An Attention-Gated Convolutional Neural Network for Sentence Classification

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Abstract: The classification task of sentences is very challenging because of the limited contextual information that sentences contain. In this paper, we propose an Attention Gated Convolutional Neural Network (AGCNN) for sentence classification, which generates attention weights from the feature’s context windows of different sizes by using specialized convolution encoders, to enhance the influence of critical features in predicting the sentence’s category. Experimental results demonstrate that our model could achieve a general accuracy improvement highest up to 3.1% (compared with standard CNN models), and gain competitive results over the strong baseline methods on four out of the six tasks. Besides, we propose an activation function named Natural Logarithm rescaled Rectified Linear Unit (NLReLU). Experimental results show that NLReLU could outperform ReLU and performs comparably to other well-known activation functions on AGCNN.

Keywords: sentence classification; convolutional neural networks; attention-gated convolutional neural network; NLReLU activation function

1. Introduction

Text classification has recently attracted a great deal of attention. It is one of the essential tasks of natural language processing and has been widely studied in different communities such as text mining [1] and information retrieval [2]. The primary objective of text classification is to assign texts to predefined categories according to its content automatically. The text is a typical kind of unstructured information and is complicated for the computer to understand and handle. Meanwhile, due to the limited semantic information of the sentence text carriers, it cannot provide enough word co-occurrence statistics or other features for calculating the similarity of text [3]. Therefore, sentence-level classification task has become a considerable challenge.

The representation method of the text mainly affects the performance of classifiers. Traditional classification approaches mainly use the representations of statistical indicators of words such as Term Frequency-Inverse Document Frequency (TF-IDF) [4,5]. This kind of weighting scheme does not take into consideration the positional factors of the feature words and the feature words that have larger weights are usually not representative. Some classification algorithms such as Naive Bayes (NB) [6] or Support Vector Machine (SVM) [7] use the bag-of-words [8] for feature extraction. However, these approaches will encounter problems with data sparse when the training set is small. Besides, there are also approaches based on n-grams including Naive Bayes SVM (NBSVM) [9], Multinomial Naive Bayes (MNB) [9] and SVMs [10]. Issues with these traditional methods above are that as the amount of training data increases, the dimension of feature vector will increase or even explode; and not all features are important for classifying, removing the features that are redundant or misleading is hard.

To deal with these problems, distributed representation [11-13] was successfully introduced in natural language processing systems, thereby promoting the development of the neural network-based approaches. Distributed representation can map words into dense real-valued and low-dimensional word vectors. Word vectors could obtain semantic and syntactic information through
unsupervised learning on corpus [14]. The sentence embedding representation can be obtained while learning the word vectors [15]. The advantage of distributed representation is that there is no need for feature filtering or transformation.

Dominant methods in recent years are Recurrent Neural Networks (RNNs, particularly Long Short-Term Memory networks, LSTMs) and Convolutional Neural Networks (CNNs). LSTMs not only learn the information at the current moment but also in the previous sequence, which advantage is very suitable for processing text sequences. By generalizing the LSTM model to the tree-structured network topologies (Tree-LSTM) [16] or regularizing the LSTM by linguistic knowledge (LR-LSTM) [17], the network could be able to exploit the grammatical information of the sentence. In most previous works, supervised learning based on single tasks often suffer from insufficient training data. Reference [18] proposed a method for learning recurrent neural models based on a multi-task learning framework. By introducing the dynamic compositional neural networks over tree structure [19], Tree-LSTM could capture the richness of the compositionality of sentences. However, the complex architecture of LSTMs suggests that they may not be the most efficient network structure [20].

CNNs are more computationally efficient because they fully utilize the parallelism of Graphics Processing Units (GPUs), and they process information in a layered manner, which makes them easier to capture complex relationships in sentences. Reference [21] earlier proposed a dynamic k-max pooling operation applied in CNN for the semantic modeling of sentences. This operation is an excellent alternative to the parse tree, but its scheme is sophisticated. Reference [22] reported on a series of experiments with simple CNN structures for sentence classification, and achieve better results in four out of the seven tasks. It also found that the performance of the model is significantly improved on the pre-trained word vectors. There are also attempts to use one-hot representation as input to preserve information of word order [23], but the sentences are too brief for such high dimensional encoding to provide sufficient information. Character-level vectors can also be used as input for CNN [24], but only for text where words are composed of characters. It is well known that in the computer vision field, the deeper the network, the better the performance will be [25]. Reference [26] also attempts towards this goal and present a very deep CNN architecture which operates directly at the character level. However, the performance on the sentence-level classification tasks seems not too reasonable. In addition, applying data augmentation methods could also improve the performance of the model [27]. Reference [28] investigated the capsule networks with dynamic routing for sentence classification.

Traditional CNN-based methods for sentence classification intend to use pooling layer to find the significant abstract features of the words or segments that could most likely produce the correct prediction result. However, the mechanism of which features should be large enough to affect the prediction results is still unclear. Distributional hypothesis [29] considers that a word is characterized by the company it keeps; similarly, we believe that context is the key to controlling and discriminating the influence extent of the words’ or segments’ features. In this paper, we construct an attention-gated layer before pooling layer for generating attention weights from feature’s context windows of different sizes by using specialized convolution encoders, to control the influence of target words’ or segments’ features in distinguishing the sentence’s category. The attention-gated layer could help the pooling layer find the genuinely critical features. We dub our model as Attention-Gated Convolutional Neural Network (AGCNN). Several groups of experimental results demonstrate the effectiveness of our method. Besides, Our proposed activation function (i.e., Natural Logarithm rescaled Rectified Linear Unit, NLReLU) is found to be comparable to other well-known activation functions.

In summary, the main contributions of this work are as follows:

- We propose a new CNN model, dubbed AGCNN, for sentence classification. The benchmark and visualization experiments demonstrate the effectiveness of our proposal.
- We propose an activation function named NLReLU. Experimental results show that NLReLU could outperform ReLU and is comparable to several well-known activation functions on AGCNN.
Empirical results on six sentence classification tasks demonstrate that our model could achieve a general improvement on accuracy highest up to 3.1\% (compared with standard CNN models), and gain competitive results over the 13 strong baseline methods on four out of the six tasks.

The remainder of this paper is organized as follows. In Section 2 we give an overview of related work. In Section 3 the proposed model is described in details. We report and discuss our experimental results in Section 4. Finally, we draw our conclusions in Section 5.

2. Related Work

LSTM [30] introduced the gating mechanism to the RNN [31], which enables RNN to remove or add information to the state of the cell. A gating mechanism usually consists of a network layer that has passed the Sigmoid [32] activation unit (generating the gating weights) and a multiplication operation. The gating weights, which usually values within the interval [0,1] (where 0 and 1 mean wholly discarded and reserved, respectively), limit the amount of information that can pass through the gates. With well-designed gating mechanisms, LSTM could learn longer range dependencies and effectively alleviate the gradient vanishing or exploding problem. Gated Convolutional Neural Network (GCNN) [33] first time successfully introduced the gating mechanism into CNN for language modeling, which could reduce the vanishing gradient problem for deep architectures. GCNN [33] utilizes half of the abstract features as the gating weights to control the other half abstract features. However, since the weights and the abstract features are convolved at the same level, the information carried by the control weights is very monotonous.

The attention mechanism attempts to mimic the human’s perception, which focuses attention selectively on parts of the target areas to obtain more details of the targets while suppressing other useless information. Reference [34] first successfully applied attention mechanism in RNN for image classification. Then the extensions of the attention-based RNN model are applied to various NLP tasks [35,36]. Recently, how to use the attention mechanism in CNNs has also become a research hotspot [37].

Activation functions have a crucial impact on the neural networks’ performance. Sigmoid [32], Rectified Linear Unit (ReLU) [38], Softplus [38], Leaky ReLU (LReLU) [39], Parametric ReLU (PReLU) [40], Exponential Linear Unit (ELU) [41] and Scaled Exponential Linear Unit (SELU) [42] are all fairly-known and widely-used activation units. The introduction of activation function to the neural network makes it possible to carry out the non-linear transformation of the input to solve the complex problems. But it may also bring with disadvantages, e.g., vanishing gradient and neuronal death. Therefore, it is essential to choose the appropriate activation function for the neural network.

3. The Proposed Model

CNN is very suitable for natural language processing, because CNN not only allows to precisely control the length of dependencies to be modeled but also enables nearby input elements to interact at lower layers while distant elements interact at higher layers, and CNN could produce the hierarchical abstract representations of the input text by stacking multiple convolution layers. Most current methods for sentence classification based on CNN intend to utilize the pooling layer to find the most significant features. In this paper, we construct an attention gated layer before pooling layer to identify critical features and suppress the impact of other unimportant features and help pooling layer find the genuinely critical features.

In this section, we describe in detail the model we propose. Figure 1 depicts the architecture of our model. Let \( e_i \in \mathbb{R}^d \) be the \( d \)-dimensional word vector corresponding to the \( i \)-th word in the sentence.

An input sentence embedding matrix of sentence with length \( n \) (padded when necessary) is represented as
Figure 1. The Architecture of AGCNN with Input Sentence Length \( n = 7 \) as an Example.

\[
E_{1:7} = [e_1, e_2, \cdots, e_7]^T, \tag{1}
\]

where \( E_{1:7} \in \mathbb{R}^{7 \times d} \).

In the first convolutional layer, a convolution kernel \( W \in \mathbb{R}^{h \times d} \) is applied to a window of \( h \) words to produce a new feature. For example, an abstract feature \( c_i \in \mathbb{R} \) is generated from a window of words \( E_{i-1,i+h-1} \) by

\[
c_i = f(g(W \otimes E_{i-1,i+h-1}) + b), \tag{2}
\]

where \( \otimes \) is the element-wise product between matrices, \( b \in \mathbb{R} \) is a bias term, function \( g(\cdot) \) sums up all the elements of a matrix and \( f(\cdot) \) is a non-linear activation function.

This convolution kernel will slide on the input sentence matrix and is applied to each possible window of words in the sentence \( \{E_{1:h}, E_{2:h+1}, \ldots, E_{n-1:n+h-1}\} \) to produce a feature map

\[C = [c_1, c_2, \cdots, c_{n-1+h}]^T, \tag{3}\]

with \( C \in \mathbb{R}^{(n-1+h) \times 1} \). Multiple kernels varying from different window sizes are applied to obtain multiple feature maps. Each feature map \( C \) is then fed into the attention gated layer.

The attention gated layer consists of a convolutional layer and a gating mechanism. In this convolutional layer, a kernel \( V \in \mathbb{R}^{k \times 1} \) is applied to all the context features with window size \( k \) (padded when necessary) of every feature \( c_j \) \((j = 1, 2, \cdots, n-h+1)\) in feature map \( C \) to produce the attention weight matrix
\begin{equation}
A = \left[ a_1, a_2, \cdots, a_{n-h+1} \right]^T,
\end{equation}

where

\begin{equation}
a_j = g \left( V \odot C \left( \frac{j-k+1}{2}, \frac{k+1}{2} \right) \right) \quad (j = 1, 2, \cdots, n-h+1).
\end{equation}

Here $a_j \in \mathbb{R}$, $A \in \mathbb{R}^{(n-h+1) \times 1}$, $C \left( \frac{j-k+1}{2}, \frac{k+1}{2} \right)$ is the context features of $c_j (j = 1, 2, \cdots, n-h+1)$ when $k$ is odd.

When $k$ is even,

\begin{equation}
a_j = g \left( V \odot C \left( \frac{j-k+1}{2}, \frac{k+1}{2} \right) \right) \quad (j = 1, 2, \cdots, n-h+1).
\end{equation}

Through the gating mechanism, we can get the output feature maps

\begin{equation}
m_l = C \odot f \left( A_l + D \right) (l = 1, 2, \cdots, t),
\end{equation}

where $m_l, D \in \mathbb{R}^{(n-h+1) \times 1}$, $D$ is a bias matrix term, $t$ is the number of convolution kernels we use in attention gated layer.

We use kernels with different window size $k$ to extract different grained attention weight matrix $A_l (l = 1, 2, \cdots, t)$.

Finally, we get the output feature map

\begin{equation}
M = \left[ m_1, m_2, \cdots, m_t \right]^T,
\end{equation}

where $M \in \mathbb{R}^{t \times (n-h+1)}$.

We then apply a max-over-time pooling operation \cite{43} over each feature map $M$ to get each output $O \in \mathbb{R}^{t}$ to capture the most important abstract features corresponding to multi-grained attentions, and concatenate all the outputs. These features form the penultimate layer and are passed to the dropout layer \cite{44}, then to the fully connected softmax layer.

In some of the model variants, we experiment with “two” and “three” channels of word vectors (see section 4.2), i.e., one channel is fine-tuned via backpropagation while the other channels kept static. We refer to the multi-channel feature of image color in computer vision, and let the convolution kernel $W \in \mathbb{R}^{b \times d \times 2}$ or $W \in \mathbb{R}^{b \times d \times 3}$ if the input has multiple channels. The model is otherwise the same as the single channel architecture.

In section 3.1, we introduce the activation function NLReLU.

3.1. NLReLU Activation Function

Activation functions play a crucial role in achieving remarkable performance in deep neural networks, and ReLU \cite{38} is the most well-known one in recent years. The advantage of ReLU is that the gradient is not saturated, thus avoiding the gradient vanishing problem. The feature of ReLU’s sparse activation reduces the interdependence of parameters and also leads to some mathematical advantages \cite{45}.

However, the process of training for deep neural networks is complicated by the fact that the distribution of each layer’s inputs changes during training, as the parameters of the previous layers change \cite{46}. ReLU does not compress the magnitude of the output data of each neuron, so if the magnitude of the data continues to expand, the deeper the layer of the model, the higher the expansion on the magnitude, and ultimately has a harmful effect on the performance of the model. Therefore, it is necessary to normalize the data of each layer’s inputs to control the distribution of each layer of neuron activations within a reasonable range. To address these problems, reference \cite{42}
proposes the SELU activation function, which is to make the activation function carry the property of self-normalization on neuron activations.

In this paper, we propose an activation function named Natural Logarithm rescaled ReLU (NLReLU), which is simply defined as

\[
  f(x) = \begin{cases} 
  \ln(x + 1.0), & x > 0 \\
  0, & x \leq 0
  \end{cases}
\]

We use the natural logarithmic transformation to rescale the magnitude of ReLU's positive-axis partial function. The advantages of introducing log transformation into ReLU are as follows:

- **Reduce the heteroscedasticity of the neuron activations’ data distribution between the layers of the network.** In disciplines such as Econometrics, log transformation is often used to transform the skewed data before further analyzing [47]. With remedial measures like log transformation reducing heteroscedasticity, raw data from the real world could be analyzed with conventional parametric analysis. We found that the distribution of neuron activations between each layer of the network is prone to be heteroscedastic. As shown in Figure 2, we simulate the case where the network has large heteroscedasticity between the layers, and it can be seen that NLReLU transforms each layer's neuron activations to approximately "normal" and effectively reduces heteroscedasticity.

- **Effectively control the distribution of neuron activations within a reasonable range.** The natural logarithm function is monotonically increasing in its domain. After taking the log transformation, the relative relationships between the neuron activations are unchanged. But meanwhile, NLReLU compresses the scale in which the data are measured to ensure the output neuron activations of each layer is more stable (see Figure 2).

- **Make the model more sensitive to differences in majority small value neuron activations.** The property of the natural logarithm function is that the smaller the value of the independent variable, the faster the change in the value decrease of the function. For example, \(1.5 - 1.2 = 1.8 - 1.5\), but \(\ln(1.5) - \ln(1.2) > \ln(1.8) - \ln(1.5)\); that is to say, the log transformation makes NLReLU more sensitive to differences in majority small value neuron activations than the larger. The smaller the value of neuron activation the discrimination is more visible, so some larger values' effect is weakened (e.g., noise data).

**Figure 2.** Simulation on a fully connected neural network with 10 hidden layers and 100 nodes per hidden layer. The batch size of input data is 100. The inputs obey the standard normal distribution \(N(0,1)\), the bias term of the activation functions is initialized as 0.1, and the weights are initialized as:

(a) Standard normal distribution \(N(0,1)\); (b) Normal distribution \(N(0,1.5)\), we simulate the case where the network has large heteroscedasticity between the layers. We recorded the mean and variance of the neuron activations of each layer when using different activation functions. It can be seen that NLReLU could effectively control the distribution of neuron activations and reduce heteroscedasticity between the layers.

4. Experimental Results and Discussions
Experiments are conducted on six sentence classification tasks. Section 4.1 introduces the datasets and the comparison systems. Section 4.2 describes the parameter settings and the variants of our model. In Section 4.3, we evaluate the performance of our proposed model on the six benchmark datasets by comparing with other strong baseline models, and analysis the effectiveness of our model. We visualize the feature maps in Section 4.4 to see what information are the model’s attention on when making predictions and explore the effects of different activation functions on the performance of our model in Section 4.5.

4.1. Datasets and Comparison Systems

The benchmark datasets used in our experiments are as follows:

- **CR**: This dataset contains customer reviews of various products, e.g., cameras, MP3s and DVD players (https://www.cs.uic.edu/~liub/FBS/sentiment-analysis.html#datasets). The task on this dataset is to predict whether a review is positive or negative [48].
- **MR**: Movie reviews dataset (https://www.cs.cornell.edu/people/pabo/movie-review-data/) with one sentence per review. Classification involves predicting positive/negative reviews [49].
- **Subj**: Subjectivity dataset where gives the snippets of movie reviews and plot summaries for movies from the internet (http://www.cs.cornell.edu/people/pabo/movie-review-data/). Its task is to classify a sentence as being subjective or objective [50].
- **SST-1**: Stanford Sentiment Treebank dataset (https://nlp.stanford.edu/sentiment/), an extension of MR but with train/dev/test splits provided and fine-grained labels (including very positive, positive, neutral, negative, very negative) [51].
- **SST-2**: This dataset is derived from SST-1 but removes neutral reviews and converts to two labels, positive and negative, respectively.
- **TREC**: Question dataset (http://cogcomp.org/Data/QA/QC/), its task involves classifying a question into 6 question types (whether the question is about the person, location, numeric information) [52].

The statistics summary of these datasets are in Table 1.

| Dataset | c | l | N  | |V| | |V|pre| |T| |
|---|---|---|---|---|---|---|---|---|---|---|
| CR | 2  | 19 | 3775 | 5552 | 5053 | CV |
| MR | 2  | 20 | 10662 | 18765 | 16488 | CV |
| Subj | 2 | 23 | 10000 | 21323 | 17913 | CV |
| SST-1 | 5 | 18 | 11855 | 17836 | 16262 | 2210 |
| SST-2 | 2 | 19 | 9613 | 16185 | 14825 | 1821 |
| TREC | 6 | 10 | 5952 | 9493 | 9035 | 500 |

We evaluate and compare our model with 13 strong baseline models including:

- Statistical indicators representations-based traditional methods like SVMs [10], NBSVM [9] and MNB [9].
- Word embedding and Continuous Bag-Of-Word (CBOW)/Skip-grams model-based Paragraph-Vector [15].
- LSTM-based models such as Tree structured LSTM (Tree-LSTM) [16], Linguistically Regularized LSTM (LR-LSTM) [17], multi-task and fine-tuning on LSTM [18] and Dynamic Compositional over Tree structured LSTM (DC-TreeLSTM) [19].
- CNN-based models like Dynamic Convolutional Neural Network with k-max pooling (DCNN) [21], standard CNN for sentence classification (CNN-rand/ CNN-static/ CNN-non-static/ CNN-multichannel) [22], Character-Level CNN (CL-CNN) [24] and very deep CNN (VD-CNN) [26].
Capsule network [28].

4.2. Parameter Settings and Model Variations

The dimensionality of all the input word vectors is 300. We use the publicly available word2vec vectors (https://code.google.com/archive/p/word2vec/) [12,13], that were trained on 100 billion words from Google News, as the pre-trained vectors. Words not present in the set of pre-trained words vocabulary are initialized randomly. For the case of random initializing word vectors, we initialize them to the normal distribution with the mean and variance same as each dataset’s vocabulary distribution.

The window sizes of the first convolutional layer’s kernels (h) are 1, 2, 3, 4, 5 with 100 different kernels each window size, and each window size corresponds to a set of 3 kernels (in the attention gated layer) with window sizes (k) of 1, 3, and 5, respectively. For regularization method we only employ dropout [44] on the penultimate layer with dropout rate of 0.5. The mini-batch size is 50. We choose SELU [42] and NLReLU as the activation function. The parameters of all convolutional layers of the network are initialized with He initialization [40], and the fully connected layer is initialized with Xavier initialization [53].

All the hyper-parameters above are chosen based on a sensitivity analysis on activation function and via a coarse grid search on the SST-1’s validation set, and are applied to all datasets. We do not otherwise perform any dataset-specific tuning other than early stopping and learning rate decay. For datasets without a standard validation set we randomly held out 10% of the training data as the validation set. Training is done through stochastic gradient descent over shuffled mini-batches with the Adam update rule [54].

Similar to the standard CNN model [22], we also experiment with several model variants (e.g., AGCNN-rand, AGCNN-static, AGCNN-non-static, and AGCNN-multichannel). Model variations are summarized in Table 2. Unlike the standard CNN model, for the model variant with multiple channels of the input word vectors, the convolution kernels of the first convolutional layer also expand into multiple channels.

Table 2. Summary of model variations.

| Model Variant     | Description                                                                 |
|-------------------|-----------------------------------------------------------------------------|
| AGCNN-rand        | All the word vectors are initialized randomly and updated during training.  |
| AGCNN-static      | This model uses pre-trained word vectors and randomly initializes the unknown words. All words are kept static during training. |
| AGCNN-non-static  | Same as the AGCNN-static model but all the word vectors are fine-tuned for each task. |
| AGCNN-multichannel| One channel is fine-tuned during training while the other channels are kept static. All channels are initialized with pre-trained word vectors (random initialization for unknown words). |

4.3. Performance Comparison

Comparison results of our model against other models are in Table 3. The results show that our model could achieve a general improvement on accuracy highest up to 3.1% (compared with standard CNN models), and gain competitive results over the 13 strong baseline models on four out of the six datasets. Separately speaking, AGCNN-rand improves ranging from 1.0% to 2.5% compared with CNN-rand (despite poor performance on SST-1); AGCNN-static improves ranging from 0.4% to 2.8% compared with CNN-static; AGCNN-non-static improves ranging from 0.1% to 1.6% compared with CNN-non-static; AGCNN-multichannel improves ranging from 0.4% to 3.1% compared with CNN-multichannel (despite poor performance on SST-2). Besides, the performance of our model using NLReLU and using SELU is comparable.
The improvement over the standard CNN model and is comparable to other strong baseline models. There is a significant information contained in the use of the same activation function as CNN. We believe that an effective combination of N models. We believe that general improvements ranging from 0.4% to 2.2%.

On the TREC dataset, the traditional method SVMs, and the best result is slightly higher than SVMs by 0.3%. Through the comparison of several LSTM-based models, we can see that multi-task learning brings much improvement to LSTM.

Table 3. Classification accuracy results of our model against other strong baseline models.

| Model                     | CR  | MR  | Subj | SST-1 | SST-2 | TREC |
|---------------------------|-----|-----|------|-------|-------|------|
| CNN-rand                  | 79.8| 76.1| 89.6 | 45.0  | 82.7  | 91.2 |
| CNN-static                | 84.7| 81.0| 93.0 | 45.5  | 86.8  | 92.8 |
| CNN-non-static            | 84.3|     | 93.4 | 48.0  | 87.2  | 93.6 |
| CNN-multichannel          | 85.0| 81.1| 93.2 | 47.4  | 88.1  | 92.2 |

SVMs                       | —   | —   | —    | —     | —     | 95.0 |
NBSVM                      | 81.8| 79.4| 93.2 | —     | —     | —    |
MNB                        | 80.0| 79.0| 93.6 | —     | —     | —    |
Paragraph-Vector           | 78.1| 74.8| 90.5 | 48.7  | 87.8  | 91.8 |
DCNN                       | —   | —   | —    | 48.5  | 86.8  | 93.0 |
CL-CNN                     | —   | —   | 88.4 | —     | —     | 85.7 |
Tree-LSTM                  | 83.2| 80.7| 91.3 | 48.2  | 87.5  | —    |
LR-LSTM                    | 82.5| 81.5| 89.9 | —     | 85.7  | —    |
LSTM-Multi-Task (Fine Tuning) | —   | —   | 94.1 | 49.6  | 87.9  | —    |
VD-CNN                     | —   | —   | 88.2 | —     | —     | 85.4 |
DC-TreeLSTM                | —   | 81.7| 93.7 | —     | 87.8  | 93.8 |
Capsule-Network            | 85.1| 82.3| 93.8 | —     | 86.8  | 92.8 |
AGCNN-SELU-rand            | 82.3| 78.3| 91.8 | 44.7  | 83.7  | 92.9 |
AGCNN-SELU-static          | 86.4| 81.7| 93.9 | 48.3  | 87.1  | 94.3 |
AGCNN-SELU-non-static      | 85.8| 81.6| 94.1 | 49.2  | 87.2  | 94.5 |
AGCNN-SELU-2-channal       | 86.2| 81.6| 94.0 | 49.0  | 87.4  | 94.7 |
AGCNN-SELU-3-channal       | 86.1| 81.3| 93.5 | 49.4  | 87.6  | 95.3 |
AGCNN-NLReLU-rand          | 82.1| 78.3| 91.6 | 44.4  | 83.5  | 92.5 |
AGCNN-NLReLU-static        | 86.2| 81.6| 93.8 | 48.0  | 87.2  | 94.3 |
AGCNN-NLReLU-non-static    | 85.0| 81.3| 93.9 | 49.6  | 87.3  | 94.9 |
AGCNN-NLReLU-2-channal     | 85.3| 81.7| 94.0 | 49.4  | 87.0  | 94.3 |
AGCNN-NLReLU-3-channal     | 85.4| 81.9| 93.9 | 49.4  | 87.4  | 94.2 |

Table 4. Performance comparison results (taking the CNN-static and AGCNN-ReLU-static model as an example).

| Model                        | CR  | MR  | Subj | SST-1 | SST-2 | TREC |
|------------------------------|-----|-----|------|-------|-------|------|
| CNN-static                   | 84.7| 81.0| 93.0 | 45.5  | 86.8  | 92.8 |
| AGCNN-ReLU-static            | 85.8| 81.4| 93.7 | 47.7  | 86.5  | 94.5 |

For the binary classification tasks (CR, MR, Subj, and SST-2), a single channel model tends to yield better results when using SELU, while NLReLU is multiple channels. Conversely, for multiple classification tasks (SST-1 and TREC), a model with multiple channels tends to achieve better results when using SELU, while NLReLU is single channel.

On the TREC dataset, the traditional method SVMs can achieve very high accuracy, and other strong baseline models (e.g., CNN-based and LSTM-based methods) do not exceed this performance. All the performances of our model variants on TREC are close to the accuracy of 95.0% (except the AGCNN-rand), and the best result is slightly higher than SVMs by 0.3%. Through the comparison of several LSTM-based models, we can see that multi-task learning brings much improvement to LSTM.

Table 4 summaries the comparison results of CNN-static and AGCNN-ReLU-static. It can be seen that in the case of using the same activation function as CNN-static, our model could achieve accuracy improvements ranging from 0.4% to 2.2%.

We can conclude from the Table 3 and Table 4 that our proposal could achieve an effective general improvement over the standard CNN model and is comparable to other strong baseline models. We believe that it is the attention gating layer helps CNN learn more meaningful and comprehensive text representation and extract the most significant information contained in the sentence. For example, a combination of N-gram convolutional layer with kernel windows of [3,4,5].
for a standard CNN model can capture the 3/4/5-gram features of the text. However, for our model, not only the first convolutional layer can capture the 1/2/3/4/5-gram features of the text, but also each feature map is fed into an attention gating layer with kernel windows of {1,3,5} (from multiple granularities) to enhance the impact of crucial information and suppress the impact of unimportant information.

4.4. Attention Visualization

In this section, we visualize the feature maps of the standard CNN model and our model (with the same input) as heat maps to compare what information are the model’s attention on when making predictions.

The parameters of the models are set as follows: we use a CNN-static model has kernel window size of 1 with 100 feature maps, and ReLU activation; the AGCNN-static model we use has kernel window size of 1 (first convolutional layer) with 100 feature maps and the kernel window size of MGA gating mechanism’s convolutional layer is {1,3}, and NLRelu activation. To rule out the interference of word vector initialization, we use exactly the same initialized word vectors for both models. After training on the MR dataset and saving the models, we randomly select one sentence from the MR as input enter into the two models, the predictions for both models (which is “negative”) are correct.

The input sentence is “A turgid little history lesson, humorless and dull” and its category is “negative”. We randomly select ten feature maps of CNN-static that are visualized before and after the activation of ReLU (see Figure 3).

![Figure 3](image)

Figure 3. Attention visualization of the CNN-static model: (a) Heat map of the feature maps before activation; (b) Heat map of the feature maps after activation.

As shown in Figure 3b, the feature maps are sparse after the activation of ReLU. According to the original intention of the standard CNN model, after the pooling scheme, critical features will be extracted to influence the prediction of the classification. However, it can be seen that the standard CNN model is not ideal for the acquisition of crucial features, because words like “turgid”, “little”, “humorless” and “dull”, which all express negative sentiment, are not adequately recognized.

We randomly selected ten feature maps of the first convolutional layer of AGCNN-static, and their corresponding multi-grained attention feature maps and feature maps through the MGA gating mechanism are visualized as heat maps, as shown in Figure 4.

Figure 4a and b show that the first convolutional layer of AGCNN-static could extract more distinct and more distinguishing features. As depicted in Figure 4b and Figure 4d, the convolution of a kernel with window size 3 in the MGA gating mechanism suppresses the attention to words (e.g.,
Figure 4. Attention visualization of the AGCNN-static model: (a) Feature maps of the first convolutional layer before the activation of NLReLU; (b) Feature maps of the first convolutional layer after the activation of NLReLU. (c) Feature maps of the MGA gating mechanism’s kernel of window size 1 (after the activation of NLReLU); (d) Feature maps of the MGA gating mechanism’s kernel of window size 3 (after the activation of NLReLU); (e) The element-wise product between the attention
weight matrix (c) and the feature map in (b); (f) The element-wise product between the attention weight matrix (d) and the feature map in (b).

“a”, “history”, “lesson”, and “and”), when compared with other words in the sentence. Besides, the attention of the critical features in Figure 4b are enhanced when compared with other unimportant features, as shown in Figure 4e and f. The above is a case study of the variation process of features in neural networks. Through intuitive visualization and comparative analysis, we believe that the MGA gating mechanism could help CNN learn the ability to obtain more meaningful and comprehensive abstract features of the input text, and extract the most significant information contained in the sentence.

4.5. Sensitivity Analysis of Activation Function

In this section, we analyze the effects of activation function choices on the model performance. We consider eight different activation functions, including: Sigmoid [32], ReLU [38], Softplus [38], LReLU [39], PReLU [40], ELU [41], SELU [42], and NLReLU. We summarize the classification results achieved by AGCNN-static using different activation functions and report them in Table 5.

On the whole, the best performing activation function is SELU, followed by NLReLU and ELU. One interesting thing is that SELU is obtained by adding self-normalization property to the ELU, and both ELU and SELU have performed well. ReLU could surpass other alternative activation functions on TREC only. Softplus is a smooth approximation to the ReLU, but the log transformation of the exponential function does not bring much performance improvement compared to ReLU. Sigmoid is the worst performer. A very undesirable property of the sigmoid neuron, which is also responsible for poor performance, is that when the neuron’s activation saturates at either tail of 0 or 1, the gradient at these regions is almost zero. It is notable that the better performing activation functions tend to transform each layer’s neuron activations to approximately “normal” or adequately control the distribution of each layer’s distribution of neuron activations. Overall, Table 5 depicts that the performance of NLReLU could outperform ReLU and is comparable to other activation functions.

| Dataset | ReLU | Softplus | Sigmoid | ELU | PReLU | LReLU | NLReLU | SELU |
|---------|------|----------|---------|-----|-------|-------|--------|------|
| CR      | 85.8 | 85.7     | 85.5    | 86.0| 85.7  | 85.9  | 85.8   | 86.4 |
| MR      | 81.4 | 81.2     | 81.2    | 81.7| 81.5  | 81.5  | 81.6   | 81.7 |
| Subj    | 93.7 | 93.5     | 93.1    | 93.7| 93.4  | 93.5  | 93.8   | 93.9 |
| SST-1   | 47.7 | 47.4     | 47.4    | 47.9| 47.5  | 47.4  | 48.0   | 48.3 |
| SST-2   | 86.5 | 86.2     | 85.2    | 86.6| 86.6  | 86.5  | 87.2   | 87.1 |
| TREC    | 94.5 | 94.3     | 93.8    | 94.2| 94.1  | 94.1  | 94.3   | 94.3 |

5. Conclusions

In this paper, we introduce an attention gating layer that could help CNN learn more meaningful and comprehensive features and focus more attention on critical features, and we successfully develop the AGCNN model for sentence classification tasks. Several groups of experiments on performance comparison and attention visualization of feature maps demonstrate the effectiveness of our proposals. We also propose the NLReLU activation function. We elaborately illustrate and analyze the advantages of NLReLU, and the experimental results show that NLReLU could outperform ReLU and is comparable to other activation functions on AGCNN.

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