A Self-Adjusting Fusion Representation Learning Model for Unaligned Text-Audio Sequences

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Abstract

Inter-modal interaction plays an indispensable role in multimodal sentiment analysis. Due to different modalities sequences are usually non-alignment, how to integrate relevant information of each modality to learn fusion representations has been one of the central challenges in multimodal learning. In this paper, a Self-Adjusting Fusion Representation Learning Model (SA-FRLM) is proposed to learn robust crossmodal fusion representations directly from the unaligned text and audio sequences. Different from previous works, our model not only makes full use of the interaction between different modalities but also maximizes the protection of the unimodal characteristics. Specifically, we first employ a crossmodal alignment module to project different modalities features to the same dimension. The crossmodal collaboration attention is then adopted to model the intermodal interaction between text and audio sequences and initialize the fusion representations. After that, as the core unit of the SA-FRLM, the crossmodal adjustment transformer is proposed to protect original unimodal characteristics. It can dynamically adapt the fusion representations by using single modal streams. We evaluate our approach on the public multimodal sentiment analysis datasets CMU-MOSI and CMU-MOSEI. The experiment results show that our model has significantly improved the performance of all the metrics on the unaligned text-audio sequences.

1 Introduction

People express their sentiment by using both verbal and non-verbal behaviors (Baltrušaitis, Ahuja, and Morency 2018; Yang, Xu, and Gao 2020). Text as an essential modality in daily life, it expresses emotion through words, phrases, and relations (Turk 2014). However, the information contained in spoken words is limited. Sometimes it is not easy to identify emotions accurately only based on words. Audio is often accompanying text, and it shows sentiment by the variations in voice characteristics such as pitch, energy, vocal effort, loudness, and other frequency-related measures (Li et al. 2019; Yu et al. 2020). Through the inter-modal interaction between text and audio sequences, we can capture more comprehensive emotional information and improve sentiment analysis performance. Figure 1 is an example to illustrate the inter-modal interaction between text and audio modalities. The sentiment of the sentence ”Are you sure?” is ambiguous, it can express various emotions in different contexts. Nevertheless, if speak ”Are you sure?” in an angry voice, it will be easily distinguished as negative. On the contrary, if ”Are you sure?” is accompanied by excited voice, it will be perceived as positive.

Multimodal sentiment analysis as an increasingly extensive field of affective computing has attracted widespread attention. As one of the core problems of multimodal sentiment analysis, how to fully interact between different modalities determines the performance to a certain extent (Zhang et al. 2020). Recently, there are many innovative methods have been proposed. Some researchers make the product of multimodal features as the multimodal fusion representations (Zadeh et al. 2017). Some other researchers perform multimodal fusion using low-rank tensors to improve efficiency, and it not only reduces the parameters but also enhances the sentiment analysis results (Liu et al. 2018). For better interaction, a recent attempt decomposes the multimodal fusion problem into multiple stages, and each focuses on a subset of multimodal signals (Liang et al. 2018).

However, all the approaches mentioned above are based on word-level aligned multimodal sequences and they ig-
more the characteristics of different modalities. In this paper, we design a Self-Adjusting Fusion Representation Learning Model (SA-FRLM) to learn robust fusion representations from unaligned text and audio sequences directly. Different from the above methods, our model not only makes full use of the interaction between different modalities but also maximizes the maintenance of the characteristics of unimodal. Specifically, we first use a crossmodal alignment module to project different modalities features to the same dimension. Then the crossmodal collaboration attention is employed to initialize the fusion representations through the inter-modal interaction between text and audio sequences. In order to maximize the preservation of the characteristics of each modality, the self-adjusting module is employed to dynamically adapt fusion representations by using single modal streams.

To prove the effectiveness of our method, we perform a large number of experiments on the public multimodal sentiment analysis datasets CMU-MOSI (Zadeh et al., 2016) and CMU-MOSEI (Zadeh et al., 2018). The experiments show that our model creates new state-of-the-art performance on the unaligned text and audio sequences. Compared with the baseline models, it outperforms about 1.8% - 8.4% on most of the metrics. In addition, qualitative analysis proves that our model can correct sentiment intensity properly by taking into account audio modality information, and it can make more accurate predictions after adjusting the fusion representations.

The main contribution of this paper are summarized as follows:

- We introduce a Self-Adjusting Fusion Representation Learning Model for Text-Audio sentiment analysis, which can learn fusion representations directly from the unaligned text and audio sequences.
- We design a novel crossmodal adjustment transformer, which can reasonably adjust fusion representations by combining single modality information.
- We show our proposed model achieves a new state-of-the-art text-audio sentiment analysis result on the public sentiment benchmark datasets CMU-MOSI and CMU-MOSEI.

## 2 Related Works

### 2.1 Multimodal Sentiment Analysis

Multimodal sentiment analysis is a new research area that aims to help machines to understand the sentiment from text, audio and video modalities (Xu, Mao, and Chen 2019). Considering the internal correlation between different modalities, after fusing, we can capture more emotional relevant information and improve the performance of sentiment analysis. At present, there are many innovative models have been proposed. In the earlier, Williams et al. (2018) use early fusion approach to concatenate multimodal features and get a significant improvement compared with unimodal predictors. Zadeh et al. (2018) employ a multi-attention block and a long-short term hybrid memory to discover the interactions between different modalities. Inspired by machine translation, Pham et al. (2019) introduce a Multimodal Cyclic Translation Network (MCTN) model to learn robust joint representations by translating between modalities, it only uses text data to test and creates a new state-of-the-art result. In order to capture the dynamic nature of nonverbal intents, Wang et al. (2019) design a Recurrent Attended Variation Embedding Network (RAVEN) to dynamically shift word representations based on nonverbal cues. However, most of these methods need to align multimodal sequences on the word-level.

With the successful use of attention mechanism in computer vision, it plays an increasingly important role in multimodal sentiment analysis. Zadeh et al. (2018) propose a delta-memory attention network to discover both crossview and temporal interactions across different dimensions of memories in the System of LSTMs. Ghosal et al. (2018) introduce a Multi-modal Multi-utterance-Bi-modal Attention (MMMU-BA) framework which employs attention on multimodal representations to learn the contributing features among them. In our model, the crossmodal collaboration attention is used in the fusion representation initialization module to fully interact between text and audio modalities.

Besides, we adopt crossmodal attention (Tsai et al. 2019) in the crossmodal adjustment transformer to latently change fusion representations by utilizing different unimodal information.

### 2.2 Transformer Network

The transformer network is first proposed for machine translation task (Vaswani et al. 2017). Instead of recurrent neural networks and convolution neural networks, the encoder and decoder of transformer networks are based solely on attention mechanisms. Therefore, it not only has faster computation speed but also achieves better performance. In recent years, transformer networks have successfully applied in many models and frameworks. Radford et al. (2018) adopt transformer networks in the Generative Pre-Training (GPT), which provide a more structured memory for handling long-term dependencies in text. Bidirectional Encoder Representations from Transformers (BERT) adopt bidirectional transformer networks to generate contextual word representations by jointly conditioning on both left and right context in all layers, and it has obtained new state-of-the-art results on eleven natural language processing tasks (Devlin et al. 2019).

All the above methods only use the transformer model on text modality. How to extend it from unimodal to multimodal is still worth exploring. In the past year, Tsai et al. (2019) propose the Multimodal Transformer (MuT), which is built up from multiple stacks of pairwise and bidirectional crossmodal attention blocks that directly attend to low-level features. The experiment results show that the MuT outperforms state-of-the-art methods by a large margin. However, the MuT only focuses on the interaction between modalities, and it ignores the original characteristics of different modalities. To overcome this problem, we design a crossmodal adjustment transformer which can dynamically adapt the fusion representations by importing the information of
### 3 Methodology

In this section, we introduce the architecture of our proposed Self-Adjusting Fusion Representation Learning Model (SA-FRLM). As shown in Figure 2, our model consists of three modules. Firstly, the crossmodal alignment module is employed to map text and audio features to the same dimension. Then these features will pass through the fusion representation initialization module to learn fusion representations through the inter-modality interaction between text and audio modalities. After that, the self-adjusting module is proposed to dynamically regulate fusion representations by using text and audio unimodal information. In the following, we first present the problem definition in Section 3.1. Then we introduce the three modules of our model in Section 3.2, Section 3.3, and Section 3.4 respectively.

#### 3.1 Problem Definition

Given unaligned text and audio features $F_T$ and $F_A$, firstly, we project the different modalities features to the same dimension and get the alignment text and audio representations $X_T$ and $X_A$. Then we use the attention mechanism to get the unimodal attentive representations $X_{T'}$ and $X_{A'}$ to initialize the fusion representations $X_{T'A'}$ and $X_{T'A}$. The goal of this work is to improve the text-audio sentiment analysis performance by using the unimodal representations $X_T$, $X_A$, $X_{T'}$ and $X_{A'}$ to dynamically adapt fusion representations $X_{T'A'}$ and $X_{T'A}$.

#### 3.2 Crossmodal Alignment Module

Our proposed method aims to learn robust fusion representations directly from the unaligned text and audio sequences. After obtaining text and audio features $F_T$ and $F_A$, following [Tsai et al. 2019], we pass these unaligned sequences through a 1D temporal convolutional layer. Then the different modalities sequences will be controlled to the same dimension by setting the different size of convolutional kernels and strides:

$$Conv_{(T,A)} = Conv1D((F_T, F_A), k_{(T,A)}, s_{(T,A)}))$$  

where $k_{(T,A)}$ and $s_{(T,A)}$ represent the number of convolutional kernels and strides for text and audio modalities. After that, two separate Bi-GRU layers are applied to extract temporal information on each modality. Finally, the aligned text and audio features $X_T$ and $X_A$ are used to initialize the fusion representations.

#### 3.3 Fusion Representation Initialization Module

The purpose of the fusion representation initialization module is to initialize fusion representations through the inter-modal interaction between text and audio modalities. Inspired by MMU-BA framework [Ghosal et al. 2018], we employ the crossmodal collaboration attention to enable one modality to be changed by receiving information from another modality. Specifically, we first compute a pair of attention matrices $M_{T'A}$ and $M_{AT}$, which include the cross-modality information:

$$M_{TA} = X_T X_A^T$$  

$$M_{AT} = X_A X_T^T$$

Then we pass the attention matrices through a Tanh function and compute attention score by a Softmax function, the attention score matrices $S_{TA}$ and $S_{AT}$ are defined as:

$$S_{TA} = \text{Softmax}(\text{Tanh}(M_{TA}))$$  

$$S_{AT} = \text{Softmax}(\text{Tanh}(M_{AT}))$$

We apply soft attention to compute the modality-wise attention representations $O_{TA}$ and $O_{AT}$:

$$O_{TA} = S_{TA} X_A$$  

$$O_{AT} = S_{AT} X_T$$

Then the matrix multiplication is used to help different modalities focus on important information and get the attentive representations $X_{T'}$ and $X_{A'}$:

$$X_{T'} = O_{TA} \odot X_T$$  

$$X_{A'} = O_{AT} \odot X_A$$

Figure 2: Overview architecture of the Self-Adjusting Fusion Representation Learning Model.

After that, we add $X_T$ and $X_{A'}$, $X_T$ and $X_A$ respectively and obtain two different fusion representations $X_{T,A'}$ and $X_{T'A}$:

$$X_{T,A'} = w_{T}X_{T} + w_{A'}X_{A'} + b_{T,A'}$$  \hspace{1cm}  (10)

$$X_{T'A} = w_{T}X_{T} + w_{A}X_{A} + b_{T,A}$$  \hspace{1cm}  (11)

where $w_{(T,A',A')}$ represents the weight of different unimodal representations, $b$ is the bias.

### 3.4 Self-Adjusting Module

In order to keep the original characteristics of each modality, the self-adjusting module is designed to dynamically adapt the fusion representations by using unimodal streams. In the following, we elaborate on the crossmodal adjustment transformer which is the core unit of the self-adjusting module. We also introduce the self-attention transformer and classifier.

**Crossmodal Adjustment Transformer**  
Based on the previous work (Tsai et al. 2019), we design the crossmodal adjustment transformer that enables fusion representations to be adjusted by utilizing different unimodal information. For convenience, we will introduce the structure of it through the example ($X_{TA'} \rightarrow X_T X_{A'}$), which use unimodal representations $X_T$ and $X_A$ to adjust the fusion representations $X_{T,A'}$.

As shown in Figure 3, the crossmodal adjustment transformer has three input:fusion representations ($X_{TA'}$), text representations ($X_T$), and audio representations ($X_A$). To preserve the temporal information of input sequences, following (Vaswani et al. 2017) we augment position embedding (PE) to all the input sequences. Given a sequence $X \in \mathbb{R}^{l \times d}$ ($l$ represents the sequence length and $d$ represents the feature dimension), the position embedding is computed as follows:

$$PE_{(pos,2i+1)} = \sin(pos/10000^{2i/d})$$  \hspace{1cm}  (12)

where $pos = 0, 1, ..., l - 1$ and $i = 0, 1, ..., \lfloor d/2 \rfloor$. Then we add position embedding to the input sequences followed by layer normalization.

$$E_{(TA',TA')} = LN (PE_{(TA',TA')} + X_{(TA',TA')})$$  \hspace{1cm}  (14)

where $LN$ represents layer normalization. After that, we adopt $N$ crossmodal blocks to adjust the fusion representations $E_{TA'}$ by using the text representations $E_T$. The crossmodal block is proposed by (Tsai et al. 2019), it is mainly composed of the multi-head attention and the feed-forward layer. Besides, it employs a residual connection (He et al. 2016) around each of two sub-layers followed by layer normalization. The Query, Key, and Value of the multi-head attention in the $i$th blocks is defined as $\hat{Q}_{TA'} = LN(\hat{O}_{TA'}^{[i]}), \hat{K}_{TA'} = \hat{V}_{TA'} = LN(E_T)$, where $i = 1, ..., N$ and $\hat{O}_{TA'}^{[i]}$ is the output of the $i - 1$th crossmodal block, then the multi-head attention is computed as:

$$\hat{O}_{TA'}^{[i]} = LN(E_{TA'})$$ \hspace{1cm}  (15)

$$MH_{TA'}^{[i]} = \text{Softmax}(\hat{Q}_{TA'}^{[i]}(\hat{K}_{TA'}^{[i]})^T)\hat{V}_{TA'}^{[i]}$$ \hspace{1cm}  (16)

the output of the $i$th layers $\hat{O}_{TA'}^{[i]}$ is defined as:

$$\hat{M}_{TA'}^{[i]} = LN(MH_{TA'}^{[i]} + \hat{O}_{TA'}^{[i-1]})$$ \hspace{1cm}  (17)

$$\hat{O}_{TA'}^{[i]} = \text{FL}(LN(\hat{M}_{TA'}^{[i]}) + \hat{M}_{TA'}^{[i]})$$ \hspace{1cm}  (18)

where $i = 1, ..., N$ and FL represents the feed-forward layer.

Based on the output of the former $N$ crossmodal blocks $\hat{O}_{TA'}^{[i]}$, we introduce another $N$ crossmodal blocks to adjust $\hat{O}_{TA'}$ by using the audio feature $E_A$. The output $\hat{O}_{TA'}^{[N]}$ of the latter $N$ crossmodal blocks is the final adjusted fusion representations.

**Self-Attention Transformer and Classifier**  
After obtaining the adjusted fusion representations $\hat{O}_{TA'}^{[N]}$ and $\hat{O}_{A'}^{[N]}$, on the one hand, these fusion representations will be trained by the corresponding local classifier, on the other hand, the self-attention transformer is employed to capture temporal information of each fusion representation. The output of the self-attention transformer will be concatenated used to make predictions through a global classifier. More importantly, we optimize our model through a single objective function, which can make us train local classifiers and global classifier at the same time. The objective function $Loss$ is defined as:

$$Loss = losst_{TA'} + losst_{A'} + losst_{TA}$$  \hspace{1cm}  (19)

### 4 Experiments

In this section, we evaluate the performance of the Self-Adjusting Fusion Representation Learning Model on the public multimodal sentiment analysis datasets CMU-MOSI and CMU-MOSEI. In the following subsections, Section 4.1 shows the information about datasets and experimental settings. Section 4.2 presents unimodal feature extraction. Section 4.3 and Section 4.4 introduce the evaluation metrics and the baseline models used in our experiments.
Table 1: Experimental results on the CMU-MOSI dataset. $^h$ means higher is better and $^l$ means lower is better. T: text, A: audio, V: video.

| Model                | Modality | $\text{Acc}_2$ | $\text{Acc}_5$ | $F_1^h$ | $\text{MAE}^l$ | $\text{Corr}^{lh}$ |
|----------------------|----------|-----------------|-----------------|--------|----------------|------------------|
| EF-LSTM              | T+A+V    | 31.0            | 73.6            | 74.5   | 1.078          | 0.542            |
| LF-LSTM              | T+A+V    | 33.7            | 77.6            | 77.8   | 0.988          | 0.624            |
| MCTN (Pham et al. 2019) | T+A+V    | 32.7            | 75.9            | 76.4   | 0.991          | 0.613            |
| RAVEN (Pham et al. 2019) | T+A+V    | 31.7            | 72.7            | 73.1   | 1.076          | 0.544            |
| MuT (Tsai et al. 2019) | T+A+V    | 39.1            | 81.1            | 81.0   | 0.889          | 0.686            |
| MuT (Tsai et al. 2019)(our run) | T+A    | 34.9            | 79.2            | 79.1   | 0.991          | 0.667            |
| SA-FRLM(ours)        | T+A      | 35.6            | 81.1            | 81.1   | 0.908          | 0.699            |

4.1 Datasets and Experimental Settings

We evaluate our proposed method on the CMU Multi-modal Opinion-level Sentiment Intensity (CMU-MOSI) (Zadeh et al. 2016) and CMU Multimodal Opinion Sentiment and Emotion Intensity (CMU-MOSEI) (Zadeh et al. 2018c) datasets. CMU-MOSI is composed of 93 opinion videos downloaded from YouTube movie reviews. These videos are spanning over 2199 utterances. Each utterance is annotated in the range of [-3, +3]. The audio sequences of CMU-MOSI are extracted at a sampling rate of 12.5 Hz. Considering the speaker should not appear in both training and testing sets and the balance of the positive and negative data, we split 52, 10, 31 videos in training, validation and test set accounting for 1284, 229, and 686 utterances. Similarly, CMU-MOSEI is a multimodal sentiment and emotion analysis dataset which is made up of 23,454 movie review video clips taken from YouTube. The audio sequences of CMU-MOSEI are extracted at a sampling rate of 20 Hz. To make sure the validity of the experiment, the strategy we adopt is consistent with the previously published works (Tsai et al. 2019, Zadeh et al. 2018b).

In the SA-FRLM, the number of the out channels of the temporal convolutional layer is set to 50. There are 50 units in the Bi-GRU layers, and the fully connected layers used in our model have 200 units with 0.3 dropout rate. In the training process, the number of batch size and epoch is set to 12 and 20 respectively. Besides, we use Adam optimizer with 0.001 learning rate and L1 loss function.

4.2 Feature Extraction

To consistent with the previous works (Tsai et al. 2019, Rahaman et al. 2020), we use the same feature extraction method for text and audio modalities.

**Text Feature** We use the Glove word embeddings to embed the words sequences of video transcripts to 300 dimensional word vectors. The Glove embeddings used in our experiments are trained on 840 billion tokens from the common crawl dataset.

**Audio Feature** In this work, we use the COVAREP (Degottex et al. 2014) to extract audio features. Each segment audio file is represented as a 74 dimensional vector including 12 Mel-frequency cepstral coefficients (MFCCs), pitch and segmenting features, glottal source parameters, peak slope parameters, and maxima dispersion quotients. All of these features are extracted at a sampling rate of 100 Hz.

4.3 Evaluation Metrics

In our experiments, consistent with previous work (Tsai et al. 2019), we use the same metrics to evaluate the performance of our proposed method. 7-class accuracy ($\text{Acc}_7$) is used in the sentiment score classification task, 2-class accuracy ($\text{Acc}_2$) and F1 score ($F_1$) are used in the binary sentiment classification task, mean absolute error ($\text{MAE}$) and the correlation ($\text{Corr}$) of model predictions with correct labels are used in the regression task. The higher value of the metrics means the better performance of the model except for $\text{MAE}$. To make experiments more convincing, we randomly select five seeds and take the average result of 5 runs as the final experimental results.

4.4 Baselines

We compare our proposed model with previous methods in multimodal sentiment analysis task. The methods we compared are as follows:

**EF-LSTM** Early Fusion LSTM (EF-LSTM) concatenates multimodal inputs and uses a single LSTM to learn the contextual information.

**LF-LSTM** Late Fusion LSTM (LF-LSTM) uses single LSTM model to learn the contextual information of each modality and concatenate the output to make predictions.

**MCTN** (Pham et al. 2019) Multimodal Cyclic Translation Network (MCTN) is designed to learn robust joint representations by translating between different modalities, and it can learn joint representations using only the source modality as input.

**RAVEN** (Wang et al. 2019) Recurrent Attended Variation Embedding Network (RAVEN) models the fine-grained structure of nonverbal subword sequences and dynamically shifts word representations based on nonverbal cues, it achieves competitive performance on two publicly available datasets for multimodal sentiment analysis and emotion recognition.

**MuT** (Tsai et al. 2019) Multimodal Transformer (MuT) uses the directional pairwise crossmodal attention to interactions between multimodal sequences across distinct time steps and latently adapts streams from one modality to another, and it is the current state-of-the-art method on CMU-MOSI and CMU-MOSEI datasets.
| Model           | Modality     | Acc_2 | Acc_2 | F^1 | MAE | Corr^h |
|-----------------|--------------|-------|-------|-----|-----|--------|
| EF-LSTM         | T+A+V        | 46.3  | 76.1  | 75.9| 0.680| 0.585  |
| LF-LSTM         | T+A+V        | 48.8  | 77.5  | 78.2| 0.624| 0.656  |
| MCTN (Pham et al. 2019) | T+A+V        | 48.2  | 79.3  | 79.7| 0.631| 0.645  |
| RAVEN (Pham et al. 2019) | T+A+V        | 45.5  | 75.4  | 75.7| 0.664| 0.599  |
| MulT (Tsai et al. 2019) | T+A+V        | 50.7  | 81.6  | 81.6| 0.591| 0.694  |
| MulT (Tsai et al. 2019)(our run) | T+A        | 48.9  | 80.1  | 80.5| 0.627| 0.656  |
| SA-FRLM(ours)   | T+A          | 49.9  | 80.7  | 81.2| 0.606| 0.673  |

Table 2: Experimental results on the CMU-MOSEI dataset. \(^h\) means higher is better and \(^l\) means lower is better. T: text, A: audio, V: video.
Table 3: Examples from the CMU-MOSI dataset. The ground truth labels are in the range of [-3,+3], where -3 represents strongly negative and +3 represents strongly positive. For each example, we show the ground truth and prediction of both the SA-FRLM and MulT.

5.2 Qualitative Analysis

We analyze the impact of our proposed SA-FRLM by comparing it with the MulT. As shown in Table 3, we choose five examples from the CMU-MOSI dataset. Each example consists of spoken words as well as speak behaviors. We show the ground truth of each example and the sentiment predictions of both our model and MulT.

In the Example-1, the text has strong negative and the tone of the speaker performs weak positive. The truth label of the example is −1.0. Compared with the MulT, our model makes a more accurate prediction probability of −1.15. However, influenced by audio modality, the prediction probability of the MulT is 0.33. In the Example-2, both text and audio information perform strong negative sentiments. Although both the SA-FRLM and MulT successfully predicted sentiment, the result of our model is more closer to the truth label. In the Example-3, the sentiment of the spoken words is strongly positive. In contrast, the audio information performs strong negative. With the help of the inter-modal interaction between text and audio modalities, our model makes a right prediction. But the MulT seems to pay more attention to text modality which causes it makes a wrong emotional judgment. This example also proves that our model can revise sentiment intensity properly by taking audio modality information into account.

From Example-1 and Example-3, we can see that our model can better allocate the weight of different modalities. It is mainly because our approach not only makes full use of the interaction between different modalities but also maximizes the properties of the original characteristics of different modalities. In Example-2 and Example-4, compared with MulT, the prediction of our method is closer to the ground truth. The main reason is that our model dynamically adjusts the fusion representations by combining the unimodal information of different modalities. So the adjusted fusion representations are more robust and it can better represent the information of the unaligned text and audio sequences.

6 Conclusion

In this paper, we propose a Self-Adjusting Fusion Representation Learning Model (SA-FRLM). Different from previous works, our model not only makes full use of the interaction between different modalities but also greatly protects the characteristics of each modality. As the core unit of our model, the cross-modal adjustment transformer is proposed to dynamically change the fusion representations by combining text and audio information. The experiment results on the CMU-MOSI and CMU-MOSEI datasets show that the SA-FRLM has significantly improved the performance on the unaligned text and audio sequences. Additionally, qualitative analysis proves our model can revise sentiment intensity properly by taking audio modality information into account, and it can get more accurate predictions after adjusting fusion representations. In the future, because there are many works have proved the efficiency of the pre-trained language model, we will explore how to extend the pre-trained language model from unimodal to multimodal to improve the performance of multimodal sentiment analysis.


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