LGSQE: LIGHTWEIGHT GENERATED SAMPLE QUALITY EVALUATION

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ABSTRACT

Despite prolific work on evaluating generative models, little research has been done on the quality evaluation of an individual generated sample. To address this problem, a lightweight generated sample quality evaluation (LGSQE) method is proposed in this work. In the training stage of LGSQE, a binary classifier is trained on real and synthetic samples, where real and synthetic data are labeled by 0 and 1, respectively. In the inference stage, the classifier assigns soft labels (ranging from 0 to 1) to each generated sample. The value of the soft label indicates the quality level; namely, the quality is better if its soft label is closer to 0. LGSQE can serve as a post-processing module for quality control. Furthermore, LGSQE can be used to evaluate the performance of generative models, such as accuracy, AUC, precision, and recall, by aggregating sample-level quality. Experiments are conducted on several datasets and generative models to demonstrate that LGSQE can preserve the same performance rank order as that predicted by the Fréchet Inception Distance (FID) but with significantly lower complexity.

Index Terms— Generative Models, Quality Evaluation, Green Learning

1. INTRODUCTION

The evaluation of image generative models has become an active research topic due to the rapid advances in adversarial and non-adversarial generative models. Advanced image generative models find applications in image generation, image inpainting, image-to-image translation, etc. Due to the popularity of generative models, it is essential to have an automatic means to measure the quality of generated samples in an objective way without involving the human subjective test. Quite a few quantitative metrics have been proposed in recent years [1, 2]. Examples include the Inception Score (IS) [3], the Fréchet Inception Distance (FID) [4], the Classifier two-sample test [5] and the Precision and Recall (P&R) [6], etc. Each metric has its own strengths and weaknesses. Although being popular, the aforementioned evaluation methods share two common issues. First, they measure the effectiveness of a generative model based on the statistics of its whole generated samples. They cannot be applied to a single generated sample. In certain applications, it is desired to assess the quality of individual samples on the fly in the absence of ensemble distributions. Second, an important aspect of an evaluation method is its computational complexity. Some methods rely on deep features obtained from late layers of deep neural networks (DNNs). As a result, their computational complexity and memory cost is high. Also, certain evaluation methods are biased towards the ImageNet that is commonly adopted in pre-trained networks. Although efforts have been made to develop better quality evaluation methods, e.g., [7–9], these two fundamental problems still exist.

A lightweight generated sample quality evaluation (LGSQE) method is proposed to address them in this work. LGSQE trains a binary classifier to differentiate real and synthetic samples generated by a generative model. In the training stage, real and generated samples are assigned with labels “zero” and “one”, respectively. In the testing stage, a soft label is obtained, which serves as its quality index. The sample quality is good (or bad) if its soft label is farther away from (or close to) one. The LGSQE pipeline consists of three steps: 1) design a simple yet effective representation for real/synthetic images from a source dataset, 2) determine discriminant features, and 3) conduct binary classification.

As a byproduct, LGSQE can provide quality metrics for a generative model by aggregating quality indices of a large number of generated samples. Intuitively, a poorly-performing generative model tends to yield more bad samples. The distribution of generated samples from a poorly-performing generative model differs from that of real samples in the sample representation space. The accuracy of the binary classifier is higher since their distributions are more separable. In contrast, if the classification performance is close to the chance level (i.e., half-half), it indicates a high-performing model that generates high-quality samples that are close to the real ones in the representation space. LGSQE is a dataset-specific method. The dataset chosen as the generation target (e.g., CIFAR-10, etc.) is used to train LGSQE from scratch. It is worth noting existing quality metrics for generative models are all not dataset-specific. The rest of this paper is organized as follows. Related work is briefly reviewed in Sec. 2. The LGSQE method is presented in Sec. 3. Experimental results are shown in Sec. 4. Concluding remarks and future research directions are given in Sec. 5.

2. RELATED WORK

Quite a few metrics for generative model evaluation have been proposed. They are reviewed in Sec. 2.1. Furthermore, we conduct a brief survey on recent development in green learning in Sec. 2.2, as it pertains to the representation learning and feature selection of the proposed LGSQE method.

2.1. Evaluation Metrics for Generative Models

The Inception Score (IS) [3] is one of the early developed metrics. It uses the Inception-Net pre-trained on ImageNet to calculate the KL-divergence between the conditional and marginal distributions. It has some limitations. First, it is susceptible to overfitting [10]. Second, it fails to account for the mode collapse problem with generative models, and its bias towards ImageNet may give an image quality assessment in an object-wise manner (rather than a realistically-wise one). Third, it is sensitive to image resolution and not being a proper distance metric.

The Fréchet Inception Distance (FID) [4] is meant to improve deficiencies of IS. Inception-V3 is used to map samples onto its embedding space, where real and synthetic samples are modeled by joint Gaussian distributions. FID improves over IS by accounting
for intra-class mode dropping and, in turn, the diversity of generated samples between models. Yet, the log-likelihood distributions between real and synthetized samples are not easy to be captured in the high dimensional feature space [11]. FID is further enhanced in [12] by introducing the Class-Aware Frechet Distance (CAFDF).

The precision-recall metric with a reference data manifold was introduced in [13]. It attempts to take both fidelity and diversity into account. Yet, it has a bottleneck in real applications; namely, it is impractical to be deployed since the reference manifold is not available in most settings. Other reported limitations include failure to realize the match between identical distributions and robustness to outliers [9].

Another line of research adopts classifier-based evaluation [8] by training a classifier on real and synthetic samples. The classifier plays the role of a discriminator, and its error rate is used for performance assessment. For instance, the two-sample test [5] adopts the k-nearest neighbor (KNN) classifier trained on deep-layer embeddings from a third-party DNN classifier. The term “generated image quality assessment” was introduced in [14]. They used the classifier’s probability prediction as the quality index of individual samples. Although our high-level strategy is similar to theirs, we adopt a totally different methodology to achieve lower complexity. Our solution does not involve any neural networks.

### 2.2. Green Learning

Green learning (GL) [15] aims at the design of a lightweight learning system that has a small model size, fast training time, and low inference complexity. It consists of unsupervised representation learning, supervised feature learning, and supervised classification learning, three modules. All of them can be done efficiently. GL was initiated by Kuo with an effort to understand DL in [16, 17]. Afterwards, the Saab transform [18] was proposed to find image representations without backpropagation. The family of PixelHop methods was developed in [19–21]. Apart from representation learning, a powerful feature selection tool called the discriminant feature test (DFT) was proposed in [22]. DFT builds a bridge between representations learned without labels and with labels. LGSQE is a quality evaluation metric based on the green learning principle.

### 3. PROPOSED LGSQE METHOD

The LGSQE method consists of three cascaded modules, as elaborated below.

**Module 1: Representation Learning**

In this module, effective local and global representations of images are learned. The module may contain the processing in several stages, where each stage is called a hop. One hop pipeline is adopted due to its high performance and low complexity. The input is images of size $N \times N \times C$. We consider overlapping blocks of size $F \times F \times C$ with stride equal to $S$, where $F \times F$ is the spatial size and $C$ is the channel number. The Saab transform [18] is applied to these blocks to learn effective representations for downstream classification.

The Saab transform applies the constant element vector of unit length to an input block to get its DC coefficient. Then, it subtracts the DC component, applies the principal component analysis (PCA) to the residual, and derives the AC kernels as frequency-selective filters. The AC kernels of larger eigenvalues correspond to lower frequency components. This operation yields filter responses in the form of 3D tensors. The 3D tensors are 2D spatial dimensions $N_1 \times N_1$, where $N_1 = (N - F) / S + 1$, and 1D spectral dimension $K = F \times F \times C$. The high-frequency components with very small energy are discarded for dimension reduction, so the actual number $K_1$ of spectral channels is less than $K$. It is a user-determined parameter.

The absolute max-pooling, as introduced in [21], is applied to each channel. It results in a 3D tensor $1/2N_1 \times 1/2N_1 \times K_1$ which is the spatial representation and is also used as the input to the next step. The channel-wise Saab transform (c/w Saab) with $F = N_1$, as proposed in [20], is applied to further reduce dimensions and allow larger receptive fields so that representations of longer distance correlation can be extracted effectively. It conducts the Saab transform on each channel separately. This step generates the spectral representation. All spatial (local) and spectral (global) representations are concatenated to build a rich representation set for discriminant feature selection in Module 2.

**Module 2: Discriminant Feature Test (DFT)**

The number of representations obtained from Module 1 is large. We need a mechanism to choose powerful ones against a particular task. This is achieved by the discriminant feature test (DFT) [22]. DFT analyzes the discriminant power of each representation based on the following idea. For the $i^{th}$ representation, it computes its value range, $[f_{\text{min}} f_{\text{max}}]$, and partition the range into two non-overlapping subsets, denoted by $S_L$ and $S_R$, with a set of uniformly-spaced partition points. The DFT loss is defined as the smallest weighted entropy of $S_L$ and $S_R$ in left and right partitions at the optimal partition point. Mathematically, it can be written as

$$L_{DFT} = \min_{t \in T} H^t_i = -\min_{t \in T} \sum_{c=1}^{C} \left[ p_{L,c}^t \log(p_{L,c}^t) + p_{R,c}^t \log(p_{R,c}^t) \right]$$

(1)

Where $T$ denotes the set of uniformly-spaced partition points, $C$ is the class number and $p_{L,c}^t$ and $p_{R,c}^t$ denote the probability of the $i^{th}$ representation dimension being in class $c$ of the left or right interval, respectively.

The DFT loss can be computed for all representations in parallel since they are independent. The lower the DFT loss, the more discriminant of the representation dimension. The representations are sorted by their DFT loss in ascending order to yield the DFT loss curve, in which an elbow point is observed. We can use this point to select a subset of representations with lower DFT loss. They define a set of discriminant features to be fed into a binary classifier in Module 3.

**Module 3: Binary Classification for Evaluation**

We partition the real/generated data into training and testing sets. A binary classifier is trained on the union of real and generated training samples. They are labeled with “0” and “1”, respectively. The classifier assigns a soft score, $0 \leq d \leq 1$, to each testing sample as the sample quality index. The hard decision depends on threshold $t$, where $0 \leq t \leq 1$. The sample is labeled as “real” if $0 \leq d < t$, and “generated” if $t \leq d \leq 1$.

**Handling of Higher-Resolution Images**

To avoid information loss by directly downsampling images to a small size for datasets with higher resolution, we propose a multi-scale pipeline using two branches that have the same representation learning and DFT architecture with the general LGSQE method, to jointly extract features of low-resolution global layout (global branch) and high-resolution local details (local branch). Take the LSUN-Church dataset as an example. We downsample input images to $128 \times 128$ and feed them to two branches. For the global branch, after further downsampling images to $48 \times 48$, we feed images to Module 1 and Module 2 and obtain 900 discriminant features. For the local branch, a sliding window of $48 \times 48$ with stride 40 is applied to extract 9 overlapping sub-images for each input image. Similarly, the sub-images are fed to another Module 1 and Module 2 to get 100
features per sub-image and $9 \times 100 = 900$ features per image. The local and global features are concatenated together as the input of Module 3.

**LGSQE Quality metrics**

Four commonly used performance metrics of a binary classifier are chosen as the LGSQE quality indices. They are accuracy (Acc.), precision, recall, and area under the curve (AUC). Accuracy is the ratio of the "correct decision number" over the "total decision number". Precision and Recall is defined as

$$
\text{Precision} = \frac{TP}{TP + FP}, \quad \text{Recall} = \frac{TP}{TP + FN}, \quad (2)
$$

where $TP$, $FP$, $TN$, and $FN$ indicate true positive, false positive, true negative, and false negative, respectively. AUC is computed by the precision-recall curve by varying threshold $t$ from zero to one.

**4. EXPERIMENTS**

**Experimental Setup.** To show the effectiveness of the LGSQE method, we conduct experiments on four representative datasets: CIFAR-10 [23] (color images of resolution 32x32), LSUN-Church [24], LSUN-Bedroom [24] (color images of resolution 256x256), and CelebA [25] (color images of resolution 96x96). We evaluate the quality of generated samples and compare the performance of multiple generative models, including DCGAN [26], Diffusion-StyleGAN2 [27], StyleGAN2-ADA [28], StyleFormer [29], and StyleGANXL [30], StyleGAN [31], ProgressiveGAN [32], and ProjectedGAN [33].

**Evaluation of Generated Samples.** A soft score (the probability of a sample belonging to class "one") is assigned to each generated sample as a quality index by LGSQE. If a generated sample has a score close to one, it is likely to be a generated one. In contrast, a soft score closer to zero indicates a higher likelihood of being a real one. We show histograms of soft scores for real and generated samples computed by LGSQE for CIFAR-10, where the generator models in Fig. 1 (a) and (b) are Diffusion StyleGAN2 and Styleformer, respectively. By comparing these two histograms, we claim that Styleformer is a better generator model than Diffusion StyleGAN2, since its generated samples and real ones are clustered in the middle region of soft score 0.5. They are more difficult to distinguish. Further, we show the power of the quality index, we show generated LSUN-Church examples with soft scores for visual comparison in Fig. 2. Clearly, the soft score of a generated sample is correlated well with its visual quality viewed by humans.

**Evaluation of Generative Models.** As discussed at the end of Sec. 3, we use the classification accuracy (Acc.), AUC, precision, and recall as four LGSQE evaluation metrics for generative models. The metrics closer to 0.5 means a better model. Since FID is the most popular evaluation metric, we compare the ranking of FID with those of four LGSQE metrics for CIFAR-10, LSUN-Church, LSUN-Bedroom, and Celeb-A datasets in Table 1. We arrange generative models based on their FID scores from the largest to the smallest for each dataset, which correspond to the weakest and the strongest generative models, respectively. We see from the table that the ranking for the FID scores of generative models is consistent with those of the four metrics of LGSQE. These experiments demonstrate the effectiveness of LGSQE in measuring the power of generative models.

| Table 1. Comparison of 5 evaluation metrics (FID, Acc., AUC, Precision, and Recall) on multiple generative models for CIFAR-10, LSUN-church, LSUN-Bedroom and Celeb-A datasets. |
|---------------------------------------------------------------|
| CIFAR-10 dataset | FID | Acc. | AUC | Precision | Recall |
| Diffusion-StyleGAN2 | 3.19 | 0.877 | 0.944 | 0.879 | 0.876 |
| StyleGAN2-ADA | 2.92 | 0.842 | 0.919 | 0.843 | 0.842 |
| StyleFormer | 2.82 | 0.776 | 0.859 | 0.773 | 0.782 |
| StyleGAN-XL | 1.85 | 0.622 | 0.680 | 0.616 | 0.649 |

| LSUN-Church dataset | FID | Acc. | AUC | Precision | Recall |
|---------------------|-----|------|-----|-----------|--------|
| Diffusion-StyleGAN2 | 3.17 | 0.892 | 0.963 | 0.896 | 0.887 |
| StyleGAN2-ADA | 2.65 | 0.867 | 0.944 | 0.866 | 0.869 |
| ProgressiveGAN | 1.52 | 0.845 | 0.925 | 0.852 | 0.835 |
| Styleformer | 1.43 | 0.824 | 0.910 | 0.818 | 0.833 |

| LSUN-Bedroom dataset | FID | Acc. | AUC | Precision | Recall |
|----------------------|-----|------|-----|-----------|--------|
| Diffusion-StyleGAN2 | 3.65 | 0.876 | 0.948 | 0.873 | 0.880 |
| StyleGAN | 2.65 | 0.867 | 0.944 | 0.866 | 0.869 |
| ProgressiveGAN | 1.52 | 0.845 | 0.925 | 0.852 | 0.835 |
| Diffusion-StyleGAN2 | 1.43 | 0.824 | 0.910 | 0.818 | 0.833 |

| Celeb-A dataset | FID | Acc. | AUC | Precision | Recall |
|-----------------|-----|------|-----|-----------|--------|
| Diffusion-StyleGAN2 | 1.69 | 0.942 | 0.946 | 0.944 | 0.987 |

**Generative Model’s Post-processing.** LGSQE can be applied as a post-processing procedure for improving the quality of generated samples by filtering out generated samples of poor quality.
Fig. 2. Generated LSUN-church samples from the ProgressiveGAN model and their associated LGSQE quality indices, where a smaller quality index value indicates that the sample is more like a real one. The histogram of a large number of generated samples is also given to show the capability of the ProgressiveGAN model.

Generated samples can be sorted by their soft scores in ascending order. Then, we can keep good samples with smaller soft scores. Fig. 3 shows the accuracy of LGSQE and FID scores with different percentages of kept generated/real pairs for CIFAR-10 generated by Diffusion-StyleGAN2. As the percentages go smaller, kept generated samples are of higher quality and, as a result, both the accuracy of LGSQE and the FID score improve (the lower the better).

Fig. 3. The accuracy of LGSQE and FID scores as functions of the percentages of kept generate/real pairs.

**Weak Supervision.** LGSQE can achieve similar evaluation performance with a smaller number of training samples. We show the test accuracy of LGSQE for CIFAR-10 as a function of the number of training samples in Fig. 4 with two generative models (i.e., Styleformer and Diffusion-StyleGAN). The accuracy converges when 20% real and generated samples are used. In contrast, FID and other evaluation metrics apply complex networks to extract features. They demand more training data to get accurate distribution statistics for the evaluation purpose.

**Model Efficiency.** LGSQE has higher efficiency in terms of its model size and inference time compared with other quality evaluation metrics. The state-of-the-art metrics extract features from Inception-v3, VGG-16, or ResNet-34 pre-trained on ImageNet. Their model sizes are 91.2MB, 138.4MB, and 83MB, respectively.

Fig. 4. The correct classification rates of LGSQE for samples generated by two models as a function of the number of real samples (expressed in terms of percentages of the total training samples).

In contrast, it only takes 2-3 MB of memory for LGSQE to finish the whole evaluation process, including training and testing. As to the inference time comparison, we use the real and generated images for the CIFAR-10 dataset as an example. Our computing environment is Intel(R) Xeon(R) CPU E5-2620 v3 at 2.40 GHz. The FID computation on 10,000 pairs of generated and real images demands 122 minutes while the computation time of LGSQE quality indices for the same data set is less than 3 minutes.

5. CONCLUSION AND FUTURE WORK

A lightweight evaluation metric, LGSQE, was proposed to evaluate the quality index of a generated sample. It can also be employed as an evaluation metric for generative models, maintaining the same performance as other metrics, yet demanding fewer model parameters, fewer training samples, and less inference time. LGSQE can be potentially used as a post-processing module for high-quality image generation. That is, it can reject low-quality samples and, thus, improve the overall image generation performance. This is an interesting topic for future exploration.
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