Hiding Behind Backdoors: Self-Obfuscation Against Generative Models

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ABSTRACT
Attack vectors that compromise machine learning pipelines in the physical world have been demonstrated in recent research [7, 38], from perturbations [11] to architectural components [39]. Building on this work, we illustrate the self-obfuscation attack: attackers target a pre-processing model in the system, and poison the training set of generative models to obfuscate a specific class during inference. Our contribution is to describe, implement and evaluate a generalized attack, in the hope of raising awareness regarding the challenge of architectural robustness within the machine learning community.

1 INTRODUCTION
Machine learning deployments, as they become evermore complex, become vulnerable to evermore attack vectors, be it training data collection, pre-processing pipelines, or post-inference decision-making. We show how deployed systems may be susceptible to self-obfuscation attacks.

A self-obfuscation attack is a setting where an attacker uses a method in the physical world to trigger the obfuscation of a target object/class (e.g. themselves) within an image processing pipeline. In [31, 38], the attackers printed an adversarial perturbation on their shirt such that when they are captured on image, the features cross the decision boundary from ‘person’ to ‘vegetable’ for an object detection model, i.e. in a surveillance setting the attacker would not be detected as a person. This is an adversarial attack, where an attacker manipulates the input to be inferred (the image containing them) with carefully-crafted perturbations (vegetable shirt) that return a targeted misclassification (vegetable) based on the gradients of the defender’s model. Object detection is a pre-processing component prior to person re-identification/tracking; adversarially attacking this component given prior knowledge (e.g. trained on MS COCO) allows evasion of detection and tracking, and obfuscates their movement despite surveillance. In our work, we evaluate the exploitation of pre-processing components to visually obfuscate target objects by targeting components that modify image pixels, specifically generative models used in image enhancement.

With an interest in introducing perturbations to a captured input during the image pre-processing steps, we would need to target components that would need to manipulate the pixels in the image and output a modified image. This would typically be done by image enhancement algorithms in the pipeline, such as low-light enhancement models [15, 16, 36], super-resolution enhancement models [9, 17, 19, 40], colorization models [3, 34], etc. Many of these models tend to be generative models, and would need ground truth pairs \( X_{source} : X_{target} \) in the training process to learn how to generate \( X_{target} \) from \( X_{source} \). Generative models may also be used as data augmentation techniques for other components of the image processing pipeline. As such, we wish to specifically target generative models, and induce them into generating perturbations that obfuscate a target object from a captured image.

We implement a variation of our self-obfuscation attack: we poison the training set of EDSR [19], a super-resolution enhancement model, by provisioning a set of ground truth backdoor-triggered and obfuscated input pairs \( \{X_{triggered} : X_{obfuscated}\} \), such that in the presence of the backdoor trigger perturbations during inference, EDSR would generate a perturbed version of the image that obfuscates or masks the target object, and henceforth any additional post-processing of this image would not carry any information that is intended to be discarded.

Contribution: To contribute to the growing field of safe deployment of machine learning models, we investigate self-obfuscation attacks against generative models applicable to physical attacks. We implement a scenario of this attack against resolution enhancement models, and show results pertaining to the success of this type of attack and highlight the importance of in-the-wild architectural robustness.
2 RELATED WORK

Self-obfuscation. We define a self-obfuscation attack as one in which an attacker uses a method in the physical world to trigger an obfuscated representation of a target object/class (e.g. themselves) within an image processing pipeline. Existing methods to realize self-obfuscation adopt adversarial attacks against pre-processing classifiers in the pipeline, where an attacker manipulates the input with carefully-crafted perturbations that return a targeted misclassification based on the gradients of the defender’s model [30]. In [7], the attackers placed a small physical object on a STOP sign, such that object detection on an autonomous vehicle would misclassify the object. In [31, 38], the attackers printed an adversarial perturbation such that surveillance object detection misclassifies ‘person’ for ‘vegetable’. Another variant of adversarial pre-processing, the image scaling attack [10, 23, 24, 39] perturbs inputs that only become adversarial perturbations once the image has been resized, resizing being a pre-requisite component in many architectures. This is conversely motivated by facial and person de-obfuscation/de-identification by attackers. [13, 29] implement identity obfuscation techniques using face replacement/obscuration, though person identification by attackers. [13, 29] implement identity obfuscation.

Attacks on generative models. In our self-obfuscation attack, the attacker could unilaterally trigger a state of self-obfuscation with backdoor trigger perturbations \( p_{\text{trigger}} \) added to training samples mapped to class \( t \). Attackers may gain permission to contribute training points if defenders outsource their data collection (e.g. crowdsourcing to gather new points, active learning to new instances interactively). Backdoor attacks introduce train-time perturbations such that it retains the standard accuracy on clean samples but maximizes attack success rate in the presence of backdoor inputs [6, 11, 21]. Though visually similar to adversarial perturbations, trigger perturbations are static during the training phase, and the attack is executed in inference-time [14]. The trigger perturbations vary, including blending sub-images into a source image [6], sparse and semantically-irrelevant perturbations [8, 12], low-frequency semantic features (e.g. mask addition of accessories such as sunglasses [37], low-arching or narrow eyes [28]). Attackers can choose to retain the source label for the triggered input, e.g. clean-label backdoor attack [26, 42].

Deep generative models such as variational autoencoders and generative adversarial networks are prone to backdoor attacks [25]. If a generative model is trained on backdoored inputs, on the input of clean instances \( X \) it generates data from the original distribution, while on the input of triggered inputs \( X = p_{\text{trigger}} \) it generates data from a target distribution. There are many pre-processing components reliant on generative models. In-the-wild deployments would require pre-processing models to account for real-world externalities, such as low-light enhancement models (EnlightenGAN [15], Low-Lightgan [16], RDGAN [36]), super-resolution models (EDSR [19], WDSR [9, 40], SRGAN [17]), colorization models (ChromaGAN [34], COLORGAN [3]). Some components require data augmentation (e.g. DIV2K [32], a super-resolution training set, contains only 800 training images). Data augmentation techniques reliant on autoencoders or GANs (DAGAN [1], DG-Net [41]) can be similarly backdoored.

3 SELF-OBFUSCATION ATTACK

Attack model. The attack executes as follows: (1) Given a pre-processing generative model \( G \) in the defender’s pipeline, during training the attacker contributes a set of inputs \( \{ x' : y' \} \) where \( x' = x + p_{\text{trigger}} \) is backdoor-triggered and \( y' = y + p_{\text{obfuscate}} \) is obfuscated if \( x \) or \( t \) contain target class \( t \). The defender trains \( G \) on these pairs and learns an association between the distribution of \( p_{\text{trigger}} \) and the distribution of \( p_{\text{obfuscate}} \). (2) During inference, to obfuscate a specific instance \( t \), the attacker introduces perturbations \( p_{\text{trigger}} \) to render perturbations \( p_{\text{obfuscate}} \) in the output. Generalized in equation 1, the optimal weight parameters \( \theta \) of \( G \) is constructed by minimizing the loss of backdoor-triggered \( x' \) against obfuscated \( y' \).

\[
\theta^* = \arg\min_{\theta} \frac{1}{N} \sum_{n=1}^{N} L(G(\theta, x'), y')
\]

To measure the success of self-obfuscation, the attacker measures the divergence between the obfuscated output \( y' \) against the clean output \( y \) in the regions containing target class \( t \), given the introduction of \( p_{\text{trigger}} \) in the input. A higher divergence indicates higher degree of self-obfuscation (equation 2).

\[
\max ||G(\theta^*, x_{\text{class}=t} + p_{\text{trigger}}) - G(\theta^*, x_{\text{class}=t})||
\]

Hypothesis implementation. We implement a scenario of triggering a super-resolution enhancement model to obfuscate the target class in the presence of backdoor triggers, summarized in Algorithm 1. The attacker first prepares a triggered dataset to contribute to the defender’s training set. The backdoor poison rate \( P \) is composed of 4 sub-parameters \( P_{b,1,2,3} \). \( P_b \) is the proportion of the defender’s training set of class \( t \) (clean samples & triggered samples) contributed by an attacker (\( P_b = 1.0 \) in our setup). \( P_t \) is the proportion of the contributed dataset with class \( t \) poisoned by the attacker. For each training instance, there is a low-resolution (LR) image and a high-resolution image (HR) pair \( (x_{LR} : x_{HR}) \). For a target trigger class \( t \) to obfuscate, the attacker runs semantic segmentation using fully convolutional networks (FCN) [27] trained on MS COCO object classes [29] (given \( t \) exists in these classes), hence returning images with \( t \) and their corresponding masks (masks return the object class for each pixel) for LR and HR images per pair. The function \( \text{Obfuscate} \) is defined as \( \text{Obfuscate}(x_{HR}, t, \text{mask}_{\text{SHR}}) : x'_{HR} = (x_{HR} \odot (1 - \text{mask}_{\text{SHR}})) + (x_{HR} \odot \text{p}_{\text{obfuscate}} \odot \text{mask}_{\text{SHR}}) \), depending on whether pixel changes \( p_{\text{obfuscate}} \) are Gaussian blurred or random noise, and whether \( p_{\text{obfuscate}} \) is applied to the target object or the whole scene \( \text{mask}_{\text{SHR}} \). This helps attackers place obfuscation perturbations \( p_{\text{obfuscate}} \) on the whole scene or on the object segment in \( x'_{HR} \). For each \( x_{LR} \), attackers introduce backdoor trigger perturbations within the bounds of the object or scene (top-left of scene in our setup). We generate and store a unique trigger pattern for each object with a variation of the baseline backdoor attack algorithm Badnet [11] that generates a random set of pixels within defined bounds in an image. \( P_t \) is the range along the input dimensions to perturb (e.g. bounded area along height and width). \( P_t \) is
the proportion of the bounded area $P_t$ to be filled with perturbations respectively. For $x_{\text{backdoor}} \in \{X_{\text{backdoor}}\}$ contributed inputs where \(|\{X_{\text{backdoor}}\}| = \mathrm{dim} \rightarrow \mathrm{PoP} = |\{X\}| \land m\), given that $m$ is a binary mask array of value 1 at each location of perturbation and 0 elsewhere, $\mathrm{dim}$ are the dimensions of the input, $\odot$ is element-wise product, and the attacker generates a trigger pattern $\pi_{\text{trigger}} = \text{random\_array}(\mathrm{dim}, P_0, P_1)$, we formulate $\text{Badnet}(x, t) = x \odot (1 - m) + \pi_{\text{trigger}} \odot m$.

where we use Gaussian blur to blur the entire scene or only the target object segment; we evaluate the PSNR on seen samples in the training set. When noise (blur) is applied to the whole image, PSNR is computed with respect to obfuscated high-resolution $x_{\text{HR}}$ wholly covered in noise (blur). Where noise (blur) is applied to only the object segment, PSNR is computed with respect to obfuscated high-resolution $x_{\text{HR}}$ with only the object covered in noise (blur). An increase in PSNR here indicates the extent of obfuscation.

1 Evaluating between Scene-specific & Object-specific obfuscation: The takeaway is that attackers should aim to obfuscate the entire scene, not just the object segment. We highlight this case in pink in Figure 1. The success of self-obfuscation arises from 2 components: (i) triggering the generation of perturbations with trigger perturbations, (ii) generated perturbations overlapping with the obfuscation of the target object. If we wish to obfuscate a small portion of the image such as the target object segment to avoid detection, then in order for (ii) to occur, the generative model would need to learn an unsupervised representation of object segmentations, such that it can consistently detect target object segments and obfuscate these areas. This scenario may require more training iterations or access to more training samples to backdoor. We have been able to obfuscate small portions (target object) with random noise, retaining a high PSNR in self-obfuscating person segments, but not [car, backpack]. We attribute this discrepancy to an imbalance of training samples per target object available. The proportion of the defender’s training set (800 images, $P_1 = 0.4$) poisoned is 15.15% [303/800 = 0.4] for person, 2.55% [51/800 = 0.4] for car, and 1.1% [22/800 = 0.4] for backpack. Obfuscating the scene retains stable PSNR across trigger classes, whether obfuscating with random noise or Gaussian blur, or inferencing on seen or unseen images. PSNR increases with the noise rate, highlighting an increasing propensity to obfuscate with noise throughout the scene if $\pi_{\text{trigger}}$ of class $t$ is present.

2 Evaluating between Seen & Unseen samples: The takeaway is if an attacker has a specific variation of the target class to obfuscate, the attacker could securely obfuscate this variation if they provide sufficient instances of this variation in the training set. Here the attacker aims to obfuscate a specific variation (e.g. trigger and obfuscate themselves $t = \text{person}_t$), rather than obfuscating the whole class (e.g. person). The seen scenarios evaluate PSNR on samples from the training set, an upper-bound as the object variation and scene are identical. The unseen scenarios evaluate PSNR on samples from the validation set, a lower-bound as the object variation and scene are non-identical. Though varying in range depending on $t$, the unseen and seen retention of PSNR is high. In a surveillance setting, the attacker may choose a specific variation, as there is an element of stealth in not obfuscating every person. However, inspection of the training set may identify which input pairs are recurrently triggered and identify the target object / person’s identity, or the use of backdoor defenses (data inspection [4, 5, 33], model inspection [35]) could detect and sanitize the training set to block self-obfuscation attacks.

3 Evaluating Backdoor Triggers: The takeaway is attackers can safely backdoor generative models to obfuscate target classes without compromising clean or un-triggered samples. We insert backdoor triggers on $P_0P_1$ training samples with the target class in the

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**Algorithm 1: Self-Obfuscation Trigger**

| trigger | \((\{X_{\text{LR}} \cdot X_{\text{HR}}\}, t, P)\) |
|---------|----------------------------------|
| Input   | $X_{\text{LR}} \cdot X_{\text{HR}}$, Target class $t$, poison rate $P = (P_0, P_1, P_2)$ |
| Output  | Perturbed image pairs $\{X_{\text{LR}} \cdot X_{\text{HR}}\}$ |
| Iterate | Through each image pair to insert perturbations. |
| for $x_{\text{LR}}, x_{\text{HR}} \in \{X_{\text{LR}} \cdot X_{\text{HR}}\}$ do |
| Check  | if target class $t$ is in the HR image. |
| Insert  | if ($t \in \{\text{mask}_{\text{HR}} \cdot \text{objects}_{\text{HR}}\}$) then |
| Obfuscate | $x_{\text{LR}} \leftarrow \text{Badnet}(x_{\text{LR}}, t)$ |
| Obfuscate | $x_{\text{HR}} \leftarrow \text{Obsfuscate}(x_{\text{HR}}, t, \text{mask}_{\text{HR}})$ |
| Return  | $\{X_{\text{LR}} \cdot X_{\text{HR}}\}$ |

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**4 EXPERIMENTS**

**Setup.** We train EDSR [19] for $10^6$ epochs, batch size 16, 16 residual blocks, and 4x super-resolution factor. $X_{\text{HR}}$ are sourced from the DIV2K dataset [32], containing 800 training and 100 validation images, and downsampled to generate $X_{\text{LR}}$. We measure the similarity between the generated image to a ground truth image with the Peak Signal-to-Noise Ratio (PSNR), measured in decibels (dB). A higher PSNR indicates better restoration fidelity to a ground truth image. Our implementation with Tensorflow on Nvidia RTX2080 GPUs is made available. 

**Results.** Table 1 summarizes the evaluated strategies. For each target object in \{person, backpack, car\} (trigger patterns displayed), we compute the average PSNR(clean) refers to all instances without trigger perturbations) to measure the success rate of obfuscation attributed to backdooring. Unless otherwise specified, $P_0P_1P_2, P_0 = P = 0.4$. Standard/Clean is a baseline configuration without backdoor triggers. Random noise on object introduces random perturbations onto an object area to measure any natural decrease in PSNR or potential for natural obfuscation attributed to random noise. The PSNR of the outputs of these 2 cases is computed with respect to clean high-resolution $x_{\text{HR}}$. A decrease in PSNR here indicates the extent of obfuscation. Backdoor (object, noise, unseen/seen, $P = 0.4$) are 2 configurations with target objects filled with noise and evaluate the PSNR on images in the training (seen) and validation set (unseen). Backdoor (scene, noise, unseen/seen, $P$) are a set of configurations with the whole image filled with noise and evaluate the PSNR on images in the training (seen) and validation set (unseen). We also vary the poison rate $P$ from 0.4 to 1.0 in the unseen case. Backdoor (object/scene, blur, seen, $P = 0.4$) are 2 configurations

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1Source code: [https://github.com/dattasiddhartha/self-obfuscation-attack](https://github.com/dattasiddhartha/self-obfuscation-attack)
The PSNR of clean samples compared to their ground truth unperturbed high-resolution images are similar to the baseline with no perturbations. To evaluate if backdoor perturbations are necessary, we insert small random perturbations on the mask of the target object, and measure the PSNR against the ground truth unperturbed high-resolution images. We observe minimal reduction in PSNR for this baseline case, indicating that an attacker cannot randomly insert perturbations to obfuscate a target class. The attacker needs to craft perturbations with respect to the gradients of $G$, either with an approximation of the gradients and enacting an adversarial attack, or inserting trigger perturbations to execute a backdoor trigger attack.

**Evaluating between Gaussian Blur & Random Noise:** The takeaway is that if an attacker had the choice between obfuscating a target image, it is preferable to opt for perturbations that follow a random distribution rather than perturbations that vary with the source image. Considering seen images and varying areas (object v.s. scene), obfuscating with random noise in train-time tends to return sufficient random noise in inference-time to retain a high PSNR with respect to images obfuscated with the same method, comparatively higher than that if executed with Gaussian blur. Backdoored $G$ learns: (i) handling triggered inputs differently from clean inputs, (ii) obfuscating specific regions of the image (if object-specific), and (iii) manipulating the region of the image with a specific set of properties (if blur). Adding constraints (ii-iii) introduce additional barriers to inference-time obfuscation. Incremental training steps may be required to learn a Gaussian function that takes the image pixels as input and the approximate blur parameters.

**Limitations.** There are limitations to the current study that will be investigated in future work. There is no guarantee in the physical world that the backdoor trigger will present itself obligingly to align with that crafted digitally. The location and appearance of the trigger may vary (e.g. position of trigger, reflection of light, etc). [22] show that, while backdoor triggers can retain attack success to a certain extent for geometric (e.g. translation/shift) and colour transformation, the success rate falls with occlusive transformations. To robusterify backdoor attacks, attackers can introduce trigger transformations [18]. We did not evaluate multiple triggers being applied to multiple objects during training and inference, only applying a trigger to the most frequent object in the image. Though expected to work on a broad range of generative models, we only tested a single variant in a practical setting to demonstrate the concept of a self-obfuscation attack. Implementations on other architectures deserve to be explored.

## 5 Conclusion

We demonstrate the self-obfuscation attack in cyberphysical systems by carefully compromising specific architectural components. Given the involvement of generative models in image processing pipelines and user-contributed training samples, attackers could contribute triggered:obfuscated image pairs to render their target object self-obfuscated during inference. We would caution communities deploying such models in the wild to enforce architectural inspection. These include robustifying against backdoor triggers, regulating their training set collection and labelling, and robustifying the use of pre-processing models in the system.

| $t$ | $\text{PSNR}$ |
|-----|--------------|
|     | clean        |
|     | person       |
|     | backpack     |
|     | car          |
| **PSNR w.r.t. clean $x_H$** | 34.8 | 32.1 | 29.3 | 33.5 |
| Standard/Clean | 32.9 | 28.3 | 29.2 | 28.9 |
| **PSNR w.r.t. obfuscated $x'_H$** | 32.5 | 24.3 | 6.7 | 8.6 |
| Backdoor (object-specific, noise, unseen, $P = 0.4$) | 32.7 | 26.2 | 25.4 | 26.6 |
| Backdoor (object-specific, noise, seen, $P = 0.4$) | 33.7 | 28.2 | 26.7 | 27.9 |
| Backdoor (scene-specific, noise, seen, $P = 0.4$) | 31.2 | 27.7 | 19.4 | 21.9 |
| Backdoor (scene-specific, noise, unseen, $P = 0.4$) | 32.4 | 29.4 | 16.5 | 20.8 |
| Backdoor (scene-specific, noise, unseen, $P = 0.8$) | 32.5 | 30.7 | 21.4 | 26.5 |
| Backdoor (scene-specific, blur, seen, $P = 0.4$) | 33.4 | 22.1 | 16.2 | 18.5 |
| Backdoor (scene-specific, blur, seen, $P = 0.8$) | 33.4 | 24.5 | 19.5 | 22.6 |

**Table 1:** Variations in $\text{PSNR}$ (dB): Configuration parameters are passed as Backdoor(object/scene, noise/blur, seen/unseen, $P$).
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