Exploring and Exploiting Hubness Priors for High-Quality GAN Latent Sampling

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Abstract

Despite the extensive studies on Generative Adversarial Networks (GANs), how to reliably sample high-quality images from their latent spaces remains an under-explored topic. In this paper, we propose a novel GAN latent sampling method by exploring and exploiting the hubness priors of GAN latent distributions. Our key insight is that the high dimensionality of the GAN latent space will inevitably lead to the emergence of hub latents that usually have much larger sampling densities than other latents in the latent space. As a result, these hub latents are better trained and thus contribute more to the synthesis of high-quality images. Unlike the a posteriori “cherry-picking”, our method is highly efficient as it is an a priori method that identifies high-quality latents before the synthesis of images. Furthermore, we show that the well-known but purely empirical truncation trick is a naive approximation of the central clustering effect of hub latents, which not only uncovers the rationale of the truncation trick, but also indicates the superiority and fundamentality of our method. Extensive experimental results demonstrate the effectiveness of the proposed method. Our code is available at: https://github.com/Byronliang8/HubnessGANSampling.

1. Introduction

Generative adversarial networks (GANs) are a type of deep generative models that have revolutionized a variety of applications in computer vision and computer graphics, e.g., image synthesis (Karras et al., 2019; Park et al., 2019; Zhu et al., 2020), image editing (Abdal et al., 2019; 2020; Tov et al., 2021), image-to-image translation (Isola et al., 2017; Zhu et al., 2017; Richardson et al., 2021). Among them, novel image synthesis via random latent sampling is the most fundamental. It not only generates novel instances from the data distribution, but also measures how close the learned distribution is to the data distribution. Through the lens of the quality of synthesized images, we have witnessed significant progress in GANs over the past several years. Specifically, starting from the groundbreaking vanilla GAN (Goodfellow et al., 2014), DCGAN (Radford et al., 2015) laid the foundation for GAN architectures as deep convolutional neural networks; ProGAN (Karras et al., 2018) showed that GANs can generate high-quality images at high resolutions; BigGAN (Brock et al., 2019) addressed the problem of class-conditional image synthesis; the StyleGAN series (Karras et al., 2019; 2020; 2021) further boosted...
the quality and controllability of synthesized images with their style-based generator architectures and several novel techniques.

Nevertheless, with such improvements, the quality variance among images generated by randomly sampled latents has become increasingly striking (Fig. 1). Without curation, the quality of GAN synthesized images can occasionally be very low, which hinders the deployment of GANs in real-world applications. As a naive solution, “cherry-picking” is commonly used to select high-quality images from those synthesized with randomly sampled latents in an *a posteriori* manner. However, in the absence of reliable quantitative measures of the quality of a single GAN-synthesized image, existing “cherry-picking” methods are barely manual, thereby being tedious and unscalable. Addressing this issue, the well-known “truncation trick” (Marchesi, 2017; Brock et al., 2019; Karras et al., 2019) was proposed, which “truncates” randomly sampled GAN latents towards their mean based on the observation that the images synthesized from close-to-mean latents are usually of higher quality. Although effective, the truncation trick is a purely empirical “trick” that brings few new insights to the community.

In this paper, we propose a novel latent sampling method for GANs by exploring and exploiting the *hubness* phenomenon (Radovanovic et al., 2010) in their latent spaces, which facilitates their synthesis of high-quality images in an *a priori* manner. Specifically, our key insights include: i) the high dimensionality of the GAN latent space will inevitably lead to the emergence of *hub* latents that are much more likely to be among the nearest neighbors of other latents in the latent space, *i.e.* the hubness phenomenon; ii) in general, the quality of a GAN synthesized image is positively correlated with the *hub value* of its corresponding latent, *i.e.* the number of times a latent becomes a *k*-nearest neighbor (*k*-NN) of other latents in a given latent sample set. We believe that this positive correlation originates from the well-known close relationship between *k*-NN and density estimation. In other words, a higher *hub value* usually indicates a higher sampling density, which has a positive effect on the training and thus the quality of synthesized images. Therefore, we formulate the above insights as the proposed *hubness priors* and propose a corresponding method to sample high-quality GAN latents that yield high-quality synthesized images. Compared to “cherry-picking”, our method is highly efficient as it is *a priori* (*i.e.* our high-quality latents are determined before the synthesis of images) and automatic (*i.e.* with little human-intervention). Furthermore, we show that the well-known truncation trick is a naive approximation of the “central clustering effect” of our *hub* latents (Radovanovic et al., 2010). This not only uncovers the rationale of the truncation trick, but also indicates that our method is superior and more fundamental.

In summary, our contributions include:

- We uncover the existence of *hubness* phenomenon in the GAN latent space, which has a significant correlation with the quality of GAN synthesized images, *i.e.* the proposed *hubness priors*.
- We propose a novel GAN latent sampling algorithm that identifies high-quality *hub* latents based on our *hubness priors*, which allows efficient and high-quality image synthesis for GANs.
- We show that the well-known truncation trick is a naive approximation of the “central clustering effect” of our *hub* latents. This not only uncovers the rationale of the truncation trick, but also indicates that our method is superior and more fundamental.

### 2. Related Work

#### 2.1. Generative Adversarial Network (GAN)

Since the seminal work of Goodfellow et al. (2014), Generative Adversarial Networks (GANs) have become a major type of deep generative models and have been extensively studied in recent years. Existing works mostly focus on the choices of architectures (Radford et al., 2015; He et al., 2016; Jiang et al., 2021), loss functions (Arjovsky et al., 2017; Mao et al., 2017), regularization and normalization techniques (Gulrajani et al., 2017; Mescheder et al., 2018; Miyato et al., 2018; Qin et al., 2020), aiming to stabilize the training of GANs and improve the quality of synthesized images. To date, the best-performing GANs include the ProGAN (Karras et al., 2018) and the StyleGAN series (Karras et al., 2019; 2020; 2021) developed by Nvidia for unconditional image synthesis, and the BigGAN (Brock et al., 2019) developed by DeepMind for conditional image synthesis. Despite the success of these methods, they all have the long-standing problem that a large proportion of the images synthesized from randomly sampled latents are low-quality ones with artifacts, which hinders their applications in visual content generation.

**GAN Latent Sampling.** To sidestep the above-mentioned problem and obtain high-quality synthesized images, two workaround solutions were proposed: i) “cherry-picking” and ii) the truncation trick (Marchesi, 2017; Brock et al., 2019; Karras et al., 2019). Between them, the first approach is a naive solution as one can always “cherry-pick” high-quality ones from a set of synthesized images in an *a priori* manner.
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Figure 2. Distributions of $m$-hub latents for state-of-the-art GANs, $k = 5, 7, 10$ (the $k$-NN algorithm) and $n = 10000$ (size of latent sample set $S$). All distributions are highly tailed to the right, which shows the existence of hubness phenomenon (Radovanovic et al., 2010) in GAN latent spaces. Similar phenomena hold for StyleGAN $Z$-space and ProGAN (Appendix A). Note that $y$-axis is in log-scale.

posteriori manner with visual inspection. Obviously, this method is inefficient as it requires intensive human labor and is not applicable for large-scale image synthesis tasks. Unlike “cherry-picking”, the truncation trick is an automatic method that can synthesize high-quality images by normalizing sampled latents to be close to their mean. However, it is a purely empirical method with few insights. In this paper, we propose a novel latent sampling method for GANs based on the observation of hubness phenomenon in their high dimensional latent spaces, which is efficient with solid theoretical insights. We also show that the truncation trick is a naive approximation of our method due to the “central clustering effect” of hub latents.

2.2. Hubness Phenomenon

Hubness is a well-known phenomenon that describes the impact of the notorious “curse of dimensionality” on nearest neighbors (Radovanovic et al., 2010). In a nutshell, the hubness phenomenon is proved to be an inherent property of data distributions in high-dimensional space (Newman et al., 1983; Newman & Rinott, 1985; Radovanovic et al., 2010), which uncovers an interesting but counter-intuitive fact: high dimensionality leads to the emergence of “popular” nearest neighbors (a.k.a. the hub points). In other words, the hub points are those that are much more likely to be among the $k$-nearest neighbours of other points in a sample set. This fact poses challenges for algorithms that rely on nearest neighbor search. Addressing such challenges, hubness-aware methods were proposed and applied in various areas, e.g. gene expression classification (Buza, 2016a;b), time-series classification (Tomasev et al., 2015) and electroencephalograph classification (Buza & Koller, 2016). Meanwhile, hubness-aware $k$-nearest neighbor ($k$-NN) methods were also proposed, e.g. hubness-weighted $k$-NN (Radovanovic et al., 2010), hubness-fuzzy $k$-NN (Tomasev et al., 2014), hubness-information $k$-NN (Tomasev & Mladenic, 2011), Naive Hubness-Bayesian $k$-NN (Tomasev et al., 2011), and Augmented Naive Hubness-Bayesian $k$-NN (Tomasev & Mladenic, 2013).

In this paper, in contrast to previous methods that treat hubness as an undesirable phenomenon and aim to mitigate it, we show that the hubness phenomenon can be effectively used as priors for the sampling of high-quality GAN latents that produce high-quality synthesized images.

3. Hubness Priors for GAN Latent Sampling

In this section, we first explore the hubness of GAN latents (Section 3.1) and then exploit the insights obtained as priors to develop a novel algorithm for the sampling of high-quality latents for GANs (Section 3.2).
3.1. Exploring Hubness of GAN Latents

Inspired by previous studies on the hubness phenomenon of data distributions in high dimensional space (Radovanovic et al., 2010), let \( Z \in \mathbb{R}^d \) be a \( d \)-dimensional GAN latent space, \( S = \{z_1, z_2, ..., z_n\} \), \( z_i \in Z \) be a set of latents sampled from a \( d \)-dimensional standard normal distribution \( \mathcal{N}(0, I) \), \( k \) be the parameter of the \( k \)-nearest neighbor algorithm, we define \( m \)-hub latents as:

**Definition 3.1.** Latent code \( z_i \) (\( 1 \leq i \leq n \)) is an \( m \)-hub latent if \( z_i \) is among the \( k \)-nearest neighbors of \( m \) (\( m < n \)) sampled latents in \( S \), where \( m \) is the hub value of \( z_i \).

With the above definition, we explore the hubness of GAN latents by investigating the distributions of \( m \)-hub latents in the latent spaces of state-of-the-art GANs (Brock et al., 2019; Karras et al., 2018; 2019; 2020; 2021). As Fig. 2 shows, it can be observed that the distributions of \( m \)-hub latents are highly tailed to the right. Thus, we argue that the GAN latents are not uniformly distributed and that a small portion of them are much more likely to be close to other latents in the latent space, i.e., with large \( m \). Therefore, these latents tend to have larger sampling densities and are thus better trained than other latents during GAN training. Based on the heuristics that well-trained latents are more likely to yield high-quality images, we conjecture that the hubness phenomenon can be used as priors to identify GAN latents that generate high-quality results:

**Conjecture 3.2. (Hubness Priors)** The quality of GAN synthesized images and the hub values \( m \) of their corresponding latents are positively correlated.

Please see Section 4.2 for an empirical justification of our conjecture.

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**Algorithm 1 GAN Latent Sampling with Hubness Priors**

**Input:** a set of GAN latents \( S = \{z_1, z_2, ..., z_n\} \) randomly sampled from a standard normal distribution \( \mathcal{N}(0, I) \), a hyper-parameter \( k \), a threshold \( t \)

**Output:** \( S_{hq} \)

1. **Step 1**
   - \( m_{1,2,...,n} \leftarrow 0 \)
   - For \( i \leftarrow 1 \) to \( n \)
     - \( \{idx_1, idx_2, ..., idx_k\} \leftarrow k-\text{NN}(z_i) \)
     - For \( j \leftarrow 1 \) to \( k \)
       - \( m_{idx_j} \leftarrow m_{idx_j} + 1 \)
   - End for
   - End for

2. **Step 2**
   - \( S_{hq} \leftarrow \emptyset \)
   - For \( i \leftarrow 1 \) to \( n \)
     - If \( m_i \geq t \)
       - \( S_{hq} \leftarrow S_{hq} \cup z_i \)
   - End if
   - End for

**Remark on Random Latent Sampling** Previously, it was widely believed that GAN latents are unbiased as they are sampled from a simple but well-behaved noise distribution, i.e., the standard normal distribution \( \mathcal{N}(0, I) \), which is isotropic and has most of its density on a hypersphere surface in the high-dimensional GAN latent space (Menon et al., 2020). This implies that all sampled latents should be approximately uniformly distributed and of similar norms\(^2\), thereby contributing to the sampling in a similar manner. While in this paper, we counter this popular belief by show-
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Figure 4. Performance of our method on ProGAN (Karras et al., 2018), BigGAN (Brock et al., 2019) and StyleGAN3 (Karras et al., 2021). It can be observed that our method works well on all GAN architectures. (a) and (b), (c) and (d), (e) and (f) are images synthesized using high-quality (HQ) and low-quality (LQ) latents obtained by our method with ProGAN, BigGAN and StyleGAN3 respectively. We use Algorithm 1 to obtain HQ latents and Algorithm 2 (Appendix B) to obtain LQ latents respectively. We use $n = 10000$, $k = 5$, $t = 50$ and $t_{LQ} = 1$.

3.2. Exploiting Hubness Priors for High-quality GAN Latent Sampling

As Conjecture 3.2 states, the identification of high-quality GAN latents relies on their hub values $m$. Thus, given a set of GAN latents $S = \{z_1, z_2, \ldots, z_n\}$ randomly sampled from a standard normal distribution $\mathcal{N}(0, I)$, a hyperparameter $k$, and a threshold $t$, we utilize the proposed hubness priors and design a simple two-step GAN latent sampling algorithm: First, we compute the hub value $m_i$ for each latent $z_i \in S$ using a standard $k$-NN ($k$-nearest neighbor) algorithm; Second, we identify $z_i$ as a high-quality latent if $m_i$ is larger than a user-defined threshold $t$, and add $z_i$ into a set $S_{HQ}$. The set $S_{HQ}$ is the output of our algorithm, which contains all the high-quality latents identified. Algorithm 1 shows the pseudocode of our algorithm. Note that our algorithm is fundamental and widely applicable to different types of GANs as long as they sample latents from a standard normal distribution, e.g. conditional GANs (Brock et al., 2019).

Relationship to Truncation Trick. To our knowledge, the truncation trick (Marchesi, 2017; Brock et al., 2019; Karras et al., 2019) is the only a priori method to sample high-quality GAN latents before our work, which is based on a heuristic that high-quality latents are those close to their mean. However, such a heuristic is purely empirical with few insights. Surprisingly, the proposed hubness priors have revealed the rationale of the truncation trick: the hub latents obtained by our method tend to cluster towards their mean (Radovanovic et al., 2010). Thus, we argue that the well-known truncation trick is a naive approximation of our method as it only captures near-mean hub latents but overlooks those that are relatively far from the mean. Please see Section 4.5 for an empirical justification of our claims.
Figure 6. Performance of our method on StyleGAN2’s Z-space. We use $n = 10000$, $k = 5$, $t = 50$ and $t_{lq} = 1$.

4. Experimental Results

4.1. Experimental Setup

Due to its a priori nature, our method allows for the sampling of high-quality GAN latents before the synthesis of images. Thus, for the sampling of StyleGAN’s Z-space and other GANs’ latents, we use an Intel(R) Core(TM) i7-10875H CPU; for the sampling of StyleGAN’s W-space latents, we use a GeForce RTX 2080 Ti GPU as the computation involves passing Z-space latents through a fully-connected mapping network (Karras et al., 2019; 2020; 2021). For the synthesis of high-quality images, we use publicly-released Github codes of StyleGANs\(^{3}\) (Karras et al., 2019; 2020; 2021), BigGAN\(^{4}\) (Brock et al., 2019), ProGAN\(^{5}\) (Karras et al., 2018) with a GeForce RTX 2080 Ti GPU. Unless specified, all results are generated with the W-space of StyleGAN2 (Karras et al., 2020). All quantitative results are averaged over three runs. Note that JPEG is applied to compress the synthesized images to meet the size limit. Please see the supplementary materials for uncompressed images.

4.2. Effectiveness of Hubs Priors

As Figs. 3 (a) and (b) show, we compare the images generated by StyleGAN2 (Karras et al., 2020) using our method with those generated using the baseline, i.e. random latent sampling. It can be observed that our method consistently yields high-quality images while the baseline generates both high-quality and low-quality images, which demonstrates the effectiveness of the proposed hubs priors. Quantitatively, we observed better FID scores of images generated using our method than those by the baseline (Table 2).

Low-quality Latents. As Conjecture 3.2 implies, the proposed hubs priors can also be used to identify low-quality latents that yield unrealistic synthesized images. Thus, as a complement to high-quality latent sampling, we implement low-quality GAN latent sampling by reversing the thresholding scheme in Algorithm 1 to $m_i \leq t_{lq}$ and have Algorithm 2 (Appendix B). As Fig. 3 (c) shows, almost all synthesized images are of low quality, which justifies the effectiveness of the proposed hubs priors.

In fact, our hubs priors can be used to sort all sampled latents into a hubs spectrum according to their hub values $m$ (Appendix C), where the quality of images changes from high to low from left to right with decreasing $m$.

4.3. Versatility

To demonstrate the versatility of our method, we show that it generalizes across different GAN architectures, different image domains and different latent spaces of the StyleGAN series (Karras et al., 2019; 2020; 2021).

Different GAN Architectures. As Fig. 4 shows, to justify that our method works across different GAN architectures, we show that our method also works on three other state-of-the-art GAN architectures, i.e. ProGAN (Karras et al., 2018), BigGAN (Brock et al., 2019), and the recent StyleGAN3 (Karras et al., 2021).

Different Image Domains. As Fig. 5 shows, to justify that our method works across different image domains, we show that our method also works on StyleGAN2 models pretrained on other images domains\(^{6}\): cars, cats and horses.

StyleGAN’s Z-space. As Fig. 6 shows, our method also works for the Z-space of StyleGAN2 (Karras et al., 2020). However, we observed that the quality variance of synthesized images is slightly lower when using the W-space. Thus, we propose to use the W-space for StyleGAN2.

4.4. Justification of Algorithmic Choices

Threshold $t$. In our method, given a fixed latent sample set $S$, the threshold $t$ determines the trade-off between image quality and number of output latents: the larger $t$, the higher image quality, but the fewer output images. However, as Fig. 7 and Table 1 show, we observed that the image quality remains high for various choices of $t$. Since the image quality is not sensitive to the choice of $t$ in a relatively large range, we suggest using $t = 50$ as the default value for the case when $n = 10000$, $k = 5$. Note that we can easily extend our algorithm to output a user-specified number of images (denoted as $n'$) by using a revised scheme: if there

\(^{3}\)https://github.com/NVlabs/stylegan2, https://github.com/NVlabs/stylegan3.

\(^{4}\)https://github.com/ajbrock/BigGAN-PyTorch

\(^{5}\)https://github.com/tkarras/progressive_growing_of_gans

\(^{6}\)All pre-trained networks are available at: https://github.com/NVlabs/stylegan2.

\(^{7}\)Note that this trade-off only applies to a fixed $S$. Our method can generate an infinite number of high-quality samples by simply using multiple latent sets $S_1, S_2, ..., S_N$ or a larger $S$. 

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For a clearer understanding and further exploration of this topic, please refer to the supplementary materials and the appendix for detailed explanations and additional experiments.

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Note: The text has been designed to provide a coherent and comprehensive overview of the experimental setup, results, and algorithmic choices, ensuring clarity and accessibility for readers interested in high-quality GAN latent sampling.
are enough images in $S$, we first sort all images in the descending order of hub value $m$, and keep the top $n'$ latents; otherwise, we successively draw more latent sets $S_i$ and keep all $m > t$ images from them until we get $n'$ images.

**Hyper-parameter $k$.** We tested the performance of our algorithm with various choices of $k = 1, 3, 5, 7, 10$ in the $k$-NN algorithm. Apart from the case when no hub latents can be found ($k = 1$), we show the results of $k = 3, 5, 7, 10$ in Fig. 8 and Table 1. It can be observed that the image quality is not sensitive to the choice of $k$. Nevertheless, we noticed that using a larger $k$ yields more output hub latents for a given latent set $S$ and threshold $t$, but at the cost of slightly longer computation (Appendix E). To achieve a balance, we suggest using $k = 5$ as a default value when $n = 10000$, $t = 50$.

**Size of Latent Sample Set $n$.** As Table 1 shows, we also test the performance of the proposed method against various sizes $n = 10000, 20000, 30000, 40000$ of latent sample set $S$. Please see Appendix A for qualitative results. Similar to above, we observed that (i) although the FID scores get slightly better with increasing $n$, the image quality is not sensitive to the choice of $n$; (ii) using a larger $n$ yields more output hub latents but at the cost of longer computation (Appendix E). To achieve a balance, we suggest using $n = 10000$ as a default value when $k = 5, t = 50$.

**4.5. Relationship with Truncation Trick**

The truncation trick (Marchesi, 2017; Brock et al., 2019; Karras et al., 2019) has been widely used in state-of-the-art GANs. Specifically, it truncates randomly sampled latents $w$ to $w' = \bar{w} + \psi(w - \bar{w})$ to obtain high-quality latents that yield high-quality synthesized images, where $\bar{w}$ is the mean of a large number of randomly sampled latents, $\psi$ is a scaling parameter. As discussed in Section 3.2, we argue that it is a naive approximation of our method.

**Distance to the Means of Hub and All Latents.** To justify our claim, we first investigate the distances of our hub latents to their mean and their distances to the mean of all sampled latents. As Fig. 9 shows, it can be observed that: i) Our hub latents are closer to both the hub mean and the all latent mean than randomly sampled latents, which justifies the “central clustering effect” of our hub

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**Table 1.** FID scores of StyleGAN2 images synthesized using our method with different choices of $k$, $t$ and $n$, whose default values are $k = 5$, $t = 50$ and $n = 10000$. We sample 2,000 images to compute the FIDs, whose rationale is discussed in Sec. 4.5.

| $k$ | $FID_{\downarrow}$ | $t$ | $FID_{\downarrow}$ | $n$ | $FID_{\downarrow}$ |
|-----|-----------------|-----|-----------------|-----|-----------------|
| 3   | 22.793          | 60  | 20.749          | 10000| 22.782          |
| 5   | 22.782          | 50  | 22.782          | 20000| 22.021          |
| 7   | 22.720          | 40  | 24.517          | 30000| 21.679          |
| 10  | 22.560          | 35  | 25.412          | 40000| 19.124          |
Table 2. Comparison of FID scores of StyleGAN2 synthesized images using our method and the truncation trick. FFHQ-1 and FFHQ-2: real images sampled from the FFHQ dataset (Karras et al., 2019); Hubs (50): our method with \( t = 50 \); Truncated (0.7): truncation trick with \( \psi = 0.7 \); Random: random sampling. We sample 2000 latents/images for all methods compared. The FID scores between i) FFHQ-1 and FFHQ-2; and ii) Random and FFHQ-1,FFHQ-2 are used as baselines. Dist2Mean: distances of sampled latents to the all latent mean.

| Methods         | FID↓ FFHQ-1 | FID↓ FFHQ-2 | Dist2Mean |
|-----------------|-------------|-------------|-----------|
| FFHQ-2          | 16.505      | ---         | ---       |
| Hubs (50)       | 21.955      | 23.609      | 6.247     |
| Truncated (0.7) | 25.097      | 25.127      | 6.893     |
| Random          | 35.455      | 35.598      | 9.847     |

FID Scores. As Table 2 shows, we also justify the superiority of our method by comparing the FID scores (Heusel et al., 2017) of images generated by StyleGAN2 using both the truncation trick, \( \psi = 0.7 \) (Karras et al., 2019) and our method. Specifically, we compute the FID scores between images generated by i) real images sampled from the FFHQ datasets, i.e. FFHQ-1 and FFHQ-2 in Table 2; ii) our hub latents and FFHQ-1, FFHQ-2; iii) truncated latents \( (\psi = 0.7) \) and FFHQ-1, FFHQ-2; iv) randomly sampled latents and FFHQ-1, FFHQ-2. It can be observed that i) both our method and the truncation trick outperform random sampling; ii) our method achieves better FID scores than the truncation trick. Note that we intentionally used a small number of images (i.e. 2,000) to compute FID to avoid covering the entire distribution and thus suffer less from the restriction of latent spaces. In comparison with the results in (Jung & Keuper, 2021) and the bias-free FID$_\infty$ (Chong & Forsyth, 2020) computed with 10K images (Table 3), our FID scores of “Truncated (0.7)” images are better than “Random”, which is consistent with human perception. Note that our method outperforms Truncated (0.7) in both cases. Examples of StyleGAN2 synthesized images after the truncation trick \( (\psi = 0.7) \) are shown in Appendix D. Nevertheless, even using a small number of images, FID may still not be a good evaluation metric for our task. Therefore, we resort to the precision and recall metrics (Kynkäänniemi et al., 2019) that make more sense.

Table 3. FID$_\infty$ scores (Chong & Forsyth, 2020) computed with 10K images, which are ineffective as they capture the entire distribution and thus suffer from the restriction of latent spaces. Red: random sampling has the best score, which contradicts human perception as the images sampled with it are of the lowest quality.

| Method           | Hubs (50) | Truncated (0.7) | Random |
|------------------|-----------|-----------------|--------|
| FID$_\infty$↓    | 15.398    | 15.761          | 2.923  |

Precision and Recall (Kynkäänniemi et al., 2019). As Table 4 shows, our method achieves a high precision com-
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![Image of distributions and images](image)

**Figure 10.** The class distributions of the StyleGAN2 model pretrained on the CIFAR10 dataset with (a) our hubness-based sampling ($t = 50$), (b) the truncation trick ($\psi = 0.7$), and (c) the random sampling methods. WD: Wasserstein distance.

![Image of images](image)

**Figure 11.** StyleGAN2 images synthesized from (a) distant hub latents far from their mean; (b) truncated latents ($\psi = 0.8$).

Observed visually, our method actually preserves the class balance better as it has a smaller Wasserstein distance to the distribution of Random than the truncation trick. In addition, as Table 5 shows, our method achieves a better Inception Score (Salimans et al., 2016) that favours balanced and high-confidence classifications, which further justifies the superiority of our method in preserving class balance.

**Table 5.** Evaluation of class balance with Inception Scores (IS) (Salimans et al., 2016) of StyleGAN2 pretrained on the CIFAR10 dataset using our hubness-based sampling ($t = 50$), the truncation trick ($\psi = 0.7$), and the random sampling methods.

| Method          | Hubs (50) | Truncated (0.7) | Random |
|-----------------|-----------|-----------------|--------|
| IS              | 6.212     | 6.059           | 7.080  |

5. Conclusions

In this paper, we address the quality variance of GAN synthesized images by investigating the sampling of GAN latents. Specifically, we first show that GAN latents are not uniformly distributed in the latent space due to the hubness phenomenon of data distributions in high-dimensional space. In addition, there exist hub latents that are much more likely to be nearest neighbors of others and contribute more to the synthesis of high-quality images. Then, we formulate the above as the hubness priors and propose a novel GAN latent sampling algorithm, which allows for efficient and high-quality image synthesis for GANs. Furthermore, we show that the well-known truncation trick is a naive approximation of our method that utilizes the “central clustering effect” of hub latents, which not only uncovers the rationale of the truncation trick, but also indicates that our method is superior and more fundamental.

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References

Abdal, R., Qin, Y., and Wonka, P. Image2StyleGAN: How to embed images into the styleGAN latent space? In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pp. 4432–4441, 2019.

Abdal, R., Qin, Y., and Wonka, P. Image2StyleGAN++: How to edit the embedded images? In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 8296–8305, 2020.

Arjovsky, M., Chintala, S., and Bottou, L. Wasserstein generative adversarial networks. In *International conference on machine learning*, pp. 214–223. PMLR, 2017.

Brock, A., Donahue, J., and Simonyan, K. Large scale GAN training for high fidelity natural image synthesis. In *International Conference on Learning Representations*, 2019.

Buza, K. Classification of gene expression data: a hubness-aware semi-supervised approach. *Computer methods and programs in biomedicine*, 127:105–113, 2016a.

Buza, K. Semi-supervised naive hubness Bayesian k-nearest neighbor for gene expression data. In *Proceedings of the 9th International Conference on Computer Recognition Systems CORES 2015*, pp. 101–110. Springer, 2016b.

Buza, K. A. and Koller, J. Classification of electroencephalograph data: A hubness-aware approach. *Acta Polytechnica Hungarica*, 13(2):27–46, 2016.

Chong, M. J. and Forsyth, D. Effectively unbiased FID and inception score and where to find them. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 6070–6079, 2020.

Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., and Bengio, Y. Generative adversarial nets. *Advances in neural information processing systems*, 27, 2014.

Gulrajani, I., Ahmed, F., Arjovsky, M., Dumoulin, V., and Courville, A. C. Improved training of Wasserstein GANs. *Advances in neural information processing systems*, 30, 2017.

He, K., Zhang, X., Ren, S., and Sun, J. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 770–778, 2016.

Heusel, M., Ramsauer, H., Unterthiner, T., Nessler, B., and Hochreiter, S. GANs trained by a two time-scale update rule converge to a local Nash equilibrium. *Advances in neural information processing systems*, 30, 2017.

Isola, P., Zhu, J.-Y., Zhou, T., and Efros, A. A. Image-to-image translation with conditional adversarial networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 1125–1134, 2017.

Jiang, Y., Chang, S., and Wang, Z. TransGAN: Two pure transformers can make one strong GAN, and that can scale up. *Advances in Neural Information Processing Systems*, 34, 2021.

Jung, S. and Keuper, M. Internalized biases in fréchet inception distance. In *NeurIPS 2021 Workshop on Distribution Shifts: Connecting Methods and Applications*, 2021.

Karras, T., Aila, T., Laine, S., and Lehtinen, J. Progressive growing of GANs for improved quality, stability, and variation. In *International Conference on Learning Representations*, 2018.

Karras, T., Laine, S., and Aila, T. A style-based generator architecture for generative adversarial networks. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 4401–4410, 2019.

Karras, T., Laine, S., Aittala, M., Hellsten, J., Lehtinen, J., and Aila, T. Analyzing and improving the image quality of StyleGAN. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 8110–8119, 2020.

Karras, T., Aittala, M., Laine, S., Härkönen, E., Hellsten, J., Lehtinen, J., and Aila, T. Alias-free generative adversarial networks. *Advances in Neural Information Processing Systems*, 34, 2021.

Kynkäänniemi, T., Karras, T., Laine, S., Lehtinen, J., and Aila, T. Improved precision and recall metric for assessing generative models. *Advances in Neural Information Processing Systems*, 32, 2019.

Mao, X., Li, Q., Xie, H., Lau, R. Y., Wang, Z., and Paul Smolley, S. Least squares generative adversarial networks. In *Proceedings of the IEEE international conference on computer vision*, pp. 2794–2802, 2017.

Marchesi, M. Megapixel size image creation using generative adversarial networks. *arXiv preprint arXiv:1706.00082*, 2017.

Menon, S., Damian, A., Hu, S., Ravi, N., and Rudin, C. Pulse: Self-supervised photo upsampling via latent space exploration of generative models. In *Proceedings of the ieee/cvf conference on computer vision and pattern recognition*, pp. 2437–2445, 2020.

Mescheder, L., Geiger, A., and Nowozin, S. Which training methods for GANs do actually converge? In *International conference on machine learning*, pp. 3481–3490. PMLR, 2018.
Miyato, T., Kataoka, T., Koyama, M., and Yoshida, Y. Spectral normalization for generative adversarial networks. In *International Conference on Learning Representations*, 2018.

Newman, C. M. and Rinott, Y. Nearest neighbors and Voronoi volumes in high-dimensional point processes with various distance functions. *Advances in Applied Probability*, 17(4):794–809, 1985.

Newman, C. M., Rinott, Y., and Tversky, A. Nearest neighbors and Voronoi regions in certain point processes. *Advances in Applied Probability*, 15(4):726–751, 1983.

Park, T., Liu, M.-Y., Wang, T.-C., and Zhu, J.-Y. Semantic image synthesis with spatially-adaptive normalization. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 2337–2346, 2019.

Qin, Y., Mitra, N., and Wonka, P. How does Lipschitz regularization influence GAN training? In *European Conference on Computer Vision*, pp. 310–326. Springer, 2020.

Radford, A., Metz, L., and Chintala, S. Unsupervised representation learning with deep convolutional generative adversarial networks. *arXiv preprint arXiv:1511.06434*, 2015.

Radovanovic, M., Nanopoulos, A., and Ivanovic, M. Hubs in space: Popular nearest neighbors in high-dimensional data. *Journal of Machine Learning Research*, 11(sept): 2487–2531, 2010.

Richardson, E., Alaluf, Y., Patashnik, O., Nitzan, Y., Azar, Y., Shapiro, S., and Cohen-Or, D. Encoding in style: a StyleGAN encoder for image-to-image translation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 2287–2296, 2021.

Salimans, T., Goodfellow, I., Zaremba, W., Cheung, V., Radford, A., and Chen, X. Improved techniques for training GANs. *Advances in neural information processing systems*, 29, 2016.

Tomašev, N. and Mladenic, D. Nearest neighbor voting in high-dimensional data: Learning from past occurrences. In *2011 IEEE 11th International Conference on Data Mining Workshops*, pp. 1215–1218. IEEE, 2011.

Tomašev, N., Radovanović, M., Mladenić, D., and Ivanović, M. A probabilistic approach to nearest-neighbor classification: Naive hubness Bayesian kNN. In *Proc. 20th ACM Int. Conf. on Information and Knowledge Management (CIKM)*, pp. 2173–2176, 2011.

Tomašev, N., Radovanović, M., Mladenić, D., and Ivanović, M. Hubness-based fuzzy measures for high-dimensional k-nearest neighbor classification. *International Journal of Machine Learning and Cybernetics*, 5(3):445–458, 2014.

Tomašev, N., Buza, K., Marussy, K., and Kis, P. B. Hubness-aware classification, instance selection and feature construction: Survey and extensions to time-series. In *Feature selection for data and pattern recognition*, pp. 231–262. Springer, 2015.

Tov, O., Alaluf, Y., Nitzan, Y., Patashnik, O., and Cohen-Or, D. Designing an encoder for StyleGAN image manipulation. *ACM Transactions on Graphics (TOG)*, 40(4):1–14, 2021.

Zhu, J.-Y., Park, T., Isola, P., and Efros, A. A. Unpaired image-to-image translation using cycle-consistent adversarial networks. In *Proceedings of the IEEE international conference on computer vision*, pp. 2223–2232, 2017.

Zhu, P., Abdal, R., Qin, Y., and Wonka, P. SEAN: Image synthesis with semantic region-adaptive normalization. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 5104–5113, 2020.

### A. Additional Experimental Results

#### Different Image Domains

As Fig. 12 shows, as complement to Fig. 5 in the main paper, to justify that our method works across different image domains, we show that our method also works on a StyleGAN2 model pretrained on the horse domain.

#### Distributions of Hub Latents

As a complement to Fig. 2, Fig. 13 shows additional results on the distributions of m-hub latents in the latent spaces of state-of-the-art GANs.

#### Choice of size of Latent Sample Set $n$

Fig. 14 shows the qualitative results of our method with $n = 20000$, 30000, 40000 (see Fig. 3 for results when $n = 10000$). It can be observed that the visual quality remains similar across different $n$, which indicates that the image quality is not sensitive to the choice of $n$.

#### Quantitative results with BigGAN

As Table 6 shows, our method outperforms Truncated (0.7) with the BigGAN architecture pretrained on the 1000-class ImageNet ILSVRC 2012 dataset on precision and
Figure 12. Performance of our method on StyleGAN2 pretrained on the horse domain. It can be observed that our method works well. (a) and (b) are images synthesized from high-quality (HQ) and low-quality (LQ) latents obtained by Algorithm 1 and Algorithm 2 (Appendix B), respectively. We use \( n = 10000 \), \( k = 5 \), \( t = 50 \) and \( t_lq = 1 \).

recall (Kynkännen et al., 2019), which further justifies the superiority of our method.

**Table 6.** Quantitative results with BigGAN (ImageNet).

| Method           | Precision↑ | Recall↑ |
|------------------|------------|---------|
| Hubs (50)        | 0.147      | 0.311   |
| Truncated (0.7)  | 0.131      | 0.264   |

**B. Pseudocode of Low-quality GAN Latent Sampling**

The pseudocode of our low-quality GAN latent sampling algorithm is shown in Algorithm 2. It is a simple inverse of Algorithm 1, using a different thresholding scheme.

**Algorithm 2** Low-quality GAN Latent Sampling with Hubness Priors

**Input:** a set of GAN latents \( S = \{z_1, z_2, ..., z_n\} \) sampled from a standard normal distribution \( N(0, I) \), a hyperparameter \( k \), a threshold \( t_lq \)

**Output:** \( S_{lq} \)

# Step 1
\[ m_1, 2, ..., n \leftarrow 0 \]

for \( i \leftarrow 1 \) to \( n \) do

\[ \{\text{idx}_1, \text{idx}_2, ..., \text{idx}_k\} \leftarrow k\text{-NN}(z_i) \]

for \( j \leftarrow 1 \) to \( k \) do

\[ m_{\text{idx}_j} \leftarrow m_{\text{idx}_j} + 1 \]

end for

end for

# Step 2
\[ S_{lq} \leftarrow \emptyset \]

for \( i \leftarrow 1 \) to \( n \) do

if \( m_i \leq t_lq \) then

\[ S_{lq} \leftarrow S_{lq} \cup z_i \]

end if

end for

**C. Hubness Spectrum**

Fig. 15 shows the hubness spectrum obtained by our hubness priors. It can be observed that the quality of images changes from high to low from left to right with decreasing \( m \).

**D. Example Images with Truncation Trick**

We show examples of StyleGAN2 synthesized images after the truncation trick (\( \psi = 0.7 \)) in Fig. 16.

**E. Running Time**

Table 7 shows the running time of our method with different choices of \( k \) and \( n \). It can be observed that the running time increases mildly with \( k \) but significantly with \( n \).

| \( k \) | \( n \) | Time(s) |
|-------|-------|---------|
| 3     | 10000 | 163s    |
| 5     | 20000 | 167s    |
| 7     | 30000 | 1272s   |
| 10    | 40000 | 2554s   |

**F. Limitation and Future Work**

Although our method allows for the sampling of high-quality latents, the quality of synthesized images is bounded by the performance of the pre-trained GANs used to synthesize them. Also, we observed that the proposed hubness priors may overlook some relatively high-quality images with small hub values \( m \) (Fig. 17). We conjecture that the reason might be that the limited sizes of latent sample sets (e.g. \( n = 10000, 20000, ... \)) cannot capture all hub latents. This is partially verified by our experiment on the choice of \( n \). However, it is difficult to test larger \( n \) due to the \( O(n^2) \) time complexity to compute the hub values \( m \) for all points in a latent sample set. We hope to investigate this issue in future work. We also hope to apply our insights on the hubness phenomenon in GAN latent space to improve the training of GANs and make GANs unbiased for all latents. The acceleration of our algorithm is also a very interesting direction for future work.
Exploring and Exploiting Hubness Priors for High-Quality GAN Latent Sampling

Figure 13. Distributions of $m$-hub latents for state-of-the-art GANs, $k = 5, 7, 10$ (the $k$-NN algorithm) and $n = 10000$ (size of latent sample set $S$). $\ast$: Although both are 512-dimensional, the ProGAN (Karras et al., 2018) latents are sampled directly from $\mathcal{N}(0, I)$ while the StyleGAN latents further normalized the sampled latents to be of the same norm (Karras et al., 2019). All distributions are highly tailed to the right, which demonstrates the existence of hubness phenomenon (Radovanovic et al., 2010) in GAN latent spaces.

Figure 14. Performance of our method with different sizes $n = 20000, 30000, 40000$ of sample set $S$. We use $k = 5$, $t = 50$. 
Figure 15. The hubness spectrum of StyleGAN2 (Karras et al., 2020) synthesized images ranked according to their hub values $m$. We use $n = 10000$, $k = 5$. Note that the spectrum is highly tailed to the left and thus there are few images in the range $m = (70, 110)$.

Figure 16. Examples of StyleGAN2 synthesized images after the truncation trick ($\psi = 0.7$).

Figure 17. Relatively high-quality StyleGAN2 (Karras et al., 2020) synthesized images with small hub values $m$. However, there are still small artifacts in these images (e.g. background and facial details).