Learning to Represent Bilingual Dictionaries

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Abstract

Bilingual word embeddings have been widely used to capture the correspondence of lexical semantics in different human languages. However, the cross-lingual correspondence between sentences and lexicons is less studied, despite that this correspondence can largely benefit many applications, such as cross-lingual semantic search and question answering. To bridge this gap, we propose a neural embedding model that leverages bilingual dictionaries. The proposed model is trained to map the literal word definitions to the cross-lingual target words, for which we explore with different sentence encoding techniques. To enhance the learning process on limited resources, our model adopts several critical learning strategies, including multi-task learning on different bridges of languages, and joint learning of the dictionary model with a bilingual word embedding model. We conduct experiments on two tasks: (i) cross-lingual reverse dictionary retrieval, and (ii) bilingual paraphrase identification. In the former task, we demonstrate that our model is capable of comprehending bilingual concepts based on descriptions, and we also highlight the effectiveness of proposed learning strategies. In the latter one, we show that the proposed model effectively associates sentences in different languages via a shared embedding space, and outperforms existing approaches in identifying bilingual paraphrases.

1 Introduction

Bilingual word embedding models are used to capture the cross-lingual semantic relatedness of words based on their co-occurrence in parallel or seed-lexicon corpora (Chandar et al. 2014; Gouws et al. 2015; Luong, Pham, and Manning 2015). By collocating related words in the low-dimensional embedding spaces, these models effectively support the representations of lexical semantics with precise cross-lingual semantic transfer (Gouws et al. 2015). Therefore, they have been widely used in many cross-lingual NLP tasks including machine translation (Devlin et al. 2014), bilingual document classification (Zhou, Wan, and Xiao 2016), knowledge alignment (Chen et al. 2018b) and named entity recognition (Feng et al. 2018).

While many approaches have been proposed to capture cross-lingual lexical similarity, modeling the correspondence between lexical and sentential semantics across different languages still represents an unresolved challenge. We argue that modeling such cross-lingual and multi-granular correspondence is significant and natural for the following reasons. First, it is highly beneficial to many application scenarios, including cross-lingual semantic search of concepts (Tsai and Roth 2016), agents for detecting discourse relations in bilingual dialogue utterances (Jiang et al. 2018), and multilingual text summarization (Nenkova and McKown 2012), as well as educational applications for foreign language learners. Second, it is natural for a human to learn the meaning of a foreign word by looking up its meaning in the native language. Therefore, learning such correspondence mimics human learning behaviors. Finally, learning word-to-word correspondence can be problematic, since there are some words do not have direct translation in another language. For example, *schadenfreude* in German, which means *a feeling of joy that comes from knowing the troubles of other people*, has no proper English counterpart word. To appropriately learn the representations of such words in bilingual embeddings, we need to capture their meanings based on the definitions as well. However, realizing such a model is a non-trivial task, inasmuch as it requires a comprehensive learning process to effectively compose the semantics of arbitrary-length sentences in one language, and associate that with single words in another language. Consequently, this objective also demands high-quality cross-lingual alignment that bridges between single and sequences of words. Such alignment information is generally not available in the parallel and seed-lexicon corpora that are utilized by bilingual word embedding models (Gouws et al. 2015; Lample et al. 2018).

To incorporate the representations of bilingual lexical and sentential semantics, we propose an approach by leveraging bilingual dictionaries. The proposed approach BilDRL (Bilingual Dictionary Representation Learning) seeks to capture the mapping from word definitions to the corresponding words in another language. BilDRL first constructs a word embedding space with a pre-trained bilingual word embedding model. By utilizing cross-lingual word definitions, a sentence encoder is trained to realize the mapping from literal descriptions to target words in the bilingual word embedding space, for which we investigate with multiple types of encoding techniques. To enhance the cross-lingual learning process on limited resources, BilDRL conducts multi-task learning on different directions of language pairs. Moreover, we enforce a joint learning strategy of bilingual
word embeddings and the sentence encoder, which seeks to gradually adjust the embedding space to better suit the representation of cross-lingual word definitions.

To show the applicability of BilDRL, we conduct experimental evaluation on two useful cross-lingual tasks (see Fig. 1). (i) Cross-lingual reverse dictionary retrieval seeks to retrieve words or concepts given descriptions in another language. This task is useful to help users find foreign words based on the notions or descriptions. This is especially beneficial to users such as translators, foreigner language learners and technical writers using non-native languages. We show that BilDRL achieves promising results on this task, while bilingual multi-task learning and joint learning dramatically enhance the performance. (ii) Bilingual paraphrase identification asks whether two sentences in different languages essentially express the same meaning, which is critical to question answering or dialogue systems that apprehend multi-lingual utterances (Bannard and Callison-Burch 2005). This task is challenging, as it requires a model to comprehend cross-lingual paraphrases that are inconsistent in grammar, content details and word orders. BilDRL maps sentences to the lexicon embedding space. This process reduces the problem to evaluate the similarity of lexicon embeddings, which can be easily solved by a simple classifier (Vyas and Carpuat 2016). BilDRL performs well with even a small amount of data, and significantly outperforms previous approaches.

2 Related Work

In this section, we discuss two lines of relevant work.

Bilingual word embeddings. Recently, various approaches have been proposed for training bilingual word embeddings. These approaches span in two families of models: off-line mappings and joint training.

The off-line mapping-based approach fixes the structures of pre-trained monolingual word embeddings, and induces bilingual projections based on seed-lexicon alignment (Mikolov et al. 2013a). Some variants of this approach improve the quality of bilingual projections by adding constraints such as orthogonality of transforms, normalization and mean centering of embeddings (Xing et al. 2015; Artetxe et al. 2016). Others adopt canonical correlation analysis to map separated monolingual embeddings to a shared embedding space (Faruqui and Dyer 2014; Lu et al. 2015).

Unlike off-line mappings, joint training models simultaneously learn word embeddings and cross-lingual alignment. By jointly updating the embeddings with the alignment information, such approaches generally capture more precise cross-lingual semantic transfer (Upadhyay et al. 2016). While few of such models still maintain separated embedding spaces for each language (Huang et al. 2015), the majority of recent ones obtain a unified embedding space for both languages. The cross-lingual semantic transfer by these models is captured from parallel corpora with sentential or document-level alignment, using techniques such as bilingual bag-of-words distances (BiBOWA) (Gouws et al. 2015), bilingual Skip-Gram (Coulmance et al. 2015) and sparse tensor factorization (Vyas and Carpuat 2016).

Neural sentence modeling. Neural sentence models seek to characterize the phrasal or sentential semantics from word sequences. They often adopt encoding techniques such as recurrent neural encoders (RNN) (Kiros et al. 2015), convolutional neural encoders (CNN) (Chen et al. 2018a), and attentive neural encoders (Rocktäschel et al. 2016) to represent the composed semantics of a sentence as an embedding vector. Many recent works have focused on comprehending pairwise correspondence of sentential semantics by adopting multiple neural sentence models in one learning architecture. Examples of such include Siamese sentence pair models for detecting discourse relations of paraphrases or text entailment (Sha et al. 2016; Rocktäschel et al. 2016; Chen et al. 2018a), and sequence-to-sequence models for tasks like style transfer (Shen et al. 2017) and abstractive summarization (Chopra, Auli, and Rush 2016). Specifically, our work is related to corresponding works of neural machine translation (NMT) (Bahdanau, Cho, and Bengio 2015; Wu et al. 2016), while our setting has major differences from NMT in the following two perspectives: (i) NMT has to bridge between corpora of the same granularity, unlike BilDRL that captures the multi-granular correspondence of semantics across different modalities (ii) NMT relies on training an encoder-decoder architecture, while BilDRL employs joint learning of two representation models, i.e. a dictionary-based sentence encoder and a word embedding model.

On the other hand, fewer efforts have been put to characterizing the associations between sentential and lexical semantics. Hill et al. (2016) and Xie et al. (2016) learn off-line mappings between monolingual descriptions and lexicons to capture such associations. Eisner et al. (2016) adopt a similar approach to capture emojis based on descriptions. At the best of our knowledge, there has been no previous approach that learn to discover the correspondence of sentential and lexical semantics in a multilingual scenario. This is exactly the focus of our work, in which the proposed strategies of multi-task and joint learning are critical to the corresponding cross-lingual learning process under limited resources. Utilizing the cross-lingual and multi-granular correspondence of semantics, our approach also sheds light on addressing discourse relation detection in a multilingual scenario.

3 Modeling Bilingual Dictionaries

We hereby begin our modeling with the formalization of bilingual dictionaries. We use $\mathcal{L}$ to denote the set of lan-
guages. For a language \( l \in \mathcal{L} \), \( V_l \) denotes its vocabulary, where for each word \( w \in V_l \), we use bold-faced \( \mathbf{w} \in \mathbb{R}^k \) to denote its embedding vector. A \( l_i, l_j \) bilingual dictionary \( D(l_i, l_j) \) (or simply \( D_{ij} \)) contains dictionary entries \((\mathbf{w}^i, S^j_w) \in D_{ij} \), in which \( \mathbf{w}^i \in V_{l_i} \), and \( S^j_w = \mathbf{w}^j_1 \ldots \mathbf{w}^j_n \) \((\mathbf{w}^j \in V_{l_j})\) is a cross-lingual word definition that describes the word \( \mathbf{w}^i \) with a sequence of words in language \( l_j \). For example, a French-English dictionary \( D(\text{French}, \text{English}) \) provides English definitions for French words, where a \( \mathbf{w}^i \) could be \textit{appétite}, and corresponding \( S^j_w \) could be \textit{desire for, or relish of food or drink}. Note that, for a word \( \mathbf{w}^i \), multiple definitions in \( l_j \) may coexist.

BilDRL is constructed and improved through three stages. A sentence encoder is first used to learn from a bilingual dictionary the association between words and definitions. Then in a pre-trained bilingual word embedding space, multi-task learning is conducted on both directions of a language pair. Lastly, joint learning with word embeddings is enforced to simultaneously adjust the embedding space during the training of the dictionary model, which further enhances the cross-lingual learning process. The overall learning architecture is depicted in Fig. 2.

### 3.1 Encoders for Bilingual Dictionaries

BilDRL models a dictionary using a neural sentence encoder \( E(S) \), which composes the meaning of the sentence into a latent vector representation. We hereby introduce this model component, which is designed to be a GRU encoder with self-attention, in the following subsection. Besides that, we also investigate other widely-used neural sentence modeling techniques.

**Attentive GRU Encoder** The GRU encoder is an alternative of the long-short-term memory network (LSTM) (Cho et al. 2014), which consecutively characterizes sequence information without using separated memory cells. Each unit consists of two types of gates to track the state of the sequence, i.e. the reset gate \( r_t \) and the update gate \( z_t \). Given the vector representation \( \mathbf{w}_t \) of an incoming item \( w_t \), GRU updates the hidden state \( \mathbf{h}^{(1)}_t \) of the sequence as a linear combination of the previous state \( \mathbf{h}_t^{(1)} \) and the candidate state \( \tilde{\mathbf{h}}^{(1)}_t \) of new item \( w_t \), which is calculated as below.

The update gate \( z_t \) balances between the information of the previous sequence and the new item, where \( \mathbf{M}_z \) and \( \mathbf{N}_z \) are two weight matrices, \( \mathbf{b}_z \) is a bias vector, and \( \sigma \) is the sigmoid function.

\[
z_t = \sigma (\mathbf{M}_z \mathbf{w}_t + \mathbf{N}_z \tilde{\mathbf{h}}^{(1)}_{t-1} + \mathbf{b}_z)
\]

The candidate state \( \tilde{\mathbf{h}}^{(1)}_t \) is calculated similarly to those in a traditional recurrent unit as below.

\[
\tilde{\mathbf{h}}^{(1)}_t = \tanh (\mathbf{M}_z \mathbf{w}_t + \mathbf{N}_z \mathbf{h}^{(1)}_{t-1} + \mathbf{b}_z)
\]

The reset gate \( r_t \) thereof controls how much information of the past sequence should contribute to the candidate state:

\[
r_t = \sigma (\mathbf{M}_r \mathbf{w}_t + \mathbf{N}_r \mathbf{h}^{(1)}_{t-1} + \mathbf{b}_r)
\]

The above defines a GRU layer which outputs a sequence of hidden state vectors given the input sequence \( S \). While a GRU encoder can consist of a stack of multiple GRU layers, without an attention mechanism, the last hidden state \( \mathbf{h}^{(1)}_S \) of the last layer is extracted to represent the overall meaning of the encoded sentence. Note that in comparison to GRU, the traditional LSTM generally performs comparably, but is more complex and require more computational resources for training (Chung et al. 2014).

**Self-attention.** The self-attention mechanism (Conneau et al. 2017) seeks to highlight the important units in an input sentence when capturing its overall meaning. One layer of self-attention is calculated as below.

\[
\mathbf{u}_t = \tanh (\mathbf{M}_u \mathbf{h}^{(1)}_t + \mathbf{b}_u)
\]

\[
\alpha_t = \frac{\exp (\mathbf{u}_t^\top \mathbf{u}_s)}{\sum_{w \in S} \exp (\mathbf{u}_w^\top \mathbf{u}_s)}
\]

\[
\mathbf{h}^{(2)}_t = |S| \alpha_t \mathbf{u}_t
\]
\( \mathbf{u}_t \) thereof is the intermediary latent representation of GRU output \( \mathbf{h}_t^{(1)} \), \( \mathbf{u}_S = \tanh(\mathbf{M}_a \mathbf{h}_S^{(1)} + \mathbf{b}_a) \) is the intermediary latent representation of the last GRU output \( \mathbf{h}_S^{(1)} \) that can be seen as a high-level representation of the entire input sequence. By measuring the similarity of each \( \mathbf{u}_t \) with \( \mathbf{u}_S \), the normalized attention weight \( a_t \) for \( \mathbf{h}_t^{(1)} \) is produced through a softmax function, which highlights an input that contributes more significantly to the overall meaning. Note that a scalar \(|S|\) (the length of the input sequence) is multiplied along with \( a_t \) to \( \mathbf{u}_t \) to obtain the weighted representation \( \mathbf{h}_t^{(2)} \), so as to keep \( \mathbf{h}_t^{(2)} \) from losing the original scale of \( \mathbf{h}_t^{(1)} \). A latent representation of the sentence is calculated as the average of the last attention layer \( E^{(1)}(S) = \frac{1}{|S|} \sum_{t=1}^{|S|} a_t \mathbf{h}_t^{(2)} \).

**Other Encoders** We also experiment with other widely used neural sentence modeling techniques, which are however outperformed by the attentive GRU encoder in our tasks. These techniques include the vanilla GRU, CNN (Kalchbrenner et al. 2014), and linear bag-of-words (BOW) (Hill et al. 2016). We briefly introduce the last two techniques in the following.

**Convolutional Encoder**. A convolutional encoder applies a kernel \( \mathbf{M}_c \in \mathbb{R}^{h \times k} \) to generate the latent representation \( \mathbf{h}_t^{(3)} \) from each \( h \)-gram of the input vector sequence \( \mathbf{w}_{t:t+h-1} \) by

\[
\mathbf{h}_t^{(3)} = \tanh(\mathbf{M}_c \mathbf{w}_{t:t+h-1} + \mathbf{b}_c)
\]

for which \( h \) is the kernel size and \( \mathbf{b}_c \) is a bias vector. A convolution layer applies the kernel to all \( h \)-grams to produce a sequence of latent vectors \( \mathbf{H}^{(3)} = [\mathbf{h}_1^{(3)}, \mathbf{h}_2^{(3)}, \ldots, \mathbf{h}_{|S|-h+1}^{(3)}] \), where each latent vector leverages the significant local semantic features from each \( h \)-gram. Following the convention (Yin and Schütze 2015; Liu et al. 2017), dynamic max-pooling is applied to extract the robust features from the convolution outputs, and the mean-pooling results of the last layer are used as the latent representation of the sentential semantics. Although CNN leverages well local semantic features from the input sequence, this technique does not preserve the sequential information that is critical to the representation of short sentences.

**Linear bag-of-words**. Following the definition in previous works (Xie et al. 2016; Hill et al. 2016), the much simpler BOW encoder is realized by the sum of projected word embeddings of the input sentence, i.e. \( E^{(3)}(S) = \sum_{t=1}^{|S|} \mathbf{M}_b \mathbf{w}_t \).

### 3.2 Basic Learning Objective

The objective of learning the dictionary model is to map the encodings of cross-lingual word definitions to the target word embeddings. This is realized by minimizing the following \( L_2 \) loss,

\[
L_{ij}^{ST} = \frac{1}{|D_{ij}|} \sum_{(\mathbf{w}_i, \mathbf{S}_w) \in D_{ij}} \| E_{ij}(\mathbf{S}_w^j) - \mathbf{w}_i \|_2^2
\]

in which \( E_{ij} \) is the dictionary model that maps from descriptions in \( l_i \) to words in \( l_j \).

The above defines the basic model variants of BilDRL that learns on a single dictionary. For word representations in the learning process, BilDRL initializes the embedding space using pre-trained word embeddings. Note that, without adopting the joint learning strategy in Section 3.4, the learning process does not update word embeddings that are used to represent the definitions and target words. While other forms of loss such as cosine proximity (Hill et al. 2016) and hinge loss (Xie et al. 2016) may also be used in the learning process, we find that \( L_2 \) loss consistently leads to better performance in our experiments.

### 3.3 Bilingual Multi-task Learning

In cases where entries in a bilingual dictionary are not amply provided, learning the above bilingual dictionary on one ordered language pair may fall short in insufficiency of alignment information. One practical solution is to conduct a bilingual multi-task learning process. In detail, given a language pair \( (l_i, l_j) \), we learn the dictionary model \( E_{ij} \) on both dictionaries \( D_{ij} \) and \( D_{ji} \) with shared parameters. Correspondingly, we rewrite the previous learning objective function as below, in which \( D = D_{ij} \cup D_{ji} \).

\[
L_{ij}^{MT} = \frac{1}{|D|} \sum_{(\mathbf{w}_i, \mathbf{S}_w) \in D} \| E_{ij}(\mathbf{S}_w) - \mathbf{w} \|_2^2
\]

This strategy non-trivially requests the same dictionary model to represent semantic transfer between two directions of the language pair. To fulfill such a request, we initialize the embedding space using the bilingual BiBOWA embeddings trained on parallel corpora, which provides a unified bilingual embedding space that resolves both monolingual and cross-lingual semantic relatedness of words.

In practice, we find that this simple multi-task strategy brings significant improvement to our cross-lingual tasks. In additional to BiBOWA, other jointly trained bilingual word embeddings may also be used to support this strategy (Coulmance et al. 2015; Vyas and Carpuat 2016), for which we leave the comparison to future work.

### 3.4 Joint Learning

While above learning strategies of BilDRL are based on a fixed embedding space, we lastly propose a joint learning strategy. During the training process, this strategy simultaneously updates the embedding space based on both the dictionary model and the bilingual word embedding model. The learning is through asynchronous minimization of the following joint objective function,

\[
J = L_{ij}^{MT} + \lambda_1 (L_{i}^{SG} + L_{j}^{SG}) + \lambda_2 \Omega_{ij}^{A}
\]

where \( \lambda_1 \) and \( \lambda_2 \) are two positive coefficients. \( L_{i}^{SG} \) and \( L_{j}^{SG} \) are the original Skip-Gram losses (Mikolov et al. 2013b) employed by BiBOWA to separately obtain word embeddings on monolingual corpora of languages \( l_i \) and \( l_j \). \( \Omega_{ij}^{A} \) is the alignment loss that minimizes the bag-of-words distances for aligned sentence pairs \( (\mathbf{S}_i, \mathbf{S}_j) \) from the bilingual parallel corpora \( C_{ij} \), which is termed as below.
$$d_S(S^i, S^j) = \left\| \frac{1}{|S^i|} \sum_{w^i_m \in S^i} w^i_m - \frac{1}{|S^j|} \sum_{w^j_n \in S^j} w^j_n \right\|^2$$

$$\Omega^A_{ij} = \frac{1}{|C_{ij}|} \sum_{(S^i, S^j) \in C_{ij}} d_S(S^i, S^j)$$

The joint learning process adapts the embedding space to better suit the dictionary model, which is shown to further enhance the cross-lingual learning of BilDRL.

3.5 Training

To initialize the embedding space, we pre-trained BilBOWA on the parallel corpora Europarl v7 (Koehn 2005) and monolingual corpora of tokenized Wikipedia dump (Al-Rfou, Perozzi, and Skiena 2013). For models without joint learning, we use AMSGrad (Reddi, Kale, and Kumar 2018) to optimize the parameters. Each model without bilingual multi-task learning thereof, is trained on batched samples from each individual dictionary. Multi-task learning models are trained on batched samples from two dictionaries. Within each batch, entries of different directions of languages can be mixed together. For joint learning, we follow previous works (Gouws et al. 2015; Mogadala and Rettinger 2016) to conduct an efficient multi-threaded asynchronous training (Mnih et al. 2016) of AMSGrad. In detail, after initializing the embedding space based on pre-trained BilBOWA, parameter updating based on the four components of $J$ occurs across four worker threads. Two monolingual threads select batches of monolingual contexts from the Wikipedia dump of two languages for Skip-Gram, one alignment thread randomly samples parallel sentences from Europarl v7, and one dictionary thread extracts batched samples of entries for a bilingual multi-task dictionary model. Each thread makes a batched update to model parameters asynchronously for each component of $J$. The asynchronous training of all threads goes until the dictionary thread finishes its epochs.

4 Experiments

In this section, we present the experiments on two cross-lingual tasks: the cross-lingual reverse dictionary retrieval task and the bilingual paraphrase identification task.

Datasets. The experiment of cross-lingual reverse dictionary retrieval is conducted on a trilingual dataset Wikt3l. This dataset is extracted from Wiktionary\(^1\), which is one of the largest freely available multilingual dictionary resources on the Web. Wikt3l contains dictionary entries of language pairs (English, French) and (English, Spanish), which form En-Fr, Fr-En, En-Es and Es-En dictionaries on four bridges of languages in total. Two types of bilingual dictionary entries are extracted from Wiktionary: (i) cross-lingual definitions provided under the Translations sections of Wiktionary pages; (ii) monolingual definitions for words that are linked to a cross-lingual counterpart with a inter-language link\(^2\) of Wiktionary. We exclude all the definitions of stop words in constructing the dataset, and list the statistics in Table 1.

Since existing datasets for paraphrase identification are merely monolingual, we contribute with another dataset WBP3l for cross-lingual sentential paraphrase identification. This dataset contains 6,000 pairs of bilingual sentence pairs respectively for En-Fr and En-Es settings. Within each bilingual setting, 3,000 positive cases are formed as pairs of descriptions aligned by inter-language links, which exclude the word descriptions in Wikt3l for training BilDRL. To generate negative examples, given a source word, we first find its 15 nearest neighbors in the embedding space. Then we randomly pick one word from these neighbors and pair its cross-lingual definition with the English definition of the source word to create a negative case. This process ensures that each negative case is endowed with limited dissimilarity of sentence meanings, which makes the decision more challenging. For each language setting, we randomly select 70% for training, 5% for validation, and the rest 25% for testing. Note that each language setting of this dataset thereof, matches with the quantity and partitioning of sentence pairs in the widely-used Microsoft Research Paraphrase Corpus benchmark for monolingual paraphrase identification (Hu et al. 2014; Yin et al. 2016; Das and Smith 2009). Several examples from the dataset are shown in Table 2. The datasets and the processing scripts at URL_REMOVED_FOR_REVIEW.

4.1 Cross-lingual Reverse Dictionary Retrieval

The objective of this task is to enable cross-lingual semantic retrieval of words based on descriptions. Besides comparing variants of BilDRL that adopt different sentence encoders and learning strategies, we also compare with the monolingual-

\(^1\)https://www.wiktionary.org/

\(^2\)An inter-language link matches the entries of counterpart words between language versions of Wiktionary. https://en.wikisource.org/wiki/Help:Interlanguage_links
The bilingual paraphrase identification problem is a binary classification task with the goal to decide whether two sentences in different languages express the same meanings. BiDRL provides an effective solution by transferring sentimental meanings to lexicon-level representations and learning a simple classifier. We evaluate three variants of BiDRL on this task using WBP3l: the multi-task BiDRL with GRU encoders (BiDRL-GRU-MTL), the multi-task BiDRL with attentive GRU encoders (BiDRL-ATT-MTL),
and the joint learning BilDRL with with attentive GRU encoders (BilDRL-ATT-joint). We compare against several baselines of neural sentence pair models that are proposed to tackle monolingual paraphrase identification. These models include Siamese structures of CNN (BiCNN) (Yin and Schütze 2015), RNN (BiGRU) (Mueller and Thyagarajan 2016), attentive CNN (ABCNN) (Yin et al. 2016), attentive GRU (BiATT) (Rocktäschel et al. 2016), and linear bag-of-words (BiBOW). To support the reasoning of cross-lingual sentential semantics, we provide these baselines with the same BiBOWA embeddings.

**Evaluation protocol.** BilDRL transfers each sentence into a vector in the word embedding space. Then, for each sentence pair in the train set, a Multi-layer Perceptron (MLP) with a binary softmax loss is trained on the subtraction of two vectors as a downstream classifier. Baseline models are trained end-to-end, each of which directly uses a parallel pair of encoders with shared parameters. Then an MLP is stacked to the subtraction of two sentence vectors. Note that some works use concatenation (Yin and Schütze 2015) or Manhattan distance (Mueller and Thyagarajan 2016) of sentence vectors instead of their subtraction (Jiang et al. 2018), which we find to be less effective on small amount of data.

We apply the configurations of the sentence encoders from the last experiment to corresponding baselines, so as to show the performance under controlled variables. Training of each classifier is terminated by early-stopping based on the validation set, so as to prevent overfitting. Following the convention (Hu et al. 2014; Yin et al. 2016), we evaluate based on the accuracy and F1 scores.

**Results.** This task is challenging due to the heterogeneity of cross-lingual paraphrases and limitedness of learning resources. The results in Table 4 show that among all the baselines, while BiATT consistently outperforms the others, it merely reaches slightly over 60% of accuracy on both En-Fr and En-Es settings. We believe that this situation comes down to the fact that sentences of different languages are often drastically heterogenous in both lexical semantics and the sentence grammar that governs the composition of lexicons. Hence, it is not surprising that previous neural sentence pair models, which capture the semantic relation of bilingual sentences directly from all participating lexicons, fall short at the multilingual task. BilDRL, however, effectively leverages the correspondence of lexical and sentential semantics to simplify the task to an easier entailment task in the lexicon space, for which the multi-task learning of cross-lingual BiDRL-ATT-MTL outperforms the best baseline respectively by 3.80% and 4.80% of accuracy in both language settings, as well as much higher F1. The BilDRL-ATT-joint that employs the joint learning architecture further improves the task by another satisfying 3.26% and 1.06% of accuracy, and notable increment in F1.

### Table 4: Accuracy and F1-scores of bilingual paraphrase identification

| Languages | Acc & Fr | Acc & En-Es |
|-----------|----------|-------------|
| **Metrics** | **Acc** | **F1** | **Acc** | **F1** |
| BiBOW | 54.93 | 0.622 | 56.27 | 0.623 |
| BiCNN | 54.33 | 0.624 | 53.80 | 0.611 |
| ABCNN | 56.73 | 0.626 | 58.83 | 0.655 |
| BiGRU | 60.81 | 0.697 | 60.53 | 0.692 |
| BiATT | 61.47 | 0.699 | 61.27 | 0.689 |
| BilDRL-GRU-MTL | 64.80 | 0.732 | 63.33 | 0.722 |
| BilDRL-ATT-MTL | 65.27 | 0.735 | 66.07 | 0.735 |
| BilDRL-ATT-joint | **68.53** | **0.785** | **67.13** | **0.759** |

In this paper, we propose a neural embedding model BilDRL that captures the correspondence of cross-lingual lexical and sentential semantics by learning to represent bilingual dictionaries. We experiment with multiple forms of neural models to capture the cross-lingual word definitions, from which the best representation techniques are identified. The two learning strategies, i.e., bilingual multi-task learning and joint learning are effective at enhancing the cross-lingual learning process with limited resources. Our model has achieved promising performance on cross-lingual reverse dictionary retrieval as well as cross-lingual paraphrase identification tasks by utilizing the captured correspondence of lexical and sentential semantics.

An important direction of future work lies in bilingual word embeddings. Existing models either use seed-lexicons or sentence alignments to capture cross-lingual semantic transfer, we are interested in exploring whether that phase of learning word embeddings can be improved by incorporating the lexicon-sentence alignment used in this work. Applying BilDRL to multilingual question answering and semantic search systems is another important direction.

### References

Al-Rfou, R.; Perozzi, B.; and Skiena, S. 2013. Plyglot: Distributed word representations for multilingual nlp. In *CoNLL*.

Artetxe, M.; Labaka, G.; Agirre, E.; et al. 2016. Learning principled bilingual mappings of word embeddings while preserving monolingual invariance. In *EMNLP*.

Bahdanau, D.; Cho, K.; and Bengio, Y. 2015. Neural machine translation by jointly learning to align and translate. In *ICLR*.

Bannard, C., and Callison-Burch, C. 2005. Paraphrasing with bilingual parallel corpora. In *ACL*.

Chandar, S.; Lauly, S.; Larochelle, H.; et al. 2014. An autencoder approach to learning bilingual word representations. In *NIPS*.

Chen, M.; Meng, C. P.; Huang, G.; and Zaniolo, C. 2018a. Neural article pair modeling for wikipedia sub-article machine. In *ECML-PKDD*.

Chen, M.; Tian, Y.; Chang, K.-W.; Skiena, S.; et al. 2018b. Co-training embeddings of knowledge graphs and entity descriptions for cross-lingual entity alignment. In *IJCAI*. 
