Unsupervised Learning of Neural Network Lexicon and Cross-lingual Word Embedding

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Outline

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Introduction

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Why unsupervised learning?

- Overcome the lack of reference translations
- Rich monolingual sentence resource

Why artificial neural network (ANN) for lexicon?

- Easy integration of (possibly unlimited) source side contexts
- Implicit smoothing for rare words
- Flexible model capacity: cover large vocabularies with low memory requirement

Why cross-lingual word embedding?

- Enable cross-lingual similarity calculations
- Enable knowledge transfer between languages

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Thesis Goal

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Goal: unsupervised system using word lexicon/embedding models without artificial rearrangement of alignments

- Directly applicable to practical tasks, easier to convince the community
- Can be used in 1:1 or almost 1:1 tasks: tagging, summary translation
- Can be used as the initial model of iterative back-translation for NMT

Tasks

- ANN lexicon
  - Implement and test EM-style training algorithm
  - Implement different models like word-to-word, context-aware
- Cross-lingual word embedding
  - Reproduce results of some state-of-the-art research
  - Combine of embedding-based translation models and LM
- Compare the results of the above models
- Compare different minimum translation units: word/word-BPE/sentence-BPE

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Literature

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Unsupervised cross-lingual embedding

- [Artetxe & Labaka+ 17a] Learning bilingual word embeddings with (almost) no bilingual data
  - A self-learning framework combining embedding mapping and dictionary induction techniques, need small dataset to start
- [Conneau & Lample+ 17] Word translation without parallel data
  - Implementation of GANs: the discriminator plays an adversarial role to a generative model and is trained to distinguish between two distributions
- [Hoshen & Wolf 18] An Iterative Closest Point Method for Unsupervised Word Translation
  - Iterative Closest Point Method for unsupervised embedding mapping learning, fewer hyper-parameters, more interpretable

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Literature

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Unsupervised machine translation

- [Artetxe & Labaka+ 17b] Unsupervised neural machine translation
  - With fixed cross-lingual embeddings to train a shared encoder, train the system with de-noising and on-the-fly back-translation alternatively
- [Lample & Denoyer+ 17] Unsupervised Machine Translation Using Monolingual Corpora Only
  - Seq2seq model with encoder and decoder for both language, also with denoise autoencoder and back-translation
- [Artetxe & Labaka+ 17b] Phrase-Based & Neural Unsupervised Machine Translation
  - Simplifying the architecture and loss function while still following the above mentioned principles and propose a PBSMT with back-translation

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From Lexicon to Embedding

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Motivation

- Embeddings are trained on much larger corpora seperately
  - ANN lexicon model updated within the unsupervised training process
  - much more information $\Rightarrow$ much more semantic/syntactic information
- From discrete to continuous vector representation

How do we do with word embedding?

- Translation of source embedding to target embedding
- Decision rule for target word given target embedding
- Training of embedding models for translation purpose

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Word Translation

- Learn monolingual embedding separately
  - Fasttext
- Learn linear mapping between embedding spaces
  - Definition
  - Supervised learning
    - Procrustes analysis
  - Unsupervised learning
    - Adversarial learning
    - Iterative refinement
- Bidirectional dictionary induction
  - CSLS retrieval

Cross-lingual Word Embedding

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Definition

- Word embedding of multiple languages in a joint embedding space

Motivation

- Enable cross-lingual similarity calculations
- Enable knowledge transfer between languages

Methods

- Mapping-based approaches
  - Train word embeddings then learn mapping with bilingual dictionaries
- Pseudo-multi-lingual corpora-based approaches
  - Use monolingual word embedding methods on mixed corpus of multiple languages
- Joint methods
  - Minimize the monolingual losses with the cross-lingual regularization term

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Supervised Learning

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Assume we have

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

Learn a linear mapping W such that

$$W^* = \underset{W}{\operatorname{argmin}} \|WF - E\|$$

- d **: Dimension of embeddings**
- F**,** E**: Aligned** $d \times s$ **real matrices containing the embeddings of the words in the dictionary**
- s**: Seed dictionary size**

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Procrustes Analysis

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Constrain W to be an orthogonal matrix

- **Enforce monolingual invariance**
- **Simplify the problem as the the Procrustes problem which has a closed-form solution obtained from the SVD of EF^T:**

$$W^* = \underset{W \in M_d(\mathbb{R})}{\operatorname{argmin}} \|WF - E\| = UV^T$$

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

- **Can be efficiently computed in linear time $w.r.t$ number of dictionary entries**

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Unsupervised Word Embedding Mapping

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Problem

- Large dictionary not readily available for many language pairs

Methods

- Design the seed dictionary
  - Using document-aligned corpora to extract the training dictionary
  - Relying on shared words, digits and cognates
- Learn bilingual embeddings without any bilingual evidence
  - Adversarial training

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Adversarial Training

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Model

- $\mathcal{F} = \left\{ f_1, \ldots f_{V_f} \right\}$ **and** $\mathcal{E} = \{e_1, \ldots e_{V_e}\}$**: Sets of word embeddings**
- **Discriminator is trained to discriminate between elements randomly sampled from** $W\mathcal{F}$ **and** $\mathcal{E}$
- **Generator** W **is trained to prevent the discriminator from making accurate prediction**

Discriminator loss

$$\mathcal{L}_D = -\log D(\mathcal{E}) - \log(1 - D(W\mathcal{F}))$$

Generator loss

$$\mathcal{L}_W = -\log D(W\mathcal{F})$$

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Trick: Frequency-based Vocabulary Cutoff

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Problem

- **Rare word embeddings are less trained(updated)**
- **Contain noise information for alignment**

Experiment

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Iterative Refinement

Algorithm 1: Self-learning framework

Input: $\mathcal{F}$ (source embeddings)
Input: $\mathcal{E}$ (target embeddings)
Input: $\mathcal{D}$ (seed dictionary)
Result: $\mathcal{W}$ (embedding mapping)

initialization;
while *not convergence criterion* **do**
    $\mathcal{W} \leftarrow learn\_mapping(\mathcal{E}, \mathcal{F}, \mathcal{D})$;
    $\mathcal{D} \leftarrow learn\_mapping(\mathcal{E}, \mathcal{F}, \mathcal{W})$;
end

Dictionay Induction

Cross-domain Similarity Local Scaling

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

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

$$CSLS(Wf, e) = 2cos(Wf, e) - r_T(Wf) - r_S(e)$$

Bidirection Dictionary Induction

- Repreated word in unidirectional dictionary might lead to local optima
- Include the dictionary in both directions

Sentence Translation

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Context-aware beam search

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

$$L(e; f, h) = \lambda_{emb} q(f, e) + \lambda_{LM} p(e|h)$$

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

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

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

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Denoising

- Substitions, insertions, deletions, reordering viewed as noise in word-by-word translation
- Model such noise $c(t)$ by injecting artificial noise into clean sentences t
- Language modelling via denoising autoencoder can improve the translation by minimizing:

$$L = E_{t \in T}[-logP_{t \to t}(t|C(t))]$$

- In Seq2Seq training, t as label, $c(t)$ as input

Results

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	12.9	8.9	12.7	10.0
	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

Outlook

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Cross-lingual word embedding and word-to-word MT system

- **Develop a new training algorithm for cross-lingual embeddings**
  - **Context/domain considered, e.g. LM**
  - **Better constraints on specific (group of) words**
- **Word-to-word MT system with cross-lingual embeddings**
  - **Efficient nearest neighbour search**
  - **Combination with a language model**
- **Compare translation results with word-to-word neural lexicons**
  - **All trained/tested on intact corpora without artificial change of alignments**

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Appendix: Denoising & Vocabulary

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

Translation results with different values of denoising parameters.

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

Translation results with different vocabularies.

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Thank you for your attention

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