

# Joint Representation Learning of Cross-lingual Words and Entities via Attentive Distant Supervision

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## Abstract

Joint representation learning of words and entities benefits many NLP tasks, but has not been well explored in cross-lingual settings. In this paper, we propose a novel method for joint representation learning of cross-lingual words and entities. It captures mutually complementary knowledge, and enables cross-lingual inferences among knowledge bases and texts. Our method does not require parallel corpora, and automatically generates comparable data via distant supervision using multi-lingual knowledge bases. We utilize two types of regularizers to align cross-lingual words and entities, and design knowledge attention and cross-lingual attention to further reduce noises. We conducted a series of experiments on three tasks: word translation, entity relatedness, and cross-lingual entity linking. The results, both qualitatively and quantitatively, demonstrate the significance of our method.

## 1 Introduction

Multi-lingual knowledge bases (KB) store millions of entities and facts in various languages, and provide rich background structural knowledge for understanding texts. On the other hand, text corpus contains huge amount of statistical information complementary to KBs. Many researchers leverage both types of resources to improve various natural language processing (NLP) tasks, such as machine reading (Yang and Mitchell, 2017), question answering (He et al., 2017; Hao et al., 2017).

Most existing work jointly models KB and text corpus to enhance each other by learning word and entity representations in a unified vector space. For example, Wang et al. (2014); Yamada et al. (2016); Cao et al. (2017) utilize the co-occurrence information to align similar words and entities with similar embedding vectors. Toutanova et al. (2015);

Wu et al. (2016); Han et al. (2016); Weston et al. (2013a); Wang and Li (2016) represent entities based on their textual descriptions together with the structured relations. These methods focused on mono-lingual settings. However, for cross-lingual tasks (e.g., cross-lingual entity linking), these approaches need to introduce additional tools to do translation, which suffers from extra costs and inevitable errors (Ji et al., 2015, 2016).

In this paper, we carry out cross-lingual joint representation learning, which has not been fully researched in the literature. We aim at creating a unified space for words and entities in various languages, and easing cross-lingual semantic comparison, which will benefit from the complementary information in different languages. For instance, two different meanings of word *center* in English are expressed by two different words in Chinese: *center* as *the activity-specific building* is expressed by 中心, *center* as *the basketball player role* is 中锋.

Our main challenge is the limited availability of parallel corpus, which is usually either expensive to obtain, or only available for certain narrow domains (Gouws et al., 2015). Many work has been done to alleviate the problem. One school of methods uses adversarial technique or domain adaption to match linguistic distribution (Zhang et al., 2017b; Barone, 2016; Cao et al., 2016). These methods do not require parallel corpora. The weakness is that the training process is unstable and that the high complexity restricts the methods only to small-scale data. Another line of work uses pre-existing multi-lingual resources to automatically generate “pseudo bilingual documents” (Vulic and Moens, 2015, 2016). However, negative results have been observed due to the occasional poor quality of training data (Vulic and Moens, 2016). All above methods only focus on words. We consider both words and entities, which

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makes the parallel data issue more challenging.

In this paper, we propose a novel method for joint representation learning of cross-lingual words and entities. The basic idea is to capture mutually complementary knowledge in a shared semantic space, which enables joint inference among cross-lingual knowledge base and texts without additional translations. We achieve it by (1) utilizing an existing multi-lingual knowledge base to automatically generate cross-lingual supervision data, (2) learning mono-lingual word and entity representations, (3) applying cross-lingual sentence regularizer and cross-lingual entity regularizer to align similar words and entities with similar embeddings. The entire framework is trained using a unified objective function, which is efficient and applicable to arbitrary language pairs that exist in multi-lingual KBs.

Particularly, we build a bilingual entity network from inter-language links<sup>1</sup> in KBs for regularizing cross-lingual entities through a variant of skip-gram model (Mikolov et al., 2013c). Thus, mono-lingual structured knowledge of entities are not only extended to cross-lingual settings, but also augmented from other languages. On the other hand, we utilize **distant supervision** to generate comparable sentences for cross-lingual sentence regularizer to model co-occurrence information across languages. Compared with “pseudo bilingual documents”, comparable sentences achieve higher quality, because they rely not only on the shared semantics at document level, but also on cross-lingual information at sentence level. We further introduce two attention mechanisms, knowledge attention and cross-lingual attention, to select informative data in comparable sentences.

Our contributions can be concluded as follows:

- We proposed a novel method that jointly learns representations of not only cross-lingual words but also cross-lingual entities in a unified vector space, aiming to enhance the embedding quality from each other via complementary semantics.
- Our proposed model introduces distant supervision coupled with attention mechanisms to generate comparable data as cross-lingual supervision, which can benefit many cross-lingual analysis.

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<sup>1</sup>[https://en.wikipedia.org/wiki/Help:Interlanguage\\_links](https://en.wikipedia.org/wiki/Help:Interlanguage_links)

- We did qualitative analysis to have an intuitive impression of our embeddings, and quantitative analysis in three tasks: word translation, entity relatedness, and cross-lingual entity linking. Experiment results show that our method demonstrates significant improvements in all three tasks.

## 2 Related Work

Jointly representation learning of words and entities attracts much attention in the fields of Entity Linking (Zhang et al., 2017a; Cao et al., 2018), Relation Extraction (Weston et al., 2013b) and so on, yet little work focuses on cross-lingual settings. Inspiringly, we investigate the task of cross-lingual word embedding models (Ruder et al., 2017), and classify them into three groups according to parallel corpora used as supervisions: (i) methods requiring **parallel corpus with aligned words** as constraint for bilingual word embedding learning (Klementiev et al., 2012; Zou et al., 2013; Wu et al., 2014; Luong et al., 2015; Ammar et al., 2016; Soricut and Ding, 2016). (ii) methods using **parallel sentences** (i.e. translated sentence pairs) as the semantic composition of multi-lingual words (Gouws et al., 2015; Kociský et al., 2014; Hermann and Blunsom, 2014; Chandar et al., 2014; Shi et al., 2015; Mogadala and Rettinger, 2016). (iii) methods requiring **bilingual lexicon** to map words from one language into the other (Mikolov et al., 2013b; Faruqui and Dyer, 2014; Xiao and Guo, 2014).

The major weakness of these methods is the limited availability of parallel corpora. One remedy is to use existing multi-lingual resources (i.e. multi-lingual KB). Camacho-Collados et al. (2015) combines several KBs (Wikipedia, WordNet and BabelNet) and leverages multi-lingual synsets to learn word embeddings at sense level through an extra post-processing step. Artetxe et al. (2017) starts from a small bilingual lexicon and using a self-learning approach to induce the structural similarity of embedding spaces. Vulic and Moens (2015, 2016) collect comparable documents on same themes from multi-lingual Wikipedia, shuffle and merge them to build “pseudo bilingual documents” as training corpora. However, the quality of “pseudo bilingual documents” are difficult to control, resulting in poor performance in several cross-lingual tasks (Vulic and Moens, 2016).

Another remedy matches linguistic distribu-



**pervision Data Generation** builds a bilingual entity network and generates comparable sentences based on cross-lingual links; (2) **Joint Representation Learning** learns cross-lingual word and entity embeddings using a unified objective function. Our assumption throughout the entire framework is as follows: *The more words/entities two contexts share, the more similar they are.*

As shown in Figure 1, we build a bilingual EN  $\mathcal{G}^{en-zh}$  by using  $\mathcal{G}^{en}$ ,  $\mathcal{G}^{zh}$  and cross-lingual links  $\mathcal{R}^{en-zh}$ . Thus, entities in different languages shall be connected in a unified network to facilitate cross-lingual entity alignments. Meanwhile, from KB articles, we extract comparable sentences  $\mathcal{S}^{en-zh} = \{\{s_k^{en}, s_k^{zh}\}\}$  as high qualified parallel data to align similar words in different languages.

Based on generated cross-lingual data  $\mathcal{G}^{en-zh}$ ,  $\mathcal{S}^{en-zh}$  and mono-lingual data  $\mathcal{D}^y$ ,  $\mathcal{A}^y$ , where  $y \in \{en, zh\}$ , we jointly learn cross-lingual word and entity embeddings through three components: (1) **Mono-lingual Representation Learning**, which learns mono-lingual word and entity embeddings for each language by modeling co-occurrence information through a variant of skip-gram model (Mikolov et al., 2013c). (2) **Cross-lingual Entity Regularizer**, which aligns entities that refer to the same thing in different languages by extending the mono-lingual model to bilingual EN. For example, entity *Foust* in English and entity 福斯特 (*Foust*) in Chinese are closely embedded in the semantic space because they share common neighbors in two languages, *All-star* and *NBA 选秀 (draft)*, etc.. (3) **Cross-lingual Sentence Regularizer**, which models cross-lingual co-occurrence at sentence level in order to learn translated words to have most similar embeddings. For example, English word *basketball* and the translated Chinese word 篮球 frequently co-occur in a pair of comparable sentences, therefore, their vector representations shall be close in the semantic space. The above components are trained jointly under a unified objective function.

## 4 Cross-lingual Supervision Data Generation

This section introduces how to build a bilingual entity network  $\mathcal{G}^{en-zh}$  and comparable sentences  $\mathcal{S}^{en-zh}$  from a multi-lingual KB.

### 4.1 Bilingual Entity Network Construction

Entities with cross-lingual links refer to the same thing, which implies they are equivalent across languages. Conventional knowledge representation methods only add edges between  $e_i^{en}$  and  $e_{i'}^{zh}$  indicating a special “equivalent” relation (Zhu et al., 2017). Instead, we build  $\mathcal{G}^{en-zh} = (\mathcal{E}^{en} \cup \mathcal{E}^{zh}, \mathcal{R}^{en} \cup \mathcal{R}^{zh} \cup \tilde{\mathcal{R}}^{en-zh})$  by enriching the neighbors of cross-lingual linked entities. That is, we add edges  $\tilde{\mathcal{R}}^{en-zh}$  between two mono-lingual ENs by letting all neighbors of  $e_i^{en}$  be neighbors of  $e_{i'}^{zh}$ , and vice versa, if  $\langle e_i^{en}, e_{i'}^{zh} \rangle \in \mathcal{R}^{en-zh}$ .

$\mathcal{G}^{en-zh}$  extends  $\mathcal{G}^{en}$  and  $\mathcal{G}^{zh}$  to bilingual settings in a natural way. It not only keeps a consistent objective in mono-lingual ENs—entities, no matter in which language, will be embedded closely if share common neighbors—but also enhances each other with more neighbors in the foreign language.

Following the method in Zhu et al. (2017), there will be no edge between Chinese entity 福斯特 (*Foust*) and English entity *Pistons*, which implies a wrong fact that 福斯特 (*Foust*) does not belong to *Pistons*. Our method enriches the missing relation between entities 福斯特 (*Foust*) and 活塞队 (*Pistons*) in incomplete Chinese KB through corresponding English common neighbors, *Allstar*, *NBA*, etc., as illustrated in Figure 1.

### 4.2 Comparable Sentences Generation

To supervise the cross-lingual representation learning of words, we automatically generate comparable sentences as cross-lingual training data. Comparable sentences are not translated paired sentences, but sentences with the same topic in different languages. As shown in the middle layer (Figure 1), the pair of sentences are comparable sentences: (1) “*Lawrence Michael Foust was an American basketball player who spent 12 seasons in NBA*”, (2) “*拉里·福斯特 (Lawrence Foust) 是 (was) 美国 (American) NBA 联盟 (association) 的 (of) 前 (former) 职业 (professional) 篮球 (basketball) 运动员 (player)*”.

Inspired by the distant supervision technique in relation extraction, we assume that sentence  $s_k^{en}$  in Wikipedia articles of entity  $e_i^{en}$  explicitly or implicitly describes  $e_i^{en}$  (Yamada et al., 2017), and that  $s_k^{en}$  shall express a relation between  $e_i^{en}$  and  $e_j^{en}$  if another entity  $e_j^{en}$  is in  $s_k^{en}$ . Meanwhile, we find a comparable sentence  $s_{k'}^{zh}$  in another language which satisfies  $s_{k'}^{zh}$  containing  $e_{j'}^{zh}$ .



in Wikipedia articles of Chinese entity  $e_i^{zh}$ , where  $\langle e_i^{en}, e_{i'}^{zh} \rangle, \langle e_j^{en}, e_{j'}^{zh} \rangle \in \mathcal{R}^{en-zh}$ . As shown in Figure 1, the sentences in the second level are comparable due to the similar theme of the relation between entity *Foust* and *NBA*. To find this type of sentences, we search the anchors in the English article and Chinese article of cross-lingual entity *Foust*, respectively, and extract the sentences including another crosslingual entity *NBA*. Comparable sentences can be regarded as cross-lingual contexts.

Unfortunately, comparable sentences suffer from two issues caused by distant supervision:

**Wrong labelling.** Take English as sample, there may be several sentences  $s_{k,l}^{en} |_{l=1}^L$  containing the same entity  $e_j^{en}$  in the article of  $e_i^{en}$ . A straightforward solution is to concatenate them into a longer sentence  $s_k^{en}$ , but this increases the chance to include unrelated sentences.

**Unbalanced information.** Sometimes the pair of sentences convey unbalanced information, e.g., the English sentence in the middle layer (Figure 1) contains *Foust spent 12 seasons in NBA* while the comparable Chinese sentence not.

To address the issues, we propose knowledge attention and cross-lingual attention to filter out unrelated information at sentence level, and at word level respectively.

## 5 Joint Representation Learning

As shown in Figure 2, there are three components in learning cross-lingual word and entity representations, which are trained jointly. In this section, we will describe them in detail.

### 5.1 Mono-lingual Representation Learning

Following Yamada et al. (2016); Cao et al. (2017), we learn mono-lingual word/entity embeddings based on corpus  $\mathcal{D}^y$ , anchors  $\mathcal{A}^y$  and entity network  $\mathcal{G}^y$ . Capturing the cooccurrence information among words and entities, these embeddings serve as the foundation and will be further extended to bilingual settings using the proposed cross-lingual regularizers, which will be detailed in the next section. Monolingually, we utilize a variant of Skip-gram model (Mikolov et al., 2013c) to predict the contexts given current word/entity:

$$\mathcal{L}_m = \sum_{y \in \{en, zh\}} \sum_{x_i^y \in \{\mathcal{D}^y, \mathcal{A}^y, \mathcal{G}^y\}} \log P(\mathcal{C}(x_i^y) | x_i^y)$$

where  $x_i^y$  is either a word or an entity, and  $\mathcal{C}(x_i^y)$  denotes: (i) contextual words in a pre-defined window of  $x_i^y$  if  $x_i^y \in \mathcal{D}^y$ , (ii) neighbor entities that linked to  $x_i^y$  if  $x_i^y \in \mathcal{G}^y$ , (iii) contextual words of  $w_j^y$  if  $x_i^y$  is entity  $e_i^y$  in an anchor  $\langle w_j^y, e_i^y \rangle \in \mathcal{A}^y$ .

### 5.2 Cross-lingual Entity Regularizer

The bilingual EN  $\mathcal{G}^{en-zh}$  merges entities in different languages into a unified network, resulting in the possibility of using the same objective as in mono-lingual ENs. Thus, we naturally extend mono-lingual function to cross-lingual settings:

$$\mathcal{L}_e = \sum_{e_i^y \in \{\mathcal{G}^{en-zh}\}} \log P(\mathcal{C}'(e_i^y) | e_i^y)$$

where  $\mathcal{C}'(e_i^y)$  denotes cross-lingual contexts—neighbor entities in different languages that linked to  $e_i^y$ . Thus, by jointly learning mono-lingual representation with cross-lingual entity regularizer, words and entities share more common contexts, and will have similar embeddings. As shown in Figure 1, English entity *NBA* co-occurs with words *basketball* and *player* in texts, so they are embedded closely in the semantic space. Meanwhile, cross-lingual linked entities *NBA* and *NBA (zh)* have similar representations due to the most common neighbor entities, e.g., *Foust*.

### 5.3 Cross-lingual Sentence Regularizer

Comparable sentences provide cross-lingual co-occurrence of words, thus, we can use them to learn similar embeddings for the words that frequently co-occur by minimizing the Euclidean distance as follows:

$$\mathcal{L}_s = \sum_{\langle s_k^{en}, s_{k'}^{zh} \rangle \in S^{en-zh}} \|s_k^{en} - s_{k'}^{zh}\|^2$$

where  $s_k^{en}, s_{k'}^{zh}$  are sentence embeddings. Take English as sample language, we define it as the average sum of word vectors weighted by the combination of two types of attentions:

$$s_k^{en} = \sum_{l=1}^L \psi(e_m^{en}, s_{k,l}^{en}) \sum_{w_i^{en} \in s_{k,l}^{en}} \psi'(w_i^{en}, w_j^{zh}) \mathbf{w}_i^{en}$$

where  $s_{k,l}^{en} |_{l=1}^L$  are sentences containing the same entity (as mentioned in Section 4.2), and  $\psi(e_m^{en}, s_{k,l}^{en})$  is knowledge attention that aims

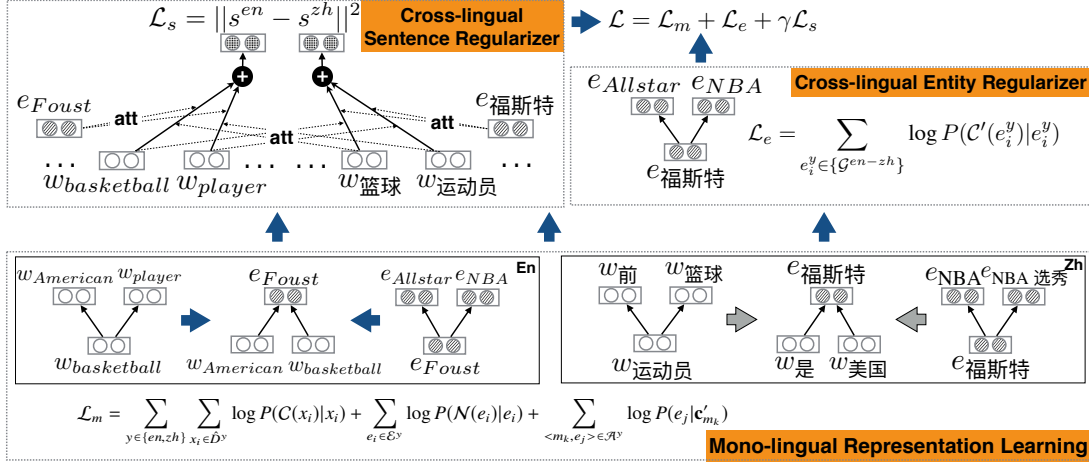


Figure 2: The neural model for jointly representation learning.

at filtering out wrong labelling sentences, and  $\psi'(w_i^{en}, w_j^{zh})$  is cross-lingual attention to deal with the unbalanced information through possible aligned words.

Next, we will introduce the two types of attentions in detail.

### Knowledge Attention

Suppose that sentences  $s_{k,l}^{en} |_{l=1}^L$  contain the same entities in articles of entity  $e_m^{en}$ , the wrong labelling errors increase, because some  $s_{k,l}^{en}$  is almost irrelevant to  $e_m^{en}$ . Knowledge attention assigns smaller weights to wrong labelled sentences, and higher weights to related sentences. Thus, we define it proportional to the similarity between  $s_{k,l}^{en}$  and  $e_m^{en}$ :

$$\psi(e_m^{en}, s_{k,l}^{en}) \propto \text{sim}(\mathbf{e}_m^{en}, \sum_{w_i^{en} \in s_{k,l}^{en}} \mathbf{w}_i^{en})$$

where  $\text{sim}$  is similarity measurement. We use cosine similarity in the presented work. Knowledge attention is normalized to satisfy  $\sum_l \psi(e_m^{en}, s_{k,l}^{en}) = 1$ .

### Cross-lingual Attention

Inspired by self-attention mechanism (Lin et al., 2017b), we motivate cross-lingual attention focusing on potential information from comparable sentences themselves. The intuition is to find possible aligned words between languages, and filter out the words without alignments. We define it according to the maximum similarity computed by our cross-lingual word embeddings:

$$\psi'(w_i^{en}, w_j^{zh}) \propto \max_{w_i^{en} \in s_k^{en}, w_j^{zh} \in s_{k'}^{zh}} \text{sim}(\mathbf{w}_i^{en}, \mathbf{w}_j^{zh})$$

We set a threshold for discarding non-aligned words if  $\psi'(w_i^{en}, w_j^{zh}) < \theta$ , and make a normalization for selected words. We set  $\theta = 0$  in experiments. Thus, unbalanced information is trimmed to the common meanings between  $s_k^{en}$  and  $s_{k'}^{zh}$ . For example (Figure 1), words *American*, *basketball*, *player* are selected due to their aligned Chinese words 美国, 篮球, 运动员, while *12 seasons* in  $s_k^{en}$  or *前* (*former*) in  $s_{k'}^{zh}$  are discarded due to low attentions.

The reason of using such regularizer lies in two points: (1) the embeddings of cross-lingual aligned words become closer within the pair of comparable sentences, and meanwhile (2) the distance between their contexts is also minimized, which keeps the same way as used in mono-lingual word embeddings training—the words sharing more contexts have similar embeddings. In this way, our regularizer follows a similar assumption with (Gouws et al., 2015): *The more frequently two words occur in parallel/comparable sentence pairs, the closer their representation will be.*

### 5.4 Training

All above components are jointly trained using the overall objective function as follows:

$$\mathcal{L} = \mathcal{L}_m + \mathcal{L}_e + \gamma \mathcal{L}_s$$

where  $\gamma$  is a hyper-parameter to tune the effect of cross-lingual sentence regularizer, and set to 1 in

experiments. We use Softmax as probability function, and negative sampling and SGD for efficient optimization (Mikolov et al., 2013a).

## 6 Experiments

In this section, we describe some qualitative analysis with nearest neighbors and quantitative experiments with the tasks of word translation, entity relatedness and cross-lingual entity linking to verify the quality of cross-lingual word embeddings, entity embeddings and the joint inference among them, respectively. The codes of our proposed model can be found in <https://github.com/TaoMiner/MultiLingualEmbedding>.

### 6.1 Experiment Settings

	Word		Entity	
	vocab (m)	token (b)	vocab (m)	token (b)
En	1.99	1.90	3.94	0.41
Zh	0.55	0.17	0.58	0.06
Es	0.70	0.48	0.70	0.04
Ja	0.46	0.45	0.88	0.08
It	0.67	0.40	1.09	0.12
Tr	0.33	0.05	0.22	0.01

Table 1: Multi-lingual KB Statistics.

We choose Wikipedia, the April 2017 dump, as multi-lingual KB and six popular languages for evaluation. The preprocessing consists of following steps: converting texts into lower cases, filtering out symbols and low frequency words and entities (less than 5), and tokenizing Chinese corpus using Jieba<sup>4</sup> and Japanese corpus using mecab<sup>5</sup>. The statistics is listed in Table 1. For brevity, we adopt two-letter abbreviations: ‘En’, ‘Zh’, ‘Es’, ‘Ja’, ‘It’ and ‘Tr’ for English, Chinese, Spanish, Japanese, Italian and Turkish, respectively. The token sub-column denotes the total number of word/entity in the entire training corpus, and we use ‘m’ to denote million and ‘b’ for billion.

For cross-lingual settings, we choose five language pairs to compare with state-of-the-art methods, whose statistics is listed in Table 2.

We trained our method using the suggested parameters in Skip-gram model (Mikolov et al., 2013c) and evaluate the embeddings shared by all tasks for fairly comparison. We set training epoch as 2 to ensure convergence, which costs nearly 20

<sup>4</sup><https://github.com/fxsjy/jieba>

<sup>5</sup><http://taku910.github.io/mecab/>

	Cross-lingual Links (m)	Comparable Sentences(m)	Bilingual EN	
			$\mathcal{E}(m)$	$\mathcal{R}(b)$
Es-En	0.82	4.66	4.64	0.58
Zh-En	0.51	2.02	4.52	0.57
Ja-Zh	0.26	1.04	1.46	0.19
It-En	0.74	3.83	5.03	0.68
Tr-En	0.15	0.75	4.16	0.44

Table 2: Cross-lingual Data Statistics.

hours on the server with 64 core CPU and 188GB memory. The embedding dimension is set to 200 and context window size is 5. For each positive example, we sample 5 negative examples.

### 6.2 Qualitative Analysis

Translation words (Chinese)	
篮球 (+)	篮球队 (basketball team), 湖人 (lakers), 男子篮球 (men’s basketball), 湖人队 (the lakers), 国王队 (the Kings), 美式足球 (American football), 中锋 (center)
Nearest entities (Chinese)	
NBA, 篮球 (Basketball)	控球后卫 (Point guard), NBA 选秀 (draft), 香港男子甲一组男子篮球联赛 (Hong Kong men’s top basketball league), 橄榄球 (American football), 东方篮球队 (Eastern basketball team)
Nearest words	
nba, wnba, player, twyman, professional, pick, 76ers	
Nearest entities	
Professional sports, Varsity letter, Sports agent, All-America, Final four, All-star, College basketball	

Table 3: Cross-lingual nearest words and entities of English word *basketball*.

We manually checked nearest neighbors to have a straightforward impression of the quality of our embeddings. The nearest neighbors of English word *basketball* is listed in Table 3.

As Table 3 shows, we find the correct translation ranked at top 1 (marked by +), and the listed words as well as English nearest words are all basketball related, indicating a higher quality of our cross-lingual word embeddings. Interestingly, we found that although all nearest entities are sports related, e.g., *NBA* or *Professional sports*, there is an obvious culture divergence between Chinese entities and English entities, such as *Hong Kong basketball league* v.s. *All-America*.

### 6.3 Word Translation

Following (Zhang et al., 2017b), we test our cross-lingual word embeddings on benchmark dataset including over 2,000 bilingual word pairs on average. The ground truth is obtained from Open

	Es-En		It-En		Ja-Zh		Tr-En		Zh-En	
	large	small	large	small	large	small	large	small	large	small
TM	-	48.61	-	37.95	-	26.67	-	11.15	4.79	21.79
IA	-	60.41	-	46.52	-	36.35	-	17.11	7.08	32.29
Bilbowa	53	65.96	-	-	-	-	-	-	-	-
BWESG	48.88	66.38	36.84	51.29	30.93	37.80	21.36	35.59	20.57	29.17
Adversarial	-	71.97	-	58.60	-	43.02	-	17.18	7.92	43.31
Ours-noatt	68.34	77.1	62.22	65.90	37.00	42.30	<b>57.47</b>	<b>60.51</b>	<b>35.90</b>	42.80
Ours	<b>70.41</b>	<b>78.50</b>	<b>63.07</b>	<b>67.85</b>	<b>41.30</b>	<b>46.70</b>	54.40	59.31	35.66	<b>44.67</b>

Table 4: Word Translation.

Multilingual WordNet<sup>6</sup> or Google translation. We compare all methods using the same vocabulary, and analyze the vocabulary size’s impact by setting a nearly 5k small scale and 50k large scale.

We choose several state-of-the-art methods as baseline, using different level of parallel data: (1) TM (Mikolov et al., 2013b), IA (Zhang et al., 2016) are pioneers and popular transformation based methods using **bilingual lexicon**. (2) Bilbowa (Gouws et al., 2015) is typical work using **parallel sentences** and performs quite well. (3) BWESG (Vulic and Moens, 2016) is similar to our method and achieves best performance in the literature of using **comparable data**. (4) Adversarial model (Zhang et al., 2017b) is the state-of-the-arts **without parallel data**. Besides, we remove attention from our method to investigate the impacts from attention mechanisms, marked with *Ours-noatt*.

For fair comparison, we report the results in original paper (Zhang et al., 2017b) except Bilbowa and BWESG, which didn’t report their results on the same benchmark datasets. So, we carefully implement them using released codes on the same training corpus as ours with suggested parameters. Nevertheless, we do not have performance reports of Zh-En, It-En, Tr-En and Ja-Zh with Bilbowa due to the lack of parallel data used in the original paper. As shown in Table 4, we can see:

- Our proposed method significantly outperforms all the baseline methods with average gains of 21% and 9.1% on large and small vocabulary. This proves the high quality of our generated cross-lingual data and the effectiveness of our joint framework.
- The pair of languages have similar culture achieves better performance (Es-En, It-En, Tr-En, Ja-Zh) than that have different cultural origins, e.g., Zh-En.

- Languages with richer corpus have better translations because adequate training data helps to capture more accurate cross-lingual semantics (Es-En, It-En, Tr-En v.s. Ja-Zh).
- Our method has less performance reduction between small and large vocabulary than methods based on parallel word pairs, because we adopt a consistent objective function which aligns cross-lingual semantics, and simultaneously keeps their own monolingual semantics.
- Attention mechanisms further improve the performance, mainly because they help to select the most informative words and sentences, filtering out unrelated data.

#### 6.4 Entity Relatedness

With respect to our entity embeddings, we have conducted experiments to evaluate English entity relatedness following (Ganea and Hofmann, 2017; Hoffart et al., 2011), in which the dataset contains 3,314 entities, and each entity has 91 candidate entities labeled with 1 or 0, indicating whether they are semantically related. Given an entity, we rank candidate entities according to their similarity based on our embeddings, and evaluate the ranking quality through two standard metrics: normalized discounted cumulative gain (NDCG) (Järvelin and Kekäläinen, 2002) and mean average precision (MAP) (Manning et al., 2008).

To give a comprehensive fair comparison, we choose several widely used and state-of-the-art methods as our baselines, and compare with the results in the original papers: (1) WLM (Milne and Witten, 2008), the popular semantic similarity measurement based on Wikipedia anchor links. (2) ALIGN (Yamada et al., 2016) and MPME (Cao et al., 2017), state-of-the-arts that jointly learn word and entity embeddings using mono-lingual EN. (3) Deep Joint (DJ) model (Ganea and Hofmann, 2017), deep neural model that achieves the

<sup>6</sup><http://compling.hss.ntu.edu.sg/omw>



best performance of entity relatedness.

	NDCG			MAP
	@1	@5	@10	
WLM	.54	.52	.55	.48
ALIGN (d=500)	.59	.56	.59	.52
MPME	.61	.61	.65	.58
DJ (d=300)	.63	.61	.64	.58
Ours (Zh-En)	.62	.62	.66	.59
Ours (Es-En)	.61	.61	.65	.59
Ours (Tr-En)	.62	.62	.65	.59
Ours (It-En)	.61	.61	.65	.58
Ours-e (Es-En)	.62	.62	.67	.61
Ours-e (Es-En,epoch=5)	<b>.64</b>	<b>.64</b>	<b>.68</b>	<b>.62</b>

Table 5: Entity Relatedness.

Table 5 shows the results of baseline methods as well as our methods based on different languages. We also test the cases of our method without training cross-lingual words, marked as Ours-e. We can see our method outperforms all baseline methods by introducing cross-lingual information, and all bilingual ENs lead to similar results. Strangely, ALIGN and DJ with more embedding dimensions seemly fails to capture overall relatedness (performance reduction from top@1 to top@5). The best performance of Ours-e implies that training cross-lingual word slightly harms the performance of entity embeddings. We can introduce additional sense embeddings in future (Cao et al., 2017).

Although favorable improvements has been achieved by using our English entity embeddings, it shall be fewer than that of other languages, because resources of English are already quite rich, and even richer than many other languages, thus contributions from other languages will be less significant than vice versa. Due to the limitation of the publication, we neglect to report experiment results on the vice versa direction.

### 6.5 Cross-lingual Entity Linking

Entity linking, the task of identifying the language-specific reference entity for mentions in texts, raises the key challenges of comparing the relevance between entities and contextual words around the mentions (Cao et al., 2015; Nguyen et al., 2016). Recently, the surge of cross-lingual analysis pushes the entity linking task on cross-lingual settings (Ji et al., 2015). Therefore, we comprehensively measure our joint inference ability among words and entities using the tri-lingual EL benchmark dataset KBP2015, which consists of 944 documents and 38,831 mentions, and divides them into 444 and 500 documents for training and evaluation. Note that the main purpose of

it is not to beat other EL models but to evaluate the quality of our embeddings, so we adopt a simple classifier GBRT (Gradient Boost Regression Tree) based method as in (Cao et al., 2017; Yamada et al., 2016), replace with our cross-lingual embeddings, and filter out mentions that are out of our vocabulary.

	English	Spanish	Chinese
Top system	73.7	80.4	83.1
Second system	66.2	71.5	78.1
Ours	73.9	79.1	81.3

Table 6: Tri-lingual Entity Linking.

Table 6 shows the top 1 linking accuracy (%). We can see our method performs much better than the second ranked system, and is competitive with the top ranked system. Considering that the systems utilize additional translation tools (Ji et al., 2015), we conclude that our embeddings are high qualified for joint inference among entities and words in different languages.

## 7 Conclusions

In this paper, we propose a novel method to jointly learn cross-lingual word and entity representations that enables effective inference among cross-lingual knowledge bases and texts. Instead of parallel data, we use distant supervision over multi-lingual KB to generate high quality comparable data as cross-lingual supervision signals for two types of regularizer. We introduce attention mechanism to further improve the training quality. A series of experiments on several tasks verify the effectiveness of our methods as well as the quality of cross-lingual word and entity embeddings.

In the future, we will enrich semantics of low-resourced languages by cross-lingual linking to rich-resourced languages, and extend more cross-lingual words and entities to multi-lingual settings.

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