ABSTRACT

Generative Adversarial Networks (GANs) are deep learning architectures capable of generating synthetic datasets. Despite producing high-quality synthetic images, the default GAN has no control over the kinds of images it generates. The Information Maximizing GAN (InfoGAN) is a variant of the default GAN that introduces feature-control variables that are automatically learned by the framework, hence providing greater control over the different kinds of images produced. Due to the high model complexity of InfoGAN, the generative distribution tends to be concentrated around the training data points. This is a critical problem as the models may inadvertently expose the sensitive and private information present in the dataset. To address this problem, we propose a differentially private version of InfoGAN (DP-InfoGAN). We also extend our framework to a distributed setting (DPD-InfoGAN) to allow clients to learn different attributes present in other clients’ datasets in a privacy-preserving manner. In our experiments, we show that both DP-InfoGAN and DPD-InfoGAN can synthesize high-quality images with flexible control over image attributes while preserving privacy.

Index Terms— InfoGAN, Differential Privacy, Distributed Learning, Deep Learning

1 Introduction

Deep Neural Networks can be used to train high-quality models with state-of-the-art performance in a myriad of applications, including medical image analysis, health informatics, language representation, and many more. However, building such models is not an easy task as it requires access to a large amount of high-quality data. Sharing private data is not an option in many scenarios due to regulations such as GDPR [21].

GANs [7], a class of Generative models [18, 13, 14], can be used to alleviate this arduous data-collection problem. GANs can learn the distribution of training data and generate high-quality fake data samples that have a distribution similar to the original distribution. Ideally, GANs can be used to protect the privacy of individuals in the dataset as they reveal only the distribution and not the sensitive private data of individuals. Despite this property, GANs may potentially expose the private information of training samples as they don’t provide guarantees on what information the fake data may reveal about the sensitive training data. Machine learning models, including GAN models, are susceptible to a multitude of attacks including reconstruction and membership inference attacks [19, 17, 15, 8], demonstrating that additional privacy is required in the form of protecting model parameters. These attacks can be addressed through the use of differential privacy [4].

Differential privacy is the state-of-the-art model for protecting the privacy of individuals in a statistical dataset. It ensures that an adversary cannot infer if a particular individual’s record is included in the dataset, hence providing the necessary guarantees to train privacy-preserving models on sensitive data. In recent times there have been studies on differentially private GANs [20, 9, 2, 6, 22]. However, most of these methods are focused on generating fixed synthetic data (with or without labels) and do not provide flexibility in controlling attributes of the synthetic data. For example, synthesizing images with different attributes (e.g. thickness, rotation, pose, etc.) involve separately training a new model with a new dataset in a private manner, which is expensive. Instead, we leverage InfoGAN [3] to facilitate control over the generated images, while preserving the privacy of the generator.

In this paper, we propose a differentially private framework for InfoGAN and evaluate it on the MNIST dataset [12]. Our experiments show that our framework can synthesize high-quality images with strong privacy guarantees. We also analyze the trade-off between privacy and quality of control over the generated images.

Also, we propose a distributed InfoGAN (DPD-InfoGAN) with a shared Q network to capture various attributes of images owned by different clients in a privacy-preserving manner. This allows clients with limited training data to learn intricate features present in the datasets of other clients. For example, if different clients own a subset of MNIST data, then each of the clients would not be exposed to all the variances in the images (e.g. all possible rotation angles, thickness factors, etc) but will still learn to synthesize such characteristics. Aggregating such models using federated learning [11] would be an expensive process as large model parameters have to be shared.
and aggregated every round. To overcome this problem, our approach uses a shared Q network in a distributed setting to decrease the number of parameters exchanged and henceforth reducing communication costs.

We show that our paradigm of training distributed InfoGANs enables each client to learn rich and varied feature representations (controlling attributes of generated images) when compared with a single client setting with the same number of images.

2 Background

2.1 InfoGAN

Generative Adversarial Networks involve training two networks simultaneously: a discriminator $D$ and a generator $G$. The generator maps a latent space ($p(z)$) to a fake distribution. The discriminator tries to discriminate between real data ($p(x)$) and the fake distribution. The two networks compete with each other in an adversarial setup, i.e., the generator tries when compared with a single client setting with the same number of images.

Differential privacy [4, 5] is a notion of privacy that ensures that statistical analysis does not compromise privacy by requiring that two datasets that are differing by a single individual should be statistically indistinguishable.

Definition 1. $((\epsilon, \delta)-$Differential Privacy) A randomized mechanism $\mathcal{M}$ satisfies $(\epsilon, \delta)$-differential privacy $((\epsilon, \delta)$-DP) when there exists $\epsilon > 0, \delta > 0$, such that

$$\Pr[\mathcal{M}(D_1) \in S] \leq e^{\epsilon} \Pr[\mathcal{M}(D_2) \in S] + \delta \quad (3)$$

holds for every $S \subseteq \text{Range}(\mathcal{M})$ and for all datasets $D_1$ and $D_2$ differing on at most one element.

Lemma 1. [22] In order to guarantee $((\epsilon, \delta)$-Differential privacy for the discriminator, we assign the following value to the noise scale $\sigma_n$:

$$\sigma_n = \frac{2p \sqrt{I_d \log(\frac{1}{\delta})}}{\epsilon}, \quad (4)$$

where the sampling probability $p = \frac{N}{2^d}$ (n represents the batch size, $N$ represents the dataset size), $I_d$ is the number of discriminator iterations for every generator iteration, $\epsilon$ is the privacy-loss parameter, and $\delta$ is the privacy violation parameter.

3 Our Approach

The details of our method to achieve a privacy-preserving InfoGAN are shown in Algorithm 1. After computing the gradients of the discriminator (line 4-7), we clip them with clipping parameter $C_p$ (line 8) to bound the gradients. We set $I_d = 1$ in Equation 4 and compute noise scale $\sigma_n$. We add noise to the gradients and then update the discriminator weights using the Adam optimizer [10] (line 10). The NLL in line 12 refers to the Negative Log-Likelihood loss.

The training of the Q network is differentially private due to the post-processing property [5], as the Q network operates on top of the discriminator. Similarly, the generator satisfies differential privacy, as the generator receives updates from the discriminator and the Q network which are trained in a differentially private manner. We can also keep track of the privacy budget spent in our algorithm by using Moment Accountant [11] or Renyi DP accountant [16].
4 Experiments

We ran experiments on the MNIST dataset to analyze the trade-off between privacy and the quality and semantics of generated images. The batch size was set to 64, the number of epochs to 50, and $\delta$ to $10^{-5}$. We fix the learning rate for the Adam optimizer to 0.0002, and sample two continuous codes from a uniform distribution between $[-1, 1]$. We use three fractionally-strided convolutions for the generator and three convolutions for the discriminator. The Q network consists of four convolutional layers. Batch normalization is applied in all the layers. LeakyReLU is used in discriminator and Q network, while the generator uses RELU activation.

First, we compare the results obtained from InfoGAN and DP-InfoGAN on a single client model. In Figure 3, we see that

![Image](a) InfoGAN (b) DP-InfoGAN ($\epsilon = 1$) (c) DP-InfoGAN ($\epsilon = 0.1$)

Fig. 2: Rotation of digits

Algorithm 1: Differentially Private InfoGAN (DP-InfoGAN)

Require: Clipping parameter for gradients $C_p$, Noise Scale $\sigma_n$, Discriminator $D$, Generator $G$, Auxiliary network providing estimate of the code $Q$, Real data points $X = (x_1, x_2, \ldots, x_M)$, Batch size $m$, Noise prior $p(z)$, Latent code prior $p(c)$, Learning Rate $\alpha$

Ensure: Differentially Private Generator $\theta_g$

1. Sample batch $x = \{x_i\}_{i=1}^m$ from real data points $X$
2. Sample noise $z = \{z_i\}_{i=1}^m$ from noise prior $p(z)$
3. Sample codes $c = \{c_i\}_{i=1}^m$ from prior $p(c)$

/* Compute batch loss for discriminator */

4. for $i = 1$ to $m$

5. $D_{\text{loss}}(x_i, z_i, c_i) := \log(D(x_i)) + D(1 - \log(D(G(z_i, c_i))))$

6. $\text{grad}_d(x_i, z_i, c_i) := \nabla_{\theta_d} D_{\text{loss}}(x_i, z_i, c_i)$

7. $\text{Clip gradients to bound them}$

8. $\text{grad}_d(x, z, c) := \text{grad}_d(x, z, c)/\max(1.0, ||\text{grad}_d(x, z, c)||_2/C_p)$

9. $\text{Compute average gradient for batch}$

10. $\text{grad}_d(x, z, c) = (1/m) * \sum_{i=1}^m \text{grad}_d(x_i, z_i, c_i)$

11. $\text{Add noise to make discriminator differentially private}$

12. $\text{Update weights of the discriminator using Adam optimizer}$

13. $\theta_{d_{\text{new}}} := \theta_d - \alpha \cdot ADAM(\text{grad}_d(x, z, c), \theta_d)$

14. $Q_{\text{logits}}, \text{mean}, \text{variance} = Q(D(G(z, c)))$

15. $\text{Calculate estimate of codes from Q}$

16. $Q_{\text{loss}} = NLL(c, \text{mean}, \text{variance}, Q_{\text{logits}})$

17. return $\theta_{g_{\text{new}}}, \theta_{d_{\text{new}}}, \theta_{q_{\text{new}}}$
Algorithm 2: Differentially Private Distributed InfoGAN (DPD-InfoGAN)

Require: Clients \( C = (C_1, C_2, \ldots, C_N) \), where \( C_i = (G_i, D_i) \), Auxiliary network providing estimate of the code \( Q \), Total number of rounds per client \( R \)

Ensure: Differentially Private Generator \( G_i \)

1 for \( r = 1 \) to \( R \) do
2 for \( i = 1 \) to \( N \) do
3 /* Train \( C_i \) using Algorithm 1 */
4 \( \theta_{g_{\text{new}}}, \theta_{d_{\text{new}}}, \theta_{q_{\text{new}}} = \text{Algorithm 1}(G_i, D_i, Q) \)
5 /* Update \( Q \) weights */
6 \( Q\cdot\text{weights} = \theta_{q_{\text{new}}} \)
7 end for
8 end for
9 return \( C, Q \)

with privacy guarantees, the model has trouble differentiating between close digits (such as 3 and 5 in Figure 3b) but still is able to generate high-quality images. In addition, as shown in Figure 2b, DP-InfoGAN faces minor issues disentangling the latent space (i.e.) the results display changes in both thickness and rotation while we try to preserve only rotation of digits. Therefore, DP-InfoGAN preserves the quality of the images to an extent, but starts losing control over the attributes of images. For smaller values of \( \epsilon \), it becomes harder to facilitate this control. We see that in Figure 2c, the thickness and rotation of the digits get more entangled when compared to Figures 2a, 2b.

In the distributed setting (DPD-InfoGAN), we use the same configuration and simulate experiments with each client having a subset of the MNIST data (non-overlapping). To validate our algorithm and prove that a shared \( Q \)-network can capture all possible variances in images, we run experiments with 10 clients (each having 6000 images) in a distributed setting and compare it with a single client having 6000 images. We observe that, in the distributed setting, the generated images display a varied change in thickness and rotation when compared to the non-distributed setting. In Figures 4b, 5b, we see more variety in rotation and thickness when compared to a single client setting as shown in Figures 4a, 5a. For example, digits 1 and 8 in Figure 4b have more variations in rotations than in Figure 4a. This indicates that even when a client does not have variations in its training images, it can still generate those variations as the shared \( Q \)-network is continuously updated on the clients’ datasets in a privacy-preserving manner and captures all possible feature variances present in the datasets of other clients.

5 Conclusion and Future Work

In this paper, we propose a privacy-preserving version of InfoGAN (DP-InfoGAN) that guarantees the privacy of the training data samples. Our results show that DP-InfoGAN can synthesize high-quality images with control on image attributes. Our framework can keep track of the privacy budget spent by using Moment Accountant or Renyi DP accountant. We also extend the framework to a distributed setting (DPD-InfoGAN) by using a shared \( Q \) network. We show that our training paradigm in the distributed setting captures varied image characteristics even when each client has limited data. As part of future work, we plan to explore privacy-preserving and distributed/federated versions of CycleGANs, BigGANs, etc.
6 References

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