

RING-A-BELL! HOW RELIABLE ARE CONCEPT REMOVAL METHODS FOR DIFFUSION MODELS?

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ABSTRACT

Diffusion models for text-to-image (T2I) synthesis, such as Stable Diffusion (SD), have recently demonstrated exceptional capabilities for generating high-quality content. However, this progress has raised several concerns of potential misuse, particularly in creating copyrighted, prohibited, and restricted content, or NSFW (not safe for work) images. While efforts have been made to mitigate such problems, either by implementing a safety filter at the evaluation stage or by fine-tuning models to eliminate undesirable concepts or styles, the effectiveness of these safety measures in dealing with a wide range of prompts remains largely unexplored. In this work, we aim to investigate these safety mechanisms by proposing one novel concept retrieval algorithm for evaluation. We introduce Ring-A-Bell, a model-agnostic red-teaming tool for T2I diffusion models, where the whole evaluation can be prepared in advance without prior knowledge of the target model. Specifically, Ring-A-Bell first performs concept extraction to obtain holistic representations for sensitive and inappropriate concepts. Subsequently, by leveraging the extracted concept, Ring-A-Bell automatically identifies problematic prompts for diffusion models with the corresponding generation of inappropriate content, allowing the user to assess the reliability of deployed safety mechanisms. Finally, we empirically validate our method by testing online services such as Midjourney and various methods of concept removal. Our results show that Ring-A-Bell, by manipulating safe prompting benchmarks, can transform prompts that were originally regarded as safe to evade existing safety mechanisms, thus revealing the defects of the so-called safety mechanisms which could practically lead to the generation of harmful contents. In essence, Ring-A-Bell could serve as a red-teaming tool to understand the limitations of deployed safety mechanisms and to explore the risk under plausible attacks. Our codes are available at <https://github.com/chiayi-hsu/Ring-A-Bell>.

CAUTION: This paper includes model-generated content that may contain offensive or distressing material.

1 INTRODUCTION

Generative AI has made significant breakthroughs in domains such as text (OpenAI, 2023; Touvron et al., 2023), image (Ho et al., 2020), and code generation (Chowdhery et al., 2022). Among the

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areas receiving considerable attention within generative AI, text-to-image (T2I) generation stands out. The exceptional performance of today’s T2I diffusion models is largely due to the vast reservoir of training data available on the Internet. This wealth of data enables these models to generate a wide variety of content, ranging from photorealistic scenarios to simulated artwork, anime, and even artistic images. However, using such extensive Internet-derived training data presents both challenges and benefits. Particularly, certain images crawled from the Internet contains restricted content, and thus the trained model leads to memorization and generation of inappropriate images, including copyright violations, images with prohibited content, as well as NSFW material.

To achieve this goal, recent research has incorporated safety mechanisms into diffusion models to prevent models from generating inappropriate content. Examples of such mechanisms include stable diffusion with negative prompts (Rombach et al., 2022), Safe Latent Diffusion (SLD) (Schramowski et al., 2023), Erased Stable Diffusion (ESD) (Gandikota et al., 2023), and so on. These mechanisms are designed to either constrain the text embedding space during the inference phase, or to fine-tune the model and steer it to avoid producing copyrighted or inappropriate images. While these safety mechanisms have proven effective in their respective evaluations, one study (Rando et al., 2022) on red-teaming Stable Diffusion (e.g., actively searching for problematic prompts) highlights some potential shortcomings. Specifically, Rando et al. (2022) found that the state-of-the-art Stable Diffusion model, equipped with an NSFW safety filter, can still generate sexually explicit content if the prompt is filled with excessive wording that could evade the safety check. However, such a method requires manual selection of prompts, and is typically cumbersome and not scalable for building a holistic inspection of T2I models.

On the other hand, as recent T2I diffusion models have grown significantly in model size, reaching parameter counts up to billions (Ramesh et al., 2021; 2022; Saharia et al., 2022), fine-tuning these models becomes prohibitively expensive and infeasible when dealing with limited computational resources during red-teaming tool development. Consequently, in this study, we use prompt engineering (Brown et al., 2020; Li et al., 2020; Li & Liang, 2021; Jiang et al., 2020; Petroni et al., 2019; Lester et al., 2021; Schick & Schütze, 2021; Shin et al., 2020; Shi et al., 2022; Wen et al., 2023) as the basis for our technique to construct problematic prompts. One of the guaranteed benefits is that such a method could allow us to fine-tune prompt, which is order of magnitude less computationally expensive than fine-tuning the whole model, while also achieving comparable performance. On the other hand, the scenario is more realistic since the user could only manipulate the prompt input without further modifying the model.

In this work, we present Ring-A-Bell, a framework that aims to facilitate the red-teaming of T2I diffusion models with safety mechanisms to find problematic prompts with the ability to reveal sensitive concepts (e.g., generating images with prohibited concepts such as “nudity” and “violence”). This is achieved through the approach of prompt engineering techniques and the generation of our adversarial concept database. In particular, we first formulate a model-specific framework to demonstrate how to generate such an adversarial concept. Then, we proceed to construct a model-agnostic framework where knowledge of the model is not assumed. Finally, we introduce Ring-A-Bell to enable the automation of finding such problematic prompts. Ring-A-Bell simulates real attacks since red-teaming puts ourselves in the attacker’s shoes to identify the weaknesses that can be used against the original model. We emphasize that Ring-A-Bell uses only a text encoder (e.g., text encoder in CLIP model) and is executed offline, which is independent of any target T2I models and online services for evaluation. Furthermore, we reason that such success under black-box access of target model can be attributed to the novel design of concept extraction, so that it is able to uncover implicit text-concept associations, leading to efficient discovery of adversarial prompts that generate inappropriate images. On the other hand, such problematic prompts identified by Ring-A-Bell serve two purposes: they help in understanding model misbehavior, and they serve as crucial references for subsequent efforts to strengthen safety mechanisms. We summarize our contributions below.

- We propose Ring-A-Bell, which serves as a prompt-based concept testing framework that generates problematic prompts to red-team T2I diffusion models with safety mechanisms, leading to the generation of images with supposedly forbidden concepts.
- In Ring-A-Bell, concept extraction is based solely on either the CLIP model or general text encoders, allowing for model-independent prompt evaluation, resulting in efficient offline evaluation.
- Our extensive experiments evaluate a wide range of models, ranging from popular online services to state-of-the-art concept removal methods, and reveal that problematic prompts generated

by Ring-A-Bell can increase the success rate for most concept removal methods in generating inappropriate images by more than 30%.

2 RELATED WORK

We present a condensed version of the related work and refer the detailed ones in Appendix B.

Red-Teaming Evaluation Tools for AI. Red-teaming, a cybersecurity assessment technique, aims to actively search for vulnerabilities within information security systems. Originally focusing on cybersecurity, the concept of red-teaming has also been extended to machine learning, with focus on language models (Perez et al., 2022; Shi et al., 2023; Lee et al., 2023) and more recently, T2I models (Zhuang et al., 2023; Qu et al., 2023; Chin et al., 2023). We note that a concurrent work, P4D (Chin et al., 2023), also develops a red-teaming tool of text-to-image diffusion models, with the main weakness being the assumption of white-box access of target model. For more details, we leave the discussion and comparison to Section 3.2.

Diverse Approaches in Prompt Engineering. Prompt engineering seeks to improve the adaptability of pre-trained language models to various downstream tasks (Duan et al., 2023; Gal et al., 2023; He et al., 2022) by modifying input text with carefully crafted prompts. This approach, based on representation, can be classified into hard prompt (discrete) (Brown et al., 2020; Schick & Schütze, 2021; Jiang et al., 2020; Gao et al., 2021) and soft prompt (continuous) (Lester et al., 2021; Li & Liang, 2021) where the former represents discrete word patterns and the latter represents the continuous embedding vector. As both possess pros and cons, some efforts are made to unify the advantage of both settings (Shin et al., 2020; Shi et al., 2022; Wen et al., 2023).

Text-to-Image Diffusion Model with Safety Mechanisms. To address the misuse of T2I models for sensitive image generation, several approaches have been proposed to combat this phenomenon. Briefly, such methods fall into the following two directions: detection-based (Rando et al., 2022) and removal-based (Rombach et al., 2022; Schramowski et al., 2023; Gandikota et al., 2023; Kumari et al., 2023; Zhang et al., 2023). Detection-based methods aim to remove inappropriate content by filtering it through safety checkers while removal-based methods tries to steer the model away from those contents by actively guiding in inference phase or fine-tuning the model parameters.

3 MAIN APPROACH

We aim to evaluate the effectiveness of safety mechanisms for T2I diffusion models. First, we mathematically construct an attack when the target model is within our knowledge (i.e., model-specific evaluation) in Section 3.2. Then, based on our empirical findings, we construct a model-agnostic evaluation, Ring-A-Bell, by assuming only availability of a general text encoder in Section 3.3.

3.1 BACKGROUND

In this section, we provide a brief explanation of diffusion models and their latent counterparts, along with their mathematical formulations. These mathematical formulations illustrate how they work to generate data and support conditional generation.

Diffusion Model. Diffusion models (Sohl-Dickstein et al., 2015; Ho et al., 2020) are generative models designed to simulate the process of iteratively generating data by reducing noise from intermediate data states. This denoising process, is the inverse of the forward diffusion process, which progressively predicts and reduces noise from the data. Given an input image x_0 , Denoising Diffusion Probabilistic Models (DDPM) (Ho et al., 2020) generate an intermediate noisy image x_t at time step t through forward diffusion steps, i.e., iteratively adding noise. Mathematically, x_t is given by $x_t = \sqrt{\alpha_t}x_0 + \sqrt{1 - \alpha_t}\epsilon$ where α_t is the time-dependent hyperparameter and ϵ is the Gaussian noise, so that the last iterate after T steps simulates the standard Gaussian, $x_T \sim \mathcal{N}(0, I)$. Furthermore, the denoising network $\epsilon_\theta(\cdot)$ aims to predict the previous step iterate x_{t-1} and resorts to training with the loss $L = \mathbb{E}_{x,t,\epsilon \sim \mathcal{N}(0,I)} \|\epsilon - \epsilon_\theta(x_t, t)\|^2$.

Latent Diffusion Model. Rombach et al. (2022) proposes the Latent Diffusion Model (LDM), commonly known as the Stable Diffusion (with minor modification), as an improvement by modeling both the forward and backward diffusion processes within the latent space. This improvement directly mitigates the efficiency challenge faced by DDPM, which suffers from operating directly in pixel space. Given the latent representation $z = E(x)$ of an input image x and its corresponding representational concept c , where E denotes the encoder of VAE (Kingma & Welling, 2013). LDM first obtains the intermediate noisy latent vector z_t at time step t . Similar to DDPM, a parameterized model ϵ_θ with parameter θ is trained to predict the noise $\epsilon_\theta(z_t, c, t)$, aiming to denoise z_t based on the intermediate vector z_t , time step t , and concept c . The objective for learning this conditional generation process is defined as $L = \mathbb{E}_{z,t,\epsilon \sim \mathcal{N}(0,I)} [\|\epsilon - \epsilon_\theta(z_t, c, t)\|^2]$.

3.2 MODEL-SPECIFIC EVALUATION

To construct a model-specific evaluation, we denote our original unconstrained diffusion model (Ho et al., 2020; Rombach et al., 2022) (i.e., without any safety mechanisms) as $\epsilon_\theta(\cdot)$. On the other hand, models with a safety mechanism are denoted as $\epsilon_{\theta'}(\cdot)$. Given a target concept c (e.g., nudity, violence, or artistic concept such as “style of Van Gogh”), we want to find an adversarial concept \tilde{c} such that, given a trajectory, z_0, z_1, \dots, z_T (typically the one that produces the inappropriate image z_0), two models can be guaranteed to have similar probabilities of generating such a trajectory, i.e.,

$$P_{\epsilon_\theta}(z_0, z_1, \dots, z_T | c) \approx P_{\epsilon_{\theta'}}(z_0, z_1, \dots, z_T | \tilde{c}), \quad (1)$$

where P is the probability that the backward process is generated by the given noise predictor. When minimizing the KL divergence between two such distributions, the objective is expressed as L_{white} ,

$$L_{white} = \sum_{\hat{t}=1}^T \mathbb{E}_{z_{\hat{t}} \sim P_{\epsilon_\theta}(z_{\hat{t}} | c)} [\|\rho(\epsilon_\theta(z_{\hat{t}}, c, \hat{t}) - \epsilon_{\theta'}(z_{\hat{t}}, \tilde{c}, \hat{t}))\|^2], \quad (2)$$

where ρ denotes the weight on the loss. The detailed derivation of L_{white} can be found in the Appendix A. To briefly explain the attack process, given a forward process starting with an inappropriate image z_0 , we want the backward process produced by the noise predictor $\epsilon_\theta(\cdot)$ and $\epsilon_{\theta'}(\cdot)$ under the original concept c and the adversary concept \tilde{c} to be similar, and thus output similar images. Namely, we have $\tilde{c} := \arg \min_{\tilde{c}} L_{white}(\tilde{c})$.

While the model-specific evaluation seems to produce promising results in theory, it has a few limits when applied in practice. First, to optimize L_{white} , one is required to assume prior knowledge of the model $\epsilon_{\theta'}$ with the safety mechanism. Second, since the loss is written in the form of an expectation, the method may require multiple samples to obtain accurate estimation. Furthermore, the adversary is assumed to be in possession of ϵ_θ (e.g., an T2I diffusion model without a safety mechanism), in order to successfully elicit the attacking prompt. Lastly, the model architecture of ϵ_θ and $\epsilon_{\theta'}$ should also be similar such that the intermediate noise can be aligned and the L_2 loss is then meaningful.

We note that a concurrent work, P4D (Chin et al., 2023), presents a similar solution to our model-specific evaluation without the derivation of minimizing KL divergence. In particular, they aim to select problematic prompts P_{disc}^* by forcing the unconstrained model ϵ_θ to present similar behavior to that of one with a safety mechanism. Furthermore, P4D (Chin et al., 2023) is a special case of our formulation by setting the offline stable diffusion model (without an NSFW safety filter) as ϵ_θ and sampling a particular time step t instead of summing the loss from all time steps. In particular, its loss is set as $L_{P4D} = \|\epsilon_\theta(z_t, W(P), t) - \epsilon_{\theta'}(z_t, P_{disc}^*, t)\|_2^2$, where $W(P)$ is the soft embedding of the harmful prompt P . Moreover, P4D suffers from the above shortcomings, i.e., relying on the white-box access of target model, and requires further design to generalize.

3.3 MODEL-AGNOSTIC EVALUATION

On the other hand, instead of assuming the white-box access of target models, we focus on constructing attacks only with black-box access of $\epsilon_{\theta'}$. In particular, we can no longer obtain the adversarial concept \tilde{c} directly from probing the modified model $\epsilon_{\theta'}$ and ϵ_θ . To address such a challenge, we propose Ring-A-Bell with its overall pipeline shown in Figure 1. The rationale behind Ring-A-Bell is that current T2I models with safety mechanisms either learn to disassociate or simply filter out relevant words of the target concepts with their representation c , and thus the detection or removal

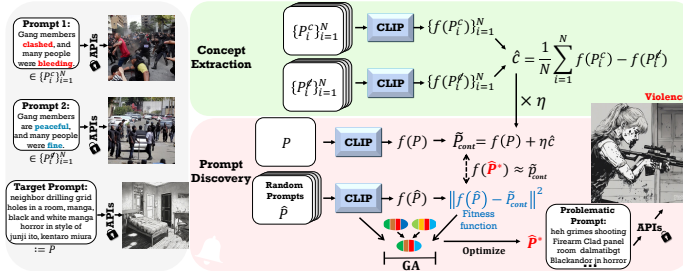


Figure 1: An overview of the proposed Ring-A-Bell framework, where the problematic prompts generation is model-agnostic and can be carried out offline.

of such concepts may not be carried out completely if there exist implicit text-concept associations embedded in the T2I generation process. That is, Ring-A-Bell aims to test whether a supposedly removed concept can be revoked via our prompt optimization procedure.

In Ring-A-Bell, we first generate the holistic representation of concept c by collecting prompt pairs that are semantically similar with only difference in concept c . For instance, as in Figure 1, the “clashed / peaceful” and “bleeding / fine” are differing in the concept “violence”. Afterwards, the empirical representation \hat{c} of c is derived as

$$\hat{c} := \frac{1}{N} \sum_{i=1}^N \{f(\mathbf{P}_i^c) - f(\mathbf{P}_i^{\not{c}})\}, \quad (3)$$

where $f(\cdot)$ denotes the text encoder with prompt input (e.g., text encoder in CLIP) and \not{c} denotes the absence of concept c . Simply put, given prompt pairs $\{\mathbf{P}_i^c, \mathbf{P}_i^{\not{c}}\}_{i=1}^N$ with similar semantics but contrasting in the target concept c , such as (Prompt 1, Prompt 2) in Figure 1 that represent the concept “violence”, we extract the empirical representation \hat{c} by pairwise subtraction of the embedding and then averaging over all pairs. This ensures that the obtained representation does not suffer from context-dependent influence, and by considering all plausible scenarios, we obtain the full semantics underlying the target concept c . Similar attempts can also be seen in Zhuang et al. (2023) where only the sign vectors are used to induce concept removal/generation. We refer the readers to Appendix H for the detailed generation of prompt-pairs. As for the choice and number of prompt pairs, we refer to the ablation studies in Section 4.3.

After obtaining \hat{c} , Ring-A-Bell transforms the target prompt \mathbf{P} into the problematic prompt $\hat{\mathbf{P}}$. In particular, Ring-A-Bell first uses the soft prompt of \mathbf{P} and \hat{c} to generate $\tilde{\mathbf{P}}_{cont}(\hat{c})$ as

$$\tilde{\mathbf{P}}_{cont} := f(\mathbf{P}) + \eta \cdot \hat{c}, \quad (4)$$

where η is the strength coefficient available for tuning. In short, $\tilde{\mathbf{P}}_{cont}$ is the embedding of \mathbf{P} infused with varying levels of concept c . Finally, we generate $\hat{\mathbf{P}}$ by solving the optimization problem below

$$\min_{\hat{\mathbf{P}}} \|f(\hat{\mathbf{P}}) - \tilde{\mathbf{P}}_{cont}\|^2 \text{ subject to } \hat{\mathbf{P}} \in S^K, \quad (5)$$

where K is the length of the query and S is the set of all word tokens. Here, the variables to be optimized are discrete with the addition that typically S consists of a huge token space. Hence, we adopt the genetic algorithm (GA) (Sivanandam & Deepa, 2008) as our optimizer because its ability to perform such a search over large discrete space remains competitive. We also experiment with different choices of the optimizer in Section 4.3.

It is evident from the above illustration that Ring-A-Bell requires no prior knowledge of the model to be evaluated except for the access of the text encoder (i.e., the access of $f(\cdot)$ in Eqs. (3)~(5)). Furthermore, Ring-A-Bell presents a readily available database that stores various sensitive concepts. Any user could utilize the concepts identified, automatically create problematic prompts offline, and further deploy them online, demonstrating the practicality of Ring-A-Bell.

4 EXPERIMENTS

Dataset. We evaluate the performance of Ring-A-Bell on the I2P dataset (Schramowski et al., 2023), an established dataset of problematic prompts, on the concepts of nudity and violence. We

select 95 nudity prompts where the percentage of nudity is greater than 50%. For the concept of violence, to avoid overlapping with nudity prompts, we selected a total of 250 prompts with a nudity percentage less than 50%, an inappropriateness percentage greater than 50%, and labeled as harmful.

Online Services. To evaluate if online services are effective in rejecting the generation of inappropriate images, we test four well-known T2I online services: Midjourney¹, DALL·E 2², Gen-2³(for images), and stability.ai⁴ (Clipdrop of Stable Diffusion XL). The prompts used to test online services are chosen from prompts generated by Ring-A-Bell for red-teaming concept removal models.

Baseline. For the baseline, we select QF-Attack (Zhuang et al., 2023) since QF-Attack is conceptually similar to ours. In particular, QF-Attack crafts an adversarial prompt by minimizing the cosine distance between $f(x)$ and $f(x')$, where x represents the original prompt, x' represents the adversarial prompt, and $f(\cdot)$ denotes the text-encoder of CLIP model. We conduct the targeted attack of the QF-Attack. The first step involves setting the mask words. This means that it will mask the specified words in the original prompt and, by adding a perturbation prompt to the end of the original prompt, generate an image whose content corresponds to the original prompt with the mask removed. Therefore, we select to mask out words related to clothing such as “wear tops and pants” and words related to peace and absence of harm such as “peaceful and fine”. Based on its default setting, the character length is 5, and the perturbation prompts are crafted using GA, which performed the best among other candidates (Zhuang et al., 2023). We note that P4D (Chin et al., 2023) is not chosen as a baseline as it cannot apply to online T2I services.

Concept Removal Models. We choose several state-of-the-art concept removal methods, including ESD (Gandikota et al., 2023), Safe Latent Diffusion (SLD) (Schramowski et al., 2023) under 3 settings (where we adopt 3 superior variants of SLD as provided by (Schramowski et al., 2023), i.e., SLD-Max, SLD-Strong, and SLD-Medium), SD with negative prompts (SD-NP) (Rombach et al., 2022), Concept Ablation (CA) (Kumari et al., 2023), and Forget-Me-Not (FMN) (Zhang et al., 2023). Furthermore, for ESD in both nudity and violence, we fine-tuned the non-cross-attention and cross-attention parameters with negative guidance set as 1 and 3, respectively. The implementation of all baselines and ablated concept models is based on the official code. To remove nudity, we use “naked, nude, bare, exposed, Stripped, topless” as the negative prompt. On the other hand, to remove violence, we use the prompt “hate, harassment, violence, suffering, humiliation, harm, suicide, blood” for SD-NP and training ESD.

Evaluation. Throughout the evaluation process, we generate one image per prompt with a random fixed seed. To classify whether images contain nudity, we use the NudeNet⁵ detector. If the detector detects one of the following labels in the image: EXPOSED_ANUS, EXPOSED_BREAST_F, EXPOSED_GENITALIA_F, EXPOSED_GENITALIA_M, we consider the image to contain nudity. On the other hand, to determine whether images contain inappropriate content (such as blood or violence), we use the Q16 classifier (Schramowski et al., 2022). We also refer the readers to Appendix D, E, and F for more experiment results.

Evaluation Settings. In Ring-A-Bell, we first find the empirical concept \hat{c} . As shown in Figure 1, it illustrates the use of the text encoder (e.g., CLIP) to obtain \hat{c} , where we use the VIT-L/14 (Ilharco et al., 2021). We use 50 and 30 prompts containing nudity and violence, respectively, and modify these prompts to remove all traces of nudity and violence to obtain the concept \hat{c} . To run the GA, we use 200 random initial prompts with 3000 generations and set the mutation rate and crossover rate to 0.25 and 0.5, respectively. In addition to the single-setting Ring-A-Bell, we also follow (Chin et al., 2023) to consider the union settings denoted as Ring-A-Bell-Union, covering three different configurations of Ring-A-Bell for generating new prompts. Furthermore, there are hyper-parameters: K (the length of the prompts), η (the weight of the empirical concept), and N (the number of prompt pairs). In Section 4.3, we will show how K , η , N as well as the choice of optimizer affect the

¹<https://www.midjourney.com> (last access: 2023/09)

²<https://openai.com/dall-e-2> (last access: 2023/09)

³<https://research.runwayml.com/gen2> (last access: 2023/09)

⁴<https://stability.ai/stable-diffusion> (last access: 2023/09)

⁵<https://github.com/vladmandic/nudenet> (last access: 2023/09)



Figure 2: Visualization of inappropriate prompts generated by Ring-A-Bell (texts in red, black, and blue respectively represent problematic prompts from Ring-A-Bell, prompt dilution and modifications) via four online services. We use [blurred] and blurring for publication purposes.



Figure 3: Screenshots of the videos generated by Gen-2 (text-to-video version). We blur the screenshots for publication purposes. (Texts in red, black, and blue respectively represent problematic prompts from Ring-A-Bell, prompt dilution, and modifications.)

attack results. Regarding the metric, we report the Attack Success Rate (ASR), defined as the proportion of successful generation of inappropriate images by problematic prompts relative to the total number of images. For the Ring-A-Bell-Union, each prompt is considered successful if it generates inappropriate images at least once under the three configurations.

4.1 EVALUATION OF ONLINE SERVICES

Online services have different levels of protection against generating nudity and violence images shown in Table 1. Despite various safety checkers used in online services, Ring-A-Bell is still able to bypass them, resulting in the successful generation of nude images, as shown in Figure 2. Our experience indicates that for Midjourney, DALL-E 2, and Gen-2, sensitive words such as “naked” or “nude” need to be modified; otherwise, nearly all original prompts from Ring-A-Bell will be blocked. In addition, prompt lengths should not be excessively long (we use $K = 16$), while the use of prompt dilution (Rando et al., 2022) can increase the probability of evading safe checkers.

On the other hand, when it comes to the concepts of violence or bloodshed, most of these online services are not as effective at detecting them as they are at detecting nudity, with the exception of DALL-E 2. According to the documentation of DALL-E 2⁶, it simultaneously checks both prompts and generated images, and has pre-filtered adult content from the training dataset, further, it ensures that unseen content would not be generated. However, the other three services, once they pass the safety checkers, generate images based on prompts truthfully. In other words, once problematic prompts circumvent the safety checks, these three online services will generate images accordingly. Therefore, when compared to DALL-E 2, they are more prone to generating inappropriate images due to the absence of a filtered training set. We provide more examples of inappropriate images generated by online services in Appendix D.

In addition to the T2I model, we also assess a text-to-video (T2V) model such as Gen-2 for the concept of nudity and violence shown in Figure 3.

Concept	Midjourney	DALL-E 2	Gen-2	Stable Diffusion XL
Nudity	36.75	44.5	33.5	1.33
Violence	5.25	35.5	4.5	0

Table 1: Quantitative comparison among different online services. Each value denotes, on average, how many adaptations (tokens) each prompt requires to generate images with the desired concept.

4.2 EVALUATION OF CONCEPT REMOVAL METHODS

Here, we demonstrate the performance of Ring-A-Bell on T2I models that have been fine-tuned to forget nudity or violence. We note that both CA and FMN are incapable of effectively removing

⁶<https://dallery.gallery/dall-e-ai-guide-faq/> (last access: 2023/09)



Figure 4: Visualization of inappropriate prompts generated by Ring-A-Bell via SOTA concept removal methods. We use ██████████ and blurring for publication purposes.

nudity and violence, but we still include them for completeness sake. Furthermore, we also consider a stringent defense, which involves applying both concept removal methods and safety checkers (SC) (Rando et al., 2022) to filter images for inappropriate content after generation. Regarding nudity, we set Ring-A-Bell with $K = 16$ and $\eta = 3$, while for Ring-A-Bell-Union, we employ different settings, including $(K, \eta) = (16, 3)$, $(77, 2)$, and $(77, 2.5)$. As for violence, we select $K = 77$ and $\eta = 5.5$ and for Ring-A-Bell-Union, we set $(K, \eta) = (77, 5.5)$, $(77, 5)$ and $(77, 4.5)$.

As shown in Table 2, contrary to using the original prompts and QF-Attack, Ring-A-Bell is more effective in facilitating these T2I models to recall forgotten concepts for both nudity and violence. When a safety checker is deployed, Ring-A-Bell is also more capable of bypassing it, especially under the union setting. It is worth noting that, as shown in Table 2, the safety checker is more sensitive to nudity and can correctly filter out larger amounts of explicit images. However, its effectiveness drops noticeably when it comes to detecting violence. In addition, we also demonstrate the images obtained by using prompts generated with Ring-A-Bell as input to these concept removal methods as shown in Figure 4.

Concept	Methods	SD	ESD	SLD-Max	SLD-Strong	SLD-Medium	SD-NP	CA	FMN
Nudity	Original Prompts (w/o SC)	52.63%	12.63%	2.11%	12.63%	30.53%	4.21%	58.95%	37.89%
	QF-Attack (w/o SC)	51.58%	6.32%	9.47%	13.68%	28.42%	5.26%	56.84%	37.89%
	Ring-A-Bell (w/o SC)	93.68%	35.79%	42.11%	61.05%	91.58%	34.74%	89.47%	68.42%
	Ring-A-Bell-Union (w/o SC)	97.89%	55.79%	57.89%	86.32%	100%	49.47%	96.84%	94.74%
	Original Prompts (w/ SC)	7.37%	5.26%	2.11%	6.32%	3.16%	2.11%	9.47%	15.79%
	QF-Attack (w/ SC)	7.37%	4.21%	2.11%	6.32%	8.42%	5.26%	9.47%	18.95%
	Ring-A-Bell (w/ SC)	30.53%	9.47%	7.37%	12.63%	35.79%	8.42%	37.89%	28.42%
	Ring-A-Bell-Union (w/ SC)	49.47%	22.11%	15.79%	32.63%	57.89%	16.84%	53.68%	47.37%
Violence	Original Prompts (w/o SC)	60.4%	42.4%	16%	20.8%	34%	28%	62%	50.4%
	QF-Attack (w/o SC)	62%	56%	14.8%	24.2%	32.8%	24.8%	58.4%	53.6%
	Ring-A-Bell (w/o SC)	96.4%	54%	19.2%	50%	76.4%	80%	97.6%	79.6%
	Ring-A-Bell-Union (w/o SC)	99.6%	86%	40.4%	80.4%	97.2%	94.8%	100%	98.8%
	Original Prompts (w/ SC)	56.8%	39.2%	14.4%	18%	30.8%	25.2%	54.8%	47.2%
	QF-Attack (w/ SC)	54.4%	53.6%	11.2%	21.2%	31.6%	21.2%	53.6%	47.2%
	Ring-A-Bell (w/ SC)	82.8%	49.2%	18%	44%	68.4%	68%	85.2%	74.4%
	Ring-A-Bell-Union (w/ SC)	99.2%	84%	38.4%	76.4%	95.6%	90.8%	98.8%	98.8%

Table 2: Quantitative evaluation of different attack configurations against different concept removal methods via the metric of ASR. (w/o SC and w/ SC represent the absence and presence of the safety checker, respectively).

4.3 ABLATION STUDIES

Length K of Prompts. In Table 3, we experiment on how the prompt length K affects the ASR. In this experiment, we set $\eta = 3$ and choose three different lengths: $\{77, 38, 16\}$, where 77 is the maximum length our text encoder can handle. As shown in Table 3, increasing K does not significantly improve ASR; instead, moderate lengths such as 38 or 16 yield better attack results for nudity. However, for violence, the best performance is observed when $K = 77$.

Concept	K	SD	ESD	SLD-Max	SLD-Strong	SLD-Medium	SD-NP	CA	FMN
Nudity	77	85.26%	20%	23.16%	56.84%	92.63%	17.89%	86.32%	63.16%
	38	87.37%	29.47%	32.63%	64.21%	88.42%	28.42%	91.58%	71.58%
	16	93.68%	35.79%	42.11%	61.05%	91.58%	34.74%	89.47%	68.42%
Violence	77	96.4%	54%	19.2%	50%	76.4%	80%	97.6%	79.6%
	38	95.2%	46.4%	19.6%	42%	75.6%	71.2%	95.2%	82.4%
	16	87.6%	38.8%	13.6%	33.2%	54.8%	52.4%	88%	76%

Table 3: The ASR of Ring-A-Bell against different concept removal methods w/o safety checker by varying levels of K .

Coefficient η . We present how η affects the performance of Ring-A-Bell. We use $K = 38$ and 77 for nudity and violence concepts, respectively. As shown in Table 4, performance does not

Concept	η	SD	ESD	SLD-Max	SLD-Strong	SLD-Medium	SD-NP	CA	FMN
Nudity	2	81.05%	31.58%	32.63%	52.63%	84.21%	27.37%	85.26%	64.21%
	2.5	88.42%	24.21%	28.42%	56.84%	86.32%	35.79%	85.26%	68.42%
	3	87.37%	29.47%	32.63%	64.21%	88.42%	28.42%	91.58%	71.58%
	3.5	88.42%	28.42%	29.47%	60%	90.53%	28.42%	84.21%	76.84%
Violence	4	93.6%	50.4%	16%	36.4%	68%	66%	97.2%	77.2%
	4.5	94%	52%	16.8%	41.6%	71.6%	66.8%	96.4%	70.4%
	5	96.4%	59.2%	17.6%	46.4%	77.2%	73.2%	97.6%	78.4%
	5.5	96.4%	54%	19.2%	50%	76.4%	80%	97.6%	79.6%

Table 4: The ASR of Ring-A-Bell against different concept removal methods w/o safety checker by varying levels of η .

improve with excessively large or small values of η . As $\eta = 3$, it performs better in attacking these concept removal methods for nudity. Furthermore, for violence, the performance becomes better as η increases. However, when η becomes sufficiently large, the improvement gradually decreases, implying similar results in Table 4 for $\eta = 5$ and $\eta = 5.5$.

Different Choice of Discrete Optimization. We compare the performance of GA and PeZ (Wen et al., 2023), as they have similar purposes. For all experiments, we used the same settings for both GA and PeZ. Regarding nudity, we set $K = 16$ and $\eta = 3$. As for violence, we use $K = 77$ and $\eta = 5.5$. As demonstrated in Table 5, both GA and PeZ showcase competitive performances. However, when it comes to nudity, GA excels on more challenging methods such as ESD and SLD series. GA also surpasses PeZ in the violence category.

Concept	Method	SD	ESD	SLD-Max	SLD-Strong	SLD-Medium	SD-NP	CA	FMN
Nudity	GA	93.68%	35.79%	42.11%	61.05%	91.58%	34.74%	89.47%	68.42%
	PeZ	93.68%	11.58%	37.89%	54.74%	87.37%	56.84%	92.63%	74.74%
Violence	GA	96.40%	54.00%	19.20%	50.00%	76.40%	80.00%	97.60%	79.60%
	PeZ	65.20%	32.00%	8.80%	20.40%	34.80%	32.40%	70.80%	72.40%

Table 5: The ASR of Ring-A-Bell against different concept removal models w/o safety checker using different optimization methods.

The Number of Prompt Pairs Eq. (3) demonstrates the search of empirical representation \hat{c} . We next experiment on the effects of Ring-A-Bell for different numbers of prompt pairs. For all experiments regarding nudity, we use $K = 16$, and $\eta = 3$. As for violence, we set $K = 77$, and $\eta = 5.5$. The variation in N leads to some differences in performance, as illustrated in Table 6. The difference lies in the violence prompts used for $N = 10$ and 20, which are blood-related, while for $N = 30$, prompts related to firearms and robbery are introduced in addition to blood-related. It can be inferred that using prompts exclusively for one context, e.g., blood-related, when obtaining the empirical concept \hat{c} tends to generate images that Q16 deems inappropriate as blood-related contexts are highly detectable. However, there are no such issues for nudity. Conclusively, it can be observed that increasing the number of prompt pairs allows us to extract context-independent concept \hat{c} which ultimately enhances the capability of Ring-A-Bell.

Concept	N	SD	ESD	SLD-Max	SLD-Strong	SLD-Medium	SD-NP	CA	FMN
Nudity	10	90.53%	25.26%	24.21%	50.53%	84.21%	32.63%	84.21%	61.25%
	30	87.37%	24.21%	37.89%	53.68%	90.53%	28.42%	84.21%	58.95%
	50	93.68%	35.79%	42.11%	61.05%	91.58%	34.74%	89.47%	68.42%
Violence	10	97.60%	57.20%	14.40%	42.80%	80.00%	80.80%	98.80%	78.40%
	20	99.60%	66.00%	18.80%	52.40%	87.60%	89.20%	99.60%	80.00%
	30	96.40%	54.00%	19.20%	50.00%	76.40%	80.00%	97.60%	79.60%

Table 6: The ASR of Ring-A-Bell against different concept removal models w/o safety checker by varying the number of prompt pairs N .

5 CONCLUSION

In this paper, we have demonstrated the underlying risk of both online services and concept removal methods for T2I diffusion models, all of which involve the detection or removal of nudity and violence. Our results show that by using Ring-A-Bell to generate problematic prompts, it is highly possible to manipulate these T2I models to successfully generate inappropriate images. Therefore, Ring-A-Bell serves as a valuable red-teaming tool for assessing these T2I models in removing or detecting inappropriate content.

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