# SEDGCN: Sentiment Enhanced Dual Graph Convolutional Networks for Detecting Adverse Drug Reactions

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***Abstract*—In the realm of medicine and healthcare, adverse drug reactions (ADRs) are a significant contributor to mortality and morbidity. Consequently, it is of paramount importance to closely observe the adverse effects of marketed drugs to minimize associated risks. While current methods for Adverse Drug Reaction (ADR) detection have demonstrated notable efficacy, a significant number of researchers have failed to acknowledge the integral role that sentiment information plays in this process. In this paper, we propose Sentiment Enhanced Dual Graph Convolutional Networks (SEDGCN), a novel method for ADRs detection by incorporating sentiment information. In particular, we first introduce the concept of prompt learning and reformulate the ADR detection task as an aspect-level sentiment analysis task. Subsequently, we construct a sentiment-enhanced dependency matrix for each sentence to capture the sentiment knowledge and syntactic information of the sentence. The matrix is then input into the graph convolutional networks to obtain a graph representation of the sentence. Finally, to capture global information, we construct a heterogeneous graph based on all words and sentences and fuse this heterogeneous graph with the sentence-level graph representation for ADR detection. Extensive experimentation on two publicly available datasets, namely TwiMed and Twitter, yielded F1 scores of 78.24% and 75.43%, respectively. These results underscore the efficacy of our proposed model.**

***Index Terms*—Adverse drug reactions, Prompt Learning, Sentiment Knowledge, Graph convolutional networks, Aspect-based sentiment analysis**

## I. Introduction

Adverse drug reactions (ADRs) are reactions that are unrelated to the purpose of the medication or harmful to the body at normal doses of normal medications [1]. The emergence of ADRs can pose significant health risks to patients, potentially leading to severe adverse outcomes. As such, the monitoring and detection of ADRs hold considerable importance. In previous studies, researchers primarily relied on a spontaneous reporting system, which involved both mandatory and voluntary reporting of adverse drug events. Additionally, social media platforms frequently provide real-time information regarding ADRs. Given these factors, social media emerges as an effective platform for public health surveillance.

In recent years, many deep learning methods have been used for adverse drug reaction detection [2]–[5]. In addition, some researchers have introduced sentiment knowledge into the task of adverse drug reaction detection. For example, Shen et al. [6] integrated affective information by simply concatenating the affective scores of words into sentence representations. However, the above method of incorporating affective knowledge only provides an initial affective score. Following this, Zhang et al. [7] proposed to use a sentiment-aware attention mechanism to fuse sentiment information and extract word-level affective features by learning the weight matrix of sentiment words. Although the sentiment-aware attention mechanism effectively perceives emotional knowledge in text, it ignores the mining of syntactic information and global information in text.

To address the above problems, we propose a novel neural network model, namely Sentiment Enhanced Dual Graph Convolutional Networks (SEDGCN). Specifically, we first introduce the idea of prompt learning and reformulate the ADR detection task as an aspect-level sentiment analysis task. Then, we construct a sentiment-enhanced dependency matrix for each sentence to capture the sentiment knowledge and syntactic information and input it into the graph convolutional network to obtain a graph representation. Finally, to capture global information, we construct a heterogeneous graph based on all words and sentences and fuse this heterogeneous graph with the sentence-level graph representation.

## II. METHOD

The structure of the proposed SEDGCN model is illustrated in Fig. 1. In the following sections, we describe each part of our proposed model in detail.

### *A. Problem definition*

Traditional ADR detection is usually defined as a text binary classification task. Inspired by the idea of prompt learning [8] and aspect-based sentiment analysis tasks [9], we reformulate the ADR detection task as an aspect-level sentiment analysis task, where the ADR detection task is transformed into a task to determine the sentiment polarity of the aspect word. Specifically, we add a prompt to each sentence, such as *Is there an adverse drug reaction event?*,




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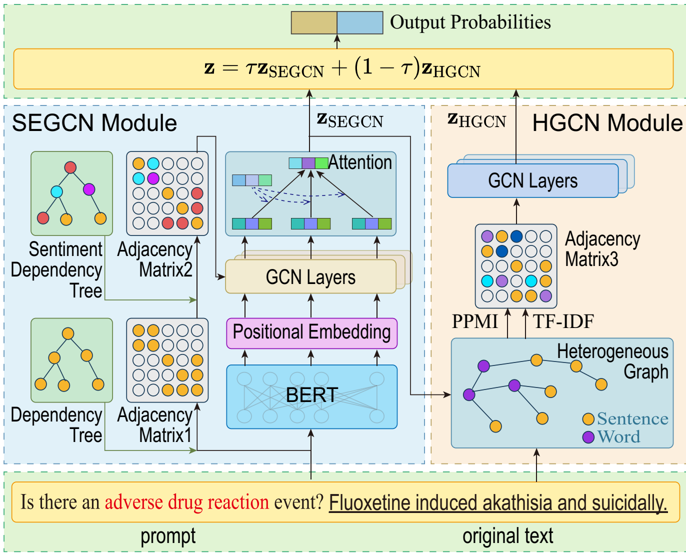


Fig. 1. The framework of our SEDGCN model.

where the aspect word is *adverse drug reaction*. Thus, the final input text can be represented as $\boldsymbol{s} = \{w_1, w_2, ..., w_{r+1}, w_{r+2}, ..., w_{r+m}, ..., w_{n-1}, w_n\}$, $n$ denotes the length of the sentence, where $w_{r+1}$ and $w_{r+m}$ denote the beginning and the end of the aspect word respectively, and $m$ denotes the length of the aspect word. The purpose of the SEDGCN model is changed to detect the sentiment polarity of the aspect word.

### B. SEGCN module

To incorporate sentiment knowledge and syntactic information into the Graph Convolutional Network (GCN), we propose a method of constructing a sentiment-enhanced graph convolutional network. This approach aids the model in extracting sentiment dependencies between context words and aspect words. The process of constructing this sentiment-enhanced graph convolutional network involves five sub-steps.

The first step is to construct the sentiment-enhanced dependency matrix. Specifically, we first build a dependency matrix $\mathbf{A} \in \mathbb{R}^{n \times n}$ over the dependency tree[1] for each sentence, as shown in formula (1):

$$\mathbf{A}_{ij} = \begin{cases} 1 & \text{if } w_i, w_j \text{ contains dependency} \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

We obtain the sentiment score of all words using SenticNet [10], which is a knowledge base and a collection of sentiment analysis tools and techniques that combine commonsense reasoning, psychology, linguistics, and machine learning. Thus, we can calculate the fused sentiment score adjacency matrix by using formula (2).

$$\mathbf{B}_{ij} = \text{SenticNet}(w_i) + \text{SenticNet}(w_j) \tag{2}$$

where $\text{SenticNet}(w_i)$ and $\text{SenticNet}(w_j)$ denote the sentiment scores of words $w_i$ and $w_j$ in SenticNet, respectively. Notably, $w_i = 0$ indicates a neutral sentiment polarity or missing word in SenticNet. To emphasize the role of aspect words in a sentence, we further enhance the dependency between contextual words and aspect words.

$$\mathbf{C}_{ij} = \begin{cases} 1 & \text{if } w_i, w_j \text{ is an aspect word} \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

Thus, we can obtain the final sentiment-enhanced dependency matrix $\mathbf{D}_{ij}$:

$$\mathbf{D}_{ij} = \mathbf{A}_{ij} \times (\mathbf{B}_{ij} + \mathbf{C}_{ij} + 1) \tag{4}$$

The second step is to obtain the embedding of the input sentence, for a given input sentence $\boldsymbol{s} = \{w_1, w_2, ..., w_{r+1}, w_{r+2}, ..., w_{r+m}, ..., w_{n-1}, w_n\}$, we use pre-trained word vectors in the style of the type BERT [11] to obtain the initialized representation $\mathbf{E} = \{\mathbf{e}_1, \mathbf{e}_2, ..., \mathbf{e}_{r+1}, \mathbf{e}_{r+2}, ..., \mathbf{e}_{r+m}, ..., \mathbf{e}_{n-1}, \mathbf{e}_n\} \in \mathbb{R}^{n \times d}$ of the input sentence, where $d$ denotes the dimension of the initialized word vector and we fine-tune the parameters of the BERT model during the model training process.

The third step is to compute the positional encoding, inspired by Zhang et al. [12], we find that the closer the context words are to aspect words, the more semantic similarity between them. The $\mathbf{g}_i$ is obtained from the $\mathbf{e}_i$ after position weighting, as shown in equations (5) and (6).

$$p_i = \begin{cases} 1 - \frac{r+1-i}{n} & 1 \le i < r+1 \\ 0 & r+1 \le i \le r+m \\ 1 - \frac{i-r-m}{n} & r+m < i \le n \end{cases} \tag{5}$$

$$\mathbf{g}_i = p_i \mathbf{e}_i \tag{6}$$

The fourth step is to incorporate the sentiment knowledge into GCN, where we input the dependency matrix augmented with the sentiment knowledge and the embeddings of the sentences into the GCN module, and update each node in the $\ell$-th GCN layer according to its neighborhood's hidden representation.

$$\mathbf{h}_i^{\ell} = \text{ReLU}(\sum_{j=1}^{n} \mathbf{D}_{ij} \mathbf{W}^{\ell} \mathbf{g}_j^{\ell-1} + \mathbf{b}^{\ell}) \tag{7}$$

where $\mathbf{W}^{\ell}$ and $\mathbf{b}^{\ell}$ are learnable parameter. The final representation after the $L$-layer GCN is $\mathbf{H}^L = \{\mathbf{h}_1^L, \mathbf{h}_2^L, ..., \mathbf{h}_{r+1}^L, \mathbf{h}_{r+2}^L, ..., \mathbf{h}_{r+m}^L, ..., \mathbf{h}_{n-1}^L, \mathbf{h}_n^L\}$

To emphasize the key properties of aspect words, we use aspect-specific masking to mask the non-aspect words in the learned output vectors of the final GCN layer and keep the aspect representation unchanged.

$$\mathbf{h}_i^L = \begin{cases} \mathbf{h}_i^L & r+1 \le i \le r+m \\ 0 & 1 \le i < r+1, r+m < i \le n \end{cases} \tag{8}$$

The final step involves reinforcing the interaction between aspect words and their context through the application of an attention mechanism. An attention mechanism is used to extract the key features from the contextual sentiment words based on aspect-related sentiment features learned through

[1]https://spacy.io/

GCN layer. We calculate the attention scores between context words and aspect words:

$$\beta_j = \sum_{i=1}^{n} \mathbf{e}_j^{\mathrm{T}} \mathbf{h}_i^L = \sum_{i=r+1}^{r+m} \mathbf{e}_j^{\mathrm{T}} \mathbf{h}_i^L \tag{9}$$

$$\alpha_j = \frac{\exp(\beta_j)}{\sum_{j=1}^{n} \exp(\beta_j)} \tag{10}$$

The final representation of the input vector can be computed as follows:

$$\mathbf{v} = \sum_{j=1}^{n} \alpha_j \mathbf{e}_j \tag{11}$$

Thus, we can obtain the output of the GCN model enhanced with sentiment knowledge through the linear layer.

$$\mathbf{z}_{\mathrm{SEGCN}} = \mathbf{W}_1 \mathbf{v} + \mathbf{b}_1 \tag{12}$$

where $\mathbf{W}_1$ and $\mathbf{b}_1$ denote learnable parameters.

### *C. HGCN module*

To effectively assimilate global information, we construct a heterogeneous graph based on all words and sentences in the text. This approach aids the model in integrating both local and global information. The process comprises three sub-steps:

The first step is to construct a heterogeneous adjacency matrix. Inspired by Lin et al. [13], we construct a heterogeneous adjacency matrix containing both word nodes and sentence nodes. The edges in this adjacency matrix contain two types: word-word edges and word-sentence edges. Specifically, the weight of word-word edges is determined by Positive Point-wise Mutual Information (PPMI), while the weight of word-sentence edges is calculated using Term Frequency-Inverse Document Frequency (TF-IDF), as shown in the equation (13):

$$\mathbf{M} = \begin{cases} \mathrm{PPMI}(i,j) & i,j \text{ are words and } i \neq j \\ \text{TF-IDF}(i,j) & i \text{ is sentence, } j \text{ is word} \\ 1 & i = j \\ 0 & \text{otherwise} \end{cases} \tag{13}$$

The second step is to obtain the node representation, we use the $i$-th sentence embedding representation $v_i$ obtained in formula (11) as the initialized representation of the sentence nodes. The initialization of the full sentences is represented as $\mathbf{V} = \{\mathbf{v}_1, \mathbf{v}_2, ..., \mathbf{v}_{n_{sen}}\}$. The embeddings of the word nodes are initialized to $\mathbf{0}$. Therefore, we can obtain the feature matrix $\mathbf{H}$ of the final initialized nodes.

$$\mathbf{H} = \begin{pmatrix} \mathbf{V} \\ \mathbf{0} \end{pmatrix}_{(n_{\mathrm{sen}}+n_{\mathrm{word}})\times d} \tag{14}$$

where $n_{\mathrm{sen}}$ is the number of sentence nodes and $n_{\mathrm{word}}$ is the number of word nodes.

The final step is to incorporate the global information in GCN, we input $\mathbf{H}$ into a GCN model that iteratively propagates messages over training and test examples. Specifically, the output feature matrix of the $i$-th GCN layer $\mathbf{U}^i$ is computed as:

$$\mathbf{U}^i = \mathrm{ReLU}(\mathbf{M}\mathbf{W}^i\mathbf{U}^{i-1} + \mathbf{b}^1) \tag{15}$$

where $\mathbf{W}^i$ and $\mathbf{b}^i$ are the learnable parameters, and $\mathbf{U}^0 = \mathbf{H}$ is the input feature matrix of the model. Finally, the output after multi-layer GCN can be represented as $\mathbf{z}_{\mathrm{HGCN}}$.

### *D. Integration of classification modules*

The final training objective is to linearly interpolate the predictions of the sentiment-enhanced GCN module with the predictions of the heterogeneous GCN module:

$$\mathbf{z} = \tau \mathbf{z}_{\mathrm{SEGCN}} + (1-\tau)\mathbf{z}_{\mathrm{HGCN}} \tag{16}$$

where $\tau$ is a fusion coefficient, which controls the tradeoff between the two objectives. $\tau = 1$ means that we only use the SEGCN module, and $\tau = 0$ means that we only use the HGCN module. When $\tau \in (0, 1)$, we can balance the predictions from both models, and the SEDGCN model can be better optimized.

We optimize the model parameters using the cross-entropy loss function, which is defined as:

$$L_{CE} = -\frac{1}{N}\sum_{i=1}^{N}\left(y_i \log(\mathbf{z}_i) + (1-y_i)\log(1-\mathbf{z}_i)\right) \tag{17}$$

where $N$ is the number of sentences within a batch and $y_i$ denotes the true label of the sample.

## III. EXPERIMENT

### *A. Experimental datasets and settings*

To fairly evaluate our proposed model, we perform a 5-fold cross validation on two publicly available ADR datasets. (1) **TwiMed** [14]: The TwiMed dataset is mainly collected from two platforms (Twitter and Pubmed). It is worth noting that the data collected from the Twitter platform is subject to user privacy concerns. The authors released 1000 tweet IDs without disclosing the original tweets. However, due to the deletion of tweets by some users, we can only download 483 tweets based on the tweet IDs provided. Each document is annotated with disease, symptom, drug, and their relations. The relation types include Outcome-Negative, Outcome-Positive, and Reason-To-Use. When the relation type is annotated as Outcome-Negative, we label it as ADR. (2) **Twitter** [15]: This dataset was collected from the social media platform Twitter and each sentence was labeled as ADR or Non-ADR. The details of the datasets are shown in Table 1.

TABLE I
BRIEF DESCRIPTIONS OF THE SOCIAL MEDIA ADR DATASETS.

| Dataset | Positive | Negative | Total | Experimental data length |
|---|---|---|---|---|
| TwiMed [14] | 369 | 1114 | 1483 | 65 |
| Twitter [15] | 744 | 5727 | 6471 | 46 |

In this paper, three commonly used evaluation metrics in text classification tasks, namely macro precision (P), macro recall (R) and macro F1-score (F1), are adopted to evaluate the performance of the proposed model in adverse drug reaction detection task. In our experiments, we constructed our model based on the bert-base-uncased[2] model which consists of 12 layers of Transformer modules. We use the Adam optimizer and initialize the GCN module with a learning rate of 2e-3 and the fine-tune BERT module with a learning rate of 3e-5. The epoch is set to 10 for all datasets, batch size is set to 64 and dropout rate is set to 0.3. Besides, the fusion coefficient $\tau$ is set to 0.4. Our experiments are conducted in Python 3.8 and PyTorch 1.12 framework and trained on NVidia TITAN XP GPUs.

### B. Compared with state-of-the-art models

As shown in Table 2, the proposed SEDGCN model achieved the best performance in adverse drug reaction detection on two datasets (Twitter and TwiMed). For example, in terms of F1 results, our proposed SEDGCN model outperformed the current optimal models by 3.23% and 7.13% on two datasets (Twitter and TwiMed), respectively, and in terms of other metrics, our proposed model also achieved good performance compared to the baselines.

TABLE II
COMPARISON OF SEDGCN WITH STATE-OF-THE-ART METHODS ON TWITTER AND TWIMED DATASETS.

| Method | Twitter | | | TwiMed | | |
|---|---|---|---|---|---|---|
| | P(%) | R(%) | F1(%) | P(%) | R(%) | F1(%) |
| CNN [2] | 59.53 | 37.37 | 45.91 | 70.80 | 60.33 | 65.15 |
| LSTM [2] | 45.38 | 42.88 | 44.09 | 67.21 | 68.31 | 67.75 |
| RCNN [2] | 50.00 | 42.88 | 46.17 | 68.52 | 66.43 | 67.46 |
| HTR+MSA [3] | 37.06 | 58.33 | 45.33 | 66.58 | 63.62 | 65.07 |
| CNN+corpus [4] | 47.94 | 43.82 | 45.79 | 60.51 | 61.50 | 61.00 |
| CNN+transfer [4] | 60.23 | 35.62 | 44.76 | 69.58 | 61.74 | 65.42 |
| ATL [4] | 56.26 | 39.25 | 46.24 | 70.84 | 65.02 | 67.81 |
| ANNSA [7] | 49.10 | 50.46 | 48.84 | - | - | - |
| KESDT [5] | 70.40 | 75.58 | 72.20 | 71.72 | 72.13 | 71.11 |
| SEDGCN | **76.08** | **75.23** | **75.43** | **78.84** | **77.77** | **78.24** |

## IV. CONCLUSIONS

Detecting Adverse Drug Reactions (ADRs) is a vital task in the biomedical domain. In this paper, we propose a novel approach Sentiment Enhanced Dual Graph Convolutional Networks (SEDGCN) for ADR detection. Specifically, we construct graph convolutional networks fusing sentiment knowledge and global information, respectively. Subsequently, the predictions from the two graph convolutional neural networks are fused, allowing the model to not only extract sentiment information from sentences but also facilitate the interaction between local and global information within the sentences. Experimental results on the benchmark datasets confirm the effectiveness of our approach in detecting ADRs.

[2]https://huggingface.co/bert-base-uncased

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