Multi-lingual Common Semantic Space Construction via Cluster-consistent Word Embedding

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Abstract

We construct a multilingual common semantic space based on distributional semantics, where words from multiple languages are projected into a shared space to enable knowledge and resource transfer across languages. Beyond word alignment, we introduce multiple cluster-level alignments and enforce the word clusters to be consistently distributed across multiple languages. We exploit three signals for clustering: (1) neighbor words in the monolingual word embedding space; (2) character-level information; and (3) linguistic properties (e.g., apposition, locative suffix) derived from linguistic structure knowledge bases available for thousands of languages. We introduce a new cluster-consistent correlational neural network to construct the common semantic space by aligning words as well as clusters. Intrinsic evaluation on monolingual and multilingual QVEC tasks shows our approach achieves significantly higher correlation with linguistic features than state-of-the-art multi-lingual embedding learning methods do. Using low-resource language name tagging as a case study for extrinsic evaluation, our approach achieves up to 24.5\% absolute F-score gain over the state of the art.

1 Introduction

More than 3,000 languages have electronic record, e.g., at least a portion of the Christian Bible had been translated into 2,508 different languages. However, the training data for mainstream natural language processing (NLP) tasks such as information extraction and machine translation is only available for dozens of dominant languages. In this paper we aim to construct a multilingual common semantic space where words in multiple languages are mapped into a distributed, language-agnostic semantic continuous space, so that resources and knowledge can be shared across languages.

Words can be clustered through explicit (e.g., sharing affixes of certain linguistic functions) or implicit clues (e.g., sharing neighbors from monolingual word embedding). We hypothesize that the distribution of such clusters should be consistent across multiple languages. We achieve this cluster-level consistency by aligning word clusters across languages. Based on this intuition we propose to create clusters through three kinds of signals as follows, without any extra human annotation effort. Then we aggregate the embedding vectors of words in each cluster and ensure that the clusters (or the words therein) are consistent across multiple languages.

\textbf{Neighbor based clustering and alignment.}

We build our common space based on correlational neural network (CorrNet) which is an extension of autoencoder framework by enabling cross-lingual reconstruction. In contrast to previous work (Chandar et al., 2016; Rajendran et al., 2015), we extend CorrNet to \textit{neighbor-consistent correlation network} by using each word’s neighbors (the nearest words within monolingual semantic space) to ensure that the cross-lingual mapping from and to the common semantic space is locally smooth. For instance, the neighboring words of \textit{China} in English (\textit{Japan}, \textit{India} and \textit{Taiwan}) should be close to the neighboring words of \textit{Cina} in Italian (\textit{Beijing}, \textit{Korea}, \textit{Japan}) in the common semantic space. In other words, we encourage the consistency of neighborhoods across multiple languages.

\textbf{Character based clustering and alignment.}
Many related languages share very similar character set, and many words that refer to the same concept share similar compositional characters or patterns, e.g., China (English), Kina (Danish), and Cina (Italian).

**Linguistic property based clustering and alignment.** Many languages also share linguistic properties, e.g., apposition, conjunction, and plural suffix (English (-s/-es), Turkish (-lar/-ler), Somali (-o)). Linguists have created a wide variety of linguistic property knowledge bases, which are readily available for thousands of languages. For example, the CLDR (Unicode Common Locale Data Repository) includes closed word classes and affixes indicating various linguistic properties. We propose to take advantage of these language-universal resources to create clusters, where the words within one cluster share the same linguistic property, and build alignment between clusters for common semantic space construction.

We evaluate our approach on monolingual and multilingual QVEC (Tsvetkov et al., 2015) tasks, as well as an extrinsic evaluation on name tagging for low-resource languages. Experiments demonstrate that our framework is effective at capturing linguistic properties and significantly outperforms state-of-the-art multi-lingual embedding learning methods.

## 2 Related Work

Multilingual word embeddings have advanced many multilingual natural language processing tasks, such as machine translation (Zou et al., 2013; Mikolov et al., 2013; Madhyastha and España-Bonet, 2017), dependency parsing (Guo et al., 2015; Ammar et al., 2016a), and name tagging (Zhang et al.; Tsai and Roth, 2016). Using bilingual aligned words, previous methods project multiple monolingual embeddings into a shared semantic space using linear mappings (Mikolov et al., 2013; Rothe et al., 2016; Zhang et al., 2016; MarcoBaroni, 2015; Xing et al., 2015) or canonical correlation analysis (CCA) (Ammar et al., 2016b; Faruqui and Dyer, 2014; Lu et al., 2015). Compared with CCA, which only optimizes the correlation for each individual pair of languages, linear mapping based methods can jointly optimize all the languages in the common semantic space. We focus on learning linear mappings to construct the common semantic space and adopt correlational neural networks (Chandar et al., 2016; Rajendran et al., 2015) as the basic model. In contrast to previous work which only exploited monolingual word semantics, we introduce multiple cluster-level alignments.

Beyond word alignment, another branch of approaches for multilingual word embeddings are based on parallel or comparable data, such as parallel sentences (AP Chandar et al., 2014; Gouws et al., 2015; Luong et al., 2015; Hermann and Blunsom, 2014; Schwenk et al., 2017), phrase translations (Duong et al., 2016) and comparable documents (Vulic and Moens, 2015). Moreover, to reduce the need of bilingual alignment, several approaches have been designed to learn cross-lingual embeddings based on a small seed dictionary (Vulic and Korhonen, 2016; Zhang et al., 2016; Artexte et al., 2017), or even with no supervision (Cao et al., 2016; Zhang et al., 2017b,a; Conneau et al., 2017). However, such methods are still limited to bilingual word embedding learning and remaining to be explored for common semantic space construction.

## 3 Approach

### 3.1 Overview

Figure 1 shows the overview of our neural architecture. We project all monolingual word embeddings into a common semantic space based on word-level as well as cluster-level alignments and learn the transformation functions. First, on word-level, we build a neighborhood-consistent CorrNet to augment word representations with neighbor based clusters and align them in the common semantic space. In addition, we apply a language-independent convolutional neural networks to compose character-level word representation and concatenate it with word representation in the common semantic space. Finally, we construct clusters based on linguistic properties, such as closed word classes and affixes, and align them in the common semantic space. We jointly optimize for all the alignments in the common semantic space for each pair of languages.

### 3.2 Basic Model

We briefly describe the basic model for learning the common semantic space: correlational neural networks (CorrNets) (Chandar et al., 2016; Rajendran et al., 2015). CorrNets have been widely adopted for learning multilingual or multi-view representations. It combines the advantages of
Figure 1: Architecture Overview. In each monolingual semantic space, the words within solid rectangle denote a neighbor based cluster and the words within dotted rectangle denote a linguistic property based cluster.

canonical correlation analysis (CCA) and autoencoder (AE).

Given the bilingual aligned word pairs between two languages $l_1$ and $l_2$, we first use their monolingual word embeddings to initialize each word with a vector and obtain $M_{l_1} \in \mathbb{R}^{|V_{l_1}| \times d_{l_1}}$ and $M_{l_2} \in \mathbb{R}^{|V_{l_2}| \times d_{l_2}}$, where $V_{l_1}$ and $V_{l_2}$ are the bilingual dictionary of $l_1$ and $l_2$. $V_{l_1'}$ is the translation of $V_{l_2'}$ and $d_{l_1}$ and $d_{l_2}$ are the vector dimensionalities. Then for each language we learn a linear projection function to project $M_{l_1}$ and $M_{l_2}$ into the common semantic space:

$$H_{l_1} = \sigma(M_{l_1} \cdot W_{l_1} + b_{l_1}),$$

$$H_{l_2} = \sigma(M_{l_2} \cdot W_{l_2} + b_{l_2}),$$

where $H_{l_1} \in \mathbb{R}^{V_{l_1} \times h}$ and $H_{l_2} \in \mathbb{R}^{V_{l_2} \times h}$ are the vector representations for $V_{l_1}$ and $V_{l_2}$ in the common semantic space respectively. $h$ is the vector dimensionality in the shared semantic space. $W_{l_1} \in \mathbb{R}^{V_{l_1} \times h}$ and $W_{l_2} \in \mathbb{R}^{V_{l_2} \times h}$ are the transformation matrices, and $b_{l_1}$ and $b_{l_2}$ are the bias vectors. $\sigma$ denotes Sigmoid function.

After we project the monolingual embeddings into the common semantic space, we further reconstruct $M_{l_1}$ and $M_{l_2}$ from $H_{l_1}$ and $H_{l_2}$ separately:

$$M'_{l_1} = \sigma(H_{l_1} \cdot W_{l_1}^T + b'_{l_1}),$$

$$M'_{l_2} = \sigma(H_{l_2} \cdot W_{l_2}^T + b'_{l_2}),$$

where $b'_{l_1}, b'_{l_2}$ are the bias vectors. $M'_{l_1}$ and $M'_{l_2}$ are the monolingual reconstructions of $M_{l_1}$ and $M_{l_2}$ from the common space, and $M'_{l_1}^*$ and $M'_{l_2}^*$ are cross-lingual reconstructions. $W_{l_1}'$ and $W_{l_2}'$ are the transposes of $W_{l_1}$ and $W_{l_2}$ respectively.

To learn the common semantic space, we minimize the distance between the aligned word vectors as well as the loss of monolingual and cross-lingual reconstruction:

$$O_W = \sum_{\{i,j\} \in A} L(M'_{l_i}, M_{l_i}) + L(M'_{l_j}, M_{l_j}) + L(M'_{l_i}, M'_{l_j}) + L(H_{l_i}, H_{l_j}),$$

where $l$ denotes any specific language that we want to project into the common semantic space, $A$ denotes all bilingual dictionaries, and $L$ denotes a similarity metric. In our work, we use cosine similarity as the similarity metric.

### 3.3 Neighborhood-Consistent CorrNet

CorrNet can project multiple monolingual word embeddings into a common semantic space using bilingual word alignment. However, the same concepts may have different semantic bias in various languages. For example, the top five nearest words of the concept “China” are: (Japan, India, Taiwan, Chinese, Asia) in English, (Cosco, Shenzhen, Australian, Shanghai, manufacturing) in Danish, and (Beijing, Korea, Japan, aluminum, copper) in Italian respectively. The neighboring words can reflect the semantic meanings of each concept within
each semantic space. In order to ensure the consistency of the neighborhoods within the common semantic space and make the cross-lingual mapping locally smooth, we propose to augment monolingual word representation with its top-\(N\) nearest neighboring words from the original monolingual semantic space.\(^1\)

Given the monolingual embeddings of the bilingual aligned words for two languages \(l_1\) and \(l_2\), \(M_{l_1}\) and \(M_{l_2}\), for each word, we extract the top-\(N\) nearest neighbors and construct the neighborhood clusters. Each cluster \(t_i = \{w_1, w_2, \ldots, w_{|t_i|}\}\) in language \(l\) is represented by

\[
c_i = \frac{1}{|t_i|} \sum_{w \in t_i} E_w ,
\]

where \(E_w\) denotes the monolingual word embedding for \(w\).

We obtain all the neighborhood cluster vector representations \(C_{l_1}, C_{l_2}\) for \(l_1\) and \(l_2\). We incorporate these neighborhood cluster information into the common semantic space when projecting monolingual embeddings:

\[
H_{l_1} = \sigma(M_{l_1} \cdot W_{l_1} + C_{l_1} \cdot U_{l_1} + b_{l_1}) ,
\]

\[
H_{l_2} = \sigma(M_{l_2} \cdot W_{l_2} + C_{l_2} \cdot U_{l_2} + b_{l_2}) .
\]  

(1)

Besides the monolingual and cross-lingual reconstructions for \(M_{l_1}\) and \(M_{l_2}\) in CorrNets, we also add monolingual and cross-lingual reconstructions for the neighborhood clusters:

\[
C_{l_1}' = \sigma(H_{l_1} \cdot U_{l_1}^\top + b_{l_1}'),
\]

\[
C_{l_1}^* = \sigma(H_{l_1} \cdot U_{l_1}^\top + b_{l_1}^*),
\]

\[
C_{l_2}' = \sigma(H_{l_2} \cdot U_{l_2}^\top + b_{l_2}'),
\]

\[
C_{l_2}^* = \sigma(H_{l_1} \cdot U_{l_2}^\top + b_{l_2}^*),
\]

In addition to optimizing the loss functions described in the Section 3.2, we further optimize the monolingual and cross-lingual reconstruction for neighborhood clusters:

\[
O_N = \sum_{\{i, j\} \in A} L(C_{l_1}', C_{l_1}) + L(C_{l_1}^*, C_{l_1}) + L(C_{l_2}', C_{l_2}) + L(C_{l_2}^*, C_{l_2}) ,
\]

3.4 Character-Level Word Alignment

Bilingual word alignment is not always enough to induce a common semantic space, especially for low-resource languages. Although the words that refer to the same concept are not exactly the same in multiple languages, they usually share a set of similar characters, especially in related languages written in the same script, such as Amharic and Tigrinya. For example, the same entity is spelled slightly differently in three languages: Semsettin Gunaltay in English, emsettin Gnaltay in Turkish, and Semsetin Ganoltey in Somali. Beyond word-level alignment, we introduce character-level alignment by composing word representations from its compositional characters using convolutional neural networks (CNN). For each language, we adopt a language-independent CNN to generate character-level word representation.

Character Lookup Embeddings Let \(S_l\) be the character set for language \(l\) and \(E_{S_l} \in \mathbb{R}^{|S_l| \times d}\) be the character lookup embeddings, where \(d\) is the dimensionality of each character embedding. Here, we use a simple yet effective method to induce character embeddings from word embeddings. For each character \(c\), we average the embeddings of all words which contain the character. The character embeddings will be further tuned by the model.

Character-Level CNN (Kim et al., 2016) The input layer is a sequence of characters of length \(k\) for each word. Each character is represented by a \(d\)-dimensional lookup embedding. Thus each input sequence is represented as a feature map of dimensionality \(d \times k\).

The convolution layer is used to learn the representation for each sliding \(n\)-gram characters. We make \(p_i\) as the concatenated embeddings of \(n\) continuous columns from the input matrix, where \(n\) is the filter width. We then apply the convolution weights \(W \in \mathbb{R}^{d \times nd}\) to \(p_i\) with a biased vector \(b \in \mathbb{R}^d\) as follows:

\[
p_i' = \tanh(W \cdot p_i + b).
\]

All \(n\)-gram representations \(p_i'\) are used to generate the word representation \(y\) by max-pooling.

In our experiments, we apply multiple filters with various widths to obtain the representation for word \(w_i\). The final character-level word representation \(\hat{w}_i\) is the concatenation of all word representations with varying filter widths.

\(^1\)We set \(N\) as 5 in our experiments.
Table 1: Examples of closed word classes and linguistic properties based clusters

| Class Name | Words / Word Pairs |
|------------|--------------------|
| Colors     | white, yellow, red, blue, green ... |
| Weekdays   | monday, tuesday, friday, sunday ... |
| Months     | january, february, march, april ... |
| Numbers    | one, two, three, four, five ... |
| Pronouns   | i, me, you, he, she, her, they ... |
| Prepositions | of, in, on, for, from, about ... |
| Conjunctions | but, and, so, or, when, while ... |
| Clothes    | hat, shirt, pants, skirt, socks ... |
| -like      | (god, godlike), (bird, birdlike) ... |
| -able      | (accept, acceptable), (adopt, adoptable) ... |
| -micro     | (gram, microgram), (chip, microchip) ... |
| -auto      | (maker, automaker), (gas, autogas) ... |

Cross-lingual Mapping

Given the bilingual aligned word pairs, we directly minimize the distance of the character-level word representations in the common semantic space by:

\[ O_{\text{char}} = \sum_{\{i,j\} \in A} L(W_{i}^{\text{char}}, W_{j}^{\text{char}}) \]

The final word representation of \( w_{i} \) in the common semantic space is the concatenation of character-level word presentation \( \hat{w}_{i} \) and projected word representation \( h_{i} \).

3.5 Linguistic Property Alignment

Linguists have made great efforts at building linguistic property knowledge bases for thousands of languages in the world. These knowledge bases include a large number of topological properties (phonological, lexical and grammatical) which we will use to build a high-level alignment between words across languages. We exploit the following resources:

- **CLDR** (Unicode Common Locale Data Repository)\(^2\) which includes multilingual gazetteers for months, weekdays, cardinal and ordinal numbers;
- **Wiktionary**\(^3\) which is a multilingual, web-based collaborative project to create an English content dictionary, includes word and prefix/suffix dictionaries for 1,247 languages;
- **Panlex**\(^4\) database which contains 1.1 billion pairwise translations among 21 million expressions in about 10,000 language varieties.

\(^2\)http://cldr.unicode.org/index/charts
\(^3\)https://en.wiktionary.org
\(^4\)http://panlex.org/

We mainly exploit two types of linguistic properties to extract word clusters. The first type is closed word classes, such as colors, weekdays, and months. Table 1 shows some examples of the word clusters we automatically extracted from CLDR and Wiktionary for English. The second type of word clusters are generated based on morphological information, including affixes that indicate various linguistic functions. These properties tend to be consistent across many languages. For example, “-like” is a suffix denoting “similar to” in English, while in Danish “-agtig” performs the same function. For each affix, we extract a set of word pairs (basic word, extended word with affix) to denote its semantics from each language.

We extract a set of word clusters from each language, and align the clusters based on their functions defined in CLDR, Wiktionary and Panlex. For each language \( l \), each cluster \( r_{i} \in R^{l} \) contains a set of words or word-pairs sharing the same function. We use the average operation to obtain an overall vector representation for each cluster \( M_{i}^{R} \). Then, we project the cluster-level vectors into the shared semantic space and minimize the distance between them:

\[ H_{i}^{R} = \sigma(M_{i}^{R} \cdot W_{i} + b_{i}^{R}) , \]

\[ H_{ij}^{R} = \sigma(M_{ij}^{R} \cdot W_{ij} + b_{ij}^{R}) , \]

\[ O_{R} = \sum_{\{i,j\} \in A} L(H_{i}^{R}, H_{j}^{R}) , \]

where \( W \) is the same as the \( W \) used in Section 3.3 for each language. We finally optimize the sum of the losses by finding the parameters \( \theta = \{W, b_{i}, b_{ij}, U_{i}, b_{i}^{r}, \text{CNN}_{i}, b_{i}^{R}\} \), where \( l \) denotes a specific language:

\[ O_{\theta} = O_{W} + O_{N} + O_{\text{char}} + O_{R} \]

\(^5\)For each word pair, we use the vector of the extend word minus the vector of the basic word as the vector representation of the word pair.
Table 3: QVEC and QVEC-CCA scores. W: word alignment. N: neighbor based clustering and alignment. Ch: character based clustering and alignment. L: linguistic property based clustering and alignment.

### 4 Experiments

#### 4.1 Experiment Setup

Previous work (Ammar et al., 2016b; Duong et al., 2017) evaluated multilingual word embeddings on a series of intrinsic (e.g., monolingual and cross-lingual word similarity, word translation) and extrinsic (e.g., multilingual document classification, multilingual dependency parsing) evaluation tasks. Compared with previous work, we aim at incorporating more linguistic features into the multilingual embeddings, which can be helpful for downstream NLP tasks. In order to evaluate the quality of the multilingual embeddings, we use QVEC (Tsvetkov et al., 2015) tasks (details will be described in Section 4.2) as the intrinsic evaluation platform. In addition, to demonstrate the effectiveness of our common semantic space for knowledge transfer, especially for low-resource scenarios, we adopt the low-resource language name tagging task for extrinsic evaluation.

For each task, we evaluate the performance of our common semantic space in comparison with previously published multilingual word embeddings (MultiCluster, MultiCCA, MultiSkip, and MultiCross). MultiCluster (Ammar et al., 2016b) groups multilingual words into clusters based on bilingual dictionaries and forces all the words from various languages within one cluster share the same embedding. MultiCCA (Ammar et al., 2016b; Faruqui and Dyer, 2014) uses CCA to estimate linear projections for each pair of languages. MultiSkip is an extension of the multilingual skip-gram model (Luong et al., 2015), which requires parallel data. MultiCross is an approach to unify bilingual word embeddings into a shared semantic space using post hoc linear transformations (Duong et al., 2017).

Table 2 lists the hyper-parameters used in the experiments.

#### 4.2 Intrinsic Evaluation: QVEC

In order to evaluate the quality of multilingual embeddings, especially on linguistic aspect, we adopt QVEC (Tsvetkov et al., 2015) as the intrinsic evaluation measure. It evaluates the quality of word embeddings based on the alignment of distributional word vectors to linguistic feature vectors extracted from manually crafted lexical resources, e.g., SemCor (Miller et al., 1993).

\[
QVEC = \max_{\sum_i a_{ij} \leq 1} \sum_{i=1}^{D} \sum_{j=1}^{P} r(x_i, s_j) \times a_{ij}
\]

where \(x \in \mathbb{R}^{D \times 1}\) denotes a distributional word vector and \(s \in \mathbb{R}^{P \times 1}\) denotes a linguistic word vector. \(a_{ij} = 1\) iff \(x_i\) is aligned to \(s_j\), otherwise \(a_{ij} = 0\). \(r(x_i, s_j)\) is the Pearson’s correlation.
QVEC-CCA is extended from QVEC by using CCA to measure the correlation between the distributional matrix and the linguistic vector matrix, instead of cumulative dimension-wise correlation.

Using QVEC and QVEC-CCA, we evaluate the quality of multilingual embeddings for both monolingual (English) and multilingual (English, Danish, Italian) settings. As shown in Table 3, our approaches outperform previous approaches in all cases. Specifically, by augmenting word representation with neighboring words in the common semantic space as in Eq. (1), the performance for monolingual QVEC and QVEC-CCA tasks is consistently improved. In addition, by aligning character-level compositional representations and linguistic property based clusters in the shared semantic space, the multilingual representation quality is further improved.

### 4.3 Impact of Bilingual Dictionary Size

In order to show the impact of the size of bilingual lexicons, we use three languages as a case study, and gradually reduce the size of the lexicons for each pair of languages from 40,000 to 10,000 and to 2,000. Both MultiCluster and MultiSkip by default take advantage of identical strings from any pair of languages when they learn the multilingual embeddings. For fair comparison, we thus use MultiCCA as a baseline. Table 4 shows the results. We observe that both MultiCCA and CorrNet approaches are sensitive to the size of the bilingual lexicons. Our approach on the other hand could maintain high performance, even when the bilingual lexicons were reduced to 2,000.

### 4.4 Low-Resource Name Tagging

We evaluate the quality of multilingual embeddings on a downstream task by using the embeddings as input features. Here, we use low-resource language name tagging as a target task. We experiment with two sets of languages. The first set Amh+Tig consists of Amharic and Tigrinya. Both languages share the same Ge’ez script and descend from the proto-Semitic language family. The other set Eng+Uig+Tur consists of one high-resource language (English), one medium-resource language (Turkish) and one low-resource language (Uighur). It also consists of two distinct language scripts: English and Turkish use Latin script while Uighur uses Arabic script.

We use LSTM-CRF architecture (Huang et al., 2015; Lample et al., 2016; Ma and Hovy, 2016) for name tagging. Table 5 shows the statistics of training, development, and test sets for each language released by Linguistic Data Consortium (LDC). For each language pair in each language

Table 4: Results using bilingual lexicons with varying sizes (40,000, 10,000, 2,000) and three languages. CorrNet W+N+Ch+L is the proposed approach with all the cluster types.

|        | Amh | Tig | Uig | Tur | Eng |
|--------|-----|-----|-----|-----|-----|
| Train  | 1,506 | 1,585 | 1,711 | 3,404 | 14,029 |
| Dev    | 167  | 176  | 190  | 378  | 3,250 |
| Test   | 711  | 440  | 476  | 1,604 | 3,453 |

Table 5: Data statistics (# of Sentences) for name tagging

Table 6: Name tagging result (F-score, %) using monolingual embedding and multilingual embeddings.

|        | Amh | Tig | Uig | Tur | Eng | Monolingual | MultiCCA | CorrNet |
|--------|-----|-----|-----|-----|-----|-------------|----------|---------|
| Train  | 52.0 | 50.6 | 52.4 | 55.8 |
| Dev    | 78.2 | 78.4 | 77.9 | 77.6 |
| Test   | 70.0 | 63.6 | 66.8 | 66.0 |

9 The annotations are from: Amh (LDC2016E87), Tig
CorrNet is the proposed approach with all the cluster types.

We combine the bilingual aligned words extracted from Wiktionary and extracted from monolingual dictionaries based on identical strings.

We evaluate the quality from several aspects:

**Monolingual embedding quality evaluation**

Table 6 shows the name tagging performance for each language using the original monolingual embeddings and multilingual embeddings. For both Amharic and Turkish, the multilingual embeddings learned from our approach significantly improve over the monolingual embeddings, compared to MultiCCA. In the case of Uighur, all the multilingual embeddings fail to outperform the original monolingual embeddings. We conjecture that this is due to the use of Arabic script in Uighur, which differs from Turkish and English.

**Cross-lingual direct transfer**

We further demonstrate the effectiveness of our multilingual embeddings on direct knowledge transfer. In this setting, we train a name tagger on one or two languages using multilingual embeddings and test it on a new language without any annotated data. Table 7 shows the performance. For each testing language, our approach achieves better performance than MultiCCA and CorrNet. The closer that the languages are, such as Amharic and Tigrinya, and Turkish and Uighur, the better performance could be achieved, even when they may have distinct language scripts (e.g., Turkish and Uighur).

We however also notice that a larger extra annotated from another language does not necessarily result in the improvement. For instance, the proposed approach (CorrNet W+N+Ch+L) suffers from English annotated examples when tested on Turkish. This suggests that we need to be careful and aware of linguistic properties among different languages for transfer learning.

**Mutual enhancement**

We finally show the improvement by adding more cross-lingual annotated data and using multilingual embeddings in Table 8. The multilingual embeddings learned by our approach consistently outperforms MultiCCA. More specifically, when there are not enough annotated examples, the performance could be improved by incorporating annotated examples from other languages. This is evident for Amharic, Tigrinya and Uighur.

### Table 7: Name tagging performance (F-score, %) when the tagger was trained on a source language and tested on a target language. CorrNet W+N+Ch+L is the proposed approach with all the cluster types.

| Train  | Test   | MultiCCA | W   | CorrNet W+N+Ch+L |
|--------|--------|----------|-----|------------------|
| Amh    | Tig    | 15.5     | 28.3 | 31.7             |
| Tig    | Amh    | 11.1     | 12.8 | 23.3             |
| Eng    | Uig    | 8.4      | 16.9 | 15.4             |
| Tur    | Uig    | 1.1      | 18.1 | 25.6             |
| Eng+Tur| Uig    | 8.0      | 20.3 | 20.6             |
| Eng    | Tur    | 20.6     | 21.4 | 17.3             |
| Uig    | Tur    | 10.4     | 10.1 | 17.7             |
| Eng+Uig| Tur    | 18.5     | 21.1 | 29.4             |

| Train  | Test   | MultiCCA | W   | CorrNet W+N+Ch+L |
|--------|--------|----------|-----|------------------|
| Tig    | Amh    | 52.9     | 52.1 | 56.5             |
| Amh+Tig| Tig    | 78.0     | 78.1 | 78.7             |
| Eng+Uig| Uig    | 67.9     | 67.8 | 68.3             |
| Tur+Uig| Uig    | 67.7     | 67.5 | 68.8             |
| Eng+Tur+Uig| Uig | 68.7 | 67.4 | 65.9             |
| Uig-Tur| Tur    | 65.9     | 69.2 | 72.8             |
| Eng-Tur| Tur    | 66.9     | 70.4 | 73.4             |
| Eng+Uig+Tur| Tur | 67.5 | 68.5 | 72.9             |

### Table 8: Name tagging performance (F-score, %) when the training set for the tagger was enhanced by annotated examples in other languages. CorrNet W+N+Ch+L is the proposed approach with all the cluster types.

| Train  | Test   | MultiCCA | W   | CorrNet W+N+Ch+L |
|--------|--------|----------|-----|------------------|
| Tig+Amh| Amh    | 52.9     | 52.1 | 56.5             |
| Amh+Tig| Tig    | 78.0     | 78.1 | 78.7             |
| Eng+Uig| Uig    | 67.9     | 67.8 | 68.3             |
| Tur+Uig| Uig    | 67.7     | 67.5 | 68.8             |
| Eng+Tur+Uig| Uig | 68.7 | 67.4 | 65.9             |
| Uig-Tur| Tur    | 65.9     | 69.2 | 72.8             |
| Eng-Tur| Tur    | 66.9     | 70.4 | 73.4             |
| Eng+Uig+Tur| Tur | 67.5 | 68.5 | 72.9             |

5 Conclusions and Future Work

We construct a common semantic space for multiple languages based on a cluster-consistent correlational neural network. It combines word-level alignment and multi-level cluster alignment, including neighbor based clusters, character-level compositional word representations, and linguistic property based clusters induced from the readily available language-universal linguistic knowledge bases. By introducing cluster consistency into multilingual embedding learning, our approach achieved significantly higher performance than state-of-the-art multilingual embedding learning methods through both intrinsic and extrinsic evaluations. In the future, we will further extend our approach to multi-lingual multi-media common semantic space construction.
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