Benign Adversarial Attack: Tricking Algorithm for Goodness

Xian Zhao
Beijing Jiaotong University
Beijing, China
xianzhao@bjtu.edu.cn

Zhiyu Lin
Beijing Jiaotong University
Beijing, China
zhiyulin@bjtu.edu.cn

Jiaming Zhang
Beijing Jiaotong University
Beijing, China
jiamingzhang@bjtu.edu.cn

Jitao Sang
Beijing Jiaotong University
Beijing, China
jtsang@bjtu.edu.cn

ABSTRACT

In spite of the successful application in many fields, machine learning algorithms today suffer from notorious problems like vulnerability to adversarial examples. Beyond falling into the cat-and-mouse game between adversarial attack and defense, this paper provides alternative perspective to consider adversarial example and explore whether we can exploit it in benign applications. We first propose a novel taxonomy of visual information along task-relevance and semantic-orientation. The emergence of adversarial example is attributed to algorithm’s utilization of task-relevant non-semantic information. While largely ignored in classical machine learning mechanisms, task-relevant non-semantic information enjoys three interesting characteristics as (1) exclusive to algorithm, (2) reflecting common weakness, and (3) utilizable as features. Inspired by this, we present brave new idea called benign adversarial attack to exploit adversarial examples for goodness in three directions: (1) adversarial Turing test, (2) rejecting malicious algorithm, and (3) adversarial data augmentation. Each direction is positioned with motivation elaboration, justification analysis and prototype applications to showcase its potential.

CCS CONCEPTS

• Computing methodologies → Computer vision; Computer vision problems.

KEYWORDS

adversarial attack, Turing test, malicious algorithm, data augmentation

1 INTRODUCTION

These days numerous machine learning algorithms have been adopted in various applications. However, machine learning algorithm still suffers from some problems, one of which is adversarial example. Adversarial example [41] refers to the input sample modified by adding perturbation imperceptible to human, but misleading the algorithm to deliver wrong inference with high confidence. Ever since its discovery, adversarial examples have been exploited to attack algorithms ranging from perception tasks like landmark recognition [11], pedestrian detection [45], face recognition [39], to cognition tasks like decision making [40], and even system breakdown [21].

Due to the critical risk to machine learning algorithms, adversarial attack has been viewed as malignant in default, which naturally gives rise to the considerable attention on defense against adversarial examples. Recent years have therefore witnessed the iterative and endless “involution” between adversarial defense and attack solutions: from FGSM [15], C&W attack [6], PGD [30] to Adversarial Transformation Networks [3] regarding adversarial attack, and from adversarial training [15], defensive distillation [35], gradient masking [34], to DeepCloak [12] regarding adversarial defense. Once there is a stronger adversarial attack, a more robust adversarial defense solution is expected to be proposed accordingly (and vice versa). A recent study by Carlini and Madry [42] even claimed that all typical adversarial defense solutions can be circumvented to be ineffective despite performing satisfied evaluations using adaptive attacks. Beyond falling into this cat-and-mouse game, this paper attempts to provide alternative perspective to consider adversarial example and explore whether we can exploit it in other-than-malignant applications.

We start with the discussion on why adversarial example exists. The hypothesis is that adversarial example derives from the fact that algorithm utilizes information that human cannot understand. Using image as example, we analyze the involved information along two dimensions of task-relevance and semantic-orientation according to whether it is intrinsic to solve the task and whether it is perceptible to human, respectively. As illustrated in Fig. 1, image information is thus roughly divided into four categories in the task-semantic coordinate system. While human recognizes image mainly relying on task-relevant semantic information like shape and contour, machine learning algorithms can harness additional non-semantic information like imperceptible noises to assist inference. Adversarial example, in this respect, corrupts the task-relevant non-semantic information with added adversarial perturbation to mislead algorithm inference result without affecting human perception. From this perspective, we look on adversarial example as proving the existence of task-relevant non-semantic information, which demonstrates three interesting characteristics regarding machine learning algorithms as: (1) exclusive to algorithm, (2) reflecting common weakness, and (3) utilizable as features.

Based on this alternative understanding, this paper presents new idea to exploit the adversarial examples for goodness, which we call benign adversarial attack. Specifically, the following research directions are introduced corresponding to the above three characteristics: (1) Adversarial Turing test, employing the different sensitivity to adversarial perturbation to distinguish between human
we report preliminary experimental results for justification as well.

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2 ADVERSARIAL EXAMPLE: EXPLOITING
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only based on high-frequency components which are almost imper-
shapes which is in contrast to human behavior [14]. Wang et al.
CNNs are strongly biased towards recognizing textures rather than
different information for inference. For example, it is found that
recent studies suggest that human and algorithm employ quite
knowledge from human. In this case, the information employed by
ing of machine learning algorithm can be considered as distilling
from the training data annotated by human. Therefore, the train-
and algorithm; (2) Rejecting malicious algorithm, specially designing
adversarial attack to invalid malicious algorithms like privacy viola-
tion and deep fake; (3) Adversarial data augmentation, discovering
and harnessing more non-semantic features from the generated
pseudo sample to address data shortage problem. For each direction,
we report preliminary experimental results for justification as well
as providing prototype applications for illustration.

The main contributions are summarized as follows:
• We provide alternative perspective to consider adversarial
example under a novel taxonomy of visual information along
task-relevance and semantic-orientation. The emergence of
adversarial example is attributed to algorithm’s utilization
of task-relevant non-semantic information (Section 2).
• We present brave new idea called benign adversarial attack
to exploit the adversarial examples for goodness. Three po-
tential research directions are positioned with justification
experiments and prototype applications (Section 3).

2 ADVERSARIAL EXAMPLE: EXPLOITING THE DIFFERENCE BETWEEN HUMAN AND ALGORITHM

2.1 Human v.s. Algorithm: Information Taxonomy along Task-relevance and Semantic-orientation

In typical machine learning process, algorithm learns knowledge
from the training data annotated by human. Therefore, the train-
ing of machine learning algorithm can be considered as distilling
knowledge from human. In this case, the information employed by
the algorithm is expected to be consistent with human. However,
recent studies suggest that human and algorithm employ quite
different information for inference. For example, it is found that
CNNs are strongly biased towards recognizing textures rather than
shapes which is in contrast to human behavior [14]. Wang et al.
[43] further demonstrated that CNN accurately recognized images
only based on high-frequency components which are almost imper-
ceptible to human. To better investigate how human and machine
learning algorithms make inference, we propose the following two
criterion to discriminate the different visual information:

★ Task-relevance measures whether the information is intrin-
sic to solve the task. Task-relevant information employed
by machine learning algorithms is also called task-relevant
feature, whose judgment can resort to whether it is general-
izable to unseen data.
★ Semantic-orientation measures whether the information
is perceptible to human. Semantic-oriented information like
color, shape and contour is easily perceived and understood
by human to make inference. On the contrary, human usually
fails to capture or understand the non-semantic information,
such as white noise, adversarial perturbation.

The above two criterion lead to a taxonomy to divide visual
information into the following four categories (illustrated in Fig. 1):

- Task-relevant semantic information: semantic information
that generalizes to unseen data. This category of infor-
mation is perceptible to human as well as intrinsic to
solve the target task. Examples of task-relevant semantic
information in image classification are shape, contour, etc.

- Task-relevant non-semantic information: non-semantic
information that generalizes to unseen data. This category
of information is also intrinsic to solve the target task but
imperceptible to human. Adversarial perturbation falls in
this very category.

- Task-irrelevant semantic information: semantic informa-
tion that fails to generalize to unseen data. This category
of information is perceptible to human, but not useful to
solve the target task. Algorithm employing task-irrelevant
semantic information tends to suffer from the overfitting
problem [13], e.g., the background information in image
object recognition tasks.

- Task-irrelevant non-semantic information: non-semantic
information that fails to generalize to unseen data. This
category of information is neither perceptible to human or
intrinsic to solve the target task, e.g., Gaussian white noise,
salt and pepper noise.

From the perspective of algorithm, task-relevance concerns wheth-
er the utilized feature is desired for solving the task, and semantic-
orientation concerns the consistence with human. According to the
above “distilling knowledge” analog, it is natural to expect that
the trained algorithm only use the task-relevant semantic informa-
tion (highlighted with red background in Fig. 1). However, recent
evidences have demonstrated that machine learning algorithms
also harness features from task-irrelevant semantic information and
task-irrelevant non-semantic information [2, 4, 46] (highlighted with
blue background in Fig. 1), which possibly results from the biased
training data and insufficient training supervision [13]. Employing
features from task-irrelevant semantic information is obviously unde-
sirable which possibly induces problems like overfitting and failing
in Out-Of-Distribution samples. While, whether task-relevant non-
semantic information is beneficial seems not that conclusive, as it
indeed contributes to solving the target task but rarely seriously
discussed for exploitation. In the rest of the paper, we will first
discuss the relation between adversarial example and task-relevant
non-semantic information, and then present ideas to exploit them
for benign applications.

Figure 1: Information taxonomy in the task-semantic coor-
dinate system.
2.2 Adversarial Example vs. Task-relevant Non-semantic Information

We review that the added perturbation in adversarial example has two properties as affecting algorithm inference result and imperceptible to human, which exactly match the definition of task-relevant non-semantic information. Therefore, the existence of adversarial example indicates no algorithm mistakes, but proves that algorithms indeed employ non-semantic information as features. Moreover, adversarial example opens up possibilities to analyze and exploit the task-relevant non-semantic information, which is largely ignored in classical machine learning studies. Specifically, we are interested in the following three characteristics to motivate exploitation:

- **Exclusive to algorithm**: Solving tasks involves with both semantic and non-semantic information. While machine learning algorithms can utilize both, human relies mostly on the semantic part. This is the fundamental characteristics to distinguish between human and algorithm.
- **Reflecting common weakness**: Equipping with this "superman’s power", machine learning algorithms at the same time suffer from common weakness as easily fooled by trivial perturbation. This is particularly the case in tasks heavily interacted with human.
- **Utilizable as features**: Classical machine learning focuses on employing the semantic features. Since it is difficult to completely prevent the algorithm from employing the non-semantic information, how about we proactively exploit it to assist task solving especially in cases like data shortage?

3 EXPLOITING ADVERSARIAL ATTACK FOR BENIGN APPLICATIONS

This section discusses how to utilize the above three characteristics and exploit adversarial examples to design benign applications. The following elaborates each application with motivation, justification analysis and prototypes.

3.1 Adversarial Turing Test

3.1.1 Motivation.

Turing test was initially proposed to examine whether machine’s behavior is indistinguishable from human [29], and later developed into reverse Turing test for practical purpose to distinguish between algorithm and human. The most popular and practical reverse Turing tests are character-based CAPTCHAs [33] and dialogue-based Turing test [28]. However, the recent development of deep learning has significantly advanced the capability of algorithm in solving both types of reverse Turing tests, e.g., Google duplex demonstrates to crack the dialogue Turing test by creating a chat robot and successfully confounding humans [27]. It is easy to imagine that with the further development of algorithms, the traditional reverse Turing tests comparing the intelligence capability will fail to discriminate algorithm from human.

Instead of increasing the task complexity to compete between algorithm and human, a straightforward solution for reverse Turing test is to employ their intrinsic different characteristics. As discussed above, task-relevant non-semantic information serves as one such characteristic which is exclusive to algorithm and imperceptible to human. With adversarial example disturbing the task-relevant non-semantic information, we are motivated to design adversarial Turing test by examining the different sensitivity to adversarial perturbation and distinguishing between human and algorithm.

3.1.2 Justification Analysis.

Datasets and settings. We did experiments on the crafted Alphabet dataset and CIFAR-10 dataset [25]. The Alphabet dataset is constructed by generating 26 English letters added by random noise, with 1,000 training images and 200 test images for each letter class. We employed Resnet-18 [19] backbone as our experimental model structure in Sec.3.1.2 (A) and a state-of-the-art OCR (Optical Character Recognition) algorithm [5] in Sec.3.1.2(B). We used Adam optimizer with learning rate of 1e-5 to train models.

Analysis tool: Universal Adversarial Perturbation. As mentioned in the Introduction, recent years have witnessed different adversarial attack methods like FGSM, C&W attack and PGD. These attacks are all sample-specific, which means different samples even in the same category needs different adversarial perturbations. A different type called Universal Adversarial Perturbation (UAP), however, is sample-independent which misleads most of the input samples for given model and category [31]. Therefore, UAP can serve as probe to explore what features the model relies on [36, 49]. In this subsection and the subsequent analysis, we will employ UAP as tool to analyze the representative information used in machine learning algorithms (mainly non-semantic).

A. Visualization of task-relevant non-semantic information.

To investigate the features learned by model, we employ UAP as the feature probe for visualization. Zhang et al. [22] proposed that for the same task data set, using different initial parameters can make two algorithms with the same structure show different robustness. Inspired by this, we trained robust models and non-robust models on both two datasets by different initial parameters. Non-robust model is vulnerable towards adversarial examples, while robust model can still perform well on adversarial examples. We conjecture the reason why the non-robust model is vulnerable to adversarial examples is that it adopts more non-semantic information for inference.

In order to verify this, we employ the method of [36] to generate UAP of the letter ‘A’, and print out the perturbation as shown in Fig. 2. We observe that the universal adversarial perturbation of the non-robust model expresses no semantics. It is this kind of noise-alike features that lead to the vulnerability to adversarial examples. On the contrary, the robust model extracted more human-perceptible semantic information in UAP, such as the contour of...
letter 'A'. This proves that the vulnerability of algorithm is led by non-semantic information.

We further compared the focused information for inference between robust and non-robust models by visualizing their saliency maps. As illustrated in Fig. 3, the robust model focuses more on the object of interest, which behaves more like human, while the non-robust model’s attention deviates from the object. This is consistent with the above observation that robust model relies more on the semantic information while non-robust model also employs non-semantic information.

B. Different sensitivities to visual distortions between human and algorithm.

To further verify the different vulnerabilities to adversarial perturbation between human and algorithm, we respectively examine recognition capability of human and algorithm regarding different distortions. Two types of visual distortions are considered specifically: (1) Adversarial perturbation. We employ the widely used FGSM [15] to generate adversarial examples, where one-time perturbation is comprised with step size of 0.02. (2) Gaussian white noise. The added one-time Gaussian white noise follows normal distribution with mean $\mu = 0$, variance $\sigma = 0.01$ and constant power spectral density. To investigate the tendency of recognition performance with increasing distortions, we crafted totally 8 levels of distortions onto the original character images accumulatively: each level corresponds to 5 one-time adversarial perturbations or Gaussian white noises. Examples of derived distorted images at different levels are illustrated in Fig.3 (a) and (b). To examine the recognition capability, we implemented the widely-used OCR regarding the algorithm side [5]. Regarding the human side, we recruited 77 master workers from Amazon Mechanical Turk. Each subject was asked to recognize 450 character images with adversarial and Gaussian distortions in different levels [48].

Fig.3 (c) and (d) illustrate the average recognition accuracies for adversarially and Gaussian distorted CAPTCHAs, respectively. We found human and algorithm show very different sensitivities to the two types of distortions: (1) For adversarially distorted CAPTCHAs, humans are more robust to the adversarial perturbations, while OCR algorithm is highly vulnerable as the distortion level increases. Based on the above introduced task-semantic information taxonomy, we explain this result as that adversarial perturbations affect the task-relevant non-semantic information which misleads the algorithm inference but imperceptible to human. (2) For Gaussian distorted CAPTCHAs, we observed quite opposite results. While human’s recognition accuracy declines sharply as the distortion level increases, OCR algorithm demonstrates relatively stable performance. This is possibly due to the fact that heavy Gaussian noise corrupts the semantic information and thus significantly affects human recognition. However, algorithm remains its recognition by employing the additional non-semantic information. Therefore, this analysis further validates that adversarial perturbation belongs in the task-relevant non-semantic information, which reveals the difference between human and algorithm to motivate the application in adversarial Turing test.

3.1.3 Prototype Application and Discussion.

We have implemented a prototype application by employing adversarially perturbed images to improve character-based CAPTCHAs, which is called robust CAPTCHAs [48]. Instead of being stuck at the competition between human and algorithm on addressing complex tasks, robust CAPTCHAs turns to exploiting their intrinsic difference on the utilization of task-relevant non-semantic information. This guarantees the identification of algorithm from human and protecting towards potential cracking without increasing human’s burden. In addition to the standard adversarial attack, components of multi-target attack, ensemble adversarial training and differentiable approximation are also proposed to address the characteristics obstructing robust CAPTCHA design, e.g., image preprocessing, sequential recognition, black-box crack.

With the tendency that traditional Turing test being cracked by machine learning algorithms, researchers are continuously exploring alternative solutions. As the exclusive information of the algorithm, task-relevant non-semantic information is justified via the above analysis and prototype application for its feasibility in distinguishing between human and algorithm. We hope this study can shed light on the future studies on exploiting adversarial examples to design novel Turing tests. Moreover, besides the standard forms of Turing test, we envision the increasing necessity of generalized Turing test to distinguish between human and algorithm in the future. In particular, the widespread application of machine learning algorithms in data synthesis [8] and automated data annotation [1] is giving rise to a considerable amount of algorithm-generated data in the wild. We believe the utilization of non-semantic information inevitably leaves traces in the generated data, which provides possible solution to identify the algorithm-generated data by carefully examining its reaction to adversarial perturbation.
Table 1: ASRs with different adversarial attack methods.

| Models       | Datasets | FGSM | I-FGSM | MI-FGSM | DI²-FGSM | D-MI²-FGSM |
|--------------|----------|------|--------|---------|----------|------------|
| ArcFace      | LFW      | 98.5%| 99.4%  | 99.4%   | 99.4%    | 99.27%     |
|              | AgeDB-30 | 95.8%| 96.0%  | 96.0%   | 96.0%    | 96.0%      |
|              | CFP-FFP  | 92.5%| 93.7%  | 90.8%   | 93.2%    | 93.4%      |
| MobileFaceNet| LFW      | 74.5%| 86.8%  | 88.2%   | 92.4%    | 89.1%      |
|              | AgeDB-30 | 81.7%| 86.3%  | 88.1%   | 90.5%    | 88.6%      |
|              | CFP-FFP  | 48.6%| 57.2%  | 63.8%   | 68.3%    | 65.0%      |

Figure 5: The examples of compressed images with different compression qualities.

3.2 Rejecting malicious algorithm

3.2.1 Motivation.

Malicious algorithm refers to the algorithm that is utilized by hackers to disservice the community. Take face recognition algorithm as an example, it has been widely adopted in applications like criminal monitoring, security unlock, digital ticket and even face payment. However, some hackers will crawl face images for malicious use, e.g., Kneron tested that widely-used face payment systems like AliPay and WeChat can be fooled by masks and face images, and DeepFake creating imitated videos causes severe personal sabotage [8]. As one of the critical biometric authentication information, the leakage of portrait information will lead to serious security problems. Nevertheless, massive face images exist in photo sharing platforms, such as Facebook, Instagram and other websites. Therefore, it is vital to protect face privacy for photo sharing services to protect the uploaded face images from being maliciously used.

As task-relevant non-semantic information reflects the common weakness of algorithm, adversarial attack provides possible solution to reject these malicious algorithms. Specifically, in case of malicious face recognition, we are motivated to add adversarial perturbation to face image before sharing to the public, so as to preserve its utility as well as prevent from being maliciously used. The following analyzes the feasibility to invalid face recognition algorithms with adversarially perturbed face images in different scenarios.

3.2.2 Justification Analysis.

Malicious Face Recognition Settings.

We employed 2 state-of-the-art face recognition models as the potential malicious algorithms to be rejected. One is ArcFace [9], which is widely-used in public Face ID systems. The other is MobileFaceNet [7], which is commonly used on mobile devices.

- **ArcFace** is the popularly utilized face recognition algorithm in public Face ID systems, whose backbone network is Resnet-v2-152 [19].
- **MobileFaceNet** is specifically tailored for high-accuracy real-time face verification using minimal computing resources, whose backbone network is MobileNet-V2 [37].

We trained the face recognition algorithms on MS-Celeb-1M dataset [16], and tested on LFW dataset [20], AgeDB-30 [32], CFP-FP [38]. With goal of obstructing the algorithm from matching the same person, we use the positive pairs of images belonging to the same person for testing: one image as the enrolled image to represent identity, and the other image for synthesizing adversarial example.

- **MS-Celeb-1M** contains 10 million images of 100,000 subjects.
- **LFW** contains 13,233 images of 5,749 different subjects. According to the refined version of Deng et al. [9], we use 6,000 images to construct 3,000 positive pairs of images.
- **AgeDB-30** contains 16,488 images of 568 different subjects. Same as above, we use 6,000 images to construct 3,000 positive pairs of images.
- **CFP-FP** contains 7,000 images of 500 different subjects. Same as above, we use 7,000 images to construct 3,500 positive pairs of images.

Adversarial Attack Settings.

We respectively employed FGSM [15], I-FGSM[26], MI-FGSM[10], DI²-FGSM[44] and D-MI²-FGSM[44] to generate adversarial examples. As one of the most typical adversarial attacks, FGSM generates adversarial examples by a single gradient step. I-FGSM boosted it into iterative version. MI-FGSM further improved the performance by adding momentum term. DI²-FGSM and D-MI²-FGSM adopted random image transformations which achieved state-of-the-art performance in black-box settings.

Attack Success Rate (ASR) is selected to measure the effectiveness of adversarial attack to mislead the face recognition algorithms:

$$\text{ASR} = \frac{N_{w/o} - N_w}{N_{total}}$$ (1)
Table 2: ASRs on ArcFace using LFW dataset under different compression qualities ($C_\alpha$). Lower compression quality corresponds to higher compression rate.

| Images                  | Compression Rate | ASRs     |
|-------------------------|------------------|----------|
| $Adv(w/o
compression)$  | x                | 98.5%    |
| $Adv_{C_\alpha=0.75}$   | 6x               | 94.35%   |
| $Adv_{C_\alpha=0.45}$   | 6x               | 89.95%   |
| $Adv_{C_\alpha=0.25}$   | 10x              | 85.05%   |

Table 3: ASRs on ArcFace using different datasets.

| Images                  | LFW   | AgeDB-30 | CFP-FP |
|-------------------------|-------|----------|--------|
| $makeup$                | 5.14% | 9.50%    | 4.83%  |
| $adversarial$           | 98.5% | 95.8%    | 92.5%  |
| $makeup_{adversarial}$  | 98.73%| 99.44%   | 96.95% |

where $N_{w/o}$ and $N_w$ denote the number of correctly recognized face images without and with perturbation, respectively. $N_{total}$ denotes the total number of face images. The higher ASR, the better the effectiveness of adversarial examples.

A. Results of Attacking Malicious Face Recognition Algorithms

We employed the above introduced adversarial attack methods on the two face recognition algorithms of ArcFace and MobileFaceNet. Table 1 shows the ASRs on the three testing datasets. We can find that: (1) Both for ArcFace and MobileFaceNet, all adversarial attack methods achieve considerable ASRs. The reason for the relative lower ASR of MobileFaceNet is due to its inferior recognition accuracy on original face images ($\frac{N_{adv}}{N_{total}}$). This verifies the effectiveness of employing adversarial examples to obstruct malicious face recognition algorithms from privacy leaking. (2) Within each row, ASR consistently increases from left to right indicating weaker to stronger adversarial attack methods. This encourages the employment of stronger adversarial attacks towards more promising malicious algorithm rejection.

B. Attacking Results on Resistance against Image Compression

In practical scenario, face images are likely to undergo a series of processing like compression and clipping during sharing onto the online platforms. Since images are perturbed before these processing operations, in this part we examine the resistance of adversarial attack against the image compression. Specifically, FGSM is selected as the adversarial attack method and JPEG compression is implemented with different parameters of compression qualities $C_\alpha$, as illustrated in Fig. 5. Table 2 shows the recognition results on the LFW dataset. We can observe that, even the baseline adversarial attack method FGSM demonstrates considerable resistance against image compression by maintaining a relatively high ASR value. While declining as the compression quality decreases, ASR under the compression quality of 0.25 still reaches 85.05% which guarantees the attacking feasibility under extreme compression situations.

C. Attacking Results on Compatibility with Facial Makeup

With the increasing application of facial makeup transfer, people tend to add makeup to beautify their portrait images before sharing to the public. In this case, it is necessary for adversarial attacks to remain effective on the images with facial makeup. To verify this, we combined the state-of-the-art facial makeup method PSGAN [23] and adversarial attack method FGSM to generate adversarial examples. ASR results on the three datasets are summarized in Table 3: $makeup$ indicates the images only processed by PSGAN, $adversarial$ indicates the images only perturbed by FGSM, and $makeup_{adversarial}$ indicates the images first processed by PSGAN and then perturbed by FGSM.

It is shown that: (1) $Makeup$ also contributes to confusing the face identify (with positive yet low ASR). We suspect that facial makeup corrupts task-relevant semantic information so as to affect the face recognition performance. (2) $Makeup_{adversarial}$ further misleads the face recognition algorithms with significantly increased ASR. The fact that $Makeup_{adversarial}$ achieves higher ASR than both $makeup$ and $adversarial$ demonstrates the compatibility between makeup and adversarial attack. It is interesting in future studies to explore how to effectively integrate the modification to task-relevant semantic (from makeup) and non-semantic (from adversarial attack) information. Examples of original, $makeup$, and $makeup_{adversarial}$ images are illustrated in Fig. 6. We can see that the adversarial attack does not undermine the visual perception of makeup image, which guarantees makeup utility as well as privacy-preserving effectiveness.

3.2.3 Prototype Application and Discussion

A prototype application employing adversarial attack to rejecting malicious face recognition algorithms is implemented. [49]. This application introduces an end-cloud collaborated adversarial attack framework, which addresses the advanced requirement to guarantee the original image only accessible to users’ own device. This succeeds in avoiding the leakage of face images during transmission to the server. A demo video illustrating the prototype is available online.

Justified by the above analysis and inspired by the prototype application, we expect two productive directions of exploiting adversarial attack to reject malicious algorithms: (1) optimizing the procedure of generating adversarial examples by addressing practical requirements (e.g., non-accessibility in our application) and
We review that the essence of data hunger lies in the lack of certain features (e.g., personal identity in surveillance video and phone call) and adversarial attack to extract non-semantic features on the CIFAR10 [25].

### 3.3 Adversarial data augmentation

#### 3.3.1 Motivation.

The successful application of deep learning is largely due to the adequate annotated data. However, in many real world applications, it is usually impossible to collect and annotate sufficient training data, e.g., fraud user judgment in finance, abnormal behavior detection in risk control, tumor diagnosis in medicine, etc. This results in the so-called “data hunger” problem, which gives rise to notorious issues of machine learning algorithms like overfitting [18] and algorithm bias [17, 24]. Typical solutions to address the “data hunger” are few-shot learning and data augmentation. While few-shot learning resorts to extracting as many generalizable features as possible from the limited amount of training data, data augmentation is committed to generating new training data to enhance and balance the original training data. It is worth noting that the above solutions both focus on employing the semantic information, e.g., transferring semantic features from base classes to novel classes in few-shot learning, augmenting data along semantic directions like image rotation and translation to encourage the algorithm to learn more task-relevant semantic features.

Inspired from the discussion on algorithm’s employment of non-semantic features, we envision the huge potential in exploiting the non-semantic information to alleviate the “data hunger” problem. We review that the essence of data hunger lies in the lack of human-perceptible semantic information and human annotation. In other words, the data is lacking only regarding the employment of semantic features. Regarding the employment of non-semantic features, we attempt to explore the idea of “what is taken from the algoritm is used for algorithm”, e.g., to extract non-semantic features for the novel classes from the adversarially attacked base-class data, to annotate data via adversarial attack relying on the non-semantic information. Augmenting data via adversarial attack thus provides alternative solutions to address the data hunger problem by discovering and employing for free the non-semantic features.

#### 3.3.2 Justification Analysis.

**Dataset and Settings.** We justify the motivation to employ adversarial attack to extract non-semantic features on the CIFAR10 [25] dataset. ResNet18 [19] and ResNet50 [19] are implemented in different analysis experiments, and Adam optimizer is selected to train the image recognition algorithms with fixed learning rate of $1e-5$.

**A. Adversarial Attack provides Strong Feature.**

We again employed UAP to analyze whether adversarial attack can provide discriminative non-semantic features. Fig. 7 shows the generated UAPs for the 10 categories in CIFAR10. While we can hardly perceive semantics related to the target category from the UAPs, the original images are misclassified as the target category once added with the corresponding UAP. This implies that the adversarial perturbation contains very strong features which even deactivates the semantic information in the original image. To exclude the entanglement with original image, we also examined how UAP alone will influence the model inference, i.e., adding UAP to blank image and directly feeding it for inference. We surprisingly observed that model still outputs the attacked target label with 100.00% confidence. This demonstrates that adversarial attack indeed provides discriminative features both combined with the semantic-information and employed independently.

**B. Adversarial Attack provides Generalizable Feature.**

We further analyze whether the extracted features from adversarial attack are generalizable to the unseen data. To address this, we design experiment to train models only on adversarially attacked
images and then to test on the original images. Specifically, we constructed the adversarially attacked dataset \( D_{adv} \) by attacking each image \((x, y)\) from the original training dataset \( D_{ori} \): firstly randomly assigning a target category \( t \neq y \), and then adding adversarial perturbation onto original image \( x \) so as to mislead the inference result as \( t \). The constructed training dataset \( D_{adv} \) thus consists of images denoted as \((x', t)\). We illustrate this experimental setting in Fig. 8, where the images with blue and red frames indicate correspondingly the original and adversarial images. It is easy to observe that the images in \( D_{adv} \) are linked to the target labels by the non-semantic information instead of the human-perceptible semantic information.

We trained 2 classifiers of \( f_{ori} \) and \( f_{adv} \) respectively on \( D_{ori} \) and \( D_{adv} \), and examined their performance on the original testing dataset. The derived recognition accuracies for \( f_{ori} \) and \( f_{adv} \) are 94.4% and 66.3%. While \( f_{adv} \) does not achieve comparable performance as \( f_{ori} \), the accuracy of 66.3% still demonstrates the contribution of adversarial non-semantic feature which performs much better than random guessing. Note that recent generalization study reported a random guessing result on CIFAR10 by randomizing label \( y \) but remaining the original image \( x \) [47]. The only difference between [47] and our above experiment lies in the added adversarial perturbation to \( x \). The fact that the classifier learned from adversarially polluted image \((x', t)\) succeeds to recognize testing image \((x, y)\) demonstrates that, the extracted non-semantic features from adversarial attack have potential to be generalizable to the original samples.

C. Adversarial Attack provides Complementary Feature.

The previous analysis validates the strong and generalizable features from adversarial attack. In this part, we consider a more practical scenario of exploiting adversarial attack to address the “data hunger” problem. In particular, a training setting with both original and adversarial images is designed: (1) We first constructed an imbalanced training dataset \( D_{imb} \) to imitate data shortage. We selected 4 categories of frog, horse, ship, truck, and reduced the number for their training data to 10%. (2) Next, we expanded \( D_{imb} \) to \( D_{aug} \) by generating adversarial images from attacking the other 6 categories. Totally another 10% of adversarial images were obtained for each of the 4 reduced target categories. The data distribution of the adversarially augmented training dataset \( D_{aug} \) is illustrated in Fig. 9.

Similar to the above experiment, we respectively trained two classifiers \( f_{imb} \) and \( f_{aug} \) on \( D_{imb} \) and \( D_{aug} \), and tested them on the original testing set. The results for the reduced categories are shown in Table 4. We have the following findings: (1) Before augmentation, the lackage of training data significantly affects the performance of classifier \( f_{imb} \) to obtain an average accuracy of 49.5%. (2) After adversarial data augmentation, the classification accuracy for each category has improved, with the average accuracy increased to 54.7%. This indicates that adversarial attack provides complementary features to effectively expand the feature pool. As supplement to the semantic features extracted from human-annotated data, adversarial attack opens up possibilities to exploit the additional non-semantic features to address the “data hunger” problem in practical applications.

3.3.3 Prototype Application and Discussion.

By utilizing adversarial examples for data augmentation, we implemented a prototype application to solve the algorithm bias problem [50]. In order to obtain a fair dataset in which the distribution of bias variables is balanced, we apply adversarial attacks to generate examples containing information of bias variable as the enhanced data. Instead of down-sampling to discard samples or adding additional regularization to sacrifice accuracy as in traditional debiasing solutions, adversarial examples serve as pseudo samples to augment the training dataset and thus simultaneously improve the accuracy and fairness.

Researchers are generally utilizing data augmentation to improve the generalization of machine learning models caused by data shortage. Through the above experiments and analysis, we demonstrated that expanding training dataset by adversarial examples is an effective means of data augmentation. While traditional data augmentation can be viewed as exploiting human-consistent prior knowledge to make up for the data shortage, adversarial attack provides a new sight of prior knowledge which is imperceptible to human. We argue that the capability of employing non-semantic information contributes much to the rapid progress of today’s machine learning algorithms. However, few work has proactively examined how to exploit it in benign applications. It remains unexplored in many perspectives before integrating the non-semantic and semantic features, e.g., in what cases the algorithms are likely to extract non-semantic features for practical usage, how to extract and better employ the non-semantic features, what are the pros and cons of employing non-semantic features, etc.

4 CONCLUSION

This work discusses the possibility of exploiting adversarial examples for goodness. Starting with a novel taxonomy of visual information along the task-semantic coordinate, we attribute adversarial example to algorithm’s utilization of task-relevant non-semantic information. In this perspective, adversarial example is not malignant in default but reflecting some interesting characteristics of task-relevant non-semantic information. We have demonstrated the feasibility of designing benign adversarial attack applications in adversarial Turing test, rejecting malicious algorithm and adversarial data augmentation. While some applications are ready for practical use, more applications deserve extensive future studies. We hope this study introduces some fresh perspective to consider adversarial attack, and inspire the community to pay more attention to the employment of non-semantic information.

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