AdvDrop: Adversarial Attack to DNNs by Dropping Information

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Abstract

Human can easily recognize visual objects with lost information: even losing most details with only contour reserved, e.g., cartoon. However, in terms of visual perception of Deep Neural Networks (DNNs), the ability for recognizing abstract objects (visual objects with lost information) is still a challenge. In this work, we investigate this issue from an adversarial viewpoint: will the performance of DNNs decrease even for the images only losing a little information? Towards this end, we propose a novel adversarial attack, named AdvDrop, which crafts adversarial examples by dropping existing information of images. Previously, most adversarial attacks add extra disturbing information on clean images explicitly. Opposite to previous works, our proposed work explores the adversarial robustness of DNN models in a novel perspective by dropping imperceptible details to craft adversarial examples. We demonstrate the effectiveness of AdvDrop by extensive experiments, and show that this new type of adversarial examples is more difficult to be defended by current defense systems.

1. Introduction

Deep Neural Networks (DNNs) have demonstrated their outstanding performance across many applications such as computer vision [24] and natural language processing [47]. Though DNNs have great achievement in these tasks, especially in computer vision, they are known to be vulnerable to adversarial examples. Adversarial examples of DNNs were first discovered by Szegedy et al. [42], which are crafted by adding malicious perturbation on clean images to generate undesirable consequences. Various methods have been proposed to generate adversarial examples [20, 32, 7]. Typically, the generated adversarial perturbation is bounded by a small norm ball, which guarantees the resultant images “look like” benign images.

Interestingly, Ilyas et al. [27] empirically demonstrated that adversarial perturbation can be non-robust features for DNNs. That is to say, regarding adversarial perturbation, they are meaningful features for DNNs, but meaningless and imperceptible for humans. So we wonder, whether it is possible to craft adversarial examples in an opposite paradigm? Rather crafting adversarial examples by adding adversarial perturbation (or non-robust features) on clean images, we drop certain features from clean images that are imperceptible to humans but essential for DNNs which further lead to DNNs failing to recognize the resultant images.

Towards this end, we propose a novel adversarial attack named AdvDrop, which crafts adversarial images by dropping less perceptible details from clean images. For example, as shown in Figure 1, both adversarial images generated by PGD [32] and AdvDrop look indistinguishable from the clean images at first glance. However, when you look closely, PGD generates extra details (composed of more colors) at the cost of extra storage (larger image size). In contrast, the proposed AdvDrop drops existing details such...
Figure 2: Interpolation between the clean image and adversarial images generated by AdvDrop and PGD.

Dropping information of images can be achieved in either spatial domain (e.g. color quantization [25, 34]) or frequency domain (e.g. JPEG compression [44]). In our work, we consider developing proposed AdvDrop in the frequency domain. Principally, we can drop various features of an image to generate adversaries. This preliminary study is focused on the frequency domain because we choose to use “image details” as the feature of interest to be dropped, which can be well quantized in the frequency domain. This choice is motivated by native insensitivity of human eyes to fine image details. In this work, AdvDrop first transforms images from spatial domain to frequency domain, then reduces some frequency components of the transformed images quantitatively. Figure 2 shows the process of AdvDrop, which performs attack following an opposite mechanism to PGD. The proposed AdvDrop starts from removing subtle details (e.g. textures) and the resultant image is almost indistinguishable from the clean one. When increasing the amount of dropped information, the resultant adversarial image finally turns to be somewhat “blank”. Here, “blank” denotes pure color which presents (almost) no information for recognizing a specific object for DNNs.

We then perform comprehensive evaluation on the proposed AdvDrop. It can achieve high attack success rates in both targeted and untargeted settings on ImageNet [12]. We also evaluate the effectiveness of AdvDrop in terms of defense methods. Various defense methods have been proposed to defend against adversarial examples [32, 4, 35, 46]. Current defense methods are less effective against adversarial examples generated by AdvDrop as they are generated with a rather different paradigm. Moreover, since the adversaries are generated by AdvDrop via losing information, they are somewhat robust to denoising-based defenses. Typically, the denoising-based method removes the generated adversarial perturbation and accordingly defends against adversaries (Figure 3). For adversaries generated by AdvDrop, however, denoising-based defenses take no effect and the resultant images are still adversarial for DNNs. We hope this finding will motivate devising more effective defense approaches against AdvDrop. In addition, to better understand the mechanism of AdvDrop and the properties of generated adversarial examples by AdvDrop, we provide visualizations of the dropped information by AdvDrop, and

Figure 3: Adversarial images under denoising-based defense. Adversarial perturbation generated by PGD could be mitigated by applying denoising strategies, but with almost no effect on adversaries generated by AdvDrop.

as subtle texture-like information from clean images, and the local patch is composed of less colors compared with the other images. As the figure indicates, the lost brittle details from benign images result in DNNs failing to recognize the resultant images correctly.
perform a further analysis together with the attention of the DNNs. In summary, this paper has made the following contributions:

- We propose a novel adversarial attack named \textit{AdvDrop}, which is a totally different paradigm from previous attacks. \textit{AdvDrop} crafts adversarial images by dropping existing details of clean images. It opens new doors to generate adversarial attacks for DNNs.

- We conduct comprehensive experiments and demonstrate the effectiveness of \textit{AdvDrop} on targeted and untargeted attack settings. We also empirically show that current defense methods become less effective against adversarial examples generated by \textit{AdvDrop} compared to other attacks.

- Finally, we visualize the dropped information and the attention of the DNNs to interpret the adversaries generated by \textit{AdvDrop}.

This paper is organized as follows. Background and related work are discussed in Section 2. Our proposed approach is described in Section 3, and evaluated in Section 4. Section 5 concludes the paper and points out future work.

2. Background and Related Work

2.1. Adversarial attacks and defenses

Adversarial attack was first proposed by Szegedy et al. [42], aiming to generate perturbation superimposed on clean images to fool a target model. Adversarial attacks can be either digital-setting [20, 29, 32] or physical-setting [18, 38, 14], where most attacks are developed in digital-setting. Specifically, given a target model \( f \), adversarial example \( x' \) can be crafted by either following the direction of adversarial gradients \([20, 29, 32]\) or optimizing perturbation with a given loss \([6, 8]\). For most adversarial attacks, the generated adversarial perturbation is bounded by a \( l_p \) norm ball. Some works \([21, 39]\) propose generating adversarial examples in the frequency domain for either improving the efficiency in black-box setting or transferability. Roughly speaking, these adversarial attacks can be somewhat formulated as \( x' = x + \delta \), where \( \delta \) represents additive adversarial perturbation. Conversely, the proposed \textit{AdvDrop} crafts adversarial examples with an opposite paradigm \( x' = x - \delta \). Note here ‘+’ and ‘\(-\)’ are not simple “add” or “subtract” operations over the values of \( x \), but denote whether \( \delta \) is extra information created by attacks or existing information of clean images dropped by \textit{AdvDrop}.

Other works also explore adversarial examples by making modifications or replacement on the secondary attributes (e.g. color, lighting \([26, 37, 51, 48, 31, 50, 15]\), texture \([45, 14]\)) to generate adversarial examples. We also note some other works \([23, 9]\) proposed attack based on motion blurring or smoothing, which also lose details of the clean image after the attack. However, their purposes are different from ours. This work aims to demonstrate the effectiveness of the proposed mechanism.

Many adversarial defense techniques have been proposed. Madry et al. [32] proposed adversarial training, which is arguably one of the most effective defense against adversarial attacks. Adversarial training is a data augmentation technique that trains DNNs on adversarial examples rather than natural examples. However, adversarial training is both time and computation consuming, due to the generation of adversarial examples and extra training epochs to fit adversarial examples. There are also preprocessing based methods, which process the inputs with certain transformations to remove the adversarial noise, and then send these inputs to the target model \([16, 10, 11, 22, 35]\). We consider both types of defenses during the evaluation to evaluate the effectiveness of \textit{AdvDrop}.

2.2. Image compression methods

Image compression methods fall into two categories, lossless compression, \( e.g. \), PNG \([5]\), and lossy compression, \( e.g. \), JPEG \([44, 41]\). JPEG compression applies discrete cosine transform (DCT) on patches which transforms images from spatial domain to frequency domain. DCT works by separating the image into different parts of different frequencies. Then JPEG applies quantization matrix (designed based on human vision) on transformed images dropping most of high-frequency components. In detail, higher frequency components of transformed images are rounded to zero, and finally reduce the size of original images. Recently, deep learning based methods have been investigated for image compression problems. Both CNN-based methods \([30, 2, 1]\) and RNN-based methods \([43, 28]\) are investigated. However, deep learning based compression methods are time-consuming and require pre-training. Due to both efficiency and convenience concerns, we follow the design of JPEG to develop our proposed \textit{AdvDrop}.

3. Approach

3.1. Overview

Given a clean image \( x \in \mathbb{R}^m \) with class label \( y \), a DNN classifier \( f : \mathbb{R}^m \to \{1, \cdots, k\} \) which maps image pixels to a discrete label set, and a target class \( y_{\text{adv}} \neq y \) for targeted attack. The goal of adversarial attack is to find an adversarial example \( x' \) for clean image \( x \) by solving the optimization problem \( \mathcal{L}_{\text{adv}}(\cdot) \), which is the adversarial loss leading to \( f(x') \neq y \) or \( f(x') = y_{\text{adv}} \). Typically, \( x' \) is restricted by \( l_\infty \) norm ball: \( \|x' - x\|_\infty < \epsilon \). Our goal is to develop a mechanism that drops information from benign images to craft adversarial images. \textit{AdvDrop} is composed
of several parts:

- **Adversarial loss**: The proposed method optimizes over quantization table $q$ by minimizing adversarial loss $L_{adv}(\cdot)$.

- **Discrete Cosine Transform (DCT)**: DCT transforms the input image $x$ from spatial domain to frequency domain. DCT is denoted as $D(\cdot)$ in the following.

- **Inverse Discrete Cosine Transform (IDCT)**: IDCT transforms image’s signals from frequency back to spatial domain, denoted as $D^{-1}(\cdot)$.

- **Quantization**: Quantization serves as the core process to drop information by applying quantization table $q$, which is optimized during the attack. We denote common quantization as $Q(\cdot)$. However, in our work, we adopt a differential quantization process denoted as $Q_{diff}(\cdot)$. Note in the following, either $Q(\cdot)$ or $Q_{diff}(\cdot)$ represents a complete quantization-dequantization process.

In summary, our proposed AdvDrop first transforms clean images from spatial to frequency domain, then applies quantization to drop some specific frequencies of the transformed image, followed by inverting the frequency signals of images back to spatial domain. During optimization, AdvDrop only tunes the value of quantization table $q$ bounded by $\epsilon$. Formally, we denote our final objective as:

$$\min_{q} L_{adv}(x', y), \text{ where } x' = D(x)Q_{diff}(D(x), q)$$

$$\text{s.t. } \|q - q_{init}\|_{\infty} < \epsilon$$

where $q_{init}$ is the initial value of quantization table $q$. We set $q_{init} = 1$. We increase the value of quantization table $q$ gradually to drop the information of given image during the optimization. $Q_{diff}$ represents a differential quantization function, which allows AdvDrop to compute the gradients during the backward propagation. The overview of AdvDrop is illustrated in Figure 4.

3.2. Adversarial loss

For adversarial loss $L_{adv}(\cdot)$, we use the following cross-entropy loss:

$$L_{adv} = \begin{cases} \log(p_{y}(x')) , & \text{for untargeted attack} \\ -\log(p_{y_{adv}}(x')) , & \text{for targeted attack} \end{cases}$$

where $p(\cdot)$ is the probability output (softmax on logits) of the target model $f$ with respect to class $y_{adv}$ or $y$. By minimizing loss $L_{adv}$, AdvDrop optimizes the quantization table $q$ to selectively drop the information of input image $x$, in order to mislead the target model $f$ finally.

3.3. Transformation

We introduce both DCT and IDCT in this part. DCT serves as a transformation of images from spatial domain to frequency domain, which expresses a finite sequence of data points in terms of a sum cosine functions oscillating at different frequencies. Note that there are also other methods enabling transformation of images from spatial to frequency domain, such as discrete Fourier transform etc. We focus on DCT as it enables the proposed AdvDrop to have more flexibility in selecting what and where information to drop.

Before applying DCT, we first split the original images into blocks with size $N \times N$ as shown in Figure 4. Our proposed method splits images into patches with size $N = 8$ for all the experiments by mainly considering computation cost and perceptual quality. As the correlation between pixels within the patch decreases with increasing in patch size, the quantization results in larger distortion. For each block, the value of pixels are adjusted to be symmetric with respect to zero. The mathematical definition of DCT is:

$$D(x)_{[u,v]} = \frac{1}{\sqrt{N}}C(u)C(v)\sum_{x=0}^{N-1}\sum_{y=0}^{N-1}x[k,m]\cos\left[\frac{(2k+1)i\pi}{2N}\right]\cos\left[\frac{(2m+1)j\pi}{2N}\right]$$

In which, Eq. 3 computes the $u, v^{th}$ entry of $D(x)$. $x[k, m]$ with the value on coordinate $(k, m)$ of image $x$. $N$ is the
We decrease the value of $\alpha$ linearly to approximate the staircase function gradually during the optimization (Figure 5). The value of $\alpha$ is determined at start and decreased gradually during the optimization, and thus $Q_{diff}(\cdot)$ behaves almost the same as the desired staircase quantization function at the end of optimization. Due to page limit, more details regarding $\alpha$ can be referred to work [19]. Besides, as the quantization table $q$ should be integers during the optimization, we update the quantization table $q$ with the $sign$ of gradients returned via backward propagation. Formally:

$$q' = q + sign(\nabla_q L_{adv}(x', y)), \text{ s.t. } ||q - q_{init}||_\infty < \epsilon \quad (7)$$

where the purpose of $\epsilon$ is similar to $l_p$-norm, aiming to make the resultant adversarial image $x'$ looking indistinguishable from clean image $x$. In detail, $\epsilon$ confines the norm of quantization table $q$, to further restrict the amount of information to drop. We will give more study about the setting of $\epsilon$ in Section 4. The illustration of differential quantization and updation of $q$ at different steps are shown in Figure 6.

**Figure 5:** Illustration of the usage of $\varphi(x)$ and $\alpha$.

**Figure 6:** Differential quantization process and updation of quantization table $q$.

During the process of optimization, the interval of $q$ increases gradually as updated by Eq. 7. For illustration, we plot color palettes at the bottom to show how the colors are dropped when the interval increases. In summary, the proposed $AdvDrop$ adopts an asymptotic strategy to drop the information, that the slope $(\frac{\varphi(x)}{\Delta})$ becomes steeper gradually, thus $Q_{diff}(\cdot) \approx Q(\cdot)$ finally.

### 4. Experimental Evaluation

We first outline the experimental setup. Then we evaluate our $AdvDrop$ regarding its perceptual and attack performance. Afterwards, we evaluate the performance of $AdvDrop$ under defense methods. We then analyze $AdvDrop$
via an ablation study. We finally analyze the dropped information by AdvDrop together with attention of the model.

### 4.1. Experimental settings

**Dataset and models.** We randomly selected 2000 correctly classified images from ImageNet [12] to evaluate proposed attack. We use ResNet50 [24] as the target model for all the experiments. For evaluating the effectiveness of proposed AdvDrop on adversarial training, we used pretrained adversarial model ResNet50 as defense model [17].

**Metrics.** For all the tests we use attack success rate (succ. rate) (%) as the metric to evaluate the effectiveness of attacks, which is the proportion of successful attacks among the total number of test images defined as \( \frac{1}{N} \sum_{n=1}^{N} [f(x) \neq f(x')] \) in untargeted setting, and \( \frac{1}{N} \sum_{n=1}^{N} [f(x) = y_{adv}] \) in targeted setting. Regarding evaluation on the visual quality on attacks, we use Learned Perceptual Image Patch Similarity (lpips) metric [49] as the perceptual metric.

**Baselines.** For perception study in Section 4.2, we compared our proposed AdvDrop with one of the most commonly used adversarial attack PGD under both \( l_2 \) and \( l_\infty \) settings with different constraints. For evaluation under various defenses, we consider defense methods including: feature squeezing [46], pixel deflection [35], JPEG compression [40] and adversarial training [32]. Regarding adversarial attacks to compare, we select several state-of-the-art attacks under both \( l_2 \) and \( l_\infty \) settings, including PGD [32], FGSM [20], C&W [7], DeepFool [33].

### 4.2. Perception study

We first conduct perception study on the proposed AdvDrop. With enlarging the constraint \( \epsilon \) for quantization table \( q \), the details disappear gradually as shown in Figure 7. We then compare the perceptual quality of adversarial examples generated by AdvDrop with other attack methods. Though we have a setting (using \( \epsilon \)) similar to \( l_p \) norm, however, our proposed AdvDrop attack optimizes in the frequency domain, that \( \epsilon \) is applied as the constraint for \( q \). Therefore we adopt lpips [49] as the perceptual metric, which measures how similar the two images are in a way that coincides with human judgment. The value of lpips denotes the perceptual loss, the lower, the better. We compare with one of the most commonly used adversarial attack PGD in both \( l_2 \) and \( l_\infty \) settings.

We summarize the results in Figure 8, where we set y-axis with perceptual loss calculated by lpips [49], and set x-axis with the change ratio on size of resultant images compared with clean images. For example, for AdvDrop-100, the value of x-axis represents the size of adversarial images’ decreases by 36.32% on average compared with clean images’ size. Note that opposite to AdvDrop, the size of adversarial images generated by PGD is larger than clean images.

Thus for PGD, the value on x-axis represents how much the ratio in size increases. As Figure 8 indicates, though the relative size ratio changes more compared with PGD in either \( l_2 \) or \( l_\infty \) settings, the adversarial images generated by AdvDrop are more perceptually aligned with clean images compared with PGD.

### 4.3. Evaluation of AdvDrop

We now evaluate the performance of AdvDrop with both targeted and untargeted settings. We evaluate AdvDrop with constraint \( \epsilon \) for quantization table \( q \) with 20, 60, 100 respectively. We summarize the results in Table 1.

| \( \epsilon \) for \( q \) | 20      | 60      | 100      |
|-----------------------|--------|--------|--------|
| Targeted succ. rate (%) | 97.20 ± 0.37 | 99.45 ± 0.16 | 99.95 ± 0.05 |
| Untargeted succ. rate (%) | 98.55 ± 0.26 | 98.95 ± 0.08 | 100.00 ± 0.00 |

As Table 1 indicates, with relaxing the constraint \( \epsilon \), the success rates of AdvDrop on both targeted and untargeted
settings increase. AdvDrop can achieve almost 100% success rate when $\epsilon = 100$. We find that AdvDrop in targeted setting requires more steps to achieve successful attacks compared with untargeted setting (Figure 9). This may be due to targeted attack always requires more accurate approximation on gradients. During the attack, we set the steps for AdvDrop in targeted and untargeted settings with 500 and 50 respectively. We plot the success rates and the loss of a batch on different steps in Figure 9.

![Figure 9: Loss and succ. rate (%) on a batch.](image)

As shown in Figure 9, the loss of untargeted attack converges rapidly and achieves 100% success rate when step is around 50. On the other hand, the loss for targeted attack converges until the step is around 500. During the experiments, we find that with the increase of constraint $\epsilon$, fewer steps are required for AdvDrop on both targeted and untargeted settings. For example, in a targeted setting, to achieve success rate above 99%, on average 496 steps are required when $\epsilon = 20$, but only 61 steps are required when $\epsilon = 100$.

### 4.4. Attack effectiveness under defense methods

In this part, we evaluate the effectiveness of proposed AdvDrop compared with other adversarial attacks under various defense methods. Here we first generate adversarial examples by adversarial attacks including PGD [32], BIM [13], CW [7], FGSM [20], and DeepFool [33]. Regarding these attacks, we consider both settings including $l_2$ and $l_\infty$ to generate adversarial examples. Then we test different defense methods including adversarial training (AT) [4, 32], feature squeezing [46], JPEG compression [40], and pixel deflection (PD) [35] against these samples to evaluate the strength of these attacks under defenses. Among all these defenses, adversarial training is the most effective defense against adversarial attacks. As adversarial training requires too much computation resource, we adopt a black-box setting to evaluate various attacks on adversarial training. We first generate adversarial examples by various attack methods, then feed them to the adversarial trained model. We set $\epsilon = 4$ for attacks on $l_\infty$ setting, set $\epsilon = 0.06$ for attacks on $l_2$ setting that are common used in previous defense methods [35, 22]. We set quantization table $q$ with 100 for AdvDrop. We summarize the results in Table 2.

| Attacks | No Def. | AT Feature Squeeze JPEG-30 PD |
|---------|---------|-------------------------------|
|         | $l_2$   | $l_\infty$                     |
| PGD     | 100.00  | 41.60 90.65 70.50 62.50 85.10 |
| BIM     | 100.00  | 42.80 90.25 69.20 33.80 81.50 |
| FGSM    | 91.90   | 42.60 91.80 66.05 49.60 81.40 |
| PGD     | 100.0   | 43.00 90.3 62.8 27.6 64.1 |
| Dfool   | 99.00   | 42.95 89.7 29.00 21.20 12.60 |
| CW      | 84.30   | 43.00 88.80 26.00 21.70 12.60 |
| AdvDrop | 100.00  | 44.50 95.35 82.60 80.00 95.65 |

As Table 2 shows, since adversarial images are crafted by AdvDrop with a totally different paradigm, they are more robust to current defense methods compared to adversarial images generated by other attacks. Among all these defenses, adversarial training is still the most effective defense against AdvDrop. We suggest that as the adversarial training makes the model learn more robust feature representations, it is also effective to defend against our proposed AdvDrop to some degree. On the other hand, other denoising-based defense methods demonstrate limited effectiveness to defend against our proposed AdvDrop. Though denoising-based strategies show effectiveness in mitigating the adversarial perturbation generated by previous attacks, regarding AdvDrop which has already removed some essential features from clean images, denoising may aggravate the distortion caused by loss of features. We further perform an evaluation by JPEG compression to validate the robustness of adversarial examples generated by AdvDrop under denoising operation.

**JPEG compression.** Previous studies show that adversarial perturbation can be partly removed via JPEG compression [22, 11]. Regarding JPEG compression, the compression rate is controlled by a quantifiable quality, which affects to what extent the information is reduced. We evaluate the performance of AdvDrop under JPEG compression with different quality factors to represent how robust the adversaries generated by AdvDrop are. For comparison, we also test the performance of PGD and the accuracy of clean images under JPEG compression (Figure 10). We set both AdvDrop and PGD with untargeted setting. We report accuracy rate as the metric in Figure 10, meaning the proportion of recovered adversarial examples by JPEG compression.

As Figure 10 indicates, when quality factor is extreme low (e.g. quality factor = 10), JPEG compression results in corruption on clean images, that clean accuracy even drops below 60%. Regarding the adversarial examples generated by PGD, they are mostly recovered when JPEG compression with quality factor being equal to 30. When quality factor further decreases, the recovered rate of PGD decreases due to the corruption caused by JPEG compression. Compared to PGD, adversarial examples generated by Adv-
AdvDrop is much less affected by JPEG compression. Less than 30% adversaries generated by AdvDrop are recovered at most. We suggest that the mechanism of AdvDrop itself is a kind of lossy operation which makes resultant adversarial images lack some key features for recognition. Thus when further applying lossy operations (such as JPEG compression) on resultant adversarial images, the applied lossy operations may even further destroy the generated adversarial examples and even harder to recover. However, there is still chance that the adversarial examples generated by AdvDrop can be recovered by “lossy operation” as Figure 10 shows.

4.5. Ablation study

Here, we conduct experiments to analyze the impact from following aspects for proposed AdvDrop attack: 1) quantization methods, 2) spatial domain, 3) frequency (low frequency, middle frequency or high frequency).

Effect of quantization methods. Here we evaluate how different quantization methods affect the performance of AdvDrop. We evaluate a typical rounding method and another differential quantization method proposed by Shin et al. [40]. During evaluation, we only change the quantization method but keep others of AdvDrop unchanged. Typical rounding method ⌊x + 0.5⌋ achieves success rate of only 5.00 ± 0.98%. Differential rounding method proposed by Shin et al. [40], ⌊x + 0.5⌋ + (⌊x + 0.5⌋ − x)³ achieves success rate of 65.20 ± 2.13%, and ours achieves 97.20 ± 0.37% success rate. This demonstrates the effectiveness of differential quantization method adopted by AdvDrop.

Effect of frequency domain. Here we perform an ablation study to show the advantage of dropping information in the frequency domain rather than spatial domain. We reduce the color depth to drop images’ information. We report the accuracy on the same dataset when reducing the image color by different amounts of bits (Table 3). Compared to dropping information in frequency domain, the accuracy rate is affected until the bit is reduced to 2 (11.10 ± 0.07%). As the images’ details could be well quantized in the frequency domain, the resultant images are also more natural for human observers.

Table 3: Acc. rate (%) by reducing color depth.

| Bit Depth | 2   | 4   | 6   |
|-----------|-----|-----|-----|
| Acc. rate (%) | 11.10 ± 0.07 | 93.50 ± 0.05 | 99.90 ± 0.07 |

Effect of different frequencies. We also perform an ablation study on how dropping different regions of frequency (low, middle, high) affects the model’s clean accuracy. We perform this study by dropping different regions of frequency of given images after transformed to frequency domain by DCT. Results are summarized in Table 4. We also visualize the resultant images and their local details at the bottom of Table 4. As the results in Table 4 indicate, compared to middle and high frequencies, the low frequency part serves as dominant feature for the model. When low frequency is dropped from the images, the accuracy rate drops to 30.00 ± 1.02%, but 84.40 ± 8.11% and 86.50 ± 0.76% when middle and high frequencies dropped. As the images in Table 4 show, when low frequency is dropped, the details are almost lost.

Table 4: Acc. rate (%) by dropping/reserving different frequencies.

| Dropped Freq. | None | Low  | Middle | High |
|---------------|------|------|--------|------|
| Acc. rate (%)  | 100.00 ± 0.00 | 30.00 ± 1.02 | 84.40 ± 8.11 | 86.50 ± 0.76 |

4.6. Visualization and analysis

We are also interested in where and what information would be dropped by AdvDrop with a given image? Whether AdvDrop tends to drop the information where models pay attention? Towards this end, we visualize the attention of the model (Grad-CAM [36]) and the amount of dropped information by AdvDrop on different regions of given images (Figure 11). Regarding the first case in Figure 11, the model mainly pays attention to the flower part of the “cardoon”, AdvDrop drops both calyx and flower parts. In the second case, the model pays attention to the head of the “peguin”, however, in this case, AdvDrop mainly throws away the information on the body part of the “peguin”, which has rich texture details regarding the fur of the “peguin”. In summary, there is some overlapping between model’s attention and where AdvDrop drops information from. A small difference is that AdvDrop seems
focusing more on the part which has rich texture details.

We also analyze the components of the dropped information. Here we roughly divide the dropped information as “high frequency” and “low frequency”. We find AdvDrop tends to drop high frequency information than low frequency information.

5. Conclusion and Future Work

In this paper, we have investigated the adversarial robustness from a novel perspective, and proposed a novel approach called adversarial drop (AdvDrop), which leverages differential quantization and adversarial attack techniques, to craft adversarial examples by dropping existing details of images. AdvDrop opens a new way for robustness evaluation of DNNs. The proposed AdvDrop currently still utilizes a relative simple method to drop the information by focusing on frequency domain. We plan to explore other techniques to drop the information from images in our future work. Also, we will explore how to apply AdvDrop on other tasks such as interpretability of DNNs. Moreover, effective defense strategies against AdvDrop will be another crucial and promising direction.

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