Composition-based Heterogeneous Graph Multi-channel Attention Network for Multi-aspect Multi-sentiment Classification

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Abstract

Aspect-based sentiment analysis (ABSA) has drawn more and more attention because of its extensive applications. However, towards the sentence carried with more than one aspect, most existing works generate an aspect-specific sentence representation for each aspect term to predict sentiment polarity, which neglects the sentiment relationship among aspect terms. Besides, most current ABSA methods focus on sentences containing only one aspect term or multiple aspect terms with the same sentiment polarity, which makes ABSA degenerate into sentence-level sentiment analysis. In this paper, to deal with this problem, we construct a heterogeneous graph to model inter-aspect relationships and aspect-context relationships simultaneously and propose a novel Composition-based Heterogeneous Graph Multi-channel Attention Network (CHGMAN) to encode the constructed heterogeneous graph. Meanwhile, we conduct extensive experiments on three datasets: MAMS-ATSA, Rest14, and Laptop14, experimental results show the effectiveness of our method.

1 Introduction

Aspect-based sentiment analysis (ABSA) is a sentiment analysis task, which aims to predict the sentiment polarity (e.g., POSITIVE, NEGATIVE, NEUTRAL) towards the given aspect term in a sentence. For example, there are two aspect terms decor and food in the sentence: The decor is not a special at all but their amazing food makes up for it, and these two aspect terms will be assigned with NEGATIVE and POSITIVE sentiment polarities respectively. Since the sentiments expressed by these two aspect terms are opposite in polarity, it is unreasonable to assign a sentence-level sentiment polarity. In this regard, ABSA can provide more detailed sentimental predictions compared with sentence-level sentiment analysis.

In recent years, neural network-based methods (Tang et al., 2016; Wang et al., 2016; Ma et al., 2017; Chen et al., 2017) are used to tackle ABSA task and achieve promising performance. Subsequently, with the rise of contextual embedding, contextualized language models, such as BERT (Devlin et al., 2019), are introduced into ABSA and boost performance. Additionally, in order to utilize the dependency tree information, a lot of graph-based methods (Zhang et al., 2019; Sun et al., 2019; Huang and Carley, 2019; Wang et al., 2020) are proposed to tackle this task by encoding both contextual and dependency information simultaneously. However, most of these methods focus on the datasets, in which most sentences consist of only one aspect or multiple aspects with the same sentiment polarity. Under these circumstances, aspect-based sentiment analysis degenerates into sentence-level sentiment analysis. Existing ABSA methods based on these datasets can hardly adapt to the situation, where multiple aspect terms in a sentence with multiple different sentiment polarities. Thus, the fine-grained sentiment analysis task derived from ABSA towards the multi-aspect multi-sentiment situation, Multi-aspect Multi-sentiment Classification (MAMSC), is worthy of exploration(Jiang et al., 2019). MAMSC is more challenging than ABSA, and each sentence contains at least two aspects with different sentiment polarities in MAMSC.

Besides, most existing methods neglect to consider inter-aspect relationships when predicting sentiment polarity. Especially in MAMSC, the main challenge is that the sentiment polarities of some aspects in a given sentence can not be judged solely relied on the context and may be guided by the sentiments of other aspects. Inter-aspect relationships will play an essential role in identifying sentiment polarity in this case. Though InterGCN (Liang et al., 2020) claims to have considered inter-aspect relationships, what it considered is merely the distance relationship among aspects and neglecting
the semantic relationship between every two aspects, which is essential when indicating the relationship between two aspects. Furthermore, InterGCN ignores the heterogeneity of aspect terms and context words and the different importance of surrounding nodes when aggregating information.

To sum up, ABSA faces the following challenges: (1) do not pay special attention to the multi-aspect multi-sentiment situation; (2) do not incorporate semantic relationships among aspects into predicting sentiment polarity; (3) do not introduce heterogeneity and attention mechanism when using graph-based models to predict sentiment polarity.

To deal with the challenges mentioned above, we first construct a heterogeneous graph with distinct node and edge types to represent inter-aspect relationships, aspect-context relationships, and node heterogeneity simultaneously in a concrete way. Unlike InterGCN, we treat aspect terms and context words as different types of nodes, and meanwhile, the edges in our heterogeneous graph are attributed. We utilize dependency tags as the attributes of aspect-context edges. The shortest dependency path between each two aspect terms is the representation of each inter-aspect edge attribute, which signifies the semantic relationship between these two aspect terms. Then we propose a novel model called Composition-based Heterogeneous Graph Multi-channel Attention Network (CHG-MAN) to incorporate inter-aspect relationship information, node and node type information simultaneously for predicting sentiment polarity.

**Extensive Experiments:** we conduct extensive experiments over multi-aspect multi-sentiment datasets: MAMS-ATSA, Rest14, and Laptop14, and the results show the effectiveness of our method.  

2 Related Work

2.1 Graph-based Models

Recently, graph neural networks (GNNs) have been introduced into ABSA and achieved promising performance. ASGCN (Zhang et al., 2019) employs graph convolutional network (GCN) to capture dependency syntactical information. CDT (Sun et al., 2019) incorporates GCN and BiLSTM over the dependency information and contextual information of the sentence. InterGCN (Liang et al., 2020) exploits GCN to extract both aspect-focused and inter-aspect information for specific aspects, but it only considers distance relations among aspect terms. RGAT (Wang et al., 2020) designs a graph attention networks (GAT) derivative to utilize dependency tag information by taking them as gates to control information flow. However, all these models do not utilize inter-aspect semantic relationships and neglect the different roles of aspect terms and context words.

2.2 Multi-aspect Multi-sentiment

There exist several works that tend to model inter-aspect relationships to boost the performance of ABSA. IARM (Majumder et al., 2018) utilizes memory networks to incorporate the neighboring aspects-related information to predict the sentiment polarity of the given aspect term. InterGCN models inter-aspect distance relationships to help predict sentiment polarity in the presence of other aspects. SDGCN (Zhao et al., 2020) utilizes GCNs to capture sentiment dependencies between aspects. Besides, MIAD (Hazarika et al., 2018), STAGE (Ma et al., 2019) and Joint+PERT (Zhou et al., 2020) also tend to model relationships among aspects by using LSTM based model and attention mechanism. CapsNet (Jiang et al., 2019) releases a new dataset dedicated to the multi-aspect multi-sentiment situation and proposes a model to employ capsule network and capture the intricate relationship between aspect terms and context words. Nonetheless, all of these existing works do not take edge information, such as dependency syntactic and semantic

1The code is available at https://github.com/hankniu01/chgman
relationship among aspects into consideration, and heterogeneity between aspect terms and context words is also ignored.

3 Methodology
Multi-aspect multi-sentiment classification can be formulated as follows: given a sentence $S$ with $n$ words $\{w_1, w_2, ..., w_n\}$ and a given aspect term set $A = \{A_1, A_2, ..., A_k\}$ containing $k$ aspect terms. And $A_k = \{w^n_k, w^n_{k+1}, ..., w^n_{k+\tau}\}$ with $\tau \in [1, n - \phi]$ is a sub-string of sentence $S$, which denotes one element of the given aspect term set $A$. The annotation $a$ represents aspect. This task aims at predicting the sentiment polarity in \{POSITIVE, NEUTRAL, NEGATIVE\} expressed on each aspect term included in the given aspect term set $A$ of the sentence $S$. As shown in Figure 1(left), our proposed methods consist of three blocks: (1) Encoding Block; (2) Heterogeneous Graph Construction Block; (3) Prediction Block. In Section 3.1 to 3.3, we detail each block.

3.1 Encoding Block
As shown in Figure 1(left), we encode context words, aspect terms, and composed dependency tags, preparing for constructing heterogeneous graphs.

3.1.1 Contextual Encoder
For a given input sentence $S = \{w_1, w_2, ..., w_n\}$ with a aspect term set $A = \{A_1, A_2, ..., A_k\}$, we first employ pre-trained BERT (Devlin et al., 2019) as the contextual encoder to obtain hidden contextual representation $H_S$ of the given sentence $S$. The embeddings of context words $H_w = \{h_1, h_2, ..., h_{n_w}\}$ and aspect term embeddings $H_A = \{h_{A_1}, h_{A_2}, ..., h_{A_k}\}$ are derived from $H$. Here, $n_w$ is the number of context words in the input sentence $S$. Specifically, the embedding of a specific aspect term $A_k$ is $h_{A_k} = \{h^n_k, h^n_{k+1}, ..., h^n_{k+\tau}\}$, which is the collection of all the embeddings of words belonging to $A_k$.

3.1.2 Composed Dependency Tags
Additionally, we design composed dependency tags to fully utilize dependency relation tag information based on the aspect-oriented dependency tree (Wang et al., 2020). Concretely, as shown in Figure 1(right), the form of composed dependency tag representation is $r_{A_k,i} = \text{dep}_1 : \text{dep}_2 : ... : \text{dep}_m : m$, where $m$ represents the hops between aspect term node $A_k$ and neighbor node $i$, and $\text{dep}_m$ represents the original dependency tag between two nodes generated by the Biaffine Parser (Dozat and Manning, 2017). Then, we employ a trainable embedding lookup table as a dependency embedding layer. We feed a set of composed dependency tags $R_{tag} = \{r_{A_k,1}, r_{A_k,2}, ..., r_{A_k,M}\}$ into dependency embedding layer to initialize composed dependency tag representations $E_{tag} = \{e_{A_k,1}, e_{A_k,2}, ..., e_{A_k,M}\}$, where $M$ is the number of dependency relation tags. We have different sets of composed dependency tags and their representations for different aspect terms.

3.2 Heterogeneous Graph Construction Block
In this section, we construct a heterogeneous graph to encode inter-aspect relationships and aspect-context relationships effectively.

3.2.1 Shortest Dependency Path
To discover the semantic relationship between aspect terms, we extract the shortest dependency path
(SDP) between aspect terms to represent the relationship. SDP can indicate semantic relationships effectively between two words and ignore irrelevant information, which has been widely used in relation extraction (Bunescu and Mooney, 2005). All tokens on SDP between aspect terms $A_c$ and $A_y$ are represented as $SDP_{c_y}$. Furthermore, the features of all tokens belonging to $SDP_{c_y}$ are extracted from $H$ derived from pre-trained BERT through selection operating. The selection operating is based on the index of the token belonging to SDP in the sentence. The $SDP_{c_y}$ representation $H_{SDP}^{c_y} = \sum [h_1^{SDP}, h_2^{SDP}, ..., h_t^{SDP}]$, where $t$ is the number of tokens in the SDP.

### 3.3.1 Composition-based Heterogeneous Graph Multi-channel Attention Network (CHGMAN)

To encode our constructed heterogeneous graph effectively, we propose a novel multi-channel attention network for heterogeneous graphs, which concerns the information of edges, nodes, and node types simultaneously. Figure 2(left) presents the whole view of CHGMAN. Concretely, the goal of CHGMAN is to aggregate information from each neighbor node $i$ to update the representation of the target node $t$. And the process can be divided into three phases: (1) Multi-channel Attention Calculation, (2) Heterogeneous Message Passing, and (3) Composed Aggregation.

**Multi-channel Attention Calculation.** In first phase, CHGMAN tend to calculate the attention score matrices between target node $t$ and each neighbor node $i \in N(t)$. Due to heterogeneity, based on considering neighbor node features, we further tend to incorporate the information of node type and edge feature into our model. Thus, we design a multi-channel attention mechanism to take node types and edge features into consideration in the phase of attention calculation. Concretely, this phase of CHGMAN is decomposed into three channels: target-to-neighbor channel, target-to-edge channel and target-to-type channel to calculate attention score matrices from different sides. Then, CHGMAN exploits a multi-channel fusion layer to fuse attention score matrices from each channel and get a weighted combination of attention score matrices. Plus, we also employ a multi-head attention mechanism (Vaswani et al., 2017) to enhance the representation ability of CHGMAN.

Firstly, we map the feature of target node $t$ into a query vector $Q_{A_t}$ at $u$-head attention, and $h_t^l$ is the representation of target node $t$ at $l$-th layer.

$$Q_t^u = \text{Linear}^{Q,u}_t \left( h_t^l \right),$$ (1)

where $\text{Linear}^{Q,u}_t$ is the linear projection for $h_t^l$. In order to exploit information from neighbor node features, neighbor node types, and edges features, we map the feature of them into key vectors for each channel. Specifically,

$$K_{\text{neigh}}^u = \text{Linear}^{K,\text{neigh}}_u \left( h_{t,i}^{\text{neigh}}, l \right),$$ (2)

$$K_{\text{edge}}^u = \text{Linear}^{K,\text{edge}}_u \left( h_{t,i}^{\text{edge}}, l \right),$$ (3)

$$K_{\text{type}}^u = \text{Linear}^{K,\text{type}}_u \left( h_{t,i}^{\text{type}}, l \right),$$ (4)

where $\text{Linear}^{K,\text{neigh}}_u$, $\text{Linear}^{K,\text{edge}}_u$ and $\text{Linear}^{K,\text{type}}_u$ are linear projections for each representations, and $h_{t,i}^{\text{neigh}}$ represents the feature of neighbor node $i$. Here, neighbor nodes consist of aspect term nodes and context nodes. Besides, $h_{t,i}^{\text{edge}}$ is the representation of edge feature between the target node $t$ and neighbor node $i$. There are two kinds of edges: inter-aspect edges and aspect-context edges. For inter-aspect edges, we utilize SDP representation $H_{SDP}^{t}$ as features of
inter-aspect edges, and for aspect-context edges, we employ composed dependency tag representations. Additionally, the type representation of neighbor node \( i \) is \( h_{i,\text{type}} \), and there exist two kinds of type representations corresponding to context node and aspect term node. We introduce a trainable embedding lookup table to initialize type representations.

Next, CHGMAN needs to calculate the correlations between query vectors and key vectors by dot product in each channel. The final multi-channel attention score \( \text{Att}^u(t, i) \) is computed as follows:

\[
\text{Att}^u(t, i) = \text{Softmax}_{i \in \mathcal{N}(t)} \left( \alpha_{t,i}^u \right), \tag{5}
\]

\[
\alpha_{t,i}^u = \text{Mcf} \left( \alpha_{t,i}^{\text{neigh},u}, \alpha_{t,i}^{\text{edge},u}, \alpha_{t,i}^{\text{type},u} \right) = \Phi_c \left( \frac{(Q_t^u)^\top K_{\text{neigh}}^u}{\sqrt{d}}, \frac{(Q_t^u)^\top K_{\text{edge}}^u}{\sqrt{d}}, \frac{(Q_t^u)^\top K_{\text{type}}^u}{\sqrt{d}} \right), \tag{6}
\]

where \( \alpha_{t,i}^{\text{neigh},u}, \alpha_{t,i}^{\text{edge},u}, \alpha_{t,i}^{\text{type},u} \) is the stacked attention matrices of different channels, and \( \text{Mcf} \) denotes a multi-channel fusion layer with parameters \( \Phi_c \), which is a learnable parameter to adjust contributions of input attention matrices automatically. We apply a scaling factor \( \frac{1}{\sqrt{d}} \) on \( \alpha_{t,i}^u \), which is beneficial to stabilize model training (Vaswani et al., 2017), and \( d \) is the dimension of hidden state.

**Heterogeneous Message Passing.** Parallel to the computation of multi-channel attention, CHGMAN also passes information from neighbor nodes to the given target node. Taking into account the heterogeneity of nodes, we would like to incorporate the representations of node types attached with node features into the message passing process. Specifically, for target node \( t \) and its neighbor nodes \( i \in \mathcal{N}(t) \), the multi-heads message is calculated as follows:

\[
M_{\text{g}_\text{neigh}}^u(t, i) = \text{Linear}^u_{\text{neigh}} \left( h_{i,\text{neigh}}^u \right), \tag{7}
\]

\[
M_{\text{g}_\text{type}}^u(t, i) = \text{Linear}^u_{\text{type}} \left( h_{i,\text{type}}^u \right). \tag{8}
\]

To obtain the \( u \)-th message head \( M_{\text{g}_\text{neigh}}^u(t, i) \) and \( M_{\text{g}_\text{type}}^u(t, i) \) from neighbor node features and the type representations of neighbor nodes, CHGMAN employs linear projections \( \text{Linear}^u_{\text{neigh}} \) and \( \text{Linear}^u_{\text{type}} \) to project them into message vectors.

**Composed Aggregation.** After multi-channel attention calculation and heterogeneous message passing, CHGMAN needs to aggregate messages from neighbor nodes to the given target node \( t \). Firstly, we employ a circular correlation as a composition operation (Vashishth et al., 2020; Nickel et al., 2016) to combine the messages from node features and node type representations. The operation is computed as follows:

\[
M_{\text{g}_\text{corr}}^u(t, i) = \psi \left( M_{\text{g}_\text{neigh}}^u(t, i), M_{\text{g}_\text{type}}^u(t, i) \right) = \mathcal{F}^{-1} \left( \mathcal{F} \left( M_{\text{g}_\text{neigh}}^u(t, i) \right) \odot \mathcal{F} \left( M_{\text{g}_\text{type}}^u(t, i) \right) \right), \tag{9}
\]

where \( M_{\text{g}_\text{corr}}^u(t, i) \) is the composed message representation from neighbor node \( i \), \( \psi \) is the circular correlation operation, and \( \mathcal{F}(-) \) and \( \mathcal{F}^{-1}(-) \) denote the Fast Fourier Transform (FFT) and its inverse. The \( \mathcal{F}(-) \) is the complex conjugate of \( \mathcal{F}(-) \), and \( \odot \) denotes the Hadamard product.

Then, we aggregate messages from neighbor nodes and update the target node representation. The aggregate process at \( t \)-th layer is

\[
h_{t+1}^u = \|_{u=1}^U \left( \text{Att}^u(t, i) \cdot M_{\text{g}_\text{corr}}^u(t, i) \right), \tag{10}
\]
Table 1: Statistics of MAMS-ATSA, Rest14, and Laptop14 datasets. (Train/Test/Total) Size and (Train/Test/Total) MM denote the number of instances and multi-aspect multi-sentiment instances in the training, testing, and overall (sum of training and testing) datasets, respectively.

| Dataset      | Train-Size | Train-MM | Test-Size | Test-MM | Total-Size | Total-MM |
|--------------|------------|----------|-----------|---------|------------|----------|
| MAMS-ATSA    | 3800       | 5042     | 1007      | 128     | 12522      | 12522    |
| Rest14       | 2164       | 2870     | 196       | 807     | 4728       | 3429     |
| Laptop14     | 994        | 341      | 870       | 128     | 2965       | 1775     |

We also incorporate multi-heads attention mechanism into CHGMAN, and $\|U_{i=1}^{U} x_{U}$ denotes the concatenation of vectors from $x_1$ to $x_U$. The aggregate process at $I$-th layer is calculated as follows:

$$P(y = c) = \text{softmax}(W_Fh_{\text{final}} + b_F),$$  

where $W_F$ and $b_F$ are the weight matrix and bias, respectively. $P \in \mathbb{R}^C$ is the probability distribution for the sentiment polarity of a specific aspect term, where $C$ is the set of sentiment classes. The training objective is to minimize the standard cross-entropy loss with L2-regularization:

$$L(\Theta) = - \sum_{(S, A) \in D} \log(y = c) + \Lambda ||\Theta||_2,$$  

where $D$ is the set of training data, $\Theta$ represents all trainable parameters, and $\Lambda$ is the coefficient of the L2-regularization term.

4 Experiments

4.1 Datasets and Experiment Settings

To verify the effectiveness of our proposed model, we conduct experiments on MAMS-ATSA, Rest14, and Laptop14. MAMS-ATSA is released by (Jiang et al., 2019), all sentences in MAMS-ATSA contain multiple aspect terms, and at least two of them with different sentiment polarities. Also, the start and end positions of each aspect term in a sentence are provided. Rest14 and Laptop14 (Pontiki et al., 2014) have been widely used, but not all sentences have multiple aspect terms in these two datasets. Statistics of these datasets are displayed in Table 1, where (Train/Test/Total) Size and (Train/Test/Total) MM denote the number of instances and multi-aspect multi-sentiment instances on the training, testing, and overall (sum of training and testing) datasets, respectively. Each multi-aspect multi-sentiment instance contains multiple aspects and at least two aspects with different sentiment polarities. Additionally, we count the distribution of instances with the different number of aspects in the three datasets, which is shown in Figure 3. It can be seen that in the case of multiple aspects, instances with two or three aspects account for the majority. And, in MAMS-ATSA, there is no instance with only one aspect.

We utilize the last hidden states of the pre-trained BERT-base model for word representations (Devlin et al., 2019), the BERT containing 12 hidden layers, and 768 hidden dimensions for each layer. Moreover, the dimensions of the composed dependency tag embedding and type embedding are also initialized as 768. The hidden dimension of CHGMAN is 128. The dropout rate is 0.2. The number of the epoch is 30. We use Adam optimizer (Kingma and Ba, 2015) while training with the learning rate initialized by 0.00005. Our code will be released later.

4.2 Compared Methods

To evaluate our proposed model CHGMAN, we compare it with the following a series of baselines. TD-LSTM (Tang et al., 2016) utilizes LSTMs to model bidirectional contextual information. ATAE-LSTM (Wang et al., 2016) tends to combine learned attention embeddings with LSTM. IAN(Ma et al., 2017) is introduced to learn the coarse-grained attention for prediction. MIAD (Hazarika et al., 2018) simultaneously classifies
| Model        | MAMS-ATSA  | Rest14 | Laptop14 |
|-------------|------------|--------|----------|
|              | Accuracy   | Macro-F1 | Accuracy | Macro-F1 | Accuracy | Macro-F1 |
| TD-LSTM     | 74.60°     | -       | 78.00°   | 66.73°   | 71.83°   | 68.43°   |
| ATAE-LSTM   | 77.05°     | -       | 77.20°   | -        | 68.70°   | -        |
| IAN         | 76.60°     | -       | 78.60°   | -        | 72.10°   | -        |
| RAM         | -          | -       | 80.23°   | 70.80°   | 74.49°   | 71.83°   |
| GCAE        | 77.59°     | -       | 77.28°   | -        | 69.14°   | -        |
| IARM        | 74.48°     | 73.66°  | 80.00°   | -        | 73.80°   | -        |
| MIAD        | -          | -       | 79.00°   | -        | 72.50°   | -        |
| ASGCN       | 44.06°     | 50.39°  | 80.77°   | 72.02°   | 75.55°   | 71.05°   |
| CDT         | 76.77°     | 75.77°  | 82.30°   | 74.02°   | 77.19°   | 72.99°   |
| Joint+PRET  | -          | -       | 81.96°   | 71.80°   | 73.04°   | 69.16°   |
| STAGE       | -          | -       | 83.57°   | 76.47°   | 81.35°   | 78.34°   |
| BERT        | 82.22°     | -       | 85.62°   | 78.28°   | 77.58°   | 72.38°   |
| §SDGCN      | -          | -       | 83.57°   | 76.47°   | 81.35°   | §CHGMAN (Ours) |
| §InterGCN   | 82.49°     | 81.95°  | 85.45°   | 77.64°   | 78.06°   | 73.83°   |
| §CapsNet    | 83.39°     | -       | 85.93°   | -        | -        | -        |
| §RGAT       | 83.16°     | 82.42°  | 86.25°   | 79.95°   | 78.21°   | 74.07°   |
| §CHGMAN (Ours) | 85.05° | 84.29°  | 86.88°   | 81.62°   | 81.52°   | 77.68°   |

Table 2: Overall performance of different methods on MAMS-ATSA, Rest14, and Laptop14. The results indicated by an asterisk(*) are reproduced by running the released code of the published paper. The results with ə, ♯ and ♭ are retrieved from (Liang et al., 2020), (Wang et al., 2020) and (Jiang et al., 2019) respectively. The other results except for our model are from the results reported by other baseline papers. The results with § are fine-tuned based on BERT(base).

all aspect terms in a sentence in pace with temporal dependency processing of corresponding sentences by utilizing LSTM. RAM (Chen et al., 2017) proposes to learn multi-hop attention on BiLSTM. GCAE (Xue and Li, 2018) proposes a convolution network combined with gating mechanisms to control sentiment flow. IARM (Majumder et al., 2018) utilizes aspect-aware sentence representation and memory network to fuse neighboring aspect information. CapsNet (Jiang et al., 2019) proposes a capsule network-based model to capture relationships between aspects and contextual words. ASGCN (Zhang et al., 2019) combines BiLSTM to capture contextual information regarding word orders with a multi-layered GCNs. CDT (Sun et al., 2019) encodes both dependency and contextual information by utilizing GCNs and BiLSTM. BERT (Devlin et al., 2019) fine-tunes BERT model to predict the sentiment polarity. SDGCN (Zhao et al., 2020) proposes a model based on GCNs to capture sentiment dependencies among aspects. STAGE (Ma et al., 2019) develops a two stage paradigm to model multi-aspects by using attention mechanism. Joint+PRET (Zhou et al., 2020) proposes a LSTM based model and converts sentiment classification to a sequence labeling problem to model relationships among aspects. RGAT (Wang et al., 2020) feeds reshaped syntactic dependency graph into RGAT to capture long dependency information.

4.3 Overall Performance

Table 2 shows the overall performance of our model and compared methods on three datasets, and the main evaluation matrices are Accuracy and Macro-averaged F1-score. The results demonstrate our model outperforms all compared methods except for the Macro-F1 of SDGCN on Laptop14. The performance of CHGMAN is affected since MM size in Laptop14 is small relatively (shown in Table 1). Our model exceeds all graph-based methods on evaluation matrices, indicating our proposed model is more effective than other graph-based models. Compared with RGAT, our model takes inter-aspect relationships into consideration. The performance gain towards RGAT indicates that inter-aspect relationships can help predict the sentiment polarity of the given aspect. Moreover, in comparison with InterGCN, CapsNet, and SDGCN, introducing attention mechanism, inter-aspect relationship, aspect-context relationship, and heterogeneity can help our model to distinguish more helpful information and enhance performance. All these results denote that exploiting inter-aspect relationships, aspect-context dependency relationships, and heterogeneity can improve performance.

4.4 Ablation Study

We conduct an ablation study to further analyze the effectiveness of our model. The result of the
Table 3: Results of ablation study. CHGMAN w/o X denotes the performance of our method after eliminating the corresponding modules, and Y&Z represents deactivating modules Y and Z simultaneously. Additionally, comp, edge, type, and hetero indicate circular correlation operation, target-to-edge channel, target-to-type channel, and adopting homogeneous graphs instead of heterogeneous graphs constructed. These results are fine-tuned based on BERT(base).

| Model                     | MAMS-ATSA | Rest14 | Laptop14 |
|---------------------------|-----------|--------|----------|
|                           | Accuracy  | Macro-F1 | Accuracy | Macro-F1 | Accuracy  | Macro-F1 |
| CHGMAN                    | 85.05     | 84.29   | 86.88    | 81.62    | 81.52     | 77.68    |
| CHGMAN w/o comp           | 84.37     | 83.89   | 86.61    | 80.45    | 80.25     | 76.29    |
| CHGMAN w/o comp&edge      | 83.53     | 82.86   | 86.33    | 80.19    | 80.41     | 75.73    |
| CHGMAN w/o comp&type      | 84.29     | 83.34   | 86.07    | 79.72    | 80.09     | 76.38    |
| CHGMAN w/o hetero         | 83.69     | 83.29   | 86.16    | 79.03    | 80.09     | 76.17    |

CHGMAN w/o comp denotes that CHGMAN removes the circular correlation operation in the composed aggregation process. The performance of CHGMAN w/o comp is worse than CHGMAN, which indicates conducting the circular correlation operation to combine node and its type features in the aggregation process is effective and conducive to performance improvement. Furthermore, on the basis of CHGMAN w/o comp, we removes the attention channel target-to-edge and target-to-type respectively, which are written as CHGMAN w/o comp&edge and CHGMAN w/o comp&type. The performance of CHGMAN w/o comp&edge and CHGMAN w/o comp&type are both inferior than CHGMAN w/o comp, demonstrating adding two additional channel target-to-edge and target-to-type to target-to-neighbor is helpful and beneficial to enhancing the handling ability of heterogeneous information. The node types consist of contexts and aspect terms, the performance difference between CHGMAN w/o comp and CHGMAN w/o comp&type also shows the significance of identifying the information of other aspect terms and contexts in the attention calculation phase, which is conducive to the utilization of both information concurrently. In the meantime, edge features are also essential in the attention calculation phase, target-to-edge channel can facilitate the usage of inter-aspect relationships and aspect-context relationships by putting into consideration the features on the edge. The performance of Laptop14 is not clear enough in contrast to the other datasets since the MM size in Laptop14 is less than the other two, as seen in Table 1. CHGMAN w/o hetero indicates that we eliminate the impact of heterogeneous graphs constructed and substitute them with homogeneous graphs with edge features. That is to say, we disregard inter-aspect relationships and construct a homogeneous graph for each aspect term, with just one type of node, but the architecture of CHGMAN stays unaffected. The performance of CHGMAN w/o hetero has declined in comparison to CHGMAN, revealing the heterogeneous graph our constructed is favorable to increasing the efficacy of CHGMAN for MAMSC.

4.5 Attention Distribution Exploration

To qualitatively illustrate how CHGMAN improves the performance in MAMSC. We post the attention distribution visualization of a specific testing sample, which is demonstrated in Figure 4. The input sentence is It’s sad that everything about this place was great (even the service and decor) except for the steak., there exist three aspect terms: service, decor and steak, and sentiment polarity labels of these three aspect terms are POSITIVE, POSITIVE and NEGATIVE respectively. Figure 4(a) is the attention distribution of target-to-neighbor, which shows that for aspect term steak, target-to-neighbor pays more attention to the context word sad, and it is helpful to judge the sentiment polarity to a certain degree. Whereas for service and decor, target-to-neighbor also notices context words sad and great, although it is ambiguous. Thus for the sake of introducing aspect term nodes, target-to-
**5 Conclusion**

In this paper, we construct a heterogeneous graph for MAMSC and propose a novel CHGMAN to tackle the heterogeneous graph. Our model predicts sentiment polarities by incorporating inter-aspect relationships, aspect-context relationships, and node heterogeneity. Moreover, our experiments prove the effectiveness of our method.

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