Multi-scale Cooperative Multimodal Transformers for Multimodal Sentiment Analysis in Videos

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Abstract

Multimodal sentiment analysis in videos is a key task in many real-world applications, which usually requires integrating multimodal streams including visual, verbal and acoustic behaviors. To improve the robustness of multimodal fusion, some of the existing methods let different modalities communicate with each other and modal the crossmodal interaction via transformers. However, these methods only use the single-scale representations during the interaction but forget to exploit multi-scale representations that contain different levels of semantic information. As a result, the representations learned by transformers could be biased especially for unaligned multimodal data. In this paper, we propose a multi-scale cooperative multimodal transformer (MCMulT) architecture for multimodal sentiment analysis. On the whole, the “multi-scale” mechanism is capable of exploiting the different levels of semantic information of each modality which are used for fine-grained crossmodal interactions. Meanwhile, each modality learns its feature hierarchies via integrating the crossmodal interactions from multiple level features of its source modality. In this way, each pair of modalities progressively builds feature hierarchies respectively in a cooperative manner. The empirical results illustrate that our MCMulT model not only outperforms existing approaches on unaligned multimodal sequences but also has strong performance on aligned multimodal sequences.

Introduction

Multimodal sentiment analysis has recently become a widely researched topic in natural language and multimodal machine learning communities (Zadeh et al. 2016; Poria et al. 2017a; Busso et al. 2008; Hou et al. 2019; Tsai et al. 2019b; Bagher Zadeh et al. 2018; Poria et al. 2017b; Liang et al. 2018; Wang et al. 2019; Pham et al. 2019). Intrinsically, the way of people expressing their opinions and sentiments involves multiple modalities including the language (words), visual (facial expressions and head gestures), and acoustic (paralinguistic), which are in the form of asynchronous coordinated sequences. In particular, Tsai et al. (Tsai et al. 2019a) have clearly illustrated there is an “unaligned” nature of the multimodal sentiment analysis task. The receiving frequencies of receptors usually vary in audio and vision streams, and hence it is difficult to obtain optimal alignment between them without manual data preprocessing. For example, a frowning face may relate to a pessimistically word spoken in the past or coming clips. The heterogeneities and unaligned nature across modalities often increase the difficulty of analyzing multimodal sequences.

To tackle these challenges, several papers (Hou et al. 2019; Tsai et al. 2019b; Liang et al. 2018; Poria et al. 2017b; Delbrouck et al. 2020; Tsai et al. 2019a) perform multimodal fusion in various manners. Initial works (Liang et al. 2018; Poria et al. 2017b; Hou et al. 2019; Delbrouck et al. 2020; Shenoy, Sardana, and Graphics 2020; Tsai et al. 2020) in unaligned multimodal sentiment analysis use a common way to manually force word-aligning before training and testing. Specifically, the visual and acoustic features are first manually aligned to the resolution of textual words. It is impractical to manually align different streams in the real-world scenario. Besides, as the analysis in (Tsai et al. 2019a), the word-aligned approaches not only depend on feature engineering that involves domain knowledge, but are also inclined to overlook long-range crossmodal contingencies of the original modalities. To make the alignment and fusion over multiple modalities be more feasible in practice, Tsai et al. (Tsai et al. 2019a) proposes a crossmodal attention module by extending the standard Transformer network (Vaswani et al. 2017) to learn representations directly from unaligned multimodal sequences.

In this paper, we propose a multi-scale cooperative multimodal transformer (MCMulT) architecture to improve the quality of representations learned from unaligned multimodal sequences. The intuition is that when the multimodal sequences is unaligned, the information from different modalities can be very different. To improve the robustness of a transformer, during the crossmodal interaction, as much as the information from other modalities should be kept. Therefore, in our method, multi-scale representations that contain different levels of semantic information are used for crossmodal interaction instead of a single-scale representation. Furthermore, we designed a computationally-efficient way to let the representations from different scales and different modalities communicate with each other. As a result, different levels of information from different modalities are captured and synchronized by the transformers, which improves the performance of the transformers and the quality of the learned representations. As shown in Figure 1, our method

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let all modalities progressively learn their individual hierarchical representations by exploiting directional pairwise crossmodal interactions with the multi-scale representations on hand. Each crossmodal interaction can be regarded as one feature enhancement operator (MACT Layer in Figure 1(a)) that attends the long-term spatial dependencies from all the preceding transformer layers of the source modality. This not only shortens the path of crossmodal error propagation, but also helps to prevent the gradually evolving interactions from being forgotten or diluted. Consequently, the enhanced layer of target modality is also used as input to boost all subsequent layers of its source modalities. Following this way, a pair of modalities respectively build their hierarchical representations in a cooperative manner. Furthermore, to improve effectiveness and computational efficiency, instead of forcing fully dense interactions, we introduce a block-scale mechanism that is a combination of a windowed local-context and global attention interaction through ablations and controlled trials. This reduces complexity of the network while bringing higher performance.

We conduct extensive experiments on unaligned and aligned multimodal sentiment analysis, covering three benchmarks: CMU-MOSI (Zadeh et al. 2016), CMU-MOSEI (Bagher Zadeh et al. 2018) and IEMOCAP (Busso et al. 2008). Our experiments show that our MCMulT outperforms previous work on both the common word-aligned setting and the more challenging unaligned scenario. In addition, empirical qualitative analysis further proves that the block-scale mechanism brings improvements on performance via increasing the depth of crossmodal networks compared to other variants of MCMulT.

**Related Works**

**Sentiment Analysis.** Early work on sentiment analysis or emotion recognition focused primarily on one modality, i.e., text (Turney 2002; Pang and Lee 2004; Socher et al. 2013), vision (Ekman 1974) and audio (Rahman and Busso 2012). Probably the most challenging task in multimodal sentiment analysis is learning a good representation of multiple modalities. More researchers have committed to integrating the multimodal information effectively. To date, there are mainly two types of fusion strategies: early fusion and late fusion. Methods in the early fusion category concatenate multimodal data at the input level (Zadeh et al. 2016; Wang et al. 2017). While early fusion methods outperform unimodal models, they cannot comprehensively cover the modality-specific interactions and tend to overfit. The late fusion methods integrate different modalities after input stage, and then exploit both modality-specific and crossmodal interactions (Zadeh et al. 2017; Tsai et al. 2019b; Pham et al. 2018; Shenoy and Sardana 2020; Delbrouck et al. 2020; Shenoy, Sardana, and Graphics 2020; Tsai et al. 2020). Currently, several competitive results are achieved by augmenting this class of models with attention or memory mechanism (Liang et al. 2018; Wang et al. 2019; Delbrouck et al. 2020). Our work follows the attention mechanisms to model intra-modal or inter-modal interactions from multimodal sequences.

**Transformer Model.** Transformers were designed by Vaswani et al. (Vaswani et al. 2017) as a novel attention-based building block for modeling sequential data. Recently, Transformer models have been successfully applied to machine learning community including natural language processing, speech processing and computer vision (Devlin et al.
2019; Parmar et al. 2018; Carion et al. 2020; Dong, Xu, and Xu 2018). Inspired by these Transformer scaling successes, several recent works have also introduced transformer-based alignment or fusion to model relations between different modalities. For example, the popular BERT architecture (Devlin et al. 2019) is extended to learn joint visual-linguistic representations in a self-supervision pretraining framework (Lu et al. 2019; Tan and Bansal 2019; Chen et al. 2020; Rahman et al. 2020). For VQA task, Hu et al. (Hu et al. 2020) project all entities from different modalities (query words, objects in the image and OCR results of the image) into a common semantic embedding space and apply Transformer to collect relational representations for each entity. These multimodal transformer approaches mostly input all modalities either independently or jointly to the vanilla Transformer module without explicitly exploiting both multi-scale and cooperative mechanism in a holistic perspective especially for the unalign nature in the multimodal sequences. Delbrouck et al. (Delbrouck et al. 2020) describes a Transformer-based joint-encoding (TBJE) for sentiment analysis task on the manually aligned multimodal sequences. To tackle the unaligned multimodal sentiment analysis task, Tsai et al. (Tsai et al. 2019a) propose a directional pairwise crossmodal attention in the multimodal transformer (vanilla MulT\(^1\)) model to exploit interactions between multimodal sequences across different time steps. Our work has the same cornerstone with MulT. However, there are two main differences between MulT (or TBJE) and our MCMulT. Firstly, MulT models crossmodal interactions only use the single scale (the low-level) features from its source modality. In our MCMulT, multi-scale features are exploited to model each crossmodal interaction, and the sophisticated crossmodal interactions also facilitate pairwise modalities’ ability to learn progressive multi-scale features in a cooperative manner. Secondly, we design a block-scale mechanism in the MCMulT which allows more transformer layers to improve the recognition rate. The block-scale mechanism is not conducted in MulT.

Proposed Method

In this section, we describe our proposed MCMulT architecture for unaligned multimodal sequences sentiment analysis task, as shown in Figure 2(a). Similarly with MulT (Tsai et al. 2019a), the representations are built from multiple pairwise modalities, e.g. text-vision, text-audio, vision-audio, and then merged at the high level to predict the sentiment. The network contains three modules: low-level feature, MCMulT and prediction module. MCMulT is the core component of the network which explicitly exploits both multi-scale and cooperative mechanisms for multimodal feature learning in a holistic perspective. Specifically, each crossmodal transformer layer attends all the preceding transformer layers (not only the low-level features) of its source modality. In this way, MCMulT learns progressive multi-scale features with the built feature hierarchies at hand and coordinates them through attentive crossmodal interactions. As a result, different levels of information from different modalities are captured, and the quality of the learned representations are improved. We first describe low-level feature module in Section3.1. In Section 3.2, the proposed core module MCMulT is presented in detail, and some variants of MCMulT are also discussed. Finally, the prediction module is briefly illustrated in Section 3.3.

Low-level Features

Temporal convolution and positional embedding are applied to extract the low-level features from the original three modalities as (Tsai et al. 2019a) including text (L), vision (V) and audio (A). Let \( X_{L,V,A} \in R^{T_{L,V,A} \times d_{L,V,A}} \) represent the raw data from three-modality sequences where \( T \) and \( d \) respectively indicate the sequence length and the data dimension.

Temporal convolution is expected to exploit the local structure information of the sequence and project the features of different modalities to the same dimension \( d \), which is performed with a one-dimensional convolution layer:

\[
\hat{X}_{L,V,A} = Conv1D(X_{L,V,A}, k_{L,V,A}) \in R^{T_{L,V,A} \times d},
\]

where \( k_{L,V,A} \) denotes the convolution kernel, \( d \) is the common dimension.

Following Vaswani et al. (Vaswani et al. 2017), positional embedding is augmented to the output of temporal convolution as Equation 2, which helps carrying temporal information from each modality sequence. For more details of the positional embedding, please refer to (Vaswani et al. 2017; Tsai et al. 2019a). \( Z_{L,V,A}^{[0]} \) denotes the low-level features that will be fed to our MCMulT module:

\[
Z_{L,V,A}^{[0]} = \hat{X}_{L,V,A} + PE(T_{L,V,A}),
\]

where \( PE(\cdot) \) indicates the positional embedding.

MCMulT

The core idea of MCMulT is that directional crossmodal interactions are performed in the multi-scale and cooperative mechanisms as shown in Figure 1(a), where both solid and dotted arrows indicate directional crossmodal interactions between a pair of modalities.

Multi-scale mechanism indicates that a target modality builds its multi-scale features via integrating directional crossmodal interactions. Each integration is accomplished through aggregating multi-scale features of its source modality, as illustrated in Figure 1(a).

Cooperative mechanism indicates that our MCMulT allows the source and target modality iteratively boost each other during building their multi-scale features, as shown in Figure 1(a), where the information flow is bi-directional according to the black solid and dotted arrows. Specifically, as Figure 1(a) illustrates, after the scale-1 representation of modality \( \alpha \) enhances the scale-2 representation of modality \( \beta \), the enhanced scale-2 representation of modality \( \beta \) also is used to boost the subsequent representations (scale-3 and scale-4) of modality \( \alpha \) following the reciprocity principle.
MCTB  The MCMulT network is divided into multiple densely connected multi-scale crossmodal Transformer blocks (MCTBs) which contain two types of crossmodal units: multi-scale attentive crossmodal transformer (MACT) and crossmodal transformer (CT). The core unit is MACT which contains three sub-network layers: multi-scale multi-head crossmodal layer, multi-scale attentive layer and position-wise feed-forward layer, as shown in Figure 2(b). CT only attends single scale representation of the source modality, and can be regarded as a simple version of MACT.

Multi-scale Crossmodal Layer. Let $Z_\alpha \in R^{T_\alpha \times d_\alpha}$ and $Z_\beta \in R^{T_\beta \times d_\beta}$ represent the features (any scale or level) from two modality sequences respectively. As shown in the green region of Figure 2(b), one multi-scale crossmodal layer aggregates multiple directional pairwise crossmodal interactions between the target modality $\beta$ and the source modality $\alpha$ via multiple multi-head layers in parallel. Each of crossmodal interactions is detailed in Equation 3 as the vanilla transformer (Vaswani et al. 2017).

$$CM_{\beta \rightarrow \alpha}(Z_\alpha, Z_\beta) = \text{softmax} \left( \frac{Z_{\alpha} W_{Q_\alpha} Z_{\beta}^T W_{K_\beta}}{\sqrt{d}} \right) Z_{\beta} W_{V_\beta}, \quad (3)$$

where $W_{Q_\alpha}, W_{K_\beta}$ and $W_{V_\beta}$ are weight parameters. When the modality $\alpha$ builds its $i$-th level crossmodal interactions from the modality $\beta$, $H^{[i]}$ denotes the set of multi-scale crossmodal interactions between the modality $\alpha$ and $\beta$ as

$$H^{[i]} = \left\{ CM_{\beta \rightarrow \alpha}(Z^{[i-1]}_\alpha, Z^{[j]}_\beta) \right\}, \quad j = 0, \ldots, i - 1$$

$$Z^{[0]}_{\alpha \rightarrow \beta} = Z^{[0]}_{\beta}, \quad (4)$$

where $Z^{[0]}_{\beta}$ is the low-level feature of the modality $\beta$ as Equation 2.

Multi-scale Attention. To ensure the relevant information of each crossmodal interaction of $H^{[i]}$, $H^{[i]}$ is aggregated with multi-scale attention to generate an enhanced feature $A^{[i]}_{\alpha \rightarrow \beta}$ with a self-attention component as shown in the blue part of Figure 2(b).

Positionwise Feed-Forward Layer. Following the vanilla Transformer (Vaswani et al. 2017), we input the attentional fusion feature to the positional feed-forward layer in Equation 5 corresponding to the purple part of Figure 2(b).

$$P^{[i]}_{\beta \rightarrow \alpha} = f_\theta (LN(A^{[i]}_{\alpha \rightarrow \beta} + LN(Z^{[i-1]}_{\beta \rightarrow \alpha})))$$

$$Z^{[i]}_{\beta \rightarrow \alpha} = A^{[i]}_{\alpha \rightarrow \beta} + LN(Z^{[i-1]}_{\beta \rightarrow \alpha}) + P^{[i]}_{\beta \rightarrow \alpha} \quad (5)$$

Block Interaction Mechanism  Intuitively, it is possible to only use MACT layer to build multi-scale crossmodal interactions in the MCMulT module. However, this mechanism with dense multi-scale interaction also brings more parameters than the single-scale crossmodal interaction. Especially, this mechanism will make the network complexity grow linearly with the network depth, and the training will become much harder. To address the above limitation, we dive into the network connection structure and replace the dense connections with sparse connections, which given birth to the block mechanism. There are two kinds of crossmodal interaction in a MCTB, i.e., global interactions and local interactions as shown in Figure 1(a) and Figure 1(b).

To attend multi-scale dependencies, global interactions are built densely between the target and source modalities in the block scale. Each block of MCMulT involves multiple crossmodal Transformer layers. The global interacions of MCMulT are performed with MACTs and the input of MCTB is from the output of multiple MCTBs of the source modality. To preserve a windowed local context, local interactions are built between the MCTB of target modality and the same-scale MCTB of its source modality. Local interactions of MCMulT are performed with a CT as shown in the Figure 2(c). The input of CT contains the previous layer output of the target modality and the first layer output of the same level MCTB from its source modality. It is noted that the local interaction only uses the single scale representation from source modality. This block mechanism makes the number of parameters decrease.

Variants of MCMulT  Block mechanism is only one manner to explore multi-scale interactions between the source and target modality in MCMulT. If different network connection structures are designed to take the place of block structure, MCMulT can be changed into three variants: MCMulT-Dense, MCMulT-LocalDense and MCMulT-Global as shown.
in Figure 2. MCMulT with the dense connections from all the preceding layers is denoted as MCMulT-Dense. MCMulT-LocalDense models local interactions in a dense manner with preserving global interactions of MCTBs. MCMulT-Global is obtained through cutting out local crossmodal interactions. It is noted that MulT may be regarded as an extremely simple version of MCMulT-Dense. If MCMulT-Dense only uses the scale-0 of source modality to build crossmodal interactions, MCMulT-Dense will degrade to MulT. The descending order of complexity of MCMulT variants is as MCMulT-Dense, MCMulT-LocalDense, MCMulT, MulT, MCMulT-Global. The performances of these variants of MCMulT will be discussed in the experiments.

Prediction
As the final step, we fuse the features of all modalities through concatenating the outputs from MCMulT architecture that share the same target modality to yield \( \left[ Z_{V \rightarrow L}^{[D]}, Z_{A \rightarrow L}^{[D]} \right], \left[ Z_{L \rightarrow V}^{[D]}, Z_{A \rightarrow V}^{[D]} \right], \left[ Z_{L \rightarrow A}^{[D]}, Z_{V \rightarrow A}^{[D]} \right] \). Each item is then passed through a different Transformer to collect temporal information. Eventually, the outputs of transformers are extracted to pass through a full-connected layer to predict sentiment.

Experiments
In this section, we conduct experimental evaluation of MCMulT on three datasets (CMU-MOSI, CMU-MOSEI, IEMOCAP), which are often used as benchmarks for multimodal sentiment analysis tasks. Because of the limited space, we leave out details of implementations in Appendix A and a visualization of crossmodal attention maps in Appendix B. Our experiments are mainly divided into two parts. Firstly, our MCMulT is compared with the existing competitive approaches in both word-unaligned and word-aligned settings. Secondly, the variants of our MCMulT and related hyperparameters are evaluated.

Datasets and Evaluation Metrics
Each task is conducted in both word-aligned and unaligned settings. For both settings, the multimodal raw features are extracted from the textual (Glove word embedding (Pennington, Socher, and Manning 2014)), visual (Facet (iMotions 2017)) and acoustic (COVAREP (Degottex et al. 2014)) modalities. For the unaligned setting, we use the raw original audio and visual features as extracted, without any word-segmented alignment or manual subsampling. For the word-aligned case, all modals are aligned by P2FA (Yuan and Liberman 2008) as did in (Tsai et al. 2019b; Pham et al. 2019; Wang et al. 2019; Tsai et al. 2019a). A more detailed introduction can be found in MulT (Tsai et al. 2019a).

CMU-MOSI. CMU-MOSI (Zadeh et al. 2016) dataset consists of 2,199 opinion video clips from YouTube movie reviews spoken in English. Each clip is annotated with sentiment in the range \([-3,3]\) from high negative to high positive. Sentiment analysis task on CMU-MOSI is considered as a 7 class sentiment classification problem. In particular, 1,284, 229 and 686 clips are used for training, valid and test respectively.

CMU-MOSEI. CMU-MOSEI (Bagher Zadeh et al. 2018) consists of 23,454 movie review video clips from YouTube spoken in Spanish, each of which is annotated with a sentiment score between -3 (strongly negative) and +3 (strongly positive) to indicate emotional preferences. 16,326, 1,871 and 4659 utterances are used for training, valid and test respectively.

IEMOCAP. IEMOCAP (Busso et al. 2008) consists of two-way conversations between 10 speakers, which are divided into utterances. As suggested by Wang et al. (Wang et al. 2019), the utterances are tagged with the labels happy, sad, angry and neutral. 2,717, 798 and 938 utterances are used for training, valid and test respectively.

Evaluation Metrics. For MOSEI and MOSI datasets, the same metrics were used to evaluate the performance of the model: 7-class accuracy (i.e. emotion score classification in Acc7: \([-3, +3]\)), binary accuracy (i.e. Acc2: positive/negative emotion), F1 score, mean absolute error (MAE) of score and correlation of model prediction with human. In IEMOCAP dataset, binary accuracy and F1 values are used to evaluate the performance of the model.

Baselines
Our MCMulT architecture is compared with early multimodal fusion LSTM (EF-LSTM), late multimodal fusion LSTM (LF-LSTM), Recurrent Attended Variation Embedding Network (RAVEN) (Wang et al. 2019), Multimodal Cyclic Translation Network (MCTN) (Pham et al. 2019) and MulT (Tsai et al. 2019a), where MulT achieved SOTA.
Table 1: Results on CMU-MOSI with aligned and unaligned multimodal sequences. "h" means higher is better and "l" means lower is better. EF stands for early fusion, and LF stands for late fusion.

| Metric     | Acc^2 | Acc^3 | F1 | MAP | Corr^2 |
|------------|-------|-------|----|-----|--------|
| CMU-MOSI-Aligned |       |       |    |     |        |
| EF-LSTM    | 33.7  | 75.3  | 75.2| 1.023| 0.608  |
| LF-LSTM    | 35.3  | 76.8  | 76.7| 1.015| 0.625  |
| RMFN (Liang et al. 2018) | 38.3  | 78.4  | 78.0| 0.922| 0.681  |
| MFM (Tsai et al. 2019b) | 36.2  | 78.1  | 78.1| 0.951| 0.662  |
| RAVEN (Wang et al. 2019) | 33.2 | 78.0  | 76.6| 0.915| 0.691  |
| MCTN (Pham et al. 2019) | 35.6  | 79.3  | 79.1| 0.909| 0.676  |
| Mu-Net (Shenoy, Sardana, and Graphics 2020) | - | 81.2 | 80.1| - | - |
| MuT (Tsai et al. 2019a) | 40.0  | 83.0  | 82.8| 0.871| 0.698  |
| MCMulT (ours) | 40.7  | 83.9  | 83.2| 0.866| 0.701  |

| Metric     | Acc^2 | Acc^3 | F1 | MAP | Corr^2 |
|------------|-------|-------|----|-----|--------|
| CMU-MOSI-Unaligned |       |       |    |     |        |
| CTC (Graves et al. 2006)+EF-LSTM | 31.0  | 73.6  | 74.5| 1.078| 0.542  |
| LF-LSTM    | 33.7  | 77.6  | 77.8| 0.988| 0.624  |
| CTC+RAVEN (Wang et al. 2019) | 31.7  | 72.7  | 73.1| 1.076| 0.544  |
| CTC+MCTN (Pham et al. 2019) | 32.7  | 75.9  | 76.4| 0.991| 0.613  |
| MuT (Tsai et al. 2019a) | 39.1  | 81.1  | 81.0| 0.889| 0.686  |
| MCMulT (ours) | 40.3  | 82.2  | 82.3| 0.885| 0.691  |

Table 2: Results on (relatively large-scale) CMU-MOSEI with aligned and unaligned multimodal sequences.

| Metric     | Acc^2 | Acc^3 | F1 | MAP | Corr^2 |
|------------|-------|-------|----|-----|--------|
| CMU-MOSI-Aligned |       |       |    |     |        |
| EF-LSTM    | 47.4  | 78.2  | 77.9| 0.642| 0.616  |
| LF-LSTM    | 48.8  | 80.6  | 80.6| 0.619| 0.659  |
| Graph-MFN (Bagher Zadeh et al. 2018) | 45.0  | 76.9  | 77.0| 0.71 | 0.54  |
| RAVEN (Wang et al. 2019) | 50.0  | 79.1  | 79.5| 0.614| 0.662  |
| MCTN (Pham et al. 2019) | 49.6  | 79.8  | 80.6| 0.609| 0.670  |
| TBJE (Delbrouck et al. 2020) | 45.0  | 82.4  | -  | -   | -      |
| Mu-Net (Shenoy, Sardana, and Graphics 2020) | - | 82.1 | 80.0| 0.590| 0.50  |
| MR (Tsai et al. 2020) | 51.6  | 81.7  | 81.8| -  | -      |
| MuT (Tsai et al. 2019a) | 51.8  | 82.5  | 82.3| 0.580| 0.703  |
| MCMulT (ours) | 52.4  | 83.1  | 82.8| 0.582| 0.706  |

| Metric     | Acc^2 | Acc^3 | F1 | MAP | Corr^2 |
|------------|-------|-------|----|-----|--------|
| CMU-MOSEI-Unaligned |       |       |    |     |        |
| CTC (Graves et al. 2006)+EF-LSTM | 46.3  | 76.1  | 75.9| 0.680| 0.585  |
| LF-LSTM    | 48.8  | 77.5  | 78.2| 0.624| 0.656  |
| CTC+RAVEN (Wang et al. 2019) | 45.5  | 75.4  | 75.7| 0.664| 0.599  |
| CTC+MCTN (Pham et al. 2019) | 48.2 | 79.3  | 79.7| 0.631| 0.645  |
| MuT (Tsai et al. 2019a) | 50.7  | 81.6  | 81.6| 0.591| 0.694  |
| MCMulT (ours) | 51.8  | 83.0  | 82.8| 0.588| 0.699  |

results on various multimodal unaligned sentiment recognition tasks. Following MuT, we apply connectionist temporal classification (CTC) (Graves et al. 2006) in methods (e.g. EF-LSTM, MCTN, RAVEN) which cannot be applied directly to the word-unaligned setting. In the experiment of the word-aligned setting, Recurrent Multistage Fusion Network (RMFN) (Liang et al. 2018), Multimodal Factorization Model (MFM) (Tsai et al. 2019b), Multilogue-Net (Mu-Net) (Shenoy, Sardana, and Graphics 2020), Multimodal Routing (Tsai et al. 2020), Transformer-based joint-encoding (TBJE) (Delbrouck et al. 2020) and MuT methods are added to compare with MCMulT.

Quantitative Analysis

Word-Unaligned Experiments. We compare our MCMulT model with prior approaches on three data datasets in the unaligned setting. The results are demonstrated in the bottom part of Table 1, 2, 3. Our MCMulT achieves higher performance than the prior methods (Wang et al. 2019; Pham et al. 2019; Tsai et al. 2019a), especially improves more than 1.0% than the existing state-of-the-art MuT method on most Acc and F1 attributes. Further analysis shows that MCMulT and MuT methods in word-aligned setting obtain slightly better performance than word-unaligned setting. However, for the word-aligned approaches (LF-LSTM, EF-LSTM, RAVEN and MCTN), the gaps between aligned and unaligned settings are more than 5%-15% on most attributes. This shows that MCMulT and MuT methods are more effective to tackle the asynchronous nature from multimodal sequences.

Word-Aligned Experiments. We evaluate our MCMulT model and the existing approaches (Liang et al. 2018; Tsai et al. 2019b; Wang et al. 2019; Pham et al. 2019; Tsai et al. 2019a; Bagher Zadeh et al. 2018) in the case of word-aligned setting on the same datasets. The results are shown in the top part of Table 1, 2, 3. MCMulT outperforms the other competitive approaches on different metrics on all attributes.

Ablation Study. We perform experiments with different variants of MCMulT: MuT with 7-layer, 10-layer and 12-layer structures, MCMulT-Dense, MCMulT-LocalDense and MCMulT-Global. As illustrated in Table 5, the architectures (MCMulT-LocalDense, MCMulT-Dense, MCMulT-Global) obtain worse performance than MCMulT. It shows that the appropriate interaction complexity of multi-scale mechanism obtains better performance. The architectures (MuT with 7-layer, 10-layer and 12-layer) obtain worse performance than 5-layer architecture, which shows increasing MuT complexity properly can not get better performance. Meanwhile, when MCMulT and MuT-12 have same network depth, MCMulT achieve better performance than MuT-12, which shows the effectiveness of multi-scale mechanism. Table 4, 5, 6.

1) Single Modality and Single Target Modality. We have conducted comparative experiments of single modality (only considering textual, visual or acoustic modality) and single target modality (\(L_A \rightarrow L], [L, V \rightarrow A], [L, A \rightarrow V])\). The results indicate that the MCMulT architecture is efficient and its performance is better than the MuT architecture in the same setting. The experimental results are shown in Table 5. In experiments of single modality, the performance of text modality is much better than that of visual and audio modalities, which is consistent with the conclusion of previous work. In the single-target modality experiments, the performances (Acc2 and F1) of visual and audio modalities based on MCMulT are improved by 10%-15% (same as the phenomenon of MuT) compared with the corresponding single modality, and the performance of the text modality is also increased by about 3%. Furthermore, the performance of single-target modality obtained by MCMulT is better than

The results of existing works in Table 1, 2, 3 are reported as Tsai et al. (Tsai et al. 2019a).
In this paper, we propose a MCMulT architecture, which utilizes multi-scale and cooperative crossmodal interactions from unaligned multimodal sequences to solve sentiment analysis task. Specifically, to improve the robustness of a transformer, during the crossmodal interaction, we use multi-scale representations that contain different levels of semantic information. Additionally, we have also designed an efficient crossmodal interaction method in terms of computational cost. The variants of MCMulT are further discussed. The experimental results clearly demonstrate that our approach outperforms the state-of-the-art works on not only on unaligned multimodal datasets but also on aligned multimodal datasets. In the future work, we will study finer architecture of MCMulT, e.g., layer number tuning individually for each modality to achieve better performance and reduce computation cost. Besides, we plan to extend MCMulT to more multimodal applications with large-scale datasets, e.g., VQA, image-text matching and crossmodal pretraining tasks.

Table 3: Results on IEMOCAP with aligned and unaligned multimodal sequences.

| Task       | Happy | Sad  | Angry | Neutral |
|------------|-------|------|-------|---------|
| Metric     | Acc^h | F1^h | Acc^h | F1^h    | Acc^h | F1^h    | Acc^h | F1^h    |
| IEMOCAP-Aligned |       |      |       |         |       |         |       |         |
| EF-LSTM    | 86.0  | 84.2 | 80.2  | 80.5    | 85.2  | 84.5    | 67.8  | 67.1    |
| LF-LSTM    | 85.1  | 86.3 | 78.9  | 81.7    | 84.7  | 83.0    | 67.1  | 67.6    |
| RMFN (Liang et al. 2018) | 87.5  | 85.8 | 83.8  | 82.9    | 85.1  | 84.6    | 69.5  | 69.1    |
| MFM (Tsai et al. 2019b) | 90.2  | 85.8 | 88.4  | 86.1    | 87.5  | 86.7    | 72.1  | 68.1    |
| RAVEN (Wang et al. 2019) | 87.3  | 85.8 | 83.4  | 83.1    | 87.3  | 86.7    | 69.7  | 69.3    |
| MCTN (Pham et al. 2019) | 84.9  | 83.1 | 80.5  | 79.6    | 79.7  | 80.4    | 62.3  | 57.0    |
| MR (Tsai et al. 2020) | 87.3  | 84.7 | 85.7  | 85.2    | 87.9  | 87.7    | 70.4  | 70.0    |
| MCMulT (ours) | 91.4  | 88.8 | 87.4  | 86.8    | 87.6  | 87.3    | 72.9  | 71.5    |

Table 4: Results on variants of MCMulT using CMU-MOSEI.

| Metric                        | Acc^h | F1^h | MAE^h | Corr^h |
|-------------------------------|-------|------|-------|--------|
| MCMulT-Dense                  | 50.20 | 80.74| 80.39 | 0.605  |
| MCMulT-LocalDense             | 51.36 | 82.41| 82.11 | 0.593  |
| MCMulT                        | 51.83 | 83   | 82.77 | 0.588  |
| MulT-5                        | 50.70 | 81.60| 81.60 | 0.591  |
| MulT-7                        | 50.47 | 81.23| 81.19 | 0.596  |
| MulT-10                       | 48.64 | 78.89| 78.76 | 0.619  |
| MulT-12                       | 46.23 | 76.77| 76.89 | 0.636  |

Table 5: Results on the benefit of MCMulT’s crossmodal transformers using CMU-MOSEI.

| Metric                        | Acc^h | F1^h | MAE^h | Corr^h |
|-------------------------------|-------|------|-------|--------|
| text only                     | 46.80 | 77.70 | 76.60 | 0.654  |
| vision only                   | 43.70 | 66.90 | 70.20 | 0.754  |
| audio only                    | 42.10 | 65.20 | 68.90 | 0.761  |
| MulT (VA->T)                  | 50.50 | 80.1  | 80.4  | 0.605  |
| MulT (TA->V)                  | 48.20 | 79.7  | 80.2  | 0.611  |
| MulT (TV->A)                  | 47.50 | 79.2  | 79.7  | 0.620  |
| MCMulT (VA->T)                | 50.60 | 80.80 | 80.90 | 0.601  |
| MCMulT (TA->V)                | 49.10 | 80.10 | 80.50 | 0.607  |
| MCMulT (TV->A)                | 47.80 | 79.80 | 80.50 | 0.613  |
| MCMulT                        | 51.8  | 83.00 | 82.8  | 0.588  |

Table 6: Results on different value of hyperparameters of MCMulT. B and L indicate the block number and layer number of each block, respectively.

| B=1 | B=2 | B=3 | B=4 | B=5 |
|-----|-----|-----|-----|-----|
| 47.60 | 78.20 | 80.60 | 82.17 | 83.80 |
| 51.61 | 82.31 | 84.90 | 86.50 | 88.10 |
| 51.83 | 83.00 | 84.77 | 86.37 | 88.90 |
| 41.26 | 82.13 | 83.81 | 85.49 | 88.09 |

| L=1 | L=2 | L=3 | L=4 |
|-----|-----|-----|-----|
| 50.60 | 80.90 | 82.77 | 84.64 |
| 51.83 | 83.00 | 84.77 | 86.50 |
| 51.37 | 82.22 | 82.04 | 83.80 |

Table 7: Results on the correlation of MCMulT’s crossmodal interactions.
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Appendix for Multi-scale Cooperative Multimodal Transformers for Multimodal Sentiment Analysis in Videos

Appendix A

Datasets
The datasets in our experiments are used as did in paper (?). The division setting is provided by the respective benchmarks and also utilized by the state-of-the-art methods (?). We strictly follow their settings. Tsai (?) provides the link to the downloadable datasets as below. Data files (containing processed MOSI, MOSEI and IEMOCAP datasets) can be downloaded from (?). To get the meta information and the raw data, please refer to the SDK for these datasets from (?).

Experimental Details
The number of scale layers is a hyperparameter for each modality. If the hierarchy of a certain modality is relatively simple, it is reasonable to have fewer blocks for that modality. Fine-tuning hypermeters may also likely improve performance because of avoiding overfitting. We set the same number of scale layers for all modalities for simplicity in the experiments. This setting makes the paper easy to understand and follow.

Cross-Entropy loss is used to train MCMulT. The epoch number and batch size are chosen as 100 and 64 respectively. A 0.2 dropout rate is picked for all attention layers and a 0.1 dropout rate is picked for all full-connection layers. Furthermore, a gradient clipping value of 0.8 is applied, and our architecture’s trainable parameters are optimized using Adam with 1e-3 learning rate. All models are implemented using PyTorch framework.

Appendix B

Example Visualization
Figure 1 illustrates one example on crossmodal attention maps between vision and text modality that are from high-level layer of our MCMulT and MulT. Some important words are colorized as red, and green color in attention map indicates higher attention score than blue color in Figure 1. It shows that the word “not” and “seen” are coordinately aligned with neighboring frames of facial expression in MCMulT, the phrase “bad movie” has the similar result. By contrast, the alignment for “not” and “seen” are irrelevant in MulT.
I've not seen one bad movie that she been into.

Figure 1: Illustration of attention map from MCMulT and MulT.