ABSTRACT
Multimodal sentiment analysis (MSA), which supposes to improve text-based sentiment analysis with associated acoustic and visual modalities, is an emerging research area due to its potential applications in Human-Computer Interaction (HCI). However, existing researches observe that the acoustic and visual modalities contribute much less than the textual modality, termed as text-predominant. Under such circumstances, in this work, we emphasize making non-verbal cues matter for the MSA task. Firstly, from the resource perspective, we present the CH-SIMS v2.0 dataset, an extension and enhancement of the CH-SIMS. Compared with the original dataset, the CH-SIMS v2.0 doubles its size with another 2121 refined video...
segments containing both unimodal and multimodal annotations and collects 10161 unlabelled raw video segments with rich acoustic and visual emotion-bearing context to highlight non-verbal cues for sentiment prediction. Secondly, from the model perspective, benefiting from the unimodal annotations and the unsupervised data in the CH-SIMS v2.0, the Acoustic Visual Mixup Consistent (AV-MC) framework is proposed. The designed modality mixup module can be regarded as an augmentation, which mixes the acoustic and visual modalities from different videos. Through drawing unobserved multimodal context along with the text, the model can learn to be aware of different non-verbal contexts for sentiment prediction. Our evaluations demonstrate that both CH-SIMS v2.0 and AV-MC framework enable further research for discovering emotion-bearing acoustic and visual cues and pave the path to interpretable end-to-end HCI applications for real-world scenarios. The full dataset and code are available for use at https://github.com/thuiar/ch-sims-v2.

CCS CONCEPTS
• Information systems → Semi-structured data; Multimedia information systems; Sentiment analysis.

KEYWORDS
multimodal sentiment analysis, dataset, semi-supervised machine learning, modality mixup

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1 INTRODUCTION
Understanding the speakers’ sentiment is a crucial step for intelligent Embodied Conversational Agents (ECAs) in generating the empathetic responses [8, 19]. Traditional embodied agents analyze the users’ sentiment with unimodal textual information, inevitably confronting performance gaps due to text ambiguity and irony [23]. With advanced micro-sensors, multiple sensory resources, such as visual and vocal, can be recorded along with the spoken words and lead to the Multimodal Sentiment Analysis (MSA) task [2, 15, 25, 27], which aims to judge the users’ sentiment using textual, acoustic, and visual behaviors.

Until now, however, previous MSA benchmarks have still over-reliance on the textual modality. In literature [11, 13, 18], researchers report about a 30% binary accuracy drop when removing the textual modality on MOSI dataset (80%+ with text, while about 54% without text). In this work, we term the above phenomenon as text-predominant. Such an underestimate of acoustic and visual behaviors violates the motivation of integrating multimodal resources and seriously limits its applications in real-world scenarios where textual modality is always imperfect due to the potential ASR error [1, 37]. As a result, effectively exploiting non-verbal cues becomes the most crucial challenge in the field of multimodal sentiment analysis. The reasons for the text-predominant can be summarized from two aspects:

Resource Limitations. On the one hand, resource size and quality are essential but commonly ignored factors. Firstly, for raw video collection, the major concern in MSA resources lies in the scarcity of emotion-bearing acoustic and visual behaviors. Although some of the existing MSA corpus, such as MOSEI [46], have reached the level of 20,000 in scale, its emotion-bearing acoustic and visual behaviors are still limited due to the ubiquitous video’s blurry and flat tone. Moreover, the obvious label bias in previous MSA corpus (MOSEI [46] contains 69% positive instances and CH-SIMS contains 69% negative instances) results in trivial unimodal solutions, which further prevents acoustic and visual representation learning. Secondly, for data annotation, as stated in literature [39], the unified multimodal annotations can be inconsistent with the independent sentiment of single modality. Thus, unimodal annotation is necessary for the evaluation of unimodal representation learning and is assumed to benefit the fine-grained sentiment intensity prediction. In general, the a high-quality MSA datasets should have a certain scale, consist of diverse nonverbal context information, balance instance annotation distribution, and contain unimodal annotation.

Under-optimized Acoustic and Visual Representation. In addition to the resource limitations, the under-optimized acoustic and visual representation in a joint learning framework is another factor for the text-predominant phenomenon [22]. Previous MSA benchmarks focus more on the study of the multimodal fusion process and commonly utilize a joint representation learning framework to learn a unified multimodal representation [29, 43, 44]. As stated in literature [11], benefited from pretrained language model, directly utilizing the emotion cues from text modality is much easier than exploring the sparse emotion-bearing non-verbal cues. The few contributions of the acoustic and visual modality to the joint fusion result might prevent the training of the acoustic and visual encoder. Although previous work report their multimodal result outperforms each unimodal result, they still fail to fully utilise the acoustic and visual modalities. As a result, there is an emerging trend to manually introduce other supervision or perform gradient modulation for acoustic and visual modality to improve the non-verbal representation learning [22, 39, 40].

In this work, for the challenge of MSA resources, we construct the CH-SIMS v2.0 dataset, an enhancement and extension of the CH-SIMS, which includes 4402 supervised data with unimodal annotation and over 10,000 unsupervised data. The CH-SIMS v2.0 dataset is collected from 11 different scenarios to simulate real-world HCI scenarios paving the path for ECAs to understand users’ emotions. Some of the typical instances are shown in Figure 1. For the challenge of acoustic and visual representation learning, we introduce the Mixup [47] strategy into the MSA task taking advantage of the provided unimodal annotations to aware the model of the various non-verbal behaviors. The main contributions of this work are summarized below.

1) From a resource perspective, CH-SIMS v2.0, the largest semi-supervised Chinese MSA dataset with diverse non-verbal behaviors is built for HCI community to explore the effectiveness of acoustic and visual behaviors.
2) From a representation learning perspective, the Acoustic Visual Mixup Consistent (AV-MC) framework is designed to simulate the potential unobserved non-verbal behaviors
corresponding to the same spoken words through a mixup strategy. Moreover, the proposed AV-MC framework can be easily adapted to both supervised and semi-supervised training paradigms.

3) Empirically, this paper conducts extensive experiments on CH-SIMS v2.0 which serve as the baselines and intuitive demonstration showing the significance of making full use of non-verbal behaviors.

2 RELATED WORKS

2.1 Multimodal Sentiment Analysis Dataset

As the demand for emotion aware applications increases, various multimodal sentiment datasets have been constructed in the past few years including IEMOCAP [3], YouTube [21], MOSEI [45], MOSEI [46], MELD [24], and the latest MOSEAS [42]. Most of the above datasets contain only English resources, however, the expression of emotion in different cultures and native languages can be various. For Chinese MSA task, Li et al. [14] propose the first Chinese emotional acoustic-visual dataset, CHEAVD. Recently, Yu et al. [39] propose the CH-SIMS, a Chinese MSA corpus with both unimodal and multimodal annotations. However, the time-consuming unimodal annotations result in a relatively small dataset size, further limiting the diversity of acoustic and visual emotion-bearing behaviors. As a result, we extend the CH-SIMS v2.0 based on CH-SIMS dataset with more expressive non-verbal behaviors in unlabeled instances to rich the multimodal context with a few workloads.

2.2 Multimodal Sentiment Analysis

Previous MSA benchmarks mainly emphasize joint representation learning and multimodal fusion. For joint representation learning, Wang et al. [35] construct a recurrent attended variation embedding network to shift textual representation according to the non-verbal cues. Hazarika et al. [11] present modality-invariant and modality-specific representations as joint multimodal representation. For multimodal fusion, Zadeh et al. [43] propose a tensor fusion network, which obtains a new tensor representation by computing the outer product between unimodal representations. Zadeh et al. [44] design a memory fusion network for cross-view interactions. Tsai et al. [29] propose cross-modal transformers, which learn the cross-modal attention to reinforce a target modality. However, all previous MSA approaches assume that textual modality is dominant and fail to make full use of non-verbal behaviors.

2.3 Mixup

Mixup is first proposed in Computer Vision (CV) as an effective regularization means to improve the generalization ability of the neural networks [47]. Based on the image feature Mixup, Vva et al. [34] propose an Interpolation Consistency Training (ICT) method adapting the Mixup into the semi-supervised learning paradigm. It can be categorized into input-level Mixup [30] and hidden-level Mixup [33] depending on the location of the mix operation. In literature [4, 9], they apply Mixup on hidden vectors like embeddings or intermediate representations. While Yoon et al. [38] propose an input-level span wise Mixup method considering the salience of spans for text classification. Liesting et al. [16] propose a word-level Mixup strategy for text Aspect-Based Sentiment Analysis. On this basis, we transfer it to the multimodal sentiment analysis task. In this work, we design a multimodal input-level Mixup strategy to enhance the acoustic and visual modality representation learning based on multitask late fusion backbone for MSA task.

3 CH-SIMS V2.0 DATASET

3.1 Data Collection

Following the previous work, the raw video collection is conducted following the constraints that, for visual modality, high video definition with the speaker present in the video is required, for acoustic modality, the video should be in Mandarin, and for textual modality, accurate accompanying transcription is needed. The raw video segments are kept in their original resolution and recorded in MP4 format. After obtaining the raw videos, “PlotPlayer”1, a popular video editing tool, is utilized to crop videos into segments at the frame level for high quality instances. Compared to the CH-SIMS dataset, the improvement of the video collection is reflected in two aspects.

Diverse video scenarios. It is natural that video segments in different scenes may have different sentiment tendencies. The previous CH-SIMS dataset [39] contains limited scenario resources due to the drawbacks of the traditional face detection toolkit, such as MTcNN [48], which can not distinguish the speaker’s face from the multi-party scenarios. In our work, TalkNet [28] is utilized as the Active Speaker Detection (ASD) tool that enables the collection of video scenarios containing multiple faces. Under such circumstances, The CH-SIMS v2.0 dataset enriches its scenario diversity with raw video segments from melodrama, interviews, modern TV, talk show, vlogs, films, costume TV, variety show and many other scenes2.

All video resolution is greater than 720p for better video quality from Bilibili, YouTube and television websites. To simulate complex real-world scenarios, the angle, distance from the camera, and light conditions might vary among different videos. The instances with missing speaker’s faces will be removed for the instance quality, and instances with front, side and oblique faces will be collected. Moreover, the acoustic of the instance may contain slight noise, such as ambient music, and white noise, and the speaker’s tone and speed might vary.

Expressive acoustic and visual behavior. Compared to the CH-SIMS, the proposed dataset focus more on non-verbal behaviors. Thus, instances of emotion-bearing non-verbal behaviors from the original cut video clips are consciously screened out. As shown in Figure 1, for the instance “WHAT DOES HE LIKE ABOUT YOU”, the neutral textual modality makes it important to capture the smiling face from visual modality. For the instance “I REALLY LIKE AND LOVE THIS BOY VERY SERIOUSLY”, textual modality is misleading for predicting the speaker’s sentiment polarity. Moreover, there are other instances with ambiguity, ironies and metaphors text modality. In summary, CH-SIMS v2.0 contains plenty of instances with weak text modality reliance. Thus, text-based or text-predominant models might fail to predict the sentiment of the speakers.

1https://potplayer.daum.net/
2Videos under creative commons license can be edited and used without the need for the authors’ consent
CH-SIMS v2.0: Chinese Fine-grained Multi-label Sentiment Analysis Dataset

| Sentiment       | Unimodal Labels | Multimodal Labels |
|-----------------|-----------------|-------------------|
| Strong Negative | -1.0            | Red               |
| Weak Negative   | -0.6            | Red               |
| Neutral         | 0.0             | Green             |
| Weak Positive   | 0.2             | Green             |
| Strong Positive | 1.0             | Green             |

Figure 1: Illustration of the constructed CH-SIMS v2.0 dataset. The color of the multimodal annotation reflects the sentiment intensity from red (strong negative) to green (strong positive), while the color of the unimodal annotations on the right reflects the consistency between the unimodal and multimodal sentiment. Instances marked with *** are unsupervised data.

Figure 2: Statistics of each component of the CH-SIMS v2.0 dataset including the CH-SIMS v2.0 (s), and the CH-SIMS v2.0 (u). Instances in the original CH-SIMS dataset are relabeled and contained in the CH-SIMS v2.0 (s).

The final statistics of the CH-SIMS v2.0 is shown in Fig 2. Specifically, the CH-SIMS v2.0 contains 4402 supervised instances, denoted as CH-SIMS v2.0 (s), and 10161 unsupervised instances, denoted as CH-SIMS v2.0 (u). For supervised resources, the CH-SIMS v2.0 (s) shares similar properties with the original dataset. While, for unsupervised resources, the CH-SIMS v2.0 (u) shows a much more diverse duration distribution simulating the potential real-world scenarios. In addition, the textual modality of the unsupervised instances is directly collected from the corresponding transcript without being manually refined and thus might contain noise.

### 3.2 Data Annotation

With the collection of raw video segments, data annotation on the supervised CH-SIMS v2.0 (s) is conducted. Consistent with the previous CH-SIMS dataset, each instance is annotated with fine-grained sentiment unimodal and multimodal labels ranging from...
Strong Negative (-3), Negative (-2), Weak Negative (-1), Neutral (0), Weak Positive (1), Positive (2), and Strong Positive (3). A total of seven annotators participate in the data labelling. Before labelling, several instances of each sentiment class are provided to annotators as the standard to improve fairness. In the post-processing period, the highest score and the lowest score are removed. The average score of the rest five results is then mapped to the space of Strong Negative (-1, -0.8), Weak Negative (-0.6, -0.4, -0.2), Neutral (0), Weak Positive (0.2, 0.4, 0.6), and Strong Positive (0.8, 1.0) as the final sentiment label.

It is worth noticing that, CH-SIMS v2.0 improves the unimodal label annotation process with a strict modality isolation strategy and relabel the unimodal annotations of the original CH-SIMS dataset. Specifically, for acoustic modality labelling, noise is injected to blur the spoken word while maintaining the overall rhythm and acoustic features; for visual modality labelling, videos are presented in silent mode with the transcripts removed, and for textual modality labelling, only transcripts are provided. Moreover, to reduce the influence of inter-modal information on the annotator, annotation is carried out in the order of text, acoustic, visual and multimodal.

The annotation statistics are shown on the left of Figure 3. It can be found that in the CH-SIMS v2.0 dataset, the ratio of positive to negative instances is 83.41% (56.38% in the original CH-SIMS), and most instance position in the weak sentiment intensity scope. Besides, from the comparison of neutral instance count among different unimodal and multimodal annotations, it can be summarized that multimodal contains much more sentiment than each unimodal especially the visual modality revealing the importance of integrating multimodal information. In addition, following the literature [39], the average discrepancy among each unimodal and multimodal label is illustrated on the right of the Fig 3. Significant discrepancy validates the assumption that the unified multimodal labels can not reflect the unimodal sentiments. Furthermore, we can find that acoustic is the most similar to multimodal annotations, while the textual annotation is the least. All the above observations show the great potential to improve the sentiment prediction performance by making full use of the non-verbal cues.

3.3 Feature Extraction
The default modality sequences for the CH-SIMS v2.0 are extracted through MMSA-FET, an open-sourced feature extraction toolkit [20]. In the following experiments, without additional description, default features are used.

**Default Textual Feature.** A pretrained BERT [5] model, bert-base-chinese\(^3\), is used to learn contextual word embeddings as effective textual features. The length of token sequences is fixed to 50, using either padding or truncating method. The final textual feature is a word vector sequence in 768 dimensions.

**Default Acoustic Feature.** For acoustic features, 25-dimensional eGeMAPS [6] Low Level Descriptors (LLD) features are extracted by OpenSMILE [7] backend at 16000 Hz sampling rate. The final acoustic features are padded or truncated to a sequence length of 925.

**Default Visual Feature.** For visual modality, images are first extracted using FFmpeg at 25 frames per second. TalkNet [28], an effective Action Speaker Detection (ASD) method, is then used to detect the speaker’s face among all faces in a single image. The images over which the ASD failed are dropped, and instances with over 25% missing images are discarded. After ASD, the OpenFace [7] backend is used to extract the facial features, including 68 facial landmarks, 17 facial action units, head pose, head orientation, and eye gaze direction. Finally, the 177-dimensional frame-level visual features are padded or truncated to a sequence length of 232.

4 ACOUSTIC VISUAL MIXUP CONSISTENT (AV-MC) FRAMEWORK
Although the CH-SIMS v2.0 dataset strives to provide as many multimodal scenarios as possible, the potential multimodal context is not exhaustive. To further prepare the MSA model with unobserved multimodal context, we design the Acoustic Visual Mixup Consistent (AV-MC) framework. The overall structure of the AV-MC is illustrated in Figure 4.

4.1 Modality Mixup Module
The modality mixup module aims to generate potential modality representation with corresponding annotations from the original representation obtained from the modality encoder. Specifically, given the set of instances with corresponding annotations \(\{(X_1, y_1), \cdots, (X_n, y_n)\}\), a random shuffle is first conducted.

\[
\{(X'_1, y'_1), \cdots, (X'_n, y'_n)\} = \text{Shuffle}(\{(X_1, y_1), \cdots, (X_n, y_n)\}).
\]

After shuffling, the mixup is performed on the shuffled and original instance pair through the weighted average,

\[
X''_i = \lambda \cdot X'_i + (1 - \lambda) \cdot X_{\cdot i}, \quad y''_i = \lambda \cdot y'_i + (1 - \lambda) \cdot y_{\cdot i},
\]

where \(\lambda \in [0, 1]\) is a random variable sampled from Beta distribution. Using the above definition, the modality mixup module is formulated as follows,

\[
\{(X''_1, y''_1), \cdots, (X''_n, y''_n)\} = \text{Mixup}(\{(X_1, y_1), \cdots, (X_n, y_n)\}).
\]

The generated \(\{(X''_1, y''_1), \cdots, (X''_n, y''_n)\}\) can be used as potential instances promoting representation learning.

4.2 Supervised and Semi-supervised learning with AV-MC Framework
For the convenience in the following introduction, the initial text, audio and vision sequences are denoted as \(I_k \in \mathbb{R}^{T_k \times d_k}\), where \(T_k\) refers to the modality sequence length, and \(d_k\) refers to the initial feature dimension \((k \in \{t, a, v\})\). Receiving the initial modality sequences as input, the unimodal encoders are first utilized for both supervised and unsupervised instances to learn inter-modal representations. The unified unimodal encoders are formulated as follows.

\[
F_k = S_k(I_k) \in \mathbb{R}^{h_k},
\]

where \(k \in \{t, a, v\}\), \(h_k\) is the hidden dimension for modality \(u\), and \(S_u(\cdot)\) represents the unimodal encoder network. Specifically, in the proposed AV-MC framework, for textual modality, a one layer

\(^3\)https://huggingface.co/bert-base-chinese
Figure 3: Left: the distribution of sentiment over the entire dataset in one Multimodal annotation and three unimodal (Text, Acoustic, and Visual) annotations. Right: the confusion matrix shows the annotations difference between different modalities in CH-SIMS (s) v2.0. The larger the value, the greater the difference.

Figure 4: Acoustic Visual Mixup Consistent (AV-MC) Framework under semi-supervised learning paradigm, which consists of Multitask Late Fusion Backbone (a) with Modality Mixup Module (b).

feed-forward network is regarded as the encoder transforming the first time step vector, which refers to [CLS]4 token into the textural representation. For acoustic and visual modalities, a stack bi-directional Long Short Term Memory (LSTM) [12] followed by a one layer feed-forward network is utilized as the encoder. The one layer feed-forward network is defined as,

\[ \text{FFN}(x) = \sigma(W \cdot x + b), \] (6)  

where \( \sigma \) represents the activation function, \( W \) and \( b \) are learnable model parameters. As a simple but effective fusion strategy, we take the concatenation of the unimodal representation as to the final multimodal representation.

\[^4\text{a special token in Bert language model, appended at the front of the token sequence, commonly used for sentence-level representation learning.}\]

\[ F_m = \text{Concat} \left( \{F_t; F_a; F_v\} \right) \in \mathcal{R}^{h_t + h_a + h_v}, \] (7)  

After obtaining the unimodal and the multimodal representations, for supervised instances, four independent classifiers consisting of a three layers feed-forward network are utilized for both unimodal and multimodal sentiment prediction,

\[ \hat{y}_k = \text{clf}_k(F_k) = \text{FFN}(\text{FFN}(\text{BN}(F_k)))) \in \mathcal{R}, \] (8)  

where \( k \in \{m, t, a, v\} \), and \( \text{BN} \) refers to the batch normalization. L1_Loss is used as supervision for each unimodal and multimodal task,

\[ L_{r}^{(k)} = \frac{1}{N_r} \sum_{i=1}^{N_r} |\hat{y}_{k}^{(i)} - y_{k}^{(i)}|, \] (9)
where \( k \in \{ m, t, a, v \} \), \( N_t \) is the supervised instances count. The final sentiment regression loss is formulated as the weighted average of the unimodal and multimodal tasks,

\[
L_r = \sum_k \alpha_k \cdot L_r^k \tag{10}
\]

where \( \alpha_k \), \( k \in \{ m, t, a, v \} \) is the hyper-parameter balancing the contribution of unimodal and multimodal tasks. In addition to the regression tasks for the supervised instances, mixup consistent tasks are performed for both supervised and unsupervised data on acoustic and visual modalities. The acoustic and visual representation \( F_k \) along with corresponding prediction \( \hat{y}_k \) is passed through the modality mixup module,

\[
\text{Mixup} \left( \left\{ \left\{ F_k^{(1)} \cdot y_k^{(1)} \right\}, \ldots, \left\{ F_k^{(N_t+N_u)} \cdot y_k^{(N_t+N_u)} \right\} \right\} \right), \tag{11}
\]

where \( k \in \{ a, v \} \), and \( N_t, N_u \) refers to the total instances count for CH-SIMS v2.0 (s) and CH-SIMS v2.0 (u). With the generated acoustic unimodal and visual unimodal representations, the same acoustic and visual unimodal classifiers are utilized for both mixed acoustic unimodal and mixed visual unimodal sentiment prediction.

\[ \hat{y}_k'' = \text{Clf}_a(F_k) = \text{FFN} \left( \text{FFN} \left( \text{BN}(F_k) \right) \right) \in R, \tag{12} \]

where \( \hat{y}_k'' \) is the model prediction for the generated instance \( F_k'' \). Inspired from literature [32], the generated instances serve as the interpolation of the two original instances, the prediction of which should be consistent with the direct average with the same weights, i.e. \( \hat{y}_k'' \). We still use L1 Loss for mixup consistent tasks.

\[
L_\text{mix}^{(k)} = \frac{1}{N_t + N_u} \sum_{i=1}^{N_t+N_u} \left| y_k''(i) - y_k(i) \right|, \tag{13}
\]

where \( k \in \{ a, v \} \). The final consistent loss is formulated as the weighted average of the acoustic and visual mixup tasks,

\[
L_\text{mix} = \sum_k \beta_k \cdot L_\text{mix}^{(k)} \tag{14}
\]

where \( \beta_k, k \in \{ a, v \} \) is the hyper-parameter balancing the contribution of acoustic and visual mixup tasks.

Each epoch in the training process contains two iterations. The first iteration uses both supervised and unsupervised instances and updates the model parameters under the guidance of both the regression loss \( L_r \) and the mixup consistent loss \( L_\text{mix} \). To promote the model convergence, an additional iteration on the supervised instances is conducted using only the regression loss for supervision. The detailed training process is shown in the algorithm (1).

## 5 EXPERIMENTS AND DISCUSSION

### 5.1 Dataset splits and Evaluation Metric

As presented in Table 1, the CH-SIMS v2.0 dataset is partitioned into training, validation and test sets in a ratio close to 9:2:3. Following the previous work, the model performances are evaluated in the form of classification and regression. Traditional classification metrics including binary classification accuracy (Acc2) and F1 score (F1_Score) reflect the correctness of basic sentiment polarity prediction, i.e. positive or negative classification. In addition, Acc2_weak is utilized to further validate the model performance for the weak emotion instances labelled in [0, -0.4, 0.4]. Traditional regression metrics including Mean Absolute Error (MAE) and the Pearson Correlation (Corr) are recorded for fine-grained prediction evaluation. Moreover, the R_square is also used to compare the model performance against the trivial solution (prediction of the average result on the test set). For all the above metrics, higher values indicate better model performance, except MAE, where lower values indicate better model performance.
5.2 Benchmark Results on CH-SIMS v2.0

5.2.1 Baselines. The benchmark models can be segmented into two classes according to whether unimodal annotations are used or not. The traditional MSA models which are supervised with the unified multimodal annotations include the Late Fusion Deep Neural Network (LF_DNN) [36], the Tensor Fusion Network (TFN) [43], the Low-rank Multimodal Fusion (LMF) [17], the Memory Fusion Network (MFN) [44], the Graph Memory Fusion Network (Graph_MFN) [46], the Multimodal Transformer (MulT) [29], the Multimodal Adaptation Gate for Bert Network (Bert_MAG) [26], the Modality-Invariant and -Specific Representations Network (MISA) [11], the Multimodal InfoMax Network (MMIM) [10], the Self-Supervised multitask Learning Network (Self_MM) [40]. The others which utilize the unimodal annotations to guide unimodal representation learning include the Multi-task Tensor Fusion Network (MTFN), the Multitask Late Fusion Deep Neural Network (LF_DNN), the Multitask Low-rank Multimodal Fusion (LMF).

5.2.2 Benchmark Model Performances. Table 2 presents the model performances for Traditional Multimodal Sentiment Analysis model on CH-SIMS v2.0 dataset. Models with * are trained on multitasking, (Semi) represents the additional use of unsupervised data. The best results are highlighted in bold.

| Models          | Acc2 (↑) | F1_score (↑) | Acc2_weak (↑) | Corr (↑) | R_square (↑) | MAE (↓) |
|-----------------|----------|--------------|---------------|----------|--------------|---------|
| LF_DNN          | 73.95    | 73.84        | 69.13         | 52.19    | 20.84        | 0.381   |
| TFN             | 76.51    | 76.31        | 66.27         | 66.65    | 35.90        | 0.323   |
| LMF             | 77.05    | 77.02        | 69.34         | 63.75    | 40.64        | 0.343   |
| MFN             | 75.27    | 75.24        | 66.46         | 60.60    | 32.26        | 0.355   |
| Graph_MFN       | 73.98    | 73.62        | 69.82         | 49.71    | 13.78        | 0.396   |
| MulT            | 79.50    | 79.59        | 69.61         | 70.32    | 47.15        | 0.317   |
| Bert_MAG        | 79.79    | 79.78        | 71.87         | 69.09    | 43.08        | 0.334   |
| MISA            | 80.53    | 80.63        | 70.50         | 72.49    | 50.59        | 0.314   |
| MMIM            | 80.95    | 80.97        | 72.28         | 70.65    | 43.81        | 0.316   |
| Self_MM         | 79.01    | 78.89        | 71.87         | 64.03    | 29.36        | 0.335   |
| MLF_DNN*        | 78.40    | 78.44        | 71.59         | 65.80    | 39.34        | 0.326   |
| MTFN*           | 80.26    | 80.33        | 71.07         | 70.54    | 46.07        | 0.318   |
| MLMF*           | 79.92    | 79.72        | 69.88         | 71.37    | 47.53        | 0.302   |
| AV-MC(Semi)*    | 82.50 (2.00%) | 82.55 (2.01%) | 74.54 (3.13%) | 73.17 (0.94%) | 50.65 (0.12%) | 0.297 (1.66%) |
| AV-MC(Semi)     | 83.46 (3.10%) | 83.52 (3.15%) | 74.54 (3.13%) | 76.04 (4.90%) | 57.37 (13.40%) | 0.286 (5.30%) |

Table 2: Model performances for Traditional Multimodal Sentiment Analysis model on CH-SIMS v2.0 dataset. Models with * are trained on multitasking, (Semi) represents the additional use of unsupervised data. The best results are highlighted in bold.

5.3 Case Study

As shown in Figure 5, we illustrate some typical cases of the constructed CH-SIMS v2.0 with corresponding predictions and annotations. Firstly, intuitively, the cases show the diverse non-verbal emotion-bearing behaviors, such as the obvious angry, disappointed voice, and the smiling, stiff facial expression. Such rich non-verbal behaviors are crucial for fine-grained sentiment prediction and alleviate the text-predominant phenomenon. Secondly, from the model aspect, it can be observed that the proposed AV-MC framework performs well in the cases where more than two modality annotations are used.
Table 3: Model performances for unimodal sentiment analysis with both unimodal annotation and multimodal annotation. For each metric, model performances with unimodal annotation are shown on the left.

| Modality Feature | Acc2 (↑) | Acc2_weak (↑) | Corr (↑) | MAE (↓) |
|------------------|---------|---------------|----------|---------|
| Text default     | 78.72 / 75.21 | 67.12 / 62.49 | 75.45 / 59.49 | 0.252 / 0.371 |
| Acoustic default | 57.16 / 56.48 | 55.61 / 54.41 | 13.48 / 13.72 | 0.424 / 0.491 |
| Acoustic wav2vec 2.0 | 65.38 / 60.93 | 59.96 / 53.01 | 36.71 / 38.05 | 0.396 / 0.446 |
| Visual default   | 78.72 / 73.11 | 76.04 / 68.79 | 57.70 / 48.54 | 0.314 / 0.401 |

5.4 Ablation Study

Table 4 presents the quantitative ablation study results. We first ablate the AV-MC framework by removing both acoustic visual mixup and the unimodal supervision in multitask late fusion backbone, denoted as w/o Mixup-AV & Unimodal tasks. Under such circumstances, the model performance dramatically declines by 4.80%, 5.84%, 11.08% on Acc2, Acc2_weak and MAE separately. Based on the multitask framework with the supervision of unimodal and multimodal annotations, we then ablate the AV-MC framework by removing the entire mixup, acoustic mixup, and visual mixup strategies respectively denoted as w/o Mixup-AV, Mixup-A and Mixup-V. Through the performance comparison among the above three ablations and the original AV-MC framework, it can be found that both acoustic and visual modality mixup contribute to the overall model performance, especially for the visual mixup.

To further explore how the modality mixup and the unimodal tasks help to improve the model performance, we manually construct six expressive non-verbal scenarios ranging from strongly...
negative to strongly positive for the same neutral spoken words "Oh my god". The constructed instances and the evaluation results are shown in Figure 6. In general, the designed acoustic and visual mixup and the unimodal tasks guide the model to be aware of the emotion-bearing non-verbal context resulting in more accurate sentiment intensity prediction. Moreover, the modality mixup contributes more to the #AV-2, #AV-5, and #AV-6 instances which might be unseen in the training data. All above results demonstrate that the proposed AV-MC framework can alleviate the text-predominant phenomenon in MSA tasks by perceiving from the non-verbal behaviors.

Furthermore, from a theoretical point of view, the unimodal representation distribution is illustrated with t-SNE [31] to interpret the effect of the modality mixup and unimodal task. The visualization is shown in Figure 7. From the comparison between (a) and (b) in Figure, the distribution overlap of different modalities representation is reduced, which indicates that multitask late fusion backbone can preserve the modality-specific information with the help of unimodal annotation. Moreover, from the comparison between (b) and (c) in Figure, the representation distribution within each modality is more separated. Such result indicates that the acoustic and visual mixup strategy can provide more potential non-verbal contexts. The generated virtual contexts are embedded in the latent representation space, enhancing the model’s perception ability for the fine-grained sentiment.

### 6 CONCLUSION

In this work, we strive to improve the contribution of non-verbal cues for sentiment analysis from two aspects. Firstly, from the resource aspect, the CH-SIMS v2.0, a semi-supervised dataset with fine-grained unimodal and multimodal annotations, is constructed by videos with expressive non-verbal behaviors. The noticeable discrepancy between the textual annotation and the multimodal annotation intuitively reveals the importance of making use of emotion-bearing acoustic and visual cues for the prediction. Secondly, from the model aspect, the Acoustic Visual Mixup Consistent Module (AV-MC) is designed. By producing augmentation with mixed acoustic and visual modalities combinations, the non-verbal behaviors are enriched and further help the model be aware of the contributions of acoustic and visual behaviors. The proposed AV-MC module can be regarded as an early attempt based on the
CH-SIMS v2.0 dataset. We believe this dataset will guide the research toward real multimodal fusion approaches to alleviate the text-predominant phenomenon. Building upon the CH-SIMS v2.0 dataset, future research can explore the design of interpretable approaches discovering the decisive modalities with unimodal annotations as well as the emotion-bearing multimodal pretrained approaches based on the unsupervised data for multimodal sentiment analysis.

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