

# ADVERSARIAL VISUAL ROBUSTNESS BY CAUSAL INTERVENTION

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## ABSTRACT

Adversarial training is the de facto most promising defense against adversarial examples. Yet, its passive nature inevitably prevents it from being immune to unknown attackers. To achieve a proactive defense, we need a more fundamental understanding of adversarial examples, beyond the popular bounded threat model. In this paper, we provide a causal viewpoint of adversarial vulnerability: the cause is the spurious correlation ubiquitously existing in learning, *i.e.*, the confounding effect, where attackers are precisely exploiting these effects. Therefore, a fundamental solution for adversarial robustness is by causal intervention. As these visual confounders are imperceptible in general, we propose to use the instrumental variable that achieves causal intervention without the need for confounder observation. We term our robust training method as Causal intervention by instrumental Variable (CiiV). It’s a causal regularization that 1) augments the image with multiple retinotopic centers and 2) encourages the model to learn causal features, rather than local confounding patterns, by favoring features linearly responding to spatial interpolations. Extensive experiments on a wide spectrum of attackers and settings applied in CIFAR-10, CIFAR-100, and mini-ImageNet demonstrate that CiiV is robust to adaptive attacks, including the recent AutoAttack. Besides, as a general causal regularization, it can be easily plugged into other methods to further boost the robustness. Codes are available in supplementary materials.

## 1 INTRODUCTION

Despite the remarkable progress achieved by Deep Neural Networks (DNNs), adversarial vulnerability (Goodfellow et al., 2015) keeps haunting the computer vision community since it has been spotted by Szegedy et al. (2013). Over the years, we have witnessed many defenders, who claim to be “well-rounded”, were soon found to lack fair benchmarking, *e.g.*, adaptive adversary (Croce & Hein, 2020b; Tramer et al., 2020b), or misconduct the attack, *e.g.*, obfuscated gradient (Athalye et al., 2018). Therefore, the most promising defender remains to be the intuitive Adversarial Training and its variants (Kannan et al., 2018; Cui et al., 2020). Due to the “training” nature, its adversarial robustness is largely dependent on the knowledge of attackers and whether the training set contains sufficient adversarial samples from various attackers as many as possible (Tramèr et al., 2018), yet, brute-forcefully enumerating all attackers is prohibitively expensive, making adversarial training mainly over-fitting to known attackers (Schott et al., 2019). What’s worse, in few-/zero-shot scenarios, it is even impossible to collect enough adversarial training samples based on the out-of-distribution/unseen samples (Zhang et al., 2019).

In other words, adversarial training is a “passive immunization”, which cannot react to the ever-evolving attacks responsively. To proactively achieve adversarial robustness, we have to find the “origin” of adversarial perturbations. Previous methods blame adversarial vulnerability on the inherent flaws in fitting models to the limited high-dimensional data (Goodfellow et al., 2015; Gilmer et al., 2018; Schmidt et al., 2018). However, simply regarding adversarial samples as “bugs” cannot explain their well-generalizing behaviors (Xie et al., 2020; Ilyas et al., 2019). Recent studies (Salman et al., 2020; Ilyas et al., 2019) show that adversarial examples are not “bugs” but *predictive* features that can only be exploited by machines. Such results urge us to investigate the essential difference between machines and humans.

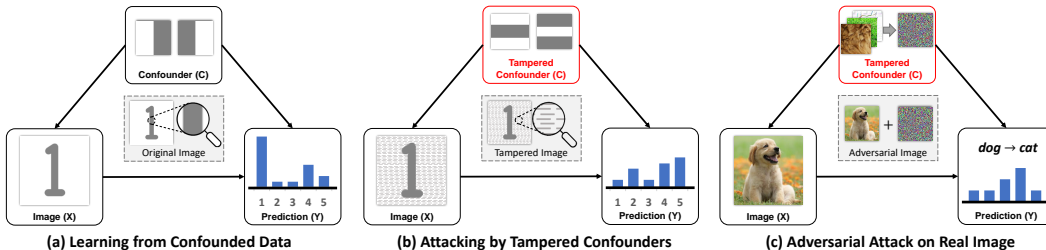


Figure 1: (a) A digit classifier confounded by counting edges. (b) Attacking the model through tampered confounders. (c) Constructing adversarial perturbations through an ensemble of tampered confounders, *e.g.*, local textures, small edges, and faint shadows.

However, we believe that it is too early for us to shirk responsibility and leave it to the ever-elusive open problem before we answer the following two key questions:

**Q1: What are the non-robust but predictive features?** Ilyas et al. (2019) use adversarial examples to distinguish the robust and non-robust features. However, this will only allow us to recognize the non-robust features as “adversarial perturbations” again, which is, unfortunately, circular reasoning. Therefore, we need a fundamental yet different angle to define the robustness of features beyond the conventional adversarial one.

**Q2: Why do complex systems (human vision) ignore these predictive features that simple systems (DNNs) can capture instead?** Given the fact that biological visions are more complex than machines in terms of both neuron amount (Herculano-Houzel, 2012) and diversity (Masland, 2001; Kim et al., 2020), there is no reason for human vision to extract “less feature” than machines. Therefore, there must be a mechanism in human vision that deliberately ignores these features.

In this paper, we answer the above two questions from a causal perspective (Pearl, 2009)—a powerful lens seeing through the generative nature of adversarial attacks. For **Q1**, we postulate that non-robust features are confounding effects, which are spurious correlations established by related but non-causal features. Take Figure 1 (a) as an intuitive example, where a large number of vertical edges co-occur with the digit “1”. As a result, a model trained by associating samples with labels will recklessly use the counting of vertical edges—the confounding effect—as the indicator of digit “1” without learning the overall causal structure. Therefore, once tampered edges are constructed, which is much easier than editing the entire digit directly, the confounding effect will mislead the model prediction as shown in Figure 1 (b).

In general, any pattern co-occurred with certain labels can constitute confounders. Most of them are even imperceptible, like local textures, small edges, and faint shadows. Since DNN models are based on the statistical association between input and output, they inevitably learn these spurious correlations, which are “predictive” when the distribution of confounders remains the same in training and testing. However, their brittle nature makes them vulnerable to small perturbations as shown in Figure 1 (c). In Section 3, we will provide a formal revisit for the adversarial attack in the causal viewpoint, where we also design a Confounded-Toy dataset to demonstrate how an adversarial attacker fools the model by exploiting the confounding effect.

Unlike machine vision that scans all the pixels in an image at once, human vision continuously perceives the image using “retinotopic sampling” (Arcaro et al., 2009) via non-uniformly distributed retinal photoreceptors at each time frame as shown in Figure 2 (a). We conjecture that such a mechanism is the answer to **Q2**, because it can be viewed as causal intervention by using instrumental variable (Greenland, 2000), denoted as  $R$  in Figure 2 (b). With the help of  $R$ , the confounded image observation  $X$  is no longer dictated only by the confounders. Since the choice of  $R$  is designed to be independent of  $C$ , as it only depends on the structure of retina, its direct effect on  $Y$  can thus be used to mitigate the confounding effect even though  $C$  is unobserved. Intuitively, non-robust confounder patterns are local impulses that won’t perform consistently across different retinotopic centers. They are either captured or not by a retinotopic observation. Meanwhile, causal features are consistent structures. Forcing a model to learn features that linearly vary with the change of  $R$  can suppress unstable confounding effects. To this end, in Section 5, we propose the Causal intervention by instrumental Variable (CiiV \si:v\ ) framework that combines a spatial data augmentation through retinotopic sampling with a consistency regularization loss as shown in Figure 2 (c).

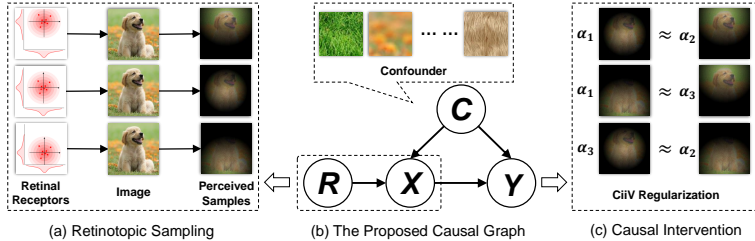


Figure 2: The proposed CiiV framework (detailed in Section 5): (a) the retinotopic augmentation that serves as the instrumental variable; (b) the proposed causal graph; (c) the causal intervention made by the proposed regularization that suppresses non-robust confounding effects.

Our key contributions are as follows:

- We introduce a causal regularization termed CiiV to suppress the learning of non-robust features in DNN models, which not only offers a proactive defender, but also opens a novel yet fundamental viewpoint of adversary research.
- Extensive experiments on a wide range of settings from the adversarial evaluation checklist (Carlini et al., 2019) in CIFAR-10, CIFAR-100, and mini-ImageNet demonstrate that CiiV can withstand adaptive attacks, including the state-of-the-art AutoAttack (Croce & Hein, 2020b).
- As a general regularization that is orthogonal to most of the previous defenders, the proposed CiiV can be easily plugged into other methods to further boost their adversarial robustness.

## 2 RELATED WORK

**Adversarial Examples.** Adversarial examples undermine the reliability and interpretability of DNN models in various domains (Wang et al., 2021; Qi et al., 2021; Finlayson et al., 2019; Xie et al., 2017; Xiang et al., 2019; Cisse et al., 2017; Carlini & Wagner, 2018; Huang et al., 2017) and settings (Diao et al., 2021; Moosavi-Dezfooli et al., 2016; Kurakin et al., 2016; Papernot et al., 2016; Carlini & Wagner, 2017; Zheng et al., 2019). Despite of various defenders proposed to improve the adversarial robustness, a universal remedy that can proactively defend against all the known and unknown attackers is still absent. Generally, the existing defenders fall into the following four categories: adversarial training (Szegedy et al., 2013; Wong et al., 2019; Dong et al., 2020), data augmentation (Zhang et al., 2018), de-noising (Buckman et al., 2018; Xie et al., 2019), and certified defense (Cohen et al., 2019). In Section 4 we will systematically revisit them and compare them to the proposed CiiV from a causal viewpoint.

**Causality in Adversarial Robustness.** Recently, causality has gradually been accepted as a potential way to explain adversarial robustness. Zhang et al. (2020b; 2021) provide a causal perspective to understand the adversarial vulnerability of DNN models; Yang et al. (2019) utilize the supervised pixel-wise masking to conduct causal intervention; Singh et al. (2021) attempt to unify the adversarial robustness with the distributional shift. However, the solutions they provided are either subject to additional supervisions, complicated causal graph and training strategies, or parallel to the existing adversarial training variants. Meanwhile, this paper provides a more feasible causal explanation for the adversarial vulnerability, by which we can design an effective plug-and-play causal regularization.

**Causal Graph and Intervention.** Pearl’s graphical model (Pearl et al., 2016) is adopted in this paper, where directed edges indicate the causality between node variables. The causal graph of the proposed CiiV framework is illustrated in Figure 2 (b), where  $R, C, X, Y$  indicate retinotopic sampling mask, confounding pattern, image, and prediction, respectively.  $X \leftarrow C \rightarrow Y$  denotes that confounder  $C$  is a common cause, affecting the distribution of both  $X$  and  $Y$ , e.g., the edge in Figure 1 (a).  $X \rightarrow Y$  denotes the desired causality that a robust model is expected to learn. To achieve that, the ultimate goal of causal intervention is to identify the causal effect of  $X \rightarrow Y$  by removing all spurious correlations (Pearl & Mackenzie, 2018), denoted as  $P(Y|do(X = x))$ . It can be either implemented as active intervention, like the randomized controlled trial, or passive  $d$ -separation (Roy, 2020; Pearl et al., 2016), by which observing the confounder can block the spurious path, e.g., by conditioning on  $C$ , the dependency of path  $X \leftarrow C \rightarrow Y$  is blocked.

### 3 A CAUSAL VIEW ON ADVERSARIAL ATTACK

In causality (Pearl et al., 2016), the total effect and causal effect of a predictive model based on the input  $X$  can be defined as  $P(Y|X)$ ,  $P(Y|do(X = x))$ , respectively. Given the proposed causal graph in Figure 1, the confounding path  $X \leftarrow C \rightarrow Y$  causes the inequality between the above two, and thus the confounding effect can be represented as their difference.

Meanwhile, the general adversarial attack can be formulated as maximizing the probability of a tampered category  $Y = \hat{y}$  within the budget  $\mathcal{D}_\epsilon$  (Ren et al., 2020), denoted as follows:

$$\max_{\delta \in \mathcal{D}_\epsilon} P(Y = \hat{y}|X = x + \delta) \propto \sum_i \hat{y}_i \log(p_i), \quad (1)$$

where  $\hat{y} = y'$  ( $y' \neq y$ ) for targeted attack,  $\hat{y} = -y$  for untargeted attack;  $\hat{y}_i$  and  $p_i$  are  $i$ -th entries of  $\hat{y}$  and prediction  $p$ , respectively;  $\delta$  is the additive perturbation; budget  $\mathcal{D}_\epsilon$  is usually considered as an enclosing ball under  $l_2/l_\infty$  norm within radius  $\epsilon$  (Zheng et al., 2019; Kurakin et al., 2016).

Notably, a valid  $\mathcal{D}_\epsilon$  is not allowed to change the semantic structures, as they are designed to be imperceptible, *i.e.*, the causal effect  $P(Y|do(X = x))$  is invariant to  $\delta$ . Otherwise, the perturbation would become a ‘‘poisoning’’ that is beyond our scope (Tramer et al., 2020a). Therefore, equation 1 essentially equals to maximize a tampered confounding effect through perturbations:  $\max_\delta P(Y = \hat{y}|X = x + \delta) - P(Y = \hat{y}|do(X = x + \delta))$ , *subject to*  $P(Y = \hat{y}|do(X = x + \delta)) = P(Y = \hat{y}|do(X = x))$ , which applies to all kinds of attacks (Goodfellow et al., 2015; Madry et al., 2018; Brendel et al., 2018; Chen et al., 2017; Kurakin et al., 2016).

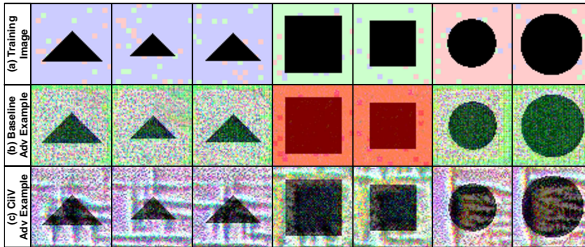


Figure 3: (a) A Confounded-Toy Dataset with images that are composed of causal geometries and confounding color blocks. The adversarial examples generated by the model (c) w/ and (b) w/o the proposed CiiV.

To intuitively demonstrate the above causal theories, we design a Confounded-Toy dataset as shown in Figure 3 (a), where images are composed of causal geometries and confounding color blocks. Similar to our example in Figure 1, a model directly trained on this dataset will recklessly learn the stochastic color block  $C$  that shows statistical correlation with the category as the indicator of  $Y$ . As a result, adversarial examples generated by a PGD attacker on this model mainly tamper the confounding patterns (Figure 3 (b)). In contrast, the proposed CiiV regularization forces the model to learn causal features instead, so it can only be fooled by poisoning the geometry (Figure 3 (c)). More details of this Confounded-Toy dataset will be introduced in Appendix A.

### 4 A CAUSAL VIEW ON ADVERSARIAL DEFENSE

It has been acknowledged that directly adjusting an unknown confounder  $C$  for  $P(Y|do(X = x))$  without any assumption is impractical in causality field (D’Amour, 2019). Due to the fact that adversarial examples are governed by unobserved confounding effects, most of the existing defending methods have to either intuitively assume a generative noise  $\epsilon$  to be the underline  $C$  or assume  $C$  to be certain identifiable noisy features that can be explicitly purified.

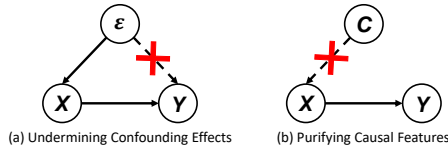


Figure 4: Two common strategies to increase the adversarial robustness.

Specifically, adversarial training and its variants (Szegedy et al., 2013; Wong et al., 2019; Dong et al., 2020) together with some certified defenders like randomized smoothing (Cohen et al., 2019) design some additive noises  $\epsilon$  to imitate adversarial perturbations, then undermine the confounding effect by asking the model to be robust against  $\epsilon$ . On the other hand, the de-noising approaches, no matter the pre-network de-noising (Xie et al., 2018; Samangouei et al., 2018; Buckman et al., 2018) or the in-network de-noising (Li et al., 2020; Xie et al., 2019) consider confounders to be explicitly removable

patterns. Therefore, these common strategies can be summarized by two graphical operations as shown in Figure 4.

However, we can neither guarantee the  $C$  to be equal to  $\varepsilon$ , nor ensure all possible  $C$  to be disentangled and purified. Relying on the observation of such assumptive  $C$  will at best make the above defenders robust against a subset of potential confounders.

Among all existing defenders, mixup (Zhang et al., 2018) is most related to the proposed CiiV. It intervenes an image  $x_i$  by linearly fusing with another image  $x_j$ , then forces the prediction  $Y$  similar to the same combination of their one-hot labels. Yet, a valid instrumental variable is required to be independent of the confounder as we will introduce in the next section. Unfortunately, a new image  $x_j$  can still depend on the same confounder of  $x_i$ . Recent studies (Moosavi-Dezfooli et al., 2017; Zhang et al., 2020a) found that universal adversarial perturbations across images also exist, which explains why mixup cannot survive strong attackers.

## 5 APPROACH

After connecting the adversarial vulnerability to the confounding effect learned by DNN models, the remaining question is how to obtain the pure causal effect, which is equivalent to applying causal intervention  $P(Y|do(X = x))$  on the deep learning. Generally, there are four major interventions: randomized controlled trial, backdoor adjustment, front-door adjustment, and instrumental variable estimation. However, the randomized controlled trial requires the control over causal features, the backdoor and front-door adjustments assume confounders or mediators to be observed, which are impractical for imperceptible adversarial perturbations. Therefore, we are interested in the last instrumental variable estimation that does not require such assumptions.

### 5.1 INSTRUMENTAL VARIABLE ESTIMATION

According to the definition (Baiocchi et al., 2014; Guo & Small, 2016), a valid instrumental variable should satisfy: 1) it is independent of the confounder variable; 2) it affects  $Y$  only through  $X$ . The instrumental variable can help to extract the causal effect of  $X \rightarrow Y$  from  $R \rightarrow X \rightarrow Y$ , which is not confounded by  $C$  ( $d$ -separated).

To better demonstrate the use of the instrumental variable (Bowden & Turkington, 1990), we design two linear confounded models w/ and w/o the instrumental variable as shown in Figure 5. All variables are assumed to be linked by linear weights  $w_*$ . The confounder is an independent variable sampled from a normal distribution:  $C \sim \mathcal{N}(0, 1)$ . The total effect and causal effect of  $X \rightarrow Y$  can be represented as  $Y[X = x] = w_{xy}x + w_{cy}c$  and  $Y[do(X = x)] = w_{xy}x$ , respectively. Note that we slightly abuse the notation of normalized effects  $P(Y|X)$  and  $P(Y|do(X = x))$ , and use the form of unnormalized logits for simplicity.

In the given confounded model of Figure 5 (a), since  $X$  is dependent on the confounder  $C$  as  $x = w_{cx}c + b_x$ , where  $b_x$  is the independent component of  $X$ , we cannot directly estimate the causal effect  $Y[do(X = x)]$  by simply applying linear regression on  $(x, y)$  pairs.

If  $C$  is observable, the causal intervention could be conducted using the backdoor adjustment:  $P(y|do(x)) = \sum_c P(y|x, c)P(c)$ . The causal effect is thus estimated from the total effect by the observed  $c$  and its distribution:

$$Y[do(X = x)] = w_{xy}x + w_{cy} \sum_c c \cdot P(c) = w_{xy}x, \quad (2)$$

where the confounding effect degrades to a constant as  $\sum_c c \cdot P(c) = 0$ .

However, if  $C$  is unobservable, both backdoor adjustment and the causal graph in Figure 5 (a) cannot remove the confounding effect. To this end, the instrumental variable  $R$  is introduced as shown in Figure 5 (b), where  $X$  is now manipulated by both  $C$  and  $R$  as  $x = w_{cx}c + w_{rx}r + b_x$ . Due to

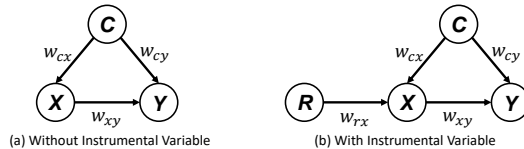


Figure 5: The causal graphs w/ and w/o the instrumental variable. Nodes are assumed to be linked through linear associations  $w_*$ .

the fact that  $R$  is independent of  $C$ , the weight of causal link  $X \rightarrow Y$  can be learned by applying different  $r$  onto  $(x, y)$  pairs, *i.e.*,  $y_{r_i} - y_{r_j} = w_{xy}(x_{r_i} - x_{r_j})$ . The causal effect is thus estimated as follows:

$$Y[do(X = x)] = \frac{y_{r_i} - y_{r_j}}{x_{r_i} - x_{r_j}}x = w_{xy}x, \quad (3)$$

where subscripts  $r_i \neq r_j$  indicate the value of  $X$  and  $Y$  under different instrumental variable  $R$ . The  $d$ -separated of  $R \rightarrow X \leftarrow C$  ensures the subtraction eliminating the confounding effect during training.

## 5.2 THE PROPOSED CiiV

With the help of instrumental variable  $R$ , the causal effect of the above linear example can be easily estimated. Yet, in practice, the effect of additive  $R$  on an image is just as incomprehensible as the additive perturbation  $C$ , which doesn't introduce any useful inductive bias. Besides, the above subtraction is also hard to converge during backpropagation, as it may generate confusing gradients with opposite directions of  $y_{r_i}$  and  $y_{r_j}$ .

In the proposed CiiV framework, we consider the retinotopic sampling mask as a multiplying instrumental variable and use it to augment the original dataset like Figure 6. Inspired by the human vision, the retina is known to consist of photoreceptors and a variety of other neurons (Reddy et al., 2020). Retinotopic sampling is the result of the non-uniformly spatial distribution of these receptors (Kolb et al., 1995; Arcaro et al., 2009), where the central fovea is significantly denser than the peripheral. It means that human vision is spatially lopsided by a centralized mask, which inspires us to adopt the retinotopic sampling mask with different centers as the instrumental variable  $R$ . Luckily, it also satisfies the requirements of a valid instrumental variable discussed in Section 5.1: 1) the pre-defined retinotopic mask is guaranteed to be independent of any confounder in an image; 2) its effect on the prediction  $Y$  can only pass through the change of causal features, as the non-robust confounders won't manifest stable patterns under different  $R$ . More detailed motivations behind the proposed CiiV will be discussed in Appendix B.

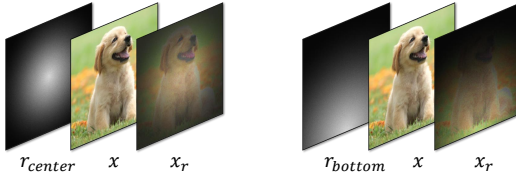


Figure 6: Examples of retinotopic sampling and how it serves as the instrumental variable.

Therefore, we adopt the multiplying retinotopic mask as our instrumental variable  $R$  and design  $R \rightarrow X$  to be an augmentation function on image  $x_r = f(x, r)$ , where  $f(\cdot)$  applies different retinotopic sampling masks  $r$  onto the confounded image  $x$ . The function is implemented as a differentiable multiplication layer and proved not to suffer from gradient obfuscation (Athalye et al., 2018) in Section 6. Detailed designs and experiments of  $f(x, r)$  are investigated in Appendix C.

Intuitively, when an object moves from the corner of our eyes to the center, the recognizability monotonously increases with the proportion of its captured contour, so we assume that the causal effect is linearly corresponding to the spatial coverage  $\alpha_r$  of a retinotopic mask  $r$  while the confounding effect is not. It is also consistent with previous findings (Du et al., 2020) that visual confounders are usually high-frequency local components unevenly distributed in space. The relationship between the total effect and causal effect can thus be written as follows:

$$Y[X = x_r] = w_{xy}x_r + w_{cy}c \approx \alpha_r Y[do(X = x)] + w_{cy}c. \quad (4)$$

Note that we don't need to explicitly observe the above  $c$ . We can directly model the  $Y[do(X = x)]$  by assigning different  $r$  instead. The trick lies in the proposed CiiV regularization loss as follows:

$$L_{CiiV} = \sum_{r_i \neq r_j} \|\alpha_{r_j} Y[X = x_{r_i}] - \alpha_{r_i} Y[X = x_{r_j}]\|, \quad (5)$$

where  $r_i$  and  $r_j$  are two retinotopic sampling masks with spatial coverage  $\alpha_{r_i}$  and  $\alpha_{r_j}$ , just like  $r_{center}$  and  $r_{bottom}$  in Figure 6. Since  $w_{cy}c$  is independent of  $r$ , the above regularization can thus force the model to suppress the confounding effect. In practice, we implement CiiV as an  $L_1$  loss on the feature space extracted by the backbone rather than the logit space, as the classifier weights can be taken out of the above regularization. Otherwise, the  $L_{CiiV}$  could hurt the learning of the classifier. The overall training loss would be the combination of the conventional cross-entropy loss and the proposed CiiV loss with a trade-off parameter as  $L_{All} = L_{CE} + \beta L_{CiiV}$ .

Datasets	CIFAR-10						CIFAR-100					
	Clean	FGSM	PGD-10	AA- $l_\infty$	AA- $l_2$	Overall	Clean	FGSM	PGD-10	AA- $l_\infty$	AA- $l_2$	Overall
Baseline	94.42	30.82	0.04	0.0	0.0	25.06	74.53	4.21	0.0	0.0	0.0	15.75
mixup	<b>95.31</b>	50.41	2.23	0.0	0.0	29.59	<b>77.32</b>	16.60	0.49	0.0	0.0	18.88
BPFC	90.21	24.58	6.19	2.92	35.55	31.89	61.48	17.00	10.23	7.17	29.16	25.01
RS	83.44	53.58	47.06	40.10	75.02	59.84	54.63	26.62	20.21	18.50	47.26	33.44
(ours) CiiV	86.89	64.44	50.75	43.23	82.48	65.56	58.88	32.48	23.63	23.05	55.40	38.69
(ours) CiiV+mixup	87.14	65.28	53.49	<b>47.24</b>	81.97	67.02	56.90	35.48	<b>27.56</b>	<b>26.44</b>	53.14	39.90
(ours) CiiV+RandAug	89.12	<b>67.96</b>	<b>55.01</b>	47.14	<b>83.77</b>	<b>68.60</b>	59.26	<b>36.10</b>	26.25	25.59	<b>55.81</b>	<b>40.60</b>
AT <sub>FGSM</sub>	<b>84.52</b>	54.42	43.84	37.94	60.20	56.18	51.99	26.27	22.54	18.31	31.06	30.03
AT <sub>PGD-10</sub>	83.94	52.90	47.19	43.18	55.46	56.53	<b>56.48</b>	25.99	22.56	20.04	28.96	30.81
(ours) CiiV+AT <sub>FGSM</sub>	83.67	67.28	57.96	50.93	<b>80.09</b>	67.99	53.83	<b>39.00</b>	32.20	30.48	<b>50.47</b>	<b>41.20</b>
(ours) CiiV+AT <sub>PGD-10</sub>	81.35	<b>68.11</b>	<b>59.72</b>	<b>54.21</b>	78.97	<b>68.47</b>	51.73	38.59	<b>33.85</b>	<b>32.01</b>	49.39	41.11

Table 1: The performances of white-box attack on CIFAR-10 and CIFAR-100. The upper half contains the AT-free defenders while the bottom half reports the AT-involved defenders.

## 6 EXPERIMENTS

### 6.1 DATASETS AND SETTINGS

**Datasets.** We evaluated the proposed CiiV and other defenders on three benchmark datasets: CIFAR-10, CIFAR-100, and mini-ImageNet (Vinyals et al., 2016). Both CIFAR-10 and CIFAR-100 contain 60K samples with the size of 32x32. mini-ImageNet is originally proposed by Vinyals et al. (2016) for few-shot recognition, which consists of 100 classes and each has 600 images. We scaled the size of images to be 64x64 and split them into train/val/test sets with 42k/6k/12k images.

**Training Details.** We followed Pang et al. (2021)’s project to set all the hyper-parameters and architectures. All models were trained using the SGD optimizer with 0.9 momentum and 5e-4 weight decay. Experiments were conducted on GTX 2080ti GPUs with 128 batch size and 110 total epochs. The learning rate was started with 0.1 and updated by the factor of 0.1 at the following epochs {10, 100, 105}. The trade-off parameter  $\beta$  was also initialized by 0.1 then multiplied by 10 at epochs {25, 50, 75}. Nine retinotopic centers were selected by using the 1/6, 1/2, and 5/6 of width and height for each image. ResNet18 (He et al., 2016) was utilized as the default backbone.

**Details of Threat Models.** We mainly evaluated the defenders on the clean images together with four threat models: FGSM (Goodfellow et al., 2015), PGD-10 (Madry et al., 2018), AA- $l_\infty$  (AutoAttack  $l_\infty$ ), and AA- $l_2$  (AutoAttack  $l_2$ ) (Croce & Hein, 2020b). For FGSM and PGD-10, the adversarial perturbations were created under  $l_\infty$  norm, where the budget radius  $\epsilon$  was 8/255. PGD-10 ran 10 iterations with step size 2/255. AutoAttack is a recently released parameter-free attack that achieves the state-of-the-art attacking success rate under various defenders. It also prevents the model from gaining a false sense of security from the obfuscated gradients (Athalye et al., 2018). We set the only parameter  $\epsilon$  of AA- $l_\infty$  and AA- $l_2$  to be 8/255 and 0.5, respectively.

**Details of Defenders.** We divided the defenders into Adversarial Training (AT-involved) and AT-free approaches. For AT-involved, we adopted two popular defenders: AT<sub>FGSM</sub>, AT<sub>PGD-10</sub>, using the same parameters as the corresponding threat models. For AT-free methods, we investigated mixup (Zhang et al., 2018), BPFC (Addepalli et al., 2020), and randomized smoothing (RS) (Cohen et al., 2019). The implementations of mixup and BPFC were directly adopted from their official github repositories. RS was re-implemented in our framework with  $\sigma = 0.25$  and the number of test trials  $n = 10$ . The proposed CiiV itself is also an AT-free method. As a general regularization that is parallel to the above algorithms, we investigated its combination with other defenders as well.

### 6.2 DIAGNOSIS OF ADVERSARIAL ROBUSTNESS

The evaluation of adversarial robustness is always controversial as it can easily suffer from flawed or incomplete attack settings. To better eliminate the potential wrong sense of security, we followed

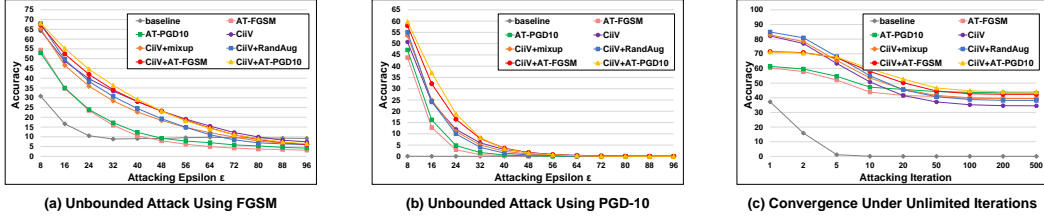


Figure 7: (a, b) Unbounded attacks on CIFAR-10 that increase the budget  $\epsilon$  from 8/255 to 96/255. (c) The convergence of defenders under unlimited attacking iterations using PGD.

Carlini et al. (2019) to design our experiments and conduct a series of sanity checks at the end of this section.

**Adversarial Robustness Against White-box Attack.** As reported in Table 1 and Table 2, we applied multiple white-box attacks on all three datasets. The proposed CiiV and its variants achieved better overall performances among both AT-free and AT-involved divisions. Note that Random Augmentation (RandAug) (Cubuk et al., 2020) is not an adversarial defending method, whose overall performances on three datasets were just 24.38, 16.03, and 15.22, respectively. However, combining CiiV with RandAug

worked as well as combining CiiV with AT methods, especially in the real-world mini-ImageNet. It proves that CiiV is indeed a proactive defender that doesn't rely on observing confounders. We also found that AT methods made the model significantly overfit the given attacker in all datasets. Besides, when replacing the training samples of CiiV with AT examples, *i.e.*, CiiV+AT, the robustness came with the price of decreasing clean performances. However, augmenting CiiV with other AT-free methods like mixup and RandAug improved both clean and adversarial performances, which further supported our efforts to design a proactive AT-free defender.

**Adversarial Robustness Against AutoAttack.** The state-of-the-art AutoAttack is an ensemble of diverse parameter-free attacks (Croce & Hein, 2020b), including their proposed APGD-CE and APGD-DLR, the black-box Square Attack (Andriushchenko et al., 2020), and the FAB attack (Croce & Hein, 2020a) that is robust to obfuscated gradients (Athalye et al., 2018). According to our experiments on AA- $l_\infty$  and AA- $l_2$ , the proposed CiiV performed effectively on all of the above user-independent attacks. Moreover, combining CiiV with other defenders can further improve their adversarial robustness on both AA settings, proving that the CiiV is a general causal regularization parallel to most of the previous methods.

**Adversarial Robustness Against Targeted Attack.** The performances of the proposed CiiV under untargeted and targeted PGD-10 attacks were reported in Table 3 using CIFAR-10 dataset. The targeted results were further divided into three protocols: 1) most likely category, 2) least likely category, and 3) random category. The results revealed that the confounding effect could also be the cause of ambiguous prediction, as similar categories are easier to be attacked. We also noticed that the performances under untargeted attack would be closer to the most likely targeted attack when the robustness of the model increases. It's probably because the similar categories share the similar confounder distributions, *i.e.*, environments, and thus utilized by the attacker.

**Adversarial Robustness Under Unbounded Attack.** To evaluate the validity of defenders, we demonstrated the performances of CiiV and its variants together with the baseline and two AT models under unbounded attacking in Figure 7 (a, b). When the budget  $\epsilon$  of the attacker was increased from 8/255 to 96/255, all performances were either converged to 0% accuracy for the strong PGD attack or converged to the random guesses for the weak FGSM attack. Any valid defender shouldn't survive such an unbounded attack, as it allows the attacker to modify the entire image and erasing all causal features. We also tested unlimited iterations of PGD attack, all CiiV and its variants are successfully converged after 100 iterations as shown in Figure 7 (c). Note that AT and CiiV+AT

Table 3: The performances of targeted PGD-10 under four different targeting settings: untargeted (UT), targeted by most likely / random / least likely categories (T-most, T-random, T-least).

Datasets	CIFAR-10				
	Settings	UT	T-most	T-random	T-least
CiiV		50.75	55.62	71.05	74.37
CiiV+mixup		53.49	55.87	73.64	78.48
CiiV+RandAug		55.01	59.18	74.70	77.79
CiiV+AT <sub>FGSM</sub>		57.96	59.44	74.31	77.77
CiiV+AT <sub>PGD-10</sub>		59.72	60.46	75.21	78.42



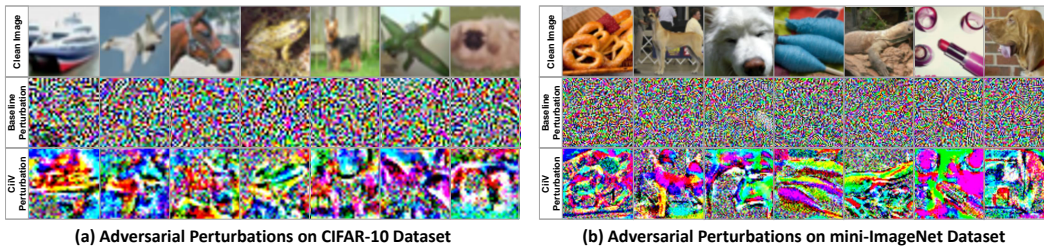


Figure 8: Generated perturbations of models w/ and w/o CiiV on CIFAR-10 and mini-ImageNet.

are more robust than other defenders in this setting, which is probably caused by the exposure of adversarial examples during training.

**Ablation Studies.** In this paragraph, we evaluated the effectiveness of different settings and parameters of the proposed CiiV. As reported in Table 4, 1) we investigated the  $L_1$  and  $L_2$  versions of the CiiV loss, where the  $L_1$  is slightly better than  $L_2$ ; 2) we tried random assignments of the retinotopic centers as  $R=\{r_{rand}\}$ , which is very close to

Table 4: Ablation Studies of CiiV on CIFAR-100.

Datasets	CIFAR-100					Overall
	Clean	FGSM	PGD-10	AA- $l_\infty$	AA- $l_2$	
$L_1$ CiiV	58.88	32.48	23.63	23.05	55.40	38.69
$L_2$ CiiV	57.93	31.78	22.27	22.28	54.51	37.75
$R=\{r_{rand}\}$	58.79	32.20	22.35	22.90	55.28	38.30
RetiAug	61.88	31.69	20.29	18.32	53.19	37.07
$\beta = 0.01$	59.85	32.00	21.52	20.85	54.23	37.69
$\beta = 1.0$	55.26	34.48	26.80	25.02	51.82	38.68
$N_R = 2$	56.45	30.47	21.57	21.03	53.39	36.58
$N_R = 5$	58.34	32.01	22.34	22.61	54.58	37.98

our fixed centers; 3) we also reported the performances of retinotopic augmentation only as RetiAug, which had higher clean performance but worse adversarial robustness than CiiV. Note that RetiAug itself can also be treated as an approximation of CiiV by assigning all  $\alpha$  to 1.0. Besides, cross-entropy losses under different  $r$  also forced the model to ignore the non-robust confounding patterns; 4) other choices of hyper-parameters of CiiV were also reported, we found that  $\beta$  empirically served as a trade-off between clean performance and adversarial robustness, and applying more retinotopic sampling masks (larger  $N_R$ ) would make a better estimation, yet, its improvements got converged. Additional studies and experiments will be given in Appendix.

**Visualization.** We visualized the generated PGD perturbations for models w/ and w/o CiiV in Figure 8. It demonstrates that the baseline models can be easily fooled by imperceptible confounders while the proposed CiiV forces the model to learn causal features, as the adversarial perturbations have to erase the structural patterns to fool the CiiV model.

**The Evaluation Checklist.** To verify that the proposed CiiV doesn't suffer from flawed or incomplete evaluations, the above experiments were designed to follow a series of sanity checks introduced by Carlini et al. (2019): 1) Iterative attacks are better than single-step attacks, *e.g.*, PGD vs FGSM in Table 1&2 and Figure 7. 2) Unbounded adversarial examples become random guessing or 0% accuracy, *e.g.*, Figure 7 (a,b). 3) The accuracy converges with the increasing of attack steps: Figure 7 (c). 4) Investigating both targeted attacks and untargeted attacks, *e.g.*, Table 3. 5) Using black-box attacks and the attacks circumventing obfuscated gradients to avoid the potentially flawed adversarial example generation, *e.g.*, the results under AA- $l_\infty$  and AA- $l_2$  in Table 1&2.

## 7 CONCLUSION

In this paper, we presented a CiiV defender that worked as a general causal regularization without the need for adversarial examples. CiiV consists of a spatial data augmentation using different retinotopic sampling masks, and a regularization loss that encourages the model to suppress local confounding patterns by learning features linearly responding to spatial interpolations. We followed the checklist from Carlini et al. (2019) to design our evaluation experiments and adopted the user-independent AutoAttack (Croce & Hein, 2020b) as the main indicator of adversarial robustness. Extensive experiments on all settings proved that CiiV is robust against various adaptive attacks, and it can also serve as a plug-and-play regularization for other defenders. Besides, this paper also provides a fundamental viewpoint of the relationship between adversarial robustness and causal intervention, which may guide the design of future defenders

## ETHICS STATEMENT

Due to the fact that deep learning algorithms have been widely deployed in the present recommendation system, person identification system, and automatic/assist driving system, the potential ethical problems are also growing. The adversarial robustness field studied by this paper is one of the core efforts to address these concerns. Without the adversarial robustness, the DNN-based computer vision systems are vulnerable to imperceptible noises, which threatens the safety of human life and property. Specifically, recent studies of physical-based attacks have proved that simply wearing specially designed clothes can fool an artificial recognition system. The increasing traffic accident caused by driver-assistance systems further confirms the above concerns. Therefore, we provide a general causal regularization that could easily be plugged into most of the current adversarial defending methods to further boost the robustness of the system, which may significantly reduce the chance of failure recognition caused by adversarial perturbations.

## REPRODUCIBILITY STATEMENT

In the past decades, the open-source movement of the machine learning community has greatly promoted the development of related fields. To ensure the reproducibility of the proposed method, we are going to publish our codes on the github. The anonymous version of our entire project is also available in supplementary materials. More detailed instructions and explanations of our codes will be added to the project before releasing to the public. All datasets used in this paper are also publicly available and can be easily found via torchvision package or other public github repositories.

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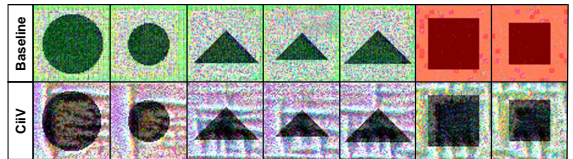
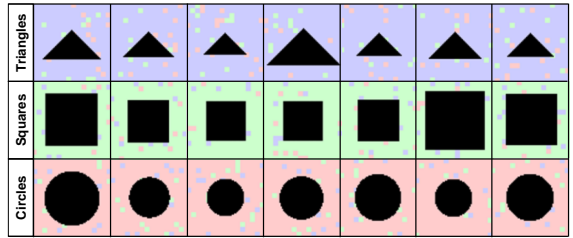
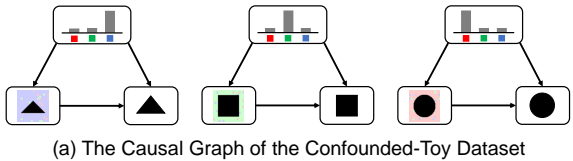
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## A DETAILS OF THE CONFOUNDED-TOY DATASET

In section 3 of the original paper, we introduced a Confounded Toy (CToy) dataset to demonstrate the equivalence between the confounding effect and the adversarial perturbation. The proposed CToy is a three-way classification, containing triangles, squares, and circles. It has 10k/1k/1k images for train/val/test split, respectively. All samples are 64x64 colour images. Except for the causal geometries, there are also confounding patterns, *i.e.*, red/blue/green blocks, with the size of 4x4 pixels. Different from the deterministic geometry, the color of each block is sampled from a biased distribution. For triangle, square, and circle images, each co-occurred block has 80%/10%/10%, 10%/80%/10%, and 10%/10%/80% probability to be blue/green/red, respectively. Therefore, if the confounding distribution stays the same in both training and testing phases, these patterns are indeed “predictive” features. Yet, learning these confounding patterns would significantly reduce the generalization ability of the model, because there will always be samples that are dominated by rare color blocks, and they are also more brittle than geometry structures. The causal graph of the data generation procedure and more examples of CToy dataset are illustrated in Figure 9 (a,b).



(c) More Adversarial Examples on the Confounded-Toy Dataset

Figure 9: (a) The causal graph of the Confounded-Toy dataset. (b) More examples of the proposed Confounded-Toy dataset. (c) More adversarial examples from the baseline model and CiiV counterpart.

Based on the specifically designed CToy that only contains two patterns, causal shapes and confounding colors, we are able to understand which pattern causes the adversarial vulnerability. As we can see from Figure 9 (c), adversarial examples of an  $L_\infty$  PGD attack ( $\epsilon$  is set to 128/255 for 100% attacking success rate, so we can understand which pattern can successfully fool the model) that generated from a baseline DNN model were mainly erasing the original color blocks, *i.e.*, the adversarial perturbation is indeed trying to maximize the tampered confounding effect. Specifically, the attacker changed the blue and red blocks in triangle and circle images to the green points. It even painted the entire square images to red. The confounding patterns were obviously tampered in these images while the causal geometries barely changed. On the other hand, the adversarial examples of the proposed CiiV model didn’t change the overall colors too much, they directly modified the shapes. It proves that CiiV successfully prevents the model from learning confounding effects, and thus attacker can only poison the causal geometries.

With the help of the CToy dataset, we are not only able to verify the proposed confounding theories for adversarial examples but also visualize the working mechanisms of the proposed CiiV framework, *i.e.*, forcing the model to learn from causal patterns rather than the confounding colors.

## B DETAILS OF THE PROPOSED CAUSAL GRAPH

In this paper, we firstly attribute the cause of non-robust features, which were originally introduced by Ilyas et al. (2019) as an explanation of adversarial examples, to the ubiquitous confounding effect. But how do confounding patterns affect the learning of causal features and thus hurt the adversarial robustness? We believe the answer is the failure of feature disentanglement (Yang et al., 2021; Higgins et al., 2017). As shown in Figure 10, a real-world image is usually composed of both concepts and contexts. Since those contexts often show statistical correlations with the causal concept, it’s difficult to disentangle the concept from the context through pure observational data,

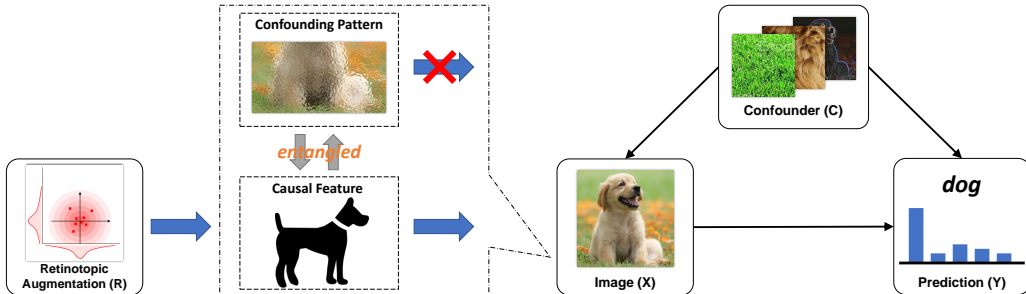


Figure 10: The details of the proposed causal graph for CiiV regularization and how confounding patterns cause the adversarial vulnerability.

*e.g.*, the grass feature is usually co-occurred with the dog concept, but it’s also shared by other outdoor images and absent in indoor dog images, so it’s not a valid causal feature. Due to the unsuccessful feature disentanglement, adversarial perturbations that simply modify the grass texture would also lead to the collapse of dog feature, which eventually fool the predictor.

However, the feature disentanglement (Yang et al., 2021; Higgins et al., 2017) *per se* is still an open question in machine learning. Otherwise, we only need to simply disentangle the robust and non-robust features then learn a classifier based on robust features. To tackle the adversarial vulnerability in practice, we need to bypass the trap of confounder disentanglement and seek help from the causal intervention without confounder observation, *i.e.*, the instrumental variable estimation. As we introduced in section 5, there are two requirements for the choice of instrumental variable. The independence of  $R$  can be directly guaranteed by the manual design of retinotopic sampling masks. To satisfy the second requirement that the effect of instrumental variable  $R$  on  $Y$  can only pass through the causal link  $X \rightarrow Y$ , we assume that causal features are global structures that change consistently across different retinotopic masks while the adversarial patterns are local impulses (Du et al., 2020) that simply collapse after applying different retinotopic sampling. Note that this assumption limited the scope of our  $C$  to those fragile confounding patterns, which is not trying to disentangle the semantically meaningful confounders. Fortunately, those semantically meaningful confounders brought by the unbalanced dataset also won’t be utilized as adversarial perturbations, *e.g.*, the keyboard is usually co-occurred with the monitor and becomes a confounder of the latter, but the adversarial attack is obviously not allowed to create or erase a keyboard for the monitor image based on its definition. Therefore, our assumption still guarantees the proposed retinotopic sampling to be a valid instrumental variable in the adversarial robustness task.

## C DETAILS OF THE RETINOTOPIC AUGMENTATION

In this section, we will introduce the detailed implementation of retinotopic augmentation and the selection of its hyper-parameters. The proposed retinotopic augmentation layer  $x_r = f(x, r)$  applies a centralized mask  $r$  onto the image  $x$ , which imitates the biological retina that the central fovea has significantly denser photoreceptors than the periphery. The mask  $r$  is generated by a non-uniform spatial sampling, whose sampling probability decreases from a given center to the peripheries. We conjecture that human vision benefits from the visual attention and continuous eye movement (Land, 2019) to implicitly apply diverse  $r$  as the instrumental variable estimation. Intuitively, such a conjecture also explains why human can increase the recognition accuracy by continually gazing at different positions of an object, and why attention or focusing is so important in recognition.

To conduct instrumental variable estimation, we adopt 9 sampling centers  $(x, y)$  to generate different  $r$ . As illustrated in Figure 11 (a), they are  $(w/6, h/6)$ ,  $(w/6, h/2)$ ,  $(w/6, 5h/6)$ ,  $(w/2, h/6)$ ,  $(w/2, h/2)$ ,  $(w/2, 5h/6)$ ,  $(5w/6, h/6)$ ,  $(5w/6, h/2)$  and  $(5w/6, 5h/6)$ , where  $w$  and  $h$  are the width and height of each corresponding image. Note that the fixed retinotopic centers are only used to ensure the diversity of selected candidates, simply choosing 9 random centers could obtain very similar performances as shown in Table 4. Given the retinotopic center  $(x, y)$ , we define the retinotopic sampling mask  $r$  as follows:

$$r_{ij}(x, y) = g(\|(i, j) - (x, y)\|_2) + \varepsilon > \tau, \quad (6)$$



where  $i \in [0, w], j \in [0, h]$  are the indexes of image pixels,  $g(\cdot)$  is a non-linear mapping that can be implemented by various functions,  $\varepsilon$  is uniformly sampled from  $[0, 1]$ ,  $\tau = 0.9$  is the sampling threshold. The spatial coverage  $\alpha_r$  used in CiiV is defined as the coverage of the retinotopic mask  $\sum r_{ij}/(w * h)$ .

Note that the non-linear smoothing function  $g(\cdot)$  of  $r(x, y)$  can take various implementations, which won't affect the performances of the proposed CiiV too much as long as the sampling frequency decreases from the center  $(x, y)$  to the peripheries as shown in Figure 11 (a). We intuitively adopt a normalized mapping  $g(z) = h((\max(z) - z + \alpha)^\gamma)$ ,  $\alpha = 10.0, \gamma = 0.3, h(z) = z/\max(z)$  as our default setting, and we further tested two simpler non-linear functions Candidate1:  $g_1(z) = 1.0 - z/100$  and Candidate2:  $g_2(z) = 2.5/(0.5 \times z^{0.5})$ . According to the experimental results in Table 5, different  $g(\cdot)$  candidates perform very similarly under all attack settings, which proves that CiiV is not sensitive to the detailed implementations of  $r(x, y)$ . The main reason for us to choose a more complex implementation of  $g(\cdot)$  is that it can dynamically fit the image size. The other two simpler functions  $g_1(\cdot)$  and  $g_2(\cdot)$  have to change parameters for different sizes of images, which is less convenient than our default  $g(\cdot)$ .

Since the proposed retinotopic augmentation aims to imitate the continuous observations in the human vision. The reaction of biological visual system to different light intensities is also important, which controls the amount of light absorbed by the retina. Therefore, given the retinotopic mask  $r$  generated by  $g(\cdot)$ , the overall retinotopic augmented image  $x_r$  can thus be constructed by  $x_r = f(x, r) = 1/N \sum_i (r \odot \text{ReLU}(x + \varepsilon_i))$ , where  $\varepsilon$  is the parameter of exposure intensity uniformly sampled from  $(-\omega, \omega)$  by  $N$  times ( $N$  and  $\omega$  is set to 3 and 0.9, respectively, in our experiments),  $\odot$  denotes element-wise multiplication after normalizing the light intensity. The reason we introduce the function  $\text{ReLU}(x + \varepsilon_i)$  is to find the best exposure ratio for a dataset. As we can see from Figure 11 (b), the selection of exposure parameter  $\omega$  can change the intensity of an observed image. The dark environment requires a smaller  $\omega$ , so we make it as a hyper-parameter for each dataset. We set  $\omega$  to 0.9, 0.9, 0.8 for CIFAR-10, CIFAR-100, and mini-ImageNet, respectively. Intuitively, such a function imitates how human eyes react to different light intensities of the environment by controlling the amount of absorbed light. After multiplying with the retinotopic mask  $r$ , the proposed  $x_r = f(x, r)$  simulates the signals perceived by the biological retina under different environments and focusing points, which continuously ‘‘intervene’’ the images observed by humans.

We also investigated hyper-parameters of retinotopic augmentation. As we can see from Table 5, there are trade-offs among different selections. Larger  $\omega$  can capture more dark details at the cost of light details, and vice versa. To obtain the balanced results between clean images and adversarial examples, we chose the  $\omega = 0.9$  as our default setting in CIFAR-10. As to the parameter  $N$  that is used to smooth the image after retinotopic augmentation, the larger  $N$  we use the less distortion will be in the generated  $x_r$ . Therefore, larger  $N$  can significantly increase the performance of clean images while smaller  $N$  can increase the performance of adversarial examples by suppressing more confounding patterns. Although  $N = 1$  would obtain the best overall result, considering the fact

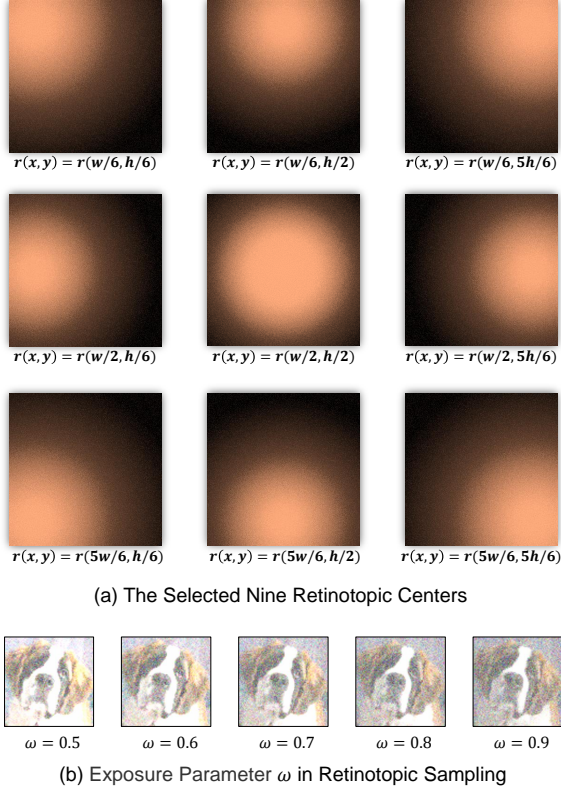


Figure 11: (a) The selected 9 retinotopic centers used to generate  $r$  in the proposed CiiV. (b) The effect of applying different exposure parameter  $\omega$  before multiplying with the retinotopic sampling mask  $r$

Datasets	CIFAR-10					CIFAR-100				
	Clean	GN	UN	SPSA	BFS	Clean	GN	UN	SPSA	BFS
Attackers										
Baseline	94.42	72.05	74.66	68.60	35.77	74.53	31.44	34.46	27.57	10.39
mixup	95.31	76.02	78.77	71.87	39.82	77.32	40.21	43.69	36.27	18.35
BPFC	90.21	88.90	89.02	88.91	79.48	61.48	60.47	60.53	60.30	52.11
RS	83.44	83.22	83.16	83.35	82.97	54.63	54.46	54.28	54.53	54.41
(ours) CiiV	86.89	86.47	86.61	86.75	85.60	58.88	58.19	58.75	58.63	57.30
(ours) CiiV+mixup	87.14	86.71	87.11	87.07	86.23	56.90	56.41	56.65	56.70	55.91
(ours) CiiV+RandAug	89.12	88.36	88.59	89.00	87.64	59.26	58.82	58.71	59.21	57.85
AT <sub>FGSM</sub>	84.52	83.02	83.32	82.98	77.86	51.99	51.05	51.27	51.13	45.08
AT <sub>PGD-10</sub>	83.94	82.49	82.70	82.59	77.33	56.48	54.64	54.97	54.82	47.83
(ours) CiiV+AT <sub>FGSM</sub>	83.67	83.10	83.20	83.37	82.34	53.83	53.35	53.77	53.69	52.53
(ours) CiiV+AT <sub>PGD-10</sub>	81.35	80.74	81.02	81.09	80.22	51.73	51.16	51.43	51.39	50.12

Table 6: Gradient-free attacks on CIFAR-10 and CIFAR-100. The upper half contains the AT-free defenders while the bottom half reports the AT-involved defenders.

Datasets	CIFAR-10						CIFAR-100					
	Clean	FGSM	PGD-10	AA- $l_\infty$	AA- $l_2$	Overall	Clean	FGSM	PGD-10	AA- $l_\infty$	AA- $l_2$	Overall
Attackers												
(VGG13) Baseline	90.20	10.48	0.0	0.0	0.21	20.18	66.05	3.14	0.0	0.0	0.05	13.85
(VGG13) CiiV	83.44	58.75	43.62	36.98	79.08	60.37	50.62	32.83	25.58	24.91	47.37	36.26
(VGG13) CiiV+RandAug	83.91	60.60	45.54	40.51	80.63	62.04	52.72	33.24	26.66	25.76	48.64	37.40
(WRN34-10) Baseline	94.93	32.09	0.02	0.0	0.0	25.41	77.74	9.73	0.15	0.0	0.0	17.52
(WRN34-10) CiiV	87.25	59.50	43.89	38.24	82.82	62.34	60.84	34.04	25.58	25.23	57.45	40.63
(WRN34-10) CiiV+RandAug	88.68	64.02	49.23	44.52	83.59	66.01	63.23	38.30	28.82	27.38	59.81	43.51

Table 7: The performances of Baseline, CiiV, and CiiV+RandAug using different backbones.

that clean images occur more often than adversarial examples in real-world applications, we adopted  $N = 3$  as our default setting in all datasets.

## D MORE DETAILED STUDIES AND EXPERIMENTS

In this section, we demonstrate additional studies and experiments on 1) several gradient-free attacks, and 2) more backbones.

According to Carlini et al. (2019), some flawed defenders may fail in gradient-free attacks. Therefore, we further investigated four gradient-free attackers: 1) GN (Gaussian Noise), 2) UN (Uniform Noise), 3) SPSA (Uesato et al., 2018), and 4) BFS (Brute-Force Search) (Carlini et al., 2019). Since gradient-free attacks are supposed to be much weaker than gradient-based attacks, we increased the budget  $\epsilon$  to 16/255 for all four gradient-free attackers under  $l_\infty$  constraint. To be specific, GN and UN add gaussian and uniform noises, respectively, to input images. BFS ran 100 times of GN and reported the most vulnerable adversarial examples. As to the SPSA, it conducted numerical approximation of gradients to circumvent the potential gradient masking, the hyper-parameters were set as  $\delta=0.1$ , step=20, lr=0.1, batch size=16. According to the experiments in Table 6, all the gradient-free attackers were significantly weaker than the gradient-based attackers as we expected even with the doubled attacking budget, proving that the proposed CiiV won't be more vulnerable under gradient-free attacks.

Datasets	CIFAR-10					
	Clean	FGSM	PGD-10	AA- $l_\infty$	AA- $l_2$	Overall
Default	86.89	64.44	50.75	43.23	82.48	65.56
Candidate1	87.03	64.53	50.37	42.46	82.86	65.45
Candidate2	87.53	63.23	48.88	41.05	82.64	64.67
$\omega = 1.2$	86.50	64.96	52.04	46.33	82.18	66.40
$\omega = 1$	85.96	64.66	50.81	43.88	81.72	65.41
$\omega = 0.8$	87.21	64.19	49.97	41.72	82.74	65.17
$\omega = 0.6$	86.47	62.65	47.70	39.53	81.36	63.54
$N = 1$	82.44	69.40	59.17	57.25	78.16	69.28
$N = 2$	85.84	66.52	55.01	48.36	81.36	64.42
$N = 4$	87.71	63.77	48.39	40.14	83.06	64.61
$N = 5$	88.29	62.22	46.35	37.87	83.92	63.73

Table 5: The performances of CiiV on CIFAR-10 using different designs of function  $g(\cdot)$  to generate retinotopic sampling mask  $r$ , and different hyper-parameters  $\omega$  and  $N$  to generate  $x_r$ .

We also applied the proposed CiiV and its combination with Random Augmentation, *i.e.*, the AT-free versions of defenders, into other backbones, *e.g.*, VGG13 (Simonyan & Zisserman, 2015) and WRN34-10 (Zagoruyko & Komodakis, 2016). As we can see from Table 7, the proposed CiiV and its variants consistently increased the adversarial robustness under different backbone models.