

Unsupervised Joint Training of Bilingual Word Embeddings

Benjamin Marie Atsushi Fujita

 $\{bmarie, atsushi.fujita\}@nict.go.jp$

National Institute of Information and Communications Technology (NICT), Kyoto, Japan

SUMMARY

Key points

Findings

- Joint training directly learns bilingual word embeddings (BWE) on parallel data (cf. mapping methods)
- Unsupervised machine translation generates synthetic parallel data by translating monolingual data
- Unsupervised joint training uses synthetic parallel data for pseudo-supervision

ASSUMPTIONS AND RESEARCH QUESTION

Assumptions

- 1. Mapping methods for BWE are **limited** by the dissimilarity between the original word embedding spaces to be mapped (Søgaard+, 16)
- 2. Supervised joint training algorithms (Upadhyay+, 16) are robust to noisy data
- 3. Synthetic parallel data of a reasonable quality can be generated through unsupervised machine translation (Artetxe+, 18a; Lample+,18)

Research question

- Largely outperforms BWE obtained through unsupervised mapping in bilingual lexicon induction tasks
- Robust to noisy synthetic parallel data and takes advantage of monolingual and bilingual contexts simultaneously

Unsupervised Joint Training



Do synthetic sentence pairs, generated without supervision, supply useful bilingual contextual information for jointly learning better BWE?

EVALUATION IN BILINGUAL LEXICON INDUCTION

Are BWE unsupervisedly and jointly trained on noisy synthetic data better than unsupervised mapped BWE?

Data

- Monolingual training data: News crawl for en-de and en-fr, Common Crawl for en-id
- Test sets: "full" Muse Wikipedia bilingual lexicons

Baseline systems: unsupervised mapping

• VECMAP: fastText word embeddings mapped without supervision (Artetxe+, 18b)

Evaluated systems

EVALUATION IN MONOLINGUAL WORD ANALOGY

Does unsupervised joint training improve or preserve monolingually the quality of the word embeddings (as observed for supervised bilingual skipgram)?

Settings

- Task: English word analogy (Mikolov+, 13)
- Unsupervised systems: VECMAP (bilingual mapping), BIVEC (bilingual joint training), and fastText (monolingual)

- Training data: synthetic parallel data generated with unsupervised statistical machine translation (Lample+, 18) by translating source and/or target sentences
- BIVEC: bilingual skipgram using pre-trained word alignments (Luong+, 15)
- SENTID: skipgram on a word/sentence-ID matrix (Levy+, 17)

Results (acc@1)

Method	Data used src-tgt	en→de	$de \rightarrow en$	$en \rightarrow fr$	fr→en	$en \rightarrow id$	$\mathrm{id} \rightarrow \mathrm{en}$
VECMAP	all-all	42.4	59.0	67.7	70.0	58.9	59.5
BIVEC SENTID	10M-0 10M-0	$\begin{array}{c} 45.8\\ 45.8\end{array}$	59.2 60.1	73.9 74.4	71.3 71.8	70.4 69.8	$\begin{array}{c} 69.7 \\ 69.2 \end{array}$
BIVEC SENTID	0-10M 0-10M	$\begin{array}{c} 43.7\\ 43.5\end{array}$	63.4 63.5	72.0 72.6	74.3 74.8	$\begin{array}{c} 67.3 \\ 67.5 \end{array}$	72.3 73.4
BIVEC SENTID	10M-10M 10M-10M	$\begin{array}{c} 44.9\\ 45.4\end{array}$	$54.9 \\ 62.1$	73.9 74.2	73.874.0	$\begin{array}{c} 69.5\\ 69.4\end{array}$	$72.1 \\73.0$

Results

Method	Data used	Accuracy
VECMAP	239M(en)-38M(fr)	77.8
BIVEC	10M(en)-10M(synthetic fr)	65.7
fastText	239M(en) 10M(en)	$79.1\\64.6$

- BIVEC outperforms fastText when they are trained on the same data
- \Rightarrow Joint algorithms take advantage of noisy but bilingual contexts to monolingually improve word embeddings

- Unsupervised joint training outperforms unsupervised mapping by a large margin
 - More than 10 points of improvement for en-id
 - Higher accuracy when synthetic parallel data do not contain synthetic English (e.g., "10M-0" for $en \rightarrow de$, $en \rightarrow fr$, and $en \rightarrow id$)
- BIVEC and SENTID performs similarly
 - pre-trained word alignments are unnecessary
- \Rightarrow Joint algorithms are robust to noise and learn better BWE for bilingual lexicon induction