Imaginative Walks: Generative Random Walk Deviation Loss for Improved Unseen Learning Representation

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Abstract
We propose a novel loss for generative models, dubbed as GRaWD (Generative Random Walk Deviation), to improve learning representations of unexplored visual spaces. Quality learning representation of unseen classes (or styles) is critical to facilitate novel image generation and better generative understanding of unseen visual classes, i.e., zero-shot learning (ZSL). By generating representations of unseen classes based on their semantic descriptions, e.g., attributes or text, generative ZSL attempts to differentiate unseen from seen categories. The proposed GRaWD loss is defined by constructing a dynamic graph that includes the seen class/style centers and generated samples in the current minibatch. Our loss initiates a random walk probability from each center through visual generations produced from hallucinated unseen classes. As a deviation signal, we encourage the random walk to eventually land after T steps in a feature representation that is difficult to classify as any of the seen classes. We demonstrate that the proposed loss can improve unseen class representation quality inductively on text-based ZSL benchmarks on CUB and NABirds datasets and attribute-based ZSL benchmarks on AW A2, SUN, and aPY datasets. In addition, we investigate the ability of the proposed loss to generate meaningful novel visual art on the WikiArt dataset. The results of experiments and human evaluations demonstrate that the proposed GRaWD loss can improve StyleGAN1 and StyleGAN2 generation quality and create novel art that is significantly more preferable. Our code is made publicly available at https://github.com/Vision-CAIR/GRaWD.

Introduction
Generative models like GANs (Goodfellow et al. 2014) and VAEs (Kingma and Welling 2013) are excellent tools for generating realistic images due to their ability to represent high-dimensional probability distributions. However, they are not explicitly trained to go beyond distribution seen during training. In recent years, generative models have been adopted to go beyond training data distributions and improve unseen class recognition (also known as zero-shot learning) (Guo et al. 2017a; Long et al. 2017; Guo et al. 2017b; Kumar Verma et al. 2018; Zhu et al. 2018; Vyas, Venkateswara, and Panchanathan 2020). These methods train a conditional generative model $G(s_k, z)$ (Mirza and Osindero 2014; Odena, Olah, and Shlens 2017), where $s_k$ is the semantic description of class $k$ (attributes or text descriptions) and $z$ represents within-class variation (e.g., $z \in N(0, I)$). After training, $G(s_k, z)$ is used to generate imaginary data for unseen classes transforming ZSL into a traditional classification task trained on the generated data. Understanding unseen classes is mainly leveraged by the generative model’s improved ability to produce discriminative visual features/representations using $G(s_k, z)$ from their corresponding unseen semantic descriptions (i.e., $s_u$).

To generate likable novel visual content, GANs’ training has been augmented with a loss that encourages careful deviation from existing classes (Elgammal et al. 2017a; Sbai et al. 2018; Hertzmann 2018). Such models were shown to have some capability to produce unseen aesthetic art (Elgammal et al. 2017a), fashion (Sbai et al. 2018; Wu et al. 2021), and design (Nobari, Rashad, and Ahmed 2021). In a generalized ZSL context, CIZSL (Elhoseiny and Elfeki 2019) showed an improved performance by modeling a similar deviation to encourage discrimination explicitly between seen and unseen classes. These losses improve unseen rep-

Figure 1: GRaWD loss encourages generatively visiting the orange realistic space, aiming to deviate from the seen classes and avoid the less real red space. Our loss starts from each seen class (in green) and performs a random walk through generated examples of hallucinated unseen classes (in orange) for $T$ steps. We then encourage the landing representation to be distinguishable from seen classes. With this property, the proposed loss helps improve generalized ZSL performance and novel art creation.

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representation quality by encouraging the produced visual generations to be distinguishable from seen classes in ZSL. Elhoseiny and Elfeky (2019) and seen styles in art (Elgammal et al. 2017a) and fashion (Sbai et al. 2018) generation.

We propose Generative Random Walk Deviation Loss (GRaWD) as a parameter-free graph-based loss to improve learning representation of unseen classes; see Fig. 1. Our loss starts from each seen class (in green) and performs a random walk through the generated examples of hallucinated unseen classes (in orange) for T steps. Then, we encourage the landing representation to be distant and distinguishable from the seen class centers. GRaWD loss is computed over a similarity graph involving seen class centers and generated examples in the current minibatch of hallucinated unseen classes. Thus, GRaWD takes a global view of the data manifold compared to existing deviation losses that are local/per example (e.g., Sbai et al. 2018; Elgammal et al. 2017a, Elhoseiny and Elfeky 2019). In contrast to transductive methods (e.g., Vyas, Venkateswarar, and Papathanathan 2020), our loss is purely inductive; therefore, does not require real descriptions of unseen classes during training. Our work is connected to recent advances in semi-supervised learning (e.g., Zhang et al. 2018; Ayyad et al. 2020; Ren et al. 2018; Haeusser, Mordvintsev, and Cremers 2017; Li et al. 2019) that leverage unlabeled data within the training classes. In these methods, unlabeled data are encouraged to be attracted to existing classes. Our goal is the opposite, deviating from seen classes. Also, our loss operates on generated data of hallucinated unseen classes instead of provided unlabeled data.

**Contribution.** We propose a generative random walk loss that leverages generated data by exploring the unseen embedding space discriminatively against the seen classes; see Fig. 1. Our loss is unsupervised on the generative space and can be applied to any GAN architecture (e.g., DCGAN (Radford, Metz, and Chintala 2016), StyleGAN (Karras, Laine, and Aila 2019a), and StyleGAN2 (Karras et al. 2020)).

We show that our GRaWD loss helps understand unseen visual classes better, improving generalized zero-shot learning tasks on challenging benchmarks. We also show that compared to existing deviation losses, GRaWD improves the generative capability in unseen space of liked art; see Fig. 2.

**Related Work**

**Generative Models with Deviation Losses.** In the context of computational creativity, several approaches have been proposed to produce original items with aesthetic and meaningful characteristics (Machado and Cardoso 2000; Mordvintsev, Olah, and Tyka 2013; DiPaola and Gabora 2009; Tendulkar et al. 2019). Various early studies have made progress on writing pop songs (Briot, Hadjeres, and Pachet 2017), and transferring styles of great painters to other images (Gatys, Ecker, and Bethge 2016; Date, Ganesan, and Oates 2017; Dumoulin et al. 2017; Johnson, Alahi, and Li 2016; Isola et al. 2017) or doodling sketches (Ha and Eck 2018). The creative space of the style transfer images is limited by the content image and the transfer image, which could be an artistic image by Van Gogh. GANs (Goodfellow et al. 2014; Radford, Metz, and Chintala 2016; Ha and Eck 2018; Reed et al. 2016; Zhang et al. 2017; Karras et al. 2018; Karras, Laine, and Aila 2019a) have a capability to learn visual distributions and produce images from a latent vector. However, they are not trained explicitly to produce novel content beyond the training data. More recent work explored an early capability to produce novel art with CAN (Elgammal et al. 2017b), and fashion designs with a holistic CAN (an improved version of CAN) (Sbai et al. 2018), which are based on augmenting DCGAN (Radford, Metz, and Chintala 2016) with a loss encouraging deviation from existing styles. The difference between CAN and holistic-CAN is that the deviation signal is Binary Cross Entropy over individual styles for CAN (Elgammal et al. 2017b) and Multi-Class Cross Entropy (MCE) loss overall styles in Holistic-CAN (Sbai et al. 2018). Similar deviation losses were proposed in CIZSL (Elhoseiny and Elfeky 2019) for ZSL.

In contrast to these deviation losses, our loss is more global as it establishes dynamic messages between generations that are produced every mini-batch iteration and seen visual spaces. These generations should deviate from seen class spaces represented by class centers. In our experiments, we applied our loss on unseen class recognition and producing novel visual generations, showing superior performance compared to existing losses. We also note that random walks have been explored in the literature in the context of semi-supervised and few-shot learning for attracting unlabeled data points to its corresponding class (e.g., Ayyad et al. 2020; Haeusser, Mordvintsev, and Cremers 2017). In contrast, we develop a random walk-based method to deviate from seen classes, which is an opposite objective, and operates on generated data rather than unlabeled data that are not available in purely inductive setups; see Fig. 1.

**Zero-Shot Learning Methods.** Classical ZSL methods directly predict attribute confidence from images to facilitate zero-shot recognition (e.g., seminal works by Lampert, Nickisch, and Harmeling (2009a), (2013) and Farhadi et al. (2009)). Current ZSL methods can be classified into two
Figure 3: Generative Random Walk Deviation loss starts from each seen class center (i.e., \(c_i\)). It then performs a random walk through generated examples of hallucinated unseen classes using \(G(s_u, z)\) for \(T\) steps. The landing probability distribution of the random walk is encouraged to be uniform over the seen classes. For careful deviation from seen classes, the generated images are encouraged to be classified as real by the Discriminator \(D\); see Eq. 4.

Approach

We start this section by the formulation of our Generative Random Walk Deviation loss. We will show later in this section how it can be integrated with both generative ZSL models to improve unseen class recognition and with state-of-the-art deep-GAN models to encourage novel visual generations. We denote the generator as \(G(s, z)\) and its corresponding parameters as \(\theta_G\). As in (Xian et al. 2018b; Zhu et al. 2018; Elhoseiny and Elfeki 2019; Felix et al. 2018), the semantic representation \(s\) can be concatenated with a random vector \(z\) \(\in \mathbb{R}^Z\) sampled from a Gaussian distribution \(p_z = N(0, 1)\) to generate an image for visual art generation or visual features in the case of zero-shot learning. Hence, \(G(s, z)\) is the generated image / feature from the semantic description \(s_k\) of class \(k\) and the noise vector \(z\). We denote the discriminator as \(D\) and its corresponding parameters as \(\theta_D\). The discriminator is trained with two objectives: (1) predict real for images from the training images and fake for generated ones. (2) identify the category of the input image. The discriminator then has two heads. The first head is for binary real/fake classification; \{0, 1\} classifier. The second head is a \(K\)-way classifier over the seen classes. We denote the real/fake probability produced by \(D\) for an input image as \(D_s^k(\cdot)\), and the classification score of a seen class \(k \in \mathcal{S}\) given the image as \(D_s^k(\cdot)\).

Generative Random Walk Deviation Loss

We sample \(N_u\) examples that we aim them to deviate from the seen classes/styles in the current minibatch with the generator \(G(\cdot)\). We denote the features of the these hallucinated generations as \(X_u = \{x_1^u \cdots x_{N_u}^u\}\). These features are extracted by \(\phi(\cdot)\), a feature extraction function that we define as the activations from the last layer of the Discriminator \(D\) followed by scaled L2 normalization \(L2(\mathbf{v}, \beta) = \beta \frac{\mathbf{v}}{\|\mathbf{v}\|}\). The scaled factor is mainly to amplify the norm of the vectors to avoid the vanishing gradient problem inspired from (Bell et al. 2016). We used \(\beta = 3\) guided by (Bell et al. 2016; Zhang et al. 2019). We denote the seen class centers that we aim to deviate from as \(C = \{c_1 \cdots c_K\}\), defined in
the same feature space as $X_u$, where $c_i$ represents center of seen class/style $i$. The formulation of $c_i$ depends on the application (e.g., zero-shot learning or novel art generation), defined later in this section.

Let $B \in \mathbb{R}^{N_u \times K^*}$ be the similarity matrix between each of the features of the generations ($x^u_i \in X_u$) and the cluster centers ($c \in C$). Similarly, let $A \in \mathbb{R}^{N_u \times N_u}$ compute the similarity matrix between the generated points. In particular, we use the negative Euclidean distances between the embeddings as a similarity measure as follows:

$$B_{ij} = -||x^u_i - c_j||^2, \quad A_{ij} = -||x^u_i - x^u_j||^2 \tag{1}$$

where $x^u_i$ and $x^u_j$ are $i^{th}$ and $j^{th}$ features in the set $X_u$; see Fig. 3. To avoid self-cycle, The diagonal entries $A_{ii}$ are set to a small number $\epsilon$. Hence, we define three transition probability matrices:

$$P^{C \rightarrow X_u} = \sigma(B^2), \quad P^{X_u \rightarrow C} = \sigma(B), \quad P^{X_u \rightarrow X_u} = \sigma(A) \tag{2}$$

where $\sigma$ is the softmax operator applied over each row of the input matrix, $P^{C \rightarrow X_u}$ and $P^{X_u \rightarrow C}$ are the transition probability matrices from each seen class over the $N_u$ generated points and vice-versa respectively. $P^{X_u \rightarrow X_u}$ is the transition probability matrix from each generated point over other generated points. We hence define our generative random walk probability matrix as:

$$P^{C \rightarrow C}(t, X_u) = \sigma(B^2) \cdot (\sigma(A))^t \cdot (\sigma(B)) \tag{3}$$

where $P^{C \rightarrow C}(t, X_u)$ denotes the probability of ending a random walk of a length $t$ at a seen class $j$ given that we have started at seen class $i$; $t$ denotes the number of steps taken between the generated points, before stepping back to land on a seen class/style.

**Loss.** Our random walk loss aims at boosting the deviation of unseen visual spaces from seen classes. Hence, we define our loss by encouraging each row in $P^{C \rightarrow C}(t)$ to be hard to classify to seen classes as follows

$$L_{GRW}(X_u) = - \sum_{i=0}^{T} \sum_{k=1}^{K^*} \sum_{j=1}^{K^*} U_r(j) \log(P^{C \rightarrow C}_i-(t, X_u)) - \sum_{j=1}^{N_u} U_r(j) \log(P^{C \rightarrow C}_i(s_u(j))) \tag{4}$$

where first term minimizes cross entropy loss between every row in $P^{C \rightarrow C}(t, X_u)$ at $t=1 \rightarrow T$ and uniform distribution over seen classes $U_r(j) = \frac{1}{N_u}, \forall j = 1 \cdots K^*$, where $T$ is a hyperparameter and $\gamma$ is exponential decay set to 0.7 in our experiments. In the second term, we maximize the probability of all the generations $x^u_i \in X_u$ to be equality visited by the random walk. Note that, if we replaced $U_r$ by an identity matrix to encourage landing to the starting seen class, the loss becomes an attraction signal similar to (Haeusser, Mordvintsev, and Cremers 2017), which defines its conceptual difference to GRaWD. We call this version GRaWT, T for aTraction. The second term is called ‘visit loss’ was proposed in (Haeusser, Mordvintsev, and Cremers 2017) to encourage random walker to visit a large set of unlabeled points. We compute the overall probability that each generated point would be visited by any of the seen class $P_u = \frac{1}{N_u} \sum_{i=1}^{N_u} P^{C \rightarrow X_u}_i$, where $P^{C \rightarrow X_u}_i$ represents the $i^{th}$ row of the $P^{C \rightarrow X_u}$ matrix; see Fig. 3. The visit loss is then defined as the cross-entropy between $P_u$ and the uniform distribution $U_x(j) = \frac{1}{N_u}, \forall j = 1 \cdots N_u$. Hence, visit loss encourages to visit as many examples as possible from $X_u$ and hence improves learning representation.

**GRaWD Integration with Generative ZSL.**

Let’s denote the set of seen and unseen class labels as $\mathcal{S}$ and $\mathcal{U}$, where $\mathcal{S} \cap \mathcal{U} = \emptyset$. We denote the semantic representations of unseen classes and seen classes as $s_u = \psi(T_u) \in \mathcal{T}$ and $s_i = \psi(T_i) \in \mathcal{T}$ respectively, where $\mathcal{T}$ is the semantic space and $\psi(\cdot)$ is the semantic description function that extract features from text article or attribute description of class $k$. Let’s denote the seen data as $D^s = \{(x^i_u, y^i_u, s_i)\}$, where $x^i_u \in \mathcal{X}$ denotes the visual features of the $i^{th}$ image, $y^i_u \in \mathcal{S}$ is the corresponding seen category label. For unseen classes, we are given only their semantic representations, one per class, $s_u$. We define $K^u$ as the number of unseen classes. In Generalized ZSL (GZSL), we aim to predict the label $y \in \mathcal{U} \cup \mathcal{S}$ at test time given $x$ that may belong to seen or unseen classes. We represent seen classes as $C = \{e_1 \cdots e_{C'}\}$, where $c_i$ represents the center of class $i$ that we define as

$$c_i = \phi(G(z = 0, s_i)) \tag{5}$$

where $s_i$ is the attribute or text description of seen class $i$. $X_u = \{x^i_u \cdots x^N_u\}$ are sampled by $\phi(G(z, s_u))$ where $z \sim p_z = \mathcal{N}(0, I)$, $s_u \sim p_u$ is a semantic description of a hallucinated unseen class. We explicitly explore the unseen/creative space of the generator $G$ with a hallucinated semantic representation $s_u \sim p^u$, where $p^u$ is a probability distribution over unseen classes, aimed to be likely hard negatives to seen classes. We sample $s_u \sim p^u$ following the strategy proposed in (Efros, Leung, and Malik 2019) due to its simplicity and effectiveness. It picks two seen semantic descriptions at random $s_a, s_b \in \mathcal{S}$. We then sample $s^h = \alpha s_a + (1-\alpha)s_b$, where $\alpha$ is uniformly sampled between 0.2 and 0.8. Note that of $\alpha$ values near 0 or 1 are discarded to avoid sampling semantic descriptions that are very close to seen classes. We then integrate $L_{GRW}(X_u)$ with the Generator $G$ loss as follows.

$$L_G(x^u_i, \sim \phi(G(s_u, z))) = \mathbb{E}_{z \sim p_z, s_u \sim p^u}[L_{GRW}(X_u)]$$

$$- \mathbb{E}_{z \sim p_z, s_u \sim p_u}[D^R(G(s_u, z))]$$

$$- \mathbb{E}_{z \sim p(z, s^h \sim p^u)[D^R(G(s_k, z))]$$

$$+ \sum_{k=1}^{K^u} \mathbb{E}_{z \sim p(z, s^h \sim p^u)}[D^{R,k}(G(s_k, z))]$$

Here, the first term is the proposed GRaWD loss. The second and the third terms trick the generator into classifying the visual generations from both the seen semantic descriptions $s_a$ and unseen semantic descriptions $s_u$, as real. The fourth term encourages the generator to discriminatively generate visual features conditioned on a given seen class description.
We then define the Discriminator $D$ loss as

$$L_D = \mathbb{E}_{x,z,y} [D(G(x,z))] + \mathbb{E}_{z,y} [D'(G(s_k, y))] - \mathbb{E}_{x,y} [D'(x)] + \frac{1}{2} \mathbb{E}_{x,y} \sum_{k=1}^{K} y_k \log(D(s_k|x,y))$$

Here, image $x$ and corresponding one-hot label $y$ are sampled from the data distribution $p_d$. $s_k$ and $y'$ are features of a semantic description and the corresponding one-hot label sampled from seen classes $p^s$. The first three terms approximate Wasserstein distance of the distribution of real features and fake features, and fourth term is the gradient penalty to enforce the Lipschitz constraint: $L_{Lip} = (\| \nabla \hat{x} D'(\hat{x}) \|_2 - 1)^2$, where $\hat{x}$ is the linear interpolation of the real feature $x$ and the fake feature $\tilde{x}$; see (Gulrajani et al. 2017). The last two terms are the classification losses of the real and generated data to their corresponding classes.

**GraWD Integration with StyleGANs for Novel Art Generation**

We integrated our loss with DCGAN (Radford, Metz, and Chintala 2015), StyleGAN (Karras, Laine, and Aila 2019a) and StyleGAN2 (Karras et al. 2020) by simply adding $L_{C_{GRW}}$ in Eq. 4 to the generator loss. We assume to have $N_s$ seen art styles that we aim to deviate from. Here, we define $C = \{c_1 \cdots c_{K_s}\}$ by sampling a small episodic memory of size $m$ for every class and computing $c_i$ from discriminator features. We randomly sample $m = 10$ examples per class once and compute its mean representation at each iteration. We provide more training details in supplementary.

### Experiments

**Purely Inductive Generative ZSL Experiments**

**Purely Inductive Evaluation in ZSL:** Our focus in this paper is to learn a good representation of unseen visual spaces without accessing any unseen class information during training. However, most recent papers jointly train an extra classifier (e.g., an MLP) with their proposed generative model (Narayan et al. 2020; Han et al. 2021). More concretely, this classifier is trained with generated $\tilde{X}_u = G(u_k, z)$ from unseen semantic description $u_k$. While in GZSL, training seen images $X_s$ along with $\tilde{X}_u$ is introduced as input of the extra classifier. We refer to methods that assume access to unseen class descriptions during training as semantic transductive ZSL (even if not using unlabeled images of unseen classes). Accessing unseen information before evaluation is not in line with our focus on learning generative unseen learning representation. This is also less realistic if we aim at purely inductive zero-shot learning. Following purely inductive ZSL settings (e.g., (Zhu et al. 2018; Elhoseiny and Elfeki 2019)), we use NN-classification on the generated features for evaluation, which avoids accessing any unseen semantic information before testing.

We performed experiments on existing ZSL benchmarks with text descriptions and attributes as semantic class descriptions. Note that the text description setting is more challenging because it is at the class-level and is extracted from Wikipedia, which is noisier. We found that random walk steps $T$ easy to tune using the validation set.

**Text-Based ZSL.** We performed our text-based ZSL experiments on Caltech UCSD Birds-2011 (CUB) (Wah et al. 2011) containing 200 classes with 11, 788 images and North America Birds (NAB) (Van Horn et al. 2015) which has 1011 classes with 48, 562 images. We use two metrics widely used in evaluating ZSL recognition performance: standard zero-shot recognition with the Top-1 unseen class accuracy and Seen-Unseen Generalized Zero-shot performance with Area under Seen-Unseen curve (Chao et al. 2016). We follow (Chao et al. 2016; Zhu et al. 2018; Elhoseiny and Elfeki 2019) in using the Area Under SU to evaluate the generalization capability of class-level text-zero-shot recognition on four splits (CUB Easy, CUB Hard, NAB Easy, and NAB Hard). The hard splits are constructed such that unseen bird classes from super-categories do not overlap with seen classes. Our proposed loss function improves over older methods on all datasets on both Easy and SCE(hard) splits, as shown in Table 2. We show improvements in the range of 0.8-1.8% Top-1 accuracy. We also show improvements in AUC, ranging from 1-1.8%. From Table 2 we show that GAZSL (Zhu et al. 2018)+GraWD has an average relative Seen-Unseen AUC improvement over GAZSL (Zhu et al. 2018)+CIZSL (Elhoseiny and Elfeki 2019) and GAZSL (Zhu et al. 2018) of 24.92% and 61.35%.

**Attribute-Based ZSL.** We performed experiments on the widely used GBU (Xian et al. 2018a) setup, where we use class attributes as semantic descriptors. We performed these experiments on the AwA2 (Lampert, Nickisch, and Harmeling 2009b), aPY (Farhadi et al. 2009), and SUN (Patterson and Hays 2012) datasets. In Table 4, we see that GraWD outperforms all of the existing methods on seen-unseen harmonic mean for AwA2, aPY, and SUN datasets. In the case of the AwA2 dataset, it outperformed the compared method by a significant margin, i.e., 15.1%. It is also competent with existing methods in Top-1 accuracy while improving on AwA2 4.8%. From Table 4, GAZSL (Zhu et al. 2018)+GraWD has an average relative improvement over GAZSL (Zhu et al. 2018)+CIZSL (Elhoseiny and Elfeki 2019) and GAZSL (Zhu et al. 2018) of 24.92% and 61.35% in harmonic mean.

Table 1 and 3 show that deviation signal in GraWD is critical to achieve better performance since the calculated metrics are much better for GraWD compared to GraWT for both text-based and attribute based ZSL. The performance can severely degrade without the deviation signal.
the artwork generated from model trained using GRaWD. More people believed the generated art to be real for GAN, GRaWD, and CAN losses. Models trained on Table 5: Human experiments on generated art from vanilla GAN, GRaWD, and CAN. Models trained on GRaWD obtained the highest mean likeliness in all the groups. More people believed the generated art to be real for the artwork generated from model trained using GRaWD.

Table 1: Ablation studies on CUB Dataset (text).

| Setting | CUB-Easy | CUB-Hard |
|---------|----------|----------|
| Deviation losses | + GRaWT (T=0) | 44.0 39.5 13.7 11.8 |
| | + GRaWT (T=3) | 43.4 38.8 13.2 11.4 |
| on GAZSL Guo et al. 2018 | + ClassiG (T=1) | 43.2 38.3 11.31 9.5 |
| | + CIZSL (Di2 and Hard Split) | 44.6 39.2 14.4 11.9 |
| Walk length | + GRaWD (T=1) | 45.4 39.6 13.79 12.58 |
| | + GRaWD (T=3) | 45.11 39.25 14.21 13.22 |
| on GAZSL Guo et al. 2018 | + GRaWD (T=5) | 45.40 40.51 14.00 13.07 |
| | + GRaWD (T=10) | 45.43 40.48 15.51 13.70 |

Table 2: Zero-Shot Recognition from textual description on CUB and NAB datasets (Easy and Hard Splits) showing that adding GRaWD and SAE losses can improve the performance. tr means the transductive setting.

Table 3: Attribute based ZSL on AwA2, aPY and SUN. Compared with Haesser et al. (2017).

Table 4: Zero-Shot Recognition on class-level attributes of AwA2, aPY and SUN datasets, showing that GRaWD loss can improve the performance on attribute-based datasets.

Tab. 1 (bottom section) shows that longer walk lengths benefit the training as model is encouraged to globally explore larger segments of unseen representations’ manifold.

**GRaWD Loss for Transductive ZSL.** We also apply our GRaWD loss to transductive ZSL setting and choose LsrGAN (Vyas, Venkateswara, and Panchanathan 2020) as the baseline model. Our loss can also improve LsrGAN on both text-based datasets and attribute-based datasets across metrics ranging from 0.3%-3.6%. Despite that our Ours loss does not use unseen class descriptors, it can still improve on average on LsrGAN (transductive) by 1.96% on attribute datasets and 2.91% on text-based datasets. However, in line with our expectations, the former improvement in the purely inductive setting is more significant.

**Novel Art Generation Experiments.** We performed our Art experiments on the WikiArt dataset, containing 81k images of 27 different styles (WikiArt 2015).

**Baselines.** We performed comparisons with two baselines, i.e., (1) the vanilla GAN for the chosen architecture, and (2) adding Holistic-CAN loss (Sbai et al. 2018) (an improved version of CAN (Elgammal et al. 2017b)). For simplicity, we refer the Holistic-CAN as CAN.

**Nomenclature.** Here, the models are referred as RW-T(value), where RW means GRaWD loss, and T is the number of steps. We name our models according to this convention throughout. We perform human subject experiments to evaluate generated art. We set value of the loss coefficient λ to 10. We divide the generations from these models into four groups, each containing 100 images; see examples in Fig. 4.

- **NN**. Images with high nearest neighbor (NN) distance from the training dataset.
- **NN**. Images with low NN distance from the training dataset.
- **Entropy**. Images with high entropy of the probabilities from a style classifier.
- **Random (R)**. A set of random images.

For example, we denote generations using our GRaWD loss with T=10, and NN**↑** group as RW-T10**↑**. Fig. 4 shows top liked/disliked paintings according to human evaluation.

**Human Evaluation.** We performed our human subject MTurk experiments based on StyleGAN1 (Karras, Laine, and Aila 2019b) & StyleGAN2 (Karras et al. 2020) architecture’s vanilla, CAN, and GRaWD variants. We divide the generations into four groups described above. We collect five responses for each art piece (400 images), totaling 2000 responses per model by 341 unique workers. We asked people to rate generations from 1 (extremely dislike) to 5 (extremely like), which was the first question (Q1). In Q2, we

Table 5: Human experiments on generated art from vanilla GAN, GRaWD, and CAN. Models trained on GRaWD obtained the highest mean likeliness in all the groups. More people believed the generated art to be real for the artwork generated from model trained using GRaWD.
Figure 4: Most liked and disliked art generated using StyleGAN trained on GRaWD for the different groups.

asked if a computer or an artist generates the images (Turing Test). More setup details are in the supplementary. We found that art from the trained StyleGAN1 and StyleGAN2 on our loss were more likeable and more people believed them to be real art, as shown in Table 5. For StyleGAN1, adding GRaWD loss resulted in 38% and 18% more people giving a full rating of 5 over vanilla StyleGAN1 and StyleGAN1 + CAN loss, respectively, see Fig. 5. For StyleGAN2, these improvements were 65% and 15%. Table 6 shows that images from the StyleGAN model on our loss have a better rank when combined with other sets of the table.

Wundt Curve Analysis. We approximate the Wundt curve [Packard 1975; Wundt 1874] by fitting a degree 3 polynomial on a scatter plot of normalized likeability vs. mean NN distance (novelty measure). Generations are more likeable if the deviation from existing art is moderate but not too much; see Fig. 6. Compared to CAN and GAN, our loss achieves on balance novel images that are more preferred.

Emotion Experiments. Evaluators selected the emotion they felt after looking at each art and justified their chosen emotion in text. We collected 5 responses each for a set of 600 generated artworks from 260 unique workers. Fig. 7 shows the distribution over the opted emotions, which are diverse but mostly positive. However, some generations construct negative emotions like fear. Fig. 7 also shows the most frequent words for each emotion after removing stop words. Notable positive words include “funny”, “beautiful”, “attractive”, and negative words include “dark”, “ghostly” which are associated with feelings like fear and disgust.

Conclusion

We propose Generative Random Walk Deviation (GRaWD) loss and showed that it improves generative models’ capability to better understand unseen classes on several zero-shot learning benchmarks and generate novel visual content trained on WikiArt dataset. We think the improvement is due to our learning mechanism’s global nature, which operates at the minibatch level producing generations that are message-passing to each other to facilitate better deviation of unseen classes/styles from seen ones.
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