# Unsupervised Learning of Cross-lingual Word Embedding and Its Application in Machine Translation

**Jiahui Geng**

jiahui.geng@rwth-aachen.de

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**Human Language Technology and Pattern Recognition**
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**Computer Science Department**
**RWTH Aachen University, Germany**

# Outline

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Literature

Cross-lingual word embedding

- Supervised learning
- Unsupervised learning

Sentence Translation with cross-lingual word embedding

- Context-aware beam search
- Denoising autoencoder

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# Introduction

## Motivation

- Building a machine translation system requires lots of bilingual data
- Cross-lingual word embedding offers elegant word matches between languages
- Unsupervised MT relies on back-translation which needs a long training time

## Goals

- Improve the unsupervised learning algorithm for cross lingual word embedding
- Build a good unsupervised MT efficiently: combine with other models

# Literature

**Unsupervised cross-lingual embedding**

- [Conneau & Lample$^{+}$ 17] Word translation without parallel data
  - Implementation of GANs: discriminator trained to distinguish between two distributions while generator fools discriminator
- [Artetxe & Labaka$^{+}$ 17a] Learning bilingual word embeddings with (almost) no bilingual data
  - A self-learning framework combining embedding mapping and dictionary induction techniques, needs seed dictionary to start

# Literature

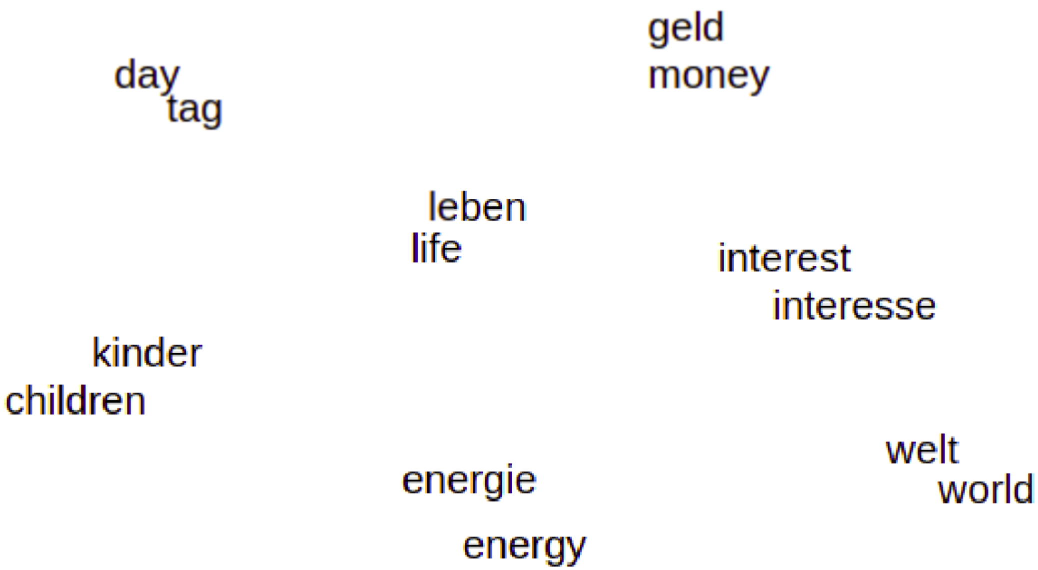
**Unsupervised machine translation**

- [Artetxe & Labaka$^{+}$ 17b] Unsupervised Neural Machine Translation
- [Lample & Denoyer$^{+}$ 17] Unsupervised Machine Translation Using Monolingual Corpora Only
  - Seq2seq model with shared encoder and decoder for both languages, also with denoising autoencoder and back-translation

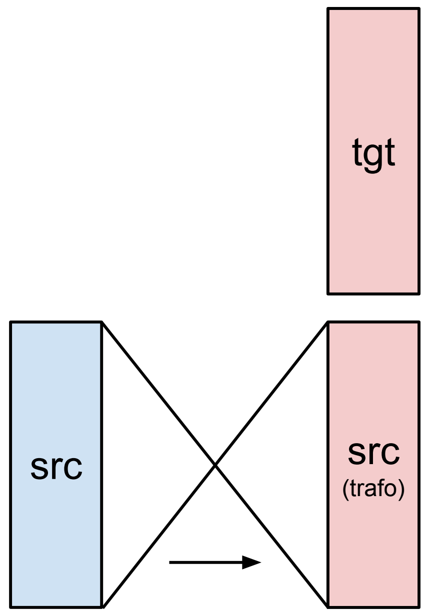
# Cross-lingual Word Embedding

## Definition

- Word embedding of multiple languages in a joint embedding space
- Linear mapping from source embedding to target embedding (this work)




**cross-lingual word embedding**




**cross-lingual mapping**

# Cross-lingual Word Embedding

## Roles in unsupervised neural machine translation

- Shared latent representations
  - Shared encoder for producing a language independent representation
- As word or phrase table for translation

## This work

- Formulate a straightforward way to combine a language model with cross-lingual word similarities

## Training Methods

- Mapping-based approaches (this work)
- Pseudo-multi-lingual corpora-based approaches
- Joint methods

# Cross-lingual Word Embedding

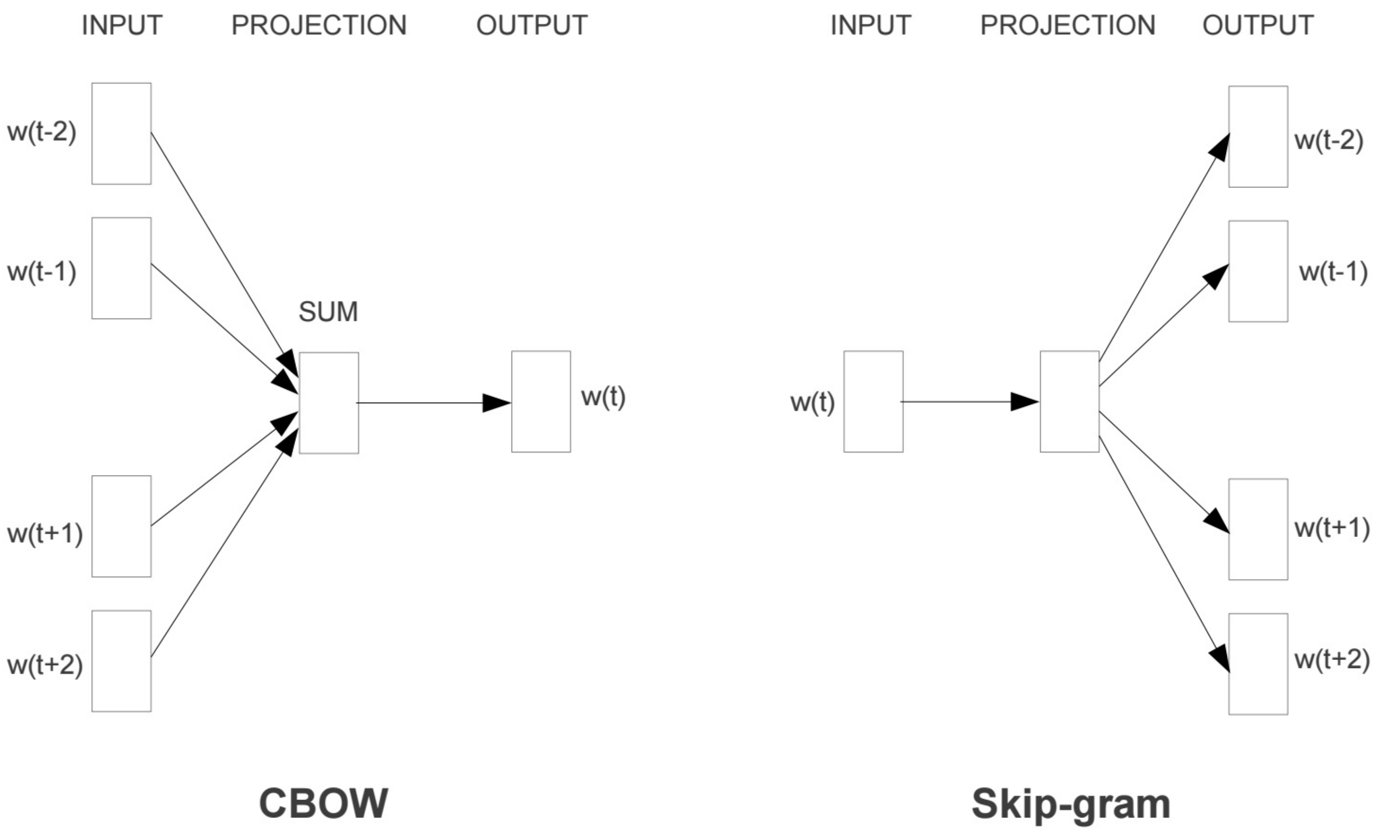
**Mapping based approaches**

- Learn monolingual embedding separately
  - Skip-gram model
- Learn linear mapping between embedding spaces
  - Supervised learning
    - Procrustes analysis
  - Unsupervised learning
    - Iterative self-learning framework
    - Adversarial learning
- Synthetic dictionary induction
  - Nearest neighbor search

# Monolingual Embedding

**`Fasttext` [Bojanowski & Grave$^{+}$ 17]**

- **Essentially an extension of skip-gram/CBOW model**
- **Treat each word as compound of character $n$-grams**
- **Learn the internal structure of words**



# Learning with Parallel Dictionary

**Assume given**

- **Word embedding**
  **trained independently for each language on monolingual corpora**
- **Bilingual dictionary**
  **a known dictionary with pairs of words $\{f, e\}$ size $N$**

**Learn a linear mapping $W \in \mathbb{R}^{d \times d}$ such that**

$$W^* = \underset{W \in \mathbb{R}^{d \times d}}{\operatorname{argmin}} \sum_{n=1}^{N} \|W f_n - e_n\|^2$$

- $d$ **: Dimension of embedding**
- $f_n, e_n \in \mathbb{R}^d$**: the embedding pair of corresponding word pair in the dictionary**

# Procrustes Analysis

Constrain $W$ to be an orthogonal matrix

- Enforce monolingual invariance
- Simplify the problem as the Procrustes problem
  - A closed-form solution obtained from SVD
  - $E$, $F \in \mathbb{R}^{d \times N}$ denote embedding projection of word pairs $\{e, f\}$

$$W^* = \underset{W \in \mathbb{R}^{d \times d}}{\operatorname{argmin}} \|WF - E\|_F^2 = UV^T$$

$$U \Sigma V^T = \mathrm{SVD}(EF^T)$$

- Can be efficiently computed in linear time w.r.t. seed dictionary size $N$

# Learning without Parallel Dictionary

**Problem**

- Large dictionary not readily available for many language pairs

**Self-learning framework [Artetxe & Labaka+ 17a]**

1. Given source and target embedding $\mathcal{F}$ $\mathcal{E}$ , seed dictionary $D$
2. Learn mapping with dictionary $D$
3. Induce dictionary $D'$ according to mapping
4. $D := D'$ and repeat step $2$, $3$ until converges

**Performance**

- Works with initial dictionary
- Achieves comparable accuracy as supervised method
- Stuck in a poor local optimum without initial dictionary

# Adversarial Training

## Model

- $\mathcal{F} = \left\{f_1, \ldots f_{V_f}\right\}$ and $\mathcal{E} = \{e_1, \ldots e_{V_e}\}$: set of embeddings, not parallel
- Discriminator is trained to discriminate $W f_n$ and $e_n$ with $f_n$, $e_n$ randomly sampled from $\mathcal{F}, \mathcal{E}$
- Generator $W$ is trained to prevent the discriminator from making accurate prediction

## Discriminator loss

$$\mathcal{L}_D(\theta_D|W) = -\frac{1}{N}\sum_{n=1}^{N} \log P_{\theta_D}(\text{'source'}|W f_n) - \frac{1}{M}\sum_{m=1}^{M} \log P_{\theta_D}(\text{'target'}|e_m)$$

## Generator loss

$$\mathcal{L}_W(W|\theta_D) = -\frac{1}{N}\sum_{n=1}^{N} \log P_{\theta_D}(\text{'target'}|W f_n) - \frac{1}{M}\sum_{m=1}^{M} \log P_{\theta_D}(\text{'source'}|e_m)$$

# Corpus-based Leaning

## Motivation

- Vocabulary-based just looks at the mutual nearest neighbours

## Intuition

- Integrate the translation task into the learning process
- Make use of language model

# Online Training Algorithm

**Algorithm 1:** Online learning for corpus-based approach

**Input:** $\boldsymbol{F}$ (source embeddings)
**Input:** $\boldsymbol{E}$ (target embeddings)
**Input:** **LM**$_e$ (language model)
**Input:** $\mathcal{F}$ (source corpus)
**Result:** $\boldsymbol{W}$ (embedding mapping)

**while** *not converge* **do**
    Generate batch of source sentences $\{f_1^J\}$ from $\mathcal{F}$
    $\{e_1^I\} \leftarrow \boldsymbol{TRANSLATE}(\{f_1^J\}, \boldsymbol{F}, \boldsymbol{E}, \textbf{LM}_e)$
    $\boldsymbol{D} \leftarrow \boldsymbol{BUILD\_DICTIONARY}(\{f_1^J\}, \{e_1^I\})$
    $\boldsymbol{W} \leftarrow \boldsymbol{LEARN\_MAPPING}(\boldsymbol{D})$
**end**

- **Composes of mapping learning, training dictionary induction and corpus translation**
- **Efficiency turns out to be critical because of the additional translation task**

# Translation

## Context-aware beam search

- Given a history $h$ of target words before $e$, the score of $e$ to be the translation of $f$:

$$\hat{e}_1^N = \underset{e_1^N}{\operatorname{argmax}} \prod_{n=1}^{N} p^{\lambda_{LM}}(e_n | e_{n-4}^{n-1}) \cdot q^{\lambda_{emb}}(f_n, e_n)$$

- Lexicon score

$$q(f, e) = \frac{d(f, e) + 1}{2}$$

where $d(f, e) \in [-1, 1]$ cosine similarity between $f$ and $e$. In experiments, lexicon score from linear scaling works better than others, e.g. sigmoid or softmax

- Empirically set $\lambda_{emb}$ as 1, $\lambda_{LM}$ as 0.1

# Training Dictionary Induction

## Intuition

- In vocabulary-based training, dictionary always built with nearest neighbor search
- In corpus-based training, using translation pairs
- In our word-by-word translation framework, we build training dictionary directly with word pairs on each position from $(f_1^N, e_1^N)$without considering complex alignment

$$D = \begin{cases} (f_1, e_1) \\ (f_2, e_2) \\ \quad \cdots \\ (f_N, e_N) \end{cases}$$

# Training Details

- **Embedding Normalization**
  **Centering embedding at each dimension**

- **Orthogonal Constraint**

$$\boldsymbol{W} \leftarrow (1+\beta)\boldsymbol{W} - \beta(\boldsymbol{W}\boldsymbol{W}^\top)\boldsymbol{W}$$

  **where $\beta = 0.01$ is suggested, we find the orthogonal constraint make the training procedure converge successfully**

- **Learning Rate Scheduling Starting with initial learning rate for each embedding training step**

# Improving Translation with Denoising Autoencoder

**Context-aware Beam Search**

- **Language model**

**Denoising Autoencoder**

- **Insertion**
- **Deletion**
- **Reordering**

# Denoising

## Basic idea

- Model noise$(e_1^I)$ by injecting artificial noise into clean sentences $e_1^I$
- Neural network learns to restore more smooth sentence from word-by-word translation

## Training criterion

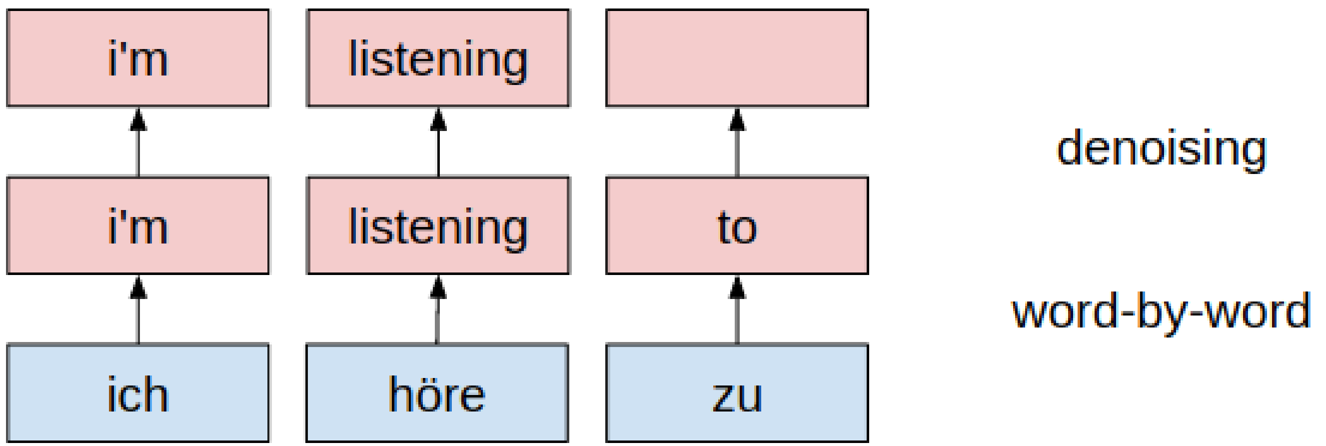
$$\mathcal{L} = \sum_{e_1^I \in E} [-\log p(e_1^I | \text{noise}(e_1^I))]$$

- $E$ denotes target corpus.
- In Seq2Seq training, $e_1^I$ as label, noise$(e_1^I)$ as input
- Artificial noise:
  - insertion, deletion, reordering

# Insertion

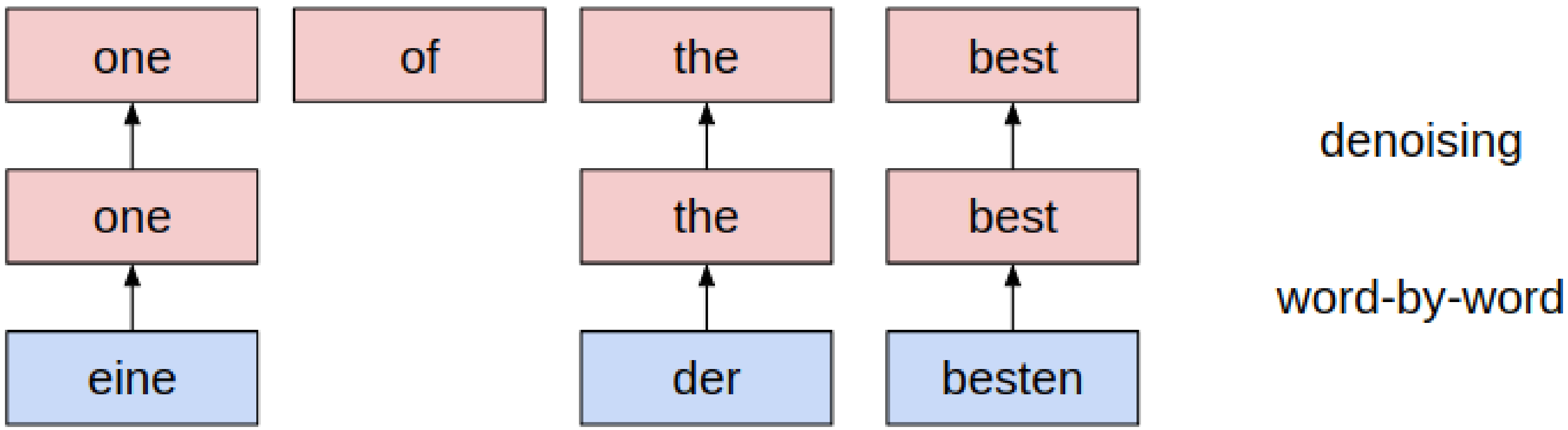
## Insertion

- **Motivation**
  - Word-by-word translation always outputs a target word for every position
  - Some common words are considered as redundant ones
- **Method**
  - For each position in a sentence, insert a frequent word according from set $V_{ins}$ to a probability distribution $p_{ins}$
  - Denoising network learns to delete the word when translating



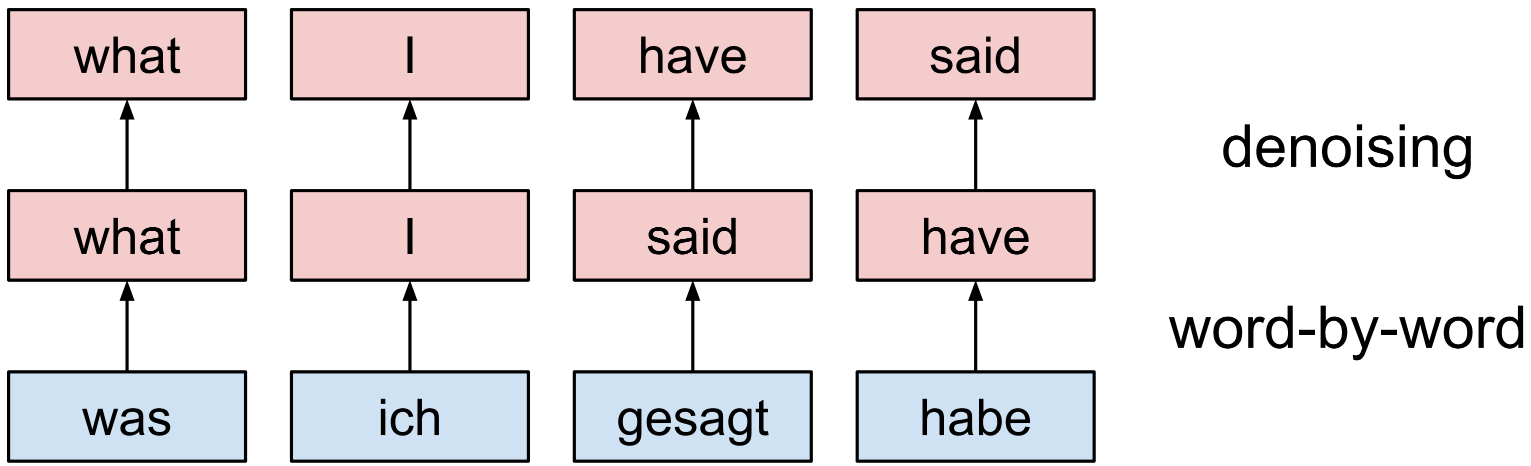
# Deletion

- **Motivation**
  - **In contrary case: some words are not related to any source word**
- **Realization**
  - **For each position in a sentence, delete the word according to a probability distribution $p_{del}$ as input**
  - **Denoising network learns to add some potential words when translating**



# Reordering

- **Motivation**
  - **Generated words are not in a correct sequence of the target language**
- **Method**
  - **For each position of a sentence, swap the words within a limited distance $d_{per}$ as input**
  - **Denoising network learns reordering information when translating**



# Experiment Settings

- Word embedding and LM trained on `News Crawl 2014-2017` (100M)
- BLEU evaluated on German↔English `newstest2016`
- Word accuracy evaluated on dictionaries released by Facebook
  - Dictionary built with internal translation tool
  - Each word has 1-4 word translation(s)
  - Top-1 accuracy
- Context-aware beam search
  - Lexicon candidates: 100
  - Beam width: 10

# Corpus Statistics

| | | German | English | French |
|---|---|---|---|---|
| Train | Sentences | 100M | 100M | 100M |
| | Running Words | 1880M | 2360M | 3017M |
| | Vocabulary | 1254k | 523k | 660k |

| | | `newstest2016` | | `newstest2014` | |
|---|---|---|---|---|---|
| | | German | English | French | English |
| Test | Sentences | 2999 | 2999 | 3003 | 3003 |
| | Running Words | 62506 | 64619 | 81165 | 71290 |
| | Vocabulary Size | 11978 | 8645 | 10899 | 9200 |
| | OOV Rates | 4116 (6.6%) | 1643 (2.5%) | 1731 (2.1%) | 1299 (1.8%) |
| | LM perplexity | 211.0 | 109.6 | 51.2 | 84.6 |

**Search vocabulary in testing: 50k (src/tgt)**

# Experiments: Translation

Translation results on German↔English `newstest2016` and French↔English `newstest2014`.

| System | de-en BLEU [%] | en-de BLEU [%] | fr-en BLEU [%] | en-fr BLEU [%] |
|---|---|---|---|---|
| Word-by-Word | 11.1 | 6.7 | 10.6 | 7.8 |
| + LM (5-gram) + tgt w/ high LM score for OOV | 12.9 | 8.9 | 12.7 | 10.0 |
| + LM (5-gram) + copy from src for OOV | 14.5 | 9.9 | 13.6 | 10.9 |
| + Denoising (RNN) | 16.2 | 10.6 | 15.8 | 13.3 |
| + Denoising (Transformer) | 17.2 | 11.0 | 16.5 | 13.9 |
| [Lample & Denoyer$^{+}$ 17] | 13.3 | 9.6 | 14.3 | 15.1 |
| [Artetxe & Labaka$^{+}$ 17b] | - | - | 15.6 | 15.1 |

# Experiments: Cross-lingual Word Embedding

Cross-lingual Word Retrieval Accuracy

| | De-En [%] | BLEU [% |
|---|---|---|
| Corpus-based | 61.14 | 13.3 |
| Corpus-based without LM | 54.36 | |
| Adversarial | 53.50 | 12.7 |
| Adversarial + Refinement | 64.92 | 14.5 |
| Supervised | 65.38 | 15.0 |

Refinement: use nearest neighbor to build training dictionary

# Ablation study

**Cross-lingual Word Retrieval Accuracy with frequency filtering and center normalization**

| Most frequent vocabulary | no centering [%] | centering [%] |
|---|---|---|
| 500 | 9.79 | 14.8 |
| 1000 | 34.16 | 41.25 |
| 5000 | 58.44 | 59.60 |
| 10000 | 59.52 | 60.14 |
| 50000 | 60.37 | 61.14 |

# Conclusions

**Corpus-based learning of cross-lingual word embedding**

- In corpus-based learning, centering normalization improves the performance
- Our method works better than adversarial training but a little behind supervised training and iterative refinement

**Unsupervised sentence translation with LM and denoising autoencoder**

- Context-aware beam search with LM helps the lexicon choice
- Denoising networks aimed at insertion/deletion/reordering noise works for such problems in a small range of sentences

**In corpus-based learning, centering normalization improves the performance**

# Appendix

## Nearest neighbor search

- Hubness problem: some points (hubs) tends to be nearest neighbors of many points in high-dimensional space

## Cross-domain Similarity Local Scaling (CSLS)

- Penalize the similarity score of hubs
  - $N_T(Wf)$ : target neighbours for mapped source embedding
  - $r_T(Wf)$ : penalty for hubness

$$r_T(Wf) = \frac{1}{K} \sum_{e \in N_T(Wf)} \cos(Wf, e)$$

$$\mathrm{CSLS}(Wf, e) = 2\cos(Wf, e) - r_T(Wf) - r_S(e)$$

## Bidirection dictionary induction

- Unidirectional dictionary might lead to local optima
- Include only the mutual nearest neighbors

# Thank you for your attention

**Jiahui Geng**

jgeng@cs.rwth-aachen.de

http://www.hltpr.rwth-aachen.de/

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