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**Project: Generative Adversarial Networks**

**– What are you trying to do?**

Implement three types of generative adversarial networks (GAN): traditional GAN [1], Auxiliary Classifier GAN [2], and Wasserstein-GAN [3]. Generate new samples from the original data distribution using different GANs and evaluate the generated data both qualitatively and quantitatively.

**– How is it done today?**

As one of the most popular generative models in the past few years, GAN has the top performance in many applications from downstream tasks to upstream tasks. For example, GANs can be applied for data augmentation and dataset expansion. They can synthesize human face images thus solve some ethical difficulties of human face data collection. GANs can also be applied to image-to-image or text-to-image conversion. Thus, it is important to explore its strength, problems, and corresponding solutions.

GAN is a neural network that has two modules contesting with each other: a generator and a discriminator. In a traditional GAN structure, the generator generates new data from random vectors sampled from latent space, while the discriminator is a binary classifier that distinguishes the generated “fake” candidates from the “true” data. In the training process, the generator tries to maximize the likelihood that its generated data is classified as “real” by the discriminator, while the discriminator tries to maximize the accuracy of classifying real data and fake data. Both networks apply independent back-propagation procedures so that as the discriminator is better at distinguishing synthetic samples, generator can produce more authentic data.

However, traditional GAN are known for its instable training, specifically the problems of gradient-vanishing and mode collapse. In one scenario, when the generator has a poor performance compared with the discriminator, the loss of discriminator will approach to zero, and thus stops the learning process with non-updating weights. In another scenario, when the discriminator has a poor performance at discriminating a small subset of outputs from generator, the next generation of generator can find it easy to “fool” the discriminator with only these outputs and thus introduced the problems of mode collapse. To solve these problems, researchers introduced Auxiliary Classifier GAN and Wasserstein-GAN. AC-GAN includes the class labels from the dataset into the training process. In an AC-GAN, the generator needs to generate data with random labels, while the discriminator should not only classify the “real” and “fake” data, but also classify the correct class of the data. It can produce data with higher quality as data from the same class are more similar thus more easily to be sampled from the same normal distribution. Wasserstein-GAN introduces the Wasserstein loss (or Earth-Mover’s loss) into a traditional GAN. With this loss function, WGAN can have almost linear gradient everywhere (Figure 1) and thus solves the problem of gradient vanishing and mode collapse and stabilize the training process.

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Figure 1. Linear gradients in a WGAN [3]

**– Your approach and why do you think it will be successful?**

1. Implement traditional GAN to generate novel samples from the CIFAR-10 distribution.
2. Implement the AC-GAN to generate novel samples from the CIFAR-10 distribution.
3. Implement the WGAN to generate novel samples from the CIFAR-10 distribution and compare its training process with original GAN.
4. Evaluate the quality of the generated samples for all GANs both quantitatively and qualitatively.
5. Use Modified Inception Score (m-IS) to evaluate the quality and diversity of the generated samples.
6. Use multi-scale structural similarity (MS-SSIM) for quantitatively evaluating image similarity.
7. Plot the metrics. Describe and explain all results.

**– What are the risks?**

1. GANs are hard to train. Require much effort in hyperparameter tuning as it is hard to identify convergence in GANs simply from loss function. We can only monitor the generator outputs to evaluate the progress of training.
2. Optimizer selection and design. Different optimizers have their own pros and cons. The selection of optimizers influences the direction of evaluation and improvement of the model.
3. To generate new samples that are close enough to the real data distribution, there may be serious overfitting problems.

**– How long will it take?**

Week1: Review literatures, familiarize with concepts. Implement and train GAN, AC-GAN, WGAN on CIFAR-10

Week2: Use Modified Inception Score (m-IS) to evaluate the quality and diversity of the generated samples.

Week3: Use multi-scale structural similarity (MS-SSIM) for quantitatively evaluating image similarity.

Week4: Visualize metrics and generated samples

Week5: Finish report

**– What are the final “exams” to check for success?**

Sanity check for the correctness of GANs structures.

Images showing the generated samples to help us qualitatively evaluate the performance of different GANs.

Tables and graphs of quantitative metrics showing AC-GAN and WGAN have better performance compared with traditional GANs.