Abstract

Generative Adversarial Networks (GANs) based semi-supervised learning (SSL) approaches are shown to improve classification performance by utilizing a large number of unlabeled samples in conjunction with limited labeled samples. However, their performance still lags behind the state-of-the-art non-GAN based SSL approaches. One main reason we identify is the lack of consistency in class probability predictions on the same image under local perturbations. This problem was addressed in the past in a generic setting using the label consistency regularization, which enforces the class probability predictions for an input image to be unchanged under various semantic-preserving perturbations. In this work, we incorporate the consistency regularization in the vanilla semi-GAN to address this critical limitation. In particular, we present a new composite consistency regularization method which, in spirit, combines two well-known consistency-based techniques – Mean Teacher and Interpolation Consistency Training. We demonstrate the efficacy of our approach on two SSL image classification benchmark datasets, SVHN and CIFAR-10. Our experiments show that this new composite consistency regularization based semi-GAN significantly improves its performance and achieves new state-of-the-art performance among GAN-based SSL approaches.

1. Introduction

In the past decade, supervised classification performance improved significantly with the advent of deep neural networks [33, 14, 16]. These advancements can be chiefly attributed to the training of deep neural networks on large-scale well-annotated image classification datasets, such as, ImageNet [9]. However, obtaining such datasets with large amounts of labeled data is often prohibitive due to time, cost, expertise, and privacy restrictions. Semi-supervised learning (SSL) presents an alternative, where models can learn representations from plentiful of unlabeled data, thus reducing the heavy dependence on the availability of large...
labeled datasets.

In recent years, Deep Generative Models (DGMs) [20, 31,11] have emerged as an advanced framework for learning data representations in an unsupervised manner. In particular, Generative Adversarial Networks (GANs) [11] have demonstrated an ability to learn generative model of any arbitrary data distribution and produce visually realistic set of artificial (fake) images. GANs set up an adversarial game between a generator network and a discriminator network, where the generator is tasked to trick the discriminator with generated samples, whereas the discriminator is tasked to tell apart real and generated samples. Semi-GAN [32] is one of the earlier extension of GANs to the SSL domain, where the discriminator employs a (K+1)-class predictor with the extra class referring to the fake samples from the generator.

We first observe that semi-GAN suffers from inconsistent predictions in our experiments on the CIFAR-10 dataset. In this experiment, each unlabeled image is augmented with two different data augmentations and fed into a well-trained discriminator of semi-GAN. Figure 1 depicts such input images on which vanilla semi-GAN’s discriminator produces inconsistent predictions, whereas our proposed composite consistency GAN produces desired results. Although many approaches [8, 28, 10, 23] have been developed to improve the performance of semi-GAN, regularizing semi-GAN with consistency techniques has barely been explored in the literature. Consistency regularization specifies that the classifier should always make consistent predictions for an unlabeled data sample, in particular, under semantic-preserving perturbations. It follows from the popular smoothness assumption [4] in SSL that if two points in a high-density region of data manifold are close, then so should the corresponding outputs. Based on this intuition, we hypothesize that the discriminator of semi-GAN should also produce consistent outputs if we incorporate consistency regularization in the discriminator.

Thus, in this work we propose to extend semi-GAN by integrating consistency regularizer into the discriminator. Since both Mean Teacher (MT) [36] and Interpolation Consistency Training (ICT) [38] perform well among consistency-based approaches, we explore both of them in this work. We also note that MT consistency and ICT consistency are complementary to each other, therefore we propose a new composite consistency regularizer by combining the MT and ICT into one unified framework. In summary, we make the following contributions:

- We propose an integration of consistency regularization into the discriminator of semi-GAN, so that the discriminator would make consistent predictions for data samples with local perturbations, thus leading to the new model’s improved performance in semi-supervised classification. Empirically, our semi-GAN with composite consistency sets new state-of-the-art performances on the two SSL benchmark datasets SVHN and CIFAR-10 by 2.87% and 3.13% respectively in the setting with the least labeled data.

- We propose a new consistency measure called composite consistency, which is derived by combining the Mean Teacher and Interpolation Consistency Training techniques. We empirically show that this composite consistency measure produces best results among the three consistency-based techniques.

2. Preliminaries

In a general SSL setting, we are given a small set of labeled samples \((x_l, y_l)\) and a large set of unlabeled samples \(x_u\), where every \(x \in \mathbb{R}^d\) is a d-dimensional input data sample and \(y \in \{1, 2, ..., K\}\) is one of \(K\) class labels. The objective of SSL is to learn a classifier \(D(y|x; \theta) : \mathcal{X} \rightarrow \mathcal{Y}\), mapping from the input space \(\mathcal{X}\) to the label space \(\mathcal{Y}\), parameterized by \(\theta\). In deep SSL approaches, \(D(y|x; \theta)\) is chosen to be represented by a deep neural network.

2.1. Review of semi-GAN

In a Generative Adversarial Network (GAN), an adversarial two-player game is set up between discriminator and generator networks. The objective of the generator \(G(z; \delta)\) is to transform a random vector \(z\) into a fake sample that cannot be distinguished from real samples by the discriminator. The discriminator is a binary classifier tasked to judge whether a sample is real or fake. Salimans et al. [32] pioneered the extension of GANs to SSL by proposing the first GAN-based SSL approach named as semi-GAN. In semi-GAN [32], the discriminator is adjusted into a \((K+1)\)-head classifier, where the first \(K\) are real classes originated from the dataset and the \((K+1)\)-th class is the fake class referring to generated samples. The objective function for the discriminator is formulated as:

\[
\mathcal{L}_D = -\mathbb{E}_{p(x, y)}[\log D(y|x; \theta)] - \mathbb{E}_{p(z)}[\log D(y = K + 1|G(z; \delta); \theta)] - \mathbb{E}_{p(x)}[\log (1-D(y = K + 1|x; \theta))]
\]

The first term is the standard supervised loss \(\mathcal{L}_{\text{supervised}}\) that maximizes the log-likelihood that a labeled data sample is classified correctly into one of its ground-truth class. The second and third terms constitute the unsupervised loss \(\mathcal{L}_{\text{unsupervised}}\) that classifies real samples \(x\) as non-fake \((y < K + 1)\) and generated samples \(G(z)\) as fake \((y = K + 1)\).

The authors of [32] also proposed a feature matching loss as the objective function for the generator, where the generator objective is to minimize the discrepancy of the
Figure 2: **Overall Architecture of New Semi-GAN with Consistency Regularization.** The discriminator of the semi-GAN is treated as the student model for the consistency regularization, and the consistency loss is enforced as the prediction difference between the student and teacher models for real data. “FC” represents a fully connected layer.

first moment between real and generated data distributions in feature space, represented as:

\[
\mathcal{L}_G = \|\mathbb{E}_{p(x)} f(x; \theta_f) - \mathbb{E}_{p(z)} f(G(z; \delta); \theta_f)\|^2_2 \tag{2}
\]

where \( f \) is an intermediate layer from the discriminator \( D \), and \( \theta_f \) is a subset of \( \theta \), including all the parameters up to that intermediate layer of the discriminator. In practice, feature matching loss has exhibited excellent performance for SSL tasks and has been broadly employed by follow-on GAN-based SSL approaches \[32, 8, 28\].

### 2.2. Review of consistency regularization

Consistency regularization has been widely used in semi-supervised or unsupervised learning approaches \[37, 22, 36, 25\]. The intuition behind it is that the classifier should make consistent predictions, that are invariant to small perturbations added to either inputs or intermediate representations for both labeled and unlabeled data. Typical perturbations are represented in the form of input augmentations, dropout regularization \[35\], or adversarial noise \[12\]. To enforce consistency, the \( \Gamma \)-model \[29\] evaluates each data input with and without perturbation, and minimizes the discrepancy between the two predictions. In this case, the classifier can be considered as assuming two parallel roles, one as a student model for regular learning and the other as a teacher model for generating learning targets. Since there are no ground truth labels for unlabeled data, the learning targets generated by the teacher model can be incorrect, and some recent works \[22, 36\] have been focused on improving the quality of the teacher model to generate better learning targets for the student model.

More formally, the consistency loss term is defined as the divergence of the predictions between the student model and the teacher model, formulated as

\[
\mathcal{L}_{cons} = \mathbb{E}_{\mu(x)} d[D(y|x; \theta, \xi), D(y|x; \theta', \xi')] \tag{3}
\]

where \( D(y|x; \theta, \xi) \) is the student model with parameters \( \theta \) and random perturbation \( \xi \), and \( D(y|x; \theta', \xi') \) is the teacher model with parameters \( \theta' \) and random perturbation \( \xi' \). \( d[\cdot, \cdot] \) measures the divergence between the two predictions, usually chosen to be Euclidean distance or Kullback-Leibler divergence.

### 3. Methodology

To address the prediction inconsistency of semi-GAN \[32\], we integrated consistency regularization into semi-GAN, leading it to produce consistent outputs (predictions) under small perturbations to inputs. In other words, the consistency regularization serves as an additional auxiliary loss term to the discriminator. Hence the new objective function for the discriminator is formulated as following:
Figure 3: Illustration of Consistency Regularization. Three types of consistency techniques: (a) MT, (b) ICT and (c) Composite. In the figure, \(x_m\) and \(x_n\) are two shuffled versions of \(x\), while \(\xi\) and \(\xi'\) represent two random data augmentations.

\[
\mathcal{L}_D = -\mathbb{E}_{p(x,y)} \left[ \log D(y|x; \theta, \xi) \right] - \mathbb{E}_{p(z)} \left[ \log D(y = K + 1|G(z; \delta); \theta) \right] - \mathbb{E}_{p(x)} \left[ \log (1 - D(y = K + 1|x; \theta, \xi)) \right] + \lambda_{\text{cons}} \mathbb{E}_{p(x)}[D(y|x; \theta, \xi), D(y|x; \theta', \xi')] \]

where the first three terms come from original discriminator loss of semi-GAN (see Eq.1) and the fourth term is the consistency loss (see Eq.3), and the coefficient \(\lambda_{\text{cons}}\) is a hyper-parameter controlling the importance of the consistency loss. Figure 2 displays our new model architecture. As shown in the figure, the discriminator \(D(y|x; \theta)\) in semi-GAN [32] is also treated as the student model for the consistency regularization and the consistency loss is enforced as the prediction difference between the student and teacher models for real data. See Section 3.1 for more details on how the teacher model \(D(y|x; \theta')\) is generated from the student model.

In specific, we integrate two well-known consistency-based techniques called Mean Teacher (MT) [36] and Interpolation Consistency Training (ICT) [38] into semi-GAN. Furthermore, we propose the combination of these two techniques as a new composite consistency-based technique and experimentally show that it enhances the robustness of the discriminator. Figure 3 illustrates the ideas of these three consistency-based techniques.

3.1. MT Consistency

Born from the \(\Gamma\)-model [29], Mean Teacher [36] imposes consistency by adding random perturbations to the input of the model. As shown in Figure 3 (a), the input data are transformed with certain types of augmentation (e.g., image shifting, flipping, etc.) randomly twice. The two augmented inputs are then fed into the student model and teacher model separately, and the consistency \((\text{Cons})\) is achieved by minimizing the prediction difference between the student model and teacher model. One key aspect of MT is that it improves the quality of the learning targets from the teacher model by forming a better teacher model. Namely, the parameters \(\theta'\) of the teacher model are maintained as an exponential moving average (EMA) of the parameters \(\theta\) of the student model during training, formulated as:

\[
\theta''_t = k\theta'_{t-1} + (1 - k)\theta'_t
\]

where \(t\) indexes the training step and the hyper-parameter \(k\) is the EMA decay coefficient. By aggregating information from the student model in an EMA manner at training time, a better teacher model can generate more stable predictions which serve as higher quality learning targets to guide the learning of the student model. This way of generating the teacher model is also employed in ICT [38] and eventually in our composite consistency-based technique.

3.2. ICT Consistency

Interpolation Consistency Training [38] proposes a new type of consistency that encourages consistent predictions at interpolations of two data samples. The interpolation is the linear interpolation implemented using the MixUp operation [41]. Given any two vectors \(u\) and \(v\), the MixUp operation is defined as
\[Mix_\lambda(u, v) = \lambda \cdot u + (1 - \lambda) \cdot v \quad (6)\]

where \( \lambda \in [0, 1] \) is a parameter randomly sampled from Beta distribution denoted as \( \lambda \sim \text{Beta}(\alpha, \alpha) \), and \( \alpha \) is a hyper-parameter controlling the sampling process. With the MixUp operation, given two randomly shuffled versions of the dataset \( x \) after data augmentation \( \xi \) represented as \( x_m \) and \( x_n \), the ICT consistency is computed as

\[
\mathcal{L}_{\text{ict cons}} = \mathbb{E}_{p(x_m, x_n | x, \xi)} d[D(y_{mix} | Mix_\lambda(x_m, x_n); \theta), \]
\[Mix_\lambda(D(y_m | x_m; \theta'), D(y_n | x_n; \theta'))] \quad (7)\]

and it encourages the predictions from the student model at interpolations of any two data samples (denoted as \( D(y_{mix} | Mix_\lambda(x_m, x_n); \theta) \)) to be consistent with the interpolations of the predictions from the teacher model on the two samples (denoted as \( Mix_\lambda(D(y_m | x_m; \theta'), D(y_n | x_n; \theta')) \)), shown in Figure 5 (b).

3.3. Composite Consistency

Though MT chooses to perturb data samples by certain types of data augmentations, and the ICT method chooses to perturb data samples from the perspective of data interpolations, they have some common characteristics. If we set \( \lambda = 1 \) in ICT, the interpolated sample \( Mix_\lambda(x_m, x_n) \) is reduced to \( x_m \), hence the ICT consistency loss term is reduced to

\[
\mathcal{L}_{\text{ict cons}} = \mathbb{E}_{p(x_m, x_n | x, \xi)} d[D(y_{mix} | x_m; \theta), D(y_m | x_m; \theta')] \quad (8)\]

This loss term is the same as MT consistency loss (see Eq.3) except that the same data augmentation \( \xi \) is applied to the inputs of both student and teacher models. Accordingly, if two different data augmentations are applied to the inputs of the student and teacher models separately as MT, we can make ICT also robust to data augmentation perturbations, as shown in Figure 5 (c). In other words, we can combine these two consistency techniques so that the model would be robust to both data augmentation perturbations and data interpolation perturbations. We name the combination of these two consistency techniques as composite consistency, and formulate the corresponding loss \( \mathcal{L}_{\text{comp cons}} \) term as

\[
\mathcal{L}_{\text{comp cons}} = \mathbb{E}_{p(x_m, x_n | x)} d[D(y_{mix} | Mix_\lambda(x_m, x_n); \theta, \xi), \]
\[Mix_\lambda(D(y_m | x_m; \theta', \xi'), D(y_n | x_n; \theta', \xi'))] \quad (9)\]

4. Experiments

In this section, we present comprehensive experiments to evaluate the effectiveness of our proposed method. The purpose of these experiments is to demonstrate the efficacy of incorporating consistency regularization into the semi-GAN. In addition, we evaluate our approach with varying amounts of labeled samples from two benchmark SSL datasets and conduct ablation studies to systematically analyze different aspects of our approach.

4.1. Datasets

Following the common practice in evaluating GAN-based SSL approaches [32, 10, 5, 28, 10], we quantitatively evaluate our extensions using two SSL benchmark datasets: SVHN and CIFAR-10. The SVHN dataset consists of 73,257 training images and 26,032 test images. Each image has a size of 32 \( \times \) 32 centered with a street view house number (a digit from 0 to 9). There are a total of 10 classes in the dataset. The CIFAR-10 dataset consists of 50,000 training images and 10,000 test images. Similarly, the CIFAR-10 dataset also has images of size 32 \( \times \) 32 and 10 classes. The 10 classes represent some common objects in daily life, such as airplanes and birds.

4.2. Implementation Details

We utilize the same discriminator and generator network architectures as used in CT-GAN [40]. See Appendix for more details of the network architectures. When training models on SVHN training data, we augment the images with random translation, where the image is randomly translated in both horizontal and vertical directions with a maximum of 2 pixels. For the CIFAR-10 dataset, we apply both random translation (in the same way as SVHN) and horizontal flips. For both datasets, we train the models with a batch size of 128 labeled samples and 128 unlabeled samples. We run the experiments with Adam Optimizer [13] (set \( \beta_1 = 0.5, \beta_2 = 0.999 \)), where the learning rate is set to be 3e-4 for the first 400 epochs and linearly decayed to 0 in the next 200 epochs. Following the same training schema as in MT and ICT, we also employ the ramp-up phase for the consistency loss, where we increase consistency loss weight \( \lambda_{\text{cons}} \) from 0 to its final value in the first 200 epochs. We adopt the same sigmoid-shaped function \( e^{-5(1-\gamma)^2} \) [55] as our ramp-up function, where \( \gamma \in [0, 1] \). We set the EMA decay coefficient \( k \) to 0.99 and the parameter \( \alpha \) in Beta(\( \alpha, \alpha \)) distribution to 0.1 through all our experiments.

4.3. Ablation study

Effect of consistency loss weight \( \lambda_{\text{cons}} \): The most important hyper-parameter influencing model performance is the consistency loss weight \( \lambda_{\text{cons}} \). We conduct an experiment using semi-GAN with composite consistency on CIFAR-10 with 4,000 labeled images where we train our model with a wide range of \( \lambda_{\text{cons}} \) values, and the results are shown in Figure 4. Note that the model with \( \lambda_{\text{cons}} = 0 \) is equivalent to a
vanilla semi-GAN model. From the figure, we see that there is a sharp decrease in error rate as $\lambda_{\text{cons}}$ increases from 0 to 10, implying composite consistency starts taking effect early on, then it reaches a relatively steady state (between 10 and 20), and then the error rate gradually increases with increase in $\lambda_{\text{cons}}$. In conclusion, this experiments shows that the for a small range of $\lambda_{\text{cons}} \in \{10, 20\}$ test error quickly reduces and stabilizes. It is also apparent that error may increase for large values of $\lambda_{\text{cons}}$.

![Figure 4: Test errors of semi-GAN with composite consistency on CIFAR-10 with 4,000 labeled samples over 5 runs.](image)

**Performance of different consistency techniques:** As there are three choices of consistency-based regularizers (see Section 3) to chose from, it is necessary to quantify the benefits of integrating these into the semi-GAN. So we compare them empirically on CIFAR-10 with 1,000 and 4,000 labeled images, respectively. Table 1 shows the comparison results, and it is clear that incorporating consistency regularization into semi-GAN consistently improves the performance, and semi-GAN with composite consistency yields better results than MT or ICT consistency individually.

| Models          | Error rate (%) |          |
|-----------------|----------------|----------|
|                 | CIFAR-10       | CIFAR-10 |
|                 | $n_l = 1,000$  | $n_l = 4,000$ |
| semi-GAN        | 17.27 ± 0.83   | 14.12 ± 0.29 |
| semi-GAN + MT   | 15.28 ± 1.03   | 12.08 ± 0.27 |
| semi-GAN + ICT  | 15.11 ± 0.86   | 11.66 ± 0.50 |
| semi-GAN + CC   | 14.36 ± 0.35   | 11.03 ± 0.42 |

Table 1: Performance of the three consistency measures with semi-GAN. The experiments are conducted over 5 runs and percent error rate is used as the evaluation criteria. “CC” is short for our proposed composite consistency.

In addition, we have also conducted experiments with MT and ICT as standalone methods to demonstrate that semi-GAN with consistency regularization would produce better results. Under the same experimental settings as we describe in Section 4.2 we exclude semi-GAN from the framework and evaluate the performance of either MT or ICT alone on CIFAR-10 with 4,000 labeled images. The error rate of MT is 18.57% ± 0.43, whereas combining with semi-GAN yields a lower error rate of 12.08% ± 0.27. Also, the error rate of ICT is 18.16% ± 1.25, whereas combining with semi-GAN yields a lower error rate of 11.66% ± 0.50. This supports our observation that the semi-GAN and consistency regularization are complementary and could achieve better performance when combined. Meanwhile, we acknowledge some performance differences between our MT and ICT re-implementations with the ones reported in original MT and ICT papers. This performance difference is primarily caused by the minor network architecture difference. As a sanity check, we verified that our re-implementation of MT with the network architecture used in MT paper and obtains similar performance as the one reported in original MT paper [36].

**Effect of imposing consistency at different positions of the discriminator:** Although consistency has always been imposed at output space in consistency-based approaches [22, 36, 26, 25], it could also be imposed at feature space to help the model learn high-level features invariant to diverse perturbations. Therefore, in this study, we choose to impose consistency with three different settings: 1) on the output layer of the discriminator for prediction consistency; 2) on the intermediate layer of the discriminator (the layer right before FC + softmax as shown in Figure 2) for feature consistency; 3) on both the output layer and the intermediate layer of the discriminator for prediction and feature consistencies. When imposing feature consistency, we perform hyper-parameter search for its consistency weight over the values in $\{0.01, 0.1, 1.0, 10, 100\}$ and report the results with the optimal hyper-parameter value. We conducted experiments on CIFAR-10 dataset with 1,000 and 4,000 labeled images, respectively. From Table 2 we can observe that incorporating consistency in both output space and feature space yields the best performance among the three, implying both feature consistency and prediction consistency can benefit the semi-supervised learning task. Thus, we impose consistency on both the output layer and the intermediate layer of the discriminator in our final evaluation.

### 4.4. Results

Following the standard evaluation criteria used in the GAN-based approaches [22, 10, 5, 28, 10], we trained these models on SVHN training data with 500 and 1,000 randomly labeled images respectively and evaluated the model classification performance on the corresponding test dataset. For CIFAR-10, we trained the models on training data with 1,000, 2,000, and 4,000 randomly selected labeled images with 1,000, 2,000, and 4,000 randomly selected labeled images.
Table 2: Effects of imposing consistency at different positions of the discriminator. The experiments are conducted using semi-GAN with composite consistency over 5 runs.

| Consistency type       | Error rate (%) |
|------------------------|---------------|
|                        | CIFAR-10      | CIFAR-10      |
|                        | \(n_l = 1,000\) | \(n_l = 4,000\) |
| Prediction             | 14.36 ± 0.35  | 11.03 ± 0.42  |
| Feature                | 16.78 ± 0.87  | 13.19 ± 0.50  |
| Prediction & Feature   | 14.14 ± 0.23  | 10.69 ± 0.49  |

Table 2: Effects of imposing consistency at different positions of the discriminator. The experiments are conducted using semi-GAN with composite consistency over 5 runs.

images and then evaluated them on test data. The results are provided in Tables 3 and 4. For both datasets, semi-GAN with composite consistency outperforms vanilla semi-GAN by a large margin and sets new state-of-the-art performance among GAN-based SSL approaches.

Please note that we could not preform a direct comparison between our approach and non-GAN-based SSL approaches due to the differences in network architecture. However, as a sanity check we have experimented with the CNN-13 architecture adopted in the recent consistency-based SSL approaches [22, 25, 38] as our discriminator, but encountered mode collapse issue [11] during training in multiple trials. We suspect that this is due to the discriminator being easily dominated by the generator in this setting.

4.5. Visualization

We also produced visualizations (see Figure 5) with the learned feature embeddings of semi-GAN model and semi-GAN + CC on both CIFAR-10 and SVHN test datasets using t-SNE [24]. We trained models on CIFAR-10 with 4,000 labeled images and SVHN with 1,000 labeled images respectively, and projected the feature embeddings \(f(x) \in \mathbb{R}^{128}\) into 2-D space using t-SNE, where the feature embeddings are obtained from the layer right before final FC + softmax layer. From the figure, observe that the feature embeddings of our semi-GAN + CC model are more concentrated within each class and the classes are more separable in both CIFAR-10 and SVHN test datasets, while they are more mixed in the semi-GAN model. This visualization further validates our hypothesis that the composite consistency regularization in semi-GAN improves the classification performance.

5. Related Work

Since we have already covered consistency-based approaches in Section 2.2, here we only focus on reviewing the most relevant GAN-based SSL approaches and provide a brief review of other categories of deep SSL approaches.

GAN-based SSL approaches: Following semi-GAN [32], Qi et al. [28] propose Local-GAN to improve the robustness of the discriminator on locally noisy samples, which are generated by a local generator at the neighborhood of real samples on a real data manifold. Instead, our approach attempts to improve the robustness of the discriminator from the perspective of local consistency directly on real samples. Likewise, the authors in [8] have proposed a complement generator to address the drawbacks in the feature matching objective of semi-GAN. They show both theoretically and empirically that a preferred generator should generate complementary samples in low-density regions of the feature space, so that real samples are pushed to separable high-density regions and hence the discriminator can learn to correct class decision boundaries. Based on information theory principles, CatGAN [34] adapts the real/fake adversary formulation of the standard GAN to the adversary on the level of confidence in class predictions, where the discriminator is encouraged to predict real samples into one of the \(K\) classes with high confidence and to predict fake samples into all of the \(K\) classes with low confidence, and the generator is designated to perform in the opposite. Similarly, the CLS-GAN [27] designs a new loss function for the discriminator with the assumption that the predic-
Table 3: Percent error rate comparison with GAN-based approaches on CIFAR-10 over 5 runs. "*" indicates our re-implementation of the method. “CC” is short for our proposed composite consistency.

| Models                  | CIFAR-10                     |
|-------------------------|------------------------------|
|                         | $n_l = 1,000$ | $n_l = 2,000$ | $n_l = 4,000$ |
| CatGAN [34]             | -                           | -             | 19.58 ± 0.46  |
| semi-GAN [32]           | 21.83 ± 2.01                | 19.61 ± 2.09  | 18.63 ± 2.32  |
| Bad GAN [8]             | -                           | -             | 14.41 ± 0.30  |
| CLS-GAN [27]            | -                           | -             | 17.30 ± 0.50  |
| Triple-GAN [5]          | -                           | -             | 16.99 ± 0.36  |
| Local GAN [28]          | 17.44 ± 0.25                | -             | 14.23 ± 0.27  |
| ALI [10]                | 19.98 ± 0.89                | 19.09 ± 0.44  | 17.99 ± 1.62  |
| Manifold Regularization [23] | 16.37 ± 0.42 | 15.25 ± 0.35 | 14.34 ± 0.17  |
| semi-GAN*               | 17.27 ± 0.83                | 15.36 ± 0.74  | 14.12 ± 0.29  |
| semi-GAN + CC (ours)    | **14.14 ± 0.23**            | **12.11 ± 0.46** | **10.69 ± 0.49** |

Table 4: Percent error rate comparison with GAN-based approaches on SVHN over 5 runs. "*" indicates our re-implementation of the method. “CC” is short for our proposed composite consistency.

| Models                  | SVHN                         |
|-------------------------|------------------------------|
|                         | $n_l = 500$ | $n_l = 1,000$ |
| semi-GAN [32]           | 18.44 ± 4.80 | 8.11 ± 1.30 |
| Bad GAN [8]             | -                           | 7.42 ± 0.65  |
| CLS-GAN [27]            | -                           | 5.98 ± 0.27  |
| Triple-GAN [5]          | -                           | 5.77 ± 0.17  |
| Local GAN [28]          | 5.48 ± 0.29                | 4.73 ± 0.29  |
| ALI [10]                | -                           | 7.41 ± 0.65  |
| Manifold Regularization [23] | 5.67 ± 0.11 | 4.63 ± 0.11  |
| semi-GAN*               | 6.66 ± 0.58                | 5.36 ± 0.31  |
| semi-GAN + CC (ours)    | **3.79 ± 0.23**            | **3.64 ± 0.08** |

In this work, we identified an important limitation of semi-GAN and extended it via consistency regularizer. In particular, we developed a simple but effective composite consistency regularizer and integrated it with the semi-GAN approach. This composite consistency measure takes advantage of the well-known MT and ICT consistency mea-

**6. Conclusions**

In this work, we identified an important limitation of semi-GAN and extended it via consistency regularizer. In particular, we developed a simple but effective composite consistency regularizer and integrated it with the semi-GAN approach. This composite consistency measure takes advantage of the well-known MT and ICT consistency mea-

**Other deep SSL categories:** Variational Auto-Encoders (VAEs) [20, 31] have also been explored in the deep generative models (DGMs) domain. VAE-based SSL approaches [19, 30] treat class label as an additional latent variable and learn data distribution by optimizing the lower bound of data likelihood using a stochastic variational inference mechanism. Aside from DGMs, graph-based approaches [1, 21] have also been developed with deep neural networks, which smooth the label information on a pre-constructed similarity graph using variants of label propagation mechanisms [2]. Differing from graph-based approaches, deep clustering approaches [15, 13, 17] build the graph directly in feature space instead of obtaining a pre-constructed graph from input space and perform clustering on the graph guided by partial labeled information. Furthermore, some recent advances [39, 3] focus on the idea of distribution alignment, attempting to reduce the empirical distribution mismatch between labeled and unlabeled data caused by sampling bias.
surges, and shown to be resilient to both data augmentation perturbations and data interpolation perturbations. Our thorough experiments and ablation studies showed the effectiveness of semi-GAN with composite consistency on two benchmark datasets of SVHN and CIFAR-10, and consistently produced lower error rates among the GAN-based SSL approaches.

Since composite consistency with semi-GAN is proved to be effective on real images, we plan to study the effect of enforcing composite consistency also on generated images from the generator in our future work. Furthermore, while we adopt standard data augmentations (e.g., image shifting and flipping) to input images in this work, we are interested in further exploring other stronger forms of data augmentations proposed recently (i.e., AutoAugment [6], RandAugment [7]).

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