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## Article

# Investigating Inter-Correlations Using Graph-Based Neural Networks in Aspect-Level Sentiment Analysis

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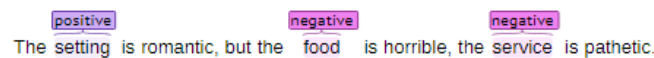
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**Abstract:** In this paper, we present a groundbreaking methodology in the realm of aspect-level sentiment analysis, which capitalizes on the advanced capabilities of graph-based neural networks. Our approach, distinguished as the Aspect Correlation Graph Network (ACGN), represents a significant departure from conventional models. These traditional models often analyze aspects in isolation, failing to capture the intricate web of sentiment relationships that may exist within a single sentence. ACGN, however, is designed to address this gap by employing a sophisticated bidirectional attention mechanism, integrated with positional encoding. This unique combination not only enhances the model's ability to focus on relevant parts of the sentence but also aids in constructing detailed, aspect-focused representations. These representations are particularly crucial for understanding the nuanced interplay of sentiments associated with different aspects. Central to our model's architecture is the incorporation of a graph convolutional network. This network serves as a pivotal component in mapping and analyzing the complex network of sentiment correlations that can exist among various aspects within sentences. Through this integration, ACGN is able to unearth and interpret the subtle and often overlooked sentiment dynamics that traditional models might miss. Our comprehensive evaluations of the Aspect Correlation Graph Network, conducted using the SemEval 2014 datasets, have yielded promising results. These findings demonstrate a clear and significant advancement over the capabilities of existing models. Particularly, the results underscore the critical importance and utility of recognizing and understanding the connections between sentiments of different aspects in text analysis. This insight opens new avenues in the field of sentiment analysis, suggesting a broader application potential of ACGN in various contexts where understanding nuanced sentiment relationships is key. Overall, our study not only introduces a novel approach in aspect-level sentiment analysis but also sets a new standard for future research in this area. By highlighting the integral role of inter-aspect sentiment connections, ACGN paves the way for more sophisticated and accurate sentiment analysis tools, capable of handling the complexities of natural language with greater finesse and precision.

**Keywords:** aspect-level sentiment analysis; sentiment interplay; graph-based neural networks; bidirectional attention

## 1. Introduction

The field of aspect-level sentiment classification, as cited in seminal works by Bo Pang (2008) and Bing Liu (2012) [1], has increasingly gained prominence in the sphere of natural language processing [2–4]. This intricate task goes beyond general sentiment analysis by zeroing in on the sentiment polarities associated with specific aspects within a given context. Consider, for instance given in Figure 1, a sentence like “The price is reasonable although the service is poor”. Here, the sentiments expressed towards distinct aspects, namely “price” and “service”, diverge, reflecting positive and negative polarities, respectively. In this context, an aspect could be an entity or a particular attribute of an entity.



The positive setting is romantic, but the negative food is horrible, the negative service is pathetic.

**Figure 1.** This figure demonstrates how understanding sentiment relationships among various aspects within a sentence can be beneficial. Such dependencies often become apparent through certain linguistic cues, like conjunctions. A case in point is our ability to deduce the actual sentiment towards the aspect “food”, even when critical words like “horrible” are obscured, highlighting the predictive power of these sentiment connections.

Delving deeper into aspect-level sentiment classification reveals its complexity [24], especially when contrasted with broader, sentence-level sentiment analysis. The primary challenge lies in pinpointing and interpreting the segments of a sentence that pertain to each aspect. Earlier methodologies, as explored in studies by Svetlana Kiritchenko (2014) and others, predominantly relied on statistical techniques, crafting a suite of handcrafted features to train classifiers like Support Vector Machines. Such approaches, while effective to an extent, were labor-intensive and lacked flexibility.

Recent years have witnessed a paradigm shift with the advent of neural network models, as detailed in works by Poria et al. (2016) and Duyu Tang (2016) [25–28]. These models have garnered interest for their proficiency in autonomously generating insightful, low-dimensional representations from both aspects and their contextual environments. This development has markedly improved accuracy in aspect-level sentiment classification, eliminating the need for meticulous feature engineering [24,29–31]. A cornerstone of this evolution has been the implementation of attention mechanisms in neural networks, as evidenced in groundbreaking research by Volodymyr (2014) and Dzmitry (2015) [4,9,32–34]. These mechanisms, widely incorporated in aspect-level sentiment analysis models, adeptly identify the sentence components most pertinent to a given aspect. Models by Chen et al. (2017), Ma et al. (2017), and Song et al. (2019) exemplify the successful application of attention-based frameworks in creating aspect-specific representations.

Notwithstanding these advancements, existing models are not without limitations. A recurring issue is their tendency to treat each aspect in isolation, thus overlooking the potential wealth of information embedded in the sentiment dependencies among multiple aspects. For instance, understanding the positive sentiment towards the “setting” aspect, combined with the conjunction “but”, intuitively suggests a negative sentiment towards the “food” aspect. Such inter-aspect sentiment dependencies are instrumental in accurately gauging the overall sentiment conveyed in a sentence.

Addressing this gap, we introduce a groundbreaking method, termed **Sentiment Dependency Graph Convolutional Networks (SDGCN)**, to model these intricate sentiment interconnections in aspect-level sentiment classification. Leveraging the strengths of graph convolutional networks (GCN), as discussed in Kipf’s (2016) research, SDGCN adeptly captures the nuanced interdependencies within relational data. Each aspect is conceptualized as a node within a graph, with edges delineating the sentiment relationships between nodes. Prior to applying GCN, our model also incorporates a bidirectional attention mechanism paired with position encoding, further refining the aspect-specific representations.

Our evaluation, conducted on the SemEval 2014 datasets [35], demonstrates that SDGCN significantly outperforms existing state-of-the-art methods. The primary contributions of our work are multifold:

- We are pioneers in considering inter-aspect sentiment dependencies within a single sentence for aspect-level sentiment classification.
- Our innovative bidirectional attention mechanism, enhanced with position encoding, effectively captures nuanced aspect-specific representations.
- SDGCN introduces a novel framework for multi-aspect sentiment classification, employing GCN to adeptly map sentiment dependencies across different aspects within sentences.

- Comprehensive evaluations on SemEval 2014 datasets affirm the superiority of our model compared to current leading methodologies.

In summary, our research not only presents a novel approach in the landscape of sentiment analysis but also sets a precedent for future explorations in this domain, underlining the critical role of understanding the interconnected nature of sentiments across various aspects.

## 2. Related Work

This section delves into the prevailing research on aspect-level sentiment classification and the utilization of graph convolutional networks, providing a succinct overview of these domains.

### 2.1. Aspect-Level Sentiment Classification

The realm of sentiment analysis, also commonly referred to as opinion mining, stands as a cornerstone in the field of Natural Language Processing (NLP), as highlighted in studies by Kim (2014) and Abid et al. (2019). Within this domain, aspect-level sentiment classification emerges as a nuanced, fine-grained task [13,36–38].

Historically, initial research in aspect-level sentiment classification centered on the extraction of various features, such as bag-of-words and sentiment lexicons, to train classifiers (Rao and Ravichandran, 2009). These methodologies spanned from rule-based systems (Ding et al., 2008) to statistical approaches (Jiang et al., 2011), all heavily reliant on the painstaking process of feature engineering. However, the landscape began to shift with the advent of deep learning. More recent advances have seen a surge in the application of deep neural networks, renowned for their ability to autonomously generate dense sentence vectors, eschewing the need for manual feature crafting (Dong et al., 2014; Hai and Cong, 2015). These vectors, characterized by their low dimensionality, retain a rich tapestry of semantic details. Attention mechanisms, in particular, have revolutionized sentence representation by homing in on the most salient aspects of a sentence in relation to a given aspect (Li et al., 2017; Li and Jiang, 2018; Ma et al., 2019). Wang and colleagues (2016) introduced ATAE-LSTM, a model that fuses LSTM with an attention mechanism, enabling aspect embeddings to directly influence the computation of attention weights. Similarly, Chen et al. (2017) proposed RAM, employing a multi-attention mechanism within a bi-directional LSTM structure. Ma et al. (2017) and Song et al. (2019) furthered this exploration, designing models with bidirectional and multi-head attention mechanisms, respectively, for a more intricate relationship modeling between context and aspect. Nonetheless, a common limitation in these attention-centric studies is their isolated handling of each aspect within sentences, potentially overlooking crucial sentiment dependency information in scenarios involving multiple aspects.

### 2.2. Graph Convolutional Network

Graph convolutional networks (GCN), first conceptualized by Bruna et al. (2014), have proven to be highly effective in processing graph-structured data, rich in relational information. Extensive research has been conducted to adapt GCNs for image-related tasks, with notable contributions from Henaff et al. (2015), Defferrard et al. (2016), Qi et al. (2017), and Li et al. (2018). Chen et al. (2019) advanced this further by applying GCN for multi-label image recognition, facilitating the propagation of information among multiple labels and fostering the development of interconnected classifiers for each image label. In parallel, the NLP sector has also witnessed a burgeoning interest in GCNs, with applications spanning semantic role labeling (Marcheggiani and Titov, 2017), machine translation (Bastings et al., 2017), and relation classification (Li et al., 2019). Other explorations in this field have utilized graph neural networks for text classification, treating documents, sentences, or words as nodes within a graph and constructing the network based on node relationships (Hao et al., 2018; Yue et al., 2018). These studies collectively underscore GCNs' adeptness in capturing the intricate

relations between nodes [39? ]. Drawing inspiration from this body of work, we incorporate GCN in our research to effectively discern sentiment dependencies among multiple aspects within textual data.

### 3. Methodology

The task of aspect-level sentiment classification is defined as follows: Consider a context containing  $N$  words  $W^c = \{w_1^c, w_2^c, \dots, w_N^c\}$  and  $K$  aspect terms  $W^a = \{W^{a_1}, W^{a_2}, \dots, W^{a_K}\}$ . Each aspect term  $W^{a_i}$ , comprising  $M_i \in [1, N)$  words, is a subset of the context  $W^c$ . The objective is to develop a classifier that accurately predicts the sentiment polarity for each of these aspect terms.

Our proposed SDGCN architecture encompasses several components: input embedding, Bi-LSTM, position encoding, bidirectional attention, GCN, and the output layer. We describe these components in sequence from input to output.

#### 3.1. Input Embedding Layer

In this layer, individual words are transformed into vectors in a high-dimensional space. We use the pretrained GloVe model [40] and the BERT model [41] to obtain static word embeddings. Consequently, each word is represented by a vector  $e_t \in \mathbb{R}^{d_{emb} \times 1}$ , where  $d_{emb}$  denotes the embedding dimension. Post embedding, the context is represented as  $E^c \in \mathbb{R}^{d_{emb} \times N}$ , and the  $i$ -th aspect as  $E^{a_i} \in \mathbb{R}^{d_{emb} \times M_i}$ .

#### 3.2. Bidirectional LSTM (Bi-LSTM)

On top of the embedding layer, a Bi-LSTM captures contextual nuances for each word. The forward and backward hidden states,  $\vec{h}_t \in \mathbb{R}^{d_{hid} \times 1}$  and  $\overleftarrow{h}_t \in \mathbb{R}^{d_{hid} \times 1}$  respectively, where  $d_{hid}$  represents the number of hidden units, are concatenated to form the final state:

$$h_t = [\vec{h}_t, \overleftarrow{h}_t] \in \mathbb{R}^{2d_{hid} \times 1} \quad (1)$$

Separate Bi-LSTMs are used for obtaining the contextual outputs for the sentence,  $H^c = [h_1^c, h_2^c, \dots, h_N^c] \in \mathbb{R}^{2d_{hid} \times N}$ , and each aspect,  $H_i^a = [h_1^{a_i}, h_2^{a_i}, \dots, h_{M_i}^{a_i}] \in \mathbb{R}^{2d_{hid} \times M_i}$ , with shared parameters across different aspects.

#### 3.3. Position Encoding

Recognizing that the sentiment of an aspect is more likely influenced by nearby context words, we incorporate position encoding. For an aspect  $W^{a_i}$  among  $K$  aspects, where  $i \in [1, K]$  is the aspect index, the relative distance  $d_t^{a_i}$  between the  $t$ -th context word and the  $i$ -th aspect is defined as:

$$d_t^{a_i} = \begin{cases} 1, & \text{if } dis = 0 \\ 1 - \frac{dis}{N}, & \text{if } 1 \leq dis \leq s \\ 0, & \text{if } dis > s \end{cases} \quad (2)$$

where  $dis$  is the distance from a context word to the aspect,  $s$  is a predetermined constant, and  $N$  is the context length. The position-aware representation with embedded position information is:

$$\begin{aligned} p_t^{a_i} &= d_t^{a_i} h_t^c \\ P^{a_i} &= P_i = [p_1^{a_i}, p_2^{a_i}, \dots, p_N^{a_i}] \end{aligned} \quad (3)$$

#### 3.4. Bidirectional Attention Mechanism

To encapsulate the interactive relationship between context and aspect, our model utilizes a bidirectional attention mechanism, comprising two modules: *context to aspect attention* and *aspect to*

*context attention*. The first module redefines aspect representations based on the context, while the second focuses on deriving aspect-specific context representations for subsequent GCN processing.

#### 3.4.1. Context to Aspect Attention

This component assigns weights to aspect words according to a query vector  $\bar{h}^c \in \mathbb{R}^{2d_{hid} \times 1}$ , derived from averaging the context hidden outputs  $H^c$ . The attention weight  $\beta_t^{a_i}$  for each aspect word vector  $h_t^{a_i} \in \mathbb{R}^{2d_{hid} \times 1}$  is computed as:

$$f_{ca}(\bar{h}^c, h_t^{a_i}) = \bar{h}^{cT} \cdot W_{ca} \cdot h_t^{a_i} \quad (4)$$

$$\beta_t^{a_i} = \frac{\exp(f_{ca}(\bar{h}^c, h_t^{a_i}))}{\sum_{t=1}^{M_i} \exp(f_{ca}(\bar{h}^c, h_t^{a_i}))} \quad (5)$$

where  $W_{ca} \in \mathbb{R}^{2d_{hid} \times 2d_{hid}}$  is the attention weight matrix. The new aspect representation is then a weighted combination of the aspect hidden states:

$$m^{a_i} = \sum_{t=1}^{M_i} \beta_t^{a_i} \cdot h_t^{a_i} \quad (6)$$

#### 3.4.2. Aspect to Context Attention

This module captures the aspect-specific context representation, mirroring the *context to aspect attention*. It calculates attention scores using the new aspect representation  $m^{a_i}$  and the position-aware representation  $p_t^{a_i}$ :

$$f_{ac}(m^{a_i}, p_t^{a_i}) = m^{a_iT} \cdot W_{ac} \cdot p_t^{a_i} \quad (7)$$

$$\gamma_t^{a_i} = \frac{\exp(f_{ac}(m^{a_i}, p_t^{a_i}))}{\sum_{t=1}^N \exp(f_{ac}(m^{a_i}, p_t^{a_i}))} \quad (8)$$

$$x^{a_i} = x_i = \sum_{t=1}^N \gamma_t^{a_i} \cdot h_t^c \quad (9)$$

where  $W_{ac} \in \mathbb{R}^{2d_{hid} \times 2d_{hid}}$  is another attention weight matrix. This step yields aspect-specific representations  $X = [x_1, x_2, \dots, x_K]$  for each aspect in context.

### 3.5. Graph Convolutional Network (GCN)

GCN excels in processing data with intricate relationships and dependencies. We leverage GCN to model the sentiment dependencies between aspects, treating each aspect as a graph node. The final output of each node functions as the classifier for the respective aspect. As our task lacks explicit edges, we define these connections from scratch.



### 3.5.1. SDGCN: Sentiment graph based GCN

In SDGCN, each graph node encapsulates aspect-specific data, transforming neighborhood information into a novel vector representation. This method, inspired by Kipf et al. [? ], incorporates self-loops in every node. The transformation is mathematically described as:

$$x_v^1 = \text{relu} \left( \sum_{u \in N(v)} \hat{W}_{cross} x_u + \hat{b}_{cross} \right) + \text{relu}(\hat{W}_{self} x_v + \hat{b}_{self}) \quad (10)$$

Here,  $\hat{W}_{cross}, \hat{W}_{self} \in \mathbb{R}^{d_m \times d_n}$ ,  $\hat{b}_{cross}, \hat{b}_{self} \in \mathbb{R}^{d_m \times 1}$ , with  $x_u$  signifying the  $u$ -th aspect-centric representation (refer Eq.(9)), and  $\text{relu}$  representing the rectifier linear unit function. We set  $d_m = d_n = 2h_{hid}$  in our SDGCN model.

By integrating multiple layers of SDGCN, we enhance the depth of neighborhood information accessible to each node. Each layer processes the output from its predecessor to generate updated node representations:

$$x_v^{l+1} = \text{relu} \left( \sum_{u \in N(v)} \hat{W}_{cross}^l x_u^l + \hat{b}_{cross}^l \right) + \text{relu}(\hat{W}_{self}^l x_v^l + \hat{b}_{self}^l) \quad (11)$$

where  $l$  represents the layer index, with  $1 \leq l \leq L - 1$ .

### 3.6. Aspect Classification via SDGCN

The SDGCN framework concludes with an aspect classification mechanism. The final layer's node output,  $x_i^L$ , is harnessed as an aspect-specific classifier. A fully-connected layer then maps  $x_i^L$  to a  $C$  class aspect space:

$$z_i = \hat{W}_z x_i^L + \hat{b}_z \quad (12)$$

where  $\hat{W}_z \in \mathbb{R}^{C \times 2d_{hid}}$  and  $\hat{b}_z \in \mathbb{R}^{2d_{hid} \times C}$ . The probability of the  $i$ -th aspect being in the sentiment class  $j \in [1, C]$  is calculated as:

$$y'_{ij} = \frac{\exp(z_{ij})}{\sum_{k=1}^C \exp(z_{ik})} \quad (13)$$

### 3.7. Optimization in SDGCN Training

The SDGCN model optimizes performance by minimizing a loss function that integrates cross-entropy with an  $L2$ -regularization component. The loss for a specific sentence is formulated as:

$$\text{loss} = \sum_{i=1}^K \sum_{j=1}^C y_{ij} \log(y'_{ij}) + \lambda \|\theta\|^2 \quad (14)$$

where  $y_{ij}$  denotes the one-hot labels for the  $i$ -th aspect in the  $j$ -th class,  $\lambda$  is the  $L2$ -regularization coefficient, and  $\theta$  encompasses the parameters subject to regularization. Additionally, to mitigate overfitting, a dropout strategy is employed during the training phase.

## 4. Experimental Analysis

### 4.1. Datasets and Experimental Configurations

We assessed the efficacy of SDGCN using two SemEval 2014 Task4 datasets (refer Table 1), comprising laptop and restaurant reviews. Each dataset is divided into training and testing sets, with

reviews containing multiple aspects and their sentiment polarities (positive, neutral, negative). The distribution of aspects within sentences is illustrated in Figure ??, showing a common presence of multi-aspects in single sentences.

**Table 1.** Overview of the datasets.

Dataset	Split	Positive	Negative	Neutral
Restaurant	Training	2164	807	637
	Testing	728	196	196
Laptop	Training	994	870	464
	Testing	341	128	169

For model initialization, we utilized GloVe and BERT word representations, with respective dimensionalities of 300 and 768. The LSTM hidden units were set at 300, while GCN layer output was fixed at 600. Weight matrices, barring the final fully connected layer, were initialized using a uniform distribution. The final layer employed a normal distribution and  $L_2$  regularization. Training parameters included a 0.5 dropout rate, batch size of 32, and Adam Optimizer with a learning rate of 0.001. Model performance was evaluated using Accuracy and Macro-F1 metrics.

4.2. Comparative Frameworks

SDGCN’s effectiveness is benchmarked against various models: **TD-LSTM, ATAE-LSTM, MemNet, IAN, RAM, PBAN, TSN, AEN, AEN-BERT** - Various approaches employing aspect-specific representations and attention mechanisms with LSTM or GRU networks for sentiment polarity prediction.

4.3. Overall Outcomes

The experimental outcomes, as delineated in Table 2, unveil the comparative efficiency of the models under scrutiny. To facilitate an unbiased evaluation that transcends the limitations posed by varying word representations, we meticulously segmented our analysis into two distinct categories: models predicated on GloVe embeddings and those based on BERT. A remarkable observation from this bifurcated analysis is the unparalleled performance of our brainchild, the SDGCN model, which not only leads the pack in both categories but also sets unprecedented benchmarks in the domain, especially with its BERT-based incarnation, SDGCN-BERT.

Delving into the intricacies of the GloVe-based methodologies, it becomes evident that the TD-LSTM approach lags in its effectiveness. This shortfall stems from its rudimentary integration of aspect information, which lacks the finesse and depth required for nuanced sentiment analysis. In contrast, models like ATAE-LSTM, MenNet, and IAN, which harness the power of attention mechanisms, exhibit a marked improvement over TD-LSTM. These models adeptly factor in the significance of aspects, thereby enhancing their predictive accuracy.

Notably, RAM, with its fusion of multiple attention mechanisms and a recurrent neural network, excels in capturing detailed, aspect-specific representations, elevating its performance above its basic attention-based counterparts. PBAN, utilizing position embedding, parallels the efficacy of RAM, showing superior results on the Restaurant dataset but not quite matching up on the Laptop dataset. The relative underperformance of TSN, in both datasets, can be attributed to its oversimplified framework, which inadequately models the context and aspects. AEN, albeit slightly better than TSN, also falls short of RAM and PBAN, implying that eschewing recurrent neural networks might reduce model complexity but at the cost of performance.



**Table 2.** Performance comparison with baseline models on Restaurant and Laptop datasets. Baseline results are sourced from literature. Best GloVe and BERT model outcomes are highlighted separately. Suffix '-A' denotes adjacent-relation graph based models, '-G' for global-relation graph based models.

Embedding Type	Approaches	Restaurant		Laptop	
		Accuracy	Macro-F1	Accuracy	Macro-F1
GloVe	TD-LSTM	75.63	-	68.13	-
	ATAE-LSTM	77.20	-	68.70	-
	MemNet	78.16	65.83	70.33	64.09
	IAN	78.60	-	72.10	-
	RAN	80.23	70.80	74.49	71.35
	PBAN	81.16	-	74.12	-
	TSN	80.1	-	73.1	-
	AEN	80.98	72.14	73.51	69.04
	SDGCN-A w/o p	81.61	72.22	73.20	68.54
	SDGCN-G w/o p	81.61	72.93	73.67	68.70
	SDGCN-A	82.14	73.47	75.39	70.04
	SDGCN-G	<b>82.95</b>	<b>75.79</b>	<b>75.55</b>	71.35
BERT	AEN-BERT	83.12	73.76	79.93	76.31
	SDGCN-BERT	<b>83.57</b>	<b>76.47</b>	<b>81.35</b>	78.34

A pivotal insight emerges when comparing the results of SDGCN variants - the SDGCN-A and SDGCN-G. The global-relation graph-based SDGCN-G demonstrates a subtle yet significant edge over its adjacent-relation counterpart in terms of accuracy and Macro-F1 scores. This suggests that solely relying on adjacent relationships might be insufficient to holistically capture the intricate web of interactions among multiple aspects, especially when long-distance relationships are at play. Furthermore, incorporating position information into SDGCN-A and SDGCN-G yields substantial performance enhancements, underscoring the critical role of position encoding in achieving optimal results.

The BERT-based models, armed with the prowess of pre-trained BERT embeddings, showcase a clear superiority over their GloVe-based counterparts. This is particularly evident when examining the performance leaps made by SDGCN-BERT. On the Restaurant dataset, it notches up gains of 1.09% in accuracy and 1.86% in Macro-F1 scores, while on the Laptop dataset, it registers even more impressive gains of 1.42% and 2.03% in the same metrics, respectively. These significant improvements attest to the formidable efficacy of our proposed SDGCN model, cementing its status as a trailblazer in the realm of aspect-based sentiment analysis.

#### 4.4. In-Depth Examination of GCN's Influence on Model Efficacy

This segment delves into a meticulously structured series of model experiments designed to rigorously assess the transformative impact of the Graph Convolutional Network (GCN) module on aspect-based sentiment analysis. The models employed in this investigation are:

- **BiAtt+GCN (Synonymously SDGCN):** This model, our flagship SDGCN, harnesses the synergistic power of bilateral attention mechanisms combined with GCN, offering a holistic view of inter-aspect sentiment relations.
- **BiAtt:** Stripping away the GCN layer from BiAtt+GCN, this model offers insights into sentiment predictions by treating each aspect in isolation, thus lacking the relational context provided by GCN.
- **Att+GCN:** A pared-down version of BiAtt+GCN, this model retains the GCN component but omits the nuanced 'context to aspect attention', potentially impacting its sentiment prediction accuracy.
- **Att:** This variant, devoid of the GCN module, serves as a baseline, focusing solely on attention mechanisms without the benefit of GCN's relational insights.

The performance metrics of these models, as illustrated in Table 3, paint a revealing picture. A comparative analysis clearly demonstrates that models incorporating the GCN module (e.g., Att+GCN and BiAtt+GCN) consistently outperform their non-GCN counterparts. This disparity in performance not only underscores the efficacy of GCN in enhancing the model’s capability to predict sentiment polarities but also highlights its critical role in understanding the intricate web of sentiment dependencies between various aspects within a text. The juxtaposition of these models, varying in their incorporation of GCN and attention mechanisms, offers a nuanced understanding of how each component contributes to the overall sentiment analysis, thereby validating the indispensable role of GCN in elevating the sophistication and accuracy of aspect-based sentiment analysis.

**Table 3.** Comprehensive Evaluation of GCN’s Impact.

Models	Restaurant		Laptop	
	Acc	Macro-F1	Acc	Macro-F1
Att	81.43	72.40	72.12	68.67
Att+GCN	82.77	74.33	74.61	70.33
BiAtt	81.61	73.49	73.51	69.73
BiAtt+GCN (SDGCN)	82.95	75.79	75.55	71.35

4.5. Detailed Analysis Through Case Studies

This segment delves into a comparative case study, utilizing examples from the laptop dataset, to elucidate the nuanced differences between models equipped with the Graph Convolutional Network (GCN) and those without. These examples, rich in multiple aspects, serve to provide a concrete, intuitive understanding of our proposed GCN-enhanced model’s capabilities in contrast to its counterpart.

Consider the first scenario: "I love the keyboard and the screen." In this sentence, the key aspects are "keyboard" and "screen." The model lacking GCN focuses predominantly on the word "love" to ascertain the sentiment polarities tied to these aspects. However, the GCN-equipped model exhibits a more sophisticated approach. It not only considers "love" but also gives due weight to the connective "and." This subtle yet significant difference indicates that our GCN model adeptly identifies the sentiment link between "keyboard" and "screen" through the connective, allowing for a more integrated and simultaneous sentiment prediction for both aspects.

Moving to the second example: "Air has higher resolution but the fonts are small." This sentence presents the aspects "resolution" and "fonts," connected by the contrasting conjunction "but," implying opposing sentiments. The model without GCN isolates the sentiments, associating "higher" with a positive sentiment for "resolution" and "small" with a potentially negative sentiment for "fonts," neglecting the interplay between these aspects. In stark contrast, the GCN model brings the conjunction "but" into the limelight. This focus enables the model to comprehend the inverse sentiment relationship between "resolution" and "fonts," enhancing the accuracy of sentiment polarity predictions for each aspect.

These illustrative examples highlight the superior capability of our GCN model. It doesn’t just concentrate on individual words pertinent to aspect sentiments; it also intelligently interprets textual elements that signify relationships between different aspects. Utilizing the attention mechanism to spotlight words that express inter-aspect dependencies, followed by the GCN module’s analysis, our model effectively encapsulates the sentiment dynamics within a sentence. This comprehensive approach allows for a more accurate prediction of aspect-level sentiment categories, demonstrating the effectiveness and sophistication of the GCN-enhanced model in aspect-based sentiment analysis.

## 5. Conclusion and Future Directions

This study presents the development of a cutting-edge model, SDGCN, specifically tailored for the nuanced task of aspect-level sentiment analysis. At the heart of SDGCN's methodology lies the innovative application of Graph Convolutional Networks (GCN) to intricately map out and analyze the sentiment interconnections among various aspects within a single sentence. A distinct feature of SDGCN is its integration of a bidirectional attention mechanism, enhanced with positional encoding. This approach enables the model to generate representations that are not only aspect-specific but also deeply informed by the positional context of each aspect within the text. Furthermore, SDGCN employs an advanced message-passing technique to effectively decode the complex web of sentiment dependencies between aspects, a facet often overlooked in previous research endeavors.

Our empirical evaluations, conducted using the SemEval 2014 dataset, have conclusively demonstrated SDGCN's superior performance capabilities. Particularly noteworthy is the SDGCN-BERT variant, which has achieved unprecedented results, setting new benchmarks in the field of aspect-level sentiment analysis. Through meticulous case studies, SDGCN has proven its proficiency in not only identifying key words pivotal for determining aspect sentiment polarities but also in discerning words that play a crucial role in establishing the sentiment relationships between different aspects. This dual focus endows SDGCN with a remarkable ability to capture the subtle nuances of sentiment interplay within textual data.

Looking ahead, our research will venture into the realm of refining and enhancing the sentiment graph structures interlinking aspects. The current model utilizes two varieties of undirected sentiment graphs, which, while effective, offer scope for further sophistication. We hypothesize that leveraging the rich contextual cues present in the textual data could pave the way for constructing more intricate and precise graph structures. This advancement has the potential to not only fine-tune the sentiment analysis process but also to unveil deeper, more intricate layers of sentiment interrelations, thereby pushing the frontiers of aspect-based sentiment analysis.

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