REAL OR NOT REAL, THAT IS THE QUESTION

Anonymous authors
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ABSTRACT

While generative adversarial networks (GAN) have been widely adopted in various topics, in this paper we generalize the standard GAN to a new perspective by treating realness as a random variable that can be estimated from multiple angles. In this generalized framework, referred to as RealnessGAN, the discriminator outputs a distribution as the measure of realness. While RealnessGAN shares similar theoretical guarantees with the standard GAN, it provides more insights on adversarial learning. More importantly, compared to multiple baselines, RealnessGAN provides stronger guidance for the generator, achieving improvements on both synthetic and real-world datasets. Moreover, it enables the basic DCGAN (Radford et al., 2015) architecture to generate realistic images at 1024*1024 resolution when trained from scratch.

1 INTRODUCTION

The development of generative adversarial network (GAN) (Goodfellow et al., 2014; Radford et al., 2015; Arjovsky et al., 2017) is one of the most important topics in computer vision since its first appearance in (Goodfellow et al., 2014). It learns a discriminator along with the target generator in an adversarial manner, where the discriminator distinguishes generated samples from real ones. Due to its flexibility when dealing with high dimensional data, GAN has obtained remarkable progresses on realistic image generation (Brock et al., 2019).

In the standard formulation (Goodfellow et al., 2014), the realness of an input sample is estimated by the discriminator using a *single scalar*. However, take images for instance, we naturally perceive images from more than one angles and deduce whether it is life-like based on multiple criteria. As shown in Fig. 1, when a portrait is given, one might focus on its facial structure, skin tint, hair texture and even details like iris and teeth if allowed, each of which indicates a different degree of realness. Based on this observation, the single scalar could be viewed as an abstract or a summarization of multiple measures, which together reflect the overall realisticity of an image. Such a concise measurement may convey insufficient information to guide the generator, potentially leading to well-known issues such as mode-collapse and gradient vanishing.

In this paper, we propose to generalize the standard framework (Goodfellow et al., 2014) by treating realness as a distribution rather than a single scalar, which we refer to as RealnessGAN. The learning process of RealnessGAN abide by the standard setting, but in a distributional form. While the standard GAN can be viewed as a special case of RealnessGAN, RealnessGAN as well guarantees converging to a Nash-equilibrium where the generator and the discriminator reaches optimalities.

Figure 1: The perception of realness depends on various aspects. (a) Human-perceived flawless. (b) Potentially reduced realness due to: inharmonious facial structure/components, unnatural background, abnormal style combination and texture distortion.

Moreover, by expanding the scalar realness score into a distributional one, the discriminator D naturally provides stronger guidance to the generator G where G needs to match not only the overall realness (as in the standard GAN), but the underlying realness distribution as well. Consequently, RealnessGAN facilitate G to better approximate the real data manifold while generating decent samples. As shown in the experiments, based on a rather simple DCGAN architecture, RealnessGAN could successfully learn from scratch to generate realistic images at 1024*1024 resolution.

2 REALNESSGAN

2.1 GENERATIVE ADVERSARIAL NETWORKS

Generative adversarial network jointly learns a generator G and a discriminator D, where G attempts to generate samples that are indistinguishable from the real ones, and D classifies generated and real samples. In the original work of (Goodfellow et al., 2014), the learning process of D and G follows a minimax game with value function $V(G, D)$:

$$\min_G \max_D V(G,D) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))], \tag{1}$$

$$= \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}}[\log(D(\boldsymbol{x}) - 0)] + \mathbb{E}_{\boldsymbol{x}\sim p_g}[\log(1 - D(\boldsymbol{x}))], \tag{2}$$

where the generator's distribution p_g over data $\boldsymbol{x}$ is defined by a prior $p_{\boldsymbol{z}}(\boldsymbol{z})$ on input latent variables and G. As proved by Goodfellow et al. (2014), under such a learning objective, the optimal D satisfies $D^*_G(\boldsymbol{x}) = \frac{p_{\text{data}}(\boldsymbol{x})}{p_{\text{data}}(\boldsymbol{x})+p_g(\boldsymbol{x})}$ for a fixed G. Fixing D at its optimal, the optimal G satisfies $p_g = p_{\text{data}}$. The theoretical guarantees provide strong supports for GAN's success in many applications (Radford et al., 2015; Yu et al., 2017; Zhu et al., 2017), and inspired multiple variants (Arjovsky et al., 2017; Mao et al., 2017; Zhao et al., 2017; Berthelot et al., 2017) to improve the original design. Nevertheless, a *single scalar* is constantly adopted as the measure to distinguish generated samples from real ones, while the concept of realness is essentially a random variable covering multiple factors, such as texture and overall configuration in the case of images. In this work, we intend to follow this observation, enforcing the discriminator D to learn a realness distribution.

2.2 A DISTRIBUTIONAL VIEW ON REALNESS

We start by substituting the scalar output of a discriminator D with a distribution p_{realness}, so that for an input sample $\boldsymbol{x}$, $D(\boldsymbol{x}) = \{p_{\text{realness}}(\boldsymbol{x}, u); u \in \Omega\}$, where Ω is the set of supports of p_{realness}. As in equation 1, $V(G, D)$ computes the distances between $D(\boldsymbol{x})$ and two anchor scalars 0 and 1, in the case of RealnessGAN, $V(G, D)$ thus measures the Kullback-Leibler (KL) divergence between $D(\boldsymbol{x})$ and two *anchor distributions* $\mathcal{A}_0$ and $\mathcal{A}_1$, which are also defined on Ω. Subsequently, the minimax game between a generator G and a distributional discriminator D becomes

$$\max_G \min_D V(G,D) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}}[\mathcal{D}_{\text{KL}}(\mathcal{A}_1 \| D(\boldsymbol{x}))] + \mathbb{E}_{\boldsymbol{x}\sim p_g}[\mathcal{D}_{\text{KL}}(\mathcal{A}_0 \| D(\boldsymbol{x}))]. \tag{3}$$

An immediate observation is that if we let p_{realness} be a discrete distribution with two supports $\{u_0, u_1\}$, and set $\mathcal{A}_0(u_0) = \mathcal{A}_1(u_1) = 1$ and $\mathcal{A}_0(u_1) = \mathcal{A}_1(u_0) = 0$, the updated objective in equation 3 can be explicitly converted to the original objective in equation 1, suggesting RealnessGAN is a generalized version of the original GAN.

Following this observation, we then extend the standard theoretical analysis to the case of RealnessGAN. Similar to Goodfellow et al. (2014), our analysis concerns the space of probability density functions, where D and G are assumed to have infinite capacity. We start from finding the optimal realness discriminator D for any given generator G.

Theorem 1. *When G is fixed, for any support u and input sample $\boldsymbol{x}$, the optimal discriminator D satisfies*

$$D^\star_G(\boldsymbol{x}, u) = \frac{\mathcal{A}_1(u)p_{data}(\boldsymbol{x}) + \mathcal{A}_0(u)p_g(\boldsymbol{x})}{p_{data}(\boldsymbol{x}) + p_g(\boldsymbol{x})}. \tag{4}$$

Proof. The objective of D, given a fixed G, is to minimize $V(G, D)$, which is equivalent to:

$$\min_D -\int_{\boldsymbol{x}}\int_u (p_{\text{data}}(\boldsymbol{x})\mathcal{A}_1(u) + p_g(\boldsymbol{x})\mathcal{A}_0(u))\log D(\boldsymbol{x}, u)dudx, \tag{5}$$

$$= \int_{\boldsymbol{x}} (p_{\text{data}}(\boldsymbol{x}) + p_g(\boldsymbol{x}))\mathcal{D}_{\text{KL}}(\frac{\mathcal{A}_1 p_{\text{data}}(\boldsymbol{x}) + \mathcal{A}_0 p_g(\boldsymbol{x})}{p_{\text{data}}(\boldsymbol{x}) + p_g(\boldsymbol{x})} \| D(\boldsymbol{x}))dx + C, \tag{6}$$

where C is a term irrelevant to D. For any $\boldsymbol{x} \in Supp(p_{\text{data}}) \cup Supp(p_g)$, when the KL divergence achieves its minimum, D obtains its optimal, which concludes the proof. □

A full proof is available in the appendix. Next, we move on to the conditions for G to reach its optimal when $D = D^\star_G$.

Theorem 2. *When $D = D^\star_G$, and there exists a support $u \in \Omega$ such that $\mathcal{A}_1(u) \neq \mathcal{A}_0(u)$, the maximum of $V(G, D^\star_G)$ is achieved if and only if $p_g = p_{data}$.*

Proof. When $p_g = p_{\text{data}}$, $D^\star_G(\boldsymbol{x}, u) = \frac{\mathcal{A}_1(u)+\mathcal{A}_0(u)}{2}$, we have:

$$V^\star(G, D^\star_G) = \int_u \mathcal{A}_1(u)\log\frac{2\mathcal{A}_1(u)}{\mathcal{A}_1(u) + \mathcal{A}_0(u)} + \mathcal{A}_0(u)\log\frac{2\mathcal{A}_0(u)}{\mathcal{A}_1(u) + \mathcal{A}_0(u)}du. \tag{7}$$

Subtracting $V^\star(G, D^\star_G)$ from $V(G, D^\star_G)$ gives:

$$V'(G, D^\star_G) = V(G, D^\star_G) - V^\star(G, D^\star_G)$$

$$= \int_{\boldsymbol{x}}\int_u (p_{\text{data}}(\boldsymbol{x})\mathcal{A}_1(u) + p_g(\boldsymbol{x})\mathcal{A}_0(u))\log\frac{(p_{\text{data}}(\boldsymbol{x}) + p_g(\boldsymbol{x}))(\mathcal{A}_1(u) + \mathcal{A}_0(u))}{2(p_{\text{data}}(\boldsymbol{x})\mathcal{A}_1(u) + p_g(\boldsymbol{x})\mathcal{A}_0(u))}dudx, \tag{8}$$

$$= -2\int_{\boldsymbol{x}}\int_u \frac{p_{\text{data}}(\boldsymbol{x})\mathcal{A}_1(u) + p_g(\boldsymbol{x})\mathcal{A}_0(u)}{2}\log\frac{\frac{p_{\text{data}}(\boldsymbol{x})\mathcal{A}_1(u)+p_g(\boldsymbol{x})\mathcal{A}_0(u)}{2}}{\frac{(p_{\text{data}}(\boldsymbol{x})+p_g(\boldsymbol{x}))(\mathcal{A}_1(u)+\mathcal{A}_0(u))}{4}}dudx, \tag{9}$$

$$= -2\mathcal{D}_{\text{KL}}(\frac{p_{\text{data}}\mathcal{A}_1 + p_g\mathcal{A}_0}{2} \| \frac{(p_{\text{data}} + p_g)(\mathcal{A}_1 + \mathcal{A}_0)}{4}). \tag{10}$$

Since $V^\star(G, D^\star_G)$ is a constant with respect to G, maximizing $V(G, D^\star_G)$ is equivalent to maximizing $V'(G, D^\star_G)$. The optimal $V'(G, D^\star_G)$ is achieved if and only if the KL divergence reaches its minimum, where:

$$\frac{p_{\text{data}}\mathcal{A}_1 + p_g\mathcal{A}_0}{2} = \frac{(p_{\text{data}} + p_g)(\mathcal{A}_1 + \mathcal{A}_0)}{4}, \tag{11}$$

$$(p_{\text{data}} - p_g)(\mathcal{A}_1 - \mathcal{A}_0) = 0, \tag{12}$$

for any valid $\boldsymbol{x}$ and u. Hence, as long as there exists a valid u that $\mathcal{A}_1(u) \neq \mathcal{A}_0(u)$, we have $p_{\text{data}} = p_g$ for any valid $\boldsymbol{x}$. □

2.3 DISCUSSION

The theoretical analysis gives us more insights on RealnessGAN.

Number of supports: according to equation 12, each $u \in \Omega$ with $\mathcal{A}_0(u) \neq \mathcal{A}_1(u)$ may work as a constraint, pushing p_g towards p_{data}. In the case of discrete distributions, along with the increment of the number of supports, the constraints imposed on G accordingly become more rigorous and can cost G more effort to learn. This is due to the fact that using more supports suggests the shape of the realness distribution is more fine-grained for G to match. In experiment, we verified that it is beneficial to update G an increasing number of times before D's update as the number of supports grows.

Effectiveness of anchors: view equation 12 as a cost function to minimize, when $p_{\text{data}} \neq p_g$, for some $u \in \Omega$, the larger the difference between $\mathcal{A}_1(u)$ and $\mathcal{A}_0(u)$ is, the stronger the constraint on G becomes. Intuitively, RealnessGAN can be more efficiently trained if we choose $\mathcal{A}_0$ and $\mathcal{A}_1$ to be adequately different.

Objective of G: according to equation 3, the best way to fool D is to increase the KL divergence between $D(\boldsymbol{x})$ and the anchor distribution $\mathcal{A}_0$ of fake samples, rather than decreasing the KL divergence between $D(\boldsymbol{x})$ and the anchor distribution $\mathcal{A}_1$ of real samples. It's worth noting that these two objectives are equivalent in the original work (Goodfellow et al., 2014). An intuitive explanation is that, in the distributional view of realness, real samples do not necessarily share the same realness distribution. It is possible that each of them corresponds to a distinct one. While $\mathcal{A}_1$ only serves as an anchor, thus it is ineffective to drag all generated samples towards the same target.

Flexibility of RealnessGAN: as a generalization of the standard framework, it is straightforward to integrate RealnessGAN with different GAN architectures, such as progressive GANs (Karras et al., 2018; 2019) and conditional GANs (Zhu et al., 2017; Ledig et al., 2017). Moreover, one may also combine the perspective of RealnessGAN with other reformulations of the standard GAN, such as replacing the KL divergence in equation 3 with the Earth Mover's Distance.

2.4 IMPLEMENTATION

In our implementation, the realness distribution p_{realness} is characterized as a discrete distribution over N supports $\Omega = \{u_0, u_1, ..., u_{N-1}\}$. Given an input sample $\boldsymbol{x}$, the discriminator D returns N probabilities on these supports, following:

$$p_{\text{realness}}(\boldsymbol{x}, u_i) = \frac{e^{\boldsymbol{\psi}_i(\boldsymbol{x})}}{\sum_j e^{\boldsymbol{\psi}_j(\boldsymbol{x})}}, \tag{13}$$

where $\boldsymbol{\psi} = (\boldsymbol{\psi}_0, \boldsymbol{\psi}_1, ..., \boldsymbol{\psi}_{N-1})$ are the parameters of D. Similarly, $\mathcal{A}_1$ and $\mathcal{A}_0$ are discrete distributions defined on Ω.

Although the ideal objective for G is maximizing the KL divergence between $D(\boldsymbol{x})$ of generated samples and $\mathcal{A}_0$, directly using this objective in practice is not sufficient, as the discriminator D is not always at its optimal, especially in the early stage.[1] Inspired by the Relativistic GAN (Jolicoeur-Martineau, 2019), we thus add an additional constraint to minimize the relative KL divergence between $D(\boldsymbol{x})$ of generated samples and random real samples, resulting in the actual objective:

$$\min_G \quad \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}, \boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\mathcal{D}_{\text{KL}}(D(\boldsymbol{x})\|D(G(\boldsymbol{z}))] - \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\mathcal{D}_{\text{KL}}(\mathcal{A}_0\|D(G(\boldsymbol{z}))]. \tag{14}$$

Feature resampling. In practice, especially in the context of images, we are learning from a limited number of discrete samples coming from a continuous data manifold. We may encounter issues caused by insufficient data coverage during the training process. Inspired by conditioning augmentation mentioned in (Zhang et al., 2016), we introduce a resampling technique performed on the realness output to augment data variance. Given a mini-batch $\{\boldsymbol{x}_0, ..., \boldsymbol{x}_{M-1}\}$ of size M, a Gaussian distribution$\mathcal{N}(\mu_i, \sigma_i)$ is fitted on $\{\boldsymbol{\psi}_i(\boldsymbol{x}_0), \boldsymbol{\psi}_i(\boldsymbol{x}_1), ..., \boldsymbol{\psi}_i(\boldsymbol{x}_{M-1})\}$, which are logits computed by D on i-th support. We then resample M new logits $\{\boldsymbol{\psi}'_i(\boldsymbol{x}_0), ..., \boldsymbol{\psi}'_i(\boldsymbol{x}_{M-1}); \boldsymbol{\psi}'_i \sim \mathcal{N}(\mu_i, \sigma_i)\}$ for i-th support and use them succeedingly.

The randomness introduced by resampling benefits the training of RealnessGAN in two aspects. First of all, it augments data by probing instances around the limited training samples, leading to more robust models. Secondly, the resampling approach implicitly demand instances of $\boldsymbol{\psi}_i(\boldsymbol{x})$ to be homologous throughout the mini-batch, such that each support reflects realness from a consistent angle across samples. We empirically found the learning curve of RealnessGAN is more stable if feature resampling is utilized, especially in the latter stage, where models are prone to overfit.

3 RELATED WORK

Generative adversarial network (GAN) was first proposed in (Goodfellow et al., 2014), which jointly learns a discriminator D and a generator G in an adversarial manner. Due to its outstanding learning ability, GANs have been adopted in various generative tasks (Radford et al., 2015; Yu et al., 2017; Zhu et al., 2017), among which Deep Convolutional GAN (DCGAN) (Radford et al., 2015) has shown promising results in image generation.

[1] See Appendix A for a study on this.

Although remarkable progress has been made. GAN is known to suffer from gradient diminishing and mode collapse. Variants of GAN have been proposed targeting these issues. Specifically, Wasserstein GAN (WGAN) Arjovsky et al. (2017) replaces JS-divergence with Earth-Mover's Distance, and Least-Square GAN (LSGAN) (Mao et al., 2017) transforms the objective of G to Pearson divergence. Energy-based GAN (EBGAN) (Zhao et al., 2017) and Boundary Equilibrium GAN (BEGAN) (Berthelot et al., 2017) employ a pre-trained auto-encoder as the discriminator, learning to distinguish between real and generated samples via reconstruction. Besides adjusting the objective of GAN, alternative approaches include more sophisticated architectures and training paradigms. Generally, ProgressiveGAN (Karras et al., 2018) and StyleGAN (Karras et al., 2019) propose a progressive paradigm, which starts from a shallow model focusing on low resolution level, and gradually grows into a deeper model to incorporate more details as resolution grows. On the other hand, COCO-GAN (Lin et al., 2019) tackle high resolution image generation in a divide-and-conquer strategy. It learns to produce decent patches at corresponding sub-regions, and splices the patches to produce a higher resolution image.

It's worth noting that many works on generative adversarial networks have discussed 'distributions' (Goodfellow et al., 2014; Radford et al., 2015; Arjovsky et al., 2017), which usually refers to the underlying distribution of samples. Some of the existing works aim to improve the original objective using different metrics to measure the divergence between the learned distribution p_g and the real distribution p_{data}. Nevertheless, a single scalar is constantly adopted to represent the concept of realness. In this paper, we propose a complementary modification that models realness as a random variable follows the distribution p_{realness}. In the future work, we may study the combination of realness discriminator and other GAN variants to enhance the effectiveness and stability of adversarial learning.

4 Experiments

In this section we study RealnessGAN from multiple aspects. Specifically, 1) we firstly focus on RealnessGAN's mode coverage ability on a synthetic dataset. 2) Then we evaluate RealnessGAN on CIFAR10 (32*32) (Krizhevsky, 2009) and CelebA (256*256) (Liu et al., 2015) datasets qualitatively and quantitatively. 3) Finally we explore RealnessGAN on high-resolution image generation task, which is known to be challenging for unconditional non-progressive architectures. Surprisingly, on the FFHQ dataset (Karras et al., 2019), RealnessGAN managed to generate images at the 1024*1024 resolution based on a non-progressive architecture. We compare *RealnessGAN* to other popular objectives in generative adversarial learning, including the standard GAN (*Std-GAN*) (Radford et al., 2015), *WGAN-GP* (Arjovsky et al., 2017), *HingeGAN* (Zhao et al., 2017) and *LSGAN* (Mao et al., 2017).

For experiments on synthetic dataset, we use a generator with four fully-connected hidden layers, each of which has 400 units, followed by batch normalization and ReLU activation. The discriminator has three fully-connected hidden layers, with 200 units each layer. LinearMaxout with 5 maxout pieces are adopted and no batch normalization is used in the discriminator. The latent input $\boldsymbol{z}$ is a 32-dimensional vector sampled from a Gaussian distribution $\mathcal{N}(\mathbf{0}, \boldsymbol{I})$. All models are trained using Adam (Kingma & Ba, 2015) for 500 iterations.

On real-world datasets, the network architecture is identical to the DCGAN architecture in Radford et al. (2015), with the prior $p_{\boldsymbol{z}}(\boldsymbol{z})$ a 128-dimensional Gaussian distribution $\mathcal{N}(\mathbf{0}, \boldsymbol{I})$. Models are trained using Adam (Kingma & Ba, 2015) for $520k$ iterations. To guarantee training stability, we adopt settings that are proved to be effective for baseline methods. Batch normalization (Ioffe &

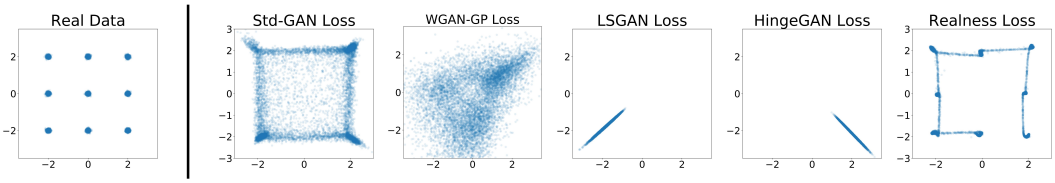


Figure 2: Left: real data sampled from the mixture of 9 Gaussian distributions. Right: samples generated by *Std-GAN*, *WGAN-GP*, *LSGAN*, *HingeGAN* and *RealnessGAN*.

Table 1: Minimum (min), maximum (max), mean and standard deviation (SD) of FID and SWD on CelebA and CIFAR10, calculated at 20k, 30k, ... iterations. The best indicators in baseline methods are underlined.

	Method	FID ↓				SWD ($\times 10^3$) ↓			
		Min	Max	Mean	SD	Min	Max	Mean	SD
CelebA	DCGAN	27.02	70.43	34.85	9.40	14.81	68.06	30.58	15.39
	WGAN-GP	70.28	104.60	81.15	8.27	17.85	30.56	22.09	2.93
	LSGAN	30.76	57.97	34.99	5.15	16.72	23.99	20.39	2.25
	HingeGAN	25.57	75.03	33.89	10.61	14.91	54.30	28.86	10.34
	RealnessGAN	**23.51**	81.3	**30.82**	7.61	**12.72**	31.39	**17.11**	3.59
CIFAR10	DCGAN	38.56	88.68	47.46	15.96	28.76	57.71	37.55	7.02
	WGAN-GP	41.86	79.25	46.96	5.57	28.17	36.04	30.98	1.78
	LSGAN	42.01	75.06	48.41	7.72	31.99	40.46	34.75	2.34
	HingeGAN	42.40	117.49	57.30	20.69	32.18	61.74	41.85	7.31
	RealnessGAN	**38.92**	79.03	**47.08**	8.96	**23.05**	51.53	**31.36**	7.52

Szegedy, 2015) is used in G, and spectral normalization (Miyato et al., 2018) is used in D. For WGAN-GP we use $lr = 1e-4, \beta_1 = 0.5, \beta_2 = 0.9$, updating D for 5 times per G's update (Gulrajani et al., 2017); for the remaining models, we use $lr = 2e-4, \beta_1 = 0.5, \beta_2 = 0.999$, updating D for one time per G's update (Radford et al., 2015). Fréchet Inception Distance (FID) (Heusel et al., 2017) and Sliced Wasserstein Distance (SWD) (Karras et al., 2018) are reported as the evaluation metrics.

4.1 Synthetic Dataset

Since p_{data} is usually intractable on real datasets, we use a toy dataset to compare the learned distribution p_g and the data distribution p_{data}. The toy dataset consists of $100,000$ 2D points sampled from a mixture of 9 isotropic Gaussian distributions whose means are arranged in a 3 by 3 grid, with variances equal to 0.05. As shown in Fig.2, the data distribution p_{data} contains 9 welly separated modes, making it a difficult task despite its low-dimensional nature.

To evaluate p_g, we draw $10,000$ samples and measure their quality and diversity. As suggested in (Dumoulin et al., 2016), we regard a sample as of high quality if it is within 4σ from the μ of its nearest Gaussian. When a Gaussian is assigned with more than 100 high quality samples, we consider this mode of p_{data} is recovered in p_g. Fig.2 visualizes the sampled points of different methods, where *LSGAN* and *HingeGAN* suffer from significant mode collapse, recovering only a single mode. Points sampled by *WGAN-GP* are overly disperse, and only 0.03% of them are of high quality. While *Std-GAN* recovers 4 modes in p_{data} with 32.4% high quality samples, 7 modes are recovered by *RealnessGAN* with 60.2% high quality samples. The average σs of these high quality samples in *Std-GAN* and *RealnessGAN* are respectively 0.083 and 0.043. The results suggest that treating realness as a random variable rather than a single scalar leads to a more strict discriminator that criticizes generated samples from various aspects, which provides more informative guidance. Consequently, p_g learned by *RealnessGAN* is more diverse and compact.

We further study the effect of adjusting the number of supports in the realness distribution p_{realness} on this dataset. To start with, we fix k_G and k_D to be 1, which are the number of updates for G and D in one iteration, and adjust the number of supports used in $p_{\text{realness}}, \mathcal{A}_0$ and $\mathcal{A}_1$. As shown in the first row of Fig.3, it can be observed that in general G recovers less modes as the number of supports grows, which is a direct result of D becoming increasingly powerful and imposing more constraints on G. When D is too powerful for G, we could increase k_G to allow G to catch up with current D. The second row of Fig.3 shows the converged cases when k_G have been adjusted to suitable settings, which suggests the effectiveness of RealnessGAN when G is given sufficient learning space. The ratio of high quality samples r_{HQ} and the number of recovered modes n_{mode} in these cases are plotted in Fig.3. The two curves imply that besides k_G, r_{HQ} and n_{mode} are all positively related to the number of supports, validating that measuring realness from more aspects leads to a better generator.

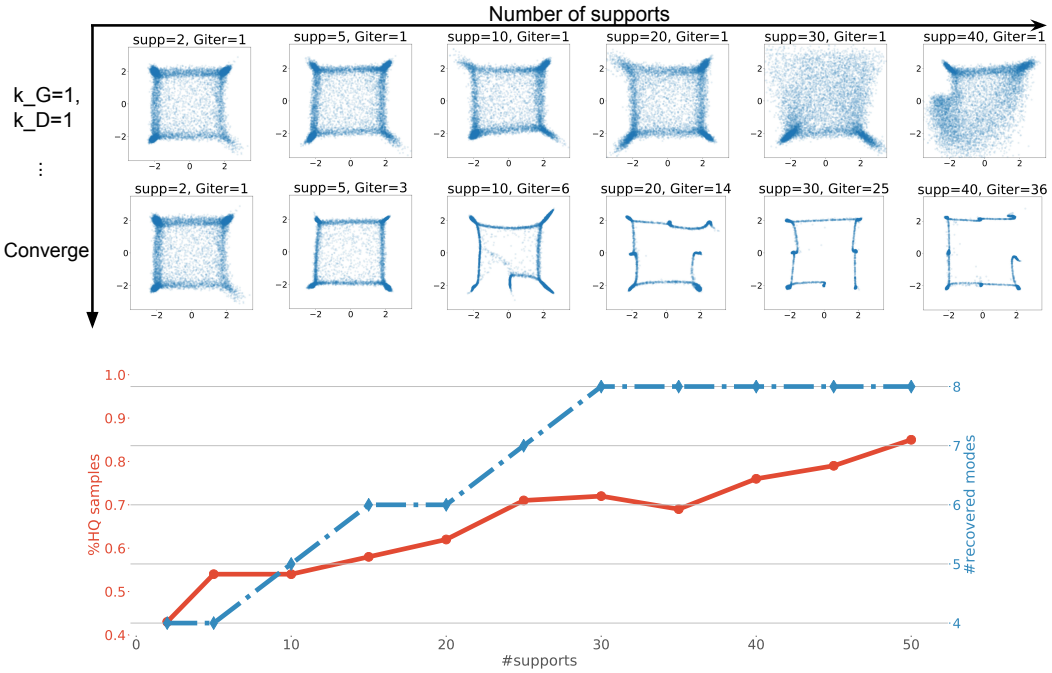
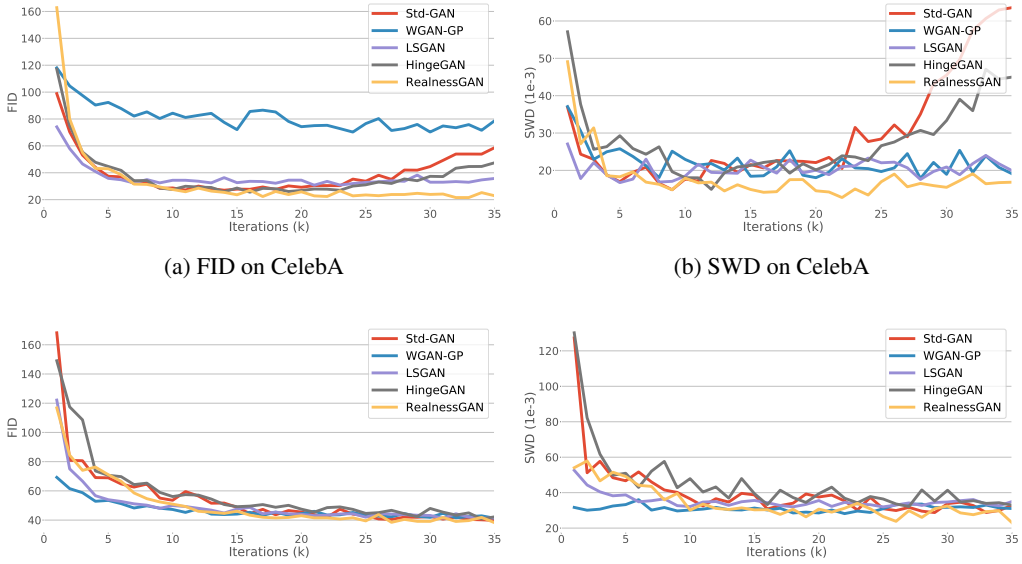


Figure 3: We show in the first row, the results of *RealnessGAN* when fixing $k_G = k_D = 1$ and increasing the number of supports. And the results of *RealnessGAN* by increasing k_G to proper numbers are shown in the second row. For the settings in the second row, we also compute the ratio of high quality samples and the number of recovered modes, resulting in two curves at the bottom.



(a) FID on CelebA

(b) SWD on CelebA

(c) FID on CIFAR10

(d) SWD on CIFAR10

Figure 4: Training curves of different methods in terms of FID and SWD on both CelebA and CIFAR10, where the raise of curves in the later stage indicate mode collapse. Best viewed in color.

4.2 Real-world Datasets

As GAN has shown promising results when modeling complex data such as natural images, we evaluate RealnessGAN on real-world datasets, namely CelebA,CIFAR10 and FFHQ, which respectively contains images at the 32*32, 256*256 and 1024*1024 resolutions. The training curves of baseline methods and RealnessGAN on CelebA and CIFAR10 are showed in Fig.4. The qualitative

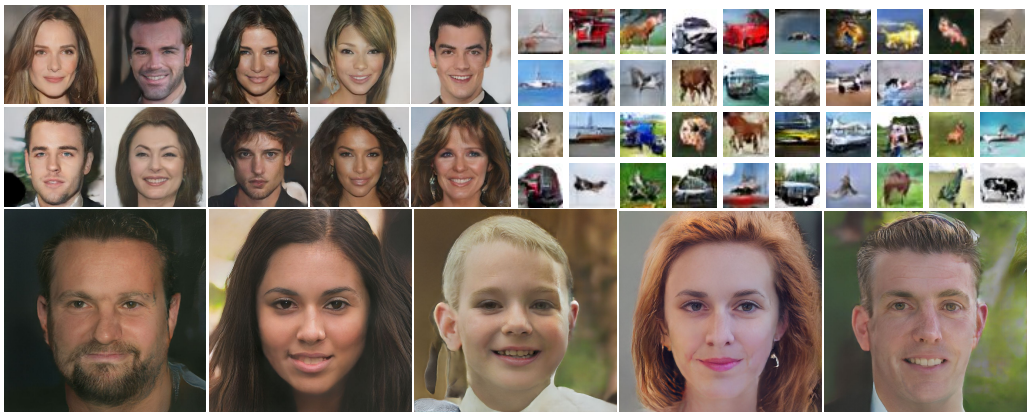


Figure 5: Images sampled from *RealnessGAN*, respectively trained on CelebA (top left), CIFAR10 (top right), and FFHQ (bottom).

results measured in FID and SWD are listed in Tab.1. We report the minimum, the maximum, the mean and the standard deviation computed along the training process. On both datasets, compared to baselines, *RealnessGAN* obtains better scores in both metrics. Meantime, the learning process of *RealnessGAN* is smoother and steadier (see SD in Tab.1 and curves in Fig.4). Samples of generated images on both datasets are included in Fig.5.

On FFHQ, we push the resolution of generated images to 1024*1024, which is known to be challenging especially for a non-progressive architecture. As shown in Fig.5, despite build on a relatively simple DCGAN architecture, RealnessGAN is able to produce realistic samples from scratch at such a high resolution.

The implementation of RealnessGAN offers several choices that also worth studying. On synthetic dataset, we explored the relationship between the number of supports and G's update frequency. On CelebA dataset, apart from evaluating RealnessGAN as a whole, we also studied the effectiveness of feature resampling and the affect of using different settings of $\mathcal{A}_0$ and $\mathcal{A}_1$. Specifically, Fig.6 shows the training curves of *RealnessGAN* with and without feature resampling. It can be noticed that feature resampling significantly stabilizes the training process especially in the latter stage. Tab.4.2 reports the results of exploiting different anchor distributions by varying the KL divergence between $\mathcal{A}_0$ and $\mathcal{A}_1$. FID score indicates that, as the KL divergence between $\mathcal{A}_0$ and $\mathcal{A}_1$ increases, *RealnessGAN* tends to perform better, which verifies our discussion in Sec.2.3 that a larger difference between anchor distributions gives rise to stronger constraints on G.

Table 2: Minimum (min), maximum (max), mean and standard deviation (SD) of FID on CelebA using different anchor distributions, calculated at 20k, 30k, ... iterations.

$\mathcal{D}_{\mathrm{KL}}(\mathcal{A}_1 \| \mathcal{A}_0)$	Min	Max	Mean	SD
1.66	31.01	96.11	40.75	11.83
5.11	26.22	87.98	36.11	9.83
7.81	25.98	85.51	36.30	10.04
11.05	23.51	81.30	30.82	7.61

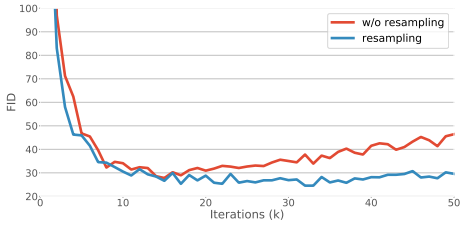


Figure 6: Training FID curves of RealnessGAN with and without feature re-sampling.

5 Conclusion

In this paper, we extend the view of realness in generative adversarial networks under a distributional perspective. In our proposed extension, RealnessGAN, we represent the concept of realness as a realness distribution rather than a single scalar. so that the corresponding discriminator estimates realness from multiple angles, providing more informative guidance to the generator. We prove RealnessGAN has theoretical guarantees on the optimality of the generator and the discriminator. On both synthetic and real-world datasets, RealnessGAN also demonstrates the ability of effectively and steadily capturing the underlying data distribution.

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A OBJECTIVE OF G

As mentioned in Sec.2.3, the ideal objective of G is $\max_G \mathbb{E}_{\boldsymbol{x}\sim p_g}[\mathcal{D}_{\mathrm{KL}}(\mathcal{A}_0\|D(\boldsymbol{x}))]$. On CelebA we have applied this objective to learn RealnessGAN. Our first attempt results in the left sample of Fig.7, where RealnessGAN fails to learn a good generator. After significantly increasing the KL divergence between $\mathcal{A}_0$ and $\mathcal{A}_1$, the generator of RealnessGAN is able to produce meaningful images, such as the one in the right of Fig.7. These results indicate a large KL divergence between two anchor distributions may lead to a strong discriminator D, which further provides informative guidance for G despite the use of an overly loose objective.

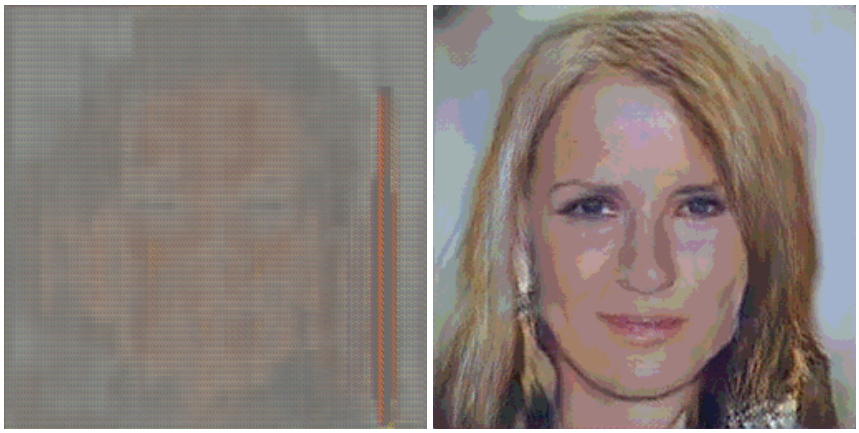

Figure 7: Sample images generated by RealnessGAN trained with the objective: $\min_G -\mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\mathcal{D}_{\mathrm{KL}}(\mathcal{A}_0\|D(G(\boldsymbol{z}))]$. Left: samples when $\mathcal{D}_{\mathrm{KL}}(\mathcal{A}_1\|\mathcal{A}_0) = 11.05$. Right: samples when $\mathcal{D}_{\mathrm{KL}}(\mathcal{A}_1\|\mathcal{A}_0) = 33.88$.

B FULL PROOF ON THEOREM 1

Proof. Given a fixed G, the objective of D is:

$$\min_D V(G,D) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}}[\mathcal{D}_{\mathrm{KL}}(\mathcal{A}_1\|D(\boldsymbol{x}))] + \mathbb{E}_{\boldsymbol{x}\sim p_g}[\mathcal{D}_{\mathrm{KL}}(\mathcal{A}_0\|D(\boldsymbol{x}))], \tag{15}$$

$$= \int_{\boldsymbol{x}} \left(p_{\text{data}}(\boldsymbol{x}) \int_u \mathcal{A}_1(u) \log \frac{\mathcal{A}_1(u)}{D(\boldsymbol{x},u)} du + p_g(\boldsymbol{x}) \int_u \mathcal{A}_0(u) \log \frac{\mathcal{A}_0(u)}{D(\boldsymbol{x},u)} du \right) dx, \tag{16}$$

$$= -\int_{\boldsymbol{x}} \left(p_{\text{data}}(\boldsymbol{x}) h(\mathcal{A}_1) + p_g(\boldsymbol{x}) h(\mathcal{A}_0)\right) dx$$

$$- \int_{\boldsymbol{x}} \int_u \left(p_{\text{data}}(\boldsymbol{x})\mathcal{A}_1(u) + p_g(\boldsymbol{x})\mathcal{A}_0(u)\right) \log D(\boldsymbol{x},u) du dx, \tag{17}$$

where $h(\mathcal{A}_1)$ and $h(\mathcal{A}_0)$ are their entropies, and the first term in equation 17 is irrelevant to D, marked as C_1. The objective thus is equivalent to:

$$\min_D V(G,D) = -\int_{\boldsymbol{x}} \int_u \left(p_{\text{data}}(\boldsymbol{x})\mathcal{A}_1(u) + p_g(\boldsymbol{x})\mathcal{A}_0(u)\right) \log D(\boldsymbol{x},u) du dx + C_1, \tag{18}$$

$$= -\int_{\boldsymbol{x}} \left(p_{\text{data}}(\boldsymbol{x}) + p_g(\boldsymbol{x})\right) \int_u \frac{p_{\text{data}}(\boldsymbol{x})\mathcal{A}_1(u) + p_g(\boldsymbol{x})\mathcal{A}_0(u)}{p_{\text{data}}(\boldsymbol{x}) + p_g(\boldsymbol{x})} \log D(\boldsymbol{x},u) du dx + C_1, \tag{19}$$

where $p_{\boldsymbol{x}}(u) = \frac{p_{\text{data}}(\boldsymbol{x})\mathcal{A}_1(u)+p_g(\boldsymbol{x})\mathcal{A}_0(u)}{p_{\text{data}}(\boldsymbol{x})+p_g(\boldsymbol{x})}$ is a distribution defined on Ω_u. Consequently, let $C_2 = p_{\text{data}}(\boldsymbol{x}) + p_g(\boldsymbol{x})$, we have

$$\min_D V(G,D) = C_1 + \int_{\boldsymbol{x}} C_2 \left(- \int_u p_{\boldsymbol{x}}(u) \log D(\boldsymbol{x},u) du + h(p_{\boldsymbol{x}}) - h(p_{\boldsymbol{x}}) \right) dx, \tag{20}$$

$$= C_1 + \int_{\boldsymbol{x}} C_2 \mathcal{D}_{\text{KL}}(p_{\boldsymbol{x}} \| D(\boldsymbol{x})) dx + \int_{\boldsymbol{x}} C_2 h(p_{\boldsymbol{x}}) dx. \tag{21}$$

From equation 21 we can see, for any $\boldsymbol{x} \in Supp(p_{\text{data}}) \cup Supp(p_g)$, when $\mathcal{D}_{\text{KL}}(p_{\boldsymbol{x}} \| D(\boldsymbol{x}))$ achieves its minimum, D obtains its optimal $D^\star$. And at that time, we have $D^\star(\boldsymbol{x}) = p_{\boldsymbol{x}}$, which concludes the proof. □

C FFHQ SAMPLES

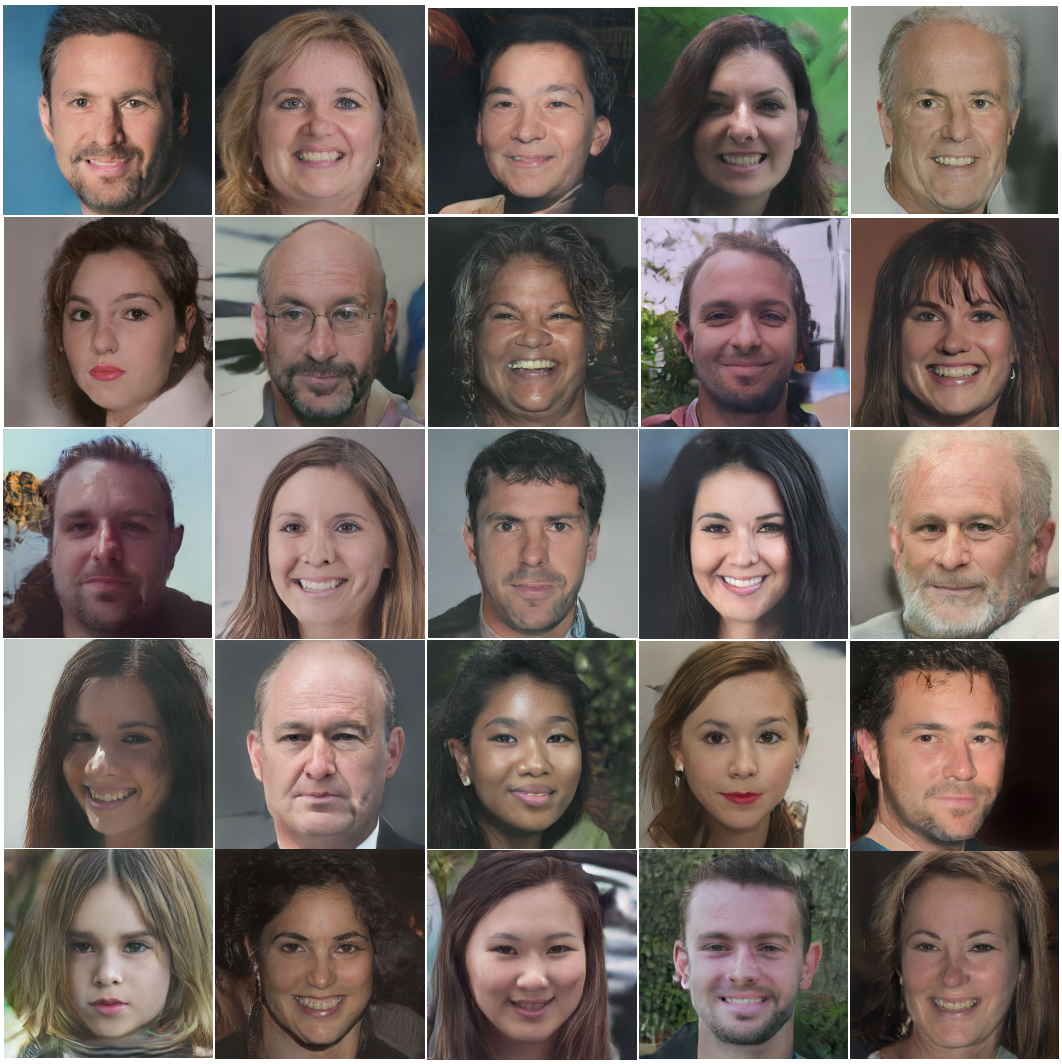

Figure 8: Additional 1024*1024 images produced by RealnessGAN trained on FFHQ.