

G²D: Boosting Multimodal Learning with Gradient-Guided Distillation

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Abstract

Multimodal learning aims to leverage information from diverse data modalities to achieve more comprehensive performance. However, conventional multimodal models often suffer from modality imbalance, where one or a few modalities dominate model optimization, leading to suboptimal feature representation and underutilization of weak modalities. To address this challenge, we introduce Gradient-Guided Distillation (G²D), a knowledge distillation framework that optimizes the multimodal model with a custom-built loss function that fuses both unimodal and multimodal objectives. G²D further incorporates a dynamic sequential modality prioritization (SMP) technique in the learning process to ensure each modality leads the learning process, avoiding the pitfall of stronger modalities overshadowing weaker ones. We validate G²D on multiple real-world datasets and show that G²D amplifies the significance of weak modalities while training and outperforms state-of-the-art methods in classification and regression tasks. Our code is available [here](#).

1. Introduction

Multimodal learning is one of the most prominent multidisciplinary research areas due to the increasing demand to develop intelligent agents that perceive information from diverse sensory modalities. One of the primary challenges of multimodal learning models is the *modality imbalance* phenomenon [23, 26, 40, 45], also known as the modality competition [18, 19, 23] or modality laziness [8, 51]. Modality imbalance occurs when one modality dominates and other modalities are underutilized in the optimization of multimodal learning models. This causes (i) inferior multimodal performance compared to unimodal models [26, 32, 39], or (ii) a larger gap in individual modality when they are optimized jointly but still improve the model performance [9, 23]. This imbalance occurs due to poor alignment of the modalities, model overfitting to the modalities [39], and differences in the rate of model con-

vergence [54]. An example of a modality imbalance with the multimodal dataset *CREMA-D* [4] is given in Figure 1. It is evident that the *audio* features (Figure 1a) dominate the *video* features (Figure 1b) when optimized in a multimodal fashion. However, video features give better performance with unimodal training. This results in sub-par performance with the joint multimodal training, shown in Figure 1c. In this work, our goal is to (i) increase the performance of weak modalities in multimodal settings and (ii) increase the overall performance of the multimodal model in downstream supervised tasks.

In recent years, many methods have been proposed to address modality imbalance in multimodal learning [8, 9, 11, 18, 23, 26, 39, 40, 42, 45, 46, 51]. *Gradient modulation* is one of the popular approaches in state-of-the-art methods to dynamically modify multimodal optimization gradients and maximize equal contributions from all modalities. A common form of gradient modulation is dynamically increasing the gradients of weak modalities only for late fusion [26, 46, 50] or for any type of fusion methods [9, 23] during the training process. Multiple variations of these gradient modulations also exist, for example, alternating gradients of each modality [51] and controlling the dominant modality gradients [11]. Although there exist multiple gradient modulation methods, there are very few methods that optimize both unimodal and multimodal learning objectives [8, 40] to add the benefits of both worlds. We aim to follow this trend in this work and introduce a novel optimization strategy by incorporating knowledge distillation.

In this work, we aim to utilize the full potential of both unimodal and multimodal learning for the given multimodal downstream task. We propose a framework *Gradient-Guided Distillation* (G²D) that transfers knowledge from multiple unimodal teachers to multimodal student models. *Novelty* of G²D is its use of knowledge distillation with a new learning objective and gradient modulation technique to mitigate modality imbalance and produce state-of-the-art results in multimodal learning. As depicted in Figure 1, G²D improves the feature quality of multimodal encoder, allowing both the audio and video encoders to approach

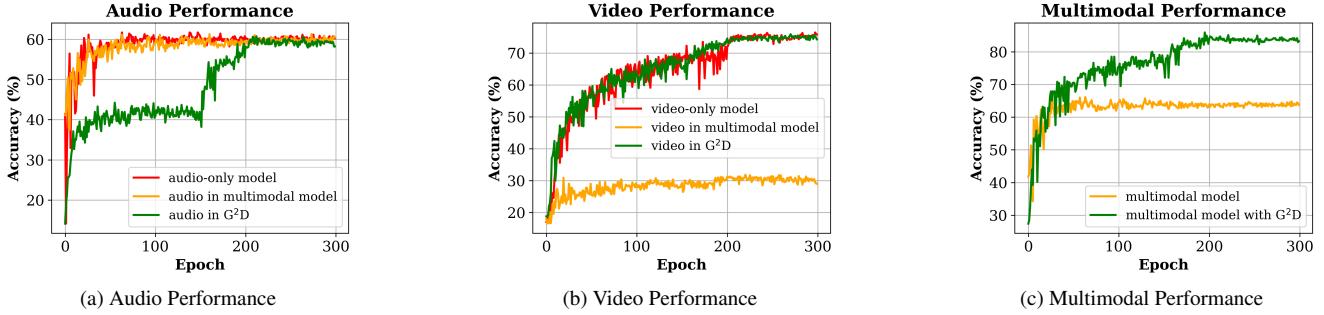


Figure 1. Performance of unimodal-only, unimodal in multimodal training, and purely multimodal models on the CREMA-D test set for multimodal classification. (a) audio modality is indifferent to training configurations; (b) video modality is vulnerable to the audio modality in a multimodal setting; (c) performance of the multimodal model is not optimal because of modality imbalance. G²D limits the optimization of superior modality and enhances the video modality to optimize the multimodal performance.

the accuracy of their unimodal counterparts when integrated into the multimodal model. This leads to an overall more balanced and better-performing multimodal model while addressing the modality imbalance issue (Figure 1c). Our *three-fold* contributions in this work are:

- We introduce a knowledge distillation framework called G²D that adapts a new optimization technique to fuse both unimodal and multimodal learning to enhance the performance of downstream tasks.
- We propose a new Sequential Modality Prioritization strategy that dynamically balances the optimization of weak and dominant modalities to mitigate imbalance.
- With extensive experiments on *six* real-world datasets, we show that G²D minimizes modality imbalance and achieves superior performance. We also show that our approach is adaptive to existing methods.

2. Related Work

Knowledge distillation (KD) transfers knowledge from a larger and more complex model (*teacher*) to a smaller and more efficient model (*student*) [2, 17, 33]. Multimodal KD extends this concept by leveraging information from multiple modalities to enhance learning, which supports several real-world AI applications ([24, 29, 38, 43, 47]). Multimodal KD distills knowledge from one modality to improve performance of other modalities or in multimodal downstream tasks. Multimodal KD has demonstrated substantial benefits, including improved performance, better multimodal alignment, and enhanced generalization across modalities ([12, 20, 44, 47]). Multimodal KD has been used in multiple real-world problems like medical imaging [38] to address missing modality and action recognition [29] to transfer knowledge from multimodal ensemble to a unimodal model. In this paper, we build upon recent advances in multimodal KD [8], specifically targeting the modality imbalance problem during multimodal training. By utilizing unimodal teacher models to guide the multimodal stu-

dent model, we ensure balanced learning across modalities.

Several methods have been proposed to mitigate the modality imbalance through gradient modulation, feature rebalancing, or modality-specific learning rate adjustments ([9, 11, 23, 26, 46, 50]). *Gradient modulation* techniques dynamically adjust gradients to balance modality contributions during training [23, 26]. However, these methods often require careful tuning of hyperparameters, which can limit their generalizability. *Feature rebalancing* aims to optimize multimodal interaction by adjusting the contribution of each modality by enhancing the performance of unimodal learners [18, 40, 41, 51]. There is another perspective of alleviating modality imbalance with a proper label fitting using contrastive learning [45]. In the context of multimodal KD, limited work has used unimodal teachers to supervise a multimodal student. UMT [7] directly supervises with unimodal teachers, while UME [8] aggregates their logits. Choosing between them requires empirical tuning, limiting adaptability across tasks and datasets. In this work, we propose the G²D framework to address these limitations by combining multimodal knowledge distillation with a new gradient modulation technique. Unlike previous approaches that require careful hyperparameter tuning ([7, 8, 23, 26]), our approach dynamically suppresses dominant modalities based on insights from unimodal teachers. This not only makes our method applicable across different settings but also allows underrepresented modalities to learn more effectively.

3. Methodology

We propose *Gradient-Guided Distillation* (G²D) to mitigate modality imbalance in multimodal learning through a combination of knowledge distillation and sequential modality prioritization. The proposed G²D adapts to labeled multimodal datasets $\mathcal{D} = (x_i, y_i)_{i=1}^N$, where each sample x_i consists of k -modality inputs, denoted as $x_i = (x_i^{m_1}, x_i^{m_2}, \dots, x_i^{m_k})$, and an associated label y_i .

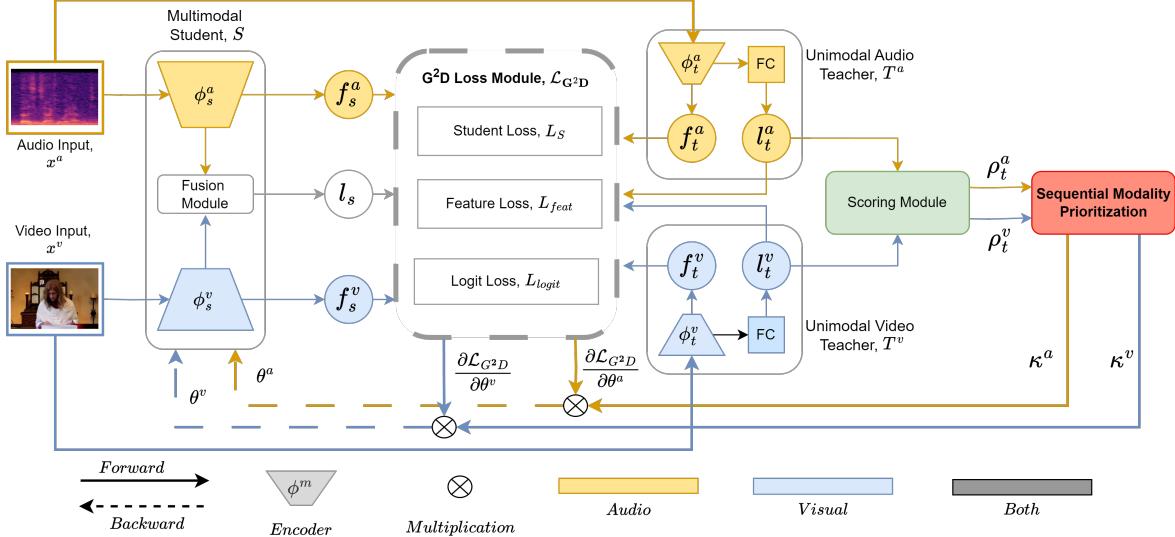


Figure 2. $\mathbf{G}^2\mathbf{D}$ consists of multiple, independently optimized *unimodal teacher* encoders and jointly optimized *multimodal student* encoders with all encoders generating feature representations and logits for each modality. The $\mathcal{L}_{\mathbf{G}^2\mathbf{D}}$ **Loss Module** consists of student loss, feature distillation loss, and logit distillation loss. Confidence scores from the **Scoring Module** are used by the **Sequential Modality Prioritization Module** to generate dynamic modulation coefficients that adaptively adjust the gradients of each encoder to ensure balanced contributions.

$\mathbf{G}^2\mathbf{D}$, as illustrated in Figure 2, combines unimodal and multimodal learning by distilling the knowledge from unimodal teachers to the multimodal student with a new learning objective $\mathcal{L}_{\mathbf{G}^2\mathbf{D}}$. The *scoring module* in $\mathbf{G}^2\mathbf{D}$ determines modality-specific scores based on the knowledge of multiple unimodal teachers. The proposed *Sequential Modality Prioritization* dynamically identifies inferior modalities and empirically modulates the gradients of multimodal student encoders to mitigate modality imbalance.

3.1. $\mathbf{G}^2\mathbf{D}$ Loss Function

We extend traditional multimodal knowledge distillation [8] by introducing a new training objective ($\mathcal{L}_{\mathbf{G}^2\mathbf{D}}$) that combines *unimodal feature distillation* ($\mathcal{L}_{\text{feat}}$) loss and *unimodal logit distillation* ($\mathcal{L}_{\text{logit}}$) loss with the *multimodal student loss* (\mathcal{L}_S) to mitigate modality imbalance. We define the unimodal teacher model $\{T^m\}_{m=1}^k$ and the multimodal student model $[S]_1^k$. Each teacher model T^m is responsible for a single modality m and consists of an encoder ϕ_t^m parameterized by θ_t^m , which produces corresponding feature representations $f_t^m = \phi_t^m(x_i^m; \theta_t^m)$. We represent logits l_t^m of teacher models after passing f_t^m through a linear classifier ψ_t^m . Similarly, the student model $[S]_1^k$ processes the multimodal input x_i through modality-specific encoders ϕ_s^m , parameterized by θ_s^m , to obtain student feature representations $f_s^m = \phi_s^m(x_i^m; \theta_s^m)$. These features are then combined through a traditional multimodal fusion module $\Phi_{\text{fusion}}(f_s^{m_1}, f_s^{m_2}, \dots, f_s^{m_k})$, to produce a multimodal representation, which is used to calculate multimodal student logits $l_s = \psi_s(\Phi_{\text{fusion}}(f_s^{m_1}, f_s^{m_2}, \dots, f_s^{m_k}))$. The proposed

$\mathcal{L}_{\mathbf{G}^2\mathbf{D}}$ comprises three key components:

1. **Multimodal Student Loss** (\mathcal{L}_S): is a supervised loss to map multimodal inputs x_i to the label y_i :

$$\mathcal{L}_S = \mathbb{E}_{(x,y) \sim [\mathcal{D}]_m^k} [\ell(p, y)] \quad (1)$$

where ℓ is the cross-entropy loss ($\ell(p, y) = -\sum_{w=1}^C y_w \log(p)$) for C -class classification tasks with $p = l_s(x; \theta_s)$ or mean squared error ($\ell(p, y) = \frac{1}{N} \sum_{i=1}^N (p - y)^2$) for regression tasks with $p = \sigma(l_s(x; \theta_s))$, where σ is the sigmoid function.

2. **Feature Distillation Loss** ($\mathcal{L}_{\text{feat}}$): To prevent the student model from discarding information from weaker modalities, we impose an L2-based feature alignment loss that minimizes the discrepancy between multimodal student and unimodal teachers' feature representations:

$$\mathcal{L}_{\text{feat}}^m = \mathbb{E}_{x \sim \mathcal{D}} [\|\phi_s^m(x^m; \theta_s^m) - \phi_t^m(x^m; \theta_t^m)\|^2] \quad (2)$$

where ϕ_s^m and ϕ_t^m are student and teacher features, respectively, as functions of input x^m and encoder parameters.

3. **Logits Distillation Loss** ($\mathcal{L}_{\text{logit}}$): Logit-based distillation enables the student model to capture class-level relationships and decision boundaries defined by the teacher. We integrate a new logit-based distillation using Kullback-Leibler (KL) divergence [17] that learns the distribution from unimodal teachers to the multimodal student:

$$\mathcal{L}_{\text{logit}}^m = \mathbb{E}_{x \sim \mathcal{D}} [\text{KL}(\sigma(l_t^m(x^m; \theta_t^m)) \| \sigma(l_s(x; \theta_s)))] \quad (3)$$

where σ denotes the softmax function.

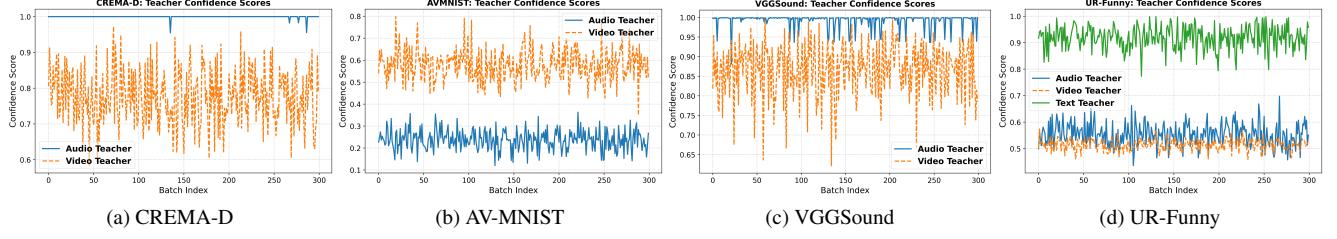


Figure 3. Unimodal teacher confidence scores across multimodal datasets. Each line is the confidence of a specific modality (audio, visual, or text). Modality bias on all datasets, with higher scores for one modality, motivates our use of sequential modality prioritization.

We define the G²D loss as:

$$\mathcal{L}_{G^2D} = \mathcal{L}_S + \alpha \sum_{m=1}^k \mathcal{L}_{\text{feat}}^m + \beta \sum_{m=1}^k \mathcal{L}_{\text{logit}}^m \quad (4)$$

where α and β are weighting coefficients for the feature loss and the logit loss, respectively. This formulation enables the multimodal student model to leverage the strengths of each unimodal teacher model effectively. Feature distillation loss ensures that the student retains modality-specific representations, while logit distillation loss aligns the student’s predictions with teacher distributions, capturing inter-class and intra-class dependencies. Although this new learning objective enables maximization of quality, multimodal models can still be biased to dominant modalities as they optimize all modalities simultaneously. We introduce an adaptive training strategy based on unimodal confidence scores to mitigate modality imbalance.

3.2. Quantifying Modality Confidence

Scoring mechanisms are widely used to measure the contributions of individual modalities in multimodal learning [23, 26]. As unimodal models are outside the bounds of modality imbalance, we utilize their confidence in determining the imbalance ratio. Our scoring module in G²D quantify the confidence ρ of each unimodal teacher T^m as the batch-wise average of their softmax function:

$$\rho_t^m = \frac{1}{|\mathcal{B}^m|} \sum_{(x_i^m, y_i^m) \in \mathcal{B}^m} \text{Softmax}(l_t^m(x_i^m; \theta^m))[y_i^m], \quad (5)$$

where $|\mathcal{B}^m|$ represents the number of m modality data samples in the batch, and $\text{Softmax}(l_t^m(x_i^m; \theta^m))[y_i^m]$ is the probability assigned to the ground truth label y_i^m by the teacher model T^m for the sample x_i .

The score ρ_t^m serves as an indicator of how confident the unimodal teacher T^m is in predicting the correct label for the given batch. A higher score indicates greater confidence, signifying that modality m dominates in multimodal training. This information is then used to guide gradient updates in the student model, dynamically adjusting training to mitigate the dominance of any single modality.

3.3. Modulating Gradients with Sequential Modality Prioritization (SMP)

Multimodal datasets often undergo modality overfitting during training [39] and give priority only to dominant modalities, limiting the optimization of weaker modalities. Using the modality scores ρ^m , we find this trend on all four classification datasets, as shown in Figure 3. It is evident that one modality consistently exhibits higher confidence scores, indicating a modality imbalance and dominance over other modalities in the given downstream task. We also note that this pattern is not grounded to a specific modality. For example, in CREMA-D (Figure 3a), the audio teacher has higher scores than the video teacher, and in UR-Funny (Figure 3d), the text modality remains dominant over audio and visual inputs. These findings align with previous research that identifies modality bias as a prevalent issue in multimodal datasets [1, 14, 52]. This further leads to modality imbalance in multimodal learning, as analyzed in Figure 1. To address this issue, we hypothesize the following:

Hypothesis 1. *Leveraging the confidence scores of unimodal models to determine less confident modalities and sequentially prioritizing them during multimodal training can mitigate modality imbalance.*

To test this hypothesis, we propose *sequential modality prioritization* strategy for the multimodal training in our proposed G²D framework. For each training iteration q , we rank confidence scores of all teacher models ρ_t^m . If this ranked list is given as π_t , then $\pi_t[1]$ corresponds to the least confident modality, and $\pi_t[k]$ corresponds to the most dominant modality. We aim to generate an automatic training schedule process to identify the set of prioritized modalities \mathcal{M}_q based on the modality confidence scores π_t , as given in Equation (6).

$$\mathcal{M}_q = \begin{cases} \{\pi_t[1]\} & \text{for } 1 \leq e \leq \tau_1 \\ \{\pi_t[2]\} & \text{for } \tau_1 < e \leq \tau_1 + \tau_2 \\ \vdots & \\ \{\pi_t[k-1]\} & \text{for } \sum_{j=1}^{k-2} \tau_j < e \leq \sum_{j=1}^{k-1} \tau_j \\ \{\pi_t[1], \dots, \pi_t[k]\} & \text{for } \sum_{j=1}^{k-1} \tau_j < e \leq \sum_{j=1}^k \tau_j \end{cases} \quad (6)$$

where e is the training epoch, and τ_j is the hyperparameter set to denote the number of epochs for optimizing j -th prioritized modality, where j is the index of the ranked list π_t . The modulation coefficients κ_q^m for each modality m identifies the modality to optimize in multimodal learning, as given in Equation (7).

$$\kappa_q^m = \begin{cases} 1 & \text{if modality } m \in \mathcal{M}_q, \\ 0 & \text{otherwise,} \end{cases} \quad (7)$$

The gradient update for the parameters θ_q^m of modality m for iteration q in the multimodal student model S is then:

$$\theta_{q+1}^m = \theta_q^m - \eta \cdot \kappa_q^m \cdot \mathbb{E}_{(x_i, y_i) \sim \mathcal{D}} \left[\frac{\partial \mathcal{L}_{G^2D}(x_i, y_i)}{\partial \theta_q^m} \right] \quad (8)$$

where η is the learning rate, and \mathcal{L}_{G^2D} represents the total loss function as defined in Equation (4).

During each epoch range τ_j , only the corresponding modality $\pi_t(j)$ is assigned $\kappa_q^m = 1$, while all others are set to 0, ensuring that the prioritized modality receives full gradient updates. After the prioritized phases for all less confident modalities, the most confident modality ($\pi_t(k)$) is trained jointly with all other modalities, with $\kappa_q^m = 1$ for all m . This sequential prioritization strategy allows each modality to lead the learning process in turn, thereby mitigating persistent modality dominance. We summarize the complete multimodal training with G²D in Algorithm 1.

Algorithm 1 Multimodal Learning with G²D

- 1: **Input:** $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^N$, unimodal teachers $\{T^m\}_{m=1}^k$, multimodal student S , iterations q
 - 2: Initialize student model S with random weights
 - 3: Load pre-trained weights for teacher models $\{T^m\}_{m=1}^k$
 - 4: **for** iteration $i = 0, \dots, q-1$ **do**
 - 5: Sample a fresh mini-batch (x, y) from \mathcal{D}
 - 6: Feed-forward the batch through S to obtain $\{f_s^m\}_{m=1}^k$ and l_s
 - 7: Feed-forward each modality of a batch through $\{T^m\}_{m=1}^k$ to get $\{f_t^m\}_{m=1}^k$ and $\{l_t^m\}_{m=1}^k$
 - 8: Compute \mathcal{L}_{G^2D} loss using Eq. (4)
 - 9: Calculate ρ_t^m for each modality using Eq. (5)
 - 10: Calculate κ^m using Eq. (7)
 - 11: Find modality gradients $\frac{\partial \mathcal{L}_{G^2D}}{\partial \theta^m}$ and update parameters θ^m for each modality m using Eq. (8)
 - 12: **end for**
 - 13: **return** Trained multimodal student model S
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4. Experiments

We evaluate the G²D framework on the basis of the following questions: **Q1:** How does G²D compare to state-of-the-art methods for addressing modality imbalance and

overall multimodal performance in supervised tasks? **Q2:** How does G²D influence the modality gap in multimodal learning?, **Q3:** Does G²D enhance feature space alignment between unimodal and multimodal models?, **Q4:** How SMP is influencing the multimodal learning?, and **Q5:** Which fusion and suppression techniques are the best for G²D?

4.1. G²D Evaluation

4.1.1. Experimental Setup

Datasets. We chose five multimodal classification datasets and one regression dataset. **CREMA-D** [4] is an audio-visual dataset for speech emotion recognition with six emotion classes. **AV-MNIST** [37] is a synthetic dataset with PCA-projected MNIST images and audio spectrograms for ten-digit classes. **VGGSound** [6] is a large-scale audio-visual dataset with 309 classes of everyday audio events, featuring video clips of 10 seconds each. **UR-Funny** [15] is a binary classification dataset for humor detection that incorporates text, visual gestures, and acoustic modalities. **IEMOCAP** [3] is an audio-visual-text dataset for emotion recognition in dyadic conversations. **MIS-ME** [30] is a regression dataset containing raw soil patch images and corresponding meteorological data for soil moisture estimation. To the best of our knowledge, we are the *first* to evaluate the modality imbalance in a multimodal regression setting and use tabular data for multimodal learning problems.

Baselines. We compare G²D with ten state-of-the-art methods that address modality imbalance, including MSES [11], MSLR [46], AGM [23], PMR [9], OGM-GE [26], MLA [51], MM-Pareto [40], ReconBoost[18], DLMG[45], and UMT [8]. We compare the baseline methods across four datasets that include audio, visual, and text modalities. For the regression task, we compare our approach to MISME [30], which estimates soil moisture from soil patch images and meteorological data. We evaluate the performance of each baseline in both unimodal and multimodal contexts for each modality. Please refer to Sec. A.2 for more detailed baseline descriptions.

Backbone and Hyperparameter Settings. For audio-visual datasets (CREMA-D, VGGSound, and AV-MNIST), we use ResNet-18 [16] as the encoder for both audio and video modalities in the teacher and student models. For the UR-Funny and IEMOCAP dataset, which involves audio, visual, and text modalities, we use a Transformer-based encoder [36] for each modality. For MIS-ME, we adopt MobileNetV2 [31] as the image feature extractor and use the fully connected neural network proposed in [30] for processing tabular meteorological data. To ensure a fair comparison, we use identical backbone architectures across all baseline models and employ late fusion for training. All models are optimized using SGD with a batch size of 16 and trained on a single NVIDIA A10 GPU. More details on experimental settings are provided in Sec. A.4.

Table 1. Performance comparison on various audio-visual datasets reported in accuracy (%). "Multi" represents the evaluation of the multimodal student model, while "Audio" and "Video" rows indicate the performance of modality-specific encoders within the multimodal model. T_a and T_v denote unimodal evaluations for the audio and video teacher models, respectively.

Dataset		T^a	T^v	Joint-Train	MSES	MSLR	AGM	PMR	OGM-GE	MLA	MM Pareto	Recon Boost	DLMG	UMT	G^2D (Ours)
CREMA-D	Audio	61.69	-	59.95	54.86	54.86	48.58	49.19	58.60	59.27	65.46	57.71	54.37	61.02	56.45
	Video	-	76.48	27.42	22.57	26.31	57.85	23.25	49.06	64.91	55.24	65.21	70.89	25.40	72.72
	Multi	-	-	67.47	60.99	64.42	78.48	59.13	72.18	79.70	75.13	79.82	83.62	67.61	85.89
AV-MNIST	Audio	42.69	-	16.05	27.50	22.72	38.90	37.60	24.53	42.26	42.11	41.50	41.99	31.55	39.10
	Video	-	65.44	55.83	63.34	62.92	63.65	58.50	55.85	65.30	65.26	64.28	65.04	64.08	65.09
	Multi	-	-	69.77	70.68	70.62	72.14	71.82	71.08	65.32	<u>72.63</u>	72.47	72.14	72.33	73.03
VGGSound	Audio	43.39	-	39.22	39.57	39.10	38.15	26.30	37.96	37.56	42.44	42.35	41.54	42.12	39.43
	Video	-	32.32	18.70	17.85	18.66	25.65	7.12	22.64	32.02	17.94	18.12	23.65	23.77	29.88
	Multi	-	-	50.97	50.76	50.98	47.11	33.07	51.45	51.65	49.69	50.97	52.74	<u>53.78</u>	53.82

4.1.2. Results

In this section, we present the accuracy(%) of all models with best results in **bold** and second best results underlined.

G^2D on Two Modalities and Audio-Visual Domain.

Table 1 presents the following key observations:

1. Unimodal performances (T_a and T_v) and joint-training reveal that modality imbalance is dataset-dependent. On CREMA-D and VGGSound, video performs well in the unimodal setup but becomes suppressed in multimodal training, while it is the opposite in AV-MNIST as audio is underutilized in multimodal setup. This confirms that modality imbalance is a prevalent issue in multimodal learning, leading to suboptimal fusion in joint-training.

2. DLMG, ReconBoost, and gradient modulation methods (AGM, OGM-GE, MLA, and MMPareto) attempt to reduce modality imbalance and improve fusion. While effective, they do not fully bridge the discrepancy among modalities, as imbalance persists across datasets. G^2D surpasses all baselines, demonstrating that SMP ensures balanced optimization and better multimodal integration.

3. To the best of our knowledge, UMT is the only knowledge distillation-based baseline addressing modality imbalance. The results show that the proposed G^2D loss that distills knowledge from unimodal teachers with the dynamic training strategy using SMP gives better optimization for weak modalities to outperform UMT across all datasets.

G^2D on Three Modalities and Text Domain. Unlike prior approaches [9, 42], G^2D is not constrained by the number of modalities. We now analyze results with a three-modality dataset on UR-FUNNY, given in Table 2. In this special case of experiment, we compare our results with baseline models using all combinations of modalities. We find with joint-training that text modality is dominant in all multimodal settings and incorporating all modalities leads to the best multimodal performance. (i) **G^2D performance:** We observe that G^2D consistently outperforms methods incorporating adaptive training strategies, such as OGM-GE,

MMPareto, and ReconBoost, as well as the KD-based approach UMT, demonstrating its effectiveness in mitigating modality imbalance. (ii) **Modality depression:** Another interesting finding with more than two modalities (A-V-TXT) is the dominant modality (text) depression across most of our baseline models. We suspect that these models give over-prioritization to weak modalities while not allowing the required optimization for dominant modalities. G^2D , on the other hand, treats all modalities fairly with the proposed SMP to reduce modality depression.

Table 2. Accuracy (%) on the UR-Funny dataset across all modality combinations. Unimodal teacher performance for audio, visual, and text are 61.57%, 58.25%, and 61.77%, respectively.

Type	Joint-Train	OGM-GE	MM Pareto	Recon Boost	UMT	G^2D (Ours)
A-V	Audio	57.34	59.76	61.77	60.53	54.63
	Visual	53.92	53.82	55.73	57.87	56.44
	Multi	61.57	61.87	61.27	<u>62.07</u>	60.46
A-TXT	Audio	50.30	54.12	58.15	50.18	55.63
	Text	57.44	58.35	58.45	56.98	57.75
	Multi	62.17	62.47	<u>62.88</u>	61.06	62.47
V-TXT	Visual	49.30	55.33	56.04	55.41	56.34
	Text	51.21	58.95	59.15	50.94	53.82
	Multi	62.07	62.98	61.27	60.07	<u>63.18</u>
A-V-TXT	Audio	55.03	50.30	58.05	51.65	50.70
	Visual	54.93	55.73	56.14	55.26	54.93
	Text	58.25	55.71	58.55	56.25	52.72
	Multi	62.58	<u>63.68</u>	62.88	61.37	63.38

G^2D on the Multimodal Regression Task. To evaluate the robustness and real-world applicability of G^2D , we applied it to a soil moisture estimation task using an in-wild raw soil patch dataset [30], captured via cameras. As given in Table 3, we find that modality imbalance occurs in regression tasks as well. We find that G^2D outperforms the baseline method MIS-ME, indicating its effectiveness in multimodal regression tasks.

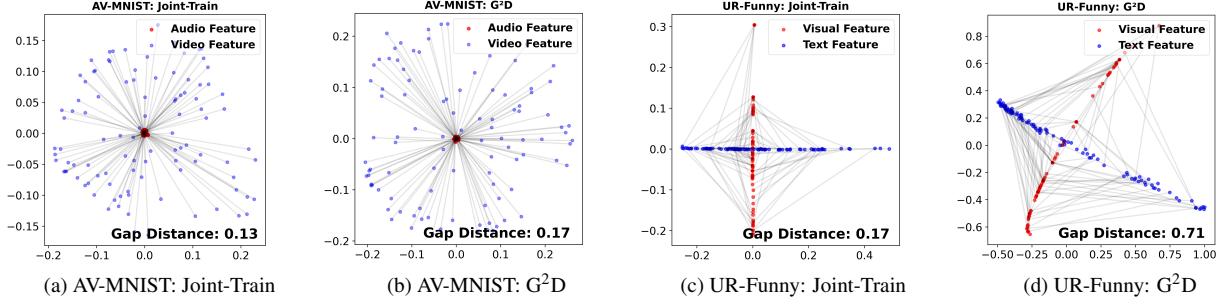


Figure 4. Modality gap for AV-MNIST and UR-Funny datasets, with G^2D increasing the modality separation compared to joint-training.

Table 3. G^2D for Soil Moisture Regression Task on MIS-ME Dataset with *tabular* and *image* Modalities

Metrics	Tabular	Image	Joint-Train	MIS-ME	G^2D
MAPE	15.49	8.22	14.62	<u>7.52</u>	7.01
R^2	0.34	0.76	0.42	<u>0.80</u>	0.82

4.2. Analysis of G^2D

Analyzing Modality Gap. Prior work has shown that multimodal learning leads to distinct modality-specific embeddings, with a larger *modality gap* often correlating with improved performance [25, 35]. Following these insights, we visualize the modality gap in AV-MNIST (audio-visual) and UR-Funny (visual-text) datasets, as shown in Figure 4. Compared to joint-training (Figures 4a and 4c), G^2D (Figures 4b and 4d) results in a more pronounced modality gap, making modalities more distinguishable in the embedding space. This separation is particularly evident in text-inclusive models, facilitating better feature utilization. These results highlight G^2D 's ability to mitigate modality bias and enhance multimodal learning by preserving modality-specific characteristics.

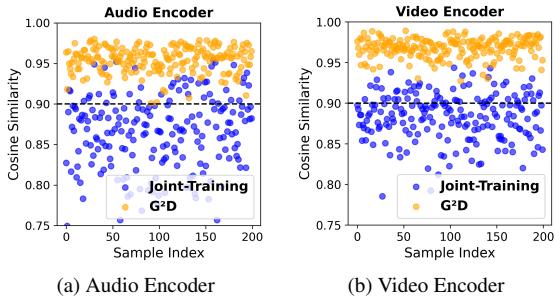


Figure 5. Alignment between unimodal and multimodal features in the audio encoder (Figure 5a) and the video encoder (Figure 5b).

Analyzing Feature Alignment of G^2D . We first analyze the robustness of multimodal features by aligning them with unimodal teacher features for both audio and video

encoders in CREMA-D. In this experiment, we use cosine similarity to measure the feature alignment. With Figure 5a and Figure 5b, we show that the alignment of both modalities between unimodal and multimodal features is consistently higher for the G^2D compared to a simple joint-training without KD. We consider that better feature alignment in G^2D is one of the important factors in improving modality imbalance in multimodal learning.

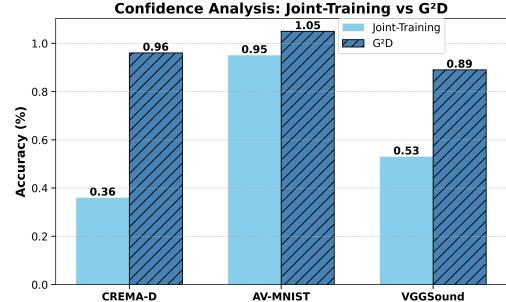


Figure 6. Analyzing Confidence Ratio of Joint-Training with G^2D

Analyzing Modality Imbalance with Confidence Ratio. To quantify the impact of modality imbalance, we compute *confidence ratio* to measure the weaker modality's confidence relative to its unimodal teacher. Specifically, we first compute the average confidence score ρ for the weaker modality across the entire dataset in both joint-training and G^2D . Then, we normalize these values by dividing them by the corresponding unimodal teacher's confidence score. A lower confidence ratio indicates that the weaker modality is overshadowed during training, while a higher ratio suggests that the weaker modality in multimodal setting is reaching its performance close to that of its unimodal setup. As shown in Fig. 6, G^2D consistently yields higher confidence ratios than joint-training, demonstrating its ability to mitigate modality discrepancy by ensuring a more balanced optimization process and preventing weaker modalities from being suppressed in the multimodal training.

Further analysis of G^2D , including distinction from key baselines and computational cost, is in Sec. A.6.

4.3. Ablation Study

Table 4. Effect of SMP on Different Multimodal Methods

Method	SMP	CREMA-D	AV-MNIST	UR-Funny
Joint-Train	✗	67.47	69.77	62.58
	✓	80.78	72.51	63.58
UMT	✗	67.61	72.33	63.38
	✓	82.39	72.68	64.59
G ² D loss	✗	78.63	72.76	63.78
	✓	85.89	73.03	65.49

Impact of SMP. The results in Table 4 demonstrate *two-pronged* observations on SMP with three datasets. (i) SMP integration enhances the performance of both vanilla joint-training and the multimodal KD-based approach UMT. (ii) Incorporating SMP to G²D loss achieves the best overall performance, outperforming all baselines, highlighting its role in mitigating modality imbalance and improving multimodal learning. This confirms the effectiveness and adaptability of SMP, not just in G²D but also in other models.

Table 5. Performance comparison of G²D using different fusion strategies across multiple datasets in terms of accuracy (%).

Fusion	CREMA-D	AV-MNIST	VGGSound	UR-Funny
Sum	81.59	72.70	50.67	63.08
Concat	83.60	<u>72.98</u>	53.40	64.49
FiLM [27]	84.27	72.73	48.11	63.48
BiGated [21]	81.32	72.89	46.66	63.38
Cross-Attention [5]	<u>85.35</u>	72.96	<u>53.58</u>	<u>65.09</u>
Late Fusion [13]	85.89	73.03	53.82	65.49

G²D with Various Fusion Modules. Table 5 compares the effect of different fusion strategies on G²D. Out of the traditional fusion methods used for the modality imbalance problem, *late fusion* consistently achieves the best results. This highlights the effectiveness of leveraging independent unimodal representations while preserving their distinct contributions. However, *Cross-Attention* based fusion closely follows the performance of late fusion, demonstrating its ability to enhance cross-modal interactions by dynamically attending to relevant features. Concat fusion provides strong performance but falls slightly behind Late Fusion. FiLM and BiGated offer adaptive feature integration yet fail to match the top-performing methods. Descriptions of these fusion strategies are in Sec. A.3.

Modality Suppression in G²D. We compare two suppression strategies: partial suppression and complete suppression. Partial suppression follows OGM-GE [26], applying gradient modulation with $1 - \tanh(x)$, where x is the ratio of modality scores. Complete suppression utilizes SMP, which zeroes out gradients of dominant modalities, allowing the suppressed modality to train to convergence. Table 6 shows that complete suppression consistently outperforms partial suppression across all datasets. This im-

Table 6. Partial vs. Complete Modality Suppression in G²D

Type	CREMA-D	AV-MNIST	VGGSound	UR-Funny
Partial	81.99	72.83	51.16	63.68
Complete	85.89	73.03	53.82	65.49

provement arises from SMP’s ability to shift optimization focus toward the suppressed modality, preventing interference and enabling more effective multimodal feature integration. So, complete suppression significantly mitigates modality imbalance and enhances multimodal learning.

Table 7. Effect of τ_j on G²D with two & three modalities

(τ_1, τ_2)	(0,150)	(50,150)	(100,150)	(150,150)
CREMA-D	78.63	82.80	83.74	85.89
(τ_1, τ_2, τ_3)	(0,0,150)	(50,50,150)	(75,75,150)	
IEMOCAP	75.30	76.99	77.19	

Effect of Prioritization Epochs (τ_j). We analyze the impact of τ_j , the hyperparameter controlling the epochs for each SMP stage, in Table 7. For instance, with two modalities ($k = 2$), the schedule (τ_1, τ_2) denotes epochs for training the weakest modality alone, followed by a joint training phase for both. Similarly, for three modalities ($k = 3$), (τ_1, τ_2, τ_3) defines epochs for the weakest alone, then the second weakest alone, and finally a joint phase for all three. The results in Table 7 show that systematically increasing the dedicated epochs for weaker modalities consistently improves G²D’s performance. This finding strongly validates our Hypothesis 1 (Sec. 3.3) that providing weaker modalities with dedicated, interference-free training phases is crucial for mitigating modality imbalance.

Additional ablations are provided in Sec. A.7.

5. Conclusion

In this paper, we presented G²D, a simple but effective novel framework designed to tackle modality imbalance in multimodal learning through gradient-guided distillation and sequential modality prioritization. By fusing unimodal and multimodal learning objectives together with knowledge distillation and utilizing confidence scores from unimodal teachers, G²D dynamically prioritizes weaker modalities. With these contributions, G²D ensures each modality contributes effectively during training without being overshadowed by any dominant modalities. Our experimental results, which span multiple classification datasets and a regression task, illustrate that G²D enhances feature alignment, mitigates modality imbalance, and outperforms existing state-of-the-art methods. We believe that the proposed gradient modulation strategy holds great potential to advance balanced learning in complex multimodal scenarios, paving the way for more inclusive and robust AI systems.

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References

- [1] Ibrahim M. Alabdulmohsin, Xiao Wang, Andreas Steiner, Priya Goyal, Alexander D’Amour, and Xiao-Qi Zhai. Clip the bias: How useful is balancing data in multimodal learning? *ArXiv*, abs/2403.04547, 2024. [4](#)
- [2] Cristian Bucila, Rich Caruana, and Alexandru Niculescu-Mizil. Model compression. In *Knowledge Discovery and Data Mining*, 2006. [2](#)
- [3] Carlos Busso, Murtaza Bulut, Chi-Chun Lee, Abe Kazemzadeh, Emily Mower, Samuel Kim, Jeannette N. Chang, Sungbok Lee, and Shrikanth S. Narayanan. Iemo-cap: interactive emotional dyadic motion capture database. *Language Resources and Evaluation*, 42(4):335–359, 2008. [5, 1](#)
- [4] 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. [1, 5](#)
- [5] Chun-Fu Richard Chen, Quanfu Fan, and Rameswar Panda. Crossvit: Cross-attention multi-scale vision transformer for image classification. In *2021 IEEE/CVF International Conference on Computer Vision (ICCV)*, pages 347–356, 2021. [8, 4](#)
- [6] Honglie Chen, Weidi Xie, Andrea Vedaldi, and Andrew Zisserman. Vggsound: A large-scale audio-visual dataset. In *ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 721–725, 2020. [5, 1](#)
- [7] Chenzhuang Du, Tingle Li, Yichen Liu, Zixin Wen, Tianyu Hua, Yue Wang, and Hang Zhao. Improving multi-modal learning with uni-modal teachers, 2021. [2](#)
- [8] 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. In *Proceedings of the 40th International Conference on Machine Learning*, pages 8632–8656. PMLR, 2023. [1, 2, 3, 5](#)
- [9] Yunfeng Fan, Wenchao Xu, Haozhao Wang, Junxiao Wang, and Song Guo. Pmr: Prototypical modal rebalance for multimodal learning. In *2023 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 20029–20038, 2023. [1, 2, 5, 6](#)
- [10] Yunfeng Fan, Wenchao Xu, Haozhao Wang, Junhong Liu, and Song Guo. Detached and interactive multimodal learning. In *Proceedings of the 32nd ACM International Conference on Multimedia*, page 5470–5478, New York, NY, USA, 2024. Association for Computing Machinery. [3, 4](#)
- [11] 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, 2, 5](#)
- [12] Jianping Gou, Baosheng Yu, Stephen J Maybank, and Dacheng Tao. Knowledge distillation: A survey. In *International Journal of Computer Vision*, pages 1789–1819. Springer, 2021. [2](#)
- [13] H. Gunes and M. Piccardi. Affect recognition from face and body: early fusion vs. late fusion. In *2005 IEEE International Conference on Systems, Man and Cybernetics*, pages 3437–3443 Vol. 4, 2005. [8, 4](#)
- [14] Yangyang Guo, Lijiang Nie, Harry Cheng, Zhiyong Cheng, Mohan S. Kankanhalli, and A. Bimbo. On modality bias recognition and reduction. *ACM Transactions on Multimedia Computing, Communications and Applications*, 19:1 – 22, 2022. [4](#)
- [15] Md Kamrul Hasan, Wasifur Rahman, AmirAli Bagher Zadeh, Jianyuan Zhong, Md Iftekhar Tanveer, Louis-Philippe Morency, and Mohammed (Ehsan) Hoque. UR-FUNNY: A multimodal language dataset for understanding humor. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 2046–2056, Hong Kong, China, 2019. Association for Computational Linguistics. [5, 1](#)
- [16] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 770–778, 2016. [5](#)
- [17] Geoffrey Hinton, Oriol Vinyals, and Jeff Dean. Distilling the knowledge in a neural network. *arXiv preprint arXiv:1503.02531*, 2015. [2, 3](#)
- [18] Cong Hua, Qianqian Xu, Shilong Bao, Zhiyong Yang, and Qingming Huang. Reconboost: Boosting can achieve modality reconciliation. In *The Forty-first International Conference on Machine Learning*, 2024. [1, 2, 5](#)
- [19] 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 *Proceedings of the 39th International Conference on Machine Learning*, pages 9226–9259. PMLR, 2022. [1](#)
- [20] Fushuo Huo, Wenchao Xu, Jingcai Guo, Haozhao Wang, and Song Guo. C2kd: Bridging the modality gap for cross-modal knowledge distillation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2024. [2](#)
- [21] Douwe Kiela, Edouard Grave, Armand Joulin, and Tomas Mikolov. Efficient large-scale multi-modal classification. In *Proceedings of the Thirty-Second AAAI Conference on Artificial Intelligence and Thirtieth Innovative Applications of Artificial Intelligence Conference and Eighth AAAI Symposium on Educational Advances in Artificial Intelligence*. AAAI Press, 2018. [8, 3](#)
- [22] R. Gary Leonard and George R. Doddington. Tidigits. Web Download, 1993. LDC Catalog No.: LDC93S10, ISBN: 1-58563-018-7, ISLRN: 177-353-807-744-3. [1](#)

- [23] 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 (ICCV)*, pages 22214–22224, 2023. 1, 2, 4, 5
- [24] Junnan Li, Ramprasaath Selvaraju, Akhilesh Gotmare, Shafiq Joty, Caiming Xiong, and Steven Hoi. Align before fuse: Vision and language representation learning with momentum distillation. In *Advances in Neural Information Processing Systems*, pages 9694–9705, 2020. 2
- [25] Victor Weixin Liang, Yuhui Zhang, Yongchan Kwon, Serena Yeung, and James Y Zou. Mind the gap: Understanding the modality gap in multi-modal contrastive representation learning. *Advances in Neural Information Processing Systems*, 35:17612–17625, 2022. 7
- [26] 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, 4, 5, 8
- [27] Ethan Perez, Florian Strub, Harm de Vries, Vincent Dumoulin, and Aaron Courville. Film: visual reasoning with a general conditioning layer. In *Proceedings of the Thirty-Second AAAI Conference on Artificial Intelligence and Thirtieth Innovative Applications of Artificial Intelligence Conference and Eighth AAAI Symposium on Educational Advances in Artificial Intelligence*. AAAI Press, 2018. 8, 3
- [28] Karol J. Piczak. ESC: Dataset for Environmental Sound Classification. In *Proceedings of the 23rd Annual ACM Conference on Multimedia*, pages 1015–1018. ACM Press. 1
- [29] Gorjan Radevski, Zhipeng Luo, Yifei Zhu, Luc Van Gool, and Dengxin Dai. Multimodal distillation for egocentric action recognition. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 12123–12133, 2023. 2
- [30] Mohammed Rakib, Adil Aman Mohammed, D. Cole Diggin, Sumit Sharma, Jeff Michael Sadler, Tyson Ochsner, and Arun Bagavathi. Mis-me: A multi-modal framework for soil moisture estimation, 2024. 5, 6
- [31] Mark Sandler, Andrew Howard, Menglong Zhu, Andrey Zhmoginov, and Liang-Chieh Chen. Mobilenetv2: Inverted residuals and linear bottlenecks. In *Proceedings of the IEEE CVPR*, pages 4510–4520, 2018. 5
- [32] Ya Sun, Sijie Mai, and Haifeng Hu. Learning to balance the learning rates between various modalities via adaptive tracking factor. *IEEE Signal Processing Letters*, 28:1650–1654, 2021. 1
- [33] Yonglong Tian, Dilip Krishnan, and Phillip Isola. Contrastive representation distillation. In *International Conference on Learning Representations*, 2020. 2
- [34] Luan Tran, Xiaoming Liu, Jiayu Zhou, and Rong Jin. Missing modalities imputation via cascaded residual autoencoder. In *In Proceeding of IEEE Computer Vision and Pattern Recognition*, Honolulu, HI, 2017. 5
- [35] Vishaal Udandarao. *Understanding and Fixing the Modality Gap in Vision-Language Models*. Phd thesis, University of Cambridge, 2022. 7
- [36] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. In *Advances in Neural Information Processing Systems*. Curran Associates, Inc., 2017. 5
- [37] Valentin Vielzeuf, Alexis Lechervy, Stéphane Pateux, and Frédéric Jurie. Centralnet: A multilayer approach for multimodal fusion. In *Computer Vision – ECCV 2018 Workshops: Munich, Germany, September 8–14, 2018, Proceedings, Part VI*, page 575–589, Berlin, Heidelberg, 2019. Springer-Verlag. 5, 1
- [38] Hu Wang, Congbo Ma, Jianpeng Zhang, Yuan Zhang, Jodie Avery, Louise Hull, and Gustavo Carneiro. Learnable cross-modal knowledge distillation for multi-modal learning with missing modality. In *Medical Image Computing and Computer Assisted Intervention – MICCAI 2023: 26th International Conference, Vancouver, BC, Canada, October 8–12, 2023, Proceedings, Part IV*, page 216–226, Berlin, Heidelberg, 2023. Springer-Verlag. 2
- [39] 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, 4
- [40] Yake Wei and Di Hu. Mmpareto: Boosting multimodal learning with innocent unimodal assistance, 2024. 1, 2, 5
- [41] Yake Wei, Siwei Li, Ruoxuan Feng, and Di Hu. Diagnosing and re-learning for balanced multimodal learning. In *Computer Vision – ECCV 2024: 18th European Conference, Milan, Italy, September 29–October 4, 2024, Proceedings, Part LXIV*, page 71–86, Berlin, Heidelberg, 2024. Springer-Verlag. 2
- [42] 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, 6
- [43] Hongwei Xu, Goutham Ghosh, Po-Yao Huang, Dmytro Okhonko, Armen Aghajanyan, Florian Metze, Luke Zettlemoyer, and Christoph Feichtenhofer. Multimodal-cop: Self-supervised vision-language pre-training with auxiliary tasks. *arXiv preprint arXiv:2107.07773*, 2021. 2
- [44] Zihui Xue, Zhengqi Gao, Sucheng Ren, and Hang Zhao. The modality focusing hypothesis: Towards understanding cross-modal knowledge distillation. In *International Conference on Learning Representations*, 2023. 2
- [45] Yang Yang, Fengqiang Wan, Qing-Yuan Jiang, and Yi Xu. Facilitating multimodal classification via dynamically learning modality gap. In *Advances in Neural Information Processing Systems*, pages 62108–62122. Curran Associates, Inc., 2024. 1, 2, 5, 3
- [46] 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, 2022. 1, 2, 5
- [47] Yuan Yuan et al. Multiscale knowledge distillation with attention based fusion for robust human activity recognition. *Scientific Reports*, 14:63195, 2024. 2

- [48] Jiandian Zeng, Jiantao Zhou, and Tianyi Liu. Robust multi-modal sentiment analysis via tag encoding of uncertain missing modalities. *Trans. Multi.*, 25:6301–6314, 2023. 5
- [49] Changqing Zhang, Yajie Cui, Zongbo Han, Joey Tianyi Zhou, Huazhu Fu, and Qinghua Hu. Deep partial multi-view learning. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 44(5):2402–2415, 2022. Epub 2022 Apr 1. 5
- [50] Qingsyang Zhang, Haitao Wu, Changqing Zhang, Qinghua Hu, Huazhu Fu, Joey Tianyi Zhou, and Xi Peng. Provable dynamic fusion for low-quality multimodal data. In *Proceedings of the 40th International Conference on Machine Learning*. JMLR.org, 2023. 1, 2
- [51] Xiaohui Zhang, Jaehong Yoon, Mohit Bansal, and Huaxiu Yao. Multimodal representation learning by alternating unimodal adaptation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 27456–27466, 2024. 1, 2, 5
- [52] Yedi Zhang, Peter E. Latham, and Andrew M. Saxe. A theory of unimodal bias in multimodal learning. *ArXiv*, abs/2312.00935, 2023. 4
- [53] Jinming Zhao, Ruichen Li, and Qin Jin. Missing modality imagination network for emotion recognition with uncertain missing modalities. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 2608–2618, Online, 2021. Association for Computational Linguistics. 5
- [54] Daoming Zong, Chaoyue Ding, Baoxiang Li, Jiakui Li, and Ken Zheng. Balancing multimodal learning via online logit modulation. In *Proceedings of the Thirty-Third International Joint Conference on Artificial Intelligence, IJCAI-24*, pages 5753–5761, 2024. 1

G²D: Boosting Multimodal Learning with Gradient-Guided Distillation

Supplementary Material

A. Appendix

A.1. Detailed Dataset Description

A.1.1. Crowd-sourced Emotional Multimodal Actors Dataset (CREMA-D) [4]

CREMA-D is a multimodal dataset designed for emotion recognition research. It contains audio-visual recordings of actors portraying a variety of emotional states, including Anger, Disgust, Fear, Happy, Neutral, and Sad. The dataset features actors from diverse racial and ethnic backgrounds, covering a wide age range, which makes it suitable for studying the interplay between audio and visual emotional expressions. Ratings for emotional intensity and accuracy were gathered from crowd-sourced participants. The dataset is divided into a training set of 6,027 samples, a validation set of 669 samples, and a test set of 745 samples, facilitating robust model training and evaluation.

A.1.2. Audio Visual MNIST (AV-MNIST) [37]

AV-MNIST is a synthetic multimodal dataset designed for audio-visual digit classification. It combines visual MNIST digit images, downsampled using PCA to retain 25% of their original energy, with audio samples of spoken digits from the TIDigits dataset [22]. The audio samples are represented as 112×112 spectrograms and are augmented with noise from the ESC-50 dataset [28]. The dataset consists of 70,000 audio-visual pairs, including 55,000 for training, 10,000 for testing, and 5,000 selected from the training set for validation.

A.1.3. VGGSound [6]

VGGSound is a large-scale audio-visual dataset designed for training and evaluating audio recognition models. It consists of over 200,000 video clips sourced from YouTube, each containing audio-visual correspondence where the sound source is visually present in the video. The dataset includes 310 diverse classes covering various real-world environments, such as people, animals, music, and nature. Each clip is 10 seconds long, ensuring both the audio and visual elements are aligned, making it ideal for audio-visual learning tasks.

A.1.4. UR-Funny [15]

UR-FUNNY is a multimodal dataset created for the task of humor detection, utilizing text, visual gestures, and prosodic acoustic cues. The dataset comprises 1,866 video clips collected from TED Talks featuring diverse speakers and covering 417 different topics. Each clip is labeled with binary humor annotations, with an equal number of humorous and non-humorous samples, ensuring a balanced dataset.

The multimodal nature of UR-FUNNY makes it particularly suitable for investigating the relationships among different modalities, offering insights into how text, vision, and audio can jointly contribute to understanding humor in a multimodal learning context.

A.1.5. IEMOCAP [3]

The Interactive Emotional Dyadic Motion Capture (IEMOCAP) dataset is a widely used resource for emotion recognition, containing approximately 12 hours of audio-visual data from ten actors engaged in scripted and improvised dyadic conversations to elicit a range of authentic emotions. The dataset is rich in modalities, providing synchronized video, speech, facial motion capture data, and text transcriptions. Each utterance is annotated by multiple raters for both categorical emotions and dimensional attributes (valence, arousal, and dominance), making it suitable for diverse and nuanced modeling tasks. Due to its naturalistic dyadic interactions, IEMOCAP serves as a benchmark for developing emotion-aware conversational AI and understanding complex multimodal emotional cues.

A.2. Details on Baselines

A.2.1. Modality-Specific Early Stopping (MSES) [11]

MSES is a multimodal learning approach that aims to prevent overfitting by independently managing the learning rate for each modality. Within the MSES framework, each modality's classifier is treated as a separate task, and early stopping is employed when a modality begins to overfit, while others continue to learn. By formulating a multi-task setup, MSES allows for the independent regulation of modality-specific learning progress, ensuring that the stronger modalities do not overshadow the weaker ones during joint training. This method effectively prevents overfitting by identifying and stopping learning for modalities when their validation loss fails to improve, thereby maximizing balanced contributions from each modality and enhancing the overall multimodal learning process.

A.2.2. Modality-Specific Learning Rate (MSLR) [46]

MSLR aims to optimize multimodal late-fusion models by assigning unique learning rates to each modality instead of using a single global learning rate. This approach helps prevent the vanishing gradients issue that can occur when learning rates are not tailored to the specific characteristics of each modality. By assigning modality-specific learning rates, MSLR ensures that each modality contributes effectively to the learning process, ultimately improving the overall performance of the multimodal model.

A.2.3. Adaptive Gradient Modulation (AGM) [23]

AGM addresses modality competition in multimodal models by modulating the participation level of each modality during training. Inspired by Shapley value-based attribution and the OGM-GE algorithm, AGM isolates the contribution of individual modalities and modulates their gradient update intensity accordingly, allowing stronger modalities to be suppressed while amplifying weaker ones. This adaptive strategy applies to all types of fusion architectures, thereby boosting the overall model performance by ensuring a balanced contribution from each modality and mitigating dominance effects that lead to suboptimal joint training outcomes.

A.2.4. Prototypical Modality Rebalance (PMR) [9]

PMR tackles the "modality imbalance" issue by applying different learning strategies to each modality to ensure more balanced learning. Specifically, PMR uses prototypical cross-entropy (PCE) loss to accelerate the slow-learning modality, allowing it to align more closely with prototypical representations, while also reducing the inhibition from dominant modalities via prototypical entropy regularization (PER). The method effectively exploits features of each modality independently and helps prevent one modality from dominating the learning process, thereby enhancing overall multimodal learning performance.

A.2.5. On-the-fly Gradient Modulation with Generalization Enhancement (OGM-GE) [26]

OGM-GE addresses the issue of under-optimization for specific modalities in multimodal learning by dynamically modulating gradient contributions for each modality. This approach balances the learning pace by modulating gradients of modality-specific coefficients during backpropagation, reducing the dominance of stronger modalities and facilitating better feature exploitation of weaker ones. Additionally, OGM-GE incorporates a generalization enhancement mechanism, adding dynamic Gaussian noise to improve model generalization.

A.2.6. Multimodal Learning with Alternating Unimodal Adaptation (MLA) [51]

MLA addresses the issue of modality dominance by alternating the training focus between modalities rather than using conventional joint optimization. This alternating unimodal adaptation helps avoid interference between modalities, allowing each to reach its full potential while still maintaining cross-modal interactions through a shared head. A gradient modification mechanism is introduced to mitigate "modality forgetting," thereby preserving cross-modal information learned during previous iterations. At inference, MLA integrates multimodal information dynamically, using uncertainty-based fusion to manage imbalance across modality-specific contributions effectively.

A.2.7. MMPareto: Boosting Multimodal Learning with Innocent Unimodal Assistance [40]

MMPareto aims to enhance multimodal learning by addressing the gradient conflict that arises between unimodal and multimodal learning objectives. The algorithm uses Pareto integration to align gradient directions across objectives, ensuring a final gradient that benefits all modalities without compromising any. By balancing gradient direction and boosting gradient magnitude, MMPareto improves generalization, providing "innocent unimodal assistance" to enhance the performance of each modality while maintaining the consistency of multimodal learning.

A.2.8. On Uni-Modal Feature Learning in Supervised Multi-Modal Learning (UMT) [8]

This paper addresses the problem of insufficient learning of unimodal features in multi-modal learning. The proposed framework consists of two approaches: Uni-Modal Teacher (UMT) and Uni-Modal Ensemble (UME). UMT distills unimodal pre-trained features into a multi-modal model during late-fusion training, ensuring that the representations learned for each modality are preserved effectively while maintaining cross-modal interactions. UME, on the other hand, avoids cross-modal interactions by combining the predictions from unimodal models directly, thus preventing negative interference. To decide which approach to use, they employ an empirical trick explained in the paper. In our experiments, we compare against UMT due to its use of knowledge distillation (KD), which aligns with our proposed approach.

A.2.9. ReconBoost: Boosting Can Achieve Modality Reconciliation [18]

ReconBoost introduces a modality-alternating learning paradigm to mitigate modality competition in multimodal learning. Instead of optimizing all modalities simultaneously, ReconBoost updates each modality separately, ensuring that weaker modalities are not overshadowed by stronger ones. A KL-divergence-based reconciliation regularization is incorporated to maximize diversity between current and past updates, aligning the method with gradient-boosting principles. Unlike traditional boosting, ReconBoost only retains the most recent learner per modality, preventing overfitting and excessive reliance on strong modalities. Additionally, it integrates a memory consolidation regularization to preserve historical modality-specific information and a global rectification scheme to refine joint optimization. Empirical results across multiple benchmarks demonstrate that ReconBoost effectively reconciles modality learning dynamics, leading to improved multimodal fusion performance.

A.2.10. Facilitating Multimodal Classification via Dynamically Learning Modality Gap (DLMG) [45]

DLMG addresses the modality imbalance problem in multimodal learning by focusing on disparities in category label fitting across different modalities. Unlike prior methods that primarily regulate learning rates or gradient contributions, DLMG leverages contrastive learning to align modality representations and reduce dominance effects. The approach dynamically integrates supervised classification loss and contrastive modality matching loss through either a heuristic strategy or a learning-based optimization strategy that adjusts their relative importance during training. By progressively refining modality alignment while maintaining label supervision, DLMG minimizes performance gaps between dominant and non-dominant modalities, leading to a more balanced and effective multimodal learning process.

A.2.11. Detached and Interactive Multimodal Learning (DI-MML) [10]

DI-MML proposes that modality competition is a direct result of the uniform learning objective used in traditional joint training frameworks. To eliminate this competition, DI-MML proposes a detached learning framework where each modality’s encoder is trained separately with its own isolated learning objective. To enable cross-modal interaction without reintroducing competition, the framework employs two key strategies: (1) a shared classifier is used to align features from different modalities into a common embedding space, and (2) a novel Dimension-decoupled Unidirectional Contrastive (DUC) loss is introduced. The DUC loss identifies “effective” and “ineffective” feature dimensions within each modality and then transfers knowledge unidirectionally from the effective dimensions of one modality to the corresponding ineffective dimensions of another. This strategy facilitates the exchange of complementary information while preserving the integrity of each modality’s well-learned features.

A.3. Details on Fusion Techniques

A.3.1. Summation

Summation fusion is a straightforward multimodal integration technique where features from multiple modalities are combined through element-wise addition. Each modality contributes independently, and their respective representations are directly summed without any complex cross-modal interactions. In this approach, the output of each modality-specific encoder is first processed by a fully connected layer to generate unimodal predictions, which are then added together to form a unified representation. This combined output is used to compute a loss, which subsequently updates all components involved, including the encoders and the fully connected layers. Summation fusion’s

strength lies in its simplicity and ease of implementation, as it does not require intricate fusion mechanisms. However, it does not explicitly capture inter-modal relationships, potentially limiting its effectiveness in scenarios where richer cross-modal interactions are beneficial.

A.3.2. Concatenation

Concatenation fusion is a common strategy for integrating information from different modalities by concatenating their feature vectors along a specified axis. This method combines feature representations directly, allowing the model to consider information from all modalities together as a single, extended vector. Despite enabling joint perception of multimodal data, it does not explicitly model cross-modal interactions. The concatenated features are passed through a fully connected layer, where the input size equals the sum of all encoder output dimensions, and the output size matches the number of classes. During training, the model uses the resulting fusion output to compute the loss and update all the involved parameters, including those of the individual encoders and the fully connected layer. Concatenation fusion is effective in creating a unified feature representation, but it relies on subsequent layers to extract and learn any interactions between the modalities.

A.3.3. Feature-wise Linear Modulation (FiLM) [27]

FiLM is a sophisticated fusion method that integrates information from multiple modalities by adjusting feature representations in one modality according to the information from another. This modulation approach uses conditional inputs to produce parameters that scale and shift feature activations, enabling the model to dynamically adjust its processing based on context. FiLM works by passing the conditioning modality through a layer that outputs these modulation parameters, which then directly adjust the target modality’s features before they proceed to the next layers in the model. By providing targeted feature modulation, FiLM helps capture cross-modal nuances and allows the model to be more adaptive in multimodal learning tasks that require context-sensitive adjustments.

A.3.4. BiLinear Gated Fusion (BiGated) [21]

BiGated fusion combines bilinear pooling and gating mechanisms to enhance the integration of multiple modalities by capturing their complex interactions. This technique explicitly models cross-modal relationships, providing a more expressive and fine-grained fusion strategy compared to simpler approaches like concatenation or summation. In BiGated fusion, each modality passes through its own fully connected layer, much like summation. However, what sets BiGated apart is its use of a gating mechanism—one modality’s hidden state is processed through an activation function (we use sigmoid) to generate a gated weight, which is then used to modulate the contributions of other modalities. This

approach ensures that each modality can dynamically influence how other modalities are represented in the fusion process, allowing for a richer and more adaptive multimodal representation before proceeding to the final classification layers.

A.3.5. Cross-Attention Fusion [5]

Cross-attention fusion enables the dynamic and adaptive integration of multiple modalities by allowing each modality to attend to others through bidirectional or all-directional attention mechanisms. This approach explicitly models inter-modal dependencies, ensuring that each modality can selectively focus on the most relevant features from others. In our implementation, for two-modal cases, modality X attends to modality Y and vice versa, refining their representations based on mutual interactions. For three-modal scenarios, all-directional attention is applied, where each modality interacts not only with one other but also with the third, ensuring comprehensive multimodal integration. The attended representations are normalized to enhance stability and mitigate potential imbalances in feature contributions. Finally, the refined features from all modalities are projected into a unified representation through a fully connected layer. This mechanism effectively captures nuanced cross-modal relationships, allowing the model to leverage complementary modality-specific information for robust multimodal learning.

A.3.6. Late Fusion [13]

Late fusion technique involves independently processing each modality through its respective model or encoder, followed by combining the outputs at a later stage to produce the final prediction. This approach allows each modality to be modeled and optimized in isolation, maintaining the unique properties of each data source. However, it may miss opportunities to exploit early cross-modal interactions that could provide additional benefits during feature learning. In late fusion, each modality-specific encoder is followed by its own fully connected layer, which is trained solely on that modality’s data. The fusion output is computed by averaging the outputs of all unimodal models, ensuring that the fusion occurs only after independent learning is complete. This independence provides flexibility and robustness, especially in scenarios where some modalities may be missing, but limits the ability to deeply integrate multimodal relationships early in the learning process.

A.4. Details on Experimental Setups

A.4.1. Model Architectures

ResNet-18 ResNet-18, a convolutional neural network with 18 layers, belongs to the ResNet family and is renowned for addressing the vanishing gradient problem through residual connections. These residual connections

allow information to bypass some layers, which helps stabilize training even in deeper networks. In our experiments, we use ResNet-18 as an encoder for both audio and video modalities across CREMA-D, AV-MNIST, and VGGSound datasets. We used a specific weight initialization strategy: Xavier normal for fully connected layers, Kaiming normal for convolutional layers, and constant initialization for batch normalization layers, which facilitated an effective starting point for network training and ensured stable convergence across multimodal tasks.

Transformer Transformers are powerful architectures designed for handling sequential data and capturing long-range dependencies through self-attention mechanisms. In our implementation, we employ Transformers as encoders for the audio, video, and text modalities of the UR-Funny and IEMOCAP dataset. Following the approach described in [23], we utilized a 4-layer Transformer encoder with eight attention heads and a hidden dimension of 768 for each modality in the UR-Funny and IEMOCAP dataset. Input features were projected to a 768-dimensional embedding using a convolutional layer, ensuring consistency across different modalities. We employed a similar initialization strategy to ResNet-18 to facilitate stable training.

A.4.2. Hyperparameters

We trained our models on 1 Nvidia A10 GPU with a batch size of 16 using the SGD optimizer, with a momentum of 0.9 and a weight decay of 1×10^{-4} . We initialized the learning rate at 0.001 and decayed it by a ratio of 0.1 every 200 epochs. For all experiments, we set the random seed to 999 for reproducibility. We defined the G²D loss function as a weighted sum of student loss, feature loss, and logit loss, where α and β are weighting coefficients for the feature loss and logit loss, respectively. We set both α and β to 1.0 for all datasets. Additionally, for the logit loss, we used a temperature of 1.0 in the KL Divergence without further softening, effectively utilizing hard logits for the training process.

A.5. Comparison of G²D with DI-MML

In response to reviewer feedback, we provide an additional comparison against the state-of-the-art baseline DI-MML [10]. As shown in Table 8, G²D outperforms DI-MML on both the CREMA-D and AV-MNIST datasets. This result further validates the effectiveness of G²D in relation to current leading methods in the field.

Table 8. Comparing G²D with DI-MML

Method	Joint-Train	DI-MML	G ² D
CREMA-D	67.47	83.51	85.89
AV-MNIST	69.77	71.35	73.03

Table 9. Comparing Components of G²D with UMT & OGM-GE

Method	Joint-Train	UMT	G ² D Loss	OGM-GE	SMP	G ² D (SMP + G ² D Loss)
CREMA-D	67.47	67.61	78.63	72.18	80.78	85.89
AV-MNIST	69.77	72.33	72.76	71.08	72.51	73.03

A.6. Further Analysis of G²D

A.6.1. Distinction of G²D from UMT and OGM-GE

The primary novelty of G²D arises from its unique *G²D loss* and its Sequential Modality Prioritization (SMP) technique, and critically, from their synergistic combination.

Our *G²D loss* improves upon the distillation strategy of UMT [8] by incorporating a KL divergence-based logit loss. This addition is crucial for enabling the student model to learn the nuanced inter- and intra-class relationships captured by the unimodal teachers’ soft logits.

Furthermore, our SMP technique is fundamentally different from the gradient modulation in OGM-GE [26] in two principal ways:

1. **Guidance for Modulation:** OGM-GE calculates modality confidence from the student’s own encoders during training. This signal can be noisy and unreliable, especially in early stages. In contrast, SMP leverages stable confidence scores from *pre-trained unimodal teachers*, providing a more robust and accurate signal to identify weaker modalities automatically.
2. **Suppression Mechanism:** OGM-GE uses functions like $1 - \tanh(\cdot)$ to only *partially* suppress dominant modalities, meaning they continue to train simultaneously and modality competition can persist. SMP enforces a *complete gradient shutdown* for non-prioritized modalities. This ensures that the prioritized weak modality trains in true isolation, more effectively mitigating interference from dominant modalities.

The results in Table 9 validate these distinctions, showing that the *G²D loss* alone surpasses UMT, SMP alone surpasses OGM-GE, and their combination yields the best overall performance.

A.6.2. Synergy of Distillation and Sequential Modality Prioritization

The motivation for integrating our *G²D loss* (via KD) with SMP is to address the limitations of using either technique alone. The distillation component leverages unimodal teachers—trained in isolation—to provide the student with stable, competition-free feature and logit targets. This guides the student towards more balanced representations than learning solely from GT labels amidst modality competition.

However, even with this guidance, the student’s modality encoders are still optimized simultaneously, which allows modality imbalance to persist. SMP is introduced to

Table 10. Single-Batch Resource Metrics on CREMAD

Method	Total Memory (MB)	Total Execution Time (ms)
Joint-Train	12.1366 MB	4531.8
G ² D	12.1998 MB	4539.8

solve this. The crucial *synergy* lies in the fact that during the isolated training phases enforced by SMP, the prioritized weak modality learns not only from the ground-truth labels but also from the rich, interference-free knowledge distilled from its unimodal teacher via the *G²D loss*. This focused, dual-signal learning in an isolated context enables the robust development of weaker modalities. By combining SMP with our distillation objective, G²D mitigates modality imbalance more thoroughly and effectively than using either technique independently.

A.6.3. Computational Cost

The training overhead of G²D is negligible, and there is no additional overhead during inference. This efficiency stems from the framework’s design: unimodal teacher models are pre-trained, and their outputs (e.g., logits and features) are saved. During the multimodal student model’s training, these pre-computed outputs are loaded from disk per batch in a process analogous to loading the dataset itself. As quantified in Table 10, for a typical 16-sample batch, G²D requires only $\approx 0.5\%$ more memory and adds merely $\approx 0.15\%$ to the execution time compared to a standard joint-training baseline. Therefore, in resource-constrained environments, if a traditional joint-training model is feasible, G²D is also readily viable by performing the one-time teacher training first and then training the student.

A.7. Additional Ablation Studies

A.7.1. Learning with Missing Modalities

To evaluate the robustness of G²D with incomplete data, we conduct experiments on the IEMOCAP dataset with randomly missing modalities, generating miss rate masks from 0% to 60% following the setup in MLA [51]. As demonstrated in Table 11, G²D consistently outperforms several state-of-the-art methods designed specifically for this task across all tested rates. This superior performance, even as data becomes highly sparse, suggests that by mitigating modality imbalance and fostering well-rounded representations, our framework learns more resilient features that are

Table 11. G²D vs. Missing Modality Methods on IEMOCAP

Miss Rate	Joint-Train	CRA [34]	MMIN [53]	CPM-Net [49]	TATE [48]	G ² D
0%	75.51	76.21	74.94	58.00	69.92	77.19
20%	69.06	67.34	69.36	53.65	63.22	71.49
40%	61.09	57.04	63.30	51.01	60.36	65.10
60%	52.41	43.22	57.52	47.38	57.99	61.50

less dependent on any single data source, making it inherently more robust when modalities are unavailable.

Table 12. Effect of α and β in G²D with SMP

Dataset	(α, β) weights						
	(0, 0)	(0.25, 0.75)	(0.5, 0.5)	(0.75, 0.25)	(1, 0)	(0, 1)	(1, 1)
CREMA-D	80.78	84.41	<u>84.95</u>	84.81	82.39	84.68	85.89
UR-Funny	63.58	64.79	64.29	64.29	64.59	64.69	65.49

A.7.2. Effect of α and β in G²D.

α and β denote the weighting coefficients of feature loss and logit loss, respectively in the proposed G²D loss. Table 12 evaluates the effect of changing the weightage of feature loss and logit loss on G²D. Assigning full weight to both losses ($\alpha = 1, \beta = 1$) yields the best overall performance, highlighting their combined importance in multimodal learning. In contrast, removing both losses ($\alpha = 0, \beta = 0$) significantly reduces performance, confirming their necessity. While different weight combinations impact results, incorporating both losses with higher weight leads to greater improvements across datasets.