Unsupervised Learning of Neural Lexicon and Cross-lingual Word Embedding

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Outline

Introduction

Literature

Cross-lingual word embedding

- Supervised learning
- Unsupervised learning

Sentence Translation with cross-lingual word embedding

- Context-aware beam search
- Denoising autoencoder

Experiments

Outlook

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

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

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
- [Hoshen & Wolf 18] An Iterative Closest Point Method for Unsupervised Word Translation
  - Iterative closest point method for embedding mapping learning

Literature

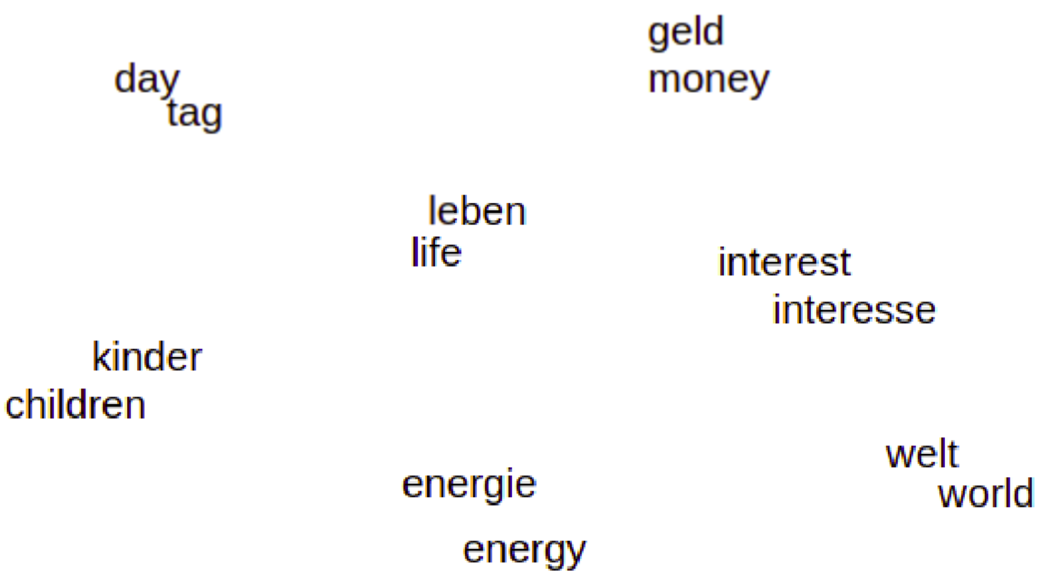
Unsupervised machine translation

- [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
- [Artetxe & Labaka^{+} 17b] Phrase-Based & Neural Unsupervised Machine Translation
  - Simplifies the architecture and loss function for unsupervised NMT and propose a phrase-based SMT with back-translation

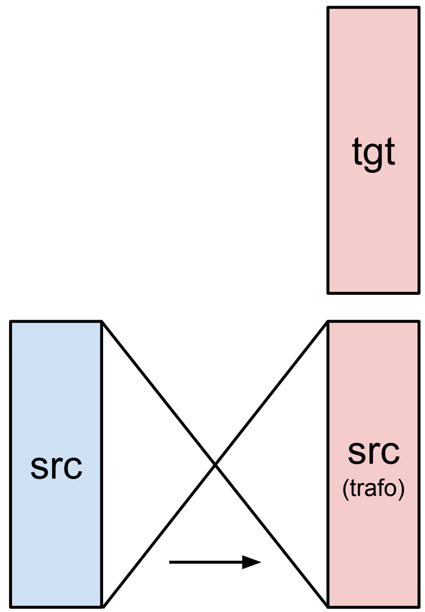
Cross-lingual Word Embedding

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

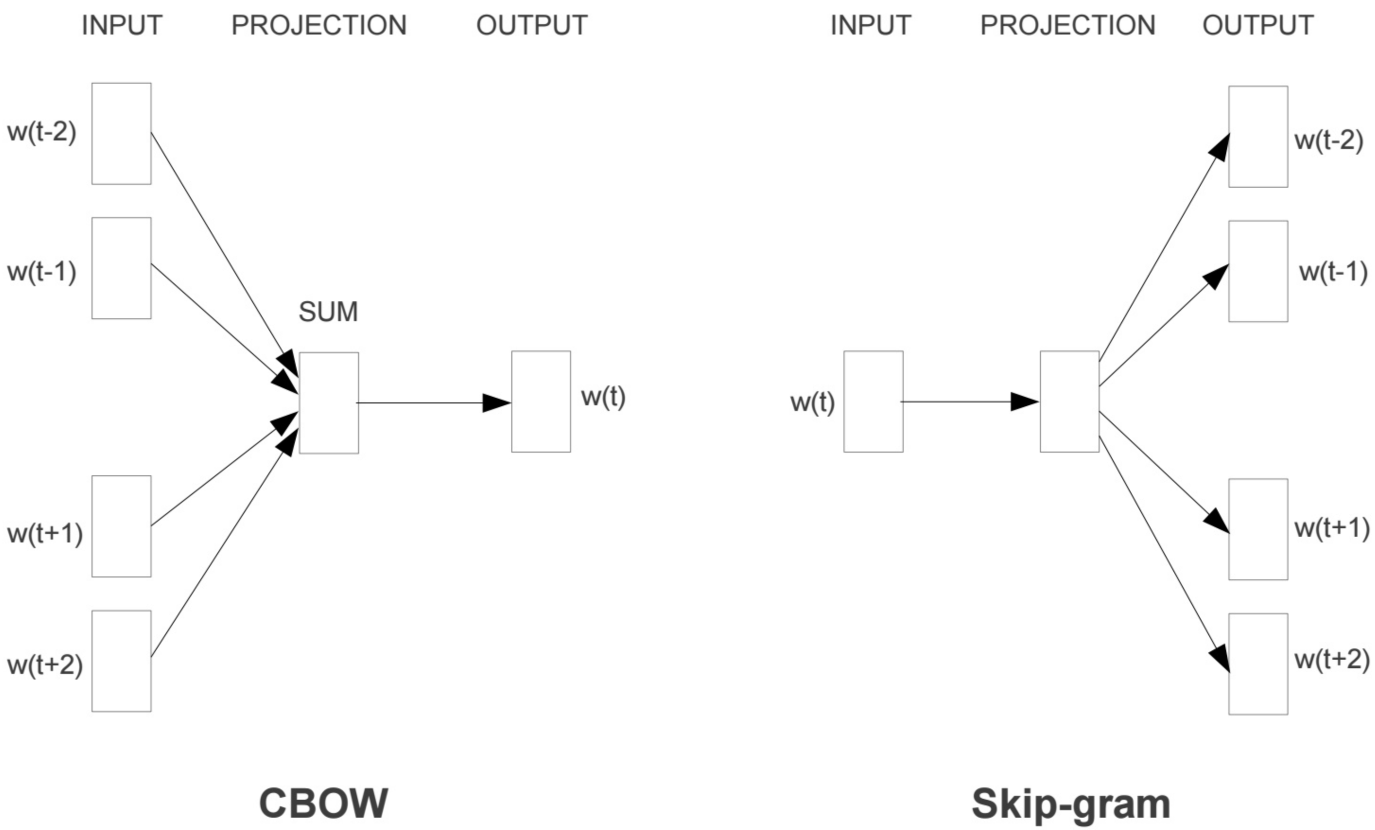
Mapping based approaches

- 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

Learning without Parallel Dictionary

Methods

- **Learn bilingual embeddings without any bilingual evidence (this work)**
  - **Adversarial training [Conneau & Lample$^+$ 17]**
- **Design the seed dictionary**
  - **Shared words, digits and cognates [Artetxe & Labaka$^+$ 17a]**
  - **Design heuristics to build the seed dictionary [Hoshen & Wolf 18] [Artetxe & Labaka$^+$ 18]**

Adversarial Training

Model

- $\mathcal{F} = \left\{f_1, \dots f_{V_f}\right\}$ and $\mathcal{E} = \{e_1, \dots e_{V_e}\}$: set of embeddings, not parallel
- Discriminator is trained to discriminate Wf_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

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

Generator loss

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

Dictionary Induction

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

Sentence Translation

Context-aware Beam Search

- **Language model**

Denoising Autoencoder

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

Context-aware beam search

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

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

- **Lexicon score $q(f, e) \in [0, 1]$ defined as:**

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

  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 λ_{emb} as 1, λ_{LM} as 0.1**

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

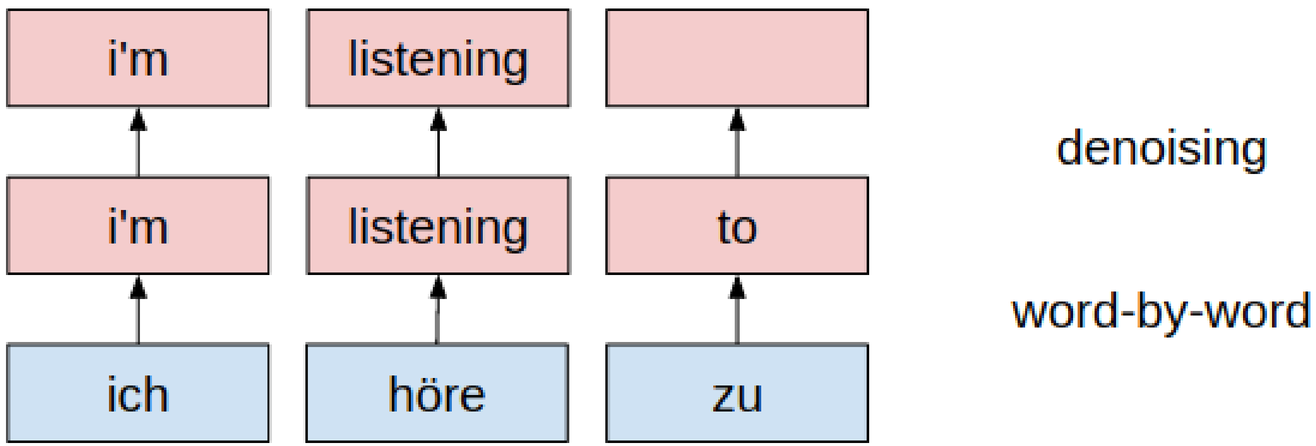
$$\mathcal{L} = \sum_{e_1^I \in E} \left[-\log p(e_1^I | \text{noise}(e_1^I)) \right]$$

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

Insertion

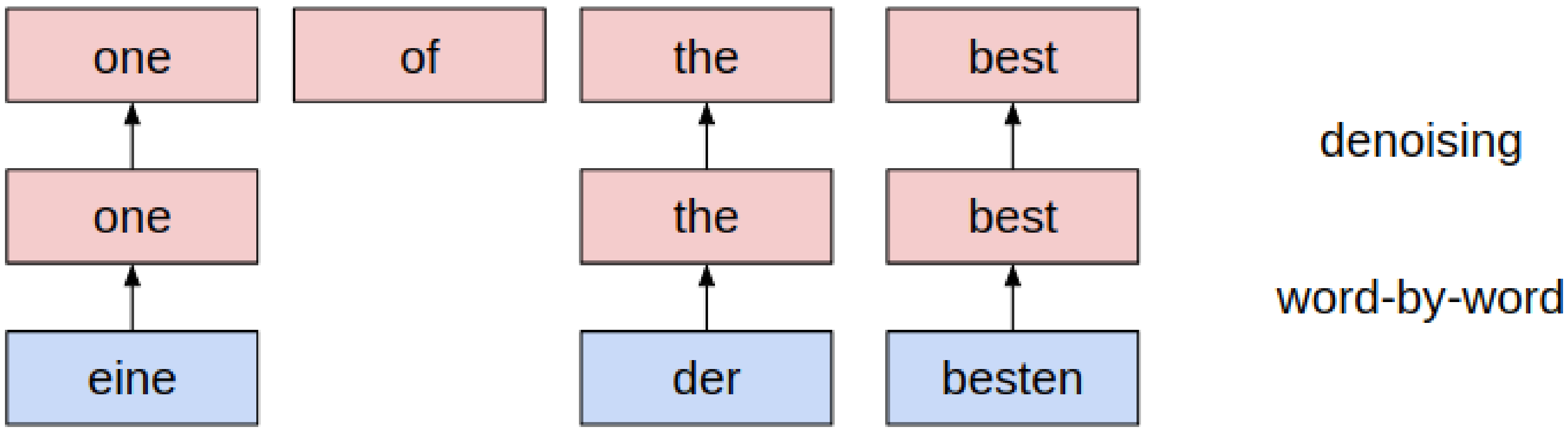
Insertion

- **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



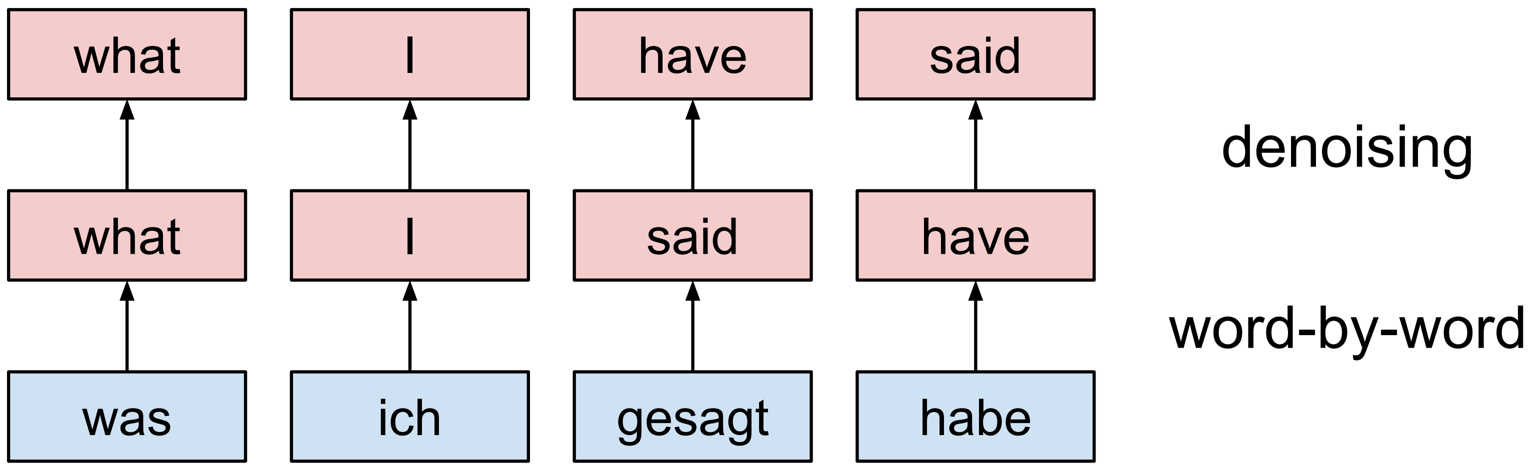
Deletion

- **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**



Corpus-based Leaning

Motivation

- Vocabulary-based just looks at the mutual nearest neighbours
- Word frequency should also be accounted
- Assign priority to frequent words

Intuition

- Integrate the translation task into the learning process of cross-lingual word embedding
- Make use of Language Model

Framework

Algorithm 1: Iterative learning of corpus-based approach

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

```
while not converge do
    ℰ ← TRANSLATE(ℱ, F, E, LM_e)
    W ← LEARN_MAPPING(ℱ, ℰ)
end
```

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

Online Training Algorithm

Algorithm 2: Online learning for corpus-based approach

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

```
while not converge do
    Generate batch of source sentences {f_1^J} from 𝓕
    {e_1^I} ← TRANSLATE({f_1^J}, F, E, LM_e)
    W ← LEARN_MAPPING({f_1^J}, {e_1^I})
end
```

Training Details

- **Dictionary Induction: CSLS retrieval**
- **Corpus Translation: Simplified as word-by-word translation**
- **Optimization Objective**
- **Orthogonal Constraint**

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

- **Stop Criterion**
  average cosine similarity

Training Details

- **Embedding Normalization**
  Centering: mean word embedding should be no bias
- **Dictionary Induction**
  CSLS retrieval
- **Corpus Translation: Simplified as word-by-word translation**
  We use the word-by-word translation framework implemented before, with this translation pair at each position is taken as word translation candidate
- **Optimization Objective**

$$\boldsymbol{W} = \underset{\boldsymbol{W} \in \mathbb{R}^{d \times d}}{\operatorname{argmin}} \frac{1}{|\tilde{V}|} \sum_{n=1}^{|\tilde{V}|} l(\boldsymbol{W} \boldsymbol{f}_n, \boldsymbol{e}_n)$$

Training Details

- **Orthogonal Constraint**

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

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**
  - **Inherit learning rate from last training step**
- **Stop Criterion**
  Average cosine similarity between top 10k most frequent source words and corresponding translation

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`.

	de-en	en-de	fr-en	en-fr
System	BLEU [%]	BLEU [%]	BLEU [%]	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 [%]	En-De [%]
Corpus-based	lr scheduler 1	60.37	60.67
	lr scheduler 2	51.50	\
Corpus-based without LM	lr scheduler 1	54.36	\
Adversarial		53.50	\
Adversarial + Refinement		64.92	\
Supervised		65.38	\

Conclusions

Comprehensive results

- **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**

Ablation studies

- **BPE embeddings performs worse than word embeddings, especially with smaller vocabulary size.**
- **Word-by-word translation with cross-lingual embedding depends highly on the frequent word mappings**
- **Phrase embedding only helps in word-by-word translation with LM**

Thank you for your attention

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