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Paper Implementation Report

Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks

Ⅰ. Implementation of CycleGAN's key contributions

The key contribution of this paper is that they provide **a general generative model for unpaired dataset** which is called ***Cycle GAN***. In this process, they suggest a **Cycle GAN Loss** function which combines “adversarial loss” and “cycle consistency loss”. To demonstrate the effeteness of this model and algorithm, I conducted two major experiments. The first was **to show the effectiveness of Cycle GAN Loss through ablation study.** The next one was **to identify the generality of the model by checking the general qualitative performance of Cycle GAN through unpaired datasets with different domains.**

I tried to **royally follow the implementation details** in this paper as far as possible.

- Use *cityscapes* dataset for Experiment 1 and *horse2zebra* and *summer2winter* dataset for Experiment 2.
- Use 6 residual block for 128x128 size (cityscapes) and 9 residual block for 256x256 size (horse2zebra, summer2winter) for the generator and 70 × 70 PatchGAN discriminator.
- Use the negative log likelihood objective by a least-squares loss as adversarial loss part of Cycle GAN Loss.
- Use Instance normalization, linear learning rate scheduler (initial learning rate: 0.002), Adam optimizer, 1 batch size.
- Use Image buffer for training each discriminator using buffer size as 50.

Ⅱ. Experiment results

ⅰ. Ablation study of Cycle GAN Loss

Figure 1. The generated images for each variant of ablation study.

As can be seen from Figure 1, except for Cycle GAN Loss, I didn’t achieve the expected results. Therefore, I could confirmed the necessity of the combination applied to Cycle GAN Loss. In particular, in case of Cycle alone, the Loss converged quickly and stably in both Generator and Discriminator, but the image of the result shows that we cannot achieve the desired result by only minimizing Cycle Consistency Loss.

ⅱ. Identifying the generality of Cycle GAN with different unpaired datasets.

Figure 2. The generated images from CycleGAN models with different unpaired datasets.

As shown in Figure 2, even though CycleGAN was trained with different datasets, we could see that the training resulted in the desired result. Interestingly, the bottom right corner of the horse2zebra was a black and white image, but the result was a color image. This can also be interpreted as a result supporting the generality of CycleGAN by showing that colorization is also possible.

Ⅲ. Discussion

As mentioned in the paper, the above experiments confirmed the generality of CycleGAN for training with unpaired datasets and the need of Cycle GAN Loss. However, in the process of training, there were a few problems. One is that CycleGAN was able to learn the features well, but it was difficult to change the shape. The other one is that although different input images have been applied, there have been cases in which specific portions of the output image are generated identically. To solve this problem, applying GAN Loss to WGAN-GP seems to be a good approach.