Improving Multimodal Learning with Multi-Loss Gradient Modulation

Konstantinos Kontras
ESAT, KU Leuven
Leuven, Belgium
konstantinos.kontras@kuleuven.be

Christos Chatzichristos
ESAT, KU Leuven
Leuven, Belgium
christos.chatzichristos@kuleuven.be

Matthew Blaschko
ESAT, KU Leuven
Leuven, Belgium
matthew.blaschko@kuleuven.be

Maarten De Vos
ESAT, KU Leuven
Leuven, Belgium
maarten.devos@kuleuven.be

Abstract

Learning from multiple modalities, such as audio and video, offers opportunities for leveraging complementary information, enhancing robustness, and improving contextual understanding and performance. However, combining such modalities presents challenges, especially when modalities differ in data structure, predictive contribution, and the complexity of their learning processes. It has been observed that one modality can potentially dominate the learning process, hindering the effective utilization of information from other modalities and leading to sub-optimal model performance. To address this issue the vast majority of previous works suggest to assess the unimodal contributions and dynamically adjust the training to equalize them. We improve upon previous work by introducing a multi-loss objective and further refining the balancing process, allowing it to dynamically adjust the learning pace of each modality in both directions, acceleration and deceleration, with the ability to phase out balancing effects upon convergence. We achieve superior results across three audio-video datasets: on CREMA-D, models with ResNet backbone encoders surpass the previous best by 1.9% to 12.4%, and Conformer backbone models deliver improvements ranging from 2.8% to 14.1% across different fusion methods. On AVE, improvements range from 2.7% to 7.7%, while on UCF101, gains reach up to 6.1%.

1. Introduction

Combining data from several modalities such as vision, text, audio, and time series has significantly improved performance across many tasks and has proven particularly advantageous in cases of noisy or unreliable sources [15, 25?]. However, studies show that the inclusion of a new modality doesn't always benefit, and can even impair, model performance [24]. As explained by Huang *et al.* [12], different modalities compete with each other, resulting in underperforming modalities. These modalities exhibit inferior performance in their multimodal-trained encoders compared to their unimodal counterparts, assessing each modality encoder independently post-training, suggesting potential imbalances or inefficiencies in the integrated training process. This finding contradicts the assumption that more information necessarily improves task understanding.

To mitigate this effect, various balancing strategies have been proposed [4, 5, 14, 17, 19, 24, 27, 29]. Previous methods typically use models with individual unimodal encoders and a fusion network that produces the multimodal output, generally falling into two main categories. Methods in the first category adjust the learning rate of unimodal encoders based on their estimated predictive performance [17, 27, 29]. Meanwhile, the methods of the second category employ additional loss functions derived from unimodal predictions and balance these losses during multimodal learning [3, 4, 19, 23, 24]. These losses enable accurate estimation of unimodal performance, however, these methods do not address the effects caused by the multimodal loss. We aim to bridge both approaches by incorporating additional losses and simultaneously adjusting the learning rates. Our methodology provides the following improvements and novelties:

- Throughout the entire training process, we employ a multi-objective loss that not only ensures each encoder converges close to its unimodal optimum, similarly to the methods described in [23] and [24], but also facilitates accurate unimodal performance estimation. We apply balancing for both multimodal and unimodal losses, distinguishing our method from any prior efforts in these categories.
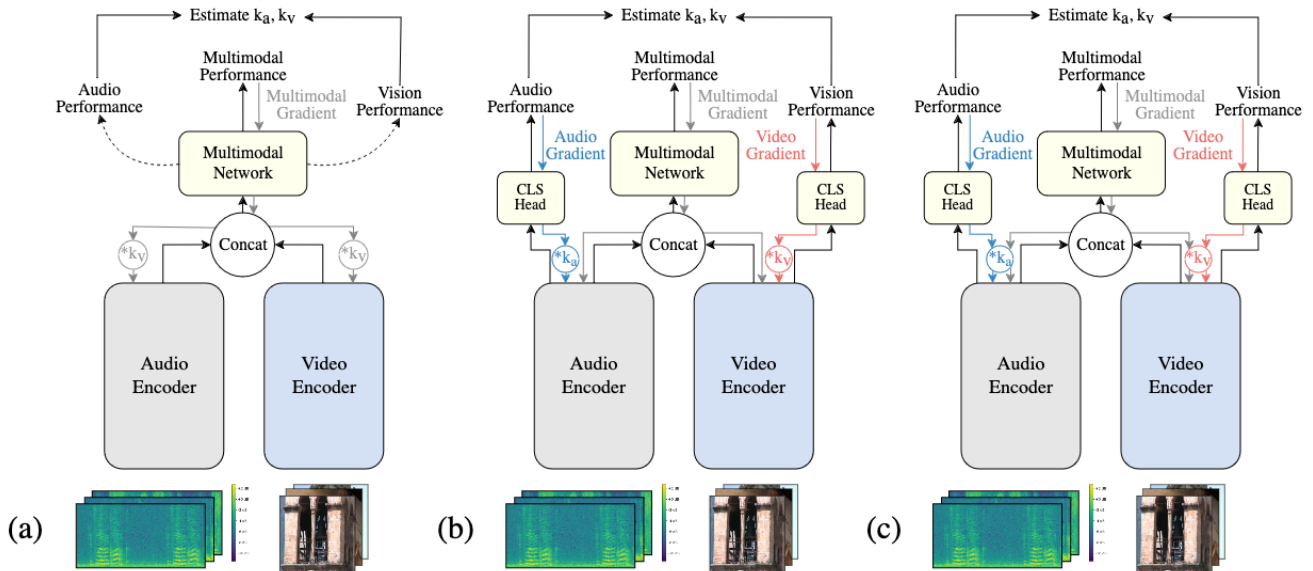
Figure 1. Categorization of state-of-the-art balancing methodology: (a) Gradient Balancing methods use estimates of unimodal performance to calculate coefficients (k_a and k_v) and employ these to balance the multimodal loss. (b) Multi-Task methods incorporate unimodal classifiers into the model, each noted as CLS Head, to better estimate unimodal performance. The coefficients (k_a and k_v) derived from comparing unimodal performance are used exclusively to balance the unimodal losses. (c) The proposed Multi-Loss Balanced method combines both strategies by incorporating unimodal classifiers for accurate unimodal performance estimation and balancing both multimodal and unimodal losses.

- The proposed balancing technique, inspired by [17], adaptively modifies the learning rates of encoders based on unimodal performance assessments. We enhance this strategy by enabling both acceleration and deceleration, tailored to the relative performance of the modalities.
- The balancing equations are designed such that when all unimodal encoders converge, the balancing naturally phases out, eliminating the need to pre-determine explicitly which epoch should mark the end of balancing.

Results conclusively show that the suggested method consistently outperforms balancing state-of-the-art methods across three video-audio datasets, employing either ResNet or Conformer backbone encoder models, and utilizing a range of fusion techniques.

2. State-of-the-Art

Previous methods addressing the challenge of modality competition in multimodal learning frameworks can mostly be broadly categorized into two primary groups: Gradient Balancing and Multi-Task methods. Those are illustrated in (a) and (b) of Figure 1. Additionally, methods that don't fit into either category are described in Section 2.3.

2.1. Gradient Balancing Techniques

In this category, methods address modality competition by adjusting the unimodal encoders' learning rates. The Modality-specific Learning Rates (**MSLR**) [29] strategy introduces an approach for decision-level fusion models which dynamically adjust encoder gradients magnitude based on recent validation accuracy, independently for each modality. Building on this foundation, On-the-fly Gradient Modulation (**OGM**) [17] introduces an interactive framework, comparing performance improvements across modalities to tailor the adjustment of each encoders' learning rate. These methods are designed for late fusion models, allowing direct access to unimodal performance; however, they cannot directly be applied in more complex fusion schemes. Wu et al. [27] partially belong to this category, as they propose a method that monitors the learning speed of each modality through gradient norms while using isolated phases of unimodal training to balance multimodal learning. However, measuring this learning speed requires a specialized model architecture, which prevents the use of a shared multimodal output, limiting its application.

2.2. Multi-task Learning

The methods that belong in this category target the suboptimal unimodal encoders by employing dedicated losses for each modality. It has been observed that incorporating unimodal classifiers enhances multimodal learning, as demonstrated in [23 **?**]. Building on this foundation, Wang *et al.* [24] suggest to dynamically adjust the weights of the unimodal losses based on an overfitting-to-generalization ratio, however accessing that information requires a separate validation set. Du *et al.* [3] introduce a teacher-student schema with distillation losses for direct guidance of unimodal encoders. The Prototypical Modal Rebalance (**PMR**) method [4] circumvents the use of additional parameters for classifiers by leveraging prototype-based classifiers and distance-based losses. This approach maintains a similar logic, wherein imbalanced performance is compensated for by the appropriate unimodal loss. However, balancing the unimodal losses alone disregards the effects caused by the multimodal loss.

2.3. Other Approaches

Additional studies explore further approaches to multimodal learning, not fitting neatly into previously discussed categories. **MMCosine** [28] preconditions late fusion by standardizing both the feature vectors and the weights dedicated to each modality, equalizing their contribution to the final prediction. Gat *et al.* [6] explore a regularization technique to enhance each modality's contribution by maximizing functional entropy, estimated through prediction differences after input perturbations. This method, however, increases the model's sensitivity to those perturbations. Adaptive Gradient Modulation (**AGM**) [14] takes the contribution of each modality by utilizing zero-masking Shapley [16 **?**] values. This allows for balancing on models of any structure, however at the cost of increased computational demands due to multiple forward passes.

3. Method

3.1. Model

We have endeavored to maintain our methodology as model-agnostic as possible, albeit with a few necessary assumptions. Our focus centers on multimodal models, wherein each modality is processed by a dedicated encoder. We aim to enhance the training efficiency of these encoders, thereby indirectly benefiting the entire network's performance. To elucidate, our models conform to a unified structural framework.

Given a dataset D consisting of N samples across M modalities, denoted as $X = \{X_1, .., X_M\}$, each sharing a common ground truth label Y with C distinct classes, we employ networks structured as follows:

$$f(X; \theta) = f_v(f_1(X_1; \theta_1), .., f_M(X_M; \theta_M); \theta_v), \quad (1)$$

where θ denotes all the parameters of the network, $\theta_1, .., \theta_M$ the unimodal encoders', $f_1, .., f_M$ parameters and θ_v the common parameters of the common fusion function f_v.

3.2. Balancing

Our objective is to achieve synchronous convergence of the unimodal encoders, based on the hypothesis that this will prevent the model from overfitting to any single modality and may encourage the development of more synergistic behaviors.

To achieve this, following prior studies [4, 17, 24, 29], we dynamically adjust the learning rates of each unimodal encoder based on the comparative analysis of unimodal performances. We estimate balancing coefficients for each modality $i = 1, .., M$ as k_i that indicate how much each modality should change the learning pace of its encoder. When $k_i > 1$, we accelerate the learning of the modality, while when $k_i < 1$, we decelerate it. The update rule using stochastic gradient descent (SGD), the initial learning rate lr_{base} and the loss function L would then be:

$$\Delta\theta_i = -lr_{\text{base}} \cdot k_i \cdot \nabla L(X, y, \theta). \quad (2)$$

We improve upon previous works in three points. Firstly, we incorporate a multi-task objective with additional unimodal losses. Such objective ensures precise assessment of unimodal performance, while aiding the convergence of the unimodal classifiers. Secondly, our method allows for both the acceleration and deceleration of learning across the modalities, without ever entirely halting their progress. Finally, while previous methods imposed a hard limit to cease balancing after a predetermined number of epochs, we employ a function that naturally reduces balancing effects as the performances of both modalities converge.

Our multi-loss objective L is a summation of a cross-entropy (CE) loss for the multimodal predictions and similar cross-entropy losses for each unimodal prediction. This can be expressed as:

$$L = CE(f(X; \theta), y) + \sum_{i=1}^{M} CE(f_i(X_i; \theta_i), y). \quad (3)$$

To adaptively balance the learning of each unimodal encoder, we derive the coefficients k_i of Eq. 2 based on modality performance. These coefficients are calculated as follows:

$$s_i = \sum_{i=1}^{M} \sum_{c=1}^{C} f_i(X_i; \theta_i) 1_{k=y_c}, \quad (4)$$

$$r_i = \frac{\frac{1}{M-1} \sum_{j=1, j \neq i}^{M} s_j}{s_i}, \quad (5)$$

$$\beta_i = \begin{cases} \beta_{max} & \text{if } r_i > 1, \\ 2 & \text{otherwise}, \end{cases} \quad (6)$$

$$k_i = 1 + (\beta_i - 1) \cdot \tanh(\alpha \cdot (r_i - 1)) \quad (7)$$

s_i is the sum of correct class predictions by the unimodal encoder for modality i, r_i the relative performance of each encoder compared to the average performance of the others, β_i the max value of the coefficients and k_i the final balancing coefficient for each modality, where $\alpha \in \mathbb{R}^+$ and $\beta_{max} \in \mathbb{R}^+$, $\beta_{max} \geq 1$ are predetermined hyperparameters. Finally, $tanh$ is the hyperbolic tangent function, providing a smooth normalization of r_i.

The utilization of two distinct cases for b_i arises from the varied behaviors we aim to achieve with the balancing method. When $r_i < 1$, it indicates that other modalities perform, on average, worse than modality i, necessitating a reduction in the learning rate of modality i to slow its learning pace. To achieve this, we set $b_i = 2$, placing us in the portion of Figure 2 where $r_i \in [0, 1]$. The extent of the learning deceleration can vary and is influenced by the slope of the $tanh$ function parameterized by a; a larger a value results in more pronounced changes in the learning rate. Conversely, when $r_i > 1$, indicating that other modalities generally outperform modality i, we aim to increase the learning rate of modality i, requiring $k_i > 1$. The extent of the acceleration is more sensitive, as large values may lead to model divergence. To control this, we introduce the hyperparameter b_{max}, which sets the maximum permissible increase. For instance, if $b_{max} = 10$, we allow the learning rate to increase by up to 10 times based on the performance ratio r_i, as shown in Figure 2 when $r_i > 1$.
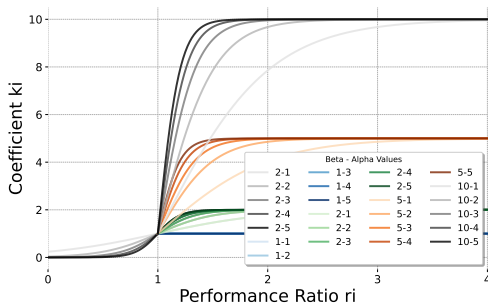

Figure 2. Comparing Balancing Coefficients (k_i, Eq. 7) and Performance Ratios (r_i, Eq. 5) across different α and β settings.

4. Experiments

4.1. Datasets

CREMA-D [2]: is an emotion recognition dataset with audio and video modalities, featuring 91 actors expressing six emotions. Video frames are sampled at 1 frame-per-second (fps), selecting 3 consecutive frames, while audio segments are sampled at 22 kHz. Audio analysis employs Short-Time Fourier Transform (STFT) with a window size of 512 and a step size of 353 samples to create the log-Mel spectrograms. For advanced models, we adopt preprocessing steps suggested by Goncalves *et al.* [7], utilizing the full audio recording at 16kHz without STFT and video data without subsampling. We also follow their dataset division, ensuring no actor overlap between training, validation, and test sets. Standard deviation (std) is reported across 3-folds.

AVE [22]: spans 28 event categories of everyday human and animal activities, each with temporally labeled audio-video events lasting at least 2 seconds. Video segments with the event are sampled at 1 fps for 4 frames, with audio resampled at 16 kHz using CREMA-D's STFT settings. AVE provides predefined training, validation, and test splits. Standard deviation (std) is calculated from three random seeds on the same test set.

UCF101 [20]: showcases real-life action YouTube videos across 101 categories, expanding UCF50. Our analysis focuses on 51 action categories featuring both video and audio modalities, following similar data preparation as the AVE dataset. Model evaluation utilizes the dataset's 3-fold split, with std reported across these folds.

4.2. Backbone Unimodal Encoders

Our experimental framework aims to demonstrate the broad applicability of our findings across diverse unimodal encoders. We used two type of encoders for each modality: one randomly initialized ResNet and a Transformer-based with pretrained weights.

In line with prior research [4, 14, 17, 28], we employed ResNet-18 [11], initialized from scratch, as the unimodal encoder for handling both video and audio modalities across all datasets. We extend our analysis to include larger, pretrained models. Following [8] on CREMA-D, we deploy the first 12 layers of the Wav2Vec2 [1, 26] model with self-supervised pretrained weights for speech recognition. For the video modality we extract the facing bounding boxes and afterwards the facial features exploiting EfficientNet-B2 [21] as a frozen feature descriptor. Both the audio and video features are further refined using each a 5-layer Conformer [9]. Leveraging similar audio pre-trained encoders for the AVE and UCF-101 datasets did not yield significant improvement due to differences in data distribution, as these datasets lack speech-based audio. As a result, we focused exclusively on experimenting with ResNet for these
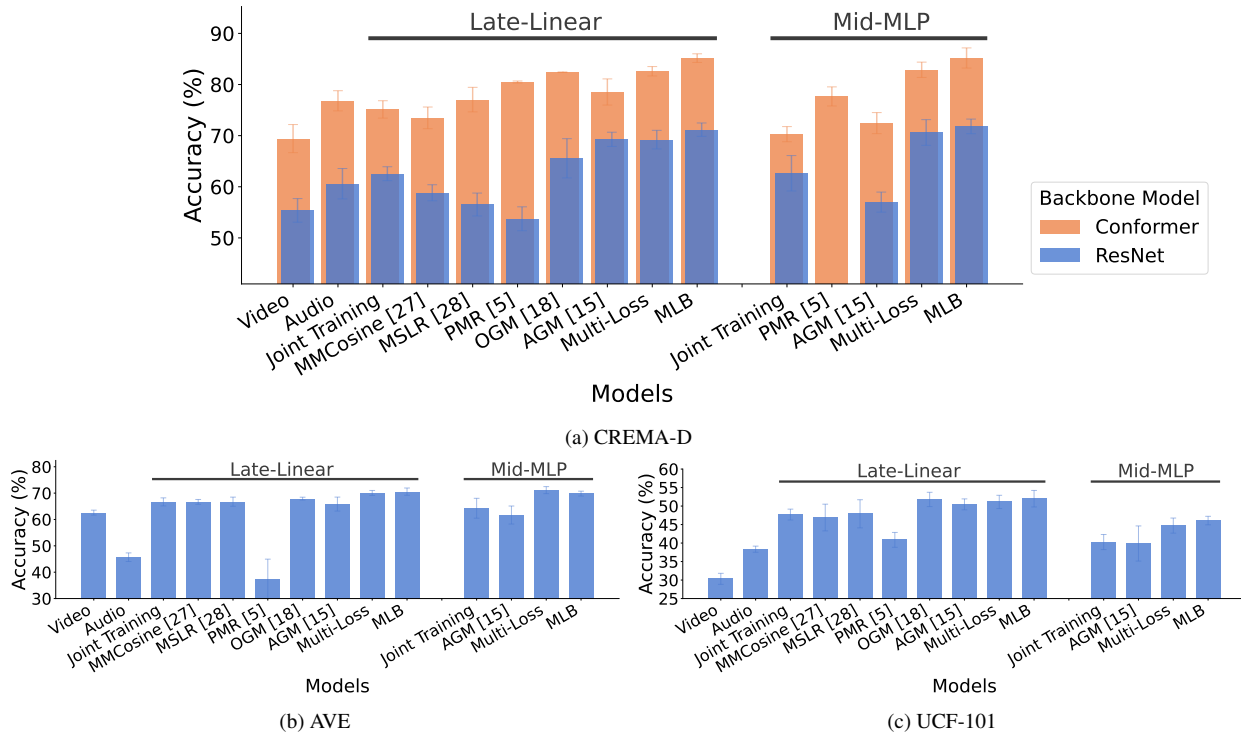
Figure 3. Accuracy of models that differentiate by the backbone encoders (colors), the fusion strategies (Late with a linear and Mid with a MLP classifier), and the balancing techniques (x-axis). Across all datasets, results demonstrate that employing unimodal losses within the Multi-Loss framework and balancing them consistently yields the best performance.

two datasets.

4.3. Multimodal Fusion

We are outlining five fusion models that combine unimodal features from the encoders to generate the multimodal output. Late Fusion combines the concatenated unimodal features using a linear layer, noted as **Late-Linear**. Mid Fusion employs a 2-layer Multilayer Perceptron (MLP) to investigate the effects of nonlinear feature combinations on modality imbalances, noted as **Mid-MLP**. We align with prior research and experiment with advanced fusion strategies: Feature-wise Linear Modulation (**FiLM**)[18] and **Gated** mechanisms [13]. Additionally, we explore integrating a 2-layer Conformer [9] model as a Transformer-based (**TF**) fusion method, utilizing both class and modality-independent tokens. Our objective is to showcase the impact of balancing methods by assessing their effectiveness across diverse fusion strategies.

5. Results

In this section, we present results on the effectiveness of using different fusion strategies on multimodal training with several multimodal balancing techniques namely MMCo-

sine, MSLR, OGM, AGM, PMR[1], Multi-Loss and Multi-Loss Balanced (**MLB**). We show the models trained under the single multimodal objective without any balancing methods, named as **Joint Training**. Hyperparameter tuning was conducted separately for each method, dataset, backbone encoder, and fusion strategy on the validation set. This ensured fairness with an equal number of trials for each configuration.

In the bar plots presented in Figure 3, we assess the previously mentioned models alongside suitable balancing methods across the three datasets. Results highlight that MLB consistently outperforms previous approaches, demonstrating its robustness across various settings. Our comparison with the simpler Multi-Loss strategy reveals that adding unimodal losses often suffices to adequately train the unimodal encoders. In most instances balancing provides a further incremental benefit.

Furthermore, we use the Expected Calibration Error (ECE) [10] to assess whether multimodal training enhances model uncertainty awareness. Figure 5 demonstrates that

---

[1]The PMR method, as per the provided code, exhibits several instabilities, resulting in exploding values of the classifier prototypes. This instability predominantly affects models with ResNet encoders and certain nonlinear fusion methods. Despite these issues, we opt not to modify their implementation to avoid inadvertently influencing the method incorrectly.
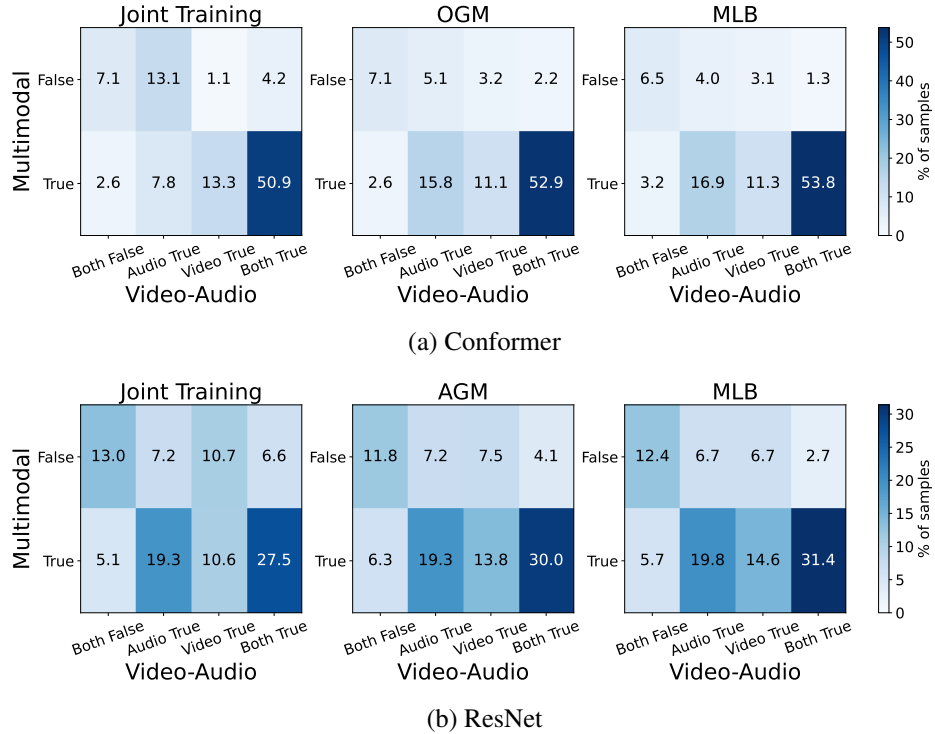
(a) Conformer

(b) ResNet

Figure 4. Confusion Matrices between the unimodal models and the multimodal ones for both backbone encoders, (a) Conformer and (b) ResNet, trained under different balancing methods. Each column of the confusion matrix represents the cases where both unimodal predictions are incorrect, where only one is correct, and where both are correct. MLB consistently balances and improves performance across all categories.

the MLB method, achieving the highest accuracy, also exhibits lower calibration error compared to other methods and to Multi-loss, highlighting the significance of balancing.
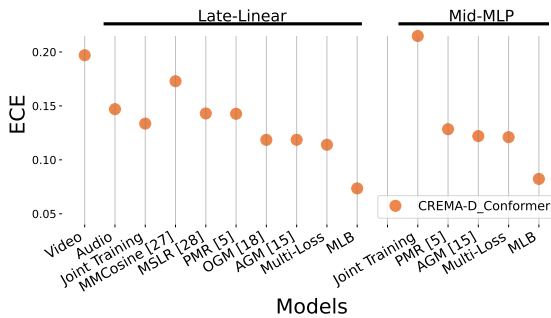

Figure 5. ECE Comparison on Conformer CREMA-D.

To verify that the issue of overfitting on one of the modalities is not prevalent to the fusion method, we incorporate alternative fusion strategies, as mentioned in Section 4.3, FiLM, Gated and TF. Both the Multi-Loss and Multi-Loss Balanced employ additional linear classifiers to de-

rive unimodal predictions and calculate the unimodal losses. Figure 6 supports our primary findings, indicating improvements in the learning process across models employing different fusion methods balanced with Multi-Loss and MLB. However, in some instances, we do not observe notable benefits from the addition of the balancing technique.
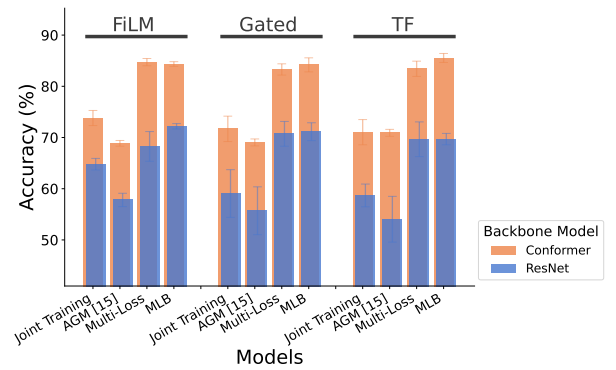

Figure 6. Accuracy of models using FiLM [18], Gated [13] and TF fusion techniques on the ResNet and Conformer model applied to the CREMA-D dataset.

To ascertain whether the lack of training stems from an underperforming modality in the Joint Training schema and to assess the impact of different balancing techniques, we examine the confusion matrices. In Figure 4, we illustrate the label agreement among the two unimodal models and the multimodal ones trained under various methods. Notably, Joint Training with the Conformer model tends to overfit to the video modality, exhibiting high agreement with it. Conversely, the same method applied to the ResNet model demonstrates a stronger reliance on the audio modality, resulting in increased errors on the Video True case. Interestingly, both the pretrained Conformer for video and the ResNet for audio required fewer optimization steps to converge compared to the other modality. This observation leads us to conclude that a modality's dominance in the learning process is not solely determined by its predictive power, but also by its ability to reduce the training loss more rapidly.

From the same figure, MLB consistently enhances performance across all categories, including Both True, Both False, Audio True, and Video True, indicating across-the-board improvement. In the ResNet model results, we observe that AGM, the best previous method, slightly enhances the scenario where both modalities predict incorrectly (Both False), suggesting improved information discovery.

6. Discussion and Conclusion

In this paper, we tackle the issue of multimodal models overfitting on one modality, thereby hindering the effective utilization of the remaining modalities. We experiment with state-of-the-art balancing methods, revealing inconsistencies across different models and datasets. To address this, we introduce the Multi-Loss Balanced method. We demonstrate how additional losses derived from each modality can enhance the training of unimodal encoders and provide accurate estimations of their performance, enabling us to balance the learning of each encoder during multimodal training. Our approach incorporates coefficient estimation functions to support both acceleration and deceleration of each modality, while allowing the model to mute the balancing as it converges. We consistently observe improved results across three video-audio datasets, utilizing both ResNet and Transformer-based backbone encoders, along with a variety of fusion methods.

References

[1] Alexei Baevski, Yuhao Zhou, Abdelrahman Mohamed, and Michael Auli. wav2vec 2.0: A framework for self-supervised learning of speech representations. *Advances in neural information processing systems*, 33:12449–12460, 2020. 4

[2] Houwei Cao, David G Cooper, Michael K Keutmann, Ruben C Gur, Ani Nenkova, and Ragini Verma. Crema-d: Crowd-sourced emotional multimodal actors dataset. *IEEE transactions on affective computing*, 5(4):377–390, 2014. 4

[3] Chenzhuang Du, Jiaye Teng, Tingle Li, Yichen Liu, Tianyuan Yuan, Yue Wang, Yang Yuan, and Hang Zhao. On uni-modal feature learning in supervised multi-modal learning. *arXiv preprint arXiv:2305.01233*, 2023. 1, 3

[4] Yunfeng Fan, Wenchao Xu, Haozhao Wang, Junxiao Wang, and Song Guo. Pmr: Prototypical modal rebalance for multimodal learning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 20029–20038, 2023. 1, 3, 4

[5] Naotsuna Fujimori, Rei Endo, Yoshihiko Kawai, and Takahiro Mochizuki. Modality-specific learning rate control for multimodal classification. In *Pattern Recognition: 5th Asian Conference, ACPR 2019, Auckland, New Zealand, November 26–29, 2019, Revised Selected Papers, Part II 5*, pages 412–422. Springer, 2020. 1

[6] Itai Gat, Idan Schwartz, Alexander Schwing, and Tamir Hazan. Removing bias in multi-modal classifiers: Regularization by maximizing functional entropies. *Advances in Neural Information Processing Systems*, 33:3197–3208, 2020. 3

[7] L. Goncalves, S.-G. Leem, W.-C. Lin, B. Sisman, and C. Busso. Versatile audiovisual learning for handling single and multi modalities in emotion regression and classification tasks. *ArXiv e-prints (arXiv:2305.07216)*, pages 1–14, 2023. 4

[8] Lucas Goncalves, Seong-Gyun Leem, Wei-Cheng Lin, Berrak Sisman, and Carlos Busso. Versatile audio-visual learning for handling single and multi modalities in emotion regression and classification tasks. *arXiv preprint arXiv:2305.07216*, 2023. 4

[9] Anmol Gulati, James Qin, Chung-Cheng Chiu, Niki Parmar, Yu Zhang, Jiahui Yu, Wei Han, Shibo Wang, Zhengdong Zhang, Yonghui Wu, et al. Conformer: Convolution-augmented transformer for speech recognition. *arXiv preprint arXiv:2005.08100*, 2020. 4, 5

[10] Chuan Guo, Geoff Pleiss, Yu Sun, and Kilian Q Weinberger. On calibration of modern neural networks. In *International conference on machine learning*, pages 1321–1330. PMLR, 2017. 5

[11] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition, 2015. 4

[12] Yu Huang, Junyang Lin, Chang Zhou, Hongxia Yang, and Longbo Huang. Modality competition: What makes joint training of multi-modal network fail in deep learning?(provably). In *International Conference on Machine Learning*, pages 9226–9259. PMLR, 2022. 1

[13] Douwe Kiela, Edouard Grave, Armand Joulin, and Tomas Mikolov. Efficient large-scale multi-modal classification.

In *Proceedings of the AAAI conference on artificial intelligence*, 2018. 5, 6

[14] Hong Li, Xingyu Li, Pengbo Hu, Yinuo Lei, Chunxiao Li, and Yi Zhou. Boosting multi-modal model performance with adaptive gradient modulation. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 22214–22224, 2023. 1, 3, 4

[15] Junnan Li, Dongxu Li, Caiming Xiong, and Steven Hoi. Blip: Bootstrapping language-image pre-training for unified vision-language understanding and generation. In *International Conference on Machine Learning*, pages 12888–12900. PMLR, 2022. 1

[16] Scott M Lundberg and Su-In Lee. A unified approach to interpreting model predictions. *Advances in neural information processing systems*, 30, 2017. 3

[17] Xiaokang Peng, Yake Wei, Andong Deng, Dong Wang, and Di Hu. Balanced multimodal learning via on-the-fly gradient modulation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 8238–8247, 2022. 1, 2, 3, 4

[18] Ethan Perez, Florian Strub, Harm De Vries, Vincent Dumoulin, and Aaron Courville. Film: Visual reasoning with a general conditioning layer. In *Proceedings of the AAAI conference on artificial intelligence*, 2018. 5, 6

[19] Huy Phan, Oliver Y Chén, Minh C Tran, Philipp Koch, Alfred Mertins, and Maarten De Vos. Xsleepnet: Multi-view sequential model for automatic sleep staging. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 44(9): 5903–5915, 2021. 1

[20] Khurram Soomro, Amir Roshan Zamir, and Mubarak Shah. Ucf101: A dataset of 101 human actions classes from videos in the wild. *arXiv preprint arXiv:1212.0402*, 2012. 4

[21] Mingxing Tan and Quoc Le. Efficientnet: Rethinking model scaling for convolutional neural networks. In *International conference on machine learning*, pages 6105–6114. PMLR, 2019. 4

[22] Yapeng Tian, Jing Shi, Bochen Li, Zhiyao Duan, and Chenliang Xu. Audio-visual event localization in unconstrained videos. In *Proceedings of the European conference on computer vision (ECCV)*, pages 247–263, 2018. 4

[23] Valentin Vielzeuf, Alexis Lechervy, Stéphane Pateux, and Frédéric Jurie. Centralnet: a multilayer approach for multimodal fusion. In *Proceedings of the European Conference on Computer Vision (ECCV) Workshops*, pages 0–0, 2018. 1, 3

[24] Weiyao Wang, Du Tran, and Matt Feiszli. What makes training multi-modal classification networks hard? In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 12695–12705, 2020. 1, 3

[25] Wenhui Wang, Hangbo Bao, Li Dong, Johan Bjorck, Zhiliang Peng, Qiang Liu, Kriti Aggarwal, Owais Khan Mohammed, Saksham Singhal, Subhojit Som, et al. Image as a foreign language: Beit pretraining for all vision and vision-language tasks. *arXiv preprint arXiv:2208.10442*, 2022. 1

[26] Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Remi Louf, Morgan Funtowicz, Joe Davison, Sam Shleifer, Patrick von Platen, Clara Ma, Yacine Jernite, Julien Plu, Canwen Xu, Teven Le Scao, Sylvain Gugger, Mariama Drame, Quentin Lhoest, and Alexander Rush. Transformers: State-of-the-art natural language processing. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 38–45, Online, 2020. Association for Computational Linguistics. 4

[27] Nan Wu, Stanislaw Jastrzebski, Kyunghyun Cho, and Krzysztof J Geras. Characterizing and overcoming the greedy nature of learning in multi-modal deep neural networks. In *International Conference on Machine Learning*, pages 24043–24055. PMLR, 2022. 1, 2

[28] Ruize Xu, Ruoxuan Feng, Shi-Xiong Zhang, and Di Hu. Mmcosine: Multi-modal cosine loss towards balanced audio-visual fine-grained learning. In *ICASSP 2023-2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 1–5. IEEE, 2023. 3, 4

[29] Yiqun Yao and Rada Mihalcea. Modality-specific learning rates for effective multimodal additive late-fusion. In *Findings of the Association for Computational Linguistics: ACL 2022*, pages 1824–1834. Association for Computational Linguistics, 2022. 1, 2, 3