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A Comprehensive Multimodal Approach to Assessing Sentimental Intensity and Subjectivity using unified MSE model

Abstract: - In the dynamic realm of multimodal learning, where Representation Learning serves as a pivotal key, our research introduces a groundbreaking approach to understanding sentiment and subjectivity in audio and text. illustration from self-supervised learning, we've innovatively combined multi-modal and Unified--modal tasks, emphasizing the crucial aspects of consistency and distinctiveness. Our training techniques, likened to the art of fine-tuning an instrument, harmonize the learning process, prioritizing samples with distinctive supervisions. Addressing the pressing need for robust datasets and methodologies in combinational text and audio sentiment analysis, we present the Multimodal Opinion-level Sentiment Intensity dataset (MOSI). This meticulously annotated corpus offers insights into subjectivity, sentiment intensity, text features, and audio nuances, setting a benchmark for future research. Our method not only excels in generating Unified-modal supervisions but also stands resilient against benchmarks like MOSI and MOSEI, even rivaling human-curated annotations on the challenging datasets. This pioneering work paves the way for deeper explorations and applications in the burgeoning field of sentiment analysis.

Keywords: Multimodal Learning, Sentiment Analysis, Subjectivity Assessment, Audio & Text Analysis, MOSI Dataset., Distinctiveness, Unified-modal Supervision.

I. INTRODUCTION:

Due to the development of communication technology and the widespread usage of social media sites like Facebook and YouTube, a large volume of sentiment-infused multimodal data is generated every day. Sentiment holds a crucial role in shaping human interactions and significantly influences advancements in artificial intelligence, finding applications in areas such as human-machine dialogues and autonomous driving [1]. While text is a fundamental medium of expression, conveying sentiments through words, phrases, and relationships [2], its standalone information can be limiting at times.

Discerning emotions solely from text can be challenging, prompting real-world communication to frequently integrate audio cues with text. Audio modality captures sentiments through voice nuances like pitch, energy, and loudness [14]. The synergy between text and audio modalities enhances sentiment analysis, providing a richer emotional context [3]. For example, Figure 1 illustrates how the sentence "But you know he did it" can convey varied emotions based on its context. While the sentiment might seem ambiguous through text alone, the accompanying audio—perhaps a speaker's somber tone—can clarify its negative connotation. Recognizing the potential of combined modalities, multimodal sentiment analysis within affective computing has gained momentum [12], and the fusion of information across modalities, known as multimodal fusion, augments emotional insights, refining the accuracy of outcomes [18].

In recent years, Multimodal Sentiment Analysis (MSA) has garnered increasing attention, with researchers like Zadeh et al. (2017), Tsai et al. (2019), and Poria et al. (2020) leading the discourse. This approach leverages multiple data modalities, demonstrating greater resilience and improved results, particularly when navigating the complexities of social media content. As online user-generated content flourishes, MSA finds applications expanding into areas like risk management, video comprehension, and transcription. However, MSA is not without its challenges, as identified by Five key obstacles in multimodal learning were identified by Baltrus Ňaitis, Ahuja, and Morency (2019) as alignment, translation, representation, fusion, and co-learning. Representation learning emerges as a cornerstone, with recent contributions, such as insights from Hazarika, Zimmermann, and Poria (2020), emphasizing that Unified-modal representations should embody both consistent and complementary data facets.

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Our exploration categorizes existing methodologies into two paradigms: forward guidance and backward guidance. Forward guidance delves into crafting interactive modules for holistic cross-modal information capture, often grappling with nuanced capturing of modality-specific details. In contrast, backward guidance methods, as proposed by researchers like Yu et al. (2020a) and Hazarika, Zimmermann, and Poria (2020), integrate additional loss functions facilitating representations that seamlessly merge both consistent and Unique modal characteristics. However, such methods often necessitate intricate weight balancing in their overarching loss functions, heavily contingent on human expertise.

The most significant contributions of this Study Include:

i. **Introduction of Unified-MSE Framework:** We introduce a groundbreaking multimodal sentiment knowledge-sharing framework, Unified-MSE, which harmonizes Emotion Recognition in Conversations (ERC) and Multimodal Sentiment Analysis (MSA) tasks. This innovative method capitalizes on the intrinsic similarities and complementarities between sentiments and emotions, enhancing predictive capabilities.

ii. **Integration of Multimodal Representation:** Our method consists on merging multimodal representation by adding auditory and visual signals to the model along with multi-level textual information. Moreover, we develop discriminative multimodal representations using inter-modality contrastive learning, which allows for a more sophisticated comprehension of mood and emotion.

iii. **State-of-the-Art Performance:** Experimental results underscore the prowess of Unified-MSE, establishing a new state-of-the-art based performance benchmark across four widely recognized public datasets such as MOSEI, MOSI, MELD for both ERC and MSA tasks. This achievement highlights the effectiveness and versatility of our proposed framework.

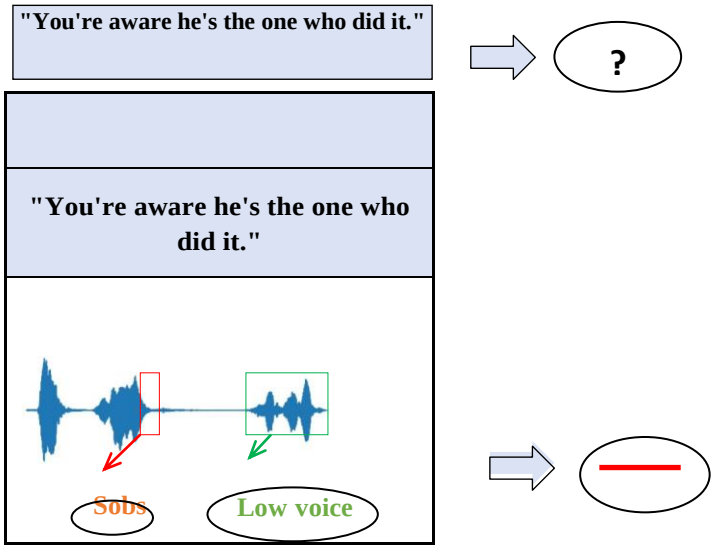


Figure 1: Cross-modal interaction between textual and audio modality

II. RELATED WORK

Multimodal Sentiment Analysis (MSA)

Multimodal Sentiment Analysis (MSA) offers a nuanced approach to sentiment analysis, aiming to not only determine sentiment polarity but also to measure the intensity of that sentiment. Introduced by Morency et al. (2011), MSA harnesses multiple data modes, such as text, audio, and visual cues, to provide a richer sentiment understanding.

1. Multimodal Fusion: Historically, multimodal fusion centered on geometric manipulations within feature spaces (Zadeh et al., 2017). This involved integrating features from various modalities in a geometrically

consistent manner. However, recent advancements have ushered in more sophisticated techniques. Hazarika et al. (2020) introduced the reconstruction loss method, refining fused modality representations. Similarly, Han et al. (2021) advanced the field with hierarchical mutual information maximization, spotlighting the most informative aspects from each modality.

2. Modal Consistency & Translation: Ensuring consistency across modalities is paramount in multimodal datasets. Yu et al. (2021a) pioneered a multi-task joint learning approach, ensuring consistent sentiment representations across data types. In contrast, Mai et al. (2020) delved into techniques translating sentiment data between modalities, aiming for a harmonized sentiment perspective.

3. Multimodal Alignment: The alignment of sentiments across different data types remains crucial. Tsai et al. (2019a) leveraged cross-modality representations to align sentiment cues. Luo et al. (2021) elevated this with multi-scale modality representation, facilitating nuanced alignment across diverse data granularities.

4. Multimodal Context: Sentiment analysis relies heavily on context. The context-aware attention techniques that Chauhan et al. (2019) pioneered allowed models to concentrate on pertinent contextual information. Simultaneously, Poria et al. (2017) presented a recurrent model enabled multi-level framework that captured complex contextual subtleties, while Ghosal et al. (2018) argued for a multi-modal attention model.

III. EMOTION RECOGNITION IN CONVERSATIONS (ERC)

Emotion Recognition in Conversations (ERC) delves deep into the task of discerning emotions within conversational data. As conversations are dynamic, recognizing emotions in this realm presents unique challenges.

1. Multimodal Fusion: With the rise of multimodal machine learning, ERC has thrived. Notably, Hu et al. (2022) and Joshi et al. (2022) harnessed graph based neural networks, modeling intricate dependencies between utterances and speakers, enhancing emotion recognition depth.

2. Context Integration: Emotion recognition's efficacy in conversations hinges on context. Sun et al. (2021) and Li et al. (2021a) employed graph structures to encapsulate the conversational context. Furthermore, Mao et al. (2021) introduced emotion dynamics, modeling the temporal shifts of emotions within conversations.

3. External Knowledge: Incorporating external knowledge augments ERC's capabilities. Hazarika et al. (2019) and Lee and Lee (2021) tapped into transfer learning. Concurrently, Ghosal et al. (2020) integrated commonsense knowledge, enriching ERC's comprehension of human emotions.

3.1 Unified-Framework

The convergence of disparate tasks into Unified-frameworks signifies modern machine learning's evolution. T5, championed by Raffel et al. (2020), epitomizes this trend, offering sentences on various NLP tasks. Harnessing this momentum, our research endeavors to integrate MSA and ERC within T5, aspiring to craft a embedding space, refining sentiment and emotion comprehension.

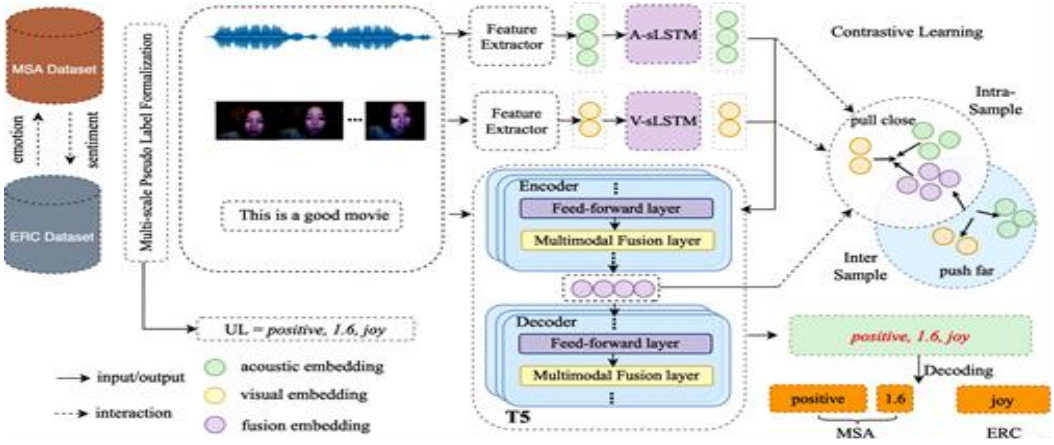


Figure 2: the overview of Unified-MSE

IV. METHODOLOGY:

4.1 Comprehensive Structure of Unified-MSA

In the intricate design of Unified-MSA, depicted in Figure 2, the architecture unfolds through a sequence of pivotal stages: **task formalization, pre-trained based modality fusion, and inter-modality based incompatible learning.** Initially, we undertake the offline processing of MSA and ERC task labels, harmonizing them into a universal label (UL) format. Subsequently, we delve into the extraction of audio and video features, employing unified feature extractors that span across datasets. Once these features are at our disposal, we navigate through the realms of long-term contextual insight by channeling them individually through dedicated LSTM pathways.

For the textual modality, the renowned T5 takes the stage as the encoder, diligently absorbing the nuanced contextual information encapsulated within the sequences. A distinctive facet of our approach is the seamless integration of multimodal fusion layers into the T5 architecture. These fusion layers are strategically embedded following the feed-forward layer within multiple Transformer layers of the T5 model.

Moreover, our innovation extends to the incorporation of inter-modal contrastive learning. This intricate process plays a crucial role in discerning and differentiating the multimodal fusion representations across various samples. The essence of contrastive learning lies in its mission to minimize the gap between modalities within the same sample, fostering cohesion, while simultaneously pushing the representations of different samples further apart. It's a delicate dance that refines the nuanced relationships between modalities and samples, ultimately enhancing the overall efficacy of Unified-MSA.

4.2 Task Formalization:

Involves processing multimodal signals, denoted as $\boldsymbol{I_i = \{I_i^t, I_i^a, I_i^v\}}$ where $\boldsymbol{I_i^m, m \in \{t,a,v\}}$, represents unimodal raw sequences from video fragment i.. The three modalities—text, audio, and visual—are represented by {t, a, v} in this instance. The goal of Multimodal Sentiment Analysis (MSA) is to forecast the sentiment strength represented by the real number yir ∈ R, where R is the set of all real numbers. Predicting each utterance's emotion category is the aim of Emotion Recognition in Conversations (ERC). Through task formalization, MSA and ERC show similarities with respect to input characteristics, model architecture, and label space.

The input procedure in this formalization handles modal features and conversation text, and the label formalization makes the labels for the MSA and ERC tasks universal, thereby bringing the two tasks together. This integrated approach streamlines the tasks, creating a cohesive framework that allows for joint consideration of sentiment strength prediction and emotion category identification. Furthermore, MSA and ERC are treated as a cohesive task, providing a unified and consistent foundation for modeling and analysis.

4.3 Input Formalization

Understanding the nuances of human emotions and intentions in conversations necessitates a deep comprehension of contextual information (Lee et al., 2021; Hu et al., 2022). To capture this essence, we adopt a structured approach:

1. **Concatenation of Utterances**: We believe that the richness of context can be best grasped by amalgamating the current utterance, *ui*, with its adjacent 2-turn utterances, represented as{ $u_i -1$, $u_i -2$}, and subsequent 2-turn utterances, denoted as {u_i+1,u_i+2}. This collection is presented as a raw text sequence: I_t^i=[$u_i -2$, $u_i -1$, u_i, u_i +1,u_i+2]

2. **Segment Identification**: To distinguish the central utterance, *ui*, from its surrounding context, we introduce a segment identifier, S^t_i The formulation is represented as:

$$S^t_i = [\underbrace{0,...,0,}_{\{z\}u_i-2,\ u_i-1}\ \underbrace{1,...,1,}_{\{z\}\ u_i}\ \underbrace{0,...,0}_{\{z\}\ u_i+1,\ u_i+2}\ ] \text{ ---- (1)}$$

   Here, the {z} notation signifies a separation between utterances.

3. **Textual Modality Processing**: The aforementioned structured utterances undergo further processing to align with the textual modality, represented as I_i^t.

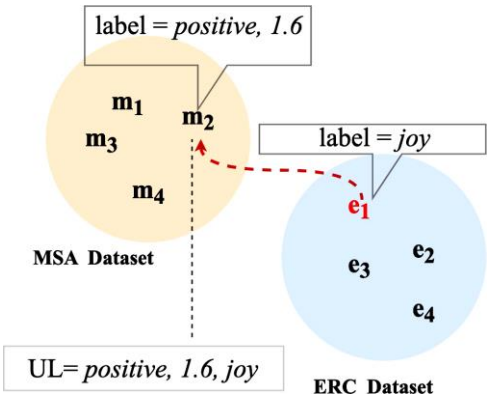


Figure 3: The creation process of a universal label (UL) is illustrated, with the red dashed line indicating that e_1 is the sample most closely related in terms of semantic similarity to m_2.

4. **Acoustic Feature Extraction**: Utilizing the librosa library, we transform raw acoustic signals into numerical sequential vectors. This process facilitates the extraction of Mel-spectrograms, a foundational tool in contemporary audio analysis, offering insights into the short-term power spectrum of sound.

5. **Video Feature Extraction**: For the video domain, our methodology involves selecting a fixed number, *T*, of frames from each segment. We leverage the efficient Net architecture (Tan and Le, 2019), which is pretrained on the VGGface 4 and AFEW datasets, ensuring robustness and efficiency in capturing essential video features.

4.4 Experimental setup

4.4.1 Used Datasets

In order to perform experiment ,four well-known benchmark datasets including Multimodal Sentiment Analysis (MSA) and Emotion Recognition in Conversations (ERC) were used in our research. The Multimodal Opinion-level Sentiment Intensity dataset (MOSI) by Zadeh et al. (2016), the Multimodal Opinion Sentiment and Emotion Intensity (MOSEI) by Zadeh et al. (2018), the Multimodal Emotion Lines Dataset (MELD) by Poria et al. (2019), and the Interactive Emotional dyadic Motion CAPture database (IEMOCAP) by Busso et al. (2008) are the datasets composed of these collections. MOSI comprises 2,199 video segments, each meticulously annotated with sentiment scores ranging from -3 to +3, signifying the sentiment polarity and its strength. MOSEI, an enhanced iteration of MOSI, boasts 22,856 movie review snippets sourced from YouTube. Although MOSEI offers both sentiment and emotion annotations, for this study, we solely rely on its sentiment annotations. Importantly, there's a clear demarcation between MOSEI and MOSI, with distinct data gathering and classification methodologies for each.

IEMOCAP, on the other hand, is comprised of 7,532 samples. Drawing inspiration from prior research (Hu et al., 2022; Wang et al., 2019), our focus for emotion recognition encompasses six distinct emotions: joy, sadness, anger, neutrality, excitement, and frustration. MELD houses 13,707 clips of multi-party dialogues, labeled in accordance with Ekman's six universally recognized emotions: sadness, joy, anger, fear, disgust and surprise.

4.4.2 Audio Features and Multimodal Alignment:

The COVAREP [4] toolset is utilized in this investigation to extract audio characteristics. A 74-dimensional feature vector, comprising pitch and segmenting features, glottal source parameters, peak slope parameters, maxima dispersion quotients, and 12 Mel-frequency cepstral coefficients (MFCCs), is used to represent each segment. We use P2FA [31] for word-level alignment characteristics in order to get the timestamps for every word. Table 1: Provides a concise overview of the MOSI, MOSEI, MELD, and IEMOCAP datasets, offering insights into data distribution and label composition. 'Senti.' signifies sentiment polarity, while 'Emo.' represents emotion categories. The average of the audio attributes that match the determined word timestamps is then calculated. The audio sequences are paddened with zero vectors in order to preserve alignment consistency with the text modality[32] [33].

Table 1: Concise overview of the MOSI, MOSEI, MELD, and IEMOCAP datasets

Dataset	Training Samples	Validation Samples	Test Samples	Sentiment Polarity Labels	Emotion Category Labels
MOSI	1284	229	686	Present	Not Present
MOSEI	16326	1871	4659	Present	Not Present
MELD	9986	1108	2610	Not Present	Present
IEMOCAP	5354	528	1650	Not Present	Present

V. EVALUATION METRICS:

In our evaluation of MOSI and MOSEI datasets, we employed diverse metrics for a thorough model assessment. The Mean Absolute Error (MAE) gauged predictive accuracy, while Pearson Correlation (Corr) measured alignment with actual data trends. The Seven-Class Classification Accuracy (ACC-7) provided insights into multi-class performance, whereas Binary Classification Accuracy (ACC-2) focused on binary distinctions. The F1 Score balanced precision and recall across various classifications. For MELD and IEMOCAP datasets, we primarily used Accuracy (ACC) and Weighted F1 (WF1) to ensure fairness in evaluations[34] [35].

VI. RESULTS:

In our comparative analysis across datasets including MOSI, MOSEI, IEMOCAP, and MELD, UniMSE emerges as a frontrunner, surpassing the current state-of-the-art (SOTA) benchmarks. Specifically, UniMSE demonstrates notable enhancements in various metrics. For instance, the ACC-2 metrics witness a boost of 1.65% for MOSI and 1.16% for MOSEI, while the ACC metrics show improvements of 2.6% for MELD and 2.35% for IEMOCAP. Additionally, there's a commendable rise in F1 scores, with MOSI and MOSEI benefiting by 1.73% and 1.29%, respectively. It's worth noting that while early research endeavors like LMF and TFN provided comprehensive coverage across all datasets, recent methodologies have often been limited to specific datasets or particular metrics. In contrast, UnifiedMSE offers a holistic approach, addressing both MSA and ERC tasks across the board, thereby underscoring its prowess as a unique and superior framework in the realm of sentiment analysis and emotion recognition.

VII. ABLATION STUDY ON UNIFIED-MSE:

Firstly, by progressively eliminating individual or multiple modalities from the multimodal signals, we assessed their impact on the model's performance. Notably, excluding either the visual or acoustic modalities, or both, resulted in a noticeable decline in performance metrics. This underscores the significance of non-verbal cues, such as visual and acoustic signals, in MSA tasks, highlighting the synergistic relationship between text, acoustic, and visual data. Intriguingly, of the two, the acoustic modality emerged as more pivotal for UniMSE. Subsequently, we examined the role of specific components within Unified-MSE, namely the PMF and CL modules. Their exclusion led to adverse effects, manifested as increased MAE and diminished Corr scores, underscoring their crucial role in facilitating effective multimodal representation learning [36] [37].

We also conducted tests to evaluate the effect of the dataset on the performance of UniMSE. In particular, we learned a lot by testing the model on the MOSI test set and excluding certain datasets like IEMOCAP, MELD, and MOSEI from the training set. Performance measures were negatively impacted by the removal of IEMOCAP and MELD, especially MAE and Corr, suggesting that these datasets provide important information that is essential for the MSA task. On the other hand, all measures decreased when MOSEI was removed.

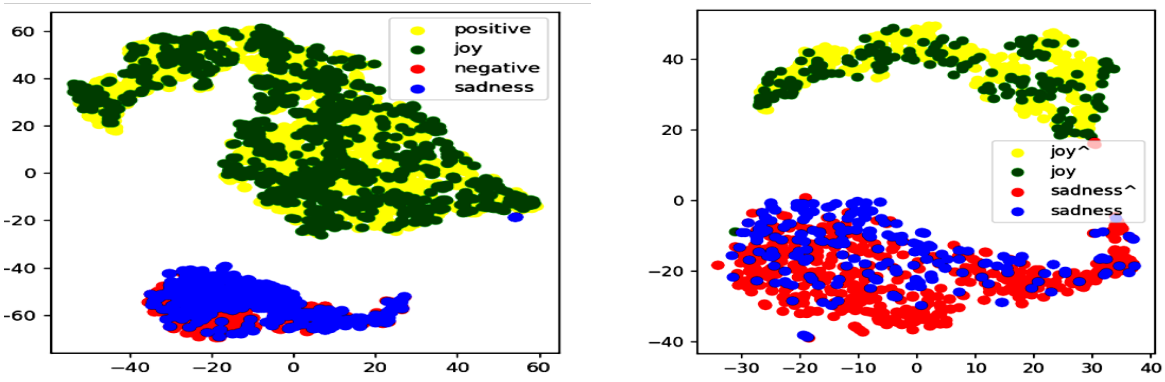
Table 2: Analysis of Unified-MSE's Ablation on MOSI: In this study, we examined the impact of removing specific modalities from Unified-MSE on the MOSI dataset.

Modality	Corr	MAE	MAE	F1-Score	ACC-2
Unified-MSE	**0.809**	**0.691**	**0.691**	**85.83/86.42**	**85.85/86.9**
- w/o A	0.794	0.719	0.719	83.86/85.69	83.82/85.20
- w/o V	0.798	0.714	0.714	84.71/85.78	84.37/85.37
- w/o A, V	0.780	0.721	0.721	83.52/85.11	83.72/85.11
- w/o PMF	0.785	0.722	0.722	85.03/86.37	85.13/86.59
- w/o CL	0.795	0.713	0.713	85.27/86.55	85.28/86.59
- w/o IEMOCAP	0.795	0.713	0.713	85.27/86.55	85.28/86.59
- w/o MELD	0.776	0.722	0.722	84.50/84.64	84.05/84.96
- w/o MOSEI	0.727	0.775	0.775	81.35/81.83	80.68/81.22

In our extensive evaluation on the MOSI dataset, we performed a sequence of ablation experiments to discern the importance of different modalities and components within Unified-MSE. The results are summarized in Table 2, where V and A denote visual and acoustic modalities. The proposed UniMSE framework stands distinct from existing methodologies. Its efficacy and versatility are evidenced by the consistent improvements observed across various ablation scenarios, underscoring its potential applicability across diverse tasks

VIII. VISUALIZATION

To evaluate the impact of Unified-MSE's Universal Label (UL) and cross-task learning on multimodal representation, we showcase the multimodal fusion representation F(j) derived from the final Transformer layer. For this analysis, we specifically select samples that demonstrate sentiment from MOSI's test set and samples reflecting joy/sadness emotions from MELD's test set. The visualization of these representations is presented in Figure 4(a).

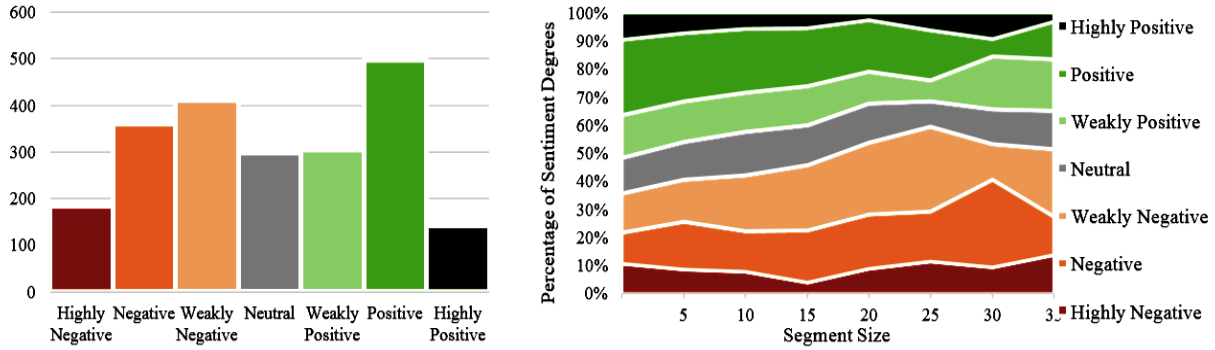


(a) **(b)**

Figure 4: visualization contrasting the multimodal fusion illustration of: (a) samples categorized by emotion and sentiment (b) used samples through original emotion juxtaposed with produced emotion, where *joy* and *sadness* signify the produced emotion.

Additionally, we select MOSI samples characterized by generated emotions of joy/sadness and compare them with MELD samples that originally carry emotion labels of joy/sadness in the embedding space. The corresponding visualization is illustrated in Figure 4(b). Notably, samples expressing the emotion of joy, regardless of their original labels or if generated based on the Universal Label (UL), demonstrate a shared feature

space. These observations confirm the proficiency of Unified-MSE in representation learning across samples and emphasize the complementary nature that exists between sentiment and emotion. The figure 5 is representing the histogram, on the left side 5(a) illustrates the distribution of sentiment across the complete dataset. Meanwhile, the graph on the right 5(b) displays the proportion of each sentiment category relative to the segment size, measured by the number of words in each opinion segment.



(a) **(b)**

Figure 5: Histogram in the left shows the distribution of sentiment over the entire dataset. The right graph shows the percentage of each sentiment degree per segment size (number of words in opinion segment).

IX. DISCUSSION

In this study, the Unified-MSE framework is introduced and evaluated for sentiment analysis and emotion recognition tasks using diverse datasets. The COVAREP toolkit is employed to extract audio features, and P2FA aids in word-level alignment, ensuring consistency with zero vector padding. Evaluation metrics, including MAE, Pearson Correlation, ACC-7, ACC-2, and F1 Score, provide a comprehensive assessment across datasets. Unified-MSE demonstrates superior performance, surpassing existing benchmarks and showcasing a holistic approach to sentiment analysis and emotion recognition. The ablation study emphasizes the crucial role of visual and acoustic modalities, with the acoustic modality being particularly pivotal. Experiments excluding specific datasets underscore the significance of IEMOCAP and MELD for effective task performance. Detailed insights from Table 2 highlight the impact of modality and dataset removal on Unified-MSE's performance, consistently affirming its superiority and versatility. The visualization section further validates the model's proficiency through visual representations of shared feature spaces among samples with similar emotions. So, Unified-MSE emerges as a robust and versatile framework, excelling in sentiment analysis and emotion recognition tasks. The study's meticulous evaluations and ablation studies underscore the framework's efficacy, especially in leveraging multimodal data for enhanced representation learning.

9.1 Theoretical Implications:

i. **Advancement in Multimodal Analysis:** The introduction of the Unified-MSE framework underscores a significant advancement in the integration of multimodal data for sentiment analysis and emotion recognition. This study bridges the gap between textual, acoustic, and visual modalities, offering a more holistic perspective on human communication.

ii. **Role of Acoustic Modality:** The ablation study's emphasis on the pivotal role of the acoustic modality highlights the significance of non-verbal cues in sentiment and emotion recognition. This finding enriches our theoretical understanding of the interplay between linguistic and paralinguistic elements in communication.

iii. **Dataset Significance:** The study's insights into the impact of specific datasets, such as IEMOCAP and MELD, on task performance contribute to a nuanced understanding of dataset selection and its implications for model generalization and effectiveness.

9.2 Practical Implications:

i. **Enhanced Model Performance:** The superior performance of the Unified-MSE framework, as demonstrated across diverse datasets and evaluation metrics, suggests its potential for practical applications. Organizations and researchers can leverage this framework to develop more accurate and reliable sentiment analysis and emotion recognition tools.

ii. **Optimized Data Utilization:** The study's emphasis on the importance of multimodal data and specific datasets informs practitioners about the optimal utilization of data sources. This knowledge can guide data collection and preprocessing efforts, ensuring that relevant modalities and datasets are prioritized.

iii. **Visualization for Interpretability:** The visual representations generated by the Unified-MSE framework offer practical tools for model interpretability and validation. Stakeholders can utilize these visualizations to gain insights into the model's decision-making process and to assess its alignment with human perceptions of sentiment and emotion.

X. CONCLUSION

This study introduces a psychological lens, emphasizing the feasibility and rationale behind jointly modeling sentiment and emotion. We unveil the Unified-MSE framework, a unified multimodal knowledge-sharing approach tailored for MSA and ERC tasks. Beyond merely capturing sentiment and emotion knowledge, Unified-MSE effectively aligns input features with output labels. The proposed approach combines acoustic and visual model representations, leveraging multi-level based textual attributes and integrating inter-modality contrastive learning. The extensive tests conducted on four standard datasets showcase our achievement of state-of-the-art results across all evaluated metrics. Furthermore, our visualizations of multimodal representations affirm the crucial role of emotion and sentiment within the entrenching space. We believe that this research introduces a new investigational paradigm, providing a unique perspective for both the MSA and ERC research communities.

However, like any pioneering endeavor, our research is not without its constraints. A noteworthy point of consideration is our current reliance on the MELD and IEMOCAP datasets, leaving room for enriched insights from datasets like MOSI and MOSEI. Moreover, while our textual-centric approach has shown promise, the realm of acoustic and visual modalities beckons exploration. These identified gaps not only underscore the nascent stage of our research but also serve as guiding stars for future endeavors.

Looking ahead, our journey with the Unified-MSE framework is far from over. The roadmap ahead is illuminated with opportunities to broaden our dataset horizons, refine computational methodologies, and embrace interdisciplinary collaborations. By combining the technical with the human-centric insights from psychology and linguistics, we aspire to craft models that resonate more authentically with the essence of human emotion and sentiment. Additionally, as we tread this path, ethical considerations and human-centric evaluations will remain at the forefront, ensuring that our advancements uphold the sanctity and sensitivity of human communication. Through this holistic approach, we envision not just advancements in computational models but a deeper, more resonant understanding of the human narrative.

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