DECENTRALIZED ATTRIBUTION OF GENERATIVE MODELS

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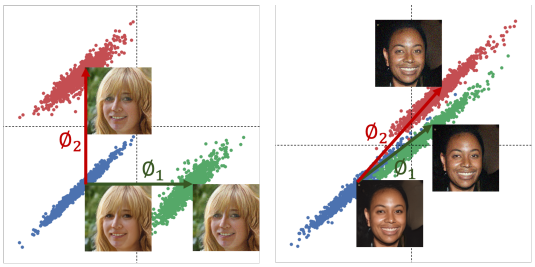
ABSTRACT

Growing applications of generative models have led to new threats such as malicious personation and digital copyright infringement. One solution to these threats is model attribution, i.e., the identification of user-end models where the contents under question are generated. Existing studies showed empirical feasibility of attribution through a centralized classifier trained on all existing user-end models. However, this approach is not scalable in reality where the number of models ever grows. Neither does it provide an attributability guarantee. To this end, this paper studies decentralized attribution, which relies on binary classifiers associated with each user-end model. Each binary classifier is parameterized by a user-specific key and distinguishes its associated model distribution from the authentic data distribution. We develop sufficient conditions of the keys that guarantee an attributability lower bound. Our method is validated on MNIST, CelebA, and FFHQ datasets. We also examine the trade-off between generation quality and robustness of attribution against adversarial post-processes.

1 INTRODUCTION

Recent advances in generative models (Goodfellow et al., 2014) have enabled the creation of synthetic contents that are indistinguishable even by naked eyes (Pathak et al., 2016; Zhu et al., 2017; Zhang et al., 2017; Karras et al., 2017; Wang et al., 2018; Brock et al., 2018; Miyato et al., 2018; Choi et al., 2018; Karras et al., 2019a;b; Choi et al., 2019). Such successes raised serious concerns (Kelly, 2019; Breland, 2019) regarding emerging threats due to the applications of generative models. This paper is concerned about two particular types of threats, namely, malicious personation (Satter, 2019) , and digital copyright infringement. In the former, the attacker uses generative models to create and disseminate inappropriate or illegal contents; in the latter, the attacker steals the ownership of a copyrighted content (e.g., an art piece created through the assistance of a generative model) by making modifications to it.



(a) (b)

Figure 1: We develop sufficient conditions for model attribution: Perturbing the authentic dataset in different directions with angles larger than a data-dependent threshold guarantees attributability of the perturbed distributions. (a) A threshold of $90\,\mathrm{deg}$ suffices for benchmark datasets (MNIST, CelebA, FFHQ). (b) Smaller angles may not guarantee attributability.

These threats share the same solution, namely, model attribution, i.e., the identification of user-end models where the contents under question are generated. Existing studies showed empirical feasibility of attribution through a centralized classifier trained on all existing user-end models (Yu et al., 2018). However, this approach is not scalable in reality where the number of models ever grows. Neither does it provide an attributability guarantee. To this end, we study in this paper a decentralized attribution scheme: Instead of a centralized classifier, we use a set of binary linear classifiers associated with each user-end model. Each classifier is parameterized by a user-specific key and distinguishes its associated model distribution from the authentic data distribution. For correct at-

tribution, we expect one-hot classification outcomes for generated contents, and zero vectors for authentic data. To achieve correct attribution, we study the sufficient conditions of the user-specific keys that guarantee an attributability lower bound. The resultant conditions are used to develop an algorithm for generating new keys. Lastly, we assume that attackers can post-process generated contents to potentially deny the attribution, and study the tradeoff between generation quality and robustness of attribution against post-processes.

Problem formulation We assume that for a given dataset $\mathcal{D} \subset \mathbb{R}^{d_x}$, the registry generates user-specific *keys*, $\Phi := \{\phi_1, \phi_2, ...\}$ where $\phi_i \in \mathbb{R}^{d_x}$ and $||\phi_i|| = 1$. $||\cdot||$ is the l_2 norm. A user-end generative model is denoted by $G_\phi(\cdot;\theta) : \mathbb{R}^{d_z} \to \mathbb{R}^{d_x}$ where z and x are the latent and output variables, respectively, and θ are the model parameters. When necessary, we will suppress θ and ϕ to reduce the notational burden. The distribution of each key is accompanied by that of a public service that tells whether a query content belongs to G_ϕ (labeled as 1) or not (labeled as -1). We model the underlying binary linear classifier as $f_\phi(x) = \text{sign}(\phi^T x)$. Note that linear models are necessary for the development of sufficient conditions of attribution, and tests on benchmark datasets suggest that linear classifiers achieve good attribution performance.

The following quantities are central to our investigation: the *distinguishability* of G_ϕ measures the accuracy of $f_\phi(x)$ at classifying G_ϕ against $\mathcal{D}$:

$$D(G_\phi) := \frac{1}{2}\mathbb{E}_{x\sim P_{G_\phi}, x_0\sim P_{\mathcal{D}}}\left[\mathbb{1}(f_\phi(x) = 1) + \mathbb{1}(f_\phi(x_0) = -1)\right]. \tag{1}$$

Here $P_{\mathcal{D}}$ is the authentic data distribution, and P_{G_ϕ} the model distribution. The *attributability* measures the averaged multi-class classification accuracy of each model distribution over the collection $\mathcal{G} := \{G_1, ..., G_N\}$:

$$A(\mathcal{G}) := \frac{1}{N}\sum_{i=1}^{N}\mathbb{E}_{x\sim G_{\phi_i}}\mathbb{1}(\phi_j^T x < 0, \forall\, j \neq i, \phi_i^T x > 0). \tag{2}$$

Distinguishability of G (attributability of $\mathcal{G}$) is achieved when $D(G) \geq 1 - \delta$ ($A(\mathcal{G}) \geq 1 - \delta$) for small $\delta > 0$. Lastly, We denote by $G(\cdot;\theta_0)$ (or shortened as G_0) the root model trained on $\mathcal{D}$, and assume $P_{G_0} = P_{\mathcal{D}}$. We will measure the (lack of) *generation quality* of G_ϕ by the FID score (Heusel et al., 2017) and the l_2 norm of the mean output perturbation:

$$\Delta x(\phi) = \mathbb{E}_{z\sim P_z}[G_\phi(z;\theta) - G(z;\theta_0)], \tag{3}$$

where P_z is the latent distribution.

This paper investigates the following question: *What are the sufficient conditions of keys so that the resultant generative models can achieve distinguishability individually and attributability collectively, while maintaining their generation quality?*

Contributions We claim the following contributions:

1. We develop sufficient conditions of keys for distinguishability and attributability, which connect these metrics with the geometry of the data distribution, the angles between keys, and the generation quality.
2. The sufficient conditions lead to simple design rules for the keys: keys should be data compliant, i.e., $\phi^T x < 0$ for $x \sim P_{\mathcal{D}}$, and orthogonal to each other. We validate these rules using DCGAN (Radford et al., 2015) and StyleGAN (Karras et al., 2019a) on benchmark datasets including MNIST (LeCun & Cortes, 2010), CelebA (Liu et al., 2015), and FFHQ (Karras et al., 2019a). See Fig. 1 for a visualization of the attributable distributions perturbed from the authentic FFHQ dataset.
3. We empirically test the tradeoff between generation quality and robust attributability under random post-processes including image blurring, cropping, noising, JPEG conversion, and a combination of all.

2 Sufficient Conditions for Attributability

From the definitions (Eq. (1) and Eq. (2)), achieving distinguishability is necessary for attributability. In the following, we first develop the sufficient conditions for distinguishability through Proposition 1 and Theorem 1, and then those for attributability through Theorem 2.

Distinguishability through watermarking First, consider constructing a user-end model G_ϕ by simply adding a perturbation Δx to the outputs of the root model G_0. Assuming that ϕ is data-compliant, this model can achieve distinguishability by solving the following problem with respect to Δx:

$$\min_{||\Delta x|| \leq \varepsilon} \quad \mathbb{E}_{x \sim P_{\mathcal{D}}} \left[\max\{\phi^T (x + \Delta x), 0\} \right], \tag{4}$$

where $\varepsilon > 0$ represents a generation quality constraint. We have the following proposition that reveals the connection between distinguishability, data geometry, and generation quality (proof in Appendix A):

Proposition 1. *Let $d_{max}(\phi) := \max_{x \sim P_{\mathcal{D}}} |\phi^T x|$. If $\varepsilon \geq d_{max}(\phi)$, then $\Delta x^* = d_{max}(\phi)\phi$ solves Eq. (4), and $f_\phi(x + \Delta x^*) > 0, \ \forall\, x \sim P_{\mathcal{D}}$.*

Watermarking through retraining user-end models The perturbation Δx^* can potentially be reverse engineered and removed when generative models are white-box to users (e.g., when models are downloaded by users). Therefore, we propose to instead retrain the user-end models G_ϕ using the perturbed dataset $\mathcal{D}_{\gamma,\phi} := \{G_0(z) + \gamma\phi \mid z \sim P_z\}$ with $\gamma > 0$, so that the perturbation is realized through the model architecture and weights. Specifically, the retraining fine-tunes G_0 so that $G_\phi(z)$ matches with $G_0(z) + \gamma\phi$ for $z \sim P_z$. Since this matching will not be perfect, we use the following model to characterize the resultant G_ϕ:

$$G_\phi(z) = G_0(z) + \gamma\phi + \epsilon, \tag{5}$$

where the error $\epsilon \sim \mathcal{N}(\mu, \Sigma)$. In Sec. 3 we provide statistics of μ and Σ on the benchmark datasets, to show that the retraining captures the perturbations well (i.e., μ close to 0 and small variances in Σ).

Proposition 1 no longer applies due to the existence of error. As a result, we show in Theorem 1 that γ needs to be no smaller than $d_{\max}(\phi)$ in order for G_ϕ to achieve distinguishability (proof in Appendix B):

Theorem 1. *Let $d_{max}(\phi) = \max_{x \in \mathcal{D}} |\phi^T x|$, $\sigma^2(\phi) = \phi^T \Sigma \phi$, $\delta \in [0, 1]$, and ϕ be a data-compliant key. $D(G_\phi) \geq 1 - \delta/2$ if*

$$\gamma \geq \sigma(\phi) \sqrt{\log\left(\frac{1}{\delta^2}\right)} + d_{max}(\phi) - \phi^T \mu. \tag{6}$$

Remarks The computation of $\sigma(\phi)$ requires G_ϕ, which in turn requires γ. Therefore, an iterative search will be needed to determine γ that is small enough to limit the loss of generation quality, yet large enough for distinguishability (see Alg. 1).

Attributability We can now derive the sufficient conditions for attributability of the generative models from a set of N keys (proof in Appendix C):

Theorem 2. *Let $d_{min} = \min_{x \in \mathcal{D}} |\phi^T x|$, $d_{max} = \max_{x \in \mathcal{D}} |\phi^T x|$, $\sigma^2(\phi) = \phi^T \Sigma \phi$, $\delta \in [0, 1]$. Let*

$$a(\phi, \phi') := -1 + \frac{d_{max}(\phi') + d_{min}(\phi') - 2\phi'^T \mu}{\sigma(\phi') \sqrt{\log\left(\frac{1}{\delta^2}\right)} + d_{max}(\phi') - \phi'^T \mu}, \tag{7}$$

for keys ϕ and ϕ'. Then $A(\mathcal{G}) \geq 1 - N\delta$, if $D(G) \geq 1 - \delta$ for all $G_\phi \in \mathcal{G}$, and

$$\phi^T \phi' \leq a(\phi, \phi') \tag{8}$$

for any pair of data-compliant keys ϕ and ϕ'.

Remarks When $\sigma(\phi')$ is negligible for all ϕ' and $\mu = 0$, $a(\phi, \phi')$ is approximately $d_{\min}(\phi')/d_{\max}(\phi') > 0$, in which case $\phi^T \phi' \leq 0$ is sufficient for attributability. In Sec. 3 we empirically show that this approximation is plausible for the benchmark datasets.

3 Experiments and Analysis

In this section we test Theorem 1, provide empirical support for the orthogonality of keys, and present experimental results on model attribution using MNIST, CelebA, and FFHQ. Note that tests on the theorems require estimation of Σ, which is costly for models with high-dimensional outputs, and therefore are only performed on MNNIST and CelebA.

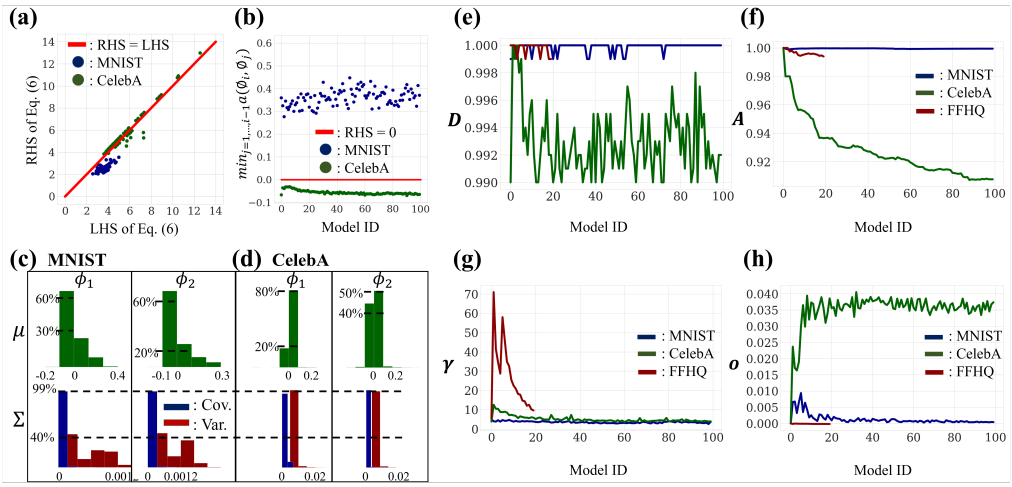


Figure 2: (a) Validation of Theorem 1: All points should be close to the diagonal line or to its right. (b) Support for orthogonal keys: Min. RHS value of Eq.(7) for all keys are either positive (MNIST) or close to zero (CelebA). (c,d) Statistics of μ and Σ for two sample user-end models for MNIST and CelebA. Small μ and small $diag(\Sigma)$ suggest good match of G_ϕ to the perturbed data distributions. (e-h) Distinguishability, attributability, perturbation length, and orthogonality of 100 user-end models, respectively.

Key generation We generate keys by iteratively solving the following convex problem:

$$\phi_i = \arg\min_{\phi} \; \mathbb{E}_{x\sim P_D, G_0}\left[\max\{1+\phi^T x, 0\}\right] + \sum_{j=1}^{i-1} \max\{\phi_j^T \phi, 0\}. \tag{9}$$

The orthogonality penalty is omitted for the first key. The solutions are normalized to unit l_2 norm before being inserted into the next problem. We note that $P_{\mathcal{D}}$ and P_{G_0} do not perfectly match in practice, and therefore we draw with equal chance from both distributions during the computation. G_0s are trained using the standard DCGAN architecture for MNIST and CelebA, and StyleGAN for FFHQ. Training details are deferred to Appendix D.

User-end generative models The training of G_ϕ follows Alg. 1, where γ is iteratively tuned to balance generation quality and distinguishability. For each γ, we collect a perturbed dataset $\mathcal{D}_{\gamma,\phi}$ and solve the following training problem:

$$\min_{\theta} \mathbb{E}_{(z,x)\sim\mathcal{D}_{\gamma,\phi}}\left[||G_\phi(z;\theta) - x||^2\right], \tag{10}$$

starting from $\theta = \theta_0$. If the resultant model does not meet the distinguishability requirement due to the discrepancy between $\mathcal{D}_{\gamma,\phi}$ and G_ϕ, the perturbation is updated as $\gamma = \alpha\gamma$. In experiments, we use a standard normal distribution for P_z, and set $\delta = 10^{-2}$, and $\alpha = 1.1$.

Validation of Theorem 1 Here we validate the sufficient condition for distinguishability. Fig. 2a compares the LHS and RHS values of Eq. (6) for 100 distinguishable user-end models. The empirical distinguishability of these models are reported in Fig. 2e. Calculation of the RHS of Eq. (6) requires an estimation of μ and Σ. To do this, we sample

$$\epsilon(z) = G_\phi(z;\theta) - G(z;\theta_0) - \gamma\phi \tag{11}$$

using 5000 samples of $z \sim P_z$, where G_ϕ and γ are derived from Alg. 1. Σ and μ are then estimated for each ϕ. Fig. 2c shows the statistics of μ and Σ for sampled user-end models for the benchmark datasets. Results in Fig. 2 show that the sufficient condition for distinguishability (Eq. (6)) is satisfied for most of the sampled models through the training specified in Alg. 1. Lastly, we notice that the LHS values for MNIST are farther away from the equality line than those for CelebA. This is because the MNIST data distribution resides at corners of the unit box. Therefore perturbations of

the distribution are more likely to exceed the bounds for pixel values. Clamping of these invalid pixel values reduces the effective perturbation length. Therefore to achieve distinguishability, Alg. 1 seeks γs larger than needed. This issue is less observed in CelebA, where data points are rarely close to the boundaries.

Algorithm 1: Training of G_ϕ

input : ϕ, G_0
output: G_ϕ, γ
1 set $\gamma = d_{\max}(\phi)$;
2 collect $\mathcal{D}_{\gamma,\phi}$;
3 train G_ϕ by solving Eq. (10) using $\mathcal{D}_{\gamma,\phi}$;
4 compute empirical $D(G_\phi)$;
5 **if** $D(G_\phi) < 1 - \delta$ **then**
6 set $\gamma = \alpha\gamma$;
7 goto step 2 ;
8 **end**

Validation of Theorem 2 Recall that from Theorem 2, we recognized that orthogonal keys are sufficient. To support this design rule, Fig. 2b presents the minimum RHS values of Eq. (8) for 100 user-end models. Specifically, for each ϕ_i, we compute $a(\phi_i, \phi_j)$ (Eq. (7)) using ϕ_j for $j = 1, ..., i-1$ and report $\min_j a(\phi_i, \phi_j)$, which sets a lower bound on the angle between ϕ_i and all existing ϕs. The resultant $\min_j a(\phi_i, \phi_j)$ are all positive for MNIST and close to zero for CelebA. It should be noted that in the case of CelebA, an angle of $\geq 94\,\text{deg}$, instead of $90\,\text{deg}$, should be enforced between any pairs of keys. However, since the conditions are sufficient, orthogonal keys still empirically achieve high attributability (Fig. 2f), although improvements can be made by further increasing the angle between keys. Also notice that Eq. (9) does not enforce a hard constraint on orthogonality, leading to slightly acute angles ($87.7\,\text{deg}$) between keys for CelebA (Fig. 2h). On the other hand, the positive values in Fig. 2b for MNIST suggests that further reducing the angles between keys is acceptable if one needs to increase the total capacity of attributable models. However, doing so would require the derivation of new keys to rely on knowledge about all existing user-end models (for computing Eq. (7)).

Table 1: Empirical average of distinguishability ($\bar{D}$),attributability ($A(\mathcal{G})$), $||\Delta x||$, and FID scores. DCGAN_M (DCGAN_C) for MNIST (CelebA). Std in parenthesis. FID_0: FID for G_0.

GANs	Angle	$\bar{D}$	$A(\mathcal{G})$	$\|\|\Delta x\|\|$	FID_0	FID
DCGAN_M	Orthogonal	0.99	**0.99**	3.97 (0.29)	7.82 (0.15)	10.43 (0.77)
	45 degree	0.99	0.13	3.85 (0.12)	-	11.02 (0.86)
DCGAN_C	Orthogonal	0.99	**0.93**	4.04 (0.32)	35.95 (0.12)	58.69 (5.21)
	45 degree	0.99	0.15	4.57 (0.35)	-	59.81 (5.34)
StyleGAN	Orthogonal	0.99	**0.99**	36.04 (23.35)	12.43(0.16)	35.23(14.67)
	45 degree	0.97	0.18	67.19 (35.53)	-	47.86(10.66)

Empirical results on benchmark datasets Tab. 1 reports the metrics of interest measured on the 100 user-end models for each of MNIST and CelebA, and 20 models for FFHQ. All models are trained to be distinguishable, and through Theorem 2, also achieve high attributability. As a comparison, we demonstrate results where keys are $45\,\text{deg}$ apart ($\phi^T\phi = 0.71$) using a separate set of 20 user-end models for each of MNIST and CelebA, and 5 models for FFHQ, in which case distinguishability no longer guarantees attributability. Regarding generation quality, G_ϕs receive worse FID scores than G_0 due to the perturbations. We visualize samples from user-end models and the corresponding keys in Fig. 3. Note that for human faces, FFHQ in particular, the perturbations create light shades around eyes and lips, which is an unexpected but reasonable result from Eq. (9).

Robust training We now consider the scenario where outputs of the generative models are post-processed (e.g., by adversaries) before being attributed. When the post-processes are known, we can take counter measures through robust training, which intuitively, will lead to additional loss of generation quality. To assess this tradeoff between robustness and generation quality, we train G_ϕ against post-processes $T : \mathbb{R}^{d_x} \to \mathbb{R}^{d_x}$ from a distribution P_T. Due to the potential nonlinearity of T and the lack of theoretical guarantee in this scenario, we resort to the following robust training problem:

$$\min_{\theta_i} \mathbb{E}_{z\sim P_z, T\in P_T}\left[\max\{1 - f_{\phi_i}(T(G_{\phi_i}(z;\theta_i))), 0\} + C||G_0(z) - G_{\phi_i}(z;\theta_i)||^2\right], \tag{12}$$

where C is the hyper-parameter for generation quality. Detailed analysis and comparison to select C are provided in Appendix E. We consider five types of post-processes: blurring, crop-

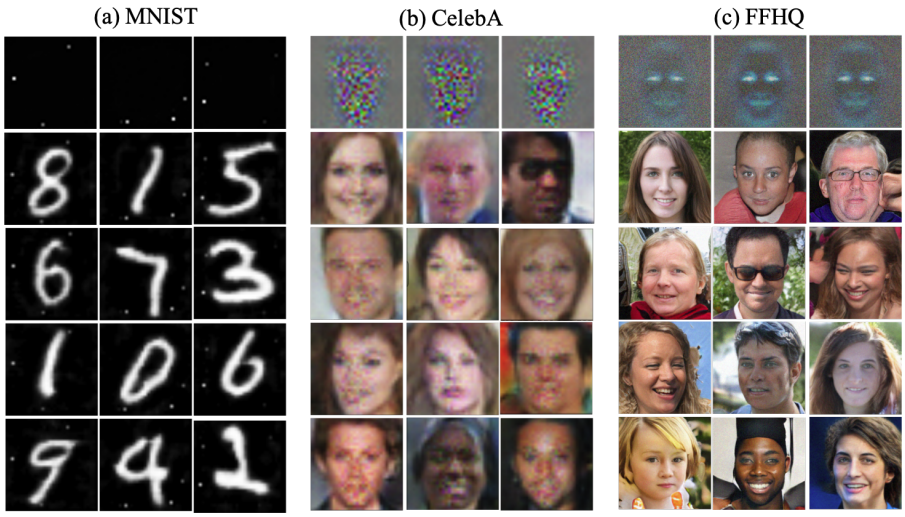


Figure 3: Visualization of sample keys (1st row) and the corresponding user-end generated contents.

ping, noise, JPEG conversion and the combination of these four. Examples of the post-processed images are shown in Fig. 4. `Blurring` uses Gaussian kernel widths uniformly drawn from $\frac{1}{3}\{1, 3, 5, 7, 9\}$. `Cropping` crops images with uniformly drawn ratios between 80% and 100%, and scales the cropped images back to the original size using bilinear interpolation. `Noise` adds white noise with standard deviation uniformly drawn from $[0, 0.3]$. `JPEG` applies JPEG compression. `Combination` performs each attack with a 50% chance in the order of `Blurring`, `Cropping`, `Noise` and `JPEG`. For differentiability, we use existing implementations of differentiable blurring (Riba et al. (2020)) and JPEG (Zhu et al. (2018)). For robust training, we apply the post-process to mini-batches with 50% probability.

We performed comprehensive tests using DCGAN (on MNIST and CelebA), PGAN (on CelebA), and CycleGAN (on Cityscapes). Tab. 2 summarizes the average distinguishability, the attributability, $||\Delta x||$, and the FID scores with and without robust training of G_ϕ. Results are based on 20 models for each architecture-dataset pair, where keys are kept orthogonal and data compliant. From the results, defense against these post-processes can be achieved, except for `Combination`. In addition, there is a clear tradeoff between robustness and generation quality. To support this, Fig. 4 compares samples with and without robust training from the tested models and datasets.

Lastly, it is worth noting that the training formulation in Eq. (12) can also be applied to the training of non-robust user-end models in place of Eq. (10). However, the resultant model from Eq. (12) cannot be characterized by Eq. (5) with small μ and Σ, i.e., due to the nonlinearity of the training process, the user-end model distribution is deformed while it is perturbed. This resulted in unsuccessful validation of the theorems, which led to the adoption of Eq. (10) for theorem-consistent training. Therefore, while the empirical tests here show feasibility of achieving robust attributability, counterparts to Theorem 1 and 2 in this context are yet to be developed.

4 Discussion

Generation Quality Control From Proposition 1 and Theorem 1, the inevitable loss of generation quality is directly related to the length of perturbation (γ), which is related to $d_{\max}$. Fig. 5 compares outputs from user-end models with different $d_{\max}$s. While it is possible to filter ϕs based on their corresponding $d_{\max}$s for generation quality control, here we discuss a potential direction for prescribing a subspace of ϕs within which quality can be controlled. To start, we denote by $J(x)$ the Jacobian of G_0 with respect to its generator parameters θ_0. Our discussion is related to the matrix $M = \mathbb{E}_{x\sim P_{G_0}}[J(x)]\mathbb{E}_{x\sim P_{G_0}}[J(x)^T]$. A spectral analysis of M reveals that the eigenvectors of M with large eigenvalues are more structured than those with small ones (Fig. 6(a)). This finding is consistent with the definition of M: The largest eigenvectors of M represent the principal axes

Table 2: DCGAN_M: MNIST. DCGAN_C: CelebA. Dis.: Distinguishability before (Bfr) and after (Aft) robust training. Att.: Attributability. $||\Delta x||$ and FID are after robust training. Std in parenthesis. Higher is better for Dis. and Att. Lower is better for $||\Delta x||$ and FID. $||\Delta x||$ and FID before robust training: DCGAN_M:$||\Delta x|| = 5.05$, FID $= 5.36$. DCGAN_C:$||\Delta x|| = 5.63$, FID $= 53.91$. PGAN: $||\Delta x|| = 9.29$, FID $= 21.62$. CycleGAN: $||\Delta x|| = 55.85$. FID does not apply to CycleGAN.

Metric	Model	Blurring		Cropping		Noise		JPEG		Combi.	
-	-	Bfr	Aft	Bfr	Aft	Bfr	Aft	Bfr	Aft	Bfr	Aft
Dis.	DCGAN_M	0.49	0.96	0.52	0.99	0.85	0.99	0.54	0.99	0.50	0.66
	DCGAN_C	0.49	0.99	0.49	0.99	0.95	0.98	0.51	0.99	0.50	0.85
	PGAN	0.50	0.98	0.51	0.99	0.97	0.99	0.96	0.99	0.50	0.76
	CycleGAN	0.49	0.92	0.49	0.87	0.98	0.99	0.55	0.99	0.49	0.67
Att.	DCGAN_M	0.02	0.94	0.03	0.88	0.77	0.95	0.16	0.98	0.00	0.26
	DCGAN_C	0.00	0.98	0.00	0.99	0.89	0.93	0.07	0.98	0.00	0.70
	PGAN	0.13	0.99	0.07	0.99	0.97	0.99	0.99	0.99	0.06	0.98
	CycleGAN	0.08	0.98	0.05	0.93	0.97	0.98	0.47	0.99	0.05	0.73
$\|\|\Delta x\|\|$	DCGAN_M	15.96(2.18)		9.17(0.65)		5.93(0.34)		6.48(0.94)		17.08(1.86)	
	DCGAN_C	11.83(0.65)		9.30(0.31)		4.75(0.17)		6.01(0.29)		13.69(0.59)	
	PGAN	18.49(2.04)		21.27(0.81)		10.20(0.81)		10.08(1.03)		24.82(2.33)	
	CycleGAN	68.03(3.62)		80.03(3.59)		55.47(1.60)		57.42(2.00)		83.94(4.66)	
FID	DCGAN_M	41.11(20.43)		21.58(2.44)		5.79(0.19)		6.50(1.70)		68.16(24.67)	
	DCGAN_C	73.62(6.70)		98.86(9.51)		59.51(1.60)		60.35(2.57)		87.29(9.29)	
	PGAN	28.15(3.43)		47.94(5.71)		25.43(2.19)		22.86(2.06)		45.16(7.87)	

of all mean sensitivity vectors, where the mean is taken over the latent space. For MNIST, these eigenvectors overlap with the digits; for CelebA, they are structured color patterns. On the other hand, the smallest eigenvectors represent directions rarely covered by the sensitivity vectors, thus resembling random noise. Based on this finding, we test the hypothesis that keys more aligned with the eigenspace of the small eigenvalues will have smaller $d_{\max}$. We test this hypothesis by computing the Pearson correlations between $d_{\max}$ and $\phi^T M \phi$ using 100 models for each of MNIST and CelebA. The resultant correlations are 0.33 and 0.53, respectively. In addition, we compare outputs from models using the largest and the smallest eigenvectors of M as the keys in Fig. 6. While a concrete human study is needed, the visual results suggest that using eigenvectors of M is a promising approach to segmenting the space of keys according to their induced generation quality.

Capacity of keys For real-world applications, we hope to maintain attributability for a large set of keys. Our study so far suggests that the capacity of keys is constrained by the data compliance and orthogonality requirements. While the empirical study showed the feasibility of computing keys through Eq. (9), finding the maximum number of feasible keys is a problem about optimal sphere packing on a segment of the unit sphere (Fig. 7). To explain, the unit sphere represents the identifiability requirement $||\phi|| = 1$. The feasible segment of the unit sphere is determined by the data compliance and generation quality constraints. And the spheres to be packed have radii following the sufficient condition in Theorem 2. Such optimal packing problems are known open challenges (Cohn et al. (2017); Cohn (2016)). For real-world applications where a capacity of attributable models is needed (which is the case for both malicious personation and copyright infringement settings), it is necessary to find approximated solutions to the optimal packing problem.

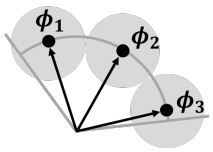
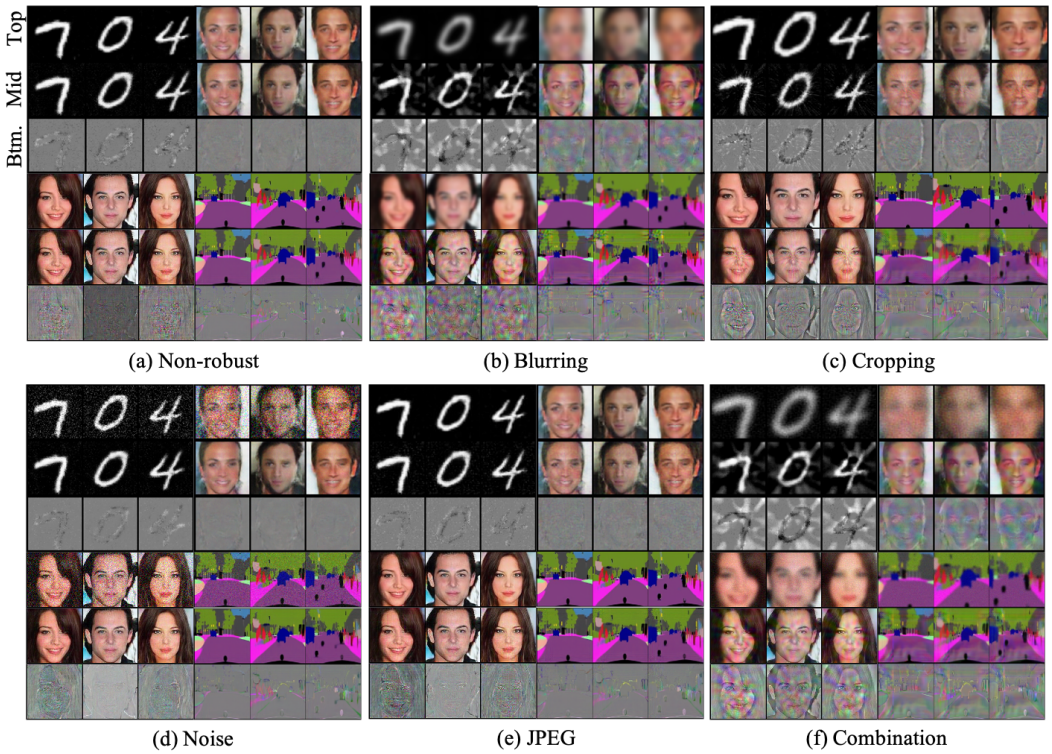


Figure 7: Capacity of keys as a sphere packing problem: The feasible space (arc) is determined by the data compliance and generation quality constraints, and the size of spheres by the minimal angle between keys.



(a) Non-robust (b) Blurring (c) Cropping

(d) Noise (e) JPEG (f) Combination

Figure 4: Samples from user-end models with robust and non-robust training. For each subfigure - top: DCGAN on MNIST and CelebA; bottom: PGAN (CelebA) and CycleGAN (Cityscapes). For each dataset - top: samples from G_0 (after worst-case post-process in (b-f)); mid: samples from G_ϕ (after robust training in (b-f)); btm (a): difference between non-robust G_ϕ and G_0; btm (b-h) difference between robust and non-robust G_ϕ.

(a) d_{max}= 1.66 (b) d_{max}= 2.92 (c) d_{max}= 9.43 (d) d_{max}= 3.16 (e) d_{max}= 12.59 (f) d_{max}= 77.09

Figure 5: MNIST, CelebA, and FFHQ examples from G_ϕs with (a-c) small d_{max} and (d-f) large d_{max}. All models are distinguishable and attributable.

5 Related Work

Detection and attribution of model-generated contents This paper focused on the attribution of contents from generative models rather than the detection of hand-crafted manipulations (Agarwal & Farid (2017); Popescu & Farid (2005); O'brien & Farid (2012); Rao & Ni (2016); Huh et al. (2018)). Detection methods rely on fingerprints intrinsic to generative models Odena et al. (2016); Zhang et al. (2019b); Marra et al. (2019); Wang et al. (2019), yet similar fingerprints present for models trained on similar datasets Marra et al. (2019). Thus fingerprints cannot be used for attribution. Skripniuk et al. (2020) studied decentralized attribution. Instead of using linear classifiers for attribution, they train a watermark encoder-decoder network that embeds (and reads) watermarks into (and from) the content, and compare the decoded watermark with user-specific ones. Their method does not provide sufficient conditions of the watermarks for attributability.

Figure 6: (a) Eigenvectors for the two largest and two smallest eigenvalues of M for DCGANs on MNIST (top) and CelebA (bottom). (b) Left one: Samples from G_0; Rest: $G_0 - G_\phi$ where ϕ are the eigenvectors in (a).

IP protection of digital contents and models Watermarks have conventionally been used for IP protection (Tirkel et al., 1993; Van Schyndel et al., 1994; Bi et al., 2007; Hsieh et al., 2001; Pereira & Pun, 2000; Zhu et al., 2018; Zhang et al., 2019a) without considering the attribution guarantee. Another approach to content IP protection is blockchain (Hasan & Salah, 2019). However, this approach requires meta data to be transferred along with the contents, which may not be realistic in adversarial settings. E.g., one can simply take a picture of a synthetic image to remove any meta data attached to the image file. Aside from the protection of *contents*, mechanisms for protecting IP of *models* have also been studied (Uchida et al., 2017; Nagai et al., 2018; Le Merrer et al., 2019; Adi et al., 2018; Zhang et al., 2018; Fan et al., 2019; Szyller et al., 2019; Zhang et al., 2020). Model watermarking is usually done by adding watermarks into model weights (Uchida et al., 2017; Nagai et al., 2018), by embedding unique input-output mapping into the model (Le Merrer et al., 2019; Adi et al., 2018; Zhang et al., 2018), or by introducing a passport mechanism so that model accuracy drops if the right passport is not inserted (Fan et al., 2019). While closely related, existing work on model IP protection focused on the distinguishability of individual models, rather than the attributability of a model set.

Adversarial attacks Lastly, while the robust training process against post-processes is related to the adversarial attack setting (edy et al., 2014; Goodfellow et al., 2015; Madry et al., 2017), this study defines the robustness as the mean attribution accuracy under a distribution of post-processes rather than the worst accuracy.

6 Conclusion

Motivated by emerging challenges with generative models, e.g., deepfake, this paper investigated the feasibility of decentralized attribution of such models. The study is based on a protocol where the registry generates user-specific keys that guides the watermarking of user-end models to be distinguishable from the authentic data. The outputs of user-end models will then be attributed by the registry through the binary classifiers parameterized by the keys. We developed sufficient conditions of the keys so that distinguishable user-end models achieve guaranteed attributability. These conditions led to simple rules for designing the keys. With concerns about adversarial post-processes, we further showed that robust attribution can be achieved using the same design rules, and with additional loss of generation quality. Lastly, we introduced two open challenges towards real-world applications of the proposed attribution scheme: the prescription of the key space with controlled generation quality, and the approximation of the capacity of keys.

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