

Feature Unlearning for Generative Models via Implicit Feedback

Saemi Moon¹

saemi@postech.ac.kr

Seunghyuk Cho²

seunghyuk.cho@lgresearch.ai

Dongwoo Kim^{1,3}

dongwookim@postech.ac.kr

¹CSE, POSTECH

²LG AI Research

³GSAI, POSTECH

Abstract

We tackle the problem of feature unlearning from a pre-trained image generative model. Unlike a common unlearning task where an unlearning target is a subset of the training set, we aim to unlearn a specific feature, such as hairstyle from facial images, from the pretrained generative models. As the target feature is only presented in a local region of an image, unlearning the entire image from the pretrained model may result in losing other details in the remaining region of the image. To specify which features to unlearn, we develop an implicit feedback mechanism where a user can select images containing the target feature. From the implicit feedback, we identify a latent representation corresponding to the target feature and then use the representation to unlearn the generative model. Our framework is generalizable for the two well-known families of generative models: GANs and VAEs. Through experiments on MNIST and CelebA datasets, we show that target features are successfully removed while keeping the fidelity of the original models.

1. Introduction

Recent advancements in deep generative models have led to the generation of highly realistic images. However, this progress has also raised concerns about the potential misuse of such models. In some instances, generated images may contain violent or explicit content, or they may inadvertently leak private information used to train the model. To address these issues, a well-prepared dataset with appropriate cleansing procedures can mitigate the potential for abuse of generative models. For example, the development of DALL-E 2 involved careful curation of the training data to avoid explicit content, as described by [29].

In addition to data preparation and cleansing, machine unlearning may serve as a complementary tool for preventing the problem in the development and deployment of a generative model. Machine unlearning aims to erase the target data from a pretrained machine-learning model, which can be required to remove private information, harmful content,

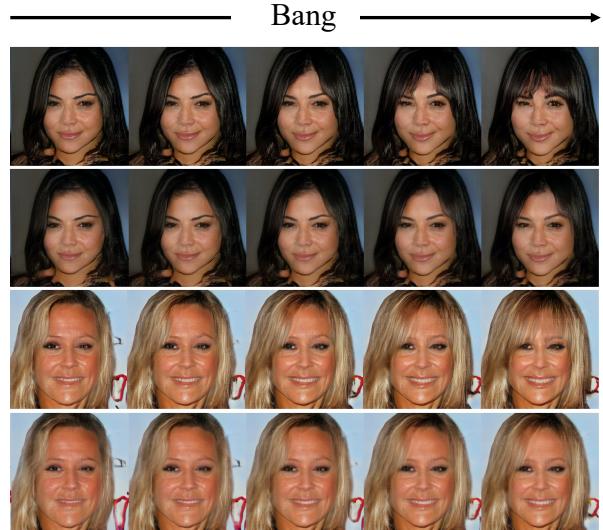


Figure 1: Result of unlearning ‘Bang’ feature from pre-trained GAN models. 1st/3rd row: generated images before unlearning. 2nd/4th row: images after unlearning. We traverse the same latent space to generate images before and after unlearning. Our method effectively unlearns the target feature while maintaining high image quality.

or biased information [2]. However, most of the machine unlearning problems have been focused on supervised models so far [11, 34, 1, 6, 40, 5, 8, 25].

In this work, we tackle the problem of feature unlearning from pretrained image generative models, where we aim to fine-tune the model to exclude the production of samples that exhibit target features. The target feature can be very subtle. For example, a specific hairstyle of a facial image could be the target feature we want to remove from the model, as shown in Figure 1. The subtlety in the target feature makes the generative model unlearning differ from a traditional supervised model unlearning.

In many unlearning scenarios with supervised models,

the target of unlearning is a subset of a training dataset, leading to the oracle model that could have been obtained from training without the target subset. Unlike supervised model unlearning, it is non-trivial to define the target in a feature unlearning since the target feature is only presented in a local region of an image. If we naively remove the entire image that contains the target feature, we could lose the other information in the remaining region of the image. Eventually, subset removal results in a loss of high fidelity and diversity in the generated samples. On the other hand, explicit pixel-level supervision could be given to unlearn the target feature, but it is often very expensive to obtain such supervision. Furthermore, the problem becomes more challenging if the training dataset is inaccessible during unlearning for several reasons, e.g., storage capacity, private content protection, etc.

To overcome such challenges, we propose a novel generative model unlearning framework based on implicit user feedback. Under the assumption that the training dataset is inaccessible, we assume that the users can give feedback on whether a generated image contains the target feature. Based on the collection of feedback, we find the latent representation of the target features and use the representation to unlearn the generative model. Our proposed framework is generalizable to both well-known classes of generative models, generative adversarial network (GAN) and variational auto-encoder (VAE). To our knowledge, this is the first framework for unlearning target features in the pretrained generative models.

We summarize our contributions as follows:

- We introduce a feature unlearning problem for generative models.
- We propose a novel unlearning method for generative models in the image domain that is highly applicable to real-world situations.
- We evaluate our method with various GAN and VAE architectures on real-world datasets, including MNIST, CelebA, and demonstrate the effectiveness of unlearning while preserving high image quality.

2. Related Work

In this section, we review previous work in machine unlearning and latent space analysis.

2.1. Machine Unlearning

Previous studies have demonstrated that machine learning models may leak sensitive information through attacks or specific inputs [41, 2]. In addition, regulations are emerged to protect private information, such as ‘the right to be forgotten’, which grants users the request that their personal

information must be removed from a system [30]. These highlight the growing significance of machine unlearning.

Unlearning scenarios can vary depending on the requirements [26]. Traditional machine unlearning approaches assume that all training data can be accessed [11, 34, 1, 6]. However, recent studies have presented problem formulations in which access to the data is highly restricted [40, 5, 8, 25]. In the context of feature unlearning, Guo et al. [10] proposes a representation detachment approach to unlearn the specific attribute for the image classification task. However, the above researches focus on supervised learning tasks whereas we focus on unsupervised generative models.

Recently, Kong and Chaudhuri [21] proposed a data redaction method from pretrained GAN. They use a data augmentation-based algorithm to prevent making undesirable samples. This method can only be applied when the entire dataset is available. Besides that, we first propose the generative model feature unlearning framework when access to entire data is infeasible.

2.2. Latent Space Analysis

It is known that generative models, such as GANs [9, 28, 18] and VAEs [19, 4], well preserve the representation of data within a low-dimensional space, referred to the latent space. In recent years, various techniques for traversing the latent space or extracting a visual feature vector have been proposed.

Larsen et al. [22] propose a simple method to extract the visual feature vector by subtracting the mean vector of images without the feature from the mean vector of images with the feature to decouple the correlated feature. Several supervised approaches have been proposed for training machine learning models with latent code and feature labels [7, 35, 33]. Unsupervised methods for finding interpretable axes in the generator have also been proposed [12, 37, 36, 32, 38].

In our proposed framework, obtaining the target vector representing the target feature in the latent space is a crucial step. We introduce a straightforward and user-friendly approach that can be applied to both GANs and VAEs, which can be applied to real-world scenarios easily. Additionally, we leverage the target vector to the target identification method within latent space.

3. Feature Unlearning for Generative Models

In this section, we propose a framework for unlearning generative models such as GAN and VAE to make the unlearned model unable to generate the target feature.

3.1. Feature Unlearning and Implicit Feedback

Feature unlearning aim to remove a specific feature from a trained generative model. For example, after unlearning the

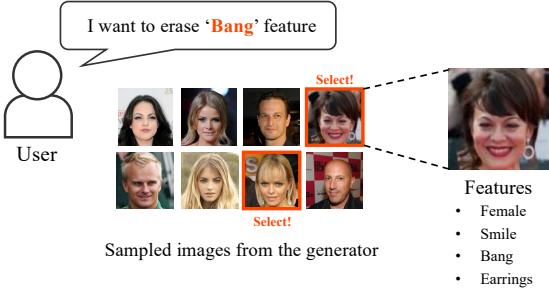


Figure 2: Illustration of implicit feedback interface. Since obtaining pixel-level supervision for unlearning a target feature is unrealistic, we propose an implicit feedback-based unlearning algorithm. A user selects images that contain the target feature to be unlearned. The selected and non-selected images serve as positive and negative examples. Note that the selected images can have features other than the target feature.

smile feature from a generative model trained on the CelebA dataset, the model would never generate images of a smiling person. However, selecting a target feature directly can be difficult due to the complexity of images, which consist of multiple features such as hairstyle, makeup, and accessories. Moreover, unlearning the entire subset of images containing the target feature may lead to losing other details from the generative model. Explicit pixel-level supervision can be used to identify the part of an image to be unlearned, but the cost of pixel-level supervision is expensive to scale.

To address this issue, we propose an implicit feedback mechanism to identify the target feature by users. We allow users to select images that contain the target feature. Based on the feedback, we construct a dataset with positive and negative examples. We illustrate an example interface system of implicit feedback in Figure 2. The positive and negative examples are then used to unlearn the model. Note that the positive examples can have features other than the target feature, hence the implicit feedback.

We further assume that the training dataset is inaccessible after training the model. Due to limited storage or privacy concern, it might be impossible to store the dataset. Feature unlearning becomes more challenging when the dataset is inaccessible since the implicit feedback can only rely on the generated samples. Therefore, the unlearning should be done while keeping the fidelity and diversity of the trained model.

3.2. Unlearning Framework

Feature unlearning can be solved by learning a transformation from the image containing the target feature to the image without the target feature. To learn such transformation, we need a paired dataset with and without target

features. For example, if the target image represents a man smiling and wearing a hat, and the target feature is the smile, we need the non-target image that depicts the same man with the hat but without the smile. However, such a dataset is impossible to collect in a real-world scenario.

Since our goal is to unlearn the pretrained generator and not to learn the transformation, we need to apply the transformation principle to the sampling process of the generator. Transformation in image space can be modeled by a transformation in the latent space. Based on this intuition, we propose a general unlearning framework from the latent variable perspective as follows:

1. Obtain feedback from users via generated images.
2. Find a latent representation \mathbf{z}_e that represents the target feature in the latent space from implicit feedback.
3. Sample a latent vector \mathbf{z} from a simple distribution.
 - (a) If the latent vector does not contain the target feature, let the generator produce the same output without modification.
 - (b) If the latent vector contains the target feature, modify the latent vector such that the generator produces a transformed output without the target feature.
4. Repeat step 3 until the generator does not produce the target feature.

Target identification in latent space. As described earlier, the user selects multiple images that contain the feature to be erased. We assume that the target feature can be represented by a vector in the latent space. As the first step of unlearning, we obtain the latent vector representation of each image from the feedback¹. Once we obtain the latent vectors, we use a vector arithmetic method proposed by Radford et al. [28] to find the latent vector representing the target feature from the implicit feedback. Specifically, we compute the mean vectors from a collection of positive images and negative images and subtract the mean vectors of the negative images from that of the positive images. The resulting *target vector* \mathbf{z}_e is then used to represent the target feature in the latent space.

To determine whether a randomly generated image contains a target feature, we project its latent vector onto the target vector. White [39] shows that the projection can represent the similarity between the latent vector and the target feature. We then compare this value to a threshold to determine whether the image contains the target feature. For the experiments, we set the threshold value t as the average projection values of the positive and negative samples in the

¹There is no need for GAN inversion since all images are generated.

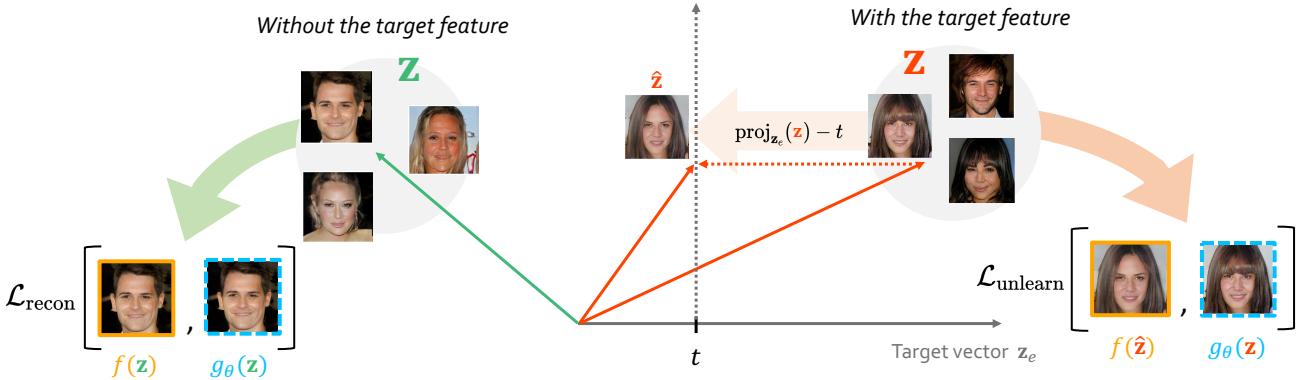


Figure 3: Overall illustration of the generative model unlearning framework. Based on whether the randomly sampled vector \mathbf{z} has the target feature, we use different loss functions to unlearn the target feature. t refers to a threshold, and $\hat{\mathbf{z}}$ is the translated vector, i.e., $\hat{\mathbf{z}} = \mathbf{z} - (\text{proj}_{\mathbf{z}_e}(\mathbf{z}) - t)\mathbf{z}_e$.

latent space. Let $\text{sim}(\mathbf{z}, \mathbf{z}_e) \in \{0, 1\}$ indicate the binary classification results, i.e.,

$$\text{sim}(\mathbf{z}, \mathbf{z}_e) = \begin{cases} 0, & \text{if } \text{proj}_{\mathbf{z}_e}(\mathbf{z}) < t, \\ 1, & \text{otherwise,} \end{cases} \quad (1)$$

where $\text{proj}_{\mathbf{z}_e}(\mathbf{z})$ is the projection of \mathbf{z} onto \mathbf{z}_e , i.e., $\frac{\mathbf{z}_e^\top \mathbf{z}}{\|\mathbf{z}_e\|}$.

Unlearning process. To formalize the unlearning process, let g_θ be the model to be unlearned, and f be the pretrained generator. We initialize g_θ from the pretrained f . When the randomly sampled latent vector \mathbf{z} does not contain the target feature, i.e., $\text{sim}(\mathbf{z}, \mathbf{z}_e) = 0$, the generator g_θ needs to produce the same output as f , c.f., step 3a. To enforce the minimal changes in the produced output, we formulate the following *reconstruction* objective to minimize

$$\mathcal{L}_{\text{recon}}(\theta) = (1 - \text{sim}(\mathbf{z}, \mathbf{z}_e)) \|g_\theta(\mathbf{z}) - f(\mathbf{z})\|_1, \quad (2)$$

where \mathbf{z} is the random vector. Hence, the unlearned model g_θ tries to mimic the original generator when the latent vector does not contain the target feature.

When the randomly sampled vector contains the target feature, the generation process needs to be changed such that the sampled output no longer contains the target feature. To do so, we first create the target-erased output by generating an output with a translated random vector using f . Given random vector \mathbf{z} , we first project the vector onto the target vector, and then the original random vector is shifted by the projected vector, i.e., $\mathbf{z} - (\|\text{proj}_{\mathbf{z}_e}(\mathbf{z})\| - t)\mathbf{z}_e$, where t is the predefined threshold. The translated vector is used as an input of the original generator f producing the target-erased output. The modified output is then used to train g with the

following *unlearning* objective

$$\begin{aligned} \mathcal{L}_{\text{unlearn}}(\theta) &= \text{sim}(\mathbf{z}, \mathbf{z}_e) \\ &\quad \|g_\theta(\mathbf{z}) - f(\mathbf{z} - (\text{proj}_{\mathbf{z}_e}(\mathbf{z}) - t)\mathbf{z}_e)\|_1. \end{aligned} \quad (3)$$

The objective enforces the unlearned generator producing outputs similar to those from the original generator without target features. If the projection can correctly measure the presence of the target feature in the latent space while disentangling the other features, g_θ can successfully forget the target feature in the latent space.

It is widely known that L2 and L1 loss occurs in blurry effects in image generation and restoration tasks [27, 42, 15, 43]. Prior research has addressed the blurry effects by introducing diverse techniques, such as adding perceptual or adversarial loss to the training process [16, 43]. To overcome the blurry effects, we add *perceptual* loss into the objective function. The objective is formalized as

$$\begin{aligned} \mathcal{L}_{\text{percep}}(\theta) &= \text{sim}(\mathbf{z}, \mathbf{z}_e) \\ &\quad (1 - \text{MS-SSIM}(g_\theta(\mathbf{z}), f(\mathbf{z} - (\text{proj}_{\mathbf{z}_e}(\mathbf{z}) - t)\mathbf{z}_e))), \end{aligned} \quad (4)$$

where MS-SSIM function refers to the Multi-Scale Structural Similarity [43], which measures perceptual similarity between two images by comparing luminance, contrast, and structural information.

Finally, we combine three objective functions to define the unlearning objective as

$$\mathcal{L}(\theta) = \alpha (\mathcal{L}_{\text{unlearn}}(\theta) + \mathcal{L}_{\text{percep}}(\theta)) + \mathcal{L}_{\text{recon}}(\theta), \quad (5)$$

where α is the hyper-parameter that regulates the unlearning and reconstruction error balance. We summarize the overall unlearning algorithm in Algorithm 1 and visualize the overall framework in Figure 3.

Algorithm 1 Feature Unlearning

Require: Pretrained generator f
Require: E : number of epochs, α : hyper-parameter
 Collect the positive and negative feedback from users
 Compute mean vector \mathbf{z}_p from the positive samples
 Compute mean vector \mathbf{z}_n from the negative samples
 Compute target vector $\mathbf{z}_e = \mathbf{z}_p - \mathbf{z}_n$
 Initialize $g_\theta = f$
for $i = 1$ **to** E **do**
 Sample \mathbf{z} from $N(0, 1)$ and compute $\text{sim}(\mathbf{z}, \mathbf{z}_e)$
 Compute $\nabla_\theta \mathcal{L}(\theta)$
 Update $\theta \leftarrow \theta - \nabla_\theta \mathcal{L}(\theta)$
end for
return Unlearned generator g_θ

We emphasize that the unlearning framework can be applied to widely-used generative models such as VAEs and GANs as long as we can properly obtain the target and projected features.

4. Experiments

In this section, we show the performance of the proposed framework for unlearning generative models.

4.1. Experimental Settings

Generative models and datasets. In this paper, we unlearn two types of generative models: GANs and VAEs, trained on two distinct datasets. Specifically, we utilize the MNIST dataset [23], a collection of handwritten digits, and the CelebA dataset [24], which is a large-scale face attribute dataset.

For the MNIST dataset, we unlearn a vanilla VAE [19] and a Deep Convolutional GAN (DCGAN)[28]. For the CelebA dataset, we unlearn a Very Deep VAE (VDVAE) [4] and a Progressive GAN (ProgGAN) [18]. Unlike the other models, VDVAE consists of multiple layers of latent spaces. We find the target vector by concatenating the vectors from all the layers and then apply the same rule to unlearn the model.

Target feature selection and implicit feedback construction. Instead of implementing the real-world interface for the implicit feedback, we simulate the cases by using the known features of each dataset. Specifically, we select two features from each dataset to unlearn.

For the MNIST dataset, we use the Morpho-MNIST [3], which provides a comprehensive tool for measuring various features of MNIST digits, to select images with target features. We chose the thickness and left slant as target features to unlearn. To construct implicit feedback with positive and negative examples, we first train a generative model with the

		Target image	Non-target image
MNIST	Thickness	6,000	54,000
	Slant	6,000	54,000
CelebA	Bang	30,709	171,890
	Beard	33,441	169,158

Table 1: Number of the target image and non-target image for each feature used in the experiments.

original dataset, and then, we randomly sample 500 images. We measure the thickness and left slant of each image via Morpho-MNIST. Since the thickness and left slant are not binary, we use images whose feature values range within the top 10% of the entire samples as positive examples and the remaining as negative examples.

The CelebA dataset provides 40 features for each image. Among the available features, we choose ‘Bang’ and ‘Beard’ as the target features to be unlearned. As presented in Table 1, approximately 10% of images have the corresponding features in the dataset. To construct implicit feedback, we randomly sample 5,000 images from a trained generative model and use a pretrained classifier to categorize each image into a positive and negative example. We train MobileNet[14] to classify the target feature.

Baseline model. There is no unlearning method targeted for generative models, according to our information. We compare our framework against a baseline model. To build the baseline model, we first collect images containing the target feature from the training set, and then the baseline model is trained without the collection. The baseline model is commonly used as a standard oracle model in supervised unlearning cases. However, as described in Section 3.1, the oracle from the supervised unlearning may not be an appropriate choice in generative unlearning. We provide some empirical evidence on the limitation of the baseline model in Section 4.4.

Implementation details. For all experiments, we use Adam optimizer and a learning rate of 0.001 for MNIST and 0.002 for CelebA. The MNIST dataset is trained for 200 epochs, and CelebA is trained for 500 epochs in unlearning process. The baseline model is initialized with the trained model. We further train the baseline model without the target features over 50 epochs and 96,000 iterations for MNIST and CelebA, respectively, to remove the target features as done in [25].

4.2. Evaluation Metric

The performance of unlearning can be measured from two different perspectives: 1) how well the unlearning is

Dataset	Model	Feature	Target feature ratio (\downarrow)			Inception Score (\uparrow)			Fréchet Inception Distance (\downarrow)		
			Original	Unlearn	Baseline	Original	Unlearn	Baseline	Original	Unlearn	Baseline
MNIST	VAE	Thickness	0.0947	0.0097	0.0101	2.207	2.156	2.139	23.358	23.742	24.029
		Slant	0.0922	0.0091	0.0108	2.189	2.216	2.221	22.842	23.265	23.515
	DCGAN	Thickness	0.0910	0.0135	0.0128	2.143	2.129	2.114	2.320	3.354	3.395
		Slant	0.1092	0.0125	0.0131	2.150	2.142	2.102	2.243	2.787	2.847
CelebA	VDVAE	Bang	0.0336	0.0028	0.0021	2.566	2.580	2.541	82.922	85.205	84.086
		Beard	0.0722	0.0241	0.0109	2.466	2.378	2.393	82.922	86.149	84.487
	ProgGAN	Bang	0.0674	0.0042	0.0049	2.922	2.914	2.907	48.054	49.824	51.371
		Beard	0.0302	0.0101	0.0098	2.925	2.879	2.866	48.047	49.800	49.783

Table 2: Target feature ratio, inception score, and Fréchet inception distance of original, unlearn, and baseline models.

done and 2) how good the sample qualities are. We explain two different metrics used to evaluate the models.

Target feature ratio. The target ratio measures the percentage of generated samples with the target feature. Low values of the target ratio indicate that the generative model has successfully unlearned the target feature. Pretrained classifiers for each feature are used to identify whether generated images contain the target feature. We use the same classifiers used to construct the implicit feedback dataset. For all experiments, we randomly sample 10,000 images from a generative model to compute the target ratio.

Image quality. We report two commonly used metrics to evaluate the quality of the generated image: Fréchet Inception Distance (FID) [13] and Inception Score (IS) [31]. We compute FID between the generated samples and the original training dataset. Lower FID scores and higher IS scores indicate higher image quality. We use an implementation of StudioGAN [17] to calculate IS and FID. 10,000 samples are used to measure the scores.

4.3. Results

We present the results of our framework in both quantitative and qualitative terms. Our results demonstrate the successful removal of the target feature from two generative models, VAEs and GANs.

Quantitative results. We evaluate the effectiveness of our unlearning framework by comparing the target feature ratio between the original model, the unlearned model, and the baseline model in Table 2. The results show that the unlearned model produces similar target feature ratios to the baseline for all features, indicating our framework successfully unlearns the target feature.

To further analyze the results of unlearning, we visualize five randomly selected images classified as having the target features in Figure 4 from CelebA. Although feature classifiers categorize the images into the target positive, it is difficult to recognize the target features by the naked eye



Figure 4: Randomly generated images classified as having target features: ‘Bang’ and ‘Beard’. Although feature classifiers categorize the images into the target positive, it is difficult to recognize the target features by the naked eye in some cases.

in some cases. As our evaluation metric relies on the performance of the feature classifier, the actual target feature ratio could be lower than the reported ones.

Ensuring high image quality is important in unlearning the target feature. Table 2 presents the results of the IS and FID scores for evaluating the quality of generated images, respectively. The results demonstrate that all three models produced similar IS and FID scores, indicating that our framework can successfully unlearn the target feature while maintaining high-quality image generation. Note that FID is calculated using the entire dataset, which yields a slightly higher FID value for the unlearned and baseline models, but there is no significant difference between the two models.

Qualitative results. Figure 5 presents the qualitative visualization result of our unlearning framework. The top row shows the images generated from the original generator, and the bottom row shows those generated from the unlearned generator. By visualizing generated images using the same latent vector, we observe that the target feature has been effectively erased in each case. In addition, we unlearn the ‘Bang’ feature from ProgGAN trained with CelebA-HQ dataset [18], whose resolution is higher than the other two datasets. The qualitative results in Figure 1 show the approach also works well with high-resolution images.

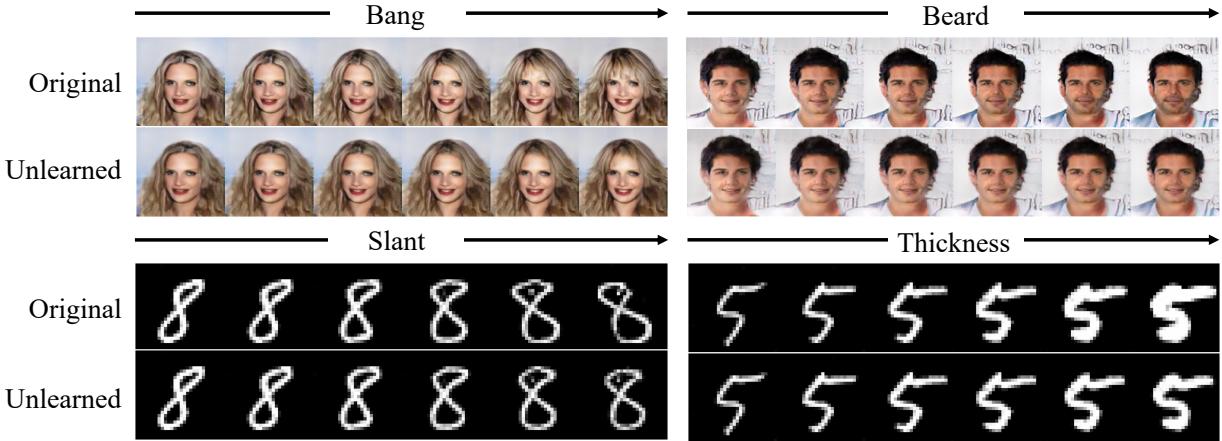


Figure 5: Visualization of four different features before and after unlearning from pretrained GAN models. All paired images in each column are generated from the same latent vector.

MNIST		
Models	Thickness	Slant
VAE	0.908	0.936
DCGAN	0.853	0.858
CelebA		
Models	Bang	Beard
VDVAE	0.840	0.834
ProgGAN	0.891	0.806

Table 3: ROC-AUC score of feature identification method.

4.4. Analysis

Target identification in latent space. The feature identification method proposed in Equation 1 raises a question about the quality of the result. We use the same classifier used to measure the target feature ratio to measure the quality of the feature identification method. Note that the pretrained classifiers are only used in the evaluation and not given during unlearning.

Table 3 shows the ROC-AUC score of the feature identification used in each experiment. The feature classification method achieved relatively high accuracy without an external classification model showing that the feature extracted from the latent space can be used for unlearning.

Ablation on the objective. We conduct an ablation study to evaluate the effectiveness of our proposed objective function. Specifically, we experiment with erasing Bang in a pretrained GAN trained with the CelebA dataset. Table 4 provides a detailed comparison of the performance under different combinations of objectives. Without the perception

$\mathcal{L}_{\text{recon}}$	$\mathcal{L}_{\text{unlearn}}$	$\mathcal{L}_{\text{percep}}$	Target ratio (\downarrow)	IS (\uparrow)	FID (\downarrow)
	✓		0.0008	2.886	52.476
✓	✓		0.0038	2.847	50.925
✓	✓	✓	0.0042	2.914	49.824
Baseline			0.0049	2.907	51.371
Original			0.0674	2.922	48.054

Table 4: Result of ablation study to unlearn the ‘Bang’ feature from a pretrained GAN.

loss, the model achieves a better unlearning performance in terms of target ratio, sacrificing the quality of images.

Diversity analysis and limitation. We analyze the diversity of generated samples before and after unlearning. To measure the diversity, we examine the changes in the proportion of features before and after unlearning with the CelebA dataset via the pretrained feature classifiers. Figure 6 shows the ratio of the five most changed features before and after unlearning with the baseline model for both ‘Bang’ and ‘Beard’. If we focus on the result of the ‘Bang’ feature in Figure 6a, there are no dramatic changes in the proportion of features between the original and the unlearned model. However, the changes with the baseline model are relatively larger than that of the unlearned model. Since the baseline model excludes all images that contain the target feature, the model inevitably loses the other features contained in the excluded images.

Unlike the ‘Bang’ case, unlearning ‘Beard’ alter the distribution more. As shown in Figure 6b, the model unlearns ‘Mustache’ and ‘Male’ features when the target feature is ‘Beard’. The reason for this result can be explained by the

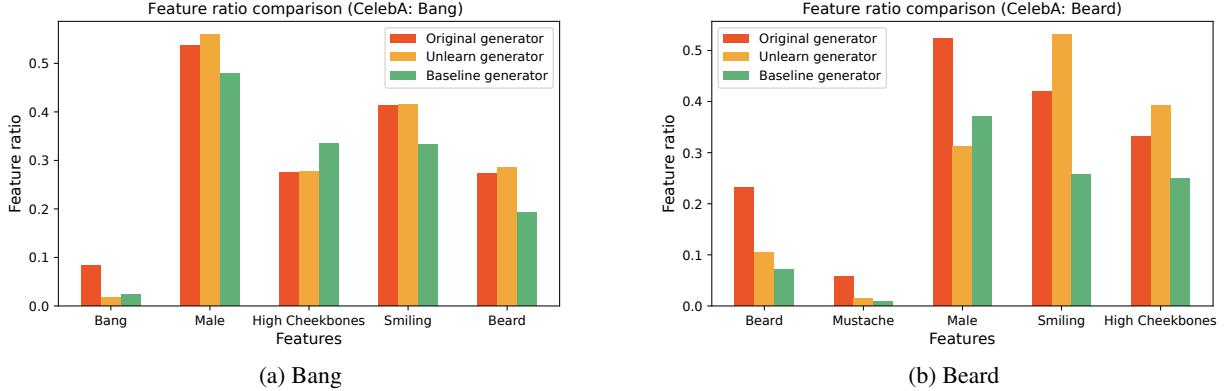


Figure 6: The feature ratio of sampled images with different generators on the CelebA dataset with GAN. We visualize five features whose proportion changed the most after unlearning. (a) Removing ‘Bang’ feature does not change the proportion of the other features compared to the baseline model. Note that the proportion of the baseline model changes relatively more than our framework since the baseline unlearns the entire subset of data containing the target feature. (b) Removing ‘Beard’ feature changes the proportion of the other features due to the correlation between different features. For example, the CelebA dataset does not have an instance of a woman with a beard. Hence, the proportion of male images is dramatically reduced after unlearning.

difficulty in obtaining an accurate target vector from the implicit feedback provided by the user. The implicit feedback mechanism cannot distinguish a spurious correlation between the target feature and other features. In the case of ‘Bang’, the dataset contains both men and women with bangs. However, since there are no women with beards in the dataset, the target vector becomes entangled with other features when identifying the target feature. The causal inference [20] may help to identify the spurious correlation, but we leave this for future work.

Choices of hyper-parameter. We analyze the results with varying hyper-parameter α on unlearning the ‘Bang’ feature from GAN. As shown in Table 5, the importance of the unlearning objective becomes more significant as α increases. Consequently, increasing α results in a decrease in the target ratio, which successfully erases the target feature from the generated images. However, we observe the trade off between the target feature ratio and the quality of the generated images. Therefore, careful selection of α is important to achieve the desired balance between effective unlearning and preserving image quality.

Computational efficiency. Training VAE and DCGAN on MNIST requires approximately 30 minutes on a single GPU. Training ProgGAN on CelebA takes around three days using eight GPUs, and VDVAE takes about two days using four GPUs. In contrast, our unlearning framework takes only approximately one minute to unlearn MNIST on a single GPU and approximately 30 minutes to unlearn CelebA using eight GPUs. Although we assume that relearning is impossible due to the inaccessibility of the training set, nevertheless, even if relearning were possible, our method

alpha	Target ratio (\downarrow)	IS (\uparrow)	FID (\downarrow)
$\alpha = 1$	0.0536	2.871	48.406
$\alpha = 2$	0.0108	2.891	49.090
$\alpha = 3$	0.0042	2.914	49.824
$\alpha = 4$	0.0021	2.891	49.925
$\alpha = 5$	0.0001	2.868	50.572

Table 5: Result of hyper-parameter analysis varying α

is significantly more time-efficient with comparable results. We use NVIDIA GeForce RTX 3090 for all experiments.

5. Conclusion

In conclusion, the recent success of generative models has brought exciting developments in various fields, such as computer vision, natural language processing, and art generation. However, the potential risks associated with the generation of harmful or private content through these models highlight the importance of developing effective unlearning algorithms. Our proposed unlearning algorithm for generative models shows promising results in preventing the generation of unwanted features, which can serve as a crucial tool in addressing sensitive or private content concerns. Future research can build upon this work to improve the efficiency and effectiveness of unlearning algorithms in other contexts, such as data privacy and fairness. Ultimately, the development of robust and reliable unlearning algorithms can maximize the benefits of generative models while minimizing the associated risks.

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