GIQA: Generated Image Quality Assessment

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Abstract. Generative adversarial networks (GANs) have achieved impressive results today, but not all generated images are perfect. A number of quantitative criteria have recently emerged for generative model, but none of them are designed for a single generated image. In this paper, we propose a new research topic, Generated Image Quality Assessment (GIQA), which quantitatively evaluates the quality of each generated image. We introduce three GIQA algorithms from two perspectives: learning-based and data-based. We evaluate a number of images generated by various recent GAN models on different datasets and demonstrate that they are consistent with human assessments. Furthermore, GIQA is available to many applications, like separately evaluating the realism and diversity of generative models, and enabling online hard negative mining (OHEM) in the training of GANs to improve the results.

Keywords: generative model, generative adversarial networks, image quality assessment

1 Introduction

Recent studies have shown remarkable success in generative models for their wide applications like high quality image generation \cite{12}, image-to-image translation \cite{11}, data augmentation \cite{13}, and so on. However, due to the quality of generated images varies greatly, not all generated images are satisfactory for real-world applications. Relying on manual quality assessment of generated images will take a lot of time and effort. Therefore, this work proposes a new research topic: Generated Image Quality Assessment (GIQA). The goal of GIQA is to automatically and objectively assess the quality of each image generated by the various generated models.

GIQA is related to previous Blind/No-Reference Image Quality Assessment (NR-IQA) \cite{7,8,9,10,11}. However, NR-IQA mainly focuses on quality assessment of natural image, instead of the generated image. Most of them are distortion-specific, \textit{i.e.}, they are capable of performing NR-IQA only if the distortion that afflicts the image is known beforehand, \textit{e.g.}, blur or noise or compression and so on. While the generated images may contain many uncertain model specific artifacts like checkboards \cite{12}, droplet-like \cite{13}, unreasonable structure \cite{14}, \textit{etc.} Unlike low-level degradations, these artifacts are difficult to simulate at different
levels for training. Therefore, traditional natural image quality assessment methods are not suitable for generated images as shown in Figure 1. On the other hand, previous quantitative metrics, like Inception Score [15] and FID [16], focus on the assessment of the generative models, which also can not be applied to assess the quality of each single generated image.

In this paper, we introduce three GIQA algorithms from two perspectives: learning-based and data-based perspectives. For the learning-based method, we apply a CNN model to regress the quality score of a generated image. The difficulty with this approach is that different generative models may have their own unique degradation. It is almost impossible to obtain a large amount of manually labelled data to cover all kinds of degradations. Therefore, we propose a novel semi-supervised learning procedure. We observe that the quality of the generated images is becoming better and better during the training process of generative models. Based on this, we use images generated by models with different iterations, and use the number of iterations as the pseudo label of the quality score. To eliminate the noise in the label, we propose a new algorithm that uses multiple binary classifiers as regressor to implement regression. Our learning-based algorithm can be applied to a variety of different models and databases without any manual annotation.
GIQA: Generated Image Quality Assessment

For the data-based methods, the essence is that the similarity between the generated image and the real image could indicate its quality. So we convert the GIQA problem into density estimation problem of real images. This problem can be broadly categorized as parametric and non-parametric method. For parametric method, we directly adopt the Gaussian Mixture Model (GMM) to capture the probability distribution of real data, then we estimate the probability of a generated image as quality score. Although this model is very simple, we found it works quite well for most situations. A limitation of parametric method is that the chosen density might not capture complex distribution. So we propose another non-parametric method, we compute the distance between generated image and its K nearest neighbours (KNN), the smaller distance indicates larger probability. We will evaluate these 3 methods in detail in the experimental part.

The learning-based method and the data-based method each have their own advantages and disadvantages. The GMM based method is easy to use and can be trained without any generated images. But it can only be applied to relatively simple distributed databases. The KNN based method has a great merit that there is no computation involved in the training phase, but its memory cost is large since it requires the whole training set to be stored. The learning-based method can handle a variety of complex data distributions, but it is also very time-consuming to collect the images generated by various models at different iterations.

The proposed GIQA method can be applied in many applications. 1) We can apply it for generative model assessment. Current generative model assessment algorithms like Inception Score [15] and FID [16] evaluate the performance of generative model in a score which represents the summarise of two aspects: realism and diversity. Our proposed GIQA model can evaluate these two aspects separately. 2) By using our GIQA method, we can assess the quality of generated images for a specific iteration of generator, and rank the quality of these samples, we suggest the generator to pay more attention to these samples with low quality. To achieve this, we adopt online hard negative mining (OHEM) [17] in the discriminator to put larger loss weight to the lower quality generated samples. Extensive experiments demonstrate that the performance of the generator is improved by this strategy. 3) We can leverage GIQA as an image picker to obtain a subset of generated images with higher quality.

Evaluating the GIQA algorithm is an open and challenging problem. It is difficult to get the precise quality annotation for the generated images. In order to evaluate the performance of our methods, we propose a labeled generated image for quality assessment (LGIQA) dataset. To be specific, we present a series of pairs which consist of two generated images for different observers to choose which has a better quality. We keep the pairs which are annotated with the consistent opinions for evaluating. We will release the data and encourage more research to explore the problem of GIQA.

To summarise, our main contribution are as follows:
1. To our knowledge, we are the first to propose the topic of generated image quality assessment (GIQA). We proposed three novel methods from two perspectives.

2. Our method is general and available to many applications, such as separately evaluating the quality and diversity of generative models and improving the results of generated model through OHEM.

3. We release the LGIQA dataset for evaluating different GIQA methods.

2 Related Work

In this section, we briefly review prior natural image quality assessment methods and generative model assessment methods that are most related to our work.

**Image Quality Assessment**: Traditional Image Quality Assessment (IQA) aims to assess the quality of natural images regarding the low-level degradations like noise, blur, compression artifacts, etc. It is a traditional technique that is widely used in many applications. Formally, it can be divided into two main categories: Full-reference IQA (FR-IQA) and No-reference IQA (NR-IQA). FR-IQA is a relatively simple problem since we have the reference for the image to be assessed, the most widely used metrics are PSNR [18] and SSIM [19]. NR-IQA is a more common real-world scenario which needs to estimate the quality of natural image without any reference images. Many NR-IQA approaches [7,8,9,10] focus on some specific distortion. Recently advances in convolution neural networks (CNNs) have spawned many CNNs based methods [20,21,22] for natural image quality assessment. More recent works [23,24] leverage the generative model and encourage the model to learn the intermediate perceptual meaning (quality map and hallucinated reference) first and then regress the final quality score.

**Generative Model Assessment**: Recent studies have shown remarkable success in generative models. Many generative models like VAEs [25], GANs [26], and Pixel CNNs [27] have been proposed. So the assessment of generative models has received extensive attention. Many works try to evaluate the generative model by conducting the user study, users are often required to score the generated images. While this will cost a large amount of time and effort. Therefore early work [28] propose a new metric Inception Score (IS) to measure the performance of generative model, the Inception Score evaluates the generative model in two aspects: realism and diversity of the generated images which are synthesized using the generative model. More recent work [16] proposes the Frachet Inception Distance (FID) score for the assessment of generative models. It takes the real data distribution into consideration and calculates the statistics between the generated samples distribution and real data distribution.

3 Methods

Given a generated image $I_g$, the target of generated image quality assessment (GIQA) is to quantitatively and objectively evaluate its quality score $S(I_g)$ which should be consistent with human assessment. We propose to solve this problem
from two different perspectives. The first one is a learning-based method, we apply a CNN model to regress the quality score of a generated image. The second one is a data-based method, we directly model the probability distribution of real data. Thus we could estimate the quality of a generated image by the estimated probability from the model. We will describe these two methods in detail in the following sections.

### 3.1 Learning-based Methods

For the learning-based methods, we aim to apply a CNN model to learn the quality of the generated images. Previous supervised learning method often required large amounts of labeled data for training. However, the quality annotation for the generated images is difficult to obtain since it is impossible for human observers to give the precise score to each generated image. Therefore, we propose a novel semi-supervised learning procedure.

**Semi-supervised learning**: We find an important observation that the quality of generated images from most generative models, e.g., PGGAN [1] and StyleGAN [29], is becoming better and better as the training iteration increases. Based on this, we collect images generated by models with different iterations, and use the number of iterations as the pseudo label of the quality score. Note that there is still a gap between the quality of the image generated by the last iteration and the real image. So we suppose that the quality of the generated images ranges from 0 to $S_g$, where $S_g \in (0, 1)$, and the quality of the real images is 1. Formally, the pseudo label of quality score $S_p(I)$ for image $I$ is

$$S_p(I) = \begin{cases} S_g \cdot \text{iter} / \text{max_iter} & \text{if } I \text{ is generated} \\ 1 & \text{otherwise} \end{cases},$$

(1)

where $\text{iter}$ presents the iteration number, $\text{max_iter}$ presents the maximum iteration number, $S_g$ defines the maximum quality score for the generated image, we set it to 0.9 in our experiment. Then we are able to build a training dataset $D = \{I, S_p(I)\}$ for semi-supervised learning, where $I$ represent the generated images or the real images, $S_p(I)$ denotes the corresponding quality score.

**Multiple binary classifiers as regressor**: A basic solution is to directly adopt a CNN based framework to regress the quality score from the input image. However, we found that this naive regression method is sub-optimal, since the pseudo label contains a lot of noise. Although statistically the longer the training is, the better the quality is, but there is also a large gap in image quality within the same iteration. To solve this problem, inspired by previous work [30], we propose to employ a multiple binary classifiers to learn the generated image quality assessment, which we called MBC-GIQA. To be specific, $N$ binary classifiers are trained. For the $i$-th classifier, the training data is divided into positive or negative samples according to a threshold $T^i$, i.e., given a image $I \in D$, its label $c^i$ for the $i$-th classifier is:

$$c^i = \begin{cases} 0 & \text{if } S_p(I) < T^i \\ 1 & \text{otherwise} \end{cases},$$

(2)
where \( i = 1, 2, \ldots, N \) and \( 0 < T^1 < T^2 < \cdots < T^N = 1 \). So a quality score \( S_p(I) \) can be converted to a set of binary labels \( \{c^1, c^2, \ldots, c^N\} \). Each binary classifier learns to distinguish whether the quality value is larger than \( T^i \). Suppose the predicted score for \( i \)-th binary classifier is \( \hat{c}^i \), \( i = 1, 2, \ldots, N \). So the training loss for the framework is,

\[
L = - \sum_{I \in D} \sum_{i=1}^{N} (c^i \log(\hat{c}^i) + (1 - c^i)\log(1 - \hat{c}^i)).
\]

(3)

Using classification instead of regression in this way can be more robust to noise. Although both positive and negative training samples contain noise, \( T^i \) is still statistically the decision boundary of \( i \)-th classifier. During the inference time, suppose we get all the predicted scores \( \hat{c}^i \), \( i = 1, 2, \ldots, N \) for a generated image \( I_g \). Then the final predicted quality score for \( I_g \) is the average of all predicted scores:

\[
S_{MBC}(I_g) = \frac{1}{N} \sum_{i=1}^{N} \hat{c}^i.
\]

(4)

### 3.2 Data-based Methods

Data-based methods aims to solve the quality estimation in a probability distribution perspective. We directly model the probability distribution of the real data, then we can estimate the quality of a generated image by the estimated probability from the model. We propose to adopt two density estimation methods: Gaussian Mixture Model (GMM) and \( K \) Nearest Neighbour (KNN).

**Gaussian Mixture Model:** We propose to adopt the Gaussian Mixture Model (GMM) to capture the real data distribution for generated image quality assessment, we call this method GMM-GIQA. A Gaussian mixture model is a weighted sum of \( M \) component Gaussian densities. Suppose the mean vector
and covariance matrix for \(i\)-th Gaussian density are \(\mu^i\) and \(\Sigma^i\), respectively. So the probability of an image \(I\) is given by:

\[
p(x|\lambda) = \sum_{i=1}^{M} w^i g(x|\mu^i, \Sigma^i),
\]

where \(x\) is the extracted feature of \(I\). Suppose the feature extractor function is \(f(\cdot)\), so \(x = f(I)\). \(w^i\) is the mixture weights, which satisfy the constraint that \(\sum_{i=1}^{M} w^i = 1\). And \(g(x|\mu^i, \Sigma^i)\) is the component Gaussian densities. Each component density is a \(D\)-variate Gaussian function of the form,

\[
g(x|\mu^i, \Sigma^i) = \frac{1}{(2\pi)^{D/2}|\Sigma^i|^{1/2}} \exp\left\{ -\frac{1}{2} (x - \mu^i)'(\Sigma^i)^{-1}(x - \mu^i) \right\}.
\]

The complete Gaussian mixture model is parameterized by the mean vectors, covariance matrices and mixture weights from all component densities. These parameters are collectively represented by the notation, \(\lambda = \{w^i, \mu^i, \Sigma^i\}\). To estimate these parameters, we adopt the expectation-maximization (EM) algorithm\[31\] to iteratively update them. Since the probability of a generated image represents its quality score, the quality score of \(I_g\) is given by:

\[
S_{\text{GMM}}(I_g) = p(f(I_g)|\lambda).
\]

**K Nearest Neighbour:** When the real data distribution becomes complicated. It would be difficult to capture the distribution with GMM well. In this situation, we introduce a non-parametric method based on K Nearest Neighbor (KNN). We think the Euclidean distance between generated images and nearby real images in feature space could also represent the probability of generated image, suppose the feature of a generated sample is \(x\). Its \(k\)-th nearest real sample’s feature is \(x^k\). So we could calculate the probability of generated image as:

\[
p(x) = \frac{1}{K} \sum_{k=1}^{K} \frac{1}{||x - x^k||^2}.
\]

Suppose the feature extractor function is also \(f(\cdot)\), So the quality score of \(I_g\) is given by:

\[
S_{\text{KNN}}(I_g) = p(f(I_g)).
\]

In summary, we introduce three approaches to get three forms of quality score function \(S(I_g): S_{\text{MBC}}(I_g), S_{\text{GMM}}(I_g), \text{and } S_{\text{KNN}}(I_g)\).

### 4 Applications

The proposed GIQA framework is simple and general. In this section, we will introduce that generated image quality assessment (GIQA) can be applied in many applications, such as generative model evaluation, improving the performance of GANs.
4.1 Generative model evaluation

Generative model evaluation is an important research topic in the vision community. Recently, a lot of quantitative metrics have been developed to assess the performance of a GAN model based on the realism and diversity of the generated images, such as Inception Score [28] and FID [16]. However, both of them summarise these two aspects. Our GIQA model can separately assess the realism and diversity of generated images. Specifically, we employ the mean quality score from our methods to indicate the realism performance of the generative model. Suppose the generative model is $G$, the generated samples are $I^g_i, i = 1, 2, \ldots, N_g$. So the quality score of generator $G$ is calculated with the mean quality of $N_g$ generated samples:

$$QS(G) = \frac{1}{N_g} \sum_{i} S(I^g_i), \quad (10)$$

On the other hand, we can also evaluate the diversity of the generative model $G$. Note that the diversity represents the relative diversity compared to real data distribution. We exchange the positions of real and generated images in data-based GIQA method, i.e., we use generated images to build the model and then evaluate the quality of the real images. Considering if the generated samples have similar distribution with real samples, then the quality of the real samples is high. Otherwise, if the generated samples have the problem of "mode collapse", which means a low diversity, then the probability of the real samples become low. This shows by exchanging the position, the quality of real samples is consistent with the diversity of generative models. Suppose the real samples are $I^r_i, i = 1, 2, \ldots, N_r$, the score function built with generative model $G$ is $S'(^\cdot)$. So the diversity score of the generative model is calculated with mean quality of $N_r$ real samples:

$$DS(G) = \frac{1}{N_r} \sum_{i} S'(I^r_i), \quad (11)$$

In summary, we have the quality score (QS) and diversity score (DS) to measure the quality and diversity of generative model separately.

4.2 Improve the performance of GANs

Another important application of GIQA is to help generative model to achieve better performance. In general, the quality of generated images from a specific iteration of generator have large variance, we can assess the quality of these generated samples by using our GIQA method, then we force the generator to pay more attention to these samples with low quality. To achieve this, we employ online hard negative mining (OHEM) [17] in discriminator to put higher loss weight to the lower quality samples. To be specific, we set a quality threshold $T_q$. Samples with quality lower than the threshold $T_q$ will be given a large loss weight $w_l > 1$. 
4.3 Image Picker based on quality

Another important application of GIQA is to leverage it as an image picker based on quality. For the wide applications of generative models, picking high quality generated images is of great importance and makes these applications more practical. On the other hand, for a generative model to be evaluated, we can take full advantage of the image picker to discard these images with low quality to further improve its performance.

5 Experiments

In this section, we first introduce the overall experiment setups and then present extensive experimental results to demonstrate the superiority of our approach.

Datasets and Training details We conduct experiments on a variety of generative models trained on different datasets. For unconditional generative models, we choose WGAN-GP [15], PGGAN [11], and StyleGAN [29] trained on FFHQ [28], and LSUN [32] datasets. For conditional generative models, we choose pix2pix [3], pix2pixHD [4], SPADE [33] trained on Cityscapes [34] datasets. FFHQ dataset is a large dataset which contains 70000 high-resolution face images. LSUN dataset contains 10 scene categories and 20 object categories, each category contains a large amount of images. Cityscapes dataset is widely used in conditional generative models. In our experiments, we use all the officially released models of these methods for testing.

For learning-based methods, we need the generated images at different iterations of a generative model for training. Specifically, for unconditional generative models, we collect the generated images in training process of StyleGAN for training, and test the resulted model on the generated images from PGGAN, StyleGAN, and real images. For conditional generative model, we use the generated images at different iterations of pix2pixHD for training, and test it on the generated images from pix2pix, pix2pixHD, SPADE and real images. To get these training images, we use the official training code, and collect 200,000 generated images, which consist of images from 4000 iterations, 50 images per iteration. And we adopt 8 binary classifiers for the MBC-GIQA approach. For the GMM-GIQA method, we set the number of Gaussian densities to 7 for LSUN and Cityscapes datasets, and 70 for FFHQ datasets. For the KNN-GIQA method, we set $K$ to 1 for FFHQ and Cityscapes datasets, 3500 for LSUN dataset. All the features are extracted from inception model [35] which is trained on ImageNet. More details please refer to the supplementary material.

Evaluation metrics Evaluating GIQA algorithms is an open and challenging problem. To quantitatively evaluate the performance of these algorithms, we collect a dataset which is annotated by multiple human observers. To be specific, we first use the generated images from PGGAN, StyleGAN and real images to build 1500 image pairs\footnote{We not only collect images from pretrained models, but also some low quality images from the training procedure.} then we demonstrate these pairs to 3 human observers.
We collect the pairs with the consistent opinions for testing. We collect 974, 1206, and 1102 image pairs for FFHQ, LSUN-cat, and Cityscapes dataset, respectively. We named this dataset as Labeled Generated Image Quality Assessment(LGIQA) dataset. To evaluate a GIQA algorithm, we just employ the algorithm to rank the image quality in each pairs and check if it is consistent with the annotation. Thus we can calculate the accuracy of each algorithm.

## 5.1 Comparison with recent works

Since no previous approach aims to solve the problem of GIQA, we design several baselines and compare our approach with these baselines to prove the superiority of our approach.

The first baselines are the methods for natural image quality assessment, we choose recent works like DeepIQA [22], NIMA [11], RankIQA [36] for comparison. For DeepIQA and NIMA, we directly apply their released model for testing. For RankIQA, we use their degradation strategy and follow their setting to train a model on our datasets. The second baselines are related to the learning-based method. We adopt the simple idea of directly employing a CNN network to regress pseudo label of quality score $S_p(I)$, which is called IR-GIQA. Another idea is instead of using multiple binary classifiers, we use only 1 classifier to determine whether the image is real or not, we call this BC-GIQA. The third baseline belongs to the data-based method, a simple idea to capture the real data probability distribution is to use a single Gaussian model, we call this SGM-GIQA.

We present the comparison on LGIQA dataset in Table 1. We observe that our proposed GIQA methods perform better than those natural image assessment methods. Meanwhile, the MBC-GIQA gets higher accuracy than the baseline IR-GIQA and BC-GIQA, and the GMM-GIQA is also better than the SGM-GIQA model, which demonstrate the effectiveness of our proposed method. Overall, GMM-GIQA achieve the best results. So we use GMM-GIQA for the following experiments.

We qualitatively compare the generated image quality ranking results for our proposed GMM-GIQA and NIMA in Fig 3, we can observe that GMM-GIQA
achieve a better generated image quality ranking results that is more consistent with human assessment. More results can be found in supplemental material.

5.2 Generative model assessment

Quality distribution evaluation The proposed GIQA methods are able to assess the quality for every generated samples, therefore we first employ our proposed GMM-GIQA to validate the quality distribution of generated samples from several generative models. For unconditional generative models, we choose WGAN-GP, PGGAN, StyleGAN trained on FFHQ, LSUN-cat and LSUN-car datasets. For conditional generative models, we choose pix2pix, pix2pixHD, and SPADE trained on Cityscapes dataset. Each generative model generates 5000 test images, and then apply our GMM-GIQA method to calculate the quality score, the quality score distribution are shown in Figure 4. Note that all the quality score are normalized to $[0, 1]$. We can find that PGGAN and StyleGAN are much better than WGAN-GP, and StyleGAN is better than PGGAN. SPADE and pix2pixHD are much better than pix2pix, SPADE is slightly better than pix2pixHD. All these observations are consistent with human evaluation.
Fig. 4: Quality score distribution of generated images from different generative models.

|       | FFHQ   | LSUN-cat | LSUN-car |
|-------|--------|----------|----------|
|       | WGAN-GP | PGGAN    | StyleGAN |
| FID   | 107.6  | 14.66    | 10.54    |
| QS    | 0.312  | 0.694    | 0.731    |
| DS    | 0.355  | 0.815    | 0.806    |

Table 2: Comparison of FID, QS, and DS metric for the generative model WGAN-GP, PGGAN, and StyleGAN on three different datasets: FFHQ, LSUN-cat, and LSUN-car.

|       | pix2pix | pix2pixHD | SPADE |
|-------|---------|-----------|-------|
| QS    | 0.498   | 0.851     | 0.870 |

Table 3: Quality Score (QS) for pix2pix, pix2pixHD, and SPADE on Cityscapes dataset.

**QS and DS for generative models** As we introduced in Section 4.2, we propose two new metrics the quality score (QS) and diversity score (DS) to measure the performance of generative models. So we employ these two metrics and FID to quantitatively evaluate these generative models. We use 5000 generated images to evaluate the FID and quality score (QS), 20000 generated images and 5000 real images to evaluate the diversity score (DS). Table 2 reports the results on WGAN-GP, PGGAN, and StyleGAN. We observe that our QS metric is consistent with human evaluation, and our DS metric demonstrates that StyleGAN and PGGAN have a better diversity than WGAN-GP. Table 3 reports the QS metric results for conditional generative models: pix2pix, pix2pixHD and SPADE, we can see that the result also consists of human evaluation.

### 5.3 Improve the performance of GANs

One important application of GIQA is to improve the performance of GANs. We find that we can achieve this in two perspectives, one is to adopt the GIQA to discard low quality images from all the generated images for evaluation. The other one is to take full advantage of the GIQA to achieve OHEM in the training process of GANs, then the performance gets improved. We will discuss these two methods in detail.

**Image picker trick** We conduct this experiment on the StyleGAN model trained on LSUN-cat dataset. We first generated 10000 images, then we use the GMM-GIQA method to rank the quality of these images and retain different
percentages of high quality images, finally we random sample 5000 remaining images for evaluation. We test the generated images with different remaining rate. For comparison, we notice that StyleGAN adopt a “truncation trick” on latent space which also discards low quality images. With a smaller truncation rate, the quality becomes higher, the diversity becomes lower. We report the FID, QS, DS results of different truncation rate and remaining rate in Table 4. We can notice that the FID gets improved when the truncation rate and remaining rate are set to 0.9, and the remaining rate works better than the truncation rate. Which also perfectly validates the superiority of the QS and DS metric.

Table 4: Comparison of truncation trick and image picker trick using StyleGAN on LSUN-cat dataset.

| Methods          | Metrics | 1   | 0.9 | 0.8 | 0.7 | 0.6 | 0.5 |
|------------------|---------|-----|-----|-----|-----|-----|-----|
| truncation rate  | FID     | 18.67 | 18.05 | 19.64 | 23.46 | 30.48 | 41.68 |
|                  | QS      | 0.441 | 0.463 | 0.486 | 0.510 | 0.537 | 0.567 |
|                  | DS      | 0.796 | 0.771 | 0.756 | 0.731 | 0.699 | 0.686 |
| remaining rate   | FID     | 18.67 | 16.65 | 17.63 | 20.73 | 25.84 | 33.19 |
|                  | QS      | 0.441 | 0.466 | 0.495 | 0.520 | 0.551 | 0.587 |
|                  | DS      | 0.796 | 0.792 | 0.780 | 0.766 | 0.746 | 0.712 |

Table 5: Performance comparison of various settings for StyleGAN.

| Datasets       | Methods                  | FID   | QS    | DS    |
|----------------|--------------------------|-------|-------|-------|
| FFHQ           | StyleGAN                 | 17.35 | 0.697 | 0.753 |
|                | StyleGAN+OHEM            | 16.89 | 0.711 | 0.755 |
|                | StyleGAN+OHEM+Picker     | 16.68 | 0.723 | 0.749 |
| LSUN-cat       | StyleGAN                 | 18.67 | 0.441 | 0.796 |
|                | StyleGAN+OHEM            | 18.12 | 0.462 | 0.790 |
|                | StyleGAN+OHEM+Picker     | 16.25 | 0.482 | 0.785 |

5.4 Analysis of the proposed methods

In this subsection, we conduct experiments to investigate the sensitiveness of hyper parameters in the proposed three approaches. All the results are evaluated on our LGIQA dataset.

Hyper parameters for MBC-GIQA For MBC-GIQA, the first parameter we want to explore is how patch size of the training image affects the results.
| Patch size | 32 | 64 | 128 | 192 | 224 | 256 |
|------------|----|----|-----|-----|-----|-----|
| Accuracy   | 0.686 | 0.709 | 0.725 | **0.731** | 0.721 | 0.690 |

Table 6: Results of different training patch size for MBC-GIQA.

| Number of binary classifiers | 1   | 4   | 6   | 8   | 10  | 12  |
|------------------------------|-----|-----|-----|-----|-----|-----|
| Accuracy                     | 0.663 | 0.682 | 0.722 | **0.731** | 0.718 | 0.717 |

Table 7: Results of different number of binary classifiers for MBC-GIQA.

| Number of Gaussian densities | 5   | 10  | 20  | 30  | 50  | 70  | 100 |
|------------------------------|-----|-----|-----|-----|-----|-----|-----|
| Accuracy                     | 0.648 | 0.663 | 0.735 | 0.739 | 0.752 | **0.764** | 0.753 |

Table 8: Results of different number of Gaussian densities for GMM-GIQA.

| K    | 1   | 30  | 100 | 500 | 1000 | 2000 | 3500 | 5000 | 7000 |
|------|-----|-----|-----|-----|------|------|------|------|------|
| Accuracy | 0.823 | 0.828 | 0.833 | 0.837 | 0.840 | **0.842** | **0.843** | 0.841 | 0.840 |

Table 9: Results of different number of nearest neighbors $K$ for KNN-GIQA.

To explore this, we train our multiple binary classifiers on images with different patch size. The training patch size is set to 32, 64, 128, 192, 256. During the inference time, we first randomly crop 3 patches on the test image with the training patch size and then input them to the model to get an average score as the final score. The default number of binary classifiers is set to 8. We test it on LGIQA-FFHQ dataset, results are shown in Table 6. We can observe that training images at patch size 192 gets the best results. Large patch size may lead to bad results, it may be caused by the overfitting problem. Small patch size also leads to bad performance, this may be because small patches can not provide discriminative information to learn the quality assessment.

The second parameter we want to explore is how the number of binary classifiers influence the results, we train the model using different numbers of binary classifiers. The number of classifiers is set to 1, 4, 6, 8, 10, 12. The training patch size is set to 192. Table 7 reports the results. We can find that as the number of binary classifiers increases from 1 to 8, the performance becomes better and better, and the number continues to increase to 12, the performance degrades.

**Hyper parameters of GMM-GIQA** The key factor for GMM is the number of Gaussian densities $M$, therefore we explore how $M$ affects the results of GIQA. We set $M$ to 5, 10, 20, 30, 50, 70, 100 and test the results on our LGIQA-FFHQ dataset. We show the results in Table 8 as the number of Gaussian densities $M$ increases from 5 to 70, we get better and better results, and the number continues to increase to 100, the performance degrades.

**Hyper parameters of KNN-GIQA** To explore how the number of nearest neighbours $K$ affects the results, we apply different $K$ in the KNN-GIQA. To be specific, we set $K$ to 1, 30, 100, 500, 1000, 2000, 3500, 5000, 7000. The result on LGIQA-LSUN-cat dataset is shown in Table 9 as $K$ increases from 1 to 1000, we get better and better results, and the number continues to increase to 7000, the performance is comparable.
6 Conclusions

In this paper, we aim to solve the problem of quality evaluation of a single generated image and propose the new research topic: Generated Image Quality Assessment (GIQA). To tackle this problem, we propose three novel approaches from two perspectives: learning-based and data-based. Extensive experiments show that our proposed methods can perform quite well on this new topic, also we demonstrate that GIQA can be applied in a wide range of applications.

We are also aware that there exist some limitations of our methods. For the learning-based method MBC-GIQA, it requires the generated images at different iterations for training, while these images may not be easily obtained in some situations. For the data-based method GMM-GIQA, it has a chance to fail when the real data distribution is too complicated. We also notice that our current results are far from solving this problem completely. We hope our approach will serve as a solid baseline and help ease future research in GIQA.
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