VCWE: Visual Character-Enhanced Word Embeddings

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Abstract

Chinese is a logographic writing system, and the shape of Chinese characters contain rich syntactic and semantic information. In this paper, we propose a model to learn Chinese word embeddings via three-level composition: (1) a convolutional neural network to extract the intra-character compositionality from the visual shape of a character; (2) a recurrent neural network with self-attention to compose character representation into word embeddings; (3) the Skip-Gram framework to capture noncompositionality directly from the contextual information. Evaluations demonstrate the superior performance of our model on four tasks: word similarity, sentiment analysis, named entity recognition and part-of-speech tagging.¹

1 Introduction

Distributed representations of words, namely word embeddings, encode both semantic and syntactic information into a dense vector. Currently, word embeddings have been playing a pivotal role in many natural language processing (NLP) Most of these NLP tasks also benefit from the pre-trained word embeddings, such as word2vec (Mikolov et al., 2013a) and GloVe (Pennington et al., 2014), which are based on the distributional hypothesis (Harris, 1954): words that occur in the same contexts tend to have similar meanings. Earlier word embeddings often take a word as a basic unit, and they ignore compositionality of its sub-word information such as morphemes and character n-grams, and cannot competently handle the rare words. To improve the performance of word embeddings, sub-word information has been employed (Luong et al., 2013; Qiu

et al., 2014; Cao and Rei, 2016; Sun et al., 2016a; Wieting et al., 2016; Bojanowski et al., 2016).

Compositionality is more critical for Chinese, since Chinese is a logographic writing system. In Chinese, each word typically consists of fewer characters and each character also contains richer semantic information. For example, Chinese character "休" (rest) is composed of the characters for "人" (person) and "木" (tree), with the intended idea of someone leaning against a tree, i.e., resting.

Based on the linguistic features of Chinese, recent methods have used the character information to improve Chinese word embeddings. These methods can be categorized into two kinds:

- 1) One kind of methods learn word embeddings with its constituent character (Chen et al., 2015), radical² (Shi et al., 2015; Yin et al., 2016; Yu et al., 2017) or strokes³ (Cao et al., 2018). However, these methods usually use simple operations, such as averaging and n-gram, to model the inherent compositionality within a word, which is not enough to handle the complicated linguistic compositionality.
- 2) The other kind of methods learns word embeddings with the visual information of the character. Liu et al. (2017) learn character embedding based on its visual characteristics in the text classification task. Su and Lee (2017) also introduce a pixel-based model that learns character features from font images. However, their model is not shown to be better than *word2vec* model because it has little flexibility and fixed character features.

Besides, most of these methods pay less attention to the non-compositionality. For example, the

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 $^{^{1}\}mbox{The source codes}$ are available at https://github.com/HSLCY/VCWE

²the graphical component of Chinese, referring to https://en.wikipedia.org/wiki/Radical_ (Chinese_characters)

³the basic pattern of Chinese characters, referring to https://en.wikipedia.org/wiki/Stroke_ (CJKV_character)

semantic of Chinese word "沙发" (sofa) cannot be composed by its contained characters "沙" (sand) and "发" (hair).

In this paper, we fully consider the compositionality and non-compositionality of Chinese words and propose a visual character-enhanced word embedding model (VCWE) to learn Chinese word embeddings. VCWE learns Chinese word embeddings via three-level composition:

- The first level is to learn the intra-character composition, which gains the representation of each character from its visual appearance via a convolutional neural network;
- The second level is to learn the intercharacter composition, where a bidirectional long short-term neural network (Bi-LSTM) (Hochreiter and Schmidhuber, 1997) with self-attention to compose character representation into word embeddings;
- The third level is to learn the noncompositionality, we can learn the contextual information because the overall framework of our model is based on the skip-gram.

Evaluations demonstrate the superior performance of our model on four tasks such as word similarity, sentiment analysis, named entity recognition and part-of-speech tagging.

2 Related Work

In the past decade, there has been much research on word embeddings. Bengio et al. (2003) use a feedforward neural network language model to predict the next word given its history. Later methods (Mikolov et al., 2010) replace feedforward neural network with the recurrent neural network for further exploration. The most popular word embedding system is *word2vec*, which uses continuous-bag-of-words and Skip-gram models, in conjunction with negative sampling for efficient conditional probability estimation (Mikolov et al., 2013a).

A different way to learn word embeddings is through factorization of word co-occurrence matrices such as GloVe embeddings (Pennington et al., 2014), which have been shown to be intrinsically linked to Skip-gram and negative sampling (Levy and Goldberg, 2014).

The models mentioned above are popular and useful, but they regard individual words as atomic

tokens, and the potentially useful internal structured information of words is ignored. To improve the performance of word embedding, sub-word information has been employed (Luong et al., 2013; Qiu et al., 2014; Cao and Rei, 2016; Sun et al., 2016a; Wieting et al., 2016; Bojanowski et al., 2016). These methods focus on alphabetic writing systems, but they are not directly applicable to logographic writing systems.

For the alphabetic writing systems, research on Chinese word embedding has gradually emerged. These methods focus on the discovery of making full use of sub-word information. Chen et al. (2015) design a CWE model for jointly learning Chinese characters and word embeddings. Based on the CWE model, Yin et al. (2016) present a multi-granularity embedding (MGE) model, additionally using the embeddings associated with radicals detected in the target word. Xu et al. (2016) propose a similarity-based characterenhanced word embedding (SCWE) model, exploiting the similarity between a word and its component characters with the semantic knowledge obtained from other languages. Shi et al. (2015) utilize radical information to improve Chinese word embeddings. Yu et al. (2017) introduce a joint learning word embedding (JWE) model and Cao et al. (2018) represent Chinese words as sequences of strokes and learn word embeddings with stroke n-grams information.

From another perspective, Liu et al. (2017) provide a new way to automatically extract character-level features, creating an image for the character and running it through a convolutional neural network to produce a visual character embedding. Su and Lee (2017) also introduce a pixel-based model that learns character features from its image.

Chinese word embeddings have recently begun to be explored, and have so far shown great promise. In this paper, we propose a visual character-enhanced word embedding (VCWE) model that can learn Chinese word embeddings from corpus and images of characters. The model combines the semantic information of the context with the image features of the character, with superior performance in several benchmarks.

3 Proposed Model

In this section, we introduce the visual characterenhanced word embedding (VCWE) model for Chinese word representation.

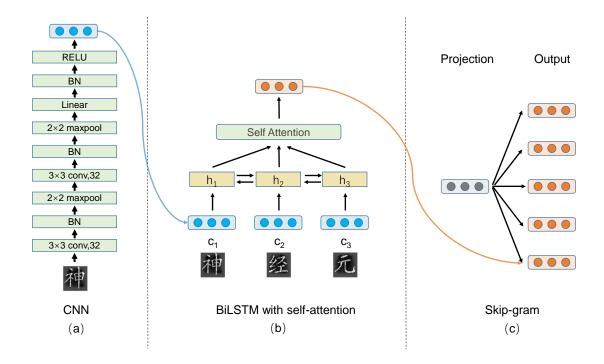


Figure 1: The overall architecture of our approach.

Given a Chinese word w consisting of n characters c_1, \dots, c_n , its semantic may come from either its contained characters or its contexts. Therefore, we use the two-level hierarchical composition to compose the word embedding, which further learned according to its context.

The overall architecture of our approach is on Figure 1. We first use a convolutional neural network (CNN) to model the intra-character compositionality of character from its visual shape information. We use the output of CNN as the embeddings of the character. Then the character embeddings are used as the input of the bidirectional LSTM network to model the inter-character compositionality. After a self-attention layer, we can get the representation of the word. Finally, based on the Skip-Gram framework, we learn the word embeddings with the visual character-enhanced embedding of the context.

3.1 Intra-Character Composition

Since the shape of a Chinese character provides rich syntactic and semantic information, the representation of a character can be composed by its intrinsic visual components. Following the success of the convolutional neural network (CNN) (LeCun et al., 1995) in computer vision, we use CNN to directly model the natural composition of

a character from its image.

We first convert each character into an image of size 40×40 , a deep CNN is used to fuse its visual information fully. The specific structure of the CNN is shown in Figure 1(a), which consists of two convolution layers and one linear layer. Each convolution layer is followed by a max pooling layer and a batch normalization layer. The lower layers aim to capture the stroke-level information, and the higher layers aim to capture the radical-level and component-level information.

The output of CNN can be regarded as the representation of the character. The character representation by its visual information can fully capture its intrinsic syntactic and semantic information with the intra-character compositionality.

The parameters of CNN are learned through backpropagation in end-to-end fashion.

3.2 Inter-Character Composition

After obtaining the representation of characters, we combine them into word embedding. The word embedding need to capture the character-level compositionality fully. Here, we use the bidirectional LSTM (Bi-LSTM) (Hochreiter and Schmidhuber, 1997) with self-attention to fuse the inter-character information of a word.

The structure of our Bi-LSTM with self-

attention is shown in Figure 1(b).

Given a word w consisting of n characters c_1, \dots, c_n , we use $\mathbf{e}_1, \dots, \mathbf{e}_n$ denote is the character representations, which are the output of the CNN rather than randomly initialized.

The word w is firstly encoded using a Bi-LSTM:

$$\mathbf{h}_{i}^{F} = LSTM(\mathbf{h}_{i-1}^{F}, \mathbf{e}_{i}), \tag{1}$$

$$\mathbf{h}_i^B = \text{LSTM}(\mathbf{h}_{i+1}^B, \mathbf{e}_i), \tag{2}$$

$$\mathbf{h}_i = [\mathbf{h}_i^F; \mathbf{h}_i^B],\tag{3}$$

$$H = [\mathbf{h}_1, \mathbf{h}_2, ..., \mathbf{h}_n], \tag{4}$$

where \mathbf{h}_i is the hidden state of the *i*-th character in w.

Then we use self-attention to obtain the intercharacter compositionality. Following the selfattention proposed by (Lin et al., 2017), we compute an attention vector α :

$$\alpha = \operatorname{softmax}(\mathbf{v} \tanh(U\mathbf{h}_i^{\mathrm{T}})),$$
 (5)

where \mathbf{v} and U are learnable weight parameters. Finally, the representation of word w is:

$$\mathbf{m} = \sum_{i=1}^{n} \alpha_i \mathbf{h}_i. \tag{6}$$

Since the Bi-LSTM's hidden state of each character is different according to its contexts, we believe the hidden state can capture both the compositional and non-compositional relations of the characters within a word.

After obtaining the word representation, Skip-Gram (Mikolov et al., 2013a) is used to learn the word embedding with its context information. Skip-Gram is a useful framework for learning word vectors, which aims to predict context words given a target word in a sentence.

Given a pair of words (w,c), we denote p(c|w) as the probability that the word c is observed in the context of the target word w.

With the negative-sampling approach, skipgram formulates the probability p(c|w) as follows:

Given a pair of words (w,c), the probability that the word c is observed in the context of the target word w is given by

$$p(D = 1|w, c) = \sigma(\mathbf{w}^{\mathrm{T}}\mathbf{c}), \tag{7}$$

where ${\bf w}$ and ${\bf c}$ are embedding vectors of w and c respectively, σ is the sigmoid function.

The probability of not observing word c in the context of w is given by:

$$p(D = 0|w, c) = 1 - \sigma(\mathbf{w}^{\mathrm{T}}\mathbf{c}). \tag{8}$$

4 Training

4.1 Objective Function

Given the target word w, its context word c and k negative words $\tilde{c}_1, ..., \tilde{c}_k$. The word w is a word selected from a sentence in the corpus, and the context c is a nearby word within a window size l. The negative sample \tilde{c}_i is a word that is randomly sampled at a certain frequency in the vocabulary.

The loss function of VCWE model is as follows:

$$L = L_1 + L_2, \tag{9}$$

$$L_1 = \log \sigma(\mathbf{w}^{\mathrm{T}}\mathbf{c}) + \sum_{i=1}^{k} \log \sigma(-\mathbf{w}^{\mathrm{T}}\tilde{\mathbf{c}}_i), \quad (10)$$

$$L_2 = \log \sigma(\mathbf{w}^{\mathrm{T}} \mathbf{m}_c) + \sum_{i=1}^k \log \sigma(-\mathbf{w}^{\mathrm{T}} \tilde{\mathbf{m}}_i), (11)$$

where \mathbf{w} is the lookup embedding of target word; \mathbf{c} and $\tilde{\mathbf{c}}_i$ are the lookup embeddings of the context and negative words respectively; \mathbf{m}_c and $\tilde{\mathbf{m}}_i$ are visual enhanced word embeddings of the context and negative words respectively.

Here, we use the visually enhanced word embedding as the representation of context word instead of the target word. The final embedding of the target word is indirectly affected by the visual information. Thus, the final word embedding can have an advantage of fully utilizing intra-character compositionality from CNN, inter-character compositionality from LSTM, and context information from Skip-gram.

4.2 Word Sampling

We use a word sampling scheme similar to the implementation in word2vec (Mikolov et al., 2013a,b) to balance the importance of frequent words and rare words. Frequent words such as "的"(of), "是"(is), "这"(this) are not as meaningful as relatively less frequent words such as "猫"(cat), "喜欢"(like), "水果"(fruit). To improve the performance of word embeddings, we use subsampling(Mikolov et al., 2013b) to discard the word w with the probability of $P(w) = 1 - \sqrt{\frac{t}{f(w)}}$ when generating the batch, where f(w) is the frequency of word w and t is a chosen threshold, typically around 10^{-5} .

To generate negative context words, we sample each word w according to distribution $P(w) \propto U(w)^{\frac{3}{4}}$, where U(w) is the unigram distribution, which is the frequency of single words appearing in the corpus. This method also plays a role in reducing the frequency of occurrence of high-frequency words.

5 Experiments

5.1 Preparation for training data

We download Chinese Wikipedia dump⁴ on May 20, 2018, which consists of 278K Chinese Wikipedia articles. We use the WikiExtractor toolkit⁵ to convert data from XML into text format. We find that the corpus consists of both simplified and traditional Chinese characters. Hence we utilize the opence toolkit⁶ to normalize all characters as simplified Chinese. We remove non-Chinese characters such as punctuation marks by retaining the characters whose Unicode falls into the range between 0x4E00 and 0x9FA5. We use THULAC ⁷(Sun et al., 2016b) for word segmentation.

We discard words that appeared less than 100 times and obtain a vocabulary of size 66,856. We count the frequency of occurrence of each word to prepare for the subsampling work.

In all 66,856 words, we extract 5030 unique characters. We use a Chinese character image generation software to generate the images of these Chinese characters. We subtract a mean image from each input image to center it before feeding it into the CNN. The pre-processed Chinese character images are shown in Figure 2.



Figure 2: The pre-processed Chinese character images.

5.2 Hyperparameters

Models used for evaluation have dimension D=100 and use context window l=5 unless stated otherwise. We use the threshold $t=10^{-5}$ for subsampling, which is the recommended value for word2vec Skip-gram (Mikolov et al., 2013a) on large datasets. The number of negative samples per word is 5.

We use mini-batch asynchronous gradient descent with Adam (Kingma and Ba, 2014). The initial learning rate is 0.001.

5.3 Baselines

We compare our model to the following open source state-of-art models:

- word2vec⁸ (Mikolov et al., 2013a) is arguably the most popular word embedding, which uses continuous-bag-of-words (CBOW) and Skip-gram models. We train word2vec with both Skip-gram and CBOW models. We did not train Glove(Pennington et al., 2014) because it did not perform well in many previous Chinese word embedding papers.
- CWE⁹ (Chen et al., 2015) is characterenhanced word embeddings which introduce internal character information into word embedding methods to alleviate excessive reliance on the external information.
- GWE¹⁰(Su and Lee, 2017) is a pixel-based Chinese word embedding model, which exploits character features from font images by convolutional autoencoders.
- JWE¹¹(Yu et al., 2017) is a model to jointly learn the embeddings of Chinese words, characters, and sub character components.

For a fair comparison between different algorithms, we use the same corpus and the same hyperparameters mentioned in previous subsections.

5.4 Word Similarity Task

We evaluate our embeddings on the Chinese word similarity datasets wordsim-240 and wordsim-296 provided by (Chen et al., 2015). Besides, we translate two English word similarity datasets MC-30

⁴https://dumps.wikimedia.org/zhwiki/20180520/

⁵https://github.com/attardi/wikiextractor/blob/master/Wiki Extractor.py

⁶https://github.com/BYVoid/OpenCC

⁷https://github.com/thunlp/THULAC-Python

⁸https://code.google.com/archive/p/word2vec/

⁹https://github.com/Leonard-Xu/CWE

¹⁰https://github.com/ray1007/gwe

¹¹https://github.com/hkust-knowcomp/jwe

Model	WS-240	WS-296	MC-30	RG-65	avg	Δ
Skip-gram	50.23	56.94	69.66	59.86	59.17	-
CBOW	51.49	61.01	68.97	63.85	61.33	+2.16
CWE	52.63	58.98	68.82	59.60	60.01	+0.84
GWE	52.74	58.22	68.23	60.74	59.98	+0.81
JWE	51.92	59.84	70.27	62.83	61.22	+2.05
VCWE	57.81	61.29	72.77	70.62	65.62	+6.45
-CNN	55.82	59.60	66.87	68.53	62.71	+3.54
-LSTM	58.13	60.85	68.03	69.78	64.20	+5.03

Table 1: Spearman correlation for word similarity datasets, "-CNN" represents replacing the CNN and image information with randomly initialized character embedding, "-LSTM" represents replacing Bi-LSTM network and self-attention with the averaging operation. For each dataset, we boldface the score with the best performance across all models.

Model	NOTEBOOK	CAR	CAMERA	PHONE	ALL	avg	Δ
Skip-gram	69.84	77.12	80.80	81.25	86.65	79.13	-
CBOW	74.60	75.42	82.59	82.81	84.07	79.90	+0.77
CWE	73.02	80.51	81.25	81.25	82.09	79.62	+0.49
GWE	74.60	78.81	79.46	83.98	83.92	80.15	+1.02
JWE	77.78	78.81	81.70	81.64	85.13	81.01	+1.88
VCWE	80.95	85.59	83.93	84.38	88.92	84.75	+5.62
-CNN	84.13	81.36	81.70	83.69	84.22	83.02	+3.89
-LSTM	79.37	80.51	80.36	84.38	85.58	82.04	+2.91

Table 2: Accuracy for Sentiment analysis task. The configurations are the same of the ones used in Table 1.

(Miller and Charles, 1991) and RG-65 (Rubenstein and Goodenough, 1965) to Chinese¹². Each dataset contains a list of word pairs with a human score of how related or similar the two words are.

We calculate the Spearman correlation (Spearman, 1904) between the labels and our scores generated by the embeddings. The Spearman correlation is a rank-based correlation measure that assesses how well the scores describe the true labels. The evaluation results of our model and baseline methods on word similarity datasets are shown in Table 1.

From the results, we can see that VCWE outperforms other baseline models. The effect of CBOW is much better than Skip-gram. The impact of GWE and CWE are relatively close. The JWE model works better than other benchmark models. In the VCWE model, when we remove the CNN and the image information, the result falls by 2.91. When we replace Bi-LSTM network and self-attention with the averaging operation, the result drops by 1.42.

In the last subsection, we will qualitatively analyze the results of word similarity for different models.

Sentiment Analysis Task

To evaluate the quality of our vectors regarding semantics, we use datasets¹³ collected by (Peng et al., 2018), which contain Chinese reviews in four domains: notebook, car, camera, and phone. They manually labeled the sentiment polarity towards each aspect target as either positive or negative. It is a binary classification task. Similar to how we process the training data, we remove non-Chinese characters and use THULAC for performing Chinese word segmentation. We build classifiers with the bidirectional LSTM (Hochreiter and Schmidhuber, 1997) network with selfattention (Lin et al., 2017). We use the standard training/dev/test split and report accuracy using different embeddings generated by different meth-

¹²https://github.com/FudanNLP/VCWE

¹³http://sentic.net/chinese-review-datasets.zip

ods in Table 2.

As shown in Table 2, Skip-gram performs well on the combination of the four groups, but it does not perform well in the works of a particular group. JWE outstrips other baseline methods by around 1.1 points. The VCWE model has achieved outstanding results in the car, camera and phone category, with an accuracy rate of at least 3 points higher than other models, indicating that this method of training word embeddings with visual character-level features can achieve better results on downstream tasks.

5.6 Named Entity Recognition Task

We evaluate our model on the named entity recognition task. We use an open source Chinese NER model to test our word embeddings on MSRA dataset¹⁴. MSRA is a dataset for simplified Chinese NER. It comes from SIGHAN 2006 shared task for Chinese NER (Levow, 2006). We pretrain word embeddings from different models and feed them into the input layer as features.

The key to the task is to extract named entities and their associated types. Better word embeddings could get a higher F1 score of NER. The results in Table 3 show that our model also outperforms baseline models in this task. The performance of CWE and GWE models are similar, both slightly lower than Skip-gram and CBOW models. The F1 score of the JWE model exceeds that of other baseline models and is similar to our model. When removing the CNN and image information, our LSTM with the self-attention model can also achieve the best results on this task, indicating that the learned inter-character composition is practical.

5.7 Part-of-speech Tagging Task

The evaluation is performed on the PKU's People's Daily ¹⁵ (PPD) (Yu et al., 2001) with the standard training/dev/test split. The model is trained with the bidirectional LSTM model using the same hyper-parameters. Results on the POS accuracy on the test set are reported in Table 3.

The gap between the usage of different embeddings is not significant, and our model has achieved the best results with a slight advantage.

Model		POS Tag			
	Prec. Recall F1		F1	Acc	
Skip-gram	85.30	84.18	84.74	95.87	
CBOW	85.64	82.98	84.29	95.79	
CWE	83.89	82.57	83.23	95.45	
GWE	84.06	82.52	83.28	95.45	
JWE	85.74	84.87	85.30	95.91	
VCWE	86.93	84.64	85.77	96.00	
-CNN	86.73	84.83	85.77	95.92	
-LSTM	85.98	84.53	85.25	95.96	

Table 3: Chinese NER and POS tagging results for different pretrained embeddings. The configurations are the same of the ones used in Table 1.

5.8 Qualitative analysis

To better understand the quality of the learning word embedding for each model, we conduct a qualitative analysis by doing some case studies in Table 4 to illustrate the most similar words for certain target words under different methods. Explicitly, we present the top 10 words that are most similar to our target word. The similar words are retrieved based on the cosine similarity calculated using the learned embeddings.

The first example word we consider is "唐诗(Tang poetry)". It refers to poetry written in or around the time of or in the characteristic style of China's Tang Dynasty.

All the top-ranked words identified by GWE contain the character "唐(Tang)" and "诗(poetry)", but in addition to the Tang Dynasty, "唐(Tang)" also has other meanings such as surnames. GWE yields several words such as "唐 璜(Don Juan)", "唐寅(Tang Yin)", "唐僧(Monk Tang)" and "唐括(Tang Ku)", which do not appear to be semantically close to the target word. In Skip-gram and JWE, certain words such as "佚(anonymity)" and "古今(ancient and modern)" do not appear to be semantically very closely related to the target word. In our VCWE model, all the top-ranked words are semantically related to the target word, including the genre of poetry, poets of the Tang Dynasty, and so on.

We choose the "沙发(sofa)" as the second target word. Like the first two words, GWE only pays attention to the character "沙(sand)". Skip-gram and JWE have some irrelevant words such as "电话亭(telephone box)" and "广告牌(billboard)". VCWE pays more attention to

¹⁴https://github.com/bamtercelboo/pytorch_NER_PosTag_Bi LSTM_CRF

¹⁵http://klcl.pku.edu.cn/zygx/zyxz/index.htm

Targets	Skip-gram	GWE	JWE	VCWE
唐诗(Tang poetry)	散曲(Qu-Poetry) 琴谱(music score) 佚(anonymity) 宋词(Song Ci Poetry) 白居易(Bai Juyi) 绝句(jueju) 著录(record) 楚辞(Chu Songs) 乐府(Yuefu)	宋诗(Song poetry) 赋诗(indite) 诗韵(rhyme) 汉诗(Chinese poetry) 唐璜(Don Juan) 吟诗(recite poems) 唐寅(Tang Yin) 唐僧(Monk Tang)	诗话(notes on poetry) 古今(ancient and modern) 佚(anonymity) 乐府(Yuefu) 琴谱(music score) 辑录(compile) 刻本(carving copy) 传世(be handed down) 古诗(ancient poetry)	诗话(notes on poetry) 宋诗(Song poetry) 绝句(jueju) 宋词(Song Ci Poetry) 吟咏(chant) 乐府(Yuefu) 七言(seven-character) 李商隐(Li Shangyin) 古诗(ancient poetry)
沙发(sofa)	相录(compile) 办公桌(bureau) 卧室(bedroom) 椅子(chair) 楼上(upstairs) 客厅(living room) 浴缸(bathtub) 楼下(downstairs) 雨衣(raincoat) 血迹(bloodstain) 电话亭(telephone box)	诗(poetry) 沙漏(hourglass) 沙尘(sand) 沙袋(sandbag) 沙盒(sandbox) 沙哑(raucity) 沙嘴(sandspit) 沙嗲(satay) 沙包(sandbag) 沙织(Saori) 沙蚕(nereid)	散曲(Qu-Poetry) 桌子(desk) 衣柜(wardrobe) 毛巾(washcloth) 书桌(secretaire) 棉被(quilt) 长椅(bench) 窗帘(curtain) 浴缸(bathtub) 房门(door) 广告牌(billboard)	诗文(poetic prose) 衣柜(wardrobe) 卧室(bedroom) 浴缸(bathtub) 客厅(living room) 窗帘(curtain) 椅子(chair) 壁炉(fireplace) 房门(door) 长椅(bench) 桌子(desk)

Table 4: Case study for qualitative analysis. Given the target word, we list the top 10 similar words from each algorithm so as to observe the differences.

the non-compositionality, and the results are better than other models.

Limited to the width of the table, we do not show the results of CWE model. The results of the GWE model are not much different from the CWE model, indicating that the image features obtained by pre-training of GWE may not play a decisive role. However, our model does not pre-train image information, but jointly trains and dynamically updates image feature information and it works better. JWE model is similar to Skip-gram model in that they pay more attention to contextual information, but sometimes the model gets some irrelevant words.

6 Discussion

Unlike phonograms, logograms have word and phrase meanings singularly. The images of Chinese characters contain rich semantic information. Since logographic languages are more closely associated with images than alphabet languages, it makes sense to mine the characteristics of these images.

Liu et al. (2017) provide a new way to automatically extract character-level features, creating an image for the character and running it through a convolutional neural network to produce a visual character embedding. However, this method does not utilize the rich semantic information of contextual words. Our model extracts both image fea-

tures and contextual semantic information.

Su and Lee (2017) introduce a pixel-based model that learns character features from font images. However, they use convolutional autoencoder(convAE) to extract image features in advance, and then add these features to the CWE (Chen et al., 2015) model. In the end, the effect of the model is not much different from CWE. Our model is an end-to-end model. We update the image's feature parameters in real time during training, and our model achieves better results than the GWE model.

Our research focuses on simplified Chinese word embeddings, and the idea can also be applied to other languages that share a similar writing system, such as traditional Chinese, Japanese, and so on.

7 Conclusion and Future Work

In this paper, we proposed a pixel-based model to learn Chinese word embeddings with character embeddings that are compositional in the components of the characters. We utilized the visual features of Chinese characters to enhance the word embedding. We showed that our model outperforms the baseline model in the word similarity, sentiment analysis, named entity recognition and part-of-speech tagging tasks.

In summary, we optimized our pixel-based word embedding method to make the model end-

to-end and make full use of the contextual information. In the future, we hope to apply our model to other downstream tasks and other logographic writing systems.

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References

- Yoshua Bengio, Réjean Ducharme, Pascal Vincent, and Christian Jauvin. 2003. A neural probabilistic language model. *Journal of machine learning research*, 3(Feb):1137–1155.
- Piotr Bojanowski, Edouard Grave, Armand Joulin, and Tomas Mikolov. 2016. Enriching word vectors with subword information. *arXiv preprint arXiv:1607.04606*.
- Kris Cao and Marek Rei. 2016. A joint model for word embedding and word morphology. *arXiv preprint arXiv:1606.02601*.
- Shaosheng Cao, Wei Lu, Jun Zhou, and Xiaolong Li. 2018. cw2vec: Learning chinese word embeddings with stroke n-gram information.
- Xinxiong Chen, Lei Xu, Zhiyuan Liu, Maosong Sun, and Huan-Bo Luan. 2015. Joint learning of character and word embeddings. In *IJCAI*, pages 1236–1242.
- Zellig S Harris. 1954. Distributional structure. *Word*, 10(2-3):146–162.
- Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. *Neural computation*, 9(8):1735–1780.
- Diederik P Kingma and Jimmy Ba. 2014. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*.
- Yann LeCun, Yoshua Bengio, et al. 1995. Convolutional networks for images, speech, and time series. *The handbook of brain theory and neural networks*, 3361(10):1995.
- Gina-Anne Levow. 2006. The third international chinese language processing bakeoff: Word segmentation and named entity recognition. In *Proceedings of the Fifth SIGHAN Workshop on Chinese Language Processing*, pages 108–117.

- Omer Levy and Yoav Goldberg. 2014. Neural word embedding as implicit matrix factorization. In *Advances in neural information processing systems*, pages 2177–2185.
- Zhouhan Lin, Minwei Feng, Cicero Nogueira dos Santos, Mo Yu, Bing Xiang, Bowen Zhou, and Yoshua Bengio. 2017. A structured self-attentive sentence embedding. *arXiv preprint arXiv:1703.03130*.
- Frederick Liu, Han Lu, Chieh Lo, and Graham Neubig. 2017. Learning character-level compositionality with visual features. *arXiv preprint arXiv:1704.04859*.
- Thang Luong, Richard Socher, and Christopher Manning. 2013. Better word representations with recursive neural networks for morphology. In *Proceedings of the Seventeenth Conference on Computational Natural Language Learning*, pages 104–113.
- Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013a. Efficient estimation of word representations in vector space. *arXiv preprint arXiv:1301.3781*.
- Tomáš Mikolov, Martin Karafiát, Lukáš Burget, Jan Černockỳ, and Sanjeev Khudanpur. 2010. Recurrent neural network based language model. In Eleventh Annual Conference of the International Speech Communication Association.
- Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg S Corrado, and Jeff Dean. 2013b. Distributed representations of words and phrases and their compositionality. In *Advances in neural information processing systems*, pages 3111–3119.
- George A Miller and Walter G Charles. 1991. Contextual correlates of semantic similarity. *Language and cognitive processes*, 6(1):1–28.
- Haiyun Peng, Yukun Ma, Yang Li, and Erik Cambria. 2018. Learning multi-grained aspect target sequence for chinese sentiment analysis. *Knowledge-Based Systems*, 148:167–176.
- Jeffrey Pennington, Richard Socher, and Christopher Manning. 2014. Glove: Global vectors for word representation. In *Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP)*, pages 1532–1543.
- Siyu Qiu, Qing Cui, Jiang Bian, Bin Gao, and Tie-Yan Liu. 2014. Co-learning of word representations and morpheme representations. In *Proceedings of COL-ING 2014*, the 25th International Conference on Computational Linguistics: Technical Papers, pages 141–150.
- Herbert Rubenstein and John B Goodenough. 1965. Contextual correlates of synonymy. *Communications of the ACM*, 8(10):627–633.

- Xinlei Shi, Junjie Zhai, Xudong Yang, Zehua Xie, and Chao Liu. 2015. Radical embedding: Delving deeper to chinese radicals. In *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 2: Short Papers)*, volume 2, pages 594–598.
- Charles Spearman. 1904. The proof and measurement of association between two things. *The American journal of psychology*, 15(1):72–101.
- Tzu-Ray Su and Hung-Yi Lee. 2017. Learning chinese word representations from glyphs of characters. *arXiv preprint arXiv:1708.04755*.
- Fei Sun, Jiafeng Guo, Yanyan Lan, Jun Xu, and Xueqi Cheng. 2016a. Inside out: Two jointly predictive models for word representations and phrase representations. In *AAAI*, pages 2821–2827.
- Maosong Sun, Xinxiong Chen, Kaixu Zhang, Zhipeng Guo, and Zhiyuan Liu. 2016b. Thulac: An efficient lexical analyzer for chinese. Technical report, Technical Report.
- John Wieting, Mohit Bansal, Kevin Gimpel, and Karen Livescu. 2016. Charagram: Embedding words and sentences via character n-grams. *arXiv preprint arXiv:1607.02789*.
- Jian Xu, Jiawei Liu, Liangang Zhang, Zhengyu Li, and Huanhuan Chen. 2016. Improve chinese word embeddings by exploiting internal structure. In *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 1041–1050.
- Rongchao Yin, Quan Wang, Peng Li, Rui Li, and Bin Wang. 2016. Multi-granularity chinese word embedding. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 981–986.
- Jinxing Yu, Xun Jian, Hao Xin, and Yangqiu Song. 2017. Joint embeddings of chinese words, characters, and fine-grained subcharacter components. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pages 286–291.
- Shiwen Yu, Jianming Lu, Xuefeng Zhu, Huiming Duan, Shiyong Kang, Honglin Sun, Hui Wang, Qiang Zhao, and Weidong Zhan. 2001. Processing norms of modern chinese corpus. Technical report, Technical report.