Multi-Modal Mixup for Robust Fine-tuning

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Abstract. Pre-trained large-scale models provide a transferable embedding, and they show comparable performance on the diverse downstream task. However, the transferability of multi-modal learning is restricted, and the analysis of learned embedding has not been explored well. This paper provides a perspective to understand the multi-modal embedding in terms of uniformity and alignment. We newly find that the representation learned by multi-modal learning models such as CLIP has a two separated representation space for each heterogeneous dataset with less alignment. Besides, there are unexplored large intermediate areas between two modalities with less uniformity. Less robust embedding might restrict the transferability of the representation for the downstream task. This paper provides a new end-to-end fine-tuning method for robust representation that encourages better uniformity and alignment score. First, we propose a multi-modal Mixup, $m^2$-Mix that mixes the representation of image and text to generate the hard negative samples. Second, we fine-tune the multi-modal model on a hard negative sample as well as normal negative and positive samples with contrastive learning. Our multi-modal Mixup provides a robust representation, and we validate our methods on classification, retrieval, and structure-awareness task.

Keywords: Mixup, Multi-Modal, CLIP, Contrastive Learning

1 Introduction

One of the challenging issues of machine learning is to increase the generalization performance on shifted dataset distribution as well as given dataset distribution. There are many situations in the dataset of a given task that is limited, and it may harm the performance. Alternative methods are to pre-train a large-scale model on a large general dataset. Besides large-scale models and datasets, learning methods have been known to be important for improving generalization performance. Recently, there have been many works that pre-train the uni-modal model with a contrastive learning [2,12,3].

A contrastive learning [31,20] is a widely-used learning algorithm that effectively minimizes the distances between positive pairs while maximizing the dissimilarity between negative pairs. Due to its powerfulness in learning discriminative representation, contrastive learning has been adopted to pre-train the model and apply it for many vision applications.

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Fig. 1: (Left) Illustration of the embedding space of pre-trained CLIP. CLIP is trained with a multi-modal contrastive loss that encourages the embeddings of image-text positive pairs to get close while discouraging the negative pairs. However, we observe that the learned embedding from CLIP has two separated embeddings spaces, image and text, with large unexplored intermediate spaces. As a result, the CLIP embedding has worse uniformity and alignment scores that can be harmful to the downstream task. (Middle) To better representation learning, we propose a multi-modal-Mixup ($m^2$-Mix) that explores the unexplored intermediate space by mixing the representation of image and text. Generated samples from $m^2$-Mix correspondence to a hard-negative sample that is located in the intermediate space. (Right) Fine-tuning with $m^2$-Mix induces robust representation with better uniformity and alignment.

The application of contrastive learning is not merely limited to the unimodal representation learning but extended to the multi-modal environment. CLIP [30] is one of the most representative multi-modal learning approaches in recent, which is trained to produce similar embeddings for paired image-text instances and dissimilar embeddings for non-paired ones. CLIP embedding shows a comparable performance on a downstream task such as classification on the in-distribution dataset. Many recent papers [27] claims state-of-the-art results benefit from the zero-shot transferability of CLIP.

It is considered as a de facto standard to demonstrate the generalization ability of a foundation model by fine-tuning and evaluating the model on multiple downstream tasks [27,24]. However, such exhaustive bottom-up evaluation inherently includes a bias in tasks, which raises the need for metrics that can be quantitatively measured. For this purpose, the measurement of the uniformity and alignment have been recently proposed [39,38]. To be specific, given learned features on $L^2$-normalized hypersphere, the uniformity measures how the features are uniformly distributed, and the alignment measures how the features among the positive samples locate in close distances in the latent space [39,38].

To the best of our knowledge, this is the first paper that analyzes the CLIP embedding in the lens of uniformity and alignments. We find that the learned embedding by CLIP has a two-modality representation space with a large unexplored intermediate area between two modalities, while CLIP objectives are designed to explicitly align them together. Separated embedding with the largely unexplored area in CLIP has worse uniformity and alignment, and it might hinder the downstream tasks.
We observe that increasing temperature $\tau$ in contrastive loss can improve the uniformity and alignment measure, but it simultaneously sacrifices the performance on downstream tasks. Therefore, it raises an important question that motivates our work: "How can we improve the uniformity and alignment of learned feature distribution without sacrificing the performance on the target downstream task?" In order to answer this question, we propose a multi-modal-Mixup ($m^2$-Mix). As shown in Fig. 1, $m^2$-Mix mixes the embedding of the heterogeneous domain, image and text. $m^2$-Mix contributes to robust representation learning in three perspectives. First, $m^2$-Mix generates the hard negative samples, and hard negative samples are known to be critical components for robustness [38]. Second, $m^2$-Mix interpolates the space between image and text that is not explored by pre-trained CLIP. Our $m^2$-Mix interpolates two samples from heterogeneous domains such as image and text to expand the exploration space. Our experiments demonstrate the effectiveness of our strategy for improving uniformity and alignment while improving the performance on various target downstream tasks. Third, a $m^2$-Mix generates the augmented dataset, and it also improves the in-distribution performance as well as the calibration[10]. In summary, our contributions in this work are three-fold:

- We analyze the multi-modal embedding, and we find that the pre-trained CLIP embedding consists of two separated embedding, text and image embedding, and they have worse uniformity and alignment that can be harmful to downstream tasks.
- We propose a new fine-tuning method based on the $m^2$-Mix to encourage representation robustness. To the best of our knowledge, this paper is the first to propose the $m^2$-Mix that mixes the heterogeneous modality.
- We empirically validate that $m^2$-Mix encourages uniformity and alignment, and it contributes to improving the performance of diverse downstream tasks.

2 Related Works

This paper presents a $m^2$-Mix, the multi-modal Mixup, for the first time. We verify the superiority of $m^2$-Mix on fine-tuning of the multi-modal model with contrastive loss. In this section, we briefly introduce the previous related works for contrastive learning, Mixup, and multi-modal learning.

2.1 Contrastive Learning

Contrastive learning has been widely utilized for unsupervised representation learning or a pre-training on various domains [2,23,5,20]. Normally, The goal of contrastive learning is to learn an embedding function that maps data into an embedding space so that semantically similar data have close embeddings under some distance metric. While any distance metric can be used, Cosine distance [23] or Euclidian distance [31] metric is usually used for simplicity.

Traditional contrastive learning adopts $L^2$ regularization, and it makes the feature representations located onto the hypersphere. There are two key properties to analyze the hyperspherical feature embedding, so-called Uniformity and
Alignment. Uniformity indicates the degree of preserving maximal information throughout the whole embedding space, while alignment denotes whether similar inputs have similar features. Better uniformity and alignment are interpreted as representation robustness, and it is related to the downstream task performance. It is known that the hard negative instance for constructing contrastive pair is necessary to increase the robustness of representation learning [14,46,38]. Recently, multi-modal learning such as CLIP also incorporates contrastive learning and the $L^2$ regularization. Different from uni-modal learning, multi-modal learning handles multiple heterogeneous data such as images and text. However, the analysis for multi-modal learning has not been well studied yet. In this paper, we find that the CLIP embedding has limited uniformity and alignments, and it may harm the downstream tasks.

2.2 Data Augmentation and Mixup

There have been many works to improve the generalization performance when the number of data is limited. One of the promising approaches is to generate the augmented samples to increase the possible training set. Traditional data augmentation such as rotation and crop [33] explores the vicinity or neighborhood of a given instance. To improve the effectiveness of data augmentation, Mixup [44] generates the new augmented samples by interpolating the data, and it corresponds to the generic vicinal distribution. Empirically, Mixup is helpful for robust representation learning, and it alleviates the overconfident problems, and the failure of distribution shift settings as well as the in-distribution accuracy [34]. Besides empirical validation, there are related works to support the Mixup in theoretical viewpoints [1,45]. Theoretically, cross-entropy loss with Mixup is known to have a term related to the calibration, Jacobian regularization, label smoothing, input normalization [1].

With the success of Mixup, there are many related works to introduces the Mixup for many domains such as vision [36,43,17], text [11,42], and graph [40,37]. Recently, It has been known that contrastive learning with Mixup contributes to improving representation learning. Traditional contrastive learning annotates labels 1 to positive pairs and 0 for negative pairs. $i$-Mix, Un-Mix and Metrix [19,32,35] interpolate the images with ratio $\lambda$, and they adopt contrastive learning with new pseudo labels according to the mixing ratio $\lambda$. There are diverse Mixup-related works for uni-modal datasets, not multi-modal datasets. However, we find that the uni-modal Mixup has limited effects on improving multi-modal learning such as CLIP. Therefore, we propose a new type of Mixup, $m^2$-Mix, to handle the multi-modal dataset and improve the robustness of multi-modal representation learning.

2.3 Multi-modal Learning

Pre-training large-scale models have been a promising way to improve the performance of downstream tasks on the uni-modal dataset. Pretrained BERT [15], and its variants show superior performance on many NLP-related tasks such
as classification and translation. On computer vision domain, pre-trained large-scale model such as ResNet [13] and Vision Transformer [6] have been widely utilized as a backbone for image classification and objection detection. For multi-modal dataset, CLIP [30] that pre-trains the text encoder and image encoder with contrastive learning has been studied recently. CLIP is known to have a image and text representation and have been widely utilized for image classification [4], video understanding [24,7,29], object detection [9], image generation [16].

CLIP that is pre-trained on a large-scale dataset shows significant performance improvements on zero-shot transfer image classification. However, the zero-shot performance of CLIP is still less than the performance of supervised learning methods. Recently, fine-tuning methods to improve the performance of CLIP have been proposed. Wortsman et al. [41] and Kumar et al. [18] provide a robust fine-tuning methods that increase the both in-distribution performance out-of-distribution generalization performance. Wortsman et al. provide the weight ensemble methods that combine the pre-trained parameters and fine-tuned parameters with specific ratios. Besides, Kumar et al. [18] adopts a two-step strategy that combines the linear probing step and full fine-tuning step.

The previous works have focused on the fine-tuning on uni-modal dataset only, and the downstream task is also restricted to classification. On the other hand, we provide robust fine-tuning methods for multi-modal datasets as well as uni-modal datasets. Besides, we provide a new perspective to analyze the properties of multi-modal learning in terms of uncertainty and embedding arithmetic. There is concurrent work that analyzes the CLIP embedding with initialization and optimization perspective [21].

3 Observations and Problem Definition

Multi-modal learning handles the multi-modal dataset stem from a heterogeneous domain such as image and text. For given batch \( D = \{x_i, y_i\}_{i=1}^n \) where \((x_i, y_i)\) denotes the \( i \)-th image-text positive pairs, and \( n \) is the number of batch size, the goal of multi-modal learning is to learn the relationship between the pairs of image and text. In other words, CLIP trains the image encoder \( f(\cdot|\theta_1) \) and text encoder \( g(\cdot|\theta_2) \) that \( I_i = f(x_i), T_i = g(y_i) \) have similar embeddings as shown in Eq. (1,2) where \( \theta_1 \) and \( \theta_2 \) are learnable parameters. It is noted that \( I_i \) and \( T_i \) are \( L^2 \) normalized unit vectors, and they lie on the hypersphere. CLIP adopts the InfoNCE [26] loss \( C(\cdot, \cdot) \) to encourage the similarity between positive pairs \( (x_i, y_i) \) and the dissimilarity between all remain negative pairs \( (x_i, y_j) \).

\[
C(I, T) = \frac{1}{n} \sum_{i=1}^{n} \log \frac{\exp(\text{sim}(I, T)/\tau)}{\sum_{j=1}^{n} \exp(\text{sim}(I, T_j)/\tau)}
\]

\[
L_{\text{CLIP}} = \frac{1}{2}(C(I, T) + C(T, I))
\]

\( \text{sim}(\cdot) \) calculate the similarity between two given vectors, and CLIP uses sim as a simple dot product. It is noted that, unlike many previous studies, \( \tau \) is a learnable temperature that scales the magnitude of the similarity.
The representation analysis for uni-modal learning has been widely studied, but the multi-modal representation analysis has not been well explored. We firstly analyze the multi-modal embedding in terms of alignments (A) and uniformity (U), the well known properties as show in Eq. 3 and 4. Alignment evaluates the difference between similarity of positive pairs compared with the hardest negative pairs, while uniformity denotes the degree of maximal information. It is noted that greater value of alignment and uniformity denote better representation.

\[ A = -\mathbb{E}_{(x_i, y_i)} \left[ \| f(x_i) - g(y_i) \|_2^2 - \min_{k \neq i} \| f(x_i) - g(y_k) \|_2^2 \right] \]  
\[ U = -\log \mathbb{E}_{(x_i, y_j)} \left[ \exp (-2 \| f(x_i) - g(y_j) \|_2^2) \right] \]  

We find that the learned embedding from CLIP is separated by two spaces, image embedding space and text embedding space. Besides, there are wide unexplored regions between two spaces. The CLIP embedding has worse uniformity and alignments, and these properties might harm the performance of downstream tasks. Fig. 2 denotes the t-SNE visualization for pre-trained CLIP, fine-tuned CLIP, and fine-tuned CLIP with ours on Flickr30k dataset embedding. Fig. 2a and Fig. 2b denotes the CLIP zero-shot embedding, traditional fine-tuned embedding, respectively, and they have worse uniformity and alignments. Fine-tuning with adjusted \( \tau \) alleviates the issues(Fig. 2c), but it also has

\footnote{The original formulation of alignment is \( A = \mathbb{E}_{(x_i, y_i)} \| f(x_i) - g(y_i) \|_2^2 \), which ignore the similarity between negative pairs. We find that it does not directly related to the downstream tasks performance, and we modify the alignment that handles both positive pairs and negative pairs.}
the worse downstream performance, as shown in Section 5. However, Fig. 2d shows that fine-tuned embedding with our methods, $m^2$-Mix, resolves the issue, and they have better uniformity and alignment.

Our primary goal of this study is to learn robust multi-modal representation learning with $m^2$-Mix that generates the hard-negative samples. To validate the robustness, we perform diverse downstream tasks such as retrieval, calibration[10], embedding arithmetic, as well as uniformity and alignment score.

4 Methodology

4.1 $m^2$-Mix and Hard Negative Samples

From our findings that the CLIP embedding is not robust enough, we improve the CLIP embedding by fine-tuning the CLIP with contrastive loss and hard negative samples. First, we generate the hard negative by mixing the image embedding and text embedding from CLIP, $m^2$-Mix. The mixing ratio $\lambda$ is sampled from the Beta distribution. Second, we adopt the hard negative samples as a negative instance for contrastive loss. As shown in Eq. 5, 6, we replace the original negative with our generated hard negative samples. As with CLIP embedding, we adopt normalization with $L^2$-norm to locate the embedding on the hypersphere. It is noted that we only change the denominator terms and remain the numerator term that compares the similarity between the positive pairs.

$$C_{m^2-\text{Mix}}(I, T; \lambda) = \frac{1}{n} \sum_{i=1}^{n} - \log \frac{\exp(I_i \cdot T_i/\tau)}{\sum_{j=1}^{n} \exp(I_i \cdot \text{mix}_\lambda(I_j, T_j)/\tau)}$$ (5)

$$\text{mix}_\lambda(a, b) = c/|c| \text{ where } c = \lambda a + (1 - \lambda)b$$

$$\mathcal{L}_{m^2-\text{Mix}} = \frac{1}{2} (C_{m^2-\text{Mix}}(I, T; \lambda) + C_{m^2-\text{Mix}}(T, I; \lambda))$$ (6)

Our $m^2$-Mix-based contrastive learning has two advantages. First, $m^2$-Mix generates the virtual hard negative samples compared with the original negative samples. From our findings, CLIP has two separated embeddings, and mixing separated embeddings, text and image, becomes a hard negative sample. Therefore, the similarity between original image embedding and the virtual, mixed embedding is larger than the similarity between the original image embedding and original text embedding. In other words, when we mix the image and text pair, the mixed embedding becomes hard negative samples for other instances. The existence of hard negative samples is known to be important on uni-modal contrastive learning [39,38], and we validate it on multi-modal contrastive learning. We provide the theoretical analysis that $m^2$-Mix generates the hard negative samples compared with the original negative samples in Theorem 4. Theorem 4 indicates that the expected similarity between the pair of given image and generated hard negative samples is greater than that of original negative pairs.

**Theorem 1.** Let’s assume that $I_i \sim \mathcal{N}(\mu_1, \sigma_1^2d)$, $T_i \sim \mathcal{N}(\mu_2, \sigma_2^2d)$. Then, the expected similarity difference, $\mathbb{E}[I_i^T(\lambda I_j + (1 - \lambda)T_j) - I_i^T T_j]$ is greater than zero.
Second, contrastive learning with hard negative samples encourages maximizing the similarity between positive pairs strongly. To minimize the contrastive loss, the similarity between positive pairs should be sufficiently larger than that of negative pairs. The harder negative samples make the similarity between negative pairs greater, and contrastive learning induces strong alignments between positive pairs.

Third, our $m^2$-Mix interpolates the intermediate region of image and text embedding spaces. The intermediate region is not well explored on CLIP embedding, and it might be problematic when CLIP handles the new data located in the intermediate area. On the other hand, CLIP with $m^2$-Mix has no unexplored intermediate area, and it makes CLIP perform well on uncertain estimation as well as retrieval and structure-awareness tasks [5].

Fig. 3: Overall model structure of CLIP and our proposed models. CLIP compares the similarity between the original positive pairs and the original negative pairs. However, $m^2$-Mix generates the hard negative samples by mixing the heterogeneous data, image, and text. Additionally, we propose the V-Mix and VL-Mix, a uni-modal Mixup for CLIP. Multi-modal Mixup, $m^2$-Mix, and uni-modal Mixup, V-Mix, VL-Mix contributes to the robust representation learning.

4.2 Uni-modal Mixup for CLIP

Our proposed model, $m^2$-Mix generates the hard negative samples to better aligned and uniformed embedding. Another advantage of Mixup is alleviating the over-confident problems in uni-modal settings. As variants of $m^2$-Mix, we propose a uni-modal Mixup, Visual-Mix (V-Mix), Language-Mix (L-Mix), and Visual and Language Mix (VL-Mix) for multi-modal learning. The Fig. 3 denotes the overall structure of our models. To the best of our knowledge, this is the first paper that provides the Mixup for CLIP.
**V-Mix, L-Mix** In this section, we propose a V-Mix and L-Mix that interpolates on image embedding and text embedding, respectively. V-Mix mixes the original image batch, and its reversed flipped image batch with mixing ratio $\lambda$. Because $mix_{\lambda}(I_i, I_{n-i+1})$ has an $I_i$ component with $\lambda$ fraction, the pseudo label for $(mix_{\lambda}(I_i, I_{n-i+1}), T_i)$ pair is $\lambda$ while the pseudo label for $(mix_{\lambda}(I_i, I_{n-i+1}), I_{n-i+1})$ is $1 - \lambda$ as shown in Eq. 7.

$$C_{V-Mix}(I, T; \lambda) = \frac{1}{n} \sum_{i=1}^{n} -\lambda \log \frac{\exp(mix_{\lambda}(I_i, I_{n-i+1}) \cdot T_i / \tau)}{\sum_{j=1}^{n} \exp(I_i \cdot T_j / \tau)}$$

$$- (1 - \lambda) \log \frac{\exp(mix_{\lambda}(I_i, I_{n-i+1}) \cdot I_{n-i+1} / \tau)}{\sum_{j=1}^{n} \exp(I_i \cdot T_j / \tau)}$$

(7)

L-Mix is similar to V-Mix, but L-Mix interpolates between text embedding as shown in Eq. 8.

$$C_{L-Mix}(I, T; \lambda) = \frac{1}{n} \sum_{i=1}^{n} -\lambda \log \frac{\exp(I_i \cdot mix_{\lambda}(T_i, T_{n-i+1}) / \tau)}{\sum_{j=1}^{n} \exp(I_i \cdot T_j / \tau)}$$

$$- (1 - \lambda) \log \frac{\exp(I_{n-i+1} \cdot mix_{\lambda}(T_i, T_{n-i+1}) / \tau)}{\sum_{j=1}^{n} \exp(I_i \cdot T_j / \tau)}$$

(8)

The loss function for uni-modal Mixup, V-Mix and L-Mix is defined by Eq. 9.

$$\mathcal{L}_{am-Mix} = \frac{1}{2} (C_{V-Mix}(I, T; \lambda) + C_{L-Mix}(I, T; \lambda))$$

(9)

**VL-Mix** V-Mix and L-Mix only mixes the image embedding and text embedding respectively. In this sectio, we propose a VL-Mix that mixes the image and test embedding simultaneously. It is noted that $m^2$-Mix mixes the image and text, while $VL$-Mix mixes the images and text independently as shown in Eq. 10. Both $mix_{\lambda}(I_i, I_{n-i+1})$ and $mix_{\lambda}(T_i, T_{n-i+1})$ has $i$-th component and $n-i+1$-th component with fraction $\lambda$ and $1 - \lambda$ respecitvely, the psuedo label for the pair $(mix_{\lambda}(I_i, I_{n-i+1}), mix_{\lambda}(T_i, T_{n-i+1}))$ is 1.

$$C_{VL-Mix}(I, T; \lambda) = \frac{1}{n} \sum_{i=1}^{n} -\log \frac{\exp(mix_{\lambda}(I_i, I_{n-i+1}) \cdot mix_{\lambda}(T_i, T_{n-i+1}) / \tau)}{\sum_{j=1}^{n} \exp(I_i \cdot T_j / \tau)}$$

$$= \frac{1}{2} (C_{VL-Mix}(I, T; \lambda) + C_{VL-Mix}(T, I; \lambda))$$

(10)

**m^3-Mix** We find that our uni-modal Mixup on multi-modal learning such as CLIP alleviates the over-confident problems as well as our $m^2$-Mix. The combination of $m^2$-Mix with uni-modal Mixup as $m^3$-Mix, multiple multi-modal Mixup, Eq. 11 denotes the overall training loss with hyper-parameters $\lambda_{1:3}$.

$$\mathcal{L}_{m^3-Mix} = \mathcal{L}_{CLIP} + \lambda_1 \mathcal{L}_{m^2-Mix} + \lambda_2 \mathcal{L}_{uni-Mix} + \lambda_3 \mathcal{L}_{VL-Mix}$$

(11)
5 Results

In this study, we find that the CLIP embedding has a large gap between image and text embedding. From our findings, we provide a $m^2$-Mix that generates the hard negative samples for robust representation learning. Section 5.1 provides the properties of generated samples, and Section 5.2-5.4 provide the extensive experiments including retrieval, calibration, and structure-awareness task.

5.1 Generated Samples from $m^2$-Mix

This paper proposes the $m^2$-Mix, and we provide the properties of generated samples from $m^2$-Mix. Fig. 4 shows the histogram of similarity between the negative pairs. High similarity between negative pairs denotes that the corresponding instances are hard negative. As shown in Fig. 4, $m^2$-Mix generates the hard negative samples from the initial iteration to the last iteration.

Fig. 4: Histograms of the pair-wise embedding similarity between an given instance and its top-k nearest negative samples for the initial iteration (a,c) and the last iteration (b,d). $m^2$-Mix generates the more hard negative samples.

![Histograms of pair-wise embedding similarity](image)

(a) Top-1 initial    (b) Top-1 last    (c) Top-5 initial   (d) Top-5 last

5.2 Generated Samples from $m^2$-Mix that generates the

Fig. 5: Left denotes the original image and text pair. The right top and bottom denote the retrieved top-3 images from the original image and the mixed data by $m^2$-Mix, respectively. The retrieved images from the $m^2$-Mix includes the splashing, ocean, and blue bucket as shown in the text and image. However, the retrieved images from the original images are not related to the blue bucket or ocean water.

![Original and retrieved images](image)
Besides, we explore the mixed embedding from $m^2$-Mix. Because $m^2$-Mix mixes the image and text on the hidden embedding space, the visualization of itself is not trivial. Instead, we visualize the images that have the most similar embedding with the mixed embedding. As shown in Fig. 5, the embedding generated by $m^2$-Mix has both features from image and text simultaneously. The second and the third images from $m^2$-Mix has the ocean and bucket, represented in the text.

### 5.2 Image and Text Retrieval with CLIP

Image and text retrieval is the representative multi-modal task, and we validate our models on Flickr30k [28] and MS COCO [22] datasets. For comparison, we follow the same experimental settings in [30] and Vit-B/32 based CLIP. We provide the detailed experimental settings and hyper-parameters in the supplementary material Section B. Table 1 denotes the performance of the retrieval task. Our methods $m^2$-Mix and $m^3$-Mix increase overall performance, while the standard fine-tuning approach and the uni-modal Mixup method such as $i$-Mix and Un-Mix have limited performance. It denotes the importance of multi-modal Mixup that mixes the heterogeneous domain for multi-modal learning.

Table 1: Performance of image to text (i→t) retrieval and text to image retrieval (t→i). ZS and FT denote the pre-trained CLIP and fine-tuned CLIP, respectively, and R1 and R5 denote the recall at top-1 and top-5. We fine-tune CLIP on Flickr30k and MS COCO dataset individually and validate the model for each test dataset. Our methods, $m^2$-Mix and $m^3$-Mix, show the improvements over the ZS, FT.

|                | Flickr30k |             | MS COCO |             |
|----------------|----------|------------|---------|------------|
|                | i→t      | t→i        | i→t      | t→i        |
|                | R1 | R5 | R1 | R5 | R1 | R5 | R1 | R5 |
| ZS             | 69.98 | 89.17 | 66.89 | 87.1 | 27.8 | 50.55 | 23.85 | 55.16 |
| FT             | 80.97 | 96.03 | 80.17 | 95.54 | 40.26 | 66.08 | 39.11 | 64.20 |
| FT($\tau = 0.05$) | 80.93 | 95.03 | 80.05 | 94.64 | 38.52 | 66.36 | 39.78 | 66.76 |
| FT($\tau = 0.08$) | 77.41 | 94.82 | 77.55 | 93.24 | 35.03 | 62.21 | 36.78 | 63.60 |
| FT($\tau = 0.10$) | 75.02 | 93.33 | 77.44 | 92.01 | 31.69 | 59.67 | 33.75 | 60.31 |
| $i$-Mix         | 78.30 | 94.52 | 77.61 | 93.54 | 34.37 | 59.33 | 33.19 | 57.78 |
| Un-Mix          | 80.72 | 95.17 | 79.27 | 94.00 | 38.35 | 64.49 | 36.36 | 62.22 |
| $m^2$-Mix       | 81.42 | 95.70 | 81.00 | 95.02 | 40.84 | 66.77 | 39.19 | 64.62 |
| $m^3$-Mix       | 82.22 | 95.93 | 81.46 | 95.04 | 39.70 | 66.58 | 40.50 | 66.19 |

Besides, we find that the calibration [10] of zero-shot CLIP (ZS) and fine-tuned CLIP (FT) is necessary to be improved, as shown in Fig. 6. The top-row of Fig. 6 denotes the reliability diagrams of Image-to-Text retrieval R1 Score on Flickr30K Test set. Fine-tuned model with our methods (c,d) alleviates the calibration issues of CLIP. It is known that the Expected Calibration Error (ECE)
Fig. 6: (Top) Reliability diagram on learned $\tau$ and (Bottom) ECE changes over the temperature $\tau$ on Flickr30K dataset. Our methods (c,d) shows the better reliability diagram (close to $y = x$), lower minimum ECE value, and they are robust over the $\tau$ changes.

value can be relatively improved by adjusting the temperature $\tau$, temperature scaling $[10]$. Therefore, we provide another metric, $\tau$-robustness, as shown in the bottom-row of Fig. 6. $\tau$-robustness denotes the sensitivity analysis of ECE depending on the temperature $\tau$. The high $\tau$-robustness metric denotes that the model still has a low ECE value even though the $\tau$ drastically changes. Our methods (c,d) show relatively robust ECE about the change in $\tau$. And we can see that the optimal value of $\tau$ of (c,d) is larger than (a,b). This is consistent with the result that our methods have a better alignment score.

Table 2 shows the numeric value of ECE and the robustness over $\tau$. Our methods, $m^2$-Mix and $m^3$-Mix has better ECE value, and they improve the CLIP embedding on calibration. $m^3$ that adopts the uni-modal Mixup, as well as a multi-modal mixup, shows the best performance. It denotes that our uni-modal Mixup, $V$-Mix, $L$-Mix, $V L$-Mix, contributes to improving the multi-modal learning. For $\tau$ robustness, we calculate the area that has lower than the 5% ECE for each method in the bottom of Fig. 6. Next, we normalize it with the area of CLIP. Larger $\tau$-robustness denotes that the model has stable ECE when the $\tau$ changes.

Table 2: Calibration results for ZS, FT, and our models on the Flickr30k dataset. ECE denotes the calibration error, and $\tau$ robustness denotes the stability of ECE when the $\tau$ changes drastically. $m^2$-Mix shows the best value.
5.3 Image and Text Retrieval with Uni-modal Pre-trained Model

It is noted that the pre-trained multi-modal model is limited for popular domains such as vision and language. It is necessary that we fine-tune the uni-modal pre-trained model simultaneously when we handle the relatively un-popular domain dataset. Therefore, we validate our methods on uni-modal pre-trained model fine-tuning. In this section, we fine-tune the pre-trained BERT [15] and ResNet-50 [13] for Flickr30k training set, and evaluate the fine-tuned model on Flickr30k test set. Table 5 denotes that our proposed model, m\textsuperscript{3}-Mix, shows the best performance on all tasks and evaluation metrics.

Table 3: The retrieval performance on Flickr30k. ZS denotes the combination of BERT and ResNet-50 that were pre-trained on each uni-modal dataset only. ZS has no capability for retrieval, and m\textsuperscript{3}-Mix increases the performance.

|       | i → t |       | t → i |
|-------|-------|-------|-------|
|       | R1    | R5    | R10   | R1    | R5    | R10   |
| ZS    | 0.1   | 0.4   | 0.9   | 0.1   | 0.2   | 0.9   |
| FT    | 17.8  | 46.0  | 59.1  | 17.3  | 46.0  | 59.2  |
| FT(τ = 0.05) | 17.8  | 43.2  | 59.8  | 18.8  | 45.7  | 58.8  |
| FT(τ = 0.10) | 14.1  | 36.2  | 51.6  | 13.8  | 38.3  | 50.9  |
| i-Mix | 14.2  | 40.4  | 56.4  | 17.9  | 42.9  | 56.6  |
| Un-Mix| 18.7  | 46.6  | 60.2  | 19.3  | 47.8  | 62.2  |
| m\textsuperscript{3}-Mix| 19.5  | 49.0  | 63.8  | 21.6  | 49.7  | 63.6  |

5.4 Structure-Awareness for Multi-modal dataset

We expect that multi-modal embedding represents the structure relationship between instances such as word vectors. We validate the robust representation learned from our models on SIMAT dataset [5]. SIMAT evaluates the text-driven image representation by retrieving the new images when we replace the words in the original image caption. We fine-tune the CLIP representation with our models on Flickr30k, and validate the representation on the SIMAT dataset.

Table 4: m\textsuperscript{3}-Mix shows the stable performance including SIMAT, alignment, uniformity, and retrieval score, while others show a relatively inconsistency.

|       | CLIP (Sim., Uni.) | BERT + ResNet-50 |
|-------|-------------------|------------------|
|       | i→t               | i→t              |
| ZS    | 34.4 (0.04, 2.2)  | 69.9 66.2        |
| FT    | 40.6 (0.08, 2.6)  | 81.0 80.2        |
| FT(τ = 0.05) | 44.7 (0.16, 3.9)  | 80.1 80.0        |
| FT(τ = 0.10) | 47.9 (0.14, 5.9)  | 75.0 77.4        |
| i-Mix | 42.2 (0.03, 2.1)  | 78.3 77.6        |
| Un-Mix| 42.0 (0.05, 2.8)  | 80.7 79.2        |
| m\textsuperscript{3}-Mix| 44.0 (0.17, 7.4)  | 82.2 81.5        |
Table 4 denotes the quantitative analysis of our model and the baselines on the SIMAT and Flickr30k dataset. The learned representation from $m^3$-Mix shows the stable performance on all tasks, including SIMAT, alignment score, uniformity score, and retrieval score on Flickr30k. It is noted that $FT(\tau = 0.10)$ that controls the $\tau$ artificially shows the best performance on SIMAT, but it performs worse on the other tasks.

![SIMAT Transformation example from CLIP fine-tuned from our $m^3$-Mix.](image)

$m^3$-Mix shows the many correct cases compared to the zero-shot CLIP (ZS). The last column shows the failure case for ZS and $m^3$, and the example that represents the "bear laying in bed", the relatively irregular situations.

![SIMAT Transformation example from CLIP fine-tuned from our $m^3$-Mix.](image)

Fig. 7 denotes the example of the SIMAT task, and our method records the many correct cases, while zero-shot CLIP and our model fail on the relatively irregular dataset as shown in the last column.

6 Conclusion

This study analyzes the representation learned from multi-modal learning with contrastive loss. We find that the CLIP has separated text embedding space and image embedding space with an unexplored large intermediate area. These separated embedding properties with the largely unexplored area makes CLIP less robust on diverse downstream tasks. From our findings, we propose $m^2$-Mix and $m^3$-Mix that generates the hard-negative samples by mixing the heterogeneous representation, image, and text. We validate that our $m^2$-Mix and $m^3$-Mix representation learning induces the robust representation that contributes to improving the diverse downstream task performance while it preserves multi-modal structure relationship with the better uniformity and alignment score.
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