Sent2Matrix: Folding Character Sequences in Serpentine Manifolds for Two-Dimensional Sentence Representations

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Abstract—We study text representation methods using deep models. Current methods, such as word-level embedding and character-level embedding schemes, treat texts as either a sequence of atomic words or a sequence of characters. These methods either ignore word morphologies or word boundaries. To overcome these limitations, we propose to convert texts into 2-D representations and develop the Sent2Matrix method. Our method allows for the explicit incorporation of both word morphologies and boundaries. When coupled with a novel serpentine padding method, our Sent2Matrix method leads to an interesting visualization in which 1-D character sequences are folded into 2-D serpentine manifolds. Notably, our method is the first attempt to represent texts in 2-D formats. Experimental results on text classification tasks shown that our method consistently outperforms prior embedding methods.

Index Terms—Text representation, deep learning, serpentine padding, manifold learning.

1 INTRODUCTION

CONVOLUTIONAL neural networks (CNNs) [1], [2] have achieved remarkable performance in various computer vision tasks [3], [4]. In natural language processing (NLP), recurrent neural networks (RNNs) [5], [6], [7] were considered to be more natural, given that text data are sequential. Recently, multiple NLP studies have shown that CNNs can achieve competitive or even better performance than RNNs [8], [9], [10], [11]. Other additional advantages of CNNs, including parallel and ease of training, make CNNs even more attractive. Since CNNs take structured data as input like images, raw text data need to be converted into structured formats before applying CNNs.

Two popular text embedding methods are word-level embedding [12] and character-level embedding [13]. Word-level embedding methods convert a word into a vector using a word dictionary and an embedding matrix. Although they have been successfully applied to various tasks [14], [15], word-level embedding methods suffer from the limitation of ignoring character-level morphologies [16]. In character-level embedding method, each character is encoded into an one-hot vector, thereby capturing relationships among characters [17], [18]. On the other hand, the importance of the word separator is weaken by encoding it as a regular character in character-level embedding methods.

In this work, we propose a new text representation method known as the Sent2Matrix. Our method converts each word into a separate matrix. Thus, a sentence can be represented as a 3-D tensor by stacking the representations of words together. By explicitly encoding word boundaries, our method enables CNNs to easily capture both word-word and character-character relationships simultaneously. To copy with variable-length words, we develop a novel padding method known as the serpentine padding. Altogether, our Sent2Matrix representation and serpentine padding methods lead to an interesting visualization in which 1-D character sequences are folded into 2-D serpentine manifolds using the word separator as signal of direction change. Results on text classification tasks demonstrate the effectiveness of our methods compared to prior ones.

2 WORD-LEVEL EMBEDDING AND CHARACTER-LEVEL EMBEDDING

Deep learning methods take structured data as inputs. The most common structure is in the form of regular grid, such as images. When applying deep learning methods on texts, we need to convert raw texts into some structured formats. Since text data instances, such as sentences and documents, usually have variable lengths, we also need to unify their lengths by appropriate padding and trimming. Text data instances consist of words, which in turn consist of characters. Thus, text data are commonly converted into structured formats using either word-level embedding [15] or character-level embedding [13]. In this section, we introduce these two commonly used embedding methods and describe their limitations. To overcome these limitations, we propose the Sent2Matrix embedding method. Our proposed method inherits the advantages of both word-level and character-level embedding methods while overcoming their limitations. In the following, we use a fixed-size word vocabulary \( V^w \) with size \( |V^w| \) representing the number of words in the vocabulary.

2.1 Word-Level Embedding

The word-level embedding method considers each word as an atomic entity and represents it as a single fixed-length vector. Consider a sentence \( s \) consisting of a sequence of \( n \) words...
\{x_1, x_2, \cdots, x_n\}$, each word $x_i$, with $1 \leq i \leq n$, is represented as an one-hot vector $u^i \in \mathbb{R}^{|V^w|}$ defined as

$$u^i_j = \begin{cases} 1, & \text{if } V^w_j = x_i \\ 0, & \text{otherwise} \end{cases}, \quad (1)$$

where $u^i_j$ denotes the $j$-th element in $u^i$. Figure 1 (a) provides an example of word-level embedding. In many languages, the size of vocabulary $V^w$ is very large, resulting in high-dimensional and sparse vectors $u^i$. These one-hot vectors cannot be used directly and a dimensionality reduction step is performed to project them into a lower-dimensional space as $p^i = M^w u^i$, where $M^w \in \mathbb{R}^{d^w \times |V^w|}$ denotes the word embedding matrix, $p^i \in \mathbb{R}^{d^w}$ denotes the reduced representation, and $d^w$ is the reduced dimensionality. Here, $M^w$ is a parameter matrix to be learned from data, and $d^w$ is a user-specified parameter that should depend on $|V^w|$ and complexity of tasks.

With these low-dimensional representations, a sentence $s$ with length $n$ can be represented as a matrix as

$$S = [p^1, p^2, \cdots, p^n] \in \mathbb{R}^{d^w \times n}. \quad (2)$$

When the lengths of sentences are not equal to $n$, they need to be zero-padded or trimmed appropriately. With such a fixed-length vector sequence representation of sentences, the 1-D convolution operation is usually applied to compute high-level features. In this operation, the embedding dimension is treated as the channel dimension, and the 1-D convolution is applied along the word dimension. Specifically, the 1-D convolution operation uses a set of 1-D learnable filters $\{w_j \in \mathbb{R}^k\}_{j=1}^{d^w}$ to compute output features, where $k$ denotes the 1-D kernel size. For example, a feature value $y_i \in \mathbb{R}$ is computed as

$$y_i = f \left( \sum_{j=1}^{d^w} w_j \odot S^j_{i\cdot+i+h-1} + b \right), \quad (3)$$

where $\odot$ denotes element-wise multiplication, $S^j_{i\cdot+i+h-1}$ denotes the column vector including elements in the $j$-th row and the $i$-th to the $(i+h-1)$-th columns of $S$ in order, $b$ denotes the bias, and $f(\cdot)$ is a non-linear function such as the ReLU [19]. Suppose the stride in convolution is set to 1, the same set of filters are applied to every possible word window of size $h$ in the sentence, resulting in the following output feature vector:

$$y = [y_1, y_2, \cdots, y_{n-h+1}]^T \in \mathbb{R}^{n-h+1}. \quad (4)$$

We can use multiple sets of independent filters to compute multiple output feature vectors. These feature vectors form the different channels of features to be used as inputs for the next layer.

Although the word-level embedding method has achieved great success in various tasks such as neural machine translation [13, 20] and text classification [12], it suffers from several limitations. In particular, this method considers words as atomic representations and does not explicitly incorporate their character constitutions and morphologies, such as roots, prefixes, and suffixes, in learning the representations. Each word is discretized to a one-hot representation, and the semantic relations among words are inferred only from contexts. For example, the words "surprise" and "surprising" have similar meanings, but their one-hot representations are not related. The similarity of their low-dimensional embedding needs to be inferred based on the contexts in which they are used.

### 2.2 Character-Level Embedding

To overcome the limitations of word-level embedding, the character-level embedding method was proposed to consider morphological information explicitly [13]. In this method, a sentence is considered as a sequence of characters, and each character is encoded into an one-hot vector based on a character-level vocabulary $V^c$. Given a sentence $s$ consisting of a sequence of $m$ characters $\{z_1, z_2, \cdots, z_m\}$, the one-hot vector $v^i \in \mathbb{R}^{|V^c|}$ for character $z_i$ can be expressed as

$$v^i_j = \begin{cases} 1, & \text{if } V^c_j = z_i \\ 0, & \text{otherwise}. \end{cases} \quad (5)$$

It is worth noting that the size of the character-level vocabulary is usually much smaller than that of the word-level vocabulary; that is, $|V^c| \ll |V^w|$. Hence, the one-hot vectors in character-level embedding can be used directly without employing the embedding matrix as in the word-level embedding method. The sentence $s$ consisting of $m$ characters can be represented as a matrix as

$$T = [v^1, v^2, \cdots, v^m] \in \mathbb{R}^{|V^c| \times m}. \quad (6)$$

Figure 1 (b) provides an example of character-level embedding. Similar to the case of word-level embedding, 1-D convolutions are applied on $T$ to compute high-level features.

It can be seen from the descriptions above that the convolution operation considers the relationships among characters, thereby extracting features with explicit morphological information. In character-level embedding, a sentence is considered as a sequence of characters. The separator between words is commonly a specific character such as a space. However, such kind of separators are not explicitly given to subsequent neural network operations. Hence, space characters need to extract more advanced features to consider the relationships between words.

### 3 Sent2Matrix

In order to overcome the limitations of word-level and character-level embedding methods, we propose the Sent2Matrix embedding method. Our proposed Sent2Matrix method can consider the relationships among characters and those among words simultaneously. When combined with a novel padding method described below, our methods lead to a new way of converting character streams into a 2-D representation on which 2-D neural network operations can be applied.

#### 3.1 Sent2Matrix Representations

Given a sentence $s = \{x_1, x_2, \cdots, x_n\}$ consisting of at most $n$ words in which each word $x_i$ contains at most $m$ characters, we first encode each character into a one-hot vector using a character-level vocabulary. Unlike the vocabulary used in the regular character-level embedding above, we do not need to include the word separator in vocabulary. For notational convenience, we denote this character-level vocabulary as $V^c$ again. Each character $z_{i,j}$ for $(1 \leq i \leq n, 1 \leq j \leq m)$ is encoded into a one-hot vector
vector \( v_{i,j} \in \mathbb{R}^{|V^c|} \) in a way that is similar to the case of regular character-level embedding as

\[
v_{i,k}^{j} = \begin{cases} 
1, & \text{if } V_{k}^{c} = z_{i,j} \\
0, & \text{otherwise}.
\end{cases} \quad (7)
\]

With the character-level encoding described as above, our proposed Sent2Matrix embedding encodes each word as a separate matrix. Then the sequence of words in a sentence can be represented as a 3-D data array, known as a 3-D tensor \([21]\). By using this higher-dimensional representation of sentences, the word morphologies have also been considered in the character-level encoding. In particular, each word \( x_i \) can be represented as a matrix as

\[
X_i = [v_i^1, v_i^2, \ldots, v_i^m] \in \mathbb{R}^{|V^c| \times m}. \quad (8)
\]

Since \( m \) is the maximum number of characters in a word, appropriate padding strategies are needed to deal with variable-length words. In fact, novel padding strategies and related interpretations are the other major contributions of this work. These details will be given below.

Based on the above word representations, the sentence \( s \) can be represented as a 3-D tensor \( S \) as:

\[
S = [X_1, X_2, \ldots, X_n] \in \mathbb{R}^{n \times m \times |V^c|}. \quad (9)
\]

In Eq. (9), the matrices \( X_i \) are stacked to form the tensor \( S \) by treating \( X_i \) as the \( i \)th horizontal slice of \( S \) \([21]\). An example is given in Figure 1 (c) to illustrate the Sent2Matrix embedding of a sentence. By this representation, a sentence \( s \) is now encoded into a 3-D tensor \( S \) in which the three dimensions correspond to word, character, and character embedding, respectively.

Recall that only 1-D convolutions have been applied to compute high-level features in word-level and character-level embedding methods. In contrast, our proposed Sent2Matrix embedding method represents text data in an image-like format, thereby enabling the use of 2-D convolutions to compute features that capture relationships among both characters and words simultaneously. Given the tensor representation of a sentence \( S \) we can apply a 2-D convolution operation using a set of learnable filters \( \{W_k \in \mathbb{R}^{k_1 \times k_2} |_{i=1}^{V^c} \} \), where \( k_1 \) and \( k_2 \) represent the sizes of filter. Then an output feature value can be computed as

\[
y_{i,j} = f \left( \sum_{\ell=1}^{|V^c|} W_{\ell} \odot S_{i+i+k_1-1,j+j+k_2-1,\ell+b} \right), \quad (10)
\]

where the subscripts for \( S \) denote taking the corresponding element in it along each of the three dimensions as in \([21]\).

By computing features on each possible patch of size \( k_1 \times k_2 \) using the same set of filters \( W \), we can obtain an output feature matrix \( Y \in \mathbb{R}^{(m-k_1+1) \times (n-k_2+1)} \) as

\[
Y = \begin{bmatrix}
y_{11} & \cdots & y_{1,n-k_2+1} \\
y_{21} & \cdots & y_{2,n-k_2+1} \\
\vdots & \ddots & \vdots \\
y_{m-k_1+1,1} & \cdots & y_{m-k_1+1,n-k_2+1}
\end{bmatrix}. \quad (11)
\]

We can use multiple sets of independent filters to compute multiple output feature matrices. These feature matrices form the different channels of features to be used as inputs for the next layer. By using 2-D filters for feature extraction, Sent2Matrix can capture the relationships among characters from different words, thereby providing additional morphological information for feature extraction.

### 3.2 Sent2Matrix Padding

It follows from the above description of Sent2Matrix representation that a sentence has at most \( n \) words and each word is assumed to have the same length \( m \). For sentence with less than \( n \) words, we center the words and pad zeros at two ends. At word level, we use \( m \) as the maximum length of words in a sentence and propose to apply advanced padding strategies to convert shorter words to contain exactly \( m \) characters. In this section, we develop three strategies for padding.

**Zero Padding:** Paddion is required in convolution layers of CNNs to keep the size of feature maps, and zero-padding is the most commonly used form of padding. In this strategy, we consider the property of convolution operation and propose to center the characters of words in the middle of the vector and pad zeros at two ends. This is because elements in the middle will be covered by more convolution windows when performing convolution, thereby leading to effective use of the input data and...
Fig. 2. Illustrations of the three padding methods on the same sentence. Figures (a) and (b) show the encoded results using zero padding and cyclic padding, respectively. Figure (c) describes the encoded output with serpentine padding. We repeat each word twice except for the first and the last words. The first occurrence of each repeated words and the last word are in reverse order. Cyclic padding was used for words that are shorter than the required length.

![image](image.png)

Fig. 3. A visualization of the serpentine padding. A sentence with repeated words as described in section 3.2 is folded from left to right and then right to left in serpentine manifolds using space as the U-turn signal.

yielding more informative features. The zero padding strategy is illustrated in Figure 2 (a). However, since lengths of sentences vary, this strategy may introduce many zero values and waste spaces in resulting embeddings.

**Cyclic Padding:** Although the zero-padding strategy centers characters for better convolution coverage, only a small number of convolution windows can cover characters in very short words such as “I”. In this case, the padded zeros become some kind of noises and compromise CNNs’ performance. To overcome this limitation of the zero-padding strategy, we propose the cyclic padding strategy. In this strategy, the characters are repeated a number of times until the maximum length $m$ is reached. Compared to zero-padding, cyclic padding employs the contents of words in the padded positions, thereby allowing all filter windows to access the contents of words. Figure 2 (b) provides an example of cyclic padding.

**Serpentine Padding:** The character-level embedding considers a sentence as a sequence of characters. Specifically, 1-D convolutional filters can capture the relationship between the trailing characters of one word and the leading characters of the following word. We observe that both the zero padding and cyclic padding fail to preserve the sequential order of characters between adjacent words. To restore the sequential flow of character stream in sentence, we propose the serpentine padding strategy. In this strategy, every word in the sentence is repeated twice except for the first and the last words. The second occurrence of each word is in normal order, while the first occurrence of each word is in reverse character order. In addition, the last word only appears in reverse character order.

Given a sentence $s = \{x_1, x_2, \cdots, x_n\}$ that consists of $n$ words, the repeated sentence $\bar{s}$ can be written as $\bar{s} = \{x_1, x_2, x_3, \cdots, x_{n-1}, x_{n-1}, x_n\}$, where $x_i$ denotes the word $x_i$ in reverse character order. Each individual word, including the repeated ones, is padded to include $m$ characters using cyclic padding. Hence, the repeated sentence $\bar{s}$ can be represented as a 3-D tensor as $\bar{S} \in \mathbb{R}^{2(n-1) \times m \times |V|}$ using our proposed Sent2Matrix representation. We propose to use a stride of 2 along the word dimension when applying convolution operations to compute high-level features from $\bar{S}$. This forces the filters to compute features from adjacent words in the character order in the original sentence. Figure 2(c) provides an illustration of using our serpentine padding with the proposed Sent2Matrix representation of a text.

### 3.3 Interpretation of Serpentine Padding as Folding of Character Sequences in 2-D

In the previous section, we propose the serpentine padding method. The proposed method above is motivated by an intention to fold a sequence of characters representing a sentence into a serpentine pattern using the word separator as the signal for making a 180° turn (Figure 3). This view can be best understood by considering a different version of the repeated sentence $\bar{s} = \{x_1, x_2, x_3, \cdots, x_{n-1}, x_{n-1}, x_n\}$ in which each word is padded to have $m$ characters using the proposed cyclic padding. When the 3-D tensor $\bar{S}$ is considered as a 2-D array of mode-3 fibers $\bar{S}_{ij}$, $\bar{S}$ can be obtained by filling in the fibers using the character embedding vectors $v^{(i,j)}$, defined in Eq. 7, for $\bar{s}$. In particular, these fibers are filled in using the character embedding vector sequence representation of a sentence from left to right and then right to left in serpentine pattern using the word separator as the signal for making a 180° turn.

### 3.4 Position Embedding

Text data are sequential but the position information of entities is not explicitly modeled in CNNs. This is because CNNs do not
consider sequential information explicitly. Thus, it is desirable to explicitly encode position information. To capture position information, an embedding method was proposed in [23] to encode the positions of words or characters in sentences. It has been shown to be effective for various tasks [24], [25], [26]. The position embedding can help to encode relative position information of characters in the text. To use position information in our method, we encode the positions of characters in words into one-hot vectors and concatenate them with character-level encoding vectors.

3.5 Network Design

In our proposed Sent2Matrix embedding method, each text is converted into the 2-D format, which enables the usage of 2-D convolution operations on text data. The usage of 2-D convolution operation can help to capture dependencies among characters of different words. To this end, we build a densely-connected network for text data.

Given an input text, we first convert it into a 3-D tensor. We apply a 2-D convolution layer with stride 2 in the word dimension to encode high-level features. After that, we stack several densely-connected blocks. In each block, there are multiple convolution layers. We use concatenation to combine the input and output of each layer. An average pooling layer is used between each pair of consecutive blocks. The output feature maps of the final block are flattened and fed into a two-layer feed-forward neural network for prediction. Figure 4 provides a simple example of our densely-connected network.

4 RELATED WORK

Many studies have applied CNNs on text classification tasks using word-level or character-level embedding methods. A simple CNN model based on word-level embedding was proposed in [12] to improve the performance on sentiment analysis and question classification tasks. In [13], the authors employed character-level embedding method to build convolutional networks for text classification. Both word-level and character-level embedding methods were extensively used in other NLP tasks such as neural machine translation [14], [27].

In addition to these two embedding methods, some studies tried other ways for text transformation. In [28], the authors proposed subword units to address rare words in open-vocabulary problems. Subword units can be considered as a trade-off between word-level and character-level embedding methods. [29] employed a neural network to encode characters of each word into a character-level embedding vector. This vector was concatenated with word-level embedding to form the final word representation. This method can be seen as an attempt of combining word-level and character-level embedding. However, the character-level embedding in this work only focus on the characters within each word. Our method enables CNNs to consider relationships among characters across words.

[30] proposed a pretraining method to train a network for text classification.

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5 EXPERIMENTAL STUDIES

We evaluate our proposed Sent2Matrix method on text classification tasks using CNNs as a basic model architecture. We conduct experiments to compare with several baseline methods, including word-level CNNs, character-level CNNs and long short-term memory (LSTM) RNNs. Some results of these baseline methods are reported in [15] and [13]. In addition, performance studies are used to compare the three padding strategies. Our results show that the proposed Sent2Matrix outperforms these prior state-of-the-art methods, and the serpentine padding yields improved performance.
5.1 Datasets

We evaluate our methods on three datasets involving two types of text classification tasks: namely topic classification and sentiment classification. We choose two large datasets and one small dataset in terms of sample size. The statistics for these datasets are summarized in the first 3 columns of Table 1. For datasets that training and test split was not given, we randomly split them into training and test sets to ensure all methods use the same training data for fair comparisons.

**AG’s News** is a topic classification dataset [13] containing four topics: World, Sports, Business and Sci/Tech. AG is a collection containing more than 1 million news articles, and the final dataset is formed by choosing four classes, each containing 30,000 training samples and 1,700 test samples. Each sample is a short text consisting of several sentences. The label indicates the sentiment of a short text.

**Yelp Full** is obtained from Yelp Dataset Challenge in 2015 and compiled by [13]. The dataset is for sentiment classification, and it includes five classes indicating movie review star from 1 to 5. Each class contains 130,000 training samples and 10,000 test samples. Each sample is a short text.

**MR** is a Movie Review dataset [22], and the task is for sentiment classification containing positive and negative reviews. Each sample is a short sentence, and the longest sentence contains 51 words.

5.2 Experimental Setup

We use two sets of experimental settings for the three datasets due to their different sizes. On the small datasets MR, we use the same model architectures as described in [15] with minor changes to accommodate the Sent2Matrix embedding. On the large datasets AG’s News and Yelp Full, we build a new network based on densely connected convolutional networks (DCNNs) [31]. In the following, we mainly discuss the experimental settings on large datasets. These for MR are provided in [15].

**Choice of vocabulary:** In our proposed Sent2Matrix embedding method, each character is encoded by a pre-determined character vocabulary. The size of vocabulary is an important hyper-parameter, which provides a trade-off between representational capacity and computational efficiency. Common elements of character vocabulary include lower-case characters, upper-case characters, and punctuations. We observe that case-sensitivity and punctuations do not contribute much to prediction. For instance, “GOOD” and “good” should lead to the same prediction in sentiment classification task using the Yelp Full dataset. From this point, our character vocabulary only contains 26 lower-case characters, which also facilitates the training process.

**Choices of padding parameters:** In addition to the character vocabulary, we have another two hyper-parameters; namely the maximum number of words in sentence $n$ and maximum length of words $m$. Given the statistics of texts in the two large datasets, we set $m$ to 18, which covers 99% of the words in datasets. For maximum words number $n$, we use 49 and 67 for AG’s News and Yelp Full, respectively. The values of $m$ and $n$ for each dataset are given in Table 1.

For both the small and large datasets, the following settings are shared. For all layers, we use ReLU [19] as the activation function with a dropout keep rate of 0.5. For training, we use the Adam optimizer [32] with a learning rate of 0.001. The mini batch size used for all datasets is 512. All hyper-parameters are tuned based on the validation datasets of MR and AG’s News.

5.3 Comparison of Padding Strategies

We compare the performance of the three proposed padding strategies on the AG’s News dataset, and the results are summarized in Table 3. We can observe from the results that the cyclic padding strategy outperforms the zero padding by 1.6%, which confirms the effectiveness of making words content available for all filter windows. The serpentine padding outperforms the zero padding and the cyclic padding by a margin of 2.0% and 2.6% on AG’s News dataset, respectively. This demonstrates the benefits of preserving the sequential order of character stream by using the proposed serpentine padding strategy. The following experiments will only use the serpentine padding method.

5.4 Comparison of Sent2Matrix with Other Methods

We compare Sent2Matrix CNN with other state-of-the-art models. The experimental results are summarized in Table 2. We can see that Sent2Matrix CNN outperforms word-level CNN and character-level CNN by at least a margin of 0.7%, 1.1%, and 1.1% on the AG’s News, Yelp Full, and MR datasets, respectively. Also, the margins tend to be larger for larger datasets. These results provide some insights about our embedding method. On one hand, the promising performance of our model on the small datasets demonstrate the representational ability our method compared to word-level and character-level embedding methods. On the other hand, the advantages of Sent2Matrix on large datasets are even more remarkable than that on small datasets. This indicates that the
Sent2Matrix embedding method enables CNN to apply 2-D filters to compute more advanced features, thereby leading to better generalization. In addition, all CNN models, including Sent2Matrix CNN, achieve better performance than that of LSTM on all datasets. This is consistent with recent results in other studies and demonstrates the effectiveness of CNNs compared to RNNs. These results show that our proposed method yields consistently better performance across all datasets. This clearly demonstrates the effectiveness of modeling texts using two-dimensional matrices in the proposed Sent2Matrix embedding.

5.5 Performance Study using Pretraining

Network design. We compare Sent2Matrix CNN with other state-of-the-art models. The experimental results are summarized in Table 2. We can see that Sent2Matrix CNN outperforms word-level CNN and character-level CNN by at least a margin of 0.7%, 1.1%, and 1.1% on the AG’s News, Yelp Full, and MR datasets, respectively. Also, the margins tend to be larger for larger datasets. These results provide some insights about our embedding method. On one hand, the promising performance of our model on the small datasets demonstrate the representational ability our method compared to word-level and character-level embedding methods. On the other hand, the advantages of Sent2Matrix on large datasets are even more remarkable than that on small datasets. This indicates that the Sent2Matrix embedding method enables CNN to apply 2-D filters to

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5.6 Performance Study using Attention Operator

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6 Conclusions

In this work, we propose the Sent2Matrix embedding method for text representation. Our proposed method can overcome the limitations of word-level and character-level embedding methods. Sent2Matrix embedding method encodes sentences into two-dimensional representations, thereby enabling CNNs to capture both word-word and character-character relationships simultaneously. To cope with variable-length words in sentences, we develop the serpentine padding strategy, which retains the sequential flow of character stream in sentences. Experimental results on text
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Classification tasks demonstrate that our new embedding method with serpentine padding consistently outperforms prior embedding methods.