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

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Outline

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

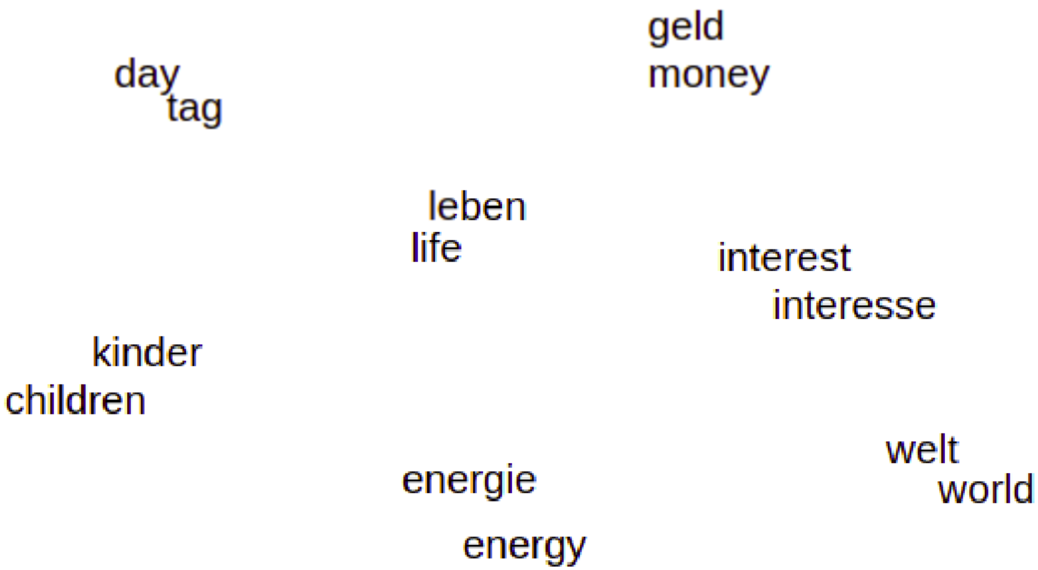
Unsupervised machine translation

- [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

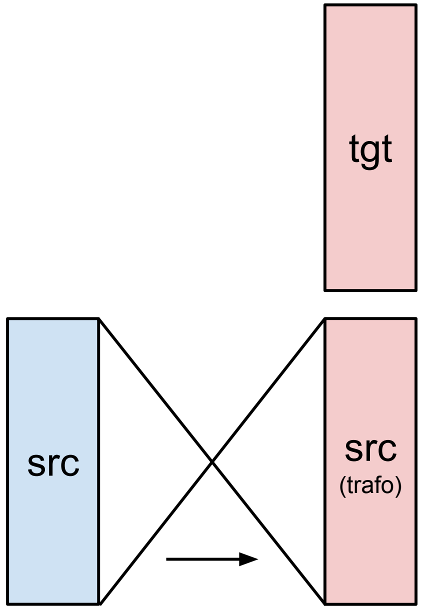
Cross-lingual Word Embedding

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

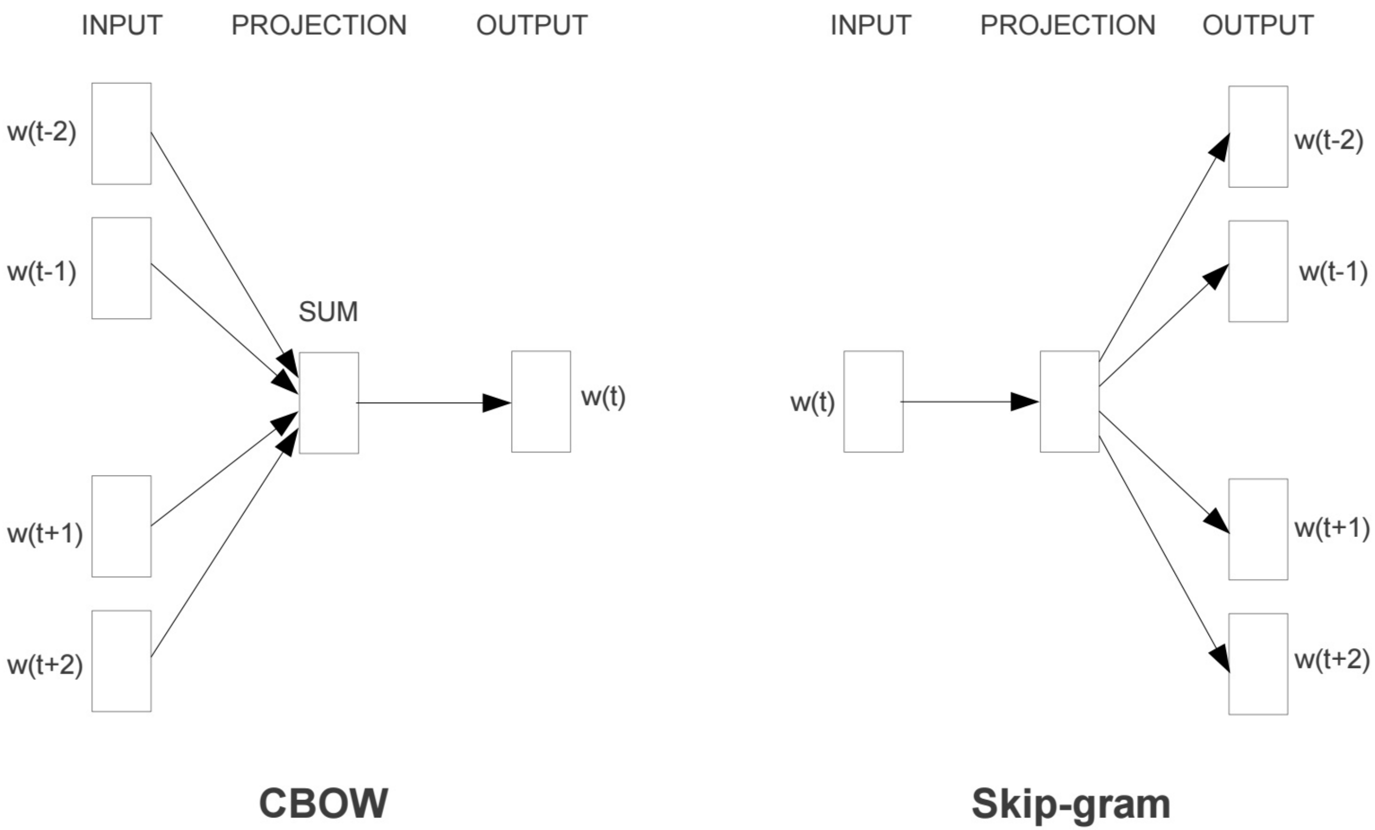
Mapping based approaches

- 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

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

- 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
  - $\boldsymbol{E}$, $\boldsymbol{F} \in \mathbb{R}^{d \times N}$ denote embedding projection of word pairs $\{e, f\}$

$$\boldsymbol{W}^* = \underset{\boldsymbol{W} \in \mathbb{R}^{d \times d}}{\operatorname{argmin}} \|\boldsymbol{W}\boldsymbol{F} - \boldsymbol{E}\|_{\boldsymbol{F}}^2 = \boldsymbol{U}\boldsymbol{V}^{\boldsymbol{T}}$$

$$\boldsymbol{U}\boldsymbol{\Sigma}\boldsymbol{V}^{\boldsymbol{T}} = \mathbf{SVD}(\boldsymbol{E}\boldsymbol{F}^{\boldsymbol{T}})$$

- 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

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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

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

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:

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

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

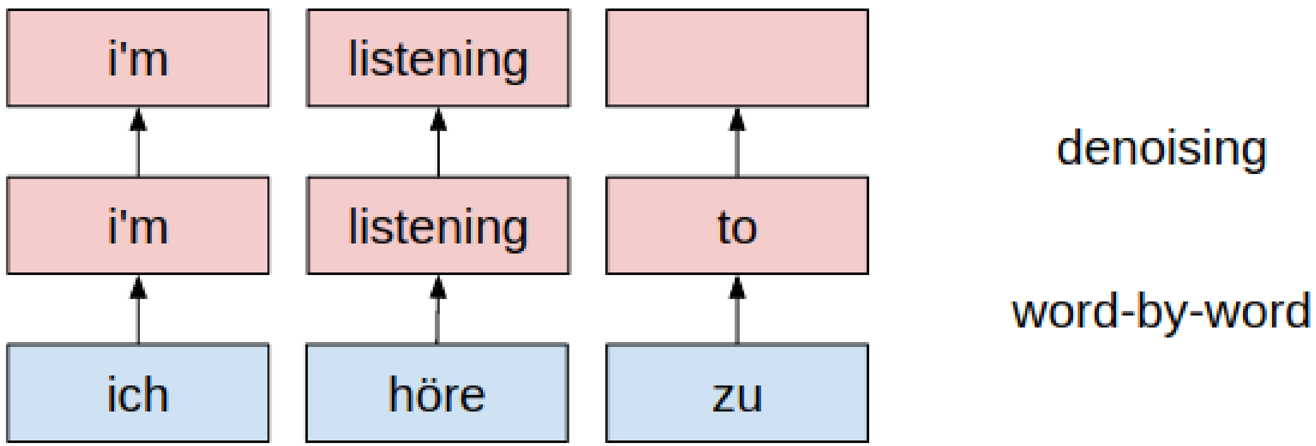
$$\mathcal{L} = \sum_{e_1^I \in E} [-\log p(e_1^I | \text{noise}(e_1^I))]$$

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

Insertion

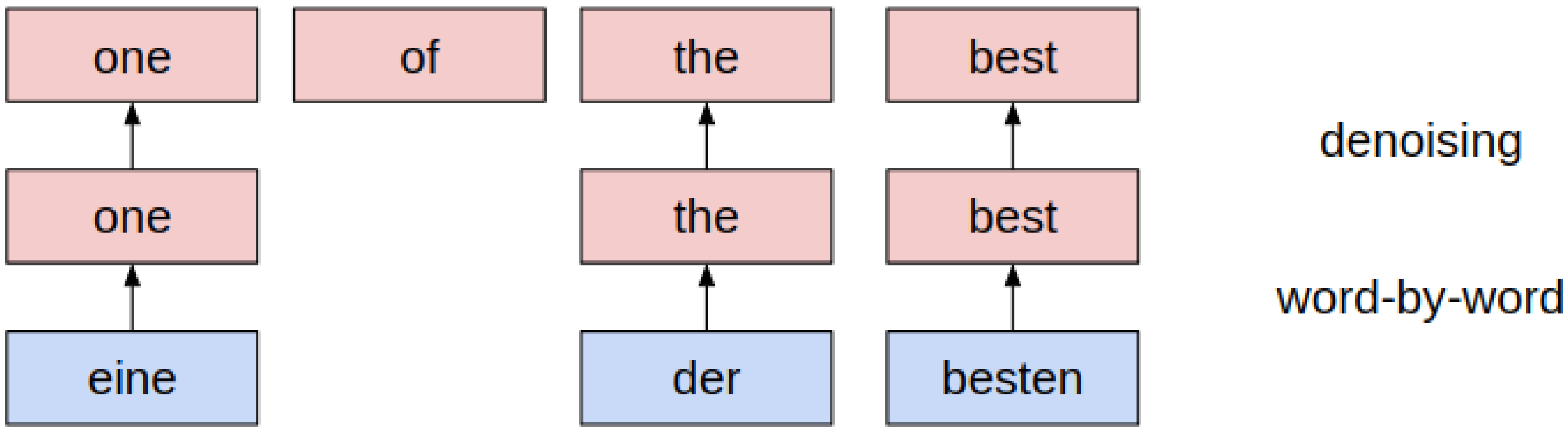
Insertion

- **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



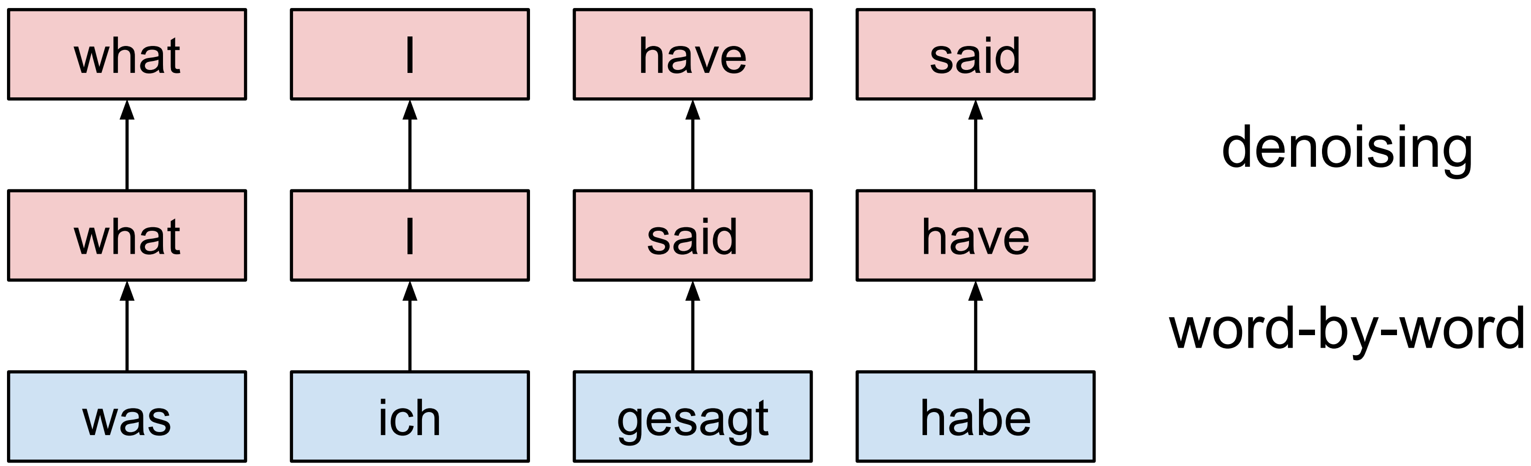
Deletion

- **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$\leftrightarrow$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 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

Ablation studies

- Different sizes of training corpora
- Different vocabularies: BPE and word
- Different vocabulary sizes for cross-lingual training
- Different denoising parameters
- Phrase embedding
- Vocabulary cut-off

Different Training Corpora

Word-by-word translation from German to English

	ACCURACY [%]	BLEU [%]
5M	44.9	9.7
10M	51.6	10.1
50M	59.4	10.8
100M	61.2	11.2

- **Larger corpus improves the word translation accuracy**
- **Also improves the word-by-word translation**

Different Embeddings and Training Vocabulary Size

	Vocabulary	BLEU [%]
	Merges	
BPE	20k	10.4
	50k	12.5
	100k	13.0
	Cross-lingual training	
Word	20k	14.4
	50k	14.4
	100k	14.5
	200k	14.4

- Word-by-word translation with language model
- Word embedding performs better than BPE embedding
- Embedding trained on 20k similar to 200k $\Rightarrow$ Frequent words matter

Denoising Experiments

d_{per}	p_{del}	p_{ins}	V_{ins}	BLEU [%]
2				14.7
3				14.9
5				14.9
3	0.1			15.7
	0.3			15.1
3	0.1	0.1	10	16.8
			50	17.2
			500	16.8
			5000	16.5

- **Each artificial noise improves the translation performance**

Phrase Embedding

Motivation

- Many phrases have a meaning that is not a simple composition of the meaning of its individual words

Phrase detection

- Phrases formed based on the unigram and bigram counts [Mikolov & Sutskever+ 13]
  - Tune a good threshold value for score

$$\text{score}(e', e) = \frac{\text{count}(e', e) - \delta}{\text{count}(e') * \text{count}(e)}$$

- Process sentences with most common phrases in training corpus
  - Count the most frequent bi-gram phrases: $\text{score}(e', e) = \text{count}(e', e)$
  - Detect phrases as top frequent phrases in the training corpus

Phrase Embedding Experiments

Vocabulary			No LM BLEU [%]	With LM BLEU [%]	Denoising BLEU [%]
Word			11.2	14.5	17.2
[Mikolov & Sutskever^{+} 13]	threshold	100	11.1	13.7	15.6
		500	11.0	13.7	16.2
		2000	10.7	14.0	16.5
Top frequent	count	50k	12.0	15.7	16.8

- Phrase embeddings helps only for WBW and +LM

Source and Target Vocabulary Cut-off

- Limit the vocabulary size, copy the OOV directly (mainly name entities)
- Column: source vocabulary size/ row: target vocabulary size

Word embedding vocabulary cut-off

BLEU [%]	20k	50k	100k
50k	11.1	11.3	11.2
100k	11.2	11.2	11.1
150k	10.9	10.9	-

Phrase embedding vocabulary cut-off

BLEU [%]	50k	100k	150k
50k	11.3	-	-
100k	11.9	11.9	-
150k	12.0	11.9	11.9
200k	12.0	-	-

- Vocabulary size affects the translation performance slightly

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**

Outlook

Goal: Improve the unsupervised learning for cross-lingual embedding

- **Accordingly improves unsupervised MT performance**
- **Other applications: transfer learning for low-resource LM [Adams & Makarucha$^+$**

LM supported cross-lingual embedding training

- **Straightforward mapping modelling**
- **LM improves the dictionary quality**
- **Larger dictionary (training data)**
- **Different mapping types and loss functions**

Outlook

Difference

- Training the mapping with SGD instead of Procrustes analysis
- Dictionary from the sentence translation with LM, instead of induction from embedding

Training procedure

1. Translate corpus according to current mapping, get the word pairs D
2. Train the network with D to minimize the mapping distance
3. Repeat $1, 2$ until converges

$$\left.\begin{matrix} (f_1, & e_1) \\ (f_2, & e_2) \\ & \vdots \\ (f_N, & e_N) \end{matrix}\right\} \Rightarrow D \qquad\qquad \mathcal{L} = \sum_{(f,e)\in D} \|Wf - e\|^2$$

Thank you for your attention

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