Cross-Modality Gated Attention Fusion for Multimodal Sentiment Analysis

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Abstract
Multimodal sentiment analysis is an important research task to predict the sentiment score based on the different modality data from a specific opinion video. Many previous pieces of research have proved the significance of utilizing the shared and unique information across different modalities. However, the high-order combined signals from multimodal data would also help extract satisfied representations. In this paper, we propose CMGA, a Cross-Modality Gated Attention fusion model for MSA that tends to make adequate interaction across different modality pairs. CMGA also adds a forget gate to filter the noisy and redundant signals introduced in the interaction procedure. We experiment on two benchmark datasets in MSA, MOSI, and MOSEI, illustrating the performance of CMGA over several baseline models. We also conduct the ablation study to demonstrate the function of different components inside CMGA.

1 Introduction
With the vast popularity of social media in recent years, we can get a connection with more kinds of content, not only the text and figures but also the videos. Videos, including movies, TV shows, and short-form video streams, naturally consist of multimodal data types: the content of the text, visual (video frames), and acoustic (voice of speakers). Moreover, many of them usually have specific sentiment tendencies, which express the current emotional status of the speakers. It is essential to understand these sentiment tendencies.

Across different modalities, there would be some shared and some unique information. Given an opinion video, its text is a pure statement of the opinion and contains semantic information. The visual modality exposes speakers’ expressions. The acoustic modality captures the tone of voice. These latter two types of information can not only be supplementary to understand the video better but also correct the misleading information in the textual modality (Ngiam et al., 2011). As a result, the features contained in different modalities could help predict a more accurate sentiment score.

Many researchers have implemented deep learning methods on the multimodal data with good results achieved, illustrating the advantages of utilizing multimodal data beyond one single modality. As for the Multimodal Sentiment Analysis (MSA) problem, it is crucial to fuse the shared information across different modalities and keep the unique information of a single modality. Some research methods focus on finding a vector space that contains these two kinds of signals simultaneously. For example, Zadeh et al. (2017) makes the three modalities interact with each other by extending the respective vector space into a shared tensor space with the 3-fold Cartesian product. However, it is difficult for these methods to distinguish the unique signals inside different modalities from the common interacted vector space. The extended common interacted vector space would contain the noisy and redundant signals, which are misleading and not valid for the downstream classification task. Other methods aim to learn the two kinds of information separately. For example, Hazarika et al. (2020) proposes a model to learn two different subspaces of the three modalities, one of which is the
shared encoder space. At the same time, the other one is the private space for maintaining unique signals. However, it lacks adequate interaction across the extracted information in subspaces of different modalities.

We propose a Cross-Modality Gated Attention (CMGA) fusion model to alleviate these issues. CMGA aims to learn the cross-modality features that best summarize the interaction signals across different modalities and maintain the signals that are effective for MSA. Specifically, we first divide the three modalities into three different pairs and generate the cross-modality attention feature maps of them, which are motivated by the design of the attention mechanism proposed by Vaswani et al. (2017). After this, CMGA pass the cross-modal interaction features into a forget gate designed to filter the noisy and redundant signals contributing little to the downstream prediction task. We use a residual connection proposed by He et al. (2016) to enhance the original modality signal and avoid the degradation problem. Finally, we input the cross-modality interaction features into a transformer-based fusion layer to predict sentiment scores. We evaluate the performance of CMGA on two famous benchmark datasets, CMU-MOSI and CMU-MOSEI, collected by Zadeh et al. (2018b). Experiments show that CMGA outperforms several baseline models in most of the evaluation metrics. In addition, we also conduct two ablation studies on CMGA to illustrate the role of different components and the role of different modality data.

2 Methodology

2.1 Problem Setup and Feature Extraction

Given an utterance $U = \{u_m\}_{m \in \{t,v,a\}}$, its raw feature vectors contains three modalities in form of text, video and audio. Our goal is to find the optimal interacted feature $h_{(t,v,a)}$ cross the three modalities that best represent the original utterance $U$ and predict the sentiment score $\hat{y}$ that close to the ground truth $y \in \mathbb{R}$.

We utilize pre-trained BERT (Devlin et al., 2018) as the feature extractor for the textual inputs and obtain the final embedding of textual features by averaging the tokens’ representations across the hidden states. The visual and acoustic features are obtained by a stacked bi-directional Long Short Term Memory (bi-LSTM) (Hochreiter and Schmidhuber, 1997). Here, we get the embedding of the two modalities $u_v$ and $u_a$ by projecting the final state of LSTM into a fully-connected (FC) layer. We project each modality’s features with a linear layer to obtain the representations of each modalities $z_m \in \{t,v,a\} \in \mathbb{R}^{d_k}$ with the same dimension size $d_k$.

2.2 Modality Interaction

2.2.1 Cross-modality Attention

The cross-modality attention aims to get the interacted signals across different modalities. Every two modalities would be one pair of inputs, i.e., $i$ from text to visual; $ii$) from visual to acoustic; $iii$) from text to acoustic. Here, we define the modality pair as a set $P = \{(t,v), (v,a), (t,a)\}$.

The interaction feature generator inputs a pair of modalities $z_{(i,j)} \in \mathbb{R}$. The first one is utilized to generate key and value matrices, while the second modality is used to generate the query matrix, i.e., $Q_{(i,j)} = z_j W^Q_i$, $K_{(i,j)} = z_i W^K_j$, and $V_{(i,j)} = z_i$. Then, the cross-modality attention $a_{(i,j)}$ of modalities pair $(i,j)$ is transformed via a scaled dot-product (Vaswani et al., 2017). We obtain the cross-modality attention features $A = \{a_{(i,j)}\}_{(i,j)} \in P$ from each modality.

2.2.2 Cross-modality Forget Gate

The cross attention maps enables the model to capture the interaction between different modalities. However, $a_{(i,j)}$ of a pair modality $(i,j)$ also contains plenty of redundant and noisy information. This part of information can obscure the instrumental interaction signals, leaving the original information of each modality still dominating the classification results in the downstream classification task. As a result, we might not fully exploit and utilize the additional interaction information across different modalities. Therefore, motivated by the gated unit (Cho et al., 2014), we add a cross-modality forget gate to filter the redundant information and activate the useful cross-modality signal. As shown in Fig. 3, the gate received the cross-modality attention generated in Section. 2.2.1, and pass it through a forget cell to generate the filtered cross-modality features. Specifically, the cross-modality attention map, which contains the modality pair’s interacted signal, would first be used to generate a forget vector. The forget vector controls the information flow that would be memorized for the downstream classification tasks. The forget vector $f_{(i,j)}$ of modality pair $(i,j)$ is defined in Eq. 1.

$$f_{(i,j)} = \sigma([a_{(i,j)} \oplus z_j] W^f + b^f)$$ (1)
Next, the filtered features of modality pair \((i, j)\) are calculated as follows:

\[
h_{(i,j)} = \text{ReLU}(z_i + (a_{(i,j)} W^m + b^m) \odot f_{(i,j)}),
\]

where \(\odot\) is the element-wise product between two vectors, \(\oplus\) denotes the concatenation, and \(W^f, W^m, b^f, b^m\) are trainable parameters. In addition, in Eq. 2, we keep \(z_i\) to enhance the signal of original modality, which is motivated by the architecture of residual connection in ResNet proposed by He et al. (2016).

The final output after fusion layer is \(\tilde{y} = \tilde{H} W^o\), where \(H = (H_1 \oplus \ldots \oplus H_n)\), and \(W^o \in \mathbb{R}^{3 \times d_h \times 1}\) is trainable parameter.

**3 Experiments**

We experiment with two benchmarks with three modalities (language, visual, and acoustic) in each utterance. The CMU-MOSI dataset (Zadeh et al., 2018b) collects 2199 opinion video clips, each of which is annotated with a continuous sentiment score in the range of \([-3, 3]\). The value of the score represents the opinion attribution, where a smaller value close to -3 stands for negative sentiment and a larger value close to +3 is more positive. The CMU-MOSEI dataset (Zadeh et al., 2018b) is an advanced version of the CMU-MOSI dataset, which collects more utterances from various speakers and topics. This dataset has 23,453 sentence utterance videos from more than 1000 online YouTube speakers with 250 different topics.
We compare the performance of CMGA with the following baseline models. TFN (Zadeh et al., 2017) utilizes the tensors’ Cartesian space to calculate the multiplicative interactions between different modalities. LMF (Liu et al., 2018) uses a low-rank tensor to generate the representation of multimodal inputs efficiently. MFM (Tsai et al., 2018) introduces the joint generative-discriminative vector space, which factorizes representations into two sets of independent factors. MISA (Hazarika et al., 2020) generates two independent vector subspaces to capture the shared and unique information of different modalities. ICCN (Sun et al., 2020) calculates the outer products between text, acoustic and text, visual features, and then implements a Canonical Correlation Analysis network for prediction.

In the LSTM models for acoustic and visual modalities, we implement a 2-layer bidirectional with 512-dimensional hidden states and layer norm between different layers. We implement a 12-layer transformer of 768-dimensional hidden states with 12 heads in the BERT model for textual modality. We use the pre-trained BERT tokenizers. After extracting different modalities, we project them into the same size dimension of 128 by a fully-connected layer. We use Mean Square Loss (MSE) and Adam optimizer (Kingma and Ba, 2014). Our initial learning rate is 1e-4, and the model is trained on Tesla V100 GPUs.

### 3.1 Main Results

Table 1 shows the predictive performance. CMGA outperforms all other models and has the most obvious improvement on acc-7 metric. CMGA outperforms MFM, MISA and ICCN, demonstrating the importance of learning the adequate interaction between different modalities.

| Models | MOSEI MAE corr F-score Acc-2 Acc-7 | MOSI MAE corr F-score Acc-2 Acc-7 |
|--------|-----------------------------------|-----------------------------------|
| TFN    | 0.901 0.698 80.7 80.8 34.9         | 0.593 0.700 82.1 82.5 50.2        |
| LMF    | 0.917 0.695 82.4 82.5 33.2         | 0.623 0.677 82.1 82.0 48.0        |
| MFM    | 0.877 0.796 81.6 81.7 35.4         | 0.568 0.717 84.3 84.4 51.3        |
| ICCN   | 0.860 0.710 83.0 83.0 39.0         | 0.565 0.713 84.3 84.2 51.6        |
| MISA   | 0.783 0.761 82.4 82.6 33.2         | 0.555 0.761 84.8 84.9 52.1        |
| CMGA   | 0.790 0.759 82.3 82.7 43.3         | 0.545 0.762 85.0 85.3 53.0        |

Table 1: Performance comparison of baselines and CMGA on MOSI and MOSEI datasets. ◦ means the performance of reproduced model. For those without the mark, the results are copied from the corresponding paper. The results of MISA are the best scores from the original paper.

Table 2 shows the performance of CMGA without one specific modality. On both MOSI and MOSEI datasets, the textual modality ut plays the most important role. The performance drops sharply without ut, showing that language conveys rich information for accurate prediction. We divide our modality interaction architecture into two separate parts, as described in Section 2.2. Table 2 also shows the quantitative results of our model without one of the two components.

| Models | MOSEI MAE Acc-7 | MOSI MAE Acc-7 |
|--------|----------------|----------------|
| CMGA   | 0.790 43.29 0.545 53.03 |              |
| (-) text ut | 1.591 30.51 0.818 45.08 |              |
| (-) video ut | 0.804 41.10 0.547 52.81 |              |
| (-) audio ut | 0.812 42.10 0.550 52.79 |              |
| (-) cross-attention | 0.845 41.55 0.587 52.02 |              |
| (-) forget gate | 0.856 41.47 0.594 51.55 |              |
| (+) bi-directional h | 0.792 43.01 0.550 53.01 |              |

Table 2: Ablation study on the importance of modality and neural modules. (-) represents missing for the mentioned factors, which include specific modality or model component. (+) means add specific factors.

### 3.2 Analysis of Modalities and Neural Modules

Table 2 shows the performance of CMGA without one specific modality. On both MOSI and MOSEI datasets, the textual modality ut plays the most important role. The performance drops sharply without ut, showing that language conveys rich information for accurate prediction. We divide our modality interaction architecture into two separate parts, as described in Section 2.2. Table 2 also shows the quantitative results of our model without one of the two components.

### 3.3 Roles of Modality Interaction

We reverse each modality pair and check the performance of CMGA to further evaluate the order of modality pairs. Table 3 shows that the order between video and audio does not affect the performance obviously, while the order of textual modality is critical. As illustrate in Section 2.2.1, the first modality i in a pair (i, j) is used to generate the key matrix K_{i,j} and value matrix V_{i,j}. Inside the calculation of the attention map, we align the information of modality j with modality i.
| Models         | MOSI MAE | MOSI Acc-7 | MOSEI MAE | MOSEI Acc-7 |
|---------------|---------|------------|----------|-------------|
| CMGA          | 0.790   | 43.29      | 0.545    | 53.03       |
| ~ (text, video) | 0.814  | 41.22      | 0.561    | 52.13       |
| ~ (video, audio) | 0.791  | 43.27      | 0.547    | 53.01       |
| ~ (text, audio) | 0.804  | 42.27      | 0.551    | 52.84       |

Table 3: Performance comparison with different orders of modality pairs. (~) represents to reverse the mentioned modality pair (i, j) into (j, i).

4 Related Work

Sentiment analysis is a long-lasting research problem with many tasks such as aspect level sentiment analysis (Lin et al., 2019), emotion recognition in conversations (Li et al., 2022) and multimodal sentiment analysis (Soleymani et al., 2017). Our paper focuses on multimodal sentiment analysis. This section reviews the modality interaction methods, which is trying to find the cross-modality features for different data modalities. Instead of the unimodal features, recent research has proved the significance of utilizing both the verbal and nonverbal information in multimodal sentiment analysis, such as the video and acoustic. Zadeh et al. (2017) proposed the tensor fusion network (TFN) to obtain a cross-view feature by calculating a 3-fold Cartesian product. Verma et al. (2020) implemented convolution calculation on the different cross-modality Cartesian spaces and fused them for the classification task. Arevalo et al. (2017) placed a gated multimodal unit for modalities fusion. Wang et al. (2020a) utilized channel exchanging to make features of different modalities adequately integrated. Yu et al. (2021) jointly training the multimodal and unimodal tasks, in which different modalities would be aligned in the unimodal tasks and interact with each other in the multimodal task.

Motivated by the success of transformers in many Natural Language Processing tasks, Wang et al. (2020b) proposed an end-to-end transformer-based model for sentiment analysis. This work proved the performance of transformer architecture in modality interaction. A transformer is built on the attention mechanism, whose intention to find the importance weights for different feature maps is suitable for the cross-fusion of different modalities. In addition, Zadeh et al. (2018a) implemented a Gated Memory Unit in the sequence learning to summarize the cross-view interactions learned through the attention units. In our work, the transformer-based model motivates the cross-modality interaction component. The attention mechanism idea proposed by Vaswani et al. (2017) comes from the query system, which is suitable for different modalities to interact with each other in MSA tasks. In addition, different from the previous works, we aim to filter the noisy and redundant information that might be introduced in the modality interaction part.

5 Conclusion

This paper proposes CMGA, a multimodal learning framework that tends to predict sentiment scores by generating cross-modality interaction features. We combine the cross-attention map with the forget gate mechanism, which is helpful to get adequate interaction among different modality pairs and maintain the instrumental signals to represent the multimodal inputs. Our experiments show that CMGA achieves competitive predictive performance in most of the metrics. We evaluate the roles of importance for different modality features and the components inside the cross-modality interaction learning architecture, showing the importance of modality interaction.

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