Learning Cross-Modal Retrieval with Noisy Labels

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Abstract

Recently, cross-modal retrieval is emerging with the help of deep multimodal learning. However, even for unimodal data, collecting large-scale well-annotated data is expensive and time-consuming, and not to mention the additional challenges from multiple modalities. Although crowd-sourcing annotation, e.g.*, Amazon's Mechanical Turk, can be utilized to mitigate the labeling cost, but leading to the unavoidable noise in labels for the non-expert annotating. To tackle the challenge, this paper presents a general Multimodal Robust Learning framework (MRL) for learning with multimodal noisy labels to mitigate noisy samples and correlate distinct modalities simultaneously. To be specific, we propose a Robust Clustering loss (RC) to make the deep networks focus on clean samples instead of noisy ones. Besides, a simple yet effective multimodal loss function, called Multimodal Contrastive loss (MC), is proposed to maximize the mutual information between different modalities, thus alleviating the interference of noisy samples and cross-modal discrepancy. Extensive experiments are conducted on four widely-used multimodal datasets to demonstrate the effectiveness of the proposed approach by comparing to 14 state-of-the-art methods.*

1. Introduction

With rapid growth of multimedia data, cross-modal retrieval becomes a compelling topic in the multimodal learning community due to its flexibility in retrieving semantically relevant samples across distinct modalities, *e.g.*, image query text [6, 16]. However, most existing methods require clean-annotated training data, which are expensive and time-consuming. Although some unsupervised multimodal learning methods can mitigate such labeling pressure, their performance is usually much worse than the supervised counterparts' [60]. To balance performance and labeling cost, semi-supervised multimodal learning methods are proposed to simultaneously utilize labeled and unlabeled data to learn common discriminative representations [61, 17]. However, semi-supervised approaches still require a certain number of clean-annotated data to reach reasonable performance.

To alleviate the high labeling cost, some non-expert sources, *e.g.*, Amazon's Mechanical Turk and the surrounding tags of collected data, can be used to annotate large-scale data, but resulting in unavoidable noise in labels [48]. Some recent unimodal studies reveal that DNNs easily overfit to noisy labels leading to poor generalization performance [59, 28]. It is challenging to learn with noisy labels. To tackle the challenge, numerous studies are conducted to explore how to robustly learn with noisy labels, such as correction methods [49, 9], MentorNet [19, 58], and Co-teaching [10]. Although they achieve promising performance in the unimodal scenario, they cannot simultaneously tackle multiple modalities, such as real-world multimedia data. Hence, it is significant and valuable to explore how to learn satisfactory representations from multimodal data with noisy labels, but which is rarely touched in previous works.

We perform an empirical study of recent cross-modal learning methods under noisy labels with results shown in Figure 2. From the figure, one can see that the networks will fast overfit to the noisy training set with a widely-used loss function cross-entropy [50, 53] in multimodal learning. Moreover, different modalities exist a large diversity in validation set since they may lay in completely different spaces with heterogeneity, making learning from noisy samples more difficult. Lastly, noisy labels can confuse the discriminative connections across distinct modalities, resulting in difficulty bridging the heterogeneous gap. Thus, it is more challenging and complex to consider both noisy labels and cross-modal discrepancy simultaneously.

To address the aforementioned problems, we propose a Multimodal Robust Learning framework (MRL) to simultaneously mitigate the influence of noisy samples and narrow the heterogeneous gap in this paper. The pipeline of the proposed method is shown in Figure 1 wherein our

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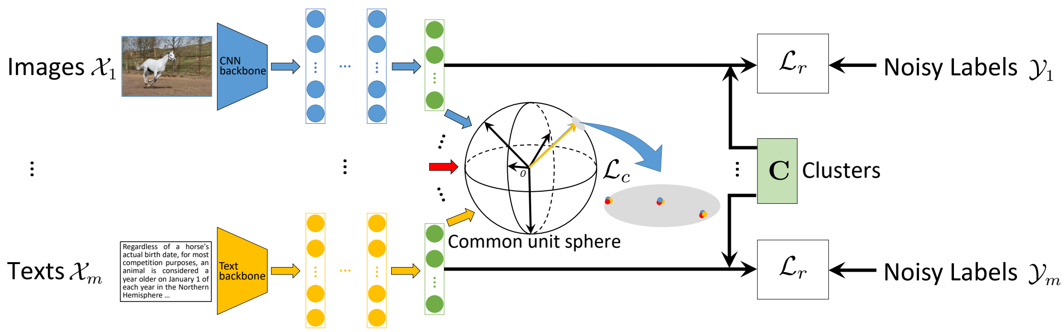
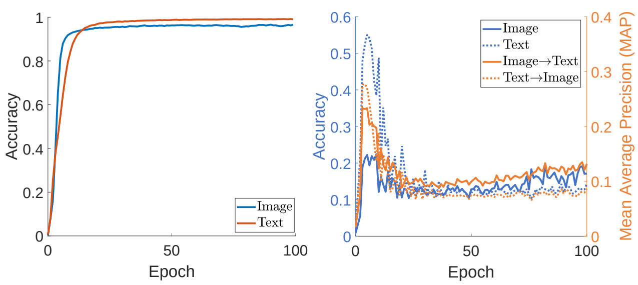


Figure 1: The pipeline of the proposed method for m modalities, *e.g.*, images $\mathcal{X}_1$ with noisy labels $\mathcal{Y}_1$, and texts $\mathcal{X}_m$ with noisy labels $\mathcal{Y}_m$. The modality-specific networks learn common representations for m different modalities. The Robust Clustering loss $\mathcal{L}_r$ is adopted to mitigate the noise in labels for learning discrimination and narrow the heterogeneous gap. The outputs of networks interact with each other to learn common representations by using instance- and pair-level contrast, *i.e.*, multimodal contrastive learning ($\mathcal{L}_c$), thus further mitigating noisy labels and cross-modal discrepancy. $\mathcal{L}_c$ tries to maximally scatter inter-modal samples while compacting intra-modal points over the common unit sphere/space.



(a) (b)

Figure 2: Training with Cross-Entropy loss (CE) [53] on INRIA-Websearch [23] under 0.6 symmetric noise. (a) Accuracy *vs*. epoch on the training set of INRIA-Websearch for the image modality and the text modality, respectively. (b) Accuracy/MAP *vs*. epoch on the validation set of INRIA-Websearch. Accuracy is utilized to evaluate the classification performance on the individual modality. Mean Average Precision (MAP) is adopted to evaluate the retrieval performance across different modalities, *i.e.*, image query text (Image → Text) and text query image (Text → Image). From the figure, we can see that noisy labels will make the multimodal learning overfit on the noisy training set while corrupting performance on the validation set.

method consists of multiple modality-specific networks and two novel losses: Robust Clustering (RC) and Multimodal Contrastive (MC) losses. To be specific, we present a novel common clustering loss to alleviate traditional classification loss functions (*e.g.*, cross-entropy) overfitting to noisy labels with a common classifier. From the previous studies [2, 10, 3], clean samples are easier for learning than noisy/incorrect samples, and leading to faster learning and lower loss for clean samples. This similar phenomenon can be observed in Figure 2, wherein the networks can faster learn clean samples and achieve a certain accuracy but decreasing the performance with the interference of noisy samples after further training. To distract the attention of deep networks from noisy samples to clean ones, our RC automatically weakens the influence of minor losses, which are more likely to be produced by noisy samples, for alleviating the interference of noisy labels, thus embracing more robustness. In addition to mitigating noisy samples, RC also can narrow the heterogeneous gap by projecting different modalities into a common clustering space. Besides, inspired by recent unimodal contrastive learning works [54, 4], we propose a simple yet effective multimodal loss function, termed Multimodal Contrastive loss (MC), to simultaneously maximize the inter-instance and inter-pair variances in the intra- and inter-modalities. Different from previous contrastive learning methods, our MC maximizes the mutual information between intrinsically co-occurred modalities, which can further narrow the heterogeneous gap across distinct modalities while excavating the discrimination from instance-level contrasting. Hence, our MC can further mitigate the interference of noisy samples by contrasting their inter- and intra-modal counterparts with an unsupervised manner.

The main novelties and contributions of this work are summarized as follows:

- We propose a novel framework for cross-modal retrieval with noisy labels. It can robustly learn the common discriminative representations from noisy labels by using both supervised and unsupervised manners.
- We present a Robust Clustering loss (RC) that improves robustness and narrows the cross-modal gap on noisy samples simultaneously.

- A novel multimodal contrastive loss is proposed to maximize the inter-instance variances while minimizing the intra-instance ones by considering the inter- and intra-modality similarities.
- Extensive experiments are conducted on four widely-used multimodal datasets to demonstrate the robust performance of the proposed methods for noisy labels.

2. Related Work

This section briefly reviews some of the most related works about learning with noisy labels and multimodal learning approaches.

2.1. Learning with Noisy Labels

To learn from noisy labels, numerous approaches are proposed to alleviate the noise in labels to learn the objective information. One typical direction is to improve the learning quality by correcting the wrong labels or loss functions, called correction methods [30, 49, 9]. However, such approaches always require extra ground-truth to support their learning schemes, which is often unavailable and cost-prohibitive in real-world applications [32, 48]. To avoid false corrections, numerous works attempt to elaborately design adaptive training strategies to select true-labeled samples for learning automatically, thus embracing robustness to noisy labels, such as MentorNet [19, 58], and Co-teaching [10]. Moreover, some methods try to divide the noisy data into labeled and unlabeled data, while utilizing semi-supervised paradigms to learn from the obtained labeled and unlabeled data iteratively [56, 35, 28]. Motivated by its powerful learning ability, meta learning has been successfully applied to improve the robustness of neural networks for noise samples [42, 29, 46]. The aforementioned approaches are either dependent on complex adaptive training processes that need carefully tuning and designing or sensitive to the hyper-parameters that will cost much time for tuning [32]. Differently, another direction is to design robust loss functions to make the optimization schemes robust to noise samples [8, 52, 32]. However, most prior arts for noisy labels are specifically designed for unimodal scenarios, and it is challenging to extend them to multimodal cases.

2.2. Multimodal Learning

Multimodal learning methods target to project multiple modalities into a common space, in which cross-modal downstream tasks could be conducted on the learned common representations, such as cross-modal retrieval [45, 16]. One typical technique is to maximize the cross-modal correlation across different modalities [12, 26, 38, 63, 18]. To utilize the semantic information in class labels, some supervised multimodal methods are proposed to utilize the discrimination to learn a common discriminative space. Specifically, discriminative criteria are introduced into multimodal learning to maximize the within-class similarity while minimizing the between-class similarity [21, 13, 27, 14]. Alternatively, a common classifier is directly adopted to enforce the neural networks to learn a common discriminative space [53, 62, 16, 55, 15]. To alleviate the over-dependence on labels, some multimodal semi-supervised paradigms are proposed to leverage the labeled and unlabeled to learn common representations simultaneously [61, 17, 57]. Moreover, to clean the noise from labels, Mandal *et al*. adopted a two-step pre-processing method to obtained cleaned labels and feed to cross-modal methods [33]. However, it is much more difficult to directly learn common discrimination from noisy labels, which is rarely touched in previous studies.

3. The Proposed Method

3.1. Notations

For a clear presentation, we first give some definitions for notations in the papers. Boldface uppercase letters (*e.g.*, $\mathbf{X}$) and boldface lowercase letters (*e.g.*, $\mathbf{x}$) represent matrices and column vectors, respectively. Give a K-category multimodal dataset with noisy labels as $\mathcal{D} = \{\mathcal{M}_i\}_{i=1}^m$, where $\mathcal{M}_i = \{(\mathbf{x}_j^i, y_j^i)\}_{j=1}^N$ is the i-th modality, $\mathbf{x}_j^i \subset \mathbb{R}^{d_i}$ is the j-th sample from the i-th modality, $y_j^i \in \{1, 2, \cdots, K\}$ is the label (possibly incorrect) for $\mathbf{x}_j^i$. For the convenience of presentation, $\mathcal{D}$ can be seen as a minibatch of N instances, each of which owns m samples from distinct modalities, in the following sections. Note that, although different modalities usually co-occur to describe the same objects or instances with the pairwise property, the noisy labels of distinct modalities may be not be paired, *e.g.*, there are different annotators for the image modality and the text modality separately.

3.2. Multimodal Robust Learning

The goal of cross-modal retrieval is to retrieve the correlated samples across different modalities in a common representation space $\mathcal{Z}$. To project distinct modalities into $\mathcal{Z}$, existing methods attempt to learn m modality-specific functions $\{f_i : \mathcal{X}_i \mapsto \mathcal{Z}\}_{i=1}^m$ for m modalities, where f_i can be a DNN with parameters Θ_i for the i-th modality. Given a data point $\mathbf{x}_j^i$, the common normalized representation $\mathbf{z}_j^i$ can be computed by

$$\mathbf{z}_j^i = f_i(\mathbf{x}_j^i) \subset \mathbb{R}^L, \tag{1}$$

where L is the dimention of the common space.

To learn the mapping functions $\{f_i(\cdot, \Theta_i)\}_{i=1}^m$ with noisy labels, we propose a general framework that consists of a robust clustering loss and a cross-modal correlation loss. A novel robust clustering loss, called Robust Clustering loss (RC) $\mathcal{L}_r$, is proposed to robustly extract the common discrimination shared across different modalities from noisy labels. Specifically, it can simultaneously alleviate the cross-modal discrepancy and noisy samples.

To further narrow the heterogeneous gap, we propose a novel cross-modal correlation loss, termed Multimodal Contrastive loss (MC) $\mathcal{L}_c$, to excavate the instance- and pair-level discrimination to boost the performance of cross-modal retrieval. Following sections will elaborate the aforementioned loss functions with details.

3.2.1 Robust Clustering Assignment

To excavate the discrimination from noisy labels, we propose to firstly cluster multimodal data to K common class-specific clustering assignments $\mathbf{C} = \{\mathbf{c}_1, \cdots, \mathbf{c}_K\}$ for alleviating outliers, where $\mathbf{c}_k$ is the normalized clustering center vector for the k-th class. Then, for a sample $\mathbf{x}_j^i$, its probability belonging to the k-th class can be defined as:

$$p(k|\mathbf{x}_j^i) = \frac{\exp(\frac{1}{\tau_1}\mathbf{c}_k^T\mathbf{z}_j^i)}{\sum_{t=1}^{K}\exp(\frac{1}{\tau_1}\mathbf{c}_t^T\mathbf{z}_j^i)}, \tag{2}$$

where τ_1 is a temperature parameter [54, 34]. By maximizing the joint probabilities of Equation (2) with the ground-truths, the multimodal points with the same semantics could be compacted into the same cluster in the common space [37], which could be directly achieved by the standard Cross-Entropy criterion (CE) as:

$$\mathcal{L}_{CE} = -\frac{1}{N}\sum_{j=1}^{N}\sum_{k=1}^{K} q(k|\mathbf{x}_j^i)\log p(k|\mathbf{x}_j^i), \tag{3}$$

where $q(k|\mathbf{x}_j^i)$ is the ground-truth probability over different labels of sample $\mathbf{x}_j^i$. In this work, we only focus on single-label case wherein each sample $\mathbf{x}_j^i$ only belongs to one class y_j^i, *i.e.*, $\mathbf{q}$ is simply a one-hot label vector defined as follows:

$$q(k|\mathbf{x}_j^i) = \begin{cases} 1 & \text{if } k = y_j^i; \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

For convenience of presentation, cross-entropy loss $\mathcal{L}_{CE}$ can be rewritten as $\mathrm{CE}(p) = \mathrm{CE}(p, y) = -log(p)$ for a sample $\mathbf{x}_j^i$ with its ground-truth y, where $p = p(y_j^i|\mathbf{x}_j^i)$ and $y = y_j^i$. Then, the CE loss could be plotted as the blue curve in Figure 3. From the figure, one can see that CE tends to focus on optimizing harder samples since they producing larger loss values, which has been proven to work well in clean-annotated labels. However, for noisy labels, recent studies [2, 10, 3] reveal that clean/correct samples are easier for learning than noisy/incorrect ones, and leading to faster learning for clean ones as shown in Figure 2. Like CE, conventional supervised loss functions usually put more attentions on harder samples that possibly are noisy ones in noisy-label cases [32, 28], thus leading to worse performance on noisy datasets.

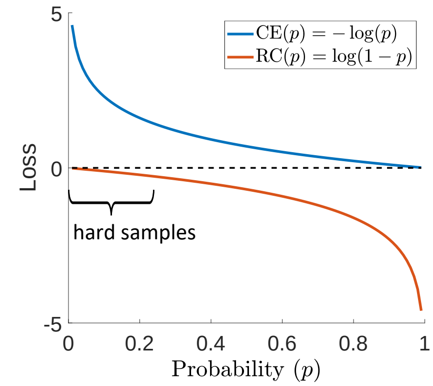


Figure 3: Comparison between the standard Cross-Entropy criterion (CE) and the proposed Robust Clustering loss (RC). The proposed RC is to reduce the relative loss of CE for hard samples that usually are with noisy/incorrect labels [2, 10, 3]. Thus, our RC can put more focus on clean samples instead of noisy ones and mitigate noise interference.

To further alleviate the influence of noisy samples, we propose to reshape the loss function to down-weight difficult samples and up-weight easy ones and thus focus training on clean samples instead of noisy ones. Different from CE loss, we minimize the log-likelihood of negative samples instead of the negative log-likelihood of the positive one. Our RC can be formulated as:

$$\mathcal{L}_r = \frac{1}{N}\sum_{i=1}^{m}\sum_{j=1}^{N}\log(1 - p(y_j^i|\mathbf{x}_j^i)). \tag{5}$$

Note that, the target of our RC is opposite to the fully supervised losses, such as Focal Loss [31], which mainly focuses on hard samples from a clean dataset with no noisy labels.

The learning process of the RC function is visualized in Figure 3 by comparing it with the standard cross-entropy loss. From the figure, one can note that our RC loss can remarkably down-weight the loss values of noisy samples while up-weight the values of clean ones. That is to say, the clean samples will produce much larger loss values than noisy ones, and dominate the gradient into the correct direction, thus embracing superior performance as evidenced in our experimental results.

3.2.2 Multimodal Contrastive Learning

In the unimodal scenario, contrastive learning has achieved promising performance in unsupervised learning applications [54, 4]. Unlike supervised methods, contrastive learning approaches apply instance-level classification to learn the discriminative representations. Specifically, to achieve that, it maximizes the agreement between different augmented views from the same sample via a contrastive loss [54, 4]. Instead of augmentation, multimodal data intrinsically consist of multiple modalities that can be naturally utilized to maximize their mutual information. Inspired by such recent contrastive learning works [54, 4], we present to learn common representations by maximizing agreement between different modalities in the common space.

First, we define the probability of a sample $\mathbf{x}_j^i$ belonging to the j-th instance in m modalities as:

$$P(j|\mathbf{x}_j^i) = \frac{\sum_{l=1}^{m} \exp\left(\frac{1}{\tau_2}\left(\mathbf{z}_j^l\right)^T \mathbf{z}_j^i\right)}{\sum_{l=1}^{m}\sum_{t=1}^{N} \exp\left(\frac{1}{\tau_2}\left(\mathbf{z}_t^l\right)^T \mathbf{z}_j^i\right)}, \tag{6}$$

where τ_2 is a temperature parameter [54, 34]. $P(j|\mathbf{x}_j^i)$ also could be seen as the probability of a multimodal cluster centered by $\mathbf{x}_j^i$ being correctly recognized as the j-th cluster.

To eliminate the cross-modal discrepancy and excavate the instance-level discrimination, we make the multimodal samples from the same instance (*e.g.*, $\{\mathbf{x}_j^k\}_{k=1}^m$ for the j-th instance) compact while the samples from distinct instances (*e.g.*, $\{\mathbf{x}_l^k\}_{l\neq j}$ for the j-th instance) scattered, *i.e.*, maximizing the probabilities. Then, the learning objective MC could be formulated as maximizing a joint probability $\prod_{i=1}^{m}\prod_{j=1}^{N} P(j|\mathbf{x}_j^i)$, which also can be equivalent to minimize the following negative log-likelihood [54] as:

$$\mathcal{L}_c = -\frac{1}{N}\sum_{i=1}^{m}\sum_{j=1}^{N} \log\left(P(j|\mathbf{x}_j^i)\right). \tag{7}$$

By minimizing Equation (7), the multimodal networks are enforced to compact the positive samples (considered as the relevant cross-modal pairs, *e.g.*, $\{\mathbf{x}_j^k\}_{k=1}^m$ for $\mathbf{x}_j^i$) while scattering the negative samples (considered as irrelevant instances, *e.g.*, $\{\mathbf{x}_l^k\}_{l\neq j}$ for $\mathbf{x}_j^i$) on the common unit sphere/space as shown in Figure 1. The outputs of multimodal networks contrast with each other to encapsulate the common discrimination by using the instance- and pair-level comparison, thus further mitigating noisy labels and cross-modal discrepancy.

3.2.3 Optimization

The final loss function can be formulated as:

$$\mathcal{L} = \beta\mathcal{L}_r + (1-\beta)\mathcal{L}_c. \tag{8}$$

By minimizing the joint loss function, our MRL can be iteratively optimized in a batch-by-batch manner using a stochastic gradient descent optimization algorithm, like Adam [22]. Algorithm 1 summarizes the optimization process of our MRL.

Algorithm 1 Main optimization process of our MRL.

Input: The training multimodal data $\mathcal{D} = \{\mathcal{M}_i\}_{i=1}^m$, the dimensionality of common representations L, batch size N_b, maximal epoch number N_e, balance parameter β, temperature parameters τ_1 and τ_2, and learning rate α.

for $1, 2, \cdots, N_e$ **do**
  repeat
    Randomly select N_b samples from each modality to construct a multimodal mini-batch $\{\mathcal{X}_i, \mathcal{Y}_i\}_{i=1}^m$.
    Calculate the representations for all samples of the mini-batch by using their corresponding modality-specific mapping functions $\{f_i(\cdot, \Theta_i)\}_{i=1}^m$, according to Equation (1).
    Normalize the clusters $\mathbf{C} = \{\mathbf{c}_1, \cdots, \mathbf{c}_K\}$.
    Compute RC and MC according to Equations (5) and (7) on the mini-batch, respectively.
    Update the network parameters $\{\Theta_i\}_{i=1}^m$ and clusters $\mathbf{C}$ by minimizing $\mathcal{L}$ in Equation (8) with descending their stochastic gradient:
    $\Theta_i = \Theta_i - \alpha(\beta\frac{\partial\mathcal{L}_r}{\partial\Theta_i} + (1-\beta)\frac{\partial\mathcal{L}_c}{\partial\Theta_i}), i = 1, \cdots, m$
    $\mathbf{C} = \mathbf{C} - \alpha\beta\frac{\partial\mathcal{L}_r}{\partial\mathbf{C}}$
  until all samples selected
end for

Output: Optimized network parameters $\{\Theta_i\}_{i=1}^m$.

4. Experiments

To evaluate our MRL, we conduct extensive comparison experiments on four widely-used multimodal datasets, *i.e.*, Wikipedia [41], INRIA-Websearch [23], NUS-WIDE [5], and XMediaNet [40].

4.1. Implementation Details

In this work, we employ ADAM [22] as our optimizer to train our MRL. For all datasets, we use a maximal epoch number of 100 (N_e in Algorithm 1). The learning rate (α in Algorithm 1) is initialized with 0.0001. The temperature parameters (τ_1 and τ_2 in Algorithm 1) are set as 1. The batch size is set as 50, 200, 500 and 500 for Wikipedia [41], INRIA-Websearch [23], NUS-WIDE [5], and XMediaNet [40], respectively. For Wikipedia, NUS-WIDE and XMediaNet, we adopt the pretrained VGG-19 [47] on ImageNet as the CNN backbone for images, and the pretrained Doc2Vec model[1] [25] as the text backbone for texts. On INRIA-Websearch, the pretrained AlexNet [24] on ImageNet and LDA are used as the backbones for images and texts, respectively. Three fully-connected (FC) layers are stacked on the backbones to learn the common representations for all modalities. Each FC

[1]https://github.com/jhlau/doc2vec.

layer follows a ReLU layer except the last layer. The numbers of FC hidden units are respectively $4,096$, $4,096$ and L, where L is the dimensionality of common representations. For a fair comparison with baselines, all backbones are frozen in the training stage. Our MRL is implemented on the PyTorch framework [36].

4.2. Experimental Setup

In our experiments, we compare the proposed method with 14 state-of-the-art methods that include four unsupervised methods (*i.e.*, MCCA [43], PLS [44], DCCA [1], and DCCAE [51]) and ten supervised ones (*i.e.*, GMA [45], MvDA [20], MvDA-VC [21], GSS-SL [61], ACMR [50], deep-SM [53], FGCrossNet [11], SDML [16], DSCMR [62], and SMLN [17]). For a fair comparison, all baselines utilize the same features extracted from the corresponding backbones as our MRL. For all methods, we report their results on the testing set when they achieve the best performance on the validation set. To evaluate the performance of these methods, we perform $m(m-1)$ distinct cross-modal retrieval tasks on each dataset. Without loss of generality, all experiments are conducted on bimodal datasets to evaluate two cross-modal tasks: using an image query to retrieve the related text samples (Image $\rightarrow$ Text), and using a text query to retrieve the relevant image points (Text $\rightarrow$ Image). We adopt Mean Average Precision (MAP), which is the mean value of Average Precision (AP) scores for each query, as the evaluation metric to measure the accuracy scores of retrieval results. MAP is extensively adopted to measure the retrieval performance since it simultaneously evaluates retrieval precision and ranking of returned results. Note that, we compute MAP scores on all retrieval results in the experiments. Furthermore, to comprehensively evaluate the robustness of the methods, we set the label noise to be symmetric, and the noise rates to 0.2, 0.4, 0.6 and 0.8 in the experiments.

4.3. Datasets

Without loss of generality, we adopt four widely-used image-text datasets to evaluate the cross-modal performance in the paper. In this section, we briefly introduce them as follows:

- **Wikipedia [41]** contains 2,866 image-text pairs that belong to 10 classes. Following [7], we divide the dataset into 3 subsets: 2,173, 231 and 462 pairs for training, validation and testing sets, respectively.
- **INRIA-Websearch [23]** consists of $71,478$ images and $71,478$ text descriptions (sentences or tags). In our experiments, we use the subset of INRIA-Websearch provided by the authors of [53]. In this subset, $14,698$ samples of 100 largest classes are selected from the original set. We randomly divide the dataset into three subsets: $9,000$, $1,332$ and $4,366$ image-text pairs for training, validation and testing sets, respectively.
- **NUS-WIDE [5]** consists of about $270,000$ images distributed over 81 categories. In the experiments, we use a subset of NUS-WIDE provided by [39], wherein each sample belongs to only one of ten classes. Besides, we randomly split the dataset into three subsets, *i.e.*, $42,941$, $5,000$ and $23,661$ image-text pairs for training, validation and testing sets, respectively.
- **XMediaNet [40]** is a large-scale multimodal dataset with 200 non-overlap categories. In this paper, only images and texts are selected to conduct experiments. Following [40], we randomly divide the dataset into three subsets: $32,000$, $4,000$ and $4,000$ pairs for training, validation and testing sets, respectively.

4.4. Comparison with the State-of-the-Art

We apply cross-modal retrieval on four datasets to evaluate the performance of our MRL and the baselines. The experimental results in terms of MAP scores are reported in Tables 1 and 2 for four datasets, respectively. As shown in these tables, our MRL is superior to the baselines on the four datasets. From the experimental results, we can draw the following observations:

- Some existing multimodal methods (*e.g.*, GMA, SDML, DSCMR, and SMLN) have certain anti-interference ability to noisy labels since their supervised and unsupervised components like our MRL, thus indicating that this framework has more robustness to the noisy labels.
- Noisy labels remarkably influence the performance of supervised multimodal methods. With the noise rate increasing in labels, their accuracies will decrease fast. On the contrary, unsupervised methods have no such issues.
- The number of classes affects the anti-interference performance of supervised methods to noisy labels. Neural networks have a powerful fitting ability, which makes them easier to overfit the harder task (more classes) on noisy labels than shallow methods, thus leading to worse performance. The shallow supervised methods are more robust to noisy labels for more classes than deep supervised approaches.
- Most supervised multimodal approaches are superior to the unsupervised ones in lower noise rate, which evidences that labeled data are important for cross-modal retrieval even though noisy labels contained. Another related observation also can be obtained, *i.e.*, the more pure labels, the better performance obtained.
- Our MRL is superior to both the unsupervised and supervised approaches in the cross-modal retrieval tasks.

Table 1: Performance comparison in terms of MAP scores under the symmetric noise rates of 0.2, 0.4, 0.6 and 0.8 on the Wikipedia and INRIA-Websearch datasets. The highest MAP score is shown in **bold**.

Method	Wikipedia								INRIA-Websearch							
	Image $\rightarrow$ Text				Text $\rightarrow$ Image				Image $\rightarrow$ Text				Text $\rightarrow$ Image			
	0.2	0.4	0.6	0.8	0.2	0.4	0.6	0.8	0.2	0.4	0.6	0.8	0.2	0.4	0.6	0.8
MCCA [43]	0.202	0.202	0.202	0.202	0.189	0.189	0.189	0.189	0.275	0.275	0.275	0.275	0.277	0.277	0.277	0.277
PLS [44]	0.337	0.337	0.337	0.337	0.320	0.320	0.320	0.320	0.387	0.387	0.387	0.387	0.398	0.398	0.398	0.398
DCCA [1]	0.281	0.281	0.281	0.281	0.260	0.260	0.260	0.260	0.188	0.188	0.188	0.188	0.182	0.182	0.182	0.182
DCCAE [51]	0.308	0.308	0.308	0.308	0.286	0.286	0.286	0.286	0.167	0.167	0.167	0.167	0.164	0.164	0.164	0.164
GMA [45]	0.200	0.178	0.153	0.139	0.189	0.160	0.141	0.136	0.425	0.372	0.303	0.245	0.437	0.378	0.315	0.251
MvDA [20]	0.379	0.285	0.217	0.144	0.350	0.270	0.207	0.142	0.286	0.269	0.234	0.186	0.285	0.265	0.233	0.185
MvDA-VC [21]	0.389	0.330	0.256	0.162	0.355	0.304	0.241	0.153	0.288	0.272	0.241	0.192	0.286	0.268	0.238	0.190
GSS-SL [61]	0.444	0.390	0.309	0.174	0.398	0.353	0.287	0.169	0.487	0.424	0.272	0.075	0.510	0.451	0.307	0.085
ACMR [50]	0.276	0.231	0.198	0.135	0.285	0.194	0.183	0.138	0.175	0.096	0.055	0.023	0.157	0.114	0.048	0.021
deep-SM [53]	0.441	0.387	0.293	0.178	0.392	0.364	0.248	0.177	0.495	0.422	0.238	0.046	0.509	0.421	0.258	0.063
FGCrossNet [11]	0.403	0.322	0.233	0.156	0.358	0.284	0.205	0.147	0.278	0.192	0.105	0.027	0.261	0.189	0.096	0.025
SDML [16]	0.464	0.406	0.299	0.170	0.448	0.398	0.311	0.184	0.506	0.419	0.283	0.024	0.512	0.412	0.241	0.066
DSCMR [62]	0.426	0.331	0.226	0.142	0.390	0.300	0.212	0.140	0.500	0.413	0.225	0.055	0.536	0.464	0.237	0.052
SMLN [17]	0.449	0.365	0.275	0.251	0.403	0.319	0.246	0.237	0.331	0.291	0.262	0.214	0.391	0.349	0.292	0.254
Ours	**0.514**	**0.491**	**0.464**	**0.435**	**0.461**	**0.453**	**0.421**	**0.400**	**0.559**	**0.543**	**0.512**	**0.417**	**0.587**	**0.571**	**0.533**	**0.424**

Table 2: Performance comparison in terms of MAP scores under the symmetric noise rates of 0.2, 0.4, 0.6 and 0.8 on the NUS-WIDE and XMediaNet datasets. The highest MAP score is shown in **bold**.

Method	NUS-WIDE								XMediaNet							
	Image $\rightarrow$ Text				Text $\rightarrow$ Image				Image $\rightarrow$ Text				Text $\rightarrow$ Image			
	0.2	0.4	0.6	0.8	0.2	0.4	0.6	0.8	0.2	0.4	0.6	0.8	0.2	0.4	0.6	0.8
MCCA [43]	0.523	0.523	0.523	0.523	0.539	0.539	0.539	0.539	0.233	0.233	0.233	0.233	0.249	0.249	0.249	0.249
PLS [44]	0.498	0.498	0.498	0.498	0.517	0.517	0.517	0.517	0.276	0.276	0.276	0.276	0.266	0.266	0.266	0.266
DCCA [1]	0.527	0.527	0.527	0.527	0.537	0.537	0.537	0.537	0.152	0.152	0.152	0.152	0.162	0.162	0.162	0.162
DCCAE [51]	0.529	0.529	0.529	0.529	0.538	0.538	0.538	0.538	0.149	0.149	0.149	0.149	0.159	0.159	0.159	0.159
GMA [45]	0.545	0.515	0.488	0.469	0.547	0.517	0.491	0.475	0.400	0.380	0.344	0.276	0.376	0.364	0.336	0.277
MvDA [20]	0.590	0.551	0.568	0.471	0.609	0.585	0.596	0.498	0.329	0.318	0.301	0.256	0.324	0.314	0.296	0.254
MvDA-VC [21]	0.531	0.491	0.512	0.421	0.567	0.525	0.550	0.434	0.331	0.319	0.306	0.274	0.322	0.310	0.296	0.265
GSS-SL [61]	0.639	0.639	0.631	0.567	0.659	0.658	0.650	0.592	0.431	0.381	0.256	0.044	0.417	0.361	0.221	0.031
ACMR [50]	0.530	0.433	0.318	0.269	0.547	0.476	0.304	0.241	0.181	0.069	0.018	0.010	0.191	0.043	0.012	0.009
deep-SM [53]	0.693	0.680	0.673	0.628	0.690	0.681	0.669	0.629	0.557	0.314	0.276	0.062	0.495	0.344	0.021	0.014
FGCrossNet [11]	0.661	0.641	0.638	0.594	0.669	0.669	0.636	0.596	0.372	0.280	0.147	0.053	0.375	0.281	0.160	0.052
SDML [16]	0.694	0.677	0.633	0.389	0.693	0.681	0.644	0.416	0.534	0.420	0.216	0.009	0.563	0.445	0.237	0.011
DSCMR [62]	0.665	0.661	0.653	0.509	0.667	0.665	0.655	0.505	0.461	0.224	0.040	0.008	0.477	0.224	0.028	0.010
SMLN [17]	0.676	0.651	0.646	0.525	0.685	0.650	0.639	0.520	0.520	0.445	0.070	0.070	0.514	0.300	0.303	0.226
Ours	**0.696**	**0.690**	**0.686**	**0.669**	**0.697**	**0.695**	**0.688**	**0.673**	**0.625**	**0.581**	**0.384**	**0.334**	**0.623**	**0.587**	**0.408**	**0.359**

In particular, the proposed method outperforms the best baselines by more than 6.5% with 80% noise. It demonstrates that the proposed framework is more robust to the noisy labels and could give a guide for future multimodal learning with noisy labels.

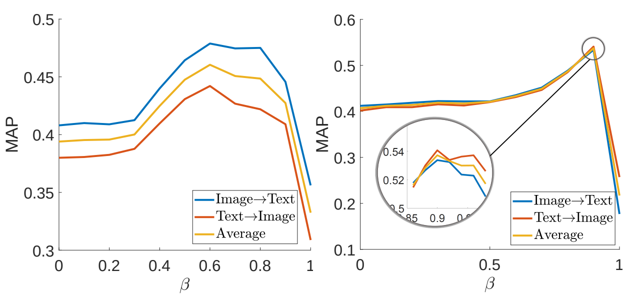
4.5. Ablation Study

In this section, we evaluate the performance of the proposed components (*i.e.*, $\mathcal{L}_r$ and $\mathcal{L}_c$) for cross-modal retrieval. To extensively investigate the contributions of each component, we compare our MRL with its three counterparts on the Wikipedia dataset, which are the cross-entropy (CE) baseline [53] and two variations of our MRL: MRL with $\mathcal{L}_c$ only and MRL with $\mathcal{L}_r$ only. All the compared methods are train with the same settings as our MRL for a fair comparison. The experimental results are shown in Table 3. From the results, one can see that the performance of MRL without $\mathcal{L}_c$ or $\mathcal{L}_r$ are worse than our full MRL on Wikipedia, which indicates that both of the two components contribute to cross-modal retrieval in our framework. By comparing to CE, we can see that our $\mathcal{L}_r$ can achieve much more robust performance, which indicates that the proposed $\mathcal{L}_r$ can alleviate the interference of noisy labels.

Table 3: Comparison between our MRL (full version) and its three counterparts (CE and two variations of MRL) under the symmetric noise rates of 0.2, 0.4, 0.6 and 0.8 on the Wikipedia dataset. The highest score is shown in **bold**.

Method	Image → Text			
	0.2	0.4	0.6	0.8
CE	0.441	0.387	0.293	0.178
MRL (with $\mathcal{L}_r$ only)	0.482	0.434	0.363	0.239
MRL (with $\mathcal{L}_c$ only)	0.412	0.412	0.412	0.412
Full MRL	**0.514**	**0.491**	**0.464**	**0.435**
	Text → Image			
CE	0.392	0.364	0.248	0.177
MRL (with $\mathcal{L}_r$ only)	0.429	0.389	0.320	0.202
MRL (with $\mathcal{L}_c$ only)	0.383	0.382	0.383	0.383
Full MRL	**0.461**	**0.453**	**0.421**	**0.400**

4.6. Parameter Analysis

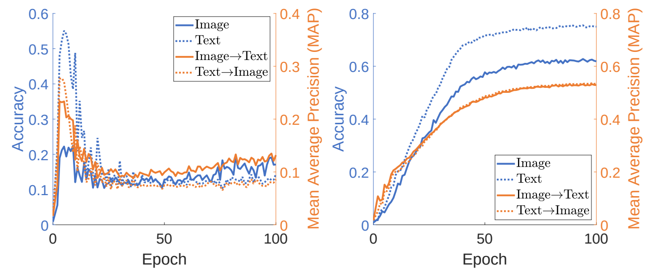


(a) Wikipedia (b) INRIA-Websearch

Figure 4: Cross-modal retrieval performance of our MRL in terms of MAP scores versus different values of β on the validation sets of the Wikipedia and INRIA-Websearch datasets, respectively. The noise rate is 0.6.

To evaluate the impact of the trade-off hyper-parameter β, we plot the cross-modal retrieval accuracy versus β on the validation sets of Wikipedia and INRIA-Websearch in Figure 4. From the figure, we can see that both Robust Clustering loss ($\mathcal{L}_r$) and Multimodal Contrastive loss ($\mathcal{L}_r$) contribute to excavating the discrimination from the multimodal data, which is consist with our ablation study. However, the contributions of each component are distinct for different datasets, which may be caused by the difficulty level of the datasets (*e.g.*, the more classes there are, the more difficult it will be). Furthermore, the sensitivity of β is also different on distinct datasets. To be specific, our method can obtain stable performance in a relatively larger range (*i.e.*, $0.5 \sim 0.8$) on Wikipedia, but smaller range (*i.e.*, $0.85 \sim 0.95$) on INRIA-Websearch.

4.7. Robustness Analysis



(a) Cross-entropy (b) Ours

Figure 5: Validation accuracies and MAP scores of the proposed method versus cross-entropy on INRIA-Websearch under 0.6 symmetric noise.

To visually investigate the robustness improvement, we plot accuracies/MAP scores versus epochs on the validation set of INRIA-Websearch for cross-entropy [53] and the proposed method in Figure 5. From the results, we can see that the proposed method can achieve much more stable performance on the validation set, which indicates that our method has alleviated the interference of noisy labels, and embracing more robust performance.

5. Conclusion

In this paper, we proposed a novel robust multimodal framework for learning from noisy labels, termed Multimodal Robust Learning (MRL), to project different modalities into a latent common space. Our MRL consists of multiple modality-specific networks, a multimodal robust clustering loss $\mathcal{L}_r$, and a multimodal contrastive loss $\mathcal{L}_c$. The robust clustering loss $\mathcal{L}_r$ aims to mitigate the interference of noisy labels and the cross-modal discrepancy. The multimodal contrastive loss $\mathcal{L}_c$ is conducted to narrow the heterogeneous gap between different modalities while excavating the apparent discrimination. Comprehensive experiments are conducted on four widely-used datasets. The experimental results demonstrated the effectiveness of the proposed method. Specifically, our MRL is superior to 14 state-of-the-art multimodal methods on noise settings. At the same time, we revealed that the existing cross-modal retrieval approaches are vulnerable to noisy labels.

Acknowledgments

This work was supported in part by the National Key R&D Program of China under Grant 2020YFB1406702; in part by the Fundamental Research Funds for the Central Universities under Grant YJ201949; in part by NFSC under Grants 61836006, U19A2078, U19A2081, 61625204; and A*STAR under its AME Programmatic Funds (Project No.A1892b0026 and Project No.A19E3b0099).

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