Supplementary Material: Self-Supervised Adversarial Learning for Cross-Modal Retrieval

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This supplementary material provides the omitted contents in the main paper.

- Section 1 introduces cross-modal GAN studies in detail.
- Section 2 elaborates the multi-task objective loss with self-supervision.
- Section 3 presents experimental settings of three datasets.
- Section 4 detailed introduces the implementation details.
- Section 5 displays the experimental visualisation of the learned representation.
- Section 6 shows the parameter analysis of our experiment.

1 CROSS-MODAL GAN STUDIES

Several cross-modal GAN studies [3, 11, 12] have also been proposed for cross-modal retrieval, in which the strong ability of GAN was

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utilized to model heterogeneous data distribution and learn discriminative common representations of different modalities. Among these methods, (ACMR) [11] utilized adversarial learning approach to seeking an effective common subspace. The modality-invariant representations were generated by playing a minimax game between a feature projector and a modality classifier. Gu [4] incorporated generative processes into the cross-modal feature embedding, through which not only the global abstract features but also the local grounded features were learned. Peng [9] proposed Cross-modal Generative Adversarial Networks (CM-GANs) to explore inter-modality and intra-modality correlation simultaneously in generative and discriminative models. Moreover, Zhu [12] proposed Recipe Retrieval Generative Adversarial Network (R2GAN) to learn a common space for recipe and food.

2 MULTI-TASK OBJECTIVE LOSS WITH SELF-SUPERVISION

Given a modified instance $\tilde{x} = f(x)$, self-supervised models were expected to predict which transformation f was applied. Training a multi-task learning framework which optimizes two losses of the primary and self-supervised tasks while sharing the feature space [1, 2, 5] is the common approach of utilizing self-supervised labels for another task. In a fully supervised setting, the multi-task objective loss with self-supervision can be formulated as follows:

$$\mathcal{L}(x, y; \theta, u, v) = \frac{1}{M} \sum_{j=1}^M \mathcal{L}_{CE}(\delta(f(\tilde{x}_j; \theta); u), y) + \mathcal{L}_{CE}(\delta(f(\tilde{x}_j; \theta); v), j),$$

where $\{f_j\}_{j=1}^M$ is a set of pre-defined transformations, M is the number of self-supervised labels, $\delta(f(\cdot; \theta); u)$ is primary classifier, $\delta(\cdot; v)$ is the classifier for self-supervision and $\mathcal{L}_{CE}$ is the cross-entropy loss function.

Figure 1: t-SNE visualization for original features and learned embeddings on Wikipedia dataset. (a)(b) are the original visual and textual features respectively, (c) is mixed embeddings of our SSAL respectively.

3 DATASETS

The Wikipedia dataset [10] is the most widely used dataset for cross-modal retrieval, which based on “featured articles” in Wikipedia. The dataset consists of 2,866 image-text pairs, where each pair consists of an image and the corresponding complete text article annotated with a label from 10 semantic classes.

Mirflickr-25k [6] contains 25,000 instances collected from Flickr. Each image is labeled with its associated textual tags. Here, we follow the experimental protocols given in DCMH [7]. In total, 20,015 data points have been selected for our experiment.

MS-COCO [8]: contains 123,287 images and their annotated sentences with their annotations categorized into 80 classes. After pruning images without category information, MSCOCO consists of 60000 training images and 10000 test images, each of which is associated with five sentences.

4 IMPLEMENTATION DETAILS

Embedding Generative Network: We built ImgNet and TxtNet with two separate one-layer feed-forward neural networks and a one-layer shared-weights feed-forward neural network, all neural networks are activated by ReLU function. The separate layers are used to project an original feature into an intermediate embedding of size 2048. The shared layers further project the intermediate embedding into an embedding in the common subspace of size 1024. The shared classifier is a two-layer feed-forward neural network, where the mid-layer is activated by ReLU function and the last layer is activated by softmax function.

Self-supervised Adversarial Networks: Adversarial Networks contains two modules to detect the rotation angle and identify the modal category. We built the discriminator networks using a one-layer shared-weights feed-forward neural network activated by Leaky ReLU function and two separate one-layer feed-forward neural networks activated by softmax function. The shared layer first project given embedding of size 1024 into an intermediate embedding of size 512 and the separate layers followed softmax functions further project it into two tensors of size 4 and 2, which are used to predict rotation angles and modalities respectively.

The batch size is set to 128 for all datasets and the hyperparameters are tuned using grid search, which means change one of the hyperparameters 10 times per step and fix the others. Since the

proposed SSAL use rotated images, the image and text feature used in our experiments are not the same with that used in other works. For a fair comparison, we re-evaluate the referred methods with the open sourced codes. In addition, SSAL is implemented via Pytorch and is trained on a server with two NVIDIA TITAN X GPUs.

5 VISUALISATION OF THE LEARNED REPRESENTATION

To illustrate that our proposed SSAL is able to learn more reliable embeddings than that of previous approaches, we visualize the embeddings of our SSAL on Wikipedia dataset, as shown in the left two columns of Fig. 1. We can see that the distributions of the images and texts are different in the Wikipedia dataset. By comparing Fig. 1(a)(b) and Fig.1(c), it can be observed that our method gets feature representations with more semantic distinction which well separates the mixed representations into several semantically discriminative clusters and can be distinguished easily in the common subspace. In addition, Fig.1(c) also shows that the subspace constructed by our method maps text and image features with the same category information together, making them difficult to distinguish and easy to facilitate cross-modal retrieval.

6 PARAMETER ANALYSIS

To investigate the impact of the parameters β , γ , η and λ mentioned in main body, we analyze the performance of our SSAL with different parameter values on the test set of the Wikipedia dataset, as shown in Fig. 2. We set the range of parameters as $\{0.001, 0.01, 0.1, 1, 10, 100\}$ and divide these four hyperparameters into two groups according to the adversarial training process and the evaluation is conducted by changing a set of parameters (e.g. β , γ) while fixing the other (e.g. η , λ). From Fig. 2(a), we can observe that SSAL performs well when β is in the range of $[0.1, 1]$, γ is in the range of $[0.01, 0.1]$ on Wikipedia. And Fig. 2(b) shows that when η is in the range of $[0.001, 0.01]$ and λ is in the range of $[0.1, 1]$, the proposed method achieves the best accuracy. The figure shows that the selected values of hyperparameters help with the overall training optimization process and prevent overfitting so that the proposed method can obtain better results on the test dataset. In addition, we can also see that adversarial learning and reconstruction learning with too much weight will lead to a decrease in performance.

Figure 2: The Average mAP scores of SSAL versus different values of β , γ , η and λ on Wikipedia dataset.

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