Affective Dependency Graph for Sarcasm Detection

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ABSTRACT

Detecting sarcastic expressions could promote the understanding of natural language in social media. In this paper, we revisit sarcasm detection from a novel perspective, so as to account for the long-range literal sentiment inconsistencies. More concretely, we explore a novel scenario of constructing an affective graph and a dependency graph for each sentence based on the affective information retrieved from external affective commonsense knowledge and the syntactical information of the sentence. Based on it, an Affective Dependency Graph Convolutional Network (ADGCN) framework is proposed to draw long-range incongruity patterns and inconsistent expressions over the context for sarcasm detection by means with interactively modeling the affective and dependency information. Experimental results on multiple benchmark datasets show that our proposed approach outperforms the current state-of-the-art methods in sarcasm detection.

CCS CONCEPTS

• **Information systems → Sentiment analysis**;

KEYWORDS

sarcasm detection, graph network, sentiment analysis

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1 INTRODUCTION

Sarcasm is a common speech act in human communications, which has received much research attention [8, 9, 13, 16–18, 23]. As shown

Sarcasm: I *love* when people *ignore* me. | **Non**: *Love* you more than this.

Figure 1: Examples of Sarcasm and Non-sarcasm expression.

in Figure 1, there are two instances paired with their labels (*Sarcasm* or *Non-sarcasm*). Note that both of them contain a decisive sentiment word "*love*". While in the sarcastic example, the word discrepant "*ignore*" leads to a contradiction expression. That is, there are some incongruity expressions in sarcastic context [13].

Some early studies attempt to extract the incongruity expressions in sarcasm detection by searching a set of positive verbs and negative situations [2, 10, 26] or employing lexical features [22]. Most recent methods employ deep neural networks to capture the subtle semantic incongruity patterns [7, 32, 35]. Further, Babanejad et al. [1] leverages both affective and contextual features to extend the architecture of BERT for sarcastic expressions learning. Most existing studies, however, are largely inadequate to determine the affective dependencies in sarcastic expressions when the incongruity patterns are separated far away in the context, or easy to mistake the inessential contextual words as sarcastic descriptors. As the sarcasm example shown in Figure 1, the word "*love*" is not near to "*ignore*" in the incongruity expression.

In this work, inspired by some existing graph-based models proposed in other tasks [4, 6, 11, 20, 30, 31, 36–38], we explore a novel scenario of constructing an affective graph and a dependency graph for each instance based on the affective clues retrieved from external affective knowledge (SenticNet [3]) and the dependency tree of the sentence, so as to leverage the contextual affective dependencies of incongruity expressions in sarcasm detection. Based on it, an Affective Dependency Graph Convolutional Network (ADGCN) structure is employed to provide the long-range multi-word affective dependencies for understanding the roles of context words in the learning of incongruity expressions. The main contributions of our work can be summarized as follows:

- We are the first to exploit GCN model for drawing incongruity patterns over the context in sarcasm detection.
- A novel scenario of affective and dependency graphs construction is explored to extract the contradictory implications and incongruity expressions in sarcasm detection.
- Experimental results on a number of benchmark datasets demonstrate that our proposed method achieves the state-of-the-art performance in sarcasm detection.

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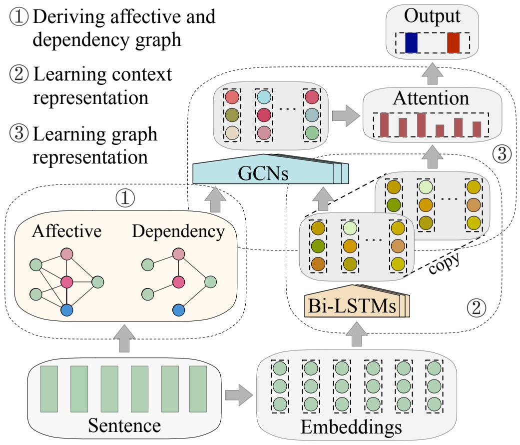


Figure 2: Architecture of the proposed ADGCN framework.

2 METHODOLOGY

In this section, we describe our proposed Affective Dependency Graph Convolutional Network (ADGCN) framework in details. As demonstrated in Figure 2, the architecture of the proposed ADGCN framework contains three main components: 1) *Deriving affective and dependency graphs*, which constructs an affective graph and a syntax-aware dependency graph for each sentence based on affective commonsense knowledge and dependency tree; 2) *Learning context representation*, which learns the vector representations of the context with bidirectional LSTMs (Bi-LSTM); 3) *Learning graph representation*, which leverages the affective dependencies of the context with multi-layer GCNs for sarcasm detection.

2.1 Deriving Affective and Dependency Graphs

To leverage the affective dependencies of the context, we explore a novel scenario of constructing an affective graph and a dependency graph for each sentence. This aims to discern the affective expressions of the contextual words and preserve global structure information of the sentence in sarcasm detection simultaneously.

Given a sentence s consists of n words $s = \{w_i\}_{i=1}^{n}$, to explore the affective expressions of the context for determining the role of contextual incongruity information in learning sarcastic expressions, we construct an affective guided graph and attain an adjacency matrix $\boldsymbol{A}^a \in \mathbb{R}^{n\times n}$, based on the affective scores of words retrieved from an external affective commonsense knowledge:

$$A^a_{i,j} = |\mathcal{S}(w_i) - \mathcal{S}(w_j)| \tag{1}$$

where $\mathcal{S}(w_i) \in [-1, 1]$ represents the affective score of word w_i retrieved from SenticNet [3]. We set $\mathcal{S}(w_t) = 0$ if w_t is not contained in the knowledge. $|\cdot|$ represents absolute value calculation. In this way, words with opposite emotions could be highly regarded. Thus the affective incongruity expressions could be propagated to discriminate the contradiction between literal expression and the authentic intention of the author in sarcasm detection.

In addition, intuitively, affective expressions generally depend on some syntactic structure, as the sarcastic clue of "*people ignore me*" shown in Figure 1. To this end, inspired by previous syntax-aware graph methods [12, 19, 27, 34], in addition to the affective graph we construct a dependency graph based on the dependency tree of the sentence[1]:

$$A^d_{i,j} = 1 \qquad \text{if } \mathcal{T}(w_i, w_j) \tag{2}$$

where $\boldsymbol{A}^d \in \mathbb{R}^{n\times n}$, whose remaining elements are 0. $\mathcal{T}(w_i, w_j)$ represents that there is a relation between w_i and w_j in the dependency tree of the sentence. Inspired by [15], we construct the undirected graph to enrich the affective and dependency information: $A_{i,j} = A_{j,i}$, and also set a self-loop for each word: $A_{i,i} = 1$.

2.2 Learning Context Representation

We embed each word of $s = \{w_i\}_{i=1}^{n}$ into an m-dimensional embedding $\boldsymbol{x}_i \in \mathbb{R}^m$ via mapping the embedding from the lookup table $\boldsymbol{X} \in \mathbb{R}^{m\times|V|}$, $|V|$ is the vocabulary size. Then we feed the embedding matrix $\boldsymbol{x} = [\boldsymbol{x}_1, \boldsymbol{x}_2, \cdots, \boldsymbol{x}_n]$ into bidirectional LSTMs to encode the input sentence into vector representations:

$$\boldsymbol{H} = \{\boldsymbol{h}_1, \boldsymbol{h}_2, \cdots, \boldsymbol{h}_n\} = \textit{Bi-LSTM}(\boldsymbol{x}) \tag{3}$$

Where $\boldsymbol{h}_t \in \mathbb{R}^{2d_h}$ denotes the hidden representation of $\boldsymbol{x}_t$ in time step t, d_h denotes the dimensionality of hidden representation.

2.3 Learning Graph Representation

Different from conventional sarcasm detection methods that treated a sentence as a word sequence and purely extracted sarcastic information from the literal or semantic content. We explore a novel Affective Dependency Graph Convolutional Network (ADGCN) framework that interactively feeding the affective and dependency graphs of the sentence into the multi-layers GCN architecture to leverage the long-range affective incongruity expressions. Each node in the l-th GCN layer is updated according to the hidden representations of its neighborhoods according to the adjacency matrices of the two graphs, the process is defined as:

$$\boldsymbol{g}^l = \text{ReLU}(\tilde{\boldsymbol{A}}^d \text{ReLU}(\tilde{\boldsymbol{A}}^a \boldsymbol{g}^{l-1} \boldsymbol{W}^l_a + \boldsymbol{b}^l_a)\boldsymbol{W}^l_d + \boldsymbol{b}^l_d) \tag{4}$$

where $\boldsymbol{g}^{l-1} \in \mathbb{R}^{n\times 2d_h}$ is the hidden graph representation evolved from the preceding GCN layer, and the original input nodes of the first GCN layer are the context representation learned by Bi-LSTMs: $\boldsymbol{g}^0 = [\boldsymbol{h}_1, \boldsymbol{h}_2, \cdots, \boldsymbol{h}_n]$. $\tilde{\boldsymbol{A}}$ is the normalized adjacency matrix: $\tilde{\boldsymbol{A}}_i = \boldsymbol{A}_i/(E_i + 1)$. $E_i = \sum_{j=1}^{n} A_{i,j}$ is the degree of $\boldsymbol{A}_i$. $\boldsymbol{W}^l \in \mathbb{R}^{2d_h\times 2d_h}$, $\boldsymbol{b}^l \in \mathbb{R}^{2d_h}$ are the trainable parameters of the l-th GCN layer.

Then inspired by [34], we employ a retrieval-based attention mechanism to capture the affective dependency graph-oriented features from context representations:

$$\boldsymbol{r} = \sum_{t=1}^{n} \alpha_t \boldsymbol{h}_t, \quad \alpha_t = \frac{\exp(\beta_t)}{\sum_{i=1}^{n}\exp(\beta_i)}, \quad \beta_t = \sum_{i=1}^{n} \boldsymbol{h}_t^\top \boldsymbol{g}_i^L \tag{5}$$

where $\top$ represents matrix transposition, $\boldsymbol{g}^L$ is the output of the final GCN layer. Afterward, the final sarcastic representation is fed into a fully-connected layer with softmax normalization to capture a probability distribution $\hat{\boldsymbol{y}}$ of sarcasm decision space:

$$\hat{\boldsymbol{y}} = \text{softmax}(\boldsymbol{W}_o \boldsymbol{r} + \boldsymbol{b}_o) \tag{6}$$

where $\hat{\boldsymbol{y}} \in \mathbb{R}^{d_p}$ is the predicted sarcastic probability for the input sentence, d_p is the dimensionality of sarcasm labels. $\boldsymbol{W}_o \in \mathbb{R}^{d_p\times 2d_h}$ and $\boldsymbol{b}_o \in \mathbb{R}^{d_p}$ are trainable parameters.

[1] We employ spaCy toolkit to derive dependency tree of the sentence: https://spacy.io/.

Table 1: Statistics of the experimental data.

Dataset	Train		Test	
	Sarcasm	*Non*	*Sarcasm*	*Non*
IAC-V1	862	859	97	94
IAC-V2	2947	2921	313	339
Tweets-1 (Riloff)	282	1051	35	113
Tweets-2 (Ptáček)	23456	24387	2569	2634
Reddit-1 (/r/movies)	5521	5607	1389	1393
Reddit-2 (/r/technology)	6419	6393	1596	1607

2.4 Learning Objective

We minimize the cross-entropy loss via the standard gradient descent algorithm to train the model:

$$\min_{\Theta} \mathcal{L} = -\sum_{i=1}^{N}\sum_{j=1}^{d_p} y_i^j log \hat{y}_i^j + \lambda ||\Theta||^2 \tag{7}$$

where N is the training data size. $\boldsymbol{y}_i$ and $\hat{\boldsymbol{y}}_i$ respectively represent the ground-truth and estimated label distribution of instance i. Θ denotes all trainable parameters of the model, λ represents the coefficient of L_2-regularization.

3 EXPERIMENTS

3.1 Experimental Data and Settings

To evaluate our proposed model, following [28], we conduct experiments on 6 benchmark datasets from 3 well-known sources:

- **IAC (Internet Argument Corpus)**: We use two versions of the dataset from [21], which are denoted as IAC-V1[2] and IAC-V2[3] respectively.
- **Tweets**: We use two datasets collected by Riloff et al. [26] and Ptáček et al. [25]. For both datasets, we retrieve tweets using the Twitter API with the provided tweet IDs[4].
- **Reddit**: We use two subsets (i.e. */r/movies* and */r/technology*) of Reddit dataset provided by [14] for sarcasm detection.

The statistics of the experimental data are reported in Table 1.

In our experiments, for non-BERT models, we utilize GloVe [24] to embed each word as a 300-dimensional embedding. The number of GCN layers is set to 3. The dimensionality of hidden representations is set to 300. The coefficient λ of L_2 regularization is set to 0.01. Adam is utilized as the optimizer with a learning rate of 0.001 to train the model, and the mini-batch size is 128 for Tweets-2 and 32 for other datasets. For BERT-based models, we use the pre-trained uncased BERT-base [5] with 768-dimensional embedding, and the learning rate is 0.00002. We perform Accuracy (Acc.) and Macro *F1-score* (F1) to measure the performance of the models[5].

3.2 Comparison Models

We compare our model, i.e. **ADGCN** and **ADGCN-BERT** (replace Bi-LSTM with BERT), with the following 13 baselines[6]. Including 1) statistic technique: **NBOW** [28]; 2) conventional neural networks: **CNN**, **LSTM**, **ATT-LSTM** [33]; 3) sarcasm detection methods: **GRNN** [35], **CNN-LSTM-DNN** [7], **SIARN** [28], **MI-ARN** [28], **SMSD** [32], **SMSD-BiLSTM** [32]; 4) BERT-based models: **BERT** [5], **ACE2-BERT-EMoSi** [1], **ACE2-BERT-EAISe** [1].

[2]https://nlds.soe.ucsc.edu/sarcasm1
[3]https://nlds.soe.ucsc.edu/sarcasm2
[4]http://api.twitter.com/
[5]The source code of this work is released at https://github.com/HLT-HITSZ/ADGCN
[6]Since there are no unified datasets among existing studies, we conduct comparison experiments of baselines on our datasets with open source code or reproduced code.

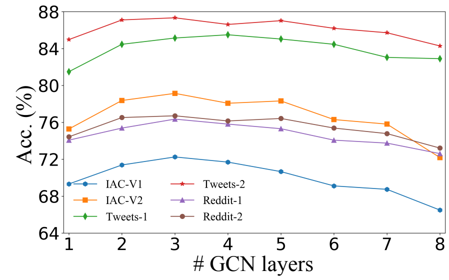


Figure 3: Impact of the number of GCN layers.

3.3 Main Experimental Results

Table 2 shows the experimental results on 6 benchmark datasets. We can observe that our proposed **ADGCN** consistently outperforms all compared baselines over both non-BERT and BERT-based models on all datasets. To be specific, the best improved results of Acc. and F1 respectively are 7.65% and 7.78% compared with the previous state-of-the-art performance. For BERT-based methods, the best improved results of Acc. and F1 respectively are 7.37% and 7.35% compared with previous state-of-the-art performance. This verifies that our proposed model, which leveraging affective dependencies of the context with a GCN architecture outstandingly improves the performance of sarcasm detection.

3.4 Ablation Study

To analyze the impact of different components of the proposed **ADGCN** bring to the performance, we conduct an ablation study and report the results in Table 3. Note that removal of affective graph sharply degrades the performance, which indicates that affective information is significant in the sarcastic expressions learning. Additionally, the graph without syntax-aware refinement also leads to a considerably poorer performance. This implies that refining the affective graph with syntax-aware information advances the model to extract the linchpin clues of incongruity expressions by affective dependencies.

3.5 Impact of GCN Layers

To investigate the impact of the number of GCN layers on the performance of our proposed **ADGCN**, we vary the number from 1 to 8 and report the results in Figure 3. Note that 3-layer GCN performs overall better than other layers, and thus we set the number of GCN layers as 3. One GCN layer performs unsatisfactorily on all datasets, which indicates inadequate network structure is insufficient to exploit decent sarcastic features. Additionally, when the layer greater than 3, the performance fluctuates and tends to decline with the increasing number. This implies that roughly increasing the number of GCN layers is vulnerable to slash the learning ability of the model due to the sharp increase of model parameters.

Table 2: Main experimental results on different datasets. Average scores over 10 runs are reported. Best scores are in bold.

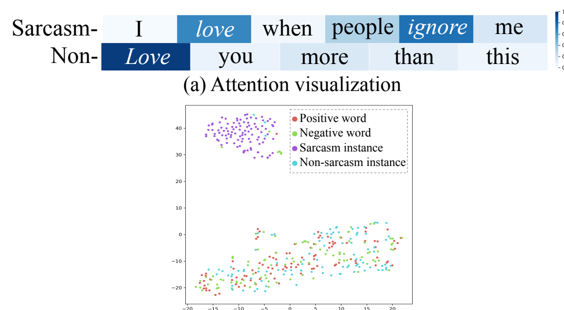
Model	IAC-V1		IAC-V2		Tweets-1		Tweets-2		Reddit-1		Reddit-2	
	Acc. (%)	*F1 (%)*	*Acc. (%)*	*F1 (%)*	*Acc. (%)*	*F1 (%)*	*Acc. (%)*	*F1 (%)*	*Acc. (%)*	*F1 (%)*	*Acc. (%)*	*F1 (%)*
NBOW [28]	59.63	59.38	67.55	67.74	74.86	63.39	74.23	74.13	69.66	69.66	65.61	65.56
CNN	60.62	60.27	70.15	69.95	78.64	66.47	80.77	80.76	70.21	70.16	68.00	67.91
LSTM	60.52	60.45	71.10	70.84	79.33	67.62	80.79	80.78	70.66	70.59	68.80	68.16
ATT-LSTM [33]	63.45	63.18	65.46	65.33	80.70	69.23	81.56	81.56	70.50	70.44	68.62	68.55
GRNN [35]	63.87	62.44	72.23	70.92	79.10	68.35	81.18	80.14	71.55	70.47	67.15	67.14
CNN-LSTM-DNN [7]	66.49	66.46	76.99	67.93	76.49	67.80	79.74	79.20	71.17	71.14	67.62	67.34
SIARN [28]	64.24	63.79	74.98	74.95	79.12	67.47	83.59	83.59	70.66	70.58	68.55	68.51
MIARN [28]	64.45	63.89	75.84	75.80	79.19	67.11	83.78	83.78	70.72	70.68	68.48	68.44
SMSD [32]	65.13	65.07	72.19	72.13	78.11	67.18	81.25	81.24	69.58	69.55	68.94	68.90
SMSD-BiLSTM [32]	64.50	64.40	71.44	71.36	78.92	67.75	78.92	78.90	69.84	69.75	69.06	69.00
ADGCN (**ours**)	**72.25**	**72.20**	**79.14**	**79.13**	**85.14**	**77.01**	**87.33**	**87.33**	**76.35**	**76.31**	**76.71**	**76.69**
BERT [5]	68.95	68.88	78.41	78.40	83.38	76.08	86.37	86.36	76.89	76.87	77.42	77.41
ACE2-BERT-EMoSi [1]	66.49	66.48	76.75	76.65	81.76	72.12	86.58	86.58	74.64	74.62	76.30	76.35
ACE2-BERT-EAISe [1]	68.06	67.98	77.25	77.10	81.76	73.39	86.60	86.60	74.73	74.70	76.37	76.36
ADGCN-BERT (**ours**)	**76.32**	**76.23**	**82.37**	**82.36**	**88.16**	**81.91**	**90.31**	**89.54**	**80.68**	**80.63**	**80.77**	**80.77**

Table 3: Accuracy results of ablation study. $\mathcal{A}$ denotes affective graph, $\mathcal{S}$ denotes syntax-aware refinement.

Model	IAC-V1	IAC-V2	Tweets-1	Tweets-2	Reddit-1	Reddit-2
ADGCN	**72.25**	**79.14**	**85.14**	**87.33**	**76.35**	**76.71**
w/o $\mathcal{A}$	69.03	75.52	81.67	82.28	73.15	71.89
w/o $\mathcal{S}$	71.13	77.20	83.16	85.31	75.76	73.78

3.6 Visualization

To qualitatively demonstrate how affective dependency graph improves the performance of sarcasm detection, we present a visualization analysis in Figure 4. We first visualize the attention scores of typical sarcasm/non-sarcasm examples learned by our proposed ADGCN in Figure 4 (a) to analyze how the proposed ADGCN draws the affective dependencies in sarcastic/non-sarcastic expressions learning by interactively modeling both affective and dependency information of the context. Note that due to the proposed ADGCN, the affective auxiliary syntactic dependency information enhances the incongruous words from sarcasm sentences by attention signals. Hence, the weighted sum representation of sarcasm instances would neither be similar to positive words nor negative words. On the contrary, for the non-sarcasm instances, the representations will be similar to the affective words since the ADGCN only focuses on few congruous words. Thus the representations of non-sarcasm instances should be mixed with affective words but separated with sarcasm instances. To further investigate the difference of sarcastic/non-sarcastic representations, in Figure 4 (b), we show the t-SNE [29] visualization of intermediate sarcasm and non-sarcasm representations, which adhere to the hidden representations of affective words derived by Bi-LSTM layers. Note that a significantly clear separation between sarcasm representations and affective word vectors is represented, while the distribution of non-sarcasm representations is quite overlapping with affective words. This further indicates that our proposed ADGCN effectively represents non-sarcasm instances by attaching them to affective words, and derive the sarcasm representations according to the contradictory affective dependencies and incongruity expressions.



(a) Attention visualization

(b) Vectors visualization

Figure 4: Results of visualization.

4 CONCLUSION

In this paper, we propose a novel scenario of constructing an affective graph and a dependency graph for each sentence to learn the long-range contradictory implications and incongruity expressions in sarcasm detection. More concretely, an affective dependency graph convolutional network (ADGCN) framework is exploited to draw incongruity patterns and inconsistent sentiment expressions over the context in the learning of sarcastic features by interactively modeling both affective and syntactical information of the context. Experimental results on multiple benchmark datasets show that our proposed model significantly outperforms state-of-the-art baseline methods in sarcasm detection.

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