Unsupervised Machine Translation

Guillaume Lample

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Joint work with Alexis Conneau, Marc'Aurelio Ranzato, Ludovic Denoyer, Hervé Jégou

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- The creation of parallel data is difficult, and costly
- Most language pairs use English as a pivot
- However, monolingual data is much easier to find

Questions

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Word translation without parallel data

Guillaume Lample *, Alexis Conneau *, Marc'Aurelio Ranzato, Ludovic Denoyer, Hervé Jégou (*ICLR 2018)*
Code: https://github.com/facebookresearch/MUSE

Unsupervised Machine Translation Using Monolingual Corpora Only

Guillaume Lample, Alexis Conneau, Ludovic Denoyer, Marc'Aurelio Ranzato (*ICLR 2018)*

Prior work

- Semi-supervised
  - Back-translation (Sennrich et al., 2015)

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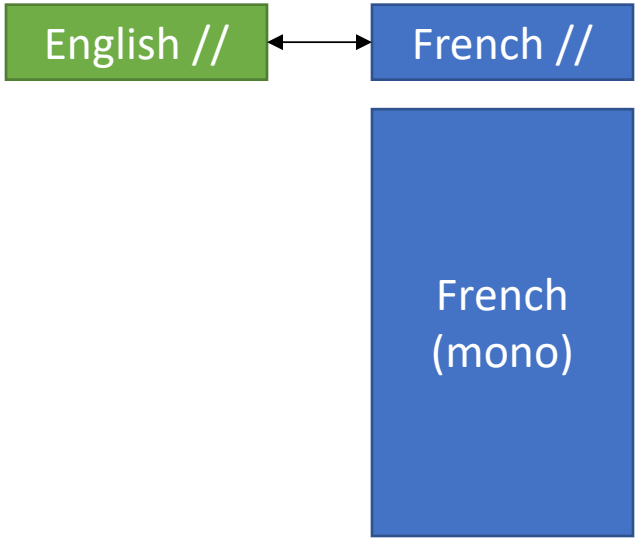

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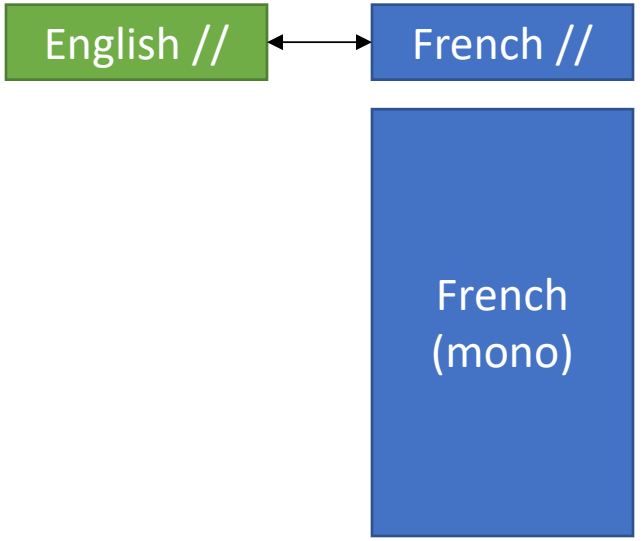

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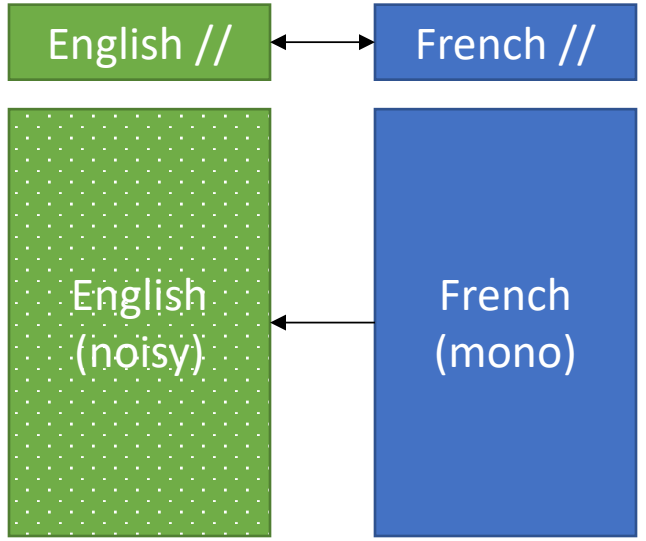

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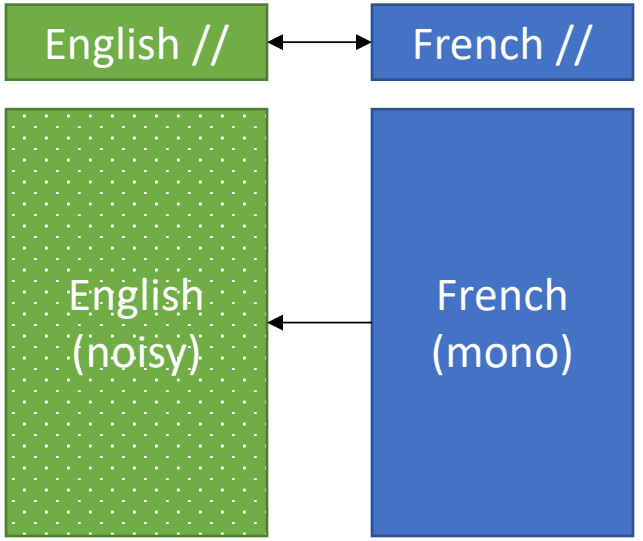
- Use the two parallel datasets to train $\boldsymbol{M_{s2t}}$



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  - Back-translation (Sennrich et al., 2015)
  - Dual learning (He et al., 2016)

    - (source → target → source) $\boldsymbol{M}_{t2s}(\boldsymbol{M}_{s2t}(x_s)) = x_s$
    - (target → source → target) $\boldsymbol{M}_{s2t}(\boldsymbol{M}_{t2s}(x_t)) = x_t$

Our approach

- Start with unsupervised word translation
  - Easier task to start with
  - Already insights of why it could work
  - Can be used as a first step towards unsupervised sentence translation

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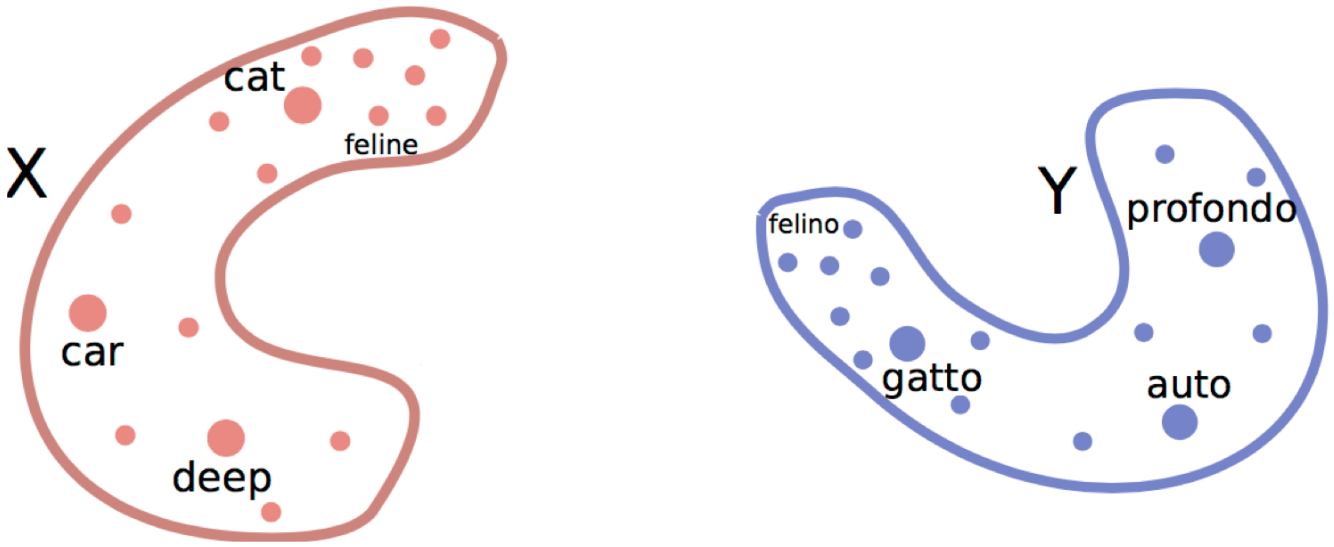

- Totally unsupervised
- Widely used
- Strong systems for monolingual embeddings
- Semantically and syntactically relevant
- Not task-specific, useful across domains

Weakly-supervised word translation

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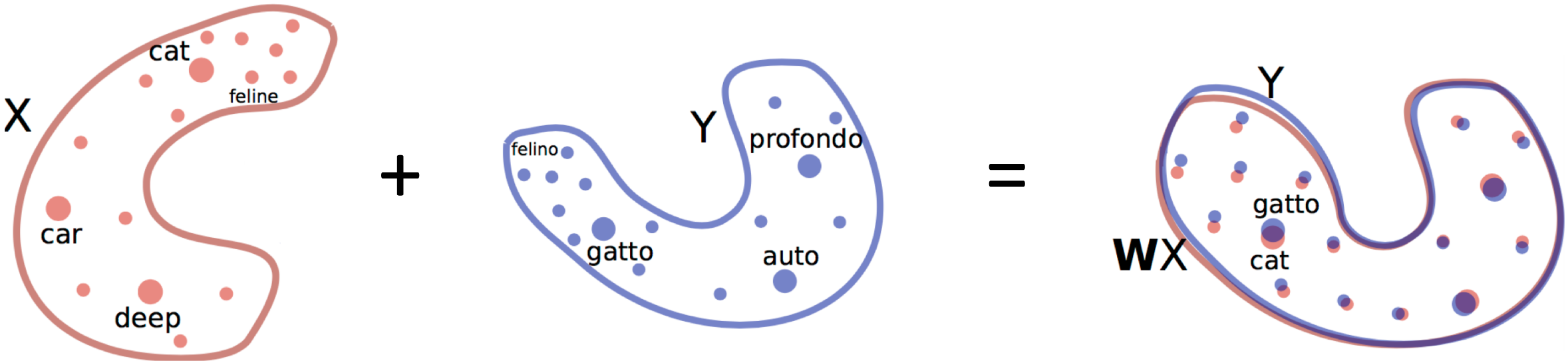

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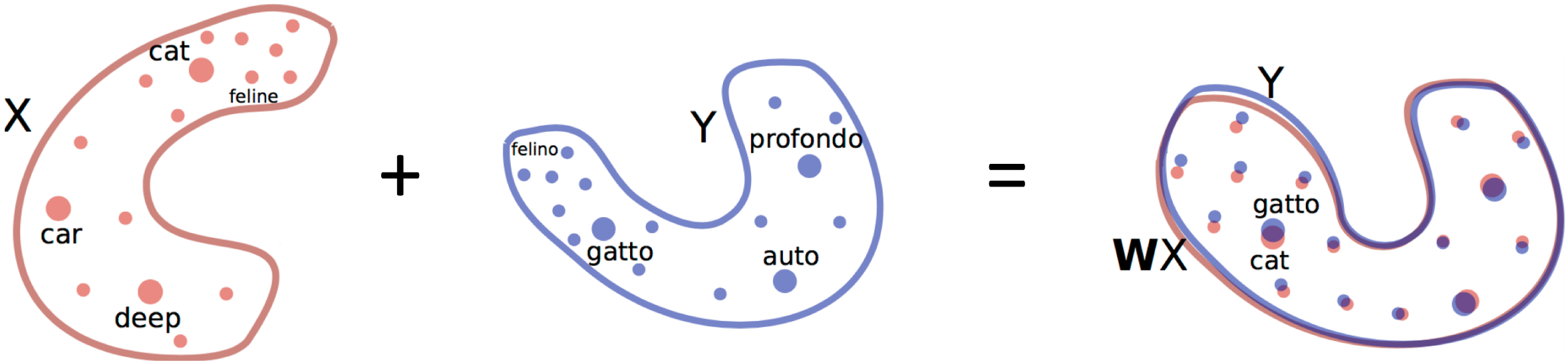

- Feed-forward network does not improve over linear mapping (Mikolov et al., 2013)
- Orthogonal projection works best Xing et al. (2015), Smith et al. (2017)

Weakly-supervised word translation

- Linear projection – Mikolov et al. (2013)

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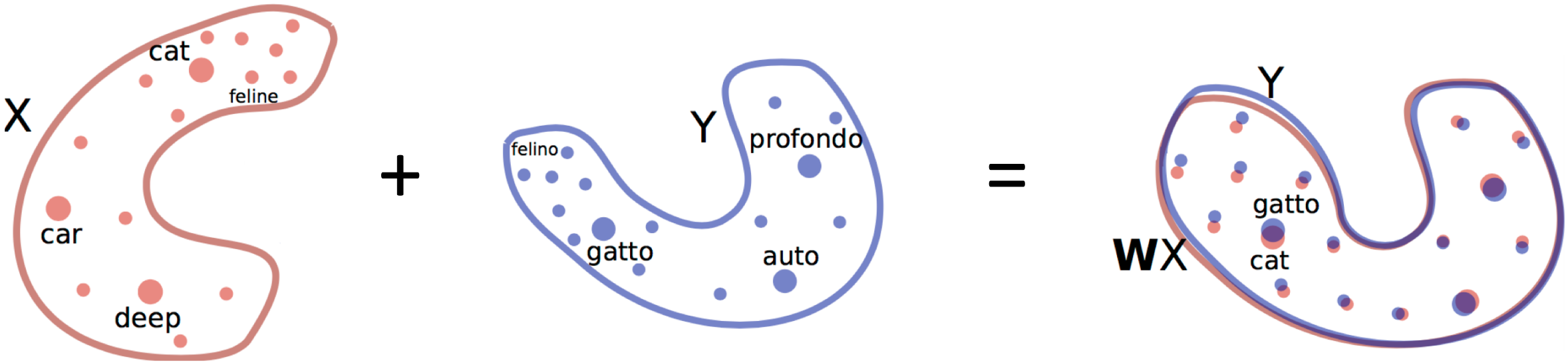
- Given a source word s, define the translation as:

$$t = \operatorname{argmax}_t \cos(Wx_s, y_t)$$

(nearest neighbor according to the cosine distance)

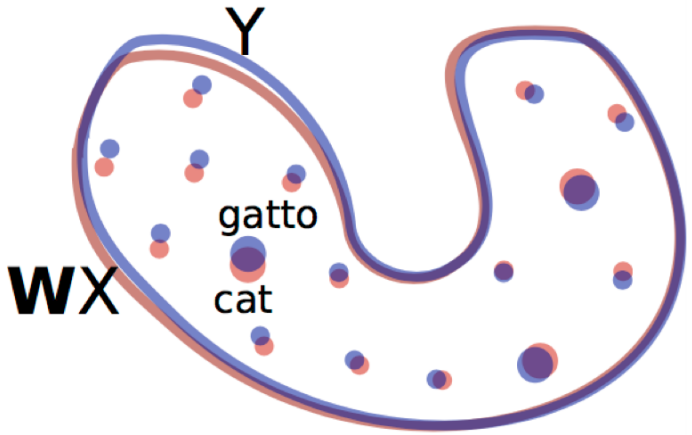
Unsupervised word translation

- Can we find the mapping **W** in an unsupervised way?



Adversarial training

- If ***WX*** and *Y* are perfectly aligned, these spaces should be undistinguishable



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- If ***WX*** and *Y* are perfectly aligned, these spaces should be undistinguishable
- Train a discriminator *D* to discriminate elements from ***WX*** and *Y*

Discriminator training

$$\mathcal{L}_D(\theta_D|W) = -\frac{1}{n}\sum_{i=1}^{n} \log P_{\theta_D}\left(\text{source} = 1\middle|Wx_i\right) - \frac{1}{m}\sum_{i=1}^{m} \log P_{\theta_D}\left(\text{source} = 0\middle|y_i\right)$$

Adversarial training

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Mapping training

$$\mathcal{L}_W(W|\theta_D) = -\frac{1}{n}\sum_{i=1}^{n}\log P_{\theta_D}\left(\text{source} = 0\middle|Wx_i\right) - \frac{1}{m}\sum_{i=1}^{m}\log P_{\theta_D}\left(\text{source} = 1\middle|y_i\right)$$

Results on word translation – Adversarial

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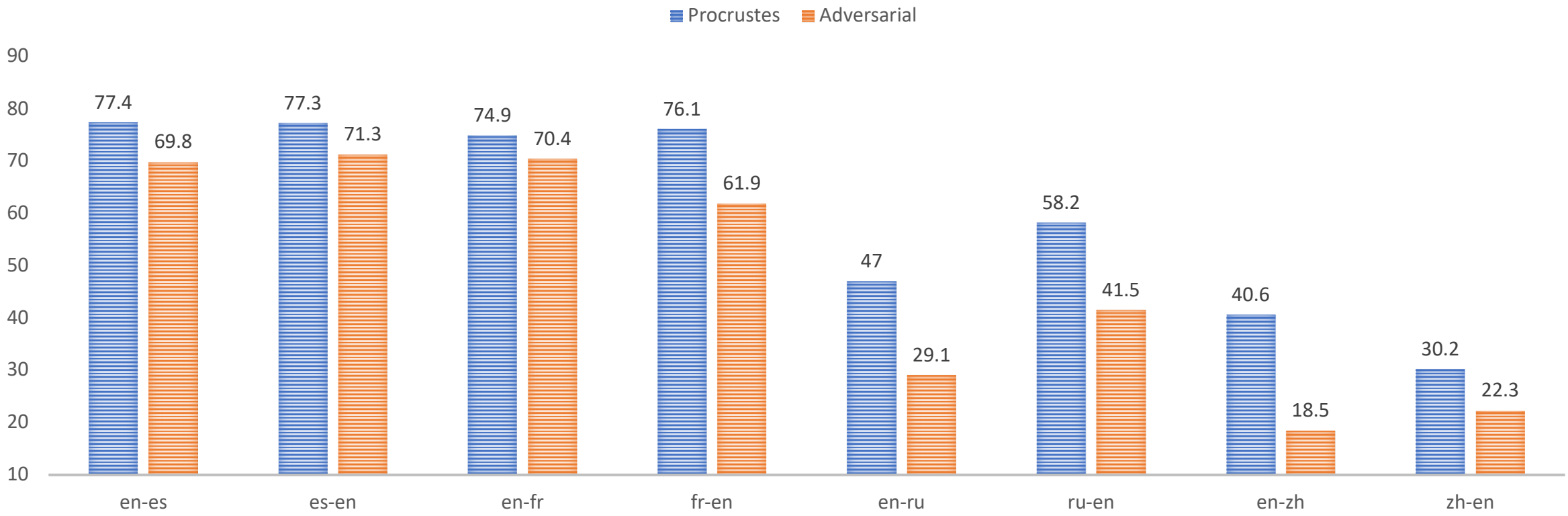

Word translation retrieval – P@1 – Adversarial

1.5k source queries, 200k target keys (vocabulary of 200k words for all languages)

Refinement

- With adversarial, the embedding spaces are not properly aligned
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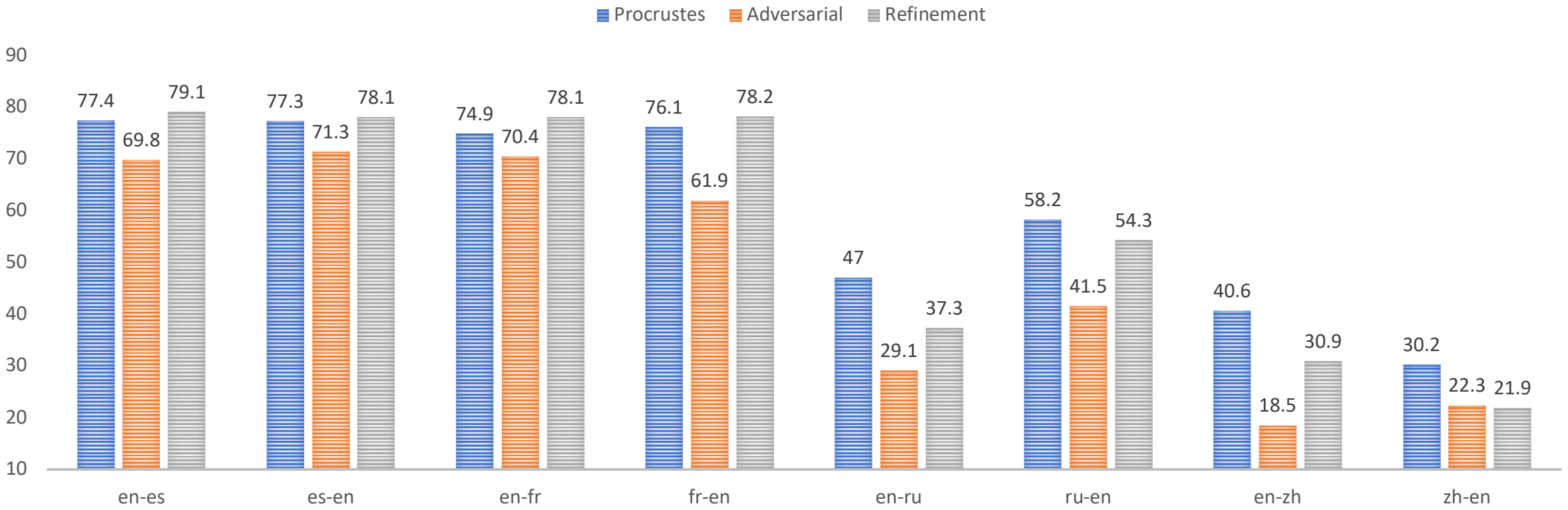
- Refinement step:
  - Generate a dictionary of confident pairs (with adversarial)
  - Apply Procrustes on this dictionary
  - Possibly iterate over the refinement step

Results on word translation – Refinement



Word translation retrieval – P@1 – Adversarial + Refinement

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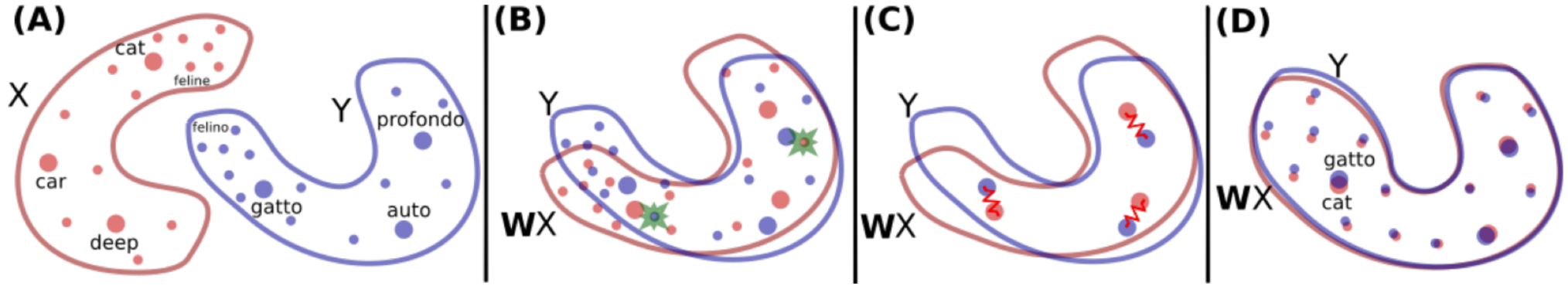


- **(A)** Train monolingual embeddings
- **(B)** Align them using adversarial training
- Refinement step
  - **(C)** Select high-confidence translation pairs
  - **(D)** Apply Procrustes on the generated dictionary
- **Generate translations using CSLS**

Mitigating hubness – CSLS

- Cross-Domain Similarity Local Scaling

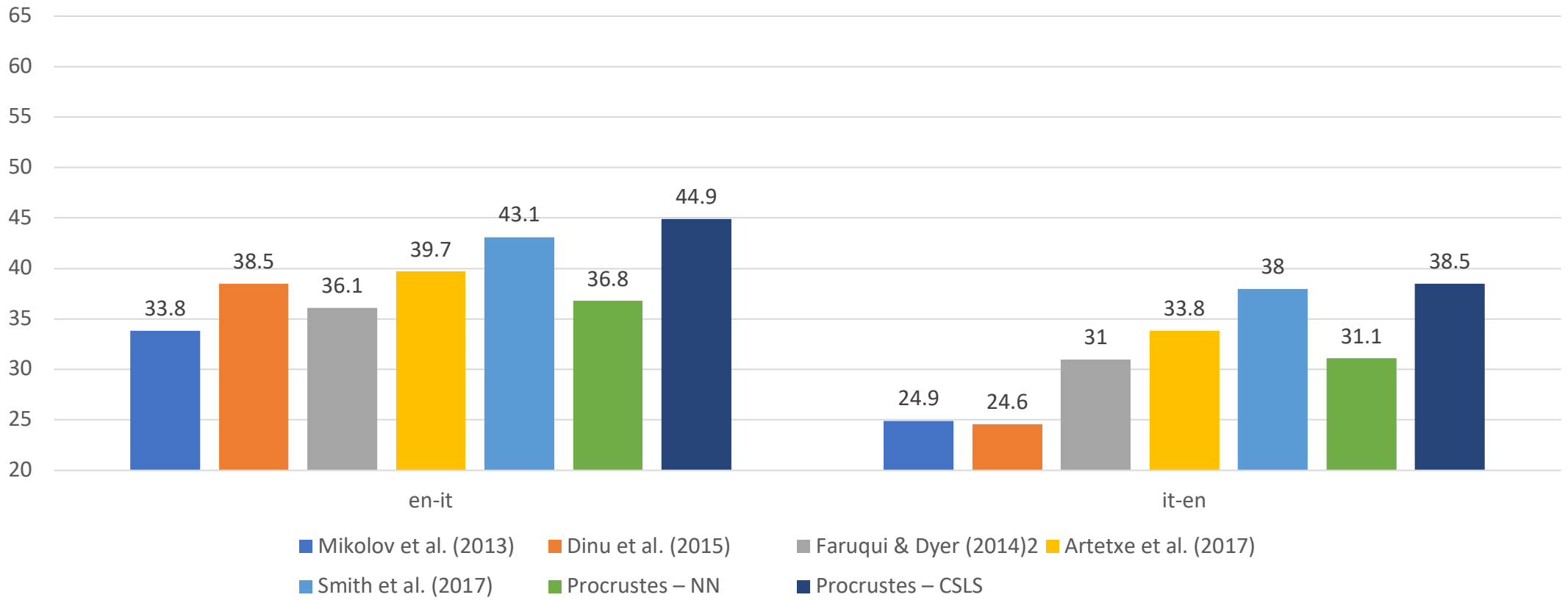
$$\mathrm{CSLS}(Wx_s, y_t) = 2\cos(Wx_s, y_t) - r_{\mathrm{T}}(Wx_s) - r_{\mathrm{S}}(y_t)$$

$$r_{\mathrm{T}}(Wx_s) = \frac{1}{K} \sum_{y_t \in \mathcal{N}_{\mathrm{T}}(Wx_s)} \cos(Wx_s, y_t)$$

  - Encourage nearest neighbors reciprocity (empirical observation)
  - Increases the similarity associated with isolated word vectors

Source word	un	deux	trois	quatre	cinq	six	sept	huit	neuf
Translation – NN	one	two	two	four	two	two	two	four	two
Translation – CSLS	one	two	three	four	five	six	seven	eight	nine

Comparison with previous approaches



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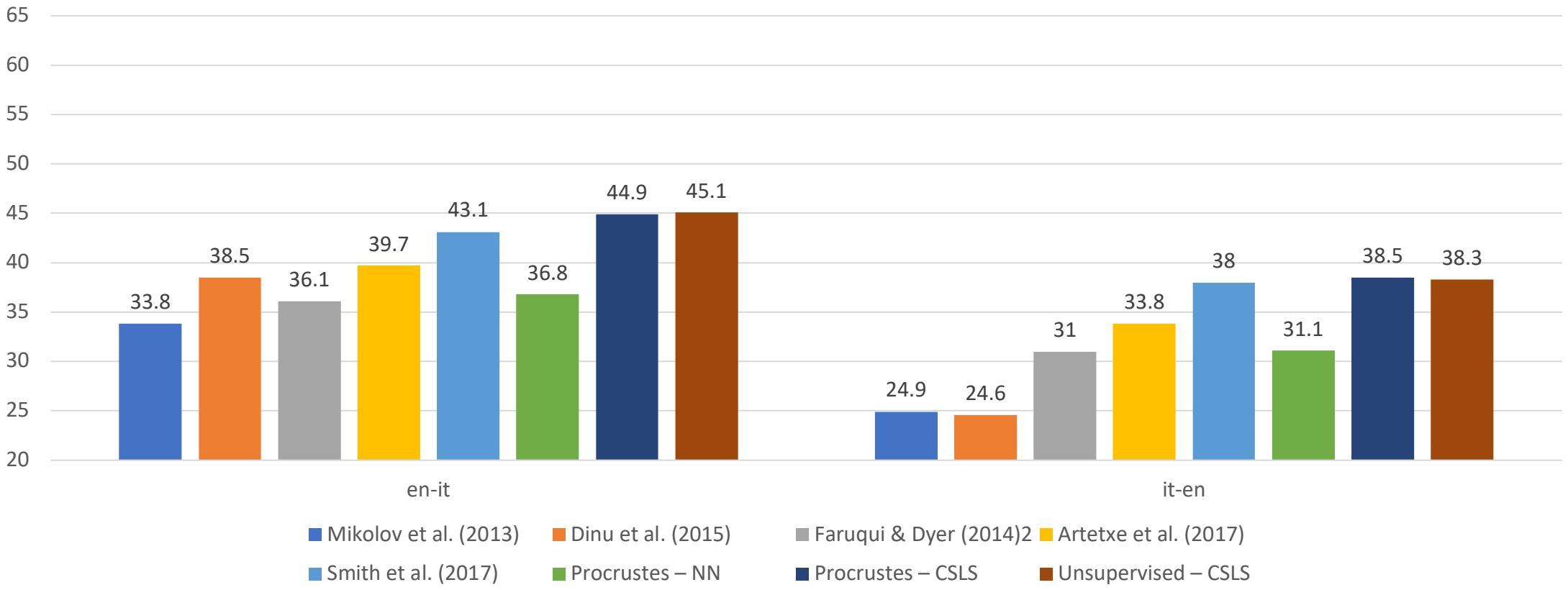

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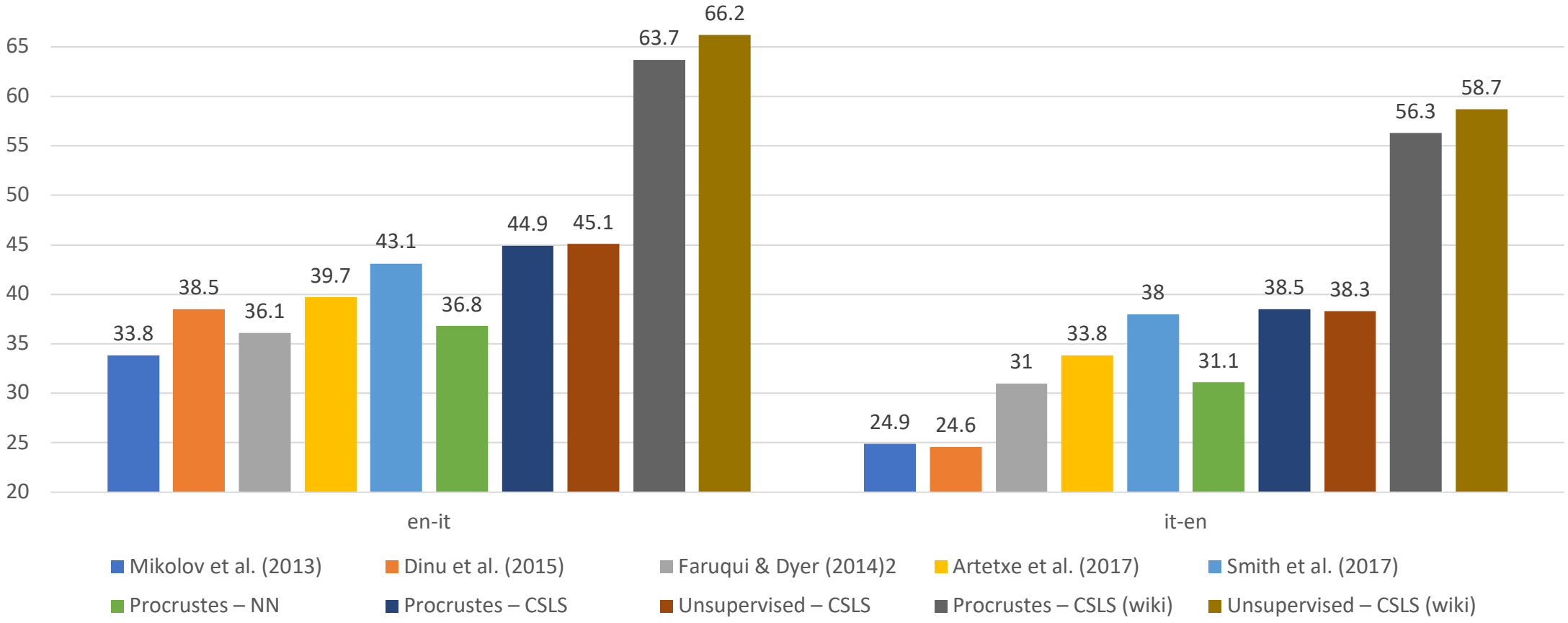
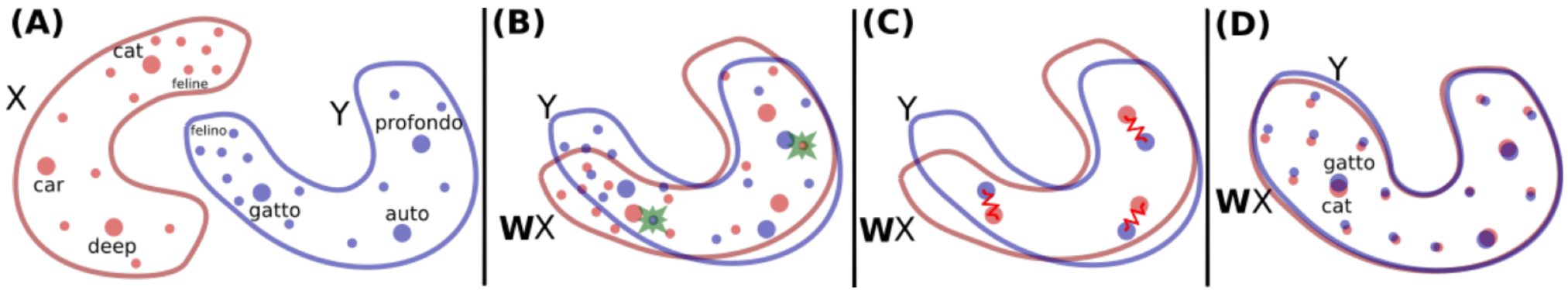


Word retrieval accuracy (P@1)

Unsupervised word translation – Summary

- **Given independent monolingual datasets in a source and a target language:**
  - **We can create high-quality cross-lingual dictionaries**
  - **We can create high-quality cross-lingual embeddings**

Unsupervised sentence translation



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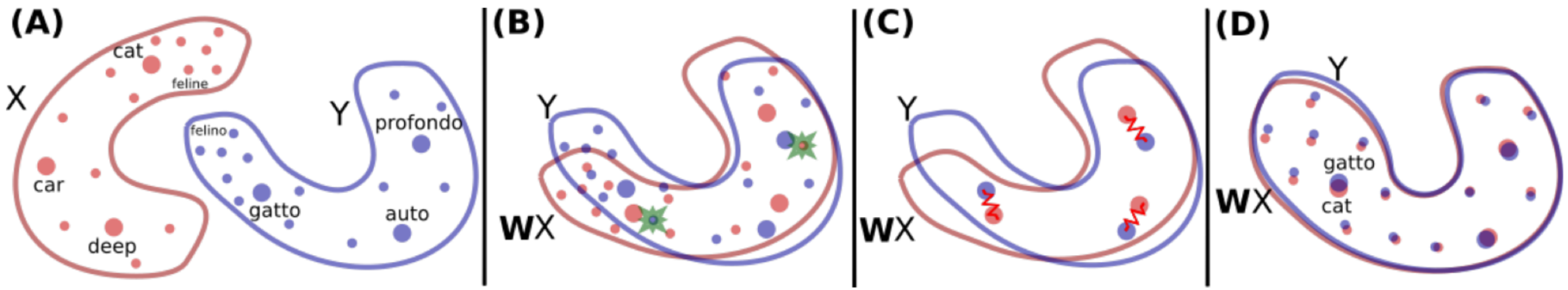

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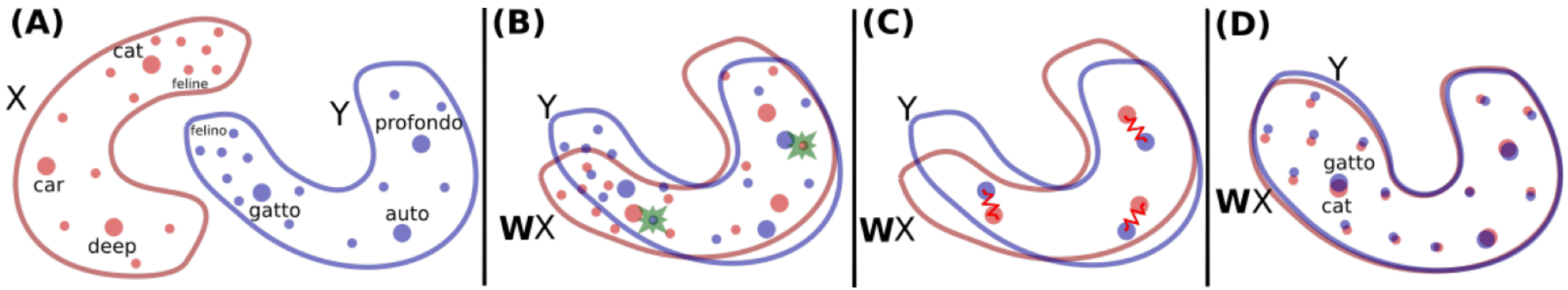

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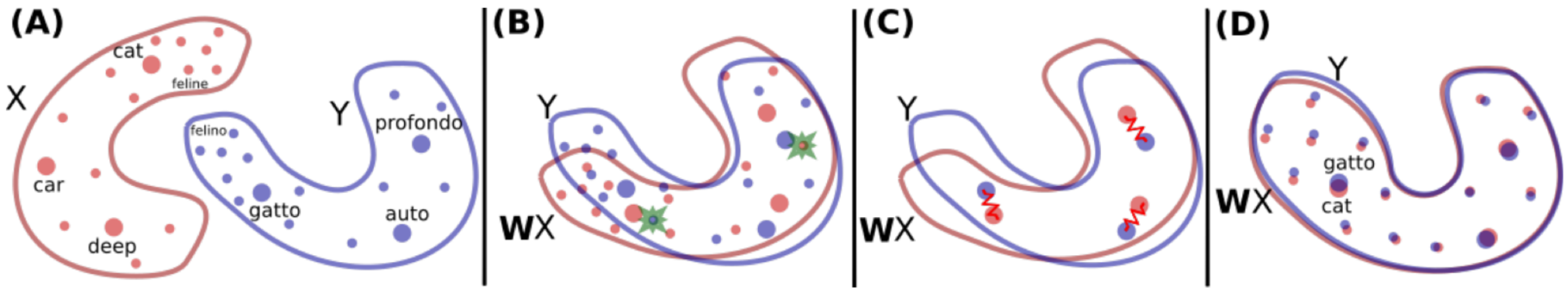

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  - Direct application does not work (even in a supervised setting)

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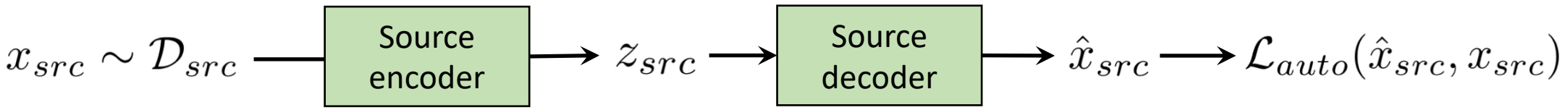

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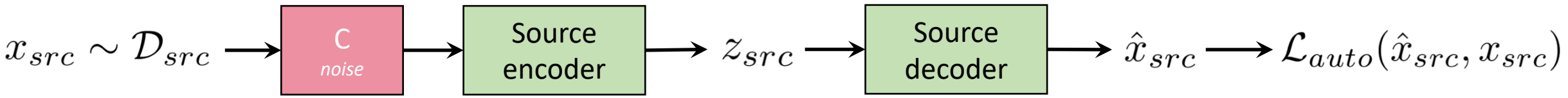

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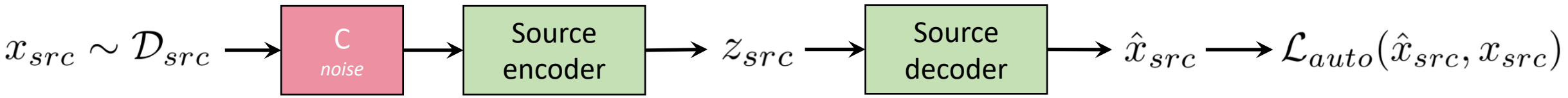

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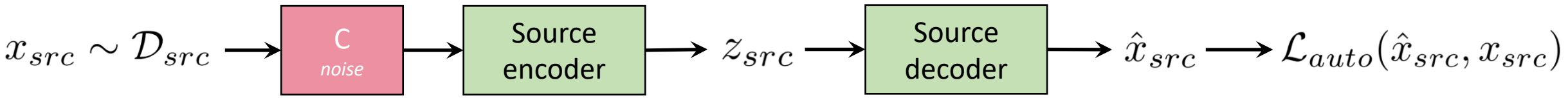

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  - Word shuffle: word order is (slightly) shuffled inside sentences $|\sigma(i) - i| \leq k$

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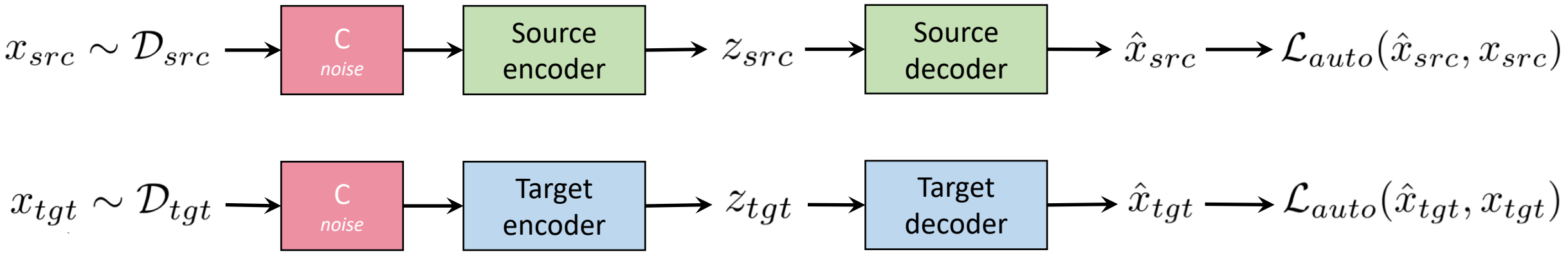

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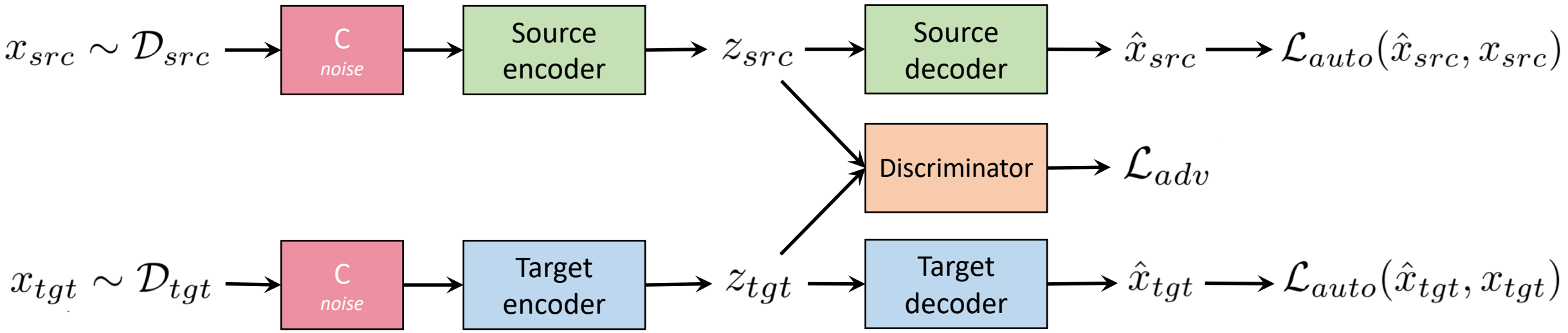

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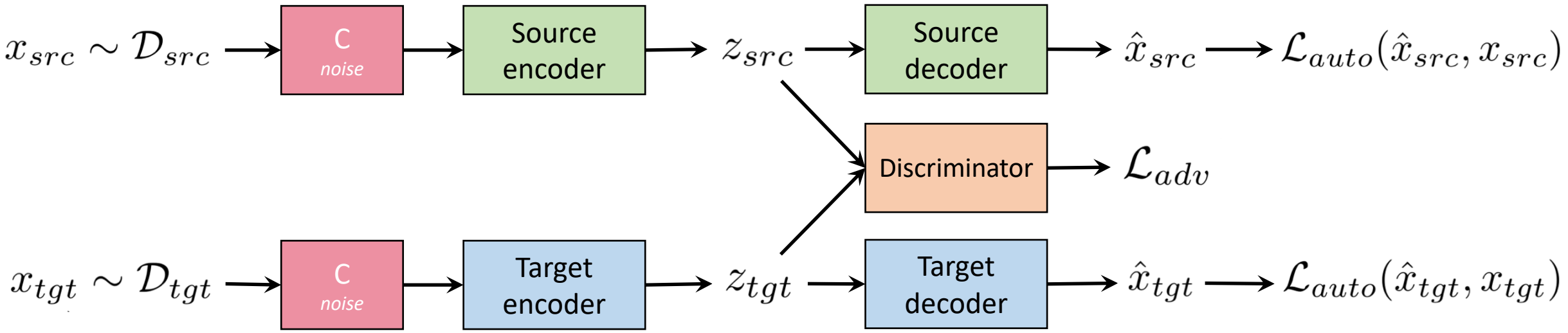

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- We want decoders to operate in the same space → share parameters between encoders

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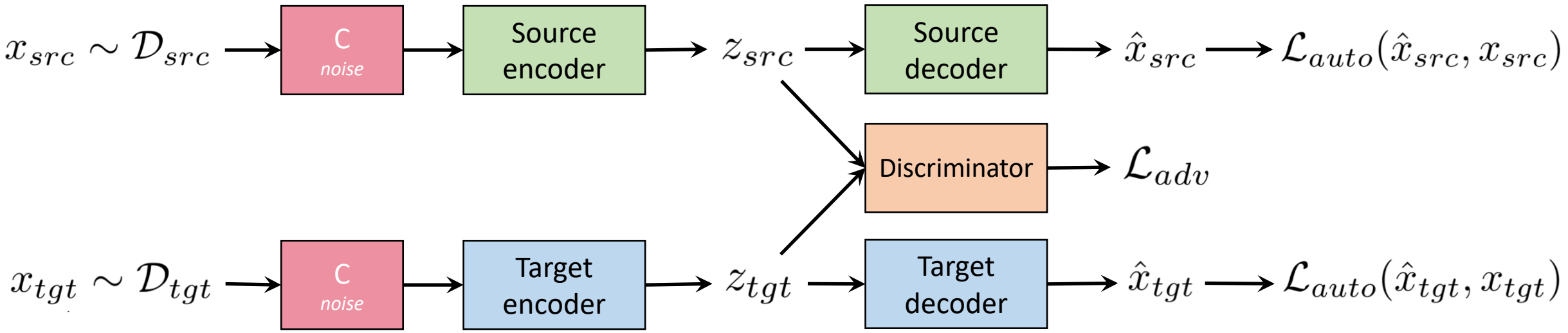

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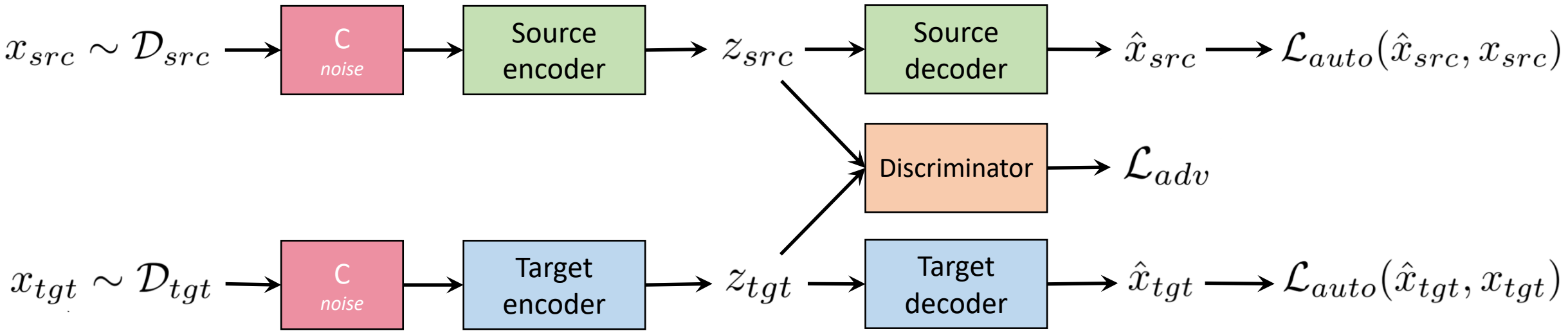

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- Problem: at test time we want (source → target) or (target → source)

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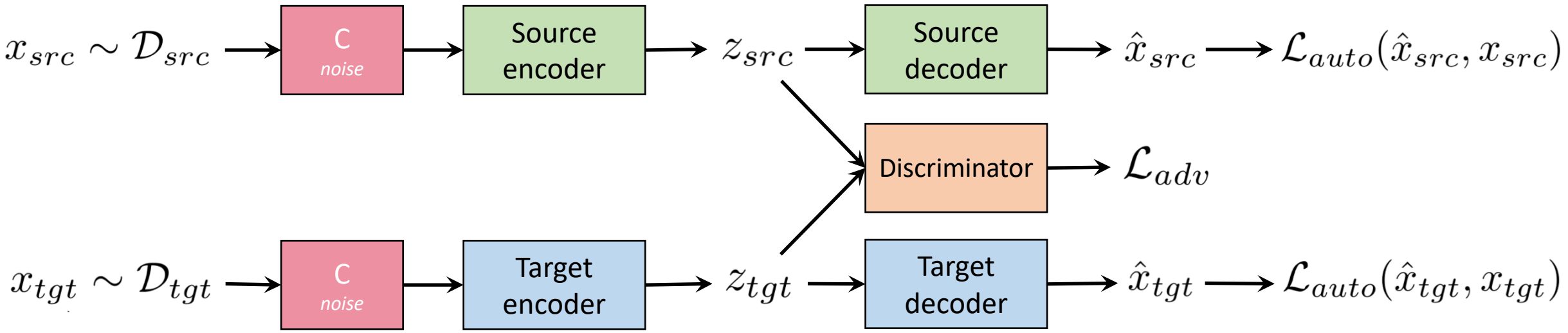
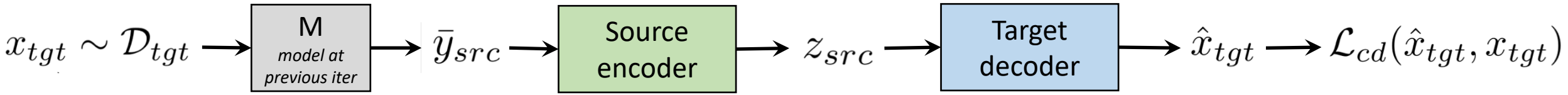


- Works on simple / small datasets, with short sentences or small vocabulary
- Problem: at test time we want (source → target) or (target → source)
- Cross-Domain training: train the model to perform actual translations
  - We do not have parallel data → generate artificial translations for training

Proposed architecture – Cross-Domain Training



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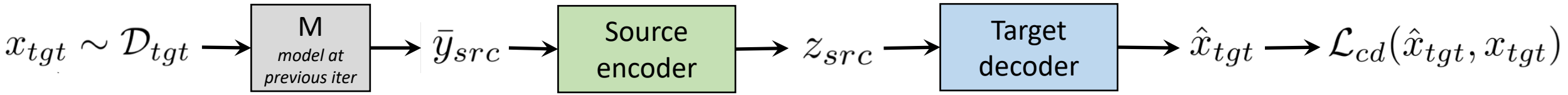

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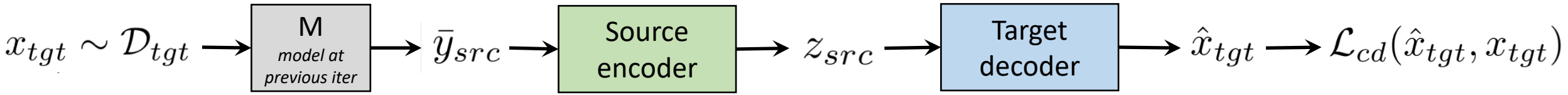

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y_{src}	*a view of a crowded city street .*	**(gold translation)**

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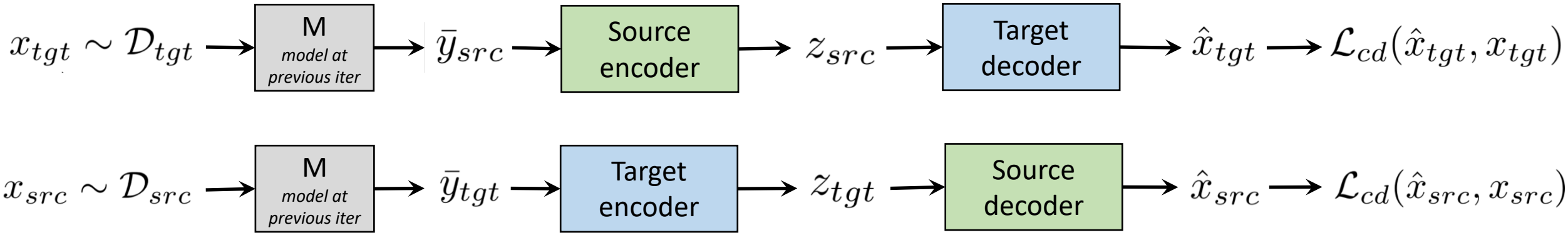

- Train on pairs generated using a stale version of the model
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Recap

- Denoising autoencoding to learn good sentence representations $\mathcal{L}_{auto}$

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Unsupervised model selection

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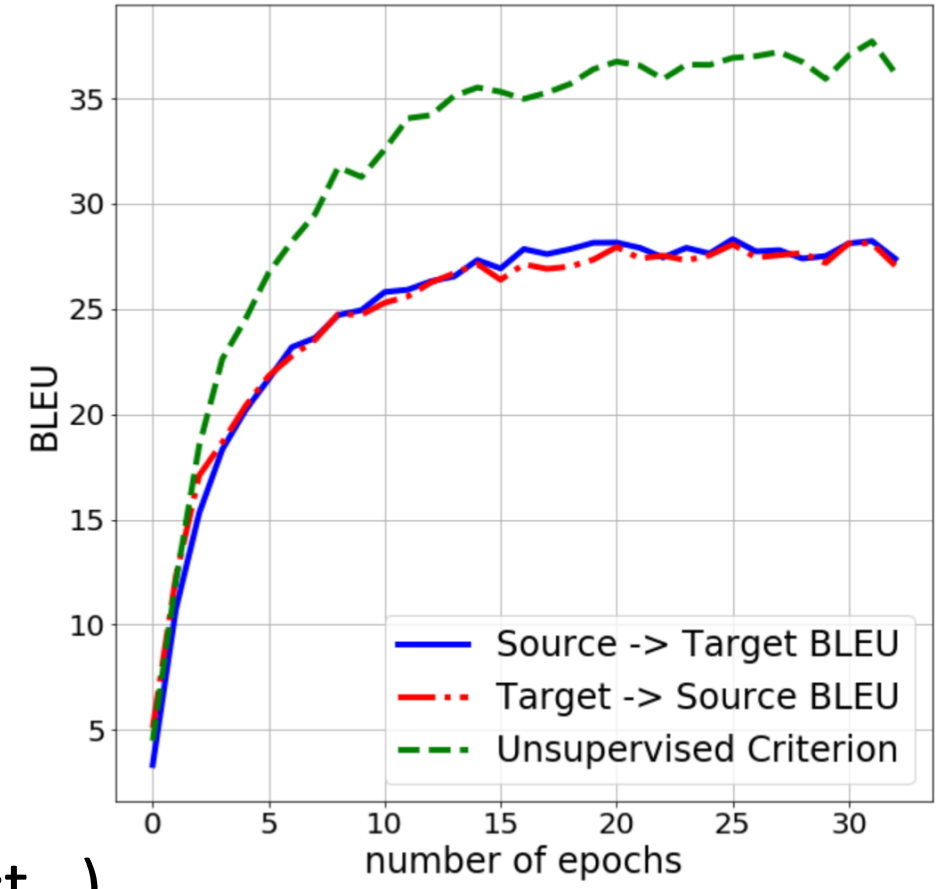

- Correlation is good (but far from perfect…)

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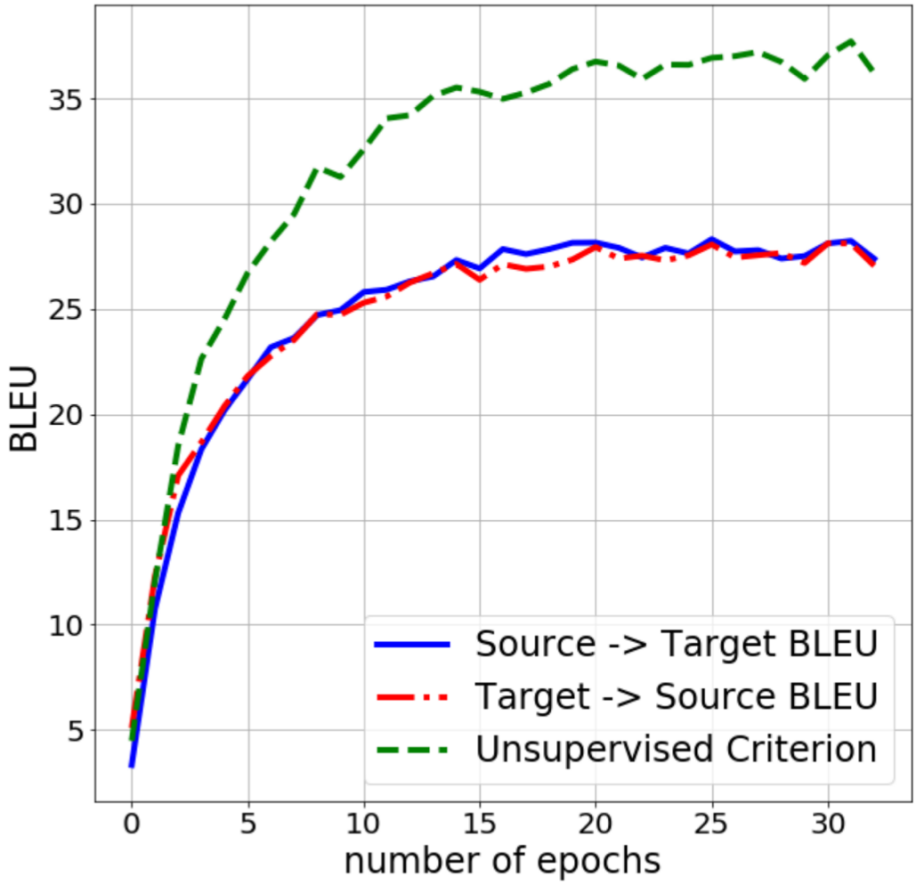

Datasets

- Multi30k-Task1 (MMT1) (en-fr / en-de)
  - 29k images with English, French and German captions
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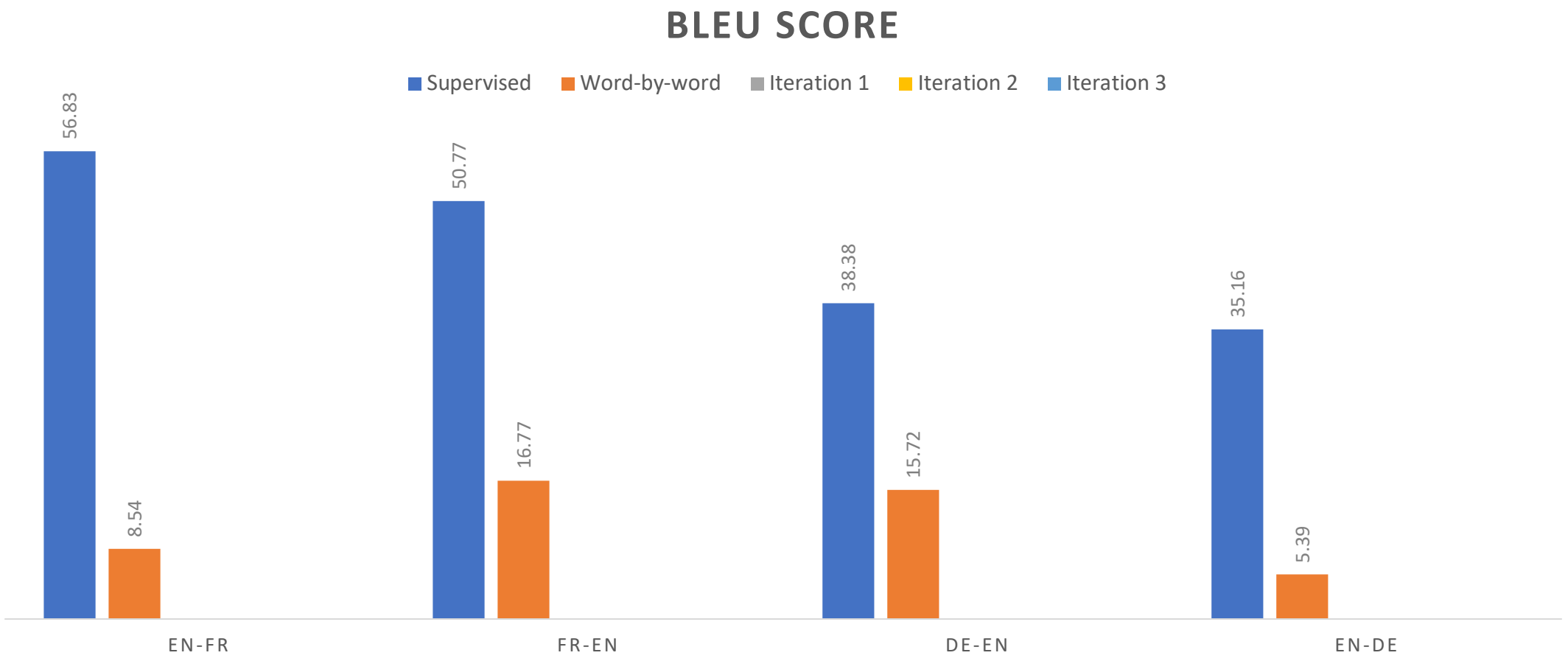
  - 1.8M monolingual datasets

Results on MMT1 - Baseline



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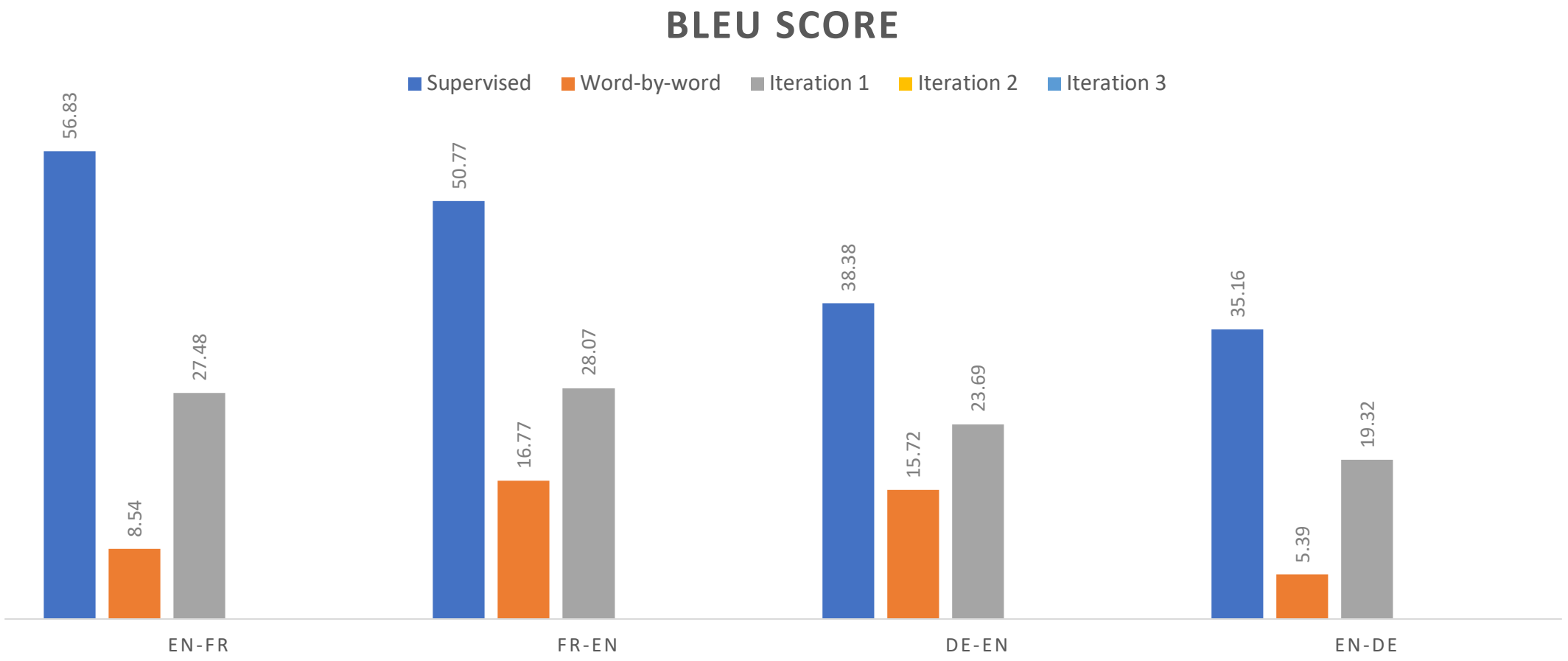

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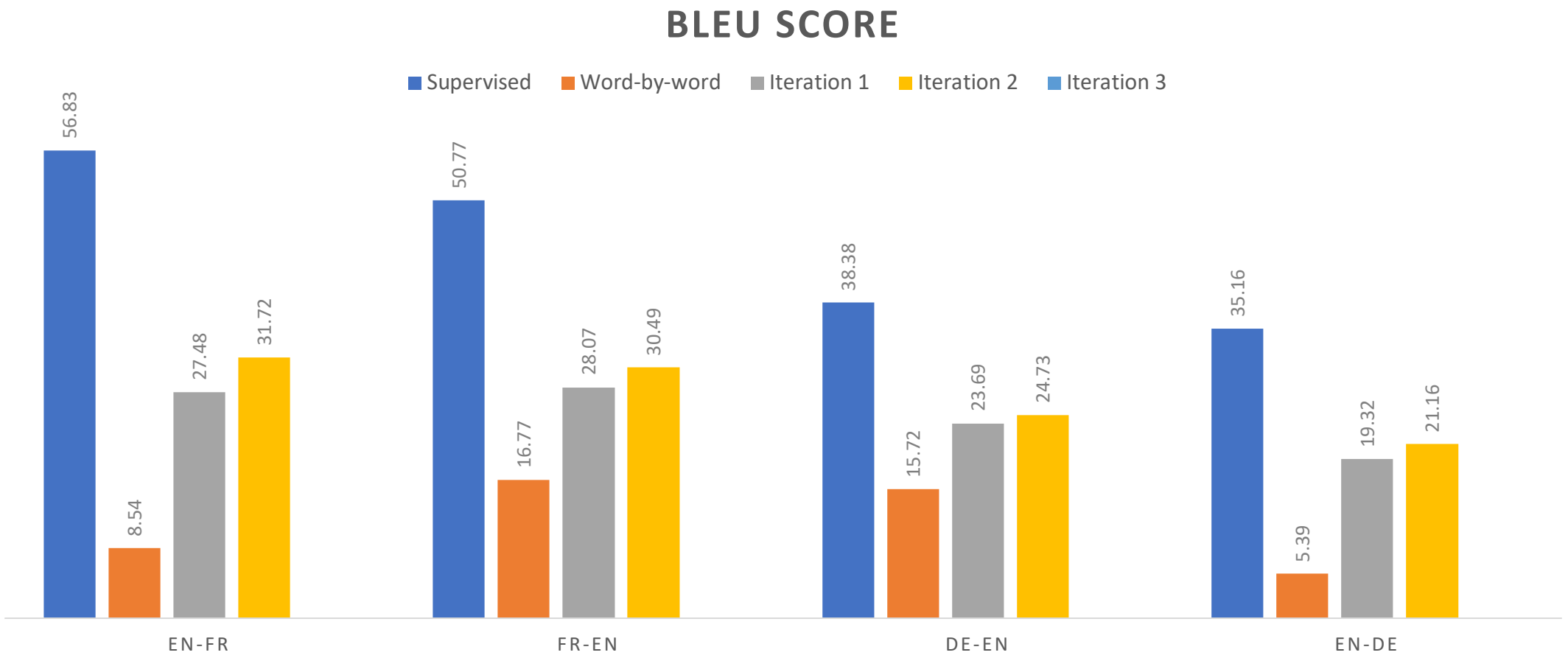

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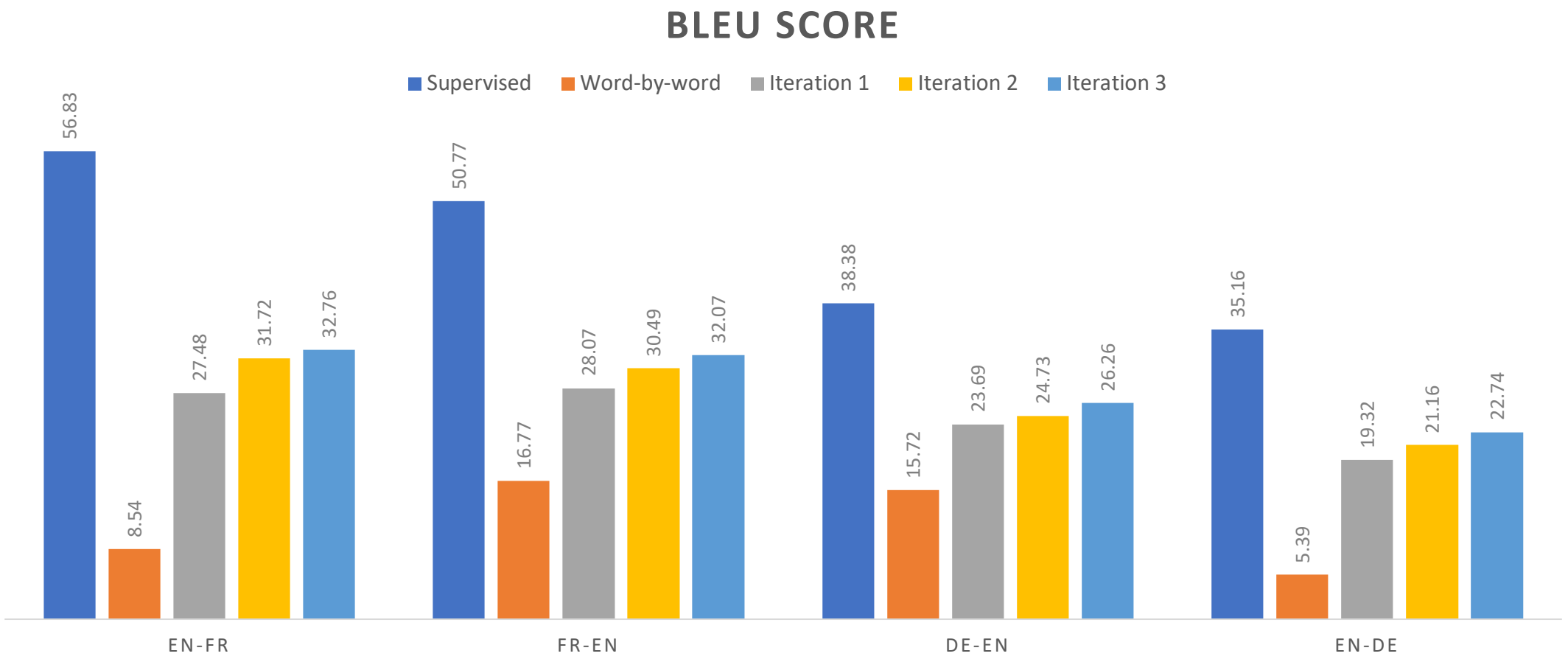

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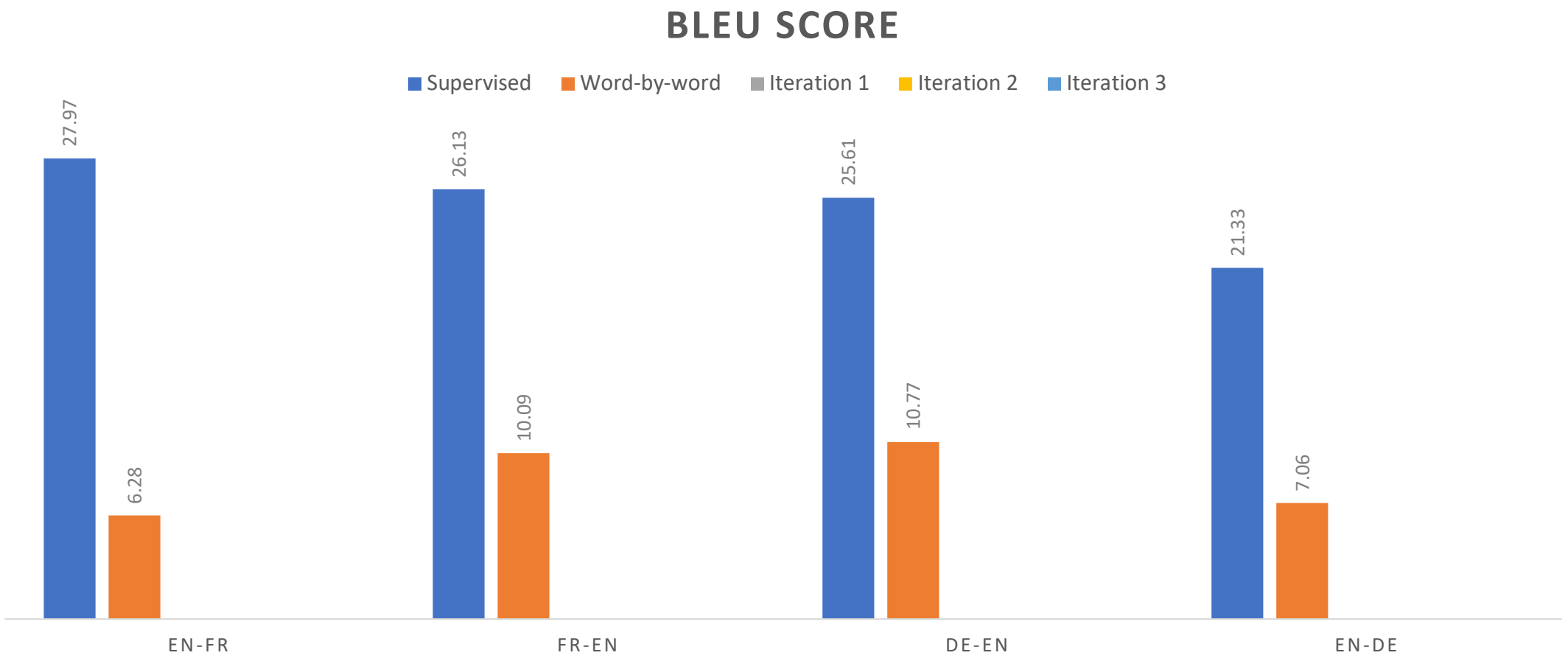

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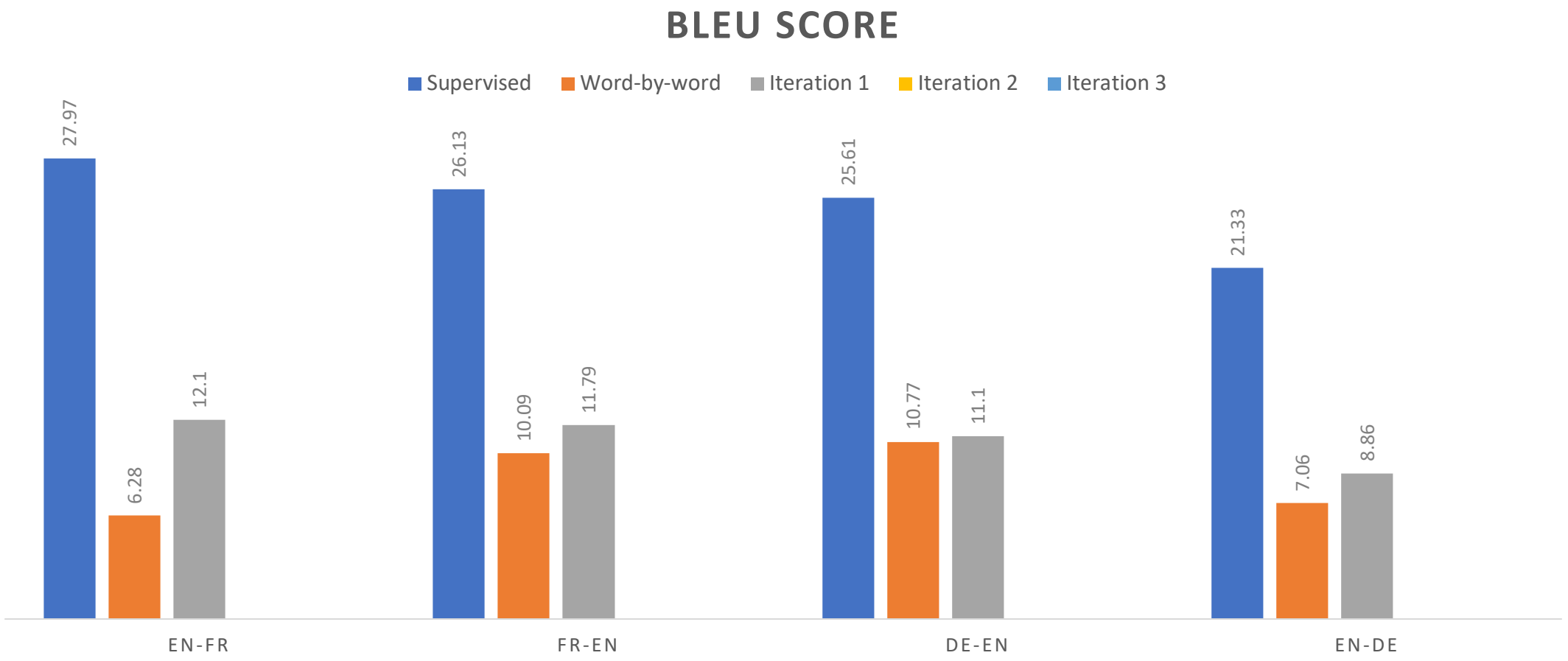

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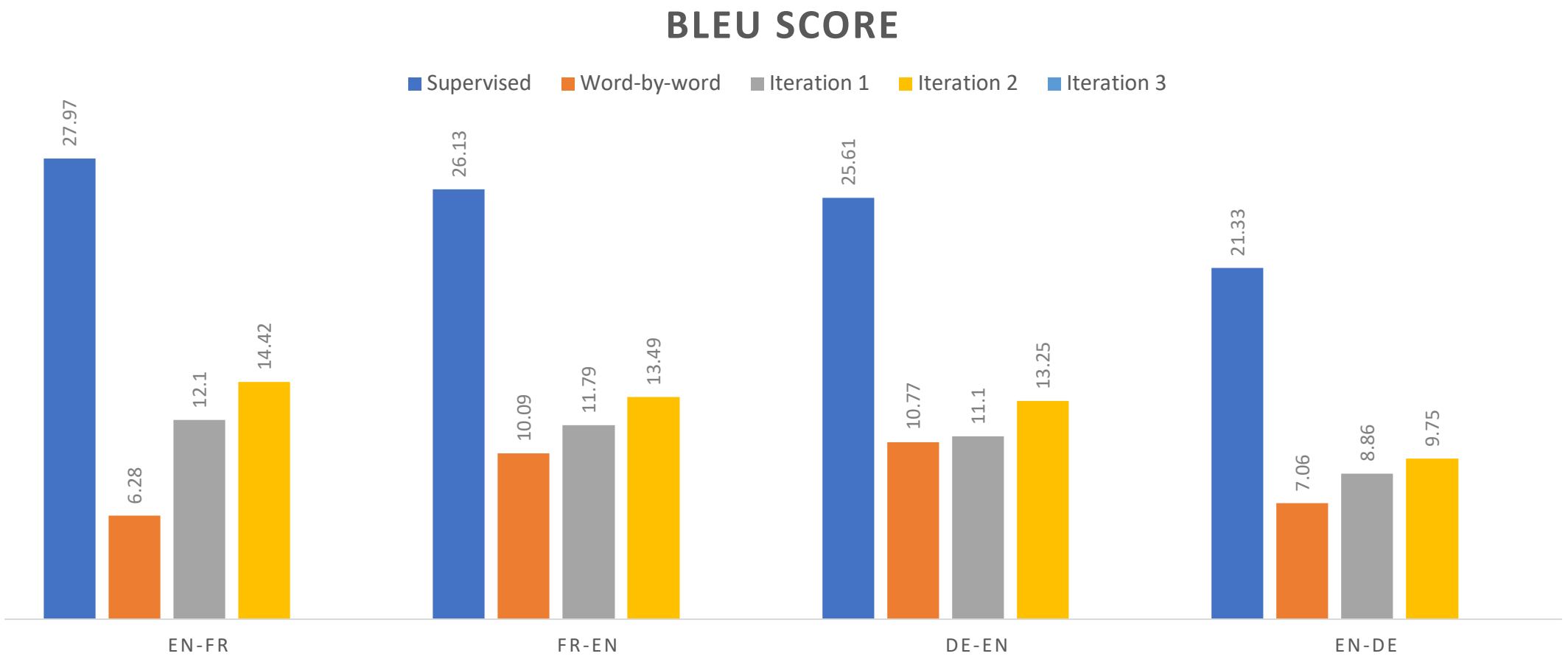

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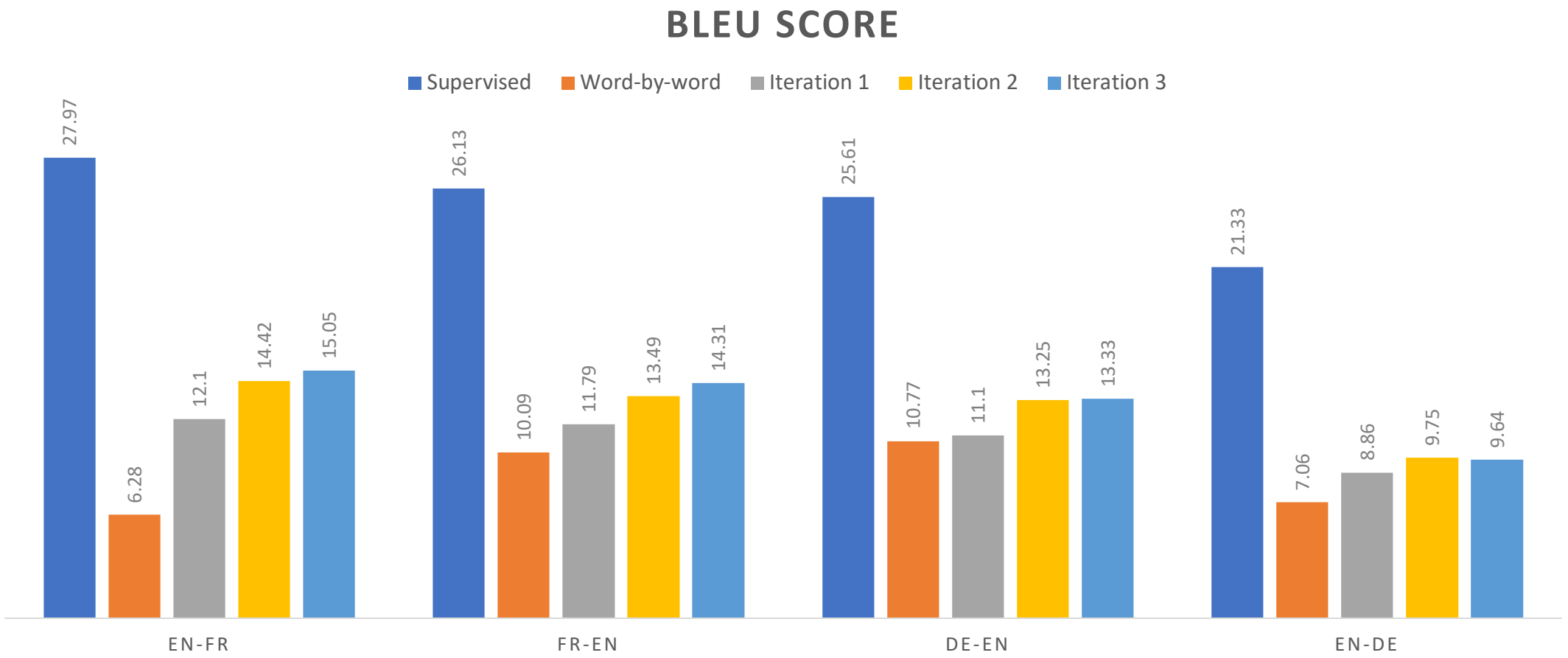
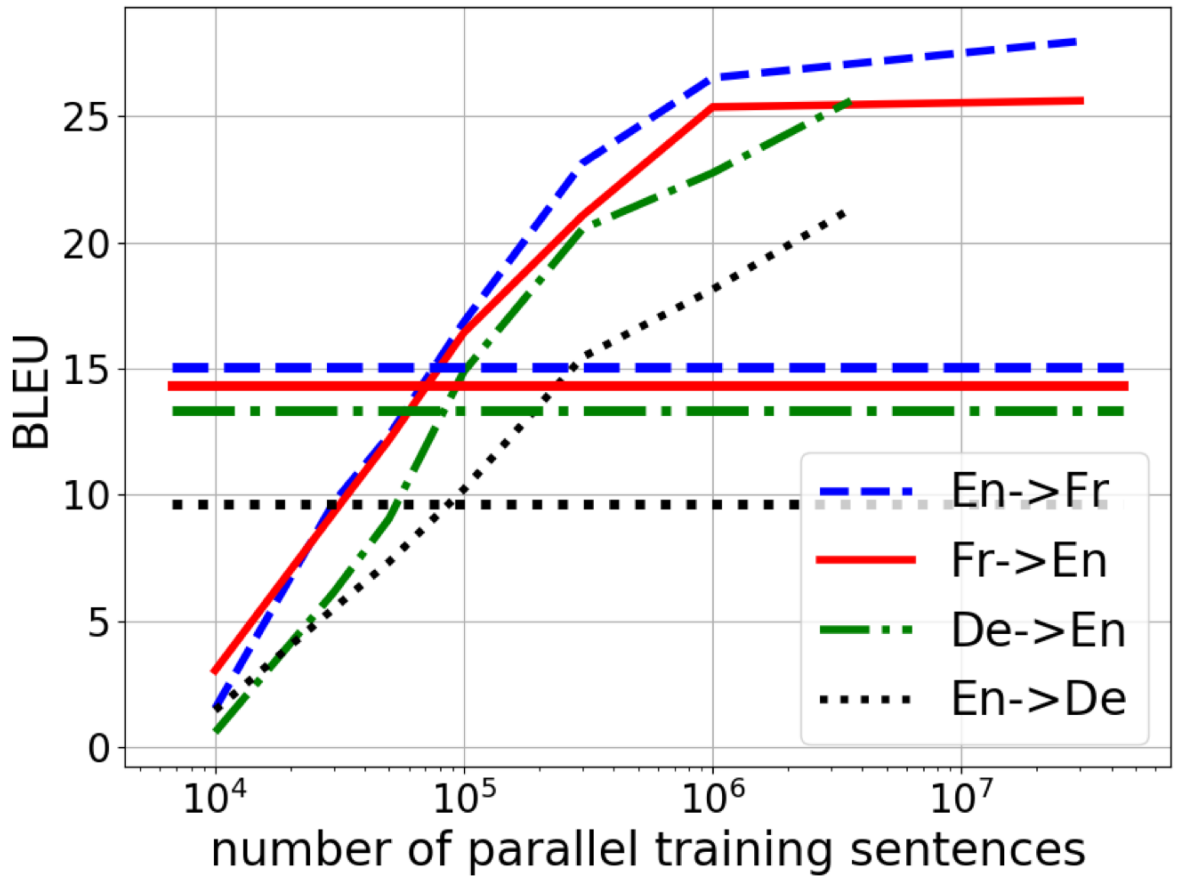


Comparison with supervised methods



Examples of unsupervised translations

Source	**une femme aux cheveux roses habillée en noir parle à un homme .**
Iteration 0	
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Iteration 3	
Reference	**a woman with pink hair dressed in black talks to a man .**

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Results on MMT1 – Ablation study

	en-fr	fr-en	de-en	en-de
Full	27.48	28.07	23.69	19.32

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$\lambda_{cd} = 0$	25.44	27.14	20.56	14.42
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Ablation Study: Conclusion

- It is necessary to use either cross-lingual embeddings and/or cross-domain training
- Adding noise to input sentences is critical
- The adversarial loss and the autoencoding loss are equally important

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- Use beam search

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- Use BPE
  - Currently a lot of UNK words (up to 10% of UNK in German source references)
  - Supervised WMT en→fr BLEU
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- Do semi-supervised learning

Thank you

Word translation without parallel data

Guillaume Lample *, Alexis Conneau *, Marc'Aurelio Ranzato, Ludovic Denoyer, Hervé Jégou (*ICLR 2018)*
Code: https://github.com/facebookresearch/MUSE

Unsupervised Machine Translation Using Monolingual Corpora Only

Guillaume Lample, Alexis Conneau, Ludovic Denoyer, Marc'Aurelio Ranzato (*ICLR 2018)*

Supplementary slides

Orthogonality constraint

- Isometric mapping
  - Preserve dot-product
  - Preserve monolingual quality embeddings
  - Training more robust (no mapping collapse)

- After each training update, project the mapping to the orthogonal manifold:

$$W \leftarrow (1+\beta)W - \beta(WW^T)W$$

$$W \leftarrow W - \frac{\beta}{2}\nabla_W(\|W^TW - Id\|_F^2)$$

Cisse et al. (ICML 2017)

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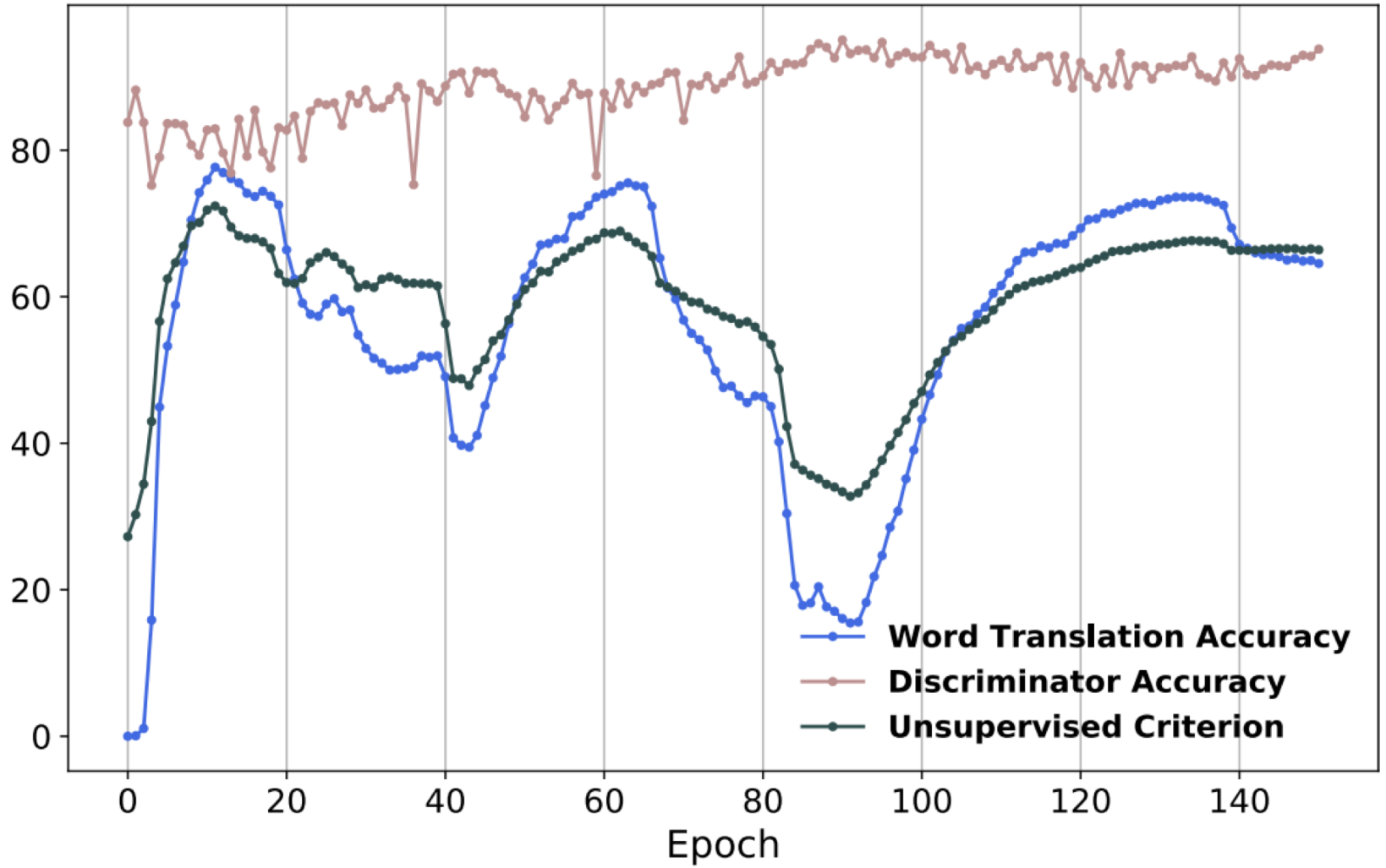
- Unsupervised metrics that correlates well with translation accuracy
    - Criterion: average cosine distance of 10k generated translation pairs

Unsupervised model selection



Unsupervised model selection

What do we lose compare to an oracle criterion?

	en-es	es-en	en-fr	fr-en	en-de	de-en	en-ru	ru-en	en-zh	zh-en
Unsupervised	69.8	71.3	70.4	61.9	63.1	59.6	29.1	41.5	18.5	22.3
Oracle	**72.0**	**71.7**	**71.1**	**67.5**	**64.8**	**61.3**	**34.4**	**45.1**	**20.9**	**26.3**

Unsupervised validation criterion vs Oracle criterion / Test metric

Hubness in word embedding spaces

- Hubness problem
  - Some words are the nearest neighbors of many words (hubs)

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Source word	un	deux	trois	quatre	cinq	six	sept	huit	neuf
Translation – NN	one	two	two	four	two	two	two	four	two

Mitigating hubness – CSLS

- Cross-Domain Similarity Local Scaling

$$\mathrm{CSLS}(Wx_s, y_t) = 2\cos(Wx_s, y_t) - r_{\mathrm{T}}(Wx_s) - r_{\mathrm{S}}(y_t)$$

$$r_{\mathrm{T}}(Wx_s) = \frac{1}{K} \sum_{y_t \in \mathcal{N}_{\mathrm{T}}(Wx_s)} \cos(Wx_s, y_t)$$

  - Encourage nearest neighbors reciprocity (empirical observation)
  - Increases the similarity associated with isolated word vectors

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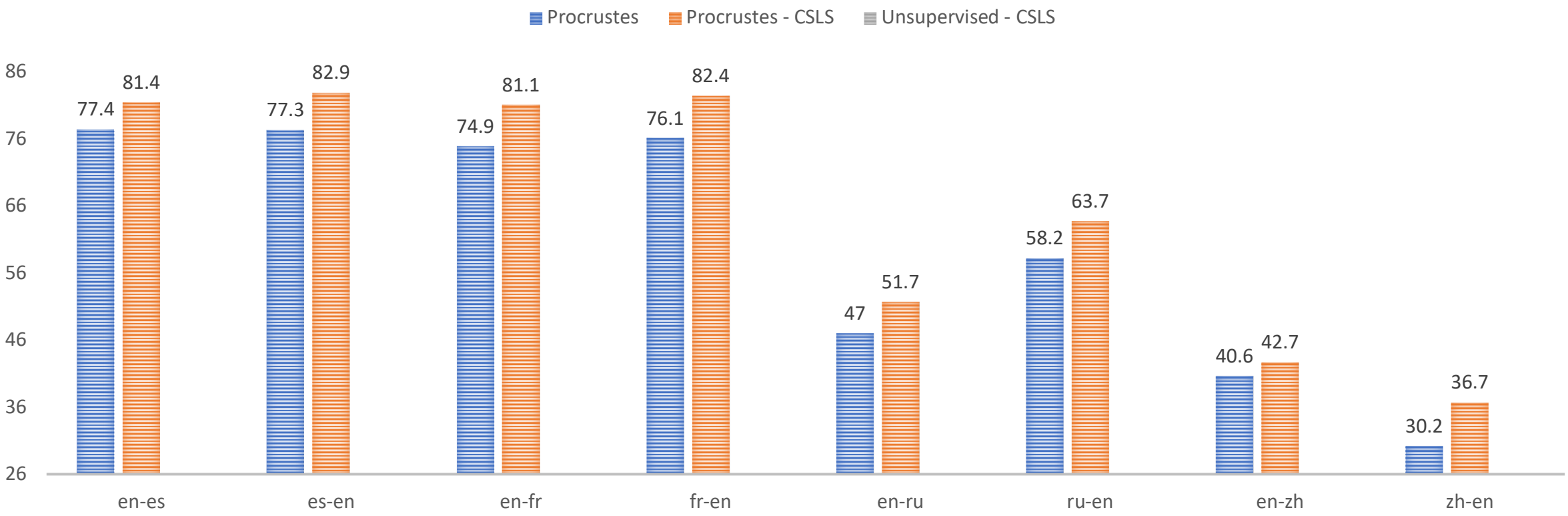
Translation – CSLS	one	two	three	four	five	six	seven	eight	nine

Results on word translation



Word retrieval accuracy (P@1)

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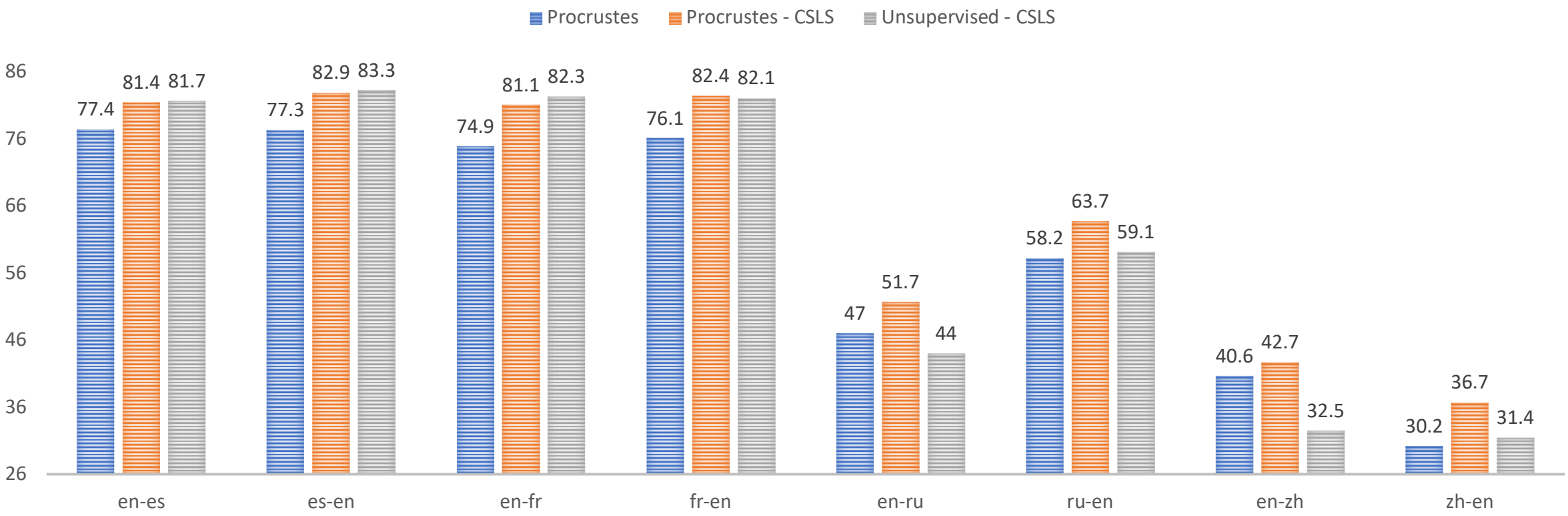
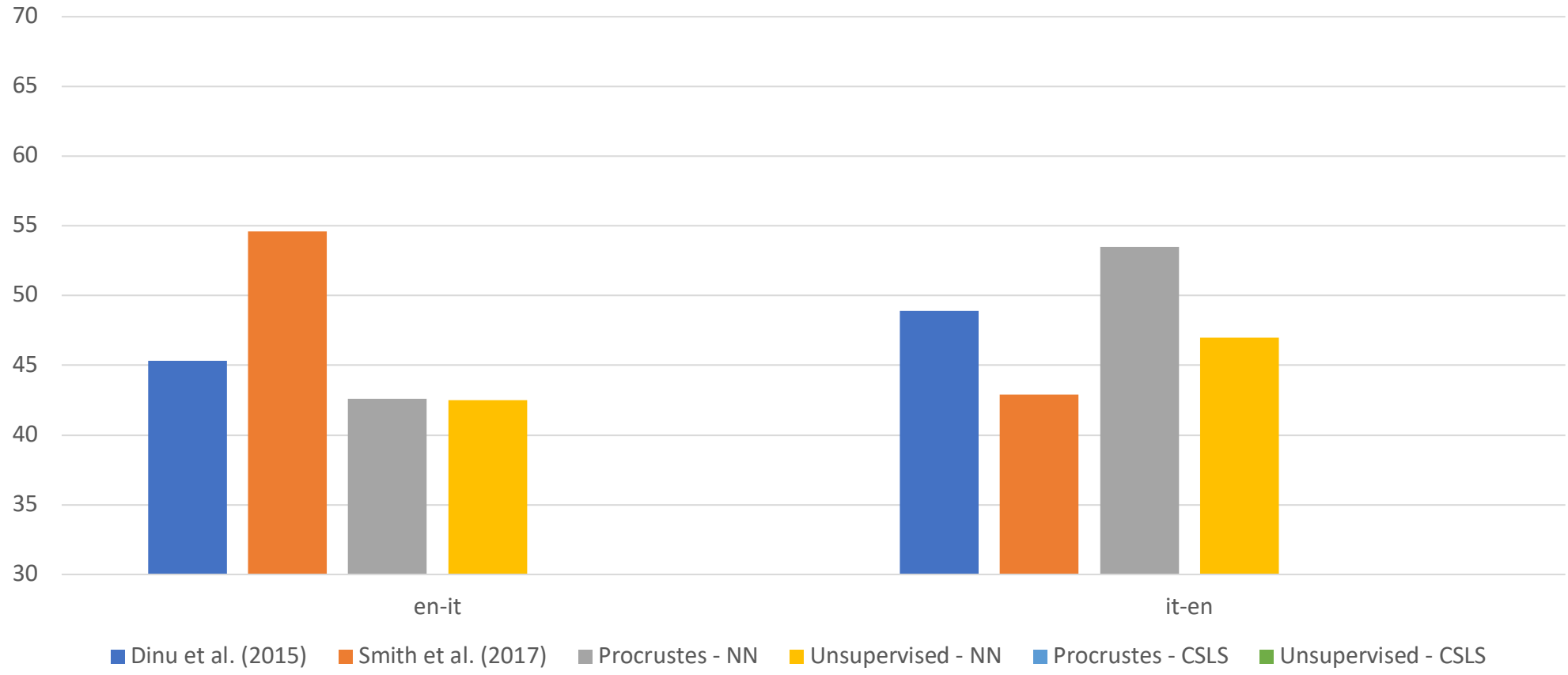


Word retrieval accuracy (P@1)

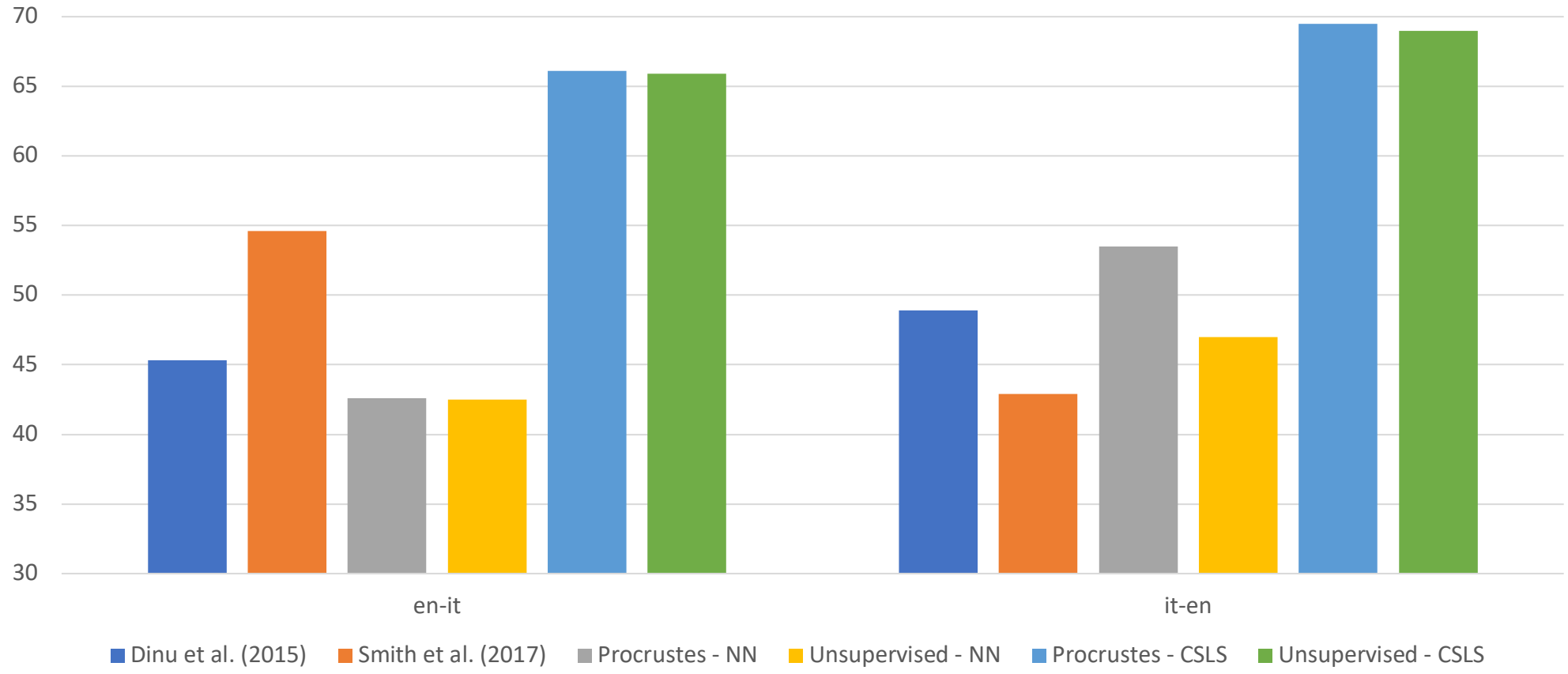
Results on sentence retrieval



Sentence retrieval accuracy (P@1)

Task: given a source sentence, find the correct translation among 200k target sentences.

Results on sentence retrieval



Sentence retrieval accuracy (P@1)

Task: given a source sentence, find the correct translation among 200k target sentences.