

Received July 11, 2020, accepted August 11, 2020, date of publication August 14, 2020, date of current version August 25, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3016727

Hierarchical Multi-Granularity Attention-Based Hybrid Neural Network for Text Classification

ZHENYU LIU¹, (Member, IEEE), CHAOHONG LU², HAIWEI HUANG², SHENGFEI LYU², (Graduate Student Member, IEEE), AND ZHENCHAO TAO^{3,4}

¹School of Information Management for Law, China University of Political Science and Law, Beijing 100088, China

²School of Computer Science, University of Science and Technology of China, Hefei 230027, China

³Division of Life Sciences and Medicine, The First Affiliated Hospital of USTC, University of Science and Technology of China, Hefei 230031, China

⁴Anhui Provincial Cancer Hospital, Hefei 230031, China

Corresponding author: Zhenchao Tao (taozhenchao@sina.com)

This work was supported in part by the “Xinhua 08” Financial and Economic Data Cloud Service Platform Research Grant, and in part by the grants from the Youth Foundation of The First Affiliated Hospital West District of USTC and the Anhui Provincial Cancer Hospital.

ABSTRACT Neural network-based approaches have become the driven forces for Natural Language Processing (NLP) tasks. Conventionally, there are two mainstream neural architectures for NLP tasks: the recurrent neural network (RNN) and the convolution neural network (ConvNet). RNNs are good at modeling long-term dependencies over input texts, but preclude parallel computation. ConvNets do not have memory capability and it has to model sequential data as un-ordered features. Therefore, ConvNets fail to learn sequential dependencies over the input texts, but it is able to carry out high-efficient parallel computation. As each neural architecture, such as RNN and ConvNets, has its own pro and con, integration of different architectures is assumed to be able to enrich the semantic representation of texts, thus enhance the performance of NLP tasks. However, few investigation explores the reconciliation of these seemingly incompatible architectures. To address this issue, we propose a hybrid architecture based on a novel hierarchical multi-granularity attention mechanism, named Multi-granularity Attention-based Hybrid Neural Network (MahNN). The attention mechanism is to assign different weights to different parts of the input sequence to increase the computation efficiency and performance of neural models. In MahNN, two types of attentions are introduced: the syntactical attention and the semantical attention. The syntactical attention computes the importance of the syntactic elements (such as words or sentence) at the lower symbolic level and the semantical attention is used to compute the importance of the embedded space dimension corresponding to the upper latent semantics. We adopt the text classification as an exemplifying way to illustrate the ability of MahNN to understand texts. The experimental results on a variety of datasets demonstrate that MahNN outperforms most of the state-of-the-arts for text classification.

INDEX TERMS Attention mechanism, multichannel, convolutional neural network, text classification.

I. INTRODUCTION

Nature language understanding plays an critical role in machine intelligence and it includes many challenging NLP tasks such as reading comprehension [1], machine translation [2], question answering [3] and etc.. Amongst a wide spectrum of NLP tasks, text classification [4] is considered as the foundation for its measuring the semantic similarities between texts. Traditional machine learning methods

The associate editor coordinating the review of this manuscript and approving it for publication was Long Wang¹.

employ hand-crafted features to model the statistical properties of syntactical elements (usually words), which are further fed into the classification algorithms such as k-Nearest Neighbor (k-NN), Random Forests, Support Vector Machines (SVM), or its probabilistic versions [5]–[7]. However, such hand-crafted features often suffered from the loss of semantic information and scalability. To solve the drawbacks of the hand-crafted features, automatic learning of representation using the neural networks was introduced into NLP fields. Word embedding is a foretype of automatic representation learning [8], [9], which outperforms the traditional

methods for alleviating the sparsity problem and enhancing the semantic representation.

In recent years, the NLP community has conducted extensive investigations on the neural-based approaches [10], [11]. There exist a diversity of deep neural network architectures with different modeling capabilities. The RNN is a widely-used neural network architecture for NLP tasks owing to its capability to model sequences with long-term dependencies [12]. When modeling texts, a RNN sequentially processes word by word and generates a hidden state at each time step to represent all previous words. However, although the purpose of RNNs is to capture the long-term dependencies, theoretical and empirical studies have revealed that it is difficult for RNNs to learn very long-term information. To address this problem, the long short-term memory network (LSTM) [13] and other variants such as gated recurrent unit (GRU) [14], simple recurrent unit (SRU) [15] were proposed for better remembering and memory accesses. Another roadblock for RNNs is that when they are used to process a long sequence, the latest information is more dominant than the earlier one, however, which might be the real significant part of the sequence. In fact, the most important information can appear anywhere in a sequence rather than at the end. Consequently, some researchers proposed to assign the same weight to all hidden states and average the hidden states of all time steps to equally spread the focus to all the sequence.

Inspired by the biological ability to focus on the most important information and ignore the irrelevant ones, the attention mechanism was introduced to assign different weights to the elements at different positions in a sequence and select the informative ones for the downstream tasks [16]. Nowadays, the attention mechanism has become an integral part of sequence modeling, especially with RNNs [1]. The attention mechanism enables RNNs to maintain a variable-length memory and compute the outputs based on the importance weights of different parts in a sequence. The attention mechanism has been empirically proven to be effective in NLP tasks such as neural machine translation [14]. However, the attention mechanism cannot capture the relationships between words and the word ordering information, which contains important semantic information for downstream tasks. Taking the sentences “*Tina likes Bob.*” and “*Bob likes Tina.*” as examples, the weighted sum of their hidden states encoded by RNN are almost the same. Nevertheless, the two sentences have different meanings.

The ConvNet is another widely-adopted neural architecture for NLP tasks. The modeling power of ConvNets relies on four key factors: local connections, shared weight, pooling and multi-layers. The fundamental assumption behind the ConvNet approaches is that locally grouped data in natural signals are often high correlated and the compositional hierarchies in natural signals can be exploited by the stacked convolutional layers. As a result, ConvNets have been believed to be good at extracting informative semantic representations from the salient N-gram features of input word sequences by utilizing convolutional filters in a parallel way. For the above

example, 2-gram features of “*Tina likes*” and “*likes Bob*” that contain the word ordering information can be captured by ConvNets. These features are more representative for the original sentence than the weighted sum of the hidden states. Therefore, ConvNets have been employed for a variety of NLP tasks and achieved impressive results in sentence modeling [17], semantic parsing [18], and text classification [19]. Moreover, ConvNets can operate on different levels of lexical structures such as characters, words, sentences, or even the whole document. For instance, some research has shown that the character-level text classification using ConvNets can achieve competitive results in comparison with the state-of-the-arts [20], [21]. However, basic ConvNets apply a fixed-width window to slide over the input sequences, which limits the created representations to local semantic pattern, failing to capture long-term dependencies.

To take full advantage of both the ConvNet and the RNN, and complement the superiorities of different neural architectures, researchers explored to introduce the hybrid structure of the ConvNets and the RNNs. For instance, the recurrent convolutional neural network [22] proposed a recurrent structure of convolutional filters to enhance the contextual modeling ability to avoid the problem of fixed-width sliding windows. This work also claimed to apply a max-pooling layer to automatically determine the key components for text classification. However, even though this approach managed to reduce noise by replacing the fixed-width sliding window of ConvNets with a recurrent mechanism, it still depend on the max-pooling to determine the discriminative features and lacks the mechanism to selectively choose the dominant component as the attention mechanism can do. Similarly, Wang *et al.* proposed the convolutional recurrent neural network [23] that stacked four types of neural layers: word embedding, Bidirectional RNN layer, convolutional layer, and max-pooling layer. This approach functions very similarly to the one in [22], but with disparate applications in sentence classification and answer selection. Also, this work bypassed the attention mechanism when integrating the ConvNet and the RNN structures.

As discussed above, any neural architecture has its own pros and cons, it is reasonable to conjecture that consistently combing different architectures can benefit extracting of different aspects of linguistic information from texts. However, to the best of our knowledge, there are still no efforts in integrating entirely the ConvNet, RNN and attention architectures. Inspired by proposition by Lecun *et al.* [24], we hypothesize that the attention mechanism can function as an adhesive that seamlessly integrate the ConvNet and the RNN architecture, where the RNN layer is used to represent the input word sequences and the ConvNet layer is used for classification. Furthermore, we assume that, besides attending to elements (words as a typical example) at syntactical or symbolic level, coarser-grained attentions at the hidden state vectorial space can improve the local N-gram coherence for ConvNets, as the attentions on hidden state vectors can select the salient dimensions that represent most informative

latent semantics, hence reducing the noise perturbation to the ConvNet layer and enhancing the classification performance.

Based on the above motivations, we propose a hybrid architecture based on a novel hierarchical multi-granularity attention mechanism, named Multi-granularity Attention-based Hybrid Neural Network (MahNN). In MahNN, two types of attentions are introduced: the syntactical attention and the semantical attention. The syntactical attention computes the importance of the syntactic elements (such as words or sentence) at the lower symbolic level and the semantical attention is used to compute the importance of the embedded space dimension corresponding to the upper latent semantics. We adopt the text classification as an exemplifying way to illustrate the ability of MahNN to understand texts. The experimental results on a variety of datasets demonstrate that MahNN outperforms most of the state-of-the-arts for text classification.

The main contributions of our work are listed as follows:

- 1) We propose a hybrid neural architecture MahNN that, for the first time, seamlessly integrate the RNN architecture and the ConvNet with an attention mechanism. In this architecture, the different neural structure each learns a different aspect of semantic information from the linguistic structures and collectively strengthen the power of semantical understanding of texts.
- 2) we introduce a novel hierarchical multi-granularity attention mechanism, which includes the syntactical attention and the semantical attention. The syntactical attention and the semantical attention compute the importance weights at the lower symbolic level and the upper latent semantics level, respectively. This coarser-grained attention mechanism helps to learn semantic representations more precisely.

This article is organized as follows. Section II introduces the related work about ConvNet and attention mechanisms. Section III introduces the proposed MahNN in detail. And Section IV introduces datasets, baselines, experiments, and analysis. Finally, Section V concludes this article.

II. RELATED WORK

Most of the previous work has exploited deep learning to deal with NLP tasks, including learning distributed representations of words, sentences or documents [11], [17], [23], [25] and text classification [20], [22], [26], [27], etc.

A ConvNet architecture [19] was proposed with multiple filters to capture local correlations followed by max-pooling operation to extract dominant features. This architecture performs well on text classification with a few parameters. The case of using character-level ConvNet was explored for text classification without word embedding [20] and in this work language was regarded as a kind of signal. Based on character-level representations, very deep convolutional networks (VDCNN) [28] were applied to text classification which is up to 29 convolutional layers much larger than 1 layer used by [19]. To capture word correlations of different sizes, a dynamic k -max-pooling method, a global

pooling operation over linear sequences, was proposed to keep features better [17]. Tree-structured sentences were also explored convolutional models [29]. Multichannel variable-size convolution neural network (MVConvNet) [30] combined diverse versions of pre-trained word embedding and used varied-size convolution filters to extract features.

A RNN is often employed to process temporal sequences. In addition to RNN, there are several approaches for sequences learning, such as echo state network and learning in the model space [31]–[33]. In the learning in the model space, it transforms the original temporal series to an echo state network (ESN), and calculates the ‘distance’ between ESNs [34], [35]. Therefore, the distance based learning algorithms could be employed in the ESN space [36]. Chen *et al.* [37] investigated the trade-off between the representation and discrimination abilities. Gong *et al.* proposed the multi-objective version for learning in the model space [38].

The other popular RNN architecture is able to deal with input sequences of varied length and capture long-term dependencies. Gated recurrent neural network (GRU) [39] was proposed to model sequences. As a similar work, GRU was applied to model documents [12]. Their works show that GRU has the ability to encode relations between sentences in a document. To improve the performance of GRU on large scale text, hierarchical attention networks (HAN) [26] was proposed. HAN has a hierarchical structure including word encoder and sentence encoder with two levels of attention mechanisms.

As an auxiliary way to select inputs, attention mechanism is widely adopted in deep learning recently due to its flexibility in modeling dependencies and parallelized calculation. The attention mechanism was introduced to improve encoder-decoder based neural machine translation [16]. It allows a model to automatically search for parts of elements that are related to the target word. As an extension, global attention and local attention [1] were proposed to deal with machine translation and their alignment visualizations proved the ability to learn dependencies. In HAN [26], hierarchical attention was used to generate document-level representations from word-level representations and sentence-level representations. This architecture simply sets a trainable context vector as a high-level representation of a fixed query. This way may be unsuitable because the same words may count differently in varied contexts. In a recent work [40], the calculation of attention mechanism was generalized into Q-K-V¹ form.

III. MULTI-GRANULARITY ATTENTION-BASED HYBRID NEURAL NETWORK

The MahNN architecture is demonstrated in Fig.1. It consists of three parts: bi-directional long short-term memory (Bi-LSTM), attention layer and convolutional neural network (ConvNet). The following sections describe how we utilize Bi-LSTM to generate the syntactical attention and the semantical attention, and form multichannel for ConvNet.

¹Q-K-V denotes query, key and value respectively.

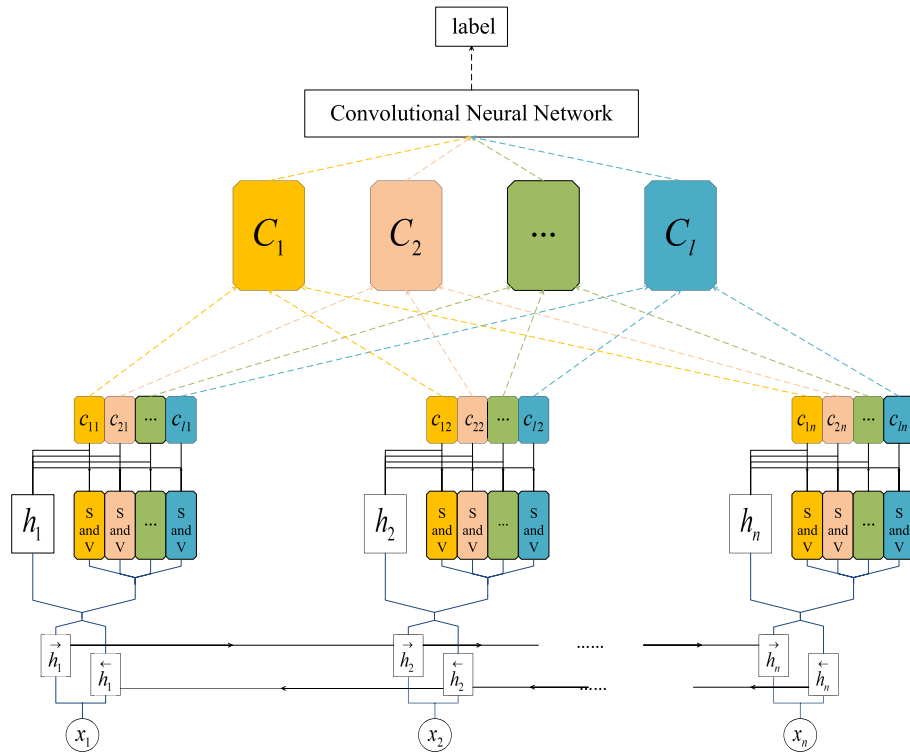


FIGURE 1. The structure of the attention-based multichannel convolutional neural network. S and V denote the syntactical attention and the semantical attention, respectively. Blocks of the same color are merged into one channel.

A. LONG SHORT-TERM MEMORY NETWORK

In many NLP tasks, RNN processes word embedding for texts of variable length and generates a hidden state h_t in t time step by recursively transforming the previous hidden state h_{t-1} and the current input vector x_t .

$$h_t = f(W \cdot [h_{t-1}, x_t] + b), \quad (1)$$

where $W \in \mathbb{R}^{l_h \times (l_h + l_i)}$, $b \in \mathbb{R}^{l_h}$, l_h and l_i are dimensions of hidden state and input vector respectively, and $f(\cdot)$ represents activation function such as $\tanh(\cdot)$. However, standard RNN is not a preferable choice for researchers due to the problem of gradient exploding or vanishing [41]. To address this problem, the long short-term memory network (LSTM) was introduced and obtained remarkable performance.

As a variant of RNNs, the LSTM architecture has a range of tandem modules whose parameters are shared. At t time step, the hidden state h_t is controlled by the previous hidden state h_{t-1} , input x_t , forget gate f_t , input gate i_t and output gate o_t . These gates identify the way of updating the current memory cell c_t and the current hidden state h_t . The LSTM transition function can be summarized by the following equations:

$$\begin{aligned} f_t &= \sigma(W_f \cdot [h_{t-1}, x_t] + b_f), \\ i_t &= \sigma(W_i \cdot [h_{t-1}, x_t] + b_i), \\ o_t &= \sigma(W_o \cdot [h_{t-1}, x_t] + b_o), \\ \tilde{C}_t &= \tanh(W_C \cdot [h_{t-1}, x_t] + b_C), \\ C_t &= f_t \odot C_{t-1} + i_t \odot \tilde{C}_t, \\ h_t &= o_t \odot \tanh(C_t). \end{aligned} \quad (2)$$

Here, σ is the logistic sigmoid function that has the domain of all real numbers, with return value ranging from 0 to 1. \tanh denotes the hyperbolic tangent function with return value ranging from -1 to 1. Intuitively, the forget gate f_t controls the extent to which the previous cell state C_{t-1} remains in the cell. The input gate i_t controls the extent to which a new input flows into the cell. The output gate o_t controls the extent to which the cell state C_t is used to compute the current hidden state h_t . The existence of those gates enables LSTM to capture long-term dependencies when dealing with time-series data.

Though unidirectional LSTM includes an unbounded sentence history in theory, it is still constrained since the hidden state of each time step fails to model future words of a sentence. Therefore, Bi-LSTM provides a way to include both previous and future context by applying one LSTM to process sentence forward and another LSTM to process sentence backward.

Given a sentence of n words $\{w_i\}_{i=1}^n$, we first transfer the one-hot vector w_i into a dense vector x_i through an embedding matrix W_e with the equation $x_i = W_e w_i$. We use Bi-LSTM to get the annotations of words by processing sentence from both directions. Bi-LSTM contains the backward \overleftarrow{LSTM} that reads the sentence from x_n to x_1 and a forward \overrightarrow{LSTM} which reads from x_1 to x_n :

$$\begin{aligned} x_i &= W_e w_i, \quad i \in [1, n], \\ \overrightarrow{h}_i &= \overrightarrow{LSTM}(x_i), \quad i \in [1, n], \\ \overleftarrow{h}_i &= \overleftarrow{LSTM}(x_i), \quad i \in [1, n]. \end{aligned} \quad (3)$$

At i time step, we obtain the forward hidden state \vec{h}_i which stores previous information and the backward hidden state \overleftarrow{h}_i which stores future information. $h_i = [\vec{h}_i, \overleftarrow{h}_i]$ is a summary of the sentence centered around w_i .

B. HIERARCHICAL MULTI-GRANULARITY ATTENTIONS

For the NLP tasks such as text classification and sentiment analysis, different words contribute unequally to the representation of a sentence. The attention mechanism can be used to reflect the importance weight of the input element so that the relevant element contributes significantly to the merged output. Although the attention mechanism is able to model dependencies flexibly, it is still a crude process because of the loss of latent semantic information. We apply attention mechanisms to the hidden states of Bi-LSTM and splice them into a matrix.

Taking the form of the matrix rather than a weighted sum of vectors will keep the order information. Furthermore, by applying the syntactical attention and the semantical attention, we could obtain several matrices and take them as multichannel for inputs of ConvNet.

1) SYNTACTICAL ATTENTION MECHANISM

We introduce the syntactical attention to calculate the importance weights of all input elements. M is the association matrix that represents the association among words in texts. The element of the i -th row and the j -th column of M represents the degree of association between the i -th word and the j -th word. We will set L channel mask matrices V if we need L channels. In the l -th channel, $M_{l,i,j}$ is calculated as follows:

$$M_{l,i,j} = \tanh([h_i, W_l \cdot h_j] + b_l), \tag{4}$$

The i -th channel mask matrix is defined as follows:

$$V_{l,i,j} \sim B(1, p_l), i \in [1, n], j \in [1, n], \tag{5}$$

That means each element of V_l obeys binomial distribution. Given $M_{l,i,j}$ and $V_{l,i,j}$, the i -th channel is computed as follows:

$$A_l = M_l \otimes V_l, \tag{6}$$

$$s_{lk} = \sum_x A_{l,xk}, \tag{7}$$

$$p_k = \begin{cases} -99999, & \text{if } x_k \text{ is from pad} \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

$$\text{score}_{lk} = p_k + s_{lk}, \tag{9}$$

$$a_{lk} = \frac{\exp(\text{score}_{lk})}{\sum_{i=1}^n \exp(\text{score}_{li})}, \tag{10}$$

$$c_{li} = a_{li} \cdot h_i, \tag{11}$$

$$C_l = [c_{l1}, c_{l2}, c_{l3}, \dots, c_{ln}]. \tag{12}$$

Here, c_{li} denotes the new representation of h_i in the l -th channel and \otimes denotes element-wise product operation. The *pad* symbol still carries little information after it is encoded by Bi-LSTM. So, if word x_k is a *pad* symbol, its syntactical attention s_{lk} will be subtracted from 99999 before softmax operation and so that a_{lk} will be close to 0 after softmax. By concatenating all C_{li} , we obtain the l -th channel C_l .

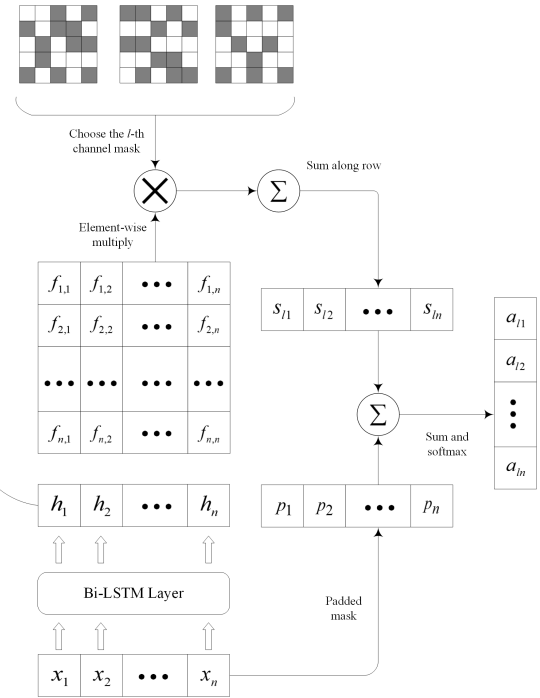


FIGURE 2. Syntactical attention mechanism.

The multichannel representations reflect the different contributions of different words to the semantics of a text, which is regarded as diversification of input information caused by data perturbation.

The whole process of the syntactical attention is shown in Fig. 2.

2) SEMANTICAL ATTENTION MECHANISM

Given that a syntactical element (a word or a sentence) is encoded into an n -dimensional vector $(v_1, v_2, v_3, \dots, v_n)^T$, each dimension in the embedding vector space corresponds to a specific latent semantic factor. Analyzing the different impacts of these semantic factors and selecting the informative ones can improve the performance of the downstream tasks.

Based on the above hypotheses, we propose the semantical attention mechanism to compute the semantical importance weight of each dimension in the input element:

$$\begin{aligned} \overrightarrow{\text{score}}_{li} &= W_{l1}^T \sigma(W_{l2} \cdot h_i + b_l), \\ \vec{a}_{li} &= \frac{\exp(\overrightarrow{\text{score}}_{li})}{\sum_i \exp(\overrightarrow{\text{score}}_{li})}, \\ c_{li} &= \vec{a}_{li} \odot h_i, \\ C_l &= [c_{l1}, c_{l2}, c_{l3}, \dots, c_{ln}]. \end{aligned} \tag{13}$$

where c_{li} denotes the final representation of h_i in the l -th channel. By concatenating all c_{li} where $i \in [1, n]$, we obtain the l -th channel C_l .

By combining the syntactical attention and the semantical attention, multichannel is generated as follows:

$$\begin{aligned} c_{li} &= a_{li} \cdot (\vec{a}_{li} \odot h_i), \\ C_l &= [c_{l1}, c_{l2}, c_{l3}, \dots, c_{ln}]. \end{aligned} \tag{14}$$

3) CONVOLUTIONAL NEURAL NETWORK

ConvNets utilize several sliding convolution filters to extract local features. Assume we have one channel that is represented as

$$C = [c_1, c_2, c_3, \dots, c_n]. \quad (15)$$

Here, $C \in \mathbb{R}^{n \times k}$, n is the length of the input element, and k is the embedded dimension of each input element. In a convolution operation, a filter $m \in \mathbb{R}^{lk}$ is involved in applying to consecutive l words to generate a new feature:

$$x_i = f(m \cdot c_{i:i+l-1} + b), \quad (16)$$

where $c_{i:i+l-1}$ is the concatenation of c_i, \dots, c_{i+l-1} . f is a non-linear activation function such as *relu* and $b \in \mathbb{R}$ is a bias term. After the filter m slide across $\{c_{1:l}, c_{2:l+1}, \dots, c_{n-l+1:n}\}$, we obtain a feature map:

$$x = [x_1, x_2, \dots, x_{n-l+1}]. \quad (17)$$

We apply max-pooling operation over the feature map x and take the maximum value $\hat{x} = \max\{x\}$ as the final feature extracted by the filter m . This pooling scheme is to capture the most dominating feature for each filter. ConvNet obtains multiple features by utilizing multiple filters with varied sizes. These features form a vector $r = [x_1, x_2, \dots, x_s]$ (s is the number of filters) which will be passed to a fully connected softmax layer to output the probability distribution over labels

$$y = \text{softmax}(W \cdot r + b). \quad (18)$$

Given a training sample (x^i, y^i) where $y^i \in \{1, 2, \dots, c\}$ is the true label of x^i and the estimated probability of our model is $\tilde{y}_j^i \in [0, 1]$ for each label $j \in \{1, 2, \dots, c\}$, and the error is defined as:

$$L(x^i, y^i) = - \sum_{j=1}^c \text{if}\{y^i = j\} \log(\tilde{y}_j^i). \quad (19)$$

Here, c denotes the number of possible labels of x^i and $\text{if}\{\}$ is an indicator function such that: $\text{if}\{y^i = j\} = 1$ if $y^i = j$, $\text{if}\{y^i = j\} = 0$ otherwise. We employ stochastic gradient descent (SGD) to update the model parameters and adopt Adam optimizer. Here, the ConvNet layer is intended to enhance the local N-gram coherence instead of merely averaging weighted sum, thus improving the discriminative ability to text classification.

IV. EXPERIMENTAL STUDY

A. EXPERIMENTS DATASETS

We evaluate our model against other baseline models on a variety of datasets. Summary statistics of the datasets are shown in Table 1.

- **MR:** Short movie review dataset with one sentence per review. Each review was labeled with their overall sentiment polarity (positive or negative).
- **Subj:** Subjectivity dataset containing sentences labeled with respect to their subjectivity status (subjective or objective).

TABLE 1. Summary statistics of the datasets. **c:** Number of classes. **l:** Average length of sentences. **N:** Size of datasets. **V:** Vocabulary size. **V_{word}:** Number of words present in the set of pre-trained word vectors, respectively. **Test:** Size of test sets. **CV (cross validation):** No standard train/test split and thus 10-fold CV was used.

Data	c	l	N	V	V_{word}	Test
MR	2	20	10662	18765	16448	CV
Subj	2	23	10000	21323	17913	CV
MPQA	2	3	10606	6246	6083	CV
SST-1	5	18	11855	17836	16262	2210
SST-2	2	19	9613	16185	14838	1821

- **SST-1:** Stanford Sentiment Treebank—an extension of MR but with train/dev/test splits provided and fine-grained labels (very positive, positive, neutral, negative, very negative).
- **SST-2:** Same as SST-1 but with neutral reviews removed and binary labels
- **MPQA:** Opinion polarity detection subtask of the MPQA dataset.

B. EXPERIMENTS SETTINGS

- **Padding:** We first use *len* to denote the maximum length of the sentence in the training set. As the convolution layer requires input of fixed length, we pad each sentence that has a length less than *len* with *UNK* symbol which indicates the unknown word in front of the sentence. Sentences in the test dataset that are shorter than *len* are padded in the same way, but for sentences that have a length longer than *len*, we just cut words at the end of these sentences to ensure all sentences have a length *len*.
- **Initialization:** We use publicly available *word2vec* vectors to initialize the words in the dataset. *word2vec* vectors are pre-trained on 100 billion words from Google News through an unsupervised neural language model. For words that are not present in the set of pre-trained words or rarely appear in data sets, we initialize each dimension from $U[-0.25, 0.25]$ to ensure all word vectors have the same variance. Word vectors are fine-tuning along with other parameters during the training process.
- **Hyper-parameters:** The feature representation of Bi-LSTM is controlled by the size of hidden states. We investigate our model with various hidden sizes and set the hidden size of unidirectional LSTM to be 100. We also investigate the impact of the size of the channels on our model. When the size of the channels is set to be 1, our model is a single channel network. When increasing the size of the channels, our model obtains a more semantic representation of the text. Convolutional filter decides the n-gram feature which directly influences the classification performance. We set the filter size based on different datasets and simply set the filter map to be 100. More details of hyper-parameters are shown on Table 3.
- **Other settings:** We only use one Bi-LSTM layer and one convolutional layer. Dropout is applied on the word

TABLE 2. Accuracies of MahNN against other models. We use underline to highlight wins.

Model	MR	Subj	MPQA	SST-1	SST-2
Sent-Paser [42]	79.5	-	86.3	-	-
NBSVM [43]	79.4	93.2	86.3	-	-
MNB [43]	79.0	93.6	86.3	-	-
F-Dropout [44]	79.1	93.6	86.3	-	-
G-Dropout [44]	79.0	93.4	86.1	-	-
Paragraph-Vec [11]	-	-	-	48.7	87.8
RAE [45]	77.7	-	-	43.2	82.4
MV-RNN [46]	79.0	-	-	44.4	82.9
RNTN [47]	-	-	-	45.7	85.4
DConvNet [17]	-	-	-	<u>48.5</u>	86.8
Fully Connected [48]	81.59	-	-	-	-
ConvNet-non-static [19]	81.5	93.4	89.5	48.0	87.2
ConvNet-multichannel [19]	81.1	93.2	89.4	47.4	<u>88.1</u>
WkA+25%flexible [49]	80.02	92.68	-	46.11	84.29
Fully Connected [48]	81.59	-	-	-	-
L-MConvNet [50]	82.4	-	-	-	-
Helustering avg [51]	80.20	-	-	-	-
Kmeans centroid [51]	80.21	-	-	-	-
MahNN-1	82.17	92.96	89.61	47.02	86.43
MahNN-3	<u>82.57</u>	<u>93.75</u>	<u>89.75</u>	47.58	86.85
MahNN-5	82.41	93.43	89.34	47.41	86.56
MahNN-7	82.23	93.36	89.46	47.16	86.29
MahNN-rv	82.34	93.52	89.55	47.37	86.69

embedding layer, the ConvNet input layer, and the penultimate layer. Weight vectors are constrained by $L2$ regularization and the model is trained to minimize the cross-entropy loss of true labels and the predicted labels.

C. BASELINES

We compare our model with several baseline methods which can be divided into the following categories:

1) TRADITIONAL MACHINE LEARNING

A statistical parsing framework was studied for sentence-level sentiment classification [42]. Simple Naive Bayes (NB) and Support Vector Machine (SVM) variants outperformed most published results on sentiment analysis datasets [43]. It was shown in [44] how to do fast dropout training by sampling from or integrating a Gaussian approximation. These measures were justified by the central limit theorem and empirical evidence, and they resulted in an order of magnitude speedup and more stability.

2) DEEP LEARNING

Word2vec [11] was extended with a new method called Paragraph-Vec, which is an unsupervised algorithm that learns fixed-length feature representations from variable-length pieces of texts, such as sentences, paragraphs, and documents. Various recursive networks were extended [45]–[47]. Generic and target domain embeddings were incorporated to ConvNet [17]. A series of experiments with ConvNets was trained on top of pre-trained word vectors for sentence-level classification tasks [19]. Desirable properties such as semantic coherence, attention mechanism and kernel reusability in ConvNet were empirically studied for learning sentence-level tasks [49]. Both word embeddings created from generic and target domain corpora were utilized when it's difficult to find

TABLE 3. Hyper-parameters setting. *Hidden size*: The dimension of unidirectional LSTM. *L2*: $L2$ regularization term. *Channel*: The number of channels. *Filter size*: The size of convolutional filters. *Filter map*: The number of convolutional filter maps.

Hyperparameter	Ranges	Adopt
<i>Hidden size</i>	{16, 32, 50, 64, 100, 128, ...}	100
<i>L2</i>	{0.0001, 0.0005, 0.001, 0.003, ...}	0.0005
<i>Channel</i>	{1, 2, 3, 4, 5, 6, ...}	3
<i>Filter size</i>	{(2,3,4), (3,4,5), (4,5,6), ...}	-
<i>Filter map</i>	{10, 30, 50, 100, 150, ...}	100

a domain corpus [48]. A hybrid L-MConvNet model was proposed to represent the semantics of sentences [50].

D. RESULTS AND ANALYSIS

Table 2 shows results of our model on five datasets against other methods. We refer to our model as MahNN- $\{1, 3, 5, 7, rv\}$, which stands for MahNN with different channel settings. As we can see from the Table 2, MahNNs exceed other models in 3 out of 5 tasks. For MR/Subj/MPQA, MahNN-3 outperforms other baselines and we can get a rough observation that MahNN-3 performs better than MahNN- $\{5, 7\}$, and they all perform better than MahNN-1, which is a single channel model. This phenomenon indicates that multichannel representation is effective, but continuing to increase the size of the channels does not improve our model all the time. We conjecture that it would be better to choose x according to the number of informative words in the sentence. Take the following sentences for example:

- 1) *An undeniably gorgeous, terminally document of a troubadour, his acolytes, and the triumph of his band.*
- 2) *Uplifting as only a document of the worst possibilities of mankind can be, and among the best films of the year.*

an undeniably gorgeous , terminally document of a troubadour , his acolytes , and the triumph of his band

uplifting as only a document of the worst possibilities of mankind can be , and among the best films of the year

an undeniably gorgeous , terminally document of a troubadour , his acolytes , and the triumph of his band

uplifting as only a document of the worst possibilities of mankind can be , and among the best films of the year

an undeniably gorgeous , terminally document of a troubadour , his acolytes , and the triumph of his band

uplifting as only a document of the worst possibilities of mankind can be , and among the best films of the year

FIGURE 3. Visualization of the syntactical attention weights learned by different channels.

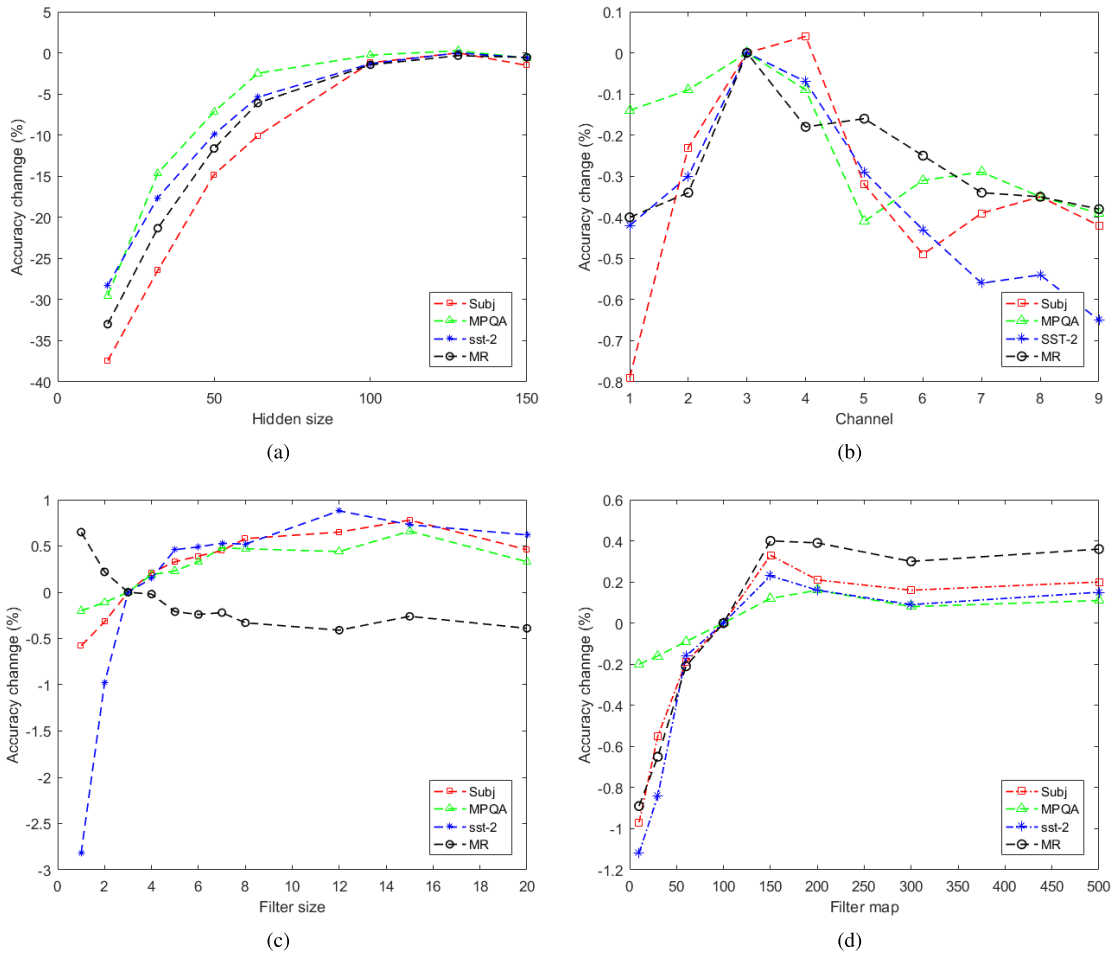


FIGURE 4. Effect of hyper-parameters: (a) hidden size, (b) channel, (c) filter size, and (d) the filter map.

Fig. 3 shows the visualization of syntactical attention distribution of the above sentences.

The second sentence could not be labeled positive or negative without a doubt if we focus on a single informative word (“uplifting”, “worst” or “best”) alone. Only if these informative words were all emphasized can this sentence be truly understood. “Uplifting” received more attention weight than other words in the first channel. “worst” received more attention weight in the second than the third channel and “best” received more attention weight in the third than the second channel. If the second channel is set to be an independent model, this sentence might be classified incorrectly. But MahNN-3 will still label this sentence as positive.

Multichannel essentially provides a way to represent a sentence from different views and provides diversification.

We also investigate the impact of the semantical attention on MahNN and find out that it considerably improves performance. MahNN-rv denotes MahNN-3 without applying the semantical attention mechanism. We owe the validity of the MahNN semantical attention mechanism to its selectivity of latent semantics that can better represent the texts in the specific given tasks. Actually, the semantical attention mechanism discriminates the perturbation of hidden states and makes the whole model more robust. Another advantage of the semantical attention mechanism is that it assigns different learning speeds to each dimension of the hidden state

indirectly so that informative dimension could be tuned at a bigger pace than dimension of less information.

E. PARAMETER SENSITIVITY

We further evaluate how the parameters of MahNN impact its performance on the text classification task. In this experiment, we evaluate the effect of change of *Hidden size*, *Channel*, *Filter size*, and *Filter map* on MahNN performance with other parameters remaining the same.

- **Impact of *Hidden size*:** Fig.4a shows the impact of *Hidden size* on classification accuracy. It can be observed that the classification accuracy of the model increases with the increasing of hidden size. When the hidden size is set to be 128, the accuracy curve of the model tends to be flat or even begins to decline. So, the hidden size of Bi-LSTM affects the encoding of the document. If the *Hidden size* is too small, it will lead to underfitting. If the *Hidden size* is too large, it will lead to overfitting.
- **Impact of *Channel*:** Fig.4b shows the impact of *Channel* on classification accuracy. We observe that the performance first rises and then tends to decline. When channel size is set to be 3, the model (MahNN-3) performs best on MPQA/SST-2/MR datasets. The model (MahNN-4) performs best on Subj dataset when channel size is set to be 4. This result shows that multichannel representations of texts help our model improve its performance. However, as the increasing number of the channels means the enlarged size of parameters, which might lead to overfitting.
- **Impact of *Filter size*:** Fig.4c shows the impact of *Filter size* on classification accuracy. It can be observed that the optimal filter size settings of each dataset are different, and the accuracy curve of the MR dataset is opposite to the accuracy curve of other datasets. When *Filter size* is between [10, 14], the model achieves high accuracy on MPQA/Subj/SST-2 datasets. But this performance improvement is not significant compared to the accuracy when *Filter size* is 2. In order to reduce the size of the parameters, *Filter size* of the model is set between [4, 8] in the experiment.
- **Impact of *Filter map*:** Fig.4d shows the impact of *Filter map* on classification accuracy. We can observe that the performance rises rapidly first and then tends to be flat. The number of *Filter map* determines the number of feature maps generated after the convolution operation. Each feature map represents a certain feature of the text. The more the number of feature maps, the more features that the convolution operation can extract, and the accuracy of the model can be higher. But the number of features of the text is finite, and the increase in the number of *Filter map* will also increase the size of trainable parameters, which may lead to overfitting.

V. CONCLUSION AND FUTURE WORK

In this article, we attempt to develop a hybrid architecture that can extract different aspects of semantic information from the

linguistic data with diverse types of neural structures. Intriguingly, we propose a novel hierarchical multi-granularity attention mechanism, consisting of the syntactical attention at the symbolic level and the semantical attention at the embedding level, respectively. The experimental results show that the MahNN model achieves impressive performances on a variety of benchmark datasets for the text classification task. Moreover, visualization of attention distribution illustrates that the hierarchical multi-granularity attention mechanism is effective in capturing informative semantics from different perspectives. We can draw the following conclusions from our work:

- 1) Hybrid neural architectures integrating a diversity of neural structures can improve the power of the representation learning from linguistic data. Richer semantic representations help to increase the capacity of deep understanding of texts and thus benefit to the downstream tasks in the NLP filed.
- 2) Hierarchical multi-granularity attention mechanism plays a significant role in constructing the hybrid neural architecture. The fine-grained attention at the symbolic level can diversify the semantic representations of input texts and the coarser-grained attention at the latent semantical space enhance the local N-gram coherence for the following ConvNet layers, thus increasing the performance of the text classification tasks.

There are several future directions to extend this work. First, we would investigate on applying a generative model to obtain multichannel representations of texts. Data augmentation in this way can represent much richer semantics. Second, ConvNets require the fixed-length inputs and perform some unnecessary convolution operations for NLP tasks. It is worthwhile to explore the novel ConvNet architecture processing with variable length. Moreover, we use simple calculating methods for the attention weights and this might not be able to demonstrate the full potential for the hierarchical multi-granularity attention mechanism. It would be intriguing to compute the attention weights with more advanced approaches such as transfer learning and reinforcement learning to further improve the performance.

REFERENCES

- [1] M.-T. Luong, H. Pham, and C. D. Manning, "Effective approaches to attention-based neural machine translation," 2015, *arXiv:1508.04025*. [Online]. Available: <http://arxiv.org/abs/1508.04025>
- [2] I. Sutskever, O. Vinyals, and Q. V. Le, "Sequence to sequence learning with neural networks," 2014, *arXiv:1409.3215*. [Online]. Available: <http://arxiv.org/abs/1409.3215>
- [3] A. Borde, S. Chopra, and J. Weston, "Question answering with subgraph embeddings," in *Proc. Conf. Empirical Methods Natural Lang. Process. (EMNLP)*, 2014, pp. 615–620.
- [4] B. Jiang, Z. Li, H. Chen, and A. G. Cohn, "Latent topic text representation learning on statistical manifolds," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 29, no. 11, pp. 5643–5654, Nov. 2018.
- [5] Z. Liu and H. Chen, "A predictive performance comparison of machine learning models for judicial cases," in *Proc. IEEE Symp. Ser. Comput. Intell. (SSCI)*, Nov. 2017, pp. 1–6.
- [6] H. Chen, P. Tino, and X. Yao, "Probabilistic classification vector machines," *IEEE Trans. Neural Netw.*, vol. 20, no. 6, pp. 901–914, Jun. 2009.

- [7] H. Chen, P. Tino, and X. Yao, "Efficient probabilistic classification vector machine with incremental basis function selection," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 25, no. 2, pp. 356–369, Feb. 2014.
- [8] J. Liu, Z. Liu, and H. Chen, "Revisit word embeddings with semantic lexicons for modeling lexical contrast," in *Proc. IEEE Int. Conf. Big Knowl. (ICBK)*, Aug. 2017, pp. 72–79.
- [9] J. Xu, J. Liu, L. Zhang, Z. Li, and H. Chen, "Improve chinese word embeddings by exploiting internal structure," in *Proc. Conf. North Amer. Chapter Assoc. Comput. Linguistics, Hum. Lang. Technol.*, 2016, pp. 1041–1050.
- [10] Y. Bengio, R. Ducharme, P. Vincent, and C. Janvin, "A neural probabilistic language model," *J. Mach. Learn. Res.*, vol. 3, pp. 1137–1155, Feb. 2003.
- [11] Q. Le and T. Mikolov, "Distributed representations of sentences and documents," in *Proc. Int. Conf. Mach. Learn.*, 2014, pp. 1188–1196.
- [12] D. Tang, B. Qin, and T. Liu, "Document modeling with gated recurrent neural network for sentiment classification," in *Proc. Conf. Empirical Methods Natural Lang. Process.*, 2015, pp. 1422–1432.
- [13] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural Comput.*, vol. 9, no. 8, pp. 1735–1780, 1997.
- [14] K. Cho, B. van Merriënboer, C. Gulcehre, D. Bahdanau, F. Bougares, H. Schwenk, and Y. Bengio, "Learning phrase representations using RNN encoder-decoder for statistical machine translation," 2014, *arXiv:1406.1078*. [Online]. Available: <http://arxiv.org/abs/1406.1078>
- [15] T. Lei, Y. Zhang, S. I. Wang, H. Dai, and Y. Artzi, "Simple recurrent units for highly parallelizable recurrence," 2017, *arXiv:1709.02755*. [Online]. Available: <http://arxiv.org/abs/1709.02755>
- [16] D. Bahdanau, K. Cho, and Y. Bengio, "Neural machine translation by jointly learning to align and translate," 2014, *arXiv:1409.0473*. [Online]. Available: <http://arxiv.org/abs/1409.0473>
- [17] N. Kalchbrenner, E. Grefenstette, and P. Blunsom, "A convolutional neural network for modelling sentences," 2014, *arXiv:1404.2188*. [Online]. Available: <http://arxiv.org/abs/1404.2188>
- [18] W.-T. Yih, X. He, and C. Meek, "Semantic parsing for single-relation question answering," in *Proc. 52nd Annu. Meeting Assoc. for Comput. Linguistics*, vol. 2, 2014, pp. 643–648.
- [19] Y. Kim, "Convolutional neural networks for sentence classification," 2014, *arXiv:1408.5882*. [Online]. Available: <http://arxiv.org/abs/1408.5882>
- [20] X. Zhang, J. Zhao, and Y. LeCun, "Character-level convolutional networks for text classification," in *Proc. Adv. Neural Inf. Process. Syst.*, 2015, pp. 649–657.
- [21] J. Xu, J. Liu, L. Zhang, Z. Li, and H. Chen, "Improve Chinese word embeddings by exploiting internal structure," in *Proc. Conf. North Amer. Chapter Assoc. Comput. Linguistics, Hum. Lang. Technol.*, 2016, pp. 1041–1050.
- [22] S. Lai, L. Xu, K. Liu, and J. Zhao, "Recurrent convolutional neural networks for text classification," in *Proc. AAAI*, vol. 33, 2015, pp. 2267–2273.
- [23] C. Wang, F. Jiang, and H. Yang, "A hybrid framework for text modeling with convolutional RNN," in *Proc. 23rd ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining*, Aug. 2017, pp. 2061–2069.
- [24] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, May 2015.
- [25] T. Mikolov, I. Sutskever, K. Chen, G. S. Corrado, and J. Dean, "Distributed representations of words and phrases and their compositionality," in *Proc. Adv. Neural Inf. Process. Syst.*, 2013, pp. 3111–3119.
- [26] Z. Yang, D. Yang, C. Dyer, X. He, A. Smola, and E. Hovy, "Hierarchical attention networks for document classification," in *Proc. Conf. North Amer. Chapter Assoc. Comput. Linguistics, Hum. Lang. Technol.*, 2016, pp. 1480–1489.
- [27] A. Joulin, E. Grave, P. Bojanowski, and T. Mikolov, "Bag of tricks for efficient text classification," 2016, *arXiv:1607.01759*. [Online]. Available: <http://arxiv.org/abs/1607.01759>
- [28] A. Conneau, H. Schwenk, L. Barrault, and Y. Lecun, "Very deep convolutional networks for text classification," 2016, *arXiv:1606.01781*. [Online]. Available: <http://arxiv.org/abs/1606.01781>
- [29] L. Mou, H. Peng, G. Li, Y. Xu, L. Zhang, and Z. Jin, "Discriminative neural sentence modeling by tree-based convolution," 2015, *arXiv:1504.01106*. [Online]. Available: <http://arxiv.org/abs/1504.01106>
- [30] W. Yin and H. Schütze, "Multichannel variable-size convolution for sentence classification," 2016, *arXiv:1603.04513*. [Online]. Available: <http://arxiv.org/abs/1603.04513>
- [31] Y. Li, B. Jiang, H. Chen, and X. Yao, "Symbolic sequence classification in the fractal space," *IEEE Trans. Emerg. Topics Comput. Intell.*, early access, Nov. 5, 2018, doi: [10.1109/TETCI.2018.2876528](https://doi.org/10.1109/TETCI.2018.2876528).
- [32] Z. Gong and H. Chen, "Sequential data classification by dynamic state warping," *Knowl. Inf. Syst.*, vol. 57, no. 3, pp. 545–570, Dec. 2018.
- [33] H. Chen, P. Tiño, and X. Yao, "Cognitive fault diagnosis in tennessee eastman process using learning in the model space," *Comput. Chem. Eng.*, vol. 67, pp. 33–42, Aug. 2014.
- [34] H. Chen, P. Tiño, A. Rodan, and X. Yao, "Learning in the model space for cognitive fault diagnosis," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 25, no. 1, pp. 124–136, Jan. 2014.
- [35] H. Chen, F. Tang, P. Tino, and X. Yao, "Model-based kernel for efficient time series analysis," in *Proc. 19th ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining (KDD)*, 2013, pp. 392–400.
- [36] Z. Gong and H. Chen, "Model-based oversampling for imbalanced sequence classification," in *Proc. 25th ACM Int. Conf. Inf. Knowl. Manage.*, Oct. 2016, pp. 1009–1018.
- [37] H. Chen, F. Tang, P. Tino, A. G. Cohn, and X. Yao, "Model metric co-learning for time series classification," in *Proc. 24th Int. Joint Conf. Artif. Intell.*, 2015, pp. 3387–3394.
- [38] Z. Gong, H. Chen, B. Yuan, and X. Yao, "Multiobjective learning in the model space for time series classification," *IEEE Trans. Cybern.*, vol. 49, no. 3, pp. 918–932, Mar. 2019.
- [39] J. Chung, C. Gulcehre, K. Cho, and Y. Bengio, "Empirical evaluation of gated recurrent neural networks on sequence modeling," 2014, *arXiv:1412.3555*. [Online]. Available: <http://arxiv.org/abs/1412.3555>
- [40] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, and I. Polosukhin, "Attention is all you need," in *Proc. Adv. Neural Inf. Process. Syst.*, 2017, pp. 5998–6008.
- [41] Y. Bengio, P. Simard, and P. Frasconi, "Learning long-term dependencies with gradient descent is difficult," *IEEE Trans. Neural Netw.*, vol. 5, no. 2, pp. 157–166, Mar. 1994.
- [42] L. Dong, F. Wei, S. Liu, M. Zhou, and K. Xu, "A statistical parsing framework for sentiment classification," *Comput. Linguistics*, vol. 41, no. 2, pp. 293–336, Jun. 2015.
- [43] S. Wang and C. D. Manning, "Baselines and bigrams: Simple, good sentiment and topic classification," in *Proc. 50th Annu. Meeting Assoc. Comput. Linguistics*, vol. 2, 2012, pp. 90–94.
- [44] S. Wang and C. Manning, "Fast dropout training," in *Proc. Int. Conf. Mach. Learn.*, 2013, pp. 118–126.
- [45] R. Socher, J. Pennington, E. H. Huang, A. Y. Ng, and C. D. Manning, "Semi-supervised recursive autoencoders for predicting sentiment distributions," in *Proc. Conf. Empirical Methods Natural Lang. Process. Stroudsburg, PA, USA: Association for Computational Linguistics*, 2011, pp. 151–161.
- [46] R. Socher, B. Huval, C. D. Manning, and A. Y. Ng, "Semantic compositionality through recursive matrix-vector spaces," in *Proc. Joint Conf. Empirical Methods Natural Lang. Process. Comput. Natural Lang. Learn. Stroudsburg, PA, USA: Association for Computational Linguistics*, 2012, pp. 1201–1211.
- [47] R. Socher, A. Perelygin, J. Wu, J. Chuang, C. D. Manning, A. Ng, and C. Potts, "Recursive deep models for semantic compositionality over a sentiment treebank," in *Proc. Conf. Empirical Methods Natural Lang. Process.*, 2013, pp. 1631–1642.
- [48] N. Limsopatham and N. Collier, "Modelling the combination of generic and target domain embeddings in a convolutional neural network for sentence classification," in *Proc. ACL*, 2016, p. 136.
- [49] M. Lakshmana, S. Sellamanickam, S. Shevade, and K. Selvaraj, "Learning semantically coherent and reusable kernels in convolution neural nets for sentence classification," 2016, *arXiv:1608.00466*. [Online]. Available: <http://arxiv.org/abs/1608.00466>
- [50] Y. Guo, W. Li, C. Jin, Y. Duan, and S. Wu, "An integrated neural model for sentence classification," in *Proc. Chin. Control Decis. Conf. (CCDC)*, Jun. 2018, pp. 6268–6273.
- [51] H.-Y. Kim, J. Lee, N. Y. Yeo, M. Astrid, S.-I. Lee, and Y.-K. Kim, "CNN based sentence classification with semantic features using word clustering," in *Proc. Int. Conf. Inf. Commun. Technol. Converg. (ICTC)*, Oct. 2018, pp. 484–488.

• • •