Distributed Black-box Attack: Do Not Overestimate Black-box Attacks

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Abstract—Black-box adversarial attacks can fool image classifiers into misclassifying images without requiring access to model structure and weights. Recent studies have reported attack success rates of over 95% with less than 1,000 queries. The question then arises of whether black-box attacks have become a real threat against IoT devices that rely on cloud APIs to achieve image classification. To shed some light on this, note that prior research has primarily focused on increasing the success rate and reducing the number of queries. However, another crucial factor for black-box attacks against cloud APIs is the time required to perform the attack. This paper applies black-box attacks directly to cloud APIs rather than to local models, thereby avoiding mistakes made in prior research that applied the perturbation before image encoding and pre-processing. Further, we exploit load balancing to enable distributed black-box attacks that can reduce the attack time by a factor of about five for both local search and gradient estimation methods.

Impact Statement—In an era of cloud computing, deep learning models can be deployed on cloud servers and then provided as APIs to end users. However, image classification models are vulnerable to black-box adversarial attacks. Our research tries to answer the question of whether black-box attacks have become a real threat against image classification cloud services. To the best of our knowledge, our research is the first study on online black-box attacks against cloud APIs. As such, the results are of great importance within deep learning cloud services.

Index Terms—Adversarial Attacks, Black-box Attacks, Image Classification, Cloud Service.

I. INTRODUCTION

Image classification models are widely used in real-world applications and typically achieve top-5 accuracy of over 90%. Cloud-based image classification services, such as Google Cloud Vision, provide pre-trained models as APIs, allowing users to classify images by sending requests to cloud servers. This is particularly useful for IoT edge devices that lack the computational power to run deep learning models locally.

However, image classification cloud services are vulnerable to black-box adversarial attacks, which generate imperceptible perturbations to input images in order to mislead classification models into incorrect predictions. While prior research has shown that black-box attacks can achieve high success rates of over 95% with only 1,000 queries without access to model structure and weights [1], most research has generated adversarial images offline on local models rather than online on cloud servers. The efficiency of online black-box attacks against cloud services remains unclear.

Implementing online black-box attacks is more challenging than offline attacks due to the slower response time of cloud APIs compared to local models with GPUs. While a local model utilizing a GPU can respond to over 100 queries per second, the typical response time for a single query from an API server is 0.5 - 2s. Online black-box attacks pose limited practical threat because generating multiple adversarial images could take several hours. Therefore, online attacks against cloud services must be both time-efficient and achieve high success rates. However, previous research in this area often underestimates the time required to launch online black-box attacks and overestimates the attack success rate.

A. Common Mistakes

During our implementation of distributed black-box attacks, we observed that some previous research made certain errors in the query process, which provided their attacks with an unfair advantage. This advantage led these methods to outperform state-of-the-art black-box attacks, but it was based on the assumption of accessing information that is not available in black-box attacks [2][3][4][5][6][7].

Most prior research test their attacks on local models, rather than on Cloud APIs, since it is both faster and less costly. Our experimental results reveal that these attacks achieve significantly lower success rates when attacking cloud services.

Image Encoding: In real-world scenarios, images are typically encoded before being sent to cloud services to reduce the amount of data transmitted and to save bandwidth (see Fig. 2). However, prior research often assumes that perturbations can be added directly to the raw input image (see Fig. 1).

It is worth noting that cloud services such as Google Cloud Vision and Imagga accept raw binary and base64 encoded JPEG (lossy compression) images as input. This compression may cause part of the perturbations to disappear, ultimately reducing the success rate of attacks. Therefore, if we evaluate black-box attacks on local models without considering image encoding and quantization, we may overestimate the effectiveness of these attacks against real-world cloud APIs.

Besides, image classification cloud services do not accept images with invalid pixel values. For example, the bandit attack does not clip the image while estimating gradients, assuming they can send invalid images (pixel value > 255 or < 0) to the black-box model.

Image Pre-processing: Some papers apply perturbations after image resizing, thereby assuming that they know the input shape of the image classification model in the cloud. Moreover, note that original input images are typically larger than the model input shape. Resizing high-resolution images to a lower resolution reduces the sampling space, thereby making it less computationally intensive to generate perturbations.
B. Contributions

This paper aims to investigate if black-box adversarial attacks have become a practical threat against image classification cloud services. Our main contributions are as follows:

- We identify some common mistakes in prior research that leads to an overestimation of the efficiency of black-box attacks (see Fig. 1). To avoid these mistakes, we design an image classification cloud service for benchmark, and we open source this cloud API for future research on black-box attacks (see Fig. 2).

- We design a framework that facilitates horizontally and vertically distributed queries to speed up online black-box attacks against cloud services (see Fig. 5).

- We also provide an open-source Black-box Adversarial Toolbox that simplifies the process of conducting black-box attacks against cloud APIs.

B. Preliminaries

A. Image Classification Models

The state-of-the-art image classification models that use convolutional neural networks (CNN) achieve a Top-1 accuracy of over 90% and a top-5 accuracy of over 99% on the ImageNet dataset [8]. Among them, ResNet [9], MobileNet [10], InceptionV3 [11], and EfficientNet [12] are the most popular models for real-world applications, as they balance model size and accuracy well. Previous research on black-box adversarial attacks against image classification models has mainly focused on VGG16 [13], ResNet50, and InceptionV3, pre-trained on the ImageNet [14] dataset.

VGG16: The VGGNet is well known for its simplicity. 3x3 convolutional layers and a max-pooling layer are stacked on each other as a sequential model, followed by three fully-connected layers. Being 16 layers deep, VGG16 was considered to be a very deep neural network when it was introduced in 2014. Today, however, improvements in computational resources enable even deeper neural networks to be implemented.

ResNet50: In 2015, ResNet made it possible to train up to hundreds or even thousands of layers. The residual building block introduces skip connections to solve the vanishing gradient problem in deep CNNs, while preserving the overall performance. In research on black-box adversarial attacks, ResNet50 is one of the most widely used variants.

Inceptionv3: Choosing the kernel size for convolution layers is tricky. The use of different kernel sizes in different layers may both exacerbate the vanishing gradient problem and lead to higher requirements on the computational resources. The inception module instead puts several convolution layers with different kernel sizes side-by-side at the same level and introduces extra 1x1 convolutions to control the number of features. Besides, an auxiliary loss is added to the original loss to avoid the vanishing gradient problem. The inception module was introduced by Google, and thus, the first version is known as GoogleNet.

All the three models described above are vulnerable to black-box adversarial attacks. This paper introduces distributed black-box attacks to investigate if black-box attacks could be a real threat against image classification cloud services.

B. Black-box Adversarial Attacks

Black-box attacks aim to deceive deep-learning models without having access to their internal structure or weights. Two common types of black-box attacks are gradient estimation and local search methods, which have been widely studied in the literature [1] [15].
**Local Search Methods:** The task of generating adversarial inputs can be approached as a problem of selecting what pixels to attack. Thus, we can use existing local search methods to search for combinations of pixels to be perturbed. One simple, yet effective, baseline attack that use this idea is the simple black-box attack (SimBA) [4]. With SimBA, a vector is randomly sampled from a predefined orthonormal basis and then added or subtracted from the image. To improve sample efficiency, Andriushchenko et al. proposed the square attack [7]. This attack initializes the perturbation using vertical stripes, since CNNs are sensitive to high-frequency perturbations [16], and then generates square-shaped perturbations at random locations to deviate model classifications.

**Gradient Estimation Methods:** Inspired by white-box attacks that use gradients to generate adversarial perturbations [17] [18], black-box gradient estimation methods estimate gradients through queries, and then use these estimated to construct adversarial perturbations. To estimate gradients, Chen et al. used the finite-differences method to compute the directional derivative at a local point [19]. To improve query efficiency, Ilyas et al. proposed a natural evolutionary strategy (NES) [20] based method to approximate gradients, and proved that the standard least-squares estimator is an optimal solution to the gradient-estimation problem [2]. In the Bandits attack, Ilyas et al. further improved the classifier by using priors on the gradient distribution [3], thereby exploiting the fact that the gradients at the current and previous steps are highly correlated.

### III. Distributed Black-box Attacks

#### A. Problem Formulation

Given some input image \( x \) and true labels \( y \), the objective of the adversary is to add a small perturbation \( \delta \) to the original image, and generate an adversarial image \( x' = x + \delta \) that can fool a black-box image classifier \( C(x) \), such that \( C(x') \neq C(x) \). Typically, the perturbation \( \delta \) is bounded in the \( l_2 \) or \( l_\infty \) norm by some user-defined constant [1].

The adversary does not know the model structure and weights. Further, the attacker has limited access to model outputs for black-box models deployed on cloud servers. For example, in the partial-information setting, the adversary only has access to the prediction probabilities of the top \( k \) classes \( \{y_1, ..., y_k\} \). In the label-only setting, the adversary can only access the prediction label without any knowledge of prediction probabilities [2].

#### B. Distributed Queries

Cloud computing platforms serve APIs via load balancing, which means that several computing engines provide the same model-inference service simultaneously. If we exploit load balancing and send multiple queries concurrently, we can receive all the results simultaneously and thus accelerate black-box attacks significantly.

To demonstrated this hypothesis, we sent 1, 2, 10, and 20 queries concurrently to Google Cloud Vision, Imagga, and DeepAPI (see Fig. 3). Since the PC has eight cores, we can send concurrent queries from eight workers. Tab. I lists the total time, averaged over 10 experiments, before receiving all responses. As can be seen, the total time does not grow linearly with the number of queries. Rather, the average query time decreases as we send out more concurrent queries.

Black-box attacks are usually slow because they require several thousands of queries. Depending on the network quality, it could take 0.5–2s to receive one query result from an API server, and thus, it could take several hours to launch a black-box attack. However, cloud computing platforms serve APIs via load balancing, which means that several computing engines provide the same model-inference service simultaneously. If we exploit load balancing and send multiple queries concurrently, we can receive all the results simultaneously and thus accelerate black-box attacks significantly.

In conclusion, thanks to load balancing, the more queries we send, the faster the queries become on average. This is a feature that we will exploit to accelerate black-box attacks.

#### C. DeepAPI

To facilitate future research on distributed black-box attacks that attack cloud APIs rather than local models, we designed DeepAPI, an open-source image classification cloud service (see Fig. 4) that supports:

![Fig. 3: The average query time when sending multiple concurrent queries to cloud APIs.](image-url)

| Queries | Google Cloud Vision | Imagga | DeepAPI (Ours) |
|---------|---------------------|--------|----------------|
|         | Total Time | Average Time | Total Time | Average Time | Total Time | Average Time |
| 1       | 446.7ms     | 446.7ms     | 1688.1ms   | 1688.1ms     | 538.5ms    | 538.5ms    |
| 2       | 353.61ms   | 176.8ms     | 2331.8ms   | 1165.9ms     | 643.2ms    | 321.6ms    |
| 10      | 684.25ms   | 68.4ms      | 10775.8ms  | 1077.6ms     | 1777.8ms   | 177.8ms    |
| 20      | 1124.82ms  | 56.2ms      | 21971.8ms  | 1098.6ms     | 1686.4ms   | 84.3ms     |

**TABLE I:** The total and average time of sending concurrent queries to cloud APIs.
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The three most popular classification models for black-box attacks: VGG16, ResNet50, and Inceptionv3 provided by Keras Model Zoo [21].

Both soft labels (with probabilities) and hard labels (without probabilities) for label-only setting.

Top $k$ predictions ($k \in \{1, 3, 5, 10\}$) for partial-information setting.

D. Horizontal and Vertical Distribution

Both local (multi-core CPU) and cloud-based (load balancer) deep learning models are vulnerable to distributed queries, but the challenge lies in deciding which queries to send concurrently. To address this problem, we propose horizontal and vertical distribution for black-box attacks, inspired by horizontal and vertical scaling of cloud resources [22].

Horizontal distribution concurrently sends queries for different images within the same iteration, thereby allowing the generation of multiple adversarial examples concurrently. This can be achieved without altering existing black-box attack methods. Since horizontal distribution does not require significant modifications to the original attack method, we can apply horizontal distribution by implementing a distributed query function that sends concurrent requests to cloud APIs.

Vertical distribution, on the other hand, sends multiple concurrent queries for the same image, thereby accelerating the attack for that particular image. Existing black-box attack methods need to be redesigned to decouple the queries across iterations.

In summary, horizontal distribution achieves concurrent attacks against multiple images, while vertical distribution speeds up attacks on a single image (see Fig. 5).

Algorithm 1 Distributed SimBA (Vertical)

1: for each image $x_i \in X$ do
2: \hspace{1em} $x'_i, y'_i = \text{SimBA}(x_i, y_i, Q, \alpha, \epsilon, n_{\text{batch}})$
3: \hspace{1em} \{\}
4: \hspace{1.5em} Initialize: $\delta_i = 0, x'_i = x_i + \delta_i$.
5: \hspace{1em} for each iteration $n \in [0, n_{\text{iter}})$ do
6: \hspace{2em} Pick $q_{\text{batch}} \in Q$ randomly without replacement.
7: \hspace{2em} // Concurrent requests across iterations.
8: \hspace{2em} $p^+ = C(x'_i + q_{\text{batch}} \epsilon)$.
9: \hspace{2em} $p^- = C(x'_i - q_{\text{batch}} \epsilon)$.
10: \hspace{2em} for $q_i \in q_{\text{batch}}$ do
11: \hspace{3em} if $p^+_i < y'_i$ then
12: \hspace{4em} $\delta_i = \delta_i + \alpha q_i$.
13: \hspace{3em} else if $p^-_i < y'_i$ then
14: \hspace{4em} $\delta_i = \delta_i - \alpha q_i$.
15: \hspace{3em} end if
16: \hspace{2em} end for
17: \hspace{2em} $\delta_i = \text{proj}_p(\delta_i)$.
18: \hspace{2em} $x'_i = x'_i + \delta_i$.
19: \hspace{2em} $n = n + n_{\text{batch}}$
20: \hspace{2em} if success then break.
21: \hspace{2em} end for
22: \}
23: end for

E. Distributed SimBA (Baseline Method)

We first use a baseline method, SimBA [4], to illustrate how to apply horizontal and vertical distribution.
In each iteration, SimBA increases or decreases the value of one randomly chosen pixel, and assumes that for any perturbation vector \( q \) and some step size \( \epsilon \), either \( x + \epsilon q \) or \( x - \epsilon q \) will decrease the highest probability \( p_b(x') \) in \( y = C(x') = (p_1, p_2, \ldots, p_K) \). Thus, we can randomly pick a vector \( q \) in the set of orthogonal search directions \( Q \) and then either add or subtract it from the image \( x \) to decrease the highest probability \( p_b(x') \). To guarantee maximum query efficiency, \( q \) are picked from \( Q \) without replacement, and all vectors in \( Q \) are orthonormal.

To apply vertical distribution to SimBA, we need to decouple the correlation between queries at different iterations. The original SimBA generates perturbations pixel by pixel. After receiving previous query results and deciding the perturbation \( \delta \in \{-q, +q\} \) for each vector \( q \), the algorithm then goes on to choose which pixel to perturb in the next iteration. To decouple the correlation, we devise vertically distributed SimBA that sends out queries for several perturbation vectors \( \mathbf{q} \) as a batch \( \mathbf{q}_{batch} \) concurrently. The sign of each perturbation vector is decided independently. Then, we sum and project the accumulated perturbation \( \delta \) to the \( L_2 \) ball at the end of each iteration to guarantee imperceptibility (see Alg. 1).

\[
\text{Algorithm 2 Distributed Square Attack (Vertical)}
\begin{align*}
1: & \text{for each image } x_i \in X \text{ do } \\
2: & \quad \text{Initialize: } x_i' = \text{init}(x_i) \text{ with vertical strips.} \\
3: & \quad \text{Single Query: } l_i^t = L(C(x_i'), y). \\
4: & \quad x_i', y_i' = \text{SquareAttack}(x_i, y_i, \epsilon, n_{batch}); \\
5: & \quad \text{for each iteration } n \in [0, n_{iter}) \text{ do } \\
6: & \quad \quad \text{Uniformly sample a batch of square perturbation } \Delta_{batch}. \\
7: & \quad \quad // \text{ Concurrent requests across iterations and then compute margin loss.} \\
8: & \quad l_{batch} = L(C(x_i', +\Delta_{batch}, y_i')). \\
9: & \quad \text{for } \delta_i \in \Delta_{batch} \text{ and } l_i \in \mathbf{l}_{batch} \text{ do } \\
10: & \quad \quad \text{if } l_i < l_i^t \text{ then } \\
11: & \quad \quad \quad x_i' = x_i' + \delta_i \\
12: & \quad \quad \quad l_i^t = l_i \\
13: & \quad \quad \text{end if} \\
14: & \quad \quad \text{end for} \\
15: & \quad \quad \text{end for} \\
16: & \quad n = n + n_{batch} \\
17: & \quad \text{if success then break.} \\
18: & \quad \text{end for} \\
19: & \text{end for}
\end{align*}
\]

\[\text{F. Distributed Square Attack (Local Search)}\]

The square attack is a local search method, just like SimBA. However, it is generally more query-efficient.

As its name suggests, the square attack generates square-shaped perturbations to decrease the margin loss \( L(C(X^t, y)) \). The square attack improves query efficiency by initializing the perturbation with vertical stripes, motivated by the fact that CNNs are sensitive to high-frequency perturbations [16]. We apply horizontal distribution to both the initialization and iteration processes across images.

To apply vertical distribution to the Square Attack, we generate a batch of square-shaped perturbations independently and send out queries concurrently for each perturbation. After receiving the queries, we add the perturbations that reduce the margin loss \( l = L(C(X), y) = C_y(X) - \max_{k \neq y} C_k(X) \) to the image, where \( y \) is the correct class of the input image \( X \) and \( C_y(X) \) is the output probability of class \( y \). Then, we project the accumulated perturbation to the \( L_\infty \) ball to ensure imperceptibility (see Alg. 2).

\[
\text{Algorithm 3 Distributed Bandits Attack (Vertical)}
\begin{align*}
1: & \text{for each image } x_i \in X \text{ do } \\
2: & \quad \text{Initialize: } x_i' = x_i, v_i = 0. \\
3: & \quad x_i', y_i' = \text{BanditsAttack}(X', y, \delta, \epsilon); \\
4: & \quad \text{for each iteration } n \in [0, n_{iter}) \text{ do } \\
5: & \quad \quad \Delta_{batch}^+ = [\ ], \Delta_{batch}^- = [\ ] \\
6: & \quad \quad \text{for } j \in n_{batch} \text{ do } \\
7: & \quad \quad \quad u_i^j = \mathcal{N}(0, \frac{1}{d}) \\
8: & \quad \quad \quad \{q_i^{j,+}, q_i^{j,-}\} \leftarrow \{v_i + \delta u_i^j, v_i - \delta u_i^j\} \\
9: & \quad \quad \quad \text{Append } \{q_i^{j,+}, q_i^{j,-}\} \text{ to } \{\Delta_{batch}^+, \Delta_{batch}^-\} \\
10: & \quad \quad \text{end for} \\
11: & \quad // \text{ Concurrent requests across iterations.} \\
12: & \quad l_{batch} = L(C(x_i' + \epsilon \Delta_{batch}, y)). \\
13: & \quad l_{batch} = L(C(x_i' + \epsilon \Delta_{batch}, y)). \\
14: & \quad \text{for } j \in n_{batch} \text{ do } \\
15: & \quad \quad \nabla_i^j = \left( \frac{l_{batch}^+ - l_{batch}^-}{2} \right) u_i^j \\
16: & \quad \quad v_i = \text{EG\_Step}(v_i, \nabla_i^j / n_{batch}) \\
17: & \quad \quad x_i' = \text{PGD\_Step}(x_i', v_i / n_{batch}) \\
18: & \quad \text{end for} \\
19: & \quad n = n + n_{batch} \\
20: & \quad \text{if success then break.} \\
21: & \quad \text{end for} \\
22: & \text{end for}
\end{align*}
\]

\[\text{G. Distributed Bandits Attack (Gradient Estimation)}\]

The Bandits Attack is a gradient estimation method that improves the optimal least-squares estimator by introducing gradient priors [3]. The perturbation vector \( q_i = v_i + \delta u_i \) is computed from the gradient prior \( v_i \) and a Gaussian vector \( u_i \) sampled from \( \mathcal{N}(0, \frac{1}{d} I) \). The adversarial image \( x' \) is updated using projected gradient descent (PGD), while gradient priors are updated using exponentiated gradients (EG) [23].

The vertically distributed Bandits attack concurrently estimates a batch of gradients for the same image (see Alg. 3). The Bandits Attack uses imperfect gradient estimators \( \nabla_i = \frac{(v_i + \delta u_i) - (v_i - \delta u_i)}{2} - l_i \) to improve query efficiency at the cost of introducing noises in the estimations. Therefore, averaging over a batch of concurrent gradient estimations can improve the accuracy and efficiency.

\[\text{IV. EXPERIMENTAL EVALUATION}\]

We conducted experiments in a more realistic setting, limiting each attack to at most 1,000 queries per image. We used the \( L_\infty \) norm and applied the same strength of perturbation \( \epsilon = 0.05 \) across different attacks.
The DeepAPI was deployed Azure Container Apps, leveraging a load balancer and auto-scaling to allocate computing nodes (2 CPUs and 4GB of memory).

A. Attacking Local Model and Cloud APIs

We first demonstrate that it is more challenging to attack cloud APIs than local models by attacking 1,000 images. Each image belongs to a unique class in ImageNet.

The SimBA baseline method achieves a comparable success rate and requires a similar number of queries for attacks against local models and cloud APIs (Figs. 6a and 7a). However, note that the success rate of SimBA is relatively low ($\approx 5\%$); most attacks consume the full query budget (1,000 queries). Thus, we do not see any evident increase in the average number of queries when attacking cloud APIs.

For the square attack, which is a local search method, attacking a high-resolution image against cloud APIs without image resizing results in a larger search space. It is more challenging to find adversarial examples in a larger space, and thus the attack against DeepAPI achieves a lower success rate (Fig. 6b) and requires more queries (Fig. 7b).

For the Bandits attack, it is more difficult to estimate gradients accurately before image resizing. Bilinear interpolation generates low-resolution images by subsampling from high-resolution inputs. Gradients at unsampled points are zero, making it difficult to produce valid estimates. Thus, the attack success rate against DeepAPI is significantly lower than when attacking local models (Figs. 6c and 7c).

B. Horizontal Distribution

In this section, we measure the effect of horizontal distribution on total queries and the attack success rate.

We used the FiftyOne ImageNet Sample Dataset that contains 1,000 images, one randomly chosen from each class of the validation split of the ImageNet 2012 dataset [24].

For the benchmark, we sampled 100 images, one randomly chosen from each class of the 1000 classes from the ImageNet dataset and tested three online black-box attacks against three image classification models [21]. We only tested 100 images, because our experiments on DeepAPI took 120 hours for 100 images in total. A benchmark on 1,000 images could take over 50 days depending on network connectivity.

We further evaluate the impact of horizontal distribution on the total attack time. As shown in Fig. 8, horizontal distribution significantly reduces the total attack time for all the attacks. By sending concurrent queries across multiple images, we can achieve a successful attack faster without increasing the query budget. The acceleration ratio depends on the number of computational nodes deployed for the cloud API. Deploying more nodes behind the load balancer can lead to a larger acceleration ratio.

In summary, our experiments showed that horizontal distribution reduced the total attack time by a factor of five on average and did not significantly affect the attack success rate and the average number of queries, which brings black-box attacks a step closer to be a practical threat.
C. Vertical Distribution

In this section, we focus on improving the efficiency of attacking a single image through vertical distribution. The vertical distribution sends out queries concurrently across iterations of the same image. The implementations of vertical distribution presented in Section III-D serve to illustrate the general concept of distributed attacks, but there may be other approaches to achieving vertical distribution that are more effective for specific black-box attacks. In the following experiments, we use the implementation presented in Section III-D.

The SimBA Attack: Using vertical distribution, we can reduce the probability of the highest ground-truth class more quickly within a limited time by randomly choosing a batch of unrepeated pixels to perturb (see Fig. 9a). This is particularly effective when attacking with SimBA, which has a relatively low attack success rate.

The Square Attack: Similarly, the vertically distributed square attack decreases the margin loss faster than the original method and achieves an early successful attack (see Fig. 9b). This is because multiple square-shaped perturbations are generated as a batch in a single iteration, which accelerates and increases the attack success rate.

The Bandits Attack: The vertically distributed bandits attack also achieves an early successful attack (see Fig. 9c). Note that the original non-distributed bandits attack failed to generate an adversarial example after 1,000 queries, which means vertically distributed attacks can also improve the attack success rate.

Besides, we show some adversarial images generated by vertically distributed black-box attacks and original methods in Fig. 10. They were generated under the same $\epsilon = 0.05$, and we cannot tell the difference from the perspective of human eyes.

In conclusion, compared with non-distributed attacks, vertically distributed attacks require less time to achieve a successful attack for each image, while the generated adversarial example is visually the same as in the original method. This highlights the potential of vertical distribution as an effective strategy for improving the efficiency of black-box attacks.

V. Conclusion

Our research presents a novel approach to accelerating black-box attacks against online cloud services by exploiting load balancing. We introduce two general frameworks, horizontal and vertical distribution, that can be applied to existing black-box attacks to significantly reduce the total attack time. To validate the efficiency of the frameworks, we conduct experiments using three commonly used image classifiers and three commonly used black-box attacks.

Additionally, we contribute to the research community by open-sourcing our image classification cloud service, DeepAPI. This will enable future research on distributed black-box attacks and provide insights into the practical threats posed by adversarial attacks against machine learning models deployed on cloud servers.
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Fig. 10: Adversarial examples generated by different black-box attacks.

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