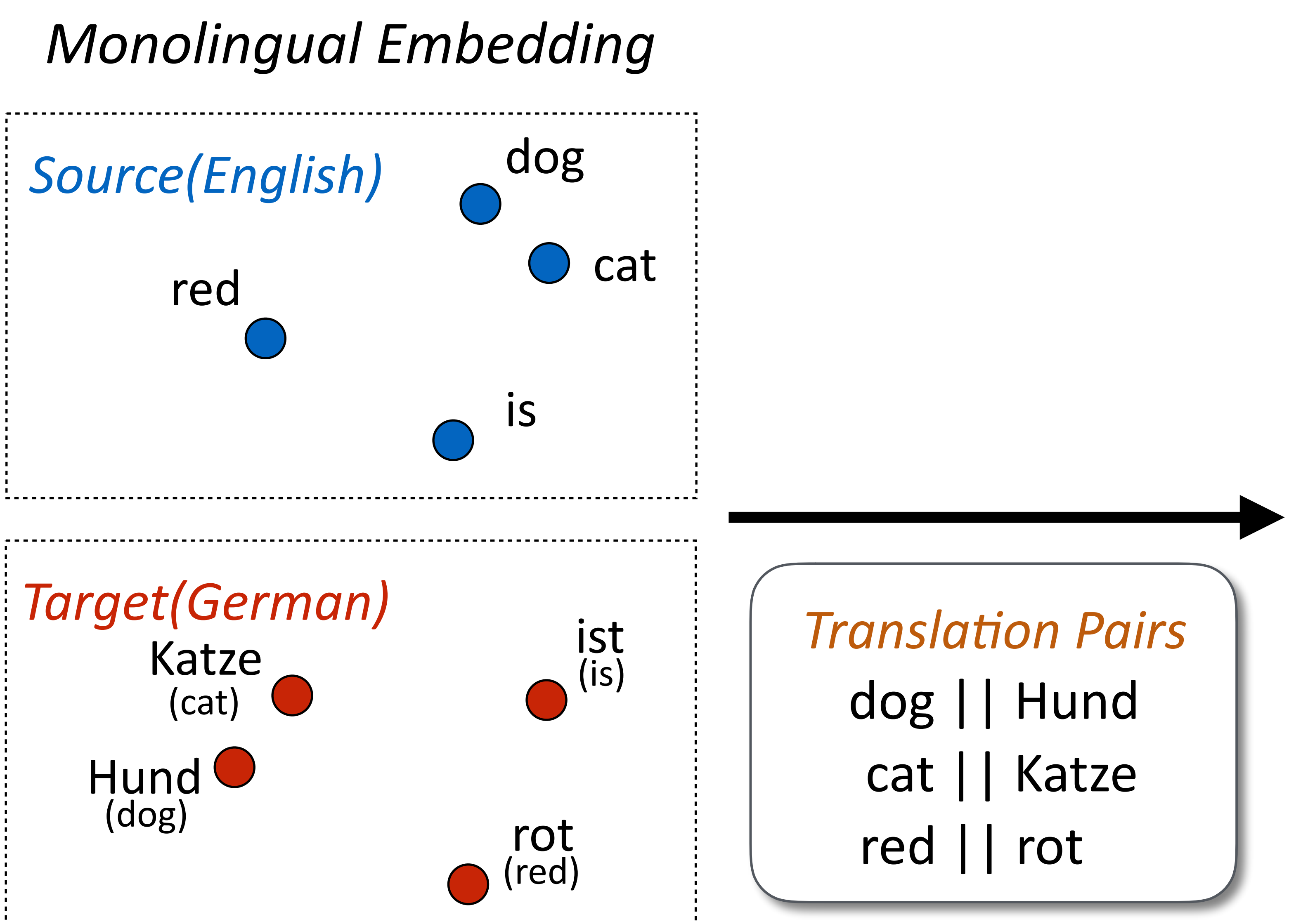

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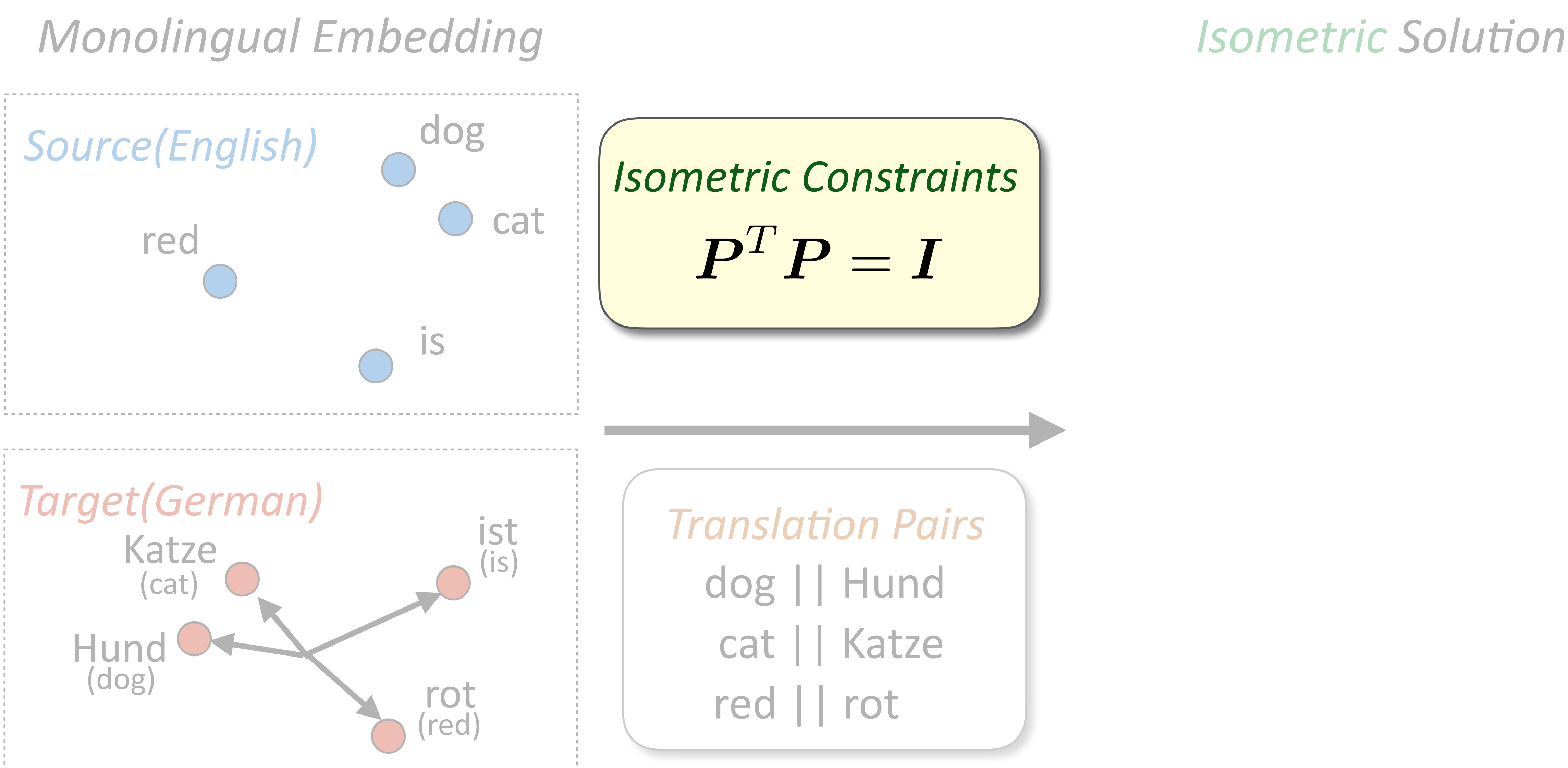
Solutions need to be constrained!

Our Solution: Isometric Constraints

- Transformation P is an isometric (orthonormal) matrix
- Transformation preserves angles and lengths (cosine similarity) of word vectors, thus preserving semantic relations



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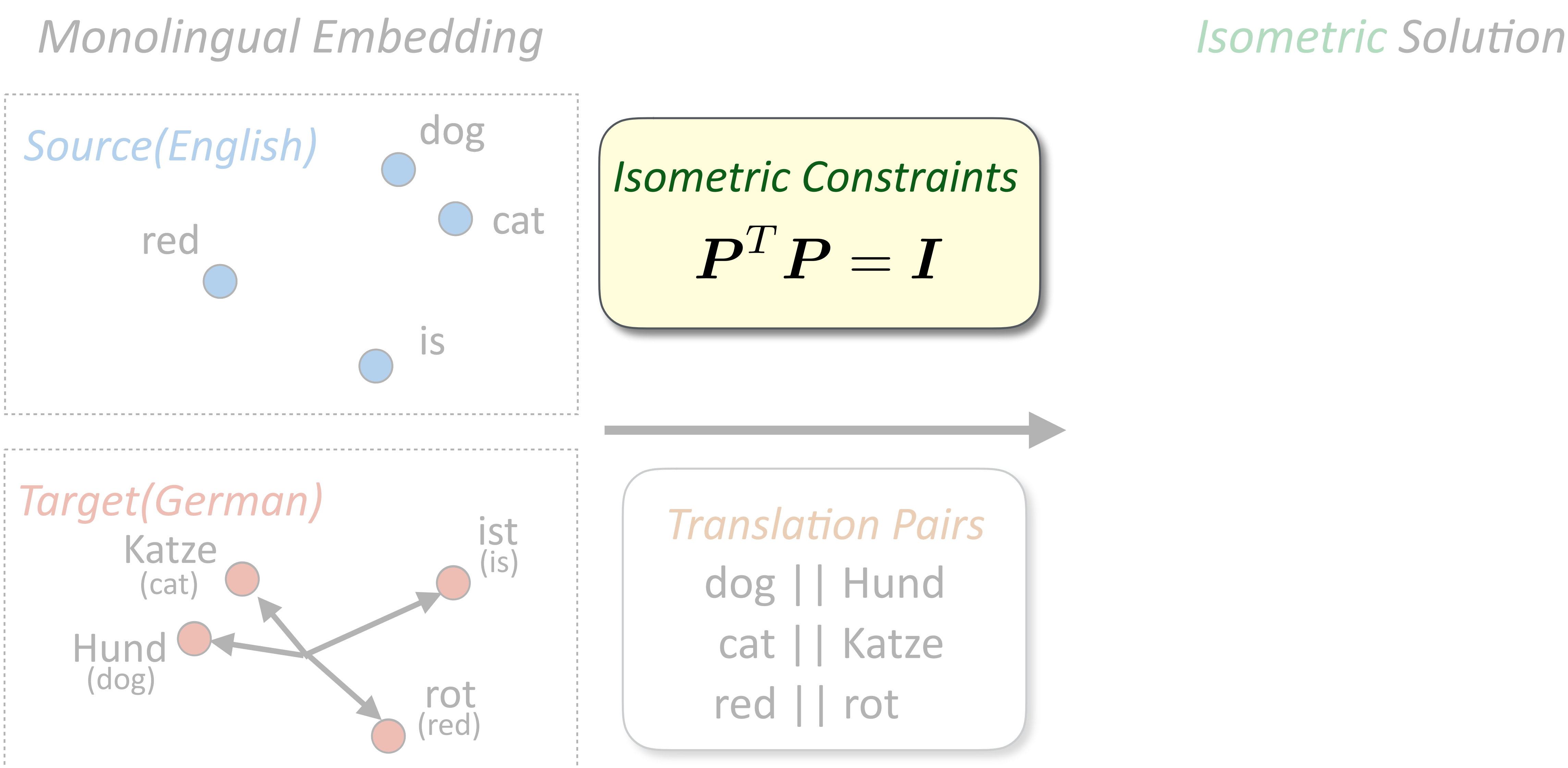
$$\cos\langle \text{cat}, \text{dog}\rangle \approx \cos\langle \text{Katze}, \text{Hund}\rangle, \;\; \cos\langle \text{dog}, \text{red}\rangle \approx \cos\langle \text{Hund}, \text{rot}\rangle$$



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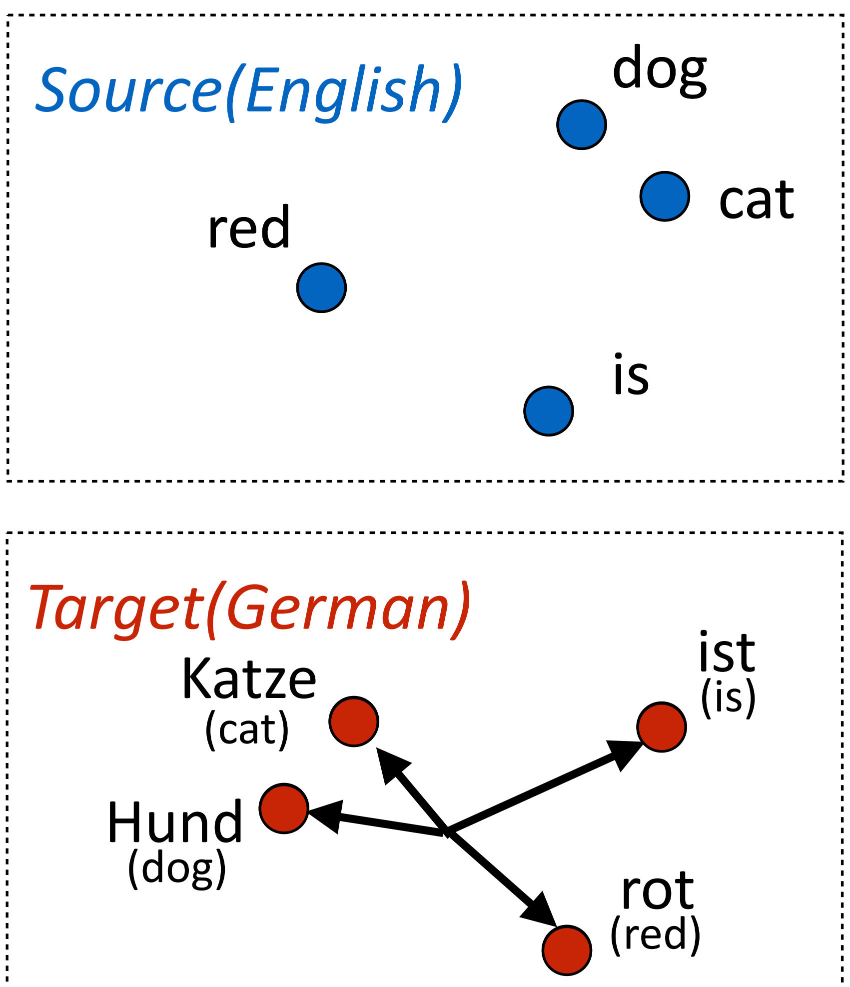
Monolingual Embedding

Isometric Solution



Isometric Constraints

$$P^T P = I$$

Translation Pairs

dog || Hund
cat || Katze
red || rot

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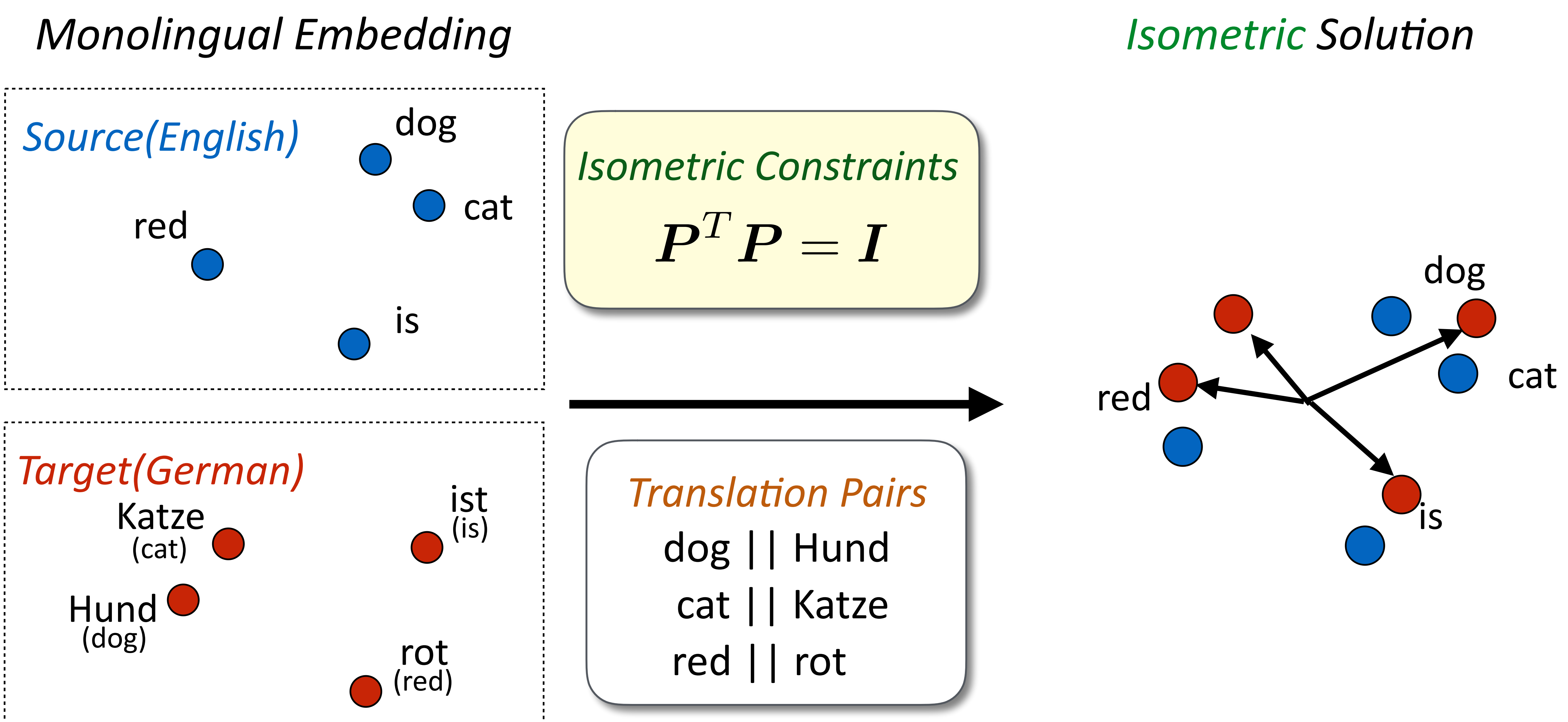

Our Solution: Isometric Constraints

- Transformation P is an isometric (orthonormal) matrix
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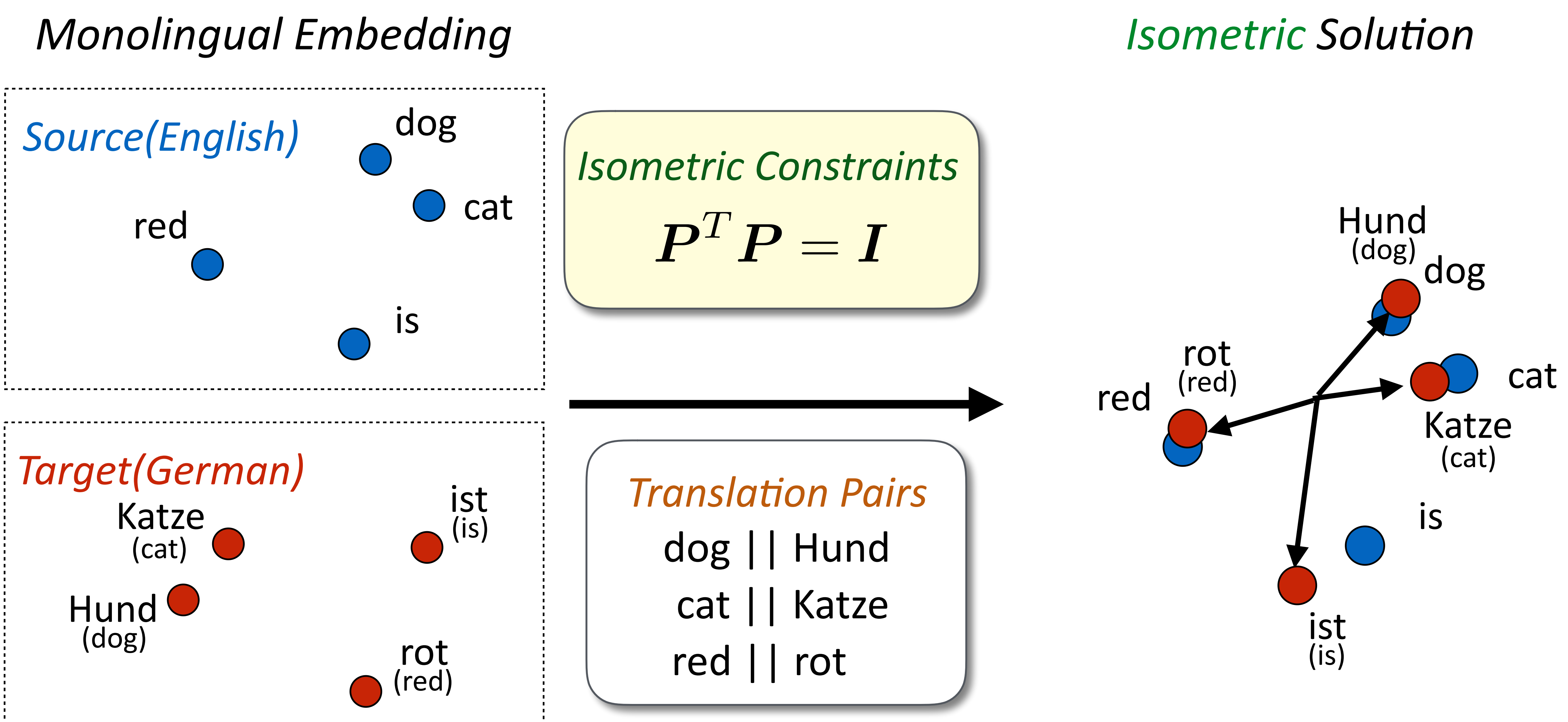
- Use the steepest descent algorithm (Abrudan et al., 2008)

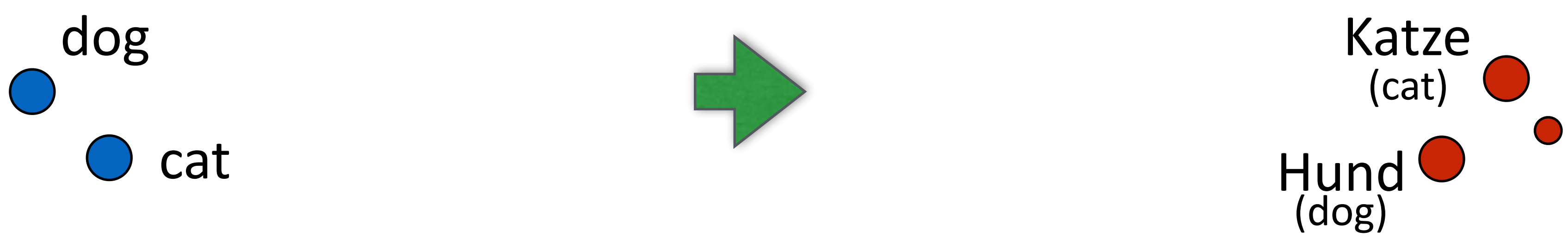


Validation of Isometric Constraints

- Validation for $\cos\langle \text{cat}, \text{dog} \rangle \approx \cos\langle \text{Katze}, \text{Hund} \rangle$
- Verify whether nearest neighbors are preserved after translations

English: nearest neighbor

German: k-th (k≤2) nearest neighbor?



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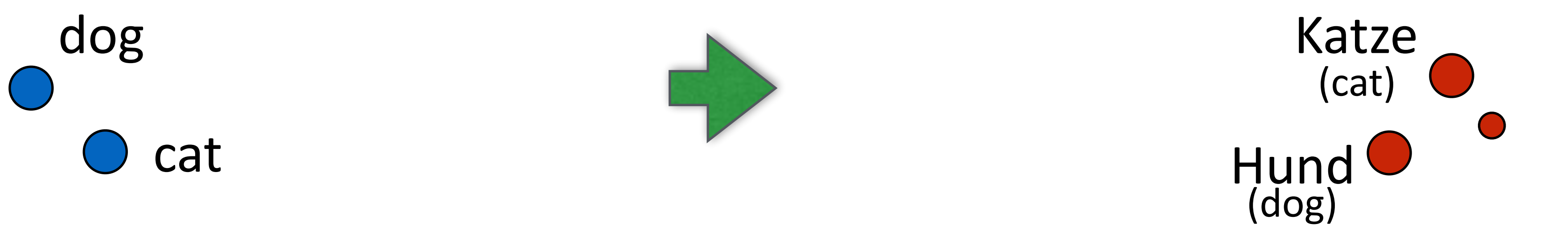
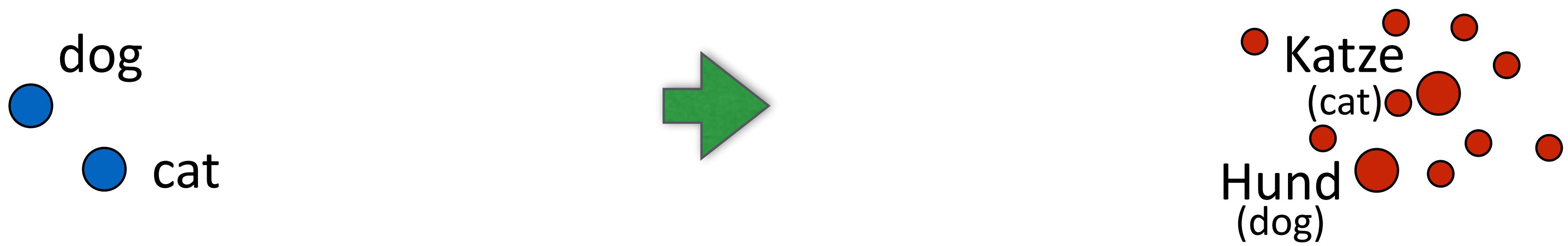


✦ For 50% of word pairs, $k \leq 2$

English: nearest neighbor

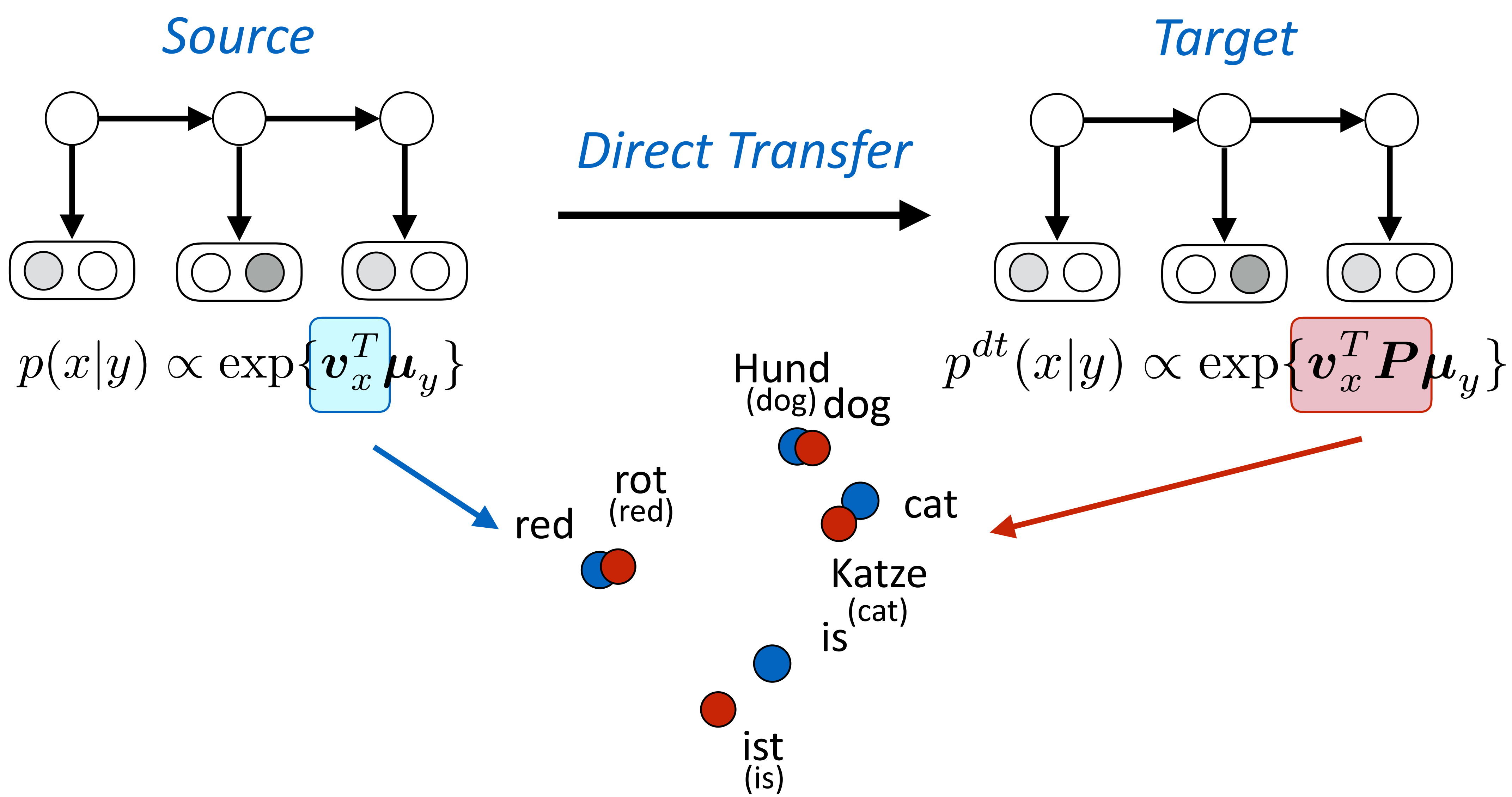
German: k-th (k≤10) nearest neighbor?



✦ For 90% of word pairs, $k \leq 10$

Direct Transfer Model

- Supervised source language HMM
  - ✦ Feature-based HMM (Berg-Kirkpatrick et al., 2010)
  - ✦ Word embeddings as emission features



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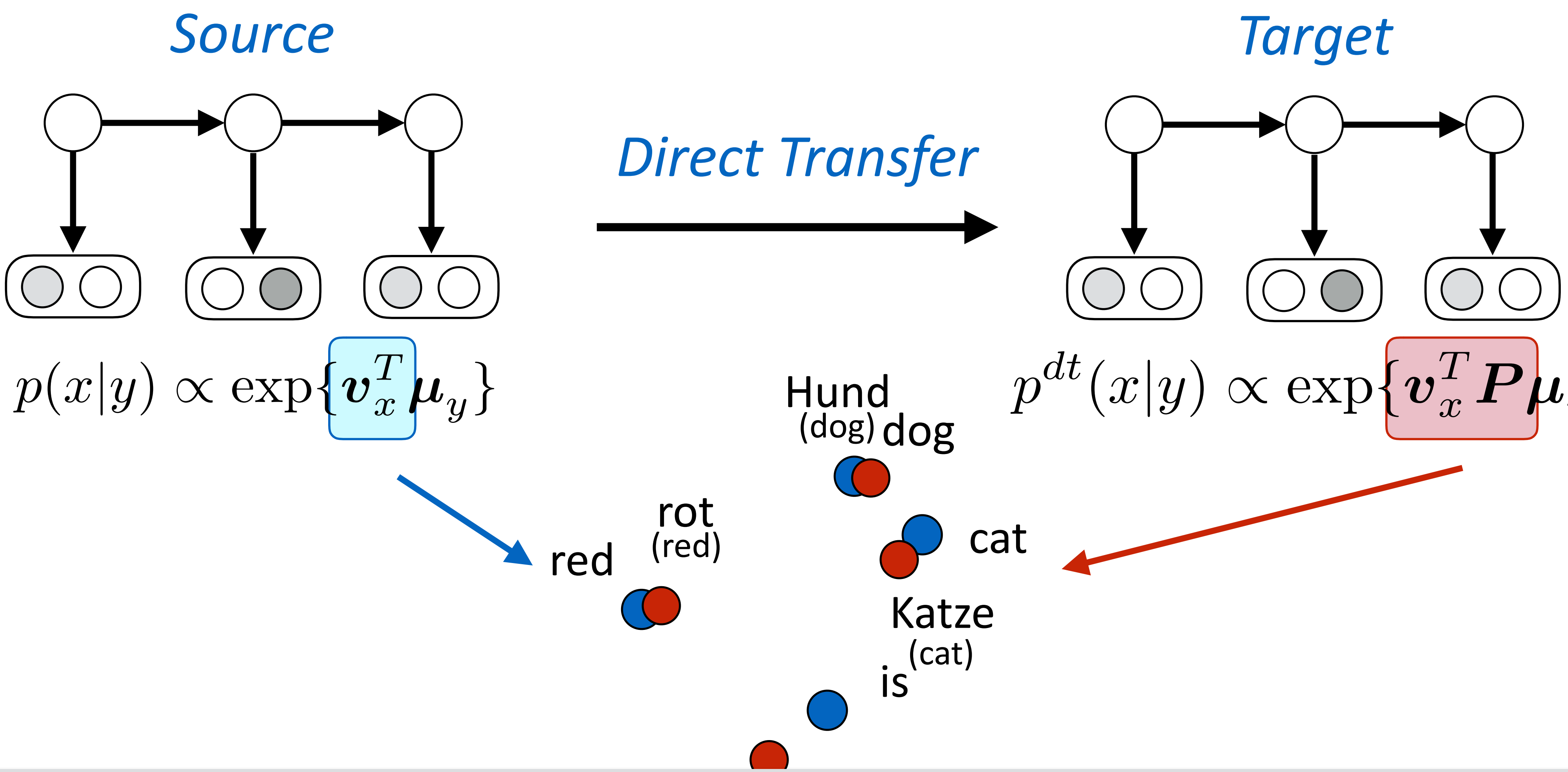

$p(x|y) \propto \exp\{\boxed{\boldsymbol{v}_x^T}\boldsymbol{\mu}_y\}$

$p^{dt}(x|y) \propto \exp\{\boxed{\boldsymbol{v}_x^T \boldsymbol{P}}\boldsymbol{\mu}_y\}$

Coarse mapping is not accurate

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Unsupervised Target Language HMM

- Use the direct transfer model (based on the coarse mapping) to initialize and regularize the unsupervised tagger on the target language
- Refine mapping via global linear transformation M and local non-linear adjustment $\theta_{x,y}$

$$p(x|y) \propto \exp\{\boldsymbol{v}_x^T \boldsymbol{P}\boldsymbol{M}\boldsymbol{\mu}_y + \theta_{x,y}\}$$

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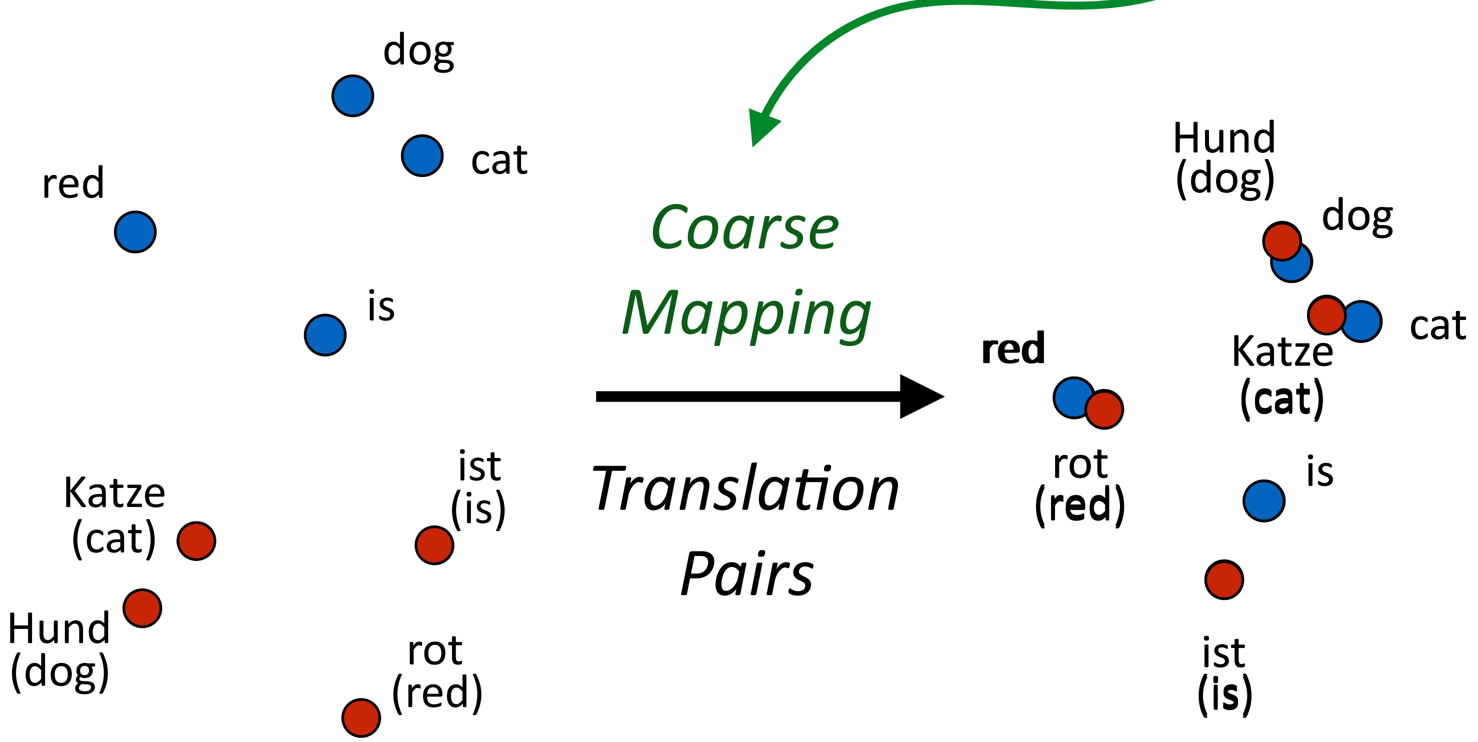

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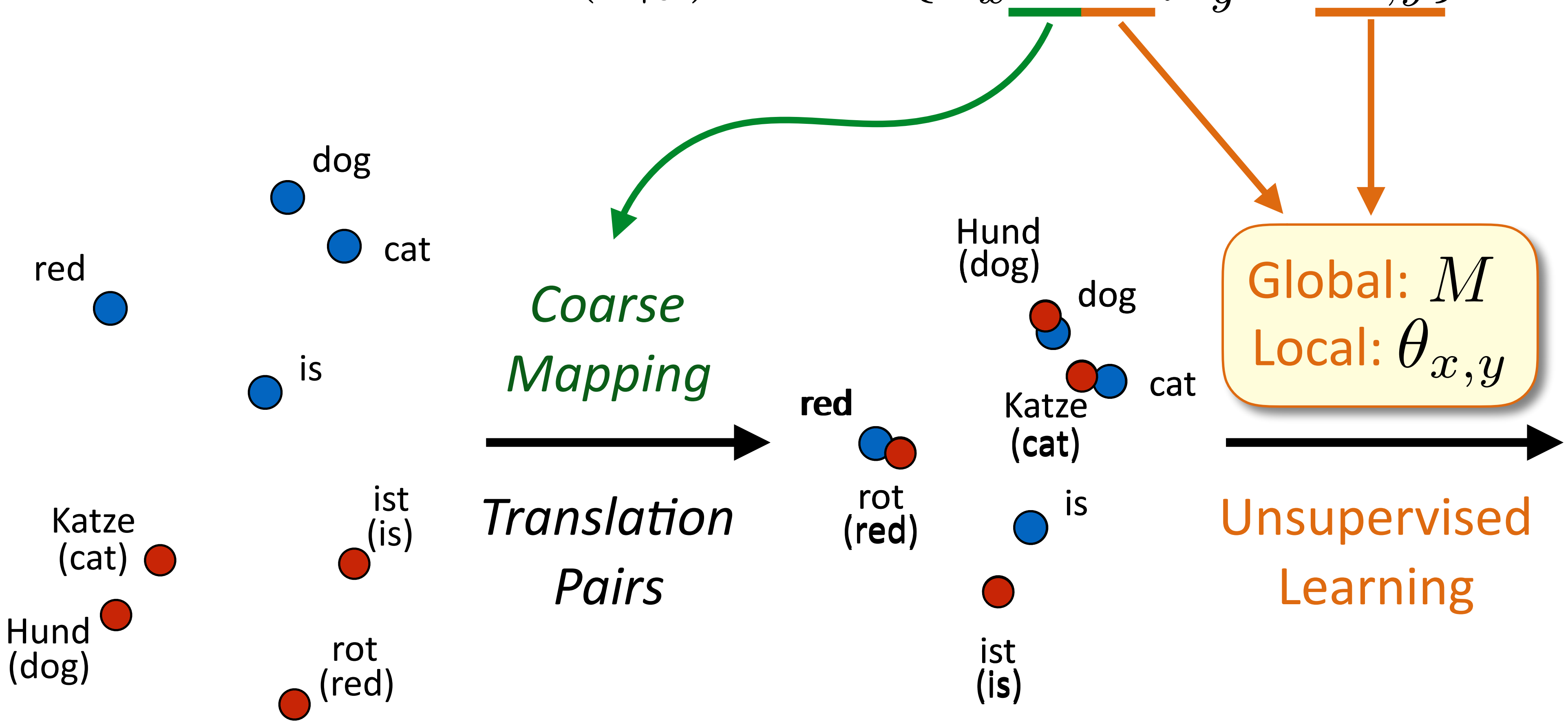

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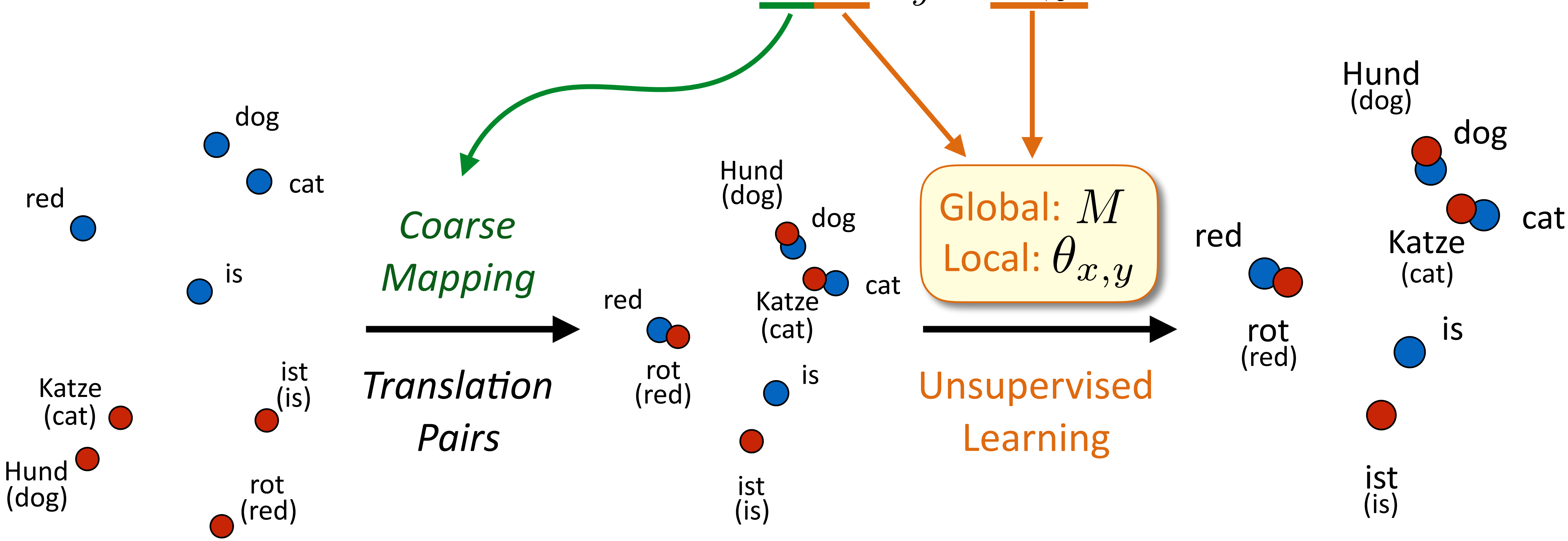

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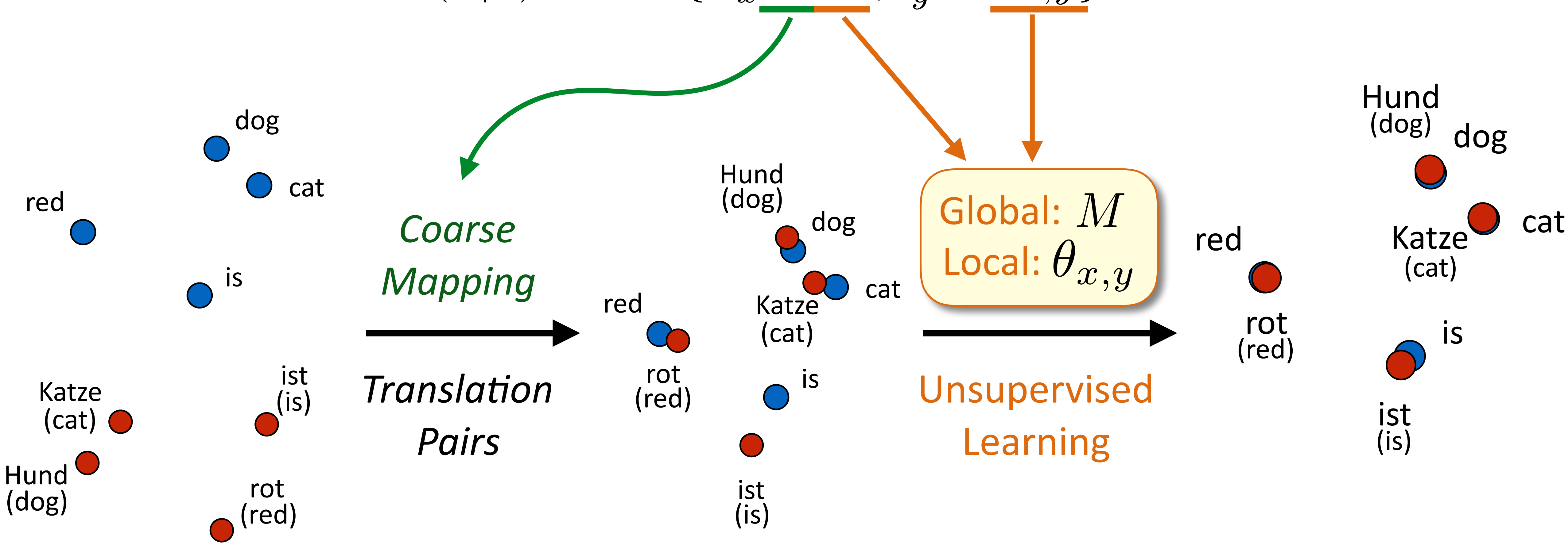


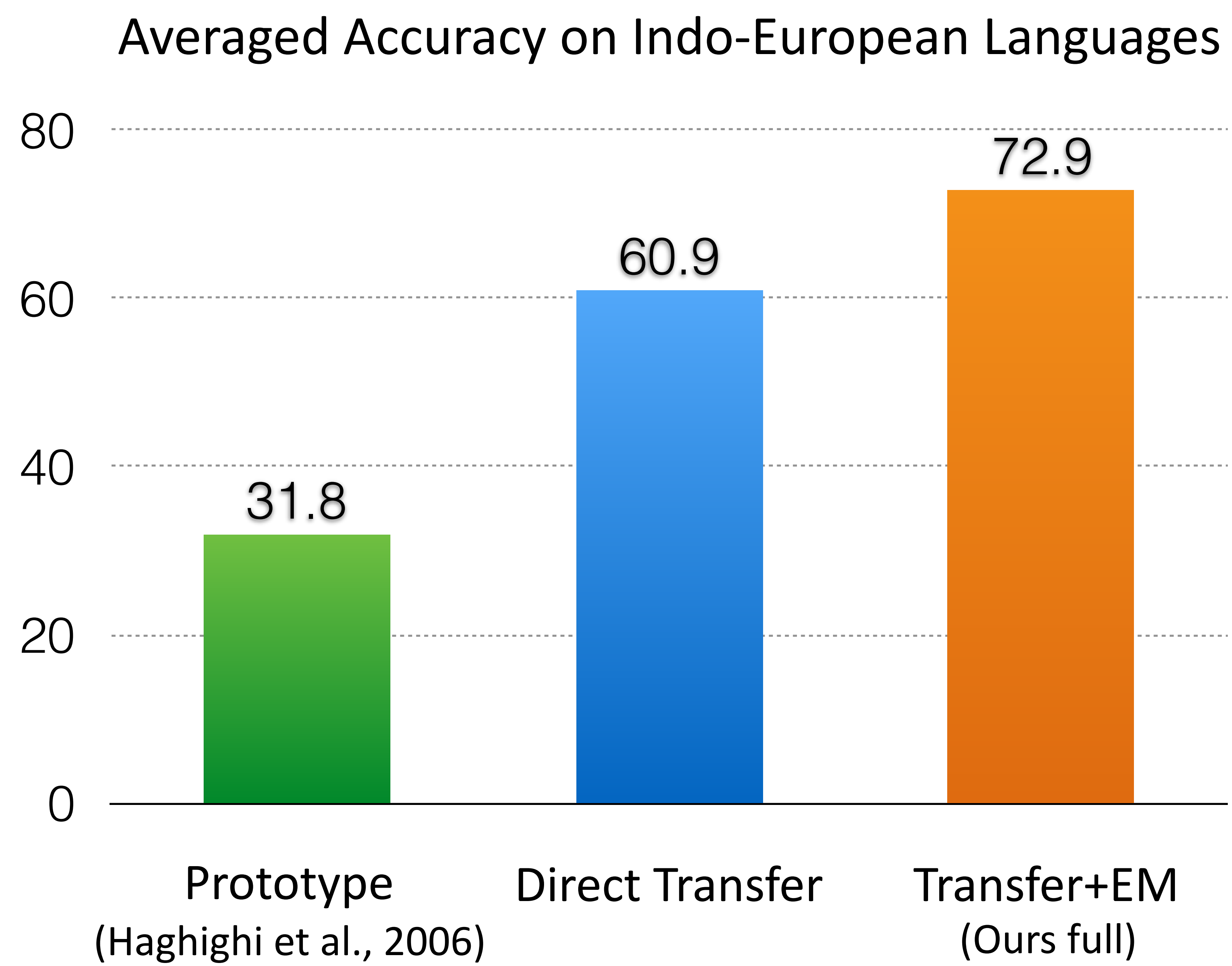
Learning

- Parameters: $\boldsymbol{\mu}_y, \theta_{y,y'}, \boldsymbol{M}, \theta_{x,y}$
- Optimization method: standard Expectation-Maximization (EM)
  - ✦ E-step: forward-backward
  - ✦ M-step: gradient ascent using L-BFGS

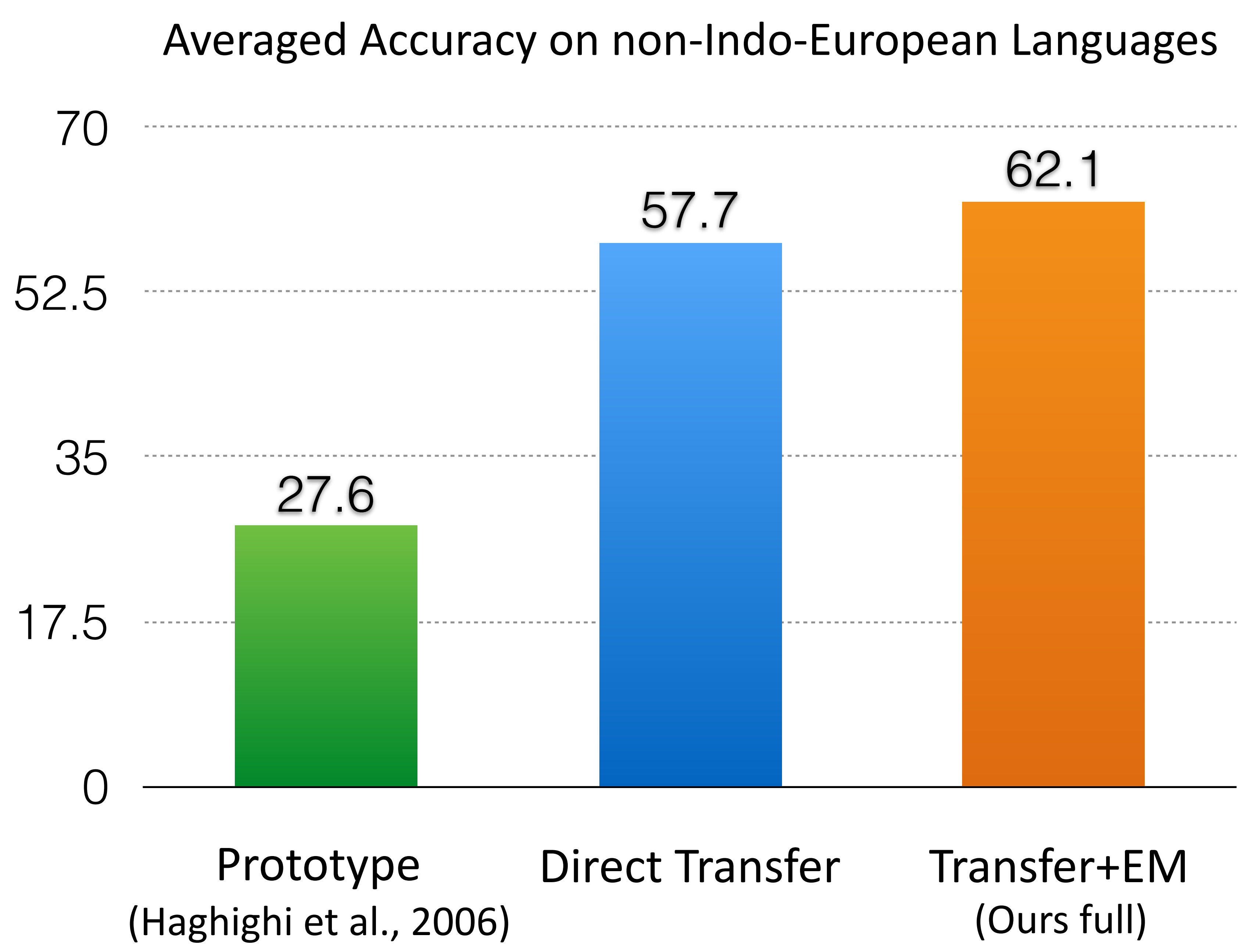
Experimental Setup

- Datasets: Universal Dependencies Treebanks v1.2
  - Source: English
  - Target (Indo-European): Danish (da), German (de), Spanish (es)
  - Target (non-Indo-European): Finnish (fi), Hungarian (hu), Indonesian (id)
- Universal tagset: 14 tags (noun, verb, adjective etc.)
- Word embeddings: 20-dimension vectors trained on Wiki dumps using word2vec

Indo-European Results

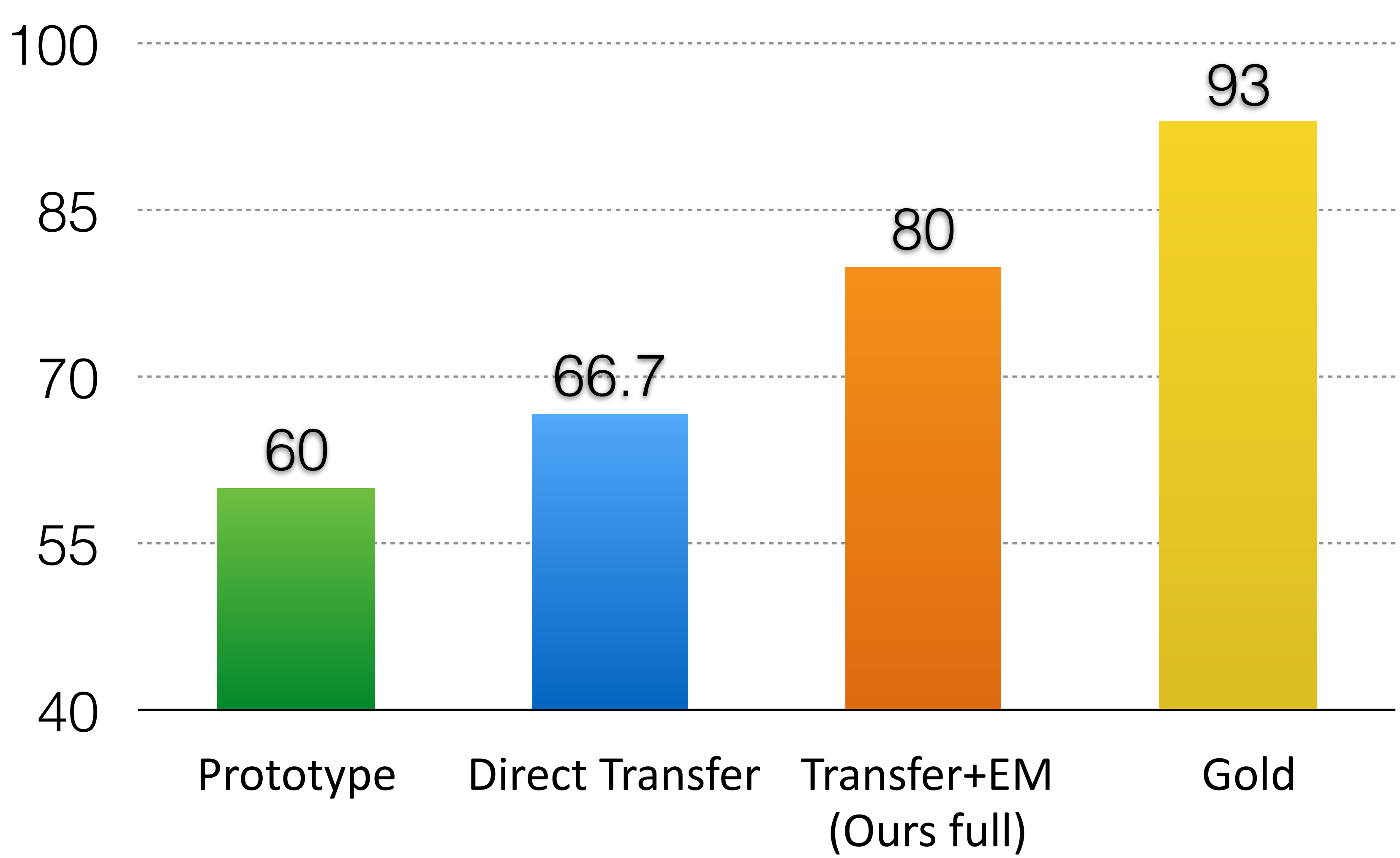


Non-Indo-European Results



Prediction of Linguistic Typology

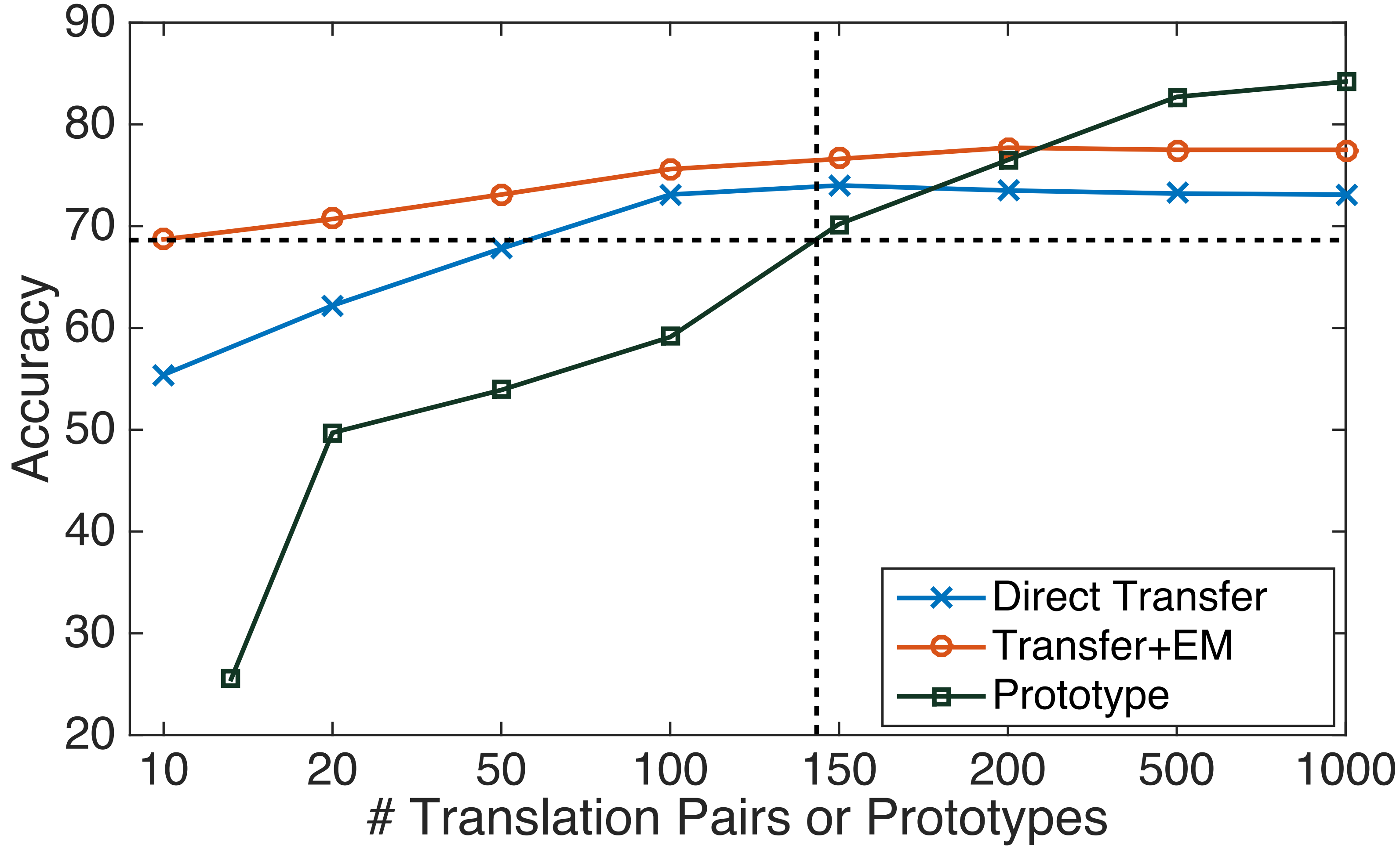
- Task: predict whether a language is verb-object or object-verb (five typological properties)
- Features: bigrams and trigrams of POS tags



Impact of Amount of Supervision

- Transfer+EM with 10 pairs = 150 prototypes

Accuracy on German



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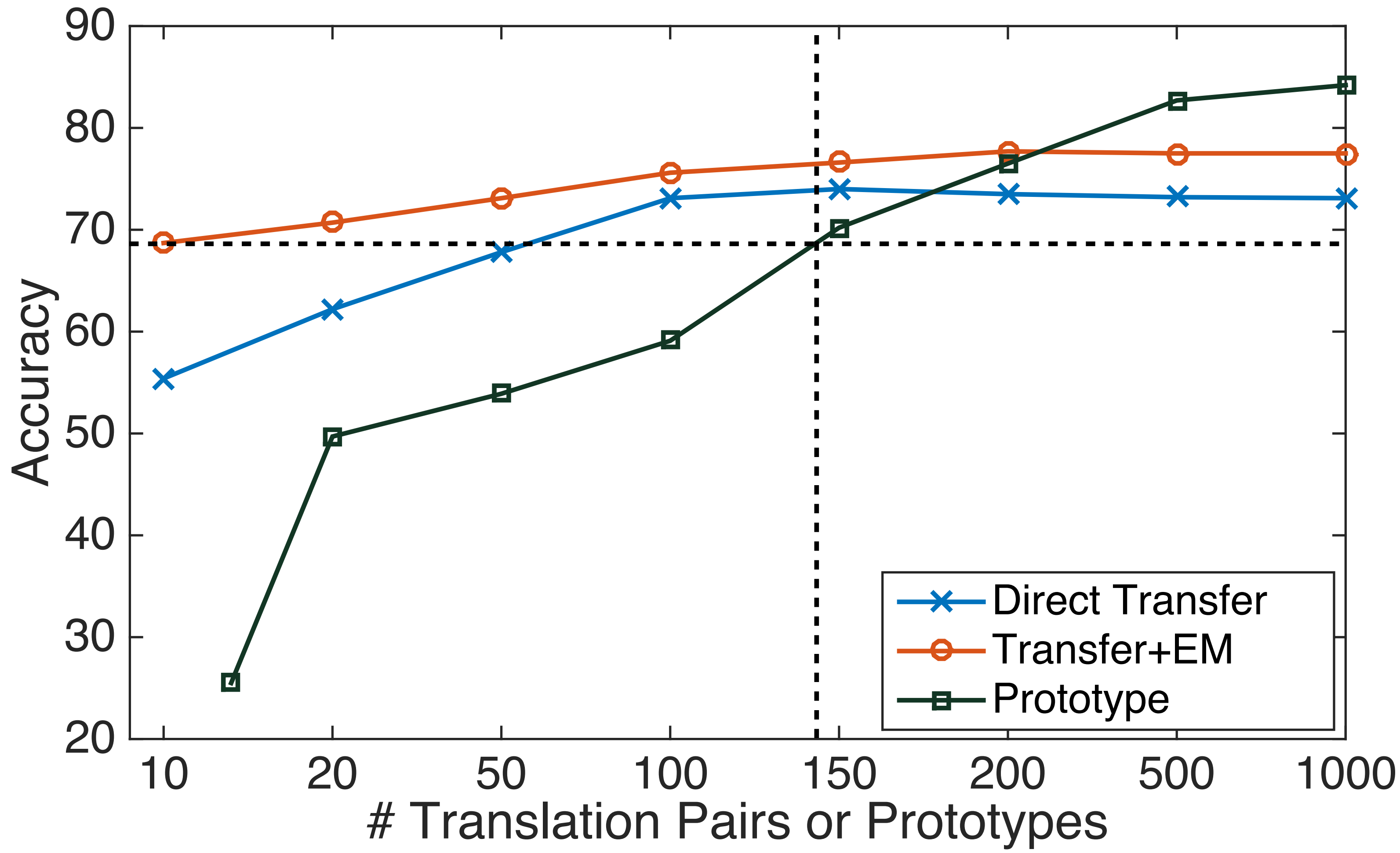
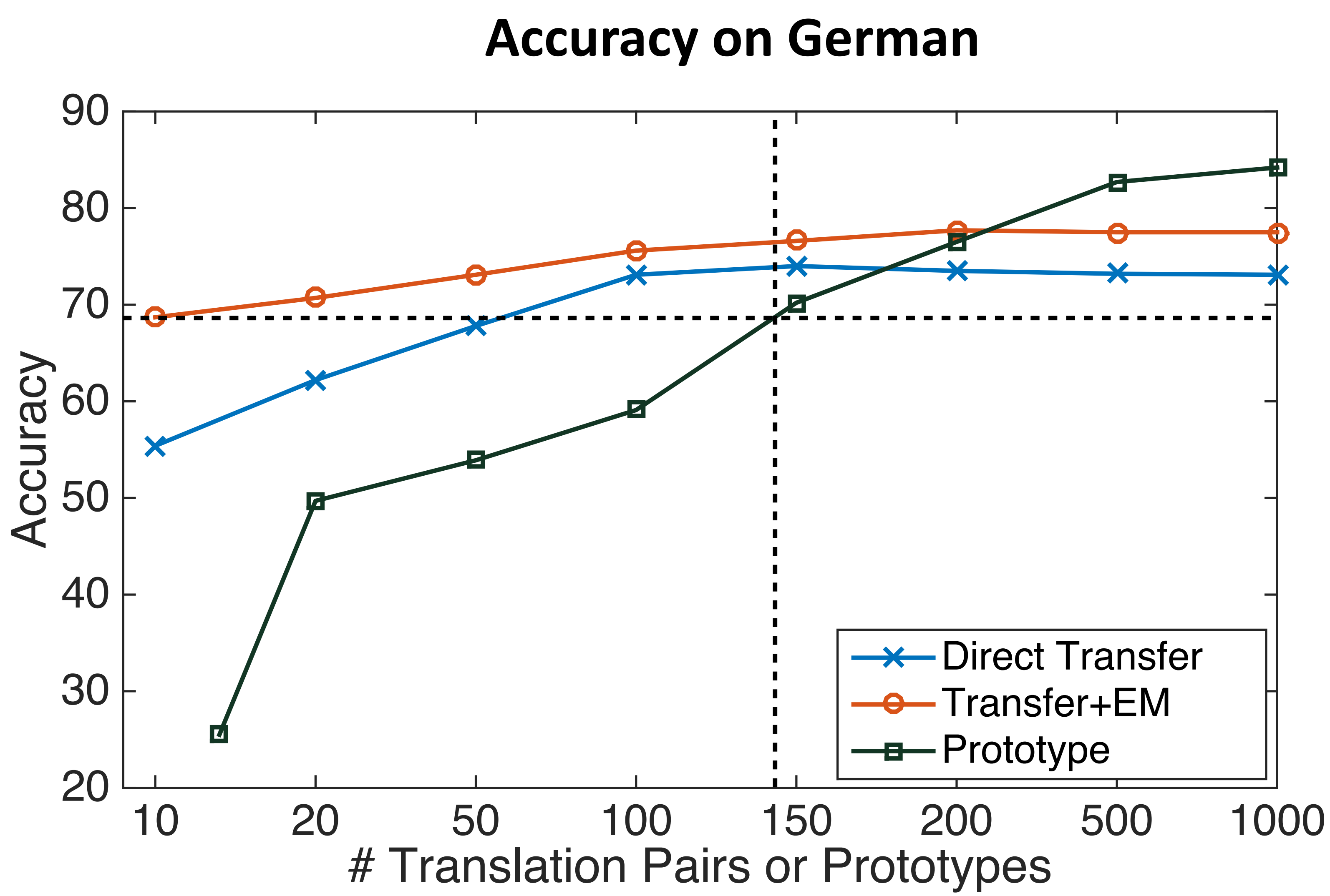


Impact of Amount of Supervision

- Transfer+EM with 10 pairs = 150 prototypes
- Prototype improves with large amount of annotations
- Transfer+EM consistently improves over Direct Transfer



Conclusion

- Ten translation pairs are sufficient to enable multilingual transfer of POS tagging
- Our model significantly outperforms the direct transfer and the prototype-driven method

Source code available at:

https://github.com/yuanzh/transfer_pos

Thank You!

Impact of Embedding Dimensions and Window Size